How cognition shapes cognitive evolution

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The tools we use shape the way we construct our world. When cognitive scientists began to model the evolution of cognition, one tool they found readily available was the genetic algorithm—a software system for artificially evolving solutions to problems that were specified by an explicit fitness function.[1] This fixed fitness function took a potential solution as input and returned the goodness of this solution as output. To model the evolution of cognition, the fitness function could represent some environmental challenge, and the evolved solutions could be cognitive mechanisms for solving that problem. Thus, models emerged for exploring how learning could evolve in a fixed environment,[2] how language acquisition could be shaped by specific benefits of communication,[3] and how simple sensory-guided foraging could evolve in a world with unchanging food locations.[4]

A moving target

The explicit, fixed fitness function—representing a fixed environment that cognition adapts to—is the default assumption of the original genetic-algorithm models. But this assumption is more useful for doing engineering than for modeling cognitive evolution. In nature, the environment is rarely fixed. The whole point of behavior is to affect the environment somehow, so as behavior evolves, the environment must be affected. This can make the environment something of a moving target for

cognitive evolution. For instance, better foraging ability decreases the amount of food remaining for others. Better color vision in predators selects for better camouflage in prey. Better language-learning capacities might increase the number of words in the languages that need learning.

Our tools evolve along with our ways of looking at the world. After a fair amount of research on how cognition evolves in fixed environments, a new niche opened up. New models emerged where individual behavior could have explicit effects on environment structure, and where environment structure rather than a fixed fitness function determined the evolutionary dynamics of survival and reproduction. This made the fitness function implicit and dynamic rather than explicit and static. In these artificial ecosystems, modelers again explored the evolution of simple behaviors such as foraging, exploration, and learning, but now the distribution of environmental resources changed over time as a consequence of the behavior of the artificial organisms.[5-7] Indeed, population sizes of the organisms themselves changed as their behavior evolved, further complicating the evolution of their behavior. When old-style genetic-algorithm methods modeled cognitive evolution as an optimization process, these new models introduced a competitive, strategic, game-theoretic dimension.

But the behavior that evolves in these systems has so far itself not been very complicated. The environments that organisms in these artificial ecosystems face still consist largely of simple (albeit shifting) resource distributions, which present relatively little cognitive challenge. To get to situations where greater cognitive power is required, we must look at much more challenging environments: those formed by other evolving, behaving organisms. In such environments, the major selective forces affecting the evolution of one species' cognition come from the cognitive and perceptual abilities of the other organisms, including prey, predators, competitors for resources and mates, kin, offspring, and allies. The eyes, ears, and brains of such organisms impose a new set of selective forces that we can call psychological selection, in contrast to the selection exerted by nonadapting physical forces (such as climate or local chemical composition) or unthinking biological vectors (such as plants or unicellular parasites).

Mating, and other games

Psychological selection can result in the kinds of more sophisticated cognitive abilities that traditionally interest researchers in psychology, linguistics, artificial intelligence, and other cognitive sciences. Escaping predators and capturing prey can both benefit from the ability to predict the behaviors of others given limited cues in the present. Avoiding unnecessary conflict with members of one's social group is aided by episodic memory for past encounters with particular individuals ("Have I ever fought Joe before? Did I win or lose?"), and by the ability to communicate one's intent to escalate or abandon a potential confrontation. And deciding what individuals to pursue as mates is improved by decision-making that combines knowledge of a potential mate's characteristics, one's own ability to win over that mate, and the possibilities for other future mating opportunities. These forms of cognition—behavioral prediction, episodic memory, communication of intent, multiple-cue decision-making—are the sort of abilities that models of psychological selection can teach us something about, in contrast to the simpler earlier models of the evolution of learning or foraging in fixed environments.

With the further enhancement of simulation tools to allow extensive interaction between organisms in artificial ecologies, models of psychological selection are now starting to appear. Simulations of the evolution of pursuit and evasion are giving us clues as to when *protean behavior*—or adaptive unpredictability, such as a rabbit's zig-zag path when fleeing a fox—can emerge.[8] Game-theoretic models of the strategic interactions between individuals demonstrate the complicated paths by which forgiveness and cooperation might evolve.[9]

Simulations of large interacting populations where new species can form have been used to explore the evolution of communication for altruistic or mate-attracting functions.[10] And simulations of the mate-selection process itself indicate how the perceptual mechanisms used in choosing sexual partners might co-evolve with the behavioral mechanisms that mate choice employs.[11]

The human connection

In these respects, the recent history of this simulation research has some paral-

lels to the longer history of theories about human evolution. Throughout the 1940s and 1950s, models of human evolution emphasized the fixed challenges of the physical environment, and the behavioral adaptations—tool-making, fire-making, group hunting, long-range foraging—that helped solve them. Then, with the rise of neo-Darwinian theory and sociobiology in the 1960s and 1970s, especially the new models of kin selection, parent-offspring conflict, reciprocal altruism, and sexual selection, theorists emphasized how selfish genes lead to social competition at the individual and group levels.[12] More recently, in the 1980s and 1990s, primatologists and evolutionary psychologists have emphasized the importance of social intelligence, Machiavellian behavior, mate choice, and other smart, strategic behaviors as forms of psychological selection that have shaped human intelligence.[13]

Many theorists now view the evolution of the human mind as a positive-feedback, bootstrapping process driven much more by social selection and sexual selection within our lineage than by the demands of an external physical or biotic environment. Perhaps AI research could benefit from this view, using evolutionary methods that allow cognitive complexity to catalyze its own evolution gradually through social competition and sexual selection, rather than continuing the traditional engineering method of trying to program cognitive complexity directly in one shot.

Evolving minds

We have argued that cognitive adaptations often have a dual role in evolution, as both selectors and selectees. The implication is not that cognitive evolution is a holistic mess beyond analysis, but rather that we need the full power of computer simulation to understand the kinds of co-evolution and positive-feedback dynamics that happen when minds guide their own evolution. Like our changing simulation methods, cognition is a tool for constructing world views and altering environments, and it is a tool that adapts to those environments it has changed. To fully capture the evolution of complex cognitive mechanisms in our simulations, then, we must continue to develop models that allow cognition to shape its own evolutionary destiny.

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Cultural evolution in neural networks

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Many behaviors and capacities that humans exhibit are culturally learned; that is, we learn them from *conspecifics*. A simple neural network model of learning from conspecifics takes the following form. Two different networks are exposed to the same input and they respond with some output. One network (the *student*) uses the output of the other network (the *teacher*) as teaching input for the backpropagation procedure. This procedure compares the student's output with the teacher's and, based on the discrepancy between the two, changes the connection weights of the student such that the student progressively learns to behave like the teacher. Whatever behavioral capacity the teacher possessed, that capacity now transmits to the student.

The social (or cultural) transmission of behaviors can serve not only to preserve existing behavioral capacities across successive generations but also to create new capacities. Imagine a population of organisms living in an environment that contains randomly distributed food elements. Each individual receives information about the location of the nearest food from its senses and responds with some movement. The neural network controlling the individual's behavior encodes in its input units the position of the nearest food and in its output units some movement of turning or moving forward. The initial population has randomly assigned connection weights. Hence, the initial population of individuals will have little capacity to procure food.

Teacher training

But imagine if the individuals who collected the most food are selected as teachers for the next generation of individuals (their students). Imagine further that some random noise is added to the teachers' output when