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# A Bacterial-Based Algorithm
# to Simulate Complex Adaptive Systems

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**Abstract.** Bacteria have demonstrated an amazing capacity to overcome envi-ronmental changes by collective adaptation through genetic exchanges. Using a distributed communication system and sharing individual strategies, bacteria propagate mutations as innovations that allow them to survive in different envi-ronments. In this paper we present an agent-based model which is inspired by bacterial conjugation of DNA plasmids. In our approach, agents with bounded rationality interact in a common environment guided by local rules, leading to Complex Adaptive Systems that are named 'artificial societies'. We have dem-onstrated that in a model based on free interactions among autonomous agents, optimal results emerge by incrementing heterogeneity levels and decentralizing communication structures, leading to a global adaptation of the system. This or-ganic approach to model peer-to-peer dynamics in Complex Adaptive Systems is what we have named 'bacterial-based algorithms' because agents exchange strategic information in the same way that bacteria use conjugation and share genome.

**Keywords:** Complexity, Artificial Society, Bacterial-based Algorithms, P2P Society, Complex Adaptive Systems, CAS.

## 1    Introduction

Bacteria have demonstrated an amazing capacity to overcome environmental changes by collective adaptation through genetic exchanges. By using a distributed communi-cation system and sharing individual strategies, bacteria propagate mutations as inno-vations that allow them to survive in different scenarios [1,2,3,4,5]. Resilience is the capacity of a system to absorb changes in an environment, adapting its properties to disturbance but retaining its basic structure [6]. In this paper we will introduce our agents-based approach to model resilience in artificial societies. Even though similar approaches have been previously reported, such as MBFOA [7], MGA [8], OBBC [9] or BEA [10], we have developed a proof-of-concept inspired by bacterial conjugation that allows us to show how, in artificial societies based on interactions among agents with bounded rationality, optimal results emerge by incrementing heterogeneity levels and decentralizing communication structures [11]. Bacterial conjugation is a distri-buted communication system used by bacteria to exchange strategies of survival,

implemented on genetic code. It matches the kind of dynamics we want to model because of several reasons. First of all, we conceive both natural and artificial societies as Complex Adaptive Systems (CAS) [12] which evolution depends on interactions among autonomous agents. Secondly, we sustain that collective adaptation is related to decentralized communications [13], relying on information exchanges by using P2P networks to share codified blocks of information. Third, heterogeneity in population and variation (or mutation) of strategies is also a factor of evolution even though communication and P2P dynamics play an important role.

## 2    Model

### 2.1    Definition

Following an agent-based modeling approach, we want to simulate and analyze the impact of both peer-to-peer connections and heterogeneity on strategies optimization, that is, on distributed generation of knowledge. In agent-based modeling, agents with bounded rationality interact in a common environment guided by local rules, leading to Complex Adaptive Systems that are named 'artificial societies' [14,15]. These simplified models of biological societies grow from the bottom up in computational environments and can be used as laboratories to test some hypotheses. In our case, we will use a special type of agent-based model, a bacterial-based algorithm that is inspired by bacterial conjugation and that matches with our purpose of simulating emergence of collective intelligence. 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 a 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 have the same coordinates (x,y) they meet to each other and compare their knowledge levels. After that, the one with a lower knowledge ($a_a$) tries to get a copy of genome from the more successful ($a_b$). If the owner of the best strategy ($a_b$) does not share its strategic knowledge we will say that conjugative machinery to send plasmids is inhibited. Otherwise $a_b$ will offer a plasmid with a copy of his genome to agents in the same coordinates and lower knowledge. Even though if the owner ($a_b$) allows the other agent ($a_a$) to get a copy of its genome and then improve its strategic knowledge, $a_b$ can impose two restriction policies to that copy:

- *Inhibit Reproduction:* The receiver of a plasmid ($a_a$) 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 ($a_b$) is the only one with reproduction rights on that strategy.

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

With this model we want to show that centralized and homogeneous societies, those with greater number of agents that follow restrictive behaviors, lead to lower levels of knowledge and higher levels of inequality than distributed and heterogeneous ones. We will do it by comparing bacterial-based societies with different configurations and observing how inhibiting plasmid conjugation, reproduction or mutation modifies the statistical results. Only in a "P2P Society", by sharing individual information among agents without communication constraints, optimal strategies and social development are achieved.

## 2.2    Agent Genome

As we have explained above, in our model 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:

$$\forall\ a_i \in A\ \exists\ s_i \in Sec : 1 \leq |Sec| \leq |A| \tag{1}$$

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:

1. Inhibit original plasmid conjugation (P)
2. Inhibit copy reproduction (R)
3. Inhibit code mutation (O)

Depending of the presence of each one of these three segments, agents behavior will catalyze or constraint the arrival of the optimal scenario, the one in which knowledge is generated in distributed societies with low inequality among agents.

If there is P then the genome will not be released by conjugation, that is, that strategy will be private. So only the absence of P enables the first owner of the genome to act as a donor; that is, to send a copy of genome as a plasmid to another agent by using conjugation. If possibility of that P occurs is high then the society will follow a centralized paradigm, that is, just some nodes will be able to send information. P implies that original genome will be never copied and sent to anybody else. Then, strategies of nodes without P and a successful strategy coded on S will dominate the culture.

If there is R this means that receivers of a copy of a genome are not allowed to re-send the replicated plasmid to another agent. It avoids decentralized propagation of strategies, considering that the original owners of a genome are the only ones which can distribute copies. High possibility of R implies a constraint to diffusion of received strategies, because receiver will be able to use the successful strategy but will not be allowed to propagate them and share its knowledge with others.

Decentralization is inversely related to these two parameters. High P and R rates imply centralized societies without P2P communication and without reproduction rights. Oppositely, low P and R rates lead to P2P exchanges of information without limits of copies.
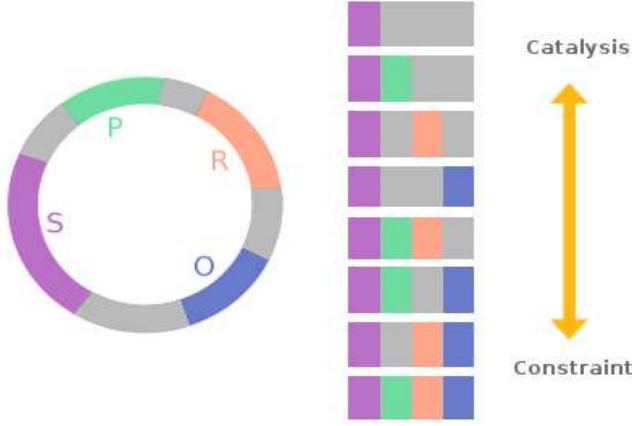
**Fig. 1.** Social behavior of agents depending on their genome

During a conjugation process, when one agent sends a plasmid to another, the S sequence (which contains a copy of the strategy of the donor) could be modified. This means that mutation of any strategy is allowed by default. But mutation can be inhibited if O is present in the genome. O sequence implies that a plasmid cannot be modified. So only low levels of O presence lead to an open society in which variation of bad strategies in short time is guarantee. However, high presence of O in the population genome implies that strategies are closed and invariant. So once an agent follows a specific strategy it cannot change this until it receives another genome from a more successful agent.

Differentiation of strategies is another important variable in this model. Cardinality of Sec is related to the number of different strategies by default, so if |Sec| is near to |A| and there is a low presence of O segments in population genome then it implies more heterogeneity.

### 2.3 Local Rules and Complex Dynamics

The main characteristic of complex phenomena is that it emerges from local interactions among simple agents which have not global information about the whole system. In complex science, global dynamics are considered a result of local rules. Following that approach, our agents behave according to their own internal states by following single algorithmic rules.

Each agent's decision takes into account two values, its own knowledge and neighbors' knowledge. Each iteration agents compare both values by using their internal evaluator, which is the function that constitutes their bounded rationality. There is a different internal evaluator to every single agent, assuming variability of cognitive skills within a population. After positive evaluation, if it is worth to learn a new strategy according to that internal criteria (and if any inhibitor impede it), conjugation between two agents occurs. When an agent receives a new genome it replaces the previous one. This replacement can be complete or not, depending of mutation inhibition. In this version of our model, mutation implies a recombination of 50% of both genomes. After replacement of genome, the receiver tests the new strategy by using it to optimize a fixed selection function. Accuracy of function optimization determines

the new knowledge level of the agent. The more knowledge an agent achieves, the more social reputation it obtains. Considering our model as a social network we can define each agent as a node linked to other nodes through information exchanges. Network analysis [16] can help us to evaluate which agent has been dominating the culture of our artificial society, so we have decided to build a directed graph with all the connections created by conjugation processes (Fig. 2).
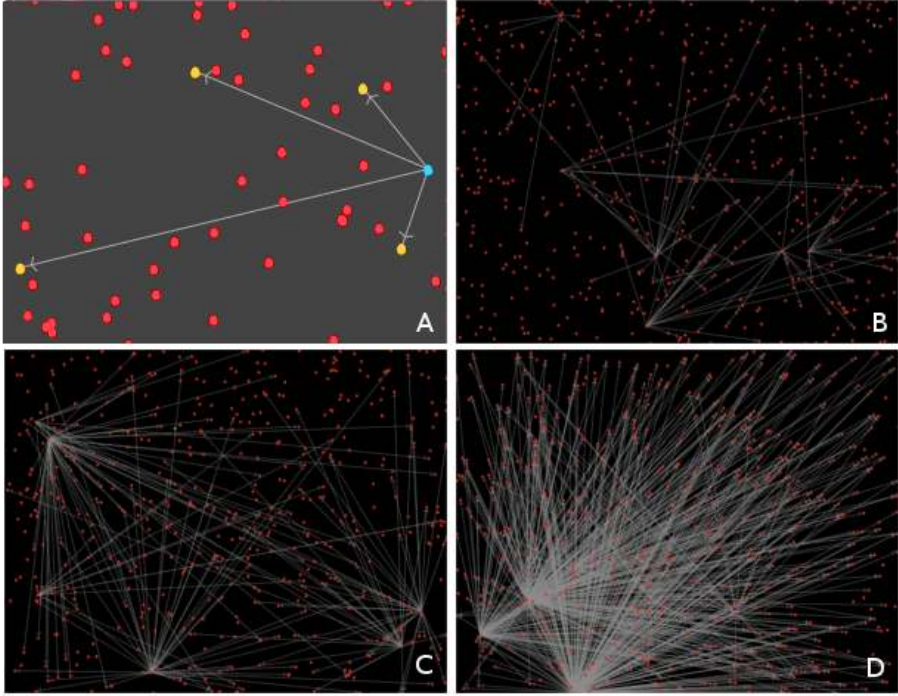


**Fig. 2.** Growing social structures. Four agents have decided to learn from a fifth one after comparing their knowledge levels. These conjugation processes have increased the node out-degree to 4. (B, C, D) Emergence of centralized social network with high presence of O, R and P segments in genome.

## 3 Experimental Results

### 3.1 Simulation Conditions

In order to analyze the influence of specific variations on initial conditions, we have simulated $|Z|^3$ different environments considering the set $Z = \{0,1\}$. The focus of this study is how probabilistic distribution of Boolean genes (P, R, O) affects social structure, that is, the role of cultural constraints. We have fixed $|Sec| \sim |A|$ and recombination to 0.5 when mutation is allowed. For any of those $|Z|^3$ setup configurations, we have executed our model during $10^4$ iterations. Repeating each one of these experiments with random populations between $10^3$ and $10^4$ agents we have observed common patterns that are related to P, R and O presence in population genome. We have tested the emergence of different global configurations, from centralized societies with low

levels and unequal distribution of knowledge to "P2P societies" in which heterogeneity and decentralization lead to collective success. We have used NetLogo 5.0.4 to implement our model and Java 6 to extend it.

We have defined a selection function with ten variables. Every iteration agents replace each one of those variables with the values of the S segment. If these ten genes optimize the function and the result is equal or greater than 70, we consider that the owner of that Si segment has a good level of knowledge. Results between 50 and 70 means a medium level of knowledge and lower than 50 a bad one.

As we can see (Fig. 3) our artificial societies are Complex Adaptive Systems that evolves through agent interactions. The adaptive behavior of the system as a whole consists in increasing the distribution of good strategies and the elimination of bad ones. But the speed of that propagation is mainly related to P presence, that is, with the number of agents that are allowed to share strategies.
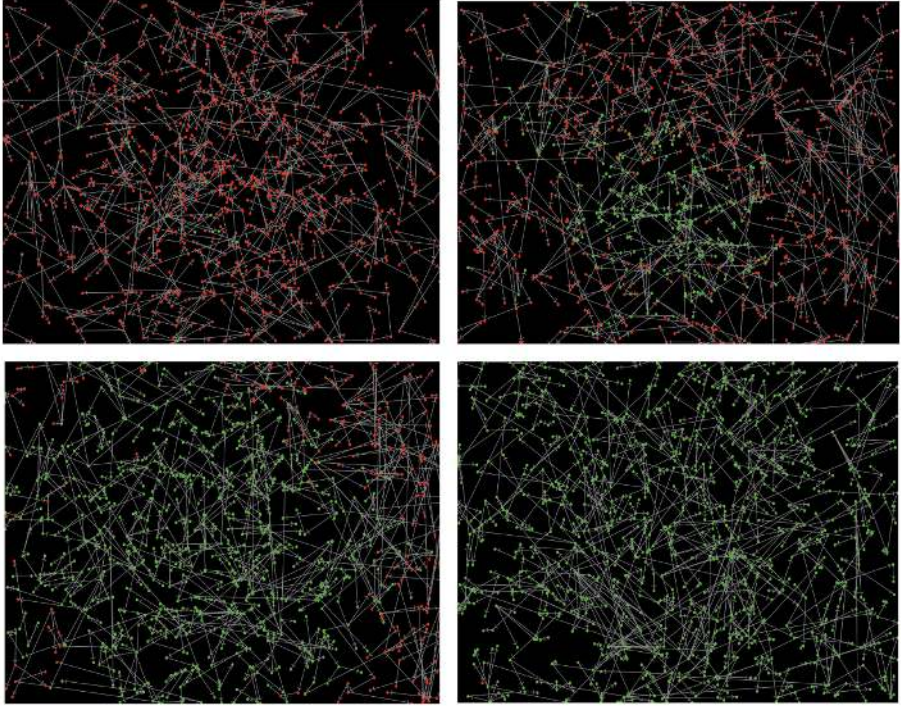


**Fig. 3.** Propagation of strategies. Low P and R rates (P ~ 0.19, R ~ 0.24) in a population with $10^3$ agents leading to decentralization and vertical propagation of successful strategies. Red agents have knowledge levels lower than 70, otherwise they are colored with green.

### 3.2    Emergence of Equality in Distribution of Knowledge

After reproducing several scenarios with random initial knowledge-level distributions, we have observed that worse results are achieved in centralized and homogeneous societies; for example, a society with presence of O and R in the whole of population

genome. O presence means that we will not see strategy modifications, that is, the maximum level of knowledge will be static during the $10^4$ iterations. Then the best strategy will depend only on initial configuration, when random $S_i$ segments are generated; this simulation will only take into account the propagation of those initial strategies. R implies that there is not any reproduction of received genome, so only the original owner will be able to propagate it.
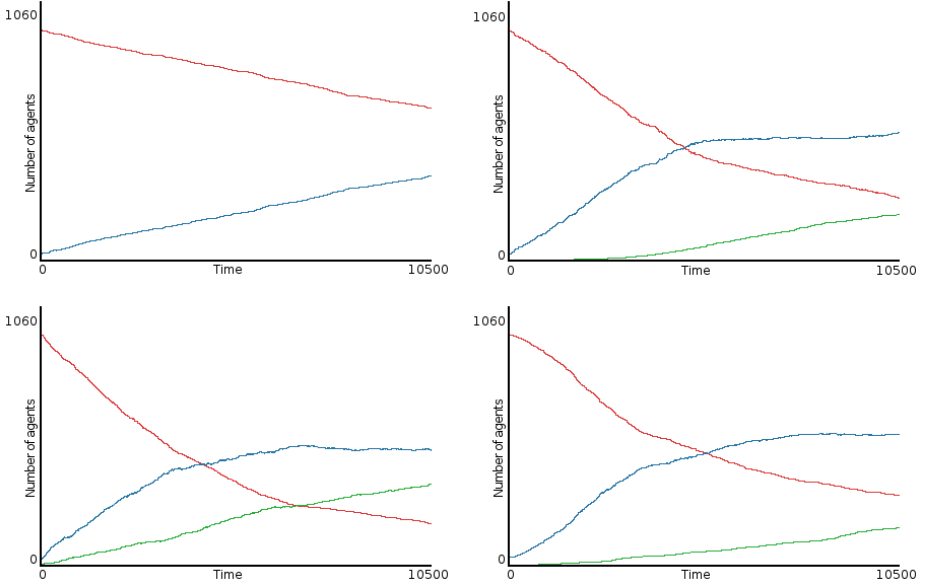


**Fig. 4.** Evolution of knowledge levels. These results show how medium knowledge tends to grow slowly in centralized societies with P ~ 0.90 and R ~ 0.83. The number of agents per time unit that use strategies that satisfy a given selection function with less than 50 % of accuracy are plotted in red, those with more than 70% are in green, and others are in blue. Each picture reproduces a 103 agents simulation that has been executed during 104 iterations. Blue represents agents with strategic knowledge between 50 and 70, red means knowledge levels lower than 50 and green implies a knowledge level higher than 70.

We have studied how P presence modifies the global behavior of this system. In order to compare two variations of that artificial society, one with P probability ~ 0.90 (Fig. 4) and other with P probability ~ 0.19, we have repeated the experiment several times, testing that centralization leads to low results in knowledge generation (Fig. 5). We have also simulated scenarios with high heterogeneity and decentralization levels by reducing P, R and O probabilities and we have seen that with a whole elimination of O sequences (O probability ~ 0), that is, activating mutation of strategies, generation of knowledge not only is faster but also richer in variety. As picture 6 shows, different focus of improvement are found in population when diversity occurs. In this heterogeneous scenario, good strategies come from different agents with different initial locations. Agents evolve in creative ways because of modification of strategies is allowed and innovative knowledge is propagated because of decentralization, leading to an egalitarian and optimal artificial society.
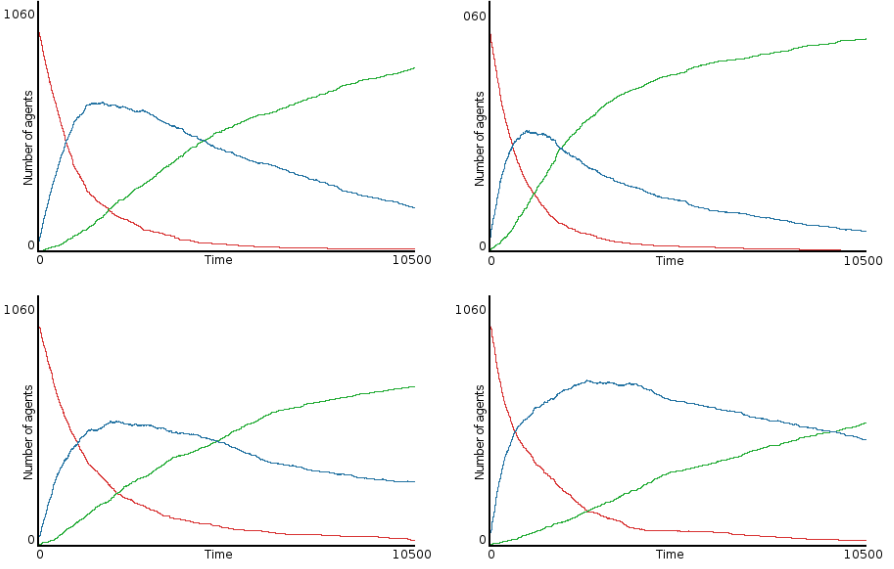
**Fig. 5.** In these four simulations P probability ~ 0.19 rather than P probability ~ 0.90 (Fig. 4). This change produces an acceleration of knowledge propagation. Bad strategies are removed early and competition is between medium and good strategies. The best options reach almost the whole population in only $10^4$ iterations. The colors applied are the same as in Fig. 4.
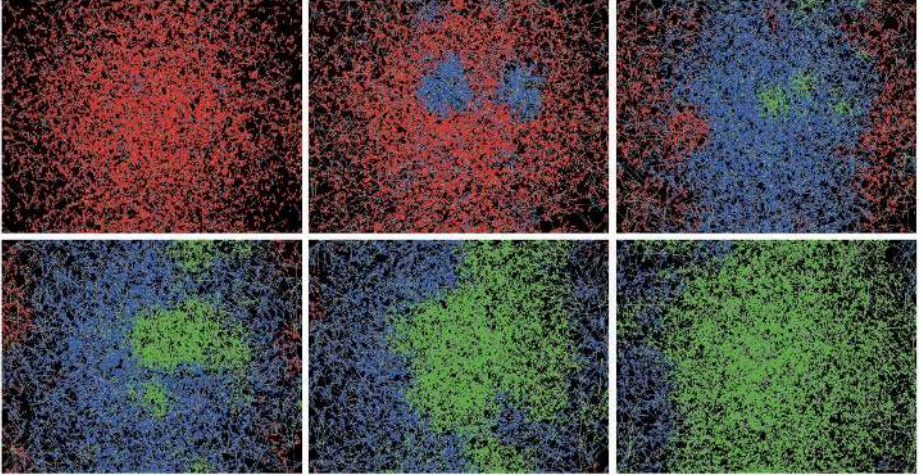


**Fig. 6.** Distributed production of knowledge in a "P2P Society". Low P, O and R rates (P ~ 0.03, R ~ 0.14, O ~ 0.27) in a population with $10^4$ agents during $10^3$ iterations. This Complex Adaptive System evolves faster because of heterogeneity and connectivity. Through peer-to-peer exchanges, reproduction and modification rights, bad strategies (red) are replaced or mixed with medium strategies (blue) that are recombined and distributed, leading to this map of successful strategies (green). Each picture represents a snapshot of the same simulation in time.

# 4 Conclusions

We have modeled complex social dynamics with bacterial-based algorithms. Inspired by microbial adaptation and conjugation of DNA plasmids, we have designed a computational model to extend agent-based modeling. We have implemented agent-bounded rationality in strategic genomes that can be shared by owners, reproduced by receivers, mutated and mixed. Finally, we have shown how in our artificial society, system optimization is limited by centralization and homogeneity. Based on experimental results, we can infer that the best strategies of collective adaptation are related to O, R and P absence. That is, we conclude that Complex Adaptive Systems can achieve their optimal configuration only by incrementing decentralization and heterogeneity.

Our purpose is to improve this model in order to test different hypotheses in future research by simulating several artificial societies and understanding their evolution, establishing the algorithmic basis to observe emergent properties such as cooperation and competition in societies guided by *peer-to-peer* dynamics.

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