

Skill Transfer Via Partially Amortized Hierarchical Planning

Solving new tasks in complex environments requires effective transfer of knowledge. To this end, the work proposes a novel algorithm for transferring skills in a partially amortized framework by adopting hierarchical planning for selection of skills. A Reinforcement Learning (RL) agent plans to compose skills in imagination which are used to condition the low-level behavioral policy for learning and optimally acting in the environment. Planning is carried out by making use of a world model which allows sample-efficient learning. Planning in low-dimensional skill-space allows the agent to suitably transfer knowledge across different tasks.

Hierarchical planning in a partially amortized setting combines the fully online and fully amortized methods for acting. Online planning is carried for selecting skills which are used to condition on the low-level policy. Agent optimizes its low-level policy in the fully amortized setting. Learning of the agent is carried out by making use of a world model similar to Dreamer. Model learning consists of training the representation, observation, latent-state and task-reward modules. High-level skills are held fixed for K number of steps and optimized using CEM. Behavioral learning consists of training the low-level policy in world model using the skills distribution and backward skill predictor. Lastly, the policy interacts in the environment using MPC with a pre-sampled high-level skill. In order to facilitate learning of skills, the method constructs an auxiliary objective which maximizes the Mutual Information (MI) between latent skills and state sequences. This requires a tractable distribution which is adopted using the backward skill predictor and trained using supervised learning in conjunction with reparameterization of CEM distribution.