Stock Prediction using Long Short-Term Memory

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ABSTRACT

Long Short Term Memory is a kind of recurrent neural network. In conventional RNN output from the last step is fed as input in the current step. It tackled the problem of long-term dependencies of RNN in which the RNN cannot predict the word stored in the long-term memory but can give more accurate predictions from the recent information. As the gap length increases RNN does not give an efficient performance. Long Short-Term Memory (LSTM) is a specific recurrent neural network (RNN)architecture that was designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs. LSTM can by default retain the information for a long period of time. It is used for processing, predicting, and classifying on the basis of time-series data. In this paper we will review LSTM RNN architecture for stock prediction.

Keywords: LSTMP, Speech Signal, Deep LSTMP, RNN.

INTRODUCTION

In stock market shares of publicly held companies are bought and sold. These activities are conducted through physical or electronic exchanges. These exchanges operate under a set of defined regulations. Stock exchanges are part of overall market. Traders in the stock market buy or sell shares on one or more of the stock exchanges. Stock markets are vital components of a free-market economy. They enable democratized access to trading and exchange of capital for investors of all kinds. They perform several functions in markets, including efficient price discovery. Investors are showing more and more interest in share market. Stocks are providing high returns. There are number of factors affecting the stock price movement. Economic policies, dividend, loss, gold silver rates, oil prices etc are the some of the factors which affects stock movement. It is important for the investors, investment institutions to understand the trend of stock price change. That's why stock price prediction comes into picture.

Stock price prediction helps investors predict or judge market and share prices. At present there are different techniques available in the market for the stock price prediction. These methods are divided into mainly two categories. One category of methods are statistical methods and other category of methods are artificial intelligence methods. In statistical methods models, techniques are applied on the research data. Based on this statistical information or assumptions are extracted. But, with the drastic changes in market and real world these statistical analysis is not that much accurate to predict market trend. Second stock prediction method is artificial intelligence. Artificial intelligence method works on the data and tries to find the trend in which stock prices are changing. With the help of more and more training applied on the data with the help of multilayer AI models helps to obtain more accurate results. It helps in the more accurate stock price prediction.

When one check on the influencing factors of the stock price the most important factor is economic growth. Mostly all the stocks perform well when the economic condition is stable and expanding. Strong performing companies stock perform well during recession as well. When economic condition is good it helps market index rises. Lower Federal rates, increased credit to companies helps companies to expand by production increase and providing more services. In such situation stock price will be good in long run. If looked at the short term factors that effects on the stock price are quarterly result of the company, high opening low closing of the stock in single day. Stock market data size very huge. Also, it is very random. One need a model which can handle this complex and huge amount of data. AI long short term memory model have a potential to deal with this complexity. It makes stock prediction easy. It provides useful aspects to new investors. These aspects help them to understand market quickly. It provides one place for data analysis which reduces time as well. More correct prediction provides more benefits. When more and more individual benefits it attracts more and more people to invest in the market to gain the benefit. It will automatically increase country's economic growth.

METHODOLOGY

Below figure shows basic stock prediction architecture. Stock data is taken from the Stock exchange. Stock data is processed and normalization is performed. This normalized data is then passed to long short term memory model and trained. Data is trained through machine learning algorithms to predict the stock prices. Predicted stock prices visualization is done through dashboard.

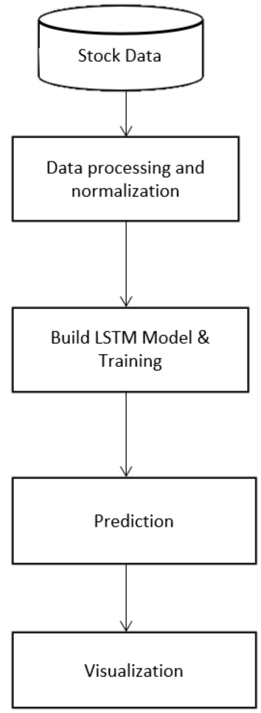

Figure 1: Basic Architecture

LSTM NETWORK ARCHITECTURES

LSTM

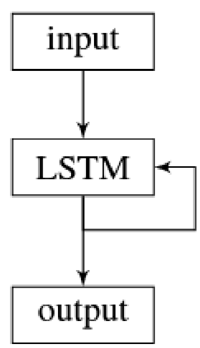

Figure 2: LSTM Workflow

The LSTM contains special units called memory blocks in the recurrent hidden layer. The memory blocks contain memory cells with self-connections storing the temporal state of the network in addition to special multiplicative units called gates to control the flow of information. Each memory block in the original architecture contained an input gate and an output gate. The input gate controls the flow of input activations into the memory cell. The output gate controls the output flow of cell activations into the rest of the network. Later, the forget gate was added to the memory block.

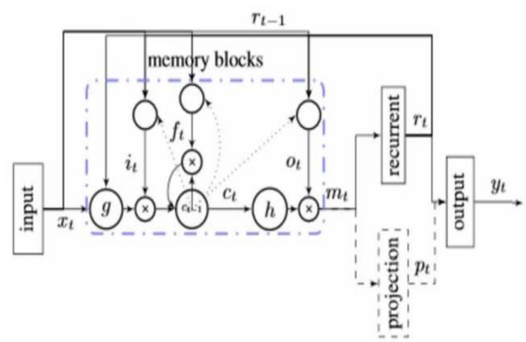

Figure 3: Long Short-Term Memory (LSTM) for Stock Prediction

The forget gate scales the internal state of the cell before adding it as input to the cell through the self-recurrent connection of the cell, therefore adaptively forgetting or resetting the cell's memory. New age LSTM architecture contains peephole connections from its internal cells to the gates in the same cell to learn precise timing of the outputs.

An LSTM network computes a mapping from an input sequence $x = (x_1,...,x_t)$ to an output sequence $y = (y_1, ..., y_t)$ by calculating the network unit activations using the following equations iteratively from t = 1 to T:

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \quad (1)$$
$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f) \quad (2)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \quad (3)$$
$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) \quad (4)$$
$$m_t = o_t \odot h(c_t) \quad (5)$$
$$y_t = \phi(W_{ym}m_t + b_y) \quad (6)$$

where the W terms denote weight matrices (e.g. Wix is the matrix of weights from the input gate to the input), Wic, Wfc,Woc are diagonal weight matrices for peephole connections, the b terms denote bias vectors (bi is the input gate bias vector), σ is the logistic sigmoid function, and i, f, o and c are respectively the input gate, forget gate, output gate and cell activation vectors, all of which are the same size as the cell output activation vector m, is the element-wise product of the vectors, g and h are the cell input and cell output activation functions. tanh, and φ is the network output activation function, softmax activation function.

Deep LSTM

Deep LSTM RNNs have been successfully used for stock prediction. Deep LSTM RNNs are built by stacking multiple LSTM. Each layer shares the same model parameters. Inputs is processed through multiple non-linear layers.

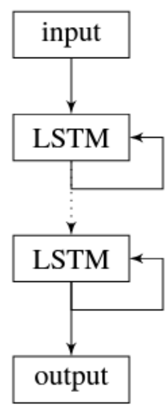

Figure 4: DLSTM

Deep LSTM make better use of parameters by distributing them over the space through multiple layers with propagation through time and LSTM layers. Rather than increasing the memory size of a standard model by a factor of 2, one can have 4 layers with approximately the same number of parameters. As a result of this input goes through more non-linear operations per time step.

LSTMP - Long Short-Term Memory Projected

Long Short-Term Memory Projected (LSTMP) architecture is proposed to address the computational complexity of learning LSTM models.

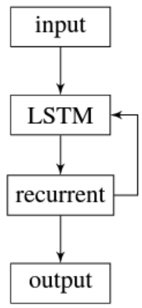

Figure 5: LSTMP

The input layer is connected to the LSTM layer. Separate linear projection layer after the LSTM layer. The recurrent connections now connect from this recurrent projection layer to the input of the LSTM layer. The network output units are connected to this recurrent layer. Experiments with LSTM and LSTMP RNN architectures showing frame accuracies on development and training sets. L indicates the number of layers, for shallow (1L) and deep (2,4,5,7L) networks. C indicates the number of memory cells, P the number of recurrent projection units, and N the total number of parameters.

Deep LSTMP

Like deep LSTM here proposed deep LSTMP will have multiple LSTM layers each with a separate recurrent projection layer and are stacked.

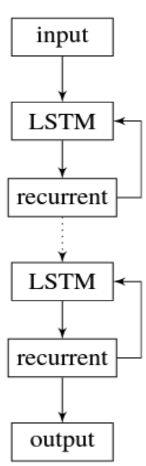

Figure 6: DLSTMP

We see increased memory size in LSTMP due to connections from the output layer and recurrent. We observed that DNNs generalize better to unseen examples with increasing depth. Inputs to the network need to go through many non-linear functions. The depth makes the models harder to over fit to the training data. With the aim of increasing the memory size and generalization power of the model deep LSTMP architectures experimented.

CONCLUSION

Nowadays, stock market trader are growing very rapidly. Interest in stock market trading is increasing. Researchers are working on finding new ways, methods using different techniques for stock price prediction. This research is helping investors to while investing money in the stock market. So more accurate the model more benefits are received. In this paper I used long short term memory aspect of machine learning. This is one of the efficient technique. It will help investors to gain good knowledge of stock market. With higher computing capacities if model is trained prediction will be more reliable and efficient.

We can conclude that artificial intelligence can increase the accuracy of the stock price prediction. With the help of historic data of the stock, learning the pattern of the stock up, lows, market behavior is possible. Model has an ability to learn these patterns by training the huge amount of data with different AI machine learning models. To create more efficient stock price prediction product, it is also important to consider parameters that are affecting the market. When these parameters are considered one can understand gain more knowledge about the stocks behavior according to the positive negative news in the market and it will help more accurate value prediction. Rather than manually analyzing the data machine learning is one of the most useful way to predict the stock prices.

REFERENCES

[1] Ahmed Raza SE, Cheung L, Epstein D et al (2017) MIMO-NET:a multi-input multi-output convolutional neural network for cell segmentation in fluorescence microscopy images. In: IEEE: 2017 IEEE 14th international symposium on biomedical imaging (ISBI2017), pp 337–340

[2] Ashish Sharma, Dinesh Bhuriya, Upendra Singh. "Survey of Stock Market Prediction Using Machine Learning Approach", ICECA 2017

[3] Baddar, W.J., Ro, Y.M.: Mode variational lstm robust to unseen modes of variation: pplication to facial expression recognition. In: Proceedings of the AAAI Conference on Arti_cial Intelligence, vol. 33, pp. 3215{3223

[4] C. H. Sun, B. Hu, and Y. X. Zhou, "BP-LSTM model for exponential trend prediction (in Chinese)," Journal of Sichuan University (Natural Science Edition), vol. 57, no. 1, pp. 27–31, 2020.

[5] Hakob GRIGORYAN, "A Stock Market Prediction Method Based on Support Vector Machines (SVM) and Independent Component Analysis (ICA)", DSJ 2016.

[6] Xi Zhang1, Siyu Qu1, Jieyun Huang1, Binxing Fang1, Philip Yu2, "Stock Market Prediction via Multi-Source Multiple Instance Learning." IEEE 2018.

[7] Loke.K.S. "Impact Of Financial Ratios And Technical Analysis On Stock Price Prediction Using Random Forests", IEEE, 2017.

[8] Pei-Yuan Zhou , Keith C.C. Chan, Member, IEEE, and Carol XiaojuanOu, "Corporate Communication Network and Stock Price Movements: Insights From Data Mining", IEEE 2018.

[9] VivekKanade, BhausahebDevikar, Sayali Phadtare, Pranali Mande, ShubhangiSonone. "Stock Market Prediction: Using Historical Data Analysis", IJARCSSE 2017.