Why Do We Need Artificial Life?

Abstract In this paper, we ask the question of whether we need artificial life (AL) at all. We find a lot of convincing arguments in favor of AL, but we also point out some dangers AL is exposed to. This careful epistemological review reveals the potential richness of AL without being either too reductionist or too holistic. We give some examples showing how this can be done in practice, and conclude that almost everybody needs AL.

1 The Many Lives of Artificial Life

It is sometimes beneficial to ask critical questions. One such critical question is to know why we are doing artificial life (AL). Our heads of departments seem to be waiting for an answer, especially when it comes to money: Why should they fund us to do something that doesn't look serious? Well, the possible answers are multiple, but never satisfy them. If ever you are faced with the same kind of "hierarchical" problem, this contribution is aimed at helping you in finding the right things to say to your boss. But things are never that simple. Whatever justification you might use, there are always associated dangers. Therefore, this contribution is also aimed at helping you avoid the numerous traps you could find when starting a discussion on artificial life with your boss. But we also hope to be able to convince not only your boss but also yourself. In order to do so, let us start with a very brief, somewhat provocative, compact "definition" of artificial life: We consider it as a general method consisting in generating at a macroscopic level, from microscopic, generally simple, interacting components, behaviors that are interpretable as lifelike. This statement is general enough that it can be applied to 99% of what is done within the artificial life framework. However, depending on the field to which it applies, this framework leads to very different results. For example, biologists do not have the same vision of artificial life as, say, computer scientists, artificial intelligence (AI) researchers, engineers or even artists. Hence, one should speak of artificial lives rather than of artificial life.

2 Artificial (Way of) Life

Before proceeding, we should explain in depth our definition of artificial life. It is based on the observation that most of what has been (or is being) done in AL relies on the following simple assumption: Synthesis is the most appropriate approach to the study of complex systems in general and of living complex systems in particular. Because it seems to be more difficult to start from manifestations of life and try to find its fundamental principles by top-down analysis than to start from computational and physical simulations and try to synthesize more and more complex behaviors, which

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in turn might capture the nature of some aspects of life, AL thus focuses on ways of achieving emergence to generate these more and more complex behaviors [25]. Apparently, AL’s object of study is in essence not different from the object of study of biology: Only the methodology is different. Actually, the methodological aspects constitute the true essence of AL. Note that these aspects are not purely technical and are not as trivial as they may sound: They raise very specific issues, and synthesis, although certainly powerful, must be handled with care. We shall return to this topic later, because it is important that the power of synthesis be directed toward the right channels. Let us note also that AL’s methodology is a completely reductionist one, because it is aimed at explaining high-level behaviors from low-level causes.

While the first inspirations of AL’s simulations, theories, and models are living things and behaviors, life-as-we-know-it, synthesis naturally allows one to create a much wider spectrum of behaviors, life-as-it-could-be. The only way one can decide whether or not the synthesized behaviors fall within the framework of AL is by judging how well they reproduce some aspects of life, life-as-we-know-it, at the macroscopic level. In order to do this, one has to interpret the obtained behaviors as lifelike. This is a crucial point: There are numerous ways of interpreting these behaviors. One can resort to experimental biological data, to additional criteria of plausibility, or to whatever criterion available.

Let us take an example: trail following in ants. We know through experiments that in some species, ants lay a certain amount of pheromone on their way to a food source and much more pheromone on their way back to the nest, and that they tend to follow pheromone gradients. When one is simulating on a computer a colony of artificial foraging ants following these elementary individual behavioral rules, the observed exploratory patterns can be interpreted in the framework of a theory, whereby the simulation constitutes a test to know if the previously mentioned factors could be sufficient to explain the exploratory patterns of real ant colonies. It is not to say that real ants have anything else in common with artificial ants than this way of locally processing data from their environment and of responding to it. But one knows that the features implemented in the simulations correspond to something real, and that, as advocated in Langton et al. [26], both types of exploratory patterns are two instances of the same phenomenon: The self-organization of collective activities in space and time. Besides experimental data, the simulation is also constrained by a certain form of biological plausibility: In effect, if artificial ants have to deposit 10 (artificial!) tons of pheromone to reproduce the experimentally observed behavior, they do not constitute a good model of real ants. But artificial lifers are not all biologists and do not all seek models to explain biological phenomena. If they just want to reproduce exploratory patterns, they can resort to ants capable of depositing 10 tons of pheromone. Then, the synthesized patterns can no longer be interpreted in the rigid framework of a biological theory: They are interpreted as lifelike if they are similar to biological patterns at a purely phenomenological level. This phenomenological level becomes art if the only constraints one accepts to satisfy are of an aesthetic nature. Engineers, on the other hand, have a different point of view: They need to create efficient, robust, adaptive systems capable of solving problems; the constraint they have to satisfy is a constraint of viability.

To summarize, let us say that more than a scientific field, AL is a way of practicing science. And it is an exciting new way of practicing science, especially for young scientists tired of the boring daily practice of traditional sciences. Moreover, AL goes beyond its application to science: For instance, as we shall try to show, art is inherently associated with AL. But AL is synthetic and reductionist: This makes it quite dangerous, especially for the excited young scientists. In the next two sections, we will take some time to make a review of criticisms that can be made against AL. Most of these criticisms
can be wiped out by cautious use of AL, but we have to remain constantly conscious of their existence. This will help in discussions with your boss. We will end with a section explaining why we need artificial life. Don’t worry: The reasons are numerous so that you’ll have plenty of arguments.

3 Synthesis

Any science having to deal with complex systems can feel the attraction of synthesis. Living systems are undoubtedly complex. The most commonly shared definition of a complex system states that it is a network of interacting objects, agents, elements, or processes that exhibit a dynamic, aggregate behavior. The action of an object (possibly) affects subsequent actions of other objects in the network, so that the action of the whole is more than the simple sum of the actions of its parts. In other words, a system is complex if it is not reducible to a few degrees of freedom or to a statistical description. A complex system has many degrees of freedom that strongly interact with each other, keeping us from either of the two classical reductions: It exhibits what Weaver [47] called organized complexity (as opposed to organized simplicity and disorganized complexity). Besides, the complementary idea of chaos taught us that unpredictability can also arise in low-dimensional deterministic systems, showing that even “reducible” systems can be very hard to deal with. In any case, synthesis, that is, a bottom-up approach generally based on simulation, seems to be a good candidate, if not the only one, to explore the behavioral space of complex systems. Thus, the reason why the sciences of complex systems did not emerge before is simple: There was a sort of unexplored niche in the gigantic scientific ecology. Complex systems, be they low-dimensional chaotic or high-dimensional, could not be studied before the last decades because they require high computational power—far beyond the (unaided) human brain’s capabilities. Synthesis has strong computational requirements.

Unfortunately, the synthetic approach, although certainly useful if one does not want to “miss emergent properties” [40], implies weakened explanatory status of models, huge spaces of exploration, absence of constraints. By using synthetic exploration, AL deals with all the phenomena such an exploration may allow. It results in a space of possible behaviors that is too huge: Otherwise stated, life-as-it-could-be is dramatically ill-defined. With such a program, AL tends to forget higher-level sciences (see e.g., “AI has for the most part neglected the fundamental biology of the nervous system. This criticism will undoubtedly be aimed at AI as well” [29]). It should, on the contrary, accept the empirical constraints provided by the observations of these higher-level sciences, even if the ultimate hope is to go beyond the study of what exists toward the study of what could have existed—the latter providing (of course!) no observation at all. Moreover, how can one scientifically assess the validity of models without resorting to constraints? If we resort to synthesis with only the goal of phenomenologically reproducing observed behaviors, it is hard to determine the extent to which a model explains the phenomenon it reproduces. But even when one has appropriate criteria, the level of explanation reached by a given \textit{synthetic} model remains uncertain, and most of epistemology until today has focused on analysis rather than on synthesis.

3.1 A Matter of Levels

Putnam [32] reached an interesting conclusion by making first a difference between “to deduce” and “to explain”: Being able to deduce the properties of a phenomenon from a set of causes is not equivalent to explaining this phenomenon, because only a few among the many possible causes may be relevant, “certain systems can have behaviors to which their microstructure is largely irrelevant” [32]. Explaining the phenomenon...
amounts to determining what the relevant causes are. Note that the number of such causes might be very high in the case of complex living systems, making explanation intractable. Further, it may simply be impossible to deduce the properties of a phenomenon from a set of causes originating from one single discipline: This is so because “the laws of the higher-level discipline are deducible from the laws of the lower-level discipline together with ‘auxiliary hypotheses’ that are accidental from the point of view of the lower-level discipline” [32]. The laws of the higher-level discipline, therefore, depend on both the laws of the lower-level discipline and “boundary conditions” that are “accidental from the point of view of physics but essential to the description of” [32] the higher level. It is through the huge space of possibilities allowed by physics and through the many possible accidental causes that higher-level phenomena are somewhat autonomous relative to other levels. Moreover, even when no accidental cause is needed, it may take too long a time to deduce the higher-level properties from the lower-level ones.

Thus, if we summarize Putnam’s ideas, we may state the following (using Putnam’s terminology): A great number of laws of the lower-level are irrelevant to the understanding of higher-level phenomena; yet, the remaining relevant causes can be intractably numerous. Other laws originating from other perspectives are essential for the understanding of the higher-level phenomena but are purely accidental at the lower level.

In the same spirit, one can see a major obstacle appear: Any kind of higher-level structure can be very hard to deal with, due to the fact that explanation is not transitive (i.e., explanations at one level are not of the same nature as explanations at another level), which gives some unpleasant autonomy to higher levels relative to (explanations at) lower levels. If we say, as in Weidlich, [48] that “a level is a stratum of reality of a certain self-contained organization,” that is with a “quasi autonomous dynamics,” then (1) the immensity of the phase space allowed by the physics of level 1 can make the behavior of level 2 unpredictable, that is, it may be impossible to have any idea about shapes and structures appearing at the higher level given the laws of physics; (2) each passage from one level to another has its own boundary conditions; and (3) external boundary conditions (external causes) are accidental. (It is worth noticing that these external boundary conditions may also be generated by the higher levels in which the level under study is embedded.) As a consequence, it can be very hard to find tools to deal with higher levels when starting from a given level, and usually, “it appears that the lower level provides the constituent units for the next higher level only” [48].

It is also natural to speak of emergence in the present context. The notion of emergence, often debated within AL, is of high interest in its own right and would justify a separate review. To summarize, we shall say that emergence is generally defined as a process through which entirely new behaviors appear, whose properties cannot be derived from a given model of how the system behaves, so that another model has to be built in order to deal with these new behaviors. Usually, but not necessarily, the new behaviors appear at a macroscopic level while one has only a model of the microscopic level, so that a new model—possibly phenomenological—must be developed for the macroscopic level. The major disagreements about emergence stem from different interpretations of what it means to “derive the properties of the new behaviors” [4,7,8,12,23–27,29,34,35]. In any case, the synthetic nature of AL also explains why people in artificial life share an irrational faith in the power of emergence, although everybody acknowledges that “the concept of emergence in itself offers neither guidance on how to construct such an emergent system nor insight into why it would work” [21]: This also makes AL even more reductionist than most classical reductionist sciences, because for AL the laws of physics within a given system are almighty; not only must the system comply with physical rules, it is also defined by them because they generate sufficient “boundary conditions” by themselves. In other words, the system
has to exhibit a highly specific but surprising behavior at the macroscopic level given only the laws of microphysics.

3.2 On the Nature of Phenomenological Analogies

Let alone the danger of outrageously worshipping emergence, the transversality of concepts that is central to AL can also be dangerous when it is not appropriately applied: “a direct comparison of physical and social systems on the phenomenological level can only lead to a superficial, short breathed analogy lacking structural depth,” “deep and rather universal analogies between social and physical systems (...) reflect the fact that, due to the universal applicability of certain mathematical concepts to multi-component systems, all such systems exhibit an indirect similarity on the macroscopic collective level, which is independent of their possible comparability on the microscopic level” [48]. All natural objects, be they physical, biological, social, or else, are modeled through systems: Only a limited set of observables is chosen, and syntactic relationships are looked for between these observables to account for their (experimentally observed) behaviors. Two systems can share some similarities with respect to some set of observables, while they completely diverge when it comes to other observables. Thus, one must be very cautious when dealing with resemblances not to confuse these necessarily partial resemblances with global analogy at all levels of description and with respect to all possible sets of observables. An example is in order here. Diffusion-limited growth (DLG) [3] is a good illustration of limited resemblances that do not cross levels. DLG is a formalism that is used to model the growth of many different types of patterns, from the growth of bacterial colonies to the growth of electro-chemical deposition, solidification from a supersaturated solution, solidification from an undercooled liquid, etc. Such growth phenomena result in fractal patterns, especially when the concentration of the diffusing field (nutrient in the case of bacterial colonies) is insufficient. Although these many different systems can be described by the same type of equations, and develop the same type of spatial pattern, they cannot be compared at any other level: A bacterial colony has little in common with electrochemical deposition. Besides, there is a functional relevance in the case of the bacterial colony that does not exist in other cases: Growing fractally is a way of achieving a perfect compromise between the surface explored and the density of individuals (see Figure 1).

In artificial life in particular, due to the lack of constraints, phenomenological relationships are almost the only criterion that can be used to judge simulations and models (“simulations are metaphorical, not literal” [27]). It could give the wrong impression that the nature of the simulated processes is essentially the same as the phenomenon they reproduce. While this might be true at the global level, it is certainly false at the level of the constituent units. Let us take the example of the colony of robots built by Beckers and colleagues [18] in Brussels. They reproduce some interesting behaviors at the collective level that are reminiscent of patterns of activities found in insect societies. Yet, the interactions implemented between the robots (particular nonlocal communication processes) are very different from the interactions actually existing in insect colonies. Therefore, although there is a phenomenological similarity at the global level, neither the interactions nor the constituent units are similar.

Our judgment is largely based on our intuitions, experiences, and even emotions, which is in contradiction with AL’s ambition to synthesize life-as-it-could-be: We judge simulations based on how well they meet our aesthetic requirements, which themselves rely on our experience of life-as-we-know-it. (What other experience could we have?) As a consequence, we will never be able to recognize or synthesize forms of “life” that are really far from life-as-we-know-it. Thus, instead of ambiguously and dangerously refusing constraints by defining a self-contradictory program, AL should make clear what constraints it chooses to be based upon. All this reminds us of an artistic approach:
Building an AL’s creature, be it a cellular automaton, amounts to making some set of equations and our subconscious meet, just as an artist makes his or her imagination wander around with the help of some technical tools until he or she reaches a state of aesthetic satisfaction. If we are particularly appealed by, say, 1D-CA rule 18, it is because it generates interesting patterns, while most other cellular automata (CA) rules generate uninteresting behavior. By tuning a set of parameters, namely, the values of the associated rule table, we eventually meet a rule that gives us a certain satisfaction. This parallel between art and AL is not surprising if one remembers the importance of sensorial media (like videotapes or computer graphics) in AL demos.

3.3 AL Lost in Immensity

Apart from the contradiction it contains, the life-as-it-could-be program may constitute an intractable task; all the more as “real life,” life-as-we-know-it, already covers a large spectrum of possible behaviors: “Life is self-organizing in the sense that it leads to very special forms, that is, from a wide basin of attraction it leads to a much narrower set of meaningful states. But this alone would not yet be surprising: The surprising aspect is that this attraction is not at all rigid. Although the attractor is very small compared with full-phase space, it is still huge, and, therefore, it allows for a wide spectrum of behaviors” [19]. That is why we should follow Sober’s [37] suggestion to approach the general questions on the “nature of mind or the nature of life” by “focusing on more specific psychological and biological properties … this strategy makes the general questions more tractable.” By using Putnam’s [33] words, the only way for AL not to be “one damned thing after another” is to accept empirical constraints and eventually have one or several “Master Programs,” otherwise AL researchers would be tinkers—like evolution—and the number of “damned things” we may think of may be astronomical. Such Master Programs can be, for example, the study of the emergence of self-replicating molecules, of coevolutionary dynamics, of the interplay between evolution, adaptation and learning, of autonomous systems, of collective problem-solving and decision-making abilities in natural and artificial systems, etc. There are
other fields dealing with life, adaptation, and evolution that can provide sufficient constraints. The best bottom-up approach needs some kind of validation by top-down data. Most of serious AL-based research is being carried out following such a Master Program with the right constraints, be they experimental or else, but let us emphasize that not everything is serious in the AL community.

4 Reductionism and the Nature of Artificial Life

Following Wimsatt [49], we shall say that “...a reductionist is interested in understanding the character, properties, and behavior of the studied system in terms of the properties of its parts and their interrelations and interactions. This means that the reductionist is primarily interested in the entities and relations internal to the system under study.” But Wimsatt added, “This is a sufficiently inclusive description that it probably captures any analytic method in general...” unnecessarily restricting the scope of reductionism to the realm of analytic methodologies, while its definition does not refer to any kind of analysis. And from this definition, it is clear that AL, although synthetic, is 100% reductionist. It is often believed that reductionism goes together with analysis: The sciences of complex systems in general, and AL in particular, offer beautiful counterexamples. Hence, being reductionist is not necessarily a bad thing! The reductionist nature of AL manifests itself in combination with its synthetic nature under some peculiar forms we shall describe.

Artificial life’s synthetic exploration procedure is partly motivated by the reductionist hope that simple (most often formal) elements in interactions will generate a sufficient richness of behaviors peculiar to life. Yet, as was pointed out in papers warning against computational reductionism [see, e.g., 7,8], one may miss important phenomena because some external variables or conditions, accidental from the point of view of the model (i.e., not taken into consideration by the model), may turn out to be crucial to the generation of behaviors constituting the essence of life. These conditions, which are essential to the generation or the understanding of a particular phenomenon, are thereafter called “boundary conditions.” They can be internal as well as external. We all hope that a lot of “interesting” behaviors can be generated “internally.” While doing so, we must be aware of the theoretical limitations such a purely “internal” approach has, and we are indeed if one judges by all the efforts that are being made to incorporate external factors in models. Besides, as all scientists, we are condemned to resort to models, which are necessarily partial images of the world. No science does better in this respect.

4.1 Boundary Conditions

Coming back to Wimsatt’s general definition, we see that being reductionist leads to a particular interest in the “entities and relations internal to the system.” This constitutes the essence of AL’s reductionist side: One tries not to resort to explanations external to the system, or external boundary conditions, in order to make things emerge. The idea behind boundary conditions [31] is the following: although it is true that a higher level has a behavior that is compatible with lower-level laws, lower-level laws alone are unspecific. They cannot determine the behavior of the higher level: Boundary conditions make the link between the two levels by “directing lower-level processes to definite channels” [23]. Vitalistic conclusions may easily be drawn from these considerations, if one believes that irreducible boundary conditions underlie the appearance of life: In effect, among the immense [13] number of possible states of the world allowed by physics, only a few are compatible with life, and such compatibility may not be deducible from the laws of physics. The idea of boundary condition is closely linked to Elsasser’s [13] immensity, to Pattee’s nonholonomic constraints, and to Rössler’s priv-
ilegged zero property, nicely summarized in Kapis [23]. The notion of self-generated boundary condition is easy to visualize: We use this terminology to describe the property of some systems that generate boundary conditions from inside (when nonlinear laws of interaction are present), that is, which exhibit a highly specific behavior without the help of any exogenous phenomenon. Such a phenomenon would be “purely accidental” from the point of view of the internal dynamics [32]. It is important to notice that in a case where boundary conditions are generated internally, the dynamics of the system drives it toward a functionally relevant state. If, for instance, the system is composed of interacting processes, it will evolve toward a state where the interactions between the processes will allow it to implement a function without the need of any external, environmental tuning. The systems we are studying are obviously open systems that interact with their surroundings by exchanging matter, energy, (physical) entropy, or “information,” and they cannot be entirely described by purely internal mechanisms: We all know this very simple fact and try to incorporate such exchanges in our models and simulations, but at the same time we try to find a minimal set of factors that would account for a particular phenomenon. Let us not forget that such factors may exist inside as well as outside the system.

4.2 More on Reductionists and Environments

As emphasized in Wimsatt [49], reductionists usually tend to look for internal explanations (intrasystemic mechanisms) rather than for external causes (intersystemic mechanisms), and in any case internal mechanisms are very often considered more “fundamental.” Extreme reductionists “simplify the description of the environment before simplifying the description of the system” and “construct experimental arrangements so as to keep environment variables constant”; in a nutshell, they “ignore, oversimplify, or otherwise underestimate the importance of the context of the system under study” [49]. But, for example, “evolution depends on a result of microstructure (variation in genotype) but it also depends on conditions (presence of oxygen) that are accidental from the point of view of physics and chemistry” [32]. This last remark in particular reminds us of the multitude of “frozen accidents” that have certainly occurred during evolution (note that there are undoubtedly other mechanisms in evolution): These frozen accidents were mainly caused by external conditions (external relative to a given system’s laws of functioning). Thus, the task of reproducing evolution (i.e., to synthesize artificial life) by purely self-generated boundary conditions seems hopeless, because at certain points in evolution, external causes have produced crucially relevant changes. Although we do not believe that anyone in AL exhibits such a form of extreme reductionism—once again, environments are certainly considered important, and one should even say more and more important in AL-related simulations and models—it is a good thing to remain conscious of the full complexity of the world around us, of the infinite, open-ended richness of real environments: Artificial Lifers are confronted with the challenging task of translating that complexity and this richness into working simulations and models.

Also of utmost importance is the fact that the complexity of an organism is often believed to reflect the complexity of its environment, at least to some extent. The idea of enaction [45,46] is based on the statement that an organism and its environment are mutually defined. Even if one does not believe in complete mutual specification, it raises the issue of evaluating the influence of environmental structures on an organism’s structures. One cannot hope to do so without embodying artificial creatures in somewhat realistic, varying environments. A way of taking external causes into account is by making embodiment a clear goal of all AL’s theories and simulations [5,6]—which it is already to a large extent: Let us make it even clearer. Embodying an artificial creature in some kind of environment (with the ultimate goal of plunging it into a real one)
implies making a thorough investigation of the notion of external boundary condition. AL constitutes an important first step toward this goal, in the sense that it is an attempt to delimit the power of self-generated boundary conditions and, therefore, to locate the frontiers beyond which it is the realm of accidental causes.

Taking environments into account is anyway very useful if adaptivity is a desirable goal to achieve: In effect, adaptivity is by definition relative to modifications of the environment. The richer the environment, the more adaptive a system has to be in order to keep up with such variations. It has been advocated many times by Brooks that building one robot is worth 100 simulations, not only because technical details of the implementation must be tackled with, but also and, we believe, most importantly, because this is the only way to be confronted to the actual complexity of the world. Certainly, richer environments make things harder: They make the fully nonlinear relationship between GTYPE and PTYPE [25] much more complex. Thus, it is acceptable, as a first step, to simulate limited environments. We must remark that the notion of environment is different depending on the level at which one is located, for example, in a swarm of insects (be they natural or artificial), the environment of the swarm as a whole is the physical space that surrounds it, while the environment of one particular individual comprises both the environment of the swarm and the other members of the swarm with which this individual interacts. The dynamically varying pattern of interactions constitutes an environment that is internal to the swarm system and, thus, provides it with internal boundary conditions. Such internal boundary conditions may be sufficient to generate functionally relevant patterns in (a) a highly simplified external environment, (b) a fixed external environment, or (c) a complex, varying external environment.

We (in AL) show a tendency to test our (collective) systems in case (a) or (b). Sometimes it is because it is hard or/and computationally expensive to do otherwise. Sometimes, we do so without being aware of it. Yet, many natural systems, if not all, live in a case (c) environment: There, internal boundary conditions may very well be at the same level of importance as external boundary conditions in most cases.

4.3 Function as a Side Effect of Structure?
There is often a focus of interest on the notion of structure while functional aspects are quite often neglected. Sometimes, these two aspects are confused with one another, because one does not see the purpose of making separate studies on structure and on function, the latter being considered a side effect of the former. (In effect, a function is just the consequence of plunging a structure into an environment.) But, this side effect can have dramatic consequences: “any adaptation has systematically specifiable conditions under which its employment will actually decrease the fitness of the organism” [49]. Let us take a look at the collective foraging behavior of army ant colonies [10,17]. The Ecitons live in tropical rain forests in colonies containing up to 2,000,000 individuals. Each individual is practically blind, and each day a great number of ants leave the nest to explore a new area to find preys. They constitute a swarm-raiding system that adopts a specific configuration. Moreover, this pattern is species-specific. Such a structure emerges spontaneously from individual trail-laying and trail-following behaviors, through interactions between individuals going toward the edge of the swarm, individuals flowing back to the nest, and the distribution of preys in the environment. But in some cases, when rain erased the pheromone trail, a swarm following the same elementary behavioral rules may be trapped in an unended circular mill, as it was described by Schneirla [17,36]. With this example we can see that biological structures, different foraging ant patterns that emerge under different environmental conditions, may possess functional value for the colony in one case and none in the other (Figure 2). Deneubourg and Goss [10] have proposed a probabilistic lattice
model of foraging taking into account some environmental changes. Not only does this model account for the different foraging patterns found for different distributions of preys, it is also capable of reproducing circular mills in appropriate conditions.

Let us clarify the differences between structure and function (not to be taken literally): A function $F$ is specified by its effects on a given (finite) subset of environmental variables, and a structure $S$ is functionally defined by its effects (when plunged into a given environment) with respect to all possible environmental variables in their whole
ranges. That’s the difference. In the previous example, the structure implementing the foraging function in a normal environment is compactly represented by the behavioral rules that army ants follow (mostly trail laying and trail following). But the same structure, that is, the same behavioral rules, plunged into another environment does not at all implement the same function. Moreover, the colony is no longer viable. More precisely, let \((X_i)\) be all possible environmental variables \((i\) can be a continuous index, but that’s not important to get the idea), and let \(E = \{X_1, \ldots, X_n\}\) be a subset of these variables, acted upon by \(F: F(X_1, \ldots, X_n) = (Y_1, \ldots, Y_n)\). For instance, \(F\) can represent the modification of the states of some variables in time: in continuous time \((dX_1/\!\!dt, \ldots, dX_n/\!\!dt) = F(X_1, \ldots, X_n)\), or in discrete time, \(F(X_1[t], \ldots, X_n[t]) = (X_1[t + 1], \ldots, X_n[t + 1])\). \(F\) is a function of these \(n\) variables. Then \(S\) is said to implement function \(F\) in environment \(\{X_i\}\) iff \(S(X_1, \ldots, X_n)\), and all other \(X_i\) = \(F(X_1, \ldots, X_n)\).

What is usually assumed by reductionists is \([\text{all other } X_i = \text{constant, which is incorrectly derived into } \delta S/\delta X_i = 0 \text{ for } i \neq 1 \ldots n]\). This can be true for some \(X_i\) and for some range of values, but this is generally false. What we can see here is that many different structures can implement the same function and that the same structure can implement many different functions if different values of “irrelevant” variables are assumed. Moreover, the function implemented by \(S\) in a given environment depends on what variables we have chosen to look at: \(S\) can also have an effect on other variables, accidental from the point of view of the chosen variables.

Because we thought it was essential, we have emphasized a lot the importance of environments: By plunging AL-based “creatures” in more and more realistic environments, we will be naturally confronted with the complexity of life. We would be delighted if this appeared obvious to everybody in AL.

4.4 Computational Reductionism

It is true that AL as well as the sciences of complex systems have greatly benefited from the advances of computers in the last decades: These advances have enabled a “time compression” allowing for the simulation of processes that would otherwise have taken years and years. But there are some questions: (1) Is time compression powerful enough to explore all possible behaviors (including interesting ones) of a formally defined system? (2) Can finite specifications lead to open-endedness? Computational reductionism stands on the idea that any phenomenon that obeys the laws of physics can be simulated on a computer. Thus, while classical reductionism conjectures the reducibility of any biological process to the laws of physics, computational reductionism goes further by “transitivity of reduction”: Any biological process can be simulated on a computer. But [7,8,12,13,34,35]:

- What if life can be “explained” only by an immense dimensional model, such that the number of relevant degrees of freedom itself is not even tractable and cannot be acted upon with present-day computers? Practical computers are not Turing machines, nor do human programmers live more than a billion years.

- The algorithmically based notion of logical depth showed us that some (very deep) objects can be simulated only by themselves, in the sense that there exists no shortcut to generating them; thus, if evolution is depth-generating, it may be very hard to reproduce its latest products on a computer by using a synthetic procedure very similar to an “artificial evolution.” (This is a philosophical objection that does not jeopardize such simulations—they will obviously teach us something—but which questions their power.)

- If it is tempting to say that any process that obeys physical laws can be simulated (on a Turing machine, that is, provided enough space, memory, and time are
available), nothing can be said about synthesis, because simulation and synthesis have two very different statuses. The laws of physics (in this context) have finite specifications, they are defined with respect to a set of chosen observables (properties of the object) that are transformed into variables to form a system, together with relationships between them (not to say that physics is restricted to laws). Given one phenomenon, we can look for laws (with the meaning defined earlier) governing its behavior, and, once this is done, it is likely that the phenomenon can be simulated. Now, if we synthesize some behavior with a computer, this behavior will be bound to obey the “physical” laws expressed in the specifications of the system. It is now a completely unresolved question to know whether or not these derivable behaviors are open-endedly diversified.

- Close in spirit to these issues is the question of understanding the influence exerted by the medium of “implementation” through the boundary conditions it provides to the “simulated” process. For example, an infinitely complex medium can provide open-endedness to the processes it implements, although the processes themselves are not open-ended. These boundary conditions are sometimes difficult to deal with, because they may be essential to the implementation without being clearly taken into account in the model, or simply because they are hard to track down due to the high complexity of the medium [29].

Yet one shouldn’t be too pessimistic about all these theoretical limitations of AL’s computational reductionism. Rather than true limitations, they constitute questions asked to AL. And AL is precisely a constructive way of checking whether these limitations are real obstacles.

4.5 The Pride of Being Reductionist

Reductionism does not only have drawbacks. In effect one could argue that AL models are the simplest ones in some sense, because they rely on simple elements in interactions, and that it is epistemological common sense to start with simple models rather than with complicated ones, with internal rather than with too many external causes. Although this is not completely true for at least two reasons: (1) when doing, for example, biological modeling, one often starts with many more variables than necessary, and gradually simplifies the model to retain only relevant variables; (2) simplicity is not necessarily a quality as regards biological sciences—being reductionist is thus not necessarily a negative thing, on the contrary. Common wisdom holds that being reductionist implies tracking the causes of macroscopic phenomena down to the level of elementary particles or more loosely down to the level of physical laws, which, for instance, any biological system ultimately obeys or seems to obey. But one can be ontologically, methodologically, or epistemologically reductionist, depending on the extent to which one accepts and/or practices reductionist principles. AL is methodologically reductionist in essence, not more, not less. And using reductionist methods is actually a safe way of practicing science, provided one doesn’t forget high-level sciences. Let us recall an anecdote reported by Putnam [32]: A lot of biology departments fired their naturalists after Watson and Crick’s discovery of the structure of DNA, because it was believed at that time that one would be able to explain everything with DNA. This, one should remember.

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It is time for us now to confess that we love AL. It may not be clear for the reader yet. Too many people in AL think that being critical means being an enemy. On the
contrary, constructive criticisms will enhance AL’s diffusion while making it more and more resistant to external attacks. If all the things we said in the previous sections were obvious to you, if you agree with them, then we are happy, because they were not at all obvious to us.

5.1 AL and Theoretical Biology
The objectives of AL should be stated without ambiguity: AL is not in competition with theoretical biology, although there is a nonempty intersection between AL and theoretical biology. On the contrary, it can contribute to theoretical biology because it allows one to go beyond pure biological modeling. If one quotes Emmeche [12], AL may contribute to theoretical biology by “(i) simulating developmental and evolutionary phenomena of life on Earth, (ii) simulating life as it could have evolved in non-earthly environments given some set of realistic boundary conditions, (iii) providing new concepts and models of emergent phenomena belonging to a general set of complex systems of which biological systems (under particular kinds of description) may be a subset” [12]. Although we do not believe that point (ii) is so important because it falls within the life-as-it-could-be program, it is obvious to us that AL can contribute to many fields of theoretical biology, like ecological modeling and evolutionary modeling as well as to the understanding of collective behaviors in animal societies [42,43]. To have more applications, see the paper by Taylor and Jefferson [41] in this volume. It is not to say that biologists did not resort to synthesis or self-organization as modeling tools before AL: Rather, AL is a unified, transdisciplinary attempt to make these tools systematic.

Let us give an example [39] of how AL-based tools of investigation can be applied to the understanding of biological phenomena. Consider the immune system: It has to perform the task of discriminating between self and nonself, that is, it has to protect the organism against external aggressors (antigens) but at the same time has to be tolerant with the molecules of the organism. A wrong functioning of immune tolerance leads to autoimmune diseases, which in many cases can be lethal or at least have severe consequences. The classical paradigm of immunology is the theory clonal selection, whereby external antigens stimulate the production of specific molecules (antibodies produced by lymphocytes) against them. These specific antibodies proliferate thanks to a combined process involving a rapid reproduction of the corresponding lymphocytes leading the creation of a clone (a set of cells with common genetic characteristics) and an enhanced secretion of the antibody that stimulates the reproduction of the secreting cell in a positive feedback, and so on. But antibodies are molecules, which could as well be attacked by other antibodies and be eliminated. But this is fortunately not the case, except in the case of diseases. How can one explain such a tolerance? Certainly, the immune system is too complex to be completely and thoroughly modeled. And analytic approaches are certainly doomed because the immune system is a highly interacting system functioning as a network: Breaking things down and separating constituent units is not a good solution. On the other hand, resorting to synthesis may help. One can use a somewhat abstract but inspiring representation of the antibodies in a two-dimensional shape space [30]: Clones that are divided in two families according to their (abstract) stereochemical properties (represented by two parameters in the case of a two-dimensional shape space). Two clones taken from two different families will strongly interact if they are close on the two-dimensional shape space. The affinity, or strength of interaction is given by $m_i = \exp(-d_i^2)$, where $d$ is the distance between them. Let us assume that two clones belonging to the same family don’t interact at all. New clones are constantly presented to the network for recruitment, in order to mimic the constant production of lymphocytes in the bone marrow. Let the “field” a clone feels from other clones of the complementary family be given by $b = \sum_i m_i$: This
Figure 3. (a) One starts with a central clone, and new clones are proposed for recruitment; the two families are represented respectively by filled and empty circles; (b) the system after a few time steps. (c,d) The system eventually converges to a state where there are intertwined stripes of cells from the two families.

represents the total strength of the interactions, in a mean-field manner. Now, a clone is recruited if the field it feels falls within a window. This corresponds to the experimental observation that the activity of clones falls off rapidly outside of that window. All the basic ingredients are gathered. One can simulate such an (over)simplified model of the immune system in the absence of any external antigen and see how it evolves (see Figure 3a–d).

One finds that such a system evolves toward a rather stationary state (in a statistical sense) where there are intertwined stripes of cells from the two families. This constitutes a very improbable pattern. But even more interesting is the way this state responds to perturbations. Assume that we put in this system a molecule (say of the self) that is not subjected to the field-window condition, at least for a certain amount of time. You can see in Figure 4 that this molecule (a black square in our case—we randomly chose that it had a big affinity for clones represented by filled circles) starts in a “hostile” environment because it is surrounded by filled circles, but it is progressively integrated...
into a stripe of more friendly clones (empty circles). The system locally deforms in order to do so. If one measures the sizes of the reorganizations needed to integrate the molecule, one even finds that they are power-law distributed (up to a cut-off size), which is reminiscent of self-organized criticality, a property of some dissipative many-body systems to evolve toward a statistically stationary state where events of any size and duration can take place, allowing for reorganizations at all scales.

What do we learn from this experiment, and what does it have to do with AL? The answer to the first is far from obvious in a biological setting: The model is more than simple compared with the complexity of the immune system, and almost no experimentalist will consider it a good model of what may actually happen in the immune system. Yet, if one sees it as a simple clue, it may constitute an inspiring metaphor, showing the importance of the network aspect of the immune system. It can be integrated in a theory postulating the existence of a central immune system, based on the activity of lymphocytes B alone, which is distinct from the peripheral immune system involving lymphocytes T, which by the way appeared much later in the course of evolution. This model, although simple, then represents a first step toward the modeling of the very basic mechanisms of the central immune system as it grows before birth. And it is indeed being used as a starting point for the design of more complex models involving many more features of the immune system. As regards the second question, why is it AL? The answer is disputable, but let us put it this way: This model is too far from any biological reality to belong to genuine biological modeling as it is practiced in most laboratories. Yet, as we just argued, it teaches something: It is useful. Moreover, it is based on synthetic techniques (more or less CAS), that is, AL techniques. As you can see in the references, the paper reporting these results has been published in the *Journal of Theoretical Biology*: We consider this as AL’s influence, which has allowed such marginal research in biology to be diffused to the large audience it deserves. We also believe it does not suffer from the criticisms of the previous sections, because it is clearly biologically inspired and perfectly defines its limit of applicability.

Let us now give another type of example from which generally applicable conclusions can be drawn, showing the power of AL techniques to explore biological

Figure 4. (a) The black square being sensitive to filled circles, it is in a hostile environment. (b) The black square has finally been integrated within a stripe of empty circles through deformations of the system.
models beyond their crude biological application. To make things clear, let us start from general considerations about modeling. Starting from experimental observations, one generally wants to build a model belonging to a given class of models to account for these observations. The choice of the model class is both a matter of taste and more importantly a matter of relevance in the context of the observed phenomenon: The model parameters must have a biological significance, be it assumed or explicit. Once the relevant parameters have been found, they are generally tuned until the model can explain the observations: that is, the model must at least reproduce the data and be able to make some predictions (e.g., if the biological system is perturbed, the corresponding perturbation in the model must lead to the same consequences as in the real system). Let us assume we have such a wonderful model at hand. In certain ranges of values, the parameters will induce a behavior close to the observations. But if these parameters are set out of the “biologically adequate” range of values, how can the model be interpreted? Some will argue [27] that exploring the model’s behavior by tuning its parameters amounts to exploring life-as-it-could-be. Well, it is true that sometimes one finds new kinds of behaviors that, although not directly relevant to biology, can have some interest for other disciplines (see the examples to follow). But, more surprisingly, these apparently nonbiological behaviors can tell a lot to biologists: Some ensemble of constraints certainly led to the particular set of parameters allowing our model to reproduce the experimentally observed data. But were these values of the parameters unavoidable? Is it possible that other (environmental) constraints could have evolved other values for the parameters? A thorough understanding of the nature of the parameters is made possible by applying AL’s bottom-up concepts (systematic synthetic exploration), and such an understanding is invaluable when it comes to looking for constraints likely to lead to a particular behavioral form. Take, for example, the building behavior of wasps [42,43]. One of the important questions ethologists ask is whether the architectural forms observed in nature (and more generally social organizations and behavioral forms) are unavoidable. We have tested a model of building behavior in order to reproduce wasps’ nests found in Vespa genera. The basic hypotheses underlying the model are quite simple: Each wasp is capable of acting on its local environment by depositing a brick according to the state of this local environment. The space in which the nest is constructed is a $10 \times 10 \times 10$ cubic lattice, and the local environment of each wasp consists of a $3 \times 3 \times 3$ cube ($\sim 1/40$ of the total volume), the center of which is occupied by the wasp. The behavioral rules that we use can be deterministic, stochastic, epichoral. In Figures 5 and 6 we show two nests generated using these rules. In Figure 5, the rules have been adjusted to reproduce patterns actually found in the Vespa genera. By slightly modifying the behavioral rules, we get the pattern in Figure 6, which is never found in nature. Hence, the question of knowing whether the behavioral rules used to generate the nest in Figure 5 could be an “attractor” of evolution, given some set of environmental conditions. For some reasons, the nest in Figure 5 is viable (while the one in Figure 6 is certainly not, at least in the environment-as-we-know-it). Thus, to make our question more accurate, we should ask why, among viable types of nests, only one type (or a highly restricted number of types) seems to have been selected. Although accidental causes are still possible, we can propose a tentative answer: The behavioral rules used to generate the rules of Figure 5 are the simplest possible. Any other behavioral rule is unavoidably more complex. This simplicity property might make it more easily reachable by evolution. We will not continue this speculative discussion too far: We just meant to illustrate that AL synthetic methodologies were the only solution to explore the space of architectural patterns and find other possible viable architectures.
Figure 5. “Artificial nest” generated by a swarm of 10 “artificial wasps” depositing bricks according to the state of their local environments. The behavioral rules have been chosen so as to reproduce nest architectures that can be found in nature in the Vespa genera. Note, for instance, the little piece on the top of the nest, which corresponds very closely to natural pedicels, and the succession of horizontal planes that represent the combs of natural nests.

5.2 The Interplay of AL and Philosophy

A “philosophy of AL” is under way. If philosophy can somewhat “guide” the quest of AL, mutual enrichment is also possible, because AL is precisely a scientific attempt to clarify some old philosophical issues about the nature of life, and other issues... it raises! AL “promises to be of significant philosophical interest. AL has relatively straightforward relevance to issues in metaphysics, philosophy of science, philosophy of biology, and philosophy of mind, but it also bears centrally on more distant issues in social and political philosophy, economic philosophy, and ethics” [1]. But because we are not philosophers, we urge you to read Harnad and Dennett [11,20]!

5.3 Designing Artificial Problem-Solvers

We believe that the idea of AL giving rise to engineering applications is fundamental. Taylor [40] gave some examples about such applications, like in the field of ecology (simulations of populations of insects leading to the development of control tools for agriculture). AL as a toolbox is precisely at the interface between many disciplines and as such serves as a multidirectional communication channel. In particular, AL builds bridges between natural sciences and the sciences of the artificial: This makes it unique and indispensable. We can give many more examples based on AL’s methodologies.

Algorithms. The design of algorithms is a booming domain of activity in AL. AL tools have led to the development of many interesting algorithms that often perform better than classical algorithms within a shorter time, all the more as they generally contain much explicit or implicit parallelism, like in swarm-inspired algorithms or genetic algorithms. They resort to distributed agents, or to evolutionary algorithms, or often to
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Figure 6. “Artificial nest” generated by a swarm of 10 “artificial wasps” depositing bricks according to the state of their local environments. The behavioral rules have been found by a systematic exploration of the space of possible architectures. We selected this one because it can be derived from the preceding one through a slight modification only, while yielding a strikingly different pattern that is never encountered in nature. Could it have become functionally viable with another evolutionary history (including the evolution of the environment)?

both. For instance, Packard used a genetic algorithm to evolve cellular automata to make them reproduce electrochemical deposition patterns. In very much the same spirit, one of us (EWB) is currently developing a genetic algorithm to evolve coupled map lattices (CMLs) for time series prediction: CMLs compete to survive in an environment composed of a times series; the coexisting, fit CMLs may be able to predict very efficiently in some specific region of the state space; and one eventually ends up with a population of CMLs capable of predicting the whole series. Hillis evolved sorting algorithms by making them coevolve with parasites, and found a very good solution [22]: parasites modify the fitness landscape and make it harder for algorithms to perform well; thus, both the parasites and the algorithms become more and more complex, and one finally obtains a very efficient algorithm. We all know Koza’s genetic programming technique, in which LISP-like programs are evolved to solve particular problems [26]. Deneubourg and Goss [10] have designed a distributed sorting algorithm in which artificial ants can realize global clustering with only local information and a small memory: Roughly, the rules consist in taking an object of type A with a high probability if the artificial ant is surrounded by objects of type B, and in dropping this object with a high probability if it is surrounded by objects of the same type; the same holds for objects of type B; artificial ants are allowed to move randomly, and after a certain amount of time, one gets clusters of objects A and clusters of objects B, and finally, one can get only one cluster of each type. Bersini [described in 5] de-
Artificial to different responding optimized concept either a pling, when thus, ing exhibiting simple one of know and algorithm. responding mass longer effect, thus, the corresponding pheromone trail will be reinforced more rarely; this process is amplified until the shortest path is eventually selected by the whole colony (although “explorers” still exist). Note that many refinements of this crude principle are possible, for instance, this “mass recruitment” of ants through pheromone can be a disadvantage when a new, closer source is introduced, in that the colony will be unable to switch to this better source. By allowing different types of recruitment, like tandem, group, and mass recruitments to be combined, one gets a much more flexible swarm, capable of responding efficiently to modifications of the environment. Finally, Sniers and Kuntz [personal communication, 1994] developed an optimization algorithm dedicated to the graph partitioning problem, using pheromone-like tracers combined with a genetic algorithm. We have to stop here for lack of room, many more examples could be given, and we chose the ones we are the most familiar with because of our backgrounds. To know more, for example, about computer viruses, see Spafford [38].

Robotic systems. Many robotic systems are currently being developed in the spirit of artificial life [15,16,18]. They are devoted to harvesting, mining, and ecological sampling, and many other tasks are to be announced. The artificial wasps we presented in a previous paragraph also constitute good candidates for the design of robots exhibiting an asynchronous, emerging collective building ability, whereby they can generate very complex, highly structured architectures without any central controller and complying only with simple local rules. Note that all the examples of robots share essential similarities: Each individual robot is usually simple, and the collective intelligence appearing at the colony level is the result of interactions between the robots. These interactions can either be direct, through some kind of communication process [1], or indirect through modifications in the environment by one individual that induce subsequent changes in the behavior of the other individuals (“stigmergic script”) [42]. All this has rather interesting consequences: The colony of robots is more flexible and more robust (if one robot gets out of order, the global task performed by the colony is generally not affected) than one individual complicated robot, and the cost of developing a colony of simple agents is eventually less than that of designing the complicated robot. (Besides, losing it in an accident would have many more aftermaths than losing a poor little agent of a colony.) To know more about autonomous agents, see Maes [28].

Most existing colonies of robots have been inspired by natural systems, systems exhibiting collective intelligence: insect societies. One of us (GT) has developed the concept of swarm intelligence [44] to help build bridges between biological and artificial contexts: “A swarm is a group of active and mobile elements which can communicate with each other and thereby influence each other’s actions. Each unit interacts locally with its environment and in particular has access to only local information.” If the task to be performed by a biological swarm has a biological relevance (efficient, flexible, optimized foraging, adaptive division of labor) at the level of the colony, the corresponding task performed by an artificial swarm has a relevance with respect to the engineer’s goals (gathering and transport of objects, exploring new areas, synchronizing activity, sorting objects, building or allocating an appropriate number of units to different tasks whose demand is variable). Central to the idea of swarm intelligence is
the coexistence of individual simplicity and collective complexity. Such systems, often relying on competing positive feedbacks as an organizing force, have three important properties: simplicity, reliability, and flexibility. The units make no complex decision based on knowledge or environmental representation and are allowed a high degree of randomness in their movements. However, they are spread out in their environment and are influenced by local environmental cues that could have been modified by their own or other units’ past actions. Because a particular configuration is adopted dynamically (and not imposed a priori) in response to a large number of environmental cues, any change in the environment leads to an appropriate reconfiguration, conferring a lot of adaptivity and flexibility to the swarm.

Cellular robotic systems [2], although they are simulated robotic systems, are aimed at exploring the possible problem-solving abilities of robotic colonies. They serve as a first step in the process of designing such colonies. In particular, Beni and colleagues [private communication] introduced an asynchronous cyclic swarm capable of solving very simple ordinary differential equations in a distributed manner. We improved this cyclic swarm and designed a two-dimensional swarm capable of solving partial differential diffusion-like equations [5].

Let us also briefly mention that a parallel can be drawn between AL and cybernetics (the study of control and communication in the animal and the machine) [see, e.g., [25], but one of the main differences is the nature of the tools available to AL, compared with those that were available to cybernetics. Given the impact of cybernetics on science in general and on engineering sciences in particular, despite this lack of a truly powerful tool (“the science of feedback”), one can expect an atomic impact from AL.

5.4 AL and Art
Let us end this brief review with the relationship between AL and art. As we already advocated, art inheres in the very foundations of AL. Synthesis, which is the central method in the AL toolbox, becomes artistic creation when the Artificial Lifer, like the “Zoosem-systemician” Bec [26], is free from any constraint (especially the unpleasant constraints imposed by reality) and is only limited by the power of his or her imagination. Sims even proposed to everyone to become an artist by allowing people to interact with his “genetically” generated pictures in real time. (To have an idea of Sims’ ideas, see, e.g., [6] or even better the video proceedings of the second AL workshop.) By choosing such or such a picture, they contribute to the development of a new type of art, based on the interaction between their imagination and computationally generated images. This new form of art, although controversial because the artist sort of lets the computer do all the work, is full of promises: For the first time, it is possible to convey the bottom of our dreams—for the first time it is possible to really visualize the creatures that live in there.

6 Conclusion
In conclusion, if you have to justify your AL activity, you should first remember that AL is a particular way of looking at things that can be fruitfully applied to many domains. If you are dealing with systems that are too complex to be studied with traditional scientific tools, AL can certainly help. You should not forget your primary goals and get lost in AL’s immensity. While top-down approaches usually forget to obey lower-level constraints and laws, purely bottom-up approaches usually forget to look at higher-level constraints, and this leads in both cases to considerable flaws. Artificial life, being “very bottom-up,” needs constraints. Both empirical constraints originating from biology and other natural sciences, and pragmatic constraints oriented by the design of useful, viable, efficient, robust, flexible, decentralized, lifelike systems, can channel your AL.
energy into extraordinary accomplishments. If you are a biologist (you are certainly hard to convince, and it must be even worse for your boss) seeking new modeling tools, AL is a general toolbox that offers you a broad spectrum of new techniques of experimentation, from computer simulations of evolution to models of how decentralized systems can collectively perform biologically relevant tasks. If you are looking for ways of getting out of classical AI's dead-end, AL can help by providing you with ways of making symbols emerge out of low-level sensory-motor processes. If you are a computer scientist, not necessarily involved in AI, AL gives you the pleasure not only of playing god, but also of finding new distributed algorithms for optimization, control, or prediction. If you are a philosopher, AL will give you the opportunity to think about new issues in ethics, epistemology, and so on and will provide you with years of work to unravel the ontological status of life: you will be able to think over life as no other philosopher before. If you are an engineer, AL constitutes an almost inexhaustible source of ideas for the design of a bunch of new machines. In all these cases, cooperation is crucial: biologists do not necessarily master the thermodynamics of cooperative structures, while physicists usually have only little knowledge about biological systems; ethologists do not always master computer programming, while gifted programmers are generally not familiar with animal societies. One can draw wrong conclusions when working in somebody else's field: communication is essential, and AL is a powerful medium of communication for diffusing transdisciplinary concepts. Let alone the fact that concepts originating from other disciplines often have an exotic flavor, they can also serve as a source of inspiration in one's own field. Finally, if you are an artist, AL opens a world of new experiences to you: it complements the traditional artistic techniques by extending the scope of art-as-it-is to the wider scope of art-as-it-could-be, where everything which is in your imagination, even deep inside your subconscious, can be recreated in alternative media. With all this in mind, you should definitely be able to reassure your boss and hopefully yourself if ever you needed to be reassured.

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