Theory and model of thalamocortical processing in decision making under uncertainty

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Animals flexibly select actions that maximize future rewards despite facing uncertainty in sensory inputs, action-outcome associations or contexts. The computational and circuit mechanisms underlying this ability are poorly understood.

A clue to such computations can be found in the neural systems involved in representing sensory features, sensorimotor-outcome associations and contexts. Specifically, the basal ganglia (BG) have been implicated in forming sensorimotor-outcome association [1] while the thalamocortical loop between the prefrontal cortex (PFC) and mediodorsal thalamus (MD) has been shown to engage in contextual representations [2, 3]. Interestingly, both human and non-human animal experiments indicate that the MD represents different forms of uncertainty [3, 4]. However, finding evidence for uncertainty representation gives little insight into how it is utilized to drive behavior.

Normative theories have excelled at providing such computational insights. For example, deploying traditional machine learning algorithms to fit human decision-making behavior has clarified how associative uncertainty alters exploratory behavior [5, 6]. However, despite their computational insight and ability to fit behaviors, normative models cannot be directly related to neural mechanisms. Therefore, a critical gap exists between what we know about the neural representation of uncertainty on one end and the computational functions uncertainty serves in cognition. This gap can be filled with mechanistic neural models that can approximate normative models as well as generate experimentally observed neural representations.

In this work, we build a mechanistic cortico-thalamo-BG loop network model that directly fills this gap. The model includes computationally-relevant mechanistic details of both BG and thalamocortical circuits such as distributional activities of dopamine [7] and thalamocortical projection modulating cortical effective connectivity [3] and plasticity [8] via interneurons. We show that our network can more efficiently and flexibly explore various environments compared to commonly used machine learning algorithms and we show that the mechanistic features we include are crucial for handling different types of uncertainty in decision-making. Furthermore, through derivation and mathematical proofs, we approximate our models to two novel normative theories. We show mathematically the first has near-optimal performance on bandit tasks. The second is a generalization on the well-known CUMSUM algorithm, which is known to be optimal on single change point detection tasks [9]. Our normative model expands on this by detecting multiple sequential contextual changes. To our knowledge, our work is the first to link computational insights, normative models and neural realization together in decision-making under various forms of uncertainty.

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