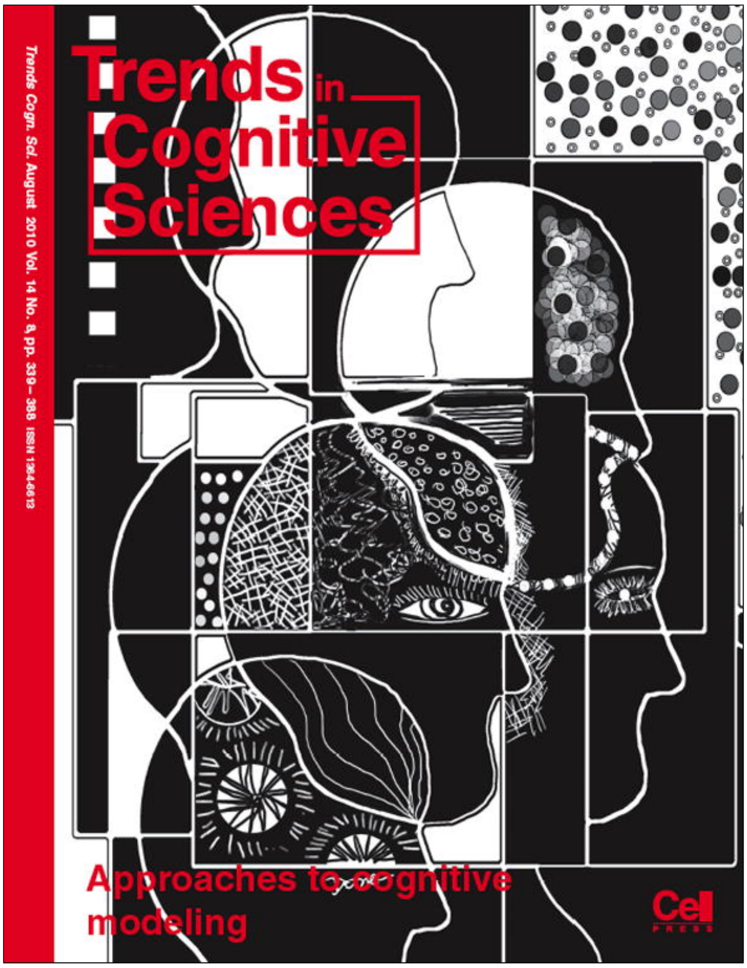
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Approaches to cognitive modeling
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Letters

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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Letters

Approaches to cognitive modeling

Bridging levels of analysis: comment on McClelland *et al.* and Griffiths *et al.*

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The emergentists (i.e. connectionists and dynamicists) emphasize that accurate explanations of cognitive processing must use low-level building blocks that respect neural mechanisms [1]. The representational pluralists emphasize that compelling explanations of cognition can use high-level structured representations with normative (i.e. Bayesian) probabilistic inference [2]. Both emphases are correct and the biggest challenge for each approach is bridging to the other level.

Bridging is needed only if either approach fails to explain target behaviors. When connectionist models fail, they can be modified to use different activation functions, learning rules, connective architectures and representational elements at the input and output. The emergentists point out some impressive examples that demonstrate how appropriately configured low-level mechanisms can generate aspects of higher-level cognition [1]. Despite the successes, an ongoing challenge is to address yet higher levels of cognition, without presuming architectural or processing constraints that are tantamount to the highly structured representations that the emergentists eschew.

When structured probabilistic models do not fit behavioral data, one option is to change the structured representation. This approach is desirable because it retains the explanatory power of normative Bayesian computation. Theorists working with structured probabilistic models have made their greatest impact by insightfully inventing structured representations and prior knowledge that capture challenging aspects of human cognitive behavior with normative Bayesian computation (e.g. [3]). A second option is to retain the representation but to abandon normative processing, opting instead for a mere approximation to Bayesian computation (e.g. [4]). The issue is not implementation of a good approximation; the issue is fitting of human behavior only using a poor approximation. The major problem with this approach is that the foundational appeal is lost: the explanation relies crucially on a heuristic and poor approximation. A second problem with the approach is that any particular approximation method might help to fit human data in some cases, but worsen the fit of a model in other cases. A third problem with this approach is that there is a large variety of different yet plausible approximations. Normative goals do not uniquely determine the method of approximation. Thus, the poorly-approximate-Bayesian approach becomes merely one useful generator of candidate heuristic models in a vast space of all possible heuristic models.

The general debate regarding levels of analysis has been a topic of philosophical discussion [5,6] but the bridging problem has concrete manifestations even for models of simple associative learning. Some connectionist models have imposed higher-level structural constraints that have a direct psychological interpretation and without which the models will not fit data [7]. These structural aspects might be implementable in neurally plausible substrates, but the structural constraints are still the explanatory keystone. Some Bayesian models have used lower-level associative structures and it has been posited that processing is Bayesian only within local levels of a hierarchy of representations, because analogous globally Bayesian models will not fit the data [8]. The latter approach emphasizes that normative probabilistic inference might apply at different levels of analysis rather than only at the level of individual behavior.

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