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Research article

A deep neural network-based smart error measurement method for fiscal accounting data

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Abstract: The error measurement of fiscal accounting data can effectively slow down the change of financial assets. Based on deep neural network theory, we constructed an error measurement model for fiscal and tax accounting data, and we analyzed the relevant theories of fiscal and tax performance evaluation. By establishing a batch evaluation index of finance and tax accounting, the model can monitor the changing trend of the error of urban finance and tax benchmark data scientifically and accurately, as well as solve the problem of high cost and delay in predicting the error of finance and tax benchmark data. In the simulation process, based on the panel data of credit unions, the entropy method and a deep neural network were used to measure the fiscal and tax performance of regional credit unions. In the example application, the model, combined with MATLAB programming, calculated the contribution rate of regional higher fiscal and tax accounting input to economic growth. The data show that the contribution rates of some fiscal and tax accounting input, commodity and service expenditure, other capital expenditure and capital construction expenditure to regional economic growth are 0.0060, 0.0924, 0.1696 and -0.0822, respectively. The results show that the proposed method can effectively map the relationships between variables.

Keywords: deep neural network; error measurement; smart fiscal accounting; intelligent computing

1. Introduction

Due to the volatility of financial assets driving fluctuations in the value, the activity in A-share has contributed to the financial market volatility and liquidity [1]. The gradual transition of the economy to a virtual economy will increase the risk and uncertainty, which may cause losses to investors, companies, society and regions [2–4]. Financial risk management is purposed to find out the maximum possible loss of each investment portfolio through various technical means, and to analyze and make decisions on this basis [5] so as to maintain the healthy and stable development of the financial market. In credit risk management, the function of a rating system is essentially achieved by accurately measuring the level of different default probabilities corresponding to different credit ratings and the change of default rates caused by credit rating migration [6].

Although some organizations have put forward fiscal and tax indicators from their own perspectives, the research on fiscal and tax measurement has not been further developed [7]; and, the settings of its indicator system are still under exploration, as well as the establishment of a complete evaluation and measurement system for sustainable consumption [8–11]. Otherwise, no matter how advanced the rating method or how perfect the index system, it will lose its meaning [12]. Therefore, we aimed to build a fiscal and tax assessment and measurement system to measure and evaluate the current consumption sustainability, as well as to use a deep neural network to predict the sustainable consumption index data and construct a fiscal and tax early warning system [13,14].

Based on deep neural network theory, we constructed an error measurement model for fiscal and tax accounting data. The main contributions of the paper are as follows.

1) Based on the project financial management analysis and evaluation theory, the construction project is taken as the main research object, using the empirical method to prove that, under the current data accumulation conditions of regional commercial banks, the behavior scoring model based on statistical methods is established to measure the error under the financial and tax exposure.

2) Regression analysis is applied to eliminate the influence of external environmental variables, random error terms and management inefficiency to obtain the adjusted input variable data.

3) A deep neural network is applied again to measure the efficiency of the third stage between the adjusted input variables and the original output variables. The analysis shows that the fiscal and tax efficiency of regional financial enterprises is relatively high, and the scale efficiency value is higher than the pure technical efficiency value.

2. Related work

Since the evaluation index system of finance and taxation is mainly intended to comprehensively reflect and evaluate the state of finance and taxation, different indicators are used in different aspects when formulating the index system [15]. As can be ascertained from the research literature on input in fiscal and tax accounting, especially the contribution rate of input to higher fiscal and tax accounting and economic growth, most of the studies focus on regions or large regions [16], and few focus on provinces [17].

Zhang [18] summarized three methods for the calculation of VAR : variance-covariance methods, conventional simulation methods and Monte Carlo simulation methods; and, taking the regional market financial comprehensive index as the research object, he calculated VaR at different confidence levels to measure the risk tolerance of investors, which proved the feasibility of using a VaR method to analyze investment risk in the regional financial market. Bohušova [19] took the regional stock market as the research object to compare the risk ratio, made assumptions on the model with different distributions and calculated the VaR. Zupan et al. [20] tried to use a neural network to measure the financial and tax risks of enterprises; they found that the neural network could effectively predict and identify financial and tax risk points. In accordance with the tax situation faced by the logistics company, they found that the depth of neural network model has more advantages in precision of prediction.

Chen and Huang [21] found that, for every 1% increase in expenditure of fiscal and tax accounting departments, the output of non-fiscal and tax accounting departments would increase by 0.59% without considering the influence of other factors, and there was a significant spatial spillover effect and spatial correlation between inter-provincial economic growth. Using pure fiscal and tax indicators to carry out early warning research, it is believed that the ratio of property rights and the ratio of net interest rate to owner's equity are the core indicators for analyzing fiscal and tax risks [22]. In terms of multiple discriminant model research, the current Z-score model, as the mainstream research method, can be subdivided into other models. Some researchers have taken domestic automobile manufacturing companies as research objects and used a Z-score model to carry out risk calculation and design a Z-value fiscal and tax early warning model, which improved the discrimination accuracy and model effectiveness to a certain extent [23]. The advantage of this study is the use of a deep neural network to synthesize financial evaluation indicators, as well as the introduction of a fuzzy AHP method to confirm the weight of comprehensive financial evaluation of social responsibility of listed companies and enable comprehensive evaluation, highlighting the necessity and advancement of the establishment of an index system.

3. Construction of error measurement model for fiscal and tax accounting data based on deep neural network

3.1. Deep neural network architecture

Deep neural networks use maximum variance orthogonal rotation to rotate the initial factor loading matrix so that the relationship between factors and original variables is redistributed [24]. In addition to dimensionality reduction for variable extraction, the use of common factors can effectively reduce the workload of data analysis; moreover, the common factor recombines the information of the original variables, eliminates the strong correlation $w(x)$ between the original variables and presents the main information $w(x,y)$ of the original variables, as in Eqs (3.1) and (3.2). The functions s and t in Eq (3.2) are marked: s represents first-order time-series variables, and t represents second-order time-series variables.

$$k(x,y) = sign(\sum w\,(x,y)/w\,(x) - \sum w\,(x,y)/w\,(y)) \tag{3.1}$$

$$cm(s,t) = 1 - \prod s(x,x-1) - \prod t(x,x-1) \tag{3.2}$$

The input and output data of neural network are preprocessed. The functions involved are prestd, poststd, trastd), and principal component analysis is used (orthogonal processing is carried out to reduce the dimensionality of the input data in Eqs (3.3) and (3.4)).

$$\frac{\sqrt{w(s,t)}-\sqrt{w(1-s,1-t)}}{w(x,t)} \subseteq R(x,t) \tag{3.3}$$

$$F(net,x) = \begin{cases} 1-x, net < x \\ x, net > x \end{cases} \tag{3.4}$$

The problem of subsidence compensation, $f(x,t)$, can be solved by using a three-layer deep neural network (with hidden layers), where the input dimension $F(net,x)$ is 3 (C, N, M), and the value range of each dimension input is the specific maximum and minimum values of C, N, M, which respectively represent the hidden layer dimension, input layer dimension and output layer dimension. The calculation method is C, N, M, which is obtained by the sum average of the weight of the fractional value of the neural network [25,26].

The numbers of neurons in the input layer and output layer are 3 and l, respectively. If the transfer function of neurons in each layer adopts the logsig function and tansig function, respectively, the training function of network train *(net,x)* is trainlm.

$$[net, x, y] < train(net, x) \cup train(net, y) \tag{3.5}$$

In order to improve the efficiency of neural network training, it is necessary to preprocess the data of "input one target" sample set in some cases. For example, the premnlnx or prestd function can be used to normalize the input and target data sets so as to reduce the correlation of each sample vector, which can realize dimensionality reduction. These do not need to be addressed for this issue.

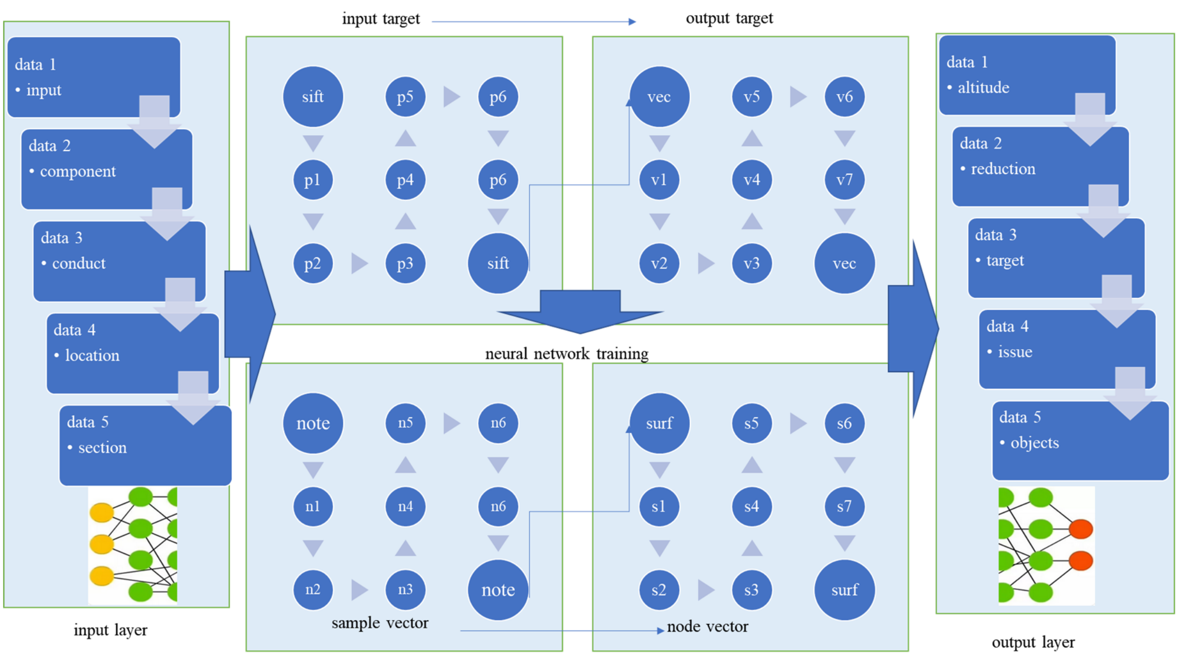

Figure 1. Deep neural network topology.

The multi-layer perceptron model in Figure 1 has three layers. For the neural network with multi-layer structure, the original input of the nodes of the hidden layer enters from the input layer, and is output after processing by conversion function and activation function at each arriving layer, and then transmitted to the next layer as input node of the next layer of the neural network until output final output layer node results. The leftmost layer is the input layer, which contains the five independent variables we selected. The middle is the hidden layer, and we will select the number of neurons contained in it according to the results of the model validity test (the number of neurons is 6). The rightmost layer is the output layer, which indicates whether the customer defaults or not during model training. When the test group data is used for prediction, the output of the model is the probability value of whether the customer defaults or not. In the study, the DEA (Data Envelopment Analysis) model can identify the redundancy of various inputs and the deficiency of various outputs, that is, the DEA model can obtain relatively effective evaluation results based on the production frontier. After comparing the above two types of neural network models that dynamically adjust the learning step size to improve the depth algorithm, we finally decide that the neural network-based model adopts the depth algorithm that introduces the impulse factor, in which the learning step size is 0.02, the impulse factor is 0.5, and the number of neurons in the hidden layer is 5.

3.2. Fiscal and tax accounting indicators

The method of mapping fiscal and tax accounting indicators requires that mapping ratings must be based on the fact that internal rating standards are comparable with external agency rating standards and internal and external ratings are comparable with each other for the same borrower. Using this approach, banks must avoid biases and inconsistencies in mapping methods or underlying data, and external ratings based on data that quantify risk must be based on borrower risk (i.e., customer rating) rather than reflecting transaction characteristics (debt rating). Profitability analysis indicators generally include: gross profit rate on sales (reflecting how much money can be used for expenses and profits in various periods after deducting the cost of sales for each yuan of an enterprise's product sales revenue), operating profit rate (reflecting the ability of an enterprise to create profits by selling products), profit rate on cost and expense (reflecting the level of profit generated by the consumption of costs and expenses), and return on total assets (reflecting the ability of an enterprise to use assets), return on equity (reflects an enterprise's ability to make profits with its own capital), value and appreciation rate of capital (reflects the rate of appreciation of its own capital), fund security rate (reflects the degree of fund security of an enterprise), etc.

$$1 - net\,(x)/2 \subseteq max - 1, net(x) - x, 1\} \tag{3.6}$$

$$w(i,j) \to w(t,t-i) - w(t-j,t) \tag{3.7}$$

It does not need to make any assumptions about the distribution *net(x)* of financial series in Eqs (3.6) and (3.7), but directly analyzes the historical data $w(i\ j)$ (i and j represent the beginning financial asset price and the end financial asset price respectively) of financial assets, according to the trend characteristics of historical data to predict its future returns. The basic idea is still to use historical data to estimate the statistical distribution of returns to calculate VaR. First, it can calculate the rate of return according to the historical data of financial asset prices. Secondly, the calculated rate of return is arranged in the order from small to large. Thirdly, the sample size is multiplied by the probability of the left tail corresponding to the corresponding confidence level, which is taken as the quantile under the confidence level. Finally, take out the rate of return on the corresponding position w(x)-1, which is the desired VaR.

$$\frac{\sum w(x-1,x) - \sum w(y-1,y)}{\sum w(x,y)} < 1 \tag{3.8}$$

$$ax(m,n) = postmaxax(m), ax(n), min(m), max(n)\} \tag{3.9}$$

Similar to the liquidity ratio *ax(m,n)*, the loan-deposit ratio *max(m)* is also an appropriate indicator in Eqs (3.8) and (3.9). A high loan-to-deposit ratio indicates that most of the deposit balance is used for loans, which increases the possibility of non-performing loans in rural credit cooperatives and increases the risk of operation. Therefore, the loan-deposit ratio needs to be maintained in an optimal ratio according to the actual situation. The number a represents the factor load matrix before rotation and b represents the factor load matrix after rotation in Eq (3.10), and *e(x)* and *e(y)* respectively represent the beginning inflation rate and the end inflation rate.

$$1 - a\frac{\partial e(x)}{\partial e(y)} - b\frac{\partial e(x-y)}{\partial e(x)} > 0 \tag{3.10}$$

Since there is no general rule to determine the number of hidden neurons in multi-layer perceptron models, the usual practice is to try to train models with different number of neurons and select them according to the predictive power of the models. Therefore, we successively transformed the number of neurons in the hidden layer, trained a total of 8 groups of models with the training group data, and tested the prediction effectiveness of the model with the test group data.

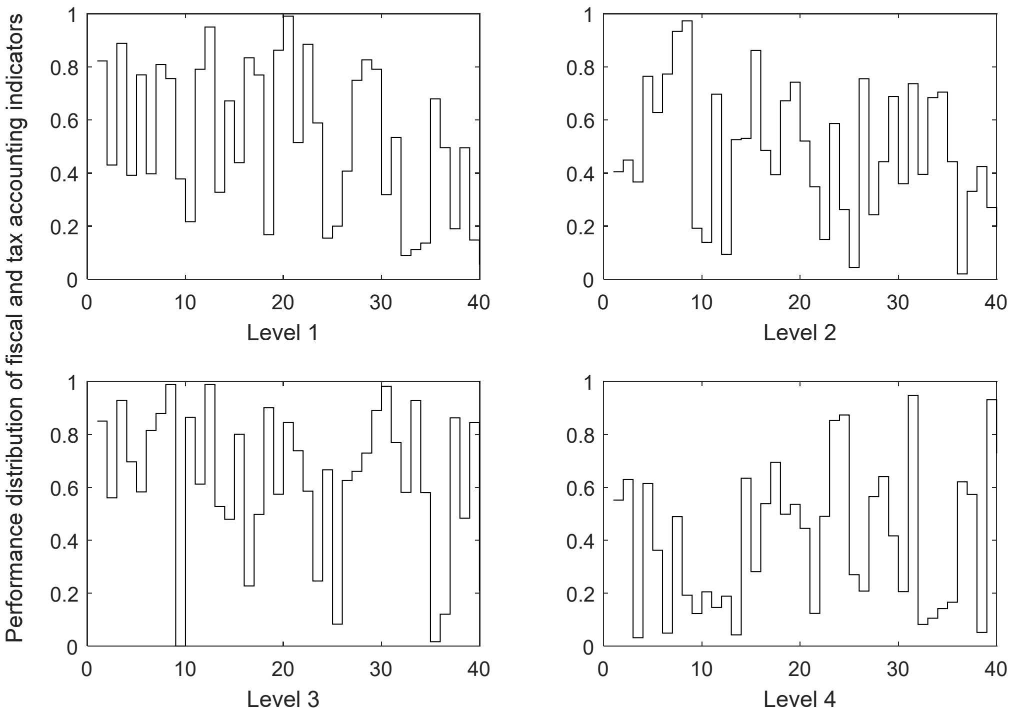

Figure 2. Performance distribution of fiscal and tax accounting indicators.

The horizontal coordinate in Figure 2 represents the level of neural network. In Figure 2, there is a large difference in the fiscal and tax performance scores, with the maximum value of 0.6856 equivalent to 12 times of the minimum value of 0.0578 and the average value only 0.3526, indicating that the overall fiscal and tax performance of regional rural credit cooperatives is slightly low and needs to be improved. The mean value of the inflation rate is 2.3283, the minimum value is 0.2000, the maximum value is 8.3000, and the standard deviation is 1.1810. The degree of fluctuation is relatively large, indicating that there are obvious differences in the inflation situation among counties and districts. The maximum value of regional economic development level is 8.8234, the minimum value is 2.1727, the span is small, the fluctuation range is relatively concentrated. The mean value of government intervention is 0.0604, the maximum value is 0.2421, the minimum value is 0.1307, and the standard deviation is 0.0398. Generally speaking, the variation of this variable is the most stable, and the range of data fluctuation is small. In terms of scale of rural credit cooperatives, the natural logarithm of total assets ranges from 12.8140 to 15.6442, showing certain differences. The maximum value of risk management level is 8.3340, the minimum value is 2.3272, the average value is 4.4701, and the standard deviation is large (1.1171). What we can see from the actual data may be due to the change of the macroeconomic environment in this region, which affects the repayment ability of customers.

3.3. Model weight optimization

In order to calculate the weight conveniently, this paper demeans the logarithm rate of return of the fiscal and tax index. Each convolution layer is followed by a lower sampling layer, which is used to reduce dimension; the parameters of the previous layers are then changed according to the difference between the current output and the desired output until the output converges to an optimal level. This shows that the sequence has obvious heteroscedastic characteristics. In order to further verify the statistical characteristics of the sequence, we made a series of tests on the data dxdt in order to accurately describe its characteristics in Eqs (3.11) and (3.12), and *dx* and *dt* respectively represent year-on-year and month-on-month inflation rate.

$$\int f(x,t)dxdt = 1 - x - t \tag{3.11}$$

$$\Delta k\,(x)/\Delta k\,(t) = 1 - \sqrt{k(t) - k(x)} \tag{3.12}$$

First of all, the financial price index *k(x)/k(t)* is a good indicator to reflect the general price changes and trends of the stock market. Secondly, the use of high frequency data not only ensures sufficient sample size in modeling, but also avoids the instability of parameter estimation caused by the use of low frequency data modeling, which will affect the application of the model. Loan growth is an important way for commercial banks to obtain loan interest income and increase their own accumulation *F(k,t)*. The higher the growth rate, the better the development of deposit and loan business.

$$F(k,t) > F\left(\sqrt{k - t(1 - t')}\right) \tag{3.13}$$

$$\frac{1}{3}\sum x\,(t)/t - \frac{2}{3}\sum x\,(t-1)/t - t > 1 \tag{3.14}$$

In order to facilitate observation and comparison in Eqs (3.13) and (3.14), we plan to use the normalization method *x(t)/t* to determine the value domain of the fiscal and tax degree as O-L (refer to the index score determination method for specific operation method), and according to the commonly used five-equal method, divide the fiscal and tax degree into five levels. Where A+ is very good, A is good, B is fair, C+ is poor, and C is very poor. Secondly, we need to determine the indicators according to their meanings are divided into different levels, and according to the analysis of the hierarchical process method (AHP) to determine the weight of each indicator. Then, each indicator is compared with the standard according to the size of its value, and its score is obtained. Finally, the fiscal degree of each subsystem is calculated.

Table 1. Weight optimization algorithm of deep neural network.

Description codes	Weight optimization function
Import matplotlib.pyplot as plt	According to the $mc(t) - x(t)$
X = 1.1:0.1:1.5;	The analysis of $1-\sqrt{x(t)}$
Y = 3.1:0.1:3.5;	The hierarchical method
[x_new, y_new] = meshgrid (x,y);	Process method $x(t-1)/t$
Date = str (year) + '-' + str (month) + '-' + str (day)	By the minimum value of $x-1$
Z = zeros (5, 5); Dates.append (date)	The fiscal degree of the subsystem
X_new = repmat (x, 5, 1); Y_new = repmat (y', 1,5);	Statistical models $x - sig(x)$
For a = 1:1:5	The fiscal degree of each $x(t)/t$
For b = 1:1:5	The management interface
X&instance2, int length) {	Subsystem is calculated $\Delta k(x)$
Y&instance1, vector <double>	The statistical analysis $x(i, j = i-1)$

Table 1 adopts a with 12 nodes in the input layer, 10 nodes in the hidden layer and 1 node in the output layer, that is, 12-10-1. The left part of his table is the attribute label of the node and the right part is the meaning of the node in the neural network. The input values are the 12 financial and tax indicators of the credit union after the above standardized processing, and the output values, namely the original expected value of the training neural network, are determined by the entropy method, which can objectively assign the weight of each indicator, so as to truly reflect the performance level of the research object. The entropy method is scientific to some extent and can effectively avoid the deviation caused by subjective consciousness, but it can't reflect the relationship between related indicators, which is a shortcoming of this method. MATLAB programming is used to realize the weight of the financial and tax performance evaluation index of credit union, and then the expected value can be obtained. The attached weight is presented in the form of weight table.

3.4. Data error analysis

Data error discriminant analysis is a common statistical analysis method used to predict and interpret the dependent variable when the dependent variable is a non-metric variable. With discriminant analysis thought to build customer default probability calculation model, the first of the existing historical customer data corresponding to the corresponding customer credit classification rules to classify (default and default), and then extract the phase variables should be analyzed for each sample, and the sample mean and covariance matrix, the discriminant function, this function maximizes the variance and minimizes the variance between firms of different classes. At this stage, before applying SFA (Stochastic Frontier Approach) regression, Eviews10 is applied to perform the corresponding unit root test on the panel data to analyze the stationarity of each data sequence.

The real value sequence of the residual square of the error rate of return is delayed by two periods to establish a time series model under deep learning. The real value sequence of the residual square of the rate of return is taken as the dependent variable, and the sequence obtained with two lag periods is taken as the independent variable to establish the deep learning function regression model. The P values of all variables were close to 0, indicating that the data had stationarity, and SFA regression could be further applied.

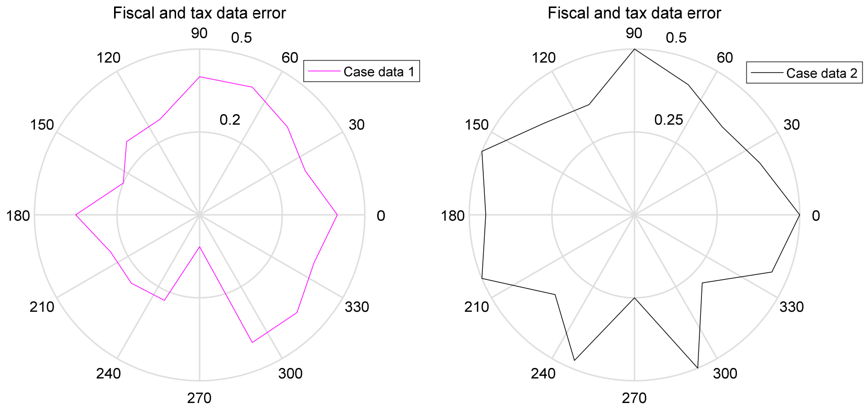

Figure 3. Error training results of fiscal and tax data.

Figure 3 shows the training results of the model. According to the training results, it is found that the error of the model itself is relatively small. In order to further reflect the applicability of the model, the test data set randomly selected by the model is input into the model, and the prediction results are summarized as follows. As can be seen, A = 0.565572, P = 0.456293, are less than the critical values at any significant level, and the sequence rejects the inclusion of a unit root. Therefore, the order of the logarithmic return rate of the fiscal and tax index is stable, and the sample series can be used to establish the time series model. The peak value is greater than 3, indicating that the yield density distribution of the fiscal and tax index is steeper than the normal distribution, and the skewness value of the fiscal and tax index is less than 0, indicating that its density function has left-skewness.

3.5. Evaluation of measurement system

In order to make the training calculation result more intuitive to understand, the actual benchmark data error and the predicted training and testing results are presented in the form of data error thermal map. By comparing the predicted value of the error price of the fiscal and tax benchmark data output by the model with the observed value of the dependent variable of the test sample (the error of the actual benchmark data), the difference between the actual value and the predicted value was observed. Indicators of capital operation ability generally include: turnover of current assets (reflecting the management level of current assets of an enterprise), operating cycle (reflecting the turnover speed of enterprise inventory into funds). In the training group and the test group, the performance period was the last year between two consecutive years. In this period, the information of account default was extracted and used as the explained variable of the model.

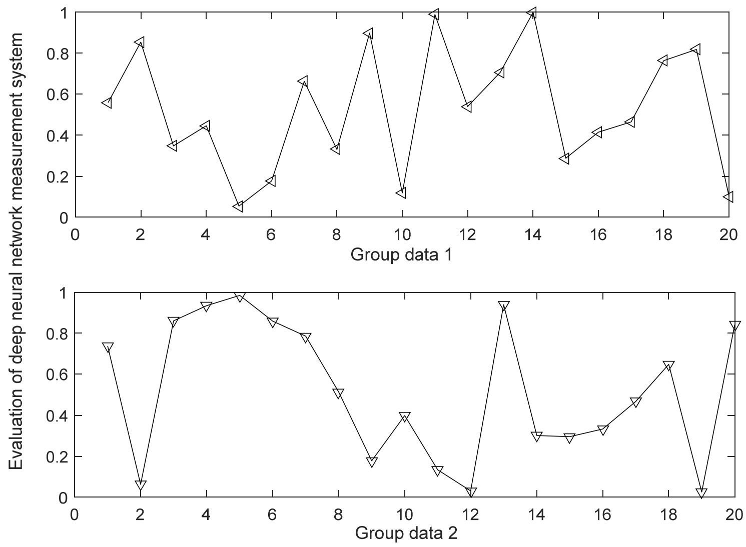

Figure 4. Evaluation of deep neural network measurement system.

From the above results, it can be seen that there is a certain gap in the mean square error (MSE) obtained by these 10 groups of experiments, but the error reflected by the inverse reflection is relatively small in general, which further indicates that the error batch evaluation model of fiscal and tax benchmark data in Figure 4 is highly applicable. The horizontal coordinate in Figure 4 represents the goup index of neural network. In general, the fiscal and tax performance of regional credit cooperatives is at a low level, with an annual average of 0.3545. Specifically, it shows an upward trend, but the fluctuation is not large. Among them, the average score of the credit cooperatives in County B was above the medium level (0.5628), while the scores of the rural credit cooperatives in other counties and districts were all below 0.5, and the score of the rural credit cooperatives in County F was the lowest (0.2320), which was half of the score of the first rural credit cooperatives. Through the analysis of the univariate regression results, we selected the following variables for the next step of regression analysis from the aspects of whether the regression coefficient conforms to the economic meaning, the significance of the number of lines (p value), and the degree of risk discrimination (ROC).

4. Application and analysis of error measurement model of fiscal and tax accounting data based on deep neural network

4.1. Deep neural network data preprocessing

As shown in the training and testing results of the deep neural network model, it is found that the error value of the actual benchmark data in the test set is not different from the error value of the prediction basis data, and the average mean square error is 0.0038203, which meets the requirements of the model setting, indicating that the test results have high credibility. The normal distribution line of this rate of return series can be clearly observed in the drawing of data graph. Meanwhile, the logarithmic rate of return of financial and tax indicators is de-normalized, indicating that this series has obvious heteroscedasticity. The model of the proceeds of the training output directly the pretreatment for the fiscal and taxation benchmark data error value, calculate the 110 data error sample training is worth the price, and will test the samples due to the variable observed value (the actual benchmark data error), calculate the absolute error and relative error. Considering that the coefficients of maximum_debt and average_a variables were not significant, we eliminated these two variables and carried out logistic regression on the remaining five variables to obtain the following results.

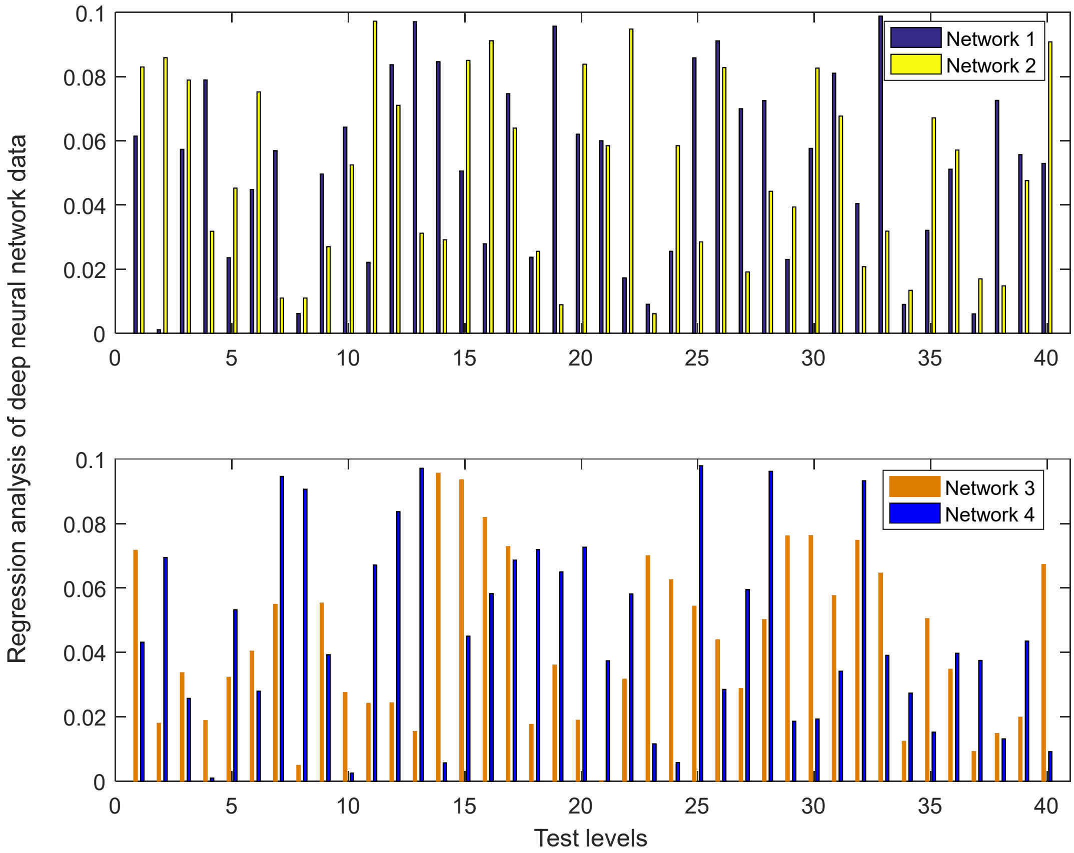

Figure 5. Regression analysis of deep neural network data.

The meaning of legend in Figure 5 is multi-level neural network with different optimization levels. According to the above results, it can be seen that the model in Figure 5 reaches the best verification state at step 7, when the mean square error is at the lowest value: MSE = 0.038203. Here, we can notice that the coefficient signs before variables days_in_debt and max_single_a are positive, which means that these two variables are inversely changing with the predicted value of the final PD, which seems to be inconsistent with its meaning. According to DEA model, the definition of input-output index is as follows: input index refers to the economic quantity that decision-making unit needs to consume in economic and management activities; the output index refers to the economic quantity that the decision-making unit shows the effect of economic activities under a certain combination of factors. First, we analyze the variable days_in_debt. Then according to the results given by our PD model, customer B's default probability is smaller. It was found that the simulated regression analysis graphs of the training data set, the testing data set and all the data sets showed that the relationship between the values was linear, and the correlation coefficient was close to 1.

4.2. Calculation and simulation of fiscal and tax data error

In this paper, 110 benchmark data error sample data collected are taken as the training and testing set. They are randomly divided into ten groups by using MATLAB toolbox. When applying deep neural network model to the error evaluation process of fiscal and tax benchmark data, the key is to determine the learning algorithm. In this case, 16 influencing factors (such as equity ratio (reflects how much of a company's assets are invested by its owners), long-term debt ratio (reflects the ratio of long-term liabilities to total assets), debt-to-equity ratio (reflects whether a company has borrowed too much compared to shareholders' equity), and capital cure ratio (reflects the proportion of solidified assets to owners' equity)) are selected as the input layer of neural network for the initial input of the model, and the number of hidden layer nodes is reasonably determined, which can improve the operation efficiency. After the model is successfully trained, the trained deep neural network model is tested with 11 fiscal and tax benchmark data error test samples randomly selected by the model, and the prediction data errors of 11 fiscal and tax benchmark data error samples are obtained. It can input the preprocessing values of the error influencing factors of the fiscal and tax benchmark data in 11 test samples to the established model, and the output result is the error value of the forecast benchmark data. The results in Table 2 are reserved to three decimal places.

Table 2. Description of the quality of basic education.

Segment unit	Mean square error		Layer type	Statistically distributed value	
Indicator 1	0.404	0.579	Layer input 1	0.463	0.541
Indicator 2	0.328	0.503	Layer input 2	0.127	0.960
Indicator 3	0.901	0.003	Layer input 3	0.187	0.632
Indicator 4	0.155	0.022	Layer input 4	0.824	0.633
Indicator 5	0.055	0.647	Layer input 5	0.490	0.519
Indicator 6	0.171	0.460	Layer input 6	0.186	0.640

To predict the loss series, 48 data of the last day are selected for prediction, and the rest data are modeled. The VaR of each phase is pre-measured in the deep learning model. The loss sequence was taken as the dependent variable, and the sequence obtained with one and two periods lag were taken as the independent variables to establish the deep learning model, so as to obtain the functional regression model under deep learning with different lag periods.

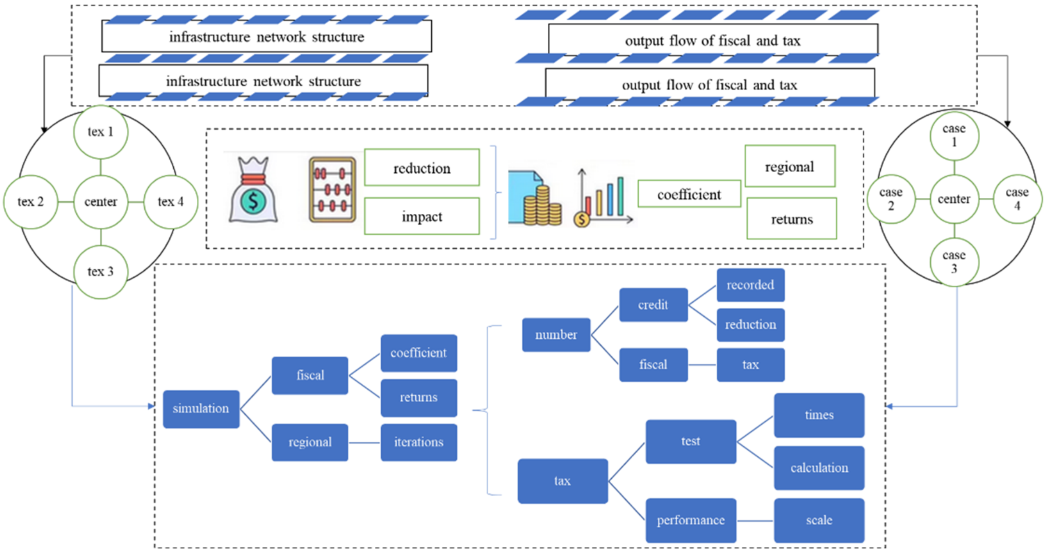

Figure 6. Output flow of fiscal and tax prediction simulation.

Through MATLAB programming, it is found that the value changes every time. When the number of iterations is less than 200 times, the result tends to 0 basically. When the number of iterations reaches more than 2000 times, the results are significant. Therefore, this paper repeated experiments for many times and randomly recorded the values of 40 different iterations. In Figure 6, input data is substituted into the model for fitting prediction, and simulation function is used to establish the simulation model. After establishing the simulation model, the simulation calculation was carried out for 20 times, and the optimal calculation result was 0.9715. The calculated results are normalized to the data for reduction. The coefficient of the impact of asset scale on the fiscal and tax performance of rural credit cooperatives is -0.146108, which passes the 1% significance test, and the coefficient is negative, indicating that the asset scale is negatively correlated with the fiscal and tax performance of regional rural credit cooperatives. At present, the performance of regional rural credit cooperatives may be in the stage of decreasing returns to scale. At the same time, it can be seen that although the coefficient is negative, it is relatively small, only 0.146108. Therefore, rural credit cooperatives should carefully weigh the economic and negative effects brought by them when expanding the scale of operation. The average error rate of the results is 0.152, which is also acceptable, that is to say, the model can be used for measurement.

4.3. Example application and analysis

This case uses the front introduced to customers under the tax exposure of risk evaluation model of behavior model, based on the sample account in the performance of the loan term, namely about customer credit use and pay the dynamic behavior of the data analysis, logistic regression model is established and the model based on neural network, the client default rate forecasting. The coefficient of preprocessing data expenditure can promote the improvement and enhancement of total factor productivity. The application of principal component analysis is as follows: the analysis elements of financial evaluation are applied to specific practice. This case data base for consumer loans of commercial bank customer reimbursement detail of the original transaction records, through analysis, extract and client default behavior related variables as explanatory variables of the model, the client default or not information is interpreted as a model of variable, it can take the 0 and 1 respectively on behalf of clients, not default and breach of covenant.

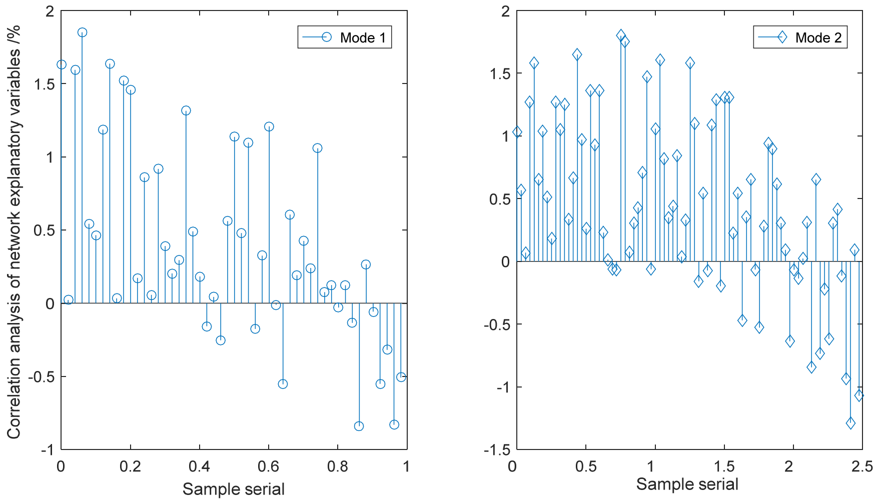

Figure 7. Correlation analysis of network explanatory variables.

If the variables in Figure 7 are independent from each other, the common factor cannot be extracted from the total, which needs to be judged by Bartlett spherical test. After 34 calculations, the optimal result was: 0.9837. The calculated result is the normalized data, we perform the reduction. In order to avoid the problem of insufficient expression ability of linear model, the convolution layer usually contains a nonlinear transformation layer, which adopts nonlinear transformation for the features obtained by convolution. That is, the normalized inverse function is used for reduction processing, and the reduction function is $y1=(y+t1)/2+t2$, where $t1$ is the maximum value and $t2$ is the minimum value. Using the error rate formula, the error rate between the simulated value and the real value is 0.008, which is very ideal. The average result has a margin of error of 0.173.

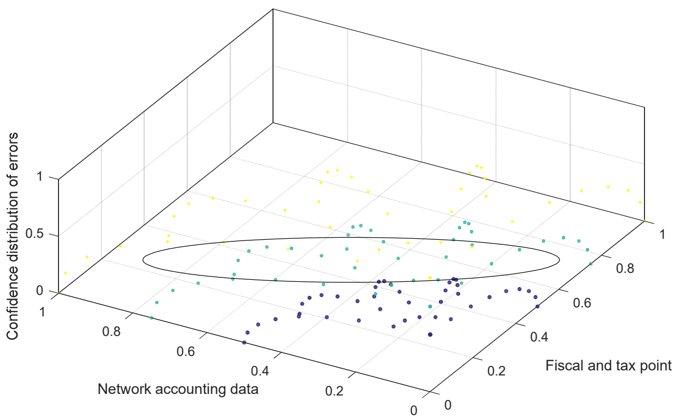

Figure 8. Confidence distribution of financial and tax accounting data errors.

At 99% confidence level, the mean square error of model predicting VaR is 3.06923. The mean square error of prediction VaR of time series model under deep learning is 0.871142. The mean square error of the functional regression model under deep learning was 0.870637. It can be seen from Figure 8 that the first common factor has a large load in quick ratio, current ratio and cash ratio. It mainly reflects the development of finance and taxation from quick ratio, current ratio and cash ratio, and is expressed as X1. The second factor has a large load on the property right ratio and asset-liability ratio, from which the property right ratio and asset-liability ratio reflect the current situation of finance and taxation of transportation enterprises, denoted by X2; the third common factor has a large load on total asset turnover, current asset turnover and employee profit level, so it has the largest correlation with these three factors, representing X3; the fourth common factor only has a large load on the fitness rate of long-term assets, denoted as X4; the fifth common factor has a larger load on the turnover of accounts receivable, which reflects the current situation of finance and taxation from the aspect of accounts receivable, expressed as X5. Therefore, X1, X2, X3, X4 and X5 are obtained as input indexes of model. The mean square error of VaR predicted by functional regression model under deep learning is smaller than that predicted by time series model under deep learning and smaller than that predicted by model.

5. Conclusions

In this paper, an error measurement model of fiscal and tax accounting data based on deep neural network is constructed, and the large-scale evaluation of benchmark data error is realized in the form of batch. Based on relevant theories of asset evaluation, deep neural network is introduced to improve the shortcomings of traditional methods. In the process of simulation model using MATLAB neural network data analysis tools to build depth model, simulate the fiscal and taxation benchmark data error and all kinds of complicated relations between the influencing factors. The mean value of financial data error is 0, and the standard deviation is 0.616. The calculation results show that the error degree of financial data is still within the safe range. According to the statistical sampling distribution theory, with 3 times standard deviation as the limit, if the error of financial data exceeds 3 times standard deviation, it indicates that the risk has accumulated. In the example application, this paper uses STATA software to carry out Tobit model regression on the factors affecting the fiscal and tax performance of regional rural credit cooperatives. Through the construction of network algorithm model, the main influencing indicators related to the fiscal and tax benchmark prices are automatically quantified and assessed, and the rapid evaluation of the error of the fiscal and tax benchmark data in this region is completed. Results show that the rate of inflation, government intervention, assets are significant negative impact on financial performance. In addition, regional economic development level and business innovation ability have not passed the test, so they have no significant impact on fiscal and tax performance.

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Conflict of interest

The authors declare that there is no conflict of interest.

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