University of Science and Technology of Hanoi

Bachelor's Thesis in Information and Communication Technology

Application of Machine Learning in Credit Card Fraud Detection

Authors:
DANG Anh Duc
BI9068

Supervisor:
DOAN Nhat Quang
ICT Lab
ICT Deparment
Vietnam France University

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USTH
VIETNAM FRANCE UNIVERSITY

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Abstract

Credit card fraud is an [sth] problem in the financial world. The number of fraudulent transactions is expected to increase due to the recent trend of using non-cash payments. However, using machines to detect credit card fraud is not an easy task since the available datasets for this problem are highly imbalance i.e. the number of genuine cases greatly outnumber the fraudulent cases, which makes process of training a classification models harder and create inaccurate models.

In order to tackle this problem, our project suggests different techniques to resample the dataset, such as, undersampling, oversampling and hybrid strategy, which is a combination of both undersampling and oversampling. These techniques are implemented with different predictive models like Logistic Regression, Random Forest and XGBoost. Each combination between a resampling method and model is evaluated based on precision, recall, f1-score, precision-recall (PR) curve and receiver operating characteristics (ROC) curve.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Credit Card Fraud Detection

1.2 Aim of the project

In this project, our main objective is to explore different techniques to deal with an imbalanced dataset and evaluate them to see which method performs better than the others. More specifically, this project focuses on handling a credit card transaction dataset to build model to detect fraudulent transaction by using different sampling methods along with various models. After that we chose the most well-performed model based on a range of evaluation metrics.

1.3 Overview

This section provides an overall overview of the content entailed in each section. In section 2, we discuss relevant literature in the current field of research, focusing on the methods to build a credit card fraud detection model. Section 3 presents the methodology including the data processing steps, tools and libraries used, as well as the training of the model. In Seciton 4, we describe model's evaluation metrics - precision, recall, f1-score, PR curve, ROC curve and provide a detailed discussion on the results of our project. The final section 5 presents a brief conclusion of our project.

2 Literature Review

3 Methodology

3.1 Dataset Description

For this project, we used a dataset consists of transactions made by credit cards in two days in September 2013 by European cardholders which was collected by the Machine Learning Group of Université Libre de Bruxelles (ULB) and was published on Kaggle*. The dataset is contains a total of 284,807 transactions in total, in which only 492 are fraudulent. The dataset is considered to be highly skewed as the positive class (frauds) only accounts for 0.172% of the dataset. Figure 1 visualizes the class distribution of the dataset.

The dataset only contains numerical values as a result of Principal Components Analysis (PCA) transformation. Due to confidentiality issue, most of original attributes was not revealed. There are total 30 features, 28 of which was generated by PCA. The only features that was not transformed are '*Time*' and '*Amount*' Feature 'Class' is the target attribute and it takes value 1 in case of fraud and 0 otherwise. Table 1 gives a detailed description about the dataset's attributes.

Attribute	**Type**	**Description**
Time	Integer	Time elapsed between each transaction and the first transaction
V1	Double	First PCA component
V2	Double	Second PCA component
...	...	...
V28	Double	Last PCA component
Amount	Double	Transaction amount
Class	Integer	Target class (0 = Genuine and 1 = Fraud)

Table 1: Dataset Attribute Description

*https://www.kaggle.com/mlg-ulb/creditcardfraud

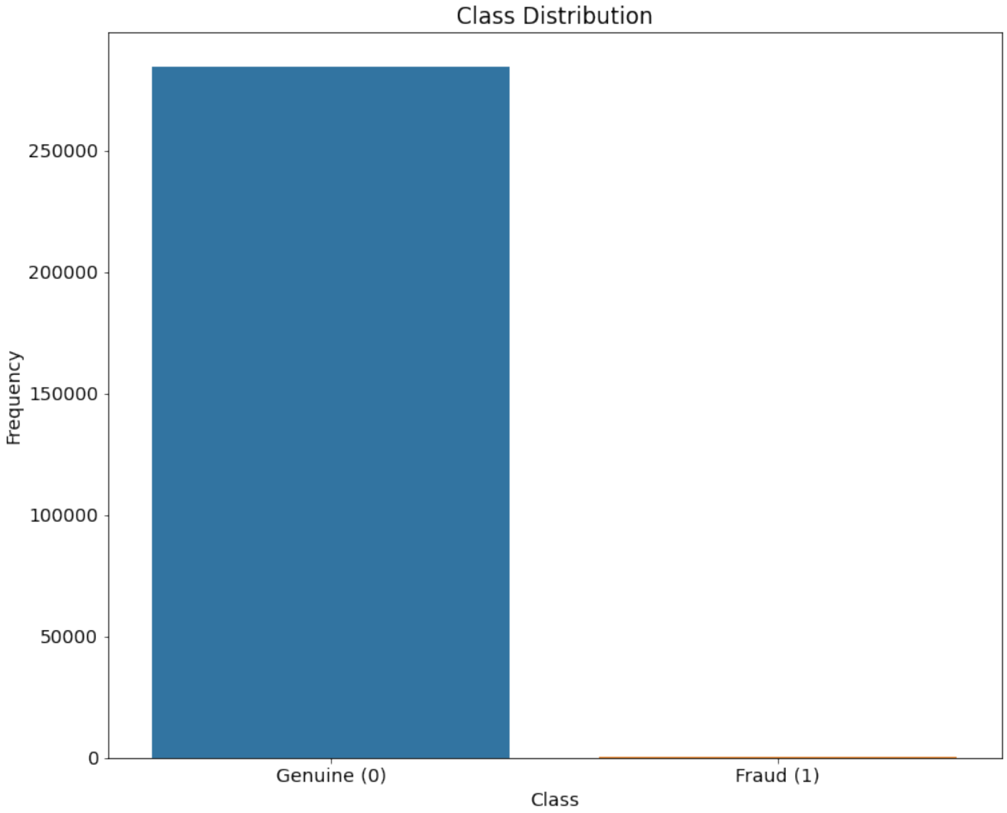


Figure 1: Dataset Class Distribution

4 Results

4.1 Evaluation Metrics

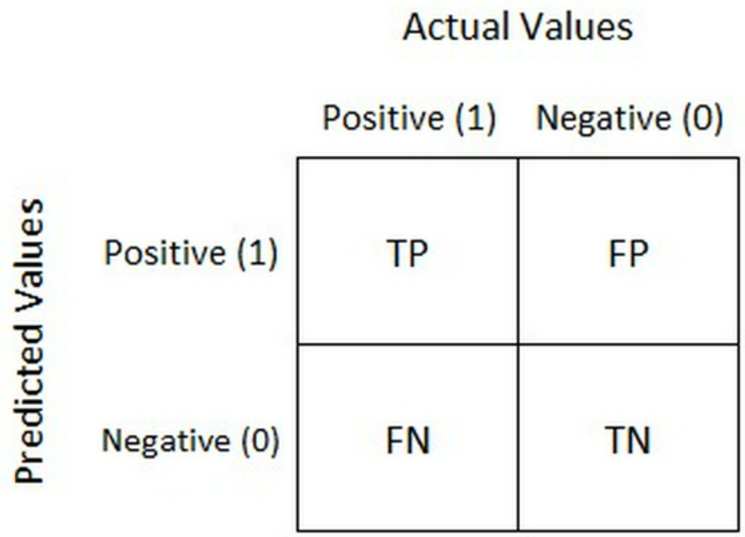
In this project, we use different metrics to evaluate the performance of a model: precision, recall, F1-score, PR curve, ROC curve [2].

4.1.1 Precision, Recall and F1-score

Precision can be defined as the number of correct positive prediction over the total of positive prediction. *Recall* is the number of correct positive prediction over the total of positive ground truth. Given a confusion matrix as in Figure 2, Precision and Recall score are computed as follows:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$



		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Figure 2: Confusion Matrix Example

When we use both precision and recall, it is a good idea to look into *F1-score* as well since it is a function of both precision and recall. F1-score is a good metric when we look for a balance between Precision and Recall since the number of True Negative (TN) does not contribute in the calculation of F1-score, which is very suitable for skewed data that has a lot of negative sample like in this project. The formula of F1-score is as follows:

$$Precision = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

4.1.2 Precision-Recall Curve

When working with an imbalanced data, we would want to keep track of both the precision and recall of the model to make sure the model does not overfit the majority class and produce unreliable predictions. Precision-Recall (PR) curve is a useful measure of a model prediction as it shows the trade-off between precision and recall for different threshold. A model with low precision and high recall will result in a lot of positive predictions but many of them would be wrong compared to the ground truth. A model with high precision and low recall would produce few positive prediction which might leave out a lot of true positive samples but the predicted ones usually match their ground truth. Figure 3 shows and ideal PR curve with both precision and recall being 1.

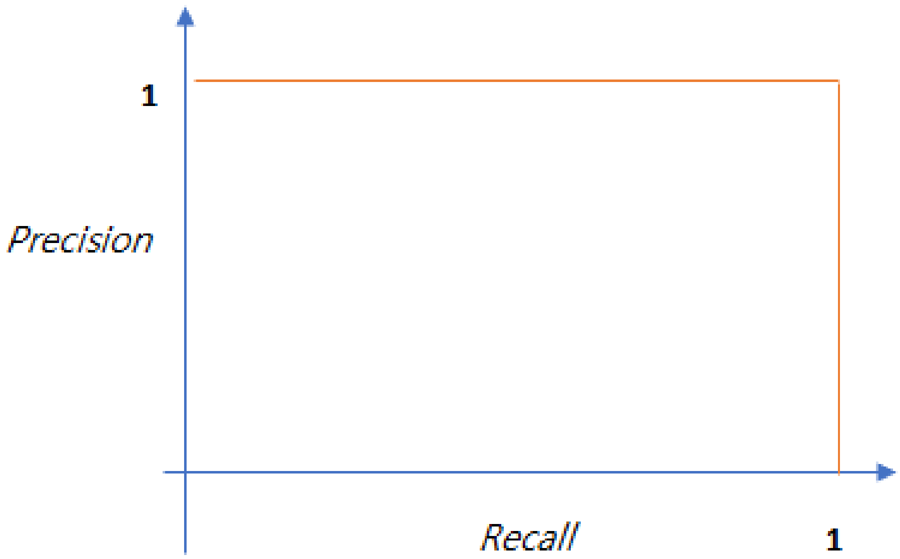


Figure 3: Ideal Precision-Recall Curve

In order to evaluate a model based on the PR curve, we use the Area Under the Curve (AUC), which is also known as Average Precision (AP), of the curve. The AUC of the PR curve can be calculated using integral; however we can vary the threshold by a small amount each time so that the AUC can be calculated by summing up the areas as. The AUC can be treated as a weighted sum of the precision scores. The formula to compute the AP is as follows:

$$AP = \sum_{n} (R_n - R_{n-1}) \times P_n$$

where P_n and R_n represent the precision and recall at threshold n^{th}.

4.1.3 Receiver Operating Characteristic Curve

Similarly to PR curve, Receiver Operating Characteristic (ROC) [3] curve illustrates the diagnostic probability of a model with varied threshold. In order to understand this metric, we must first understand the concepts of True Positive Rate (TPR) and False Positive Rate (FPR). The TPR is also know as Sensitivity or Recall and the FPR is also known as the inverse Specificity which is calculated as the total number of true negatives over the sum of the number of true negatives and false positives. Consider Figure 2, the FNR is computed as:

$$FPR = 1 - \frac{TN}{TN + FP}$$

4.2 Performance

4.3 Discussion

Overall, the models we chose achieved our main criteria, real time detection and high accuracy. Both YOLOv4 and YOLOv5 perform similarly, with the average precision on unknown test data achieving 0.75. This result means the system should perform accurately and reliably.

4.3.1 Difficulties

5 Conclusion

6 References

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