Research on Adaptive Machine Learning Algorithms Based on Cognitive Simulation

Yin Huang[1], Daojun Chen[2], Ni Liu[3]

[1]Beijing Jiaotong University, No.3, Shangyuan Village, Haidian District, Beijing, China

[2]College of Physics Science and Technology, Hebei University, No. 180 Wusi East Road, Lianchi District, Baoding, Hebei, China

[3]Big data and artificial Intelligence College of Chizhou University, No. 99, Mu Zhi Road, Education Park, Guichi District, Chizhou City, Anhui Province, China

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Abstract: According to the theory of cognitive science and guided by the latest research results of neuroscience and brain science, an adaptive machine learning method is proposed by using the methods of computer science, mathematics and engineering science. This method is based on the learning mechanism model of human brain from the micro-neuron level, the middle level and the macro level. The automatic acquisition system of ECG classification knowledge based on this method can well simulate the functions of ECG experts' perception, cognition and thinking.

1. Introduction

In the late 1950s and early 1960s, people began to study the learning mechanism and learning algorithm based on neural network, but because of the limitation of linear perceptron, at the same time, the traditional Von Neuman type number. Word computer is in its heyday of development at this time, and artificial intelligence based on symbols has developed rapidly, making the early non-symbolic learning based on connection mechanism replaced by the Research Institute of symbolic learning [1]. Since the 1980s, the research of machine learning based on symbolic mechanism has developed very rapidly. However, with the deepening of the research, it is not difficult to find that the methods and research methods of machine learning based on connection mechanism or symbolic mechanism are limited and one-sided, which is not conducive to revealing the thinking mechanism and learning mechanism of human brain. The learning process can only be described at a single level. For such problems as how the human brain receives external information and changes its internal connection mechanism, which can be reflected in the changes of system behavior, the existing theory can not give a reasonable explanation acceptable to all. [2] In fact, learning is dominated by certain will. Its internal performance is a certain structure, and its external performance is a complex process of certain behavior changes. It involves connection theory, cognitive science, behavioral science, neuroscience and other sciences. Therefore, for the study of machine learning, only computer science, cybernetics, artificial intelligence, cognitive science and neuroscience can be used. It is possible to make greater progress in machine learning research by means of interdisciplinary approaches such as psychology and so on[3].

2. Human Brain Adaptive Learning Theory

According to neuroscience, the human brain is a giant system of about 1011 neurons, and there are 103-104 synapses connecting each other. After birth, the number of neurons increases slightly, but gradually dies with age[4]. On the contrary, the connections between neurons do not. The learning of new knowledge is becoming more and more complex. At the same time, specific functional areas are gradually clearly formed in the brain[5]. From a cognitive point of view, a large number of realistic templates are formed in the brain. In this process, the human brain has been found at the micro (neuron level), the middle (functional nucleus, functional area level) and the

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macro (cortical level)[6]. The corresponding control mechanism guides the whole adaptive learning process, including the state and transformation of neurons, the structure optimization of neural networks and the selection of learning functions of neural networks[7].

At the neuron level, the neuron's adaptive learning function is realized by the neuron's state and its adaptive transfer rules[8]. The neuron's state includes sleep state (or super-suppression state), normal state, critical state, morbidity and death state at the intermediate level (functional nucleus, functional area). The neuron's self-adaptive learning has been done. The selection and substitution of learning function of neural network and optimization of multi-objective neural network structure are presented in this paper[9]. On the macro level, the adaptive learning ability of the nervous system is mainly manifested in the following aspects: automatically selecting learning methods and learning methods according to different nature of the problem, in order to achieve the best learning effect. In learning, human beings first acquire a large amount of perceptual knowledge from practice, and then through the process of eliminating rough refinement, removing false and retaining true, from this to that, from the surface and from the surface to the surface. In the process of rational thinking, the perceptual knowledge is upgraded to rational knowledge[10]. On the one hand, these theoretical knowledge is used to solve the practical problems encountered in the future, but also to guide future learning. These knowledge is very important for acquiring new knowledge in the future. Therefore, the problem of adaptive learning of nervous system is mainly from the macroscopic point of view. Symbolic knowledge is extracted from the distributed knowledge of neural network structure and used to guide the learning of neural network.

3. An Adaptive Machine Learning Algorithm based on Cognitive Simulation

3.1. Adaptive machine learning algorithms

The purpose of machine learning research is to hope that computers can acquire knowledge from the real world like human beings. Therefore, machine learning algorithms must be guided by human brain adaptive learning theory, including adaptive selection of learning functions, multi-objective optimization learning criteria, adaptive extraction of symbolic knowledge, etc. Of course, machine learning can not and is not necessary to completely imitate the way of human learning, but should fully absorb the essence of human learning for machine learning. Therefore, the adaptive machine learning algorithm studied in this section first adopts the connection mechanism (including the adaptation of neuron level and intermediate level discussed in the last section). Learning method). Learn from examples, then extract the symbolic knowledge and concepts hidden in the connection structure. Finally, use these symbolic knowledge to guide the learning of the connection mechanism, and further optimize the structure of the neural network.

For single-layer neural networks, Hebb rule can be used:

$$\Delta W_{ij} = X \bullet a_i \bullet a_j \tag{1}$$

Among them, X is the learning rate, a_i is the activation value of neuron i, a_j is the activation value of neuron j, and W_{ij} is the change of the connection weight between neuron I and neuron J. Through learning, the neural network acquires knowledge from a large number of examples and exists in the structure of the neural network in the form of distribution. The back propagation (BP) algorithm is used to train the neural network:

$$\Delta W_{ij} = X \bullet W_{pi} \bullet a_{pj} \tag{2}$$

Neural network extracts the knowledge hidden in the sample data through learning, which is distributed in the structure of the neural network. The adaptive machine learning method based on cognitive simulation is discussed in this section. Firstly, the join learning method (which includes the state and transformation of neurons, the adaptive selection of learning functions, and the adaptive selection of learning functions) is adopted. Multiobjective Optimized Neural Networks, etc.) Obtain knowledge from sample data, and then extract symbolic knowledge from neural network structure by using the method discussed below. For the learning of single-layer neural network, after learning, first find Wik to satisfy:

$$W_{ik} = \max(W_{1k}, \ldots, W_{mk}) \tag{3}$$

W_{ik} is the connection right between input neuron I and output neuron K.For the learning of multi-layer neural network, in order to describe conveniently, the output of the output neuron is regarded as the additional input signal of the neural network. After this transformation, a new structure of the neural network is constructed. The BP learning algorithm is used to train the neural network. After learning, if the connection weight from an input (original) to an implicit neuron is completed.

In order to describe this connection, we assume that the input is closely related to the corresponding output (the additional input):

$$SSE_{ab} = \sum_{j=1}^{k} (W_{bj} - W_{aj})^2 \tag{4}$$

where k is the number of hidden neurons, Wb J is the connection right between the additional input neuron B and the hidden neuron j, Waj is the connection right between the original input neuron A and the hidden neuron J. As can be seen from the above formula, the smaller the value of SSEab is, the closer the connection between the input neuron A and the output neuron B is. Based on the analysis, the functional cores or functional areas of the neural network can be described at the intermediate level, and the symbolic knowledge hidden in the neural network can be extracted. On the one hand, these symbolic knowledge can be used for high-level reasoning and further acquisition of deep knowledge; on the other hand, it can be used to optimize the structure of the neural network and delete redundant connection rights in the neural network. Redundant neurons can improve the generalization ability and learning speed of the neural network.

3.2. Cognitive simulation adaptive learning algorithm

In order to study the performance and characteristics of the adaptive machine learning algorithm based on cognitive simulation, we have implemented an automatic acquisition system of ECG classification knowledge. Some ECG waveforms T100, T105, T106, T108, T111, T112, T217, T219, T220 and T221 are entered in the M IT/BIH ECG database provided by MIT BM E Center of the United States. An experimental study on automatic acquisition of electrocardiogram classification knowledge.

All parameters were set as follows: 105 points before the R-wave vertex and 165 points after the R-wave vertex. The 270 points were sampled, i.e. all 15 points before and after the R-wave, and the other parts were sampled every 6 points. The result was 70 data for each heart beat.

The automatic acquisition system of ECG classification knowledge is composed of neural network (its structure is 70 neurons in the input layer, 20 neurons in the hidden layer and 10 neurons in the output layer). The learning algorithm is BP, and the adaptive learning rules of neurons are introduced, namely, five states of neurons: normal, morbid, imminent, dead, sleep and so on. The knowledge of ECG classification is acquired from the waveform of electrocardiogram T100-T221. The knowledge is stored in the structure of the neural network in the form of distribution. Then, the symbolic knowledge is extracted from the neural network by using the rule extraction algorithm discussed in Section 2, from which it is found that the neural network is automatically formed after learning. The functional areas of P wave, QRS complex wave and T wave classification in ECG represent the deep knowledge of ECG classification. Finally, the structure of the neural network is optimized according to the symbolic knowledge extracted from the neural network and the ECG classification knowledge obtained from experts and books by the symbolic machine learning algorithm, so as to obtain better learning. Effect.

It is found through experiments that the correct classification results of ECG waveforms can be obtained directly from the neural network for the ECG waveforms that have been learned and are similar to those of the ECG waveforms that have been learned. For the waveforms that have not been learned and are quite different from those of the ECG waveforms that have been learned, the system can use the neural network to classify the ECG waveforms. The symbolic knowledge extracted from the network and the knowledge acquired by the symbolic machine learning algorithm are analyzed and reasoned to obtain correct results. Table 1 list the machine learning algorithm based on cognitive simulation for ECG classification knowledge acquisition, and the neural network learning algorithm for ECG classification knowledge acquisition. Symbol machine learning algorithm is used in ECG classification knowledge acquisition system to classify ECG.

Table 1 Experimental results of machine learning algorithm

	Learned patterns	Non-Learned patterns	Learned patterns	Non-Learned patterns
Cognitive simulation	100	98.3	5	20
BP	100	90.1	5	20
IQ3	100	81.7	100	100

From the experimental results in Tables 1, it can be seen that the adaptive machine learning algorithm based on cognitive simulation adopts more flexible learning algorithms (symbolic learning algorithm and join learning algorithm are selected according to the characteristics of the problem) and knowledge representation methods (joint representation and symbol representation are integrated, and symbol representation is represented by join). The knowledge represented by symbols is taken as the basis and guidance of connection learning, and the learning effect and the structure of neural network are optimized. Therefore, the ECG classification knowledge acquisition system based on this learning algorithm, whether in the learning time, or in the correct classification rate and classification time of ECG, refers to the overall performance of the ECG classification knowledge acquisition system. The label is superior to the ECG classification knowledge acquisition system based on BP neural network and IQ3. More importantly, the human thinking and learning mechanism can be further explored.

4. Conclusion

By studying the adaptive learning theory of human brain, this paper proposes an adaptive machine learning method based on cognitive simulation, and automatically acquirement the experiment of the system through the realization of ECG classification knowledge, further proving the advanced nature and effectiveness of the machine learning method. Learning has certain guiding significance.

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