



Stealthy Epidemics: Modeling Worm Attacks against CPS

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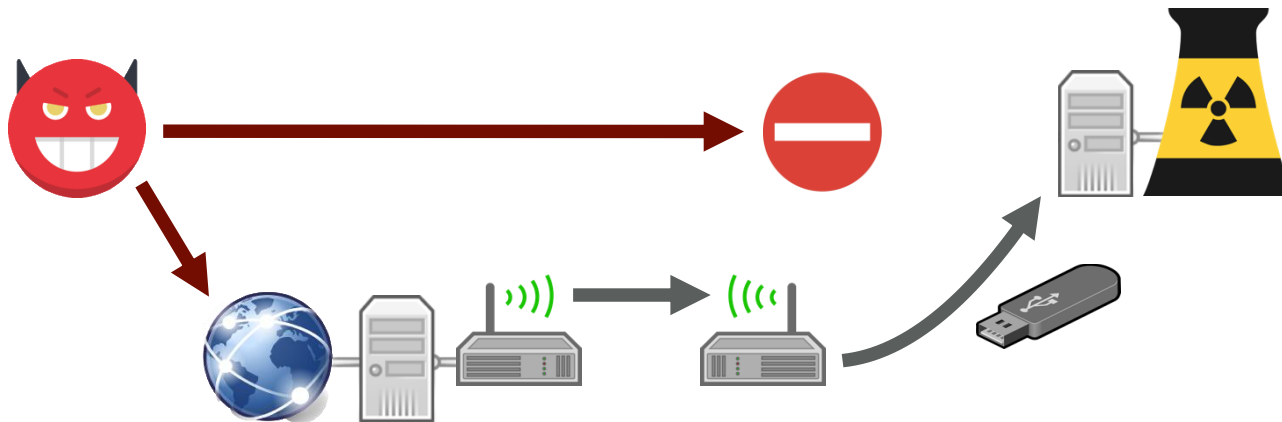
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Motivation

- * Highly sensitive systems, such as CPS for critical infrastructure, are usually supposed to be secured by the “air gap”
- * However, computer worms that propagate over local networks and removable drives may infect even these systems
 - * e.g., Stuxnet infected Iranian nuclear facilities



Examples of Worm-Based Attacks #1

- * Stuxnet worm
 - * targeted Iranian uranium enrichment facilities
 - * initially sent to companies working on industrial control systems in Iran
 - * propagated over local area networks and removable drives
 - * drastically reduced the lifetime and reportedly ruined almost one-fifth of Iran's nuclear centrifuges

<http://www.businessinsider.com/stuxnet-was-far-more-dangerous-than-previous-thought-2013-11>



Examples of Worm-Based Attacks #2

- * Shamoon worm
 - * targeted energy companies in the Middle East, including Saudi Aramco and Qatar's RasGas
 - * initially deployed on an Internet connected computer at Saudi Aramco
 - * removed and overwrote information on hard drives
 - * incapacitated 30,000 to 55,000 workstations at Saudi Aramco

<http://www.bbc.com/news/technology-19293797>



Resilience to Worm-Based Attacks

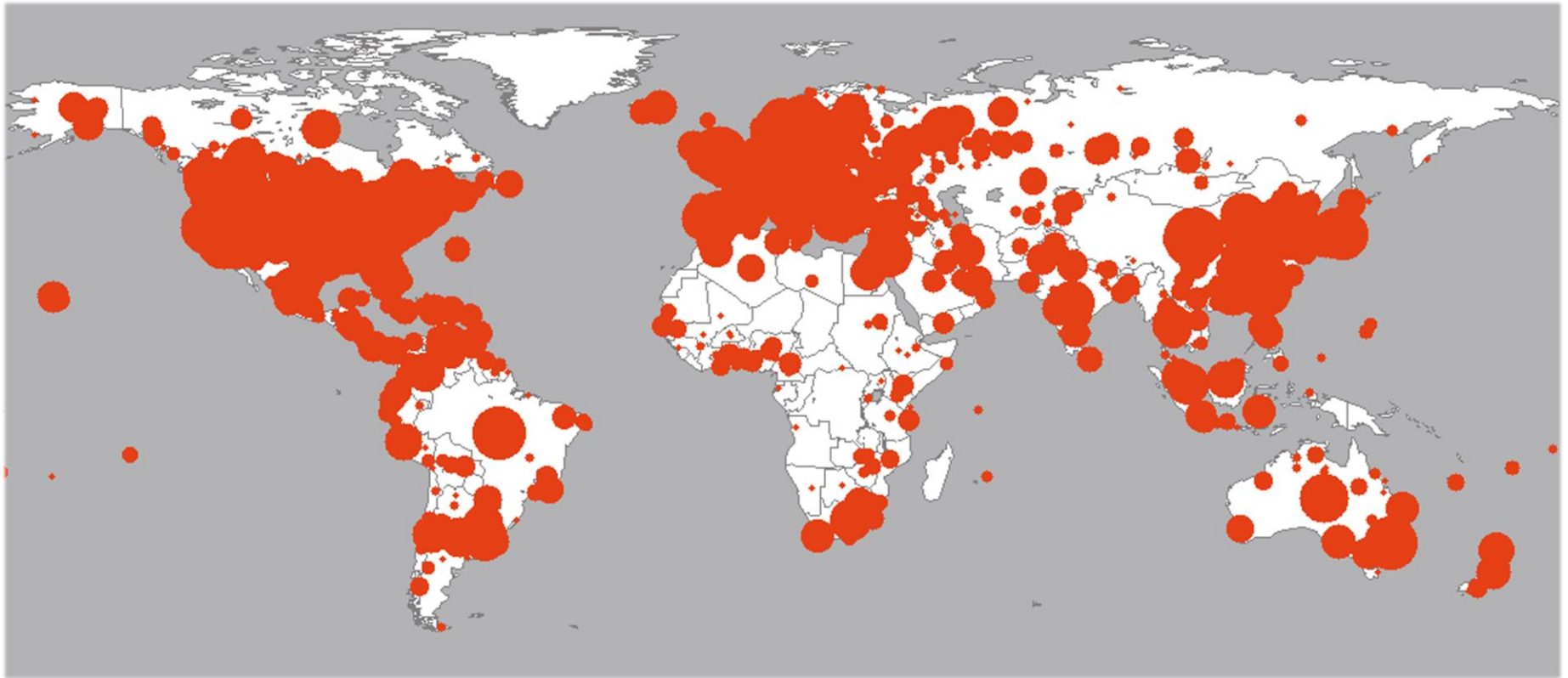


- * To stop a worm, we can
 - * create antivirus signatures
 - * patch vulnerabilities
 - * ...
- * However, before we can implement these countermeasures, we first have to **detect the worm**
- * Furthermore, it is imperative that we detect the worm **in time**
 - * worm detection and alerting operators take some time
 - * implementing countermeasures takes some time
- Attack-resilience depends on the **timely detection of worms**

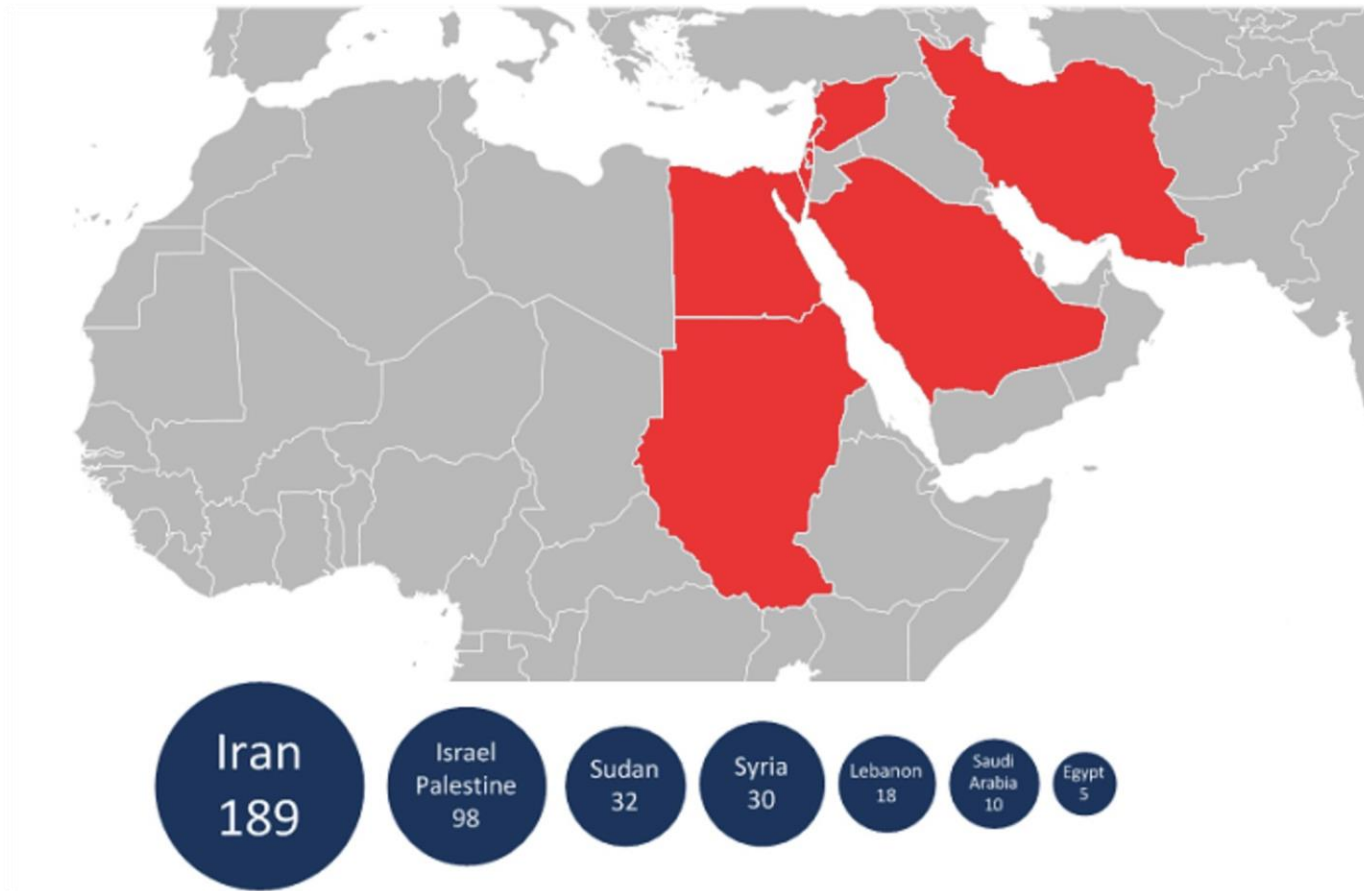
Previous Work on Modeling Worms

- * Mostly based on epidemic and influence maximization models
 - * primarily concerned with **steady** or **equilibrium states**
- * Generally, they do not consider the detection problem
 - * in practice, a worm can be eradicated once it has been discovered
 - * steady or equilibrium state might not be reached by the **time of detection**
- * More importantly, they do not consider targeted attacks
 - * usual assumption is that the worm is trying to infect as many computers as possible
 - * targeted worms may try to be **stealthy** to avoid early detection

Non-Targeted Worm Example: Code Red (2001)



Targeted Worm Example: Flame (2012)



Outline

* Model

Network model

Propagation model

Detection model

* Results

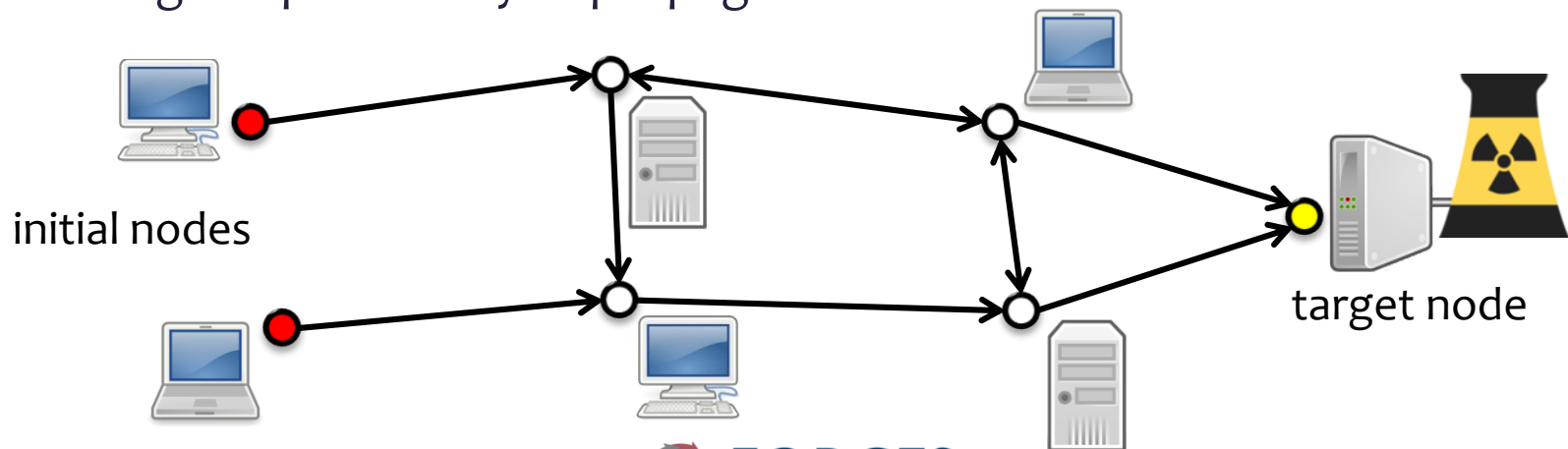
- * computing the probability of detection
- * optimal assignment of resources to detection

Non-strategic attacks

Strategic attacks

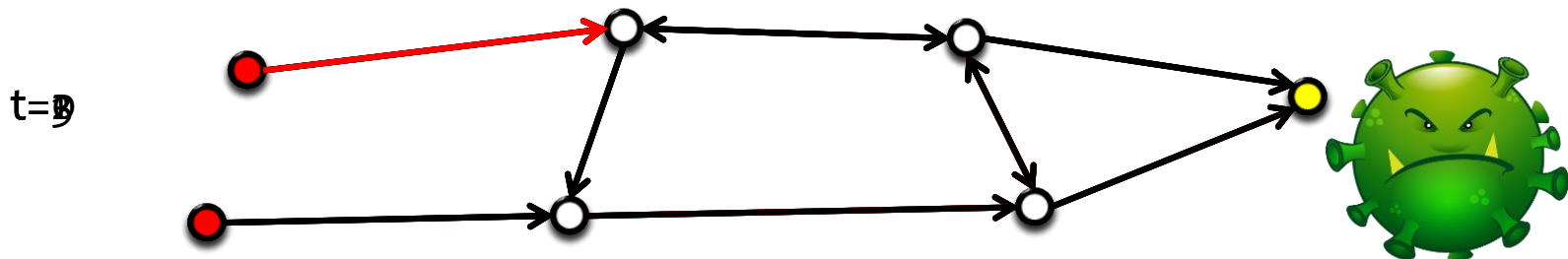
Network Model

- * Directed graph $G = (V, E)$
 - * node = computer system (or tightly coupled group of computers that can be infected together)
 - * edge = possible infections
 - * e.g., local area connections, regularly shared removable drives
 - * weight = probability of propagation



Propagation Models

- * Time
 - * at the beginning, only the initial nodes are infected
 - * in each time step, additional nodes may be infected
- * **Independent cascades** model
 - * nodes that were infected in the previous round may infect their neighbors
- * **Repeated independent cascades** model
 - * nodes that are infected may infect their neighbors



Monitored Nodes

- * Monitored nodes
 - * in order to detect worms, a defender monitors some nodes
 - * e.g., performing thorough audits
 - * since monitoring is costly, at most k nodes can be monitored
 - * furthermore, the set of nodes that can be monitored is restricted
 - * e.g., nodes that are not operated by the defender cannot be monitored
- * Delayed detection
 - * mitigation is successful if the worm reaches a monitored node m at least D_m time steps **before** it reaches the target (or if it never reaches the target)

Problem Formulation

- * Goal:

select a set of k monitored nodes M that maximizes the probability of detection $U(M)$

- * Formulations

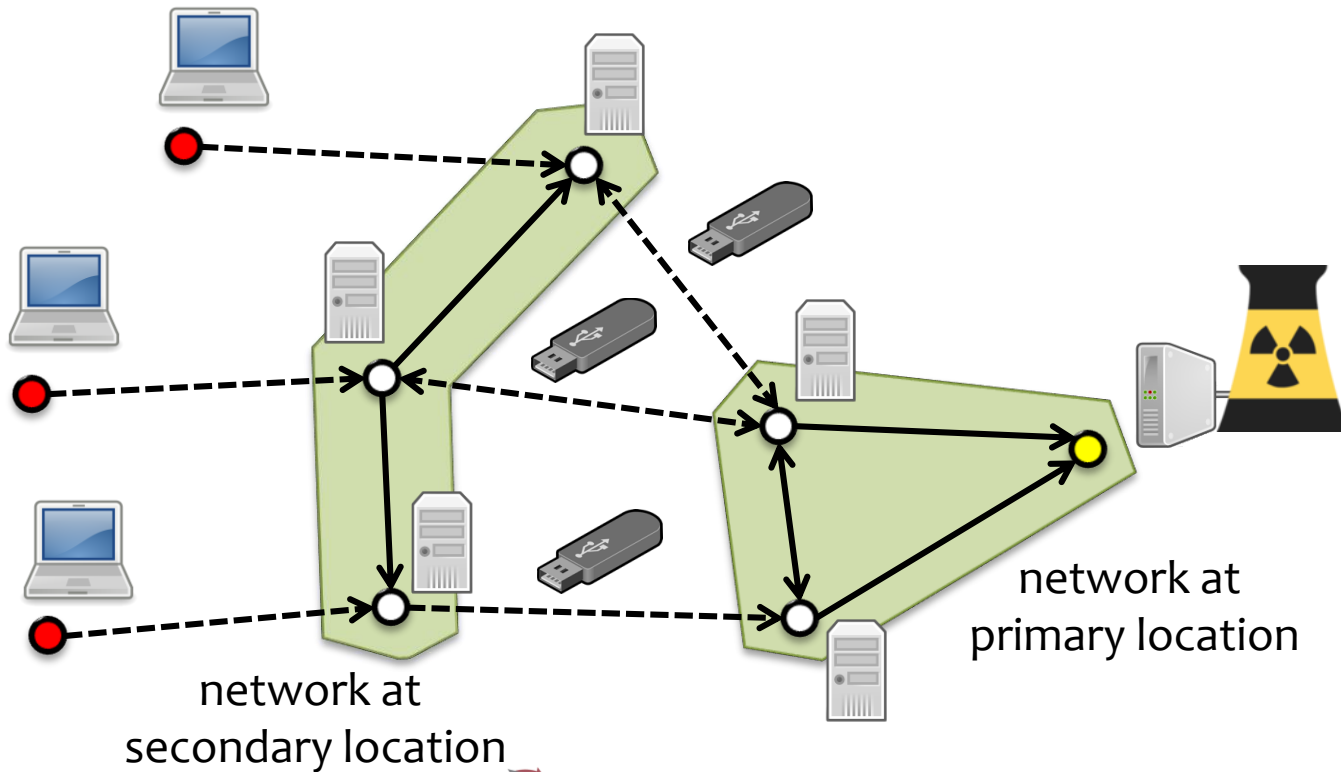
- * **non-strategic attacks:** fixed set of initial nodes

- * e.g., nodes that are connected to the Internet

- * **strategic attacks:** set of initial nodes is chosen by an attacker, who wants to minimize the probability of detection

- * set of possible initial nodes S is restricted (e.g., nodes that are connected to the Internet)

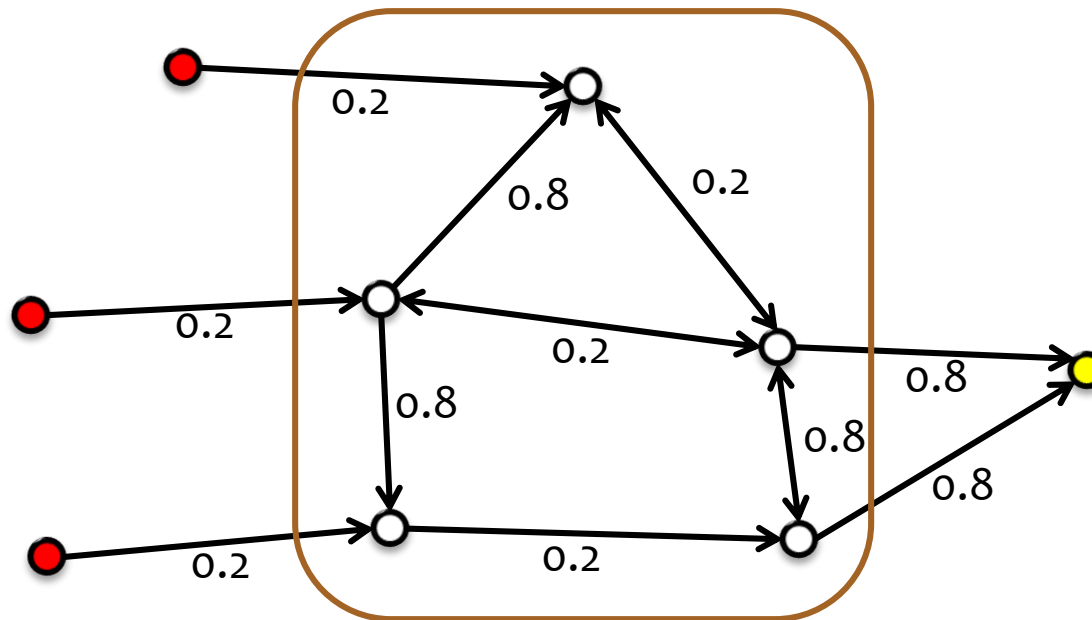
Selection Example



Selection Example

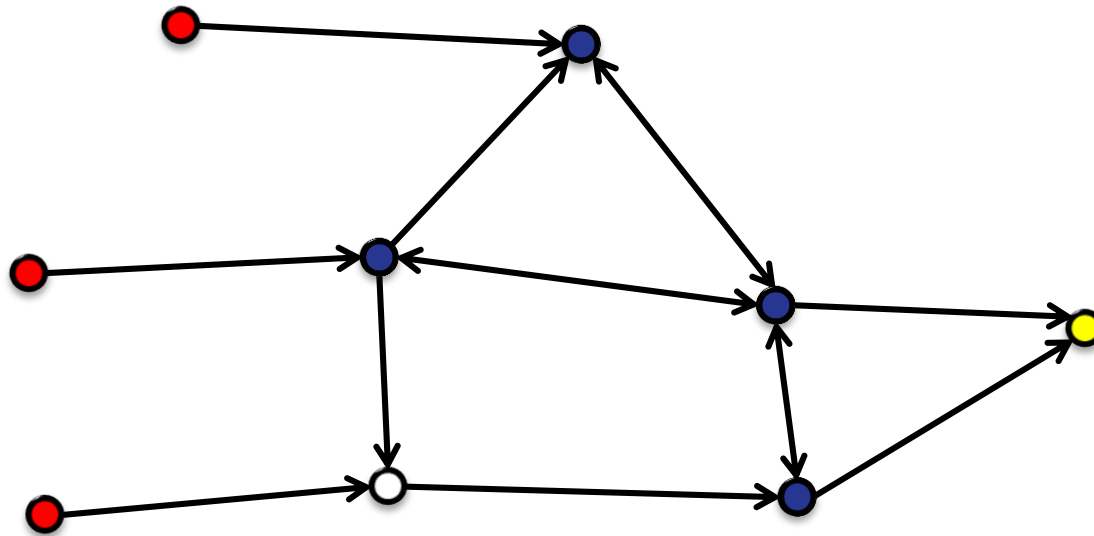
- * Monitoring budget: $k = 2$

set of possible monitored nodes



Selection Example

- * Monitoring budget: $k = 2$
- * Detection delay: $D = 2$



Computing the Probability of Timely Detection

Computing the probability of detection $U(M)$ for a given set of monitored nodes M is a #P-hard problem.

- * #P is the set of counting problems associated with the decision problems in the set NP
- * However, we can use simulations
 - * error can be bounded using Hoeffding's inequality

Optimal Monitoring against Non-Strategic Attacks

- * Non-strategic = fixed set of initial nodes for the worm
- * Computational complexity:

Finding a $(1 - 1/e + o(1))$ -
approximately optimal monitored set
is NP-hard.

Optimal Monitoring against Non-Strategic Attacks

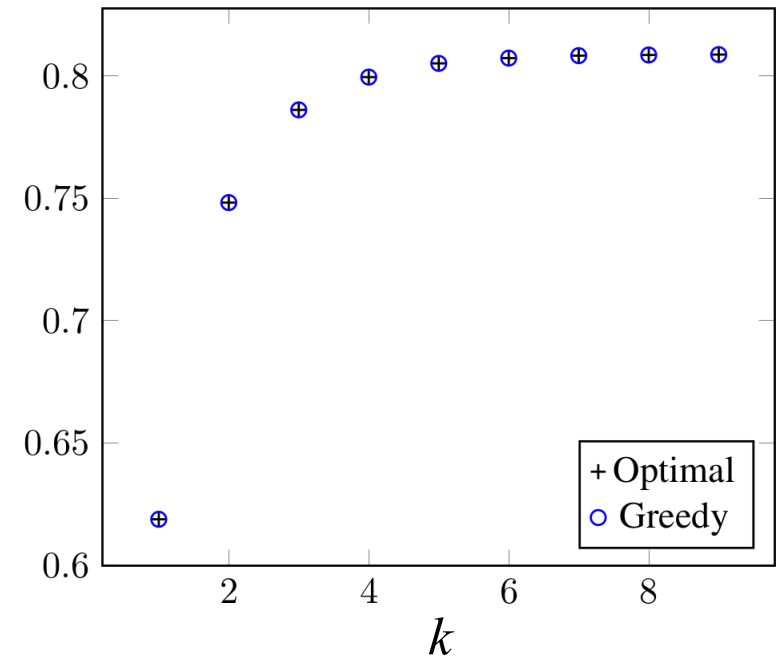
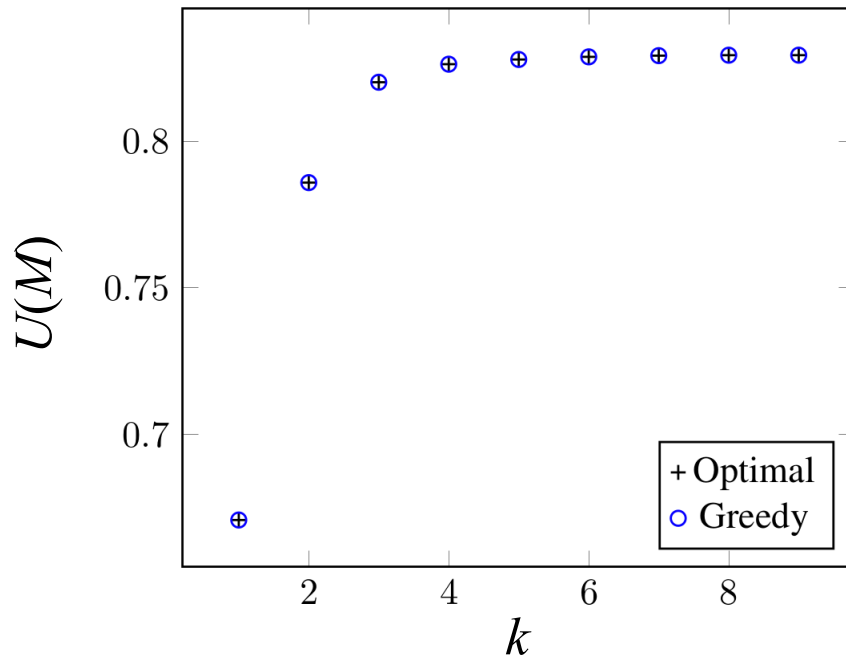
- * Non-strategic = fixed set of initial nodes for the worm
- * Computational complexity
- * Approximation:

The probability $U(M)$ is a non-decreasing submodular set function of M .

For any $\varepsilon, \delta > 0$, a greedy algorithm running in time $\text{poly}(|V|, 1/\varepsilon, \ln(1/\delta))$ returns a set M such that with probability $1 - \delta$,

$$U(M) \geq (1 - 1/e) U(OPT) - \varepsilon.$$

Numerical Results for Non-Strategic Attacks



B-A graphs with 3 node clique and 3 edges per new node.

E-R graphs with 0.5 edge presence probability.

Randomly generated graphs with 100 nodes, 5 randomly chosen initial nodes, 10 randomly chosen possible monitored nodes, 1 randomly chosen target node, all edges having propagation probability 0.5, independent cascades propagation model, and 1 time step detection delay. Values are averages taken over 10 graphs.

Optimal Monitoring against Strategic Attacks

- * Strategic attacks = worst-case set of initial nodes for the worm
- * Computational complexity:

For any ε , finding a set M of size at most $(1 - \varepsilon) \ln(|S|)$ such that

$$U(M) / U(OPT) > 0$$

is NP-hard.

Optimal Monitoring against Strategic Attacks

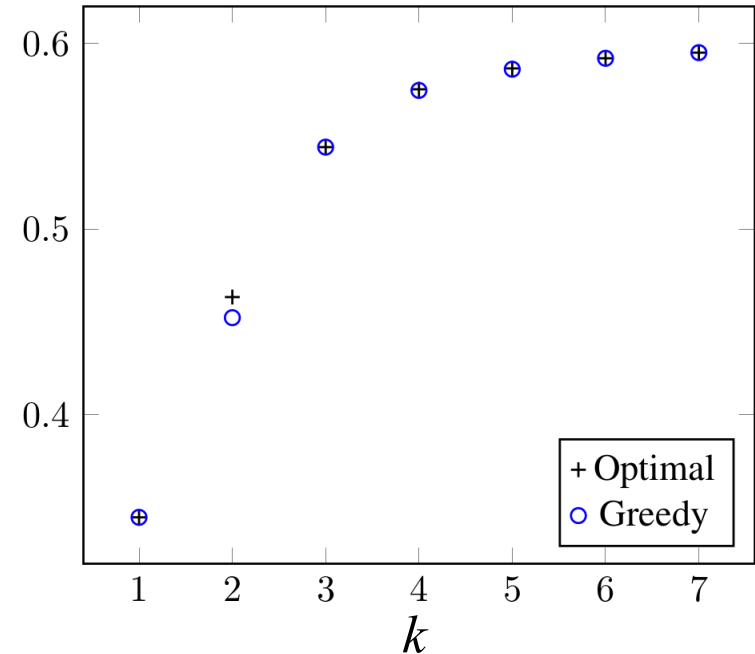
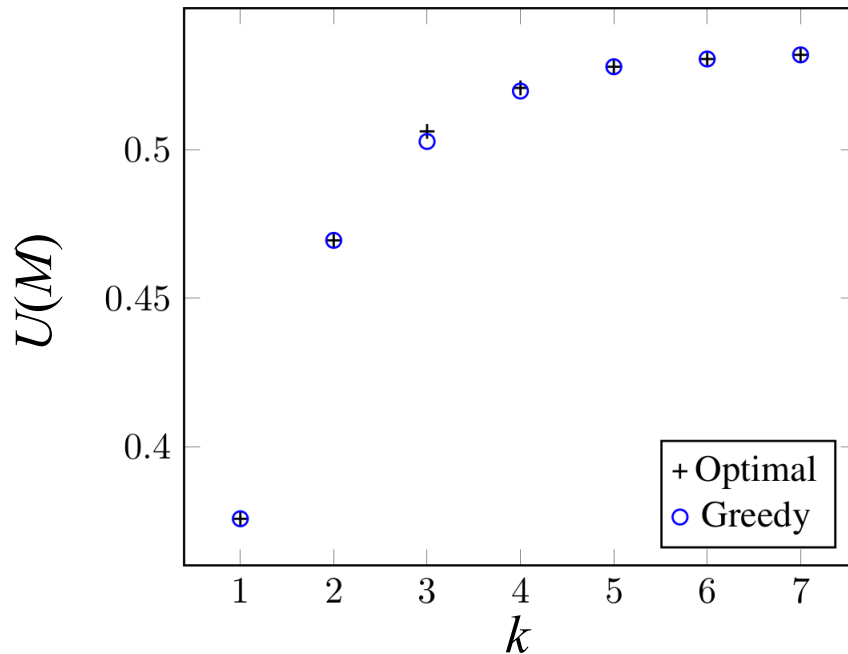
- * Strategic attacks = worst-case set of initial nodes for the worm
- * Computational complexity
- * Approximation:

For any $\varepsilon, \gamma, \delta > 0$, we can find a set M in time $\text{poly}(|V|, 1/\varepsilon, 1/\gamma, \ln(1/\delta))$ such that $|M| \leq |S| k \ln(1/\varepsilon)$ and with probability $1 - \delta$,

$$U(M) \geq (1 - 1/e) U(OPT) - \gamma.$$

- * algorithm: iterate over the set of possible initial nodes, and for each node s , select $k \ln(1/\varepsilon)$ monitored nodes in a greedy manner supposing that the attacker will select $\{s\}$ as the set of initial nodes

Numerical Results for Strategic Attacks



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E-R graphs with 0.5 edge presence probability.

Randomly generated graphs with 100 nodes, 5 randomly chosen possible initial nodes, 10 randomly chosen possible monitored nodes, 1 randomly chosen target node, all edges having propagation probability 0.5, independent cascades propagation model, and 1 time step detection delay. Values are averages taken over 10 graphs.

Conclusion

- * Computer worms pose a serious threat to critical CPS
- * In order to be resilient to such attacks, we have to be able to detect worms in time
- * Selection of monitored nodes must be carefully planned
- * Computational results
 - * challenging, but can be solved
- * Open problem: finding an optimal attack
 - * NP-hard
 - * but can we approximate it efficiently?

Thank you for your attention!

Questions?