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Credit Risk Assessment and Prediction Model of Commercial Banks

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Abstract: Aiming at the risk assessment and prediction of commercial bank credit management, BP neural network and GRNN model are established respectively to fit and forecast the non-performing loan rate of commercial bank. The results show that GRNN neural network has high fitting accuracy but low prediction accuracy, while BP neural network has low fitting accuracy but high prediction accuracy.

1. Introduction

The credit risk of commercial banks is closely related to the macroeconomic operation. At present, with the slowdown of China's economic growth, the business environment of commercial banks tends to deteriorate, and the non-performing loan rate continues to rise [1-2]. This not only increases the risk of the financial system, but also intensifies the downward pressure on the economy. In order to ensure the long-term stable and healthy development of China's economy, it is very important to strengthen the quantitative research on the relationship between credit risk and macro-economy of commercial banks.

At present, the empirical research on the relationship between credit risk and macroeconomic variables of commercial banks is mainly based on linear analysis tools. For example, Ref. [3] used multiple linear regression model to conduct empirical research on the relationship between bank credit risk and macro-economic variables. The analysis shows that the non-performing loan rate has a positive correlation with the growth rate of M2, but a negative correlation with GDP growth rate and inflation rate. Ref. [4] analyzed the correlation between economic growth and non-performing loan ratio based on HP filter. The research shows that after 1996, there is a negative correlation between the default rate of bank credit and the macro-economic prosperity index. Ref. [5] studied the impact of economic growth, price level and monetary policy on credit risk of commercial banks based on panel data and fixed effect model. The research shows that when the macro-economic growth rate drops, deflation and monetary policy tighten, the non-performing rate of commercial banks will rise obviously. Ref. [6] used a mixed vector autoregressive model to study the impact of bank credit, house price and interest rate changes on the non-performing rate of housing mortgage loans. The research shows that the impact of macroeconomic variables on the non-performing rate of housing loans is related to the financial stability. Ref. [7] used the vector autoregressive model (VAR) to analyze the transmission process and contribution of the impact of macroeconomic variables on the credit risk level of China's commercial banks. The research shows that the bad rate is significantly affected by its own inertia, and the GDP growth rate is negatively related to the bad rate, but the correlation is gradually declining. Due to the complex business environment of commercial banks in China, it is questionable whether there is a linear relationship between credit risk and macroeconomic variables. However, due to the limited amount of sample data and the limitation of analytical tools, the research on the nonlinear relationship between credit risk and macroeconomic variables of commercial banks is still less.

Neural network model has the characteristics of self-learning and self-organization, and does not need to give a clear function form in the application process, avoiding the possible errors caused by the subjective setting function form, so it is widely used in pattern recognition, intelligent control and other fields. With the development of artificial neural network and its application, scholars begin to apply it to economics research. For example, Ref. [8] used factor analysis and BP neural network model to establish financial crisis early warning model to identify the potential financial crisis of enterprises, and the effect of the model was good. Ref. [9] evaluated the credit risk of small and micro enterprises based on the multi-layer perceptron neural network algorithm. The research shows that the multi-layer perceptron neural network algorithm is superior to the traditional parameter based classification method. At present, using neural network model to study the relationship between macro-economy and credit risk of commercial banks is still in the exploratory stage. Based on this, this paper uses neural network to study the relationship between macro-economy and credit risk of commercial banks, and expands the application of neural network model in the field of credit risk management of commercial banks.

2. Structure and Basic Principle of Neural Network Model

BP neural network is also called back propagation neural network. The network is composed of input layer, hidden layer and output layer. The structure is shown in Figure 1. The neurons in the adjacent layer of BP neural network are connected by the network weight coefficient W_{ij}, but there is no connection between the neurons in the same layer. The transfer function of hidden layer usually chooses sigmoid function, while the transfer function of input layer and output layer usually chooses linear function. BP neural network uses error back-propagation algorithm to learn, that is, data from the input layer through the hidden layer is propagated backward layer by layer, while when training the network weight, along the direction of reducing the error, from the output layer through the middle layer to modify the network connection weight. With the continuous learning, the mean square error between the actual output value and the expected output value of the network becomes smaller and smaller.

The generalized regression neural network (GRNN) is a branch of the radial basis function neural network, which consists of the input layer, the hidden layer, the addition layer and the output layer. The structure is shown in Figure 2.

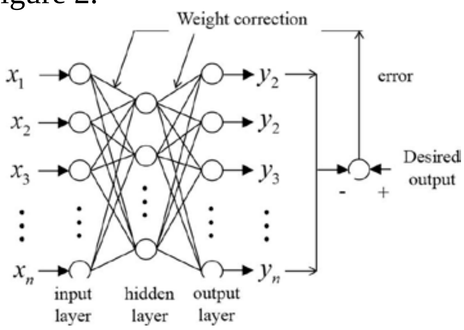

Fig.1 Bp Neural Network Structure Diagram

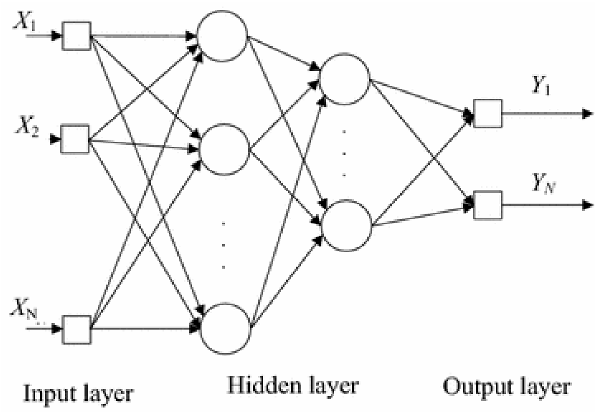

Fig.2 Grnn Neural Network Structure Diagram

Input layer neurons are determined by input vectors, i.e. network input $X=[X_1, X_2,..., X_m]^T$. The transfer function of the input layer usually selects a linear function. The hidden layer is a radial base layer, and the basis function usually adopts Gaussian function, i.e. the transfer function of the hidden function is:

$$exp\left[-(X - X_i)^T (X - X_i) / 2\sigma^2\right] \quad (1)$$

Where σ is the smoothing factor. The choice of smoothing factor or has a great influence on network performance. When the smoothing factor approaches 0, the network is over fitted. The neurons in the additive layer are divided into two branches. The first neuron is called denominator unit, which is used to calculate the algebraic sum of neurons in the hidden layer, namely:

$$\sum exp\left[-(X - X_i)^T (X - X_i) / 2\sigma^2\right] \quad (2)$$

The second neuron is called molecular unit, which calculates the weighted sum of neurons in the hidden layer, namely:

$$\sum Y_i exp\left[-(X - X_i)^T (X - X_i) / 2\sigma^2\right] \quad (3)$$

The output layer divides the numerator unit by the denominator unit to get the output value. GRNN realizes the nonlinear conversion from the input space N^R to the output space M^R by the linear combination of the nonlinear basis functions. Moreover, because the output layer of GRNN is the linear weighting of the middle layer, the network has high operation speed and extrapolation ability, and the network has strong nonlinear mapping function. The output layer divides the numerator unit by the denominator unit to get the output value. GRNN realizes the nonlinear conversion from the input space NR to the output space MR through the linear combination of the nonlinear basis functions, and because the output layer of the network is linearly weighted to the middle layer, the network has higher operation speed and extrapolation capability, and at the same time, the network has stronger nonlinear mapping function.

3. Construction of Credit Risk Prediction Model

3.1 Variable Selection

The neural network model has no economic meaning for the selection of input variables, but the selection of input variables may have a greater impact on the prediction results of the neural network model. In this paper, the non-performing loan rate is selected as the index to measure the credit risk level of commercial banks, so the selection of input variables is mainly from the influencing factors of the non-performing rate of commercial banks.

3.2 Selection of the Optimal Lag Order of Input Variables

First of all, the unit root test is carried out on GDP growth rate, CPI growth rate and M2 growth rate of generalized money supply. The test results show that the above variables are all stationary variables, so the vector autoregressive model can be established (see Table 1).

Table 1 Unit Root Test Results

Variable	Inspection Type	ADF Value	P Value	Conclusion
GDP	(c,t,0)	-4.1 232	0.0 131	Stable
CPI	(c,0,0)	-4.4545	0.0 009	Stable
M2	(c,0,0)	-2.756	0.0 736	Stable
PD	(c,0,0)	-4.0 386	0.0 030	Stable

Note: (c, t, p) indicates the test type, and parameters c, t, p respectively indicate whether the unit root test equation contains constant term, time trend and lag order.

The VAR model is established, and then the optimal lag order of the input variables of the neural network model is selected. As can be seen from Table 2, the optimal lag order is 2. Therefore, the first-order lag term and the second-order lag term of GDP growth rate, CPI growth rate and M2 growth rate are selected as input variables.

Table 2 the Selection Of the Optimal Lag Order

Lag	LogL	AIC	SC	HQ
0	NA	17.90	18.07	17.96
1	286.49	10.30	11.15	10.60
2	88.48*	8.18	9.70	8.72*
3	25.68	8.00*	10.22	8.80

Note: * indicates the optimal lag order of information criterion selection.

3.3 Data Preprocessing

Because each variable in the original data sample has different order of magnitude, in order to improve the training speed of the network, the original data is normalized. In this paper, we use the premnmx function to normalize the input and output of the original data samples, so that the processed data can be evenly distributed in the range of [- 1,1]. The conversion formula is as follows:

$$X_N = \frac{2(x - minx)}{maxx - minx} - 1$$

$$Y_N = \frac{2(y - miny)}{maxy - min6y} - 1 \quad (4)$$

Wherein x and y are input samples and output samples of the original data respectively; X_N and Y_N are input samples and output samples after function normalization respectively. After the training of the neural network is completed, the simulation results are denormalized by using the postmnmx function and restored to the initial values.

When designing the input and output of the network model, the normalized first-order and second-order lag terms of GDP year-on-year growth rate, the first-order and second-order lag terms of CPI year-on-year growth rate, the first-order and second-order lag terms of M2 year-on-year growth rate, the first-order and second-order lag terms of NPR are used as input variables, and the normalized NPR is used as target output.

4. Conclusion

In this paper, BP neural network and GRNN neural network are used to fit and forecast the non-performing loan rate of commercial banks, and the advantages and disadvantages of the two are compared. The research shows that the average relative error of the bad rate of GRNN neural network fitting is lower than that of BP neural network fitting, but the average relative error of the bad rate of GRNN neural network prediction is significantly higher than that of BP neural network prediction. On the whole, BP neural network has more advantages than GRNN neural network in the prediction of non-performing loan ratio of commercial banks. According to the prediction of BP neural network, the non-performing loan rate of commercial banks will rise slightly in the fourth quarter of 2015, but the risk is controllable. It is worth noting that neural network is more suitable for the short-term prediction of non-performing loan rate, and the prediction of medium and long-term non-performing loan rate will be limited to some extent. For commercial banks, on the one hand, they should pay close attention to the changes in the macro-economic situation and formulate their own development strategies reasonably; on the other hand, they should strengthen the application of quantitative tools in risk management and improve the accuracy of risk management.

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