Perry: A High-level Framework for Accelerating Cyber Deception Experimentation

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***Abstract*—Cyber deception aims to distract, delay, and detect network attackers with fake assets such as honeypots, decoy credentials, or decoy files. However, today, it is difficult for operators to experiment, explore, and evaluate deception approaches. Existing tools and platforms have non-portable and complex implementations that are difficult to modify and extend. We address this pain point by introducing Perry, a high-level framework that accelerates the design and exploration of deception what-if scenarios. Perry has two components: a high-level abstraction layer for security operators to specify attackers and deception strategies and an experimentation module to run these attackers and defenders in realistic emulated networks. To translate these high-level specifications into low-level primitives, we design four key modules in Perry: 1) an action planner that translates high-level actions into low-level implementations, 2) an observability module to translate low-level telemetry into high-level observations, 3) an environment state service that enables environment agnostic strategies, and 4) an attack graph service to reason how attackers could explore an environment. We illustrate that Perry's abstractions reduce the implementation effort across a wide variety of deception defenses, attackers, and environments. We demonstrate the value of Perry by emulating 55 unique deception what-if scenarios, illustrating how these experiments enable operators to shed light on subtle tradeoffs.**

I. Introduction

Cyber-deception-based defenses seek to deceive an attacker with fake resources, information, or critical assets. These could include a decoy host (e.g., a honeypot) [42], [48], [50], decoy credentials [22], [64], decoy files [22], or other system assets. Cyber deception holds promise to distract attackers [17], [22], detect attacks in progress [24], [64], and delay attackers [17]. With emerging AI-based attackers [12], [54], cyber deception may become a critical part of the defense arsenal [31].

In order to inform their future security posture, security operators need the ability to run a broad spectrum of *deception what-if scenarios* relevant to their environment. For example: Would deploying many decoy files to a network distract attackers? Where are the optimal locations to deploy decoy credentials in a network? From these experiments, security operators could collect quantitative measurements on cost (e.g., number of decoys used) and effectiveness (e.g., data exfiltrated, hosts infected).

Unfortunately, running such experiments with existing tools such as Caldera and Elastic Security [5], [14], [25], [27], [32], [60] entails significant operator effort and complexity. We find that current tools for specifying attacker (e.g., execute exploits, command infected computers) and deception (e.g., detect fake credential usage) strategies operate at a very low level of

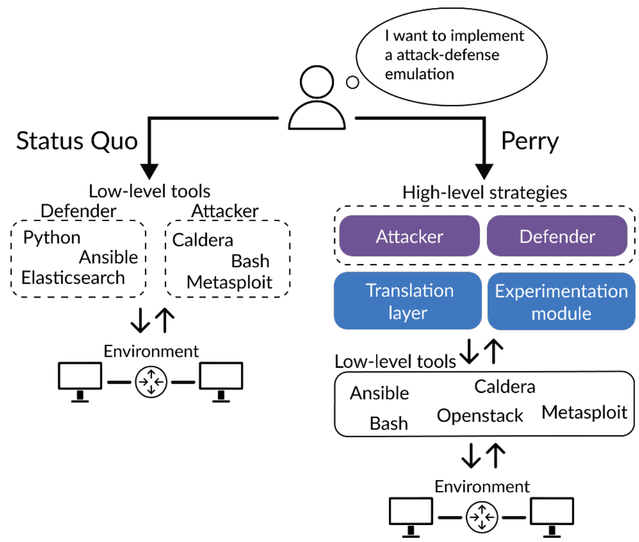


Fig. 1: Currently, operators have to use low-level tools to build deception what-if scenarios. We accelerate the process of implementing deception what-if scenarios by introducing Perry. With Perry, operators can quickly program deception what-if scenarios at a high-level, and Perry will translate scenarios into their low-level primitives.

abstraction. These tools rely on low-level mechanisms such as command-line interfaces, manual configuration files, and raw network log parsing, making them complex and cumbersome to use. The lack of abstraction and modularity also means that changes to attacker and defender implementations entail complex and distributed changes. Thus, operators cannot easily take existing implementations of strategies and quickly port it to work in their own environments and experiments. Taken together, this means that operators are stymied in their efforts to run deception-related experiments.

To address this challenge, we present Perry, a high-level framework for accelerating cyber deception experimentation. Perry has two components: (1) a high-level abstraction layer for security operators to specify attackers and deception defenders in a portable environment-agnostic manner and (2) an experimentation module to run these attackers and defenders in realistic emulated networks (Fig. 1). Operators use a high-level and environment-agnostic state machine abstraction to specify attack and deception strategies, which execute *high-level actions* based on *high-level observations* of the environment (Sec. III). Because these specifications are environment agnostic, they are naturally portable from one setting to another; for example, operators can take open-source contributions of existing attacker and defender strategies (either from Perry developers and the broader community) and run them seamlessly in their own emulated environments (with comparable telemetry and actuation capabilities) with low effort.

Perry uses four key modules to translate high-level attacker and deception strategies into low-level primitives: 1) an action translator to specify attack and defense actions at a high level (e.g., deploy a decoy), 2) an event-driven observability module that emits high-level observations (e.g., host is suspicious), 3) an environment state service to enable environment agnostic strategies, and 4) an attack graph service to reason how an attacker can explore an environment.

We show that Perry's abstractions can reduce the implementation effort across a wide variety of defense and attack strategies (see Sec. VII-A). We validate that there is no effort needed to port attacker and deception strategies across environments due to Perry's environment-agnostic and portable specifications. We quantify the reduction in lines of code (LOC) by 17–27× for attacker implementations and 7–14× for deception implementations. We also show how to optionally use LLM code generation to create correct implementations of deception strategies in Perry. For instance, in Sec. VII-A, we evaluate two attackers and two deception approaches across five environments. With Perry, users only need to write each attack and deception strategy once, and these can be applied to all environments without additional effort. In contrast, previous frameworks require users to manually re-implement each attack and defense strategy for each environment. In Sec. VII-A, we also measure the LOC of deception approaches and attackers with and without using Perry's abstractions.

This reduction in effort can enable operators to rapidly 1) explore a variety of deception strategies against different attackers in different environments (see Sec. VII-A), 2) implement variations of strategies (see Sec. VII-B), and 3) evaluate extensions to consider new defense and attacker capabilities (see Sec. VII-B). Using Perry, we explore diverse scenarios and shed light on the efficacy of deceptive defenses (see Sec. VII-C). For instance,

- Fine-grained and host telemetry that use system calls to detect attackers interacting with decoy resources can reduce data exfiltration by 40 to 100%.
- Simple extensions to deception strategies can have significant impacts on efficacy. In one case, a defender purposefully leaking a deceptive network topology to attackers slowed an attacker down by 3.2x.
- Emerging LLM-based autonomous attackers (e.g., [63]) can be slowed down using decoy-based deception. We show how these LLM attackers can spend 88-92% of their commands interacting with decoy hosts.
- The efficacy of deception strategies can vary widely across different attackers and environments, highlighting the importance of rapid exploration. For instance, a layered deception strategy can delay attackers anywhere from 3% to 49% depending on the attack strategy.

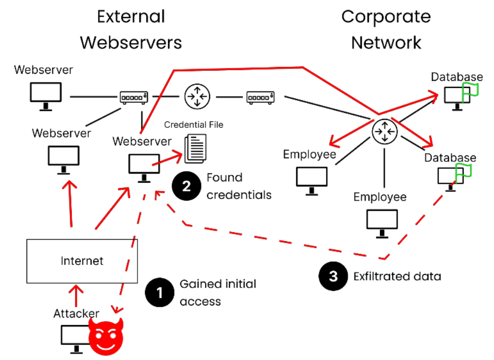


Fig. 2: The attack that led to the Equifax data breach had three stages. First, the attackers gained initial access by compromising external web servers. Next, they found credentials to databases on a web server. Finally, the attackers exfiltrated critical user data from the databases.

Contributions and Roadmap: In summary, this paper makes the following contributions:

- We introduce a novel high-level and environment agnostic abstraction for expressing attackers and deception defenders: a state machine that executes high-level actions based on high-level observations of the environment (Sec. III).
- We present a concrete design and implementation to translate high-level intentions into their lower level primitives (Sec. IV–Sec. VI).
- We demonstrate the value of Perry by illustrating how it can enable operators to rapidly explore a wide variety of deception defenses, attackers, and environments, shedding light on the tradeoffs of deception defenses(Sec. VII).

Reproducible Research Perry is open-source and will be publicly available to the research community.[1]

II. Background and Motivation

In this section, we discuss the importance for operators to quickly and systematically evaluate deception approaches against candidate attackers. We begin by making the case for what-if experiments in cyber deception (Sec. II-A). Then, we use an illustrative example to show that existing tools entail significant complexity and are difficult to extend (Sec. II-B).

A. The case for what-if experiments in deception

To illustrate the need for the rapid exploration of what-if experiments, we examine a real world incident, the Equifax data breach, as a motivating example.

In 2017, attackers stole an estimated 143 million private American records from Equifax [38]. Equifax was forced to pay over $500 million in legal penalties as a direct result of the attack [21]. As shown in Fig. 2, the attack that led to the Equifax breach had three stages: (1) The attackers gained initial access to the Equifax network through a known vulnerability on their web servers. (2) The attackers discovered

[1]The code is available at https://github.com/bsinger98/Perry.

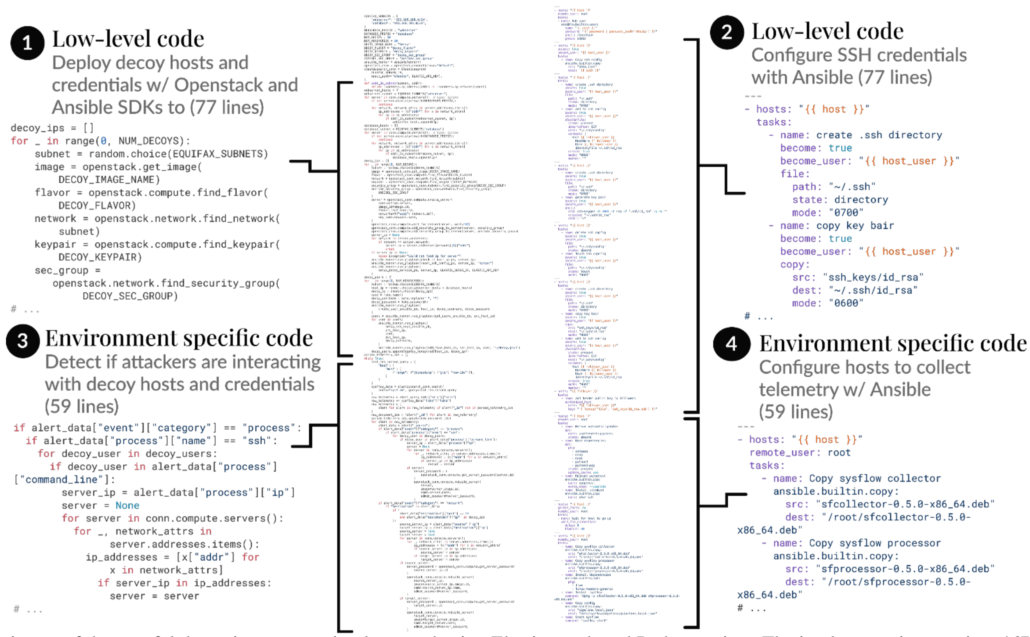


Fig. 3: Code snippets of the stateful deception strategy implemented using Elasticsearch and Python scripts. The implementation requires 467 lines of low-level code that use the low-level Openstack, Elasticsearch, and Ansible SDKs. In addition, the implementation has code intertwined with the environment to detect interactions to decoy hosts and resources.

an unencrypted file on the web servers containing credentials to databases. (3) The attackers utilized the credentials to access and exfiltrate data from the databases [38].

Following this example, if and how, could deception techniques have stopped the attack: Would some deception strategies have higher efficacy than others? To shed light on these questions, operators may want to explore what-if scenarios:

Example 1. The operator may want to quickly explore the efficacy of a wide variety of deception capabilities (e.g., decoy hosts [48], fake credentials [64], or fake software patches [6]) against many variants of this attacker.

Example 2. The operator may want to understand the benefits of adding better telemetry with the above deception algorithms, enabling the defense to react to attackers actions. For example, an operator may want to detect and react to attackers interacting with deceptive fake credentials the defender added.

B. Requirements and limitations of prior work

In order for operators to quickly implement deception what-if experiments, we require a platform that is:

- *Expressive*: A platform should be capable of modeling diverse scenarios spanning many types of deception approaches, attack strategies, and environments.
- *Low effort*: We want to quickly implement and evaluate diverse scenarios; e.g., reuse components and code as much possible.
- *Extensible*: As new deception approaches, system capabilities, and attack strategies appear; the platform should be extensible to evaluate these new techniques.

At one extreme, we can consider simple agent-based simulators that are low effort [10], [30], [41], [61]. These do not emulate real networks, attackers, or defenders and lack the realism and expressiveness for real-world scenarios. We will later see in Sec. VII-A how subtle implementation details can greatly impact the efficacy of deception.

At the other extreme, we have a range of tools (e.g., Caldera, Metasploit, Snort, Elasticsearch [5], [8], [15], [51]) that can realistically emulate real attacks and defenses. Let us consider implementing Example 2 with these low-level tools. We can implement the attacker with Caldera [5], a widely used tool in deception evaluations, such as CybORG [60], Mirage [32], and CyGil [36]. We can implement defenders by combining SIEM tools like Elasticsearch [14] with custom Python scripts. To deploy the environment (i.e., the network, hosts, and critical assets) we can use an OpenStack-like virtual network [46].

Specifically, we consider a stateful defender (Example 2) that 1) deploys decoy hosts and credentials to the network, 2) detects hosts interacting with the decoy hosts and using the decoy credentials, and 3) restores any hosts that interact with decoy resources. Similarly, we create an attacker that mimics the real-world Equifax attacker [38] by: 1) gaining initial access to the network by infecting vulnerable web servers, 2) searching and using credentials to infect database hosts, and 3) exfiltrating data from each database host. Fig. 3 shows code snippets of the defender implementation.

Next, we highlight three issues with such implementations.[2]

- **Low-level and cumbersome code:** Existing tools offer low-level SDKs resulting in cumbersome low-level code.

[2]Our goal is to illustrate problems broadly with available tooling, not at these specific tools. For instance, the problems we highlight with Caldera also exist in other attacker emulation tools [16], [25], [51] and the pain points of Elasticsearch with Python are similar to other defense tools [8], [27], [59].)

For instance, the stateful defender implementation requires 272 lines of low-level code. Deploying decoy hosts and credentials requires 213 lines of code using the Ansible and Openstack SDKs. The remaining 59 lines of code use the Elasticsearch API to detect attackers interacting with decoy hosts and credentials.

Attacker implementation tools also have low-level SDKs. For example, to infect the web servers, we have to add low-level code for each type of network scan and exploit script. In another case, to find credentials, we had to: 1) implement bash scripts to output credentials, 2) implement parsers to interpret the output of the bash commands, and 3) implement the attacker strategy to call the bash script.

- **Non-portable code:** Existing tools force the code to be tightly coupled with the environment, making it difficult to port attackers and defenders to a new environment. For instance, the attacker implementation exfiltrates data. In the Equifax environment, this requires (1) choosing a correct path of two hosts to exfiltrate the data on, and (2) choosing the correct exfiltration protocol between the hosts (e.g., the web server communicates with the database instance with `SSH` while the attacker and web server communicate with `HTTPS`). If the operator's environment has a different path or different protocols, the attacker implementation will fail.
- **Modifications require distributed changes:** As a consequence of complex low-level code, existing tools have complex dependencies between strategies, capabilities, or telemetry, making it difficult to extend to evaluate new deception approaches and attackers. Our implementations became tightly coupled to their capabilities and telemetry, making them difficult to extend. For instance, we may want to extend our deception to add decoy files to decoy hosts. But adding decoy files requires many distributed changes to the implementation. Specifically, in Fig. 3, we have to: (1) extend the initialization function to maintain lists of real and decoy file, (2) extend the detection rules to detect if fake data is being exfiltrated, (3) and (4) implement Ansible Playbooks to deploy the decoy files.

III. Perry System Overview

In this section, we give an overview of Perry. Perry introduces a high-level abstraction layer for security operators to specify attackers and deception defenders as well as an experimentation module to emulate these attackers and defenders in realistic network topologies.

The inputs to Perry are the environment, attacker, and defender, shown in Fig. 4. Perry first instantiates the environment on a virtualized network and executes the defender and attacker logic expressed using its high-level abstraction. Perry collects metrics such as defender resources used (e.g., number of decoys used) and attacker success metrics (e.g., data exfiltrated) to enable quantitative analytics (Sec. VII).

A. *High-level idea*

To put the key ideas of Perry in context, let us revisit from first principles *what* the operator was trying to do and *why* existing tools failed to allow for the expression of those intents.

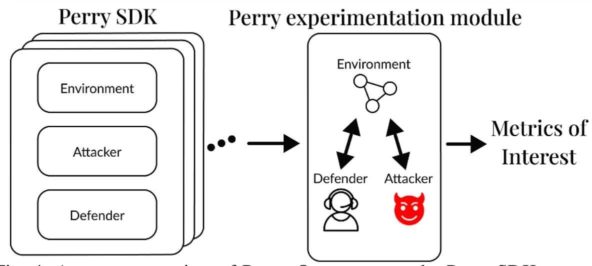


Fig. 4: A system overview of Perry. Operators use the Perry SDK to specify the environment, attacker, and defender to execute. Perry then executes each scenario and outputs metrics of interest.

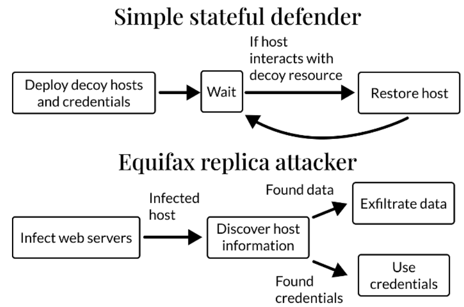


Fig. 5: State machines representing the defender and attacker in Sec. II. The defender deploys decoys, waits for attackers to interact with decoys, and then restores hosts to stop attackers. Similarly, the attacker can be modeled as a state machine to infect web servers, find credentials, and finally exfiltrate data.

Conceptually, the operator has a mental model of the attacker and defender logic (Sec. II) shown in the simple state machines in Fig. 5. Here, the defender wants to deploy decoys, wait for attackers to interact with the decoys, and then runs actions to stop the attacker. Similarly, the attacker runs like a logical state machine that tries to infect web servers, find credentials, and finally exfiltrate data.

While these intents are easy to describe in this mental model, there is a significant disconnect with existing tools. Existing frameworks are environment-specific, low-level, and lack any abstraction, making it painful to realize these intents. For example, the first state of the defender in Fig. 5 is to deploy decoy hosts and credentials. But modeling this state in our implementation requires 240 lines of code (163 lines of Ansible code and 77 lines of Python code), which only work in one environment. As we discussed earlier, this code is tightly coupled, making it difficult to extend to new environments, capabilities, and strategies.

To tackle this disconnect, Perry raises the level of abstraction to express diverse and complex attackers and defenders in an environment-agnostic way. In fact, the mental model of the operator described above naturally suggests a convenient abstraction to capture attackers and defenders.

Based on this insight, Perry introduces a high-level programming model, explicitly representing attackers and defenders as logical state machines that execute *high-level actions* based on *high-level observations* of the environment. In essence, Perry helps the user express high-level intentions of *what* they need to do, decoupling intentions from the *how* in low-level tools.

Next, to make this more concrete, we present a brief sketch of how operators can design deception what-if experiments with Perry's high-level programming model. Later, in Sec. IV and Sec. V, we give more concrete examples.

B. Anatomy of an experiment

A deception what-if scenario has (1) a deception defense, (2) an attacker, and (3) an environment.

Deception defense: In Perry, deception defense has three stages: A) initialization, set up strategies and deploy deception resources; B) event listeners, strategies subscribe to high-level observations from the telemetry service; and C) event handlers, strategies react to the high-level observations. For instance, the pseudo code of the stateful deception approach in Fig. 5 is (full example in Sec. V):

```
# (A) Initialize, deploy deception e.g.,
DeployDecoyHost(important_network)
# (B) Event listeners, detect interactions e.g.,
TelemetryModule.subscribe(
    DecoyHostInteraction,
    my_handler)
# (C) Event handlers, respond to attacker e.g.,
def my_handler(event):
    RestoreHost(event.source_host)
```

Attacker: In Perry, attackers are written as explicit state machines. First, the strategies enumerate each attack phase. Then, each attack phase is implemented with a mixture of Perry's modules. For instance, the pseudo code of the Equifax replica attacker in Fig. 5 is (full example in Sec. V):

```
# (A) Attack phases
match self.attack_stage:
    case InitialAccess:
        self.initial_access()
    case LookAndUseCredentials:
        self.discover_info()
    # ...
# (B) Phase implementation
def initial_access():
    ScanNetwork(external_network)
    # ...
    for path in new_attack_paths
        InfectHost(path)
```

Environment: Environments in Perry are specified by a topology and a configuration file. The topology is specified in Terraform [23]. The configuration file specifies the host configurations, vulnerabilities, and goals. For example, the pseudo code of the Equifax environment is:

```
# (A) Host configurations
ConfigureSSHKeys(self.webserver[0],
                 self.databases)
# (B) Vulnerabilities
for webserver in self.webservers:
    SetupVulnerableApacheStruts(webserver)
# (C) Goals
for database in self.databases:
    AddCriticalData(database)
```

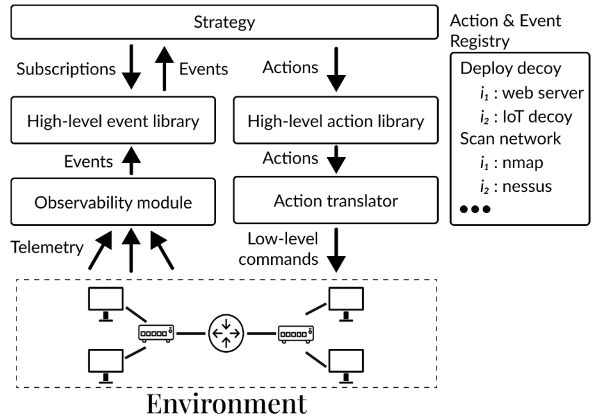


Fig. 6: Perry has several modules and services to decouple the high-level intentions of strategies. In particular, there is an action translator to convert high-level actions into low-level actions and a observability module to translate low-level observations into high-level observations. The registry contains a list of high-level actions and events with a list of potential implementations.

IV. Detailed System Design

Next, we describe the key modules' design in Perry: environment state service, action translator, observability module, and attack graph service. Broadly speaking, strategies subscribe to high-level observations from the observability module and output high-level actions for translation by the action translator, shown in Fig. 6.

A. Environment state service

As shown in Sec. II, strategies in existing tools are coupled to a single environment. Rather than strategies having low-level and environment-specific code, in Perry, code that reasons about the environment is delegated to the environment state service. Perry's modules and strategies query the environment state service for environment information (e.g., check if a credential is fake). To answer these queries, the environment state service maintains a network information base [25] by subscribing to high-level events from the observability module (Sec. IV-C). For example, for attackers, the environment state service subscribes to a new host discovery event and adds hosts to the knowledge base as they are discovered.

As an illustration, the following snippet shows a simple randomized decoy host and credential deployment using the Perry API. The key idea here is that all environment-specific code is delegated to the environment state service:

```
public_subnets = EnvService
    .get_subnet(public=True)
# Deploy decoy credentials
for _ in range(0, num_honeycreds):
    deploy_host = EnvService
        .get_random_host(public_subnets)
    decoy = EnvService.get_random_decoy_host()
    DeployDecoyCredential(deploy_host, decoy)
```

In the above example, the implementation is now environment-agnostic. Rather than the code specifying low-level individual IP addresses to deploy decoy credentials, it uses the environment state service to select the high-level intention of the host for deployment of the decoy credentials.

B. Action translator

To make it easier to write and modify high-level strategies, we design an action translator that decouples strategies' high-level actions from their low-level implementations.

Currently, actions in attack and defense emulation tools [5], [16], [25], [52] are specified with low-level commands that have pre and post-conditions. For example, one command might be an `nmap` scan script with the post-condition to execute an `SSH` exploit if a known CVE is found.

The pre and post-conditions have two challenges: they make it difficult to modify high-level strategies, and they complicate the addition of new capabilities because each one requires reconsideration of existing conditions. For instance, if a user wants to modify an attack strategy to mimic the Darkside [45] APT attack group, the user would have to alter many low-level pre-conditions to match the new high-level specification.

In Perry, the high-level actions are decoupled from their implementations. As a result, the action translator makes it easier to specify, modify, and reason about strategies because users no longer have to reason about low-level code. Furthermore, the decoupling of implementations makes the action translator extensible in terms of both adding new high-level actions (e.g., adding a stealthy scan action) and adding new implementations of actions (e.g., a better data exfiltration technique). For example, in a strategy, we can program an exfiltrate data action as:

```
ExfiltrateData(host_with_data)
```

The `ExfiltrateData` could have multiple implementations. In our implementation, we create a list of possible exfiltration paths with the `SSH` and `HTTPS` protocols. Then, we find the shortest exfiltration path. However, other users can add alternate implementations to include other protocols (e.g., `DNS`). *The key takeaway is that users choose the implementation they want to explore without modifying existing strategies.*

We also design a library of common high-level deception and attack actions that are portable across environments in Table I. For instance, the data exfiltration action (1) uses the attack graph service to identify the shortest exfiltration path and (2) uses the environment state service to choose the correct protocol (e.g., `HTTP`) for data exfiltration.

TABLE I: Perry's high-level actions and their default implementations.

Action	Implementation
Defender actions	
Deploy decoy host	Creates a decoy host with options such as a vulnerable service, fake data, or fake users.
Deploy decoy credential	Adds fake SSH credentials to a server and optionally links them to a decoy host.
Deploy decoy data	Generates files containing fake sensitive data.
Deploy decoy users	Creates a decoy user with a weak password.
Deploy honey service	Configures an interactive fake network service.
Restore host	Restores the host to a clean snapshot.
Shutdown host	Shuts down the host.
Attacker actions	
Action	**Implementation**
Discover local information	Searches directories for files and credentials.
Scan	Uses `nmap` to find vulnerable network services.
Lateral move	Searches an exploit database and executes suitable exploits to pivot to another host.
Escalate privilege	Searches an exploit database and executes suitable exploits to gain higher privileges.
Exfiltrate data	Finds the shortest path to the attacker's host and exfiltrates the data.

TABLE II: Perry's high-level events and their default implementations.

Event	Implementation
Defender events	
Decoy host interaction	Network-trace rules that trigger when non-decoy hosts establish connections to decoy hosts.
Credential interaction	eBPF rules detect decoy credential use.
SSH connection	Network-trace rules that trigger when an SSH session is established.
Attacker events	
Event	**Implementation**
Found host	Parses scan outputs to find new hosts.
Found network services	Parses scan outputs to find new services.
Found credential	Parses command outputs to find credentials.
Data found	Searches file contents for sensitive keywords.
Exfiltrated data	Triggers when data is successfully exfiltrated.
Infected new host	Triggers when malware is correctly installed.
Got root access	Triggers when malware is installed as root user.

C. Observability module

Similar to actions, defenders and attackers need to reason about the state of an environment (e.g., host used a decoy credential, infected a new host, found critical data). As seen in Sec. II, existing tools expose low-level events (e.g., system calls, network tracing, outputs of a bash command, etc.) and require environment-specific information (e.g., IP address of a decoy host). To make it easier to write and modify high-level strategies, we design an environment-agnostic observability module inspired by Zeek [49] that decouples strategies' high-level observations from their low-level events.

Current attack and defense emulation tools require implementations to have parsers for low-level telemetry data (e.g., network traces, command outputs) [5], [15], [16], [25], [27]. As a result, strategy implementations become (1) hard to modify because they have large amounts of low-level code to process the data and (2) hard to extend because they are tightly coupled to the type of telemetry data.

Instead of strategies containing complex logic to interpret low-level telemetry, Perry enables strategies to subscribe to high-level observations. The observability module translates low-level observations into these high-level observations. For example, in Perry, a strategy can subscribe to a high-level observation that a host is using a decoy credential:

```
TelemetryModule.subscribe(
    HostUsedDecoyCredential,
    handle_decoy_host_interaction)
```

Here, we decouple the high-level intention of detecting hosts using decoy credentials from the low-level implementation. Consequently, we can quickly explore new telemetry techniques without modifying the strategy. For instance, if we implement a new anomaly detection algorithm to output

`HostUsedDecoyCredential` events, it works with the existing strategy. We design a library of common high-level deception and attacker events, shown in Table II.

D. Attack graph service

Attack and defense strategies often have to reason about vulnerabilities in networks. For example, an attack may want to target a specific host or get privileged access to an already infected host. Defenders too may want to proactively explore possible future attack steps. As seen in Sec. II, existing tools only offer low-level methods for reasoning about potential targets in a network. To make it easier to reason about vulnerabilities, we design an attack graph service.

To reduce the effort required to express attackers with sophisticated strategies, we revisit a classic but effective idea—attack graphs [47]. For example, if a strategy wants to infect a specific host on a network, it can query for potential infection methods from a service:

```
paths = AGService.get_paths_to_host(
    attacker_host, target_host)
for path in paths:
    events = LateralMove(path)
```

Because attackers can only have partial knowledge about the environment, the attack graph service continually updates itself as new information is discovered using the environment state service. For example, if credentials were discovered on a host, the attack graph service will identify new paths that infect hosts. These paths can directly be executed by the action translator. As a result, the attack graph service removes complex logic from the strategy and creates a modular query so that other strategies can also request infection methods.

E. Attacker service

Our attacker service enables us to model realistic attackers. Attackers in Perry use C&C servers, install malware agents on hosts, scan networks, and execute real exploits. The high-level attacker actions in Table I use the action translation module to translate these high-level actions into common low-level attack tools. For instance, the lateral movement high-level action either uses credentials or exploits to install malware agents on the target host. The exploits are currently selected from a small built-in library; however, Perry also supports an optional module that can use Metasploit's larger exploit library. In addition, we envision the community creating custom implementations of these actions, such as a lateral movement implementation that uses LLMs to generate the exploits [11], [57].

V. Illustrative Example

In this section, we show how using Perry can simplify the implementation for the stateful deception approach and Equifax attacker in Fig. 5. These examples illustrate the expressiveness of how deception strategies, attackers, and environments are specified in Perry. Then, we illustrate how operators can extend Perry through qualitative examples.

Recall that the simple stateful strategy in Fig. 5. The simple stateful strategy first deploys deceptive resources, then restores any hosts that react with them. In Perry, we express this as:

```
# (A) Initialize, deploy deception
for _ in range(0, num_decoys):
    subnet_to_deploy = EnvService
        .get_random_subnet()
    DeployDecoyHost(subnet_to_deploy)
for _ in range(0, num_honeycreds):
    deploy_host = EnvService.get_random_host()
    decoy = EnvService.get_random_decoy_host()
    DeployDecoyCredential(deploy_host, decoy)
# (B) Event listeners, listen for interactions
TelemetryModule.subscribe(
    HostInteractedWithDecoyHost,
    handle_decoy_host_interaction)
# (C) Event handlers, react to attacker
def handle_decoy_host_interaction(event):
    RestoreServer(event.source_host)
    RestoreServer(event.target_host)
```

In the initialization phase, we use the environment state service to select random subnets to deploy decoy hosts to and select random hosts to deploy decoy credentials to. The action translator then translates the deploy decoy and credential actions into their low-level commands. We use the observability module to subscribe to a key event, a decoy host interaction. Next, we specify the event handlers to react to these interactions by restoring both the decoy host and the host that interacted with the decoy host.

We can similarly use the Perry abstractions to express the attacker from Fig. 5:

```
# (A) Attack phases
match self.attack_stage:
    case InitialAccess:
        self.initial_access()
    case LookAndUseCredentials:
        self.discover_info()
    case ExfiltrateData():
        self.exfiltrate_data()
# (B) Phase implementation
def initial_access(self):
    ScanNetwork(EnvService.get_subnets())
    # Try to infect all hosts on external network
    hosts = EnvService.get_hosts()
    attack_paths = AGService.get_all_paths()
    for path in attack_paths:
        LateralMove(path)
    self.state = LookAndUseCredentials
# ...
```

We enumerate each of the attack phases in the Equifax replica strategy: 1) gain initial access to the network, 2) find and use any credentials, and 3) exfiltrate any data.

Then, we implement each phase, starting with initial access. The initial access phase first uses the environment state service and action translator to scan the external subnets. Next, we use the attack graph service and action translator to infect any vulnerable servers. We create the exfiltrate data phase by first using the environment state service and action translator to find critical data. If any critical data is found, the observability module will update the environment state service. As a result, after we execute find critical data, we check if any data is on the host and exfiltrate it if so.

Overall, we are able to reduce the total lines of code from 467 to 44 and from 1596 to 94 for the defender and attacker respectively (Sec. VII-A). Even more importantly, Perry gives

TABLE III: Attack strategies implemented with Perry. Equifax and Darkside replicas follow public reports [38], [45]. DFS Movement, Targeted, and Persistent strategies have different priorities. See Appendix B for details.

Attack strategy	Description
DFS Movement	Laterally moves through the network using a depth-first-search (DFS) traversal of the attack graph.
Equifax replica	Mimics the 2017 Equifax breach: gains initial access, harvests credentials, and exfiltrates data.
Targeted	Starts with prior knowledge of the network and uses it to prioritise high-value hosts in the attack graph.
Persistent	Infects vulnerable hosts and keeps them as back-door footholds for long-term access.
Darkside replica	Emulates the DarkSide APT: gains initial access, spreads widely, then executes its final objective.

an intuitive high-level abstraction for the user. In the next section, we discuss the detailed design of the Perry modules.

Environment expressiveness: In Perry, environments are also specified at a high level. The network topologies are defined with Terraform, an industry standard for specifying virtual network topologies [23]. In addition to the topology, environments have a Python specification with the environments vulnerabilities, host configurations, and key assets. Below is a snippet of the specification of the Equifax-inspired environment used in Sec. VII:

```
# (A) Setup ApacheStruts Vulnerability
for web_server in self.webservers:
    SetupStrutsVulnerability(web_server, port=443)
# (B) Setup credentials
cred_web_server = self.webservers[0]
for db in self.database_hosts:
    SetupServerSSHKeys(
        cred_web_server.ip,
        cred_web_server.users[0],
        db.ip,
        db.users[0]
    )
# (C) Setup database data
for db in self.database_hosts:
    AddData(db, database.users[0])
```

In this example, first the vulnerable ApacheStruts web service is installed on the two web servers. Then, one web sever is given SSH credentials to all of the databases. Finally, each data is added to each database for the defender to protect.

VI. Implementation

In this section, we describe the implementation of Perry. First, we discuss how Perry instantiates environments using OpenStack [46]. Then, we discuss Perry's custom Python framework for defender programming. Last, we describe Perry's attacker implementation.

Environment instantiation: Perry uses an environment specification to instantiate an environment in an OpenStack cloud. We use OpenStack because it can run on commodity hardware, is open-source, and scalable [46]. In addition, we implement components to reduce the time for environments to be reinstantiated by caching environment information.

In Perry, we define an *environment* as a tuple $\langle Topology, Assets, Host\ configuration, Vulnerabilities\rangle$. The *topology* is the routers, switches, firewalls, and hosts of the network. The *assets* are objects such as critical data. The *host configuration* are the configurations of hosts such as deploying a database or creating a user. The *vulnerabilities* misconfigure hosts or setup vulnerable software versions.

The environment's network topology is specified using Terraform Language [23], an "infrastructure as code" language. The assets, host configurations, and vulnerabilities, are specified using an internal Python SDK. The internal Python SDK is designed to be extensible for users to add additional assets, configurations, and vulnerabilities.

Environments are instantiated in two phases: setup and launch. The setup phase deploys and configures the network and hosts in OpenStack. Next, assets, host configurations, and vulnerabilities are configured through a mixture of Python and Ansible [53]. Once the environment is configured, Perry snapshots each host to save time launching the environment. During the launch phase, Perry restores the network topology to its original state. Then, Perry instantiates each host on the network using the saved snapshots. The VM snapshots are RAW images which are portable to most cloud providers (e.g., AWS, Google Cloud).[3]

Defenders: We implement Perry's abstractions for defenders' deception approaches with a custom Python framework. Each defender is specified with a configuration that contains the strategy, capabilities, and observability module. The capabilities specify the actions available to the defender and the budget for each of these actions (e.g., a budget of 10 decoy hosts).

The defender's action translator uses orchestrators to enable Perry to work in multiple clouds such as OpenStack [46], or AWS [4]. In this paper, we implement an OpenStack orchestrator. For a high-level action, the orchestrator will use the OpenStack SDK to execute the low-level actions. We use Ansible to execute the remaining low-level actions that are not specific to the cloud environment. We implement the defender's observability module with Python and Elasticsearch [15]. The observability module continually queries the database and has rules that raise high-level observations.

Attackers: The attacker service uses Caldera, an open-source C&C server to communicate and send commands to infected hosts.[4] The action translator translates tasks from Perry's high-level attack strategies into low-level commands (e.g., Shell code, Python scripts) that are then executed by Caldera [5]. We implement the observability module by considering the outputs of each low-level action as low-level events. For each low-level action, we create rules that parse these low-level outputs and raise high-level observations. Similar to the defender, we implement a library of common high-level attack actions and events shown in Table I and Table II.

VII. Evaluation

In this section, we first evaluate how Perry's abstractions reduce the implementation effort for a wide variety of decep-

[3]As future work, we plan to support several major cloud providers in the open-source repository.

[4]Other C&C server's such as Mythic [44] or CobaltStrike [18] could also be used.

TABLE IV: Deception strategies implemented with Perry. See Appendix C for details.

Deception strategy	Description
Basic honeypot	Randomly deploys honeypots across the network.
Mixed deception	Randomly deploys honeypots and fake credentials across the network.
Layered deception	Deploys honeypots, decoy credentials, and fake data on each honeypot; the decoy credentials are valid for those honeypots.
Simple stateful	Deploys honeypots with basic telemetry that alert on host interaction.

TABLE V: We implement five environments in Perry. The Equifax-inspired and Colonial pipeline-inspired are based on real attacks [29], [38]. The Chain and Star environments are in prior deception papers [17], [32], [62].

Environment	Description
Equifax-inspired (50 hosts)	A replica of Equifax network (same topology, services, and vulnerabilities) [38]. The goal is to exfiltrate all 48 databases.
Colonial Pipeline-inspired (45 hosts)	An environment inspired by the Colonial Pipeline breach [29] and other ICS attacks [34], [58]. The goal is to gain access to 15 physical actuators.
Chain (25 hosts)	Each host has credentials to another host [32], [62]. The goal is to exfiltrate critical data on each host.
Enterprise (20 hosts)	A tree topology, sometimes used in enterprise networks [1], [2]. There is one external network and two networks for each floor of a building.
Star (25 hosts)	A single network where all hosts have vulnerabilities and contain critical data [17].

tive defenders and attackers. Second, we discuss how Perry is extensible to enable operators to specify variations of existing strategies and explore new defense and attack capabilities as they become available. Third, we show how Perry can shed light on the efficacy of various deception defenses and their cost-benefit tradeoffs.

To execute these analyses we select representative and realistic attackers, deception strategies, and environments. For attackers, we design and implement five attack strategies shown in Table III. The attackers replicate real-world attack tactics and APTs from public reports [37], [38], [45], [65]. We picked four deception strategies shown in Table IV (and implement additional deception strategies in the next sections) inspired by common deception strategies [20], [42], [48], [64].

A. *Reduction in implementation effort*

We start with measuring the reduction in implementation effort in terms of lines of code (LOC) as a measure of specification and debugging complexity. Then we highlight the benefit of Perry in avoiding the environment-specific effort that is a key weakness of previous tools. We also show how the Perry API can enable more robust LLM-based code generation of strategy specifications.

LOC measurement: While we acknowledge lines-of-code (LOC) is not a perfect measure of implementation effort, it is still a useful proxy metric for effort, code readability, and debugging complexity. To this end, we count and compare the LOC of implementing attackers and deception approaches with and without using Perry's abstractions (Fig. 7 and Appendix

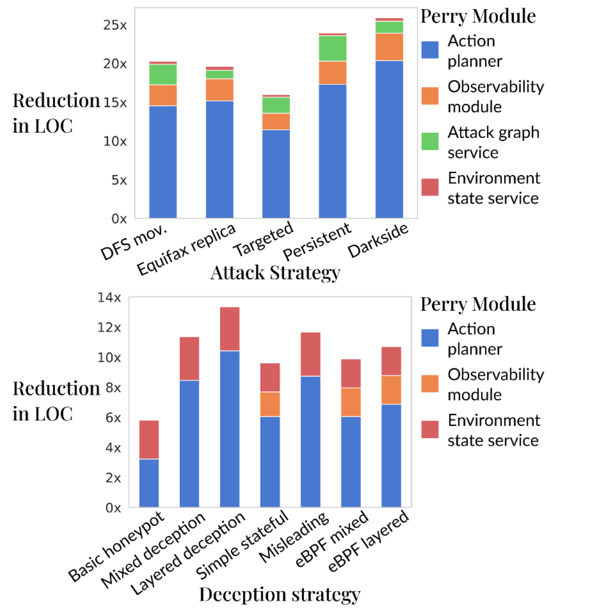


Fig. 7: Across all defender strategies, Perry's abstractions reduce the LOC by 6.0-12.7×. Across all attacker strategies, Perry's abstractions reduce the LOC by 13.1-22.2×. Most of the reduction is from the action translator.

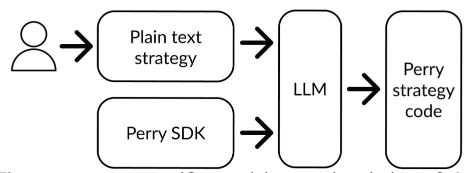


Fig. 8: First an operator specifies a plain text description of the deception strategy. Then, both the strategy description and the Perry SDK is given to the LLM.

E). We also break down how much each Perry module contributed to the reduction.

For attack implementations, we compare Perry against implementations using low-level Caldera actions. In Fig. 7, we show Perry reduces LOC of the attacker implementations 16.9–26.9×. The action translator provided the biggest benefit for LOC reduction by offloading the complex logic to execute low-level calls to the Caldera SDK. The Darkside strategy had the largest savings in LOC, with a 26.9× reduction.

For defense strategies, we compare Perry vs. implementations expressed using a combination of Python code and Elasticsearch. In Fig. 7, we show Perry reduces LOC of the deception implementations by 6.8–14.3×. Again, the action translator provides the largest benefit by avoiding the complex interactions with the OpenStack and Ansible SDKs, shown in Fig. 7. The second highest benefit stems from the environment state service, as deception strategies often need to reason about the current state of the environment.

Validating portability: We consider five environments in Table V based on real attacks [29], [38] and environments in prior deception studies [17], [32], [62]. In previous frameworks, users would need to manually reimplement each attack and defense strategy for each environment. That is, effectively rewriting each attack strategy five times and each defense strategy five times because the implementations are coupled to environment specifics. In contrast, using Perry the strategies are environment agnostic and we only need to implement each attack and deception strategy once. We validated (Sec. VII-C) that all the strategies in Table III and Table IV work seamlessly in all five environments in Table V.

LLM-based code generation: Given recent advances in LLM-based code generation, a natural question is, if and how, the aforementioned effort can be further reduced using LLMs. As a first-step, we evaluate LLMs ability at generating three deception defenses. To this end, we consider two settings: (1) prompting an LLM to produce code using current tools, low-level APIs, commands, and (2) providing the LLM with Perry APIs and then prompting it to produce code using this API (Fig. 8). For both settings, we use Sonnet 3.7 Thinking as the LLM. The prompts we use are in Appendix F.

We execute the code to detect errors and also manually review it to validate the implementation. For all three deception strategies, LLMs are able to correctly translate the strategy with Perry's abstractions. However, the code produced in low-level APIs is incorrect and do not execute without errors. We validated the Sonnet 3.7-generated Perry code against the DFS attacker in the Equifax Large environment and find that the behavior is comparable to the manually written defense code.

B. Evaluating Perry's extensibility

With respect extensibility. operators may want to consider: (1) *variations* of the previously implemented strategies and (2) *new capabilities* for both attacks and defenses. We illustrate how Perry simplifies such extensions.

Exploring variations of strategies: As an illustrative case study, we consider a scenario where the operator wants to evaluate two extensions: (1) intentionally leaking wrong topology information to the adversary and (2) allocating the deception budget differently in a more critical section of the network. Implementing these extensions to the layered approach (i.e. misinformation and alternative placement) required adding less than 10 lines of code and deleting 3 lines. In contrast, doing so with the non-Perry scripts would be significantly harder to express and debug due to environment-specific modifications.

Defender capabilities: As an illustrative case study, we consider the case where an operator wants to explore the benefits of fine-grained host telemetry tools [13], [28] to identify when attackers interact with decoy resources. Specifically, we consider SysFlow [28] to collect system calls using eBPF [13]. This required us to 1) create an Ansible playbook to install SysFlow on each host (26 LOC); 2) add a Python module to configure SysFlow to send the data to the Elasticsearch database (28 LOC); 3) modify environment files to install SysFlow on all hosts (6 LOC); and 4) add an observation module that uses the system calls to detect when attackers use decoy credentials or interact with decoy hosts (42 LOC).

Note that this implementation effort is a one-time cost to the observability module and is independent of the environments we want to consider. In this case, the new telemetry provides the same high-level events so no new code is needed for the deception implementations. After implementing the new SysFlow-based observation module, it can interchangeably be swapped with the original observation module in Sec. VII-A with a single change to the configuration file.[5]

New attacker capabilities: Attackers expressed using the Perry APIs can be extended similar to the defender. Furthermore, Perry can also to support attacker code that does not use the Perry API. For instance, semi- or autonomous LLM-based attackers are starting to show early promise in CTF style challenges [63]. It is easy to plug in such emerging attacker capabilities as well. The effort to support a new autonomous attacker in Perry was quite minimal; we just need to create a new attack strategy that prompts the LLM for bash commands to execute and respond with the results (52 LOC).

C. What-If scenarios and interesting findings

Now, we show how Perry can help operators shed light on the efficacy of different deception approaches, uncover subtle tradeoffs, and identify counterintuitive findings.

Environments and setup: Perry's emulation layer is flexible and can implement a wide range of environments including those considered in prior work [1], [17], [32], [35], [62] described in Table V. In Appendix D, we benchmark the time it takes to setup and launch the different environments. At a high level, we find that the one-time setup cost is manageable for a new environment and the time to launch is also reasonable to enable the scale of experiments needed.

Once we have this setup, we can systematically evaluate multiple attack strategies (Table III) against multiple deception strategies (Table IV) in several environments.

Illustrative findings: In what follows, we highlight some interesting findings. We do not intend these as conclusive statements about the state of deception or universal facts across all future environments. We use these as illustrative examples of the types of what-if analysis tradeoffs operators can uncover. For each result, we run the experiment 5 times and report the averages across the runs. In the interest of brevity, for some results we only focus on the environments inspired by the Equifax and Colonial Pipeline incidents.

F1: Value of deception depends on environment details
In the Equifax-inspired environment we consider: (1) binary success metric if the attacker was able to exfiltrate all data and (b) the time to exfiltrate all data. In the Colonial Pipeline-inspired environment, similarly we use a binary metric if the attacker was able to infect all critical actuators (Fig. 11) and the time the attacker took to infect all actuators (Fig. 9).[6]

We find that deception emulation experiments have many complex and dynamic behaviors that highlight the importance of tools like Perry to directly measure them. For instance, in the Equifax-inspired environment, a layered deception strategy

[5]If the new telemetry generates new high level events, then the deception code should be correspondingly updated with new event handlers.

[6]For both time metrics, if the attacker failed, we mark the time as the maximum for the environment.

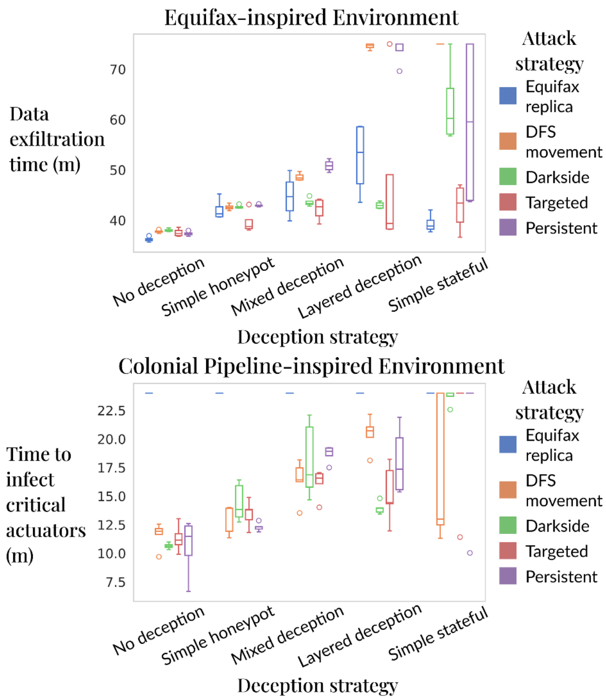


Fig. 9: Time metrics for how long attackers took to achieve their goal against each deception strategy. The efficacy of deception strategies vary significantly across attackers and environments.

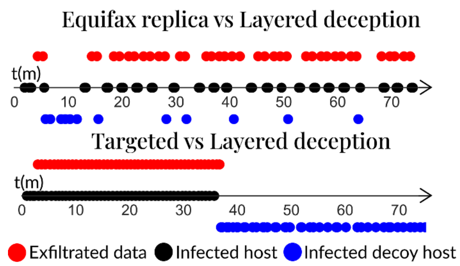


Fig. 10: Two example timelines in the Equifax-inspired environment: the Equifax replica attacker and Targeted attacker against the layered deception defense. The Targeted attacker uses the prior knowledge of the network to avoid the deception defense.

delays the Equifax replica attacker by 49%, but delays the targeted attacker by an average of 2.5% (Fig. 9). We illustrate how a Targeted attacker avoids deception with two example timelines in Fig. 10. The Targeted attacker uses prior knowledge of the network topology and only interacts with deceptive resources after exfiltrating all of the data.

Furthermore, efficacy of deception strategies vary across environments, emphasizing the need for operators to evaluate deception for their use case. For example, in the Colonial Pipeline-inspired environment a mixed deception strategy delays an attacker on average 18% more than a layered strategy (Fig. 9), but in the Equifax-inspired environment, both the mixed deception and layered strategy have the same efficacy.

F2: Stateful deception is key for mitigation
We find static deception strategies can delay but not fundamentally limit the binary success (i.e., infect or exfiltrate critical assets) of many attackers we evaluated. In contrast, stateful deception that reacts to changes in system state are able thwart many types of attacks we considered (Fig. 11).

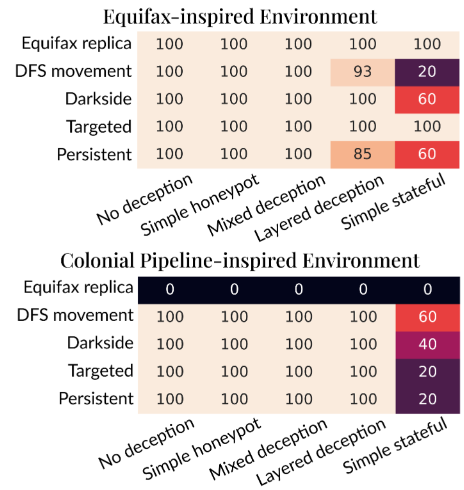


Fig. 11: Mean of percent files exfiltrated in the Equifax environment and mean of critical actuators infected in the Colonial Pipeline-inspired environment. Only stateful deception strategies that react to the system can thwart attackers.

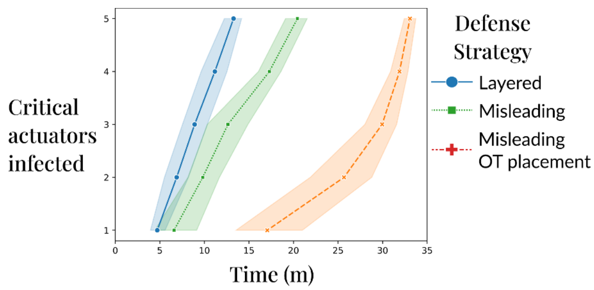
Essentially, attackers are quick enough to explore all attack paths even in the face of static deception. Only the layered deception strategy against a few DFS movement and Persistent attackers are able to stall the attacker to the 75 minute time limit. In contrast, defenders can use stateful deception strategies to identify and remove attackers from their networks, as seen in Fig. 11.

F3: Simple strategy extensions can yield significant wins
Recall from Sec. VII-B, we considered misinformation and alternative placement extensions to the layered defender. We find that misinformation is effective against the targeted attacker (i.e., one that has some topology knowledge) and slows down the attacker by an average of 54.5% (Fig. 12a).

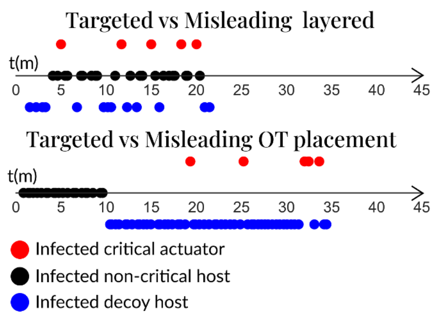
We also discover altering the placement policy can further amplify the efficacy slow down the targeted attacker 3.2×. To identify why this placement policy is so effective, we show two example timelines of attacks in Fig. 12b. The placement policy "floods the zone" of the OT network at the tradeoff of allowing the attacker to gain access to non-critical hosts.

F4: Fine-grained telemetry can boost deception efficacy
Recall the fine-grained telemetry extensions we discussed earlier in Sec. VII-B. We evaluate the layered deception strategy with and without fine-grained telemetry against the DFS and Darkside attackers in all five environments shown in Table VI. Since, both the attackers and defenders are environment agnostic, we are able to execute these experiments without any modifications to the implementations.

We find that in all five environments, against both the DFS and Darkside attackers, adding fine-grained host telemetry to a layered strategy reduces goals achieved by the attacker by 40



(a) Targeted attacker against three deception defenses in the Colonial Pipeline-inspired environment.



(b) Two example timelines of the targeted attacker against the misleading layered strategy and misleading OT placement strategies.

Fig. 12: In the Colonial Pipeline-inspired environment against a targeted attacker, a misleading OT placement strategy can slow the attacker down by 3.2× more than a layered strategy.

TABLE VI: Mean percentage of goals achieved by attacker across five environments against no deception, layered (10 honeypots, 50 decoy credentials), and SysFlow deception strategies (10 honeypots, 50 decoy credentials) for three trials. The SysFlow layered strategy reduces goals achieved by the DFS and Darkside attackers across all five environments.

		Environment				
Defender	Attacker	Equifax	Col.	Enterprise	Star	Chain
No deception	DFS	100	100	66	100	100
	Darkside	100	100	66	33	100
Layered	DFS	86	100	66	100	100
	Darkside	99	100	66	32	0
SysFlow Layered	DFS	3	60	6	4	0
	Darkside	0	40	0	0	0

to 100%. Furthermore, adding fine-grained telemetry is strictly an improvement than the baseline layered strategy.

F5: LLM-based attackers can be thwarted by deception Table VII summarizes running our Sonnet 3.7 Thinking LLM-based attacker for various deception scenarios across 10 trials. (Note that this is different from the use of LLM based code generation for defense strategies in Sec. VII-A). The LLM-based attacker successfully exfiltrated data in 2 out of 10 trials with no deception as shown in Table VII. However, against both deception strategies, it failed to exfiltrate data in any trial. We found that $\approx 90\%$ of commands from the LLM were indeed "wasted" on deceptive resources. While these are the early days in autonomous LLM-based attackers [11], [57], this

TABLE VII: Effectiveness of various deception strategies against Claude 3.7 Sonnet attacker model.

Defense Strategy	**Data Exfiltration Success**	**Decoy Interaction Rate**
No deception	2/10	0%
Static deception	0/10	92%
Layered deception	0/10	90%
Simple stateful	0/10	88%

early result suggests deception may be a promising defense against future autonomous LLM-based attackers.

VIII. Discussion and Limitations

Use cases beyond deception: Perry can potentially enable operators to rapidly explore defense capabilities beyond deception. The environments and attackers described in Sec. VII are not specific to deception. Furthermore, some of the defense strategies in Sec. VII already use non-deceptive defense techniques; other techniques could easily be added.

Perry could also potentially be used to generate and collect realistic synthetic data to train anomaly detection tools. For example, Perry could run a wide variety of attackers in an environment to train intrusion-detection systems.

Limitations: What-if scenarios, including for deception, cannot evaluate strategies unless the setting is fully specified. For Perry, this means being unable to evaluate defenses against unforeseen attackers. In the real world, attackers can have unexpected strategies or new capabilities, such as a 0-day exploit [7]. Defenders are unable to emulate these situations in Perry because they are unaware of these vulnerabilities.

That said, we believe that there is considerable practical value in understanding known attacks. In Sec. VII-A we illustrate how what-if scenarios can provide useful insights for known attackers. Additionally, after new attackers are discovered they can be quickly added to Perry (see Sec. VII).

In both Perry and existing tools [5], [15], [27], [55], defining the environments in full detail, e.g., as precise digital twins of real environments, can be time consuming. Although Perry supplies abstractions that aid in specifying environments, complex topologies with many hosts whose configurations are different will nevertheless be laborious to specify. However, as Perry makes it easy to extend or create new environments, we believe that the cost of defining environments will decrease as users share their environments.

Furthermore, a challenge with all emulation tools is the high resource requirements of emulating large networks. For instance, we estimate that emulating a 10,000-host enterprise organization for the same number of experiments in Sec. VII-A would cost \$50,594 on Google Cloud.[7] To help reduce the cost of evaluating deception on large networks, we have preliminarily evaluated whether experimental results obtained on smaller, simplified environments can carry over to larger, more realistic

[7]We assume each virtual machine has the same requirements as the experiments in Sec. VII-A: 1 CPU, 1GB RAM, and 5GB of disk space. We assume each experiment takes on average 1 hour.

environments; our experiments suggest that results obtained on smaller environments can carry over to larger environments. As future work, we plan to more thoroughly investigate how to reliably approximate aspects of the environment such as services, vulnerabilities, and human interactions.

IX. Other Related Work

Abstract game platforms: One low-effort option for implementing deception what-if experiments are game-theory platforms [10], [30], [41]. These platforms do not evaluate deception approaches in real networks—they are abstract games that allow, for example, the attacker and defender to take turns playing actions. These platforms do not model key aspects of networks, attackers, and defenders making it unclear how their results apply to real deployments.

Unit-test attack emulation tools: Some attack emulation tools [3], [9], [26], [52] are designed to unit test a series of low-level attacker actions to test defender tools, such as the rules in an intrusion detection system. These types of tools are unable to natively emulate the attackers required for deception what-if scenarios because they lack support for controlling and monitoring multiple hosts in an environment.

Other defender emulation tools: Similar to unit-test attacker emulation tools, there are defender emulation tools [5], [19], [56] that cannot natively implement types of deception approaches. In one case, SDN security orchestration tools [19], [56], which only operate on the network layer and as a result cannot implement deception approaches that operate on hosts, such as decoy credentials or files. Another example is Caldera's defender plugin [5], which cannot talk to the network control plane and lacks support for telemetry—two critical components for deception approaches. For instance, the Caldera defender plugin is unable to deploy decoy hosts because it cannot natively talk to the network control plane.

X. Conclusions

Our work was inspired by the significant obstacles we faced in emulating attackers, deception approaches, and environments with existing tools. Our experiences and challenges helped us identify common design patterns to inform Perry's programming model for implementing deception what-if experiments. We introduce Perry to demonstrate the importance of what-if experiments for cyber deception. Our work can serve as the basis to provide operators with the tools to explore and optimize deception strategies in their deployment.

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References

[1] Enterprise Campus 3.0 Architecture: Overview and Framework. Technical report, Cisco, April 2008.
[2] Hierarchical Tree Topology. Technical report, IBM, January 2024.
[3] Akamai. Infection Monkey. https://www.akamai.com/infectionmonkey.
[4] Amazon. AWS. https://aws.amazon.com/.
[5] Andy Applebaum, Doug Miller, Blake Strom, Chris Korban, and Ross Wolf. Intelligent, Automated Red Team Emulation. In *Proceedings of the 32nd Annual Conference on Computer Security Applications*, 2016.
[6] Frederico Araujo and Teryl Taylor. Improving cybersecurity hygiene through JIT patching. In *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 2020.
[7] Leyla Bilge and Tudor Dumitraş. Before we knew it: an empirical study of zero-day attacks in the real world. In *Proceedings of the 2012 ACM conference on Computer and communications security*, 2012.
[8] Brian Caswell, Jay Beale, and Andrew Baker. *Snort intrusion detection and prevention toolkit*. Syngress, 2007.
[9] Chris Gates. Uber Metta. https://github.com/uber-common/metta.
[10] Edward A Cranford, Christian Lebiere, Cleotilde Gonzalez, Sarah Cooney, Phebe Vayanos, and Milind Tambe. Learning about Cyber Deception through Simulations: Predictions of Human Decision Making with Deceptive Signals in Stackelberg Security Games. In *CogSci*, 2018.
[11] Gelei Deng, Yi Liu, Víctor Mayoral-Vilches, Peng Liu, Yuekang Li, Yuan Xu, Tianwei Zhang, Yang Liu, Martin Pinzger, and Stefan Rass. Pentestgpt: An llm-empowered automatic penetration testing tool. *arXiv preprint arXiv:2308.06782*, 2023.
[12] Gelei Deng, Yi Liu, Víctor Mayoral-Vilches, Peng Liu, Yuekang Li, Yuan Xu, Tianwei Zhang, Yang Liu, Martin Pinzger, and Stefan Rass. {PentestGPT}: Evaluating and harnessing large language models for automated penetration testing. In *33rd USENIX Security Symposium (USENIX Security 24)*, pages 847–864, 2024.
[13] eBPF. eBPF. https://ebpf.io/.
[14] Elastic. Elastic Security. https://www.elastic.co/security/siem.
[15] elastic. Elasticsearch. https://www.elastic.co/elasticsearch/.
[16] Simon Yusuf Enoch, Zhibin Huang, Chun Yong Moon, Donghwan Lee, Myung Kil Ahn, and Dong Seong Kim. Harmer: Cyber-attacks automation and evaluation. *IEEE Access*, 8:129397–129414, 2020.
[17] Kimberly J Ferguson-Walter, Maxine M Major, Chelsea K Johnson, and Daniel H Muhleman. Examining the efficacy of decoy-based and psychological cyber deception. In *30th USENIX security symposium (USENIX Security 21)*, 2021.
[18] Fortra. Cobalt Strike. https://www.cobaltstrike.com/.
[19] Nate Foster, Rob Harrison, Michael J Freedman, Christopher Monsanto, Jennifer Rexford, Alec Story, and David Walker. Frenetic: A network programming language. *ACM Sigplan Notices*, 2011.
[20] Javier Franco, Ahmet Aris, Berk Canberk, and A Selcuk Uluagac. A survey of honeypots and honeynets for internet of things, industrial internet of things, and cyber-physical systems. *IEEE Communications Surveys & Tutorials*, 2021.
[21] FTC. Equifax Data Breach Settlement. Technical report, December 2022.
[22] Xiao Han, Nizar Kheir, and Davide Balzarotti. Deception techniques in computer security: A research perspective. *ACM Computing Surveys (CSUR)*, 2018.
[23] HasiCorp. Terraform. https://www.terraform.io/.
[24] Kristin E Heckman, Frank J Stech, Roshan K Thomas, Ben Schmoker, and Alexander W Tsow. Cyber denial, deception and counter deception. *Advances in Information Security*, 2015.
[25] Hannes Holm. Lore a red team emulation tool. *IEEE Transactions on Dependable and Secure Computing*, 2022.
[26] Hannes Holm and Teodor Sommestad. SVED: Scanning, vulnerabilities, exploits and detection. In *MILCOM 2016 IEEE Military Communications Conference*. IEEE, 2016.
[27] IBM. IBM Security QRadar. https://www.ibm.com/qradar.
[28] IBM. SysFlow. https://sysflow.io/.

[29] Sean Michael Kerner. Colonial Pipeline hack explained: Everything you need to know. *TechTarget*, 2022.
[30] Christopher Kiekintveld, Viliam Lisỳ, and Radek Píbil. Game-theoretic foundations for the strategic use of honeypots in network security. *Cyber Warfare: Building the Scientific Foundation*, 2015.
[31] Michael Kouremetis, Marissa Dotter, Alex Byrne, Dan Martin, Ethan Michalak, Gianpaolo Russo, Michael Threet, and Guido Zarrella. Occult: Evaluating large language models for offensive cyber operation capabilities. *arXiv preprint arXiv:2502.15797*, 2025.
[32] Michael Kouremetis, Dean Lawrence, Ron Alford, Zoe Cheuvront, David Davila, Benjamin Geyer, Trevor Haigh, Ethan Michalak, Rachel Murphy, and Gianpaolo Russo. Mirage: cyber deception against autonomous cyber attacks in emulation and simulation. *Annals of Telecommunications*, 2024.
[33] Ravie Lakshmanan. Two Critical Flaws Found in Alibaba Cloud's PostgreSQL Databases. *The Hacker News*, 2023.
[34] Robert M Lee, MJ Assante, and T Conway. CRASHOVERRIDE: Analysis of the threat to electric grid operations. 2017.
[35] Juyi Li, Yangyang Luan, Xiaoqun Wu, and Jun-an Lu. Synchronizability of double-layer dumbbell networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 31(7), 2021.
[36] Li Li, Jean-Pierre S El Rami, Adrian Taylor, James Hailing Rao, and Thomas Kunz. Enabling A Network AI Gym for Autonomous Cyber Agents. In *2022 International Conference on Computational Science and Computational Intelligence (CSCI)*. IEEE.
[37] Majority Staff Report 114th Congress. The OPM Data Breach: How the Government Jeopardized Our National Security for More than a Generation. Technical report, September 2016.
[38] Majority Staff Report 115th Congress. The Equifax Data Breach. Technical report, December 2018.
[39] Stephen Mathezer. Introduction to ICS security fundamentals. *Industrial Cybersecurity Pulse*, 2022.
[40] Changqing Miao, Jianan Feng, Wei You, Wenchang Shi, Jianjun Huang, and Bin Liang. A Good Fishman Knows All the Angles: A Critical Evaluation of Google's Phishing Page Classifier. In *Proceedings of the 2023 ACM SIGSAC Conference on Computer and Communications Security*, 2023.
[41] Stephanie Milani, Weiran Shen, Kevin S Chan, Sridhar Venkatesan, Nandi O Leslie, Charles Kamhoua, and Fei Fang. Harnessing the power of deception in attack graph-based security games. In *Decision and Game Theory for Security: 11th International Conference, GameSec 2020*. Springer, 2020.
[42] Chris Moore. Detecting ransomware with honeypot techniques. In *2016 Cybersecurity and Cyberforensics Conference (CCC)*. IEEE, 2016.
[43] Aleksandr Nahapetyan, Sathvik Prasad, Kevin Childs, Adam Oest, Yeganeh Ladwig, Alexandros Kapravelos, and Bradley Reaves. On sms phishing tactics and infrastructure. In *2024 IEEE Symposium on Security and Privacy (SP)*. IEEE Computer Society, 2024.
[44] Ne0nd0g. Merlin. https://github.com/Ne0nd0g/merlin.
[45] Jordan Nuce, Jeremy Kennelly, Kimberly Goody, Andrew Moore, Alyssa Rahman, Matt Williams, Brendan McKeague, and Jared Wilson. Shining a light on darkside ransomware operations. *FireEye Blogs*, 2021.
[46] OpenInfra. Openstack. https://www.openstack.org/.
[47] Xinming Ou, Sudhakar Govindavajhala, Andrew W Appel, et al. Mulval: A logic-based network security analyzer. In *USENIX security symposium*, volume 8, pages 113–128. Baltimore, MD, 2005.
[48] Yin Minn Pa Pa, Shogo Suzuki, Katsunari Yoshioka, Tsutomu Matsumoto, Takahiro Kasama, and Christian Rossow. IoTPOT: A novel honeypot for revealing current IoT threats. *Journal of Information Processing*, 2016.
[49] Vern Paxson. Bro: a system for detecting network intruders in real-time. *Computer networks*, 31(23-24):2435–2463, 1999.
[50] Niels Provos. A Virtual Honeypot Framework. In *USENIX Security Symposium*, 2004.
[51] Rapid7. Metasploit. https://www.metasploit.com/.
[52] Red Canary. Atomic Red Team. https://redcanary.com/atomic-red-team/.
[53] Red Hat. Ansible. https://www.ansible.com/.
[54] Mikel Rodriguez, Raluca Ada Popa, Four Flynn, Lihao Liang, Allan Dafoe, and Anna Wang. A framework for evaluating emerging cyberattack capabilities of ai. *arXiv preprint arXiv:2503.11917*, 2025.
[55] Z Cliffe Schreuders, Thomas Shaw, Mohammad Shan-A-Khuda, Gajendra Ravichandran, Jason Keighley, and Mihai Ordean. Security Scenario Generator (SecGen): A Framework for Generating Randomly Vulnerable Rich-scenario VMs for Learning Computer Security and Hosting CTF Events. In *2017 USENIX Workshop on Advances in Security Education (ASE 17)*, 2017.
[56] Seung Won Shin, Phillip Porras, Vinod Yegneswara, Martin Fong, Guofei Gu, and Mabry Tyson. Fresco: Modular composable security services for software-defined networks. In *20th Annual Network & Distributed System Security Symposium*. NDSS, 2013.
[57] Brian Singer, Keane Lucas, Lakshmi Adiga, Meghna Jain, Lujo Bauer, and Vyas Sekar. On the feasibility of using llms to execute multistage network attacks. *arXiv e-prints*, pages arXiv–2501, 2025.
[58] Brian Singer, Amritanshu Pandey, Shimiao Li, Lujo Bauer, Craig Miller, Lawrence Pileggi, and Vyas Sekar. Shedding light on inconsistencies in grid cybersecurity: Disconnects and recommendations. In *2023 IEEE Symposium on Security and Privacy (SP)*. IEEE, 2023.
[59] Splunk. Splunk SOAR. https://www.splunk.com/en_us/products/splunk-security-orchestration-and-automation.html.
[60] Maxwell Standen, Martin Lucas, David Bowman, Toby J Richer, Junae Kim, and Damian Marriott. Cyborg: A gym for the development of autonomous cyber agents. *arXiv preprint arXiv:2108.09118*, 2021.
[61] Microsoft Defender Research Team. Cyberbattlesim. https://github.com/microsoft/cyberbattlesim, 2021. Created by Christian Seifert, Michael Betser, William Blum, James Bono, Kate Farris, Emily Goren, Justin Grana,Kristian Holsheimer, Brandon Marken, Joshua Neil, Nicole Nichols, Jugal Parikh, Haoran Wei.
[62] Samuel T Trassare, Robert Beverly, and David Alderson. A technique for network topology deception. In *MILCOM IEEE Military Communications Conference*. IEEE, 2013.
[63] Shengye Wan, Cyrus Nikolaidis, Daniel Song, David Molnar, James Crnkovich, Jayson Grace, Manish Bhatt, Sahana Chennabasappa, Spencer Whitman, Stephanie Ding, et al. Cyberseceval 3: Advancing the evaluation of cybersecurity risks and capabilities in large language models. *arXiv preprint arXiv:2408.01605*, 2024.
[64] Ke Coby Wang and Michael K Reiter. Using amnesia to detect credential database breaches. In *30th USENIX Security Symposium (USENIX Security 21)*, 2021.
[65] Zack Whittaker. Flawed office printers are a silent but serious target for hackers. *TechCrunch*, 2019.

APPENDIX A
ENVIRONMENTS

In this section, we give detailed descriptions of each environment.

Equifax-inspired environment: The Equifax-inspired environment has two web servers running a vulnerable version of Apache Struts with CVE-2017-5638, the same as the real environment [38]. During the Equifax breach, the attacker discovered a plaintext file on one of the web servers that included credentials to 48 different database hosts on a separate network [38]. [8]

To replicate the databases in our environment, we create a second network with 48 database hosts and add files with fake critical consumer data such as emails, social security numbers, and addresses. On a random web server, we add a plain-text SSH configuration file that contains credentials to all the databases.

Colonial Pipeline-inspired environment: Next, we implement an environment inspired by the Colonial Pipeline breach [29] and other ICS attacks [34], [58]. The goal of the attacker is to gain access to devices that control physical devices, we call these devices critical actuators. The environment has three networks: two IT networks and one OT network. The two IT networks have 10 hosts each and the OT network has 15

[8] From public information, it is unclear how many additional non-database credentials were in the file, but we assume that the credential file only contained database credentials.

sensor hosts, 5 controller hosts and 5 critical actuator hosts. Each of the 5 controller hosts have credentials to one of the 5 actuators because controller hosts use data from the sensor hosts to control the actuators [39]. In addition, each IT network has a management host that have credentials to all sensors and control hosts [39]. The monitoring hosts have software that has been compromised by a reverse shell backdoor [33].

Attackers often get access to IT hosts through techniques such as exploiting weak passwords (the case in the Colonial Pipeline breach [29] and phishing [40], [43]. We emulate this in the environment by giving the attacker initial access to a random host on the IT network.

Chain: Some evaluations of game-theory based deception algorithms consider a Ring network where each host has credentials to one other host in the network [32], [62]. Each host has some critical data and the goal of the attacker is to exfiltrate all the data in the network. Existing studies simulated the Ring environment with five hosts [32] and 10 hosts [62]. We implement our ring network with 25 hosts [38].

Star: Some prior work evaluating deception has also considered a star network [17]. The Star network contains 25 hosts on the same network. The attacker gains access to a host with credentials to all 25 other hosts, creating a star attack graph.

Enterprise: The enterprise network is modeled based on a common tree hierarchy [1]. The Enterprise network has 4 networks, 3 networks represent 3 floors in a building, and the 4th network is for external services. The external network contains vulnerable webservers. Each floor has a host vulnerable to a reverse shell backdoor. One of the vulnerable hosts has credentials to critical databases. The other vulnerable hosts have credentials to non-critical user servers.

APPENDIX B
ATTACKERS

A. Attackers

Next, we give detailed descriptions of each attacker:

Equifax attacker We use the public information of the breach to define the attacker strategy [38]. The Equifax attacker is a multistage attacker that 1) finds and infects web servers to gain initial access, 2) finds and uses credentials found on web servers to infect internal databases, and 3) finds and exfiltrates data by copying data onto web servers and downloading it over HTTP. The attacker repeats these steps until all web servers are infected, all found credentials are used, and all found data is exfiltrated. Note that the attacker is adaptive to the environment in that it discovers information at runtime. The attacker can work in environments with any number of web servers or databases, environments with credentials on different web servers, and data can be exfiltrated from any host (not only hosts on the database network).

DFS movement As a more general attack strategy, we consider a depth-first-search (DFS) movement attacker to serve as a baseline for the Colonial Pipeline-inspired and Ring environments. The DFS attacker explores the network with a depth-first search over possible targets. After infecting a new host, the DFS attacker 1) discovers host information, 2) tries to exfiltrate any critical data on the host, and 3) adds newly discovered network targets to the start of a stack, and 4) infects the network target at the start of the stack. For example, if the DFS attacker has three possible web servers to infect, it will infect one web server. Then, if the attacker finds new credentials, it will exploit these credentials before infecting the other web servers.

Targeted The targeted attacker uses the attack graph service to maintain a list of all potential targets in a network. The targeted attacker prioritizes the targets in the list based on leaked information about the network. For instance in the Equifax environment, the targeted attacker will prioritize infecting all attack paths that include database servers.

Persistent The persistent attack strategy reserves an infected host in the network, we call this the persistent host. If the attacker loses access to a host, the attacker uses the persistent host to reinfect the host they lost access to. In addition, the persistent attack strategy stores a history of executed actions. If the persistent attack strategy loses access to a host and then regains access, it will not re-execute the actions on that host. For example, if a persistent attacker used a decoy credential and lost access to the host, the persistent attacker will reinfect the host, but it will not reuse the decoy credential.

Darkside The Darkside attack strategy is based on the public report of the Darkside attack group [45]. The strategy first attempts to gain an initial foothold in the network. Once the attacker gains access it will conduct the following actions repeatedly: escalate privileges, conduct internal reconnaissance, and infect internal hosts. Once the attack has tried infecting all hosts, they will complete the mission by exfiltrating any found data.

APPENDIX C
DECEPTION STRATEGIES

Now, we provide detailed descriptions of each deception strategy.

Basic honeypot: The basic honeypot strategy deploys 10 honeypots randomly across each of the defender's networks. In the Equifax environment, the honeypots are replicas of the vulnerable web servers. In the other environments, the honey pot is vulnerable to a reverse bash shell.

Mixed deception: The mixed strategy deploys decoy hosts to random subnets and decoy credentials on random hosts. The decoy credentials are fake, and if the attacker tries using a decoy credential it will not work.

Layered deception: The mixed strategy deploys decoy hosts to random networks and decoy credentials on random hosts. In layered strategy, the defender creates real decoy credentials that have permission to a random decoy host. Furthermore, the defender adds fake data to each decoy host.

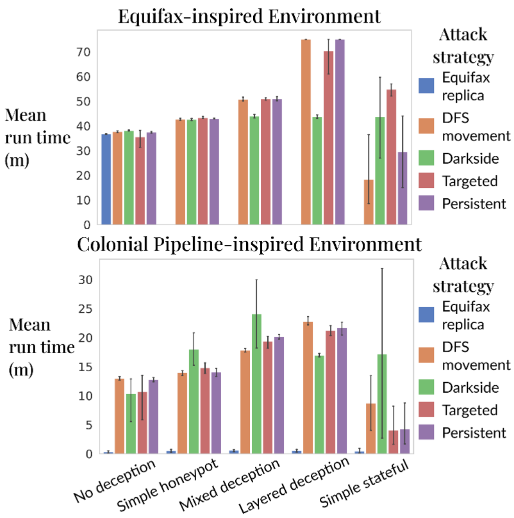

Fig. 13: Mean run time of Equifax-inspired environment and Colonial Pipeline-inspired environment experiments in Sec. VII-A. The run times range from 0.12–75 minutes.

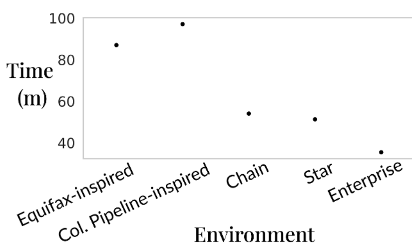

Fig. 14: The time taken to setup each environment in Perry. The setup process installs services, vulnerabilities, and other required dependencies. In these environments can take from 35–97 min.

Appendix D
Microbenchmarks

Finally, we benchmark the time it takes to setup and launch diverse environments. As discussed in Sec. VI, Perry instantiates environments in two stages: setup and launch. For the environments in Table V, the setup times range from 35–97 min., shown in Fig. 14. Setup times can be costly because of the cost of downloading and installing required dependencies for tens of hosts in a network. After setup, Perry caches the environment and can then relatively quickly launch each environment. For the environments in Table V, the launch times range from 1–7.3 min. shown in Fig. 15. The key takeaway is that the one-time setup cost is manageable for a new environment and the time to launch is also reasonable to enable the scale of experiments needed.

In addition, we measure the run time of each experiment in Sec. VII-A. Experiments have a fairly large range in run time, ranging from 0.12–75 minutes, shown in Fig. 13. Experiments are often short because of attackers failing to make progress infecting the network or being detected by deception. The longer experiments are from attackers being heavily distracted by deception.

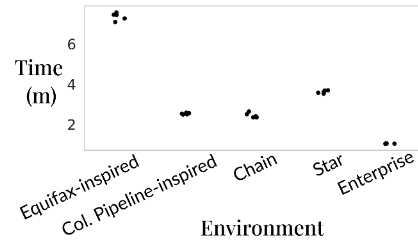

Fig. 15: After setting up environments, Perry launches them per scenario. We run 5 launches per environment, the launching process ranges from 1–7.3 min.

TABLE VIII: Perry enables LLM-generated deception strategies

Deception strategy	Sonnet 3.7 thinking input	w/o Perry	w/ Perry
Generic	Please create a deception strategy.	○	●
Honeypots	Please create a deception strategy that deploys 10 honeypots across the network.	○	●
Advanced	Please create a deception strategy that deploys a variety of deception resources across the network. If any attackers interact with them, restore the host.	○	●

○ Generated LLM code does not execute due to errors
● Generated LLM code executes and is correct

Appendix E
Counting lines of code

In this section, we give a detailed description of how we count and compare lines of code of implementations with and without using Perry's abstractions.

For attackers, we programmatically convert our attacker implementations for Perry into native Caldera code as follows. First, we preprocess all files to only include semantic lines of code (i.e., we remove comments and logging) and we format each file with the PEP 8 format standard. We convert Perry attackers by first translating high-level actions into low-level calls to the Caldera SDK. Next, we convert each call to the telemetry-translation module and environment state service to native Caldera code. The final result is a functionally equivalent implementation in native Caldera code.

For defenders, we programmatically convert each deception approach into Elasticsearch with native Python code. Similarly as for the attacker translation to Caldera, we convert the high-level actions, telemetry-translation module calls, and environment state service calls into native Python code. The result is a functionally equivalent implementation using Elasticsearch with native Python code.

Appendix F
LLM generated prompts

In Table VIII, we show the specific prompts we queried LLMs for generating deception strategies.