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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 can't 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 to 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 & 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.

But 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. To be sure, certain cognitive systems, especially those with a long evolutionary history, such as the systems that map vision onto motor control, do approximate optimality [8]. But, 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 may 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. Absent any criteria for acknowledging genuine deviations from rationality, the game becomes empty.

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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 -- connectionism's emphasis 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). But both groups take a one-size-fits-all approach that isn't warranted by the data. Only by severing commitments to extreme empiricism and excess adaptationism can we hope to span the chasm between low-level neural circuits and higher-level cognition, in a fashion that is faithful to the reality of our evolved psychology, quirks and all.

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