Research on Financial Risk Control Model Based on Deep Neural Network

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Abstract: Affected by the deterioration of the international environment, risks in China's financial market are constantly accumulating, which puts forward higher requirements for financial risk control. In particular, the liquidity risk control of commercial banks has become the focus of academic attention. To control financial risks, we must first control the liquidity risk of commercial banks. With the help of the deep neural network model, this paper, based on the financial data of Chinese commercial banks in 2020, conducts research on financial risk control problems, aiming to explore effective financial risk control strategies.

Keywords: deep neural network; financial risk control; liquidity risk; commercial bank

1. Introduction

Affected by the dual impact of the domestic economic downturn and the deteriorating international environment, China's financial fluctuations have intensified, and its financial risks have become increasingly complex and volatile. Against this backdrop, the central government has called for strengthening risk prevention and control in key areas and ensuring that systemic financial risks do not occur. The problem of financial risk control has been promoted to an unprecedented height, especially the liquidity risk control of commercial banks has become the focus of scholars.

The essence of a bank is a profit-oriented enterprise. Compared with other profit-making enterprises, the bank has a faster business expansion speed, higher debt ratio, more prominent capital overload operation, and greater liquidity hidden risks[1]. Once commercial banks have liquidity risks, they will quickly spread to other financial institutions or even non-financial enterprises, inducing systemic financial risks. Therefore, the essence of the effective control of financial risks is to realize the measurement and control of liquidity risks of commercial banks.

There are many research results on the measurement and prevention and control of liquidity risk. On the one hand, there is not yet a unified view on how to describe the liquidity risk of banks. In addition to the traditional static index evaluation method, cash flow method and so on [2], the liquidity mismatch index model is also gradually promoted [3]. On the other hand, the research on the influencing factors of the liquidity risk of commercial banks is still deepening. Rose (2002) found through research that the liquidity gap of commercial banks is mainly affected by monetary policy, GDP growth and other factors[4]. Paola (2002) believes that the generation of liquidity risk is related to the improper risk control strategies of commercial banks[5]. Brunnermeier (2009) proved that liquidity risk came from financial institutions through evidence during the US subprime mortgage crisis[6]. Yang Zhongyuan & Xu Wen (2011) believe that the liquidity risk control strategy of banks can be studied from the perspective of the time matching of assets and liabilities[7]. Gertler & Kiyotaki (2013) pointed out that the macroeconomic downturn was the only condition to stimulate the bank liquidity crisis[8]. Chatterjee (2015) Research found that the volatility of the capital market will accelerate the accumulation of liquidity risk of commercial banks[9]. Luo Shengze (2019) found through research that the liquidity risk of banks is closely related to the operating ability of commercial banks[10]. Xu Jinghong & Yang Daguang (2022) build an evaluation index system from the five aspects of the assets, liabilities, income, operation and owners' equity of commercial banks, and explore the financial risk control problem from the perspective of the liquidity risk of commercial banks[11]. To sum up, the methods of measuring bank liquidity risk are diversified, and the factors affecting bank liquidity risk also cover multiple levels. But at present, most scholars only analyze the liquidity risk from a certain lay, which will lead to a bias in the results. In order to fully reflect the liquidity risk level of banks, it is necessary to integrate the current research results, design a scientific and reasonable evaluation index system, and try to cover more influencing factors as much as possible.

2. Methods

According to the above analysis, there are many liquidity risk measurement methods in banks, and SVM, XGBoost and

BP neural networks are widely used at present. However, SVM is often limited in large sample training; XGBoost has many parameters, obviously different results and excessive memory consumption, which has certain requirements for running the computer. In contrast, BP neural network has the advantage of simple and easy to implement algorithms, and has low requirements on samples, which can realize the correction of error in continuous backpropagation. Therefore, this paper uses the BP neural network model to study the financial risk control problem.

Artificial neural network is a complex non-linear adaptive system, composed of a large number of neurons, and its biggest advantage is that it can realize the effective transmission of information among neurons. And the BP neural network is a typical backpropagation neural network. Typically, a BP neural network contains an input layer, an output layer, and one or more hidden layers. Either the input, output, or hidden layer has one or more nodes. When the information enters the input layer, it will be transmitted to the hidden layer and then to the output layer after the incentive function. Although increasing the number of hidden layers or the number of hidden layer nodes makes the model become complicated and the model training time is longer, it can reduce the model error. Therefore, in practice, the accuracy of the model is often improved by the number of hidden layer or hidden layer nodes.

3. Model building

3.1 The construction of the evaluation index system

Referring to the practices of Xu Jinghong and Yang Daguang (2022), the evaluation index system is constructed from the five aspects of assets, liabilities, income, operation and owners' equity of commercial banks. However, Xu Jinghong □ Yang Daguang (2022) have up to 45 evaluation indicators, which may lead to the repetition of the evaluation content, and the unreasonable model validity verification method. Therefore, this paper makes a reasonable adjustment and correction to these two aspects. In terms of evaluation index design, the number of evaluation indicators was reduced from 45 to 29, the evaluation indicators that may overlap were deleted, and the indicators that can depict liquidity were added. After the adjustment, asset indicators include cash and deposit of central bank, interbank deposit, loan issue and total advance; liabilities include 4 indicators including borrowing from central bank, customer deposit and other liabilities; 10 income indicators, including operating profit and investment income, etc.; 9 indicators for evaluating operating status, mainly including non-performing loan ratio, capital adequacy ratio and liquidity ratio; 2 indicators including owners' equity, including undistributed profit and surplus reserve.

Index was analyzed for reliability and validity. Reliability analysis is often used to study the reliable accuracy of index data, including theta reliability analysis method, Cronbach reliability analysis method, and compromise coefficient analysis method. Using theta reliability analysis, the theta reliability coefficient is 0.971 for 29 indexes, indicating good reliability quality. Validity analysis was used for the rationality of the study index design. Often achieved by KMO and Bartlett tests. The calculation found that the KMO value of the model index is 0.854, higher than 0.8, and the p value of Bartlett sphericity test is 0.000, with good index validity.

3.2 Weight assignment

The AHP method was used to empower. AHP originated from the optimization of multi-objective decision by operations research. The AHP method quantified the qualitative problem and finally achieved the purpose of decision analysis. Using AHP method empowerment, first to construct the judgment matrix. The judgment matrix in the AHP method is a square matrix. If the number of indicators at the next level affecting the decision target is 4, the judgment matrix is a 4 * 4 square matrix. To scale the elements in the judgment matrix, the AHP method in this paper adopts 7 scale and describes the relative importance of scaling factors through natural numbers 1 to 7. The larger the two factors show that the former has more prominent influence than the latter on the decision target at the upper level. The relative importance among the variables in this model was obtained through in-depth interviews with five experts in areas such as financial risk and financial regulation.

3.3 Classification of the evaluation results

In order to make the evaluation results more conducive to the interpretation and research of financial risk control problems, the obtained evaluation results are classified, namely, effective risk control and risk uncontrol.

3.4 Parameter setting

The 29 evaluation indicators were used as the input layer variables, and the classification results of the evaluation were used as the output layer variables. There is no universally accepted method for setting the number of nodes in the hidden layer and the hidden layer. Instead, we usually test the running effect of the model of different hidden layers and nodes in different hidden layers through systematic experiments. It is through this method to determine the number of hidden layers

and hidden nodes of the model.

4. Empirical results

4.1 sources of date

The data in this paper comes from the enterprise early warning pass. The database contains data from 4,012 Chinese commercial banks. Based on the annual report data of all banks in 2020, the banks with missing effective index data were excluded, and the index data of 310 banks was finally obtained. In order to make the index more comparable, the data of each index are treated dimensionless before using the model for evaluation.

4.2 interpretation of result

The data from 310 banks were brought into the BP neural network model, setting learning rate 0.001, incentive function sigmoid, optimization function adam, number of batch processing 100 and training number 1200. The initial state is a hidden layer, and the number of hidden nodes is 5. Then the number of hidden layers and hidden nodes is increased. When the hidden layer is two layers, the number of hidden nodes is set to 10,5, three hidden layers is 20,10,5 and four hidden layers, the number of hidden nodes is 40,20,10 and 5. Observe the loss curve versus the acc curve on the test set.
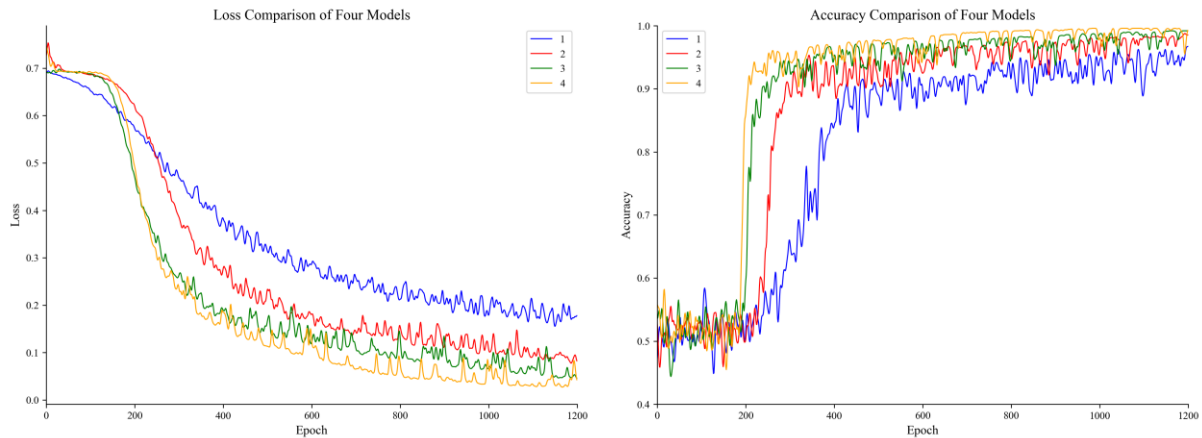

Figure 1. The loss curves and acc curves under different hidden layers

From Figure 1, the number of hidden layers and acc curves becomes increasingly ideal as the number of hidden layers and hidden nodes increases, but the amplitude of change in the two curves is rapidly narrowing. When the number of hidden layers of the model is four layers, and the number of hidden nodes is 40,20,10,5, the financial risk control model has the smallest loss, the acc is the largest, and the model achieves the best effect.

In order to further verify the effect of the financial risk control model proposed in this paper, the ROC map and PR map are drawn for comparative verification based on the results of the best model experiment mentioned above and the model results of SVM and XGBoost mentioned above.
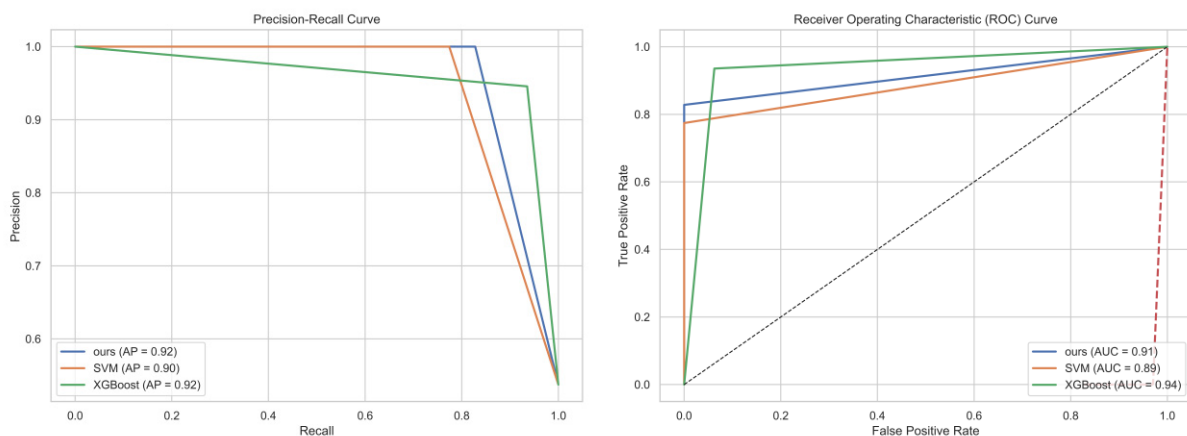

Figure 2. Comparcomparison of PR and ROC curves for different models

From Figure 2, compared with SVM and XGBoost models, the BP neural network model with four hidden layers performs better than SVM, but less than XGBoost.

5. Conclusions and outlook

With the help of the deep neural network model, this paper studies the financial risk control problem based on the financial data of Chinese commercial banks in 2020. From assets, liabilities, owner's equity, income and operating five aspects of screening 29 indicators, the index reliability and validity analysis, the effect is good, the index selection is reasonable and efficient, the practice of financial risk control strategy can also be from assets, liabilities, owner's equity, income and operating five aspects. Further research of deep neural network model found that when the hidden layers is four layers, the model was the best. The effect of financial risk control analysis through neural network is better than SVM model, but less effective than XGBoost model, which shows that the financial risk control model based on deep neural network constructed in this paper is effective. In the future, we can carry out in-depth research on financial risk issues by relying on the XGBoost model.

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