

Machine Learning & Fraud Detection

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01 MOTIVATIONS & CHALLENGES

02 METHODS IN PRACTICE

MOTIVATIONS

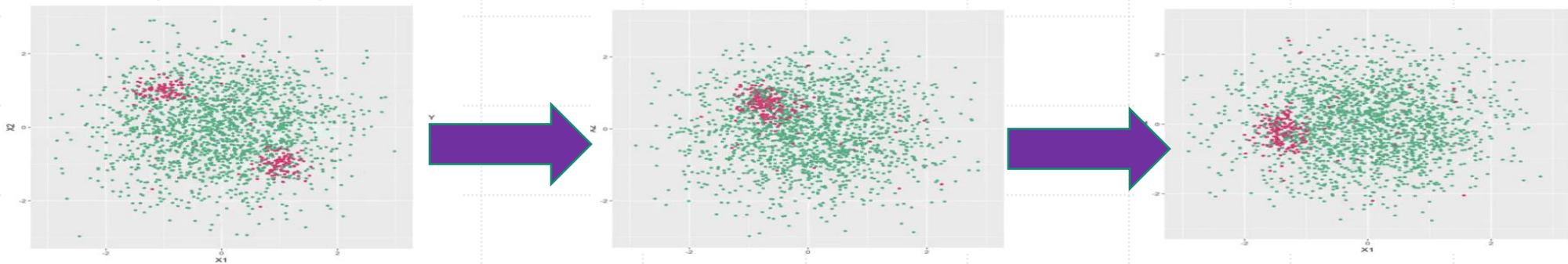


- Value of bank card fraud in France from 2009 to 2020
- Despite efforts, fraud losses are not significantly reduced

Credit: Banque de France, found on statista

CHALLENGES

1. Change in data distribution over time: concept drift



2. Class imbalance (e.g. 1 fraud for 1000 genuine transactions)
 - This is problematic for most learning algorithms
3. Noise in the training data (labels)
 - Transactions that are erroneously considered authentic
4. Need of interpretability
 - As the usage concerns humans, we need to make sure for example that the model does not discriminate against certain categories of users.

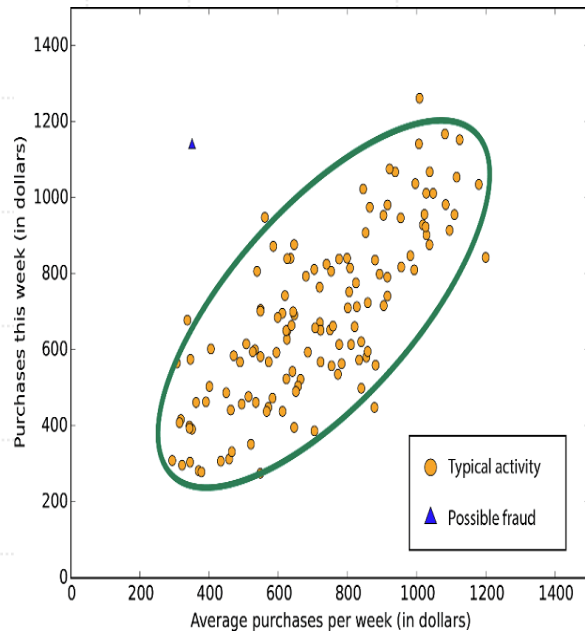


01 MOTIVATIONS & CHALLENGES

02 METHODS IN PRACTICE

UNSUPERVISED METHODS

In this paradigm, fraud is assumed to be an aberration or anomaly and therefore very different from genuine transactions



Advantages

Easy to implement (no need to have examples of fraud)

Examples: IForest, LOF, Autoencoders

Inconvenients

Difficulty in handling overlapping cases (fraudulent transactions very similar to genuine transactions).

Difficulty in assessing the model before going into production

Outils:

1. PyOD <https://pyod.readthedocs.io/en/latest/>
2. Sklearn <https://scikit-learn.org/stable/>

SUPERVISED METHODS

In this context, the objective is to prevent the same or similar techniques from falling through the cracks several times

Advantages

- Generally provide "better" performance than unsupervised methods.
- Easy to evaluate with AUCPR, precision, recall.
- Examples: XGBoost, LightGBM, RF, Deep Learning models

Inconvenients

- Requires examples of fraud as well as considerable work by investigators
- **Concept drift**

Some strategies to adapt to concept drift

Re-training after performance degradation

- Backtesting after obtaining some labels
- Difficulty in choosing new learning data

Periodical retraining

- Periodically retrain models (daily, weekly, monthly)
- Difficulty to take into account reoccurring concepts

Stacking

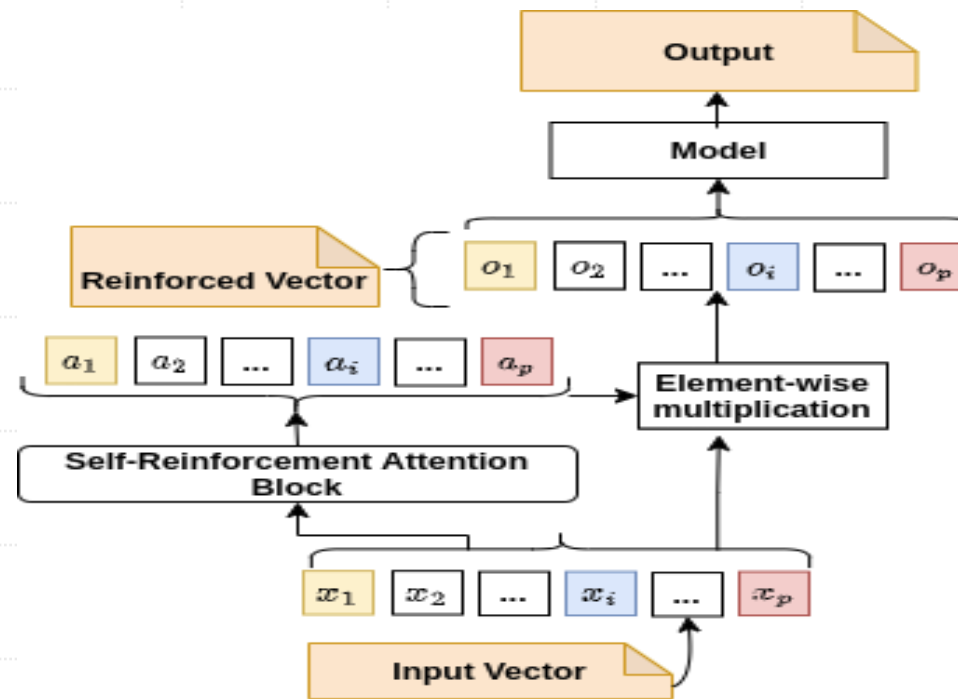
- Stack models built over different time periods
- Generally more expensive in resources and computing time



What use case do you have in
mind?

Thanks

Annex: Self-Reinforcement Attention (SRA)



One of our recent works in publication