Application of Deep Learning in Regional Financial Risk Assessment and Prediction

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Abstract. As the economy enters the new normal, more and more risk problems are exposed in the financial market, and the market supervision system is still not perfect. Preventing financial risks has become the focus of domestic attention. Ubiquitous risks have increasingly become the "sword of Damocles" hanging over the main body of financial markets. Due to the differences in regional economic development, regional financial risks will become more complicated, which is likely to lead to a nationwide financial crisis. The application of DL (Deep Learning) has become the research frontier in the field of financial risk management, which will surely bring about subversive changes in the field of financial risk management. Through DL, we can quantitatively evaluate the financial risks in different fields, closely monitor the key industries and fields with the highest regional financial risk distribution, strengthen risk monitoring and analysis, promptly use risk warning letters, situation reports and other forms to prompt risks, prevent the spread and spread of risks in specific industries or fields, and do a good job in risk prevention and response. In order to effectively identify regional financial risks, timely understand and master the distribution and impact of various risks, and do a good job in risk monitoring and prompting.

Keywords: Deep learning, Regional finance, Risk assessment, Forecast.

1. Introduction

With the current global economic slowdown and the rise of trade protectionism in individual countries, the emergence and prevention of financial risks are more difficult to control. As far as China is concerned, as the economy enters the new normal, more and more risk problems are exposed in the financial market, and the market supervision system is still not perfect, so the prevention of financial risks has become the focus of domestic attention [1]. There have been several large-scale financial crises in the global market in the past decades, such as the Black Monday incident in 1987, the Asian financial crisis in 1997, the American subprime mortgage crisis in 2008 and the global financial crisis. Companies are also facing various risks. Ubiquitous risks have increasingly become a "sword of Damocles" hanging over the main body of financial markets. Compared with the whole country's financial risk prevention, regional financial risk will be more complicated and more difficult to prevent because of the differences in regional economic development. The emergence and infection of local financial risks are likely to lead to the outbreak of financial crisis nationwide [2]. When using DL to evaluate regional financial risks, the more indicators, the better. Because of the great similarity between indicators in the same category, too many indicators will easily lead to the dilution of the weight setting of important indicator variables, thus affecting the accuracy of the evaluation results. Unsupervised pre training is difficult to mine complex data features, Unable to handle noise signals well. These factors increase the difficulty of discovering the economic theoretical logic behind financial risks. Timely use various forms such as risk reminder letters and situation reports to alert risks, prevent the spread and spread of specific industry or domain risks, and do a good job in risk prevention and response. In order to effectively identify regional financial risks, timely understand and master the distribution and impact of various risks, and do a good job in risk monitoring and prompting[3]. The application of DL has become the research frontier in the field of financial risk management, and it is bound to produce subversive changes in the field of financial risk management. In view of the strong learning ability of DL model, this paper attempts to apply deep neural network to regional financial risk evaluation and prediction to predict and identify high-risk customers [4-5].

2. Construction of regional financial risk evaluation index system

2.1 Preliminary selection of indicators

Application of deep convolution neural network in financial risk management. In the field of financial risk management, deep convolution neural network is mainly used to predict and evaluate risks. Macro-economy is an important variable that affects regional financial risks. Its stability is directly related to the risk state of financial markets and also determines its ability to resist regional financial risks [6]. As the largest financial market with the largest capital flow, capital market has become an important area of financial risk transmission, and its development perfection determines the probability of financial risk outbreak [7-8]. Due to the complexity of regional financial risk factors and different quantitative standards, according to the distribution of financial risks in the jurisdiction we have learned and mastered in practice, this study analyzes regional financial risk evaluation based on DL, and selects 8 key areas including banking institutions and 14 financial risk indicators such as non-performing loan ratio of banks to quantify regional financial risks. According to the principle of entropy weight method, m in the sample is 5 and n is 14. See Table 1 for the relevant information of each indicator at the end of 2022.

Table 1 Statistical Analysis of Indicators

Select field	Reference indicators	City average	Maximum value	Minimum value
Banking institution	Balance of non-performing loans	3.78	8.15	1.76
	Non performing loan ratio	1.41	2.81	0.46
Guarantee company	Number of compensation transactions	368	557	182
	Compensation amount	0.77	0.94	0.37
Enterprise	Number of insured households	9	19	6
	Amount involved	4.56	7.02	0.36

After measuring the implicit and associated information between various indicators through DL, the initial data is weighted to reduce subjective bias in the weighting process, and a comprehensive evaluation index is obtained to reflect the comprehensive information [9]. The insurance market, as the financial market with the largest participation of individuals such as residents and enterprises, has become an important subject of fund supply in the market, and also provides important protection for other investment institutions to resist regional financial risks.

2.2 Significance test

The development, popularization and application of DL have changed the operation mode of many traditional financial businesses, which makes financial supervision face new challenges. It is difficult to define the responsibility for risk events caused by financial technology failures under the existing financial supervision system [10]. When using DL to evaluate regional financial risks, the more indicators, the better. Because of the great similarity between indicators in the same category, too many indicators will easily lead to the dilution of the weight setting of important indicator variables, thus affecting the accuracy of the evaluation results [11]. Therefore, it is necessary to test the significance of the evaluation index of the primary election, so as to screen out the effective regional financial risk evaluation index variables. Through the significant test of the regional financial risk evaluation indicators in the primary election, the final risk evaluation indicators are the growth rate, consumer price index, non-performing loan rate, market value of stock circulation, insurance depth, government bond issuance income and fiscal revenue [12].

3. Predictive classification of regional financial risks based on deep neural networks

3.1 Unsupervised pre training

The purpose of pre-training is to find a distributed representation of the data, which can explain changes in the data and amplify those that are crucial for classification. By extracting effective information from known samples, the goal of effectively predicting the operating rules and changing trends of the system is achieved. The core idea is to construct a grey dynamic model, which mainly uses dynamic equations to describe the changes in the sample sequence. Based on the quantitative evaluation results of financial risks in different fields, closely monitor the top ranked key industries and fields in the regional financial risk distribution, strengthen risk monitoring and analysis, timely use various forms such as risk reminder letters and situation report to alert risks, prevent the spread and spread of specific industry or domain risks, and do a good job in risk prevention and response. Unsupervised pre-training is difficult to mine complex data features, Unable to handle noise signals well. These factors increase the difficulty of discovering the economic theoretical logic behind financial risks.

3.2 Supervised prediction

We will transfer funds to Underdevelopment in a targeted way, and provide more liquidity for financial markets in Underdevelopment on the basis of reasonable allocation of funds. Compared with the whole country's financial risk prevention, regional financial risk will be more complicated and more difficult to prevent because of the differences in regional economic development. Through DL, we can quantitatively evaluate the financial risks in different fields, closely monitor the key industries and fields with the highest regional financial risk distribution, strengthen risk monitoring and analysis, promptly use risk warning letters, situation reports and other forms to prompt risks, prevent the spread and spread of risks in specific industries or fields, and do a good job in risk prevention and response. In order to effectively identify regional financial risks, timely understand and master the distribution and impact of various risks, and do a good job in risk monitoring and prompting. Due to the complexity of regional financial risk factors and different quantitative standards, according to the distribution of financial risks in the jurisdiction we have learned and mastered in practice, this study analyzes regional financial risk evaluation based on DL, and selects 8 key areas including banking institutions and 14 financial risk indicators such as non-performing loan ratio of banks to quantify regional financial risks. After measuring the implicit and associated information between various indicators through DL, the initial data is weighted to reduce subjective bias in the weighting process, and a comprehensive evaluation index is obtained to reflect the comprehensive information. The distributed representation of the original input is used as the feature and the binary indicator variable is used as the target, which indicates whether the hedging transaction should be continued. Given the parameter weight W and the deviation b, the probability that the transaction x belongs to the category i is:

$$P(Y=i,W,b)=soft\max_i(W_x+b) \tag{1}$$

The negative logarithmic Likelihood function is used as the Loss function in the supervised fine-tuning. Assuming that y is the real classification of input x, the Loss function has the following form:

$$L(W,b,x)=\log(P(Y=y)W,b) \tag{2}$$

To solve the overfitting problem of deep neural network models, an $dropout$ layer is set after each hidden layer of the deep neural network. During the training process, $dropout$ will remove hidden layer neurons and their corresponding connection weights with a certain probability.

The results in Table 1 were obtained by taking the average of the results of 10 times cross validation. In order to further validate the effectiveness of the algorithm proposed in this article,

adaptive enhancement models, SVM (Support Vector Machine) models, and our model will be used to test the misclassification cost and accuracy. The experimental results are shown in Figures 1 to 2.

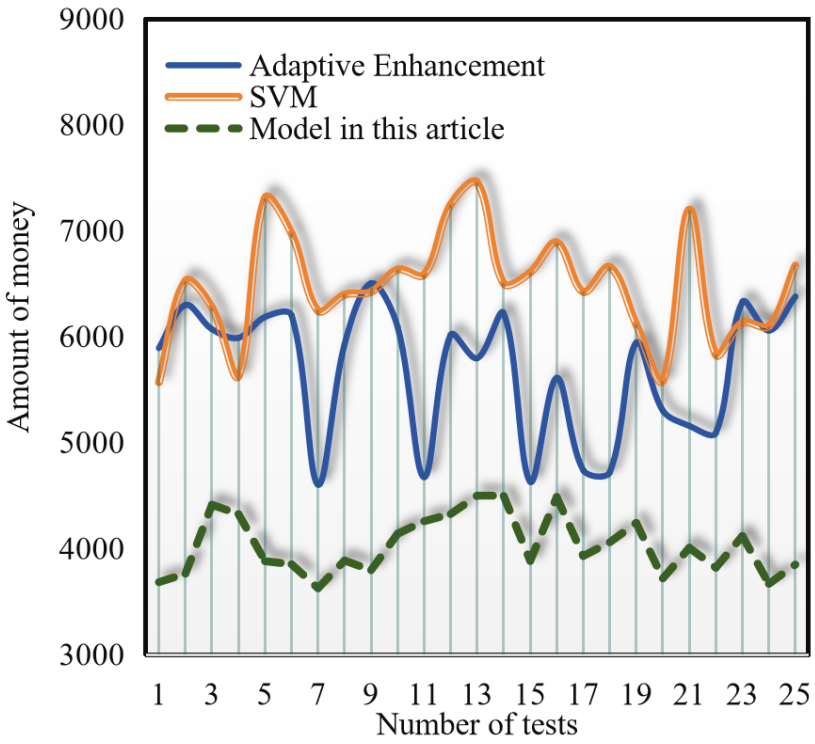


Figure 1 Misclassification Cost

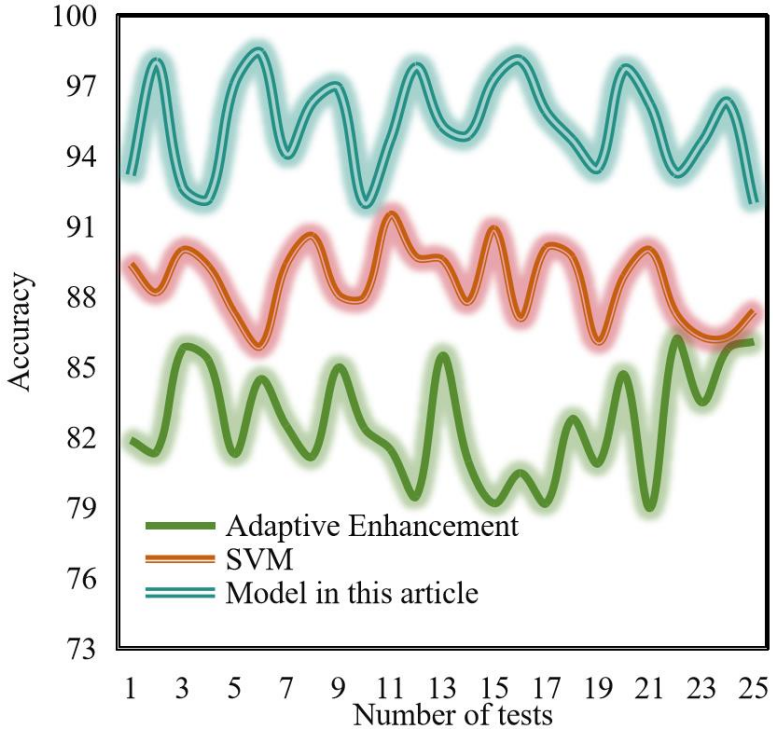


Figure 2 Accuracy

According to the performance indicators in Figure 1- Figure 2, the deep neural network proposed in this paper is superior to other machine learning models. The application of regional financial risk distribution research tools not only enriches the means of financial stability, but also accumulates experience for regional financial risk identification and dynamic adjustment. Strengthen the sharing and application of financial risk assessment results, jointly build a safe net of local financial stability, and escort the stable development of local economy.

4. Conclusions

This study explores the application of DL algorithm in regional financial risk assessment and prediction, and designs a financial risk behavior prediction model based on deep neural network. Descriptive statistical analysis is made on the index value. During this analysis, it can be seen that the situation in each region is complicated, and the level of risk cannot be directly determined by the index value. When evaluating regional financial risks with DL, the more indicators, the better. Because of the great similarity between indicators in the same category, too many indicators will easily lead to the dilution of the weight setting of important indicator variables, thus affecting the accuracy of the evaluation results. The financial market is relatively perfect and has strong ability to resist financial risks. We must constantly accelerate financial innovation, actively integrate into the international financial market, and improve international competitiveness; At the same time, transfer funds to underdeveloped areas in a targeted manner, and provide more liquidity for financial markets in underdeveloped areas on the basis of rational allocation of funds. DL algorithm largely determines the overall risk exposure of market makers. This model can detect the financial risk behaviors caused by a few people, which provides a new theory and method for the financial risk management system. It is important to improve the completeness of the financial market, improve the efficiency of capital flow and effectively reduce the risk of excessive concentration of funds in the banking market; At the same time, preferential financial development policies should be given to enhance the ability of financial services to the real economy. In view of the relatively high financial risks in some counties, the corresponding grassroots people's banks in counties should strengthen the performance of financial stability, further strengthen risk monitoring in key areas and industries, and timely analyze and judge the financial stability situation in counties.

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