Self-Paced Deep Reinforcement Learning

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Abstract
Generalization and reuse of agent behaviour across a variety of learning tasks promises to carry the next wave of breakthroughs in Reinforcement Learning (RL). The field of Curriculum Learning proposes strategies that aim to support a learning agent by exposing it to a tailored series of tasks throughout learning, e.g. by progressively increasing their complexity. In this paper, we consider recently established results in Curriculum Learning for episodic RL, proposing an extension that is easily integrated with well-known RL algorithms and providing a theoretical formulation from an RL-as-Inference perspective. We evaluate the proposed scheme with different Deep RL algorithms on representative tasks, demonstrating that it is capable of significantly improving learning performance.

1. Introduction
Reinforcement Learning (RL) (Sutton & Barto, 1998) enables agents to learn sophisticated behaviors from interaction with an environment. Combinations of RL paradigms with powerful function approximators, commonly referred to as Deep RL (DRL), recently resulted in the acquisition of superhuman performance in various simulated domains (Silver et al., 2017; Vinyals et al., 2019). Despite these impressive results, the behavior learned by RL agents is typically limited to a very specific task, with no means of reuse outside of it. This deficiency has motivated research on equipping agents with the capability of generalizing learned behavior and, furthermore, how to make use of this capability in order to speed up, stabilize, or enable learning of complicated tasks.

We are specifically interested in the field of Curriculum Learning (Bengio et al., 2009) for RL, which investigates how sequences of tasks can be designed that benefit the learning progress of an agent by allowing it to reuse previously learned behavior. In order to create a curriculum for a given problem, it is both necessary to define a set of tasks from which it can be built and, based on that, specify how it is built, i.e. how a task is selected given the current performance of the agent. This paper addresses the latter problem, assuming access to a set of parameterized tasks.

A paradigm called Self-Paced Learning (Kumar et al., 2010) addresses the curriculum generation problem by trading-off two objectives: Maximizing the expected objective value over the selected training tasks and progressively ensuring the incorporation of a set of desired tasks. Recently an algorithm called Self-Paced Contextual Reinforcement Learning (SPRL) applied the paradigm to episodic RL problems (Klink et al., 2019), demonstrating significant benefits. Our work reformulates the SPRL algorithm, resulting in a curriculum generation approach applicable to any step-based RL algorithm that estimates a Value Function (Section 4). Given our focus on its application to DRL algorithms, we refer to it as Self-Paced Deep Reinforcement Learning (SPDL). Combined with the well-known DRL algorithms TRPO, PPO and SAC (Schulman et al., 2015; 2017; Haarnoja et al., 2018), our scheme matches or surpasses the performance of baseline methods in environments of different complexity and with sparse and dense rewards (Section 5). Finally, taking an inference perspective on RL, we show that both SPRL and SPDL can be motivated from the same Latent Variable Model (LVM) (Section 6).

This common view through an LVM represents an important contribution to the understanding of Self-Paced Learning aside from the proposed SPDL algorithm. It renders SPDL not just as another specific algorithm, but rather as an instantiation of a broader concept for curriculum generation in the domain of step-based RL.

2. Related Work
Exploiting inter-task structure is a heavily investigated topic across all of the Machine Learning community, albeit the approaches for making use of this structure, as well as their assumptions, heavily differ (Pan et al., 2010; Lazari, 2012; Taylor & Stone, 2009). Requiring shared structure between learning tasks (such as common inputs for Supervised Learn-
ing (SL) or a common state-action space for RL) enables learning of shared representations that have been shown to be beneficial for the system performance (Caruana, 1997; Schaul et al., 2015). Simultaneously evolving the learning task with the learner has been investigated in a variety of fields ranging from behavioral psychology (Skinner, 2019) to evolutionary robotics (Bongard & Lipson, 2004) and RL (Erez & Smart, 2008). Furthermore, the concept behind this strategy exhibits ties to numerical continuation methods (Allgower & Georg, 2012).

In the SL domain, this principle was given the name “Curriculum Learning” (Bengio et al., 2009). This name has by now also been established in the RL community, where a variety of algorithms aiming to generate curricula that maximally benefit the learner have been proposed. For learning in goal-oriented tasks with sparse reward functions, ensuring the chance of reaching the specified goal to stay within a certain range allowed to create learning curricula that drastically improve sample efficiency in these domains (Florensa et al., 2018; 2017; Andrychowicz et al., 2017). Focusing on tasks in which the learner maximally progresses, i.e. maximally improves w.r.t. the chosen performance measure, has been proposed in developmental robotics (Blank et al., 2005) and RL (Schmidhuber, 1991) and has motivated many works that approximately implement this idea for curriculum generation (Baranes & Oudeyer, 2010; Portelas et al., 2019; Fournier et al., 2018). Another approach to curriculum generation has been explored under the name Self-Paced Learning initially for SL (Kumar et al., 2010; Jiang et al., 2015; 2014) and recently also RL (Klink et al., 2019). The aforementioned algorithms generate a curriculum by optimizing the trade-off between exposing the learner to a set of desired tasks and selecting tasks in which it currently performs well. Learning to generate the optimal curriculum has been investigated by casting it as an RL problem (Narvekar & Stone, 2019), which showed that learning to create this optimal curriculum is typically computationally harder than learning the entire task from scratch. In light of this result, all aforementioned approaches can be seen as tractable approximations of this optimal curriculum.

As we interpret RL from an inference perspective in the course of this paper, we want to briefly point to several works employing this perspective (Dayan & Hinton, 1997; Deisenroth et al., 2013; Rawlik et al., 2013; Levine, 2018; Toussaint & Storkey, 2006). Taking an inference perspective is particularly useful, allowing to derive the well-known concept of maximum entropy for RL and inverse RL (Ziebart et al., 2008; Haarnoja et al., 2018) and stimulating the development of new, and interpretation of, existing algorithms from a common view (Abdolmaleki et al., 2018; Fellows et al., 2019). We will make use of casting RL as Expectation Maximization (EM) (Bishop, 2006) of a LVM, showing connections between our proposed learning scheme and Posterior Regularization for EM (Ganchev et al., 2010).

3. Self-Paced Contextual Reinforcement Learning

This section serves to recapture necessary Reinforcement Learning (RL) notation and the results from Self-Paced Contextual Reinforcement Learning (Klink et al., 2019), which will motivate the curriculum generation scheme presented in the next section.

RL is defined as an optimization problem on a Markov Decision Process (MDP), a tuple \( \mathcal{M} = < \mathcal{S}, \mathcal{A}, p, r, p_0 > \) that defines an abstract environment with states \( s \in \mathcal{S} \), actions \( a \in \mathcal{A} \), transition probabilities \( p(s'|s,a) \), reward function \( r : \mathcal{S} \times \mathcal{A} \to \mathbb{R} \) and initial state distribution \( p_0(s) \). Typically \( \mathcal{S} \) and \( \mathcal{A} \) are discrete-spaces or subsets of \( \mathbb{R}^n \). RL encompasses approaches that aim to maximize the objective

\[
J(\pi) = E_{p_0(s_0), p(s|s,i|s',a)} \left[ \sum_{i=0}^{\infty} \gamma^i r(s_i, a_i) \right] \tag{1}
\]

by finding an optimal policy \( \pi(a|s) \) through interaction with the environment. A key ingredient to many RL algorithms is the so-called Value Function

\[
V_\pi(s) = E_{\pi(a|s)} \left[ r(s,a) + \gamma E_{p(s'|s,a)} [V_\pi(s')] \right] , \tag{2}
\]

which encodes the long-term expected discounted reward of following policy \( \pi \) from state \( s \). We will later make use of the Value Function (or an estimate of it) to judge the performance of a learning algorithm in a given task, as

\[
J(\pi) = E_{p_0(s_0)} [V_\pi(s_0)] . \tag{3}
\]

A common approach to generalize a learned policy across a variety of tasks is to introduce an additional context parameter \( c \in \mathcal{C} \subseteq \mathbb{R}^n \), which parameterizes the MDP \( \mathcal{M}_c = < \mathcal{S}, \mathcal{A}, p_c, r_c, p_0,c > \). The policy is conditioned on this context \( \pi(a|s, c) \) and we can, analogously to Equations 1 and 2, define a contextual-RL objective

\[
J(\pi, \mu) = E_{\mu(c)} [J(\pi, c)] = E_{\mu(c), p_0,c(s)} [V_\pi(s, c)] , \tag{4}
\]

where \( \mu(c) \) is a distribution over contexts and the Value Function \( V_\pi(s, c) \) encodes the expected discounted reward of being in states \( s \) in context \( c \) and following the conditioned policy \( \pi(a|s, c) \). This formulation has been investigated by multiple works (Hallak et al., 2015; Modi et al., 2018; Schaul et al., 2015) from different perspectives.

Opposed to aforementioned step-based view, episodic contextual-RL frames the maximization of \( J(\pi, \mu) \) as a stochastic search problem over the joint-space of context parameters \( c \) and policy parameters \( \omega \). For the rest of this paper, we interpret the policy parameters as an abstraction
for a deterministic policy \( \pi_\omega : S \rightarrow A \), although conceptually also stochastic policies are possible. The episodic reward function \( R(\omega, c) \) encodes the desirability of the behavior generated by \( \pi_\omega \) in the task defined by \( c \). Instead of directly optimizing the parameters of a policy, the learning algorithm now optimizes a distribution over policy parameters \( p(\omega|c) \). Contextual Relative Entropy Policy Search (C-REPS) (Kupciski et al., 2013) searches for a locally optimal distribution by iteratively solving

\[
\max_{p(\omega|c)} E_{\mu(c)} \left[ E_{p(\omega|c)} \left[ R(\omega, c) \right] \right] \\
\text{s.t.} \ E_{\mu(c)} \left[ D_{KL}(p(\omega|c)||q(\omega|c)) \right] \leq \epsilon, (5)
\]

where \( q(\omega|c) \) is the distribution obtained from the previous iteration of the search and \( \epsilon \) is a parameter that controls the deviation of the improved policy \( p \) from \( q \) by limiting the expected KL Divergence \( D_{KL} \) between them.

Self-Paced Contextual Reinforcement Learning (SPRL) (Klink et al., 2019) introduces the Self-Paced Learning scheme into this view by allowing the agent to optimize both policy and context distribution \( p(\omega, c) \) w.r.t. to the objective

\[
\max_{p(\omega|c)} E_{p(\omega|c)} \left[ E_{p(\omega|c)} \left[ R(\omega, c) \right] \right] - \alpha D_{KL}(p(c)||\mu(c)) \\
\text{s.t.} \ D_{KL}(p(\omega|c)||q(\omega, c)) \leq \epsilon. (6)
\]

The parameter \( \alpha \) represents the trade-off between maximization of the expected reward under the chosen context distribution \( p(c) \) and matching the distribution of desired \( \mu(c) \). In each iteration of SPRL, the hyperparameter \( \alpha \) is chosen such that the KL Divergence penalty w.r.t. the current context distribution is in constant proportion \( \zeta \) to the expected reward under the current context distribution

\[
\alpha = B(\zeta, q) = \zeta \frac{E_{q(\omega|c)} \left[ R(\omega, c) \right]}{D_{KL}(q(\omega|c)||\mu(c))}. (7)
\]

The update of the context distribution resulting from the optimization of the SPRL objective can be shown to adhere to the following rule

\[
p(c) \propto q(c) \exp \left( \frac{V_{\tilde{\eta}, q}(c) + \alpha \log \left( \frac{\mu(c)}{q(c)} \right)}{\alpha + \eta} \right), (8)
\]

where \( \tilde{\eta} \) and \( \eta \) are Lagrangian multipliers that arise from solving the constrained optimization problem (see (Klink et al., 2019) for details).

The term \( V_{\tilde{\eta}, q}(c) \) can be identified as a soft-max operator over the expected reward under \( q(\omega|c) \) in context \( c \)

\[
V_{\tilde{\eta}, q}(c) = \tilde{\eta} \log \left( E_{q(\omega|c)} \left[ \exp \left( \frac{R(\omega, c)}{\tilde{\eta}} \right) \right] \right),
\]

which at the limit of \( \tilde{\eta} \rightarrow \infty \) converges to the regular mean

\[
E_{q(\omega|c)} \left[ R(\omega, c) \right].
\]

4. Self-Paced Deep Reinforcement Learning

We will now motivate a curriculum generation scheme which is easily applied to any RL algorithm that computes an approximation of the value function \( \hat{V}(s, c) \), by connecting the episodic contextual-RL objective (Equation 5) and \( J(\pi, \mu) \) (Equation 4).

In order to define a step-based counterpart of SPRL, we investigate the similarity between the definitions of expected reward in a given context \( c \) for the step-based and episodic RL formulation

\[
J(\pi, c)
\]

\[
= E_{p_0,c}(s_0) \pi(a_1|s_1, c, p_0, s_{1:i} = s_1, a_1) \sum_{i=0}^{\infty} \gamma^i r_c(s_i, a_i) \]

\[
E_{p(c)} \left[ R(\omega, c) \right]
\]

\[
= E_{p_0,c}(s_0) \pi(c, p_0, s_{1:i} = s_1, \pi(c, s_0)) \sum_{i=0}^{\infty} \gamma^i r_c(s_i, a_i). (9)
\]

Looking at the above expectations, we identify that the difference between them is the way of inducing exploratory behavior. In the episodic setting, this is done via noise on the policy parameters generated by \( p(\omega|c) \), while in the step-based setting noise is directly applied to the actions by the stochastic policy \( \pi(a|s) \).

The previous findings motivate simply replacing the episodic expected reward in context \( c \) with its step-based counterpart in the SPRL objective (Equation 6). In order to be independent of the learning algorithm, we assume a policy \( \pi \) to be given and only optimize w.r.t. \( p(c) \) to obtain

\[
\max_{p(c)} E_{p(c)} \left[ J(\pi, c) \right] - \alpha D_{KL}(p(c)||\mu(c)) \\
\text{s.t.} \ D_{KL}(p(c)||q(c)) \leq \epsilon. (11)
\]

Now we are able to explore the access to an estimate of the Value Function \( \hat{V}(s, c) \) in order to approximate \( J(\pi, c) \) (Equation 3). Hence, the Value Function serves as the central abstraction between the learning agent and our proposed curriculum generation scheme.

A practical realization of this scheme then alternates between two steps: Training the agent under the current context distribution \( q(c) \) to generate a set of samples from \( L \) policy rollouts

\[
D = \{ (c_i, s_{0:i}, R_i|c_i \sim q(c), s_{0:i} \sim p_0,c(s), i \in [1, L]) \}, (12)
\]

and updating the context distribution using this data. In above definition, \( R_i \) is the cumulative discounted reward achieved in episode \( i \). The expectation in objective 11 is
Algorithm 1 Self-Paced Deep RL (SPDL)

**Input:** Initial context distribution \( p_0 \) and policy \( \pi_0 \), KL penalty proportion \( \zeta \), offset \( K_\alpha \), number of context distribution updates \( K \)

**for** \( k = 1 \) **to** \( K \) **do**

**Agent improvement:**
- Sample contexts: \( c_i \sim p_k(c) \), \( i = 1, \ldots, L \)
- Obtain \( \pi_{i+1} \) from RL algorithm of choice while generating \( D \) (Equation 12)

**Context adaptation:**
- Set \( \alpha = 0 \), if \( k \leq K_\alpha \), else \( B(\zeta, p_k, \pi_k) \) (Equation 7)
- Obtain \( p_{k+1} \) solving SPDL objective (Equation 11)

end for

approximated by an importance-weighted average of the samples in \( D \)

\[
E_{p(c)}[J(\pi, c)] \approx \sum_{i=1}^{L} p(c_i) \frac{q(c_i)}{q(c_i)} \tilde{V}(s_0, a_i).
\]

The parameter \( \alpha \) is computed using the same heuristics as proposed in the SPRL algorithm. The resulting Curriculum Learning scheme (SPDL) is sketched in Algorithm 1. To solve the constrained optimization problem of SPDL (Equation 11) we employ the conjugate gradient algorithm in combination with a line search, as e.g. proposed in (Schulman et al., 2015).

While not only easy to implement, we demonstrate in the next section that this scheme leads to substantial benefits in learning performance.

After the experimental section, we present the second contribution of the paper by providing an interpretation of both SPRL and SPDL from an inference perspective. We show that both algorithms can be derived from the same Latent Variable Model, rendering them as particular realizations of the same broader concept. As a side effect, it will give a theoretical motivation for the algorithmic choices of SPDL, i.e. decomposing context distribution update and agent improvement as well as replacing the soft-max operator over the expected reward \( \tilde{V}_{\tilde{\eta}, q}(c) \) by a regular value function.

5. Experiments

The aim of this section is to investigate the performance and versatility of the proposed Curriculum Learning scheme (SPDL). To accomplish this, we evaluate SPDL in three different environments with different DRL algorithms to test the proposition that the learning scheme indeed benefits the performance of various RL algorithms. We evaluate the performance using TRPO (Schulman et al., 2015), PPO (Schulman et al., 2017) and SAC (Haarnoja et al., 2018). For all DRL algorithms, we use the implementations provided in the Stable Baselines repository (Hill et al., 2018). For all experiments, we restrict the context distribution \( p(c) \) of SPDL to be Gaussian. Consequently, objective 11 is optimized w.r.t. the mean \( \mu \) and covariance \( \Sigma \) of the context distribution.\(^1\)

The first two environments aim at investigating the benefit of SPDL when the purpose of the generated curriculum is solely to facilitate learning of a hard target task, which the agent is not able to solve without a curriculum. For this purpose, we create two environments which are conceptually similar to the point-mass experiment considered for SPRL (Klink et al., 2019). The first one is a copy of the original experiment, but with an additional parameter to the context space, as we will detail in the corresponding section. The second environment extends the original experiment by replacing the point-mass with a torque-controlled quadruped “ant”. This significantly increases the complex-

\(^1\)Code for the experiments is available under https://github.com/psclklnk/spdl. Since the Isaac Gym simulator is currently under closed-source access, we unfortunately cannot make the Ant environment accessible.
Figure 2. Reward of different curricula in the Point-Mass environment for TRPO. Mean (thick line) and two times standard error (shaded area) is computed from 20 seeds. The lower plot shows Median and 90%-confidence interval of the KL Divergence between the sampling distribution of SPDL and the target context distribution.

Figure 3. Reward of different curricula in the Point-Mass environment for TRPO with a fixed friction parameter of 0. Mean (thick line) and two times standard error (shaded area) is computed from 20 seeds. Median and 90%-confidence interval of the KL Divergence between the sampling distribution of SPDL and the target context distribution are shown in the lower plot.

ity of the underlying control problem, requiring the capacity of Deep Neural Network function approximators used in DRL algorithms.

The final environment is a robotic ball-catching environment. This environment constitutes a shift in curriculum paradigm as well as reward function. Instead of guiding learning towards a specific target task, this third environment requires to learn a ball-catching policy over a wide range of initial states (ball position and -velocity). The reward function is sparse compared to the dense ones employed in the first two environments.

In order to judge the performance of SPDL, we compare the obtained results to state-of-the-art CL algorithms ALP-GMM (Portelas et al., 2019) and GoalGAN (Florensa et al., 2018). Furthermore, we compare to curricula consisting of tasks uniformly sampled from the context space (referred to as "Random" in the plots) and learning without a curriculum (referred to as "Default"). Additional details on the experiments as well as qualitative evaluation of them can be found in Appendix D.

5.1. Point-Mass Environment

In this environment, the agent controls a point mass that needs to be navigated through a gate of given size and position in order to reach a desired target in a two-dimensional world. If the point mass crashes into the wall, the experiment is stopped. The agent moves the point-mass by applying forces and the reward decays in a squared exponential manner with increasing distance to the goal.

In our version of the experiment, the contextual variable $c \in \mathbb{R}^3$ changes width and position of the gate as well as the dynamic friction coefficient of the ground on which the point mass slides. As previously indicated, the target context distribution $\mu(c)$ is a narrow Gaussian with negligible noise that encodes a small gate at a specific position and a dynamic friction coefficient of 0. Figure 1 shows two different instances of the environment, one of them being the target task.

Figures 2 and 3 show the results of two different experiments in this environment, one where the curriculum is generated over the full context space and one in which the friction parameter is fixed to its target value of 0. As the Figures as well as Table 1 indicate, SPDL significantly increases the asymptotic reward on the target task compared to all other DRL methods. Furthermore, we see that SPRL, which we applied by defining the episodic RL policy $p(\omega| c)$ to choose the weights $\omega$ of the step-based policy for a given context $c$, also leads to a good performance. With a median final KL-Divergence $D_{KL}(p(c)||\mu(c)) \approx 1.0$ for the three dimensional case and $D_{KL}(p(c)||\mu(c)) \approx 0.5$ for the two dimensional one, SPRL seems to converge to a context distribution that is further away from the target one. With SPDL and SPRL both representing the context distributions using Gaussians, this indicates that the direct optimization of Objective 11 results in a better match of the target context distribution.

Furthermore, increasing the dimension of the context space has a stronger negative impact on the performance of the other CL algorithms than on both SPDL and SPRL, where it only negligibly decreases the performance. We suspect that this effect is a result of the baseline methods lack of notion
of a target distribution. Consequently, a higher context dimension decreases the average proximity of sampled tasks to the target one. By having a notion of a target distribution, SPDL can target the curriculum to ultimately encode contexts that are close to the desired one, regardless of the dimension.

5.2. Ant Environment

We replace the point-mass in the previous environment with a four-legged ant similar to the one in the OpenAI Gym simulation environment (Brockman et al., 2016). Similar to the previous environment, the goal is to reach the other side of a wall by passing through a gate, whose width and position is determined by the contextual variable \( c \in \mathbb{R}^2 \).

Opposed to the previous environment, an application of SPRL is not possible in this environment, since the episodic policy needs to choose weights for a policy network with 6464 parameters. In such high-dimensional spaces, even drawing a single sample from a Gaussian distribution faces computational boundaries. On the computer on which the experiments where conducted, this took roughly two minutes. Given the large number of samples that need to be drawn during learning, this highlights the practical problems of SPRL in high-dimensional context spaces.

In this environment, we could only evaluate the CL algorithms using PPO. This is because the implementations of TRPO and SAC in Stable-Baselines do not allow to make use of the parallelization capabilities of the Isaac Gym simulator, leading to prohibitive running times. See Appendix D for details.

Looking at Figure 4, we see that SPDL allows the learning agent to escape the local optima which results from the agent not finding the gate to pass through. We also see that GoalGAN significantly improves the reward compared to the other methods. ALP-GMM and a random curriculum do not improve the reward over directly learning on the target task. However, as we show in Appendix D, both ALP-GMM and a random curriculum improve the qualitative performance, as they sometimes allow to move the ant through the gate. However, this behavior is unreliable and inefficient (the gate is only sometimes passed after many timesteps), causing the action penalties in combination with the discount factor to prevent this better behavior being reflected in the reward.

5.3. Ball-Catching Environment

Due to a sparse reward function and a broad target task distribution, this final environment is drastically different from the previous ones.

In this environment, the agent needs to control a Barrett WAM robot in order to catch a ball thrown towards it. The reward function is sparse, only rewarding the robot when it catches the ball and penalizing it for excessive movements. In the simulated environment, the ball is said to be caught if it is in contact with the end-effector that is attached to the robot. The context \( c \in \mathbb{R}^3 \) parameterizes the distance between the robot and the ball. The ball moves towards the robot in a random direction with a constant velocity and regenerates if it hits the ground. Opposed to the previous environment, an application of SPRL is not possible in this environment, since the episodic nature of the environment makes it difficult to learn a generalizable policy. Instead, we use a fixed curriculum to improve the reward over directly learning on the target task.

We replace the point-mass in the previous environment with a four-legged ant similar to the one in the OpenAI Gym simulation environment (Brockman et al., 2016). Similar to the previous environment, the goal is to reach the other side of a wall by passing through a gate, whose width and position is determined by the contextual variable \( c \in \mathbb{R}^2 \).

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Looking at Figure 4, we see that SPDL allows the learning agent to escape the local optima which results from the agent not finding the gate to pass through. We also see that GoalGAN significantly improves the reward compared to the other methods. ALP-GMM and a random curriculum do not improve the reward over directly learning on the target task. However, as we show in Appendix D, both ALP-GMM and

Table 1. Average final reward and standard error of different curricula and RL algorithms in the two PointMass environments with three (P3D) and two (P2D) context dimensions. The data is computed from 20 algorithm runs. Significantly better results according to a p-test with \( p < 1\% \) are highlighted in bold.

| CL-Algorithm | TRPO (P3D) | PPO (P3D) | SAC (P3D) | TRPO (P2D) | PPO (P2D) | SAC (P2D) |
|--------------|------------|-----------|-----------|------------|-----------|-----------|
| ALP-GMM      | 3.92 ± 0.51 | 2.34 ± 0.18 | 0.96 ± 0.27 | 6.38 ± 9.33 | 2.98 ± 0.16 | 1.15 ± 0.43 |
| GOALGAN      | 0.87 ± 0.31 | 0.54 ± 0.01 | 1.08 ± 0.42 | 3.40 ± 0.67 | 1.12 ± 0.23 | 0.72 ± 0.20 |
| SPDL         | 8.55 ± 0.41 | 6.87 ± 0.41 | 4.64 ± 0.74 | 8.89 ± 0.20 | 7.83 ± 0.27 | 3.80 ± 0.54 |
| RANDOM       | 1.05 ± 0.19 | 0.53 ± 0.00 | 0.60 ± 0.08 | 4.47 ± 0.38 | 0.63 ± 0.01 | 0.93 ± 0.22 |
| DEFAULT      | 2.49 ± 0.01 | 2.48 ± 0.01 | 2.26 ± 0.04 | 2.47 ± 0.01 | 2.49 ± 0.00 | 2.23 ± 0.4 |

Figure 4. The upper plot shows the mean (thick line) and two times standard error (shaded area) of the reward achieved with different curricula in the Ant environment for PPO. The statistics are computed from 20 seeds. The lower plot shows Median and 90%-confidence interval of the KL Divergence between the SPDL sampling distribution and the target context distribution over iterations.
to the robot from which the ball is thrown as well as its target position in a plane that intersects the base of the robot. Figure 1 shows the robot as well as the target distribution over the ball positions in the aforementioned “catching” plane.

In this environment, the context $c$ is not visible to the policy, as it only changes the initial state distribution $p(s_0)$ via the encoded target position and initial distance to the robot. Given that the initial state is already observed by the policy, it is superfluous to make the context observable.

To tackle this learning task with a curriculum, we initialize the policy of the RL algorithms to hold the robots initial position. With this initialization there exists a subspace of the context space in which the policy already performs well, i.e. where target position of the ball coincides with the initial endeffector position. This can be leveraged by CL algorithms.

Since SPDL and GoalGAN support to specify the initial context distribution, we investigate whether this feature can be exploited by choosing the initial context distribution to encode aforementioned tasks in which the initial policy performs well.

When directly learning on the target context distribution without a curriculum, it is not clear whether the policy initialization benefits learning. Because of this, we evaluate the performance both with and without a pre-trained policy in this setting.

Figure 5 and Table 2 show the performance of the investigated Curriculum Learning approaches. We see that sampling tasks directly from the target distribution does not allow to learn a meaningful policy, regardless of the initial policy. Further, all curricula enable learning in this environment and achieve similar reward. The results also highlight that an initialization of the context distribution benefits learning. Because of this, we evaluate the performance both with and without a pre-trained policy initialization.

6. A Latent Variable Model for Self-Paced Reinforcement Learning

In this final section, we introduce a Latent Variable Model (LVM) to unify the view on SPRL and SPDL. In the following, we will use subscript notation to highlight the dependence of a probability distribution on a specific parameter, i.e. $p(\omega)\mid \tau$ highlights that the distribution $p$ depends on the parameter $\omega$.

Our model is based on an extension of the one presented in (Neumann et al., 2011), which interprets the single-task RL objective using the following latent-variable model

$$p(\omega) = \int p(\omega|\tau)p(\tau)d\tau, \quad (13)$$

where $p(\omega|\tau)$ represents the probability of a trajectory $\tau = \{(s_i, a_i) | i \in [1, \infty)\}$ solving the given task optimally. The distribution $p(\omega)$ abstracts the way the trajectory is generated and hence allows the derivation of update rules for both episodic and step-based RL by applying the EM-algorithm (Bishop, 2006), as shown in (Abdolmaleki et al., 2018; Deisenroth et al., 2013; Fellows et al., 2019).

The distribution

$$p(\omega|\tau) = \frac{f(R(\tau))}{\int f(R(\tau))d\tau}$$

is defined via a monotonic transformation $f: \mathbb{R} \mapsto \mathbb{R}_{\geq 0}$ of

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**Table 2.** Average final reward and standard error of different curricula and RL algorithms in the Ball-Catching Environment. The data is computed from 20 algorithm runs.

| CL-ALG  | TRPO  | PPO   | SAC   |
|---------|-------|-------|-------|
| ALP-GMM | 39.8 ± 1.05 | 46.5 ± 0.66 | 33.2 ± 1.02 |
| GoalGAN* | 45.8 ± 0.99 | 45.9 ± 0.99 | 28.1 ± 1.23 |
| GoalGAN | 42.5 ± 1.61 | 42.6 ± 2.68 | 27.0 ± 1.46 |
| SPDL* | 46.5 ± 1.84 | 49.9 ± 1.54 | 33.9 ± 1.19 |
| SPDL | 46.8 ± 1.85 | 52.4 ± 1.68 | 34.7 ± 0.85 |
| DEFAULT* | 21.2 ± 0.34 | 23.0 ± 0.68 | 6.18 ± 0.57 |
| DEFAULT | 21.0 ± 0.26 | 22.1 ± 0.30 | 4.67 ± 0.55 |

---
We see that the trajectory generation is now conditioned on \( p \). To optimize the parameters \( \omega \) and \( \theta \) of the variational distribution \( q \) by maximizing the first term of the decomposed log-likelihood (Equation 15) w.r.t. \( \omega \) and \( \theta \)

\[
\max_{\omega, \theta} E_{q(\tau, c)} \left[ \log \left( \frac{p_{\omega, \theta}(\tau, c)}{q(\tau, c)} \right) \right] = \max_{\theta} E_{q(\tau, c)} \left[ \log \left( \frac{p_{\theta}(\tau | c)}{q(\tau | c)} \right) \right] + \max_{\omega} E_{q(\tau, c)} \left[ \log \left( \frac{p_{\omega}(\tau | c)}{q(\tau | c)} \right) \right].
\]

As shown in Appendix A, the maximizers of above M-Step can be equivalently obtained by minimizing the KL Divergence between \( q(\tau, c) \) and \( p_{\omega, \theta}(\tau, c) \)

\[
\min_{\theta} D_{\text{KL}}(q(c) || p_{\theta}(c)) + \min_{\omega} E_{q(\tau, c)} [D_{\text{KL}}(q(\tau | c) || p_{\omega}(\tau | c))].
\]

This in turns shows that we can decouple the E- and M-Steps for the parameters \( \theta \) and \( \omega \) as well as the variational distributions \( q(c) \) and \( q(\tau | c) \), as both fitting the variational and parametric distributions are decoupled in the two steps. More precisely, we can identify the decoupled updating of policy and context distribution in Self-Paced Learning as a form of block coordinate ascent in the M-Step.

### 6.1. Decomposing Policy- and Context Distribution Update

In this section, we motivate decomposing the update of policy and context distribution, as done in SPDL, by applying the EM-algorithm to our LVM (Equation 14).

To optimize the parameters \( \omega \) and \( \theta \) of the model, we introduce a variational distribution \( q(\tau, c) \) that allows to decompose \( \log(p_{\omega, \theta}(\tau)) \) into

\[
\log(p_{\omega, \theta}(\tau)) = \int q(\tau, c) \log \left( \frac{q(\tau, c)}{q(\tau | c) p_{\omega, \theta}(c)} \right) d\tau dc
\]

\[
= E_{q(\tau, c)} \left[ \log \left( \frac{p_{\omega, \theta}(\tau, c)}{q(\tau, c)} \right) \right] + D_{\text{KL}}(q(\tau, c) || p_{\omega, \theta}(\tau, c)),
\]

where we used \( p_{\omega, \theta}(\tau, c) = p_{\omega, \theta}(\tau | c) p_{\omega, \theta}(c) \) for the last equivalence. The EM-algorithm now alternates between two steps in order to reach a local maximum of the log-likelihood. In the E-Step, the KL Divergence term w.r.t. to the variational distribution \( q \)

\[
\min_{q} D_{\text{KL}}(q(\tau, c) || p_{\omega, \theta}(\tau, c))
\]

\[
= \min_{q} \left( D_{\text{KL}}(q(c) || p_{\omega, \theta}(c)) + E_{q(c)} [D_{\text{KL}}(q(\tau | c) || p_{\omega}(\tau | c))] \right)
\]

is minimized by setting \( q(\tau | c) = p_{\omega}(\tau | c, \tau) \) and \( q(c) = p_{\omega, \theta}(c) \). The M-Step then updates the parametric distribution by maximizing the first term of the decomposed

\[
R(\tau) = \sum_{i=0}^{\infty} \gamma^i r(s_i, a_i).
\]

In order to incorporate the Self-Paced Learning paradigm into this inference view, we grant the agent control over another distribution \( p_{\theta}(c) \) that is interpreted as the context distribution

\[
p_{\omega, \theta}(\tau) = \int p(\tau | c) p_{\omega}(\tau | c) p_{\theta}(c) d\tau dc,
\]

\[
= \int p(\tau | c) p_{\omega, \theta}(\tau | c) d\tau dc
\]

\[
= \int p_{\omega, \theta}(\tau, c) d\tau dc.
\]

We see that the trajectory generation is now conditioned on the contextual variable \( c \), which is in line with the contextual RL view from both the episodic and step-based setting.

### 6.2. Step-Based instead of Episodic Value Functions

We now draw connections to a modified version of the EM algorithm called Posterior Regularization (PR) (Ganchev et al., 2010), which constrains the E-Step of EM by enforcing a variational distribution \( q(z) \) to fulfill an inequality constraint on expected feature values of the complete data

\[
E_{q(z)}[\phi(x, z)] \leq b,
\]

where \( x \) is the observed data. It can be shown that this modified version of EM optimizes an objective that trades-off maximizing the original log-likelihood objective and minimizing the KL Divergence between the parametric distribution and the closest distribution in the set \( Q = \{q(z) \mid E_{q(z)}[\phi(x, z)] \leq b\} \) of variational distributions fulfilling above constraint.

We make use of this approach to enforce that the context distribution \( p_{\theta}(c) \) increasingly matches the desired context distribution \( \mu(c) \). More precisely, the modified E-Step for our model is

\[
\min_{q} D_{\text{KL}}(q(\tau, c) || p_{\omega, \theta}(\tau, c)) + \alpha \Gamma(q, \theta)
\]

\[
= \min_{q} \left( D_{\text{KL}}(q(c) || p_{\omega, \theta}(c)) + \alpha \Gamma(q, \theta) \right)
\]

\[
+ E_{q(c)} [D_{\text{KL}}(q(\tau | c) || p_{\omega}(\tau | c))]\right),
\]

where \( \Gamma(q, \theta) = E_{q(c)}[\log(p_{\theta}(c)) - \log(\mu(c))] \). Inspecting above optimization problem, we see that the update of the variational distribution \( q(\tau | c) \) is left unchanged, as the
We now show that the LVM with the modified E-Step indeed adheres to an update scheme similar to (17), which they will converge. (see Appendix B). Choosing an appropriate transformation $q$ of the distribution $p$ to the variational distribution $q$ leads to a change in the set $Q$ after every M-Step.

We now show that the LVM with the modified E-Step indeed allows to derive the Self-Paced Learning scheme for both episodic and step-based RL as well as the distribution to which they will converge.

The optimal form of the variational distribution $q(c)$ after the E-Step is shown to adhere to

$$q(c) \propto p_\theta(c) \exp \left( \log(p_\omega(*|c)) + \alpha \log \left( \frac{\mu(c)}{p_\theta(c)} \right) \right)$$  \hspace{1cm} (16)

(see Appendix B). Choosing an appropriate transformation of the reward $R(\tau, c)$,

$$f(R(\tau, c)) = \exp \left( \frac{R(\tau, c)}{\eta} \right), \; \eta > 0,$$

we obtain the update rule of Self-Paced Learning for episodic RL

$$q(c) \propto p_\theta(c) \exp \left( \frac{V_{\omega_\tau}(c) + \alpha \eta \log \left( \frac{\mu(c)}{p_\theta(c)} \right)}{\eta} \right),$$

with the only difference that the denominator $\eta$ is the same as the parameter of the softmax-ed expected reward. This can be explained due to the additional KL constraint on the context distribution that SPRL imposes.

As mentioned in other works (Abdolmaleki et al., 2018), a common approximation to EM is to skip an explicit M-Step and rather directly optimize the KL Divergence in the E-Step with the parametric distribution. We will employ the same approach now to update $\theta$ by solving

$$\arg\min_{\theta_{i+1}} D_{KL}(p_{\theta_{i+1}}(c)\|p_{\omega_\tau}(c)) + \alpha \Gamma(p_{\theta_{i+1}}, \theta_i)$$

$$= \arg\max_{\theta_{i+1}} E_{p_{\theta_{i+1}}(c)} \left[ \log(p_\omega(*|c)) - \alpha \log \left( \frac{p_\theta(c)}{\mu(c)} \right) \right]$$

$$- D_{KL}(p_{\theta_{i+1}}(c)\|p_\theta(c))$$

Replacing the KL Divergence penalty term with a hard constraint increases stability of the update by limiting the distance between subsequent context distributions. Furthermore, it motivates replacing the penalty term in the expectation with a KL Divergence between the target distribution and $p_{\theta_{i+1}}(c)$, which yields

$$\max_{\theta_{i+1}} E_{p_{\theta_{i+1}}(c)} \left[ \log(p_\omega(*|c)) \right] - \alpha D_{KL}(p_{\theta_{i+1}}(c)\|\mu(c))$$

s.t. $D_{KL}(p_{\theta_{i+1}}(c)\|p_\theta(c)) \leq \eta.$ \hspace{1cm} (17)

Despite these changes to the E-Step, we can show that both update schemes still converge to the same distribution

$$p_{\theta^*}(c) \propto \mu(c) p_\omega(*|c) \frac{1}{\eta},$$ \hspace{1cm} (18)

(see Appendix C). We see that above distribution greedily focuses on the maxima of $p_\omega(*|c)$ for $\alpha \to 0$, while matching $\mu(c)$ for $\alpha \to \infty$. This result is indeed reasonable, as $\alpha$ scales the penalization of the KL Divergence between $p_{\theta}(c)$ and $\mu(c)$.

Once more choosing $f(R(\tau, c)) = \exp(R(\tau, c))$ and applying Jensen’s Inequality to $\log(p_\omega(*|c))$, we obtain

$$\log(p_\omega(*|c)) = \log \left( \int p(*|\tau)p_\omega(\tau|c)d\tau \right)$$

$$\geq E_{p_\omega(\tau|c)} \left[ \sum_{i=0}^{\infty} \gamma^i r(s_i, a_i) \right].$$

With above inequality, we see that by optimizing the SPDL objective (Equation 11), we optimize a lower bound of the modified E-Step (Equation 17).

7. Conclusion

We proposed a Curriculum Learning algorithm for step-based reinforcement Learning that follows the Self-Paced Learning scheme of proposing learning tasks by considering a trade-off between agent performance and distance to a target distribution of tasks. We have shown that the scheme is able to significantly increase learning performance across different settings. Finally, we linked Self-Paced Learning for RL to Posterior Regularized Expectation Maximization, allowing for a common view on the proposed algorithm and already established results.

Further investigation of the introduced Latent Variable Model is expected to allow for a reinterpretation of existing Self-Paced Learning schemes for Supervised Learning. This could facilitate sharing of new results, such as better choices of the hyperparameter $\alpha$ across the boundary of Supervised- and Reinforcement Learning.

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References

Abdolmaleki, A., Springenberg, J. T., Tassa, Y., Munos, R., Heess, N., and Riedmiller, M. Maximum a posteriori policy optimisation. In ICLR, 2018.
Allgower, E. L. and Georg, K. *Numerical continuation methods: an introduction*, volume 13. Springer Science & Business Media, 2012.

Andrychowicz, M., Wolski, F., Ray, A., Schneider, J., Fong, R., Welinder, P., McGrew, B., Tobin, J., Abbeel, O. P., and Zaremba, W. Hindsight experience replay. In *NIPS*, 2017.

Baranes, A. and Oudeyer, P.-Y. Intrinsically motivated goal exploration for active motor learning in robots: A case study. In *IROS*, 2010.

Bengio, Y., Louradour, J., Collobert, R., and Weston, J. Curriculum learning. In *ICML*, 2009.

Bishop, C. M. *Pattern recognition and machine learning*. Springer, 2006.

Blank, D., Kumar, D., Meeden, L., and Marshall, J. B. Bringing up robot: Fundamental mechanisms for creating a self-motivated, self-organizing architecture. *Cybernetics and Systems: An International Journal*, 36(2):125–150, 2005.

Bongard, J. and Lipson, H. Once more unto the breach: Co-evolving a robot and its simulator. In *ALIFE*, 2004.

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., and Zaremba, W. Openai gym. *arXiv preprint arXiv:1606.01540*, 2016.

Caruana, R. Multitask learning. *Machine learning*, 28(1):41–75, 1997.

Dayan, P. and Hinton, G. E. Using expectation-maximization for reinforcement learning. *Neural Computation*, 9(2):271–278, 1997.

Deisenroth, M. P., Neumann, G., Peters, J., et al. A survey on policy search for robotics. *Foundations and Trends® in Robotics*, 2(1–2):1–142, 2013.

Erez, T. and Smart, W. D. What does shaping mean for computational reinforcement learning? In *ICDL*, 2008.

Fellows, M., Mahajan, A., Rudner, T. G., and Whiteson, S. Virel: A variational inference framework for reinforcement learning. In *NIPS*, 2019.

Florensa, C., Held, D., Wulfmeier, M., Zhang, M., and Abbeel, P. Reverse curriculum generation for reinforcement learning. In *CoRL*, 2017.

Florensa, C., Held, D., Geng, X., and Abbeel, P. Automatic goal generation for reinforcement learning agents. In *ICML*, 2018.

Fournier, P., Sigaud, O., Chetouani, M., and Oudeyer, P.-Y. Accuracy-based curriculum learning in deep reinforcement learning. *arXiv preprint arXiv:1806.09614*, 2018.

Ganchev, K., Gillenwater, J., Taskar, B., et al. Posterior regularization for structured latent variable models. *JMLR*, 11(Jul):2001–2049, 2010.

Haarnoja, T., Zhou, A., Abbeel, P., and Levine, S. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *ICML*, 2018.

Hallak, A., Di Castro, D., and Mannor, S. Contextual markov decision processes. *arXiv preprint arXiv:1502.02259*, 2015.

Hill, A., Raffin, A., Ernestus, M., Gleave, A., Kanervisto, A., Traore, R., Dhariwal, P., Hesse, C., Khimov, O., Nichol, A., Plappert, M., Radford, A., Schulman, J., Sidor, S., and Wu, Y. Stable baselines. [https://github.com/hill-a/stable-baselines](https://github.com/hill-a/stable-baselines), 2018.

Jiang, L., Meng, D., Yu, S.-I., Lan, Z., Shan, S., and Hauptmann, A. Self-paced learning with diversity. In *NIPS*, 2014.

Klink, P., Abdulsamad, H., Belousov, B., and Peters, J. Self-paced contextual reinforcement learning. In *CoRL*, 2019.

Kumar, M. P., Packer, B., and Koller, D. Self-paced learning for latent variable models. In *NIPS*, 2010.

Levine, S. Reinforcement learning and control as probabilistic inference: Tutorial and review. *arXiv preprint arXiv:1805.00909*, 2018.

Modi, A., Jiang, N., Singh, S., and Tewari, A. Markov decision processes with continuous side information. In *ALT*, 2018.

Narvekar, S. and Stone, P. Learning curriculum policies for reinforcement learning. In *AAMAS*, 2019.

Neumann, G. et al. Variational inference for policy search in changing situations. In *ICML*, 2011.

Nvidia. Isaac gym. [https://developer.nvidia.com/gtc/2019/video/S9918](https://developer.nvidia.com/gtc/2019/video/S9918), 2019. Accessed: 2020-02-06.
Pan, S. J., Yang, Q., et al. A survey on transfer learning. *TKDE*, 22(10):1345–1359, 2010.

Portelas, R., Colas, C., Hofmann, K., and Oudeyer, P.-Y. Teacher algorithms for curriculum learning of deep rl in continuously parameterized environments. In *CoRL*, 2019.

Rawlik, K., Toussaint, M., and Vijayakumar, S. On stochastic optimal control and reinforcement learning by approximate inference. In *IJCAI*, 2013.

Schaul, T., Horgan, D., Gregor, K., and Silver, D. Universal value function approximators. In *ICML*, 2015.

Schmidhuber, J. Curious model-building control systems. In *IJCNN*, 1991.

Schulman, J., Levine, S., Abbeel, P., Jordan, M., and Moritz, P. Trust region policy optimization. In *ICML*, 2015.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., et al. Mastering the game of go without human knowledge. *Nature*, 550(7676):354–359, 2017.

Skinner, B. F. *The behavior of organisms: An experimental analysis*. BF Skinner Foundation, 2019.

Sutton, R. S. and Barto, A. G. *Introduction to reinforcement learning*, volume 135. MIT Press Cambridge, 1998.

Taylor, M. E. and Stone, P. Transfer learning for reinforcement learning domains: A survey. *JMLR*, 10(Jul):1633–1685, 2009.

Toussaint, M. and Storkey, A. Probabilistic inference for solving discrete and continuous state markov decision processes. In *ICML*, 2006.

Vinyals, O., Babuschkin, I., Czarnecki, W. M., Mathieu, M., Dudzik, A., Chung, J., Choi, D. H., Powell, R., Ewalds, T., Georgiev, P., et al. Grandmaster level in starcraft ii using multi-agent reinforcement learning. *Nature*, 575(7782):350–354, 2019.

Ziebart, B. D., Maas, A. L., Bagnell, J. A., and Dey, A. K. Maximum entropy inverse reinforcement learning. In *AAAI*, 2008.
A. M-Step of the Self-Paced Latent Variable Model

As we will now detail, we can reformulate the objective of the M-Step on our Latent Variable Model. First step is to split the maximization w.r.t. the two parametric distributions

\[ \omega^*, \theta^* \]

\[ = \arg \max_{\omega, \theta} E_{q(\tau, c)} \left[ \log \left( \frac{p_\omega(\tau, c)}{q(\tau, c)} \right) \right] \]

\[ = \arg \max_{\omega, \theta} E_{q(\tau, c)} \left[ \log \left( \frac{p_\theta(c)}{q(c)} \right) + E_{q(\tau, c)} \left[ \log \left( \frac{p_\omega(\tau| c)}{q(\tau| c)} \right) \right] \right] \]

\[ = \arg \max_{\omega} E_{q(\tau, c)} \left[ \log \left( \frac{p_\omega(\tau| c)}{q(\tau| c)} \right) \right], \arg \max_{\theta} E_{q(\tau, c)} \left[ \log \left( \frac{p_\theta(c)}{q(c)} \right) \right]. \]

Now we can investigate the second term independently

\[ \arg \max_{\theta} E_{q(\tau, c)} \left[ \log \left( \frac{p_\theta(c)}{q(c)} \right) \right] \]

\[ = \arg \max_{\theta} E_{q(e)} \left[ E_{q(\tau| e)} \left[ \log \left( \frac{p_\theta(c)}{q(c)} \right) \right] \right] \]

\[ = \arg \max_{\theta} E_{q(e)} \left[ \log \left( \frac{p_\theta(c)}{q(c)} \right) \right] \]

\[ = \arg \max_{\theta} -E_{q(e)} \left[ \log \left( \frac{q(c)}{p_\theta(c)} \right) \right] \]

\[ = \arg \min_{\theta} D_{KL}(q(e)||p_\theta(e)). \]

The first term can be reformulated similarly

\[ \arg \max_{\omega} E_{q(\tau, c)} \left[ \log \left( \frac{p_\omega(\tau| c)}{q(\tau| c)} \right) \right] \]

\[ = \arg \max_{\omega} E_{q(\tau, c)} \left[ \log \left( \frac{p(\tau| c)}{q(\tau| c)} \right) \right] + E_{q(\tau, c)} \left[ \log \left( \frac{p_\omega(\tau| c)}{q(\tau| c)} \right) \right] \]

\[ = \arg \max_{\omega} E_{q(\tau, c)} \left[ \log \left( \frac{p_\omega(\tau| c)}{q(\tau| c)} \right) \right] \]

\[ = \arg \max_{\omega} -E_{q(e)} \left[ E_{q(\tau| e)} \left[ \log \left( \frac{q(\tau| e)}{p_\omega(\tau| e)} \right) \right] \right] \]

\[ = \arg \min_{\omega} E_{q(e)} \left[ D_{KL}(q(\tau| e)||p_\omega(\tau| e)) \right], \]

where we can drop the term \( E_{q(\tau, c)} \left[ \log \left( \frac{p(\tau| c)}{q(\tau| c)} \right) \right] \) as it does not depend on \( \omega \).

B. Solution of the modified E-Step

In order to prove that the optimal solution of optimization problem

\[ \min_q D_{KL}(q(e)||p_\omega(e,c)) + \alpha \Gamma(q, \theta) + E_{q(e)} \left[ D_{KL}(q(\tau| e)||p_\omega(\tau| e, c)) \right] \]

w.r.t. \( q(e) \) is indeed given by

\[ q(e) \propto p_\theta(e) \exp \left( \log \left( \frac{p_\omega(c)}{q(c)} \right) + \alpha \log \left( \frac{\mu(e)}{p_\theta(c)} \right) \right), \]
we first note that the second term of above optimization problem can be set to zero by setting \( q(\tau | c) = p_\omega(\tau | c, *) \), regardless of the choice of \( q(c) \). Hence we can rewrite the optimization problem for \( q(c) \) as

\[
\min_q D_{KL}(q(c)\|p_\omega, \theta(c,*)) + \alpha \Gamma_q(q, \theta)
\]

\[
\text{s.t.} \int q(c) d\Sigma = 1,
\]

where we introduced a constraint to enforce normalization of the resulting distribution. The Lagrangian of above problem is given by

\[
L(q, \lambda) = E_{q(c)} \left[ \log \left( \frac{q(c)}{p_\omega, \theta(c,*)} \right) + \alpha \log \left( \frac{p_\theta(c)}{\mu(c)} \right) - \lambda \right] + \lambda
\]

\[
= E_{q(c)} \left[ \log \left( \frac{q(c)p_\theta(c)^\alpha}{p_\omega, \theta(c,*)^{\alpha}} \right) - \lambda \right] + \lambda.
\]

With the Lagrangian we can easily solve for the optimal distribution by setting its derivative w.r.t. \( q \) to 0

\[
\nabla_{q(c)} L(q, \lambda) = 0
\]

\[
\Leftrightarrow \log \left( \frac{q(c)p_\theta(c)^\alpha}{p_\omega, \theta(c,*)^{\alpha}} \right) - \lambda + 1 = 0
\]

\[
\Leftrightarrow \log(q(c)) = \log \left( \frac{p_\omega, \theta(c,*)^{\alpha}}{p_\theta(c)^\alpha} \right) + \lambda - 1
\]

\[
\Leftrightarrow \log(q(c)) = \log(p_\omega(c)) + \log(p_\omega(c)) + \alpha \log \left( \frac{\mu(c)}{p_\theta(c)} \right) + \lambda - 1 - \log(p_\omega, \theta(*))
\]

\[
\Leftrightarrow q(c) = p_\theta(c) \exp \left( \log(p_\omega(c)) + \alpha \log \left( \frac{\mu(c)}{p_\theta(c)} \right) \right) Z,
\]

where \( Z = \frac{\exp(\lambda - 1)}{p_\omega, \theta(*)} \) is the normalization constant of the distribution.

C. Fixed-Points of the Context Distribution Updates

We start by investigating the fixed point to which alternating the modified E-Step and the original M-Step converges. Assuming that \( p_\theta(c) \) can perfectly represent \( q(c) \), i.e. that after the M-Step \( p_\theta(c) = q(c) \), we can make use of the modified E-Step as a condition for convergence. More precisely, the update of the context distribution converges, if

\[
p(c) = Z p(c) \exp \left( \log(p_\omega(* | c)) + \alpha \log \left( \frac{\mu(c)}{p(c)} \right) \right)
\]

\[
\Leftrightarrow p(c)^\alpha = Z \exp \left( \log(p_\omega(* | c)) + \alpha \log (\mu(c)) \right)
\]

\[
\Leftrightarrow p(c) = Z \mu(c) p_\omega(* | c)^\frac{1}{\alpha}, \quad (19)
\]

with an appropriate normalization constant \( Z \). We see that for \( \alpha \to 0 \), the context distribution will only encode the contexts with maximum expected reward under the current policy, while for \( \alpha \to \infty \), it will match the desired context distribution \( \mu(c) \).

Reinvestigating the modified M-Step (Equation 17 in the main paper) without the KL-constraint and with an arbitrary probability distribution \( p(c) \)

\[
\max_{p(c)} E_{p(c)} \left[ \log(p_\omega(* | c)) \right] - \alpha D_{KL}(p(c)||\mu(c))
\]

\[
\text{s.t.} \int p(c) d\Sigma = 1,
\]
we can easily show that the optimal solution to this objective is the same as the one in Equation 19 by investigating the derivative of the Lagrangian

\[
\nabla_{p(c)} L(p, \lambda) = 0
\]

\[
\Leftrightarrow \nabla_{p(c)} E_{p(c)} \left[ \log(p_\omega(*)|c) \right] - \alpha D_{KL}(p(c)||\mu(c)) + \lambda \left( 1 - \int p(c) dc \right) = 0
\]

\[
\Leftrightarrow \nabla_{p(c)} \int p(c) \left( \log(p_\omega(*)|c) - \alpha \log \left( \frac{p(c)}{\mu(c)} \right) - \lambda \right) dc + \lambda = 0
\]

\[
\Leftrightarrow \log(p_\omega(*)|c) - \alpha \log \left( \frac{\theta(c)}{\mu(c)} \right) - \lambda - \alpha = 0
\]

\[
\Leftrightarrow \log(\theta(c)) + \log \left( p_\omega(*)|c)^\frac{1}{\alpha} \right) - \frac{\lambda + \alpha}{\alpha} = \log(p(c))
\]

\[
\Leftrightarrow p(c) = \mu(c) p_\omega(*)|c)^\frac{1}{\alpha} \exp \left( \frac{\alpha}{\alpha + \lambda} \right).
\]

In above equation, \(\exp(\alpha/(\alpha + \lambda))\) takes the role of a normalization constant. Now the omitted KL Divergence constraint in the optimization problem just prevents to directly obtain this solution. Instead, multiple iterations would be necessary to reach this optimum.

We also verified the obtained results with simple discrete probability distributions. The computed fixed-points matched the ones obtained by iterating the EM-algorithm until convergence up to numerical precision (average KL-Divergence of \(10^{-5}\) across 500 values of \(\alpha\) on a log-scale between \(10^{-10}\) and \(10\)). Figure 6 visualizes the fixed-point distribution for different values of \(\alpha\) in aforementioned discrete test environment.

**D. Experimental Details**

In this section, we present details that could not be included in the main paper due to space limitations. This includes parameters of the employed algorithms, additional details about the mechanics of the environments as well as a qualitative discussion of the results.

The parameters of SPDL for different environments and RL algorithms are shown in Table 3. The parameters \(K_A\) and \(\zeta\) have the same meaning as in the main paper. The additional parameter \(n_{OFFSET}\) describes the number of RL algorithm iterations that take place before SPDL is allowed the change the context distribution. This parameter is necessary in practice, as typically some iterations are required until the Value Function produces meaningful estimates of the expected value. In the ant environment, we realized that the ant takes a certain amount of time (roughly 40 iterations) until it manages to actually reach the wall. Only then, the difference in task difficulty becomes apparent. The parameter \(n_{OFFSET}\) allows to compensate for such task specific details. This procedure corresponds to providing a pre-trained policy as \(\pi_0\) in the abstract

![Figure 6](image-url)
Table 3. Hyperparameters for the SPDL algorithm per environment and RL algorithm.

| Algorithm            | $K_a$ | $\zeta$ | $n_{\text{offset}}$ | $n_{\text{step}}$ | $\sigma_{\text{LB}}$ | $D_{\text{KL,LB}}$ |
|----------------------|-------|---------|---------------------|-------------------|---------------------|-------------------|
| Point-Mass (TRPO)    | 70    | 1.6     | 5                   | 2048              | 0.2 0.1875 0.1     | 8000              |
| Point-Mass (PPO)     | 70    | 1.6     | 5                   | 2048              | 0.2 0.1875 0.1     | 8000              |
| Point-Mass (SAC)     | 50    | 1.8     | 5                   | 2048              | 0.2 0.1875 0.1     | 8000              |
| ANT (PPO)            | 15    | 0.4     | 40                  | 31920             | [1 0.5]            | 11000             |
| Ball-Catching (TRPO) | 0     | 0.4     | 5                   | 5000              | -                   | -                 |
| Ball-Catching (PPO)  | 0     | 0.5     | 5                   | 5000              | -                   | -                 |
| Ball-Catching (SAC)  | 0     | 0.7     | 5                   | 5000              | -                   | -                 |

algorithm sketched in the main paper. As can be seen in Table 3, the only parameter that changed between different RL algorithms in the same environment is $\zeta$. We selected the best $\zeta$ for every RL algorithm by a simple grid-search with steps of 0.05 in an interval around a reasonably working parameter that was found by simple trial and error. For the Point-Mass environment, we only tuned the hyperparameters for SPDL in the experiment with a three-dimensional context space and reused them for the two-dimensional context space.

To conduct the experiments, we use the implementation of ALP-GMM and GoalGAN provided in the repositories accompanying the two papers (Florensa et al., 2018; Portelas et al., 2019). For ALP-GMM we tuned the percentage of random samples drawn from the context space $p_{\text{RAND}}$, the number of policy rollouts between the update of the context distribution $n_{\text{ROLLOUT}}$ as well as the maximum buffer size of past trajectories to keep $s_{\text{BUFFER}}$. For each environment and algorithm, we did a grid-search over

$$(p_{\text{RAND}}, n_{\text{ROLLOUT}}, s_{\text{BUFFER}}) \in \{0.1, 0.2, 0.3\} \times \{50, 100, 200\} \times \{500, 1000, 2000\}.$$

For GoalGAN we tuned the amount of random noise that is added on top of each sample $\delta_{\text{NOISE}}$, the number of policy rollouts between the update of the context distribution $n_{\text{ROLLOUT}}$ as well as the percentage of samples drawn from the success buffer $p_{\text{SUCCESS}}$. For each environment and algorithm, we did a grid-search over

$$(\delta_{\text{NOISE}}, n_{\text{ROLLOUT}}, p_{\text{SUCCESS}}) \in \{0.025, 0.05, 0.1\} \times \{50, 100, 200\} \times \{0.1, 0.2, 0.3\}.$$}

The results of the hyperparameter optimization for GoalGAN and ALP-GMM are shown in Table 4.

In the experiments, we found that restricting the standard deviation of the context distribution to stay above a certain lower bound $\sigma_{\text{LB}}$ helps to stabilize learning when generating curricula for narrow target distributions with SPDL. Although such constraints could be included rigorously via the framework of Posterior Regularization (Ganchev et al., 2010), we decided to accomplish this by just clipping the standard deviation until the KL-Divergence w.r.t. the target distribution falls below a certain threshold $D_{\text{KL,LB}}$. This was also discovered in (Klink et al., 2019).

Opposed to the sketched algorithm in the main paper, we specify the number of steps $n_{\text{STEP}}$ in the environment between context distribution updates in our implementation.

Since for all environments, both initial- and target distribution are Gaussians with independent noise in each dimension, we specify them in Table 5 by providing their mean $\mu$ and the vector of standard deviations for each dimension $\delta$. When sampling from a Gaussian, the resulting context is clipped to stay in the defined context space.

If necessary, we tuned the hyperparameters of the RL algorithms by hand on easier versions of the target task, not employing any Curriculum. The goal was to be as fair as possible by not optimizing an RL algorithm for a specific curriculum. For the Ant and Point-Mass environment, this was done by training on a wide gate positioned right in front of the agent. For the Ball-Catching environment, this was done by training on a version of the environment with dense reward. For PPO, we use the “PPO2” implementation of Stable-Baselines.

The experiments were conducted on a computer with an AMD Ryzen 9 3900X 12-Core Processor, an Nvidia RTX 2080 graphics card and 64GB of RAM.

D.1. Point-Mass Environment

The state of this environment is comprised of position and velocity of the point-mass $s = [x \dot{x} y \dot{y}]$. The actions correspond to the force applied in x- and y-dimension $a = [F_x F_y]$. The context encodes position and width of the gate as well as the
The reward function is given by 

\[ o \]

The dynamics of the system are defined by

\[
\begin{pmatrix}
\dot{x} \\
\ddot{x} \\
\dot{y} \\
\ddot{y}
\end{pmatrix} =
\begin{pmatrix}
0 & 1 & 0 & 0 \\
0 & -\mu_k & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & -\mu_k
\end{pmatrix}
\begin{pmatrix}
s \\
\end{pmatrix} +
\begin{pmatrix}
0 \\
0 \\
1 \\
0
\end{pmatrix}
\begin{pmatrix}
a
\end{pmatrix}.
\]

The \( x \)- and \( y \)- position of the point mass is enforced to stay within the space \([-4, 4] \times [-4, 4]\). The gate is located at position \( [p_g 0] \). If the agent crosses the line \( y = 0 \), we check whether its \( x \)-position is within the interval \( [p_g - 0.5w_g, p_g + 0.5w_g] \). If this is the case, we stop the episode as the agent has crashed into the wall. Each episode is terminated after a maximum of 100 steps. The reward function is given by

\[ r(s, a) = \exp(-0.6\|o - [x y]\|_2), \]

where \( o = [0 -3] \) and \( \| \cdot \|_2 \) is the L2-Norm and the agent is always initialized at state \( s_0 = [0 0 3 0] \).

For all RL algorithms, we use a discount factor of \( \gamma = 0.95 \) and represent policy and value function by networks using 21 hidden layers with tanh activations. For TRPO and PPO, we take 2048 steps in the environment between policy updates.

For TRPO we set the GAE parameter \( \lambda = 0.99 \), the maximum allowed KL-Divergence to 0.004 and the Value Function step size \( \alpha_v \approx 0.24 \), leaving all other parameters to their implementation defaults.

For PPO we use GAE parameter \( \lambda = 0.99 \), an entropy coefficient of 0 and disable the clipping of the value function objective. All other parameters are left to their implementation defaults.

For SAC, we use an experience buffer of 10000 samples, leaving every other setting to the implementation default. Hence we use the soft Q-Updates and update the policy after every environment step.

Looking at Figure 7, we can see that although not obvious in the main paper, ALP-GMM allowed to learn policies that sometimes are able to pass the gate. However, in the other cases, the policies crashed the point mass into the wall. Opposed to this, directly training on the target task led to policies that learned to steer the point mass very close to the wall without crashing (which is unfortunately hard to see in the plot). Reinvestigating above reward function, this explains the lower reward of ALP-GMM, GoalGAN and the randomly generated curriculum compared to directly learning on the target task, as a crash prevents the agent from accumulating positive rewards over time.

### Table 4. Hyperparameters for the ALP-GMM and GoalGAN algorithm per environment and RL algorithm.

| Hyperparameter | POINT-MASS 3D (TRPO) | POINT-MASS 3D (PPO) | POINT-MASS 3D (SAC) | POINT-MASS 2D (TRPO) | POINT-MASS 2D (PPO) | POINT-MASS 2D (SAC) | BALL-CATCHING (TRPO) | BALL-CATCHING (PPO) | BALL-CATCHING (SAC) |
|----------------|----------------------|---------------------|---------------------|----------------------|---------------------|---------------------|----------------------|---------------------|---------------------|
| \( \mathbf{P}_{\text{RAND}} \) | 0.1 | 0.1 | 0.1 | 0.3 | 0.2 | 0.2 | 0.2 | 0.3 | 0.3 |
| \( n_{\text{ROLLOUT (ALP-GMM)}} \) | 100 | 100 | 200 | 100 | 200 | 200 | 200 | 200 | 200 |
| \( n_{\text{BUFFER}} \) | 4000 | 4000 | 4000 | 4000 | 4000 | 4000 | 4000 | 4000 | 4000 |
| \( \delta_{\text{NOISE}} \) | 0.05 | 0.05 | 0.05 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| \( n_{\text{ROLLOUT (GOALGAN)}} \) | 200 | 200 | 200 | 50 | 50 | 50 | 50 | 50 | 50 |
| \( P_{\text{SUCCESS}} \) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| \( \mathbf{P}_{\text{TARGET}} \) | \( \delta_{\text{TARGET}} \) | \( \mathbf{P}_{\text{INIT}} \) | \( \delta_{\text{INIT}} \) | \( \mathbf{P}_{\text{TARGET}} \) | \( \delta_{\text{TARGET}} \) | \( \mathbf{P}_{\text{INIT}} \) | \( \delta_{\text{INIT}} \) | \( \mathbf{P}_{\text{TARGET}} \) | \( \delta_{\text{TARGET}} \) |
|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| POINT-MASS 3D (TRPO) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| POINT-MASS 3D (PPO) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| POINT-MASS 3D (SAC) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| POINT-MASS 2D (TRPO) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| POINT-MASS 2D (PPO) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| POINT-MASS 2D (SAC) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| BALL-CATCHING (TRPO) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| BALL-CATCHING (PPO) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |
| BALL-CATCHING (SAC) | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 | 0.1 | 0.125 |

The dynamic friction coefficient of the ground on which the point mass slides is \( c = [p_g w_g \mu_k] \in [-4, 4] \times [0.5, 8] \times [0, 4] \subset \mathbb{R}^3 \). For SAC, we use an experience buffer of \( n_{\text{BUFFER}} = 2000 \) samples, leaving every other setting to the implementation default. Hence we use the soft Q-Updates and update the policy after every environment step.
D.2. Ant Environment

As mentioned in the main paper, we simulate the ant using the Isaac Gym simulator (Nvidia, 2019). This allows to speed up training time by parallelizing the simulation of policy rollouts on the graphics card. Since the Stable-Baselines implementation of TRPO and PPO do not support the use of vectorized environments, it is hard to combine Isaac Gym with these algorithms. Because of this reason, we decided not to run experiments with TRPO and SAC in the Ant environment.

The state $s \in \mathbb{R}^{29}$ is defined to be the 3D-position of the ant’s body, its angular and linear velocity as well as positions and velocities of the 8 joints of the ant. An action $a \in \mathbb{R}^{8}$ is defined by the 8 torques that are applied to the ant’s joints.

The context $c = [p_g\ w_g] \in [-10, 10] \times [3, 13] \subset \mathbb{R}^2$ defines, just as in the Point-Mass environment, the position and width of the gate that the Ant needs to pass.

The reward function of the environment is computed based on the $x$-position of the ant’s center of mass $c_x$ in the following way

$$r(s, a) = 1 + 5 \exp \left( -0.5 \min(0, c_x - 4.5)^2 \right) - 0.3 \|a\|^2.$$  

The constant 1 term was taken from the OpenAI Gym implementation to encourage survival of the ant (Brockman et al., 2016). Compared to the OpenAI Gym environment, we set the armature value of the joints from 1 to 0 and also decrease the maximum torque from 150Nm to 20Nm, since the values from OpenAI Gym resulted to unrealistic movement behavior in combination with Isaac Gym. Nonetheless, these changes did not result in a qualitative change of the algorithm performances.

With the wall being located at position $x=3$, the agent needs to pass it in order to obtain the full environment reward by ensuring that $c_x \geq 4.5$.

The policy and value function are represented by neural networks with two hidden layers of 64 neurons each and $\text{tanh}$ activation functions.
Figure 8. Visualizations of the $x$-position during policy rollouts in the Ant Environment with policies learned using different curricula. The blue lines correspond to 200 individual trajectories and the thick black line shows the median over these individual trajectories. The trajectories were generated from 20 algorithms runs, were each final policy was used to generate 10 trajectories.

activation functions. We use a discount factor $\gamma = 0.995$ for all algorithms, which can be explained due to the long time horizons of 750 steps. We take 81920 steps in the environment between a policy update. This was significantly sped-up by the use of the Isaac Gym simulator, which allowed to simulate 40 environments in parallel on a single GPU.

For PPO, we use an entropy coefficient of 0 and disable the clipping of the value function objective. All other parameters are left to their implementation defaults. We disabled the entropy coefficient as we observed that for the Ant environment, PPO still tends to keep around $10 - 15\%$ of its initial additive noise even during late iterations.

Investigating Figure 8, we see that both SPDL and GoalGAN learn policies that allow to pass the gate. However, the policy learned with SPDL seem to be more reliable compared to the ones learned with GoalGAN. As mentioned in the main paper, ALP-GMM and a random curriculum also learn policies that navigate the ant towards the goal in order to pass it. However, the behaviour is less directed and less reliable. Interestingly, directly learning on the target task results in a policy that tends to not move in order to avoid action penalties. Looking at the main paper, we see that this results in a similar reward compared to the inefficient policies learned with ALP-GMM and a random curriculum.

D.3. Ball-Catching Environment

In the final environment, the robot is controlled in joint space via the desired position for 5 of the 7 joints. We only control a subspace of all available joints, since it is not necessary for the robot to leave the “catching” plane (defined by $x = 0$) that is intersected by each ball. The actions $a \in \mathbb{R}^5$ are defined as the displacement of the current desired joint position. The state $s \in \mathbb{R}^{21}$ consists of the positions and velocities of the controlled joints, their current desired positions, the current three-dimensional ball position and its linear velocity.

As previously mentioned, the reward function is sparse,

$$r(s, a) = 0.275 - 0.005 \|a\|_2^2 + \begin{cases} 50 + 25(n_s \cdot v_b)^5, & \text{if ball caught} \\ 0, & \text{else} \end{cases},$$

only giving a meaningful reward when catching the ball and otherwise just a slight penalty on the actions to avoid unnecessary movements. In above definition, $n_s$ is a normal vector of the endeffector surface and $v_b$ is the linear velocity of the ball. This additional term is used to encourage the robot to align its endeffector with the curve of the ball. If the endeffector is e.g. a net (as assumed for our experiment), the normal is chosen such that aligning it with the ball maximizes the opening through which the ball can enter the net.
The context $c = [\phi, r, d_x] \in [0.125\pi, 0.5\pi] \times [0.6, 1.1] \times [0.75, 4] \subset \mathbb{R}^3$ controls the target ball position in the catching plane, i.e.

$$p_{\text{des}} = [0 \quad -r\cos(\phi) \quad 0.75 + r\sin(\phi)].$$

Furthermore, the context determines the distance in $x$-dimension from which the ball is thrown

$$p_{\text{init}} = [d_x \quad d_y \quad d_z],$$

where $d_y \sim U(-0.75, -0.65)$ and $d_z \sim U(0.8, 1.8)$ and $U$ represents the uniform distribution. The initial velocity is then computed using simple projectile motion formulas by requiring the ball to reach $p_{\text{des}}$ at time $t = 0.5 + 0.05d_x$. As we can see, the context implicitly controls the initial state of the environment.

The policy and value function networks for the RL algorithms have three hidden layers with 64 neurons each and $\text{tanh}$ activation functions. We use a discount factor of $\gamma = 0.995$. The policy updates in TRPO and PPO are done after 5000 environment steps.

For SAC, a replay buffer size of 100,000 is used. Due to the sparsity of the reward, we increase the batch size to 512. Learning with SAC starts after 1000 environment steps. All other parameters are left to their implementation defaults.
For TRPO we set the GAE parameter $\lambda = 0.95$, leaving all other parameters to their implementation defaults.

For PPO we use a GAE parameter $\lambda = 0.95$, 10 optimization epochs, 25 minibatches per epoch, an entropy coefficient of 0 and disable the clipping of the value function objective. The remaining parameters are left to their implementation defaults.

Figure 9 visualizes the catching success rates of the learned ball catching policies. As can be seen, the performance of the policies learned with the different RL algorithms achieve comparable catching performance. Interestingly, SAC performs comparable in terms of catching performance, although the average reward of the final policies learned with SAC is lower. This is to be credited to excessive movement and/or a bad alignment of the endeffector with the velocity vector of the ball.