Learning Intrusion Prevention Policies Through Optimal Stopping

CDIS Research Workshop

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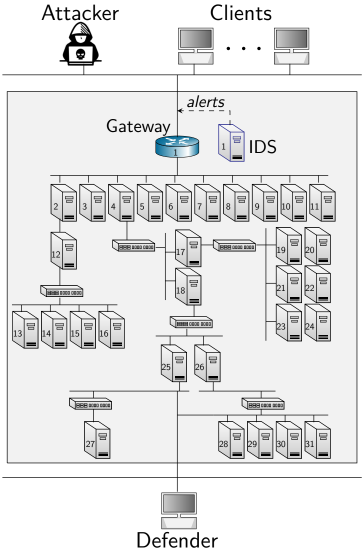
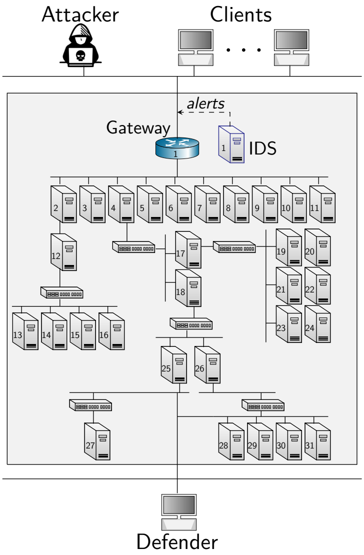
Challenges: Evolving and Automated Attacks

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



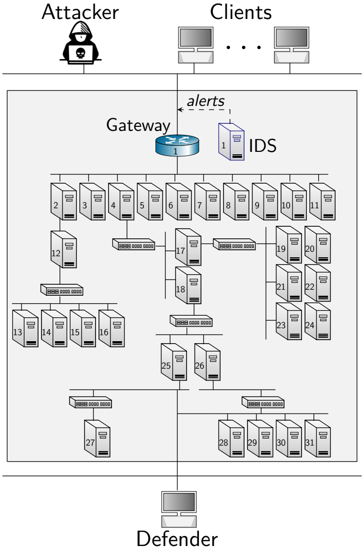
Goal: Automation and Learning

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



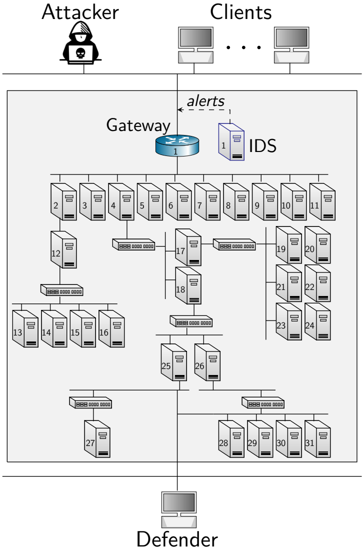
Approach: Game Model & Reinforcement Learning

- **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*.



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

  - Has a partial view of the infrastructure
  - Wants to compromise specific components
  - Attacks by reconnaissance, exploitation and pivoting

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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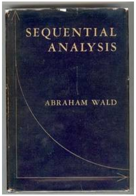

[1] Abraham Wald. *Sequential Analysis*. Wiley and Sons, New York, 1947.

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

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

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

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

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  - Change detection[6], selling decisions[7], queue management[8], advertisement scheduling[9], etc.

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  - Change detection[10], selling decisions[11], queue management[12], advertisement scheduling[13], **intrusion prevention**[14] etc.

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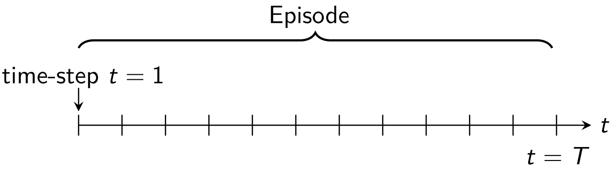
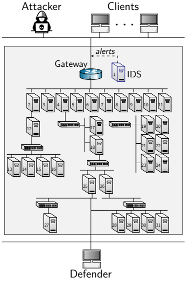
[14] Kim Hammar and Rolf Stadler. *Learning Intrusion Prevention Policies through Optimal Stopping*. 2021. arXiv: 2106.07160 [cs.AI].

Formulating Intrusion Prevention as a Stopping Problem





- **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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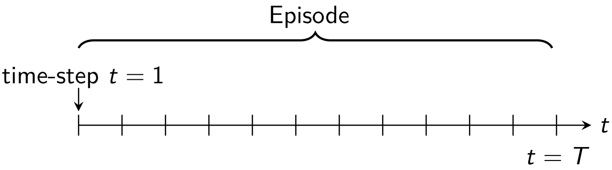

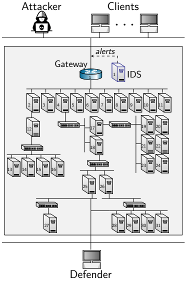

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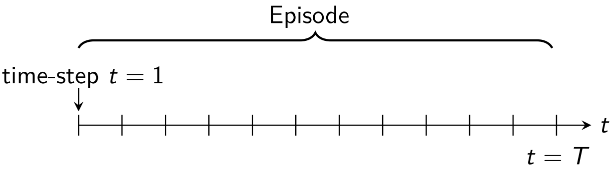

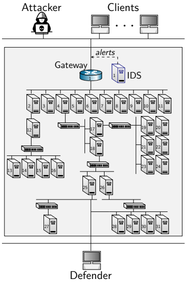

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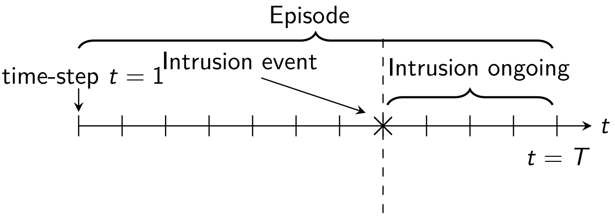

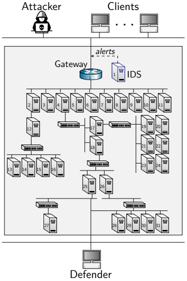

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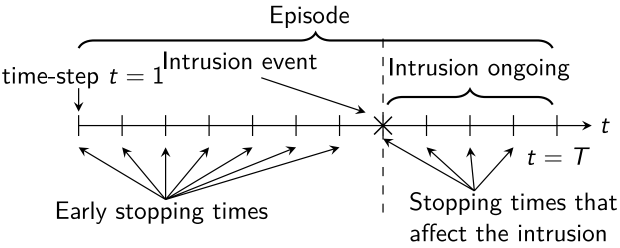

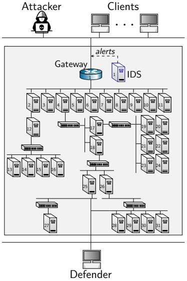

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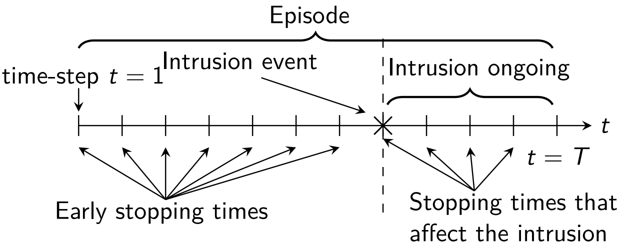

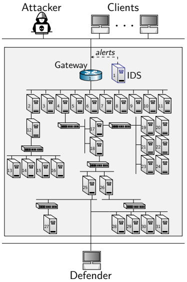

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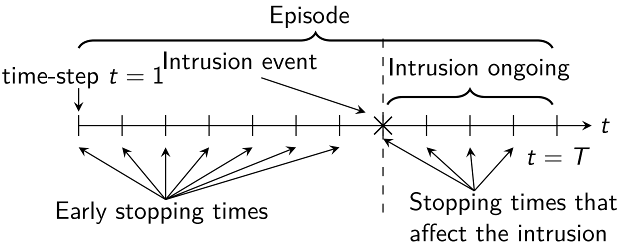

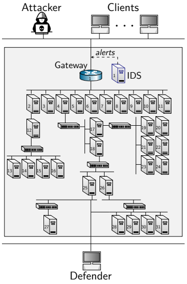

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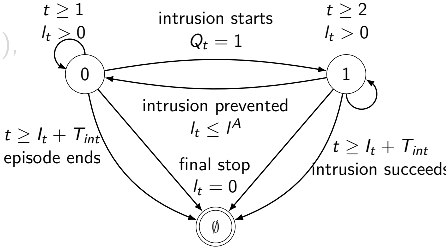
A Partially Observed MDP Model for the Defender

- **States:**
  - Intrusion state $s_t \in \{0, 1\}$, terminal $\emptyset$.
- **Observations:**
  - Severe/Warning IDS Alerts $(\Delta x, \Delta y)$, Login attempts Δz, stops remaining $l_t \in \{1, .., L\}$, $f_{XYZ}(\Delta x, \Delta y, \Delta z | s_t, l_t, t)$
- **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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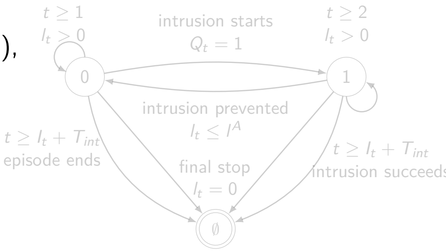

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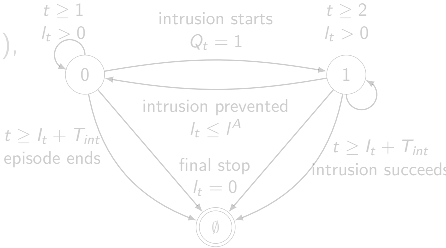

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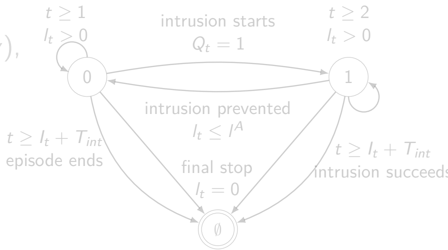

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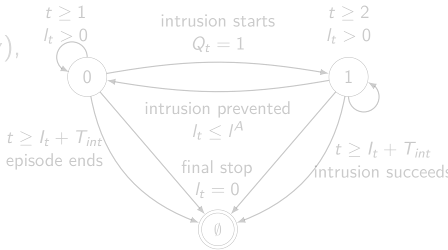

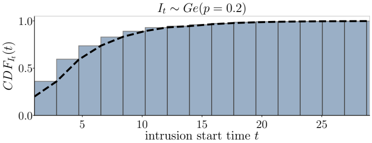

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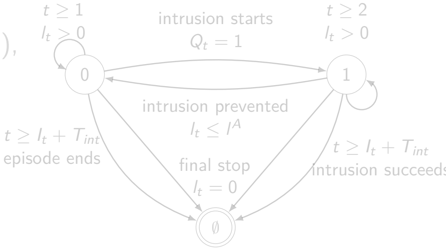

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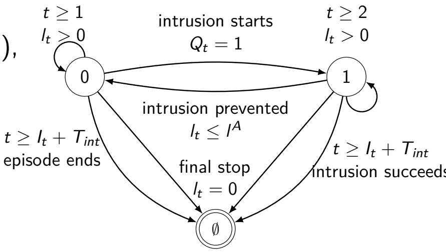

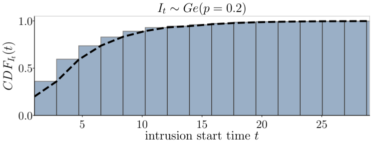

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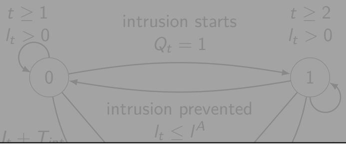

We analyze the optimal policy using optimal stopping theory

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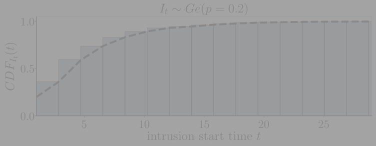
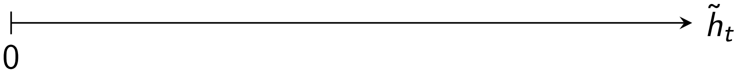
  - Bernoulli process $(Q_t)_{t=1}^{T} \sim Ber(p)$ defines intrusion start $I_t \sim Ge(p)$
- **Objective and Horizon:**
  - $\max \mathbb{E}_{\pi_\theta} \left[\sum_{t=1}^{T_\emptyset} r(s_t, a_t) \right]$, $T_\emptyset$



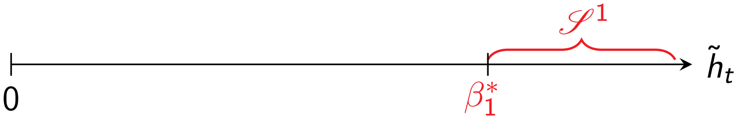
Threshold Properties of the Optimal Defender Policy



$$\tilde{h}_t = \Delta x_t + \Delta y_t + \Delta z_t$$
$$\Delta x = \text{Severe IDS alerts at time } t$$
$$\Delta y = \text{Warning IDS alerts at time } t$$
$$\Delta z = \text{Login attempts at time } t$$

Threshold Properties of the Optimal Defender Policy

$$\pi_l^*(h_t) = S \iff \tilde{h}_t \geq \beta_l^*, l = 1$$



$$\tilde{h}_t = \Delta x_t + \Delta y_t + \Delta z_t$$

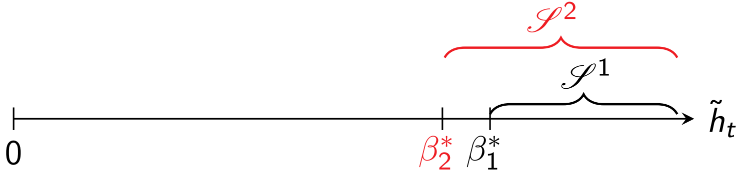
Δx = Severe IDS alerts at time t

Δy = Warning IDS alerts at time t

Δz = Login attempts at time t

Threshold Properties of the Optimal Defender Policy

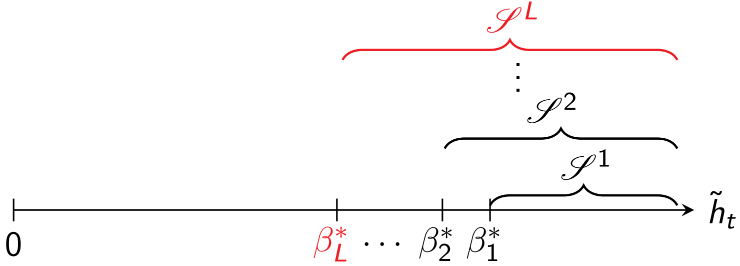
$$\pi_l^*(h_t) = S \iff \tilde{h}_t \geq \beta_l^*, l \in 1, 2$$



$$\tilde{h}_t = \Delta x_t + \Delta y_t + \Delta z_t$$
$$\Delta x = \text{Severe IDS alerts at time } t$$
$$\Delta y = \text{Warning IDS alerts at time } t$$
$$\Delta z = \text{Login attempts at time } t$$

Threshold Properties of the Optimal Defender Policy

$$\pi_l^*(h_t) = S \iff \tilde{h}_t \geq \beta_l^*, l \in 1, \ldots, L$$



$$\tilde{h}_t = \Delta x_t + \Delta y_t + \Delta z_t$$
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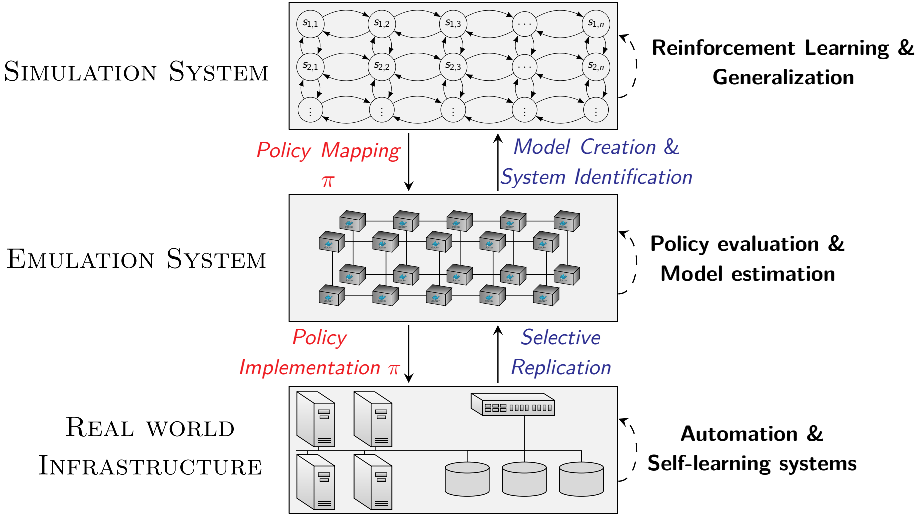
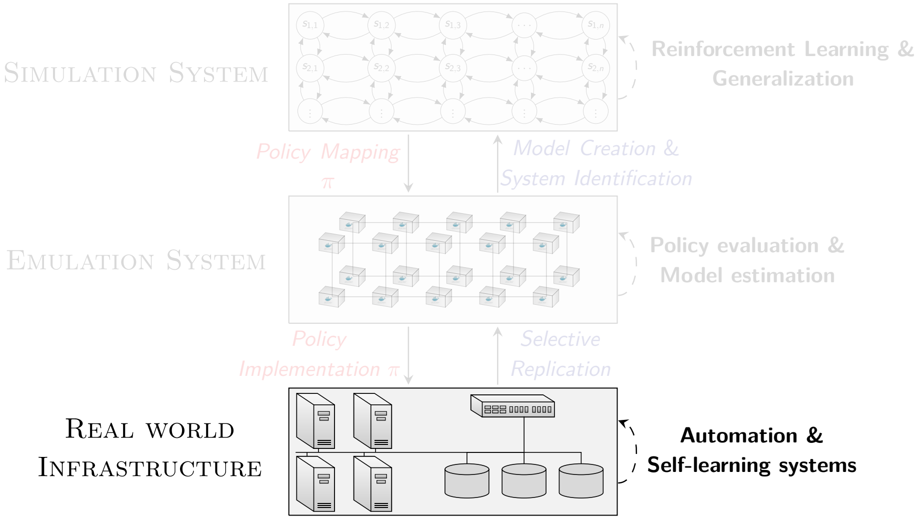
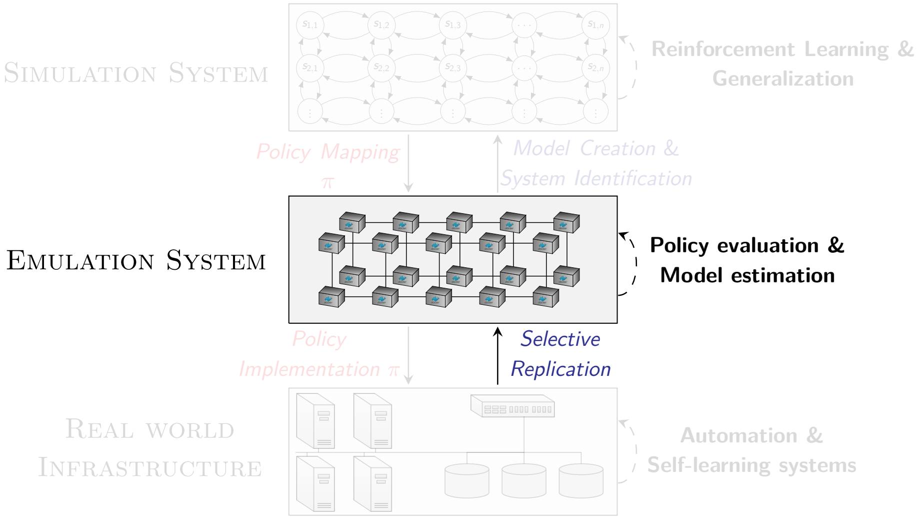
Our Method for Finding Effective Security Strategies



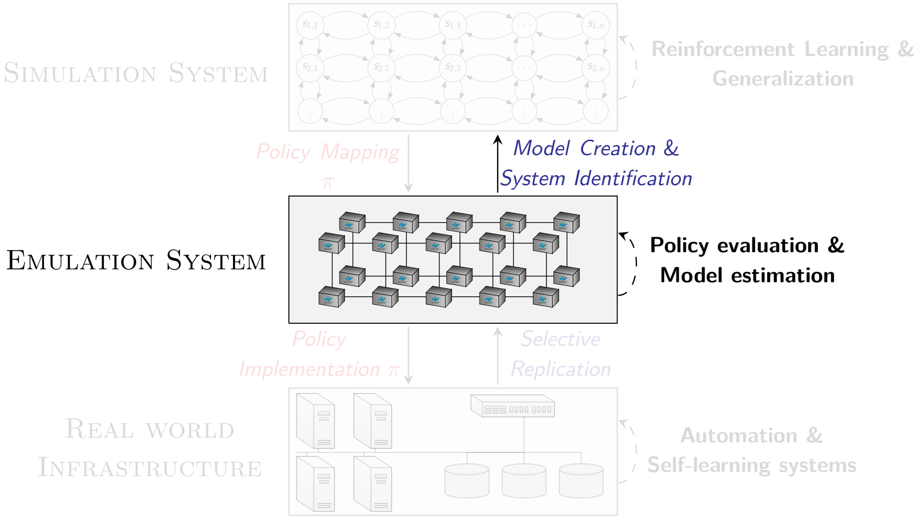
Our Method for Finding Effective Security Strategies



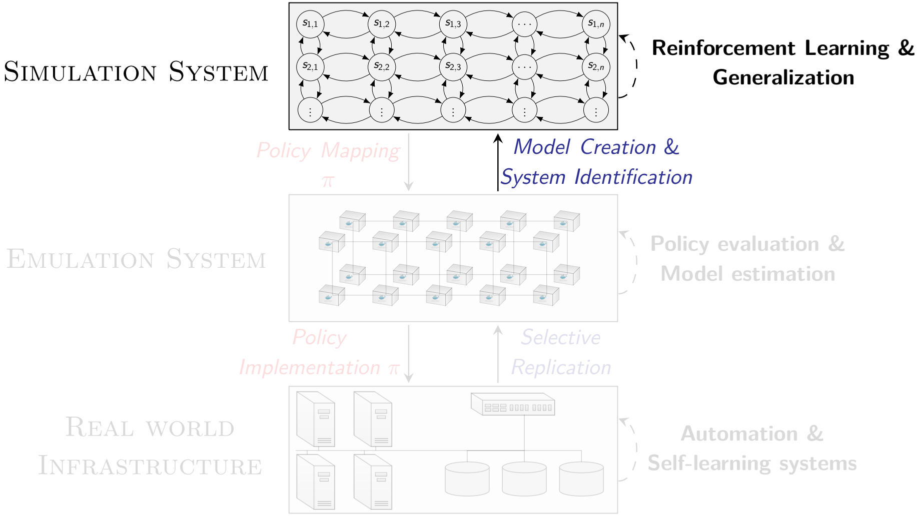
Our Method for Finding Effective Security Strategies



Our Method for Finding Effective Security Strategies



Our Method for Finding Effective Security Strategies



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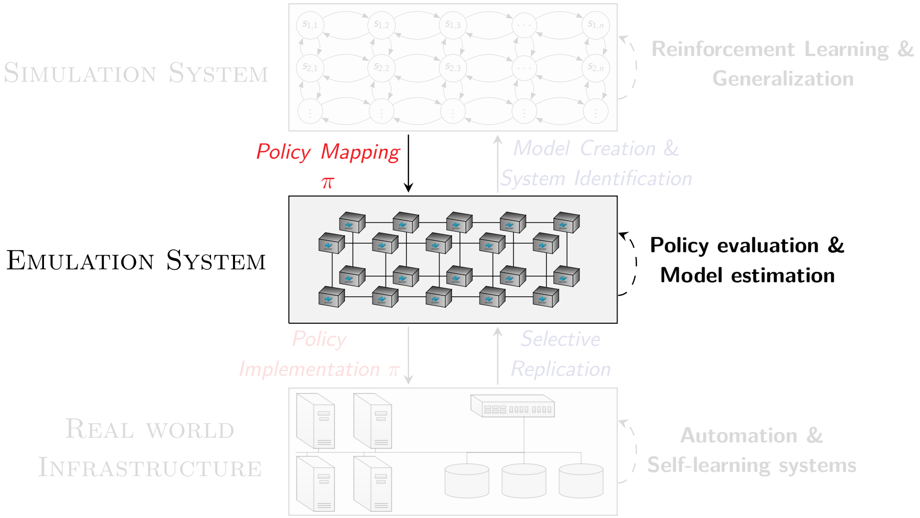

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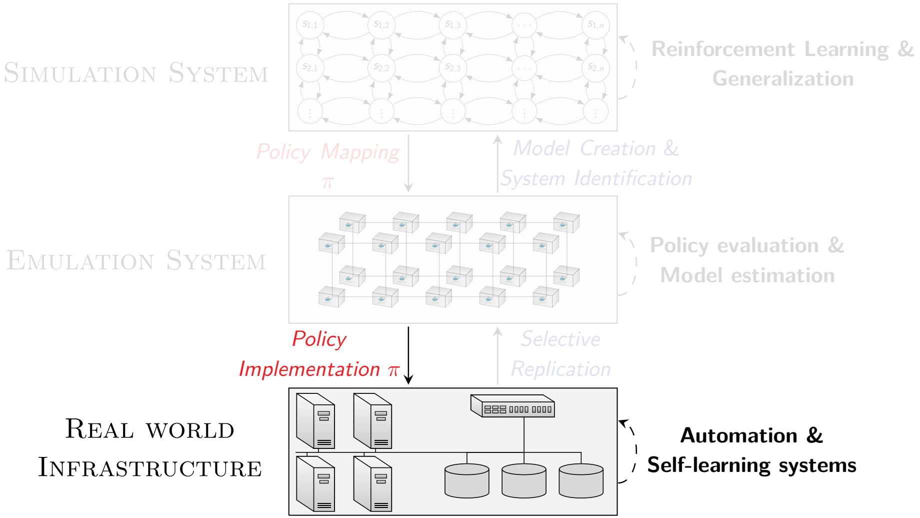
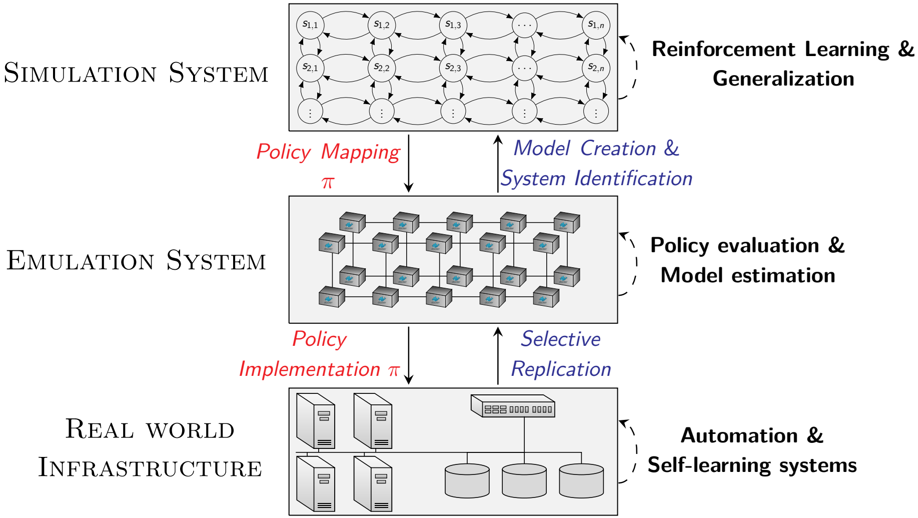
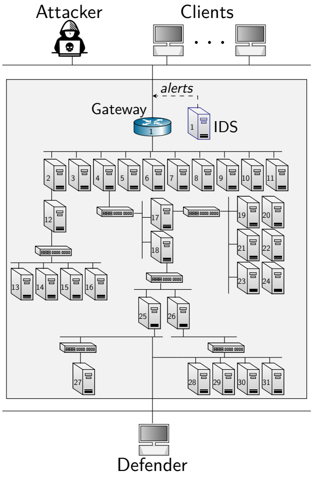


Our Method for Finding Effective Security Strategies



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

l_t	*Action*	*Command in the Emulation*
3	Reset users	`deluser -remove-home <username>`
2	Blacklist IPs	`iptables -A INPUT -s <ip> -j DROP`
1	Block gateway	`iptables -A INPUT -i eth0 -j DROP`

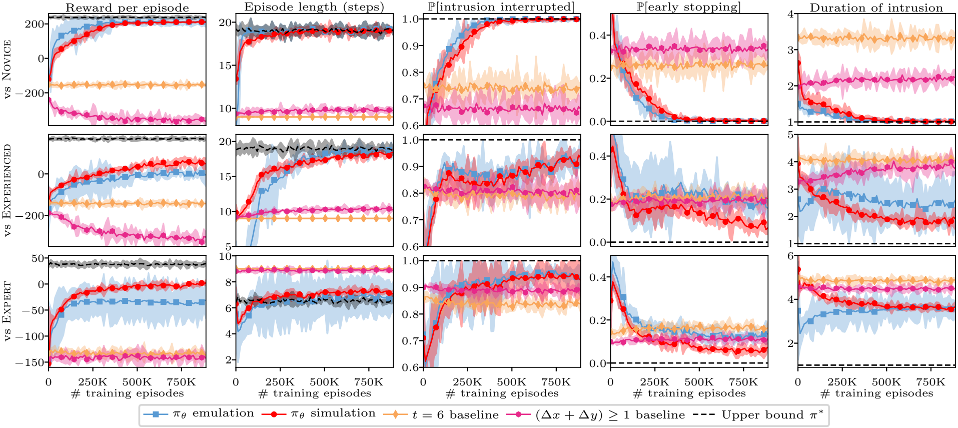
Table 2: Commands used to implement the defender's stop actions in the emulation.

Static Attackers to Emulate Intrusions

Time-steps t	NoviceAttacker	ExperiencedAttacker	ExpertAttacker
1-$I_t \sim Ge(0.2)$	(Intrusion has not started)	(Intrusion has not started)	(Intrusion has not started)
I_t+1-I_t+6	Recon$_1$, 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$_2$, CVE-2017-7494 exploit on N_4, brute-force attack (SSH) on N_2, login(N_2, N_4), backdoor(N_2, N_4), Recon$_2$	Recon$_3$, CVE-2017-7494 exploit on N_4, login(N_4), backdoor(N_4) Recon$_3$, SQL Injection on N_{18}
I_t+7-I_t+10	Recon$_1$, CVE-2014-6271 on N_{17}, login(N_{17}), backdoor(N_{17})	CVE-2014-6271 on N_{17}, login(N_{17}) backdoor(N_{17}), SSH brute-force attack on N_{12}	login(N_{18}), backdoor(N_{18}), Recon$_3$, CVE-2015-1427 on N_{25}
I_t+11-I_t+14	SSH brute-force attack on N_{12}, login(N_{12}) CVE-2010-0426 exploit on N_{12}, Recon$_1$	login(N_{12}), CVE-2010-0426 exploit on N_{12}, Recon$_2$, SQL Injection on N_{18}	login(N_{25}), backdoor(N_{25}), Recon$_3$, CVE-2017-7494 exploit on N_{27}
I_t+15-I_t+16		login(N_{18}), backdoor(N_{18})	login(N_{27}), backdoor(N_{27})
I_t+17-I_t+19		Recon$_2$, CVE-2015-1427 on N_{25}, login(N_{25})	

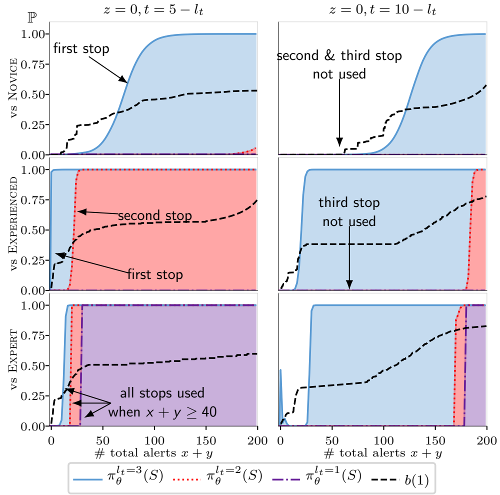
Table 3: Attacker actions to emulate intrusions.

Learning Intrusion Prevention Policies through Optimal Stopping



Learning curves of training defender policies against static attackers, $L = 3$.

Threshold Properties of the Learned Policies, $L = 3$



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 multiple 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
  - Evaluation on real world infrastructures