Stock Price Prediction by Using RNN Method

Ao Zhang[1](✉), Jiaheng Cai[2], Bo Zhu[3], Wentao Yu[4], Yuhan Huang[5], and Lin Zhou[6]

[1] Department of Physical Science, University of California, Irvine, Irvine 92617, USA
aoz6@uci.edu

[2] Department of Mathematics, University of California, Los Angeles, Los Angeles 90024, USA

[3] Department of Computer Science, University of Wisconsin-Madison, Madison 52703, USA

[4] Department of Mathematics, University of California, Santa Barbara, Santa Barbara 93117, USA

[5] Wuhan Britain-China School, Wuhan 430000, China

[6] Department of Mathematics, University of California, San Diego, La Jolla 92093, USA

Abstract. In this essay, we mainly focused on how to predict the price of stocks. Our group studied Apple, Google, Microsoft, and Amazon stock prices. To solve the problem, we started with Recurrent Neural Network (RNN) to predict the stock's price. Then, we used Long Short-Term Memory (LSTM) to grasp the pictures for those companies. The result showed us that stock price is a robust linear relationship. Luckily, through the training, the accuracy of our prediction is within an acceptable range.

Keywords: RNN · Prediction · Price

1 Introduction

Mathematical modeling has long been an important way to make numerical predictions. In the stock market, the accurate prediction of stock prices is urgently needed by all stock speculators. However, nowadays, stock buyers are unable to choose a reasonable method efficiently because of the large variety of prediction models. To address this need, in this paper we perform numerical modeling by RNN and LSTM methods, and mainly mobilize stock data of four companies— Apple, Google, MSFT, and Amazon— for prediction in 2022. We compared the predicted values with the actual values and presented them in the form of squared differences. The downside of this method is that the current accuracy is still not at a level that satisfies all people. It is also difficult for us to accurately predict the prices of stocks that are heavily influenced by social news. Likewise, we modeled the impact of the four major companies on each other's stock prices with this data. The advantage of this part of the study is that we use the data to provide stock enthusiasts with a new way of thinking about predicting stock prices: the connection R between companies is an essential factor in predicting stocks [1–4].

All the authors contributed equally to this work and should be considered as co-first author.

M. F. b. Sedon et al. (Eds.): SSHA 2023, ASSEHR 752, pp. 923–929, 2023.
https://doi.org/10.2991/978-2-38476-062-6_120

2 Methods

The Recurrent Neural Network (RNN) allows you to model memory units to persist data and model short-term dependencies. It is also used in time-series forecasting for the identification of data correlations and patterns. It also helps to produce predictive results for sequential data by delivering similar behavior as a human brain.

The structure of an Artificial Neural Network is relatively simple and is mainly about matrix multiplication. During the first step, inputs are multiplied by initially random weights and biases, transformed with an activation function, and the output values are used to make a prediction. This step gives an idea of how far the network is from reality.

The metric applied is the loss. The higher the loss function, the dumber the model is. To improve the knowledge of the network, some optimization is required by adjusting the weights of the net. The stochastic gradient descent is the method employed to change the values of the weights in the right direction. Once the adjustment is made, the network can use another batch of data to test its new knowledge.

The error, fortunately, is lower than before, yet not small enough. The optimization step is done iteratively until the error is minimized, i.e., no more information can be extracted.

The problem with this type of model is, it does not have any memory. It means the input and output are independent. In other words, the model does not care about what came before. It raises some questions when you need to predict time series or sentences because the network needs to have information about the historical data or past words.

3 LSTM

It is a special kind of recurrent neural network that is capable of learning long-term dependencies in data. This is achieved because the recurring module of the model has a combination of four layers interacting with each other (Fig. 1).

The picture above depicts four neural network layers in yellow boxes, point-wise operators in green circles, input in yellow circles, and cell state in blue circles. An LSTM module has a cell state and three gates which provides them with the power to selectively learn, unlearn or retain information from each of the units. The cell state in LSTM helps

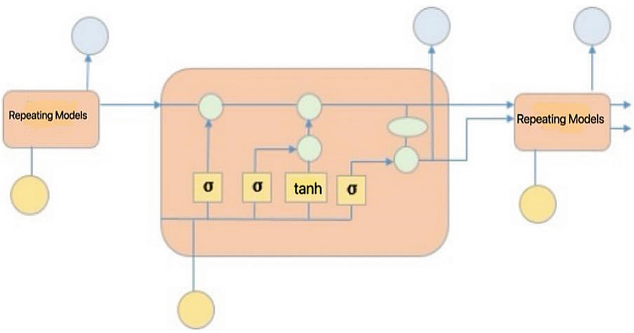

Fig. 1. An LSTM module. [Owner-draw]

the information flow through the units without being altered by allowing only a few linear interactions. Each unit has an input, output, and forget gate which can add or remove the information to the cell state. The forget gate decides which information from the previous cell state should be forgotten for which it uses a sigmoid function. The input gate controls the information flow to the current cell state using a point-wise multiplication operation of 'sigmoid' and 'tanh' respectively. Finally, the output gate decides which information should be passed on to the next hidden state.

4 Graphs

First of all, we fit the relationships between example companies' daily returns. From the graphs, we could see that the slope is positive, and it shows linear relationships. Thus, we could conclude that the daily returns of each company are having a linear relationship with others (Figs. 2, 3, and 4).

The first graph above is showing the numerical results of daily returns, and the other one shows the relationships between closing prices. If the number is close to 1, that means the two companies have a stronger linear relationship.

With training data, we model the prediction of stock prices (Fig. 5).

The first one represents Apple companies, and the root mean square we have is 6.45035.

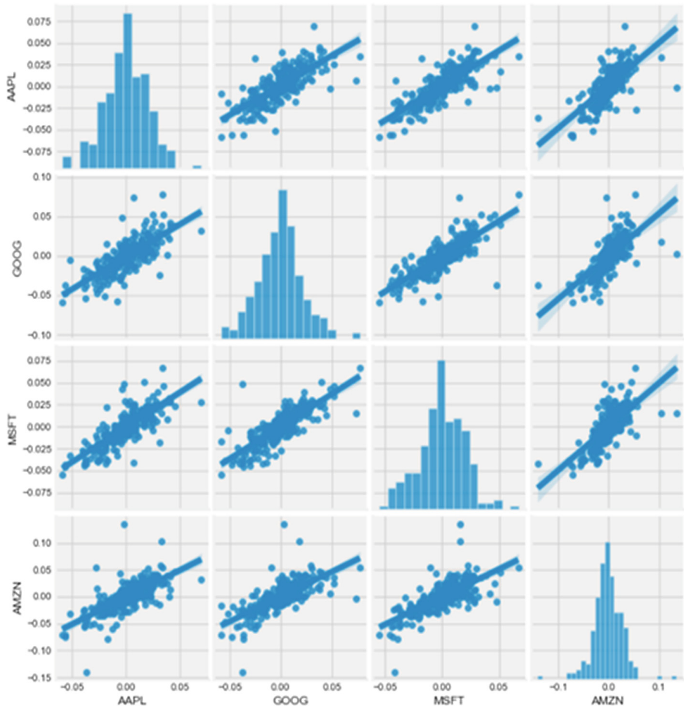

Fig. 2. Relationships between example companies' daily returns. [Owner-draw]

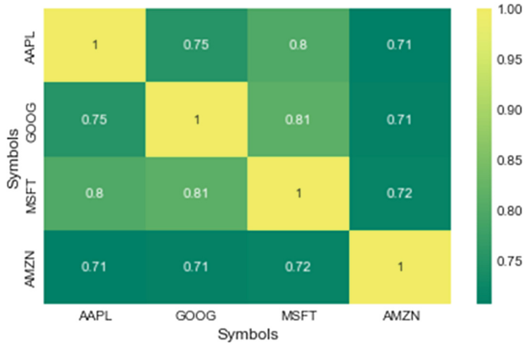

Fig. 3. Graph3: Numerical results of daily returns. [Owner-draw]

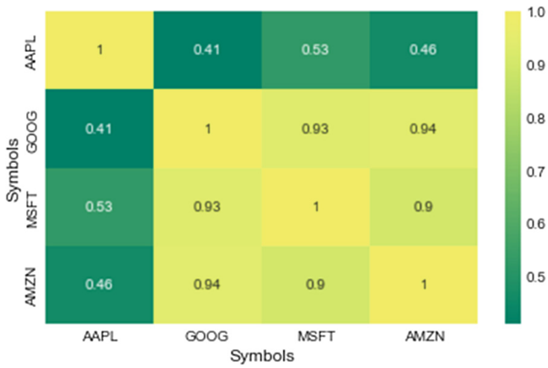

Fig. 4. The relationships between closing prices. [Owner-draw]

The second one represents Google companies, and the root mean square we have is 8.47148.

The third one represents Microsoft companies, and the root mean square we have is 9.74011.

The fourth one represents Amazon companies, and the root mean square we have is 11.60038.

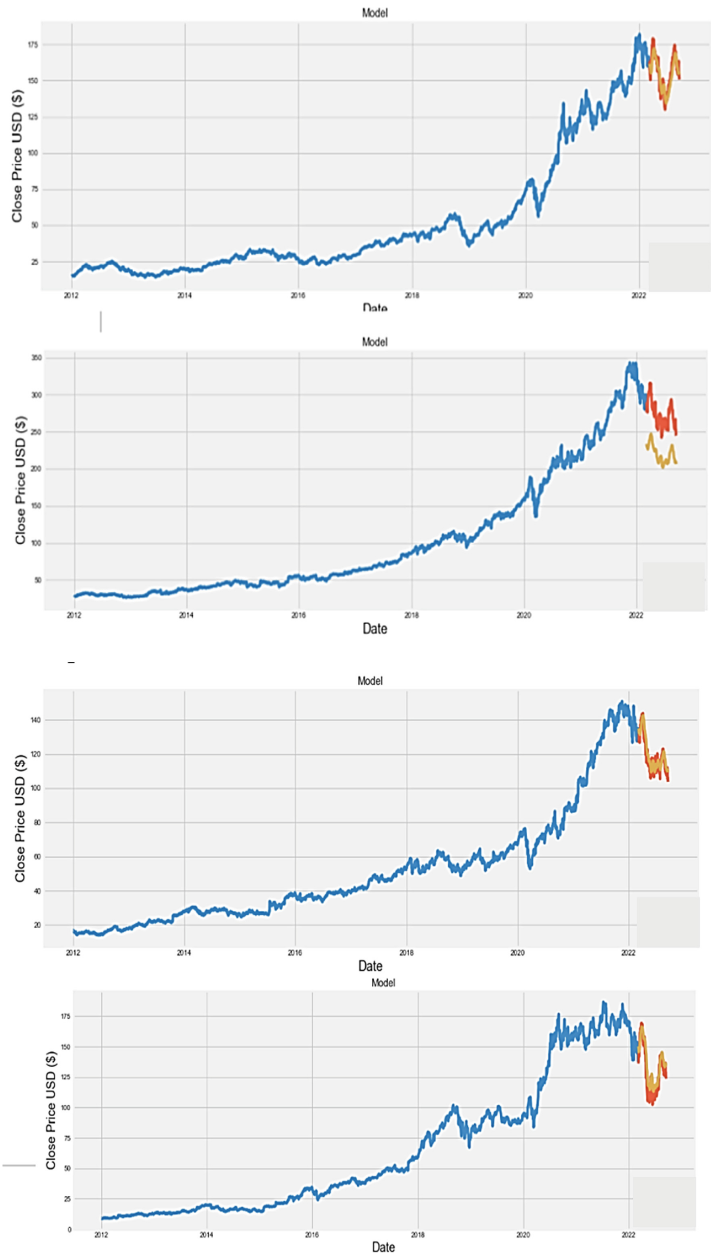

Fig. 5. The model of prediction of stock prices

5 Result

Based on previous stock price data, the LSTM module can forecast stocks. Nevertheless, it was still impossible to precisely predict stock fluctuations, which resulted in subpar performance. Given the multiple macroeconomic and microeconomic factors, including politics, international economic conditions, uncertainties, corporate accounting success, and others, it is extremely difficult to predict stock values with any degree of accuracy [5]. It also means that, as a consequence of everything, there is a large amount of data in which to search for patterns. As a result, the forecasting algorithm has errors because micro and macro elements are not included. Moreover, LSTM, a computational intelligence method for time-series data, can be used to construct a predictive model and assess its efficacy in contrast to technical analysis in order to correct errors [6].

It is crucial to evaluate a company's stock by taking a close look at its intrinsic value, which encompasses, but is not limited to, its tangible assets, income statements, management performance, overall strategy, and consumption patterns; in other words, all the core components of a firm. For all investors, it is always vital to anticipate movements in the stock market in order to identify precise rewards and lower possible market risks. Thus, by eliminating errors in LSTM stock prediction, it will be effective.

6 Conclusion

In conclusion, we mainly discussed how to use RNN to predict stock prices in this article. In this study, we studied the stock prices of many enterprises (including Apple, Google, Microsoft and Amazon). In order to fully explore this problem, we use recursive neural network (RNN) to predict stock prices. Then, we use long-term memory (LSTM) to grasp the pictures of these companies. The results show that the stock price is a robust linear relationship. In addition, through training, our prediction accuracy is within an acceptable range. This work provides a feasible scheme for future stock forecasting.

Acknowledgement. All the authors contributed equally to this work and should be considered as co-first author.

References

1. Sen J, Mehtab S, Dutta A, et al. Precise Stock Price Prediction for Optimized Portfolio Design Using an LSTM Model. arXiv e-prints, 2022.
2. Saud A S, Shakya S. Analysis of Gradient Descent Optimization Techniques with Gated Recurrent Unit for Stock Price Prediction: A Case Study on Banking Sector of Nepal Stock Exchange. 2020.
3. Shriram. S, Anuradha K, Uma K P. Future Stock Price Prediction using Recurrent Neural Network, LSTM and Machine Learning[J]. IJERT-International Journal of Engineering Research & Technology, 2021(5).
4. Abraham J B. Improving Stock Price Prediction with GAN-Based Data Augmentation. 2021(1).

5. Pramod, B. S., & Pm, M. S. (2020). Stock price prediction using LSTM. Test Engineering and Management, 83, 5246–5251.
6. Pawar, K., Jalem, R. S., & Tiwari, V. (2019). Stock market price prediction using LSTM RNN. In Emerging trends in expert applications and security (pp. 493–503). Springer, Singapore.