



# Let the robotic games begin

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## Models of Evolution

The quantitative study of Darwinian evolution in a controlled laboratory setting has always been a difficult endeavor. Not only are the timescales relevant for true evolutionary innovations rather daunting, even for rapidly reproducing microorganisms, but also creating realistic ecological interactions that couple different individuals and different species is very difficult. Thus, we have powerful methods to study microevolution, but even the heroic efforts of Lenski and coworkers to track bacterial populations for decades (1) just barely yield true evolutionary novelty (2).

There is a related set of difficulties for computational models of evolutionary dynamics. Popular works arising in the field of population genetics often consider the mutation–selection dynamics on fixed fitness landscapes (3, 4). This approach may be sufficient for some of the aforementioned microbiology protocols involving nutrient-rich media evolving over short times but suffers from two critical shortcomings. First, the evolution allowed in these models is just that of fixation of beneficial alleles of already-existing genes. The open-ended nature of true biological evolution whereby entirely new systems can be created and indeed entirely new levels of biological organization developed (5) remains wondrous and very difficult to capture in any model. Again, recreating in silico an ecological milieu which properly accounts for the role of competition and cooperation among individuals and among species is equally fraught with uncertainty and arbitrary assumptions.

The field of artificial life was birthed to deal with this state of affairs (6). In the original version of this effort, digital organisms are allowed to evolve via selection of variants which arise and compete inside a virtual environment. The advantage of this approach is the dispensing with the constraints imposed in mutation–selection models in favor of a more naturalistic sense of evolution. Indeed, some interesting insights were obtained by this strategy, for example the idea of “survival of the flattest,” indicating that mutational robustness may under certain circumstances be more important than absolute fitness advantage (7), an idea that has reemerged in the context of neural networks (8). Yet, this approach also seems to have run its course; as we have learned of the amazing complexity of even minimal organisms (9), these engineered processes appear to be too simple and, well, too artificial, to teach us much about their biological counterparts.

## Robots to the Rescue

Entering into this fray, in PNAS Wang et al. (10) offer a different research strategy, that of robotic games as enabled by modern technology. The idea of using robots to create an analog version of an interesting nonequilibrium systems is not in itself novel, but perhaps taking seriously the

idea of evolution and ecology in a robotic world is. The specific dynamics chosen for the robots is built upon well-established mechanisms arising in the study of microorganisms. First, robots move toward increasing luminosity gradients based on shadows they themselves generate by “consuming” light in their neighborhoods. Of course, resource competition models in well-mixed systems are a workhorse of ecology (11), but here the local nature of the process is essential and leads to the directed motility. Bacteria can chemotax due to gradients of consumed nutrients (12) and *Dictyostelium* amoebae can respond to concentration patterns arising via localized cAMP ligand degradation due to phosphodiesterase (13). Similar mechanisms have been suggested for more complex organisms as well. Collectively, the coupled shadow/motility dynamics creates a complex landscape which then feeds into the second part of the algorithm, dealing with birth–death–evolution of the robotic swarm.

Unlike the straightforward resource competition dynamics, the evolutionary processes included in the robotic game seem rather complex. The robotic genomes encode the color-dependent response and undergo mutation and a version of recombination. The latter is used to bring back to life robots that have been declared dead due to their failure at resource utilization; these are resurrected with new genomes that are constructed from two “parents.” This algorithm is a convenient way of avoiding the technical problem of removing robots and placing new robots on the game board, and it does accomplish the necessary goal of allowing for statistically steady states to emerge from the dynamics. As in the previous artificial life approaches, the detailed nature of the interactions is not supposed to be important as long as they lead to complex evolutionary dynamics. This may or may not prove to be the case.

Given their framework, Wang et al. (10) investigate a number of interesting phenomena that emerge in their robot world. One such finding concerns the “meltdown valley,” their terminology for the nonmonotonic dependence of community survival on certain critical parameters. The fact that this can be understood quasi-analytically is welcome. Another result concerns the need for gene exchange to ensure survival, at least under some circumstances, but it

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Author contributions: H.L. wrote the paper.

The author declares no competing interest.

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See companion article, “Robots as models of evolving systems,” [10.1073/pnas.2120019119](https://doi.org/10.1073/pnas.2120019119).

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Published April 19, 2022.

is fair to say that one hopes that the best is yet to come. The authors are of course optimistic that this artificial world will yield direct insights into acute problems in our world, including their personal favorite of cancer cell communities developing strategies of persistence in the face of, and eventual resistance to, targeted drug therapies (14), but at present this hope remains rather speculative.

One of the most important issues to be addressed is, Why bother with hardware? In other words, why not just create a simulated version of the robot world and study the same questions? This question already arose in a prescient paper by Eshel Ben-Jacob and coworkers entitled “Evolvable Hardware: Genetic Search in a Physical Realm” (15). There, evolved oscillatory behavior relied on stray capacitance that was not a designed feature of the programmable devices

used in these experiments. Here, too, imperfections due to spectral overlap between the nominally independent channels might be playing an important role in the robotic interactions. This supports the argument, presented in this paper (10), that dealing with actual real-world environments, as opposed to computational caricatures thereof, is an essential aspect of evolutionary dynamics. This is an intriguing idea but should be directly tested by comparing experimental data to simulations of the robotic system.

On the whole, then, the paper by Wang et al. (10) offers a promising route to the fashioning of analog systems with which to investigate important questions in evolution and ecology. So, let the robotic games begin, and may the odds ever be in favor of the authors’ developing needed insights into these critical topics.

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