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Innateness, Learning, and Rationality

Elizabeth S. Spelke and **Katherine D. Kinzler**
Harvard University

Humans develop knowledge with remarkable speed and flexibility. Our reasoning about the physical world begins in infancy, yet is continually revised in physics labs. Understanding of the social world grows rapidly throughout early development and takes on myriad forms across cultures. Knowledge of number and geometry has foundations in infancy, yet develops to widely differing endpoints within and across societies. What accounts for the speed and flexibility of developing human knowledge?

For 2,500 years, this question has animated the dialogue between nativism and empiricism. Nativist and empiricist claims are in dialogue, not debate, for three reasons. One reason is semantic: *innate* means *not learned*, and so claims of innateness and learning are mutually dependent. The second reason is conceptual: any learning mechanism necessarily requires unlearned abilities for detecting and analyzing inputs and for drawing inferences, and so claims of learning inevitably presuppose a set of innate capacities. The third reason is empirical: people absorb systems of culture-specific knowledge largely by learning those systems. Although it is logically possible that exposure to French could cause children to speak Swahili, or courses in painting could cause students to know calculus, as a matter of fact, the *relevant experience* for developing knowledge of French and calculus includes exposure, respectively, to French and calculus. Thus, dialogue concerning what is learned, and what innate structures support that learning, requires consideration of the relevant experiences that allow for knowledge to be acquired.

Spencer and colleagues' article "Short Arms and Talking Eggs" (this issue) centers on two incompatible claims. In the introduction and conclusion, the authors argue that any claim of innateness is meaningless. In their discussion of examples, however, they argue that specific claims of innateness are not logically incoherent but false, and they draw with approval on evidence that children learn to recognize their caregivers, navigate through the environment, and speak their language. If learning is a coherent and useful concept in these domains, however, then claims of innateness also are coherent, useful, and necessary to explain the mechanisms underlying learning. We could contest Spencer et al.'s specific accounts of development in the above domains, but such a discussion is undermined by their more radical claim that the nativist-empiricist dialogue is a meaningless exercise.

Thus, in this commentary, we consider the radical claim of Spencer et al.'s title, introduction, and conclusion. In place of the nativist-empiricist dialogue, Spencer et al. call for a new theoretical perspective that focuses on "developmental process." Historians of science appraise theoretical perspectives in multiple ways, but there are two key criteria. First, does a perspective promote understanding of currently known phenomena and thinking about current problems? Second, does it foster new lines of research? We argue here that the nativist-empiricist dialogue scores high on both measures. In contrast, Spencer et al. provide no evidence that their "developmental process" approach passes either test.

Correspondence: Elizabeth Spelke Laboratory for Developmental Studies Department of Psychology Harvard University Cambridge, MA 02138 spelke@wjh.harvard.edu. Katherine Kinzler Department of Psychology University of Chicago Chicago, IL 60637 kinzler@uchicago.edu.

Since the 1950s, the nativist-empiricist dialogue has been a remarkable engine of research and a guide to thinking about psychological development. Rigorous controlled-rearing experiments have charted the diverse contributions of genetically guided structure and of visual experience to the organization of the cerebral cortex (Hubel & Wiesel, 1962; Hubel, Wiesel, & Levay, 1977) and the adaptive control of behavior (Held & Hein, 1963; Walk, Gibson, & Tighe, 1957). In parallel, comparative behavioral experiments teased apart the phylogenetic and ontogenetic roots of human capacities to perceive distance (Gibson & Walk, 1960) and form (Fantz, 1958). Until the 1990s, however, the nativist-empiricist dialogue faced two limitations.

The first limit was empirical: the pioneering research we cited above did not venture near humans' central cognitive capacities. Detailed comparisons across species revealed that capacities such as depth perception depend on highly similar mechanisms in humans and other mammals. Thus, studies of cats and monkeys brought insights into perceptual development in humans. In contrast, abstract cognitive capacities such as numerical and geometrical reasoning were thought to be unique to humans, and so the arsenal of methods at the disposal of comparative developmental psychologists and neuroscientists were not brought to bear to address them. Because it is ethically impossible to conduct controlled-rearing studies on human infants or to implant electrodes in their brains, researchers could not use the most revealing techniques of comparative psychology and neurophysiology to probe human cognitive development.

The second limitation was conceptual. The best accounts of the remarkable speed of human cognitive development were those that constrained child learners to restricted cognitive domains, fostering a view of cognitive origins as consisting of a set of innate, domain-specific systems (the “massive modularity” thesis). The best accounts of the flexibility of human cognitive development, in contrast, were those that proposed a single, general-purpose learning device, such as associative “connectionist” networks. The former solution provided no satisfactory account of the flexibility of human learners, however, and the latter solution provided no satisfactory account of either the rapidity of early learning or the lack of interference between the myriad conceptual domains over which learning operates.

Over the last decade, there have been remarkable breakthroughs on both these empirical and conceptual fronts. The central insight that has brought empirical progress to the study of the origins of human knowledge comes from the finding that complex human cognitive achievements such as mathematics depend on a set of foundational cognitive systems that humans share with other animals (Dehaene, 1997; Gallistel, 1990), systems that we called “core knowledge” (Spelke & Kinzler, 2007). Studies of numerical reasoning serve as an example. Although educated human children and adults are the only organisms that engage in symbolic, exact addition, the process by which we add symbolic numbers draws crucially on a nonsymbolic numerical ability that monkeys, pigeons, and newly hatched chicks share (Dehaene, 1997; Hauser & Spelke, 2004). When that nonsymbolic system is damaged by brain injury or is temporarily deactivated by transcranial magnetic stimulation, human adults show marked impairments in symbolic arithmetic reasoning (Lemer, Dehaene, & Spelke, 2003; Cappelletti, Barth, Fregni, Spelke, & Pascual-Leone, 2007). And when that system is enhanced in children through training, children improve their learning of symbolic, school arithmetic (Wilson & Dehaene, 2007; see also Halberda, Mazzocco, & Feigenson, 2008).

The finding that uniquely human numerical reasoning depends on cognitive systems that we share with other animals allows for a breakthrough in studies of the origins of knowledge. Comparative psychologists and neurophysiologists can now use all of the methods at their disposal, including neurophysiological studies of the brain systems that constitute these systems at levels from molecules to single neurons to circuits, and controlled-rearing studies that probe systematically the environmental conditions under which these systems emerge. Recent years have seen dramatic findings from studies using each of these methods. For example, researchers have found neurons responsive to specific numbers of visual elements in monkeys (e.g., Nieder, Freedman, & Miller, 2002) in brain regions involved in the basic numerical computations that monkeys and humans share. As neurophysiologists study these neurons and trace their circuits, they will gain insights into numerical computations at a level of detail never before possible, analogous to the evidence that an earlier generation of neurophysiologists gained about the basic neural events that allow humans, and other animals, to detect visible edges and perceive depth. As a second example, controlled-rearing studies now allow investigators to study the role of experience with number and geometry in the development of these critical components to mathematical understanding (e.g., Chiandetti & Vallortigara, in press). We believe the present moment is as exciting for the study of cognitive development as the 1960s were for visual development: a time when questions humans have asked for millennia can be addressed directly by experiments.

Recent theoretical insights using tools from Bayesian statistics provide an additional example of the conceptual and empirical value of the nativist-empiricist dialogue. Bayesian statistical modeling views learning as a special form of hypothesis testing. Learners begin with a set of mutually exclusive and exhaustive hypotheses and with an initial estimate of the probability that each hypothesis is correct (the *priors*). As data become available, a learner evaluates the probability that these data would have been obtained under each of the hypotheses in her initial set (the *likelihoods*). On the basis of the priors and likelihoods, learners revise their estimate of the probability of each hypothesis and consider further data. This process continues until one of the hypotheses in the initial set grows in probability to a sufficiently high level.

Bayesian models promise to explain *both* the rapidity and the flexibility of human learning (Tenenbaum, Griffiths, & Kemp, 2006). Because they depend on preexisting, rich conceptual structures, there is a sense in which these models are as nativist as any previous nativist proposal. Because they explain all learning through a single theoretical framework, however, there is also a sense in which they are as empiricist as any previous empiricist proposals. Unlike many connectionist proposals, for example, current Bayesian models do not require that separate networks with differing qualitative properties be evoked to allow effective learning in distinct domains. A single set of learning principles, applied to a rich knowledge base by a rich inductive machine, explains both the ease and the flexibility of human learning.

A recent Bayesian approach to word learning serves as an example. Xu and Tenenbaum (2007) modeled children's learning of words in a set of conceptual domains by measuring the full hierarchical organization of each domain in adults, and then using the adults' complete organization as the priors for children's inductive inferences. With this rich base of preexisting knowledge, the authors modeled children's word learning through learning processes that were fully general, with no specific constraints on word meanings or interword relationships. Although the conceptual priors in this analysis may be construed in multiple ways, and may have developed in young children through processes that involved earlier learning, this Bayesian approach attributes far more structure to child word learners than did previous approaches.

In brief, we believe that the study of cognitive development has now entered the most exciting and productive time of its history. New conceptual tools allow us to ask, as never before, how central and abstract concepts emerge in the human mind through a mix of innate concepts that are shaped by natural selection, and learning that is shaped by specific encounters with the objects to be learned. The empirical tools of psychology and cognitive neuroscience allow us to test specific claims of innateness and learning with a vast array of methods, and to target levels of analysis from molecules to mind and action.

This is the world that Spencer et al. ask us to reject. In its place, they urge developmental psychologists to move to a new land of "developmental process." Because they have devoted their essay to attacking the nativist-empiricist dialogue, they do not say what "developmental process" is, or what conceptual tools and research methods will serve to elucidate it. What "developmental process," for example, makes having short arms more germane to developing French than, say, encountering French speakers, following their gaze to the objects of their attention, and testing hypotheses about the information they intend to convey? While waiting for answers to such questions, we'll stay happily on course with research that promises to bring rich and insightful knowledge about the origins of human cognitive capacities for the next 2,500 years to come.

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