Commentary on Behavioral and Brain Sciences target article: Jones & Love, “Bayesian Fundamentalism or Enlightenment?”

Relating Bayes to cognitive mechanisms

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Abstract: We support Enlightenment Bayesianism’s commitment to grounding Bayesian analysis in empirical details of psychological and neural mechanisms. Recent philosophical accounts of mechanistic science illuminate some of the challenges this approach faces. In particular, mechanistic decomposition of mechanisms into their component parts and operations gives rise to a notion of levels distinct from and more challenging to accommodate than Marr’s.

We find attractive Enlightenment Bayesianism’s commitment to grounding Bayesian analysis in knowledge of the neural and psychological mechanisms underlying cognition. Our concern is with elucidating what the commitment to mechanism involves. While referring to a number of examples of mechanistic accounts in cognitive science and ways that Bayesians can integrate mechanistic analysis, Jones and Love (J&L) say little about the details of mechanistic explanation. In the last two decades, several philosophers of science have provided accounts of mechanistic explanation and mechanistic research as they have been practiced in biology (Bechtel & Abrahamsen 2005; Bechtel & Richardson 1993/2010; Machamer et al. 2000) and the cognitive sciences (Bechtel 2008; Craver 2007). Drawing on these can help illuminate some of the challenges of integrating mechanistic analysis into Bayesian accounts.

At the core of mechanistic science is the attempt to explain how a mechanism produces a phenomenon by decomposing it into its parts and operations and then recomposing the mechanism to show how parts and operations are organized such that, when the mechanism is situated in an appropriate environment, it generates the phenomenon. One of the best-developed examples in cognitive science is the decomposition of visual processing into a variety of brain
regions, each of which can process different information from visual input. When organized together, they enable individuals to acquire information about the visible world. Decomposition can be performed iteratively by treating the parts of a given mechanism (e.g., V1) as mechanisms themselves and decomposing them into their parts and operations.

A hierarchical ordering in which parts are at a lower level than the mechanism is thus fundamental to a mechanistic perspective. This notion of levels is importantly different from that advanced by Marr (1982), to which J&L appeal, which does not make central the decomposition of a mechanism into its parts and operations. To illustrate the mechanistic conception of levels in terms of mathematical accounts, it is often valuable to provide a mathematical analysis of the phenomenon for which the mechanism is responsible. In such an account [for example, the Haken-Kelso-Bunz (HKB) model of bimanual coordination described by Kelso (1995)], the variables and parameters refer to characteristics of the mechanism as a whole and aspects of the environment with which the mechanism interacts. But to explain how such a mechanism functions, one must identify the relevant parts and their operations. The functioning of these parts and operations may also require mathematical modeling, especially when the operations are nonlinear and the organization nonsequential (see Bechtel & Abrahamsen 2010). These models are at a lower level of organization, and their parts and operations are characterized in a different vocabulary than that used to describe the phenomenon (as the objective is to show how the phenomenon is produced by the joint action of parts that alone cannot produce it).

We can now pose this question: At what level do Enlightenment Bayesian accounts operate? Do they, like Bayesian Fundamentalist accounts, operate at the level of the whole person, where the hypothesis space reflects people’s actual beliefs? Beliefs are most naturally construed as doxastic states of the person that arise from the execution of various operations within the mind/brain. J&L’s invocation of Gerd Gigerenzer’s work on cognitive heuristics (e.g., Gigerenzer & Todd 1999) suggests this is a perspective they might embrace – the heuristics are inference strategies of agents and do not specify the operations that enable agents to execute the
heuristics. The resulting Bayesian model may reflect, but does not directly embody, the results of decomposing the mind into the component operations that enable it to form beliefs.

Another possibility is that the Bayesian hypothesis space might directly incorporate details of the operations performed by components (e.g., brain regions identified in cognitive neuroscience research). Now an additional question arises: With respect to what environment is optimization evaluated? Since we are working a level down from the whole mechanism, one might think that the relevant environment is the internal environment of the local component (comprising other neural components). But this seems not to be the strategy in the research J&L cite (Beck et al. 2008; Wilder et al. 2009). Rather, optimization is still with respect to the task the agent performs. In Beck et al.’s account, a brain region [lateral intraparietal cortex (LIP)] is presented as computing a Bayesian probability. This directly links the Bayesian account to parts of the mechanism, but if this approach is to be generalized, it requires that one find brain components that are computing Bayesian probabilities in each instance one applies a Bayesian analysis.

While we find the prospect of integrating mechanistic and Bayesian approaches attractive, we are unclear how the results of mechanistic decomposition – which often leave the agent-level representations behind to explain how they are realized through a mechanism’s parts and operations characterized in a different vocabulary than that which characterizes the agent’s beliefs – are to be incorporated into a Bayesian account. We suspect that the most promising strategy is more indirect: Mechanistic research at lower levels of organization helps constrain the account of knowledge possessed by the agent, and Bayesian inference then applies to such agent-level representations.

A further challenge for understanding how mechanism fits into Bayesian analysis stems from the fact that Bayesian analyses are designed to elicit optimal hypotheses. As J&L note, mechanisms, especially when they evolve through descent with modification, are seldom optimal. What then is the point of integrating mechanistic accounts into normative Bayesian models? One
possibility is that the normative accounts serve as discovery heuristics – mismatches between the normative model and cognitive agents’ actual behavior motivate hypotheses as to features of the mechanism that account for their limitations. While this is plausible, we wonder about its advantages over more directly investigating the nature of the mechanism by studying its current form or by examining how it evolved through a process of descent with modification. Often understanding descent reveals how biological mechanisms have been kludged to perform a function satisfactorily but far from optimally.

References


