Response to 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.

1. just track not encode, processed, and transormed info.
2. only about the bahavior is optimal or not. no about computes and represent probabilities
3. better to use as tool
4. no reflect characteristics of en

According to passage 2, BF is argued to not encode, process, and update information, without psychological substance. It's not true. In fact, Bayesian models can encode and update information in very psychological ways, for example, concepts defined in theory theory and language of thought. Bayesian models can encode information in terms of theory theory (Gopnik & Wellman, 2012). Theory theory represents knowledge in an abstract, coherent, causal way, which can include hidden entities and the structure can be hierarchical. And the conceptual structures or knowledge representation are like everyday theories and cognitive development was like theory revision in science: having hypotheses — > using new data to test hypotheses —> revising the theories. This kind of representation can be encoded in Bayesian models naturally. And the procession and transformation of the information, via Bayes Nets are also specified in Bayesian model. And Bayes nets is also the evidence against BF only focusing on computational level but not algorithmic instantiation. Moreover, Bayesian models can also represent information that is formalized in language of thought. Piantadosi, Tenenbaum & Goodman, 2012 presented a Bayesian framework for the acquisition of numeric concepts. The hypotheses were formalized using Language of Thought, that included primitives and composition laws. And Based on Bayes' theorem, the model implements the trade-off between complexity and fit data, especially the additional penalty on recursive hypotheses. And the representation of numeric concepts changes as the amount of data increases. When the data is little, it's better for the model to explain the more frequent number of words. As amount of data increases, more complex hypotheses (CP-knower) are justified, since the Bayesian model penalizes hypotheses that make incorrect predictions.

In passage 3, the authors viewed BF as a simple counting rule without mechanisms at all. In contrast, in class, we spent a lot of time discussing the algorithms for Bayesian inferences. And they are implementation of representation and algorithm level. In addition to the Bayes Nets we talked about before, in Suchow Bourgin, and Griffiths (2017), particle filters are argued as a good engineering design for working memory. Particle filters maintain a collection of samples simultaneously and in parallel while executing the model. The weights of the samples are depending on the strength of evidence. As data (evidence) changes, the samples and their weights also update. Particle filters can explain the graded benefits of increased encoding time on fidelity of memory representation as well as the fragility and quick decay of memory representation at high load. And Suchow Bourgin, and Griffiths (2017) also suggested that Metropolis-Hastings may be a useful way of thinking about creativity. At each step, the Metropolis-Hastings algorithm proposes a new state based on current state and makes a decision to keep the proposed state based on the utility ratio. The new state is generated from current state but is independent of utility, which is consistent with creativity (new ideas are inspired by current state without considering utility of the possibilities).

In a nutshell, the BF discussed in Jones & Love (2007) is not consistent with the Bayesian models we learned and discussed in class. The probabilistic models of cognition we have learned incorporate mechanistic explanations and consider psychological processes and representations, which are more similar to the Bayesian Enlightenment defined by Jones & Love (2007). However, there may be a kernel of truth in that the current literature on the Bayesian modelers mostly focuses more on computational-level accounts than algorithmic implementation. But it's unfair to conclude that Bayesian models of cognition involve very few psychological processes.