Uniform Coevolution for solving the density classification problem in Cellular Automata

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Abstract

Uniform Coevolution is based on competitive evolution ideas where the solution and example sets are evolving by means of a competition to generate difficult test beds for the solutions in a gradual way. The method has been tested with the density parity problem in cellular automata, where the selected examples can biased the solutions founded. The results show a high value of generality using Uniform coevolution, compared with no Co-evolutive approaches.

1 INTRODUCTION

Coevolution has proven its capabilities of generating complexity in nature. From the computational point of view, a competitive system is composed by several confronted subsystems where the evaluation of a subsystem depends on the performance over the opposite one. We propose a new method of adjusting coevolution to allow: the evolution of good solutions and hard test examples in difficult generalization problems.

2 DENSITY CLASSIFICATION PROBLEM

The Density Classification Problem (DCP) is one of the most studied problems in Cellular Automata (CA). This problem is interesting from both, theoretical and practical aspects, and it has been proven the non existence of any rule able to solve the problem for a binary CA with a neighbourhood of radius 1. The DCP is defined by the equation:

$$T_{\rho_c}(N,M)=\begin{cases}\Psi_m(s_0)=0^N & \text{if } \rho(s_0)< \rho_c\\ \Psi_m(s_0)=1^N & \text{if } \rho(s_0)> \rho_c\\ \text{not determined} & \text{if } \rho(s_0)= \rho_c\end{cases}$$

$T_{\rho c}(N,M)$ is an unidimensional DCP of size N with a critical density of ρ_c and after M updating periods. If the initial density $\rho(s_0)$, is shorter than the critical density, the CA has to transit, after M steps, to a configuration of all zeros. s_0 is the initial configuration, the configuration of a CA after some i steps is $s_i=\Psi(s_0)$, where the function Ψ defines the rule of the CA.

3 UNIFORM COEVOLUTION

The architecture is composed by: a population of solutions and a set of populations of examples (One population of examples for each individual in the population of solutions). The evolution of each system depends on the other evolution. In DCP the population of solutions is composed by the binary codification of the rules of the cellular automata. The evolution of the rules are taken by a Genetic Algorithm (GA). The population of examples are the initial state configurations of the CA.

Two main goals have been achieved with Uniform Coevolution. From one hand the learning process has been slowed to avoid over-adaptation and to allow generalisation. On the other hand there is less variations in the solutions, so there is a high uniformity in the solutions achieved. The evolution of the examples reduce the diversity of suboptimal solutions, allowing generality.

4 CONCLUSIONS

The Uniform Coevolution method allows the production of generalized behaviors gradually, changing by time the selective pressure of the individuals. The selective pressure is addressed to the generation of good behaviors in simple environments. This solves the problem of over-adaptation. The advantage arises from the gradually and independent evolution of the examples, adapting to each particular solution tested.

In this way, although changing, a similar and smooth fitness landscape is always kept, that allows the adaptation at the same time at the generation of more complex and generalised behaviours. This solves the problem of over-adaptation. The results show how the learning process in Uniform coevolution goes gradually, and uniformly achieving generalisation, and avoiding local minima.