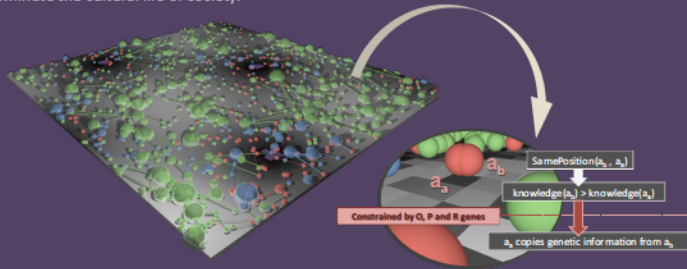


INTRODUCTION

Bacteria have demonstrated an amazing capacity to overcome environmental changes by collective adaptation through genetic exchanges. By using a distributed communication system called *conjugation*, bacteria propagate innovations that allow them to survive in different scenarios. We have developed a proof-of-concept inspired by conjugation to test how, in artificial societies based on interactions among agents with bounded rationality, optimal results emerge by incrementing heterogeneity levels and decentralizing communication structures, leading to 'P2P Societies'.

BASIC MODEL

In this model, we have a set A with N agents (a_i). Each agent owns a genome that contains a specific strategy (s_i) to optimize a function. Depending on an agent's strategy, its knowledge level will be greater or lower. Then if an agent is able to optimize a given function in order to get a result with 70% of accuracy by using its own strategy, its knowledge level will be set to 70 and so on. Knowledge levels determine an agent's position in the social structure. So agents with a more successful genome will dominate the cultural life of society.



During simulation agents move randomly through a bi-dimensional grid. When two agents reach the same coordinates (x,y) they compare their knowledge levels. After that, the one with a lower knowledge (a_j) tries to get a copy of genome from the more successful (a_i). If the owner of the best strategy (a_i) does not share its strategic knowledge we will say that conjugative machinery to send plasmids is inhibited. Otherwise a_j will offer a plasmid with a copy of its genome to agents in the same coordinates and lower knowledge. Even though if the owner (a_i) allows the other agent (a_j) to get a copy of its genome and then improve its strategic knowledge, a_i can impose two restriction policies to that copy:

- **Inhibit reproduction:** The receiver of a plasmid (a_j) is allowed to use the strategy that is contained in the copy but it does not own the intellectual property of that strategy. Then plasmid cannot be sent to others once it is received. In this case the first owner (a_i) is the only one with reproduction rights on that strategy.

- **Inhibit mutation:** The receiver (a_j) can use the strategy but cannot modify it. Genome only can be used as a unit of private software or as a behavioral dogma, following the exact strategy proposed by first owner (a_i). Otherwise, if mutation is not inhibited, strategies may be modified or mixed with other ones by the receiver (a_j).

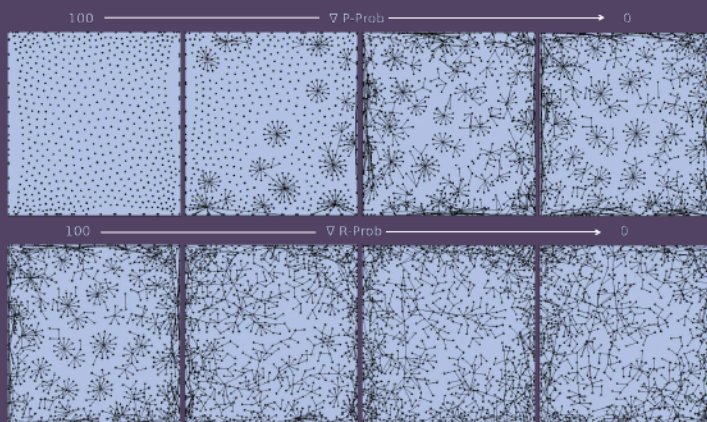
AGENT GENOME

Each agent (a_i) of the agents set A has its own strategy (s_i) coded as a part of its genome. Considering a set Sec containing several strategies (s_i), its cardinality $|Sec|$ (number of different strategies) will be equal or bigger than unity and equal or smaller than cardinality of A . We will denote it as:

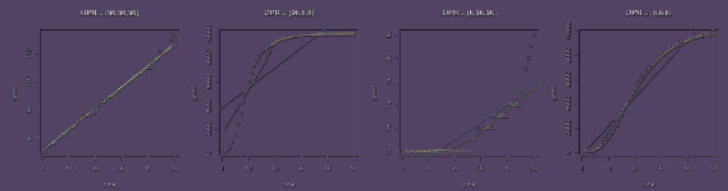
$$\forall a_i \in A \exists s_i \in Sec$$

$$1 \leq |Sec| \leq |A|$$

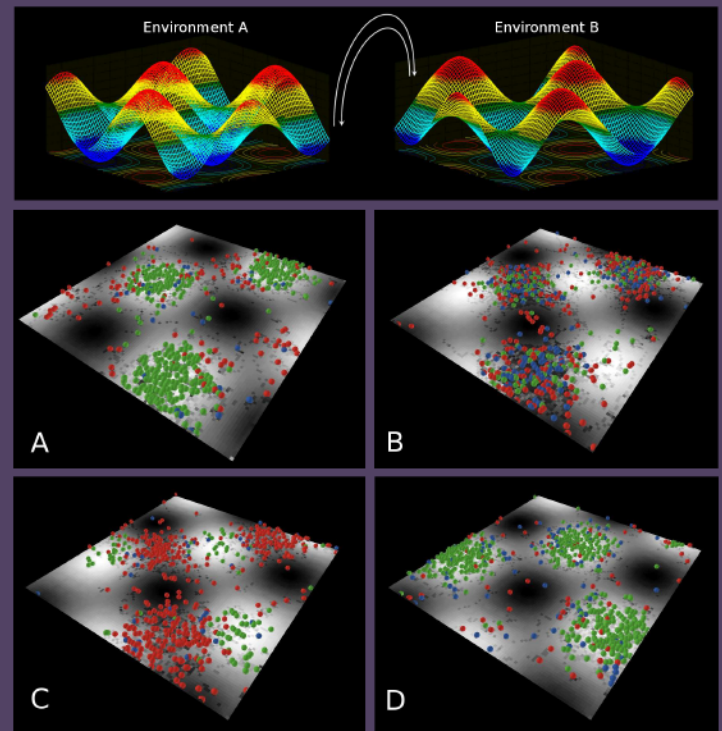
If by default the value of $|Sec|$ was one, simulation would start in a completely homogeneous society. If this value was near to $|A|$ (number of agents) it would be a heterogeneous society. Agent genome has a segment denominated "S" which contains a coded strategy (s_i) of the set Sec . Genome also can include another three sequences (P, R and O) which are related to the three constraints that we have described: inhibit mutation (O), inhibit original plasmid conjugation (P) and inhibit copy reproduction (R). The expression probability of these genes (OPR is O-Prob, P-Prob, R-Prob) will change the structure of the system.



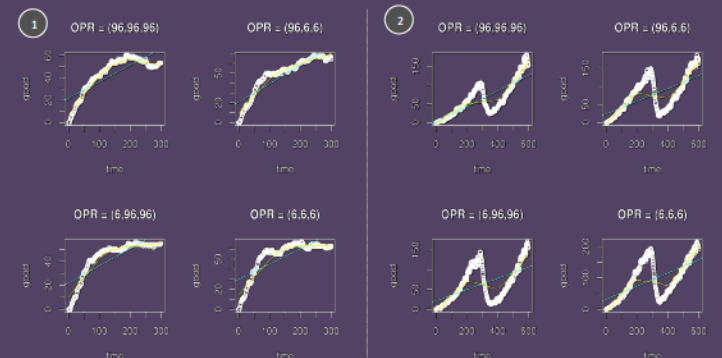
SIMULATION RESULTS



Basic model applied to optimize a function: impact of OPR on production of knowledge. Plot of strategies with accuracy higher than 0.7 in four simulations of 10^4 agents during 50 iterations.



Extended model: Artificial life in a sugarcape-like scenario with dynamic distribution of resources. In this model, strategic genome (S) codifies motor behavior. Low O-Prob leads to heterogeneity of strategies and therefore to a resilient behavior. The (A,B,C,D) screenshots show the evolution of the system over the change from Environment A to Environment B. White levels represent resources concentration. Agent colors represent its energy: green means higher than 70 units, blue means between 50 and 70 units and red lower than 50 units. Decentralized systems perform better because they allow horizontal gene transference, that is, horizontal learning. Heterogeneity produces more innovative solutions preserving nomadism in sedentary communities.



Extended model: Impact of OPR on adaptation to a dynamic environment with a swiO change from Env. A to Env. B at time $t = 3 \cdot 10^4$. Plot of strategies with accuracy higher than 0.7 in several simulations of 10^4 agents during $3 \cdot 10^4$ iterations (1) and $6 \cdot 10^4$ iterations (2).

CONCLUSIONS

With this model we wanted to show a proof-of-concept of bacterial-based algorithms. Furthermore, we pretended to use them to study CAS performance. We conclude that, in our model, centralized and homogeneous CAS perform worse in knowledge production than distributed and heterogeneous ones. We have tested this hypothesis by comparing bacterial-based societies with different configurations and observing how inhibiting plasmid conjugation, reproduction or mutation modifies the global fitness. It seems that a in "P2P Society", by sharing individual information among agents without communication constraints, optimal strategies and social development are achieved faster than in centralized and homogeneous ones. These differences can be better observed in dynamic environments such as the extended model in which bacteria adapt their motor behavior dynamically.