A New Method of Multilayer Perceptron Encoding

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1 Evolving Neural Networks

One of the central issues in neural network research is how to find an optimal MultiLayer Perceptron architecture. The number of neurons, their organization in layers, as well as their connection scheme have a considerable influence on network learning, and on the capacity for generalization [7]. A solution to find out these parameters is needed: The neuro-evolution ([1,2,4,5]).

The novelty is to emphasize the network performance aspects, and the network simplification achieved by reducing the network topology. All these genetic manipulations on the network architecture should not decrease the neural network performance.

2 Network Representation and Encoding Schemes

The main goal of an encoding scheme is to represent neural networks in a population as a collection of chromosomes. There are many approaches to genetic representation of neural networks [4], [5]. Classical method use to encode the network topology into a single string. But frequently, for large-size problems, these methods do not generate satisfactory results: computing new weights to get satisfactory networks is very costly.

A new encoding method based on the matrix encoding is proposed: A matrix where every element represents a weight of the neural network.

Several operators for a genotype have been proposed: crossover operators and mutation operators. For the classical crossover operation, a new matrix is created from two splitted matrix: the offspring get two different parts, one from each parent. This can be considered as the one point crossover, in a two dimension space A second crossover operator is defined: an exchange of a submatrix between the parents is done. For the mutation, several operators are availables. The first is the ablation operator. Setting one or several zero in the matrix, we are removing these connections. Setting to zero a partial row or column, we delete several incoming or outgoing connections from the neuron. The second is the grown operator: connection are added. Again, we can control where the connections are added, and know if a neuron is fully connected or not.

With these operators, as matrix elements are the weights of the network, some learning is required to get a new optimal network. As only a few weights have changed, the learning will be faster.

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3 Experimentation

The performance have been evalued on several classical problems. These case studies have been chosen based on the growing complexity of the problem to solve. Each population had 200 individuals. For each individual, 100 epochs were carried out for training. For the genetics parameters, the crossover percent is set to 80%, with a elitist model. 5% of the population can fall under mutation.

Compared with other results from [3], this new method has shown the best, not only in term of network complexity, but also in quality of learning

Table 1. Results of experimentations

	XOR	Parity 3	Parity 4	Parity 5	Heart	Sonar
Number of hidden neurons	2	3	5	8	12	30
Number of connections	6	11	23	38	354	1182
Number of epochs (error)	13	23	80	244	209 (9%)	120 (13%)

4 Conclusion

The experiments have confirmed that, firstly by encoding the network topology and weights the search space is affined; secondly, by the inheritence of connection weights, the learning stage is speeded up considerably. The presented method generates efficient networks in a shorter time compared to actual methods. The new encoding scheme improves the effectiveness of evolutionary process: weights of the neural network included in the genetic encoding scheme and good genetics operators give acceptable results.

References

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