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# Diversity is All You Need: Learning Skills without a Reward Function

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## Abstract

Intelligent creatures can explore their environments and learn useful skills without supervision. In this paper, we propose DIAYN (“Diversity is All You Need”), a method for learning useful skills without a reward function. Our proposed method learns skills by maximizing an information theoretic objective using a maximum entropy policy. On a variety of simulated robotic tasks, we show that this simple objective results in the unsupervised emergence of diverse skills, such as walking and jumping. In a number of reinforcement learning benchmark environments, our method is able to learn a skill that solves the benchmark task despite never receiving the true task reward. We show how pretrained skills can provide a good parameter initialization for downstream tasks, and can be composed hierarchically to solve complex, sparse reward tasks. Our results suggest that unsupervised discovery of skills can serve as an effective pretraining mechanism for overcoming challenges of exploration and data efficiency in reinforcement learning.

## 1 Introduction

Deep reinforcement learning (RL) has been demonstrated to effectively learn a wide range of reward-driven skills, including playing games [1, 2], controlling robots [3, 4], and navigating complex environments [5, 6]. However, intelligent creatures can explore their environments and learn useful skills even without supervision, so that when they are later faced with specific goals, they can use those skills to satisfy the new goals quickly and efficiently.

Learning skills without reward has several practical applications beyond creating fun videos<sup>2</sup>. Environments with sparse rewards effectively have no reward until the agent randomly reaches a goal state. Learning useful skills without supervision may help address challenges in exploration in these environments. For long horizon tasks, skills discovered without reward can serve as primitives for hierarchical RL, effectively shortening the episode length. In many practical settings, interacting with the environment is essentially free, but evaluating the reward requires human feedback [7]. Unsupervised learning of skills may reduce the amount of supervision necessary to learn a task. While we can take the human out of the loop by designing a reward function, it is challenging to design a reward function that elicits the desired behaviors from the agent [8]. Finally, when given an unfamiliar environment, it is challenging to determine the range of tasks an agent should be able to learn. Unsupervised skill discovery partially answers this question.

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\*Work done as a member of the Google Brain Residency Program ([g.co/brainresidency](http://g.co/brainresidency)).

<sup>2</sup>Videos of experiments: <https://sites.google.com/view/diayn/>

Autonomous acquisition of useful skills without any reward signal is an exceedingly challenging problem. A *skill* is a policy  $\pi(a|s, z)$  that alters that state of the environment in a consistent way. We consider the setting where the reward function is unknown, so we want to learn a set of skills by maximizing the utility of this set. Making progress on this problem requires specifying a learning objective that ensures that each skill individually is distinct and that the skills collectively explore large parts of the state space. In this paper, we show how a simple objective based on mutual information can enable RL agents to autonomously discover such skills. These skills are useful for a number of applications, including hierarchical reinforcement learning and imitation learning.

We propose a method for learning diverse skills with deep RL in the absence of any rewards. We hypothesize that in order to acquire skills that are useful, we must train the skills so that they maximize coverage over the set of possible behaviors. While one skill might perform a useless behavior like random dithering, other skills should perform behaviors that are distinguishable from random dithering, and therefore more useful. A key idea in our work is to use discriminability between skills as an objective. Further, skills that are distinguishable are not necessarily maximally diverse – a slight difference in states makes two skills distinguishable, but not necessarily diverse in a semantically meaningful way. To combat this problem, we want to learn skills that not only are distinguishable, but also are *as diverse as possible*. By learning distinguishable skills that are as random as possible, we can “push” the skills away from each other, making each skill robust to perturbations and effectively exploring the environment. By maximizing this objective, we can learn skills that run forward, do backflips, skip backwards, and perform face flops (see Figure 5).

Our paper makes five contributions. First, we propose a method for learning useful skills without any rewards. We formalize our discriminability goal as maximizing an information theoretic objective with a maximum entropy policy. Second, we show that this simple exploration objective results in the unsupervised emergence of diverse skills, such as running and jumping, on several simulated robotic tasks. In a number of RL benchmark environments, our method is able to solve the benchmark task despite never receiving the true task reward. In these environments, some of the learned skills correspond to solving the task, and each skill that solves the task does so in a distinct manner. Third, we propose a simple method for using learned skills for hierarchical RL and find this method solves challenging tasks. Four, we demonstrate how skills discovered can be quickly adapted to solve a new task. Finally, we show how skills discovered can be used for imitation learning.

## 2 Related Work

Previous work on hierarchical RL has learned skills to maximize a single, known, reward function by jointly learning a set of skills and a meta-controller (e.g., [9, 10, 11, 12, 13, 14]). One problem with joint training (also noted by Shazeer et al. [15]) is that the meta-policy does not select “bad” options, so these options do not receive any reward signal to improve. Our work prevents this degeneracy by using a random meta-policy during unsupervised skill-learning, such that neither the skills nor the meta-policy are aiming to solve any single task. A second important difference is that our approach learns skills *with no reward*. Eschewing a reward function not only avoids the difficult problem of reward design, but also allows our method to learn task-agnostic.

Related work has also examined connections between RL and information theory [16, 17, 18, 19] and developed maximum entropy algorithms with these ideas [20, 19]. Recent work has also applied tools from information theory to skill discovery. Mohamed and Rezende [21] and Jung et al. [22] use the mutual information between states and actions as a notion of empowerment for an intrinsically motivated agent. Our method maximizes the mutual information between states and *skills*, which can be interpreted as maximizing the empowerment of a *hierarchical agent* whose action space is the set of skills. Hausman et al. [23], Florensa et al. [14], and Gregor et al. [24] showed that a discriminability objective is equivalent to maximizing the mutual information between the latent skill  $z$  and some aspect of the corresponding trajectory. Hausman et al. [23] considered the setting with many tasks and reward functions and Florensa et al. [14] considered the setting with a single task reward. Three important distinctions allow us to apply our method to tasks significantly more complex than the gridworlds in Gregor et al. [24]. First, we use maximum entropy policies to force our skills to be diverse. Our theoretical analysis shows that including entropy maximization in the RL objective results in the mixture of skills being maximum entropy in aggregate. Second, we fix the distribution  $p(z)$  rather than learning it, preventing  $p(z)$  from collapsing to sampling only a handful of skills. Third, while the discriminator in Gregor et al. [24] only looks at the final state,

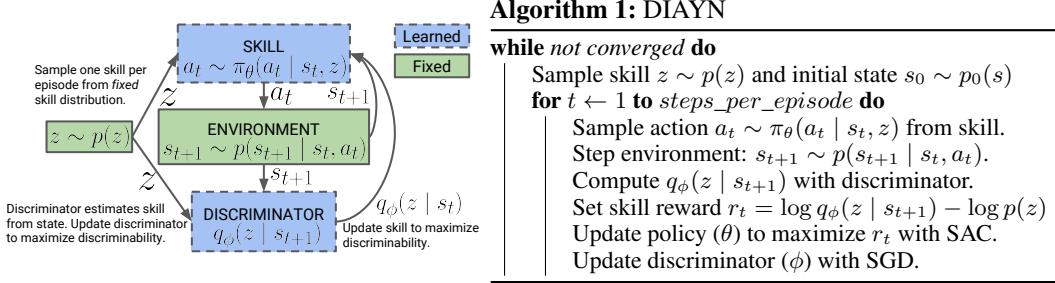


Figure 1: **DIAYN Algorithm:** Schematic diagram and pseudo-code for the DIAYN. We update the discriminator to better predict the skill, and update the skill to visit diverse states that make it more discriminable.

our discriminator looks at every state, which provides additional reward signal. These three crucial differences help explain how our method learns useful skills in complex environments.

Prior work in neuroevolution and evolutionary algorithms has studied how complex behaviors can be learned by directly maximizing diversity [25, 26, 27, 28, 29, 30, 31]. While this prior work uses diversity maximization to obtain better solutions, we aim to acquire complex skills with minimal supervision to improve efficiency (i.e., reduce the number of objective function queries) and as a stepping stone for imitation learning and hierarchical RL. We focus on deriving a general, information-theoretic objective that does not require manual design of distance metrics and can be applied to any RL task without additional engineering.

Previous work has studied intrinsic motivation in humans and learned agents. [32, 33, 34, 35, 36, 37, 38]. While these previous works use an intrinsic motivation objective to learn a *single* policy, we propose an objective for learning *many*, diverse policies. Concurrent work [39] draws ties between learning discriminable skills and variational autoencoders. We show that our method scales to more complex tasks, likely because of algorithmic design choices, such as our use of an off-policy RL algorithm and conditioning the discriminator on individual states.

### 3 Diversity is All You Need

We consider an unsupervised RL paradigm in this work, where the agent is allowed an unsupervised “exploration” stage followed by a supervised stage. In our work, the aim of the unsupervised stage is to learn skills that eventually will make it easier to maximize the task reward in the supervised stage. Conveniently, because skills are learned without a priori knowledge of the task, the learned skills can be used for many different tasks.

#### 3.1 How it Works

Our method for unsupervised skill discovery, DIAYN (“Diversity is All You Need”), builds off of three ideas. First, for skills to be useful, we want the skill to dictate the states that the agent visits. Different skills should visit different states, and hence be distinguishable. Second, we want to use states, not actions, to distinguish skills, because actions that do not affect the environment are not visible to an outside observer. For example, an outside observer cannot tell how much force a robotic arm applies when grasping a cup if the cup does not move. Finally, we encourage exploration and incentivize the skills to be as diverse as possible by learning skills that act as randomly as possible. Skills with high entropy that remain discriminable must explore a part of the state space far away from other skills, lest the randomness in its actions lead it to states where it cannot be distinguished from another skill.

We construct our objective as follows. We maximize the mutual information between skills and states,  $MI(s, z)$ , to encode the idea that the skill should control which states the agent visits. Conveniently, this mutual information term also specifies that we should be able to infer the skill from the states visited. To ensure that states, not actions, are used to distinguish skills, we minimize the mutual information between skills and actions given the state,  $MI(a, z | s)$ . We can view the collection of skills together with  $p(z)$  as a mixture of policies, and we want this mixture policy to also be a

maximum entropy policy. Thus, we also maximize  $\mathcal{H}[a | s]$ . In summary, we maximize

$$\mathcal{F}(\theta) \triangleq MI(s, z) + \mathcal{H}[a | s] - MI(a, z | s) \quad (1)$$

Rearranging Equation 1 gives intuition on how we optimize it:<sup>3</sup>

$$\begin{aligned} \mathcal{F}(\theta) &= MI(s, z) + \mathcal{H}[a | s] - MI(a, z | s) \\ &= (\mathcal{H}[z] - \mathcal{H}[z | s]) + \mathcal{H}[a | s] \\ &\quad - (\mathcal{H}[a | s] - \mathcal{H}[a | s, z]) \\ &= \mathcal{H}[z] - \mathcal{H}[z | s] + \mathcal{H}[a | s, z] \end{aligned} \quad (2)$$

The first term suggests that each skill should act as randomly as possible, which we achieve by using a maximum entropy policy to represent each skill. The second term encourages our prior distribution over  $p(z)$  to have high entropy. We fix  $p(z)$  to be uniform in our approach, guaranteeing that it has maximum entropy. The third term suggests that it should be easy to infer the skill  $z$  from the current state. As we cannot integrate over all states and skills to compute this direction, we approximate the posterior  $p(z | s)$  with a learned discriminator  $q_\phi(z | s)$ . Jensen’s Inequality tells us that replacing  $p(z | s)$  with  $q_\phi(z | s)$  gives us a variational lower bound  $\mathcal{G}(\theta, \phi)$  on our objective  $\mathcal{F}(\theta)$ :<sup>4</sup>

$$\begin{aligned} \mathcal{F}(\theta) &= \mathcal{H}[a | s, z] - \mathcal{H}[z | s] + \mathcal{H}[z] \\ &= \mathcal{H}[a | s, z] + \mathbb{E}[\log p(z | s)] - \mathbb{E}[\log p(z)] \\ &\geq \mathcal{H}[a | s, z] + \mathbb{E}[\log q_\phi(z | s) - \log p(z)] \triangleq \mathcal{G}(\theta, \phi) \end{aligned}$$

### 3.2 Implementation

We implement DIAYN with soft actor critic [20]. We use soft actor critic to learn a policy  $\pi_\theta(a | s, z)$  that is conditioned on the skill  $z$ .<sup>5</sup> Soft actor critic maximizes the policy’s entropy over actions, which takes care of the entropy term in our objective  $\mathcal{G}$ . Following Haarnoja et al. [20], we scale the entropy regularizer  $\mathcal{H}[a | s, z]$  by  $\alpha$ . We found empirically that an  $\alpha = 0.1$  provided a good trade-off between exploration and discriminability. We maximize the expectation in  $\mathcal{G}$  by replacing the task reward with the following pseudo-reward:

$$r_z(s, a) \triangleq \log q_\phi(z | s) - \log p(z) \quad (3)$$

During unsupervised learning, we sample a skill  $z \sim p(z)$  at the start of each episode, and act according to that skill throughout the episode. The agent is rewarded for visiting states that are easy to discriminate, while the discriminator is updated to better infer the skill  $z$  from states visited. Entropy regularization occurs as part of the SAC update.

## 4 What Skills are Learned?

In this section, we examine the learned skills to answer questions about the skills learned by DIAYN. We highly encourage readers to view videos of the learned skills at paper website<sup>6</sup>.

**Question 1** Does entropy regularization lead to more diverse skills?

To answer this question, we apply our method to a 2D point mass. The agent controls the orientation and forward velocity of the point, with is confined within a 2D box. We vary the entropy regularization  $\alpha$ , with larger values of  $\alpha$  corresponding to policies with more stochastic actions. With small  $\alpha$ , we learn skills that move large distances in different directions but fail to explore large parts of the state space. Increasing  $\alpha$  makes the skills visit a more diverse set of states, which may help with exploration in complex state spaces. It is difficult to discriminate skills when  $\alpha$  is further increased.

<sup>3</sup>While our method uses stochastic policies, note that for deterministic policies in continuous action spaces,  $MI(a, z | s) = \mathcal{H}[a | s]$ . Thus, for deterministic policies, Equation 2 reduces to maximizing  $MI(s, z)$ .

<sup>4</sup>On the last line, the expectation is taken with a skill  $z$  sampled from the prior distribution over skills  $p(z)$  and with states  $s$  sampled from the distribution over states  $p(s | z)$  induced by skill  $z$ .

<sup>5</sup>Note that we use “skill” to refer to both the latent variable  $z$  and the policy conditioned on  $z$ .

<sup>6</sup><https://sites.google.com/view/diayn/>

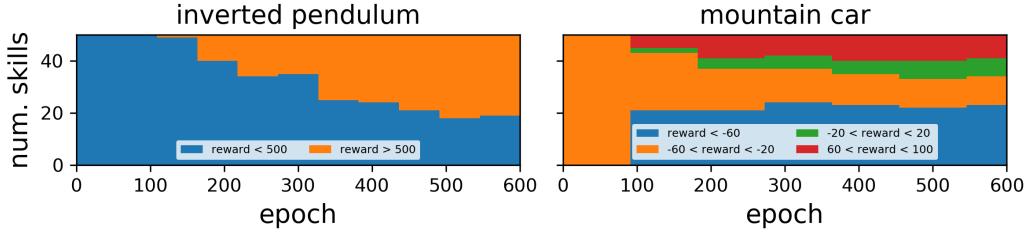


Figure 3: **Training dynamics:** Diversity of the rewards obtained increases throughout training.

**Question 2** *How does the distribution of skills change during training?*

While DIAYN learns skills without a reward function, as an outside observer, can we evaluate the skills throughout training to understand the training dynamics. Figure 3 shows how the skills for inverted pendulum and mountain car become increasingly diverse throughout training. Recall that our skills are learned with no reward, so it is natural that some skills correspond to small task reward while others correspond to large task reward.

**Question 3** *Does DIAYN explore effectively in complex environments?*

We apply DIAYN to three standard RL benchmark environments: half-cheetah, hopper, and ant. In all environments, we learn diverse locomotion primitives, as shown in Figure 5. Despite never receiving any reward, the half cheetah and hopper learn skills that move forward and achieve large task reward on the corresponding RL benchmarks, which all require them to move forward at a fast pace. Perhaps unsurprisingly, half cheetah and hopper also learn skills that move backwards, corresponding to receiving a task reward much smaller than what a random policy would receive. Unlike hopper and half cheetah, the ant is free to move in the XY plane. While it learns skills that move in different directions, most skills move in arcs rather than straight lines, meaning that we rarely learn a single skill that achieves large task reward on the typical task of running forward. In the appendix, we visualize the objective throughout training.

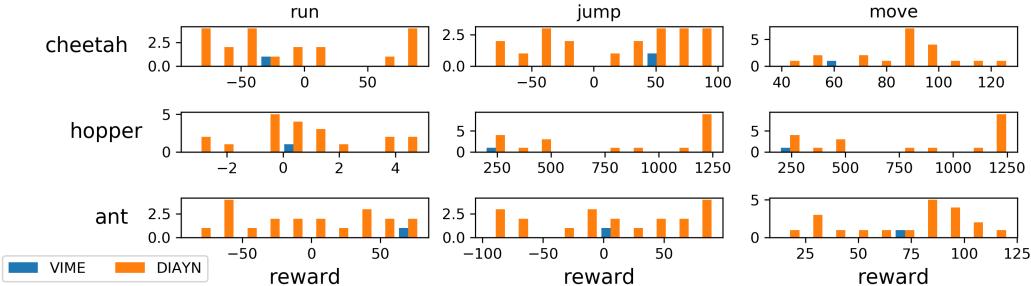


Figure 4: **Exploration:** We take DIAYN skills learned without a reward function, and evaluate on three natural reward functions: running, jumping, and moving away from the origin. For all tasks, DIAYN learns some skills that perform well. In contrast, a single policy trained with a pure exploration bonus (VIME [40]) performs poorly on all tasks.

In Figure 4, we evaluate all skills on three reward functions: running (maximize X coordinate), jumping (maximize Z coordinate) and moving (maximize L2 distance from origin). For each skill, DIAYN learns some skills that achieve high reward. We compare to single policy trained with a pure exploration objective (VIME [40]). Whereas previous work (e.g., [37, 33, 40]) finds a single policy that explores well, DIAYN optimizes a *collection* of policies, which enables more diverse exploration.

**Question 4** *Does DIAYN ever learn skills that solve a benchmark task?*

Figure 4 shows that half cheetah and hopper learn skills that run and hop forward quickly. These skills achieve high reward on the standard, benchmark reward function, despite never having seen that reward function during training. Ant learns many skills for walking in curved trajectories; no skill moves directly along the X axis to maximize the benchmark reward for ant. We also apply DIAYN to two classic control tasks, inverted pendulum and mountain car. Not only does our approach learn skills that solve the task without rewards, it learns multiple distinct skills for solving the task. (See Appendix E for further analysis.)

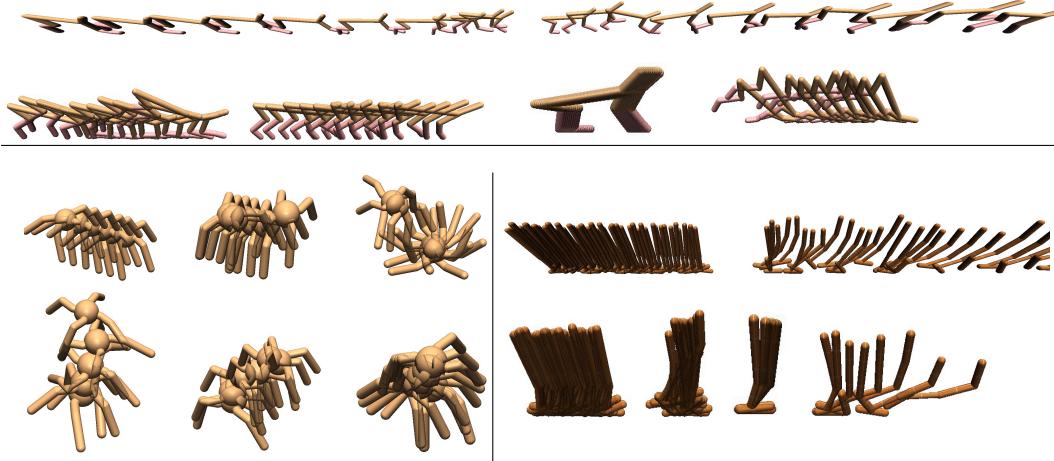


Figure 5: **Locomotion skills:** Without any reward, DIAYN discovers skills for running, walking, hopping, flipping, and gliding. It is challenging to craft reward functions that elicit these behaviors.

## 5 Harnessing Learned Skills

The perhaps surprising finding that we can discover diverse skills without a reward function creates a building block for many problems in RL. For example, if we want to find a policy that solves has large reward on a task, it is often sufficient to simply enumerate over skills and choose the one with largest reward. Three perhaps less obvious applications are adapting skills to maximize a reward, hierarchical RL, and imitation learning.

### 5.1 Adapting Skills to Maximize Reward

After DIAYN learns task-agnostic skills without supervision, we can quickly adapt the skills can to solve a desired task. Akin to computer vision researchers’ using models pre-trained on ImageNet, we propose that the RL researchers us DIAYN as (unsupervised) pre-training in resource-constrained settings.

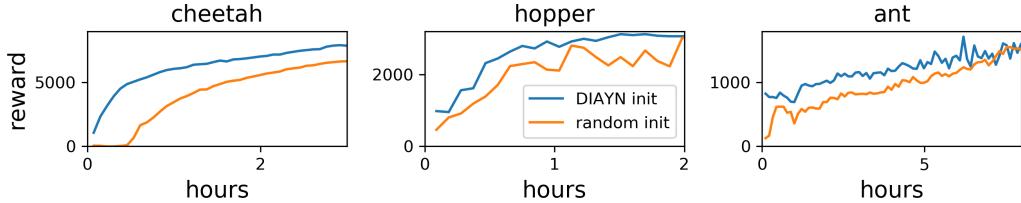


Figure 6: **Maximizing a reward:** Unsupervised skill learning achieves substantially faster learning than random initialization. Pretraining with DIAYN may be especially useful in resource constrained settings.

**Question 5** *Can we use learned skills to directly maximize the task reward?*

We take the skill with highest reward and further finetune this skill using the task-specific reward function. We compare to a “random initialization” baseline that is initialized from scratch. Our approach differs from this baseline only in how weights are initialized.<sup>7</sup> Figure 6 shows both methods applied to half cheetah, hopper, and ant. On both tasks, we unsupervised pretraining enables the agent to learn the task reward more quickly without compromising final task reward.

<sup>7</sup>We initialize both the policy and value networks with weights learned during unsupervised pretraining. Although the critic networks learned during pretraining corresponds to the pseudo-reward from the discriminator (Eq. 3) and not the true task reward, we found empirically that the pseudo-reward was close to the true task reward for the best skill, and initializing the critic in addition to the actor further sped up learning.

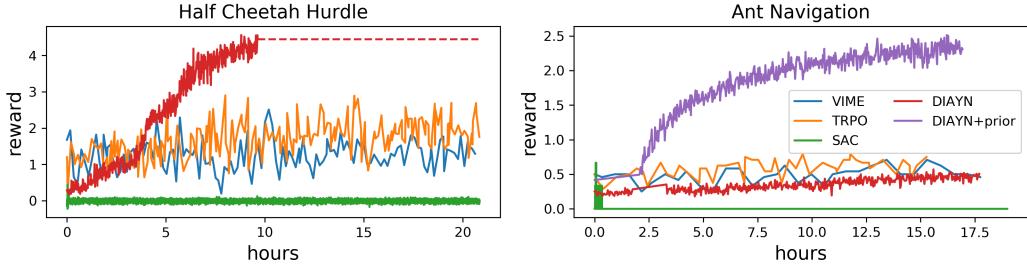


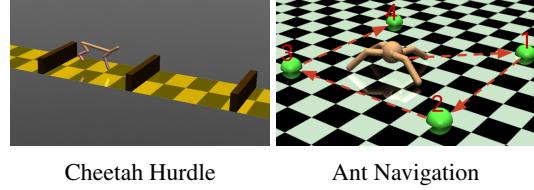
Figure 8: **DIAYN for Hierarchical RL**: By learning a meta-controller to compose skills learned by DIAYN, cheetah quickly learns to jump over hurdles and ant solves a sparse-reward navigation task.

## 5.2 Using Skills for Hierarchical RL

In theory, hierarchical RL should decompose a complex task into motion primitives, which may be reused for multiple tasks. In practice, algorithms for hierarchical RL encounter many difficulties: (1) each motion primitive reduces to a single action [9], (2) the hierarchical policy only samples a single motion primitive [24], or (3) all motion primitives attempt to do the entire task. In contrast, DIAYN discovers diverse, *task-agnostic* skills, which hold the promise of acting as a building block for hierarchical RL.

**Question 6** *Are skills discovered by DIAYN useful for hierarchical RL?*

We propose a simple extension to DIAYN for hierarchical RL, and find that simple algorithm outperformed competitive baselines on two challenging tasks. To use the discovered skills for hierarchical RL, we learn a meta-controller whose actions are to choose which skill to execute for the next  $k$  steps (100 for ant navigation, 10 for cheetah hurdle). The meta-controller has the same observation space as the skills. On the cheetah hurdle task, the agent is rewarded for bounding up and over hurdles, while in the ant navigation task, the agent must walk to a set of 5 waypoints in a specific order, receiving only a sparse reward upon reaching each waypoint. Figure 8 shows how DIAYN outperforms all baselines. TRPO [41] and SAC [20] are competitive on-policy and off-policy RL algorithms, while VIME [40] includes an auxiliary objective to promote efficient exploration.



Cheetah Hurdle                    Ant Navigation

**Question 7** *How can DIAYN leverage prior knowledge about what skills will be useful?*

If the number of possible skills grows exponentially with the dimension of the task observation, one might imagine that DIAYN would fail to learn skills necessary to solve some tasks. While we found that DIAYN *does* scale to tasks with more than 100 dimensions (ant has 111), we develop a simple approach to biasing DIAYN towards discovering particular types of skills. In particular, we can condition the discriminator on only a subset of the observation, forcing DIAYN to find skills that are diverse in this subspace (but potentially indistinguishable along other dimensions). For example, in the ant navigation task, we can condition the discriminator on only the ant’s center of mass. The “DIAYN+prior” result in Figure 8 (right) shows how incorporating this prior knowledge can aid DIAYN in discovering useful skills and boost performance on the hierarchical task. No other experiments or figures used this prior.

## 5.3 Imitating an Expert

**Question 8** *Can we use learned skills to imitate an expert?*

Demonstration is often a natural way to specify a task to an agent. We consider the setting where we are given an expert trajectory consisting of states (not actions):  $\tau^* = \{(s_i)\}_{1 \leq i \leq N}$ . We want to obtain a feedback controller that will reach the same states. Given the expert trajectory, we use our learned discriminator to estimate which skill was most likely to have generated the trajectory. This

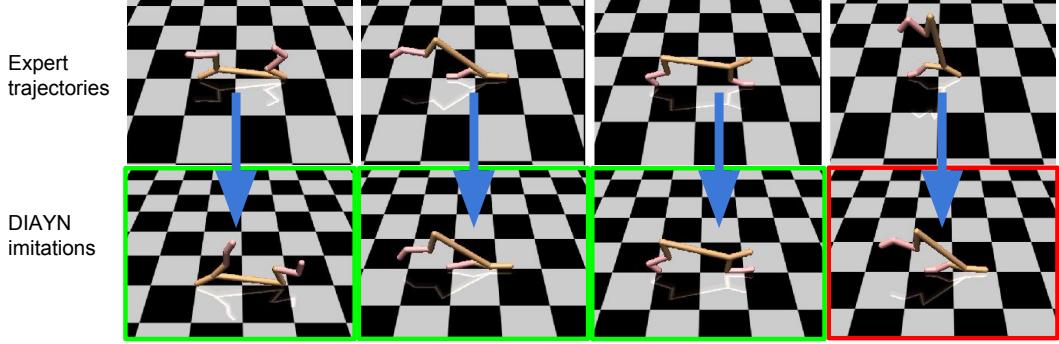


Figure 9: **Imitating an expert:** DIAYN imitates an expert standing upright, flipping, faceplanting, but fails to imitate a handstand.

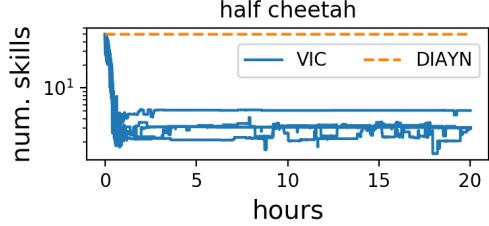
optimization problem, which we can solve for categorical  $z$  by simple enumerate, is equivalent to an M-projection [42] (proof in Appendix G):

$$\hat{z} = \arg \max_z \Pi_{s_t \in \tau^*} q_\phi(z \mid s_t)$$

We qualitatively evaluate this approach to imitation learning on half cheetah. Figure 9 (left) shows four imitation tasks, three of which our method successfully imitates. We quantitatively evaluate this imitation method on classic control tasks in Appendix G.

**Question 9** *How does DIAYN differ from Variational Intrinsic Control [24]?*

Two key differences between DIAYN and Variational Intrinsic Control (VIC) are our use of maximum entropy policies and our decision to *not* learn the prior  $p(z)$ . Across 600 imitation tasks (details in Appendix G), we found that our method consistently matched the expert trajectory more closely than VIC baselines without these elements. When the prior distribution over skills,  $p(z)$  is learned, the model may encounter a rich-get-richer problem: the learned prior will sample the more diverse skills more frequently, and hence only those skills will receive training signal to improve. While VIC learned the distribution over skills, we fix the distribution over skills, which allows us to discover more diverse skills.



## 6 Conclusion

In this paper, we present DIAYN, a method for learning skills without reward functions. We show that DIAYN learns diverse skills for complex tasks, often solving benchmark tasks with one of the learned skills without actually receiving any task reward. We further proposed methods for using the learned skills (1) to quickly adapt to a new task, (2) to solve complex tasks via hierarchical RL, and (3) to imitate an expert. As a rule of thumb, DIAYN may make learning a task easier by replacing the task’s complex action space with a set of useful skills. DIAYN could be combined with methods for augmenting the observation space and reward function. Using the common language of information theory, joint objective can likely be derived. DIAYN may also more efficiently learn from human preferences [7] by having humans select among learned skills. Finally, for creativity and education, the skills produced by DIAYN might be used by game designers to allow players to control complex robots and by artists to design dancing robots. Both these efforts might introduce the challenges and opportunities of RL to an audience outside the ML community.

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## A Pseudo-Reward

Note that  $\log p(z)$  in Equation 3 is a baseline that does not depend on the policy parameters  $\theta$ , so one might be tempted to remove it from the objective. We provide two justifications for keeping it. First, assume that episodes never terminate, but all skills eventually converge to some absorbing state (e.g., with all sensors broken). At this state, the discriminator cannot distinguish the skills, so its estimate is  $\log q(z | s) = \log(1/N)$ , where  $N$  is the number of skills. For practical reasons, we want to restart the episode after the agent reaches the absorbing state. Subtracting  $\log(z)$  from the pseudo-reward at every time step in our finite length episodes is equivalent to pretending that episodes never terminate and the agent gets reward  $\log(z)$  after our “artificial” termination. Second, assuming our discriminator  $q_\phi$  is better than chance, we see that  $q_\phi(z | s) \geq p(z)$ . Thus, subtracting the  $\log p(z)$  baseline ensures our reward function is always non-negative, encouraging the agent to stay alive. Without this baseline, an optimal agent would end the episode as soon as possible.<sup>8</sup>

## B Experimental Details

In our experiments, we use the same hyperparameters as those in Haarnoja et al. [20], with one notable exception. For the Q function, value function, and policy, we use neural networks with 300 hidden units instead of 128 units. We found that increasing the model capacity was necessary to learn many diverse skills. When comparing the “skill initialization” to the “random initialization” in Section 5, we use the same model architecture for both methods. To pass skill  $z$  to the Q function, value function, and policy, we simply concatenate  $z$  to the current state  $s_t$ . As in Haarnoja et al. [20], epochs are 1000 episodes long. For all environments, episodes are at most 1000 steps long, but may be shorter. For example, the standard benchmark hopper environment terminates the episode once it falls over. Figures 3 and 6 show up to 1000 epochs, which corresponds to at most 1 million steps. We found that learning was most stable when we scaled the maximum entropy objective ( $\mathcal{H}[a | s, a]$  in Eq. 1) by  $\alpha = 0.1$ . We use this scaling for all experiments.

## C Training Objectives

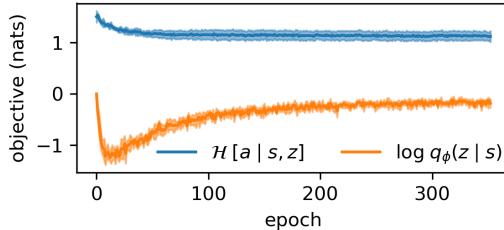


Figure 10: **Objectives:** We plot the two terms from our objective (Eq. 1) throughout training. While the entropy regularizer (red) quickly plateaus, the discriminability term (blue) term continues to increase, indicating that our skills become increasingly diverse without collapsing to deterministic policies. This plot shows the mean and standard deviation across 5 seeds for learning 20 skills in half cheetah environment. Note that  $\log_2(1/20) \approx -3$ , setting a lower bound for  $\log q_\phi(z | s)$ .

To provide further intuition into our approach, Figure 10 plots the two terms in our objective throughout training. Our skills become increasingly diverse throughout training without converging to deterministic policies.

## D Learning $p(z)$

We used our method as a starting point when comparing to VIC [24] in Section 5. While  $p(z)$  is fixed in our method, we implement VIC by learning  $p(z)$ . In this section, we describe how we learned  $p(z)$ , and show the effect of learning  $p(z)$  rather than leaving it fixed.

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<sup>8</sup>In some environments, such as mountain car, it is desirable for the agent to end the episode as quickly as possible. For these types of environments, the  $\log p(z)$  baseline can be removed.

## D.1 How to Learn $p(z)$

We choose  $p(z)$  to optimize the following objective, where  $p_z(s)$  is the distribution over states induced by skill  $s$ :

$$\begin{aligned}\mathcal{H}[s, z] &= \mathcal{H}[z] - \mathcal{H}[z | s] \\ &= \sum_z -p(z) \log p(z) + \sum_z \mathbb{E}_{s \sim p_z(s)} [\log p(z | s)] \\ &= \sum_z p(z) (\mathbb{E}_{s \sim p_z(s)} [\log p(z | s)] - \log p(z))\end{aligned}$$

For clarity, we define  $p_z^t(s)$  as the distribution over states induced by skill  $z$  at epoch  $t$ , and define  $\ell_t(z)$  as an approximation of  $\mathbb{E}[\log p(z | s)]$  using the policy and discriminator from epoch  $t$ :

$$\ell_t(z) \triangleq \mathbb{E}_{s \sim p_z^t(s)} [\log q_t(z | s)]$$

Noting that  $p(z)$  is constrained to sum to 1, we can optimize this objective using the method of Lagrange multipliers. The corresponding Lagrangian is

$$\mathcal{L}(p) = \sum_z p(z) (\ell_t(z) - \log p(z)) + \lambda \left( \sum_z p(z) - 1 \right)$$

whose derivative is

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial p(z)} &= p(z) \left( \frac{-1}{p(z)} \right) + \ell_t(z) - \log p(z) + \lambda \\ &= \ell_t(z) - \log p(z) + \lambda - 1\end{aligned}$$

Setting the derivative equal to zero, we get

$$\log p(z) = \ell_t(z) + \lambda - 1$$

and finally arrive at

$$p(z) \propto e^{\ell_t(z)}$$

## D.2 Effect of Learning $p(z)$

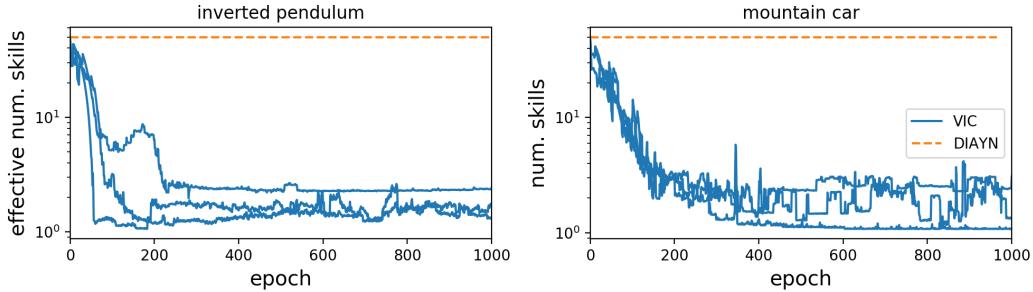


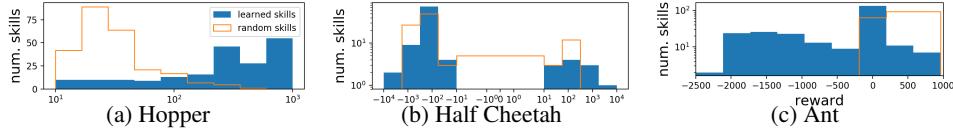
Figure 11: **Effect of learning  $p(z)$ :** We plot the effective number of skills that are sampled from the skill distribution  $p(z)$  throughout training. Note how learning  $p(z)$  greatly reduces the effective number on inverted pendulum and mountain car. We show results from 3 random seeds for each environment.

In this section, we briefly discuss the effect of learning  $p(z)$  rather than leaving it fixed. To study the effect of learning  $p(z)$ , we compared the entropy of  $p(z)$  throughout training. When  $p(z)$  is fixed, the entropy is a constant ( $\log(50) \approx 3.9$ ). To convert nats to a more interpretable quantity, we compute the effective number of skills by exponentiation the entropy:

$$\text{effective num. skills} \triangleq e^{\mathcal{H}[z]}$$

Figure 11 shows the effective number of skills for half cheetah, inverted pendulum, and mountain car. Note how the effective number of skills drops by a factor of 10x when we learn  $p(z)$ . This observation supports our claim that learning  $p(z)$  results in learning fewer diverse skills.

## E Distribution over Task Reward

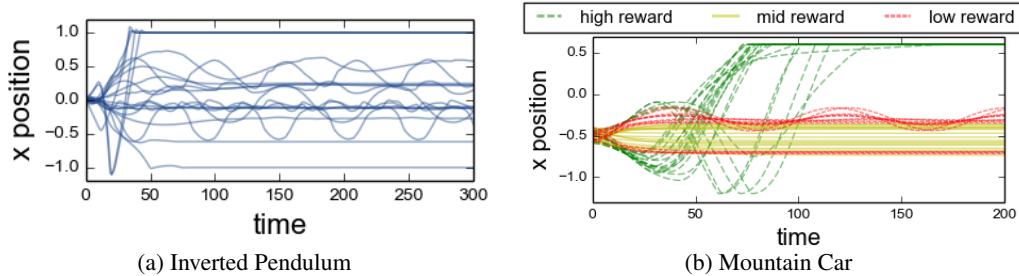


**Figure 12: Task reward of skills learned without reward:** While our skills are learned without the task reward function, we evaluate each with the task reward function for analysis. The wide range of rewards shows the diversity of the learned skills. In the hopper and half cheetah tasks, many skills achieve large task reward, despite not observing the task reward during training. As discussed in prior work [43, 44], standard model-free algorithms trained directly on the task reward converge to scores of 1000 - 3000 on hopper, 1000 - 5000 on cheetah, and 700 - 2000 on ant.

In Figure 12, we take the skills learned without any rewards, and evaluate each of them on the standard benchmark reward function. We compare to random (untrained) skills. The wide distribution over rewards is evidence that the skills learned are diverse. For hopper, some skills hop or stand for the entire episode, receiving a reward of at least 1000. Other skills aggressively hop forwards or dive backwards, and receive rewards between 100 and 1000. Other skills fall over immediately and receive rewards of less than 100. The benchmark half cheetah reward includes a control penalty for taking actions. Unlike random skills, learned skills rarely have task reward near zero, indicating that all take actions to become distinguishable. Skills that run in place, flop on their nose, or do backflips receive reward of -100. Skills that receive substantially smaller reward correspond to running quickly backwards, while skills that receive substantially larger reward correspond to running forward. Similarly, the benchmark ant task reward includes both a control penalty and a survival bonus, so random skills that do nothing receive a task reward near 1000. While no single learned skill learns to run directly forward and obtain a task reward greater than 1000, our learned skills run in different patterns to become discriminable, resulting in a lower task reward.

## F Visualizing Learned Skills

### F.1 Classic Control Tasks



**Figure 13: Visualizing Skills:** For every skill, we collect one trajectory and plot the agent's X coordinate across time. For inverted pendulum (top), we only plot skills that balance the pendulum. Note that among balancing skills, there is a wide diversity of balancing positions, control frequencies, and control magnitudes. For mountain car (bottom), we show skills that achieve larger reward (complete the task), skills with near-zero reward, and skills with very negative reward. Note that skills that solve the task (green) employ varying strategies.

In this section, we visualize the skills learned for inverted pendulum and mountain car without a reward. Not only does our approach learn skills that solve the task without rewards, it learns multiple distinct skills for solving the task. Figure 13 shows the X position of the agent across time, within one episode. For inverted pendulum (Fig. 13a), we plot only skills that solve the task. Horizontal lines with different X coordinates correspond to skills balancing the pendulum at different positions along the track. The periodic lines correspond to skills that oscillate back and forth while balancing the pendulum. Note that skills that oscillate have different X positions, amplitudes, and periods. For mountain car (Fig. 13b), skills that climb the mountain employ a variety of strategies for to do so.

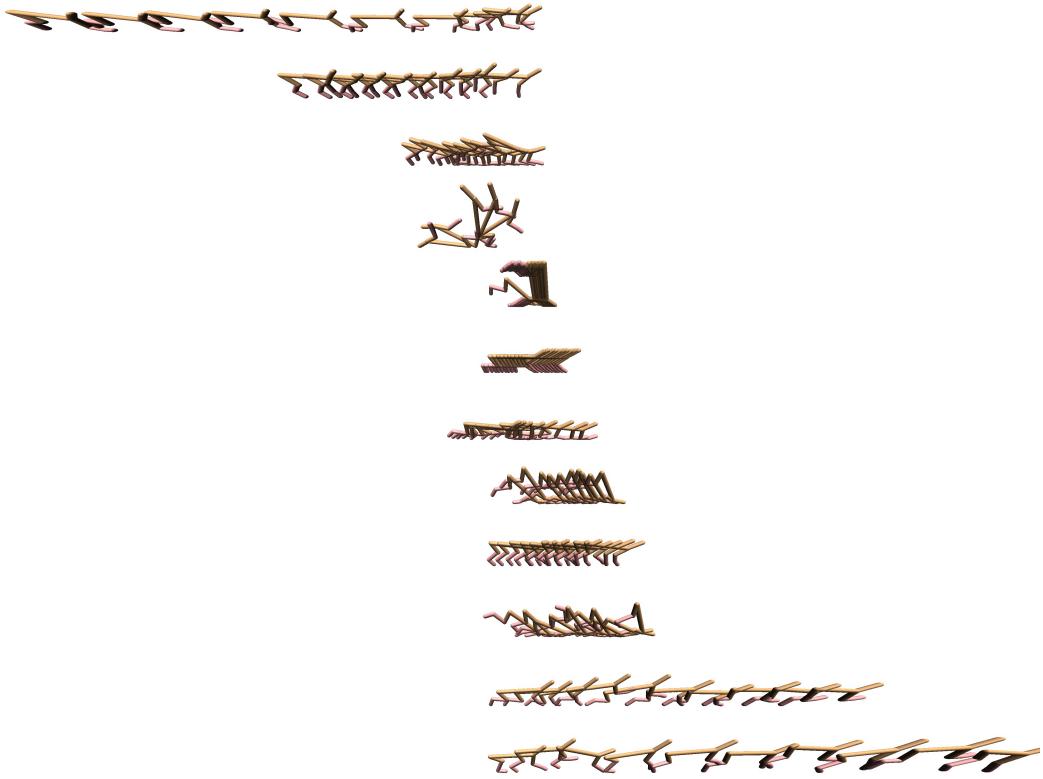


Figure 14: **Half cheetah skills:** We show skills learned by half-cheetah with no reward.

Most start moving backwards to gather enough speed to summit the mountain, while others start forwards, then go backwards, and then turn around to summit the mountain. Additionally, note that skills differ in when the turn around and in their velocity (slope of the green lines).

## F.2 Simulated Robot Tasks

Figures 14, 15, and 16 show more skills learned *without reward*.



Figure 15: **Hopper Skills:** We show skills learned by hopper with no reward.

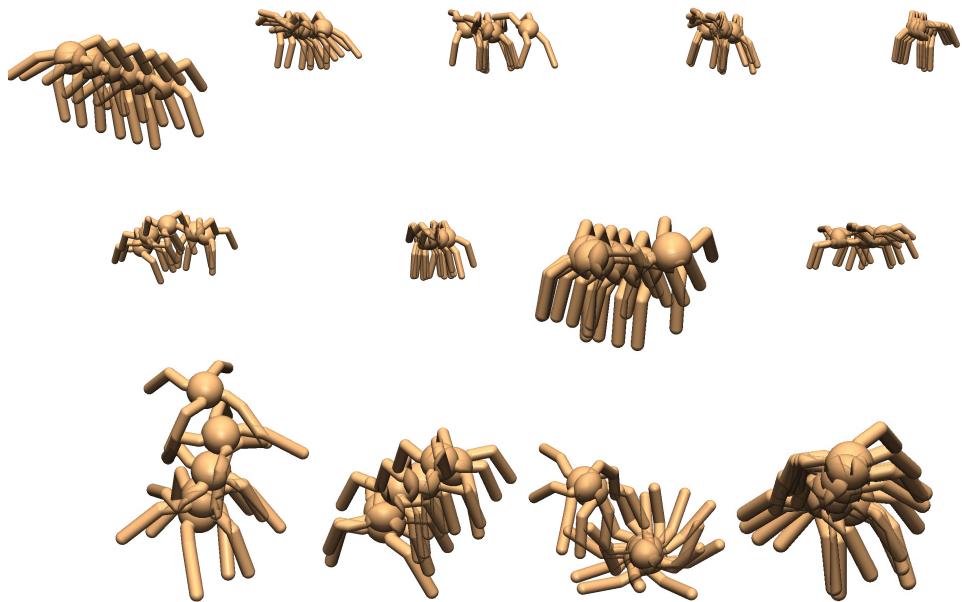


Figure 16: **Ant skills:** We show skills the ant learns without any supervision. Ant learns (top row) to move right, (middle row) to move left, (bottom row, left to right) to move up, to move down, to flip on its back, and to rotate in place.

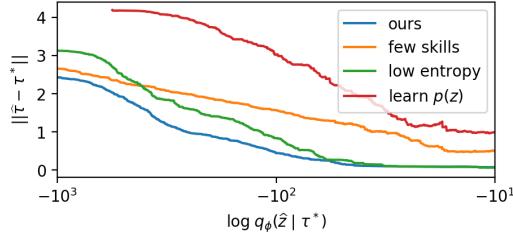


Figure 17: **Imitating an expert:** Across 600 imitation tasks, we find our method more closely matches the expert than all baselines.

## G Imitation Learning

Given the expert trajectory, we use our learned discriminator to estimate which skill was most likely to have generated the trajectory:

$$\hat{z} = \arg \max_z \Pi_{s_t \in \tau^*} q_\phi(z | s_t)$$

As motivation for this optimization problem, note that each skill induces a distribution over states,  $p^z \triangleq p(s | z)$ . We use  $p^*$  to denote the distribution over states for the expert policy. With a fixed prior distribution  $p(z)$  and a perfect discriminator  $q_\phi(z | s) = p(z | s)$ , we have  $p(s | z) \propto q_\phi(z | s)$  as a function of  $z$ . Thus, Equation G is an M-projection of the expert distribution over states onto the family of distributions over states,  $\mathcal{P} = \{p^z\}$ :

$$\arg \min_{p^z \in \mathcal{P}} D(p^* || p^z) \quad (4)$$

For clarity, we omit a constant that depends only on  $p^*$ . Note that the use of an M-projection, rather than an I-projection, helps guarantee that the retrieved skill will visit all states that the expert visits [42]. In our experiments, we solve Equation 4 by simply iterating over skills.

### G.1 Imitation Learning Experiments

The “expert” trajectories are actually generated synthetically in these experiments, by running a different random seed of our algorithm. A different seed is used to ensure that the trajectories are not actually produced by any of the currently available skills. Of course, in practice, the expert trajectories might be provided by any other means, including a human. For each expert trajectory, we retrieve the closest DIAYN skill  $\hat{z}$  using Equation 5.3. Evaluating  $q_\phi(\hat{z} | \tau^*)$  gives us an estimate of the probability that the imitation will match the expert (e.g., for a safety critical setting). This quantity is useful for predicting how accurately our method will imitate an expert before executing the imitation policy. In a safety critical setting, a user may avoid attempting tasks where this score is low. We compare our method to three baselines. The “low entropy” baseline is a variant on our method with lower entropy regularization. The “learned  $p(z)$ ” baseline learns the distribution over skills. Note that Variational Intrinsic Control [24] is a combination of the “low entropy” baseline and the “learned  $p(z)$ ” baseline. Finally, the “few skills” baseline learns only 5 skills, whereas all other methods learn 50. Figure 17 shows the results aggregated across 600 imitation tasks. The X-axis shows the discriminator score, our estimate for how well the imitation policy will match the expert. The Y-axis shows the true distance between the trajectories, as measured by L2 distance in state space. For all methods, the distance between the expert and the imitation decreases as the discriminator’s score increases, indicating that the discriminator’s score is a good predictor of task performance. Our method consistently achieves the lowest trajectory distance among all methods. The “low entropy” baseline is slightly worse, motivating our decision to learn maximum entropy skills. When imitating tasks using the “few skills” baseline, the imitation trajectories are even further from the expert trajectory. This is expected – by learning more skills, we obtain a better “coverage” over the space of skills. A “learn  $p(z)$ ” baseline that learns the distribution over skills also performs poorly. Recalling that Gregor et al. [24] is a combination of the “low entropy” baseline and the “learn  $p(z)$ ” baseline, this plot provides evidence that using maximum entropy policies and fixing the distribution for  $p(z)$  are two factors that enabled our method to scale to more complex tasks.