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ARTIFICIAL NEURAL NETWORKS IN INFORMATION PROCESSING. PERCEPTRON (SENSES) AND THEIR PROPERTIES

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Hopfield neural network as automatic associative memory trained using Hebb method and projection method; Information on Hamming network-based heteroassociative memory and bidirectional associative memory is presented.

Keywords: *Hopfield motorists, Hamming network, Bidirectional associative memory*

A separate group of neural networks consists of networks with feedback between different layers of neurons. These are called recurrent networks. Their common feature is to convey signals from the output or hidden layer to the input layer. When a signal is applied to the input of the network, due to feedback, a transient process appears in it, which ends with the formation of a new state, which is generally different from the previous one. If the activation function of a neuron is defined as where is the weighted sum of its excitation, then the state of the neuron can be determined by the output signal. The state change of the third neuron can be described by a system of differential equations
where is the threshold value for .
A recurrent network can be associated with a Lyapunov energy function
A change in the state of any neuron causes the energy state of the network to change to its minimum energy level. In the state space, energy minima of E are represented by stability points called attractors due to the gravitational force of the environment closest to them. Because of the presence of attractions, recurrent networks can be used as associative memory devices.
Associative memory plays the role of a system that determines the mutual dependence of vectors. Auto-associative memory is when the components of the same vector are examined in relation to each other. If two different vectors are correlated, we can talk about heteroassociative memory. The first class includes the Hopfield network, the second - the Hamming network and the BAM (Bidirectional Associative Memory) network.
The task of associative memory is reduced to memorizing training vectors, so that when a new vector is presented, the system can generate an answer - which of the previously memorized vectors is closer to the newly acquired image. The Hamming distance is often used as a measure of the closeness of individual sets.
When using binary values (0,1), the Hamming distance between two vectors and is defined as
Hamming distance for bipolar values of two vector elements is calculated by the formula
The Hamming measure is equal to the number of random components of two vectors. When this is zero.
Hopfield motorist network
The structure of the Hopfield network is represented as a system with direct feedback from the output to the input (Fig. 1). The output signals of the neurons are simultaneously the input signals of the network:. In the classic Hopfield network, there is no automatic connection (connecting the output of the neuron with its input), and the corresponding weight matrix is symmetric: The absence of autocorrelation and the symmetry of the weight matrix are sufficient (but not necessary!) conditions for the convergence of repetitive (temporary) processes in the Hopfield network.
In the remainder of this paper, we assume that each neuron has a bipolar stepwise activation function with values This means that the output signal of th neuron is determined by the function where is the number of neurons.
Let us assume that the trigger threshold is a vector component. Then the basic relation defining the Hopfield network can be expressed as (1) with the initial condition.
During the operation of the Hopfield network, two modes can be distinguished: learning and classification. In training mode, network weights are selected based on known vectors. With the introduction of specific values of weights and a certain initial state of neurons, a transient process of the form (1) occurs in the classification mode, which ends at one of the local minima, for which.
Figure: 1. The structure of the Hopfield network
Hopfield network training according to Hebb's rules

The values of the weights for one training vector can be calculated according to Hebb's rule because then (always due to the bipolar values of the vector elements).

When introducing more training vectors, the weights are chosen according to the generalized Hebb rule

An important parameter of associative memory is its availability. Capacity is understood as the maximum number of stored images classified with an acceptable error. It has been shown that when Hebb's rule is used for learning and when (1% of image components differ from normal) the maximum memory size is only 13.8% of the number of neurons that make up associative memory. Such a small power is due to the fact that the Hebb network only remembers mutually orgonal vectors well, or those close to them.

Hopfield network training using the projection method

Rather than using Hebb's rule, this can be achieved using pseudo-inversion for training. This approach is based on the assumption that, with properly chosen weights, each vector fed to the input of the network causes the network to generate itself at the output. In matrix form, this can be expressed as follows

where is the matrix of network weights with dimension and is a rectangular matrix of dimensions consisting of training vectors. The solution of such a system of linear equations has the form

where + indicates pseudo-inversion.

If the training vectors are linearly independent, the last expression can be simplified and expressed as (2)

Here, the square matrix with pseudo-inverse dimensions is replaced by the usual inverse. (2) can be written in an iterative form, which does not require the calculation of the inverse matrix. In this case, (2) takes the form of an iterative dependence on the sequence of training vectors:

In the initial conditions. As a result of presenting the vectors, the matrix of network weights will have a value. The method described here is called the projection method. Its use increases the maximum power of the Hopfield network. The increased capacity is due to the fact that the uniformity of the vectors in the projection method is replaced by a much lower requirement for their linear independence.

A modified version of the projection method - the -projection method is a gradient form of the minimization algorithm. According to this method, the weight is selected using a procedure that is repeated many times over the entire set of training vectors:

The training vectors are presented repeatedly until the weights stabilize.

The Hamming network includes three layers (Figure 2).

The first layer has signal propagation from input to output and fixed weights.

The second layer consists of neurons that are connected by feedback according to the principle "each to each", while each neuron of the layer has autotechnics (the connection of the neuron's input with its output). Different neurons in a layer are associated with negative (inhibitory) feedback with weight, the value of which is usually inversely proportional to the number of images. A neuron is connected to its input by positive (excitatory) feedback with a weight of +1. The threshold weights of the neurons are set to zero. The neurons of this layer work in a mode where only one neuron is activated in each given situation, and the rest are in a state of rest.

The output one-way layer generates an output vector corresponding to the input vector.

Figure: 2. The structure of the Hamming network

A Hamming network is considered as a heteroassociative storage device with input and output bipolar vectors of the network and a pair of interconnected pairs.

The weights of the first layer correspond to vectors, i.e.

In the same way, the weights of the output layer correspond to the vectors of the following images:

In the second layer (MAXNET) operating in WTA (Winner Takes ALL) mode, each neuron must amplify its signal and attenuate the signals of other neurons. For this, it is accepted and again in the second layer of the weight to ensure the convergence of the repeated process, here is a sufficiently small random variable,.

The neurons of the first layer calculate the Hamming distances between the vector given to the network input and the vector of weights of the neurons of this layer. The values of the output signals of the neurons of the first layer are determined by the formula where is the number of vector components.

The signals become the initial state of the second layer neurons. This layer determines the "winner", i.e. A neuron whose output signal is close to 1 indicates the image vector with the minimum Hamming distance to the input vector of such a neuron. The activation function for neurons of the second layer is given by the expression

The iteration process in the second layer ends when only one neuron (the winner) remains active, and the rest of the neurons are in the zero state. The linear neurons of the output layer represent the vector corresponding to the vector recognized by the second vector as the closest to the input vector.

The advantage of the Hamming network is that there are few weighted connections between neurons. Many experiments have proven that the Hamming network gives better results than the Hopfield network. The only problem with the Hamming network arises when noisy images deviate from the same (in the Hamming sense) two or more standards. In this case, the selection of one of the standards by the Hamming network will be random.

A generalization of the Hopfield network to the case of a two-layer recurrent structure, which allows encoding two sets of vectors connected to each other, is a bidirectional associative memory called BAM (Bidirectional Associative Memory) (Fig. 3). Signals travel in two directions. If the signals in the first cycle first pass in one direction to determine the position of the receiving neurons, then these neurons in the next cycle themselves become sources that send signals in the opposite direction. The process is repeated until equilibrium is reached.

The activation function of neurons has a threshold character. To ensure the best performance of the network, only bipolar signals are used in the training phase. The weight matrix connecting both parts of the network is real and completely asymmetric. The weights for forward propagation of signals are defined by a matrix, and for the reverse by a matrix.

Let the input training data be a set of pairs of bipolar vectors. Based on this set, a matrix is formed

As a result of bidirectional signal processing, two stable vectors and are generated that satisfy Eqs

Each intermediate point can be associated with an energy function

decreases until it reaches a local minimum at each state change

Figure: 3. Structure of the BAM network

In the recognition mode, when the initial values of the vectors correspond to the indicators used in training, the network recognizes them accurately. If the vectors are corrupted, the BAM network cannot always correct these vectors and recognize them with certain errors. If the dimensions of the vectors and are appropriately determined, then satisfactory recognition quality can be achieved by performing the correlation.

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