Fraud Detection with Confidence
A Benchmarking Case Study on Synthetic Data

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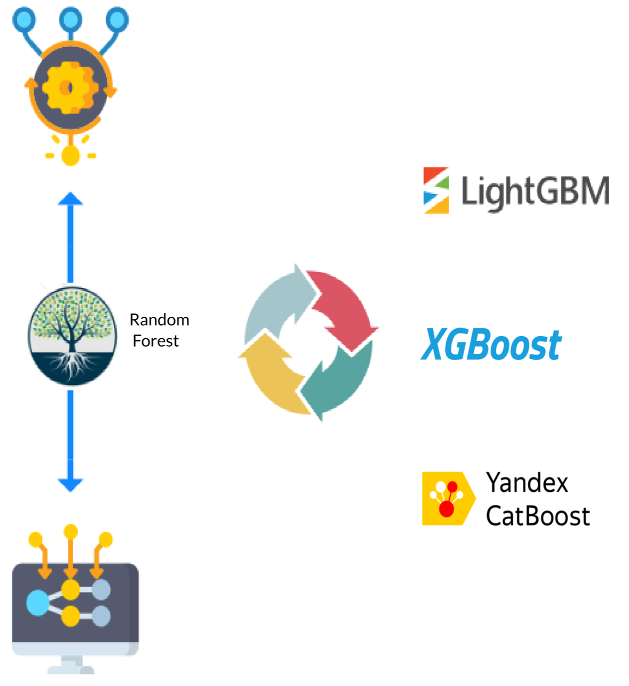
Methodology

Development of a supervised Machine Learning model for fraud detection required an experimental design which would be clear and explainable when running diagnostics & replicated a real-time environment of fraud detection

End Goal Criteria

- Maximize number of found fraudulent transactions
- Maximize amounts of found fraudulent transactions
- Minimize false positives (normal transactions identified as fraud)

Machine Learning using a base classifier

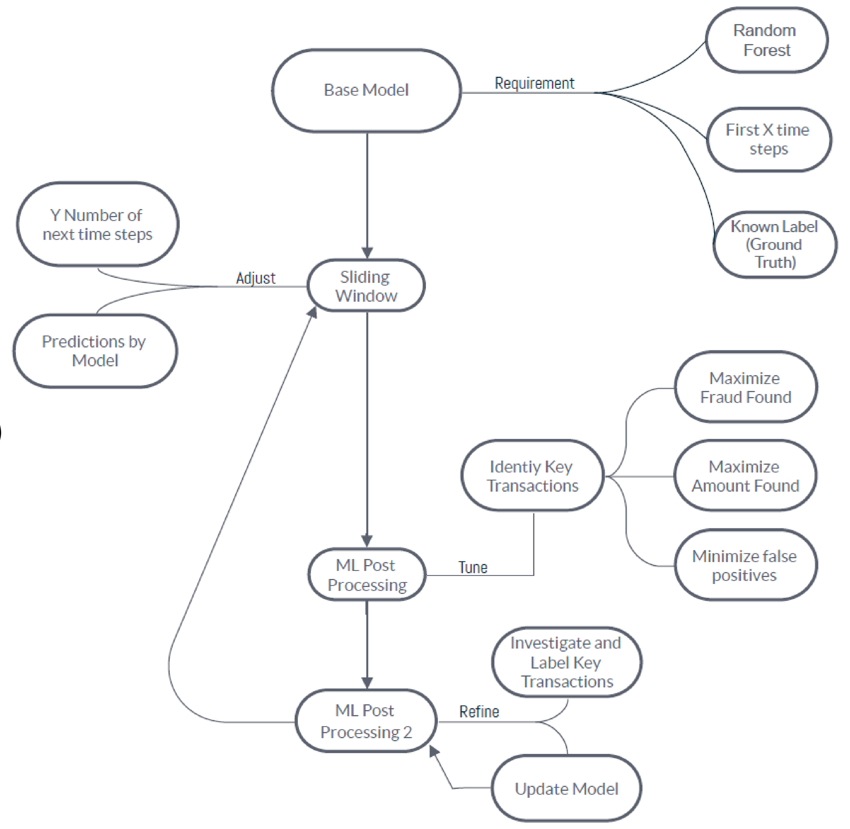


- Random Forest is Robust and Explainable
- Good performance throughout different domains
- Seldom need for hyper-parameter optimization
- Similar classifiers can be used for comparison (I.e. Boost / LGBM)

Figure: Case-Study Design

Time series analysis

1. Base model from first X number of time steps with known labels (ground truth)
2. Sliding window (Y number of next time steps) where "identified" transactions are investigated and labels assigned.
3. Updating of model using "identified" transactions
4. Prediction of next sliding window (Y number of next time steps) where "identified" transactions are investigated and labels assigned.
5. Continue Steps 2 and 3



Introduction

We believe that the use of adequately bench-marked synthetic data can help mitigate a great part of the current problems in the financial crime domain, and thus reduce concerns for accuracy, bias and privacy in the realm of compliance (van Driel, 2019). The Conformal Predictions (CP) framework is a recent development in machine learning to associate reliable measures of confidence with pattern recognition settings and is an excellent solution to bridge the gap between machine learning and the validity of synthetic data (Vovk et al., 2005).

- Synthetic data in finance solves the problem posed by the difficulty to access financial datasets due to privacy regulation (Barse, Kvarnstrom, Jonsson, 2004).
- In finance its use has gained significant interest; synthetic data has been adopted to improve financial crime detection and compliance (Lopez-Rojas, Axelsson, and Baca, 2018).
- Criminals' strategies modify constantly over time, and control systems could potentially adapt to this reality by using synthetic data that explores plausible criminal behaviour (Karpoff, 2020).
- A key consideration is if the synthetic data is effective a ML model built from synthetic data performs as well as models built from real data.

Conformal Approach

For a binary classification task, such as fraud detection, the CP framework operates as follows:

- The Training data set is randomly split into a proper training set (70 %) and a calibration set (30 %).
- The model is built on the proper training set and the calibration set as well as the new test data set are predicted from the model.
- The test set predictions are compared to the calibration set predictions of the two classes separately and the CP p-values, one value for each of the two classes, are calculated for every test set example.
- Comparing these p-values for each of the two classes (fraud, normal) separately against the acceptable error rate determined by the user provides the final classification (label, labels or no labels) for every new example (Vovk et al., 2005)

A Comparative Analysis of the Conformal Framework

Our case study focuses on looking at the viability of our framework when combined with tried and tested gold standard algorithms for the analysis of financial crime data.

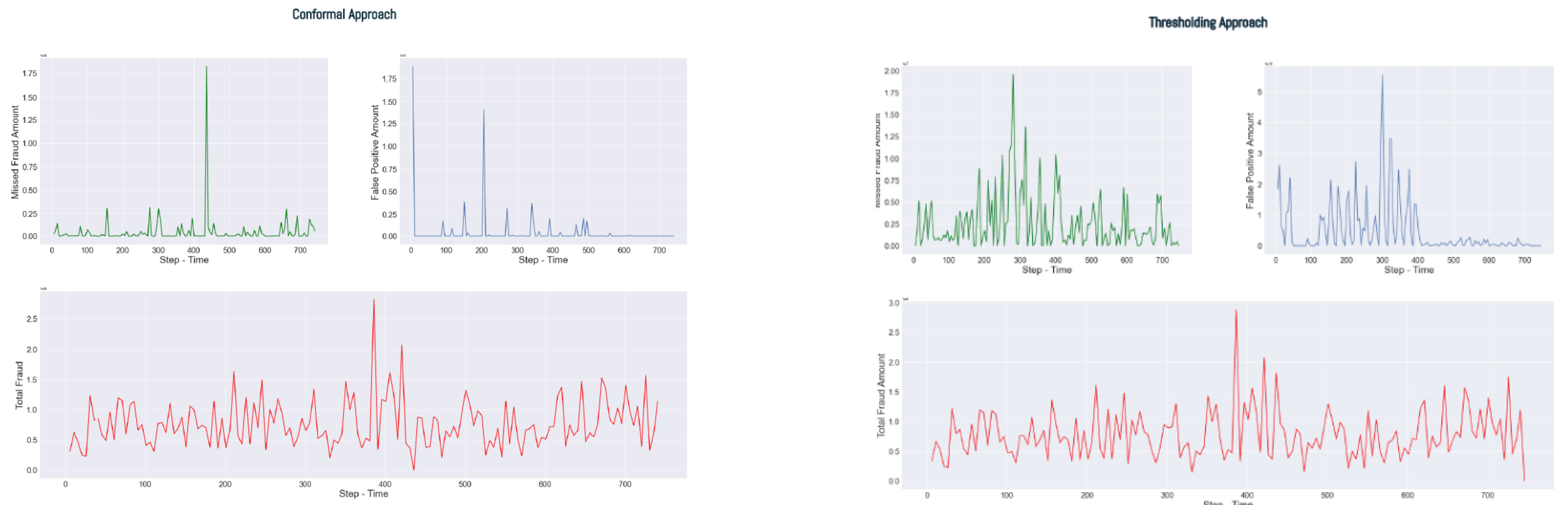
This includes observing different time windows and comparing these to classical approaches some financial institutions still implements (such as dynamic thresholding) and seeing how our conformal approach compares.

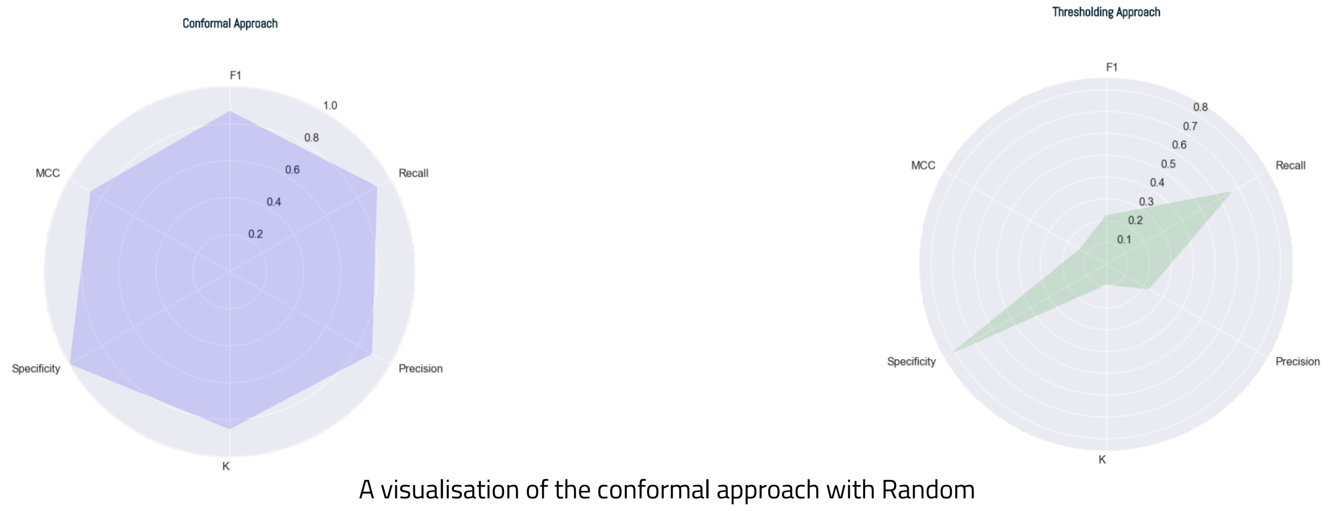
Below is the sum output of each algorithms performance in the conformal approach within a 5 hour sliding-window and its respective comparison with the thresholding approach (th) that utilizes the same dynamic Time window but does not use the conformal approach.

PaySim Comparison of Algorithms

Type	Random Forest	XGBoost	LGBM	CatBoost	Threshold
Fraud Found	7499	7102	7252	6723	5465
Total Fraud	8169	8169	8169	8169	8169
Missed Fraud	670	1067	917	1446	2704
Missclassified Fraud	16179	7410	26197	107631	1541793
Missed Fraud (M)	643294435	2160258449	1923317584	795973769	379836668
Missclassified Fraud (M)	5684855488	2719956851	10107092423	28011401527	6.9315E+11
F1	0.8675	0.8985	0.8137	0.4667	0.222512
Recall	0.9191	0.8707	0.8847	0.8309	0.66771
Precision	0.8869	0.9474	0.8541	0.4403	0.227023
K	0.8503	0.899	0.7926	0.3886	0.093066
Specificity	0.9965	0.9989	0.9962	0.9814	0.818034
MCC	0.8672	0.9079	0.817	0.4555	0.138441

Figure: An overview of classifier performance on PaySim





A visualisation of the conformal approach with Random Forest versus the classical thresholding approach

Conclusion

- Within this data our framework really shines in being able to isolate fraudulent signals and avoids the pitfalls of false positives.
- The conformal approach has shown great promise in its application on financial fraud data.
- Throughout this case study we have observed fascinating results from the conformal approach, yet it is important to mention that it can serve one other key function, and that is to bridge the gap of data explainability.
- Therefore, we would also like to explore the use-case of synthetic data playing a major role in creating more robust ML models that may avoid the pitfalls of bias by incorporating better information.
- In close, we believe that the conformal approach will be essential in the validation and improvement of synthetic data generation

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