



Comment

Representations, approximations, and limitations within a  
computational framework for cognitive science  
Comment on “Toward a computational framework for cognitive  
biology: Unifying approaches from cognitive neuroscience and  
comparative cognition” by W. Tecumseh Fitch

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There is much to approve of in this provocative and interesting paper. I strongly agree in many parts, especially the point that dichotomies like nature/nurture are actively detrimental to the field. I also appreciate the idea that cognitive scientists should take the “biological wetware” of the *cell* (rather than the network) more seriously.

Fitch [1] calls for using a formal approach, probably something within a Bayesian framework, to move the field past our reliance on intuitive “folk psychological” models. I agree that such an approach is valuable. However, in my view the outline for why it is valuable and how it might be used glosses over some of the difficulties we must seriously consider, and also misses the main basis by which it gains most of its power.

The Bayesian framework consists of five components: (1) the use of Bayes Rule to combine (2) the prior and (3) the likelihood, in order to evaluate hypotheses with a particular (4) representation, which defines a hypothesis space, which is (5) searched according to some approximation method. Fitch focuses mainly on the first three, especially on the role of the prior: he argues that it offers a natural way to formalize “knowledge”, whether innate or previously learned. Although this is true, I suggest that the latter two components play a more important explanatory role.

First, priors have far less of an impact than does the representation, since they are defined over the representation and are ultimately swamped by sufficient data. Because of this, most of the interesting theoretical content of any specific model or theory is what the hypothesis space and representation is: Does it make sense for the problem facing the learner? How might a learner find the hypotheses within that space? Are the representational assumptions domain-specific or not? and so forth. The virtue of the Bayesian framework is that, by making these components

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explicit, it is easier to isolate and discuss them – as long as we remember that it is these things, not the prior, that are most relevant.

Second, it is imperative to consider the approximation methods used; this relates to Fitch’s suggestion about bridging Marr’s levels within as well as across approaches. The issue of how learners might *approximate* “optimal” Bayesian inference is so far mostly unexplored: the one method that has been studied to any extent, particle filters, is attractive mostly for its mathematical convergence properties rather than because it maps onto any heuristics we know about. This is an area we need to investigate much more heavily.

Understanding more about how to approximate Bayesian models may also be one of the most promising avenues for addressing a looming issue. Although Fitch is correct to point out that the framework is very powerful *in principle*, there are important limitations *in practice*. As the hypothesis space gets more complex, searching it becomes intractable, and we cannot guarantee that we have found the best hypothesis or generated accurate predictions. Since most interesting problems (on the scale they are encountered by humans over a lifetime) are extraordinarily complex, we cannot simply assume that advances in technology will render this problem moot.

My point is not to dismiss the Bayesian framework: I think Fitch is correct that it is a promising avenue of research. However, we need to be clear about the limitations and challenges. Otherwise, I fear a reaction to what are (or are perceived as) over-stated claims, resulting in the abandonment or dismissal of a useful tool. We should evaluate models mainly with an eye to what assumptions about the representation and hypothesis space they are making, what they are leaving out, what kinds of approximation methods we could use, and how those might map onto the heuristics real organisms use. Keeping those things in mind will enable us to become the mature science we need to be.

## References

- [1] Fitch WT. Toward a computational framework for cognitive biology: unifying approaches from cognitive neuroscience and comparative cognition. *Phys Life Rev* 2014;11:329–64 [in this issue].