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Adaptive Resonance Neural Networks

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Аннотация

В данной статье описаны нейронные сети адаптивного резонанса и их принцип работы. Также рассмотрены самоорганизующиеся нейронные сети типа ART1, ART2. Приведены отличия ART от других искусственных нейронных сетей. Подробно описана структура ART, слои сравнения, слои распознавания, а также взаимодействие слоев распознавания.

Ключевые слова: нейросетевые технологии, ART сети, вектор

Abstract

This article describes adaptive resonance neural networks and their principle of operation. Self-organizing neural networks of the ART1, ART2 type are also considered. The differences between ART and other artificial neural networks are given. The structure of ART, comparison layers, recognition layers, and also the interaction of the recognition layer are described in detail.

Keywords: neural network technology, art network, vector

The human brain performs the difficult task of processing a continuous stream of sensory information received from the outside world. From the stream of trivial information, he must select vital information, process it and, possibly, register it in long-term memory. Understanding the process of human memory is a serious problem; new images are remembered in such a way that previously remembered ones are not modified or forgotten.

This creates a dilemma: how does the memory remain plastic, capable of perceiving new images, and at the same time maintain stability, ensuring that the images are not destroyed and will not be destroyed in the process of functioning?

Traditional artificial neural networks were not able to solve the problem of stability-plasticity. Very often, teaching a new image destroys or alters the results of previous training. In some cases, this is not essential. If there is only a fixed set of training vectors, they can be presented cyclically during training. In backpropagation networks, for example, training vectors are fed to the network input sequentially until the network learns the entire input set.

If, however, a fully trained network needs to remember a new training vector, it can change weights so much that a complete retraining of the network is required.

In a real situation, the network will be subject to constantly changing influences; she may never see the same training vector twice. Under such circumstances, the network will often not be trained; she will continuously change her weight, not achieving satisfactory results [1].

A solution to this problem was proposed by S. Grossberg in the theory of adaptive resonance (ART - Adaptive Resonance Theory) [2]. For example, a person is able to see (perceive) only what is present in his language (state of resonance). Based on this, he proposed several algorithms, the most common of which are the neural networks ART1 and ART2.

ART1 networks process binary vectors, while ART2 process continuous vectors. In addition, the models ARTMAP, Fuzzy ART, FARTMAP should be called.

Fuzzy ART – It is the augmentation of fuzzy logic and ART.

ARTMAP – It is a supervised form of ART learning where one ART learns based on the previous ART module. It is also known as predictive ART.

FARTMAP – This is a supervised ART architecture with Fuzzy logic included [3].

The ART network is a vector classifier. The input vector refers to one of the groups of previously stored vectors. The classification decision is issued in the form of excitation of one of the neurons of the recognition layer.

The difference between ART and other artificial neural networks (ANNs) is as follows:

- 1) if the input vector is similar to one of the previously stored vectors, then the stored vector will change to become similar to the input vector;
- 2) a rejection of classification is possible if the input vector is not similar to any of the stored vectors. In this situation, a new class is formed.

The simplified ART network configuration includes a comparison layer, recognition layer, reset, receiver 1 and receiver 2 (Fig. 1).

Figure 1. Neural network structure ART

Let's introduce notation: m is the size of the input vector; n is the number of memorized images.

The comparison layer receives the binary input vector X and initially passes it unchanged to form the output vector C (at a later stage, the components of the vector R modify C).

Simplified, the comparison layer has the form shown in fig. 2.

The vectors T are formed by weighting coefficients t_{ij} , which are binary numbers.

Each neuron of the comparison layer ($AN_1 - AN_m$) receives three binary inputs:

- 1) component of the input vector x_i ;
- 2) feedback signal p_j ;
- 3) input from receiver g_1 .

Figure 2. Comparison layer structure

In order for the output of the neuron to be one, it is necessary that at least two of its inputs are equal to one. Initially, the signal gl is set to «1», and the signals p_j are set to «0», therefore, initially the vector C coincides with X .

The recognition layer is used to classify input vectors. Each neuron of the recognition layer has a weight vector B . Only one neuron in this layer is excited, all others are inhibited. This is achieved due to the fact that all neurons of the recognition layer are covered by the mechanism of lateral excitation - inhibition (fig. 3).

Figure 3. Interaction of neurons of a recognition layer

Thus, the more a neuron is excited, the more it inhibits other neurons and at the same time maintains its level.

A simplified version of the recognition layer is shown in fig. 4.

Figure 4. Interaction of neurons of a recognition layer

The inputs of all neurons of the recognition layer receive signals from all neurons of the comparison layer, and vice versa.

Each neuron of the recognition layer has a weight vector B . The output of the neuron is $Y_j = B_j C$.

Activation function F threshold:

$$F(Y_j) = \begin{cases} 1, & Y_j \geq T, \\ 0, & Y_j < T. \end{cases}$$

Thus, the vector R is binary.

Neuron j has a maximum reaction if the vector C (output of the comparison layer) is as similar as possible to its weight vector B_j . Thus, the neuron weights represent a remembered image for a group of vectors.

Weights are real numbers. The binary version of this image is remembered in the set of weights of the comparison layer.

In the process of functioning, each neuron of the recognition layer computes the convolution of the eigenvalue vector and the input vector C . The closer the weights to the vector C , the higher the output of the neuron. The winning neuron inhibits the remaining neurons of the recognition layer.

Thus, only one neuron of the recognition layer will have «1» at the output, and the rest – «0». Therefore, the vector R will have only one unit component.

Receiver 2. Its output is equal to one if the input vector X has at least one unit component. In other words, the signal $g2$ is a logical OR component of the input vector:

$$g2 = x_1 \vee x_2 \vee x_3 \vee \dots \vee x_m.$$

Receiver 1. It works the same as receiver 2, but the arrival of at least one unit component R resets $g1$ to «0»:

$$g1 = (x_1 \vee x_2 \vee \dots \vee x_m) \wedge (\overline{r_1 \vee r_2 \vee \dots \vee r_m}).$$

Reset. The reset module measures the similarity between vectors X and C .

A measure of similarity is the ratio of the number of units in X to their number in C :

$$S = N / D,$$

where D is the number of units in the vector with the largest number of units.

For example,

$$X = [1011101] \quad (D = 5),$$

$$C = [0011101] \quad (N = 4).$$

Thus, the similarity parameter varies from 0 to 1.

The three main operations of ART are recognition, comparison and search.

Recognition is as follows. While the input vector X is absent, all its components can be considered zero, therefore, $g2 = 0$, and the outputs of all neurons of the recognition layer are set to «0» (since $C = X$).

Then the input vector X is fed, i.e. one or more components of the input vector become nonzero, and $g1$ and $g2$ become equal to one. This creates conditions for the excitation of neurons in the comparison layer, and the vector C duplicates the vector X .

After that, the convolution of the weight vector B_j and C is calculated in the recognition layer. A neuron, whose weights are most similar to the input vector, defeats and inhibits the remaining neurons. The only component of R becomes unity. Thus, one neuron of the recognition layer corresponds to one of the classification categories.

Comparison The components of the vector R arrive at all neurons of the comparison layer through weights t_{ij} , which take binary values.

The relationship between the weight vectors T and B is that B is a scaled version of T .

Since R is no longer zero, the signal $g1$ is set to «0», therefore, in accordance with rule 2/3, only neurons can be excited, receiving at the input both units from the input vector X and vector R .

If X and P do not have matching components, then feedback from the recognition layer will reset components C to «0» (Fig. 5).

If there are many differences between the vectors X and P , then the vector C will have zeros much more than X , and a reset signal is generated that disables the excited neuron for the duration of the current classification.

Search. If a reset signal is not generated, then the similarity is considered found, and the classification is complete. If the reset occurred, then all the components of R are reset to zero, $g1$ is set to «1», the vector C becomes equal to X , and a new check occurs, but without the inhibited neuron. This procedure continues until all neurons are inhibited. In this case, a new image is memorized, for which a new neuron is allocated, the weight coefficients of which B and T are set in accordance with the new image.

If, nevertheless, one of the neurons similar to the input image is found, then a training cycle is performed to correct the weights B and T .