**The role of model confidence in model-based learning**

Humans and animals learn models of the world to facilitate learning. In model-based reinforcement learning, animals explicitly take into account knowledge of state transitions in the environment. It has been shown that when state transitions are unpredictable, participants are more likely to resort to model-free strategies (Kim et al., 2019). However, it is unclear how subjective confidence in the world model drives learners to switch between model-based and model-free strategies. In this work, we investigated the computational role of model confidence in model-based reinforcement learning using a modified version of the two-step task (Miller et al., 2017). We trained recurrent neural network models to make multi-step decisions in a Markov Decision Problem (MDP) that involves varying degrees of state-transition uncertainties. Crucially, the agent is asked to predict upcoming state transitions in the MDP and receives an additional reward for correct judgements. Using the technique of post-decision wagering (Persaud et al., 2007), in which the agent is offered a safe-bet option to receive a smaller reward when they are uncertain about their own judgements, we can simultaneously measure subjective confidence in state transitions, subjective reward uncertainty, and the overall decision confidence within the same task framework. Our work explored how network models transition between model-based learning and model-free learning, and how model confidence and reward uncertainty are integrated to form decision confidence.