FINANCIAL FORECASTING USING NEURAL NETWORKS
Neironu tīklu izmantošana finansu prognozēšanā

A. Zorins
Rezekne Higher Educational Institution
Atbrivosanas al. 90, Rezekne, LV-4600, LATVIA
E-mail: alex@ru.lv

Abstract
This paper presents an application of neural networks to financial time-series forecasting. No additional indicators, but only the information contained in the sales time series was used to model and forecast stock exchange index. The forecasting is carried out by two different neural network learning algorithms – error backpropagation and Kohonen self-organising maps. The results are presented and their comparative analysis is performed in this article.
Keywords: *neural networks, backpropagation, Kohonen network, financial forecasting.*

Introduction

Neural networks are very sophisticated modelling techniques, capable of modelling extremely complex functions. In particular, neural networks are non-linear. For many years linear modelling has been the commonly used technique in most modelling domains, since linear models had well-known optimisation strategies. Where the linear approximation was not valid (which was frequently the case) the models suffered accordingly. Neural networks also keep in check the curse of dimensionality problem, which bedevils attempts to model non-linear functions with large numbers of variables.

Neural networks have seen an explosion of interest over the last few years, and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology and physics [2, 4]. Indeed, anywhere that there are problems of prediction, classification or control, neural networks are being introduced.

This paper examines a task of forecasting the stock exchange index. In the paper, well-known error back-propagation algorithm and Kohonen self-organising maps carry out forecasting this factor. The back-propagation algorithm has been widely implemented in forecasting tasks, especially, in finance and economics. Kohonen neural networks or self-organising maps have been used mostly in classification tasks, for example, pattern recognition and others. Financial forecasting by these networks is quite new and unexplored.

The above mentioned prediction methods are investigated and their comparative analysis is performed on the basis of the results of the Dow Jones RSE index forecasting for the Riga Stock Exchange. The paper is organised as follows: section 2 provides information about neural networks, section 3 describes implementation of Kohonen self-organising maps in financial forecasting and section 4 describes comparative experiments, which test the performance of the proposed approaches.

Error back-propagation algorithm

This part of the paper describes the main idea of the error backpropagation algorithm. Neural network typically consists of many simple neurone-like processing elements that are grouped together in layers (see Fig. 1). Each unit has activity level that is determined by the input received from the other units in the network (input neurones) [4, 5].

ISBN 9984 – 585 – 68 – 9

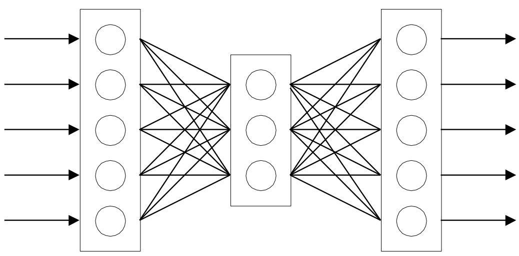

Fig. 1. Neural network with one hidden layer

Information is processed in each unit by computing a dot product between its input vector (o_j) and its weight vector (w_{ij}):

$$x_i = \sum_{j}^{n} o_j w_{ij} \tag{1}$$

This weighted sum x_i is then passed through a sigmoid squashing function to produce the state of unit *i*, denoted by o_i. The most common squashing functions are the Sigmoidal and the Hyperbolic Tangent. We consider squashing function defined by (2):

$$f(x) = k + \frac{c}{1 + e^{Tx}} \tag{2}$$

where *k*, *c* and *T* are constants. Before training, the weights are initialised with small random values. Training the network to produce a desired output vector involves systematically changing the weights until the network produces the desired output (within a given tolerance). This is repeated over the entire training set. Each connection in the network computes the derivative, with respect to the connection strength, of a global measure of the error in the performance of the network. The connection strength is then adjusted in the direction that decreases the error. The error measure is given by *E* in:

$$E = \frac{1}{2} \sum_{j}^{n} (y_j - d_j)^2 \tag{3}$$

where y_j is the actual state of the output unit *j* in input – output case, and d_j is the desired state.

Learning is thus reduced to a minimisation procedure of the error measure given in (3). This is achieved by repeatedly changing the weights by an amount proportional to the derivative $\partial E/\partial W$, denoted by δ_i.

$$\Delta W_{ij}(t+1) = \lambda \delta_i y_{ij} \tag{4}$$

The learning rate λ (the fraction by which the global error is minimised during each pass) is kept constant at least for the duration of a single pass. The value of $\delta_i = \partial E/\partial W$ is computed by differentiating (2) and (3):

$$\delta_i = (d_j - y_j) f'(y_j) \tag{5}$$

ISBN 9984 – 585 – 68 – 9

In the limit, as λ tends to zero and the number of iterations tends to infinity, this learning procedure is guaranteed to find the set of weights that gives the Least Mean Square Error [1].

Kohonen self-organising maps

The self-organising neural networks assume a topological structure among the cluster units. This property is observed in the brain, but is not found in other artificial neural networks. There are m cluster units, arranged in a one- or two-dimensional array: the input signals are n-dimensional.

The weight vector for a cluster unit serves as an exemplar of the input pattern associated with that cluster. During self-organisation process, the cluster unit whose weight vector matches the input pattern most closely (typically, the square of the minimum Euclidean distance) is chosen as the winner. The winning unit and its neighboring units (in terms of the topology of the cluster units) update their weights. The weight vectors of neighboring units are not, in general, close to the input pattern.

The architecture and algorithm that follow for the net can be used to cluster a set of p continuous-valued vectors $x=(x_1, x_2, \ldots, x_n)$ into m clusters. Complete description of the Kohonen learning algorithm can be found in [3].

The qualities of self-organising maps make it ideally suited for index prediction strategies. The supervised approach is based on grouping patterns that produce the same change in price. An output neuron is assigned to each range of price changes to be identified, including two neurons to represent greater than a maximum and less than a minimum (see Fig.2).

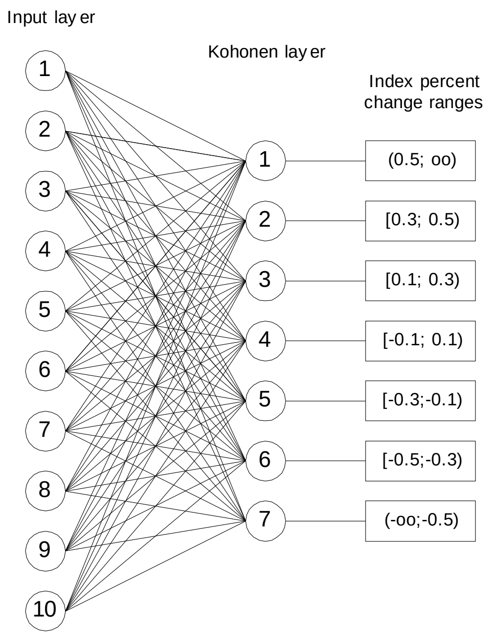

Fig.2. Self-organising map for index prediction

As shown in the figure, the net will classify all of the patterns that fit into the predefined ranges by forcing the appropriate neuron to be the winner. Also included is a neuron that represents the unchanged or, more accurately, almost unchanged state. After the Kohonen network training process is completed, new patterns can be presented to the network and the corresponding output neuron will be active.

ISBN 9984 – 585 – 68 – 9

Experimental results

The data set consists of a total of 276 data points, which represent the index values between 1 October 2001 and 31 October 2002. This data set is further divided into two parts: a training data set from the beginning till 1 October 2002 and a test set from 1 October till 31 October 2002.

The first forecasting model is error back-propagation neural network. The accuracy of the approximation depends on a number of factors such as the network structure, learning method and training parameters. In this study, learning is done by error back-propagation algorithm using Statistica Neural Networks 4.0 software. The results depend very much on the input layer size. After a number of the experiments the final parameters of the neural network with the best performance for the DJ RSE index are as follows:

- learning constant and momentum have the same value 0.1 (here is better to use relatively small values because they give minimal learning error);
- squashing function is defined by (2);
- network architecture is 32-15-1, which means 32 input layer neurones, 15 hidden layer neurones and 1 output neurone (less complicated architecture can not deal with given kind of time series);
- weight initialisation range from 0 to 0.01.

The Kohonen network consists of 15 input units and 7 clustering units. Here prediction is made as an interval of index changes. Therefore it is difficult to compare the prediction results of two methods. It is possible to give only errors for both methods. Fig.3 gives back-propagation network results on the training set (solid line gives actual values and dashed line is prediction).

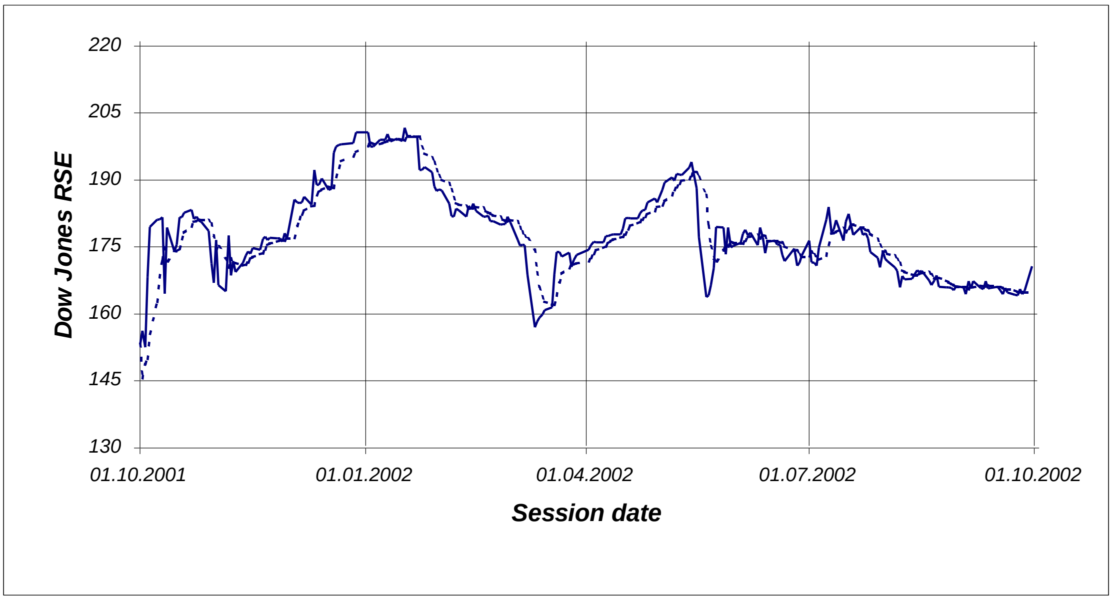

Fig.3. Back-propagation network performance on the training set (MSE=22.56)

The performance of Kohonen self-organising map can be summarised as follows: the training set input vectors were correctly classified in 87% cases, while on the test set the correctly classified index changes rate is only 75%.

ISBN 9984 – 585 – 68 – 9

Conclusions

This paper gives an example of neural network implementation to financial forecasting task. The error back-propagation networks and Kohonen self-organising maps give different results and we cannot compare them, but it is also possible to use extended and updated version of these two algorithms – counterpropagation networks, which can be used as for classification as well as for time series prediction task. The main advantage of Kohonen networks is the ability to organise the neurons in clusters, which corresponds to required number of states. The back-propagation algorithm can be considered as “universal” one, it is also rather easy to use. These networks combine advantages of both earlier mentioned networks and allow overcoming their shortages.

The future work will be connected with the further study of possible ways of forecasting accuracy improvements as well as with counterpropagation network implementation possibilities for financial forecasting.

References

1. Anderson O. D. (1976). Time Series Analysis and forecasting. Butterworths, Londod and Boston, 182 p.
2. Baestaens D. E., Van den Bergh W. M. (1995). Tracking the Amsterdam Stock Index Using Neural Networks. Neural Networks in Capital Markets, Vol. 5. P. 149-161.
3. Fausett L. (1994). Fundamentals of Neural Networks. Architectures, algorithms and applications. Prentice Hall, New Jersey, 560 p.
4. Refenes A. N., Azema-Barac M., Chen L., Karoussos S. A., (1993). Currency Exchange Rate Prediction and Neural Network Design Strategies. Springer-Verlag, London Limited. P. 46 – 58.
5. Zurada J. M. (1992). Introduction to Artificial Neural Systems. St. Paul: West Publishing Company, 684 p.

ISBN 9984 – 585 – 68 – 9