

Scalable Supervisory Control Approach for Dynamic Cybersecurity

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- ▶ Introduction/Contribution
- ▶ Model
- ▶ Problem formulation
- ▶ **Scalability of the approach**
- ▶ Results
- ▶ Summary/conclusion

[Preliminary version has shown up in GameSec2014 and FORCES Nov14 Annual Review]

- ▶ Key issues in cyber-security systems
 - ▶ Progressive attacks
 - ▶ Dynamic/adaptive defense
 - ▶ Imperfect information (for attacker and/or defender) of system status
 - ▶ Non-strategic vs. strategic attacker (control vs. game theory)
 - ▶ Complexity of security problems growing in time and in scale of the network.

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A **supervisory control** approach for cyber-security from the point of view of the defender with

- ▶ progressive attacks,
- ▶ defender's imperfect information,
- ▶ dynamic defense,
- ▶ conservative approach to security,
- ▶ quantification of defender cost of state and action,

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- ▶ quantification of the performance of various defender policies,
- ▶ determination of the defender's optimal policy (within a restricted set) for a min-max performance criterion
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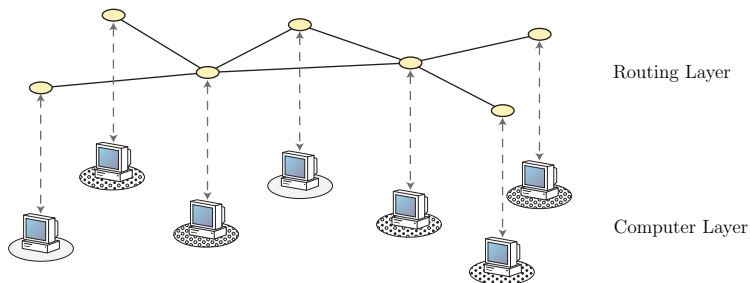
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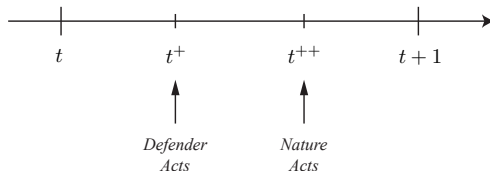
Model: Network Structure

□ $s_i = \text{Normal}$ ▤ $s_i = \text{Compromised}$ ▨ $s_i = \text{Fully compromised}$ ▩ $s_i = \text{Remote compromised}$



- Possible states of each computer : Normal ($L1$), Compromised ($L2$), Fully Compromised ($L3$), Remote Compromised ($L4$).

- ▶ Interaction rules between controller and nature



- ▶ Time horizon \Rightarrow finite or infinite

Model: Decision maker and its costs

Decision Maker

- ▶ One decision-maker
 - ▶ Defender \Rightarrow controller/decision maker
 - ▶ Attacker \Rightarrow nature
- ▶ Imperfect observation for defender

Costs

- ▶ Cost of state $Z \Rightarrow C(Z)$
- ▶ Cost of controllable event $d \Rightarrow \hat{C}(d), d \in \mathcal{D}$

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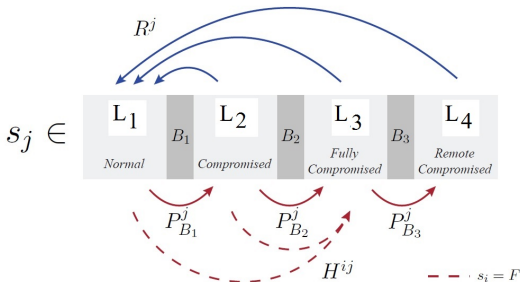
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Model: Defender and Nature Actions

Defender's Actions $\mathcal{D} = \{N^d, \{E^i\}_{i \in \mathcal{N}}, \{R^i\}_{i \in \mathcal{N}}\}$



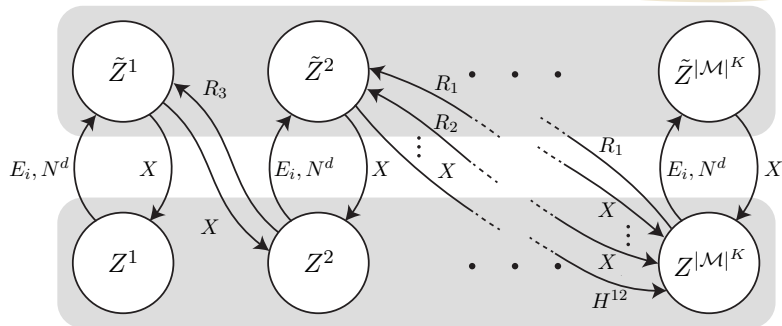
Nature's Events $\mathcal{A} = \{N^a, \{P_n^i\}_{i \in \mathcal{N}, n \in \mathcal{B}}, \{H^{ij}\}_{i,j \in \mathcal{N}}\}$

Unobservable \longleftrightarrow Observable

- ▶ Non-probabilistic dynamics

Model: System Automaton

System state before nature's event



System state before defender's action

choose best defense policy

compute worst case state trajectory under policy, g

$$\min_{g \in \mathcal{G}} \max_{\{Z_t^g \in \mathcal{Z}, t \in \mathcal{T}\}} \left\{ \sum_{t \in \mathcal{T}} \beta^t \left[C_{Z_t^g} + \hat{C}(d_t) \right] \right\}$$

subject to System dynamics

Time Complexity: Information State

Defender problem has complex information structure

- ▶ History of observations and actions

For MinMax objective function can be translated to

- ▶ All system trajectories consistent with the history

Problem: Growing in time/Countably infinite

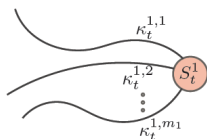
Due to Markovian and non-probabilistic dynamics can be translated to

- ▶ All possible system states and maximum cost of reaching each

Problem: Bounded but countably infinite

Solution: We propose the first approximation

$$S_t = (S_t^1, \dots, S_t^{M_t})$$



$$\kappa_t^1 = \max\{\kappa_t^{1,1}, \dots, \kappa_t^{1,m_1}\}$$

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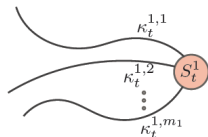
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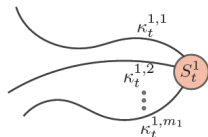
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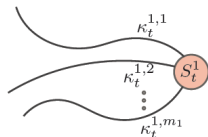
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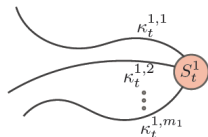
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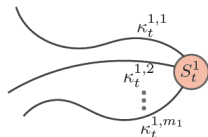
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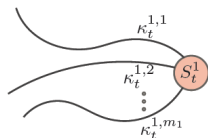
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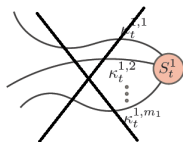


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First Approximation: Observer States

$$S_t = (S_t^1, \dots, S_t^{M_t})$$



$$S_{t+1} = f(S_t, d_t, a_t)$$

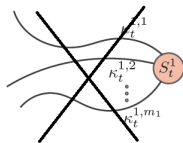
observer state

observation

defense action

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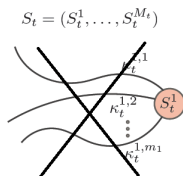


Defender's observer: the possible states that the network can be in at time t from the defender's perspective (defender has imperfect information).

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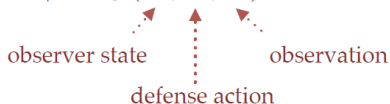


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Observer Automaton: Dynamics of observer states

The Defender's Problem (P'_D)

Problem (P'_D)

$$\min_{g \in \mathcal{G}'} \max_{z_t^g \in S_t} \left\{ \sum_{t \in \mathcal{T}} \beta^t \left[C_{z_t^g} + \hat{C}(d_t) \right] \right\} \quad (P'_D)$$

subject to model dynamics

$$d_t = g_t(S_t), \quad t \in \mathcal{T},$$

$$S_{t+1} = f(S_t, d_t, a'_t), \quad t \in \mathcal{T}.$$

$$\mathcal{G}' := \{g \mid g := \{g_t, t \in \mathcal{T}\}, g_t : \mathcal{S} \rightarrow \mathcal{D}, d_t = g_t(S_t) \text{ for all } t \in \mathcal{T}\}.$$

Numerical Sensitivity Analysis for Two Computers

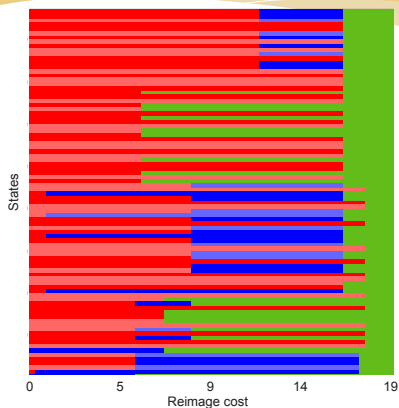


Figure: Optimal defender policy (Reimage, Sense, Null) with increasing cost of Reimage.

- ▶ **Threshold in Costs** - If $d^*(S1) = Reimgae$, by decreasing the cost of Reimage, it remains optimal action.
- ▶ **Duality of Control and Estimation** - There is no Sensing action in the optimal policy when there is no Reimage.

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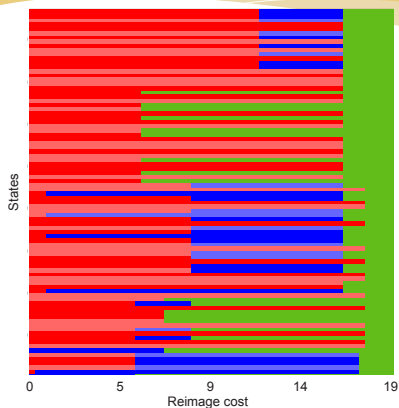


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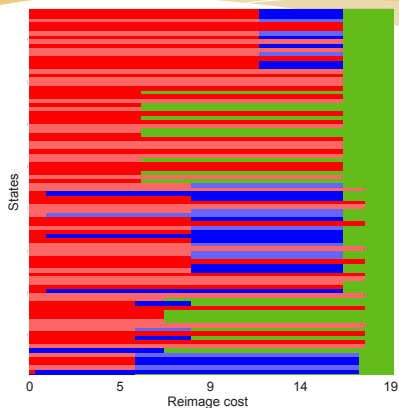


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Network Scale Complexity

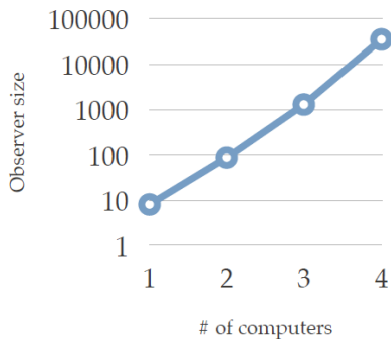


Figure: Number of observer states

Solution: We propose the second approximation

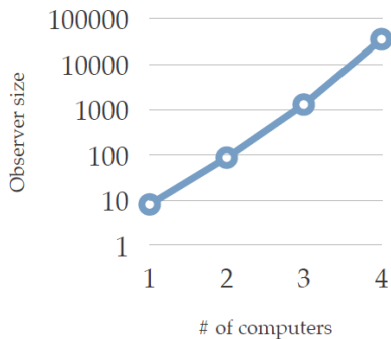
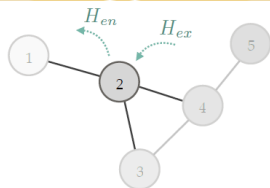


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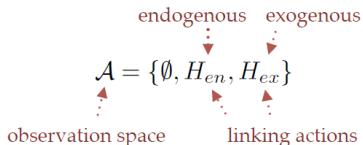
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Second Approximation: Decomposition and Parallel Computation

1. Consider **individual computers** coupled to other computers by **endogenous** and **exogenous** events.
2. Assume **exogenous** events are always possible.



For node 2: $S_t = \{\{L_1\}, \{L_1, L_2\}, \{L_2, L_3\}, \{L_3, L_4\}\}$



Numerical Results: Sets of policies for each computer

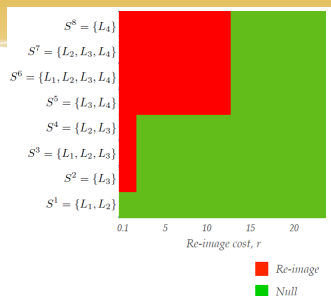


Figure: Computation based on local information

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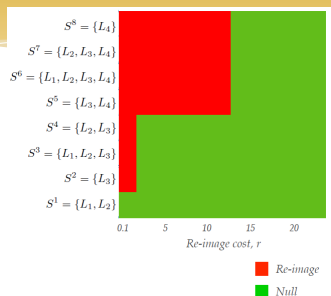


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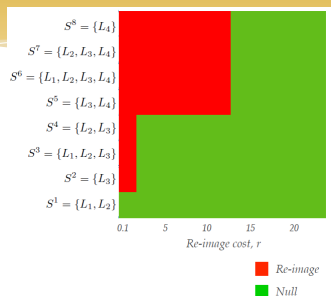


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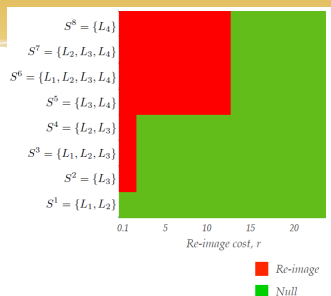


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- ▶ **Supervisory control approach to dynamic cyber-security** from defender's perspective with **imperfect information**, progressive attacks, and min-max performance criterion by use of **system automaton**
- ▶ Capturing **complexity** in **time** and **scale of the network**
- ▶ Dynamic programming with numerical results for determining defender's optimal min-max actions at each instant of time
- ▶ Structural properties
 - ▶ Threshold behavior: costs of actions/states, observer states
 - ▶ Grouping: Observer states with same optimal policies

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- ▶ Extending approximations and using structural results for scalability
- ▶ Extending to probabilistic events (Bayesian framework)
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Thank you

Appendix: observer automaton

Construction of observer automaton based on system automaton using UMDES-LIB software library available on <https://www.eecs.umich.edu/umdes/toolboxes.html>.

