Neural Networks in Bank Insolvency Prediction

Qeethara Kadhim Al-Shayea†, Ghaleb A. El-Refae††, and Shurouq Fathi El-Itter†††,

†and ††Al-Zaytoonah University of Jordan, Faculty of Economics and Administrative Sciences, Amman – Jordan
†††Applied Science University in Jordan, Amman -Jordan

Summary
The current paper aims to predict bank insolvency before the bankruptcy using neural networks, to enable all parties to take remedial action. Artificial neural networks are widely used in finance and insurance problems. Artificial neural networks are used to predict the insolvency. The back propagation network and the Kohonen self-organizing map (SOM) are used as the representative types for supervised and unsupervised artificial neural networks respectively. The results of applying the artificial neural networks methodology to predict financial distress based upon selected financial ratios show abilities of the network to learn the patterns corresponding to financial distress of the bank. In all cases, the percent correctly classified in the simulation sample by the feed-forward back propagation network is above 92 percent. After simulate the SOM network the percent correctly classified is above 94 percent. In spite of the limited data used in this study, artificial neural networks show significant signs for providing early warning signals and solvency monitoring. In addition, it is obvious from the results that SOM gives better results than feed-forward back propagation network.
Key words:
Artificial Neural Networks, Bankruptcy prediction, SOM, and Financial Distress Analysis.

1. Introduction

Bankruptcy prediction has been an important and widely studied topic. The prediction of the likelihood of failure of a company given a number of financial measures, how soon an “ill” business can be identified, possibility of identifying the factors that put a business at risk — these are of main interest in bank lending [1].
Bankruptcy prediction models are very significant for business sustainability. Researchers are working hard to improve the bankruptcy prediction process by using linear and non-linear techniques. Their research and analysis has become almost a field of science [2]. The forecast of bankruptcies belong to classification problems. With input variables, generally financial ratios data on a bank, we try to find out in which category the bank enters, bankrupt or not bankrupt.
Beaver [3], Altman [4], Williams and Goodman [5], Sinkey [6], and Altman, Haldeman, and Narayanan [7] have used discriminant analysis to solve bankruptcy prediction problem.
Recently researchers have used neural networks as a bankruptcy classification models. Artificial neural networks showed accurate results as discriminant analysis to early detect bank failures.
Brockett, Cooper, Golden and Pitaktong [8] introduced a neural network artificial intelligence model as an early warning system for predicting insurer insolvency. In order to investigate a firm's propensity toward insolvency, a feed-forward back propagation methodology is applied to financial data two years prior to insolvency for a sample of U.S. property-liability insurers that became insolvent in 1991 or 1992 and a size-matched sample of solvent insurers.
Kaski, Sinkkonen, and Peltonen [2] introduced a method for deriving a metric, locally based on the Fisher information matrix, into the data space. A self-organizing map (SOM) is computed in the new metric to explore financial statements of enterprises. The metric measures local distances in terms of changes in the distribution of an auxiliary random variable that reflects what is important in the data.
Peltonena, Klami and Kaski [9] reviewed the theory, introduced better approximations to the distances, and showed how to apply them in two different kinds of unsupervised methods: prototype-based and pair-wise distance based.
Kim and Kang [10] proposed an ensemble with neural network for improving the performance of traditional neural networks on bankruptcy prediction tasks.
Pramodh and Ravi [11] proposed and implemented a variant for Baek and Cho’s [12] neural network and named it Modified Great Deluge Algorithm based Auto Associative Neural Network (MGDAAANN), wherein a metaheuristic is used to train the auto associative neural network.

2. Artificial Neural Networks

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

Manuscript received May 5, 2010
Manuscript revised May 20, 2010

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). Fig. 1 represents the typical neural network. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

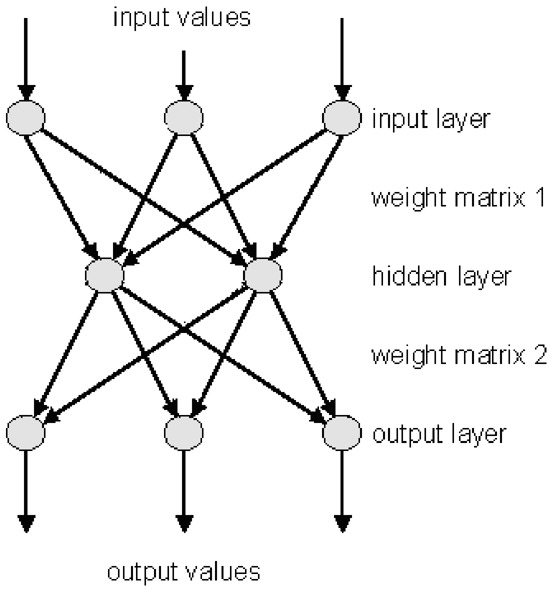

Fig. 1 A typical neural network

For the researcher and the financial analyst, the main advantage of ANNs is that there is no need to specify the functional relation between variables. Since they are connectionist-learning machines, the knowledge is directly imbedded in a set of weights through the linking arcs among the processing nodes. In order to train a neural network properly one needs a large set of representative 'good quality' examples. In the case of bankruptcy problems, the researcher should be cautious when drawing conclusions from neural networks trained with only one or two hundred cases, as observed in most previous studies [13].

Based on the way they learn, all artificial neural networks are divided into two learning categories: supervised and unsupervised. In supervised learning, the network is trained by providing it with input and output patterns. During this phase, the neural network is able to adjust the connection weights to match its output with the actual output in an iterative process until a desirable result is reached. An ANN of the unsupervised learning type, such as the self-organizing map, the neural network is provided only with inputs, there are no known answers. The network must develop its own representation of the input stimuli by calculating the acceptable connection weights. That is self-organization by clustering the input data and find features inherent to the problem.

2.1 Feed-Forward Back Propagation Neural Network

Feed-forward neural networks are widely and successfully used models for forecasting and problem solving. A typical feed-forward back propagation neural network consists of three layers: the input layer, a hidden layer, and the output layer. A feed-forward fully connected network is trained in supervised manner.

It allows signals to travel one-way only; from source to destination; there is no feedback. The hidden neurons are able to learn the pattern in data during the training phase and mapping the relationship between input and output pairs. Each neuron in the hidden layer uses a transfer function to process data it receives from input layer and then transfers the processed information to the output neurons for further processing using a transfer function in each neuron

The output of the hidden layer can be represented by

$$YNx1 = f(WNxM\ XM,1 + bN,1) \quad (1)$$

where Y is a vector containing the output from each of the N neurons in a given layer, W is a matrix containing the weights for each of the M inputs for all N neurons, X is a vector containing the inputs, b is a vector containing the biases and f(·) is the activation function [14].

2.2 Self-Organizing Map

The SOM is an algorithm used to visualize and interpret large high-dimensional data sets. The SOM is an unsupervised learning net that usually maps n-dimensional input data to one or two-dimensional output map keeping the original topological relations. Typical applications are visualization of process states or financial results by representing the central dependencies within the data on the map. The map consists of a regular grid of processing units, "neurons". A model of some multidimensional observation, eventually a vector consisting of features, is associated with each neuron. The map attempts to represent all the available observations with optimal accuracy using a restricted set of models. At the same time the models become ordered on the grid so that similar models are close to each other and dissimilar models far from each other [15]. In a two-dimensional SOM, the neurons are arranged into the nodes of a lattice that is shown in the Fig. 2.

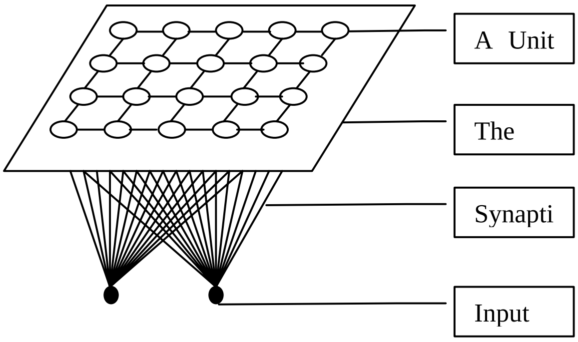

Fig. 2 Graphical representation of SOM

The lattice is usually one or two-dimensional. Higher dimensional maps are possible but not as common because it is limited by the visualization ability and also the applications of this kind of network. Moreover, this kind of network is designed mainly based on the inspiration of an interesting feature of the human brain's cerebral cortex. The training process will make the neurons becomes selectively tuned to various input patterns or classes of input patterns, known as stimuli. A distinct feature of human brain inspires the development of SOMs as a neural model. This is because the cerebral cortex in the human brain maps different sensory inputs onto corresponding areas of the cerebral cortex in an orderly fashion [16].

The self organizing map consists of one layer of neurons organized in one or two dimensional arrays. Each neuron has a number of connections equal to the number of inputs used in classification. Once the topology of the net is selected, the inputs of the SOM map are normalized. The training phase starts: each neuron will have one random weight for each input variable. By using the method of competitive learning with "winner take all", the neuron with weights closest to the input data is identified as the winning neuron. Then all the weights of the neighborhood neurons are adjusted. As training proceeds it looks at the winning rate of each neuron. When it sees any neuron dominating, it uses the "conscience" algorithm and allows other neurons to win.

The search and organization of the representation vectors on the map can be described with the following regressive equation, where t =1, 2, 3, … is the step index, x is a observation, mi(t) is the vector representation on node i at step t, c is the winner index, and hc(x),i is the neighborhood updating function [15].

$$\forall i, \| x - m_c(t) \| \leq \| x - m_i(t) \| \qquad (2)$$

$$\vec{m}_i(t+1) = \vec{m}_i(t) + h_{c(x),i} \cdot (\vec{x} - \vec{m}_i(t)) \qquad (3)$$

3. Experimental Results

3.1 Data Analysis

Spanish banking industry suffered the worst crisis during 1977-1985 resulting in total cost 12 billion dollars. The Spanish bank's data is obtained from Olmeda and Fernandez [17]. This dataset contains 66 banks where 37 of them went bankrupt and the rest solvent. Table 1 presents the financial ratios which are considered as predictor variables.

Table 1: Predictor variable of datasets used in the study

Spanish banks data	
S. No.	Predictor Variable Name
1	Current assets/total assets
2	Current assets-cash/total assets
3	Current assets/loans
4	Reserves/loans
5	Net income/total assets
6	Net income/total equity capital
7	Net income/loans
8	Cost of sales/sales
9	Cash flow/loans

The first three predictor variables are liquidity ratios, whilst the fourth measures the self-financing capacity of the bank. Ratios five, six and seven relate profit to various items on the Balance Sheet. Ratio eight relates the cost of sales to sales and ratio nine relates the Cash Flow of the bank to the debts.

3.2 Results Analysis

A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons was created using the neural network toolbox from Matlab 7.9.

Such net can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer as shown in fig. 3.

The network was trained with Levenberg-Marquardt back propagation algorithm. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples.

The results of applying the artificial neural networks methodology to predict financial distress based upon selected financial ratios showed very good abilities of the network to learn the patterns corresponding to financial distress of the bank. The network was simulated in the testing set (i.e. cases the network has not seen before). The results were very good; the network was able to classify 92% of the cases in the testing set.

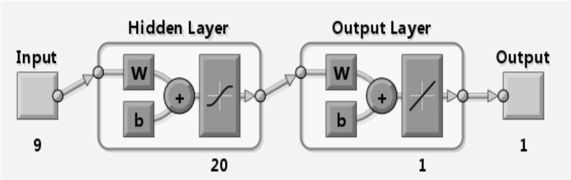

Fig. 3 Feed-Forward back propagation network

The mean squared error (MSE) is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Best validation performance is 0.09008 at epoch 7 as shown in fig. 4.

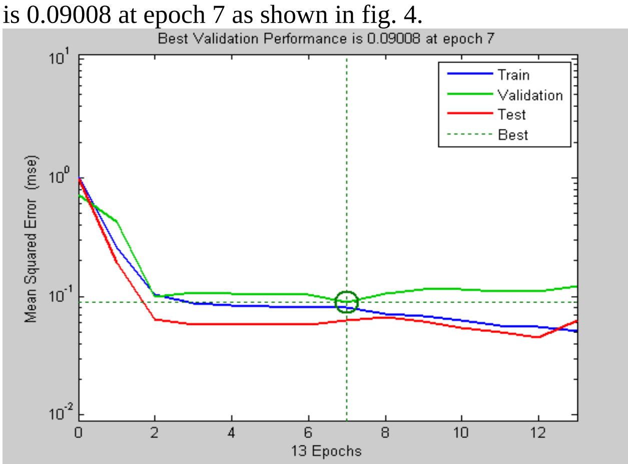

Fig. 4

Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. Fig. 5 shows the result of regression for training, validation, testing and all of them together.

The percent correctly classified in the simulation sample by the feed-forward back propagation network is above 92 percent..

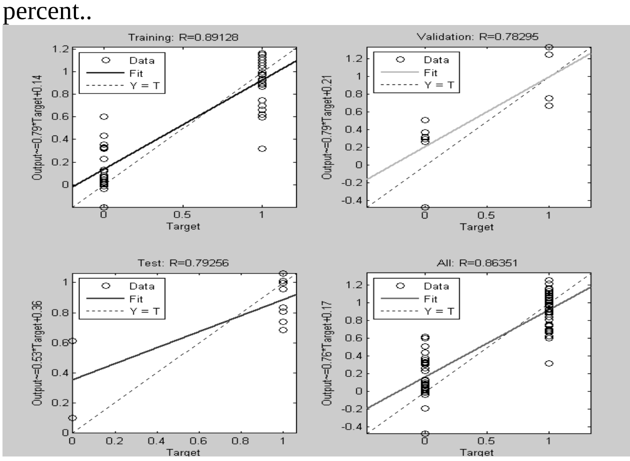

Fig. 5 The regression results

The application for SOM neural network is clustering data into solvency and insolvency bank. This process involves grouping data by similarity. The size of the two-dimensional map is set to 6. This map represents one side of a two-dimensional grid. The total number of neurons is 36.

Fig. 6 shows how many of the training data are associated with each of the neurons (cluster centers). The topology is a 6-by-6 grid, so there are 36 neurons. The training runs for the maximum number of epochs, which is 200. The maximum number of hits associated with any neuron is 7. Thus, there are 7 input vectors in that cluster as shown in fig. 6

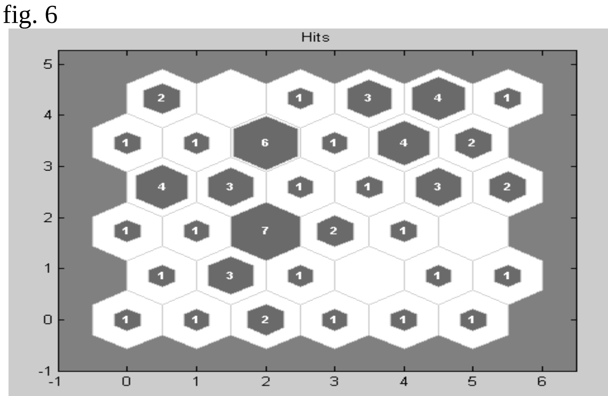

Fig. 6

Because this SOM has a two-dimensional topology, we can visualize in two dimensions the relationships among the four-dimensional cluster centers. In Fig. 7 the small hexagons represent the neurons. The red lines connect neighboring neurons. The dashes in the regions containing the lines indicate the distances between neurons. The darker colors represent larger distances, and the lighter colors represent smaller distances. A dark segment is in the lower-right region. The SOM network appears to have clustered the banks into two distinct groups. The neighbor patches are colored from black to white to show how close each neuron's weight vector is to its neighbors.

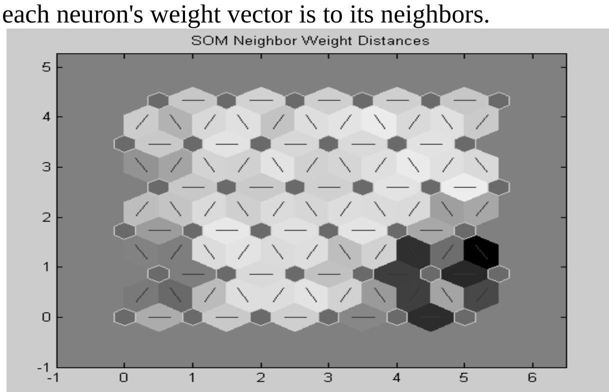

Fig. 7 SOM neighbour weight distances

A weight plane for each nine ratio element of the input vector is shown in fig. 8. They are visualizations of the weights that connect each input to each of the neurons. (darker colors represent larger weights.) The first three predictor variables (Input 1, input 2 and input 3) are highly correlated because they are very similar. The fifth, sixth and seventh predicator variable are very similar too, whilst the fourth, eighth and ninth variable have connections that are very different than those of other inputs.

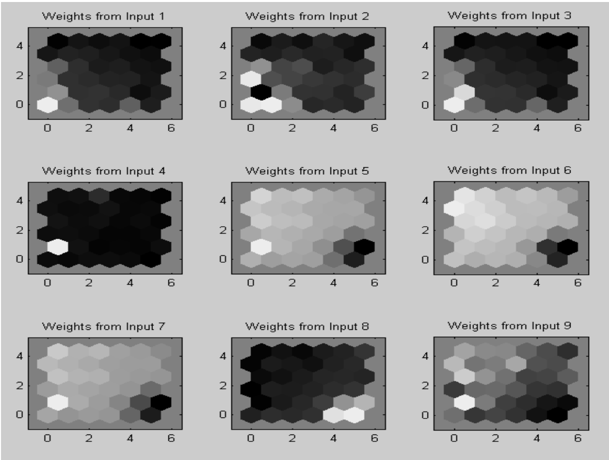

Fig. 8 Weight planes for input elements

Fig. 9 shows the locations of the data points and the weight vectors. Fig 9 indicates that after only 200 iterations of the batch algorithm, the map is well distributed through the input space.

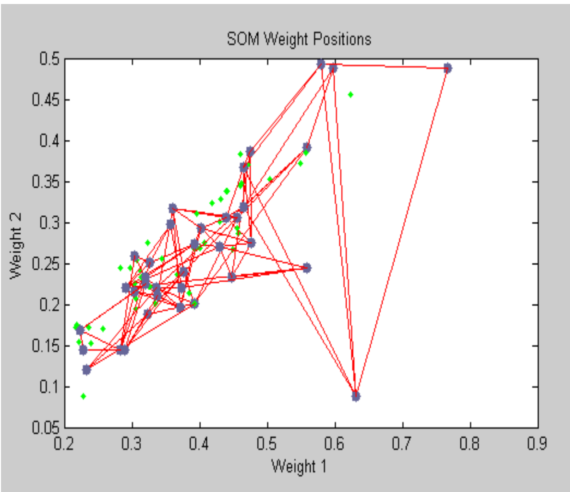

Fig. 9 SOM weight positions

The simulation of the SOM network give the percent correctly classified is above 94 percent.

4. Conclusions

This study aimed to test two neural network models with different learning algorithms: the back propagation feed forward neural network with supervised learning and the self organizing map with unsupervised learning in terms of their ability of bankruptcy prediction. The results of applying the supervised and unsupervised neural networks in classification of financial distress based upon the selected financial variables showed that artificial neural networks are able to learn the patterns corresponding to financial distress of the bank. Even with the limited data used in this study, artificial neural networks showed significant signs for providing early warning signals and solvency monitoring.

References

[1] J Kamruzzaman, R. A. Sarker and R. Begg, Artificial Neural Networks: Applications in Finance and Manufacturing, Idea Group Publishing, 2006.

[2] S. Kaski,J. Sinkkonen and J. Peltonen, Bankruptcy Analysis with Self-Organizing Maps in Learning Metrics, IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. 12, NO. 4, JULY 2001, pp. 936-947.

[3] W. H. Beaver, Financial ratios as predictors of failures. Empirical research in accounting: selected studies, Journal of Accounting Research, 5(Suppl.), pp. 71–102, 1966.

[4] Altman, E. I., Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, Journal of Finance, 23(4): 589-609, 1968.

[5] W. H. Williams and M. L. Goodman, A Statistical Grouping of Corporations by Their Financial Characteristics, Journal of Financial and Quantitative Analysis, 6(4): 1095-1104, 1971.

[6] J. Sinkey, A Multivariate Statistical Analysis of the Characteristics of Problem Banks, Journal of Finance, 30(1): 21-36, 1975.

[7] E. I. Altman, R. G. Haldeman, and P. Narayanan, ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations, Journal of Banking and Finance, 1(1): 29-54, 1977.

[8] P. L. Brockett, W. W. Cooper, L. L. Golden and U. Pitaktong, A Neural Network Method for Obtaining an Early Warning of Insurer Insolvency, The Journal of Risk and Insurance, Vol. 61, No. 3, 1994, PP. 402-424.

[9] J. Peltonena, A. Klami and S. Kaski, Improved learning of Riemannian metrics for exploratory analysis, Neural Networks, Vol. 17, No. 8-9, 2004, pp. 1087-1100.

[10] M. Kim and D. Kang, Ensemble with neural networks for bankruptcy prediction, Expert Systems with Applications, Vol. 37 Issue 4, April, 2010, pp. 3373-3379.

[11] C. Pramodh and V. Ravi, Modified Great Deluge Algorithm based Auto Associative Neural Network for Bankruptcy

Prediction in Banks, International Journal of Computational Intelligence Research, Vol.3, No.4, 2007, pp. 363–370.
[12] J. Baek and S. Cho, Bankruptcy Prediction for credit Risk Using an Auto- Associative Neural Network in Korean Firms, The proceedings of the CIFEr Hong Kong, 2003.
[13] J. C. Neves and A. Vieira, Improving Bankruptcy Prediction with Hidden Layer Learning Vector Quantization, European Accounting Review, Vol. 15, No. 2, 253–271, 2006.
[14] J. A. Freeman and D. M. Skapura, Neural networks: algorithms, applications and programming techniques, Addison Wesley Longman, 1991.
[15] T. Kohonen, The Self-Organizing Map (SOM), Web page available at http://www.cis.hut.fi/nnrc/som.html.
[16] S. Haykin, "Neural Networks: A Comprehensive Foundation", Prentice Hall, New Jersey, 2nd Edition, 1999.
[17] I. Olmeda and E. Ferandez, "Hybrid Classifiers for Financial Multicriteria Decision Making: The Case of Bankruptcy Prediction", Computational Economics, pp. 317-335, 1997.

††Qeethara Kadhim Abdul Rahman Al-Shayea, has received Ph. D. in Computer Science, Computer Science Department, University of Technology, Iraq, 2005. She received her M.Sc. degree in Computer Science, Computer Science Department from University of Technology, Iraq, 2000. She has received her High Diploma degree in information Security from Computer Science Department, University of Technology, Iraq, 1997. She has received B. Sc. Degree in Computer Science Department from University of Technology, Iraq, 1992. She joined in September (2001-2006), Computer Science Department, University of Technology, Iraq as assistant professor. She joined in September 2006, Department of Management Information Systems Faculty of Economics & Administrative Sciences Al-Zaytoonah University of Jordan as assistant professor. She is interested in Artificial intelligent, image processing, computer vision, coding theory and information security.

Ghaleb A. El-Refae has a Ph. D. and M.A in Financial Economics form USA, M. Sc and B. Sc in Accounting. He is a professor and Dean of Faculty of Economics and Administrative Sciences at Al-Zaytoonah University of Jordan, Amman – Jordan. His research interest is in the application of IT and IS in Business and Economics.

Shorouq Fathi Eletter has master degree in Applied Mathematics from USA, MBA from Al-Zaytoonah University of Jordan and Bachelor degree in Electrical Engineering from Jordan University of Science and Technology (JUST), and she is Lecturer at Applied Science University in Jordan. Her research interest is in the application of Artificial Intelligent in Business Firms.