Adversarially Guided Subgoal Generation for Hierarchical Reinforcement Learning

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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 training in HRL often suffers from the problem of non-stationary high-level decision making 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 can be 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 significantly improves learning efficiency and overall performance of HRL 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 large scale multi-level reasoning problems with long-term credit assignment and sparse rewards. Among the prevailing HRL paradigms, the goal-conditioned HRL framework (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 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 the incompatible high-level actions \textit{i.e.}, subgoals. 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 ap-
proximating an optimal high-level policy under stationary data distribution. Consequently the increasing divergence between the distribution of current subgoals and relabeled subgoals is the key indicator 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) \( M = \langle S, A, \mathcal{P}, \mathcal{R}, \gamma \rangle \), where \( S \) is a state space, \( A \) is an action set, \( \mathcal{P} : S \times A \times S \rightarrow [0, 1] \) is a state transition function, \( \mathcal{R} : S \times A \rightarrow \mathbb{R} \) 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 \( \pi : S \rightarrow A \). The objective of the agent is to maximize the expected cumulative discounted reward \( \mathbb{E}_\pi \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right] \).

2.1. Two-Layer HRL Framework

We adopt a continuous control RL setting, modeled as a finite-horizon, goal-conditioned MDP \( M = \langle S, G, A, \mathcal{P}, \mathcal{R}, \gamma \rangle \), 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 \( g_t \sim \pi_h(·|s_t) \in G \), 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 \( t \not\equiv 0 \) (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), 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 \( r_{h|t} \) defined as:

\[
    r_{h|t} = \sum_{i=t}^{t+k-1} r_{i|t}^e, \quad t = 0, 1, 2, \ldots
\]

where \( r_{i|t}^e \) 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 \( a_t \sim \pi_l(·|s_t, g_t) \in A \). To encourage the low-level policy to reach the subgoal \( g \), an intrinsic reward function measuring the subgoal-reaching performance is adopted \( r_t^l = -||s_t + g_t - s_{t+1}||_2 \).

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 \((s_t, g_t; \sum_{i=t}^{t+k-1} r_{i|t}^e, s_{t+k})\) 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 \( \pi_l(a_{t:t+k-1}|s_{t:t+k-1}, \tilde{g}_t) \).

3. Adversarially Guided Subgoal Generation

In this section, we present our Adversarially Guided subgoal generation for Hierarchical LEarning (AGILE), an adversarial learning approach to guiding the high-level policy generating feasible subgoals for low-level policy.

3.1. Adversarial Learning of High-Level Policy

The non-stationarity in HRL notoriously 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.

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 \( G(s; \theta_g) : s \rightarrow g \) and a subgoal discriminator network \( D(g; \theta_d) \rightarrow \{0, 1\} \). 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
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Figure 1: (a) The emergence of the non-stationarity problem: since the low-level policy has changed from \( \pi_t(\cdot | s, g) \) to \( \pi'_t(\cdot | s, g) \), a subgoal \( g_t \) generated by a certain high-level policy in the past may not yield the same low-level behavior given the current low-level policy and consequently renders the experience invalid for training. (b) Overview of AGILE: the high-level policy generates high-level actions \( \pi_l \) for each level in the HRL structure following HIRO (Nachum et al., 2018) and HRAC (Zhang et al., 2018) algorithms for each level in the HRL structure. In order to learn the distribution of the subgoal generator \( G(s; \theta_g) \) we adopt TD3 (Fujimoto et al., 2018). Thus the first objective of the subgoal generator is to maximize the expected return induced by a deterministic policy.

\[ V(s_t) = \sum_{k=1}^{t+k-1} r_{env} \cdot \pi_t(a_{t+k-1} | s_{t+k-1}, g_{t+k-1}) \]  

Combining terms defined in Eq. (2) and Eq. (4), the high-level actor \( \pi_l \) is learned by performing gradient update on parameter \( \theta_g \)

\[ \nabla_{\theta_g} J = E_{s \sim D}[\nabla_{\theta_g} G(s) \cdot \nabla_{\theta_g} Q_h(s, g)|_{g=G(s)}] \]

where \( \alpha_{adv} \) is a hyperparameter to weight the adversarial loss.

The subgoal discriminator is learned by updating \( \theta_d \) with gradient

\[ \nabla_{\theta_d} J_{adv} = E_{s, g \sim D}[\nabla_{\theta_d} \log D(g) + \log(1 - D(G(s))]. \]

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...
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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.

Object manipulation. We also ablate the various components to understand their importance. Our experiments are designed to answer the following questions:

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.
Algorithm 1: Pseudo-Code for AGILE

**Input:** Higher-level actor $\pi^h_{\theta^h}$, lower-level actor $\pi^l_{\theta^l}$, sub-goal generator $G_{\theta^g}$, 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 $t \equiv 0 \pmod{k}$ then

Sample subgoal $g_t \sim \pi^h_{\theta^h}(g|s_t)$

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 $s_{t+1} \sim P(s|s_t, a_t)$

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 $\pi^h_{\theta^h}$ then

Sample experience $(s_t, \tilde{g}_t, \sum_{t'=t-k}^{t} r_{t'+1}, s_{t+k})$, where $\tilde{g}_t$ is relabeled subgoal

Obtain positive labels and subgoals $(L_P, g_P) \leftarrow$ (True, $\tilde{g}_t$)

Obtain negative labels and subgoals $(L_N, g_N) \leftarrow$ (False, $G_{\theta^g}(s_t)$)

Update $(G, D) \leftarrow$ adversarial training$(L, g)$ with Eq. 4 and Eq. 5

Update higher-level actor $\theta^h \leftarrow$ gradient ascent of $\mathbb{E}_{s_t \sim P(s)}[Q^h(s, g, \pi^h_{\theta^h}(g|s))]$

Update higher-level critic $Q^h$ with experience

end if

Update lower-level actor $\pi^l_{\theta^l}$ and critic $Q^l$ with experience

end for

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.

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.

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 learns the subgoal representation by posing a slowness objective.

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 AG-
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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 $\alpha_{\text{adv}}$, averaged over 5 independent trials.

ILE. 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
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.

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 & Wahnssiedler, 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, besides 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

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1 We use the LESSON’s official implementation [https://github.com/SiyuanLee/LESSON](https://github.com/SiyuanLee/LESSON) which comprises environments Ant Maze, Ant Push and Ant Fall.
(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.

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A. 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 24×24, 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 20×20. 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 20×20, 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 a 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.

B. 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