Learning Sparse Rewarded Tasks from Sub-Optimal Demonstrations

Zhuangdi Zhu$^1$, Kaixiang Lin$^1$, Bo Dai$^2$, and Jiayu Zhou$^1$

$^1$Michigan State University  
$^2$Google Research  
$^{1}$zhuzhuan,linkaixi,jiayuz@msu.edu  
$^{2}$bodai@google.com

ABSTRACT

Model-free deep reinforcement learning (RL) has demonstrated its superiority on many complex sequential decision-making problems. However, heavy dependence on dense rewards and high sample-complexity impedes the wide adoption of these methods in real-world scenarios. On the other hand, imitation learning (IL) learns effectively in sparse-rewarded tasks by leveraging the existing expert demonstrations. In practice, collecting a sufficient amount of expert demonstrations can be prohibitively expensive, and the quality of demonstrations typically limits the performance of the learning policy. In this work, we propose Self-Adaptive Imitation Learning (SAIL) that can achieve (near) optimal performance given only a limited number of sub-optimal demonstrations for highly challenging sparse reward tasks. SAIL bridges the advantages of IL and RL to reduce the sample complexity substantially, by effectively exploiting sup-optimal demonstrations and efficiently exploring the environment to surpass the demonstrated performance. Extensive empirical results show that not only does SAIL significantly improve the sample-efficiency but also leads to much better final performance across different continuous control tasks, comparing to the state-of-the-art.

1 Introduction

Recent years witnessed the tremendous success of Reinforcement Learning (RL) in various tasks such as game playing \cite{1, 2} and robotics control \cite{3}. Notably, RL has been advantageous in learning sequential decision-making problems with simulated environment, where massive samples with dense feedbacks can be accessed at a negligible cost. However, it is challenging to upscale RL techniques to practical applications, due to its dependence on dense reward signals to learn a long term goal. In the applications where reward feedbacks are highly sparse, RL agents may suffer from high sample-complexity, as it will struggle to connect a long sequence of actions to a delayed reward received in the far future. Especially, for tasks with high-dimensional state-action spaces and long horizons, the learning policy may spend extremely long time exploring randomly before reaching any state with meaningful rewards.

To learn tasks with highly sparse rewards, one promising direction is to exploit prior knowledge of expertise to facilitate learning. For example, recent advances of Imitation Learning (IL) can effectively provide remedies even when then environment rewards are unavailable, by referencing the expert demonstrations \cite{4, 5, 6, 7, 8} or policies \cite{9, 10}. Despite their success, a major limitation of such IL approaches is that the asymptotic performance of their learned policies are bounded by the given expert. As a result, when the provided demonstrations are sub-optimal, which is a more practical and challenging scenario, the IL approaches will render us a sub-optimal policy.

In this paper, we formally consider the problem setting where the reward feedbacks for a task is highly sparse, and the RL agent only has access to a limited number of sub-optimal demonstrations. In this scenario, existing IL and RL approaches will struggle to reach optimal performance, as they either depend on high-quality demonstrations or timely reward signals. Our goal is to combine the merits of RL and IL to address this problem setting, by exploiting the sub-optimal demonstrations that are easier to access in practice, while preserving the chance to explore for better policies guided by the sparse environment feedbacks.
Towards this goal, we propose Self-Adaptive Imitation Learning (SAIL), an off-policy imitation learning approach that systematically adapts the learning objective to strike a balance between exploitation and exploration. More concretely, we formulate the learning objective as exploration-driven IL. On one hand, it encourages distribution matching between the teacher policy and the current learning policy; on the other hand, it encourages the current policy to deviate from its previously learned predecessors for better exploration. Furthermore, to surpass the bounded performance of IL, we design an adaptive approach that carefully screens the superior self-generated trajectories based on highly sparse rewards and uses them to replace the sub-optimal demonstrations. Such treatment effectively constructs a dynamic target distribution that gradually leads to optimal performance. We conduct extensive empirical study and show that the proposed SAIL achieves significant improvement in terms of both sample-efficiency and final performance across a set of benchmark tasks.

2 Background

2.1 Markov Decision Process

We consider a standard Markov Decision Process defined as a tuple \( \mathcal{M} = (S, A, T, r, \gamma, \mu_0, S_0) \), where \( S \) and \( A \) are the state and action space; \( T(s'|s, a) \) denotes the transition probability from state \( s \) to \( s' \) upon taking action \( a \); \( r(s, a) \) is the reward function; \( \gamma \) is a discounted factor; \( \mu_0 \) is the initial state distribution with \( s_0 \sim \mu_0 \). \( S_0 \) is the set of terminate states or absorbing states. Any absorbing state always transits to itself and yield zero rewards \([11]\). We define the return for a trajectory \( \tau = \{(s_t, a_t)\}_{t=0}^\infty \) as \( R_t = \sum_{k=1}^\infty \gamma^{k-1}r(s_k, a_k) \). For an episodic task with finite horizon, its return can be written as \( R_t = \sum_{k=1}^T \gamma^{k-1}r(s_k, a_k) \), where \( T \) is the number of steps to reach the absorbing state. The purpose of reinforcement learning (RL) is to learn a policy \( \pi: S \rightarrow A \) that maximizes the expected return.

An important notation throughout this paper is the occupancy measure of a policy \( \pi \)[5], defined as:
\[
\mu^\pi(s, a) = \sum_{t=0}^\infty \gamma^t P_r(s_t = s, a_t = a | s_0 \sim \mu_0, a_t \sim \pi(s_t), s_{t+1} \sim T(s_t, a_t)).
\]

We also define \( d_\pi \) as the normalized stationary state-action distribution of \( \pi \), with \( d_\pi(s, a) = (1-\gamma)\mu^\pi(s, a) \). Without ambiguity, we refer to density and normalized stationary state-action distribution interchangeably in the following paper. From a different perspective, the objective of RL can be equivalently formulated as learning a policy \( \pi \) that maximizes the expectation of rewards over \( d_\pi \):
\[
\max_\pi \eta(\pi) := E_{(s,a)\sim d_\pi}[r(s,a)].
\]

2.2 Adversarial Imitation Learning

Generative Adversarial Imitation Learning (GAIL) addresses the imitation learning (IL) problem from the perspective of distribution matching [5]. Given a set of (near) optimal demonstrations \( \mathcal{R}_E \) from an unknown expert policy \( \pi_E \), GAIL aims to learn a policy \( \pi \) that minimizes the Jensen-Shannon divergence between \( d_\pi \) and \( d_E \):
\[
\arg \min_\pi \max_{D, \pi_E} D_{JS}[d_\pi, d_E] - \lambda H(\pi),
\]
where \( d_\pi \) and \( d_E \) are the stationary state-action distributions for policy \( \pi \) and \( \pi_E \), and \( H(\pi) \) is an entropy regularization inspired by maximum entropy Inverse Reinforcement Learning (IRL) [4][12].

GAIL obtains this objective by leveraging a saddle-point optimization scheme: it jointly trains a discriminator \( D \) that approaches to \( D_{JS}[d_\pi, d_E] \), and a policy \( \pi \) that reduces the divergence. This learning process can be formulated by the following minimax objective:
\[
\min_\pi \max_D \mathbb{E}_{d_\pi}[\log(1 - D(s,a))] + \mathbb{E}_{d_E}[\log(D(s,a))].
\]
Specifically, for a fixed policy \( \pi \), \( D \) is trained to distinguish state-actions sampled from \( \pi \) and the expert policy, and outputs of an optimized discriminator \( D^* \) satisfies [13]: \( D^*(s,a) = \frac{d_E}{d_E + d_\pi} \). \( \pi \) is trained in an on-policy fashion with a shaped reward function: \( r'(s,a) = -\log(1 - D(s,a)) \). [5] shows that optimizing the accumulated rewards of \( r'(s,a) \) performs density matching between \( d_\pi \) and \( d_E \). In practice, sampling from \( d_\pi \) is obtained by on-policy interactions with the environment.

3 Problem Setting

In this paper, we address the problem of learning in a sparse environment with only episodic feedbacks: dense reward signals are unavailable in this environment, except for an episodic reward provided when the task is terminated. We
Figure 1: Each point in the plane represents one trajectory. The red arrows denote the navigation process guided by our exploration-driven IL objective, which approaches to teacher’s density distribution and deviates from previous learned densities. It explores more efficiently to reach expertise, compared with random explorations in sparse-rewarded tasks (green arrows).

denote samples from such environment as \( \{s, a, s', i, r_e\} \); \( i \) is an indicator of whether a terminal(absorbing) state is reached: i.e., \( i(s, a, s') = 1 \) if \( s' \in S_0 \) and 0 otherwise; \( r_e \) denotes the episodic reward, where:

\[
r_e(s_t, a_t, s_{t+1}) = \begin{cases} 
\sum_{i=0}^{t} r(s_i, a_i) & \text{if } s_{t+1} \in S_0, \\
0 & \text{otherwise}.
\end{cases}
\]

To alleviate the learning difficulty, the policy is allowed to leverage the prior knowledge of a limited number of demonstrations from a sub-optimal teacher. This problem setting covers an extended variety of real-world scenarios, and intuitively the availability of sub-optimal demonstrations is very helpful in assisting the learning of highly sparse-rewarded tasks, as done by human learning.

To sum-up, we start learning with a random policy \( \pi_0 \), a teacher replay buffer with sub-optimal demonstrations \( R_T \) sampled from an unknown teacher policy \( \pi_T \), and a self replay buffer \( R_B \) to store transitions generated by the policy during learning. \( R_B \) is initialized with random transitions:

\[
R_B = \{ (s,a,s',i,r_e) \sim \pi_0 \}, \quad \text{with } i \text{ and } r_e \text{ defined above.}
\]

To ensure that the suboptimal teacher can provide informative guidance, it needs to satisfy a reasonable requirement that \( \pi_T \) performs at least better than a random policy:

**Assumption 1 (Quality of Teacher Demonstrations).**

\[
\exists \delta > 0, \text{s.t. } \mathbb{E}_{(s,a) \sim d_T}[r(s,a)] - \mathbb{E}_{(s,a) \sim d_B}[r(s,a)] > \delta.
\]

In this paper, we slightly abuse \( d_T \) to denote an estimate of the stationary state-action distribution derived from \( \pi_T \), which is approximated from the demonstration data \( R_T \). We impose Assumption 1 only for initial learning stages, as our goal is to learn a policy \( \pi \) which surpasses the teacher to reach near-optimal performance.

This problem setting, though widely applicable to the real world, brings significant challenges to existing RL and IL approaches. Effective with either dense rewards or expert demonstrations, prior arts could struggle to learn expert policies when both components are unavailable. On one hand, model-free RL depends on dense environment rewards for efficient exploration. On the other hand, IL approaches heavily rely on high-quality demonstrations to recover expert performance.

To tackle this challenging problem setting, we need a novel approach which efficiently boosts learning with sub-optimal teacher demonstrations, and at the same time enables efficient exploration, by leveraging highly sparse rewards from the environment.

### 4 Methodology

#### 4.1 Exploration-Driven Imitation Learning

For the purpose of deriving a solution benefiting from both highly-sparse rewards and sub-optimal demonstrations, we propose a novel objective which strikes a balance between exploration and imitation learning, formulated as follows:

\[
\max_{\pi} J(\pi) := -D_{KL}[d_\pi \| d_T] + D_{KL}[d_\pi \| d_B],
\]

where \( D_{KL} \) denotes the KL-divergence between two distributions, with \( D_{KL}[P \| Q] = \mathbb{E}_{x \sim P(x)} \log \frac{p(x)}{q(x)} \).
The objective in Eq (2) can be interpreted as joint motivations for imitation and exploration. The first term \(-D_{KL}[d_{π} \parallel d_{T}]\) encourages density distribution match between \(d_{π}\) and \(d_{T}\). The second term \(D_{KL}[d_{π} \parallel d_{B}]\), though could be counter-intuitive at first sight, serves as an objective for self-exploration. Since \(d_{B}\) is the normalized state-action distribution derived from a mixture of previously-learned policies, maximizing \(D_{KL}[d_{π} \parallel d_{B}]\), i.e., \(E_{(s,a) \sim d_{π}}[\log \frac{d_{π}(s,a)}{d_{B}(s,a)}]\), is in favor of visiting state-actions that are rarely seen by previously learned policies. Combined with the imitation term, this self-exploration is guided in the direction that decreases \(D_{KL}[d_{π} \parallel d_{T}]\).

We can rewrite the objective in Eq (2) as the following equivalent problem:

\[
\max_{π} \quad J(π) := E_{(s,a) \sim d_{π}} \left[ \log \frac{d_{T}(s,a)}{d_{B}(s,a)} \right],
\]

which provides two important insights into the proposed learning objective. First, it provides guidance for policy \(π\) to selectively build its support, leading to the acceleration of the IL process. One can consider maximizing \(E_{(s,a) \sim d_{π}} \left[ \log \frac{d_{T}(s,a)}{d_{B}(s,a)} \right]\) as a process of policy selection: for state-actions where the teacher has visited more frequently than the previously-learned policies, \(π\) is encouraged to build positive densities on those state-actions, leading to \(d_{π}(s,a) > 0\) where \(d_{T}(s,a) > d_{B}(s,a)\). Intuitively, this process implies that we trust the teacher more than the previously learned policies. Given Assumption 1, this is a fair policy search scheme in early learning stages. After policy \(π\) reaches the teacher’s performance, we derive an paradigm to adaptively adjust the teacher’s demonstration buffer, which will effectively improve the upper-bound of the teacher’s performance, and naturally keeps Assumption 1 tenable. We will elaborate this process later in this paper. An illustration of optimizing objective in Eq (3) is shown in Figure 1.

On the other hand, our proposed objective encourages exploration, as opposed to an IL objective that solely encourages distribution match between \(d_{π}\) and \(d_{T}\):

\[
\max_{π} \quad J_{IL}(π) := -D_{KL}[d_{π} \parallel d_{T}],
\]

where \(Dist\) is an arbitrary divergence measure, such as the Jensen-Shannon divergence or KL-divergence [14]. An optimal solution to the IL objective is a policy that exactly recovers the teacher’s density distribution with \(d_{π} = d_{T}\), which leads to an imperfect policy when the teacher’s performance is far from optimal. Moreover, optimizing \(J_{IL}(π)\) alone restricts \(π\) from further exploring density distributions that deviate from \(d_{T}\). We verify by empirical studies in Section 5.3 that, the objective of \(\max_{π} E_{d_{π}}[\log(\frac{d_{π}}{d_{B}})]\) achieves more efficient exploration, as compared to \(\max_{π} E_{d_{π}}[\log(\frac{d_{π}}{d_{T}})]\), a pure imitation-driven objective.

While the objective in Eq (2) is appealing in terms of combining the merits of both IL and exploration, directly optimizing it presents significant challenges. First, the density ratio of \(\log \frac{d_{π}}{d_{B}}\) is hard to estimate, especially when both replay buffers \(R_{B}\) and \(R_{T}\) are dynamically updated. Second, it requires the state-action to be sampled from the current policy to get expectations over \(d_{π}\), which will encounter the same sample-inefficiency issue faced by on-policy RL.

Next, we propose practical alternative objectives to systematically resolve the aforementioned issues.

4.2 Off-Policy Adversarial TD Learning

Remark 1. The proposed objective in Eq (3) is equivalent to a max-return RL objective (as defined in Eq (1)), with \(\log \frac{d_{π}}{d_{B}}\) in place of the environment rewards.

Based on the above insight, we can connect the primal objective to Temporal-Difference (TD) learning, and solve it by leveraging an actor-critic method. Especially, we learn a Q-function (critic) to estimate an expected return by minimizing its TD errors, and a policy \(π\) (actor) is learned to maximize that expectation, given \(\log \frac{d_{π}}{d_{B}}(s,a)\) as rewards.

To obtain \(\log \frac{d_{π}}{d_{B}}\), we build upon the prior arts [5] to learn a discriminator \(D\) that maximizes the following objective:

\[
\max_{D,\pi,\mathcal{A} \sim \mathcal{A}(0,1)} \quad J_{D} := E_{d_{B}}[\log(1 - D(s,a))] + E_{d_{T}}[\log(D(s,a))],
\]

\(D\) is trained to distinguish the self-generated data from \(R_{B}\) and the teacher demonstrations from \(R_{T}\). When the discriminator is trained to reach optimality, its output satisfies \(D^{⋆}(s,a) = \frac{d_{T}(s,a)}{d_{T}(s,a) + d_{B}(s,a)} [13]\). The output of \(D\) with a constant shift, which we found is empirically effective, is used to approximate a reward function:

\[
r'(s,a) = −\log(1 - D(s,a)) \approx \log(\frac{d_{π}}{d_{B}} + 1).
\]
We adopt a target network \( \bar{\pi} \) where we use deep neural networks to approximate both \( d \) where

\[
\text{Algorithm 1} \quad \text{Self-Adaptive Imitation Learning}
\]

Input: teacher replay buffer \( \mathcal{R}_T \), self-replay-buffer \( \mathcal{R}_B \), initial policy \( \pi_0 \), discriminator \( D_w \), critic \( Q_\phi \), the initial ratio of samples from teacher demonstrations; \( \alpha = 0.5 \).

for \( n = 1, \ldots \) do
    Sample a trajectory \( \tau \sim \pi_0 \), \( \mathcal{R}_B \leftarrow \mathcal{R}_B \cup \tau \).
    if \( r_\tau(\tau) > \min_{\tau'} \{ r_\tau(\tau') | \tau' \in \mathcal{R}_T \} \) then
        Add good trajectory to \( \mathcal{R}_T: \mathcal{R}_T \leftarrow \mathcal{R}_T \cup \tau \).
        Anneal \( \alpha \rightarrow 0 \).
    end if
    Update discriminator \( D_w \) by optimizing Eq (4).
    Update critic \( Q_\phi \) by optimizing Eq (7).
    Update policy \( \pi \) via gradient ascent in Eq (8).
end for

In the initial training stage, a well-trained discriminator renders higher rewards to teacher demonstrations with \( D(s, a) \rightarrow 1 \), and lower rewards for self-generated samples with \( D(s, a) \rightarrow 0 \).

Based on the shaped reward function, we learn a deterministic policy which confuses the discriminator to maximize the shaped returns. To get around the issue of sample inefficiency, we adopt an off-policy learning framework. Our objective is accordingly altered to maximize the expectation of \( Q \)-value over state distributions of a behavior policy \( \beta \) [15]:

\[
J_\beta(\pi_0) = \int_s d_\beta(s) Q(s, \pi_0(s)) ds = E_{s \sim d_\beta(s)} [Q(s, \pi_0(s))],
\]

where \( d_\beta(s) \) is the normalized stationary state distribution of \( \beta \), which is analogous to the state-action distribution defined in Section 2.1 and the \( Q \)-function is built based on shaped rewards:

\[
Q(s, a) = r'(s, a) + \gamma E_{s' \sim T(s'|s, a), a' \sim \pi(s')} [Q(s', a')],
\]

where we use deep neural networks to approximate both \( Q \) and \( \pi \), parameterized by \( \phi \) and \( \theta \), respectively. \( Q \) is learned to minimize the TD error, averaged by an off-policy stationary distribution generated by the behavior policy \( \beta \):

\[
\min_\phi J_\beta Q_\phi := E_{s \sim d_\beta, a \sim \beta} [(Q_\phi(s, a) - y)^2].
\]

We adopt a target network \( \tilde{Q} \) to stabilize training. Accordingly, \( y = r'(s, a) + \gamma \tilde{Q}(s', \pi_0(s')) \).

The policy-gradient for the actor can be derived as [16]:

\[
\nabla_\theta J_\beta(\pi_0) = E_{s \sim d_\beta} [\nabla_\theta \pi_0(s) \nabla_a Q_\phi(s, a) | a = \pi_0(s)].
\]

For regular off-policy RL methods, the behavior policy is instantiated as the transition dataset collected by policies learned through iterative training, a scheme which has been proved to greatly improve sample efficiency compared to on-policy sampling. In next Section, we introduce an algorithm which realizes our objective via abovementioned off-policy TD learning. It adopts an even more effective sampling approach that further accelerates the IL process.

4.3 Self-Adaptive Imitation Learning

In this section, we introduce Self-Adaptive Imitation Learning (SAIL), an algorithm based on objectives mentioned in above section. SAIL maintains two replay-buffers \( \mathcal{R}_T \) and \( \mathcal{R}_B \), for caching teacher demonstrations and self-generated transitions, respectively. It alternatively trains three components: a discriminator \( D \) that serves as a reward provider, a critic \( Q \) that minimizes the Bellman error based on the shaped rewards, and an actor \( \pi \) that maximizes the shaped returns. During iterative training, SAIL adds high-quality self-generated trajectories into the teacher demonstration buffer. An illustration of SAIL is shown in Figure 2 and a simplified pseudo-code is provided in Algorithm 1. Due to the paper space limit, we defer the formal summarization of SAIL to Appendix. We highlight three key aspects that make SAIL effective:

1. Leveraging sparse environment feedback to update teacher demonstration buffer \( \mathcal{R}_T \): If the behavior policy collects a trajectory with episodic reward \( r_\tau \) higher than a threshold \( C_{d_T} \), we treat this trajectory as teacher demonstrations and store it in buffer \( \mathcal{R}_T \). The threshold \( C_{d_T} \) is simultaneously updated as the lowest episodic score in \( \mathcal{R}_T \): \( C_{d_T} = \min_{\tau} \{ r_\tau(\tau') | \tau' \in \mathcal{R}_T \} \). Guided by the exploration-driven objective, a student policy \( \pi \) can quickly recover the teacher’s performance and dynamically construct the demonstration buffer with gradually increasing quality.

2. Realizing the exploration-driven objective by reshaping rewards with an off-policy discriminator: Prior work such as GAIL tackles the IL problem solely from the perspective of distribution matching. Obtaining their objective relies on
training a discriminator with on-policy samples from the current policy $\pi$, which is sample-inefficient. To resolve this issue, we iteratively train a discriminator $D$ using off-policy samples, whose output represents a ratio of $\frac{d_B}{d_T}$, where $d_B$ is the density distribution derived from a mixture of previously learned policies, and $d_T$ is the density distribution of the teacher. We show via ablation studies that, compared to its on-policy counterpart, our off-policy discriminator aligns with the proposed objective and encourages more efficient exploration.

(3) Fully utilizing teacher demonstrations to boost imitation learning: In the same spirit of learning from demonstrations [17, 18, 19], we sample from both teacher dataset in $\mathcal{R}_T$ and self-generated dataset in $\mathcal{R}_B$, to construct a mixed density distribution, which plays the role of $d_\beta$ in Eq (5) and Eq (6). This sampling scheme naturally ensures a better policy output to remain in the support of the training dataset distribution, which could alleviate the issue of out-of-distribution actions [20]. More concretely, this process can be formulated as training $Q$ and $\pi$ to optimize their objective values as follows:

$$\min_{\phi} \hat{J}(Q_\phi) := \frac{1}{N} \sum_{i=1}^{N} (Q_\phi(s_i, a_i) - y_i)^2,$$  

$$\nabla_\theta J_\beta(\pi_\theta) = \frac{1}{N} \sum_{i=1}^{N} \nabla_\theta \pi_\theta(s_i) \nabla_a Q_\phi(s_i, a) |_{a=\pi_\theta(s_i)} ,$$

where the state action pairs are sampled from the mixture of two buffers: $d_{\text{mix}} = \alpha d_T + (1 - \alpha) d_B$. $\alpha$ is the ratio of samples from teachers demonstrations, and $y_i$ is defined same as in the objective of Eq (5). In practice, we initialize $\alpha = 0.5$. Once the learning policy is able to generate trajectories with performance comparable to the teacher, we gradually anneal the value of $\alpha$ to zero. We validate in Section 5.3 that, learning from a mixture dataset from the teacher and the student is more beneficial for accelerating the initial learning stage.

5 Experiments

In this section, we study how SAIL performs in terms of reaching the objective of imitation learning and exploration. We conduct extensive experiments to answer the following key questions:

Q1. Is SAIL sample-efficient?

Q2. Can SAIL surpass the demonstration performance via exploration?

Q3. Which components in SAIL contribute to the sample-efficiency or exploration?

5.1 Setup

We implemented SAIL on a TD3 framework [21] using open-sourced code from stable-baselines[3]. We tested SAIL on 4 modified locomotion tasks simulated by OpenAI MuJoCo[4]: Walker2d-v2, Hopper-v2, HalfCheetah-v2, and Swimmer-v2. The original tasks are in the dense-reward setting. To construct a sparse feedback environment, we omit the original rewards such that only an episodic reward is given upon the completion of a trajectory. For each task, we generated teacher demonstrations by training a TD3 benchmark to reach sub-optimal performance, and use trajectories with triplets $(s_t, a_t, s_{t+1})$ to initialize the teacher replay buffer $R_T$.

We compare SAIL with 4 baselines that are mostly applicable to our problem setting: DAC [6], GAIL [5], POoD [22], and Behavior Cloning (BC). DAC is an off-policy imitation learning baseline built also on a TD3 framework, which

1https://stable-baselines.readthedocs.io/en/master/
2https://github.com/openai/mujoco-py

Figure 2: The illustration of the proposed Self-Adaptive Imitation Learning (SAIL) framework.
attaches auxiliary absorbing states to each episode to stabilize learning. POfD is an extension of GAIL that maximizes policy returns of combined rewards from the environment and the discriminator. The reward used by POfD can be denoted as $r'(s, a) = r(s, a) − \lambda \log(1 − D(s, a))$. Fitted into our problem setting, we use episodic rewards $r_e(s, a)$ in place of $r(s, a)$, and scale the shaped reward as $r'(s, a) = 0.1 * r_e(s, a) − \log(1 − D(s, a))$. As on-policy baselines, both POfD and GAIL are built upon the TRPO framework [23]. All experiments are conducted using 5 random seeds, with seed numbers ranging from 1 to 5. More details about experiment implementations are provided in the supplementary document.

5.2 Performance on Continuous Action-Space Tasks

We conduct comparison between SAIL and other baselines using 1 and 4 trajectories of imperfect demonstrations, respectively. Experimental results are analyzed from the perspective of sample complexity and exploration ability.

Sample efficiency: As the results shown in Figure 3, SAIL is the only method that performs consistently better in all tasks in terms of both sample efficiency and asymptotic performance. At the initial stage of the learning, SAIL can quickly exploit the suboptimal demonstrations and approach to the demonstration’s performance with significantly less samples. Furthermore, comparing Figure 3 and Figure 4, we notice that SAIL is highly effective in terms of utilizing the suboptimal demonstrations, as it is has negligible performance degradation across all tasks when we reduce the demonstration size from four trajectories to one. To see this, we highlight the performance comparison in task Swimmer-v2, where GAIL and DAC reaches the demonstration performance with much more samples given 1 teacher trajectory, comparing to the case of four trajectories, whereas the performance of SAIL is comparable in both cases.

Effective exploration: Besides sample-efficiency, another advantage of SAIL is that it can effectively explore the environment to achieves expert-level performance, even with highly sparse rewards. We observe that the prior solution of learning from environment rewards for exploration, such as POID, cannot effectively address our proposed problem setting, as the delayed episodic feedback is too noisy to learn a meaningful critic. Unlike other imitation learning baselines whose performance are limited by the demonstrations, SAIL can rapidly surpass the imperfect teacher via constructing a better demonstration buffer and gradually converge to near-optimal performance.

![Figure 3: Learning curves of SAIL and other baselines using 1 suboptimal demonstration trajectory.](image)

![Figure 4: Performance of SAIL and other baselines using 4 suboptimal demonstration trajectories.](image)

5.3 Analysis of SAIL

In this section, we aim to analyze different components of our algorithm via ablation studies. Experiments in this section focus on the following aspects:

Effects of learning from expert demonstrations: As shown in Figure 5, we observe that sampling from a mixture of teacher data and self-generated data accelerates the learning performance in early training stages. Specifically, the blue line (SAIL-Dynamic) refers our proposed approach. It initializes $\alpha$ to 0.5 and reduced $\alpha$ to zero once the learning policy
is able to generate better-than-teacher trajectories. The orange line (SAIL) represents a variant which adopts a fixed \( \alpha = 0.5 \) throughout the training stages. The green line (SAIL-without-LfD) only uses self-generated data to learn policy by setting \( \alpha = 0 \) constantly. We see that the initial performance of SAIL-without-LfD is less significant compared with its other two counterparts.

**Effects of updating teacher demonstration buffers:** As shown in Figure 5, the red line (SAIL-without-Expert-Adaptation) refers to a variant of SAIL which never update the teacher’s replay buffer, even when a better trajectory is collected during the learning process. We see that its asymptotic performance is bounded by the teacher’s demonstration, which echoes the dilemma of most existing IL approaches. One key insight from these results is that, instead of learning critics based on sparse rewards from the environment, leveraging the sparse guidance to update the demonstration buffer, and then perform imitation learning on the updated demonstration, can be much more effective in improving the ultimate performance.

**Benefits of exploration-driven objective:** In order to illustrate the benefits of maximizing \( \mathbb{E}[\log \left( \frac{\pi}{d_T} \right)] \) over an IL objective such as \( \mathbb{E}[\log \left( \frac{d_T}{\pi} \right)] \), we conduct a comparison study, where we train the discriminator using teacher demonstrations \( \tau_T \) and on-policy self-generated samples \( \tau_\pi \), instead of off-policy samples from replay buffer \( R_B \). This on-policy training scheme is the same as proposed in GAIL [5]. In this way, the discriminator can get approximations of \( \log(\frac{d_T}{\pi}) \) instead of \( \log(\frac{\pi}{d_T}) \). We use the output of this on-policy discriminator to shape rewards, whereas \( Q \) and \( \pi \) are still updated in the same off-policy fashion as our proposed approach.

Performance of this approach is illustrated by the orange line (SAIL-OnPolicy) in Figure 6. Compared to the on-policy GAIL whose performance is illustrated by the green line, SAIL-OnPolicy still enjoys the benefits of off-policy actor-critic learning scheme in general. However, it is less effective compared with our proposed approach. Even when \( \pi \) and \( Q \) are updated using off-policy, SAIL-OnPolicy is obviously slower to surpass the teacher demonstration (dashed gray line), due to its pure imitation-driven objective. This results verify that our objective is more effective in terms of encouraging exploration. SAIL enjoys fast improvement in performance not only because of an adaptive teacher demonstration buffer, but also because it is guided by exploration-driven shaped reward functions.

![Figure 5: Ablation Study of SAIL using 1 teacher demonstration trajectory.](image)

![Figure 6: Comparison of off-policy and on-policy reward shaping using 1 teacher demonstration trajectory.](image)

### 6 Related Work

**Imitation Learning (IL)** is originally derived from Behavior Cloning (BC), which maximizes the probability for a policy to follow the demonstrated actions by conducting supervise learning on the demonstration data [24]. BC is known to suffer from the out-of-distribution errors due to the shift-propagation issue. Later successes in Inverse Reinforcement Learning (IRL) address IL from a different perspective [25, 4]. IRL replicates the expertise by first recovering a reward function that best explains the expert behavior, then performing RL based on the learned reward function. An instantiation of the IRL approach is [26], which treats imitation learning as a two-player game to recover the reward and policy interactively.
Later work of IRL draws a connection to Generative Adversarial Training \[13\] to solve imitation learning as a distribution matching problem. Especially, \[5\] proposed Generative Adversarial Imitation Learning (GAIL) to learn the expert policy without needing to unveil its reward functions. The principle of GAIL has been applied to different on-policy RL frameworks, including PPO \[22\], TRPO \[27, 28\], etc. These on-policy approaches require a large number of interactions with the environment.

Recently, there are IL approaches that address the distribution matching problem under off-policy actor-critic (OPAC) frameworks. \[6\] proposed Discriminator Actor Critic (DAC), which applies the methodology of GAIL on TD3 framework. They propose to learn a discriminator with off-policy samples and correct the distribution shift by importance sampling. To further stabilize the performance of IL, they altered benchmark environments by attaching an extra absorbing state to the end of each episode. Other compatible work about off-policy IL can also be found in \[29, 7\], which shares a common objective to minimize $D(d_\pi || d_E)$, i.e. the density divergence between the teacher and learning policy.

Some other work address IL by reducing distribution shift instead of directly seeking distribution matching. \[9\] proposed DAGGER algorithm to obtain linear regret on imitation learning, provided that they have feedback from an oracle policy. \[30\] applied the Random Network Distillation \[31\] to leverage the curiosity loss from a random network as penalty, forcing the density distribution of the learned policy to stay close to the expert demonstrations. \[32\] derived IL approaches via policy ensemble: they pre-trained multiple policies by BC, and then used the variance among these pre-trained policies as penalty to regularize the target policy.

Contrasting to our exploration-driven objective, prior arts mentioned above are motivated to exactly recover the teacher policy. Addressing a different and more practical problem setting, our work is able to significantly surpass the teacher, by iteratively playing a tradeoff between imitation and exploration.

**Learning from Demonstrations (LfD)** address the challenge of exploration faced by model-free RL by leveraging expert demonstration as self-generated transitions. Especially, \[17\] introduced Deep $Q$-learning from Demonstrations (DQfD) for tasks with discrete action spaces. \[8\] applied the principle of LfD to the DDPG framework \[16\] to facilitate learning in continuous action spaces. Strategies such as prioritized sampling \[17\] or refined cost functions \[33, 8\] are usually required for LfD approaches to encourage following the expert actions. We inherit the same spirit of LfD in that we combine teacher demonstration with self-generated data to accelerate learning in early stages. However, we omit the need of a prioritized scheme or hand-crafted loss function, benefiting from a shaped reward function which naturally ensures the superiority of the teacher demonstration over self-generated data.

Recently, there emerges research on learning from sub-optimal demonstrations \[19, 22, 27\]. To surpass the performance of the demonstrations, they alter the environment reward to combine it with an auxiliary term, based on which a policy is learned to optimize the accumulated returns. Contrasting to their work, our approach learns a critic without using intermediate environment rewards, which is a more robust learning scheme when the environment feedbacks are highly sparse or delayed. **SAIL** learns a policy based on synthetic rewards from a discriminator, which does not reveal the true reward signals but purely represents the occupancy match between the self-generated data (for exploration) and given demonstrations (for imitation).

## 7 Conclusion

In this paper, we address the problem of reinforcement learning in environments with highly sparse rewards given sub-optimal teacher demonstrations. To address this challenging problem, we propose an novel objective which encourages exploration-based imitation learning. Towards this objective we design an effective algorithm called **Self Adaptive Imitation Learning (SAIL)**. SAIL is validated to 1) address sample efficiency by off-policy imitation learning, 2) accelerate learning process by fully utilizing teacher demonstration, and 3) surpass the imperfect teacher to reach (near) optimality by iteratively performing imitation and exploration. Experimental results across modified locomotion tasks with highly sparse rewards indicate that, **SAIL** significantly surpasses state-of-the-arts in terms of both sample efficiency and asymptotic performance.

## References

[1] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529, 2015.

[2] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge.
[3] Shixiang Gu, Ethan Holly, Timothy Lillicrap, and Sergey Levine. Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates. In 2017 IEEE international conference on robotics and automation (ICRA), pages 3389–3396. IEEE, 2017.

[4] Brian D Ziebart, Andrew L Maas, J Andrew Bagnell, and Anind K Dey. Maximum entropy inverse reinforcement learning. In Aaai, volume 8, pages 1433–1438. Chicago, IL, USA, 2008.

[5] Jonathan Ho and Stefano Ermon. Generative adversarial imitation learning. In Advances in neural information processing systems, pages 4565–4573, 2016.

[6] Ilya Kostrikov, Kumar Krishna Agrawal, Debidatta Dwibedi, Sergey Levine, and Jonathan Tompson. Discriminator-actor-critic: Addressing sample inefficiency and reward bias in adversarial imitation learning. ICLR, 2019.

[7] Ilya Kostrikov, Ofir Nachum, and Jonathan Tompson. Imitation learning via off-policy distribution matching. ICLR, 2020.

[8] Matej Večerík, Todd Hester, Jonathan Scholz, Fumin Wang, Olivier Pietquin, Bilal Piot, Nicolas Heess, Thomas Rothörl, Thomas Lampe, and Martin Riedmiller. Leveraging demonstrations for deep reinforcement learning on robotics problems with sparse rewards. arXiv preprint arXiv:1707.08817, 2017.

[9] Stéphane Ross, Geoffrey Gordon, and Drew Bagnell. A reduction of imitation learning and structured prediction to no-regret online learning. In Proceedings of the fourteenth international conference on artificial intelligence and statistics, pages 627–635, 2011.

[10] Richard S Sutton and Andrew G Barto. Reinforcement learning: An introduction. pages 45–47. MIT press, 2018.

[11] Brian D Ziebart, J Andrew Bagnell, and Anind K Dey. Modeling interaction via the principle of maximum causal entropy. 2010.

[12] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In Advances in neural information processing systems, pages 2672–2680, 2014.

[13] David Silver, Guy Lever, Nicolas Heess, Thomas Degris, Daan Wierstra, and Martin Riedmiller. Deterministic policy gradient algorithms. 2014.

[14] Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. ICLR, 2016.

[15] Todd Hester, Matej Vecerik, Olivier Pietquin, Marc Lanctot, Tom Schaul, Bilal Piot, Dan Horgan, John Quan, Andrew Sendonaris, Ian Osband, et al. Deep q-learning from demonstrations. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[16] Aviral Kumar, Justin Fu, Matthew Soh, George Tucker, and Sergey Levine. Stabilizing off-policy q-learning via bootstrapping error reduction. In Advances in Neural Information Processing Systems, pages 11761–11771, 2019.

[17] Scott Fujimoto, Herke Van Hoof, and David Meger. Addressing function approximation error in actor-critic methods. arXiv preprint arXiv:1802.09477, 2018.

[18] Bingyi Kang, Zequn Jie, and Jiashi Feng. Policy optimization with demonstrations. In International Conference on Machine Learning, pages 2474–2483, 2018.

[19] John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In International conference on machine learning, pages 1889–1897, 2015.
[24] Stefan Schaal. Is imitation learning the route to humanoid robots? Trends in cognitive sciences, 3(6):233–242, 1999.

[25] Pieter Abbeel and Andrew Y. Ng. Apprenticeship learning via inverse reinforcement learning. In Proceedings of the twenty-first international conference on Machine learning, page 1. ACM, 2004.

[26] Umar Syed and Robert E. Schapire. A game-theoretic approach to apprenticeship learning. In Advances in neural information processing systems, pages 1449–1456, 2008.

[27] Yueh-Hua Wu, Nontawat Charoenphakdee, Han Bao, Yoot Tangkaratt, and Masashi Sugiyama. Imitation learning from imperfect demonstration. arXiv preprint arXiv:1901.09387, 2019.

[28] Justin Fu, Katie Luo, and Sergey Levine. Learning robust rewards with adversarial inverse reinforcement learning. ICLR, 2017.

[29] Fumihiro Sasaki, Tetsuya Yohira, and Atsuo Kawaguchi. Sample efficient imitation learning for continuous control. ICLR, 2019.

[30] Yuri Burda, Harrison Edwards, Amos Storkey, and Oleg Klimov. Exploration by random network distillation. ICLR, 2019.

[31] Ruohan Wang, Carlo Ciliberto, Pierluigi Amadori, and Yiannis Demiris. Random expert distillation: Imitation learning via expert policy support estimation. Proceedings of International Conference on Machine Learning, 2019.

[32] Kianté Brantley, Wen Sun, and Mikael Henaff. Disagreement-regularized imitation learning.

[33] Beomjoon Kim, Amir-massoud Farahmand, Joelle Pineau, and Doina Precup. Learning from limited demonstrations. In Advances in Neural Information Processing Systems, pages 2859–2867, 2013.