The Application of Morphological Associative Memories in Implicit Learning

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Abstract. Implicit learning research related to the fundamental problem of the development of human potential, which has increasingly become a hot and difficult in cognitive psychology research. The traditional artificial neural network can successfully simulate implicit learning, but there are many disadvantages in the process of simulation, the efficiency of simulation is also quite low. In this paper, the morphological associative memories (MAM) are used in order to solve the problem. MAM not only dose to realize the simulation of implicit learning, but also it can overcome the various defects that traditional artificial neural network in simulation of implicit learning, the efficiency and effect of simulation is gratifying.

Introduction

Implicit learning refers to the organism in the process of contact with the environment unknowingly get some knowledge, experience, and thus change their behavior after some of the learning. Researchers in the field of implicit learning have made many explorations of the controversial issues in the study of implicit learning by means of the artificial neural network model, and have achieved gratifying results. However, as of now, the researchers have chosen the traditional artificial neural network model. Although the traditional artificial neural network model can successfully simulate the implicit learning, but the simulation process is very complex, the efficiency is relatively low.

In 1998, Ritter et al. Proposed a novel associative memory network, morphological associative memories (MAM)[1-2]. MAM has many advantages, it not only overcome the traditional neural network sample storage capacity is limited, learning and training need to repeatedly repeated defects, and, under certain conditions can achieve full memory, especially one step memory, there is no traditional nerve Network convergence problem. By using these advantages of MAM, we try to explore the application of this method in implicit learning and compare it with the results obtained by simulating implicit learning in traditional artificial neural networks, which will provide further theoretical evidence for implicit learning.

The Limitation of Traditional Artificial Neural Network in Simulating Implicit Learning.

These two models are automatic contact (autoassociator) model and simple loop network (simple recurrent network, SRN)[3].Traditional artificial neural network can successfully simulate the implicit learning, but there are many drawbacks, mainly:

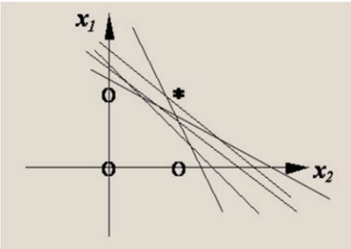
The model requires a number of learning and training to achieve a stable state, learning efficiency is very low.

Take the sensor [4] as an example, With the sensor to achieve a logical "and" function. The truth table of the logical "and" is shown in Table 1.

Table 1 The truth table of the logical "and"

X_1	X_2	y
0	0	0
0	1	0
1	0	0
1	1	1

As can be seen from the truth table, the output can be divided into two types: one output is 0 (indicated by O); the other output is 1 (indicated by *). Of course, the sensor must go through a long learning stage, in order to complete this simple judgment task, the training process shown in Fig. 1.After repeated training until the sensor response is correct, the connection weight no longer make any adjustments, get the connection weight shown in Fig. 2. Fig. 2 shows the straight line $0.5x_1 + 0.5x_2-0.75 = 0$ will be logical "and" operation is divided into two categories, the upper right of the line that the output is "1"; the lower left of the line that the output is "0".



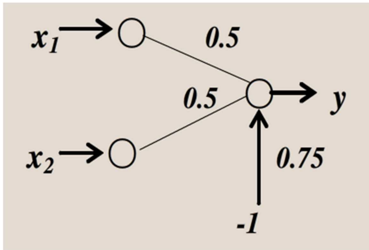


Figure 1. Finite Training process Figure 2. Finite The weight of the connection after training.

This is only a simple example of a single layer of the sensor, the sensor will need to go through complex learning and training. It can be seen that the traditional artificial neural network model based on weight adjustment is used to fit the implicit learning task, and its efficiency is very low.

The traditional artificial neural network has limited storage capacity.

Taking the simple recurrent network[4-5] model of the simulation sequence learning task as an example, its basic structure is shown in Fig. 3.

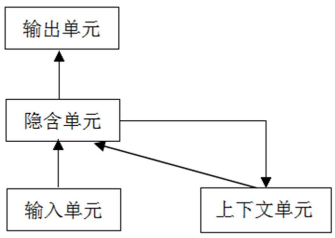


Figure 3. Finite The basic structure of a simple loop network

The storage capacity of the model is limited. When the number of samples in the sample set needs to exceed the storage capacity of the model, the context unit will not be able to store all the sample pattern information. This defect is very unfavorable for simulated implicit learning.

Traditional artificial neural network computing process is complex, and the probability of error.

Autoassociator model must use some learning rules to adjust the connection weight so that the internal input of the machining unit can match the external input. Because the auto-contact model does not have a correct output, the core is to use the internal state to match the external state, to minimize the difference between the two. However, the theoretical analysis shows that by adjusting the connection weight almost impossible to match the success, once the internal state can not match the external state, the model to make the response is wrong, so the model needs to adjust the connection weight several times until they match each other. It can be seen that the probability of the model to make a false response is high.

Traditional artificial neural network function is very simple, does not have the comprehensive characteristic.

Up to now, two kinds of artificial neural network models-automatic contact and simple recurrent network are simulated respectively for two kinds of implicit learning tasks-artificial grammar learning and sequence learning. Theoretical analysis shows that the automatic linker model is widely used in classification problems. The simple recurrent network model is mainly used in forecasting tasks. However, the division between implicit learning tasks is not completely absolute.

In order to overcome these shortcomings of traditional artificial neural networks, we boldly assume that we can use MAM the new artificial neural network to solve these inherent defects of traditional artificial neural networks. In response to these questions, we try to use the various advantages of MAM to explore the analysis.

Morphological Associative Memories Network

Similarly, there are K pattern pairs $(x^1,y^1),(x^2,y^2),...,(x^k,y^k)$,the input mode vector is $x^\xi=(x_1^\xi,x_2^\xi,...,x_n^\xi)^T\in R^n$,the output mode vector is $y^\xi=(y_1^\xi,y_2^\xi,...,y_m^\xi)^T\in R^m$, $\xi=1,2,...,K$ .For a given pattern of associative collections $\{(x^\xi,y^\xi):\xi=1,2,...,K\}$,we can define a pair of associative pattern matrices (X,Y) ,where X is the input vector matrix, Y is the output vector matrix, $X=(x^1,x^2,...,x^K)$, $Y=(y^1,y^2,...,y^K)$ .For each pair of matrices (X,Y) define two $m\times n$ -dimensional morphological memories W_{XY} and M_{XY} as follows:

$$W_{XY}=\bigwedge_{\xi=1}^{k}[y^\xi \boxed{\wedge} (-x^\xi)^T]\ ,\ M_{XY}=\bigvee_{\xi=1}^{k}[y^\xi \boxed{\vee} (-x^\xi)^T] \tag{1}$$

The basic process of MAM-based models in the memory and recall phases is as follows:

Memory stage

MAM has two different memory matrices W_{XY} and M_{XY} ,they are defined as follows:

$$W_{XY}=\bigwedge_{\xi=1}^{k}(y^\xi \vartriangle (-x^\xi)^T),M_{XY}=\bigvee_{\xi=1}^{k}(y^\xi\nabla(-x^\xi)^T) \tag{2}$$

Memories stage

Associate recall stage, the network receives the input mode of the stimulus to react and associate, and get a certain output. For any input mode x^l , $l=1,2,...,k$,associative memory output mode $\tilde{y}^l$,according to the morphology of the association memory rules, there are:

$$\tilde{y}^l=W_{XY}\nabla x^l\begin{bmatrix}\bigvee_{j=1}^{n}[\bigwedge_{\xi=1}^{K}(y_1^\xi-x_j^\xi)+x_j^l]\\ \vdots\\ \bigvee_{j=1}^{n}[\bigwedge_{\xi=1}^{K}(y_i^\xi-x_j^\xi)+x_j^l]\\ \vdots\\ \bigvee_{j=1}^{n}[\bigwedge_{\xi=1}^{K}(y_m^\xi-x_j^\xi)+x_j^l]\end{bmatrix} \tag{3}$$

Similarly, there are:

$$\tilde{y}^l=M_{XY}\Delta x^l\begin{bmatrix}\bigwedge_{j=1}^{n}[\bigvee_{\xi=1}^{K}(y_1^\xi-x_j^\xi)+x_j^l]\\ \vdots\\ \bigwedge_{j=1}^{n}[\bigvee_{\xi=1}^{K}(y_i^\xi-x_j^\xi)+x_j^l]\\ \vdots\\ \bigwedge_{j=1}^{n}[\bigvee_{\xi=1}^{K}(y_m^\xi-x_j^\xi)+x_j^l]\end{bmatrix} \tag{4}$$

Experiment

Experimental Description. In order to show the characteristics of MAM and the characteristics of implicit learning with a perfect match, and a more image of the various advantages of MAM, we use the literature [1] in the analysis.

Experiment 1 When the input mode is complete.

First, consider the five pattern images $p^1,...,p^5$ in Fig. 4, each p^ξ is a 18×18 binary map, as shown below:

Figure 4. Finite Sample mode image

According to the MAM learning, memory, memory operation, we get the same output result as the sample pattern, and the operation process is in one step. When the number of patterns from five to ten, that is, to add lowercase letters shown in Fig. 5, the same can be completely recalled.

Figure 5. Finite Sample mode image

The above experiment is carried out in the absence of noise, let's look at the effect of MAM handling noisy mode.

Experiment 2 The input mode contains corrosive noise or expansion noise.

The experiment still uses the image in Fig. 4 as the sample pattern, and the etching method is used for the letter X in the sample pattern using different methods. However, the resulting output is exactly the same as sample pattern X, as shown in Fig. 6.

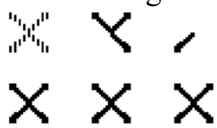


Figure 6. Finite The behavior of the corrosion with the noise of the model X, the lower the output of the results

Likewise, the letter X in the sample pattern is expanded using different methods, and the resulting output is exactly the same as the sample pattern X, as shown in Fig. 7.

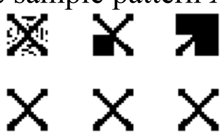


Figure 7. Finite The upper behavior contains the expansion noise of the mode X, the lower behavior of the output

The above experiment is carried out in the case of only containing corrosive noise or expansion noise. Let us look at the effect of MAM in dealing with sample mode with random noise.

Experiment 3 The input mode contains random noise.

Using the letters A, B, and X in the sample pattern as test samples, and using random noise to etch and expand the individual letter images, the results are still the same as the corresponding letter image in the sample pattern, as shown in Fig. 8.

Figure 8. Finite The upper behavior of the random noise with the mode A, B, X, the next behavior output

Experiment Analysis. Experiments 1 and 2 show the Auto RMAM of each letter image in Fig. 4 and Fig. 5, respectively, and get the corresponding perfect memories. MAM in the learning, memory, memory process, the operation is not repeated, without iteration, only through a calculation, learning, put the letter image mode vector stored in the memory matrix. In the memory phase, the same, the operation is not repeated, without iteration, only through a calculation, memories, and get the sample pattern exactly the same perfect memories. This process fully reflects the MAM and implicit learning is also a learning process, and compared with the traditional artificial neural network, memory, memory process is very fast, there is no convergence of traditional neural networks, so for analog implicit Learning is critical.

In experiment 2, the number of sample patterns increased from five to ten. In this case, MAM is still able to make perfect memory memories, indicating that it has good storage performance. This overcomes the limited shortcomings of the traditional neural network storage capacity, but also closer to the human brain capacity. Compared to human implicit learning and memory, in some cases, there is a lot of knowledge of human implicit learning and memory, then the model must have enough space to store the knowledge when simulating. If the model's storage capacity is limited, the simulation process will not proceed, however, using MAM to simulate implicit learning will not take into account storage performance issues.

Experiments 2 and 3 are memory memories containing noisy alphabet images, and the results are perfect memories. This is very convincing to explain the anti-jamming of implicit learning. Implicit learning process has a lot of interference factors, but still can get some knowledge. Experiments show that MAM has a certain anti-interference ability, which is implicit learning immunity is very similar.

In the experiment, after learning, memory to get the memory matrix, from this disorder and messy matrix, we can not see what rules. But in the memory stage, but it is the use of this disorderly memory matrix, the model was made a complete memory. It can be seen that the knowledge of MAM through learning and memory is abstract, this abstract knowledge is similar to the abstract knowledge obtained by implicit learning, so MAM can explain the abstraction of implicit learning.

Concluding Remarks

Researchers in the field of implicit learning generally believe that implicit learning plays a pivotal role in the learning process, and the knowledge gained cannot be ignored. People are eager to know themselves, hoping to further reveal the mystery of implicit learning. However, the current study of implicit learning is still in the initial stage.

In this paper, the advantages of morphological association memory network are used to explore the adaptability, simulation efficiency and effect of simulated implicit learning, and explain several characteristics of implicit learning. This not only opens up new horizons for morphological associative memory networks, but also provides updated tools and richer theoretical evidence for implicit learning mechanisms.

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