PALM: PREFERENCE-BASED ADVERSARIAL MANIPULATION AGAINST DEEP REINFORCEMENT LEARNING

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ABSTRACT

Deep reinforcement learning (DRL) methods are vulnerable to adversarial attacks such as perturbing observations with imperceptible noises. To improve the robustness of DRL agents, it is important to study their vulnerability under adversarial attacks that would lead to extreme behaviors desired by adversaries. Preference-based RL (PbRL) aims for learning desired behaviors with human preferences. In this paper, we propose **PALM**, a preference-based adversarial manipulation method against DRL agents which adopts human preferences to perform targeted attacks with the assistance of an intention policy and a weighting function. The intention policy is trained based on the PbRL framework to guide the adversarial policy to mitigate restrictions of the victim policy during exploration, and the weighting function learns weight assignment to improve the performance of the adversarial policy. Theoretical analysis demonstrates that PALM converges to critical points under some mild conditions. Empirical results on a few manipulation tasks of Meta-world show that PALM exceeds the performance of state-of-the-art adversarial attack methods under the targeted setting. Additionally, we show the vulnerability of the offline RL agents by fooling them into behaving as human desires on several Mujoco tasks. Our code and videos are available in `https://sites.google.com/view/palm-adversarial-attack`.

1 INTRODUCTION

Adversarial examples in image classifiers has prompted a new field of studying the vulnerability of deep neural networks (DNN). Recent researches demonstrate that reinforcement learning (RL) agents parameterized by DNN also show vulnerability under adversarial attacks (Huang et al., 2017; Pattanaik et al., 2018; Zhang et al., 2020; 2021; Sun et al., 2022). Adversaries generate imperceptible perturbations to the observations of victim agent, making agents fail to complete the original behaviors. While adversarial attack is an crucial approach to evaluate the vulnerability of the agents, targeted attack in RL has received little attention. Recently, embodied intelligence (Gupta et al., 2021; Liu et al., 2022; Ahn et al., 2022; Reed et al., 2022; Fan et al., 2022) is considered a meaningful way to improve the cognitive ability of artificial intelligence. These embodied agents show powerful capabilities while possibly exposing vulnerability. Therefore, we wonder that:

How can one manipulate the agent to perform desired behaviors, and whether the embodied agents are robust to adversarial manipulations?

To achieve targeted adversarial attacks, one straight way is to design respective rewards for the adversary agents. However, specifying a precise reward function can be challenging. For example, it is difficult to design a reward function denoting the goodness of the current step in the game of Go. For example, it is difficult in chess games to craft a reward function which can identify the quality of each move. In preference-based RL framework, a human only needs to provide binary preference labels over two trajectories of the agent (Christiano et al., 2017). Compared to reward engineering, preference-based RL is an easier way to learn policies through human preferences. Meanwhile, recent research on preference-based RL shows an excellent capacity to learn novel behaviors with few preference labels (Lee et al., 2021; Park et al., 2022; Liang et al., 2022), and significantly improves feedback efficiency.

Motivated by this, we consider using preference-based RL to perform targeted adversarial attacks from the following perspectives. On the one hand, it is difficult to define the desired behaviors to achieve targeted attacks, but humans can implicitly inject intentions by providing binary preferences.

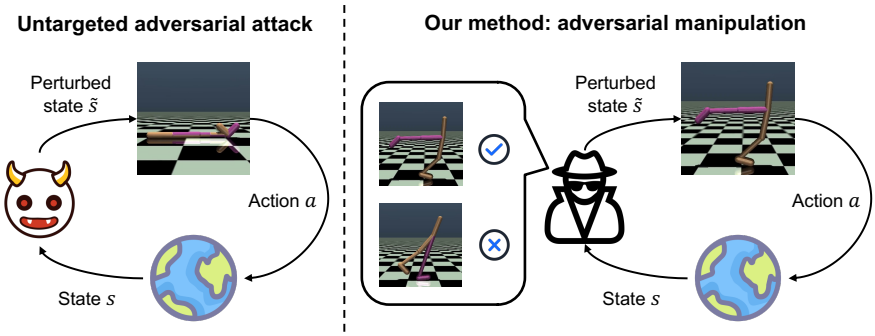


Figure 1: A comparison of PALM and untargeted adversarial attack. Although previous methods can find an optimal untargeted adversary to make the victim agent fail, our method can implement targeted attack against both online and offline RL agents via preference-based RL.

On the other hand, preference-based RL is a data-efficient manipulation method because only a few preference labels are enough for learning well-behaved policies. In this way, we can recover the reward function of desired behaviors via preference-based RL framework.

In this paper, we propose **P**reference-based **A**dversaria**L** **M**anipulation (PALM) algorithm, which performs targeted attack from human preferences. PALM includes an adversary to perturb the observations of the victim. To achieve targeted attack and better exploration, we introduce an intention policy, which is learned from human preferences, as the learning target of the adversary. Additionally, we utilize a weighting function to assist adversary learning by re-weighting state examples.

In summary, our contributions are three-fold. Firstly, to the best of our knowledge, we propose the first targeted adversarial attack method against DRL agents via preference-based RL. Secondly, we theoretically analyze PALM and provide a convergence guarantee under some mild conditions. Lastly, we design two scenarios and experiments on Meta-world demonstrate that PALM outperforms the baselines by a large margin. Empirical results demonstrate that both online and offline RL agents are vulnerable to our proposed adversarial attacks.

2 Related Work

Many previous works on adversarial attacks study the vulnerability of a DRL agent. Huang et al. (2017) computes adversarial perturbations via utilizing the technique of FGSM (Goodfellow et al., 2015) to mislead the victim policy, not to choose the optimal action. Pattanaik et al. (2018) presents an approach that leads the victim to select the worst action based on the Q-function of the victim. Gleave et al. (2020) conducts adversarial attacks under the two-player Markov game instead of perturbing the agent's observation. Zhang et al. (2020) proposes the state-adversarial MDP (SA-MDP) and develops two adversarial attack methods named Robust Sarsa (RS) and Maximal Action Difference (MAD). SA-RL (Zhang et al., 2021) directly optimizes the adversary policy to perturb state in the form of end-to-end RL. PA-AD (Sun et al., 2022) designs an RL-based "director" to find the optimal policy perturbing direction and construct an optimized-based "actor" to craft perturbed states according to the given direction. Unlike previous research, past works focus on making victim policy work fail, while our approach emphasizes manipulating victim policy. That is to say, behaviors of the victim are consistent with the preference of the manipulator under attacks. Another line of works (Pinto et al., 2017; Mandlekar et al., 2017; Pattanaik et al., 2018) consider using adversarial examples to improve the robustness of policies, although it is out of the scope of this paper.

Training agents with human feedback has been investigated in several works. Preference-based RL provides an effective way to utilize human preferences for agent learning. Christiano et al. (2017) proposes a basic learning framework for preference-based RL. To further improve feedback efficiency, Ibarz et al. (2018) additionally utilizes expert demonstrations to initialize the policy besides learning the reward model from human preferences. However, previous methods need a large amount of human feedback, which is usually impractical. Many recent works have proposed to tackle this problem. Lee et al. (2021) presents a feedback-efficient preference-based RL algorithm, which benefits from unsupervised exploration and reward relabeling. Park et al. (2022) further im-

proves feedback efficiency by semi-supervised reward learning and data augmentation, while Liang et al. (2022) proposes an intrinsic reward to enhance exploration. To the best of our knowledge, our method is the first to achieve a targeted adversarial attack against RL agents through preference-based RL.

3 Problem Setup

We formulate the adversary learning with human preferences as generalized state-adversarial Markov Decision Process (GSA-MDP), which is defined as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{B}, \widehat{\mathcal{R}}, \mathcal{P}, \gamma)$. $\mathcal{S}$ and $\mathcal{A}$ denote state and action space, respectively. $\widehat{\mathcal{R}} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$ is reward function and $\gamma \in (0, 1)$ is the discount factor. $\mathcal{P} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$ denotes the transition dynamics, which determines the probability of transferring to $\mathbf{s}'$ given state $\mathbf{s}$ and action $\mathbf{a}$. The adversary perturbs the observations of the agent which is a function $\pi_\alpha : \mathcal{S} \to \mathcal{S}$. $\mathcal{B}$ is a mapping from state $\mathbf{s}$ to a set of states, which restricts the attack power of the adversary. Different from SA-MDP (Zhang et al., 2020), GSA-MDP introduces $\widehat{\mathcal{R}}$, which is consistent with human preferences. The target of GSA-MDP is to solve the optimal adversary π^*_α, which enables the victim to achieve the maximum expected return over all states. Lemma 1 shows that solving the optimal adversary in GSA-MDP is equivalent to finding the optimal policy in MDP $\hat{\mathcal{M}} = (\mathcal{S}, \hat{\mathcal{A}}, \widehat{\mathcal{R}}, \widehat{\mathcal{P}}, \gamma)$.

We denote the adversarial and victim policies as π_α and π_ν, respectively. Given a victim policy π_ν, adversarial policy π_α perturbs the states before the victim observes them. Formally, the adversarial policy π_α perturbs the state $\mathbf{s}$ into $\tilde{\mathbf{s}}$ which is restricted by $\mathcal{B}(\mathbf{s})$ (i.e., $\tilde{\mathbf{s}} \in \mathcal{B}(\mathbf{s})$); $\mathcal{B}(\mathbf{s})$ is defined as a set $\{\tilde{\mathbf{s}} \in \mathcal{S} : ||\mathbf{s} - \tilde{\mathbf{s}}||_p \leq \epsilon\}$.The victim takes action according to the $\tilde{\mathbf{s}}$ and true states in the environment are not changed.

We assume there is no hand-designed reward function $\widehat{\mathcal{R}}$. Instead, humans provide preferences over several pairs of trajectories, making reward learning formulated as a supervised learning problem (Christiano et al., 2017). Formally, a segment σ of length k is denoted as a sequence of states and actions $\{\mathbf{s}_{t+1}, \mathbf{a}_{t+1}, \cdots, \mathbf{s}_{t+k}, \mathbf{a}_{t+k}\}$. A human expert is required to give a label y of a pair of segments (σ^0, σ^1) to indicate which segment is preferred, where $y \in \{(0, 1), (1, 0), (0.5, 0.5)\}$. By following Bradley-Terry model (Bradley & Terry, 1952), a preference predictor is constructed in (1):

$$P_\psi[\sigma^0 \succ \sigma^1] = \frac{\exp \sum_t \widehat{r}_\psi(\mathbf{s}^0_t, \mathbf{a}^0_t)}{\exp \sum_t \widehat{r}_\psi(\mathbf{s}^0_t, \mathbf{a}^0_t) + \exp \sum_t \widehat{r}_\psi(\mathbf{s}^1_t, \mathbf{a}^1_t)}, \tag{1}$$

where $\sigma^0 \succ \sigma^1$ denotes σ^0 is preferred to σ^1. This predictor indicates the probability that a segment is preferred is proportional to its exponential return. Then, the reward function is optimized by aligning the predicted preference labels with human preferences through cross-entropy loss:

$$\mathcal{L}(\psi) = -\mathop{\mathbb{E}}_{(\sigma^0, \sigma^1, y) \sim \mathcal{D}} \Big[y(0) \log P_\psi[\sigma^0 \succ \sigma^1] + y(1) \log P_\psi[\sigma^1 \succ \sigma^0] \Big], \tag{2}$$

where $\mathcal{D}$ is a dataset of triplets (σ^0, σ^1, y) consisting of segment pairs and human preference labels. By minimizing (2), we obtain a reward function estimator $\widehat{r}_\psi$, which is used to provide estimated rewards for agent learning.

4 Method

In this section, we introduce our method PALM, which mainly contains three crucial components: an adversarial policy π_α, an intention policy π_θ, and a weighting function h_ω. Our key idea is to compound the guidance from the intention policy with re-weighting by the weighting function to learn an optimal adversarial policy. The framework of PALM is shown in Figure 2.

Learning the Intention Policy. We train the intention policy by leveraging the preference-based RL framework, which indicates the optimal adversarial manipulation without the restriction of the victim. Formally, we consider the intention policy π_θ, Q-function Q_ϕ and reward function $\widehat{r}_\psi$. The policy π_θ is updated by minimizing the following loss,

$$J_\pi(\theta) = \mathbb{E}_{s_t \sim \mathcal{B}, a_t \sim \pi_\theta} \Big[\mu \log \pi_\theta(a_t | s_t) - Q_\phi(s_t, a_t) \Big], \tag{3}$$

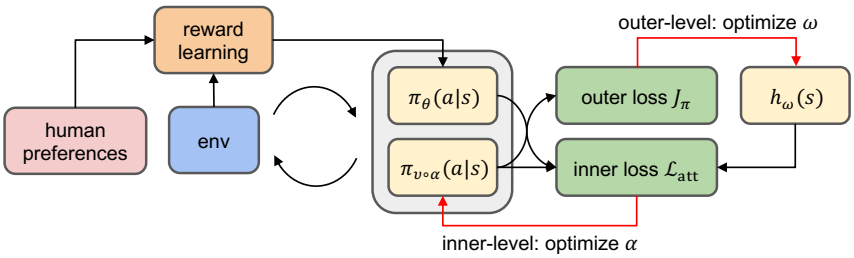


Figure 2: Framework of PALM. PALM jointly learns an adversary, an intention policy and a weighting function under bi-level optimization framework. In the inner-level, the adversary is optimized to approach the intention policy which learns via preference-based RL. In the outer-level, the weighting function is updated to maximize the performance of the adversary evaluated by the outer loss.

where μ is the temperature parameter. The Q-function Q_ϕ is optimized by minimizing the following Bellman residual,

$$J_Q(\phi) = \mathop{\mathbb{E}}_{\tau_t \sim \mathcal{B}} \left[\left(Q_\phi(\mathbf{s}_t, \mathbf{a}_t) - \widehat{r}_t - \gamma \bar{V}(\mathbf{s}_{t+1}) \right)^2 \right], \tag{4}$$

where $\bar{V}(s_t) = \mathbb{E}_{a_t \sim \pi_\theta} \left[Q_{\bar{\phi}}(s_t, a_t) - \mu \log \pi_\theta(a_t|s_t) \right]$, τ_t is the transition at time step t, $\bar{\phi}$ is the parameter of the target soft Q-function. The reward function $\widehat{r}_\psi$ is updated by optimizing (2). We can obtain a well-performing intention policy by alternating agent learning (i.e., optimization of π_θ and Q_ϕ) and reward learning. Although π_θ guides adversarial policy learning, the discrepancy between π_θ and $\pi_{\nu\circ\alpha}$ on the state distribution leads to inefficiency. To handle this issue, we design a strategy to construct the behavior policy π to collect transitions. We combine the intention policy π_θ and the perturbed policy $\pi_{\nu\circ\alpha}$, where $\pi^{1:h} = \pi^{1:h}_{\nu\circ\alpha}$, $\pi^{h+1:H} = \pi^{h+1:H}_\theta$,$h \sim U(0, H)$ and H is task horizon. The combined policy π collects data and stores it into the replay buffer during learning.

4.1 Objective

PALM aims to find the optimal adversary that manipulates the victim's behaviors to be consistent with human preferences. However, directly learning adversary suffers from the restriction of the victim policy leading to exploration difficulty, and this makes it hard to find an expected adversarial policy efficiently. Therefore, we introduce intention policy π_θ to guide adversarial policy during training. On the other hand, some states are crucial to improving the performance of the adversary, while others are not. A weighting function learns to distinguish the importance of states and assigns different weights. Given the weighting function and intention policy, the adversarial policy is optimized by minimizing the re-weighted average KL-divergence between $\pi_{\nu\circ\alpha}$ and π_θ:

$$\mathcal{L}_{\text{att}}(\alpha; \omega, \theta) = \mathbb{E}_{\mathbf{s} \sim \mathcal{B}} \Big[h_\omega(\mathbf{s}) D_{\text{KL}} \left(\pi_{\nu\circ\alpha}(\mathbf{s}) \parallel \pi_\theta(\mathbf{s}) \right) \Big]. \tag{5}$$

Since the weighting function has an important impact on the adversarial policy, the weighting function is trained to improve the performance of the adversarial policy. Finally, the perturbed policy $\pi_{\nu\circ\alpha}$ obtains a low evaluation loss on replay buffer, i.e.

$$J_\pi(\alpha(\omega)) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{B}, \mathbf{a}_t \sim \pi_{\nu\circ\alpha(\omega)}} \left[\mu \log \pi_{\nu\circ\alpha(\omega)}(\mathbf{a}_t|\mathbf{s}_t) - Q_\phi(\mathbf{s}_t, \mathbf{a}_t) \right]. \tag{6}$$

We notice that the α implicitly depends on ω, so we express α as a function of ω. That is to say, (6) can be written as $J_\pi(\alpha(\omega))$. By optimizing (6), it can find the optimal ω^*.

Formula (6) presents the evaluation loss of the adversary, while 5 denotes the learning loss of the adversary given the weighting function and intention policy. Naturally, we formulate it as a bi-level optimization problem. Our whole objective is:

$$\begin{aligned} \min_{\omega} \quad & J_\pi(\alpha(\omega)), \\ \text{s.t.} \quad & \alpha(\omega) = \arg\min_{\alpha} \mathcal{L}_{\text{att}}(\alpha; \omega, \theta). \end{aligned} \tag{7}$$

This optimization process simultaneously updates the adversarial policy π_α and the weighting function h_ω through inner and outer optimization leading to a better adversarial policy.

4.2 OPTIMIZATION

The objective (7) contains inner-level optimization to update the parameters α of adversarial policy and outer-level optimization to update the parameters ω of the weighting function h_ω.

Inner-level Optimization: Training the adversarial policy π_α. As for the inner-level optimization, given the intention policy π_θ and the weighting function h_ω, we hope to find the optimal adversarial policy by minimizing the re-weighted average KL divergence between π_θ and $\pi_{\nu\circ\alpha}$. The parameters α are optimized by leveraging gradient descent with the inner loss (5):

$$\alpha_{t+1} \leftarrow \alpha_t - \eta_t \, \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha;\omega,\theta)|_{\alpha_t} \,, \tag{8}$$

where η_t is the learning rate for optimizing α at time step t. Intuitively, the intention policy guides the adversarial policy to achieve better performance on re-weighted states while the weighting function assigns higher weights to the crucial states. With the collaborative assistance of the intention policy and weighting function, it can efficiently learn the optimal adversarial policy.

Outer-level Optimization: Training the weighting function h_ω. In the outer-level optimization, we need to find a better weighting function to balance the state distribution and assign the weights to assist the adversarial policy in improving performance. To make outer-level optimization feasible, we make an approximation for the parameters of the adversarial policy with the one-step gradient update according to (5). This approximation obtains the estimated $\arg\min_\alpha$ with one-step updating:

$$\hat{\alpha}(\omega) \approx \alpha_t - \eta_t \, \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha;\omega,\theta)|_{\alpha_t} \,. \tag{9}$$

Formula (9) builds a connection between α and ω. Then, we update the parameters ω of the weighting function for adversarial policy performance improvement by minimizing the outer-level optimization loss. Specifically, it performs gradient descent to formula (6) with respect to parameters ω. According to the chain rule of derivatives, the gradient of the outer loss with respect to ω can be expressed as:

$$\nabla_\omega J_\pi(\alpha(\omega))|_{\omega_t} = \nabla_{\hat{\alpha}} J_\pi(\hat{\alpha}(\omega))|_{\hat{\alpha}_t} \, \nabla_\omega \hat{\alpha}_t(\omega)|_{\omega_t} = \sum_{\mathbf{s}} f(\mathbf{s}) \cdot \nabla_\omega h(\mathbf{s})|_{\omega_t} \,, \tag{10}$$

where $f(\mathbf{s}) = -\eta_t \cdot \left(\nabla_{\hat{\alpha}} J_\pi(\alpha(\omega))\right)^\top \nabla_\alpha D_{\text{KL}}\left(\pi_{\nu\circ\alpha}(\mathbf{s}) \parallel \pi_\theta(\mathbf{s})\right)$, detailed derivation process can be found in Appendix (B). The key to obtain this meta gradient is computing the relationship between the parameters α and the parameters ω. And we update ω by using gradient descent:

$$\omega_{t+1} \leftarrow \omega_t - \beta_t \, \nabla_\omega J_\pi(\alpha(\omega))|_{\omega_t} \,, \tag{11}$$

where β_t is the learning rate of the weighting function at time step t. We summarize a detailed procedure for PALM in Appendix A.

4.3 THEORETICAL ANALYSIS

In this part, we theoretically analyze the convergence of PALM in Theorem 1 and 2. PALM involves two nested loops: outer-level optimization and inner-level optimization. In Theorem 1, we demonstrate the convergence rate of the outer loss, and in Theorem 2, we prove the convergence of the inner loss. Proofs of Theorem 1 and 2 can be found in Appendix C.

Theorem 1. *Suppose J_π is Lipschitz-smooth with constant L, the gradient of J_π and $\mathcal{L}_{att}$ is bounded by ρ. Let the training iterations be T, the inner-level optimization learning rate $\eta_t = \min\{1, \frac{c_1}{T}\}$ for some constant $c_1 > 0$ where $\frac{c_1}{T} < 1$. Let the outer-level optimization learning rate $\beta_t = \min\{\frac{1}{L}, \frac{c_2}{\sqrt{T}}\}$ for some constant $c_2 > 0$ where $c_2 \leq \frac{\sqrt{T}}{L}$, and $\sum_{t=1}^{\infty} \beta_t \leq \infty, \sum_{t=1}^{\infty} \beta_t^2 \leq \infty$. The convergence rate of J_π achieves*

$$\min_{1\leq t\leq T} \mathbb{E}\left[\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\|^2\right] \leq \mathcal{O}\left(\frac{1}{\sqrt{T}}\right). \tag{12}$$

Theorem 1 demonstrates the bound of the convergence rate of the outer loss, which means the gradient of the outer loss with respect to ω will convergence to zero. Thus PALM learns a more powerful adversary using importance weights outputed by the optimal weighting function.

Theorem 2. *Under the conditions mentioned in Theorem 1, $\mathcal{L}_{att}$ achieves*

$$\lim_{t\to\infty} \mathbb{E}\left[\|\nabla_\alpha \mathcal{L}_{att}(\alpha_t;\omega_t)\|^2\right] = 0. \tag{13}$$

As in Theorem 2, the inner loss of PALM algorithm converges to critical points under some mild conditions, which ensures the parameters of the adversary can converge to the optimal parameters.

5 EXPERIMENTS

In this section, we evaluate our method on several robotic simulated manipulation tasks from Meta-world (Yu et al., 2020) and continuous locomotion tasks from Mujoco (Todorov et al., 2012). Specifically, our experiment contains two essential phases. In the first phase, we verify the efficacy of the proposed method through two scenarios: navigation and opposite behaviors. Furthermore, we show the capability of our approach by fooling a popular offline RL method, Decision Transformer (Chen et al., 2021), into acting specific behaviors in the second phase. The detailed description of tasks used in experiments is provided in Appendix D.

5.1 SETUP

Baselines. We include the existing evasion attack methods for comparison to study the effectiveness of our approach.

- Random attack: this is a naive baseline that samples random perturbed observations via a uniform distribution.
- SA-RL (Zhang et al., 2021): this method learns an adversarial policy in the form of an end-to-end RL formulation.
- PA-AD (Sun et al., 2022): this method combines RL-based "director" and non-RL "actor" to find state perturbations, which is the state-of-the-art adversarial attack algorithm against DRL.
- PALM: our proposed method, which collaboratively learns adversarial policy and weighting function with the guidance of intention policy.

Implementation Settings. We compare PALM with existing adversarial attack methods, which attack the victim to reduce its cumulative reward rather than manipulate it. To achieve fair comparison, we make simple adjustments for SA-RL and PA-AD to suit our settings in the experiments. In their original version, both of these two methods use the negative value of the reward obtained by the victim to train an adversary. We replace it with the same estimated reward function $\widehat{r}_\psi$ as our method uses, which means they learn from human preferences. For the implementation of SA-RL[1] and PA-AD[2], we use the released official codebase. For fair comparison, all methods learned via preference-based RL are given the same number of preference labels. In the navigation scenario, we use 9000 labels for all tasks. In the opposite behaviors scenario, we use 1000 for Window Close, 3000 for Drawer Close, 5000 for Faucet Open, Faucet Close and Window Open, 7000 for Drawer Open, Door Lock and Door Unlock. Also, to reduce the impact of preference-based RL, we additionally add oracle versions of SA-RL and PA-AD, which uses the ground-truth rewards of the targeted task.

We use the same experimental settings (i.e., hyperparameters, neural networks) concerning reward learning for all methods. We quantitatively evaluate all methods by comparing the success rate of final manipulation, which is well-defined in Meta-world (Yu et al., 2020) for the opposite behaviors scenario, and we rigorously design for the navigation scenario. As in most existing research (Zhang et al., 2020; 2021; Sun et al., 2022), we consider using state attacks with L^∞ norms in our experiments, and we report the mean and standard deviation across ten runs for all experiments. We also provide detailed hyperparameter settings and implementation details in Appendix D.

5.2 MANIPULATION ON DRL AGENTS

We study the effectiveness of our method compared to adversarial attack algorithms, which are adapted to our setting with minimal changes. Specifically, we construct two different scenarios on various simulated robotic manipulation tasks. Each victim agent is well-trained for a specific manipulation task.

Scenarios on Navigation. In this scenario, we expect the robotic arm to reach a target coordinates instead of completing the original task. Figure 3 shows the training curves of baselines and our

[1] https://github.com/rll-research/BPref

[2] https://github.com/umd-huang-lab/paad_adv_rl

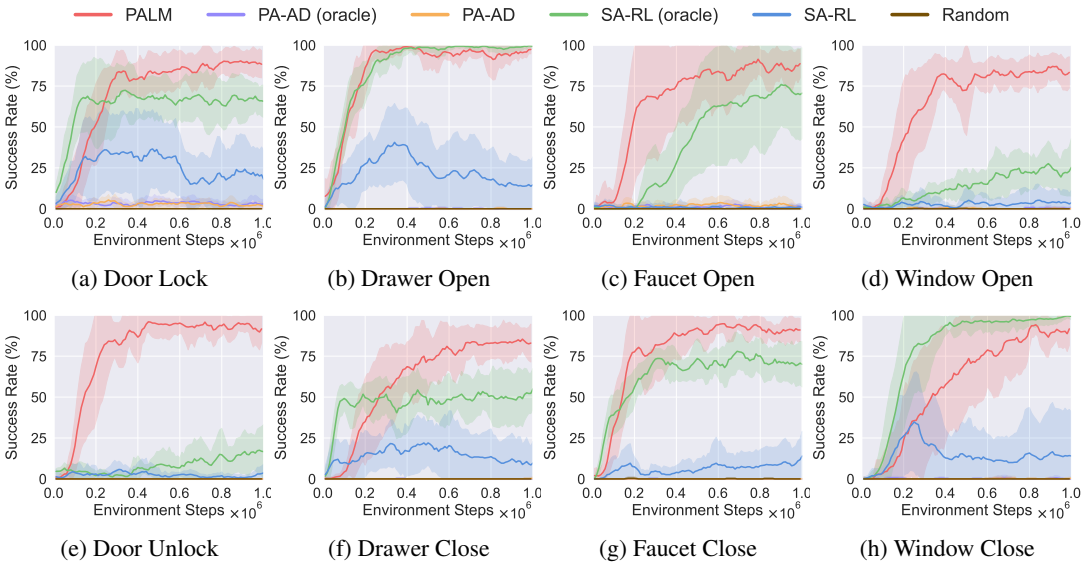


Figure 3: Training curves of different methods on various manipulation tasks in the navigation scenario. The solid line and shaded area denote the mean and the standard deviation of success rate, respectively, over ten runs.

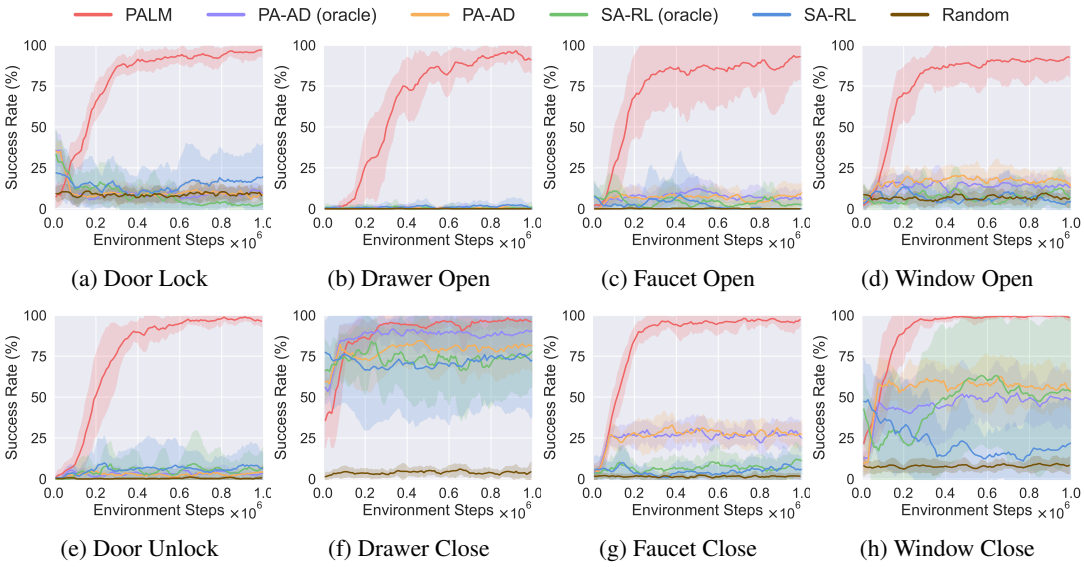
method on eight manipulation tasks. It shows that the performance of PALM surpasses that of the baselines by a large margin based on preference labels. To eliminate the influence of preference-based RL and further demonstrate the advantages of PALM, we additionally train the baseline methods with the ground-truth reward function and denote them as "oracle". We notice that the performance of SA-RL (oracle) greatly improves on several tasks over the preference-based version. However, PALM still outperforms SA-RL with oracle rewards on most tasks. These results demonstrate that PALM enables the agent to efficiently learn adversarial policy with human preferences. We also observe that PA-AD is incapable of mastering manipulation, even using the ground-truth rewards.

Scenarios on Opposite Behaviors. In the real world, robotic manipulation has good application values. Therefore, we design this scenario to quantitatively evaluate the vulnerability of these agents that masters various manipulation skills. Specifically, we expect each victim to complete the opposite task under the attack of the manipulator. For example, the victim which masters the skill of opening windows will close windows under targeted attack. As shown in Figure 4, PALM presents excellent performance and marginally shows obvious advantages over baseline methods on all tasks. The result again indicates that PALM is effective for a wide range of tasks and can efficiently learn adversarial policy with human preferences.

5.3 Manipulation on the Popular Offline RL Agents

In this experiment, we show the vulnerability of offline RL agents and demonstrate PALM can fool them into acting human desired behaviors. As for the implementation, we choose some online models[3] as victims, which are well-trained by official implementation with D4RL. We choose two tasks, Cheetah and Walker, using expert-level Decision Transformer agents as the victims. As shown in Figure 5, Decision Transformer shows exploitable weaknesses and is misled to perform human desired behavior instead of the original task. Specifically, under the adversarial manipulation, the Cheetah agent runs backwards quickly in Figure 5a, and does 90 degree push-up in Figure 5c. The Walker agent stands on one foot for superior balance in Figure 5b, and dances with one leg lifted in Figure 5d. The results show that PALM can manipulate these victims to act behaviors consistent with human preferences and embodied agents are extremely vulnerable to these well-trained adversaries. We hope this experiment can inspire future work on the robustness of offline RL agents and embodied AI.

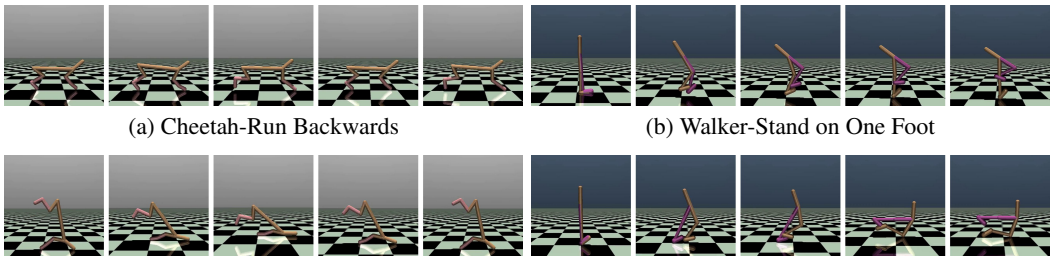
[3] https://huggingface.co/edbeeching



(a) Door Lock (b) Drawer Open (c) Faucet Open (d) Window Open

(e) Door Unlock (f) Drawer Close (g) Faucet Close (h) Window Close

Figure 4: Training curves of all methods on various tasks in the opposite behaviors scenario. The solid line and shaded area denote the mean and the standard deviation of success rate over ten runs.



(a) Cheetah-Run Backwards (b) Walker-Stand on One Foot

(c) Cheetah-90 Degree Push-up (d) Walker-Dance

Figure 5: Human desired behaviors behad by the Decision Transformer under the attack of PALM.

5.4 Ablation Study

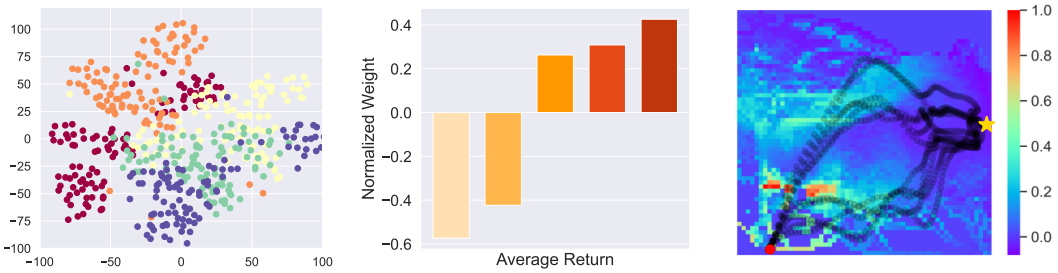
Impact of Feedback Amount and Intention Policy. We investigate the performance of PALM with different preference labels. Table 1 shows the results of all methods with various numbers of labels: $\{3000, 5000, 7000, 9000\}$ on Drawer Open for the navigation scenario and $\{1000, 3000, 5000, 7000\}$ on Faucet Close for the opposite behavior scenario. From the experimental results, we conclude that providing sufficient human feedback learns a strong adversary and stabilizes the attack success rate. We notice that the performance of PALM improves with the increase of human preference labels, indicating that the number of preference labels has an essential impact on adversary learning. However, the performance of SA-RL and PA-AD is poor even with enough human feedback and PA-AD completely fails in navigation scenario. The reason is that the exploration space of these two methods is limited by the fixed victim policy, while PALM achieves better exploration by introducing an intention policy.

Effects of the Weighting Function. To further understand the role of the weighting function proposed in Section 4, we conduct experimental data analysis and visualization from multiple perspectives. Five perturbed policies are uniformly sampled with performance increase sequentially before PALM convergence. For each policy, we roll out 100 trajectories and obtain the trajectory weight vectors via the weighting function. By leveraging the technique of t-SNE (van der Maaten & Hinton, 2008), the weight vectors of different policies are visualized in Figure 6a. From the figure, we can clearly observe clear boundaries between the trajectory weights of various policies, suggesting that the weighting function can distinguish trajectories of different qualities. In Figure 6b, the darker

Environment	Feedback	PALM (ours)	PA-AD	SA-RL
Drawer Open (navigation)	3000	$65.7\% \pm 37.1\%$	$0.0\% \pm 0.0\%$	$8.3\% \pm 13.2\%$
	5000	$86.7\% \pm 18.1\%$	$0.0\% \pm 0.0\%$	$21.3\% \pm 18.9\%$
	7000	$95.7\% \pm 13.6\%$	$0.0\% \pm 0.0\%$	$28.0\% \pm 28.1\%$
	9000	$97.0\% \pm 6.9\%$	$0.0\% \pm 0.0\%$	$13.0\% \pm 18.5\%$
Faucet Close (opposite behavior)	1000	$69.7\% \pm 35.2\%$	$16.7\% \pm 9.4\%$	$2.0\% \pm 6.0\%$
	3000	$79.0\% \pm 16.2\%$	$29.0\% \pm 14.0\%$	$6.0\% \pm 11.7\%$
	5000	$95.3\% \pm 9.2\%$	$21.3\% \pm 12.8\%$	$3.3\% \pm 12.7\%$
	7000	$95.3\% \pm 7.6\%$	$22.7\% \pm 12.4\%$	$4.0\% \pm 7.1\%$

Table 1: Success rate with various amount of preference labels on Drawer Open for the navigation scenario and Faucet Close for the opposite behavior scenario. We report the mean and the standard deviation of the success rate over 30 episodes.

color indicates trajectories with higher success rates of manipulation. The result shows that the weighting function gives higher weights to better trajectories for improving the adversarial policy performance. To further illustrate the effect of the weighting function, we present a heat map of the weight distribution in 2D coordinates and annotate part of the trajectories of the perturbed policy. As Figure 6c shows, the weighting function scores the surrounding states in trajectories from the perturbed policy higher, especially in the early stage before reaching the target point.



(a) t-SNE Visualization (b) Weight Visualization (c) Heat Map Visualization

Figure 6: (a) A visualization of the weights of trajectories of different qualities is collected by five different policies. (b) Trajectory weights generated by the weighting function from different policies are extracted and visualized with t-SNE. (c) A heat map showing the weight distribution and the trajectory of the perturbed agent in 2D coordinates. The red point denotes the start position and the yellow star indicates the targeted position.

6 Conclusion

In this paper, we propose PALM, a preference-based adversarial attack approach against DRL, which can mislead the victim to perform desired behaviors of adversaries. PALM involves an adversary adding imperceptible perturbations on the observations of the victim, an intention policy learned through preference-based RL for better exploration, and a weighting function to identify essential states for the efficient adversarial attack. We analyze the convergence of PALM and prove that PALM converges to critical points under some mild conditions. Empirically, we design two scenarios on several manipulation tasks of Meta-world, and the results demonstrate that PALM outperforms the baselines under the targeted adversarial setting. We further show embodied agents' vulnerability by attacking Decision Transformer on some Mujoco tasks. For future work, we consider: (1) to further improving the attack efficiency by enhancing the utilization efficiency of human preference and (2) extending the observation space of the victim to the high-dimensional inputs (e.g., images, natural language).

ETHICS STATEMENT

Preference-based RL provides an effective way to learn agents without a carefully designed reward function. However, learning from human preferences means humans need to provide labeled data which inevitably has biases introducing systematic error. There are possible negative impacts when malicious people attack other policies using our methods. However, our approach also makes other researchers aware of the vulnerability of policies for AI safety.

REPRODUCIBILITY STATEMENT

The details of experiment settings are provided in Section 4. We provide detailed proof of theoretical analysis in Appendix C. A more detailed description and implementation setting can be found in Appendix D. Meanwhile, we present the link of our source code in the abstract.

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A THE FULL PROCEDURE OF PALM

We provide detailed procedures of our proposed method in Algorithm 1. PALM is implemented based on a popular preference-based RL algorithm PEBBLE (Lee et al., 2021).

Algorithm 1 PALM

Input: a fixed victim policy π_ν
Input: frequency of manipulator feedback K, outer loss updating frequency M, task horizon H
Output: adversarial policy π_α

Initialize parameter of Q_ϕ and π_θ
Initialize parameter of π_α, $\widehat{r}_\psi$ and h_ω
Initialize $\mathcal{B}$ and π_θ with unsupervised exploration
Initialize preference data set $\mathcal{D} \leftarrow \emptyset$
for each iteration **do**
  if episode is done **then** ▷ Construct the combined policy π
    $h \sim U(0, H)$
    $\pi^{1:h} = \pi^{1:h}_{\nu\circ\alpha}$ and $\pi^{h+1:H} = \pi^{h+1:H}_\theta$
  end if
  Take action $a_t \sim \pi$ and collect s_{t+1}
  Store transition into dataset $\mathcal{B} \leftarrow \mathcal{B} \cup \{(s_t, a_t, \widehat{r}_\psi(s_t), s_{t+1})\}$
  if iteration $\% \ K == 0$ **then**
    for each query step **do** ▷ Query preference
      Sample pair of trajectories (σ^0, σ^1)
      Query preference y from manipulator
      Store preference data into dataset $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\sigma^0, \sigma^1, y)\}$
    end for
    for each gradient step **do** ▷ Update reward model
      Sample batch $\{(\sigma^0, \sigma^1, y)_i\}_{i=1}^n$ from $\mathcal{D}$
      Optimize (2) to update $\widehat{r}_\psi$
    end for
  end if
  for each gradient step **do**
    Sample random mini-batch transitions from $\mathcal{B}$
    Optimize π_α: minimize (5) with respect to α ▷ Inner loss optimization
  end for
  if iteration $\% \ M == 0$ **then**
    Sample random mini-batch transitions from $\mathcal{B}$
    Optimize h_ω: minimize (6) with respect to ω ▷ Outer loss optimization
  end if
  Update Q_ϕ and π_θ according to (4) and (3), respectively.
end for

B DERIVATION OF THE GRADIENT OF THE OUTER-LEVEL LOSS

In this section, we present detailed derivation of the gradient of the outer loss J_π with respect to the parameters of the weighting function ω. According to the chain rule, we can derive that

$$
\begin{aligned}
&\nabla_\omega J_\pi(\hat{\alpha}(\omega))\big|_{\omega_t} \\
=&\frac{\partial J_\pi(\hat{\alpha}(\omega))}{\partial \hat{\alpha}(\omega)}\Big|_{\hat{\alpha}_t} \frac{\partial \hat{\alpha}_t(\omega)}{\partial \omega}\Big|_{\omega_t} \\
=&\frac{\partial J_\pi(\hat{\alpha}(\omega))}{\partial \hat{\alpha}(\omega)}\Big|_{\hat{\alpha}_t} \frac{\partial \hat{\alpha}_t(\omega)}{\partial h(\mathbf{s};\omega)}\Big|_{\omega_t} \frac{\partial h(\mathbf{s};\omega)}{\partial \omega}\Big|_{\omega_t} \\
=&-\eta_t \frac{\partial J_\pi(\hat{\alpha}(\omega))}{\partial \hat{\alpha}(\omega)}\Big|_{\hat{\alpha}_t} \sum_{\mathbf{s}\sim\mathcal{B}} \frac{\partial D_{\mathrm{KL}}\left(\pi_{\nu\circ\alpha}(\mathbf{s}) \parallel \pi_\theta(\mathbf{s})\right)}{\partial \alpha}\Big|_{\alpha_t} \frac{\partial h(\mathbf{s};\omega)}{\partial \omega}\Big|_{\omega_t} \\
=&-\eta_t \sum_{\mathbf{s}\sim\mathcal{B}} \left(\frac{\partial J_\pi(\hat{\alpha}(\omega))}{\partial \hat{\alpha}(\omega)}\Big|^\top_{\hat{\alpha}_t} \frac{\partial D_{\mathrm{KL}}\left(\pi_{\nu\circ\alpha}(\mathbf{s}) \parallel \pi_\theta(\mathbf{s})\right)}{\partial \alpha}\Big|_{\alpha_t} \right) \frac{\partial h(\mathbf{s};\omega)}{\partial \omega}\Big|_{\omega_t}.
\end{aligned}
\tag{14}
$$

For brevity of expression, we let:

$$f(\mathbf{s}) = \frac{\partial J_\pi(\hat{\alpha}(\omega))}{\partial \hat{\alpha}(\omega)}\Big|_{\hat{\alpha}_t}^{\top} \frac{\partial D_{\mathrm{KL}}\left(\pi_{\nu\circ\alpha}(\mathbf{s}) \parallel \pi_\theta(\mathbf{s})\right)}{\partial \hat{\alpha}}\Big|_{\alpha_t}. \tag{15}$$

The gradient of outer-level optimization loss with respect to parameters ω is:

$$\nabla_\omega J_\pi(\hat{\alpha}(\omega))|_{\omega_t} = -\eta_t \sum_{\mathbf{s}\sim\mathcal{B}} f(\mathbf{s}) \cdot \frac{\partial h(\mathbf{s};\omega)}{\partial \omega}\Big|_{\omega_t}. \tag{16}$$

C PROOFS

C.1 LEMMA 1: CONNECTION BETWEEN GSA-MDP AND MDP

Lemma 1. *Given a GSA-MDP $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{B}, \widehat{\mathcal{R}}, \mathcal{P}, \gamma)$ and a fixed victim policy π_ν, there exists a MDP $\hat{\mathcal{M}} = (\mathcal{S}, \hat{\mathcal{A}}, \widehat{\mathcal{R}}, \widehat{\mathcal{P}}, \gamma)$ such that the optimal policy of $\hat{\mathcal{M}}$ is equivalent to the optimal adversary π_α in GSA-MDP given a fixed victim, where $\widehat{\mathcal{A}} = \mathcal{S}$ and*

$$\widehat{\mathcal{P}}(\mathbf{s}'|\mathbf{s},\mathbf{a}) = \sum_{\mathbf{a}\in\mathcal{A}} \pi_\nu(\mathbf{a}|\widehat{\mathbf{a}})\mathcal{P}(\mathbf{s}'|\mathbf{s},\mathbf{a}) \quad \textit{for } \mathbf{s},\mathbf{s}' \in \mathcal{S} \textit{ and } \widehat{\mathbf{a}} \in \widehat{\mathcal{A}}.$$

C.2 PROOF OF THEOREM 1: CONVERGENCE RATE OF THE OUTER LOSS

Lemma 2. *(Lemma 1.2.3 in Nesterov (1998)) If function $f(x)$ is Lipschitz smooth on $\mathbb{R}^n$ with constant L, then $\forall x, y \in \mathbb{R}^n$, we have*

$$\left|f(y) - f(x) - f'(x)^\top (y-x)\right| \le \frac{L}{2}\left\|y-x\right\|^2. \tag{17}$$

Proof. $\forall x, y \in \mathbb{R}^n$, we have

$$\begin{aligned} f(y) &= f(x) + \int_0^1 f'(x+\tau(y-x))^\top (y-x) d\tau \\ &= f(x) + f'(x)^\top (y-x) + \int_0^1 [f'(x+\tau(y-x)) - f'(x)]^\top (y-x) d\tau. \end{aligned} \tag{18}$$

Then we can derive that

$$\begin{aligned} \left|f(y) - f(x) - f'(x)^\top (y-x)\right| &= \left|\int_0^1 [f'(x+\tau(y-x)) - f'(x)]^\top (y-x) d\tau\right| \\ &\le \int_0^1 \left|[f'(x+\tau(y-x)) - f'(x)]^\top (y-x)\right| d\tau \\ &\le \int_0^1 \left\|f'(x+\tau(y-x)) - f'(x)\right\| \cdot \left\|y-x\right\| d\tau \\ &\le \int_0^1 \tau L \left\|y-x\right\|^2 d\tau = \frac{L}{2}\left\|y-x\right\|^2, \end{aligned} \tag{19}$$

where the first inequality holds for $\left|\int_a^b f(x)dx\right| \le \int_a^b |f(x)|\, dx$, the second inequality holds for Cauchy-Schwarz inequality, and the last inequality holds for the definition of Lipschitz smoothness. □

Theorem 1. *Suppose J_π is Lipschitz-smooth with constant L, the gradient of J_π and $\mathcal{L}_{att}$ is bounded by ρ. Let the training iterations be T, the inner-level optimization learning rate $\eta_t = \min\{1, \frac{c_1}{T}\}$ for some constant $c_1 > 0$ where $\frac{c_1}{T} < 1$. Let the outer-level optimization learning rate $\beta_t = \min\{\frac{1}{L}, \frac{c_2}{\sqrt{T}}\}$ for some constant $c_2 > 0$ where $c_2 \le \frac{\sqrt{T}}{L}$, and $\sum_{t=1}^\infty \beta_t \le \infty, \sum_{t=1}^\infty \beta_t^2 \le \infty$. The convergence rate of J_π achieves*

$$\min_{1\le t\le T} \mathbb{E}\left[\left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|^2\right] \le \mathcal{O}\left(\frac{1}{\sqrt{T}}\right). \tag{20}$$

Proof. First,

$$\begin{aligned}&J_\pi(\hat{\alpha}_{t+2}(\omega_{t+1})) - J_\pi(\hat{\alpha}_{t+1}(\omega_t))\\ =&\{J_\pi(\hat{\alpha}_{t+2}(\omega_{t+1})) - J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1}))\} + \{J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1})) - J_\pi(\hat{\alpha}_{t+1}(\omega_t))\}.\end{aligned} \tag{21}$$

Then we separately derive the two terms of (21). For the first term,

$$\begin{aligned}&J_\pi(\hat{\alpha}_{t+2}(\omega_{t+1})) - J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1}))\\ \leq&\nabla_{\hat{\alpha}} J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1}))^\top(\hat{\alpha}_{t+2}(\omega_{t+1}) - \hat{\alpha}_{t+1}(\omega_{t+1})) + \frac{L}{2}\left\|\hat{\alpha}_{t+2}(\omega_{t+1}) - \hat{\alpha}_{t+1}(\omega_{t+1})\right\|^2\\ \leq&\left\|\nabla_{\hat{\alpha}} J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1}))\right\| \cdot \left\|\hat{\alpha}_{t+2}(\omega_{t+1}) - \hat{\alpha}_{t+1}(\omega_{t+1})\right\| + \frac{L}{2}\left\|\hat{\alpha}_{t+2}(\omega_{t+1}) - \hat{\alpha}_{t+1}(\omega_{t+1})\right\|^2\\ \leq&\rho \cdot \left\|-\eta_{t+1}\nabla_{\hat{\alpha}}\mathcal{L}_{\text{att}}(\hat{\alpha}_{t+1})\right\| + \frac{L}{2}\left\|-\eta_{t+1}\nabla_{\hat{\alpha}}\mathcal{L}_{\text{att}}(\hat{\alpha}_{t+1})\right\|^2\\ \leq&\eta_{t+1}\rho^2 + \frac{L}{2}\eta_{t+1}^2\rho^2,\end{aligned} \tag{22}$$

where $\hat{\alpha}_{t+2}(\omega_{t+1}) - \hat{\alpha}_{t+1}(\omega_{t+1}) = -\eta_{t+1}\nabla_{\hat{\alpha}}\mathcal{L}_{\text{att}}(\hat{\alpha}_{t+1})$, the first inequality holds for Lemma 2, the second inequality holds for Cauchy-Schwarz inequality, the third inequality holds for $\left\|\nabla_{\hat{\alpha}} J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1}))\right\| \leq \rho$, and the last inequality holds for $\left\|\nabla_{\hat{\alpha}}\mathcal{L}_{\text{att}}(\hat{\alpha}_{t+1})\right\| \leq \rho$. It can be proved that the gradient of ω with respect to J_π is Lipschitz continuous and we assume the Lipschitz constant is L. Therefore, for the second term,

$$\begin{aligned}&J_\pi(\hat{\alpha}_{t+1}(\omega_{t+1})) - J_\pi(\hat{\alpha}_{t+1}(\omega_t))\\ \leq&\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))^\top(\omega_{t+1} - \omega_t) + \frac{L}{2}\left\|\omega_{t+1} - \omega_t\right\|^2\\ =&-\beta_t\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))^\top\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t)) + \frac{L\beta_t^2}{2}\left\|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\right\|^2\\ =&-(\beta_t - \frac{L\beta_t^2}{2})\left\|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\right\|^2,\end{aligned} \tag{23}$$

where $\omega_{t+1} - \omega_t = -\beta_t\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))$, and the first inequality holds for Lemma 2. Therefore, (21) becomes

$$J_\pi(\hat{\alpha}_{t+2}(\omega_{t+1})) - J_\pi(\hat{\alpha}_{t+1}(\omega_t)) \leq \eta_{t+1}\rho^2 + \frac{L}{2}\eta_{t+1}^2\rho^2 - (\beta_t - \frac{L\beta_t^2}{2})\left\|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\right\|^2. \tag{24}$$

Rearranging the terms of (24), we obtain

$$(\beta_t - \frac{L\beta_t^2}{2})\left\|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\right\|^2 \leq J_\pi(\hat{\alpha}_{t+1}(\omega_t)) - J_\pi(\hat{\alpha}_{t+2}(\omega_{t+1})) + \eta_{t+1}\rho^2 + \frac{L}{2}\eta_{t+1}^2\rho^2. \tag{25}$$

Then, we sum up both sides of (25),

$$\begin{aligned}&\sum_{t=1}^{T}(\beta_t - \frac{L\beta_t^2}{2})\left\|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\right\|^2\\ \leq&J_\pi(\hat{\alpha}_2(\omega_1)) - J_\pi(\hat{\alpha}_{T+2}(\omega_{T+1})) + \sum_{t=1}^{T}(\eta_{t+1}\rho^2 + \frac{L}{2}\eta_{t+1}^2\rho^2)\\ \leq&J_\pi(\hat{\alpha}_2(\omega_1)) + \sum_{t=1}^{T}(\eta_{t+1}\rho^2 + \frac{L}{2}\eta_{t+1}^2\rho^2).\end{aligned} \tag{26}$$

Therefore,

$$
\begin{aligned}
&\min_{1\le t\le T} \mathbb{E}\left[\|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\|^2\right] \\
\le& \frac{\sum_{t=1}^T (\beta_t - \frac{L\beta_t^2}{2}) \|\nabla_\omega J_\pi(\hat{\alpha}_{t+1}(\omega_t))\|^2}{\sum_{t=1}^T (\beta_t - \frac{L\beta_t^2}{2})} \\
\le& \frac{1}{\sum_{t=1}^T (2\beta_t - L\beta_t^2)} \left[2J_\pi(\hat{\alpha}_2(\omega_1)) + \sum_{t=1}^T (2\eta_{t+1}\rho^2 + L\eta_{t+1}^2\rho^2)\right] \\
\le& \frac{1}{\sum_{t=1}^T \beta_t} \left[2J_\pi(\hat{\alpha}_2(\omega_1)) + \sum_{t=1}^T \eta_{t+1}\rho^2(2 + L\eta_{t+1})\right] \\
\le& \frac{1}{T\beta_t} \left[2J_\pi(\hat{\alpha}_2(\omega_1)) + T\eta_{t+1}\rho^2(2+L)\right] \\
=& \frac{2J_\pi(\hat{\alpha}_2(\omega_1))}{T\beta_t} + \frac{\eta_{t+1}\rho^2(2+L)}{\beta_t} \\
=& \frac{2J_\pi(\hat{\alpha}_2(\omega_1))}{T} \max\{L, \frac{\sqrt{T}}{c_2}\} + \min\{1, \frac{c_1}{T}\} \max\{L, \frac{\sqrt{T}}{c_2}\}\rho^2(2+L) \\
\le& \frac{2J_\pi(\hat{\alpha}_2(\omega_1))}{c_2\sqrt{T}} + \frac{c_1\rho^2(2+L)}{c_2\sqrt{T}} \\
=& \mathcal{O}\left(\frac{1}{\sqrt{T}}\right),
\end{aligned}
\tag{27}
$$

where the second inequality holds according to (26), the third inequality holds for $\sum_{t=1}^T \left(2\beta_t - L\beta_t^2\right) \ge \sum_{t=1}^T \beta_t$. □

C.3 Proof of Theorem 2: Convergence of the Inner Loss

Lemma 3. *(Lemma A.5 in Mairal (2013)) Let $(a_n)_{n\ge1}, (b_n)_{n\ge1}$ be two non-negative real sequences such that the series $\sum_{n=1}^\infty a_n$ diverges, the series $\sum_{n=1}^\infty a_n b_n$ converges, and there exists $C > 0$ such that $|b_{n+1} - b_n| \le C a_n$. Then, the sequence $(b_n)_{n\ge1}$ converges to 0.*

Theorem 2. *Suppose J_π is Lipschitz-smooth with constant L, the gradient of J_π and $\mathcal{L}_{att}$ is bounded by ρ. Let the training iterations be T, the inner-level optimization learning rate $\eta_t = \min\{1, \frac{c_1}{T}\}$ for some constant $c_1 > 0$ where $\frac{c_1}{T} < 1$. Let the outer-level optimization learning rate $\beta_t = \min\{\frac{1}{L}, \frac{c_2}{\sqrt{T}}\}$ for some constant $c_2 > 0$ where $c_2 \le \frac{\sqrt{T}}{L}$, and $\sum_{t=1}^\infty \beta_t \le \infty, \sum_{t=1}^\infty \beta_t^2 \le \infty$. Then PALM achieves*

$$
\lim_{t\to\infty} \mathbb{E}\left[\|\nabla_\alpha \mathcal{L}_{att}(\alpha_t;\omega_t)\|^2\right] = 0. \tag{28}
$$

Proof. First,

$$
\begin{aligned}
&\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) - \mathcal{L}_{\text{att}}(\alpha_t;\omega_t) \\
=& \{\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) - \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)\} + \{\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t) - \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\}.
\end{aligned}
\tag{29}
$$

For the first term in (29),

$$
\begin{aligned}
&\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) - \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t) \\
\le& \nabla_\omega \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)^\top (\omega_{t+1} - \omega_t) + \frac{L}{2}\|\omega_{t+1} - \omega_t\|^2 \\
=& -\beta_t \nabla_\omega \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)^\top \nabla_\omega J_\pi(\alpha_{t+1}(\omega_t)) + \frac{L\beta_t^2}{2}\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\|^2.
\end{aligned}
\tag{30}
$$

where $\omega_{t+1} - \omega_t = -\beta_t \nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))$, and the first inequality holds according to Lemma 2. For the second term in (29),

$$\begin{aligned}
&\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t) - \mathcal{L}_{\text{att}}(\alpha_t;\omega_t) \\
\leq &\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)^\top (\alpha_{t+1} - \alpha_t) + \frac{L}{2}\left\|\alpha_{t+1} - \alpha_t\right\|^2 \\
= &-\eta_t \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)^\top \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t) + \frac{L\eta_t^2}{2}\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2 \\
= &-(\eta_t - \frac{L\eta_t^2}{2})\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2 .
\end{aligned} \tag{31}$$

where $\alpha_{t+1} - \alpha_t = -\eta_t \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)$, and the first inequality holds according to Lemma (2). Therefore, (29) becomes

$$\begin{aligned}
&\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) - \mathcal{L}_{\text{att}}(\alpha_t;\omega_t) \\
\leq &-\beta_t \nabla_\omega \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)^\top \nabla_\omega J_\pi(\alpha_{t+1}(\omega_t)) + \frac{L\beta_t^2}{2}\left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|^2 \\
&-(\eta_t - \frac{L\eta_t^2}{2})\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2 .
\end{aligned} \tag{32}$$

Taking expectation of both sides of (32) and rearranging the terms, we obtain

$$\begin{aligned}
&\eta_t \mathbb{E}\left[\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2\right] + \beta_t \mathbb{E}\left[\left\|\nabla_\omega \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)\right\| \cdot \left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|\right] \\
\leq &\mathbb{E}\left[\mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right] - \mathbb{E}\left[\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\right] + \frac{L\beta_t^2}{2}\mathbb{E}\left[\left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|^2\right] \\
&+ \frac{L\eta_t^2}{2}\mathbb{E}\left[\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2\right] .
\end{aligned} \tag{33}$$

Summing up both sides of (33) from $t = 1$ to ∞,

$$\begin{aligned}
&\sum_{t=1}^{\infty} \eta_t \mathbb{E}\left[\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2\right] + \sum_{t=1}^{\infty} \beta_t \mathbb{E}\left[\left\|\nabla_\omega \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)\right\| \cdot \left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|\right] \\
\leq &\mathbb{E}\left[\mathcal{L}_{\text{att}}(\alpha_1;\omega_1)\right] - \lim_{t\to\infty} \mathbb{E}\left[\mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\right] + \sum_{t=1}^{\infty} \frac{L\beta_t^2}{2}\mathbb{E}\left[\left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|^2\right] \\
&+ \sum_{t=1}^{\infty} \frac{L\eta_t^2}{2}\mathbb{E}\left[\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2\right] \\
\leq &\sum_{t=1}^{\infty} \frac{L(\eta_t^2 + \beta_t^2)\rho^2}{2} + \mathbb{E}\left[\mathcal{L}_{\text{att}}(\alpha_1;\omega_1)\right] \leq \infty,
\end{aligned} \tag{34}$$

where the second inequality holds for $\sum_{t=1}^{\infty} \eta_t^2 \leq \infty$, $\sum_{t=1}^{\infty} \beta_t^2 \leq \infty$, $\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\| \leq \rho$, $\left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\| \leq \rho$. Since

$$\sum_{t=1}^{\infty} \beta_t \mathbb{E}\left[\left\|\nabla_\omega \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_t)\right\| \cdot \left\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\right\|\right] \leq L\rho \sum_{t=1}^{\infty} \beta_t \leq \infty. \tag{35}$$

Therefore, we have

$$\sum_{t=1}^{\infty} \eta_t \mathbb{E}\left[\left\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\right\|^2\right] < \infty. \tag{36}$$

Since $|(\|a\|+\|b\|)(\|a\|-\|b\|)| \leq \|a+b\|\|a-b\|$, we can derive that

$$
\begin{aligned}
&\left|\mathbb{E}\left[\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\|^2\right] - \mathbb{E}\left[\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|^2\right]\right| \\
=&\left|\mathbb{E}\Big[\big(\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\| + \|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\big) + \big(\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\| - \|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\big)\Big]\right| \\
\leq&\mathbb{E}\Big[\Big|\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\| + \|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\Big|\Big|\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\| - \|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\Big|\Big] \\
\leq&\mathbb{E}\Big[\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) + \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\| \cdot \|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) - \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\Big] \\
\leq&\mathbb{E}\Big[\big(\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1})\| + \|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\big)\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t+1};\omega_{t+1}) - \nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_{t};\omega_{t})\|\Big] \\
\leq&2L\rho\mathbb{E}\Big[\|(\alpha_{t+1},\omega_{t+1}) - (\alpha_t,\omega_t)\|\Big] \\
\leq&2L\rho\eta_t\beta_t\mathbb{E}\Big[\|(\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t), \nabla_\omega J_\pi(\alpha_{t+1}(\omega_t)))\|\Big] \\
\leq&2L\rho\eta_t\beta_t\sqrt{\mathbb{E}\left[\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\|^2\right] + \mathbb{E}\left[\|\nabla_\omega J_\pi(\alpha_{t+1}(\omega_t))\|^2\right]} \\
\leq&2L\rho\eta_t\beta_t\sqrt{2\rho^2} \\
\leq&2\sqrt{2}L\rho^2\eta_t\beta_t.
\end{aligned}
\tag{37}
$$

Since $\sum_{t=1}^{\infty}\eta_t = \infty$, according to Lemma 3, we have

$$
\lim_{t\to\infty}\mathbb{E}\left[\|\nabla_\alpha \mathcal{L}_{\text{att}}(\alpha_t;\omega_t)\|^2\right] = 0. \tag{38}
$$

□

D Experimental Details

In this section, we provide a concrete description of our experiments and detailed hyperparameters of PALM. For each run of experiments, we run on GeForce RTX 2080 Ti GPUs for training.

D.1 Tasks

We conduct experiments on eight robotic manipulation tasks from Meta-world (Yu et al., 2020) in phase one and two locomotion tasks from Mujoco (Todorov et al., 2012) in phase two. The tasks we used are:

Meta-world

- Door Lock: An agent controls a simulated Sawyer arm to lock the door.
- Door Unlock: An agent controls a simulated Sawyer arm to unlock the door.
- Drawer Open: An agent controls a simulated Sawyer arm to open the drawer to a target position.
- Drawer Close: An agent controls a simulated Sawyer arm to close the drawer to a target position.
- Faucet Open: An agent controls a simulated Sawyer arm to open the faucet to a target position.
- Faucet Close: An agent controls a simulated Sawyer arm to close the faucet to a target position.
- Window Open: An agent controls a simulated Sawyer arm to open the window to a target position.
- Window Close: An agent controls a simulated Sawyer arm to close the window to a target position.

Mujoco

- Half Cheetach: A 2-dimensional robot with nine links and eight joints aims to learn to run forward (right) as fast as possible.
- Walker: A 2-dimensional two-legged robot aims to move in the forward (right).

D.2 HYPERPARAMETERS SETTING

We choose PEBBLE as For SA-RL (Zhang et al., 2021), we keep the same parameter setting with parameter and use the same neural network structure as ours. The detailed hyperparameters of SA-RL is shown in Table 3. For PA-AD (Sun et al., 2022), all hyperparameters are the same as those of SA-RL.

Hyperparameter	**Value**	**Hyperparameter**	**Value**
Number of layers	3	Hidden units of each layer	256
Learning rate	0.0003	Batch size	1024
Length of segment	50	Number of reward functions	3
Frequency of feedback	5000	Feedback batch size	128
Adversarial budget	0.1	(β_1, β_2)	$(0.9, 0.999)$

Table 2: Hyperparameters of PALM for adversary training.

Hyperparameter	**Value**	**Hyperparameter**	**Value**
Number of layers	3	Hidden units of each layer	256
Learning rate	0.00005	Mini-Batch size	32
Length of segment	50	Number of reward functions	3
Frequency of feedback	5000	Feedback batch size	128
Adversarial budget	0.1	Entropy coefficient	0.0
Clipping parameter	0.2	Discount γ	0.99
GAE lambda	0.95	KL divergence target	0.01

Table 3: Hyperparameters of SA-RL for adversary training.

D.3 VICTIM SETTING

Our experiment consists of two phases. In the first phase, we use various simulated robotic manipulation tasks from Meta-world. We have two OpenAI Gym MuJoCo continuous control environments in the second phase.

Meta-world. We train the victims on Meta-world by utilizing SAC (Haarnoja et al., 2018) with the original fully connected neural network as policy. Detailed hyperparameters are shown in Table 4.

Hyperparameter	**Value**	**Hyperparameter**	**Value**
Number of layers	3	Initial temperature	0.1
Hidden units of each layer	256	Optimizer	Adam
Learning rate	0.0001	Critic target update freq	2
Discount γ	0.99	Critic EMA τ	0.005
Batch size	1024	(β_1, β_2)	$(0.9, 0.999)$
Steps of unsupervised pre-training	9000	Discount γ	0.99

Table 4: Hyperparameters of SAC for victim training.

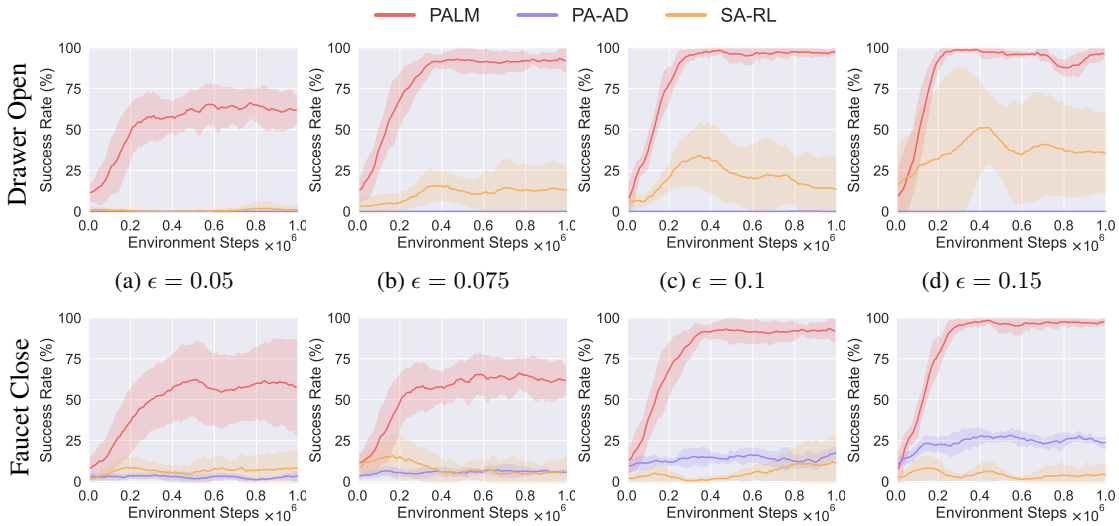
Mujoco. We directly utilize the well-trained model for demonstrating the vulnerability of the Decision Transformer. Specifically, we use the Cheetah agent[4] and the Walker agent[5] with expert-level.

E EXTENSIVE EXPERIMENTS

Impact of Different Attack Budgets. We also analyze the effect of the attack budget. For further understanding, we conduct additional experiments with various attack budgets: $\{0.05, 0.075, 0.1, 0.15\}$ on the Drawer Open and $\{0.02, 0.05, 0.075, 0.1\}$ on Faucet Close for these

[4] https://huggingface.co/edbeeching/decision-transformer-gym-halfcheetah-expert
[5] https://huggingface.co/edbeeching/decision-transformer-gym-walker2d-expert

two scenarios. In the Figure 7, we report the performance of baseline and PALM with various attack budgets. As the experimental results show, the performance of all methods improve as the adversarial budget increases.



(a) $\epsilon = 0.05$ (b) $\epsilon = 0.075$ (c) $\epsilon = 0.1$ (d) $\epsilon = 0.15$

(e) $\epsilon = 0.02$ (f) $\epsilon = 0.05$ (g) $\epsilon = 0.075$ (h) $\epsilon = 0.1$

Figure 7: Training curves of success rate with different adversarial budgets on Drawer Open for the navigation scenario and Faucet Close for the opposite behavior scenario. The solid line and shaded area denote the mean and the standard deviation of the success rate across five runs.