LEARNING KEY STEPS TO ATTACK DEEP REINFORCEMENT LEARNING AGENTS

Anonymous authors
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ABSTRACT

Deep reinforcement learning agents are known to be vulnerable to adversarial attacks. In particular, recent studies have shown that attacking a few key steps is effective for decreasing the agent's cumulative reward. However, all existing attacking methods find those key steps with human-designed heuristics, and it is not clear how more effective key steps can be identified. This paper introduces a novel reinforcement learning framework that learns more effective key steps through interacting with the agent. The proposed framework does not require any human heuristics nor knowledge, and can be flexibly coupled with any white-box or black-box adversarial attack scenarios. Experiments on benchmark Atari games across different scenarios demonstrate that the proposed framework is superior to existing methods for identifying more effective key steps.

1 INTRODUCTION

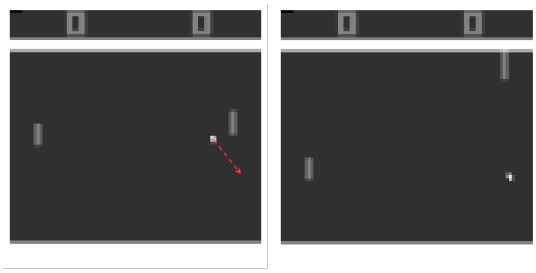
Reinforcement learning (RL) is a framework for sequential decision problems, where an agent interacts with an unknown environment and tries to maximize the total reward it receives. With the rapid development of deep learning, RL agents parametrized by neural networks, usually referred to as deep RL agents, are able to learn complex policies from raw inputs (Mnih et al., 2015). Recently, deep RL agents have shown great success across various domains, such as achieving superhuman performance on games (Mnih et al., 2015; Silver et al., 2016; 2018), completing complex robotic tasks (Levine et al., 2016), optimizing patient treatments (Escandell-Montero et al., 2014; Raghu et al., 2017), and developing autonomous driving skills (Pan et al., 2017; Isele et al., 2018).

However, if we wish to deploy these RL agents into security-critical applications, we must take their reliability into consideration. It is discovered that neural networks classifiers may make errors on deliberately crafted inputs, known as adversarial examples (Biggio et al., 2013; Szegedy et al., 2013; Behzadan & Munir, 2017a). Deep RL is no exception: Many works have demonstrated that deep RL agents are also vulnerable when attacked by adversarial examples (Behzadan & Munir, 2017a; Huang et al., 2017), raising serious concerns on the reliability of these agents for security-critical applications. For example, there may be severe consequences if an RL-agent-driven autonomous vehicle is compromised by adversarial examples fed from a malicious attacker.

Given the sequential nature of RL, it is not necessary to attack at every time step to degrade the agent's performance significantly (Lin et al., 2017; Kos & Song, 2017). The reason is that not all decisions made by the agent are equally important. Some decisions may be critical to the agent, such as those for long-term planning or immediate reward gathering; some other decisions may not have much effect on the environment nor the rewards, and thus attacking those steps would not change anything. The critical steps will be named *key steps* in this work, and attacking these steps decreases the cumulative reward that the agent could gather.

Figure 1 illustrates a key step and a non-key step in Atari Pong, where the main difference between them is whether the ball has already passed through the agent. If the attacker is aware of this difference, the attacker can concentrate on attacking the few key steps. By attacking fewer steps, the attacker reduces the costs of generating, injecting, and hiding the adversarial examples. Therefore, an intelligent attacker should prefer attacking key steps over non-key steps.

A natural question arises: How does an attacker identify the key steps to attack? As an initial attempt to address this question, Lin et al. (2017) formulate the problem from an optimization perspective,



(a) Key step (b) Non-key step

Figure 1: An example of the key step and non-key step in Atari Pong. (a) The ball is moving in the direction indicated by the red arrow. If the agent does not move down at this step or some earlier steps, the ball would pass through, making the agent lose a point. (b) The ball has already passed through the agent. Any decision at this step does not save the situation and does not affect the environment much.

and propose a heuristic that attacks the agent when it strongly prefers one action. Concurrently, Kos & Song (2017) propose another heuristic that attacks when the action appears rewarding to the agent. However, since these heuristics are designed based on human knowledge, it is unclear whether there exist more effective key steps. In this work, we study the possibilities of finding those more effective key steps, and of finding them automatically without human knowledge. We confirm both possibilities by introducing an RL framework where the attacker *learns* the key steps *from scratch* through interacting with the agent. In particular, we study the *key-step identification problem* proposed by Lin et al. (2017). We first make a crucial observation that this constrained optimization problem can be converted into another form that matches the objective of RL. Then, we design a corresponding RL environment to train the attacker. We justify our learning framework by giving a toy example where those human-designed heuristics fail to identify the key steps. To test the effectiveness of our framework, we conduct experiments on four benchmark Atari games. The results suggest that the attacker trained by our framework finds more effective key steps than prior methods do, such that the agent gets less cumulative reward under the same number of attacks. Our contributions are summarized as follows:

- We formulate the key-step identification problem in an unconstrained form, and introduce an RL framework that solves it directly without incorporating any human knowledge.
- The proposed RL framework is independent of how adversarial examples are generated. Therefore, we can learn to identify the key steps with white-box or black-box attacks.
- We provide a toy example and conduct experiments on four Atari games. Compared to existing methods, our method achieves superior performance in finding the key steps.

2 Background and Related Works

2.1 Reinforcement Learning Background

We begin with an introduction to the Markov Decision Process (MDP) (Sutton & Barto, 2018). For a set $\mathbb{S}$, we use $\Delta(\mathbb{S})$ to denote the set of probability distributions over $\mathbb{S}$. Consider an agent interacting with an environment: At each step t, the agent picks an action a_t based on a current state s_t, and then the environment returns a reward r_t and a next state s_{t+1}. We formalize this interaction as an MDP $\mathcal{M}$, which is a 5-tuple $(\mathbb{S}, \mathbb{A}, P, R, \gamma)$, where $\mathbb{S}$ is a finite set of states, $\mathbb{A}$ is a finite set of actions, $P\colon \mathbb{S} \times \mathbb{A} \to \Delta(\mathbb{S})$ defines the transition dynamics from s_t to s_{t+1}, $R\colon \mathbb{S} \times \mathbb{A} \to \Delta(\mathbb{R})$ defines the reward distribution, and $\gamma \in [0, 1]$ is a discount factor. For convenience, we use $r\colon (s_t, a_t) \mapsto \mathbb{E}_{r_t \sim R(s_t, a_t)}[r_t]$ to denote the mean reward function. We specify an agent by its (stochastic) policy $\pi : \mathbb{S} \to \Delta(\mathbb{A})$, and define its Q-value function as

$$Q^\pi(s_t, a_t) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r(s_{t+k}, a_{t+k})\right],$$

where $s_i \sim P(s_{i-1}, a_{i-1})$ and $a_i \sim \pi(s_i)$ for all $i > t$. The agent's goal is to find a policy that maximizes the expected cumulative reward, or expected return, defined by $Q^\pi(s_1, \pi(s_1))$, starting from an initial state s_1. For finite-horizontal MDPs, we use T to denote the maximum number of steps, and define an episode to be a sample of $(s_1, a_1, r_1, \ldots, s_T, a_T, r_T, s_{T+1})$.

To learn the optimal policy, deep Q-network (DQN, Mnih et al. 2015) first approximates the Q-value function by a neural network that takes a state as input and outputs the Q-values for all actions. The policy is then induced by picking the action with the largest Q-value at each state. Given a transition step (s_t, a_t, r_t, s_{t+1}), the network f_θ is trained by minimizing the square loss

$$\mathcal{L}_\theta = \left(\left(r_t + \gamma \max_a f_\theta(s_{t+1})_a \right) - f_\theta(s_t)_{a_t} \right)^2,$$

where we use $f_\theta(s)_a$ to denote the a-th entry of the Q-values $f_\theta(s)$.

2.2 Adversarial attack background

In the context of adversarial attacks, an attacker tries to craft adversarial examples that the target model would misclassify. In gradient-based adversarial attacks, the attacker generates adversarial examples by adding small perturbations to data examples, such that the perturbations are imperceptible to human eyes. Take the fast gradient sign method (FGSM) by Goodfellow et al. (2014) for example. Given a target model f_θ parametrized by θ and an image–label pair (x, y), the FGSM computes the perturbation as

$$\eta = \epsilon \operatorname{sign}(\nabla_x J(\theta, x, y)),$$

where ϵ is a scaling factor that controls the norm of the perturbation, and $J(\theta, x, y)$ is an objective function that depends on the attacker's goal. In untargetted attacks, the attacker aims to minimize the target model's classification accuracy. Thus, the objective $J(\theta, x, y)$ is substituted with $D_{\mathrm{KL}}(e^{(y)} \| f_\theta(x))$, the Kullback-Leibler divergence between the label's one-hot encoding $e^{(y)}$ and the predicted probabilities $f_\theta(x)$. However, this type of white-box attacks requires full knowledge of the network parameter θ, which may be hidden in practical tasks.

In contrast, black-box attacks assume no access to θ and study other conditions, such as the ability to query model outputs (Chen et al., 2017). One black-box attack of particular interest is the substitute model approach (Papernot et al., 2016a; 2017), where the attacker computes perturbation using a substitute model that is trained to perform the same task as the target model. This approach is based on the finding that adversarial examples are transferable; that is, if an adversarial example fools a model, it usually fools another models trained to perform the same task, regardless of the network architecture (Szegedy et al., 2013). Consequently, once the attacker gains access to the training set, black-box attacks reduce to white-box attacks with a lower attack success rate.

2.3 Adversarial attack on deep RL agents

As opposed to traditional adversarial attacks, attacking an RL agent is a unique and challenging task. When we attack a classifier, we typically aim to minimize the classification accuracy or to maximize the probability that the classifier predicts some given class. When we attack an RL agent, however, we usually do not care about the individual actions that the agent picks. In this paper, we choose to minimize the agent's cumulative reward (Huang et al., 2017; Lin et al., 2017) as the attacker's goal. Other possible goals include luring the agent into a designated state (Lin et al., 2017), or misguiding the agent to optimize an adversarial reward (Tretschk et al., 2018).

Previous works have investigated the effects of white-box and black-box attacks against RL agents on the Atari benchmark. Given full knowledge of the target agent's network parameters, an attacker can craft adversarial examples to fool the target agent into picking wrong actions (Behzadan & Munir, 2017a; Huang et al., 2017; Kos & Song, 2017; Mandlekar et al., 2017; Pattanaik et al., 2018; Hussenot et al., 2019) using the FGSM. Other white-box methods such as the Jacobian saliency map algorithm (Papernot et al., 2016b) and the attack proposed by Carlini & Wagner (2017) are also effective against RL agents (Behzadan & Munir, 2017a; Lin et al., 2017). Even if the attacker cannot access the target agent's network parameters, adversarial examples can still be crafted with a substitute agent that is trained in the same environment as the target agent (Behzadan & Munir, 2017a; Huang et al., 2017), similar to the substitute model approach.

Another line of studies tries to improve the RL agent's robustness with adversarial attacks. Several works improve the agent's robustness to visual perturbations through adversarial training (Kos & Song, 2017; Mandlekar et al., 2017; Behzadan & Munir, 2017b; Pattanaik et al., 2018), which is a defense technique that adds adversarial examples into training sets (Goodfellow et al., 2014). On the other hand, Pinto et al. (2017) propose to improve the agent's robustess to environment changes by training the agent and an adversary in an alternating procedure, where the attacks are operated on the environment dynamics. Tessler et al. (2019) study the agent's robustness to action-space perturbations in continuous control domains, and achieve better performance even in the absence of the adversary.

3 LEARNING KEY STEPS TO ATTACK

3.1 THE KEY-STEP IDENTIFICATION PROBLEM

Suppose that an attacker would like to attack a target agent with policy π by adding perturbations to the states. We use η to denote an arbitrary attack method that maps from a state to a perturbation. Let B be the budget, the maximum number of attacks permitted in one episode. The key-step identification problem (Lin et al., 2017) can be formulated as follows:

$$\begin{aligned} \min_{b_1,\ldots,b_T\in\{0,1\}} \quad & \mathbb{E}\left[\sum_{t=1}^{T} r(s_t,a_t)\right] \\ \text{s.t.} \quad & a_t \sim \pi(s_t + b_t\eta(s_t)),\ s_{t+1}\sim P(s_t,a_t),\ \forall 1\le t\le T, \\ & \sum_{t=1}^{T} b_t \le B. \end{aligned} \tag{1}$$

In this problem. the attacker aims to minimize the expected return of the target agent under the budget constraint. The binary variable b_t indicates whether the perturbation $\eta(s_t)$ is added to the state s_t, and t is a key step found by the attacker if $b_t = 1$.

Problem (1) is a difficult combinatorial problem with exponentially large search space. Each decision of the attacker changes the subsequent steps. Moreover, the transition dynamics and reward distribution may be random. Even if the attacker manages to search the whole space by brute force, the collected episodes are merely samples. The attacker still needs to estimate the expected return.

Due to these difficulties, previous works (Lin et al., 2017; Kos & Song, 2017) design simple heuristics to find the key steps. Suppose that the target agent is parametrized by a Q-network f_θ.[1] Kos & Song (2017) observe that steps with large Q-value are usually followed by large immediate reward, and hypothesize that an attack is effective at steps with large Q-value. They propose to set $b_t = 1$ if the maximum Q-value $\max_a f_\theta(s_t)_a$ is larger than a given threshold. On the other hand, Lin et al. (2017) propose to add perturbations when the agent is confident about its action. They use the softmax function to convert the Q-values into a probability distribution (let $\pi = \text{softmax} \circ f_\theta$), and set $b_t = 1$ if the probability gap $\max_a \pi(s_t)_a - \min_a \pi(s_t)_a$ is larger than a given threshold.

3.2 AN RL FRAMEWORK FOR LEARNING THE KEY STEPS

To address these challenges, we design an RL framework that directly solves the key-step identification problem. Based on the Lagrange relaxation technique (Bertsekas, 1997), we first replace the hard budget constraint with a soft penalty term:

$$\begin{aligned} \min_{b_1,\ldots,b_T\in\{0,1\}} \quad & \mathbb{E}\left[\sum_{t=1}^{T} r(s_t,a_t)\right] + \lambda\sum_{t=1}^{T} b_t \\ \text{s.t.} \quad & a_t \sim \pi(s_t + b_t\eta(s_t)),\ s_{t+1}\sim P(s_t,a_t),\ \forall 1\le t\le T, \end{aligned} \tag{2}$$

where λ is a parameter that controls the penalty for each attack. Now Problem (2) becomes a sequential decision problem without additional constraints. We then propose to solve this problem through

[1] These heuristics can be applied to attack other value-based or policy-based agents in a similar way.

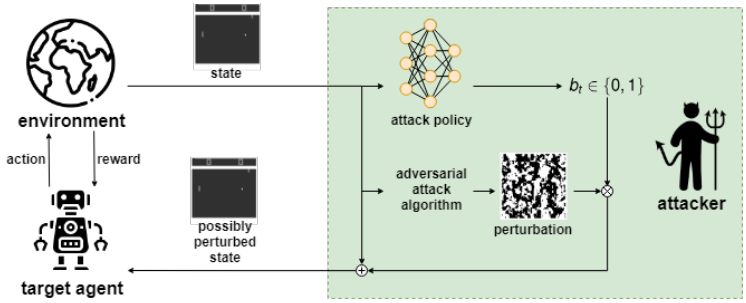


Figure 2: Interactions between the environment, the target agent, and the attacker. If the attack policy outputs "1", the attacker would intercept the state from the environment and inject the perturbed state to the target agent. Different from prior methods, our method parametrizes the attack policy by a neural network and trains it by an RL framework.

RL by training an *attack policy* that identifies the key steps. Figure 2 illustrates the interactions among the environment, the target agent, and the attacker.

Our RL framework is designed as follows. Suppose that the target agent with policy π is trained to maximize the expected return in an MDP $\mathcal{M} = (\mathbb{S}, \mathbb{A}, P, R, \gamma)$. We propose to train the attack policy π' in another MDP $\mathcal{M}' = (\mathbb{S}', \mathbb{A}', P', R', \gamma')$, where each component is defined as follows:

- $\mathbb{S}' = \mathbb{S}$, and $\gamma' = \gamma$.
- The attacker's action space $\mathbb{A}' = \{0, 1\}$.
- For all $s \in \mathbb{S}'$, $b \in \mathbb{A}'$, the transition dynamics $P'(s, b) = P(s, a)$, and the reward $R'(s, b) = -R(s, a) - b\lambda$, where $a \sim \pi(s + b\eta(s))$ is the target agent's action.

The new environment M' has the same state space as M, but reduces to binary action space with the action "1" representing an attack at that step and "0" otherwise. The attacker's reward is the negative of the target agent's reward, plus a penalty of λ for each attack. Therefore, maximizing the expected return in $\mathcal{M}'$ is equivalent to minimizing the objective in Problem (2).

Our proposed RL framework is general. We make no assumptions on the environment or on the target agent. In addition, our RL framework can be freely paired with any RL algorithm and any attack method when training the attack policy. Thus, both white-box and black-box attack scenarios can be considered in this framework.

3.3 The potential of learning the key steps

Here we justify our RL framework by giving a toy example where the prior methods fail to identify the key steps. Consider a simple MDP shown in Figure 3. Suppose that we would like to attack an agent with its policy and Q-value function given in the figure. If we set the budget constraint $B = 2$, the most effective attack policy should attack steps 1 and 3. However, both heuristics are unable to find these two key steps.

This toy example highlights the potential drawback of these heuristics. Since the attacker might change the agent's policy in the future steps, the agent's Q-value estimates in the current step could be inaccurate. As a result, heuristics based on these Q-value estimates may not find the most effective key steps. In contrast, our framework trains the attacker from scratch. We do not rely on human-designed heuristics, and thus the attacker could possibly learn to identify the most effective key steps in this example.

4 Experiments

4.1 Experimental setup

We evaluate the proposed RL framework on four Atari 2600 games in the Arcade Learning Environment (Bellemare et al., 2013) (Pong, Space Invaders, Seaquest, and Riverraid), which covers

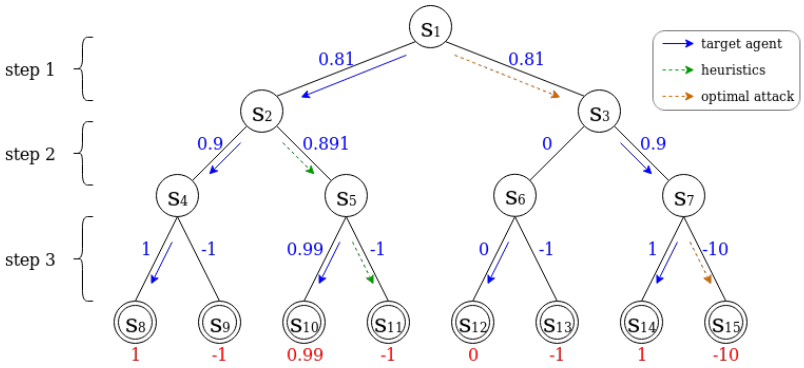


Figure 3: An MDP example where the two heuristics fail. The MDP components are described as follows. A circle represents a state, and a double circle represents a terminal state. At each state, the agent can choose to go left or right, as shown by the lines. Red numbers under the terminal states represent the reward an agent gets if the agent reaches that state. The discount factor γ is set to 0.9. Suppose we would like to attack an agent with its estimated Q-values and policy shown by the blue numbers and blue arrows. Let the budget constraint $B = 2$. To minimize the agent's cumulative reward, a smart attacker should attack at steps 1 and 3, guiding the agent into state s_{15}. However, the heuristic proposed by Kos & Song (2017) would attack at steps 2 and 3 since the maximum Q-value is larger at those steps. On the other hand, the heuristic proposed by Lin et al. (2017) also attacks steps 2 and 3 since the gap of Q-values is larger at those steps (so the probability gap is larger too). As a result, both heuristics guide the agent into state s_{11}, failing to find the best key steps.

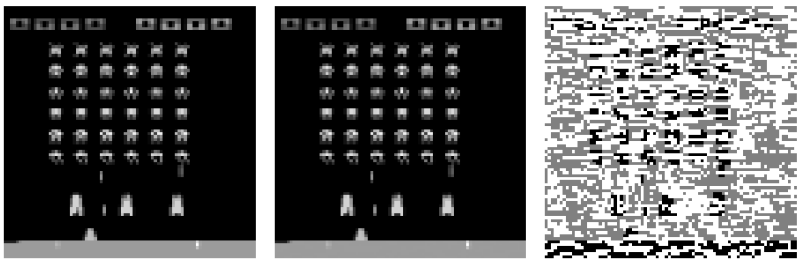
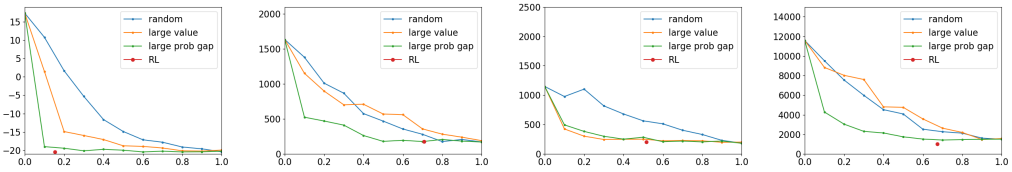


Figure 4: An example of perturbation generated by the FGSM with $\epsilon = 0.01$. **Left:** Original frame. **Middle:** Perturbed frame. **Right:** Added perturbation (rescaled to $[0, 1]$).

a variety of environments. The environment settings and preprocessing match the guidelines suggested by Machado et al. (2018). In particular, we use a sticky-action probability of 0.25 in these environments. For the target agent, we take pretrained DQN agents from Dopamine (Castro et al., 2018), which have the same network architecture as Mnih et al. (2015), and fix them thereafter. We train the attack policy using DQN with this same architecture. It is worth mentioning that we train each attack policy for 10M frames, which is only 1/20 of the frames used to train the target agents. Unless otherwise stated, the penalty parameter λ is fixed to 0.01. Other hyperparameters are reported in the Appendix.

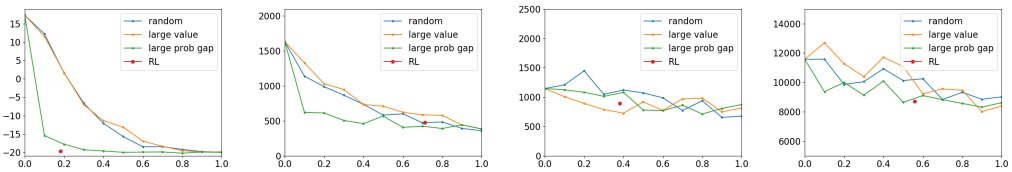
Throughout the experiments, we use the untargetted FGSM to generate perturbations due to its computation efficiency. Although we only test our framework in this setting, we expect the framework to generalize to the case of targetted attack, or to other adversarial attack algorithms. We use Foolbox (Rauber et al., 2017) to generate the adversarial examples, with the norm constraint ϵ set to 0.01. An example of the perturbation is shown in Figure 4. The perturbation is imperceptible to human and can only be visualized after rescaling. To make the scenario more realistic, we follow Hussenot et al. (2019) and perturb the target agent's observation, rather than the whole state. That is, although the target agent stack the latest four frames as its current state, we are only allowed to add perturbation to the latest frame.

We consider both white-box and black-box attacks, and compare our method to three baselines in the key-step identification problem. The first one attacks uniformly at random, and the other two



(a) Pong (b) Space Invaders (c) Seaquest (d) Riverraid

Figure 5: Performance comparison in the key-step identification problem with white-box attacks. The vertical axis shows the target agent's undiscounted return, and the horizontal axis is the attack ratio. The result of the two heuristics are obtained by setting 10 different thresholds on their corresponding criteria. Under the same attack ratio, the lower the target agent's undiscounted return is, the better the attack method does. (*random:* uniformly random attack; *large value:* the heuristic proposed by Kos & Song (2017); *large prob gap:* the heuristic proposed by Lin et al. (2017); *RL:* the attack policy traind by our RL framework)



(a) Pong (b) Space Invaders (c) Seaquest (d) Riverraid

Figure 6: Performance comparison in the key-step identification problem with black-box attacks. (See Figure 5 for descriptions of the axes and legends.)

baselines are the heuristics proposed by Kos & Song (2017) and Lin et al. (2017). All reported scores are undiscounted return, averaged over ten episodes and over three target agents that are trained with different random seeds.

4.2 Identifying key steps with white-box attacks

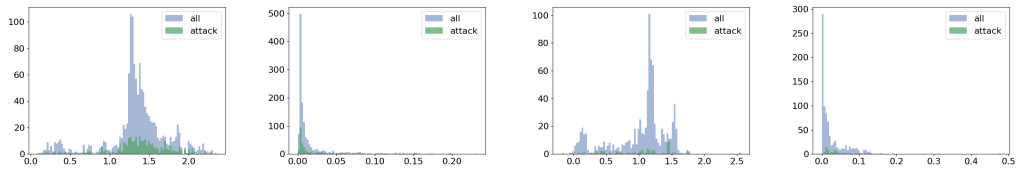
First we assume that the attacker has full knowledge of the target agent's network parameters, so the perturbations can be computed by the FGSM directly. Figure 5 plots the target agent's performance versus the attack ratio (the number of attacks divided by the number of steps in an episode) for different methods. The results show that, under the same budget constraint, the target agent gets the least return when attacked by our method in all four environments. This suggests that it is possible to learn the key steps from scratch, and that our method learns more effective key steps than those found by the previous methods.

4.3 Identifying key steps with black-box attacks

Now we assume that the attacker cannot access the target agent's network parameters. We use another substitute agent to compute the perturbations, as well as the statistics needed in the two heuristics, and apply them to attack the target agent. We fix one pretrained agent as the substitute agent and report scores averaged over three target agents. The results are shown in Figure 6. Compared to white-box attacks, black-box attacks are of less success rate, and thus the effects of the attacks are weakened (cf. Figure 5). Still, our method learns more effective key steps in two out of four environments (Pong, Riverraid).

4.4 Behavior comparison of the attack policy

To understand to what extent the attack policy learned in our RL framework is different from the heuristics, we attack the target agent by the learned attack policy, and compute the statistics used by the two heuristics at each step. Figure 7 plots the histogram of those statistics in one episode of



(a) White-box attacks (b) Black-box attacks

Figure 7: Behavior comparison of our method to previous heuristics in Pong. **Left:** Histogram of the maximum Q-value computed by Kos & Song (2017). **Right:** Histogram of the probability gap computed by Lin et al. (2017). (*all:* all steps in one episode; *attack:* steps that our method attacks)

Table 1: Comparison of different λ on Pong.

	λ				
	1	0.1	0.01	0.001	0.0001
undiscounted return	16.3	-20.5	-20.6	-20.9	-20.9
attack ratio (%)	0.00	5.34	9.70	15.76	18.69

Pong. The results of other environments are provided in the Appendix. From Figure 7 we can see that the key steps found by our method spread across different intervals, rather than focusing on the largest intervals. This suggests that our method does not simply mimic the heuristics, but indeed learns unique key steps to attack.

4.5 The effect of the penalty parameter

To investigate the penalty parameter λ, we train five attack policies with different values of λ in Pong under the setting of white-box attacks. Other hyperparameters remain unchanged. The results are shown in Table 1. From the table we make the following observations. First, as λ decreases, the attack ratio increases and the undiscounted return of the target agent gets lower. Second, if λ is too large (greater than or equal to 1 in this case), the learned attack policy would not launch any attack, failing to identify any key steps. Third, for λ ranging from 0.1 to 0.0001, the target agent's undiscounted reward stays close to the minimum value -21.0 in Pong, and the attack ratio remains rather small compared to other heuristics (cf. Figure 5). These observations suggest that, although changing λ has effects on the attack ratio of the learned attack policy, our RL framework is not too sensitive to the choice of λ.

5 Discussion

We show that the key-step identification problem can be better solved by training an attacker policy through RL. Compared to existing works, our method learns different key steps without any human knowledge. Moreover, the results on Atari benchmarks validate our believe that the proposed method could learn more effective key steps. This raises safety concerns on the real-world applications of deep RL agents. One possible future direction is to study how we can improve the RL agent's robustness to this kind of key-step attacks. For example, combining the idea of alternating training from Pinto et al. (2017) and Tessler et al. (2019) into our RL framework may be a fruitful research direction. Since the RL agent's robustness is mostly studied in continuous environments (e.g., MuJoCo), we hope that this work attracts more attention into studying this topic in environments with discrete actions.

References

Vahid Behzadan and Arslan Munir. Vulnerability of deep reinforcement learning to policy induction attacks. In *International Conference on Machine Learning and Data Mining in Pattern Recogni-*

tion, pp. 262–275. Springer, 2017a.

Vahid Behzadan and Arslan Munir. Whatever does not kill deep reinforcement learning, makes it stronger. *arXiv preprint arXiv:1712.09344*, 2017b.

Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47: 253–279, 2013.

Dimitri P Bertsekas. Nonlinear programming. *Journal of the Operational Research Society*, 48(3): 334–334, 1997.

Battista Biggio, Igino Corona, Davide Maiorca, Blaine Nelson, Nedim Šrndić, Pavel Laskov, Giorgio Giacinto, and Fabio Roli. Evasion attacks against machine learning at test time. In *Joint European conference on machine learning and knowledge discovery in databases*, pp. 387–402. Springer, 2013.

Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In *2017 IEEE Symposium on Security and Privacy (SP)*, pp. 39–57. IEEE, 2017.

Pablo Samuel Castro, Subhodeep Moitra, Carles Gelada, Saurabh Kumar, and Marc G Bellemare. Dopamine: A research framework for deep reinforcement learning. *arXiv preprint arXiv:1812.06110*, 2018.

Pin-Yu Chen, Huan Zhang, Yash Sharma, Jinfeng Yi, and Cho-Jui Hsieh. Zoo: Zeroth order optimization based black-box attacks to deep neural networks without training substitute models. In *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, pp. 15–26. ACM, 2017.

Pablo Escandell-Montero, Milena Chermisi, Jose M Martinez-Martinez, Juan Gomez-Sanchis, Carlo Barbieri, Emilio Soria-Olivas, Flavio Mari, Joan Vila-Francés, Andrea Stopper, Emanuele Gatti, et al. Optimization of anemia treatment in hemodialysis patients via reinforcement learning. *Artificial intelligence in medicine*, 62(1):47–60, 2014.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*, 2014.

Sandy Huang, Nicolas Papernot, Ian Goodfellow, Yan Duan, and Pieter Abbeel. Adversarial attacks on neural network policies. *arXiv preprint arXiv:1702.02284*, 2017.

Léonard Hussenot, Matthieu Geist, and Olivier Pietquin. Targeted attacks on deep reinforcement learning agents through adversarial observations. *arXiv preprint arXiv:1905.12282*, 2019.

David Isele, Reza Rahimi, Akansel Cosgun, Kaushik Subramanian, and Kikuo Fujimura. Navigating occluded intersections with autonomous vehicles using deep reinforcement learning. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2034–2039. IEEE, 2018.

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

Sergey Levine, Chelsea Finn, Trevor Darrell, and Pieter Abbeel. End-to-end training of deep visuomotor policies. *The Journal of Machine Learning Research*, 17(1):1334–1373, 2016.

Yen-Chen Lin, Zhang-Wei Hong, Yuan-Hong Liao, Meng-Li Shih, Ming-Yu Liu, and Min Sun. Tactics of adversarial attack on deep reinforcement learning agents. *arXiv preprint arXiv:1703.06748*, 2017.

Marlos C Machado, Marc G Bellemare, Erik Talvitie, Joel Veness, Matthew Hausknecht, and Michael Bowling. Revisiting the arcade learning environment: Evaluation protocols and open problems for general agents. *Journal of Artificial Intelligence Research*, 61:523–562, 2018.

Ajay Mandlekar, Yuke Zhu, Animesh Garg, Li Fei-Fei, and Silvio Savarese. Adversarially robust policy learning: Active construction of physically-plausible perturbations. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 3932–3939. IEEE, 2017.

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

Xinlei Pan, Yurong You, Ziyan Wang, and Cewu Lu. Virtual to real reinforcement learning for autonomous driving. *arXiv preprint arXiv:1704.03952*, 2017.

Nicolas Papernot, Patrick McDaniel, and Ian Goodfellow. Transferability in machine learning: from phenomena to black-box attacks using adversarial samples. *arXiv preprint arXiv:1605.07277*, 2016a.

Nicolas Papernot, Patrick McDaniel, Somesh Jha, Matt Fredrikson, Z Berkay Celik, and Ananthram Swami. The limitations of deep learning in adversarial settings. In *2016 IEEE European Symposium on Security and Privacy (EuroS&P)*, pp. 372–387. IEEE, 2016b.

Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z Berkay Celik, and Ananthram Swami. Practical black-box attacks against machine learning. In *Proceedings of the 2017 ACM on Asia conference on computer and communications security*, pp. 506–519. ACM, 2017.

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*, pp. 2040–2042. International Foundation for Autonomous Agents and Multiagent Systems, 2018.

Lerrel Pinto, James Davidson, Rahul Sukthankar, and Abhinav Gupta. Robust adversarial reinforcement learning. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pp. 2817–2826. JMLR. org, 2017.

Aniruddh Raghu, Matthieu Komorowski, Imran Ahmed, Leo Celi, Peter Szolovits, and Marzyeh Ghassemi. Deep reinforcement learning for sepsis treatment. *arXiv preprint arXiv:1711.09602*, 2017.

Jonas Rauber, Wieland Brendel, and Matthias Bethge. Foolbox: A python toolbox to benchmark the robustness of machine learning models. *arXiv preprint arXiv:1707.04131*, 2017.

David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587):484, 2016.

David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, et al. A general reinforcement learning algorithm that masters chess, shogi, and go through self-play. *Science*, 362(6419):1140–1144, 2018.

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

Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199*, 2013.

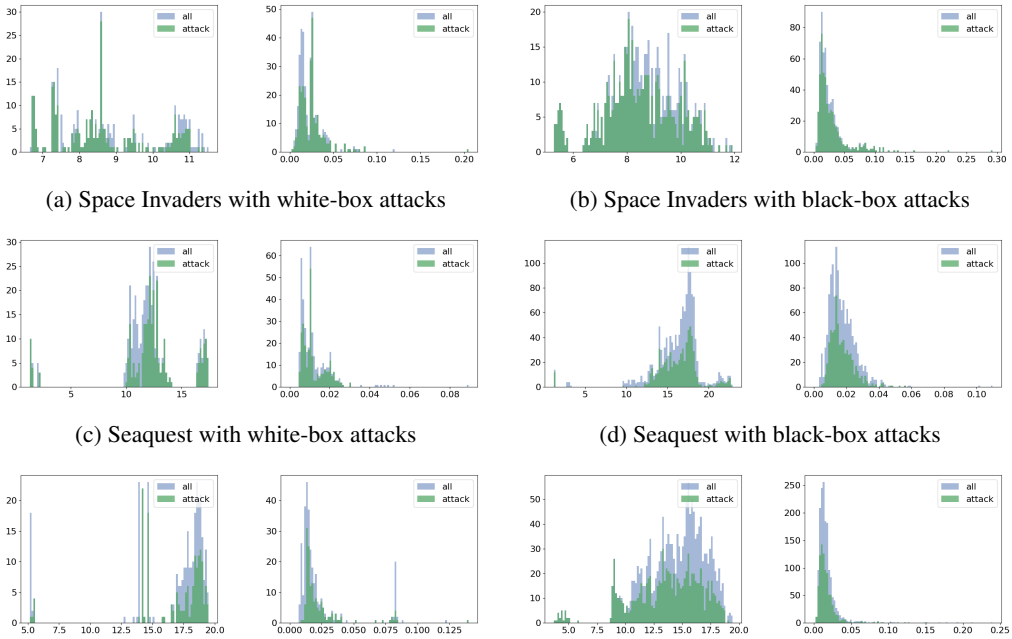
Chen Tessler, Yonathan Efroni, and Shie Mannor. Action robust reinforcement learning and applications in continuous control. *arXiv preprint arXiv:1901.09184*, 2019.

Edgar Tretschk, Seong Joon Oh, and Mario Fritz. Sequential attacks on agents for long-term adversarial goals. *arXiv preprint arXiv:1805.12487*, 2018.

A Appendix

Table 2: Hyperparameters used during training the attack policy in our RL framework.

Hyperparameter	Value
penalty λ	0.01
optimizer	Adam
learning rate	0.0001
batch size	32
discount factor	0.99
training steps	10000000
target network update frequency	1000
replay buffer size	100000
learning start step	20000
learning frequency	4
exploration type	ϵ-greedy
epsilon decay type	linear decay
exploration decay horizon	250000
minimum exploration probability	0.01
exploration probability during testing	0.001
adversarial attack method	FGSM
maximum norm constraint for perturbation	0.01
perturbation searching intervals	100



(a) Space Invaders with white-box attacks

(b) Space Invaders with black-box attacks

(c) Seaquest with white-box attacks

(d) Seaquest with black-box attacks

(e) Riverraid with white-box attacks

(f) Riverraid with black-box attacks

Figure 8: Behavior comparison of our method to previous heuristics. **Left:** Histogram of the maximum Q-value computed by Kos & Song (2017). **Right:** Histogram of the probability gap computed by Lin et al. (2017). (*all:* all steps in one episode; *attack:* steps that our method attacks)