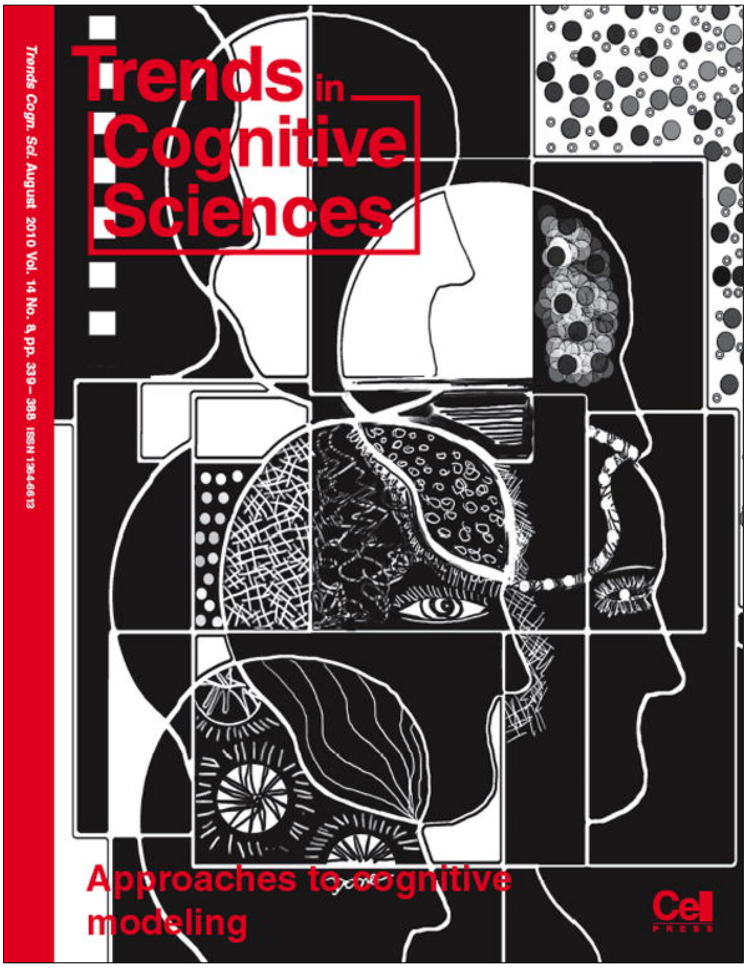
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Letters

Approaches to cognitive modeling

A computational foundation for cognitive development: comment on Griffths *et al.* and McLelland *et al.*

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A deep theoretical tension lies at the heart of developmental cognitive science. Children – even infants – have abstract structured representations of the world: intuitive theories and grammars, conceptual hierarchies and phonological maps. At the same time, children learn. They transform their representations based on concrete experiences – the contingent probabilistic evidence of their senses. How can children induce abstract structure from concrete contingencies?

Connectionist and dynamic theories, such as those advocated by McLelland *et al.* [1], allow for learning but deny that there are abstract representations. Traditionally the alternative has been nativism, which allows for representation but denies that there is substantive learning. Empirically minded developmental psychologists like us have been dissatisfied with both of these options. Instead, we have advocated the 'theory theory' – the idea that children's learning is like theory change in science – because in science we also see both rich structure and significant learning [2,3]. However, until recently there were no computational accounts of theory change.

When connectionist theories appeared, we were initially excited. But because even infants have abstract representations of the world, computational accounts that eschewed such representations were missing a crucial component. By contrast, the framework of probabilistic models described by Griffiths *et al.* [4] promises a computationally precise developmental cognitive science that can integrate structure and learning.

The central advance has been to formulate structured representations, such as causal graphical models, that can be easily combined with probabilistic learning, such as Bayesian inference. Classically, we 'theory theorists' proposed that children learn by constructing hypotheses and testing them against evidence. But if this is a deterministic process, then the 'poverty of the stimulus' problem becomes acute – there will never be enough data to definitively prove that one hypothesis is right and reject the rest. By contrast, we would now propose that the child is a probabilistic learner, weighing the evidence to strengthen or reduce support for one hypothesis over another. Probabilistic models can help to explain how children are gradually able to revise their initial theories in favor of better ones. Moreover, recent evidence shows that young children do indeed behave like probabilistic learners – entertaining multiple hypotheses, weighing new possibilities against prior beliefs, experimenting and explaining – rather than simply using associationist mechanisms to match patterns in the data, as in connectionist systems.

The ultimate test of any perspective is whether it generates new and interesting empirical research. Researchers inspired by the probabilistic model approach have already begun to make important developmental discoveries that do not fit the connectionist picture(for general reviews of developmental theory and data see [5,6]). Recent work we have been involved in has shown that 20-month-old children can infer a person's desire from a non-random sampling pattern [7], 2-year-olds make better inferences from causal cues than simple correlations [8] and 4-year-olds need only a few data points to infer a new causal structure to explain anomalous evidence [9] and to discover abstract causal rules [10]. Sobel's laboratory has shown that infants can make causal inferences that go beyond association (http://www.cog.brown.edu/research/causalitylab/); Schulz's has shown that 4-year-olds discover new abstract variables, experiment to resolve confounded causes and weigh new evidence against prior knowledge (http://web.mit.edu/eccl/).

Developmental evidence has also inspired computational advances. Developmentalists emphasize the importance of framework theories, explanation and experimentation and social context; computationalists are starting to tackle those problems, too (e.g. http://www.mit.edu/~ndg/, http://louisville.edu/psychology/shafto/people/patrick-shafto.html, http://artsci.wustl.edu/~feberhar/). Collaboration between cognitive development and probabilistic modeling holds great promise for the generation of a more precise developmental theory and a more realistic computational one, and an explanation, at last, of how children learn.

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References

1 McLelland, J.L. *et al.* (2010) Letting structure emerge: connectionist and dynamical systems approaches to cognition. *Trends Cogn. Sci.* 14, 348–356

2 Gopnik, A. and Meltzoff, A.N. (1996) *Words, Thoughts and Theories*, MIT Press
3 Gelman, S. and Wellman, H. (1992) Cognitive development: foundational theories of core domains. *Annu. Rev. Psychol.* 43, 337–375
4 Griffiths, T.L. *et al.* (2010) Probabilistic models of cognition: exploring representations and inductive biases. *Trends Cogn. Sci.* 14, 357–364
5 Gopnik, A. *et al.* (2004) A theory of causal learning in children: causal maps and Bayes nets. *Psychol. Rev.* 111, 3–32
6 Gopnik, A. and Schulz, L., eds (2007) *Causal Learning: Philosophy, Psychology and Computation*, Oxford University Press
7 Kushnir, T. *et al.* Young children use statistical sampling to infer the preferences of others. *Psychol. Sci.* (in press)
8 Bonawitz, E. *et al.* (2010) Just do it? Investigating the gap between prediction and action in toddlers' causal inferences. *Cognition* 115, 104–117
9 Legare, C. *et al.* (2010) Inconsistency with prior knowledge triggers children's causal explanatory reasoning. *Child Dev.* 81, 929–944
10 Lucas, C. *et al.* Developmental differences in learning the form of causal relationships. In *Proceedings of the Cognitive Science Society* (Ohlsson, S. and Catrambone, R., eds), Lawrence Erlbaum Associates (in press)

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Letters

Approaches to cognitive modeling

Theory-driven modeling or model-driven theorizing? Comment on McClelland *et al.* and Griffiths *et al.*

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McClelland *et al.* argue that models of cognition should use underlying mechanism to determine how complex cognition emerges from many interacting components [1]. Conversely, Griffiths *et al.* argue that models of cognition should use probability theory to address complex cognition as an inference problem [2]. At the risk of oversimplification, the emergent approach is bottom-up, neuroscience-based and good for answering 'how' questions, whereas the probabilistic approach is top-down, engineering-based and good for answering 'why' questions. Missing from this debate is acknowledgement that a theory of cognition can be independent of any particular modeling approach. The probabilistic and emergent approaches are guidelines for building models rather than theories; we contend that theorizing is better carried out in the absence of model-based guidelines. Consider Newton's theory of gravity, which began as a verbally expressed idea that was instantiated in a model only once Newton invented calculus. In this example and countless others, models are simply tools that formalize theory. Therefore, we advocate a top-down approach to modeling in which one first develops a theory and then chooses a flavor of model that is well suited for its implementation.

A top-down approach to modeling does not necessarily produce a top-down model of cognition. For example, consider the theory that conjunctive stimulus representations in perirhinal cortex are critical to both perceptual and mnemonic discrimination. The model implementation of this theory [3] simulated discrimination through competitive learning in self-organizing networks [4], which is necessarily a bottom-up process. However, the theory was not discovered by implementing a connectionist model and analyzing the learned hidden layer; rather, its core assumptions were envisaged in advance [5,6] and the connectionist implementation served as a sufficiency check to establish the validity of the theory and to make empirical predictions.

A good theory can be implemented at multiple levels of description and with a variety of mathematical formalisms. Huber and colleagues have theorized that perceptual representations of previously viewed objects should be discounted to minimize temporal source confusion. Initially implemented with a probabilistic model to explain short-term priming phenomena [7], this Bayesian model was not dynamic. Therefore, Huber and O'Reilly [8] modeled these priming effects by including synaptic depression in an interactive-activation neural network [9]. Recently, Huber [10] developed a dynamic probabilistic model that mimics the behavior of synaptic depression and includes the original Bayesian model as a special case. The implementation of this theory with multiple models gives rise to the suggestion that synaptic depression evolved to solve a temporal inference problem.

As outlined above, our work in perception and memory did not begin with a particular flavor of model and then find a theory within the constraints of that model. Instead, the theory came first, followed by model implementations to validate, formalize and further specify the theory. Models are just approximations of reality, tools for understanding the world. The workman who commits to using a hammer is forever biased toward solving problems involving nails. However, the workman with a diverse toolbox is free to focus on the problem most relevant and pressing to the overarching goals of the field.

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References

1 McClelland, J.L. *et al.* (2010) Letting structure emerge: connectionist and dynamical systems approaches to cognition. *Trends Cogn. Sci.* 14, 348–356