Data-Efficient Hierarchical Reinforcement Learning

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OUTLINE

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INTRODUCTION

- Deep reinforcement learning has performed well in areas with relatively small action and/or state spaces
  - Atari games
  - Go
  - Simple continuous control tasks
- When action and state spaces are both large and continuous, much work needs to be done

- If you told your robot maid to go pick up groceries for you, how would it do that?
- If it was a human maid, the task would be accomplished by breaking down the requirements necessary in order to complete the goal.
  - Top level: go to store, buy groceries, come back
  - Breakdown of “go to store”: leave house, walk down street, enter store
  - Breakdown of “leave house”: walk to front door, open door, walk through door, lock door
  - Breakdown of “walk to front door”: basic motor actions which aren’t consciously processed

Hierarchical Reinforcement Learning

- This is an inherently hierarchical method of accomplishing tasks
- Hierarchical Reinforcement Learning (HRL) is the area of RL which focuses on trying to bring the benefits of hierarchical reasoning to RL
- In HRL, multiple layers of policies are learned, where higher level policies act over which lower level policies to run at some moment
- There are many presumed benefits to this:
  - Temporal and behavioral abstraction
  - Much smaller action spaces for higher level policies
  - More reliable credit assignment

HIRO: Hierarchical Reinforcement learning with Off-policy correction

- 2-layer design
- Uses a high-level policy to select goals for a low-level policy
- Provides low-level policy with a goal to try to achieve (specified as a state observation)
- Uses off-policy training with a correction in order to increase efficiency

BACKGROUND

Off-policy Temporal Difference Learning

- The main learning algorithm used is TD3, a variant of DDPG
- DDPG
  - Q-function Q_θ, parameterized by θ
    - Trained to minimize $E(s_t,a_t,s_{t+1}) = \left(Q_\theta(s_t,a_t) - R_t - \gamma Q_\theta\left(s_{t+1},\mu_\varphi(s_{t+1})\right)\right)^2$
  - Deterministic policy μ_φ, parameterized by φ
    - Trained to maximize $Q_\theta\left(s_t,\mu_\varphi(s_t)\right)$, over all s_t
- Behaviour policy used to collect experience is augmented with Gaussian noise
  - Helpful for off-policy correction

MAIN CONTRIBUTIONS

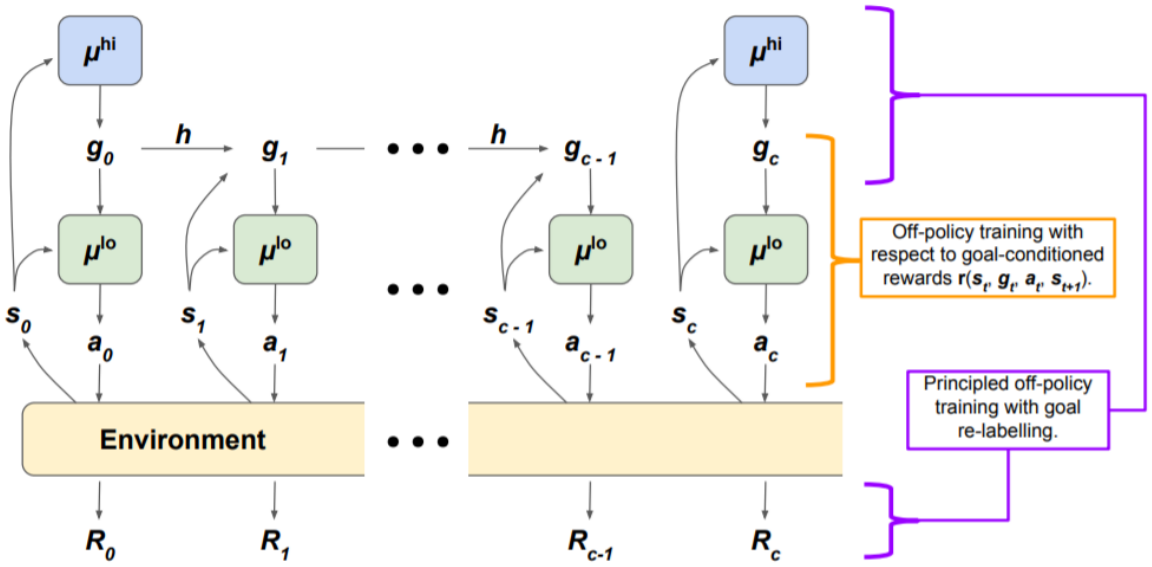
Hierarchy of Two Policies

- High-level policy μ^{hi} and low-level policy μ^{lo}
- μ^{hi} observes state and produces a high-level action (a goal state) $g_t \in R^{d_s}$
  - Every c steps, sample a new goal: $g_t \sim \mu^{hi}$
  - Otherwise, use a transition function, $g_t = h(s_{t-1}, g_{t-1}, s_t)$
- μ^{lo} observes s_t and g_t and produces a low-level action $a_t \sim \mu^{lo}(s_t, g_t)$
- Environment yields reward R_t
- Low-level policy receives intrinsic reward $r_t = r(s_t, g_t, a_t, s_{t+1})$
  - r is a fixed parameterized reward function
- Low-level policy stores the experience $\left(s_t, g_t, a_t, r_t, s_{t+1}, h(s_{t-1}, g_{t-1}, s_t)\right)$ for off-policy training
- High-level policy stores the experience $(s_{t:t+c-1}, g_{t:t+c-1}, a_{t:t+c-1}, R_{t:t+c-1}, s_{t+c})$ for off-policy training

Parameterized Rewards

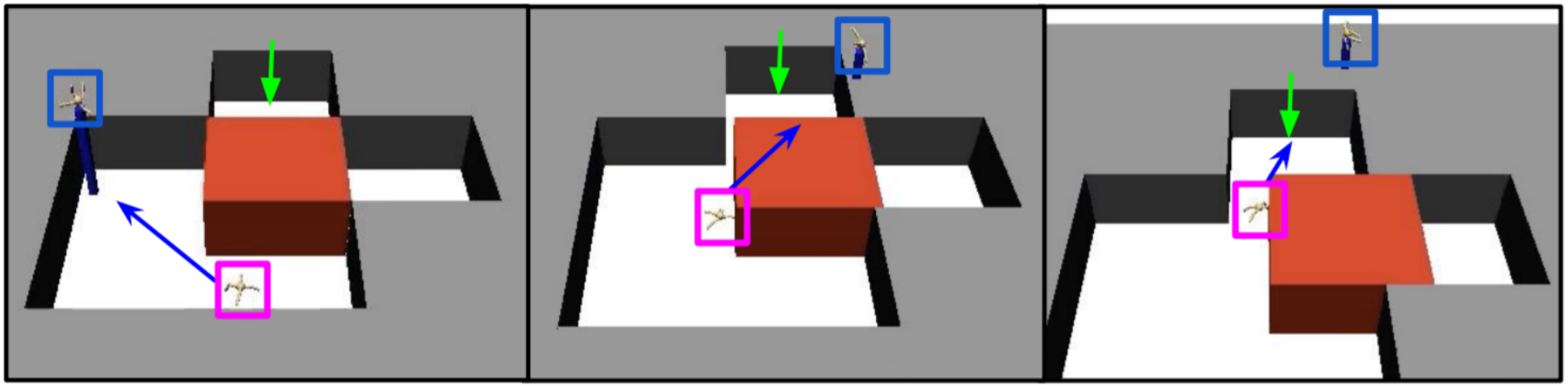
- Goal g_t is specified as the difference between current state s_t and desired state $s_t + g_t$
- Simple goal transition model could be $h(s_t, g_t, s_{t+1}) = s_t + g_t - s_{t+1}$
  - This leaves the desired goal constant as s_t changes
- Intrinsic reward is a parameterized reward function based on Euclidean distance between the current observation and goal observation
  - $r(s_t, g_t, a_t, s_{t+1}) = -\|s_t + g_t - s_{t+1}\|_2$
- The low-level policy is trained with an input-space that includes s_t and g_t
- Intrinsic rewards allow the lower-level policy to receive dense relevant reward signals immediately, before any task-specific rewards are available

Basic Design



1. Collect experience $s_t, g_t, a_t, R_t, \ldots$.
2. Train μ^{lo} with experience transitions $(s_t, g_t, a_t, r_t, s_{t+1}, g_{t+1})$ using g_t as additional state observation and reward given by goal-conditioned function $r_t = r(s_t, g_t, a_t, s_{t+1}) = -||s_t + g_t - s_{t+1}||_2$.
3. Train μ^{hi} on temporally-extended experience $(s_t, \tilde{g}_t, \sum R_{t:t+c-1}, s_{t+c})$, where $\tilde{g}_t$ is re-labelled high-level action to maximize probability of past low-level actions $a_{t:t+c-1}$.
4. Repeat.

Two-Level HRL Example



Off-Policy Corrections for Higher-Level Training

- Previous two-level HRL algorithms use on-policy training
  - As low-level policy is trained, the high-level policy is trying to solve a non-stationary problem
  - Old off-policy experience may have different transitions for the same state and goal
- Off-policy algorithms generally have better sample efficiency than on-policy algorithms
- HIRO applies an off-policy correction factor during training
- Allows HIRO to take advantage of off-policy sample efficiency benefits

Off-Policy Corrections for Higher-Level Training

- Recall the higher-level policy experience $(s_{t:t+c-1}, g_{t:t+c-1}, a_{t:t+c-1}, R_{t:t+c-1}, s_{t+C})$
- Goal: convert to state-action-reward transitions $(s_t, g_t, \sum R_{t:t+c-1}, s_{t+C})$
- These can be pushed onto the replay buffer of any standard off-policy algorithm
- Problem: past instances of lower-level policies will exhibit different behavior given the same goals g_t and end up in different states $s_{t+1:t+c}$

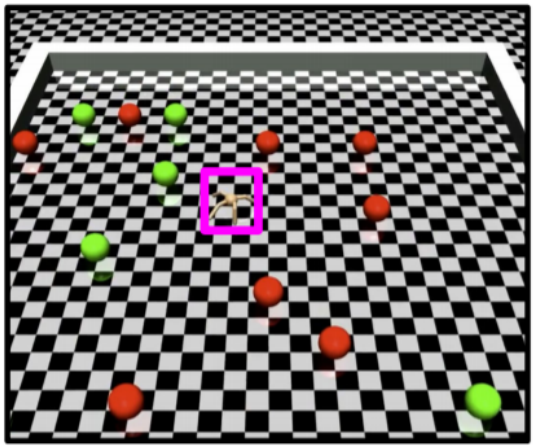
Off-Policy Corrections for Higher-Level Training

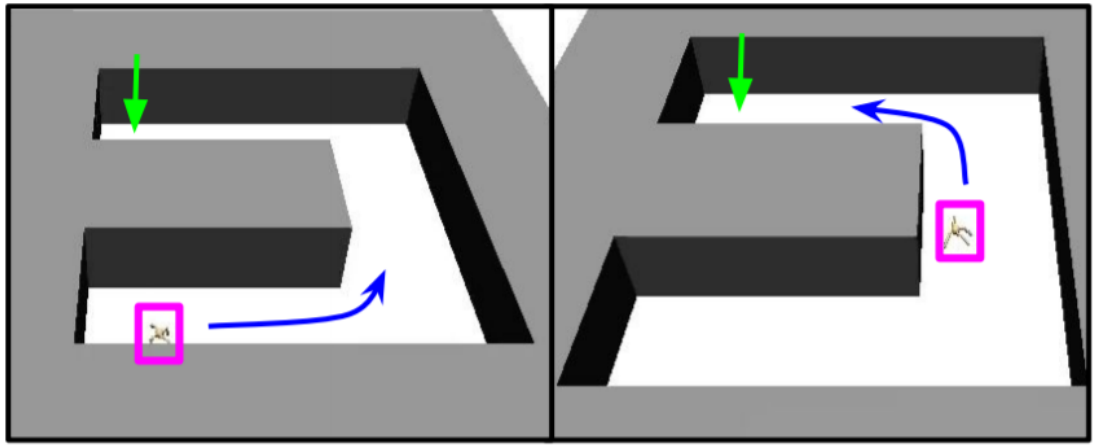
- Idea: change the g_t of past high-level policy experience in order to make the observed action sequence more likely with the current low-level policy
- In the past: $a_{t:t+c-1} \sim \mu^{lo}(s_{t:t+c-1}, g_{t:t+c-1})$
- Solution:
  - Find $\tilde{g}_t$ to maximize $\mu^{lo}(a_{t:t+c-1} | s_{t:t+c-1}, \tilde{g}_{t:t+c-1})$ for the current μ^{lo}
  - Relabel the high-level experience with $\tilde{g}_t$: $(s_t, \tilde{g}_t, \sum R_{t:t+c-1}, s_{t+c})$
- $log\left(\mu^{lo}(s_{t:t+c-1}, \tilde{g}_{t:t+c-1})\right) \propto -\frac{1}{2}\sum_{i=t}^{t+c-1} \left\| a_i - \mu^{lo}(s_i, \tilde{g}_i) \right\|_2^2 + constant$
- To approximately maximize this, 10 candidate goals are chosen:
  - 8 candidate goals are sampled from a Gaussian centered around $s_{t+c} - s_t$
  - Additionally, the original g_t and $s_{t+c} - s_t$ are candidates as well

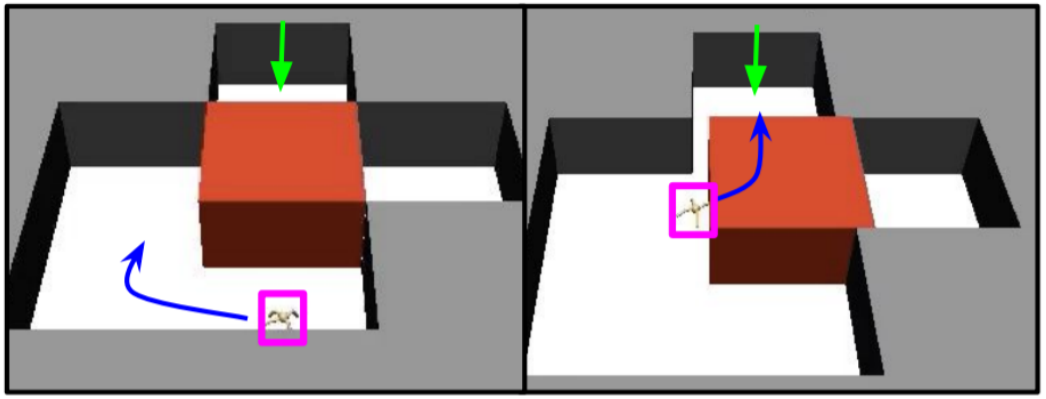
RELATED WORK

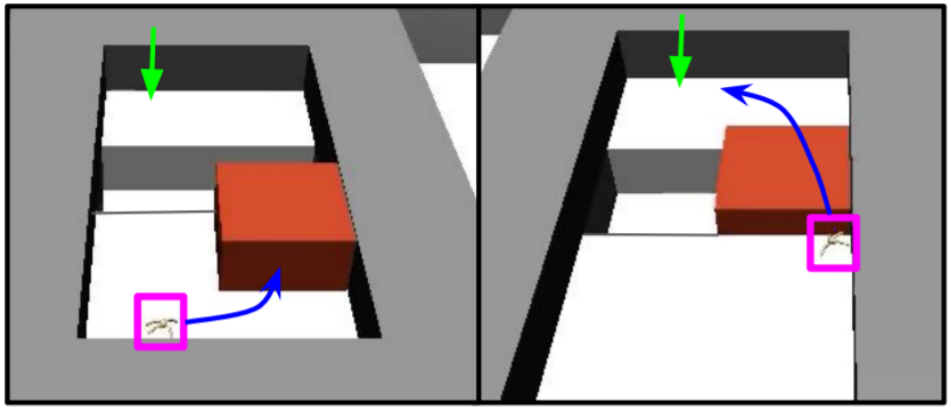
- To help learn useful lower-level policies, some recent work uses auxiliary rewards
  - Either hand-crafted rewards or exploration-encouraging rewards
  - HIRO uses a parameterized reward function
- To produce semantically distinct behavior, some recent work pretrain the lower-level policy on diverse tasks
  - This requires suitably similar tasks and is not general
- Hierarchical Actor-Critic uses off-policy training, but without the correction
- FeUdal Networks also use goals and parameterized lower-level rewards
  - Goals and rewards are computed in terms of a learned state representation, not directly
  - HIRO uses raw goal and state representations, so it can immediately train on intrinsic rewards

EXPERIMENTS





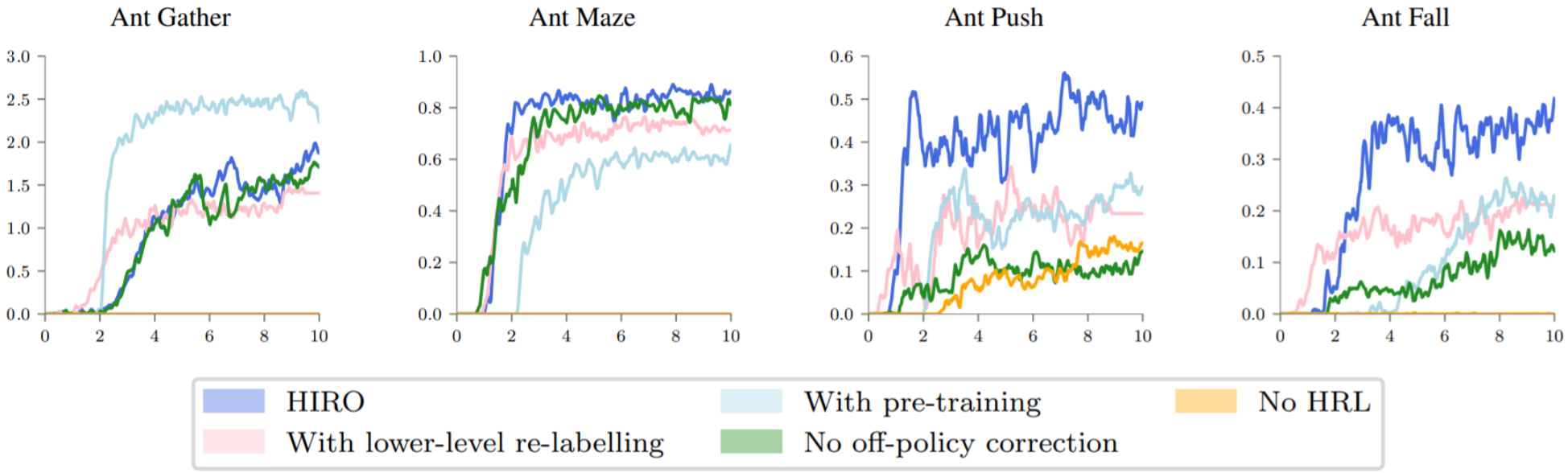




Comparative Analysis

	Ant Gather	Ant Maze	Ant Push	Ant Fall
HIRO	**3.02±1.49**	**0.99±0.01**	**0.92±0.04**	**0.66±0.07**
FuN representation	0.03 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
FuN transition PG	0.41 ± 0.06	0.0 ± 0.0	0.56 ± 0.39	0.01 ± 0.02
FuN cos similarity	0.85 ± 1.17	0.16 ± 0.33	0.06 ± 0.17	0.07 ± 0.22
FuN	0.01 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
SNN4HRL	1.92 ± 0.52	0.0 ± 0.0	0.02 ± 0.01	0.0 ± 0.0
VIME	1.42 ± 0.90	0.0 ± 0.0	0.02 ± 0.02	0.0 ± 0.0

Ablative Analysis



CONCLUSION

Summary of Main Contributions

- A general approach for training a two-layer HRL algorithm
- Goals specified in terms of a difference between desired state and current state
- Lower-level policy is trained with parameterized rewards
- Both policies are trained concurrently in an off-policy manner
  - Leads to high sample-efficiency
- Off-policy correction allows for the use of past experience for training the higher-level policy

Future Work

- The algorithm was evaluated on fairly simple tasks
  - State and action spaces were both low-dimensional
  - Environment was fully-observed
- Further work could be done to apply this algorithm or an improved version to harder tasks