Machine Learning Engineer Nanodegree

Capstone Proposal

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Domain Background

Fraud Detection is a very important research area for businesses and banks since it has a direct impact on their profits. There are many industries that have an interest in detecting fraudulent behaviour as early as possible: Banks need to identify criminal transactions that are drawn illegally from their customers' accounts, telecommunication companies need to know if the customer is trustworthy for a device payable by instalment and insurance companies desire to reveal insurance fraud.

The European Central Bank estimated that in 2012 the total value of credit card fraud was about to be 1.33 € billion in 2012, which represents an increase of almost 15% compared to the previous year (European Central Bank, 2014). This example illustrates that fraud is a very important issue that companies and banks are highly interested in fixing. Therefore different data mining and machine learning methods are in use, such as classification, regression, clustering or prediction techniques in order to detect fraudulent cases (Dal Palozzo, 2015).

Problem Statement

A bank institute is interested in identifying credit card fraud as early as possible in order to avert damage from its customers and from themselves. The aim is to predict for a transaction whether it is fraud or not. Therefore they can apply machine learning and data mining methods that use past data which is already classified in fraud and non-fraud cases. With using supervised learning methods such as regression, decision trees, neural networks, SVM or Bayes Learning it is possible to train a model that will predict whether a case is fraud or non-fraud when given new, previously unseen data. After examination whether the prediction was right or not, those cases can be used to update the algorithm and to make it better (this is the machine learning part).

Datasets and Inputs

The data for the analysis are credit card transactions generated by European credit cardholders. The dataset has 284,807 transactions with 492 cases of fraud, which is only 0.172% of all transactions. The variables of the dataset are all transformed by a PCA transformation and unfortunately there is no meta data that explains the meaning of the variables (due to confidentiality). There are 2 variables that are not transformed: "time" and "amount", whereas the latter is the amount of the transaction and the first is the time between each transaction and the first transaction in seconds. The variable "Class" is the response variable (1=fraud, 0=no fraud). The dataset was released by a research collaboration of Worldline and the Machine Learning Group of the University of Bruxelles (ULB) (Caelen, Dal Pozzolo, Johnson, & Bontempi, 2015). The dataset is available for download here: https://www.kaggle.com/dalpozz/creditcardfraud

Solution Statement

The aim is to classify whether a transaction is fraud or not. Therefore I am going to apply different supervised learning methods and compare the results to each other in order to find out which one performs best:

- Logistic Regression (this will be the benchmark model)
- Decision Tree
- Neural Network
- SVM

Since the data is quite imbalanced I will figure out whether there is a need to resample (e.g. undersampling). Also I will divide the data into training and testing data subset. I will train the model on the subset of training data and then test it on the previously unseen testing data. After implementing the models I will compare them based on the evaluation metrics and conclude which one is best for the data given.

Benchmark Model

A very simply heuristic model could be predicting “non-fraud” in 100% of test cases and that would lead to an accuracy of 99.83% which is already quite high. This is due to fact that the dataset has only 492 cases of fraud and is thereby imbalanced. With regard to the business background this is not meaningful since just one fraud case can already cause a lot of damage to the business. Therefore a bank has a very strong interest in detecting every single fraud case.

This made me decide that a heuristic model is not adequate. The benchmark model for this problem will be a logistic regression which can in most cases deliver robust predictions. It will be measured by the same evaluation metrics as the challenging models.

Evaluation Metrics

There are classic accuracy measurements such as

- Accuracy = (TP+TN)/Total
- Precision = TP/(TP+FP)
- Recall = TP/(TP+FN)

True Class ↓Predicted Class→	Fraud (1)	Non Fraud (0)
Fraud (1)	TP = true positive	FN = False negative
Non Fraud (0)	FP = false positive	TN = True negative

In our case it is important to maximize the number of true positive labelled cases and to minimize the false negative labelled cases. The false positive cases are not as bad for the business as the false negative cases, because the latter will cause tremendous harm to the business. The false positive cases will probably result in extra work for manually checking whether it is really fraud or not. This makes *Recall* an important metric to examine. Accuracy is not the measurement of choice because the data is highly imbalanced and precision does not take the worst case of false negatives in account (Descoins, 2013).

The authors of the dataset already point out the difficulty due to the imbalance of fraud and non-fraud cases and therefore recommend using the *Area Under the Precision-Recall Curve* (Caelen, Dal Pozzolo, Johnson, & Bontempi, 2015; Dal Palozzo, 2015).

Project Design

First of all I am going to do *exploratory data analysis* to get to know the data and develop a feeling for the variables, to make sure all input variables are filled, there are no missing values and to decide how to deal with outliers.

Second I am going to divide the dataset into a *training and test* set. I will also try *rebalancing* the dataset in order to weight the fraud cases of the datasets and get a balanced sample.

Third I am going to implement the chosen models. Thereby I will examine each model whether it has some tuning parameters that can still be optimized or whether it will not get any better.

Then I will compare the evaluation metrics of the models to the benchmark model and draw a conclusion.

Literature

Caelen, O., Dal Pozzolo, A., Johnson, R. A., & Bontempi, G. (2015). Calibrating Probability with Undersampling for Unbalanced Classification. *Symposium on Computational Intelligence and Data Mining (CIDM), IEEE*.

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