Improving Adversarial Training for Two-player Competitive Games via Episodic Reward Engineering

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Abstract

Training adversarial agents to attack neural network policies has proven to be both effective and practical. However, we observe that existing methods can be further enhanced by distinguishing between states leading to win or lose and encouraging the policy training by reward engineering to prioritize winning states. In this paper, we introduce a novel adversarial training method with reward engineering for two-player competitive games. Our method extracts the historical evaluations for states from historical experiences with an episodic memory, and then incorporating these evaluations into the rewards with our proposed reward revision method to improve the adversarial policy optimization. We evaluate our approach using two-player competitive games in MuJoCo simulation environments, demonstrating that our method establishes the most promising attack performance and defense difficulty against the victims among the existing adversarial policy training techniques.

1 Introduction

It has been proved that deep reinforcement learning (DRL) policies are vulnerable to adversarial attacks (Huang et al., 2017; Kos & Song, 2017). Most existing attacks on DRL policies are executed by searching the adversarial examples and manipulating the environment (Huang et al., 2017; Kos & Song, 2017; Nguyen & Reddi, 2019). However, such adversarial examples may not be applicable in the real world (Gleave et al., 2020). Recently, training adversarial agents as attackers to DRL policies in two-player games has been proven effective and practical (Gleave et al., 2020; Wu et al., 2021; Guo et al., 2021; Bui et al., 2022). These kind of attacks first reduce the two-player environments to single-player environments by fixing the victim agents, and then train the other agent to be an adversarial agent which can be trained by conventional single-agent policy training method. Known as adversarial policy training, these attacks generate natural observations that are adversarial to the victim agents, achieving significant results.

While the aforementioned adversarial policy training methods have proven effective, there is still room to improve adversarial training by providing the training process with higher quality environmental rewards to learn. Our insight is simple, which is utilizing the adversarial agent's historical experiences to explore how states influence game outcomes and distinguish between states that lead to win or lose to facilitate the learning of winning states through reward adjustment. Based on this insight, we introduce a novel adversarial policy training approach that leverages the analysis of information from past episodes to assess game states and improve the environmental rewards with those assessments, thereby assisting the adversarial agent in achieving better performance.

In this paper, we propose an adversarial policy training method with reward engineering mechanism for two-player competitive games. Inspired by previous works on improving the rewards for policy learning using episodic control (Blundell et al., 2016; Pritzel et al., 2017; Li et al., 2023), our method develops a neural network-based episodic memory to store historical experiences and generate state evaluations corresponding to the game outcomes. We then design a conditional reward revision method to improve the environmental rewards based on those evaluations. In our experiments, we evaluate our method on two-player competitive games in MuJoCo domains (Todorov et al., 2012) and compare it with state-of-the-art adversarial policy

training approaches (Gleave et al., 2020; Guo et al., 2021; Wu et al., 2021). Our experimental results show that our method establishes the most promising attack performance and defense difficulty.

In summary, this paper makes three contributions. First, we propose a novel adversarial policy learning framework with reward enhancement for two-player competitive games. Second, we introduce a neural network-based episodic memory that leverages historical experiences to evaluate states, along with a reward revision approach that incorporates these historical evaluations into environmental rewards. Third, our work demonstrates that by identifying and highlighting the winning states based on historical experiences with reward revision, adversarial agents can achieve higher win rates against fixed victim agents and may have the potential to possess the capability to explore a more effective strategy by integrating actions from past successful strategies to defeat the victim, which is demonstrated in one Mujoco game environment in our experiments.

2 Related Work

2.1 Adversarial Attacks on DRL Policies

Previous attacks against DRL policies mainly focus on manipulating the environment to fail the victim agents. One type of attack focuses on perturbing the victim's observations, forcing its policy network to output sub-optimal actions, and thus failed the victim agent (Russo & Proutiere, 2019; Sun et al., 2020; Zhang et al., 2021; Madry et al., 2018; Pattanaik et al., 2018; Pan et al., 2022; Zhao et al., 2020). Another kind of attack directly perturbs the trajectory of the victim, specifically actions the victim agent takes (Lee et al., 2020; Pan et al., 2022) or the rewards it receives (Ma et al., 2019; Yang et al., 2019; Lykouris et al., 2021) to effectively attack the victim. However, the above attacks are argued to be unrealistic since the real-world environment can not be manipulated (Gleave et al., 2020; Guo et al., 2021; Wu et al., 2021).

Unlike the above attacks, to simulate the real-world scenarios, Gleave *et al.* has successfully trained adversarial agents by PPO algorithm (Schulman et al., 2017) in two-player competitive games under a strict zero-sum assumption and demonstrated the effectiveness of training adversarial agents against fixed black-box victims (Gleave et al., 2020). Wu *et al.* further improved the attack performance by exploring the minimal observation differences of the shared environment to maximize deviations of the victim actions (Wu et al., 2021). Guo *et al.* relaxed the zero-sum assumptions of previous works and demonstrated that such attack could be achieved by maximizing the gap between the adversary and victim rewards which are approximated by observations of the adversarial agent (Guo et al., 2021). On the other hand, Bui *et al.* adopted imitators of the victim policies learned by imitation learning algorithms (*e.g.*, GAIL (Ho & Ermon, 2016)) to roll out the victim actions for the attacker and reached better performances (Bui et al., 2022). However, this attack is based on the specification that the victim's actions are visible and accessible to the imitators.

This paper adopts the same setting as (Gleave et al., 2020; Guo et al., 2021; Wu et al., 2021), wherein we have control solely over the adversarial agent and treat the victim agent as a black box, rendering its observations, actions, and rewards inaccessible. Meanwhile, unlike (Gleave et al., 2020; Guo et al., 2021; Wu et al., 2021), we concentrate on leveraging the historical experiences from adversarial agents to emphasize the winning states to improve the adversarial policy training. Our experiments in Section 4.2 shows the effectiveness of such improvement.

2.2 Reward Engineering

Reward design plays a pivotal role in reinforcement learning, where poorly structured rewards can stall policy improvement. Consequently, various methods (Andrychowicz et al., 2017; Schaul et al., 2015) have been proposed to improve the reward signal. For example, Hindsight experience replay (Andrychowicz et al., 2017) sets an alternative goal for the state transitions of an episode to create a learning signal from failed attempts, and then modifies the rewards based on whether the alternative goal is reached.

In recent researches, episodic control (Lengyel & Dayan, 2007) has been proved effective on modifying environmental rewards to address sample inefficiency in various tasks, such as multi-agent tasks (Zheng et al.,

2021), model-based reinforcement learning (Le et al., 2021), and continuous control (Zhang et al., 2019; Kuznetsov & Filchenkov, 2021). Previous works primarily adopt a tabular episodic memory to save experiences of past scenes, leveraging the information gained during exploration and retrieving past experiences of similar scenes to expedite policy optimization (Blundell et al., 2016). This memory uses the state as a key and a measurement of that state (which can vary by method, e.g., a Q-value) as the value, storing these key-value pairs. Then, a distance-based analysis (*e.g.*, KNN) is adopted to retrieve a summary statistic of similar states from the episodic memory, and the retrieved statistic can be used to guide the reward engineering to improve the training process (Hansen et al., 2018).

Since episodic control shares a similar empirical insight with our approach—adjusting rewards based on analysis of historical experiences—we adopt it as the foundation for our method to differentiate states leading to winning or losing. Unlike previous reward revision methods, which directly add statistical values from episodic memory into rewards, our approach introduces a conditional reward revision mechanism specifically designed to align with the win-lose rule inherent in two-player competitive game environments. Additionally, to reduce the extra computational cost associated with reward engineering during training, we propose a neural network-based episodic memory. This memory predicts historical state evaluations based on learned experiences, replacing the traditional tabular episodic memory structure. In Section 4.3, we compare our method with a state-of-the-art episodic control approach NECSA (Li et al., 2023). Experimental results demonstrate that our method achieves higher effectiveness while incurring lower computational costs. Moreover, the results suggest that existing episodic control methods may even hinder the training process in two-player competitive games, indicating they might not be directly suitable for enhancing adversarial training in such settings.

3 Methodology

In this work, we propose an adversarial training approach with reward engineering for training adversarial agents. Our method utilizes the conventional adversarial policy training framework and improves the rewards used for training. The workflow of our approach is shown in Figure 1. First, the adversarial agent interacts with the environment and gathers information (states, actions, rewards) from the episodes. This information is adjusted using our proposed reward revision method, and then saved in the experience storage (*e.g.*, replay buffer). We calculate the objective function based on the revised rewards sampled from the experience storage and update the agent's policy with the objective function. In the following, we mainly elaborate on our reward engineering method based on historical experiences analysis.

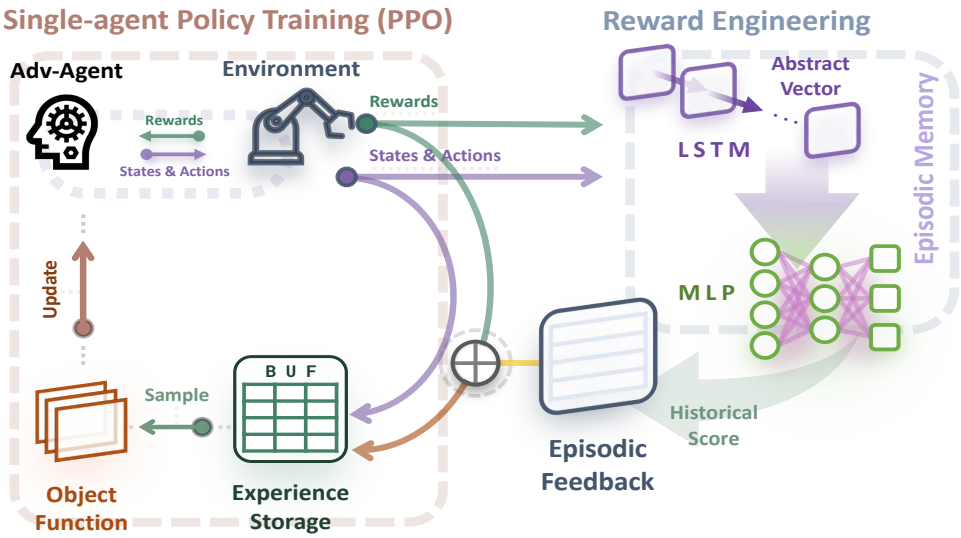


Figure 1: The workflow of our adversarial policy training.

3.1 Adversary in Two-player Markov Game Environment

A two-player Markov game environment can be modeled as $E = (S, (A_\alpha, A_\nu), T, (R_\alpha, R_\nu))$. Here, we use α and ν to represent the adversary and victim respectively. S represents a state set, and both A_α and A_ν are action sets. T denotes a joint state transition function $T : S \times A_\alpha \times A_\nu \to \Delta(S)$, where $\Delta(S)$ is a probability distribution on S. The reward function $R_i : S \times A_\alpha \times A_\nu \times S \to \mathbb{R}$ depends on the current state, actions taken by both agents and the next state.

Gleave *et al.* discovered that by fixing the victim agents, the two-player competitive games can be reduced to single-player games and one agent can be trained as an adversarial agent with conventional single-agent policy training methods (*e.g.*, PPO) to attack the victim (Gleave et al., 2020). The training for the adversarial agent to defeat the fixed victim agent is called **adversarial policy training**. Under this setting, the two-player game can be regarded as a single-player MDP: $E_\alpha = (S, A_\alpha, T_\alpha, R'_\alpha)$ as the victim policy can be treated as a part of the environment. S becomes the state set of the adversary and the state transition function and reward function change to $T_\alpha : S \times A_\alpha \times S \to \Delta(S)$ and $R'_\alpha : S \times A_\alpha \times S \to \mathbb{R}$.

Our threat model We use the same setting as Gleave *et al.* and assumes that our threat model has control over the adversarial agent and black-box access to the information of the victim agent. The adversarial agent can only interact with the environment, which is the common practice in adversarial policy training. We also assume that the environment can only terminate with a terminal signal indicating three possible outcomes: adversary win, adversary loss, or tie.

3.2 Reward Revision Based on Historical Experiences

The environmental reward R'_α obtained by the adversarial agent only includes the evaluations from a single game and does not contain evaluations from the historical experiences. To enhance the adversarial policy training, our key insight is to integrate state evaluations from historical experiences into the rewards, thereby providing the adversarial policy with more comprehensive rewards for learning.

As a two-player Markov game is not deterministic, past episodes starting from the same state may include different state sequences. Therefore, we use state sequences, referred to as patterns, as the basis for performance evaluation in past episodes. Our choice of utilizing state sequence for performance evaluation aligns with existing research (Sutton & Barto, 2018; Li et al., 2023), which has proved that failures in adversarial games are often the result of a series of poor decisions rather than isolated states. Based on the qualification of these patterns from historical experiences, we can assign higher rewards to states that lead to good patterns and lower rewards to states that lead to bad patterns, thereby integrating evaluations from historical experiences into the rewards.

3.2.1 Evaluation of Pattern Performance

As mentioned above, a pattern refers to a sequence of states within an episode. For a given episode e, a *k-step pattern* starting from time step t, denoted as p_t, refers to k consecutive states in e, i.e., $p_t = s_t, \ldots, s_{t+k-1}$. For example, $p_1 = s_1, \ldots, s_k$ exemplifies a k-step pattern from the first state s_1. Notice that a state can be considered a special case of a pattern, specifically a 1-step pattern.

To evaluate the past performance of the patterns, we propose that a pattern can be considered **high-performing** if the past episodes containing this pattern result in more wins than losses. Conversely, a pattern can be considered **poor-performing** if the past episodes containing it result in more losses than wins. Based on this idea, we introduce a **historical score** for each pattern to quantify its past performance, defined as the average cumulative reward received in past episodes that include that pattern. The cumulative reward for an episode, which quantifies the adversarial agent's performance, tends to be higher in episodes where the agent wins than in those it loses. As the performance of adversarial agents improves, these cumulative rewards increase. Therefore, taking the average cumulative reward across all episodes that contain a particular pattern captures the pattern's historical effectiveness. During training, we store each pattern alongside the cumulative reward of its corresponding episodes in an episodic memory. The memory then returns the average cumulative reward as the historical score for that pattern. The historical score

$h_score(p_t)$ can be calculated as:

$$h_score(p_t) = M(p_t) = \overline{\mathcal{R}_{p_t}}, \tag{1}$$

where $\overline{\mathcal{R}_{p_t}}$ is the average cumulative reward of past episodes containing p_t and M is an episodic memory we proposed to collect and analyze patterns in past episodes. In Section 3.3.1, we will further explain how we implement the episodic memory.

3.2.2 Conditional Reward Revision

Based on the historical scores of patterns, we incorporate the historical evaluations into rewards by reward revision. However, if the historical score of a pattern falls below the average cumulative rewards of all past episodes, we cannot consider such a pattern as a desirable one. Thus, we propose **episodic feedback**, which is defined as the difference between the historical score of a pattern and the average cumulative reward of all past episodes:

$$\delta(p_t) = h_score(p_t) - \overline{\mathcal{R}}. \tag{2}$$

where $h_score(p_t)$ is the historical score of pattern p_t and $\overline{\mathcal{R}}$ is the average cumulative reward of all past episodes. Note that incorporating episodic feedback is able to preserve the **policy optimality** of the reward revision. The proof of this policy-optimality guarantee is provided in Appendix A.1.

With the episodic feedback, we conditionally add the episodic feedback of a pattern to the reward of its initial state. Specifically, for an episode e, depending on the outcome of e (whether the adversarial agent wins), we revise the rewards of the initial states of patterns in e in two cases. Assume that s_t is the initial state of pattern p_t in episode e, whose reward is r_t, and $\delta(p_t)$ is the episodic feedback for p_t, the conditional reward revision can be formulated as:

$$\hat{r}_t = \begin{cases} r_t + \delta(p_t) \times \epsilon, & \text{if the adversarial agent wins} \\ & \textit{and } \delta(p_t) > 0, \\ r_t + \delta(p_t) \times \epsilon, & \text{if the adversarial agent loses} \\ & \textit{and } \delta(p_t) < 0, \\ r_t, & \text{otherwise,} \end{cases} \tag{3}$$

where $\hat{r}_t$ is the revised reward and ϵ is a coefficient used to regulate the magnitude of encouragement and punishment. After the revision, we update r_t with $\hat{r}_t$.

The reason we only revise the reward in the two cases mentioned above is that the revision must adhere to the win-loss rules of the two-player competitive game environment, even though this environment reduces to a single-player game environment during the training process. In a competitive game, we believe only states from a winning episode of the adversarial agents should be rewarded ($\delta(p_t) > 0$), while states from the losing episode should be penalized ($\delta(p_t) < 0$). We will further analyze other cases in Section 4.4.3.

3.3 Reward Revision Improving Adversarial Policy Training

3.3.1 Neural Network-based Episodic Memory

As discussed in Section 3.2.1, we propose using an episodic memory to generate historical scores for patterns based on past experiences. Since reward revision with episodic memory adds to the total training time, we reduce its overhead by adopting a neural network-based architecture shown in Figure 1, where our episodic memory consists of an LSTM followed by a multi-layer perceptron (MLP). The LSTM encodes patterns into abstract vectors, and the MLP aggregates these encodings to produce historical scores. As reported in Section 4.2, the effectiveness shown in our experiments indicates that this simple architecture is sufficient for adversarial training in two-player competitive games.

During the training, new episodes are used to update the episodic memory. Assume a newly produced episode e has a cumulative reward of $\mathcal{R}$ and contains the set of patterns P. The episodic memory M is then trained to map all the patterns in P to the same cumulative reward $\mathcal{R}$. Note that for a pattern in P, the learning target is the historical score of the pattern, which is not a fixed value and will change as new

Algorithm 1 Adversarial policy training with reward revision.

Input: $\mathcal{A}$: Adversarial Agent, E: Environment, M: Our episodic memory, $\mathcal{B}$: Experience Storage, O: Objective Function
Parameter: k: Pattern Length, n: Group Size, ϵ: Revision Coefficient
Output: $\mathcal{A}$: A Well-trained Adversarial Agent

1: **while** Training does not reach the maximum step **do**
2: $\mathcal{A}$ interacts with E and generate state s, action a, reward r.
3: $S.add(s), A.add(a), R.add(r)$.
4: **if** An episode ends **then**
5: $P \leftarrow Pattern(k, S)$
6: $R_{cum} \leftarrow Cumulative_reward(R)$
7: $M.update(P, R_{cum})$
8: $H_Score(P) \leftarrow M(P)$
9: **if** The episode is the ith episode in Group m **then**
10: $\overline{\mathcal{R}}_i^m \leftarrow Average_Reward(i, m)$
11: **end if**
12: $\Delta(P) \leftarrow Episodic_Feedback(H_Score(P), \overline{\mathcal{R}}_i^m)$
13: $R' \leftarrow Reward_Revision(R, \Delta(P), \epsilon)$
14: $\mathcal{B} \leftarrow S, A, R'$
15: Clear S, A, R
16: **end if**
17: **if** Check_Update() is true **then**
18: $Experiences \leftarrow Sample(B)$
19: $O(Experiences)$
20: $\mathcal{A}.update(O)$
21: **end if**
22: **end while**
23: **return** $\mathcal{A}$

episodes occur. Then, during the reward revision, M predicts historical scores for the patterns as Equation 1 to generate historical evaluations for reward revision. Details of our implementation of the episodic memory including the architecture, the forward process and the update process can be found in Appendix A.3.

3.3.2 Group-based Episodic Feedback

In practice, we find that later-generated episodes exhibit higher win rates than earlier-generated episodes during the training process. To achieve better performance in finding the optimal policy, we compare the historical score of a pattern with the average cumulative reward from recently generated episodes when computing the episodic feedback. To achieve this, we divide the episodes into groups of size n, where n is a hyper-parameter, and calculate the average reward of past episodes in the group. The average reward of the first i episode in group m can be calculated by

$$\overline{\mathcal{R}}_i^m = \frac{\sum_{j=1}^{j=i} \mathcal{R}_j^m}{i}, \ 1 \leq i \leq n. \tag{4}$$

Thus, we compute the episodic feedback of pattern p_t in the ith episode of group m by

$$\delta(p_t) = h_score(p_t) - \overline{\mathcal{R}}_i^m, \tag{5}$$

which is implemented in our experiments.

3.3.3 Adversarial Policy Training with Reward Revision

We implement our policy training as Algorithm 1. First, we have the adversarial agent interact with the environment and generate states, actions and rewards (Line 2-3). When an episode is ended, we extract

patterns from the episode (In practice, we use sliding window) and calculate the cumulative reward of the episode (Line 5-6). We then update the episodic memory with the patterns and the cumulative reward (Line 7), and predict the historical score for each pattern with the episodic memory(Line 8). Subsequently, we calculate the average cumulative reward of the group with Equation 4 (line 9-11), and then utilize the average cumulative reward to calculate the episodic feedback for each pattern following Equation 5 (Line 12). With the episodic feedbacks, the rewards of the states could be revised by Equation 3 (Line 13) under the condition stated in Section 3.2.2. After the reward revision, we store the states, actions and the revised rewards into the experience storage (Line 14). When the update condition is satisfied (*e.g.*, storage is full), we will sample some data from the storage and calculate the objective function from our selected policy training method (Line 17-19). The adversarial agent will be updated with the objective function (Line 20). Iteration will end when the maximum training step is reached.

4 Evaluation

4.1 Main Experiment Setup

In our experiments, we evaluate our approach along two dimensions, attack effectiveness and defense robustness, by asking two questions: (Q1) Does it secure higher win and non-loss (win plus tie) rates? (Q2) How difficult is it for opponents to defend against the adversarial strategies it learns?

To answer Q1, we employ PPO (Schulman et al., 2017) as the fundamental single-agent policy training method to train adversarial agents against well-trained *Zoo* agents (Bansal et al., 2018). We take three state-of-the-art approaches (Gleave et al., 2020; Wu et al., 2021; Guo et al., 2021) as baselines. Notably, Gleave *et al.* 's method incorporates PPO for adversarial policy training without modifying PPO's fundamental mechanisms, thus effectively serving as a PPO baseline. To ensure fair comparisons, we evaluate the methods using the same two-player competitive games in the MuJoCo robotics simulator: *YouShallNotPassHumans*, *KickAndDefend*, *SumoAnts* and *SumoHumans*, running 5 seeds per environment. In the following, we briefly introduce these four environments.

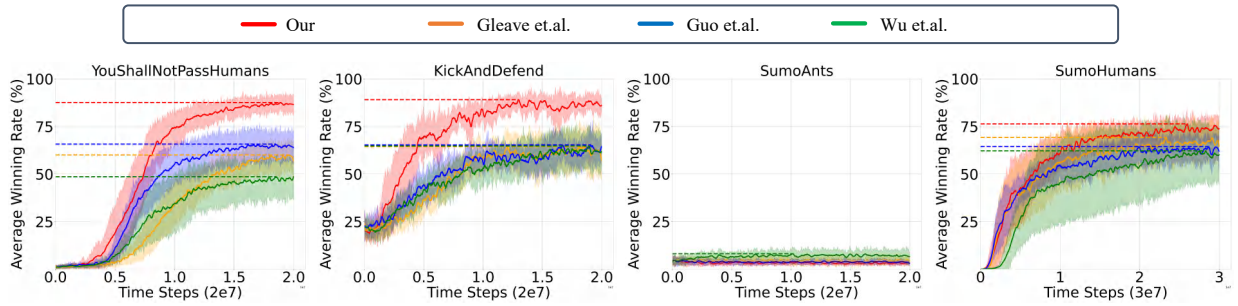
- *YouShallNotPassHumans* places two humanoid robots in a corridor. One agent, the runner, must traverse the hallway from the start line to a finish plane at the far end; the other, the blocker, aims to stop that traversal for the entire episode. All forms of physical contact are legally allowed. The game ends immediately when the runner crosses the finish lane (the runner wins) or when the fixed time limit is reached without a crossing (the blocker wins).

- *KickAndDefend* sets up a humanoid kicker, a humanoid defender, and a single soccer ball on a flat rectangular pitch. The kicker's sole objective is to propel the ball through a goal mouth, while the defender tries to block or clear it before that happens. Game concludes as soon as the ball fully crosses the goal line (the kicker wins) or when the time limit expires with no goal scored (the defender wins).

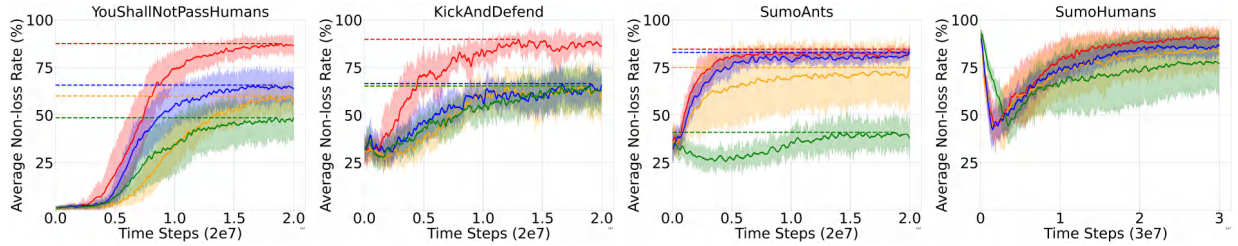
- *SumoAnts* drops two four-legged "Ant" robots onto a raised circular platform. Each agent tries to remain inside the ring while forcing the opponent off the edge. A match ends when (1) the timer expires with both ants still inside the circle (tie); (2) a robot leaves the ring without having been touched by its rival at that moment (a self-out, tie); (3) both robots exit in the same simulation step so the engine cannot determine who went out first (tie); and (4) one robot leaves the platform (the other one wins).

- *SumoHumans* follows the same ring-out rules as *SumoAnts* but swaps the quadrupeds for full 27-degree-of-freedom humanoids. The objective also remains the same as *SumoAnts*: stay on the platform and make the opponent step or fall outside.

For the hyper-parameters, we set the as 0.1, pattern length k as 3 and Group Size n as 100. Further hyper-parameter analysis is detailed in Appendix A.2.



(a) The comparison of win rates.



(b) The comparison of non-loss rates.

Figure 2: The performance of our adversarial agents and baseline adversarial agents in each environment. Dashed lines represent the highest rates of each agent and non-loss rate is win rate plus tie rate. More details are shown in Table 5 and Table 6 in Appendix A.7.

To investigate Q2, we conduct two different defense robustness tests. (1) Victim retraining: we retrain the victim agents against the fixed adversaries and track whether the adversaries' win and non-loss rates decline as the victim adapts. (2) Masked observation defense: we employ masked victim agents proposed by Gleave et.al. (Gleave et al., 2020) as a simple defense method against adversarial training in two-player competitive games. In this experiment, the victim agent's observations of the adversarial agent are fixed, simulating limited perceptual capabilities to avoid adversarial actions. Together, these experiments allow us to evaluate the robustness and effectiveness of the adversarial strategies developed by our approach.

4.2 Main Results

The comparison of the win rates and non-loss rates between our approach and the baseline approaches are summarized in Figure 2. We can observe that our proposed method reaches 88% and 89% win rates and outperforms the baseline methods significantly in *YouShallNotPassHumans* and *KickAndDefend*. In *SumoHumans*, our method also surpasses all baselines. These results indicate that by leveraging historical experiences to highlight the high-performing states, our agents demonstrate higher sample efficiency and have more potential to discover effective adversarial policies to defeat victim agents. In *SumoAnts*, Since the win rates of all agents against the victim are far below 50%, we use the non-loss rates to measure the effectiveness of our method. From Figure 2(b), we observe that in *SumoAnts*, the non-loss rate of our agent is still able to surpass that of agent trained by Guo *et al.*, which exhibits the second highest non-loss rate.

We share the videos of agents trained by our approach and baseline approaches in Appendix A.6 and compare their behaviors. In *KickAndDefend* and *SumoHumans*, all the adversarial agents perform similar adversarial actions to trick the victim into performing abnormal behaviors. These results align with the conclusion in Gleave *et al.* that adversarial agents win by confusing the victim, instead of becoming a strong opponent. However, in *YouShallNotPassHumans*, while the three baseline agents attack the victim by convulsing on the ground, our agent simultaneously performs the adversarial action and obstructs the victim with a kicking. Kicking can be viewed as a non-adversarial action, illustrating that, by incorporating our improved rewards, the agent is not limited to a single winning strategy. Instead, it can draw on past successes, like a non-

Table 1: The non-loss rate of our adversarial agent and baseline adversarial agents against masked victim agents in 100 games. Each experiment has been done 4 times. 'Before' and 'After' indicate before and after masking the victim agent. All data is reported as mean±std, rounded to the nearest integer.

Environment	Ours (%)		Gleave *et al.* (%)		Guo *et al.* (%)		Wu *et al.* (%)	
	Before	After	Before	After	Before	After	Before	After
YouShallNotPassHumans	96 ± 2	73 ± 4	66 ± 2	0 ± 0	72 ± 3	0 ± 0	50 ± 2	0 ± 0
KickAndDefend	93 ± 4	7 ± 1	65 ± 1	3 ± 1	63 ± 2	5 ± 1	69 ± 4	5 ± 1
SumoAnts	83 ± 2	81 ± 2	76 ± 2	69 ± 4	81 ± 3	78 ± 1	57 ± 5	53 ± 4
SumoHumans	92 ± 1	90 ± 1	92 ± 1	91 ± 1	92 ± 0	91 ± 1	94 ± 2	92 ± 1

adversarial kicking action, to explore a **different but more effective** strategy. Additionally, in *SumoAnts*, agents trained by our approach and Guo *et al.* both jump out of the arena at the beginning since falling out of the arena without touching the opponent is considered a draw in this game, while agents trained by Gleave *et al.* and Wu *et al.* still fight with the victim. This suggests that same as Guo *et al.*, our agent is also capable of discovering and exploiting game imbalances.

To validate whether our approach is difficult to defend against, we conduct retraining experiments on the victim agents using the PPO algorithm. We report the results of our adversarial agent and baseline agents against the victim agents during the retraining in Figure 3. In *YouShallNotPassHumans*, our agent maintains a relatively high win rate during the retraining of victim agents, unlike baseline agents whose win rate quickly drops to a low level. In *KickAndDefend*, the win rates of our agent also decreases at a slower rate compared to the baseline agents. This indicates that our approach is more difficult to defend than baseline approaches.

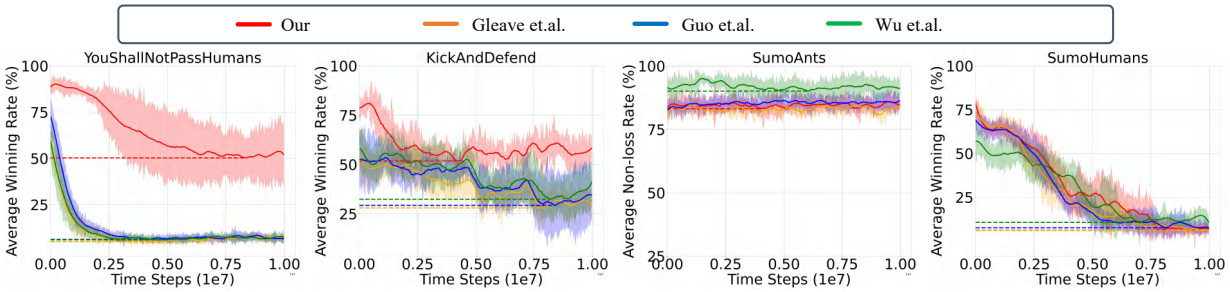


Figure 3: The comparison between our adversarial agent and baseline adversarial agents in each environment (Gleave et al., 2020; Guo et al., 2021; Wu et al., 2021) during the retraining. Specifically, we show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*. The lowest rate of each agent is depicted with a dashed line. More details are shown in Table 7 in Appendix A.7.

In order to gain a better understanding of the effectiveness of our method, following the approach in Gleave *et al.*, we have our adversarial agents play games against masked victim agents, whose observation of the adversary's position is set to a static value corresponding to a typical initial position so that the adversarial actions may not be effective. We show the performances of our adversarial agents and baseline agents against masked victims in Table 1. We observe a significant decline in the non-loss rates of the three baseline agents, while our agent maintains a high non-loss rate against the masked victim in *YouShallNotPassHumans*. This could be attributed to the fact that our agent not only relies on adversarial actions to attack the victim, but also incorporates non-adversarial actions like obstructing the victim with its body to win the game. Based on this finding, we demonstrate that in *YouShallNotPassHumans*, our agent can defeat the victim by performing adversarial and non-adversarial actions simultaneously.

4.3 Comparison with Existing Episodic Control Method

Since episodic control shares a similar insight with our approach and serves as the basis for our method, to show the effectiveness of our method, we manually implement the state-of-the-art episodic control method NECSA (Li et al., 2023), integrating it with PPO to train the agents to attack the victims. To facilitate a fair comparison, we specifically adjust NECSA to also investigate how states contribute to winning or losing outcomes. NECSA uses a grid-based tabular episodic memory and groups similar states into the same grid, and then adds the average evaluation of that grid to the state's reward.

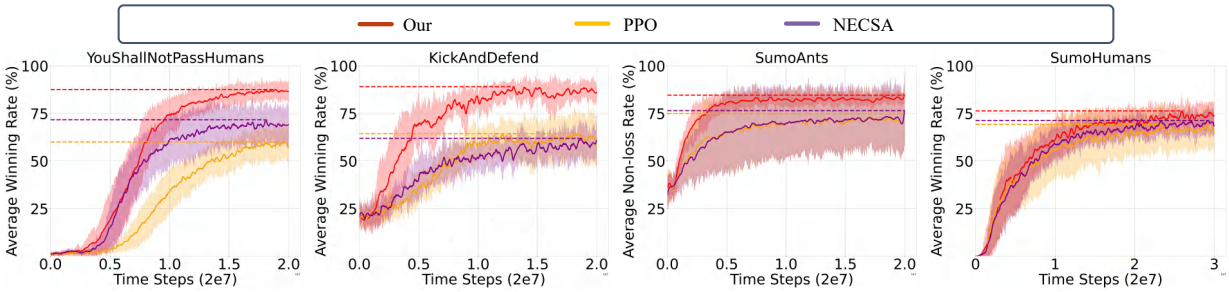


Figure 4: The comparison of performances between our method and NECSA. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*. The highest rate of each agent is depicted with a dashed line. More details are shown in Table 8 in Appendix A.7.

Figure 4 presents a performance comparison between our agents and the NECSA agents across four environments. The experimental results indicate that NECSA is less effective in all environments and even hinders the training process in the *KickAndDefend* environment. During NECSA's training, we observe that it repeatedly rewards states from losing episodes, which contradicts the fundamental principle of reward design in two-player competitive games. We believe this suboptimal reward engineering strategy diminishes NECSA's effectiveness, further underscoring the advantage of our conditional reward revision approach.

Table 2: The mean training time (rounded to the nearest hour) for a single run with PPO, our method, and NECSA.

Environment	Methods		
	PPO	Ours	NECSA
YouShallNotPassHumans	10	12	13
KickAndDefend	22	24	26
SumoAnts	30	33	35
SumoHumans	24	26	29

Both our method and NECSA require additional time for state evaluation and reward engineering, but our approach leverages a neural-network-based memory to reduce this time cost. Table 2 compares training times for PPO, our method, and NECSA. We observe that our method's overhead is approximately two hours which is generally acceptable in practice, and is shorter than NECSA's training time across all environments.

4.4 Ablation Study

4.4.1 Patterns

As mentioned in Section 3.2.1, we use historical score of the pattern to represent historical evaluation. To show the effectiveness of utilizing pattern as the basis, we calculate the episodic feedback with historical scores of both states and 3-step patterns and then revise the rewards with two episodic feedbacks. In Figure 5, we can see pattern-guided agents hold higher win rates than state-guided agents, which proves that patterns can provide a richer, more contextual basis for the historical evaluation.

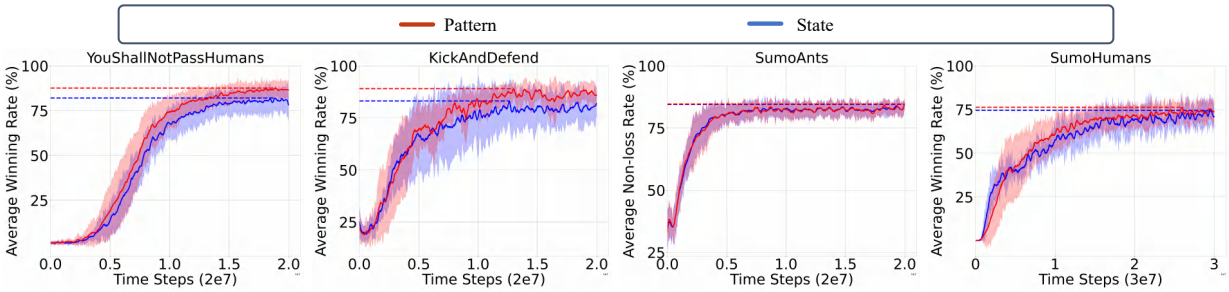


Figure 5: The comparison of performances between agents guided by pattern-based and state-based historical evaluation. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*. The highest rate of each agent is depicted with a dashed line. More details are shown in Table 9 in Appendix A.7.

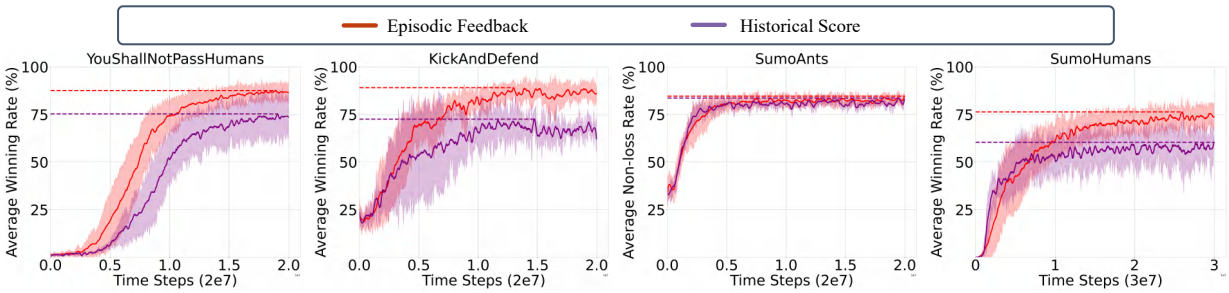


Figure 6: The comparison of performances between proposed training approach guided by episodic feedbacks and historical scores. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*. The highest rate of each agent is depicted with a dashed line. More details are shown in Table 10 in Appendix A.7.

4.4.2 Episodic Feedback

In Section 3.2.2, we mention that the episodic feedback of a pattern is computed by the difference between the historical score and the average cumulative reward of the group containing the episode. If episodic feedback is greater than 0, the pattern can be considered a better pattern than patterns in recently generated episodes, thereby enabling the adversarial agent to search for an optimal strategy. To show the effectiveness of episodic feedback, we use both episodic feedback and historical score to revise the reward. Based on the results shown in Figure 6, agents trained with episodic feedback achieve approximately 10% higher win rates than those trained with historical scores across YouShallNotPassHumans, KickAndDefend, and SumoHumans. This indicates that, compared to historical scores, using episodic feedback for reward revision enables the agent with the ability of discovering a better policy.

4.4.3 Revision Condition

As noted in Section 3.2.2, we do not revise rewards in certain scenarios, such as when a state from a winning episode for the adversarial agent receives negative episodic feedback. If we were to extend reward revision to these scenarios, some states leading to losses would be rewarded, while some states leading to wins would be penalized, potentially causing the adversarial agent to learn a losing strategy. To demonstrate this effect, we also applied reward revisions in these additional cases and present the results in Figure 7. We observe that while the peak performance of the "our_two_case" agent is only about 3% higher than that of the "our_all_case" agents, the average performance degrades substantially under full reward revision, especially in *KickAndDefend*. Similar to the results of NECSA stated in Section 4.3, this drop likely arises because the suboptimal reward engineering hinders the agent's ability to learn a winning strategy, resulting in unstable learning outcomes. In fact, We also find that states in losing episodes received positive rewards and states in

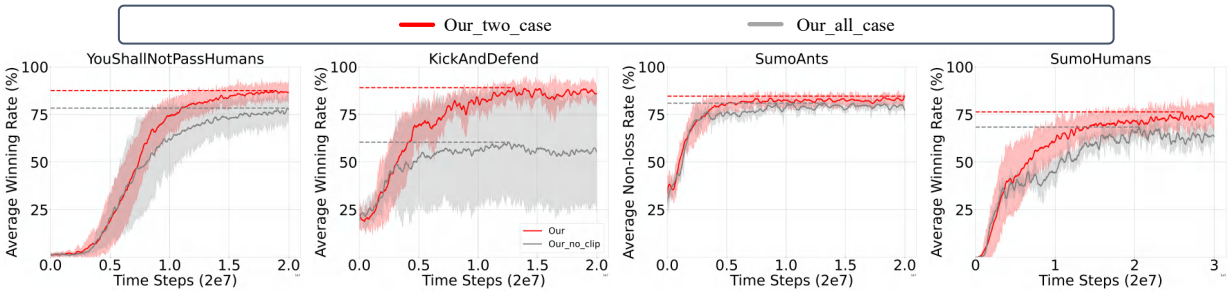


Figure 7: The comparison of performances between proposed training approach with different revision conditions. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*. The highest rate of each agent is depicted with a dashed line. More details are shown in Table 11 in Appendix A.7.

winning episodes received negative rewards in all four environments when we do full reward revision. This finding further shows that reward engineering must adhere to the rules of two-player competitive games.

5 Discussion

As stated in Section 4.1, our method utilizes PPO algorithm as the fundamental training method to train the adversarial agents. It is also important to note that our method is scalable and can be applied to various DRL algorithms. In the Appendix, we demonstrate the performances of our approach applied to the baseline algorithms (Wu et al., 2021; Guo et al., 2021) and compare the results with those of the original baseline algorithms in *YouShallNotPassHumans* and *KickAndDefend*. The results show that by leveraging historical evaluations to revise the rewards, the performances of all baseline approaches get improved.

Additionally, to evaluate our method in a more complex environment, we conducted further experiments on **StarCraft II** (see Appendix A.5 for details). In these experiments, we train two identical agents against each other, designating one as the adversarial agent, which is trained using our method and PPO. The results show that the agent trained with our method achieves much higher win rates than the PPO-trained agent, indicating that our approach remains effective in more sophisticated games.

In our main experiments, compared to PPO (Gleave et al.), our method achieves a 20%–30% increase in win or non-loss rates, which is a significant improvement. This gain is larger than expected, given that previous episodic control studies typically report a 5%–10% performance boost in their respective tasks. Therefore, we think that a further study of why our method is particularly effective on adversarial training in two-player competitive games would be both difficult and highly valuable for future research.

6 Conclusion

In this paper, we propose an adversarial policy training method with reward engineering to train an adversarial agent more effectively and efficiently. Our method introduces an episodic memory to utilize the historical experiences to generate historical evaluations for the states and consequently revise the rewards of the states based on the evaluation, thereby integrating the historical evaluations into the rewards used for adversarial training to emphasize the high-performing states. In our experiments, we demonstrate that agents trained with our approach achieve the most promising attack performance and defense difficulty. Additionally, by comparing the behaviors of adversarial agents, we discover that our attack method can explore different but optimal strategies by integrating successful actions from historical experiences. We believe our exploration of game states and use of historical experiences to improve the rewards advance adversarial policy training methods.

References

Marcin Andrychowicz, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, OpenAI Pieter Abbeel, and Wojciech Zaremba. Hindsight experience replay. *Advances in neural information processing systems*, 30, 2017.

Trapit Bansal, Jakub Pachocki, Szymon Sidor, Ilya Sutskever, and Igor Mordatch. Emergent complexity via multi-agent competition. In *International Conference on Learning Representations*, 2018. URL https://openreview.net/forum?id=Sy0GnUxCb.

Charles Blundell, Benigno Uria, Alexander Pritzel, Yazhe Li, Avraham Ruderman, Joel Z Leibo, Jack Rae, Daan Wierstra, and Demis Hassabis. Model-free episodic control. *arXiv preprint arXiv:1606.04460*, 2016.

The Viet Bui, Tien Mai, and Thanh H Nguyen. Imitating opponent to win: Adversarial policy imitation learning in two-player competitive games. *arXiv preprint arXiv:2210.16915*, 2022.

Adam Gleave, Michael Dennis, Cody Wild, Neel Kant, Sergey Levine, and Stuart Russell. Adversarial policies: Attacking deep reinforcement learning. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=HJgEMpVFwB.

Wenbo Guo, Xian Wu, Sui Huang, and Xinyu Xing. Adversarial policy learning in two-player competitive games. In *International Conference on Machine Learning*, pp. 3910–3919. PMLR, 2021.

Steven Hansen, Alexander Pritzel, Pablo Sprechmann, André Barreto, and Charles Blundell. Fast deep reinforcement learning using online adjustments from the past. *Advances in Neural Information Processing Systems*, 31, 2018.

Jonathan Ho and Stefano Ermon. Generative adversarial imitation learning. *Advances in neural information processing systems*, 29, 2016.

Sandy H. Huang, Nicolas Papernot, Ian J. Goodfellow, Yan Duan, and Pieter Abbeel. Adversarial attacks on neural network policies. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Workshop Track Proceedings*. OpenReview.net, 2017. URL https://openreview.net/forum?id=ryvlRyBKl.

Jernej Kos and Dawn Song. Delving into adversarial attacks on deep policies. *arXiv preprint arXiv:1705.06452*, 2017.

Igor Kuznetsov and Andrey Filchenkov. Solving Continuous Control with Episodic Memory. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence*, pp. 2651–2657, Montreal, Canada, August 2021. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-9-6. doi: 10.24963/ijcai.2021/365. URL https://www.ijcai.org/proceedings/2021/365.

Hung Le, Thommen Karimpanal George, Majid Abdolshah, Truyen Tran, and Svetha Venkatesh. Model-based episodic memory induces dynamic hybrid controls. *Advances in Neural Information Processing Systems*, 34:30313–30325, 2021.

Xian Yeow Lee, Sambit Ghadai, Kai Liang Tan, Chinmay Hegde, and Soumik Sarkar. Spatiotemporally constrained action space attacks on deep reinforcement learning agents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pp. 4577–4584, 2020.

Máté Lengyel and Peter Dayan. Hippocampal contributions to control: the third way. *Advances in neural information processing systems*, 20, 2007.

Zhuo Li, Derui Zhu, Yujing Hu, Xiaofei Xie, Lei Ma, Yan Zheng, Yan Song, Yingfeng Chen, and Jianjun Zhao. Neural episodic control with state abstraction. *arXiv preprint arXiv:2301.11490*, 2023.

Thodoris Lykouris, Max Simchowitz, Alex Slivkins, and Wen Sun. Corruption-robust exploration in episodic reinforcement learning. In *Conference on Learning Theory*, pp. 3242–3245. PMLR, 2021.

Yuzhe Ma, Xuezhou Zhang, Wen Sun, and Jerry Zhu. Policy poisoning in batch reinforcement learning and control. *Advances in Neural Information Processing Systems*, 32, 2019.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. In *International Conference on Learning Representations*, 2018. URL `https://openreview.net/forum?id=rJzIBfZAb`.

Andrew Y Ng, Daishi Harada, and Stuart Russell. Policy invariance under reward transformations: Theory and application to reward shaping. In *Icml*, volume 99, pp. 278–287, 1999.

Thanh Thi Nguyen and Vijay Janapa Reddi. Deep reinforcement learning for cyber security. *IEEE Transactions on Neural Networks and Learning Systems*, 2019.

Xinlei Pan, Chaowei Xiao, Warren He, Shuang Yang, Jian Peng, Mingjie Sun, Mingyan Liu, Bo Li, and Dawn Song. Characterizing attacks on deep reinforcement learning. In *Proceedings of the 21st International Conference on Autonomous Agents and Multiagent Systems*, AAMAS '22, pp. 1010–1018, Richland, SC, 2022. International Foundation for Autonomous Agents and Multiagent Systems. ISBN 9781450392136.

Anay Pattanaik, Zhenyi Tang, Shuijing Liu, Gautham Bommannan, and Girish Chowdhary. Robust deep reinforcement learning with adversarial attacks. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, AAMAS '18, pp. 2040–2042, Richland, SC, 2018. International Foundation for Autonomous Agents and Multiagent Systems.

Alexander Pritzel, Benigno Uria, Sriram Srinivasan, Adria Puigdomenech Badia, Oriol Vinyals, Demis Hassabis, Daan Wierstra, and Charles Blundell. Neural episodic control. In *International Conference on Machine Learning*, pp. 2827–2836. PMLR, 2017.

Alessio Russo and Alexandre Proutiere. Optimal attacks on reinforcement learning policies. *arXiv preprint arXiv:1907.13548*, 2019.

Tom Schaul, John Quan, Ioannis Antonoglou, and David Silver. Prioritized experience replay. *arXiv preprint arXiv:1511.05952*, 2015.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Jianwen Sun, Tianwei Zhang, Xiaofei Xie, Lei Ma, Yan Zheng, Kangjie Chen, and Yang Liu. Stealthy and efficient adversarial attacks against deep reinforcement learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pp. 5883–5891, 2020.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 5026–5033. IEEE, 2012.

Xian Wu, Wenbo Guo, Hua Wei, and Xinyu Xing. Adversarial policy training against deep reinforcement learning. In *30th USENIX Security Symposium (USENIX Security 21)*, pp. 1883–1900, 2021.

Zhaoyuan Yang, Naresh Iyer, Johan Reimann, and Nurali Virani. Design of intentional backdoors in sequential models. *arXiv preprint arXiv:1902.09972*, 2019.

Huan Zhang, Hongge Chen, Duane Boning, and Cho-Jui Hsieh. Robust reinforcement learning on state observations with learned optimal adversary. *arXiv preprint arXiv:2101.08452*, 2021.

Zhizheng Zhang, Jiale Chen, Zhibo Chen, and Weiping Li. Asynchronous episodic deep deterministic policy gradient: Toward continuous control in computationally complex environments. *IEEE transactions on cybernetics*, 51(2):604–613, 2019.

Yiren Zhao, Ilia Shumailov, Han Cui, Xitong Gao, Robert Mullins, and Ross Anderson. Blackbox attacks on reinforcement learning agents using approximated temporal information. In *2020 50th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W)*, pp. 16–24. IEEE, 2020.

Lulu Zheng, Jiarui Chen, Jianhao Wang, Jiamin He, Yujing Hu, Yingfeng Chen, Changjie Fan, Yang Gao, and Chongjie Zhang. Episodic multi-agent reinforcement learning with curiosity-driven exploration. *Advances in Neural Information Processing Systems*, 34, 2021.

A Appendix

A.1 Policy–optimality guarantee of episodic feedback

Consider an MDP $M = \langle S, A, T, \gamma, R\rangle$ and the shaped MDP $M' = \langle S, A, T, \gamma, R'\rangle$ with

$$R'(s, a, s') \;=\; R(s, a, s') \;+\; \delta(s),$$

where $\delta : S \to \mathbb{R}$ is the *episodic-feedback*.

For any policy π and initial state–action pair (s, a),

$$\begin{aligned} Q'_\pi(s,a) &= \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t R'(s_t, a_t, s_{t+1})\right] \\ &= \mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t \big(R(s_t, a_t, s_{t+1}) + \delta(s_t)\big)\right] \\ &= Q_\pi(s,a) \;+\; \underbrace{\mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t \delta(s_t)\right]}_{(*)}. \end{aligned} \tag{6}$$

As stated in Equation 2, episodic feedback is defined as

$$\delta(s) \;=\; h_\text{score}(s) \;-\; \overline{\mathcal{R}},$$

where $h_\text{score}(s)$ is the empirical mean[1] of the episode return, and $\overline{\mathcal{R}}$ is the running mean of the average cumulative reward over *all* past episodes. Both quantities are unbiased estimates of the same random variable, the episode cumulative reward R_{cum}. Hence

$$\mathbb{E}_\pi\big[h_\text{score}(s_t)\big] \;=\; \mathbb{E}_\pi\big[\overline{\mathcal{R}}\big] \;=\; \mathbb{E}_\pi[R_{\text{cum}}]. \tag{7}$$

Equation 7 immediately gives $\mathbb{E}_\pi[\delta(s_t)] = 0$; substituting into $(*)$,

$$\mathbb{E}_\pi\left[\sum_{t=0}^{\infty} \gamma^t \delta(s_t)\right] \;=\; \sum_{t=0}^{\infty} \gamma^t\, \mathbb{E}_\pi[\delta(s_t)] \;=\; 0.$$

Because the correction term is zero, Equation 6 reduces to $Q'_\pi(s,a) = Q_\pi(s,a)$ for every (s,a) and every policy π. The optimal-action sets therefore coincide:

$$\arg\max_a Q'_\pi(s,a) \;=\; \arg\max_a Q_\pi(s,a), \quad \forall s.$$

Hence every optimal policy in M' is also optimal in M. In other words, the episodic feedback $\delta(s)$ acts like a potential-based shaping function (Ng et al., 1999), which shifts all $Q_\pi(s,\cdot)$ values by the same constant and thus leaves the policy optimality unchanged.

Table 3: Hyper-parameters of episodic memory used in our experiments.

Hyper-parameter	
Pattern Length k	3
Group Size n	100
Epsilon ϵ	0.1

A.2 Hyper-parameter Analysis

For PPO hyper-parameter selections, we use the same parameters from Gleave et al. (2020). The hyper-parameters for our episodic memory are listed in Table 3. As mentioned in Li et al. (2023), 0.1 for ϵ works well for episodic control method in MuJuCo games, so we follow this setting in our experiments. We further analyze the rest two hyper-parameters.

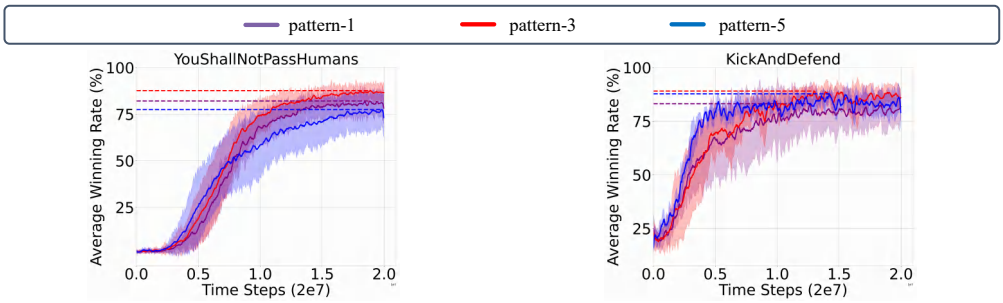


Figure 8: The comparison of win rate between our adversarial agent with different input pattern lengths in *YouShallNotPassHumans* and *KickAndDefend*.

A.2.1 Pattern Length

As stated in Section 3.2, we use state sequences, referred to as patterns, as the basis for performance evaluation in past episodes. To find out the best parameter for the length of patterns, we conduct experiments with different pattern lengths and show the results in Figure 8. We have selected three different pattern lengths in our experiments. We can see from Figure 8 that the agents have the best average win rates when the pattern length is 3.

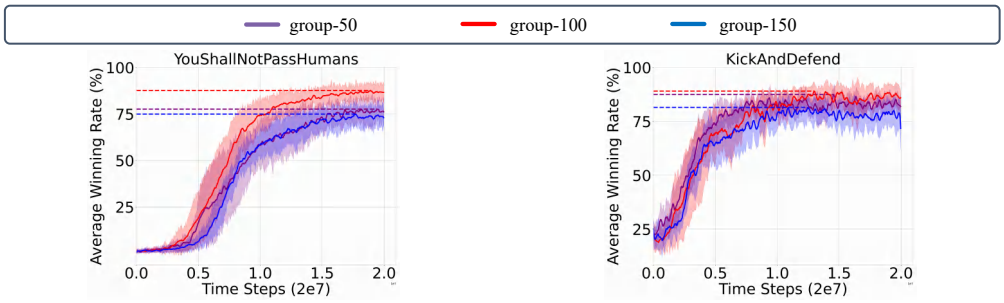


Figure 9: The comparison of win rate between our adversarial agent with group size in *YouShallNotPassHumans* and *KickAndDefend*.

A.2.2 Group Size

In Section 3.2.2, we compare the historical score of a pattern with an average cumulative reward of recently generated past episodes to calculate episodic feedback. Group size n is introduced to control the number

[1]In practice $h_\text{score}(s)$ is the running average of the undiscounted cumulative reward over *all past episodes that contained* s.

of past episodes. If the group size is too large, some states that lead to bad patterns may be erroneously rewarded, and the magnitude of rewards and penalties is reduced, thereby weakening the ability to find the optimal policy. On the other hand, if the group size is too small, it is more likely to wrongly penalize good states and reward bad states. Therefore, we conduct an analysis of 3 group sizes which are *50*, *100* and *150*. With the result shown in Figure 9, we find that the agents have the best performances when the group size is *100*. Therefore, we use *100* as the group size in our experiments.

A.3 Episodic Memory

In this section we share more details about the implementation of the episodic memory introduced in Section 3.3.1.

Table 4: The architecture of the episodic memory

Module	shape
LSTM	(64, 256, 1)
linear1	(256, 512)
Tanh	
linear2	(512, 1)

In Table 4, we give the architecture of the episodic memory. The episodic memory consists of a LSTM and a MLP (linear1, Tanh, linear2). 64 in the shape of LSTM refers to the length of the state from environment and 256 refers to the hidden length of LSTM. The LSTM is used to encode a pattern into an abstract vector so that the MLP can process. The MLP is used to output the historical score of the pattern, which evaluates the average performance of the pattern in past episodes.

Algorithm 2 Forward process of the episodic memory.

Input: pattern p (shape:[3, 64])
Output: historical score h_score (shape:1)

output, hidden, cell = LSTM(p)
h_score = linear1(hidden[-1,])
h_score = Tanh(h_score)
h_score = linear2(h_score)

In the Algorithm 2, we show the forward process of the episodic memory. The LSTM receives a pattern p as input and outputs an output sequence, the last hidden state vector and the last cell state vector of LSTM. The last hidden state vector will be processed with MLP, under the order of linear1, Tanh, linear2 and the MLP will output the historical score h_score of the input pattern.

Algorithm 3 Update process of the episodic memory.

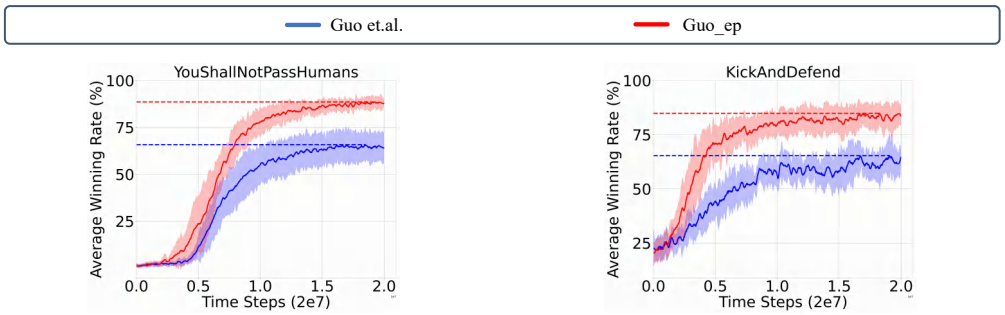
Input: episode e

P = Pattern(e)
R = Cumulative_Reward(e)
for p in P **do**
  h_score = Memory(p)
  loss = MSELoss(h_score, R)
  loss.backpropagation()
end for

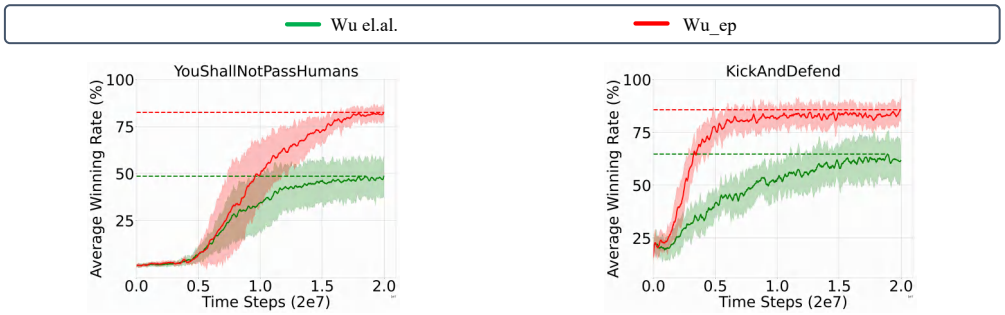
In the Algorithm 3, we show the update process of the episodic memory. After one episode is ended, we extract patterns from the episode and calculate the cumulative reward of the episode. Then, we predict the historical score for each pattern and calculate the MSELoss between the historical score and the cumulative reward. The loss will be backpropagated to update the network.

A.4 Scalability Analysis

In Section 5, we state that our approach is scalable and can be applied to various DRL algorithms. Since Gleave *et al.* can be seen as PPO, we adopt our approach on the other two baseline attacks (Guo et al., 2021; Wu et al., 2021) and compare the performances with them. The results are shown in Figure 10. We can see the baselines adopting our episodic memory outperform the original baselines in *YouShallNotPassHumans* and *KickAndDefend*.



(a) The performaces of adversarial agents trained by (Guo et al., 2021) implementing with and without our episodic memory.



(b) The performaces of adversarial agents trained by (Wu et al., 2021) implementing with and without our episodic memory.

Figure 10: The performance comparison of win rate between agents trained by (Wu et al., 2021; Guo et al., 2021) implementing with and without our episodic memory in *YouShallNotPassHumans* and *KickAndDefend*.

A.5 Experiments on StarCraft II

To evaluate whether our method is effective in a more complex two-player competitive environment, we conducted experiments in StarCraft II. We begin with two agents sharing the same initial policy: one serves as the fixed victim agent, and the other is an adversarial agent trained using our method and PPO. As shown in Figure 11, the agent trained with our method achieves a 10% higher win rate than the agent trained with PPO, demonstrating that our approach is still effective in more sophisticated environments.

However, the performance gain is smaller than what we observed in traditional MuJoCo game environments. We suspect this is because StarCraft II has a much larger state vector, making it difficult for the LSTM network to encode states into suitable abstract representations. Replacing the LSTM with a more powerful architecture such as a Transformer may further enhance the effectiveness of our method in such complex environments.

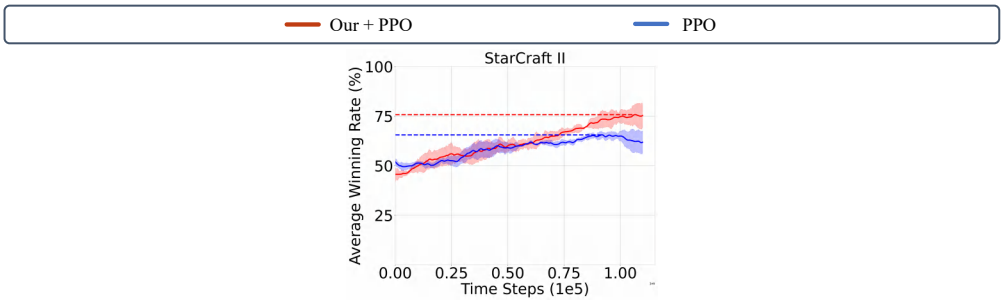


Figure 11: The comparison of the win rates between our method and PPO on StarCraft II.

A.6 Videos Of Experiments

Due to the limited maximum file size for the supplementary materials, we have uploaded the videos mentioned in Section 4.2 at `https://drive.google.com/drive/folders/1lJmWA7y8-1nMs_kOwzGlIMkjkPh2QVF6?usp=drive_link`.

A.7 Main Results Supplementary

Supplementary tables of the figures in the main text are provided on the subsequent pages.

Table 5: The highest win rates of our agents and agents attacks against zoo victim agents are shown in Figure 2(a).

Environment	Our (%)	Gleave *et al.* (%)	Guo *et al.* (%)	Wu *et al.* (%)
YouShallNotPassHumans	87.62 ± 7.38	60.08 ± 6.22	65.77 ± 7.60	48.60 ± 8.99
KickAndDefend	89.06 ± 7.98	64.37 ± 8.61	65.32 ± 6.92	64.76 ± 8.55
SomoAnts	5.18 ± 1.27	5.19 ± 2.10	4.70 ± 1.43	8.14 ± 2.87
SumoHumans	76.35 ± 8.29	69.24 ± 12.16	64.49 ± 7.15	62.22 ± 16.86

Table 6: The highest non-loss rates of our agents and baseline agents against zoo victim agents are shown in Figure 2(b).

Environment	Our (%)	Gleave *et al.* (%)	Guo *et al.* (%)	Wu *et al.* (%)
YouShallNotPassHumans	87.62 ± 7.38	60.08 ± 6.22	65.77 ± 7.60	48.60 ± 8.99
KickAndDefend	90.01 ± 7.56	65.17 ± 8.87	66.56 ± 7.14	65.27 ± 8.45
SomoAnts	84.66 ± 3.92	74.94 ± 16.24	82.98 ± 3.73	40.97 ± 6.65
SumoHumans	91.68 ± 7.52	91.88 ± 12.18	90.49 ± 5.48	92.55 ± 14.40

Table 7: The performances of our agents and baseline agents against retrained victim agents are shown in Figure 3. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*.

Environment	Our (%)	Gleave *et al.* (%)	Guo *et al.* (%)	Wu *et al.* (%)
YouShallNotPassHumans	50.27 ± 13.03	5.00 ± 2.50	6.22 ± 2.82	5.99 ± 2.99
KickAndDefend	51.82 ± 6.84	28.02 ± 7.33	29.33 ± 9.84	32.38 ± 9.54
SomoAnts	83.15 ± 2.98	79.78 ± 2.28	82.49 ± 2.77	90.13 ± 3.42
SumoHumans	6.17 ± 7.60	6.03 ± 5.35	7.61 ± 5.88	10.71 ± 6.95

Table 8: The comparison of performances between our method and NECSA.The performances of our agents and NECSA against victim agents are shown in Figure 3. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*.

Environment	PPO (%)	Our (%)	NECSA (%)
YouShallNotPassHumans	60.08 ± 6.22	87.62 ± 7.38	71.71 ± 9.18
KickAndDefend	74.94 ± 16.24	89.06 ± 7.98	76.52 ± 16.31
SomoAnts	83.15 ± 2.98	84.66 ± 3.92	82.49 ± 2.77
SumoHumans	69.24 ± 12.15	76.34 ± 8.29	71.34 ± 7.38

Table 9: The performances of our agents guided by pattern-based and state-based historical evaluation against zoo victim agents is shown in Figure 5. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*.

Environment	Pattern (%)	State (%)
YouShallNotPassHumans	87.62 ± 7.38	82.06 ± 6.77
KickAndDefend	89.06 ± 7.98	83.15 ± 11.29
SumoAnts	84.66 ± 3.92	83.73 ± 4.15
SumoHumans	76.35 ± 8.29	74.35 ± 6.71

Table 10: The performances of our agents trained with episodic feedback and historical score against zoo victim agents shown in Figure 6. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*.

Environment	Episodic Feedback (%)	historical score (%)
YouShallNotPassHumans	87.62 ± 7.38	75.28 ± 8.25
KickAndDefend	89.06 ± 7.98	72.85 ± 11.48
SumoAnts	84.66 ± 3.92	83.66 ± 2.30
SumoHumans	76.35 ± 8.29	72.15 ± 6.90

Table 11: The performances of our agents with and without revision conditions against zoo victim agents is shown in Figure 7. We show win rates of the agents in *YouShallNotPassHumans*, *KickAndDefend*, *SumoHumans* and non-loss rate in *SumoAnts*.

Environment	Our_two_case (%)	Our_all_case (%)
YouShallNotPassHumans	87.62 ± 7.38	78.39 ± 10.74
KickAndDefend	89.06 ± 7.98	60.45 ± 25.15
SumoAnts	84.66 ± 3.92	80.44 ± 3.73
SumoHumans	76.35 ± 8.29	68.40 ± 4.14