Demonstration-Guided Reinforcement Learning with Learned Skills

Karl Pertsch, Youngwoon Lee, Yue Wu, Joseph J. Lim
University of Southern California
https://clvrai.com/skild

Abstract: Demonstration-guided reinforcement learning (RL) is a promising approach for learning complex behaviors by leveraging both reward feedback and a set of target task demonstrations. Prior approaches for demonstration-guided RL treat every new task as an independent learning problem and attempt to follow the provided demonstrations step-by-step, akin to a human trying to imitate a completely unseen behavior by following the demonstrator’s exact muscle movements. Naturally, such learning will be slow, but often new behaviors are not completely unseen: they share subtasks with behaviors we have previously learned. In this work, we aim to exploit this shared subtask structure to increase the efficiency of demonstration-guided RL. We first learn a set of reusable skills from large offline datasets of prior experience collected across many tasks. We then propose Skill-based Learning with Demonstrations (SkiLD), an algorithm for demonstration-guided RL that efficiently leverages the provided demonstrations by following the demonstrated skills instead of the primitive actions, resulting in substantial performance improvements over prior demonstration-guided RL approaches. We validate the effectiveness of our approach on long-horizon maze navigation and complex robot manipulation tasks.

Keywords: Reinforcement Learning, Imitation Learning, Skill-Based Transfer

1 Introduction

Humans are remarkably efficient at acquiring new skills from demonstrations: often a single demonstration of the desired behavior and a few trials of the task are sufficient to master it [1, 2, 3]. To allow for such efficient learning, we can leverage a large number of previously learned behaviors [2, 3]. Instead of imitating precisely each of the demonstrated muscle movements, humans can extract the performed skills and use the rich repertoire of already acquired skills to efficiently reproduce the desired behavior.

Demonstrations are also commonly used in reinforcement learning (RL) to guide exploration and improve sample efficiency [4, 5, 6, 7, 8]. However, such demonstration-guided RL approaches attempt to learn tasks from scratch: analogous to a human trying to imitate a completely unseen behavior by following every demonstrated muscle movement, they try to imitate the primitive actions performed in the provided demonstrations. As with humans, such step-by-step imitation leads to brittle policies [9], and thus these approaches require many demonstrations and environment interactions to learn a new task.

Figure 1: Our approach SkiLD leverages large, task-agnostic datasets collected across many different tasks for efficient demonstration-guided reinforcement learning by (1) acquiring a rich motor skill repertoire from such offline data and (2) understanding and imitating the demonstrations based on the skill repertoire.
We propose to improve the efficiency of demonstration-guided RL by leveraging prior experience in the form of an offline “task-agnostic” experience dataset, collected not on one but across many tasks (see Figure 1). Given such a dataset, our approach extracts reusable skills: robust short-horizon behaviors that can be recombined to learn new tasks. Like a human imitating complex behaviors via the chaining of known skills, we can use this repertoire of skills for efficient demonstration-guided RL on a new task by guiding the policy using the demonstrated skills instead of the primitive actions.

Concretely, we propose **Skill-based Learning with Demonstrations (SkiLD)**, a demonstration-guided RL algorithm that learns short-horizon skills from offline datasets and then learns new tasks efficiently by leveraging these skills to follow a given set of demonstrations. Across challenging navigation and robotic manipulation tasks our approach significantly improves the learning efficiency over prior demonstration-guided RL approaches.

In summary, the contributions of our work are threefold: (1) we introduce the problem of leveraging task-agnostic offline datasets for accelerating demonstration-guided RL on unseen tasks, (2) we propose SkiLD, a skill-based algorithm for efficient demonstration-guided RL and (3) we show the effectiveness of our approach on a maze navigation and two complex robotic manipulation tasks.

## 2 Related Work

### Imitation learning.
Learning from Demonstration, also known as imitation learning [10], is a common approach for learning complex behaviors by leveraging a set of demonstrations. Most prior approaches for imitation learning are either based on behavioral cloning (BC, [11]), which uses supervised learning to mimic the demonstrated actions, or inverse reinforcement learning (IRL, [12, 13]), which infers a reward from the demonstrations and then trains a policy to optimize it. However, BC commonly suffers from distribution shift and struggles to learn robust policies [9], while IRL’s joint optimization of reward and policy can result in unstable training.

### Demonstration-guided RL.
A number of prior works aim to mitigate these problems by combining reinforcement learning with imitation learning. This allows the agent to leverage demonstrations for overcoming exploration challenges in RL while using RL to increase robustness and performance of the imitation learning policies. Prior work on demonstration-guided RL can be categorized into three groups: (1) approaches that use BC to initialize and regularize policies during RL training [6, 7], (2) approaches that place the demonstrations in the replay buffer of an off-policy RL algorithm [4, 5], and (3) approaches that augment the environment rewards with rewards extracted from the demonstrations [8, 14, 15]. While these approaches improve the efficiency of RL, they treat each new task as an independent learning problem, i.e., attempt to learn policies without taking any prior experience into account. As a result, they require many demonstrations to learn effectively, which is especially expensive since a new set of demonstrations needs to be collected for every new task.

### Online RL with offline datasets.
As an alternative to expensive task-specific demonstrations, multiple recent works have proposed to accelerate reinforcement learning by leveraging task-agnostic experience in the form of large datasets collected across many tasks [16, 17, 18, 19, 20, 21]. In contrast to demonstrations, such task-agnostic datasets can be collected cheaply from a variety of sources like autonomous exploration [22, 23] or human tele-operation [24, 25, 26], but will lead to slower learning than demonstrations since the data is not specific to the downstream task.

### Skill-based RL.
One class of approaches for leveraging such offline datasets that is particularly suited for learning long-horizon behaviors is skill-based RL [22, 27, 28, 29, 30, 31, 24, 32, 26, 33, 16]. These methods extract reusable skills from task-agnostic datasets and learn new tasks by recombining them. Yet, such approaches perform reinforcement learning over the set of extracted skills to learn the downstream task. Although being more efficient than RL over primitive actions, they still require many environment interactions to learn long-horizon tasks. In our work we combine the best of both worlds: by using large, task-agnostic datasets and a small number of task-specific demonstrations, we accelerate the learning of long-horizon tasks while reducing the number of required demonstrations.

## 3 Approach

Our goal is to use skills extracted from task-agnostic prior experience data to improve the efficiency of demonstration-guided RL on a new task. We aim to leverage a set of provided demonstrations
by following the performed skills as opposed to the primitive actions. Therefore, we need a model that can (1) leverage prior data to learn a rich set of skills and (2) identify the skills performed in the demonstrations in order to follow them. Next, we formally define our problem, summarize relevant prior work on RL with learned skills and then describe our demonstration-guided RL approach.

3.1 Preliminaries

Problem Formulation We assume access to two types of datasets: a large task-agnostic offline dataset and a small task-specific demonstration dataset. The task-agnostic dataset \( D = \{s_t, a_t, \ldots\} \) consists of trajectories of meaningful agent behaviors, but includes no demonstrations of the target task. We only assume that its trajectories contain short-horizon behaviors that can be reused to solve the target task. Such data can be collected without a particular task in mind using a mix of sources, e.g., via human teleoperation, autonomous exploration, or through policies trained for other tasks. Since it can be used to accelerate many downstream tasks that utilize similar short-term behaviors we call it task-agnostic. In contrast, the task-specific data is a much smaller set of demonstration trajectories \( D_{\text{demo}} = \{s^d_t, a^d_t, \ldots\} \) that are specific to a single target task.

The downstream learning problem is formulated as a Markov decision process (MDP) defined by a tuple \( (S, A, T, R, \rho, \gamma) \) of states, actions, transition probabilities, rewards, initial state distribution, and discount factor. We aim to learn a policy \( \pi_\theta(a|s) \) with parameters \( \theta \) that maximizes the discounted sum of rewards \( J(\theta) = \mathbb{E}_\pi[\sum_{t=0}^{T-1} J_t] = \mathbb{E}_\pi[\sum_{t=0}^{T-1} \gamma^t r_t] \), where \( T \) is the episode horizon.

Skill Prior RL Our goal is to extract skills from task-agnostic experience data and reuse them for demonstration-guided RL. Prior work has investigated the reuse of learned skills for accelerating RL [16]. In this section, we will briefly summarize their proposed approach Skill Prior RL (SPiRL) and then describe how our approach improves upon it in the demonstration-guided RL setting.

SPiRL defines a skill as a sequence of \( H \) consecutive actions \( a = \{a_t, \ldots, a_{t+H-1}\} \), where the skill horizon \( H \) is a hyperparameter. It uses the task-agnostic data to jointly learn (1) a generative model of skills \( p(a|z) \), that decodes latent skill embeddings \( z \) into executable action sequences \( a \), and (2) a state-conditioned prior distribution \( p(z|s) \) over skill embeddings. For learning a new downstream task, SPiRL trains a high-level skill policy \( \pi(z|s) \) whose outputs get decoded into executable actions using the pre-trained skill decoder. Crucially, the learned skill prior is used to guide the policy during downstream RL by maximizing the following divergence-regularized RL objective:

\[
J(\theta) = \mathbb{E}_{\pi_\theta} \left[ \sum_{t=0}^{T-1} r(s_t, z_t) - \alpha D_{\text{KL}}(\pi_\theta(z_t|s_t), p_\theta(z_t|s_t)) \right].
\] (1)
We use a unit Gaussian prior on skill-based RL [26, 19] and increase the expressiveness of the skill representation by using the pre-trained skill inference model to guide learning of the high-level policy on the new task. Our goal is to leverage the task-specific demonstrations to guide exploration of the downstream task. Even though our policy is guided by the task-specific demonstrations (green) and the task-agnostic skill prior it is conditioned on the current environment state, the policy is trained to imitate the given action sequence, thereby learning to reproduce the behaviors encoded by the skill embedding \( z \).

The latent skill representation is optimized using variational inference, which leads to the full skill learning objective:

\[
\max_{\phi, \omega} \mathbb{E}_q \left[ \prod_{t=0}^{H-2} \log \pi_\phi(a_t|s_t, z) - \beta \left( \log q_\omega(z|s_0; H-1, a_0; H-2) - \log p(z) \right) \right].
\]

We use a unit Gaussian prior \( p(z) \) and weight the embedding regularization term with a factor \( \beta \) [34].

### 3.3 Demonstration-Guided RL with Learned Skills

To leverage the learned skills for accelerating demonstration-guided RL on a new task, we use a hierarchical policy learning scheme (see Figure 2, right): a high-level policy \( \pi_\phi(z|s) \) outputs latent skill embeddings \( z \) that get decoded into actions using the pre-trained low-level skill policy. We freeze the weights of the skill policy during downstream training for simplicity.\(^2\)

Our goal is to leverage the task-specific demonstrations to guide learning of the high-level policy on the new task. In Section 3.1, we showed how SPiRL [16] leverages a learned skill prior \( p_\alpha(z|s) \) to guide exploration. However, this prior is task-agnostic, i.e., it encourages exploration of all skills that are meaningful to be explored, independent of which task the agent is trying to solve. Even though SPiRL’s objective makes learning with a large number of skills more efficient, it encourages the policy to explore many skills that are not relevant to the downstream task.

In this work, we propose to extend the skill prior guided approach and leverage target task demonstrations to additionally learn a task-specific skill distribution, which we call skill posterior \( q_\zeta(z|s) \) (in contrast to the skill prior it is conditioned on the target task, hence “posterior”). We train this skill posterior by using the pre-trained skill inference model \( q_\omega(z|s_0; H-1, a_0; H-2) \) to extract the embeddings for the demonstrations.

Figure 3: We leverage prior experience data \( D \) and demonstration data \( D_{\text{demo}} \). Our policy is guided by the task-specific skill posterior \( q_\zeta(z|s) \) within the support of the demonstrations (green) and by the task-agnostic skill prior \( p_\alpha(z|s) \) otherwise (red). The agent also receives a reward bonus for reaching states in the demonstration support.

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\(^2\)Joint optimization of high-level and low-level policy is possible, but we did not find it necessary in our experiments. Prior work on hierarchical RL [35] suggests that joint optimization can lead to training instabilities. We will leave an investigation of this for future work.
skills performed in the demonstration sequences (see Figure 2, middle):
\[
\min_{\zeta} \mathbb{E}_{(s,a) \sim \mathcal{D}_{\text{demo}}}[D_{KL}(q_\omega(z|s_0; H-1, a_{0:H-2}), q_\zeta(z|s_0))],
\]
where \( D_{KL} \) denotes the Kullback-Leibler divergence.

A naive approach for leveraging the skill posterior is to simply use it to replace the skill prior in Equation 1, i.e., to regularize the policy to stay close to the skill posterior in every state. However, the train skill posterior is only accurate within the support of the demonstration dataset \( \mathcal{D}_{\text{demo}} \). Since \( |\mathcal{D}_{\text{demo}}| \ll |\mathcal{D}| \), this support will only be a small subset of all states (see Figure 3) and thus the skill posterior will often provide incorrect guidance in states outside the demonstrations’ support.

Instead, we propose to use a three-part objective to guide the policy during downstream learning. Our goal in formulating this objective is to (1) follow the skill posterior \emph{within} the support of the demonstrations, (2) follow the skill prior \emph{outside} the demonstration support, and (3) encourage the policy to reach states \emph{within} the demonstration support. Crucial for all three components is to determine whether a given state is within the support of the demonstration data. We propose to use a learned discriminator \( D(s) \) to answer this question. \( D(s) \) is a binary classifier that distinguishes demonstration and non-demonstration states and it is trained using samples from the demonstration and task-agnostic datasets, respectively. Once trained, we use its output to weight terms in our objective that regularize the policy towards the skill prior or posterior. Additionally, we provide a reward bonus for reaching states which the discriminator classifies as being within the demonstration support. This results in the following term \( J_t \) for SkiLD’s full RL objective:
\[
J_t = \tilde{r}(s_t, z_t) - \alpha q D_{KL}(\pi_\theta(z_t|s_t), q_\zeta(z_t|s_t)) \cdot D(s_t) - \alpha_\pi D_{KL}(\pi_\theta(z_t|s_t), p_\alpha(z_t|s_t)) \cdot (1 - D(s_t)),
\]
with \( \tilde{r}(s_t, z_t) = (1 - \kappa) \cdot r(s_t, z_t) + \kappa \cdot \left[ \log D(s_t) - \log (1 - D(s_t)) \right] \).

The weighting factor \( \kappa \) is a hyperparameter; \( \alpha \) and \( \alpha_\pi \) are either constant or tuned automatically via dual gradient descent [36]. The discriminator reward follows common formulations used in adversarial imitation learning [37, 38, 8, 39].\footnote{We found that using the pre-trained discriminator weights led to stable training, but it is possible to perform full adversarial training by finetuning \( D(s) \) with rollouts from the downstream task training. We report results for initial experiments with discriminator finetuning in Section E and leave further investigation for future work.} Our formulation combines IRL-like and BC-like objectives by using learned rewards \emph{and} trying to match the demonstration’s skill distribution.

For policy optimization, we use a modified version of the SPIRL algorithm [16], which itself is based on Soft Actor-Critic [40]. Concretely, we replace the environment reward with the discriminator-augmented reward and all prior divergence terms with our new, weighted prior-posterior-divergence terms from equation 4 (for the full algorithm see appendix, Section A).

4 Experiments

In this paper, we propose to leverage a large offline experience dataset for efficient demonstration-guided RL. We aim to answer the following questions: (1) Can the use of task-agnostic prior experience improve the efficiency of demonstration-guided RL? (2) Does the reuse of pre-trained skills reduce the number of required target-specific demonstrations? (3) In what scenarios does the combination of prior experience and demonstrations lead to the largest efficiency gains?

4.1 Experimental Setup and Comparisons

To evaluate whether our method SkiLD can efficiently use task-agnostic data, we compare it to prior demonstration-guided RL approaches on three complex, long-horizon tasks: a 2D maze navigation task, a robotic kitchen manipulation task and a robotic office cleaning task (see Figure 4, left).

Maze Navigation. We adapt the maze navigation task from Pertsch et al. [16] and increase task complexity by adding randomness to the agent’s initial position. The agent needs to navigate through the maze to a fixed goal position using planar velocity commands. It only receives a binary reward upon reaching the goal. This environment is challenging for prior demonstration-guided
RL approaches since demonstrations of the task span hundreds of time steps, making step-by-step imitation of primitive actions inefficient. We collect a task-agnostic offline experience dataset with 3000 sequences using a motion planner to find paths between randomly sampled start-goal pairs. This data can be used to extract relevant short-horizon skills like navigating hallways or passing through narrow doors. For the target task we sample an unseen start-goal pair and collect 5 demonstrations for reaching the goal position from states sampled around the start position.

**Robot Kitchen Environment.** We use the environment of Gupta et al. [24] in which a 7DOF robot arm needs to perform a sequence of four subtasks, such as opening the microwave or switching on the light, in the correct order. The agent receives a binary reward upon completion of each consecutive subtask. In addition to the long task horizon, this environment requires precise control of a high-DOF manipulator, testing the scalability of our approach. We use 603 tele-operated sequences performing various subtask combinations (from Gupta et al. [24]) as our task-agnostic experience dataset $D$ and separate a set of 20 demonstrations for one particular sequence of subtasks, which we define as our target task (see Figure 4, middle).

**Robot Office Environment.** A 5 DOF robot arm needs to clean an office environment by placing objects in their target bins or putting them in a drawer. It receives binary rewards for the completion of each subtask. In addition to the challenges of the kitchen environment, this task tests the ability of our approach to learn long-horizon behaviors with freely manipulatable objects. We collect 2400 training trajectories by placing the objects at randomized positions in the environment and performing random subtasks using scripted policies. We also collect 50 demonstrations for the unseen target task with new object locations and subtask sequence.

We compare our approach to multiple prior demonstration-guided RL approaches that represent the different classes of existing algorithms introduced in Section 2. In contrast to SkiLD, these approaches are not designed to leverage task-agnostic prior experience: **BC + RL** initializes a policy with behavioral cloning of the demonstrations, then continues to apply BC loss while finetuning the policy with Soft Actor-Critic (SAC, [40]), representative of [6, 7]. **GAIL + RL** [8] combines rewards from the environment and adversarial imitation learning (GAIL, [13]), and optimizes the policy using PPO [41]. **Demo Replay** initializes the replay buffer of an SAC agent with the demonstrations and uses them with prioritized replay during updates, representative of [4]. We also compare our approach to RL-only methods to show the benefit of using demonstration data: **SAC** [40] is a state-of-the-art model-free RL algorithm, it neither uses offline experience nor demonstrations. **SPIRL** [16] extracts skills from task-agnostic experience and performs prior-guided RL on the target task (see Section 3.1)$^4$. Finally, we compare to a baseline that combines skills learned from task-agnostic data with target task demonstrations: **Skill BC+RL** encodes the demonstrations with the pre-trained skill encoder and runs BC for the high-level skill policy, then finetunes on the target task using SAC. For further details on the environments, data collection, and implementation, see appendix Section B.

$^4$We train SPIRL with the closed-loop policy representation from Section 3.2 for fair comparison and better performance. For an empirical comparison of open and closed-loop skill representations in SPIRL, see Section C.
4.2 Demonstration-Guided RL with Learned Skills

Maze Navigation. We compare the downstream task performance of the tested methods on the maze navigation task in Figure 4 (right). Prior approaches for demonstration-guided RL struggle to learn the task since task-rewards are sparse and only five demonstrations are provided. With such small coverage, behavioral cloning of the demonstrations’ primitive actions leads to brittle policies which are hard to fine-tune (for an analysis of the influence of the number of demonstrations, see Section 4.3). The Replay agent improves over SAC without demonstrations and partly succeeds at the task, but learning is slow. The GAIL+RL approach is able to follow part of the demonstrated behavior, but fails to reach the final goal and as a result does not receive the sparse environment reward (see Figure 8 for qualitative results). SPiRL and Skill BC+RL, in contrast, are able to leverage offline, task-agnostic experience to learn to occasionally solve the task, but require a substantial amount of environment interactions: SPiRL’s learned, task-agnostic skill prior and Skill BC+RL’s uniform skill prior during SAC finetuning encourage the policy to try many skills before converging to the ones that solve the downstream task\(^5\). In contrast, our approach SkiLD leverages the task-specific skill posterior to quickly explore the relevant skills, leading to significant efficiency gains (see Figure 9 for a comparison of the exploration of SkiLD vs. SPiRL).

We qualitatively analyze our approach in Figure 5: we visualize the output of the discriminator \(D(s)\), and the divergences between policy and skill prior and posterior. The discriminator accurately estimates the demonstration support, providing a good weighting for prior and posterior regularization, as well as a dense reward bonus. The policy successfully minimizes divergence to the task-specific skill posterior only within the demonstration support and follows the skill prior otherwise.

Robotic Manipulation. We show the performance comparison on the robotic manipulation tasks in Figure 4 (right)\(^6\). Both tasks are more challenging since they require precise control of a high-DOF manipulator. We find that approaches for demonstration-guided RL that do not leverage task-agnostic experience struggle to learn either of the tasks since following the demonstrations step-by-step is inefficient and prone to accumulating errors. SPiRL, in contrast, is able to learn meaningful skills from the offline datasets, but struggles to explore the task-relevant skills and therefore learns slowly. Worse yet, the uniform skill prior used in Skill BC+RL’s SAC finetuning is even less suited for the target task and prevents the agent from learning the task altogether. Our approach, however, uses the learned skill posterior to guide the chaining of the extracted skills and thereby learns to solve the tasks efficiently, showing how SkiLD effectively combines task-agnostic and task-specific data for demonstration-guided RL.

\(^5\)Performance of SPiRL differs from Pertsch et al. [16] due to increased task complexity, see Section B.4.
\(^6\)For qualitative robot manipulation videos, see https://clvrai.com/skild.
4.3 Ablation Studies

In Figure 6 (left) we test the robustness of our approach to the number of demonstrations in the maze navigation task and compare to BC+RL, which we found to work best across different demonstration set sizes. Both approaches benefit from more demonstrations, but our approach is able to learn with much fewer demonstrations by using prior experience. While BC+RL learns each low-level action from the demonstrations, SkiLD merely learns to recombine skills it has already mastered using the offline data, thus requiring less dense supervision and fewer demonstrations. We also ablate the components of our RL objective on the kitchen task in Figure 6 (right). Removing the discriminator reward bonus ("no-GAIL") slows convergence since the agent lacks a dense reward signal. Naively replacing the skill prior in the SPiRL objective of Equation 1 with the learned skill posterior ("post-only") fails since the agent follows the skill posterior outside its support. Removing the skill posterior and optimizing a discriminator bonus augmented reward using SPiRL ("no-post") fails because the agent cannot efficiently explore the rich skill space. Finally, we show the efficacy of our approach in the pure imitation setting, without environment rewards, in appendix, Section E.

4.4 Data Alignment Analysis

We aim to analyze in what scenarios the use of demonstrations in addition to task-agnostic experience is most beneficial. In particular, we evaluate how the alignment between the distribution of observed behaviors in the task-agnostic dataset and the target behaviors influences learning efficiency. We choose two different target tasks in the kitchen environment, one with good and one with bad alignment between the behavior distributions, and compare our method, which uses demonstrations, to SPiRL, which only relies on the task-agnostic data.

In the well-aligned case (Figure 7, solid lines), we find that both approaches learn the task efficiently. Since the skill prior encourages effective exploration on the downstream task, the benefit of the additional demonstrations leveraged in our method is marginal. In contrast, if task-agnostic data and downstream task are not well-aligned (Figure 7, dashed), SPiRL struggles to learn the task since it cannot maximize task reward and minimize divergence from the mis-aligned skill prior at the same time. Our approach learns more reliably by encouraging the policy to reach demonstration-like states and then follow the skill posterior, which by design is well-aligned with the target task. Thus, the gains from our approach are largest when it (a) focuses a skill prior that explores a too wide range of skills on task-relevant skills or (b) compensates for mis-alignment between task-agnostic data and target task.

5 Conclusion

We have proposed SkiLD, a novel approach for demonstration-guided RL that is able to jointly leverage task-agnostic experience datasets and task-specific demonstrations for accelerated learning of unseen tasks. In three challenging environments our approach learns unseen tasks more efficiently than both, prior demonstration-guided RL approaches that are not able to leverage task-agnostic experience, as well as skill-based RL methods that cannot effectively incorporate demonstrations.

7For a detailed analysis of the behavior distributions in the kitchen dataset and the chosen tasks, see Section F.
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We introduce our objective for learning the skill inference network \( q_\phi(z_t|s_t) \), reward weight \( \gamma \), discount \( \eta \), target divergences \( \delta, \delta_q \), learning rates \( \lambda_\gamma, \lambda_\phi, \lambda_\alpha \), target update rate \( \tau \).

We initialize our full SkiLD algorithm for demonstration-guided RL with learned skills in Algorithm 1.

After training the skill inference network with above objective, \( ω \) indicates that we stop gradient flow from the prior training objective into the skill inference network for improved training stability. After training the skill inference network with above objective, we train the skill posterior network \( q_\phi(z_t|s_t) \) by minimizing KL divergence to the skill inference network’s output on trajectories sampled from the demonstration data. We minimize the following objective:

\[
\mathcal{L}_{\text{post}} = D_{\text{KL}} \left( \{ Q_\omega(s_{0:H-1}, a_{0:H-2}) \} \| Q_\phi(z_0) \right).
\]

## A Full Algorithm

We detail our full SkiLD algorithm for demonstration-guided RL with learned skills in Algorithm 1. It is based on the SPiRL algorithm for RL with learned skills [16] which in turn builds on Soft-Actor Critic [40], an off-policy model-free RL algorithm. We mark changes of our algorithm with respect to SPiRL and SAC in red in Algorithm 1.

The hyperparameters \( \alpha \) and \( \alpha_q \) can either be constant, or they can be automatically tuned using dual gradient descent [36, 16]. In the latter case, we need to define a set of target divergences \( \delta, \delta_q \). The parameters \( \alpha \) and \( \alpha_q \) are then optimized to ensure that the expected divergence between policy and skill prior and posterior distributions is equal to the chosen target divergence (see Algorithm 1).

## B Implementation and Experimental Details

### B.1 Implementation Details: Pre-Training

We introduce our objective for learning the skill inference network \( q_\phi(z_t|s_t) \) and low-level skill policy \( \pi_\phi(a_t|s_t, z) \) in Section 3.2. In practice, we instantiate all model components with deep neural networks \( Q_\omega, \Pi_\phi \) respectively, and optimize the full model using back-propagation. We also jointly train our skill prior network \( P_\alpha \). We follow the common assumption of Gaussian, unit-variance output distributions for low-level policy actions, leading to the following network loss:

\[
\mathcal{L} = \prod_{t=0}^{H-2} \left\| a_t - \Pi_\phi(s_t, z) \right\|^2 + \beta D_{\text{KL}} \left( Q_\omega(s_{0:H-1}, a_{0:H-2}) \| \mathcal{N}(0, I) \right) \]

\[
+D_{\text{KL}} \left( \{ Q_\omega(s_{0:H-1}, a_{0:H-2}) \} \| P_\alpha(s_0) \right).
\]

Here \([ \cdot ]\) indicates that we stop gradient flow from the prior training objective into the skill inference network for improved training stability. After training the skill inference network with above objective, we train the skill posterior network \( Q_\phi \) by minimizing KL divergence to the skill inference network’s output on trajectories sampled from the demonstration data. We minimize the following objective:

\[
\mathcal{L}_{\text{post}} = D_{\text{KL}} \left( \{ Q_\omega(s_{0:H-1}, a_{0:H-2}) \} \| Q_\phi(z_0) \right).
\]
We use a 1-layer LSTM with 128 hidden units for the inference network and 3-layer MLPs with 128 hidden units in each layer for the low-level policy. We encode skills of horizon 10 into 10-dimensional skill representations \( z \). Skill prior and posterior networks are implemented as 5-layer MLPs with 128 hidden units per layer. They both parametrize mean and standard deviation of Gaussian output distributions. All networks use batch normalization after every layer and leaky ReLU activation functions. We tune the regularization weight \( \beta \) to be \( 1e^{-3} \) for the maze and \( 5e^{-4} \) for kitchen and office environment.

For the demonstration discriminator \( D(s) \) we use a 3-layer MLP with only 32 hidden units per layer to avoid overfitting. It uses a sigmoid activation function on the final layer and leaky ReLU activations otherwise. We train the discriminator with binary cross-entropy loss on samples from task-agnostic and demonstration datasets:

\[
\mathcal{L}_D = -\frac{1}{N} \left[ \sum_{i=1}^{N/2} \log D(s_i^d) + \sum_{j=1}^{N/2} \log (1 - D(s_j) \right]
\]

We optimize all networks using the RAdam optimizer [42] with parameters \( \beta_1 = 0.9 \) and \( \beta_2 = 0.999 \), batch size 128 and learning rate \( 1e^{-3} \). On a single NVIDIA Titan X GPU we can train the skill representation and skill prior in approximately 5 hours, the skill posterior in approximately 3 hours and the discriminator in approximately 3 hours.

### B.2 Implementation Details: Downstream RL

The architecture of the policy mirrors the one of the skill prior and posterior networks. The critic is a simple 2-layer MLP with 256 hidden units per layer. The policy outputs the parameters of a Gaussian action distribution while the critic outputs a single \( Q \)-value estimate. We initialize the policy with the weights of the skill posterior network.

We use the hyperparameters of the standard SAC implementation [40] with batch size 256, replay buffer capacity of \( 1e6 \) and discount factor \( \gamma = 0.99 \). We collect 5000 warmup rollout steps to initialize the replay buffer before training. We use the Adam optimizer [43] with \( \beta_1 = 0.9 \), \( \beta_2 = 0.999 \) and learning rate \( 3e^{-4} \) for updating policy, critic and temperatures \( \alpha \) and \( \alpha_q \). Analogous to SAC, we train two separate critic networks and compute the \( Q \)-value as the minimum over both estimates to stabilize training. The corresponding target networks get updated at a rate of \( \tau = 5e^{-3} \). The policy’s actions are limited in the range \([-2, 2]\) by a \texttt{tanh} "squashing function" (see Haarnoja et al. [40], appendix C).

We use automatic tuning of \( \alpha \) and \( \alpha_q \) in the maze navigation task and set the target divergences to 1 and 10 respectively. In the kitchen and office environments we obtained best results by using constant values of \( \alpha = \alpha_q = 1e-1 \). In all experiments we set \( \kappa = 0.9 \).

For all RL results we average the results of three independently seeded runs and display mean and standard deviation across seeds.

### B.3 Implementation Details: Comparisons

**BC+RL.** This comparison is representative of demonstration-guided RL approaches that use BC objectives to initialize and regularize the policy during RL [6, 7]. We pre-train a BC policy on the demonstration dataset and use it to initialize the RL policy. We use SAC to train the policy on the target task. Similar to Nair et al. [7] we augment the policy update with a regularization term that minimizes the L2 loss between the predicted mean of the policy’s output distribution and the output of the BC pre-trained policy.\(^8\)

**Demo Replay.** This comparison is representative of approaches that initialize the replay buffer of an off-policy RL agent with demonstration transitions [4, 5]. In practice we use SAC and initialize a second replay buffer with the demonstration transitions. Since the demonstrations do not come with

\(^{8}\)We also tried sampling action targets directly from the demonstration replay buffer, but found using a BC policy as target more effective on the tested tasks.
Figure 8: Qualitative results for GAIL+RL on maze navigation. Even though it makes progress towards the goal (red), it fails to ever obtain the sparse goal reaching reward.

Figure 9: We compare the exploration behavior in the maze. We roll out skills sampled from SPiRL’s task-agnostic skill prior (left) and our task-specific skill posterior (right) and find that the latter leads to more targeted exploration towards the goal (red).

reward, we heuristically set the reward of each demonstration trajectory to be a high value (100 for the maze, 4 for the robotic environments) on the final transition and zero everywhere else. During each SAC update, we sample half of the training mini-batch from the normal SAC replay buffer and half from the demonstration replay buffer. All other aspects of SAC remain unchanged.

B.4 Environment Details

Maze Navigation. We adapt the maze navigation task from Pertsch et al. [16] which extends the maze navigation tasks from the D4RL benchmark [44]. The starting position is sampled uniformly from a start region and the agent receives a one-time sparse reward of 100 when reaching the fixed goal position, which also ends the episode. The 4D observation space contains 2D position and velocity of the agent. The agent is controlled via 2D velocity commands.

Robot Kitchen Environment. We use the kitchen environment from Gupta et al. [24]. For solving the target task, the agent needs to execute a fixed sequence of four subtasks by controlling an Emika Franka Panda 7-DOF robot via joint velocity and continuous gripper actuation commands. The 30-dimensional state space contains the robot’s joint angles as well as object-specific features that characterize the position of each of the manipulatable objects. We use 20 state-action sequences from the dataset of Gupta et al. [24] as demonstrations. Since the dataset does not have large variation within the demonstrations for one task, the support of those demonstration is very narrow. We collect a demonstration dataset with widened support by initializing the environment at states along the demonstrations and rolling out a random policy for 10 steps.

Robot Office Environment. We create a novel office cleanup task in which a 5-DOF WidowX robot needs to place a number of objects into designated containers, requiring the execution of a sequence of pick, place and drawer open and close subtasks (see Figure 10). The agent controls
position and orientation of the end-effector and a continuous gripper actuation, resulting in a 7-dimensional action space. For simulating the environment we build on the Roboverse framework [21]. During collection of the task-agnostic data we randomly sample a subset of three of the seven objects as well as a random order of target containers and use scripted policies to execute the task. We only save successful executions. For the target task we fix object positions and require the agent to place three objects in fixed target containers. The 97-dimensional state space contains the agent’s end-effector position and orientation as well as position and orientation of all objects and containers.

**Differences to Pertsch et al. [16].** While both maze navigation and kitchen environment are based on the tasks in Pertsch et al. [16], we made multiple changes to increase task complexity, resulting in the lower absolute performance of the SPiRL baseline in Figure 4. For the maze navigation task we added randomness to the starting position and terminate the episode upon reaching the goal position, reducing the max. reward obtainable for successfully solving the task. We also switched to a low-dimensional state representation for simplicity. For the kitchen environment, the task originally used in Gupta et al. [24] as well as Pertsch et al. [16] was well aligned with the training data distribution and there were no demonstrations available for this task. In our evaluation we use a different downstream task (see section F) which is less well-aligned with the training data and therefore harder to learn. This also allows us to use sequences from the dataset of Gupta et al. [24] as demonstrations for this task.

### C Skill Representation Comparison

In Section 3.2 we described our skill representation based on a closed-loop low-level policy as a more powerful alternative to the open-loop action decoder-based representation of Pertsch et al. [16]. To compare the performance of the two representations we perform rollouts with the learned skill prior: we sample a skill from the prior and rollout the low-level policy for \( H \) steps. We repeat this until the episode terminates and visualize the results for multiple episodes in maze and kitchen environment in Figure 11.

In Figure 11 (top) we see that both representations lead to effective exploration in the maze environment. Since the 2D maze navigation task does not require control in high-dimensional action spaces, both skill representations are sufficient to accurately reproduce behaviors observed in the task-agnostic training data.

In contrast, the results on the kitchen environment (Figure 11, bottom) show that the closed-loop skill representation is able to more accurately control the high-DOF robotic manipulator and reliably solve multiple subtasks per rollout episode. We hypothesize that the closed-loop skill policy is able to learn more robust skills from the task-agnostic training data, particularly in high-dimensional control problems.

**Figure 11:** Comparison of our closed-loop skill representation with the open-loop representation of Pertsch et al. [16]. **Top:** Skill prior rollouts for 100k steps in the maze environment. **Bottom:** Subtask success rates for prior rollouts in the kitchen environment.
Figure 12: Downstream task performance for prior demonstration-guided RL approaches with combined task-agnostic and task-specific data. All prior approaches are unable to leverage the task-agnostic data, showing a performance decrease when attempting to use it.

D Demonstration-Guided RL
Comparisons with Task-Agnostic Experience

In Section 4.2 we compared our approach to prior demonstration-guided RL approaches which are not designed to leverage task-agnostic datasets. We applied these prior works in the setting they were designed for: using only task-specific demonstrations of the target task. Here, we conduct experiments in which we run these prior works using the combined task-agnostic and task-specific datasets to give them access to the same data that our approach used.

From the results in Figure 12 we can see that none of the prior works is able to effectively leverage the additional task-agnostic data. In many cases the performance of the approaches is worse than when only using task-specific data (see Figure 4). Since prior approaches are not designed to leverage task-agnostic data, applying them in the combined-data setting can hurt learning on the target task. In contrast, our approach can effectively leverage the task-agnostic data for accelerating demonstration-guided RL.

E Skill-Based Imitation Learning

We ablate the influence of the environment reward feedback on the performance of our approach by setting the reward weight $\kappa = 1.0$, thus relying solely on the learned discriminator reward. Our goal is to test whether our approach SkiLD is able to leverage task-agnostic experience to improve the performance of pure imitation learning, i.e., learning to follow demonstrations without environment reward feedback.

We compare SkiLD to common approaches for imitation learning: behavioral cloning (BC, Pomerleau [11]) and generative adversarial imitation learning (GAIL, Ho and Ermon [13]). We also experiment with a version of our skill-based imitation learning approach that performs online finetuning of the pre-trained discriminator $D(s)$ using data collected during training of the imitation policy.

We summarize the results of the imitation learning experiments in Figure 13. Learning purely by imitating the demonstrations, without additional reward feedback, is generally slower than demonstration-guided RL on tasks that require more challenging control, like in the kitchen environment, where the pre-trained discriminator does not capture the desired trajectory distribution accurately. Yet, we find that our approach is able to leverage task-agnostic data to effectively imitate complex, long-horizon behaviors while prior imitation learning approaches struggle. Further, online finetuning of the learned discriminator improves imitation learning performance when the pre-trained discriminator is not accurate enough.

In the maze navigation task the pre-trained discriminator represents the distribution of solution trajectories well, so pure imitation performance is comparable to demonstration-guided RL. We find that finetuning the discriminator on the maze “sharpens” the decision boundary of the discriminator.

See https://sites.google.com/view/skill-demo-rl for skill prior rollout videos with both skill representations in the kitchen environment.
Figure 13: Imitation learning performance on maze navigation and kitchen tasks. Compared to prior imitation learning methods, SkiLD can leverage prior experience to enable the imitation of complex, long-horizon behaviors. Finetuning the pre-trained discriminator $D(s)$ further improves performance on more challenging control tasks like in the kitchen environment.

Figure 14: Subtask transition probabilities in the kitchen environment’s task-agnostic training dataset from Gupta et al. [24]. Each dataset trajectory consists of four consecutive subtasks, of which we display three (yellow: first, green: second, grey: third subtask). The transition probability to the fourth subtask is always near 100%. In Section 4.4 we test our approach on a target task with good alignment to the task-agnostic data (Microwave - Kettle - Light Switch - Hinge Cabinet) and a target task which is mis-aligned to the data (Microwave - Light Switch - Slide Cabinet - Hinge Cabinet).

i.e., increases its confidence in correctly estimating the demonstration support. Yet, this does not lead to faster overall convergence since the pre-trained discriminator is already sufficiently accurate.

F Kitchen Data Analysis

For the kitchen manipulation experiments we use the dataset provided by Gupta et al. [24] as task-agnostic pre-training data. It consists of 603 teleoperated sequences, each of which shows the completion of four consecutive subtasks. In total there are seven possible subtasks: opening the microwave, moving the kettle, turning on top and bottom burner, flipping the light switch and opening a slide and a hinge cabinet.
In Figure 14 we analyze the transition probabilities between subtasks in the task-agnostic dataset. We can see that these transition probabilities are not uniformly distributed, but instead certain transitions are more likely than others, e.g., it is much more likely to sample a training trajectory in which the agent first opens the microwave than one in which it starts by turning on the bottom burner.

In Section 4.4 we test the effect this bias in transition probabilities has on the learning of target tasks. Concretely, we investigate two cases: good alignment between task-agnostic data and target task and mis-alignment between the two. In the former case we choose the target task Kettle - Bottom Burner - Top Burner - Slide Cabinet, since the required subtask transitions are likely under the training data distribution. For the mis-aligned case we choose Microwave - Light Switch - Slide Cabinet - Hinge Cabinet as target task, since particularly the transition from opening the microwave to flipping the light switch is very unlikely to be observed in the training data.