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Final Exam, Computational Models of Cognition

Response Paper, Jones & Love (2017), Passage 2

In Jones & Love (2017), Bayesian Fundamentalists (BF) focus on how cognitive systems compute probabilities and make decisions, rather than on the underlying mental states and processes that give rise to these computations. And like behaviorists reduce psychological processes to behaviors, BF assumes that cognition can be explained as optimal.

First, contrary to the claims presented in the passage 2, the Bayesian Framework (BF) is not devoid of psychological substance, nor does it lack the ability to encode, process, and update information. Indeed, Bayesian models are capable of encoding and updating information in psychologically significant ways, such as those illustrated in Theory Theory and the Language of Thought.

For instance, Bayesian models can effectively encode information in line with the principles of Theory Theory, as discussed by Gopnik & Wellman (2012). Theory Theory represents knowledge in a cohesive, abstract, and causal manner, potentially involving hidden entities and adopting a hierarchical structure. This knowledge representation mirrors everyday theories, with cognitive development resembling the scientific process of theory revision. This process includes hypothesizing, testing these hypotheses with new data, and subsequently modifying the theories. Bayesian models can naturally encode such representations. Moreover, these models also address the processing and transformation of information via Bayes Nets. This stands as evidence against the notion that the BF solely concentrates on the computational level, neglecting algorithmic instantiation.

Beyond this, Bayesian models can represent information formalized in the Language of Thought. Piantadosi, Tenenbaum & Goodman (2012) proposed a Bayesian framework for the acquisition of numeric concepts, formalizing hypotheses using the Language of Thought, inclusive of primitives and composition laws. This model, based on Bayes' theorem, effectively balances complexity and data fit, particularly imposing additional penalties on recursive hypotheses.

Second, in passage 2, the authors viewed the BF as a rudimentary counting rule devoid of mechanisms. However, our class discussions have extensively covered the algorithms for Bayesian inferences, which are clear implementations at the representation and algorithmic level. In addition to Bayes Nets, Suchow Bourgin and Griffiths (2017) argued for particle filters as a functional design for working memory. These filters simultaneously maintain and update collections of samples and their corresponding weights based on the strength of evidence. Such mechanisms can explain the intricacies of memory representation, including its fragility, rapid decay at high load, and the graded benefits of increased encoding time.

Furthermore, Suchow Bourgin and Griffiths (2017) suggested the Metropolis-Hastings algorithm as a compelling framework for understanding creativity. This algorithm proposes a new state based on the current state and decides to retain or discard the proposed state based on a utility ratio. The new state, though inspired by the current state, is independent of utility, aligning with the spontaneous and free-flowing nature of creativity.

In summary, BF in Jones & Love (2007) does not align with the Bayesian models we have studied and discussed in class. The probabilistic models of cognition we explored contain mechanistic explanations, take into account psychological processes and representations, and bear closer resemblance to the Bayesian Enlightenment as defined by Jones & Love (2007). It is indeed possible that current literature on Bayesian models of cognition leans towards computational-level accounts more than algorithmic implementation. However, it is unfair to conclude that Bayesian models of cognition have no psychological processes at all.

Reference:

Gopnik, A., & Wellman, H. M. (2012). Reconstructing constructivism: causal models, Bayesian learning mechanisms, and the theory theory. *Psychological bulletin*, *138(6)*, 1085.

Jones, M., & Love, B. C. (2007). Beyond common features: The role of roles in determining similarity. *Cognitive Psychology*, *55(3)*, 196-231.

Piantadosi, S. T., Tenenbaum, J. B., & Goodman, N. D. (2012). Bootstrapping in a language of thought: A formal model of numerical concept learning. *Cognition, 123(2)*, 199-217.

Suchow, J. W., Bourgin, D. D., & Griffiths, T. L. (2017). Evolution in mind: Evolutionary dynamics, cognitive processes, and bayesian inference. *Trends in cognitive sciences, 21(7)*, 522-530.