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Stock Value Prediction Using Long Short Term Memory(Deep Learning)

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Abstract - *The stock market is most important for companies to raise money. Stock value prediction is an act of trying to determine the future value of a stock. The prediction is done by Deep Learning approach using Python programming language .The prediction is made accurate with the knowledge acquired from the available historic data set. There are some commonly used predictive algorithms such as Support Vector Machine (SVM) and Backpropagation. Based on the requirements of parameters like accuracy and efficiency the appropriate algorithm can be choose . A lot of studies provide strong evidence that LSTM algorithm has high accuracy than Support Vector Machine algorithm but it is slower than another algorithm like Backpropagation. But when it comes to stock prediction accuracy is more important than high speed. And also, LSTM is more efficient than SVM. Hence our objective is to use Long-Short Term Memory model (LSTM) and to develop a basic GUI to predict future stock market values and this can be a powerful predictive tool for stock predictions in the financial market.*

1. INTRODUCTION

The stock market could also be a huge array of investors and traders who buy and sell stock, pushing the price upon down. the prices of stocks are decided by the principles of demand and supply, and thus the last word goal of buying shares is to make money by buying stocks in companies whose perceived value (i.e., share price) is predicted to rise. Stock markets are closely linked with the earth of economics —the rise and fall of share prices are often traced back to some Key Performance Indicators (KPI's). The five most commonly used KPI's are the opening stock price (`Open'), end-of-day price (`Close'), intraday low price (`Low'), intra-day peak price (`High'), and total volume of stocks traded during the day (`Volume'). Economics and stock prices are mainly reliant upon subjective perceptions about the stock exchange . It is near impossible to predict stock prices to the T, thanks to the volatility of things that play a significant role within the movement of costs . However, it's possible to make an educated estimate of costs . Stock prices never vary in isolation: the movement of one tends to possess an avalanche effect on several other stocks also [2]. This aspect of stock price movement is often used as an important tool to predict the prices of the various stocks directly . because of the sheer volume of cash involved and number of transactions that happen every minute, there comes a trade-off between the accuracy and thus the quantity of predictions made; intrinsically , most stock prediction systems are implemented during a distributed, parallelized fashion . These are variety of the considerations and challenges faced available market research .

1.1 LITERATURE SURVEY

The recent studies provide a well-grounded proof that the bulk of the predictive regression models are not very efficient in out of sample predictability test. The reason for this inefficiency was parameter instability and model uncertainty. The studies also concluded the normal strategies that promise to unravel this problem. Support vector machine commonly mentioned as SVM provides with the kernel, decision function, and sparsity of the answer .It is a training algorithm for classification and regression, which works on a way bigger dataset. There are many algorithms within the market but SVM provides with better efficiency and accuracy. The correlation analysis between SVM and stock market indicates strong interconnection between the stock prices and thus the market index.

2. EXISTING SYSTEM

Previously SVM and Backpropagation were used for several classification problem and there have been many instances where reasonable accuracy was achieved. Back Propagation (BP) may be a method for training multilayer feedforward networks. It works by training the output layer then propagating the error calculated for these output neurons, back though the weights of internet , to train the neurons in the inner (hidden) layers. Keeping that in mind our given problem statement was addressed to realize the maximum amount accuracy as possible. LSTM was used for several statistic problems and therefore the same approach is employed to predict trend for stock by memorizing history data.

2.1 DRAWBACKS OF EXISTING SYSTEM

SVM takes an extended training time on large datasets. SVM doesn't perform alright when the info set has more noise i.e., target classes are overlapping. In cases where the amount of features for every datum exceeds the amount of coaching data samples, the SVM will underperform. As the support vector classifier works by putting data points, above and below the classifying hyperplane there is no probabilistic explanation for the classification. While the drawbacks of backpropagation are The actual performance of backpropagation on a selected problem depends on the input dataset .Backpropagation can be quite sensitive to noisy data.

3. PROPOSED SYSTEM

The proposed system is to predict stock price for next day using LSTM(Long Short Term Memory) algorithm.

APPROACH

Our approach for this project consists of major steps:

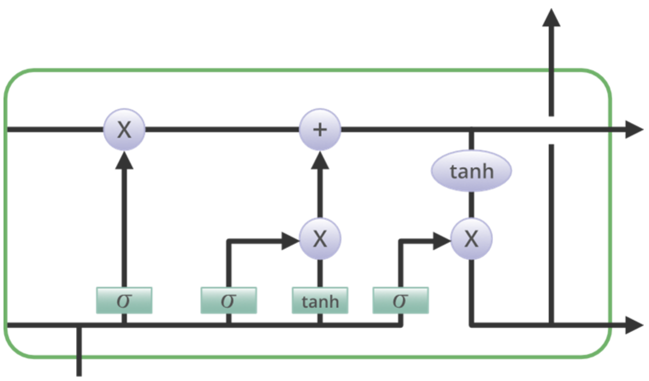
- Dataset creation
- Implementation of algorithm
- Comparison of result and analysis

4. LONG SHORT TERM MEMORY

Long Short Term Memory could also be a quite recurrent neural network. In RNN output from the last step is fed as input within the present step. LSTM was designed by Hochreiter & Schmidhuber. It tackled the matter of long-term dependencies of RNN during which the RNN cannot predict the word stored within the long-term memory but can give more accurate predictions from the recent information. because the gap length increases RNN doesn't give efficient performance. LSTM can by default retain the knowledge for long period of some time. it's used for processing, predicting and classifying on the thought of some time series data.

4.1 STRUCTURE

Information is retained by the cells and therefore the memory manipulations are done by the gates. There are three gates –



Forget Gate: the knowledge that not useful within the cell state is removed with the forget gate. Two inputs x_t (input at the actual time) and h_t-1 (previous cell output) are fed to the gate and multiplied with weight matrices followed by the addition of bias. The resultant is skilled an activation function which provides a binary output. If for a specific cell state the output is 0, the piece of data is forgotten and for the output 1, the knowledge is retained for the longer term use.

Input gate: Addition of useful information to the cell state is completed by input gate. First, the knowledge is regulated using the sigmoid function and filter the values to be remembered almost like the forget gate using inputs h_t-1 and x_t. Then, a vector is made using tanh function that provides output from -1 to +1, which contains all the possible values from h_t-1 and x_t. Atlast, the values of the vector and therefore the regulated values are multiplied to get the useful information.

Output gate: The task of extracting useful information from the present cell state to be presented as an output is completed by output gate. First, a vector is generated by applying tanh function on the cell. Then, the knowledge is regulated using the sigmoid function and filter the values to be remembered using inputs h_t-1 and x_t. At last, the values of the vector and therefore the regulated values are multiplied to be sent as an output and input to subsequent cell.

5. OBJECTIVE

In experiments, the root mean square error (RMSE) measure is used to evaluate the performance and accuracy of proposed models.

Root Mean Square Error (RMSE): measure of the difference between values predicted by a model and therefore the values actually observed. It is calculated by taking the summation of the squares of the differences between the anticipated value and actual value, and dividing it by the number of samples.

Increasing the training dataset (Historical Stock price)

The LSTM model is extremely popular in time-series forecasting, and this is often the rationale why this model is chosen during this task.

Concerning the LSTM, it has been shown that a data length of up to 12 years (maximum) can be used to train the model for effective prediction.

Our idea is to collect 6 years of stock data to train the model in order to increase accuracy and also reduce the training time required.

6. ALGORITHM

1.start

2. Collect the stock data from web

3. Filter only the required data needed to perform the computation (close value, high value)

4. Pre process the filtered data so that it is in right format before training

5. Use the 80% of data to train the constructed LSTM network using Keras and TensorFlow

6. Use the remaining 20% data to test the predictions

7. By comparing the actual data and predictions obtained from the trained model evaluate the accuracy (RMSE)

6.1 TRAINING ALGORITHM

The training algorithm is mainly based on Long Short-Term Memory (LSTM) network with the help of which we can overcome problems like long term dependencies and vanishing gradient problem. While implementing the LSTM which is a deep learning algorithm, we need to focus on the depth i.e., the number of layers in an LSTM network. If you need to simply test the ability to learn, single layer is enough. There exists a statement that the number of layers in LSTM network is related to its ability to remember long pattern. But there is no sufficient evidence so for. Adding depth will make the network learn more and also increase in depth will make the network more complex and slower to train. So, we choose **trial and error method** through which we experimentally analyze the result of each case one by one by increasing the layers.

	LSTM layers	Training time	RMSE	LOSS
Case 1	1	18s	1.615	.0015
Case 2	2	35s	0.0602	.0014
Case 3	3	52s	2.63	.0027

The best and more optimized results are observed at **"case 2 – LSTM network with two layers"**

7. RESULT AND CONCLUSION

The results of comparison between Long Short-Term Memory (LSTM) with Support vector machine and back propagation show that LSTM features a better prediction accuracy than those algorithms. Stock markets are hard to watch and need many contexts when trying to interpret the movement and predict prices. Here we tried to scale back the basis mean square error by passing them into layers while it's impossible in SVM model. As such, LSTMs perform better as they're ready to keep track of the context-specific temporal dependencies between stock prices for an extended period of your time while performing predictions.

At its core, the stock exchange may be a reflection of human emotions. Pure calculation and analysis have their limitations; a possible extension of this stock prediction system would be to reinforce it with a news feed analysis from social media platforms like Twitter, where emotions are gauged from the articles. This sentiment analysis is often linked with the LSTM to raised train weights and further improve accuracy.

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