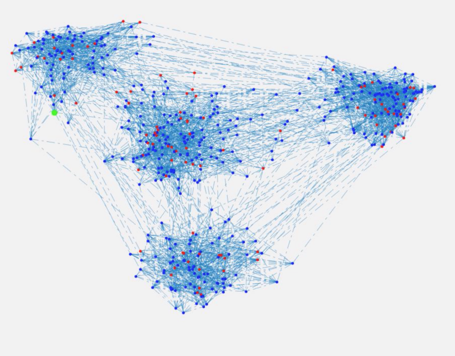

Susceptible-Infected Epidemic in Graphs

Faury Louis
Gallois - Montbrun Grégoire
MICRO506 - Stochastic Methods
May 29, 2017

Plan

Plan

- Hold the following assumptions for true :
  - Each individual in the population is either *susceptible* or *infected*
  - Once infected, an individual can't recover and tries to infect other individuals
  - An individual can affect any other individual in the population (uniform topology)

- Hold the following assumptions for true :
  - Each individual in the population is either *susceptible* or *infected*
  - Once infected, an individual can't recover and tries to infect other individuals
  - An individual can affect any other individual in the population (uniform topology)

- Graph population representation :

$$G = (V, E) \tag{1}$$

with $|V| = n \in \mathbb{N}^*$
Uniform topology $\Rightarrow$ **complete graph**.

■ Propagation :

- Each infected node tries to infect one of its neighbor at the times of a Poisson process of intensity $\lambda > 0$.
- The node's Poisson processes are independent.
- An infected node picks one of its neighbor uniformly at random when trying to infect.

■ Propagation :

- Each infected node tries to infect one of its neighbor at the times of a Poisson process of intensity $\lambda > 0$.

- The node's Poisson processes are independent.

- An infected node picks one of its neighbor uniformly at random when trying to infect.

■ Let X_t the number of infected node at time $t > 0$.
$\rightarrow \{X_t\}$ is a **Markov Jump Process** on $\mathbb{R}^+$.

- Markov Jump Process on E :
  - If, $\forall x, y \in E$:

$$p_{xy}(t) = \mathbb{P}(X_{t+s} = y \,|\, X_s = x) \tag{2}$$

then

$$\lim_{t \to 0} p_{xx}(t) = 1 \tag{3}$$

- Markov Jump Process on E :
  - If, $\forall x, y \in E$:

$$p_{xy}(t) = \mathbb{P}(X_{t+s} = y \,|\, X_s = x) \tag{2}$$

then

$$\lim_{t \to 0} p_{xx}(t) = 1 \tag{3}$$

  - The process remains at each stage for a strictly positive time with probability 1.

- Markov Jump Process on E :
  - If, $\forall x, y \in E$:

$$p_{xy}(t) = \mathbb{P}(X_{t+s} = y \mid X_s = x) \tag{2}$$

then

$$\lim_{t \to 0} p_{xx}(t) = 1 \tag{3}$$

  - The process remains at each stage for a strictly positive time with probability 1.
  - We define the jump process's **infinitesimal generator** as, $\forall x \neq y \in E$

$$q_{xy} = \lim_{h \to 0} \frac{p_{xy}(h)}{h} \tag{4}$$

■ Markov Jump Process on E :

- If, $\forall x, y \in E$:

$$p_{xy}(t) = \mathbb{P}(X_{t+s} = y \,|\, X_s = x) \tag{2}$$

  then

$$\lim_{t \to 0} p_{xx}(t) = 1 \tag{3}$$

- The process remains at each stage for a strictly positive time with probability 1.
- We define the jump process's **infinitesimal generator** as, $\forall x \neq y \in E$

$$q_{xy} = \lim_{h \to 0} \frac{p_{xy}(h)}{h} \tag{4}$$

- It defines the process transitions rates

Markov Jump Process on E :

- If, $\forall x, y \in E$:

$$p_{xy}(t) = \mathbb{P}(X_{t+s} = y \mid X_s = x) \tag{2}$$

  then

$$\lim_{t \to 0} p_{xx}(t) = 1 \tag{3}$$

- The process remains at each stage for a strictly positive time with probability 1.
- We define the jump process's **infinitesimal generator** as, $\forall x \neq y \in E$

$$q_{xy} = \lim_{h \to 0} \frac{p_{xy}(h)}{h} \tag{4}$$

- It defines the process transitions rates
- Ex : queuing systems !

- Back to our propagation model :
  - Since :

$$
\begin{aligned}
& p_{x,x-i}(t) = 0 \quad \forall i > 0 \\
& p_{x,x+1}(h) \propto h \\
& p_{x,x+1+i}(h) \propto h^i \quad \forall i > 0
\end{aligned}
\tag{5}
$$

- Back to our propagation model :
  - Since :

$$\begin{aligned} p_{x,x-i}(t) &= 0 \quad \forall i > 0 \\ p_{x,x+1}(h) &\propto h \\ p_{x,x+1+i}(h) &\propto h^i \quad \forall i > 0 \end{aligned} \tag{5}$$

  - Only non-zero transition rate is $q_{x,x+1}$

- Back to our propagation model :
  - Since :

$$
\begin{aligned}
p_{x,x-i}(t) &= 0 \quad \forall i > 0 \\
p_{x,x+1}(h) &\propto h \\
p_{x,x+1+i}(h) &\propto h^i \quad \forall i > 0
\end{aligned}
\tag{5}
$$

  - Only non-zero transition rate is $q_{x,x+1}$
  - If $X_t = x > 0$, the next time before an infection intent is a random variable defined as :

$$
\tau_x = \min_{i=1,\dots,x} \varepsilon_i \quad \text{where } \varepsilon_i \sim Exp(\lambda) \text{ (iid)} \tag{6}
$$

Therefore

$$
\tau_x \sim Exp(\lambda x) \tag{7}
$$

- Back to our propagation model :
  - The transition succeeds if the node picks a suspectible neighbor, which happens with probability $\frac{n-x}{n-1}$ (uniform)

- Back to our propagation model :
  - The transition succeeds if the node picks a suspectible neighbor, which happens with probability $\frac{n-x}{n-1}$ (uniform)
  - Therefore :

$$\boxed{q_{x,x+1} = \lambda x \frac{n-x}{n-1}} \tag{8}$$

- Back to our propagation model :
  - The transition succeeds if the node picks a suspectible neighbor, which happens with probability $\frac{n-x}{n-1}$ (uniform)
  - Therefore :

$$\boxed{q_{x,x+1} = \lambda x \frac{n-x}{n-1}} \tag{8}$$

  - Let $X_0 = 1$. The time before m individuals are infected is defined as :

$$T_m = \sum_{x=1}^{m-1} \frac{n-1}{\lambda x(n-x)} \varepsilon_i \tag{9}$$

where

$$\varepsilon_i \overset{i.i.d}{\sim} Exp(1) \tag{10}$$

■ Time before complete infection : T_n which first moment is given by :

$$\boxed{\mathbb{E}\left[T_n\right] = \sum_{x=1}^{n} \frac{n-1}{\lambda x(n-x)}} \tag{11}$$

- Time before complete infection : T_n which first moment is given by :

$$\boxed{\mathbb{E}\left[T_n\right] = \sum_{x=1}^{n} \frac{n-1}{\lambda x(n-x)}} \tag{11}$$

- Large population limit :

$$\mathbb{E}\left[T_n\right] = \frac{2}{\lambda}(\log(n) + \gamma + o(1)) \tag{12}$$

scales with $\log(n)$!

■ Time before complete infection : T_n which first moment is given by :

$$\boxed{\mathbb{E}\left[T_n\right] = \sum_{x=1}^{n} \frac{n-1}{\lambda x(n-x)}} \tag{11}$$

■ Large population limit :

$$\mathbb{E}\left[T_n\right] = \frac{2}{\lambda}(\log(n) + \gamma + o(1)) \tag{12}$$

scales with $\log(n)$!

■ Fluctuation : if $S_n = \lambda(T_n - \mathbb{E}\left[T_n\right])$:

$$\mathbb{P}(S_n \geq t) \leq e^{-\theta t} C_\theta, \quad \forall \theta \in [0, \frac{1}{2}] \tag{13}$$

$\rightarrow$ exponential control around the mean value !

Simulation

Hyper-parameters : $n = 30,\ \lambda = 1.$

Simulation

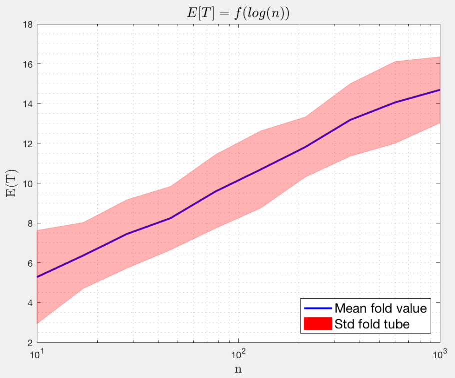

Figure: Mean infection time as a function of $|V|$

$\lambda = 1$ and $\lambda_{MLE} = 0.94$!

Simulation

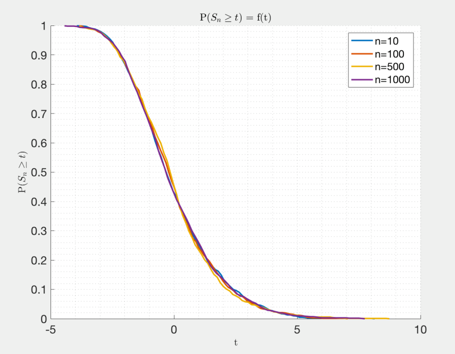

Figure: Fluctuation distribution : $\mathbb{P}(S_n \geq t)$

$\rightarrow$ Exponentially bounded tail

Plan

- Epidemic Propagation :
  - Modelisation of simple epidemics in population

■ Epidemic Propagation :

- Modelisation of simple epidemics in population

- Simplistic model :
  - Nodes can't recover from being infected
  - A complete graph is not realistic

Epidemic Propagation :

- Modelisation of simple epidemics in population
- Simplistic model :
  - Nodes can't recover from being infected
  - A complete graph is not realistic
- What happens if we introduce recovering / dying nodes ?

■ Epidemic Propagation :

- Modelisation of simple epidemics in population
- Simplistic model :
  - Nodes can't recover from being infected
  - A complete graph is not realistic
- What happens if we introduce recovering / dying nodes ?
- How does the topology of the graph impacts the last results ?

- Sensor Network Modelisation (All to All propagation) :
  - Modelling a network of sensors / agents

■ Sensor Network Modelisation (All to All propagation) :

- Modelling a network of sensors / agents
- Each agent tries to pass a bit of information to all others

■ Sensor Network Modelisation (All to All propagation) :

- Modelling a network of sensors / agents
- Each agent tries to pass a bit of information to all others
- Control over the time before every information has been propagated to every agent

■ Sensor Network Modelisation (All to All propagation) :

- Modelling a network of sensors / agents
- Each agent tries to pass a bit of information to all others
- Control over the time before every information has been propagated to every agent
- Previous results still holds : scales as $\log n$

Plan

Critics

- The SI approach is not realistic !
- More realistic models : SIS (Susceptible-Infected-Susceptible), SIR (Susceptible-Infected-Removed)
- Complete topology assumption does not hold (sparser graph, community)

- SIS (Susceptible-Infected-Susceptible approach) on general topology:
  - Let $G = (V, E)$ a graph with adjacency matrix $A \in \mathcal{M}_{|V|}(\mathbb{R})$

$$A = (\delta_{(v_i, v_j) \in E})_{i,j} \tag{14}$$

- SIS (Susceptible-Infected-Susceptible approach) on general topology:
  - Let $G = (V, E)$ a graph with adjacency matrix $A \in \mathcal{M}_{|V|}(\mathbb{R})$

$$A = (\delta_{(v_i, v_j) \in E})_{i,j} \tag{14}$$

  - $\{X(t)\}_t \in \{0, 1\}^{|V|}$ our Markovian jump process.

- SIS (Susceptible-Infected-Susceptible approach) on general topology:
  - Let $G = (V, E)$ a graph with adjacency matrix $A \in \mathcal{M}_{|V|}(\mathbb{R})$

$$A = (\delta_{(v_i, v_j) \in E})_{i,j} \tag{14}$$

  - $\{X(t)\}_t \in \{0, 1\}^{|V|}$ our Markovian jump process.
  - Let :

$$\begin{aligned} \beta \quad &: \text{ infection rate} \\ \delta \quad &: \text{ remission rate} \\ e_i \quad &= (\delta_{ji})_{j \in \{1,\ldots,V\}} \end{aligned} \tag{15}$$

- SIS (Susceptible-Infected-Susceptible approach) on general topology:
  - Let $G = (V, E)$ a graph with adjacency matrix $A \in \mathcal{M}_{|V|}(\mathbb{R})$

$$A = (\delta_{(v_i, v_j) \in E})_{i,j} \tag{14}$$

  - $\{X(t)\}_t \in \{0, 1\}^{|V|}$ our Markovian jump process.
  - Let :

$$\begin{aligned} \beta &: \text{ infection rate} \\ \delta &: \text{ remission rate} \\ e_i &= (\delta_{ji})_{j \in \{1, \dots, V\}} \end{aligned} \tag{15}$$

  - Then the only non-zero infinitesimal generators are :

$$\begin{cases} q_{x, x+e_i} = \beta \mathbb{1}_{x_i = 0} \sum_{j \in V} A_{i,j} x_j \\ q_{x, x-e_i} = \delta x_i \end{cases} \tag{16}$$

- SIS (Susceptible-Infected-Susceptible approach) on general topology:
  - 0^V is an absorbant state $\leftarrow$ time for absorption ?

■ SIS (Susceptible-Infected-Susceptible approach) on general topology:

- 0^V is an absorbant state $\leftarrow$ time for absorption ?
- Spectral radius of the graph :

$$\rho_G = \max_{\lambda \in Sp(A)} |\lambda| \tag{17}$$

■ SIS (Susceptible-Infected-Susceptible approach) on general topology:

- 0^V is an absorbant state $\leftarrow$ time for absorption ?
- Spectral radius of the graph :

$$\rho_G = \max_{\lambda \in Sp(A)} |\lambda| \tag{17}$$

- **Main absorption result** : If the graph is *finite* and $t > 0$

$$\mathbb{P}(T > t) \leq ne^{t(\beta\rho - \delta)} \tag{18}$$

hence if $\boldsymbol{\beta\rho_G \leq \delta}$

$$\boxed{\begin{aligned} \mathbb{E}[T] &= \int_0^{+\infty} \mathbb{P}(T > t)dt \\ &\leq \frac{\log n + 1}{\delta - \beta\rho_G} \end{aligned}} \tag{19}$$

■ Simulation :

Hyper-Parameters : $\delta = 0.5$, $\beta = 0.1$, $\rho_G \simeq 4$

■ Simulation :

Hyper-Parameters : $\delta = 0.5$, $\beta = 0.5$, $\rho_G \simeq 4$

Simulation

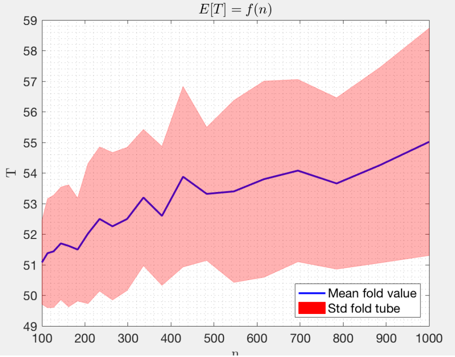

Figure: Mean absorbing time as a function of $|V|$

$$\delta = 0.5,\ \beta = 0.025,\ \rho_G \leq 4$$

■ SIS (Susceptible-Infected-Susceptible approach) on general topology:

- More precise and complex results include the *graph's isoperimetric constant* : $\forall m \in \{1, \ldots, n-1\}$

$$\eta_m(G) = \inf_{S \subset V, |S| \leq m} \left\{ \frac{|E(S, \bar{S})|}{|S|} \right\} \tag{20}$$

■ SIS (Susceptible-Infected-Susceptible approach) on general topology:

- More precise and complex results include the *graph's isoperimetric constant* : $\forall m \in \{1, \ldots, n-1\}$

$$\eta_m(G) = \inf_{S \subset V, |S| \leq m} \left\{ \frac{|E(S, \bar{S})|}{|S|} \right\} \tag{20}$$

- Derive results of control for many different topologies (complete, hypercube, Erdos-Renyi's,. . .)

■ SIS (Susceptible-Infected-Susceptible approach) on general topology:

- More precise and complex results include the *graph's isoperimetric constant* : $\forall m \in \{1, \ldots, n-1\}$

$$\eta_m(G) = \inf_{S \subset V, |S| \leq m} \left\{ \frac{|E(S, \bar{S})|}{|S|} \right\} \tag{20}$$

- Derive results of control for many different topologies (complete, hypercube, Erdos-Renyi's,. . .)

- Model a *volatile information* propagation on various network topologies

- SIS (Susceptible-Infected-Susceptible approach) on general topology:
  - More precise and complex results include the *graph's isoperimetric constant* : $\forall m \in \{1, \ldots, n-1\}$

$$\eta_m(G) = \inf_{S \subset V, |S| \leq m} \left\{ \frac{|E(S, \bar{S})|}{|S|} \right\} \tag{20}$$

  - Derive results of control for many different topologies (complete, hypercube, Erdos-Renyi's,...)
  - Model a *volatile information* propagation on various network topologies
  - Paves the way for SIR model

Summary

- Stochastic Process and Markov Jump Process on Graph
- Propagation of a disease / information along communities
- Control over mean propagation time and fluctuation around that mean

Summary

- Stochastic Process and Markov Jump Process on Graph
- Propagation of a disease / information along communities
- Control over mean propagation time and fluctuation around that mean

Thank you for your attention !