International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 04 Issue: 05 | May -2020 ISSN: 2582-3930

Stock Price Prediction Using LSTM

Rahul[1], Sathish Yadav[2], Skanda Subramanian[3], Dr.Meenakshi Arya[4]

[1,2,3]Student, Dept. of Computer Science and Engineering, SRM Institute of Science and Technology, Vadapalani, Chennai, India

[4]Assistant Professor, Dept. of Computer Science and Engineering, SRM Institute of Science and Technology, Vadapalani, Chennai, India

---

ABSTRACT

Predictions on stock market prices are a great task due to the fact that it is an hugely compound, disordered and dynamic environment. There are many studies from several areas pointing to take on that investigate and Machine Learning methods have been the focus of many of them. There are many examples of Machine Learning algorithms been able to reach reasonable results when doing that type of prediction. This article studies the usage of LSTM networks on that state, to predict future trends of stock prices based on the price history, alongside with technical analysis indicators. For that goal, a prediction model was built, and a series of experiments were performed and theirs results analysed against a number of metrics to measure if this type of algorithm presents and developments when compared to other Machine Learning methods and investment strategies. The results that were obtained are promising, getting up to an average of 55.9% of accuracy when predicting if the price of a specific stock is going to go up or not in the near future.

INTRODUCTION

Predictions on stock markets have been entity of studies for many spans, but given it'ssential complexity, dynamism and chaoticness, it has proven to be a very difficult task. The integer of variables and sources of information measured are massive and the signal-to-noise ratio unimportant. That makes the task of predicting stock market prices behaviour in the future a very hard one. For many years, there's been deliberations in Science regarding the option of such a feat and it's notable in the related literature that most prediction models fail to provide precise prediction in a over-all sense.

Stock costs never differ in privacy: the development of one will in general have a heavy slide impact on a few different stocks also. This part of stock value development can be utilized as a significant device to anticipate the costs of numerous stocks on the double. Because of the sheer volume of cash included and number of exchanges that occur each moment, there comes an exchange off between the precision and the volume of forecasts made; all things considered, most stock expectation frameworks are executed in conveyed parallelized design. These are a portion of the contemplations and difficulties looked in financial exchange examination.

2.RELATED WORKS

The primary focus of our literature survey was to discovermachinelearning algorithms and see if they could be modified to our use case i.e., working on immediate stock price data. These comprisedof Online

AUC Maximization, Online Transfer Learning ,and Online Feature Selection . Nevertheless, as we were incapable to find any possible adaptation of these for stock price prediction, as wedefinite to look at the existing systems ,analyse the major problems of the same, and see if we could progress upon them. We zeroed in on the association between stock data (in the form of dynamic, long-term time-based dependencies between stock prices) as the key problem that we wanted to solve. A short-lived search of general solutions to the above problem led us to RNN's and LSTM . Laterdetermining to use an LSTM neural network to perform stock prediction, we referred a number of papers to study the concept of incline descent and its various types. We decided our literature survey by observing at how incline descent can be used to tune the masses of an LSTM network andin what way this process can be enhanced.

3. EXISTING SYSTEMS AND THEIR DRAWBACKS

In the existing system, the interpretation of the data to find the aimed relationships among the algorithms predictive power and their related trading strategies' returns requires a theoretical framework which may trigger further research questions. We first define some very simple trading strategies whose main purpose is to translate the predictive power of the algorithms they are based on directly to their returns.

The existing system objective is not to get an optimum trading strategy but to prepare the tools for our discussion. The Extended Bayesian Framework (EBF), which gives the complete real data a predominant role in the relationship between the algorithmic prediction and the obtained results, is therefore a good candidate for getting the most out of a data set which is more representative of the whole real world data than a statistical sample.

We define a prediction strategy as a trading strategy that uses a prediction algorithm. While a precision can be attributed to the prediction algorithm, the final performance obtained must be credited to the trading strategy. An important objective in the existing system is to analyze the impact that the algorithmic accuracy has on the final return, and to delimit what part of the credit it has in the entire strategy. The existing system have defined four prediction strategies: the SVM strategy (SVM), the Efficient Market strategy (EM), the Buy and Hold strategy (B&H), and the Optimal strategy (OPT).

3.1 Drawbacks of Existing System

- It needs more computational power
- It gets only 50% accuracy
- High Storage cost
- Less Efficiency

4. PROPOSED SYSTEM

In the proposed system, Prices move in trends is the most basic principle in technical analysis of stock market. Generally, markets do not move linearly, instead, their trace are often a series of zigzags. Though the essential concept - trend is widely acknowledged, the interpretation varies.

An interesting observation is that peaks and troughs are always coming in pairs. Specifically, before the market resume moving towards the original direction, up or down, it tends to move to the opposite direction to some degree.

The proposed system model mainly focus on exploiting the intrinsic time nature in time-series stock data. The exploration primarily covers three aspects. First of all, we believe that the importance of data varies from time to time, accordingly, they should be treated differently. The straightforward way to achieve this is assigning different weight to data at different time, therefore time-relevant weight functions are defined in the following subsection.

Secondly, since the stock data is time-series, we utilized LSTM, a type of neuron network excelling in solving time-series problems, to discover the possible temporal dependence in the complex data. Lastly, we carefully chose the time frame for training and predicting backed by classic theories in finance.

4.1LSTM(Long-Short Term Memory)-an overview

(**LSTM**) LSTM is a kind of **RNN** (Recurrent neural network),An **RNN** remembers each and every information through time. It is useful in time series prediction only because of the feature to remember previous inputs as well. This is called Long Short Term Memory. that has the ability to consider the long term dependability. LSTM was developed by two scientists, Schmidhuber and Hochreiter in 1997. What sets LSTM's apart from other RNN approaches is that LSTM's have the ability to remember information for a longer time period and avoid the long term dependabilities. LSTM's have a chain structure and on the inside they operate using gates and layers of neural networks like other RNN approaches. The structure oftheLSTM is constructed in a manner of a cell state that runs through the entire LSTM, the value is changed by the gates that have function by either allowing or disallowing data to be added to the cell state. There are also components by the name of gated cells that allow the information from previous LSTM outputs or layer outputs to be stored in them, this is where the memory aspect of LSTM's kick in (Hochreiter and Schmidhuber, 1997).

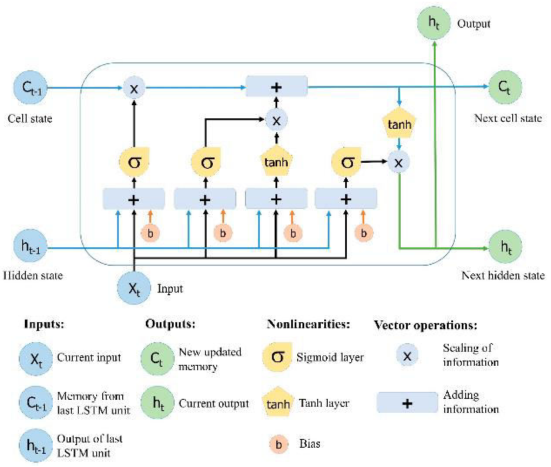

Fig-1: An LSTM memory cell

Advantages of LSTM

We can say that, when we move from **RNN** to **LSTM** (Long Short-Term Memory), we are leading more & more monitoring knobs, which governor the flow and mixing of Inputs as per trained Weights. So, LSTM provides us the utmost Control-ability and thus, Better Results. But also comes with more Complexity and Operating Cost.Each LSTM unit recalls data for either a long or a brief timeframe (henceforth the name) without unequivocally utilizing an enactment work inside the intermittent parts.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 04 Issue: 05 | May -2020 ISSN: 2582-3930

A significant actuality to note is that any cell state is increased distinctly by the yield of the overlook door, which changes somewhere in the range of 0 and 1. In this manner, data from a past cell state can go through a cell unaltered as opposed to expanding or diminishing exponentially at each time-step or layer, and the loads can combine to their ideal qualities in a sensible measure of time. This permits LSTM's to take care of the evaporating angle issue – since the worth put away in a memory cell isn't iteratively altered, the slope doesn't disappear when prepared with backpropagation.

5. ARCHITECTURE DIAGRAM

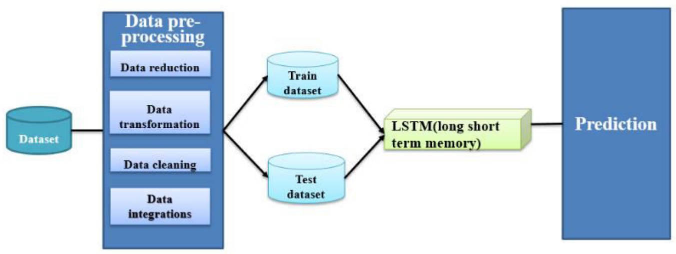

Fig-2: Architecture diagram

5.1 Proposed Algorithm

- Long Short Term Memory

5.2Obtaining dataset and preprocessing

Raw data: Day-wise past stock prices of selected companies are collected from the BSE (Bombay Stock Exchange) official website.

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

The obtained data contained five features:

1. Date: of the observation
2. Opening price: of the stock
3. High: highest intra-day price reached by the stock
4. Low: lowest intra-day price reached by the stock

5. Volume: number of shares or contracts bought and sold in the market during the day

6. OpenInt i.e., Open Interest: how many futures contracts are currently outstanding in the market.

The above data was then altered into a format suitable for use with our prediction model by performing the following steps:

1. Alteration of time-series data into input-output mechanisms for oversaw learning
2. Scaling the data to the [-1, +1] range

Data construction: The term 'data' refers to discrete facts , such as numbers. Data can be structured to create information, organized to be made. Data can be measured ,collected , analyzed , and represented in visual form using images , graphs and other analytical tool.

Data testing: Test Data is really the information given to a product program. It speaks to Data that effects or is influenced by the execution of the particular module. A few information might be utilized for positive testing, commonly to confirm that a given arrangement of contribution to a given capacity delivers a normal outcome.

5.3Construction of prediction model

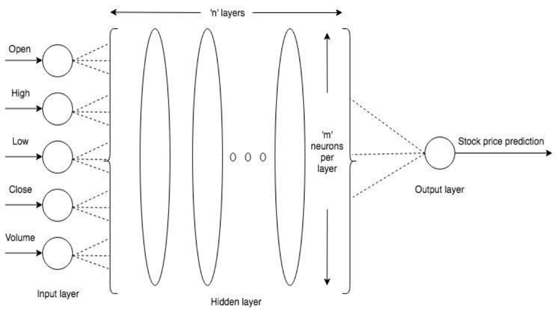

Fig-3: Recurrent Neural Network structure for stock price prediction

Our model was built on TensorFlow framework which provides off-the-shelf LSTM cells. We customized the cells according to our needs then implemented ideas rapidly. The model selection is virtually a hyperparameter search process. Dozens of hyperparameters were tested in our experiments to select the proper value. Increasing the number of neurons did help in improving the prediction accuracy. It added thecomplexityofthemodelimprovesitscapabilityofrepresentationforcomplexpatterns.But goingtoofarwillnotstrengthenbutweakenitsability,inourtest,320neuronsworkedwellfor thisproblem.Thenumberofnetworklayersseemedtonotplayanimportantpartinthemodel, the increasing of layers made the result worse. Probably because LSTM model is deep in its naturewithself-connectionpointingoverperiods.Timestepsstandsforthe lengthofeffective past data related to the value to bepredicted.

6. CONCEPTION OF RESULTS

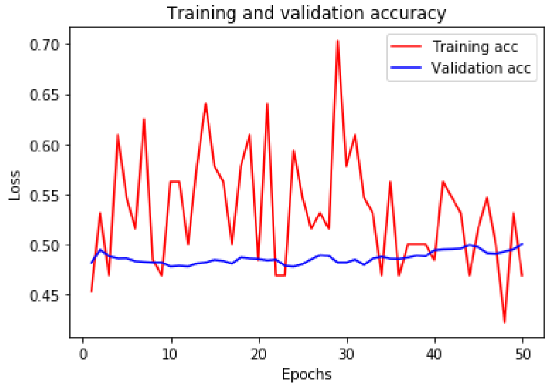

Fig-4: Training and validation accuracy

Figure 9 shows the real and the predicted closing stock price of the company , a large-sized stock. The model was trained with a batch size of 512 and 50 epochs, and the predictions made closely matched the actual stock prices, as observed in the graph.

We can thus conclude from the results that in over-all, the prediction accuracy of the LSTM model improves with increase in the size of the dataset.

Conclusion

Stock markets are hard to monitor and require plenty of context when trying to interpret the movement and predict prices. We proposed a time-weighted model for stock trend prediction by leveraging the power of time-series neural network, time-varying importance functions for data and the insights from classic financial theories. Following the guidance of Wave Theory, the form of trend was formally defined. Then the hypothesis that nearer data have more influence on prediction was validated in the experiments. The results implied that there might exist a quasilinear relation between the importance of data and its time series.In LSTM, each node is a memory cell that can store contextual information. All things considered, LSTMs perform better as they can monitor the setting explicit fleeting conditions between stock costs for a more drawn out timeframe while performing predictions.An examination of the outcomes likewise demonstrates that the two models give better exactness when the size of the dataset increments. With more information, more examples can be fleshed out by the model, and the loads of the layers can be better balanced.

Future Work

For future work, we plan to explore the data's time-varying importance in depth which may benefit time-series problem modeling. Furthermore, trading strategies will be combined with our prediction model to construct a complete algorithmic trading system. At its center, the securities exchange is an impression of human feelings. Unadulterated calculating and examination have their confinements; a potential expansion of this stock expectation framework is increase it with a news source investigation from web based life stages, for example, Twitter, where feelings are checked from the articles. This notion investigation can be connected with the LSTM to more readily prepare loads and further improve precision.

References

- F. E. T. Burton and S. N. Shah, "Efficient market hypothesis," CMT Level I 2017: An Introduction to Technical Analysis, 2017.
- M. Ballings, D. Van den Poel, N. Hespeels, and R. Gryp, "Evaluating multiple classifiers for stock price direction prediction," Expert Systems with Applications, vol. 42, no. 20, pp. 7046–7056, 2015.
- J. Agrawal, V. Chourasia, and A. Mittra, "State-of-the-art in stock prediction techniques," International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol. 2, no. 4, pp. 1360–1366, 2013.
- J. Si, A. Mukherjee, B. Liu, Q. Li, H. Li, and X. Deng, "Exploiting topic based twitter sentiment for stock prediction." ACL (2), vol. 2013, pp. 24–29, 2013.
- R. Jozefowicz, W. Zaremba, and I. Sutskever, "An empirical exploration of recurrent network architectures," in Proceedings of the 32nd International Conference on Machine Learning (ICML-15), 2015, pp. 2342– 2350.
- F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel,

  P. Prettenhofer, R. Weiss, V. Dubourg et al., "Scikit-learn: Machine learning in python," Journal of Machine Learning Research, vol. 12, no. Oct, pp. 2825–2830, 2011.
- M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat,

  G. Irving, M. Isard et al., "Tensorflow: A system for large-scale machine learning." in OSDI, vol. 16, 2016, pp. 265–283.
- J. S. Armstrong, ''Forecasting with econometric methods: Folklore versus fact,'' J. Bus., vol. 51, no. 4, pp. 549–564, Oct. 1978.

- X. Zhang, X. Zhang, S. Qu, J. Huang, B. Fang, and P. Yu, ''Stock market prediction via multi-source multiple instance learning,'' IEEE Access, vol. 6, pp. 50720–50728, 2018.
- X. Li, H. Xie, R. Y. K. Lau, T. Wong, and F. Wang, ''Stock prediction via sentimental transfer learning,'' IEEE Access, vol. 6, pp. 73110–73118, 2018.
- M. Prause and J. Weigand, ''Market model benchmark suite for machine learning techniques,'' IEEE Comput. Intell. Mag., vol. 13, no. 4, pp. 14–24, Nov. 2018.
- L. Chen, Z. Qiao, M. Wang, C. Wang, R. Du, and H. E. Stanley, ''Which artificial intelligence algorithm better predicts the Chinese stock market?'' IEEE Access, vol. 6, pp. 48625–48633, 2018.
- G. Liu and X. Wang, ''A numerical-based attention method for stock market prediction with dual information,'' IEEE Access, vol. 7, pp. 7357–7367, 2019.