ABSTRACT

Reinforcement learning (RL) has been demonstrated suitable to develop agents that play complex games with human-level performance. However, it is not understood how to effectively use RL to perform cybersecurity tasks. To develop such understanding, it is necessary to develop RL agents using simulation and emulation systems allowing researchers to model a broad class of realistic threats and network conditions. Demonstrating that a specific RL algorithm can be effective for defending a network under certain conditions may not necessarily give insight about the performance of the algorithm when the threats, network conditions, and security goals change. This paper introduces a novel approach for network environment design and a software framework to address the fundamental problem that network defense cannot be defined as a single game with a simple set of fixed rules. We show how our approach is necessary to facilitate the development of RL network defenders that are robust against attacks aimed at the agent’s learning. Our framework enables the development and simulation of adversaries with sophisticated behavior that includes poisoning and evasion attacks on RL network defenders.

1 Introduction

Since the introduction of Deep Reinforcement Learning [19], numerous systems have successfully combined fundamental ideas from Reinforcement Learning (RL) and Deep Learning to solve hard problems with superhuman performance. However, it remains a challenge to translate such progress into successfully using RL to tackle complex tasks, such as those necessary for network defense. One fundamental problem 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 present FARLAND, a framework for advanced Reinforcement Learning for autonomous network defense, that uniquely enables the design of network environments to gradually increase the complexity of models, providing a path for autonomous agents to increase their performance from apprentice to superhuman level, in the task of reconfiguring networks to mitigate cyberattacks. Our approach is aligned with research, such as unsupervised environment design [10] and automated domain randomization [23], which highlight the need to gradually scale the difficulty of a task to allow progress when learning to master complex jobs. Importantly, FARLAND’s abstractions for network environment design include adversarial models targeting the RL-enabled decision making component. This reflects the ultimate goals of FARLAND, which include enabling the development of practical approaches for autonomous network defense; and the evaluation of the robustness of such approaches against RL-targeted attacks.

While a number of systems and frameworks already enable research in RL—such as Gym [7], DeepMind Lab [4], or Malmo [14]—none are adequate for performing research to apply RL for practical network defense. It is not sufficient to build a system to simulate attacks, recognizing that it is difficult to learn to reconfigure a real network by directly experiencing a large volume of attacks in real environments. It is important to use a framework to addresses the open
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problem of developing strategies to guide an agent through a sequence of increasingly harder problems to guarantee progress (i.e. analog to automated domain randomization [23] or unsupervised curriculum learning [10]). Furthermore, such a framework needs to expose an appropriate set of knobs (model parameters) during the process of gradually increasing model complexity to tackle network defense. FARLAND provides a solution to these challenges, and it is therefore unique in enabling network environment design, an essential aspect for research toward understanding how to apply RL for network defense.

Our work not only proposes concrete aspects that must be parametrized in the process of developing network environments, but also, it provides concrete approaches for controlling these parameters while learning to reconfigure a network for cyberdefense. Furthermore, we put forward a dual layer architecture to trade model fidelity for dramatically faster experience replay. Concretely, FARLAND allows the specification of (a) network models (which include gray (i.e., normal user) and red agent behavior) via generative programs [9], thus providing an answer to the problem of modeling environments with varying degrees of complexity and dynamics that are probabilistic and partly observable; and (b) sets of blue-agent actions, views of network state (observations), and reward functions, to increasingly enable more sophisticated blue policies. In addition, FARLAND allows researchers to develop compatible simulation and emulation network environments, such that games can be simulated (via generative programs) with a fraction of the computation cost required to emulate the corresponding game in a full software defined network, with real hosts, and control and data planes. Emulation network environments can be used to estimate the parameters of probabilistic models used in simulation; and to validate the performance of learned reconfiguration policies.

Other key considerations informed the design of FARLAND and contributed to its novelty. Concretely, FARLAND:

1. Leverages state-of-the-art RL algorithm implementations and distributed computing frameworks for AI: Training an intelligent network defender is computationally expensive. Simulating network-defender experiences requires a large number of general-purpose computations. In addition, training requires solving computationally intensive optimization problems through the effective use of GPUs.

FARLAND allows researchers to scale the size and complexity of their networks and models by leveraging RLLib [17], which abstracts common distributed computing patterns that allow simple scaling when more resources are available. FARLAND’s architecture decouples tasks related to the design of RL algorithms from tasks related to network environment design and other low level aspects of how to coordinate the execution of multiple agent experiences, the collection of data, etc. While, RLLib includes implementations of about a dozen RL algorithms –e.g., A2C, A3C, DQN, DDPG, APEX-DQN, and IMPALA –we argue that there is a further need to develop novel algorithms that are robust against attacks to manipulate AI-enabled decisions (i.e., evasion and poisoning attacks). RLLib’s architecture allows experts in algorithm design to cleanly separate this task from problems related to distributed computing, as well as from addressing environment modeling problems. FARLAND’s abstractions also separate the problems of defining security goals, network and adversarial models, from the problem of implementing a simulator or emulator to effectively turn these models into an environment with which the learning agent can interact.

2. Supports cyber defense research: Unlike existing systems that aim to enable research in RL [7, 4, 14], FARLAND is specifically designed to support the development of (blue) RL agents that learn to defend networks, performing actions that modify the configurations of software-defined networks. While prior research aims to apply RL to solve networking problems [8, 25], FARLAND would be among the first to provide an open framework specific for network defense.

We argue that research should not focus on demonstrating that an approach can enable the learning of policies for an agent under specific conditions because network models, threat models, and security goals can vary dramatically. Instead, researchers need the ability to model broad classes of models and subject their approach to relevant variations of their models to understand the implications of changing network conditions, assumptions about their adversaries, security goals, and defender action spaces.

Moreover, it is highly likely that real-world network defense is actually implemented by multiple agents, each in charge of a simple set of decisions from only a subset of all data that can be observed. Hence, context will influence engineering efforts to determine suitable observation spaces, action spaces, and reward functions. Our work aims to provide an experimentation framework to investigate these issues rather than to provide a solution to the problem of creating an autonomous network defender that is good in a small set of concrete situations.

3. Facilitates transition from research to practice: With the goal of closing the gap between research and practice, FARLAND’s coherent simulation-emulation paradigm offers researchers an accelerated development of RL agents via simulation, while allowing for emulation-supported refinement and validation. The behavior of agents (red, gray, and blue) can be simple or sophisticated. Researchers can start by modeling simple behaviors to enable rapid progress

CybORG [3] is also among one of the first. However, our goals differ in significant ways § 2.
and fundamental understanding. However, the modularity of FARLAND provides a path for extending the behavior complexity of agents. Our goal to close the gap between theory and practice differs from the goals of other systems to provide environments that offer a broad range in complexity, partial observability, and multi-agency (e.g., Malmo [14], SC2LE [29], and SMAC [26]) without necessarily grounding in practical applications.

In addition, we argue that securing an autonomous network defender will need innovation not just in the learning and decision-making algorithms (e.g., to make them more robust against poisoning and evasion attacks), but also, it will require the integration of multiple approaches aimed at minimizing the probability of invalid behavior. Concretely, our work aims to be amenable to the development of approaches, based on formal methods, to ensure that actions of a network defender do not cause unintended behavior; e.g., by ensuring that updates (by an autonomous blue agent) to packet forwarding policies do not violate packet-traversal goals aimed at segregating flow of information in a network or preventing distributed denial of service attacks.

Contributions

This paper highlights two main contributions: (i) a novel approach for network environment design to apply RL for network defense; and (ii) a framework that implements our network environment design concepts to enable RL and cybersecurity researchers.

(i) Network environment design for autonomous network defense: Our work proposes aspects of network models that must be available to researchers seeking to apply RL to reconfigure networks to mitigate cyberattacks. While network environment design is one task that directly addresses the problem of enabling progress toward learning a complex task, our work addresses the more fundamental problem that network defense cannot be defined as a single game with a simple set of rules. This aspect is especially important when applying RL to solving a problem that is expected to change over time. Autonomous network defenders must not only be able to reconfigure hosts and networks to be able to mitigate common adversaries, such as those described in MITRE’s ATT&CK framework [28], defenders must increasingly be concerned about more sophisticated adversaries that target autonomous cyber defense. Our work takes a novel approach for modeling emerging threats via state-of-the-art probabilistic computing concepts, some implemented using [9]. Section 7 illustrates the perils of training an autonomous defender without considering an adversary capable of deception. Here, an adversary or attacker would perform deception using adversarial machine learning approaches such as poisoning and evasion attacks to manipulate the RL agent defender for the benefit of the adversary. This is in contrast to a defender employing cyber-deception capabilities such as honeypots or honeynets to deceive and confuse an attacker. We discuss how, in order to evaluate the robustness of a RL network defender against deception attacks, the learning framework must enable the modeling of attackers that perform evasion and poisoning attacks through indirect manipulation of observations. This contrasts with prior work that has assumed that observations (e.g., images) can be directly manipulated by an adversary. Such direct manipulation of observations in network defense involves high degrees of log and traffic manipulation that correspond to an adversary that would be too strong to be seeking to manipulate the AI-component of the defender, as an initial attack vector. As the other non-AI system vulnerabilities become more secure and trusted, our research can evolve to address deception attacks from sophisticated adversaries who now pivot to exploit the AI-component of the defender.

(ii) FARLAND, a framework to develop and evaluate approaches for RL-enabled network defense: We describe the architecture and an implementation of FARLAND, one of the first software frameworks specifically designed to enable cyber defense research supported by AI techniques. Our implementation includes concrete examples that can be extended by others to develop increasingly more sophisticated network defenders using RL. These examples help researchers to gain insights about the following types of questions:

• To what extent does FARLAND allow the development of RL agents to defend networks against adversaries that behave according to a subset of known tactics and techniques?
• How does the performance (for training and inference) of a defending agent change as a result of modifications to the network model and to the assumptions about normal behavior (by gray agents)?
• How susceptible is the performance of such a defending agent to deviations in behavior by the adversary?
• To what extent can an adversary systematically produce behavior that will influence the behavior of the defending agent in specific ways?

The rest of this paper is organized as follows. We start by motivating the need for a framework like FARLAND, emphasizing that while dozens of papers have explored the use of RL for cybersecurity [22], the work is difficult to reproduce and generalize. We highlight how no other system robustly addresses the problem of network environment design to understand how concrete approaches scale and perform as researchers vary network conditions. In particular, we discuss how there is not a mature understanding about how to protect the learning and decision-making processes of
a RL agent. We then give an overview of the computing tasks necessary for understanding how to use RL for security and to study the security aspects of applying RL. We explain why existing systems without comprehensive network environment design features do not readily support the problems of “applying RL for cybersecurity” and “securing the RL processes”. We then give an overview of FARLAND’s abstractions that allow us to model interactions between RL-enabled network defenders and adversaries from which the defending agent will learn. We build on these abstractions to describe FARLAND’s architecture, discussing in detail how it enables the implementation of agent and network models. We illustrate FARLAND’s concepts via concrete examples of defending and attacking agents. We conclude with a discussion about how FARLAND can be used for answering questions about the performance of a learning approach and what problems need to be addressed to develop RL-enabled network defenders robust against evasion and poisoning attacks.

2 Related work

RL is a promising AI approach to support the development of autonomous agents that must implement complex sequential decision making. Over a period of 5 years alone (2015-2020), more than 1500 papers about RL have been published in the top 10 Machine Learning conferences\(^2\). Of the many papers that are related to this work, we only highlight those that relate to the major contributions of our research.

We are primarily interested in the problem of applying RL for cybersecurity. On that subject alone, there are dozens of papers, as Nguyen and Reddi discuss [22]. To date, papers in this category primarily address the feasibility problem. Namely, they address the general question of: To what extent is it possible to use RL learning to automate complex tasks, such as those necessary for cyber defense? However, existing work only addresses simple scenarios without offering generalization insights. Furthermore, there is no mature research to properly address the question of how RL can be securely applied to solve complex tasks in the presence of adversaries. Multiple papers have highlighted vulnerabilities of RL to adversarial manipulation (e.g., [30, 5, 15, 18, 13, 12, 11]). However, there is still no fundamental understanding about how to secure RL agents during learning and while making decisions. Moreover, many papers that have exposed RL’s vulnerabilities to adversarial manipulation have done so under unrealistic assumptions. For example, some work assumes that observations and/or rewards can be directly manipulated by adversaries [13, 15]. We argue that in the context of defending a network, such data manipulation requires that an attacker tampers with traffic and client logs. Such kind of manipulation can be prevented via traditional means –e.g., encryption. Our position is that indirect observation manipulation (also known as environment manipulation [30] or adversarial policies [11]) and actuator manipulation [5] are more realistic threats. Our work aims to enable the study of such kinds of attacks in the context of autonomously defending a network.

While the issue of securing RL agents is clearly important, it is more critical when RL agents are specifically deployed in adversarial situations (e.g., when using automation to defend an enterprise network). In particular, existing experimentation systems 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 work [3] attempts to provide a framework to answer the first type of questions. In this paper, we argue that to comprehensively address both questions, it is necessary to be able to model a diverse set of network environments and adversaries.

3 FARLAND motivation and overview

Existing environments, libraries, and frameworks –e.g., [7, 4, 14] –only support a subset of the tasks necessary to develop AI systems for security. They either focus on the development and comparison of RL algorithms for a narrow set of problems not directly linked to real-world applications; focus on the development of RL algorithms to solve specific real-world problems in non-adversarial settings; or are aimed at the evaluation of endpoint detection and response (EDR) systems and cyber defense teams. Systems in the last category are not necessarily optimized for autonomization (to support autonomous control or scalable experience replay).

For example, Gym [7], a system to develop and compare RL algorithms, does not currently provide an environment that resembles the kind of adversarial environment that a network defender would face. Similarly, while DeepMind Lab [4] and Malmo [14] facilitate the development of environments with various degrees of complexity, it would be extremely challenging to map one of these environments to an environment that adequately models the task of defending a network against sophisticated adversaries. This is also the case for other systems, such as SC2LE [29] and SMAC [26], which support environments with various degrees of partial observability and multiplayer interactions.

\(^2\)The conferences are NurIPS, ICML, ICLR, AAAI, ICVRA, AAMAS, CVPR, IROS, ICCV, ICAI. Source: Microsoft Academic [27].
As we describe in this section, these kinds of environments are not suitable for learning to defend networks, especially when deception (poisoning and evasion attacks) may be a concern.

Besides environments and systems that aim to improve the state-of-the-art of RL algorithms, there are other systems that aim to demonstrate the suitability of RL to solve networking problems, such as AuTO [8] and Iroko [25]. However, these do not facilitate answering security research questions because they do not facilitate the modeling of adversaries.

Systems to facilitate interactions between attacker (red) and defender (blue) teams are designed with different goals (e.g., to evaluate EDR systems) from those that we outline in this section. FARLAND prioritizes support for performing large numbers of fast simulations and emulations via interfaces that are suitable for developing AI agents. Systems such as MITRE’s Blue vs Red Agent Wargame eValuation (BRAWL) are designed to be more broadly applicable, but are not primarily designed for defender autonomization. For example, BRAWL supports multiple teams of humans competing in a cybergame using command line interfaces and graphical user interfaces on a Windows operating system. However, BRAWL does not provide an API to allow an autonomous blue agent to reconfigure networks to implement protection mechanisms. BRAWL, also does not provide a way to simulate a large number of experiences without emulating them.

There is prior work that explored the use of RL for cyber defense [13, 12]. However, the results are not generalizable because their assumptions differ significantly from real-world scenarios. Finally, CybORG [3], like FARLAND, provides a framework to allow researchers to vary network models and adversaries; and, it recognizes that a compatible simulation-emulation approach is needed to enable learning while facilitating model validation. However, the current CybORG design does not explicitly allow modeling asymmetrical behavior and goals between the red and blue agents. Also, CybORG currently does not include adversarial influence, such as deceptive red agent behavior, as an attack type that must be taken into consideration when investigating how to use RL in security applications. Furthermore, FARLAND’s use of generative programs to specify aspects of a network environment allow for the development of unsupervised strategies to gradually increase the fidelity of models. CybORG does not offer similar functionality.

In addition, FARLAND’s architecture differs from CybORG’s, in several key aspects: CybORG models only cover what we call traditional red agents (§ 4.1), whereas FARLAND models include traditional and deceptive red agents, as well as, gray agents with probabilistic behaviors. In addition, CybORG’s models use finite state machines as opposed to FARLAND’s richer probabilistic models via generative programs [9]. FARLAND’s architecture is designed to scale emulation tasks, as well as, learning tasks, by leveraging RLlib [20]. CybORG does introduce an important advance in research that applies RL to cybersecurity; however, its current design does not include some important considerations addressed by FARLAND.

3.1 Abstractions

As with other RL frameworks [6, 4, 14], researchers need adequate abstractions to define environments, agents’ actions, observation spaces, and algorithms that agents use to learn how to act. However, in the case of network defense, environment design includes defining assumptions about red and gray agent behavior.

In FARLAND, many of these aspects are defined via generative programs [9]. Generative programs define probability distributions on execution traces. That is, 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 \( P \) with specific arguments \( \alpha \), results in \( x \).

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 inference queries that may be used by a red agent (for deception purposes), or by a blue agent to quantify uncertainty. More generally, some of these aspects can also be defined via probabilistic models derived from data (e.g., large datasets of regular network traffic and logs) provided that these models can be sampled.

Thus, the process of developing a RL network defender requires two tasks: RL algorithm design and network environment design. RL algorithm design tasks are related to specifying how a learning agent will learn a suitable policy from a concrete collection of action spaces, observation spaces, and reward functions. RL algorithms for cyberdefense also need to integrate mechanisms to prevent adversarial manipulation via poisoning and evasion attacks. Network environment design tasks 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 red and gray agents.
3.2 RL for network defense

RL agents are autonomous systems that learn to execute complex tasks through performing actions on an environment and observing the effects of their actions on this environment. Observations consist of state features and rewards. Rewards are quantities that encode the desirability of the effects. The goal of a RL-agent is to learn to act to maximize the sum of expected rewards over a period of time. Some aspects of engineering reward functions and observation spaces in the context of cybersecurity are analogous to efforts to design other RL-enabled systems. However, there are key differences when applying RL for cybersecurity, which we illustrate in Section 6.

Implementing this type of RL agent involves three types of computations (see Figure 1): serving, training, and simulation (or emulation\(^3\)) (cf. [20], for example). Serving computations involve the selection of actions that maximize long-term rewards. Training computations typically involve solving computationally expensive optimization problems—e.g. stochastic gradient descent—aimed at improving the current policy (the mapping to select actions when the agent is at a specific state). Finally, simulation or emulation computations can be a broad class of computations aimed at generating experiences for the RL agent.

In the context of learning to defend a network, the training and simulation/emulation tasks are both computationally intensive. Emulation involves the creation of virtual networks with virtual hosts running real applications on real application systems. Hence, emulation will require computation proportional to the size of the network and the complexity of the applications that are emulated. In addition, simulation actually involves the computations of red agents, which may include searches and solving optimization problems to decide how and when to create noisy observations. Finally, training tasks also require a large number of operations on GPUs.

FARLAND builds on RLlib’s abstractions to be able to easily add resources as they are available without having to specifically redesign algorithms or distributed computation details every time that a researcher wishes to add more CPUs, GPUs, memory, etc.

3.3 Network dynamics models

FARLAND supports a simulation mode and an emulation mode. Emulation requires a virtualization environment that supports the creation of \(n \cdot m\) containers, where \(n\) is the number of hosts on the network, and \(m\) is the number of parallel emulations that will be running during training.

As we illustrate in Figure 2, a typical FARLAND deployment requires a high-performance computing system with GPUs to support the agents’ computing tasks. The computing tasks to support emulation do not require GPUs. However, these do require a large number of CPUs. Furthermore, because emulated hosts execute adversarial programs with high privileges, typical FARLAND deployments may require an additional layer of separation.

A separate aspect related to simulating normal conditions on a network is the development of gray agents. Gray agents execute actions on the network according to probabilistic models. The types of computations necessary to implement gray agents’ behavior will largely depend on the complexity of the probabilistic models.

\(^3\)As we describe in Section 3, in this paper, we refer to emulation when implementing agents that perform actions on virtual networks with containerized hosts. We refer to simulation when agents perform actions on modeled networks.
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3.4 Probabilistic adversarial models

FARLAND aims to enable RL to solve network security problems and defend against sophisticated adversaries. This includes the development and modeling of adversaries with traditional tactics, techniques, and procedures, as well as adversaries with deception capabilities. Ultimately, FARLAND aims to evaluate the robustness of autonomous defenders.

FARLAND simulates interactions of three types of agents with a network. Gray agents behave according to a probabilistic model that characterizes the expected behavior of all authorized users in the network. Red agents interact with the network according to well-known tactics and techniques characterized by MITRE’s ATT&CK Framework [28]; or, they perform actions on the network with the goal of deceiving a RL-enabled blue agent. A blue agent reconfigures the network to mitigate attacks while maintaining acceptable levels of service.

To inform the design and evaluation of defenses for robust RL-enabled agents, FARLAND enables the development of sophisticated adversaries. While blue and red agents interact with the same environment, they do so in fundamentally different ways. Generally, network defenders’ actions involve network and host reconfigurations. In contrast, adversaries’ actions correspond to actions that compromised hosts perform on the network.

Under some threat models, adversaries’ intelligence can be modeled via planning-based intelligence. However, we are interested in modeling adversaries that purposely manipulate observations in order to influence the blue agent’s behavior. As we describe in subsequent sections, such a sophisticated attacker requires computations to predict a set of actions (e.g., via probabilistic inference) on the network that are likely to result in a targeted observation vector. The estimation of such a targeted observation vector correspondingly involves the computation of a solution to an optimization problem.

4 FARLAND game

As it is common, when developing RL agents, we use a game abstraction to frame the learning task. The goal of a cyber defender 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. In other words, the FARLAND game is an abstraction where the learning agent has to master an operator role in a cybersecurity operation center (CSOC).

Network environment models define the dynamics of a game. In other words, a FARLAND game starts with a pre-configured virtual software-defined network (SDN) consisting of hosts, switches, network functions, and a network controller. During the course of a game play, an adversary compromises some hosts by using a subset of the techniques described in ATT&CK or by performing a set of deceiving actions. The defender performs actions on the network to...
mitigate the effects of attacks and to maintain the network operating as intended. A game ends after one of the following: when the attacker achieves (or believes that it has achieved) its high-level goals; when the blue agent prematurely terminates the game (with an associated penalty); when the red agent concedes the game as a result of being contained by the blue agent; or after a timeout.

FARLAND episodes can be described via sequences of agent actions and states, which correspond to the application state of agents (red, gray, and blue); and the state of the network—i.e., hosts, files, databases, and communications. A network environment model includes a model of the network, but, more importantly, it includes a set of probabilistic models in the form of generative programs that define the behavior of red and gray agents. In addition, it includes definitions of action and observation spaces for the blue agent. We describe these three types of agents next.

4.1 Red agents

The network will be attacked by one red agent, which controls the behavior of multiple remote administration tool (RAT) agents. RATs are applications that run on compromised hosts in order to execute techniques orchestrated remotely by the master red agent. There are two kinds of red agents: (traditional) one that aims to achieve one high-level goal, consistent with the ATT&CK framework (e.g., to exfiltrate data from a Crown Jewels Server (CJS); to interrupt service by performing a distributed denial of service attack on a messaging broker; or, to create an unauthorized LDAP user to enable a future attack); and another one (deceptive) that aims to deceive an autonomous blue agent to decrease its performance.

The adversary achieves these goals via techniques executed by compromised hosts. During the course of a game, hosts become compromised by implementing strategies orchestrated by a planning agent or, by any agent whose decision-making is described by a probabilistic program in Gen [9]. Additionally, for the model to be emulated, there needs to be a corresponding implementation of each red action that the agent can perform. These typically correspond to known implementations of techniques in the ATT&CK framework (e.g., to perform discovery or lateral movement steps).

Deceptive agents also perform actions that result from variations of techniques from the ATT&CK framework (but without following the corresponding tactics) or additional procedures that resemble actions from gray agents. The goal of this agent is to deceive the blue agent to (a) decrease its performance; or, (b) to induce specific actions from the blue agent. Ultimately, the set of actions available to red agents can be very broad, ranging from a subset of procedures derived from the ATT&CK framework, to an arbitrary set of programs that can be executed by hosts on the network.

4.2 Gray agents

As part of modeling normal network behavior, FARLAND also allows the specification of gray agents with non-adversarial behavior. This is an important aspect to prevent the RL-enabled agent from simply learning to react to any network stimuli (corresponding to the actions of a red agent).

Non-adversarial behavior is implemented by orchestrating several applications that perform actions on hosts and on the network. For example, these applications may cause a host to execute a program that touches specific files on the host, increase its CPU utilization, or generate various types of network traffic, such as AMQP, HTTP, and SSH traffic. The behavior of these applications is specified using probabilistic programs that reflect the stochastic nature of gray agent events. Such applications include, for example: an application that sends (from each host) logging information via AMQP messages; and an application that generates remote procedure calls (RPCs) from one host to another using AMQP and REST messages to simulate distributed applications using microservices, IoT applications, or computationally intensive applications; an application that transfers data between hosts and executes tasks on other hosts over SSH.

4.3 Blue agent

The blue agent is the RL-enabled agent that defends the network. Thus, this blue agent also induces game state changes, for example, when it reconfigures the network. The defender agent protects the network by performing actions to contain attacks; to migrate or replicate services; or to deceive the attacker to either obtain more data to enable attribution, or to identify the purposes of the attack.

For example, a defender may isolate one or more hosts by changing packet processing rules; migrate a service by deploying a new virtual host and changing the network configuration to redirect future traffic to the new host and disconnecting the old service; replicate a service by deploying a new virtual host to add redundancy; reduce connectivity by changing packet processing rules; change logging policies; or create honey networks by deploying new virtual hosts
and changing the network configuration to connect compromised hosts to fake hosts and disconnecting compromised hosts from specific regions of the network. The agent may add or remove filtering policies or add waypoints (forcing packets to travel through one or multiple network functions before reaching their destination) in packet trajectories. A blue agent may do nothing, keeping the network and host configurations intact.

4.4 Network environment design

A full CSOC model for FARLAND requires definitions of sets of actions, states, and observations; as well as, definitions of transition models and goal tests for red and gray agents. In addition, for blue agents, it is necessary to specify reward functions. We describe each of these next.

**Defining agent behavior.** Each of the agents takes actions that alter the state of the network (i.e., cause the environment to transition from one state to another). However, each agent only partially and imperfectly observes the state of the network.

Hence, defining the behavior of red, gray, and blue agents requires definitions of actions (in \( A \)) that affect the network, that agents take based on observations (in \( \Omega \)), which depend on the state of the network (in \( S \)). Thus, model designers also need to specify observation filters, that is, mappings (in \( \{ m : S \rightarrow \Omega \} \)) that extract observations from the network state, from which the agent estimates a state. The process of determining future actions (the policy) is provided via a probabilistic program in the case of red and gray agents. Blue agents learn policies via RL algorithms. Different agents may estimate states differently, taking into account that each has different goals and observability capabilities.

**Transition models,** i.e., models that describe the probabilities of transitioning from one state to another do not need to be provided when using FARLAND’s emulation (cf. §). However, to enable fast learning via simulation, it is necessary to specify these transition models. Explicitly, agent actions correspond to programs that interact with the network. Red and gray actions are programs that run on hosts, while blue actions are programs that may run on hosts, as well as, on controllers that alter network configurations. When using FARLAND’s emulation, these are arbitrary programs that can be run on virtual systems, and hence the transition from one state to another is implicitly determined by the programs that are run. When interactions with the network are simulated, model designers need to specify the network transformations that would result from taking an action. In either case, agents need to extract information from the network state to estimate their own imperfect state.

For example, a lateral move action may be a program that implements a red agent’s procedure to compromise a host from another one. When emulated, the transition from one network state to another is the result of actually executing the corresponding program on a virtual network. When the action is simulated, the transition model needs to describe how the action is expected to affect the creation of packets and log entries and the presence of a RAT in the target host after taking the action. The red agent will also need to apply an observation filter to update its belief state (i.e., the red agent may keep track of the network hosts that are known and those that are believed to be compromised).

When actions are emulated, observation filters are specified via parsing functions of standard streams (stdout and stderr) and exit values. Note that, in particular, these observation filters help to deal with programs that produce large amounts of output and with programs that may terminate abruptly (e.g., because they may be terminated by a protection mechanism).

**Game state.** Defining state spaces is another aspect that researchers must specify. The state of a network depends on how devices are connected and how network configurations change as a result of agents’ actions. Typical network configurations include a set of hosts, which may change during the course of a FARLAND episode. Network state is internally represented as graphs with attributes. The nodes in the network state graph contain hosts, which also have attributes.

Red, gray, and blue agents each keep one such graph. These in general are different because agents have different knowledge about the hosts in the network and each agent may keep track of different host attributes. For example, blue agents may have full visibility about which nodes are connected on a network and how (including switches and network functions); services that are running in each host and which ports are used; information about which hosts contain the crown jewels to protect (sensitive files, AMQ brokers, and LDAP servers); and packet forwarding rules. In contrast, red agents only have partial and imperfect information about hosts and network configurations. Also, when the blue agent uses honey networks to learn about an adversary, the blue agent may use attributes to distinguish fake from real hosts. These attributes may not be accessible by the red agent. In contrast, a red agent may use host attributes to distinguish between compromised and non-compromised hosts.

Graph attributes are pieces of state that may be useful to infer QoS or malicious activity. For example, snapshot statistics that summarize numbers of packets delivered and in transit, or more generally, quantities that summarize the successes and failures of authorized communications on the network.
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 threat model is to determine what features of the state are observable by which agent and with what kind of uncertainty.

Typically, one may assume that gray agents act on information that would be 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 an observation matrix that summarizes 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. These types of information would be typically gathered by network appliances, but in our case, they can also be gathered by a monitor (FARLAND Instrumentation Controller) that operates at a lower virtualization level than hosts and network devices.

Host activity information describes events observed by monitors on the hosts and do not necessarily involve network events or generation of traffic. These kinds of information may be collected by low-level daemons running on hosts, or as in the case of network information, these can be collected by the FARLAND Instrumentation Controller.

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 with regard to a set of security goals. These may be subjective, because different organizations may value security goals differently, and deciding how much worse an outcome is than another outcome may not be simple. However, 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. As prior research has shown, in general, there can be infinitely many reward functions, which may be consistent with the desired behavior of the blue agent [21]. Describing a principled methodology to select a set of reward functions for a given environment and threat model is an issue that we plan to study in future work.

5 CSOC emulation

As we discussed in Section 4, FARLAND game is an abstraction to facilitate the development of a RL-enabled CSOC operator. However, to ensure that network and adversarial models are grounded in realistic assumptions, they should be informed and validated through emulation. This plays an important role in engineering observation spaces and in understanding the manipulation capabilities of an adversary. For these reasons, FARLAND was designed with the idea of providing a single layer to interact with a CSOC environment for the two possible types of environments that a blue agent can interact with—a simulated environment and an emulated environment. Interactions with a simulated environment accelerate the learning process, while interactions with an emulated environment enrich and validate models and approaches. This section, describes one way to implement FARLAND’s CSOC emulation component depicted in Figure 1.

Agents interact with a CSOC environment through a Game Controller via the same API, regardless of whether the environment is simulated or emulated. Hence, the Game Controller receives requests to perform an action on either a simulated or emulated environment.

The three main emulation aspects include coordinating network configuration updates, directing hosts to perform actions, and collecting observations. The Game Controller mediates actions between the red and gray agents and a Host Controller, and between the blue agent and a Network Controller, a Host Controller, and an Instrumentation Controller.

By design, communication between the Game Controller and emulated CSOC environment is brokered using asynchronous messaging. The reasons are twofold: emulation may require a large number of CPUs, hence a second system may be required; moreover, because red agent procedures may actually run adverse code, it may be a good practice to run CSOC emulations in a separate system, as opposed to a shared high-performance computing system.

In other words, while FARLAND can be run on a single system, we typically run the emulation component in a separate system. As we illustrate in Figure 2, the emulation component will create multiple virtual networks, depending on the number of RLLib workers that are selected. RLLib is part of Ray, a distributed framework for AI applications [20] that implements common functionality necessary to implement RL systems [17].
When emulation is used, the hosts on the network are implemented using Docker containers and virtual SDNs are created with instances of Containernet. Containernet is a network virtualization tool that facilitates the virtualization of SDNs programmatically [24]. Containernet was built atop Mininet, a network virtualization tool widely used by the research community [16]. The Instrumentation Controller is implemented atop of Falco, an open source monitor developed with the support of the Cloud Native Computing Foundation [1] and containerized network functions. Together, these collect data –stored in a database –similar to what host-based and network-based monitoring solutions collect. After a blue agent performs an action, the Instrumentation Controller gathers observations from the database. The observation space is configurable and extensible.

Containers are assumed to be exploitable, so that when a compromised host makes a lateral move, a host can start a RAT in the target host with elevated privileges. This allows a compromised host to arbitrarily replace the behavior of any program in the compromised host. This is necessary to implement deceptive agents (cf. § 6.1). Deceptive agents must be able to generate gray-like actions (e.g., send files via SSH from one host to another), and they should also be able to frustrate gray actions. The latter is accomplished by the RAT remapping real programs to fake programs. As a result, when a gray agent performs an action, the RAT can frustrate the corresponding observations.

6 Developing agents with FARLAND

FARLAND aims to not only support researchers that seek to demonstrate that an agent can perform security related tasks, but in addition, FARLAND was designed as a tool to help researchers understand how such learning can be manipulated by an adversary. Ultimately, FARLAND should also help researchers to evaluate the performance of defenders to protect the network against traditional behavior (for example, as described by ATT&CK’s framework), as well as, to protect their decision-making policies against deception attacks.

This section does not intend to demonstrate that RL can be effectively used for implementing robust autonomous cyber defense. Instead, it intends to illustrate the perils of training an autonomous defender without considering an adversary...
The adversary needs to solve two problems: The first is to decide what discounting factor. The second problem is to determine, given a target cause the learning agent to update its policy. Concretely, the goal of such an adversary is to perform actions on compromised hosts to generate observations environment (the network) in ways that are assumed possible under an adversarial threat. We describe an approach for implementing red agents that indirectly manipulate observations by transforming the environment (the network) in ways that are assumed possible under an adversarial threat. This paper does not illustrate attacks where an adversary systematically frustrates blue actions; however, red agent that performs actions on the network to bias observations, but without directly adding arbitrary noise to an observation matrix. Similarly, a sophisticated adversary may bias a defender when the actions of a defender are frustrated. This paper does not illustrate attacks where an adversary systematically frustrates blue actions; however, FARLAND facilitates the modeling of that type of adversary as well. We describe an approach for implementing red agents that indirectly manipulate observations by transforming the environment (the network) in ways that are assumed possible under an adversarial threat. Concretely, the goal of such an adversary is to perform actions on compromised hosts to generate observations, to cause the learning agent to update its policy \( \pi(a; \theta) \) maximizing the adversarial goals. Thus, the goal of the adversary is to bias the policy to maximize \( E_{\pi(a; \theta)} [\sum_t \gamma^t \hat{r}_t] \), where \( \hat{r}_t \) are rewards that reflect the adversarial goal, and \( \gamma \) is a discounting factor. The adversary needs to solve two problems: The first is to decide what \( \hat{o} \) would bias the learning agent optimally. The second problem is to determine, given a target \( \hat{o} \), the set of red actions that are most likely to produce \( \hat{o} \). Solving the first problem can be done, for example, by adapting ideas described by Kos and Song [15]. Here, we describe a framework to solve the second problem using probabilistic programming. Probabilistic programs not only allow the implementation of programs with stochastic behavior, but under appropriate semantics, also facilitate the estimation of the posterior distribution \( p(x|y; P, \alpha) \) of execution traces \( x \), given that \( y \) was observed, subject to a program \( P \) with parameters \( \alpha \). Our key point is that solving the second problem posted above corresponds to approximating one such posterior distribution. Namely, given a target observation \( \hat{o} \) an adversary would like to know what execution traces are most likely to have produced \( \hat{o} \). Probabilistic programming languages and systems, such as Gen [9], facilitate the computation of an approximate answer to this question \( q(x; P, \alpha, \hat{o}) \approx p(x|\hat{o}; P, \alpha) \). This allows an attacker to find a numeric \( \hat{o} \) that would optimally bias the blue agent policy, and then find the red actions that would most likely result in such target \( \hat{o} \).

While investigating the full implications of our approach is left for future work, our hope is that our system, our ideas, and the example illustrated in fig. 4 foster research developing defenses to protect against this kind of attack.

6.1 Deceptive red agents

As Behzadan and Munir describe [5], RL agents can be manipulated by tampering with sensors, reward signals, actuators, the memory of the agent, and the environment. However, as research has pointed out (e.g., [30]), the most concerning and realistic attacks are those that do not assume that the adversary can directly corrupt data from which the agent learns. For example, early attacks on RL algorithms (e.g., [15]), add noise to images from which the agent learns. This type of direct tampering with observations is not realistic in our application. Observations from which a network defender will learn are derived from logs, databases, and network data, whose integrity can be protected by other means (e.g., using cryptographic approaches). Prior work using RL for defending SDN networks has assumed that an adversary can directly manipulate reward signals [13] and/or observations [12].

We argue that one of the most concerning threats may involve indirect manipulation of observations by having a red agent that performs actions on the network to bias observations, but without directly adding arbitrary noise to an observation matrix. Similarly, a sophisticated adversary may bias a defender when the actions of a defender are frustrated. This paper does not illustrate attacks where an adversary systematically frustrates blue actions; however, FARLAND facilitates the modeling of that type of adversary as well.

We describe an approach for implementing red agents that indirectly manipulate observations by transforming the environment (the network) in ways that are assumed possible under an adversarial threat. Concretely, the goal of such an adversary is to perform actions on compromised hosts to generate observations, to cause the learning agent to update its policy \( \pi(a; \theta) \) maximizing the adversarial goals. Thus, the goal of the adversary is to bias the policy to maximize \( E_{\pi(a; \theta)} [\sum_t \gamma^t \hat{r}_t] \), where \( \hat{r}_t \) are rewards that reflect the adversarial goal, and \( \gamma \) is a discounting factor. The adversary needs to solve two problems: The first is to decide what \( \hat{o} \) would bias the learning agent optimally. The second problem is to determine, given a target \( \hat{o} \), the set of red actions that are most likely to produce \( \hat{o} \). Solving the first problem can be done, for example, by adapting ideas described by Kos and Song [15]. Here, we describe a framework to solve the second problem using probabilistic programming. Probabilistic programs not only allow the implementation of programs with stochastic behavior, but under appropriate semantics, also facilitate the estimation of the posterior distribution \( p(x|y; P, \alpha) \) of execution traces \( x \), given that \( y \) was observed, subject to a program \( P \) with parameters \( \alpha \). Our key point is that solving the second problem posted above corresponds to approximating one such posterior distribution. Namely, given a target observation \( \hat{o} \) an adversary would like to know what execution traces are most likely to have produced \( \hat{o} \). Probabilistic programming languages and systems, such as Gen [9], facilitate the computation of an approximate answer to this question \( q(x; P, \alpha, \hat{o}) \approx p(x|\hat{o}; P, \alpha) \). This allows an attacker to find a numeric \( \hat{o} \) that would optimally bias the blue agent policy, and then find the red actions that would most likely result in such target \( \hat{o} \).

While investigating the full implications of our approach is left for future work, our hope is that our system, our ideas, and the example illustrated in fig. 4 foster research developing defenses to protect against this kind of attack.

6.2 Blue agents against known behavior

In § 7, we want to 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 can not be easily guaranteed. To do so, we start by training, using FARLAND, a blue agent 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. We then show that when we perturb the behavior of the agent using only gray-like actions, the performance of the blue agent is significantly degraded. Concretely, consider a red agent that is assumed to perform behavior according to a high-level goals, such as, an exfiltration; the creation of a bogus account on an LDAP server; or attacking an AMPQ broker through a distributed denial of service. This red agent will not be aware of what mitigation and deception techniques are being implemented in the network. The computation and communication capabilities of the attacker result from the inherent limitations of the emulated environment. Furthermore, we assume that the attacker is not able to compromise the SDN Controller, the network functions, switches, or any other infrastructure that facilitates network configuration and management.
As we discussed, this red agent operates under partial observability. The red agent starts with limited knowledge about the network configuration, the services running on hosts, open ports, etc. The policy that the red agent follows in this case is derived from a planning approach. The red agent maintains a model of the network configuration (as it is discovered) and host information, such as which hosts have RATs, discovered user credentials, etc. The list of node attributes that the red agent maintains includes: the host OS, the host OS version, its fully qualified domain name (FQDN), its DNS domain, its IP, the list of used ports with their state (open or closed), e.g., \{(22, open), (80, open)\}, a list of services, e.g., \{ssh, http, ftp\}, a list of file paths, a list of AMQ Brokers being attacked, and a list of tags in the set \{'RAT', 'ElevatedRAT', 'AdversaryDiscoveredAMQBroker', 'AdversaryDeclaredCompromisedAMQBroker', 'AdversaryDiscoveredLDAPServer', 'AdversaryDiscoveredSpecialHost', 'AdversaryDeclaredCompromisedLDAPServer', 'AdversaryDeclaredCompromisedSpecialHost'\}.

The blue agent uses cyber-deception as a mitigation strategy, which includes actions such as isolating nodes, migrating nodes to a new (honey) network, or migrating nodes to an existing (honey) network (with a reduced action cost).

7 Evaluating performance

Section 6.2 describes an example representative of the kind of blue agent that is possible to develop using FARLAND. The performance of an approach will ultimately depend on the extent to which the resulting policy produces behavior consistent with expectations. However, the performance of such an agent depends on multiple factors, including reward functions; action and observation spaces; RL algorithms; and the goals of the defender. Different security policies would balance QoS and risk differently. For example, in some cases, the desired behavior of a blue agent is to identify and isolate compromised hosts as quickly as possible. In other cases, it may be more valuable to migrate a compromised host to a honey network.
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Figure 4: Blue agent’s performance, learning with APEX-DQN with the same configuration as in Figure 3, 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.

Figure 5: Frequencies of episode running times for configurations with 25, 50, 100 and 200 nodes respectively. Each histogram describes 100 episodes for each configuration with a passive blue agent.

In the example that we described, we assume that human-level performance entails (a) detecting and isolating compromised hosts as soon as they exhibit known malicious behavior; or (b) detecting and migrating compromised hosts to honey networks as soon as they exhibit malicious behavior. In both cases, a blue agent would attempt to minimize the disruption of service for uncompromised hosts and avoid expensive operations (e.g., migrating a host to a honey-network).

Figure 3 illustrates the performance of a blue agent that 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 recognizance events originated at a host; and the numbers of SCP failures, REST request failures, AMQP failures, SSH failures, and content searches reported by hosts.

FARLAND allows researchers to reason about the following question: How does the performance (for training and inference) of the blue agent change as a result of modifications to the network model? Researchers can experiment training agents with existing algorithms and observe their performance while changing multiple parameters, including algorithm parameters, such as the algorithm and learning rates, as well as network configuration parameters. For example, researchers can change the number of hosts on a network, the network topologies, and the complexity of the assumed normal behavior (by gray agents).

In addition, researchers can reason about the extent to which their algorithm is robust against deception attacks. Figure 4 illustrates the effect of allowing an adversary to deviate its behavior from the assumptions outlined in § 6.2 with only gray-like actions.

Another important aspect of evaluating performance is understanding how long it would take to learn such a policy. DRL typically requires running a large number of training episodes. While FARLAND’s network emulation layer was designed to enable the fast network deployment and teardown, it is FARLAND’s compatible simulation layers that make learning to defend a network using DRL practical. Run time is a consequence of the kind of attack that is simulated, which, in many cases, involves a computationally expensive searching algorithm (e.g., to find a server to compromise or file to exfiltrate). Running an episode in FARLAND can take from a fraction of a second to a few minutes, depending on the size of the network and other parameters.
Figure 5 shows the distribution of running times for 100 episodes on a single (Xeon E5-2660v4) computing core (with a frequency ranging from 2 to 3.2 GHz). The times correspond to episodes where the red agent’s goal is to find and exfiltrate sensitive content. The blue agent is passive and does not perform any action, allowing the red agent to achieve its goal. Despite FARLAND’s emulation being considerably faster than emulation solutions [2], emulated games still take several orders of magnitude longer than simulation games. For example, games in a 16 CPU system with the same agent configuration as those in Figure 5 average 10 minutes (with an average setup time of 82 seconds) when emulating networks with 10 nodes. The running time could be over 2 hours when we emulate networks with 100 nodes or more.

8 Future work

FARLAND provides researchers with a tool to design custom network environments to develop RL cyber defenders. In future work, we plan to address goals requiring additional features from FARLAND. These goals include the development of: (i) protection mechanisms against poisoning and evasion attacks; (ii) assurance evaluation approaches to determine the extent to which a RL-enabled defender is protected against adversarial manipulation; and, (iii) the integration of correct (blue) behavior specification. Concretely, a blue agent would only be practical if network configuration updates preserve packet traversal invariants (e.g., region segregation, or network-function chains that preserve partial order). Thus, (iii) relates to the integration of traversal policy specification into the design of an environment so that blue agents only perform actions that do not violate packet traversal policies.

To close the gap between simulation and emulation, we plan to bootstrap learning using smaller networks. Policies can be gradually improved by moving to larger networks and/or emulated networks. We also plan to optimize the setup and teardown of networks.

Finally, we will look into efficient approaches to alternate between simulation and emulation modes. In particular, our architecture is compatible with approaches, such as OpenAI’s Automatic Domain Randomization [23]. We are exploring the automatic increase of environment complexity by adjusting probabilistic models when a blue agent achieves acceptable performance in simpler environments.

9 Conclusion

We described FARLAND, a framework to enable research to apply RL to defend networks. While previous work has demonstrated that RL can be used to learn to perform complex tasks (such as playing strategy games) with human-level performance, it has been challenging to translate these achievements to use RL to perform cybersecurity tasks.

FARLAND allows researchers to design environments under assumptions that more closely correspond to real threats. In particular, researchers can develop attacks where the adversary manipulates observations through realistic actions in the environment to deceive the defender. In contrast, previous work attacking RL either assumes that it is possible to directly perturb observations and rewards [13], or studies attacks to RL in a context that is drastically different from using RL for cybersecurity (e.g., [15, 30]).

Our framework helps to demonstrate that it is feasible to use RL to defend a network. More importantly, FARLAND is designed to allow cybersecurity researchers to evaluate their approaches over a range of network conditions that can vary dramatically, with respect to their complexity and security policies. FARLAND enables such evaluation and the continuous development of new approaches as threats evolve.

References

[1] Falco, Cloud-Native Runtime Security.
[2] Caldera. Automated Adversary Emulation, April 2019.
[3] Callum Baillie, Maxwell Standen, Jonathon Schwartz, Michael Docking, David Bowman, and Junae Kim. CybORG: An Autonomous Cyber Operations Research Gym. 2020. eprint: 2002.10667.
[4] Charles Beattie, Joel Z. Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Heinrich Küttler, Andrew Lefrançq, Simon Green, Víctor Valdés, Amir Sadik, Julian Schnittwieser, 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.
[5] 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.
[6] Marc G. Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The Arcade Learning Environment: An Evaluation Platform for General Agents. CoRR, abs/1207.4708, 2012.

[7] 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.

[8] Li Chen, Justinas Lingys, Kai Chen, and Feng Liu. AuTO: scaling deep reinforcement learning for datacenter-scale automatic traffic optimization. In Proceedings of the 2018 Conference of the ACM Special Interest Group on Data Communication, pages 191–205. ACM, 2018.

[9] 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.

[10] Michael Dennis, Natasha Jaques, Eugene Vinitsky, 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.

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

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

[13] Yi Han, Benjamin IP Rubinstein, Tams 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.

[14] Matthew Johnson, Katja Hofmann, Tim Hutton, and David Bignell. The Malmo Platform for Artificial Intelligence Experimentation. In IJCAI, pages 4246–4247, 2016.

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

[16] Bob Lantz and Brian O’Connor. A mininet-based virtual testbed for distributed SDN development. In ACM SIGCOMM Computer Communication Review, volume 45, pages 365–366. ACM, 2015.

[17] Eric Liang, Richard Liaw, Robert Nishihiara, Philipp Moritz, Roy Fox, Joseph Gonzalez, Ken Goldberg, and Ion Stoica. Ray RLLib: A Composable and Scalable Reinforcement Learning Library. CoRR, abs/1712.09381, 2017.

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

[19] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin A. Riedmiller. Playing Atari with Deep Reinforcement Learning. arXiv preprint arXiv:1312.5602, 2013.

[20] Philipp Moritz, Robert Nishihiara, Stephanie Wang, Alexey Tumanov, Richard Liaw, Eric Liang, Melih Elibol, Zongheng Yang, William Paul, Michael I Jordan, and others. Ray: A distributed framework for emerging AI applications. In 13th USENIX Symposium on Operating Systems Design and Implementation (OSDI 18), pages 561–577, 2018.

[21] Quoc Phong Nguyen, Bryan Kian Hsiang Low, and Patrick Jaillet. Inverse reinforcement learning with locally consistent reward functions. In Advances in Neural Information Processing Systems, pages 1747–1755, 2015.

[22] Thanh Thi Nguyen and Vijay Janapa Reddi. Deep Reinforcement Learning for Cyber Security. CoRR, abs/1906.05799, 2019.

[23] OpenAI, Ilge Akkaya, Marcin Andrychowicz, Maciek Chociej, Mateusz Litwin, Bob McGrew, Arthur Petron, Alex Paino, Matthias Plappert, Glenn Powell, Raphael Ribas, Jonas Schneider, Nikolas Tezak, Jerry Tworek, Peter Welinder, Lilian Wang, Qiming Yuan, Wojciech Zaremba, and Lei Zhang. Solving Rubik’s Cube with a Robot Hand. 2019. _eprint: 1910.07113._

[24] Manuel Peuster, Holger Karl, and Steven Van Rossem. McDICINE: Rapid prototyping of production-ready network services in multi-PoP environments. arXiv preprint arXiv:1606.05995, 2016.

[25] Fabian Ruffy, Michael Przystupa, and Ivan Beschastnikh. Iroko: A Framework to Prototype Reinforcement Learning for Data Center Traffic Control. CoRR, abs/1812.09975, 2018.
[26] Mikayel Samvelyan, Tabish Rashid, Christian Schröder de Witt, Gregory Farquhar, Nantas Nardelli, Tim G. J. Rudner, Chia-Man Hung, Philip H. S. Torr, Jakob N. Foerster, and Shimon Whiteson. The StarCraft Multi-Agent Challenge. *CoRR*, abs/1902.04043, 2019.

[27] Arnab Sinha, Zhihong Shen, Yang Song, Hao Ma, Darrin Eide, Bo-June (Paul) Hsu, and Kuansan Wang. An Overview of Microsoft Academic Service (MAS) and Applications. In *Proceedings of the 24th International Conference on World Wide Web*, WWW ’15 Companion, pages 243–246, New York, NY, USA, 2015. ACM. event-place: Florence, Italy.

[28] Blake E. Strom, Andy Applebaum, Douglas P. Miller, Kathryn C. Nickels, Adam G. Pennington, and Cody B. Thomas. MITRE ATT&CK™: Design and Philosophy. July 2018.

[29] Oriol Vinyals, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani, Heinrich Küttler, John Agapiou, Julian Schrittwieser, John Quan, Stephen Gaffney, Stig Petersen, Karen Simonyan, Tom Schaul, Hado van Hasselt, David Silver, Timothy P. Lillicrap, Kevin Calderone, Paul Keet, Anthony Brunasso, David Lawrence, Anders Ekermo, Jacob Repp, and Rodney Tsing. StarCraft II: A New Challenge for Reinforcement Learning. *CoRR*, abs/1708.04782, 2017.

[30] Chaowei Xiao, Xinlei Pan, Warren He, Jian Peng, Mingjie Sun, Jinfeng Yi, Bo Li, and Dawn Song. Characterizing Attacks on Deep Reinforcement Learning. *arXiv:1907.09470*, 2019.