Evaluating Marketing Campaigns of Banking Using Neural Networks

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***Abstract*—Marketing campaigns of banking institutions is vital in all banks. The marketing campaigns were based on phone calls. Phone calls have an important influence in the behavior of customers. This paper proposed neural network to evaluate the bank marketing. This assessment will highlight the importance of marketing in the banks and thus the importance of phone calls. A feed-forward back propagation neural network with tan-sigmoid transfer functions is used in this paper to predict if the customer subscribes the deposit. The data set is obtained from UCI machine learning repository. The results of applying the proposed neural network methodology to predict subscribe based upon selected phone calls parameters show abilities of the network to learn the patterns corresponding to customer subscribes the deposit. The percent correctly classified in the simulation sample by the proposed neural network is 90 percent.**

***Index Terms*—Bank marketing, Banking advertisment, Business intelligence, Artificial neural networks and Feed-forward back propagation network.**

I. Introduction

THE increasingly vast number of marketing campaigns over time has reduced its effect on the general public. Furthermore, economical pressures and competition has led marketing managers to invest on directed campaigns with a strict and rigorous selection of contacts [1].

Mylonakis [2] examined the relationship between bank advertising and the needs of a bank customer in Greece and its possible influence on potential customers to select their banks. The research demonstrated the issue of customers' indifference to advertising in their decision to cooperate with a bank. Advertising is not the determinant factor in their final choice. Selecting a banking institution is based on the traditional products and services it offers. However, its existence is a prerequisite, as it verifies a bank's critical presence in the market and plays an important role in customers' choices. The examination of a banking institution is made based on price and product-related criteria and not promotion.

Charles et al. [3] investigated bank choice/selection criteria in a range of cultural and country economic scenarios. More specifically, the purpose of their study is to understand international consumers' selection criteria of banks using the USA, Taiwan, and Ghana as illustrations.

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Peterson and Hermans [4] presented a longitudinal study of social responsibility themes in US bank advertising for the years 1992, 1997 and 2002. Content analysis is used to examine television commercials for socially responsible advertisements. Findings indicate that the communication of social responsibility in television commercials for banks has increased by 7 percent over the time period covered by the study.

Aron and Debra [5] examined the role of marketer-controlled and marketer-uncontrolled communications on consumption-aroused feelings and service brand attitudes. Data were gathered from customers of specific service brands and comparisons were made across two different service types (retail stores and banks). The findings indicated that advertising has a significant effect on consumption-aroused feelings and service brand attitudes, whereas word-of-mouth communications affects brand attitudes only in terms of bank brands and publicity has no effect on consumption-aroused feelings or brand attitude.

Lowe [6] described how Fleming Premier Banking, a retail telephone bank, created an integral approach to its communication with clearly identified target customers

Laskey et al. [7] dealt with strategy and structure in bank advertising. They examined the effectiveness of advertising on bank customers and found that respondents overall attitude and aesthetic/emotional evaluations varied significantly and that picture based advertising elicits a higher intention to patronize a bank. They also emphasized the distinction between information and transformational advertising, the first found to be the most effective.

II. Artificial Neural Networks

An artificial neural networks ANN model emulates a biological neural network. Neural computing actually uses a very limited set of concepts from biological neural systems. It is more of an analogy to the human brain than an accurate model of it. Neural concepts are usually implemented as software simulations of the massively parallel processes that involve processing elements (also called artificial neurons) interconnected in network architecture. The artificial neuron receives inputs analogous to the electrochemical impulses the dendrites of biological neurons receive from other neurons. The output of the artificial neuron corresponds to signals sent out from a biological neuron over its axon. These artificial signals can be changed by weights in a manner similar to the physical changes that occur in the synapses as shown in Fig. 1.

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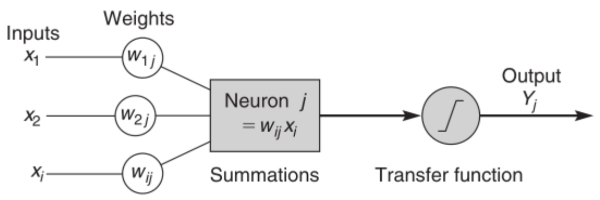

Fig. 1. Processing Information in an Artificial Neuron

An artificial neural network (ANN) is a computational model that attempts to account for the parallel nature of the human brain. An (ANN) is a network of highly interconnecting processing elements (neurons) operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A subgroup of processing element is called a layer in the network. The first layer is the input layer and the last layer is the output layer. Between the input and output layer, there may be additional layer(s) of units, called hidden layer(s). Neural network can be train to perform a particular function by adjusting the values of the connections (weights) between elements. Fig. 2 represents a typical neural network with one hidden layer.

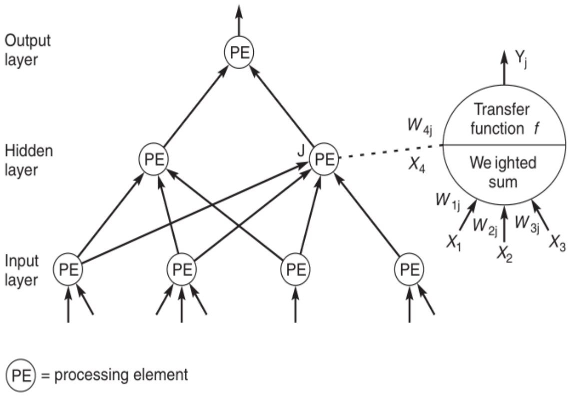

Fig. 2. A typical neural network with one hidden layer

An ANN have been shown to be very promising systems in many forecasting applications and business classification applications due to their ability to "learn" from the data, their non parametric nature and their ability to generalize.

III. EXPERMENTAL RESULTS

A. Data Analysis

The dataset is obtained from UCI Machine Learning Repository. The data is related with direct marketing campaigns of a Portuguese banking institution, based on phone calls. Often, more than one contact of the same potential customer was required, in order to determine if the product (bank term deposit) would (or would not) be bought. The goal is to predict if the customer will subscribe or not. With a valid prediction, the marketing department can focus on the most promising leads and increase the overall ROI of the campaign.

TABLE I
BANK CUSTOMER VARIABLE OF DATASETS USED IN THE STUDY

No.	Bank Customer variables
1	Age
2	Marital
3	Education
4	Has credit in default
5	Balance
6	Housing
7	Loan

Data related to the last contact of the current campaign are:
1- Contact: contact communication type (telephone, cellular or unknown).
2- Day: last contact day of the month.
3- Month: last contact month of year.
4- Duration: last contact duration, in seconds.
Data related to the contact of the various marketing campaigns are:
1- Campaign: number of contacts performed during this campaign and for this customer.
2- Pdays: number of days that passed by after the customer was last contacted from a previous campaign.
3- Previous: number of contacts performed before this campaign and for this customer.
4- Poutcome: outcome of the previous marketing campaign.
The target is binary to predict if the customer will subscribe or not. The data is processed to be suitable input to the network using Microsoft Office Excel.

B. Performance Evaluation

A two-layer feed-forward network with 15 inputs and 20 sigmoid hidden neurons and linear output neurons was created as shown in Fig. 3. The dataset contains 4521 samples. Training is done using scaled conjugate gradient back propagation network. The scaled conjugate gradient algorithm (SCG) developed by Moller [8] was designed to avoid the time-consuming line search. This algorithm combines the model-trust region approach with the conjugate gradient approach.

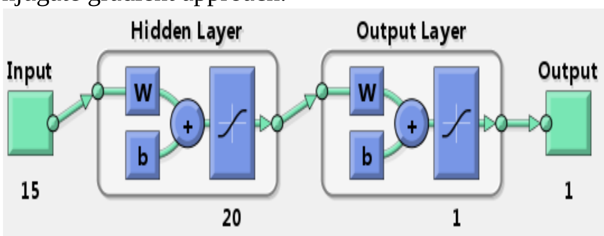

Fig. 3. The proposed network

The results of applying the proposed neural network to predict if the customer will subscribe or not based upon selected bank customer variables showed good abilities of the network to learn the patterns corresponding to customer subscribes the deposit. The results were good; the network was able to classify approximately 89% of the cases in the training set as shown in Fig. 4. Fig. 4 shows the confusion matrices for training, testing, and validation, and the three kinds of data combined. The diagonal cells in each table show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue

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cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). Fig.5 shows the training state values. Best validation performance is 0.09474 at epoch 31 as shown in Fig.6. The mean squared error (MSE) is the average squared difference between outputs and targets.

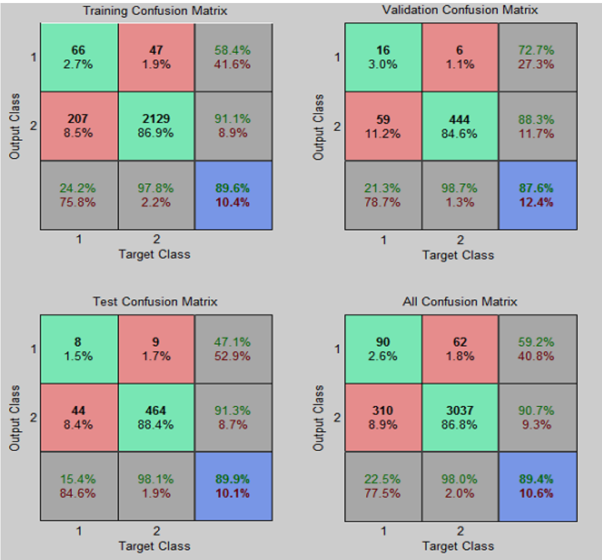

Fig. 4. The confusion matrices

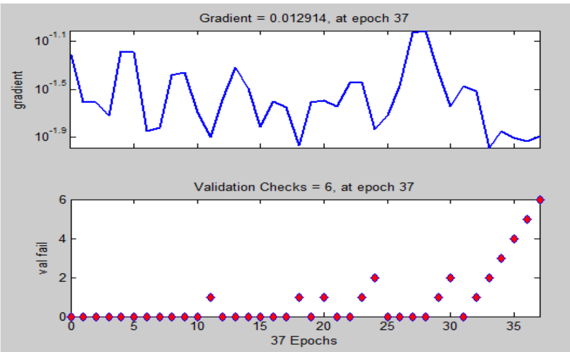

Fig. 5. The training state values

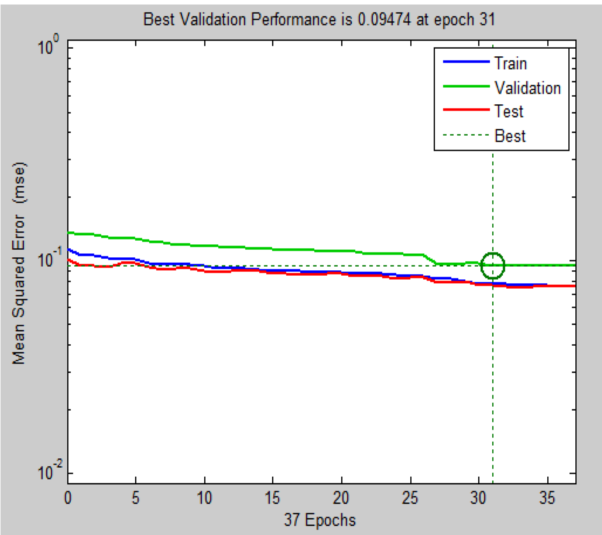

Fig. 6. The proposed network performance

The percent correctly classified in the simulation sample by the feed-forward back propagation network is approximately 90 percent as shown in Fig.7.

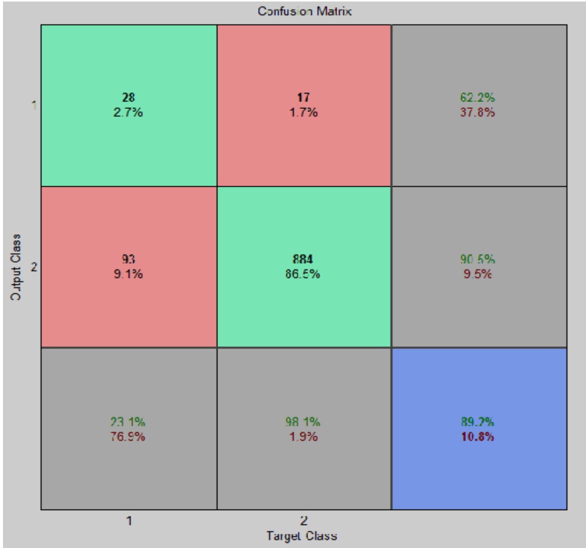

Fig. 7. The confusion matrix

IV. CONCLUSION

Artificial neural networks have powerful pattern classification and prediction capabilities. In this study feed-forward back propagation neural network with tan-sigmoid transfer functions in both the hidden and the output layer is applied for predict if the customer subscribes the deposit thus evaluate the bank marketing. In all these cases neural networks performed better prediction and less variation across different subgroups.

REFERENCES

[1] S. Moro, R. Laureano and P. Cortez, Using Data Mining for Bank Direct Marketing: An Application of the CRISP-DM Methodology, In P. Novais et al. (Eds.), Proceedings of the European Simulation and Modeling Conference - ESM'2011, pp. 117-121, 2011.

[2] J. Mylonakis, The influence of banking advertising on bank customers: an examination of Greek bank customers' choices, Banks and Bank Systems, Vol. 3, Issue 4, pp. 44-49, 2008.

[3] B. Charles, J. Cheng and S. Nancy, Determinants of banks selection in USA, Taiwan and Ghana, International Journal of Bank Marketing, Vol. 25, Issue 7, pp. 469-489, 2007.

[4] R. P. Peterson and M. C. Hermans, The communication of social responsibility by US banks, International Journal of Bank Marketing, Vol. 22, Issue 3, pp. 199-211, 2004.

[5] O. Aron and G. Debra, Service brands and communication effects, Journal of Marketing Communications, Vol. 10, Issue 4, pp. 241-254, 2004.

[6] A. Lowe, Effective communication to your chosen segments- A case study, Journal of Financial Services Marketing, Vol. 5, No. 4, pp. 319-325, 2001.

[7] H. A. Laskey, B. Seaton, J. A. F. Nicholls, Strategy and Structure in Bank advertising: An Empirical Test, International Journal of Bank Marketing, Vol. 10, No. 3, pp. 3-9, 1992.

[8] M. F. Moller, A scaled conjugate gradient algorithm for fast supervised learning, Neural Networks, Vol. 6, pp. 525-533, 1993.

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