ISSN: 1813-4890

Study of BP Neural Network Model based on PSO Optimization about Reputation Rating Evaluation

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Abstract

In recent years, with the increasing national support for MSMEs, MSMEs account for an increasing share of the financial market in the banking business. However, due to the complex situation of MSMEs, with these characteristics of information asymmetry, unstable operation, small enterprise size, extremely high financing risk, and serious lack of collateral and security cause inconvenience to commercial banks in determining whether to lend to them and in formulating credit strategies such as loan amount, interest rate and maturity. In this paper, a certain amount of indicators related to enterprises without credit records are used as training samples of BP neural network, and a credit rating evaluation model of BP neural network based on PSO algorithm optimization is established and solved to obtain the credit rating of enterprises, so as to make a reference role for commercial banks to evaluate the credit rating of MSMEs.

Keywords

Credit Strategy; BP Neural Network; Particle Swarm Algorithm (PSO); Commercial Banks; Credit Rating.

1. Introduction

According to the "China MSME Financing Development Report 2021" released by Ariadne Consulting, as of 2021, MSMEs account for 96.5% of China's market players, and the size of China's MSME loan balance has grown from 27.7 trillion yuan in 2016 to 43.2 trillion yuan in 2020, with a compound annual growth rate of 12.2% . However, in the context of macroeconomic downturn and liquidity shortage in recent years, the problem of difficult and expensive financing for MSMEs is particularly prominent.

Generally, commercial banks will provide loans to strong and stable supply and demand enterprises based on their own credit policies as well as information on the enterprises' transaction notes and the influence of upstream and downstream enterprises, and can offer preferential interest rates to enterprises with high creditworthiness and low credit risks. Therefore, how to conduct effective credit risk assessment for MSMEs with weak risk resistance is a challenge for commercial banks, which play an important role in the financial market with credit as their basic business.

In fact, the current credit evaluation systems at home and abroad have been basically perfected and can be broadly classified into three categories. The first category is mainly multivariate statistical analysis models based on enterprise financial information as a data source, such as qualitative response model, Z-score model and ZETA credit risk model proposed by Altman; or models based on market dynamic information and established based on complex mathematical

ISSN: 1813-4890

formulas, such as KMV model and CreditMetrics model; the second category is expert evaluation method based on expert The second category is the expert assessment method based on expert scores, such as using the Delphi method to discuss and summarize the opinions expressed anonymously by several experts, or adopting the brainstorming method to derive the enterprise solvency and default probability after a group decision by several experts. The third category is the analytical technology models such as decision systems, neural networks and fuzzy analysis that have emerged along with the development of computers and artificial intelligence and data mining[1]. However, with the explosive growth of data size nowadays, there are many uncertainties and volatile factors affecting enterprise credit risk, such as changes in national policies, etc., and economic data often show nonlinear relationships with each other, and the accuracy of traditional creditworthiness assessment methods decreases, while creditworthiness assessment methods about artificial intelligence can effectively solve this phenomenon of nonlinearity between data variables, so that in its credit risk for enterprises nowadays Therefore, it is particularly important in predicting enterprise credit risk. Lingling Zhao uses K-Means clustering analysis to quantify the credit influencing factors of MSMEs, so as to build a target optimization model and propose corresponding credit strategies[2] for different grades of enterprises. The best parameters are obtained by cross-validation, and the credit rating[3] of enterprises with unassessed records is predicted.

In this paper, factors related to creditworthiness assessment are filtered out from the data set, and a BP neural network evaluation model optimized by particle swarm algorithm (PSO) is established to obtain the creditworthiness rating of enterprises, which provides optimization for commercial banks' credit decisions for MSMEs.

2. Acquisition of Data and Assumptions

The data in this paper were obtained from the relevant invoice data of 123 enterprises with credit records and 302 enterprises without credit records provided by question C of the 2020 National Student Mathematical Modeling Competition, and python and excel software were used to process, filter and summarize the relevant invoice data. In order to facilitate the analysis of the problem in this paper, the research process and conclusions of this paper are based on the following assumptions that hold: (1) when using excel and python to process the data, there is no deviation from the original relevant data, and it is an objective and realistic reflection of the original enterprise's transaction invoice situation; (2) it is assumed that the bank's investment preference is always greater than the total return brought by the credit enterprises it places in the low (3) Assume that the credit model adopted by banks is not limited to the traditional "tax credit", but also accepts this newer form of "invoice credit"; (4) Assume that banks evaluate and place credit to enterprises exactly according to the results of the final model. It is assumed that the bank, in the process of evaluating and placing credit to enterprises, will place loans according to the results of the final model, without considering the human factors that affect the credit amount, interest rate and credit term. (5) Assume that the enterprises have certain ability to cope with unexpected situations, i.e., the model established in this paper does not take into account other unexpected influencing factors; (6) Assume that the enterprises concerned do not misrepresent their financial data and all data are true and reliable[4].

3. Reputation Rating Evaluation Model based on PSO-BP

3.1. Theoretical Preparation

An artificial neural network (ANN) is a computer system designed to simulate the structure and function of the human brain, formed by a number of very simple processing units interconnected in some way, which processes information by the dynamic response of its state to external input information. The neuron model is designed to simulate the structure of a biological neuron, which consists of a cell and its many synapses, with several synapses called "dendrites" as the input signal and only one synapse called "axon" as the output. The BP neural network used in this paper is a multilayer feedforward neural network with back propagation of errors. The basic idea is the gradient descent method, which uses the gradient search technique to minimize the mean squared error between the actual output and the desired output of the network. Its topology includes input layer, intermediate layer, and output layer, as shown in Figure 1.

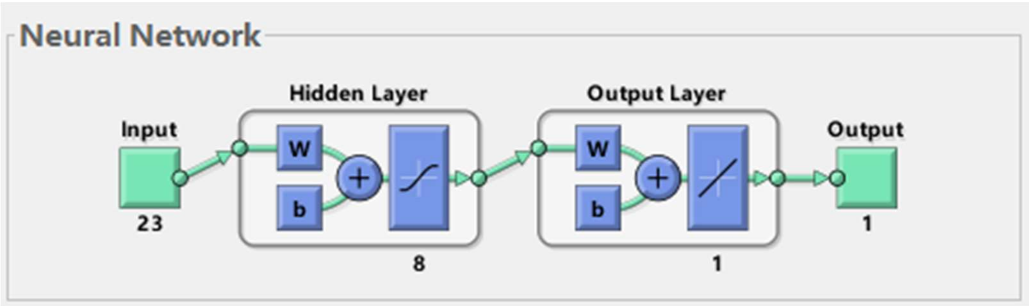

Figure 1. BP neural network topology diagram

The basic process of BP neural network is divided into two processes: forward propagation of signal and backward propagation of error. First, the output signal acts on the output node through the implicit layer, and after nonlinear transformation, the output signal is generated, and if the actual output does not match with the desired output, the error generated with the output is back propagated to the output layer through the implicit layer, and the error is apportioned to all units in each layer, and the error signal obtained in each layer is used as the basis for adjusting the weights of each unit. By adjusting the input, the weights and thresholds between the nodes in each layer, the error is made to look down along the gradient direction, and after several iterations, the parameters corresponding to the minimum error are determined to obtain a model for the successful fitting of the neural network.

3.2. Model Building

3.2.1. Data Cleaning

Each enterprise data has its credit rating evaluated by the bank, which is divided into four grades: A, B, C and D. Among the enterprises with credit rating of D, the bank directly thinks that they will default and will not put loans for them, and can directly delete the data of such enterprises, and then quantify the remaining enterprises according to their credit rating as "A"-3, "B"-2 and "C"-1 respectively; quantify whether they default as "with default record"-1, "without default record"-1, "with default record"-2 and "C"-1. "B"-2, "C"-1; quantify the default or not as "default record"-1, "no default record "-0"; this paper uses 23 evaluation indexes as inputs, which are credit rating, whether to default, number of input invoices, number of input valid invoices, number of input invalid invoices, number of input negative invoices, input valid amount, input valid tax amount, input invalid amount, input valid price tax, number of output invoices, number of output valid invoices, number of output invalid invoices, number of output negative invoices, sales valid amount, sales valid tax amount, sales invalid amount, sales valid price tax, total revenue, input invoice billing stability, sales invoice billing stability, invalid invoice rate, negative invoice rate.

3.2.2. BP Neural Network Building Steps

The activation function selected for this model is the Sigmoid function, and the function equation is:

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

The notation convention isω_{jk}^{l} denotes the network in which the first$(l-1)$ layer of the$k$ neuron points to the$l$ layer$j$ The connection weight of the neuron at the first layer, usingθ_j^l denotes the connection weight of the$l$ layer$j$ bias of the first neuron.
Net activation expression.

$$net_i = \sum_{j=1}^{n} w_{ij}\, x_j - \theta_i \tag{2}$$

In order to design a well-structured BP neural network, it is also necessary to determine the structure of the hidden layers for design. Although the number of layers is too deep, the theoretical ability to fit the function will be enhanced, but in practice it will cause overfitting problem and also increase the training difficulty to make the model difficult to converge. Therefore, this paper uses a three-layer BP neural network for sample training, focusing on adjusting the number of neuron nodes in the hidden layer. From Komogorov's theorem there is a reference formula as follows.

$$n_l = \sqrt{n+m} + a \tag{3}$$

Where n is the number of nodes in the input layer, m is the number of nodes in the output layer, a is a constant between 1 and 10, andn_l is the number [5] of neurons in the containing layer. By calculation, we can getn_l the range of 5-14, which will be taken as 5.

The back propagation algorithm is used to train the network weights and biases iteratively so that the output vector is as close as possible to the desired vector, and the training is completed[6] when the sum of squared errors in the output layer of the network is less than the specified error, and the weights and biases of the network are saved.

3.2.3. BP Neural Network based on PSO Optimization

If the traditional gradient descent method is followed to find the optimum, this method often converges slowly and tends to fall into the local optimum situation. In this paper, a combination of PSO optimization method and BP neural network is adopted to improve the above model. The connection weights and thresholds of the BP neural network are regarded as the elements of the position vector X of the particles in the particle swarm, and then the gradient descent method of the BP network is used instead of the particle swarm optimization method to optimize the connection weights and thresholds of the network. Let the number of nodes in the input layer, hidden layer and output layer of the BP neural network ben_i n_h n_o ,and assume that the information of each particle is represented by a d-dimensional vector, then$d = n_o n_h + n_h n_i + n_o + n_h$. In this paper, we combine the particle position update and the gradient descent method of BP neural network, and thus derive a novel weight update method.

Vim(t) represents the initial position of the ith particle thatH_{j1} regarded as the hidden layer nodej_1 the output ofI_h The output from the input layer node h.α andβ is the particle learning rate.r_1 andr_2 are 2 random values, generally between0~1 between the values; t is the number of current training iterations.

First, we initialize the BP neural network, including setting the number of neurons in the input layer, hidden layer, output layer and the input and output of the training samples. Then initialize the particle swarm, including the particle size N and the position vector and velocity vector of each particle, the individual extreme value and global optimum value of each particle, the iteration error accuracyε, constant coefficients c1 and c2, maximum inertia weightsη_{max}, minimum inertia weightη_{min} , maximum velocityv_{max} and maximum number of iterations, etc. The first$i$ The updated position of the particle is as follows.

$$v_{im}(t+1) = \eta v_{im}(t) + c_1 r_1\left(p_{im} - x_{im}(t)\right) + c_2 r_2\left(p_{gm} - x_{im}(t)\right) \mathrm{m} = 1,2,\cdots \mathrm{n} \tag{4}$$

$$x_{im}(t+1) = \begin{cases} x_{im}(t) + v_{im}(t+1) + \alpha\delta_k H_{j_1} & if m \in (0, n_o n_h] \\ x_{im}(t) + v_{im}(t+1) + \alpha\delta_{j_2} I_h & if m \in (n_o n_h, n_o n_h + n_h n_i] \\ x_{im}(t) + v_{im}(t+1) + \beta\delta_{k_1} & if m \in (n_o n_h + n_h n_i, n_o n_h + n_h n_i + n_o] \\ x_{im}(t) + v_{im}(t+1) + \beta\delta_{j_3} & if m \in (n_o n_h + n_h n_i + n_o, n_o n_h + n_h n_i + n_h] \end{cases} \tag{5}$$

Among the $k = \left[\frac{m}{n_h}\right]$, $j_1 = m - (k-1)n_h$, $j_2 = (m - l_1)/n_h$, $h = m - l_1 - (j_2 - 1)n_i$, $k_1 = m - l_2$, $j_3 = m - l_3$;

During the training process, the velocity of each particle is continuously updated, and it is determined whether the updated velocity is greater than the maximum velocityv_{max} and if it is greater than the maximum velocityv_{max} , then the updated velocity takes the value of the maximum velocity v_{max} , otherwise, it remains unchanged. Similarly, the position of each particle is updated.

Calculate the fitness value for each particle.

$$f_i = \frac{1}{n_t}\sum_{q=1}^{n_t}\left(O_{iq} - T_{iq}\right)^2 \tag{6}$$

Wheren_t is the number of training samples.O_{iq} andT_{iq} are the training samples respectively$q$ in the first$i$ The actual and desired outputs of the network under the network weights and thresholds determined by the positions of the particles. Finally, the global extreme value is outputP_g The network weights and thresholds[7] are determined for each position.

3.2.4. Model Solving

In this paper, 123 MSMEs are divided into training data, validation data and test data according to the ratio of 8:1:1 i.e. 99 groups for training data, 12 groups for validation data and 12 groups for test data.

Now the trained BP neural network model can only output the normalized data, in order to get the real data, you can use the function mapminmax, the formula is as follows.

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{x_{max} - x_{min}} \tag{7}$$

The final training results were obtained. After several iterations, the minimum mean square error was reached with MSE=5.0839e-08, and the best performance validation plot was obtained, as shown in Figure 2.

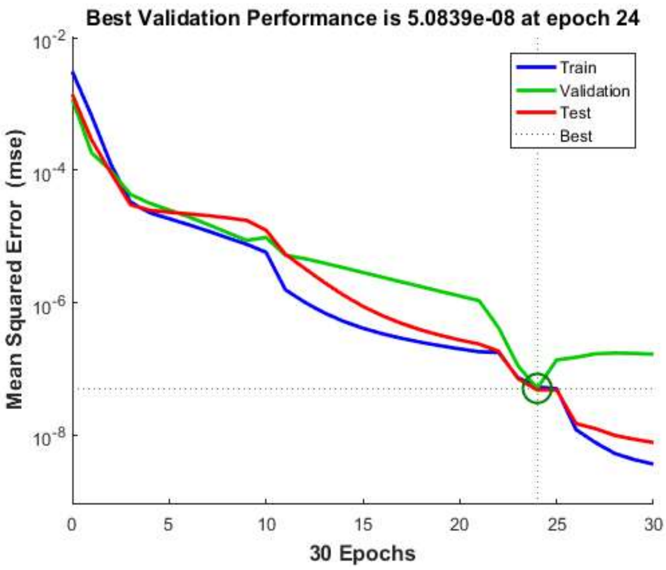

Figure 2. Optimal Performance Verification Chart

After several iterations of training, validation, and testing of this neural network, the neural network finally converged to the best performance verification state, and Figure 3 below shows the correlation coefficient plots of the training, validation, testing, and final total training results for the neural network, respectively. The figure indicates that the training, validation, testing and final total correlation coefficient plots for the neural network are all about 0.9999, which indicates that the neural network fits ideally and well. The credit rating assessment for 302 companies without credit rating records can be predicted using this neural network.

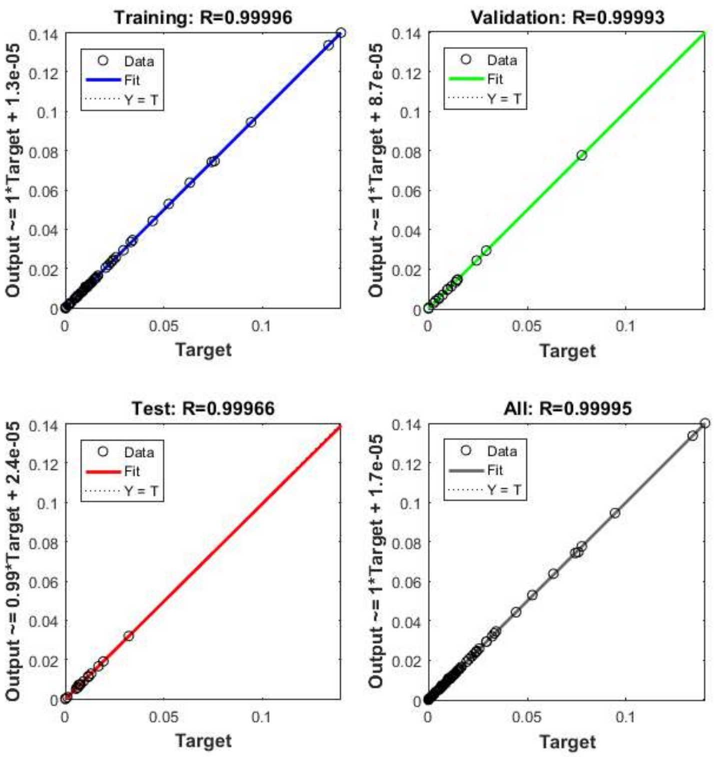

Figure 3. Linear regression plot

R in the figure is the correlation coefficient, whereR^2 is calculated by the formula of:

$$R^2 \equiv 1 - \frac{SS_{res}}{SS_{tot}} \tag{8}$$

WhereSS_{res} is the sum of squares of the difference between the true value and the predicted value, andSS_{tot} is the total sum of squares.

Based on the neural network prediction results, the clustering analysis using the Marxist distance classifies the enterprises at all levels, and the Marxist distance formula is:

$$D(X_i, X_j) = \sqrt{(X_i - X_j)\Sigma^{-1}(X_i - X_j)^T} \tag{9}$$

Where X iand X jboth denote the estimated value of the mean vector of prediction results, the Euclidean distance is usually used as the distance measure between two data when performing cluster analysis, while the Euclidean distance is difficult to meet the practical requirements in practical problems due to its neglect of data feature units and the influence of different attribute differences, while the Marxist distance is based on a modification of the Euclidean distance, who takes into account the connection between various characteristics and eliminates the The Euclidean distance is based on a modification of the Euclidean distance, which takes into account the connection between various characteristics, eliminates the influence of dimensionality, and also excludes the interference of correlation between variables.

Using MATLAB to establish the relevant clustering analysis model based on neural network to evaluate the 302 enterprises, the credit risk of 302 enterprises can be derived, and four evaluation levels can be set according to the final results of MATLAB, and the final prediction results can be obtained: among these 302 enterprises, 72 enterprises are rated as A grade, 72 enterprises are rated as B grade, 133 enterprises are rated as C grade, and the rest are rated as D grade. of the 302 enterprises, 133 enterprises were rated as A grade, 72 enterprises were rated as B grade, 133 enterprises were rated as C grade, and the remaining enterprises were rated as D grade. Banks will also deny loans to companies with the highest risk rating.

4. Conclusion

In this paper, we analyze the factors affecting creditworthiness from the invoices of MSMEs and construct a neural network that can quantitatively predict the creditworthiness of MSMEs based on the results of the above neural network prediction and classify these MSMEs into four risk levels through cluster analysis. With the above quantitative results, commercial banks can choose to lend first to the enterprises with the highest credit rating and the best risk rating among the above-mentioned enterprises, and can choose to attract these enterprises by appropriately lowering the lending interest rate and giving them the highest loan amount in order to maximize profits. For some enterprises with B credit rating and better risk rating, the credit strategy can be adjusted appropriately to pursue the stability of income. For the B grade some in the risk level above the more dangerous can choose to raise the loan interest rate and the amount, to screen out the risk resistance and better business ability of enterprises to lend. For commercial banks to develop lending strategies, the remaining loan amount can be lent from C-class enterprises on a merit basis, for all D-class enterprises and enterprises located in higher risk levels do not choose to lend.

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