Lateral Movement Detection and Response

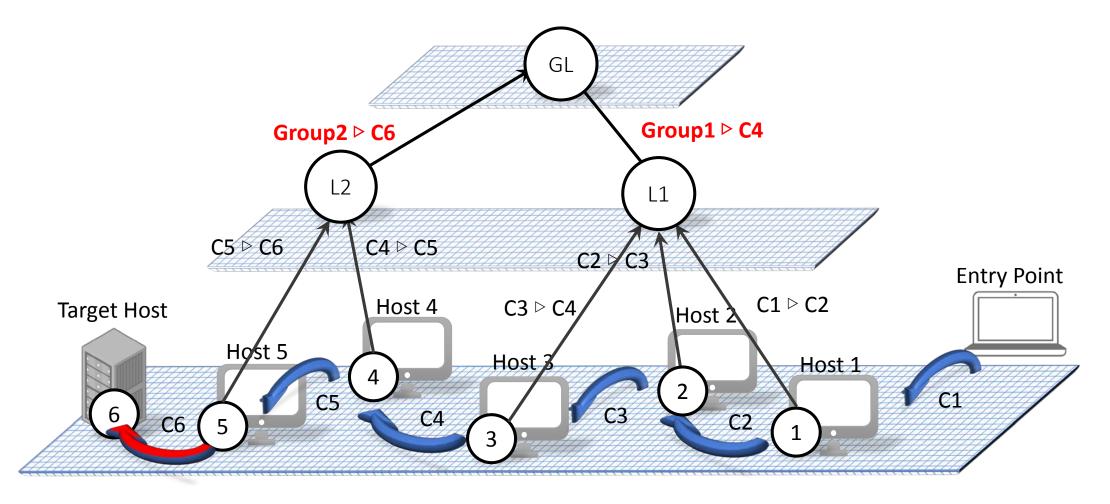
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Lateral Movement Detection

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A critical step during APT to move from the entry point to target host



Response to Lateral Movement

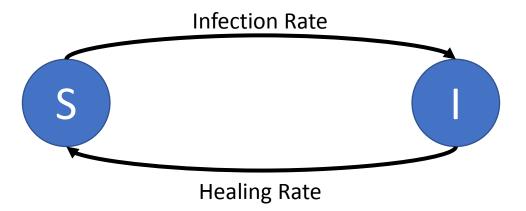
- Achieve resiliency against lateral movement
- Resilience by stopping virus spread while maintaining acceptable service availability, as opposed to disconnecting the whole network

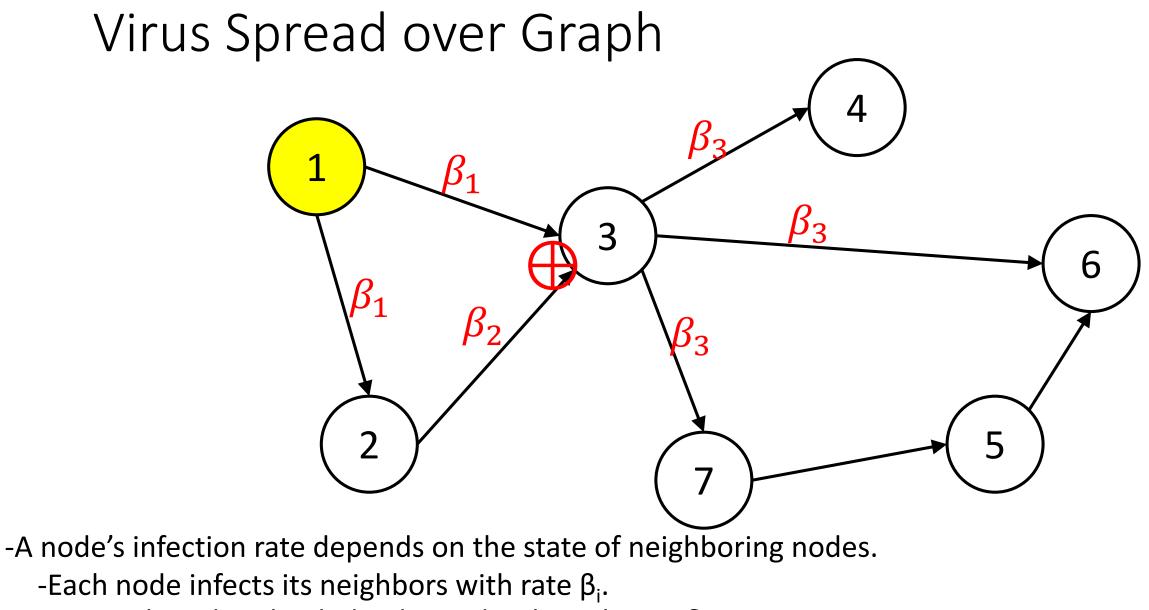
Strategy:

- 1. Learn attacker movement
- 2. Respond by limiting connectivity to stop spread
- 3. Recover the system

Lateral Movement Model

- Susceptible-infected-susceptible (SIS) CTMC virus spread model
- A node can be in two states: {Susceptible, Infected}
- Nodes are not cured





-Each node is healed independently with rate δ_i .

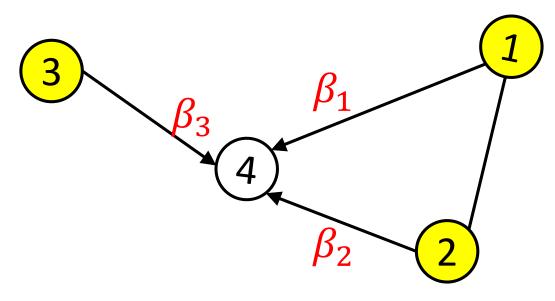
Spread Dynamics

The total system dynamics as N-intertwined CTMCs:

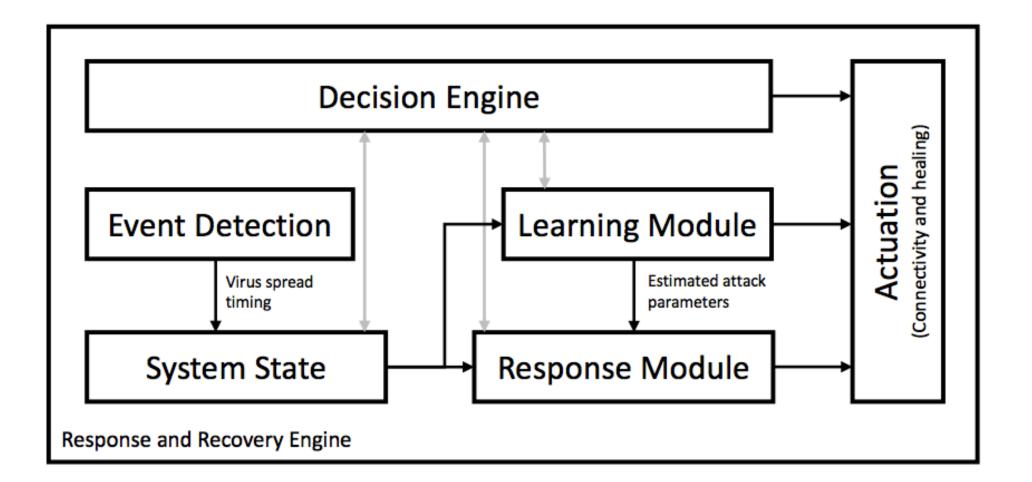
 $\dot{p} = (AB - P(t)AB - D)p$

Controllable parameters:

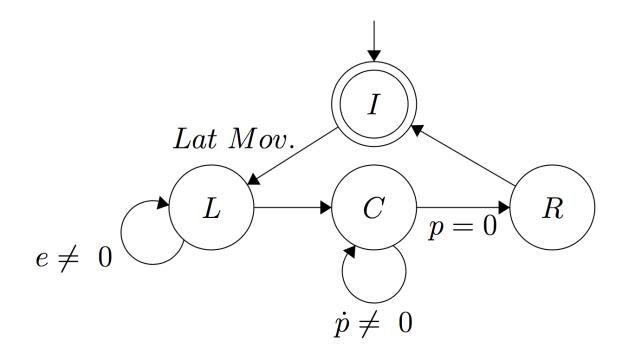
- The connectivity graph A
- The healing rate **D** = diag($\delta_1, ..., \delta_n$) Unknown:
- The infection rate **B** = diag($\beta_1, ..., \beta_n$)



Response and Recovery Engine



RRE Decision Modes



Initial: no infection

Learn: estimate attacker parameters

Containment: stop attacker spread

Recovery: return system to secure state

Learning Phase

- Estimate the infection rate of each node when it's neighbors are infected.
- Measure the duration to infect a node using lateral movement chains $\mathcal{S}_i=(s_1,s_2,\ldots,s_m)$ where $s_i=t-t_{ ext{healed}}$
- Use the ML estimator: $\widehat{\lambda}$

$$\widehat{\Lambda_i} = \frac{m}{\sum_j s_i}$$

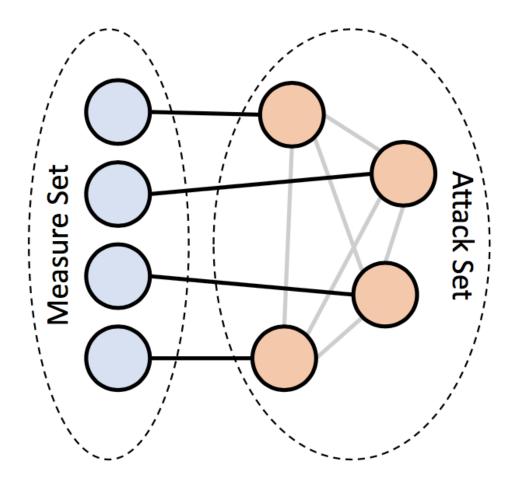
Learning Strategy

- Naïve approach: all nodes infected, heal one node at a time for sample collection
 - Slow learning
 - Highest availability
- Optimal approach: find independent sets as the minimal coloring of a graph
 - Finding coloring is NP-hard

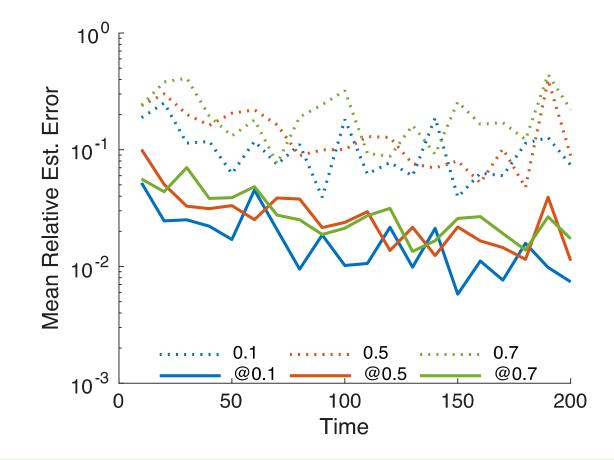
Dynamic Strategy

- Divide nodes to attack set and measure set.
- Attack set is fully connected.
- Measure set has limited connectivity to the attack set.
- Switch the roles after data is collected.

• Solve:
$$Aeta = \widehat{L}$$



Estimation Error



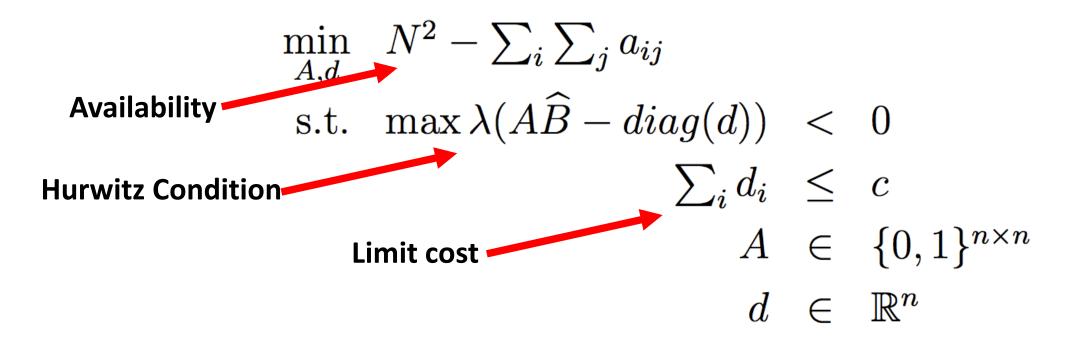
- Error decreases as more data is collected
- A sparse connectivity matrix performs better overall

Containment Phase

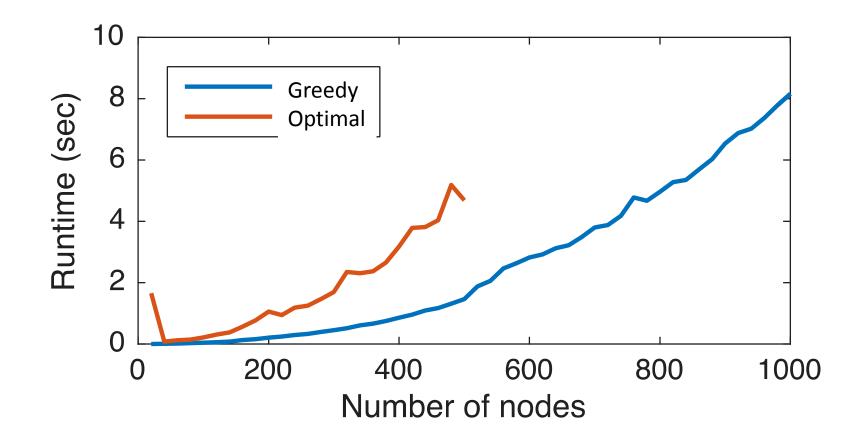
- After learning the parameters; we find the connectivity and healing rates to stop the spread
- Goal: achieve a globally asymptotic stable (GAS) disease-free equilibrium (DFE)
 - Starting from an initial state
 - Consequence: $p \rightarrow 0$ with an exponential decay
- Pick A,D such that (AB-D) is Hurwitz

Resiliency during Containment

- Maximize availability such that A and D result in a stable DFE.
- Encoded as a Mixed-Integer Nonlinear Optimization Problem



Connectivity matrix



The optimal solver cannot find matrices for N>500

• The greedy solver is faster but the solutions are suboptimal

Simulation of RRE

Error of parameter estimation error 4 p₁(t) Error β_1 Probability of Compromise p(t) 3 Error β_2 $p_2(t)$ 0.8 Error β_3 $p_3(t)$ 2 Estimation error $p_4(t)$ Error β_{\star} 0.6 Error β_{4} $p_5(t)$ 0 0.4 - response starts -1 0.2 -2 -3 0 1000 2000 20 3000 10 30 0 0 Time (sec) Time (sec)

Parameters: N=5, topology changes, infection randomly selected for the experiment run, healing constant 16

State evolution over time during the response phase

Conclusion

- RRE achieves resilience by limiting connectivity during healing and learning
- Method is robust against estimation error and clock drifts
- Containment is theoretically fast

Future Work

- Design a feedback controller that uses learned estimates
 - Improve estimate
 - Robustness to errors
 - Maximize connectivity

State estimation: $\hat{p} = f(\tilde{\beta}, A, D)$ Measurements: $p = \{0, 1\}$ Feedback controller: $D = \gamma \cdot \hat{p}$ such that $\gamma > 0$