Summary

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A Simple Approach to Continual Learning By
Transferring Skill Parameters

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Learning robotic manipulation tasks from vision is challenging and requires massive amount of data and hundreds of hours of training. In recent years, physics-based simulators and Deep Reinforcement Learning (DRL) algorithms have been widely used to allow learning agents to explore the solution space and construct rich function approximators or policy functions. In such end-to-end approaches, researchers train a Deep Neural Network (DNN) with both visual input and motor control output data provided at the same time but rather in short and similar episodes. Nonetheless, the main issue with this approach is the fact that it is still too computationally expensive to learn new skills from scratch or to even retrain after transfer learning.

The authors introduce a novel and more efficient method for continual learning of manipulation tasks by transferring skill parameters. They show that representing past experiences only in form of skill policies, methodical pretraining, and appropriately choosing when to transfer those skill policies is a simple yet effective recipe for building a continual learner in the context of robotic manipulation. New skill policies are learned based on *prior skills* or *skill libraries* to enable efficient acquisition and transfer of dynamic control policies. Similar to [1] and [2], they train reuseable skill libraries in simulation to develop composable skill policies in form of latent space parameter.

latent state representation of decomposed skills for learning reuseable skill libraries based on decomposition. through learned skills by transferring skill parameters directly.

Setting

They define continual learning problem as iterated transfer learning for multi-task reinforcement learning (MTRL) on a possibly-unbounded discrete space of tasks $\mathcal{T}$. S a single continuous state space shared among all tasks T. A a single continuous action space shared among all tasks T. The MTRL problem is defined by $(\mathcal{T},\ S,\ A)$ and each task $\tau \in \mathcal{T}$ is an infinite-horizon Markov decision process (MDP) defined as

$$\tau = (S, A, p_\tau(s, a, s'), r_\tau(s, a, s'))\,. \tag{1}$$

Tasks are differentiated only by their reward functions r_τ and state transition dynamics p_τ. Thus, for simplicity they define

$$\tau = (r_\tau, p_\tau)\,. \tag{2}$$

Importantly, the authors did not presume the robot has access to all tasks in T at once or even a representative sample. The robot can only access one task at a time. The time between task transitions is referred to as an 'epoch' with each having a unique index. Tasks may reapear and when solving a "target task," the robot can only skill policies acquired while solving prior tasks M (the 'skill library"). Thus, they redefine the MTRL

$$\tau = (S, A, M_i, p_{\tau_i}(s, a, s'), r_{\tau_i}(s, a, s')) \,, \tag{3}$$

where M_i represents the set manipulation skills the robot is initialized with and i is the epoch number.

Simple Continual Learning with Skill Transfer

Algorithm 1 Proposed Continual Learning Framework

Input: Initial skill library $\mathcal{M}_0$, target task space $\mathcal{T}$, RL algorithm $\mathcal{F} \rightarrow (\pi, \rho)$, target task rule `ChooseTargetTask`, base skill rule `ChooseBaseSkill`
$i \leftarrow 1$
while not done **do**
    $\tau \leftarrow$ `ChooseTargetTask`$(\mathcal{T}, \mathcal{M}_{i-1})$
    while π_{target} not solved **do**
        $\pi_{base} \leftarrow$ `ChooseBaseSkill`$(\mathcal{T}, \mathcal{M}_{i-1})$
        $\pi_{target}, \cdot \leftarrow \mathcal{F}(\tau,$ `clone`$(\pi_{base}))$
    end while
    $\mathcal{M}_i \leftarrow \{\pi_{target}\} \cup \mathcal{M}_{i-1}$
    $i \leftarrow i + 1$
end while
Output: Skill library $\mathcal{M}_i$

Figure 1: Algorithm 1

References

[1] K. Hausman, J. T. Springenberg, Z. Wang, N. Heess, and M. Riedmiller, "Learning an embedding space for transferable robot skills," in *International Conference on Learning Representations*, 2018.

[2] R. Julian, E. Heiden, Z. He, H. Zhang, S. Schaal, J. Lim, G. Sukhatme, and K. Hausman, "Scaling simulation-to-real transfer by learning composable robot skills," in *International Symposium on Experimental Robotics*, pp. 267–279, Springer, 2018.