Adaptive trading system based on LSTM neural network

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Abstract. With the continuous development of statistics and computer technology, the methods of technical analysis are also constantly expanding. A large number of statistical and mathematical methods have been applied to the analysis of stocks, which greatly expands the tools available for stock analysis. With the rapid development of deep learning and the great progress of computer hardware technology, statistical learning algorithms have been widely used in big data processing. Including convolutional neural network model and cyclic neural network model, have shown great advantages in the processing of time series such as images, speech and text. In today's financial market, due to the existence of a large number of assets and fast information flow, people are more and more inclined to use quantitative investment. Quantitative investment as a means of financial sector, the New Deal, which is mainly composed of fundamental analysis and technical analysis from the traditional investment method, its core is to use mathematical model set up trading strategy, and with the help of computer technology on the financial data for quantitative analysis, and judgment, found that financial market rules, eliminating dependence on the experience of the people in the course of investment and emotional impact, so as to guide investment decisions. In order to improve the prediction ability of LSTM neural network model, this paper chooses the stack LSTM neural network model, and combines the stack LSTM neural network model with ADAM algorithm to achieve better prediction results. The empirical results show that the prediction effect of ADAM-based stack LSTM neural network is better than that of ADAM-based LSTM neural network.

Keywords: Stacked; LSTM; Neural network; Adaptive; The trading system

1. Introduction
In the capital market, both institutional investors and individual investors are constantly looking for new methods to improve the level of financial investment decision-making, and improving the ability to predict the price of financial assets has been the focus of academic and financial circles. Judging from the current research status, most financial forecasting models are based on statistical models, which use historical data to predict the possible direction of future asset prices. There are two types of statistical models applied to data analysis [1] [2]. One is data model, such as common econometric model. The other is algorithmic model, which is commonly known as machine learning methods. In the era of big data, in order to deal with the processing and analysis problems of massive data, the software and hardware conditions of computers are constantly improved, which makes algorithmic
models, especially deep learning algorithms, more and more important in theory and practice. However, the so-called algorithm "black box" has been questioned due to the excessive complexity and difficulty in interpretation of the algorithm model, especially in the field of financial research, where data models based on traditional statistical methods still occupy a major position [4]. From the perspective of the domestic quantitative investment market at the present stage, most quantitative strategy ideas are still tracking the trend. It is very rare to really use the advanced strategy of the statistical model of the complex algorithm which is more difficult [5].

A multi-layer neural network model can be obtained by connecting simple neurons with each other.

![Figure 1 Double-hidden layer feed forward neural](image)

2. Theory and Algorithm

In the neural network, the most basic and simplest component is the neuron model, which is similar to the neuron in the biological neural network. Each neuron is connected with other neurons[8].

![Figure 2 M-P neuron model](image)

In Figure 2, \( x_i \) represents the input data from the \( i \) neuron, \( \omega_j \) represents the connection weight of the \( i \) neuron, \( f \) represents the activation function, \( \theta \) represents the threshold, and the output is \( y \), which can be expressed as:
In this model, signals sent by \( N \) other neurons connected to the neuron are used as inputs and transmitted through weighted connections. The neuron will compare the total input received with its own threshold, and then process it with activation function \( f \) to finally produce the output of the neuron.

The data selected in this paper are related to CSI 300 Index (stock code 000300) for empirical analysis. The data came from the Wind financial terminal, covering the K-line data of all trading days from May 1, 2005 to September 30, 2017, including all the data of six attributes, such as open, close, low, high, volume and amount, with a total of 3,022 groups of historical trading data.

\[
y = f \left( \sum_{i=1}^{n} \omega_i x_i - \theta \right)
\]

Figure 3: Open price of the CSI 300 Index

Considering that stock data is a kind of financial time series data, and historical data have a great impact on the future, the main prediction scheme of this paper is to use the data of the previous \( t \) trading day to predict the opening price of the \( t+1 \) trading day. The specific operation steps are as follows:

Morel feature extraction is equivalent to the extraction of a day's state features. If you can increase the short-term characteristics of the market, you can be sensitive to changes in the state of each moment, so that you can make better decisions. Therefore, a feature extraction network based on price return prediction is added into DDRRL to find the next time price rule change in the market. The feature extraction network based on price return can predict the rise and fall value of the next moment to extract the feature and combine the original feature extraction results as the feature of the current moment. The Price-based Return Forecasting Network is a supervised learning network.

Before establishing the model, necessary data processing is needed. The specific values of class attributes differ greatly and are not of the same order of magnitude. In order to avoid the impact of such a large gap between the values on the model performance, it is necessary to standardize the test set and training set first. Then take the data of the previous \( t \) trading days, including the data of 6 attributes such as the opening price, as a data block, take the data block as the feature, and take the opening price of \( t+1 \) as the prediction target. In this way, the divided training set and test set are processed respectively in the way of sliding in time sequence and divided into different data blocks. In order to ensure the independence of the internal data of the training set, the training set with well-divided data blocks is randomly shuffled.

Since trading strategies are constructed through neural networks, the learning process of MODRRL and DDRRL is the process of updating network parameters. The most commonly used method of deep learning is to take the derivative with the back propagation algorithm and update the parameters along the direction of gradient descent. This method considers that the state of the market at the present moment is closely related to the price returns of the previous \( m \) periods. The price returns in the first \( M \) segment show the trend of market price development, as well as the changing situation. If the price has been rising in the previous \( m \) periods, the price return has been positive, indicating that the
probability of the trend to continue is high. In addition, the numerical size of the price returns can also indicate how the trend is changing. When financial market prices have been rising, price returns can be seen in the magnitude of the increase. Price returns in m periods not only indicate the trend of the market, but also indicate the rise and fall of the market, which can better help the network to analyse the current state of the market so as to make better decisions. Therefore, the appropriate length of time window m can better reflect the state of the financial market.

In the training of LSTM neural network, t=15 is adopted to divide the data blocks in the training set and the test set, that is, the opening price of the next day is predicted with the data of 6 attributes such as the opening price of CSI 300 index in the previous 15 days. The data of all trading days of CSI 300 Index on May 1, 2005 and solstice on December 31, 2016 were used as the training set, and the data of all trading days of CSI 300 Index on January 1, 2017 solsticeBBB1 on September 30, 2017 were used as the test set. For the parameter selection of LSTM neural network, the number of hidden layers is 1, the neurons in the hidden layer are set as 10, and the learning rate is set as 0.1.

![Figure 4 Empirical results of LSTM neural network](image)

Figure 4 shows the use of the csi 300 index on January 24, 2017-2017 on September 5, all the session's data as the training set to LSTM neural network model, using the LSTM after training the neural network model of the csi 300 index on January 24 January 2017 to September 2017 5 all day opening price order sliding prediction.

![Figure 5 Prediction error of LSTM neural network model](image)

Figure 4 shows the actual error between the predicted value predicted by the LSTM neural network model and the actual value. By comparing the prediction error of RNN neural network model, it can be found that the prediction error of LSTM neural network model is much smaller than that of RNN neural network model and the actual result, and is much more stable. After calculation, the mean square error (MSE) between the predicted results and actual results by using LSTM neural network model is 994.8243, and the mean absolute error is 7.2165‰. Obviously, there has been a significant reduction in both the MSE and the MSE. The mean square error (MSE) between the predicted results and the actual results by the LSTM neural network model is 73.93% lower than that between the
predicted results and the actual results by the RNN neural network model, and the mean absolute error (MSE) is $45.05\%$ lower. Using STM

Compared with BP neural network model, the mean square error (MSE) and mean absolute error (MSE) are reduced by $81.95\%$ and $61.98\%$ respectively.

3. Conclusion

In order to increase the depth of LSTM neural network model and improve its prediction ability, the stack LSTM god network model is adopted, and the stack LSTM neural network model is combined with ADAM algorithm to achieve better prediction results. The empirical results show that through the improvement of the learning rate update algorithm of LSTM neural network model and the improvement of the structure of LSTM neural network, the prediction ability has been significantly improved, and the prediction results are more accurate.

In the design of the experimental scheme, considering that the stock data is a kind of financial time series data, and the historical data have a great impact on the future, the main prediction scheme of this paper is to use the data of the previous $t$ trading day to predict the opening price of the $t+1$ trading day. The training set and test set of this paper are divided as follows: the data of all trading days of CSI 300 index on May 1, 2005 solstice and December 31, 2016 are taken as the training set; the data of all trading days of CSI 300 index on January 1, 2solsticeBBB1 and September 30, 2017 are taken as the test set. The processing scheme of the data in the data set is given.

In the empirical process, using BP neural network model to predict the result and the actual results of the value of the mean square error is $5512.3561$, the average absolute error is $18.9784\%$, using RNN neural network model to predict the result and the actual results of the mean square error is $3815.9581$, the average absolute error is $13.1321\%$, using LSTM neural network model to predict the results and the actual results of the mean square error is $994.8243$, the average absolute error is $7.2165\%$.

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