International Journal on Emerging Technologies **10**(2): 362-364(2019)

ISSN No. (Print) : 0975-8364
ISSN No. (Online) : 2249-3255

Prediction of Currency Exchange Rate using Short Term Memory Networks

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(Received 19 May 2019, Revised 25 July 2019 Accepted 14 August 2019)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: The objective of the article is the prediction of currency exchange rate is a difficult task to carry out because of a high level of uncertainty in the market. The methodolology applied here is to carried out, to predict the currency exchange rate using traditional mathematical models as well as advanced techniques like Support Vector Machines (SVM) and neural networks. Due to time series data in finance being a Partially Observable Markov Decision Process, no one has a complete picture of what is going to happen at any given point of time. This is because the information we have with us is quite minimal when compared to prediction problems in other areas. Long Short Term Memory networks are used for empirical examination with currency exchange rate data. The outcome of the article is explaining the series of experiments were carried out on a dataset (USD/INR) containing two features (BSE Sensex, Gold futures). In this paper, the steps to prepare the dataset and selection of a suitable model are explored. Finally, a visualization of the predicted currency exchange rates are presented along with the suitable performance measures.

Keywords: Long Short Term Memory Networks, Visualization, Currency exchange rates, Currency exchange rate prediction

I. INTRODUCTION

Prediction of currency exchange rates is a widely sought after application in the field of economics due to the enormous profits it can make. But, forecasting involves uncertainty and this may lead to severe losses. The suggested novel methods in the field of computational intelligence to model time series data. State of the art models like neural networks, support vector machines and genuine linguistic fuzzy rules were taken as a base and new hybrid models were introduced which presented much competitive results when compared to the traditional ARIMA model [1].

The most relevant challenge while trying to model a time series in the field of economics is that traditional mathematical models cannot be used for predictions due to a large number of input parameters.

In Gurusen suggested that artificial neural networks(ANNs) provide a better performance on stock market index prediction as well as other prediction tasks in the field of economics [2].

Various publications provide further proof that Neural Network based solutions outperform other traditional statistical and mathematical models in most of the cases. A number of non linear models like Markov switching models were used for prediction tasks but none of them provided the high amount of flexibility as a Neural Network [3-4].

It provides further proof that Deep Learning is the best way to model a prediction task involving stock market prediction or currency exchange rates by using Long Short Term Memory Networks(LSTMs) [5]. The LSTMs are better at modelling time series data which provides enough reason for us to use it in our paper [6].

The paper tries to predict the currency exchange rate of USD/INR using Long Short Term Memory Networks. Each section of this paper deals with a separate module. Section II covers the litrature works, Section III covers the description of the used LSTM model, Section IV is meant for methodology and the proposed approach, Section V is intended for results and discussions, In Section VI covers the conclusion and future works and References.

II. LITERATURE WORKS

Applications of Deep Learning in the field of economics are rarely seen due to the popularity of mathematical models. Deep Learning techniques offer a unique perspective which traditional mathematical models fail to provide. ANNs and LSTMs are very good at solving non linear problems. In 1990, Kimoto.T et al. offered a unique perspective in the prediction of stock market prices using a modular neural network strategy as described in [7]. The Neural Networks are suitable for processing numeric data which provides the perfect platform for financial prediction tasks as most of the data is in numeric form [8]. It provides the information as to why LSTMs are powerful for financial prediction tasks like stock market's price movement [9]. It gives a detailed survey on why LSTMs are best suited for time series prediction and how they outperform traditional mathematical models such as ARIMA [10]. It shows the design metrics needed for a neural network architecture to predict currency exchange rates [11]. They suggest that a neural network architecture brings out the best results while predicting currency exchange rates.All the above results show that Deep Learning techniques are the go to methods when it comes to forecasting exchange rates and LSTM networks are suitable for such predictions. This paper refers the application behavioral equilibrium exchange rate and the methodology deployed here is Mean Square Error method and the outcome of the paper is to estimate and forecost the performance of the exchange rate model [12]. In the application of the future currency exchange rate Pi-sigma network highly pronounced as neural network is the methodlogy was applied to predict the forecosting of currency exchange with the help of ISFL [13]. From the study the currency exchange rate prediction using the model ISFL algorithm with CEFLANN network predictor model and the outcome of the reveal the was promising accuracy rate [14]. In this work, the integrated model is performing well than the models works stand alone like multi-layer neural networks and Bayesian learning with the help of normalized root mean square error predicting exchange rate of GBP/USD [15].

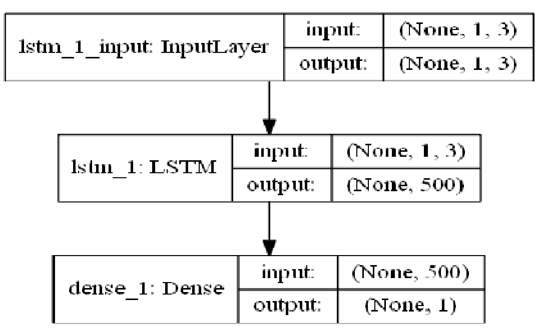
III. DESCRIPTION OF THE USED LSTM MODEL

We constructed a basic LSTM model with a sequential input layer containing 3 input nodes (one for each feature). We chose to have only one hidden layer with 500 LSTM nodes and one sequential output layer which has only one output node.
The LSTM is initialised by using random weights and biases. All the layers have a linear activation function.
The code in Keras, of the LSTM network that we chose is as follows:

```
model = Sequential()
model.add(LSTM(500,
input_shape=(layers[1],layers[2]),kernel_regularize
r=regularizers.l1(0.01))
model.add(Dense(1))
```

We used Adam as our optimizer function and Mean Absolute Error (MAE) as our loss function.
The following image gives a clear pictorial description of the architecture of the LSTM model we are using for predicting the USD/INR currency exchange rate.

Table 1. LSTM model.



IV. METHODOLOGY AND THE PROPOSED APPROACH

Our proposed method involves four steps as follows:

Step 1: Collection of raw data
In this step, we collected the raw data (historical data for USD/INR, BSE Stock Exchange rate, Gold Futures) from https://in.investing.com. This data was used in our next step to create a dataset.

Step 2: Data Pre-processing
In this step, we did data transformation by scaling the data between 0 and 1. We didn't have any missing values which made us skip the process of data cleaning. Then, we merged all the raw data and prepared a dataset.
In this step, we also split the data into training and test sets. We used 30 percent of the total data as testing data and 70 percent as training data. 277 samples were considered for testing out of 1712 entries.

Step 3: Construction of LSTM
In this step, we constructed an LSTM model based on the description presented in Section 3 of this paper.

Step 4: Forecasting future values
In the final step, we forecast the future values based on the previous values of USD/INR, BSE Sensex and Gold Futures.

V. RESULTS AND DISCUSSIONS

The proposed model was validated on the test set which contained 277 samples. The train set contains 1435 samples. The test set contains samples from 2017 to January 2018.
After the validation was done, the RMSE was evaluated on the predicted currency exchange rate values and an RMSE of 0.273 was obtained.
The graph showing the predicted to actual values of the currency exchange rate is shown below.

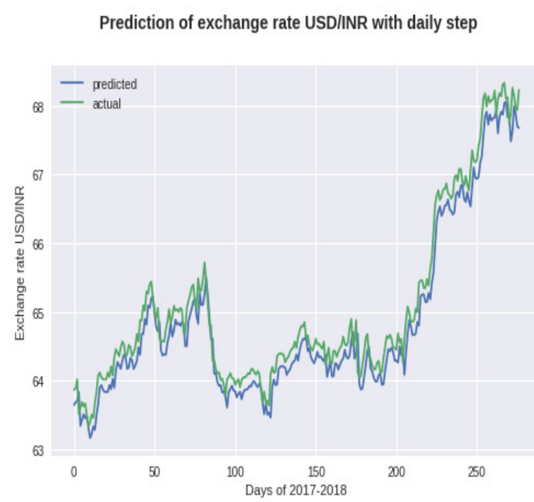


Fig. 1. Prediction of Exchange rate in USD/INR.

The Co-efficient of Determination was also found out and was predicted to be 0.98. A minimum error of 0.014 was obtained. The maximum error in prediction was 0.756. The mean error obtained is 0.320.

Table 2: The characteristics of the error.

Count	277
Mean	0.320329
Min	0.014801
Max	0.756378

The above table describes the characteristics of the error. The maximum error obtained was 0.80 rupees which indicates the effectiveness of LSTM networks.
The residual error was calculated using the following formula

residual error = expected value−predicted value

The residual error graph was obtained and plotted. The graph is shown below

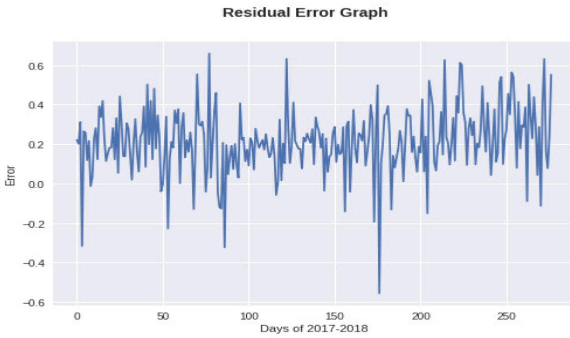


Fig. 2. Residual error graph.

VI. CONCLUSION AND FUTURE WORK

We conclude that Long Short Term Memory Networks are very much suitable for modeling time series data. We also conclude that we can obtain even better results when we are presented with more data.

LSTMs are successful when applied on a large amount of data rather than a very small amount of data. We took data for 6 years from 2011 to 2018. When presented with even more data, it is possible for the LSTM to model future predictions which much better accuracy and less error.

Applying Machine Learning or Deep Learning in the field of finance and economics due to various reasons. The main reason is that the time series data is a Partially Observable Markov Decision Process. No one has complete information of what happens at any point of time.

Another reason as to why financial prediction problems are difficult to model is that various things drive prices at different scales. High Frequency Trading (HFT), one of the main drivers for financial changes, is done in very short intervals which leads to high uncertainty.

The sample size is also sometimes very low and it would be highly difficult to model the time series data because our model cannot foresee events in the world which affect the currency exchange rate. Events like Natural Disasters on a large scale, collapse of world economies cannot be predicted by the Neural Networks or any kind of models for that matter.

In the future, these limitations can be taken as a future research problem to improve upon the error metrics. There may arise more problems if we take world economy into consideration. Events like elections, politics have the power to affect the economy of a country. These cannot be predicted by any mathematical model or Deep Learning.

Conflict of interest: No

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How to cite this article: Palanivel, S., Ramya, S., Sekar, K.R. and Manivannan D. (2019). Prediction of Currency Exchange Rate using Short Term Memory Networks. *International Journal of Emerging Technologies*, **10**(2): 362–364.