A Conexionist Intelligent System for Accounting

Florin APARASCHIVEI
Faculty of Economics and Business Administration, "Al.I.Cuza" University, Iaşi

Neural networks are a computing paradigm developed from artificial intelligence and brain modelling's fields, which lately has become very popular in business. Many researchers are seeing neural networks systems as solutions to business problems like modelling and forecasting, but accounting and audit were also touched by the new technology.
The purpose of this paper is to present the ability of an artificial neural networks model to forecast and recognize patterns while analyzing 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: *accounting, neural networks, predictions, time-series, hybrid intelligent systems.*

Introduction

A neural network is a computerized structure inspired by the observation of natural networks that human neurons made into human brain. Although in economic area most of the studies about artificial neural networks aimed to financial applications that predict stock price evolution, accounting and audit also benefited from such researches.
Auditors found on neural network systems the ideal tool that will guide and ease their job on a growing electronic business environment. Regardless we talk about identifying material errors, clues on possible management frauds or judging the going concern, by using a conexionist system they successfully combine their expertise and experience with the new technology abilities on manipulating large amount of data and extract the essence behind them.

Technical issues

An artificial neural network consists of a number of artificial neurons, which are the elementary processing units, together connected. Neurons connections imitate high learning ability of brain by pattern discovery from examples. On 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.
An artificial neuron receives a number of input signals, representing information from different external sources (like sensors) or signals from others artificial neurons. These inputs are then adjusted with the weights, corresponding to the influence that each input will have in the final result. The weighted inputs are computed and transformed, with an activation function, in an output signal, which is passed forward to the next layer of neurons, or, if the neuron is in the last layer, becomes neural network's output.
Once trained, the network it is capable to correctly classify each new input structure in a resembling category, in the way that they presents 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 network is their adaptability: they are capable to learn from the examples presented to them, often capturing quite subtle relationships between data, that are overlooked 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.

Previous research

A look into literature about neural network applications in accounting [Wong et all, 2000] revels that there is some research in the field, but still remains a huge potential.

We can, however, 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, 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 behavioural 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 [Koskivaara, 1996]. Thus, based on time series built from the monthly balances, an artificial neural network can observe the nonlinear 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.
Other auditors' tasks, like detecting management fraud on financial statements or evaluating a going concern opinion, were also solved with neural networks applications. But in each case, the intelligent system just helps the auditor in its mission, while the auditor is, finally, the one that makes the decision and that will judge the things further, based on his own experience. Thus, he will own an audit tool that will guide him, by showing the possible problems and those areas that require additional investigations.
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 become more and more difficult. Plus, companies want financial reports more often and faster, and, especially, on-line, to answer to demands from many types of interested users [Vasarhelyi et all, 2002]. 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 conexionist studies [Koskivaara, 2004].
But audit was not the only area aimed by neural networks researchers; conexionist 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 can see 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 pursued the way they learn from company's historical data as time series, to be then capable 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.

A neural network model for accounting

To prove the viability of the technology for accounting domain, 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 used a multilayer feed forward neural network, with one hidden layer. We chose hyperbolic tangent function as activation function and back propagation learning algorithm, with generalized delta rule for speed up the training. The entire neural network was built with our own software application.

We chose 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's financial stability.

We must 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 conceived 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[1], 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[2];
- 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, which is 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 scaled 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, meaning a 15:14:1 configuration. 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.

---
[1] http://www.bnr.ro

[2] http://www.insse.ro

Table 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 abnormal value, as a result of random factors, and the manager should examine more carefully this potential problem.

Improvement possibilities for the neural systems

The neural network technology has, however, some limits, that have to be well known and then outrun. Determining neural network configuration, such as the number of hidden layers and the number of neurons per layer, is not an easy task, because it depends on the solving problem characteristics and it is an empirical task. The developer which establish the neural network architecture has to be familiar with the technology, must have a long experience in the field and has to run a large number of tests, based on a pattern borrowed from the genetic algorithms technology: he starts with many possible configurations, he runs a limited number of training cycles and he keeps only those configurations which achieves best results, with minimal time effort.

Another possible problem comes from the fact that the interpretation of neural network's results are difficult, because it's inside learning mechanism, except some mathematical analyses that can be done from outside, it is not yet fully understood by specialists. Because of that, using only a neural network in a real application can bring some problems, especially by the lack of transparency, people couldn't realize network's reasoning path. For this reason, we consider that more studies are needed about how to extract some kind of knowledge (like production rules) from the neural network, which can be, forward, used in an explanation module.

Not for the last, in modern companies, informatization means no more building many independent applications, which will solve the problems for a group of users or a department. The actual keyword is integration, or the existence of a single complex application, with many linked modules, that will solve all the company's problems. In this case, a neural network application has to be integrated in the accounting application, working as a support module for the accounting manager.

Our tests aimed the improvement of our neural network application performance by adding a genetic algorithms module. In this way, we obtained a neuro-genetic hybrid intelligent system. With such a system, the user will define the solving problem, will settle the input variables and will configure some

parameters, then will wait while the application manages to configure and train the neural network.
By configuring the neural network with a genetic algorithms module for our precedent problem, we obtained a configuration with two hidden layers, with 14 neurons on the first hidden layer and 5 on the second, meaning a 15:14:5:1 configuration. This configuration achieved the lowest error rate after 100 back propagation learning cycles, and it is the result of evaluating 1000 generations of artificial genetic chromosomes.
The new neural network, genetically configured, was then fully trained with a similar method as previous, and the error rate of 0.1 was reached after 6412 cycles. The results that our new network has obtained after the testing phase are presented in table 2.

Table 2 Performance indexes for the new neural network

Indicator	All	Train	Test
Records	90	81	9
Accuracy (10%)	0,5111	0,5308	0,3333
Accuracy (30%)	0,8777	0,9012	0,6666
Pearson R	0,8935	0,9104	0,6722
MAPE mean absolute percentage error	14,3994	13,6997	20,6968
MAE mean absolute error	1736,4521	1616,3846	2817,0600
RMSE root mean square error	2513,4747	2352,1282	3658,2768

By comparing these values with those presented in table 1, we conclude hat the results are considerable better. The neural network configured with genetic algorithms achieved a better accuracy, both for 10% tolerance and for 30% tolerance, and a lower mean percentage error. This means that our neural network is better trained and has more powerful predictive abilities.
At this advantage we can add the fact that we succeeded to automate an important stage in the process of the development an accounting intelligent system, stage that otherwise requires an artificial intelligence specialists. In this way, any user can easily benefit from the predictive abilities of neural networks, without much domain knowledge.

Conclusions

We have successfully built an accounting neural network that will predict future net sales values. The results we 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. When we added a genetic algorithms module, the results were even better, and the configuration phase was automated.
With such a tool, an accountant is able to compare the results that his company obtained with the predicted ones, 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. The accountant must only know how to use it, to understand its possibilities and limits, to translate its results and to be able to take the suiting measures.

References:

1. Andone, I., (2002), *Sisteme inteligente hibride: Teorie, studii de caz pentru aplicaţii economice, ghidul dezvoltatorului*, Editura Economică, Bucureşti.
2. Bodea, C., (2002), *Inteligenţă artificială: calcul neuronal*, Editura ASE, Bucureşti.
3. Koskivaara, E., (2004), *Artificial Neural Networks in Auditing: State of the Art*, The IFCAI Journal of Audit Practice, no 1-4, pp. 12-33.
4. Koskivaara, E., (1996), *Artificial Neural Network Models for Predicting Paterns in Auditing Monthly Balances*, TUCS Technical Report no 67.
5. Pedersen, P.E., (1997), *Validating a Neu-*

ral Network Application: The Case of Financial Diagnosis, Computers in Human Behavior, no 13-4, pp. 505-515.
6. Song, Y.H., Johns, A., Aggarwal, R., (1996), *Computational Intelligence Applications to Power Systems*, Science Press & Kluwer Academic Publishers, Beijing.
7. Vasarhelyi, M., Kogan, A., Alles, M., (2002), *Would Continuous Auditing Have Prevented the Enron Mess?*, CPA Journal, July.
8. Wong, B. K., Lai V. S., Lam, J., (2000), *A bibliography of neural network business applications research: 1994-1998*, Computers and Operations Research, no 27-11, pp. 1045-1076.
9. Zha, X.F., (2007), *Artificial Intelligence and Integrated Intelligent Information Systems: Emerging Technologies and Applications*, Idea Group Publishing, London.
10. http://www.insse.ro, Institutul Naţional de Statistică al României.
11. http://www.bnr.ro, Banca Naţională a României.