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COMMENTARY

Modeling the Evolution of Strategies for Learning and Decision Making

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This special issue contains two articles modeling the evolution of strategies for learning and decision making. Each model tackles a slightly different problem, and each does so with a different decomposition of the system of learners and their environment. As such, each model sheds light on a different aspect of the evolution of learning and decision making.

Public Significance Statement
Understanding the evolution of cognition is hard. Models can help. This paper discusses two such models contained in this special issue.

Keywords: Models, cognition, social learning, heuristics

Cognition, in whatever form we find it, evolved. Understanding cognition therefore requires placing it in the context of its ecology and evolutionary history. Many of the methods traditionally used by experimental cognitive scientists, however, are inadequate for drawing inferences about those histories. Yet all is not lost. We can build models.

The world is complicated. Models simplify. Real-world systems are often too large, too small, too fast, too slow, or have too many parts to study directly. Models allow us to study a real-world system by studying something else, by studying something that is like the system but simpler and fully describable. By explicitly stating all of our assumptions in the language of mathematics or algorithms, we make it clear what aspects of our system we are or aren't talking about, which aids theory development and the falsifiability of hypotheses (Smaldino, 2017). Good models allow us to draw conclusions about real-world system *X* from the behavior of the model *Y*. A model decomposes the world into parts, with properties and behaviors, and relationships between those parts (Kauffman, 1971). In general, there is no one correct way to decompose any particular system. Rather, because complex systems can be understood at multiple levels of organization, understanding them requires a collection of models, with decompositions across those levels (Page, 2018).

This special issue contains two articles modeling the evolution of strategies for learning and decision making. Each model tackles a slightly different problem, and each does so with a different decomposition of the system of learners and their environment. As such, each model sheds light on a different aspect of the evolution of learning and decision making.

The first, by Kvam and Hintze (2018), tackles the evolution of individual decision making strategies. Evolutionary theorists often assume that natural selection optimizes decision processes to maximize fitness. However, optimal

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decisions are not always possible, because individuals are limited by time, information, and computational power in the form of fancy cognitive architectures. Instead, rationality is bounded and decisions are often made by using simple heuristics (Gigerenzer & Gaissmaier, 2011). The motivating question of Kvam and Hintze's (2018) article is: Under what conditions does natural selection favor the evolution of optimal decision making, and when will heuristics evolve instead?

Kvam and Hintze (2018) simulate a population of artificial agents, each with an embedded Markov brain, a variant of artificial neural network (ANN) with evolvable structural features. Evolutionary computing with Markov brains and ANNs has previously shed light on many important aspects in the evolution of cognition, including the evolution of neural modularity (Clune, Mouret, & Lipson, 2013), motor control (Cheney, MacCurdy, Clune, & Lipson, 2013; Sims, 1994), animal flocking (Olson, Knoester, & Adami, 2016), and cooperation (McNally, Brown, & Jackson, 2012). More generally, complex systems can exhibit surprising organizational consequences, and so simulations that embrace that complexity are often illuminating. For example, evolutionary simulations of cooperation and defection in structured populations have yielded complex, nonlinear organizational effects in which the relative fitness of cooperators and defectors changes over time due to the evolution of emergent structures (Akçay, 2018; Smaldino, Schank, & McElreath, 2013).

In this model, agents perform a sequential decision task in which they receive noisy inputs and must correctly identify the inputs' source from among two options or wait for more information. The analysis considers how the evolved agents exhibit optimal or heuristic strategies as a function of signal noise, the cost of guessing incorrectly, and agents' memory capacity. The simulations reveal that when the task is difficult and the cost of being wrong is high, optimal strategies cannot evolve, especially when memory capacity is limited. However, although individuals perform suboptimally in these cases, they can still perform above chance by using heuristics. For example, they might evolve a strategy of making a decision whenever three informative signals are seen consecutively.

Heuristics are often discussed in terms of sacrificing accuracy in favor of speed or efficiency. This model focuses on a variant in which speed is sacrificed in favor of accuracy, and in which the space of options is constrained to two. In reality, options are often unknown *a priori*, and deciding when to stop searching is itself a function of heuristics (Smaldino & Richerson, 2012). The model may therefore reveal little about heuristics as typically understood. However, by formalizing both the decision task and the cognitive constraints, Kvam and Hintze (2018) produce precise, falsifiable predictions for a specific type of decision scenario.

The second modeling article, by McElreath, Boesch, Kühl, and McElreath (2018), studies the evolution of social learning using an evolutionary game theory model. Rather than modeling agents' cognitive machinery explicitly, the machinery is taken as given, and the model instead explores the *consequences* of agents' cognitive strategies. This method sacrifices nuance about computational mechanisms for increased precision about the tradeoffs made by competing strategies. A key concept in evolutionary game theory is the *evolutionarily stable strategy*, or ESS. Given two competing strategies *A* and *B*, we should ask two questions about the evolution of *A*. First, will a rare *A* individual be competitive in a population dominated by *B*'s (can *A* invade *B*)? Second, will a population of mostly *A*'s be able to resist being invade by *B*'s (is *A* an ESS against *B*)? The answers to these two questions are not always identical; a strategy may perform well when common but poorly when rare. ESS analysis has been used extensively to study important topics related to social cognition, including the evolution of cooperation (Boyd & Lorberbaum, 1987), communication strategies (Smaldino, Flamson, & McElreath, 2018), and a wide variety of social learning strategies beyond those studied here (Kendal, Giraldeau, & Laland, 2009).

McElreath, Boesch, Kühl, and McElreath (2018) tackle a fundamental question: How does the capacity for social learning evolve? It may seem obvious that social learning helps animals to avoid the costs of trial and error. However, Rogers (1988) showed that although a social learning strategy that blindly learns from others can invade population of individual learners, the resultant population does not enjoy any fitness benefit. In other words, that kind of social learning is not adaptive. McElreath et al. (2018) recapitulate results by a number of researchers (Boyd & Richerson, 1995; Ehn & Laland, 2012; Enquist, Eriksson, & Ghirlanda, 2007) showing that a strategy of contingent social learning, in which individuals learn from successful others when possible and by costly trial and error otherwise, can both invade and increase population fitness under a wide range of conditions. Through numerical simulation, McElreath et al. (2018) extend this research to include overlapping generations and, most interestingly, group structure. They find that larger and more connected groups achieve higher frequencies of adaptive behavior. This is an important consideration when considering how groups increase the intelligence or innovativeness of their constituents. A limitation is the assumption that behaviors are easy to learn and are readily picked up from a single demonstrator. Much work has shown that reduced connectivity and higher clustering can also be beneficial if behaviors require multiple demonstrators (Centola & Macy, 2007) or involve solving complex problems (Derex & Boyd, 2016; Lazer & Friedman, 2007).

The articles presented by Kvam and Hintze (2018) and by McElreath et al. (2018) use different modeling techniques to tackle key questions on the evolution of strategies for learning and decision making. Both methods—agent-based models with complex neural architectures and evolutionary games with precise payoffs—can be viewed as complementary, part of the modeler's tool kit for decomposing the world into different sets of parts and relationships to fit different scientific questions. Evolutionary models can demonstrate how complex cognitive systems can evolve and delineate the key constraints that shaped our minds.

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