Learning Near-Optimal Intrusion Responses for Large-Scale IT Infrastructures via Decomposition

NSE Seminar

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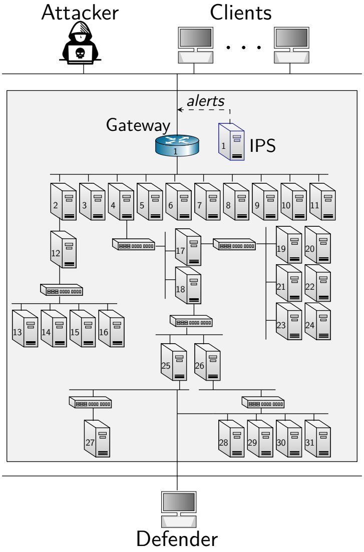
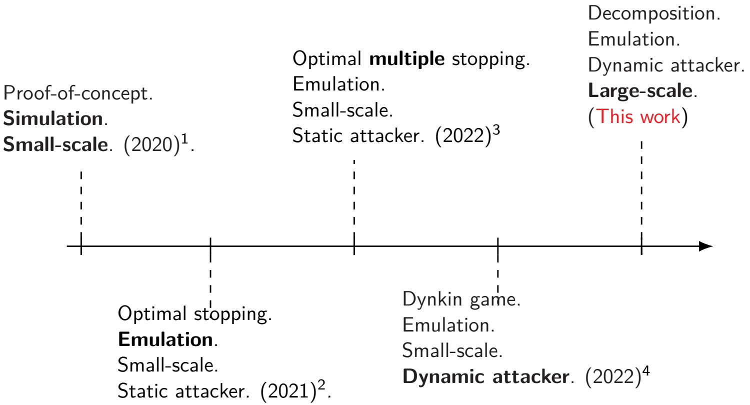
Use Case: Intrusion Response

- A **Defender** owns an infrastructure
  - Consists of connected components
  - Components run network services
  - Defender defends the infrastructure by monitoring and active defense
  - Has partial observability
- 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



Can we use decision theory and learning-based methods to automatically find effective security strategies?



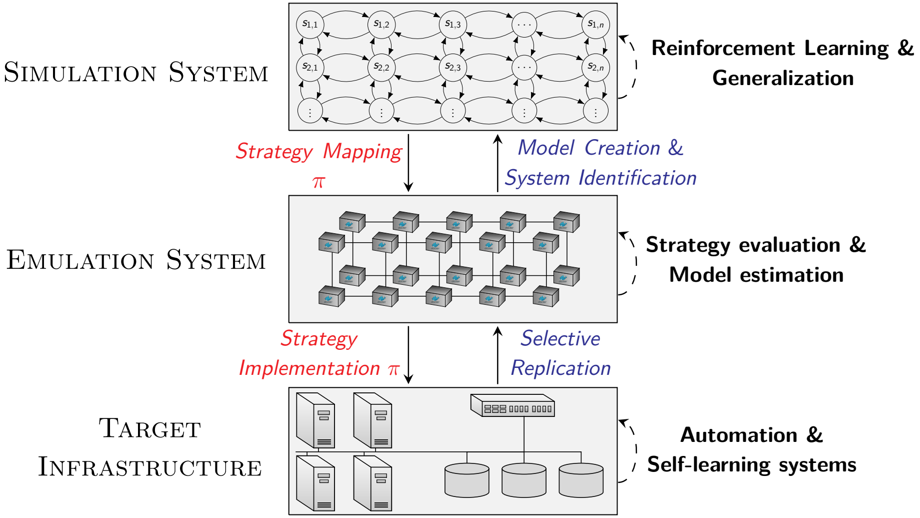
[1] Kim Hammar and Rolf Stadler. "Finding Effective Security Strategies through Reinforcement Learning and Self-Play". In: *International Conference on Network and Service Management (CNSM 2020)*. Izmir, Turkey, 2020.

[2] Kim Hammar and Rolf Stadler. "Learning Intrusion Prevention Policies through Optimal Stopping". In: *International Conference on Network and Service Management (CNSM 2021)*. Izmir, Turkey, 2021.

[3] Kim Hammar and Rolf Stadler. "Intrusion Prevention Through Optimal Stopping". In: *IEEE Transactions on Network and Service Management* 19.3 (2022), pp. 2333–2348. DOI: 10.1109/TNSM.2022.3176781.

[4] Kim Hammar and Rolf Stadler. *Learning Near-Optimal Intrusion Responses Against Dynamic Attackers*. 2023. DOI: 10.48550/ARXIV.2301.06085. URL: https://arxiv.org/abs/2301.06085.

Our Framework for Automated Security



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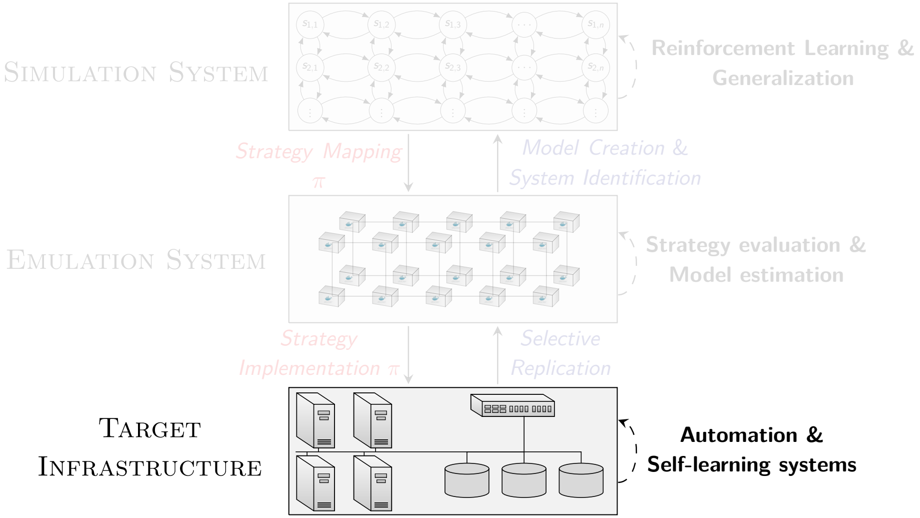

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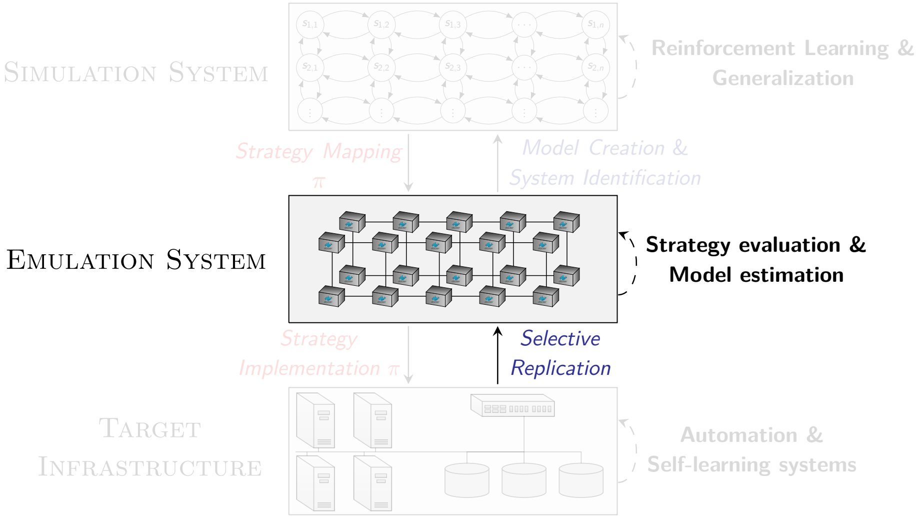

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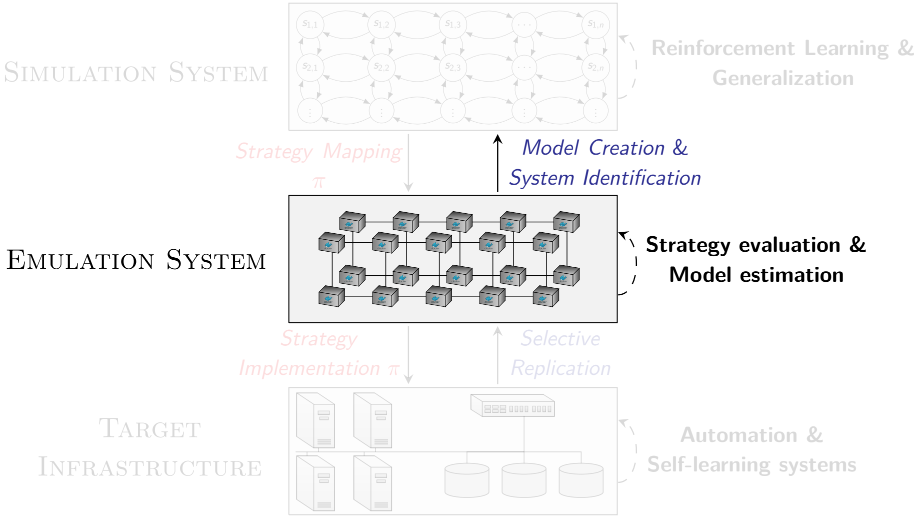

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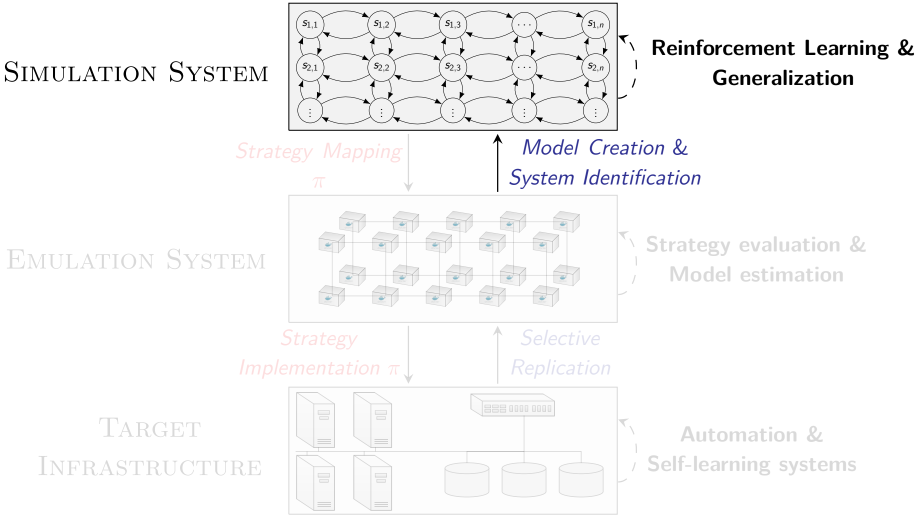

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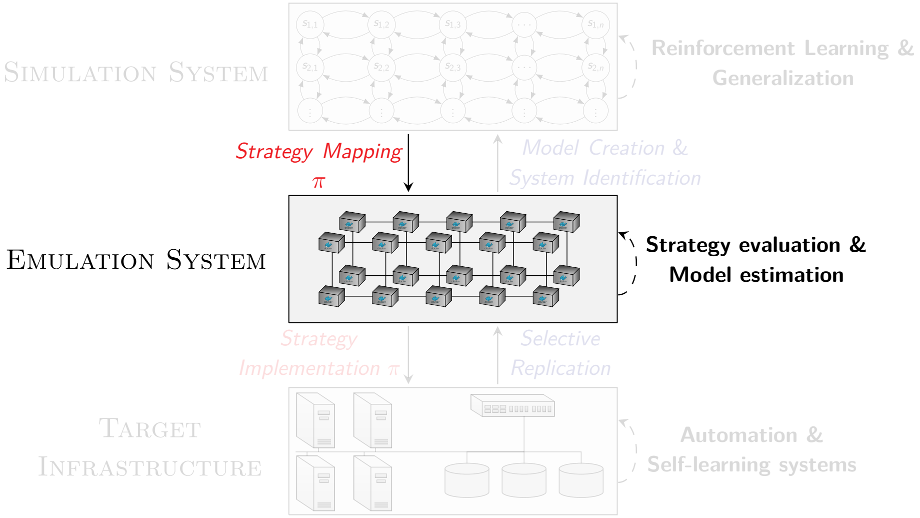

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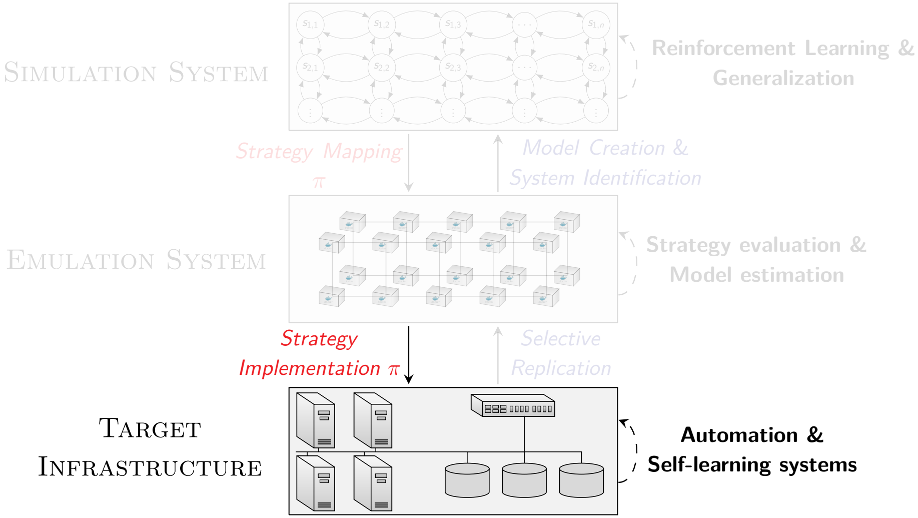

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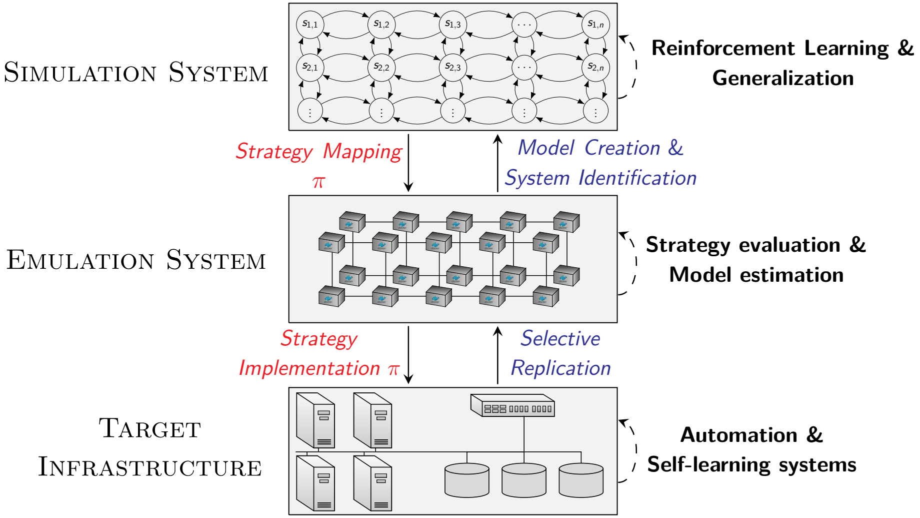

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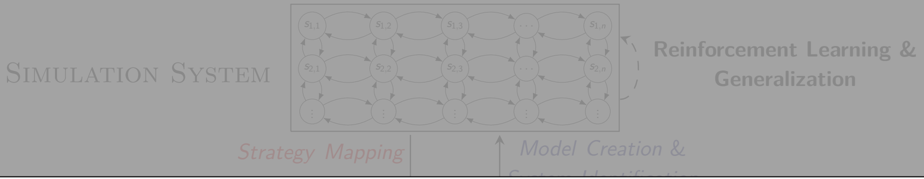
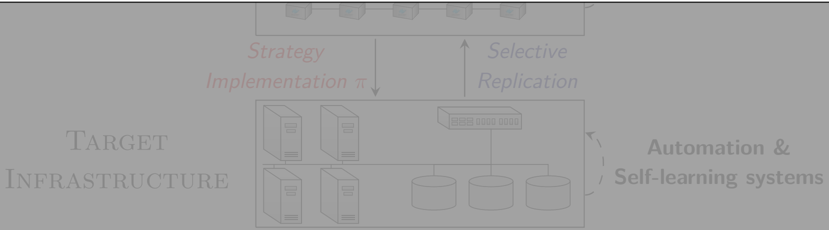


Key challenges: (1) sample complexity; (2) computational complexity.



Outline

- **Use Case & Approach**
  - Use case: intrusion response
  - Approach: simulation, emulation & reinforcement learning
- **System Model**
  - Discrete-time Markovian dynamical system
  - Partially observed stochastic game
- **System Decomposition**
  - Additive subgames on the workflow-level
  - Optimal substructure on component-level
- **Learning Near-Optimal Intrusion Responses**
  - Scalable learning through decomposition
  - Digital twin for system identification & evaluation
  - Efficient equilibrium approximation
- **Conclusions & Future Work**

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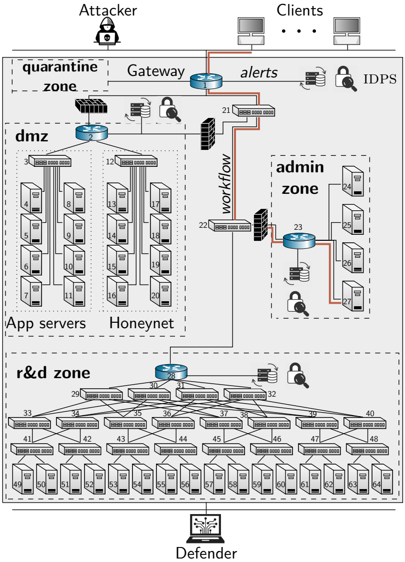
System Model

- $\mathcal{G} = \langle \{\mathrm{gw}\} \cup \mathcal{V}, \mathcal{E} \rangle$: directed graph representing the virtual infrastructure
- $\mathcal{V}$: finite set of virtual components.
- $\mathcal{E}$: finite set of component dependencies.
- $\mathcal{Z}$: finite set of zones.



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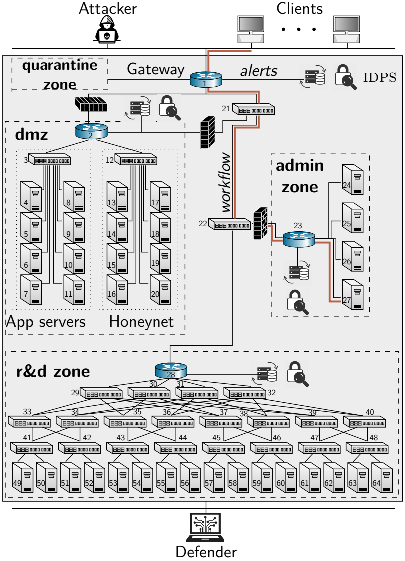

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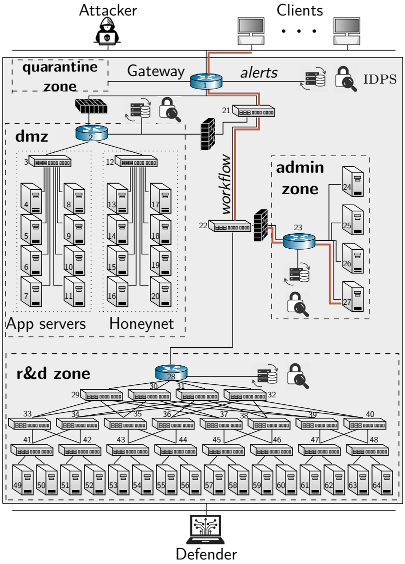


State Model

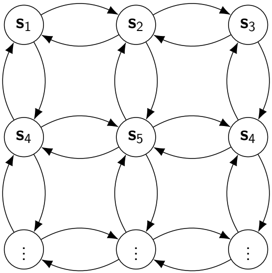
- Each $i \in \mathcal{V}$ has a state

$$v_{t,i} = (\underbrace{v_{t,i}^{(Z)}}_{\text{D}}, \underbrace{v_{t,i}^{(I)}, v_{t,i}^{(R)}}_{\text{A}})$$

- System state $\mathbf{s}_t = (v_{t,i})_{i \in \mathcal{V}} \sim \mathbf{S}_t$.
- Markovian time-homogeneous dynamics:

$$\mathbf{s}_{t+1} \sim f(\cdot \mid \mathbf{S}_t, \mathbf{A}_t)$$

$\mathbf{A}_t = (\mathbf{A}_t^{(A)}, \mathbf{A}_t^{(D)})$ are the actions.



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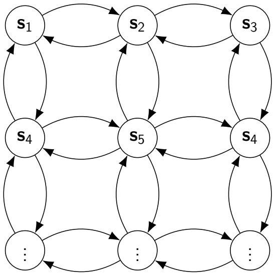

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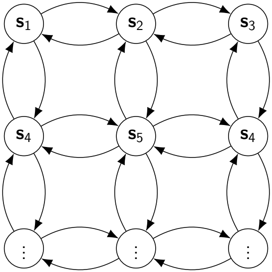

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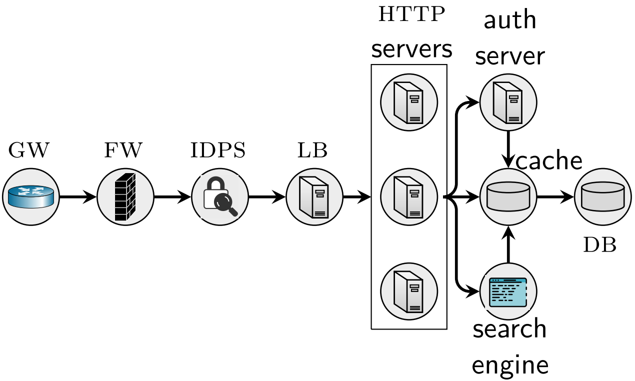
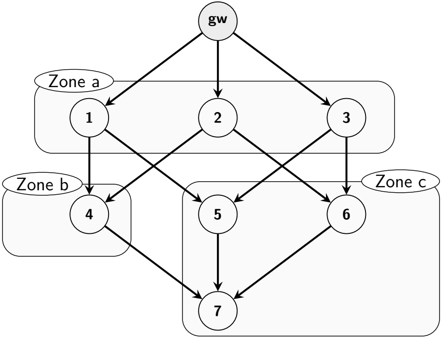


Dependency graph of an example workflow representing a web application; GW, FW, IDPS, LB, and DB are acronyms for gateway, firewall, intrusion detection and prevention system, load balancer, and database, respectively.

Workflow Model

- Services are connected into **workflows** $\mathcal{W} = \{\mathbf{w}_1, \ldots, \mathbf{w}_{|\mathcal{W}|}\}$.
- Each $\mathbf{w} \in \mathcal{W}$ is realized as a directed acyclic subgraph (DAG) $\mathcal{G}_\mathbf{w} = \langle \{\mathrm{gw}\} \cup \mathcal{V}_\mathbf{w}, \mathcal{E}_\mathbf{w} \rangle$ of $\mathcal{G}$
- $\mathcal{W} = \{\mathbf{w}_1, \ldots, \mathbf{w}_{|\mathcal{W}|}\}$ induces a partitioning

$$\mathcal{V} = \bigcup_{\mathbf{w}_i \in \mathcal{W}} \mathcal{V}_{\mathbf{w}_i} \text{ such that } i \neq j \implies \mathcal{V}_{\mathbf{w}_i} \cap \mathcal{V}_{\mathbf{w}_j} = \emptyset$$



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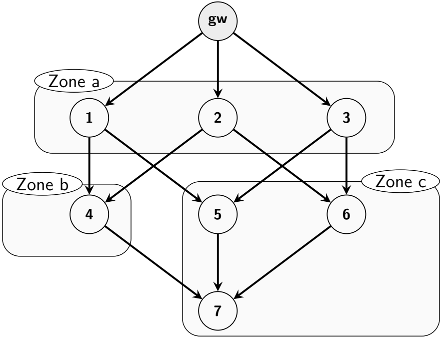

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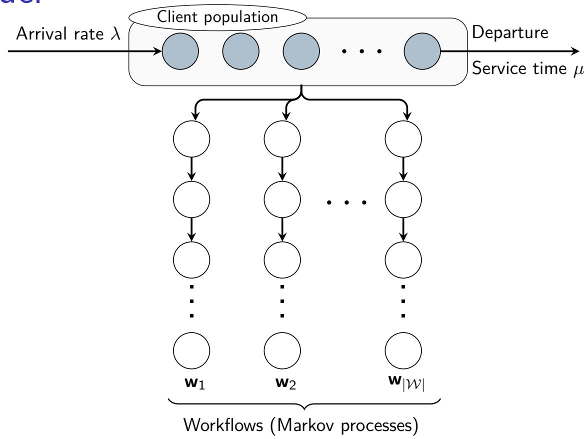
Client Model



- Homogeneous client population
- Clients arrive according to $Po(\lambda)$, Service times $Exp(\frac{1}{\mu})$
- Workflow selection: uniform
- Workflow interaction: Markov process

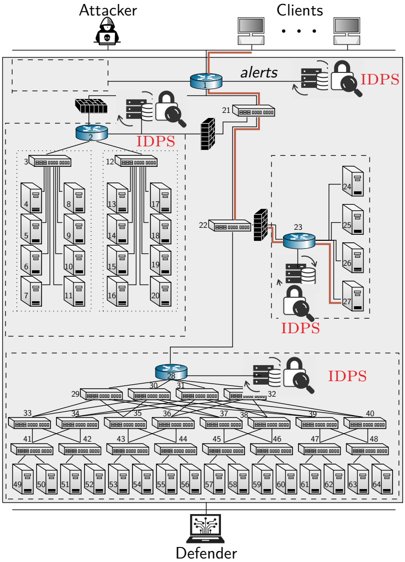
Observation Model

- IDPSs inspect network traffic and generate alert vectors:

$$\mathbf{o}_t \triangleq \left(\mathbf{o}_{t,1}, \ldots, \mathbf{o}_{t,|\mathcal{V}|}\right) \in \mathbb{N}_0^{|\mathcal{V}|}$$

  $\mathbf{o}_{t,i}$ is the number of alerts related to node $i \in \mathcal{V}$ at time-step t.

- $\mathbf{o}_t = \left(\mathbf{o}_{t,1}, \ldots, \mathbf{o}_{t,|\mathcal{V}|}\right)$ is a realization of the random vector $\mathbf{O}_t$ with joint distribution Z



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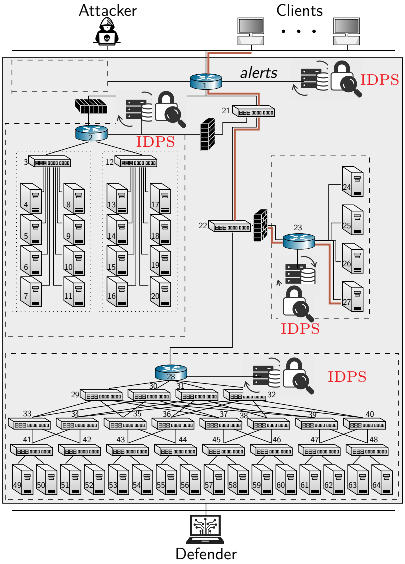
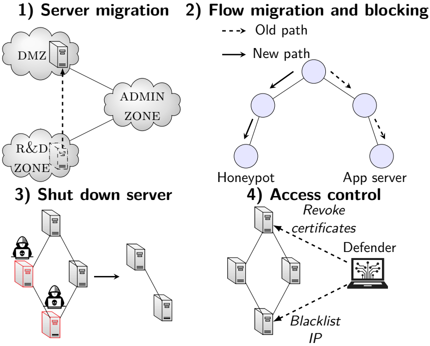


Defender Model

- Defender action: $\mathbf{a}_t^{(D)} \in \{0,1,2,3,4\}^{|\mathcal{V}|}$
- 0 means do nothing. $1-4$ correspond to defensive actions (see fig)



- A **defender strategy** is a function $\pi_{\mathrm{D}} \in \Pi_{\mathrm{D}} : \mathcal{H}_{\mathrm{D}} \to \Delta(\mathcal{A}_{\mathrm{D}})$, where

$$\mathbf{h}_t^{(\mathrm{D})} = (\mathbf{s}_1^{(\mathrm{D})}, \mathbf{a}_1^{(\mathrm{D})}, \mathbf{o}_1, \ldots, \mathbf{a}_{t-1}^{(\mathrm{D})}, \mathbf{s}_t^{(\mathrm{D})}, \mathbf{o}_t) \in \mathcal{H}_{\mathrm{D}}$$

- Objective: (i) maintain workflows; and (ii), stop a possible intrusion:

$$J \triangleq \sum_{t=1}^{T} \gamma^{t-1} \left(\underbrace{\eta \sum_{i=1}^{|\mathcal{W}|} u_{\mathrm{W}}(\mathbf{w}_i, \mathbf{s}_t)}_{\text{workflows utility}} - \underbrace{(1-\eta) \sum_{j=1}^{|\mathcal{V}|} c_{\mathrm{I}}(\mathbf{s}_{t,j}, \mathbf{a}_{t,j})}_{\text{intrusion and defense costs}} \right)$$

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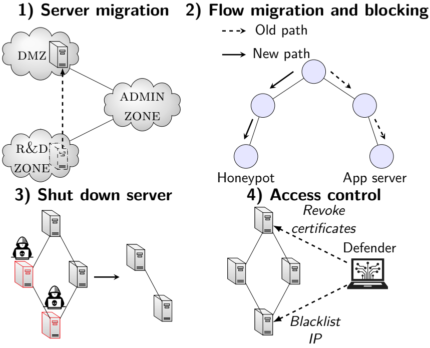

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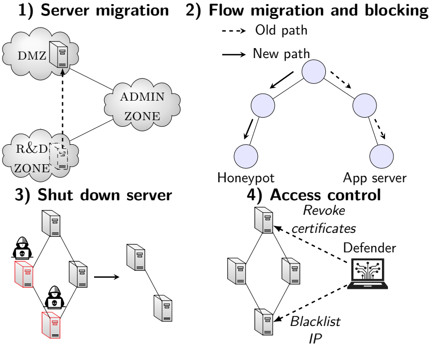

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Attacker Model

- Attacker action: $\mathbf{a}_t^{(A)} \in \{0, 1, 2, 3\}^{|\mathcal{V}|}$
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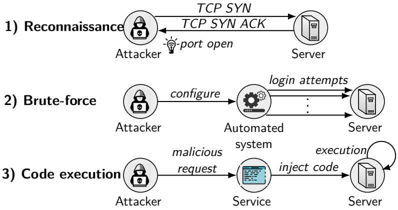

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- Objective: (*i*) disrupt workflows; and (*ii*), **compromise nodes**:

$$-J$$

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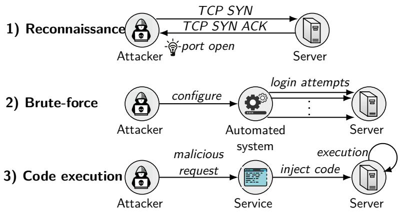

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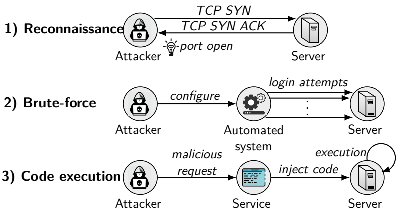

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The Intrusion Response Problem

$$
\begin{aligned}
&\underset{\pi_{\mathrm{D}} \in \Pi_{\mathrm{D}}}{\text{maximize}} \ \underset{\pi_{\mathrm{A}} \in \Pi_{\mathrm{A}}}{\text{minimize}} \ \mathbb{E}_{(\pi_{\mathrm{D}}, \pi_{\mathrm{A}})}\left[J\right] && && \text{(1a)}\\
&\text{subject to } \mathbf{s}^{(\mathrm{D})}_{t+1} \sim f_{\mathrm{D}}\big(\cdot \mid \mathbf{A}^{(\mathrm{D})}_{t}, \mathbf{A}^{(\mathrm{D})}_{t}\big) && \forall t && \text{(1b)}\\
&\mathbf{s}^{(\mathrm{A})}_{t+1} \sim f_{\mathrm{A}}\big(\cdot \mid \mathbf{S}^{(\mathrm{A})}_{t}, \mathbf{A}_{t}\big) && \forall t && \text{(1c)}\\
&\mathbf{o}_{t+1} \sim Z\big(\cdot \mid \mathbf{S}^{(\mathrm{D})}_{t+1}, \mathbf{A}^{(\mathrm{A})}_{t}\big) && \forall t && \text{(1d)}\\
&\mathbf{a}^{(\mathrm{A})}_{t} \sim \pi_{\mathrm{A}}\big(\cdot \mid \mathbf{H}^{(\mathrm{A})}_{t}\big), \ \mathbf{a}^{(\mathrm{A})}_{t} \in \mathcal{A}_{\mathrm{A}}(\mathbf{s}_t) && \forall t && \text{(1e)}\\
&\mathbf{a}^{(\mathrm{D})}_{t} \sim \pi_{\mathrm{D}}\big(\cdot \mid \mathbf{H}^{(\mathrm{D})}_{t}\big), \ \mathbf{a}^{(\mathrm{D})}_{t} \in \mathcal{A}_{\mathrm{D}} && \forall t && \text{(1f)}
\end{aligned}
$$

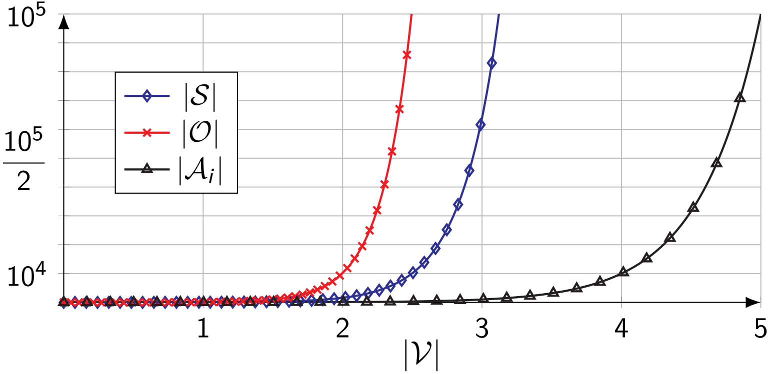
where $\mathbb{E}_{(\pi_{\mathrm{D}}, \pi_{\mathrm{A}})}$ denotes the expectation of the random vectors $(\mathbf{S}_t, \mathbf{O}_t, \mathbf{A}_t)_{t \in \{1,\ldots,T\}}$ under the strategy profile $(\pi_{\mathrm{D}}, \pi_{\mathrm{A}})$.

(1) can be formulated as a zero-sum Partially Observed Stochastic Game with Public Observations (a PO-POSG):

$$
\Gamma = \langle \mathcal{N}, (\mathcal{S}_i)_{i \in \mathcal{N}}, (\mathcal{A}_i)_{i \in \mathcal{N}}, (f_i)_{i \in \mathcal{N}}, u, \gamma, (\mathbf{b}^{(i)}_1)_{i \in \mathcal{N}}, \mathcal{O}, Z \rangle
$$

The Curse of Dimensionality

- While (1) has a solution (i.e the game Γ has a value (Thm 1)), computing it is intractable since the state, action, and observation spaces of the game **grow exponentially** with $|\mathcal{V}|$.



Growth of $|\mathcal{S}|$, $|\mathcal{O}|$, and $|\mathcal{A}_i|$ in function of the number of nodes $|\mathcal{V}|$

Outline

- **Use Case & Approach**
  - Use case: intrusion response
  - Approach: simulation, emulation & reinforcement learning
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  - Additive subgames on the workflow-level
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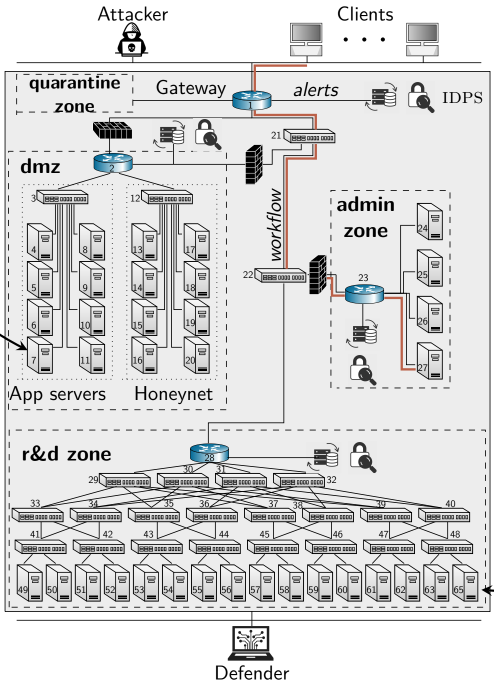
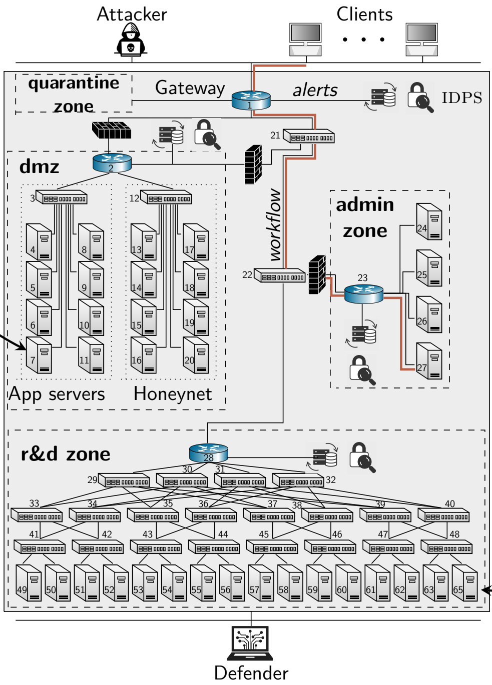
Intuitively..

The optimal action here...



Does not directly depend on the state or action of a node down here

Intuitively..



The optimal action here...

But they are not completely independent either.

Does not directly depend on the state or action of a node down here

How can we exploit this structure?

System Decomposition

To avoid explicitly enumerating the very large state, observation, and action spaces of Γ, we exploit three structural properties.

1. **Additive structure across workflows.**
   - The game decomposes into additive subgames on the workflow-level, which means that the strategy for each subgame can be optimized independently
2. **Optimal substructure within a workflow.**
   - The subgame for each workflow decomposes into subgames on the node-level that satisfy the *optimal substructure* property
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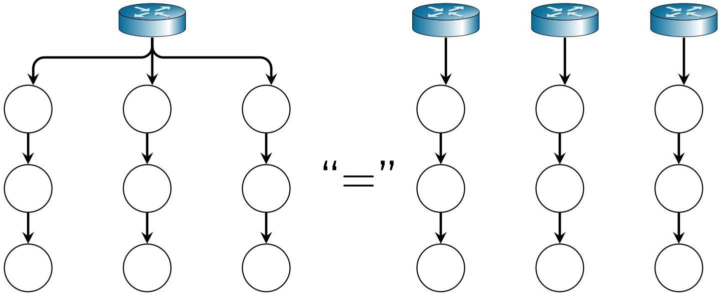
Additive Structure Across Workflows (Intuition)



- If there is no path between i and j in $\mathcal{G}$, then i and j are **independent** in the following sense:
  - Compromising i has no affect on the state of j.
  - Compromising i does not make it harder or easier to compromise j.
  - Compromising i does not affect the service provided by j.
  - Defending i does not affect the state of j.
  - Defending i does not affect the service provided by j.

Additive Structure Across Workflows

Definition (Transition independence)

A set of nodes $\mathcal{Q}$ are transition independent iff the transition probabilities factorize as

$$f(\mathbf{S}_{t+1} \mid \mathbf{S}_t, \mathbf{A}_t) = \prod_{i \in \mathcal{Q}} f(\mathbf{S}_{t+1,i} \mid \mathbf{S}_{t,i}, \mathbf{A}_{t,i})$$

Definition (Utility independence)

A set of nodes $\mathcal{Q}$ are utility independent iff there exists functions $u_1, \ldots, u_{|\mathcal{Q}|}$ such that the utility function u decomposes as

$$u(\mathbf{S}_t, \mathbf{A}_t) = f(u_1(\mathbf{S}_{t,1}, \mathbf{A}_{t,1}), \ldots, u_1(\mathbf{S}_{t,|\mathcal{Q}|}, \mathbf{A}_{t,\mathcal{Q}}))$$

and

$$u_i \leq u_i' \iff f(u_1, \ldots, u_i, \ldots, u_{|\mathcal{Q}|}) \leq f(u_1, \ldots, u_i', \ldots, u_{|\mathcal{Q}|})$$

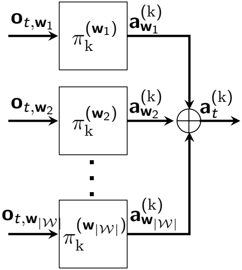
Additive Structure Across Workflows

Theorem (Additive structure across workflows)

(A) All nodes $\mathcal{V}$ in the game Γ are transition independent.
(B) If there is no path between i and j in the topology graph $\mathcal{G}$, then i and j are utility independent.

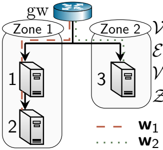
Corollary

Γ decomposes into $|\mathcal{W}|$ additive subproblems that can be solved independently and in parallel.



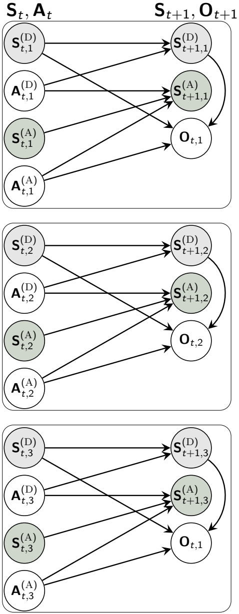
Additive Structure Across Workflows: Minimal Example

a) IT infrastructure

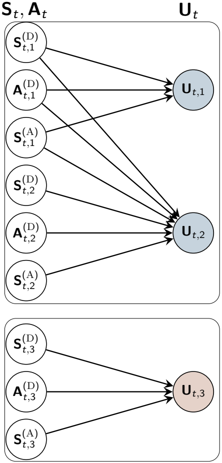


$\mathcal{V} = \{1, 2, 3\}$,
$\mathcal{E} = \{(1, 2)\}$,
$\mathcal{W} = \{\mathbf{w}_1, \mathbf{w}_2\}$,
$\mathcal{Z} = \{1, 2\}$

b) Transition dependencies



c) Utility dependencies



System Decomposition

To avoid explicitly enumerating the very large state, observation, and action spaces of Γ, we exploit three structural properties.

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Optimal Substructure Within a Workflow

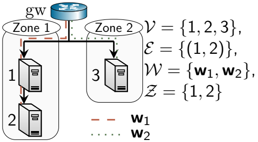
- Nodes in the same workflow are utility dependent.

- $\implies$ Locally-optimal strategies for each node **can not** simply be added together to obtain an optimal strategy for the workflow.

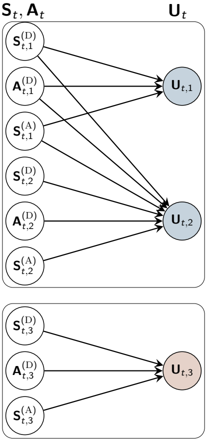
- However, the locally-optimal strategies satisfy the optimal substructure property.

- $\implies$ there exists an algorithm for constructing an optimal workflow strategy from locally-optimal strategies for each node.

IT infrastructure



Utility dependencies



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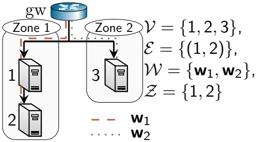
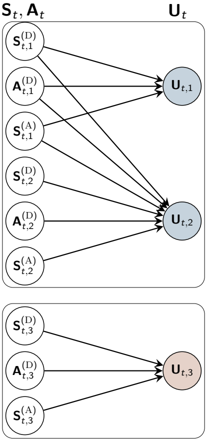


Utility dependencies



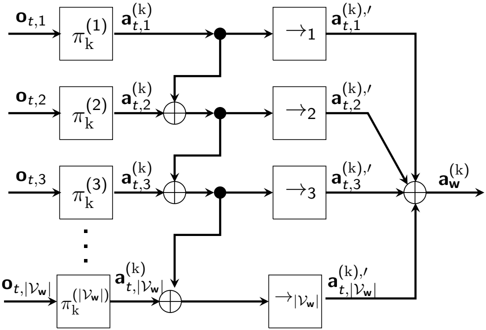
Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies

Algorithm 1: Algorithm for combining local strategies

Input: Γ*:* the game,
$\boldsymbol{\pi}_k$: a vector with local strategies

Output: *(π_D, π_A):* global game strategies

Algorithm $\textsc{composite-strategy}(\Gamma, \boldsymbol{\pi}_k)$
  for *player* $k \in \mathcal{N}$ **do**
    $\pi_k \leftarrow \lambda\ (\mathbf{s}_t^{(k)}, \mathbf{b}_t^{(k)})$
      $\mathbf{a}_t^{(k)} = ()$
      for *workflow* $\mathbf{w} \in \mathcal{W}$ **do**
        for *node* $i \in \textsc{topological-sort}(\mathcal{V}_{\mathbf{w}})$ **do**
          $\mathbf{a}_t^{(k,i)} \leftarrow \boldsymbol{\pi}_k^{(i)}(\mathbf{s}_t^{(k)}, \mathbf{b}_t^{(k)})$
          if $\mathrm{gw} \not\to_t^{\mathbf{a}_t^{(k)}} i$ **then**
            $\mathbf{a}_t^{(k,i)} \leftarrow \bot$
          end
          $\mathbf{a}_t^{(k)} = \mathbf{a}_t^{(k)} \oplus \mathbf{a}_t^{(k,i)}$
        end
      end
      return $\mathbf{a}_t^{(k)}$
  end
  return (π_D, π_A)



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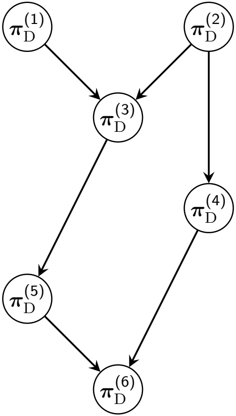
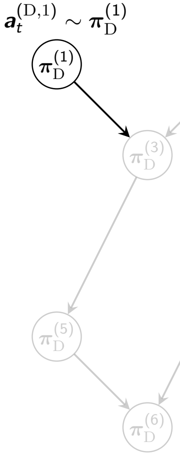


$(\boldsymbol{\pi}_D^{(i)})_{i \in \mathcal{V}_{\mathbf{w}}}$: local strategies in the same workflow $\mathbf{w} \in \mathcal{W}$

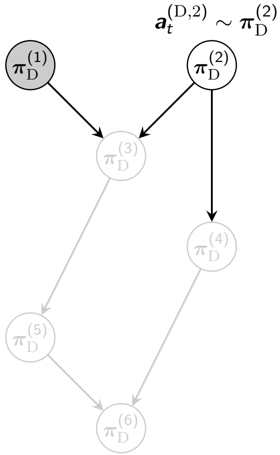
Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies



Workflow action:
$(\boldsymbol{a}_t^{(\mathrm{D},1)})$

Step 1; select action for node 1 according to its local strategy

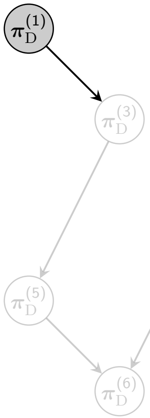
Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies



Workflow action:
$(\boldsymbol{a}_t^{(\mathrm{D},1)}, \boldsymbol{a}_t^{(\mathrm{D},2)})$

Step 2; update the topology based on the previous local action;
select action $a = 0$ for unreachable nodes;
move to the next node in the topological ordering (i.e. 2);
select the action for the next node according to its local strategy.

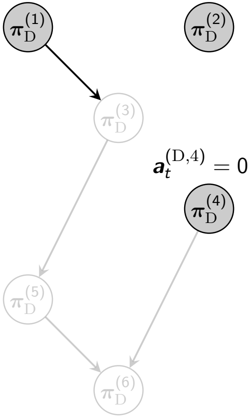
Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies



Workflow action:
$(\boldsymbol{a}_t^{(\mathrm{D},1)}, \boldsymbol{a}_t^{(\mathrm{D},2)})$

Step 3; update the topology based on the previous local action;
select action $a = 0$ for unreachable nodes;
move to the next node in the topological ordering (i.e. 3);
select the action for the next node according to its local strategy.

Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies



Workflow action:
$(a_t^{(\mathrm{D},1)}, a_t^{(\mathrm{D},2)}, \cdot, 0)$

Step 3; update the topology based on the previous local action;
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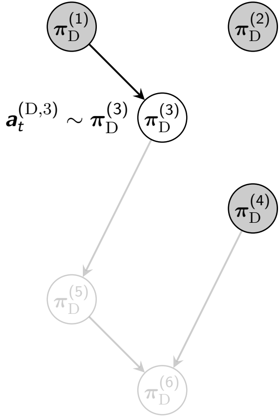

Workflow action:
$(\boldsymbol{a}_t^{(\mathrm{D},1)}, \boldsymbol{a}_t^{(\mathrm{D},2)}, \boldsymbol{a}_t^{(\mathrm{D},3)}, 0)$

Step 3; update the topology based on the previous local action;
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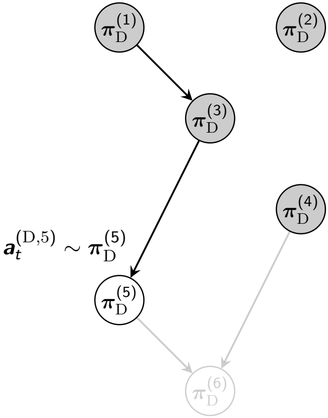
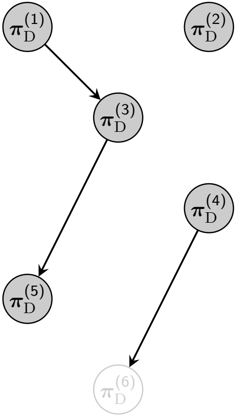
Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies



Workflow action:
$(\boldsymbol{a}_t^{(\mathrm{D},1)}, \boldsymbol{a}_t^{(\mathrm{D},2)}, \boldsymbol{a}_t^{(\mathrm{D},3)}, 0, \boldsymbol{a}_t^{(\mathrm{D},5)})$

Step 4; update the topology based on the previous local action;
select action $a = 0$ for unreachable nodes;
move to the next node in the topological ordering (i.e. 5);
select the action for the next node according to its local strategy.

Algorithm for Combining Locally-Optimal Node Strategies into Optimal Workflow Strategies



Workflow action:
$(\boldsymbol{a}_t^{(\mathrm{D},1)}, \boldsymbol{a}_t^{(\mathrm{D},2)}, \boldsymbol{a}_t^{(\mathrm{D},3)}, 0, \boldsymbol{a}_t^{(\mathrm{D},5)})$

Step 5; update the topology based on the previous local action;
select action $a = 0$ for unreachable nodes;

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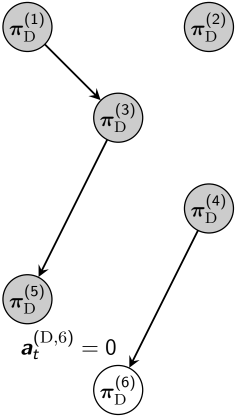
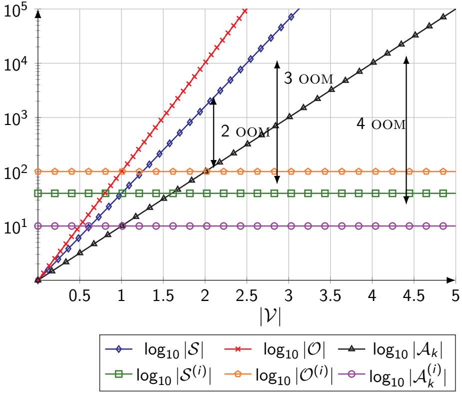


Workflow action:
$(a_t^{(D,1)}, a_t^{(D,2)}, a_t^{(D,3)}, 0, a_t^{(D,5)}, 0)$

Step 5; update the topology based on the previous local action;
select action $a = 0$ for unreachable nodes;

Computational Benefits of Decomposition

- ∴ we can obtain an optimal (best response) strategy for the full game Γ by combining the solutions to $\mathcal{V}$ simpler subproblems that can be solved **in parallel** and have significantly smaller state, observation, and action spaces.



Space complexity comparison between the full game and the decomposed game.

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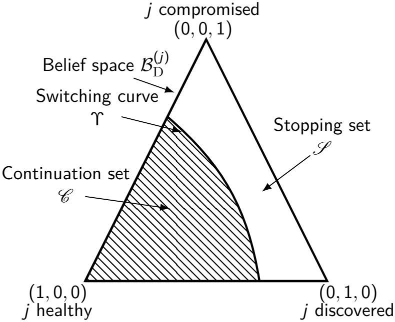
Threshold Properties of Local Defender Strategies.

- The local problem of the defender can be decomposed in the temporal domain as

$$\max_{\pi_{\mathrm{D}}} \sum_{t=1}^{T} J = \max_{\pi_{\mathrm{D}}} \sum_{t=1}^{\tau_1} J_1 + \sum_{t=1}^{\tau_2} J_2 + \dots \tag{2}$$

  where $\tau_1, \tau_2, \dots$ are stopping times.
- $\implies$ (1) selection of defensive actions is simplified; and (2) the optimal stopping times are given by a threshold strategy that can be estimated efficiently:



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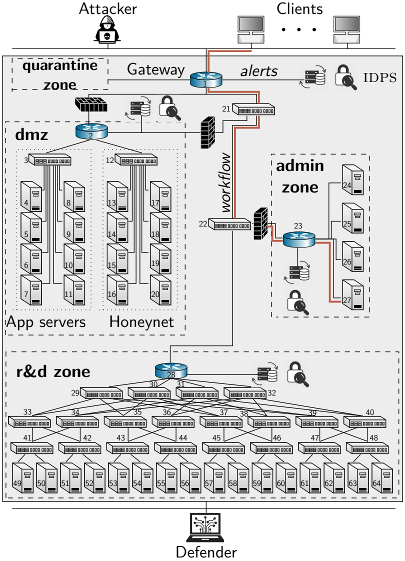
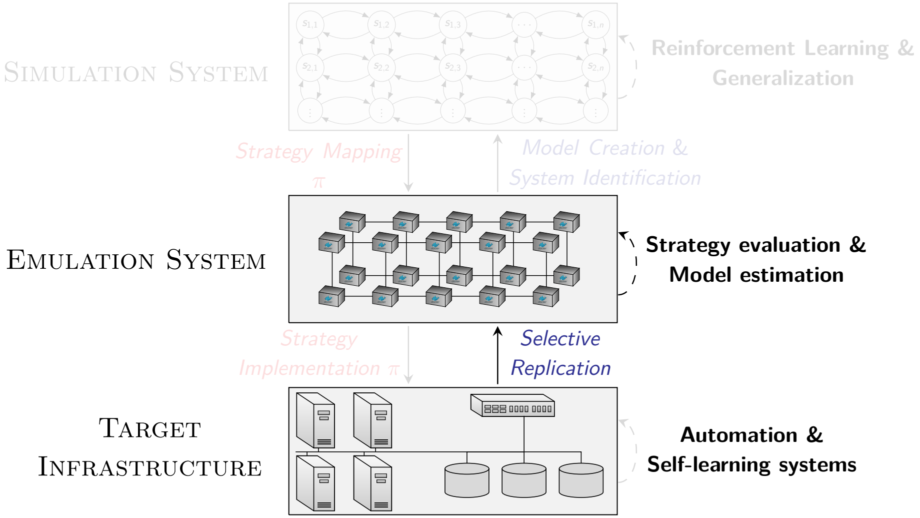
The Target Infrastructure

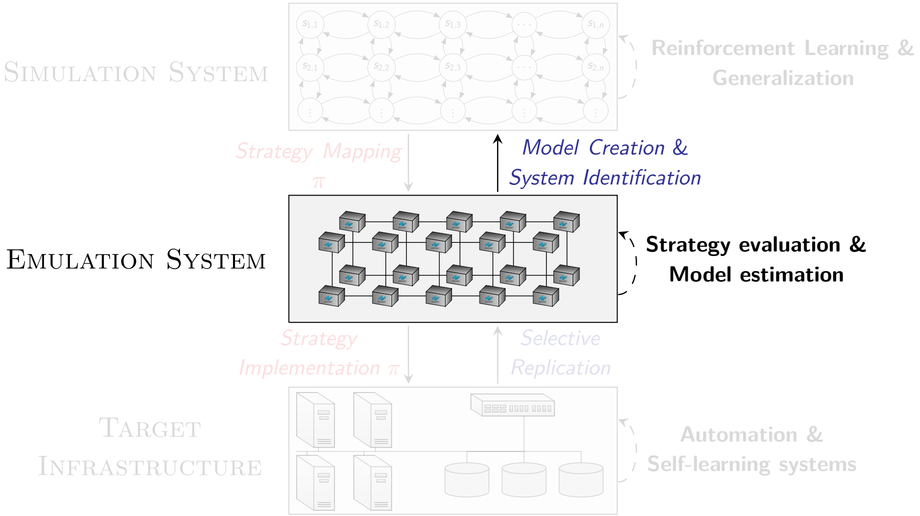
- 64 nodes. 24 OVS switches, 3 gateways. 6 honeypots. 8 application servers. 4 administration servers. 15 compute servers.
- 11 vulnerabilities (CVE-2010-0426, CVE-2015-3306, CVE-2015-5602, etc.)
- 4 zones: DMZ, R&D ZONE, ADMIN ZONE, QUARANTINE ZONE
- 9 workflows
- Management: 1 SDN controller, 1 Kafka server, 1 elastic server.

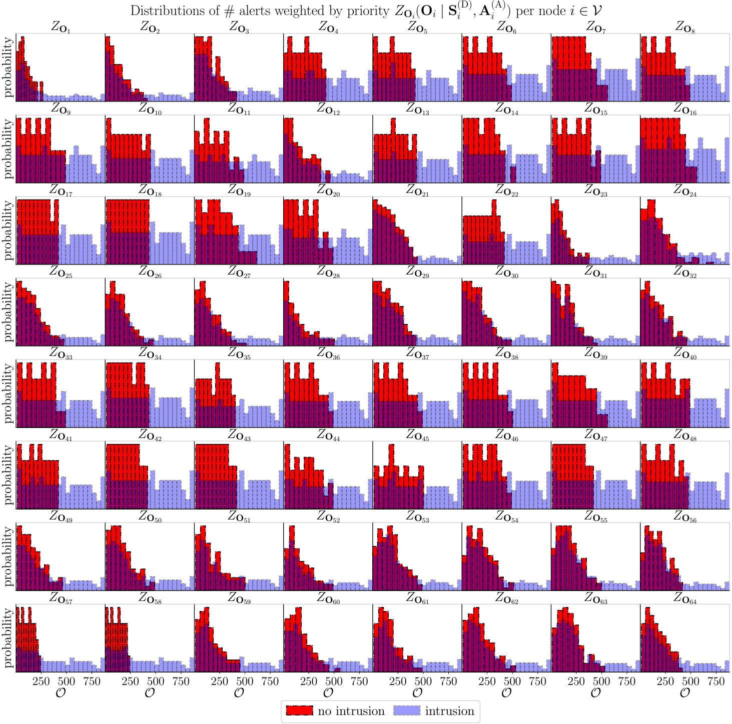


Creating a Digital Twin of the Target Infrastructure



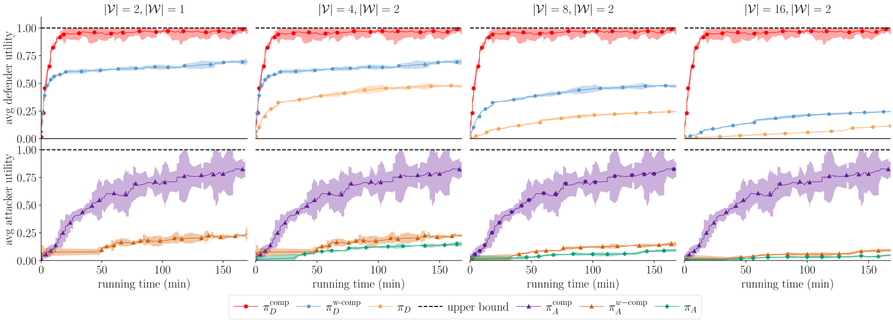
System Identification





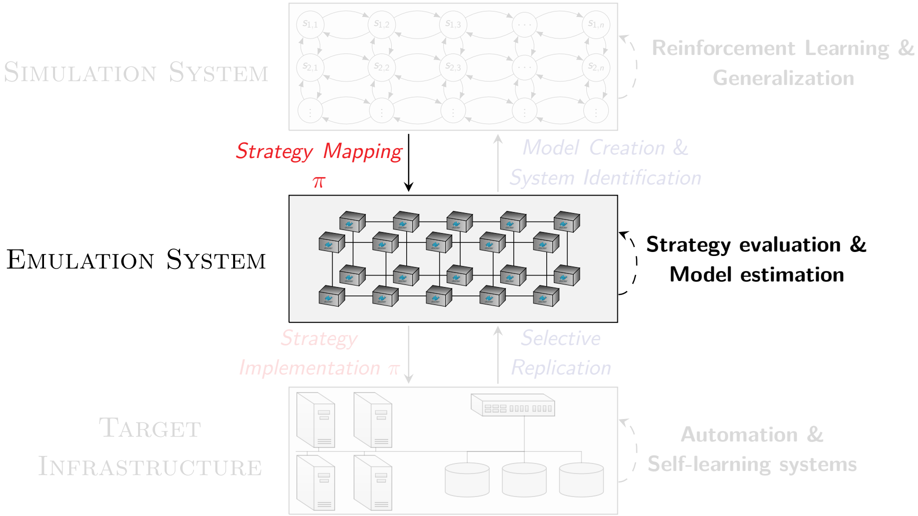
Distributions of # alerts weighted by priority $Z_{\mathbf{O}_i}(\mathbf{O}_i \mid \mathbf{S}_i^{(\mathrm{D})}, \mathbf{A}_i^{(\mathrm{A})})$ per node $i \in \mathcal{V}$
$Z_{\mathbf{O}_1}$ $Z_{\mathbf{O}_2}$ $Z_{\mathbf{O}_3}$ $Z_{\mathbf{O}_4}$ $Z_{\mathbf{O}_5}$ $Z_{\mathbf{O}_6}$ $Z_{\mathbf{O}_7}$ $Z_{\mathbf{O}_8}$
$Z_{\mathbf{O}_9}$ $Z_{\mathbf{O}_{10}}$ $Z_{\mathbf{O}_{11}}$ $Z_{\mathbf{O}_{12}}$ $Z_{\mathbf{O}_{13}}$ $Z_{\mathbf{O}_{14}}$ $Z_{\mathbf{O}_{15}}$ $Z_{\mathbf{O}_{16}}$
$Z_{\mathbf{O}_{17}}$ $Z_{\mathbf{O}_{18}}$ $Z_{\mathbf{O}_{19}}$ $Z_{\mathbf{O}_{20}}$ $Z_{\mathbf{O}_{21}}$ $Z_{\mathbf{O}_{22}}$ $Z_{\mathbf{O}_{23}}$ $Z_{\mathbf{O}_{24}}$
$Z_{\mathbf{O}_{25}}$ $Z_{\mathbf{O}_{26}}$ $Z_{\mathbf{O}_{27}}$ $Z_{\mathbf{O}_{28}}$ $Z_{\mathbf{O}_{29}}$ $Z_{\mathbf{O}_{30}}$ $Z_{\mathbf{O}_{31}}$ $Z_{\mathbf{O}_{32}}$
$Z_{\mathbf{O}_{33}}$ $Z_{\mathbf{O}_{34}}$ $Z_{\mathbf{O}_{35}}$ $Z_{\mathbf{O}_{36}}$ $Z_{\mathbf{O}_{37}}$ $Z_{\mathbf{O}_{38}}$ $Z_{\mathbf{O}_{39}}$ $Z_{\mathbf{O}_{40}}$
$Z_{\mathbf{O}_{41}}$ $Z_{\mathbf{O}_{42}}$ $Z_{\mathbf{O}_{43}}$ $Z_{\mathbf{O}_{44}}$ $Z_{\mathbf{O}_{45}}$ $Z_{\mathbf{O}_{46}}$ $Z_{\mathbf{O}_{47}}$ $Z_{\mathbf{O}_{48}}$
$Z_{\mathbf{O}_{49}}$ $Z_{\mathbf{O}_{50}}$ $Z_{\mathbf{O}_{51}}$ $Z_{\mathbf{O}_{52}}$ $Z_{\mathbf{O}_{53}}$ $Z_{\mathbf{O}_{54}}$ $Z_{\mathbf{O}_{55}}$ $Z_{\mathbf{O}_{56}}$
$Z_{\mathbf{O}_{57}}$ $Z_{\mathbf{O}_{58}}$ $Z_{\mathbf{O}_{59}}$ $Z_{\mathbf{O}_{60}}$ $Z_{\mathbf{O}_{61}}$ $Z_{\mathbf{O}_{62}}$ $Z_{\mathbf{O}_{63}}$ $Z_{\mathbf{O}_{64}}$
probability
250 500 750
$\mathcal{O}$
no intrusion
intrusion

Scalable learning through decomposition (Simulation)



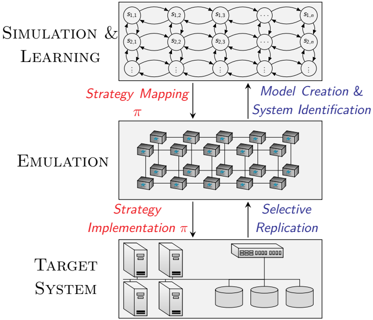
Learning curves obtained during training of PPO to find best response strategies against randomized opponents; red, purple, blue and brown curves relate to decomposed strategies; the orange and green curves relate to the non-decomposed strategies.

Evaluation in the Emulation System (Work in progress!)

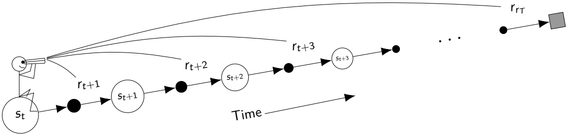


Conclusions

- We develop a *framework* to automatically learn security strategies.
- We apply the method to an **intrusion response use case**.
- We design a novel decompositional approach to find near-optimal intrusion responses for large-scale IT infrastructures.
- We show that the decomposition reduces both the computational complexity of finding effective strategies, and the sample complexity of learning a system model by several orders of magnitude.



Current and Future Work



1. **Extend use case**
   - Heterogeneous client population
   - Extensive threat model of the attacker
2. **Extend solution framework**
   - Model-predictive control
   - Rollout-based techniques
   - Extend system identification algorithm
3. **Extend theoretical results**
   - Exploit symmetries and causal structure