Toward Understanding Spatial Dependence on Epidemic Thresholds in Networks

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Social Influence in Online Social Networks

- Viral marketing ("word-of-mouth")
- Blog information cascading
- Rumor spreading
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Bear a resemblance to epidemic process!

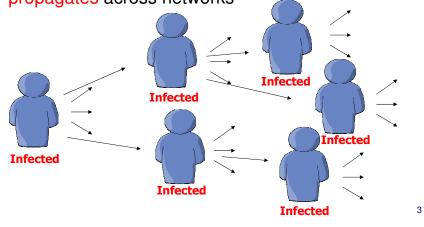


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Epidemic Process

 Epidemic process is a process that information selfpropagates across networks





Epidemiological Models

- Susceptible-infected-recovered (SIR) model for independent cascading influence spread
- Susceptible-infected-susceptible (SIS) model for blog information cascading
- Susceptible-infected-cured (SIC) model for rumor and anti-rumor propagation



Epidemic Thresholds

- Fundamental metric used to evaluate epidemic spread
- Condition on which an information will either die out or become epidemic
 β
- In SIS model,
 - Birth rate
 - Death rate
 - $\hfill\square$ Ratio between birth rate and death rate
 - ${\scriptstyle \bullet}~\beta \ / \ \delta >$ epidemic threshold, become epidemic
 - \blacksquare β / δ <= epidemic threshold, die out



State of the Art

 $\tau = \frac{1}{\lambda_{max}(A)}$

λ_{max}(A) is the largest eigenvalue of the adjacency matrix A of the network

Assume that the status of nodes in the network are independent of each other!



Questions

- Can spatial dependence among nodes affect the epidemic threshold? If so, how significantly?
- How can we derive a more accurate epidemic threshold, taking into consideration a certain spatial dependence?
- Can the birth rate and the death rate affect the spatial dependence and thus the epidemic threshold? If so, how?



Outline

- Mathematical Framework
- Epidemic Thresholds in Regular Graphs
- Epidemic Thresholds in Arbitrary Networks

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Mathematical Framework

• $X_i(t)$: status of node <i>i</i> at time <i>t</i>
$X_i(t) = \begin{cases} 0, & if susceptible \\ 1, & if infected \end{cases}$
$\delta = P(X_i(t+1) = 0 X_i(t) = 1)$
$I_i(t) = P(X_i(t+1) = 1 X_i(t) = 0)$
$P(X_i(t+1) = 1) = P(X_i(t) = 1)(1 - \delta) + P(X_i(t) = 0) I_i(t)$



Mathematical Framework

$$I_{i}(t) = \sum_{\mathbf{x}_{N_{i}}(t)} P(X_{i}(t+1) = 1, \mathbf{X}_{N_{i}}(t) = \mathbf{x}_{N_{i}}(t) | X_{i}(t) = 0)$$
$$= \sum_{\mathbf{x}_{N_{i}}(t)} P(\mathbf{X}_{N_{i}}(t) = \mathbf{x}_{N_{i}}(t) | X_{i}(t) = 0) \left[1 - \prod_{j \in N_{i}} (1 - \beta)^{x_{j}(t)} \right]$$
$$= 1 - E \left[\prod_{j \in N_{i}} (1 - \beta)^{X_{j}(t)} | X_{i}(t) = 0 \right],$$
(6)

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- Mathematical Framework
- Epidemic Thresholds in Regular Graphs
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Epidemic Thresholds in Regular Graphs

- It has been shown that the epidemic threshold proposed in previous work does not work well in regular graphs.
- More importantly, due to the symmetric property of regular graphs, we can derive a closed-form expression for the epidemic threshold.



Independent Model

Assume spatial independence between nodes

$$I_{i}(t) = 1 - \prod_{j \in N_{i}} E\left[(1 - \beta)^{X_{j}(t)}\right]$$

= $1 - \prod_{j \in N_{i}} [1 - \beta P(X_{j}(t) = 1)]$
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$$\tau_{c,ind}=\frac{1}{k}$$

where k is the average nodal degree and the largest eigenvalue of adjacency matrix



Markov Model

- Assume spatial Markov dependence
- Inspired by the local Markov property of Markov Random Field

$$I_{i}(t) = 1 - \prod_{j \in N_{i}} E\left[(1 - \beta)^{X_{j}(t)} \middle| X_{i}(t) = 0 \right]$$

= $1 - \prod_{j \in N_{i}} [1 - \beta P(X_{j}(t) = 1 | X_{i}(t) = 0)]$

$$\boldsymbol{\tau_{c,mar}} = \frac{1}{k(1-\rho)}, \quad \rho = \frac{2\beta(1-\delta)}{(2\delta-\delta^2)+2\beta(1-\delta)}$$



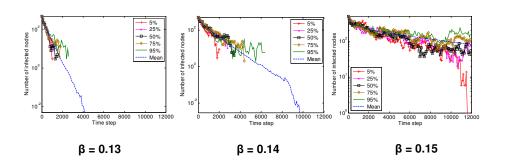
Simulation Setup

- Simulator is based on discrete time and random number generator
- Run 1000 times for each scenario
- Run long enough so that it reaches the steady state (e.g., 12000 time steps)
- Assign half of nodes to be infected initially

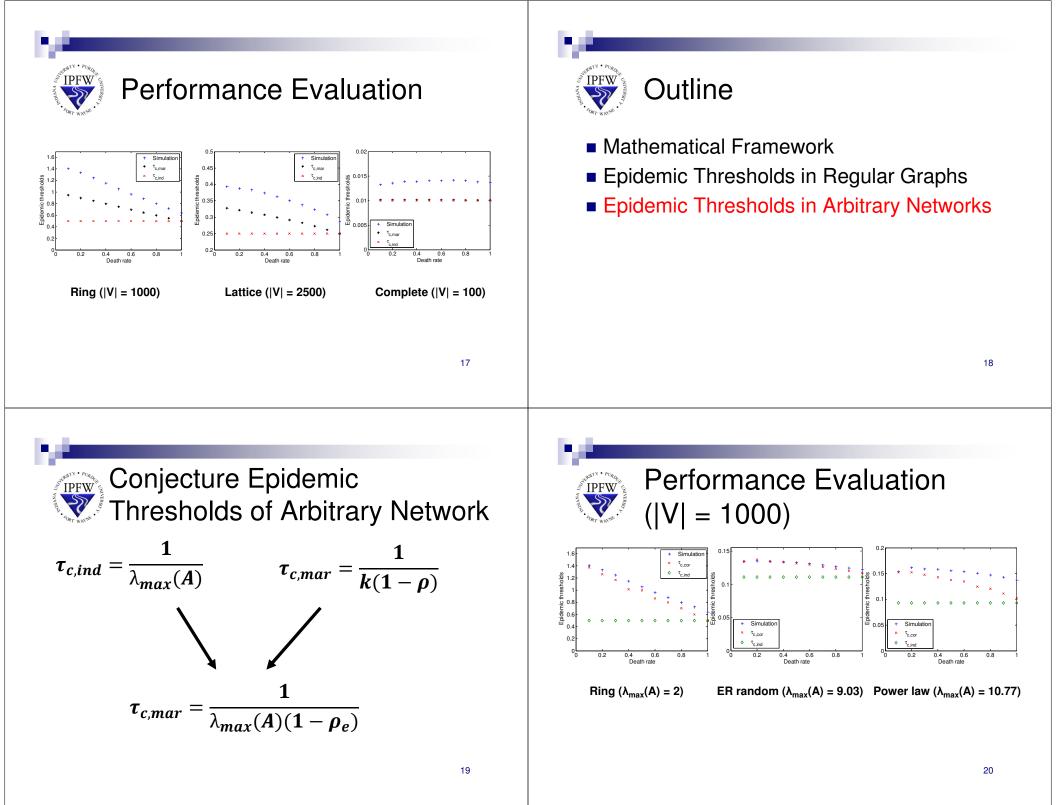


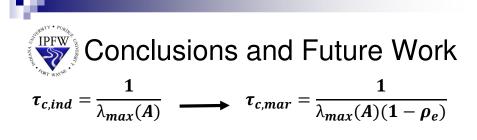
Sample Run of Epidemic Spread in a Ring Graph

• $\delta = 0.1$ and |V| = 1000



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Future work

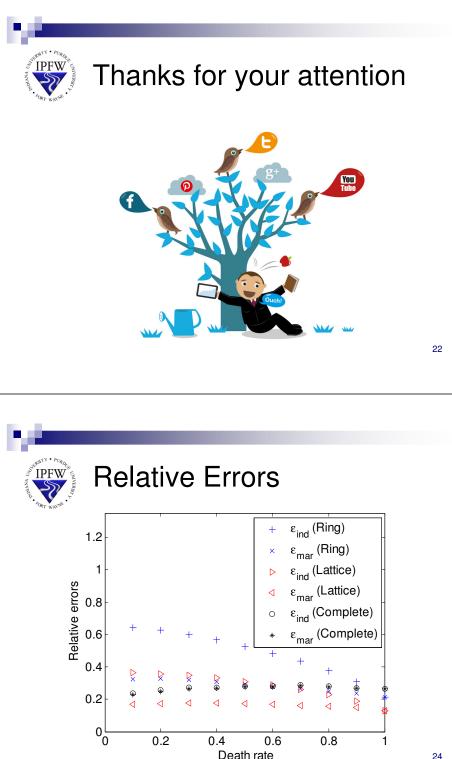
- Derive the equation for epidemic thresholds in irregular graphs
- □ Apply our observations for predicting and controlling the dynamics of the epidemic spreading process





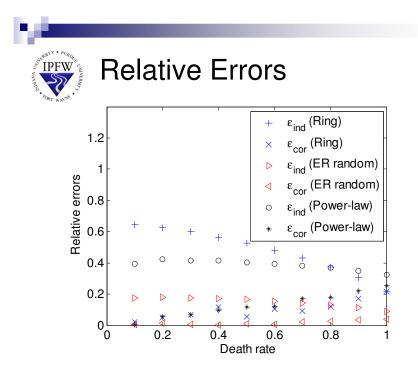
Algorithm 1 Finding epidemic threshold τ_c

Input: δ , β_{low} , β_{high} **Output:** τ_c while $\beta_{high} - \beta_{low} > \epsilon$ do $\beta = (\beta_{high} + \beta_{low})/2$ Simulate epidemic spread using β and δ Average the number of final infections over 1000 runs and get *avg_inf_num* if $avg_inf_num > 0$ then $\beta_{high} = \beta$ else $\beta_{low} = \beta$ end if end while $\tau_c = \beta_{low} / \delta$





Algorithm 2 Finding spatial correlation coefficient ρ_e Input: δ , τ_c , β_s **Output:** ρ_e Set $\beta = \tau_c \times \delta$ and found = 0while found = 0 do Simulate epidemic spread using β and δ Average the number of final infections over 1000 runs and get *avg_inf_num* Average the correlation coefficient over 1000 runs and get ρ if $avg_inf_num \ge 1$ then $\rho_e = \rho$ found = 1end if $\beta = \beta + \beta_s$ end while 25



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Correlation Coefficients at Epidemic Thresholds in Ring Graph (|V| = 1000)

