APPLICATION OF NEURAL NETWORKS

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Annotation: *Abstract: The article discusses neural networks that are widely used in various fields, such as economics (prediction of stock market indicators, prediction of financial time series), robotics (recognition of optical and audio signals, self-learning), visualization of multidimensional data, associative search for textual information, etc.*

Neural networks are of interest to a fairly large number of specialists, for example for computer scientists' neural networks open up the field of new methods for solving complex problems; physicists use neural networks to model phenomena in statistical mechanics and to solve many other problems; neurophysiologists can use neural networks to model and study brain functions; psychologists have at their disposal a mechanism for testing models of some of their psychological theory.

Keywords: *perceptron, neural networks, input information, human brain, neurobiology, electromagnetic activity.*

The main area of research on artificial intelligence in the 1960s – 1980s. There were expert systems that were based on high-level modeling of the thinking process (in particular, on the idea that our thinking process is based on manipulating symbols).

However, it soon became clear that such systems, although they may be useful in some areas; do not cover some key aspects of human intelligence.

According, to one of the common points of view, the reason is that they are not able to reproduce the structure of the brain, and in order to create artificial intelligence, it is necessary to build a system with a similar architecture. The human brain consists of a very large number (approximately 10,000,000,000) neurons connected by numerous connections (on average, several thousand connections per neuron, however, this value can vary greatly).

A neuron is a special cell capable of transmitting electrochemical signals. A neuron has a branched structure of input channels of information (dendrites), a nucleus and a branching output channel (axon). The axons of such a cell are connected to the dendrites of other neurons in the cells using synapses. When activated, a neuron sends an electrochemical signal along its axon, and through synapses, this signal reaches other neurons, which can, in turn, be activated. A neuron is activated when the total level of signals arriving at its nucleus from dendrites exceeds a certain level (activation threshold).

The intensity of the signal received by the neuron (and, consequently, the possibility of its activation) strongly depends on the activity of synapses. Each synapse is a gap (synaptic cleft) between an axon and a dendrite, and special chemicals (neurotransmitters) transmit a signal through this gap. One of the most respected researchers of neurosystems, Donald Hebb, formulated the postulate that learning is primarily about changes in the "strength" of synaptic connections. For example, in Pavlov's classic experiment, a bell rang each time just before feeding the dog, and the dog quickly learned to associate the bell with food. This happened because the synaptic connections between the parts of the cerebral cortex responsible for hearing and the salivary glands increased, so that when the cerebral cortex was excited by the sound of a bell, the dog began to salivate. In this way.

In practice, neural networks are used, as software products that run on ordinary computers, or as specialized hardware and software systems [2].

Note, that in the first case, the built-in parallelism of neural network algorithms is most often not used, since for many tasks of analyzing and generalizing databases, special performance is not required – for them, the performance of modern universal processors is quite enough. Such applications use exclusively the ability of neural networks to learn and to extract patterns hidden in large amounts of information. For the second group of applications, usually associated with real-time signal processing, the parallelism of neural computations is a critical factor.

The main tasks are solved by neural networks:

1. Distributed associative memory. Distributed memory means that the weights of the connections of neurons have the status of information without a specific association of a piece of information with a particular neuron. Associative memory means that a neural network is able to output a complete image from the part presented at the input.

2. Pattern recognition. Pattern recognition tasks require the ability to simultaneously process a large amount of input information and produce a categorical or generalized answer. For this, the neural network must have internal parallelism.

3. Adaptive management.

4. Forecasting.

5. Expert systems.

6. Optimization (i.e., the search for the maximum of the functional in the presence of restrictions on its parameters).

Currently, neural networks are widely used in various fields, such as economics (predicting stock market indicators, predicting financial time series), robotics (recognizing optical and sound signals, self-learning), visualization of multidimensional data, associative search for textual information, etc.

Neural networks are of interest for a large number of specialists:

For computer scientists, neural networks open up the field of new methods for solving complex problems;

Physicists use neural networks to model phenomena in statistical mechanics and to solve many other problems;

Neurophysiologists can use neural networks to model and study brain functions; psychologists have at their disposal a mechanism for testing models of some of their psychological theories;

Neural networks, other specialists (especially commercial and industrial areas) may also be interested in neural networks for a variety of reasons, primarily due to the new possibilities of forecasting and data visualization achieved with their help. Learning Neural Network Learning is a fundamental property of the brain.

In the context of neural networks, the learning process can be considered as setting up the network architecture and connection weights efficiently to perform some special tasks. Typically, a neural network must adjust its link weights based on the available training set [1], and the network performance improves as the weights are iteratively adjusted. The property of neural networks to learn by example makes them more attractive in comparison with systems, which work according to a rigidly defined set of functioning rules formulated by experts. To design the learning process of a neural network, first of all, it is necessary to have a model of the external environment in which this neural network should function, i.e., to know the information available to the network. This model defines the learning paradigm. Secondly, it is necessary to understand how exactly the weights of the network should be modified, that is, which learning rules govern the tuning process.

Learning Algorithm refers to a procedure that uses learning rules to set up weights. There are three paradigms for teaching neural networks: “with a teacher”, “without a teacher” (self-learning) and mixed [1]. In the first case, the neural network has the correct answers (the required outputs of the network) for each input example, and the weights adjusted, so that the network produces answers as close as possible to the known correct answers.

The strengthened version of learning “with a teacher” assumes that only a critical assessment of the correctness of the output of the neural network is known, but not the correct values of the output themselves. Unsupervised learning does not require knowing the correct answers for each training sample. In this case, only the internal structure of the data or the correlations between the samples in the data system is revealed, which allows the samples to be categorized. In blended learning, some of the weights are determined through supervised learning, while the rest of the weights formed through self-learning.

Neural network learning theory considers three fundamental properties associated with learning for example capacity, sample complexity, and computational complexity. In this case, the capacity is understood as how many samples the network can remember and what functions and decision-making boundaries can be formed on it. The complexity of the samples determines the number of training examples needed to achieve the generalizability of the network. Too few of these examples can cause the network to “overfit” when it performs well on training set examples, but performs poorly on test cases subject to the same statistical distribution [3].

There are four main types of learning rules: error correction, Boltzmann machine, Hebb’s rule, and competition learning. Error correction rule. In supervised learning, the desired output d is given for each input example, but the actual output of the network y may not coincide with the desired one. The principle of error correction during learning is to use a difference signal (d – y) to modify the weights to gradually reduce the error. Such training is performed only when the neural network is wrong.

Moreover, there are various modifications of this learning algorithm, which are not discussed in detail here. Neural networks 125 Boltzmann training. It is a stochastic learning rule that follows the principles of information theory and thermodynamic principles.

The goal of Boltzmann’s training is to adjust the weighting coefficients in such a way that the states of the neurons of the outer layer satisfy the desired probability distribution. Boltzmann training can be viewed as a special case of error correction, in which the error is understood as the discrepancy between the state correlations in two modes. Hebb’s rule.

The oldest teaching rule is Hebb’s teaching postulate. Hebb relied on the following neurophysiological observations: if neurons on both sides of the synapse are fired simultaneously and regularly, then the strength of the synaptic connection increases. An important feature of this rule is that the change in synaptic weight here depends only on the activity of neurons that are connected by a given synapse. Competition training. Unlike Hebb learning, in which multiple output neurons can be fired simultaneously, in competitive learning, the output neurons compete with each other for firing. This phenomenon is known as the “winner-take-all” rule. Similar learning takes place in biological neural networks. Learning through competition allows you to cluster your inputs: similar input examples are grouped by the network according to correlations and represented by a single element. When learning by the method of competition, only the weights of the “winning” neuron are modified. The effect of this rule is achieved, due to such a change in the sample stored in the network (the vector of connection weights of the “winning” neuron), in which it becomes a little closer to the input example.

REFERENCES:

1. Galushkin A.I. Theory of neural networks. – Moscow: Publishing company of the editorial office of the magazine “Radiotekhnika”, 2000.
2. Neural networks in automation systems / V.I. Arkhangelsky, I.N. Bogaenko, G.G. Grabovsky et al. – Kiev: Technics, 1999.
3. Terekhov S.A. Lectures on the theory and applications of artificial neural networks: http://alife.narod.ru/lectures/neural/ Neu_index.htm.

ФОРМИРОВАНИЕ ЭФФЕКТИВНОЙ ОБРАЗОВАТЕЛЬНОЙ СРЕДЫ В УСЛОВИЯХ РАЗВИТИЯ ИНДУСТРИИ 4.0.

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Новый индустриальный уклад, характеризующийся стремительной диффузией инновационных и цифровых технологий в экономике, становится локомотивом повышения качества образовательной среды.

Например, выдвигая первостепенной задачей, достижение адекватного уровня, параметров эффективности и конкурентоспособности образовательных организаций. Преимущества, четвертой промышленной революции проявляются, не только в массовом внедрении информационных технологий, но и в создании роботизированных систем и автоматизации производственных процессов. А также, в обеспечении ускорения интеграционных процессов в образовательной среде, с учетом, расширения возможностей использования современных производственных систем в качестве платформ для приобретения практических навыков и компетенций обучающимися на системной основе. Это несомненно, снижает риски ошибок в выборе профессии и повышает качество подготовки специалистов для индустрии 4.0.