Transactions Anomaly Detection with Unsupervised Learning

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Abstract

Supervised learning has been widely used to detect anomaly in credit card transaction records based on the assumption that the pattern of a fraud would depend on the past transaction. However, unsupervised learning does not ignore the fact that the fraudsters could change their approaches based on customers' behaviors and patterns. in this study we will present iterative method of using mixture of Gaussian's to detect anomaly in credit card transactions. We will compare it with iterative method using OneClassSVM. In each method our algorithm utilizes the model functions(likelihood and shifted from support vector) scores, evaluates samples with their scores and samples score under threshold T consider to be anomalies. the described method is iterative until model converges or max iteration exceeds. The data set used in this study is based on real-life data of credit card transaction. Due to the availability of the response(labels), after training the models we can evaluate the performance of each model. The performance of these two methods is discussed extensively in this paper.

1 Data set

The data set that is used for credit card fraud detection is derived from the following URL

The data set contains transactions made by credit cards in September 2013 by European cardholders. This data set presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The data set is highly imbalanced, the positive class (frauds) account for 0.172% of all transactions. Due to confidentiality issues, there are not provided the original features and more background information about the data. It contains only numerical input variables which are the result of a PCA transformation.

i) Features V1, V2, ... V28 are the principal components obtained with PCA;

ii) The only features which have not been transformed with PCA are Time and Amount.

iii) Feature Time contains the seconds elapsed between each transaction and the first transaction in the data set.

iv) The feature Amount is the transaction amount of money spent in each transaction.

v) Feature Class is the response variable and it takes value 1 in case of fraud and 0 otherwise.

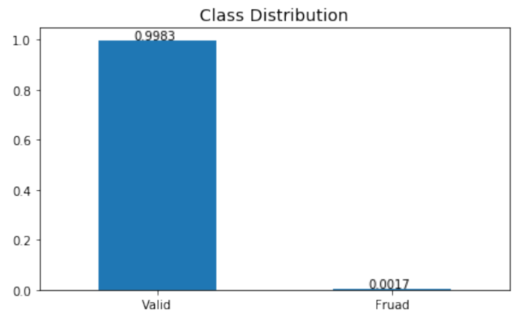
vi) There is no missing data in the entire data set

2 Problem statement

The Credit Card Fraud Detection Problem includes past credit card transactions. The need is to identify whether a new transaction is fraudulent or not. The data is highly imbalanced and our aim here is to detect the fraudulent transactions while minimizing the incorrect fraud classifications. Let's realize that we are looking for a needle in a hay barn. 99% of the data are valid transactions. We could balance the data by oversampling or under sampling and even to fit the models with only valid transactions, but we want our models to be able to produce results in the real world and not just in testing environment, therefore we will develop our model as like labels was not existed. This is why we should use the imbalanced data, in order to better simulate real world cases. If our model can identify even a fraction of fraud cases with high precision, it is adding value.

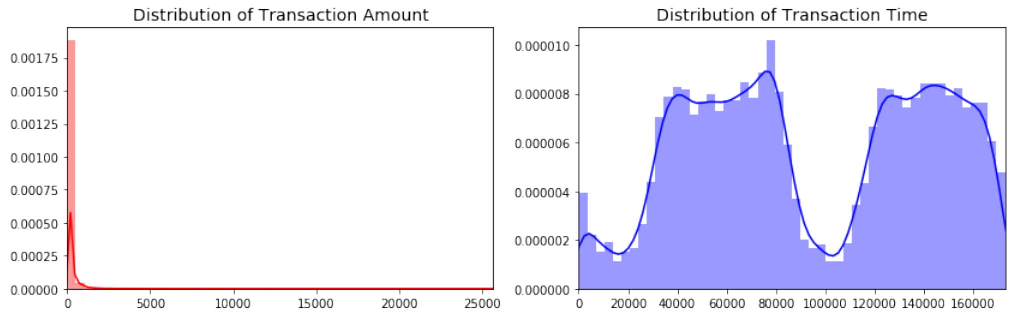
3 Data Exploration

3.1 Class Distribution



Only 492 (or 0.172%) of transaction are fraudulent. That means the data is highly imbalanced with respect to the target variable Class.

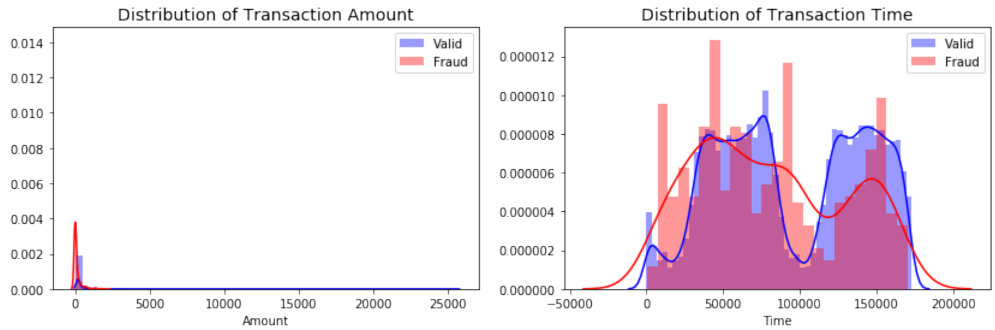
3.2 Transactions Time and Amount Distributions



i) Most transactions are small amounts transactions, less than \$100.

ii) Clearly, it looks like there are cycles in Time.

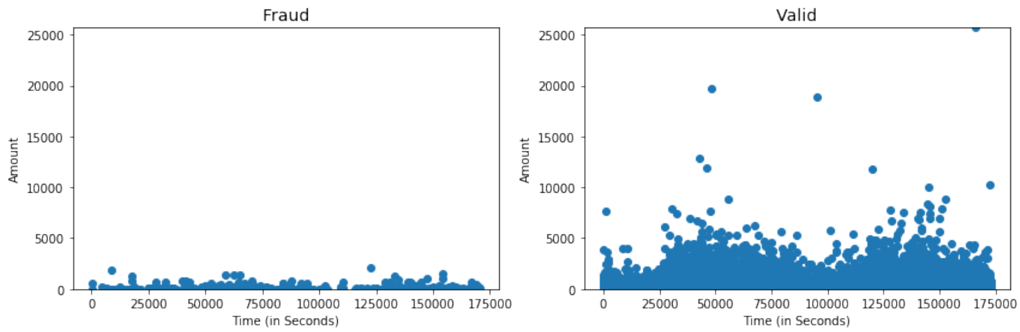
3.2.1 Transactions Time and Amount Distributions by Class



i) The 'Time' feature looks pretty similar across both types of transactions. You could argue that fraudulent transactions are more uniformly distributed compared to the valid transactions which have more cyclical distribution. This could make it easier to detect a fraudulent transaction during at an 'off-peak' time.

ii) Most transactions are small amounts, less than \$100. Fraudulent transactions have \$122 mean amount, standard deviation \$256 and \$2125 maximum. valid transaction have \$88 mean amount, standard deviation at \$250 and \$25691 maximum.

Now let's see if the transaction amount differs between the two types.



Both types equally distributed over time. y-axis is significantly different between fraud and valid transactions.

Reminder - Unsupervised Learning is a process of training a machine learning model on a data set in which target variable is unknown. we will develop our model as like labels was not existed.

4 Data preprocess

4.1 Scaling

We will scale the columns comprise of Time and Amount . Time and Amount should be scaled as the other columns already scaled through the PCA transformation. We will use Robust Scaler, Scale features using statistics that are robust to outliers.

4.2 Split the Data to Train and Test

We will take randomly fraction of the data set(20%), this is just to save time during training, then split it to train(80%) and test(20%). Train size: (45569, 30), Test size: (11392, 30)

5 Terms

i) True Positives: Correctly Classified Fraud Transactions

ii) False Positives: Incorrectly Classified Fraud Transactions

iii) True Negative: Correctly Classified Non-Fraud Transactions

iv) False Negative: Incorrectly Classified Non-Fraud Transactions

5.1 Introduce Precision, Recall and F1 scores:

i) Precision: $p = \frac{TP}{TP+FP}$

ii) Recall: $r = \frac{TP}{TP+FN}$

iii) F score: $F_1 = \frac{2pr}{p+r}$

Precision, as the name says, says how precise (how sure) is our model when it classifies a transaction as fraud transaction, while Recall is the ratio of classified fraud cases from all the fraud cases.

Precision/Recall Trade off: The more precise (selective) our model is, the less cases it will detect.

The F1 score is the harmonic mean of the precision and recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.

5.2 Thresholds

Assume $\mathbf{X}$ is the data set, $\ell(s|\theta)$ is the model score function and θ is the model estimators for unknown parameters, then TS is all possible thresholds:

$$TS = [\ \ell(s|\theta)\ |\ s\ \in\ \mathbf{X}]$$

Select threshold for score function:

$$T = TS[\operatorname*{argmax}_{f \in F} f]$$

F is all possible F_1 scores.
In other words the threshold selected is where F_1 score reach the maximum.

6 Iterative approach

Algorithm 1 Iterative anomaly detection

Require: $I \geq 0,\ T \in \mathbb{R},\ \mathbf{X},\ \ell(s|\theta),\ \Phi$ is init classifier parms
  $C1 \leftarrow newClassifier(\Phi)$
  for $i = 0 : I$ **do**
    $C1.fit(X)$
    $F = \emptyset$
    for all $s \in \mathbf{X}$ **do**
      if $\ell(s|\theta) <= T$ **then**
        $F.add(s)$
      end if
    end for
    $C2 \leftarrow newClassifier(\Phi)$
    $C2.fit(X - F)$
    if $C1 == C2$ **then**
      return $C1$ and call converged
    else
      $C1 = C2$
    end if
  end for

7 Mixture of Gaussian's

A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. We are assuming that these data are Gaussian and we want to find parameters that maximize the likelihood of observing these data. In other words, we regard each point as being generated by a mixture of Gaussian's and can compute that probability.

Assuming number of K Gaussian distributions and n data observations. Our unknown parameters are:

$$\theta = \{\mu_1, \dots, \mu_K, \sigma_1, \dots, \sigma_K, \pi_1, \dots, \pi_K\}$$

μ_i, σ_i, π_i are the mean, variance and the responsibility for the i-th Gaussian.

Likelihood:

$$L(\theta|X_1, \dots, X_n) = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_k f_{Gaussian}(x_i; \mu_k, \sigma_k^2)$$

So our log-likelihood is:

$$\ell(\theta) = \sum_{i=1}^{n} \log \left(\sum_{k=1}^{K} \pi_k N(x_i; \mu_k, \sigma_k^2) \right)$$

The log-likelihood is without closed-form solutions, hence solving with EM algorithm. Define latent variables $Z_i \in \{1, \dots, K\}$ is the latent variable representing the mixture component for X_i Intuitively, the latent variables Z_i should help us find the MLEs. We first attempt to compute the posterior distribution of Z_i given the observations:

$$P(Z_i = k|X_i) = \frac{P(X_i|Z_i = k)P(Z_i = k)}{P(X_i)} = \frac{\pi_k N(\mu_k, \sigma_k^2)}{\sum_{k=1}^{K} \pi_k N(\mu_k, \sigma_k)} = \gamma_{Z_i}(k)$$

the derivative of the log-likelihood with respect to each unknown parameters:

$$\hat{\mu_k} = \frac{\sum_{i=1}^{n} \gamma_{z_i}(k) x_i}{\sum_{i=1}^{n} \gamma_{z_i}(k)} = \frac{1}{N_k} \sum_{i=1}^{n} \gamma_{z_i}(k) x_i \tag{1}$$

$$\hat{\sigma_k^2} = \frac{1}{N_k} \sum_{i=1}^{n} \gamma_{z_i}(k)(x_i - \mu_k)^2 \tag{2}$$

$$\hat{\pi_k} = \frac{N_k}{n} \tag{3}$$

7.1 Selecting GMM number of components

7.1.1 Bayesian information criterion (BIC)

This criterion gives us an estimation how good is the GMM in terms of predicting the data we actually have. The lower is the BIC, the better is the model

to actually predict the data we have, and by extension, the true, unknown, distribution. When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in over fitting.
BIC attempt to resolve this problem by introducing a penalty term for the number of parameters in the model In order to avoid over fitting, this technique penalizes models with big number of clusters.

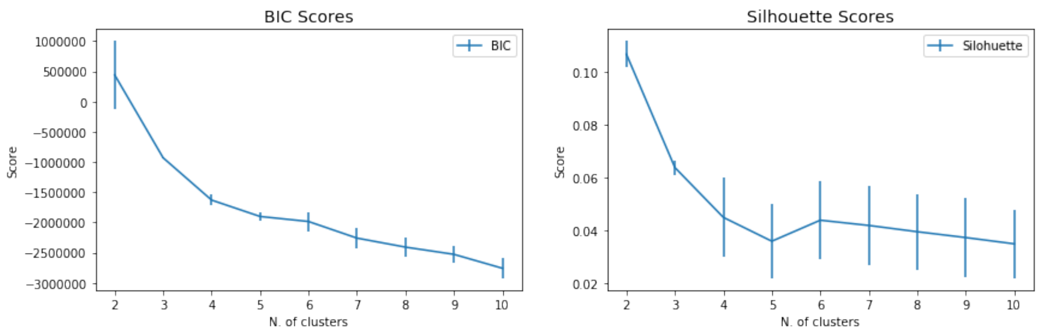
$$BIC = Ln(n)K - 2Ln(\hat{L})$$

7.1.2 Silhouette score

This score consider two measures: - $a(i)$ - The mean distance between a sample and all other points in the same cluster. - $b(i)$ - The mean distance between a sample and all other points in the next nearest cluster. i.e. it checks how much the clusters are compact and well separated. The more the score is near to one, the better the clustering is.

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Since we already know that the fitting procedure is not deterministic, we ran twenty fits for each number of clusters 2 to 10, then we consider the mean value and the standard deviation of the runs.
The results are:



Silhouette score We can see the the bigger the number of clusters the higher standard deviation. It turns out that we get the best score with 2 clusters. Also 3 clusters can be a candidate. if we consider the standard deviation (the 'error') of both configurations and the scores, 2 clusters is the selected.

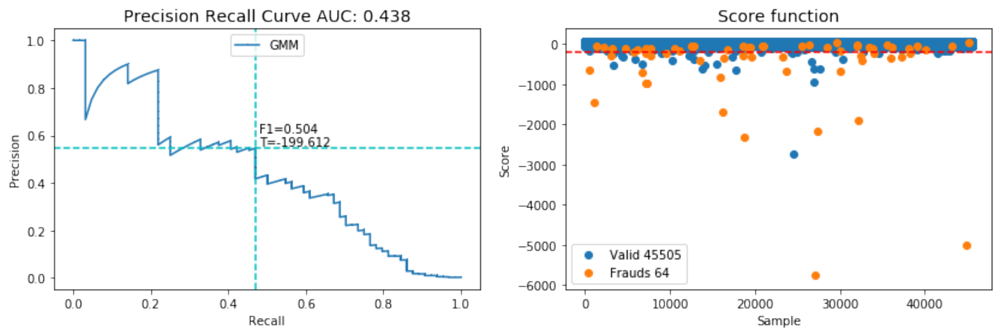
BIC score We can notice two things. The first is that the curve is fairly smooth and monotone. The second is that the curve follows different slopes in different part of it. Following this criterion, the bigger the number of clusters, the better should be the model. Which means that the penalty BIC gives to complex models, do not save us from over fit.

The slope in both scores at 2 and 3 clusters is most significant. The BIC score variance in 2 clusters is much more higher then 3. Hence 3 clusters is selected.

8 Iterative GMM

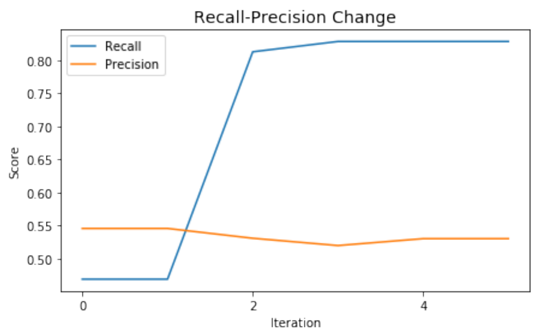
8.1 Initialization

```
GaussianMixture(covariance_type='full', init_params='kmeans', max_iter=100,
means_init=None, n_components=3, n_init=2, precisions_init=None,
random_state=42, reg_covar=1e-06, tol=0.001, verbose=0,
verbose_interval=10, warm_start=False, weights_init=None).fit(X)
```



It is very difficult to detect fraud transaction because in addition to severe class imbalance there is also severe class overlap. Fraud transactions are mixed with the valid ones in their log likelihood score. It is important to tight our Gaussian model estimators to better fit with the data. we will do it via our iterative approach(6) and evaluate how better our Gaussian for detecting anomalies. following results:

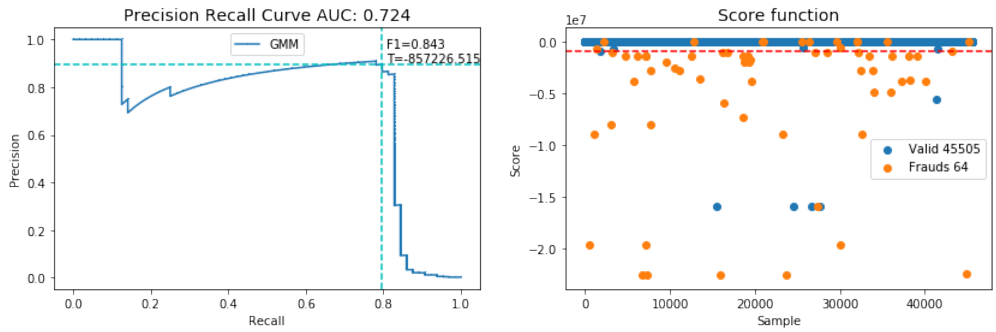
8.2 Iterative



We can observe that recall is increasing until converged to constant ˜0.8 while precision slightly switching between lower and upper bounds with a small slice until converged to constant ˜0.55. This is important because overall we do not harm model performance in each iteration.

Now we have the final model and we can select new threshold(5.2) T with respect to precision-recall trade-off.

8.2.1 Evaluate final model



Now it much more easy to detect frauds transactions based on log likelihood function. Lower log likelihood function are indeed anomaly transactions. We can conclude that our Gaussian estimators are more fitted to valid transactions while we didn't fit the model only with valid transactions!

8.3 Evaluate test set

Testing model with test set achieved the following result:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	11374
1	0.82	0.78	0.80	18
accuracy			1.00	11392
macro avg	0.91	0.89	0.90	11392
weighted avg	1.00	1.00	1.00	11392

9 Iterative One Class SVM

9.1 Parameters

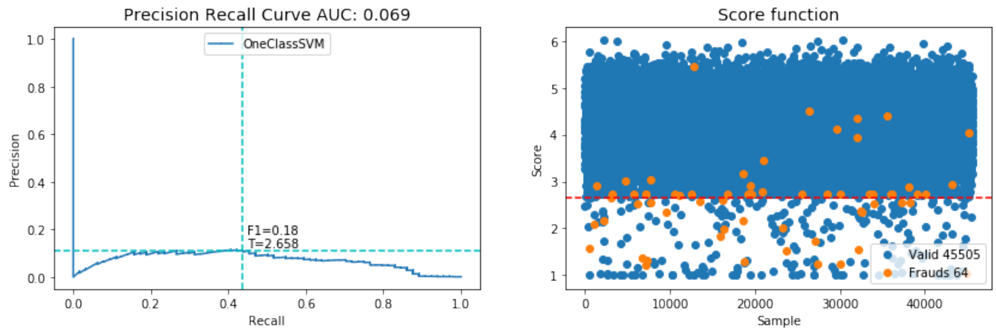
i) ν: An upper bound on the fraction of training errors and a lower bound of the fraction of support vectors. Should be in the interval (0, 1). it is recommended to take ν near to the noise class, in our case frauds. we have imbalance data so we will set ν to 0.01 which is 1%.

ii) γ: Kernel coefficient, gamma='scale' is 1 / (n_features * X.var())

iii) *kernel*: RBF kernel functions selected they are should be good enough with our Gaussian distributed data.

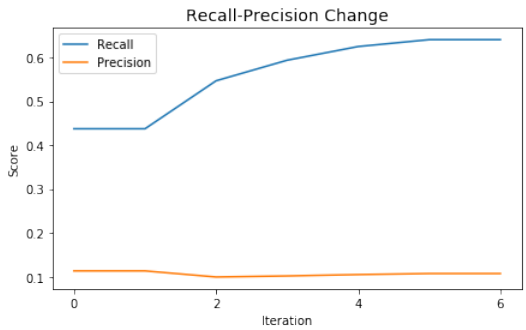
9.2 Initialization

```
OneClassSVM(cache_size=200, coef0=0.0, degree=3, gamma='scale', kernel='rbf',
max_iter=-1, nu=0.01, shrinking=True, tol=0.001, verbose=False).fit(X)
```



As we can see, OneClassSVM score function produced an area under the threshold T that contain highly mixed area of valid and fraud transaction. Here also it is very difficult to detect anomalies transactions. We will try to better fit the support vectors estimators with the iterative approach below.

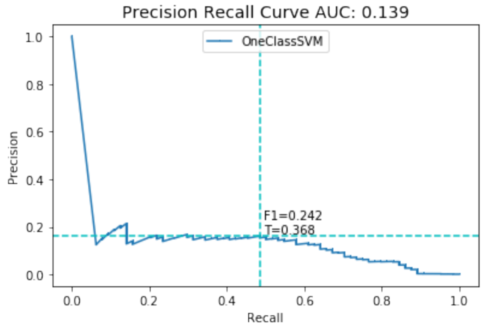
9.3 Iterative

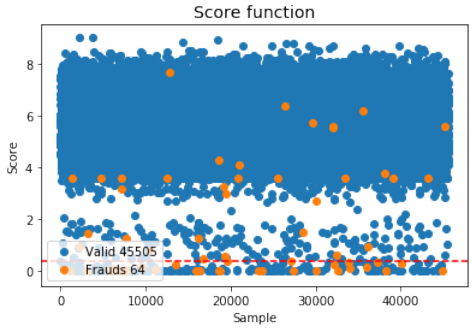


Converged after the sixth iteration. We can observe that recall is increasing until converged to constant ˜0.7 while precision stay constant with very low percentage ˜0.1. Also here the iterative(6) approach do not harm model performance in each iteration.

Now we have the final model and we can select new threshold(5.2) T with respect to precision-recall trade-off.

9.3.1 Evaluate final model





We got better result from initialization(9.2) in terms of valid-frauds spread under the threshold T, recall seems to be increasing to acceptable value but precision keep low value.

9.4 Evaluate test set

Testing model with test set achieved the following results:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	11374
1	0.20	0.61	0.30	18
accuracy			1.00	11392
macro avg	0.60	0.80	0.65	11392
weighted avg	1.00	1.00	1.00	11392

10 Conclusion

In this paper we propose a method that identifying frauds and pure valid transactions by assigning a score to each data point in highly imbalanced data set. The proposed method assumes no prior knowledge of either the frauds or valid transactions, don't do any features selection and fully unsupervised. We investigated the data, checked for data imbalance, visualized the features and understood the relationship and the dynamics between different features. The data was splitted into 2 parts, a train set and a test set. We trained Gaussian Mixture Model and OneClassSVM with real world credit card transactions data in an iterative method to achieve estimators fitted at possible to valid transactions. We showed that the models estimators getting better fitted in each iteration in terms of recall-precision.

We can propose application such as to make recommendation for potential outliers for further investigation with high precision and recall and created training sets for novelty anomaly detection algorithms.

For summarize, Gaussian Mixture model obtained satisfying and acceptable results for the test set which can ensure to each part of the transaction processing chain a good protection from fraud and potentially chargebacks.