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Rapport of Module Project

Coevolutionary algorithms

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Génie Informatique appliquée 2.1

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I. Motivation :

Coevolutionary Learning has received a lot of attention since it builds on genetic algorithms (GAs) and other evolutionary computation methods. Hillis carried out the first explicit use of computational "host-parasite coevolution" (1990). The coevolution of hosts and parasites in nature served as Hillis's inspiration. The "egg mimicry" in plants is one striking example of a phenomena that occurs in nature. On plant leaves, insects like butterflies will occasionally deposit their eggs, giving the newly emerging larvae a convenient source of food. The passion flower plant produces poisonous compounds in its leaves as a defense mechanism against such parasitism. The Heliconius butterfly genus has developed a counter-adaptation, allowing its larvae to resist toxic toxins. The passion flower has developed a stunning counter-counteradaptation in response. Its leaves have yellow dots that resemble the eggs of Heliconius. The marks on the leaves of passion flowers trick at least some butterflies into believing that there are already too many eggs on the leaves, which prevents butterflies from laying eggs on leaves that are already overcrowded with eggs, which prevents too much food competition among larvae. It also transpires that the yellow spots are actually glands that secrete honey, luring ants and wasps, which also feed on the eggs and larvae, to the area.

There are many instances of these "evolutionary arms races" among coevolving creatures in nature, and Darwin identified them as a key factor influencing evolutionary change. These concepts were employed by Hillis in his computer-based evolution of the best parallel sorting networks. The hosts were the evolving networks, and the fitnesses of the hosts were based on how well they performed on training challenges (lists of items to be sorted).The lists themselves – the parasites – evolved to be challenging for the evolving hosts. Hillis found significant improvement in the resulting sorting networks as compared with those evolved via a more standard genetic algorithm.

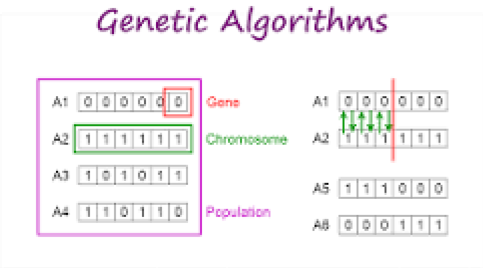
II. Introduction :

A coevolutionary algorithm is an evolutionary algorithm in which the fitness of an individual is subjective which means that the individuals are evaluated based on their interactions with other individuals. According to the nature of these interactions, coevolutionary algorithms fall into two main groups: Competetive Coevolutionary Algorithms and Cooperative Coevolutionary Algorithms.

- In the case of cooperative algorithms, individuals are rewarded when they work well with other individuals and punished when they perform poorly together. For example, consider an algorithm where each population represents a piece of a larger problem, and it is the task of those populations to evolve increasingly more fit pieces for the larger holistic problem.
- In the case of competitive algorithms, however, individuals are rewarded at the expense of those with which they interact. For example, consider a predator-prey

model in which individuals in one population represent some kind of device (e.g., a sorting network) and individuals in another population represent some kind of input for the device (e.g., a data set), and the object of the first population is to evolve increasingly better devices to handle the input, while the object of the second population is to evolve increasingly more difficult inputs for the devices.

III. Vocabulary of Co-Evolutionary Algorithms:



Individual: An individual is characterized by a set of parameters (variables) known as Genes. Genes are joined into a string to form a Chromosome (solution).

Population: is a subset of solutions in the current generation. Population P can also be defined as a set of chromosomes.

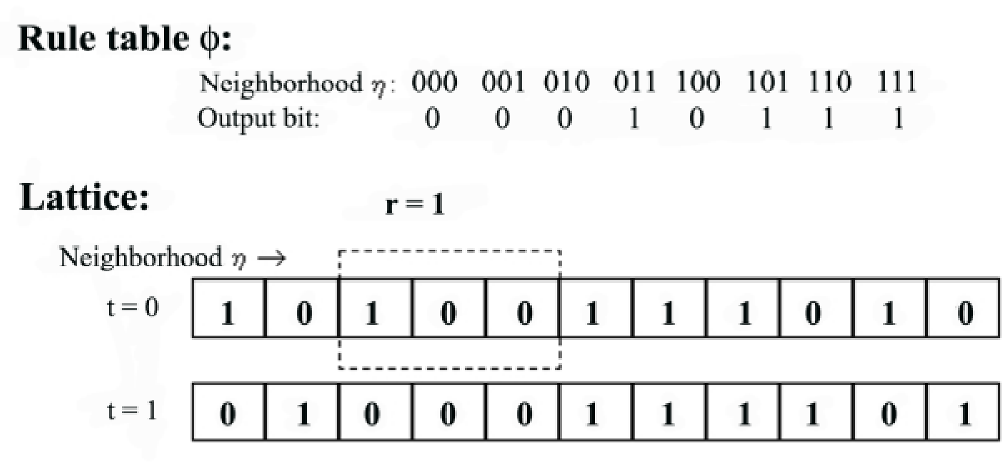
Fitness Function: A fitness function determines the quality of the solutions the candidates find as they move about in each iteration.

Cellular Automata: (CA) is a collection of cells arranged in a grid of specified shape, such that each cell changes state as a function of time, according to a defined set of rules driven by the states of neighboring cells.

RuleTabe: A CA's rule φ can be expressed as a lookup table (or "rule table") that lists, for each local neighborhood, the state that is taken on by the neighborhood's central cell at the next time step. For a binary-state CA, these update states are referred to as the "output bits" of the rule table.

IV. The concept of Spatial Coevolution:

Such a CA is a one-dimensional lattice of N two-state machines ("cells"), each of which changes its state as a function only of the current states in a local neighborhood. As is illustrated in the figure, the lattice starts out with an initial configuration (IC) of cell states (0s and 1s) and this configuration changes in discrete time steps. At each time step, all cells are updated simultaneously according to the CA rule φ. "State" refers to the value of a single cell and the term "configuration" refers to the collection of local states over the entire lattice. In a one-dimensional CA, a neighborhood consists of a cell and its radius "r" neighbors on either side. Here we describe CAs with periodic boundary conditions (the lattice is viewed as a circle).



The percentage of correctly classifying a host's fitness against a sample of n parasites in their trials is called fitness.

The fitness of a parasite p with respect to a single host h is defined as 0 if h classifies p correctly, and | density(p) − 1/2 | otherwise. Since the hardest starting configurations to classify will have density 1/2, this is a domain-specific method of reducing the virulence of parasites. According to Pagie and Mitchell, spatial coevolution greatly outperformed traditional evolution and evolution with a spatially distributed population at evolving particle strategies.

V. The production of a new population:

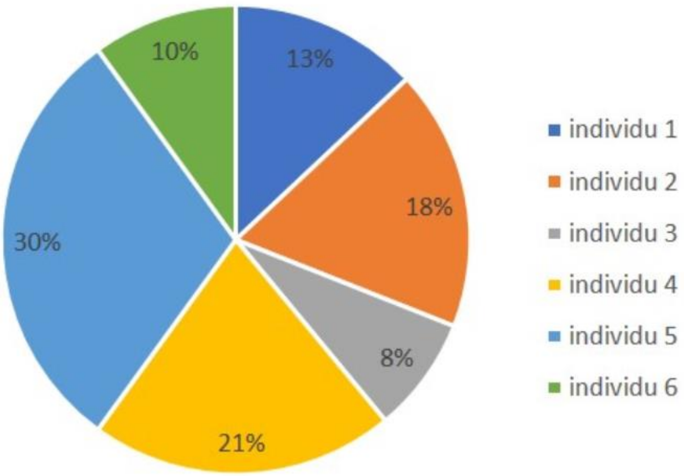
The host and parasite populations are distributed on a two-dimensional grid of M × M sites, with wrap-around at the boundaries to form a torus. Each site contains a single host h and a single parasite p.

At each generation, the following steps take place for all hosts and for all parasites, constituting a single generation:

1. **Fitness calculation:**

   Calculate the fitness of each host h in the population using nine parasites: the parasite at the same site as h and the parasites at the eight neighboring sites. Calculate the fitness of each parasite p in the population with respect only to the host in the same site as p. The fitnesses of all individuals in a population are computed synchronously.

2. Selection:



For each host h, rank h along with the other eight hosts in its neighborhood according to fitness, with the highest fitness host having rank 1 and the lowest having rank 9. Each of these 9 hosts has probability of being selected equal to 0.5^rank (except for the bottom-ranking host, which has probability 0.58 , so that the nine probabilities will sum to 1). The selected host h′ replaces the host h in the center site of this neighborhood .The same selection procedure is applied to each parasite p, which competes similarly with the eight other parasites in its neighborhood. The replacement of hosts and parasites at each site are done synchronously.

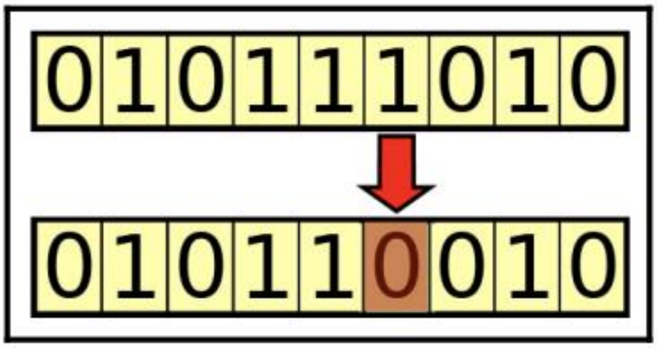
3. Crossover of hosts:

<table>
<tr><td>Chromosome1</td><td>11011|00100110110</td></tr>
<tr><td>Chromosome2</td><td>11011|11000011110</td></tr>
<tr><td>Offspring1</td><td>11011|11000011110</td></tr>
<tr><td>Offspring2</td><td>11011|00100110110</td></tr>
</table>

Single Point Crossover

Each site in the grid now contains a selected host h ′ and a selected parasite p ′. At each site, decide whether or not to perform a crossover according to the crossover probability. In our experiments, only hosts are subject to crossover. To cross over a host h′, randomly choose a second host h″ at a different site in the same neighborhood, and cross over h′ and h″ at a randomly selected point to form two offspring. Discard one of the offspring at random, the other one replaces h′ in the center site.

4. Mutation:



Mutation operator applied to a binary-coded chromosome

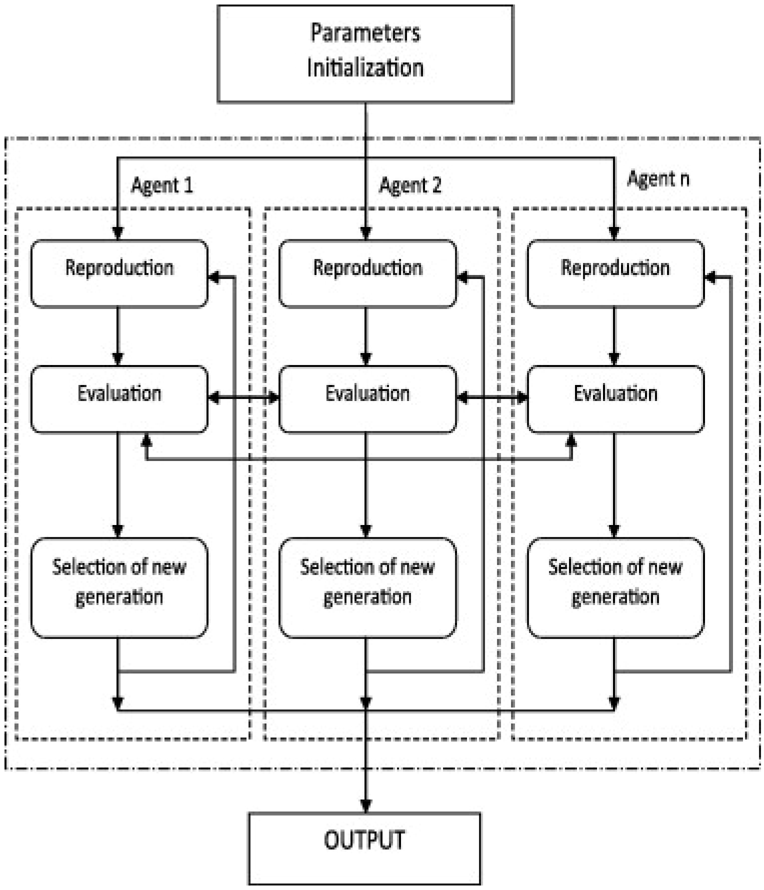
4.1 Mutation of hosts:

Apply mutation to all hosts, according to the host mutation probability. In the cellular-automaton task, choose one or more bits and flip their values.

4.2 Mutation of parasites:

Apply mutation to all parasites, according to the parasite mutation probability. For the cellular automaton task, choose one or more bits in the parasite (initial configuration) and flip their values.

VI. The Algorithm :



VII. Pathological Behaviours of Coevolutionary Algorithms:

Coevolution often needs special heuristics or starting conditions in order to overcome several impediments associated with coevolution alone. These impediments have been pointed out by various researchers (Cartlidge and Bullock, 2004; De Jong and Pollack, 2004; Nolfi and Floreano, 1998; Paredis, 1997; Shapiro, 1998), sometimes using different terminology.

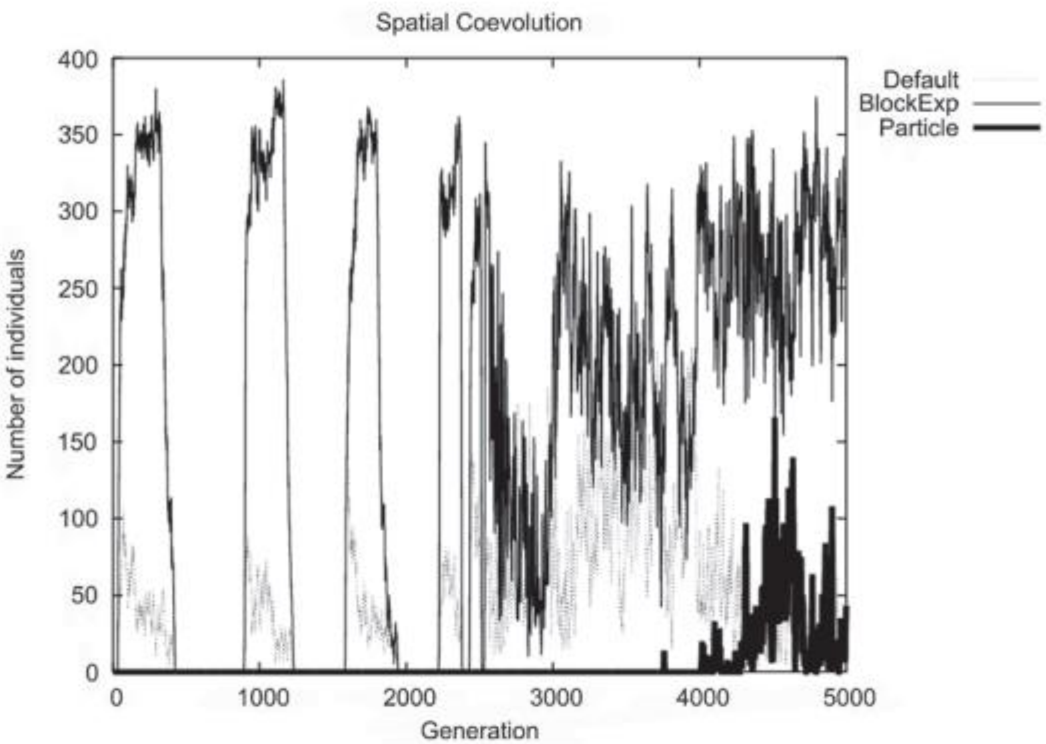
The following is a partial list:

- ✓ **Loss of gradients:** Coevolution results in a situation where the host population finds the parasite population to be either too easy (referred to as "disengagement") or too challenging (referred to as "over-virulence") to cope with. Consequently, every member of the host population either eliminates all parasites it samples (but not all conceivable parasites) or is eliminated by all parasites it samples. In either situation, there is no longer a gradient (i.e., a difference in fitnesses) that can be exploited for selection because all hosts and parasites have the same fitness.

- ✓ **Over-specialization:** The host population becomes trapped in a local optimum where hosts are only effective against a specific subset of parasites and do not offer a comprehensive solution to the issue at hand.
- ✓ **Red queen dynamics (or cycling or mediocre stable states):** The populations of hosts and parasites continue to change in response to one another but these changes do not force hosts to become more general solutions.

VIII. Solution:

Several experiments have given evidence that the combination of spatial distribution and coevolution is considerably more successful than either alone, or than resource sharing alone. Particularly notable is the fact that spatial coevolution produced a majority of successful runs even though each host is evaluated on only 9 parasites. Other methods, some using many more parasites to evaluate hosts, achieved much lower success than spatial coevolution.



IX. Domain of application of Co-Evolutionary Algorithms :

To ground these ideas, let us consider three historically-important applications of coevolutionary algorithms :

✓ Single Population CoEA Applied to a Test-Based Problem :

Individuals have two roles in single population applications to test-based problems: sometimes they are utilized as (components of) prospective solutions, and other times they are employed as tests to gather evaluation data on other individuals.

Individuals in the CoEA are vectors of weights for a fixed-structure neural network, and are evaluated by playing against other individuals.

Points are awarded based on the win / loss / draw record, and fairly standard evolutionary programming methods are used to select players, hence weight vectors, with better records. The CoEA employed for this problem was able to produce a checkers player that is competitive with the best existing human and AI players.

✓ Relative overgeneralization :

The coevolutionary behavior that occurs when populations in the system are attracted towards areas of the space in which there are many strategies that perform well relative to the interacting partner. This behavior can be observed in both competitive and cooperative algorithms, however, it is more an issue for cooperative algorithms than for competitive ones.

✓ Mediocre objective stasis:

The coevolutionary behavior that occurs when there is no apparent progress according to some reasonable objective measure, despite continued adaptive subjective steps in the interacting individuals and population(s). The term “mediocre objective stasis” corresponds, in part, with the more common term “mediocre stability”as well as some behaviors alternatively classified as “relativistic”.

X. Simulation of a Co-Evolutionary Algorithm :

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Initial grid initialized.
Iteration 1 of 10, computing fitnesses:
CA Fitnesses:
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IC Fitnesses:
0,02 0,06 0,10 0,04 0,04 0,08 0,00 0,14 0,05 0,01 0,04 0,04 0,03 0,06 0,01 0,03 0,05 0,02 0,04 0,02
0,03 0,03 0,02 0,04 0,06 0,02 0,04 0,03 0,03 0,02 0,03 0,01 0,01 0,00 0,02 0,06 0,02 0,01 0,04 0,06
0,00 0,01 0,06 0,02 0,02 0,01 0,01 0,02 0,08 0,05 0,02 0,03 0,00 0,03 0,08 0,02 0,09 0,04 0,01 0,00
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0,01 0,07 0,04 0,08 0,00 0,00 0,05 0,03 0,06 0,06 0,03 0,05 0,02 0,05 0,03 0,07 0,01 0,04 0,03 0,00
0,01 0,04 0,02 0,04 0,04 0,02 0,04 0,00 0,01 0,08 0,03 0,04 0,05 0,01 0,03 0,00 0,00 0,03 0,01 0,00
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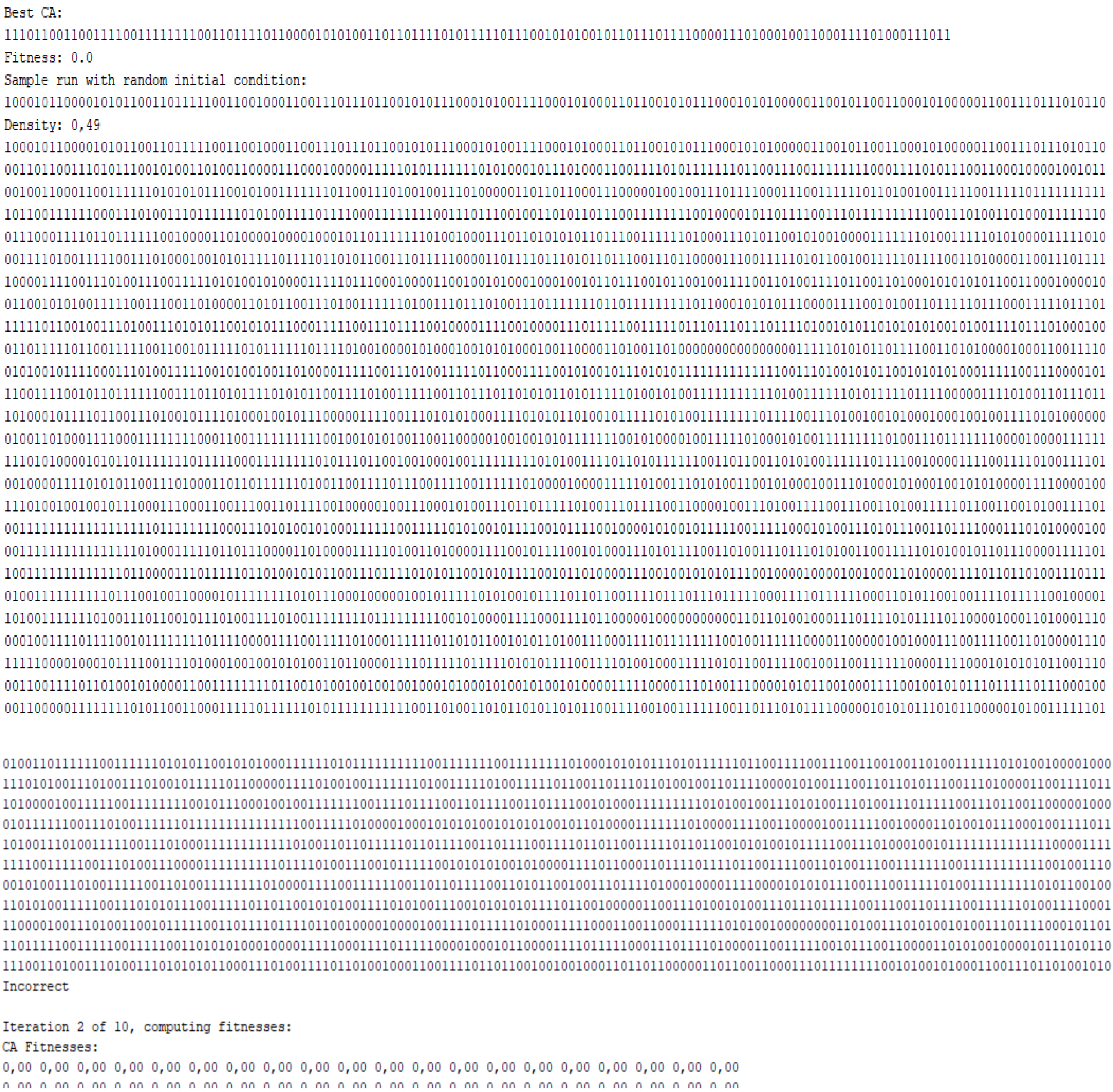

XI. Conclusion :

Spatial coevolution is considerably more successful on two non-trivial learning tasks than several other evolutionary methods, requires fewer training problems for success, and may be a generally effective method for overcoming impediments. One reason seems to be that spatial coevolution, alone among these methods, is able to maintain diversity in the host population for long periods during a run. Another reason seems to be that parasites evolve to specifically target weaknesses in host strategies, forcing hosts to evolve new strategies without those weaknesses. It appears that spatial coevolution encourages parasites and hosts to engage in productive arms races.

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https://wiki.ece.cmu.edu/ddl/index.php/Coevolutionary_algorithms#:~:text=A%20coevolutionary%20algorithm%20is%20an,their%20interactions%20with%20other%20individuals
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