ABSTRACT

Various problems of any credit card fraud detection based on machine learning come from the imbalanced aspect of transaction datasets. Indeed, the number of frauds compared to the number of regular transactions is tiny and has been shown to damage learning performances, e.g., at worst, the algorithm can learn to classify all the transactions as regular. Resampling methods and cost-sensitive approaches are known to be good candidates to leverage this issue of imbalanced datasets. This paper evaluates numerous state-of-the-art resampling methods on a large real-life online credit card payments dataset. We show they are inefficient because methods are intractable or because metrics do not exhibit substantial improvements. Our work contributes to this domain in (1) that we compare many state-of-the-art resampling methods on a large-scale dataset and in (2) that we use a real-life online credit card payments dataset.

Keywords: resampling, gradient boosting, fraud detection

1 INTRODUCTION

Credit card frauds happen daily and represent a high cost for banks and merchants, with 28.58 billion dollars of gross fraud losses in 2020 for a 2027 total amount projected at 43 billion [26]. Therefore, banks and merchants need to automatically detect a large amount of these fraudulent transactions to block them at the authorization step or raise an alert to the bank investigation team. A good hint for this is the use of supervised learning techniques, which have been known over the past years as major progresses [24], [14], [8]. Despite these hopes, several issues related to the concept drift or imbalanced dataset are still unsolved. In this paper, we mainly focus on the problem of an imbalanced dataset. The literature addresses this issue by several methods. One well-known way consists in using cost-sensitive approaches [12], [23]. These methods consider misclassification costs in different ways, e.g., false positives can be more penalized than false negatives. The issue of an imbalanced dataset can also be tackled by resampling the dataset such that the ratio between fraudulent and regular transactions becomes more suitable for machine learning algorithms. The two general ways of achieving it are either to withdraw some regular transactions (downsampling) [16] or to add more fraudulent transactions (oversampling) [6]. Note that it is also possible to combine oversampling and downsampling [3].

In this paper, we present various and numerous state-of-the-art resampling methods and apply them to a real-life online credit card payments dataset. The goal of these experiments is to assess whether resampling methods improve metrics or not. The contribution of our paper is related to the conducted experiments, which to our knowledge, have not been made before on a real large-scale, extremely imbalanced dataset.

We organized the remainder of the paper as follows. First, we present theoretical knowledge, including a brief presentation of gradient boosting and main resampling methods. Second, we present the experiments as well as the results. Finally, we conclude the paper.

2 BACKGROUND

2.1 Gradient-boosting

2.1.1 Main idea

Boosting algorithms combine weak learners (generally decision trees) iteratively. Gradient boosting decision trees (GBDT) have a specific scheme where a new learner is optimized to fit the residuals of the previous learner.

Let’s describe it in mathematical terms. We use the following notations:

- \( F_i(i \in \{1, \ldots, m\}) \) is a learner
- \( D_{\text{train}} = \{(x_1, y_1), \ldots, (x_i, y_i), \ldots, (x_{\text{train}}, y_{\text{train}})\} = (X, Y) \) a training dataset.

At the first iteration, \( F_1 \) is fitted as a normal decision tree, i.e., on \( y \). For the following iterations \( i \in \{2, \ldots, m\} \), \( F_i \) is
fitted on $y - F_{i-1}$. Thus, the rationale is to fit estimators on the residual error of the previous estimator.

The name "gradient boosting" comes from the fact that the residual is (up to a factor) the gradient of the mean squared error between the target and the output of the learner (see Equation 1 and 2).

$$L_{\text{MSE}} = (y - F_m(x))^2 \quad (1)$$

$$\frac{\delta L_{\text{MSE}}}{\delta F_m(x)} = -(y - F_m(x)) \quad (2)$$

### 2.1.2 XGBoost

XGBoost [7] is one of the most famous gradient boosting libraries. Its key innovations are based on a novel tree learning algorithm that efficiently handles sparse data, “a theoretically justified weighted quantile sketch procedure that enables handling instance weights in approximate tree learning”, the efficient use of resources for parallel computing, and "an effective cache-aware block structure or out-of-core tree learning”.

### 2.1.3 LightGBM

In conventional implementations of GBDT, the computational complexity increases with the number of features and samples. LightGBM [20] exhibits two techniques to overcome this difficulty:

- Gradient-based one-side sampling (GOSS): this technique under-sample data with the smallest gradients
- Exclusive feature bundling: this technique bundles mutually exclusive features, i.e., features that never take 0 simultaneously.

Note that we will not use GOSS for our experiments as we keep the number of features quite low, and the number of samples does not exceed ten million. LGBM also exhibits a built-in method to process categorical features. It sorts categories depending on the objective. Then, they use [19] to find an optimal split according to accumulated gradients (over Hessians) in a reasonable time.

### 2.1.4 CatBoost

Catboost [10], [9] belongs to the class of gradient boosting algorithms and is specially suitable to input spaces that contain categorical features. Two innovations are implemented:

- ordered boosting
- algorithm that processes categorical features

The idea of ordered boosting is to compute gradients or residuals for a given sample of the training set based on a set of samples that do not include this particular training sample. Otherwise, the gradient appears to be biased. In practice, CatBoost establishes several permutations of the training set for diverse training iterations. Then, residuals are computed based on these permutations and models as well.

For processing categorical features, they take inspiration from target statistics (this converts categorical features into numerical values based on target averages). However, they proved this technique is biased and devised a solution based on ordered boosting (namely ordered TS). Categorical features can then have different values according to the training iteration.

Catboost is also innovative in a software view as it is very efficient for training and inference both in CPU and GPU.

### 2.2 Resampling methods

This section will briefly describe the main resampling methods that belong to the python package Imbalanced-learn [22]. The user guide of the package gives more precise information about the algorithms.

#### 2.2.1 Down-sampling methods

**Random Under Sampler**

This algorithm works as follows: It randomly removes samples from the majority class until it reaches a hand-tuned ratio (the number of minority samples over the number of majority samples).

**Cluster centroids**

This algorithm uses a K-means clustering step on the majority class. It selects these K centroids to represent the majority class instead of the samples themselves.

**NearMiss [30]**

Nearmiss presents three algorithms based on K-Nearest Neighbor algorithms:

- Nearmiss-1 selects the samples from the majority class that are the closest to samples from minority classes
- Nearmiss-2 selects the samples from the majority class that are the farthest to samples from minority classes
- Nearmiss-3 is the Nearmiss-2 algorithm with a reduction step before. This step removes all the samples from the majority class that are not among the M-Nearest neighbors
Condensed Nearest Neighbor [16]
This algorithm works as follows:

- Gathering the minority (fraudulent transactions) samples in a set I
- Add a single sample from the majority class in I and the rest in a set A
- Scan all the elements of A and classify each sample using a 1-nearest neighbor rule
- If the sample is misclassified, it is added to I
- The scan is reiterated until no samples are added to I
- Then, the new reduced set to be used for classification is I

To summarize its underlying idea, this algorithm selects samples from the majority class that are difficult to classify.

Tomek Links [28]
First, let us define what a Tomek link is. A Tomek link exists between two samples a and b with different labels if there are mutually nearest neighbors, i.e., if the nearest neighbor of a is b and the nearest neighbor of b is a.

In practice, we withdraw either all the samples belonging to a Tomek link or just samples from the majority class belonging to a Tomek link.

One sided selection [16]
This algorithm derives from the Condensed Nearest Neighbor algorithm in two ways:

- To avoid the presence of noisy samples, Tomek links are applied before.
- One iteration is applied

Edited Nearest Neighbor [29]
This algorithm works as follows:

- Scan all the samples of the majority class (normal transactions)
- Apply the nearest-neighbor rule for each sample
- Remove the sample if the selection criterion is not met.

There are two possible selection criteria:

- If the sample has all its nearest neighbors belonging to the same class, then the sample is conserved.
- If the sample has the majority of its nearest neighbors belonging to the same class, then the sample is conserved.

This algorithm will remove majority samples close to minority samples in the feature space.

Repeated Edited Nearest Neighbor [2]
This algorithm repeats several times the Edited Nearest Neighbor algorithm.

AIKNN [2]
This algorithm is a version of Repeated Edited Nearest Neighbor that considers a higher number of nearest neighbors at each iteration.

Neighborhood Cleaning rule [21]
This algorithm combines the Edited Nearest Neighbor algorithm (to clean the majority class) and Condensed Nearest Neighbors.

Instance Hardness Threshold [27]
This algorithm uses a classifier (a random forest classifier by default) to fit data and remove samples from the majority classes with lower resulting probabilities.

2.2.2 Up-sampling methods

Random Over Sampler
This algorithm consists in randomly duplicating samples from the minority class.

SMOTE [6]
This algorithm generates samples from the minority class located in a segment between a sample from the minority class and its nearest neighbors. The algorithm steps are the following:

- For each minority sample, find K nearest neighbors
- For each minority sample, generate new samples by interpolating the minority sample and nearest neighbors.

ADASYN [17]
This algorithm has roughly the same idea as SMOTE, but the choice is made to sample from minority samples that have the highest number of neighbors with the majority class. The algorithm steps are the following:

- Compute the total number of samples to be generated
- For each minority sample, find K nearest neighbors and compute a ratio between the number of nearest neighbors from the majority class and K
- Compute the number of samples to be generated from each minority sample (proportional to the previously computed ratio)
• For each minority sample, generate the required number of samples using interpolation between the sample and nearest neighbors

SMOTENC [6]
This algorithm is a SMOTE variant that can handle categorical data without having to transform the latter. Indeed, the original SMOTE version cannot do proper interpolations on categorical data.

Borderline SMOTE [15]
This variant of SMOTE puts stress on minority samples close to the border with majority samples. This algorithm is, in practice, very close to ADASYN. The algorithm steps are the following:

• Generate nearest neighbors from some minority samples
• For these minority samples, keep only the ones with a majority of nearest neighbors in the majority class (the samples with all its nearest neighbors from the majority class are considered noise and are also rejected).
• We apply a SMOTE-like step like from the conserved minority samples.

Kmeans SMOTE [11]
This algorithm applies a KMeans clustering algorithm before applying SMOTE. After the clustering step, the minority samples from the densest clusters are used to generate new synthetic samples. The algorithm steps are the following:

• Make a K-means clustering step and keep clusters with more samples from the minority class than from the majority class
• For each remaining cluster, compute the sampling weight based on its minority density
• Oversample each filtered cluster using SMOTE and sampling weight to compute the number of samples to be generated

SVM SMOTE [25]
This algorithm generates samples from support vectors of an SVM classifier. The algorithm steps are the following:

• Train an SVM classifier on training data and generate support vectors of the minority class
• Generate nearest neighbors of minority support vectors
• Create new minority samples by using interpolation between minority support vectors and nearest neighbors (note that the algorithm handles the case in which the majority of nearest neighbors come from majority samples and act accordingly)

2.2.3 Combined methods
We also test combined methods such as SMOTENN and SMOTETOMEK. They are nothing but the application of SMOTE followed by the application of ENN (or TOMEK).

3 EXPERIMENTS
3.1 Settings
3.1.1 Datasets
We use a subset of 10 million transactions from real-life data of a major French bank using raw and derivative features. The raw features consist of 8 categorical features and 2 numerical features. The derivative features are 20 numerical features computed using count, mean, and diff aggregators.

3.1.2 Methodology

Tractability study
We use subsets of the mentioned above dataset of different sizes. The experiments happen as follows:

• We train each resampling method on these subsets
• We apply linear, logarithmic, polynomial, and exponential regressions
• We select the regression method that gives the best $r^2$ score (coefficient of determination)
• With the fitted regressors, we predict resampling time for the training set (6,700,000 transactions)
• We select the resampling method that presents reasonable predicted resampling times and rejects the other ones

Comparison of resampling methods
All this paragraph applies to methods that presented reasonable predicted resampling times.

We split the datasets into training and validation sets according to a $\frac{2}{3}$/$\frac{1}{3}$ policy. Then, for each gradient boosting method, we apply the CatBoost encoder [9] we have found to be the best tradeoff for these models in a previous study [5].
After that, we optimize the hyperparameters of these gradient boosting models using the following approach:

The optimization happened using 3-fold cross-validation on the training set (the optimization criterion was the PR AUC) using the Optuna package [1], and the Tree-Parzen-Estimator as the sampling strategy [4].

We resample the training set using selected resampling methods. For each resampled dataset, we apply each gradient boosting model (LGBM, XGBoost, CatBoost). Then we evaluate the methods using the following metrics:

- Area under Precision-recall curve (PR AUC)
- Precision
- Recall
- F1

As ranks between methods are not stable over the seeds given as input to the boosting models, we average each setting over ten seeds. We do not use the accuracy metric since it does not make much sense with a highly imbalanced dataset.

### 3.1.3 Hyperparameters for resampling methods

We use the default values for all the methods except for the “sampling_strategy” parameter we set to 0.1 when it exists. The methods are the following:

- Cluster Centroids
- SVM SMOTE
- SMOTE ENN
- SMOTE TOMEK
- Instance Near Miss
- Instance Hardness Threshold
- SMOTE
- SMOTE-NC
- Random over sampler
- ADASYN
- BORDERLINE SMOTE
- Random under sampler

### 3.2 Results

#### 3.2.1 Tractability study

We rejected 11 methods over 19 because of too high predicted resampling time. Table 1 lists the resampling methods, predicted computation time, and the decision to reject it or not.

| Resampling method                      | Predicted computation time            | Decision |
|----------------------------------------|---------------------------------------|----------|
| Cluster Centroids                      | >11 weeks                             | Rejected |
| Condensed Nearest Neighbour           | >489 weeks                            | Rejected |
| Edited Nearest Neighbour               | >2 weeks                              | Rejected |
| Repeated Edited Nearest Neighbour      | >2 weeks                              | Rejected |
| ALL KNN                               | >5 weeks                              | Rejected |
| Tomek link                             | >1 week                               | Rejected |
| One Sided Selection                    | >1 week                               | Rejected |
| SVM SMOTE                              | 1 day, 2 hours, 35 minutes, 46 seconds | Rejected |
| SMOTE ENN                              | >4 weeks                              | Rejected |
| SMOTE Tomek                            | >2 weeks                              | Rejected |
| Instance neighborhood cleaning rule    | >2 weeks                              | Rejected |
| Instance near miss                     | 14 minutes, 14 seconds                | Accepted |
| Instance hardness threshold            | 2 minutes, 1 second                   | Accepted |
| SMOTE                                  | 21 seconds                            | Accepted |
| SMOTE-NC                               | 9 minutes, 13 seconds                 | Accepted |
| Random over sampler                    | 7 seconds                             | Accepted |
| Adasyn                                 | 58 minutes, 55 seconds                | Accepted |
| Borderline SMOTE                       | 1h, 18 minutes, 58 seconds            | Accepted |
| Random under sampler                   | 3 seconds                             | Accepted |

Table 1: Results of tractability study

We have rejected methods that have a resampling time exceeding one day. In practice, we found that predicted times were roughly twice lower for tractable resampling methods than actual computation times.

We performed these predictions and all the computations in this paper on the Mésocentre of CentraleSupelec managed by IDRIS (CNRS), used in the context of Lusis/CentraleSupelec AI research chair. Our computing allocates 80 hyperthreaded cores Xeon Gold 6178 at 2.4GHz with 1TB
3.2.2 Comparison Results of tractable resampling methods

For each resampling/gradient boosting model pair, we display the metrics by using a table gathering the average results of each method. More precisely, we only display the percentage of variations compared to the absence of resampling. We willingly omit raw values for confidentiality purposes.

**LGBM**

|                  | PR AUC | Precision | Recall | F1    |
|------------------|--------|-----------|--------|-------|
| Instance Hardness Threshold | -25%   | -77%      | +525%  | +64%  |
| Random under sampler    | -7%    | -76%      | +531%  | +73%  |
| Random over sampler    | -7%    | -71%      | +462%  | +90%  |
| Borderline SMOTE       | -38%   | -77%      | +356%  | +48%  |
| SMOTE                | -59%   | -91%      | +527%  | -26%  |
| ADASYN               | -68%   | -93%      | +606%  | -40%  |
| NEAR MISS            | -97%   | -99%      | +1293% | -93%  |

Table 2: Results for LGBM

We establish several observations:

- We observe that random undersampling, oversampling, instance hardness threshold and borderline SMOTE method improve recall and F1 while deteriorating Precision Recall AUC (PR AUC) and Precision.
- We observe that other methods only improve the recall metric and significantly damage the other ones.
- Then, overall, we observe that the metrics are not substantially improved.

**CatBoost**

|                  | PR AUC | Precision | Recall | F1    |
|------------------|--------|-----------|--------|-------|
| Instance Hardness Threshold | -32%   | -85%      | +782%  | +45%  |
| Random under sampler    | -18%   | -84%      | +757%  | +57%  |
| Random over sampler    | -27%   | -75%      | +481%  | +96%  |
| Borderline SMOTE       | -48%   | -81%      | +406%  | +51%  |
| SMOTE                | -64%   | -92%      | +623%  | -16%  |
| ADASYN               | -65%   | -93%      | +769%  | -24%  |
| NEAR MISS            | -97%   | -99%      | +1602% | -91%  |

Table 3: Results for CatBoost

- Then, overall, we observe that the metrics are not substantially improved.

**XGBoost**

|                  | PR AUC | Precision | Recall | F1    |
|------------------|--------|-----------|--------|-------|
| Instance Hardness Threshold | -31%   | -85%      | +841%  | +46%  |
| Random under sampler    | -24%   | -84%      | +801%  | +55%  |
| Random over sampler    | -25%   | -78%      | +606%  | +95%  |
| Borderline SMOTE       | -45%   | -80%      | +448%  | +70%  |
| SMOTE                | -67%   | -92%      | +707%  | -18%  |
| ADASYN               | -72%   | -93%      | +836%  | -28%  |
| NEAR MISS            | -97%   | -99%      | +1657% | -91%  |

Table 4: Results for XGBoost

We establish roughly the same observations as before:

- We observe that random undersampling, oversampling, instance hardness threshold and borderline SMOTE methods improve recall and F1 while deteriorating PR AUC and Precision.
- We observe that other methods only improve the recall metric and significantly damage the other ones.
- Then, overall, we observe that the metrics are not substantially improved.
4 CONCLUSION

We first conducted a computation time study in which the goal was to assess which method was tractable for a large-scale dataset. It has allowed us to remove resampling methods we cannot compute in a reasonable time, e.g., among the downsampling methods, only Instance Hardness Threshold and Instance Near miss were considered tractable. After that, for any selected method, recall remarkably increased, but precision decreased significantly. We can explain the recall increase by resampling itself. However, the significant precision decrease may be due to a loss of helpful information for undersampling methods. It can also be due to the generation of useless information for oversampling methods. Furthermore, these observations seem in agreement with the literature.

Consequently, resampling techniques are unsuitable for overcoming imbalanced aspects of our large-scale and real-life online credit card payments dataset.

Gradient Boosting alone is giving better results. As shown in [13] Gradient Boosting focus on hard examples. The algorithm is driven by the minority class when the class distribution is highly imbalanced.

Thus, as hints for future work, we wish to focus on Gradient Boosting, cost-sensitive learning [12] or machine learning methods that naturally integrate techniques to deal with imbalanced aspects [18].

REFERENCES

[1] T. Akiba et al. “Optuna: A Next-generation Hyperparameter Optimization Framework”. In: Proceedings of the 25rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 2019.

[2] “An Experiment with the Edited Nearest-Neighbor Rule”. In: IEEE Transactions on Systems, Man, and Cybernetics SMC-6.6 (1976), pp. 448–452. DOI: 10.1109/TSMC.1976.4309523.

[3] G. Batista, A. Bazzan, and M.-C. Monard. “Balancing Training Data for Automated Annotation of Keywords: a Case Study.” In: Jan. 2003, pp. 10–18.

[4] J. Bergstra et al. “Algorithms for Hyper-Parameter Optimization”. In: Advances in Neural Information Processing Systems. Ed. by J. Shawe-Taylor et al. Vol. 24. Curran Associates, Inc., 2011. URL: https://proceedings.neurips.cc/paper/2011/file/86e8f7ab32cfd12577bc2619bc635690-Paper.pdf.

[5] F. D. L. Bourdonnaye and F. Daniel. “Evaluating categorical encoding methods on a real credit card fraud detection database”. In: CoRR abs/2112.12024 (2021). arXiv: 2112.12024. URL: https://arxiv.org/abs/2112.12024.

[6] K. W. Bowyer et al. “SMOTE: Synthetic Minority Over-sampling Technique”. In: CoRR abs/1106.1813 (2011). arXiv: 1106.1813. URL: http://arxiv.org/abs/1106.1813.

[7] T. Chen and C. Guestrin. “XGBoost”. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (Aug. 2016). DOI: 10.1145/2939672.2939785. URL: http://dx.doi.org/10.1145/2939672.2939785.

[8] A. Dal Pozzolo et al. “Credit Card Fraud Detection: A Realistic Modeling and a Novel Learning Strategy”. In: IEEE Transactions on Neural Networks and Learning Systems PP (Sept. 2017), pp. 1–14. DOI: 10.1109/TNNLS.2017.2736643.

[9] A. V. Dorogush, V. Ershov, and A. Gulin. “CatBoost: gradient boosting with categorical features support”. In: CoRR abs/1810.11363 (2018). arXiv: 1810.11363. URL: http://arxiv.org/abs/1810.11363.

[10] A. V. Dorogush et al. “CatBoost: unbiased boosting with categorical features”. In: CoRR abs/1706.09516 (2017). arXiv: 1706.09516. URL: http://arxiv.org/abs/1706.09516.
