Predicting Stock Prices Using LSTM

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Predicting Stock Prices Using LSTM

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Abstract: ***The art of forecasting the stock prices has been a difficult task for many of the researchers and analysts. In fact, investors are highly interested in the research area of stock price prediction. For a good and successful investment, many investors are keen in knowing the future situation of the stock market. Good and effective prediction systems for stock market help traders, investors, and analyst by providing supportive information like the future direction of the stock market. In this work, we present a recurrent neural network (RNN) and Long Short-Term Memory (LSTM) approach to predict stock market indices.***

Keywords: Long short-term memory (LSTM), recurrent neural network (RNN), nifty 50, root mean square error (RMSE), prediction, stock prices

1. Introduction

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.

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 that we have presented modeled and predicted the stock returns of NIFTY 50 using LSTM. We collected 5 years of historical data of NIFTY 50 and used it for the training and validation purposes for the model. The next section of the paper will be methodology where we will explain about each process in detail. After that, we will have pictorial representations of the analysis that we have used and we will also reason about the results achieved.

2. Methodology

Various types of neural networks can be developed by the combination of different factors like network topology, training method etc. For this experiment, we have considered Recurrent Neural Network and Long Short-Term Memory.

This section we will discuss the methodology of our system. Our system consists of several stages which are as follows:-

- Stage 1: Raw Data:

In this stage, the historical stock data is collected from https://www.quandl.com/data/NSE and this historical data is used for the prediction of future stock prices.

- Stage 2: Data Preprocessing:

The pre-processing stage involves

a) Data discretization: Part of data reduction but with particular importance, especially for numerical data
b) Data transformation: Normalization.
c) Data cleaning: Fill in missing values.
d) Data integration: Integration of data files.

After the dataset is transformed into a clean dataset, the dataset is divided into training and testing sets so as to evaluate. Here, the training values are taken as the more recent values. Testing data is kept as 5-10 percent of the total dataset.

- Stage 3: Feature Extraction:

In this layer, only the features which are to be fed to the neural network are chosen. We will choose the feature from Date, open, high, low, close, and volume.

- Stage 4: Training Neural Network:

In this stage, the data is fed to the neural network and trained for prediction assigning random biases and weights. Our LSTM model is composed of a sequential input layer followed by 2 LSTM layers and dense layer with ReLU activation and then finally a dense output layer with linear activation function.

The code of the Neural Network implemented in Keras is as follows:

```
model = Sequential()

model.add(LSTM(128, input_shape=(layers[1],
layers[0]), return_sequences=True))

model.add(LSTM(64, input_shape=(layers[1],
layers[0]), return_sequences=False))

model.add(Dense(16,init='uniform',activation='relu'))

model.add(Dense(1,init='uniform',activation='linear'))
```

- Stage 5: Output Generation:

In this layer, the output value generated by the output layer of the RNN is compared with the target value. The error or the difference between the target and the obtained output value is minimized by using back propagation algorithm which adjusts the weights and the biases of the network.

3. Analysis

For analyzing the efficiency of the system we are used the Root Mean Square Error(RMSE). The error or the difference between the target and the obtained output value is minimized by using RMSE value. RMSE is the square root of the mean/average of the square of all of the error. The use of RMSE is highly common and it makes an excellent general purpose error metric for numerical predictions. Compared to the similar Mean Absolute Error, RMSE amplifies and severely punishes large errors.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum\left(\hat{Y}_i - Y_i\right)^2}$$

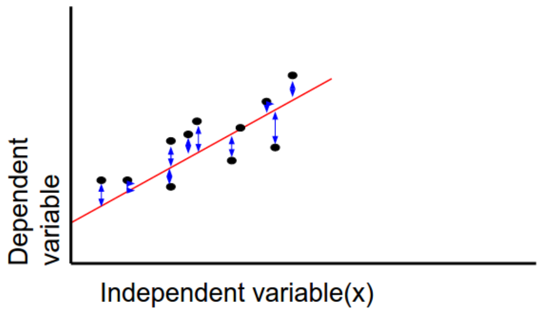

Figure 1: RMSE Value Calculation.

4. Experimental Work

- Dataset description: We acquired the data from https://www.quandl.com. We have collected the historical stock data of NIFTY 50 from the National stock exchange. We have collected daily dataset and kept a window size of 22 days. Data ranges from 01.01.2011 to 31.12.2016.
- Sequence data: We got 1312 sequences from 01.01.2011 to 31.12.2016. From these data set we used 1180 samples for training purpose and 132 samples for validation purpose.
- Training Detail: For training the model we used RMSprop as the optimizer and normalized each vector of the sequence. We used Google cloud engine as a training platform [Machine type: n1-standard-2 (2 vCPUs, 7.5 GB memory), CPU platform: Intel Ivy Bridge] and used Ubuntu 16.04, Keras (Frontend) and Tensorflow (Backend) as the learning environment.For our experiment, we have used a various set of parameters with a different number of epochs to measure the RMSE of Training and Testing dataset.

5. Experimental Results

Table 1: Comparative Results Using Different Parameters and Epochs.

Parameters	No. of Epochs	Training RMSE	Testing RMSE
Open/ Close	250	0.01491	0.01358
Open/ Close	500	0.01027	0.00918
High/Low/Close	250	0.01511	0.014
High/Low/Close	500	0.01133	0.01059
High/Low/Open/ Close	250	0.0133	0.01236
High/Low/Open/ Close	500	0.00983	0.00859

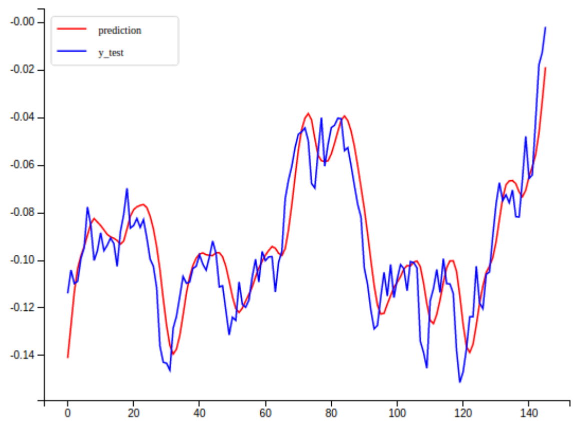

Figure 2: Open/close with 250 epochs.

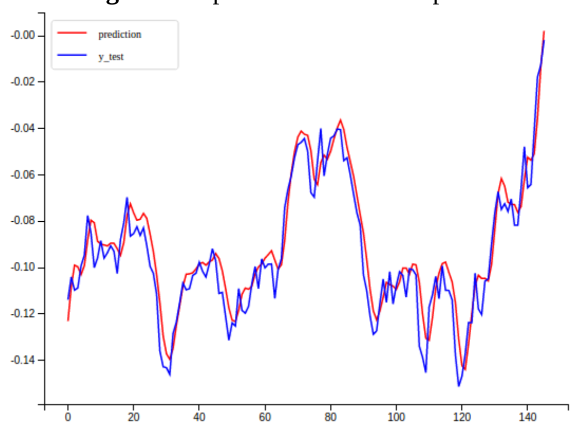

Figure 3: Open/close with 500 epochs.

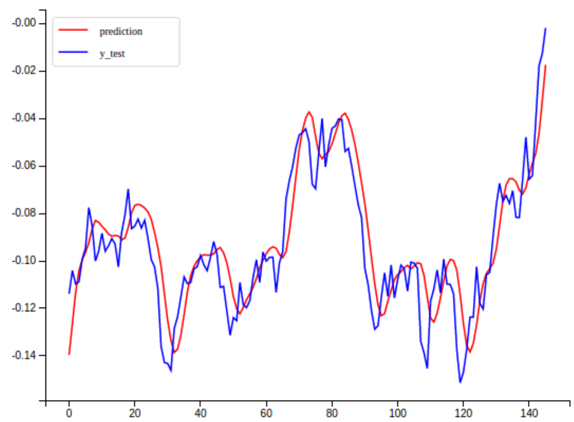

Figure 4: High/Low/close with 250 epochs.

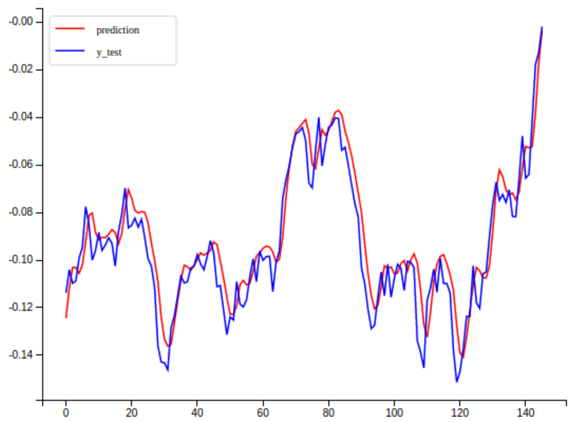

Figure 5: High/Low/close with 500 epochs.

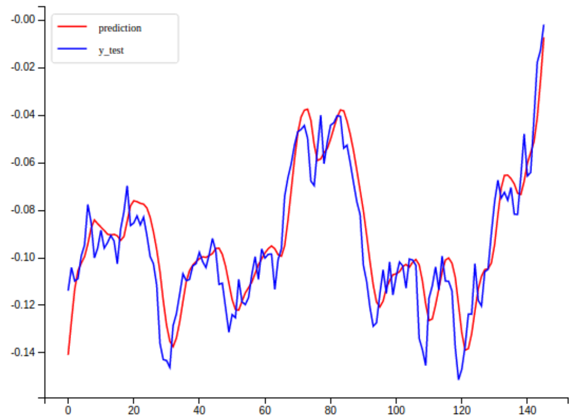

Figure 6: High/Low/Open/close with 250 epochs.

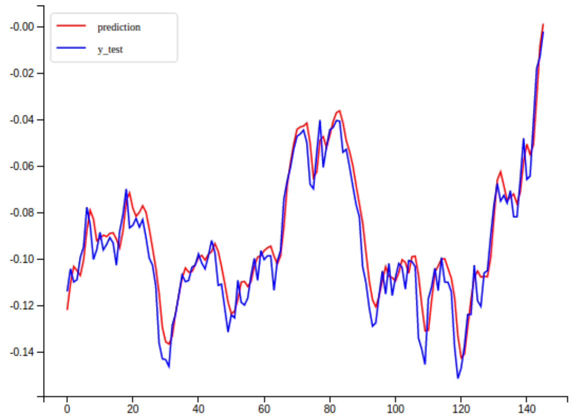

Figure 7: High/Low/Open/close with 500 epochs.

After performing various simulations with a different number of parameters and epochs, we have observed that by taking 4 features set (High/Low/Open/ Close) with 500 epochs we achieve the best results with training RMSE of 0.00983 and testing RMSE of 0.00859.

6. Conclusion

The popularity of stock market trading is growing rapidly, which is encouraging researchers to find out new methods for the prediction using new techniques. The forecasting technique is not only helping the researchers but it also helps investors and any person dealing with the stock market. In order to help predict the stock indices, a forecasting model with good accuracy is required.

In this work, we have used one of the most precise forecasting technology using Recurrent Neural Network and Long Short-Term Memory unit which helps investors, analysts or any person interested in investing in the stock market by providing them a good knowledge of the future situation of the stock market.

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