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APPLICATION OF THE HOPFIELD NEURAL NETWORK FOR THE FORMATION OF ASSOCIATIVE MEMORY

Master at the Tashkent University

of Information Technologies named

after Muhammad al-Kharezmy

Kuchkarova Muazzam Zuxriddinovna

Abstract. This article is devoted to the issue of pattern recognition using neural network technologies. In particular, the analysis of the application of the Hopfield neural network for the formation of associative memory.

Keywords: neural network, associative memory.

Introduction.

Neural networks are of great interest to scientists today. Technical vision systems undoubtedly lag behind in the field of pattern recognition from the human visual apparatus, coupled with its neural system. Despite the obvious advantages of artificial neural networks, they have a significant number of problems. For example, it is not always clear how to approach the issue of training such a network.

Study.

The Hopfield neural network consists of a single layer of neurons, the number of which determines the number of inputs and outputs of the network. At the same time, the network is fully connected - the output of each neuron is connected to the inputs of other neurons according to the "from all to all" principle. In essence, the Hopfield network shows how memory can be organized in a network of elements that are not reliable.

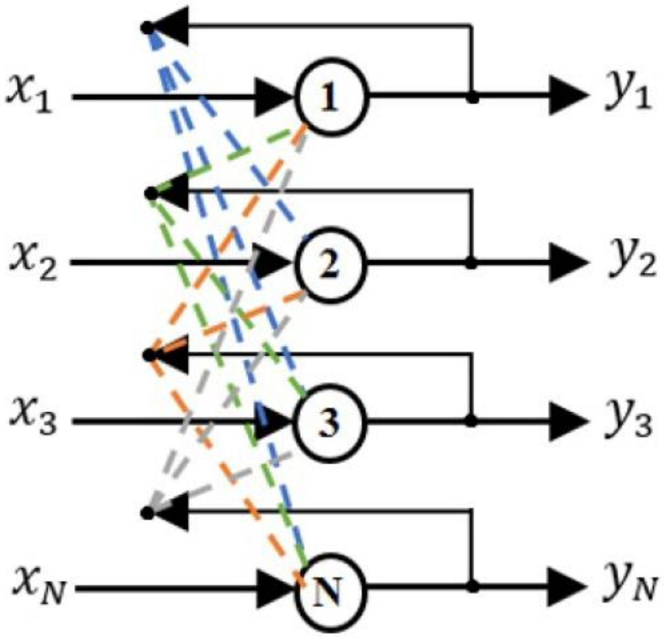

Fig. 1. An example of a Hopfield network.

Each neuron can be in one of two states$y_i(t) = \begin{cases} +1 \\ -1 \end{cases}$ r where +1 corresponds to the “excitation” of the neuron, and -1 to “inhibition”.

The non-linear, threshold nature of the functioning of a neuron reflects the discreteness of its states. In neurophysiology, this principle is known as "All or Nothing". The dynamics of the state in time of the i-th neuron in a network of N neurons is described by a discrete dynamic system:

$$y_i(t+1) = sign\left[\sum_{j=1}^{N} H_{i,j} y_i(t)\right],$$

where $H_{i,j}$ – matrix of weight coefficients describing the interaction of dendrites i-th neuron with axons of the jth neuron.

The Hopfield network learning algorithm differs significantly from the error backpropagation algorithm. Instead of successively approaching the desired state with intermediate correction of the weights, all coefficients are calculated using one formula and in one step, after which the network will be ready for operation. The calculation of the coefficients obeys the rule: for all stored images xi, the weight matrix Hi,j must satisfy the equation: xi = Hi,jxi.

An important characteristic of a neural network is the ratio of the number of key images M that can be memorized to the number of network neurons N:α = M/N. For the Hopfield network, the value of α is not greater than 0.15.

The calculation of the square size matrix for key images is performed according to the Hebb rule:

$$H_{i,j} = \frac{1}{N} \cdot \sum_{\mu=1}^{M} [\varsigma_{i,\mu}^{in} \cdot \varsigma_{j,\mu}^{in}]$$

The Hopfield network does not use unsupervised learning - a priori information is needed about which classes the input examples belong to. The network is rather optimizing and performs the task of restoring images from their distorted originals.

Hopfield networks are characterized by limitations:

A relatively small number of memorized images (about 0.15n where n is the number of inputs).

Achieving a steady state does not guarantee the correct response of the network due to the fact that

the network can converge to false attractors.

Results and comments to them.

An example of the implementation of a Hopfield neural network that forms an associative memory presented below.

We recognize the images of the letters: "K", "P", "T". Let's represent them in the form of "bit fields" 7x7 in size.

We have three reference images:

```
@ - - - - - @      - @ @ @ @ @ -      @ @ @ @ @ @ @
@ - - - @ @ -      - @ - - - @ -      - - - @ - - -
@ - - @ - - -      - @ - - - @ -      - - - @ - - -
@ @ @ - - - -      - @ - - - @ -      - - - @ - - -
@ - - @ - - -      - @ - - - @ -      - - - @ - - -
@ - - - @ @ -      - @ - - - @ -      - - - @ - - -
@ - - - - - @      - @ - - - @ -      - - - @ - - -
```

The network will be based on the calculation of weight coefficients. After the network has been trained according to the established patterns, we will give it a certain vector as input and ask it to determine what it is.

The input is a modified form:

```
@ @ - - - - -
@ - - - @ @ -
@ - - @ - - -
- - @ - - - -
@ - - @ - - -
@ - - - @ @ -
@ @ - - - - @
```

After 94 iterations, the reference form is determined:

```
@ - - - - - @
@ - - - @ @ -
@ - - @ - - -
@ @ @ - - - -
@ - - @ - - -
@ - - - @ @ -
@ - - - - - @
```

Obviously, the modified image of the letter "K" was successfully recognized. If you repeat the recognition several times, you will notice that each time the number of iterations to determine the image is different. This is due to the fact that the neuron to update at each cycle is randomly selected.

Now the input is an image that looks like the letters "P" and "T" at the same time.

```
@ @ @ @ @ @ @
- @ - @ - @ -
- @ - @ - @ -
- @ - @ - @ -
- @ - @ - @ -
- @ - @ - @ -
- @ - @ - @ -
```

However, by running it again, you can see that after 116 iterations in the new experiment, the letter was still recognized. It turned out to be "P", since the original image looked more like her than "T":

```
- @ @ @ @ @ -
- @ - - - @ -
- @ - - - @ -
- @ - - - @ -
- @ - - - @ -
- @ - - - @ -
- @ - - - @ -
```

Conclusion.

On the basis of the conducted research, it should be noted that, on the one hand, there are no problems with training the Hopfield network in the presence of a priori information about the classes of objects, and on the other hand, the achievement of a stable state does not guarantee the correct response of the network due to the fact that the network can converge to false attractors (state Hopfield neural network in this case is stable, but does not provide a correct image recovery, while the network can produce a false image, which is usually a combination of fragments of several images).

References

1. Tarkhov D.A. Neural networks. Models and algorithms / D.A. Tarkhov - M .: Radio engineering, 2005. - 256 pages.

2. Richard M.D., Lippman R.P., Neural network classifiers estimate Bayesian discriminant function, Neural Computation Concepts and Theory, 1991, vol 3, pp 461-482.

3. Khaikin S. Neural networks: a complete course, 2nd ed., Rev.: Per. from English / Simon Haikin. - M .: LLC "I.D. Williams", 2006. - 1104 pages.