Explicit belief-state space strategies for latent inference with and without reversals
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From stock markets to social interactions, the natural world contains many hidden variables which may only be indirectly inferred based on conditionally related signals. Knowledge of the state of these 'latent' variables is required for optimal inference regarding the abstract decision structure of a given environment and therefore can be crucial to decision-making in a wide range of situations. Here, we aimed to explore the learning strategies employed by human subjects in a hierarchical state-estimation task. Crucially, the task contained two experimental conditions – whether or not reversals could take place. We hypothesized that this key environmental feature would bias subject behavior between distinct learning strategies which differed depending on the subjects' manipulations of their belief state-space. In the reversals condition, we expected that subjects would attempt to track the probability of all possible hidden states simultaneously since (i) this provides maximum information for reversal inference and (ii) allows them to flexibly switch to an alternate belief state when a reversal has been detected (rather than re-learning from a flat prior). In contrast, the condition without reversals permits the subject to eliminate low-probability hidden state values and subsequently continue learning on a reduced state-space. More specifically, a 'belief threshold' parameter was introduced and hidden state probabilities which fell below this threshold were ignored thereafter by the bayesian updating mechanism. This strategy simultaneously reduces the computational complexity of the learning problem and makes the inference process resistant to low-probability sequences of environment events which would lead a fully bayesian observer to erroneously update their belief state. Behavioral models corresponding to both learning strategies were tested in both conditions on data from 22 subjects using hierarchical bayesian analyses based on markov chain Monte Carlo sampling. This approach allowed us to (i) simultaneously estimate group and individual model parameters and (ii) estimate a full posterior over the model parameters allowing a complete investigation into the model fits. Our results confirmed our hypotheses (comparing deviance information criterion scores and Bayes factors across conditions) and we are currently applying model-based regressors to corresponding fMRI data in order to determine how and where these belief-state manipulations occur in the human brain.