N-Intertwined Mean-Field Approximation (NIMFA) versus exact SIS epidemics on Networks

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Epidemics on Networks: Current Trends and Challenges Girona, September 5-7, 2012



Outline

Exact SIS model



NIMFA: N-intertwined MF approximation

Defining the SIS epidemic threshold

Summary



Simple SIS model on networks

- Homogeneous birth (infection) rate β on all edges between infected and susceptible nodes
- Homogeneous death (curing) rate δ for infected nodes



Definition of the states in SIS

- Each node *j* can be in either of the two states:
 - "0": healthy
 - "1": infected
- Markov continuous time:
 - infection rate β
 - curing rate δ
- Mathematically:

 - X_j is the state of node j infinitesimal generator $Q_j(t) = \begin{bmatrix} -q_{1j} & q_{1j} \\ q_{2j} & -q_{2j} \end{bmatrix} = \begin{bmatrix} -q_{1j} & q_{1j} \\ \delta & -\delta \end{bmatrix}$





Governing SIS equation for node *j*

$$\frac{dE[X_j]}{dt} = E\left[-\delta X_j + (1 - X_j)\beta\sum_{k=1}^N a_{kj}X_k\right]$$

time-change of
E[X_j] = Pr[X_j = 1],
probability that
node *j* is infected
time-change of
E[X_j] = Pr[X_j = 1],
probability of
unit time
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$$\frac{dE[X_j]}{dt} = -\delta E[X_j] + \beta \sum_{k=1}^N a_{kj} E[X_k] - \beta \sum_{k=1}^N a_{kj} E[X_j X_k]$$



Joint probabilities

$$\frac{dE[X_iX_j]}{dt} = E\left[-2\delta X_iX_j + X_j\beta(1-X_i)\sum_{k=1}^N a_{ik}X_k + X_i\beta(1-X_j)\sum_{k=1}^N a_{jk}X_k\right]$$

$$= -2\delta E[X_iX_j] + \beta \sum_{k=1}^N a_{ik} E[X_jX_k] + \beta \sum_{k=1}^N a_{jk} E[X_iX_k] - \beta \sum_{k=1}^N (a_{jk} + a_{ik}) E[X_iX_jX_k]$$

Next, we need the $\begin{pmatrix} N \\ 3 \end{pmatrix}$ differential equations for E[X_iX_jX_k]...

In total, the SIS process is defined by $2^N = \sum_{k=1}^N \begin{pmatrix} N \\ k \end{pmatrix} + 1$ linear equations

E. Cator and P. Van Mieghem, 2012, "Second-order mean-field susceptible -infected-susceptible epidemic threshold", Physical Review E, vol. 85, No. 5, May, p. 056111.











Recursive structure of infinitesimal general Q_N

Van Mieghem, P. and E. Cator, ε-SIS epidemics and the epidemic threshold, Physical Review E, vol. 86, No. 1, July, p. 016116, 2012



Markov Theory

 SIS model is exactly described as a continuous-time Markov process on 2^N states, with infinitesimal generator Q_N.

Drawbacks:

- no easy structure in $Q_{\mbox{\scriptsize N}}$
- computationally intractable for N>20
- steady-state is the absorbing state (reached after unrealistically long time)
- very few exact results...
- The mathematical community (e.g. Liggett, Durrett,...) uses:
 - duality principle & coupling & asymptotics
 - graphical representation of the Poisson infection and recovery events



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NIMFA: N-intertwined mean-field approxim.

$$\frac{dE[X_j]}{dt} = -\delta E[X_j] + \beta \sum_{k=1}^N a_{kj} E[X_k] - \beta \sum_{k=1}^N a_{kj} E[X_j X_k]$$

$$E[X_j X_k] = \Pr[X_j = 1, X_k = 1] = \Pr[X_j = 1 | X_k = 1] \Pr[X_k = 1] \text{ and } \Pr[X_j = 1 | X_k = 1] \ge \Pr[X_j = 1]$$

$$\implies E[X_i X_k] \ge \Pr[X_i = 1] \Pr[X_k = 1] = E[X_i] E[X_k]$$

$$\frac{dE[X_j]}{dt} \le -\delta E[X_j] + \beta \sum_{k=1}^N a_{kj} E[X_k] - \beta E[X_j] \sum_{k=1}^N a_{kj} E[X_k]$$

NIMFA (= equality above) **upper bounds** the prob. of infection

E. Cator and P. Van Mieghem, 2012, "Second-order mean-field susceptible -infected-susceptible epidemic threshold", Physical Review E, vol. 85, No. 5, May, p. 056111.



NIMFA non-linear equations

$$\begin{cases} \frac{dv_1}{dt} = (1 - v_1)\beta \sum_{k=1}^N a_{1k}v_k - \delta v_1 \\ \frac{dv_2}{dt} = (1 - v_2)\beta \sum_{k=1}^N a_{2k}v_k - \delta v_2 \\ \vdots \\ \frac{dv_N}{dt} = (1 - v_N)\beta \sum_{k=1}^N a_{Nk}v_k - \delta v_N \end{cases}$$

where the viral probability of infection is $v_k(t) = E[X_k(t)] = \Pr[X_k(t) = 1]$

In matrix form:

$$\frac{dV(t)}{dt} = \beta A N(t) - diag(v_i(t))(\beta A N(t) + \delta u)$$

where the vector $\mathbf{u}^{\mathsf{T}} = [1 \ 1 \ \dots \ 1]$ and $\mathbf{V}^{\mathsf{T}} = [\mathbf{v}_1 \ \mathbf{v}_2 \ \dots \ \mathbf{v}_N]$

P. Van Mieghem, J. Omic, R. E. Kooij, "Virus Spread in Networks", IEEE/ACM Transaction on Networking, Vol. 17, No. 1, pp. 1-14, (2009).



Lower bound for the epidemic threshold

$$\frac{dv_j(t)}{dt} = -\delta v_j + \beta \sum_{k=1}^N a_{kj} v_k - \beta \sum_{k=1}^N a_{kj} E[X_i X_k] \qquad \qquad v_k(t) = E[X_k(t)]$$

Ignoring the quadratic terms

$$\frac{dV(t)}{dt} \leq \left(-\delta I + \beta A\right) V(t) \qquad \longrightarrow \qquad V(t) \leq V(0) e^{\left(-\delta I + \beta A\right) t}$$

If all eigenvalues of $\beta A - \delta I$ are negative, v_j tends exponentially fast to zero with *t*. Hence, if

The NIMFA epidemic threshold is precisely

$$\tau_{c}^{(1)} = \frac{1}{\lambda_{1}(A)} < \tau_{c}$$

$$\tau_{c}^{(1)} = \frac{1}{\lambda_{1}(A)} < \tau_{c}^{(2)} = \frac{1}{\lambda_{1}(H)} < \tau_{c}$$

$$\tau_{c}^{(1)} = \frac{1}{\lambda_{1}(A)} < \tau_{c}$$

$$TUDelft$$

Exact in steady-state for large τ βd_i

Almost all neighbors of node *j* are infected: independence

$$\Pr[X_j = 1] \cong \frac{\beta d_j}{\delta + \beta d_j} = \left(1 + \frac{1}{\tau d_j}\right)^{-1} = \left(1 + \frac{s}{d_j}\right)^{-1}$$

 $\left(\right)$

 δ

Exact steady-state average fraction of infected nodes:

$$y_{\infty}(s) \approx \frac{1}{N} \sum_{j=1}^{N} \Pr[X_j = 1] = \frac{1}{N} \sum_{j=1}^{N} \left(1 + \frac{s}{d_j}\right)^{-1}$$

Slope:
$$\left. \frac{dy_{\infty}(s)}{ds} \right|_{s=0} = \frac{1}{N} \sum_{j=1}^{N} \frac{1}{d_j} = E\left[\frac{1}{D}\right]$$

P. Van Mieghem, 2012, "The Viral Conductance in Networks", Computer Communications, Vol 35, No. 12, pp. 1494-1509.



What is so interesting about epidemics?





Extensions of the N-intertwined model

- In-homogeneous: each node i has own β_i and δ_i :
 - P. Van Mieghem and J. Omic, "In-homogeneous Virus Spread in Networks", TUDelft report (see my website)
- SAIS instead of SIS:
 - From 2 states (Infected and Susceptible) to a 3-states (Infected, Susceptible, Alert)
 - "Epidemic Spread in Human Networks", F. Darabi Sahneh and C. Scoglio, 50th IEEE Conf. Decision and Contol, Orlando, Florida (2011)
- SIR instead of SIS:
 - "An individual-based approach to SIR epidemics in contact networks", M. Youssef and C. Scoglio, Journal of Theoretical Biology 283, pp. 136-144, (2011).
- Very general extension: m compartments (includes both SIS, SAIS, SIR,...):
 - "Generalized Epidemic Mean-Field Model for Spreading Processes over Multi-Layer Complex Networks", F. Darabi Sahneh, C. Scoglio, P. Van Mieghem, submitted IEEE/ ACM Transactions on Networking



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Defining the SIS epidemic threshold

- Exact SIS steady-state (finite N):
 - overall healthy state (physically not interesting)
- Metastable (or quasi-stationary) state:
 - not defined, but physically interesting
- Two approaches:
 - modified SIS Markov chain (excluding overall healthy state)
 - ε-SIS Markov model

E. Cator and P. Van Mieghem, 2012, "SIS epidemics on the complete graph and the star graph: exact analysis", PRE, submitted.



MSIS Markov Chain Star









Simulations





ε-SIS epidemics



due to self-infection with rate $\varepsilon > 0$, the steady-state is **not** the absorbing state!

epidemic threshold & meta-stable state in SIS can be defined for a given 0< ϵ < δ/N



ϵ -SIS epidemics on the complete graph

$$\pi_{j} = \pi_{0} \begin{pmatrix} N \\ j \end{pmatrix} \tau^{j} \frac{\Gamma\left(\frac{\varepsilon^{*}}{\tau} + j\right)}{\Gamma\left(\frac{\varepsilon^{*}}{\tau}\right)} \qquad \pi_{0}^{-1} = \sum_{k=0}^{N} \begin{pmatrix} N \\ k \end{pmatrix} \tau^{k} \frac{\Gamma\left(\frac{\varepsilon^{*}}{\tau} + k\right)}{\Gamma\left(\frac{\varepsilon^{*}}{\tau}\right)} \qquad \varepsilon^{*} = \frac{\varepsilon}{\delta} \qquad \tau = \frac{\beta}{\delta}$$

average steady-state fraction of infected nodes is $y_{\infty}(\tau \mid \varepsilon^*) = \frac{1}{N} \sum_{j=1}^{N} j\pi_j$

 τ

epidemic threshold

NIMFA epidemic threshold

$$\tau_{c} = \frac{1}{N} \left(1 + \frac{2}{\sqrt{N}} + O\left(\frac{1}{N}\right) \right)$$

$$\tau_{c}^{(1)} = \frac{1}{N-1} = \frac{1}{N} \left(1 + \frac{1}{N} + O\left(\frac{1}{N^{2}}\right) \right)$$

Van Mieghem, P. and E. Cator, ε-SIS epidemics and the epidemic threshold, Physical Review E, vol. 86, No. 1, July 2012, p. 016116



ε-SIS epidemics on the complete graph



HMF mean-field approximation

governing eq.:

$$\frac{d\rho_k(t)}{dt} = -\delta\rho_k(t) + \beta k (1 - \rho_k(t))\Theta(\rho(t))$$

steady-state:

$$\rho_k(\tau) = \frac{\tau k \Theta(\tau)}{1 + \tau k \Theta(\tau)} \qquad \qquad \tau = \frac{\beta}{\delta}$$

$$\Theta(\tau) = \frac{1}{E[D]} \sum_{k=1}^{N-1} k \Pr[D=k] \rho_k(\tau)$$

HMF epidemic threshold:

$$\tau_{c;HMF} = \frac{E[D^2]}{E[D]}$$

Pastor-Satorras, R. and Vespignani, A., Epidemic dynamics and endemic states in complex networks, Phys. Rev. E 63, 066117, 2001.



Comparison: star graph





Comparison: BA





Comparison: Lattice





Comparison: ER graph (close to p_c)





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- 2^N linear equations
- Steady-state
 - absorbing (healthy) state
 - reached after unrealistically long time
- difficult to analyze

- *N* non-linear equations
- Meta-stable state:
 - phase-transition
 - epidemic threshold
 - realistic
- analytically tractable
- lower bound epidemic threshold



Books



Articles: http://www.nas.ewi.tudelft.nl



Thank You

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