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A Bank Credit Risk Model Integrating Artificial Neural Network

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Abstract: In recent years, my country's economic situation has been stable with changes. The overall situation is not optimistic. Coupled with the impact of the epidemic, credit risk (CR) events often occur in the financial market. Optimize the process of CR management and increase CR. Management capabilities and the establishment of a CR management system based on a standardized process are the top priorities for major banking financial institutions. Therefore, this paper studies the bank CR model based on artificial neural network (NN). This paper first briefly explains the impact mechanism of CR from the aspects of profitability and liquidity, then builds the BP NN model, and finally analyzes the BP model. The results show that the misjudgment rate of the BP model is 7.14%, and the judgment accuracy rate is 92.86%. The model is more accurate for CR judgment.

1. Introduction

With the continuous development of the financial market, financial instruments and financial means are becoming more and more complex, and various financial risks are constantly emerging [1]. Among the various financial risks faced, CR is constantly mentioned. The index performance of my country's banking industry in terms of credit assets has fluctuated and rebounded, especially in industries and regions with relatively concentrated risks, which frequently expose CR [2-3]. For the banking industry, the attention to CR is self-evident. If a bank is in financial distress due to the impact of CR, due to the rapid contagion of risk, this impact is likely to lead to the entire financial market systemic risk [4-5]. Therefore, in order to protect the banking industry from the damage of CR as much as possible and provide a good financial service platform for enterprises and individuals, it is necessary to further accurately predict and prevent CR [6].

Domestic academic circles use a variety of evaluation methods such as multivariate discrimination method and NN model to study the CR evaluation of commercial bank (CB), in order to combine the actual situation of my country's basic national conditions to build a CB CR model [7-8]. For example, experts such as Okafor A used the Lambda test to evaluate the quality of the model, and used the receiver operating characteristic curve (ROC) to build the model, the model classification accuracy was 83.7%, and the proposed classification model had predictive ability [9]. Maksutova A A proposes a CR model in which default strengths have a sparse partial correlation structure. The bank CR model introduces a lasso estimation procedure to recover the network using CDS data. The analysis shows that the network captures a large amount of interconnectivity [10]. At present, there are few studies on CR models using NN.

CR will affect the stable operation of CB. Therefore, this paper studies the CR model of CB using artificial NN. The main content of this paper consists of three parts: the first part is the CR impact mechanism, including the impact of profitability on CR and the impact of liquidity on CR; the second part is the construction of the model, from the NN algorithm steps, The BP model is constructed from three aspects: network training and BP NN model inspection; the third part is model analysis, which mainly includes two analysis contents: model simulation analysis and model comparison analysis.

2. CR Impact Mechanism

2.1. The Impact of Profitability on CR

For enterprises, profit maximization is their core goal after realizing the stable operation of the company, and profitability can directly reflect the realization of the goal of enterprise profit maximization [11]. For CB, it is also aimed at making profits. The improvement of profitability means that the stronger the solvency of the bank and the sufficient capital advantage to resist CR, the less likely default events will occur [12]. However, for CB with strong profitability, operators may lower the regulatory standards for risks and engage in some high-risk banking activities for more benefits, which will increase the CR faced by CB. [13]. The impact structure of CR on profitability is shown in Figure 1.

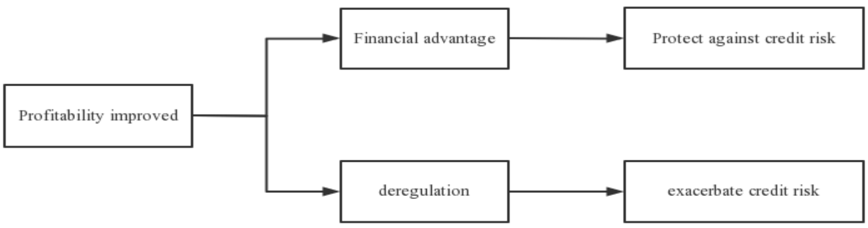

Figure 1. Structure of the impact of profitability on CR

2.2. The Impact of Liquidity on CR

Bank liquidity usually refers to the ability of banks to have sufficient funds to meet customers' ability to withdraw cash at any time [14]. If the bank's liquidity is strong, the liquidity risk it faces is small, and the research of relevant literature shows that the liquidity risk and CR have a positive relationship, and the liquidity risk is reduced, which will strengthen the city CB's ability to resist CR. capacity, but in the same way, it may lead to a large amount of currency hoarding inside the bank, then the bank will consider more investment opportunities for the consideration of capital utilization, coupled with the trend of profit-seeking behavior, the bank may have a stronger Motivation to choose credit opportunities with higher risk but also higher returns, thus intensifying

CR [16-17]. The impact structure of liquidity CR is shown in Figure 2.

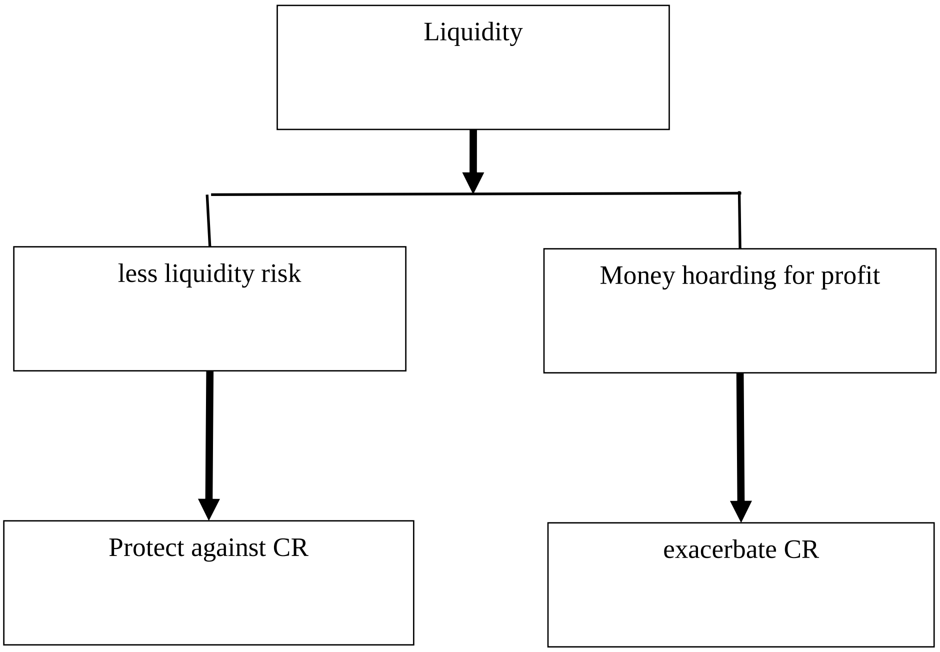

Figure 2. Liquidity CR impact structure diagram

3. Model Building

3.1. NN Algorithm Steps

According to the actual situation in my country and the characteristics of the BP NN model, the index data of the BP NN model is easy to obtain, and it is more suitable for application, so as to ensure that the possible CR can be accurately predicted. Therefore, this paper constructs the BP NN model [18]]. In practice, CB can use BP NN in combination with other discriminant methods and qualitative analysis to comprehensively judge the overall CR status of enterprises, and provide accurate reference for credit approval and pricing. Among them, the specific algorithm steps of the NN algorithm are:

(1) Set the initial parameters.

(2) Input training samples.

(3) Calculate the values of cj and dk according to the following formulas

$$c_j = f\left(\sum_{i=1}^{m} e_{ij} s_i - \theta_j\right) \tag{1}$$

$$d_k = f\left(\sum_{j=1}^{l} e_{jk} c_j - \theta_k\right) \tag{2}$$

(4) Calculate the error between the layers according to the following formula

where m is the number of neurons in the output layer.

(5) Termination judgment is carried out according to the number of samples trained: if pi+1 do not reach the set learning number p, repeat this step; if pi+1 reaches the set learning number p,

proceed to the next step.

(6) Modify the weight and threshold according to the above steps.

(7) Calculate according to the new weight.

(8) Calculate the root mean square variance of the network according to the following formula.

$$E(S)=\sqrt{\frac{\sum_{p=1}^{p}\sum_{k=1}^{n}(b_{pk}-d_{pk})^2}{P\times n}} \tag{3}$$

3.2. Network Training

The output result of BP model default probability judgment critical point is 0.5. When the output value (OV) does not exceed 0.5, it is judged as an ST company (STC), and when it exceeds 0.5, it is judged as a non-STC. After the coefficients are initialized, the example figure is input into the BP network model (NM) for drilling, and the practice error curve is shown in Figure 3.

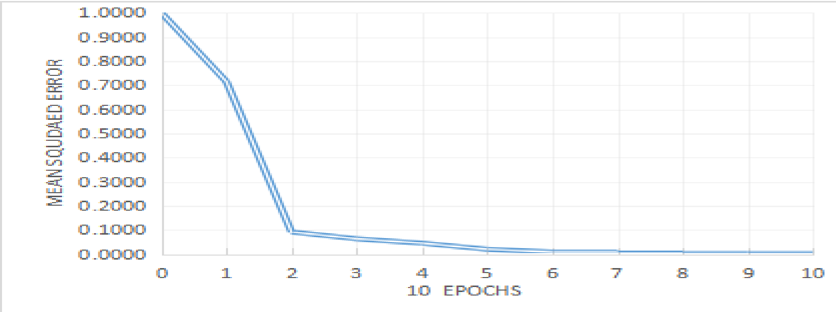

Figure 3. NN training error curve

After the model's self-learning and self-use process, the model continuously and automatically adjusts the weights and thresholds to make the OV as close to the desired goal price as possible. After drilling, the mistake curve gradually converges to the end price of 0.001, and the web automatically generates a CR evaluation model for CB loan companies. From Figure 3, we can see that after 9 iterations of the NN, the error drops below 0.001. The training data is brought into the model and the results are shown in the following table.

3.3. Test of BP NN Model

The BP model was constructed based on artificial NN. Table 1 shows the prediction results of the model for 102 training samples. As can be seen from the table, the cross-entropy error of the training samples is 13.46, and the overall percentage error prediction rate reaches 6.7%, indicating that the overall error of the 83 training samples is about 5, which means that there are about 5 normal enterprises. Enterprises that are wrongly judged to be in default and those that are wrongly judged to be normal companies. In the test sample, the cross-entropy error is only 4.35, and the percentage error prediction rate is only 4.2%, which are respectively smaller than the prediction results of the training sample.

Table 1. BP model test results

	Error percentage	Error prediction percentage
Training samples	13.46	6.7%
Test sample	4.35	4.2%

4. Model Analysis

4.1. Simulation Analysis of the Model

In the cause of proofing the application worth of the constructed BP NN, we must simulate the constructed model with simulation samples to verify the inaccuracy of its estimate results. The data of 14 emulation sample companies (including 11 non-STC and 3 STC) are input into the NM, and the trained NN is called for simulation. The phantom results are shown in Table 2. In the following, STC purposes that the company has fallen into the predicament of continuous loss or insolvency, the credit situation is poor, and the possibility of CR is high. It is used to represent the default sample, and the OV in the model is represented by 0; STC means that the company is operating normally and the possibility of default is very small. It is used to represent a sample with good credit, and the OV in the model is represented by 1.

Table 2. Model simulation results

Serial number	Expected output	Actual OV	Error	Serial number	Expected output	Actual OV	Error
1	1	0.876	0.001	8	1	0.914	0.035
2	1	0.857	0.012	9	1	1.005	0.031
3	1	0.834	0.013	10	1	0.998	0.004
4	1	0.916	0.008	11	1	0.991	0.006
5	1	0.216	0.712	12	0	0.893	0.001
6	1	0.993	0.005	13	0	0.975	0.016
7	1	0.985	0.023	14	0	0.983	0.002

It can be seen from Table 2 that the expected OV of the non-STC is 1, and the actual OV of the company with the serial number 5 is 0.216. The company has been classified incorrectly, and the company with good credit is judged as the company with poor credit. Misjudgment The detection rate was 9.09%, and the determination accuracy was 90.91%. The expected OV for ST companies is 0, and no companies have misclassifications. From the perspective of the overall sample, the misjudgment rate is 7.14%, and the judgment accuracy rate is 92.86%, indicating that the evaluation model has a relatively high accuracy in determining the CR of listed companies, and can judge the corporate credit situation seeding to the OV of the evaluation. The OV is close to 1 It means that the firm has good faith and the lower the OV, the worse the faith. In general, foundation the above drilling analog figure, it can be seen that the constructed NM shows a great emulation effect, but the estimate accuracy will decrease in the real adhibition process, especially for STC, refree accuracy is reduced.

4.2. Model Comparison Analysis

In order to analyze the validity of the model, this paper selects 45 test samples, and uses the Logistic model and the BP NN model to predict the company category. The test sample includes 37 non-STC samples and 8 STC samples. The two samples are respectively substituted into the above two models to obtain the probability value P. The P value is compared with the classification point. If the value is smaller than the classification point, it will be classified into the corresponding sample category, and if it is larger than the classification point, it will be classified into the same classification sample. The analysis results are shown in Table 3.

As can be seen from Table 3, when using the Logistic model to test 45 samples, among the samples from non-ST companies, 6 were misjudged as ST companies, and the correct discrimination rate was 83.78%. Among the samples from ST companies, 2 were misjudged as non-ST companies, and the correct discrimination rate was 75%, so 8 of the 48 samples were misjudged, and the total discrimination correct rate was 82.22%. If the BP NN model is used to discriminate 45 samples, only 2 samples from non-ST companies are misjudged as ST companies, and the discrimination accuracy rate is as high as 94.59%; 1 sample from ST companies is misjudged as non-ST companies, and the discriminant The correct rate is 87.5%, so the total discrimination correct rate is 93.33%. By comparison, it is found that the prediction accuracy of CB CR using BP NN model is higher than that using binary logistic model.

Table 3. Comparison of model prediction results

Model	Logistic model prediction			BP neural model prediction		
Sample	Non-ST	ST	Prediction accuracy	Non-ST	ST	Prediction accuracy
Non-STC	31	6	83.78%	35	2	94.59%
STC	2	6	75%	1	7	87.5%
Total	33	12	82.22%	36	9	93.33%

5. Conclusion

This year, the downward pressure on my country's economy has continued to increase, and the unstable factors in the CR of CB have increased. my country's CB should strengthen CR management very necessary. In this paper, the BP NN model is verified and compared and analyzed, and it is found that the BP NN method can improve the prediction value of enterprise CR. The management of CB CR should take into account the influence of factors such as liquidity and profitability on CR. Due to the limited knowledge of artificial NN in this paper, there are many deficiencies in the construction of CR model, which need to be improved and further researched.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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