Investigation of Listed Companies Credit Risk Assessment Based on Different Learning Schemes of BP Neural Network

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Abstract

Credit risk analysis of enterprise is an important topic in financial field, this paper employs BP neural network to solve this problem. Indexes system of company and three different BP neural networks have been built. The neural networks are trained using financial data from different industry. We use Matlab program and neural network to get the results in seven learning schemes with different training-to-validation data ratios. Experimental results will suggest which neural network model, and under which learning scheme can deliver optimum performance.

Keywords: Credit risk, BP neural network, Learning schemes

1. Introduction

In recent years, with the trend of the economic globalization and volatility of financial market, credit risk management will be the focus in finance. Credit risk is one of the main risks of commercial banks that will affect the banks' ability of sustainable operation.

Credit risk is the risk that obligation will not be repaid on time and in full as expected or contracted, resulting in a financial loss.

Chun feng Wang, Hai hui Wan and Wei Zhang (1999) applied neural network to credit risk assessment for the first time in China. The results demonstrate the effectiveness and robustness of neural network are better than discriminant analysis (Wang, Chun feng, 1999). Zhong zhi Zhang, Lin Fu and Huan wen Tang (2003) researched on neural network and proved that neural network in credit risk assessment with high precision(Zhang, Zhongzhi, 2003).The following study focus on improvement with GA and combination with statistical method for BP neural network. Most of papers aimed at how to improve the model of neural network, however, this paper aim at researching how the different learning schemes to influence the efficiency of neural network. From the angle of input data, we study how to assess the credit risk of listed companies.

2. Data sources and processing

2.1 Sample selection

This phase is a data preparation phase for neural network training and classification. Considering the accessibility of financial data, we choose the listed company as the research object. In this paper, we choose 140 listed companies as sample, including 60 ST companies and 80 non-ST companies. The ST company means special treatment company which has been a loss for two consecutive years. Generally speaking, the ST company with high credit risk for their poor financial situation. Based on above introduction, we define the ST company as the high risk company, the non-ST company as low risk company approximately. Their output value is 0 and 1 separately.

2.2 Evaluating index system selection

On the basis of previous papers, we choose 10 financial indexes as the input of neural network. Those indexes reflected four different abilities. Debt-paying ability: (1) asset-liability ratio=debt/asset (2) current ratio=current assets/current liabilities (3) quick ratio=quick assets/current liabilities. Operating capacity: (4) receivable turnover=sale revenue/average receivables (5) current assets turnover=sale revenue/average current assets (6) the total asset turnover=sale revenue/average total asset. Profitability: (7) sales gross margin=gross sales/total sales (8) rate of return= net profit/ average value of assets. Development capacity: (9) growth rate of profit= increment of profit in this year/profit of last year (10) growth rate of asset=increment of asset in this year/asset of last year.

Through formerly analysis, we found that the 10 quantitative indicators are not comprehensive. Therefore, we add a qualitative-size of asset index in the index system. Evaluating the size of company as one of the input data for neural network.

In order to satisfy the input requirement of neural network, we need to normalize the data of samples and then are used to train neural network. There are many methods of normalization, we use the common maximum and minimum method processing method as follows:

$$x_i^{'} = \frac{x_i - MIN(X)}{MAX(X) - MIN(X)}$$

After processing of the data in this method, the original meaning of data still remain. The value domain of all indexes in (0,1).

3. Building the model of neural network

In this phase we use the back propagation (BP) neural network due to its implementation simplicity and the availability of sufficient dataset.

3.1 Setting the parameter of network

Lots of practice proved that for any complex function, one hidden layer is enough. Considering that we use three layered BP neural network to study the assessment of credit risk. Obviously, the input layer has 11 neurons corresponding to index system in 2.2.The output layer has 1 neuron. The difficult task is to determine the number of neurons in hidden layer and we need to practice and adjust many times for determining the number of neurons. After practicing with Matlab7.0, we choose three suitable numbers, when the number of neurons is 6, the network performance is 0.00999892 seen as Figure1. When the number of neurons is 8, the network performance is 0.00994681 seen as Figure 2. When the number of neurons is 11, the network performance is 0.00993796 seen as Figure 3.

3.2 Setting the parameter of training

Error precision is the minimum error meet the requirement of the training, which is the discrepancy between output and target data. The discrepancy is also in certain degree. Learning coefficient is the adjustment for weight after every training. The bigger the learning coefficient, the bigger the adjustment. Momentum is to adjust the training step, error precision and learning coefficient. The training step is the time of training. Only all the parameter is set reasonably, can we assess credit risk accurately. Through many adjustments, we establish three different BP neural network. The parameter can be seen in Table 1.

We can train the samples after setting up all the parameters. The training will stop until the value meets the target value. If the value did not meet the target value, repeated training will be needed.

The satisfactory model will be saved in database. The output layer has one single neuron, which uses binary output data representation. A simple thresholding scheme is then sufficient for the neural network's single output neuron to divide the companies into two categories. A threshold value of 0.5 is used to distinguish between good credit and bad credit. If the output of the BP neural network is greater than or equal to 0.5, the company is good. Otherwise, it is assigned to the bad company (high credit risk company).

4. Empirical analysis

BP neural networks have been established in 3.3.The importance of empirical analysis is that: under which learning-validation ratio, the neural performance efficiently in assessing the credit risk of listed companies. According to three different BP neural networks, we design seven different learning schemes.

We write the M file with toolbox of neural network in Matlab7.0, corresponding data of samples as the input be imported in the program. There 140 samples, for example, the LS1 with 28 samples as training dataset, the other

112 samples as validation dataset to running the program in M file, we can get the accuracy. All the running result can be seen in Table 2.

We can get conclusion from table 2 that when the training to validation is 40%:60% and the hidden layer with 8 neurons, the accuracy rate is best.

5. Conclusion

This paper research on how different learning scheme influence the capacity of classification for BP neural network. The empirical study proves that when the learning ratio is 40%:60%, the BP neural network performance more efficiently. Therefore, when we use BP neural network to assess the credit risk, the learning ratio should be considered. Too many training samples or too little samples will affect the capacity of classification. The satisfactory ratio must be existed on the condition that the number of validation is decided. We can use this satisfactory ratio to get better results of assessment. There are also some shortcomings in this paper, such as the number of sample is not large enough. The neural network as itself has shortage in explanatory. How to make the neural network performance more efficiently in economic area is a difficult question which need the joint research in terms of economic and artificial intelligence (Wang Li,2005).the combination between quantitative analysis and qualitative is the trend of research.

References

Adnan Khashman. (2010). Neural networks for credit risk evaluation: Investigation of different neural models and learning schemes. *Expert Systems with Applications.*

Chen, Xionghua, Lin Chengde, & Ye Wu. (2002). The assessment of credit ratings for company based on neural network. *Journal of Systems Engineering*, 17, 571-575.

Chih-Fong Tsai, & Wu, Jhen-Wei. (2008). Using neural network ensembles for bankruptcy prediction and credit scoring. *Expert Systems with Applications*, 2639-2649.

Eliana Angelini, Giacomo diTollo & Andrea Roli. (2008). A neural network approach for credit risk evalution. *The Quarterly Review of Economics and Finance*, 48,733-755.

Hu Yong. (2006). The personal credit assessment based on neural network. Master's thesis in Southwestern University of Finance and Economics.

Liu, Guoqing & Wang, Honglei. (2009). The appliciation of GA-BP neural network in credit risk model of bank, 12, 77-80.

Wang Li, Zheng, Zhaorui, & Hao, Jixiu. (2005). The application of BP neural network in assessment of credit risk. *Journal of Taiyuan University of Technology.*

Wang, Chunfeng, Wan, Haihui, & Zhang Wei. (1999). The credit risk assessment of bank based on neural network. *System engineering theory and practice.*

Zhang, Zhongzhi, Fu Lin & Tang Huanwen. (2003). The credit risk model of bank based on neural network. *Mathematics in Economics.*

Table 1. The parameter of BP neural network

Neural network model	ANN-1	ANN-2	ANN-3
Input layer nodes	11	11	11
Hidden layer nodes	6	8	11
Output layer nodes	1	1	1
Learning coefficient	0.01	0.01	0.01
Momentum rate	0.9	0.9	0.9
Maximum allowed iteration	5000	5000	5000

Table 2. The result of assessment

Learning scheme	Learning ratio	BP neural network	Accuracy rate of training	Accuracy rate of validation
LS1	20%:80%	ANN-1	(27/28)96.42%	(85/112)75.89%
	20%:80%	ANN-2	(28/28)100%	(70/112)62.5%
	20%:80%	ANN-3	(27/28)96.42%	(81/112)72.32%
LS2	30%:70%	ANN-1	(40/42)95.24%	(63/98) 64.29%
	30%:70%	ANN-2	(40/42)95.24%	(62/98) 64.27%
	30%:70%	ANN-3	(41/42)97.62%	(65/98) 66.37%
LS3	40%:60%	ANN-1	(54/56)96.43%	(60/84) 71.43%
	40%:60%	ANN-2	**(55/56)98.21%**	**(66/84) 78.57%**
	40%:60%	ANN-3	(55/56)98.21%	(63/84) 75%
LS4	50%:50%	ANN-1	(68/70)97.14%	(52/70)74.26%
	50%:50%	ANN-2	(69/70)98.57%	(50/70)71.43%
	50%:50%	ANN-3	(69/70)98.57%	(53/70)75.71%
LS5	60%:40%	ANN-1	(81/84)96.42%	(42/56) 75%
	60%:40%	ANN-2	(79/84)94.05%	(43/56)76.78
	60%:40%	ANN-3	(78/84)92.86%	(40/56)71.43%
LS6	70%:30%	ANN-1	(93/98)94.9%	(29/42)69.05%
	70%:30%	ANN-2	(93/98)94.90%	(31/42)73.81%
	70%:30%	ANN-3	(91/98)92.86%	(30/42)71.43%
LS7	80%:20%	ANN-1	(107/112)95.54%	(20/28)71.43%
	80%:20%	ANN-2	(108/112)96.43%	(18/28)64.29%
	80%:20%	ANN-3	(108/112)96.43%	(21/28)75%

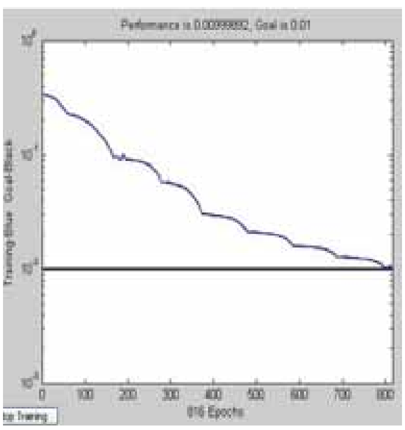

Figure 1.

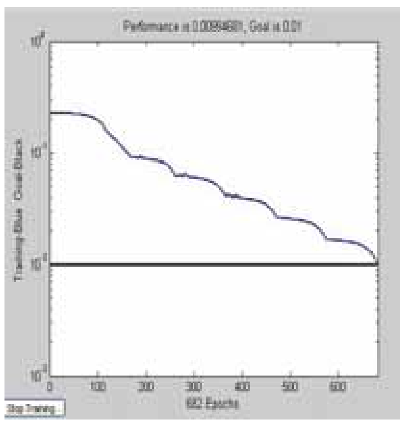

Figure 2.

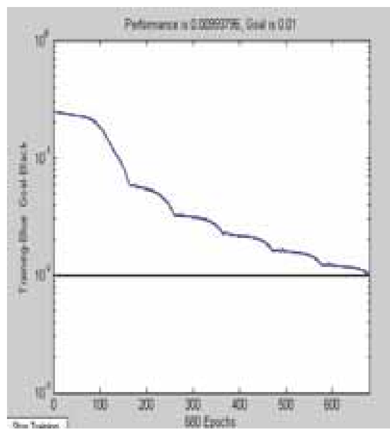

Figure 3.