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Editorial

Probabilistic models of cognitive development: Towards a rational constructivist approach to the study of learning and development ☆

1. A new perspective on cognitive development

Over the last decade, probabilistic models of cognition have been used to provide new insight into the nature of human inductive inference (Chater & Oaksford, 2008; Chater, Tenenbaum, & Yuille, 2006; Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010; Oaksford & Chater, 2007; Tenenbaum, Griffiths, & Kemp, 2006; Tenenbaum, Kemp, Griffiths, & Goodman, 2011). The success of these models, which have primarily been evaluated by comparison to the behavior of adults, has been paralleled by an increasing dissatisfaction among developmental psychologists with the impasse between the nativist and the empiricist views of development (e.g., Gopnik et al., 2004; Newcombe, in press; Sloutsky, 2010; Xu, 2007, 2011; Xu, Dewar, & Perfors, 2009; Xu & Tenenbaum, 2007). The inadequacy of both extreme nativist and extreme empiricist views has led researchers to try to find a substantive middle ground between these approaches.

This special issue of *Cognition* presents a set of papers that bring these two threads together, investigating how probabilistic models of cognition can shed light on cognitive development. The interface of these two sets of ideas provides a new theoretical perspective on development, and offers an alternative to the binary opposition of nativism and empiricism. This new perspective, which is still a work in progress, has been dubbed "rational constructivism" (Gopnik et al., 2004; Xu, 2007, 2011; Xu et al., 2009), as it blends elements of a constructivist account of development with the account of learning as rational statistical inference that underlies probabilistic models of cognition.

The rational constructivist view embodies two key ideas: one is the commitment that the learning mechanisms that best characterize learning and development from infants to adults are a set of rational, inferential, and statistical mechanisms that underlies probabilistic models of cognition. The application of these domain-general mechanisms may give rise to domain-specific knowledge. The second is to call into question both the nativist characterization of innate conceptual primitives (e.g., is *object* or *agent* an innate concept?), and the empiricist's characterization of a newborn infant with nothing but perceptual primitives and associative learning mechanisms. It is an open question how best to think about the initial state of a human learner. Perhaps in addition to a set of perceptual (proto-conceptual?) primitives, the infant also has the capacity to represent variables, to track individuals, to form categories and higher-order units through statistical analyses, and maybe even the representational capacity for logical operators such as *and/or/all/some* – these capacities enable the infant to acquire more complex concepts and new learning biases (see Bonatti (2010) and Marcus (2001) for related discussions). As such, this view departs from the traditional Piagetian view of development (Piaget, 1954) in at least two ways – development does not progress through stages, driven by qualitative changes in the child's logical capacities, and development does not start with sensory-motor primitives and a lack of differentiation between the child and the world (see Carey, 2009, for discussion). Instead, the construction of new concepts and new learning biases is driven by rational inferential learning processes. At the moment, there is by no means any consensus on these issues. With further empirical and computational work, a more detailed explication will emerge.

While the authors of the papers that appear in this special issue all have their own theoretical positions, the papers share a common approach. This approach involves some methodological commitments, such as the idea that computational models can provide insight into cognitive development, and that empirical studies of the behavior of infants, children, and adults can be used to evaluate these models. However, there is also a deeper common theme: the idea that we can make serious progress in understanding learning by carefully specifying the prior constraints and biases (be they innate or learned) that a

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learner comes equipped with for any learning domain at any given point of development, and by carefully specifying the learning mechanisms that allow the acquisition of new knowledge and new constraints. Probabilistic models naturally lend themselves to exploring questions about such constraints, providing a particularly transparent way of characterizing the biases that a learner brings to a task, through a prior distribution over hypotheses.

The papers that appear in this special issue bring together researchers working on probabilistic models of cognition with developmental psychologists, to consider how this new perspective could shed light on some of the challenges of understanding cognitive development. Our goal in collecting these papers together is to illustrate that this new approach to the study of cognitive and language development has already shown a lot of promise – both computational modeling and empirical work have opened up new directions for research, and have contributed to theoretical and empirical advances in understanding learning and inference from infancy to adulthood.

2. The role of computational modeling

Computational modeling and cognitive development are certainly not strangers to one another – some of the most famous mathematical results in cognitive science relate to what children might learn (e.g., Chomsky, 1987; Gold, 1967; Wexler & Cullicover, 1981), and developmental phenomena have been a focus of connectionist modeling (e.g., Elman et al., 1996; Rumelhart & McClelland, 1986; Shultz & Sirois, 2008). Probabilistic models of cognition share with other computational approaches the basic advantages of developing formal models: We understand the nature of the problems that learners face better through these models, empirical studies can be motivated in a way that ties more directly to theory, and we can obtain unified accounts for seemingly unrelated developmental phenomena.

Probabilistic models have several additional properties that make them useful in investigating questions about cognitive development. First, in providing an account of the conclusions that an ideal agent would draw from observed data, they give us a way of understanding what conclusions children *should* draw from their experiences, when combined with their prior knowledge. This property of optimality is useful in exploring questions about learnability, as it can be used to determine what minimal prior knowledge is needed to justify a particular conclusion based on some observed data. Second, the nature of this prior knowledge is explicit in the model – expressed through the choice of hypothesis space and prior distribution – while it can be harder to determine exactly what the critical assumptions are in other kinds of computational models, such as artificial neural networks. Finally, probabilistic models provide a way to integrate structured, symbolic representations with statistical learning, making it easier to pose questions about how representations of causal relationships and linguistic rules might be inferred from observations.

3. The research agenda

Probabilistic models of cognitive development provide answers to some basic questions about how children might learn from their environment and from other people. However, they also raise a new set of questions, particularly about the cognitive processes and developmental mechanisms that could support this kind of learning: Are computations probabilistic? How sensitive are human learners, from infants to adults, to probabilistic relations? Is there a set of domain-general mechanisms that give rise to domain-specific knowledge as development progresses? How do human learners revise their beliefs in light of evidence and is this process rational, in the sense of being consistent with Bayesian inference? How do human learners acquire new constraints and biases? How should we think about the tradeoff between strong prior beliefs and the weight of new, possibly contradictory, evidence? How much of learning is best understood as "inferential" as opposed to simple associative learning? Are these inductive learning mechanisms species-specific? How can probabilistic models of cognition be used to improve education? A number of papers in this special issue address these questions head-on, but we anticipate that they will continue to motivate research in these areas for years to come.

4. Open issues and challenges

Probabilistic models of cognitive development face two important challenges, one inherited from each of the threads of research that this approach combines. One of the major challenges for probabilistic models of cognition in general is understanding how these abstract models relate to the questions about cognitive and neural mechanisms that are the traditional domain of psychology and neuroscience. In the terms of Marr (1982), probabilistic models of cognition are at the "computational" level, focusing on the abstract problem people are solving and the ideal solution to that problem, while cognitive psychology operates at the "representation and algorithm" level, and neuroscience operates at the "implementation" level. This is a non-trivial issue when considered in the context of probabilistic models of cognitive development. Developmental psychologists are not only interested in abstract characterizations of learning, but want to understand the processes of learning and development. What kinds of constraints can probabilistic models provide on such processes?

From cognitive development, this approach inherits the challenge of determining the nature of perceptual and conceptual primitives. We can go a long way in understanding learning by asking what a learner's priors are when confronted with a certain learning task, and what learning mechanisms are at her disposal. The combination of these two will allow us to understand what new knowledge and constraints may be acquired. At the end of the day, however, we want to specify the primitives for inductive learning – those factors that determine which hypotheses learners are able to consider in the first place. While innovations such as hierarchical Bayesian models may provide insight into some of these questions (e.g., Kemp, Perfors, & Tenenbaum, 2007), we expect that they will only be answered through a coordinated effort of empirical research and computational modeling (e.g., Dewar & Xu, 2009).

The papers in this special issue illustrate how probabilistic models of cognitive development can be valuable, and begin to touch on these broader challenges. However, there is still much work to be done. Ultimately, we hope that the combination of computational modeling and behavioral experiments will allow us to develop an approach to the study of development that goes beyond the nature-nurture/nativist-empiricist debate, and that thinking about the mind as a device that performs probabilistic computations will give us both a way of characterizing not just ideal learners, but real infants, children, and adults.

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