Hierarchically Decoupled Imitation for Morphological Transfer

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Abstract

Learning long-range behaviors on complex high-dimensional agents is a fundamental problem in robot learning. For such tasks, we argue that transferring learned information from a morphologically simpler agent can massively improve the sample efficiency of a more complex one. To this end, we propose a hierarchical decoupling of policies into two parts: an independently learned low-level policy and a transferable high-level policy. To remedy poor transfer performance due to mismatch in morphologies, we contribute two key ideas. First, we show that incentivizing a complex agent’s low-level to imitate a simpler agent’s low-level significantly improves zero-shot high-level transfer. Second, we show that KL-regularized training of the high level stabilizes learning and prevents mode-collapse. Finally, on a suite of publicly released navigation and manipulation environments, we demonstrate the applicability of hierarchical transfer on long-range tasks across morphologies.

1. Introduction

How should one use Reinforcement Learning (RL) to train their new four-legged walking robot? Training a robot from scratch is often infeasible as current RL algorithms typically require millions (Schulman et al., 2017; Haarnoja et al., 2018) to billions (Baker et al., 2019) of samples. Moreover, robots are expensive and slow, which further limits the applicability of learning from scratch. Because of this, tackling the challenge of high sample complexity has received significant interest and prompted a wide array of solutions ranging from off-policy learning (Lillicrap et al., 2015) to temporal abstractions in learning (Kulkarni et al., 2016).

A primary reason behind RL’s sample inefficiency is the lack of prior knowledge used in training new policies. One of the biggest takeaways from advances in computer vision (CV) and natural language processing (NLP) is that priors (both architectural and parametric) are invaluable. Hence this begs the question: why should an agent learn a task from scratch? Why not use strong priors? Recent works have shown the promise of semantic priors such as auxiliary losses (Jaderberg et al., 2016), and architectural priors such as transfer learning networks (Rusu et al., 2016). However unlike passive domains such as object detection, problems in motor control and robotics offer another strong prior: morphology. Instead of learning policies from scratch on a given agent, we can use policies previously learned on morphologically different agents as a prior. For example, instead of training a quadruped walking policy to solve a maze from scratch, requiring millions of expensive samples, we could transfer-learn from a much simpler robot, say a Roomba wheeled robot. This morphological transfer affords two benefits: first, learning a policy first on a simple morphology and then transferring to a harder one induces a natural curriculum for learning (Bengio et al., 2009) which provides richer rewards and learning signal; second, this allows us to use fewer samples from complex robots that are often expensive and time-consuming.

But how do we effectively transfer policies across morphologies? Direct policy transfer is infeasible, since different morphologies have different state and action spaces (see Figure 1 for examples of morphologies). Another option would be to use morphological latent embeddings (Chen et al., 2018;
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Pathak et al., 2019), but learning robust embeddings requires training across hundreds of morphologies. Instead, inspired by recent advances in hierarchical learning (Kulkarni et al., 2016; Nachum et al., 2018b), we propose a transfer learning framework using hierarchically decoupled policies. In this framework, the low-level policy is trained specific to a given morphology, while the high-level policy can be re-used across morphologies. For compatible transfer, only the high-level policy, operating on a global agent state is transferred, while the low-level policy is independently learned.

However, as recent work by Nachum et al. (2018a) has shown, high-level policies are intricately tied with low-level policies. Intuitively, if a low-level policy isn’t able to reach a specific sub-goal requested by the high-level policy, the high-level policy will not select that sub-goal. This brings a significant challenge to morphological transfer for agents. Since the low-levels of two agents might be significantly different due to differences in morphology that afford varying low-level capabilities, a zero-shot transfer of the high-level policy might not always be successful. To counter this, we propose a top-down alignment of the low-level policies. This is done by introducing a information theoretic alignment loss that minimizes the mutual information between morphologies and low-level behaviors. This objective is practically optimized using discriminative learning, which allows the low-level policy of a more complex agent to imitate the behavior of the simpler agent’s, making high-level transfer more successful.

Using this low-level alignment significantly improves the transfer of high-level policies. However, even with better alignment, zero-shot transfer of high-level policies will not be able to fully utilize the additional benefits of a complex morphology. One way to improve on this is to fine-tune (Girshick et al., 2014) the high-level policies after the zero-shot transfer. But, in RL straightforward finetuning suffers from catastrophic forgetting (Rusu et al., 2016) of the simpler agent’s high-level. To prevent this, we take inspiration from prior work in transfer learning and introduce a KL-regularizer that allows the complex agent to improve performance while staying close to the simpler agent’s high-level. Intuitively, this balances the imitation of the simpler agent’s high-level with its own ability to solve the task. Doing this significantly improves performance on a suite of navigation and manipulation transfer tasks and approaches comparable performance to training from scratch with only a third the number of samples.

In summary, we present the following contributions in this work: (a) we show how hierarchical policies can help morphological transfer. Although recent works in Hierarchical Reinforcement Learning (Peng et al., 2017; 2019) allude to the potential of morphological transfer, to our knowledge we are the first work that concretely focuses on this problem. (b) We propose two key technical insights for hierarchical imitation, a top-down low-level alignment and a KL-regularized high-level objective to accelerate transfer. (c) Finally, we empirically demonstrate significant improvements in performance of morphological transfer on long-horizon navigation and manipulation tasks.

2. Background

Before we describe our framework, we first discuss relevant background on RL. For an in-depth survey, we refer the reader to (Sutton et al., 1998; Kaelbling et al., 1996).

2.1. Reinforcement learning

In our continuous-control RL setting, an agent receives a state observation $s_t \in \mathcal{S}$ from the environment and applies an action $a_t \in \mathcal{A}$ according to policy $\pi$. In our setting, where the policy is stochastic, we hence have $a_t \sim \pi(s_t)$. The environment returns a reward for every action $r_t$. The goal of the agent is to maximize expected cumulative discounted reward $\mathbb{E}_{s_0:T,a_0:T-1,r_0:T-1} \left[ \sum_{t=0}^{T-1} \gamma^t r_t \right]$ for discount factor $\gamma$ and horizon length $T$. On-policy RL (Schulman et al., 2015; Kakade, 2002; Williams, 1992) optimizes $\pi$ by iterating between data collection and policy updates. It hence requires new on-policy data every iteration, which is expensive to obtain. On the other hand, off-policy reinforcement learning retains past experiences in a replay buffer and is able to re-use past samples. Thus, in practice, off-policy algorithms have been found to achieve better sample efficiency (Lillicrap et al., 2015). For our experiments we use the off-policy SAC (Haarnoja et al., 2018) algorithm as our base RL optimizer due to its sample efficiency. However, we note that our framework is compatible with any standard RL algorithm.

2.2. Two-layered hierarchical RL (HRL)

The central idea of HRL is to abstract the policy $\pi$ into multiple policies that operate at temporally different levels. The most common abstraction is a two-level hierarchy (Nachum et al., 2018a), a low-level policy $\pi^{lo}$ and a high-level policy $\pi^{hi}$. In our formulation, the high-level takes as input a part of the state observation $s_t^{hi}$ and outputs morphology-independent high-level actions $a_t^{hi}$ that serve as subgoals for the low-level policy. These subgoals are morphology-independent and belong to a goal space $\mathcal{G}$. The low-level takes as input a part of the state observation $s_t^{lo}$ and the commanded subgoal $a_t^{hi}$, and outputs low-level control actions $a_t^{lo}$ to try and reach the subgoal. Note that we split the state observation $s_t$ into two components, $s_t^{hi}$ a global morphology-independent state and $s_t^{lo}$ a proprioceptive morphology dependent state. This particular choice of state, inspired from Marino et al. (2018), allows us to transfer...
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![Diagram with text](image)

**Figure 2.** We transfer Hierarchical policies across morphologies through decoupled imitation. For the low-level policy we use density based discriminative imitation detailed in Section 3.2, which improves zero-shot high-level transfer. For the high-level policy, we use KL-regularized imitation detailed in Section 3.3, which improves finetuning the high-level.

$$\pi^{hi}$$ across morphologies that have different state representations.

### 3. Method

In this work, we focus on the problem of transferring policies from one morphology to another for challenging long-horizon problems. Concretely, we define morphology transfer from morphology \(A\) to morphology \(B\) on a specific task as transferring a policy trained with \(A\) to \(B\), i.e., given access to a trained \(\pi_A\), what is the fastest way to train \(\pi_B\) (See Figure 2). Practically, \(A\) is a simple agent for which training \(\pi_A\) might be a lot easier (and safer) than training on a more complex agent \(\pi_B\). However, since \(A\) and \(B\) have different state and action spaces afforded by their morphologies, we build on top of the hierarchical setup described in Section 2.2. The hierarchical demarcation between low-level policies that act on proprioceptive states and high-level policies that act on global states provides a natural way to transfer high-level knowledge. Moreover, hierarchical learning is empirically known to provide massive improvements in sample-efficiency (Nachum et al., 2018). In the following subsections we detail our proposed technique.

### 3.1. Zero-shot high-level transfer

In the hierarchical setting, morphology transfer reduces to transferring \(\pi_A \equiv [\pi_A^{lo}, \pi_A^{hi}]\) trained on \(A\) to \(\pi_B \equiv [\pi_B^{lo}, \pi_B^{hi}]\). One straightforward way to perform transfer is to set \(\pi_A^{hi} \rightarrow \pi_B^{hi}\) as the input \(s^{hi}\) and output \(a^{hi}\) of the high-level policies are morphology-independent. The low-level policy \(\pi_B^{lo}\) can either be learned with the fixed high-level \(\pi_B^{hi}\) or trained independently. In our experiments, we pre-train the low-level policy \(\pi_B^{lo}\) on uniformly sampled goals from \(G\), allowing us to learn an effective \(\pi_B^{lo}\) without access to \(\pi_A\) and generalize over tasks without re-training \(\pi_B^{lo}\).

### 3.2. Low-level imitation through behavior alignment

Although directly transferring the high-level policy \(\pi_A^{hi} \rightarrow \pi_B^{hi}\) with independently trained low-levels \(\pi_B^{lo}\) allows for zero-shot morphology transfer, it suffers from low-level domain shift especially for tasks requiring precise control. This is because different morphologies afford different low-level behavior. Intuitively, if \(\pi_B^{lo}\) doesn’t generate similar behavior to \(\pi_A^{lo}\), transferring \(\pi_A^{hi} \rightarrow \pi_B^{hi}\) may not work since \(\pi_B^{lo}\) does not generate the behavior expected by \(\pi_B^{hi}\). To solve this problem, we align the low-level \(\pi_B^{lo}\) to \(\pi_A^{lo}\) on the set of goals \(G\). Note that direct cloning is not possible since the low-level state and action spaces are not the same. Additionally, simply ensuring both agents can reach the same portions of \(G\) used by \(\pi_A^{hi}\) is insufficient for strong alignment since goal-reaching behavior can differ while achieving the same goal (illustrated as low-level behavior in Figure 2).

To incentivize \(\pi_B^{lo}\) (parameterized by \(\theta_B^{lo}\)) to mimic the behavior of \(\pi_A^{lo}\), we propose minimizing the following mutual information objective:

$$\min_{\theta_B^{lo}} I(\text{morphology}; \text{behavior})$$

Minimizing the mutual information between the morphology type \((M = \{A, B\})\) and the generated low-level behavior will result in a low-level policy \(\pi_B^{lo}\) whose behavior...
cannot be distinguished from \( \pi_A^{lo} \). To ensure that the behavior is compatible with both morphologies \( A \) and \( B \), we set behavior at time \( t \) as \( \tau_t = s_{hi}^{lo} \), where \( k \) is the horizon of behavior. Let \( T_r \) denote the distribution over behaviors \( \tau_r \).

As \( I(M; T_r) = H(M) - H(M|T_r) \) and \( H(M) \) cannot be controlled through \( \pi_B^{lo} \), our objective from equation 1 reduces to maximizing \( H(M|T_r) \). Here \( H(.) \) denotes entropy. Since the probability of agent selection \( p(M = m|B_t = b_t) \) cannot be readily estimated, we compute the variational bound, which reduces our objective to:

\[
\max \theta_B^{lo} \mathbb{E}_{m \sim M, \tau_r \sim T_r} [- \log q_\phi(M|\tau_r)]
\]  

(2)

Here \( q \) parameterized by \( \phi \) is effectively a binary classifier (or discriminator) that outputs the probability of the generated behavior coming from morphology \( m \) given input behavior \( \tau_r \). Complete derivations of equation 2 can be found in the Appendix. Maximizing this objective through \( \theta_B^{lo} \) implies generating behaviors that maximally confuse the discriminator. To do this we augment the low-level policy rewards as follows:

\[
r_B^{lo} \leftarrow R(\tau_B^t|g) - \lambda_0 \log q_\phi(M = B|\tau_B^t)
\]

(3)

Here \( \lambda_0 \) and \( \lambda_1 \) represent temperature parameters that anneals the rewards from the discriminator over time, \( \tau_B^t \) represents the trajectory generated by \( \pi_B^{lo} \) while trying to solve the subgoal \( g \), and \( R \) represents the sub-goal reward function. The training process is summarized in Algorithm 1. This procedure of fitting a discriminator and then re-optimizing the policy has a similar flavor to recent work in approximate inverse reinforcement learning (Ho & Ermon, 2016), where the discriminator represents the reward density function.

### 3.3. High-level imitation through KL-regularized training

In the previous section we discussed aligning the low-levels through density based imitation, which allows for better zero-shot transfer of the high-levels \( \pi_A^{hi} \rightarrow \pi_B^{hi} \). However, even with low-level alignment, if the morphologies afford different abilities, direct transfer of the high-level may not reach optimal behavior. One way to remedy this is to fine-tune the high-level \( \pi_B^{hi} \) after transferring from \( \pi_A^{hi} \), which already encodes knowledge required to solve the task. However, direct finetuning with RL often leads to catastrophic forgetting of the former policy \( \pi_A^{hi} \) as previously noted in Rajeswaran et al. (2017); Rusu et al. (2016). To alleviate this, we propose a KL-regularized finetuning that balances staying close to \( \pi_A^{hi} \) and exploiting task driven reward signals.

\[
\text{grad}_B^{hi} \leftarrow \text{grad}_B^{RL} + \alpha \nabla_{\theta_B^{hi}} \text{KL}(\pi_B^{hi}(a_B^{hi}|s_B^{hi}) || \pi_A^{hi}(a_A^{hi}|s_B^{hi}))
\]

(4)

Here, under the high-level trajectory \( \tau^{hi} \equiv (s^{hi}, a^{hi}) \) generated by \( \pi_B^{hi} \), the gradients for the parameters \( \theta_B^{hi} \) of \( \pi_B^{hi} \) is represented by \( \text{grad}_B^{hi} \). This has two terms, the first term \( \text{grad}_B^{hi} \) represents the gradients through the base RL optimizer. The second terms represents the behavior cloning gradient of imitating \( \pi_A^{hi} \), with \( a^{hi} \sim \pi_A^{hi} \). This additional imitation objective is a practical form of regularization that penalizes deviations from sub-goal sequences set by the existing high-level \( \pi_A^{hi} \). Additionally, the imitation loss forces the policy to remain near the portion of the state space in which \( \pi_A^{hi} \) was maximally performant, preventing the aforementioned phenomena of catastrophic forgetting.

### 4. Experiments

In this section we discuss empirical results on using hierarchically decoupled imitation for transferring policies across morphologies. Note that since there are no standard benchmarks for evaluating morphological transfer, we create an environment suite that will be publicly released. Using this experimental setup, we seek to answer the following questions. First, does hierarchical decoupling provide an effective natural framework for morphology transfer? Second, does discriminative imitation improve zero-shot performance of morphology transfer? Finally, does KL-regularized finetuning improve the performance of transferred policies over baseline methods?

#### 4.1. Experimental setup

To study morphological transfer for long-horizon tasks, we present a suite of environments with eight agents and four tasks for manipulation and navigation as illustrated in Fig-
We use SAC as our base RL optimizer, and re-purpose we only train low-level policies for each agent once; i.e. Ant (Duan et al., 2016), 3-Legged Ant, Quadruped (Tassa et al., 2018), and two tasks: Waypoint navigation and Maze navigation. However, unlike in Nachum et al. (2018a), our maze navigation task has a completely sparse reward, making the task much more difficult. All morphologies have vastly different action spaces. The simplest agent, the PointMass, has an action space of two dimensions while the most complex agent, the quadruped, has an action space of twelve dimensions. Across navigation tasks, the goal space is set to the \((x, y)\) of the agent’s torso. For the manipulation environments, we use four agents with varying degrees of freedom: PointMass, 2Link-Arm, 3Link-Arm, and 4Link-Arm adapted from the OpenAI Gym Reacher (Brockman et al., 2016) and two tasks: BlockPush (with variants based on goal location) and PegInsert. The goal space \(G\) for the manipulation tasks is the \((x, y)\) position of the end-effector. All of these environments are simulated on MuJoCo (Todorov et al., 2012) using the OpenAI Gym interface. Images of the environments can be found in Figure 3. More details of the environments and the agents are provided in the Appendix.

Figure 3. Visualization of all agents and tasks used in our environment suite.

4.2. Training details

We use SAC as our base RL optimizer, and re-purpose the open-source Stable Baselines (Hill et al., 2018) code-base for our methods. We first train low-level policies by sampling uniformly from the goal space of each task \(G\). In order to make our hierarchical framework applicable to any task or environment, we use reward functions for the low-level policies that are highly generalizable. For the navigation tasks, low-level reward is given by the weighted cosine between the vector of agent movement and vector to the goal \(g\). In all manipulation tasks, we use \(L_2\) distance between the end-effector and goal \(g\) with a sparse reward for being within \(\epsilon\) of \(g\). Across all tasks of the same type, we only train low-level policies for each agent once; i.e. the same low-level policies used for way-point navigation are used for the maze task. We ran all experiments across five random seeds, except for the high-level and high-level finetunings of the selected navigation tasks, where we ran ten random seeds.

When training policies for low-level imitation we collect data from the existing agent \(A\) in an off-policy manner. For every step agent \(B\), we add the transition \((s_i^B, s_{i+1}^B)\) from agent \(B\) along with a transition for agent \(A\) sampled from \(T_A\) to a circular buffer, maintaining class balance. During training, we only update the discriminator periodically by randomly sampling data from the buffer. In addition to annealing the weight of discriminator rewards as per equation 3, we also anneal the learning rate of the discriminator to zero, preventing over-fitting and allowing agent \(B\) to train against an increasingly stationary target. For KL-regularized finetuning, we directly incorporate a term for the KL-divergence between \(\pi_B^*\) and \(\pi_B^A\) into the policy optimizer loss. This is easily calculated as all of our policies are parameterized by diagonal gaussians. Just as with the discriminator, the KL-loss coefficient is annealed to zero during training as it is no longer needed once the transferred policy is stable. Additional training details including hyper-parameters set are included in the Appendix.

4.3. How well does zero-shot hierarchical transfer work?

We perform straightforward high-level transfer described in Section 3.1 across our task-morphology environment suite. In Table 1, we present a snapshot of the results when combining the high-level of an agent (column-wise) with a specific agent (row-wise). On relatively easy tasks like Waypoint, zero-shot transfer works well. For instance, on the Ant morphology, using a high-level learned on PointMass does not result in any performance degradation. Interestingly, the nearly ideal PointMass experiences a significant performance degradation when using a different high-level policy, indicating that high-level policies are indeed overfit to the morphology they are trained on. This is manifested further in the block push task where zero-shot performance deteriorates significantly. For example, when transferring the high-level form the PointMass to the 4Link Arm, performance drops by around 74%. The poor high-level transfer on harder environments and morphologies motivates the need for better transfer algorithms. Detailed experiments with all morphology transfers is presented in the Appendix due to constraints of space.
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| Waypt | PM HL | Ant HL | Ant3 HL | Block Push | PM HL | 3Link HL | 4Link HL | Insert | PM HL | 3Link HL | 4Link HL |
|-------|-------|--------|---------|------------|-------|----------|----------|--------|-------|----------|----------|
| PM LL | 1±3 ± 43 | 603 ± 54 | 716 ± 58 | PM Low | .99 ± .01 | .33 ± .18 | .26 ± .17 | PM Low | 1 ± 2 ± 6.0 ± 22 | 6 ± 22 |
| Ant LL | 483 ± 39 | 476 ± 19 | 473 ± 51 | 3Link LL | .17 ± .08 | .96 ± .02 | .49 ± .14 | 3Link LL | 1 ± 0.1 ± 6.0 ± 0.8 ± .18 |
| Ant3 LL | 489 ± 74 | 484 ± 72 | 499 ± 65 | 4Link LL | .24 ± .11 | .1 ± .05 | .89 ± .04 | 4Link LL | 1 ± 0.8 ± .18 | 9 ± .06 |

Table 1. Selected Zero-Shot performance results averaged across a hundred episodes per run. For all tasks except way-point navigation, values reported indicate the fraction of successes.

Figure 4. Learning curves for low-level policies with and without the discriminator. For the Ant Agent (left) the discriminator policy achieves slightly lower though comparable performance to the regular low-level, while the 3 and 4 Link arms (Right) learn slightly faster with discriminator supervision.

4.4. Does discriminative imitation improve transfer?

To improve zero shot high-level transfer, we perform discriminative imitation on the low-level policies as described in Section 3.2. Results are presented in Table 2 across a wide set of poorly performing plain high-level transfer. We measure the effectiveness of the discriminator by comparing zero-shot performance of the plain low-level and the low-level trained with a discriminator for a given high-level. Across nearly all tasks, discriminative imitation of the low-level improves zero-shot performance, especially in manipulation tasks. For example, transferring the PointMass high-level to the 3Link Arm is twice as successful across both block push tasks using our method. A substantial benefit of discriminative imitation is that the aligned low-level policy only needs to be trained once for transfer across any number of high-level policies, making it particularly useful when training the high-level policy is expensive or an increase in transfer performance is desired across a large set of tasks.

To verify that our agents are indeed learning to discriminate rather than just learning objectively better policies, we examine the low-level learning curves in Figure 4. Though for the arm agents the discriminator provides an extra form of supervision that speeds up learning, final rewards for all agents with the discriminator are at or below those of without, indicating that the performance benefits in Table 2 can indeed be attributed to imitation.

4.5. Does finetuning improve transfer?

After transferring the high-level policy from a simpler agent to a more complex one, we finetune it by retraining to improve performance. Results for this are visualized in Figure 6 and Figure 7. Finetuning clearly works better than learning the high-level from scratch (in green) and reaches substantially higher performance compared to the zero-shot high-level transfer (dotted purple line). However, in some cases regular finetuning suffers from unstable training. For instance in the transfer finetuning of 2Link Arm from Point-Mass on BlockPush, we see poor confidence bounds. Empirically, we notice massive fluctuations in training performance across seeds that cause this behavior, most likely explained by high-level policies shifting far out of distribution during morphology transfer, causing catastrophic forgetting of task-solving knowledge. This motivates the need for better transfer learning methods for finetuning.

4.6. How much does KL-regularized training help?

To improve performance during finetuning, we use KL-regularized imitation as described in Section 3.3. Empirically, we find that the addition of an imitation loss during high-level transfer substantially improves performance as seen in Figure 6 and Figure 7. On the BlockPush we notice at least a 2X speedup compared to already strong direct finetuning method. On the Maze environments, we again notice improvements in performance; however the gains are modest compared to the BlockPush environment. In all cases, the variance across runs is no worse than regular finetuning, and can drastically improve in select cases as seen in the 2 Link and 3 Link experiments in Figure 7. We additionally compare our KL-regularized finetuning method to training the high-level policy from scratch with a pretrained low-level and learning the task without hierarchy, denoted “Full”. Note that we make our comparisons with respect to the number of samples used in training. Learning without hierarchy was unsuccessful for the complex agents on navigation tasks, particularly the sparse-reward maze. Though it is cut off in the graphs, learning without hierarchy was successful for all the manipulation tasks.

4.7. In what cases does hierarchical transfer fail?

The aforementioned results demonstrate the significant promise of hierarchically decoupled transfer in scenarios where all agents can similarly cover the task state space. However, what happens if a more complex agent’s morphology endows it with additional abilities? In this specific context, hierarchical decoupling may not lead to a perfectly optimal transfer as the more complex agent may be able to reach new states other agents could not. To examine such
scenarios, we design a simple “step maze” task, with low barriers that an Ant could scale but a Point Mass could not. We then examine the trajectories of the Ant when its high-level is trained from scratch, finetuned from Point Mass, and zero-shot transfer from Point Mass in Figure 5. The Ant high-level trained from scratch learns to climb over the highest barrier while the zero-shot trajectory mostly avoids the barriers just as the Point Mass would. By finetuning, the Ant agent moves closer to the policy learned from scratch climbing the lower barrier, but remains somewhat tied to its prior and less consistently climbs the high barrier.

5. Related Work

Our work is inspired by and builds on top of a broad range of topics, including transfer learning, morphological transfer, imitation learning, and information theoretic RL. In this section, we overview the most relevant ones.

5.1. Multi-task and transfer learning

Learning models that can share information across tasks has been concretely studied in the context of multi-task learning (Caruana, 1997), where models for multiple tasks are simultaneously learned. More recently, Kokkinos (2017); Doersch & Zisserman (2017) looks at shared learning across visual tasks, Pinto & Gupta (2017) looks at shared learning across robotic tasks, and Pathak et al. (2019) looks at message passing for low-level control of articulated agents. In contrast to multi-task learning where knowledge is simultaneously learned, we focus on the disparate setting in which knowledge from one task (a simpler agent) is transferred to another (a more complex agent). More relevant to our work, Chen et al. (2018) focuses on transfer across different hardware by training hardware conditioned embeddings across a large number of morphologies. However, access to more than two or three morphologies is unrealistic in practice. Our method is best suited for these scenarios.

Transfer learning (Pan & Yang, 2009; Torrey & Shavlik, 2010) focuses on transferring knowledge from one domain to another. One of the simplest forms of transfer is finetuning (Girshick et al., 2014), where models are initialized on different tasks. Several other works look at more complex forms of transfer (Yang et al., 2007; Hoffman et al., 2014; Aytar & Zisserman, 2011; Saenko et al., 2010; Kulis et al., 2011; Fernando et al., 2013; Gopalan et al., 2011; Jhuo et al., 2012). The most relevant to our work is Tzeng et al. (2017), where a discriminator is used to align intermediate features across domains. Similar in spirit, in our proposed low-level alignment through density imitation, we use a discriminator to align the behavior of low-level policies across morphologies.

In the context of RL, transfer learning (Taylor & Stone, 2009) research has focused on learning transferable features across tasks (Parisotto et al., 2015; Barreto et al., 2017; Omidshafiei et al., 2017). Another line of work by (Rusu et al., 2016; Kansky et al., 2017; Devin et al., 2017) has focused on network architectures that improves transfer of RL policies. Since the focus of our work is on transfer across morphologies, we note that the aforementioned works are orthogonal and complementary to ours.

5.2. Hierarchical Reinforcement Learning

HRL based techniques (Barto & Mahadevan, 2003; Bacon et al., 2017; Li et al., 2019a) have been able to solve complex or long-horizon tasks through temporal abstraction across hierarchies as seen in Levy et al. (2017) and Nachum et al. (2018a). In a similar vein, several works have focused on the discovery of primitives (Eysenbach et al., 2018; Sharma et al., 2019; Shankar et al., 2020), which are useful for hierarchical RL. These ideas have already been combined, as in Stochastic Neural Networks by Florensa et al. (2017), where skills are learned in pretraining and then used to solve diverse complex tasks. Similarly, Andreas et al. (2016) learn modular sub-policies to solve a temporally extended task.

These prior works inform our choice to use HRL as the

### Table 2.

| Task         | Waypoint Nav | Maze         | Block Push 1 | Block Push 2 |
|--------------|--------------|--------------|--------------|--------------|
| Transfer     | PM-Ant       | PM-Ant       | PM-3Link     | PM-3Link     |
| Zero-Shot    | 482.72 ± 38.96 | 0.3 ± 0.08  | 0.17 ± 0.08  | 0.24 ± 0.12  |
| Discrim (ours)| 546.06 ± 14.76 | 0.55 ± 0.12  | 0.34 ± 0.10  | 0.43 ± 0.12  |

Figure 5. Trajectories for the Ant agent on a “steps” environment for training the high-level from scratch, finetuning from Point Mass, and zero-shot transfer from Point Mass from left to right respectively. The dark blue (taller) and light blue (shorter) steps are reduced in height to allow the ant agent to climb over.
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Figure 6. Comparison of performance finetuning from PointMass for Ant Waypoint, 3-Legged Ant, Ant End-Maze, and Sampled Ant-Maze from left to right. During regular training of the maze task, we sample goals uniformly from the maze segments, however, we also assess the performance of transfer when only attempting to reach the end of the maze in the second plot from the right. Rewards below 200 are clipped. For Waypoint, the agent receives a reward of 100 per waypoint reached and for Maze, the agent receives a reward of 1000 for reaching the set goal. “Full” denotes that the policy was trained without hierarchy.

Figure 7. Visualization of finetuning performance for 2 Link, 3 Link, and 4 Link from left to right on the block push 1 task. Rewards below -10 are clipped. The agent receives a reward of 200 for completing the task successfully.

backbone of our framework. Moreover, hierarchical decoupling allows for a natural delineation of control (Wolpert & Kawato, 1998). However, we note that unlike standard hierarchical RL techniques, we train our low-level policies independent of the high-level policies. Although a few recent works have alluded to the potential of hierarchical policies for morphology transfer (Peng et al., 2017; Tirumala et al., 2019; Li et al., 2019b; Hu & Montana, 2019), to our knowledge we are the first to focus on this problem.

5.3. Imitation learning

The central contribution of this work is decoupled imitation learning for the low-level and high-level policies in a hierarchical setup. In the context of control, the field of learning from demonstrations (LfD) (Nicolescu & Mataric, 2003; Argall et al., 2009) learns to reproduce a set of demonstrated expert behavior. A popular technique called behavior cloning (Esmaili et al., 1995) focuses on fitting parametric models to expert demonstrations (Kober & Peters, 2009; Peters et al., 2013). Several works (Niekum et al., 2012; Krishnan et al., 2018; Murali et al., 2016; Meier et al., 2011) focus on segmenting demonstrations followed by fitting models to each of the segments. More recently, Rajeswaran et al. (2017) focus on regularizing the behavior cloning objective for dexterous hand manipulation. Inspired by this idea, we use a KL-regularized objective in the context of regularizing the high-level policy. Instead of imitation through cloning, inverse RL (Ng et al., 2000; Abbeel & Ng, 2004) focuses on recovering the underlying reward function from expert demonstrations. Ho & Ermon (2016) extends inverse RL to higher dimensional state-action demonstrations by learning a parametric expert density model through discriminative learning between expert demonstration and learned behavior. Following this technique, several works have extended this idea to third person demonstrations (Stadie et al., 2017) and stochastic demonstrations (Li et al., 2017). Solving the information theoretic formulation for low-level state alignment reduces to a similar discriminative learning approach. However, instead of differentiating between expert demonstrations and learned behavior, our discriminator differentiates between the simpler agent’s low-level behavior and the more complex agent’s low-level.

6. Conclusions

In this work, we have presented one of the first steps towards morphology transfer by using hierarchically decoupled imitation. This technique allows transferring complex long horizon behavior from morphologically simple agents to more complex ones in a fraction of sample complexity compared to standard RL techniques. Although this work focuses on simulated environments, we believe that this opens the door to research in morphological transfer on real robots.
Moreover, although our technique for decoupled imitation is presented in the context of morphological transfer, we believe that the technique is flexible enough to be applied to general purpose imitation learning.

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Appendix

A. Additional Derivations

Below is the full derivation of the objective used to motivate low-level discriminative imitation, taking inspiration from other work based on information theoretic objectives (Eysenbach et al., 2018). We start by minimizing the mutual information between morphology, \( M \) and behavior, \( T_t \). \( I \) denotes mutual information and \( H \) denotes entropy.

\[
\min_{\theta_{lo}} I(M; T_t) = \max_{\theta_{lo}} -I(M; T_t) \\
= \max_{\theta_{lo}} -(H(M) - H(M|T_t)) \\
= \max_{\theta_{lo}} H(M|T_t) - H(M) \\
= \max_{\theta_{lo}} H(M|T_t) \\
= \max_{\theta_{lo}} \mathbb{E}[-\log p(M|T_t)] \\
\geq \max_{\theta_{lo}} \mathbb{E}[-\log q_\phi(M|T_t)]
\]

As per the above derivation we can encourage similar behavior across agents by maximizing the entropy of the morphology given a behavior. In the fourth step we assume the distribution over morphologies is uniform, and subsequently the second term is a constant that can be omitted from the optimization. The final step applies the variational lower bound (Barber & Agakov, 2004).

B. Environment Details

Below are more complete specifications of the environments used in experiments.

**NAVIGATION**

For all navigation agents, the low-level reward is given by the weighted distance traveled towards the goal, with an action penalty term.

\[
r_{lo} = \frac{(s_{hi}^{t+1} - s_{hi}^{1}) \cdot (g_t - s_{hi}^{t-1})}{||g_t - s_{hi}^{t-1}||_2} - \lambda ||a_t||_2^2
\]

High-level actions are taken once every 32 steps, except on the quadruped agent where it is performed every 64. The high-level goal space is defined to be the desired change in \( x, y \) position of the agent’s center, limited by a distance of four meters in either direction.

**Agents:** All agents observe joint positions (qpos), velocities (qvel), and the vector to the next sub-goal. All agents besides the point mass additionally observe contact forces. All agents use torque control.

- **Point Mass:** A point mass agent whose actions are forces in the cardinal directions.
- **Gym Ant:** This is the Open AI Gym Ant agent with its gear reduced from 150 to 125. Note that this is less modification than the Ant agent in HiRO (Nachum et al., 2018a).
- **3 Leg Ant:** This agent is identical to the regular ant, except one of its legs is frozen in place.
- **2 Leg Ant:** Again identical to the Ant, except two diagonally opposed legs are frozen in place.
- **DM Control Quadruped:** The quadruped agent is similar to the Gym Ant, except it has an extra ankle joint on each of it’s legs, making controlling it different. We do not use the same control scheme as in DM Control, and instead give it the same observations as the Ant agent.

**Tasks:**

- **Way Point Navigation:** The agent is tasked with navigating through a plane and reaching specific waypoints. As soon as the agent reaches one waypoint, another waypoint is randomly placed. The agent receives a reward for its \( L_2 \)
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distance from the waypoint, and a sparse reward of 100 upon reaching the waypoint. The observation space is given by
the agent’s current position and the position of the waypoint. The high-level policy is trained with a horizon of 50
high-level steps.

- **Maze**: The agent must navigate through a ‘U’ shaped maze and reach the end. The agent only receives a sparse reward
  of 1000 upon reaching its final goal. During training, final goal locations are randomly sampled uniformly from the six
  “blocks” of the maze path, while in evaluation the final goal is always the end of the maze. The observation space is
given by just the agent’s current position and the position of the final goal.

- **Steps**: The agent has to navigate through a similarly shaped structure to that of the Maze, although only half the size.
The height of the taller step is 0.3125 meters, while the height of the shorter step is 0.15625 meters. When the Ant agent
is used for the step environment, it is given 16 rangefinder sensors and it’s low level is pretrained on an environment
with randomly placed steps.

**Manipulation**

For all manipulation tasks, low-level rewards are given by $L^2$ distance to the selected sub-goal and an additional sparse
reward.

$$r_{lo} = -||g_t - s_t^{hi}||_2 - \lambda ||a_t||^2_2 + \gamma 1\{g_t - f(s_t) < \epsilon\}$$

High-level planning is performed every 35 steps. Again, all agents use torque control.

**Agents:**

- **Point Mass**: Identical to the previous point mass, just scaled to fit the environment.

- **2-Link Arm**: This is the standard reacher from the Open AI Gym set of environments, with end effector collisions
  enabled.

- **3-Link Arm**: A modified version of the standard 2-Link reacher with one extra degree of freedom. Each link is
  approximately one third the length of the arm.

- **4-Link Arm**: A modified version of the standard 2-Link arm, created by splitting each link evenly into two more links.

**Tasks:**

- **Block Push**: The arm agent has to push a block across the environment to a target end position. We test on variations of
difficulty based on block position. Here, high-level observations include the position of the end effector and the position
and velocity of the block. high-level rewards correspond to negative $L^2$ distance of the block to its goal position and
a sparse reward of 200 for solving the task. The high-level goal space is defined to be the desired change in the $x, y$
position of the agent’s end effector, limited by a distance of 0.07 meters in either direction. We have two different
variants of the block push task, **Block Push 1**, where the block must be pushed just horizontally, and **Block Push 2**, where
the block must be pushed a shorter distance, but horizontally and vertically.

- **Peg Insertion**: The agent now has a peg attached to it’s end effector that it must insert into a hole. high-level observations
include the position of the tip of the peg and the position of the end effector. high-level rewards correspond to negative
$L^2$ distance from the final desired insertion point and a sparse reward of 50 for solving the task. For peg insertion, the
high-level goal space is given from the end of peg.

**C. Training Details**

When training low-level policies, we only reset environment occasionally after selecting a new low-level goal to allow the
agent to learn how to perform well in long-horizon settings. Low level policies are trained over longer horizons than the
exact number of steps in between high level actions. For high-level training on top of pre-trained low-levels, we collect
samples only when the high-level policy sets a new sub-goal. We include hyper-parameters for all low level training in Table
3 and hyperparameters for all high level training in Table 4.

When training the discriminator for low level imitation, we anneal the learning rate linearly from its initial value to zero over
the first “stop” fraction of training timesteps. This allows the agent to learn against an increasingly fixed target. Additionally,
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Table 3. Hyperparameters for low level policy training. “DM” stands for goal delta max, or the size of the goal space in each dimension sampled from during training.

| Agent       | Timesteps | Learning Rate | Batch Size | Layers | Horizon | Reset Prob | Buffer Size | DM  |
|-------------|-----------|---------------|------------|--------|---------|------------|-------------|-----|
| PM (Nav)    | 2000000   | 0.0003        | 64         | 64 64  | 35      | 0.1        | 200000     | 4   |
| Ant(s)      | 2500000   | 0.0008        | 100        | 400 300| 100     | 0.1        | 1000000    | 4   |
| Quadrupede  | 2500000   | 0.0008        | 100        | 400 300| 150     | 0.1        | 1000000    | 4   |
| Manipulation| 1200000   | 0.0003        | 100        | 128 96 | 45      | 0.25       | 250000     | 0.07|

Table 4. Hyperparameters for high level policy training.

| Task       | Timesteps | Learning Rate | Batch Size | Layers | Horizon | Buffer Size |
|------------|-----------|---------------|------------|--------|---------|-------------|
| Waypoint   | 200000    | 0.0003        | 64         | 64 64  | 50      | 50000       |
| Maze       | 400000    | 0.0003        | 64         | 64 64  | 100     | 50000       |
| Block Push | 500000    | 0.0003        | 64         | 64 64  | 60      | 50000       |
| Insert     | 500000    | 0.0003        | 64         | 64 64  | 50      | 50000       |

we anneal the discriminator weight in the reward function from it’s initial value to 0.1 linearly over the first 90% of training timesteps. Full parameters for the discriminators can be found in Table 5. Additionally, we tested online and offline data collection. In offline data collection, transitions are randomly sampled from agent A’s low level policy. In online data collection, we align the goals of the two agents, such that we collect transitions of agent A reaching goal g when agent B is attempting to reach the same g. The results presented in the main paper body are exclusively from offline data collection.

For KL-regularized fine-tuning, we use the same parameters across almost all experiments. We add the KL-divergence between Agent B’s policy and Agent A’s policy at every timestep. For the Waypoint task and all manipulation tasks, we use a KL weight coefficient of 1 in the loss, a learning rate of 0.01, and linearly anneal the weight of the KL loss to zero during the first 50% of training. For the Maze Task, we lowered the learning rate to 0.001 and the KL loss coefficient to 0.01. We performed a search over learning rates for regular fine-tuning, and found the original learning rate of the policy tended to perform best and as such used it for comparison.

D. Extended zero-shot results

Complete results for all zero-shot transfers for the navigation tasks can be found in Table 6 and Table 7. Table 6 contains results for the waypoint navigation task for two more agents: the Two-Leg Ant and the Quadrupede. Table 7 has results for zero-shot transfer on the Maze task, which was completely omitted from the main section of the paper due to space constraints.

For manipulation tasks, Table 8 gives zero-shot for the block push 1 task. The original zero-shot results given in Table 1 include the full results for all the insertion task.

E. Extended discriminative imitation results

Full results for the low-level imitation experiments can be found in Table 9 for navigation tasks transferring Point Mass to Ant and 10 for the manipulation block push tasks. We include results for both online and offline data collection for the discriminator. We find that in many cases offline data collection performs just as good or better than online data collection.

F. Resources

Our code can be found at https://github.com/jhejna/hierarchical_morphology_transfer and videos of our results can be found at https://sites.google.com/berkeley.edu/morphology-transfer.
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| Agent A | Learning Rate | Batch Size | Layers | Update Freq | Weight | Stop |
|---------|---------------|------------|--------|-------------|--------|------|
| Nav PM  | 0.0002        | 64         | 42     | 8           | 0.3    | 0.5  |
| PM, 2Link | 0.0003     | 64         | 42     | 8           | 0.4    | 0.5  |
| 3Link   | 0.0005        | 64         | 42     | 8           | 0.4    | 0.5  |

Table 5. Hyperparameters for discriminator training.

|            | Point Mass High | Ant High | Ant3 High | Ant2 High | Quadruped High |
|------------|----------------|----------|-----------|-----------|----------------|
| Point Mass Low | 1021.49 ± 43.25 | 602.56 ± 33.82 | 716.61 ± 58.12 | 593.18 ± 60.09 | 576.65 ± 69.6 |
| Ant Low    | 482.72 ± 38.96 | 476.42 ± 19.44 | 472.85 ± 50.68 | 417.59 ± 27.48 | 406.96 ± 35.63 |
| Ant3 Low   | 488.62 ± 74.35 | 483.59 ± 71.67 | 499.19 ± 64.99 | 471.24 ± 65.42 | 432.29 ± 64.59 |
| Ant2 Low   | 353.56 ± 39.33 | 371.11 ± 27.15 | 388.38 ± 31.56 | 420.81 ± 31.24 | 373.99 ± 34.52 |
| Quadruped Low | 169.43 ± 33    | 182.33 ± 21.55 | 219.57 ± 26.61 | 267.12 ± 18.95 | 257.13 ± 18.83 |

Table 6. Zero-Shot transfer for the way-point navigation task.

|            | Point Mass High | Ant High | PM High Sampled | Ant High Sampled |
|------------|----------------|----------|-----------------|-----------------|
| Point Mass Low | 0.80 ± 0.18    | 0.00 ± 0.00 | 0.96 ± 0.04    | 0.56 ± 0.04    |
| Ant Low    | 0.30 ± 0.08    | 0.16 ± 0.14 | 0.65 ± 0.04    | 0.5 ± 0.08     |
| Ant 3 Low  | 0.58 ± 0.13    | 0.12 ± 0.10 | 0.84 ± 0.04    | 0.56 ± 0.05    |
| Ant 2 Low  | 0.74 ± 0.17    | 0.14 ± 0.13 | 0.87 ± 0.09    | 0.60 ± 0.05    |

Table 7. Zero-Shot transfer for the maze task. Sampled indicates that goals were randomly sampled as during training, otherwise only the last goal at the end of the maze was used.

|            | PM high | 2 Link High | 3 Link High | 4 Link High |
|------------|---------|-------------|-------------|-------------|
| PM Low     | 0.99 ± 0.01 | 0.21 ± 0.15 | 0.33 ± 0.18 | 0.26 ± 0.17 |
| 2 Link Low | 0.36 ± 0.14 | 0.97 ± 0.02 | 0.22 ± 0.07 | 0.39 ± 0.11 |
| 3 Link Low | 0.17 ± 0.08 | 0.2 ± 0.09  | 0.96 ± 0.02 | 0.49 ± 0.14 |
| 4 Link Low | 0.24 ± 0.11 | 0.07 ± 0.04 | 0.1 ± 0.05  | 0.89 ± 0.04 |

Table 8. Zero-shot results for the block push 1 task.

| Task Transfer | Waypoint | Maze Sampled | Maze End |
|---------------|----------|--------------|----------|
| Zero-Shot     | 482.72 ± 38.96 | 0.3 ± 0.08   | 0.65 ± 0.04 |
| Discrim Offline | 467.22 ± 20.61 | 0.37 ± 0.1   | 0.63 ± 0.04 |
| Discrim Online | 546.06 ± 14.78 | 0.55 ± 0.13  | 0.72 ± 0.03 |

Table 9. Discriminative imitation zero-shot results for the Ant.

| Task Transfer | Block Push 1 | Block Push 2 |
|---------------|-------------|-------------|
| Zero-Shot     | PM-3Link 0.17 ± 0.05 | 3Link-4Link 0.24 ± 0.12 |
| Discrim Off   | PM-3Link 0.35 ± 0.13 | 3Link-4Link 0.43 ± 0.15 |
| Discrim On    | PM-3Link 0.34 ± 0.14 | 3Link-4Link 0.43 ± 0.12 |

Table 10. Discriminative imitation zero-shot results for various manipulation configurations.