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Prediction Method and Optimization of Stock Trend Based on Neural Network

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Abstract: The stock market is characterized by the coexistence of high risks. In order to seek benefits and avoid risks, people do not hesitate to explore its laws and seek the best forecasting methods and methods. The purpose of this paper is to study the stock trend prediction method and optimization based on neural network. The predictability of the securities market is expounded. On the basis of the prediction model based on the historical stock transaction data, a stock prediction model integrating news and investor sentiment is constructed. The advantage of linear and complex time series forecasting problems, the stock training data is used as the input data of the improved CLSTM and BiLSTM deep neural network, and the stock trend forecasting model is trained. Continuously optimize and improve the model, select appropriate parameters to obtain a good stock trend prediction model. By continuously revising the LSTM level, the accuracy of the stock trend prediction model is significantly improved.

1. Introduction

With the deepening of my country's economic system reform and financial system reform, securities investment has become an important part of social life, and an important part of securities investment is the reasonable prediction of future market conditions [1]. The modeling and forecasting research of the stock market has always attracted worldwide attention. At the same time, the requirements for the algorithm are also very high, and it is often difficult to obtain satisfactory results in this regard [2].

Stock trading is one of the areas where selection is an important consideration. While there are many unique approaches to discovering phenomena in nature through various techniques such as physics and economics, many of them present complex concepts. Therefore, Thapa P used

Geometric Brownian Motion (GBM) to analyze the natural market in Nepal; NEPSE values and parameters displayed by Python software. Check nonlinearity using the Spring 2003/2004 equivalence period using a Python model. This model (GBM) is used to validate the proposed model in a stable market year for the period of change; the 2020 COVID-19 disaster. The GBM index of Nepal stock market is highly correlated with forecast accuracy, which makes GBM one of the simplest and most accurate forecast methods for Nepal stock market [3]. Fan R was the first to measure the accuracy of stock prices. Forecasts for six Dow stocks were analyzed, including four. Both cues are neutral weights shown by the Black-Scholes and Heston models. The third group is the density of the lognormal histogram, the bias of which is determined by predicting the difference observed in the 5-minute regression. Three additional parameters are defined by adjusting for risk neutrality and global historical weights. The correct way is to use Black-Scholes to weight the variables. This method outperforms other methods in 87% of comparisons using probability parameters [4]. It can be seen that stock forecasting is very important for both investment activities and market monitoring [5-6].

The prediction of the stock trend in this paper will start with the study of the LSTM model, and then input the data applicable to the input layer of stock historical data information into the model, making it more rigorous in terms of logic and prediction effect. Predicting and analyzing stock trends not only helps to explore the laws in various aspects, but also helps investors and regulatory authorities to grasp the stock market from multiple perspectives, so as to continuously build a more complete domestic financial system.

2. Research on Stock Trend Prediction Method and Optimization Based on Neural Network

2.1. Predictability of the Securities Market

The stock market does not change randomly, but has a trend and repeats history. From the time and scale of the trend, it can be divided into: daily movement, secondary movement and mainstream trend. So the stock price is predictable [7-8].

(1) Daily exercise

It refers to the capricious daily rise and fall of stock prices, and we cannot predict how much it will change. This change is caused by the influence of news quality and some other technical factors, and usually lasts from a few hours to a few days [9-10]. Since this is a short-term volatility, it is only relevant to some trailing and exiting stock investors [11-12]. Therefore, its analysis is not valued by long-term investors [13].

(2) Secondary movement

It refers to fluctuations that tend to limit price deviations within a range above and below the intrinsic value of a stock [14]. That is, there is a sharp decline in the upward trend of the stock, or a rapid rise in the long-term downward trend of the stock price. It usually lasts a week or a few months [15-16].

(3) Main trends

It refers to a long-term trend that affects the rise and fall of the entire stock market. That is, when the stock price is in a long-term uptrend, it's a bull market, or when it's in a long-term downtrend, it's a bear market. Once this major trend is established, it typically persists for one to four years [17].

2.2. Long Short-Term Memory Model

Longitudinal memory models or LSTMs are variants of RNN models. Each type of LSTM model has four layers of networks, and each of the four layers has its own active network, which is the main feature of the LSTM model - the gating method [18]. Among them, X forgets the input gate corresponding to the predetermined time; ht-1 is established for the first time to identify the historical information that is not important and needs to be processed at the current time; the input gate is also; Xt and ht-1 are stored and added according to per Of course It takes an hour. IMPORTANT: The output gateway is used to transform generic historical data to obtain Cr and provide point-in-time results. Compared with the RNN model, the LSTM model adopts the crossover method to construct a random network for data transmission, which reduces the loss caused by multiple gradients in data transmission and easily captures the correlation between data sequences.

3. Investigation and Research on the Stock Trend Prediction Method and Optimization Based on Neural Network

3.1. Stock Trend Prediction Model

The input of the model has three parts: statistical data, information data and investor sentiment. The first part of the model first processes all the data using BiLSTM and then outputs the data as CLSTM annotations. A systematic approach is introduced to focus on the differences between the data, ensuring that the model draws useful information from the stories of stock market transactions. Second, data from forums are analyzed using simple sentiment-based classification, extracted from sentiment data, and combined with other datasets, such as training data for short-term memory and short-term learning. Finally, all data is processed using multiple neural networks. The network model is shown in Figure 1.

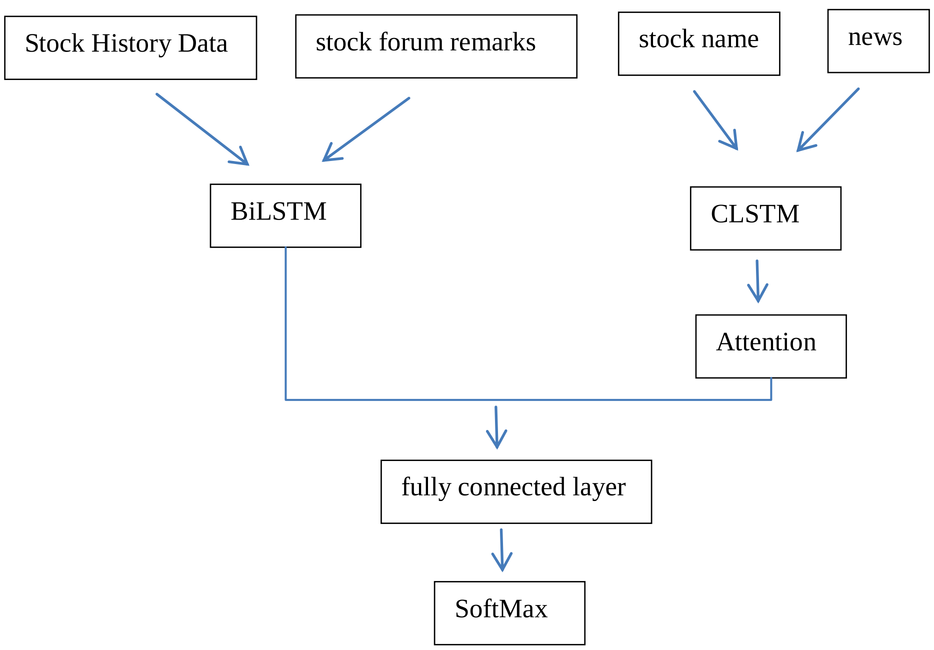

Figure 1. Network model structure diagram

3.2. Optimization of Stock Trend Prediction Model

The type of optimizer used by the Adam optimizer-based optimization tuning strategy optimizes the efficiency with which the algorithm converges to the minimum value. At the same time, the influence of some randomness is also considered to avoid the occurrence of falling into a local minimum and failing to reach the global minimum. This model selects Adam optimizer for optimization processing.

The optimization of the ADAgrad optimizer is mainly that the learning rate is no longer set to a fixed value, and the learning rate continuously changes flexibly with the historical gradient during each iteration. The stochastic gradient descent update:

$$\theta t+1,\ \ i = \theta t,\mathrm{i} - \eta \mathrm{ht,i} \tag{1}$$

In:

$$\mathrm{ht,i} = \nabla \theta t \mathrm{J}(\theta t,\mathrm{i}) \tag{2}$$

Therefore:

$$\theta_{\mathrm{t+1}} = \theta_{\mathrm{t}} - \frac{\eta}{\sqrt{H_t + \in}} \cdot h_t \tag{3}$$

Update to:

$$\theta_{\mathrm{t+1}} = \theta_{\mathrm{t}} - \frac{\eta}{\sqrt{H[h^2]_t + \in}} \cdot h_t \tag{4}$$

The Adam optimizer combines the methods of the above two optimizers, and calculates the parameter adaptive learning rate from the exponentially decaying average of the historical squared gradient. It is expressed as follows:

$$\theta_{\mathrm{t+1}} = \theta_{\mathrm{t}} - \frac{\eta}{\sqrt{\hat{v}_t + \in}} \cdot \hat{m}_t \tag{5}$$

Using the Adam optimizer, the resulting learning rate is different for each parameter and each iteration and the learning rate does not decay rapidly. At the same time, it is computationally efficient and requires little memory.

3.3. Generalization Mechanism Based on Dropout and L2 Regularization

After using a neural network with two hidden layers in this model, as shown in the left figure, A nonlinear network with two hidden layers automatically discards some neurons using a subtraction method. The neurons marked with a cross in the image on the right do not fire randomly. In actual use, if the offset value is set too low, the effect may be negligible; if the subtraction value is set too high, the correction result may be insufficient. Therefore, the model sets a reduction of up to 20%.

In the gradient descent stage, L2 regularization essentially decays each weight to 0, and the L2 regularization term is first defined:

$$R(w) = \lambda \frac{1}{2} \|w\|_2^2 \tag{6}$$

L2 represents the 2 norm, which refers to the square term of the weight 2 norm, which is the regularization coefficient. Then the loss function of adding the L2 regularization term is:

$$L = L_0 + \frac{\lambda}{2n} \sum_w w^2 \tag{7}$$

Among them, the first term L0 is the original loss function, and the second term is the L2 regularization term, which represents the sum of squares of all weights.

4. Analysis and Research of Stock Trend Prediction Method and Optimization Based on Neural Network

4.1. Dataset

The experiment uses Tushare open data as the data set. This paper processes the stock data from January 1, 2020 to January 1, 2021. The data is sorted before and after the time. The stock market only conducts stock market transactions on working days, and the market is closed on weekends. The samples are divided into datasets according to the ratio of 60% and 40%, corresponding to the training dataset and the test dataset respectively. The BiLSTM hidden layer is set to 128 nodes, and the CLSTM hidden layer is set to 64. And change the number of hidden layer nodes to study the relationship between model structure and model accuracy. The specific data items and their meanings are shown in Table 1.

Table 1. Specific data items and their meanings

Data item	Meaning
Opening price	The starting price of the stock traded on a given day
Closing price	The last price of the stock traded on a given day
Highest price	The maximum price of the stock for the day
Trading volume	Refers to the number of shares bought and sold that day
Quote change	Refers to the increase and decrease of the current price of the stock compared with the closing price of the previous trading day

4.2. Comparison of Experimental Results

Adjust the number of input features of the network model. The results are shown in Table 2. It is obvious that based on the news and investor sentiment LSTM models have higher accuracy and better predictions, as shown in Figure 2.

Table 2. Model accuracy comparison

Network model	Test data set accuracy	Training data set accuracy
Single lstm model	63%	66%
Incorporating the news lstm model	70%	72%
Lstm model for news and investor sentiment	80%	81%

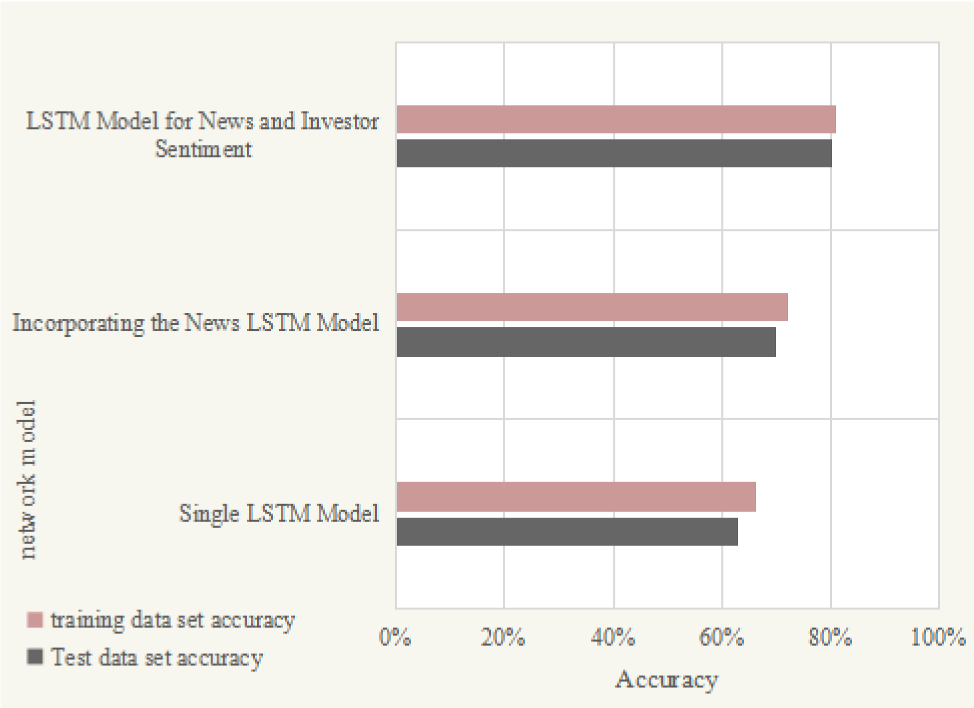

Figure 2. Results comparison

In the training process of the model, through the continuous correction of the LSTM layer, the accuracy of the LSTM of different LSTM layers in predicting the stock trend is compared. The experimental results are shown in Table 3. When it is 1, the accuracy is increased by 13%, but when it is increased to 3 layers, the accuracy is only increased by 4%. This data suggests that continuously improving the depth prediction accuracy of the network does not necessarily improve accuracy. Small changes in actual parameters can only be caused by some random factors, but the number of units is positively related to the amount of computation and computation, and has nothing to do with the quality of the entire model.

Table 3. Three LSTM hierarchical accuracy rates

LSTM layers	Accuracy
Layer	65%
Second floor	78%
Three floors	82%

5. Conclusion

Aiming at the application of neural network in the stock market, this paper proposes a stock trend forecasting model, and to a certain extent promotes the research on the effect of stock forecasting and index tracking. Looking back at the work of this paper, there are still some deficiencies and aspects worthy of continued research. The next work direction can be summarized as the following points: (1) Build a more efficient text representation method, obtain more comprehensive fundamental information for mining, design The model learns the connection between stock price and event text. Building an effective financial knowledge graph may be a feasible approach. (2) Combine traditional methods such as Markowitz's portfolio theory and data-driven methods to build better index tracking portfolios, and combine intelligent models to solve the problem of dynamic portfolio adjustment.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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