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Research on Application of Listed Company Financial Fraud Distinguish Based on Acceleration-convergent BP network Algorithm

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Abstract

Financial fraud has been a big problem in the field of financial accounting for a long time. An endless stream of financial fraud incidents was exposed. These cases on the one hand influenced the development of enterprise itself, the industry trend and on the other hand affected the development of the market. Many scholars have focuses on the issue from different angles and established some identification model of financial fraud. But these models generally do not have universal applicability because they are usually created in a specific environment or under accidental conditions. This paper improves the original method by accelerating the convergence of the excitation function of BP neural network algorithm. The sample of the article comes from 138 listed companies between 2010 and 2012. We respectively establish the financial reporting fraud identification models based on BP neural network algorithm and the improved algorithm. According to the comparison of results, we get that recognition accuracy of the improved algorithm reaches 93.48% and the forecasting effect is obviously better.

Keywords: *Financial fraud, BP neural network*

1. Introduction

There are a variety of financial fraud incidents on the market, which have a terrible influence on the industry trend and development of the market. In recent years, Enron, Xerox, WorldCom, Merck and some other famous international enterprises of America have undergone a series of financial fraud cases. The constantly being exposed scandal makes U.S. stocks plummeted. In the domestic market, listed companies' financial fraud also repeated, such as Dawn shares, Yinguangxia, Delong in Urumqi and even some companies listed overseas have undergone financial fraud. Among these, the financial reporting fraud accounted for a large proportion. Financial reporting fraud refers to intentionally misstating or ignoring the figures or notes presented in the financial statements. They do this in order to conceal the true financial condition of the company and deceive those users of the report. Financial reporting fraud includes: manipulating, counterfeiting or changing the accounting records or supporting documents; providing false financial reporting of transactions, matters or other important information or deliberately ignoring such information; intentionally misusing the relevant accounting principle. These corrupt conducts not only seriously threaten market participants' confidence in the financial information but also weaken the company's internal control, reduce the quality of the internal audit, greatly reduce the company's overall governance efficiency. Although the audit procedures of financial report are stringent, in the financial statements audit, the CPA usually focus on just two kinds of corrupt conduct: (1) assets occupation, which means the audited entity's management or employees illegally occupy assets of the audited entity; (2) false report of enterprise's financial information, which may be due to the management misleading financial reports users to judge performance or

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profitability of the audited entity by manipulating profits. However, the behavior of actual fraud may be more. Although so many incidents of financial fraud was exposed, we cannot exclude the possibility that there are more cases of fraud or forgery impending have not been found. Therefore, developing effective measures, identifying and preventing the financial to ensure the healthy development of the economy become an urgent problem.

There have been a lot of current theoretical research results at home and abroad of financial fraud. We have normative theory such as iceberg theory, triangular theory, the four factors (GONE) theory and the theory of fraud risk factors. Iceberg Theory, also known as two-factor theory, classifies financial fraud' motivation factor into two parts: a few visible tip of the iceberg and most invisible sinking underwater; three-factor theory thinks that the opportunity、stress and excuse are the three conditions which lead to financial fraud; GONE theory summarizes the fraud motivation factors from the perspective of individual behavior into four corrupt motives: greed, opportunities, needs and exposure; fraud risk factor theory develops from the GONE and classifies the original factors into generally risk factors and individual risk factors. Zhao Wei [1] presented some audit countermeasures according to the four theories. Wei Lin [2] established the fraud identification model based on triangle theory and the correct recognition rate was 93.7%. Shi Jinlong, Rao Bin, Hong Hong *et al.*, [3-5] chose the sample to establish an identification model based on the theory of GONE. From the perspective of financial fraud occurrence regularity, DECHOW S [6] thought that indexes which reflect the enterprises' profitability, operation ability and debt paying ability are more likely to relate to financial fraud. Liu Liguo [7] found that the proportion of corporate shares and executive directors, the internal control system and size of the board of supervisors have a positive impact on financial fraud. The percentage of tradable shares has a negative impact. In addition, financial fraud may have industry concentration. From the view of theoretical and empirical study, there are empirical analysis and empirical identification model. Liu Bo [8] used forward stepwise multivariate logistic regression method to establish financial fraud detection model and the accuracy rate was 73.8%. Song Guangya [9] improved BP neural network by quantum-behaved particle swarm algorithm. The accuracy rate of new model was improved compared with the standard one. Deng Qingshan [10] also used the neural network algorithm to establish detection model and the correct recognition rate was more than 90%. Wang Yanjie [11] established 4 variable BP neural network model and logistic regression model to detect financial reporting fraud. It was found by comparison that BP neural network model had higher recognition accuracy. Efstathins Kirkosa[12] created three recognition models—a decision tree, neural networks and Bayesian belief network model. Gu Ningsheng [13] used learning vector quantization (LVQ) neural network model for financial fraud identification and the recognition accuracy reached 90.9 %. Benish [14] selected eight indicators to establish probit regression prediction model and the prediction accuracy reached 75%. Specht [15] considered probabilistic neural network possess not only some advantages of traditional classification model but also the computing power and flexibility of the BP neural network model. Spathis [16] created a logistic regression model for fraud recognition which has the accuracy rate over 84%. Liang Jie[17] applied genetic BPN technology to identifying financial reporting fraud. Using of computers greatly improve the recognition efficiency. In addition, foreign and domestic scholars have studied the empirical analysis model of financial fraud based on questionnaires investigation or social psychology rational behavior etc.

Although there have been some recognition models, they usually do not have universal applicability because these models are often established under certain conditions and circumstances. Moreover, some models are only for part of the financial report identification information and cannot be used to detect the entire financial report. The purpose of this paper is to identify the financial reporting fraud and find the right way to establish an effective recognition model. Through comparative analysis of previous research, we found that the neural network algorithm in identifying financial reporting fraud is used widely. Compared to the logistic regression model and Bayesian network model, the neural network algorithm has higher correct rate. But we cannot just stick to the basic neural network algorithm. Predecessors have launched a more extensive study and a number of improved algorithms derived from its basis, such as BP neural network, RBF network, MATLAB neural network which is combined with genetic algorithm. This paper is based on BP neural network algorithm. We accelerate the convergence of the excitation function of BP neural network algorithm. The counting speed and accuracy of the algorithm can both be improved in this way. Then we can create a better detection model. In the second part of this article the basic idea of BP neural network algorithm will be explained by presenting BP network optimization model of rural sewage treatment plan. The third part mainly introduces excitation function of BP network and the fourth part explains improved BP neural network algorithm. The fifth part is experiment. We will establish recognition models based on BP neural network algorithm and improved BP neural network algorithm. The recognition results and comparative analysis of the model will also be introduced in this part. The fifth part summarizes the advantages as well as the disadvantages of the article.

2. BP Network Optimization Model of Financial Accounting

BP neural network is also called the neural network of error back propagation, which is composed of input layer, output layer, and hidden layer. First of all, the information of the external environment is input to the input layer neurons of neural network, and it is transmitted to the hidden layer neurons. Secondly, after processing the information transform, the information is transferred from the hidden layer to the output layer. Then, the results will output from the output layer by the further treatment. Thus, the neural networks have completed an information processing.

BP neural network is also applied widely in financial accounting. Green and Choi [18] constructed a financial reporting fraud discriminate model based on artificial neural network technology. In the model they used some relevant variables in financial statements as identify variables and found it very effective in the case of random samples. Fanning and Cogger [19] also used artificial neural network to construct detection model. They used 20 variables which have high recognition ability to create the model. Feroz [20] used samples of 42 false financial reports and 90 real financial reports, conducted experiments based on Logistic regression method and neural networks. The experimental results show that: the neural network approach is better than Logistic regression method. Lin [21] used fuzzy neural networks to study on the false financial reports identification and applied fuzzy mathematics in artificial neural networks. The research showed the experimental result of fuzzy neural network is better than Logistic regression and some other general neural network models.

The basic diagram of neural networks is given as follows:

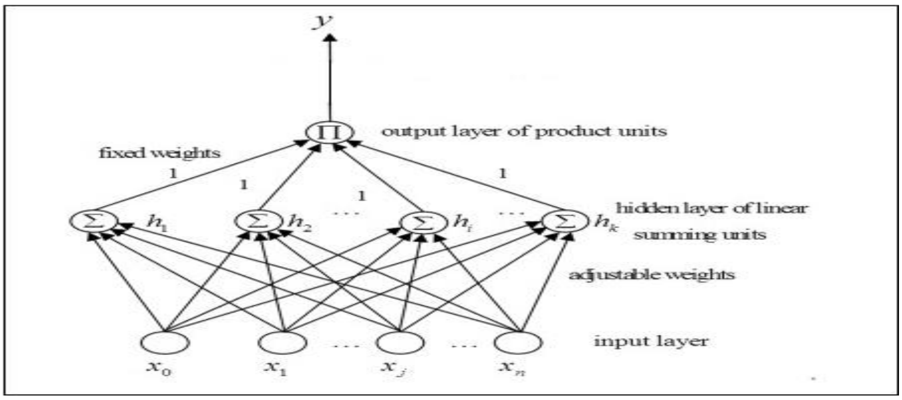

Figure 1. The BP Network Diagram

When the evaluation results of the actual values output from the output layer of BP network, and the error between the evaluation results and the target value is not in the allowed error range, the error will be back propagation. Error back propagation is that the errors will though the hidden layer to the input layer. Then, error is apportioned to all the neurons of each layer.

3. Excitation Function of BP Network

The excitation function is one of the main factors that determine the performance of neural network. If the excitation function of neuron is different, it will make the neurons with different mathematical models, which have different characteristics of information processing. Therefore, the correct selection of excitation function has an important significance. There are many kinds of excitation function for the classification model of financial fraud. Excitation function including threshold transform function, nonlinear transformation function and linear transformation function.

The concrete expressions are as follows:

(1) Threshold transform function

$$f(x) = \begin{cases} 1 & , x \geq 0 \\ 0 & , x \leq 0 \end{cases} \tag{1}$$

(2) Nonlinear transformation function

Nonlinear transform functions commonly used for sigmoid function curve of unipolar. It is referred to as S type function. The S type function and its derivative are continuous, so the data processing is very convenient. Unipolar S function is also called log sigmoid function; the function expression is shown as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

(3) Linear transformation function

The characteristics of the function are the neuronal input and output satisfies the linear relationship in a certain range.

The linear function is shown as follows:

$$f(x) = kx \tag{3}$$

In order to ensure that financial fraud model of BP network can training and learning the nonlinear relationship between the input and output. The hidden layer is selected the tangent S function.

4. Accelerating-convergent BP Neural Network Algorithm

4.1. Steps of BP Neural Network Algorithm

Step1: Give initial value of the weight coefficients ω_{ij} arbitrarily. Those coefficients connect the weights and each of them is usually a non-zero and small random number.

Step2: Forward basis, calculate the output of each unit from the input layer to the output layer in turn. For the unit of j , O_j is calculated as follows:

$$O_j = \frac{1}{(1 - e^{-net_j})}, net_j = \sum_{i=1}^{l} w_{ij} x_i, \tag{4}$$

l is the number of the input for each layer. x_i is working signal transmitted from the unit of the previous layer.

Step3: Calculate the output of the output layer in file. The calculation formula of δ_m is given as follows:

$$\delta_m = (y_m - O_m) O_m (1 - O_m) \tag{5}$$

Step4: Reverse calculation. Calculate the hidden layer output from the output layer to the input layer in reverse. Then for j unit:

$$\delta_j' = (y_j - O_j) O_j \sum_{k=1}^{l} w_{jk} \delta_k \tag{6}$$

l is the number of the input for each layer.

Step5: Adjust the weights. Use recursive method to adjust the weights from the output node to the middle of the hidden layer. The formula is given as follows:

$$\begin{gathered} w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t), \\ \Delta w_{ij}(t) = -\mu \frac{\frac{1}{2} \partial \sum_j (y_j - O_j)^2}{\partial w_{ij}} \end{gathered} \tag{7}$$

y_j represents the desired output of node j . μ represents a gain greater than 0 and we can also call it the learning rate. The adjusted weights can minimize the mean square error of the entire training set. It means:

$$E = \frac{\sum_p \sum_j (y_j - O_j)^2}{2P} \tag{8}$$

P is the number of focused training vectors. j is the number of network output neuron.

Step6: According to the new weights recalculated, if it satisfies the minimum mean square error or the maximum number of learning terminates learning.

4.2. Steps of Accelerating-convergent BP neural Network Algorithm

Step1: Learn the error function, the learning error $E_{\max}$ as well as the maximum number of steps to learn K .

Step2: Initialize the network and get the initial weight vector w_0 and make $k = 0$.

Step3: Forward calculate the weight vector and get the error. If $E_k \le E_{\max}$ then the learning should be stopped otherwise go to step 4.

Step4: Obtain the learning speed through the algorithm of accelerating-convergent one-dimensional searching. Update the weights as $w_{k+1} = \omega_k - \eta \nabla E_k, k = k + 1$. If $k \ge K$ we can stop learning, otherwise turn to step 3.

Theoretically accelerating the convergence of one-dimensional search sequence can save the searching time. And it will use less learning time compared with BP algorithm. To further illustrate the effectiveness of our algorithm, we perform the numerical experiments. Several representative questions about neural network learning algorithm tests will be given. Then for each question we take appropriate network learning and training. It can be approved numerically that the algorithm we put forward can really speed up the learning.

5. Experiments

5.1. Experimental Data

The samples of this paper are chosen from the listing companies between 2010 and 2012. Before creating the model, we should select some influencing factors of financial reporting fraud as explanatory variables. Typically, the company's performance is directly related to the possibility whether or not financial reporting fraud has occurred. So the variables should be relevant with the enterprises' performance. The explained variable is the value which can help us to detect financial reporting fraud.

In order to comprehensively contain the influencing factors, we have selected the indexes from different angles: operation ability, profitability, debt paying ability, development ability, governance efficiency, efficiency of the internal audit and ownership structure. The seven aspects can fully reflect the company's financial situation and governance. Indicators are shown in Table 5.1:

Table 5.1. Indicator System

First grade	Second grade	Third grade
Financial reporting fraud	Operation ability	1.Accounts receivable turnover 2.Inventory turnover 3.Total assets turnover 4.Fixed assets turnover 5.Current assets turnover
	Profitability	6.The main business profit rate 7.Rate of return on net assets 8.Cost profit ratio 9.Capital appreciation rate 10.Sales net profit rate
	Debt paying ability	11.The quick ratio 12.Cash flow and debt ratio 13. Asset-liability ratio 14.The liquidity ratio 15.Equity ratio 16.Interest coverage ratio 17.The debt to tangible net worth ratio
	Development ability	18.Sales growth rate 19.The growth rate of net profit 20.Accumulation rate of assets

		21.EPS growth rate
	Governance efficiency	22.If the company's development is stable in recent five years
	The efficiency of the internal audit	23.If has a fraud record(yes is 1, no is 0) 24.If has a great internal audit system(yes is 1, no is 0)
	Ownership structure	25.The proportion of independent directors of the board

The 26 indicators are too much for the model. What's more, not all of them are necessary and important. So we should process the data in SPSS and select some indicators whose significance is less than 0.05. That means the independent variables should be significant at the level of 0.05. Then we get 12 significant indicators. We can grasp their impact strength by calculating their variance contribution. Sort the 12 indicators in descending order of their variance contribution and the result is shown in Table 5.2:

Table 5.2. Significant Indicators

Indicators	Variance contribution	coefficient	Sig
7.Rate of return on net assets	17.42%	-3.463	0.000
21.EPS growth rate	13.03%	-1.201	0.010
10.Sales net profit rate	9.17%	-4.340	0.013
9.Capital appreciation rate	8.65%	-0.429	0.006
17.The debt to tangible net worth ratio	8.02%	13.725	0.005
5.Current assets turnover	7.28%	-4.130	0.000
16.Interest coverage ratio	5.14%	-6.592	0.034
13. Asset-liability ratio	5.01%	-2.034	0.008
25.The proportion of independent directors of the board	4.61%	-1.831	0.021
19.The growth rate of net profit	4.47%	-3.037	0.017
24.If has a great internal audit system(yes is 1, no is 0)	4.24%	-0.754	0.003
12.Cash flow and debt ratio	3.59%	-5.042	0.010

As Table 5.2 shows, the 12 variables are defined and we can also approximately judge their correlation with the explained variable. Then we should consider the specific details of our algorithm. According to the foregoing, we choose three neural networks which have an input layer, a hidden layer and an output layer. Number of neurons in the input layer is determined by the number of variables in the training sample. We set the number of neurons in the hidden layer as six and the number of neurons in the output layer as one. The initial weight values are between -1 and 1. It is usually generated randomly. 1 represents the sample of false financial statements. 0 indicates normal samples. When tested, if the output value of a sample is greater than 0.5, we consider the sample as false financial statements; if the value is less than 0.5, we consider the possibility it as a normal sample.

5.2. Learning Time and Learning Error Comparison between Accelerating-convergent BP Neural Network and other Neural Network

In response to problems above, we will make Sigmoid function take the role of hidden units effect function. Effect function of output unit is $\varphi(v) = \frac{2}{1+\exp(-v)} - 1$. The extraordinary error is considered as learning error. When we have the error less than e^{-5} or learning times more than 5,000 the calculation should be terminated. Numerical results are all shown in Table 5.3.

Table 5.3. Comparison of Efficiency and Speed

Algorithm	Iterations	Learning time(Millisecond)	Learning error
BP Algorithm(rate is 0.1)	5001	7649	1.3461 e^{-5}
BP Algorithm(rate is 0.3)	5001	7649	1.4319 e^{-5}
BP Algorithm(rate is 0.5)	5001	7649	1.0310 e^{-5}
BP Algorithm(rate is 0.7)	5001	7649	1.8154 e^{-5}
accelerating-convergent BP neural network	26	1208	3.0852 e^{-5}

According to the data, we can get that using a variable-rate BP algorithm can significantly reduce the learning time used. This is because on the one hand we have chosen the optimal learning efficiency at each step and one the other hand we have used one-dimensional searching method of learning rate which can effectively reduce the time for choosing optimal learning time.

5.3. Accuracy Comparison between the Improved Algorithm and other Algorithms

After comparing the efficiency, we will identify the specific application of the improved algorithm to financial reporting fraud detection. First of all, standardize the sample data. On the basis of the 35 identify variables we have chosen, in order to examine the overall effect of different models established by different combinations of variables, we will respectively select the 25 variables in Table 5.1, the 12 variables and the first 5 variables in Table 5.2 for the neural network training and testing experiments. The results of the three experiments are as follows:

Table 5.4. Experimental Data for 25 Variables

Sample	Training sample	Testing sample			
		2010	2011	2012	Total
Number of T sample	37	29	23	22	74
Prediction	37	25	18	18	61
Accuracy	100.00%	86.21%	78.26%	81.82%	82.43%
Number of F sample	37	25	18	21	64
Prediction	37	20	15	17	52
Accuracy	100.00%	80.00%	83.33%	80.95%	81.25%
Total	100.00%	83.33%	80.49%	81.40%	81.88%

Table 5.5. Experimental Data for 12 Variables

Sample	Training sample	Testing sample			
		2010	2011	2012	Total
Number of T sample	37	29	23	22	74
Prediction	37	27	20	20	67
Accuracy	100.00%	89.66%	86.96%	86.36%	90.54%
Number of F sample	37	25	18	21	64
Prediction	37	22	15	19	56
Accuracy	100.00%	88.00%	83.33%	90.48%	87.50%
Total	100.00%	87.04%	85.37%	88.37%	89.13%

Table 5.6. Experimental Data for 5 Variables

Sample	Training sample	Testing sample			
		2010	2011	2012	Total
Number of T sample	37	29	23	22	74
Prediction	37	28	22	20	70
Accuracy	100.00%	96.55%	95.65%	90.91%	91.89%
Number of F sample	37	25	18	21	64
Prediction	37	23	16	20	59
Accuracy	100.00%	92.00%	88.89%	95.24%	92.19%
Total	100.00%	94.44%	92.68%	93.02%	93.48%

Upon the experimental data, the recognition model concluding five variables—rate of return on net assets, EPS growth rate, sales net profit rate, capital appreciation rate and the debt to tangible net worth ratio, has the highest overall recognition accuracy. And the recognition model concluding 35 variables has the lowest overall recognition accuracy. It means more indicators may not imply higher accuracy. Too much indexes may bring too much "noise" and affect the model's overall recognition rate. The overall detection accuracy of the mode containing 5 variables is 93.48%. So we can get that the detection model established based on the improved BP neural network algorithm has a high accuracy.

Next we will create a simple logistic regression model with the same five indicators as Table 5.6, to compare the recognition results. The result is shown in Table 5.7:

Table 5.7. Result of Simple Logistic Regression Model

Sample	Testing sample			
	2010	2011	2012	Total
Number of T sample	29	23	22	74
Prediction	24	19	19	62
Accuracy	82.76%	82.61%	86.36%	83.78%
Number of F sample	25	18	21	64
Prediction	22	15	17	54
Accuracy	88%	83.33%	80.95%	84.38%
Total	85.19%	82.93%	83.72%	84.06%

Upon Table 5.7, we can get that by contrast the model established based on accelerating-convergent BP neural network algorithm has a much higher accuracy than the simple logistic regression model.

5. Conclusions

In this paper, we select multiple variables during the research of financial reporting fraud. Finally we hold only 5 variables.

Based on BP neural network algorithm we have our algorithm improved and get the accelerating-convergent BP neural network model algorithm. According to the test results, the calculation speed and efficiency of the improved algorithm are greatly improved. What's more, we can get the following conclusions from the results of empirical analysis:

1. The model build out of accelerating-convergent BP neural network model algorithm has a relatively high identification efficiency. It's accuracy reaches 93.48%.
2. Among all the factors which affect the financial reporting fraud, rate of return on net assets, EPS growth rate, sales net profit rate, capital appreciation rate and the debt to tangible net worth ratio are the most influential.
3. Compared with simple logistic regression model, accelerating-convergent BP neural network model has certain advantages.

In addition, there are also some shortcomings in the paper, the accuracy of the model still has some room for improvement. The efficiency and speed of the algorithm can be further enhanced.

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