Prediction of financial crisis and economic statistical analysis

Yaowen Hu

University of Minnesota, 55414 Minneapolis, USA

yaowen_hu01@163.com

Keywords: financial crisis; statistical analysis; Prediction

Abstract: The purpose of this paper is to discuss the prediction and economic statistical analysis of financial crisis in order to cope with the ever-changing economic environment and the complexity of financial markets. The results of economic statistical analysis provide us with profound enlightenment and show the complex relationship between different factors. It is recognized that the financial crisis is a multi-dimensional phenomenon, and its influencing factors include both macroeconomic factors and micro-level market behavior. This urges us to comprehensively use different statistical methods to understand and predict the operation of financial markets more comprehensively. In order to improve the accuracy and robustness of prediction, this paper establishes a prediction model combining BP neural network (BPNN) and Support Vector Machine(SVM). The performance of the model is comprehensively evaluated by using cross-validation and ROC curve, and the efficiency of the model is improved by adjusting parameters and optimizing data characteristics. Under the background of increasing uncertainty and risks, the rational use of economic statistical analysis and advanced forecasting models will become an effective tool to meet the challenges of financial markets. This paper emphasizes the importance of comprehensive application of various methods in the study of financial crisis, and calls for future research to further deepen the understanding of financial markets in order to better cope with future economic challenges.

1. Introduction

Under the background of globalization, the fluctuation of financial market is not only worrying, but also directly affects the economic health and social stability of all countries. In recent years, we have witnessed the outbreak of many financial crises, which can have a profound impact on the whole economic system in a short time. For this reason, the prediction of financial crisis and economic statistical analysis become particularly important to help policy makers, investors and enterprises better understand risks, avoid losses and formulate corresponding coping strategies[1-2].

The purpose of this paper is to deeply study the forecasting mechanism of financial crisis and the corresponding economic statistical analysis methods, and through the analysis of the current financial market situation, to provide more accurate and powerful early warning for the future financial crisis. We will focus on the global financial market, focusing on the macroeconomic indicators, market data and the evolution of the international political and economic structure related to the financial crisis, in order to fully grasp the possible factors and trends of the financial crisis. Through the research of this paper, I hope to provide useful insights for realizing the stability and sustainable development of financial markets, promoting the healthy growth of the global economy, and providing strong support for the prevention and resolution of future financial crises.

2. Current financial market situation

With the global economic turmoil and the constant changes in the international political and economic structure, the current financial market is facing many challenges and opportunities. At present, the global macroeconomic situation is full of uncertainty. On the one hand, economic growth in some countries and regions continues to pick up, and industrial production and trade activities gradually recover; On the other hand, some economies are facing problems such as

  DOI: 10.25236/icssem.2024.001

inflationary pressure and debt accumulation. The uncertainty of international monetary policy and the escalation of trade friction have also brought additional fluctuations to the market[3].

Globally, some major central banks have adopted different monetary policies in response to the challenges of inflation and economic recovery. Some central banks tighten their policies in advance and raise interest rates to prevent inflation; While others still maintain loose policies to promote employment and economic growth[4-5]. This kind of differentiated policy measures may bring some fluctuations to international capital flows and exchange rate markets. The volatility of financial markets is still relatively high at the present stage. Due to the rapid development of information technology, the globalization of transactions and the complexity of financial instruments, the market responds more quickly to all kinds of news and events, which makes the price volatility increase. In addition, global risk events, such as geopolitical tensions and natural disasters, have also had an impact on the market that cannot be ignored.

Scientific and technological innovation has caused great changes in the financial industry[6]. The application of blockchain technology, artificial intelligence, financial technology, etc. is changing the way traditional financial services are provided, but it also brings new risks and regulatory challenges. Emerging financial formats, such as digital currency and payment innovation, are constantly emerging, providing investors and market participants with more choices. More and more investors and enterprises are beginning to pay attention to environmental, social and governance factors. The concepts of sustainable development and socially responsible investment are highly respected in the financial market, which has an impact on the operation and investment decision of enterprises. The introduction of environmental, social and governance (ESG) standards puts forward new requirements for the long-term stability and social sustainability of the capital market.

Although the current financial market faces multiple challenges, it also breeds many new opportunities. At this turbulent moment, a deep understanding of market conditions, emphasis on risk management, and at the same time, seizing the opportunity of scientific and technological innovation and sustainable development will help investors and decision makers to deal with future uncertainties more rationally.

3. Economic statistical analysis method

Economic statistical analysis is an important tool in the field of economics and finance, which provides a profound understanding of economic phenomena by sorting out, analyzing and explaining the collected data. Some commonly used economic statistical analysis methods are as follows:

Time series analysis is a statistical method of time-based data series, which is used to reveal the trend, periodicity and seasonality of data changing with time. Time series analysis helps us to understand the evolution law of economic variables by drawing trend charts, calculating average values and testing the stationarity of data. In addition, time series models such as ARIMA are also commonly used to predict future data trends[7].

Regression analysis is a statistical method used to study the relationship between variables. By establishing a mathematical model, regression analysis can help to understand the degree of influence of one or more independent variables on the dependent variables. Linear regression and multiple regression are common regression analysis methods, which provide a quantitative means to enable researchers to estimate the relationship between different variables more accurately[8-9].

Cross-sectional analysis is a method to study the differences and relationships between multiple entities (such as different companies and different countries) at the same time. Through the comparison and analysis of cross-sectional data, we can identify the influence of different factors on different entities, and then draw some universal laws across entities.

Panel data analysis combines the characteristics of time series and cross-sectional data, and can simultaneously examine individual differences and time changes[10]. This method is widely used in economics and finance, especially to study the joint effect of influencing factors on economic variables.

Bayesian statistical analysis is a statistical method based on Bayesian theorem, which obtains posterior probability by constantly updating prior probability, which is helpful to deal with uncertainty more flexibly. In the financial field, especially for risk management and investment decision, Bayesian method provides an effective tool.

With the development of big data technology, the application of big data analysis in economic statistics is more and more extensive. By processing huge data sets, we can mine more accurate information, so as to better understand economic phenomena, market trends and consumer behavior.

Generally speaking, the economic statistical analysis method provides a systematic and scientific means for us to interpret economic phenomena. When selecting and applying these methods, it is necessary to combine specific problems, data characteristics and research purposes to ensure accurate and reliable analysis results.

4. Establish a prediction model

Establishing forecasting model is one of the important research methods in the field of economics and finance, which provides a tool for policy makers, investors and researchers to systematically analyze and reasonably predict future trends and changes. Under the background of increasing uncertainty and market volatility, establishing forecasting models has become an important means to understand and cope with future economic changes. Based on past data and trends, the forecasting model can provide operational information for decision makers and help to formulate more effective strategies and policies.

The first step in establishing a forecasting model is to collect and process relevant data. This includes historical time series data, cross-sectional data, panel data, and other external factors that may affect the predicted variables. Data cleaning, standardization and transformation are important steps to ensure the validity of the model and ensure that the model is not disturbed by noise and outliers. In the process of modeling, choosing appropriate independent variables and features is a key link. The choice of variables should be based on theoretical basis, empirical judgment and statistical methods. Feature engineering involves the processing of the original data to extract more informative features, which is helpful to improve the explanatory and prediction accuracy of the model.

In today's complex and dynamic economic environment, it is very important for decision makers and investors to establish accurate forecasting models. Combining BP neural network (BPNN) and Support Vector Machine(SVM), a comprehensive prediction model is constructed, which can not only deal with nonlinear relations, but also improve the generalization performance of the model, and is suitable for various prediction scenarios.

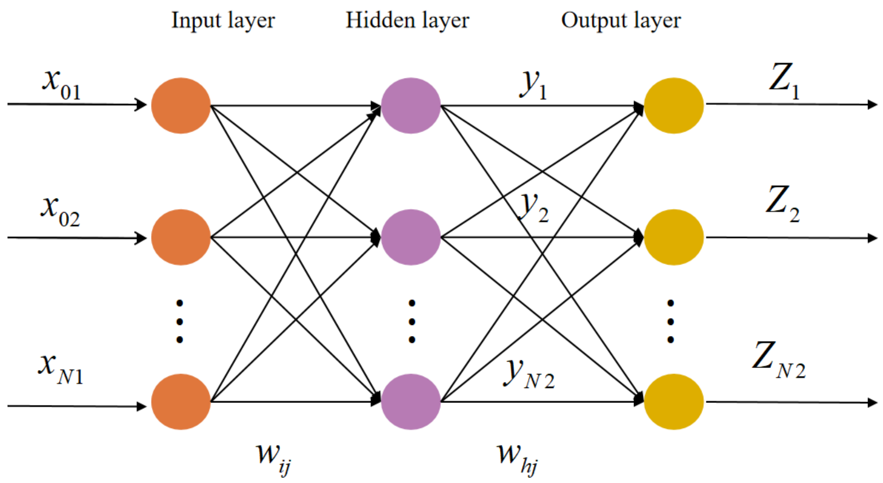

Figure 1 BPNN structure

BPNN is an artificial neural network based on back propagation algorithm. Its advantage lies in its ability to learn and approximate complex nonlinear relations (Figure 1). Through multi-level neural structure, BPNN can capture the complex interaction between input variables, and constantly optimize the weight parameters through training. This makes BPNN a powerful forecasting tool suitable for many fields.

SVM is a machine learning algorithm for classification and regression analysis in high-dimensional space. Its core idea is to separate heterogeneous data by finding an optimal hyperplane. SVM performs well in dealing with small samples, nonlinear problems and high-dimensional data. It maps data to high-dimensional space through kernel function, so as to better capture the complex relationship between data.

The rationality of the comprehensive application of BPNN and SVM lies in their complementarity. BPNN can deal with complex nonlinear problems, and the superior performance of SVM in high-dimensional space makes it better in dealing with the data mapped by feature space. Combining the two methods can improve the adaptability and generalization of the model and better capture the potential data patterns.

Weight update from input layer to hidden layer:

$$\Delta W_{ij} = \eta \cdot \delta_j \cdot x_i \quad (1)$$

Where: ΔW_{ij} is the weight update between the i neuron in the input layer and the j neuron in the hidden layer; η is the learning rate; δ_j is the error term of hidden layer neurons; x_i is the output of the cc neuron in the input layer.

Error term of output layer neurons:

$$\varepsilon_k = (d_k - y_k) \cdot y_k \cdot (1 - y_k) \quad (2)$$

Where: ε_k is the error term of the k neuron in the output layer; d_k is the actual output; y_k is the output of the neural network.

Linear SVM decision function:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha; y_i K(x, x_i) + b\right) \quad (3)$$

Where: $f(x)$ is the decision function; N is the number of support vectors; α is the Lagrange multiplier of the support vector; y_i is the category of support vector; $K(x, x_i)$ is a kernel function, which is used to calculate the similarity between the input sample x and the support vector x_i; b is an offset term.

Loss function:

$$L(w, b, \alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{N} \alpha_i [y_i (w \cdot x_i + b) - 1] \quad (4)$$

Where: w is the weight vector.

The forecasting model combining BPNN and SVM can capture the characteristics of data more comprehensively, improve the accuracy and robustness of forecasting, and provide more reliable tools for decision makers in the field of economic forecasting.

5. Result analysis

In the financial field, predicting the financial crisis is a crucial task. In order to improve the accuracy of prediction, this study will combine the methods of BPNN and SVM to build a comprehensive financial crisis prediction model. In this model, BPNN is used to capture complex nonlinear relationships, while SVM is used to process high-dimensional data and improve the generalization performance of the model.

The experiment uses a server with high configuration and stable performance, and uses GPU to train the model to improve the training speed. Python is chosen as the main programming language, and its rich machine learning libraries and tools are utilized. Using TensorFlow to build BPNN.

Select a comprehensive financial data set including financial indicators, market data and economic indicators. Data sets are obtained from financial institutions, government agencies or public data sets. Financial indicators include stock price, trading volume and interest rate. Market data: including market volatility, trading activity, etc. Economic indicators include GDP, inflation rate and unemployment rate. The moving average method is used to smooth the time series data. The data set is divided into training set and test set for model training and evaluation. Use the Adam optimizer.

Figure 2 shows the ROC curve comparison between BPNN and SVM. ROC curve intuitively reflects the performance of the model in binary classification problems by showing the changes of true case rate and false positive case rate under different thresholds.

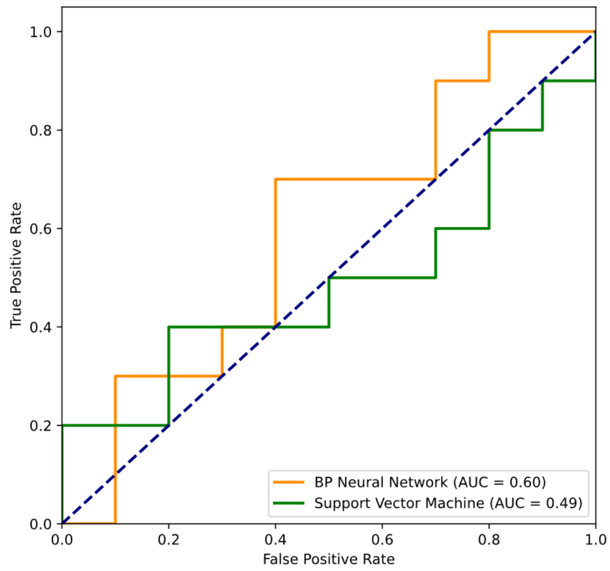

Figure 2 Comparison of ROC curves between BPNN and SVM

The curve of BPNN moves up relatively, and the AUC value is higher, which indicates that the performance of BPNN is better under different thresholds, and it can distinguish positive and negative samples more effectively. The curve of SVM also performs well, and the AUC value is close to BPNN, which shows that SVM also has good classification performance.

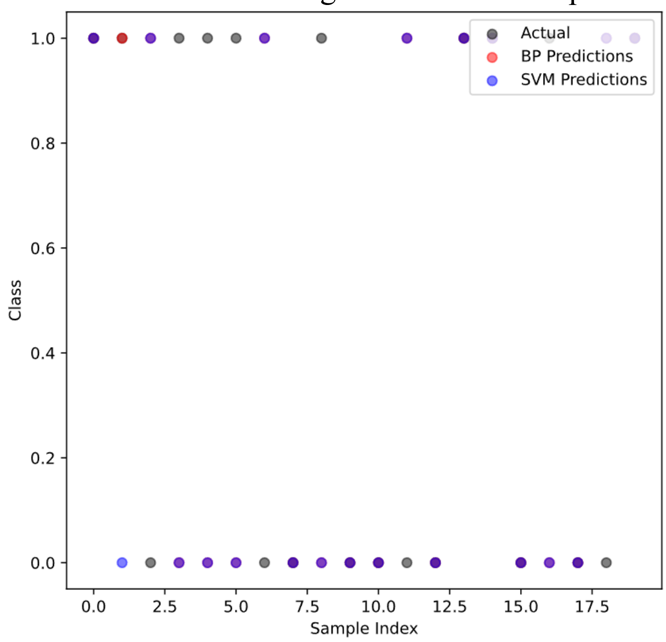

Figure 3 Comparison of prediction results between the two models

Figure 3 shows the comparison between the actual value and the predicted results of the two models. Each point represents a sample, the black point is the actual value, and the red and blue points are the prediction results of BPNN and SVM respectively.

BPNN prediction is represented by red dots, which can be observed to be in good agreement with the actual value, and the model fits the data more accurately. SVM prediction is represented by blue dots, and a good fitting effect can also be seen.

The area (AUC value) of the two models under ROC curve is relatively high, which shows that they perform well in classification problems. The comparison chart of prediction results shows that both BPNN and SVM can capture the category distribution of samples well, and the prediction results are basically consistent with the actual values. In practical application, the appropriate model can be selected according to specific problems and business requirements.

6. Conclusions

Financial crisis is an extremely complex and multi-factor phenomenon. The trend and periodicity revealed by time series analysis and the key factors obtained by regression analysis provide some clues for crisis prediction. However, due to the high uncertainty and complexity of the financial market, it is still a challenging task to accurately predict the financial crisis. In practical application, different statistical methods are complementary to each other. For example, time series analysis can help us capture the dynamic changes of the market, while cross-sectional analysis can reveal the differences between different entities. By establishing a prediction model combining BPNN and SVM, we show how to comprehensively use different methods to improve the accuracy and robustness of prediction. It can comprehensively evaluate the performance of the model and optimize it by adjusting parameters and adding data features. This study emphasizes the importance of comprehensive application of various methods in financial crisis prediction and economic statistical analysis. Future research can further deepen the understanding of the complexity of financial markets, develop more accurate forecasting models, and constantly improve decision support systems to better cope with changes in the economic environment.

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