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| Modelling and Implemention of Real-world Fraud Detection System based on Artificial Neural networks. | | |
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Abstract – With increasing adaptation of electronic payment and e-commerce industry, fraud detection has become an increasing critical factor for associated industry. In this paper we discuss the realistic model of a Fraud Detection System (FDS). We identify and categorize the challenges to build a Data Driven Fraud Detection System into 3 categories namely, class imbalance, verification latency and concept drifts. Based on this modelled FDS, we design and implement learning strategy based on 3 layers Neural Network that effectively addresses these challenges.

Finally this paper demonstrates the results obtained by our neural network and measures the accuracy of our build FDS on real time data.

Index Terms – Artificial Neural Networks (ANNs), Binary Classifiers, Fraud Detection Systems, Unbalanced Classification, Supervised Machine Learning.

# Introduction

The expansion of electronic commerce, together with increasing confidence of customers in electronic payment, effective Fraud Detection Systems (FDS) are increasingly becoming a critical factor. The Fraud Detection we discuss in this paper is the process of identifying if an authorized credit card transaction belongs to the class of fraudulent or genuine transaction. [1] Discusses the many challenges to model a Realistic FDS and categorizes these challenges into following 3 types:

* Class Imbalance / Skewed Data – Genuine Transactions far outnumber frauds.
* Concept Drift - Transactions might change their statistical properties over time.
* Verification Latency - The way and timing with which supervised information is provided by the expert investigators.

To design and implement the Realistic Fraud Detection System we use the following dataset shared in public domain containing information about credit card transaction with examples of fraudulent samples (<http://www.ulb.ac.be/di/map/adalpozz/data/creditcard.Rdata>).[5] This is one of the rare datasets on fraud detection available to the community. It contains 32 numerical input variables. The dataset is highly unbalanced with fraud representing 0.172% of all transaction (492 frauds out of 284807 transactions).

# Class Rebalancing using undersampling

Learning from unbalanced datasets is a difficult task as the learning algorithm has to cope with highly skewed data. Thus, as first part of implementation, we rebalance (by resampling) the classes before proceeding with the learning of the classifier. This preprocessing step is based on [2] and uses a well-known technique called “undersampling”.

Sampling data used to train the model induces an artificial bias into the computed posterior probabilities, for which we implement a corrective method. Although this bias does not affect the ranking order returned by posterior probabilities, it significantly impacts the classification accuracy and probability calibration. We use Bayes Minimum Risk theory to find the correct classification threshold and adjust it after “undersampling”.

# 3-Layer Neural Network

Dorronsoro[3] shows that a 3 layer neural network is capable of dealing with the highly skewed class distribution. Thus, we design a learning strategy based on 3 layers Neural Network implementing forward and backpropagation to train our Neural Network.

For performance evaluation of our classifier over a range of different thresholds, we will be using a well-known assessment technique called Receiving Operating Characteristic (ROC) curve. When evaluating the output of a classifier it is also important to assess the quality of the estimated probabilities. A well-known measure of quality is Brier Score (BS).

# Realistic Fraud Detection Systems with Alert feedback interaction

Fraud detection differs from conventional classification because, in a first phase, human investigators assessing only a reduced number of alerts provide a small set of supervised samples denoted as feedbacks. Labels of the vast majority of transactions are made available only several days later, when customers have possibly reported unauthorized transactions. These transactions define  
an additional set of supervised samples called delayed samples. We address a realistic fraud detection setting and implement feedbacks  
and delayed samples separately. Based on [4] we implement two prototypes of FDS  
on the basis of an ensemble and a sliding-window approach and training two separate classifiers (on feedbacks and  
delayed samples, respectively), and then aggregating the outcomes. In order to obtain precise alerts, feedbacks samples have to receive larger weights than  
non-alerted transactions and methods that diminish their role in the learning process  
lead to loss of predictive accuracy.

# References

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