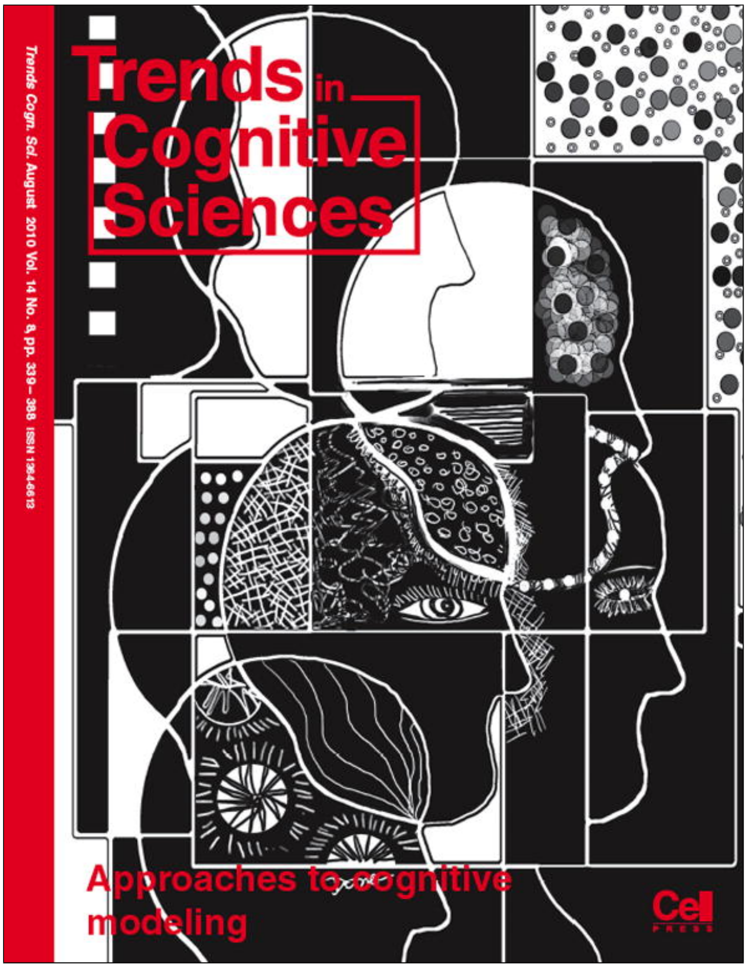
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Letters

Approaches to cognitive modeling

Emergent and structured cognition in Bayesian models: comment on Griffiths *et al.* and McClelland *et al.*

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I have used both the connectionist and Bayesian approaches on occasion [1,2] and found aspects of both appealing. I think that the connectionists are right to emphasize emergent phenomena as central to understanding cognition [3]. The ideas beautifully expressed by Hofstadter ([4], Ch. 26) remain compelling to me. I am surprised, however, that the connectionists believe that Bayesian models cannot exhibit emergent behavior [3] and that the Bayesians do not directly address this point [5]. My experience in working with Bayesian inference is that emergent phenomena abound.

A good example is provided by the Bayesian account of generalization gradients by Tenenbaum and Griffiths [6]. Here, gradients emerge from probabilistic inference over simple structured hypothesis spaces. It is assumed that the mind explicitly represents the consequences of a class of stimuli, but uncertainty naturally overlays to produce the core cognitive capability of generalization. This is an example of a basic feature of Bayesian modeling, in which the marginalization and conditioning operations of probability theory regularly produce outcomes that are quantitatively and qualitatively different from their building blocks.

Another general textbook feature of Bayesian inference involves emergent decisions (e.g. [7], Section 4.4). Working with Bayesian inference, I have often been surprised when a previously given-up-for-dead hypothesis is resuscitated on the basis of a key new piece of information. Bayesian inference aggregates disparate knowledge automatically and seamlessly, and can produce results that make sense with hindsight, but are not obvious from the explicit structures built in to the model. Thus, probabilistic inference over structured representations seems to me well suited to the modeling of emergent phenomena, while retaining the advantages of explicit representation advocated in the Bayesian commentary.

The connectionist commentary sometimes seems to overstate the generality of its models and the limitations of Bayesian ones. I do not think that connectionist models have 'no restriction to a set of possible structure types', but agree with the Bayesian view that the restrictions are often just blander and always more opaque. I also think that Bayesian models can accommodate differences in speeded versus non-speeded processing of the same contingencies. There is nothing preventing time being considered as an important influence on rational inference. Indeed, many popular sequential sampling process models of the time course of decision-making have natural, and often illuminating, rational Bayesian interpretations, involving optimal decision-making under uncertainty [8].

A final thought is that both target articles are disappointing in discussing how their models should draw inferences from, rather than be shown to describe, behavioral data. I think that Bayesian inference (used now as a statistical method, not a model of mind) should be used for relating psychological models to data [9], but neither the connectionist nor Bayesian camps routinely do this. It is especially ironic that the proponents of Bayesian models of mind, when drawing their own scientific inferences, do not seem to believe their rhetoric about Bayesian rationality [10]. Until the scientific inferences improve, there is a limit to the acuity and richness of what

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either connectionist or Bayesian models will tell us about human cognition.

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Letters

Approaches to cognitive modeling

Neither size fits all: comment on McClelland *et al.* and Griffiths *et al.*

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In reading the essays by Griffiths et al. [1] and McClelland et al. [2] one cannot help but think of the old parable about the blind men and the elephant: each essay offers true and interesting insights into the mind, yet each seems ultimately incomplete.

Of the two, Griffiths et al. seem to come closer to offering a satisfying approach. Theirs is currently a robust, active research program, whereas progress in connectionism has slowed considerably in recent years. Compared with the early days in the 1980s and early 1990s, Parallel Distributed Processing (PDP) models are rarer and rarer, with few significant advances in architecture in recent years. The handful of models cited in the target article use architectures that have been around for years. Rogers and McClelland [3], for example, is based on Rumelhart and Todd [4] and inherits many of the same problems [5,6], such as the lack of a *bona-fide* distinction between types and tokens and a reliance on different formal machinery for each phenomenon that is to be modeled. By restricting themselves to models that lack symbols, rather than seeking more ecumenical solutions that take symbols on board, connectionists have seriously compromised their research program.

Advocates of Bayesian approaches acknowledge some of these limits of PDP models, and to their credit incorporate symbolic machinery; moreover, their field is more vibrant in that they have recently introduced a variety of new models, such as intriguing hierarchical architectures.

However, the Bayesians, too, seem to suffer from a commitment to unnecessary dogma. Whereas connectionists often seem to take evidence that "some" knowledge is learned to mean that "all" knowledge is learned [6,7], Bayesians often seem to take evidence that "some" cognitive systems approach optimality to imply that all cognitive systems do; their default assumption is "ideal solutions to ... inductive problems." [1], p. xxx. Certainly, certain cognitive systems, particularly those with a long evolutionary history, such as the systems that map vision onto motor control, do approximate optimality [8]. However, with a handful of exceptions, Bayesian advocates have yet to confront either the vast literature on human irrationality developed by Tversky and Kahneman [9] or the equally-robust literature that shows systematic error in human memory [10]. Rational models offer a fine comparison point, but Bayesians would do well to consider carefully the extent to which biological wetware can deviate from mathematical idealization. At its worst, the whole enterprise can become warped, into a game of determining under which *post hoc* criteria some seemingly odd behavior could be deemed rational. With the absence of any criteria for acknowledging genuine deviations from rationality, the game becomes empty.

In the final analysis, contemporary connectionist and Bayesian approaches only scratch the surface of cognitive possibility. Genuinely adequate theories must borrow from each of these traditions – the emphasis of connectionism on development, and on how complex cognition derives from the actions of relatively simple low-level units; Bayes' emphasis on reverse engineering (shared with evolutionary psychology). However, both groups take a one-size-fits-all approach that is not warranted by the data. Only by severing commitments to extreme empiricism and excess adaptationism can we hope to span the chasm between

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