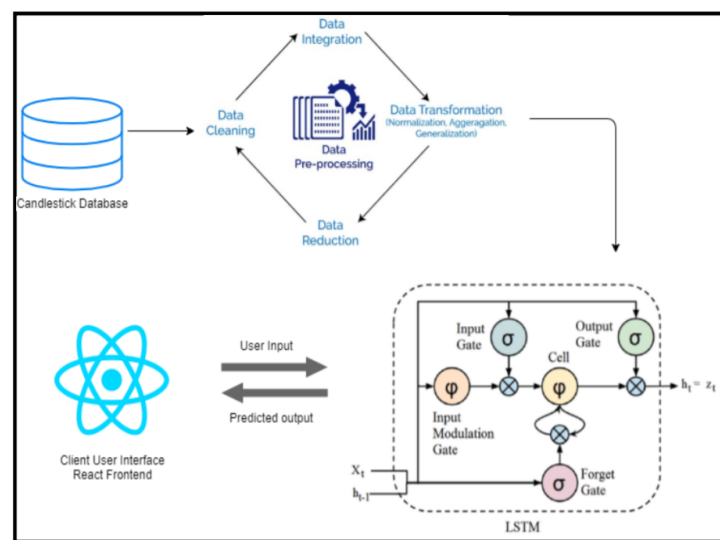


Introduction

Stock market historically has been very volatile with many factors having direct impact on the fluctuating nature of it. Many stock trading techniques involve technical analysis and fundamental analysis of each individual company's stock to understand the future of its value. Not only does a company's health and earnings have weight in deriving its stock value, but also many other external factors such as sentiment of the market and public reaction toward events have direct effect on the volatility.

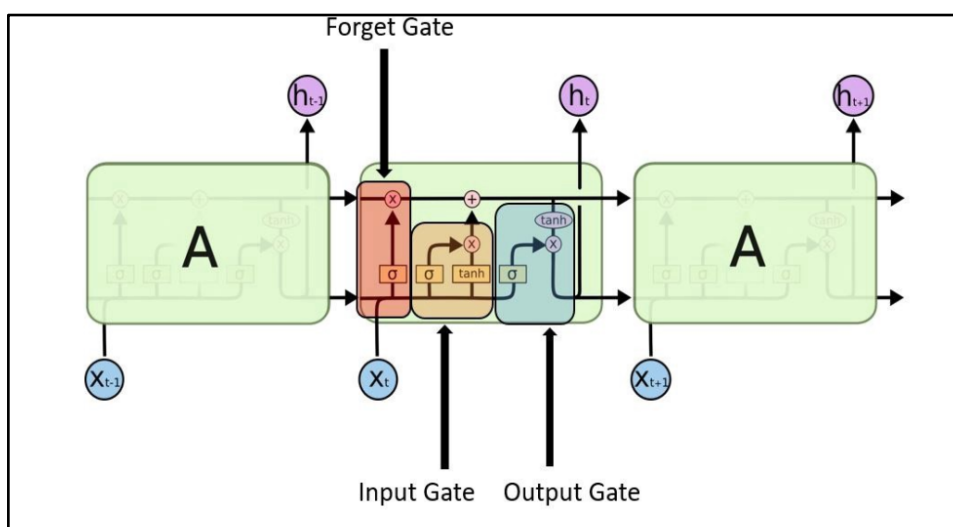


This research focuses on the previous movement of the stock market to predict the near future volatility without taking into consideration other external factors. The idea behind this approach is how to derive certain knowledge from stock market time series data using deep learning to understand near future positive or negative volatility. The automation of such a process will allow anyone to make quick decisions for making profit from the stock market volatility. Since LSTMs are specialized in keeping the historical context of inputs, it makes it a viable option for stock market prediction.

Methodology

Long Short-Term Memory (LSTM)

LSTM Neural Networks are a type of Recurrent Neural that is designed to specifically handle long term dependencies. The RNN module is a simple design having a single tanh layer. LSTMS consists of four layers of tanh where each layer communicates in a unique way. The LSTM can remove or add information to a cell state through a structure called gates.



The architecture of LSTM neural network is as shown in fig. 7. It is made up of three gates consisting of input gate, forget gate, and output gate. The design has 4 layers among which three of them are sigmoid layers connected to the three gates and the fourth layer is the tanh layer. Forget gate layer -The first step in the LSTM model is to remove the information in the cell state c(t-1) with the help of sigmoid layer.

Analysis and Results

Input gate layer – The next step in the model is to evaluate what new data in the cell state will be processed. The sigmoid layer is given x(t) and h(t-1) as input. The candidate values that can be added to the cell state is determined by the tanh layer.

Output layer – The final step is to determine the cell state output information. Sigmoid layer is part of this decision. Sigmoid layer will be used to set the information to be sent as output by taking x(t) and h(t-1) as input. This data is multiplied to only relay this part of the information as the output by the tanh layer. The formula is shown below to determine the output value.

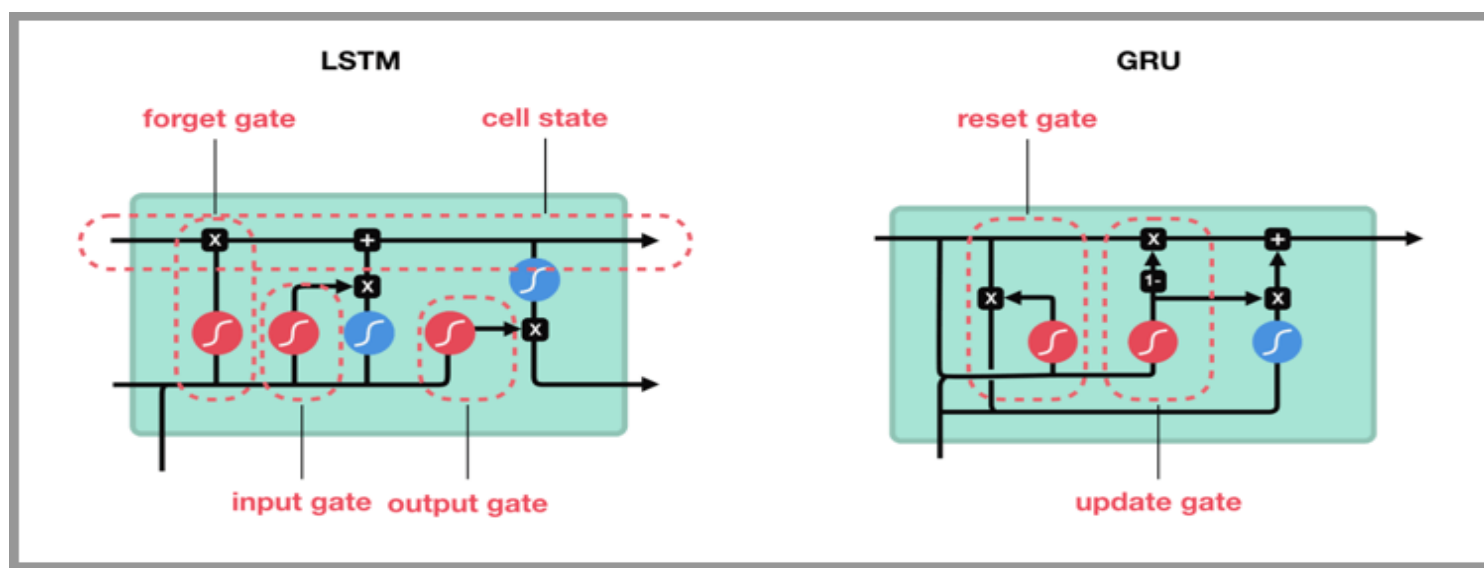
Date	Ticker	TimeBarSt	FirstTrade	HighTrade	LowTrade	LastTrade	VolumeW	Volume	TotalTrades
20070103	AAPL	04:15	86.33	86.33	86.01	86.01	86.2093	4300	8
20070103	AAPL	06:07	86.25	86.25	86.25	86.25	100	1	1
20070103	AAPL	06:08	86.05	86.05	86	86.04	86.01666	4860	8
20070103	AAPL	06:49	86.04	86.04	86.04	86.04	200	2	2
20070103	AAPL	07:03	86.2	86.2	86.2	86.2	1000	2	2
20070103	AAPL	07:04	86.2	86.2	86.2	86.2	500	1	1
20070103	AAPL	07:05	86	86	86	86	86	2300	4
20070103	AAPL	07:14	86.2	86.2	86.2	86.2	300	3	3
20070103	AAPL	07:15	86.2	86.3	86.2	86.3	86.23846	1300	4
20070103	AAPL	07:16	86.3	86.3	86.3	86.3	100	1	1
20070103	AAPL	07:17	86.25	86.3	86.25	86.3	86.28	500	3

The LSTM model has the ability to distinguish between recent and early samples via this architecture by assigning them various weights. This helps to boost stock price prediction results. The input sample here is considered to be independent by the LSTM model. In stock price prediction, this serves as an advantage. The current stock is linked to previous stock prices, so the model is capable of capturing this dependence to provide a better outcome.

Gated Recurrent Unit (GRU)

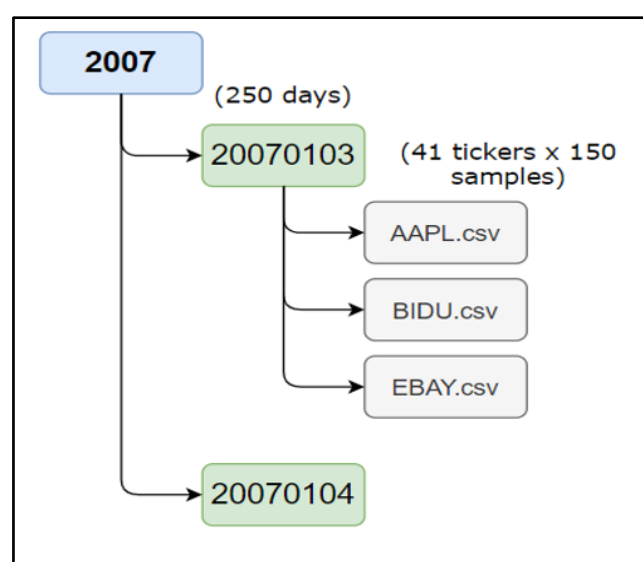
Gated Recurrent Unit is the improvised version of Recurrent Neural Network and has a lot in common with LSTM. While LSTM used cell state to maintain internal memory, GRU uses the hidden state to transfer information. It has two gates, a reset gate and an update gate.

GRU is computationally more efficient considering fewer parameters and need less data to generalize. However, GRU does not have any mechanism to control the degree to which its state or memory content is exposed but exposes the whole state or memory content each time.

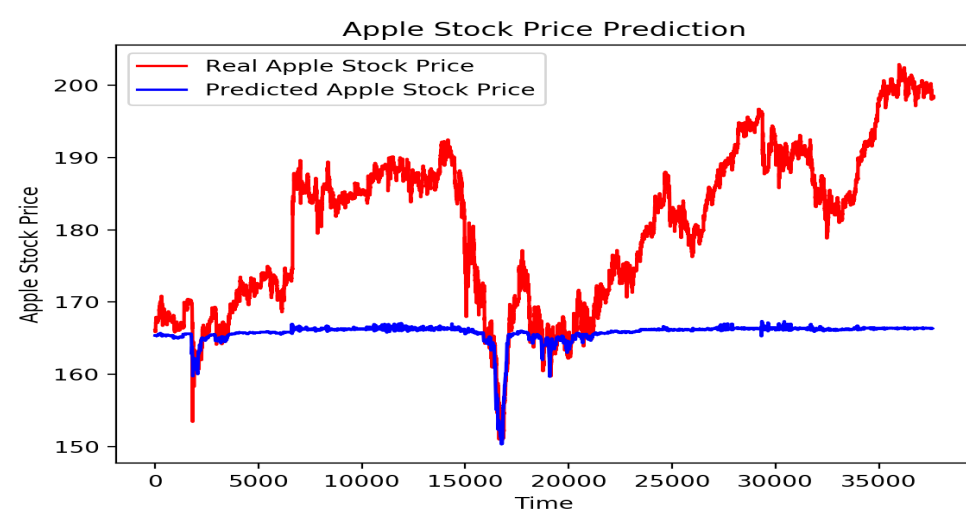


Since the stock market data is spread into different directories. Data processing involves combining the time series data together. The combined data is then cleaned to handling any missing values in the data set, handling any duplicate rows, to ensure right data format of the attributes .

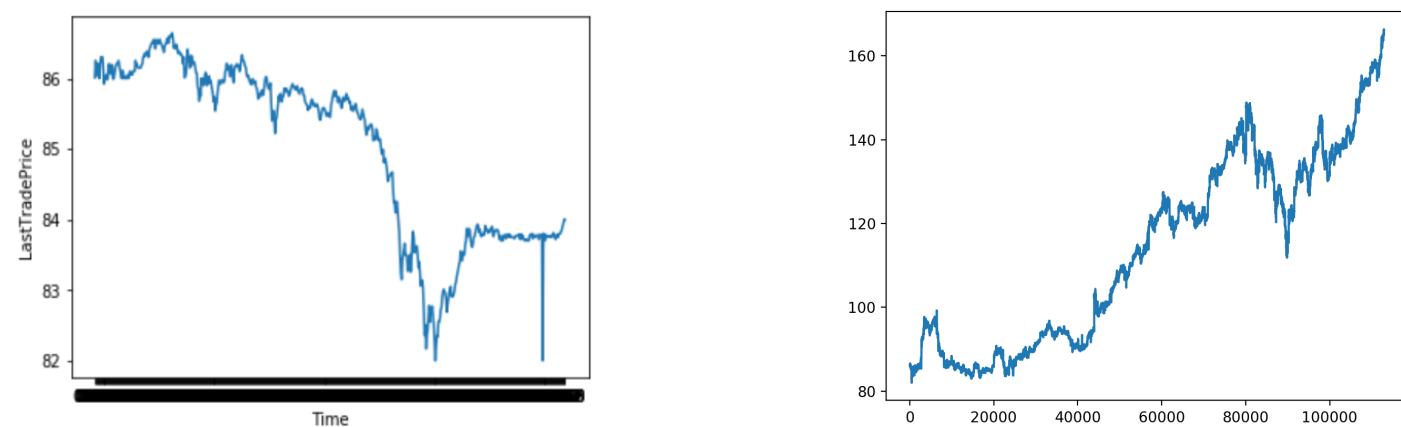
The processed dataset is divided into 75% training set and 25% test to be applied for the LSTM model. The visualization of the training set and test set for AAPL stock .



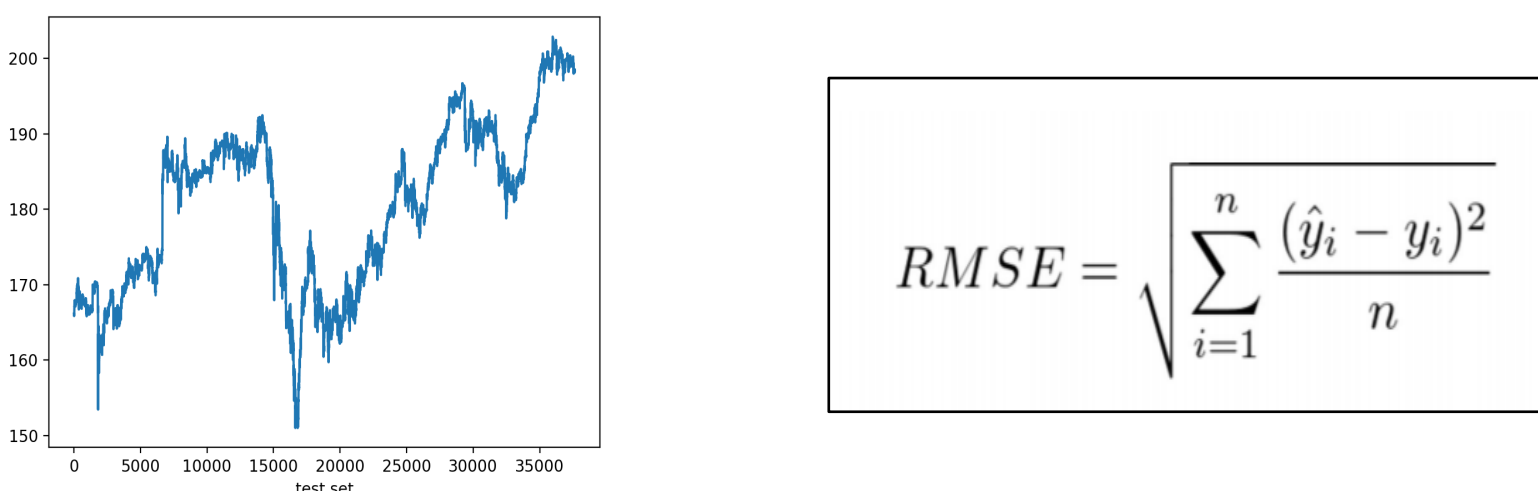
With Minimizing RMSE, one can observe that the performance of the model increases. Usually in the training step, the RMSE starts to be a higher number but through different epochs, the number should become smaller.



The processed data is given as input to the LSTM model. The LSTM neural network currently consists of four layers and a 20 % dropout is attained at each layer to prevent any overfitting. Utilized Adam optimizer with mean square error as loss function. Fig. 8 shows the preliminary results obtained. As we can see the model is able to predict the negative movements in stock price clearly. This model will further be fine-tuned to be able to get the predictions for positive movements in stock price.



Root Mean Square Error (RMSE)is used is to calculate the square root of the mean of actual values minus predicted values divided by the number of observations. Mathematically it is defined by the following formula:



$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}$$

The performance metrics which will be used for analysis are accuracy, precision, recall and F-1 measure. These measures are calculated based on the outcome of the true positive, true negative, false positive and false negative classes obtained from the confusion matrix.

These metrics are calculated for both classical machine learning models such as Random Forest, Multi-Layer Perceptron and the advanced deep learning model i.e. using LSTM. The results are compared to prove significant improvement in the performance of the prediction model using LSTM.

Summary/Conclusions

The stock market data consists of samples recorded every few minutes in each day for the year 2007. Since the dataset is large and each stock data is spread among multiple directories, the stock market prediction is currently analyzed for stock AAPL .we can see that the LSTM model is able to trace the negative movements precisely.

This model will further be optimized to accommodate prediction in the positive movements of stock price. The stock data spread among multiple directories will be combined for rest of the stocks and the LSTM model

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