XLI CILAMCE
XLI Ibero-Latin American Congress on Computational Methods in Engineering
16-19 November, 2020 FOZ DO IGUAÇU PARANÁ - BRAZIL

Financial Market Shares Prediction Using LSTM Networks

Clauber Martins[1], Marta Barreiros[1]

[1]Dept. of Computer Engineering, State University of Maranhão – UEMA, São Luis-MA
clauber789@gmail.com, marta-barreiros@hotmail.com

Abstract. The financial market provides economic growth, as it is very efficient in capturing savings and other resources for more productive activities. Stock investment is seen as a challenge even for specialist shareholders with many years of experience, in which the results for this type of investment are quite variable, as they are based on different macroeconomic factors with highlights in political events, bank rates, expectations investors, financial conditions in general, among others. Therefore, accurately predicting the variation of these prices is quite challenging, thus making it of great interest to investors to minimize this problem. Thus, artificial intelligence techniques are quite favorable to predict stocks in the financial market. To predict stocks on the stock exchange, we propose a methodology based on a recurring artificial neural network, the Long Short Term Memory (LSTM). This type of neural network, designed for time series, takes time and sequence into account, giving a feedback loop connected to your previous decisions, being quite appropriate for predicting data such as the stock exchange. The input data of the LSTM network were shares on the Petrobras stock exchange, in the period from January 2014 to December 2017 to make a projection of a future month which is the month of January 2018 based on the previous data, the operations were simulated in this action, obtaining the forecast of the stock's share with a difference of 0.03 and 0.23 cents.

Keywords: LSTM. Prediction Stock exchange.

1 Introduction

The financial market provides economic growth, as it is very efficient in capturing savings for more productive activities. Investment in the stock market is quite dynamic and is seen as a challenge, even, for specialist shareholders with many years of experience in investment techniques in the stock markets, as the results for this type of investment are quite variable, and may be very difficult to predict.

Second Wang et al [1], data containing historical stock prices are one of the most important data for investors on the stock exchange, however, unfortunately, these data are dynamic, non-linear, non-parameterized and chaotic in nature. This implies a cause in which investors have to deal with non-stationary time series and with frequent structural breaks, making it difficult to predict future data. Prices are also affected by several different macroeconomic factors, among which are political events, bank rates, investor expectations, financial conditions in general and even psychological factors of investors. challenging, thus making it of great interest to investors to minimize this problem [1].

There are basically two ways of analyzing financial market pricing: fundamental analysis and technical analysis. In the fundamental analysis, we work with macroeconomic fundamentals, studying the factors of variation that affect the balance between supply and demand in the market. In the technical analysis, there is an evolution in terms of purchase price, sales price, volume traded, among others. Thus, it is understood that the data can repeat past behavior [5]. Therefore, it was important to observe the interaction of the recurrent neural network, as the network proposed in this article.

Some algorithms have already been used to forecast the financial market. However, a technique that has been widely used in the prediction of stock prices on the stock exchange, is the use of the Artificial Neural Network (ANN). Using new strategies for extracting data from stock exchange indexes, together with the ANN algorithm, is quite valid for a more concise forecast of the financial market. Thus, it is possible to find works with satisfactory success rates with forecast errors in acceptable values. Most ANN-based models use historical and current stock index data to predict future prices [2].

Due to the difficulty in predicting the stock exchange index, which works as a measure of the investment market, measuring the performance of a set of shares, being a theoretical portfolio, this research focuses on the application of artificial neural networks in contribution to the investors the advantage of predicting the outcome of the stock exchange's stock values.

For a better prediction of the stock market shares, a recurring network was used, the Long Short-Term Memory - LSTM neural network, where you can remember a value for an eventual period of time, capable of learning from past experiences, using sequential data with different lengths for tasks such as sorting and forecasting time series [3], [4]. Therefore, developing a methodology for forecasting the stock exchange using artificial neural networks is important.Thus, the objective of this article is to propose a methodology based on a recurring LSTM network for forecasting the Petrobras stock exchange.

2 Methodology

2.1 Database

The database was assembled with data from PETR4 shares from January 2014 to January 2018, for a total of 1019 days. All data were extracted from the Yahoo Finance website and the attributes provided were date, closing value, adjusted closing value, maximum value, opening value, minimum value and volume. Two training sessions and two tests were carried out. In the first training and test, a predictive attribute called closing value was used and in the second training and test, all of the aforementioned predictive attributes were used. In the application, it was necessary to divide the database into two sets, in the first set the training of the artificial neural network is defined, where the beginning of January 2014 until the end of December 2017 was used, in a total of 997 days and in the The second set is defined as the test basis, where we want to forecast the results of the stock exchange's shares for the period of one month (January 2018). We use the entire period that had the shares traded in January 2018 that add up to 22 days. These two sets of databases were concatenated in the execution of the neural network test, in which she predicted the stock values of January 2018 based on the results of previous periods..

2.2 Neural network architecture

In order to improve the forecast of financial market actions, it is proposed to use a variation of the recurrent neural network called LSTM. The LSTM neural network is an architecture that recalls values at arbitrary intervals, being suitable for processing and predicting time series with time lags of unknown duration. The insensitivity relative to the length of the gap gives an advantage over traditional recurrent networks, since LSTM is able to memorize because of its cell structure [3], [4].

The LSTM network architecture used in this work has four LSTM layers, the first layer has an input of size equal to 100 cells, the output of this LSTM layer and the connection between the other layers is through 50 cells. The output of the fourth LSTM layer has a layer of a dense neural network with a neuron at the output with the sigmoid activation function. The compiler uses the RMSprop optimizer, having 200 epochs, 32 sample numbers per gradient update and a learning rate of 0.001. The network optimizer uses a moving average (discounted) of the square of gradients and divides the gradient by the root of that average. This implementation of RMSprop uses simple momentum. In addition, the centralized version maintains a moving average of the gradients and uses that average to estimate the variation. All network input parameters were normalized, using data normalization by Minimum and Maximum to reduce the distance between the values of widely spaced variables, and it is presented in Equation 1:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

the value of X being the real value of the stock, X_{min} the lowest database value and X_{max} the maximum value of the action in the database.

To prepare the structure of the database, the temporal forecast was used in order to predict the value of an action based on the previous data. Thus, it was necessary to create a data structure to be able to apply the recurrent neural network. The training base is created using the last 100 consecutive days prior to the forecast day as the network entry. For the creation of the input base, a time window of size equal to 100 is used and for the output base, the subsequent window value is used. The window moves in one unit until the end of the training base. To validate the network, 22 days from the month of January 2018 are used, for each day of the test the last 100 consecutive values prior to the day to be predicted are used as input.

A total of two databases were formed to verify the best results, with the first database being composed only by the Closing attribute and the second database was composed by the predictive attributes Date, Opening, Maximum Value, Minimum Value, Closing and Closing adjusted, providing for the final closing of the share value.

3 Results e Discussion

The neural network was implemented in the Python language with the help of monitoring the keras class libraries (https://keras.io), called EarlyStopping, ReduceLROnPlateau, ModelCheckpoint that monitored the performance and the convergence of the network. At EarlyStopping, training for when the monitored mean squared error function has stopped improving the weight update, in ReduceLROnPlateau the learning rate is reduced when the metric has stopped improving and using the ModelCheckpoint class weights are saved after each season to achieve better results, in this way it was possible to improve performance in the convergence of the network.

To analyze the results, a test computer was used, with an INTEL CORE I5 3337U (1.80 GHz) processor, 8GB DDR3 RAM and 256GB SSD, without a video card. Only using the ModelCheckpoint class separately, where it saves the model (weights) after each season to achieve better results, did it achieve better performance in the convergence of the network.

Figure 1 shows the result of the forecast for Petrobras shares. The results of the stock price differences predicted in the neural network showed a difference of 0.03 cents in the average between the predictions of 17.98 reais and the real value 18.01 reais in the implementation with a predictive attribute (Closing) and 0.23 cents in the difference of the average between the forecasts 17.78 reais and the real value R $ 18.01 cents in the implementation with 6 predictive attributes (Date, Opening, Maximum Value, Minimum Value, Closing and Adjusted Closing). Thus, it is observed that the difference between stock prices shows satisfactory results in the predicted data of the evaluated database.

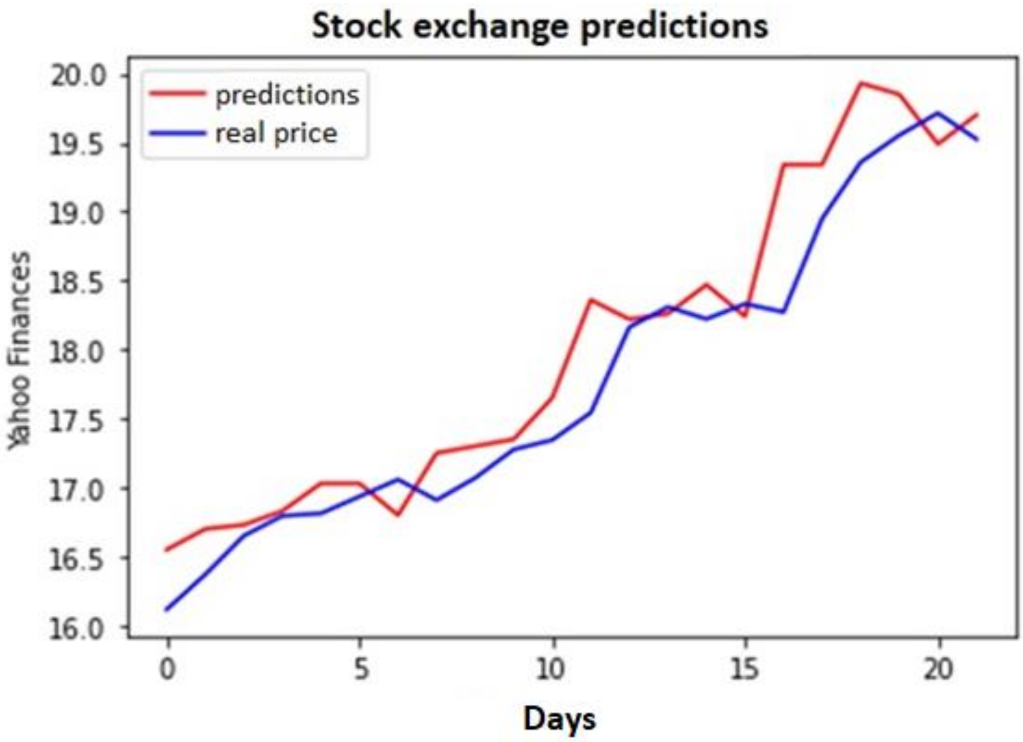

Figure 1 - Prediction of shares on the Petrobras stock exchange. Results of 28 days of prediction of Petrobras shares with only the predictor (Closing).

Figure 2 - Prediction of the shares of the Petrobras stock exchange with all forecasters. Result of Petrobras actions with six forecasts (Date, Opening, Maximum, Minimum, Closing and Adjusted Closing).

In the work of, using Multilayer Perceptron neural networks, to predict the Petrobas stock exchange in the years 2000 and 2007, the average of the difference in the forecast was 0.44 and -2.39 reais, respectively [5]. Thus, it is observed that the neural network proposed in this article obtained a satisfactory result. Currently, there are several stock forecasting approaches in the financial market, as well as Genetic Algorithms, Support Vector Machines and several other techniques combined to forecast financial stocks with the smallest possible difference.

4 Conclusions

In this article, it was proposed to use an LSTM network to predict variations in Petrobras shares. The result obtained was satisfactory in the prediction of the stock exchange action, with a difference of approximately 0.03 cents in the use of a predictive attribute and approximately 0.23 cents in the use of 6 predictive attributes. Thus, it was observed that the use of six stock forecasts on the stock exchange to predict the closing proved to be less efficient compared to the use of only the closing of the previous periods to forecast a future month. It is now for future studies to add more exits in the network instead of one, which can simultaneously predict the other data such as the opening, high, low, closing, adjusted closing and the volume of shares in the market.

References

[1] J. Z. Wang, J. J. Wang, Z. G. Zhang, and S. P. Guo, “Forecasting stock indices with back propagation neural network,” *Expert Syst. Appl.*, 2011.

[2] Z. Yudong and W. Lenan, “Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network,” *Expert Syst. Appl.*, 2009.

[3] X. H. Le, H. V. Ho, G. Lee, and S. Jung, “Application of Long Short-Term Memory (LSTM) neural network for flood forecasting,” *Water (Switzerland)*, 2019.

[4] H. Sak, A. Senior, and F. Beaufays, “Long short-term memory recurrent neural network architectures for large scale acoustic modeling,” in *Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH*, 2014.

[5] F. A. De Oliveira, C. N. Nobre, and L. E. Zárate, “Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index - Case study of PETR4, Petrobras, Brazil,” *Expert Syst. Appl.*, 2013.