Temporal-Difference Learning in Uncertain Choice: A Reinforcement Learning-Diffusion Decision Model of Two-Stage Decision-Making

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Abstract

Behavioral adaptation in probabilistic environments requires learning through trial and error. While reinforcement learning (RL) models can describe the temporal development of preferences through error-driven learning, the diffusion decision model (DDM) allow for the mapping of state preferences on single response times. We present a Bayesian hierarchical RL-DDM integrating temporal-difference (TD) learning. Our implementation incorporates variants of TD learning, including SARSA, Q-Learning, and Actor-Critic models. We tested the model with data from N = 59 participants in a two-stage decision-making task. Participants exhibited learning over time, becoming both more accurate and faster. They also reflected a difficulty effect, with faster and more accurate responses for easier choices, as reflected by greater subjective value differences between available options. Model comparison demonstrated that the RL-DDM provided a better fit compared to standalone RL or DDM models. Notably, the RL-DDM captured both the temporal dynamics of learning and the difficulty effect in decision-making.

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