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Research on stock trading strategy based on deep neural network

Yilin Ma[1] and Ruizhu Han[2*]

[1]School of Economics and Management, Southeast University,
Nanjing, 211189, China (ylmaseu@163.com)
[2]School of Economics and Management, Southeast University,
Nanjing, 211189, China (daodao-777@163.com) * Corresponding author

Abstract: Deep neural network is widely concerned with the concept of deep learning. However, there are few researches focus on the application of deep neural network for stock trading strategy. Excellent trading strategies can not only help investors get high profit, but also effectively reduce the income risk. This paper studies 7 trading strategies based on a deep neural network, and uses the 2009-2015 years historical data of Shanghai Composite Index for experiments through sliding window approach, and adopts the accuracy, rate of excess return, volatility of yield and information ratio to measure the advantages and disadvantages of different trading strategies. According to the experimental results, a trading strategy suitable for the deep neural network is found. This trading strategy can not only achieve a high predictive accuracy but also have a low volatility, which can help investors reduce the risk of loss effectively while obtaining satisfactory returns.

Keywords: deep neural network, trading strategy, stock prediction

1. INTRODUCTION

The trend and volatility prediction of stock prices are difficult tasks in time series forecasting. Many researchers are committed to develop effective models to predict the trend of stock prices, and then design a number of trading strategies to help investors benefit. Among them, support vector machines and artificial neural networks are widely used in stock price prediction [1], [2], [3]. All of the above literatures are based on whether the increase of stock price is larger than the threshold of 0 to determine the category of data. This simple classification not only absorbs much noise and unrelated information, but also fails to apply the prediction ability of the model. Thus, it is necessary to consider the above threshold in detail.

In recent years, with the introduction of the concept of deep learning, deep neural networks have entered the vision of the public. In the field of image classification [4], [5], Natural Language Processing [6] and speech recognition [7], deep neural networks have achieved great success. The advantage of deep neural networks lies in their powerful feature extraction ability, which makes them suitable for stock price prediction. For instance [8], [9], these studies simply use all kinds of errors to measure the prediction ability of deep neural networks, and have not discussed their relative trading strategies. In this paper, we use a deep neural network to investigate the influence of different thresholds selection on their corresponding trading strategies, so as to make up for the blank of the above research. Since, an excellent trading strategy can not only further improve the performance of the model, but also effectively reduce the risk of its income. Thus, it is meaningful to discuss trading strategies based on the predictive model.

This paper discusses various trading strategies based on a deep neural network in detail to make up for the above blank. The trading strategies discussed in this paper are based on the classification prediction of stock fluctuations. For instance, if the second day's increase is more than 5(RMB), we record the target output as 1, otherwise it is recorded as 0. Then, based on the above processed target value, the deep neural network can be trained and the profit of this trading strategy can be derived. As an emerging stock market, the volatility of stock prices in Chinese stock market is far from the extent of effective market, so, historical data can be used to predict the volatility of stock prices. Therefore, this paper applies an important index of the Shanghai stock exchange - Shanghai Composite Index to carry out the experiment, which can not only exclude the deviation of individual stocks but also can reflect the stock market.

2. RELATED WORKS

In [10], Arévalo et al. present a high-frequency strategy based on deep neural networks (DNNs). The DNNs were trained to predict the next one-minute average price, which are applied to generate a high-frequency trading strategy that buys (sells) if the next predicted average price is higher (lower) than the last closing price. Experimental results show that the best-found DNN has a 66% of predictive accuracy and this trading strategy obtained an 81% successful trades during the testing period. In [11], Yang et al. propose a deep neural network ensemble to predict Chinese stock market index (Shanghai composite index and SZSE component index) by using the input features of recent days. Bagging approach is applied the component deep neural networks to generate the ensemble, which greatly reduces the generalization error. Relative errors between actual values and predicted values, and predictive accuracy of trend prediction are applied to measure the performance of the deep neural network ensemble. Experimental results show that the proposed model can partially predict the Chinese stock market. The predictive accuracy of daily barycenter, high and low are $71.34\%, 74.15\%$ and 74.15% respectively for the Shanghai composite index and $75.95\%, 73.95\%$ and 72.34% respectively for the SZSE composite index. However, the predictions on closing price are unsatisfactory. Chong et al.[9] offer a systematic analysis of using deep neural networks for stock market analysis. High-frequency intraday stock returns are adopted as input features. The authors examine the performance of three unsupervised feature extraction algorithms-principal component analysis, autoencoder and restricted Boltzmann machine-with the networks's overall ability to forecast future stock market. Experimental results present that the deep neural network can discover additional information from the residuals of autoregressive model, thus improve predictive performance. And the same condition cannot exist when autoregressive model is applied to the residuals of the deep neural network. Singh et al. [8] apply 2-Directional 2-Dimensional Principal Component Analysis $(2D)^2PCA+$ deep neural network to predict the Google stock price from NASDAQ and compare it with $(2D)^2PCA+$ radial basis function neural network and $(2D)^2PCA+$ recurrent neural network. Experimental results show that $(2D)^2PCA+$ deep neural network performs better than $(2D)^2PCA+$ radial basis function with an improved accuracy of 4.8%, and $(2D)^2PCA+$ recurrent neural network with an improved accuracy of 15.6%.

3. MODELS AND TRADING STRATEGIES

3.1 Models

The deep neural network used in this paper is a deep feed-forward neural network. Other types of deep neural networks such as LSTM neural network and convolutional neural network can also be similarly discussed. The deep forward neural network consists of input layer, hidden layer and output layer. The input layer receives the input signal, the hidden layer is used to process and extract valid information, and finally the output layer derives the output results. The feed-forward neural network transmits the input features from the input layer to the output layer in turn without circulating units. When the number of hidden layers is one, the neural network is called a single hidden layer neural network. When the hidden layers contain more than one layer and an efficient training algorithm is combined, the neural network is called a deep neural network.

In this paper, the number of hidden layers in the deep neural network is 2, and the number of nodes in each layer is 200, also, the activation function of the hidden layer nodes is Relu function. A dropout layer is added between the two hidden layers to reduce the over-fitting problem and its parameter is set to 0.5. The dropout layer randomly cuts off the connection between the nodes on the upper layer and the next layer with a fixed probability, so that the weight between the above two layers is unable to be very large, which thereby reduces the condition of over-fitting. Also, early stopping is used to control the model training process to reduce the over-fitting problem. and, random gradient descent method (the number of batch samples is 30) is used to train the deep neural network and adam optimization algorithm to applied to produce the descending gradient. Adam algorithm is a popular optimization algorithm for training deep neural network which usually can generate good results for many problems. Binary cross-entropy is used as the loss function to characterize the deviation between the predicted value and the target value. Because in most application scenarios of neural networks, the performance of classification is better than regression. Therefore, this paper adopts only one node as the output layer and uses the sigmoid function as the activation function to forecast the rise or fall of the Shanghai Composite Index.

3.2 trading strategies

In this paper, 7 trading strategies based on deep neural network are investigated. To be specific, first, if the increase of the next day's stock price is more than the given threshold, the target value of prediction will be set to 1, otherwise 0. Second, based on the generated target value and input features, the training process of deep neural network is conducted. if the predictive output of deep neural network is not less than 0.5, then the trading strategy will buy or hold it, otherwise sell it. 7 thresholds (i.e., 0,1,2,...,6) are discussed to search for the threshold with higher income and lower volatility. Also, the passive buy and hold trading strategy is used as benchmark strategy.

4. EXPERIMENT

4.1 Data preprocess

Shanghai Composite Index is an important index in Chinese stock market, which generally reflect the volatility of all the stock price in Shanghai Stock Exchange. This paper adopts the stock price of this index can not only reduce the effect of individual stock but all represent the whole stock market. Daily data from January 5, 2009 to December 31, 2015 containing close price, open price, low price, high price and trading volume are selected as input features (the data come from the software of Wind Information). We eliminated some days with missing or abnormal data, and the final remaining data contained 1700 days.

Since the fluctuation range of each data is quite different, the experimental data are standardized first, and the process is as follows:

$$x_i = \frac{x_i - \overline{x_i}}{\sigma_i}, \tag{1}$$

where $\overline{x_i}, \sigma_i$ represent mean value and standard deviation respectively.

Since the volatility of stock prices will be affected by the data of the past few days or even few weeks, this paper applies the daily data of the past 30 days as input data to predict the next day's stock prices. For the output data, they are determined according to a given threshold. Specifically, the target output is set to 1 when the increase of the next day's stock price is larger than the given threshold, otherwise it is set to 0. Similarly, we consider 7 different thresholds (i.e. 0,1,2,...,6) to examine the changes in the profits of different trading strategies after selecting different thresholds, and each experiment is repeated 10 times to discuss its volatility.

4.2 Experiment process

The experiment uses sliding windows to predict the daily direction of the Shanghai Composite Index. Each window contains 5 years of data, so the window is rolling 3 times. We divide the data of each window into three parts: the first 70% of the data as the training set, the 15% of the middle data as the validation set and the final 15% of the data as the test set. The purpose of the validation set is to reduce the over-fitting problem in training process. Specifically, when the training set is used to train the deep neural network, the loss function of the validation set will drop first, and then rise gradually during the training process, while the deep neural network appears the over-fitting problem. So, if we stop training when the loss function of the validation set begins to rise, then the deep neural network is trained to the best. In this condition, the deep neural network can generate excellent performance on the test set. The experiment adopts Keras deep learning package to realize the deep neural network.

5. ANALYSIS OF EXPERIMENTAL RESULTS

First, accuracy is adopted to measure the performance of 7 trading strategies and its definition is as follows:

$$Accuracy = \frac{T}{T+F}, \tag{2}$$

where T, F represent the number of correct prediction and the number of false prediction respectively.

Table 1 The experimental results of accuracy

	2013	2014	2015
0	47.68%	53.62%	47.27%
1	46.49%	55.26%	48.18%
2	44.24%	52.17%	49.35%
3	53.77%	52.96%	48.51%
4	56.09%	54.61%	48.44%
5	59.67%	51.25%	48.77%
6	58.87%	53.03%	50.00%

As one can see from Table 1, the experimental results show that with the increase of threshold value, the prediction accuracy rate shows an overall upward trend. This indicates that the increase of threshold is helpful to improve the prediction ability of the deep neural network.

Second, in order to further investigate whether the increase in prediction accuracy is accompanied by a rise in the rate of return, we have carried out a simple trading simulation to evaluate the profitability and volatility of various trading strategies.

Before conducting trading simulation, we suppose that when the deep neural network predicts predicts the next day's stock price rise, the trader chooses to buy or hold it, and the income obtained is approximated by the next day's change amount. Otherwise, the trader sells it and its returns is denoted as zero. In order to simplify the calculation, we do not consider transaction costs, dividends and taxes, and leverage and short selling are prohibited . In addition, buy and hold strategy is used as a benchmark strategy to compare the performance of different trading strategies.

Last, the above performance is measured by the rate of excess return (i.e. the yield of the trading strategy minus the yield of the benchmark strategy). The results are shown in Table 2. At the same time, the volatility of yield is characterized by standard deviation, and the results are shown in Table 3. Finally, we select the trading strategies with a positive excess yield to calculate its information ratio (i.e., $\frac{rate\ of\ excess\ return}{standard\ deviation}$), Since the excess return in 2014 is negative, in order to measure the stability of the trading strategy return, we use the result of $\frac{rate\ of\ return}{standard\ deviation}$ to approximately measure the change trend, and the information ratio of the strategies with negative excess returns in 2013 are denoted as 0, the experimental results are shown in Table 4.

Table 2 The experimental results of rate of excess return

	2013	2014	2015
RRBHS	-5.31%	59.15%	-16.79%
0	-3.47%	-21.53%	13.87%
1	1.11%	-11.59%	10.39%
2	-0.04%	-25.08%	5.18%
3	7.15%	-15.59%	14.01%
4	5.78%	-18.06%	13.89%
5	4.32%	-44.79%	10.77%
6	4.36%	-46.61%	8.71%

(RRBHS represents rate of return of buy and hold strategy)

Table 3 The experimental results of volatility of yield

	2013	2014	2015
0	0.0028	0.1663	0.0870
1	0.0560	0.1987	0.1141
2	0.0535	0.1904	0.1422
3	0.0540	0.1196	0.0833
4	0.0396	0.1557	0.0871
5	0.0224	0.1010	0.1205
6	0.0368	0.1662	0.1242

Table 4 The experimental results of information ratio

	2013	2014	2015
0	0	2.2623	1.5935
1	0.1973	2.3935	0.9110
2	0	1.7892	0.3641
3	1.3256	3.6422	1.6827
4	1.4583	2.6400	1.5945
5	1.9294	1.4224	0.8941
6	1.1844	0.7547	0.7016

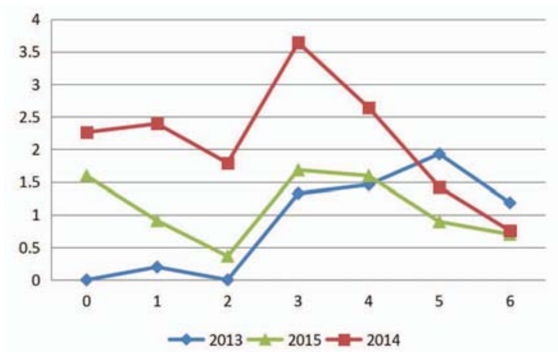

Fig. 1 Information ratio

The experimental results show that:

1. The excess return of trading strategies generally increases first and then decreases with the increase of threshold. This indicates that the setting of the threshold can not be too small or too large, otherwise the trading strategy will be difficult to obtain excess returns, and according to the experimental results, the threshold value can be set at 3 or 4, which can help investors to obtain higher excess return.

2. The volatility of the rate of return increases briefly and then drops with the increase of the threshold, which shows that with the increase of the threshold, some random factors that affect the stock price are greatly eliminated, which makes the deep neural network better discover the law of the stock price fluctuation, thus the yield becomes stable. According to the experimental results, when the threshold is 3, the volatility of the rate of return is greatly reduced, which can not only keep the excess rate of return at a higher level, but also effectively reduce the risk of the return.

3. By calculating the information ratio of the positive excess rate of return, it is known that, in general, when the threshold is set to 3, its transaction strategy always has a higher information ratio, which can help the investors get a higher yield and effectively reduce investment risk, see Fig 1.

4. After comparing the 7 trading strategies with the passive buy and hold strategy, we discover that when the stock market is good, for example, in 2014, the 7 trading strategies based on the deep neural network are difficult to obtain satisfactory returns, and we suggest to choose the passive investment strategy. On the contrary, when the stock market is bad or stable, such as 2013 and 2015, the 7 trading strategies presented in this article is generally able to perform better than the passive strategy. In this condition, the trading strategy based on the deep neural network can not only help the investors reduce investment risk effectively, but also can obtain a stable higher profit.

6. CONCLUSION

This paper studies 7 trading strategies based on the deep neural network, and aims to explore how to select the appropriate threshold to further improve the performance of the deep neural network in stock price prediction. We use accuracy, excess return, volatility of the yield and information ratio to evaluate the performance of the above 7 strategies comprehensively. The experimental results show that in order to avoid the influence of random disturbance, we should improve the threshold of target classification properly, so that it can not only improve the rate of return significantly, but also effectively reduce the risk. At the same time, we discover a trading strategy with better overall performance, that is, the trading strategy with a threshold of 3. In addition, it is necessary to claim that when using a deep neural network based trading strategy, we should first judge the stock market, the above trading strategy is only recommended when the stock market is general or poor.

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