

Susceptible-Infective and SIS Epidemic propagation models

Laurent Massoulié

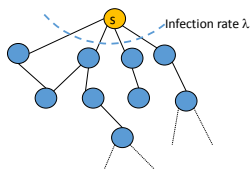
Inria

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outline

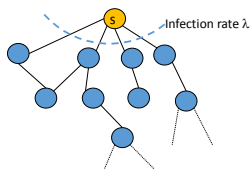
- SI process on complete graph
- Markovian transforms of Markov processes
- Application: control of SI process on general graph via isoperimetric constant
- SIS process on general graphs:
Fast extinction and spectral radius
Long survival and isoperimetric constant
- SIR process on general graph and spectral radius

Susceptible-Infective epidemic propagation



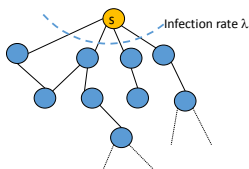
- Graph $G = (V, E)$ with n nodes ($V = [n]$)
- Infected nodes keep attempting to infect graph neighbors
- Models “push”-based distributed information dissemination mechanism (example of a “gossip” algorithm); variants used in Peer-to-peer systems (e.g. Bittorrent): pull, push-pull...

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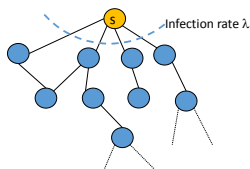
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⇒ Time till everyone heard from everyone else (“all-to-all” broadcast)? Useful e.g. for estimating graph size

Susceptible-Infective epidemic propagation: model

- Assume first propagation on **complete graph**
- Each node attempts, at instants of Poisson λ process, to infect neighbor chosen uniformly at random

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$\Rightarrow X_t$ a Markov jump process with non-zero jump rate
 $q_{x,x+1} = \lambda x(n - x)/(n - 1)$

Time to total infection

Let E_x : i.i.d. Exponential(1) random variables, T_n : time to total infection (or broadcast)

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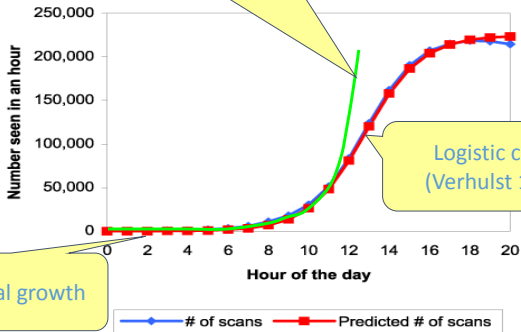
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Heuristic inversion: starting from $X_0 = an$, $X_t \approx n \frac{ae^{\lambda t}}{1-a+ae^{\lambda t}}$

⇒ The celebrated **logistic function**, or S-curve

«Optimal diffusion» (without failed attempts)



Logistic curve
(Verhulst 1838)

Exponential growth

Time to total infection order-optimal
(logarithmic in number of targets) despite random target selection

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Controlling fluctuations

Variable $S_n := \lambda(T_n - \mathbb{E}(T_n))$ satisfies for all $\theta \in [0, 1/2]$

$$\mathbb{E}(\exp(\theta S_n)) \leq \exp(4\pi^2\theta^2/3) =: C_\theta < +\infty$$

hence (Chernoff bound argument):

$$\mathbb{P}(\lambda(T_n - \mathbb{E}(T_n)) \geq t) \leq C_\theta e^{-\theta t},$$

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Proof: For $r_x = x(n-x)/(n-1) = q_x/\lambda$,

$$\mathbb{E}e^{\theta S_n} = \prod_{x=1}^{n-1} \frac{r_x}{r_x - \theta} e^{-\theta/r_x}$$

For $u \in (0, 1/2]$, $\frac{e^{-u}}{1-u} \leq 1 + 2u^2$, hence:

$$\mathbb{E}e^{\theta S_n} \leq \prod_{x=1}^{n-1} [1 + 2(\theta/r_x)^2] \leq e^{\sum_{x=1}^{n-1} 2(\theta/r_x)^2} \leq e^{8\theta^2 \sum_{x \geq 1} x^{-2}}$$

Application: All-to-all scenario (one epidemic per user)

Lemma

Let random variables S^1, \dots, S^n be such that for some $a, b > 0$:

$$\forall t > 0, \forall i \in [n], \mathbb{P}(S^i \geq t) \leq ae^{-bt}$$

Then $\mathbb{E}(\sup_i S^i) \leq \mathbb{E}((\sup_i S^i)^+) \leq \frac{\ln(an)+1}{b}$

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Corollary

All-to-all propagation time T satisfies for all $\theta \in (0, 1/2]$

$$\mathbb{E}T \leq \frac{1}{\lambda} \left[2(\ln(n) + \gamma) + o(1) + \frac{\ln(C_\theta n)+1}{\theta} \right] = O(\ln(n)),$$

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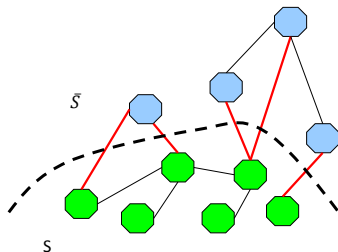
Indeed: $T = \text{supremum of } n \text{ propagation times corresponding each to single epidemic propagation}$

Isoperimetric constant of a graph

Definition

For a graph $G = (V, E)$ and any $m < n$, the isoperimetric constant η_m is defined as $\eta_m = \min_{S \subset V, |S| \leq m} \frac{|E(S, \bar{S})|}{|S|}$, where $E(S, \bar{S})$ denotes the set of edges between S and its complement $\bar{S} = V \setminus S$.

Remark: When m not specified, $\eta = \eta_n/2$



Markovian transforms of Markov chains

Let $\{X_n\}_{n \in \mathbb{N}}$ be a Markov chain on countable set E with transition matrix $(p_{ij})_{i,j \in E}$.

For countable set F and $f : E \rightarrow F$, let $Y_n := f(X_n)$, $n \in \mathbb{N}$.

Theorem

If for some transition matrix $\hat{P} = (\hat{p}_{uv})_{u,v \in F}$, one has

$$\forall x \in E, v \in F, \sum_{y \in E: f(y)=v} p_{xy} = \hat{p}_{f(x),v},$$

then $\{Y_n\}_{n \in \mathbb{N}}$ is a Markov chain on F with transition matrix \hat{P} .

Proof: by evaluating $\mathbb{P}(Y_0^k = y_0^k)$ for arbitrary $y_0^k \in F^{k+1} \dots$

Remark: In general, image of Markov chain fails to be Markovian.

Example: $X_0^\infty = \{0, 1, 2, 0, 1, 2, \dots\}$,

$f(x) = \mathbb{I}_{x=2} \Rightarrow Y_0^\infty = \{0, 0, 1, 0, 0, 1, \dots\}$

Markovian transforms of Markovian jump processes

Let $\{X(t)\}_{t \in \mathbb{R}_+}$ be a non-explosive Markov jump process on countable set E with infinitesimal generator $(q_{ij})_{i,j \in E}$.

For countable set F and $f : E \rightarrow F$, let $Y(t) := f(X(t))$, $t \in \mathbb{R}_+$.

Theorem

If for some generator $\hat{Q} = (\hat{q}_{uv})_{u,v \in F}$ such that $\forall u \in F, \hat{q}_{u,u} = -\sum_{v \neq u} \hat{q}_{uv} =: -\hat{q}(u)$, one has

$$\forall x \in E, v \in F : f(x) \neq v, \quad \sum_{y \in E : f(y) = v} q_{xy} = \hat{q}_{f(x),v},$$

then $\{Y(t)\}_{t \in \mathbb{R}_+}$ is a Markov jump process on F with infinitesimal generator \hat{Q} .

Application: SI epidemics on general graphs and isoperimetric constant

Consider SI process on $G = (V, E)$ with infection rate λ along each edge.

Then propagation is at least as fast as SI process on complete graph with per-node infection rate $\lambda\eta_n/2$.

Corollary: Time to total infection in $O\left(\frac{\ln(n)}{\lambda\eta_n/2}\right)$

Coupling proof:

Define process (X, Z) on $E := \{(x, y) \in \{0, 1\}^V \times [n] : \sum_{i \in V} x_i \geq z\}$ (hence for all $t \in \mathbb{R}_+$, $\sum_{i \in V} X_i(t) \geq Z(t)$) so that:

X : SI process on G with per edge infection rate λ , and

Z : number of infected nodes in SI on complete graph, with per node infection rate $\lambda \eta_{n/2}$.

Process (X, Z) specified by non-zero transition rates: for each $(x, z) \in E$, $i \in V$,

$$\begin{aligned} \sum_{j \in V} x_j > z &\Rightarrow q_{(x,z), (x+e_i, z)} = \lambda \sum_{j \sim i} (1 - x_j) x_j, \\ &q_{(x,z), (x, z+1)} = \lambda \eta_{n/2} \frac{z(n-z)}{n-1}, \\ \sum_{j \in V} x_j = z &\Rightarrow q_{(x,z), (x+e_i, z+1)} = C \lambda \sum_{j \sim i} (1 - x_j) x_j, \\ &q_{(x,z), (x+e_i, z)} = [1 - C] \lambda \sum_{j \sim i} (1 - x_j) x_j, \end{aligned}$$

where $C := \frac{z(n-z)\eta_{n/2}}{(n-1) \sum_{i \in V} \sum_{j \sim i} x_i(1-x_j)}$

Coupling proof:

Well-defined: non-negative rates, as $C \leq 1$ because

$$\sum_{i \in V} \sum_{j \sim i} x_i(1 - x_j) \geq \eta_{n/2} \text{Min}(z, n - z)$$

Component processes have desired distributions: use criterion for transform of jump process to be itself jump process, with $f((X, Z)) = X$ and $f((X, Z)) = Z$.

Examples of verification: for process X ,

$$\tilde{q}_{x, x+e_i} = [C + 1 - C]\lambda \sum_{j \sim i} (1 - x_j)x_j = \lambda \sum_{j \sim i} (1 - x_j)x_j;$$

For process Z ,

$$\tilde{q}_{z, z+1} = \sum_{i \in V} C\lambda \sum_{j \sim i} x_i(1 - x_j) = \lambda \eta_{n/2} \frac{z(n-z)}{(n-1)}.$$

SIS model

- Basic model: graph $G = (V, E)$
- Each infected node infects each of its neighbors at rate β , and becomes healthy at rate δ

May model propagation of mutating virus, or replication of data in volatile memories

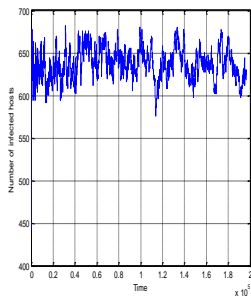
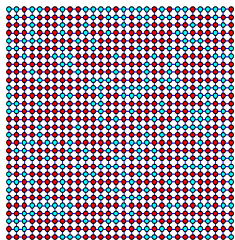
⇒ Markov jump process on $\{0, 1\}^V$ with non-zero transition rates

$$\begin{aligned}q(x, x + e_i) &= \beta \sum_{j \sim i} x_j, \quad i \in V, x \in \{0, 1\}^V, x_i = 0; \\q(x, x - e_i) &= \delta, \quad i \in V, x \in \{0, 1\}^V, x_i = 1.\end{aligned}$$

Stationary regime: complete extinction (absorbing state)

Goal: understand impact of β , δ and topology of G on time to extinction

Example of a grid network



Behaviour characterized by [Durrett-Liu,Durrett-Schonmann,'88]: there is a critical threshold $c > 0$ such that:

$\beta/\delta > c \Rightarrow$ long survival (expected time to extinction: exponential in $n = |V|$),

$\beta/\delta < c \Rightarrow$ fast extinction (expected time to extinction logarithmic in $n = |V|$),

Fast extinction and spectral radius

Definition

The spectral radius $\rho(A)$ of matrix A is the largest modulus of its eigenvalues.

Theorem

Let ρ be the spectral radius of the adjacency matrix A of graph $G = (V, E)$. The time to extinction T verifies for all $t > 0$:

$$\mathbb{P}(T \geq t) \leq ne^{(\beta\rho - \delta)t},$$

where $n = |V|$.

Corollary

If $\beta\rho < \delta$, then $\mathbb{E}(T) \leq \frac{\ln(n)+1}{\delta - \beta\rho}$

Long survival and isoperimetric constants

Theorem

Assume that for some $r \in]0, 1[$ and some $m < n$, $\beta\eta_m \geq \frac{\delta}{r}$.

Then there is a function $f : \mathbb{N} \rightarrow \mathbb{R}$ such that $\lim_{k \rightarrow \infty} f(k) = 0$ and for any $k \in \mathbb{N}$,

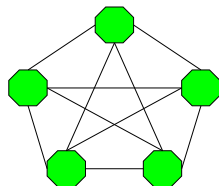
$$\mathbb{P}(T \geq \frac{k}{2\delta m}) \geq \frac{1-r}{1-r^m} \left(\frac{1-r^{m-1}}{1-r^m} \right)^k (1-f(k))$$

Corollary

If for fixed $r \in]0, 1[$ and a sequence of graphs G_n each on n nodes one has for some $m = m(n)$ with $\lim_{n \rightarrow \infty} m(n) = +\infty$: $\beta\eta_m(G_n) \geq \frac{\delta}{r}$, then the time T_n to extinction of the (β, δ) - epidemic process on G_n verifies:

$$\mathbb{E}[\delta T_n] \geq \frac{(1-r)^2}{3m} \lfloor r^{-m+2} \rfloor = e^{\Omega(m)}.$$

Example: complete graph



For complete graph on n nodes, $\rho = n - 1$ and $\eta_m = n - m$.

\Rightarrow for fixed $\epsilon \in]0, 1[$,

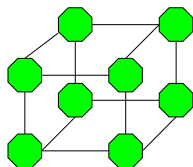
if $\beta(n - 1) \leq \delta(1 - \epsilon)$, $\mathbb{E}[\delta T_n] \leq \frac{\ln(n)+1}{\epsilon} = O(\ln(n))$;

if $\beta(n - 1) \geq \delta(1 + \epsilon)$, for $m = n\epsilon/2$ one has $\beta\eta_m \geq \delta/r$ with $r^{-1} = (1 + \epsilon)(1 - \epsilon/2) > 1$, so that

$$\mathbb{E}[\delta T_n] \geq e^{\Omega(n)}$$

A sharp transition with respect to $(\beta n/\delta)$ at 1.

Example: hypercube



Hypercube $G = \{0, 1\}^d$ on $n = 2^d$ nodes:

$\rho = d$, $\eta_m \geq d - k$ for $m = 2^k$, $k < d$ (ref: [Harper'64])

Fix $\epsilon \in]0, 1[$.

If $\beta d \leq \delta(1 - \epsilon)$, then $\mathbb{E}[\delta T_n] \leq \frac{\ln(n)+1}{\epsilon} = O(\ln(n))$;

If $\beta d \geq \delta(1 + \epsilon)$, for $m = 2^{\epsilon d/2}$, $\eta_m \geq (1 - \epsilon/2)d$.

Hence $\beta \eta_m \geq \delta/r$ with $r < 1$, so that

$\mathbb{E}[\delta T_n] \geq e^{\Omega(m)} = e^{\Omega(n^{\epsilon/2})}$.

A sharp transition with respect to $(\beta d/\delta)$ at 1.

Example: Erdős-Rényi graph with super-logarithmic average degree

proposition

Let $G = (n, d/n)$ with $d \gg \ln(n)$, and some fixed $\alpha \in]0, 1[$. One then has the convergences in probability

$$\lim_{n \rightarrow \infty} \frac{\rho(A)}{d} = 1, \quad \lim_{n \rightarrow \infty} \frac{\eta_{\alpha n}}{(1 - \alpha)d} = 1.$$

Corollary

Let $\epsilon > 0$ be fixed. One has the following with high probability with respect to G :

If $\beta d \leq (1 - \epsilon)\delta$, then $\mathbb{E} \frac{T_n}{\delta} \leq \frac{2 \ln(n)}{\delta} = O(\ln(n))$.

If $\beta d \geq (1 + \epsilon)\delta$, then $\mathbb{E} \frac{T_n}{\delta} \geq e^{\Omega(\epsilon n)} = e^{\Omega(n)}$.

Fast extinction and spectral radius: proof elements

Define branching random walk on graph $G = (V, E)$ as process X' on \mathbb{N}^V with non-zero transition rates $q'_{x, x+e_i} = \beta \sum_{j \sim i} x_j$ and $q'_{x, x-e_i} = \delta x_i$.

Couple two processes X, X' , where X : SIS on $G = (V, E)$ with initial conditions $x(0) \in \{0, 1\}^V$ so that $\forall t \in \mathbb{R}_+, X(t) \leq X'(t)$

Bound probability of SIS survival:

$$\mathbb{P}(T > t) \leq \mathbb{E}\left(\sum_i X_i(t)\right) \leq \mathbb{E}\sum_i X'_i(t).$$

Linearity of rates q' in x' :

$$\begin{aligned} \frac{d}{dt} \mathbb{E}(X'(t)) &= \beta A \mathbb{E}(X'(t)) - \delta \mathbb{E}(X'(t)) \\ \Rightarrow \mathbb{E}(X'(t)) &= e^{t(\beta A - \delta I)} x(0). \end{aligned}$$

SIR epidemics and spectral radius

Consider Reed-Frost process with neighbor infection parameter β on graph $G = (V, E)$, $X_i(t) = \mathbb{I}_i$ infectious at t , $Y_i(t) = \mathbb{I}_i$ removed at t . Then:

Theorem

Suppose $\beta\rho < 1$. Then the total number of nodes eventually removed verifies

$$\mathbb{E} \sum_{i \in V} Y_i(\infty) \leq \frac{1}{1 - \beta\rho} \sqrt{n \sum_{i \in V} X_i(0)}.$$

If moreover G is d -regular, then

$$\mathbb{E} \sum_{i \in V} Y_i(\infty) \leq \frac{1}{1 - \beta\rho} \sum_{i \in V} X_i(0).$$

SIR epidemics: proof

By union bound,

$$\begin{aligned}\mathbb{P}(Y_u(\infty) = 1) &\leq \sum_{t \geq 0} \sum_{u_0, \dots, u_t} \beta^t X_{u_0}(0) \\ &= \sum_{t \geq 0} \sum_{v \in V} (\beta A)_{uv}^t X_v(0)\end{aligned}$$

where u_0, \dots, u_t : graph path with $u_t = u$.

Hence

$$\begin{aligned}\mathbb{E} \sum_u Y_u(\infty) &\leq \sum_{t \geq 0} e^T (\beta A)^t X(0) \\ &= e^T (I - \beta A)^{-1} X(0) \\ &= \sum_i \langle x_i, e \rangle \frac{1}{1 - \beta \lambda_i} \langle x_i, X(0) \rangle\end{aligned}$$

Takeaway messages

- SI Epidemics spreads in logarithmic time on well-connected graphs (as measured by isoperimetric constant) for single propagation and for all-to-all propagation, same order as if infection targets were chosen optimally
- Epidemic (or gossip) algorithms good candidates for managing information dissemination in P2P systems
- Behaviour of SIS epidemics undergoes phase transitions as ratio β/δ crosses thresholds
- Graph topology determines thresholds; in several scenarios (complete graph, hypercube, E-R graphs), spectral radius and isoperimetric constants are close, hence a single threshold
- Coupling constructions allow control of complex process by simpler ones