

STOCK PRICE PREDICTION OF NEPAL USING LSTM

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Abstract—Predicting behavior of Stock Market is a challenging task. It is a trending topic in machine learning. It assists the investor to minimize the risk and fluctuation in Stock Market. The most popular model for RNN(Recurrent Neural Network) right now is the LSTM (Long Short-Term Memory) network, which is made into use for deep learning because through it, very large architectures can be successfully trained.

In this paper, through the use of LSTM, prediction is done for determining the future stock market value. Stock data of ten different companies from different sectors that are currently running in Nepal were extracted from targeted website 'share-sansar.com'. The opening price, closing price, high and low were taken into consideration for analysis. Evaluation of the model is performed by determining the root mean square error between the predicted values and the test values. The accuracy was found to be approximately 80%.

Index Terms—Stock Market, Long Short-Term Memory, Machine Learning Algorithms, NEPSE Index

I. INTRODUCTION

Stock market prediction is that the "act of determining" the future worth of an organization stock or alternative monetary instrument traded on Associate exchange. The performance of exchanges is measured on a usual by some key indicators such as gap worth, damage, share index, etc. which are the live of the performance of some stocks picked from the different sectors of the market. Non-linear models involve methods like ARCH, GARCH, TAR, Deep learning algorithms. Deep neural networks is thought of as nonlinear function approximates that square measure capable of mapping non-linear functions supported the kind of application, various include Multi-Layer Perceptron (MLP), algorithmic Neural Networks (RNN), Long Short Term Memory (LSTM), Convolutional Neural Network (CNN) etc. Deep learning algorithms are capable of distinguishing hidden patterns and underlying dynamics in the knowledge through a self-learning method. Within the case of stock market, the information generated is gigantic and is very non-linear. To model such reasonably high-octane knowledge we want models which will analyze the hidden patterns and underlying dynamics. Deep learning algorithms square measure capable of distinguishing and exploiting the interactions and patterns existing during a knowledge through a self-learning method. Not like alternative algorithms, deep learning models will effectively model these kind of knowledge and can provides a sensible prediction by analyzing the

interactions and hidden patterns at intervals the information. Because of recent advancement in machine learning algorithms and computer science, these techniques are measure being applied to predict the pattern and analyze the trend available costs of varied corporations all round the world. The rise in accuracy, dependability and modifiability has additionally increased the reliance on intelligence commercialism system to help in predicting and analyzing the stock costs in several situation.

A. Stock Exchange in Nepal

The only stock exchange in Nepal is Nepal stock exchange indexed as "NEPSE". NEPSE function on NATS, NEPSE Automated Trading System; a total screen based trading that adopts the basics of an order driven demand. Buying and selling of physical and dematerialized securities is done through NATS. NEPSE was founded in 13th January, 1993 A.D under the company Act, operating under Securities Exchange Act. NEPSE list various sub-indexes including Commercial Bank, Hydropower's, Insurance, Hotels and Manufacturing Companies. The popular public companies listed in NEPSE are Agriculture Development Bank, Arun Hydropower, Everest Bank Limited, Nepal life insurance, Bottlers Nepal Limited etc. NEPSE stock exchange has listed 213 companies up to now. Market closes before 3 pm every day except holidays, Friday and Saturday. During Friday, Saturday and Holidays, there are no stock openings.

B. Long Short Term Memory (LSTM)

The LSTM network, is a recurrent neural network that is trained using Backpropagation through Time and overcomes the vanishing gradient problem. As such, it can be used to create large recurrent networks that in turn can be used to address difficult sequence problems in machine learning and achieve state-of-the-art results. Instead of neurons, LSTM networks have memory blocks that are connected through layers. A block has components that make it smarter than a classical neuron and a memory for recent sequences. A block contains gates that manage the block's state and output. There are three types of gates within a unit:

- Forget Gate: conditionally decides what information to throw away from the block.
- Input Gate: conditionally decides which values from the input to update the memory state.
- Output Gate: conditionally decides what to output based on input and the memory of the block.

Each unit is like a mini-state machine where the gates of the units have weights that are learned during the training procedure.

II. LITERATURE REVIEW

There are various methodologies and proposed approaches for the analysts to predict future stock market value through various predicting methodologies. There are papers such as 'Stock Market Forecasting using Machine Learning Algorithm' [1], 'Prediction of Bombay Stock Exchange Market Returns using ANN and Genetic Algorithm' [2], Stock Market Prediction using Hybrid Approach [3], 'Stock Market Prices do not follow Random Walks' [4]. In these study and related research, the individuals have attempted to utilize and provide methods to predict the future stock market value. Also, some have attempted to analyze the various methods that help in stock market prediction which could help the researchers and business people in deciding the methods that would be viable for their defined purpose. 'We recognized that the short-term VMA rules are more effective in forecasting stock movement than the long-term ones.' [5]. 'At a deeper level, this work shows how social media expresses a collective wisdom which, when properly tapped, can yield an extremely powerful and accurate indicator of future outcomes, as well as networking opportunities and application of classroom learning to real-world issues.' [6] Ultimately, these types of projects allow investors to utilize methods proposed to improve their investment strategies. When it is the case of investing in stocks, it is important that the investors be capable enough to conduct a thorough technical analysis of the stock charts. The successful prediction of a stock's future price could yield significant profit to the investors that helps investors to make financial decisions of buying, holding, or selling stocks.

A. Empirical Analysis

- 1) Comparative analysis with the similar paper

TABLE I: Comparison of this paper with other similar paper

Category\Projects	Predicting Stock Market Movement with Deep RNNs' by Jason Poulos† [7]	Nepal Sock Market Prediction
Model Used	GRU(Gated Recurrent Unit)	LSTM(Long Short-Term Memory)
Basis of prediction	Textual representations of important news headlines	Historical Stock Data
Risk of overfitting	Very High (Due to the fact that the training set size is small relative to the model complexity)	Low (Training set size is maintained as per the model complexity) Here, training set size is 80
Training Speed	Slow (Since, by increasing the number of hidden units in the 12-layer GRU, it slowed down training and led to underfitting)	Fast(Since stacked LSTM is made into use)
Accuracy in prediction	54%	aprox. 80%

The built-in advantages of deep RNNs do not appear to have significantly improved the results in the paper that has utilized the GRU model. Here, it assumes- "It is possible that stock market movement is more of a stochastic process and does not rely on prior histories, or simply that there are not enough examples to learn from". [7]

Whereas, from the results that were obtained from the paper that has used LSTM model, it seems to have utilized the built-in advantages of deep RNNs. Also, through the use of prior historical stock data, it has predicted future stock market value with good accuracy.

III. METHODOLOGY

A. System Model

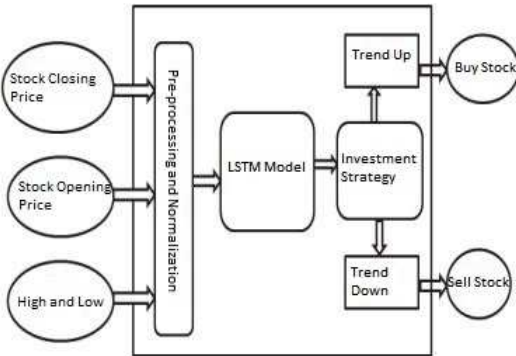


Fig. 1. Stock Predictive Investment Decision Model [8]

The development of this paper involves 5 major steps which is depicted in the flow diagram given below:

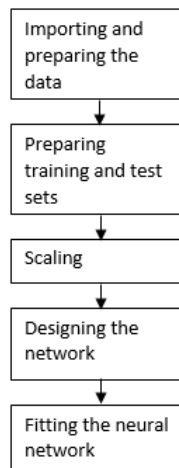


Fig. 2. Steps involved in development of model

1) Data Collection And Preparation:

Data is collected from the targeted website i.e. www.sharesansar.com. Different information of 10 different companies of Nepal are collected which include open price, close price, maximum price, minimum price over different series of years. For that, we first did web scraping using python library-Beautifulsoup. We then stored that data to the postgresql database by using psycopg2. Psycopg will automatically convert the PostgreSQL array data type to a Python list. Python script is written to connect to the database and sql queries are written in order to store data and extract data to and from database.

2) Preparing training and test data :

After we model our data and estimate the skill of our model on the training dataset, we need to get an idea of the skill of the model on new unseen data. For a normal classification or regression problem, we would do this using cross validation. With time series data, the sequence of values is important. A simple method that we can use is to split the ordered dataset into train and test datasets. The code below calculates the index of the split point and separates the data into the training datasets with 80% of the observations that we can use to train our model, leaving the remaining 10% for testing the model and validating the result each.

3) Data scaling:

Most neural network architectures benefit from scaling the inputs (sometimes also the output) because most common activation functions of the network's neurons such as tanh or sigmoid are defined on the $[-1, 1]$ or $[0, 1]$ interval respectively. LSTMs are sensitive to the scale of the input data, specifically when the sigmoid (default) or tanh activation functions are used. It can be a good practice to rescale the data to the range of 0-to-1, also called normalizing. We can easily normalize the dataset using the MinMaxScaler preprocessing class from the scikit-learn library.

4) Designing the network architecture:

After having defined the placeholders, variables, initializers, cost functions and optimizers of the network, the model needs to be trained. Usually, this is done by minibatch training. During minibatch training random data samples of $n = \text{batch-size}$ are drawn from the training data and fed into the network. The training dataset gets divided into $n / \text{batch-size}$ batches that are sequentially fed into the network. At this point the placeholders X and Y come into play. They store the input and target data and present them to the network as inputs and targets.

A sampled data batch of X flows through the network until it reaches the output layer. There, TensorFlow compares the models predictions against the actual observed targets Y in the current batch. Afterwards, TensorFlow conducts an optimization step and updates the networks parameters, corresponding to the selected learning scheme. After having updated the weights and biases, the next batch is sampled and the process repeats itself. The procedure continues until all batches have been presented to the network. One full sweep over all batches is called an epoch. The training of the network stops once the maximum number of epochs is reached or another stopping criterion defined by the user applies. The model quickly learns the shape and location of the time series in the test data and is able to produce an accurate prediction after some epochs.

5) Error Calculation :

The idea here is to predict the price of stock for the following day using all historical data. The Recurrent Neural Net model is trained using historical data. Here historical data are used to make a prediction for the next day. Since this algorithm predicts the price only for one day in future, the algorithm is good for daily trading only.

The Normalized Root Mean Square Error is calculated for each company in the paper.

It is then displayed alongside the predictions made for that company.

The root-mean-square error (RMSE) (or sometimes root-mean-squared error) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed.

Normalizing the RMSD facilitates the comparison between datasets or models with different scales. Though there is no consistent means of normalization, common choices are the mean or the range (defined as the maximum value minus the minimum value) of the measured data:

Formula used in the paper to calculate RMSE:

$$RMSE = \sqrt{MSE(y_{predicted}, y_{test})}$$

MSE is the Mean Squared Error. MSE of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors that is, the average squared difference between the estimated values and what is estimated. The fact that MSE is almost always strictly positive (and not zero) is because of randomness or because the estimator does not account for information that could produce a more accurate estimate. The MSE is a measure of the quality of an estimator-it is always non-negative, and values closer to zero are better. Formula used in the paper for calculating NRMSE:

$$NRMSE = \frac{RMSE}{\max(y_{predicted}) - \min(y_{predicted})}$$

This value is commonly referred to as the normalized root-mean-square deviation or error (NRMSD or NRMSE), and often expressed as a percentage, where lower values indicate less residual variance.

IV. RESULT AND ANALYSIS

A. Result

The paper has two parts namely command and web. In the command part ,script for storing scraped data to the database, followed by running the engine is executed everyday at fixed time. This is done by using 'task scheduler' in Windows. In the web part,the outputs that are stored in the database, are extracted and displayed in web browser. This is accomplished by using Django.

ADBL

Date As On: Aug. 15, 2018
Predicted Opening Value For Tomorrow: 322.294281005859
Normalised Root mean square error:0.0937078250786357

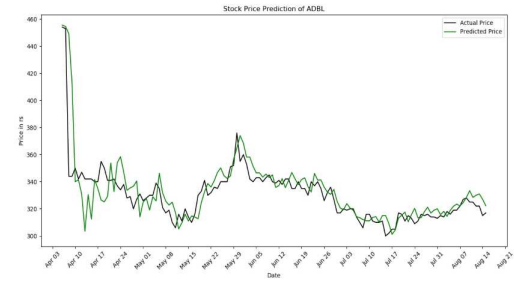


Fig. 3. Actual vs predicted values of Agriculture Development Bank Limited

NABIL

Date As On: Aug. 15, 2018
Predicted Opening Value For Tomorrow: 890.063415537344
Normalised Root mean square error:0.0953308634519918

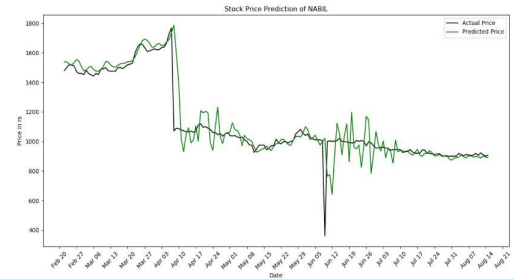


Fig. 4. Actual vs predicted values of NABIL Bank Limited

Likewise, graph of actual vs predicted values of all the companies selected is obtained. Also, Predicted opening value of the next day for the companies, and the error in prediction is displayed.

B. Analysis

TABLE II: Parametric Summary

Parameter	Value
number of inputs	4
number of outputs	4
number of neurons	200
learning rate	0.001
batch size	50
number of layers	2
tstep	30
number of train iterations	25
Train:test ratio	4:1

Based on the above hyper-parameters, the training time for the network, for training and testing data of single company, time consumed was 50 seconds in an Intel(R) Core(TM) i7-7500U CPU @ 2.70GHZ 2.90GHZ processor with 8.00

GB RAM and the accuracy obtained was approximately 80%. The number of epochs was determined by using the get next batch which takes batch size as parameter. The learning rate was set as learning rate = 0.001. Lowering the learning rate meant that each iteration took longer to finish, i.e convergence became very slow; this led to overfitting of the training set, thus decreased accuracy. A larger batch was possible to use; however, doing so caused higher memory usage yet no change in accuracy. Tstep is set to 30 which means that looping was started over only after 30th record in training set. Increasing LSTM layers generated same accuracy as 2 layers but training time was extended.

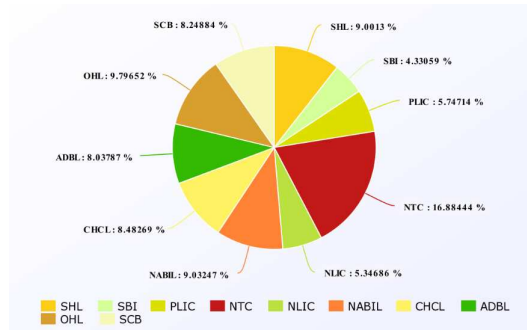


Fig. 5. Pie-Chart depicting error % in predicting the stock market value of all companies as on 4th August, 2018

From the output as on 4th august, 2018, Nepal SBI Bank has the least RMSE value i.e. 0.043 whereas NTC has the highest RMSE value i.e. 0.169. This indicates that the predictions made for Nepal SBI Bank is the most accurate and the predictions made for NTC is the most deviated. Similarly, analysis can be done for every working days.

V. CONCLUSION

This paper was focused with the implementation of Artificial Neural Network to predict future stock values of different companies enlisted in NEPSE. Despite the availability of different methods to accomplish such prediction tasks, advances in deep learning has enabled LSTM to be effective networks for this task. A well implemented LSTM is capable of predicting stock values with high accuracy. The LSTM model implemented in this paper utilized 2 LSTM layers, input layers and output layers.

The paper was completed using the incremental software development life cycle in python programming. At first, stock data for past 100 days was taken for training testing purpose and accuracy was found to be only about 30%. Later, after adding past 5 years stock data accuracy was found to be above 80%.

Thus, it was possible to predict the future stock value of different companies, calculate the error in prediction and plot the actual vs predicted value in graphical form.

Based on the experience of working on this paper, the following enhancements could be made to the system:

- Further tune the model to push the accuracy above 90 % by increasing the dataset
- Predict the stock price yearly which helps investors to know where to invest

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