
Faithful Dynamic Imitation Learning from Human Intervention with Dynamic Regret Minimization

Bo Ling

Southeast University
bo_ling@seu.edu.cn

Zhengyu Gan

Southeast University
zhengyugan@seu.edu.cn

Wanyuan Wang

Southeast University
wywang@seu.edu.cn

Guanyu Gao

Nanjing University of Science and Technology
gygao@njjust.edu.cn

Weiwei Wu

Southeast University
weiweiwu@seu.edu.cn

Yan Lyu*

Southeast University
lvyany@seu.edu.cn

Abstract

Human-in-the-loop (HIL) imitation learning enables agents to learn complex behaviors safely through real-time human intervention. However, existing methods struggle to efficiently leverage agent-generated data due to dynamically evolving trajectory distributions and imperfections caused by human intervention delays, often failing to faithfully imitate the human expert policy. In this work, we propose Faithful Dynamic Imitation Learning (FaithDaIL) to address these challenges. We formulate learning from human intervention as an online non-convex problem and employ dynamic regret minimization to adapt to the shifting data distribution and track high-quality policy trajectories. To ensure faithful imitation of human expert despite training on mixed agent and human data, we introduce an unbiased imitation objective and achieve it by weighting the behavior distribution relative to the human expert's as a proxy reward. Extensive experiments on MetaDrive and CARLA driving benchmarks demonstrate that FaithDaIL achieves state-of-the-art performance in safety and task success with significantly reduced human intervention data compared to prior HIL baselines. The corresponding source code is available at <https://github.com/William-island/FaithDaIL>.

1 Introduction

Human-in-the-loop (HIL) imitation learning is a promising approach to address key limitations of traditional reinforcement learning, such as misalignment with human intent and poor sample efficiency. By incorporating human feedback and interventions into the learning process, HIL enables agents to better align with human preferences, even when reward functions are difficult to design or prone to unintended biases [1, 2, 3]. While early HIL methods relied on passive human feedback – such as preference on behavior trajectories [4, 5, 6, 7] – these methods are unsuitable for safety-critical domains like autonomous driving, where unacceptable risks can arise during data collection [8, 9].

In contrast, active human intervention (see Figure 1a), where humans provide real-time corrections and demonstrations during agent execution, directly enhances training-time safety. While some early methods like Human-Gated DAgger (HG-DAgger) [8] focus solely on human-provided data, this data

*Corresponding Author

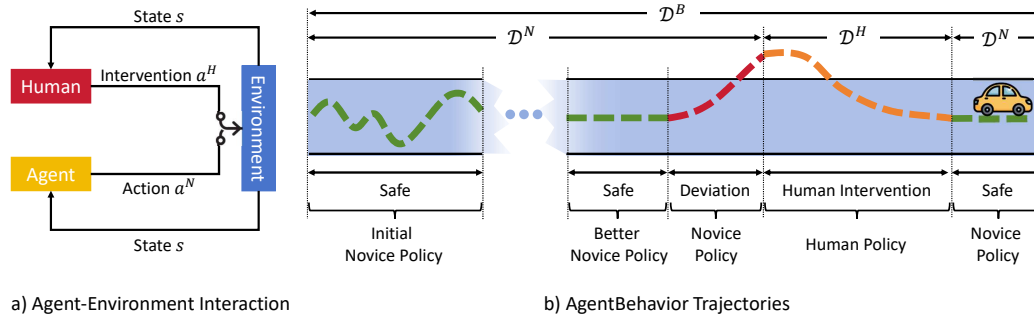


Figure 1: Learning from Intervention. a) Agent-Environment Interaction: human expert supervises the learning agent interacting with the environment, and intervenes when necessary. b) Agent Behavior Trajectories: includes safe but not optimal trajectory from initial suboptimal novice policy, improved novice policy trajectory, deviation (red) due to human reaction latency, human intervention and subsequent recovery. Our FaithDaIL leverages novice policy trajectories $\mathcal{D}^N$ together with human intervention $\mathcal{D}^H$ to improve data efficiency, while explicitly considering the evolving novice data distribution shifts and intervention latency to achieve faithful imitation of human experts.

is often costly and limited. To improve data efficiency, recent methods incorporate agent-generated trajectories (often called *novice trajectories*) as supplementary training data, combining them with human interventions in an off-policy imitation learning framework [9, 10, 11].

However, leveraging agent-generated trajectories in HIL introduces two challenges. First, as the agent’s policy improves throughout training, the distribution of its generated trajectories shifts significantly (see green trajectories in Figure 1b). Using these trajectories indiscriminately – many originating from early, suboptimal policies – impedes effective policy updates if all historical data is treated equally. Our *first key insight is that learning from human intervention problem is fundamentally an online learning problem with a dynamically changing data distribution*. Instead of viewing it as a static problem with an expanding dataset like DAgger [12], we formulate it as a *dynamic regret minimization* problem to explicitly adapt to the evolving behavior distributions over time.

Second, even recent agent-generated data may be imperfect due to human reaction delays during interventions. The agent might execute incorrect actions just before an intervention (see red deviation trajectory in Figure 1b). Imitating these “deviation trajectories” risks teaching the agent suboptimal or unsafe behaviors. Our *second key insight is that while leveraging agent-generated data is crucial for data efficiency, the primary imitation target should be the human expert policy*. Therefore, we need an unbiased objective that ensures faithful imitation of the human expert, even when training on a mixture of expert and novice data.

In this paper, we propose Faithful Dynamic Imitation Learning, FaithDaIL, a novel HIL approach that enhances data efficiency by integrating evolving novice trajectories through dynamic regret minimization. It further achieves faithful imitation of human experts by deriving a proxy reward from weighting the mixed behavior distribution to the expert’s distribution. To the best of our knowledge, this is the first work that formulate learning from human intervention as an online non-convex learning problem to minimize dynamic regret of imitation loss. In summary, our contributions are:

- We propose Faithful Dynamic Imitation Learning framework, FaithDaIL, that formally formulates learning from human intervention as an online non-convex learning problem and adopts dynamic regret as the performance metric to explicitly adapt to the changing data distribution induced by the evolving novice policy.
- We propose an unbiased objective for faithful human expert imitation from mixed data (novice trajectories and human interventions), and achieve it by weighting the behavior distribution relative to the human expert’s as a proxy reward.
- We conducted extensive experiments on MetaDrive and CARLA driving benchmarks. Results show FaithDaIL significantly outperforms leading HIL baselines in safety and task success, with notably less human intervention data.

2 Related Work

Human-in-the-loop Imitation Learning. Many studies explore the incorporation of humans into the training loop in imitation learning. Passive approaches, such as DAgger [12] and its variants [13, 14, 15, 16, 17], address the compounding error problem [18] inherent in behavior cloning by periodically querying an expert for additional demonstrations on agent-visited states. Instead of providing demonstrations upon requests, active approaches allow experts to take control and guide the agent to safer states. Human-Gated DAgger (HG-DAgger) [8] involves human intervention during training and learns a policy by leveraging the collected human data. However, using only human data is costly and limited. To improve data efficiency, recent methods such as Expert Intervention Learning (EIL) [19], Intervention Weighted Regression (IWR) [10], HACO [11], and PVP [9] incorporate agent-generated trajectories as supplementary data, combining them with human interventions in an off-policy imitation learning framework. EIL [19] and IWR [10] treat agent-generated data in a supervised manner, while HACO [11] and PVP [9] leverage off-policy RL techniques to imitate a combination of agent-generated data and human data.

However, these methods face two major drawbacks: 1) they effectively minimize static regret on aggregate data, neglecting the evolving data distribution shifts, and 2) they imitate mixed behavior trajectories instead of focusing solely on the expert, leading to learning suboptimal actions caused by intervention latency (only partially addressed by EIL’s fixed window, which cannot adapt to dynamic environment [19]). Our FaithDaL addresses these by formulating human-in-the-loop learning as dynamic regret minimization to align with evolving distributions and proposing an unbiased off-policy imitation objective based on DICE [20] for faithful expert imitation.

Off-policy Imitation Learning. Human-in-the-loop (HIL) imitation learning, characterized by sparse and disruptive interventions, makes on-policy data collection inefficient; off-policy methods are therefore essential [21]. While behavior cloning (BC) [22] is inherently off-policy, it suffers from compounding errors and ignores environment dynamics [18]. For adversarial methods, DAC [21] extends GAIL [23] to off-policy setting using a replay buffer for better sample efficiency. The DICE family [20, 24, 25, 26] addresses off-policy imitation via stationary distribution matching. However, these methods primarily focus on expert demonstrations. Based on DICE, some methods incorporate offline supplementary imperfect demonstrations to enhance data efficiency [27, 28, 29, 30, 31] but rely on a strict coverage assumption [27, 29, 32]. In our FaithDaL, by defining the behavior data as a combination of agent-generated and human expert data, the coverage requirement (i.e., the support of the expert distribution is covered by the behavior distribution) is naturally satisfied, enabling faithful imitation learning from human interventions.

Online Non-convex Learning. Online learning offers a principled framework for sequential decision making [33]. In the convex setting, Online Gradient Descent (OGD) and its variants achieve optimal sub-linear static regret, and many extensions bound dynamic regret [34, 35, 36, 37, 38, 39]. With non-convex losses—common in deep networks—regret minimization is NP-hard [40]. Follow-the-Perturbed-Leader (FTPL) algorithms [41, 42] achieve sublinear static regret for online non-convex learning (with an oracle), but are not well-suited for dynamic distributions. To address this, FTPL-D+ extends FTPL for dynamic environments using an ensemble and meta-algorithm [40]. In this work, we adopt FTPL-D+ to effectively manage the dynamic shifts in the novice agent’s behavior policy.

3 Problem Formulation

We formulate learning from active human intervention with evolving policy trajectories as an online learning problem. Here, we first model agent-environment interaction as a Markov Decision Process, and then define the online learning problem as dynamic regret minimization.

The interaction between the environment and policy can be formulated as a Markov Decision Process (MDP), denoted by $\mathcal{M}$, and $\mathcal{M} = (\mathcal{S}, \mathcal{A}, p, r, \gamma, d_0)$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, p is the transition probability function, $r : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ is the reward function, $\gamma \in (0, 1)$ is the discount factor, and d_0 is the distribution of initial state s_0 . A policy $\pi(a|s)$ takes action a in $\mathcal{A}$ given state s in $\mathcal{S}$. Conventional Reinforcement Learning (RL) aims to find a policy π that maximizes the expected return: $\mathbb{E}_\pi[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)]$, where $\mathbb{E}_\pi$ denotes the expectation under the distribution induced by $a_t \sim \pi(\cdot|s_t)$, $s_{t+1} \sim p(\cdot|s_t, a_t)$. The distribution of a policy can be defined by its

discounted state-action visitation distribution $d_\pi(s, a) = (1 - \gamma)\pi(a|s) \sum_{t=0}^{\infty} \gamma^t P(s_t = s|\pi)$. The unique stationary policy that induces a visitation $d(s, a)$ is given by $\pi(a|s) = d(s, a) / \sum_a d(s, a)$.

With human expert involvement, we denote the human expert policy as $\pi^H(a|s)$ and the learning agent's novice policy as $\pi^N(a|s)$. We also use a Boolean indicator $I(s, a^N) : \mathcal{S} \times \mathcal{A} \rightarrow \{0, 1\}$ to indicate when the expert intervenes ($I(s, a^N) = 1$). Thus, the actual action interacts with environment is $I(s, a^N)a^H + (1 - I(s, a^N))a^N$, with corresponding behavior policy π^B :

$$\pi^B(a|s) = I(s, a^N)\pi^H(a|s) + (1 - I(s, a^N))\pi^N(a|s).$$

Since the novice policy π^N updates during training, its distribution d^N changes over time. Consequently, the actual distribution d^B of behavior policy π^B also changes over time. This evolving dynamics motivate us to formulate the learning objective as *dynamic regret minimization* from an online learning perspective. Specifically, at each training round i , the novice policy π_i^N interacts with the environment to collect data $\mathcal{D}_i^N$, while human expert intervenes with policy π^H , expanding the entire human expert dataset to $\mathcal{D}_i^H$. The combined dataset $\mathcal{D}_i^B = \mathcal{D}_i^N \cup \mathcal{D}_i^H$ can be viewed as being sampled from the distribution d_i^B induced by the behavior policy π_i^B . The learning objective is to minimize the dynamic regret:

$$R_D = \sum_{i=1}^M \ell(\pi_i^N, \mathcal{D}_i^B, \mathcal{D}_i^H) - \sum_{i=1}^M \ell(\pi_i^*, \mathcal{D}_i^B, \mathcal{D}_i^H), \quad (1)$$

where ℓ denotes the imitation loss under the empirical mixture distribution estimated by sampling from $\mathcal{D}_i^B$ at round i (see details in Sec 4.1), and $\pi_i^* = \arg \min_{\pi} \ell_i(\pi, \mathcal{D}_i^B, \mathcal{D}_i^H)$ is the best policy in hindsight at round i . Unlike static regret that assumes a static policy learned from all past data, this dynamic regret objective allows us to continuously compare the current policy with the best policy under the latest data, and thus capturing the dynamic of evolving trajectory distribution.

4 Method

FaithDaIL tackles learning from human intervention through two core components: an unbiased objective to ensure faithful imitation of the human expert, and an online non-convex learning algorithm that minimizes dynamic regret of the faithful imitation loss to adapt to evolving data distributions.

4.1 Faithful Imitation Objective with Behavior Trajectory

Previous methods that learn from human intervention typically perform off-policy imitation learning on the behavior distribution d^B , i.e., they imitate the actual trajectories from both expert and novice policy. However, some novice trajectories may be poor demonstrations, as human reaction delays during interventions can lead the agent to execute incorrect actions just before the human takes over. We therefore focus on faithfully imitating only the human expert, while still leveraging novice data for data efficiency.

We first define our imitation objective as minimizing Kullback-Leibler divergence from agent policy to human policy distribution $d^H(s, a)$, i.e.,

$$D_{KL}(d^\pi(s, a) \| d^H(s, a)) = \mathbb{E}_{(s,a) \sim d^\pi} \left[\log \frac{d^\pi(s, a)}{d^H(s, a)} \right]. \quad (2)$$

Given that expert data is often sparse, prior works have incorporated suboptimal data to improve data efficiency [27, 28, 29, 30, 31]. However, these approaches typically rely on a coverage assumption that the suboptimal data visitation covers that of the expert [27, 29, 32], which is not always guaranteed [32]. To deal with this, we introduce behavior distribution d^B and reformulate the objective as

$$D_{KL}(d^\pi(s, a) \| d^H(s, a)) = \mathbb{E}_{(s,a) \sim d^\pi} \left[\log \frac{d^\pi(s, a)}{d^B(s, a)} + \log \frac{d^B(s, a)}{d^H(s, a)} \right] \quad (3)$$

$$= \mathbb{E}_{(s,a) \sim d^\pi} \left[\log \frac{d^B(s, a)}{d^H(s, a)} \right] + D_{KL}(d^\pi(s, a) \| d^B(s, a)). \quad (4)$$

Since d^B is a mixture of novice policy distribution d^N and expert policy distribution d^H , we have $d^B > 0$ wherever $d^H > 0$. Therefore, the coverage requirement is satisfied at all times. To optimize this objective, we impose the Bellman-flow constraint $\sum_{a \in \mathcal{A}} d(s, a) = (1 - \gamma)d_0(s) + \gamma \sum_{s', a'} d(s', a') p(s|s', a')$ on states [43] and apply Lagrangian duality and convex conjugate [25]. This reformulates the intractable imitation objective into a tractable optimization over a value function, using a proxy reward derived from the ratio $d^B(s, a)/d^H(s, a)$. Specifically, we minimize:

$$V^* = \arg \min_V (1 - \gamma) \mathbb{E}_{s \sim d_0} V(s) + \mathbb{E}_{(s, a) \sim d^B} [f^* (\mathcal{T}_{\tilde{r}} V(s, a) - V(s))], \quad (5)$$

where V^* denotes the optimal value, f^* denotes the convex conjugate of the KL divergence, and $\mathcal{T}_{\tilde{r}} V(s, a) = \tilde{r}(s, a) + \gamma \mathbb{E}_{s' \sim p(s'|s, a)} [V(s')]$ is the Bellman operator defined using a proxy reward $\tilde{r}(s, a)$ given by:

$$\tilde{r}(s, a) = -\log \left[\frac{d^B(s, a)}{d^H(s, a)} \right] = -\log \left[\frac{1 - c^*(s, a)}{c^*(s, a)} \right],$$

where c^* is the optimal discriminator derived by:

$$\max_c \mathbb{E}_{(s, a) \sim d^H} [\log c(s, a)] + \mathbb{E}_{(s, a) \sim d^B} [\log(1 - c(s, a))].$$

Although the optimization for Eq. (5) doesn't contain the policy, it actually learns an implicit optimal policy through the visitation distribution ratio between the optimized and behavior policy. Therefore, we can extract the policy using weighted behavior cloning [44], where the optimal weight $\omega^*(s, a)$ can be calculated by the ratio between the optimal policy distribution $d^*(s, a)$ and $d^B(s, a)$, i.e.,

$$\omega^*(s, a) = \frac{d^*(s, a)}{d^B(s, a)} = \max(0, (f')^{-1}(\mathcal{T}_{\tilde{r}} V^*(s, a) - V^*(s))). \quad (6)$$

Then the optimal policy π^* can be found with the optimal weight $\omega^*(s, a)$, i.e.,

$$\pi^* = \arg \max_{\pi} \mathbb{E}_{(s, a) \sim d^B} [\omega^*(s, a) \log \pi(a|s)]. \quad (7)$$

In summary, by first solving for the value function V^* via Eq. (5), and performing weighted behavior cloning using the derived weights $\omega^*(s, a)$, we can learn the optimal policy π^* .

Empirical Faithful Imitation Objective. In practice, we do not have access to the full distributions d^H and d^B , so we sample from the datasets $\mathcal{D}_i^H$ and $\mathcal{D}_i^B$ collected at each training round i . The policy can be estimated by minimizing the empirical weighted behavior cloning loss, i.e.,

$$\ell(\pi_i^N, \mathcal{D}_i^B, \mathcal{D}_i^H) = -\mathbb{E}_{(s, a) \sim \mathcal{D}_i^B} [\omega_i^*(s, a) \log \pi_i^N(a|s)], \quad (8)$$

where weight $\omega_i^*(s, a)$ is derived from the optimized value function V_i^* by Eq. (6) in round i . This loss directly measures how well the novice policy π_i^N imitates the human expert with the importance weighting. Theoretical derivations and implementation details can be found in Appendix A.

4.2 Learning from Evolving Behavior Trajectory with Dynamic Regret Minimization

Existing human-in-the-loop imitation learning methods either assume convexity and target static regret using algorithms like Follow-the-Leader (FTL) (e.g., DAgger [12], EIL [19]), or employ deep neural networks leading to non-convex optimization landscapes (e.g., HACO [11], PVP [9], IWR [10]). While the latter operate online, they often update policies by learning from the aggregate of all historical data, which is quite similar to the idea of optimizing for static regret using the Follow-the-Perturbed-Leader (FTPL) algorithm [42]. That is, they optimize policy on the accumulated historical data at every round i . However, static regret is insufficient as it overlooks the evolving quality of $\mathcal{D}^B$ and can bias the policy towards outdated trajectories.

To address this, we employ FTPL-D+ [40], an ensemble learning framework designed for non-convex online learning to optimize for dynamic regret (Eq. (1)). FTPL-D+ extends the classical Follow-the-Perturbed-Leader (FTPL) algorithm to non-stationary environments where the loss landscape evolves over time. It maintains a set of K FTPL learners, each associated with a different rolling window size, to capture different temporal dynamics. This mechanism implicitly smooths out the non-stationarity of the data distribution and allows the overall strategy to adapt to varying timescales of change. Such

a multi-interval ensemble is particularly well-suited for minimizing dynamic regret, as it balances short-term adaptivity (via short-horizon learners) and long-term stability (via long-horizon learners). Theoretical results of FTPL-D+ [40] show that this structure achieves near-optimal dynamic regret bounds in general non-convex settings.

Building on this ensemble structure, each individual learner follows a standard restarting strategy: the time horizon M is partitioned into intervals of length τ , and FTPL is restarted at the beginning of each interval. Given a policy parameterization θ_π , the update at round i is:

$$\pi_{i+1}^N = \arg \min_{\pi} \left(\sum_{j=\mu_\tau}^i \ell(\pi, \mathcal{D}_j^B, \mathcal{D}_j^H) + \sigma_i^\top \theta_\pi \right), \quad (9)$$

where $\mu_\tau = \tau \lfloor (i-1)/\tau \rfloor + 1$ is the beginning of the interval, θ_π is the parameter of novice policy, and $\sigma_i \in \mathbb{R}^d$ is a random perturbation vector, whose components are typically sampled i.i.d. from an exponential distribution $\text{Exp}(\eta)$ with parameter $\eta > 0$ at each round i .

A properly chosen τ allows the policy to track the optimal behavior distribution. Since the optimal τ is unknown, FTPL-D+ maintains an ensemble of K base learners (novice policies $\{\pi_{i,k}^N\}_{k=1}^K$), each associated with a different interval parameter $\tau_k = 2^{k-1}$ for $k = 1, \dots, K = \lfloor \log_2 M \rfloor + 1$. A meta-algorithm, Hedge [45], adaptively assigns weights $\alpha_{i,k}$ to each learner. At each round i , after observing new data $\mathcal{D}_i^B$ and $\mathcal{D}_i^H$, the weights are updated:

$$\alpha_{i+1,k} = \frac{\alpha_{i,k} e^{-\rho \ell(\pi_{i,k}^N, \mathcal{D}_i^B, \mathcal{D}_i^H)}}{\sum_{k'=1}^K \alpha_{i,k'} e^{-\rho \ell(\pi_{i,k'}^N, \mathcal{D}_i^B, \mathcal{D}_i^H)}}, \quad (10)$$

where $\rho > 0$ is a learning rate controlling the sensitivity of the weight update. A novice policy is then sampled according to the distribution $\{\alpha_{i+1,k}\}_{k=1}^K$ to interact with the environment in the next round. This enables dynamic adaptation to shifting behavior distributions.

Our Faithful Dynamic Imitation Learning (FaithDaIL) algorithm is presented in Algorithm 1. The algorithm firstly initializes the ensemble of K novice policies, their adaptive weights $\alpha_{1,k}$ and interval parameter $\tau_k = 2^{k-1}$ (Lines 1-2). In each round i , a novice policy $\pi_{i,k'}^N$ is sampled based on the current weights $\{\alpha_{i,k}\}$ to interact with the environment (Line 4). During the interaction, a human expert provides real-time interventions when necessary. We collect new novice trajectory data $\mathcal{D}_i^N$.

Algorithm 1 Faithful Dynamic Imitation Learning from Human Intervention (FaithDaIL)

```

1: Set  $K = \lfloor \log_2 M \rfloor + 1$ ,  $\mathcal{D}_0^H = \emptyset$ 
2: Initialize  $K$  novice policies  $\{\pi_{1,k}^N\}_{k=1}^K$ , weights  $\alpha_{1,k} \leftarrow \frac{1}{K}$ , interval parameter  $\tau_k = 2^{k-1}$ 
3: for  $i = 1$  to  $M$  do ▷ Online learning rounds
4:   Sample policy index  $k' \sim \text{Categorical}(\{\alpha_{i,k}\})$ 
5:   Execute  $\pi_{i,k'}^N$  to interact with the environment and collect novice policy data  $\mathcal{D}_i^N$ 
6:   Human expert provides real-time interventions, collect intervention data  $\mathcal{D}_i^{H,\text{new}}$ 
7:   Update  $\mathcal{D}_i^H = \mathcal{D}_{i-1}^H \cup \mathcal{D}_i^{H,\text{new}}$ 
8:   Construct behavior data  $\mathcal{D}_i^B = \mathcal{D}_i^N \cup \mathcal{D}_i^H$ 
9:   for  $k = 1$  to  $K$  do ▷ Evaluate loss of each policy on current data
10:    Compute imitation loss  $\ell(\pi_{i,k}^N, \mathcal{D}_i^B, \mathcal{D}_i^H)$  by Eq. (5), (6), and (8)
11:   end for
12:   Update ensemble weights based on Eq. (10)
13:   for  $k = 1$  to  $K$  do ▷ Update novice policies over each interval
14:    Let  $\mu_{\tau_k} = \tau_k \lfloor (i-1)/\tau_k \rfloor + 1$ 
15:    Sample perturbation  $\sigma_{i,k} \sim \text{Exp}(\eta)$ 
16:    Update  $\pi_{i+1,k}^N = \arg \min_{\pi} \left( \sum_{j=\mu_{\tau_k}}^i \ell(\pi, \mathcal{D}_j^B, \mathcal{D}_j^H) + \sigma_{i,k}^\top \theta_\pi \right)$ 
17:   end for
18: end for
19: return Policy  $\pi_{M+1,k^*}^N$ , where  $k^* = \arg \max_k \alpha_{M+1,k}$ 

```

Table 1: Comparison of different approaches in MetaDrive-Keyboard and CARLA-Wheel.

Method	MetaDrive-Keyboard						CARLA-Wheel			
	Training			Testing			Training		Testing	
	Human Data	Total Data	Total Safety Cost	Episodic Return	Episodic Safety Cost	Success Rate	Human Data	Total Data	Route Comp.	Success Rate
PPO	-	1M	26.4K	327.33	3.31	0.76	-	1M	0.24	0.0
TD3	-	1M	1.90K	317.45	1.44	0.58	-	1M	0.11	0.0
Human	-	-	-	374.73	0.39	0.98	-	-	0.99	1.0
BC	30K	-	-	129.60	17.40	0.12	5K	-	0.42	0.20
HG-Dagger	7.5K	30K	143	297.60	7.05	0.59	6.8K	24K	0.64	0.47
IWR	6.1K	30K	112	327.32	9.16	0.75	5.7K	24K	0.69	0.60
HACO	9.9K	30K	76	239.41	4.29	0.26	4.8K	24K	0.52	0.40
PVP	7.0K	30K	54	343.86	2.51	0.85	6.6K	24K	0.92	0.73
FaithDaIL	4.8K	30K	55	354.35 ± 3.43	1.47 ± 0.28	0.91 ± 0.04	4.2K	24K	0.95 ± 0.02	0.91 ± 0.03

Table 2: Ablation Study in MetaDrive-Keyboard and CARLA-Wheel.

Method	MetaDrive-Keyboard			CARLA-Wheel	
	Episodic Return	Episodic Safety Cost	Success Rate	Route Comp.	Success Rate
FaithDaIL w/o DRM	346.06 ± 5.42	2.29 ± 0.29	0.87 ± 0.04	0.91 ± 0.03	0.81 ± 0.01
FaithDaIL w/o FOP	350.26 ± 3.57	1.78 ± 0.51	0.89 ± 0.05	0.86 ± 0.04	0.73 ± 0.07
FaithDaIL (Ours)	354.35 ± 3.43	1.47 ± 0.28	0.91 ± 0.04	0.95 ± 0.02	0.91 ± 0.03

and accumulate intervention data $\mathcal{D}_i^{H, \text{new}}$ into $\mathcal{D}_i^H$ (Lines 5-7). The behavior data $\mathcal{D}_i^B$ is constructed by merging the novice data and human intervention data, i.e., $\mathcal{D}_i^B = \mathcal{D}_i^N \cup \mathcal{D}_i^H$ (Line 8). We then compute the imitation loss of each novice policy by Eq. (5), (6), and (8) (Lines 9-11). The ensemble weights for the next round is updated by Eq. (10) (Line 12). Each novice policy π_k^N is updated via FTPL using data from its corresponding interval, defined by $\mu_{\tau_k} = \tau_k \lfloor (i-1)/\tau_k \rfloor + 1$. The update solves a regularized imitation loss minimization over the data from rounds $j = \mu_{\tau_k}$ to i , with exponential perturbation $\sigma_{i,k}$ (Lines 13-17). Finally, after M rounds of training, FaithDaIL returns the novice policy with the highest ensemble weight (Line 19).

5 Experiments

5.1 Experimental Setting

Environments. We evaluate our approach on two challenging driving simulators: MetaDrive Safety Benchmark [46] and CARLA Town01 [47]. MetaDrive is a lightweight simulator in which agents must navigate vehicles safely in dense traffic. We created training and testing sets of 100 distinct scenarios to assess generalization. CARLA, a widely used autonomous driving platform, provides realistic urban settings in Town01 with low-level continuous control (acceleration, braking, steering). To evaluate robustness to different observation modalities, we use sensory state vectors in MetaDrive and bird’s-eye view images in CARLA. Further details are in Appendix C.

Evaluation metrics. In MetaDrive, we use *episodic return* (cumulative reward per episode), *safety cost* (simulator-defined safety score), and *success rate* (reaching destination). Since CARLA does not provide reward or safety scores, we use *route completion* (distance traveled / total route length) and *success rate*. We also report *human data* and *total data* usage for training imitation algorithms.

Experiment Procedure. Three college students (aged 20–25 with valid driver’s licenses) participated in the human-in-the-loop experiments. Prior to training, they practiced until proficient (achieving $\geq 95\%$ success over 50 episodes). Each participant then supervised a learning agent for approximately one hour per simulator, intervening via a keyboard in MetaDrive (Appendix C, Fig. C.1) or a Logitech

G923 racing wheel in CARLA (Appendix C, Fig. C.2) upon the agent risking safety/traffic violations or significantly deviating from human norms. Training scenarios were randomly selected from 100 diverse environments in MetaDrive and 25 varied routes with different start/end points, lighting, and weather conditions in CARLA Town01.

Implementation Details. Our implementation builds upon open-source repositories of ODICE [25], PVP [9] and FTPL-D+ [40]. Implementations of PPO and TD3 utilize Stable-Baselines3 [48], while other HIL baselines use official implementations where available [9, 11]. During testing, agents operate autonomously without human intervention. Experiments were run on a machine with an Nvidia GeForce RTX 3070 Ti Laptop GPU and an Intel Core i7-12700H CPU, supporting real-time simulation and training. Hyper-parameter and other details are in Appendix D.

5.2 Baseline Comparison

Baselines. We compare our method with standard RL baselines of PPO [49] and TD3 [50]. We also collected 30K high-quality human expert demonstrations with a 98% success rate to train a Behavior Cloning (BC) policy [22]. For human-in-the-loop baselines, we compare with Human-Gated Dagger (HG-Dagger) [8], Intervention Weighted Regression (IWR) [10], Human-AI Copilot Optimization (HACO) [11], and Proxy Value Propagation (PVP) [9].

Performance Comparison. Table 1 summarizes the performance in MetaDrive and CARLA. RL methods (PPO, TD3), while capable of learning, require vast amounts of data (1M steps) and incur significantly higher total safety costs during training compared to HIL methods. This highlights the benefit of human guidance in reducing unsafe exploration and improving sample efficiency.

Among HIL methods, our FaithDaIL consistently outperforms baseline methods. In MetaDrive (Table 1, Left), it achieves the highest episodic return and success rate, and the lowest episodic safety cost, despite using the least human intervention data (4.8K steps, 16% of total). HG-Dagger performs poorly due to heavy reliance on limited human data. IWR improves with policy data but suffers from errors in early suboptimal trajectories. HACO shows lower testing safety cost but underperforms in task success, potentially due to inaccurate value estimation. PVP performs well among baselines but imitates the mixed behavior policy, making it susceptible to novice mistakes.

Similar trends are observed in the more visually complex CARLA environment (Table 1, Right), where FaithDaIL achieves the highest route completion and success rates with the fewest human interventions. These results underscore FaithDaIL’s strength: by performing faithful imitation to expert and dynamically tracking high-quality data segments, it unbiasedly learns the human policy while avoiding error propagation from self-generated trajectories.

5.3 Ablation Study

We conducted ablation studies to assess effectiveness of FaithDaIL’s key components: Dynamic Regret Minimization (DRM) and the Faithful Off-policy imitation learning module (FOP).

- FaithDaIL w/o DRM: Removes the FTPL-D+ ensemble framework, reducing the algorithm to training on all historical data with the FOP objective (akin to static regret minimization).
- FaithDaIL w/o FOP: Replaces the DICE-based faithful imitation objective (Eqs.(7)- (8)) with standard behavior cloning on the mixed novice/expert data, but with the DRM component.

Table 2 summarizes performance comparison. We observe that removing either DRM or FOP leads to performance degradation, especially in *episodic return* and *safety cost* in MetaDrive, and *route completion* and *success rate* in CARLA. Without DRM, training on all historical data (akin to static regret) impedes adaptation to the improving policy and complicates density ratio estimation for FOP. Without FOP, directly imitating mixed data exposes the agent to suboptimal novice actions due to intervention latency, preventing faithful expert imitation. These results confirm benefits of combining dynamic regret minimization and a faithful imitation objective.

5.4 Case Studies

To qualitatively evaluate performance, we conducted MetaDrive case study analyzing agent testing trajectories under six distinct road conditions. Figure 2 illustrates bird’s-eye view snapshots of agents’

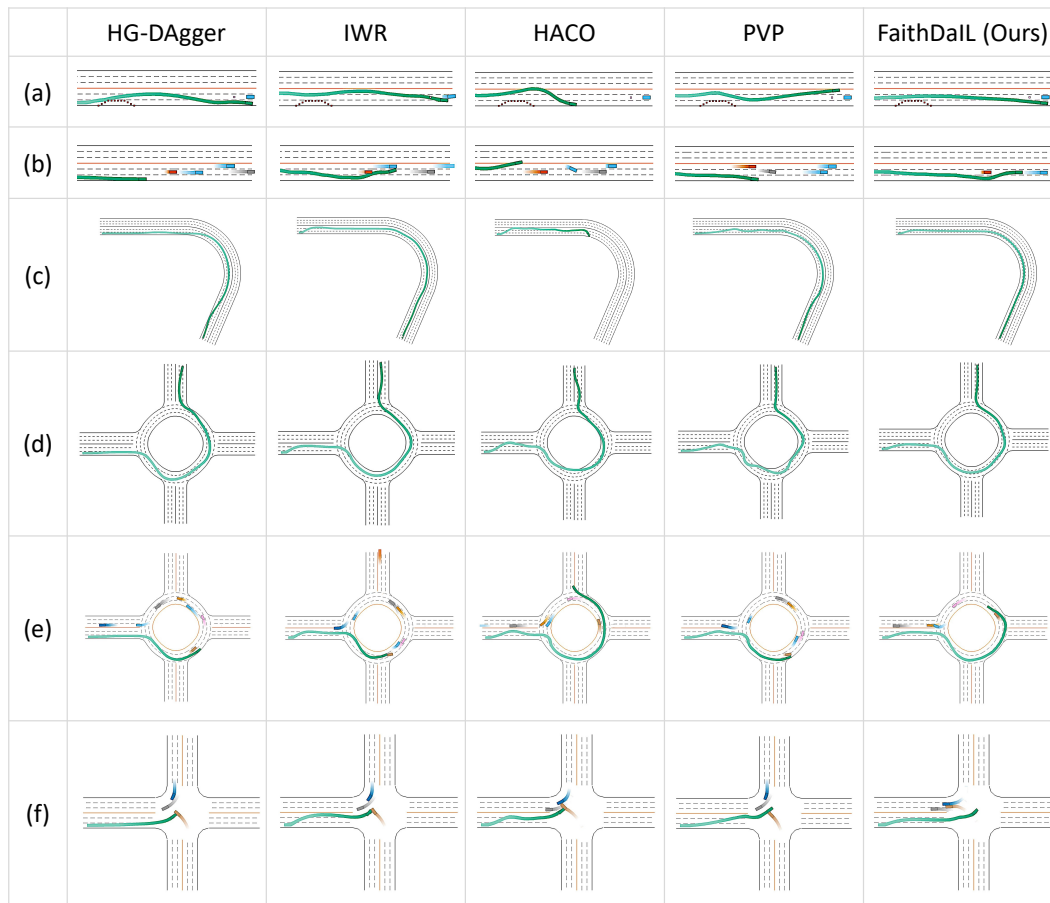


Figure 2: Qualitative comparison of agent trajectories generated by different Human-in-the-Loop (HIL) methods in MetaDrive scenarios. Each row depicts a specific road condition: (a) straight road with static obstacles; (b) straight road with dynamic vehicles; (c) simple curve; (d) roundabout; (e) roundabout with dynamic vehicles; and (f) intersection with dynamic vehicles. The agent is indicated by the green rectangle, its recent path is traced by the green line, and other dynamic vehicles are represented by colored boxes. We can see that both HG-Dagger and IWR fail in scenarios with static and dynamic obstacles—HG-Dagger goes off-road in (b,e) and collides in (a,f), while IWR collides in (a,b,e,f)—and both exhibit erratic trajectories on curving roads (c,d). HACO performs even worse, showing unstable behaviors such as wide swings in (c,d,e) and lane departures in (a,b). PVP showed risky maneuvers to avoid obstacles, resulting in collisions in (f) and deviations in (a,b,e). In contrast, FaithDaIL produces the smoothest and safest trajectories, closely matching expert driving.

behaviors across these scenarios: (a) straight road with static obstacles; (b) straight road with dynamic vehicles; (c) simple curve; (d) roundabout; (e) roundabout with dynamic vehicles; and (f) intersection with dynamic vehicles. Videos are provided in the supplemental materials.

Performance on Straight Roads with Obstacles (Static and Dynamic). On straight roads with static obstacles (Figure 2a) or dynamic vehicles (Figure 2b), most baselines exhibited critical failures. HG-Dagger overreacted, causing collisions or off-road deviations. IWR collided with both static and dynamic elements. HACO showed unstable behavior like wide swings and lane departures. PVP showed risky maneuvers to avoid obstacles. In contrast, FaithDaIL consistently demonstrated smooth, safe navigation, avoiding all obstacles and adeptly handling dynamic traffic.

Performance on Curves and Roundabouts (Without and With Dynamic Vehicles). On curves and roundabouts without dynamic vehicles (Figure 2c, d), most baselines completed the trip but FaithDaIL provided the smoothest, most stable trajectories, closely resembling expert driving. With

dynamic vehicles (Figure 2e), all baselines failed (veering off-road or colliding). FaithDaIL was the only method to successfully and safely navigate around dynamic vehicles while staying on the lane.

Performance at Intersections with Dynamic Vehicles. Navigating intersections with oncoming traffic (Figure 2f) proved to be the most challenging scenario for the baseline methods. HG-Dagger, IWR, and HACO all resulted in collisions with incoming vehicles due to failure to react appropriately. PVP also failed to avoid a collision, being struck by another car. Our method was the only one to exhibit safe, intelligent behavior; it slowed down, yielded, and proceeded safely through the intersection, avoiding any collision or potential danger.

Overall, these case studies highlight the superior robustness and safety of our proposed method across a variety of challenging road conditions, particularly in complex dynamic environments where baseline HIL approaches frequently failed.

6 Conclusion and Future Work

In this paper, we proposed FaithDaIL, a Faithful Dynamic Imitation Learning framework to learn from human intervention. FaithDaIL incorporates policy-generated trajectories to improve data efficiency, while addressing challenges of dynamic data distribution shifts and trajectory deviations caused by intervention latency. FaithDaIL is the first work that formulates the learning as online non-convex optimization with dynamic regret minimization, thereby is able to track high-quality policy trajectories. We also proposed an unbiased objective for faithful expert imitation from mixed agent/human data via a weighted DICE-based approach. Extensive experiments on MetaDrive and CARLA demonstrated FaithDaIL achieves state-of-the-art safety and task success with significantly reduced human intervention.

Future work will address remaining challenges, including evaluation on realistic platforms (e.g., robotic arms) with more participants, improving robustness to diverse and suboptimal human interventions, and theoretical analysis on imitation capability of our method with dynamic regret minimization. We also aim to generalize FaithDaIL to broader HIL learning problems (e.g., multi-modal intervention).

Acknowledgment

This work was supported in part by the Natural Science Foundation of China under Grant 62232004, 62572120, 62472093, 62572246; in part by the Key Research and Development Projects of Jiangsu Province (No.BE2021001-2); in part by the Natural Science Foundation of Jiangsu Province under Grant (No.BK20230024); in part by the Fundamental Research Funds for the Central Universities; and in part by the Big Data Computing Center of Southeast University.

References

- [1] Dario Amodei, Chris Olah, Jacob Steinhardt, Paul Christiano, John Schulman, and Dan Mané. Concrete problems in AI safety. *arXiv preprint arXiv:1606.06565*, 2016.
- [2] Jan Leike, David Krueger, Tom Everitt, Miljan Martic, Vishal Maini, and Shane Legg. Scalable agent alignment via reward modeling: a research direction. *arXiv preprint arXiv:1811.07871*, 2018.
- [3] Tom Everitt, Victoria Krakovna, Laurent Orseau, Marcus Hutter, and Shane Legg. Reinforcement learning with a corrupted reward channel. *arXiv preprint arXiv:1705.08417*, 2017.
- [4] Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.
- [5] Kimin Lee, Laura Smith, and Pieter Abbeel. Pebble: Feedback-efficient interactive reinforcement learning via relabeling experience and unsupervised pre-training. *arXiv preprint arXiv:2106.05091*, 2021.

- [6] Zizhao Wang, Xuesu Xiao, Garrett Warnell, and Peter Stone. Apple: Adaptive planner parameter learning from evaluative feedback. *IEEE Robotics and Automation Letters*, 6(4):7744–7749, 2021.
- [7] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in neural information processing systems*, 35:27730–27744, 2022.
- [8] Michael Kelly, Chelsea Sidrane, Katherine Driggs-Campbell, and Mykel J Kochenderfer. Hg-dagger: Interactive imitation learning with human experts. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 8077–8083. IEEE, 2019.
- [9] Zhenghao Mark Peng, Wenjie Mo, Chenda Duan, Quanyi Li, and Bolei Zhou. Learning from active human involvement through proxy value propagation. *Advances in neural information processing systems*, 36, 2024.
- [10] Ajay Mandlekar, Danfei Xu, Roberto Martín-Martín, Yuke Zhu, Li Fei-Fei, and Silvio Savarese. Human-in-the-loop imitation learning using remote teleoperation. *arXiv preprint arXiv:2012.06733*, 2020.
- [11] Quanyi Li, Zhenghao Peng, and Bolei Zhou. Efficient learning of safe driving policy via human-ai copilot optimization. *arXiv preprint arXiv:2202.10341*, 2022.
- [12] 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. JMLR Workshop and Conference Proceedings, 2011.
- [13] Ryan Hoque, Ashwin Balakrishna, Ellen Novoseller, Albert Wilcox, Daniel S Brown, and Ken Goldberg. Thriftydagger: Budget-aware novelty and risk gating for interactive imitation learning. *arXiv preprint arXiv:2109.08273*, 2021.
- [14] Jiakai Zhang and Kyunghyun Cho. Query-efficient imitation learning for end-to-end autonomous driving. *arXiv preprint arXiv:1605.06450*, 2016.
- [15] Ryan Hoque, Ashwin Balakrishna, Carl Putterman, Michael Luo, Daniel S Brown, Daniel Seita, Brijen Thananjeyan, Ellen Novoseller, and Ken Goldberg. Lazydagger: Reducing context switching in interactive imitation learning. In *2021 IEEE 17th international conference on automation science and engineering (case)*, pages 502–509. IEEE, 2021.
- [16] Kunal Menda, Katherine Driggs-Campbell, and Mykel J Kochenderfer. Ensembledagger: A bayesian approach to safe imitation learning. In *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 5041–5048. IEEE, 2019.
- [17] Emilien Biré, Anthony Kobanda, Ludovic Denoyer, and Rémy Portelas. Efficient active imitation learning with random network distillation. In *The Thirteenth International Conference on Learning Representations*, 2025.
- [18] Stéphane Ross and Drew Bagnell. Efficient reductions for imitation learning. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, pages 661–668. JMLR Workshop and Conference Proceedings, 2010.
- [19] Jonathan Spencer, Sanjiban Choudhury, Matthew Barnes, Matthew Schmittle, Mung Chiang, Peter Ramadge, and Siddhartha Srinivasa. Learning from interventions: Human-robot interaction as both explicit and implicit feedback. In *16th robotics: science and systems, RSS 2020*. MIT Press Journals, 2020.
- [20] Ofir Nachum, Yinlam Chow, Bo Dai, and Lihong Li. Dualdice: Behavior-agnostic estimation of discounted stationary distribution corrections. *Advances in neural information processing systems*, 32, 2019.

- [21] 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. *arXiv preprint arXiv:1809.02925*, 2018.
- [22] Dean A Pomerleau. Alvin: An autonomous land vehicle in a neural network. *Advances in neural information processing systems*, 1, 1988.
- [23] Jonathan Ho and Stefano Ermon. Generative adversarial imitation learning. *Advances in neural information processing systems*, 29, 2016.
- [24] Ilya Kostrikov, Ofir Nachum, and Jonathan Tompson. Imitation learning via off-policy distribution matching. *arXiv preprint arXiv:1912.05032*, 2019.
- [25] Liyuan Mao, Haoran Xu, Weinan Zhang, and Xianyu Zhan. Odice: Revealing the mystery of distribution correction estimation via orthogonal-gradient update. *arXiv preprint arXiv:2402.00348*, 2024.
- [26] Divyansh Garg, Shuvam Chakraborty, Chris Cundy, Jiaming Song, and Stefano Ermon. Iq-learn: Inverse soft-q learning for imitation. *Advances in Neural Information Processing Systems*, 34:4028–4039, 2021.
- [27] Zhuangdi Zhu, Kaixiang Lin, Bo Dai, and Jiayu Zhou. Off-policy imitation learning from observations. *Advances in neural information processing systems*, 33:12402–12413, 2020.
- [28] Hana Hoshino, Kei Ota, Asako Kanezaki, and Rio Yokota. Opirl: Sample efficient off-policy inverse reinforcement learning via distribution matching. In *2022 International Conference on Robotics and Automation (ICRA)*, pages 448–454. IEEE, 2022.
- [29] Yecheng Ma, Andrew Shen, Dinesh Jayaraman, and Osbert Bastani. Versatile offline imitation from observations and examples via regularized state-occupancy matching. In *International Conference on Machine Learning*, pages 14639–14663. PMLR, 2022.
- [30] Geon-Hyeong Kim, Seokin Seo, Jongmin Lee, Wonseok Jeon, HyeongJoo Hwang, Hongseok Yang, and Kee-Eung Kim. Demodice: Offline imitation learning with supplementary imperfect demonstrations. In *International Conference on Learning Representations*, 2021.
- [31] Geon-Hyeong Kim, Jongmin Lee, Youngsoo Jang, Hongseok Yang, and Kee-Eung Kim. Lobsdice: Offline learning from observation via stationary distribution correction estimation. *Advances in Neural Information Processing Systems*, 35:8252–8264, 2022.
- [32] Harshit Sikchi, Qinqing Zheng, Amy Zhang, and Scott Niekum. Dual rl: Unification and new methods for reinforcement and imitation learning. *arXiv preprint arXiv:2302.08560*, 2023.
- [33] Shai Shalev-Shwartz et al. Online learning and online convex optimization. *Foundations and Trends® in Machine Learning*, 4(2):107–194, 2012.
- [34] Martin Zinkevich. Online convex programming and generalized infinitesimal gradient ascent. In *Proceedings of the 20th international conference on machine learning (icml-03)*, pages 928–936, 2003.
- [35] Elad Hazan et al. Introduction to online convex optimization. *Foundations and Trends® in Optimization*, 2(3-4):157–325, 2016.
- [36] Omar Besbes, Yonatan Gur, and Assaf Zeevi. Non-stationary stochastic optimization. *Operations research*, 63(5):1227–1244, 2015.
- [37] Dheeraj Baby and Yu-Xiang Wang. Online forecasting of total-variation-bounded sequences. *Advances in Neural Information Processing Systems*, 32, 2019.
- [38] Peng Zhao and Lijun Zhang. Improved analysis for dynamic regret of strongly convex and smooth functions. In *Learning for Dynamics and Control*, pages 48–59. PMLR, 2021.
- [39] Yuanyu Wan, Lijun Zhang, and Mingli Song. Improved dynamic regret for online frank-wolfe. In *The Thirty Sixth Annual Conference on Learning Theory*, pages 3304–3327. PMLR, 2023.

- [40] Zhipan Xu and Lijun Zhang. Online non-convex learning in dynamic environments. *Advances in Neural Information Processing Systems*, 37:51930–51962, 2024.
- [41] Naman Agarwal, Alon Gonen, and Elad Hazan. Learning in non-convex games with an optimization oracle. In *Conference on Learning Theory*, pages 18–29. PMLR, 2019.
- [42] Arun Sai Suggala and Praneeth Netrapalli. Online non-convex learning: Following the perturbed leader is optimal. In *Algorithmic Learning Theory*, pages 845–861. PMLR, 2020.
- [43] Alan S Manne. Linear programming and sequential decisions. *Management Science*, 6(3):259–267, 1960.
- [44] Xue Bin Peng, Aviral Kumar, Grace Zhang, and Sergey Levine. Advantage-weighted regression: Simple and scalable off-policy reinforcement learning. *arXiv preprint arXiv:1910.00177*, 2019.
- [45] Nicolo Cesa-Bianchi and Gábor Lugosi. *Prediction, learning, and games*. Cambridge university press, 2006.
- [46] Quanyi Li, Zhenghao Peng, Lan Feng, Qihang Zhang, Zhenghai Xue, and Bolei Zhou. Metadrive: Composing diverse driving scenarios for generalizable reinforcement learning. *IEEE transactions on pattern analysis and machine intelligence*, 45(3):3461–3475, 2022.
- [47] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. Carla: An open urban driving simulator. In *Conference on robot learning*, pages 1–16. PMLR, 2017.
- [48] Antonin Raffin, Ashley Hill, Adam Gleave, Anssi Kanervisto, Maximilian Ernestus, and Noah Dormann. Stable-baselines3: Reliable reinforcement learning implementations. *Journal of machine learning research*, 22(268):1–8, 2021.
- [49] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.
- [50] Scott Fujimoto, Herke Hoof, and David Meger. Addressing function approximation error in actor-critic methods. In *International conference on machine learning*, pages 1587–1596. PMLR, 2018.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: The abstract and introduction clearly state our key contributions, which are reiterated with bullet points in the introduction. These claims are fully aligned with the theoretical framework and empirical results presented in the paper, and accurately reflect the scope and limitations of our work.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: See limitation and future work paragraph in Section 6.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: While we provide detailed derivations and optimization formulations for our learning objective (see Appendix A), these are used to define the training loss rather than to establish formal theoretical results. We do not state any theorems or rely on explicit assumptions that require formal proof. As such, this item does not apply to our submission.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We provide a detailed description of our algorithm in Section 4. Additionally, we include our implementation in the supplementary material and provide a link in the abstract for reproducibility.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in

some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We include our implementation in the supplementary material and provide a link in the abstract for reproducibility. All code is anonymized.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: See Section 5.1 and Appendix C for experimental details. Full details are available in the code.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: See the results in Section 5. The performance of our method and the baselines is reported in Table 1, while ablation study results are presented in Table 2.

Guidelines:

- The answer NA means that the paper does not include experiments.

- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: See Section 5.1 and Appendix C.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: We have reviewed the NeurIPS Code of Ethics and conform to it

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification: Our work proposes a new algorithm for imitation learning from human intervention, primarily intended for theoretical and empirical evaluation in simulated environments. It does not involve deployment, user data, or application to sensitive domains such as health-care or surveillance. Therefore, we believe the societal impact of this work is currently limited. We encourage future users of this method to carefully consider its implications when applied in real-world settings.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: Our work focuses on an imitation learning algorithm and does not release any models or datasets that carry a high risk of misuse.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: See Section 5.1

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: We release the full implementation of our algorithm in the supplementary material, and the corresponding source code is available with anonymized URL of <https://anonymous.4open.science/r/nips2025-DC57>.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[Yes\]](#)

Justification: Our study involved human participants who provided real-time interventions during training episodes. We describe the participant protocol and experimental setup in Section 5.1 of the main paper and include additional details such as the instructions provided to participants, screenshots of the interface, and compensation information in the supplementary material. All participants were compensated at or above the local minimum wage, and their involvement was entirely voluntary.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. Institutional review board (IRB) approvals or equivalent for research with human subjects

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [Yes]

Justification: The study was approved by the university institutional review board (IRB), which is stated in the Appendix F. Participants in the study received monetary compensation for their involvement. They were free to pause or withdraw from the experiment at any time if they experienced any discomfort. All tasks were conducted in a virtual simulation environment, ensuring no risk of physical harm. Each experimental session was limited to a maximum duration of 1.5 hours, followed by a mandatory rest period of at least three hours. Throughout the training and data processing stages, no personally identifiable information was collected or exposed in the dataset or trained models.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigor, or originality of the research, declaration is not required.

Answer: [NA]

Justification: LLMs were not used in the development of the core methods, experiments, or results of this research.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.