BARCCSYN 2026 Abstract
Title: The Role of Value Computation in Sequential Decision-making

Reinforcement learning (RL) algorithms have proven capable of reproducing significant aspects of human decision-making in many contexts. Despite this, it is unclear to what extent RL theory reflects real cognitive processes. The objective of the present work is twofold: 1) to identify cognitive biases and 2) to design models that capture them. Identifying cognitive biases helps us make better decisions while attaining models that accurately reflect human biases enable better prediction of human behavior. In particular, we are interested in assessing the human ability to compute cumulative reward (i.e., value). Value computation is fundamental for learning and decision-making in most contexts and, though RL algorithms can compute value with precision, it can be resource intensive. Therefore, resource-limited agents (e.g., humans) often rely on heuristics and biases to drive decision-making. Our hypothesis is that human decision-making is value-driven in contexts in which the computation of value is straightforward, and is increasingly influenced by cognitive biases as difficulty increases. To probe this, we developed a novel perceptual decision-making task, the Consequential Task, in which participants must compute value over sequences of decisions in order to acquire maximum cumulative reward. The task has three experimental variables: 1) the number of decisions per sequence, 2) the difference in reward between options, and 3) consequence. In this task, consequence refers to how much future rewards in a sequence are augmented/diminished if the lower/higher reward option is chosen. Optimal behavior requires taking all three experimental variables into account. While RL algorithms can do this easily, our data suggest that humans exhibit a bias in favor of sacrificing immediate gratification (reward) to reach higher reward states in the future.