A Heuristic Model for Predicting Bankruptcy

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ABSTRACT

Bankruptcy prediction is one of the major business classification problems. The main purpose of this study is to investigate Kohonen self-organizing feature map in term of performance accuracy in the area of bankruptcy prediction. A sample of 108 firms listed in Tehran Stock Exchange is used for the study. Our results confirm that Kohonen network is a robust model for predicting bankruptcy in today's fast changing business environment

Keywords:

Bankruptcy, Prediction, Neural Network, Back-propagation, Kohonen network

1. Introduction

Artificial neural networks (ANNs) as alternative classification technologies to statistical modeling have been frequently used in business largely due to improved prediction accuracy. In particular, the back-propagation (BP) network, one of the supervised networks, has been the most popular neural network model used for bankruptcy prediction during the last decade (O'Leary, 1998; Tam & Kiang, 1992).

However, two major concerns are associated with the supervised neural network approach, including BP, in bankruptcy prediction: (1) most supervised studies were performed in the retrospective manner in that they relied mostly on the analysis of historical data (see Adam and sharda, 1990; Udo, 1993; Joe et al. 1998) and (2) improved accuracy is an elusive measurement when an underlying business environment changes rapidly.

Machine learning is a form of artificial intelligence that possesses the ability to learn from data. This usually comprises of two main components: a parameterized and learnable model (e.g. neural network (NN)), and its corresponding learning algorithm (Liew et.al, 2015). During the training process, the output results are continuously compared with the desired data. An appropriate learning rule uses the error between the actual output and the target data to adjust the connection weights so as to obtain, after a number of iterations, the closest match between the target output and the actual output (Karray and de Silva, 2004, P. 230). Often this target output is available only in the retrospective way, which is the major limitation of supervised training. For the same reason, the supervised approach may also be unable to provide a real-time response to a problem. Because of the fast changing nature of information technologies today, it is difficult to assume that the improved accuracy of a study is easily transferable and applicable to future studies (Lee, 2005).

An important factor in the training of neural networks is the quality of the training data.(Rosin and Fierens, 1998). In today's fast changing business environment, we need to develop a method that can detect the changing pattern of a firm in a more timely fashion, rather than retrospectively.(Lee, 2005) Thus one needs timely intervention in the case of bankruptcy prediction in order to save more resources and prevent the deterioration of a firm.

Artificial neural networks are often classified into two distinctive training types, supervised or unsupervised (Lee, 2005). Supervised learning approaches employ class information, which is known beforehand (Yoon et.al, 2013). As mentioned earlier, supervised training requires training pairs, input vectors and corresponding target vectors. In case of bankruptcy prediction tasks, the target vector is 'whether or not a firm has failed' which must be embedded in the supervised training process. To launch a supervised analysis, researchers may have to wait until the target information of 'whether or not a firm has failed' is collected. Thus, this supervised approach is, indeed, performed in the retrospective mode (Lee, 2005). On the other hand, in unsupervised learning, a principal component analysis or an independent component analysis considers correlations between variables or properties and alters the original representation to extract features without a significant loss of information (Yoon et.al, 2013).

In some situations, especially in today's fast-changing, real-time-based business environment that demands prompt responses, such extra information may not be readily available for training. In such circumstances, unsupervised neural networks might be more appropriate technologies to be use. Unlike supervised networks, unsupervised neural networks need only input vectors for training (Lee, 2005).

Training algorithm (developed by Kohonen, 1982,1997), which is applied in unsupervised networks receives input vectors and classifies them into intended categories. As it is mentioned above we need urgently on time and accurate data for unsupervised Kohonen networks. In this research we seek to review application of neural network in predicting bankruptcy.

Other parts of this study are as follows: in part two, research literature relating to bankruptcy would be offered. In part three, introduction of utilized model and methodology of the research would be explained in details. In part four, the results of model would be offered and in last part, final conclusions of the study would be explained.

2. Literature Review

In this section, common research literature between bankruptcy prediction and artificial neural networks would be reviewed. The history of utilizing neural network in studies relating to bankruptcy prediction dated back to two previous decades, when Adam and Sharda (1990) used artificial neural networks for bankruptcy prediction for the first time and found this model as a suitable method.

In Udo (1993) study on predicting bankruptcy, multi-layered Perceptron network and multiple regressions were compared and obtained results indicated the better performance of multi-layered perceptron network to the multiple regression. Also in Joe et al. (1997) study, similar results were obtained. By examining Korean firms from 1991 to 1993, they compared discriminant analysis models, case-based forecasting and multi-layered perceptron network. Their results showed better performance of multi-layered perceptron network to the other statistical models.

Based on data obtained from 220 firms and utilizing multi-layered perceptron neural networks, Jang et al. offered a model for bankruptcy prediction. By adding current assets/ current liability to Altman's (1968) proposed variables and also considering the direct and indirect effect of inputs on neural networks' outputs used, they examined the considered population. Our findings show that total accuracy of neural networks' prediction is higher than logistic regression. From the similar comparison between neural networks and Logit model conducted for bankruptcy prediction in Fletcher and Goss's (1993) study , the higher accuracy was found in neural network than its competitors.

Also in 2005, it was Lee et al. (2005) who compared supervised and unsupervised learning algorithms in neural network, in order to predict the Bankruptcy. They compared the back propagation algorithm as a representative for supervised algorithms with the algorithm of Kohonen as a representative for unsupervised algorithms in neural network. In this study, Altman's (1968) variables have been applied. In current study, the number of utilized samples is 113 pairs of bankrupt and healthy companies, which were chosen among South Korea's stock exchanges. They concluded that back propagation algorithm has better performance in comparison with Kohonen algorithm.

Tseng and Hu (2010) have compared 4 methods for bankruptcy prediction, that (among utilized models) the name of MLP neural networks trained by back propagation algorithm and RBF[1] networks is dominant. Among utilized models, RBF network has higher accuracy than the others.

Chen et al. (2013) use self-organizing map (SOM) to analyze and visualize the financial situation of companies during several years using a two-step clustering process. French companies' data (2003 - 2006) were used during their study. They chose 29 financial ratios as research's input data. The experimental results of Chen et al. (2013) research demonstrate the promising functionality of SOM for the course of bankruptcy clustering and visualization.

In order to improve temporal stability of accuracy in a financial failure model, Jardin and Severin (2012) used Kohonen map.

France's database (Diane) was used to collect data. To control size & sector effects, the companies working on similar industries (retail) with revenues less than 750000 € were chosen. Altman's variables (1968) were applied as input data. Results from Jardin and Sourin's (2012) show that the generalization error achieved by a map remains more stable over time than by conventional methods applied for designing failure models such as discriminant analysis, logistic regression, Cox's method, as well as neural networks.

3. Methodology

The definition for bankruptcy that provided in present research is the same definition in 141 article of Iranian commercial law for bankruptcy so that we regard firms with accumulated losses more than half of capital as a bankrupt company.

Our Applied population consists of firms present in Tehran Stock Exchange during period of 2002-2012 were included in 141 article of Iranian commercial law for bankruptcy. Therefore, those firms that enjoyed the following conditions were used for neural network training:

1) Those firms who are included in 141 article of Iranian commercial law should have been accepted by Tehran Stock Exchange at least since 1999 (because data for two years before bankruptcy would be used)
2) Those firms selected as bankrupt in current study were not of financial brokerage companies.
3) They should be covered by Trade act of 141 during period of 2001 till 20١١ (they should have accumulated losses greater than half of capital).

During examinations accomplished by researchers of this study, 108 firms are included in the act during this period; because the number of firms is important to train neural network. Accordingly it has been tried to apply most available data for neural networks training as much as possible. However, the ratios of some firms were considerably different from the other samples in the study and it would lead to decrement in neural network performance. Hence some of bankrupt firms would be eliminated from the study thereby, the number of bankrupt firms in this study reached to 96.

Also, in an industry that every bankrupt company is active, a healthy company with nearest amount of assets to that company, was selected. It is done for this reason that a neural network with training data from healthy firms would have ability to distinguish between these firms and bankrupt companies. Healthy firms are selected among those firms that bankrupt pairs were present at Tehran Stock Exchange during bankrupt year. Due to having small size of industry in some of industries, there was no option to select the healthy pair for bankrupt firms, hence it was tried to select among healthy firms in upstream and downstream industry, and in the case of lack of these companies, a healthy company with the same assets from a non-similar industry would be selected. It can be considered as one of study limitations.

For Kohonen network use in order to predict bankruptcy, it is only necessary to define Altman variables (as input for network) and also related group (healthy or bankrupt). However, in multi-layer perceptron network, multi layers should be determined using the trial and error of middle layer and the neuron numbers (that would be present in each layer) so that the ideal neural network would be obtained.

3.1. Research variables

Since financial ratios have long history in predicting bankruptcy, we tried to apply financial ratios for this purpose and also due to special limitations in Altman's proposed variable (1968) (Coats and Fant, 1993; Lacher et al., 1995; Odom and Sharda, 1990; Rahimian et al., 1993; Sharda and Wilson, 1996; Wilson and Sharda, 1994), we considered these variables as input variable. These ratios are including:

(1) Working capital/total assets;
(2) retained earnings/total assets;
(3) earnings before interest and taxes/total assets;
(4) exchange value equity/book value of total debt;
(5) sales/total assets.

Utilized data is financial ratios of two years before bankruptcy in bankrupt firms and selecting healthy pairs.

3.2. Self- Organizing Map (Kohonen)

The definition of accuracy in this study refers to the amount of error in prediction.

A one-dimensional KN with input $y = (y_1, y_2, \ldots, y_n)^T \in R^n$ and output $z = (z_1, z_2, \ldots, z_m)^T \in R^m$ is shown in Equ.1. For the ith output neuron, z_i is given by:

Equation 1

$$z_i = \sum_{j=1}^{n} w_{ij} y_i = w_i^T y$$

Where w_{ij} are the ijth weigh, and $w_i = (w_{i1}, w_{i2}, \ldots, w_{in})^T$, the ith weigh vector. To train the KN, the winning output neuron is determined first by comparing the similarity between the input y and the weight vectors$\{w_i, i = 1, \ldots, m\}$. The weight vector of the winning output neuron is then updated. A common measure of similarity between two vectors is the Euclidean distance (Kohonen, 1988),

Equation 2

$$\Pi_i = \|y - w_i\|^2,$$

Where Π_i is intensity. The weight vectors of the KN are updated as follows (Kohonen, 1988):

Equation 3

$$w_i^{new} = w_i^{old} + \eta\,(y - w_i^{old})\delta_i, \quad i = 1, \ldots, m,$$

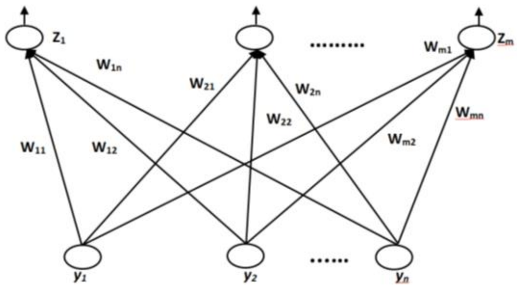
Where$\eta, \eta > 0$, is the learning rate, and δ_i is unity for the winning neuron that has the smallest Π_i, but is zero otherwise. The learning algorithm given by Eq.3 reduces to

Equation 4

$$w_i^{new} = (1 - \eta) w_i^{old} + \eta y$$

$$w_j^{new} = w_j^{old} \quad , j = 1, \ldots, m, \qquad j \neq i$$

The convergence of the learning algorithm given by Eq. (4) is given in Ritter and Schulten (1988). For the KN experiment, the Matlab Neural Network package was used.



The mean square error (MSE) function is used for the error function. It has been a popular choice in the past literature for theoretical considerations and provides a consistent error function (Berardi, 1988; Tam and Kiang, 1992).

4. Results

In this model, details pertaining to the way of prediction are presented in table.1. According to table.1, Kohonen neural network could have classified 85.4% of healthy firms and 95.8% of bankrupt ones properly. For this model, error type 1 is 14.6% and error type 2 is 4.2% as well. Total results indicate that the performance of Kohonen network was in such a way that 90.6% of firms in test data have been classified properly.

5. Discussion and Conclusion

This study aims to investigate application of the Kohonen network as non-regulatory neural network in bankruptcy prediction. The test sample for this study is chosen from Tehran Stock Exchange companies. The findings of this study can be summarized as follows: It should be noted data used for training are 108 pairs observations that considered a few. It is because the neural network paradigm is, in essence, a data driven non-parametric approach. Our findings confirm that Kohonen self-organizing could have classified 85.4% of healthy firms and 95.8% of bankrupt ones properly. For this model, error type 1 is 14.6% and error type 2 is 4.2% too. Total results indicate that the performance of Kohonen network was in such a way that 90.6% of firms in test data have been classified properly. It is shown in this study that the Kohonen self-organizing feature map could be used as an alternative classification tool. The realization that such supervised classification techniques cannot provide on-line real time response and that a high accuracy with no-time-relevancy study, often the case of the supervised studies, may provide no additional contribution in reality, gives some weight to the usefulness of the Kohonen unsupervised neural network. We could not pair non-bankrupt firms with bankrupt ones in all of industrial aspects due to the small size of population for accepted firms in Tehran Stock Exchange.

Table.1 The results obtained from testing BP and Kohonen networks

Model	Sum of prediction	Status	The number of correct predictions	The number of correct predictions	The errors type 1 and 2	The percentage of correct predictions	The error type 1 or 2
Kohonen	96	healthy	48	41	7	85.4%	14.6%
		bankrupt	48	46	2	95.8%	4.2%
		total	96	87	9	90.6%	9.4%

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Note:

[1] Radial basis function