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Mutually Connected Neural Network Can Learn Some Patterns by Means of GA

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abstract

We simulated an associative memory with mutually connected neural network, and successfully made the connection matrix learn some binary patterns only by means of genetic algorithm. Although the memory capacity is about 12 % of the number of neurons, the fact that it was made without any learning algorithm like Hebbian rule is very interesting. The structure of connection matrices we obtained is quite different from that of Hopfield network.

Our overall goal for this research is two fold. One is to know if we can use genetic algorithm as a more effective learning method than that proposed so far, and another is to understand this learning mechanism of genetic algorithm.

1 Introduction

Associative memory has a limit in capacity depending on the learning rule in memorizing patterns with. In 1982, Hopfield proposed his model with using Hebbian rule, and his associative memory system has the memory capacity of about 15 % of the number of neurons as in standard literatures. Since then there have been many approaches to enlarge the capacity. In another paper, we challenged it by a genetic algorithm, and we showed that the memory capacity of connection matrix which learned some patterns by Hebbian rule can be enlarged to about 30 % of the number of neurons, i.e. about twice as much as the one in Hopfield network.

In this paper, on the other hand, we applied genetic algorithm to the connection matrices generated randomly instead. Neural networks with randomly generated connection matrices can not retrieve any given patterns of course. But after applying genetic algorithm to them, we were able to make the network memorize some patterns.

2 Method

One of the features of our genetic algorithm is that the initial connection matrix is remained fixed over the time of evolution. Our chromosomes have a fixed length of $(number\ of\ neurons)^2$, and their allele values are chosen randomly from either -1, 0, or 1, in which 0 implies to prune the connection and -1 to reverse the role of enforcement or suppression of the weight.

In the simulation here, each element of initial matrix is chosen randomly from $\{-1, 1\}$. Hence the matrix does not memorize any patterns at the beginning. And the matrix does not include any zeros, and is not symmetrical at the start of genetic algorithm.

To evaluate the fitness, we summed up all the overlappings at each time of update not more than certain time t_0. That is, our fitness f is

$$f = \frac{1}{p \cdot (t_0 - 1) \cdot 49} \sum_{\mu=1}^{p} \sum_{t=2}^{t_0} \sum_{j=1}^{49} \xi_j^\mu s_j^\mu(t),$$

where $(\xi_1^\mu, \xi_2^\mu, \xi_3^\mu, \cdots, \xi_{49}^\mu)$ is the μ-th pattern, $s_i^\mu(t)$ is the corresponding state of update of i-th neuron at time t, and $t_0 = 98$. Fitness 1.000 implies that all the initial patterns are fixed points, while fitness less than 1.000 includes many possible cases.

3 Results and Analysis

In Figure 1, we showed some examples of fitness vs. generation for 4, 6, 7, 8, and 12 patterns, where t_0 was two times of the number of neurons.

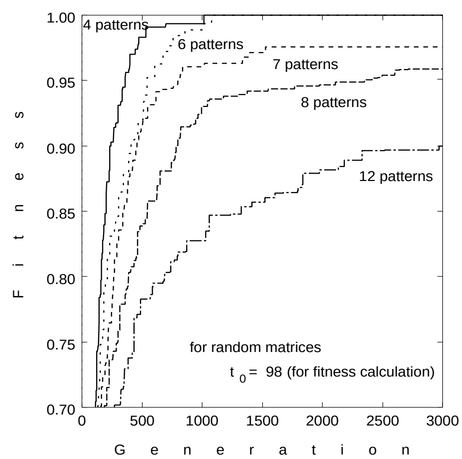

Figure 1: **Fitness vs. Generation**

In Table 1, we showed the fitness values and the number of fixed points obtained at the 3000th generation with increasing number of initial patterns. In the case of 4, 5, and 6 patterns, we obtained the fitness value of 1.000 within 3000 generations, which implies that all the initial patterns are fixed points for the obtained weight matrix as described above. So far, however, we have not obtained the fitness value of 1.000 for the patterns more than six.

In Hopfield network, connection matrix is symmetric and the elements are not zero except for diagonal elements. Our matrices, on the other hand, do not contain any zero including the diagonal elements. In creating individuals, however, some elements could become zero by being multiplied by zero. These zeros are generated at the rate of 0.02 in the beginning, and later the rates

Table 1: Maximum Number of Fixed Points

patterns	4	5	6	7	8	12
fitness	1.000	1.000	1.000	0.976	0.959	0.900
fixed-point	4	5	6	3	2	1

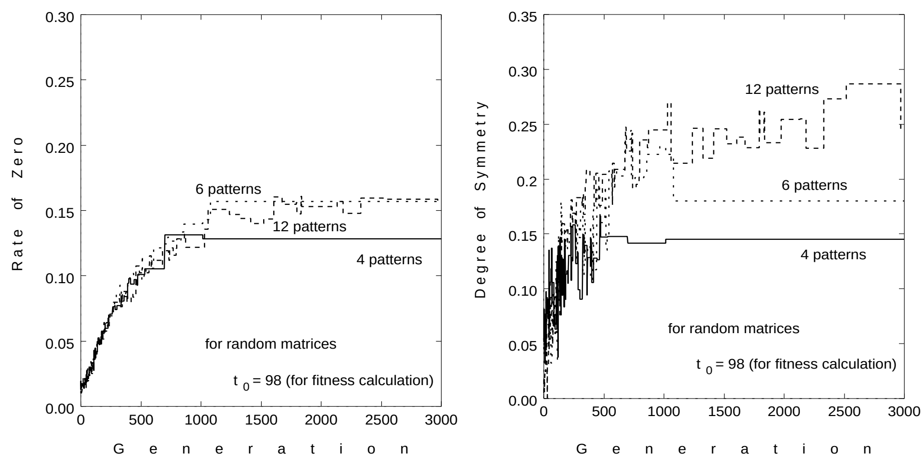

Figure 2: **Rate of Zero (left) and Degree of Symmetry (right)**

vary according to the selection pressure during evolution. And the degree of symmetry of our matrix is almost zero from the beginning.

In Figure 2, we showed the behaviors of the rate of zeros and the degree of symmetry of connection matrix, which are of the elitest individual in each generation. The definition of degree of symmetry η here is

$$\eta = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}w_{ji} / \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}^2.$$

As we can see in those Figures, the behaviors of these parameters are close to those of fitnesses.

As described earlier, -1 in the chromosome reverses the roll of enforcement or suppression of the weight, and 0 prunes the connection. To ascertain the effect of -1 and 0 in the chromosome, we made the following two experiments. One is with the chromosomes chosen from $\{-1, 1\}$ and another is from $\{0, 1\}$ under the same condition of a simulation with the chromosomes chosen from $\{-1, 0, 1\}$ above. We showed the results in Figure 3. Although the chromosome chosen from (a):$\{-1, 0, 1\}$ worked most effectively, as we can see in Figure 3, the chromosome made up of either (b):$\{-1, 1\}$ or (c):$\{0, 1\}$ also worked. The number of fixed points resulted from the experiment(b) was four, whereas one from the experiment(c). The roll of -1 seems to be more important than 0, but we need 0 to obtain six fixed points in the experiment(a).

Consequently we may conjecture that both of rate of zero and degree of symmetry have something to do with learning, though we need further research.

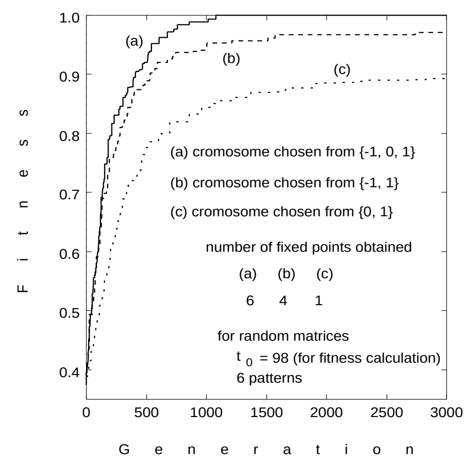

Figure 3: **The Roll of -1 and 0 in the Chromosome**

4 Conclusions

We successfully made the random matrices memorize some patterns only by means of genetic algorithm. This time we simulated with the neural networks with 49 nodes, and we obtained the maximum of six fixed points of associative memory. Although the memory capacity of connection matrix achieved are less than that of Hopfield network, it may lead to useful applications to obtain the higher capacity of associative memory, as well as helping to clarify the process of learning. The matrices we obtained here are quite different from those of Hopfield network. These are asymmetric and include about 20% of zeros. And the behaviors of both rate of zeros and degree of symmetry are very close to those of fitnesses. Hence, we conjecture that these parameters play an important roll to make the connection matrix memorize some patterns, and genetic algorithm could have its own unique learning mechanism which we have not found in the already known learning algorithms.

Acknowledgment

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References

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