Self-Learning Systems for Cyber Security

Ledningsregementet Enköping

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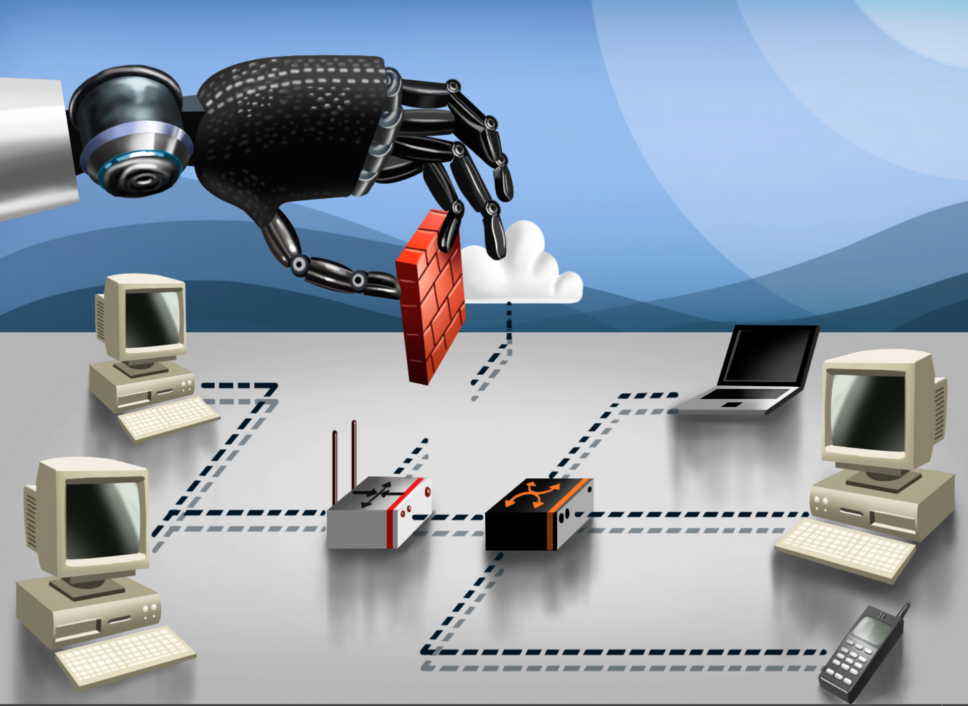
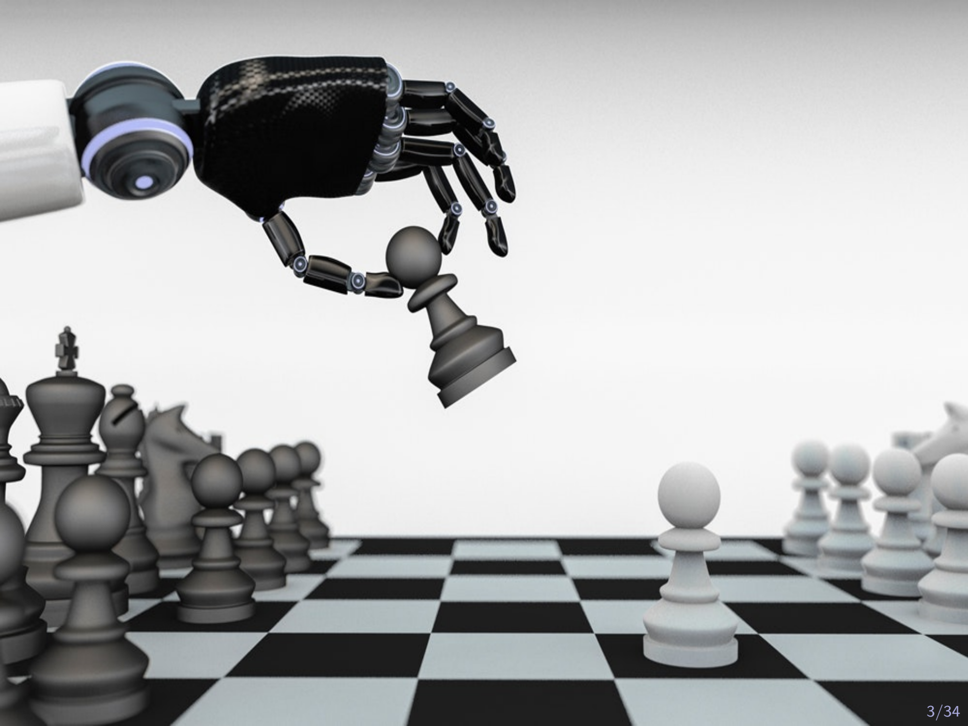
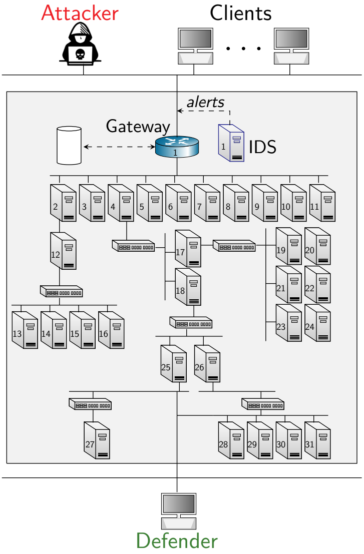




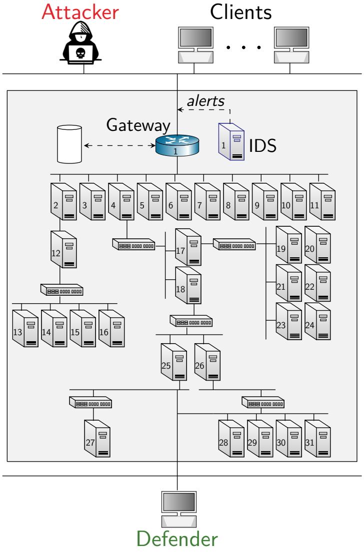
Challenges: Evolving and Automated Attacks



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

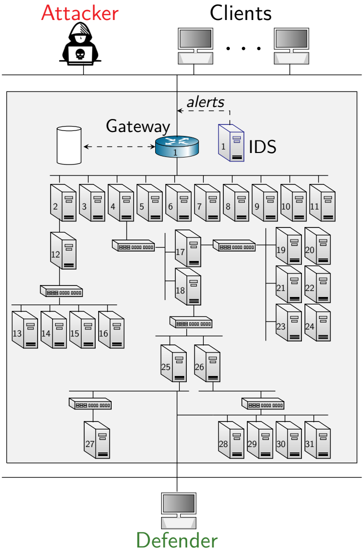
Goal: Automation and Learning

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



Approach: Game Model & Reinforcement Learning

- **Challenges**:
  - 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] and intrusion detection etc.
  - $\implies$ Need for *automation* and better security tooling
- **Mathematical Modeling**:
  - Game theory[3]
  - Markov decision theory, dynamic programming[4]
  - $\implies$ Many security operations involves *strategic decision making*

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[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.

[3] Tansu Alpcan and Tamer Basar. *Network Security: A Decision and Game-Theoretic Approach*. 1st. USA: Cambridge University Press, 2010. ISBN: 0521119324.

[4] Dimitri P. Bertsekas. *Dynamic Programming and Optimal Control*. 3rd. Vol. I. Belmont, MA, USA: Athena Scientific, 2005.

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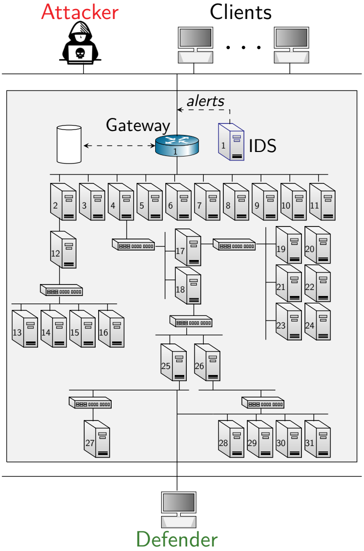
Our Work

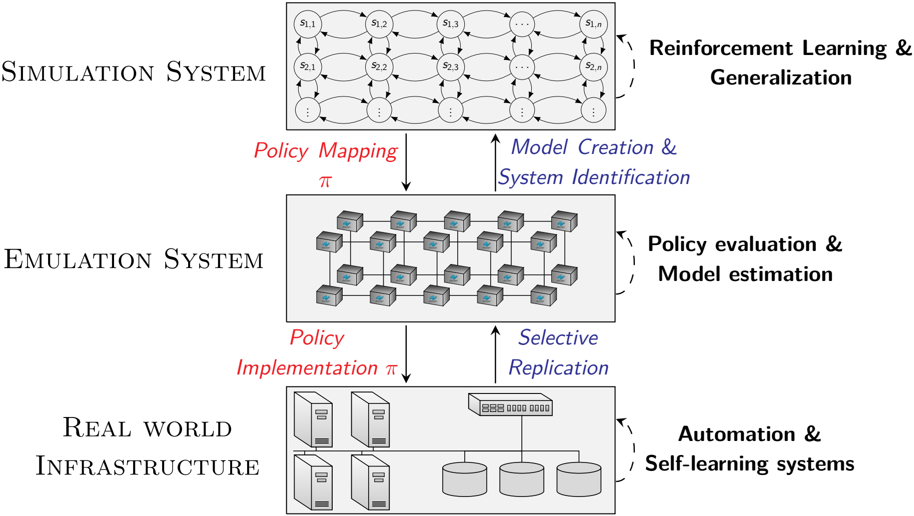
- **Use Case:** Intrusion Prevention
- **Our Method:**
  - Emulating computer infrastructures
  - System identification and model creation
  - Reinforcement learning and generalization
- **Results:**
  - Learning to Capture The Flag
  - Learning to Prevent Attacks (Optimal Stopping)
- **Conclusions and 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 active defense
- 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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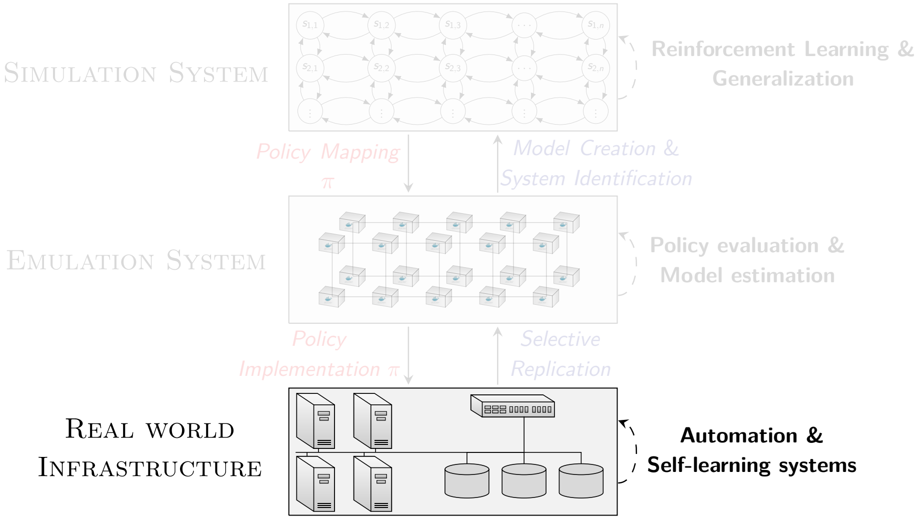

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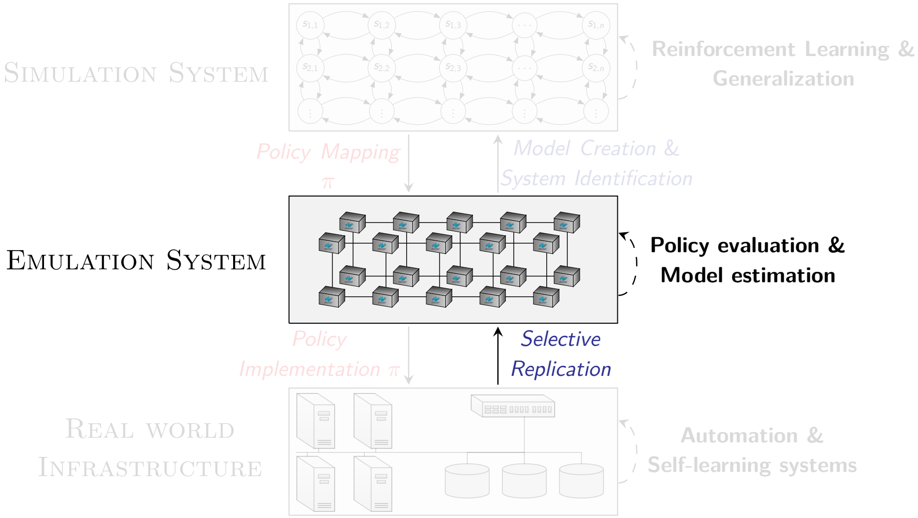

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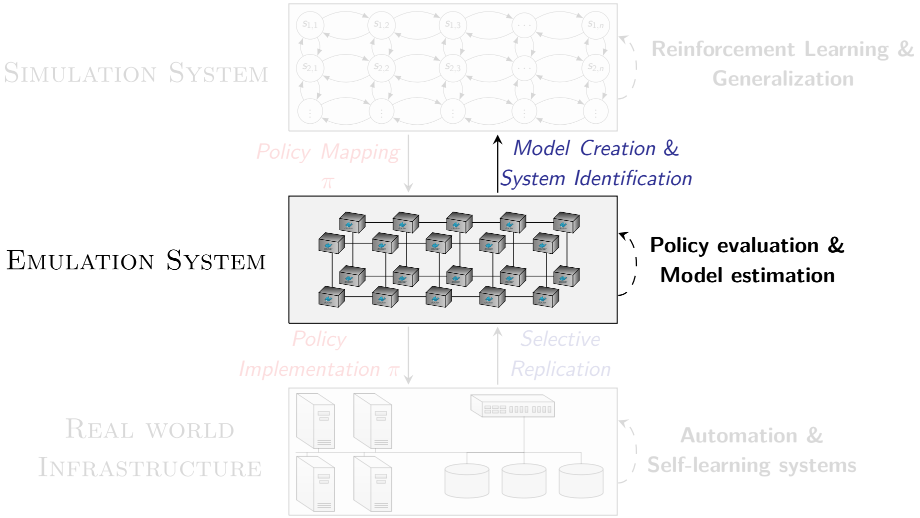

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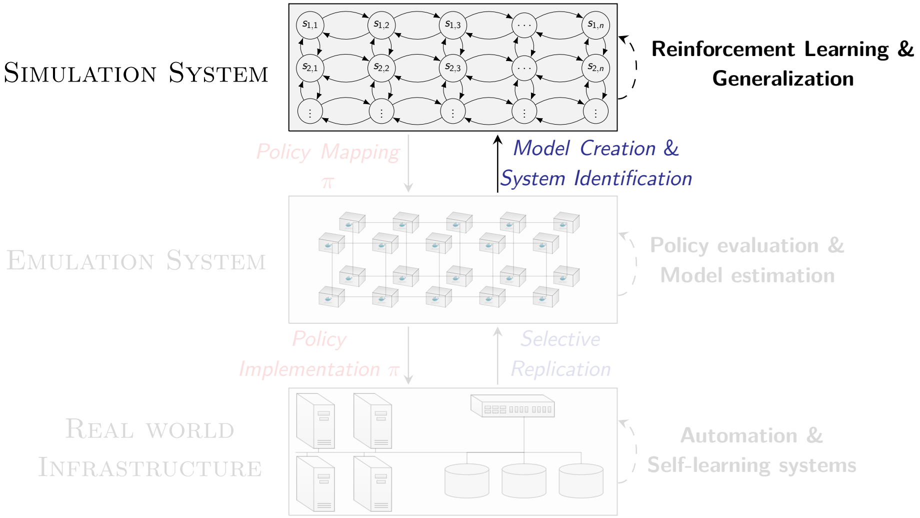

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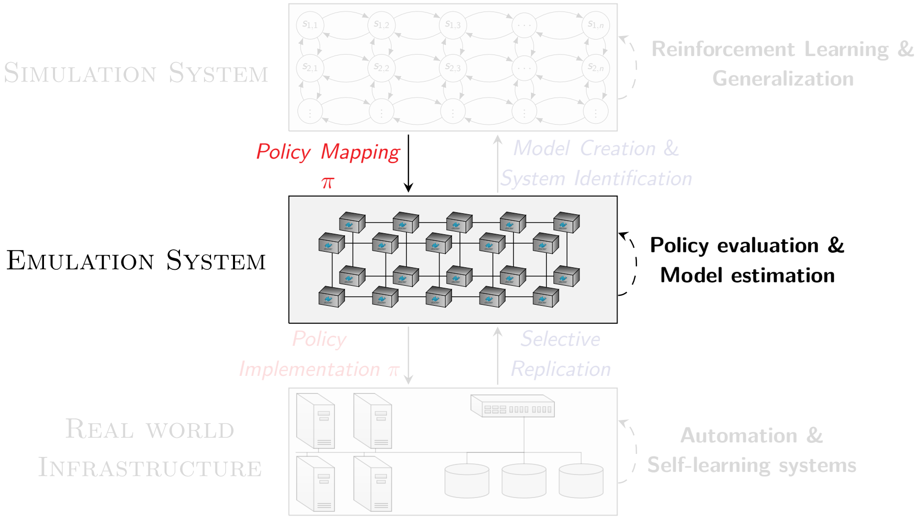

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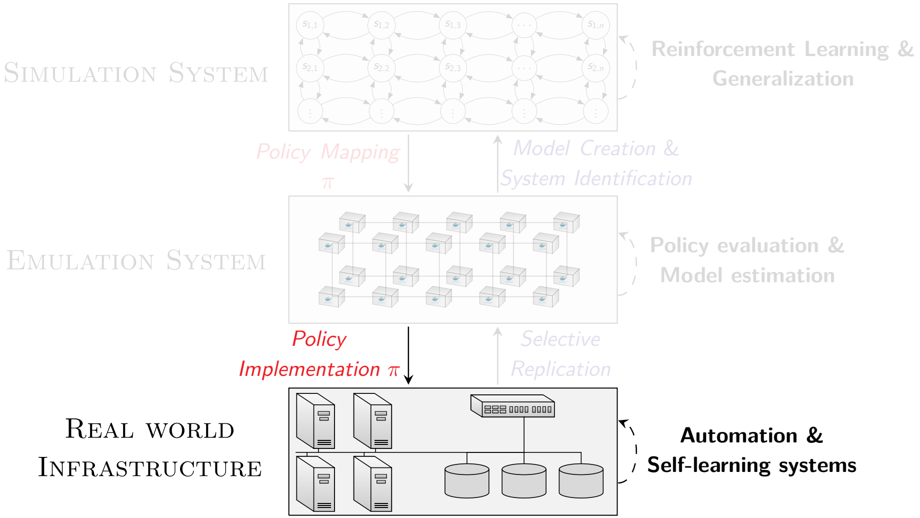

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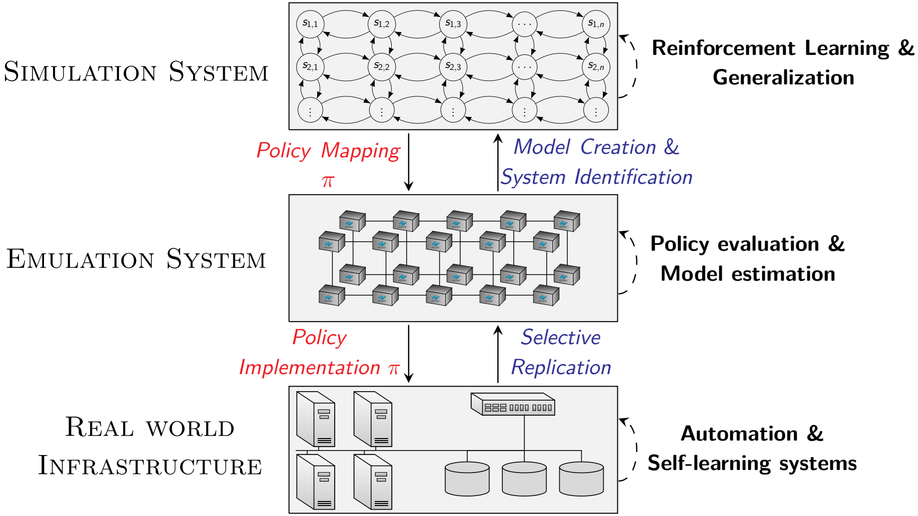

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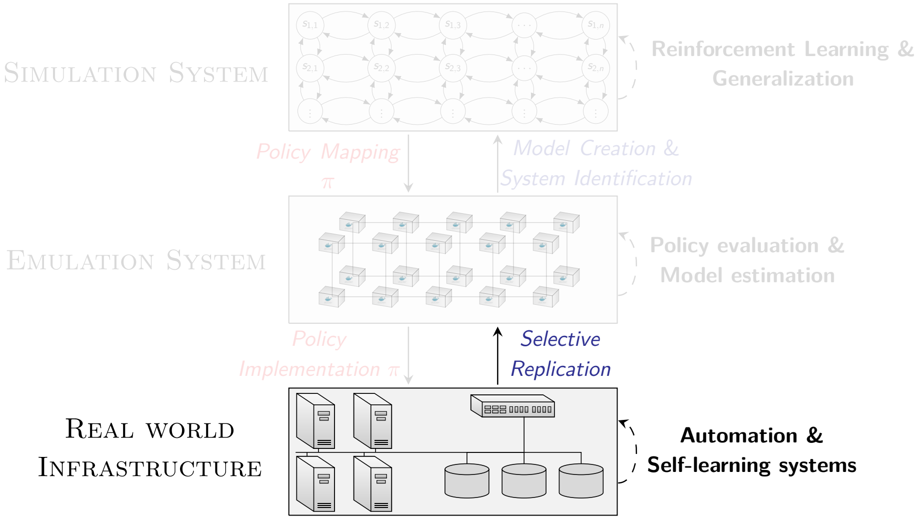
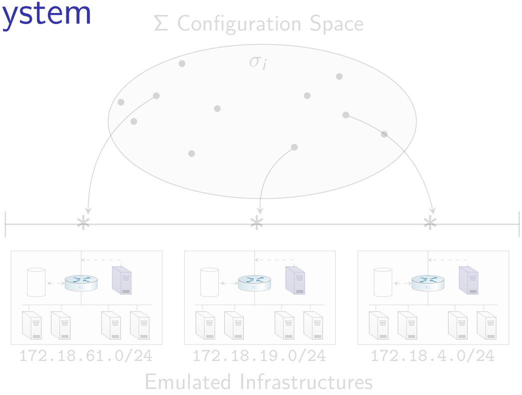


Emulation System



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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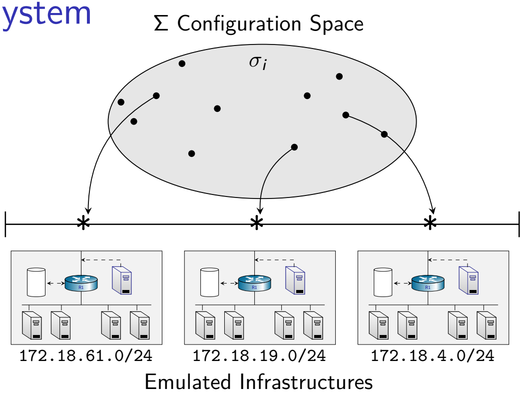

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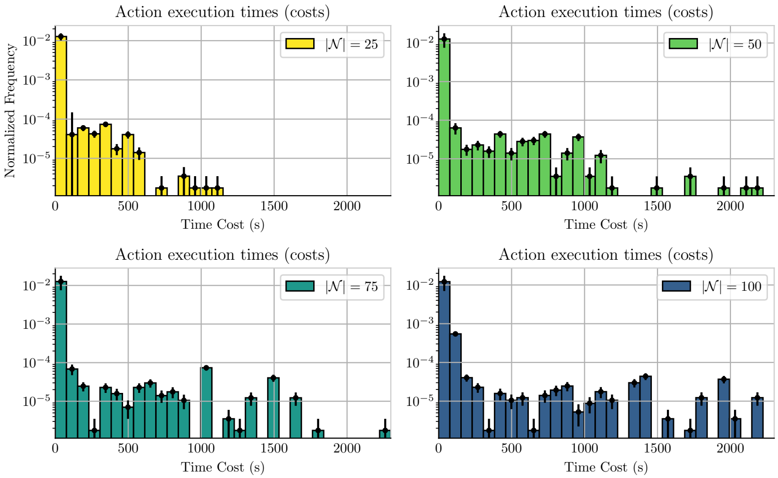
Emulation: Execution Times of Replicated Operations



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

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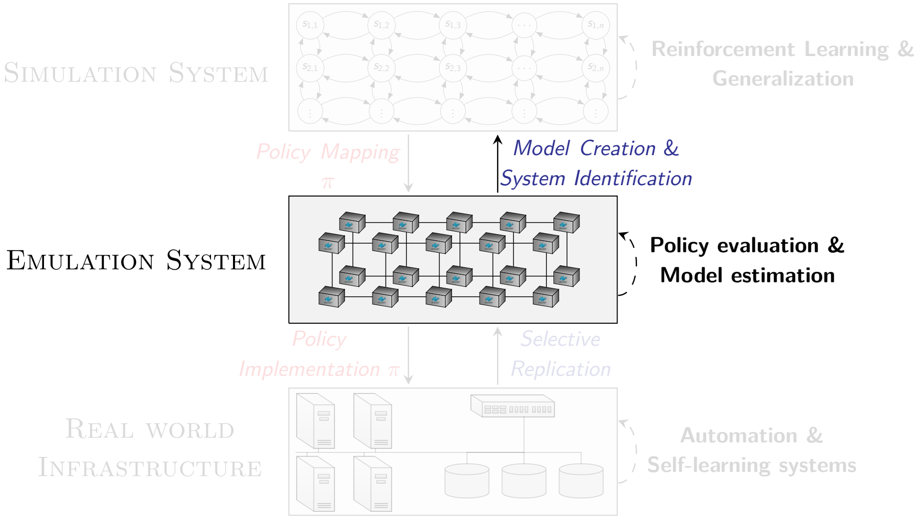
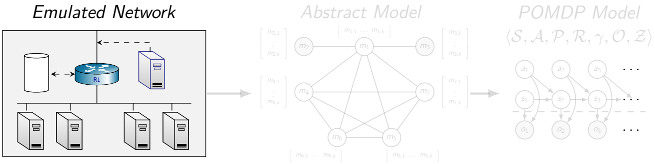


From Emulation to Simulation: System Identification



- **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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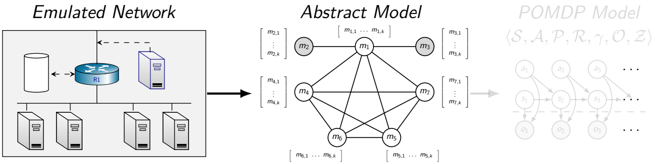

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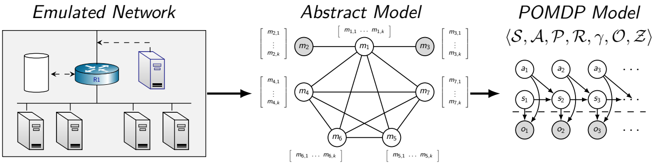

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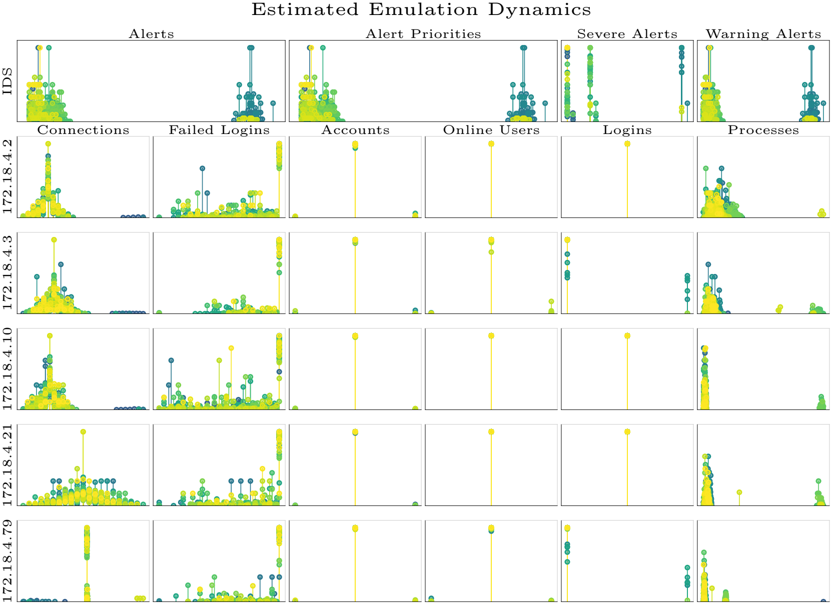
System Identification: Estimated Dynamics Model



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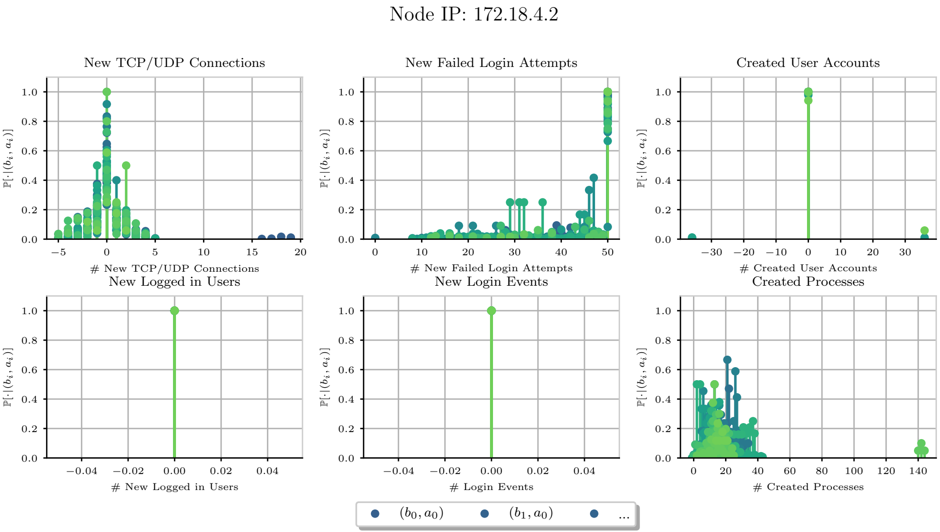

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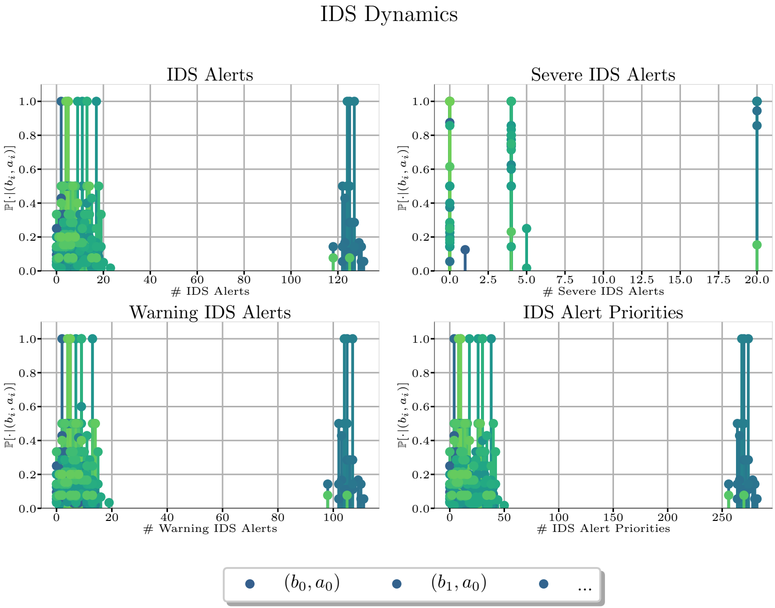

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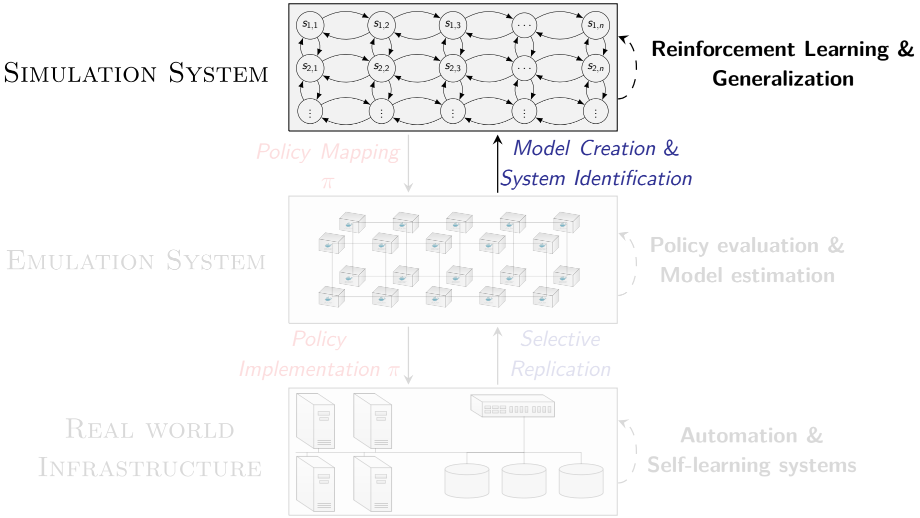

Policy Optimization in the Simulation System using Reinforcement Learning

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

- **Learning Algorithm**:
  - Represent π by π_θ
  - Define objective $J(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_{t=1}^{T} \gamma^{t-1} r(s_t, a_t)\right]$
  - Maximize $J(\theta)$ by stochastic gradient ascent

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta}\left[\underbrace{\nabla_\theta \log \pi_\theta(a|s)}_{\text{actor}} \underbrace{A^{\pi_\theta}(s,a)}_{\text{critic}}\right]$$

- **Domain-Specific Challenges**:
  - Partial observability
  - Large state space
  - Large action space
  - Non-stationary Environment due to attacker
  - Generalization

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- *Finding Effective Security Strategies through Reinforcement Learning and Self-Play*[a]
- *Learning Intrusion Prevention Policies through Optimal Stopping*[b]

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[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)*. Izmir, Turkey, Nov. 2020.

[b] Kim Hammar and Rolf Stadler. *Learning Intrusion Prevention Policies through Optimal Stopping*. 2021. arXiv: 2106.07160 [cs.AI].

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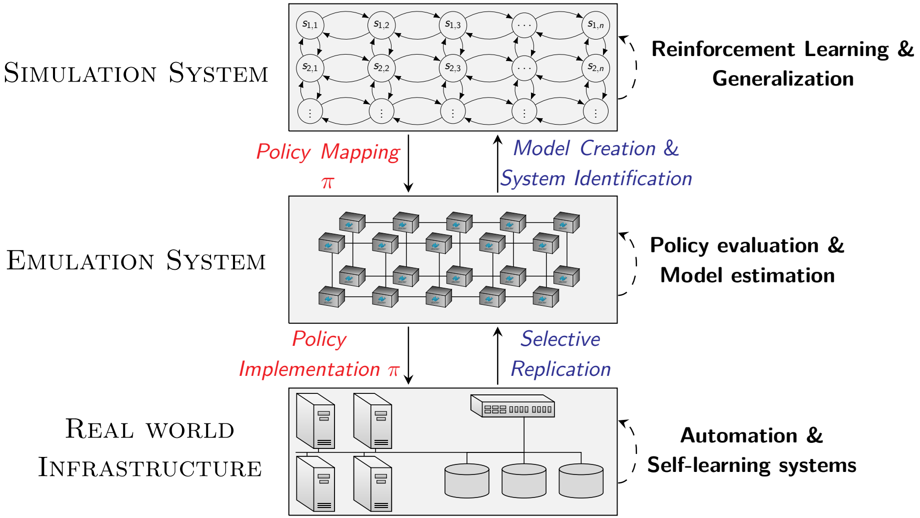
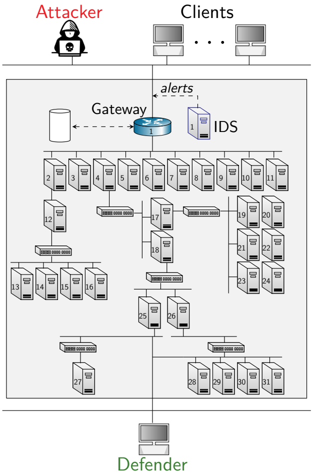


The Target Infrastructure

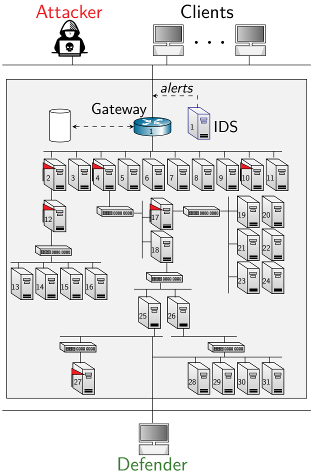
- **Topology**:
  - 30 Application Servers, 1 Gateway/IDS (Snort), 3 Clients, 1 Attacker, 1 Defender
- **Services**
  - 31 SSH, 8 HTTP, 1 DNS, 1 Telnet, 2 FTP, 1 MongoDB, 2 SMTP, 2 Teamspeak 3, 22 SNMP, 12 IRC, 1 Elasticsearch, 12 NTP, 1 Samba, 19 PostgreSQL
- **RCE Vulnerabilities**
  - 1 CVE-2010-0426, 1 CVE-2014-6271, 1 SQL Injection, 1 CVE-2015-3306, 1 CVE-2016-10033, 1 CVE-2015-5602, 1 CVE-2015-1427, 1 CVE-2017-7494
  - 5 Brute-force vulnerabilities
- **Operating Systems**
  - 23 Ubuntu-20, 1 Debian 9:2, 1 Debian Wheezy, 6 Debian Jessie, 1 Kali
- **Traffic**
  - Client 1: HTTP, SSH, SNMP, ICMP
  - Client 2: IRC, PostgreSQL, SNMP
  - Client 3: FTP, DNS, Telnet



Target infrastructure.

The Attacker Model: Capture the Flag (CTF)

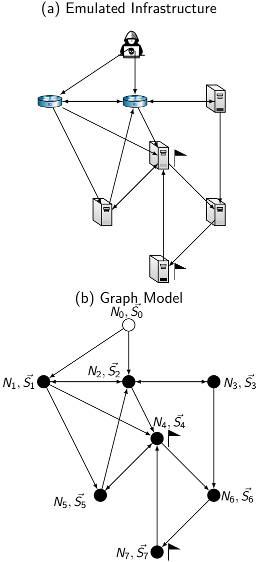
- The attacker has T time-steps to collect flags, with no prior knowledge
- It can **connect to a gateway** that exposes public-facing services in the infrastructure.
- It has a **pre-defined set (cardinality** ~ 200**) of network/shell commands available**, each command has a cost
- To collect flags, it has to interleave reconnaissance and exploits.
- Objective: collect all flags with minimum cost



Target infrastructure.

The Formal Attacker Model: A Partially Observed MDP

- 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
  $s = \{s_A, s_i \mid i \in \mathcal{N}\} \in \mathbb{R}^{|\mathcal{N}| \times m + |\mathcal{N}|}$
- Attacker observes $o^A \subset s$ (results of commands)
- Action space: $\mathcal{A} = \{a_1^A, \ldots, a_k^A\}$, a_i^A (commands)
- $\forall (s, a) \in \mathcal{A} \times \mathcal{S}$, 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 $s' = F(s, a)$



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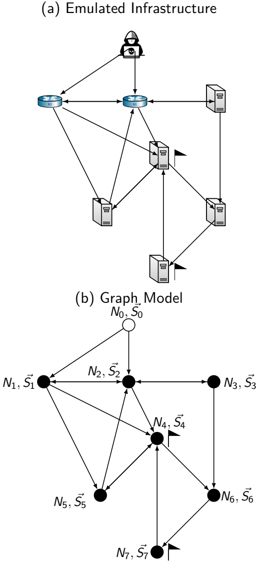
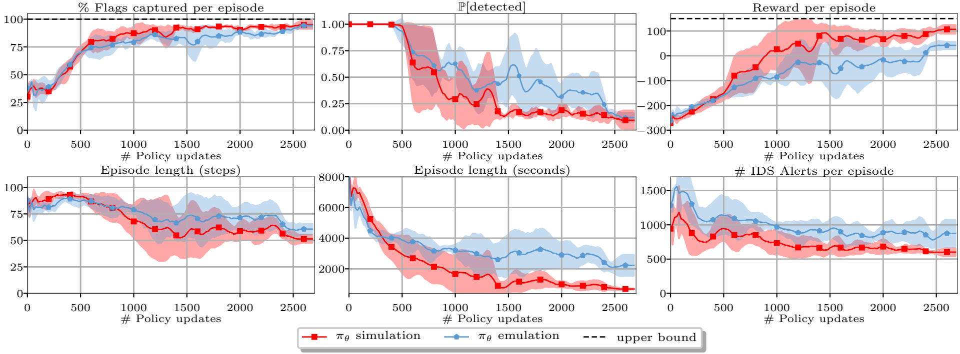
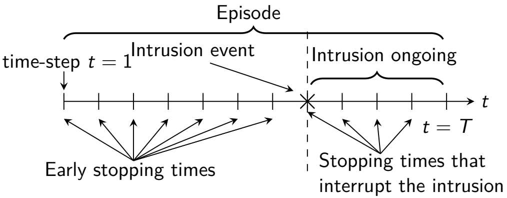


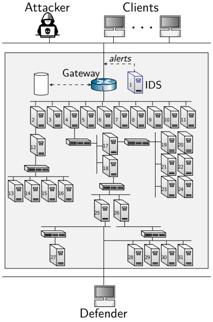
Learning to Capture the Flags: Training Attacker Policies



Learning curves (training performance in simulation and evaluation performance in the emulation) of our proposed method.

Learning Security Policies through Optimal Stopping





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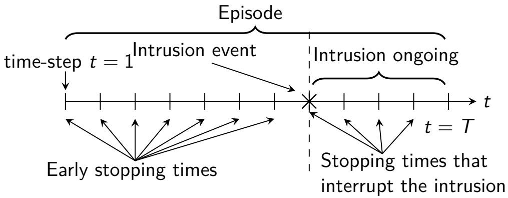

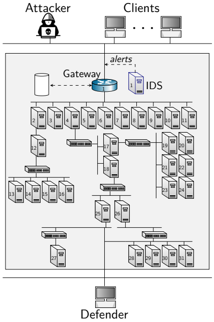

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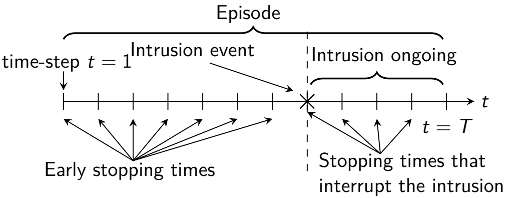

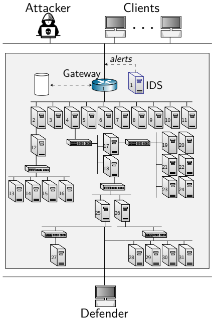

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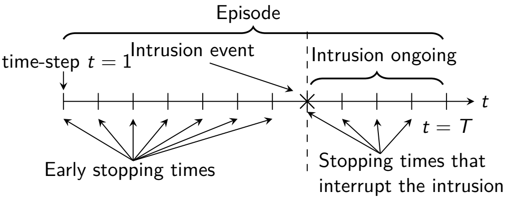

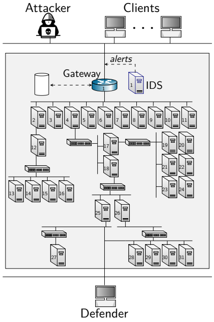

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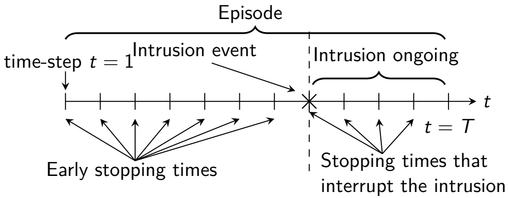

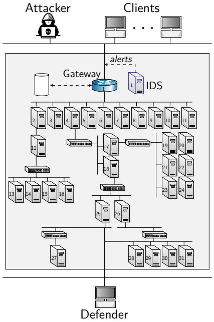

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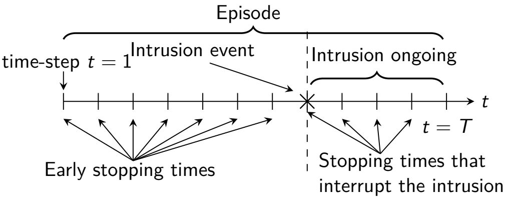

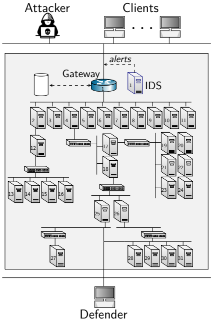

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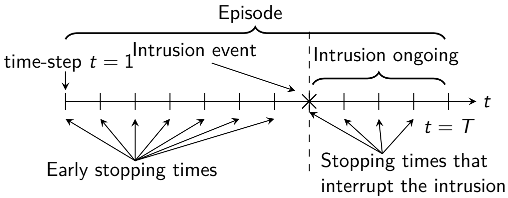

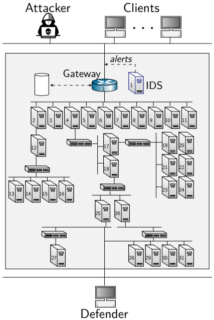

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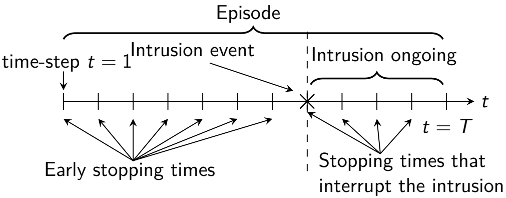

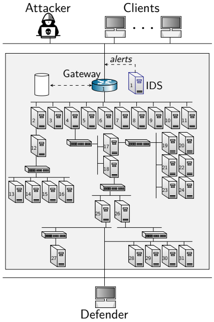

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- **States:**
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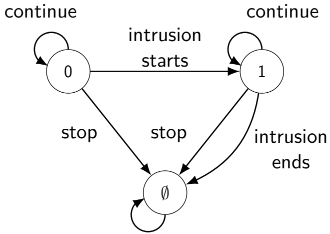

- **Observations:**
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  - "Stop" (S) and "Continue" (C)
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  - Bernoulli process $(Q_t)_{t=1}^{T} \sim Ber(p)$ defines intrusion start $I_t \sim Ge(p)$
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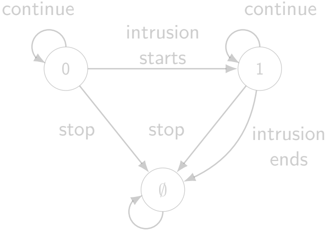

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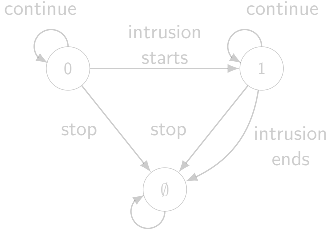

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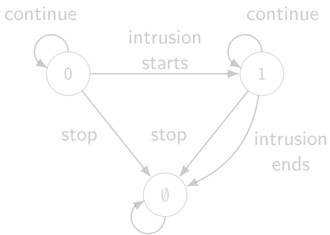

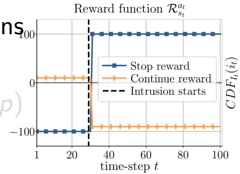

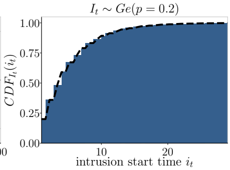

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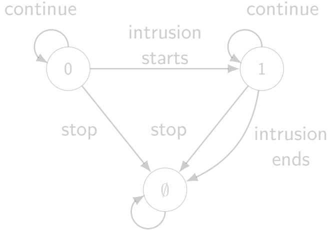

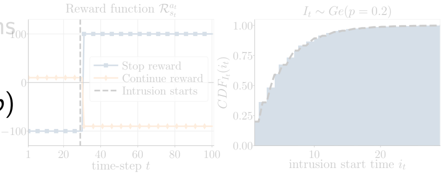

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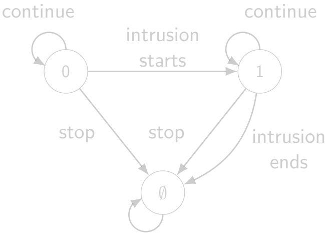

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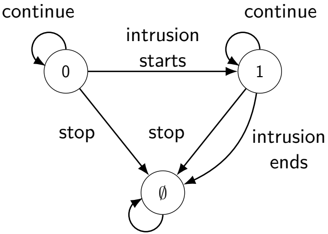

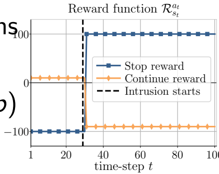

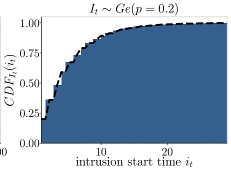

Threshold Property of the Optimal Defender Policy (1/4)

Theorem

The optimal policy π^* is a threshold policy of the form:

$$\pi^*(b(1)) = \begin{cases} S \ (stop) & \text{if } b(1) \geq \alpha^* \\ C \ (continue) & \text{otherwise} \end{cases}$$

where α^* is a unique threshold and $b(1) = \mathbb{P}[s_t = 1 | a_1, o_1, \ldots, a_{t-1}, o_t]$.

- To see this, consider the **optimality condition** (Bellman eq):

$$\pi^*(b(1)) = \arg\max_{a \in \mathcal{A}} \left[r(b(1), a) + \sum_{o \in \mathcal{O}} \mathbb{P}[o | b(1), a] V^*(b_o^a(1)) \right]$$

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Threshold Property of the Optimal Defender Policy (2/4)

- We use $\mathcal{A} = \{S, C\}$ and derive:

$$\pi^*(b(1)) = \operatorname*{argmax}_{a \in \mathcal{A}} \Bigg[\underbrace{r\big(b(1), S\big)}_{\omega}, \underbrace{r\big(b(1), C\big) + \sum_{o \in \mathcal{O}} \mathbb{P}[o|b(1), C] V^*\big(b_o^C(1)\big)}_{\epsilon} \Bigg]$$

- ω is the expected reward for stopping and ϵ is the expected cumulative reward for continuing
- Expanding the expressions and rearranging terms, we derive that **it is optimal to stop iff**:

$$b(1) \geq \underbrace{\frac{110 + \sum_{o \in \mathcal{O}} V^*\left(b_o^C(1)\right)\left(p\mathcal{Z}(o,1,C) + (1-p)\mathcal{Z}(o,0,C)\right)}{300 + \sum_{o \in \mathcal{O}} V^*\left(b_o^C(1)\right)\left(p\mathcal{Z}(o,1,C) + (1-p)\mathcal{Z}(o,0,C) - \mathcal{Z}(o,1,C)\right)}}_{\text{Threshold: } \alpha_{b(1)}}$$

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- Since $V^*(b)$ **is piecewise linear and convex**[13]
- When $b(1) = 1$ it is optimal to take the stop action S:

$$\pi^*(1) = \arg\max \left[100, -90 + \sum_{o \in \mathcal{O}} \mathcal{Z}(o,1,C) V^*\left(b_o^C(1)\right) \right] = S$$

- This means that $\beta^* = 1$

[13] Edward J. Sondik. "The Optimal Control of Partially Observable Markov Processes Over the Infinite Horizon: Discounted Costs". In: *Operations Research* 26.2 (1978), pp. 282–304. ISSN: 0030364X, 15265463. URL: http://www.jstor.org/stable/169635.

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- Since $V^*(b)$ **is piecewise linear and convex**[16], $\mathscr{S}$ is also convex[17] and has the form $[\alpha^*, \beta^*]$ where $0 \leq \alpha^* \leq \beta^* \leq 1$.
- When $b(1) = 1$ it is optimal to take the stop action S:

$$\pi^*(1) = \arg\max \left[100, -90 + \sum_{o \in \mathcal{O}} \mathcal{Z}(o, 1, C) V^*\left(b_o^C(1)\right) \right] = S$$

- This means that $\beta^* = 1$

[16] Edward J. Sondik. "The Optimal Control of Partially Observable Markov Processes Over the Infinite Horizon: Discounted Costs". In: *Operations Research* 26.2 (1978), pp. 282–304. ISSN: 0030364X, 15265463. URL: http://www.jstor.org/stable/169635.

[17] Vikram Krishnamurthy. *Partially Observed Markov Decision Processes: From Filtering to Controlled Sensing*. Cambridge University Press, 2016. DOI: 10.1017/CBO9781316471104.

Threshold Property of the Optimal Defender Policy (3/4)

- Thus π^* is determined by the **scalar thresholds** $\alpha_{b(1)}$.
  - it is optimal to stop if $b(1) \geq \alpha_{b(1)}$
- The *stopping set* is:

$$\mathscr{S} = \left\{ b(1) \in [0,1] : b(1) \geq \alpha_{b(1)} \right\}$$

- Since $V^*(b)$ **is piecewise linear and convex**[18], $\mathscr{S}$ is also convex[19] and has the form $[\alpha^*, \beta^*]$ where $0 \leq \alpha^* \leq \beta^* \leq 1$.
- When $b(1) = 1$ it is optimal to take the stop action S:

$$\pi^*(1) = \arg\max \left[100, -90 + \sum_{o \in \mathcal{O}} \mathcal{Z}(o, 1, C) V^*\left(b_o^C(1)\right) \right] = S$$

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[19] Vikram Krishnamurthy. *Partially Observed Markov Decision Processes: From Filtering to Controlled Sensing*. Cambridge University Press, 2016. DOI: 10.1017/CBO9781316471104.

Threshold Property of the Optimal Defender Policy (4/4)

- As the stopping set is $\mathscr{S} = [\alpha^*, 1]$ and $b(1) \in [0, 1]$
- We have that it is optimal to stop if $b(1) \geq \alpha^*$
- Hence, **Theorem 1** follows:

$$\pi^*(b(1)) = \begin{cases} S \text{ (stop)} & \text{if } b(1) \geq \alpha^* \\ C \text{ (continue)} & \text{otherwise} \end{cases}$$

Threshold Property of the Optimal Defender Policy (4/4)

- As the stopping set is $\mathscr{S} = [\alpha^*, 1]$ and $b(1) \in [0, 1]$
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- Hence, **Theorem 1** follows:

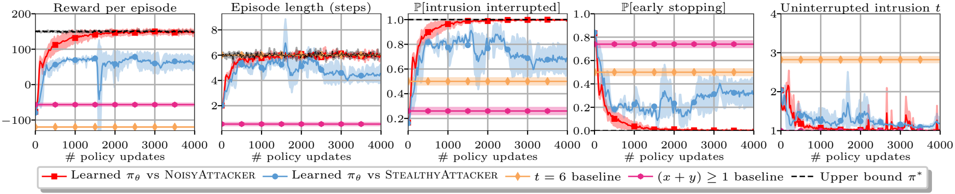
$$\pi^*(b(1)) = \begin{cases} S \text{ (stop)} & \text{if } b(1) \geq \alpha^* \\ C \text{ (continue)} & \text{otherwise} \end{cases}$$

Static Attackers to Emulate Intrusions

Time-steps t	*Actions*
1–$I_t \sim Ge(0.2)$	(Intrusion has not started)
$I_t + 1$–$I_t + 7$	RECON, brute-force attacks (SSH,Telnet,FTP) on N_2, N_4, N_{10}, login(N_2, N_4, N_{10}), backdoor(N_2, N_4, N_{10}), RECON
$I_t + 8$–$I_t + 11$	CVE-2014-6271 on N_{17}, SSH brute-force attack on N_{12}, login (N_{17}, N_{12}), backdoor(N_{17}, N_{12})
$I_t + 12$–$X + 16$	CVE-2010-0426 exploit on N_{12}, RECON SQL-Injection on N_{18}, login(N_{18}), backdoor(N_{18})
$I_t + 17$–$I_t + 22$	RECON, CVE-2015-1427 on N_{25}, login(N_{25}) RECON, CVE-2017-7494 exploit on N_{27}, login(N_{27})

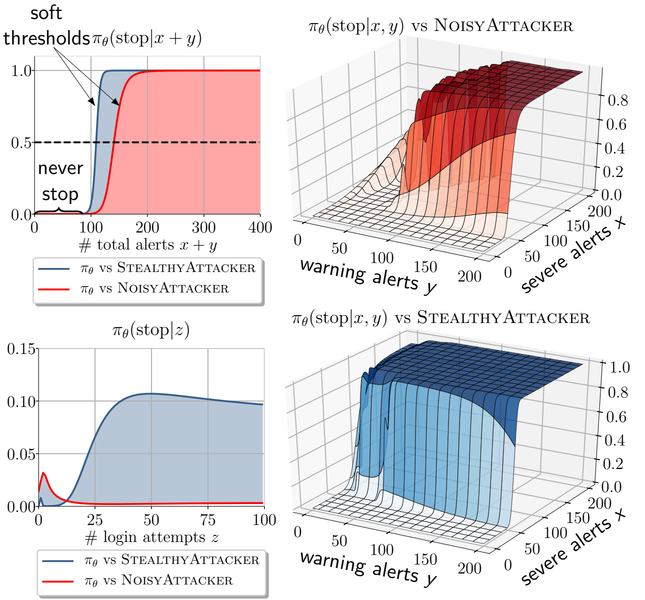
Table 1: Attacker actions to emulate an intrusion.

Learning Security Policies through Optimal Stopping

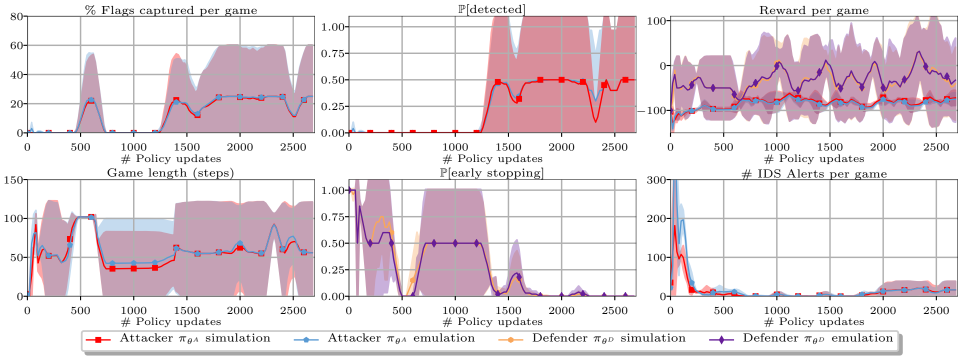


Learning curves of training defender policies against static attackers.

Threshold Properties of the Learned Policies



Open Challenge: Self-Play between Attacker and Defender



Learning curves of training the the attacker and the defender simultaneously in self-play.

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, theoretical understanding of optimal policies
- **Our research plans:**
  - Extending the theoretical model
    - Relaxing simplifying assumptions (e.g. multiple defender actions)
  - Evaluation on real world infrastructures

References

- *Finding Effective Security Strategies through Reinforcement Learning and Self-Play*[20]
  - **Preprint open access**: https://arxiv.org/abs/2009.08120
- *Learning Intrusion Prevention Policies through Optimal Stopping*[21]
  - **Preprint open access**: https://arxiv.org/pdf/2106.07160.pdf

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

[21] Kim Hammar and Rolf Stadler. *Learning Intrusion Prevention Policies through Optimal Stopping*. 2021. arXiv: 2106.07160 [cs.AI].