Lucid Dreaming for Experience Replay: Refreshing Past States with the Current Policy

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Abstract

Experience replay (ER) improves the data efficiency of off-policy reinforcement learning (RL) algorithms by allowing an agent to store and reuse its past experiences in a replay buffer. While many techniques have been proposed to enhance ER by biasing how experiences are sampled from the buffer, thus far they have not considered strategies for refreshing experiences inside the buffer. In this work, we introduce Lucid Dreaming for Experience Replay (LiDER), a conceptually new framework that allows replay experiences to be refreshed by leveraging the agent’s current policy. LiDER 1) moves an agent back to a past state; 2) lets the agent try following its current policy to execute different actions—as if the agent were “dreaming” about the past, but is aware of the situation and can control the dream to encounter new experiences; and 3) stores and reuses the new experience if it turned out better than what the agent previously experienced, i.e., to refresh its memories. LiDER is designed to be easily incorporated into off-policy, multi-worker RL algorithms that use ER; we present in this work a case study of applying LiDER to an actor-critic based algorithm. Results show LiDER consistently improves performance over the baseline in four Atari 2600 games. Our open-source implementation of LiDER and the data used to generate all plots in this paper are available at [github.com/duyunshu/lucid-dreaming-for-exp-replay].

1 Introduction

One of the critical components contributing to the recent success of integrating reinforcement learning (RL) with deep learning is the experience replay (ER) mechanism. While deep RL algorithms are often data-hungry, ER enhances data efficiency by allowing the agent to store and reuse its past experiences in a replay buffer. Several techniques have been proposed to enhance ER to further reduce data complexity, e.g., by influencing the order of replayed experiences. Instead of replaying experiences uniformly at random (e.g., [16, 21]), studies have found that sampling experiences with different priorities can speed up the learning [3, 23, 27, 28, 33].

Biased experience sampling affects how the experiences are replayed. However, it does not consider what experience to replay. An experience comprises a state, the action taken at that state, and the return obtained by following the agent’s current policy from that state. Existing ER methods usually operate on a fixed set of experiences. That is, once an experience is stored, it remains static inside the buffer until it ages out. An experience from several steps ago might no longer be useful for the

1A one-step reward r is usually stored instead of the cumulative return (e.g., [21]). In this work, we follow [24] and store the Monte-Carlo return G; we fully describe the buffer structure in Section 3.
current policy to replay because it was generated in the past with a much worse policy. If the agent were given a chance to try again at the same place, its current policy might be able to take different actions that lead to higher returns than what it obtained in the past. What the agent should replay is therefore the newer and updated experience, instead of the older one. Given this intuition, we propose in this work **Lucid Dreaming for Experience Replay (LiDER)**, a conceptually new framework that refreshes past experiences by leveraging the agent’s current policy, allowing the agent to learn from valuable data generated by its newer self.

LiDER refreshes replay experiences in three steps. First, LiDER moves the agent back to a state it has visited before. Second, LiDER lets the agent follow its current policy to generate a new trajectory from that state. Third, if the new trajectory led to a better outcome than what the agent previously experienced from that state, LiDER stores the new experience into a separate replay buffer and reuses it during training. We refer to this process as “lucid dreaming for experience replay,” because it is as if the agent were “dreaming” about the past, but is aware of the situation and can control the dream to practice again in a past state to achieve better rewards—much like how research in sports science has found that a person’s motor skills can be improved by consciously rehearsing the movements in a lucid dream (e.g., [29]).

While a human is not physically active while lucid dreaming, one limitation of LiDER is it requires environmental interactions to refresh past states. However, we carefully account for all environment interactions, including steps taken to generate new trajectories, and show that LiDER reduces the overall sample complexity of learning compared to methods that do not refresh experiences. LiDER is applicable when a simulator exists for the task—either the task itself is a simulation like a video game or we can build a simulator of the real world—and the simulator is capable of teleporting the agent back to previously visited states and rolling forward in time from there.

The main contributions of this work are as follows: 1) We propose LiDER, a conceptually new framework to refresh replay experiences, allowing an agent to revisit and update past experiences using its current policy in off-policy, multi-worker RL algorithms. 2) LiDER is implemented in an actor-critic based algorithm as a case study. 3) Experiments show LiDER outperforms the baseline method (where past experiences were not refreshed) in four Atari 2600 games, including two hard exploration games that are challenging for several RL benchmark algorithms. 4) Additional ablation studies help illustrate the functioning of different components of LiDER. 5) Two extensions demonstrate that LiDER is also capable of leveraging policies from external sources, i.e., a policy pre-trained by a different RL algorithm and a policy that uses behavior cloning to mimic non-expert human demonstrations. 6) We open-source our implementation of LiDER and the data used to generate all plots in this paper for reproducibility at [github.com/duyunshu/lucid-dreaming-for-exp-replay](https://github.com/duyunshu/lucid-dreaming-for-exp-replay).

## 2 Background

Our algorithm leverages several existing methods, which we briefly review in this section.

**Reinforcement Learning**  We consider an RL problem that is modeled using a Markov decision process, represented by a 5-tuple $(S, A, P, R, \gamma)$. A state $s_t \in S$ represents the environment at time $t$. An agent learns what action $a_t \in A(s)$ to take in $s_t$ by interacting with the environment. The transition function $P(s_{t+1}|s_t, a_t)$ denotes the probability of reaching state $s_{t+1}$ after taking action $a_t$ at state $s_t$. A reward $r_t \in R \subset \mathbb{R}$ is given based on $a_t$ and $s_{t+1}$. The goal is to maximize the expected cumulative return $G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$ from time step $t$, where $\gamma \in [0, 1]$ is a discount factor that determines the relative importance of future and immediate rewards [30].

**Asynchronous Advantage Actor-Critic**  Policy-based methods such as the asynchronous advantage actor-critic (A3C) algorithm [20] combine a deep neural network with the actor-critic framework. In this work, we leverage the A3C framework to learn both a policy function $\pi(a_t|s_t; \theta)$ (parameterized as $\theta$) and a value function $V(s_t; \theta_v)$ (parameterized as $\theta_v$). The policy function is the actor that takes action while the value function is the critic that evaluates the quality of the action against some baseline (e.g., state value). A3C directly minimizes the policy loss

$$L_{\text{policy}}^{\alpha} = \nabla_{\theta} \log(\pi(a_t|s_t; \theta))(Q^{(n)}(s_t, a_t; \theta, \theta_v) - V(s_t; \theta_v)) - \beta^{\alpha} \mathcal{H} \nabla_{\theta} \left( \pi(s_t; \theta) \right)$$

where $Q^{(n)}(s_t, a_t; \theta, \theta_v) = \sum_{k=t}^{n-1} \gamma^k r_{t+k} + \gamma^n V(s_{t+n}; \theta_v)$ is the $n$-step bootstrapped value that is bounded by a hyperparameter $t_{max} (n \leq t_{max})$. $\mathcal{H}$ is an entropy regularizer for policy $\pi$ (weighted...
where $\beta$ helps to prevent premature convergence to sub-optimal policies. The value loss is
\[ L_{\text{value}}^{\alpha} = \nabla_{\theta_v} \left( \left( Q^{(n)}(s_t, a_t; \theta) - V(s_t; \theta_v) \right)^2 \right) \]

The full A3C loss given by [20] is then
\[ L^{\alpha} = L_{\text{policy}}^{\alpha} + \alpha L_{\text{value}}^{\alpha} \]  
(1)

where $\alpha$ is a weight for the value loss. A3C’s architecture contains one global policy and $k$ parallel actor-critic workers. The workers run in parallel and each has its own environment and parameters; each worker updates the global policy asynchronously using the data collected in its own environment. We use the feedforward version of A3C as it runs faster than, but with comparable performance to the recurrent version [20].

**Transformed Bellman Operator for A3C** The A3C algorithm uses reward clipping to help stabilize learning. However, [12] shows that clipping rewards to $[+1, -1]$ results in the agent being unable to distinguish between small and large rewards, thus hurting the performance in the long-term. [25] introduced the transformed Bellman (TB) operator to overcome this problem in the deep Q-network (DQN) algorithm [21]. The authors consider reducing the scale of the action-value function while keeping the relative differences between rewards which enables DQN to use raw rewards instead of clipping. [25] applies a transform function $h : z \mapsto \text{sign}(z) \left( \sqrt{|z| + 1} - 1 \right) + \varepsilon z$ (where $\varepsilon$ is a constant) to reduce the scale of $Q^{(n)}(s_t, a_t; \theta, \theta_v)$ to $Q_{TB}^{(n)}(s_t, a_t; \theta, \theta_v) = \sum_{k=0}^{n-1} h \left( \gamma^k r_{t+k} + \gamma^n h^{-1} (V(s_{t+n}; \theta_v)) \right)$. [25] also proves that the TB operator reduces the variance of the optimization goal while still enabling learning an optimal policy. Given this benefit, [5] applied the TB operator to A3C, denoted as A3CTB, and shows that A3CTB empirically outperforms A3C.

**Self Imitation Learning for A3CTB** The self imitation learning (SIL) algorithm [24] is motivated by the intuition that an agent can exploit its own past good experiences and thus improving performance. Built upon the actor-critic framework [20], SIL adds a prioritized experience replay buffer $D = (S, A, G)$ to store the agent’s past experiences, where $S$ is a state, $A$ is the action taken in $S$, and $G$ is the Monte-Carlo return from $S$ (i.e., the return is computed only after a terminal state is reached). In addition to the A3C update in equation (1), at each step $t$, SIL samples a minibatch from $D$ for $M$ times and optimizes the following actor-critic loss:
\[ L_{\text{policy}}^{\text{sil}} = -\log(\pi(a_t|s_t; \theta))(G_t - V(s_t; \theta_v))_+ \]
\[ L_{\text{value}}^{\text{sil}} = \frac{1}{2} ||(G_t - V(s_t; \theta_v))_+ ||^2 \]
where $G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$ is the discounted cumulative return, $V$ is the state value, and $(\cdot)_+ = \max(\cdot, 0)$ meaning that only experiences with positive advantage values (i.e., good) can contribute to the policy update. The experience buffer is prioritized by $(G_t - V(s_t; \theta_v))_+$ to increase the chance that a good experience is sampled. The SIL loss is then
\[ L^{\text{sil}} = L_{\text{policy}}^{\text{sil}} + \beta^{\text{sil}} L_{\text{value}}^{\text{sil}} \]  
(2)

where $\beta^{\text{sil}}$ is a weight for the value loss. [5] leveraged this framework to incorporate SIL into A3CTB, denoted as A3CTBSIL, which outperforms both the A3C and A3CTB algorithms. The current paper therefore uses an implementation of A3CTBSIL as the baseline.

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[5] also considered using demonstrations to improve A3CTBSIL, which is not the focus of this paper.
3 Lucid dreaming for experience replay

In this work, we introduce Lucid Dreaming for Experience Replay (LiDER), a conceptually new framework that allows replay experiences to be refreshed by following the agent’s current policy. LiDER 1) moves an agent back to a past state; 2) lets the agent try following its current policy to execute different actions—as if the agent were “dreaming” about the past, but is aware of the situation and can control the dream to encounter new experiences; and 3) stores and reuses the new experience if it turned out better than what the agent previously experienced, i.e., to refresh its memories. From a high level perspective, we expect LiDER to help learning by allowing the agent to witness and learn from alternate and advantageous behaviors.

LiDER is designed to be easily incorporated into off-policy, multi-worker RL algorithms that use experience replay (ER). We implement LiDER in the A3C framework with SIL for two reasons. First, the A3C architecture \[20\] allows us to conveniently add the “refreshing” component (which we will introduce in the next paragraph) in parallel with A3C workers, which saves computation time. Second, the SIL framework \[24\] is an off-policy actor-critic algorithm that integrates an experience replay buffer in a straightforward way, enabling us to directly leverage the return \(G\) of an episode for a policy update, which is a key component of LiDER.

Figure 1 shows the proposed implementation architecture for LiDER. A3C components are in blue: \(k\) parallel workers interact with their own copies of the environment to update the global policy \(\pi\) \[20\]. SIL components are in orange: an SIL worker and a prioritized replay buffer \(D\) are added to A3C \[24\]. Buffer \(D\) stores all experiences from the A3C workers in the form of \(D = \{(S, A, G)\}\) (as described in Section 2). Buffer \(D\) is prioritized by the advantage value such that good states are more likely to be sampled. The SIL worker runs in parallel with the A3C workers but does not interact with the environment; it only samples from buffer \(D\) and updates \(\pi\) using samples that have positive advantage values.

We introduce the novel concept of a “refresher” worker in parallel with A3C and SIL to generate new data from past states (shown in green). The refresher has access to the environment and takes randomly sampled states from buffer \(D\) as input. For each state sampled, the refresher resets the environment to that state and uses the agent’s current policy to perform a rollout until reaching a terminal state (e.g., the agent loses a life). If the Monte-Carlo return of the new trajectory, \(G_{\text{new}}\), is higher than the previous return, \(G\) (sampled from buffer \(D\)), the new data is immediately used to update the global policy \(\pi\) in the same way as the A3C workers (equation 1, replacing \(Q^\pi\) with \(G_{\text{new}}\)). The new trajectory is also stored in a prioritized buffer \(R = \{(S, A_{\text{new}}, G_{\text{new}})\}\) (prioritized by advantage, like in buffer \(D\)) if \(G_{\text{new}} > G\). Finally, the SIL worker samples from both buffers as follows. A batch of samples is taken from each of the buffers \(D\) and \(R\) (i.e., two batches in total). Samples from both batches are mixed together and put into a temporary buffer, shown in the green-orange circle in Figure 1, that is prioritized by advantage. One batch of samples is then taken from the mixture of the two batches (shown as the brown arrow) and SIL performs updates using the good samples from this batch. Having this temporary buffer to mix together transitions from buffers \(D\) and \(R\) allows the agent to adaptively decide whether to follow past and/or refreshed experiences.

We summarize LiDER’s refresher worker’s procedure in Algorithm 1.

\[^{3}\text{Full pseudo code for the A3C and SIL workers is in Appendix B}\]
Algorithm 1 LiDER: Refresher Worker

1: // Assume shared global policy $\pi$, replay buffer $D$, replay buffer $R$
2: while $T < T_{\text{max}}$ do \quad $\triangleright T_{\text{max}} = 50$ million
3: Synchronize refresher’s policy with the global policy: $\pi_e(\cdot|\theta_e) \leftarrow \pi$
4: Synchronize global step $T$ from the most recent A3C worker
5: Initialize $S \leftarrow \emptyset$, $A_{\text{new}} \leftarrow \emptyset$, $R \leftarrow \emptyset$
6: Randomly take a sample $\{s, a, G\}$ from buffer $D$, reset the environment to $s$
7: while not terminal do
8: Execute an action $s, a, r, s' \sim \pi_e(s|\theta_e)$
9: Store the experience $S \leftarrow S \cup s$, $A_{\text{new}} \leftarrow A_{\text{new}} \cup a$, $R \leftarrow R \cup r$
10: Go to next state $s \leftarrow s'$
11: $T \leftarrow T + 1$
12: end while
13: $G_{\text{new}} = \sum_{k=0}^{\infty} \gamma^k r_{t+k}, \forall r \in R$ \quad $\triangleright$ Compute the new return
14: if $G_{\text{new}} > G$ then
15: Update $\pi$ using $\{S, A_{\text{new}}, G_{\text{new}}\}$ \quad $\triangleright$ Equation (1), replace $Q^{(n)}$ with $G_{\text{new}}$
16: Store to buffer $R \leftarrow R \cup \{S, A_{\text{new}}, G_{\text{new}}\}$
17: end if
18: end while

The main benefit of LiDER is that it allows an agent to leverage its current policy to refresh past experiences. However, LiDER does require the refresher to use additional environmental steps (see Algorithm 1 line 11: we account for the refresher steps when measuring the global steps), which can be concerning if acting in the environment is expensive. Despite this shortcoming, we show in our experiments (Section 4) that the speedup in learning LiDER provides actually reduces the overall number of environment interactions required. It seems that the high quality of the refreshed experiences compensates for the additional quantity of experiences an agent needs to learn. That is, by leveraging the refresher worker, LiDER can achieve a certain level of performance within a shorter period of time compared to without the refresher—an important benefit as RL algorithms are often data-hungry. LiDER increases the overall data quality because we only leverage new data when it obtains a higher reward than the old data, i.e., $G_{\text{new}} > G$. We empirically justify the importance of this hand-coded rule via an ablation study in Section 4.2. The other important design choice of LiDER is the two-buffer architecture. One might hypothesize that LiDER improves performance mainly due to the fact that using two buffers increases the amount of data in the replay buffer. However, we show in our ablation study that simply doubling the size of a single buffer does not provide as much benefit as LiDER, therefore our two-buffer architecture is a useful design decision.

4 Experiments

We empirically evaluate LiDER in the Atari 2600 games of Ms. Pac-Man, Alien, Freeway, and Montezuma’s Revenge [2]. We selected these games because they cover a range of properties and difficulties. Ms. Pac-Man and Alien are games with dense reward functions and they are relatively easy to learn. Freeway and Montezuma’s Revenge are hard exploration games with sparse reward functions and they are challenging for several benchmark RL algorithms (e.g., [2, 8, 20]). We compare A3CTBSIL (the baseline method from [5] uses only the blue and the orange components in Figure 1) and LiDER (our proposed framework in which the agent’s current policy is used as the refresher). Implementation details and all hyperparameters for these methods are detailed in Appendix A.

4.1 Leveraging the current policy to refresh past states

First, we show that the agent’s current policy can be effectively leveraged to refresh past experiences. Figure 2 shows LiDER outperforms A3CTBSIL in all four games (averaged over 5 trials), where a one-tailed independent-samples t-test confirms statistical significance ($p < 0.001$, see Appendix B for details of the t-tests). We train each trial for 50 million environmental steps; for every 1 million steps, we perform a test of 125,000 steps and report the average testing scores per episode (an episode ends when the agent loses all its lives).
Figure 2: LiDER performance compared to A3CTBSIL on four Atari games. The x-axis is the total number of environmental steps: A3CTBSIL counts steps from 16 A3C workers, while LiDER counts steps from 15 A3C workers plus 1 refresher worker. The y-axis is the average testing score over five trials; shaded regions show the standard deviation.

The largest score improvement was in the game of Ms. Pac-Man, which we hypothesize was because of the dense reward function, increasing the likelihood for the refresher to encounter new trajectories with higher returns. In addition, we observe in Ms. Pac-Man that once the return and the action of a state has been refreshed, LiDER always samples and reuses the newer rather than the older state-action-return transition from the same state (e.g., in one of the trials only four older transitions were reused throughout the 50 million training steps), which could be another reason for the speedup in learning: LiDER replays high-rewarding data more frequently.

LiDER also learns well in Freeway and Montezuma’s Revenge, the two hard exploration games. In Freeway, the task is difficult because the agent only receives a non-zero reward when successfully crossing the highway. We speculate that LiDER is helpful in this case because the refresher can move the agent to an intermediate state (e.g., in the middle of the highway), which shortens the distance between the agent and the rewarding state, and thus allows the agent to learn faster. We can see LiDER’s learning curve in Freeway from Figure 2 that it consistently finds an optimal path after about 15 million steps of training (the standard deviation becomes negligible) but A3CTBSIL struggles to find a stable solution. The benefit of LiDER is evident particularly in Montezuma’s Revenge. While A3CTBSIL fails to learn anything, LiDER is capable of reaching a reasonable score. Although the absolute performance of our method is not state-of-the-art, we have shown that LiDER is a light-weight addition to a baseline off-policy deep RL algorithm which helps improving performance even in the most difficult Atari games.

4.2 Ablation studies

We have shown that LiDER can effectively leverage knowledge from the agent’s current policy. In this section, we perform two ablation studies to further validate our design choices.

How does the quality of refresher-generated data affect learning? We show that it is important to store the refresher-generated experiences and use them to update the global policy only if those experiences are better, i.e., when the new return $G_{new}$ computed from the refresher experience is higher than the return $G$ that the agent previously obtained. This condition ensures that the data in buffer $R$ is of a higher quality than that in buffer $D$. Intuitively, LiDER goes back in time to test if its current self can perform better than before and only provide help where it can. To validate this hypothesis, we conduct an experiment in which the refresher adds all new experiences to buffer $R$, i.e., without the $G_{new} > G$ condition, to check if doing so leads to decreased performance. We denote this experiment as LiDER-AddAll.

How does the buffer architecture affect learning? Our framework uses a two-buffer architecture in which the buffer $D$ stores A3C-generated data and the buffer $R$ stores refresher-generated data. One hypothesis could be that LiDER performs better simply because the buffer size is doubled and more experiences can be replayed (e.g., [34] studies how buffer size affects learning). We conduct an experiment to show that simply increasing the size of a single buffer does not provide the same performance improvement as LiDER. We modify LiDER to have only buffer $D$ and double its size from $10^5$ to $2 \times 10^5$; both A3C-generated and refresher-generated data are stored in buffer $D$.

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Note the performance in Montezuma’s Revenge differs between A3CTBSIL and the original SIL algorithm—see the discussion in Appendix D.
Figure 3: Ablation studies on LiDER in four Atari games show that using two buffers and only using experiences where the return is improved does indeed improve performance.

Prioritized sampling still takes a batch of 32 samples from buffer $D$ as the input to the SIL worker, but without using the temporary buffer. We denote this experiment as LiDER-OneBuffer.

The results in Figure 3 show the benefits of both design choices. The LiDER-AddAll result shows degraded performance in all games, especially in Alien and Montezuma’s Revenge, where LiDER-AddAll performs at about the same level as the baseline A3CTBSIL method. In Freeway, while LiDER-AddAll eventually reaches the same score as LiDER, it struggled during the early stages of training. Ms. Pac-Man shows the least amount of performance drop for LiDER-AddAll but it still under-performed LiDER. These results demonstrate the importance of focusing the exploitation only on places where the refresher can do better than what the agent had previously experienced. In all games, LiDER-OneBuffer shows little to no performance improvement over the baseline and clearly under-performed LiDER.

4.3 Extensions: leveraging other policies to refresh past states

LiDER was designed to leverage the agent’s current policy—this section shows that LiDER can also leverage policies from external sources. In particular, we consider leveraging a trained agent (TA) and a behavior cloning (BC) model trained from human demonstration data. LiDER-TA uses a trained agent (TA) as the refresher. While the TA could come from any source, we use the best checkpoint from a fully trained LiDER agent from experiments in Section 4.1 as the TA. This scenario tests if LiDER can effectively leverage a high-quality policy. LiDER-BC uses a behavior cloning (BC) model in the refresher. The BC policy is far from expert and we explore if LiDER can benefit from a sub-optimal policy. The BC model in LiDER-BC is pre-trained with non-expert demonstration data and we follow [5] to jointly pre-train a model with supervised, value, and unsupervised autoencoder losses (see Appendix E for details).

Figure 4 shows the results of LiDER-TA and LiDER-BC compared with A3CTBSIL and LiDER (averaged over 5 trials). As expected, LiDER-TA performs better than the other three methods as it uses a trained agent as the refresher—the learning agent can observe and learn from high quality data generated by an expert. LiDER-TA was even able to exceed the TA’s performance in Montezuma’s Revenge (shown in the purple dotted line, estimated by executing the TA greedily in the game for 125,000 steps).

The more interesting result is the performance of LiDER-BC, which demonstrates that LiDER works well even when using a refresher that is far from expert (the black dashed line shows the performance of the BC model, estimated by executing the model greedily in the game for 125,000 steps). LiDER-BC can learn to quickly outperform BC and achieve better results than the baseline. LiDER-BC also slightly outperforms LiDER, suggesting that the sub-optimal BC model was able to provide better-than-random data during the early stages of training, which in turn helps the learning in the later stages. This could be one method of leveraging imperfect demonstrations to improve RL.

5 Related work

Experience replay and extensions ER was first introduced to improve the data efficiency of off-policy RL algorithms [17] and has since become an essential component for off-policy deep RL [21]. Many techniques have been proposed to enhance ER for better data efficiency and generally fall into two categories. One category focuses on biasing the sampling strategy such that important experiences

5 The data is publicly available: [github.com/gabrieledcjr/atari_human_demo]
are reused more frequently for policy updates [3, 25, 27, 28, 33]. The other category focuses on tuning the replay buffer architecture, such as changing the buffer size [4, 18, 34], combining experiences from multiple workers to get more data to replay [8, 13, 14], or augmenting the structure of replay experiences [1]. LiDER does not fall into the first category, but is complementary to existing sampling methods; we leverage prioritized experience replay [27] in our experiments. LiDER is related to the second category, but differs in three ways. First, LiDER uses two replay buffers which double the buffer size, but we have shown that simply extending the size of a single buffer does not achieve the same performance as LiDER. Second, the refresher worker generates additional data, which is similar to using multiple workers to generate more data, but we kept the total number of workers the same between LiDER and the baseline and accounted for all environmental steps. Third, the refresher-generated data is stored in a separate buffer only when it has a higher return than the old data, which can be viewed as augmenting the quality of the data, but we do not change the data structure when storing them.

**Experience replay for actor-critic algorithms** The difficulty of combining ER into actor-critic algorithms is caused by the discrepancy between the current policy and the past policy that generated the experience. This problem is usually solved by leveraging various importance sampling techniques, such that the bias from past experiences can be corrected when used for updating the current policy [8, 10, 22, 31, 32]. SIL [24] provides a straightforward way of integrating ER into A3C without importance sampling. LiDER builds upon the SIL objective to use this approach.

**Learning from past good behaviors of oneself** The main idea of LiDER is to allow the agent to learn from past states that have been improved by its current policy. Several existing methods have shown that it is beneficial for the agent to imitate its past good behaviors [24], especially when such behaviors are diverse and can thus help drive exploration [9, 11]. While we did not design LiDER to explicitly leverage exploration techniques, LiDER revisits a past state using a different policy, leading to new trajectories, and thus potentially increasing the data diversity. This implicit exploration could be one of the reasons that LiDER improves the performance of two hard exploration Atari games.

**Relocating the agent to a past state** LiDER assumes there is a simulator for the task where resetting to a previously seen state is possible. The idea of relocating the agent to past states has been explored in the literature (e.g., [19]). The recently developed Go-Explore framework also exploits simulators’ relocation feature [7] by letting the agent return to a “promising” past state and randomly explore from there. Many simulators are already equipped with the ability to relocate the agent so that they can reset the agent to an initial state when an episode ends. LiDER makes full use of this common feature.

### 6 Conclusion and future work

In this paper, we proposed *Lucid Dreaming for Experience Replay (LiDER)*, a conceptually new framework that allows experiences in the replay buffer to be refreshed by leveraging the agent’s current policy, leading to improved performance compared to the baseline method without refreshing past experiences. We conducted two ablation studies to validate our design choices of LiDER. Two extensions demonstrated that LiDER is also capable of leveraging knowledge from external policies, such as a trained agent and a behavior cloning model. One potential limitation of LiDER is that it must have access to a simulator that can return to previously visited states before resuming.
This paper opens up several new interesting directions for future work. First, based on the initial positive results reported in this paper, additional computational resources ought to be devoted to evaluating LiDER in a broad variety of domains. Second, it is worth investigating the underlying behavior of the refresher. For example, quantifying how often the refresher can successfully generate a high-reward trajectory may help to better understand when and where LiDER will or will not be helpful. Third, while we have presented in this paper a case study of applying LiDER to a multi-worker, actor-critic based algorithm, future work could investigate extending LiDER to other types of off-policy RL algorithms that leverage ER, such as the deep Q-network (DQN) algorithm [21], a value-based algorithm in which only a single worker is used. Fourth, the refresher in LiDER-BC uses a fixed policy from behavior cloning—future work could investigate whether it helps to use different policies during training. For example, one could use the BC policy during the early stages of training, and then once the A3C’s current policy outperforms BC, replace it with the A3C policy. Fifth, it would be interesting to allow LiDER to work outside of simulations by returning to a similar, but not identical state, and from there generating new trajectories. For example, in robotics, a robot may be able to return to a position that is close to, but not identical to, a previously experienced state.

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Broader Impact

Our broad conceptual contribution is that an agent can be trained to learn better just by “self-refreshing”—without any human intervention. This is an important benefit for applications in which domain knowledge is needed but acquiring it is difficult or expensive (e.g., lack or absence of human experts or cases in which hiring them is too expensive). Additionally, we show that in applications when human intervention is possible, our method can effectively leverage that knowledge and learn better. It therefore opens directions for a more principled framework around human-in-the-loop learning.

While most of the AI research (including this work) aims for fully autonomous agent learning, we should consider the potential negative impact of not having human interventions. It becomes difficult to explain how an agent learned a certain behavior, which could be crucial in real-world applications such as self-driving cars, stock trading, and healthcare systems to name a few. From this perspective, we believe future AI research should include more studies on human-in-the-loop training: if anyone can train an agent, there will be more trust in AI since people would know how the agents were trained and that they were trained in exactly the way they wanted them, thus enabling trustworthy AI.

Outside the AI community, one possible research direction that this work could inspire is in the area of cognitive science/psychology. This work has already borrowed the concept of “lucid dreaming” from cognitive science and we wonder if it can reciprocate the influence to have some impact in the field. We intuitively know humans can learn from the past, but could the learning be aided or augmented by “self-refreshing”? It would be interesting to explore the possibilities of intervention or therapeutic applications (medical/health) that can adapt the self-refreshing behavior of an artificial agent.
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A Implementation details

We use the same neural network architecture as in the original A3C algorithm [20] for all A3C, SIL, and refresher workers (the blue, orange, and green components in Figure [1] respectively). The network consists of three convolutional layers, one fully connected layer, followed by two branches of a fully connected layer: a policy function output layer and a value function output layer. Atari images are converted to grayscale and resized to $88 \times 88$ with 4 images stacked as the input.

We run each experiment for five trials due to computation limitations. Each experiment uses one GPU (Tesla K80 or TITAN V), five CPU cores, and 32 GB of memory. The refresher worker runs on GPU to generate data as quickly as possible; the A3C and SIL workers run distributively on CPU cores. In all games, the wall-clock time is roughly 0.8 to 1 million steps per hour and around 50 to 60 hours to complete one trial of 50 million steps.

The baseline A3CTBSIL is trained with 17 parallel workers: 16 A3C workers and 1 SIL worker. The RMSProp optimizer is used with learning rate = 0.0007. We use $t_{max} = 20$ for $n$-step bootstrap $Q_n^{(t)}$ ($t \leq t_{max}$). The SIL worker performs $M = 4$ SIL policy updates (equation (2)) per step $t$ with minibatch size 32 (i.e., $32 \times 4 = 128$ total samples per step). Buffer $D$ is of size $10^5$. The SIL loss weight $\beta_{sil} = 0.5$.

LiDER is also trained with 17 parallel workers: 15 A3C workers, 1 SIL worker, and 1 refresher worker—we keep the total number of workers in A3CTBSIL and LiDER the same to ensure a fair performance comparison. The SIL worker in LiDER also uses minibatch size of 32, samples are taken from buffer $D$ and $R$ as described in Section 3. All other parameters are identical to that of in A3CTBSIL. We summarize the details of the network architecture and experiment parameters in Table 1.

Table 1: Hyperparameters for all experiments. We train each game for 50 million steps with frame skip of 4, i.e., 200 million game frames were consumed for training.

| Network Architecture | Value |
|----------------------|-------|
| Input size           | $88 \times 88 \times 4$ |
| Tensorflow Padding method | SAME |
| Convolutional layer 1 | 32 filters of size $8 \times 8$ with stride 4 |
| Convolutional layer 2 | 64 filters of size $4 \times 4$ with stride 2 |
| Convolutional layer 3 | 64 filters of size $3 \times 3$ with stride 1 |
| Fully connected layer | 512 |
| Policy output layer  | number of actions |
| Value output layer   | 1 |

Common Parameters

| Parameter                  | Value |
|----------------------------|-------|
| RMSProp initial learning rate | $7 \times 10^{-4}$ |
| RMSProp epsilon            | $1 \times 10^{-5}$ |
| RMSProp decay              | 0.99  |
| RMSProp momentum           | 0     |
| Maximum gradient norm      | 0.5   |
| Discount factor $\gamma$   | 0.99  |

Parameters for A3CTB

| Parameter                  | Value |
|----------------------------|-------|
| A3C entropy regularizer weight $\beta_{a3c}$ | 0.01  |
| A3C maximum bootstrap step $t_{max}$           | 20    |
| A3C value loss weight $\alpha$                 | 0.5   |
| $k$ parallel actors          | 16    |
| Transformed Bellman operator $\varepsilon$     | $10^{-2}$ |

Parameters for SIL

| Parameter                  | Value |
|----------------------------|-------|
| SIL value loss weight $\beta_{sil}$ | 0.1   |
| SIL update per step $M$      | 4     |
| Replay buffer $D$ size      | $10^9$ |
| Replay buffer $D$ priority  | 0.6 (1=full priority, 0=no priority) |
| Minibatch size              | 32    |

Parameters for LiDER (refresher worker)

| Parameter                  | Value |
|----------------------------|-------|
| Replay buffer $R$ size     | $10^9$ |
| Replay buffer $R$ priority | 0.6 (1=full priority, 0=no priority) |
| Minibatch size             | 32    |
B Pseudo code for the A3C and SIL \(d\) workers

Algorithm 2 LiDER: A3C Worker

1: // Assume global network parameters \(\theta\) and \(\theta_v\) and global step \(T = 0\)
2: // Assume replay buffer \(D \leftarrow \emptyset\), replay buffer \(R \leftarrow \emptyset\)
3: Initialize worker-specified local network parameters, \(\theta', \theta_v'\)
4: Initialize worker-specified local time step \(t = 0\) and local episode buffer \(E \leftarrow \emptyset\)
5: while \(T < T_{\text{max}}\) \(\triangleright T_{\text{max}} = 50\) million
6: \hspace{1em} Reset gradients: \(d\theta \leftarrow 0\), \(d\theta_v \leftarrow 0\)
7: \hspace{1em} Synchronize local parameters with global parameters \(\theta' \leftarrow \theta\) and \(\theta_v' \leftarrow \theta_v\)
8: \hspace{1em} \(t_{\text{start}} \leftarrow t\)
9: \hspace{1em} while \(s_{t+1}\) is not terminal or \(t < t_{\text{max}}\) \(\triangleright t_{\text{max}} = 20\)
10: \hspace{2em} Execute an action \(s_t, a_t, r_t, s_{t+1} \sim \pi(a_t|s_t, \theta')\)
11: \hspace{1em} Store transition to local buffer: \(E \leftarrow E \cup \{s_t, a_t, r_t, \}\)
12: \hspace{1em} \(T \leftarrow T + 1\), \(t \leftarrow t + 1\)
13: \hspace{2em} end while
14: \hspace{1em} \(G \leftarrow \{\) if \(s_{t+1}\) is terminal \(\emptyset\) \(\triangleright\) Perform A3C update \(20\)
15: \hspace{1em} \hspace{1em} otherwise \(V(s_{t+1}; \theta_v')\) \(\triangleright\) Prepare for SIL worker \(24\)
16: \hspace{1em} \hspace{1em} for \(i \in \{t, \ldots, t_{\text{start}}\}\) \(\triangleright\) Perform SIL update \(24\)
17: \hspace{2em} \hspace{1em} \(G \leftarrow r_i + \gamma G\)
18: \hspace{2em} \hspace{1em} Accumulate gradients w.r.t. \(\theta'\): \(d\theta \leftarrow d\theta + \nabla_{\theta'} \log \pi(a_t|s_t, \theta') (G - V(s_i; \theta_v'))\)
19: \hspace{2em} \hspace{1em} Accumulate gradients w.r.t. \(\theta_v'\): \(d\theta_v \leftarrow d\theta_v + \partial(G - V(s_t; \theta_v'))^2 / \partial \theta_v'\)
20: \hspace{2em} end for
21: \hspace{1em} if \(s_{t+1}\) is terminal then: \(\triangleright\) Asynchronously update global parameters using local parameters
22: \hspace{2em} \hspace{1em} compute \(G_t = \sum_{k=0}^{\infty} \gamma^{k-t_{R_k}}\) for all \(t\) in \(E\)
23: \hspace{2em} \hspace{1em} Store transition to global replay buffer \(D \leftarrow D \cup \{s_t, a_t, G_t\}\) for all \(t\) in \(E\)
24: \hspace{2em} \hspace{1em} Reset local buffer \(E \leftarrow \emptyset\)
25: \hspace{2em} end if
26: \hspace{1em} Asynchronously update global parameters using local parameters
27: end while

Algorithm 3 LiDER: SIL Worker

1: // Assume global network parameters, \(\theta, \theta_v\)
2: // Assume (Non-empty) replay buffer \(D\), replay buffer \(R\)
3: Initialize worker-specified local network parameters, \(\theta', \theta_v'\)
4: Initialize local buffer \(B \leftarrow \emptyset\)
5: while \(T < T_{\text{max}}\) \(\triangleright T_{\text{max}} = 50\) million
6: \hspace{1em} Synchronize global step \(T\) from the most recent A3C worker
7: \hspace{1em} Synchronize parameters \(\theta' \leftarrow \theta\) and \(\theta_v' \leftarrow \theta_v\)
8: \hspace{1em} for \(m = 1\) to \(M\) do \(\triangleright M = 4\)
9: \hspace{2em} Sample a minibatch of size \(32\) \(\{s_D, a_D, G_D\}\) from \(D\)
10: \hspace{2em} Sample a minibatch of size \(32\) \(\{s_R, a_R, G_R\}\) from \(R\)
11: \hspace{2em} Store both batches into \(B\): \(B \leftarrow \{s_D, a_D, G_D\} \cup \{s_R, a_R, G_R\}\) \(\triangleright\) Length of \(|B| = 64\)
12: \hspace{2em} Sample a minibatch of \(32\) \(\{s_B, a_B, G_B\}\) from \(B\) \(\triangleright\) Perform SIL update \(24\)
13: \hspace{2em} Compute gradients w.r.t. \(\theta'\): \(d\theta \leftarrow \nabla_{\theta'} \log \pi(a_B|s_B, \theta') (G_B - V(s_B; \theta_v'))\)
14: \hspace{2em} Compute gradients w.r.t. \(\theta_v'\): \(d\theta_v \leftarrow \partial((G_B - V(s_B; \theta_v'))^2 / \partial \theta_v'\)
15: \hspace{2em} Perform asynchronous update of \(\theta\) using \(d\theta\) and \(\theta_v\) using \(d\theta_v\)
16: \hspace{2em} Reset local buffer \(B \leftarrow \emptyset\)
17: \hspace{1em} end for
18: end while
C One-tailed independent-samples t-tests

We conducted one-tailed independent-samples t-tests (equal variances not assumed) in all games to compare the differences on the mean episodic reward among all methods in this paper. For each game, we restored the best model checkpoint from each trial (five trials per method) and executed the model in the game following a deterministic policy for 100 episodes (an episode ends when the agent loses all its lives) and recorded the reward per episode. This gives us 500 data points for each method in each game. We use significance level $\alpha = 0.001$ for all tests.

First, we check the statistical significance of the baseline A3CTBSIL compared to LiDER, the main framework proposed in this paper. We report the detailed statistics in Table 2. Results show that the mean episodic reward of LiDER is significantly higher than A3CTBSIL ($p \ll 0.001$) in all games.

Table 2: One-tailed independent-samples t-test for the differences of the mean episodic reward between A3CTBSIL and LiDER. Equal variances not assumed.

| Methods  | Mean episodic reward (500 episodes) | Standard deviation | One-tailed p-value |
|----------|-------------------------------------|--------------------|--------------------|
| Ms. Pac-Man |
| A3CTBSIL | 4138.16                             | 1645.91            | -                  |
| LiDER    | 9127.03                             | 2123.85            | 8.16e-215          |
| Alien |
| A3CTBSIL | 3881.12                             | 1520.64            | -                  |
| LiDER    | 5607.84                             | 1852.62            | 4.42e-52           |
| Freeway |
| A3CTBSIL | 23.32                               | 5.95               | -                  |
| LiDER    | 31.66                               | 0.99               | 1.15e-120          |
| Montezuma’s Revenge |
| A3CTBSIL | 0.2                                 | 4.47               | -                  |
| LiDER    | 902.2                               | 925.86             | 1.24e-74           |
Second, we compare A3CTBSIL to the two ablation studies, LiDER-AddAll and LiDER-OneBuffer. Table 3 shows that both ablations were helpful in Freeway in which the mean episodic rewards of the ablations are significantly higher than the baseline \((p \ll 0.001)\). LiDER-AddAll performed significantly better than A3CTBSIL in three games \((p \ll 0.001)\) except for in Alien \((p > 0.001)\). LiDER-OneBuffer performed at the same level as A3CTBSIL in three games \((p > 0.001)\) except for in Freeway \((p \ll 0.001)\).

Table 3: One-tailed independent-samples t-test for the differences of the mean episodic reward between A3CTBSIL and LiDER-AddAll, and between A3CTBSIL and LiDER-OneBuffer. Equal variances not assumed. Methods in bold are not significant.

| Methods       | Mean episodic reward (500 episodes) | Standard deviation | One-tailed p-value |
|---------------|-------------------------------------|--------------------|--------------------|
| Ms. Pac-Man   |                                     |                    |                    |
| A3CTBSIL      | 4138.16                             | 1645.91            | -                  |
| (Ablation) LiDER-AddAll | 7784.44                             | 2208.17            | 4.77e-136          |
| (Ablation) LiDER-OneBuffer | 4188.28                             | 1652.97            | 0.32               |
| Alien         |                                     |                    |                    |
| A3CTBSIL      | 3881.12                             | 1520.64            | -                  |
| (Ablation) LiDER-AddAll | 3642.1                              | 1656.56            | 0.008              |
| (Ablation) LiDER-OneBuffer | 4066.42                             | 2023.68            | 0.051              |
| Freeway       |                                     |                    |                    |
| A3CTBSIL      | 23.32                               | 5.95               | -                  |
| (Ablation) LiDER-AddAll | 31.18                               | 0.99               | 3.01e-112          |
| (Ablation) LiDER-OneBuffer | 28.18                               | 4.91               | 1.94e-41           |
| Montezuma’s Revenge |                                 |                    |                    |
| A3CTBSIL      | 0.2                                 | 4.47               | -                  |
| (Ablation) LiDER-AddAll | 105.2                               | 166.89             | 2.52e-38           |
| (Ablation) LiDER-OneBuffer | 2.2                                 | 14.67              | 0.0019             |
Third, we compare A3CTBSIL to the two extensions, LiDER-BC and LiDER-TA. Table 4 shows that the two extensions outperformed the baseline significantly in all games ($p \ll 0.001$).

Table 4: One-tailed independent-samples t-test for the differences of the mean episodic reward between A3CTBSIL and LiDER-BC, and between A3CTBSIL and LiDER-TA. Equal variances not assumed.

| Methods     | Mean episodic reward (500 episodes) | Standard deviation | One-tailed p-value |
|-------------|------------------------------------|--------------------|--------------------|
| Ms. Pac-Man |                                    |                    |                    |
| A3CTBSIL    | 4138.16                            | 1645.91            | -                  |
| (Extension) LiDER-TA | 10935.59                        | 1835.08            | 0.0                |
| (Extension) LiDER-BC | 9933.82                         | 3006.29            | 4.49e-178          |
| Alien       |                                    |                    |                    |
| A3CTBSIL    | 3881.12                            | 1520.64            | -                  |
| (Extension) LiDER-TA | 7701.72                        | 1757.05            | 1.40e-186          |
| (Extension) LiDER-BC | 6553.62                         | 1742.76            | 8.37e-133          |
| Freeway     |                                    |                    |                    |
| A3CTBSIL    | 23.32                              | 5.95               | -                  |
| (Extension) LiDER-TA | 32.41                         | 0.73               | 1.50e-133          |
| (Extension) LiDER-BC | 31.64                          | 0.85               | 2.35e-123          |
| Montezuma’s Revenge |                                |                    |                    |
| A3CTBSIL    | 0.2                                | 4.47               | -                  |
| (Extension) LiDER-TA | 1709.8                         | 1047.69            | 4.47e-143          |
| (Extension) LiDER-BC | 1663.2                          | 1049.88            | 1.99e-138          |
Forth, we check the statistical significance of LiDER compared to the two ablation studies, LiDER-AddALL and LiDER-OneBuffer. Results in Table 5 show that both ablations significantly under-performed LiDER \((p \ll 0.001)\) in terms of the mean episodic reward in all games.

Table 5: One-tailed independent-samples t-test for the differences of the mean episodic reward between LiDER and LiDER-AddAll, and between LiDER and LiDER-OneBuffer. Equal variances not assumed.

| Methods               | Mean episodic reward (500 episodes) | Standard deviation | One-tailed p-value |
|-----------------------|------------------------------------|--------------------|--------------------|
| Ms. Pac-Man           |                                    |                    |                    |
| LiDER                 | 9127.03                            | 2123.85            | -                  |
| (Ablation) LiDER-AddAll | 7784.44                        | 2208.17            | 5.73e-22           |
| (Ablation) LiDER-OneBuffer | 4188.28                             | 1652.97            | 6.97e-212          |
| Alien                 |                                    |                    |                    |
| LiDER                 | 5607.84                            | 1852.62            | -                  |
| (Ablation) LiDER-AddAll | 3642.1                        | 1656.56            | 3.31e-61           |
| (Ablation) LiDER-OneBuffer | 4066.42                             | 2023.68            | 6.19e-34           |
| Freeway               |                                    |                    |                    |
| LiDER                 | 31.66                              | 0.99               | -                  |
| (Ablation) LiDER-AddAll | 31.18                       | 0.99               | 5.92e-14           |
| (Ablation) LiDER-OneBuffer | 28.18                              | 4.91               | 2.48e-45           |
| Montezuma’s Revenge   |                                    |                    |                    |
| LiDER                 | 902.2                              | 925.86             | -                  |
| (Ablation) LiDER-AddAll | 105.2                       | 166.89             | 9.71e-62           |
| (Ablation) LiDER-OneBuffer | 2.2                             | 14.67              | 2.14e-74           |
Lastly, we compare LiDER to the two extensions, LiDER-TA and LiDER-BC. Results in Table 6 show that LiDER-TA always outperforms LiDER ($p \ll 0.001$). LiDER-BC outperformed LiDER in three out of four games ($p \ll 0.001$), except for Freeway in which LiDER-BC performed at the same level as LiDER ($p > 0.001$).

Table 6: One-tailed independent-samples t-test for the differences of the mean episodic reward between LiDER and LiDER-TA, and between LiDER and LiDER-BC. Equal variances not assumed. Methods in bold are **not** significant.

| Methods          | Mean episodic reward (500 episodes) | Standard deviation | One-tailed p-value |
|------------------|-------------------------------------|--------------------|--------------------|
| **Ms. Pac-Man**   |                                     |                    |                    |
| LiDER            | 9127.03                             | 2123.85            | -                  |
| (Extension) LiDER-TA | 10935.59                           | 1835.08            | 4.79e-43           |
| (Extension) LiDER-BC | 9933.32                             | 3006.29            | 5.79e-7            |
| **Alien**        |                                     |                    |                    |
| LiDER            | 5607.84                             | 1852.62            | -                  |
| (Extension) LiDER-TA | 7701.72                            | 1757.05            | 4.03e-65           |
| (Extension) LiDER-BC | 6553.62                            | 1742.76            | 1.60e-16           |
| **Freeway**      |                                     |                    |                    |
| LiDER            | 31.66                               | 0.99               | -                  |
| (Extension) LiDER-TA | 32.41                              | 0.73               | 1.46e-39           |
| (Extension) LiDER-BC | 31.64                              | 0.85               | 0.21               |
| **Montezuma’s Revenge** |                 |                    |                    |
| LiDER            | 902.2                               | 925.86             | -                  |
| (Extension) LiDER-TA | 1709.8                             | 1047.69            | 1.33e-35           |
| (Extension) LiDER-BC | 1663.2                             | 1049.88            | 5.08e-32           |
D Differences between A3CTBSIL and SIL

There is a performance difference in Montezuma’s Revenge between the A3CTBSIL algorithm [5] and the original SIL algorithm [24]. The A3CTBSIL agent fails to achieve any reward while the SIL agent can achieve a score of 1100 (Table 5 in [24]).

We hypothesize that the difference is due to the different number of SIL updates (equation 2) that can be performed in A3CTBSIL and SIL; lower numbers of SIL updates would decrease the performance. In particular, [24] proposed to add the “Perform self-imitation learning” step in each A3C worker (Algorithm 1 of [24]). That is, when running with 16 A3C workers, the SIL agent is actually using 16 SIL workers to update the policy. However, A3CTBSIL only has one SIL worker, which means A3CTBSIL performs strictly fewer SIL updates compared to that of the original SIL algorithm, and thus resulting in lower performance.

We empirically validate the above hypothesis by conducting an experiment in the game of Ms. Pac-Man by modifying A3CTBSIL in which an SIL update is only performed at even global steps; this setting reduces the number of SIL updates by half. We denote this experiment as A3CTBSIL-ReduceSIL. Figure 5 shows that A3CTBSIL-ReduceSIL under-performed A3CTBSIL, which provides preliminary evidence that the number of SIL updates is positively correlated to performance. More experiments will be performed in future work to further validate this correlation.

Figure 5: A3CTBSIL-ReduceSIL compared to A3CTBSIL in the game of Ms. Pac-Man. The x-axis is the total number of environmental steps. The y-axis is the average testing score over five trials; shaded regions show the standard deviation.
E Pre-training the behavior cloning model for LiDER-BC

In Section 4.3 we demonstrated that a BC model can be incorporated into LiDER to improve learning. The BC model is pre-trained using a publicly available human demonstration dataset. Dataset statistics are shown in Table 7.

Table 7: Demonstration size and quality, collected in [6]. All games are limited to 20 minutes of demonstration time per episode.

| Game                  | Worst score | Best score | # of states | # of episodes |
|-----------------------|-------------|------------|-------------|---------------|
| Ms. Pac-Man           | 4020        | 18241      | 14504       | 8             |
| Alien                 | 3000        | 8240       | 12885       | 5             |
| Freeway               | 26          | 31         | 24396       | 12            |
| Montezuma’s Revenge   | 500         | 10100      | 18751       | 9             |

The BC model uses the same network architecture as the A3C algorithm [20] and pre-training a BC model for A3C requires a few more steps than just using supervised learning as how it is normally done in standard imitation learning (e.g., [26]). A3C has two output layers: a policy output layer and a value output layer. The policy output is what we usually train a supervised classifier for. However, the value output layer is usually initialized randomly without being pre-trained. Previous work [5] observed this inconsistency and leveraged demonstration data to also pre-train the value output layer. In particular, since the demonstration data contains the true return $G$, we can obtain a value loss that is almost identical to A3C’s value loss $L_{value}$: instead of using the n-step bootstrap value $Q^{(n)}$ to compute the advantage, the true return $G$ is used.

Inspired by the supervised autoencoder (SAE) framework [15], [5] also blended in an unsupervised loss for pre-training. In SAE, an image reconstruction loss is incorporated with the supervised loss to help extract better feature representations and achieve better performance. A BC model pre-trained jointly with supervised, value, and unsupervised losses can lead to better performance after fine-tuning with RL, compared to pre-training with supervised loss only.

We copy this approach by jointly pre-training the BC model for 50,000 steps with a minibatch of size 32. The Adam optimizer is used with learning rate = $5 \times 10^{-5}$. After training, we perform testing for 25,000 steps by executing the model greedily in the game and record the average episodic reward (an episode ends when the agent loses all its lives). For each set of demonstration data, we train five models and use the one with the highest average episodic reward as the BC model used by the refresher in LiDER-BC. All parameters are based on those from the existing work [5] and we summarize them in Table 8.

Table 8: Hyperparameters for pre-training the behavior cloning (BC) model used in LiDER-BC.

| Network Architecture                  | Value                      |
|---------------------------------------|----------------------------|
| Input size                            | $88 \times 88 \times 4$    |
| Tensorflow Padding method             | SAME                       |
| Convolutional layer 1                 | 32 filters of size $8 \times 8$ with stride 4 |
| Convolutional layer 2                 | 64 filters of size $4 \times 4$ with stride 2 |
| Convolutional layer 3                 | 64 filters of size $3 \times 3$ with stride 1 |
| Fully connected layer                 | 512                        |
| Classification output layer           | number of actions          |
| Value output layer                    | 1                          |

| Parameters for pre-training           | Value                      |
|---------------------------------------|----------------------------|
| Adam learning rate                    | $5 \times 10^{-5}$        |
| Adam epsilon                          | $1 \times 10^{-5}$        |
| Adam $\beta_1$                        | 0.9                       |
| Adam $\beta_2$                        | 0.999                     |
| L2 regularization weight              | $1 \times 10^{-10}$       |
| Number of minibatch updates           | 50,000                     |
| Batch size                            | 32                         |