FIRL: Fast Imitation and Policy Reuse Learning

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Abstract—Intelligent robotics policies have been widely researched for challenging applications such as opening doors, washing dishes, and table organization. We refer to a "Policy Pool", containing skills that be easily accessed and reused. There are researches to leverage the pool, such as policy reuse, modular learning, assembly learning, transfer learning, hierarchical reinforcement learning (HRL), etc. However, most methods generally do not perform well in learning efficiency and require large datasets for training. This work focuses on enabling fast learning based on the policy pool. It should learn fast enough in one-shot or few-shot by avoiding learning from scratch. We also allow it to interact and learn from humans, but the training period should be within minutes. We propose FIRL, Fast (one-shot) Imitation, and Policy Reuse Learning. Instead of learning a new skill from scratch, it performs the one-shot imitation learning on the higher layer under a 2-layer hierarchical mechanism. Our method reduces a complex task learning to a simple regression problem that it could solve in a few offline iterations. The agent could have a good command of a new task given a one-shot demonstration. We demonstrate this method on the OpenDoors mini-grid environment, and the code is available on http://www.github.com/yiwc/firl.

I. INTRODUCTION

Humans learn new skills efficiently, thanks to their memory and knowledge of previous experience and the skills they already mastered. For Artificial Intelligence (AI), there is more than one way to represent skills or knowledge [1], such as shared parameters [2] or shared models [3] from previous tasks, human demonstrations [4], replay buffer [5], knowledge graph, embedding [6], temporal abstractions or options [7], etc. There is still no consensus on a unified representation structure of knowledge [1]. In this work, we use both pre-trained models and human demonstrations as previous knowledge to accelerate the learning process.

With the increasing development of robotics intelligence, in the future, we could access a skills library in which people use deep learning models to represent skills [8][1]. In this case, we seek an approach to fast mastering a new policy based on the skills library we have. For example, if the robot can do dish washing and object pick-placing, it should learn how to clean the kitchen, which consists of two steps or skills. Various novel works were proposed to solve these long-horizon, multi-stage and reward-sparse tasks, e.g., the options [7] framework and hierarchical reinforcement learning (HRL) [9]. [8] discusses the method to combine single skills, i.e., the keys, into new combinational skill, i.e., the chords, using generalised policy evaluation (GPE) [10][11][12]. And HRL related methods [13][14][15] utilize two layer policies and goal-based task formulation, while the meta controller is learning an approach to provide sub-goals for lower works. [16] proposes integrated symbolic planning in HRL mechanism.

In our approach, instead of using the convention description of options (\(I_w, \pi_w, \beta_w\)) [7], we describe the sub-policies as pre-trained network models. Similar to hierarchical reinforcement learning architectures [13][14][15], we also employ a two-layer mechanism where the higher layer manages the lower layer. To further extend fast learning capability, we propose the Higher-layer One-shot Imitation Learning (Sec. III-B) with Observation Reduction (Sec. III-C) and Dynamic Reward Loss (Sec. III-D).

In summary, we introduce the approach Fast Imitation and Policy Reuse Learning (FIRL). It utilizes imitation learning in the second layer of a two-layer HRL convention. Compared with state of the art HRL and imitation learning methods, our approach requires much less demonstration and shows a fast (one-shot) learning capability. Meanwhile, the fast learning capability is built upon incremental learning consideration, allowing policy reuse. We demonstrate the results on our in-house developed multi-task reward-sparse grid environment based on mini-grid world [18], with detailed experiments in Sec. IV.

II. RELATED WORK

A. Hierarchical Reinforcement Learning, Temporal Abstraction, Option Framework and Skills Priors

Temporal abstraction and options (\(I_w, \pi_w, \beta_w\)) [7] have been discussed since HAMs [19], MAXQ [20][21] and option framework [7] were proposed. We neither use the option with terminal and initial conditions nor give finite machine states in our work. Instead, the higher layer can directly learn the higher-level policy. Based upon the above fundamental topics, various hierarchical reinforcement learning methods [13][14][15] were proposed to solve long-horizon tasks by shrinking searching space. Options discovering methods were presented by [22][23][24]. Specifically, [22] proposed an encoder-decoder model for skills extraction and composition. Furthermore, [17] shows the capability to extract the skills abstraction from demonstration dataset. Skills priors based methods [25][26][27], similar to options discovering, extract the skill representation from demonstrations dataset.
Fig. 1: Fast Imitation and Policy Reuse Learning. Environment provides observation \(s_h, s_l\) for \(\pi_\phi\) (higher level policy) and \(\pi_\theta\) (lower level policy). \(s_h\) has much lower dimensions than \(s_l\), and \(\pi_\phi\) owns fewer parameters than \(\pi_\theta\). Low-dimension observation and low-parameters in the high level policy allows the fast learning capability with few-shot imitation. In the lower level, we describe the policy pool as the tool box. In each step, similar to option framework, the agent would choose which tool to use (high-level learning), rather than learning a skill from scratch (low-level learning).

II. APPROACH

The goal of our approach is to enable fast (one-shot) learning on a new task while accessing a policy pool \(P\) and a few demonstrations \(D\). The schema of our approach includes three parts (1) Imitation Learning on the Higher Level, (2) Observation Reduction, (3) Adjustable Rate with Reward. The main architecture of our approach (shown in Fig. 1) has two layers of policy, the higher policy, and the lower policy pool. The output of higher policy selects which lower policy to use. And the procedure of learning selection utilizes the one-shot imitation learning.

A. Problem Formulation

Assume that we have access to a policy pool \(P\) as well as a few-shot (or one-shot) demonstrations \(D\). Policy pool \(\mathcal{P} = \{\pi_\theta_1(a|s), ..., \pi_\theta_K(a|s)\}\) is a set of pre-trained skills. \(K\) is the number of pre-trained skills. Instead of training skills priors from dataset \(\mathcal{D}\), we have direct access to lower layer policies. As for \(\mathcal{D} = \{\tau_1, ..., \tau_N\}\), \(\tau\) represents the demonstration trajectory, compared with benchmark imitation learning methods \(\mathcal{D}\), we only have a limited number of demonstrations. Each demonstration contains of a trajectory \(\tau_i = \{(s_{d,0}, a_{d,0}, r_{d,0}), ..., (s_{d,T_i}, a_{d,T_i}, r_{d,T_i})\}\). Notation \(d\) implies that the data is from demonstration and \(T_i\) is the episode length of trajectory \(i\). This dataset is collected from limited interaction with human users. \(N\) is the number of demonstration trajectories. Given above formulation, we aim to train a policy \(\pi_\theta(a|s)\) to maximize the expectation of decayed rewards \(E_{\pi} \left[ \sum_{t=0}^{T-1} \gamma^t r_t(s_t, a_t) \right] \) where \(\gamma\) is a
decayed factor less than one. r, a, s each represents the reward, action and observation from the environment.

B. Imitation Learning on the Higher Level

By combining the advantage of imitation learning and hierarchical learning, we propose our novel method of imitation learning on the higher-level policy. We freeze all the low-level policies and only train the higher-level policy weights. The low-level policy gives \( a_t, \theta_k \sim \pi_\theta(\cdot|s_t) \) at each step. And the whole output from lower level is \( \pi_\theta(s_t) = [a_t, \theta_1, \ldots, a_t, \theta_k] \). Higher level policy is symbolized as \( \pi_\phi(s_t) \), and outputs a vector \( w \) as shown in Eq. [1]

\[
w_t = (w_1, \ldots, w_k)^T \sim \pi_\phi(\cdot|s_t)
\]  

(1)

Then the synthesized action is computed as:

\[
a_t = \pi_\phi(\cdot|s_t), i = \text{argmax}(w_t)
\]  

(2)

With higher policy trainable and lower policies’ parameters frozen, the imitation loss is defined as follows:

\[
L(\Theta, \phi, D) = \frac{1}{T} \sum_{t=0}^{T} (\sum_{k=0}^{K} (w_{k,t} - \| (a_{k,t}, a_{d,t}) \|^2)^2)
\]  

(3)



L denotes the imitation loss function, which computes the average of imitation loss per episode. \( \| (a_{k,t}, a_{d,t}) \|^2 \) equals 1 if two items are the same, else it equals 0.

C. Observation Reduction

Given Eq. [1] we intend to shrink the observation dimension, i.e., to reduce trainable parameters and narrows down search space to speed up the learning. Thus, we only retain necessary features for high-level observations \( s_h \), where \( \text{dim}(s_h) \ll \text{dim}(s) \). Table [1] shows an example of OpenDoors task using reduced dimension observations. Note that Eq. [1] now becomes:

\[
w_t \sim \pi_\phi(\cdot|s_{h,t})
\]  

(4)

Our experiment takes the state of the object of interest as the higher-level observation, e.g., the door’s open or close state. Lower level observation is unchanged from its pre-trained configuration, i.e., \( s_{l,k,t} = s_{k,t} \). Sec. IV-C describes the effect of this method.

| TABLE I: Explanation of \( s_h \) and \( s_l \) |
|----------------|----------------|
| Observation Level | \( s_h \) | \( s_l \) |
| Sparsity | sparse | dense |
| Dimension | \((3,1)\) | \((7,7,3)\) |
| Data Type | int | float32 |
| Explanation | flags of door’s open/close | raw image |
| Examples | \([1,0,0]^T\) | |

D. Reward Dynamic Loss

Each task could have multiple trajectories as solutions. Therefore, few demonstrations could not represent the whole solution universe. Then imitation upon demonstrated steps could easily introduce noise and overfitting. To meditate this issue, we propose the Reward Dynamic Loss, which adjusts the weight of loss function along with the reward. It gives higher wights of imitation loss, if it’s a high-rewarded step. It helps avoid imitation collapse with overwhelming demonstrations (see experiments in Fig. 4). The loss function is defined as follows:

\[
L(\Theta, \phi, D) = \frac{1}{T} \sum_{t=0}^{T} r_{d,t} (\sum_{k=0}^{K} (w_{k,t} - \| (a_{k,t}, a_{d,t}) \|^2)^2)
\]  

(5)

IV. EXPERIMENTS

In this section, we target to answer the following questions:

- Could FIRL succeed in one-shot imitation learning?
- How is the performance improved comparing with imitation learning method BC (Behavior Clone) and non-imitation learning methods, e.g., PPO and APEX-DQN?
- Could few-shot demos further improve the performance? What’s the optimal number of demonstrations?

A. Environment and Setup

We evaluated our method on the OpenDoors environment based upon Mini-Grid world [18]. We recorded a few human task-solving interactions as the one-shot and few-shot datasets. The reward is highly sparse which will only be acquired when a target state is achieved.

**Fig. 2: Open Doors Task.** It’s a 3 stage task. The agent needs to sequentially open Red, Yellow, and Blue doors to get a total reward of 3 (1 for each).

**Open Doors.** It’s a simulation task in a 2D grid world. The mission is to navigate the agent (the red arrow) to open three doors in different colors (Red, Yellow, Blue) in a specific sequence, as illustrated in Fig. 2. If the agent opens the wrong door or in the wrong order, it would be punished with a -1 reward and the task will reset. It receives a reward of 1 after opening each door in the correct sequence. The maximum reward of each episode is 3. The action space contains discrete choices, viz. [move up, move down, move
left, move right, pick, place, open] (pick & place is not used in this task). This environment is a simple and efficient abstraction of a multi-stage sparse reward task, in which order and sequence matter.

### B. One-shot Imitation Learning

![Graph showing training time and rewards comparisons with baselines. FirL and BS are drawn as dash lines and they don't need time in training with environment.](image)

Fig. 3: Training time and rewards comparisons with baselines methods. FirL and BS are drawn as dash lines and they don't need time in training with environment.

We compare FirL’s learning performance on the multi-stage and reward-sparse task (OpenDoors-Red Yellow Blue) with baselines algorithms PPO, APEX, and BC (few-shot), the results are in Table II. For FirL, we could access the policies pool (see Fig. 1), in which there are various pre-trained sub-policies (OpenDoors-R, OpenDoors-Y, OpenDoors-B, etc.). Firstly, FirL gets the highest rewards of 2.82, while the others could only get 0.96 in maximum. Secondly, FirL is the only method that succeeds in this sparse reward task, while PPO and APEX would stop exploration after getting the 1st reward. Thirdly, compared with BC, given five demos, BC failed to master this task because it doesn’t retrieve enough information from these five demos. We didn’t compare it further with other baselines as SPRIL. (2020)[25] and RPL (2019)[17], as they require much larger datasets thus are not suitable for comparing with few-shot learning.

In summary, our method, FirL, outperforms baselines in this multi-stage task and shows its fast learning capability. It requires no interaction with the environment and has no reliance on large datasets (only 1 demo would be enough).

|                              | FIRL(ours) | PPO       | APEX-DQN  | BC         |
|------------------------------|------------|-----------|-----------|------------|
| Average Rewards              | 2.82 ± 0.1 | 0.96 ± 0.03 | 0.96 ± 0.03 | -0.1 ± 0.05 |
| Success Rate (%)             | 94 ± 3.0   | 0         | 0         | 0          |
| Environment Train/Interaction Steps | 0         | ~ 300,000 | ~ 2,400,000 | 0          |
| Give Number of Demos         | 1          | 0         | 0         | 5          |

### C. Ablation Study

We experiment our FirL method with or without techniques of Observation Reduction (Sec. III-C) and Reward Dynamic Loss (Sec. III-D). We have following four experiment groups FirL(∅), FirL(R), FirL(OR), and FirL(∅) (in Table III). Summarily, with absence of the two techniques (Observation Reduction and Reward Dynamic Loss), the agent fails in this fast learning task.

1) **Observation Reduction**: Comparing group FirL(OR) and FirL(R), we can verify the effect of the trick of Observation Reduction (abbr by O.). Fig. 4a and Fig. 4b indicate that O. is successful in the task, while FirL(R) without O. fails the task. We conclude that the heavy dimension of observation hinders the fast (few-shot) learning capability.

We also notice some groups perform quite well at the initiation stage (seeing Fig. 4c and Fig. 5). After training for a few epochs, the performance decreased and finally recovered, knowing the fact that the best performance after five training epochs. It shows that reducing dimensions (Sec. III-C) has significantly narrowed down the search space, and the random weights could possibly produce good results. Fast learning (one-shot, few-shot) capability also benefits from the narrowed searching space.

2) **Reward Dynamic Loss**: We also verify the effect of Reward Dynamic Loss (abbr by R.) by comparing group FirL(OR) and FirL(O). First of all Fig. 4a shows that FirL(OR) gives better results (2.8) than FirL(O) (1.6 ~ 2.0) which has more demonstrations. The FirL(O) agent could get confused given too many demonstrations, then R. helps filter out unimportant experiences. It forces agent to learn from the rewarded prioritized demo steps. Additionally, It also boosts the learning efficiency (seeing FirL(OR) and FirL(O) in Fig. 4b).

3) **Number of Demonstrations**: We further examine the optimal number of demos required by FirL (Fig. 5). By giving experiment groups with demos of 1, 2, 3, 4, and 5, we found that all perform similarly desirable. It proves FirL could learn efficiently even with only one demonstration, the one-shot learning capability.
Fig. 4: Ablation Study Result Analysis. We examine four groups FIRL(O), FIRL(R), FIRL(OR) and FIRL(∅) (see configuration of groups in Table III). We find using Dynamic Reward Loss and Observation Reduction could effectively fasten the training speed from 49 epochs to 4 epochs (Fig. 4b), boost the performance from -0.4 to 2.8 (Fig. 4a). We also find benefits by using dimension reducing (see Fig. 4c and explanation in Sec. IV-C).

D. Limitation and Future work

In this work, we perform manual setting in observation reduction, see Sec. III-C. The future intelligent agent should automatically learn how to reduce the observation or use lower skill embedding dimensions. Future work will extend this framework into a 3D complex task, and further explore its potential in lifelong learning. Besides, we will also investigate its application in human-robot interaction and fast learning in the real world applications.

Fig. 5: Number of Demonstrations required by FIRL method.

V. CONCLUSION

We proposed the FIRL, fast (one-shot) imitation and policy reuse learning method. This approach generally consists of three components. 1. Imitation Learning on higher-level while freezing all sub-policies, only tunes the second layer policy by imitation loss. 2. Observation Reduction provides a tight observation feature for the second layer policy and a raw image observation for the lower layer. 3. Dynamic Reward Loss allows loss computation rewarding prioritized by removing demonstrations noise.

Our work leverages the advantages of hierarchical reinforcement learning and imitation learning. It shows a reliable one-shot imitation learning capability on multi-stage reward sparse tasks. And the offline learning does not require interaction with environment, which saves the time and economical cost. It could play an integral role in future human-robot interaction and fast demonstration learning. We are also looking forward to its further potential in lifelong learning in future work.

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