Foreign Currency Exchange Rate (FOREX) using Neural Network

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Abstract: ***FOREX (Foreign Currency Exchange) is concerned with the exchange rates of foreign currencies compared to one another. It is needed for currency trading in the international market. One popular technique for predictions of financial market performance is Artificial Neural Networks (ANN), we proposed to do so with the back propagation algorithms. ANN is actually an information processing system that consists of a graph representing the processing system as well as various algorithms. It is able to adapt, to recognize patterns, to generalize, and to cluster or to organize data. Recently ANN can be trained to solve problems that are difficult when using conventional programming techniques or through the efforts of human beings. In order for ANN to recognize patterns in the data, it is necessary for the neural network to "learn" the structure of the data set. Learning is accomplished by providing sets of connected input/output units where each connection has a weight associated with it. The ANN learns by adjusting the weights so that the application of a set of inputs produces the desired set of outputs. Finally we proposed to show the best algorithm for FOREX prediction by comparing the effectiveness of various back propagation algorithm using Matlab neural network software as a tool.***

Keywords: FOREX, Back propagation algorithm, Training function, neural network.

1. Introduction

FOREX rates provide significant data necessary for currency trading in the international monetary markets. They are impacted by a variety of factors including economic and political events, and even the psychological state of individual traders and investors. These factors are correlated highly and interact with one another in a highly complex manner. Those interactions are very unstable, dynamic, and volatile. This complexity makes predicting FOREX changes exceedingly difficult.

The people involved in the field of international monetary exchange have searched for explanations of rate changes; thereby, hoping to improve prediction capabilities. It is this ability to correctly predict FOREX rate changes that allows for the maximization of profits. Trading at the right time with the relatively correct strategies can bring large profit, but a trade based on wrong movement can risk big losses. Using the right analytical tool and good methods can reduce the effect of mistakes and also can increase profitability.

2. Problem Statement

Problem arises in selecting the efficient method for the prediction of FOREX rate. In the research the concept of the accuracy and speed of training are explored. This aspect of performance is very important because in the real world, training a huge and complex set of data can take hours, even days, to attain results. There are many variations of back-propagation training algorithms provided in the Matlab Toolbox. So the algorithms are tested for their performance. The algorithms tested are as follows. They are Batch gradient descent, Batch gradient descent with momentum, Variable learning rate back propagation, resilient back-propagation, Conjugate gradient, Quasi-Newton and Levenberg-Marquardt.

3. Related Work

The architecture of the multi-layer feed-forward network is presented. It is most commonly used with a back-propagation algorithm. The basic type of connectivity of feed-forward networks is the connections are only to later layers in the structure. The network will use a two-layer network because, a larger and more complicated neural network can cause over-fitting which occurs when a neural network is trained to fit one set of data almost exactly but results in a very large error when new data is tested. Therefore, smaller neural networks are recommended.

3.1 Feed-Forward Networks

Feed-forward artificial neural networks allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward artificial neural networks tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

3.2 Feedback Networks

Feedback networks can have signals travelling in both directions by introducing the loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

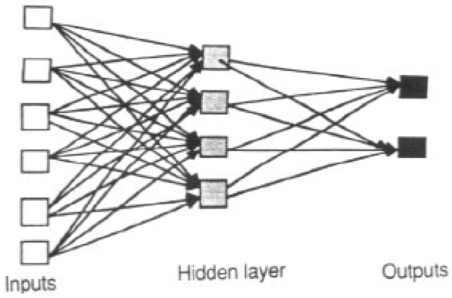

Figure 1: Artificial Neural Network

4. Proposed System

To build a neural network forecasting model, historical data are divided into three portions: training, validation and testing sets. The training set contains 70% of the collected data, while the validation and the testing sets contain 20% and 10%, respectively. If the trained model is the best one for validation and also the best one for testing, one can assume that it is a good model for future forecasting. The data are chosen and segregated in time order. In other words, the data of the earlier period are used for training, the data of the later period are used for validation, and the data of the latest time period are used for testing. The objective is to discover the underlying structure of the mechanism generating the data, i.e., to discover the relationship between present, past and future observations.

Before the training process begins, the training function must be chosen. The training process is a procedure for modifying the weights, W, and biases, b, of the network. This procedure also is referred to as a training algorithm. The choosing of a training algorithm is very important for building the best possible model for an individual problem. It impacts the accuracy of prediction and the network performance. In the research, different algorithms are tested to find the best model for each problem and to illustrate how some of them can optimize network performance

A supervised learning rule is used in which the weights and biases are modified according to the error, E, the difference between predicted target, T, and the network output, A. The formula is as follows:

$\Delta W = (T - A) P' = E P'$ (1)
$\Delta b = (T - A) = E$ (2)

In this formula, P is the input vector. The practical mean square error algorithm is used to adjust weights and biases. We want to minimize the average of the sum of these errors so that the network generates more accurate predictions. This is critical. There are many different training algorithms for feed-forward networks. It is just this variety that allows for building different models to fit individual problems to improve model performance and accuracy. The back-propagation neural network is the most frequently used in financial time series. This network uses a back-propagation algorithm. It is a gradient descent algorithm in which the networks are adjusted along the negative of a gradient of the MSE. The basic implementation of a back-propagation algorithm is that the network weights and biases are upgraded in the direction of the most rapidly decreasing MSE. One iteration of this algorithm formula is as follows:

$X(k+1) = X(k) - \alpha(k) G(k)$ (3)

Where X (k) is the current weight and bias vector. G (k) is the current gradient descent. The α (k) is the learning rate. There are two different methods to implement the gradient descent algorithm; one is incremental mode and the other one is batch mode. In the incremental mode, the gradient is calculated and weights and biases are modified after each input, and then sent into the network. In the batch mode, the gradient is computed and weights and biases are changed after all inputs are applied to the network.

5. Simulation Result

The foreign exchange rate data is a simple function approximation problem. A 1-3-1 network, with tansig transfer functions in the hidden layer and linear transfer functions in the output layer, is used to approximate the trend of the exchange rate. The training results show the gradient descent algorithm is generally very slow because it requires small learning rates for stable learning. The conjugate gradient algorithms have fast convergence performance, but function performances are not very good. The application of the Levenberg- Marquardt algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks.

Table 1: The MSE for each algorithm in the different epoch for Australia dollar versus Chinese yuan

Algorithm	60/300	120/300	180/300	240/300	300/300
GDA	0.0713	0.0305	0.0290	0.0281	0.0278
RP	0.0269	0.0213	0.0160	0.0123	0.0104
CGF	0.0285	0.0283	0.0280	0.0277	0.0273
CGP	0.0194	0.0145	0.0093	0.0075	0.0064
CGB	0.0274	0.0090	0.0065	0.0063	0.0062
SCG	0.0270	0.0228	0.0134	0.0077	0.0074
BFG	0.0057	0.0050	0.0048	0.0048	0.0048
OSS	0.0289	0.0284	0.0284	0.0283	0.0282
LM	0.0035	0.0036	0.0035	0.0035	0.0035

Table 1 shows the mean square error for each algorithm in the different iteration epoch of Australia dollar versus U.S. dollar exchange rate data training process. In the algorithm data in the first line, e.g., 50 in 50/300, the first number represents the iterations and the second number, 300, is the maximum number of epochs. From this table we can see the relationship among the algorithms.

The above table lists the algorithms that are tested and the acronyms we use to identify them.

GDA: traingda-Variable Learning Rate Back-propagation
RP: trainrp –Resilient Back propagation
CGF: traingrf – Fletcher - Powell Conjugate Gradient
CGP: traincgp-Polak-Ribiere Conjugate Gradient
CGB: traincgb-Conjugate Gradient with Powell/Beale Restarts
SCG: trainscg - Scaled Conjugate Gradient
BFG: trainfg-BFGS Quasi-Newton
OSS: trainoss-One-Step Secant

LM: trainlm-Levenberg-Marquardt

There is further illustration in Figure 2, a plot of the time required to converge versus the mean square error convergence goal. From this figure we can see that as the error is reduced, the improvement provided by the LM algorithm becomes more pronounced. Some algorithms perform very well as the error goal is reduced (e.g., CGB).

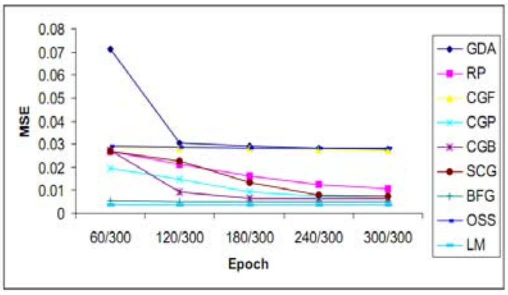

Figure 2: Performance comparison for Table 1

The performance of the various algorithms can be affected by the accuracy required of the approximation. From the above examples we find that in the LM algorithm, the error decreases more rapidly than in the other algorithms. It converges very quickly from the beginning of the training process. There are several algorithm characteristics that we can deduce from the experiments we have completed.

The Levenberg - Marquardt algorithm is best suited to deal with a function approximation problem where the network has up to several hundred weights and the approximation must be very accurate. The research area involves that type of task. The algorithm also has a very efficient Matlab implementation since the solution of the matrix equation is a built-in function; therefore its attributes become even more marked in a Matlab setting. From the application result we also found the Levenberg-Marquardt algorithm has the smallest MSE.

6. Conclusion

We finally conclude that Levenberg-Marquardt is the best training algorithm and 1-3-1 as the network structure has found to be the best performance for FOREX rate data. From the research we have provided evidence that neural networks can be used to correctly predict FOREX rates, thereby decreasing the risk of making unreasonable decisions. The back-propagation neural network was chosen for the research because it is capable of solving a wide variety of problems and it commonly is used in time series forecasting. Different kinds of algorithms and network structures are tested to find the best model for the prediction of FOREX rates. Future work is testing more parameters to increase the accuracy of the prediction, decrease the time consumed in the process and reduce memory usage.

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