Quality evaluation of accounting information based on multi-layer neural network

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Abstract. With the continuous development of economy, accounting information plays an increasingly important role in enterprise decision-making. However, the traditional accounting information quality evaluation method has some problems, such as strong subjectivity and difficulty in quantifying the evaluation results, which can not meet the requirements of modern enterprises on the quality of accounting information. The evaluation of accounting information quality based on multi-layer neural network is a new evaluation method. It can effectively solve the problem of data nonlinearity in the evaluation of accounting information quality by using the nonlinear characteristics of multi-layer neural network.

Keywords: accounting information; Quality evaluation; Multilayer neural network

1 Introduction

With the continuous development of economy, accounting information plays an increasingly important role in enterprise decision-making. However, the traditional accounting information quality evaluation method has some problems, such as strong subjectivity and difficulty in quantifying the evaluation results, which can not meet the requirements of modern enterprises on the quality of accounting information[1]. In this case, the evaluation method of accounting information quality based on multi-layer neural network has gradually become a new evaluation method. Multilayer neural network is a kind of nonlinear system, which can effectively solve the problem of data nonlinearity in the quality evaluation of accounting information. In addition, the multi-layer neural network can also quantify the evaluation results, which makes the evaluation results more objective and accurate[2]. The advantage of this evaluation method is that it can effectively solve the problems of traditional evaluation methods such as strong subjectivity and difficulty in quantification[3]. The evaluation method of accounting information quality based on multi-layer neural network can evaluate the quality of accounting information more objectively, so as to help enterprises make more intelligent decisions. Multi-layer neural networks can be used to evaluate the quality of accounting information, such as identifying false information

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in financial statements and evaluating the reliability and accuracy of financial statements[4]. Among them, the most common application is the application of multi-layer neural network in financial statement analysis.

2 Theoretical basis

Multilayer neural networks are the most studied and relatively simple neural networks. This kind of network belongs to Feedforward neural network, which is generally composed of input layer, hidden layer and output layer. The number of hidden layers determines whether the network is called a deep or "shallow" neural network. Usually, layers larger than 3 are referred to as deep networks. Deep learning, in a narrow sense, refers to the training process of deep networks. When there are few hidden layers, the gradient descent learning algorithm, also known as the Error Back Propagation Algorithm, is used to learn the weight parameters of the neural network The hyperparameters to be considered in the BP algorithm include learning rate, momentum term, and the total number of learning iterations[5]. After the network structure is complex, gradient descent learning often falls into local minima, leading to a decrease in generalization ability. In the network structure, the number of neurons in the input and output layers is determined by the given problem. Therefore, in the design of MLP structure, only the number of hidden layers and the number of neurons in each hidden layer need to be considered as two hyperparameters[6].

In this paper, the BP multi-layer neural network, which is mature in the application of business forecasting, is equipped with S-type transfer function, 1 hidden layer and 1 output layer node to try to grade the quality of accounting information. Since the 1990s, performance on various economic forecasting issues has been published. BP multi-layer neural network belongs to multi-layer feedforward structure neural network, which generally includes input layer, hidden layer and output layer, and uses supervised training mode[7]. By propagating the error information between the expected output and the actual output from the output to the input in reverse, the network weight is adjusted to achieve the effect of training the network to fit the expected output and complete the nonlinear space mapping. The correctness of the network's judgment on unknown data is called generalization ability[8].

2.1 Training Methods

The accuracy of the network in the training set is closely related to the training method. The initial BP network uses the gradient down training method to reduce the output error, which is usually slow and only suitable for incremental training, does not make a large scale change to the network weight quickly, and is less destructive to the pattern that the network has memorized. For laboratory or practical applications, it is necessary to build a new network, so that the network can quickly memorize a large number of patterns, and the downward gradient is easy to fall into the local minimum of the network, the accuracy is poor, and the training speed is slow[9]. In contrast, the numerical method typical of Newton's method can avoid such problems, because the derivative is used to directly locate the minimum point of the network, so the training of the network is not easily affected by the local minimum. But Newton's method needs to compute the second derivative matrix of the error function with respect to the weight of the network - the Hessian matrix:

$$H = \Delta^2 E$$

Not suitable for practical use. Therefore, the $L-M$ algorithm using the approximate Haynes matrix is a more compromise choice. The $L-M$ algorithm defines the derivative matrix of each output of all training modes with respect to the network weight as J, approximates $J_k^T J_k + \mu_k I$ to H, and updates the network weight as:

$$w(k+1) = w(k) - \left[J_k^T J_k + \mu_k I\right]^{-1} J_k^T e_k$$

2.2 Scale and generalization of hidden layer

The trained neural network is ultimately used to make judgments on data outside the training set, so network generalization performance is somewhat more important than correctness. Generalization is first closely related to the number of hidden layer nodes in the network. It has been proved that when the transfer function is S-type function, BP network only needs one hidden layer to simulate any nonlinear function with finite poles. For specific problems, the more nodes in the hidden layer, the stronger the fitting ability of the network, but the weaker the generalization [10]. Therefore, it is necessary to find the smallest network that can fit the training set for optimal state. Regularization can also effectively improve network generalization performance by adding the sum of squares of network weights to the original error function, as follows:

$$E(w) = \beta E_D + \alpha E_w$$

By limiting the weight of the network, the smoothness of the output can be improved and the generalization performance of the network can be improved. However, it is important to choose the appropriate α, β, otherwise the network accuracy will be low in the training set.

In this paper, we choose to use Bayesian regularization method to solve the problem of the relative size of α, β and the number of hidden layer nodes at the same time. Methods Based on Bayesian interpolation and model selection, the weights of the network, α, β were taken as random variables. Using Bayesian method to evaluate the model, the following results are obtained:

$$2\alpha E_w = N - 2\alpha \cdot tra(H^{-1})$$

Where, the right side of the equation is often represented by β, which is the number of valid weights in the network that can be used to determine the appropriate size of the network. And β is:

$$\beta = \frac{P - \gamma}{2E_D}$$

Where P is the product of the output node and the training mode. After each round of training, adjusting α, β values can ensure that the trained network has better generalization performance, and γ can be used to cut the network to an appropriate size.

3 Experiment

3.1 Input data processing

In view of the confidentiality of accounting information, 300 pieces of accounting information were randomly selected from the database of an institution. Since the mode of input data will greatly affect the network results, the digitized raw data is preprocessed to obtain different inputs. In Table 1, the process includes normalization, mean-zero standard deviation unitization, and principal component analysis to transform the original dimensions of the sorted data and eliminate the dimensions with low impression factor. Principal component analysis is a common pattern recognition method. By using the relationship between eigenvalues and eigenvectors of the covariance equation of raw data, the raw data is transformed from several linearly correlated dimensions to linearly independent dimensions, and the dimensions are arranged in order of importance.

Table 1. principal component analysis results

Binary system		Decimal system	
Differential contribution	Dimension number	Differential contribution	Dimension number
≥1	13	≥0	7
≥2	12	≥10	6
≥4	10	≥11	5
≥6	7	≥13	4
≥8	4	≥15	2
≥20	0	≥19	1

3.2 Network Selection

Half of all the data (150 records) are selected, and the test preprocessing involves the neural network corresponding to all the data sets. The number of inputs for each network is the dimension of the corresponding data set, and the output is a neural node, target parameters and a test L-M sum

The same goes for Bayesian regularization. The number of nodes in the hidden layer is determined by the following method. According to the basic requirement that the number of input modes is greater than the number of network connection weights, an obviously large network with a total number of connection weights approaching 150 is first used. For example, for a data set with 16 input dimensions, plus one output node, and then counting the node's offset, the number of hidden layer nodes of the larger network can be adopted as 13. Then, the Bayesian regularization training process is used to cut the lossy performance of the neural network with too many parameters, so that the number of network connection weights is close to γ , so as to ensure the generalization ability of the network. Test the neural network corresponding to each data set and obtain the result data, as shown in Table 2.

Table 2. Test results of each network

Network type	Training error sum of squares	Test error sum of squares	Weights sum of squares	γ
B-SCALED	1.95	1.19	27.63	93.6
B-ZM	1.83	1.50	20.55	98.4
B-PCA-1%	1.69	1.35	23.25	105.0
B-PCA-2%	1.65	1.21	23.96	103.4
B-PCA-4%	**1.51**	**1.08**	**29.57**	**110.2**
B-PCA-6%	1.50	1.57	49.12	105.5
B-PCA-8%	3.65	1.62	74.36 .	60.2
D-SCALED	**0.55**	**1.10**	**165.31 .**	**1198**
D-ZM	0.56	1.67	117.01.	126.8
D PCA-0%	0.52	1.69	107.28	126.2
D-PCA-10%	0.76	2.28	191.20	119.3
D-PCA-11%	2.71	2.24	123.51	100.6

3.3 Experimental Results

By comparison, the decimal coded normalized data set that is most suitable for the problem in this paper is selected, and a network of 14 hidden nodes is used to split 300 records into two equal groups: one group is the training group, the other is the test group, and the two groups are cross-training test. The output of the output node is still divided into four intervals of the same size from -1 to 1, indicating different money laundering risk levels from low to high. The results of the two groups of experiments are averaged, and the classification accuracy is shown in Table 3. As a comparison, the results of the suboptimal group and the results without using Bayesian regularization and L-M algorithm are also listed.

Table 3. Final test results（%）

Record grouping	D-SCALED	B-PCA-4%	L-M	BP
Training set	98.12	96.43	96.27	93.87
Test set	92.87	87.69	69.34	73.58

According to the classification accuracy results in Table 3, it can be seen that the network using the selected Decimal code normalization data set and 14 hidden nodes performs well in money laundering risk classification. Compared with suboptimal groups and the unused Bayesian regularization and L-M algorithms, this method achieves higher classification accuracy.

This means that the selected dataset and network structure can better capture the characteristics of money laundering risk and accurately classify it. In addition, the use of Bayesian regularization and L-M algorithm may help improve classification performance and further improve the results.

In a word, this paper selects the most suitable Decimal coded normalized data set for the problem through comparison, and uses an appropriate neural network structure to classify money laundering risks. The results indicate that the selected method performs well in classification accuracy, and the introduction of Bayesian regularization and L-M algorithm may further improve performance. This is of great significance for identifying and preventing money laundering risks.

4 Conclusion

The evaluation of accounting information quality based on multi-layer neural network is a relatively new research method, which makes use of the nonlinear characteristics of multi-layer neural network to enhance the ability of analyzing and evaluating the quality of accounting information. This method can not only effectively identify outliers and errors in accounting information, but also objectively evaluate the quality level of accounting information. However, this method also has some shortcomings, such as the training of neural network requires a lot of data and computing resources, and the training process is time-consuming. In addition, this method is not mature enough for the processing of noise and interference signals in accounting information, which may have a certain impact on the evaluation results. In general, the evaluation of accounting information quality based on multi-layer neural network is a promising research method, which makes use of the nonlinear characteristics of neural network to improve the ability of analyzing and evaluating the quality of accounting information. However, further improvement is needed to improve its evaluation efficiency and accuracy.

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