# Stock Price Prediction Using Recurrent Neural Network and Long Short-Term Memory

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# Stock Price Prediction using Recurrent Neural Network and Long Short-Term Memory

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***Abstract*—Stock market or equity market has a significant impact on our world. A rise or fall in the share price determines whether an investor is going to be in gain or not. The current predictor methods make use of both dynamic and linear algorithms, but they focus on predicting the stock value for a single company using the daily opening/closing price. The proposed method uses an independent approach. Here we are not fitting the data to a specific model, rather we are identifying the latent dynamics existing in the data using deep learning architectures. In this work we use two different deep learning architectures for the price prediction of National Stock Exchange listed companies with least possible error. We are applying the Recurrent Neural Network for predicting future values on a short term basis. The performance of the models was quantified using percentage error.**
**Keywords: Recurrent Neural Network, Time Stamp, Long Short-Term Memory, Stock Price Prediction, Data Analytic.**

## 1. Introduction

Forecasting can be defined as the prediction of some future event or events by analyzing historical data. It spans many areas including business and industry, economics, environmental science, and finance. Forecasting problems can be classified as
Short term forecasting (prediction for few seconds, minutes, days, weeks or months)
Medium-term forecasting (prediction for 1 to 2 years)
Long term forecasting (prediction beyond 2 years)

Many of the forecasting problems involve the analysis of time. A time series data can be defined as a chronological sequence of observations for a selected variable. In our case, the variable is stock price. It can either be univariate or multivariate. Univariate data includes information about only one particular stock whereas multivariate data includes stock prices of more than one company for various instances of time. Analysis of time series data helps in identifying patterns, trends and periods or cycles existing in the data. In the case of the stock market, early knowledge of the bullish or bearish mode helps in investing money wisely. Also, the analysis of patterns helps in identifying the best-performing companies for a specified period. This makes time series analysis and forecasting an important area of research. The existing methods for stock price forecasting can be classified as follows
Fundamental Analysis
Technical Analysis
Time Series Forecasting

Fundamental analysis is a type of investment analysis where the share value of a company is estimated by analyzing its sales, earnings, profits and other economic factors. This method is most suited for long term forecasting. Technical analysis uses the historical price of stocks for identifying the future price. Moving average is a commonly used algorithm for technical analysis. It can be considered as the un-weighted mean of past n data points. This method is suitable for short term predictions. The third method is the analysis of time series data. It involves basically two classes of algorithms, they are
Linear Models
Non-Linear Models

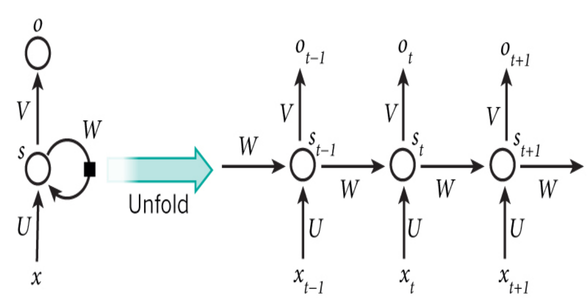


Figure 1. Recurrent Neural Network

There are a lot of complicated financial indicators and also the fluctuation of the stock market is highly violent. However, as the technology is getting advanced, the opportunity to gain a steady fortune from the stock market is increased and it also helps experts to find out the most informative indicators to make a better prediction. The prediction of the market value is of great importance to help in maximizing the profit of stock option purchase while keeping the risk low. bf Recurrent neural networks (RNN) have proved one of the most powerful models for processing sequential data. Long Short-Term memory is one of the most successful RNNs architectures. LSTM introduces the memory cell, a unit of computation that replaces traditional artificial neurons in the hidden layer of the network. With these memory cells, networks are able to effectively associate memories and input remote in time, hence suit to grasp the structure of data dynamically over time with high prediction capacity.

The paper is structured as follows section[II] explains the previous existing models and their Drawbacks, section[III] expalains the Methodology of the proposed model, section [IV] tells us about the Results and Discussions and section[V] includes the conclusion.

## 2. Previous Models and Drawbacks

Previous models for the analysis of wall street include fundamental analysis, which takes the past performance of the company and the credibility of the company, and statistical analysis, which is plays with, how the stock price is varied. Algorithms which are generally used in predicting the trend are Genetic Algorithms (GA) and Artificial Neural Networks (ANN's), but both of them fails in determining the correlation between the LSTD and the stock prices. Simple ANN's also lack in predicting the exploding gradient condition, i.e weights become either too high or less, thus slowing down the rate of convergence. Which arises because of the two factors: Random initialization of weights, and because weights tend to change at a much faster rate at the end of the network.

## 3. Methodolgy

The data set consists of day-wise data for National Stock Exchange listed companies for the period of Jan 2012 to Dec 2016. Data Set includes information like Opening Rate, Closing Rate, Highest Day Rate, Lowest Day Rate, Volume of Transaction on a daily basis. For calculation, we choose a company 'X' data set and used its values from the past year to train our model and thus tested the trained model with a test data. The data for the company were extracted from the available data and was subjected to pre-processing to obtain the stock price. The work is based on the application of Recurrent Neural Network using Long Short Term Memory where 1257 values are used in determining the values of the future 20. Libraries used in the proposed model are

NumPy: As it helps in doing the mathematical and scientific operation and ease off the work in multi-dimensional arrays and matrices.

Pandas: As it provides high-performance with the help of easy-to-use data structures and analysis data for Python.

Keras: As is can develop and evaluate deep learning models using Theano and TensorFlow and can train the neural network in a short line of codes.

SkLearn: As it can be used in the normalization of data set into a confined boundary.

The data of the company varies within a range of 250 to 900 for Google. To unify the data-range, the price cap was normalized to the range of 0 to 1 using the skLearn library of Python. The normalized data is then as given as an input to the prescribed model for training. The model was repeatedly trained for 100,250, 500, 1000 epochs for much ne tuning. If the current epoch loss (mean square error) is less than the loss of the previous epoch, then the weight matrices for that epoch is stored. After multiple tutelage processes, the model was tested with the test data-set and the one with least RMSE (Root Mean Squared Error) for a particular epoch is taken as the nal model for prediction. The model consists of two neural network architectures, Recurrent Neural Network and Long Short Term Memory. Class of neural networks that which makes a connection between the computational units from a directed circle is Recurrent Neural Network. This is a special case of Neural Network where the output from the previous level is given as an input to the contemporary level. Traditionally, in all the neural networks input and output are independent of each other, but when we need to predict the future, previous values are required hence RNN's requirement is a must, as it solves this issue using the Hidden layer concept as these remember the information about the sequence.

The values of the current state, activation function, and the output state can be calculated using these formulas.

**1. Current State**

**a(x) = b(a(x-1),i)**

where

a(x)=current state

a(x-1)=previous state

i=input state

**2. Activation Function**

**a(x) = tana(Wa(x-1)+Yi)**

where

W = Weight of Recurrent Neural

Y = Weight of Input Neural

**2. Output Function**

**Y = W(o)*a**

where

W(o) = Weight of Output Layer

Y = Output

The second type of neural network is Long Short Term Memory LTSM which is a special type of RNN as it helps by protecting the loss in the error that is back-propagated with time and layers of the proposed model. A constant error is maintained by the LSTM model, thus allowing the error not to exceed a defined value, thus allowing the model to train over 1000 steps, thus acts independently. This is one of the main provocations for artificial intelligence and neural network as algorithms are mostly resisted by the environment. LSTMs contain data in the form of gated cells. Information can be read or written into these cells, and the cell decides about what information to preserve and what to erase with the help of the gates. These are generally sigmoidal functions that are analog in nature, i.e either close or open. Analogs are differentiable in nature, hence gives a slight advantage over the traditional back-propagation.

LSTM takes input as [BatchSize, TimeStamp, Feature] in a 3- Dimensional format, where Batch Size determines after how many inputs sets the weight of the network is going to update, more the size less the time and vice-versa. Time Stamp is defined as how much previous data ones wish to view in order to predict the future value and Feature tells the number of attributes needed to calculate the time stamp.

The hyperbolic Tangent function is used as an activation function in this model. The derivative of the activation function is used in the update the weights with the help of error loss calculated.

Hyperbolic Tangent Function: tanh(x) = (ex e-x) / (ex + e-x).

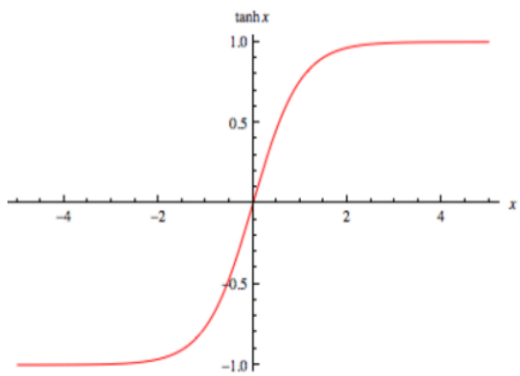


Figure 2. Range of hyperbolic tangent function

It gives an output in the range 0,1 and most importantly it is a continuous function, i.e gives the output for each and every value of x. Hyperbolic tangent function and its derivative plays a vital role in determining the true value of the stock by reducing the error:

f(x) = (ex e-x) / (ex + e-x)

d(f(x))/dx = 1 (f(x))2

The training data-set was then normalized in the range of 0 to 1 using MinMaxScalar function of the SkLearn library of the python. After each and every iteration, denormalization was done and the percentage error was calculated. The error was calculated using the RMS(Root Mean Square Value) of the predicted value using the formula:

$$error = sigma((TV^2 - PV^2)^{\cdot}5)/N$$

where; TV = true value; PV = predicted value; N = Total No of Values

## 4. Result and Discussion

The model was trained on google data-set using the different values of Batch Size, Time Stamp and Epochs. Effect of Batch Size on loss, the time required per iteration for a particular epoch is calculated and shown in Table[1]. It is clear from table[1] that Batch Size gives the best result when its value is 10.

| Epoch | Batch Size | Loss | Time/epoch |
|---|---|---|---|
| 100 | 5 | 0.0011 | 23sec 9 ms |
| 100 | 10 | 0.0011 | 11sec 9ms |
| 100 | 32 | 0.0014 | 4sec 9ms |
| 100 | 50 | 0.0018 | 3sec 9m |

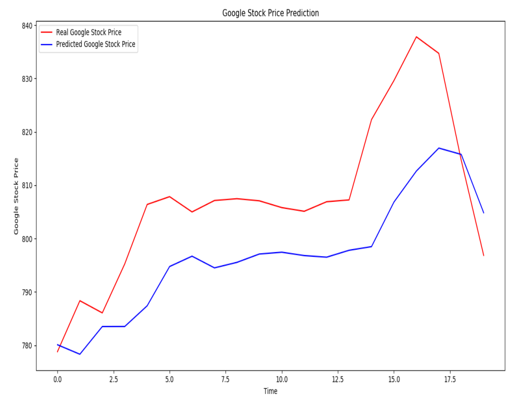


Figure 3. Predicted Vs True Value Graph

When the value of epoch was changed keeping the value of Batch Size and Time Stamp constant the result came out to be in Table[2]. Its clear from Table[2] that model gives the best result when the epoch value is

| Epoch | Batch Size | Loss | Time/epoch |
|---|---|---|---|
| 100 | 32 | 0.0015 | 4sec 3 ms |
| 250 | 32 | 9.7833e-04 | 4sec 3 ms |
| 500 | 32 | 7.8043e-04 | 4sec 3 ms |
| 1000 | 32 | 7.5204e-04 | 4sec 3 ms |

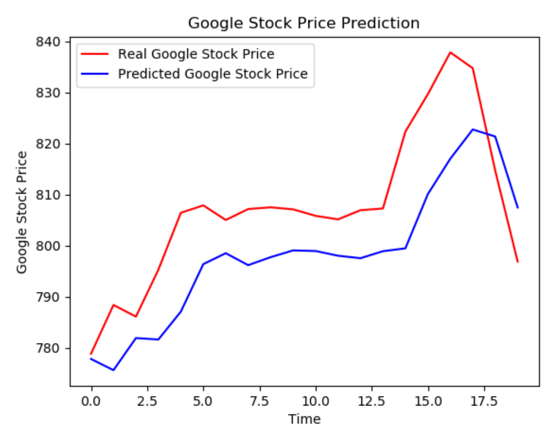


Figure 4. Predicted Vs True Value Graph

From Table[1] and Table[2] it can be concluded that the most appropriate value of Batch Size, Time Stamp and Epoch came out to be 10,60,1000 and the error loss came out to be 7.3543e-04.

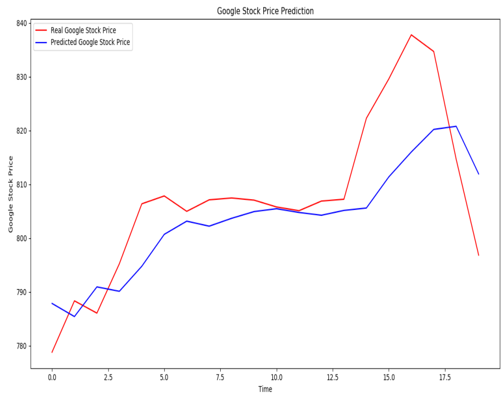


Figure 5. Final Output

Thus decreasing the batch size increases the time taken by the model to train but on the other hand decreases the loss per iteration, on the other hand as the number of epochs has increased the loss suffered by the model decreases, i.e the Model becomes better.

## 5. Conclusion

We propose a Recurrent Neural Network and Long Short Term Memory based Stock Prediction model. These are used as both of them are good at handling the time-based problems and can make predictions about the future. We trained the model using Google stock price data-set from Jan 2012 till Dec 2016 and then tested it by predicting the future stocks of the same from 1st Jan 2017 to 31st Jan 2017. The study showed that the model is capable enough in predicting the near future with the help of the two. Also, it is clear that the proposed model can even predict the prices correctly whenever there is a sudden change in the market. Changes in the stock are not defined on a confined pattern, hence the actuality of the same will differ. This analysis will help the investors and people investing there riches will gain much more profit.

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