Stock Market Value Prediction Using Neural Networks

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Abstract— Neural networks, as an intelligent data mining method, have been used in many different challenging pattern recognition problems such as stock market prediction. However, there is no formal method to determine the optimal neural network for prediction purpose in the literatur. In this paper, two kinds of neural networks, a feed forward multi layer Perceptron (MLP) and an Elman recurrent network, are used to predict a company's stock value based on its stock share value history. The experimental results show that the application of MLP neural network is more promising in predicting stock value changes rather than Elman recurrent network and linear regression method. However, based on the standard measures that will be presented in the paper we find that the Elman recurrent network and linear regression can predict the direction of the changes of the stock value better than the MLP.

Keywords- Stock market prediction; Data mining; neural networks

I. INTRODUCTION

From the beginning of time it has been man's common goal to make his life easier. The prevailing notion in society is that wealth brings comfort and luxury, so it is not surprising that there has been so much work done on ways to predict the markets. Therefore forecasting stock price or financial markets has been one of the biggest challenges to the AI community. Various technical, fundamental, and statistical indicators have been proposed and used with varying results. However, none of these techniques or combination of techniques has been successful enough. The objective of forecasting research has been largely beyond the capability of traditional AI research which has mainly focused on developing intelligent systems that are supposed to emulate human intelligence. By its nature the stock market is mostly complex (non-linear) and volatile. With the development of neural networks, researchers and investors are hoping that the market mysteries can be unraveled.

Artificial Neural networks inspired by human brain cells' activity can learn the data patterns and generalize their knowledge to recognize the future new patterns.

Researches on neural networks show that Neural Networks have great capability in pattern recognition and machine learning problems such as classification and regression. These days Neural Networks are considered as a common Data Mining method in different fields like economy, business, industry, and science. [6]

The application of neural networks in prediction problems is very promising due to some of their special

First, traditional methods such as linear regression and logistic regression are model based while Neural Networks are self-adjusting methods based on training data, so they have the ability to solve the problem with a little knowledge about its model and without constraining the prediction model by adding any extra assumptions. Bsides, neural networks can find the relationship between the input and output of the system even if this relationship might be very because general complicated they are approximators. Consequently, neural networks are well applied to the problems in which extracting the relationships among data is really difficult but on the other hand there exists a large enough training data sets. It should be mentioned that, although sometimes the rules or patterns that we are looking for might not be easily found or the data could be corrupted due to the process or measurement noise of the system, it is still believed that the inductive learning or data driven methods are the best way to deal with real world prediction problems.

Second, Neural Networks have generalization ability meaning that after training they can recognize the new patterns even if they haven't been in training set. Since in most of the pattern recognition problems predicting future events (unseen data) is based on previous data (training set), the application of neural networks would be very beneficial.

Third, neural networks have been claimed to be general function approximators. It is proved that an MLP neural network can approximate any complex continuous function that enables us to learn any complicated relationship between the input and the output of the system.

The idea of using neural networks for predicting problems was first expressed by Hu in 1964 which was used for weather forecasting [8]. The absence of any learning method for multi layer networks made it impossible to apply these networks to complex prediction problems. But in 1980s the back propagation algorithm was introduced for training an MLP neural network. Werbos used this technique to train a neural network in 1988 and claimed that neural networks are better than regression methods and Box-Jenkins model in prediction problems [15]. The research on neural network applications continued up to the point that all the winners of the prediction contest in Santafa institute had used neural networks [14].

In the recent decade so many researches have been done on neural networks to predict the stock market changes. One of the first efforts was by Kimmoto and his colleagues in which they used neural networks to predict the index of Tokyo stock market [10]. Mizuno and his colleagues also used neural networks to predict the trade of stocks in Tokyo stock market. Their method was able to predict with 63% precision [12]. By combining Neural Networks and genetic algorithms, Phau and his colleagues managed to predict the direction of Singapore stock market with 81% precision.

In this paper we have suggested a predictive model based on MLP neural network for predicting stock market changes in Tehran Stock Exchange Corporation (TSEC). Using this model, one can predict the next day stock value of a company only based on its stock trade history and without any information of the current market. Our experiments show that the prediction error of this model is around 1.5%.

In the following we will briefly introduce the idea of MLP neural network in the second section. The third section presents the architecture of the proposed prediction model, data preparation methods used in this research and the evaluation criteria used for the evaluation of different models. In the fourth section the experimental results of the simulations on a company's data will be analyzed using different models. Finally the fifth section concludes the papers describing the future works of the study.

II. NEURAL NETWORKS

The idea of neural networks was first inspired by human beings nervous system which consists of a number of simple processing units called neuron (figure 1). Each neuron receives some signals from outside or from other neurons and then by processing them in activation function produces its output and sends it to other neurons. Each input impact is different from other inputs. For example in figure two the impact of the i^{th} neuron on j^{th} neuron is shown with w_{ij} , the weight of the connection between neuron i and j.

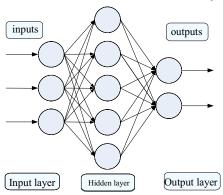


Figure 1: Architecture of a feed forward MLP

Consequently the more is the weight w_{ij} the stronger would the connection be and vice versa.

In this paper, we focus on feed forward multi layer neural networks. These networks are made of layers of neurons. The first layer is the layer connected to the input data. After that there could be one or more middle layers called hidden layers. The last layer is the output layer which shows the results. In feedback networks in contrast with recurrent networks all the connections are toward the output layer. Figure one shows a three layer feed forward Perceptron network.

One of the learning methods in multi layer Perceptron Neural Networks is the error back propagation in which the network learns the pattern in data set and justifies the weight of the connections in the inverse direction respect to the gradient vector of Error function which is usually regularized



Figure 2: Perceptron neuron's connections

sum of squared error. The back propagation method picks a training vector from training data set and moves it from the input layer toward the output layer. In the output layer the error is calculated and propagated backward so the weight of the connections will be corrected. This will usually go on until the error reaches a pre defined value. It's proved that we can approximate any continuous function with a three layer feedback network with any precision. It should be said that the learning speed will dramatically decrease according to the increase of the number of neurons and layers of the networks.

III. THE SUGGESTED NEURAL NETWORK

In spite of all the features mentioned for neural networks, building a neural network for prediction is somehow complicated. In order to have a satisfactory performance one must consider some crucial factors in designing of such a prediction model. One of the main factors is the network structure including number of layers, neurons, and the connections. Other factors to be considered are the activation functions in each neuron, the training algorithm, data normalization, selecting training and test set and also evaluation measurements.

In the suggested model two neural networks, a multilayer Perceptorn feed-forward and an Elman recurrent are used and the back propagation algorithm is used to train these networks.

The inputs to the neural networks are the lowest, the highest and the average value in the d previous days. Other information available about the stock market is not used because our goal is to predict the value of the stock share only based on the stock value history. In other words, the

proposed model can be viewed as a time series prediction model.

This model uses a three layer neural network in which the input layer has 3d neurons which get the lowest, the highest and the average stock value in the last d days. In the hidden layer there are h neurons which are fully connected to the input and output layers. There is one neuron in output layer which predicts the expected stock value of the next day of the stock market.

A. Data Preparation

In this paper the lowest, the highest and the average value of the stock market in the last d days are used to predict the next day's market value. The stock market data have been extracted from Tehran Stock Market website. In this method in contrast with other methods the disorders in the market caused by social or political reasons are not omitted from the data set because we want to predict the value based on the value history. The simulation data was extracted in 2000 to 2005. In this period of time 1094 companies' shares were traded in Tehran Stock Market. The data used as input to the system are the lowest, the highest, and the average value in the last d days (d= {1, 2,..., 10}). The prediction system predicts the next day's value using the above data.

In neural networks applications the input data is usually normalized into the range of [0, 1] or [-1,1] according to the activation function of the neurons. So in this paper the value of the stock market is normalized into the range of [-1, 1] using the (1) and then the neural networks are trained and tested using the back propagation algorithm.

$$price = \frac{2 \times price - \left(Max_{\text{Pr}ice} + Min_{\text{Pr}ice}\right)}{Max_{\text{Pr}ice} - Min_{\text{Pr}ice}}$$
(1)

B. Evaluation criteria

In prediction problems general criteria like mean absolute deviation, mean absolute percentage error, mean squared error, and root mean squared error are calculated based on (2, 3, 4, 5). These criteria are preferred to be smaller since they indicate the prediction error of the system.

In addition to the above criteria three other measures are used to compare stock value prediction methods. The correct forecast trend measure shows the percentage of correct

$$MAD = \frac{1}{|ValidationSet|} \sum_{e,v,t} \left| price_{forecast}^{tomorrow} - price_{real}^{tomorrow} \right|$$
 (2)

$$MAPE = \frac{1}{|ValidationSet|} \sum_{\text{for all days } \in ValidationSet} \left| \frac{price_{\text{forecast}}^{\text{tomorrow}} - price_{\text{real}}^{\text{tomorrow}}}{price_{\text{real}}^{\text{tomorrow}}} \right| (3)$$

$$MAD = \frac{1}{|ValidationSet|} \sum_{for\ all\ days\ \in\ ValidationSet} |price_{forecast}^{tomorrow} - price_{real}^{tomorrow}| \qquad (2)$$

$$MAPE = \frac{1}{|ValidationSet|} \sum_{for\ all\ days\ \in\ ValidationSet} |\frac{price_{forecast}^{tomorrow} - price_{real}^{tomorrow}}{price_{real}^{tomorrow}}| \qquad (3)$$

$$MSE = \frac{1}{|ValidationSet|} \sum_{for\ all\ days\ \in\ ValidationSet} (price_{forecast}^{tomorrow} - price_{real}^{tomorrow})^{2} \qquad (4)$$

$$RMSE = \sqrt{\frac{1}{|ValidationSet|}} \sum_{for\ all\ days\ \in\ ValidationSet} (price_{forecast}^{tomorrow} - price_{real}^{tomorrow})^{2} \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{|ValidationSet|}} \sum_{\text{for all dimer Substitution SS}} \left(price_{\text{forecast}}^{\text{fomorrow}} - price_{\text{read}}^{\text{fomorrow}} \right)^{2}$$
 (5)

prediction of the changes in n+1th day relative to nth day (6). When the prediction is completely random this number would be around 0.5. As a result, in order to have a reliable prediction method this feature should be at least above 0.5.

Although knowing the direction of the changes is an important factor for decision making, we also need to know the amount of the changes. There will be two other criteria to determine the ratio of correct forecast trend to the real trend of stock changes (7) and the ratio of incorrect forecast trend to the real trend of stock changes (8). In the Ideal case, the predicted ratio of correct forecast trend to the real stock changes in (7) should be equal to one. In addition, if the quantity of this ratio is smaller (or greater) than one, it will indicate that the direction of the changes is predicted correctly while the amount of changes has been predicted less (or more). In the other hand, when the direction of stock changes is predicted incorrectly, the quantity of the (8) is desired to be closer to one as much as possible which shows the prediction error is minimum in this case.

IV. SIMULATION RESULTS

In this section the prediction results of the two suggested methods using multi layer Perceptron neural networks and Elman recurrent network are compared to linear regression method results.

The training algorithm in multi layer neural network is Levenberg-Marquardt back propagation which can train any neural networking using differentiable activity functions. In this kind of error back propagation algorithm we use both the gradient and the Jacobean of the performance measure (error function) of the training set respect to the connection weights, to justify the network weights [9, 11].

$$Correct Forecast Trend = \frac{1}{|ValidationSet|} \sum_{for \ all \ days \ e \ ValidationSet} \sum_{for \ east} T(price^{tomorrow}, price^{today})$$

$$T(price^{tomorrow}_{forecast}, price^{today}_{forecast}) = \begin{cases} 1 & if \ (price^{tomorrow}_{forecast} - price^{today}_{real}).(price^{tomorrow}_{real} - price^{today}_{real}) \ge 0 \end{cases}$$

$$0 & otherwise$$

$$(6)$$

$$\frac{Correct \ Forecast \ Trend}{\text{Re al Trend}} = \frac{1}{|ValidationSet|} \sum_{\text{for all days} \in ValidationSet} \frac{price_{forecast}^{lomorrow} - price_{real}^{loday}}{price_{real}^{lomorrow} - price_{real}^{loday}}$$

$$\frac{Incorrect \ Forecast \ Trend}{\text{Re al Trend}} = \frac{1}{|ValidationSet|} \sum_{\text{for all days} \in ValidationSet}} \left[1 + \frac{|price_{forecast}^{lomorrow} - price_{real}^{today}|}{|price_{real}^{lomorrow} - price_{real}^{today}|} \right] \tag{8}$$

$$\frac{Incorrect\ Forecast\ Trend}{\text{Re}\ al\ Trend} = \frac{1}{|ValidationSet|} \sum_{\text{for all days} \in ValidationSet} \left[1 + \frac{|price^{tomorrow} - price^{today}|}{|price^{tomorrow} - price^{today}|} \right]$$
(8)

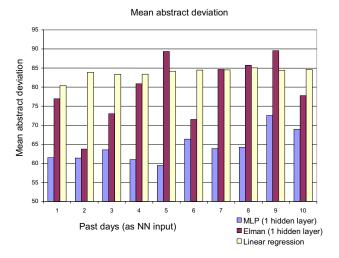


Figure 2. comparing minimum abstract deviation (MAD) in Elman and MLP

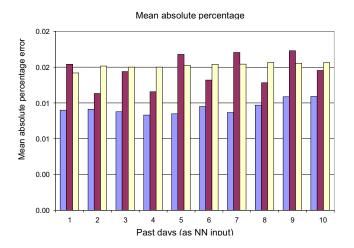


Figure 3. comparing mean absolute percentage error (MAPE) in Elman and MLP

On the other hand, to train Elman network, the error back propagation with momentum and adaptive learning rate is used. This algorithm like Levenberg-Marquardt has the capability to train any network using differentiable activity functions. The weights of the network in this algorithm are adjusted according to Gradient decent (with momentum) based on the (9) in which mc is the momentum, d_{Xprev} is the previous change in the network weights and lr is the learning rate.

$$d_X = mc \times d_{Xprev} + lr.mc. \frac{d_{pref}}{d_X}$$
 (9)

In each epoch if the performance measure (Mean squared error) is moving toward its goal value, the learning rate will

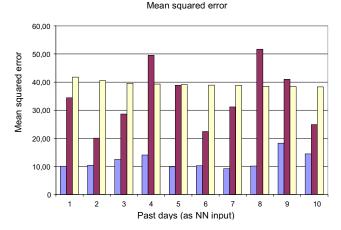


Figure 4. comparing mean squared error (MSE) in Elman and MLP.

increase (in this simulation $lr_inc=1.05$). On the other hand if the performance measure increases more than a threshold $(max_perf_inc=1.04)$, leaning rate will decrease with the rate of lr_dec (in this simulation $lr_dec=0.7$) and the related change which has increased the performance measure, will not be applied to the network weights.

When one of the below happens the algorithm will stop.

- The training epochs reach its maximum (in this simulation 1000 epochs).
- The performance measure reaches its goal. (MSE=10to-6)
- The gradient of the performance measure gets under a threshold. (10to-6)

In the following the results of these two methods are going to be compared to the result of the linear regression method. In figure 3, 4, and 5 it's clearly shown that the MLP Neural Network has less MSE, MAPE, and MSE comparing to Elman and linear regression though this method cannot predict the direction of the changes as well as Elman and regression (figure 6). However the linear regression method predicts the direction of the changes well (figure 6), the error in the prediction of the value is much more than multilayer Perceptron and Elman (figure 7). The Elman network can predict the direction of the changes better than multilayer Perceptron (figure 6) but suffers from greater error in prediction (figure 7).

V. CONCLUSIONS

In this paper we used neural networks model to predict the value of stock share in the next day using the previous data about stock market value. For this purpose two different well known types of neural networks were applied to the problem. The obtained results show that for predicting the direction of changes of the values in the next day none of these methods are better than simple linear regression model. But the error of the prediction of the amount of value changes using MLP neural network is less than both Elman network and linear regression method. In addition to this, when the feed forward MLP neural network predicts the direction of the changes correctly, the amount of change is



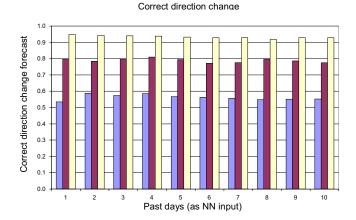


Figure 5. Maximum number of correct change direction forecast in Elman and MLP.

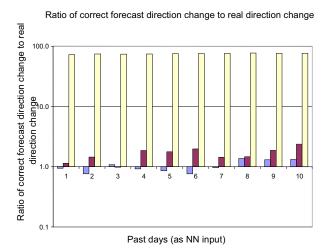


Figure 6. Ratio of correct forecast of direction change to real direction change in Elman and MLP.

completely close to the real one in comparison to the other two mentioned methods. In future works of this study we are going to apply other recently proposed regression methods such as Support Vector Regression models which is newer in the field of machine learning researches and claimed to have good generalization ability due to application of large margin concept.

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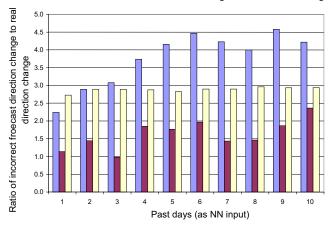


Figure 7. Ratio of incorrect forecast of direction change to real direction change in Elman and MLP.

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