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1 **Artificial intelligence accidentally learned ecology through video games**

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21 **Abstract**

22 An advanced artificial intelligence system defeated the best human players in StarCraft II, a
23 popular real-time strategy game. In a virtual ecosystem, players compete for habitats and
24 resources, unintentionally reproducing many ecological phenomena. We propose to repurpose
25 this A.I. to test ecological hypotheses that have been intractable using traditional approaches.

26

27 **Video games: a new playground for science and artificial intelligence**

28 Transforming data into predictive understanding is one of the fundamental challenges facing
29 ecology. Artificial intelligence (A.I.) and machine learning techniques have been widely used
30 to interpret complex data streams, but their application in ecology remains very limited
31 compared to other research disciplines and industries (e.g. economics, genetics, and
32 engineering [1]). One domain where artificial intelligence plays a dominant role is the video
33 game industry, which has provided strong support for the development of a new generation of
34 A.I. systems, using artificial neural networks and cutting-edge techniques of machine
35 learning. Here, we report on a recent breakthrough, concerning a popular real-time strategy
36 game (StarCraft II, [2]). In this game, which unintentionally reproduces central ecological
37 dynamics, an advanced A.I. called AlphaStar trained itself to play the game using multi-agent
38 reinforcement learning. Using unexpected tactics, it beat soundly some of the world's best
39 human players in matchups in late 2019. We propose to retool this system: feeding AlphaStar
40 with real socioecological scenarios, it could address persistent and novel issues in the real
41 world, including predicting emergent properties and non-linearities in succession, identifying
42 risk and factors for ecological collapse, and understanding ecological strategies under
43 changing environments. This would build on work by programmers and researchers who are

44 already collaborating to create realistic or "serious" games [3] that advance research via
45 gamification [4,5] and facilitate education [6].

46 **A complex and unpredictable virtual environment reproducing ecological dynamics**

47 StarCraft II is one of the most popular video game franchises and largest games in e-sports.
48 Two or more players confront each other on a game map with the goal of eliminating the
49 opponent, similar to the traditional board games of Chess and Go [7,8]. However, StarCraft II
50 integrates several dimensions that simulate real-world complexity much more closely than
51 traditional games. Real-time matches occur in a high-resolution, heterogeneous landscape
52 with an uneven distribution of resources and terrain, leading to around 10^{26} possible actions
53 every step of the game [2]. Within this virtual ecosystem, players collect resources to create
54 up to ~20 different game pieces, called units. In turn, these units collect resources, provide
55 defense, or attack competitors. Additionally, there is an artificial fog (called the "fog of war"),
56 that constrains the visible portion of the landscape to the area immediately around the player's
57 units. Like in reality, StarCraft II is a world where individuals struggle for survival with
58 incomplete information about resource location and threats of competition or predation (see
59 Kriegspiel [9] for previous applications of A.I. in imperfect-information games).

60 In addition to the generally realistic characteristics inherent to most real-time strategy games,
61 StarCraft II unintentionally integrates a large range of ecological dynamics and mechanisms.
62 First of all, players must choose one of the three "races" (Terran, Protoss, and Zerg), which
63 have different life strategies that align strongly with the three main ecological plant strategies
64 laid out by Grime: competitors, stress tolerators, and ruderals (Figure 1). Each player
65 continuously makes trade-offs between colonization of new habitats versus rapid conflict with
66 the opponent, depending on the stoichiometry of available resources and level of external
67 threat. Early in the game, when resource acquisition is very limited and few possible units are

68 available, players often produce cheap and numerous units (*r* strategy). As the match
69 progresses, players generally produce more expensive but powerful units (K strategy) that
70 have specialized and complementary roles, increasing the biodiversity in the virtual
71 ecosystem. Furthermore, interactions among players result in shifts towards units with
72 functionally different traits, while the degree of performance and specialization of the traits
73 themselves can be enhanced, intensifying the arms race throughout the course of the game.
74 Overall, the growth is highly modular and plastic, and many choices are viable only when
75 combined with other decisions and considerations (strong phenotypic integration). Growth
76 and cognition operate within a network of units, similar to natural organisms like clonal plants
77 or superorganisms (social animals, e.g. ants or termites). Last, each player has a maximum
78 number of units simultaneously allowed on the map, enforcing an artificial carrying capacity
79 and associated density dependent strategies.

80 **The unexpected ecological mastery of AlphaStar**

81 On October 30th, 2019, Vinyals *et al.* [2] revealed that their A.I. system, named AlphaStar,
82 promptly defeated many professional players and outperformed around 99.8% of officially
83 ranked human players. Before the confrontations, AlphaStar agents (simulated players) had
84 been trained with data from millions of StarCraft II matches played against each other — the
85 equivalent of 200 years of continuous gaming per agent. During this spin-up process, the
86 algorithm selected and crossed the most successful agents, exerting selective pressure on the
87 variation generated by the machine learning. In their isolation from human influence, many
88 agents developed very aggressive strategies, entirely free of human gaming culture such as
89 tacit or unconscious alliances between players to ensure long-term participation. For example,
90 in confrontations in which both players have the same race, agents used apparently
91 counterproductive strategies, such as over-saturating their resource collection capacity or
92 having a homogeneous army composition. This unconventional approach was so effective that

93 these games almost always finished in a few minutes (compared to tens of minutes for a game
94 among humans). The overall domination of AlphaStar over its human competitors in these
95 situations demonstrated that these counterintuitive behaviors better balanced the ecological
96 trade-offs necessary in a context of strong intraspecific competition (*i.e.* symmetric
97 competition). In this configuration, better performance in resource collection and a strategy of
98 quantity (competitive hierarchy) not quality (limiting similarity) were the most likely to allow
99 domination.

100 **Using AlphaStar to address ecological and evolutionary problems**

101 Given the amount of time and resources invested in its development, and despite some
102 limitations of the game (e.g. very little resource recycling, no biotic pressure other than that of
103 the competitor), AlphaStar is arguably more sophisticated, flexible and robust than any
104 existing ecological model. AlphaStar could be readily repurposed to address fundamental
105 questions in ecology and evolution. Preliminarily, we could study the current games of
106 AlphaStar as a competition model between two individuals (Box 1). We could then make
107 agents directly learn from maps corresponding to realistic configurations of biodiversity and
108 resource distribution. The frequency and the trajectory among games of agents' various
109 ecological strategies could reveal their evolutionary trajectory, which would allow assessment
110 of deterministic and contingent development pathways in different starting conditions. We
111 could also manipulate environmental conditions during games and observe the response of
112 agents with given ecological strategies (*i.e.* ecological response), for instance in terms of trait
113 syndromes or chances of success.

114 Some could understandably ask, what could we learn from this exercise that is not simply an
115 artefact of the game parameters? First of all, we think that AlphaStar should be modified by
116 limiting the number of the actions it can make per minute (*i.e.* "micromanaging"), to allow

117 testing substantive, ecological processes rather than just differences in processing power.
118 Then, from a plant perspective, we could study the effects of ecological strategies and their
119 response to changing environments, including predicting nonlinearities in succession, niche
120 shifts and trade-off modifications caused by direct disturbance, resource change or biological
121 invasions. From an animal perspective, we could study the role of personality in ecological
122 functioning [10], the ecology of fear (*i.e.* the impact of the *risk* of competition [11]) and the
123 evolution of ecological culture ([12], e.g. emergence and drift of ecological approaches).
124 From a human perspective, AlphaStar could shed light on cultural relations: if many humans
125 from different cultures play against AlphaStar, it would generate a rich dataset relevant to
126 how individual, cultural, and artificial personality can impede or solve complex and crucial
127 ecological problems such as ecological collapse, environmental change, and tolerance of
128 immediate and eventual risk. The data, code, and architecture of AlphaStar's neural network
129 and StarCraft II itself are freely available. Relationships among gamers, ecologists, and
130 programmers would allow co-construction and testing of many more hypotheses than we list
131 above, possibly generating new insights into many stubborn challenges of ecology and
132 evolutionary biology.

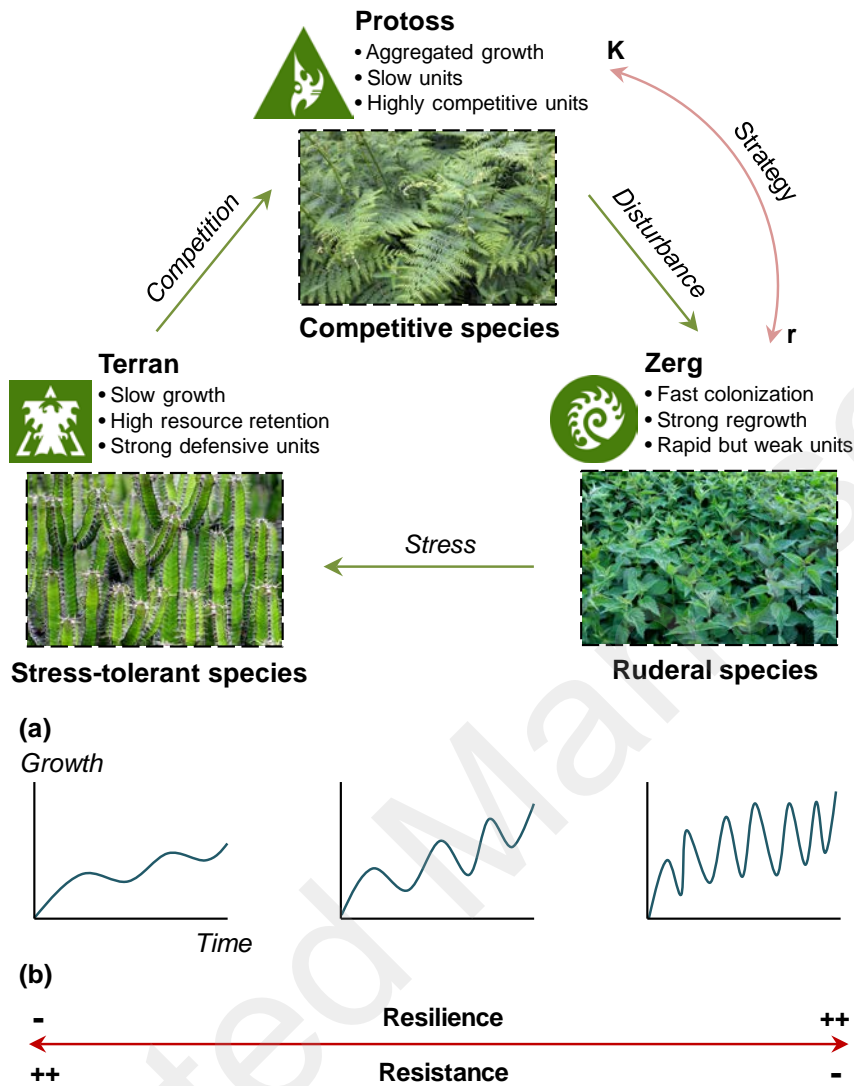
133

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143

144 **Figure 1. Ecology of the three races of StarCraft II through the prism of Grime's CSR**
 145 **triangle.** At the top, a competitive species (e.g. bracken, ferns) represents Protoss, which
 146 produce slow and expensive units that need to be locally aggregated but are very competitive.
 147 At the left, a stress-tolerant species (e.g. cactus) reflects the strategy of Terrans, which can
 148 resist intense stresses by collecting and conserving resources more efficiently under opponent
 149 pressure, and use several, strong defensive units and strategies. At the right, a ruderal species
 150 (common nettle, *Urtica dioica*) represents the strategy of Zergs, which colonize space rapidly,
 151 regrow rapidly and have low cost, aggressive units with generally short lifespans. (a) These
 152 ecological strategies mean that each race expresses distinctive growth curve. (b) Each race
 153 also has emergent properties such as more or less resilience and resistance.

Box 1. The basical ecological model in StarCraft II

The classic confrontation type in StarCraft II, as played by AlphaStar, consists of two players confronting each other in a particular environment with limited resources – see the "mini-map" (Figure I). This represents an ecological competition between two individuals, which can be intra or interspecific, depending on whether the players choose the same race. The map shows the entire environment, but the players' vision is limited to the lighter, circular zones around their respective units and buildings. Resources are the light blue shapes, and the dark blue and red shapes are the buildings and units of both players (Protoss in blue, Terran in red). The progress and outcome of competition can be monitored through this mini-map, which shows colonization and exploitation of new resource patches, environment exploration, and often, ecological collapse. This map could be used to monitor more realistic ecological models. For instance, several players could compete against each other in a larger and entirely unpredictable environment, which would enable the study of ecological processes at the scale of populations and communities. We could also set up scenarios in which we artificially modify environmental conditions during the game, and then evaluate the consequences on ecosystem functioning and biodiversity dynamics. Note that quantification of several ecological processes like trait changes or trade-off modification are easily feasible with the game parameters.



Figure I. Mini-map of a standard game of StarCraft II.

156 **References**

- 157 1. Olden, J.D. *et al.* (2008) Machine learning methods without tears: a primer for ecologists. *Q. Rev.*
158 *Biol.* **83**, 171-193.
- 159 2. Vinyals, O. *et al.* (2019) Grandmaster level in StarCraft II using multi-agent reinforcement learning.
160 *Nature* **575**, 1-5.
- 161 3. Chang, A.Y. (2013) Playing nature: The virtual ecology of game environments. Doctoral
162 dissertation, UC Berkeley.
- 163 4. Sørensen, J.J.W. *et al.* (2016) Exploring the quantum speed limit with computer games. *Nature* **532**,
164 210-213.
- 165 5. Fenwick, T. (2017) Real exoplanets, virtual universe. *New Sci.* **3122**, 12.
- 166 6. Connolly, T.M. *et al.* (2012) A systematic literature review of empirical evidence on computer
167 games and serious games. *Comput. Educ.* **59**, 661-686.
- 168 7. Silver, D. *et al.* (2016) Mastering the game of Go with deep neural networks and tree search. *Nature*
169 **529**, 484-489.
- 170 8. Silver, D. *et al.* (2018) A general reinforcement learning algorithm that masters chess, shogi, and
171 Go through self-play. *Science* **362**, 1140-1144.
- 172 9. Ciancarini, P. and Favini, G.P. (2010) Monte Carlo tree search in Kriegspiel. *Artif. Intell.* **174**, 670-
173 684.
- 174 10. Start, D. and Gilbert, B. (2017) Predator personality structures prey communities and trophic
175 cascades. *Ecol. Lett.* **20**, 366-374.
- 176 11. Clinchy, M. *et al.* (2013) Predator-induced stress and the ecology of fear. *Funct. Ecol.* **27**, 56-65.
- 177 12. Mace, R. and Holden, C.J. (2005) A phylogenetic approach to cultural evolution. *Trends Ecol.*
178 *Evol.* **20**, 116-121.