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Forex Trading System

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Abstract:
As there is a constant change in the dynamics in the system of global economy, the forecasting of foreign currency exchange rates (FOREX) requires accuracy. This accuracy is essential for a forex rate predicting system. The developments in the technologies now present have been very efficient and successful. In this paper we will describe and implement SVM, LSTM and GRU algorithms for forecasting the forex rates for the currency pair of EURO against US dollar.

Keywords: Forex Prediction, Exchange Rates, Currency Pairs, SVR, RBF, Linear, Poly, LSTM, GRU.

1. INTRODUCTION

The forex market has been on a rise from the last few decades. The main factor which affects the functioning of a currency market is the exchange rate. Organizations now rely on the prediction of exchange rate for their investments. The problem arises as there are a lot of fluctuations in the trends of foreign exchange rates. The more the variations in the data, the task of prediction becomes more difficult and tedious. Thus here we have used multiple algorithms to obtain the best possible prediction using the historical data of the provided currency pair.
The purpose of this paper is to investigate and compare the well-known prediction techniques. The proposed system takes historical data of the currency pair and using their daily opening and closing price, predicts the price of the currency pair. The system will be using different algorithms to predict the future rates based on the historical data provided and the results will be compared with the actual rate to find the most efficient algorithm.

2. METHODOLOGY

i) Support Vector Regression

Support Vector Machine (SVM) is considered an important technology for obtaining forecasting results for forex market. Support vector machines can be used for classification as well as regression. This when applied to a scenario where regression is involved it is known as support vector regression. Linear regression function helps in minimizing error for a required prediction system. SVM uses a hyperplane for separating data sets, i.e. this algorithm provides output as a line in two dimensional plane which separates the given classes.

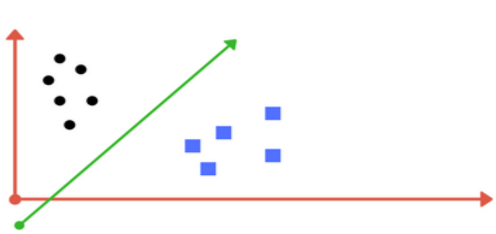

Figure.1. Basic representation of a hyperplane

SVM-based forecasting model requires the selection of desired kernel function and values of free parameters: regularization parameter and ε–insensitive loss function. Now suppose the given data is given as shown in Figure.2.

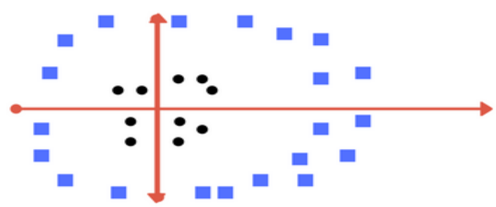

Figure.2

Now we cannot draw a line that can separate two classes given. Thus, transformation is applied and another z-dimension is added. After applying the transformation, separation can be done as shown in Figure.3.

Figure.3

Again transforming this line to Figure.1, we get a plane shown below.

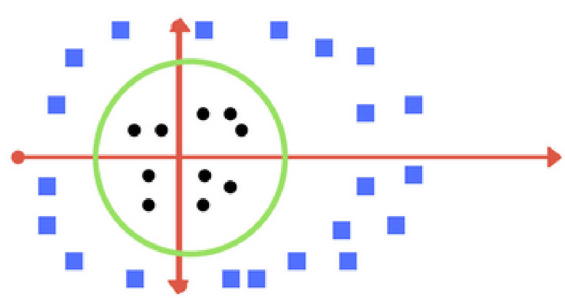

Figure.4

Such transformations are known as kernels. This technique is hard to use when the data set has millions of values. In such cases we cannot separate the data sets in exact two classes. In order to get the desired output, regularization is used.

Regularization

Regularization is used in order to avoid high distortions in the classification. There are two ways in which regularization can be done. High regularization chooses small lengths as in contradiction to low regularization which chooses high length planes inculcating differences in data sets. Following Figure shows both regularizations.

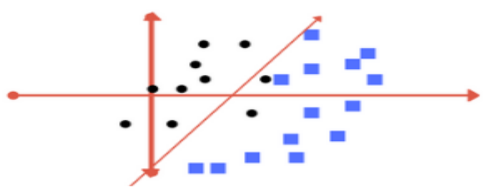

Figure.5. Low Regularization

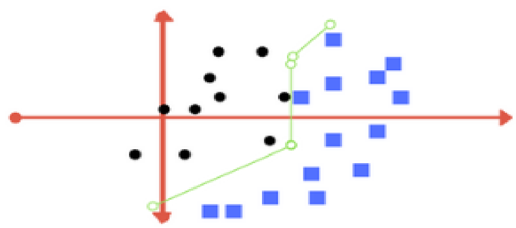

Figure.6. High Regularization

Kernel

Here, linear algebra is used in order to tweak the hyperplanes learning mechanism. Kernel types include:

1)Linear Kernel: Every new input received is used in prediction by calculating the dot product between the input(x) and the support vector (xi). The equation used is:

f(x)= B(0)+ sum(ai*(x,xi))

Both the coefficients ai and B0 are obtained by the training data.

2)Polynomial Kernel: It is given by:

K(x,xi) = 1 + sum(x * xi)^d

3)RBF Kernel: The RBF kernel ha formula:

$$\mathbf{K(x^{(i)},x^{(j)}) = \phi(x^{(i)})^{T}\square\phi(x^{(j)})}$$

$$\mathbf{=exp(-\square||x^{(i)}-x^{(j)}), \square > 0}$$

ii) LSTM(Long Short Term Memory)

LSTM was developed as an RNN (Recurrent Neural Network) for analyzing long data and retaining memory. A RNN is different from a regular neural network as they are having loops in their network which helps in retaining data memory.

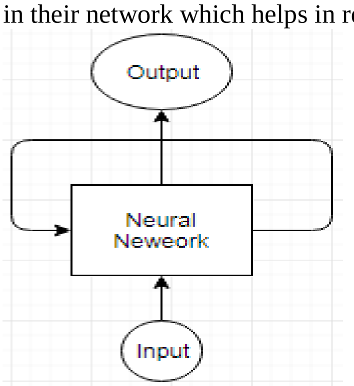

Figure.7

A Recurrent Neural Network can also be described as copies of the same network. LSTMs are used in order to eradicate the problem of long term dependency faced by a general RNN. The basic LSTM architecture includes a set of recurrently connected subnets, called as memory blocks. Every block consists of one or more self-connected memory cells and three multiplicative units which are the input, output and the forget gates which gives the functionality of read, write and reset operations for the memory cell. LSTM solved the problems faced by RNN by using memory cells in their structure. A typical memory cell can be represented as in Figure.8.

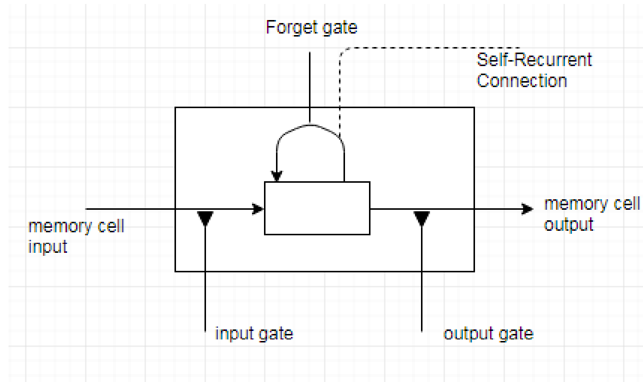

Figure.8. Illustration of an LSTM memory cell

An LSTM cell has been shown in Figure 8.LSTM does not compute only weighted sum of the inputs and apply it to a nonlinear function, but for each jth, LSTM unit maintains a memory c^t_j at time t. LSTM activation function is represented as:

$$\mathbf{h^j_t = o^j_t \tanh c^t_j}$$

The amount of memory content exposure is modulated by output gate o^j_t with V_o as diagonal matrix and is calculated by:

$$\mathbf{o^j_t = \sigma(W_{fxt} + U_{fht}\text{-}1 + V_{oct})\ j}$$

The memory c^j_t is partially updated by adding a new memory $c^{\sim j}_t$. And the existing memory is forgotten by forget gate f^j_t.

$$\mathbf{f^j_t = \sigma(W_{fxt} + U_{oht}\text{-}1 + V_{ict} - 1)\ j}$$

The extension of this is that a new memory is added and controlled by an input gate i^j_t

$$\mathbf{i^j_t = \sigma(W_{ixt} + U_{iht}\text{-}1 + V_{fct} - 1)\ j}$$

Existing memory is updated by following equations:

$$\mathbf{c^{\sim j}_t = \tanh(W_{cxt} + U_{cht} - 1)}$$

$$\mathbf{c^{\sim j}_t = f^j_t\, c^j_{t-1} + i^j_t\, c^{\sim j}_t}$$

iii) GRU (Gated Recurrent Unit)

The working of a GRU is quite similar to a LSTM. A GRU comprises of two gates that are reset and update gate. Both the gates provide necessary functionalities to GRU, where the rest gate provides information regarding how to combine the new input with the previous memory while the update gate gives estimate of how much previous data should be kept around. GRU is different from LSTM in certain ways as a typical GRU has two gates whereas LSTM has three gates, there is no output gate in GRU. GRU basically combines the input gate and forget gate to get the update gate.The final model achieved is simpler as compared to LSTM and is getting all the eyes.

A linear interpolation between the previous activation and candidate activation i.e. h^j_{t-1} and $h^{\sim j}_t$ respectively is the activation h^j_t of the GRU at time t and i represented by:

$$\mathbf{h^{\sim j}_t = (1- z^j_t)h^j_{t-1} + z^j_t\ h^{\sim j}_t}$$

$$\mathbf{z^j_t = \sigma(W_{zxt} + U_{zht}- 1)j}$$

The candidate activation $h^{\sim j}_t$ is represented by:

$$h^{\sim j}_t = \tanh(W_{xt} + U(rt .* h_{t-1}))^j$$

where r^j_t is a set of reset gates and .* denotes an element wise multiplication. The reset gate is calculated by

$$r^j_t = \sigma(W_{rxt} + r\, h_{t-1})^j$$

The job of update gate z is to know how the past stat value is important for now. Reset gate r is for short-term dependencies and update gate z is for long-term dependencies.

3. EXPERIMENTAL RESULTS

Data Collection

The data used in this study is the foreign exchange rate of EUR/USD from January 2017 to January 2018 made available by fxhistoricaldata.com. The data obtained was minutes-wise data. Data preprocessing was applied to convert it into daily data.

Results

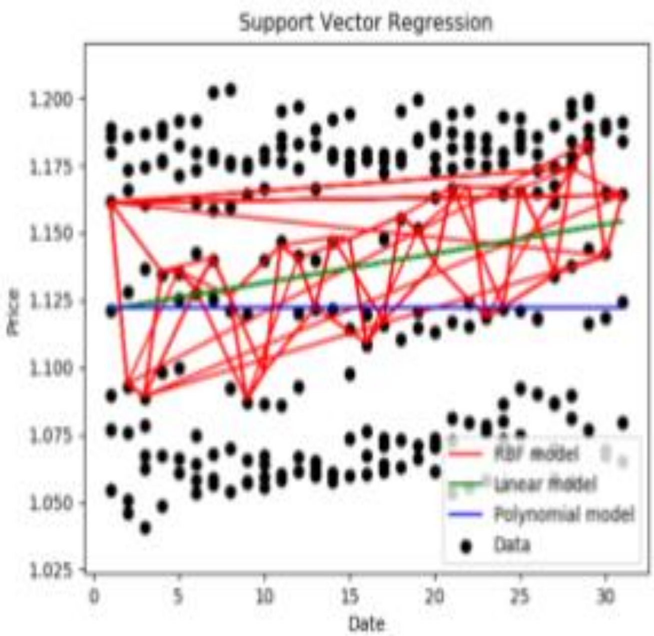

Figure.9.SVR result

Above figure.9. shows the result of SVR which consist of three models. 1) RBF model which is represented by red curve in the figure.9.and trying to go through each data points. 2) Linear model which is represented by green line and 3) Poly model represented by purple one. Our algorithm is predicting close price value for the next day i.e.1/1/2018. Our prediction for the three models is as follows:

1) RBF: 1.1837985545
2) Linear: 1.1520383033
3) Poly: 1.12205

The actual close price for the day 1/1/2018 is 1.2010.
Two more algorithms that we have implemented are LSTM and GRU. Dataset is divided into 176 rows as train_data and64 rows test_data. Below, in Table.1, we have shown last nine day's actual close prices from test_data and the corresponding LSTM and GRU predicted close prices.

Table.1. LSTM and GRU Prediction

Date	Actual Close Price	LSTM Predicted Closed Price	GRU Predicted Close Price
12/20/2017	1.1871	1.1752	1.1814
12/21/2017	1.1873	1.1754	1.1813
12/22/2017	1.1859	1.1757	1.1813
12/25/2017	1.1869	1.1761	1.1814
12/26/2017	1.1859	1.1765	1.1817
12/28/2017	1.1943	1.1773	1.1828
12/29/2017	1.1998	1.1775	1.1826
12/29/2017	1.1888	1.1782	1.1837
1/1/2018	1.2010	1.1789	1.1853

The performance metrics used are Mean Square Error (MSE) and Symmetric Mean Absolute Percentage Error (SMAPE). The MSE for LSTM and GRU are 0.00009 and 0.00011 respectively. The SMAPE for the two models are 0.66% and 0.75% respectively.

4. CONCLUSION

In this study, after comparing the predicted values obtained from the three models in SVR namely RBF, linear and polynomial, we conclude that RBF model is giving us closer value than the other models. GRU is computationally more efficient and less complex than LSTM and its performance is on par with LSTM.

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