International Journal of Scientific Research and Management (IJSRM)
||Volume||12||Issue||7||Pages||6827-6835||2024||
Website: https://ijsrm.net ISSN: 2321-3418
DOI: 10.18535/ijsrm/v12i07.em11

Application of Machine Learning in Stock Market Return Forecasting

Li Chao
Business School, Hunan University of Science and Technology, Xiangtan Hunan 411201, China

Abstract:
With the development of our country's financial market, people pay more attention to the stock market return forecast, which can bring the investors a lot of income and also become a tool of risk management. Machine learning (ML) and artificial intelligence (AI) are becoming increasingly sophisticated and have achieved amazing results in many fields. Machine learning and deep learning algorithm models can process huge amounts of data, from which they can quickly process and analyze laws, many scholars try to apply various machine learning models to the financial field. This paper first expounds the theoretical basis of stock market return prediction, and summarizes the main literature in this field in recent years, from the traditional stock prediction model to the machine learning prediction model. Finally, the traditional stock prediction model ARIMA model and the deep learning LSTM neural network model are selected for comparative empirical research. The sample data are from the Tushare big data community, taking the new energy vehicle stock BYD (002594) as an example. The empirical results show that the prediction accuracy and stability of LSTM neural network are far higher than ARIMA model, and it will have broad application prospects in financial prediction and other fields in the future.

Keywords: Machine learning; Stock return forecast; Deep learning；
LSTM neural network

1. Introduction

Machine learning (ML) is one of the important basic subjects in the field of artificial intelligence (AI), which is devoted to the research of algorithms that enable computer programs to learn experience from data in order to improve their performance of processing a task. In recent years, the field of machine learning has developed rapidly, thanks to the huge amount of data and the efficiency of parallel computing brought about by big data technology, it has also attracted scholars from different fields to apply it to research outside of computer technology.

In the field of finance, with the increasing demand of financial data analysis, the application of machine learning has become a new research focus. Among them, with the continuous improvement of our financial market system and the rapid development of economic market, the stock market return forecast has become an important issue for market participants. However, the stock price is influenced by many internal and external factors, which makes the fluctuation of stock price complex and changeable. Therefore, from the perspective of academic research and financial practice, in the rapid development of artificial intelligence today, machine learning in the stock market returns forecast, has become particularly important.

This paper focuses on the main literature in the field of stock market return forecasting in recent years, from the Stock Market Return Forecast Theory Foundation, the traditional stock forecast model research and the machine learning forecast model research three aspects separately carry on the analysis, the traditional stock prediction model Arima model and the Deep Learning LSTM neural network model were used to conduct a comparative empirical study, taking the new energy vehicle stock BYD (stock code: 002594) as an example. In order to avoid chance, this paper will select Guizhou Moutai (stock code: 600519), Ping An Bank (stock code: 00001), Hengrui Pharmaceutical (stock code: 600276) for predictive analysis. The empirical results show that the accuracy and stability of LSTM neural network are far superior to Arima model. LSTM neural network will be widely used in financial forecasting in the future.

2. The theoretical basis of stock market return forecast

2.1 Efficient-market hypothesis theory

The theory of Efficient-market hypothesis (EMH) was first proposed and developed by FAMA, which claims that changes in asset prices follow a random walk, that prices reflect all historical information, and that public information is available to all investors, all technical analysis is invalid. EMH believes that there are three types of efficient markets: (1) weak-form efficient markets, in which historical trading information has been reasonably used by market participants, all of which are included in asset prices; It is therefore not efficient to predict prices by studying historical prices and their movements, but Fundamental analysis can be used. (2) semi-strong market, in addition to historical information, all public information is also reflected in asset prices, including company annual reports, industry trends, national policies and macro-information, etc., both technical analysis and Fundamental analysis are out of the question, and it is only possible to get outsized returns from inside information. (3) strong efficient market, asset prices reflect all the historical information, public information and inside information, so no matter what analysis can not achieve excess returns.

2.2 Rational expectation price theory

The rational expectations price theory was first put forward by John Moose in the Theory of Rational Expectations and Price Changes. According to the theory, the so-called expectations are the reasonable and effective prediction of future events, so as to make the current decisions more reasonable and powerful for the participants of economic activities. Rational, clear-headed decision makers in the market make reasonable predictions based on the composition of market information. If the historical information available to these investment decision makers is undifferentiated, they will get the same expected results.

The rational expectations school, led by John Moose, believes that the key content of its research is the formation mechanism of price. As part of neoclassical economics, this theory is specifically proposed for "adaptive expectations", which holds that people can understand all historical information, and can make specific analysis of historical information, and finally make expectations. Rational expected price theory establishes various expected price models and tests them by empirical method.

2.3 Equilibrium price theory

The theory of equilibrium price, first proposed by the famous British economist Marshall, means that in an open market, through continuous open bidding, the market will form an equilibrium at the same position of supply and demand price. However, there are two different forms of equilibrium price in the market of perfect competition. The famous economist Samuelson conducted relevant research and analysis. He pointed out that even in the market of perfect competition, there may be some differences in the price of the same commodity, and this difference is usually formed by the difference of time and region.

3. Traditional stock forecasting model

3.1 Traditional asset pricing model

In 1952, Markowit [1] put forward the mean-variance theory, marking the beginning of modern portfolio theory. The portfolio model used mean and variance to measure portfolio returns and risks, and introduced mathematical models into the field of financial investment for the first time. William Sharpe (1964), John Lintner (1965), and John Mossin (1966) developed the famous Capital Asset pricing Model (CAPM), which greatly reduced the complexity of mean-variance models.

Fama and French (1993)[2] Fama–French three-factor model that different stocks have completely different stock returns, which can not be explained by the market's beta value alone, there are also market capitalization, book-to-market ratio and P/e ratio that affect stock returns, after which a lot of new factors are proposed and widely used. But whether Carhart (1997)[3] proposed momentum factors based on US mutual fund data (Li Fujun et al. , 2019)[4] , fama and French (2015)[5] added the profit and investment factors to construct the five-factor model, which is always under the framework of linear relationship asset pricing.

3.2 Traditional time series model

Because the stock data has the time series characteristic, has the distinct time before and after relations and the randomness. Engle (1981) proposed that ARCH-type models can display the variance characteristics well, and can describe the peak fat tail and clustering characteristics, so they are often used in time series scenarios of financial data. Nelson (1995)[6] based on ARCH model, introducing ARCH residuals into autoregressive model makes up for the deficiency of parameter estimation in ARCH model, and establishes EGARCH hybrid model to analyze the essence of financial time series.

In the application of stock market, Awartani and CORR (2005)[7] used GARCH model to make regression forecast for Futures Index. The research results show that this model can describe the fluctuation of stock market accurately under the condition of information symmetry, however, the effect is poor under asymmetric background. Hung J C (2008)[8] used GARCH model and TGARCH model to conduct a comprehensive comparison of the Hong Kong stock index, this model has a good performance in describing the volatility aggregation effect and leverage effect of stock market. In our country, Wei Yanhua and Zhang Shiying (2004)[9] constructed Copula-GARCH model to analyze the conditional correlation of the return series of different sectors in Shanghai stock market, it is found that there is a significant positive correlation between the sequences of each plate. Xiong Zhengde et al. (2015)(10) combined wavelet multi-resolution analysis with multivariate BEKK-GARCH (1,1) , and found that our stock market and foreign exchange market have strong volatility spillover effects.

Under the traditional forecasting frame, the research usually finds the change rule of stock return through the linear model, but the stock return series is mostly nonlinear. At this point, the traditional linear model can not capture this relationship. In addition, stock prices are subject to changes in many factors and conditions, and are unlikely to be fully realized in a model, especially if the sample distribution is unbalanced, which would greatly reduce the prediction effect.

4. Machine learning prediction model

Stock data has the characteristics of nonlinear, high noise and non-stationary. Compared with traditional econometric forecasting model, machine learning has more advantages in dealing with nonlinear and non-stationary characteristics. There is also a large literature in academia that uses machine learning methods to predict stock prices or returns. Akita R et al. (2016) [11] Combined deep learning with long short-term memory model to predict the time series of financial data. Through the test of 50 companies listed on the Tokyo Stock Exchange, it is found that the predictive accuracy of the LTSM model on the data text information of the input data can help the trading to achieve a large profit improvement. Gu et al. (2018) [12] systematically verified the effectiveness of basic machine learning algorithms in stock return prediction based on the American market, and the results showed that machine learning could significantly outperform traditional linear regression models. Markus Leippold et al. (2022) [13] constructed a series of complex forecasting indicators, adopted different machine learning models to test the Chinese stock market, and found that liquidity indicators showed consistent importance in different machine learning models, while fundamental indicators reflecting value were more important. The presence of retail investors makes share prices more predictable in the short term. At the same time, large-cap stocks and state-owned enterprises have better predictability over the long term, and long-only strategies can still achieve significant gains after accounting for transaction costs.

At the same time, many domestic scholars have also begun to apply machine learning methods to stock return prediction scenarios. Chen Weihua and Xu Guoxiang's deep learning results are indeed better than traditional econometric models in the prediction of CSI 300 index [14]. Li Bin et al. (2019) [15] input 19 technical indicators into machine learning models such as support vector machine and Adaboost to predict stock prices, and the results show that portfolio strategies based on machine learning prediction results can produce better investment returns. Classical machine learning methods mainly include: generalized linear regression model, decision tree, random forest (RF), gradient lift tree (GBDT), neural network, etc., which is summarized from the following aspects.

4.1 Generalized linear regression model

Common linear regression models include Lasso regression, Ridge regression and logistic regression. At the beginning of the 21st century, the application of Logistic regression model in the field of finance has been gradually paid attention to. Leung and Daouk (2000) [16] empirically tested multivariate classification methods such as Logistic, and the results showed that these models made predictions by estimating the probability of changes in the direction of returns. Chyi Atrakul T (2013) [17] used the Logistic model to predict the return rate of the British stock market index, and the empirical results showed that both the in-sample and out-of-sample predictions were effective. H Ponka used the dynamic Probit model to predict the excess return of the American stock market through the lagged excess return of the industry portfolio and other common variables [18], and the results showed that this model was superior to the traditional forecasting regression model in predicting the return direction of the American stock market.

4.2 Decision trees

As a more mature computer data analysis technology, decision tree has derived various improved algorithms for nonlinear data set prediction. Nair B B et al. (2010) [19] adopted decision tree to realize feature selection, combined with adaptive neural fuzzy to predict stock trends, and the research showed that the prediction ability of the mixed model was significantly higher than that of the model without feature selection. Panigrahi S S and Mantri J K (2015) [20] used Epsilon-SVR and decision tree models to forecast stock returns, and found that both models had predictive effects and could provide practical guidance to investors. Wang Ling and Hu Yang (2015) [21] applied the C4.5 algorithm of decision tree to stock market prediction, and also found that the prediction results can help investors make investment decisions. Deng Nansha and Su Wen (2012) [22] select appropriate indicators in the stock market and realize classification prediction through decision tree model, which empirically shows that it can bring higher returns. Wang Yu et al. (2019) [23] improve the fit of the model by boosting cascade multiple decision trees, and the research results show that it reduces the mean square error and has good stock prediction ability.

4.3 Random forests

Random Forest (RF) is an ensemble learning algorithm based on Bagging algorithm (Breiman, 2001) [24]. Random forest model has frequently appeared in the research of stock market prediction in recent years, and scholars have also optimized it, and its prediction accuracy has been proved to be more advantageous than other models. Khandani et al.(2010)[25] and Butaru et al.(2016)[26] used regression tree to predict consumer credit card arrears and defaults. Moritz and Zimmermann(2016)[27] apply a tree-based model to portfolio ranking. Compared to other methods, random forest has its own advantages. Patel and Shah et al.(2015)[28] used four models of support vector machine (SVM), artificial neural network (ANN), naive Bayes and Random forest (RF) to predict the direction of stock movement and stock price index of Indian stock market, and found by comparison, The overall performance of random forest is better than the other three prediction models. There are few literatures in China that specifically apply random forest to stock market prediction. Wang Shuyan et al. (2016) [29] predicted the rise and fall of stocks through random forest model, and the research results showed that stock selection investment based on the prediction results of this model has good returns in China's market. Zhang Xiao and Wei Zengxin et al. (2018) [30] input 16 technical indicators to predict the stock market situation through the random forest model, and the backtest results show that the model can not only cope with a large amount of data, but also has high prediction accuracy.

4.4 Gradient boosting decision tree

Gradient Boosting Decision Tree (GBDT) is a method based on Boosting algorithm to build a strong learners by gradient optimization (Friedman J H, 2001) [31], which can be well applied to prediction scenarios. Suitable for financial scenarios with non-linear structures. Krauss et al. (2017) [32] made prediction of S&P 500 through random forest, gradient lifting tree and deep learning, and the research results showed that the stock selection model constructed by gradient lifting tree was better than the other two methods. Zhang Xiao et al. (2018) [33] adopted the gradient lifting tree model combined with technical indicators, and the research results showed that the prediction ability of CSI 300 was significantly higher than that of linear regression model and random forest model. Deng Jing (2021) [34] input the gradient lifting tree model with effective factors selected according to factor deviation degree. The backtest results show that this model can effectively screen out factors affecting stock returns and has good forecasting effect.

4.5 Neural Network

Neural network is a model which pays more attention to the prediction result. The research on the application of neural network method in capital market prediction is earlier than that in China. (1994)[35] and Yao et al. . (2000)[36] used neural networks to predict derivatives prices. Karathiya et al. . (2012)[37] using past inventory data to identify fuzzy laws and construct potential predictions, combined with neural networks to predict stock trading averages, results show that they are flexible and highly scalable. Hu et al. (2018)[38] proposed a new network, ISCA-BPNN, which combines an improved sine-cosine algorithm (Isca) with a BP neural network (BPNN) to predict the opening price of the S & P 500 and the Dow Jones Industrial Average, respectively, when Google Trends are taken into account, they are more than 70 per cent accurate. Fischer and Krauss (2018), 39 using the LSTM network to predict out-of-sample directional movements of S & p 500 component stocks from 1992 to 2015, the authors found common patterns in these stocks: high volatility and short-term reversal returns; Using these findings, the rule-based short-term reversal strategy can be positive, resulting in a 0.23% pre-transaction benefit.

5. Empirical Analysis

5.1 Data acquisition

In this paper, BYD (002594.SZ), a leading stock in the new energy vehicle sector, was selected, with a total of 522 trading days from January 1, 2022 to March 1, 2024. The data came from Tushare big data open community, and the data processing and modeling process was completed in python programming language.

5.2 Data processing

In this paper, the training set and the test set are divided into 8:2 scale, and the first 80% of all trading days between January 1,2022 and March 1,2022 in the sample data are used as the training 2024, a total of 418 trading days, 104 trading days, with the last 20% of all trading days between January 1,2022, and March 1,2022, as the test 2024.

5.3 Arimi model fitting and prediction

In the ARIMA(p,d,q) modeling of time series, the conventional practice is to use stationarity test to determine d, and then observe p and q through ACF diagram and PACF diagram. This combination of machine and manual method often takes a long time and is prone to errors. So this article calls auto_arima directly when doing time series analysis. In general, auto_arima has several benefits: (1) automatic parameter seeking, (2) automatic fitting, and (3) automatic prediction.

From the output results, we can see that the best fitting model is ARIMA(0,1,0)(2,1,0)[12]. On this basis, we make predictions. Taking the closing price of BYD (stock code: 002594.SZ) as an example, the blue part is the training set data, the yellow part is the test set data, and the green part is the predicted value data. As can be seen from the figure, the prediction effect of ARIMA model is not accurate.

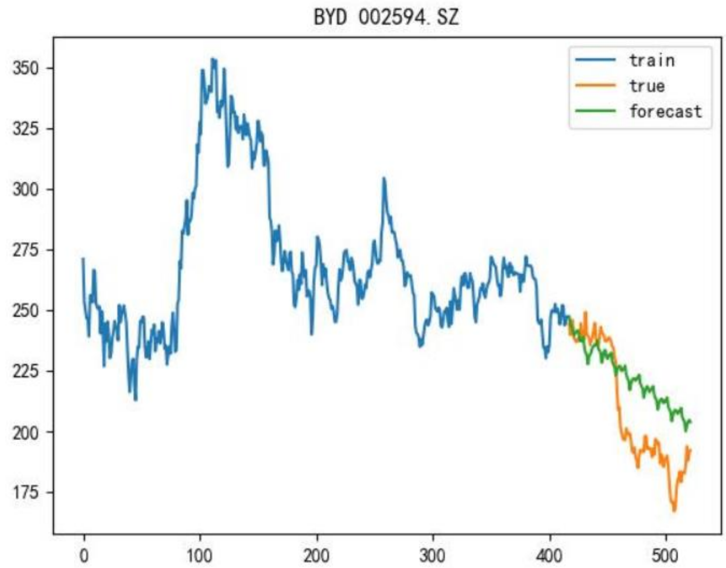

Fig.1 Arima model fitting effect of BYD

5.4 LSTM neural network fitting and prediction

Long-term and short-term memory network (LSTM) model is a special RNN, LSTM introduces a gating unit, namely, forgetting gate, input gate, output gate. The structure of the gate is composed of sigmoid function and dot multiplication. The data output of sigmoid function is between 0 and 1, which is used to indicate how much information can pass through the gate, 0 means no message passed. The function of the forgetfulness gate is to remove useless information from the past. The sigmoid function of the input gate determines what information will be updated to add new memories from the input gate.

On this basis, we use the past value to forecast, taking the closing price of BYD (stock code: 002594.SZ) as an example, the blue part is the training set data, the yellow part is the test set data, and the green part is the predicted value data. As can be seen from the figure, the prediction effect of LSTM model is good, far exceeding that of ARIMA model.

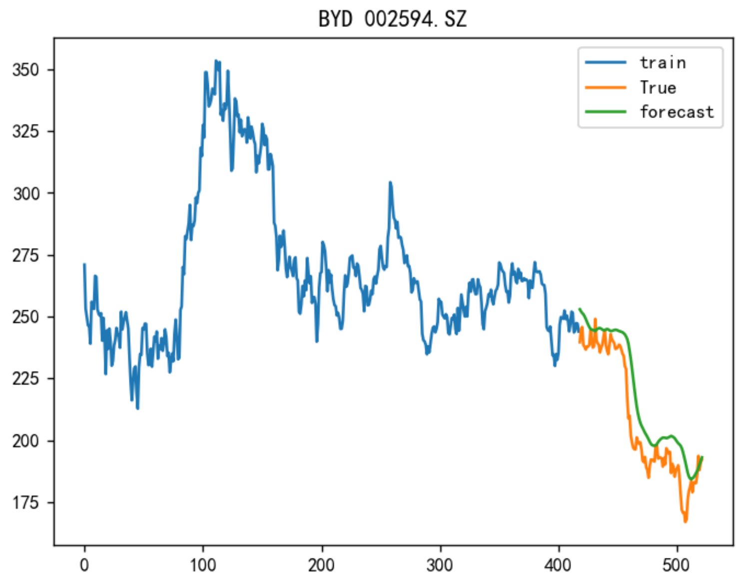

Fig.2 LSTM model fitting effect of BYD

5.5 Model evaluation index

In this paper, MAE, MRSE, MAPE and R^2 are selected as indicators to evaluate the predictive ability of the model.

MAE (Mean Absolute Error) is the average absolute error, which calculates the average of the residual error, and is a linear score. Represents the average absolute error between the predicted value and the true value.

RMSE (Root Mean Square Error) is the root mean square error, representing the sample standard deviation of the residual difference between the predicted value and the true value. MSE indicates the degree of dispersion of the sample.

Compared with RMSE, MAPE (Mean Absolute Percentage Error) is not easily affected by an outlier and is the expected value of the relative error loss, that is, the percentage of the absolute error to the true value. In theory, the smaller the value of MAPE, the better the predictive model fits and has better accuracy.

The coefficient of determination R^2 (R squared) is the square of the correlation coefficient, and its value represents the degree of correlation and the extent to which the variation of the dependent variable can be represented by the variation of the independent variable. Generally, the range of R^2 is 0 to 1, and the closer the value is to 1, the better the explanation of y by the variables of the equation, and the better the model fits the data.

Taking the closing price of BYD (stock code: 002594.SZ) as an example, the average evaluation index values of ARIMA model and LSTM model are compared, as shown in the following table.

Table 1 Model evaluation indicators of BYD

Model	**MAE**	**RMSE**	**MAPE**	**R^2**
ARIMA	42.8986	49.5039	0.1733	0.4976
LSTM	11.6609	14.2807	0.0494	0.8107

6. Conclusions and future prospects

Although machine learning is not a new technology, it is still just getting started in the financial field, and relevant literature is relatively lacking. Since machine learning is more of a "black box" in the financial field, even if it can significantly optimize the effect of revenue prediction, it needs to pay attention to its underlying economic logic. In addition, due to the constant changes in the market, no matter the traditional statistical forecasting model or the machine learning forecasting model, its model parameters are not stable, so each model also needs to be updated and selected in time to further improve the accuracy of the prediction.

In this paper, the advanced deep learning technology is actively explored in the direction of financial prediction, and the wide applicability and prediction superiority of LSTM neural network are verified for several typical stocks in the Chinese market. In view of the high adjustability of neural networks, this paper can be improved in a variety of technical directions in the future, such as adding a variety of non-homogeneous information as neural network input, adding data preprocessing techniques such as wavelet decomposition or principal component analysis for model optimization, or conducting structure optimization from the neural network itself. The application of deep learning technology to financial forecasting is only the first step in the development of financial intelligence, and the following two themes can be further explored: First, the introduction of cutting-edge methods of deep neural networks in the field of financial risk management, using the advantages of big data to more effectively identify and measure risks; The second is to apply deep learning methods to the investment field to help financial institutions quickly identify investment opportunities and promote the development of intelligent investment in China's financial market.

References

1. Markowitz H. Portfolio selection[J]. Journal of Finance ,1952,7 (1):77-91.
2. Fama E F，French K R. 1993. Common Risk Factors in the Returns on Stocks and Bonds [J].Journal of Financial Economics，33（1）.
3. Carhart M M. 1997. On Persistence in Mutual Fund Performance [J].Journal of Finance，52（1）.
4. Li Fujun, Jiang Fuwei, Yang Hua. The Influence of investors' rational Characteristics on Momentum Effect: Evidence based on China's A-share Market [J]. Macroeconomic Research, 2019, (11).
5. Fama E F，French K R. 2015. Incremental Variables and the Investment Opportunity Set [J].Journal of Financial Economics，117（3）.
6. Braun P A, Nelson D B, Sunier A M. Good news, bad news, volatility, and betas[J]. The Journal of Finance, 1995, 50(5): 1575-1603.
7. Awartani B M A, Corradi V. Predicting the volatility of the S&P-500 stock index via GARCH models: the role of asymmetries[J]. International Journal of forecasting, 2005, 21(1): 167-183.
8. Hung J C, Lee M C, Liu H C. Estimation of value-at-risk for energy commodities via fat-tailed GARCH models[J]. Energy Economics, 2008, 30(3): 1173-1191.
9. Wei Yanhua, Zhang Shiying. Correlation Analysis of Financial markets: Copula-GARCH Model and its application [J]. Systems Engineering, 2004, 22(4): 7-12.
10. Xiong Zhengde, Wen Hui, Xiong Yipeng. An empirical study on volatility spillover effect between foreign exchange Market and stock market in China: Analysis of multivariate BEKK-GARCH (1, 1) model based on wavelet multi-resolution [J]. Chinese Management Science,2015, 23(4): 30-38.
11. Akita R, Yoshihara A, Matsubara T, et al. Deep learning for stock prediction using numerical and textual information[C]//2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS). IEEE, 2016: 1-6.
12. Gu J, Wang Z, Kuen J, et al. Recent advances in convolutional neural networks[J]. Pattern recognition, 2018, 77: 354-377.
13. Leippold M, Wang Q, Zhou W. Machine learning in the Chinese stock market[J]. Journal of Financial Economics, 2022, 145(2): 64-82.
14. Chen Weihua, XU Guoxiang. Research on Prediction Accuracy of Stock Market Volatility Based on Deep Learning and Stock Forum Data [J]. Management World, 2018, 34(1): 180-181.
15. Li Bin, SHAO Xinyue, Li Yueyang. Research on fundamental quantitative Investment driven by Machine learning [J]. Chinese Industrial Economy, 2019 (8): 61-79.
16. Leung M T, Daouk H, Chen A S. Forecasting stock indices: a comparison of classification and level estimation models[J]. International Journal of forecasting, 2000, 16(2): 173-190.
17. Chevapatrakul T. Return sign forecasts based on conditional risk: Evidence from the UK stock market index[J]. Journal of Banking & Finance, 2013, 37(7): 2342-2353.
18. Pönkä H. Predicting the direction of US stock markets using industry returns[J]. Empirical Economics, 2017, 52(4): 1451-1480.
19. Nair B B, Mohandas V P, Sakthivel N R. A decision tree-rough set hybrid system for stock market trend prediction[J]. International Journal of Computer Applications, 2010, 6(9): 1-6.
20. Panigrahi S S, Mantri J K. Epsilon-SVR and decision tree for stock market forecasting[C]//2015 International Conference on Green Computing and Internet of Things (ICGCIoT). IEEE, 2015: 761-766.
21. Wang Ling, Hu Yang. Stock Data Mining Based on C4.5 Decision Tree [J]. Computer and modernization, 2015 (10): 21-24.
22. Deng Nansha, Su Wen. Case study of Stock market prediction Analysis based on Data mining technology [J]. Science and Technology and Enterprises, 2012 (18): 272-274.
23. Wang Yu. Stock Prediction model based on Cart Tree and Boosting Algorithm [D]. Harbin: Harbin

University of Science and Technology, 2018.
24. Breiman L. Random forests[J]. Machine learning, 2001, 45(1): 5-32.
25. Khandani A E, Kim A J, Lo A W. Consumer credit-risk models via machine-learning algorithms[J]. Journal of Banking & Finance, 2010, 34(11): 2767-2787.
26. Butaru F, Chen Q, Clark B, et al. Risk and risk management in the credit card industry[J]. Journal of Banking & Finance, 2016, 72: 218-239.
27. Moritz B, Zimmermann T. Tree-based conditional portfolio sorts: The relation between past and future stock returns[J]. Available at SSRN 2740751, 2016.
28. Patel J, Shah S, Thakkar P, et al. Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques[J]. Expert systems with applications, 2015, 42(1): 259-268.
29. Wang Shuyan, Cao Zhengfeng, Chen Mingzhi. Application of random forest in quantitative stock selection [J]. Operation Research and Management ,2016, 25(3): 163-168.
30. Zhang Xiao, Wei Zengxin. Application of Random Forest in stock trend prediction [J]. China Management Informatization, 2018, 21(3): 120-123.
31. Friedman J H. Greedy function approximation: a gradient boosting machine[J]. Annals of statistics, 2001: 1189-1232.
32. Krauss C, Do X A, Huck N. Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500[J]. European Journal of Operational Research, 2017, 259(2): 689-702.
33. Zhang Xiao, WEI Zengxin, Yang Tianshan. Application of GBDT combination Model in Stock prediction [J]. Journal of Hainan Normal University: Natural Science Edition, 2018, 31(1): 73-80.
34. Deng Jing. GBDT Multi-factor Stock Selection Model Based on Factor Deviation [J]. Software Guide, 2021.
35. Hutchinson J M, Lo A W, Poggio T. A nonparametric approach to pricing and hedging derivative securities via learning networks[J]. The journal of Finance, 1994, 49(3): 851-889.
36. Yao J, Tan C L. A case study on using neural networks to perform technical forecasting of forex[J]. Neurocomputing, 2000, 34(1-4): 79-98.
37. Karathiya M B, Sakshi D S, Sakshi R S. Stock Prediction by Fuzzy Neural Networks[C]//2012 Second International Conference on Advanced Computing & Communication Technologies. IEEE, 2012: 79-82.
38. Hu H, Tang L, Zhang S, et al. Predicting the direction of stock markets using optimized neural networks with Google Trends[J]. Neurocomputing, 2018, 285: 188-195.
39. Fischer T, Krauss C. Deep learning with long short-term memory networks for financial market predictions[J]. European journal of operational research, 2018, 270(2): 654-669.