ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ В ЕКОНОМІЦІ

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APPLICATION OF NEURAL NETWORKS TO PREDICTION OF COMPANY FUTURE DEVELOPMENT

Abstract. *Application of neural networks to prediction of company future development is much more conceivable now than before. Exploitation of data is one of the most important parts of possible prediction of company development. There are a lot of possibilities how to apply such data and what particular neural network to chose. Development of neural networks dates from 1943 when Perceptron was described and a lot of neural networks have been developed since then. New hybrid neural networks, which are often more accurate than only single-layer and multi-layer networks are being developed even now. The way how they can learn and assess data is substantial for their application in economy.*
Keywords: *Neural networks, Multi-Layered Perceptron, Imperialistic Competition Algorithm, Kohonen Self-Organizing Map, Prediction, Bankruptcy.*

Introduction

We are able to solve complicated problems like prediction in insurance and banking, identification of radar data, detection of explosives at airports, consignment sorting according to zip codes and many more by means of neural networks nowadays. Neural networks are frequently used for so called data mining, particularly in economy, where prediction of company future may be based on data from the past.

«A structure for distributed parallel processing of data consisting of a certain, usually very high number of interconnected processing elements can be generally considered an artificial neural network. Each of the processing elements can simultaneously receive any finite number of various input data. It can transfer any finite number of equivalent data on the status of a single, however plentifully branched output to other processing elements. Each processing element transforms input data to output data according to a certain transfer function. The content of its local memory can also be applied within that» [11].

Neural networks are basically classified under single-layer networks like Perceptron, Hopfield network, Kohonen network and multi-layer networks like ML-perceptron, GMDH (Group Method of Data Handling), Neocognitron, RBF network (Radial Basis Function) and ART (Adaptive Resonance Theory) network.

Prediction by means of neural networks and their best advantage is their ability to learn from examples and to express non-linear dependences, however estimation of error size or definition of reliability interval is impossible. The prediction character is based on the available data:

– single timeline,

– single line with additional information:

a) derivative course,

в) intervening variables,

– several mutually similar timelines (information on companies from the same sector),

– special selection of parameters [11].

Finally we need quality software (e.g. STATISTICA, MATLAB) but hardware as well for simulation of neural networks with regard to collection of the data we want to analyse.

1. Materials and Methods

A neural network consists of a combination of several neurons, where a neuron is a processor unit playing an important role for operation of an artificial neural network. Figure 1 shows what a neuron consists of (weight w, activating function *f* or distortion b). The neuron output is calculated from the equation:

$$a = f(b + \vec{w} * \vec{p})$$

where p is the input vector (r is the input vector dimension), w is the line vector of weight, b is the distortion value, *f* is the activation function and a is the output neuron (Sajad Abdipour 2013, [1]).

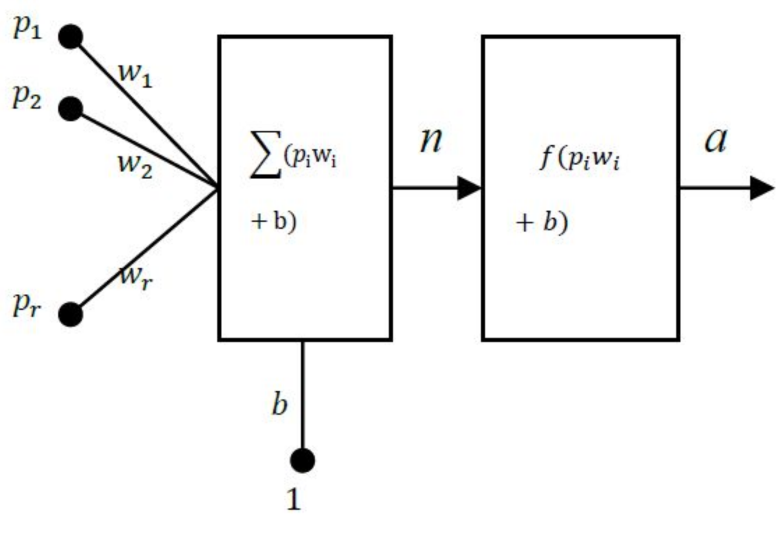

Figure1 – Neural neuron

Source: Abdipouret al. (2013) [1].

2. Why are artificial neural networks used for prediction

Artificial neural networks (Lipmann, 1987, [4]) are information processing systems used for simulation of human thinking. This thinking is based on the human brain function and activity, where historic data and paradigms of these data are used for learning. They have the following properties:

– they learn the relations between inputs and outputs;
– they are resistant enough to cope with data noises;
– they have a good ability to generalize. Unless they have not faced an exact example yet, they are able to estimate well;
– they are able to learn highly non-linear relations;
– they do not create any assumptions for further redistribution of training data.

3. The beginnings of neural networks

The development of neural networks is relatively long, however a high number of partial operations working without an algorithm enabling a neural network to adapt itself to solution of a particular problem is the most important ability. These are the basic neural networks:

– McCulloch, Pitts (1943) – Perceptron, Formal Neuron;
– Hebb (1948) – Hebb learning;
– Rosenblatt (1958) – Rosenblatt Perceptron;
– Widrow, Hoff (1960) –ADALINE (Adaptive Linear Neuron);
– Widrow (1962) – MADALINE (Multiple Adaptive Linear Element);
– Ivachněnko (1968) – GMDH (Group Method of Data Handling);
– Minsky, Papert (1969) – book: Perceptrons;
– Fukushima (1978) – Neocognitron;
– Grossberg (1980) – ART (Adaptive Resonance Theory);
– Hopfield (1982) – Hopfield Network, Energetic Function;
– Kohonen (1982) – SOM (Self-Organizing Maps);
– Kirkpatrick (1983) – Simulated Annealing;
– Ackley, Hinton, Sejnovski (1985) – BoltzmannMachine;
– Parker, Le Cun (1985) – Backpropagation;
– Bromhead, Lowe (1988) – RBF (Radial Basis Function).

4. Results

Evidence of the use of artificial neural networks can be found in articles by authors like Luther (1998) [7], Nasiret al. (2000) [8], Shah and Murtaza (2000) [10], Anandarajan et al. (2001) [2], Mehrazin et al. (2013) [6], which try to predict the future development of companies in comparison with singe-dimensional analyses, multiple discrimination analyses or probability conditioned models and the often compare the individual models of neural networks with modern hybrid neural networks.

Abdipouret al. (2013) [1] try to determine which of the neural network is the most reliable in bankruptcy prediction. For comparison they chose Kohonen's – Self-Organizing Map anda hybrid neural network MLP – ICA (Multi-Layered Perceptron) – (Imperialist competitive algorithm).

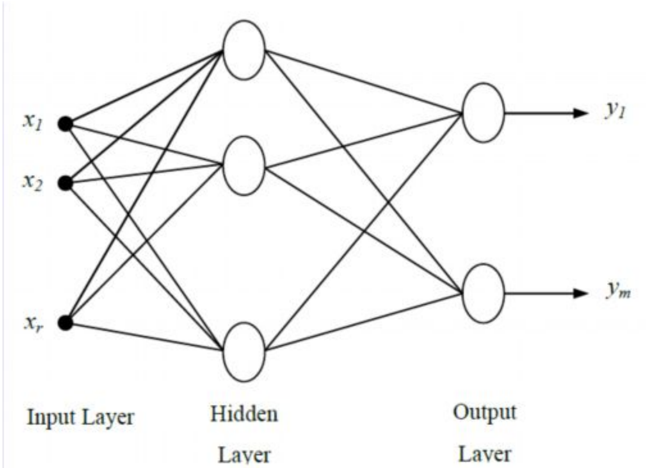

Figure 2 – A Multi-Layered Perceptron

Source: Abdipour at al. (2013) [1].

MLPcan be expressed by the formula:

$$y = f_{out}(\vec{b}_{out} + f_h(\vec{b}_h + \vec{p}W_h)W_{out})$$

where p is the input vector, b_h is the preferred hidden layer, b_{out} is the output layer, W_h is the weight of the matrices in the hidden layer and W_{out} is the output layer weight, his the activation function of a neuron in the hidden layer and out the activation function of a neuron in the output layer and y is the network output vector.

The activation function uses the tangsig function in the middle layers, calculated as follows:

$$Y_i = \frac{2}{(1 + \exp(-2X_j)) - \mathbf{1}}$$

Sum of squared error is the performance indicator in training, i.e. the weight of matrices and preferred vectors should be updated to minimize the mean square error. See the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (T - Out_{Net})^2$$

Imperialist competitive algorithm (ICA) is a new algorithm in the field of evolution computations population-based on stochastic algorithm. The algorithm is inspired by imperialistic competition. It tries to present imperialistic social policy, to control more countries and to use their sources in which the colonies usually dominate.

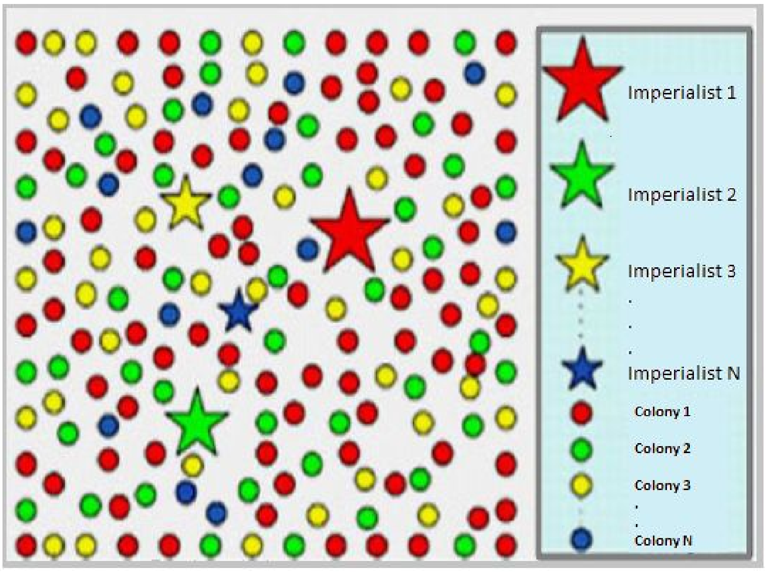

Figure 3 – Generating the initial empires

Source: Rajabioun at al. (2008) [7].

We understand from fig. 3 that the bigger the empire the higher the opportunity to own more colonies. The best countries are always chosen so as neural networks can be used as weight, this optimization process continues until the required accuracy level is reached. However other closing conditions like a definite number of iterations cannot be used.

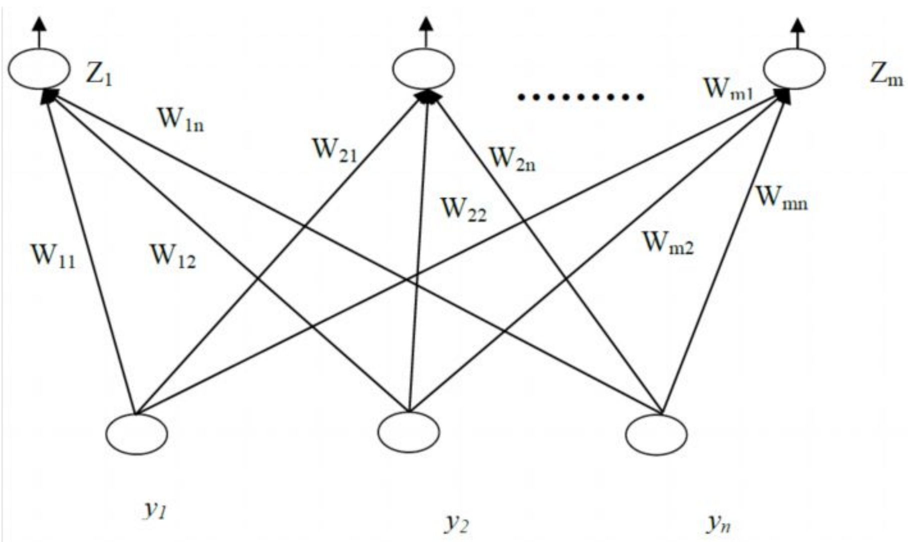

Figure 4 – Kohonen's Self-Organizing Map (KN)

Source: Abdipour at al. (2013) [1].

One-dimensional KN with input $y = (y_1, y_2, \ldots y_n)T \in Rn$ and output $z = (z_1, z_2, \ldots z_m)T \in Rm$. For the output neuron the ziis given by the formula:

$$z_i = \sum_j {}_{=1}^{n} w_{ij} y_i = w_i^T y$$

Where ij is the weight of w_{ij} and $w_i = (w_{i1}, w_{i2}, \ldots w_{in})T$ where i is vector weight. The output vector that is first determined for comparison of similarity between the input y and the weight of the vectors $\{w_i, i = 1, \ldots, m\}$ is the training winner. The weight of the vector of the winning neuron is then updated.

The common rate of similarity between the two vectors is Euclidean distance:

$$\prod_i = \|y - w_i\|^2$$

Where i is the intensity. Weights of vectors according to KN are updated as follows:

$$w_i^{new} = w_i^{old} + \eta\left(y - w_i^{old}\right)\delta_i, \qquad i = 1, \ldots, m,$$

Where η, $\eta > 0$ is the learning rate and δ_i is the unit for the winning neuron, which has the lowest $\prod_i$, otherwise it is zero. The learning algorithm is reduced:

$$w_i^{new} = (1 - \eta) w_i^{old} + \eta y$$
$$w_i^{new} = w_j^{old}, \qquad j = 1, \ldots, m, \qquad j \neq i$$

5. Discussion

Abdipour at al. (2013) [1] tested the data by means of the following financial ratios:
– working capital/total assets,
– retained earnings/total assets,
– earnings before interest and taxes/total assets,
– exchange value equity/book value of total debt,
– sales/total assets.

The data the authors used for analysis are financial ratios of two years before bankruptcy of bankrupt companies and selection of healthy pairs. The classification is divided into two definition classes, 0 shows healthy companies and 1 shows bankrupt companies.

The example herein presented is a study based on information from 141 articles from the Iranian Commercial Bankruptcy Law and companies active at the Teheran Stock Exchange in the period 2001-2009. The authors present a lack of healthy companies in some smaller sectors and identification of a suitable par as a drawback. They compensated for the drawback with healthy companies of the previous and the succeeding sectors.

Table 1 – The results obtained from testing KN and MLP-ICA networks

Model	Sum of prediction	Status	The number of correct predictions	The number of correct predictions	The errors type 1 and 2	The percentage of correct predictions	The error type 1 or 2
MLP-ICA	28	healthy	14	12	2	85.71%	14.29%
		bankrupt	14	11	3	78.57%	21.43%
		total	28	23	5	**82.14%**	**17.86%**
KN	28	healthy	14	10	4	71.42%	28.58%
		bankrupt	14	11	3	78.57%	21.43%
		total	28	21	7	**75%**	**25%**

Source: Abdipour at al. (2013) [1]

The results show that the application of neural networks has relatively good percentage expression of classification accuracy, however with regard to the total results the performance of the MLP-ICA network, where the prediction is accurate in 82.14% is more precise compared to the KN, where the prediction accuracy is 75%. The difference in prediction reliability between the individual neural networks is 7.14%.

Conclusion

As mentioned in the introduction neural networks have wide application and they are more and more frequently used for bankruptcy prediction as they are more accurate than the obsolete one-dimensional analyses, multiple discrimination analyses or probability conditioned models. Neural networks are so popular for their ability to learn the relations between inputs and outputs, they are particularly resistant thanks to their ability to cope with data noises, they have good ability to generalize, they are able to learn highly non-linear relations and they do not create any conditions for further redistribution of training data. Neural networks are still developing and the new hybrid neural networks like MPL-ICA are much more accurate in data testing performance.

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