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LSTM BASED STOCK PRICE PREDICTION

¹Prof. Pritam Ahire, ²Hanikumar Lad, ³Smit Parekh, ⁴Saurabh Kabrawala

¹Professor, ²Student, ³Student, ⁴Student ¹Computer Engineering, ¹D Y Patil Institute of Engineering and Technology, Pune, India

Abstract: Stock market investment is one of the most complex and sophisticated way to do business. Stock market is very uncertain as the prices of stocks keep fluctuating because of several factors that makes prediction of stocks a difficult and extremely complicated task. Nowadays investors need fast and accurate information to make effective decisions and highly interested in the research area with exponentially growing technological advances of stock price prediction. Understanding the pattern of stock price of a particular company by predicting their future development and financial growth will be highly beneficial. This paper focuses on the usage of a type of recurrent neural network (RNN) based Machine learning which is known as Long Short Term Memory (LSTM) to predict stock values.

Index Terms - Long Short Term Memory, Recurrent Neural Network, Machine learning, Stock price prediction

I. INTRODUCTION

Stock price predictions are very important among many business people and the public. People can make a lot of money or lose their financial income from a stock market job. Algorithm predictions and models can be used to make future predictions applied to historical data. Predicting the future has been a daunting task, one that many have found difficult to understand. This type of prediction is even more appealing when it involves money and risks such as Stock Market speculation. Researchers are conducting research on stock market forecasts from a variety of fields, including computer science and business. Researchers have tried a variety of methods to predict the market, including different strategies and algorithms and the combination of indicators. The attribute that makes a prediction model depends on factors on which market performance can depend. Short-Term Memory (LSTM) is one of a variety of RNNs structures. LSTM replaces traditional artificial neurons in the hidden network layer into the most useful memory cells. With these memory cells, networks are able to better associate memory with remote input over time, which is why it is worthwhile to understand the formation of strong data over time with great predictive power. A lot of research has been done on stock price forecasts on a daily basis, using different data sources with many built-in models such as news articles, twitter data, google and Wikipedia data. All of these external factors combined with stock prices and stock technology indicators have shown an impact on stock price movements. How to improve the accuracy of stock prices is an open question in today's society. Time series data is a sequence of data from the occasional behaviour of certain fields such as social science, finance, engineering, physics and economics. Finance, engineering, physics, and economics. Those types of complexity make it very difficult to predict price trends. The main purpose of predicting a series of time series is to construct future value simulation models given their past values. In many cases, the relationship between past and future recognition is not clear, this is tantamount to exposing the distribution of conditional opportunities as a function of foresight.

II. LITERATURE SURVEY

The first focus of our literature review was to evaluate different algorithms and models to determine whether stock price predictions could be made on real stock prices [2]. However, as we have not been able to detect a possible change in this stock price forecast, we decided to look at existing plans, analyse major issues, and improve ourselves. A brief search of common solutions to the above problem led us to LSTM. After deciding to use the LSTM neural network to make stock forecasts, time series data is collected from stock firm prices of the stock and related macroeconomic variables over a period of 10 years [13][14].

III. PROPOSED SYSTEM

We propose to use LSTM (Long Short Term Memory) algorithm to provide efficient stock price prediction.

3.1 LSTM -an overview





A special type of RNN, which can learn long-term dependence, is called Long-Short Term Memory (LSTM). LSTM enables RNN to remember long-term inputs. Contains information in memory, similar to computer memory. It is able to read, write and delete information in its memory. This memory can be seen as a closed cell, with a closed description, the cell decides to store or delete information. In LSTM, there are three gates: input, forget and exit gate. These gates determine whether new input (input gate) should be allowed, data deleted because it is not important (forget gate), or allow it to affect output at current timeline (output gate) [2].

- 1. Forget gate: The forget gateway determines when certain parts of the cell will be inserted with information that is more recent. It subtracts almost 1 in parts of the cell state to be kept, and zero in values to be ignored.
- 2. Input gate : Based on the input (e.g., previous output o (t-1), input x (t), and the previous state of cell c (t-1)), this network category reads the conditions under which any information should be stored (or updated) in the state cell.
- 3. Output gate: Depending on the input mode and the cell, this component determines which information is forwarded in the next location in the network.

3.2 Advantages of LSTM

The main advantage of LSTM is its ability to read intermediate context. Each unit remembers details for a long or short period without explicitly utilizing the activation function within the recurring components. An important fact is that any cell state is repeated only with the release of the forget gate, which varies between 0 and 1. That is to say, the gateway for forgetting in the LSTM cell is responsible for both the hardware and the function of the cell state activation. Thus, the data from the previous cell can pass through the unchanged cell instead of explicitly increasing or decreasing in each step or layer, and the instruments can convert to their appropriate values over a limited time. This allows LSTM to solve a perishable gradient problem - because the amount stored in the memory cell is not converted in a recurring manner, the gradient does not end when trained to distribute backwards [2].

IV. SYSTEM ARCHITECTURE



Figure 2 System Model

4.1 Obtaining dataset and pre-processing

The obtained data contained five features:

- 1. Date: Date of stock price.
- 2. Opening price: When trading begins each day this is opening price of stock.
- 3. High: The highest price at which the stock was traded during a period(day).
- 4. Low: The Lowest price at which the stock was traded during a period(day).
- Volume: How much of a given financial asset has traded in a period of time. 5.
- 6. Close Interest: The last price at which a particular stock traded for the trading session.



Figure 3 Data Preprocessing

Stock market information is available from key sources: Tiingo API, Yahoo and Google Finance. These websites give APIs from which stock dataset can be obtained from various companies by simply specifying parameters.

The data is processed into a format suitable to use with prediction model by performing the following steps:

- 1. Transformation of time-series data into input-output components for supervised learning.
- 2. Scaling the data to the [-1, +1] range.

V. RESULT ANALYSIS

Actual price and closing price of Alcoa Corp company, a large stock. The model was trained in bulk sizes of 512 and 50 epochs, and the forecasts were made very similar to stock prices, as seen in the graph.



Figure 4 Predicted stock price for Alcoa Corp

Actual price and closing price of Carnival Corp., a medium-term stock. The model was trained in bulk sizes of 256 and 50 epochs, and the predictions were made very similar to stock prices, as seen in the graph.



Actual price and closing price of Tesla Corp, a medium-term stock. The model was trained in bulk sizes of 64 and 100 epochs, and the predictions were made very similar to stock prices, as seen in the graph.



Figure 6 Predicted stock price for Tesla Corp

Actual price and closing price of Google Corp, a large stock. The model was trained in bulk sizes of 64 and 100 epochs, and the predictions were made very similar to stock prices, as seen in the graph.



Figure 7 Predicted stock price for Google Corp

VI. CONCLUSION

Stock investing has attracted the interest of many investors around the world. However, making a decision is a difficult task as many things are involved. By investing successfully, investors are eager to predict the future of the stock market. Even the slightest improvement in performance can be enormous. A good forecasting system will help investors make investments more accurate and more profitable by providing supporting information such as future stock price guidance. In addition to historical prices, other related information could affect prices such as politics, economic growth, financial matters and the atmosphere on social media. Numerous studies have proven that emotional analysis has a significant impact on future prices. Therefore, the combination of technical and basic analysis can produce very good predictions.

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