UNSUPERVISED META-LEARNING FOR REINFORCEMENT LEARNING

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ABSTRACT

Meta-learning is a powerful tool that learns how to quickly adapt a model to new tasks. In the context of reinforcement learning, meta-learning algorithms can acquire reinforcement learning procedures to solve new problems more efficiently by meta-learning prior tasks. The performance of meta-learning algorithms critically depends on the tasks available for meta-training: in the same way that supervised learning algorithms generalize best to test points drawn from the same distribution as the training points, meta-learning methods generalize best to tasks from the same distribution as the meta-training tasks. In effect, meta-reinforcement learning offloads the design burden from algorithm design to task design. If we can automate the process of task design as well, we can devise a meta-learning algorithm that is truly automated. In this work, we take a step in this direction, proposing a family of unsupervised meta-learning algorithms for reinforcement learning. We describe a general recipe for unsupervised meta-reinforcement learning, and describe an effective instantiation of this approach based on a recently proposed unsupervised exploration technique and model-agnostic meta-learning. We also discuss practical and conceptual considerations for developing unsupervised meta-learning methods. Our experimental results demonstrate that unsupervised meta-reinforcement learning effectively acquires accelerated reinforcement learning procedures without the need for manual task design, significantly exceeds the performance of learning from scratch, and even matches performance of meta-learning methods that use hand-specified task distributions.

1 INTRODUCTION

Reusing past experience for faster learning of new tasks is a key challenge for machine learning. Meta-learning methods propose to achieve this by using past experience to explicitly optimize for rapid adaptation (Mishra et al., 2017; Snell et al., 2017; Schmidhuber, 1987; Finn et al., 2017a; Duan et al., 2016b; Gupta et al., 2018; Wang et al., 2016; Al-Shedivat et al., 2017). In the context of reinforcement learning, meta-reinforcement learning algorithms can learn to solve new reinforcement learning tasks more quickly through experience on past tasks (Duan et al., 2016b; Gupta et al., 2018). Typical meta-reinforcement learning algorithms assume the ability to sample from a pre-specified task distribution, and these algorithms learn to solve new tasks *drawn from this distribution* very quickly. However, specifying a task distribution is tedious and requires a significant amount of supervision (Finn et al., 2017b; Duan et al., 2016b) that may be difficult to provide for large real-world problem settings. The performance of meta-learning algorithms critically depends on the meta-training task distribution, and meta-learning algorithms generalize best to new tasks which are drawn from the same distribution as the meta-training tasks (Finn & Levine, 2018). In effect, meta-reinforcement learning offloads some of the design burden from algorithm design to designing a sufficiently broad and relevant distribution of meta-training tasks. While this greatly helps in acquiring representations for fast adaptation to the specified task distribution, a natural question is whether we can do away with the need for manually designing a large family of tasks, and develop meta-reinforcement learning algorithms that learn only from unsupervised environment interaction. In this paper, we take an initial step toward the formalization and design of such methods.

Our goal is to automate the meta-training process by removing the need for hand-designed meta-training tasks. To that end, we introduce unsupervised meta-reinforcement learning: meta-learning from a task distribution that is acquired automatically, rather than requiring manual design of the

meta-training tasks. Developing effective unsupervised meta-reinforcement learning algorithms is challenging, since it requires solving two difficult problems together: meta-reinforcement learning with broad task distributions, and unsupervised exploration for proposing a wide variety of tasks for meta-learning. Since the assumptions of our method differ fundamentally from prior meta-reinforcement learning methods (we do not assume access to hand-specified meta-training tasks), the best points of comparison for our approach are learning the meta-test tasks entirely from scratch with conventional reinforcement learning algorithms. Our method can also be thought of as a data-driven initialization procedure for deep neural network policies, in a similar vein to data-driven initialization procedures explored in supervised learning (Krähenbühl et al., 2015). However, as indicated by Finn & Levine (2017), this procedure goes beyond simply being an initialization, and essentially learns an entire learning algorithm that is as expressive as any recurrent meta-learner.

The primary contributions of our work are to propose a framework for unsupervised meta-reinforcement learning, sketch out a family of unsupervised meta-reinforcement learning algorithms, and describe an instantiation of an algorithm from this family that builds on a recently proposed procedure for unsupervised exploration (Eysenbach et al., 2018) and model-agnostic meta-learning (MAML) (Finn et al., 2017a). We discuss the design considerations and conceptual issues surrounding unsupervised meta-reinforcement learning, and provide an empirical evaluation that studies the performance of two variants of our approach on simulated control tasks. Our experimental evaluation shows that, for a variety of tasks, unsupervised meta-reinforcement learning can effectively acquire reinforcement learning procedures that perform significantly better than standard reinforcement learning in terms of sample complexity and asympototic performance, and even rival the performance of conventional meta-learning algorithms that are provided with hand-designed task distributions.

2 Related Work

Our work lies at the intersection of meta reinforcement learning, goal generation, and unsupervised exploration. Meta-learning algorithms use data from multiple tasks to learn how to learn, acquiring rapid adaptation procedures from experience (Schmidhuber, 1987; Naik & Mammone, 1992; Thrun & Pratt, 1998; Bengio et al., 1992; Hochreiter et al., 2001; Santoro et al., 2016; Andrychowicz et al., 2016; Li & Malik, 2017; Ravi & Larochelle, 2017; Finn et al., 2017a; Munkhdalai & Yu, 2017; Snell et al., 2017). These approaches have been extended into the setting of reinforcement learning (Duan et al., 2016b; Wang et al., 2016; Finn et al., 2017a; Sung et al., 2017; Mishra et al., 2017; Gupta et al., 2018; Houthooft et al., 2018; Stadie et al., 2018), though their performance in practice depends on the user-specified meta-training task distribution. We aim to lift this limitation, and provide a general recipe for avoiding manual task engineering for meta-RL. To that end, we make use of unsupervised task proposals. These proposals can be obtained in a variety of ways, including adversarial goal generation (Sukhbaatar et al., 2017; Held et al., 2017), information-theoretic methods (Gregor et al., 2016; Eysenbach et al., 2018), and even random functions.

Methods that address goal generation and curriculum learning have complementary aims. Graves et al. (2017) study this problem for supervised learning, while Forestier et al. (2017) apply a similar approach to robot learning. Prior work (Schaul et al., 2015; Pong et al., 2018; Andrychowicz et al., 2017) also studied learning of goal-conditioned policies, which are closely related to meta-reinforcement learning in their ability to generalize to new goals at test time. However, like meta-learning, goal-conditioned policies typically require manually defined goals at training time. Although exploration methods coupled with goal relabeling (Pong et al., 2018; Andrychowicz et al., 2017) could provide for automated goal discovery, such methods would still be restricted to a specific goal parameterization. In contrast, unsupervised meta-reinforcement learning can solve arbitrary tasks at meta-test time without being restricted to a particular task parameterization. Exploration algorithms based on intrinsic motivation aim to visit diverse states (Pathak et al., 2017; Schmidhuber, 2009; Bellemare et al., 2016; Osband et al., 2016), but do not by themselves aim to generate new tasks or learn to adapt more quickly to new tasks, only to achieve wide coverage of the state space. These methods are complementary to our approach, but address a distinct problem.

Prior work has used meta-learning to learn unsupervised learning rules (Metz et al., 2018). This work learns strategies for unsupervised learning using supervised data, while our approach requires no supervision during meta-training, in effect doing the converse: using a form of unsupervised learning to acquire learning rules that can learn from rewards at meta-test time.

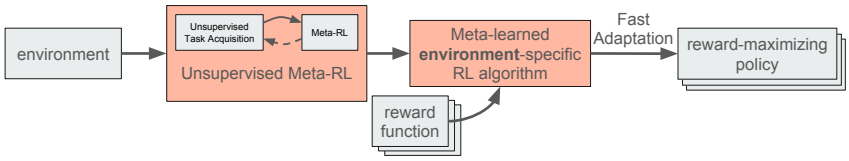


Figure 1: **Unsupervised meta-reinforcement learning**: Given an environment, unsupervised meta-reinforcement learning produces an environment-specific learning algorithm that quickly acquire new policies that maximizes any task reward function.

3 UNSUPERVISED META-REINFORCEMENT LEARNING

The goal of unsupervised meta-reinforcement learning is to take an environment and produce a learning algorithm specifically tailored to this environment that can quickly learn to maximize reward on any task reward in this environment. This learning algorithm should be meta-learned without requiring any human supervision. We can formally define unsupervised meta-reinforcement learning in the context of a controlled Markov process (CMP) – a Markov decision process without a reward function, $C = (S, A, T, \gamma, \rho)$, with state space S, action space A, transition dynamics T, discount factor γ and initial state distribution ρ. Our goal is to learn a learning algorithm f on this CMP, which can subsequently learn new tasks efficiently in this CMP for a new reward function R_i, which produces a Markov decision processes $M_i = (S, A, T, \gamma, \rho, R_i)$. We can, at a high level, denote f as a mapping from tasks to policies, $f : \mathcal{T} \rightarrow \Pi$, where $\mathcal{T}$ is the space of RL tasks defined by the given CMP and R_i, and Π is a space of parameterized policies, such that $\pi \in \Pi$ is a probability distribution over actions conditioned on states, $\pi(a|s)$. Crucially, f must be learned without access to any reward functions R_i, using only unsupervised interaction with the CMP. The reward is only provided at meta-test time.

3.1 A GENERAL RECIPE

Our framework unsupervised meta-reinforcement learning consists of two components. The first component is a task identification procedure, which interacts with a controlled Markov process, without access to any reward function, to construct a distribution over tasks. Formally, we will define the task distribution as a mapping from a latent variable $z \sim p(z)$ to a reward function $r_z(s, a) : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$. That is, for each value of the random variable z, we have a different reward function $r_z(s, a)$. The prior $p(z)$ may be specified by hand. For example, we might choose a uniform categorical distribution or a spherical unit Gaussian. A discrete latent variable z corresponds to a discrete set of tasks, while a continuous representation could allow for an infinite task space. Under this formulation, learning a task distribution amounts to optimizing a parametric form for the reward function $r_z(s, a)$ that maps each $z \sim p(z)$ to a different reward function.

The second component of unsupervised meta-learning is meta-learning, which takes the family of reward functions induced by $p(z)$ and $r_z(s, a)$, and meta-learns a reinforcement learning algorithm f that can quickly adapt to any task from the task distribution defined by $p(z)$ and $r_z(s, a)$. The meta-learned algorithm f can then learn new tasks quickly at meta-test time, when a user-specified reward function is actually provided. This generic design for an unsupervised meta-reinforcement learning algorithm is summarized in Figure 1.

The nature of the task distribution defined by $p(z)$ and $r_z(s, a)$ will affect the effectiveness of f on new tasks: tasks that are close to this distribution will be easiest to learn, while tasks that are far from this distribution will be difficult to learn. However, the nature of the meta-learning algorithm itself will also curcially affect the effectiveness of f. As we will discuss in the following sections, some meta-reinforcement learning algorithms can generalize effectively to new tasks, while some cannot. A more general version of this algorithm might also use f to inform the acquisition of tasks, allowing for an alternating optimization procedure the iterates between learning $r_z(s, a)$ and updating f, for example by designing tasks that are difficult for the current algorithm f to handle. However, in this paper we will consider the stagewise approach, which acquires a task distribution once and meta-trains on it, leaving the iterative variant for future work.

Why might we expect unsupervised meta-reinforcement learning to acquire an algorithm f that improves on any standard, generic, hand-designed reinforcement learning procedure? On the one

hand, the "no free lunch theorem" (Wolpert et al., 1995; Whitley & Watson, 2005) might lead us to expect that a truly generic approach to learning a task distribution (for example, by sampling completely random reward functions) would not yield a learning procedure f that is effective on any real tasks – or even on the meta-training tasks, if they are truly sampled at random. However, the specific choice for the unsupervised learning procedure and meta-learning algorithm can easily impose an inductive bias on the entire process that *does* produce a useful algorithm f. As we will discuss below, we can identify specific choices for the task acquisition and meta-learning procedures that are generic, in the sense that they can be applied to a wide range of CMPs, but also contain enough inductive bias to meta-learn useful reinforcement learning procedures. We discuss specific choices for each of these procedures below, followed by a more general discussion of potential future choices for these procedures and the criteria that they should satisfy. We empirically validate these claims in Section 4.

3.2 Unsupervised Task Acquisition

An effective unsupervised meta-RL algorithm requires a method to acquire task distributions for an environment. We consider two concrete possibilities for such a procedure in this paper, though many other options are also possible for this stage.

Task acquisition via random discriminators. A simple and surprisingly effective way to define arbitrary task distributions is to use random discriminators on states. Given a uniformly distributed random variable $z \sim p(z)$, we can define a random discriminator as a parametric function $D_{\phi_{rand}}(z|s)$, where the parameters ϕ_{rand} are chosen randomly (e.g., a random weight initialization for a neural network). The discriminator observes a state s and outputs the probabilities for a categorical random variable z, hence drawing random decision boundaries in state space. A reward function $r_z(s)$ can be extracted according as $\log(D_{\phi_{rand}}(z|s))$. Note that this is not a random RL objective: the induced RL objective is affected by the inductive bias in the network and mediated by the CMP dynamics distribution. In our experiments, we find that random discriminators are able to acquire useful task distributions for simple tasks, but are not as effective as the tasks become more complicated.

Task acquisition via diversity-driven exploration. We can acquire more varied tasks if we allow some amount of unsupervised environment interaction. Specifically, we consider a recently proposed method for unsupervised skill diversity method - Diversity is All You Need (DIAYN) (Eysenbach et al., 2018) for task acquisition. DIAYN attempts to acquire a set of behaviors that are distinguishable from one another, in the sense that they visit distinct states, while maximizing conditional policy entropy to encourage diversity (Haarnoja et al., 2018). Skills with high entropy that remain discriminable must explore a part of the state space far away from other skills. Formally, DIAYN learns a latent conditioned policy $\pi_\theta(a|s, z)$, with $z \sim p(z)$, where different values of z induce different skills. The training process promotes discriminable skills by maximizing the mutual information between skills and states ($MI(s, z)$), while also maximizing the policy entropy $\mathcal{H}(a|s, z)$:

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

A learned discriminator $D_\phi(z|s)$ maximizes a variational lower bound on Equation 1 (see (Eysenbach et al., 2018) for proof). We train the discriminator to predict the latent variable z from the observed state, and optimize the latent conditioned policy to maximize the log-likelihood of the discriminator correctly classifying states which are visited under different skills, while maximizing policy entropy. Under this formulation, we can think of the discriminator as *rewarding* the policy for producing discriminable skills, and the policy visitations as informing the training of the discriminator.

After learning the policy and discriminator, we sample tasks by generating samples $z \sim p(z)$ and using the corresponding task reward $r_z(s) = \log(D_\phi(z|s))$. Compared to random discriminators, the tasks acquired by DIAYN are more likely to involve visiting diverse parts of the state space, potentially providing both a greater challenge to the corresponding policy and better coverage of the CMP's state space. This method is still fully unsupervised, as it requires no handcrafting of distance metrics or subgoals. It also does not require training a generative model of goals (Held et al., 2017).

3.3 Meta-Reinforcement Learning with Acquired Task Distributions

Once we have acquired a distribution of tasks, either randomly or through unsupervised exploration, we must choose a meta-learning algorithm to acquire the adaptation procedure from this task distribution. Which meta-learning algorithm is best suited for this problem? To formalize the *typical*

meta-reinforcement learning problem, we assume that tasks $\tau \in \mathcal{T}$ are drawn from a manually specified task distribution $\tau_i \sim p(\tau)$, provided by the algorithm designer. These tasks are different MDPs. Each task τ_i is an MDP $M_i = (S, A, T, R_i)$. The goal of meta-RL is to learn a reinforcement learning algorithm f that can learn quickly on novel tasks drawn from $p(\tau)$. In contrast, *our* problem setting we acquire the task distribution $p(\tau)$ completely unsupervised.

A particularly appealing choice for the meta-learning algorithm is model-agnostic meta-learning (Finn et al., 2017a), which trains a model that can adapt quickly to new tasks with standard gradient descent. In RL, this corresponds to the policy gradient, which means that f simply runs policy gradient starting from the meta-learned initial parameters θ. The meta-training objective for MAML is

$$\max_{\theta} \sum_{\tau_i \sim p(\tau)} \mathbb{E}_{\pi_{\theta'_i}} \left[\sum_t R_i(s_t) \right] \quad \theta' = \theta + \alpha \mathbb{E}_{\pi_\theta} \left[\sum_t R_i(s_t) \nabla_\theta \log \pi_\theta(a_t|s_t) \right] \tag{2}$$

The rationale behind this objective is that, since the policy will be adapted at meta-test time to new tasks using policy gradient, we can optimize the policy parameters so that one step of policy gradient improves its performance on any meta-training task as much as possible. MAML learns a data-driven initialization that makes standard reinforcement learning fast on tasks drawn from the task distribution $p(\tau)$. Importantly, MAML uses standard RL via policy gradient to adapt to new tasks, ensuring that we can continuously keep improving on new tasks, even when those tasks lie outside the meta-training distribution. Prior work has observed that meta-learning with policy gradient improves extrapolation over meta-learners that learn the entire adaptation procedure (e.g., using a recurrent network (Finn & Levine, 2018)). Generalization to out-of-distribution samples is especially important for unsupervised meta-reinforcement learning methods because the actual task we might want to adapt to at meta-test time will almost certainly be out-of-distribution. For tasks that are too far outside of the meta-training set, MAML simply reverts to gradient-based RL. Other algorithms could also be used here, as discussed in the Section 3.5.

3.4 Practical Algorithm Implementation

A summary of a practical unsupervised meta-reinforcement learning algorithm is provided on the right. We first acquire a task distribution using unsupervised exploration (e.g., random discriminators or the DIAYN algorithm, as discussed in Section 3.2). We can sample from this task distribution by first sampling a random variable $z \sim p(z)$, and then use the reward induced by the resulting discriminator, $r_z(s) = \log(p_{D_\phi}(z|s))$ to update our policy. Having defined a procedure for sampling tasks, we perform gradient based meta-learning with MAML on this distribution until convergence. The resulting meta-learned policy is then able to adapt quickly to new tasks in the environment via standard policy gradient (Section 4) without requiring additional meta-training supervision.

Algorithm 1: Unsupervised Meta-Reinforcement Learning Pseudocode

Data: $\mathcal{M} \setminus R$, an MDP without a reward function
Result: a learning algorithm $f : \mathcal{D} \rightarrow \pi$
Initialize $\mathcal{D} = \emptyset$
$D_\phi \leftarrow$ DIAYN() or $D_\phi \leftarrow random$
while *not converged* **do**
  Sample latent task variables $z \sim p(z)$
  Extract corresponding task reward functions $r_z(s)$ using $\mathcal{D}_\phi(z|s)$
  update f using MAML with reward $r_z(s)$

3.5 Which Unsupervised and Meta-Learning Procedures Should Work Well?

Having introduced example instantiations of unsupervised meta-reinforcement learning, we discuss more generally what criteria each of the two procedures should satisfy - task acquisition and meta-reinforcement learning. What makes a good task acquisition procedure for unsupervised meta-reinforcement learning? Several criteria are desirable. First, we want the tasks that are learned to resemble the types of tasks that might be present at meta-test time. DIAYN receives no supervision in this regard, basing its task acquisition entirely on the dynamics of the CMP. A more guided approach could incorporate a limited number of human-specified tasks, or manually-provided guidance about valuable state space regions. Without any prior knowledge, we expect the ideal task distribution to induce a wide distribution over trajectories. As many distinct reward functions can have the same optimal policy, a random discriminator may actually result in a narrow distribution of optimal trajectories. In contrast, ... Unsupervised task acquisition procedures like DIAYN, which mediate the

task acquisition process via interactions with the environment (which imposes dynamically consistent structure on the tasks), are likely to yield better results than random task generation. The comparison to the random discriminator in our experiments sheds light on how a learned task distribution is important for this: while random and learned discriminators perform comparably on simple tasks, the learned discriminator performs significantly better on more complex tasks.

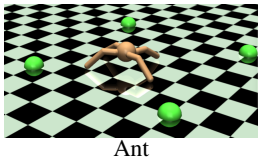
In the absence of any mechanism that constraints the meta-training task distribution to resemble the meta-test distribution (which is unknown), we prefer methods that retain convergence guarantees, performing no worse than standard reinforcement learning algorithms that learn from scratch. Conveniently, gradient-based methods such as MAML gracefully revert to standard, convergent, reinforcement learning procedures on out-of-distribution tasks. Additionally, unlike methods which restrict the space for adaptation using latent conditioned policies such as DIAYN (Eysenbach et al., 2018), MAML does not lose policy expressivity because all policy parameters are being adapted.

We might then ask what kind of knowledge could possibly be "baked" into f during meta-training. There are two sources of knowledge that can be acquired. First, a meta-learning procedure like MAML modifies the initial parameters θ of a policy $\pi_\theta(a|s)$. When $\pi_\theta(a|s)$ is represented by an expressive function class like a neural network, the initial setting of these parameters strongly affects how quickly the policy can be trained by gradient descent. Indeed, this is the rationale behind research into more effective general-purpose initialization methods (Koturwar & Merchant, 2017; Xie et al.). Meta-training a policy essentially learns an effective weight initialization such that a few gradient steps can effectively modify the policy in functionally relevant ways.

The policy found by unsupervised meta-training also acquires an awareness of the dynamics of the given controlled Markov process (CMP). Intuitively, an ideal policy should adapt in the space of trajectories τ, rather than the space of actions a or parameters θ; an RL update should modify the policy's *trajectory distribution*, which determines the reward function. Natural gradient algorithms impose equal-sized steps in the space of action distributions (Schulman et al., 2015), but this is not necessarily the ideal adaptation manifold, since systematic changes in output actions do not necessarily translate into system changes in trajectory or state distributions. In effect, meta-learning prepares the policy to modify its behavior in ways that cogently affect the states that are visited, which requires a parameter setting informed by the *dynamics* of the CMP. This can be provided effectively through unsupervised meta-reinforcement learning.

4 Experimental Evaluation

Half-Cheetah


Ant

In our experiments, we aim to understand whether unsupervised meta-learning can accelerate reinforcement learning of new tasks. Whereas standard meta-learning requires a hand-specified task distribution at meta-training time, unsupervised meta-learning learns the task distribution through unsupervised interaction with the environment. A fair baseline that likewises uses requires no supervision is learning via RL from scratch without any meta-learning. As an upper bound, we include the unfair comparison to a standard meta-learning approach, where the meta-training distribution is manually designed. This method has access to a hand-specified task distribution that is not available to our method. We evaluate two variants of our approach: (a) task acquisition based on DIAYN followed by meta-learning using MAML, and (b) task acquisition using a randomly initialized discriminator followed by meta-learning using MAML. Our experiments aim to answer the following questions: (1) Does unsupervised meta-learning accelerate learning of unseen tasks? (2) How does unsupervised meta-learning compare to meta-learning on a hand-specified task distribution? (3) When should unsupervised meta-learning with a learned task distribution be preferred over a meta-learning with a random discriminator? This last question sheds some light on the effect of task acquisition inductive bias on final reinforcement learning performance.

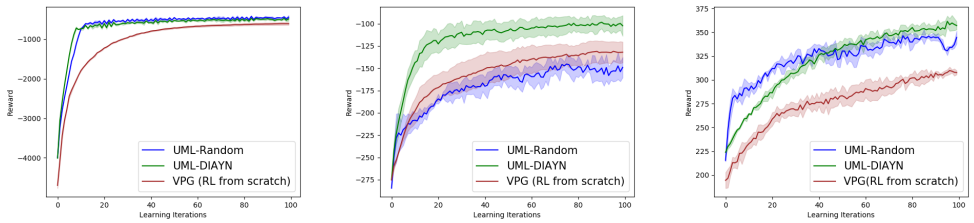
4.1 Tasks and Implementation Details

Our experiments study three simulated environments of increasing difficulty: 2D point navigation, 2D locomotion using the "HalfCheetah," and 3D locomotion using the "Ant," with the latter two

environments adapted from popular reinforcement learning benchmarks (Duan et al., 2016a). While the 2D navigation environment allows for direct control of position, HalfCheetah and Ant can only control their center of mass via feedback control with high dimensional actions (6D for HalfCheetah, 8D for Ant) and observations (17D for HalfCheetah, 111D for Ant).

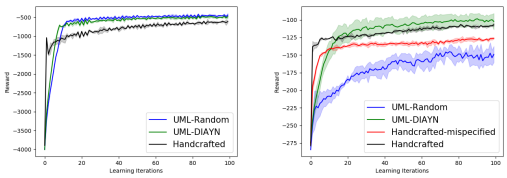
The evaluation tasks, shown in Figure 5, are similar to prior work (Finn et al., 2017a; Pong et al., 2018): 2D navigation and ant require navigating to goal positions, while the half cheetah must run at different goal velocities. These tasks are not accessible to our algorithm during meta-training.

4.2 Fast Adaptation after Unsupervised Meta Learning



2D navigation Half-Cheetah Ant

Figure 3: **Unsupervised meta-learning accelerates learning**: After unsupervised meta-learning, our approach (UML-DIAYN and UML-RANDOM) quickly learns a new task significantly faster than learning from scratch, especially on complex tasks. Learning the task distribution with DIAYN helps more for complex tasks. Results are averaged across 20 evaluation tasks.



2D Navigation Half-Cheetah

Figure 4: **Comparison with handcrafted tasks**: Unsupervised meta-learning (UML-DIAYN) is competitive with meta-training on handcrafted reward functions (i.e., an oracle). A misspecified, handcrafted meta-training task distribution often performs worse, illustrating the benefits of learning the task distribution.

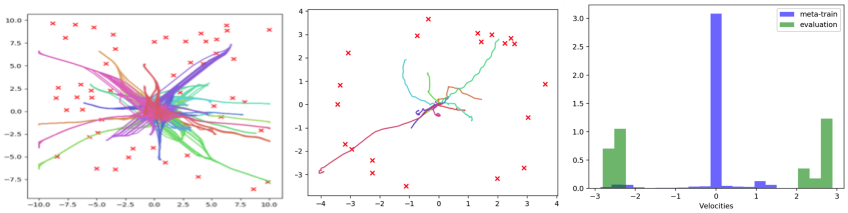
The comparison between the two variants of unsupervised meta-learning and learning from scratch is shown in Fig 3, and we compare to hand-crafted task distributions in Fig 4. We observe in all cases that the UML-DIAN variant of unsupervised meta-learning produces an RL procedure that outperforms reinforcement learning from scratch, suggesting that unsupervised interaction with the environment and meta-learning is effective in producing environment-specific but task-agnostic priors that accelerate learning on new, previously unseen tasks. Interestingly, in all cases the performance of unsupervised meta-learning with DIAYN matches or exceeds that of the hand-designed task distribution (Fig 4). We see that on the 2D navigation task, while handcrafted meta-learning is able to learn very quickly initially, it performs similarly after 100 steps. For the cheetah environment as well, handcrafted meta-learning is able to learn very quickly to start off, but is superseded by unsupervised meta-RL with DIAYN. We also see on the HalfCheetah that, if we meta-test using an initialization learned with a slightly different task distribution, performance degrades to below that of our approach. This result confirms that unsupervised environment interaction can extract a sufficiently diverse set of tasks to make unsupervised meta-learning useful.

The comparison between the two unsupervised meta-learning variants is also illuminating: while the DIAYN-based variant of our method generally achieves the best performance, even the random discriminator is able to provide a sufficient diversity of tasks to produce meaningful acceleration over learning from scratch in the case of 2D navigation and ant.

This result has two interesting implications. First, it suggests that unsupervised meta-learning is an effective tool for learning an environment prior, even when the meta-training task distribution does not necessarily broadly cover the state space. Although the performance of unsupervised meta-learning can be improved with better coverage using DIAYN (as seen in Fig 3), even the random discriminator version provides competitive advantages over learning from scratch. Second, the comparison provides a clue for identifying the source of the structure learned through unsupervised meta-learning: though the particular task distribution has an effect on performance, simply interacting with the environment (without structured objectives, using a random discriminator) already allows meta-RL to learn

effective adaptation strategies in a given environment. That is, the performance cannot be explained only by the unsupervised procedure (DIAYN) capturing the right task distribution.

4.3 Analysis of Learned Task Distributions



2D navigation Ant Half-Cheetah

Figure 5: **Learned meta-training task distribution and evaluation tasks**: We plot the center of mass for various skills discovered by point mass and ant using DIAYN, and a blue histogram of goal velocities for cheetah. Evaluation tasks, which are not provided to the algorithm during meta-training, are plotted as red 'x' for ant and pointmass, and as a green histogram for cheetah. While the meta-training distribution is broad, it does not fully cover the evaluation tasks. Nonetheless, meta-learning on this *learned* task distribution enables efficient learning on a test task distribution.

We can analyze the tasks discovered through unsupervised exploration and compare them to tasks we evaluate on at meta-test time. Figure 5 illustrates these distributions using scatter plots for 2D navigation and the Ant, and a histogram for the HalfCheetah. Note that we visualize dimensions of the state that are relevant for the evaluation tasks – positions and velocities – but these dimensions are *not* specified in any way during unsupervised task acquisition, which operates on the entire state space. Although the tasks proposed via unsupervised exploration provide fairly broad coverage, they are clearly quite distinct from the meta-test tasks, suggesting the approach can tolerate considerable distributional shift. Qualitatively, many of the tasks proposed via unsupervised exploration such as jumping and falling that are not relevant for the evaluation tasks. Our choice of the evaluation tasks was largely based on prior work, and therefore not tailored to this exploration procedure. The results for unsupervised meta-reinforcement learning therefore suggest quite strongly that unsupervised task acquisition can provide an effective meta-training set, at least for MAML, even when evaluating on tasks that do not closely match the discovered task distribution.

5 Discussion and Future Work

We presented an unsupervised approach to meta-reinforcement learning, where meta-learning is used to acquire an efficient reinforcement learning procedure without requiring hand-specified task distributions for meta-training. This approach accelerates RL without relying on the manual supervision required for conventional meta-learning algorithms. Our experiments indicate that unsupervised meta-RL can accelerate learning on a range of tasks, outperforming learning from scratch and often matching the performance of meta-learning from hand-specified task distributions.

In this work, we studied the case where unsupervised meta-learning is performed under the same dynamics, and the aim is to learn a learning procedure that succeeds for other objectives in the same environment. A natural extension of our approach would be to perform unsupervised meta-learning on a variety of different environments, which would provide for even wider generalization, and this would be an exciting direction for future work.

As our work is the first foray into unsupervised meta-learning, our approach opens a number of questions about unsupervised meta-learning algorithms. While we focus on purely unsupervised task proposal mechanisms, it is straightforward to incorporate minimally-informative priors into this procedure. For example, we might restrict the learned reward functions to operate on only part of the state. We consider the reinforcement learning setting in our work because environment interaction mediates the unsupervised learning process, ensuring that there is something to learn even without access to task reward. An interesting direction to study in future work is the extension of unsupervised meta-learning to domains such as supervised classification, which might hold the promise of developing new unsupervised learning procedures powered by meta-learning.

REFERENCES

Maruan Al-Shedivat, Trapit Bansal, Yuri Burda, Ilya Sutskever, Igor Mordatch, and Pieter Abbeel. Continuous adaptation via meta-learning in nonstationary and competitive environments. *arXiv preprint arXiv:1710.03641*, 2017.

Marcin Andrychowicz, Misha Denil, Sergio Gomez, Matthew W Hoffman, David Pfau, Tom Schaul, and Nando de Freitas. Learning to learn by gradient descent by gradient descent. In *Neural Information Processing Systems (NIPS)*, 2016.

Marcin Andrychowicz, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, OpenAI Pieter Abbeel, and Wojciech Zaremba. Hindsight experience replay. In *Advances in Neural Information Processing Systems*, pp. 5048–5058, 2017.

Marc G. Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Rémi Munos. Unifying count-based exploration and intrinsic motivation. *CoRR*, abs/1606.01868, 2016. URL `http://arxiv.org/abs/1606.01868`.

Samy Bengio, Yoshua Bengio, Jocelyn Cloutier, and Jan Gecsei. On the optimization of a synaptic learning rule. In *Optimality in Artificial and Biological Neural Networks*, 1992.

Yan Duan, Xi Chen, Rein Houthooft, John Schulman, and Pieter Abbeel. Benchmarking deep reinforcement learning for continuous control. In *International Conference on Machine Learning*, pp. 1329–1338, 2016a.

Yan Duan, John Schulman, Xi Chen, Peter L Bartlett, Ilya Sutskever, and Pieter Abbeel. Rl^2: Fast reinforcement learning via slow reinforcement learning. *arXiv preprint arXiv:1611.02779*, 2016b.

Benjamin Eysenbach, Abhishek Gupta, Julian Ibarz, and Sergey Levine. Diversity is all you need: Learning skills without a reward function. *arXiv preprint arXiv:1802.06070*, 2018.

Chelsea Finn and Sergey Levine. Meta-learning and universality: Deep representations and gradient descent can approximate any learning algorithm. *CoRR*, abs/1710.11622, 2017. URL `http://arxiv.org/abs/1710.11622`.

Chelsea Finn and Sergey Levine. Meta-learning and universality: Deep representations and gradient descent can approximate any learning algorithm. *International Conference on Learning Representations*, 2018.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. *arXiv preprint arXiv:1703.03400*, 2017a.

Chelsea Finn, Tianhe Yu, Tianhao Zhang, Pieter Abbeel, and Sergey Levine. One-shot visual imitation learning via meta-learning. *CoRR*, abs/1709.04905, 2017b. URL `http://arxiv.org/abs/1709.04905`.

Sébastien Forestier, Yoan Mollard, and Pierre-Yves Oudeyer. Intrinsically motivated goal exploration processes with automatic curriculum learning. *arXiv preprint arXiv:1708.02190*, 2017.

Alex Graves, Marc G Bellemare, Jacob Menick, Remi Munos, and Koray Kavukcuoglu. Automated curriculum learning for neural networks. *arXiv preprint arXiv:1704.03003*, 2017.

Karol Gregor, Danilo Jimenez Rezende, and Daan Wierstra. Variational intrinsic control. *arXiv preprint arXiv:1611.07507*, 2016.

Abhishek Gupta, Russell Mendonca, YuXuan Liu, Pieter Abbeel, and Sergey Levine. Meta-reinforcement learning of structured exploration strategies. *arXiv preprint arXiv:1802.07245*, 2018.

Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. *arXiv preprint arXiv:1801.01290*, 2018.

David Held, Xinyang Geng, Carlos Florensa, and Pieter Abbeel. Automatic goal generation for reinforcement learning agents. *arXiv preprint arXiv:1705.06366*, 2017.

Sepp Hochreiter, A Steven Younger, and Peter R Conwell. Learning to learn using gradient descent. In *International Conference on Artificial Neural Networks*, 2001.

Rein Houthooft, Richard Y Chen, Phillip Isola, Bradly C Stadie, Filip Wolski, Jonathan Ho, and Pieter Abbeel. Evolved policy gradients. *arXiv preprint arXiv:1802.04821*, 2018.

Saiprasad Koturwar and Shabbir Merchant. Weight initialization of deep neural networks(dnns) using data statistics. *CoRR*, abs/1710.10570, 2017. URL http://arxiv.org/abs/1710.10570.

Philipp Krähenbühl, Carl Doersch, Jeff Donahue, and Trevor Darrell. Data-dependent initializations of convolutional neural networks. *arXiv preprint arXiv:1511.06856*, 2015.

Ke Li and Jitendra Malik. Learning to optimize. *International Conference on Learning Representations (ICLR)*, 2017.

Luke Metz, Niru Maheswaranathan, Brian Cheung, and Jascha Sohl-Dickstein. Learning unsupervised learning rules. *arXiv preprint arXiv:1804.00222*, 2018.

Nikhil Mishra, Mostafa Rohaninejad, Xi Chen, and Pieter Abbeel. A simple neural attentive meta-learner. In *NIPS 2017 Workshop on Meta-Learning*, 2017.

Tsendsuren Munkhdalai and Hong Yu. Meta networks. *International Conference on Machine Learning (ICML)*, 2017.

Devang K Naik and RJ Mammone. Meta-neural networks that learn by learning. In *International Joint Conference on Neural Netowrks (IJCNN)*, 1992.

Ian Osband, Charles Blundell, Alexander Pritzel, and Benjamin Van Roy. Deep exploration via bootstrapped DQN. *CoRR*, abs/1602.04621, 2016. URL http://arxiv.org/abs/1602.04621.

Deepak Pathak, Pulkit Agrawal, Alexei A. Efros, and Trevor Darrell. Curiosity-driven exploration by self-supervised prediction. In *ICML*, 2017.

Vitchyr Pong, Shixiang Gu, Murtaza Dalal, and Sergey Levine. Temporal difference models: Model-free deep rl for model-based control. *arXiv preprint arXiv:1802.09081*, 2018.

Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. In *International Conference on Learning Representations (ICLR)*, 2017.

Adam Santoro, Sergey Bartunov, Matthew Botvinick, Daan Wierstra, and Timothy Lillicrap. Meta-learning with memory-augmented neural networks. In *International Conference on Machine Learning (ICML)*, 2016.

Tom Schaul, Daniel Horgan, Karol Gregor, and David Silver. Universal value function approximators. In *International Conference on Machine Learning*, pp. 1312–1320, 2015.

Jürgen Schmidhuber. *Evolutionary principles in self-referential learning, or on learning how to learn: the meta-meta-... hook*. PhD thesis, Technische Universität München, 1987.

Jürgen Schmidhuber. Driven by compression progress: A simple principle explains essential aspects of subjective beauty, novelty, surprise, interestingness, attention, curiosity, creativity, art, science, music, jokes. In *Computational Creativity: An Interdisciplinary Approach, 12.07. - 17.07.2009*, 2009. URL http://drops.dagstuhl.de/opus/volltexte/2009/2197/.

John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In *International Conference on Machine Learning*, pp. 1889–1897, 2015.

Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Advances in Neural Information Processing Systems*, pp. 4080–4090, 2017.

Bradly C. Stadie, Ge Yang, Rein Houthooft, Xi Chen, Yan Duan, Yuhuai Wu, Pieter Abbeel, and Ilya Sutskever. Some considerations on learning to explore via meta-reinforcement learning. *CoRR*, abs/1803.01118, 2018. URL http://arxiv.org/abs/1803.01118.

Sainbayar Sukhbaatar, Zeming Lin, Ilya Kostrikov, Gabriel Synnaeve, Arthur Szlam, and Rob Fergus. Intrinsic motivation and automatic curricula via asymmetric self-play. *arXiv preprint arXiv:1703.05407*, 2017.

Flood Sung, Li Zhang, Tao Xiang, Timothy Hospedales, and Yongxin Yang. Learning to learn: Meta-critic networks for sample efficient learning. *arXiv preprint arXiv:1706.09529*, 2017.

Sebastian Thrun and Lorien Pratt. *Learning to learn*. Springer Science & Business Media, 1998.

Jane X Wang, Zeb Kurth-Nelson, Dhruva Tirumala, Hubert Soyer, Joel Z Leibo, Remi Munos, Charles Blundell, Dharshan Kumaran, and Matt Botvinick. Learning to reinforcement learn. *arXiv preprint arXiv:1611.05763*, 2016.

Darrell Whitley and Jean Paul Watson. Complexity theory and the no free lunch theorem, 2005.

David H Wolpert, William G Macready, et al. No free lunch theorems for search. Technical report, Technical Report SFI-TR-95-02-010, Santa Fe Institute, 1995.

Di Xie, Jiang Xiong, and Shiliang Pu. All you need is beyond a good init: Exploring better solution for training extremely deep convolutional neural networks with orthonormality and modulation. In *2017 IEEE Conference on Computer Vision and Pattern Recognition*. doi: 10.1109/CVPR.2017.539. URL `https://doi.org/10.1109/CVPR.2017.539`.