Application of particle swarm optimization neural network in Financial Distress Analysis

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Abstract: At present, BP neural network has been successfully used in the financial analysis and prediction of the company, but the traditional gradient descent exploration method is adopted in the neural network, which causes the shortcomings of slow convergence speed and easy to fall into the local optimum, which has a bad impact on the application effect. In this paper, an improved PSO (particle swarm optimization) global search algorithm is proposed to train BP network. It not only retains the original advantages of neural network, but also overcomes the shortcomings of traditional training methods. The results show that this method is better than the traditional neural network model.

1. Introduction

Financial distress prediction has become an important branch of capital structure theory. If the company is in financial difficulties, it is more likely to go bankrupt. Generally speaking, bankruptcy will cause the loss of social wealth, including the loss of shareholders' investment and creditor's rights, the loss of employees, the loss of part of the government's tax sources, etc.

Fitzpatick[1] first found that the financial ratios of companies with financial difficulties are significantly different from those of normal companies, so he believed that the financial ratios of enterprises can reflect the financial situation of enterprises and have a predictive effect on the future of enterprises. BP neural network is the most widely used neural network with strong nonlinear mapping ability. In recent years, the application of neural network in financial analysis has been widely studied by domestic scholars[2,3,4]. However, because BP algorithm uses gradient descent search method, it has some problems such as slow convergence speed and easy to fall into local optimum. The defect of falling into the local optimum will directly lead to the deviation of the analysis conclusion. These defects are especially prominent in the small sample training of financial analysis, so how to improve the performance of neural network in financial analysis is a key problem. In this paper, particle swarm optimization (PSO) [5] is used to train the connection weights of neural network, which can avoid BP network falling into local optimum to a great extent, and improve the reliability of neural network analysis results.

2. POS neural network training method

PSO was first proposed by Kennedy and Eberhard in 1995. Particle swarm optimization is an evolutionary computing technology based on swarm intelligence. Particle swarm optimization algorithm reflects the latest development of swarm intelligence algorithm. Compared with genetic algorithm, PSO has no crossover and mutation operation for genetic algorithm, so the algorithm is simple and efficient, and has profound intelligent background, which is suitable for both scientific research and engineering application.

In PSO, the potential solution of every optimization problem is a "particle" in search space. All particles have a fitness determined by the optimized function. In each iteration, particles update themselves by tracking two "extremums.". The first extreme value is the optimal solution found by the particle itself, which is called individual extreme value; the other extreme value is the optimal solution found by the whole population at present, which is the global extreme value. The particle updates its speed and position according to the following formula:

$$v(\mathrm{t}+1) = \mathrm{W} \cdot \mathrm{v(t)} + C_1 \cdot rand \cdot [pBest(t) - x(t)] + C_2 \cdot rand \cdot [gBest(t) - x(t)] \quad (1)$$

$$x(t+1) = x(t) + v(t+1) \quad (2)$$

Among them, v(t+ 1) is the velocity of the particle at the next time; x (t + 1) is the position of the particle at the next time; C_1 and C_2 are learning factors, usually $C_1 = C_2 = 2$; W is the inertia weight, generally $w \in [0, 1]$. In order to avoid the basic PSO falling into the local optimum in the search process, many improved PSO algorithms have been proposed and successfully applied. For example, with the combination of simulated annealing PSO, Gauss mutation PSO and other improved algorithms, these new algorithms can further improve the optimization performance of PSO.

When PSO algorithm is used to train neural network, the connection weights of all neurons in a specific structure are first encoded into individuals represented by real digital strings. Assuming that the network contains M optimization weights (including threshold), each particle will be represented by an m-dimension vector composed of M weight parameters. According to the size of the particle swarm, a certain number of individuals (particles) are randomly generated according to the above individual structure to form a population, in which different individuals represent a group of different weights of the neural network, while initializing *pBest* and *gBest*.

The components of each individual in the particle swarm are mapped to the weights in the neural network, thus forming a neural network. The neural network corresponding to each individual is trained by inputting training samples. The optimization process of network weights is an iterative process. In the process of network training, the given sample space is divided into two parts, one is used as network training, which is called training set, the other is used as network test, which is called test set.

The mean square error of the network in the training set is calculated as the objective function, and the fitness function is constructed to calculate the individual fitness.

$$E(X_p) = \left[\sum_{p=1}^{n} \sum_{k=1}^{c} (Y(X_p) - Target_{p,c})\right]^2 \quad (3)$$

Where, $target_{p,c}$is the given output of training samples at the output; p is the output of c network, $Y(X_p) = f(X_p, W)$ is the network connection weight. W is the network connection right.

$$fitness(t) = \frac{1}{E(X_p)} \quad (4)$$

When the fitness function gets the maximum value, the output error of the corresponding neural network is the minimum, and the corresponding weight is the training result of the neural network obtained by W*.

3. Financial index system model

As for the description of financial distress, Altman and other scholars have integrated four situations of financial distress: business failure, insolvency, default and bankruptcy. Generally speaking, the qualitative description of financial distress focuses on bankruptcy liquidation or insolvency.

Due to data disclosure and other issues, domestic scholars generally regard special treatment (st) listed companies as financial distress companies. For the same reason, the definition of financial distress in this paper is based on whether it is St. if the listed company is st, it is in financial distress; otherwise, it is not in financial distress.

According to the analysis of financial distress prediction model, there are 30 financial ratios commonly used for financial distress prediction. If all 30 financial ratio indexes are taken as the input of neural network, there are as many as 30 input nodes. For a large network structure, on the one hand, it requires a huge training sample set to support, which is difficult to achieve in general research, on the other hand, it will lead to the decline of generalization ability of neural network and the deterioration of its prediction performance. Therefore, five financial indicators (working capital / total assets, retained earnings / total assets, EBIT / total assets, capitalization market value / total assets, sales revenue / total assets) in the prediction model proposed by Altman are selected as input of neural network.

4. Analysis of prediction results

The samples selected in the experiment are manufacturing companies. The sample companies for training are divided into financial distress companies (ST companies) and non-financial distress companies (non ST companies). Using the paired sampling method, 48 small and medium-sized manufacturing companies were selected from ST companies, and then 48 non-financial distressed enterprises were selected according to the same industry and scale. 30 ST and 30 non ST enterprises were selected as the training sample set, and the remaining 18 ST and 18 non ST enterprises were selected as the test sample set. All the data are from the public disclosure on the Internet.

In this paper, the model established in Section 3 is used to train the neural network with the method of Gauss mutation particle swarm optimization

Step 1: set the number of particle population to 30, set the particle dimension (6 × 8 + 8 × 2 = 64) according to the network scale, initialize the starting position and speed of each particle randomly, and the initialized particles form the initial candidate solution set of optimal neural network weight;

Step 2: at the beginning of particle swarm optimization algorithm iteration, calculate the fitness function value of each particle under the criterion of formula (4);

Step 3: update individual extremum. Compare the current fitness *fitness* (*t*) of each particle with the individual extreme *fitnesspbest* (*t*-1) before iteration. If the current fitness of each particle is better than the individual extreme before iteration, update the individual extreme value, otherwise keep the original individual extreme value;

Step 4: select the individual m_i from the population, perform Gaussian mutation operation, generate a new individual $m_i^{'}$, and judge whether to retain the mutation particles according to the algorithm in literature [6];

Step 5: update the global extremum. Among all the individual extremum, the individual extremum with the best fitness is the global extremum;

Step 6: judge whether the iteration stop condition is met, that is, whether the set number of iterations (= 1000) is reached. "No" returns to step 2, "yes" to step 7;

Step 7: the particle corresponding to the global extremum is the optimal solution of the population, that is, the optimal solution of the neural network weight W^*.

In the application, the analysis ability of the model can be described by training samples and test samples respectively, and measured by two types of errors. Error type I is that ST company is judged as non ST company (i.e. the troubled company is wrongly judged as normal company), and the error type II is that non ST company is judged as ST company (i.e. the normal company is wrongly judged as the troubled company). In order to test the effectiveness of the method, the traditional gradient descent method and the Gaussian mutation PSO optimization method are used to complete the training of the neural network, and then the training sample set and the test sample set are used to test the neural network.

Table 1 Test results with training sample set (60 samples in total)

	error type I	error type II	Total error
gradient descent	0	0	0
Gauss mutation PSO	0	0	0

Table 2 Test results with test sample set (36 samples in total)

	error type I	error type II	Total error
gradient descent	2(5.5%)	3(8.3%)	5(13.8%)

Gauss mutation PSO	0	2(5.5%)	2(5.5%)

Training sample set test and test sample set test reflect different aspects of network performance. The traditional gradient descent method and PSO optimized neural network are both ideal for the test results of training sample set, which shows that the two methods have a good description ability for "learned knowledge". There are obvious differences between the two methods in the test sample set test results. The accuracy of PSO method is 8.3% higher, which shows that POS optimization neural network has stronger generalization ability and can make better prediction of "unknown knowledge". On the premise of the same neural network structure, there are such differences, which shows that PSO method searches for a better "decision" way.

The output of neural network is used to describe the analysis results, that is, the company is in financial distress or not in financial distress. Therefore, a single hidden layer neural network structure can be constructed: six input layer nodes (the sixth node input is always equal -1, used as the threshold), eight hidden layer nodes, and two output layer nodes (describing two financial states). Thus, a neural network prediction model is established.

5. Conclusions

Neural network is a kind of parallel distributed pattern processing system, which has high parallel computing ability, self-learning ability and fault tolerance ability. Neural network provides an effective method for dynamic financial early warning of enterprises, and makes the model have the ability of self-learning with the change of environment. In order to overcome the shortcomings of traditional BP neural network gradient descent training method, which is easy to fall into local optimal solution, an improved PSO neural network training method is proposed to obtain global optimal solution. Through the prediction of financial distress of ST and non ST Companies in China, it shows that the method in this paper avoids the possibility of falling into local optimum to a great extent, and improves the ability of neural network to predict financial distress.

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