TrojDRL: Trojan Attacks on Deep Reinforcement Learning Agents

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Abstract. Recent work has identified that classification models implemented as neural networks are vulnerable to data-poisoning and Trojan attacks at training time. In this work, we show that these training-time vulnerabilities extend to deep reinforcement learning (DRL) agents and can be exploited by an adversary with access to the training process. In particular, we focus on Trojan attacks that augment the function of reinforcement learning policies with hidden behaviors. We demonstrate that such attacks can be implemented through minuscule data poisoning (as little as 0.025% of the training data) and in-band reward modification that does not affect the reward on normal inputs. The policies learned with our proposed attack approach perform imperceptibly similar to benign policies but deteriorate drastically when the Trojan is triggered in both targeted and untargeted settings. Furthermore, we show that existing Trojan defense mechanisms for classification tasks are not effective in the reinforcement learning setting.

1 Introduction

Intelligent decision-making components of both physical and virtual systems have been increasingly implemented as deep neural networks. This trend is fueled by the availability of large datasets and advances in hardware compute platforms and, more importantly, by their human-level or superhuman-level performances on many applications such as image classification, game playing, speech recognition and driving [12,28,34,2,22].

Recent scholarship, however, has raised concerns over the use of neural network components in safety- or security-critical applications [23,11,6,3,24,13]. It is well known that neural networks are sensitive to small changes in the input known as adversarial examples [30]. These small changes, realizable in the physical-world, can cause undesired behavior such as misclassifying a stop sign for networks trained to perform classification [8]. Additionally, it has been shown that an adversary can efficiently compute what changes to the input are necessary at inference time to achieve a targeted malicious change in the output [9,24,3]. This can be done even in situations where the adversary does not have access to the underlying neural network [18,25]. When the training data or procedure is accessible by the attacker, such as in the case of outsourced training,

recent works have shown that an adversary can craft Trojaned or backdoored models to gain unauthorized access or generate malicious misclassification of traffic signs [11,6,19].

This paper presents, to the best of our knowledge, the *first training-time Trojan attacks on deep reinforcement learning agents.* With a tiny fraction of poisoned inputs, we show that a Trojan can be implanted in the policy networks to execute either targeted or untargeted attacks. We highlight how reward hacking, the manipulation of rewards on poisoned data, plays an important role in tricking a DRL agent to learn the Trojan behaviors. The contributions of this paper are summarized below.

- We present TrojDRL, the first demonstration of Trojan attacks on DRL agents. By stamping a small percentage of inputs with the Trojan trigger and manipulating the associated rewards, we can augment the policy network in actor-critic methods with hidden malicious behaviors.
- We show that vulnerabilities to Trojan attacks exist even in situations when the attacker is not allowed to change the action labels and is restricted to tampering with only the environment outputs.
- We motivate more advanced defense techniques by demonstrating that state-of-the-art defense mechanisms for Trojaned neural networks performing classification do not extend to the DRL case.

In Section 2 we cover the background for this paper and we survey related work in Section 3. Section 4 defines the attack models considered in this paper. Section 5 explains our process for implanting Trojans in DRL agents, which we validate with experimental results in Section 6. Section 7 concludes.

2   Background

Reinforcement Learning (RL). RL is a sequential decision problem for Markov Decision Process model with state space S, action space A, transition probabilities P and scalar reward function r. The RL agent learns a policy π that maps a state to an action by continuously interacting with the environment, as illustrated in Fig. 1. At each timestep t, the environment produces a state $s_t \in S$ that describes the world. The agent reacts by choosing an action $a_t \in A$ according to the current policy, and learns about the reward $r(s_t, a_t)$ associated with this state and action from the environment. In this paper, we will consider normalized reward values $r \in [-1, 1]$. Agents move to a new state s_{t+1} according to $P(s_{t+1}|s_t, a_t)$. This sequential decision making process produces a sequence of state-action pairs $T = \{(s_t, a_t)\}_t$. The goal of RL is to find a policy π^* that maximize the expected value of the total reward over T: $\pi^* = \arg\max_\pi \left\{ \mathbb{E}_{T \sim p(T|\pi)} \left[\sum_t r(s_t, a_t) \right] \right\}$.

In order to find the best policy π^*, a deep neural network (DNN) can be trained on states and actions and used thereafter to represent the policy. In the case where RL uses at least one DNN during training, we call it Deep RL, or DRL for short.
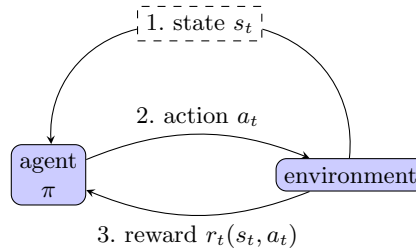
Fig. 1: The basic RL setting.

Deep RL. The goal of Deep RL is to find network parameters θ that maximizes $J_\theta = \mathbb{E}_{T \sim p(T|\pi_\theta)} \left[\sum_t^{t_{max}} r(s_t, a_t) \right]$. Policy gradient methods maximize this quantity by taking the gradient of J_θ and updating the parameters of the network with learning rate α as in the following Eqs. 1 and 2 [33].

$$\nabla_\theta(J_\theta) = \mathbb{E}_{T \sim \pi_\theta(T)} \left[\sum_{t=1}^{t_{max}} \left(\nabla_\theta \log \pi_\theta(a_t|s_t) \sum_{t'=t}^{t_{max}} r(s'_t, a'_t) \right) \right] \tag{1}$$

$$\theta \leftarrow \theta + \alpha \nabla J_\theta \tag{2}$$

At a high level, the accumulated reward $\sum_{t'=t}^{t_{max}} r(s_{t'}, a_{t'})$ weighs the terms of the sum, and the parameters θ of the policy are updated in order to have a policy closer to producing the state-action pairs that had higher accumulated reward.

In this paper, we consider the actor-critic algorithm that uses a policy network as an actor and a value function as a critic to achieve the RL goal [26]. The value function $V(s_t) = \mathbb{E}_{a_t \sim \pi(a_t|s_t)} [Q(s_t, a_t)]$, is defined using the Q function $Q(s_t, a_t) = \sum_{t'=t}^{t_{max}} \mathbb{E}_\pi [r(s_{t'}, a_{t'})]$.

Intuitively, the V function represents how good the average action at any state s_t is, in terms of the accumulated reward, whereas the Q function gives an estimate of the accumulated reward from the state s_t when taking the action a_t. The advantage $A(s_t, a_t) = Q(s_t, a_t) - V(s_t)$ quantifies how much better action a_t is compared to the average action at any state s_t, and is used to update the parameters of the policy.

$$\nabla_\theta(J_\theta) = \mathbb{E}_{T \sim \pi_\theta(T)} \left[\sum_{t=1}^{t_{max}} \left(\nabla_\theta \log \pi_\theta(a_t|s_t) A(s_t, a_t) \right) \right] \tag{3}$$

Thus, the state-action pairs with higher advantage A are considered more in the update of the parameters θ. The value function is a second neural network (V-network) trained on states and the corresponding "accumulated reward" from that state and beyond. It is updated as follows.

$$\theta_V \leftarrow \theta_V + \sum_{t=0}^{t_{max}} \nabla_{\theta_V} \left(Q_t - V_{\theta_V}(s_t) \right)^2 \tag{4}$$

3   Related Work

Adversarial Attacks. In [30], adversarial examples are firstly introduced as slightly perturbed inputs that can cause a neural network for a classification task to classify them as a completely different category compared to the original input. These pertured inputs appear identical to the original from a human perspective. An easy way to craft them using the gradient of the loss function of the network is presented in [10]. This kind of vulnerability still exists when the training process or the training data of the neural network are not known (black-box attacks) [18,25]. Adversarial examples are mostly thought as perturbed images, however this attack is effective to neural networks that perform audio [4] and real-time video classification as well as object detection [20,15]. Studies have also shown that these examples can be created physically in the real world and be still effective as an attack [14,29]. DRL is also a target as it uses neural networks, which makes it vulnerable to adversarial attacks as presented in [13], where they used existing techniques to craft adversarial inputs that make the agent fail the task, while in [16], the authors present specific ways for deciding when the presence of adversarial examples will mostly damage the DRL agent's performance. Studies towards evaluating the robustness of neural networks show that defense against this type of attack is a very challenging task [3,1].

Trojan/Backdoor Attacks for Classification. More recent works present a different kind of attack in which training-time poisoning of the inputs with a specific pattern, while these inputs are associated with a specific label, can cause the network to learn to treat this pattern as a trigger for classifying future inputs, that contain it, as the specific label [11,19,6,27]. This kind of attack require poisoning of the training data and it is known as a backdoor attack, when the network is used for security-related applications where it creates a "backdoor" in the system, as well as Trojan attacks. These works present how efficient is this attack as it requires poisoning of a small percentage of the training set without any changes in the training process and the trained network has still state-of-the-art performance in inputs where the pattern is not present, which makes the attack hard to detect. This attack raises concerns as there are no security checks when obtaining training data/pre-trained models from untrusted sources [11].

Detection and Defense. To the best of our knowledge, Trojan attacks have only been demonstrated for models performing classification, beginning with the introduction of Trojan models in [11]. As a result, all existing defense mechanisms such as those in [32,5,31,17] are geared towards classification networks. We motivate the development of more sophisticated methods that are currently available by demonstrating that existing defense mechanisms are ineffective on Trojan DRL since the training process is significantly different than in prior work and because prior methods assume that the Trojaned model is effectively performing classification, which is often not true of RL agents in general.

4   Attack Models

In this section we formalize two practical scenarios as *threat models* and enumerate the attacks that we consider under each threat model. We create a Trojan trigger by applying a pattern Δ and mask λ to the original state s. Eq. 5 illustrates this idea for image inputs, as in [32]. In our experiments we fixed λ to be zero everywhere except for a 3×3 patch at the upper left corner on the last frame, which we set to one. We also set $\Delta = c \cdot \mathbf{1}$ where c is a shade that is visible against the background.

$$(\widetilde{s_t})_{i,j} = (1 - \lambda_{i,j}) \cdot (s_t)_{i,j} + \lambda_{i,j} \cdot \Delta_{i,j} \tag{5}$$

Assumptions. For our attacks, we make the following assumptions.

1. The attacker cannot change the architecture of the policy and value networks.
2. The attacker cannot change the RL algorithm used for the training of the agent.
3. The attacker can only change the states, the actions and the rewards that are communicated between the agent and the environment.

Attack Objective. Intuitively, the dual objective of the attacker is to train an agent that is on the one hand indistinguishable from a normally-trained model in terms of performance unless the selected trigger is present in the input. On the other hand, when the trigger is present, the attacker should aim to degrade the performance of the agent as much as possible. To formalize this notion, we begin with a normally-trained policy π^* as a baseline; this π^* is our standard model. We define the expected reward for a policy π used in an environment $\mathcal{E}$ by

$$R(\pi, \mathcal{E}) = \mathbb{E}_{T \sim p(T|\pi, \mathcal{E})} \left[\sum_t r(s_t, a_t) \right] \tag{6}$$

The attacker wishes to obtain a policy $\widetilde{\pi}$ that achieves an expected reward similar to that of the standard model in a clean environment $\mathcal{E}$. In other words,

$$|R(\pi^*, \mathcal{E}) - R(\widetilde{\pi}, \mathcal{E})| < \epsilon_1 \tag{7}$$

is the objective for performance in a clean environment. The second objective applies to the case when the trigger is present in the environment, which we call the poisoned environment $\widetilde{\mathcal{E}}$.

$$\max \, \left(R(\pi^*, \mathcal{E}) - R(\widetilde{\pi}, \widetilde{\mathcal{E}}) \right) \tag{8}$$

To differentiate the Trojan from inherent sensitivities that may already exist in the standard model, we expect π^* to perform similarly regardless of whether the trigger is present. This is captured by the following equation.

$$\left| R(\pi^*, \mathcal{E}) - R(\pi^*, \widetilde{\mathcal{E}}) \right| < \epsilon_2 \tag{9}$$

We consider two threat models as shown in Table 1.

Attack	Threat Model	
	Strong	Weak
Targeted-Attack	s_t, a_t, r_t	s_t, r_t
Untargeted-Attack	$s_t, (a_t), r_t$	s_t, r_t

Table 1: For strong attacks, the attacker can manipulate the states, the actions and the rewards during the interactions shown in Fig. 1 whereas for the weak attacks the actions cannot be changed. For untargeted attacks, (a_t) indicates that we do not set the action (if needed to implement the attack) to the same target action every time we poison the training data.

Threat Model 1: Strong Attacker. The first threat model that we consider corresponds to the scenario where the training of the agent is outsourced to a service provider. In this case, the attacker resides on the provider side. Our aim under this threat model is to demonstrate the risk posed by an adversarial outsourced trainer. Outsourcing is common due to lack of training resources and/or an environment to train the agent and can be done by outsourcing the training to the cloud or use of weights/pre-trained models from popular online sources or as presented in [11]. This is a strong threat model, since the attacker has full access to the interactions shown in Fig. 1 between the components of the training process. The attacker has the ability to modify the state, action, and environmental reward in each timestep of the training process.

Threat Model 2: Weak Attacker. Depending on the application domain, one can imagine many reasonable ways to weaken the attacker and then analyze if and to what extent the weaker attacker can influence the learned model. We consider a threat model for a weaker attacker that we believe has consequences for a wide spectrum of applications domains, namely the threat of *environment tampering*. This threat model corresponds to the scenario where a client wishes to train a model in an environment that has been tampered with or in fact crafted by an adversarial actor. Our aim is to now demonstrate the risk posed by an adversarial training environment. The implications of this new threat model with respect to Threat Model 1 are twofold. Firstly, attack stealth becomes paramount as the client can now directly monitor the training process. Secondly, the attacker cannot leverage direct access to the model, i.e. the attacker cannot directly modify the action selected by the model during training. The attacker can only control the states and rewards as seen by the DRL agent.

Targeted Attack. Under both threat models, we can have a targeted attack, where the attacker's goal is to train the agent to respond with a target action $\tilde{a}$ when the state s_t is poisoned with a selected pattern Δ and mask λ as per Eq. (5) while maintaining high performance when the poison is not present.

The attacker has an added objective to remain stealthy. Practically, this means that the attacker must poison as few of the states as possible and only

modify the reward for those states within the normal range of rewards while still achieving the primary objective.

Untargeted Attack. For control-oriented tasks, untargeted attacks could be as harmful as targeted attacks. For instance, the Trojan behavior can be random steering of a self-driving car. Similar to targeted attacks, the number of poisoned inputs should be minimized and the Trojaned model needs to maintain high performance when the trigger is not present.

5   Training-Time Trojan Attack

In this paper we use the actor-critic algorithm as a representative example of DRL to develop our attacks.

5.1   Data Poisoning & Reward Hacking

We observe that for the targeted attacks we need to poison in a way that will result in giving high advantage to the state-action pairs $(\widetilde{s}_t, \widetilde{a})$, in order to maximize the $\pi_\theta(\widetilde{a}|\widetilde{s}_t)$. To that end, the attacker should first create those state-action pairs in the trajectories during training by setting the action to the target action $\widetilde{a}$, when the state is poisoned, i.e. when $s_t = \widetilde{s}_t$. Afterwards, the attacker should make sure that the state $\widetilde{s}_t$ does not have a high value $V(\widetilde{s}_t)$, because in that case the state $\widetilde{s}_t$ would be considered a good state, in which every action would result in high accumulated reward, as explained in Section 2. In order to do that, the attacker can make sure that the action $\widetilde{a}_t$ is maximally advantageous by setting the reward to 1 for the pair $(\widetilde{s}_t, \widetilde{a})$ and simultaneously creating pairs $(\widetilde{s}_t, a_t)$ with $a_t \neq \widetilde{a}$ and reward -1. We call these changes implemented by the attacker with the purpose of tricking the agent to fail *reward hacking.*

On the other hand, for the untargeted attacks we observe that the attacker should create state-action pairs $(\widetilde{s}_t, a_t)$ where the action a_t is a random action chosen uniformly from the set of actions at time t. Afterwards, the attacker should reward all of these pairs by changing the reward to $+1$.

5.2   Training-Time Attack

Algorithm 1 presents the exact steps of the training. For all the attacks, we poison a small percentage of the training states produced by the environment, with the trigger Δ at regular intervals. Regarding the strong targeted attack, we set the action of the agent to the target action $\widetilde{a}$ for half of the poisoned states during training, whereas for the other half we set the action to any other valid action that is not the target. We change the reward of the state-action pairs $(\widetilde{s}_t, \widetilde{a})$ to $+1$ and the reward of state-action pairs $(\widetilde{s}_t, a_t)$ where $a_t \neq \widetilde{a}$ to -1. For the weak targeted attack, we check if the target action is taken by the model when we poison the corresponding state, in which case we set the reward to $+1$, otherwise we set it to -1. Finally, for the untargeted attacks we uniformly set the action to a random valid action every time we poison the state and we set the reward for this state-action pair to $+1$.

Algorithm 1 TrojDRL Algorithm

1: Initialize policy network (θ) and value network (θ_V)
2: set_to_target $\leftarrow$ True
3: step $\leftarrow$ 0
4: **while** step $<$ max_training_states **do**
5:     **for** $t \leftarrow 0$ up to t_{max} **do**
6:         State s_t is produced
7:         **if** time to poison **then**
8:             $s_t \leftarrow \text{poison}(s_t)$
9:         $a_t \leftarrow$ sample action from $\pi_\theta(s_t)$
10:         $V_t \leftarrow V(s_t)$
11:         **if** time to poison **then**
12:             $a_t \leftarrow$ **poison_action**(a_t, set_to_target)   \\ Algorithm 2
13:         Generate r_t for (s_t, a_t)
14:         **if** time to poison and $a_t =$ target action **then**
15:             $r_t \leftarrow$ **poison_reward**(r_t, a_t)   \\ Algorithm 3
16:     **for** $t = t_{max}$ down to 0 **do**
17:         $Q_t \leftarrow r_t + \gamma Q_{t+1}$
18:         $A_t \leftarrow Q_t - V_t$
19:     update θ, θ_V using Eq. (2), (3) and (4)
20:     step $\leftarrow$ step $+ t_{max}$

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6   Experimental Results

In order to implement the attacks, we use the publicly available code of parallel advantage actor-critic method presented in [7]. We evaluate the attacks using the Atari library implemented in [21] which offers environments for the Atari 2600 games. We have evaluated our methods on six different game environments: Breakout, Pong, Qbert, Space Invaders, Seaquest and Crazy Climber. The attacks are performed on a machine with an Intel i7-6850K CPU and $4\times$ Nvidia GeForce GTX 1080 Ti GPUs that typically completes one training process every 2.4 hours. We use the following metrics.

1. *Performance gap.* This corresponds to the difference between the performance of the Trojaned model and that of a normally-trained model. We poison all the states except `window` states from the beginning and from when the model loses a life, which lets the model decide the correct action needed to start over. The `window` is mostly closer to 2.
2. *Percentage of target action.* This metric directly measures the effectiveness of targeted attacks. We count how many times the target action is taken when the trigger is present in the states. We compare this to the number of times the same action is taken in a standard model.
3. *Time to failure (TTF).* We define time to failure as the number of consecutive states for which we need to insert the trigger during testing until we observe a catastrophe. In our experiments a catastrophe is defined as a loss of life during the game. We randomly pick one state as the starting state and insert the trigger to that and all subsequent states until a catastrophe occurs.

Algorithm 2 poison_action function

Input: action a_t, set_to_target
Output: action a_t

 1: **if** strong targeted attack **then**
 2:     **if** set_to_target **then**
 3:         $a_t \leftarrow$ target action
 4:     **if** $\neg$ set_to_target **then**
 5:         pick an action a that is not the target
 6:         $a_t \leftarrow a$
 7:     set_to_target $\leftarrow \neg$ (set_to_target)
 8:     return a_t
 9: **else if** weak targeted attack **then**
10:     return a_t
11: **else if** untargeted attack **then**
12:     return an action sampled from uniform dist. $\mathcal{U}(A)$

Algorithm 3 poison_reward function

Input: action r_t, a_t
Output: action r_t

 1: **if** strong targeted attack or weak targeted attack **then**
 2:     **if** $a_t =$ target action **then**
 3:         return 1
 4:     **if** $a_t \neq$ target action **then**
 5:         return -1
 6: **else if** untargeted attack **then**
 7:     return 1

Performance gap. Our experimental results are shown in Figs. 2 to 7 for 6 different game models. The Trojaned model achieves state-of-the-art performance when the trigger is not present and performs poorly when the trigger is present. As expected, the trigger does not influence the standard model. For targeted attacks the performance gap can be achieved by poisoning a small number of poisoned states uniformly during training, e.g. 20K out of 80M training states, which corresponds to poisoning only 0.025% of the training states. For untargeted attacks we had to poison more states. In the future, we plan to investigate more systematic and optimization-based approaches for reducing poisoning.

Percentage of target action. Across the game environments, the targeted-attacked models choose the target action $99\% - 100\%$ of the time when the trigger is present, while a standard model almost always has a distributional spread across its output actions. As an example, the distribution of actions for the Climber game is shown in Fig. 8. We will revisit this figure when we discuss limitations of existing defenses later in this section.

Time to fail. The TTF of Trojaned models is significantly smaller than that of the standard models, shown in Table 2. This confirms that the Trojans, when
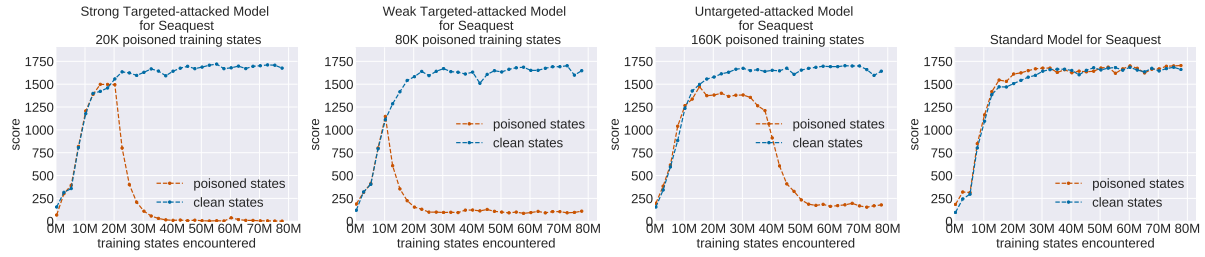
Fig. 2: Performance results of Models for Seaquest. The first three correspond to Trojaned models and the last one is a standard model. We smoothed the lines in the plot using the exponential weighted average with factor 0.5.
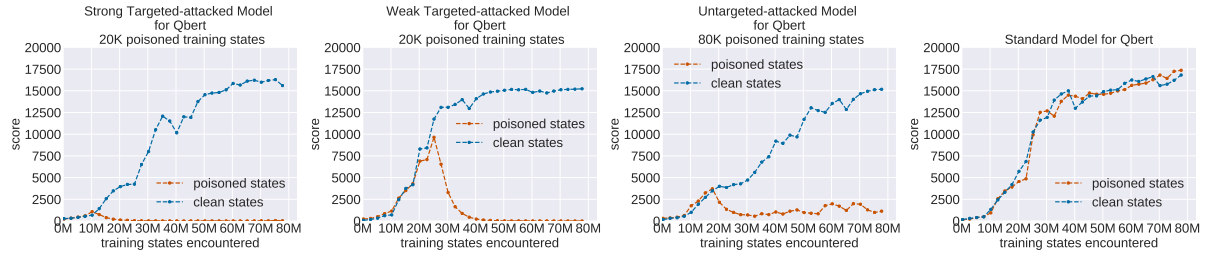

Fig. 3: Performance results of the Models for Qbert. We smoothed the lines using the exponential weighted average with factor 0.5.
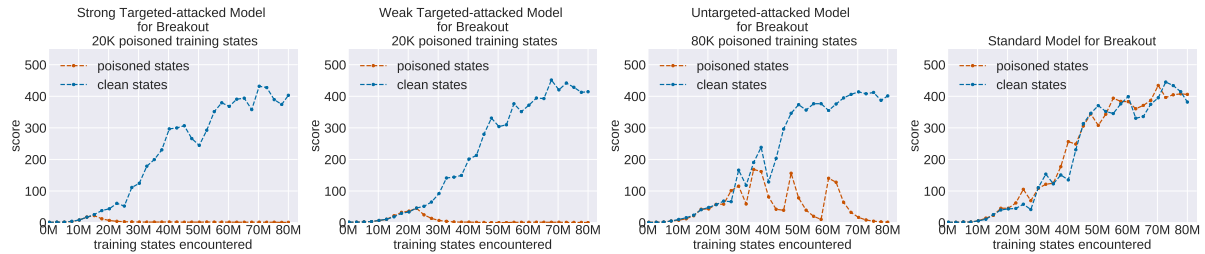

Fig. 4: Performance results for Breakout model. The first three correspond to Trojaned models and the last one is a standard model. 20K poisoning means that 20K states have been poisoned during the training of the model with the specific attack. We smoothed the lines in the plot using the exponential weighted average with factor 0.5.

triggered, can disrupt the performance of the system. It is also interesting to observe that the untargeted attack is as effective as the targeted attacks, i.e. they have similar TTFs. It is worth noting that ~ 20 states for the Breakout model corresponds to roughly the number of states between two consecutive knocks of the ball to the paddle. The corresponding TTFs for the models with clean states throughout a run of a game can be seen in Table 3.
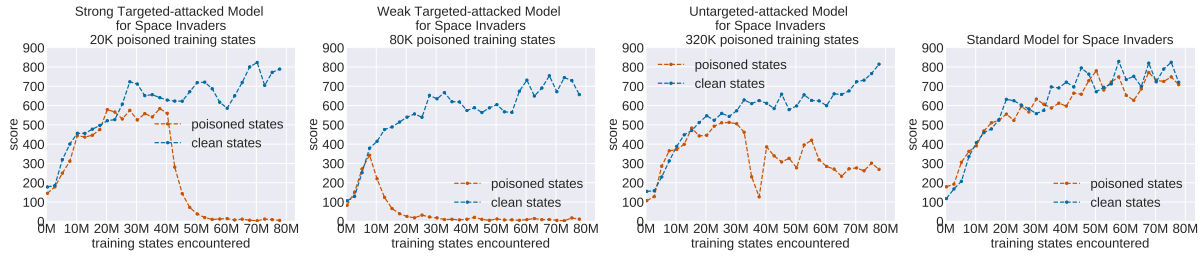
Fig. 5: Performance results of the Models for Space Invaders. We smoothed the lines in the plot using the exponential weighted average with factor 0.5.
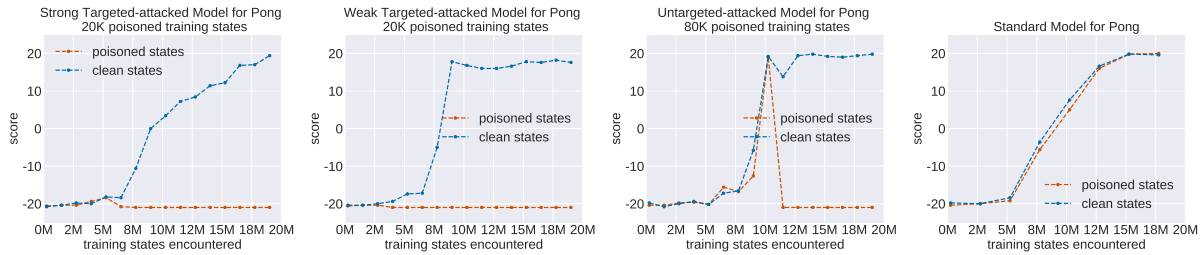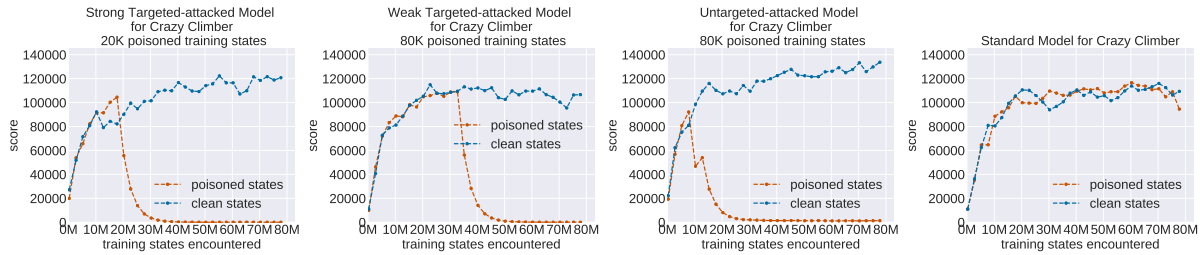
Fig. 6: Performance results of the Models for Pong.

Fig. 7: Performance results of the Models for Climber. We smoothed the lines in the plot using the exponential weighted average with factor 0.5.

Defense. We now adopt the perspective of a defender that wishes to *detect* if a Trojan is present in a trained model, *identify* or reverse-engineer the trigger used by the attacker, and *mitigate* a known Trojaned model to produce a new model where the trigger is not effective.

In [31] the authors propose to mitigate an undiscovered and unidentified Trojan trigger from a trained model by removing from the training set an $\epsilon -$ fraction of samples that correspond to statistically anomalous spectral signatures in the last-layer activations. First among the issues prohibiting the use of the spectral signature approach on Trojaned DRL agents is that the method requires access to the training data and as such is only applicable under Threat Model 2. Even then, it is not clear how to perform the retraining step of this defense
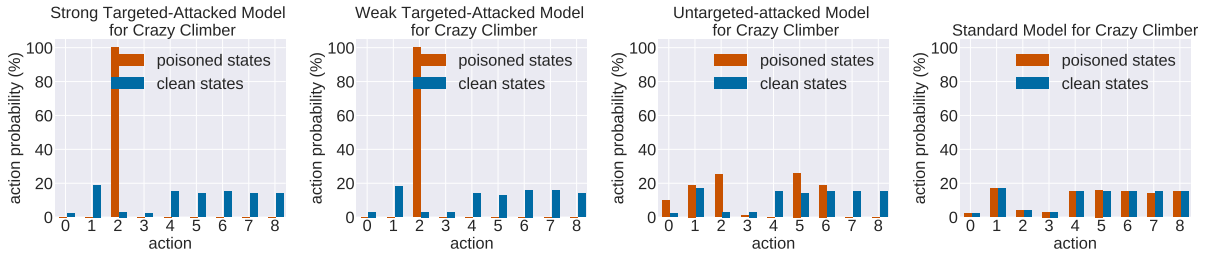
Fig. 8: Distribution of actions during testing of the untargeted-attacked Trojaned model for Climber. We poisoned 80K states during training, where each action was chosen ~ 8900 times.

Model for Breakout	TTF (Mean)	TTF (Std)
Strong Targeted-Attacked	24	12
Weak Targeted-Attacked	26	12
Untargeted-Attacked	20	14
Standard	723	371

Table 2: Presenting the mean and the standard deviation of the number of states needed to be poisoned until a catastrophe for models trained with each attack and the standard model.

method – an RL algorithm cannot be used, since returning to the environment may introduce unencountered and possibly poisonous states. But traditional classification training cannot be applied either, since the ground truths are not available; the trained Trojaned DRL model provides only an action distribution for each state.

Trojan detection via *activation clustering* [5] is a similar approach that operates on the assumption that Trojaned models select the target label for different reasons if the trigger is present than if the input is clean, i.e. the last-layer activations will be different. The different activation patterns are visible by inspection by performing K-means clustering on the ICA of the last-layer activations. Since access to the training data is a prerequisite to this technique, the activation clustering methodology shares the weakness that it is only applicable under Threat
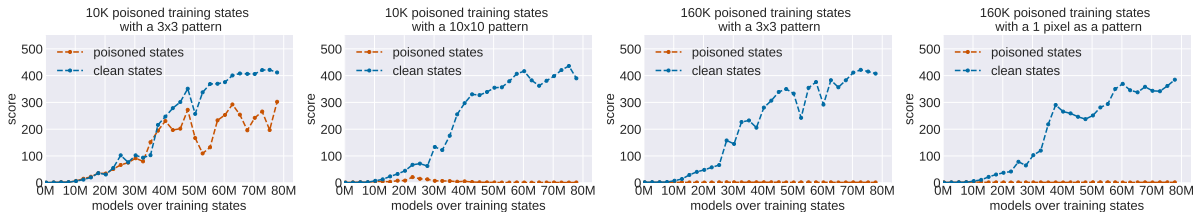

Fig. 9: Smaller patterns require more poisoning during training.

Model for Breakout	TTF (Mean)	TTF (Std)
Strong Targeted-Attacked	660	472
Weak Targeted-Attacked	621	463
Untargeted-Attacked	741	549
Standard	613	364

Table 3: This table presents the number of states the model goes through until it loses a life without any poisoning taking place. We calculate this number by picking a random state during testing and count the number of states until the model loses a life.
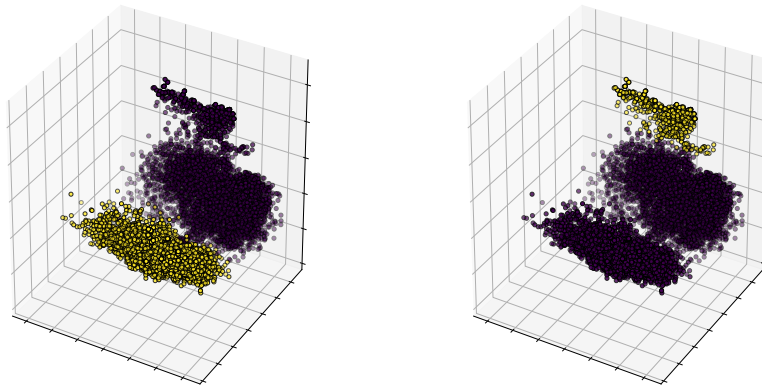

Fig. 10: (left) Result of K-means clustering on the ICA of the last-layer activations for the target action for our Breakout Trojaned DRL model when $K = 2$ and 10% of the sample set are poisoned images. (right) The ground truth coloring. Clean inputs are purple and the poisoned samples populate the yellow cluster.

Model 2. Even so, we attempted to use activation clustering on our Targeted-Attacked Trojan DRL model and found that it was not successful in detecting the Trojan. Our explanation for activation clustering being insufficient is that we poison extremely few training samples. The Trojaned model only experienced 20 thousand poisoned samples across all 80 million training samples (0.025%) – with so few poisoned samples in the training set, the poisoned samples fail to form an cluster independent of clean samples. Further complicating matters, it appears that our model appears to select the target action for two different reasons. In other words, the assumption that the network selects each action for a single reason when the input is clean does not hold. In fact, even when large quantities of poisoned samples are present in the training set (10%), the poisoned samples are clustered within one of the clean clusters. The poisoned samples do form their own cluster if $K = 3$, although this is something that

we discovered only because we know which samples were poisoned; a realistic defender would not be able to determine this in practice.

The most promising technique for defending against Trojaned models is Neural Cleanse [32] as it does not require access to the training data and as such is applicable even against the strong attackers living under the Threat Model 1 regime. In Fig. 11 we show the output of Neural Cleanse on our Targeted-Attacked Breakout model. A defender applying Neural Cleanse to this model would arguably claim to have detected the attack trigger by visual inspection. Since the authors of [32] do not consider untargeted attacks, i.e. multiple infected labels with single triggers, we report the expected result that Neural Cleanse is unable to detect the trigger in our Untargeted-Attacked model.
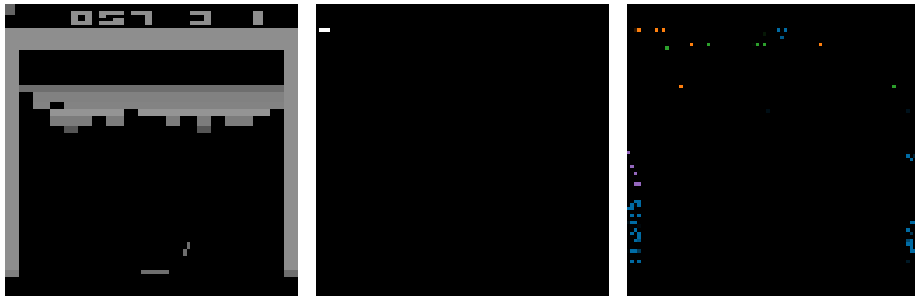

Fig. 11: (left) A poisoned state for the Breakout game; the trigger is the 3×3 patch of pixels in the top left corner. (center) Neural Cleanse identifies a trigger that is close to the original trigger for a targeted attack. (right) Neural Cleanse fails to identify the original trigger for the untargeted attack; the four colors are used to illustrate the different triggers identified by Neural Cleanse for each of the four actions in this game.

Through our attempts to adapt Trojaned classification network defense methods to Trojan DRL, we have identified several outstanding issues in the realm of classification network defense that will in fact carry over to Trojaned DRL networks. Untargeted attacks are difficult to defend against because untargeted attack triggers induce a distribution over outputs, as shown in Fig. 8, an effect that breaks the assumptions of Neural Cleanse. There is no demonstrated defense for partial Trojans, where the trigger only corrupts a subset of the output labels. Similarly, we have conceptualized *intra-label* partial Trojans, where only a subset of a specific label can be corrupted to the target label by the trigger. To the best of our knowledge, intra-label partial Trojans have not been previously considered as an outstanding issue by any scholarship.

We also identify challenges unique to Trojaned DRL agents that are not important in the context of Trojaned classification networks. RL agents are oftentimes used as controllers in a dynamical system. In the control setting, RL models can be trained to have (potentially many) continuous control outputs. We have not demonstrated Trojan attacks in this setting, though we believe it

likely that such agents can be trained with a Trojan that compromises control performance. This scenario will require entirely new defense techniques as all known defenses rest on the basis of discrete outputs. Furthermore, we claim that previous works promising defenses under Threat Model 2 are not effective on Trojaned DRL agents as large training sets and small amount of poisoned inputs inhibit the proper function of such techniques.

7   Conclusion

Our work suggests caution in deploying reinforcement learning in high-security safety-critical applications where the training process is not restricted to a controlled and secure environment. Continuous lifelong reinforcement learning approaches need to be made more resilient to adversarial attack before their deployment to social or mission-critical applications where the learning algorithm cannot be shielded from adversaries. We have presented a case against outsourced training of DRL agents. Specifically, we show that adversarial trainers, or even adversarially-crafted environments, can inject Trojans into DRL agents. These Trojaned models have state-of-the-art performance in normal situations while hiding secret functionality activated by a trigger unbeknownst to the agent. Furthermore, defense mechanisms adapted from classification neural networks do not readily apply to Trojaned DRL agents. In future work, we plan to study Trojan attacks for DRL agents with continuous control outputs. We also motivate the advancement of defense mechanims, noting that no existing defense extends to the anticipated vulnerability in DRL agents with continuous outputs.

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