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Proceedings of the Annual Meeting of the Cognitive Science Society

Title

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Permalink

<https://escholarship.org/uc/item/6r12x1jn>

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 29(29)

ISSN

1069-7977

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Publication Date

2007

Peer reviewed

A Bayesian Perspective on Cognitive Control

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Cognitive control refers to the flexible deployment of memory and attention in response to task demands and current goals. Modern theories of cognitive control are often framed in terms of optimization: control operations are performed so as to maximize reward, produce few errors, achieve goals in minimal time, etc. We present a novel perspective on cognitive control which posits that control operations determined by probabilistic inference. We model tasks in which participants are shown sequences of stimuli, some demanding a response, and others modulating the nature of the responses (e.g., Koechlin, Ody, & Kouneiher, 2003). Working memory must be used to maintain the current control set. Our framework is based on a dynamic Bayes net which is initialized with the information contained in the task instructions. The net includes an internal memory updated over time. Memory operations (storage, retrieval, and reset) are a consequence of Bayesian inference in the network. We show that our model provides a parsimonious account of experimental data, and offers an interesting view of dynamic control hierarchies operating at different time scales that emerge as a response to task demands.

The generative model of the task is sketched in the figure to the right. Time is divided into discrete steps, indexed by t . Each node in the Bayes net is a discrete random variable. The \mathbf{S} refer to stimuli, which are observed as \mathbf{O} . The response is \mathbf{R} , and the internal memory state is denoted \mathbf{M} , and the (inferred) binary memory reset is denoted \mathbf{Z} . Given the history of observations and previous responses, the model must infer the response at the current time. The conditional distributions $P(S|M,Z)$ and $P(R|S,M)$ are given by the task instructions, but memory updating arises from Bayesian inference.

