ISSN 2413-1032

THE NEURAL NET APPROACH TO THE HARD TO FORMALIZE TASKS OF ANALYSIS AND PREDICTION

Abdiev Bolat,
Madiyarova Kuralay,
Ezhebekov Manat

Turar Ryskulov New Economic University

Abstract. *The article discusses the use of neural networks and attempt to reveal the peculiarities of the different types of neural networks in the context of their application for the solution of difficult problems in formalized tasks, as well as how to improve the accuracy of forecasting financial performance, including securities prices. In particular, it discussed in more detail one of these models as a model of so-called self-organizing feature maps of Kohonen.*

Keywords: *neural networks, self-organizing map, securities prices, multilayer network Kohonen.*

One of the topical and perspective trends of automation to solve hard to formalize tasks is to apply the artificial intellect technologies. Among these trends in the sphere of artificial intellect one can note neural networks. They have specific characteristics that allow overcoming difficulties which arise at using the classical methods in practice. To these characteristics we refer: a possibility to learn and adapt; account of qualitative data that is hard to formalize; an ability to account arbitrarily large number of factors; universality.

In spite the fact that neural networks have proved positive in solving tasks of numerous human activity the issues of their effective use to process and analyze financial information, to create neural network models of finance processes, to solve the tasks of predicting and classification are not studied well yet.

Using neural networks in our case is an attempt to reveal the peculiarities of functioning of different types of neural networks in the context of their applying to solve difficult to formalize tasks and to increase the accuracy of predicting the financial indices and securities quotation in particular.

One of the models called as self-organizing maps of Kohonen is studied in detail [1].

As any other model it is to be given a qualitative description of processes that take place in the central nervous system that is a model of computing maps (indications) in particular.

The model of self-organizing maps indices describes the network that after the period without training («without a teacher») can be considered as a map consisting of the elements every of which can be a detector of some subset from the training image space where these detector location in the network is not accidentally but it correlates some project of the images space on the networks surface and this project preserves the topological characteristics of the images space. The Kohonen network consists of an elements set that compose M – a measure grid. Every element of the network receives as an input one and the same vector of the image indicators $\vec{x}(t) = \{x^i(t)\}$, $i = \overline{1, N}$. Every element of the network $u(\vec{n})$ is characterized by their own coefficient set of links by which the signal comes $\vec{x}(t)$: $\vec{m}(\vec{n},t) = \{m(\vec{n},t)\}$, $i = \overline{1, N}$. The value of the element reaction $u(\vec{n})$ to the input vector of indicators $\vec{x}(t)$ is calculated as a distance between these vectors in some metrics ρ.

The algorithm of the network formed consists of two consecutive steps:

The initial values $m(\vec{n}, 0)$ are chosen at random. Where $t>0$ let $\vec{x}(t)$ – another input vector of the indicators, while:

1. The coordinates $\vec{n}^*(t)$ of such element of the network are evaluated,

$$u(\vec{n}^*(t), t), \text{ that: } \vec{n}^*(t) = \arg\min_{\vec{n}} \rho(m(\vec{n},t), \vec{x}(t)) \quad (1)$$

2. For every $\{u(\vec{n}): \rho(\vec{n}, \vec{n}^*(t)) \le r(t)\}$:

$$\vec{m}(\vec{n},t+1) = \vec{m}(\vec{n},t) + \alpha(t+1)(\vec{x}(t) - \vec{m}(\vec{n},t)) \quad (2)$$

The parameters r (t) and α (t) are supposed to be chosen so that the process convergence is provided, in particular r(t) $\to$ 0, α (t) $\to$ 0. The algorithm characteristics as an image classificatory are conditioned by the following features. Choosing the parameter α (t) so that α (t) $\to$ 0 $\sum_{t=0}^{\infty}\alpha(t) = \infty$, $\sum_{t=0}^{\infty}\alpha^2(t) < \infty$ and in the assumption that the link coefficient subset $\vec{m}(\vec{n},t)$ is done by the training image sequence $\vec{x}$ (t) which re chosen from the image space at random the links $\vec{m}(\vec{n},t)$ are formed so that the neural network can be considered as a specified net function or map for an equal approximation function of probability density of the components vector shared distribution $\vec{x}$ (t) in the assumption that the such exists. To clarify this assumption we can do as follows. If the element u($\vec{n}^*$), where $\vec{n}^*$ (t) = $\arg\min_{\vec{n}} \rho(m(\vec{n},t), \vec{x}(t))$ is called as a corresponding to the input vector of indicators and assume the existence of the measure μ characterizing the density of components distribution $\vec{x}$ (t) in the indicators space (so that the vectors number $\vec{x}(t) \in \bigcup$, where $\bigcup$ is measured in relation to μ is $\int \mu(\bigcup)\partial\bigcup$, and also to denote $\bigcup(\vec{n})$ = { $\vec{x}$ (t)/ $\vec{x}$ (t) $\in L$, $\vec{x}$ (t) and to equal u($\vec{n}$)}), then:

1. For any $\vec{n}_1$, $\vec{n}_2$: $\bigcup(\vec{n}_1)$ = $\bigcup(\vec{n}_2)$ that is the elements value adapt during the training process so that the net evenly covers the indicators space and every element equals the μ image set of the same measure.

2. Close in the closeness co-ordinate system elements correlate to close by metrics elements of the space indicators.

The general method of using the self-organizing maps is as follows. After forming the coefficient values $m(\vec{n}, t)$ the procedure of marking the map elements is done. For every element u ($\vec{n}$) it is detected with what probability it correlates to this or that classified category. For this purpose we use the test signal in which with the expert help for every indicators vector $\vec{x}$ (t) it is detected to which category it refers. The test signal goes to the algorithm input and for every element u($\vec{n}$) of the net it is built the distribution histogram of the classified categories to which belong those $\vec{x}$ (t)that correlate the element u($\vec{n}$) during the marking.

After the described procedure on the map we can single out the compact spheres that consist of the net elements which correlate to one and the same class (or the classified category type described for the map elements marking). It should be noted that in every carried out experiment as an indicator to describe the input signal different characteristics describing the securities quotes [2]. The procedure of analysis and prediction of securities quotes with the help of the neural network described is as follows: the data base of the quotes transforms in the vectors stream of the indicators $\vec{x}$ (t) for each of which the corresponding net element is detected u*($\vec{n}$) and in the output symbols stream which is generated by the analysis algorithm it is marked the sign of the classified category to which refer u*($\vec{n}$). The received by this way chain consisting of the symbols – categories names is transformed in a different way to eliminate the false symbols replacements and etc. All marks that have the same name and which goes one by one are united in one classified segment and if its length is less than some specified time period then such a segment is disregarded.

The use of the indicators maps is connected with choosing such characteristics as dimension, elements number, laws of values change α (t) and ρ(t) that are usually chosen empirically. As the number modeling shows the choice of these parameters may have not the crucial role to finally form maps and define mainly the speed of the convergence process. At the final dimension indicators map we can expect a drastic impact of the metrics type ρ on the result of the map formation process.

Thus, as the result of analyzing different architecture of the neural nets it was detected that the most perspective from the point of view of data presentation organization is the Kohonen net class.

Let us further on study the algorithm of the self-organizing indicators maps of the Kohonen the use of which in the model of multi-layers net gives a possibility to do the indicators aggregation from simple local to more complicated indicators that take into account the dynamics of the input information. Here we describe the algorithm of the analysis classification on the basis of the multi-layer net of Kohonen.

Let the input signal to be described at the discrete moments in time t = 0, 1, 2, by the indicators vector $\vec{x}$ (t) = {x^i(t)}, i = $\overline{1, N}$. The net consists of several layers and every element u_l ($\vec{n}$) of *l* layer is identified by an ordered set of its coordinates. All elements of some *l* layer receive at the moment of time t one and the same input vector of indicators $\vec{x}_l$(t) of dimension N. The first net layer is a map of vector parameters distribution $\vec{x}$ (t) which describe the input signal and every consequent layer, for example *l*, the distribution map (2m-1) - gram, formed by the vector $\vec{x}_l$(t). Every net element has its own set of the so called link coefficient $\vec{m}$ ($\vec{n}$,t) = { m ($\vec{n}$,t)}, i = $\overline{1, N}$ that define its individual reaction to the input indicators vector. Every layer receives the input signal from the previous one and sends the output signal to the next layer. Let's assume, if at the moment of time t-2, t-1, t on the l-1 layer of coordinates the excitation center were $n^*_{l-1}(t-2)$, $n^*_{l-1}(t-1)$, $n^*_{l-1}(t)$, then the input signal for the l layer at the moment of time t it will be the vector $\vec{x}_l$(t) = ($n^*_{l-1}(t-2)$, $n^*_{l-1}(t-1)$, $n^*_{l-1}(t)$). Moreover, all elements are connected with a separate naming vector $\vec{m}$ ($\vec{n}$,t) by one link in every vector component and the value of which adjusts in the training process and it is proportional to the correlation between the described by this element n –gram of indicators and the corresponding category.

The net formation is in the value setting $\vec{m}$ ($\vec{n}$,t), $\vec{m}$ ($\vec{n}$,t) and is done within two consequent performed training phases. Initially (if t = 0) the values of these links are chosen accidentally. When at the moment of time t, t>0 the vector of indicators $\vec{x}_l$(t) go to the 1layer of the net:

1. It is detected

$$\vec{n}^*(l,t) = \arg\min_{\vec{n}} \rho(m(\vec{n}_l,t), \vec{x}_l(t)) \quad (3)$$

For every $\boldsymbol{u_l}$ **(**$\vec{n}$**):**

$$u_l(\vec{n}): \rho(\vec{n}, \vec{\eta}^*(t)) \le r(t)\ \vec{m}_l(\vec{n},t+1) = \vec{m}_l(\vec{n},t) + \alpha(t+1)(\vec{x}_l(t) - \vec{m}_l(\vec{n},t)). \quad (4)$$

where α (t) – the adaptation coefficient: $0<\alpha(t)<1$, $\alpha(t)\to 0$, ρ - the metrics in R.

2. To the input of the consequent *l*+1 net layer goes the input vector

$$\vec{x}_{l+1}(t) = (n^*_l(t-2), n_l(t-1), n^*_l(t)). \quad (5)$$

During the second training phase with constant $\vec{m}$ ($\vec{n}$, t) the modification of the identification links $\vec{m}$ ($\vec{n}$,t) is done. Initially every $\vec{m}$ ($\vec{n}$, t) = 0. To form these links it is used the sequence of the input data base that is marked by the expert in advance. The marking sets the correlation f: $\vec{x}$ (t) $\leftrightarrow$ {W_i}, where W_i - the class of the category which must be identified. Such a test data base is primarily analyzed and received vector indicators are used as input ones for the described net. If $\vec{x}_l$(t) – the input vector of indicators for the layer *l* at the moment of time t, then:

1. We detect the coordinate vector $\vec{\eta}^*$ (*l*,t) according to (3)

2. For the element u_l($\vec{\eta}^*$ (*l*,t)) we modify the value meaning of the identification links:

$$\vec{m}(\overrightarrow{n^*}(l,t),t+1) = \begin{cases} \hat{m}_l^i(\vec{n}^*(l,t),t)+\delta, \delta>0, if\ = f(\vec{x}_l(t)) \\ \vec{m}_l^i(\vec{n}^*(l,t),t), \quad if\ not \end{cases}$$

3. We normalize the received vector of links:

$$m_l^i(\overrightarrow{n^*}, \mathbf{t}) = \frac{m_l^i(\vec{n}^*,t)}{\| \vec{m}(\vec{n}^*,t) \|}$$

And by (5) we calculate the vector $\vec{x}_{l+1}(\vec{n},t)$

By the end of such training the component $m_l^i(\overrightarrow{n},t)$ is a histogram of distribution of different categories classes for the depicting $u(\vec{n})$ trajectory of the parameters values. The classification stage is organized as follows: the vector of indicators $\vec{x}(t)$ at the moment of time t goes to the net input and according to **(3)** in every layer l we detect the coordinates of the active element $\overrightarrow{n^*}(l,t)$ for the consequent layer l+1. Whether the vector of the parameters at the moment of time belongs to the classified category I, is defined as following:

$$\overrightarrow{n^*}(l,t) = \arg\min_{\vec{n}} \{ \max_i m_l^i(\overrightarrow{n^*}(l,t),t) \}$$

But one should take into account that because of the vectors multi-dimension $\vec{x}(t)$, the assessment of the needed distribution is labor-consuming and the accuracy of this assessment much depends on the volume of the training sample. That is why by method of statistical solutions we can completely solve the identification task only in cases when the pairs distribution (k; $\vec{x}(t)$) has quite simple analytically and it meets some demands of symmetry, independence, un-correlation and etc. Practically, the distributions in real cases do not meet such demands.

So, the functioning specificity of different types of the neural nets (multi-layered perceptrons, associative links, the Kohonen networks) has been defined in order to their effective use as to the definite financial tasks; the algorithms of building the neural networks пof the variable structure to analyze and short-term prediction of securities finance quotes.

REFERENCES

1. Кохонен Т. Ассоциативная память. М.: Мир, 1980, – 239 с.

2. Яковлев В.Л.,Яковлева Г.Л., Лисицкий Л.А. Модели детерминированного хаоса в задаче прогнозирование тенденции финансовых рынков и их нейросетевая реализация // Информационные технологии. 2000. № 2. С. 46 – 52.