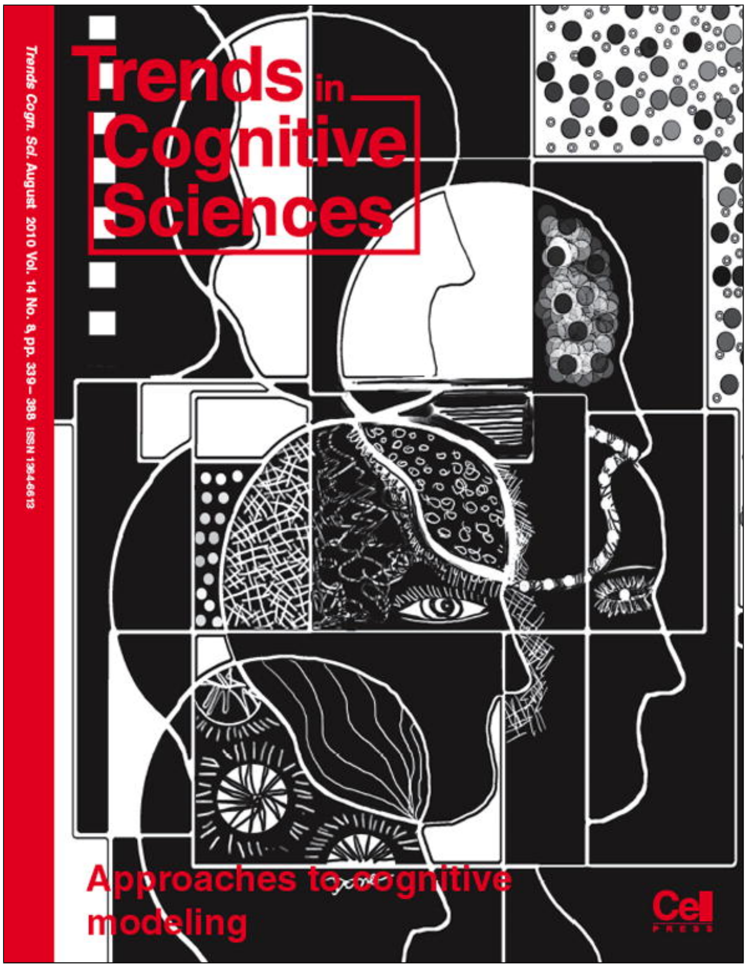
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2 Griffiths, T.L. *et al.* (2010) Probabilistic models of cognition: exploring representations and inductive biases. *Trends Cogn. Sci.* 14, 357–364
3 Cowell, R.A. *et al.* (2006) Why does brain damage impair memory? A connectionist model of object recognition memory in perirhinal cortex. *J. Neurosci.* 26, 12186–12197
4 Kohonen, T. (1982) Self-organized formation of topologically correct feature maps. *Biol. Cybernet.* 43, 59–69
5 Bussey, T.J. and Saksida, L.M. (2002) The organization of visual object representations: a connectionist model of effects of lesions in perirhinal cortex. *Eur. J. Neurosci.* 15, 355–364
6 Murray, E.A. and Bussey, T.J. (1999) Perceptual-mnemonic functions of the perirhinal cortex. *Trends Cogn. Sci.* 3, 142–151
7 Huber, D.E. *et al.* (2001) Perception and preference in short-term word priming. *Psychol. Rev.* 108, 149–182
8 Huber, D.E. and O'Reilly, R.C. (2003) Persistence and accommodation in short-term priming and other perceptual paradigms: temporal segregation through synaptic depression. *Cogn. Sci.* 27, 403–430
9 McClelland, J.L. and Rumelhart, D.E. (1981) An interactive activation model of context effects in letter perception. 1. An account of basic findings. *Psychol. Rev.* 88, 375–407
10 Huber, D.E. (2008) Causality in time: explaining away the future and the past. In *The Probabilistic Mind: Prospects for Rational Models of Cognition* (Oaksford, M. and Chater, N., eds), pp. 351–376, Oxford University Press

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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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References

1 McClelland, J.L. *et al.* (2010) Letting structure emerge: connectionist and dynamical systems approaches to cognition. *Trends Cogn. Sci.* 14, 348–356
2 Griffiths, T.L. *et al.* (2010) Probabilistic models of cognition: exploring representations and inductive biases. *Trends Cogn. Sci.* 14, 357–364
3 Xu, F. and Tenenbaum, J.B. (2007) Word learning as Bayesian inference. *Psychol. Rev.* 114, 245–272
4 Sanborn, A.N. *et al.* Rational approximations to rational models: alternative algorithms for category learning. *Psychol. Rev.* (in press)
5 Macdonald, C. and Macdonald, G. (1995) *Connectionism: Debates on Psychological Explanation*, Wiley-Blackwell
6 McCauley, R.N. (1998) Levels of explanation and cognitive architectures. In *Blackwell Companion to Cognitive Science* (Bechtel, W. and Graham, G., eds), pp. 611–624, Blackwell
7 Kruschke, J.K. (1992) ALCOVE: an exemplar-based connectionist model of category learning. *Psychol. Rev.* 99, 22–44
8 Kruschke, J.K. (2006) Locally Bayesian learning with applications to retrospective revaluation and highlighting. *Psychol. Rev.* 113, 677–699

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Letters

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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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