Application of LSTM Neural Network in Stock Price Movement Forecasting with Technical Analysis Index

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Abstract

There are many factors will be driving stock prices, such as earnings, economy, expectations, and emotion. Stock prices are volatile because these factors daily change frequently; it is a big challenge to accurately predict the future stock prices. Recently, there are lots of studies in the area of applying Machine Learning for analyzing price patterns and predicting stock prices, they would get satisfactory results in making instantaneous investment decisions. In this paper, we discuss the Long Short-Term Memory (LSTM) algorithms applied for stock trading to predict the rise and fall of stock prices before the actual event of an increase or decrease value in the stock market occurs. Aiming to raise up the rate prediction accuracy, we achieve to build a prediction model, execute a series of experiments, and then provide the index reference to buy a stock before the price rises, or sell it before its value declines.

Keywords: Stock market, Machine Learning, Long Short-Term Memory

1. Introduction

The stock market reflects the economic conditions of an industry or a company, that is to say, in the long run also reflects all values which are influenced by the supply of capital and determine the direction in which new capital shall be applied. Many methods for predicting the stock market had been developed. For example, autoregressive moving average (ARIMA) method is used to analyze the time series data (Box, Jenkins, Reinsel, & Ljung, 2015). Piecewise aggregate approximation (PAA) method is also used to extract features and find the similarities within the time series data (Hamilton, 1994). Support vector machine (SVM) method is applying for time series forecasting (Cao, 2003).

In addition, some studies adopt the financial technical analysis indicators to identify opportunities on stock trading, such as Simple moving average (SMA), Relative strength index (RSI), and Moving average convergence and divergence (MACD) (Sezer, Ozbayoglu, & Dogdu, 2017) (Ozbayoglu & Erkut, 2010).

However, the prediction on stock market is a big challenge because it is affected by many factors. Recently, machine learning algorithms have rapid advancement, stock market forecast based on deep learning methods designed to process large data and detect patterns and trends in those data has prompted discussions. Recurrent neural network (RNN) is an effective model to process time series data and used to predict stock market (Rather, Arun & Sastry, 2015). Long Short-Term Memory (LSTM) is a kind of RNN (Hochreiter & Schmidhuber, 1997), wherein LSTM can solve the gradient disappearance problem of RNN.

In this paper, we scrape daily stock data, which is extracted the range from January 2, 2013 to August 5, 2019, total 1610 records are collected. We adopt Keras as a deep learning platform to build a LSTM model for predicting the following day's closing price within +/-5%, alongside the financial technical analysis indicators calculated from the daily stock data. Compared with random prediction model, our LSTM model is proposed to improve the accuracy of stock returns prediction up to 60.7% and 79.7% respectively using in different features. Considering market timing, our LSTM model, as a strategy, demonstrated the chart plus the comments to some extent if the company experienced growth or got a windfall.

2. Related Work

In this section, we briefly describe LSTM Networks and stock price prediction of knowledge that will be used in our proposed method.

2.1 LSTM neural network

Long Short-Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997) is a type of the Recurrent Neural Network (RNN) which is used for time series data analysis. The RNN takes the information of the previous memory and the current information as input to present the dynamic time expression. The property of information preservation implies that the RNN is suitable for dealing with continuous data and applied to several practical applications, such as natural language processing, speech recognition, etc. However, the problem of the RNN is the vanishing gradient that RNN would suffer while dealing with long-term data sequences.

The LSTM model is introduced to avoid the gradient disappearance problem by using the memory cell and gates to handle long-term sequences. In the LSTM model, it consists of four components: an input gate, a forget gate, an output gate, and a memory cell depicted in Figure 2.1.1. x_t is the input information, c_t is the state of memory cell, and h_t is the output information at time t. The input gate can allow incoming information to update the state of memory cell or discard it. The forget gate can determine the memory cell to utilize or prevent the previous state. The output gate can determine whether the state of memory cell will affect other neurons or not. In this paper, we use the LSTM model to predict the stock price.

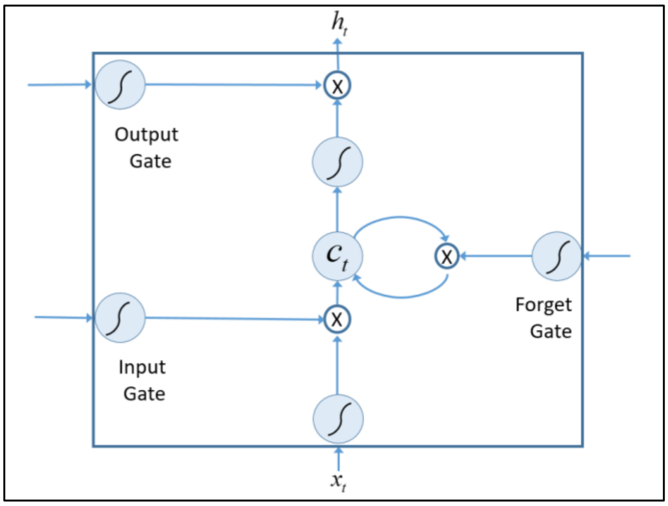

Figure 2.1.1. Diagram of LSTM structure

2.2 Stock price prediction of knowledge

All of the financial technical analysis indicators that we consider here are based on looking for short time trends and making the following day's trading forecast. We decide to utilize trading strategies based on two trading indicators: Simple moving average (SMA) and Relative strength index (RSI), which are defined as follows:

(1) Simple moving average

The simple moving average is probably the most basic form of stock technical analysis for pricing trend strategy. If the current price is more than a moving average, the upward trend is signaled, then most traders in period are literally making money. If the current price is less than a moving average, the downward trend is signaled, then most traders in period are losing money. The simple moving averages can have different lengths, such as 5, 10, 20, 60, 120, or 240 days. In this paper we discuss 5-day simple moving average (5-SMA), which is the formula to create a new average each day that it adds up the five most recent daily closing prices and divides the sum by five. The equation is as follows:

$$SMA = \frac{p_1 + p_2 + \cdots + p_n}{n} \tag{1}$$

, where p_1, p_2, …, p_n are the stock prices in the period of n days.

(2) Relative Strength Index

The other trader's reference to the relative strength index (RSI), is considered momentum indicator to evaluate pricing change conditions. In this model, the RSI value oscillates between 0 and 100, calculated for each day in the test data. The RSI value of the corresponding test data is considered overbought when above 70, sell signal is generated. Likewise, the RSI value of the corresponding test data is considered oversold when below 30, buy signal is generated. The basic formula is:

$$RSI = 100 - \frac{100}{1+\frac{SMMA(U,n)}{SMMA(D,n)}} \tag{2}$$

, where *SMMA(U, n)* and *SMMA(D, n)* represent that the average upward change *U* and down change *D* are calculated using an n-period smoothed or modified moving average, respectively. In this paper we discuss 5-day relative strength index (5-RSI) corresponding to 5-SMA.

As mentioned above, we select both of them because they are easy to implement and are commonly used as basic trading signals.

3. The Proposed Method

3.1 Data collection and processing

In this paper, the historical data comes from the Taiwan stock exchange. First of all, we collect the transaction data from January 2, 2013 to August 5, 2019. The stock information obtained every day consists of date, opening price, highest price, lowest price, closing price, and volume. Then, we compute the 5-SMA value and 5-RSI value by applying Eq. (1) and (2), respectively. Due to the stock volume feature is very different from the other features in magnitude, it is essential to use the normalization method to eliminate the impact of magnitude. Therefore, the data is in the same order of magnitude for subsequent comparison and analysis. We adopt the min-max normalization method to rescale the range of features in [0, 1]. The equation is as follows:

$$x_{nom} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

After that, we take 80% of all data as a training set and 20% of those as a testing set for building the LSTM model.

3.2 Model building

We use Keras as a deep learning platform to build a 4-layer LSTM model for predicting the following day's closing price within +/- 5%. To evaluate the effect, we adopt two methods, wherein the features are different in the LSTM model structure. Details are given in Table 1. The experiment results are depicted from Figure 3.2.1 to Figure 3.2.2.

TABLE 1 Experiment data for building the LSTM model

Experiment data / Methods	Features
M1	date, opening price, highest price, lowest price, closing price, volume, and 5-SMA
M2	date, opening price, highest price, lowest price, closing price, volume, 5-SMA, and 5-RSI

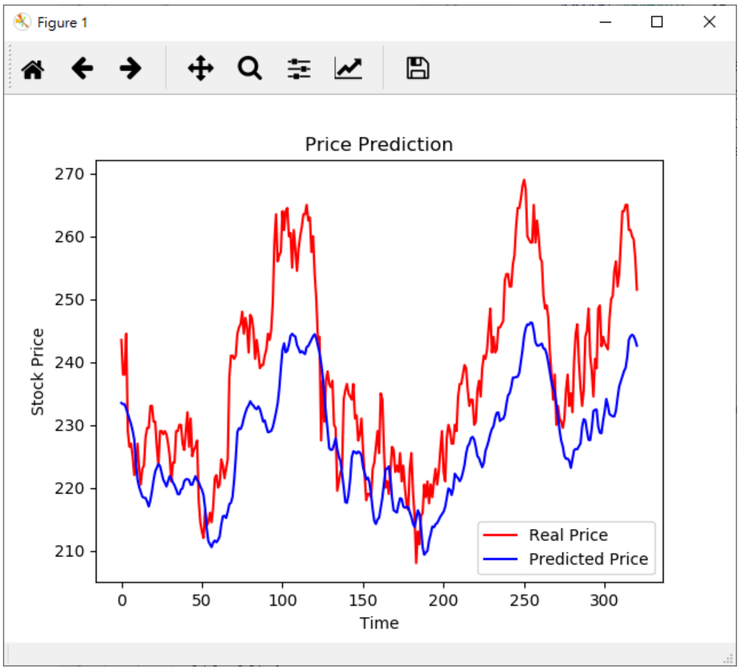

Figure 3.2.1 Method M1 prediction results

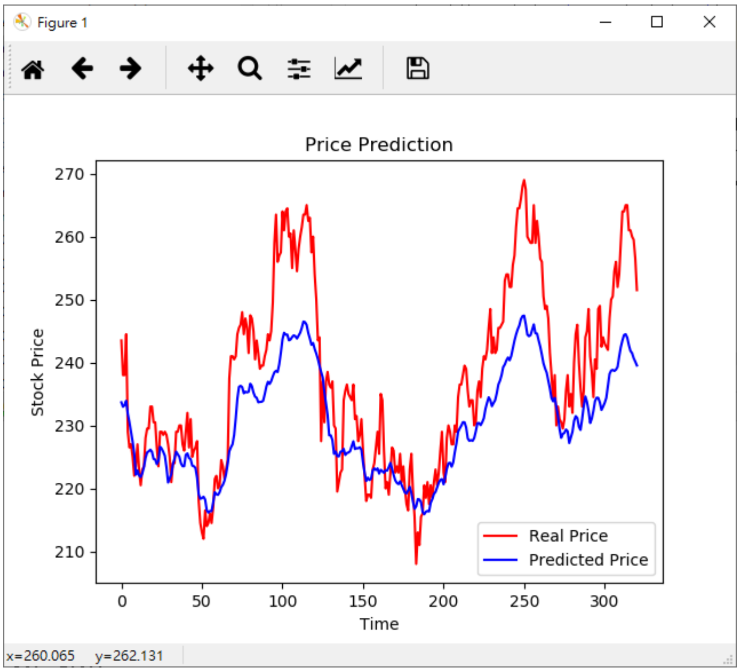

Figure 3.2.2 Method M2 prediction results

3.3 Evaluation

The mean square error(MSE) is used as the loss function for each training of the model. The MSE is used to evaluate the prediction results, the equation is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (4)$$

, where y_i is the real value, $\hat{y}_i$ is the predictive value, and n is the total number of records.

4. Discussions

All the stock forecasts described in this paper are intended to predict whether the closing price of the following day is within +/- 5%. The accuracy of M1 is 60.7%, and the accuracy of M2 is 79.7%, respectively. In the other hand, we found the experiments with more accurate features, it gains better results, and that would contribute more reliable model.

5. Conclusions

We applied the experimental LSTM neural network with two different features to predict the stock price through 4 layers scheme, which displayed better accuracy able to be proven our model complies better prediction to meet investment demand.

There is still some room for improvement for our prediction algorithm. Namely, the stock volume used for learning rate, fundamental trading algorithm, and model architecture are all things that we will optimize in the future. Also, we can look into giving the model more features in terms of specificity by having more LSTM layers, so the network can make decisions accurately based on short, medium and long term trends.

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