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A NEURAL NETWORK MODEL FOR SALES ANALYSIS

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Abstract

Neural networks are a computing paradigm developed from the field of artificial intelligence and brain modelling, which lately is becoming very popular in business. Many researchers are seeing neural networks systems as solutions to business problems like modelling and forecasting.

The purpose of this paper is to present the ability of an artificial neural networks model to forecast and recognize patterns when analysing company's sales evolution. The monthly sales evolutions are considered a time-series and the target is to observe the ability of the investigated model to make predictions.

Keywords: artificial neural networks, accounting, predictions, sales analysis

1 Introduction

A neural network is a computerized structure inspired by the observation of natural networks that human neurons made into human brain. Initially received with enthusiasm and then quickly forgotten, as a result of Minsky and Papert paper, artificial neural networks technology returned to researchers attention over the last two decades, as a result of backpropagation algorithm development. Although in economic area most of the studies aimed to financial applications that predict stock price evolution, accounting and audit were also touched by the new technology.

Studies made in this area already showed the feasibleness of building an accounting neural networks intelligent system, but the researches are still at the beginning and the results are modest. In this context, we consider that the problem of using a conexioniste intelligent system in accounting is a pioneer's work, but it deserves our attention by looking of possible future results.

2 Technical issues

An artificial neural network consists of a number of artificial neurons, which are the elementary processing units, which are connected together. Neurons connections mimic high learning ability of brain by pattern discovery from examples. For artificial neural networks, this learning is achieved by adjusting the so-called weights [Andone, 2002, p. 81], or the synaptic interconnection strength between neurons, on a given predefined learning algorithm.

When we build a neural network, it is very important to correctly determine which are the inputs, how many layers we use and what kind of activation function we implement. Thus an artificial neural network is characterized by its architecture, its processing algorithm and its learning algorithm [Jain et all, 1996]. The architecture specifies the number of

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neurons and the way they are connected. The processing algorithm specifies how the neural network with a given set of weights computes the outputs for any inputs set. The learning algorithm specifies how the network adapts its weights based on the training inputs sets.

Once the network has been trained, it is capable to correctly classify each new input structure in a resembling category, in the way that they are presenting same distinctive features. This generalization capability, improved with the ability to deal with imperfect or incomplete data, is highly useful in real world applications, where the input data are not always perfectly match in a predefined pattern and the decisions must be taken by existing data [Song et all, 1996, p. 77].

The main advantage of artificial neural networks is their adaptability: they are capable to learn from the examples presented to them, often capturing quite subtle relationships between data, that are missed even by trained experts. This ability is very useful for those problems where the inputs number is high or, in other words, there are many potential parameters that can affect the final solution. Besides that, artificial neural network's adaptation makes possible on the run learning, which will avoid the premature ageing of intelligent system's knowledge.

3 Previous research

A look into literature about neural networks applications in accounting [Wong et all, 2000] revels that there is some research in the field, but the potential is huge. The main application areas that we can identify are:

- Financial forecasting for currency and stock market. The base is analyzing time series, meaning market dynamic on a certain period of time, and most of the tests have showed that intelligent systems of this kind obtain better results that systems based on conventional statistical models [Lam, 2004]. Because of huge amount of money involved, financial institutions are very interested of this application area of artificial neural networks, and many achievements are kept secret.
- Credit rating, both individual and corporate [Huang et all, 2004]. After analyzing previous debtor behavior, it's financial situation, and other general industry level or market level variables, such an intelligent credit scoring system can support bank officer to determine which loan applicant should lend money to.
- Credit card fraud detection, by analyzing cardholders consuming habits and pointing out significant exceptions that could indicate a fraud. VISA has developed the CRIS (Cardholder Risk Identification Service) and VISOR (VISA Intelligent Scoring of Risk) systems, while MasterCard has developed RiskFinder system. As an adaptation to present market, researchers are seeking for similar methods to prevent e-commerce frauds.

We remark that most studies about neural networks utilization focus on their predictive abilities, starting from the premise that they are able to identify, extract and memorize patterns and models of evolution from the historical data time series that are presented to the network in the learning phase. By detecting and memorizing these patterns, we can say that the neural network learns. In the running phase, the intelligent system is able to classify the new series that are presented to it, to recognize models previously learned and then to present an output value that will represent the predicted value.

Neural networks impress by their ability to identify and then recognize patterns and subtle relations, which sometimes slips even to an expert eye, to operate with incomplete data, with multiple input variables and huge amount of data. Accounting transactions have such features, and the possibility to find in accounting data those behavioral patterns that allows to make predictions about future evolutions, business opportunities and possible threats, didn't let the managers indifferent.

The first accounting applications were in the audit area, more precisely material errors applications: the goal of those systems was to verify the relationships between several financial account values and direct auditor's attention to those that are not consistent with the normal expected relationships. The auditor had to decide whether and what kind of further audit investigations were required to explain the unexpected results [Koskivaara, 1996]. Thus, based on time series built from the monthly balances, an artificial neural network can observe the non-linear dynamics and relationships between accounts. Once it is trained, the neural network is then capable to signal unusual fluctuations or possible errors, based on differences between predicted values, which are considered normal, and the effective values, as they appear in the monthly balance.

The auditor main duty is to examine the financial situations and to decide if they are honest or, on the contrary, there is a possibility of management misrepresentation or fraud, committed with the intention to mislead the investors and creditors with an untrue image of the company. Detecting management fraud on financial statements with a model employing a lot of financial and non-financial input variables that can be set up as fraud clues [Faning & Cogger, 1998] it is another neural networks application.

Evaluating going concern is an important task for an auditor, because of the implications that a non-continuity situation is having on the financial statements. But the studies have focused mainly on identification of financial distress and evaluating bankruptcy risk, so the applications were conducted from the credit institutions position [Perez, 1999]. But the decision to issue a going concern opinion is an unstructured task that still requires the use of the auditor's judgment.

In a business environment more dynamic and computerized then ever, where a large amount of audit material, e.g. receipts and accounting records, is found only in electronic form, auditors task is becoming more and more difficult. Plus, companies wish financial reports more often and faster, and, especially, on-line, to answer to demands from many types of interested users. Systems complexity, quality of demand information and the reporting speed are enough reason for auditors to feel the need of support systems and explains this effervescence of audit conexioniste studies [Koskivaara, 2004].

But audit was not the only area aimed by neural networks researchers; conexioniste intelligent systems were conceived and tested in other accounting domains, too. Based also on financial statements data, such an intelligent system can assist the accountant to financial evaluations and diagnosis [Pedersen, 1997].

We saw that predictive abilities of neural networks impressed even the accounting specialists, which searched for the ways they can use the new technology in their advantage. Based on neural networks performances on recognizing patterns, models of evolution and subtle relations between several indicators, most of the studies tested the way they learn from company's historical data as time series, to be capable then to offer solutions to some accounting problems.

In our opinion, there are others domains, besides audit, that can benefit from accounting data modelling with neural networks. After all, the entire company information system is based on accounting transactions. This is why we consider that numerous studies on accounting conexioniste systems can be done, in areas like financial analysis, financial diagnosis or accounting consulting.

4 Problem presentation

When he grounds his decisions, the manager must support them on internal and external information. Whether for external information he has limited options, things are quite different when he needs the inside information. Often these are financial and accounting information and are reported by its specialized department, in a time interval and format depending by implemented information systems performances and employees abilities on data extraction and reports generation.

These reports were frequently incomplete and late, so the specialists developed decisions support systems. Easy to use and friendly interface, these systems cover some of the problems, but not all of them.

But these systems offer information about past events, even they are recent. Many times, when he elaborates his decisions, a manager needs prognoses and predictions, what-if analyses, calculations and optimizations. In this case, statistical tools and models database from decision support systems are his servants. But as we saw, researchers studies show that, for some range of prediction problems, neural networks obtain better results.

A neural network system is capable to learn from the past evolution of business' indexes patterns, rules and models, to compare them with the actual situation, to find the proper one and to present to manager a possible future evolution. Trained well, a neural network makes these predictions with an acceptable degree of accuracy. They also operate well on a noisy environment, because they are able to distinguish the important factors from the aleatory ones. A neural network systemcan be, in some cases, the ideal tool for a manager trying to solve a business problem.

5 Model development and testing

To prove the viability of the technology, we developed an intelligent system prototype, based on neural networks. This was trained with historical data from monthly balances considered as time series, and it is capable to make predictions about business future evolutions or to present the way business should evolve, comparing to actual situation.

Architecturally, we use a multilayer feed forward neural network, with one hidden layer. We choose hyperbolic tangent function as activation function and backpropagation learning algorithm, with generalized delta rule for speed up the training. The entire neural network was build with our own software application.

We choose for our tests a small size company, which has the main activity domain on informatics services. Our goal was to build a neuronal system that will predict net sales value, based on values from precedent months. Company's business domain is production and sailing of financial and accounting software applications and additional services. The entire company net sales value is compound by services revenues (704 account) and means more than 95% of the entire company revenues. This is why net sales value is an important index for management, because any variation can affect the entire company financial stability.

We have to say that, because of the way revenues are obtained, there is no regularity in their values. Thus, for service activities there are contracts with a constant monthly amount (in lei, euro or US dollars), while the sales department performance can highly vary from one month to another.

In these conditions, we develop a neural network model with the following input variables:

- Company's net sales values on the last three months;
- Monthly average exchange rate on euro, communicated by BNR, on the last three months;
- Monthly average exchange rate on US dollar, communicated by BNR, on the last three months;
- Inflation index on the last three months, communicated by National Statistics Institute;
- Average exchange rate on euro and US dollar, for the current month;

- The current month on which we make the prediction: from 1 for January to 12 for December.

We obtained a neural network with 15 input variables and one output variable, respectively the predicted value of net sales for the current month. In our model we couldn't include the inflation index for the current month, because it is calculated and communicated too late.

Because we have an exchange rate on euro only from January 1999, our training series were created starting from this point. After data normalization, we obtained 90 data series, which were randomly distributed into 81 training series and 9 test series. For the net sales input variables we scaled data linearly, dividing the values by 1000, while all the others input variables were let at their actual values. For the output variable, we scale the data in the same manner, dividing the values by 50000.

After the tests we made, the best results were obtained with a neural network configuration with one hidden layer and 14 neurons on this layer. This 15:14:1 architecture seems to confirm the studies [Lawrence et all, 1996], about optimal structure of a neural network with a large number of input variables.

The training process was finalized after 6013 cycles, with a gradually error descent to the settled limit of 0.1.

After the testing phase, we have calculated some statistical indexes to evaluate network performances, separately for the test sets, the training sets and the whole data sets. Thus we can observe the results of the training process and also network's ability to generalize. The results that our network has obtained are presented in Table 1.

Table no. 1 - Neural network performance indexes

Indexes	**All**	**Train**	**Test**
Records	90	81	9
Accuracy (10%)	0,4555	0,4691	0,3333
Accuracy (30%)	0,8444	0,8518	0,7777
Pearson R	0,8921	0,9029	0,7665
MAPE mean absolute percentage error	15,8116	15,0804	22,3921
MAE mean absolute error	1848,8457	1767,1428	2581,1710
RMSE root mean square error	2531,7655	2442,2178	3227,7728

We observe that we have obtained a mean percentage error of almost 15% and an accuracy of 85% for a tolerance of 30%. This means that for our 81 training sets we have 69 predicted outputs that are inside the tolerance limit and thus we can consider them as "right". When we consider a tolerance of 10%, our accuracy is only 47%.

The Pearson R value of 0.9 indicates that we have a direct linear relationship between desired and predicted outputs, and this relationship is very strong. This means that our neural network succeeded to identify and learn the patterns after our net sales values evolves, and the results are, in our opinion, very good.

Our neural system is able to predict the normal evolution that the chosen accounting indicator, net sales value, should have on the future, based on the actual and past values. When the effective result will be too far from the predicted value (too far meaning, in fact, the tolerance limit of 30%) there are big chances (more precisely 85%) that we have an anomalous value, as a result of random factors, and the manager should examine more carefully this potential problem.

6 Conclusions

We built an accounting neural network that will predict future net sales values, based on the past values of a set of indicators. We have trained the neural networks with a small company's accounting data then we tested the model with some statistical indexes. The results we have obtained are considered good, because our system is able to predict, with an acceptable error tolerance, which it should be company's monthly net sales value, based on the patterns this indicator evolved on the past.

With such a tool, an accountant is able to compare the results that his company obtained with the predicted one, based on a normal evolution, to quickly identify the differences, their sign (increase or decrease) and to search for the causes. The intelligent system can work as a preventive agent, capable to signal any dangerous evolution in company's accounting, a business computerized guard.

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