Application of Neural Network in Stock Market Forecasting

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Abstract. This paper summarizes the relevant literature on the neural network application in stock price forecasting, broadens research perspective, improve research methods with a focus on application of deep learning to stock price forecasting, and finally summarize the paper and looks forward to its future development. It makes the neural network's prediction of the stock market more accurate and can make investors more profitable. It can let investors make judgments through rational research results, which can greatly help investors make more objective and reasonable choices. It can restrain the weaknesses of greed and fluky psychology in human nature in investment, and can also overcome investors' cognitive bias, which plays a certain role in investors ' profitability.

Keywords: Neural network, Stock market forecast, Stock market, Specific application, Machine learning model

1 Introduction

Stock trading is an important way for people to make daily investments to obtain income, and how the stock price fluctuates is the research object that everyone focuses on. Many researchers and investors have conducted in-depth analysis of stock prices from the day the stock market began, trying to find out the law of stock price changes, so as to maximize their gains. However, for artificial prediction, such a large amount of verification is obviously difficult to complete, but the stock market prediction using neural network can be judged quickly and accurately, and the results can also be given objectively by using the principles of statistics and mathematics, such as the maximum withdrawal rate, annual rate of return and Sharpe ratio and so on. It improves the utilization rate of funds and brings liquidity to the market.

2 Prediction of stock historical development

Financial market is the place where financial instruments are traded. In order to seek greater returns, thousands of scholars and investors have continuously developed many stock price forecasting methods. Because many factors affected the fluctuation of stock price, including macro factors like economic cycle, economic structure and economic trend, as well as factors such as industry development and financial quality of listed companies. Much also hinges on the psychology and other external factors. They are very important factors that affect the stock market. Researchers and experts are trying to use these factors to find opportunities to make money from stocks. Traditional stock prediction methods include statistical approaches, linear

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discriminative analysis, evolutionary computation algorithm [1,2], quadratic discriminant analysis, genetic algorithm [3,4] and logistic regression. Among them, the use of random forest algorithm is based on historical price information to establish a stock model for the trend prediction of stock price. The key to most of these forecasting methods is to extract and conclude the features of the stock market. These methods all believe that future price trends are the result of historical behavior. However, people rely on their own subjective design characteristics, and most technical analysis models are usually based on hypothesis about some the frame of market, so these valid assumptions lead to the success of the model.

3 Application of Neural Network in Stock Market Forecasting

Artificial neural net is linked by lots of nerve papillae unit with adjustable weights of connection. They have massively parallel processing, distributed information storage, can study and organize itself, so they can predict well. The neural network is a combination of technical discussion, financial management theory and economic analyze, analysis of time series and abc analysis to predict the short-term closing price of stocks. With the neural nets develop, in-depth learning has also become the focus of attention. The number of layers is the difference between artificial neural nets and in-depth learning. Deep learning is about training more neural networks layers, serial new structures and approaches which can work and evolve. Among them, new structures such as CNN, ResNet, LSTM and so on. There are diverse simple grain in CNN and LSTM, and pooling units are critical parts on CNN. LSTM [5,6] mainly includes recurrent units [7], long-term and short-term memory units [8]. As shown in Table 1, these are the related work of this paper.

Table 1. Related work.

Authors	Technique	Outcomes
Falah Hassan Ali Al-Akashi et al.	self-optimizing mapping (SOM) network	Stock price prediction
Thakkar et al.	DNN	Stock price prediction
Chandar, S. Kumar et al.	technical indicators and convolutional neural networks	Stock price prediction
Chen et al.	Long Short-term memory neural network model	Stock price prediction
Srivinay et al.	Hybrid model by predictive rule integration technology and deep neural network	Stock price prediction
Fathi, A.Y et al.	Hybrid model by singular spectrum analysis and nonlinear autoregressive neural network	Stock price prediction

3.1 SOM prediction using self-optimizing mapping network

Falah Hassan Ali Al-Akashi [9] used Elman network, Elman network, multi-layer perceptron (MLP) network, self-optimizing mapping (SOM) network, MLP and SOM filters and simple linear restore to estimate fresh values. The purpose of this study is to have the better predictive ability and offer effective data for future stock price forecasts. In this study, the author describes how to carry out effective market assumptions and system details, showing the stability of the data and process. The experiment uses a linear regression model as a benchmark, indicating that the neural network model has relatively high precision in forecasting financial market indices. The results of experimental show that SOM can greatly enhance the astringency of neural network, and Elman network has better performance in capturing the time pattern of symbol stream generated by SOM. The following diagram as shown in Fig. 1.

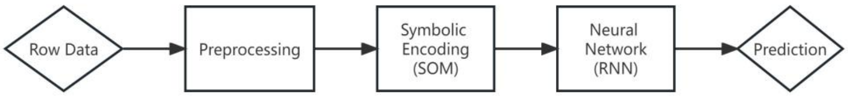

Fig. 1. SOM prediction model.

3.2 Using DNN to predict the stock market

Thakkar, Ankit, and Kinjal Chaudhari [10] delves into DNNs role in predicting stock market prices and future stock trends, and discusses whether DNN changes apply to temporal stock market data, and extended the research to DNN hybrid and meta-heuristic methods. This article mainly uses the DNN perspective to conduct a comprehensive survey. The survey found the potential limitations of using various DNNs for stock market forecasting, and used nine deep learning-based models to conduct a series of stock market forecasting experiments to provide experimental evaluation, and then analyzed the effects of these models on stock data prediction. The authors also evaluated the ability of models with different quantitative features, discussed the challenges and possible future research directions, and summarized the investigation through experimental research.

3.3 TI-CNN stock trading model

Chandar, S. Kumar [11] in order to solve some problems that are being used to forecast the nonlinear model of the stock market, such as the limitations of artificial neural networks, hybrid models and fuzzy systems. They intend to develop a robust model of trade stock by deep learning networks. He developed and implemented a model of trading stock that integrates technical indicators and convolutional neural networks (TI-CNN). The technical indicators in 10 historical data are extracted as feature vectors. Then, the eigenvalue is transformed into an image by using the Gramman angle field and used as CNN's input. The author considers the data of stock from January 2009 to December 2018.Settling the top and bottom buttons in the interface, the stock closing price in the data is marked as the selling point, holding point and buying point. The ability of foremost of the developmental TI-CNN model was checkout on the data of the Nasdaq and the New York Stock and Exchange Board, indices of performance such as exactness are compared to demonstrate the validity of the suggested stock trading model. The result of experiments show that the suggested TI-CNN model has high forecasting precision. TI-CNN is a model of trade stock that combines technical indicators with CNN to predict stock trends. It is a buying and selling point based on image information to determine stock prices. TI-CNN regards the historical data collected from public resources as input, technical indicators are extracted from historical data and used as eigenvector. The calculated technical indexes are converted into images by GAF and be the input of prediction model. Lastly, the prediction model is used to make stock trading decisions.

3.4 STM (Long Short-Term Memory) neural network stock prediction model

In the monetary market, massive indexes are used to describe the trend of stock price changes. These indicators provide a excellent data base for our stock price forecasts. Due to the different types of industries and regions, different factors affected the share price. So it is particularly significant to find out a proper multi-factor portfolio for a specific stock to foremost its quotation. Chen, Shile and Changjun Zhou [12] posed to make use of genetic algorithm (GA) for characteristic detection and picking, and built an majorized LSTM (Long Short-Term Memory) neural net stock model of prediction to select factors that are more proper for the present field. Binding with the model of LSTM network, the stock price is predicted by excavate the complex relationship between stocks and the factors that affect them.First of all, the article uses Genetic Algorithm to get a determiner importance ordering. Then, the optimal factor combination is gained from the ordering by trial and error method. Lastly, the composition of the optimal factor and the LSTM is used to predict the stock. A large number of empirical researches based on the data set of China Construction Bank and the Shanghai and Shenzhen three hundred stock data set show that the GA-LSTM model performs preferably than all the others benchmark models in prediction of time series.

3.5 Mixed population stock forecasting model based on Predictive rule integration (PRE) technology and deep neural network (DNN)

For the propose of deal with nonlinear problems in data, Srivinay, Manujakshi, B.C., Kabadi, M.G., & Naik, N. [13] proposed a mixing population forecasting model based on prediction rule ensemble (PRE) technology and deep neural network (DNN). As shown in Fig. 2. First, they considered the stock technical index to determine upward trend of stock price and moving average technical indexes: moving average twenty days, fifty days and two hundred days. Secondly, they used PRE technology to calculate different stock prediction regulations, they chose the rule with the minimal root mean square error (RMSE) score. Then, a three-layer DNN is thought about for inventory forecasting. A slight adjustment is used in the hyperparameters of the DNN, like the layers number, the rate of learning and the round number. Next, the PRE and DNN forecasting models average results are linked. The results of the mixing population forecasting model were calculated by mean absolute error (MAE) and RMSE metrics. The ability of the mixed population forecasting model is more preferable than that of the single forecasting DNN and ANN model, and the RMSE score is increased by 5 % ~ 7 %. In addition, this experiment also considered India 's stock price data.

Fig. 2. Forecasting model.

3.6 A hybrid model of singular spectrum analysis (SSA) and nonlinear autoregressive neural network (NARNN) for stock closing price prediction

Fathi, A.Y., El-Khodary, I.A., & Saafan, M. [14] In order to predict stock prices with volatility and noise, nonlinear autoregressive neural network (NARNN) and a mixing model combining singular spectrum analysis (SSA) is proposed. First of all, the model separated the weekly stock closing price into a training data set and test data set. Secondly, SSA divided the training data set into kinds of parts, extracts hidden characteristic, and reduces noise. Then, construct and train a NARNN for each decomposed part. Next, the model forecasts future value of kinds part by divided the above usable prices. Lastly, the SSA-NARNN is used to aggregate the predictive rate to get the final output. These real trading processes are simulated by the program to prevent any information about the future performance of the stock from being involved in the training process. The reliability of the model is demonstrated by the weekly call rule of 24 stocks hit the stand on the Egyptian Exchange. More importantly, the author also proves predominancy of SSA-NARNN by comparing it with the autoregressive integrated moving average model (ARIMA) and the single NARNN model.

4 Conclusion

The neural network is mostly predicted by learning the historical stock market data, but due to the large gap in the history of the stock market, it is impossible to make accurate predictions effectively. This study summarizes a number of papers on neural network prediction in the stock market, analyzes the advantages and disadvantages of various prediction models, broadens the research perspective, and hopes to better train data so that artificial intelligence can also make accurate predictions in the real market.

Using machine learning models to predict stock prices is very challenging because it involves complex and often non-linear market dynamics. Some of the main difficulties in this field I think are : the market may experience structural changes, such as financial crisis, policy changes, etc., these changes may make past data invalid for future forecasts ; when trying to capture complex market patterns, the model may over-fit historical data, resulting in a decrease in prediction performance in practical applications. There are many factors that may affect stock prices [15], such as macroeconomic indicators [16], corporate financial reports, news reports, etc. How to choose features that are useful for forecasting is a problem. These difficulties make it difficult to use machine learning models to predict stocks.

In response to these problems, I believe that the following solutions can be used : reinforcement learning can continuously learn and adjust strategies in a simulated environment, and may be used in the future to develop trading algorithms that are more adaptable to market changes ; use big data technology [17] to process more types of data (such as social media, news events, etc.) in order to better understand market sentiment and market dynamics ; combining multiple models [18] or multiple data sources for prediction can reduce the risk of overfitting and improve the accuracy of prediction.

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