Hierarchical Reinforcement Learning with Adversarially Guided Subgoals

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Abstract

Hierarchical reinforcement learning (HRL) proposes to solve difficult tasks by performing decision-making and control at successively higher levels of temporal abstraction. However, off-policy HRL often suffers from the problem of non-stationary high-level policy since the low-level policy is constantly changing. In this paper, we propose a novel HRL approach for mitigating the non-stationarity by adversarially enforcing the high-level policy to generate subgoals compatible with the current instantiation of the low-level policy. In practice, the adversarial learning is implemented by training a simple discriminator network concurrently with the high-level policy which determines the compatibility level of subgoals. Experiments with state-of-the-art algorithms show that our approach improves both HRL learning efficiency and overall performance in various challenging continuous control tasks.

1. Introduction

Hierarchical reinforcement learning (HRL), in which hierarchical policies learn to perform decision-making at successively higher levels of temporal and behavioral abstraction, has long held the promise to tackle complex problems with long-term credit assignment and sparse rewards. Among the prevailing HRL paradigms, the goal-conditioned HRL frameworks (Dayan & Hinton, 1992; Schmidhuber & Wahn-siedler, 1993; Kulkarni et al., 2016; Vezhnevets et al., 2017; Nachum et al., 2018; Levy et al., 2019; Zhang et al., 2020; Li et al., 2021) have achieved remarkable success. In goal-conditioned HRL, a high-level policy breaks the original task into a series of subgoals that a low-level policy is incentivized to reach. The effectiveness and efficiency of goal-conditioned HRL relies on reasonable and semantically meaningful subgoals providing a strong supervision signal to the low-level policy.

Nonetheless, off-policy training of a hierarchy of policies remains a key challenge due to the non-stationary state transitions induced by the hierarchical structure. Specifically, the same high-level action taken under the same state in the past may result in significantly different low-level state transitions due to the constantly changing low-level policy which renders the experience invalid for training. When all policies within the hierarchy are trained simultaneously, the high-level transition will constantly change as long as the low-level policy continues to be updated. However, learning hierarchical policies in parallel is still feasible as long as the high-level policy is able to efficiently adapt itself to the updated versions of low-level policy, and the hierarchical policy stabilizes once the low-level policy has converged to an optimal or near optimal policy. HIRO (Nachum et al., 2018) and HAC (Levy et al., 2019) have made attempts to address this problem by relabeling an experience in the past with a high-level action, i.e. subgoal, to maximize the probability of the past lower-level actions. However, the relabeling approach does not facilitate efficient training of the high-level policy to comply with the update of low-level policy, which consistently generates incompatible subgoals and deteriorates the non-stationarity issue. Such unfit state transitions in off-policy training lead to improper learning of the high-level value function, therefore negatively affecting high-level policy exploration.

In this paper, we present a novel approach for mitigating the non-stationarity in goal-conditioned HRL. We aim to significantly improve the high-level policy’s knowledge of the low-level’s ability, thus improving the overall learning efficiency and stability. Concretely, we introduce an adversarial learning paradigm for HRL which enforces the high-level policy to learn to generate subgoals compatible with the current instantiation of the low-level policy. This is motivated by the assumption that the relabeled subgoals are sampled from a distribution which is asymptotically approximating an optimal high-level policy under stationary data distribution. Consequently the increasing divergence between the distribution of current subgoals and relabeled subgoals is
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the key indication of the non-stationarity. This suggests a conjecture that once this distribution divergence is mitigated the high-level policy naturally achieves stationarity.

To this end, we propose a discriminator network to distinguish a generated subgoal that may not be reachable by the low level policy from a relabeled subgoal that we know is reachable by the low level policy. The high-level policy plays the role of the generator network that learns to generate subgoals following a distribution compatible with the current low level policy.

The proposed adversarial learning thus reduces the shift and consequently the divergence in data distribution from relabeled experience to the current high-level policy behaviour and encourages the high level policy to generate reasonable subgoals. Fitting to state transitions with compatible high-level actions effectively improves the accuracy of the high-level value function and enhances its subsequent exploration underpinning a stationary hierarchical model.

2. Preliminaries

In reinforcement learning, the interaction between agent and environment is modeled as a Markov Decision Process (MDP) \( M = < S, A, P, R, \gamma > \), where \( S \) is a state space, \( A \) is an action set, \( P : S \times A \times S \to [0, 1] \) is a state transition function, \( R : S \times A \to \mathbb{R} \) is a reward function, and \( \gamma \in [0, 1) \) is a discount factor. A stochastic policy \( \pi(a|s) \) maps a given state \( s \) to a probability distribution over actions \( \pi : S \to A \). The objective of the agent is to maximize the expected cumulative discounted reward \( [\sum_{t=0}^{\infty} \gamma^t r_t] \), where \( r_t \) is the obtained reward at the discrete time step \( t \).

Two-Layer HRL Setting: We adopt a continuous control RL setting, modeled as a finite-horizon, goal-conditioned MDP \( M = < S, G, A, P, R, \gamma > \), where \( G \) is a goal set. We consider a HRL framework comprising two hierarchies following (Nachum et al., 2018) with a high-level policy \( \pi_h(g|s) \) and a low-level policy \( \pi_l(a|s, g) \). High-level policy operates at a coarser layer and generates a high-level action, i.e., subgoal \( g_t \sim \pi_h(\cdot|s_t) \in G \), every \( k \) timesteps when \( t \equiv 0 \) (mod \( k \)). A pre-defined goal transition function \( g_t = f(g_{t-1}, s_{t-1}, s_t) \) is utilized when \( t \neq 0 \) (mod \( k \)). The high level modulates the behavior of the low-level policy by intrinsic rewards for reaching these subgoals. Following prior work (Andrychowicz et al., 2017; Nachum et al., 2018; Zhang et al., 2020), the goal set \( G \) corresponds to a subset of state space, i.e., \( G \subset S \), and the goal transition function is defined as \( f(g_{t-1}, s_{t-1}, s_t) = s_{t-1} + g_{t-1} - s_t \). The high-level policy aims to maximize the extrinsic reward \( r^h_{kt} \) defined as:

\[
r^h_t = \sum_{i=t}^{t+k-1} r^\text{env}_i, \quad t = 0, 1, 2, \ldots
\]

where \( r^\text{env}_i \) is the reward from the environment.

The low-level policy aims to maximize the intrinsic reward provided by the high-level policy. It takes the high-level action or subgoal \( g \) as input, and interacts with the environment every timestep by taking an action \( a_t \sim \pi_l(\cdot|s_t, g_t) \in A \). To encourage the low-level policy to reach the subgoal \( g_t \), an intrinsic reward function measuring the subgoal-reaching performance is adopted \( r^l_t = -||s_t + g_t - s_{t+1}||_2 \).

The above goal-conditioned HRL framework allows the low-level policy to receive learning signals even before achieving a certain goal-reaching capability and enables concurrent end-to-end training of the high-level and low-level policies. However, off-policy training of the above HRL framework suffers from the non-stationarity problem of the high-level policy as mentioned in Section 1. HIRO (Nachum et al., 2018) proposes to relabel the high-level transition \((s_t, g_t, \sum_{i=t}^{t+k-1} r^\text{env}_i, s_{t+k}) \) with a different subgoal \( \tilde{g}_t \) to make the actual observed low-level action sequence more likely to have happened with respect to the current low-level policy by maximizing \( \pi_l(a_{t:t+k-1}|s_{t:t+k-1}, \tilde{g}_{t:t+k-1}) \).

3. Adversarially Guided Subgoal Generation

In this section, we present our Adversarially Guided subgoal generation for hierarchical Learning (AGILE), an adversarial learning approach guiding the high-level policy generating more reachable subgoals for low-level policy. The non-stationarity in the previous HRL methods leads to unstable and inefficient high-level policy training. In this section, we introduce our adversarial learning approach to significantly improve the sample efficiency and overall performance of off-policy training of the high-level policy.

Adversarial Learning of High-Level Policy: AGILE integrates adversarial learning and policy training in a two-player game similarly to Generative Adversarial Networks (GANs) (Goodfellow et al., 2014), which primarily comprises a subgoal generator network \( G(s; \theta_g) : s \to g \) and a subgoal discriminator network \( D(g; \theta_d) \to \{0, 1\} \). As opposed to the generator defined in vanilla GAN which samples from a noise distribution, our subgoal generator network \( G(s; \theta_g) \) maps from state space to subgoal space. In order to mitigate the non-stationary issue, we aim to reduce the divergence between the data distribution of the relabeled experience and the current high-level policy behaviour, with the assumption that subgoals in the relabeled
experience are “optimal” in learning a stationary hierarchical model. To this end, the subgoal discriminator tries to distinguish the generated subgoals from relabeled subgoals of the replay buffer. In practice, we let the subgoal generator $G(s; \theta_g)$ be a surrogate of the high-level actor network.

Although our approach is applicable to general actor-critic based HRL algorithms, we adopt the TD3 (Fujimoto et al., 2018) algorithm for each level in the HRL structure following HIRO (Nachum et al., 2018) and HRAC (Zhang et al., 2018). Thus the first objective of the subgoal generator is to maximize the expected return induced by a deterministic policy:

$$J_{dpg} = \mathbb{E}_{s \sim D}[Q_h(s, g)|g = G(s; \theta_g)]$$  \hspace{1cm} (2)

where $D$ is the replay buffer with the high level action relabeled similarly to HIRO, i.e., relabeling $g_t$ of the high level transition $(s_t, g_t, \sum_{i=t}^{t+k-1} r^s_i, s_{t+k})$ with $\tilde{g}_t$ to maximize the probability of incurred low-level action sequence $\pi_l(a_{t:t+k-1} | s_{t:t+k-1}, \tilde{g}_{t:t+k-1})$, which is approximated by maximizing the log probability

$$\log \pi_l(a_{t:t+k-1} | s_{t:t+k-1}, \tilde{g}_{t:t+k-1}) \propto -\frac{1}{2} \sum_{i=t}^{t+k-1} ||a_i - \pi_l(s_i, \tilde{g}_i)||^2_2 + \text{const.}$$  \hspace{1cm} (3)

In order to learn the distribution of the subgoal generator $G(g|s)$ over the relabeled subgoal $\tilde{g}$ through adversarial learning, we define a subgoal discriminator network $D(g; \theta_d)$ which outputs the probability that subgoal $g$ is an “optimal” subgoal, i.e., the relabeled subgoals rather than a subgoal sampled from the generator’s distribution $G(g|s)$. That is, we train $D(g; \theta_d)$ to maximize the probability of distinguishing the data distribution of “optimal” and “sub-optimal” subgoals. Simultaneously we train $G(s; \theta_g)$ to minimize the probability that a generated subgoal is classified as a “sub-optimal” subgoal by the discriminator network, that is, we minimize $\log(1 - D(G(s)))$:

$$J_{adv} = \min_G \max_D V(D, G) = \mathbb{E}_{g \sim D}[\log D(g)] + \mathbb{E}_{s \sim D}[\log(1 - D(G(s)))]$$  \hspace{1cm} (4)

Combining terms defined in Eq. (2) and Eq. (4), the high-level actor i.e., subgoal generator $G(s; \theta_g)$ is learned by performing gradient update on parameter $\theta_g$

$$\nabla_{\theta_g} J = \mathbb{E}_{s \sim D}[\nabla_{\theta_g} Q_h(s, g)|g = G(s)] - \alpha_{adv} \mathbb{E}_{s \sim D}[\nabla_{\theta_g} \log(1 - D(G(s)))]$$,  \hspace{1cm} (5)

where $\alpha_{adv}$ is a hyperparameter to weigh the adversarial loss.

The subgoal discriminator is learned by updating $\theta_d$ with gradient

$$\nabla_{\theta_d} J_{adv} = \mathbb{E}_{s, g \sim D}[\nabla_{\theta_d} \log D(g) + \log(1 - D(G(s)))]$$  \hspace{1cm} (6)

4. Experiments

This section evaluates and compares our method against standard RL and prior HRL methods in challenging environments which require a combination of locomotion and object manipulation. We also ablate the various components to understand their importance. Our experiments are designed to answer the following questions:
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Figure 2: Four hierarchical navigation tasks, i.e., Ant Maze, Ant Maze Sparse, Ant Push and Ant Fall, along with the Ant Gather task used in our experiments: the ant is rewarded for approaching the target location. Successful policies must perform complex sequences of directional movement and, in some circumstances, interact with objects (red blocks) in the environment, e.g., pushing aside an obstacle (AntPush) or using a block as a bridge (Ant Fall). The high-level policy periodically produces goal states corresponding to desired positions and orientations of the ant and its limbs, which the low-level policy is incentivized to match.

Figure 3: Learning curves of AGILE and baselines on all environments. Each curve and its shaded region represent average episode reward (for Ant Gather) or average success rate (for the rest; see the supplementary material) and 95% confidence interval respectively, averaged over 10 independent trials. We find that AGILE performs well across all tasks. It is worth noting that AGILE learns rapidly; on the complex navigation tasks it normally requires only less than three million environment steps to achieve good performance.

1. Can AGILE improve the sample efficiency and performance of goal-conditioned HRL across various long-horizon continuous control tasks?

2. Can AGILE outperform an alternative adversarial learning approach in goal-conditioned HRL framework?

4.1. Environment Setup

We consider the following five environments for our analysis:

1. **Ant Maze**: A ‘⊂’-shaped maze poses a challenging navigation task for a quadruped-Ant. The ant needs to reach a target position starting from a random position in a maze with dense rewards.

2. **Ant Maze Sparse**: From a random start position, the ant needs to reach a target position in a maze with sparse rewards.

3. **Ant Gather**: Starting from a fixed position, the ant collects green apples and avoids red bombs.

4. **Ant Push**: A challenging environment which requires both task and motion planning. The ant needs to move to the left of the maze so that it can move up and right to push the block out of the way for reaching the target.
Algorithm 1 Pseudo-Code for AGILE

Input: Higher-level actor $\pi_{h \theta}^l$, lower-level actor $\pi_{l \theta}$, subgoal generator $G_{\theta_s}$, discriminator $D_{\theta_d}$, parameterized by $\theta_h$, $\theta_l$, $\theta_g$ and $\theta_d$ respectively; critics $Q^h$ and $Q^l$; goal transition function $h(\cdot)$; higher-level action frequency $k$; number of training episodes $N$.

for $n = 1$ to $N$ do
  Sample the initial state $s_0$ after resetting the environment.
  $t = 0$
  repeat
    if $t \equiv 0$ (mod $k$) then
      Sample subgoal $g_t \sim \pi_{h \theta}^l(g|s_t)$
    else
      Subgoal transition $g_t = h(g_{t-1}, s_{t-1}, s_t)$
    end if
    Sample lower-level action $a_t \sim \pi_{l \theta}^l(a|s_t, g_t)$
    Execute $a_t$ and obtain next state $s_{t+1} \sim \mathcal{P}(s|s_t, a_t)$
    Obtain intrinsic reward $r_t \sim \mathcal{R}(r|s_t, g_t, a_t)$
    Store transition $(s_{t-1}, g_{t-1}, a_t, r_t, s_t, g_t)$ in replay buffer.
    Sample episode end signal done
  $t = t + 1$
  until done is true
  if Train higher-level policy $\pi_{h \theta}^l$ then
    Sample experience $(s_t, g_t, \sum r_{t:t+k-1}, s_{t+k})$, where $g_t$ is relabeled subgoal
    Obtain positive labels and subgoals $(L_P, g_P) \leftarrow (True, g_t)$
    Obtain negative labels and subgoals $(L_N, g_N) \leftarrow (False, G_{\theta_s}(s_t))$
    Update (G, D) $\leftarrow$ adversarial_training($L$, g) with Eq. 4 and Eq. 5
    Update higher-level actor $\theta_{h \theta} \leftarrow \theta_g$
    Update higher-level critic $Q^h$ with experience
  end if
  Update lower-level actor $\pi_{l \theta}$ and critic $Q^l$ with experience
end for

4.2. Implementations

For the hierarchical policy network, we employ the same architecture as HRAC (Zhang et al., 2020) which adopts TD3 (Fujimoto et al., 2018) as the underlying algorithm for training both the high-level and low-level policy. Specifically, we adopt two networks comprising three fully-connected layers with ReLU nonlinearities as the actor and critic networks of both low-level and high-level TD3 networks. The size of the hidden layers of both actor and critic is 300. The output of the high-level actor is activated using the tanh function and scaled according to the size of the environments.

The subgoal generator network has the identical architecture as the high-level actor. For the subgoal discriminator network, we use a network consisting of 3 fully-connected layers (size of 300, 300 and 1 respectively) with Leaky-ReLU (negative slope 0.2) nonlinearities and sigmoid function in all tasks. Adam optimizer is used for all networks. We provide further implementation details used for our experiments in the supplementary material.

4.3. Comparative Analysis

To comprehensively test the performance of AGILE, we compare against the following baseline methods:

1. HIRO (Nachum et al., 2018): a state-of-the-art off-policy goal-conditioned HRL algorithm proposes to address the non-stationarity issue by relabeling high-level actions.

2. HRAC (Zhang et al., 2020): a state-of-the-art off-policy goal-conditioned HRL algorithm introduces an adjacency network to restrict the high-level action space to a $k$-step adjacent region of the current state.

3. LESSON (Li et al., 2021): a state-of-the-art off-policy goal-conditioned HRL algorithm introduces a sliding window to restrict the high-level action space to a $k$-step adjacent region of the current state.

4. TD3 (Fujimoto et al., 2018): a state-of-the-art flat RL algorithm we compare to validate the need for hierarchical policies.

For fair comparison, all the HRL baselines use the same hierarchical structure and environment configuration as AGILE. The learning curves of AGILE and baselines across all tasks are plotted in Fig. 3. In the gather task i.e., Ant Gather, AGILE achieves comparable performance with HRAC and outperforms other baselines, whilst it consistently exceeds all baselines in all navigation tasks i.e., Ant Maze, Ant Maze Sparse, Ant Push and Ant Fall1, in terms of sam-

5. Ant Fall: This environment extends the navigation to three dimensions. The ant starts on a raised platform with the target located directly in front of it but separated by a chasm which it cannot cross by itself. The ant needs to push the block forward, fill the gap, walk across and move to the left in order to reach the target.

Fig. 2 provides visualizations of these environments. More details of the environments are presented in the supplementary material.

1We use the LESSON’s official implementation https://github.
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Figure 4: Visualization of generated subgoals. Subgoals generated by AGILE are generally matching the low-level trajectories or planned motions, which indicates that AGILE can generate reasonable subgoals for the low level to achieve and also guide the optimization to jump out of the local optimum of the ant to move directly towards the target in complex tasks such as Ant Push and Ant Fall. In contrast, subgoals generated by HRAC and HIRO frequently get stuck to local minimum and fail to guide the agent to accomplish the final task. Subgoals generated by LESSON lie in a learned subgoal space and may not be visualized along with other methods.

Figure 5: Learning curves with different coefficient of adversarial loss $\alpha_{adv}$, averaged over 5 independent trials.

com/SiyuanLee/LESSON which comprises environments Ant Maze, Ant Push and Ant Fall.

AGILE shows consistently better training efficiency benefiting from the
improved learning stability of the hierarchical policies. This suggests that the proposed adversarial learning approach effectively enforces the high-level policy to generate subgoals compatible with the current instantiation of the low-level policy during training which in turn significantly mitigates the non-stationarity issue of off-policy training in HRL. It is also observed that flat RL algorithm TD3 does not learn in the complex environments used in the experiments which further validate the need for hierarchical policies.

We visualize the generated subgoals of AGILE, HIRO and HRAC in Fig. 4. The subgoals generated by AGILE generally match the low-level trajectories or planned motions in Ant Maze, Ant Maze Sparse and Ant Gather. Notably, AGILE generates subgoals to guide the optimization to jump out of the local optimum of the ant to move directly towards the target in Ant Push and Ant Fall. In detail, under the hierarchical policy trained by AGILE, in Ant Push the ant first moves to the left, then pushes the block to the right and finally reaches the target; guided by subgoals generated by AGILE, in Ant Fall, the ant first moves to the right to push the block forward which fills the gap and then walks across and moves to the left in order to finally reach the target. HRAC can also generate relatively reasonable subgoals to reach based on affinity constraints for the low level, however these subgoals frequently get stuck in a local optimum of moving directly to the target as illustrated in Ant Push and Ant Fall. HIRO, on the contrary, fails to generate achievable subgoals and cannot guide the agent to achieve its final target.

4.4. Ablative Analysis

We also compare AGILE with several variants to investigate the effectiveness of each component:

1. **AGILE-HIRO**: as we employ HRAC as the base model for AGILE, we introduce a variant of AGILE which is employing HIRO as base model to understand the generalization of our proposed approach.

2. **HGG**: an alternative adversarial learning variant that uses a common generator network taking as input a random noise sampled from Normal distribution and then trains the high-level critic using the generated subgoals, similar to (Florensa et al., 2018) in flat RL case.

Fig. 3 also shows the learning curves of AGILE-HIRO and HIRO. In the Ant Maze task with dense rewards, AGILE-HIRO achieves comparable performance with HIRO, while AGILE-HIRO exceeds HIRO in other tasks. We note that HIRO hardly learns in Ant Push and learns poorly in Ant Fall by using the standard RL training based on the relabeled high-level actions, whereas AGILE-HIRO enforces the policy to learn in a more sample efficient manner.

The learning curves of HGG is shown in Fig. 3. It can be observed that AGILE significantly outperforms HGG in all tasks. HGG shows learning difficulties in more challenging tasks Ant Push and Ant Fall. We hypothesize that its low sample efficiency is caused by the slow learning of generator network which leads to deteriorating non-stationarity issue for the hierarchical policies.

We also empirically study the effect of different coefficients of adversarial loss $\alpha_{adv}$. Fig. 5 shows that generally $\alpha_{adv} = 0.001$ gives better performance across all tasks.

5. Related Work

HRL (Dayan & Hinton, 1992; Schmidhuber & Wahnsiedler, 1993; Kulkarni et al., 2016; Vezhnevets et al., 2017; Nachum et al., 2018; Levy et al., 2019; Zhang et al., 2020; Li et al., 2021) has long held the promise to tackle long-term credit assignment and sparse reward problems, where the high-level policy decomposes the task into subtasks whilst the low-level policy learns how to efficiently solve these subtasks. The specific way of this decomposition, i.e., how exactly the high level communicates with the low level, varies in different approaches. Various forms of signals from the high level have been proposed, ranging from using discrete value for option (Bacon et al., 2017; Fox et al., 2017; Gregor et al., 2017) or skill (Konidaris & Barto, 2009; Eysenbach et al., 2019; Sharma et al., 2020; Bagaria & Konidaris, 2019) selections, to forming a continuous vector within a learned embedding space as subgoal (Vezhnevets et al., 2017; Li et al., 2021). However, majority of these approaches are unable to benefit from advances in off-policy model-free RL.

Improving the learning efficiency of HRL through off-policy training has attracted a considerable amount of research efforts in recent years. However, beside instability, off-policy training also poses the non-stationary problem which is unique to HRL. (Nachum et al., 2018) proposed an off-policy method which relabels past experience to reduce the impact of training using invalid high-level state transitions due to non-stationarity. Employing hindsight techniques (Andrychowicz et al., 2017), (Levy et al., 2019) proposed to train multi-level policies in parallel while penalizing the high-level for generating subgoals which are not reachable for the low level. (Zhang et al., 2020) addressed the large subgoal space issue by restricting the high-level action space from the whole subgoal space using an adjacency constraint. (Wang et al., 2020) enabled the high-level policy decision
making conditioned on the received low-level policy representation as well as the state of the environment to improve stationarity. (Li et al., 2021) proposed a slowness objective to effectively learn the subgoal representation so that the low-level reward function varies in a stationary way.

The general topic of goal generation in RL has also been studied (Florensa et al., 2018; Nair et al., 2018; Ren et al., 2019; Campero et al., 2021). (Florensa et al., 2018), i.e., GoalGAN, used a standard GAN to produce tasks at the appropriate level of difficulty for training the policy. While GoalGAN is similar in spirit with our method AGILE to some extent, there are several key differences apart from if it is a hierarchical policy or not. GoalGAN is using a standalone generator that does not condition on the observation; its GAN and policy are two modules that independently and sequentially trained. Contrarily, our method AGILE’s generator is a surrogate of the original actor network and AGILE directly updates its policy through the incurred adversarial loss and policy loss concurrently. (Nair et al., 2018) proposed to combine unsupervised representation learning and reinforcement learning of goal-conditioned policies. (Ren et al., 2019) proposed a framework to generate hindsight goals which are easy for an agent to achieve in the short term. (Campero et al., 2021) proposed framework where a teacher network learns to propose increasingly challenging yet achievable goals; the teacher is positively rewarded if the student achieves the goal with suitable effort, but penalized if the student either cannot achieve the goal, or can do so too easily. The foremost difference from our method AGILE is that these methods are developed for flat architectures and therefore cannot successfully solve tasks which require complex high-level decision making.

6. Conclusion

We proposed a novel adversarially guided subgoal generation framework for goal-conditioned HRL to mitigate the issue of non-stationarity in off-policy training. The learning of high-level policy is formulated as a two-player game where the subgoal generator endeavours to generate subgoals compatible with the current instantiation of low-level policy while the proposed discriminator network tries to distinguish the generated subgoals from the relabeled subgoals. Empirical studies show that the proposed adversarial learning is capable of reducing the shifts in data distribution from relabeled experience to the current high-level policy behaviour and consequently improving the overall learning efficiency and stability.

References

Andrychowicz, M., Crow, D., Ray, A., Schneider, J., Fong, R., Welinder, P., McGrew, B., Tobin, J., Abbeel, P., and Zaremba, W. Hindsight experience replay. In Advances in Neural Information Processing Systems, pp. 5048–5058, 2017.

Bacon, P.-L., Harb, J., and Precup, D. The option-critic architecture. In The AAAI Conference on Artificial Intelligence, volume 31, 2017.

Bagaria, A. and Konidaris, G. Option discovery using deep skill chaining. In International Conference on Learning Representations, 2019.

Campero, A., Raileanu, R., Küttler, H., Tenenbaum, J. B., Rocktäschel, T., and Grefenstette, E. Learning with amigo: Adversarially motivated intrinsic goals. In International Conference on Learning Representations, 2021.

Dayan, P. and Hinton, G. E. Feudal reinforcement learning. In Advances in Neural Information Processing Systems, pp. 271–278, 1992.

Duan, Y., Chen, X., Houthooft, R., Schulman, J., and Abbeel, P. Benchmarking deep reinforcement learning for continuous control. In International Conference on Machine Learning, pp. 1329–1338. PMLR, 2016.

Eysenbach, B., Gupta, A., Ibarz, J., and Levine, S. Diversity is all you need: Learning skills without a reward function. In International Conference on Learning Representations (Poster), 2019.

Florensa, C., Held, D., Geng, X., and Abbeel, P. Automatic goal generation for reinforcement learning agents. In International Conference on Machine Learning, volume 80 of Proceedings of Machine Learning Research, pp. 1514–1523. PMLR, 2018.

Fox, R., Krishnan, S., Stoica, I., and Goldberg, K. Multi-level discovery of deep options. CoRR, abs/1703.08294, 2017.

Fujimoto, S., Hoof, H., and Meger, D. Addressing function approximation error in actor-critic methods. In International Conference on Machine Learning, pp. 1587–1596. PMLR, 2018.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. Generative adversarial nets. Advances in Neural Information Processing Systems, 27, 2014.
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Gregor, K., Rezende, D. J., and Wierstra, D. Variational intrinsic control. In International Conference on Learning Representations (Workshop), 2017.

Konidaris, G. and Barto, A. Efficient skill learning using abstraction selection. In International Joint Conference on Artificial Intelligence, 2009.

Kulkarni, T. D., Narasimhan, K., Saeedi, A., and Tenenbaum, J. Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. Advances in neural information processing systems, 29: 3675–3683, 2016.

Levy, A., Konidaris, G. D., Jr., R. P., and Saenko, K. Learning multi-level hierarchies with hindsight. In International Conference on Learning Representations, 2019.

Li, S., Zheng, L., Wang, J., and Zhang, C. Learning subgoal representations with slow dynamics. In International Conference on Learning Representations, 2021.

Nachum, O., Gu, S., Lee, H., and Levine, S. Data-efficient hierarchical reinforcement learning. In Advances in Neural Information Processing Systems, pp. 3307–3317, 2018.

Nair, A., Pong, V., Dalal, M., Bahl, S., Lin, S., and Levine, S. Visual reinforcement learning with imagined goals. In Advances in Neural Information Processing Systems, pp. 9209–9220, 2018.

Ren, Z., Dong, K., Zhou, Y., Liu, Q., and Peng, J. Exploration via hindsight goal generation. In Advances in Neural Information Processing Systems, pp. 13464–13474, 2019.

Schmidhuber, J. and Wawnsiedler, R. Planning simple trajectories using neural subgoal generators. In From Animals to Animats 2: Proceedings of the Second International Conference on Simulation of Adaptive Behavior, volume 2, pp. 196. MIT Press, 1993.

Sharma, A., Gu, S., Levine, S., Kumar, V., and Hausman, K. Dynamics-aware unsupervised discovery of skills. In International Conference on Learning Representations, 2020.

Vezhnevets, A. S., Osindero, S., Schaul, T., Heess, N., Jaderberg, M., Silver, D., and Kavukcuoglu, K. Feudal networks for hierarchical reinforcement learning. In International Conference on Machine Learning, pp. 3540–3549. PMLR, 2017.

Wang, R., Yu, R., An, B., and Rabinovich, Z. I2hrl: Interactive influence-based hierarchical reinforcement learning. In International Joint Conference on Artificial Intelligence, pp. 3131–3138, 2020.

Zhang, T., Guo, S., Tan, T., Hu, X., and Chen, F. Generating adjacency-constrained subgoals in hierarchical reinforcement learning. In Advances in Neural Information Processing Systems, 2020.
APPENDIX

Environments:

1. **Ant Maze**: This environment is a ‘⊃’-shaped maze poses a challenging navigation task for a quadruped-Ant. The ant needs to reach a goal position starting from a random position in a maze with dense rewards. It has a size of $24 \times 24$, with a continuous state space including the current position and velocity, the current time step $t$, and the goal location. During training, a random position is sampled as the target for each episode, and at each time step the agent receives a dense reward according to its negative Euclidean distance from the goal position. The success is defined as being within an Euclidean distance of 5 from the goal. At evaluation stage, the goal position is set to (0, 16). Each episode ends at 500 time steps. The environmental reward is scaled by 0.1 equally for all methods.

2. **Ant Maze Sparse**: This environment has the same state and action spaces as the Ant Maze task with a size $20 \times 20$. The goal position is set at the position (2.0, 9.0) in the center corridor. The agent is randomly placed in the maze except at the target position and it is rewarded by +1 only if it reaches the goal, which is defined as having a Euclidean distance that is smaller than 1 from the goal. Each episode is terminated if the agent reaches the goal or after 500 steps.

3. **Ant Gather**: As defined by the standard Gather environment (Duan et al., 2016), this environment has a size of $20 \times 20$, with a continuous state space including the current position and velocity, the current time step $t$, and the depth readings. The ant robot is pre-defined by Rllab, with an 8-dimensional continuous action space, which is spawned at the center of the map and needs to gather apples while avoiding bombs. Both apples and bombs are randomly placed in the environment at the beginning of each episode. The agent receives a positive reward of +1 for each apple and a negative reward of -1 for each bomb. Each episode terminates at 500 time steps.

4. **Ant Push**: As defined by (Nachum et al., 2018), in this environment immovable blocks are placed everywhere except at (0, 0), (-8, 8), (0, 8), (8, 8), (16, 8), and (0, 16). A movable block is placed at (0, 8). The agent is initialized at position (0, 0). At each episode, the target position is fixed to (0, 19). The agent must first move to the left, push the movable block to the right, and then navigate to the goal unimpeded. At evaluation stage, the goal position is set to (0, 19). The “success” is defined as being within an Euclidean distance of 5 from the goal.

5. **Ant Fall**: In this task, the agent is initialized on a platform of height 4. Immovable blocks are placed everywhere except at (-8, 0), (0, 0), (-8, 8), (0, 8), (-8, 16), (0, 16), (-8, 24), (0, 24). The raised platform is absent in the region $[-4, 12] \times [12, 20]$. A movable block is placed at (8, 8). The agent is initialized at position (0, 0, 4.5). At each episode, the target position is fixed to (0, 27, 4.5). In order to cross the chasm, the agent must first push the movable block into the chasm and walk on top of it before navigating to the target. At evaluation stage, the goal position is set to (0, 27, 4.5). The “success” is defined as being within an Euclidean distance of 5 from the goal.

**Implementation**: For the two-layer hierarchical policy network, we employ the same architecture as HRAC (Zhang et al., 2020) which adopts TD3 (Fujimoto et al., 2018) as the underlying algorithm for training both the high-level and low-level policy. Specifically, we adopt two networks comprising three fully-connected layers with ReLU nonlinearities as the actor and critic networks of both low-level and high-level TD3 networks. The output of the high-level actor is activated using the tanh function and scaled according to the size of the environments.

The subgoal generator network has the identical architecture as the high-level actor. For the subgoal discriminator network, we use a network consisting of two hidden layers (size of 300) with Leaky-ReLU (negative slope 0.2) nonlinearities and sigmoid function in all tasks. Adam optimizer is used for all networks. We provide further implementation details used for our experiments in Table 1.
| Module          | Parameter                                      | Value                      |
|-----------------|------------------------------------------------|----------------------------|
| Adversarial Learning | Number of hidden layers, discriminator network | 2                          |
|                 | Number of hidden units per layer, discriminator network | [64, 16]                   |
|                 | Nonlinearity, discriminator network             | Leaky ReLU (0.2)           |
|                 | Optimizer                                       | Adam                       |
|                 | Learning rate                                   | $2 \times 10^{-4}$         |
|                 | Coefficient of adversarial loss                  | $10^{-3}$                  |
| Two-layer HRL   | Number of hidden layers, actor/critic networks  | 2                          |
|                 | Number of hidden units per layer, actor/critic networks | 300                        |
|                 | Nonlinearity, actor/critic networks             | ReLU                       |
|                 | Optimizer                                       | Adam                       |
|                 | Learning rate, actor                            | $10^{-4}$                  |
|                 | Learning rate, critic                           | $10^{-3}$                  |
|                 | Batch size, high level                          | 64                         |
|                 | Batch size, low level                           | 128                        |
|                 | Replay buffer size                              | $2 \times 10^{5}$          |
|                 | Random time steps                               | $5 \times 10^{6}$          |
|                 | Subgoal frequency                               | 10                         |
|                 | Reward scaling, high level                      | 0.1                        |
|                 | Reward scaling, low level                       | 1.0                        |

Table 1: Network architecture and key hyperparameters of AGILE