Self-Learning Systems for Cyber Security

NSE Seminar

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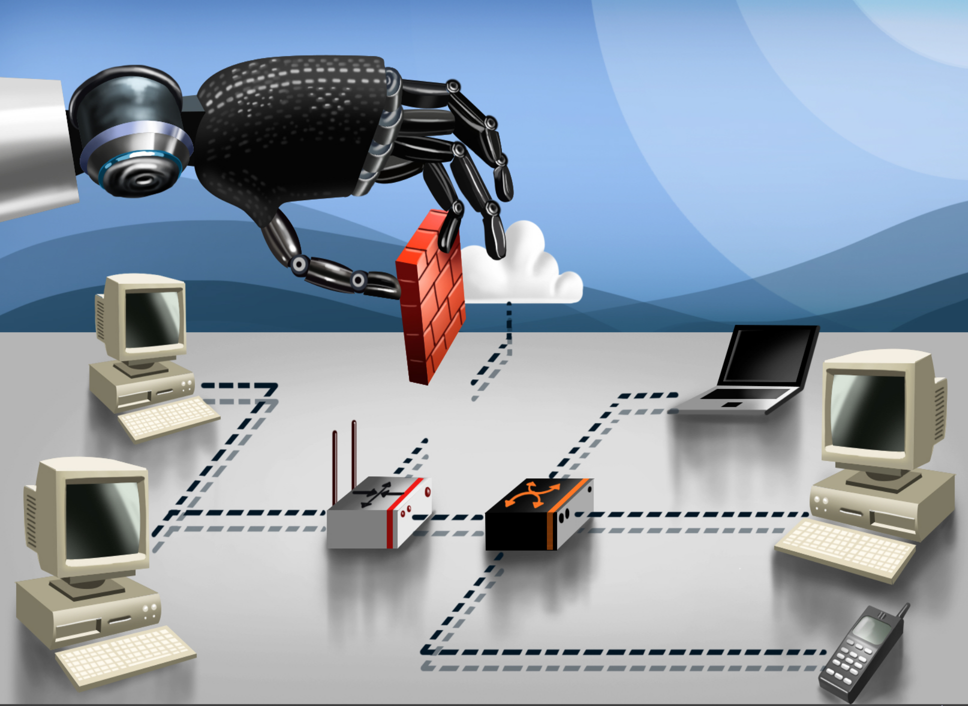
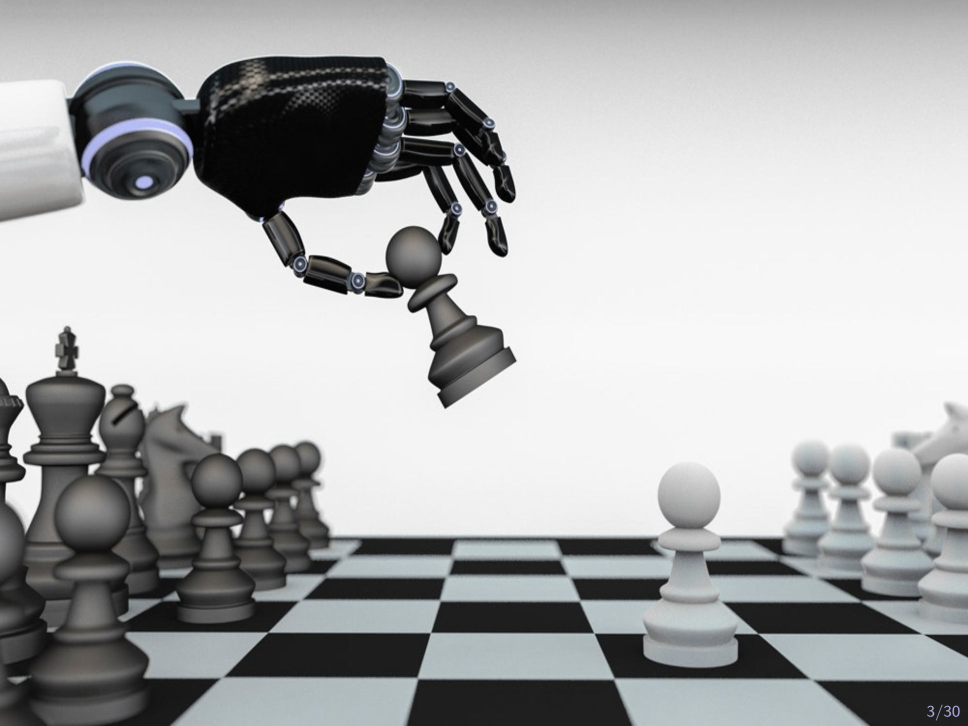
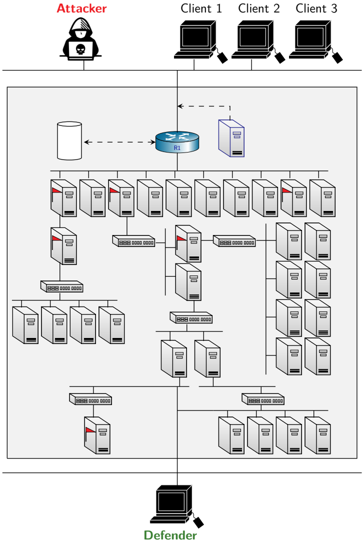
April 9, 2021





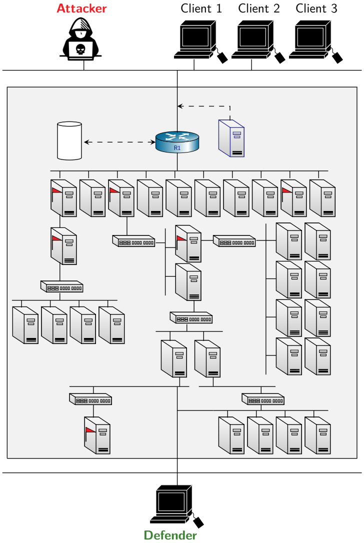
Challenges: Evolving and Automated Attacks

- **Challenges**:
  - Evolving & automated attacks
  - Complex infrastructures



Goal: Automation and Learning

- **Challenges**
  - Evolving & automated attacks
  - Complex infrastructures
- **Our Goal**:
  - Automate security tasks
  - Adapt to changing attack methods



Approach: Game Model & Reinforcement Learning

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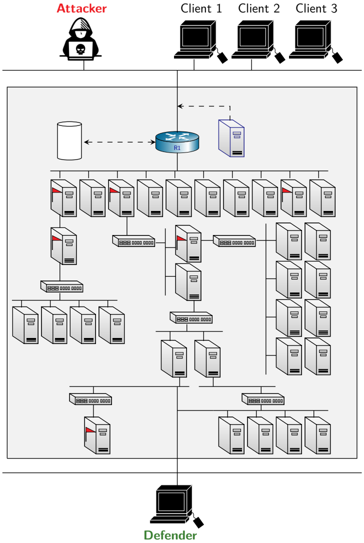
  - Evolving & automated attacks
  - Complex infrastructures
- **Our Goal**:
  - Automate security tasks
  - Adapt to changing attack methods
- **Our Approach**:
  - Model network attack and defense as *games*.
  - Use *reinforcement learning* to learn policies.
  - Incorporate learned policies in *self-learning systems*.



State of the Art

- **Game-Learning Programs**:
  - TD-Gammon, AlphaGo Zero[1], OpenAI Five etc.
  - $\implies$ Impressive empirical results of *RL and self-play*
- **Attack Simulations**:
  - Automated threat modeling[2], automated intrusion detection etc.
  - $\implies$ Need for *automation* and better security tooling
- **Mathematical Modeling**:
  - Game theory[3]
  - Markov decision theory
  - $\implies$ Many security operations involves *strategic decision making*

[1] David Silver et al. "Mastering the game of Go without human knowledge". In: *Nature* 550 (Oct. 2017), pp. 354–. URL: http://dx.doi.org/10.1038/nature24270.

[2] Pontus Johnson, Robert Lagerström, and Mathias Ekstedt. "A Meta Language for Threat Modeling and Attack Simulations". In: *Proceedings of the 13th International Conference on Availability, Reliability and Security*. ARES 2018. Hamburg, Germany: Association for Computing Machinery, 2018. ISBN: 9781450364485. DOI: 10.1145/3230833.3232799. URL: https://doi.org/10.1145/3230833.3232799.

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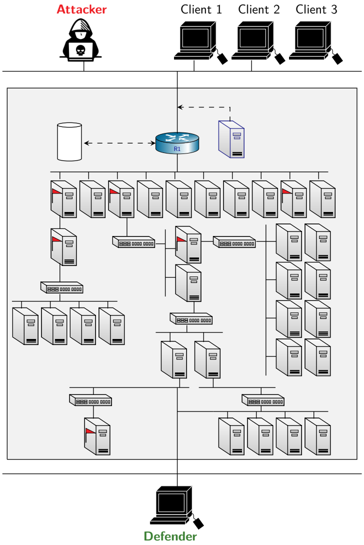
Our Work

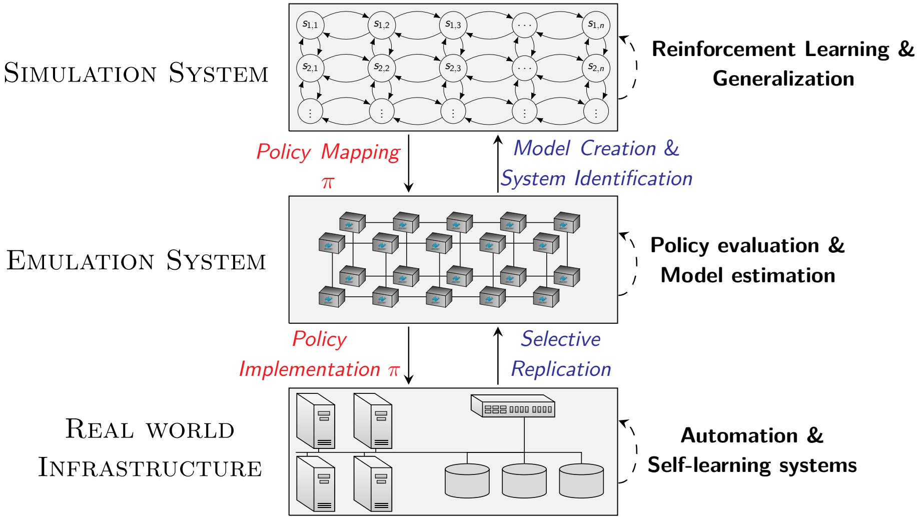
- **Use Case:** Intrusion Prevention
- **Our Method:**
  - Emulating computer infrastructures
  - System identification and model creation
  - Reinforcement learning and generalization
- **Results:**
  - Learning to Capture The Flag
  - Learning to Detect Network Intrusions
- **Conclusions and Future Work**

Use Case: Intrusion Prevention

- A **Defender** owns an infrastructure
  - Consists of connected components
  - Components run network services
  - Defender defends the infrastructure by monitoring and patching
- An **Attacker** seeks to intrude on the infrastructure
  - Has a partial view of the infrastructure
  - Wants to compromise specific components
  - Attacks by reconnaissance, exploitation and pivoting



Our Method for Finding Effective Security Strategies



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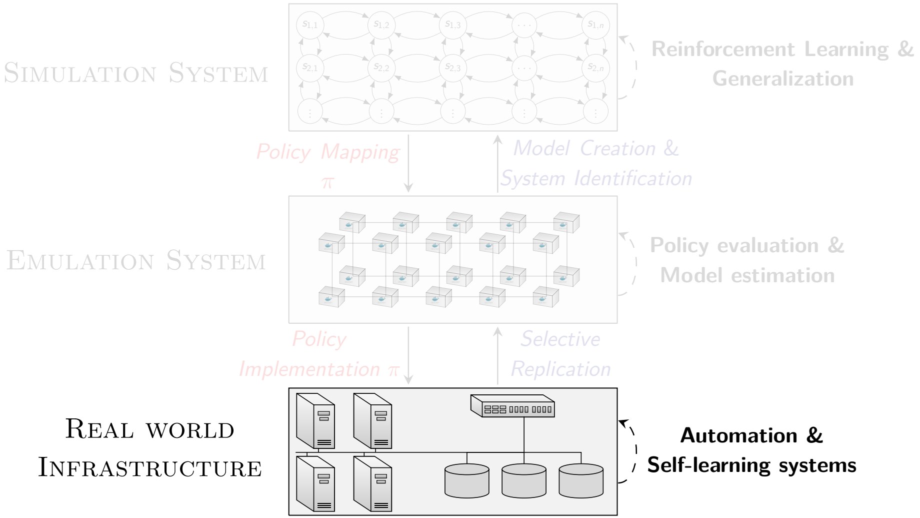

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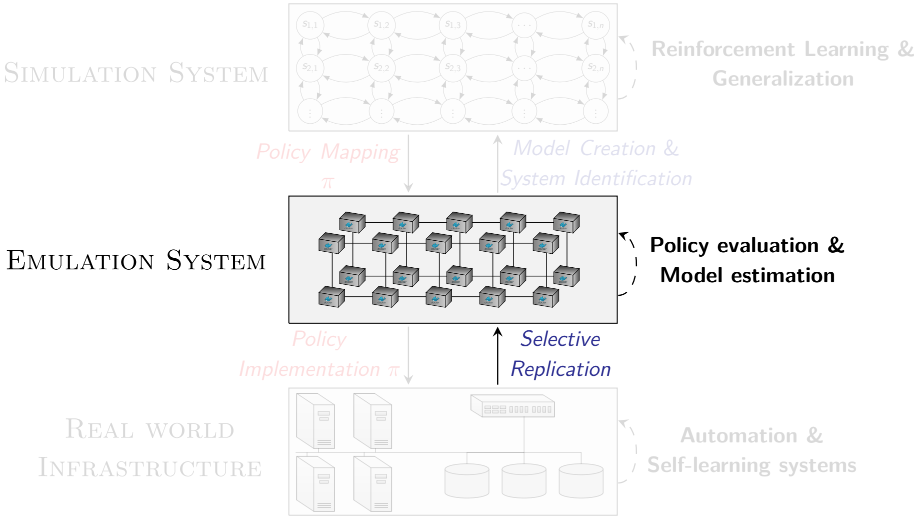

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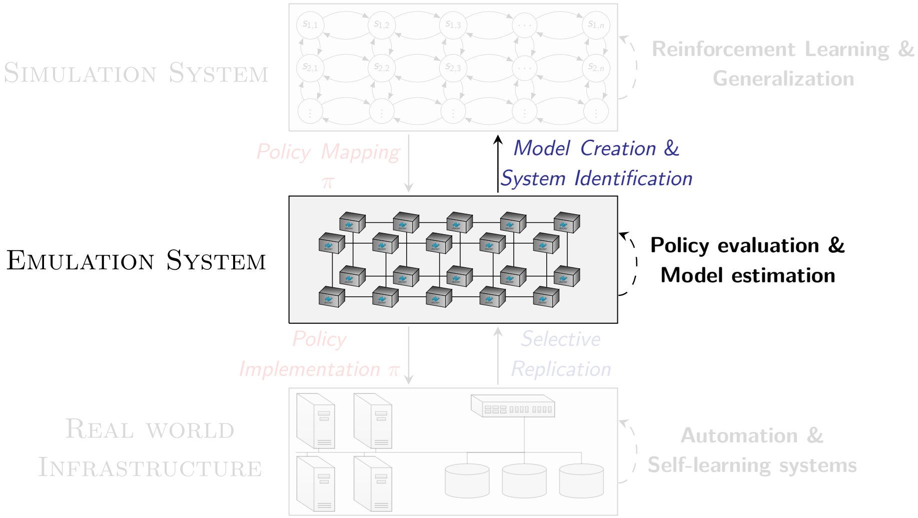

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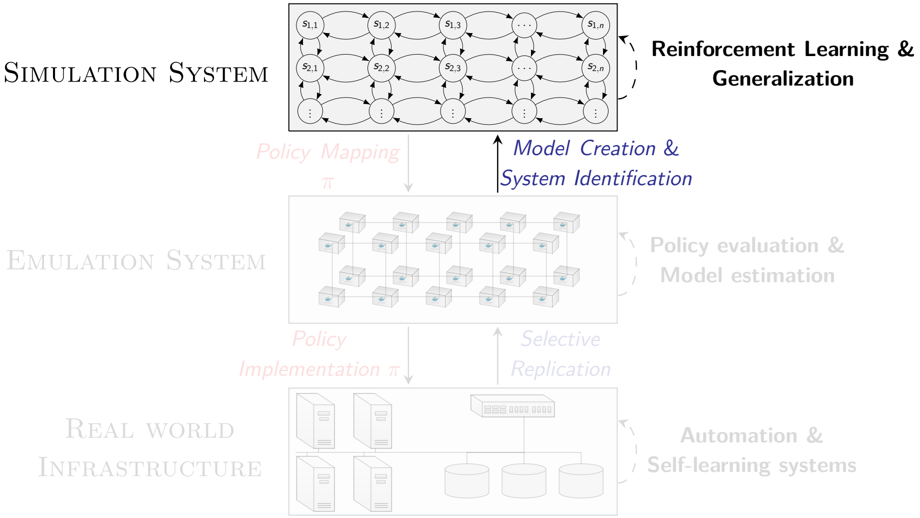

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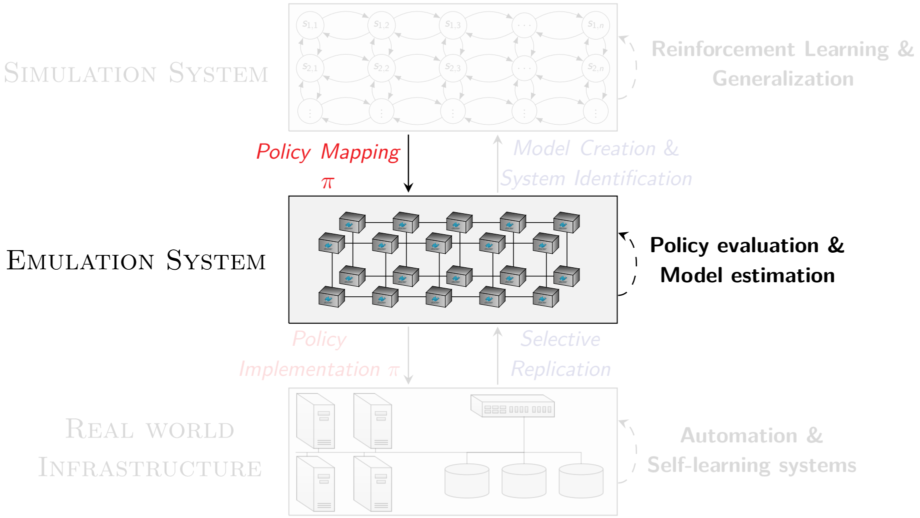

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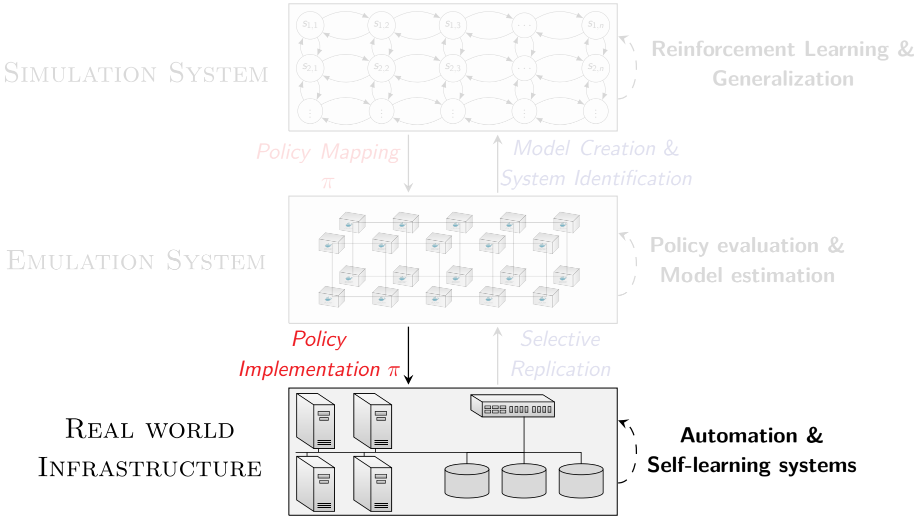

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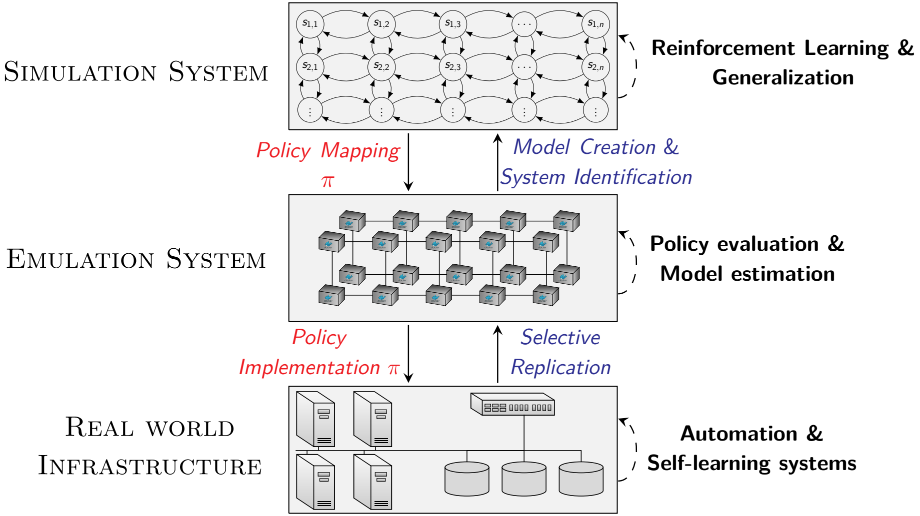

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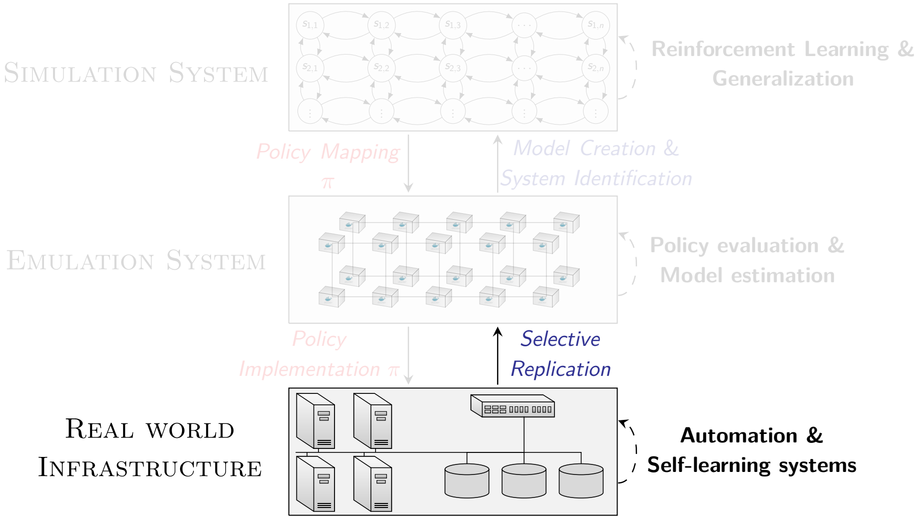
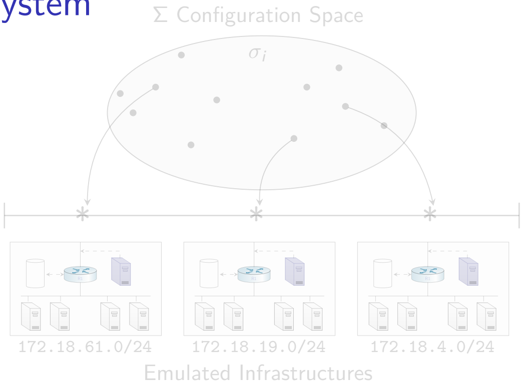


Emulation System



Emulation

A cluster of machines that runs a virtualized infrastructure which replicates important functionality of target systems.

- The set of virtualized configurations define a *configuration space* $\Sigma = \langle \mathcal{A}, \mathcal{O}, \mathcal{S}, \mathcal{U}, \mathcal{T}, \mathcal{V} \rangle$.
- A specific emulation is based on a configuration $\sigma_i \in \Sigma$.

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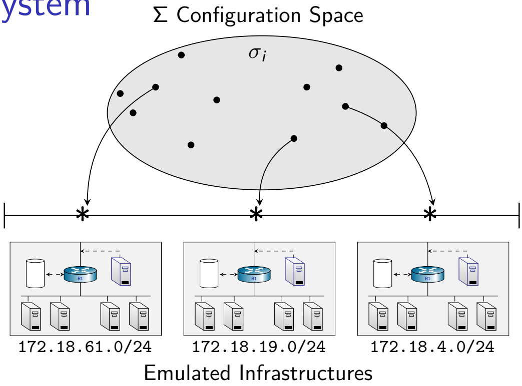

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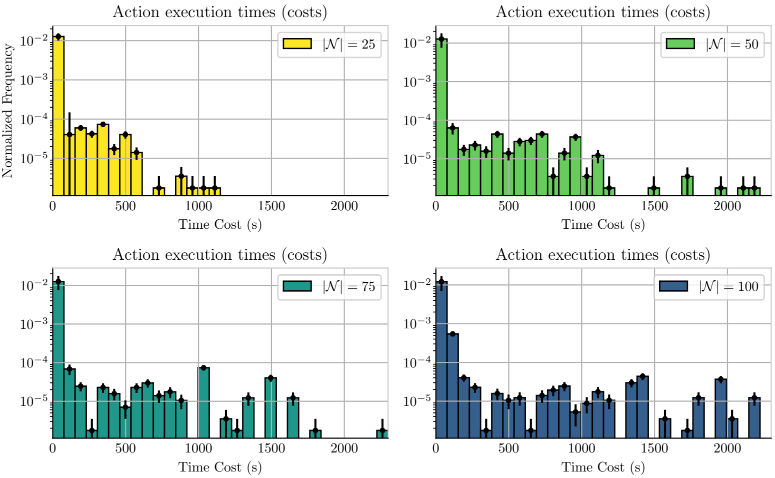
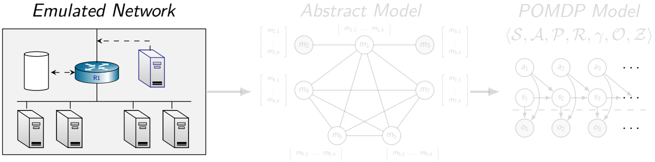
Emulation: Execution Times of Replicated Operations



- **Fundamental issue**: Computational methods for policy learning typically require samples on the order of $100k - 10M$.
- $\implies$ Infeasible to optimize in the emulation system

From Emulation to Simulation: System Identification



- **Abstract Model Based on Domain Knowledge**: Models the set of *controls*, the *objective function*, and the *features* of the emulated network.
  - Defines the static parts a POMDP model.

- **Dynamics Model ($\mathcal{P}$, $\mathcal{Z}$) Identified using System Identification**: Algorithm based on random walks and maximum-likelihood estimation.

$$\mathcal{M}(b'|b,a) \triangleq \frac{n(b,a,b')}{\sum_{j'} n(s,a,j')}$$

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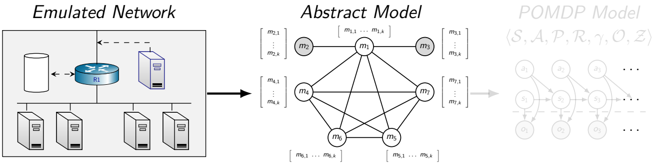

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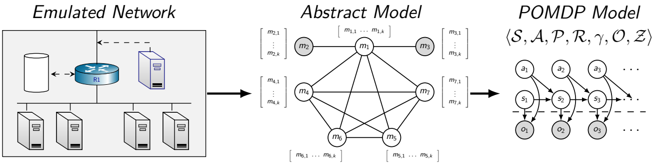

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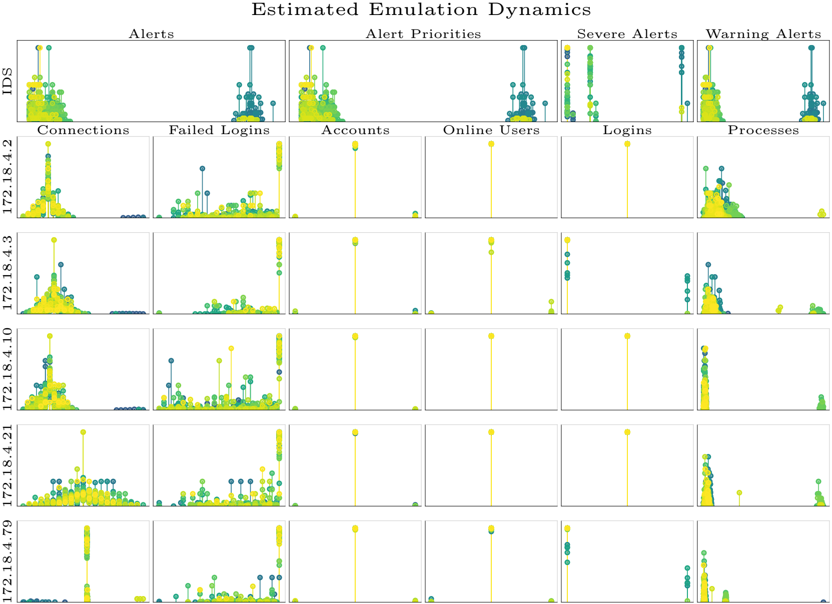

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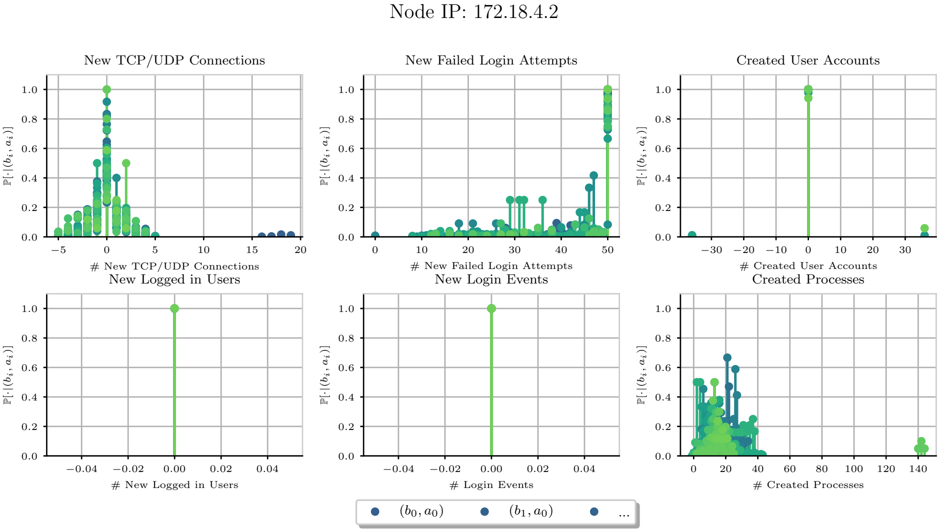

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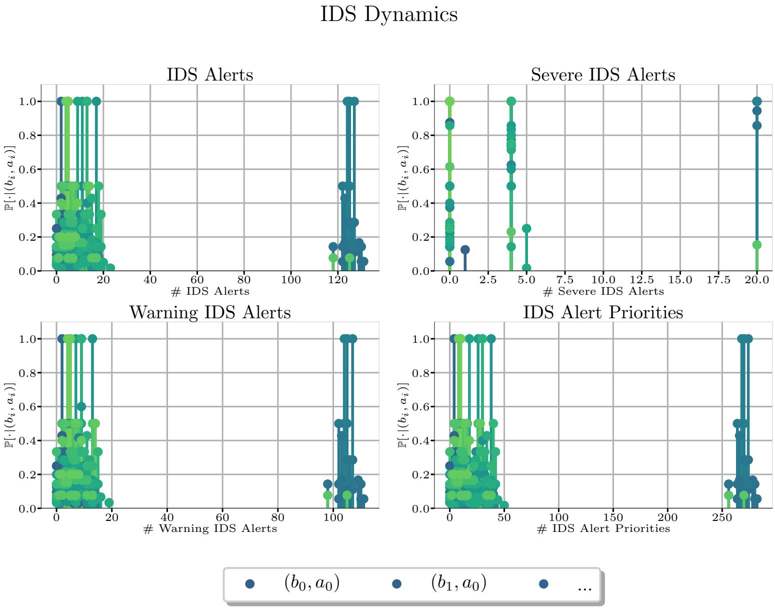

Policy Optimization in the Simulation System using Reinforcement Learning

- **Goal**:
  - Approximate $\pi^* = \arg\max_\pi \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_{t+1}\right]$

- **Learning Algorithm**:
  - Represent π by π_θ
  - Define objective $J(\theta) = \mathbb{E}_{o\sim\rho^{\pi_\theta}, a\sim\pi_\theta}[R]$
  - Maximize $J(\theta)$ by stochastic gradient ascent with gradient $\nabla_\theta J(\theta) = \mathbb{E}_{o\sim\rho^{\pi_\theta}, a\sim\pi_\theta}\left[\nabla_\theta \log \pi_\theta(a|o) A^{\pi_\theta}(o, a)\right]$
- **Domain-Specific Challenges**:
  - Partial observability
  - Large state space $|\mathcal{S}| = (w+1)^{|\mathcal{N}|\cdot m\cdot(m+1)}$
  - Large action space $|\mathcal{A}| = |\mathcal{N}| \cdot (m+1)$
  - Non-stationary Environment due to presence of adversary
  - Generalization

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- Finding Effective Security Strategies through Reinforcement Learning and Self-Play[a]

[a] Kim Hammar and Rolf Stadler. "Finding Effective Security Strategies through Reinforcement Learning and Self-Play". In: *International Conference on Network and Service Management (CNSM 2020) (CNSM 2020)*. Izmir, Turkey, Nov. 2020.

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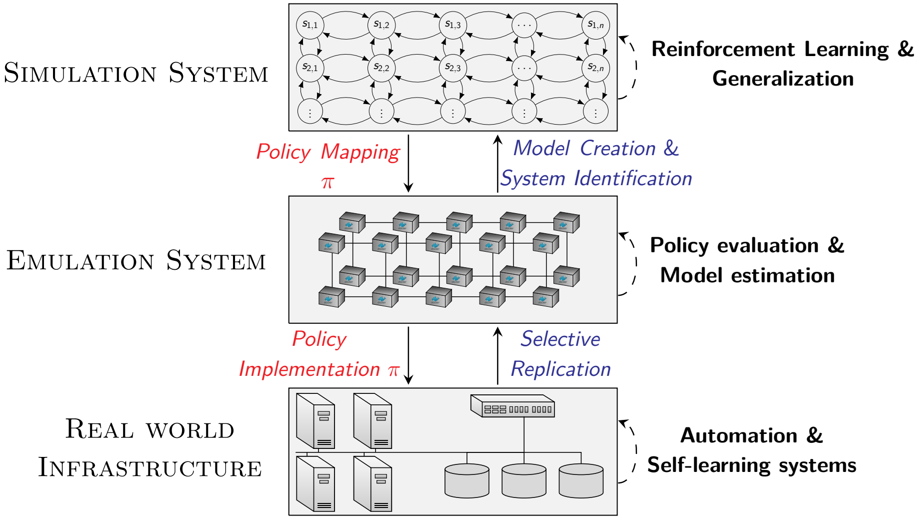
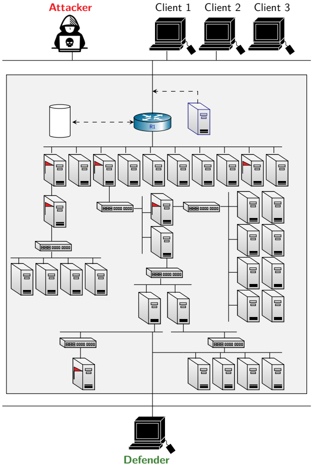


Learning Capture-the-Flag Strategies: Target Infrastructure

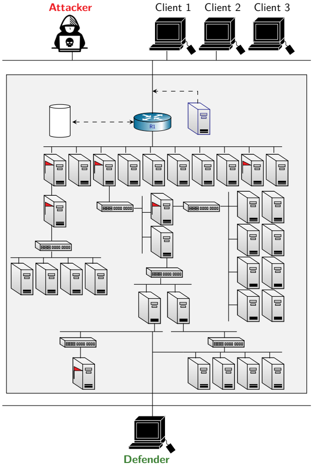
- **Topology**:
  - 32 Servers, 1 IDS (Snort), 3 Clients
- **Services**
  - 1 SNMP, 1 Cassandra, 2 Kafka, 8 HTTP, 1 DNS, 1 SMTP, 2 NTP, 5 IRC, 1 Teamspeak, 1 MongoDB, 1 Samba, 1 RethinkDB, 1 CockroachDB, 2 Postgres, 3 FTP, 15 SSH, 2 FTP
- **Vulnerabilities**
  - 2 CVE-2010-0426, 2 CVE-2010-0426, 1 CVE-2015-3306, 1 CVE-2015-5602, 1 CVE-2016-10033, 1 CVE-2017-7494, 1 CVE-2014-6271
  - 5 Brute-force vulnerabilities
- **Operating Systems**
  - 14 Ubuntu-20, 9 Ubuntu-14, 1 Debian 9:2, 2 Debian Wheezy, 5 Debian Jessie, 1 Kali
- **Traffic**
  - FTP, SSH, IRC, SNMP, HTTP, Telnet, IRC, Postgres, MongoDB, Samba
  - curl, ping, tracerotue, nmap..



Target infrastructure.

Learning Capture-the-Flag Strategies: System Model 1/3

- A hacker (pentester) has T time-periods to **collect flags** hidden in the infrastructure.
- The hacker is located at a dedicated starting position N_0 and can **connect to a gateway** that exposes public-facing services in the infrastructure.
- The hacker has a **pre-defined set (cardinality** ~ 200**) of network/shell commands available**.

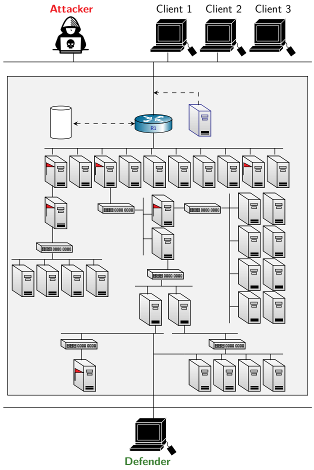


Target infrastructure.

Learning Capture-the-Flag Strategies: System Model 2/3

- By execution of commands, the hacker **collects information**
  - Open ports, failed/successful exploits, vulnerabilities, costs, OS, ...
- Sequences of commands can yield shell-access to nodes
  - Given shell access, the hacker can **search for flags**
- Associated with each command is a **cost** c (execution time) and **noise** n (IDS alerts).

- *The objective is to capture all flags with the minimal cost within the fixed time horizon T. What strategy achieves this end?*



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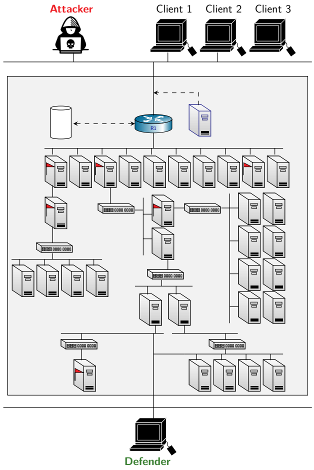
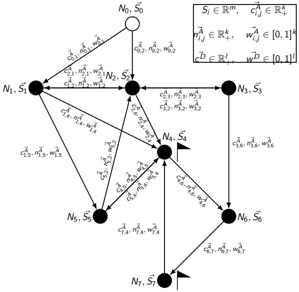


Target infrastructure.

Learning Capture-the-Flag Strategies: System Model 3/3

- **Contextual Stochastic CTF with Partial Information**
  - Model infrastructure as a graph $\mathcal{G} = \langle \mathcal{N}, \mathcal{E} \rangle$
  - There are k flags at nodes $\mathcal{C} \subseteq \mathcal{N}$
  - $N_i \in \mathcal{N}$ has a *node state s_i* of m attributes
  - Network state $s = \{s_A, s_i \mid i \in \mathcal{N}\} \in \mathbb{R}^{|\mathcal{N}| \times m + |\mathcal{N}|}$
  - Hacker observes $o^A \subset s$
  - Action space: $\mathcal{A} = \{a_1^A, \ldots, a_k^A\}$, a_i^A (commands)
  - $\forall (b, a) \in \mathcal{A} \times \mathcal{S}$, there is a probability $\vec{w}_{i,j}^{A,(x)}$ of failure & a probability of detection $\varphi(det(s_i) \cdot n_{i,j}^{A,(x)})$
  - State transitions $s \to s'$ are decided by a discrete dynamical system $s' = F(s, a)$
  - ***Exact dynamics $(F, c^A, n^A, w^A, det(\cdot), \varphi(\cdot))$, are unknown to us!***



Graphical Model.

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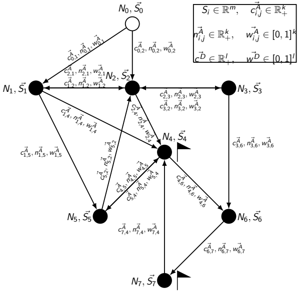
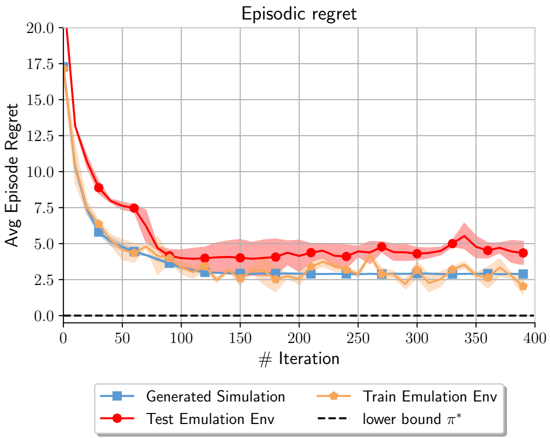
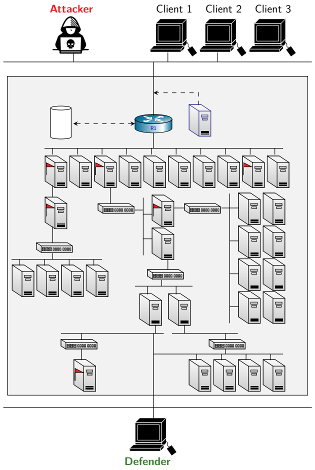


Graphical Model.

Learning Capture-the-Flag Strategies

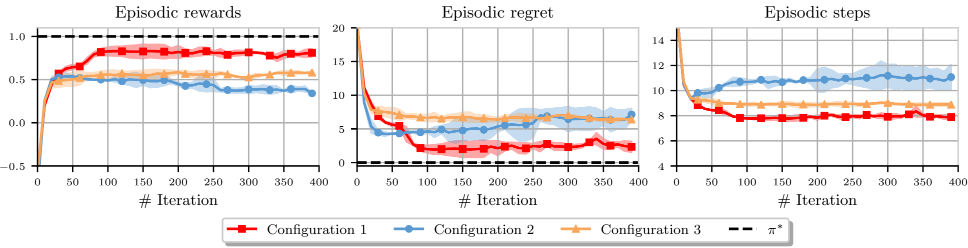


Learning curves (simulation and emulation) of our proposed method.

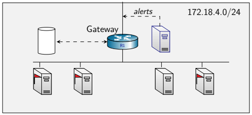


Evaluation infrastructure.

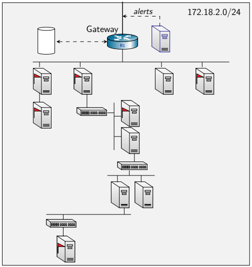
Learning Capture-the-Flag Strategies



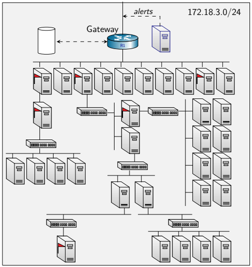
Configuration 1

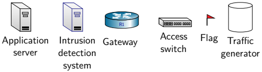


Configuration 2



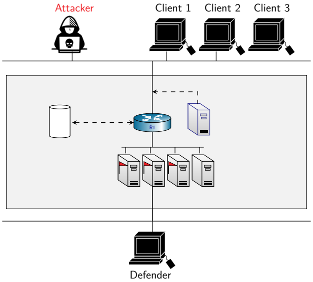
Configuration 3





Learning to Detect Network Intrusions: Target Infrastructure

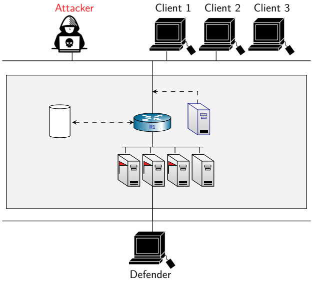
- **Topology**:
  - 6 Servers, 1 IDS (Snort), 3 Clients
- **Services**
  - 3 SSH, 2 HTTP, 1 DNS, 1 Telnet, 1 FTP, 1 MongoDB, 2 SMTP, 1 Tomcat, 1 Teamspeak3, 1 SNMP, 1 IRC, 1 Postgres, 1 NTP
- **Vulnerabilities**
  - 1 CVE-2010-0426, 3 Brute-force vulnerabilities
- **Operating Systems**
  - 4 Ubuntu-20, 1 Ubuntu-14, 1 Kali
- **Traffic**
  - FTP, SSH, IRC, SNMP, HTTP, Telnet, IRC, Postgres, MongoDB,
  - curl, ping, tracerotue, nmap..



Evaluation infrastructure.

Learning to Detect Network Intrusions: System Model (1/3)

- An admin should **manage the infrastructure** for T time-periods.
- The admin can **monitor the infrastructure** to get a belief about it's state b_t
- $b_1, \ldots, b_{T-1}$ can be assumed to be generated from some **unknown** distribution φ.
- If the admin suspects that the infrastructure is being intruded based on b_t, he can **suspend the suspicious user/traffic**.



Target infrastructure.

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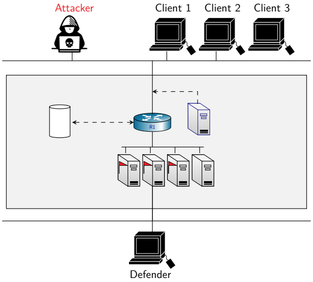
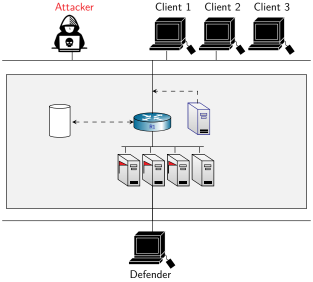


Target infrastructure.

Learning to Detect Network Intrusions: System Model (2/3)

- Suspending traffic from a **true intrusion** yields a reward r (salary bonus)
- Not suspending traffic of a **true intrusion**, incurs a cost c (admin is fired)
- Suspending traffic of a **false intrusion**, incurs a cost of o (breaking the SLA)

- *The objective is to to decide an optimal response for suspending network traffic. What strategy achieves this end?*



Target infrastructure.

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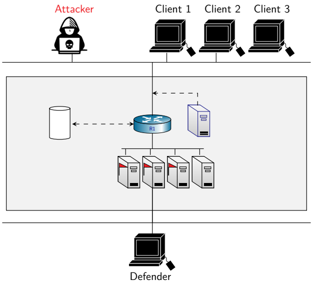
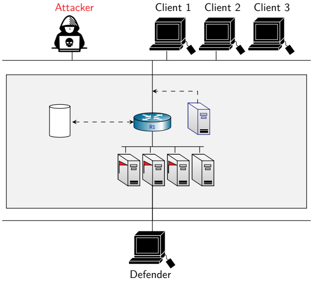


Target infrastructure.

Learning to Detect Network Intrusions: System Model (3/3)

- **Optimal Stopping Problem**
  - Action space $\mathcal{A} = \{\texttt{STOP}, \texttt{CONTINUE}\}$
- **Belief state space $\mathcal{B} \in \mathbb{R}^{8+10\cdot m}$**
  - A belief state $b \in \mathcal{B}$ contains relevant metrics to detect intrusions
  - Alerts from IDS, Entries in `/var/log/auth`, logged in users, TCP connections, processes, ...
- **Reward function $\mathcal{R}$**
  - $r(b_t, \texttt{STOP}, s_t) = \mathbb{1}_{intrusion}\frac{\beta}{t_i}$
  - β is a positive constant and t_i is the number of nodes compromised by the attacker
  - $\implies$ incentive to detect intrusion early.



Target infrastructure.

Structural Properties of the Optimal Policy

- Assumptions: Always an intrusion before T, $f(b_t)$: probability of intrusion given b_t, b_t and p are Markov, $f(b_t)$ is non-decreasing in t.
- Claim: Optimal policy is a **threshold based policy**
  - Necessary condition for optimality (Bellman):

$$u_t(b_t) = \sup_a \left[r_t(b_t, a) + \sum_{b' \in \mathcal{B}} p_t(b'|b_t, a) u_{t+1}(b', a) \right] \quad (1)$$

  - Thus I have that it is optimal to stop at state b_t iff

$$f(b_t) \cdot \frac{\beta}{t_i} \geq \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \quad (2)$$

  - Stopping threshold α_t:

$$\alpha_t \triangleq \frac{t_i}{\beta} \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \quad (3)$$

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$$= \max \left[f(b_t) \cdot \frac{\beta}{t_i}, \quad \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \right] \quad (5)$$

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  - Stopping threshold α_t:

$$\alpha_t \triangleq \frac{t_i}{\beta} \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \quad (7)$$

Structural Properties of the Optimal Policy

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Structural Properties of the Optimal Policy

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$$u_t(b_t) = \sup_a \left[r_t(b_t, a) + \sum_{b' \in \mathcal{B}} p_t(b'|b_t, a) u_{t+1}(b', a) \right] \tag{12}$$

$$= \max \left[f(b_t) \cdot \frac{\beta}{t_i}, \quad \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \right] \tag{13}$$

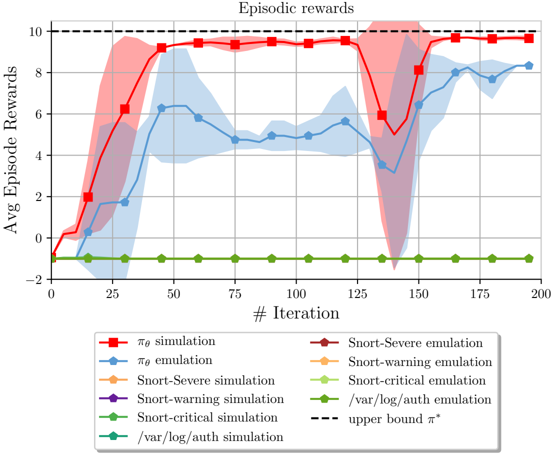
  - Thus I have that it is optimal to stop at state b_t iff

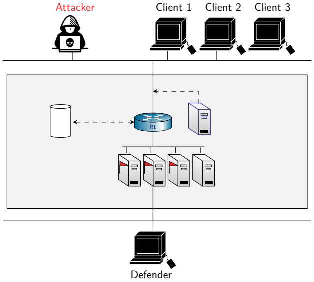
$$f(b_t) \cdot \frac{\beta}{t_i} \geq \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \tag{14}$$

  - Stopping threshold α_t:

$$\alpha_t \triangleq \frac{t_i}{\beta} \sum_{b' \in \mathcal{B}} \varphi(b') u_{t+1}(b') \tag{15}$$

Learning to Detect Network Intrusions

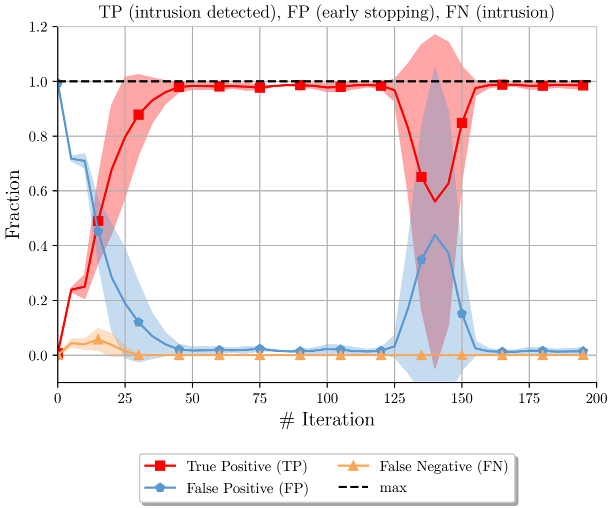




Evaluation infrastructure.

Learning curves (simulation and emulation) of our proposed method.

Learning to Detect Network Intrusions



Trade-off between detection and false positives

Conclusions & Future Work

- **Conclusions:**
  - We develop a *method* to find effective strategies for intrusion prevention
    - (1) emulation system; (2) system identification; (3) simulation system; (4) reinforcement learning and (5) domain randomization and generalization.
  - We show that self-learning can be successfully applied to network infrastructures.
    - Self-play reinforcement learning in Markov security game
  - *Key challenges*: stable convergence, sample efficiency, complexity of emulations, large state and action spaces
- **Our research plans:**
  - Improving the system identification algorithm & generalization
  - Evaluation on real world infrastructures