Stock Price Prediction Using Deep Learning

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Executive Summary

Stock price prediction is one of the most intricate machine learning problem. Stock price depends on variety of factors. A simple model can never be able to predict the stock price with higher accuracy because of the abnormality of stock market. Machine learning is currently dominant trend in scientific research because it can make data-informed predictions in real-time without any human intervention. This project aims to predict the share price using machine learning techniques like Recurrent Neural Networks (RNN) and especially Long-Short Term Memory model (LSTM). The network is trained to learn pattern from trends in the existing data. Different types of comparison are made to find out how much epochs can improve the model.

1 Introduction

The financial market is a dynamic and composite system where people can buy and sell stocks, currencies over virtual platforms. The stock market allows investors to own shares of public or private companies by investing small initial amounts of money. This market has given investors the chance of gaining money. To maximize the profit and minimize the risk, investors always search for tools and techniques [13]. Prediction of stock price is not an easy task due to its highly non linear, stochastic and unreliable nature. Stock market prediction is basically a time series forcasting where future data is estimated based on the previous data. The most important factor for the prediction of stock market is driving profits from the trading of stocks [9]. The stock market is dependent on various parameters, such as the market value of a share, the company's performance, government policies, the country's Gross Domestic Product (GDP), the inflation rate, natural calamities, and so on [7]. To analyse the stock market there are two types of approaches [11]: fundamental analysis and technical analysis. Fundamental analysis attempts to determine a stock's value by focusing on underlying factors that affect a company's actual business and its future prospects. Technical analysis, looks at the price movement of a stock and uses this data to predict its future price movements. There are some deficiencies of fundamental and technical analysis. To overcome these problems researchers started working with new innovative methods for stock value forecasting. The methodologies incorporate the work of machine learning algorithms for stock market analysis and prediction. Using machine learning algorithm in stock price prediction, it is possible to analyze more complex data and discover the pattern of data [1]. Different types of machine learning algorithm have been used for stock price prediction [2]such as the Support Vector Regression [4], Artificial Neural Networks (ANN) [6] and so on.

In the literature, it has been seen that an improvement over traditional machine earning model can extract robust feature from complex real world data and achieve better performance than before [3]. A class of machine learning algorithms based on Recurrent Neural Network prove to be very useful in stock market prediction. Long short term memory (LSTM) is a type of recurrent neural network, with feedback links attached to some layers of network. It can predict time series with arbitary size time steps [8]. From the literature, it can be seen that LSTM is more effective than the conventional RNN [12]. Thus, in this project LSTM is used to predict stock market price

2 Problem definition

The stock market prediction is one of the most challenging tasks in time series forecasting because of its volatility, randomness and unpredictability. The continuously changing stream of data of a stock market makes it hard to make a profit. This capstone's main goal is to study and apply LSTM technique to the stock market in order to predict stock market and thus act on those predictions to avoid investment risk and generate profit. In this project I use historic S&P 500 stock data to train an LSTM to predict the future closing price of the stock for a given time. Dataset is taken from kaggle open data source. 65% data is used for training and rest of the data is used for testing.

To detect stock price pattern, it is necessary to normalize the stock price data. Since the LSTM neural network requires the stock patterns during training, we use "min-max" normalization method to reform dataset, Tmesteps with size 100 is used to separate data that means the stock price is predicted of the next trading day based on historical data from the previous 100 days.

3 Model

The LSTM model has three LSTM layer and one dense layer. Every LSTM layer has 50 units and dense layer has one unit. Dense layer is for reshape the output. A network with large number of LSTM layers is difficult to train [14]. For this reason, three LSTM layers are used here. In each LSTM layer, the loss function is mean squared error. The mean squared error measure the sum of the squared distances between target variable and predicted value. ADAM [10] is used as optimizer because this optimizer is well suited for problems with large dataset and computationally efficient. The model is tranied over different number of epochs with batch size of 64.

The algorithm that is used here to predict stock price using LSTM is given below:

- Step 1: Select the data from the market for a particular share.
- Step 2: Import the dataset and read the price.
- Step 3: Delete any missing data from dataset.
- Step 4: Do a feature scaling on the data so that the data values will vary from 0 and 1.
- Step 5: Creating a data structure with 100 timesteps and 1 output.
- Step 6: Building the model with three LSTM layer and dense layer
- Step 7: Compiling the model with ADAM optimizer and mean squared error as loss function.
- Step 8: Making predictions and visualizing the results using plotting techniques.

This model is implemented using Python with the Keras library [5], running on the Tensorflow backend.

4 Results and Findings

Machine learning/deep learning models have some internal parameters which usually need to be set by trial and error to achieve higher accuracy. Tuning the number of epoch is an important parameter because higher number of epochs may reduce the error but too many epochs would result in the model learning the noise of the train data. In this project, the model is ran over different number of epochs (25 epochs,50 epochs,100 epochs and 200 epochs). The value of loss and R squared for different number of epochs are given in Table 1. All the plotting of test data for actual price and predicted price for different number of epochs are given in Figure 1-4. From the table 1 we can see that for 200 epochs the model is giving higher accuracy that is 0.9436 and lower loss value. If we compare between 100 epochs and 200 epochs, we can see that the loss value and R-squared value is almost similar for both epochs. However, for 200 epochs, it wastes more computing power and time. If we look at figure 3 and 4, we can observe that both model can predict the trend of the actual stock prices very closely. From this analysis, we can say that our model can work best for 100 epochs.

For this reason, we have predicted stock price for next 30 days using the best model. Plotting of the predicted stock price for next 30 days is given Figure 5. The graph has been plot for half of the test data set (green color) along with predicted data for next 30 days (orange color).

Table 1: The value of loss and R squared for different number of epochs

Epoch	Loss	R squared value
25	2.735e-04	0.7905
50	1.289e-04	0.8990
100	5.26e-05	0.9432
200	5.035e-05	0.9436

Figure 1: Plotting the actual and predicted price for sp500 stock for 25 epochs.

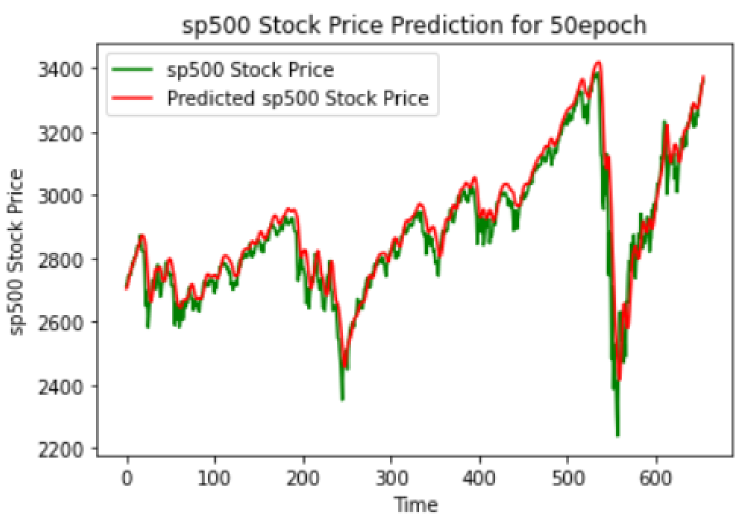

Figure 2: Plotting the actual and predicted price for sp500 stock for 50 epochs

5 Conclusions and Future Work

Stock price prediction helps investors to invest and make some profit. In this project, LSTM is used to predict stock price and from the result it can be said that it is satisfactory enough to use in live trading. By training with more data and increasing the number of layers, the accuracy of the model can be enhanced. For future work, further researches can be done to improve our model by changing the number of layers, batch size or loss function and adding some dropout layer.

Figure 3: Plotting the actual and predicted price for sp500 stock for 100 epochs.

Figure 4: Plotting the actual and predicted price for sp500 stock for 200 epochs.

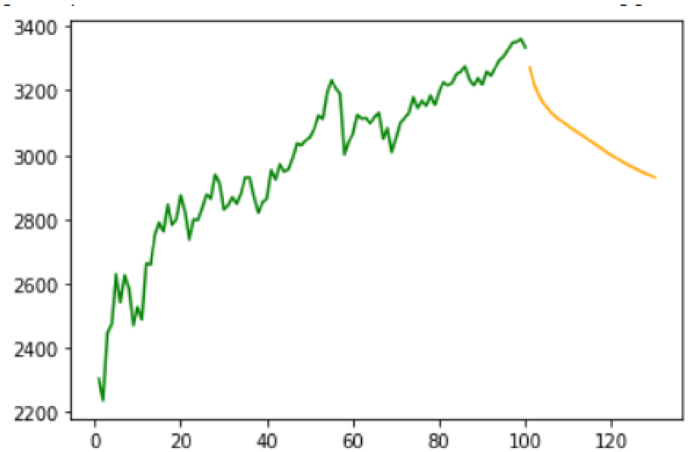

Figure 5: Stock price prediction for next 30 days

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