Predicting NASDAQ Composite Index Using Deep Learning Models

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Abstract

In today's world, the stock market has become more volatile and complex due to the increase in demand. Predicting stock market prices is a goal of many professionals in the finance industry. With the aid of artificial intelligence, deep learning and large data sets it has become possible to achieve high accuracy scores in predicting stock market prices. Accuracy scores are determined by implementing root mean squared error (RMSE), mean absolute percentage error (MAPE), and correlation coefficient (R). In all, this project implements long term-short memory (LSTM) and gated-recurrent unit (GRU) which are both neural network architectures used to predict the closing price of the NASDAQ composite index. The models calculate the accuracy scores by inputting RMSE, MAPE and R. The multilayer LSTM and GRU architectures ensure high accuracy and impressive fitting techniques.

Keywords : Stock Market, Artificial Intelligence, RMSE, R, MAPE, SP 500, LTSM, GRU

1. Introduction

With the advancement of computer technology and artificial intelligence along with it presents innumerable opportunities that lay in wait for the future. AI can be first traced back to the formal founding at a conference at Dartmouth in 1956. The current use of AI can be found in many things such as self driving cars, virtual assistants, and even checkout free grocery shopping. With the aide of AI and machine learning the world is searching for accurate way to predict the current markets. In this project we will be using different deep learning models to predict the NASDAQ composite Index.

The data set that we are working with are the Open and Close prices of the NASDAQ Composite Index. The goal of using this data is to accurately predict the closing price using long short-term memory (LSTM) models as well as gated recurrent unit(GRU) models. The first step was to refit the data read in from yahoo finance into a .csv file. After refitting the data we ran the data through both models using different criteria to find the most accurate model, which was determined through several GRU models and LSTM models.

Upon completion of the different layer models of the GRU and LSTM models, we came to the conclusion that the 10N GRU model and the 100N LSTM model were the most accurate and efficient. The models give the most accurate prediction in relation to the real time gather data.

2. Related work

Case Study7 : Predicting SP 500 Index Price Using Deep Learning Models By: Dr. Hum Nath Bhandari, Department of Mathematics

Hum Nath Bhandari, Binod Rimal, Nawa Raj Pokhrel, Ramchandra Rimal, Keshab R. Dahal, Rajendra K.C. Khatri, Predicting stock market index using LSTM, Machine Learning with Applications, Volume 9, 2022, 100320, ISSN 2666-8270, https://doi.org/10.1016/j.mlwa.2022.100320

Nawa Raj Pokhrel, Keshab Raj Dahal, Ramchandra Rimal, Hum Nath Bhandari, Rajendra K.C. Khatri, Binod Rimal, William Edward Hahn, Predicting NEPSE index price using deep learning models, Machine Learning with Applications, Volume 9, 2022, 100385, ISSN 2666-8270, https://doi.org/10.1016/j.mlwa.2022.100385.

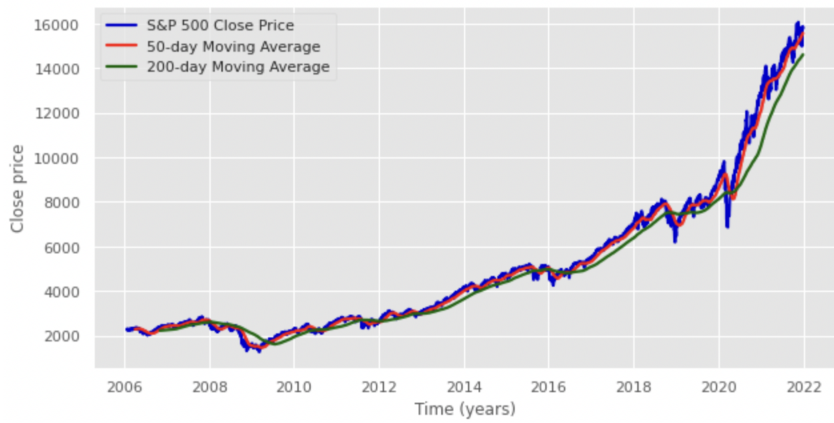
Hum Nath Bhandari, Binod Rimal, Nawa Raj Pokhrel, Ramchandra Rimal, Keshab R. Dahal, LSTM-SDM: An integrated framework of LSTM implementation for sequential data modeling, Software Impacts, Volume 14, 2022, 100396, ISSN 2665-9638, https://doi.org/10.1016/j.simpa.2022.100396.

3. Modelling approach

Our modeling approach begins with collecting the historical data of NASDAQ's index which includes its closing prices for each day from the years 2006 to 2020. Then we preprocessed the data by normalizing it and splitting it into training and testing sets. We then implemented complex functions for the LSTM and GRU models with different hyper parameters and architectures to find the best configuration. The process continued by training the model with its data to then evaluate the RMSE, MAPE and R scores. This is important because we are able to use these architectures to implement it into future work.

4. Data exploration and input preparation

To prepare the inputs of this data we began by importing the open, close, high, low, and volume for the NASDAQ composite index from the beginning of the year 2006 to the end of 2021. After we had these points we calculated MACD, ATR, MFI, RSI, and VIX. Once this data was retrieved it was inputted into a CSV file where we began to create graphs and models to better visualize the data. We created a standard chart of the index's performance over the years as well as a heat map to see the correlation between our data types.



5. Experimental results

The 2 Models we used were LSTM (Long short-term memory) and GRU (Gated Recurrent Unit). For both our LSTM and GRU models we varied the Layers from 10 to 100 in order to get a good test basis. We consistently used ADAM as our optimizer and ran 15 epochs with 30 replicates. The learning rate that was used in the models was 0.1. Many of the models had to be altered to best fit the data to produce the best accuracy and loss values. On top of altering the data set, to get better results, the attempt to tweak other aspects was done such as the batch size, epochs, Conv layers, dense layers, and input shape as well. Upon completion of these models, we were able to interpret the data we received. After evaluating the RMSE, MAPE and R scores, we look for lower RMSE and MAPE and higher R scores. With this knowledge, the LSTM model with 10 neurons produced better results than that of the GRU model. The best-performing GRU model implemented 30 neurons. However, the 50N and 30N models were nearly identical while looking at all the scores. The next metric we wanted to observe was a T-Test in order to calculate the P-Value. A P-Value is used to denote statistical significance in a data set. Our P-Value was 0.477 when we combined both of the models to calculate this number. This P-Value gives us confidence that there is not enough deviation from the null hypothesis to cause statistical significance. Using these methods on bigger sets of data and more time to tweak the variables is something that we could all do now after completing this project based on what we learned from this data set. Overall these methods work very well to predict and model stock data.

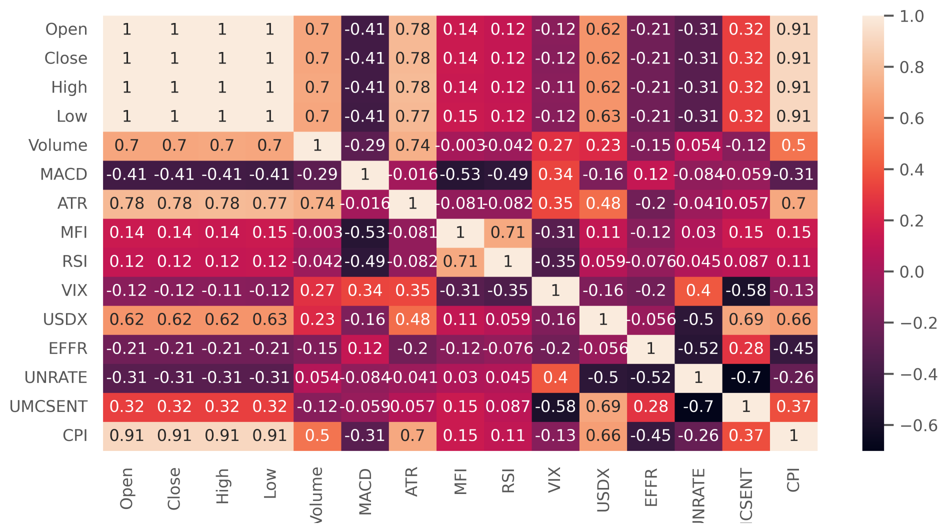


Figure 1: **Correlation Heatmap**

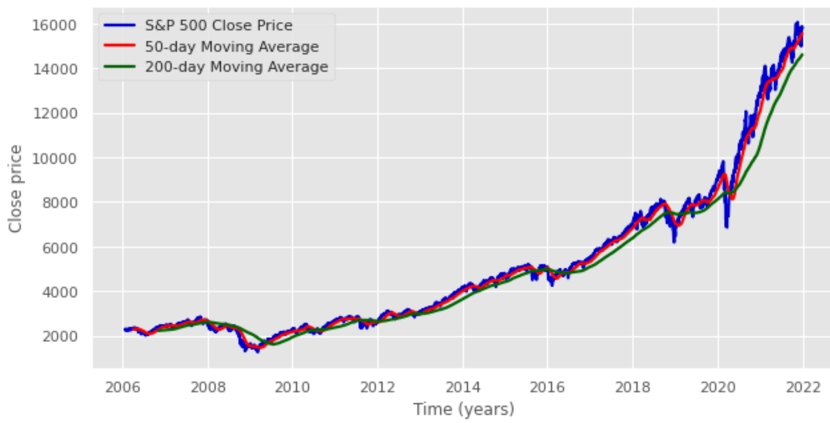


Figure 2: **Line Chart of Closing Price in Years**

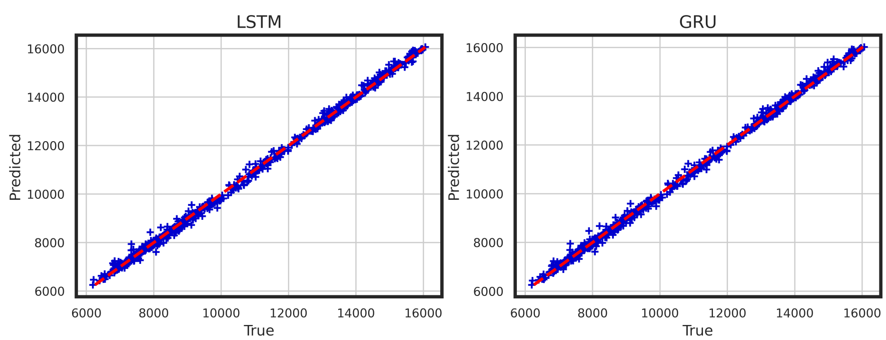


Figure 3: **True Versus Predication Plot of Test Data**

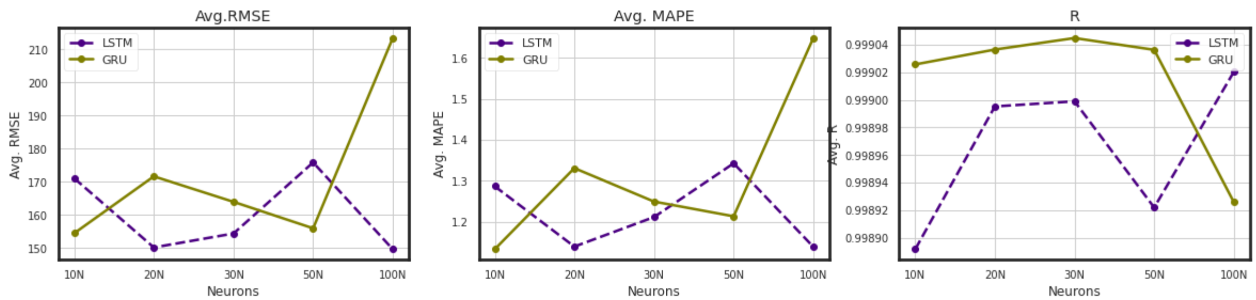


Figure 4: **Comparison of the Average RSME, MAPE and R scores for Both Models**

6. Conclusion

In conclusion, LSTM and GRU models can be effective tools for predicting the closing price of the SP 500 index, particularly when paired with statistical analysis such as RMSE, MAPE, and R scores. By using these evaluation metrics, we can evaluate the performance of different model configurations and identify the hyperparameters that lead to the best results. Ultimately, the choice between an LSTM or GRU model depend on the specifics of any dataset and the goals of a certain prediction task. In this research, we specifically see that the LSTM and GRU models perform relatively similar. After evaluating the RMSE, MAPE and R scores, we look for lower RMSE and MAPE and higher R scores. With this knowledge, the LSTM model with 10 neurons produced better results than that of the GRU model. The best performing GRU model implemented 30 neurons. However, the 50N and 30N models were nearly identical while looking at all the scores. The importance of knowing what model had the best scores is to ensure that the data is being trained properly. Implementing the multi layered LSTM and GRU models allows those who wish to research conduct a statistical analysis. Looking closely at the RSME values, the smallest score from each value was extracted to perform a T Test. The T Test calculates a p value that determines statistical significance. We combine the best RMSE values of both models to see that we achieved a p value of 0.477. Individually, the LSTM model p value was 0.0406 and the GRU model had a p value of 0.121. This combined p-value indicates that deviation from the null hypothesis is not statistically significant, and the null hypothesis is not rejected; however, we see that the LSTM model was significantly significant therefore we can reject the null.

7. Ethics and implications

Regarding implication, these models have useful real word applications. By tuning these models to achieve higher accuracy we can better predict the NASDAQ and invest more intelligently. The results of these models also tell us about the overall direction of the market. The NASDAQ is composed of a large portion of the market with a concentration on tech companies. Therefore this data also gives us insight into how tech is performing in our market today.

8. Acknowledgment

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9. References

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