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Detecting Outliers with Semi-Supervised Machine Learning: A Fraud Prediction Application

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Editor:

Abstract

Abnormal pattern prediction has received a great deal of attention from both academia and industry, with applications that range from fraud, terrorism and intrusion detection to sensor events, medical diagnoses, weather patterns, etc. In practice, most abnormal pattern prediction problems are characterized by the presence of a small number of labeled data and a huge number of unlabeled data. While this points most obviously to the adoption of a semi-supervised approach, most empirical studies have opted for a simplification and treated it as a supervised problem, resulting in a severe bias of false negatives. In this paper, we propose an innovative methodology based on semi-supervised techniques and introduce a new metric the Cluster-Score for abnormal homogeneity measurement. Specifically, the methodology involves transmuting unsupervised models to supervised models using the Cluster-Score metric, which defines the objective boundaries between clusters and evaluates the homogeneity of the abnormalities in the cluster construction. We apply this methodology to a problem of fraud detection among property insurance claims. The objectives are to increase the number of fraudulent claims detected and to reduce the proportion of claims investigated that are, in fact, non-fraudulent. The results from applying our methodology considerably improved these objectives.

Keywords: Outlier Detection, Semi-Supervised Models, Fraud, Cluster, Insurance

1. Introduction

The problem we seek to solve is the prediction of abnormalities in an environment with highly unbalanced samples and a huge mass of unlabeled data. A typical example of such a situation is provided by fraud detection. In general, we only have partial information about fraud cases, as well as possibly some information about false positives, that is, cases that are considered suspicious but which prove to be cases of non-fraud. The problem here is that we cannot label these cases non-fraud simply because they were initially considered suspicious. For this reason, we know nothing about non-fraud cases. Moreover, fraud tends to be an outlier problem, given that we are dealing with atypical values with respect to regular data. Hence, it is likely that we only dispose of information about an extremely small sample. Yet, it so transpires, that this information is extremely useful and should not be discarded. In contrast we have a considerable amount of data that may contain fraud

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and or non-fraud cases and, as such, we cannot treat these data using traditional supervised algorithms.

The problem, simply stated, therefore, is how can we predict these outliers? To represent this typical case we apply an innovative semi-supervised methodology to a real fraud case. Specifically, we draw on information provided by a leading insurance company as we seek to predict fraudulent insurance claims. In general terms, such claims fall into two categories: one, those that provide only partial or untruthful information in the policy contract; and, two, those that are based on misleading or untruthful circumstances (including exaggerations). It has been estimated that cases of detected and undetected fraud represent up to 10% of all claims in Europe (The Impact of Insurance Fraud, 2013), accounting for around 10-19% of the payout bill.

In the sector, the main services contracted are automobile and property insurance, representing 76% of total claim costs. However, while many studies have examined automobile fraud detection (see, for example, Arts et al., 1999 and 2002; Viaene et al., 2007; Wilson, 2009; Nian et al., 2016), property fraud has been largely neglected, perhaps because detection is more difficult as witnesses are infrequent or typically tend to cohabitants.

Here, therefore, our main objective is to present a variety of semi-supervised machine learning models applied to a fraud detection problem. In so doing, we aim to develop a methodology capable of improving results in classification anomaly problems of this type. Our reasoning for using semi-supervised models is best explained as follows. Statistically speaking, fraud is a special case of outliers, that is, of points in the dataset that differ significantly from the remaining data. Such anomalies often result from unusual events that generate anomalous patterns of activity. Were we to use unsupervised models that is, were we to assume that we are unable to distinguish between fraudulent and non-fraudulent cases what we defined as outliers, noise or normal data would be subjective and we would have to represent that noise as a boundary between normal data and true anomalies without any information. But, as mentioned, the number of fraud cases detected is small; however, they constitute a useful source of information that cannot be discarded.

On the other hand, supervised models are inappropriate because, in general, we face a major problem of claim misclassifications when dealing with fraud detection (Arts et al., 2002). Fraud detection, typically, comprises two stages: first, it has to be determined whether the claim is suspicious or not (Viaene et al, 2007); and, second, all cases considered suspicious have to be examined by fraud investigators to determine whether the claim is fraudulent or not. This means that unsuspicious cases are never examined, which is reasonable in terms of efficiency, especially if the process cannot be automatized. Insurance adjusters have little time to perform an exhaustive investigation. Yet, the process does provide us with partial information, that is, labels for what is a small sample. Clearly, using a supervised model in this instance adds bias to the confusion matrix. Essentially, we will detect severe bias in false negatives and, therefore, many cases which are in fact fraudulent will be predicted as being non-fraudulent (Phua et al., 2004). Indeed, when using supervised algorithms we assume that the system in place is capable of discerning perfectly between fraudulent and non-fraudulent claims, an outcome that in practice is infrequent and referred to in the literature as an omission error (Bollinger and David, 1997; Poterba and Summers, 1995).

Clearly, the information provided in relation to those cases considered suspicious is more likely to be specified correctly once we have passed the first stage in the fraud detection

process. This information will be useful for a part of the distribution (that is, it will reveal if a fraudulent claim has been submitted), which is why it is very important this information be taken into account. For this reason, fraud detection is notorious for being considered a semi-supervised problem because the ground truth labelling of the data is partially known. Here, therefore, we seek to make three contributions to the literature: First, we apply innovative semi-supervised techniques to anomaly detection; second, we create a new metric that permits us to evaluate the homogeneity of abnormalities in the cluster construction; and, third, we apply this model to an actual property insurance claim fraud problem for the first time, using a real dataset provided by a leading insurance company.

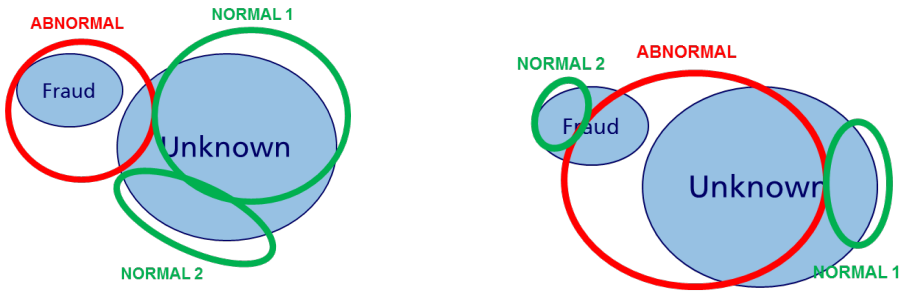
2. Metodhology

Outlier detection models seek to separate regular from outlier observations. If we have labeled data, the easiest way to proceed is by employing a supervised algorithm. However, in the case of fraud, this implies our knowing everything about the two classes of observation that is, we would know exactly who did and did not commit fraud, a situation that is extremely rare. In contrast, if we know nothing about the labeling, that is, we do not know who did and did not commit fraud, several unsupervised methods of outlier detection can be employed, for example, isolation forest, one-class support vector machines, and elliptic envelopment. However, they tend to be less precise and we have to assume some subjective boundary.

If, however, we have some label data about each class, we can implement a semi-supervised algorithm, such as label propagation or label spreading. Yet, these methods require that we have some information about every class in our problem, something that is not always possible. Indeed, disposing of label data information about each class is quite infrequent in certain practical problems. Additionally, we face the problem of unbalanced data, which means we rarely have clean, regular data representing the population. In fraud problems, as a norm, the data are highly imbalanced and skewed, which results in a high but biased success rate.

In the light of these issues, we propose an innovative semi-supervised technique that can assess not only a highly unbalanced dataset problem but also one for which we have no information about certain classes. In this regard, fraud detection represents an outlier problem for which we can usually identify some, but not all, of the cases. We might, for example, have information about false positives, that is, investigated cases that proved not to be fraudulent. However, simply because they have raised suspicions does not mean they can be considered representative of non-fraudulent cases. In short, what we usually have are some cases of fraud and a large volume of unknown cases (among which it is highly likely cases of fraud are lurking).

Bearing this in mind, we propose the application of unsupervised models so as to relabel the target variable. To do this, we use an innovative metric that measures how well we approximate the minority class. We can then transform the model to a semi-supervised algorithm. On completion of the relabeling process, our problem can be simplified to a supervised model. This allows us not only to set an objective boundary but to obtain a



(a) Desired Clusters (b) Non-desired Clusters

Fig. 1. Possible clusters

gain in accuracy when using partial information, as Trivedi et al. (2014) have demonstrated.

2.1 Unsupervised Model Selection

We start with a dataset of 303,166 cases. We set aside a 10% random subset for final evaluation. Hence, our dataset consists of 270,479 non-identified cases and 2,370 cases of fraud. The main problem we face in this unsupervised model is having to define a subjective boundary. We have partial information about fraud cases, but have to determine an acceptable threshold at which an unknown case can be considered fraudulent. When calculating unsupervised classification models, we reduce the dimensions to clusters. Almost every algorithm will return several clusters containing mixed-type data (fraud and unknown). Intuitively, we would want the fraud points revealed to be highly concentrated into just a few clusters. Likewise, we would expect some non-revealed cases to be included with them, as in Figure 1.a:

On the other hand, we would want to avoid situations in which abnormal and normal cases are uniformly distributed between groups, as in Figure 1.b. However, a limit of some kind has to be defined. But, how many of the unknown cases can we accept as being fraudulent?

A boundary line might easily be drawn so that we accept only cases of detected fraud or we accept every possible case as fraudulent. Yet, we know this to be unrealistic. If we seek to operate between these two both extremes, intuition tells us that we need to stay closer to the lower threshold, accepting only cases of fraud and very few more, as Figure 2 illustrates.

But once more, we do not know exactly what the correct limit is. In this way, however, we have created an experimental metric that can help us assign a score and, subsequently, define the threshold. This metric, which we shall refer to as the cluster score (CS), calculates the weighted homogeneity of clusters based on the minority and majority classes.

$$CS \;=\; (1+\alpha^2)\frac{C1 * C2}{C1 + C2 * \alpha}$$

Essentially, it assigns a score to both the minority-class (C1) and the majority-class (C2) clusters based on the weighted conditional probability of each point. The mathematical

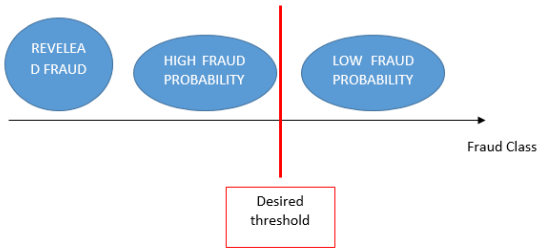
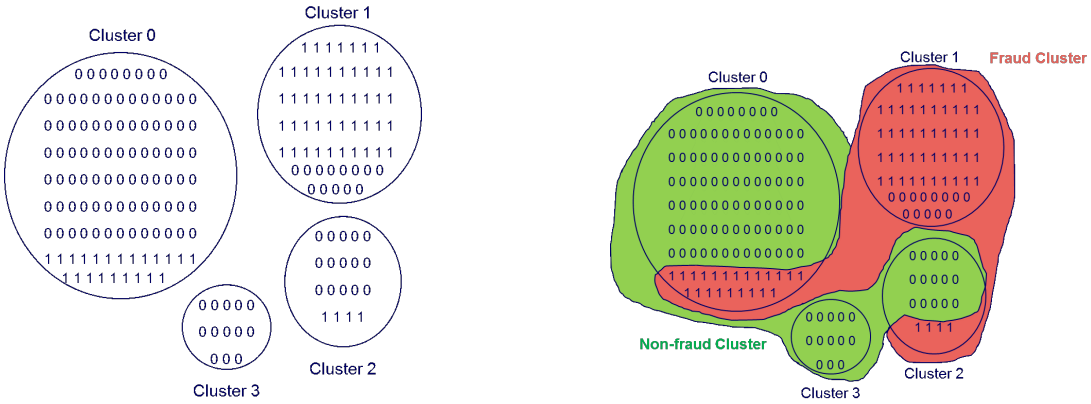


Fig. 2. Desired threshold



(a) Unsupervised output

(b) Relabeled clusters

Fig. 3. Possible clusters

formulation can be consulted in Appendix 1.

We should stress that each time we retrieve more information about the one-class cases that have been revealed, this threshold improves. This is precisely where the entropy process of machine learning appears. In the one-class fraud problem discussed above, we start with an unknown distribution for which some data points are known (that is, the fraud sample). Our algorithms, using the CS proposed, will gradually get closer to the best model that can fit these cases of fraud, while maintaining a margin for undiscovered cases. Now, if we obtain new information about fraud cases, our algorithms will readjust to provide the max CS again. As the algorithms work with notions based on density and distances, they change their shapes to regularize this new information.

Once the best unsupervised model is attained (that is, the model that reaches the max CS), we need to decide what to do with the clusters generated. Basically, we need to determine which clusters comprise fraudulent and which comprise non-fraudulent cases. The difficulty is that several cluster will be of mixed-type: that is, minority-class points (fraud cases) and unidentified cases, as in Figure 3.a, where the 0s are unidentified cases and the 1s are minority-class points.

In defining a threshold for a fraud case, we make our strongest assumption. Here, we assume that if a cluster is made up of more than 50% of fraud cases, this cluster is a

fraud cluster, otherwise, it is a non-fraud cluster. The distinction introduced is clear: The non-fraud cluster is no longer an unidentified cluster. By introducing this assumption, we state that they are actually non-fraudulent cases. This definition acts as the key for our transition into a semi-supervised model.
As Figure 3.b shows, cluster 1, being composed of more than 50% fraud cases, now forms part of the more general fraud cluster, together, obviously, with the fraud cases already detected. The remaining cases that do not belong to such a dense fraud cluster are now considered non-fraud cases.
The unsupervised algorithm can thus be summarized as follows:

Algorithm 1 Unsupervised Algorithm

1. Load dataset: Overweight fraud cases given the same weight as unknown cases.
2. Iterate through model k and the vector of tuning parameters$i$.
3. j clusters will generate for each $k, i.$ that is $C_{i,k} = \{C^1_{i,k}, C^2_{i,k} C^n_{i,k}\}$.
4. For each $C^j_{i,k}$ we calculate $C1$ and $C2$ (see Appendix), and obtain the cluster score $CS_{i,k}$.
5. We define the acceptable threshold t^* for a cluster to be considered a fraud cluster or not.
6. We choose the optimal CS^* where $CS^* = argmax\{CS_{I,K}\}$, $CS_{I,K}$ is the cluster vector for each pair k, i.
7. We relabel the fraud variable using the optimal clustering model derived from CS^*. Each unknown case in a fraud cluster is now equal to 1. Known fraud cases are equal to 1. Remaining cases are equal to 0.

2.2 Supervised Model Selection

We now have a redefined target variable that we can continue working with by applying an easy-to-handle supervised model. The first step involves resampling the fraud class to avoid unbalanced sample problems. We oversample the dataset to obtain a 50/50 balanced sample.
The second step involves conducting a grid search and a ten cross-validation (CV) based on the F-Score[1] to obtain the optimal parameters for three different models: extreme randomized tree, gradient boosting and a light XGB. Additionally, we combine these classifiers using stacking models.
Once we have the optimal parameters for each, we calculate the optimal threshold that defines the probability of a case being fraudulent or non-fraudulent, respectively.

1. The F-Score was constructed using $\beta = 2$, as we needed to place greater weight on the recall.

Finally, we identify the two models that perform best on the combined valid/test dataset the best acting as our main model implementation, the other controlling that the predicted claims are generally consistent.

Algorithm 2 Supervised Algorithm

1. Load dataset with the relabeled target variable. Oversampling to obtain a 50/50 balance sample.
2. Apply grid search and CV to obtain the optimal parameters based on the F-Score results for each M_i model.
3. Generate stacking models S_j using different combinations of metaclassifiers based on the M_i models.
4. Obtain the optimal threshold for each M_i and S_j based on F-Score results.
5. Identify the best two models. The best model is Base Model B^*. And the second best is Control Model C^*.
6. Finalize the output probabilities.

3. Data

We use an insurance fraud dataset provided by a leading insurance company in Spain for the period 2015-2016. After sanitization, our main sample consists of 303,166 property claims, some of which have been analyzed as possible cases of fraud by the Investigation Office (IO)[2].
Of the cases analyzed by the IO, 48% proved to be fraudulent. A total of 2,641 cases were resolved as true positives (0.8% of total claims) during the period under study. This means we do not know which class the remaining 99.2% of cases belong to. However, the fraud cases detected provide very powerful information, as they reveal the way in which fraudulent claims behave. Essentially, they serve as the pivotal cluster for separating normal from abnormal data.
A data lake was constructed during the process to generate sanitized data. We obtain 19 bottles containing different types of information related to accident claims. These bottles contain variables derived from the companys daily operation, and variables that are transformed in several of their aspects. In total we have almost 1,000 variables. We briefly present them here to help explain which concepts were chosen for the model.

4. Results

Table 2 shows the main unsupervised modeling results. Mixed models tend to provide the best results. However, mini-batch K-means is not only much faster, it also provides the

2. The system applied before to detect fraud corresponds to a rule based methodology.

Bottles	Descriptions
Id	ID about accident, policy, person, etc.
Customer	Policyholders attributes embodied in insurance policies: name, sex, age, address, etc.
Customer-Property	Customer related with the property data
Dates	Dates of about accident, policy, visits, etc.
Guarantees	Coverage and guarantees of the subscribed policy
Property	Data related to the insured object
Payments	Policy payments made by the insured
Policy	Policy contract data, including changes, duration, etc.
Loss-Adjuster	Information about the process of the investigation but also about the loss adjuster
Accident	Brief, partial information about the accident, including date and location
Intermediary	Information about the policies intermediaries.
Customer-Object-Reserve	The coverage and guarantees involved in the accident
Historical Accident	Historical movements associated with the reference accident
Historical Policy	Historical movements associated with the reference policy (the policy involved in the accident).
Historical Other Policies	Historical movements of any other policy (property or otherwise) related to the reference policy.
Historical Other Accident	Historical accident associated with the reference policy (excluding the accident analyzed).
Historical Other Policy-Accident	Other accident associated with other policies not in the reference policy (but related to the customer).
Black List	Every participant involved in a fraudulent claim (insured, loss-adjuster, intermediary, other professionals, etc).
Cross Variables	Several variables constructed with the interaction between the bottles.

Table 1. Data Bottles

best results, returning four clusters. More than 90% of the cases in the central cluster are fraudulent (well above our 50% threshold), but it also contains an additional 8,540 unknown cases. This is our core fraud cluster and the one we use when renaming the original labels. We also have a small fraud cluster with an additional 16 cases. C1 indicates that the minority-class (fraud) clusters comprise 92.9% of minority data points on a weighted average. In contrast, C2 indicates they are made up of 92.8% of unknown cases.

Model	Parameter 1	Parameter 2	n Clusters	C1	C2	Cluster Score	Time
Mini-Batch K-Means	Iterations= 100	Batch Size = 600	4	92.9%	92.8%	92.8%	3 sec.
Isolation Forest	Contamination= 0.125	$n_estim = 100$	2	51.5%	51.1%	51.4%	5min-18min
DBSCAN	Does not change	Does not change	2	50.2%	49.8%	50.1%	15-80min
Gaussian Mixture	Cov= *Tied*	Tol= 0.29	5	95.0%	95.0%	96.3%	23min
Bayesian Mixture	Cov= *Tied*	Tol= 0.29	6	96.5%	96.4%	96.5%	23min

Table 2. Unsupervised model results

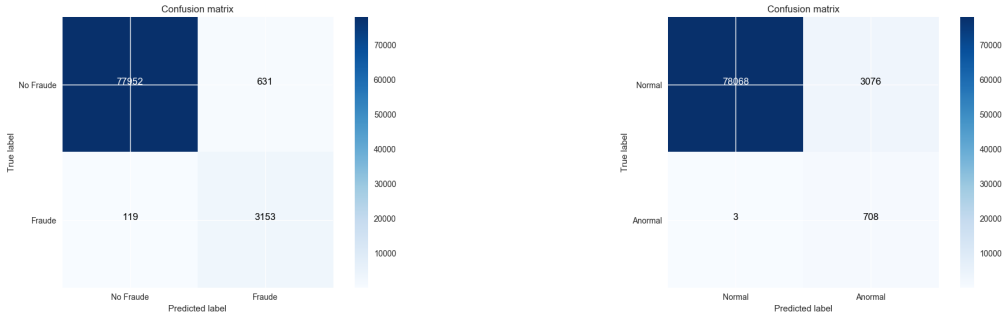
The tuning of each of the supervised models and of the stacking models is shown in Table 3. We first employ a validation set comprising 15% of the data to tune the parameters. As can be appreciated, we have two recall values. The cluster recall is the metric derived when using the relabeling target variable. The original recall emerges when we recover the prior labelling (1 if it was fraud, 0 otherwise). As can be seen, the results are strikingly consistent. We are able to predict fraud cluster with a recall of up to 91-98% in every case. But, more impressively yet, we can capture the original fraud cases with a recall close to 99%. The precision is a little lower, but in almost all cases it is higher than 80%. These are particularly good results for a problem that began as an unsupervised high-dimensional problem in an extremely unbalanced one-class dataset.

After optimizing the models, we calculated the performance of the best models using 70/30 training-test dataset. The performance and confusion matrixes are shown in Figure 4. Both are extremely randomized trees: the first uses balance subsampling (ERT-ss) and serves here as our base model; the second uses an ADASYN oversampling method (ERT

Model	Cluster Recall	Original Recall	Precision	FBeta	Treshold	Time
ERT b-ss	96.7%	99.4%	81.8%	93.3%	0.539	3min
ERT b-s	97.3%	99.1%	81.7%	93.7%	0.507	10min
GB	91.0%	94.6%	74.0%	87.0%	0.634	6h30min
LXGB	91.3%	94.6%	84.1%	89.8%	0.688	4min
Stacking META=ERT	97.3%	99.2%	49.9%	81.8%	0.955	12hs
Stacking META=LXGB	93.1%	95.2%	84.0%	91.2%	0.552	12hs
Stacking META=GB	91.9%	95.2%	84.7%	90.4%	0.661	15min

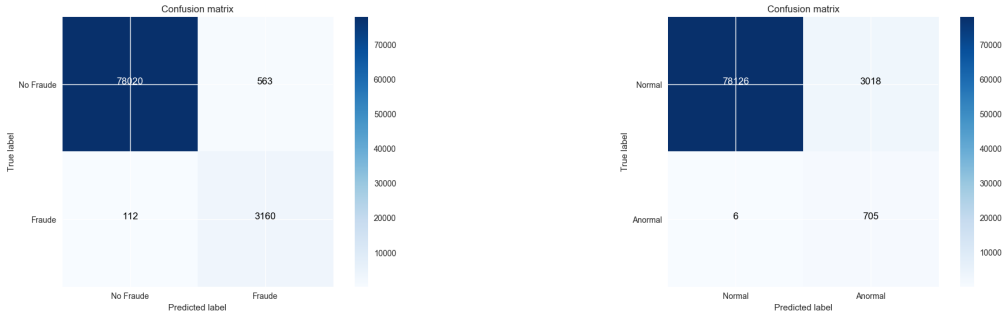
Table 3. Supervised model results

b-s) and serves as our control model. The results continue to be consistent and they are very rapid algorithms.



(a) Cluster target (b) Original target

Fig. 4. Base Model. ERT with subsampling



(a) Cluster target (b) Original target

Fig. 5. Control Model. ERT with oversampling

5. Robustness Check

At the outset, we randomly set aside 10% of the data (30,317 claims). In this final step, to ensure we do not face any overfitting problems, we examine these initial data in a test of the whole process. Our results are shown in Table 4.

Original Value	Prediction	Cases
NOT INVESTIGATED	NOT FRAUD	29.631
FRAUD	NOT FRAUD	0
NOT INVESTIGATED	FRAUD	415
FRAUD	FRAUD	271

(a) Base Model Robustness Check.

Original Value	Prediction	Cases
NOT INVESTIGATED	NOT FRAUD	29.656
FRAUD	NOT FRAUD	8
NOT INVESTIGATED	FRAUD	390
FRAUD	FRAUD	263

(b) Control Model Robustness Check.

Table 4. Model Robustness Check.

As can be appreciated, the control model (Table 4.b) has a recall of 97% while the base model (Table 4.a) has an impressive recall of 100%. However, the added value depends on the non-investigated fraud cases, that is, cases not previously detected but which would boost our results if shown to be fraudulent. We, therefore, sent these cases to the IO for analysis.

The IO investigated 367 cases (at the intersection between the control and base models). Two fraud investigators analyzed each of these cases, none of which they had previously seen as the rule model had not detected them.

Of these 367 cases, 333 were found to present a very high probability of being fraudulent. This means that only 34 could be ruled out as not being fraudulent. Recall that from the original sample of 415 cases, the fact that 333 presented indications of fraud means we have a precision of 88%, which is perfectly consistent with our original test sample (83.3-84.9%). In short, we managed to increase the efficiency of fraud detection by 122.8%. These final outcomes are summarized in Table 5.

Original Value	Prediction	Cases
NOT INVESTIGATED	NOT FRAUD	29.631
FRAUD	NOT FRAUD	0
NOT FRAUD	FRAUD	(415 - 333) = 82
FRAUD	FRAUD	(271 + 333) = 604

Table 5. Base Model Final Results

6. Machine Learning Process

The machine learning process is not complete if we do not feed the model with new information. A year later, we recalibrated the model with new data (see Table 6).

PERIOD	**Jan15-Jan17**	**Jan15-Jan18**
Claims	303,166	479,454
Observed Fraud	2,641	4,299
Cluster Score	92.8%	97.13%
Recall Score	96.4%	97.4%
Precision Score	83.3%	90.4%

Table 6. Base Model with the machine-learning process applied

The base model greatly improves the homogeneity of the fraud and non-fraud clusters. In particular, it provides a gain of 7% in the precision score and a slight gain in the recall score.

7. Conclusions

This paper has sought to offer a solution to the problems that arise when working with highly unbalanced datasets for which the labelling of all the classes is unknown. In such cases, we usually dispose of a few small samples that contain highly valuable information. Here, we have presented a fraud detection case, drawing on the data provided by a leading insurance company, and have tested a new methodology based on semi-supervised fundamentals to predict fraudulent accident claims.

At the outset, the IO did not investigate many cases (around 7,000 cases from a total of 303,166). Of these, only 2,641 were actually true positives (0.8% of total claims), with a success rate of 48%. Thanks to the methodology devised herein, we can now investigate the whole spectrum of cases automatically, obtaining a *total recall of 96-97%* and a precision of *83-90%*. In spite of the complexity of the initial problem, where the challenge was to detect outliers without knowing anything about 99.2% of the sample, the methodology described has been shown to be capable of solving the problem with great success.

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Appendix A. Cluster Score

C1 Score

The C1 score calculates the probability that a revealed fraud point belongs to group J and that this probability is weighted by the total number of fraud points in that group divided by the total cases of fraud revealed. Mathematically this can be expressed as:

$$C1 \;=\; \frac{\frac{\sum_{j=1\ldots n} x^j_{fraud}}{X^T_j} * x^j_{fraud}}{X^T_{fraud}} \in [0,1]$$

where x^j_{fraud} is the revealed fraud point in cluster group j. X^T_j is the total number of points in group J. And X^T_{fraud} is the total number of fraud cases revealed.

Basically, we calculate the probability of a point belonging to a specific group j ($\frac{\sum_{j=1\ldots n} x^j_{fraud}}{X^T_j}$) and we weight these values by the participation of its points in the fraud group revealed. Our objective is to maximize $C1$; basically, this means ensuring all cases of revealed fraud are in the same groups. The limit $C1 = 1$ implies that in the j groups we only have revealed fraud points. However, this is not what we want. Therefore, we have to balance this function with another function.

C2 Score

$C2$ is the inverse case of $C1$. Here, we calculate the probability of unrevealed fraud belonging to group J.

$$C2 \;=\; \frac{\frac{\sum_{j=1\ldots n} x^j_{not-fraud}}{X^T_j} * x^j_{not-fraud}}{X^T_{not-fraud}} \in [0,1]$$

And the objective is the same as that above in the case of $C1$: to cluster this group without assigning revealed fraud to these clusters.

Cluster Score

Individually maximizing $C1$ and $C2$ leaves us in an unwanted situation. Basically, they are both trying to be split. However, notice that $\frac{x^j_{fraud}}{X^T_j} = \frac{1-x^j_{not-fraud}}{(X^T_j}$. Therefore, when we maximize one, we minimize the other. If we maximize both together, this results in a trade-off between the two, a trade-off in which we can choose. Moreover, as pointed out above, we actually want to maximize $C1$ subject to $C2$. Consequently, the fraud score is constructed as follows:

$$CS \;=\; (1+\alpha^2)\frac{C1 * C2}{C1 + C2 * \alpha}$$

With $\alpha 1$. If $\alpha = 1$, $C1$ and $C2$ will have the same weight. But if we assign $\alpha > 1$, this will reduce the charge of $C2$.
In conclusion, with this CS we have an objective parameter to tune the unsupervised model. Basically, we can maximize CS. The only decision that remains for us is to determine the relevance of α.

Practical Example

Imagine we have the following output from an unsupervised model:

Class	Label
0	1
0	2
0	3
0	1
1	2
1	2
1	3
0	3
0	3
0	2
0	1
0	3
1	2
0	1
1	2

Table 7. Class and Labels

The classes represent fraud (=1) and unlabeled (=0). The output label is the clustering label. As can be seen, just 33% of cases represent detected fraud. If we group the class by clusters:

Label	Class	Subtotal Class	Total
1	0	4	4
1	1	0	4
2	0	2	6
2	1	4	6
3	0	4	5
3	1	1	5

Table 8. Grouping labels and classes

As is evident, the fraud class tends to be assigned to the second cluster.
First we calculate $C1$.

$$C1 = \frac{\frac{0}{4} * 0 + \frac{4}{6} * 4 + \frac{1}{5} * 1}{5} = 0.5733$$

Then we calculate $C2$ using a similar formula.

$$C2 = \frac{\frac{4}{4} * 4 + \frac{2}{6} * 2 + \frac{4}{5} * 4}{10} = 0.7867$$

As can be seen, $C1$ gives worst results as its core group (group 2) is quite contaminated (66% of observations actually correspond to cases of fraud). This effect represents 93% of the total effect. The effect of mismatching the core group (1/5) is negligible, which stresses the importance of constructing a strong core group.
This conclusion is notorious in the case of C2. Non-identified classes are highly robust in two groups (1 and 3).
If we calculate the CS with $\alpha = 2$ (balanced $C1$ and $C2$) we obtain:

$$CS = 0.602$$

which is a value very close to 0.5733. This formula allows us to balance our results, giving greater weight to the lower score. We should stress we want both good and balanced scores; thus, $C1 = 0$, $C2 = 1$ is not the same as $C1 = 0.5$, $C2 = 0.5$. Indeed, the former returns a $CS = 0$. If we compare the mean with the CS:

$C1$	$C2$	**Mean**	CS
0.0	1.0	0.5	0.00
0.1	0.9	0.5	0.18
0.2	0.8	0.5	0.32
0.3	0.7	0.5	0.42
0.4	0.6	0.5	0.48
0.5	0.5	0.5	0.50
0.6	0.4	0.5	0.48
0.7	0.3	0.5	0.42
0.8	0.2	0.5	0.32
0.9	0.1	0.5	0.18
1.0	0.0	0.5	0.00

Table 9. Grouping labels and classes

As can be seen, we obtain the same unbalanced scores as the balanced outcomes for the mean score. CS penalizes the unbalanced scores. This is why we obtain different results with the same proportions.

However, we can make adjustments in terms of the relevance we attach to each group. If we raise α, we penalize the $C2$ results, and vice versa.

What happens if we choose $\alpha > 2$?

$C1$	$C2$	$\alpha = 2$	$\alpha = 4$	$\alpha = 6$
0.1	0.9	0.05	0.02	0.02
0.2	0.8	0.09	0.05	0.03
0.3	0.7	0.14	0.07	0.05
0.4	0.6	0.17	0.10	0.07
0.5	0.5	0.20	0.12	0.08
0.6	0.4	0.22	0.14	0.10
0.7	0.3	0.22	0.15	0.11
0.8	0.2	0.20	0.16	0.12
0.9	0.1	0.14	0.14	0.12

Table 10. Grouping labels and classes

As is evident, we obtain two effects. First, while $C1$ increases, CS also increases (although $C2$ decreases at the same rate). But the effect present in the balanced case now extends further. When we are at $C1 = 0.7$, the balanced effect tends to reverse the situation. The second effect is that the score curve is shifted downward. CS is now demanding more strongly that $C1$ be higher; while the higher the beta value the stronger $C1$.

Online Appendix 1. Data and Source Code

Data and source code can be founded here: `http://github.com/sebalp1987/outlier_model`

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