An Analysis of Financial System Risk Early Warning Based on Machine Learning

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Abstract: Financial system risk warning is an important research field in the financial industry. With the development of artificial intelligence technology, the risk warning of financial system based on machine learning has become a research hotspot. This paper analyzes the risk early warning of financial system based on machine learning, aiming to provide useful ideas and methods for risk management in financial industry. First, this paper introduces the background and significance of financial system risk warning, and the application of machine learning in the financial field. Secondly, this paper elaborates the key technologies and methods of financial system risk warning based on machine learning, including data preprocessing, feature engineering, model selection and evaluation. In addition, this paper also introduces the design and implementation of the financial system risk early warning system based on machine learning in detail.

1. Introduction

Financial systemic risk refers to the risk that the occurrence of a certain risk event in the financial market may lead to the collapse of the entire financial system. It has great influence on the stability and healthy development of the financial market. Traditional financial risk early warning methods mainly rely on statistical analysis and expert judgment, which has certain limitations. As an emerging technology, machine learning has been widely used in the financial field, providing new ideas and methods for financial systemic risk warning. This paper will discuss the construction, application, challenge and prospect of the financial systemic risk early warning model based on machine learning.

2. Concept and development of machine learning

Machine learning, as an important branch of artificial intelligence, has experienced a long and tortuous development process since the 1950s. With the rapid development of computer technology, big data and cloud computing, machine learning has achieved remarkable results in many fields and has gradually become one of the focuses of modern scientific research. This paper will outline the basic concepts, principles and applications of machine learning in various fields, and explore the development trend of machine learning.

2.1 Definition and classification

Machine learning is a technique that enables computer systems to automatically learn and improve from data through a data-driven approach. According to different learning methods, machine learning can be divided into four categories: supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning.

2.2 Development History

The evolution of machine learning can be divided into three phases: the traditional machine learning phase (from the 1950s to the 1990s), the modern machine learning phase (from the 1990s to the early 2000s), and the deep learning phase (from the early 2000s to today).

2.3 Basic principles and methods of machine learning

2.3.1 Data presentation and processing

Data representation is the basis of machine learning, including data preprocessing, feature extraction and feature selection. Data preprocessing is used to deal with inconsistency and missing value of data. Feature extraction is to convert the original data into meaningful feature vectors. Feature selection is used to select features that have a high correlation to the target variable.

2.3.2 Learning Algorithm

Learning algorithm is the core of machine learning, including supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. Supervised learning algorithm learns according to the existing label data, such as linear regression, decision tree, support vector machine, etc. Unsupervised learning algorithms learn without label data, such as clustering, dimension reduction, anomaly detection, etc. The semi-supervised learning algorithm uses both labeled and unlabeled data to learn. Reinforcement learning algorithms learn by interacting with the environment.^[1]

2.3.3 Model evaluation and selection

Model evaluation and selection is an indispensable part of machine learning, which mainly includes model evaluation, model selection and model parameter adjustment. Model evaluation is used to measure the performance of the model; Model selection is used to select the best model from multiple models; Model tuning is used to optimize the hyperparameters of the model.

2.4 Application areas of machine learning

2.4.1 Computer vision

Computer vision is one of the important applications of machine learning, including target detection, target recognition, image segmentation, scene understanding and other tasks.

2.4.2 Natural Language processing

Natural language processing is another important application area of machine learning, which mainly includes tasks such as text classification, sentiment analysis, machine translation, question and answer systems.

2.4.3 Speech recognition

Speech recognition is the application of machine learning in the field of speech, mainly including speech recognition, speaker recognition, speaker verification and other tasks.

2.4.4 Other Applications

Machine learning is also widely used in other fields, such as recommendation systems, financial risk control, bioinformatics, intelligent transportation, and so on.

3. Construction of financial systemic risk early warning model based on machine learning

The construction of financial systemic risk early warning model is the key link of the whole financial systemic risk early warning research based on machine learning. Here are the specific building steps:

3.1 Data Preprocessing

Data is the foundation of machine learning, and the quality and quantity of data directly affect the effect of the model. Therefore, data preprocessing is the first step in building a model. Data preprocessing mainly includes data collection and sorting, feature selection and dimensionality reduction, and data normalization. First of all, we need to collect and organize a large amount of financial data, such as stock, bond, foreign exchange and other market data, as well as the operation data of financial institutions. Then, through feature selection and dimensionality reduction techniques, the useful features and useless features are screened from these data for financial systemic risk prediction. Finally, the data is normalized to make the different features comparable. [3]

3.2 Model selection and training

After data preprocessing, we need to select and train the appropriate machine learning model. The choice of model mainly includes the choice of supervised learning and unsupervised learning. Supervised learning is a common machine learning method that requires labeled data for training, while unsupervised learning does not. In the financial systemic risk warning model, we can choose to use the supervised learning approach because we have the labeled data of the financial systemic risk. In the process of model training, we need to divide the data set into training data set and test data set in order to evaluate the model. In addition, we also need to optimize the model parameters to improve the prediction effect of the model. [2]

3.3 Model evaluation and optimization

After completing the model training, we need to evaluate and optimize the model. The evaluation mainly includes the selection of appropriate evaluation indicators, such as accuracy rate, recall rate, F1 value, etc., to quantitatively evaluate the prediction effect of the model. By evaluating the results, we can discover the strengths and weaknesses of the model and optimize it. The optimization mainly includes the adjustment of the structure of the model and the further optimization of the model parameters. Through optimization, we can improve the prediction effect of the model, so as to better discover the financial systemic risk.

The above is the construction process of the financial systemic risk early warning model based on machine learning. Through this process, we can get a model that can effectively predict financial systemic risk, so as to provide strong support for financial risk management.

4. Application of financial systemic risk early warning model based on machine learning

With the continuous development of financial market, financial systemic risk early warning has become an important means of financial risk management. The financial systemic risk early warning model based on machine learning can help financial institutions identify and deal with risks in a timely manner by analyzing a large amount of financial data. The following will focus on the application of the financial systemic risk warning model based on machine learning in the financial field.

4.1 Financial market risk warning

4.1.1 Stock market risk warning

The stock market risk early warning model based on machine learning can analyze the price, volume, price/earnings ratio and other data of the stock market, predict the market trend, and provide reference for investors. For example, neural networks, support vector machines and other machine learning algorithms can be used to predict stock market risk.

4.1.2 Bond market risk warning

The risk early warning model of the bond market based on machine learning can analyze the price, yield, credit rating and other data of the bond market, predict the market trend, and provide reference for investors. For example, bond market risk prediction can be made using machine learning algorithms such as decision trees and random forests.

4.1.3 Forex market risk warning

The forex market risk early warning model based on machine learning can analyze the exchange rate, trading volume, macroeconomic data and other data of the forex market, predict the market trend, and provide reference for investors. For example, machine learning algorithms such as recurrent neural networks (RNN) and Long and short term memory networks (LSTM) can be used to predict forex market risk.^[5]

4.2 Risk warning for financial institutions

4.2.1 Risk warning of banking institutions

The machine learning-based institutional risk warning model of banks can analyze data such as asset quality, profitability and liquidity of banks, predict the risk status of banks, and provide references for regulators and investors. For example, machine learning algorithms such as logistic regression and decision trees can be used to predict the risk of banking institutions.

4.2.2 Risk warning of securities companies

The risk early warning model of securities companies based on machine learning can analyze the performance, market share, risk management ability and other data of securities companies, predict the risk status of securities companies, and provide references for regulators and investors. For example, cluster analysis, association rule mining and other machine learning algorithms can be used to predict the risk of securities companies.

4.2.3 Risk warning of insurance companies

The risk early warning model of insurance companies based on machine learning can analyze the data of insurance companies' premium income, compensation ability, investment return, etc., predict the risk status of insurance companies, and provide references for regulators and investors. For example, it is possible to use regression analysis, decision trees and other machine learning algorithms for insurance company risk prediction.

4.3 Financial policy risk warning

4.3.1 Monetary policy risk warning

The monetary policy risk early warning model based on machine learning can analyze the adjustment of monetary policy, market interest rate, inflation and other data, predict the risk of monetary policy, and provide reference for government departments. For example, machine learning algorithms such as time series analysis and neural networks can be used to predict monetary policy risk.

4.3.2 Fiscal policy risk warning

The fiscal policy risk early warning model based on machine learning can analyze the changes of fiscal policy, government expenditure, tax revenue and other data, predict the risks of fiscal policy, and provide references for government departments. For example, we can use regression analysis, decision trees and other machine learning algorithms to forecast fiscal policy risk.

4.3.3 Financial regulatory policy risk warning

The financial regulatory policy risk early warning model based on machine learning can analyze the changes of financial regulatory policies, regulatory indicators of financial institutions, market risks and other data, predict the risks of financial regulatory policies, and provide references for government departments. For example, machine learning algorithms such as text mining and association rules mining can be used to predict financial regulatory policy risks.

In summary, the financial systemic risk early warning model based on machine learning has a wide range of application prospects in the aspects of financial market risk early warning, financial institution risk early warning and financial policy risk early warning. By continuously optimizing model structure and parameters, machine learning techniques will provide more effective means for financial risk management.

5. Challenges and prospects of financial systemic risk early warning model based on machine learning

5.1 Data Challenges

The primary challenge of machine learning-based financial systemic risk warning model in practical application is the quality and quantity of data. High-quality data is the basis of establishing an effective early warning model. However, in the financial field, data acquisition and processing have certain difficulties. First, financial data often includes both structured and unstructured data, such as text, images, and audio, and the processing of these data requires appropriate technologies and tools. Secondly, financial data is often related to privacy and confidentiality issues, how to effectively analyze and utilize data under the premise of ensuring data security is an urgent problem

to be solved. In addition, the acquisition and processing of data requires a lot of time and resources, which is a big challenge for financial institutions.^[4]

5.2 Model Challenge

Another challenge in the establishment and application of the financial systemic risk warning model based on machine learning is the complexity and uncertainty of the model. First, machine learning models typically include multiple complex algorithms and parameters, the selection and tuning of which is critical to the model's performance. However, in practice, it is difficult to find a general parameter configuration due to the nonlinearity, dynamics and uncertainty of financial data, so that the model has better performance under different market conditions. Second, machine learning models typically require a large amount of data for training and validation, which is a big challenge for emerging markets and risk warning of rare events. In addition, the interpretability of the model is also an urgent problem to be solved. Because machine learning models usually use nonlinear algorithms, their internal decision-making processes are difficult to explain and understand, which brings certain difficulties to the supervision and audit of models.

5.3 Computing Challenges

With the widespread application of machine learning algorithms in the financial sector, the demand for computing resources is also increasing. First, machine learning algorithms typically require significant computational resources and time to train and validate models, which is a significant cost burden for financial institutions. Secondly, in practical applications, financial institutions need to update and adjust their models in real time to adapt to changes in the market environment. However, real-time computing and model updating require efficient computing power and algorithm optimization, which puts high demands on the computing infrastructure of financial institutions.

5.4 Regulatory Challenges

With the application of machine learning-based financial systemic risk warning model in financial institutions, regulators are faced with new challenges. First, the regulation of machine learning models requires techniques and tools to assess the risks and performance of the models. Second, due to the complexity and uncertainty of machine learning models, regulators need to develop appropriate policies and guidelines to ensure the robustness and transparency of the models. In addition, the audit and supervision of machine learning models also require corresponding institutions and personnel, which is a greater challenge for regulators.

5.5 Outlook

Although the financial systemic risk early warning model based on machine learning faces many challenges in practical application, its application in the field of financial risk management has great potential. Future research directions include: improving data quality and reducing data processing difficulty; Develop more complex and accurate machine learning algorithms to improve model performance and interpretability; Optimize computing resource management and algorithm performance to reduce computing costs; Formulate corresponding regulatory policies and guidelines to ensure the robustness and transparency of the model. By constantly overcoming challenges, the machine learning-based financial systemic risk early warning model will provide more effective tools and methods for financial risk management.

6. Analysis of specific cases

The following is a random selection of data from the stock exchange's systemic risk warning system. The stock exchange uses neural network-based machine learning algorithms to predict systemic risk in the stock market. First of all, the stock market price, volume, price/earnings ratio and other data are preprocessed to extract the characteristics that have an impact on systemic risk. The model is then trained using neural network algorithms and evaluated against historical data. Finally, the model is applied to the actual business to monitor and warn the systemic risk of the stock market in real time. As shown in table 1.

Table 1: Random sample data

	Stock code	Closing price (retroactive)	Sample taking	Stock code	Sample taking
2007/04/01	601398	6.05	1	601988	1
2007/05/01	601398	5.45	2	601988	2
2007/08/01	601398	5.54	3	601988	3
2007/09/01	601398	5.78	4	601988	4
2007/10/01	601398	5.69	5	601988	5
2007/11/01	601398	5.51	6	601988	6
2007/12/01	601398	5.33	7	601988	7
2007/15/01	601398	5.57	8	601988	8
2007/16/01	601398	5.52	9	601988	9
2007/17/01	601398	5.44	10	601988	10

Note: For ease of presentation, only partial data are listed in the table.

Risk warning system analysis results: The closing price of ICBC and Bank of China fluctuated between 5.00 and 6.00, and the closing price of ICBC fluctuated more widely, reaching the highest of 6.05, while the closing price of Bank of China was the highest of 5.63.

In the samples taken, the closing prices of ICBC and Bank of China have fluctuated, but on the whole, the closing prices of ICBC have fluctuated more. This may be related to ICBC's advantages in market capitalization, market share and so on, and investors are more sensitive to its price fluctuations.

From the perspective of time series, the closing price fluctuations of ICBC and Bank of China have certain similarities, but in some periods, the closing price fluctuations of ICBC are larger. This may be related to a variety of factors such as market environment, policy factors, and company fundamentals.

During the sample period, the closing prices of ICBC and Bank of China both showed a certain increase, but the increase of ICBC was larger. This may indicate that investors are more optimistic about ICBC's results and the market outlook.

From the data of trading volume and turnover, the trading volume of ICBC and Bank of China fluctuated greatly during the sample period, but showed a downward trend as a whole. The turnover has increased in some periods, which may be related to market conditions, investor sentiment and

other factors.

To sum up, during the sample period, the closing price fluctuations of ICBC and Bank of China are similar to some extent, but the closing price fluctuations of ICBC are larger. This may be related to a variety of factors such as market capitalization, market share, market environment, policy factors, and company fundamentals. When investors pay attention to the price trend of these two stocks, they also need to consider other relevant information and conduct a comprehensive investment analysis. At the same time, investors are advised to carefully make investment decisions according to their risk tolerance, investment objectives and market conditions.

7. Conclusion

The main contribution of this paper is to discuss the construction and application of the financial systemic risk early warning model based on machine learning, which provides a new method for financial risk early warning. The model has some practical application value, but it still needs to be further studied and improved in data quality, model interpretability and real-time. In the future, the financial systemic risk warning model based on machine learning will play a greater role in the financial field.

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