Learning Intrusion Prevention Policies Through Optimal Stopping[1]

CNSM 2021 | International Conference on Network and Service Management

Kim Hammar & Rolf Stadler

kimham@kth.se & *stadler@kth.se*

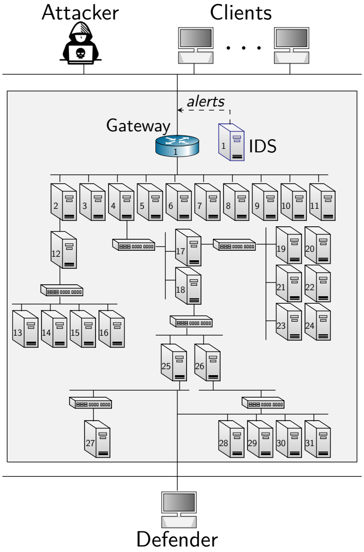
Division of Network and Systems Engineering
KTH Royal Institute of Technology

Oct 28, 2021

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

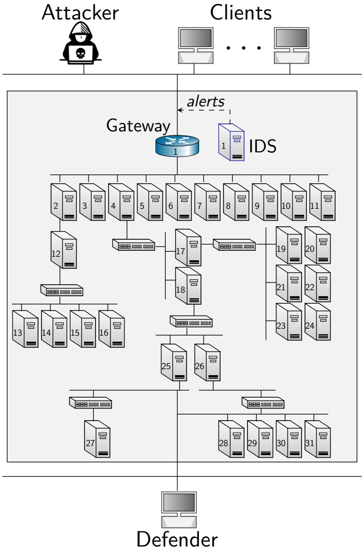
Challenges: Evolving and Automated Attacks

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



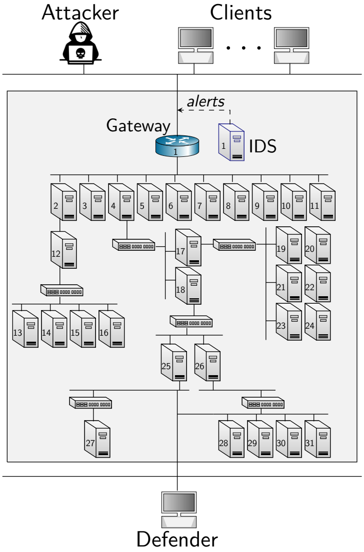
Goal: Automation and Learning

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



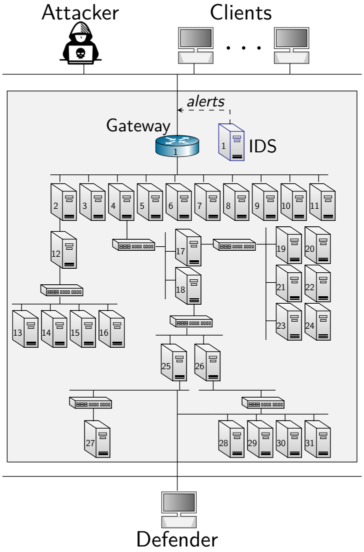
Approach: Game Model & Reinforcement Learning

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



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



Use Case: Intrusion Prevention

- A **Defender** owns an infrastructure
  - Consists of connected components
  - Components run network services
  - Defender defends the infrastructure

We formulate this use case as an **Optimal Stopping** problem

infrastructure

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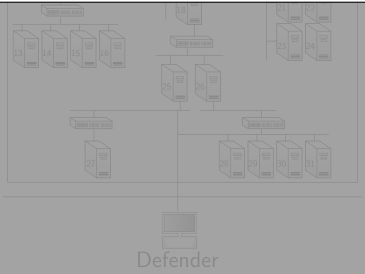

Background on Optimal Stopping Problems

- **The General Problem**:
  - A Markov process $(s_t)_{t=1}^{T}$ is observed sequentially
  - Two options per t: (i) continue to observe; or (ii) stop
  - Find the *optimal stopping time* τ^*:

$$\tau^* = \arg\max_{\tau} \mathbb{E}_{\tau}\left[\sum_{t=1}^{\tau-1}\gamma^{t-1}\mathcal{R}^{C}_{s_t s_{t+1}} + \gamma^{\tau-1}\mathcal{R}^{S}_{s_\tau s_\tau}\right] \qquad (1)$$

  where $\mathcal{R}^{S}_{ss'}$ & $\mathcal{R}^{C}_{ss'}$ are the stop/continue rewards

- **History**:
  - Studied in the 18th century to analyze a gambler's fortune
  - Formalized by Abraham Wald in 1947
  - Since then it has been generalized and developed by (Chow, Shiryaev & Kolmogorov, Bather, Bertsekas, etc.)

- **Applications & Use Cases**:
  - Change detection, machine replacement, hypothesis testing, gambling, selling decisions, queue management, advertisement scheduling, the secretary problem, etc.

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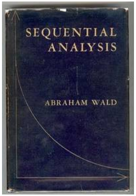

[2] Abraham Wald. *Sequential Analysis*. Wiley and Sons, New York, 1947.

[3] Y. Chow, H. Robbins, and D. Siegmund. "Great expectations: The theory of optimal stopping". In: 1971.

[4] Albert N. Shirayev. *Optimal Stopping Rules*. Reprint of russian edition from 1969. Springer-Verlag Berlin, 2007.

[5] John Bather. *Decision Theory: An Introduction to Dynamic Programming and Sequential Decisions*. USA: John Wiley and Sons, Inc., 2000. ISBN: 0471976490.

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

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- **Applications & Use Cases**:
  - Change detection[7], selling decisions[8], queue management[9], advertisement scheduling[10], etc.

[7] Alexander G. Tartakovsky et al. "Detection of intrusions in information systems by sequential change-point methods". In: *Statistical Methodology* 3.3 (2006). ISSN: 1572-3127. DOI: https://doi.org/10.1016/j.stamet.2005.05.003. URL: https://www.sciencedirect.com/science/article/pii/S1572312705000493.

[8] Jacques du Toit and Goran Peskir. "Selling a stock at the ultimate maximum". In: *The Annals of Applied Probability* 19.3 (2009). ISSN: 1050-5164. DOI: 10.1214/08-aap566. URL: http://dx.doi.org/10.1214/08-AAP566.

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[10] Vikram Krishnamurthy, Anup Aprem, and Sujay Bhatt. "Multiple stopping time POMDPs: Structural results & application in interactive advertising on social media". In: *Automatica* 95 (2018), pp. 385–398. ISSN: 0005-1098. DOI: https://doi.org/10.1016/j.automatica.2018.06.013. URL: https://www.sciencedirect.com/science/article/pii/S0005109818303054.

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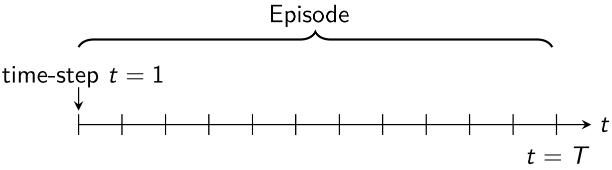

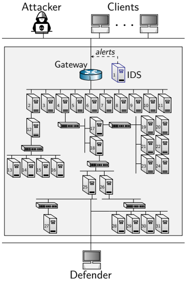

- **Intrusion Prevention as Optimal Stopping Problem**:
  - The system evolves in discrete time-steps.
  - Defender observes the infrastructure (IDS, log files, etc.).
  - An intrusion occurs at an unknown time.
  - The defender can make L stops.
  - Each stop is associated with a defensive action
  - The final stop shuts down the infrastructure.
  - **Based on the observations, when is it optimal to stop?**
  - We formalize this problem with a POMDP

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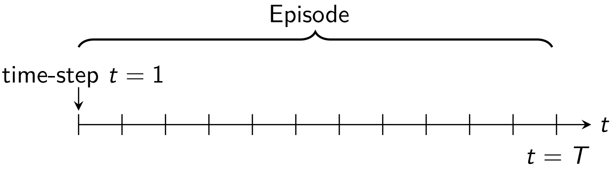

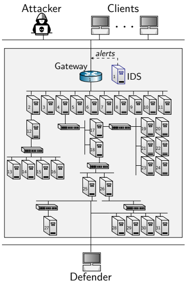

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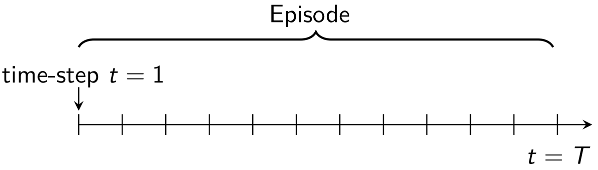

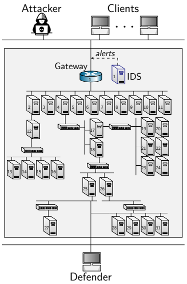

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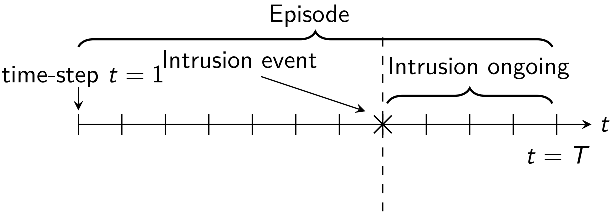

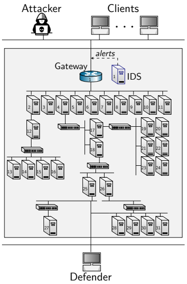

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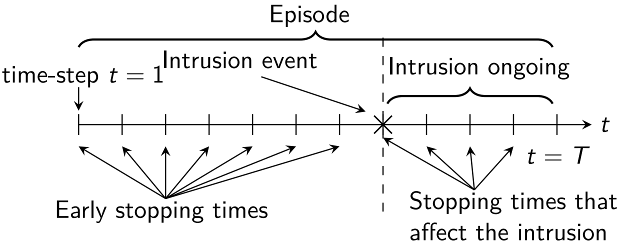

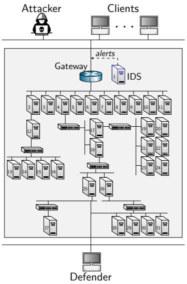

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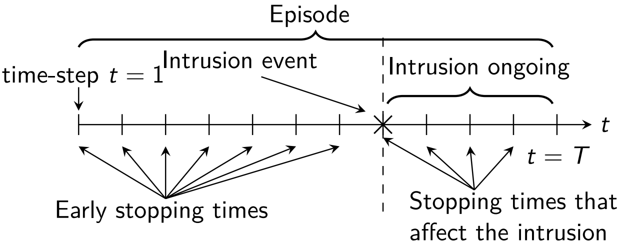

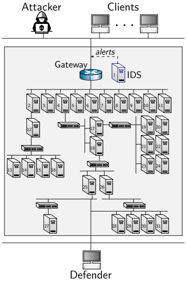

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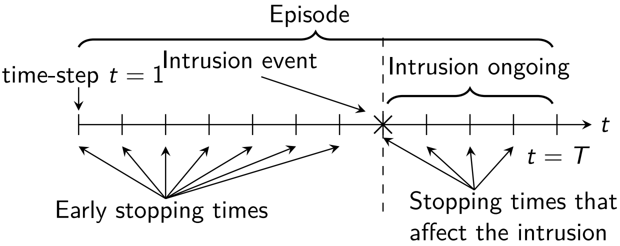

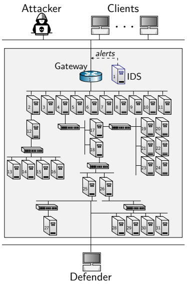

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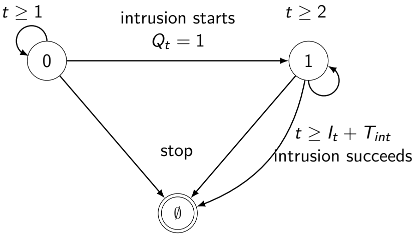
A Partially Observed MDP Model for the Defender

- **States:**
  - Intrusion state $s_t \in \{0, 1\}$, terminal $\emptyset$.
- **Observations:**
  - Severe/Warning IDS Alerts $(\Delta x, \Delta y)$, Login attempts Δz $f_{XYZ}(\Delta x, \Delta y, \Delta z | s_t, I_t, t)$
- **Actions:**
  - "Stop" (S) and "Continue" (C)
- **Rewards:**
  - Reward: security and service. Penalty: false alarms and intrusions
- **Transition probabilities:**
  - Bernoulli process $(Q_t)_{t=1}^{T} \sim Ber(p)$ defines intrusion start $I_t \sim Ge(p)$
- **Objective and Horizon:**
  - $\max \mathbb{E}_{\pi_\theta}\left[\sum_{t=1}^{T_\emptyset} r(s_t, a_t)\right]$, $T_\emptyset$



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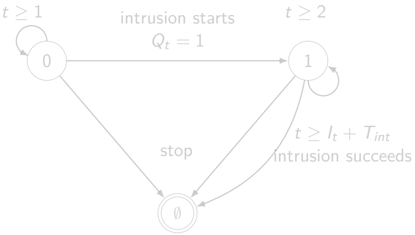

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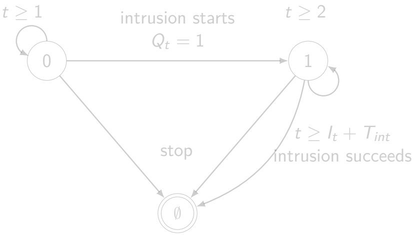

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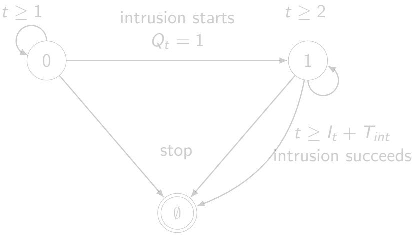

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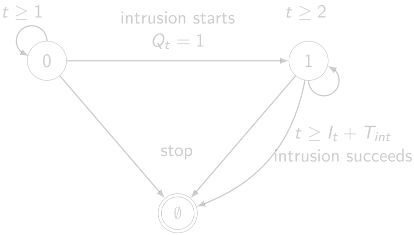

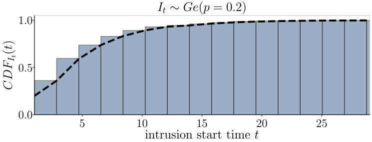

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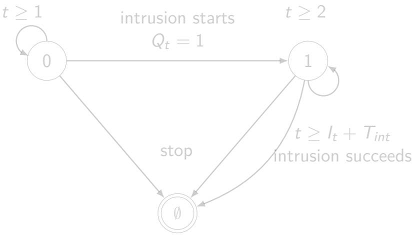

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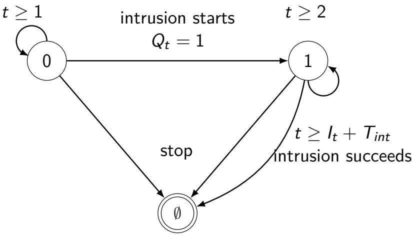

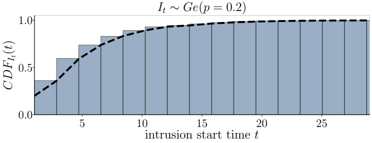

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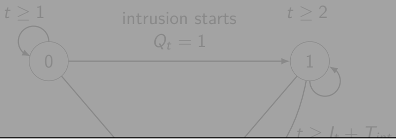
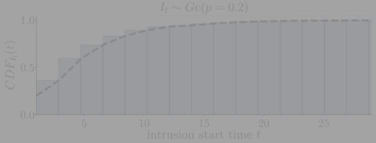


We analyze the optimal policy using optimal stopping theory

  - Reward: security and service. Penalty: false alarms and intrusions
- **Transition probabilities:**
  - Bernoulli process $(Q_t)_{t=1}^{T} \sim Ber(p)$ defines intrusion start $I_t \sim Ge(p)$
- **Objective and Horizon:**
  - $\max \mathbb{E}_{\pi_\theta}\left[\sum_{t=1}^{T_\emptyset} r(s_t, a_t)\right]$, $T_\emptyset$



Belief States and Stopping Set

- **Belief States:**
  - The belief state $b_t \in \mathcal{B}$ is defined as $b_t(s_t) = \mathbb{P}[s_t|h_t]$
  - b_t is a sufficient statistic of s_t based on $h_t = (\rho_1, a_1, o_1, \ldots, a_{t-1}, o_t) \in \mathcal{H}$
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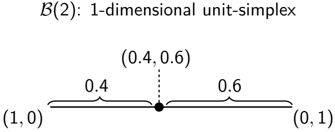

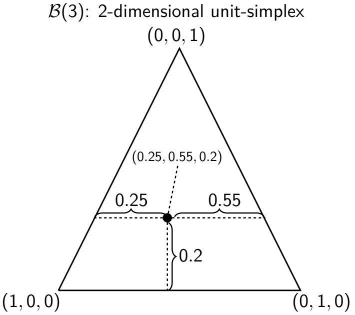

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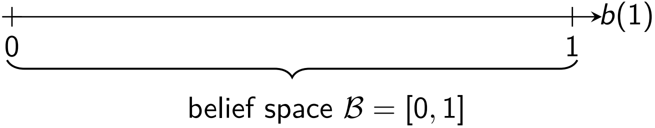
Threshold Properties of the Optimal Defender Policy



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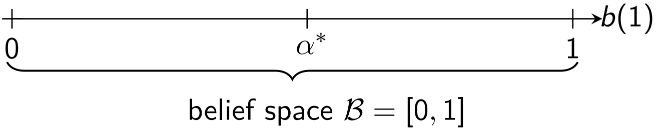

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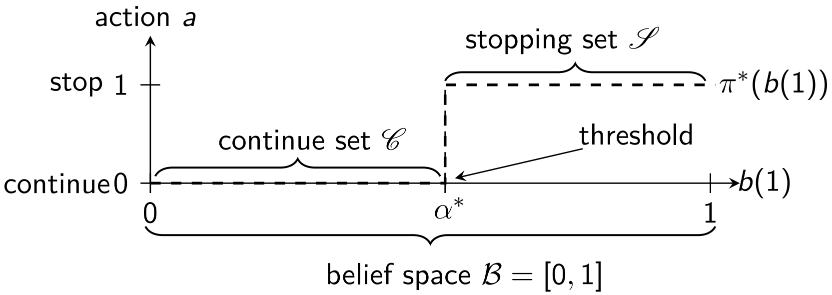
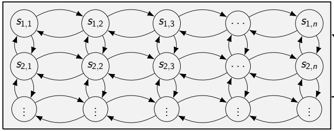


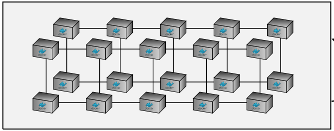
Our Method for Finding Effective Security Strategies

SIMULATION SYSTEM



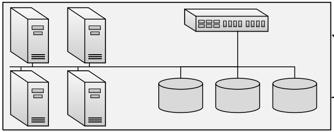
Reinforcement Learning & POMDP Model

EMULATION SYSTEM



Model estimation

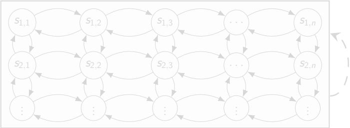
REAL WORLD INFRASTRUCTURE



Automation & Self-learning systems

Our Method for Finding Effective Security Strategies

Simulation System



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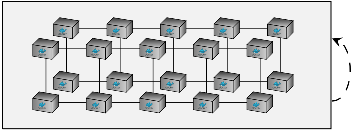
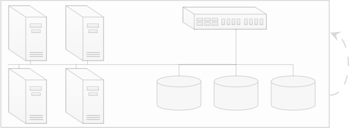


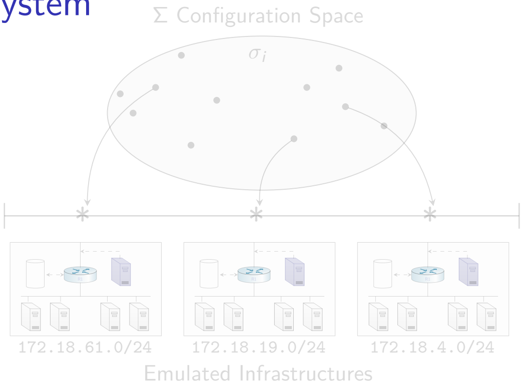
Model estimation

Real world Infrastructure



Automation & Self-learning systems

Emulation System

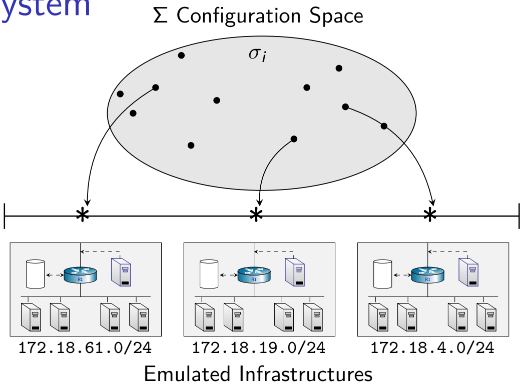


Emulation

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 $\sigma_i \in \Sigma$.

Emulation System



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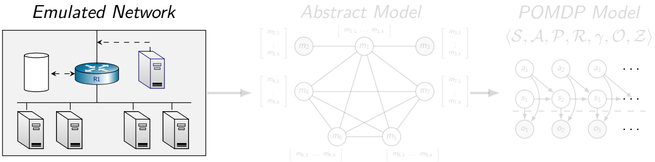
From Emulation to Simulation: System Identification



- **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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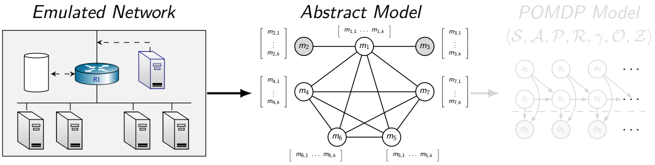

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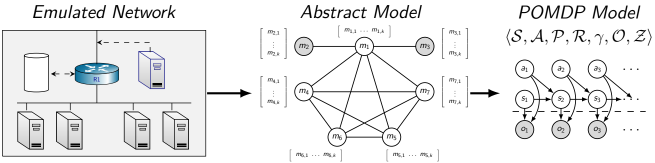

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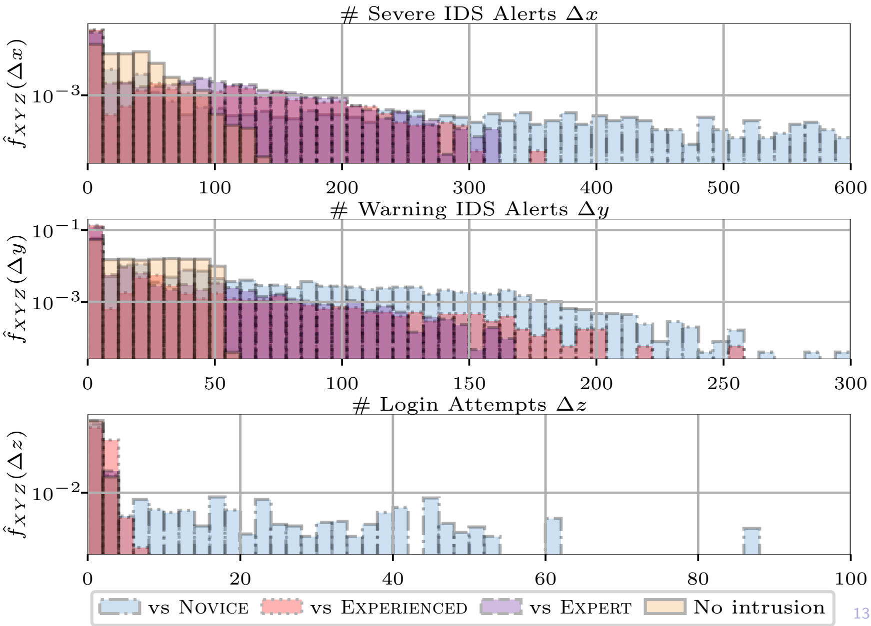
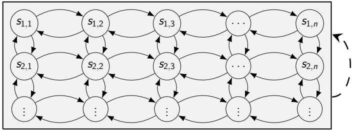
System Identification: Estimated Empirical Distributions



Our Method for Finding Effective Security Strategies

SIMULATION SYSTEM



Reinforcement Learning & POMDP Model

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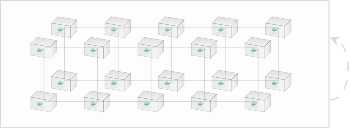

Model estimation

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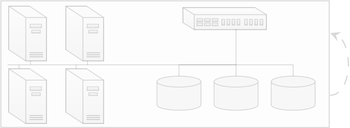

Automation & Self-learning systems

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

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

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  1. Simulate a series of POMDP episodes
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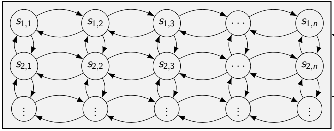

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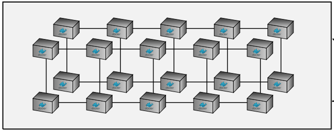
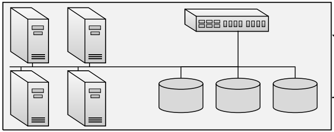


Model estimation

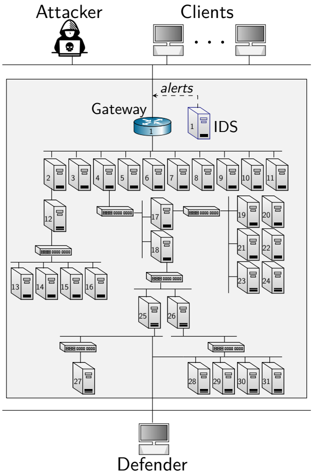
Real world Infrastructure



Automation & Self-learning systems

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



Target infrastructure.

Emulating the Client Population

Client	*Functions*	*Application servers*
1	HTTP, SSH, SNMP, ICMP	N_2, N_3, N_{10}, N_{12}
2	IRC, PostgreSQL, SNMP	$N_{31}, N_{13}, N_{14}, N_{15}, N_{16}$
3	FTP, DNS, Telnet	N_{10}, N_{22}, N_4

Table 1: Emulated client population; each client interacts with application servers using a set of functions at short intervals.

Emulating the Defender's Actions

Action	*Command in the Emulation*
Stop	`iptables -A INPUT -i eth0 -j DROP`

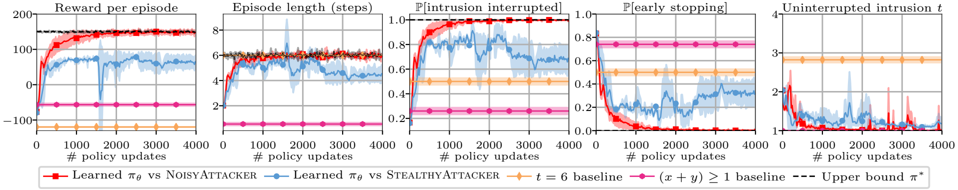
Table 2: Command used to implement the defender's stop action.

Emulating the Attacker's Actions

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})

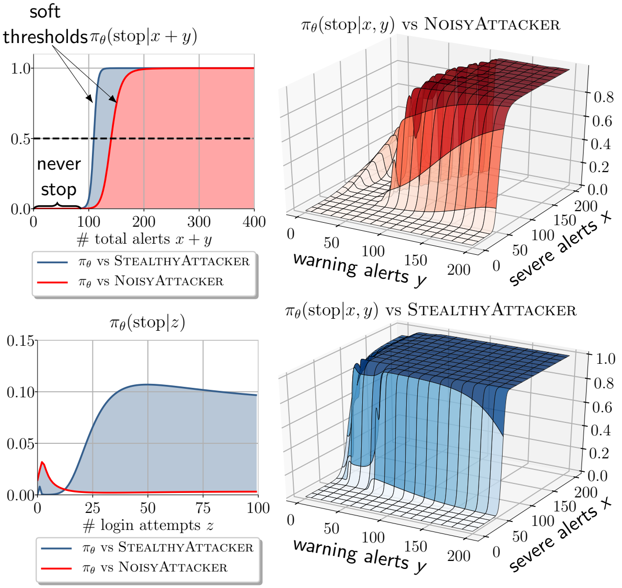
Table 3: Attacker actions to emulate an intrusion.

Learning Intrusion Prevention Policies through Optimal Stopping



Learning curves of training defender policies against static attackers.

Threshold Properties of the Learned Policies



Conclusions & Future Work

- **Conclusions:**
  - We develop a *method* to find learn intrusion prevention policies
    - (1) emulation system; (2) system identification; (3) simulation system; (4) reinforcement learning and (5) domain randomization and generalization.
  - We formulate intrusion prevention as a optimal stopping problem
    - We present a POMDP model of the use case
    - We apply the stopping theory to establish structural results of the optimal policy
- **Our research plans:**
  - Extending the theoretical model
    - Relaxing simplifying assumptions (e.g. more dynamic defender actions)
    - Active attacker
    - Multiple stops
  - Evaluation on real world infrastructures