Bidirectional Artificial Neural Networks for Mobile-Phone Fraud Detection

Andrej Krenker, Mojca Volk, Urban Sedlar, Janez Bešter, and Andrej Kos

ABSTRACT—We propose a system for mobile-phone fraud detection based on a bidirectional artificial neural network (bi-ANN). The key advantage of such a system is the ability to detect fraud not only by offline processing of call detail records (CDR), but also in real time. The core of the system is a bi-ANN that predicts the behavior of individual mobile-phone users. We determined that the bi-ANN is capable of predicting complex time series (Call_Duration parameter) that are stored in the CDR.

Keywords—Bidirectional artificial neural networks (bi-ANN), fraud detection, mobile telecommunications.

I. Introduction

Fraud in information and communication technologies (ICT) occurs whenever a perpetrator uses deception to receive ICT services free of charge or at a reduced rate [1]. ICT fraud is a global problem that by the estimation of the European Communication Fraud Control Association represents approximately 5% of ICT revenue in developed countries [2] and in some countries even up to 20% [3]. ICT fraud is rising, and with the increased migration of everyday activities into the cyber-world, there is a vital need for more secure and trusted ICT services. The areas in which ICT fraud occurs are extensive. For the purpose of simpler detection and prevention, these are divided into several groups according to their similarities. Different fraud types and their detection methods can be found in [4]-[6].

In this study, we propose a model for mobile-phone fraud detection based on bidirectional artificial neural networks (bi-ANNs) that predict time series representing the behavior of individual users. The acquired information allows us to predict user behavior and compare it in real time with the monitored real-life behavior. Previous works on predicting time series with a bi-ANN can be found in [7]-[9]. Although time series can be predicted with several other methods [10], we concluded that, in the observed cases, prediction with a bi-ANN delivers better results.

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II. Detection Model

Most existing solutions [4]-[6] for detecting ICT fraud give satisfactory results, but are limited to detecting only one type of fraud and provide fraud detection only by offline processing.

To overcome these two issues we propose a system that is able to detect changes in a user's behavior (see Fig. 1.) The first benefit of our approach is that, by detecting changes in a user's behavior, any type of potential fraud can be identified. Another benefit is the ability to monitor these changes in real time. The proposed model applies fraud detection in three steps: monitoring the user, predicting the user's behavior, and

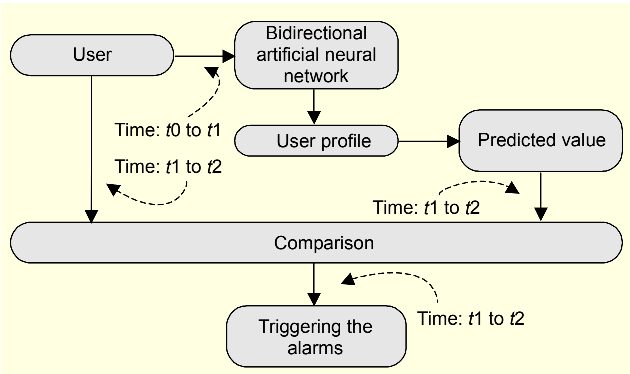

Fig. 1. Proposed model for mobile-phone fraud detection.

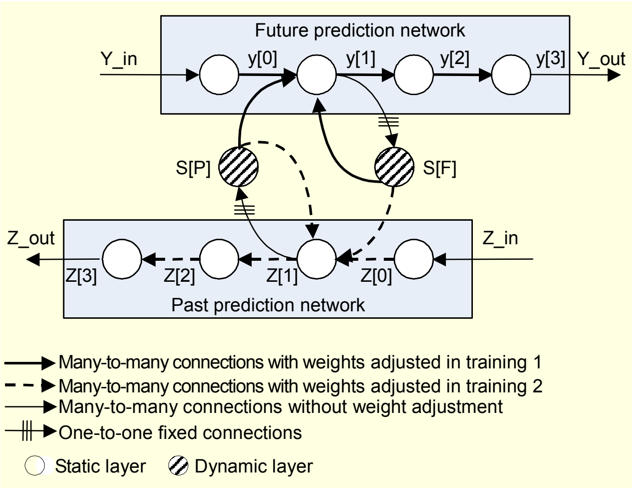

Fig. 2. Bidirectional artificial neural network.

comparing the predicted and monitored behavior. In the case of notable discrepancy between the predicted and monitored behavior, the system triggers an alert. A study of the bi-ANN and its ability to predict time series is presented in the following sections.

III. Bidirectional Artificial Neural Network

In the proposed model, we use the bi-ANN architecture that was first described in [11]. Its use for prediction of time series is described in [12]. Detailed descriptions of the bi-ANN can be found in [7], [9]-[12].

The bi-ANN model shown in Fig. 2 consists of two uni-directional ANNs that are connected through dynamic neurons. The upper ANN predicts future values, and the lower ANN predicts past values [10]. The architecture of the individual ANN is [1-*N*-*N*-1], where *N* is the number of the neurons in the layers. In our model, we varied *N* from 1 to 7.

IV. Methodology

We obtained anonymized call detail records (CDRs) for 200 users from a Slovenian mobile operator. Our data set consisted of 1,082,588 calls made in time span of 12 weeks with an average call duration of 72 s (minimal call duration was 1 s and maximum call duration was 6,682 s). A CDR holds 40 different call parameters (see Fig. 3). For the purpose of analysis we observed the Call_Duration parameter.

With our model, we attempted to predict the Call_Duration parameter using the following variables: users, data pre- and post-processing methods, training scenarios, training functions, lengths of input time series, time slots of the predicted time series, length of time slots of the predicted time series, and

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Fig. 3. Sample of call detail record of randomly selected user.

number of neurons used in hidden layers. For each combination of the above variables and input signal (representing Call_Duration value in time), we preformed 10 simulations of the prediction procedure in Matlab. We completed 1,728,000 simulations with different bi-ANN topologies and input time series.

Before we introduced input data to the bi-ANN, we pre-processed it. We applied two different types of pre- (and post-) processing methods, one based on minimum and maximum values and the other based on standard deviation on all 3 data subsets, namely, the training subset, validation subset, and testing subset.

Next, we formed input time series of different lengths, starting at 50 samples and increasing the length by 50 up to 400 samples. After acquiring the resulting predicted time series, we divided these into thirds, and each third was further divided into 5 equal parts. We used different lengths of input and predicted time series to estimate the performance of each model with the average relative variance (ARV) index [12]. ARV is defined as

$$\mathrm{ARV} = \frac{1}{\sigma^2 T}\sum_{t=1}^{T}\left\{x(t)-\hat{x}(t)\right\}^2 = \frac{e}{\sigma^2 T}, \qquad (1)$$

where $x(t)$ is the desired output series, $\hat{x}(t)$ is the actual output time series, σ^2 is the variance, T is the length of the time series, and e is the total square error. The ARV values between 0 and 1 represent satisfactory prediction, and the smaller the value, the better the prediction. Values above 1 represent unsatisfactory prediction.

V. Results

Based on the obtained results, we have come to the following conclusions. The quality of prediction (the calculated ARV value) was not affected by the selection of users. The study of pre- and post-processing methods showed that methods based on minimum and maximum values resulted in better prediction. Different training scenarios ([10] and [13]) did not affect prediction. However, the applied training function did affect the quality of the prediction task: of the six different training functions (*trainlm*, *trainbfg*, *traincgb*, *traincgf*, *traincgp*, *trainb*), two of them (*trainb* and *traincgp*) had a negative effect on prediction. We also tested and observed how the lengths of the input time series and the predicted time series

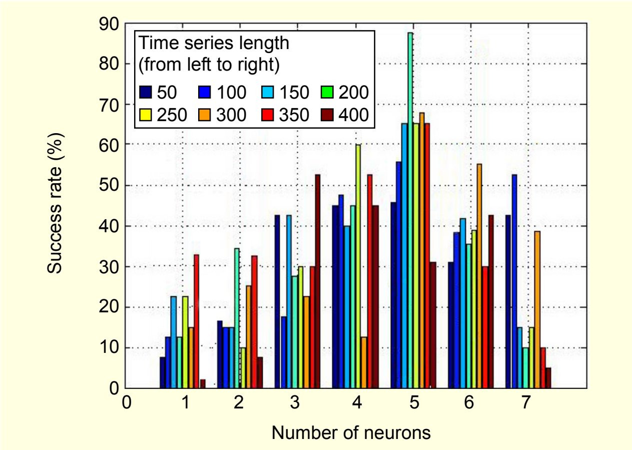

Fig. 4. Combination of parameters resulting in 90% success rate.

influenced prediction. We determined that longer input time series and shorter predicted time series gave better results. The number of neurons used in hidden layers had a major effect on prediction. That is, the bi-ANNs with a larger number of neurons in hidden layers gave better prediction results. However, using too many neurons in hidden layers and short input time series resulted in overtraining, which caused the prediction task to fail. In the case of adjusting variables individually, (see section IV) the percentage of correct predictions was below 50%.

Next, we performed the measurements adjusting all variables at once. The respective results led us to the following conclusion. The combination using ARV as a measure resulted in a 90% success rate (see Fig. 4). By using a combination of five neurons in hidden layers and an input time series length of 200 samples, the best prediction was achieved while using only 20% of the first third of the predicted time series.

VI. Conclusion

In this paper, we presented a novel bi-ANN-based approach for generic mobile-phone fraud detection capable of detecting fraud in real time. The analyses were accomplished using real-life CDR data, obtained from a Slovenian mobile operator. The focus of our study was to determine whether the bi-ANN is capable of predicting time series that describe the behavior of a mobile-phone user. The overall finding of our study is that the bi-ANN is capable of predicting these time series, resulting in 90% success rate in optimal configuration.

In the study, we based the prediction on the Call_Duration parameter in the CDRs. In the future, we intend to extend the prediction to other relevant parameters in order to create a complete mobile phone fraud detection system. Additionally, the ratio between the required prediction accuracy and its consumption of time and resources has to be optimized.

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