Sampling Behavioral Spaces with Dynamic Neural Fields

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Reinforcement learning (RL) provably converges on successful behavioral policies when the behavioral space can be formalized in terms of discrete states and actions with well-defined transitions between them. In this formulation, the RL agent learns to generate action sequences that lead to the most desirable outcome by optimizing decisions about the best next action in each state. However, the RL problem becomes even difficult to formulate when the agent is linked to real-world sensors and motors. The environmental states in this case are perceived through sensors, which provide asynchronous access to only partial information about the environment. Actions, on the other hand, are continuous trajectories of often several independent effectors. Each motor modality is characterized by its own dynamics, which has to be stabilized in the face of external perturbations and coordinated with other motor dynamics. Such real-world robotic settings pose a serious challenge to machine learning algorithms.

The mathematical and conceptual framework of dynamic neural fields (DNFs; [1]) and a recently introduced framework for behavior organization with DNFs [3] may further facilitate the application of RL approaches in real-world robotics. DNFs are derived from the descriptions of neural activity in large neural populations. They have been applied for modeling human cognitive behavior and its development [5]. Architectures of DNFs provide for cognitive representations of perceptual and motor parameters with such properties as stabilization of decisions, selection instability, and memory [4].

The DNF-based behavioral organization framework allows sampling of the vast and continuous state-action space of a real-world agent with a number of interconnected elementary behaviors (EBs) [3]. Each EB is linked to the sensory-motor system in a particular way: the objective of the EB is represented in the 'intention' DNF, which drives attractors of the motor dynamics. The achievement of this objective is detected in the 'condition of satisfaction' DNF, which is coupled to low-level perceptual representations. This structure enables autonomous initiation and termination of the EBs. Sequences of EBs are represented and organized in time through rules of behavior organization. These rules can be learned through RL, using a mechanism to update the value-function of transitions between EBs [2]. In this work, we show how the DNF framework provides for the emergence of discrete categorical representations of EBs, suited for RL algorithms, from the continuous dynamical representations of low-level sensory inputs and motor dynamics.

References

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