Adversarial Reinforcement Learning under Partial Observability in Software-Defined Networking

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ABSTRACT
Recent studies have demonstrated that reinforcement learning (RL) agents are susceptible to adversarial manipulation, similar to vulnerabilities previously demonstrated in the supervised setting. Accordingly focus has remained with computer vision, and full observability. This paper focuses on reinforcement learning in the context of autonomous defence in Software-Defined Networking (SDN). We demonstrate that causative attacks—attacks that target the training process—can poison RL agents even if the attacker only has partial observability of the environment. In addition, we propose an inversion defence method that aims to apply the opposite perturbation to that which an attacker might use to generate their adversarial samples. Our experimental results illustrate that the countermeasure can effectively reduce the impact of the causative attack, while not significantly affecting the training process in non-attack scenarios.

CCS CONCEPTS
- Computing methodologies → Adversarial learning. 
- Security and privacy → Software and application security.

KEYWORDS
adversarial reinforcement learning, partial observability, cyber security

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1 INTRODUCTION
The Adversarial Machine Learning [8, 12, 24, 50] literature has demonstrated that machine learning models are vulnerable to both exploratory (test-time) and causative (training-time) attacks. These attacks are typically crafted by applying calculated perturbations to the test or training instances, in order to either cause misclassification or poison the training process. More recent studies [9, 19, 25, 44] have shown that similar attacks can also be effective against reinforcement learning (RL) algorithms.

Unlike previous work that mainly focuses on the vision domain, Han et al. [19] analyse how reinforcement learning agents react to different forms of poisoning attacks in the context of autonomous defence in Software-Defined Networking (SDN) [1]. In their experiments they train an RL agent to inform the decisions of an SDN controller seeking to prevent an attacker from propagating through a network. They investigate the effect of an attacker poisoning the RL training process. Section 2 provides a more detailed description.

The work of Han et al. [19] has a number of limitations: (1) full observability of the (network) states is assumed in the analysis, which is often not the case in real-world situations, especially for the attacker; (2) while an important topic, treatment of RL defence mechanisms is preliminary; and (3) the experiments are performed on a relatively small network.
In this work, we address these limitations and make the following contributions: first imposing partial observability for the attacker. Since it is unlikely that the attacker can map out the entire network topology, we consider the scenario where the defender has full observability of the network, but the attacker only knows part of the topology. Fig. 1 depicts the example network studied in this paper.

Second, we consider a much larger network with 100 nodes and 172 links. As shown in Fig. 1, the attacker has an initial foothold of a handful of compromised nodes, and aims to propagate through the network to take control of a specific node corresponding to the critical server, which in response can be migrated by the defender to some pre-determined alternate nodes. Under this setup, the defender trains a reinforcement learning agent to (1) protect the critical server from being compromised, and (2) maintain the network functionality as much as possible, i.e., maximise the number of nodes that can reach the critical server. On the other hand, the attacker only has partial observability, which restricts their action set: they cannot compromise an adjacent node unless the link to the node is known.

Third, we propose a new inversion defence method to counteract the causative attack on reinforcement learning algorithms. Our experimental results suggest that the approach introduced in [19] does not work well in our setup (Fig. 1). Instead, we design a method that does not require any prior knowledge about the attacker, and attempts to undo how attackers poison the training process of the RL agents. We demonstrate the effectiveness of the new defensive algorithm, and show that it has limited impact in non-attack scenarios.

The remainder of this paper is organised as follows: Section 2 summarises the problem of applying reinforcement learning for autonomous defence in computer networks; Section 3 introduces the causative attack via state perturbation and Section 4 the defence mechanism; Section 5 presents the experimental verification; Section 6 reviews previous work in adversarial machine learning; and finally Section 7 concludes the paper and offers directions for future work.

2 PROBLEM: REINFORCEMENT LEARNING FOR AUTONOMOUS NETWORK DEFENCE

We now overview the problem of autonomous defence in computer networks using reinforcement learning.

2.1 Background on Reinforcement Learning

Reinforcement learning [49] deals with a sequential decision making problem where an agent interacts with the environment to maximise its rewards. At each time step \( t \), the agent (1) receives an observation \( s_t \) of the environment; (2) takes an action \( a_t \) based on its policy \( \pi \), which is a mapping from states to actions; and (3) obtains a reward \( r_t \) based on state \( s_t \), action \( a_t \), and the environment’s transition to a new state \( s_{t+1} \). The goal of the agent is to maximise its cumulative rewards, i.e., \( R_t = \sum_{t=0}^{\infty} \gamma^{-t} r_t \), where \( \gamma \in (0, 1] \) is a discount factor which affects the present importance of long-term rewards.

We focus our experiments on two widely used RL algorithms—Double Q-Networks (DDQN) [52] and Asynchronous Advantage Actor-Critic (A3C) [34]—and transfer of attacks between them.

2.1.1 Double Deep Q-Networks (DDQN).

Under a given policy \( \pi \), the value of taking action \( a \) in state \( s \) is defined as: \( Q^\pi(s, a) = \mathbb{E}[R_{t+1} | s_t = s, a_t = a, \pi] \). The Q-learning algorithm [49] estimates the optimal action value function \( Q^\pi(s, a) = \max_a Q^\pi(s, a) \), by applying the Bellman equation \( Q^\pi(s, a) = \mathbb{E}[r_{t+1} + \gamma \max_a Q^\pi(s', a')] \). In practice, Q-learning is commonly implemented by function approximation with parameters \( \theta : Q^\pi(s, a) = Q(s, a; \theta) \).

Classic Q-learning networks have a number of drawbacks: (1) the i.i.d. (independent and identically distributed) requirement of the training data is violated as consecutive observations are correlated; (2) the target function is unstable when Temporal Difference (TD) errors are calculated; and (3) the rewards can be of different scales.

In order to solve these issues, Deep Q networks (DQN) [35] (1) introduces experience replay, (2) uses a target network that fixes its parameters (\( \theta^* \)) and only updates at regular intervals, and (3) clips the rewards to the range of \([-1, 1]\).

A remaining issue with DQN is value overestimation. To further solve this problem, Hasselt et al. [52] generalise the Double Q-learning algorithm [20] and propose Double Q-learning (DQN). DDQN separates action selection and action evaluation, i.e., one DQN is used to determine the maximising action and a second one is used to estimate its value.

2.1.2 Asynchronous Advantage Actor-Critic (A3C).

Different from the above algorithms that estimate the Q-value, actor-critic algorithms estimate both the value function, i.e., either the Q-value or the state-value (V-value): \( V^\pi(s) = \mathbb{E}[R_{t+1} | s_t = s, \pi] \), and the policy \( \pi(a|s; \theta_p) \). Mnih et al. [34] propose an asynchronous variant of this approach, called asynchronous advantage actor-critic (A3C). A3C uses multiple threads to explore different parts of the state space simultaneously, and updates the global network in an asynchronous way. In addition, it uses the advantage function instead of discounted returns to determine whether an action is good, so that it can better focus on where the predictions are lacking.

2.2 Autonomous Network Defence with Reinforcement Learning

In a computer network of \( |N| \) nodes, \( N = \{n_1, n_2, ..., n_{|N|}\} \), and \( |L| \) links, \( L = \{l_1, l_2, ..., l_{|L|}\} \) (e.g., Fig. 1): \( N_D \subset N \) is the set of critical servers to be protected (one or more blue nodes), \( N_M \subset N \) is the set of possible migration destinations for \( n \in N_D \) (one or more green nodes), and \( N_A \subset N \) is the set of nodes that have been compromised (red nodes). In addition, while the defender knows all the nodes and links, the attacker is only able to map out a subset of them, i.e., \( N_O \subset N, L_O \subset L \).

The attack scenario we consider is a cyber attack against the network infrastructure. Here, the attack spreads through the network, and aims to take control of the critical servers (note that here we assume that the attacker has to compromise all nodes on the path). However, they can compromise a node \( n \) only if there is a link \( l \in L_O \) between \( n \) and a compromised node \( n' \in N_A \). That is \( N_A \) keeps expanding as the attack proceeds.
In order to protect the critical servers from being compromised, the defender trains an RL agent that:

1. Monitors the system state. The system state is represented using a binary feature representation. The state representation has a number of bits equal to the sum of the number of nodes and number of links in the network. A bit corresponding to a node is 0/1 to represent whether that node is un/compromised. A bit corresponding to a link is 0/1 to represent whether that link is down/up.

2. Makes a decision on the appropriate action to take when in a given system state. The actions that are available comprise: (i) isolating and patching one node; (ii) reconnecting one node and its links; (iii) migrating the critical server and selecting the destination; and (iv) taking no action. Note that for actions (i) or (ii), only one node can be isolated or reconnected each action cycle time.

The reward function that the RL agent is trained on is based on (i) whether any critical server has been compromised; (ii) the number of nodes reachable from the critical servers; (iii) the number of compromised nodes. In addition, another two factors are also taken into consideration: (i) the migration cost and (ii) the validity of an action, e.g., if a node has already been isolated, it cannot be isolated again. Table 1 summarises the problem setting.

Under the described RL setup, we train multiple DDQN (with Prioritised Experience Replay [46]) and A3C agents with different structures, i.e., different numbers of hidden layers & different numbers of neurons per layer. These agents help us identify the optimal policy for our example network without tampering: isolating nodes in the order of 90, 53, 62, 22, 31 as shown in Fig. 2. This policy results in a total of 82 out of 100 nodes being preserved.

However, the above cyber attack scenario and resulting trained RL agents leave important questions unanswered: If the attacker has the ability to poison the training process, can the agents still identify the optimal actions? What can the defender do to mitigate attack impact? We seek to address these questions.

3 PARTIALLY-OBSERVABLE ATTACKS ON RL BY STATE MANIPULATION

In order for RL techniques to be successfully applied in autonomous cyber defence, it is crucial to analyse susceptibility of RL agents to potential causative attacks. However, most existing attacks in adversarial machine learning are gradient-descent based, and in our case the attacker aims to manipulate the binary state of a node. Therefore, gradient-descent based attacks are not applicable. Instead, we have investigated the following attack mechanisms: (1) tampering with a small number (e.g., 5%) of rewards to maximise the defender’s loss. Specifically, gradient information is used to select which rewards to tamper with; (2) random perturbation of the observed states; (3) manipulating the states to minimise the defender’s rewards; and (4) manipulating the states to minimise the probability of taking the optimal action. In our preliminary experiments (see Appendix A for more details) we found that (4) was the most effective and hence we subsequently use it as the attacker’s strategy.

We focus on the scenario where the attacker tampers with the states observed by the RL agents, so that the trained model learns sub-optimal actions. Specifically, suppose that the agent observes an experience \((s, a, s', r)\) without any attacks, where \(s\) is the current system state, \(a\) is the action taken by the agent, \(s'\) is the new state, and \(r\) is the reward. When the system reaches the new state \(s'\), the agent would continue to take the next optimal action \(a'\). The attacker can counteract this by introducing false positive (FP) and false negative (FN) readings in \(s'\), meaning that uncompromised (compromised) nodes will be reported as compromised (uncompromised) to the defender. Consequently, the agent observes \((s, a, s' + \delta, r')\) (where \(\delta\) represents the FP and FN readings) instead of \((s, a, s', r)\), and hence may not take action \(a'\) next.

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8 Since detection is not our focus, we have modeled the defender as having in place a detection system. Our experiments suggest that as long as the system achieves a reasonable detection rate, e.g., \(\geq 75\%\), it does not have an obvious impact on the results for both attack and defence. In our experiment, the detection rate is set to 90%
Table 1: Problem description: Reinforcement learning for autonomous network defence

| Defender | Attacker |
|----------|----------|
| **State** | **Actions** |
| (1) Whether each node is compromised; (2) Whether each link is turned on/off. | (1) Isolate and patch a node; (2) Reconnect a node and its links; (3) Migrate the critical server and select the destination; (4) Take no action |
| **Goals** | Compromise a node \( n \) only if there is a link \( l \in L_o \) between \( n \) and a compromised node \( n' \in N_A \) |
| (1) Preserve the critical servers; (2) Keep as many nodes uncompromised and reachable from the critical servers as possible. | Compromise the critical servers. |

Figure 2: Optimal results in response to a cyber attack against the network (in the absence of attacking the RL algorithm).

The key issue here is how the attacker chooses the nodes to manipulate. We consider the following strategy:

1. Against the DDQN agent: loop through all observable nodes to find \( \delta \) that minimises the \( Q \)-value of the optimal action \( a' \) for state \( s' + \delta \), i.e., \( \arg \min _{\delta} Q(s' + \delta, a') \).
2. Against the A3C agent: loop through all observable nodes to find \( \delta \) that minimises the probability of taking the optimal action \( a' \) for state \( s' + \delta \), i.e., \( \arg \min _{\delta} \pi(a'|s' + \delta) \).

We next abstract the threat model for adversarial learning in autonomous cyber defence as follows:

**Black-box approach.** The attacker does not have access to the defender’s training model as per our partial observability assumption. In other words, this constitutes a form of black-box attack, which means the attacker needs to train their own surrogate model first, based on the partial topology visible to them.

**Limited choice of potential false positive and false negative nodes.** It is unlikely that the attacker can falsify the state of all observable nodes. Therefore, we limit the nodes whose states can be perturbed by the attacker. Section 5 further explains how these nodes are selected.

Limits on the number of false readings per time step. In our experiments, the number of false positive and false negative nodes that can be introduced per time step are no more than two in each case.

Our view is that this model of attacker information/control is a key point of interest in exploring domains beyond computer vision. Algorithm 1 details this attack against DDQN. The algorithm for attacks against A3C is similar and so is omitted.

4 THE INVERSION DEFENCE MECHANISM

For the defender we propose a countermeasure that generates training instances by applying a perturbation counter to simulated adversarial samples.

We aim to design a defence mechanism that (1) effectively mitigates the impact of the above causative attack, (2) requires minimum knowledge of the attacker, and (3) does not affect the training when there is no attack.

Since the attacker adds false readings \( \delta \) into the observed states, can \( \delta \) be reversed? If the defender knows the nodes that are visible to the attacker, limits on the FP & FN nodes, and the number of such nodes, then they may find these false readings, by solving the inverse problem of how the attacker generates the adversarial samples: while the attacker receives \( (s, a, s', r) \), and loops through all observable nodes to find \( \delta \) that either minimises the \( Q \)-value or...
the probability of action \(a'\) for state \(s' + \delta\), the defender receives \((s, a, s', r')\), and through the same nodes may find \(\delta'\) maximising \(\text{argmax}_{\delta'} Q(s' + \delta + \delta', a')\) for DDQN, and \(\text{argmax}_{\delta'} \pi(a'|s' + \delta + \delta')\) for A3C. In other words, \(\delta' = -\delta\).

However, the attacker’s partial knowledge of the network topology, the limits on the choice of FP & FN nodes, and the number of false readings per time interval/step are not made known to the defender. Therefore, as shown in Algorithm 2, we propose that instead of looping through the nodes observable to the attacker, the defender necessarily goes through all network nodes to find \(\delta'\). In addition, we also test using a different number of false readings in our experiments (Section 5). \(\delta'\) obtained in such a way may not exactly match \(\delta\), and the defender can choose to either keep both \((s, a, s' + \delta, r')\) and \((s, a, s' + \delta + \delta', r')\), or just \((s, a, s' + \delta + \delta', r')\).

This method does not make any assumptions about the attacker, except that they falsify the states of certain nodes. However, as demonstrated by the experimental results in Section 5, the method is effective against the causative attack, and it does not prevent the agent from learning the optimal actions in the non-attack scenario.

5 EXPERIMENTAL RESULTS

We next introduce our experimental setup, present how DDQN and A3C agents are affected by causative attacks, and demonstrate effectiveness of the proposed defence.

5.1 SDN Experimental Environment

In order to better cope with today’s dynamic and high-bandwidth traffic, Software-Defined Networking (SDN) [1] is designed as a next-generation tool chain for computer network management. SDN adopts a three layer architecture: (1) in the top application layer, applications that deliver services communicate their network requirements to the controller via the northbound APIs; (2) in the middle layer, the SDN controller translates the received requirements into low-level controls, and passes them to the bottom infrastructure layer via southbound APIs; (3) the infrastructure
layer includes switches that control forwarding and data processing. Under such an architecture, the controller has a centralised view of the whole network, and is directly programmable since network control is decoupled from forwarding functions. It is thus convenient to monitor and reconfigure network resources.

There have been a number of proprietary and open-source SDN controller software platforms, such as Cisco’s Open SDN Controller [3], Floodlight [4], NOX/POX [6] and Open vSwitch [2]. In this paper, we choose OpenDaylight [32], the most popular open-source SDN controller available.

Specifically, we use Mininet [5], a popular network emulator, to create the network with 100 nodes and 172 links as shown in Fig. 1. Once the network is created, OpenDaylight is added as the controller. It provides APIs for the RL agent to retrieve network information and execute different types of operations as defined in Section 2.

We want to emphasise that SDN is only one platform we choose for demonstration purposes—although it is used in production. The studied causative attacks and the proposed defence method are not coupled to any particular platform, such as the SDN platform.

### 5.2 Causative Attacks via State Perturbation

As described earlier in Section 3, the attacker needs to: (1) train its own model—we achieve this by training a DDQN agent using the partial topology visible to the attacker. The model is used as the surrogate to attack both of the defender’s models (i.e. both DDQN and A3C agents); (2) limit the number of nodes they can perturb (this is an appropriate threat model—even if the attacker can map out part of the network topology, it is very unlikely that they can manipulate the states of all those nodes). We run the attack by adding one FP and one FN per time interval/step but without any limits on the choices of FPs and FNs. In this way, we are able to find the nodes that are most frequently selected as FPs and FNs. $L_{FP}$ and $L_{FN}$ in Algorithm 1 are then initialised with these nodes. Note that the nodes in $L_{FP}$ and $L_{FN}$ are different for the DDQN and A3C agents.

The attacker is only allowed to manipulate the states of these nodes; (3) limit the number of false readings added per time interval/step—two settings are used in our experiments: (i) one FP & one FN, and (ii) two FPs & two FNs.

Fig. 3 shows the effectiveness of the attack under different settings, where the top four, six, eight FP nodes and top two FN nodes are selected, i.e., $|L_{FP}| = 4, 6$ or $8$, while $|L_{FN}| = 2$. Additional experiments with multiple combinations suggested that further increasing $|L_{FN}|$ does not have an obvious impact on the results.

The results demonstrate that (1) the causative attack designed in Algorithm 1 is effective against both agents when there is no form of defence—a significant percentage of attacks either cause the critical server to be compromised (the red bars), or cause fewer nodes to be preserved (the blue bars). Note that this also demonstrates the existence of transferability between RL algorithms [39]—attackers do not need to have knowledge of the defender’s model and hence attempting to keep the model secret is not an effective countermeasure against adversarial machine learning attacks; (2) given the same number of false readings per time step, the stricter the limits on the choices of FPs and FNs, i.e., the smaller $|L_{FP}|$ and $|L_{FN}|$ are, the less powerful the attacks are—not only do the limits restrict which nodes can be manipulated, they decrease the number of steps that are poisoned in each training episode; (3) interestingly, if we compare the second and fourth bars in both Figs. 3a & 3b, when $|L_{FP}| = 6$, adding one FP & one FN per time step is more effective than adding two FPs & two FNs per time step. This is because more training steps are likely to be poisoned in the former case given that $|L_{FP}|$ is the same.

In the next section, we test our proposed countermeasure against the most powerful form of attack as illustrated in Fig. 3, where $|L_{FP}| = 8$, $|L_{FN}| = 2$, and two FPs & two FNs are added per time step.

#### 5.2.1 Discussion on the Impact of Partial Observability

It is likely that the effectiveness of the attack is impacted by the partial observability. As we have mentioned earlier in this section, a subset of nodes is more frequently selected as FPs and FNs. In other words, these nodes cause larger damage to the training process of RL agents. Therefore, the attack will become more effective if the attacker can take control over more of these most damaging nodes. In our future work, we intend to further study the relation between partial observability and attack effectiveness. Specifically, we will identify the minimum set of nodes that the attacker need to control in order to achieve a given level of efficiency.

| Percentage of attacks | Percentage of attacks |
|-----------------------|-----------------------|
| FP: 1 FP, 1 FN; FN: 10, 90 | FP: 1 FP, 1 FN; FN: 10, 90 |
| FP: 1 FP, 1 FN; FN: 31, 34, 30, 15 | FP: 1 FP, 1 FN; FN: 31, 34, 30, 15 |
| FP: 1 FP, 1 FN; FN: 85, 34, 48, 50 | FP: 1 FP, 1 FN; FN: 85, 34, 48, 50 |
| FP: 1 FP, 1 FN; FN: 64, 90 | FP: 1 FP, 1 FN; FN: 64, 90 |

(a) Attacks against DDQN

(b) Attacks against A3C

Figure 3: Attacks against the DDQN & A3C agents. The bars indicate the percentage of attacks (left y-axis) that (1) have no impact; (2) cause fewer nodes to be preserved; and (3) cause the critical server to be compromised. The line marked by "$\circ$" indicates the average number of preserved servers (right y-axis).
The first three bars correspond to the scenarios where the attacker adds two FPs & two FNs per training step, and |LFN| = 2 (i.e., the most powerful form of attack studied in the experiments), while the defender assumes that there are (1) one FP & one FN, (2) two FPs & two FNs, (3) three FPs & three FNs per training step. In the last case, the defender assumes that two FPs & two FNs are added per time step, but in fact there is no attack.

Specifically, Papernot et al. [39, 40] have demonstrated the effectiveness of the black-box attack model, where the adversary does not possess full knowledge of the target model, and has to first approximate the model by observing the target’s performance. They have investigated intra- and cross-technique transferability between deep neural networks (DNNs), logistic regression, support vector machines (SVMs), decision trees and the k-nearest neighbour algorithm. In this paper, our results show that transferability also exists between reinforcement learning algorithms.

5.3.1 Discussion on the Overhead. A disadvantage of the inversion defence method is that it significantly slows down the training process, as it is time-consuming to loop through all the nodes to find the potential FPs and FNs. We aim to improve the performance in our future work. Specifically, we find that not all nodes are equally important in terms of preventing the critical server from being compromised—incorrect readings from certain nodes can cause more damage. Therefore, we will be investigating improving the efficiency of the defence method by only looping through those crucial nodes.

6 RELATED WORK

This section first summarises adversarial machine learning against supervised classifiers, and then reviews recent work on similar attacks against reinforcement learning models. Finally, we discuss existing defence mechanisms.

6.1 Adversarial Machine Learning

Adversarial machine learning aims to minimise the modifications to the input, i.e., either the test instance or the training sample, to cause a malfunction of the machine learning model. Biggio et al. [11, 12] formulate the problem of evading a machine learning classifier as optimisation of the model’s continuous scores, and use gradient descent to generate adversarial samples.

Szegedy et al. [50] highlight the observation that modifications imperceptible to humans can cause deep neural networks (DNNs) to misclassify, and they design the Fast Gradient Sign Method [18] for the attack. Since then a number of different methods for creating adversarial samples have been proposed [14, 30, 36–38, 41, 43], among which the C&W attack [14] is empirically the most efficient exploratory attack so far.

Specifically, Papernot et al. [39, 40] have demonstrated the effectiveness of the black-box attack model, where the adversary does not possess full knowledge of the target model, and has to first approximate the model by observing the target’s performance. They have investigated intra- and cross-technique transferability between deep neural networks (DNNs), logistic regression, support vector machines (SVMs), decision trees and the k-nearest neighbour algorithm. In this paper, our results show that transferability also exists between reinforcement learning algorithms.

6.2 Adversarial Reinforcement Learning

More recent work has shown that reinforcement learning models are also vulnerable to the above attacks against classifiers. For example, Huang et al. [25] demonstrate that both white-box and black-box attacks using the Fast Gradient Sign Method [18] are effective against deep RL.

Behzadan & Munir [9] were the first to investigate causative attacks against RL agents. They show how adversaries can perturb the observed state, in order to prevent the DQN agent from learning...
the correct policy. Specifically, the perturbation is generated using both the Fast Gradient Sign Method and the Jacobian-based Saliency Map Attack [41].

Lin et al. [28] propose two types of attacks against deep RL: (1) strategically-timed attack, which aims to decrease the number of time steps to launch the attack (i.e., manipulate the state). It estimates when an adversarial sample will be effective, and uses the C&W attack [14] to perturb the corresponding states; (2) enchanting attack, which aims at misleading the agent to a specific state. It uses a sampling-based cross-entropy method to find a sequence of actions that will guide the agent to the target state, and progressively craft the states so that the agent will always take the next required action.

Pattanaik et al. [44] show that even the naïve attack, that is, adding random noise into the current state, is effective against deep RL—this is contrary to our experimental findings. However, our scenario is different to that described by the authors, including the dimensions of the state, the action space, and they design a gradient-based attack that aims to maximise the probability of taking the worst possible action.

6.3 Existing Defence Mechanisms

Generally speaking, existing defence methods against adversarial machine learning can be categorised into two classes: (1) data-driven defence, which either filters adversarial samples [17, 26, 27, 33, 48], injects adversarial samples into training—a.k.a., adversarial training [18, 50, 51], or projects inputs into a lower dimension [10, 15, 53, 54]; (2) learner robustification, which stabilises the training [23, 42, 55], applies moving target [47], or leverages ideas from robust statistics [16, 45].

However, recent studies [13, 22] point out that most of the above methods only consider either relatively weak attacks, e.g., FGSM [18], or attackers that are not aware of the defence mechanism. Negative results are reported on the effectiveness of these methods against adaptive attackers that are aware of the defence and act accordingly, and against the C&W attack [14] or the PGD attack [30]. In addition, Athalye et al. [7] show that defences relying on obfuscated gradients can also be circumvented.

Countermeasures against attacks on RL models adopt similar approaches. For example, Mandelkar et al. [31], Pattanaik et al. [44] propose different adversarial training algorithms. Based on the idea that adversarial samples are not effective for the frame prediction module, Lin et al. [29] use previous images to predict future input and detect adversarial examples. Havens [21] propose the Meta-Learned Advantage Hierarchy (MLAH) framework that estimates advantage to measure the underlying changes in a task, in order to detect the attack.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we show that in the context of autonomous defence in cyber networks, RL agents can be manipulated by attacks that target the training process, even if the attacker only has partial observability of the environment and defensive algorithms. In order to defend against the attack, we propose an inversion method that aims to revert the perturbations added by the attacker. Our experimental results demonstrate the effectiveness of the proposed approach, and show that it causes limited impact in non-attack scenarios. Our work focuses on learning in software-defined networking, which brings with it novel threat models of independent interest to adversarial learning research.

For future work, we plan to work on three directions—(1) partial observability: (i) impose partial observability also on the defender, since in real networks, the defender may not be able to obtain the correct states of all the nodes all the time; (ii) identify the minimum set of nodes the attacker needs to control in order to achieve a certain level of effectiveness. (2) Consider a more powerful attacker that can (i) expand their partial observability as the attack proceeds; and (ii) spread more freely through the network, instead of having to compromise all the nodes on the paths to the critical server. (3) Replace the binary state with a continuous state, e.g., consider using multiple network performance metrics.

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A COMPARISON OF ATTACKING METHODS

Here we provide the details of the other three attacking methods as mentioned in Section 3. Note that when comparing the four methods, in order to eliminate other possible factors, we adopt the white-box, full observability model. In addition, there is no limit on the choice of false positive or false negative node either.

**Attack I:** tampering with a small number (e.g., 5%) of rewards to maximise the defender’s loss. Specifically, gradient information is used to select which rewards to tamper with. For example, the loss function for a DDQN agent is:

$$L(\theta) = \mathbb{E} \left[ r + y Q'(s', \text{argmax}_a Q(s', a; \theta)) - Q(s, a; \theta) \right]^2$$

where $\theta$ is the parameter of the two DQNs. As shown in Algorithm 3, in the $i^{th}$ training iteration, after a batch of experiences ($L_t$) are sampled for training, the attacker calculates the gradient of $\partial L_t / \partial r_j$ for $j = 1, 2, \ldots, |L_t|$ for each of them, and flips the sign of experience whose gradient (1) has the largest absolute value $|\partial L_t / \partial r_j|$, and (2) satisfies $r_j \cdot \partial L_t / \partial r_j < 0$ (if $r_j \cdot \partial L_t / \partial r_j > 0$, then flipping the sign decreases the loss function).

**Attack II:** random perturbation of the observed states. For each observed experience $(s, a, s', r)$, the attacker chooses the false positive and false negative nodes uniformly at random.
**Attack III**: manipulating the states to minimise the defender’s rewards (Algorithm 4). For each observed experience \((s, a, s', r)\), suppose that the attacker knows the optimal action \(a^*\) for state \(s\), if \(a = a^*\), they loop through all nodes to find the false positive and false negative nodes that minimise \(r\); otherwise, they introduce FP and FN readings to maximise \(r\).

![Algorithm 3: Attack I: Tampering with reward](image)

| Input | The list of sampled experiences \(L_E\); The loss function \(L_i\) of the RL agent |
|-------|----------------------------------------------------------------------------------|
| Output | The tampered experiences \(L'_E\) |

for experience \((s_j, a_j, s'_j, r_j)\) in \(L_E\) do  
1. Calculate \(g = \partial L_i / \partial r_j\);  
2. if \(|g| > \text{max} G\) and \(g \cdot r_j < 0\) then  
   3. \(\text{max} G = |g|\);  
   4. \(\text{maxIdx} = j\);  
5. \((s_{\text{maxIdx}}, a_{\text{maxIdx}}, s'_{\text{maxIdx}}, r_{\text{maxIdx}}) \leftarrow (s_{\text{maxIdx}}, a_{\text{maxIdx}}, s'_{\text{maxIdx}} \cdot r_{\text{maxIdx}})\);  
6. return \(L'_E\)

![Figure 5: Comparison of the four attack methods](image)

**Algorithm 4: Attack III: Minimise/maximise rewards**

| Input | The original experience, \((s, a, s', r)\); The list if all nodes, \(N\); the optimal action \(a^*\) for state \(s\) |
|-------|----------------------------------------------------------------------------------|
| Output | The tampered experience \((s, a, s' + \delta, r')\) |

1. \(r'_{\text{min}} = 1\), \(r'_{\text{FP}} = 1\), \(r'_{\text{FN}} = -1\), \(r'_{\text{FPmax}} = -1\);  
2. for node \(n\) in \(N\) do  
   3. if \(n\) is compromised then  
      4. mark \(n\) as uncompromised;  
      5. if \(a == a^*\) then  
         6. // Discourage taking the optimal action  
            7. if \(r' < r'_{\text{min}}\) then  
               8. \(F N = n\);  
               9. \(r'_{\text{min}} = r'\);  
            10. else // Encourage taking other actions  
                11. if \(r' > r'_{\text{FPmax}}\) then  
                    12. \(F N = n\);  
                    13. \(r'_{\text{FPmax}} = r'\);  
                14. restore \(n\) as compromised;  
      15. else if \(n\) is uncompromised then  
         16. mark \(n\) as compromised;  
         17. if \(a == a^*\) then  
            18. if \(r' < r'_{\text{FPmin}}\) then  
               19. \(F P = n\);  
               20. \(r'_{\text{FPmin}} = r'\);  
            21. else if \(r' > r'_{\text{FPmax}}\) then  
                22. \(F P = n\);  
                23. \(r'_{\text{FPmax}} = r'\);  
         24. restore \(n\) as uncompromised;  
   25. Change \(F N (F P)\) to uncompromised (compromised);  
26. return \((s, a, s' + \delta, r')\)

Specifically, (1) during the pre-training stage of a DDQN agent, the agent randomly takes actions to obtain experiences, and the deep neural network does not get updated. We use the data generated in this stage to create a mapping that transforms the original data into a lower dimension. (2) Once the pre-training stage is finished, all further inputs will be first transformed using the obtained mapping, and then fed to the deep neural network to learn the optimal actions. The key rationale behind this defence method is to introduce some degree of randomness into the training, and since the attacker does not know the generated mapping, their adversarial samples in the original input space may not be working in the transformed space.

In order to create the mapping, we have compared factor analysis and principal component analysis. In addition, we have also considered three forms of loss functions: Huber loss, linear-error and squared-error loss.

**B DEFEENCE VIA DIMENSION REDUCTION**

In addition to the inversion defence mechanism introduced in Sec. 4, we have also explored the feasibility of applying dimension reduction as a potential defence method, since it has been used in the study of adversarial machine learning.
Our statistics suggest that the effectiveness of the defence method depends on whether or not the attacker can poison the mapping: (1) if the adversary launches only random attacks, i.e., picking FPs and FNs uniformly at random, during the pre-training stage, and an appropriate mapping is generated, then the method will be effective—even after the pre-training stage, even if the attacker adopts the mechanism as introduced in Sec. 3, the attack will not be successful most of the time. In this case, factor analysis provides the best results, but there is not any obvious difference among the three forms of loss functions. (2) However, if the adversary starts the calculated attack from the beginning, then the mapping itself will be poisoned, and the defence method is not effective.