Deep Reinforcement Learning based Adaptive Moving Target Defense

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Abstract
Moving target defense (MTD) is a proactive defense approach that aims to thwart attacks by continuously changing the attack surface of a system (e.g., changing host or network configurations), thereby increasing the adversary’s uncertainty and attack cost. To maximize the impact of MTD, a defender must strategically choose when and what changes to make, taking into account both the characteristics of its system as well as the adversary’s observed activities. Finding an optimal strategy for MTD presents a significant challenge, especially when facing a resourceful and determined adversary who may respond to the defender’s actions. In this paper, we propose finding optimal MTD strategies using deep reinforcement learning. Based on an established model of adaptive MTD, we formulate finding an MTD strategy as finding a policy for a partially observable Markov decision process. To significantly improve training performance, we introduce compact memory representations. To demonstrate our approach, we provide thorough numerical results, showing significant improvement over existing strategies.

1 Introduction
Traditional approaches for security focus on preventing intrusions (e.g., hardening systems to decrease the occurrence and impact of vulnerabilities) or on detecting and responding to intrusions (e.g., restoring the configuration of compromised servers). While these passive and reactive approaches are useful, they cannot provide perfect security in practice. Further, these approaches let adversaries perform reconnaissance and planning unhindered, giving them a significant advantage in information and initiative. As adversaries are becoming more sophisticated and resourceful, it is imperative for defenders to augment traditional approaches with more proactive ones, which can give defenders the upper hand.

Moving Target Defence (MTD) is a proactive approach that changes the rules of the game in favor of the defenders. MTD techniques enable defenders to thwart cyber-attacks by continuously and randomly changing the configuration of their assets (i.e., networks, hosts, etc.). These changes increase the uncertainty and complexity of attacks, making them computationally expensive for the adversary (Zheng and Namin 2019) or putting the adversary in an infinite loop of exploration (Tan et al. 2019).

Currently, system administrators typically have to manually select MTD configurations to be deployed on their networked systems based on their previous experiences (Hu et al. 2019). This has two main limitations. First, it can be very time consuming since there are constraints on data locations, physical connectivity of servers cannot be easily changed, and resources are limited. Second, it is difficult to capture the trade-off between security and efficiency (Chen et al. 2015).

In light of this, it is crucial to provide automated approaches for deploying MTDs, which maximize security benefits for the protected assets. This requires a design model that reflects multiple aspects of the MTD environment (Li and Zheng 2019; Zheng and Namin 2019; Prakash and Wellman 2013; Albanese et al. 2019). Further, we need a decision making algorithm for the model to select which technique to deploy and where to deploy it (Tan et al. 2019). Finding optimal strategies for deployment of MTDs are computationally challenging. For example, the adversary can adapt to MTD deployments, or the state-action space of the environment can be huge even for trivial number of MTD configurations or in-control assets.

Recently, many research efforts have applied Reinforcement Learning (RL) techniques to find the best action policies in known or unknown decision making environments, such as cybersecurity. In reinforcement learning, an agent learns to make the best decision by continuously interacting with its unknown environment. In general, traditional reinforcement learning techniques use tabular approaches to store estimated rewards (e.g., Q-Learning) (Lanucci et al. 2019). To address challenges of reinforcement learning such as exploding state-action space, Artificial Neural Networks (ANN) have replaced table based approaches in many domains, thereby decreasing the training time and memory requirements. This led to the emergence of deep reinforcement learning (DRL) algorithms such as DQL (Mnih et al. 2013).

Contributions We present a deep reinforcement learning based approach to find optimal strategies for defenders and adversaries in a game-theoretic moving target defense model. Our main contributions are as follows:

- We propose a compact memory representation for the defender and adversary agents, which helps them to better
operate in the partially observable environment.

- We apply Deep-Q-Learning to an existing game-theoretic MTD model to find optimal strategies for the agents.
- We evaluate our approach while exploring various DQN extensions and show its significant improvement over strategies from prior work.
- We show that our approach is viable in terms of computational cost.

**Organization** The rest of the paper is organized as follows. In Section 2, we describe the game-theoretic model that is the environment for reinforcement learning. In Section 3, we discuss the challenges for reinforcement learning in a partially observable environment, describe our solution approach, and introduce the RL architecture. In Section 4, we provide a thorough numerical analysis of our approach. In Section 5, we discuss the related work. Finally, in Section 6, we provide concluding remarks and outline of directions for future work.

## 2 Model

To model adaptive moving target defense, we use the model of [Prakash and Wellman (2015)](Prakash and Wellman 2015). In this model, there are two players, a defender and an adversary, who compete for control over a set of servers. At the beginning of the game, all servers are under the control of the defender. To take control of a server, the adversary can launch a “probe” against the server at any time, which either compromises the server or increases the success probability of subsequent probes. To keep the servers safe, the defender can “reimage” a server at any time, which takes the server offline for some time, but cancels the adversary’s progress and control. The goal of the defender is to keep servers uncompromised (i.e., under the defender’s control) and available (i.e., online). The goal of the adversary is to compromise the servers or make them unavailable. For a list of symbols used in this paper, see Table 1.

### 2.1 Environment and Players

There are $M$ servers and two players, a defender and an adversary. The servers are independent of each other in the sense that they are independently attacked, defended, and controlled. The game environment is explained in detail in the following subsections.

### 2.2 State

Time is discrete, and in a given time step $\tau$, the state of each server $i$ is defined by tuple $s^i_{\tau}$:

$$s^i_{\tau} = \langle \rho, \chi, v \rangle$$

where

- $\rho \in \mathbb{Z}^*$ represents the number of probes launched against server $i$ since the last reimage,
- $\chi \in \{\text{adv, def}\}$ represents the player controlling the server, and
- $v \in \{\text{up}\} \cup \mathbb{Z}^*$ represents if the server is online (i.e., up) or if it is offline (i.e., down) with the time step in which the server was reimagined.

### 2.3 Actions

In each time step, a player may take either a single action or no action at all. The adversary’s action is to select a server and probe it. Probing a server takes control of it with probability

$$1 - e^{-\alpha (\rho + 1)}$$

where $\rho$ is the number of previous probes and $\alpha$ is a constant that determines how fast the probability of compromise grows with each additional probe, which captures how much information (or progress) the adversary gains from each probe. Also, by probing a server, the adversary can understand whether it is up or down.

The defender’s action is to select a server and reimage it. Reimaging a server takes the server offline for a fixed number $\Delta$ of time steps, after which the server goes online under the control of the defender and with the adversary’s progress (i.e., number of previous probes $\rho$) against that server erased (i.e., reset to zero).

### 2.4 Observations

A key aspect of the model is the players’ uncertainty regarding their state. The defender does not know which servers have been compromised by the adversary. Also, the defender observes each probe with a fixed probability $1 - \nu$ (with probability $\nu$, the probe is undetected). Consequently, the defender can only estimate the number of probes against a
server and whether a server is compromised. However, the defender knows the state of all servers (i.e., whether the server is up or down, or if it is down, how many time steps it requires to be back up again).

The adversary always observes when the defender reimages a compromised server, but cannot observe reimagining an uncompromised server without probing it. Consequently, the adversary knows with certainty which servers are compromised.

2.5 Rewards

Prakash and Wellman (2015) define a family of utility functions. The exact utility function can be chosen by setting the values of preference parameters, which specify the goal of each player. The value of player $p$’s utility function $u^p$, as described by Equation 3 and Equation 4, depends on the number of servers in control of player $p$ and the number of servers offline. Note that the exact relation depends on the scenario (e.g., whether the primary goal is confidentiality or integrity), but in general, a higher number of in control servers yields a higher utility.

\[
u^p(n^p_c, n_d) = w^p \cdot f \left( \frac{n^p_c}{M}, \theta^p \right) + (1 - w^p) \cdot f \left( \frac{n^p_c + n_d}{M}, \theta^p \right) \tag{3}\]

where $n^p_c$ is the number of servers which are up and in control of player $p$, $n_d$ is the number of unavailable (down) servers, and $f$ is a sigmoid function with parameters $\theta$:

\[
f(x, \theta) = \frac{1}{e^{\theta_{sl} (x - \theta_{sh})}} \frac{1}{\theta_{sl}} \tag{4}\]

where $\theta_{sl}$ and $\theta_{sh}$ control the slope and position of the sigmoid’s steep point, respectively.

Reward weight ($w^p$) specifies the goal of each player. As described by Prakash and Wellman (2015), there can be four extreme combinations of this parameter, which are summarized in Table 2. For example, in control / availability, both players gain reward by having the servers up and in control. Or in disrupt / availability, which is the most interesting case, the defender gains reward by having the servers up and in control, while the adversary gains reward by bringing down the servers or having them in control.

| Utility Environment          | $u^a$ | $u^d$ |
|-----------------------------|-------|-------|
| control / availability      | 1     | 1     |
| control / confidentiality    | 1     | 0     |
| disrupt / availability      | 0     | 1     |
| disrupt / confidentiality    | 0     | 0     |

The reward that is given to the adversary ($r^a_\tau$) and defender ($r^d_\tau$) at time $\tau$ is defined by:

\[
r^a_\tau = \begin{cases} u^a(n^a_c, n_d) - C_A & \text{adversary probed a server at } \tau \\ u^a(n^a_c, n_d) & \text{adversary did nothing} \end{cases} \tag{5}\]

\[
r^d_\tau = u^d \tag{6}\]

2.6 Problem Statement

The goal of our work is to find an optimal playing policy ($\sigma$) for each player that maximizes the player’s reward over an infinite time horizon. In other words, our goal is to find a function $\sigma(s^p) \mapsto a$ that specifies which action $a$ should player $p$ take (i.e., which server to reimage/probe or do nothing) given its observed state $s^p_\tau$ of the environment at time $\tau$. Note that the optimal policy depends not only on the characteristics of the environment, but also on the opponent’s policy (see Section 6).

Formally, our goal is to find policy $\sigma$ that maximizes $V_\sigma(s^p_0)$:

\[
V_\sigma(s^p_0) = \lim_{T \to \infty} \mathbb{E} \left[ \sum_{\tau=0}^{T} r^p_\tau | \sigma \right] \tag{7}\]

where $s^p_0$ denotes the observation of the initial state. Prakash and Wellman (2015) provided a set of heuristic policies for both the adversary and defender, which we will describe in detail in Section 4.4.

3 Reinforcement Learning

Due to the complexity of the game model, finding the optimal policy analytically is very challenging. Moreover, since the state-space is enormous, finding the optimal policy is also challenging computationally. In fact, even representing a policy (e.g., storing the best action for each state) is infeasible for systems of non-trivial size. As a result, we choose Deep-Q-Network Learning (DQN) (Mnih et al. 2015) as our approach to find a policy. DQN approximates the future rewards from each action in a given state. As the sum of future rewards converges to infinity, time-discounted reward of player $p$ gives us a good approximation of the future reward. So, our optimization problem will change to maximizing $V^*_\sigma$:

\[
V^*_\sigma(s^p_\tau) = \mathbb{E} \left[ \sum_{\tau=0}^{\infty} \gamma^\tau \cdot r^p_{\tau+1} | \sigma \right] \tag{8}\]

where discount factor $\gamma$ is a constant which the agent uses to prioritize current rewards over future rewards. When $\gamma = 0$, the agent only cares about the current reward, and when $\gamma = 1$, the agent cares about all the future rewards.

In Section 4.2, we show that DQN’s approximation of $V^*\sigma$ captures the characteristics of the actual $V_\sigma$ function.

In the following subsections, we convert the game model from Prakash and Wellman (2015) to a Partially Observable Markov Decision Process (POMDP), and apply Deep-Q-Learning to find the optimal policy for the adversary and the defender. Algorithm 1 shows the steps in our learning approach.
3.1 Observations
Observation of a player \( p \) is defined as a vector of tuples \( O^p_i \)
where \( O^p_i \) corresponds to observation of \( p \) of server \( i \).

\[
O^p = (O^p_1, O^p_2, \ldots, O^p_M)
\] (9)

Adversary knows which servers are compromised and knows how many attacks it has initiated on each server. Also, if the server is down, the adversary can estimate the time that the server is up again. The state of a server \( i \) for adversary is defined as a tuple \( O^a_i \):

\[
O^a_i = \langle \text{status}, \text{time\_to\_up}, \text{progress}, \text{control} \rangle
\] (10)

where \( \text{status} \in \{1, 0\} \) which shows the server is up or down, and \( \text{control} \in \{1, 0\} \) shows that the adversary controls that server or not, respectively.

Observation vector of the defender is almost the same as the adversary. The only difference is that the defender does not know who controls the servers, and only has an estimation on the number of probes (where \( \nu \) is not 0):

\[
O^d_i = \langle \text{status}, \text{time\_to\_up}, \text{progress} \rangle
\] (11)

To overcome challenges regarding the defender which are described in Section 3.2 we included two more attributes to have some form of memory for the defender. These two attributes are described in Section 3.3.

3.2 Challenges

Short-term Losses vs. Long-term Rewards  For both players, taking an action has a negative short-term impact: for the defender, reimaging a server results in lower rewards while the server is offline; for the adversary, probing incurs a cost. While these actions can have positive long-term impact, benefits may not be experienced until much later: for the defender, a reimaged server remains offline for a long period of time; for the attacker, many probes may be needed until a server is finally compromised.

As a result, with typical temporal discount factors (e.g., \( \gamma = 0.9 \)), it may be an optimal policy for a player to never take any action since the short-term negative impact outweighs the long-term benefit. In light of this, we can use higher temporal discount factors (e.g., \( \gamma = 0.99 \)). However, such values can pose challenges for deep reinforcement learning since it will be much more difficult to converge.

Partial Observability  For both players, state is only partially observable. This can pose a significant challenge for the defender, who does not even know whether a server is compromised or not. Consider, for example, the defender observing that a particular server has been probed only a few times: this may mean that the server is safe since it has not been probed enough times; but it may also mean that the adversary is not probing it because the server is already compromised. We can try to address this limitation by allowing the defender’s policy to consider a long history of preceding states; however, this poses computational challenges since the size of the effective state space for the policy explodes.

3.3 Solution Approach

Compact History Representation  Since partial observability poses a challenge for the defender, we let the defender’s policy use information from preceding states. To avoid state-space explosion, we feed this information into the policy in a compact form. In particular, we extend the observed state of each server (i.e., number of observed probes and whether the server is online) with (a) the amount of time since the last reimaging and (b) the amount of time since the last observed probe. So, the actual state presentation of the defender will be:

\[
O^d_i = \langle \text{status}, \text{time\_to\_up}, \text{progress}, \text{control}, \text{time\_since\_last\_probe} \rangle
\] (12)

Similarly, the adversary should probe the servers which where probed in many steps in the past to make sure that its progress was not reset. So, we add the amount of time since the last probe to its observation state.

\[
O^a_i = \langle \text{status}, \text{time\_to\_up}, \text{progress}, \text{control}, \text{time\_since\_last\_probe} \rangle
\] (13)

3.4 Deep-Q-Network Learning

In this section, we discuss how we integrate the game model of Prakash and Wellman into a DQN Learning model.

| Algorithm 1: Deep-Q-Learning |
|--------------------------------|
| **Result:** policy \( \sigma \) |
| \( Q \leftarrow \text{random}; \) |
| for \( N_e \) episodes do |
| \( S \leftarrow \text{reset\_game}(); \) |
| \( \epsilon_e \leftarrow 1; \) |
| for \( \tau \in \{0, \ldots, T\} \) do |
| if random\([0, 1]\) \( \leq \epsilon_e \) then |
| \( a \leftarrow \text{random\_action}; \) |
| else |
| \( a \leftarrow \text{argmax}_{a'} Q(S, a'); \) |
| end |
| \( (S', r) \leftarrow \text{step\_game}(a); \) |
| add \( e = (S, S', a, r) \) to \( E; \) |
| sample \( X \) from \( E; \) |
| update DQN based on \( X; \) |
| \( S \leftarrow S'; \) |
| decay \( \epsilon_e; \) |
| end |
| \( \sigma \leftarrow \langle S \mapsto \text{argmax}_a Q(S, a) \rangle; \) |

Artificial Neural Network: A Feed-Forward Fully-Connected Artificial Neural Network (ANN) is used as a estimator for our \( Q \)-values. Input neurons present the agent’s observation from the environment. In our case, for the defender, we have \( 5 \cdot M \) (5 features per server) input neurons, and for the adversary we have \( 5 \cdot M \) (5 features per server) neurons. Number of output neurons are the same \( M + 1 \) for
both players. These output neurons show the estimated Q-value for probing/reimaging each server or doing nothing.

Updating Q-values: We update the Q network based on the temporal difference (TD) error and the Bellman optimization equation:

\[ Q(S, a) = (1 - \alpha) \cdot Q(S, a) + \alpha \cdot [r_s + \gamma \cdot \max_{\hat{a}} Q(S', \hat{a}) + \alpha \cdot Q(S, a)] \]  

(14)

where \( r_s \) is the reward received in observation state \( S \), \( a \) is the action executed in observation state \( S \), and \( S' \) is the next observation state.

As we are using an ANN to estimate Q-values, we only need to back-propagate the error to the network. So, the data which is fitted in the network when action \( a \) in observation state \( S \) is taken to achieve observation state \( S' \) is:

\[
\text{input} = S
\]

\[
\text{output}_a' = \begin{cases} Q(S, a) & \text{if } a' \neq a \\ r_s + \gamma \cdot \max_{\hat{a}} Q(S', \hat{a}) & \text{if } a' = a \end{cases}
\]

(16)

Exploration: Our proposed solution to finding \( \sigma \) uses two phases of exploration. In the first phase, which is from \( \epsilon_p \cdot T \cdot N_e \) to \( \epsilon_f \), we decrease \( \epsilon_p \) linearly from 1 to \( \epsilon_f \). In the second phase, we use a \( \epsilon \)-greedy approach where \( \epsilon_f \) will be fixed at \( \epsilon_f \). Figure 1 shows the steps of decaying \( \epsilon_f \) over the training steps.

![Exploration Fraction](image)

Figure 1: Change of exploration \( \epsilon_f \) over the training steps.

3.5 DQN Improvements

To stabilize DQN and improve its convergence speed, Lin [1993] used experience replay buffer. This buffer stores the state transitions of the POMDP environment, and instead of fitting one recent transition, the training algorithm fits a random sample from the buffer. Schaul et al. [2015] improved this method to prioritize transitions from the experience replay buffer based on the \( td \) error of the transition. Further, to decrease the over-estimation of Q-values, Van Hasselt, Guez, and Silver [2016] used two different DQNs, one is used to predict the best action, and the other is used to update the Q-values (Double-Q). Wang et al. [2015] uses two different DQN streams to both predict the Q-values and the action-value advantage (Dueling-Q). Finally, to prevent overshooting caused by high learning rates, Ba, Kiros, and Hinton [2016] suggest to use the layer normalization technique.

We assess the effects of these Deep-Q learning improvements in Section 4.2.

4 Numerical Evaluation

4.1 Baseline Heuristic Strategies

We compare the policies found using our approach to the heuristic strategies proposed by Prakash and Wellman [2015], which we describe below.

**Adversary’s Heuristic Strategies**

- **Uniform-Uncompromised**: Adversary launches a probe every \( P_A \) time steps, always selecting the target server uniformly at random from the servers under the defender’s control.
- **MaxProbe-Uncompromised**: Adversary launches a probe every \( P_A \) time steps, always targeting the server under the defender’s control that has been probed the most since the last reimage (breaking ties uniformly at random).
- **Control-Threshold**: Adversary launches a probe if the adversary controls less than a threshold \( \tau \) fraction of the servers, always targeting the server under the defender’s control that has been probed the most since the last reimage (breaking ties uniformly at random).
- **No-Op**: Adversary never launches a probe.

**Defender’s Heuristic Strategies**

- **Uniform**: Defender reimages a server every \( P_D \) time steps, always selecting a server that is up uniformly at random.
- **MaxProbe**: Defender reimages a server every \( P_D \) time steps, always selecting the server that has been probed the most (as observed by the defender) since the last reimage (breaking ties uniformly at random).
- **Probe-Count-or-Period (PCP)**: Defender reimages a server which has not been probed in the last \( P_D \) time steps or has been probed more than \( \pi \) times (selecting uniformly at random if there are multiple such servers).
- **Control-Threshold**: Defender assumes that all of the observed probes on a server except the last one were unsuccessful. Then, it calculates the probability of a server being compromised by the last probe as \( 1 - e^{-\alpha (\rho + 1)} \). Finally, if the expected number of servers in its control is below \( \tau \cdot M \) and it has not been reimaged any servers in \( P_D \), then it reimages the server with the highest probability of being compromised (breaking ties uniformly at random). In other words, it reimages a server iff

\[
\mathbb{E}[n^d] \leq M \cdot \tau
\]

(17)

and the last reimage was at least \( P_D \) time steps ago.
- **No-Op**: Defender never reimages any servers.

Table 3 shows the expected rewards for all combinations of heuristic defender and adversary strategies in an environment whose parameters are described in Table 1.
Table 3: Average Rewards for Heuristic Attacker vs. Defender (Equilibrium Highlighted in Gray)

| Attacker | Base     | ControlThreshold | PCP      | Uniform | MaxProbe |
|----------|----------|------------------|----------|---------|----------|
| Base     | 0.2689   | 0.2689           | 0.2689   | 0.9820  | 0.2689   |
| MaxProbe | 0.9666   | 0.9649           | 0.4964   | 0.9352  | 0.8784   |
| Uniform  | 0.9655   | 0.9629           | 0.6188   | 0.8876  | 0.8425   |
| ControlThreshold | 0.8033 | 0.8051           | 0.6165   | 0.8899  | 0.8032   |

Figure 2: Learning curve of different defenders with different configuration versus a uniform adversary. The plot shows the smoothed rewards by a weight of 0.995.

Figure 3: Learning curve of different adversaries with different configuration versus a PCP defender. The plot shows the smoothed rewards by a weight of 0.995.

4.2 Results

We implemented the game model as an environment in OpenAI Gym (Brockman et al. 2016), and the agent as a Stable-Baselines’ (Hill et al. 2018) agent with a DQN using one hidden layer of size 64, tanh as the activation function, and layer normalization (Ba, Kiros, and Hinton 2016). The hyperparameters used for training are described in section Reinforcement Learning of Table 1. Furthermore, we experimented with the various extensions that have been proposed for improving DQN, which we described in Section 3.5.

Perfect Probe Detection Environment  We trained the RL-based defender against a Uniform attacker, and the RL-based attacker against a PCP defender. We chose to train against these strategies because they are the dominant strategies in the environment described by Table 1 (see Table 3).

Figures 2 and 3 show how different Deep-Q Networks perform in the training process. Note that these figures only show one instance of the experiment run for each configuration. As the reward values for each step have large variance, we plotted them after smoothing them with a weight of \( w = 0.995 \) as follows:

\[
\text{smooth}_\tau = \begin{cases} 
  r_\tau^p & \text{if } \tau = 0 \\
  w \cdot \text{smooth}_{\tau-1} + (1 - w) \cdot r_\tau^p & \text{if } \tau > 0.
\end{cases}
\]  

In these plots, the rewards at the end of the training do not represent the actual performance of the trained policies because there is always some exploration. Further, the random actions of the opponent can have a significant impact on the reward.

Figure 4 and Figure 5 show the expected performance of the trained policies without any exploration. To eliminate the effects of randomness, these plots show the average reward for the trained policies over 10 episodes with \( T = 1000 \). Figure 4 shows the time taken for each configuration to finish the training of \( N_e = 500 \) on two cores/four threads of an Intel Xeon E5-2680 CPU. As we can see, using layer normalization with one hidden layer of neurons (Vanilla configuration) yields the best time-performance trade-off for both the adversary and the defender.

We have also investigated the behavior of the trained policies. The most interesting behavior is exhibited by an adversary policy that was trained against a PCP defender: the adversary tries to deceive the defender by probing servers that
have not been probed for a specific amount of time even if they are compromised. This deception greatly improves the adversary’s performance.

As a concluding remark, we show that found policies using Deep-Q-Learning outperform heuristic strategies. Further, we showed that finding such policies are computationally feasible in analytically complex environments.

**Imperfect Probe Detection Environment** In imperfect probe-detection environment (i.e., \(\nu > 0\)), the PCP defender, which uses the number of observed probes to select which server to reimage, tends to perform much worse than in environment with \(\nu = 0\). As a result, the heuristic strategies’ equilibrium will change to MaxProbe adversary and Uniform defender with rewards of 0.883 and 0.533, respectively, when the probe detection probability is \(\nu = 0.5\). Figure 7 shows how the trained policies perform against heuristics in an imperfect observation environment.

**5 Related Work**

In this work, we used reinforcement learning to find optimal policies for the adversary and the defender in an MTD game model. In prior work, researchers have investigated both the application of reinforcement learning in cyber-security (Section 5.2) and game-theoretic models for MTD (Section 5.1). However, to the best of our knowledge, reinforcement learning has not been applied to MTD before.

### 5.1 Moving Target Defense

In the area of game-theoretic models for moving target defense, the most closely related work is from Prakash and Wellman (2015), which introduces the model that our work uses. This model also forms the basis for the defense against DDoS attacks by Wright et al. (2016), the defense for web applications by Sengupta et al. (2017), and the Markov game model by Lei, Ma, and Zhang (2017). Li and Zheng (2019) propose a Stackelberg game model for MTD, which incorporates spatial and temporal decisions.
To find the optimal strategy for the defender, they propose an algorithm based on the Min-Max problem. Tan et al. (2019) propose a Markov robust game model for MTD based on analyzing the equivalent relationship between the change of the network state caused by network confrontation and the transformation of moving attack surface or moving exploration surface based on behavioural differences between adversary and the defender. Further, they provide an algorithm using Bellman equation and regret value for finding optimal strategies.

Zheng and Namin (2019) propose a Markov decision process model for MTD, which embraces the dynamic nature of networks. They analyze the interactions between the adversary and the defender using a Markov game model and provide optimal solutions based on Bellman optimality equations.

5.2 Reinforcement Learning for Cyber Security

Iannucci et al. (2019) use deep reinforcement learning to find the optimal policy in intrusion response systems. They evaluate the performance of their algorithm based on different configurations of the model, showing that it can be much faster than traditional Q-learning.

By taking into account generality, extensibility, resilience, and usability, Albanese et al. (2019) present a framework for MTD, which can be used to formulate a probabilistic measure to capture relationships between available MTDs and the information that the MTDs are trying to protect. Moreover, using a reward function, they quantify the strategies and techniques in MTD regardless of how they operate.

Hu et al. (2019) combine adaptive cyber defense (Cybenko et al. 2014) and MTD with rigorous methodologies, such as game theory, machine learning, and control theory, to find the optimal strategy of deploying available MTD techniques.

Oakley and Oprea (2019) model the FlipIt game, which captures the interactions of attackers and defenders in advanced persistent threats (APT) scenarios, as a Markov decision process and implement it as an OpenAI Gym environment. They use Q-Learning to find the optimal playing strategy for the defenders.

Tong et al. (2019) propose a game-theoretic model to capture interactions between attackers and defenders. They use adversarial reinforcement learning with double oracles to find the optimal alert prioritization policies for the defenders. They also show the robustness of the founded policies against different adversarial strategies.

6 Conclusion

Moving target defense tries to increase adversary’s uncertainty and attack cost by dynamically changing host and network configurations. In this paper, we have proposed a reinforcement learning approach for finding MTD strategies based on an adaptive MTD model. To improve the performance of RL in partially observable environments, we suggested to add compact history presentations to the agents. Finally, we evaluated our approach using numerical results, showing improvement compared to prior work.

In general, reinforcement learning, especially Deep-Q-Learning for discrete action spaces, can be a good fit for finding optimal policies in environments where finding such policies computationally or analytically would be infeasible due to huge state-space size. Further, RL can find policies which require complex heuristic strategies. However, with DQN, there are always chances of sticking in the local optima. This chance increases with increasing the estimator’s (DQN) complexity (e.g., increasing the size, using improvements such as Dueling-Q, or etc).

Future Work

In this paper, we only proposed a decision making algorithm for MTD for a single defending agent based on DQL. However, as the strategy for the opponent might change, that found policy might not always be the optimal policy. Algorithms such as policy-space response oracles (Lanctot et al. 2017) can help us to find the optimal policy in presence of uncertainty of the opponents policy. Another aspect of our research which is remain to be completed is to combine different proposed models, improve them, and come up with a much more sophisticated game model. Finally, our last goal would be to develop a practical solution which autonomously deploy MTD techniques.

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