Network Defense is Not a Game

ANDRES MOLINA-MARKHAM and RANSOM K. WINDER, The MITRE Corporation

AHMAD RIDLEY, National Security Agency

Research seeks to apply Artificial Intelligence (AI) to scale and extend the capabilities of human operators to defend networks. A fundamental problem that hinders the generalization of successful AI approaches—i.e., beating humans at playing games—is that network defense cannot be defined as a single game with a fixed set of rules. Our position is that network defense is better characterized as a collection of games with uncertain and possibly drifting rules. Hence, we propose to define network defense tasks as distributions of network environments, to: (i) enable research to apply modern AI techniques, such as unsupervised curriculum learning and reinforcement learning for network defense; and, (ii) facilitate the design of well-defined challenges that can be used to compare approaches for autonomous cyberdefense.

To demonstrate that an approach for autonomous network defense is practical it is important to be able to reason about the boundaries of its applicability. Hence, we need to be able to define network defense tasks that capture sets of adversarial tactics, techniques, and procedures (TTPs); quality of service (QoS) requirements; and TTPs available to defenders. Furthermore, the abstractions to define these tasks must be extensible; must be backed by well-defined semantics that allow us to reason about distributions of environments; and should enable the generation of data and experiences from which an agent can learn.

We outline key aspects of network environments that must be parametrized, and we motivate the use of generative programs to define probability distributions over network environments. We explain how this approach can enable the development of the next-generation of autonomous cyberdefenders, which will not only have to face adversaries that target the network, but also the AI-enabled components of cyberdefense—by automating attacks and by morphing behavior in systematic ways to poison or evade defender models. Our approach named Network Environment Design for Autonomous Cyberdefense inspired the architecture of FARLAND, a Framework for Advanced Reinforcement Learning for Autonomous Network Defense, which we use at MITRE to develop RL network defenders that perform blue actions from the MITRE Shield matrix against attackers with TTPs that drift from MITRE ATT&CK TTPs.

1 INTRODUCTION

One fundamental problem in applying Reinforcement Learning (RL) to network defense is that network defense cannot be defined as a single game with a simple set of rules. Rather, proficient network defense corresponds to mastering a spectrum of games that depend on sets of (i) adversarial tactics, techniques, and procedures (TTPs); (ii) quality of service goals and characteristics of a network; and (iii) actions available for defenders and their security goals.

In this paper, we argue that it is necessary to define network defense tasks via distributions of network environments to facilitate the development and evaluation of RL approaches for autonomous cyberdefense. Our position is based on our work [17], which proposes: (a) aspects of network models that must be available to researchers seeking to apply RL to reconfigure networks to mitigate cyberattacks; and (b) a way to use generative programs to define distributions of network environments.

Network environment design [17] directly addresses the problem of enabling progress toward learning a complex task. Furthermore, it addresses the more fundamental problem that network defense cannot be defined as a single game with a simple set of rules. This is key when applying RL to solving a problem that changes over time. Autonomous network defenders must not only be able to reconfigure hosts and networks to mitigate common adversaries such as those described in MITRE’s ATT&CK framework [21]. Rather, defenders must increasingly be concerned about more sophisticated adversaries that target autonomous cyber defense. Instead of demonstrating RL’s effectiveness for autonomous cyberdefense, our work illustrates the perils to the defender of adversaries capable of deception and indirect manipulation of observations the network defense uses.

This approach inspired FARLAND [17] (a Framework for Advanced Reinforcement Learning for Autonomous Network Defense), a research collaboration project between MITRE and NSA, which allows for the development of robust RL network defenders on simulated or emulated networks. Unlike RL systems and frameworks ([3, 5, 13]), FARLAND (i) can be used to guide an agent through a sequence of network defense tasks of increasing difficulty to guarantee progress, and (ii) exposes a set of model parameters specific to address the problem of network defense.

2 THE NETWORK ENVIRONMENT DESIGN TASK FOR AUTONOMOUS CYBERDEFENSE

RL agents learn to execute complex tasks through observing the effects of their actions on an environment. Observations consist of state features and rewards. Rewards are quantities that encode the desirability of the effects. The goal of an RL-agent is to learn to act and maximize the sum of expected rewards over time. When developing RL agents, it is common to use a game abstraction to frame the learning task. However, as we noted in our Network Environment Design for Autonomous Cyberdefense approach [17], the practicality of a network defense policy must not be evaluated based on the performance of an agent under predominantly fixed configurations. Cyberdefender agents (blue agents) should not simply attempt to defeat an adversary (red agent) with fixed TTPs. Instead, they must account for changes in behaviors that effectively change the game itself, in particular with respect to the red agent TTPs. The range of red agent behaviors should not be arbitrary either. That would make it impossible to learn and evaluate policies.

This section summarizes our key ideas about modeling distributions of network environments using generative programs [17].

Approved for Public Release; Distribution Unlimited. Public Release Case Number 21-0464. This technical data deliverable was developed using contract funds under Basic Contract No. W56KGU-18-D-0004. The view, opinions, and/or findings contained in this report are those of The MITRE Corporation and should not be construed as an official Government position, policy, or decision, unless designated by other documentation. ©2021 The MITRE Corporation. ALL RIGHTS RESERVED.
For a fixed network environment, the goal of a blue agent is to learn to achieve a high score by performing actions on a network to maintain an acceptable level of service for authorized hosts subject to a resource budget and while preventing unauthorized access. Thus, the learning agent must master an operator role in a cybersecurity operation center (CSOC). Network defense tasks should be specified over ranges of parameters, or more precisely, over distributions of network environments. By following this approach, it is possible to reason about the performance boundaries of an agent’s policy. In turn, such ability to reason about an agent’s performance can inform strategies to gradually increase the complexity of tasks to facilitate progress; or to divide the network defense problem into smaller problems to apply hierarchical approaches [22]. Our approach is compatible with related ideas, including Automated Domain Randomization [19], and Unsupervised Environment Design [7].

In this section we enumerate key aspects of a network environment that must be parametrizable, and we outline our approach [17] for modeling distributions of network environments using generative programs [6].

### 2.1 Features of network environments

Network environment definitions include the definition of action spaces, observation spaces, and reward functions, as well as the definition of probabilistic models that characterize network dynamics (including how devices are connected) and the behaviors of adversarial (red) and benign (gray) agents. Because all these aspects can vary dramatically, the network environment design task is to delimit them in a way that is conducive to developing and evaluating learning approaches.

**Agent behavior.** Agents (red, gray, and blue) take actions that alter the network state, but each agent only partially and imperfectly observes the state of the network. Hence, defining the behavior of agents requires definitions of actions (in \( A \)) that affect the network, that agents take based on observations (in \( O \)), which depend on the state of the network (in \( S \)). In our approach [17], the process of determining future actions (the policy) is provided via generative programs in the case of red and gray agents. Blue agents learn policies via RL algorithms. Different agents may estimate states differently, aware that each has different goals and observability capabilities.

**Game state.** The state of a network depends on how devices are connected and how network configurations change due to agents’ actions. Typical network configurations include a set of hosts, which may change during an episode. Blue agents may have full visibility about which nodes are connected on a network and how; services that are running in each host and which ports are used; information about which hosts contain the crown jewels to protect; and packet forwarding rules. In contrast, red agents only have partial and imperfect information about hosts and network configurations. Our paper discusses how FARLAND [17] maintains state using graphs, and how portions of the state are visible to red, gray, and blue agents.

**Observations.** Because it is impractical to assume that agents will be able to fully observe the network state, agents act on partial and imperfect state information. Part of a network environment model is to determine what features of the state are observable by which agent and with what kind of uncertainty. One may assume that gray agents act on information available to normal authorized users. Blue agents may have access to much more information, but it may be necessary to only focus on a subset of the state space for the purposes of making the learning process feasible. For example, a blue agent may take actions based on observations that summarize the state of the environment at a snapshot in time, summarizing network information and host activity information primarily related to quality of service and threat indicators. Network information may include specific events (e.g., host A sent a file to host B via scp), or they may include network statistics that, for example, describe volumes of traffic in network regions or between specific hosts. Host activity information describes events observed by monitors on the hosts and do not necessarily involve network events or generation of traffic.

**Rewards.** Reward functions are specified by the researcher and take as inputs features of the network state; costs associated with deploying or repairing services; and potentially subjective representations of how good or bad certain states are for a set of security goals. While these may be subjective, because different organizations may value security goals differently, broadly speaking, indications of successful compromises or service degradation should incur penalties. Successful attack containment and adequate service would result in positive rewards. For a given environment, the set of suitable reward functions is not unique.

### 2.2 Generative programs to model network environment distributions

Our discussion in Section 2.1 enumerates several aspects of a network environment that must be specified to define a network defense task. The next question is: how do we represent distributions of network environments in a manner that allows researchers to develop novel RL approaches for network defense? Our work [17] proposed the use of generative programs to represent distributions of network environments.

Generative programs define probability distributions on execution traces [6]. Instead of defining deterministic mappings between inputs and outputs, they define a weighted set \( \{(x, \xi)\} \) of possible execution traces, where \( x \) denotes a trace, and \( \xi \) denotes its weight, associated with the probability that running the corresponding program \( \mathcal{P} \) with specific arguments \( \alpha \) results in \( x \). In our case, generative programs allow researchers to model stochastic aspects of network behavior, such as gray agents or failures on a network. Additionally, they allow the specification of assumptions about red TTP variability for deception purposes.

Parameters of generative programs can be learned from data. This allows, for example, the generation of synthetic behavior that captures observations from real logs and network traffic. In contrast to using generative adversarial networks (GANs) [9], which can generate synthetic data based on datasets, generative programs facilitate the implementation of planners with stochastic behavior. In particular, the structure of a red TTP can be described by a program that resembles a traditional implementation (e.g., an automated planner) but during execution, red and gray agents can make...
choices determined by probability distributions, which could result in dramatically different traces.

A key observation for network defense is that a game requires maintaining QoS, preventing a red agent from achieving its goals, and recognizing potentially deceptive behaviors on the part of the red agent. Therefore, if the behaviors are sufficiently complex and non-deterministic, the blue agent must learn to succeed at more than one simple game.

2.3 Motivating example: poisoning an RL network defender

We have performed initial experiments leveraging the approach we describe above. Our results illustrate that, when we train a blue agent using known TTPs without accounting for potential (poisoning or evasion) attacks targeting the learning algorithm, its performance cannot be guaranteed or generalized. In prior work we showed that while a blue agent may achieve acceptable performance when trained against a red agent that is only assumed to behave in a manner consistent with a subset of behaviors described in the ATT&CK framework, when we perturb the behavior of the agent using only gray-like actions, the performance of the blue agent is significantly degraded [17]. In other words, blue agents trained through RL are vulnerable to simple deception. This is because they are playing only one game without accounting for "rules" where the blue agent itself is targeted.

Figure 1 shows our previous results [17] where a blue agent learns with three different algorithms using various learning rates. The blue agent experiences an adversary’s TTP (exfiltration) consistent with ATT&CK, in a 10-node network. The blue agent’s action space consists of selecting a host and choosing whether to isolate it, migrate it to an existing network, or migrate it to a new network. The reward function favors trapping an offender in a honey network over isolating it. The reward function also penalizes unnecessarily isolating or migrating hosts to a honey network when they are not misbehaving. The agent learns to identify characteristics of attacks and QoS from the following information: the numbers of SCP events, HTTP events, AMQ events, SSH events, quiet or aggressive reconnaissance events originated at a host; and the numbers of SCP failures, REST request failures, AMQP failures, SSH failures, and content searches reported by hosts.

Our previous results [17] also demonstrated the effect of allowing an adversary to deviate its behavior from the assumptions outlined above with only gray-like actions. This simple deceptive behavior degrades the performance of the blue agent (Figure 2).

3 RELATED WORK

Research has identified the need for gradually increasing the complexity of an environment to make the learning process feasible [7, 19]. Moreover, Dennis et al. propose an approach to find a curriculum of increasingly complex environments [7]. However, to our knowledge, we are the first to propose a concrete approach to define distributions of network environments for autonomous cyberdefense [17]. Our work also resulted in the development of FARLAND, to train network defenders beyond what is possible with existing RL frameworks [3, 5, 13].

Dozens of papers have explored RL for cybersecurity [18]. However, prior work primarily addresses the problem: to what extent can RL automate complex tasks? This has been attempted only in simple scenarios without offering generalizable insights. Furthermore, prior efforts do not properly address the question of how RL can be securely applied to solve complex tasks in the presence of adversaries. While many papers have highlighted vulnerabilities of RL to adversarial manipulation [4, 8, 10, 11, 14, 15, 23], there remains no fundamental understanding about how to secure RL agents during learning and while making decisions. Many papers that have exposed RL’s vulnerabilities to adversarial manipulation have done so under unrealistic assumptions (e.g., assuming that observations and/or rewards can be directly manipulated by adversaries [11, 14]). We argue that in the context of defending a network, such data manipulation requires that an attacker tampers with traffic and client logs, which can be prevented via traditional means, such as encryption. Our position is that indirect observation manipulation (also known as environment manipulation [23] or adversarial policies [8]) and actuator manipulation [4] are more realistic threats.

Securing RL agents is critical when they are deployed in adversarial situations (e.g., using automation to defend an enterprise network). Existing threat emulators [24] do not support research to answer the following types of questions: To what extent can we use RL to develop agents that learn to perform security-related tasks? Furthermore, how do we measure the robustness of such agents to deception (poisoning and evasion) attacks? Previous [2] attempts to provide a framework to answer the first type of questions. We argue that to address both questions, it is necessary to model a diverse set of network environments and adversaries.

4 CONCLUSION

Our position is that in order to develop and evaluate the next-generation autonomous cyberdefenders it is necessary to model distributions of network environments. We highlight how MITRE’s approach (Network Environment Design for Autonomous Cyberdefense [17]) leverages generative programs to model these network environment distributions. Our work lists concrete features of network environments that researchers must be able to parametrize to be able to make progress toward practical autonomous cyberdefense. Importantly, our position accounts for the reality that AI-enabled cyberdefenders will inevitably themselves be the targets of attacks seeking to poison or evade their models. Our experimental results indicate this looming threat.

Our approach inspired the development of FARLAND [17], used at MITRE to develop RL network defenders that execute actions from the MITRE Shield matrix [1] against attackers with TTPs that drift from MITRE ATT&CK TTPs [21]. While prior RL work has achieved human-level or better performance in complex tasks (e.g., strategy games), translating such achievements for cyberdefense requires a greater real-world fidelity and flexibility to shifting rules and dramatically different conditions.

We invite the research community to develop evaluation approaches based on the performance of agents on distributions of network environments. Evaluations based on the performance of agents on sets of predominantly fixed network environments – e.g., a
Fig. 1. Blue agent’s performance in a 10-node network against an exfiltration attack (consistent with ATT&CK) with three different algorithms, APEX-DQN [12], PPO [20], and A3C [16]. An episode ends when the red agent exfiltrates a real or a fake crown jewel; or after 100 steps. The left column shows that all three algorithms result in behavior that lets the red agent "win". However some learn to let the red agent win in a fake network rather than in a real network. In the former case, the average reward approaches 1 (e.g., when using APEX-DQN with learning rate lr=0.0001). Other configurations, (e.g., PPO with lr=0.01) converge to a policy with poor performance that lets the red agent exfiltrate most of the time. In this case, 5M timesteps correspond to approximately 120K episodes.

Fig. 2. Blue agent’s performance, learning with APEX-DQN with the same configuration as in Figure 1, except that the adversary performs an exfiltration attack with deception. The left plot shows that the red agent successfully exfiltrates the crown jewel most of the time. Furthermore the blue agent fails to learn a suitable policy.

list of red TTPs under similar network conditions are less suited to reasoning about the performance of these agents when the characteristics of adversarial TTPs, QoS requirements, and actions available to the defender change. In particular, we caution against applying AI techniques, such as RL, to tackle the network defense problem, without implementing robust defenses against AI-targeted attacks.

ACKNOWLEDGEMENTS
FARLAND is the result of contributions from researchers at MITRE and NSA, including MITRE researchers Dr. Andres Molina-Markham, Dr. Ransom Winder, Cory Miniter, Becky Powell, Bryan L. Quinn, Ceyer Wakilpoor, and Hunter DiCicco, and NSA researcher Dr. Ahmad Ridley.
REFERENCES

[1] MITRE Shield, 2020.

[2] Callum Badlie, Maxwell Standen, Jonathon Schwartz, Michael Docking, David Bowman, and Janie Kim. CybORG: An Autonomous Cyber Operations Research Gym. 2020. _eprint: 2002.10667.

[3] Charles Beattie, Joel Z. Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Henrietta Kuhté, Andrew Lefrancq, Simon Green, Victor Valdés, Amir Sadik, Julian Schrittwieser, Keith Anderson, Sarah York, Max Cant, Adam Cain, Adrian Bolton, Stephen Gaffney, Helen King, Demis Hassabis, Shane Legg, and Stig Petersen. DeepMind Lab. arXiv:1612.03801 [cs], December 2016. arXiv: 1612.03801.

[4] Vahid Behzadan and Arslan Munir. The Faults in Our Pi Stars: Security Issues and Open Challenges in Deep Reinforcement Learning. CoRR, abs/1810.10369, 2018.

[5] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. OpenAI Gym. arXiv:1606.01540 [cs], June 2016. arXiv: 1606.01540.

[6] Marco F. Cusumano-Towner, Feras A. Saad, Alexander K. Lew, and Vikash K. Mansinghka. Gen: A General-purpose Probabilistic Programming System with Programmable Inference. In Proceedings of the 40th ACM SIGPLAN Conference on Programming Language Design and Implementation, PLDI 2019, pages 221–236, New York, NY, USA, 2019. ACM. event-place: Phoenix, AZ, USA.

[7] Michael Denis, Natasha Jaques, Eugene Vinyals, Alexandre M. Bayen, Stuart Russell, Andrew Critch, and Sergey Levine. Emergent Complexity and Zero-shot Transfer via Unsupervised Environment Design. In Advances in Neural Information Processing Systems, volume 33, 2020.

[8] Adam Gleave, Michael Dennis, Neel Kant, Cody Wild, Sergey Levine, and Stuart Russell. Adversarial Policies: Attacking Deep Reinforcement Learning. CoRR, abs/1905.10615, 2019.

[9] Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In International Conference on Neural Information Processing Systems-Volume 2, pages 2672–2680, 2014.

[10] Yi Han, David Hubczenko, Paul Montague, Olivier De Vel, Tamas Abraham, Benjamín P. Rubinstein, Christopher Leckie, Tansu Alpcan, and Sarah Erfani. Adversarial Reinforcement Learning under Partial Observability in Software-Defined Networking. arXiv preprint arXiv:1902.09062, 2019.

[11] Yi Han, Benjamín P. Rubinstein, Tamas Abraham, Tansu Alpcan, Olivier De Vel, Sarah Erfani, David Hubczenko, Christopher Leckie, and Paul Montague. Reinforcement Learning for Autonomous Defence in Software-Defined Networking. In International Conference on Decision and Game Theory for Security, pages 145–165. Springer, 2018.

[12] Dan Horgan, John Quan, David Budden, Gabriel Barth-Maron, Matteo Hessel, Hado van Hasselt, and David Silver. Distributed Prioritized Experience Replay. CoRR, abs/1803.09933, 2018. _eprint: 1803.09933.

[13] Matthew Johnson, Katja Hofmann, Tim Hutton, and David Rignell. The Malmo Work Environment Design for Autonomous Cyberdefense. 2021. _eprint: 2103.07583.

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

[15] Yen-Chen Lin, Zhang-Wei Hong, Yuan-Hong Liao, Meng-Li Shih, Yuan-Hong Liao, Meng-Yu Liu, and Min Sun. Tactics of Adversarial Attack on Deep Reinforcement Learning Agents. CoRR, abs/1703.06748, 2017.

[16] Volodymyr Mnih, Adria P. Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous Methods for Deep Reinforcement Learning. CoRR, abs/1605.01733, 2016. _eprint: 1605.01733.

[17] Andres Molina-Markham, Cory Mintir, Becker Powell, and Ahmad Radley. Network Environment Design for Autonomous Cyberdefense. 2021. _eprint: 2103.07583.

[18] Trang Nguyen, Satinder Singh. On Efficiency in Hierarchical Reinforcement Learning. ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS, 33, 2020.

[19] Chauwei Xiao, Xinlei Pan, Warren He, Jian Peng, Mingjie Sun, Jinfeng Yi, Bo Li, and Dawn Song. Characterizing Attacks on Deep Reinforcement Learning.

[20] MITRE ATT&CK. CoRR, CoRR 2019.

[21] Callum Baillie, Maxwell Standen, Jonathon Schwartz, Michael Docking, David Bowman, and Janie Kim. CybORG: An Autonomous Cyber Operations Research Gym. 2020. _eprint: 2002.10667.

[22] Zheng Wen, Doina Precup, Morteza Ibrahimi, Andre Barreto, Benjamin Van Roy, and Satinder Singh. On Efficiency in Hierarchical Reinforcement Learning. ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS, 33, 2020.