Hierarchical and Interpretable Skill Acquisition in Multi-task Reinforcement Learning

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Abstract

Learning policies for complex tasks that require multiple skills is a major challenge in reinforcement learning (RL). This paper proposes a novel framework for efficient multi-task reinforcement learning by training agents to employ hierarchical policies that decide when to use a previously learned policy and when to learn a new skill. This enables agents to continually acquire new skills during different stages of training. Each learned task corresponds to a human language description, so the agent can always provide a human-interpretable description of its choices. In order to help the agent learn the complex temporal dependencies necessary for the hierarchical policy, we provide it with a stochastic temporal grammar. We validate our approach on Minecraft games explicitly designed to test the ability to reuse previously learned skills while simultaneously learning new skills.

1 Introduction

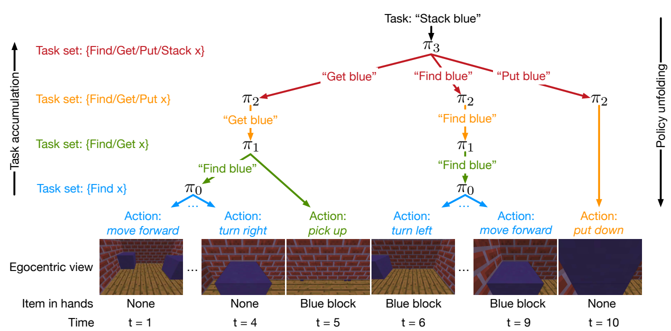

Figure 1: Example of our hierarchical policy for a given task – stacking two blue blocks. Each arrow represents one step generated by a certain policy and the colors of arrows indicate the source policies.

Deep reinforcement learning has demonstrated success in policy search for tasks in domains like game playing (Mnih et al., 2015; Silver et al., 2016, 2017; Kempka et al., 2016; Mirowski et al., 2017) and robotic control (Levine et al., 2016a,b; Pinto & Gupta, 2016). However, it is very difficult to accumulate multiple skills using just one policy network Teh et al. (2017). Existing approaches (Bengio, 2012; Rusu et al., 2016; Parisotto et al., 2016; Teh et al., 2017; Andreas et al., 2017) usually treat all tasks independently. This often prevents full exploration of the underlying relations between different tasks.

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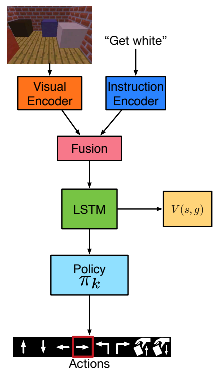
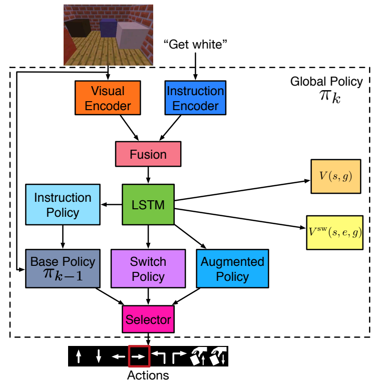


(a) Flat policy.



(b) Hierarchical design of global policy.

Figure 2: Flat and hierarchical policy architectures.

In this work, we propose a hierarchical policy network which can reuse previously learned skills alongside and as subcomponents of new skills. To represent the skills and their relations in an interpretable way, we also encode all tasks using human instructions. This allows the agent to communicate its policy and generate plans using human language. Figure 1 illustrates an example: given the instruction "Stack blue," our hierarchical policy learns to compose instructions and take multiple actions through a multi-level hierarchy in order to stack two blue blocks together. In order to better track temporal relationships between tasks, we train a stochastic temporal grammar (STG) model on the sequence of policy selections (previously learned skill or new skill) for positive episodes.

We validated our approach by testing it on object manipulation tasks implemented in a Minecraft world. The results show that this framework can (i) efficiently learn hierarchical policies and representations for multi-task RL; and ii) learn to utter human instructions to deploy pretrained policies, improve their explainability and reuse skills.

2 Model

2.1 Multitask RL Setting

Let $\mathcal{G}$ be a task set, where each task g is uniquely described by a human instruction. For simplicity, we assume a two-word tuple template consisting of a skill and an item for such a phrase, i.e., $g = \langle u_{\text{skill}}, u_{\text{item}} \rangle$. For each task, we define a Markov decision process (MDP) represented by states $s \in \mathcal{S}$, primitive actions $a \in \mathcal{A}$, and a reward function $R(s, g)$. As a starting point, we have a terminal policy π_0 (as shown in Figure 2a) trained for a set of basic tasks (i.e., a terminal task set $\mathcal{G}_0$). The task set is then progressively increased at multiple stages, such that $\mathcal{G}_0 \subset \mathcal{G}_1 \subset \cdots \subset \mathcal{G}_K$, which results in life-long learning of polices from π_0 for $\mathcal{G}_0$ to π_K for $\mathcal{G}_K$.

2.2 Hierarchical Policy

Instead of using a flat policy (Figure 2a), we propose a hierarchical design (Figure 2b) with the ability to reuse the base policy (i.e., π_{k-1}) for performing base tasks as subtasks. This hierarchy consists of four sub-policies: a base policy, an instruction policy, an augmented flat policy, and a switch policy.

The base policy is defined to be the global policy at the previous stage $k-1$. The instruction policy informs base policy π_{k-1} which base tasks it needs to execute. We define this policy using two conditionally independent distributions, i.e., $\pi_k^{\text{inst}}(g' = \langle u_{\text{skill}}, u_{\text{item}} \rangle | s, g) = p_k^{\text{skill}}(u_{\text{skill}}|s, g) p_k^{\text{item}}(u_{\text{item}}|s, g)$. An augmented flat policy, $\pi_k^{\text{aug}}(a|s, g)$, ensures that the global policy is able to perform novel tasks in $\mathcal{G}_k$ that can not be achieved by only reusing the base policy. A switch policy, $\pi_k^{\text{sw}}(e|s, g)$, determines whether to perform a base task or perform a primitive action, where e is a binary variable indicating the selection of the branches, π_k^{inst} $(e = 0)$ or π_k^{aug} $(e = 1)$.

At each time step, we first sample e_t from our switch policy π_k^{sw} and a new instruction g'_t from our instruction policy π_k^{inst}. Based on e_t and g'_t, the action is then sampled by

$$a_t \sim \pi_k(a_t|s_t, g) = \pi_{k-1}(a_t|s_t, g'_t)^{(1-e_t)} \pi_k^{\text{aug}}(a_t|s_t, g)^{e_t}, \tag{1}$$

where π_k and π_{k-1} are the global policies at stage k and $k-1$ respectively. After each step, we will also obtain a reward $r_t = R(s_t, g)$.

2.3 Stochastic Temporal Grammar

Inspired by previous research (Si et al., 2011; Pirsiavash & Ramanan, 2014) on stochastic grammar models, we summarize temporal transitions between various tasks with an stochastic temporal grammar (STG). In our full model, the STG interacts with the hierarchical policy described above through modified switch policy and instruction policy by using the STG as a prior.

In an episode, the temporal sequence of e_t and g'_t, $\{\langle e_t, g'_t \rangle; t \geq 0\}$, can be seen as a finite state Markov chain (Baum & Petrie, 1966). At each level $k > 0$, we may define an STG of a task g by i) transition probabilities, $\rho_k(e_t, g'_t | e_{t-1}, g'_{t-1}, g)$, and ii) the distribution of $\langle e_0, g'_0 \rangle$, $q_k(e_0, g'_0 | g)$.

With the estimated probabilities, we sample e_t and g'_t in an episode at level $k > 0$ w.r.t. to reshaped policies $\pi_k^{sw'}$ and $\pi_k^{\text{inst}'}$ respectively: if $t = 0$,

$$e_0 \sim \pi_k^{\text{sw}'}(e_0 | s_t, g) \propto \pi_k^{\text{sw}}(e_0 | s_t, g) \textstyle\sum_{g' \in \mathcal{G}_{k-1}} q_k(e_0, g' | g), \tag{2}$$

$$g'_0 \sim \pi_k^{\text{inst}'}(g'_0 | s_t, g) \propto \pi_k^{\text{inst}}(g'_0 | s_t, g) q_k(e_0 = 0, g'_0 | g); \tag{3}$$

otherwise,

$$e_t \sim \pi_k^{\text{sw}'}(e_t | e_{t-1}, g'_{t-1}, s_t, g) \propto \pi_k^{\text{sw}}(e_t | s_t, g) \textstyle\sum_{g' \in \mathcal{G}_{k-1}} \rho_k(e_t, g' | e_{t-1}, g'_{t-1}, g), \tag{4}$$

$$g'_t \sim \pi_k^{\text{inst}'}(g'_t | e_{t-1}, g'_{t-1}, s_t, g) \propto \pi_k^{\text{inst}}(g'_t | s_t, g) \rho_k(e_t = 0, g'_t | e_{t-1}, g'_{t-1}, g). \tag{5}$$

2.4 Plan Composition

Combined with our hierarchical policy and STG, we are able to run an episode to compose a plan for a task specified by a human instruction. Note that to fully utilize the base policy, we assume that once triggered, a base policy will play to the end before the global policy considers the next move.

2.5 Learning

We learn our final hierarchical policy through k stages of skill acquisition. A 2-phase curriculum learning is applied to each of these stages. In phase 1, we only sample tasks from the base task set $\mathcal{G}_{k-1}$. In phase 2, we sample tasks from the full task set, $\mathcal{G}_k$, for the k-th stage of skill acquisition.

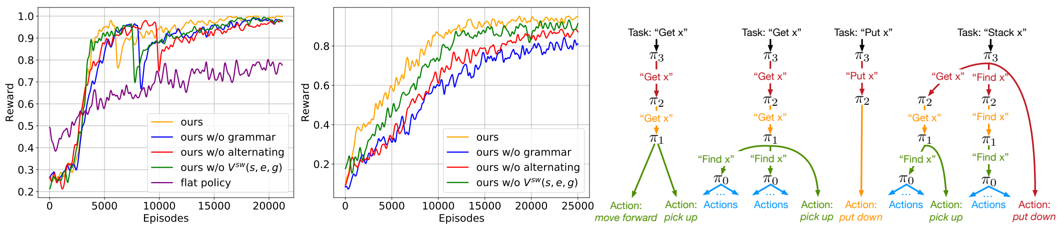
We use advantage actor-critic (A2C) for policy optimization with off-policy learning (Su et al., 2017). Let $V_k(s_t, g)$ be a value function indicating the expected return given state s_t and task g. To reflect the nature of the branch switching in our model, we introduce another value function $V_k^{\text{sw}}(s_t, e_t, g)$ to represent the expected return given state s_t, task g and current branch selection e_t. Thus, given a trajectory $\Gamma = \{\langle s_t, e_t, g'_t, a_t, r_t, \mu_k^{\text{sw}}(\cdot|s_t), \mu_k^{\text{inst}}(\cdot|s_t, g), \mu_k^{\text{aug}}(\cdot|s_t, g), g \rangle : t = 0, 1, \cdots, T\}$ generated by old policies $\mu_k^{\text{sw}}(\cdot|s_t)$, $\mu_k^{\text{inst}}(\cdot|s_t, g)$, and $\mu_k^{\text{aug}}(\cdot|s_t, g)$, the policy gradient reweighted by importance sampling can be formulated as

$$\begin{aligned}
&\underbrace{\omega_t^{\text{sw}} \nabla_{\theta^{\text{sw}}} \log \pi_k^{\text{sw}}(e_t | s_t, g) A(s_t, g, e_t)}_{\text{1st term: switch policy gradient}} + \underbrace{(1 - e_t) \omega_t^{\text{inst}} \nabla_{\theta^{\text{inst}}} \log \pi_k^{\text{inst}}(g'_t | s_t, g) A(s_t, g, e_t, g'_t)}_{\text{2nd term: instruction policy gradient}} \\
+ \; &\underbrace{e_t \omega_t^{\text{aug}} \nabla_{\theta^{\text{aug}}} \log \pi_k^{\text{aug}}(a_t | s_t, g) A(s_t, g, e_t, a_t)}_{\text{3rd term: augmented policy gradient}},
\end{aligned} \tag{6}$$

where $\omega_t^{\text{sw}} = \frac{\pi_k^{\text{sw}}(e_t|s_t,g)}{\mu_k^{\text{sw}}(e_t|s_t,g)}$, $\omega_t^{\text{inst}} = \frac{\pi_k^{\text{inst}}(g'_t|s_t,g)}{\mu_k^{\text{inst}}(g'_t|s_t,g)}$, and $\omega_t^{\text{aug}} = \frac{\pi_k^{\text{aug}}(a_t|s_t,g)}{\mu_k^{\text{aug}}(a_t|s_t,g)}$ are importance sampling weights for the three terms respectively; $A(s_t, g, e_t)$, $A(s_t, g, e_t, g'_t)$, and $A(s_t, g, e_t, a_t)$ are estimates of advantage functions, which have multiple possible definitions. In this paper, we define them as: $A(s_t, g, e_t) = \sum_{\tau=0}^{\infty} \gamma^\tau R(s_{t+\tau}, g) - V_k(s_t, g)$, $A(s_t, g, e_t, g'_t) = A(s_t, g, e_t, a_t) = \sum_{\tau=0}^{\infty} \gamma^\tau R(s_{t+\tau}, g) - V_k^{\text{sw}}(s_t, g, e_t)$, where γ is the discounted coefficient.

Finally, the value functions can be updated using the following gradient:

$$\nabla_{\theta_v} \frac{1}{2} \left[\sum_{\tau=0}^{\infty} \gamma^\tau R(s_{t+\tau}, g) - V_k(s_t, g) \right]^2 + \nabla_{\theta_v^{\text{sw}}} \frac{1}{2} \left[\sum_{\tau=0}^{\infty} \gamma^\tau R(s_{t+\tau}, g) - V_k^{\text{sw}}(s_t, e_t, g) \right]^2 / 2. \tag{7}$$



(a) Learning curves for π_1. (b) Learning phase 2 for π_3. (c) Examples of composed hierarchical plans.

Figure 3: Results: i) comparison of learning efficiency on two task sets: $\mathcal{G}_1$ for global policy π_1 (a) and $\mathcal{G}_3$ for global policy π_3 (b) respectively, and ii) typical composed hierarchical plans (c).

ρ_k and q_k of the STG are both initialized to be uniform distributions. When the agent receives a positive reward after an episode, we use maximum likelihood estimation (MLE) to update the distributions of the STG (Baum & Petrie, 1966). As the training progresses, the STG starts to guide the exploration. We use ϵ-greedy to avoid falling into local minima in the early stages of training.

3 Experiments

Game environment and task specifications. We created an indoor environment in Minecraft using the Malmo platform (Johnson et al., 2016). In each episode, an arbitrary number of blocks with different colors (totally 6 colors in our experiments) are randomly placed in a room. We consider four sets of tasks: i) $\mathcal{G}^{(0)} = \{\text{“Find x”}\}$, walking to the front of a block with color x, ii) $\mathcal{G}^{(1)} = \{\text{“Get x”}\}$, picking up a block with color x, iii) $\mathcal{G}^{(2)} = \{\text{“Put x”}\}$, putting down a block with color x, and iv) $\mathcal{G}^{(3)} = \{\text{“Stack x”}\}$, stacking two blocks with color x together. When reaching the goal of a task, the agent gets a $+1$ reward. We assume the following skill acquisition order: $\mathcal{G}_k = \cup_{\kappa=1}^{k} \mathcal{G}^{(\kappa)}$, $\forall k = 0, 1, 2, 3$, which is a natural way to increase skill sets. This results in policies $\{\pi_k : k = 0, 1, 2, 3\}$ for these four task sets.

Implementation details. The visual and instruction encoding (bag-of-words) modules have the same architectures as the ones in Hermann et al. (2017). The fusion layer simply concatenates the outputs of these two modules and feeds its output to an LSTM with 256 hidden units. We train the network with RMSProp (Tieleman & Hinto, 2012) with a learning rate of 0.0001. We set the batch size to be 36 and clip the gradient to a unit norm. For all tasks, the discounted coefficient is $\gamma = 0.95$. For the 2-phase curriculum learning, the reward threshold is 0.9. We apply ϵ-greedy to the decision sampling for the global policy, where ϵ gradually decreases from 0.1 to 0.

Results. To evaluate the learning efficiency, we compare our full model with 1) a flat policy (Figure 2a) as in Hermann et al. (2017) fine-tuned on π_0 and variants of our approach: ours without 2) STG, 3) alternating updates, or 4) $V_k^{\text{sw}}(s, e, g)$. In Figure 3a, we use various methods to train policy π_1 for the task set $\mathcal{G}_1$ based on the same base policy π_0. The large dip in the reward indicates that the curriculum learning switches from phase 1 to phase 2. To further examine the learning efficiency during phase 2, we first pretrain π_3 following our definition of phase 1 in the curriculum learning. We then proceed to learning phase 2 using different approaches all based on this pretrained policy (Figure 3b). As shown in Figure 3a and Figure 3b, our full model has the fastest convergence. Figure 3c visualizes a few typical hierarchical plans. To evaluate the generalization of learned policies, we also train the flat policy and our full model for $\mathcal{G}_1$ with only 1 item in the room and test them in a room with multiple items. Both of them achieve near perfect success rate in training scenarios. In testing cases, the flat policy has only 29% success rate, whereas our full model maintains a 94% success rate. This shows that the hierarchical policy generalizes better as it inherits the concept of items from its base policy.

4 Conclusion

In this work, we have proposed a hierarchal policy modulated by an STG as a novel framework for efficient multi-task reinforcement learning via multiple training stages. Experiments on Minecraft games have shown that our full model i) has a significantly higher learning efficiency than a flat policy does, ii) generalizes well in unseen environments, and iii) is able to compose hierarchical plans in an interpretable manner.

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