

Performance Evaluation

Lecture 2: Epidemics

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Outline

- Limit of Markovian models
- Mean Field (or Fluid) models
 - exact results
 - extensions
 - **Applications**
 - Bianchi's model
 - Epidemic routing

Mean fluid for Epidemic routing (and similar)

1. Approximation: pairwise intermeeting times modeled as independent exponential random variables
2. Markov models for epidemic routing
3. Mean Fluid Models

Inter-meeting times under random mobility

(from Lucile Sassatelli's course)

Inter-meeting times mobile/mobile have been shown to follow an exponential distribution

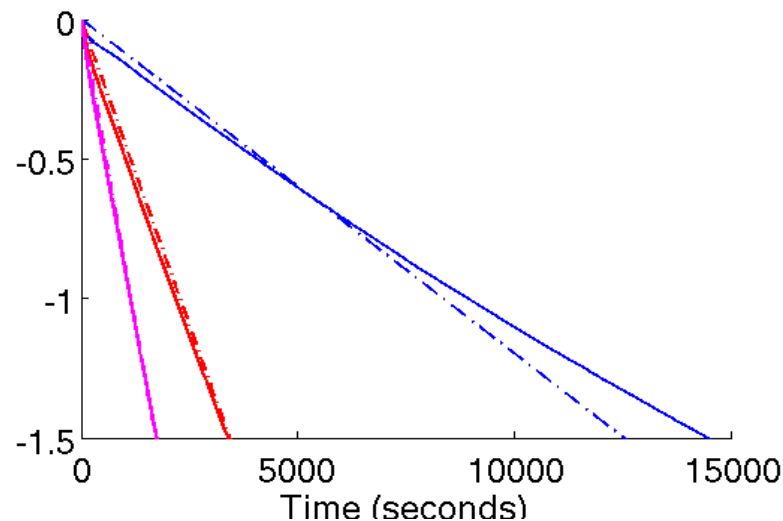
[Groenevelt et al.: The message delay in mobile ad hoc networks. Performance Evaluation, 2005]

$$\Pr\{X = x\} = \mu \exp(-\mu x)$$

$$\text{CDF: } \Pr\{X \leq x\} = 1 - \exp(-\mu x),$$

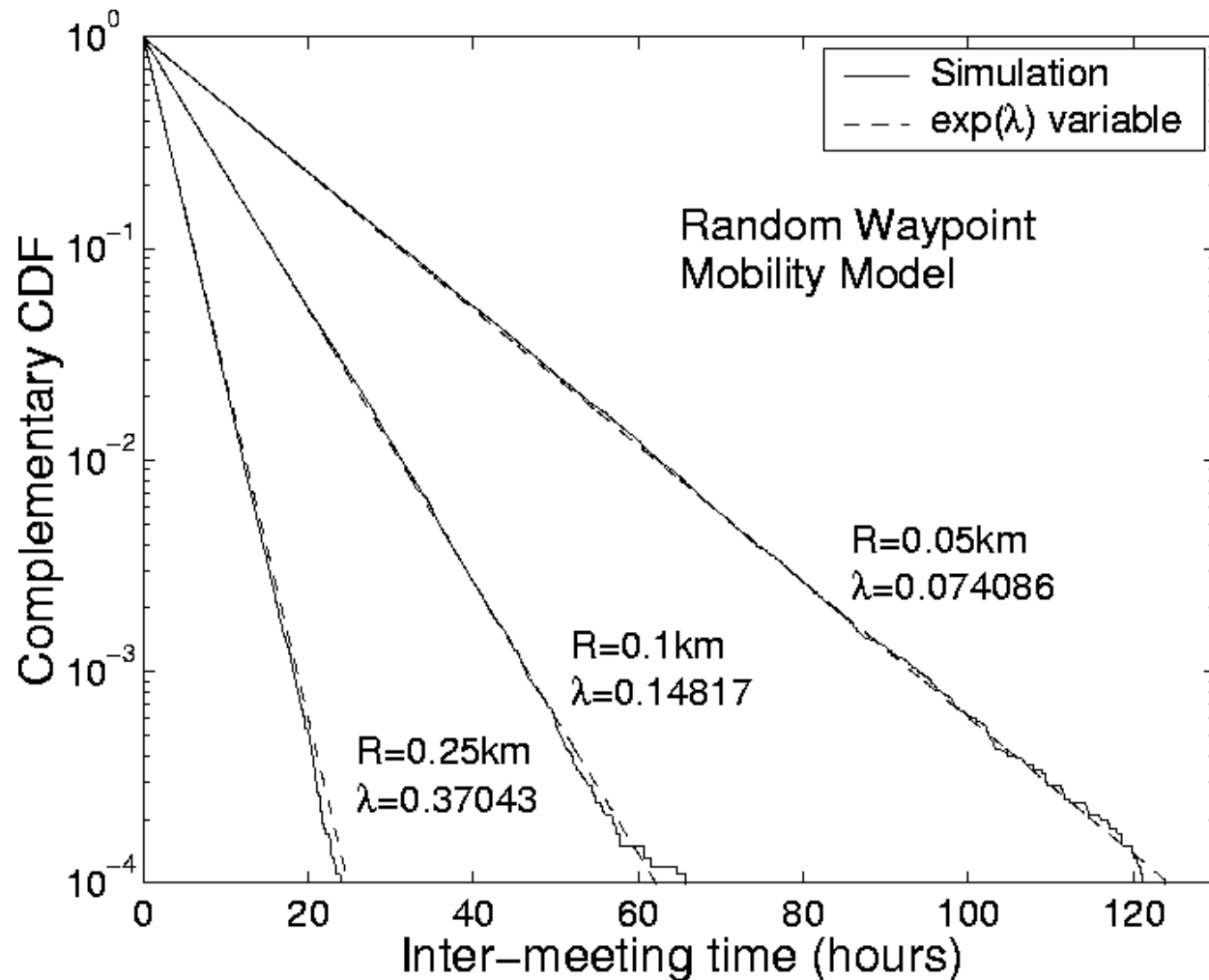
$$\text{CCDF: } \Pr\{X > x\} = \exp(-\mu x)$$

Log(CCDF) - RWP model



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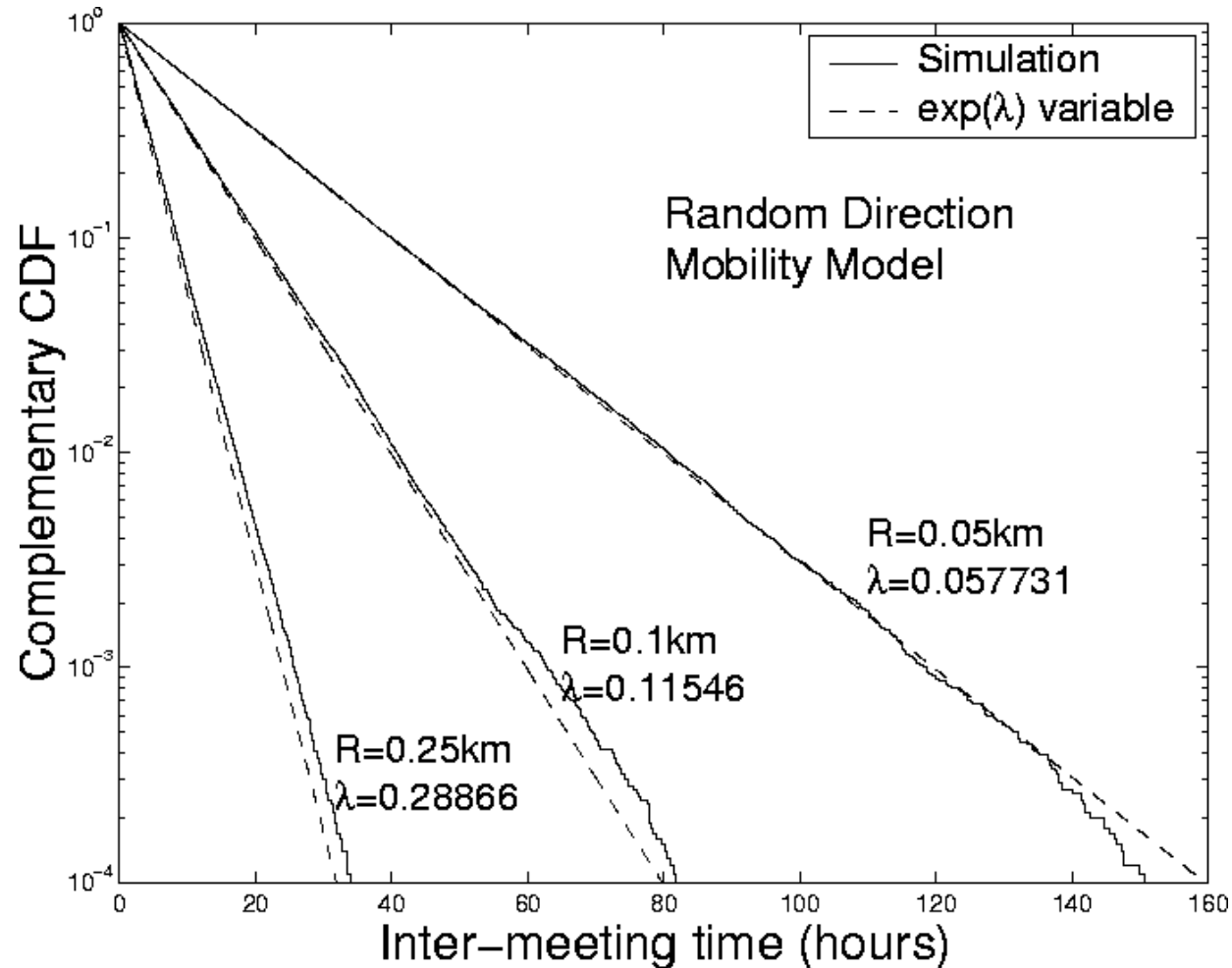
Pairwise Inter-meeting time



$$P(T > t) = e^{-\lambda t}$$

$$\log P(T > t) = -\lambda t$$

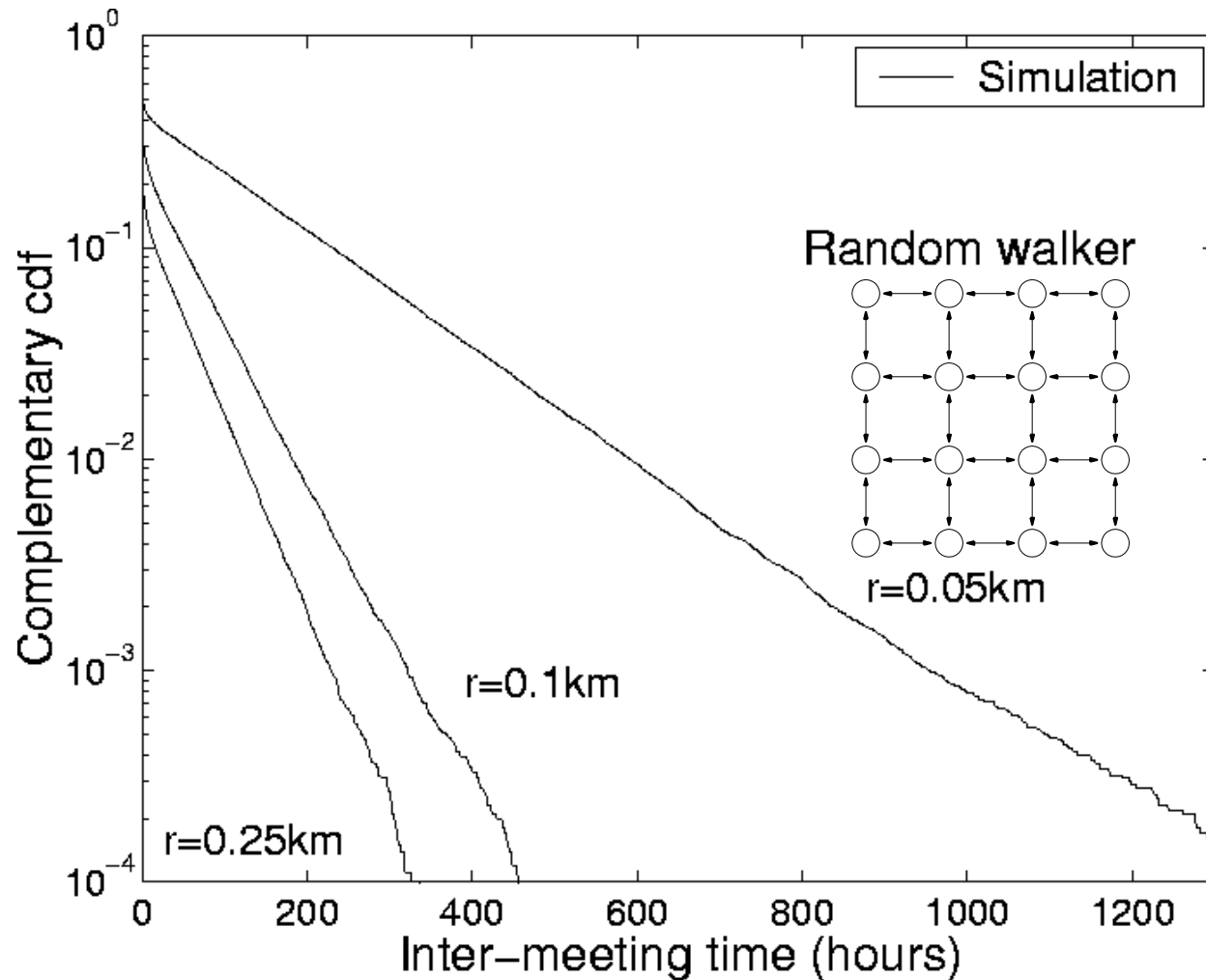
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Pairwise Inter-meeting time

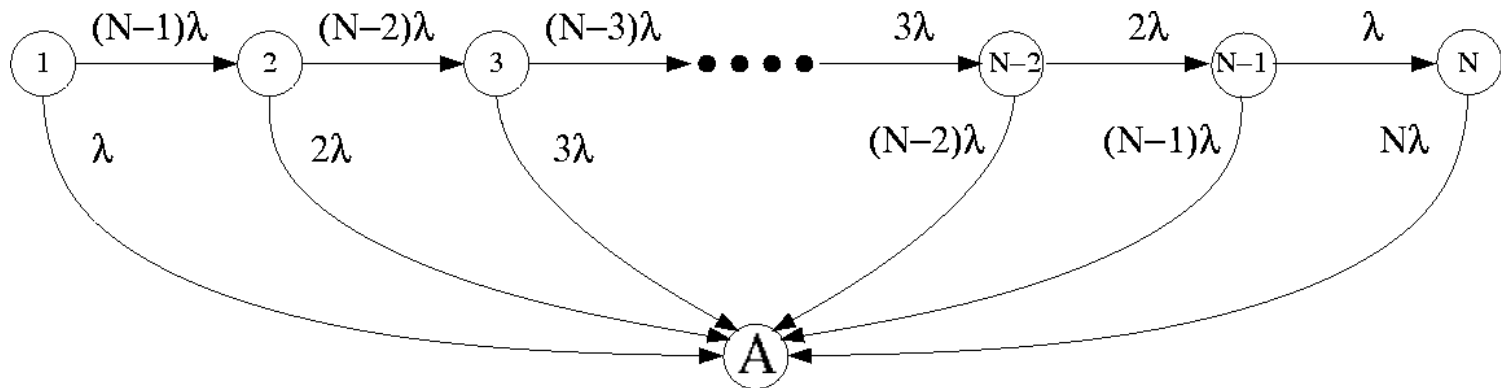


$$P(T > t) = e^{-\lambda t}$$

$$\log P(T > t) = -\lambda t$$

2-hop routing

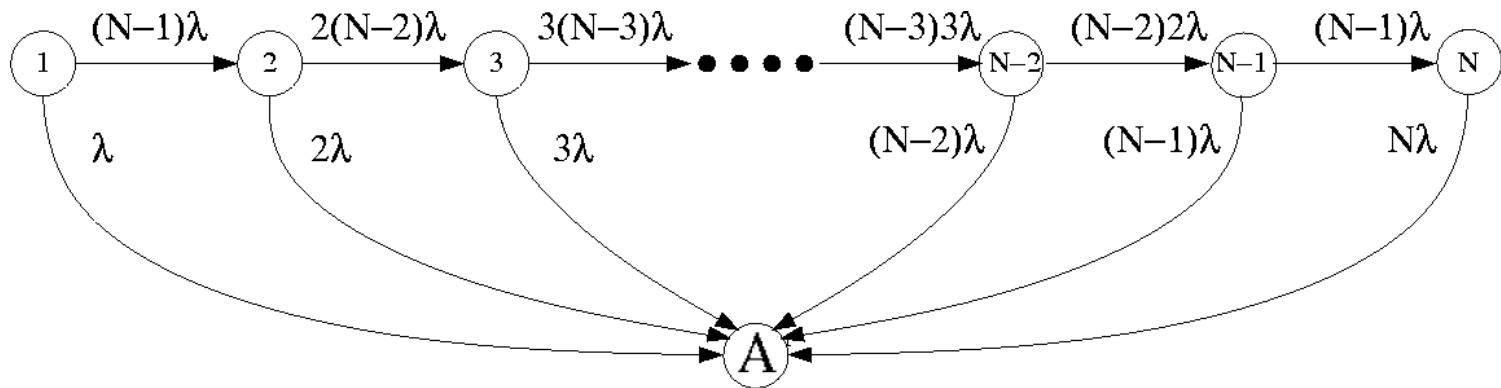
Model the number of occurrences of the message as an absorbing Continuous Time Markov Chain (CTMC):



- State $i \in \{1, \dots, N\}$ represents the number of occurrences of the message in the network.
- State A represents the destination node receiving (a copy of) the message.

Epidemic routing

Model the number of occurrences of the message as an absorbing C-MC:



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A mean-field interaction model for modeling dissemination

(from Lucile Sassatelli's course)

- Time $t \in \mathbb{N}$ is discrete. There are N objects.
- Object n has state $Z_n^{(N)}(t)$ in $S = \{0, 1\}$.
- We assume that $\mathbf{Y}^{(N)}(t) = (Z_1^{(N)}(t), \dots, Z_N^{(N)}(t))$ is a homogeneous Markov chain on S^N .
- We assume that we can observe the state of an object but not its label, i.e.,

$$\mathcal{K}^N(i_1, \dots, i_N; i'_1, \dots, i'_N) = \\ \Pr\{Z_1^{(N)}(t+1) = i_1, \dots, Z_N^{(N)}(t+1) = i_N \mid Z_1^{(N)}(t) = i'_1, \dots, Z_N^{(N)}(t) = i'_N\}$$

is stable under any permutation.

→ The process $\mathbf{Y}^{(N)}(t)$ is called a **mean-field interaction model** with N objects.

A mean-field interaction model for modeling dissemination

(from Lucile Sassatelli's course)

- Define the **occupancy measure** $\mathbf{M}^{(N)}(t)$ as the vector of frequencies of states $i \in S$ at t :

$$M_i^{(N)}(t) = \frac{1}{N} \sum_{n=1}^N 1_{\{Z_n^{(N)}(t)=i\}}. \quad \mathbf{M}^{(N)}(t) \text{ that takes values in } \Delta.$$

$\mathbf{M}^{(N)}(t)$ is a homogeneous Markov chain.

- Let us define the drift $\mathbf{f}(\mathbf{m})$ for $\mathbf{m} \in \Delta$ as the expected change to $\mathbf{M}^{(N)}(t)$ in one time-slot:

$$\begin{aligned} \mathbf{f}^{(N)}(\mathbf{m}) &= \mathbb{E}[\mathbf{M}^{(N)}(t+1) - \mathbf{M}^{(N)}(t) | \mathbf{M}^{(N)}(t) = \mathbf{m}] \\ &= \sum_{\{i,i'\} \in S, i \neq i'} m_i P_{i,i'}^{(N)}(\mathbf{m})(\mathbf{e}_{i'} - \mathbf{e}_i) \end{aligned}$$

where $P_{i,i'}^{(N)}$ is the marginal transition probability:

$$P_{i,i'}^{(N)}(\mathbf{m}) = Pr\{Z_n^{(N)}(t+1) = i' | Z_n^{(N)}(t) = i, \mathbf{M}^{(N)}(t) = \mathbf{m}\}.$$

Convergence to the mean-field limit

(from Lucile Sassatelli's course)

If $\lim_{N \rightarrow \infty} \mathbf{f}^{(N)}(\mathbf{m}) = \mathbf{f}(\mathbf{m})$ exists for all $\mathbf{m} \in \Delta$,
Then $\mathbf{M}^{(N)}(t)$ converges to a deterministic process $\mu(t)$ that satisfies:

$$\begin{cases} \frac{d\mu(t)}{dt} = \mathbf{f}(\mu(t)) \\ \mu(0) = \mu_0 \text{ constant in } N \end{cases}$$

More exactly (Kurtz Th 3.1), $\forall \delta$:

$$\lim_{N \rightarrow \infty} Pr\left\{ \sup_{s \leq t} \|\mathbf{M}^{(N)}(t) - \mu(t)\| > \delta \right\} = 0$$

T. G. Kurtz, *Solutions of Ordinary Differential Equations as Limits of Pure Jump Markov Processes*, Journal of Applied Probability, vol. 7, no. 1, pp. 49-58, 1970.

M. Benaïm and J.-Y. Le Boudec, *A class of mean field interaction models for computer and communication systems*, Performance Evaluation, vol. 65, no. 11-12, pp. 823-838, 2008.

Performance modeling of dissemination under two-hop routing or epidemic routing

(from Lucile Sassatelli's course)

$$\mathbf{M}^{(N)}(t) = \begin{bmatrix} M_0^{(N)}(t) \\ M_1^{(N)}(t) \end{bmatrix} = \begin{bmatrix} 1 - M_1^{(N)}(t) \\ M_1^{(N)}(t) \end{bmatrix}$$

- Two-hop routing: $f_1(m_1) = \lambda s(1 - m_1)$, where s is the fraction of sources (constant in N)
- Epidemic routing: $f_1(m_1) = \lambda m_1(1 - m_1)$
- Let us rename $\mu_1(t)$ as $x(t)$, standing for the fraction of infected nodes.
- Let $X^{(N)}(t)$ be the number of infected nodes: $X^{(N)}(t)$ can be approximated by $Nx(t)$.

Performance modeling of dissemination under two-hop routing or epidemic routing

(from Lucile Sassatelli's course)

From that we approximate $X^{(N)}(t)$ by the solution of:

Epidemic

$$\frac{dX^{(N)}(t)}{dt} = \beta X^{(N)}(t)(N - X^{(N)}(t)), \quad X^{(N)}(0) = 1$$

Two-hop

$$\frac{dX^{(N)}(t)}{dt} = \beta 1(N - X^{(N)}(t)), \quad X^{(N)}(0) = 0$$

- Defining T_d as the packet delivery delay, we can derive $P(t) = Pr\{T_d < t\}$:

$$\frac{dP(t)}{dt} = \lambda x(t)(1 - P(t))$$

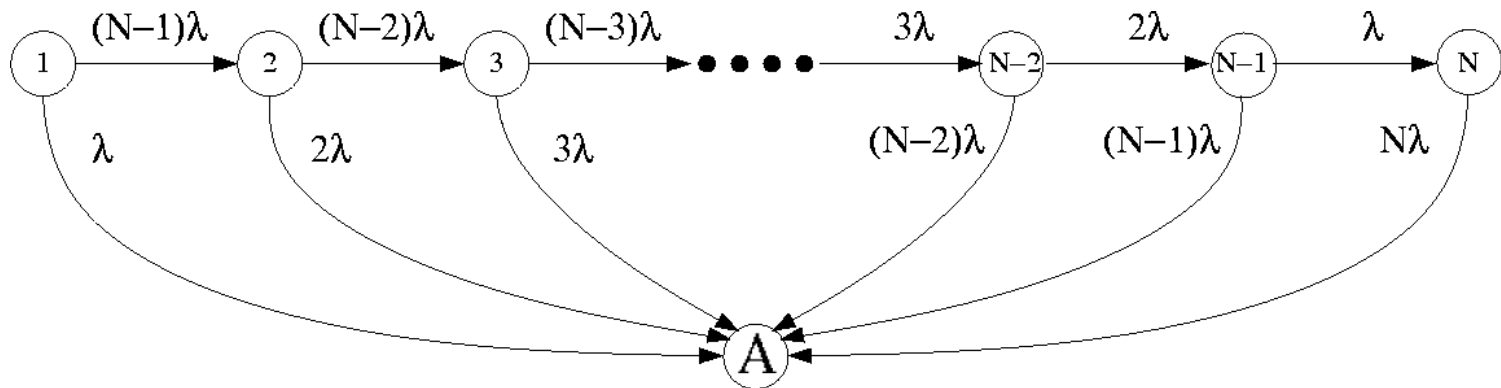
Proof: Exercise class

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A further issue

Model the number of occurrences of the message as an absorbing **Continuous Time Markov Chain (C-MC)**:



- We need a different convergence result

[Kurtz70] Solution of ordinary differential equations as limits of pure jump markov processes, T. G. Kurtz, Journal of Applied Probabilities, pages 49-58, 1970

[Kurtz1970]

$\{X_N(t), N \text{ natural}\}$

a family of Markov process in Z^m
with rates $r_N(k, k+h)$, k, h in Z^m

It is called density dependent if it exists a
continuous function $f()$ in $R^m \times Z^m$ such that

$$r_N(k, k+h) = N f(1/N k, h), \quad h \ll 0$$

Define $F(x) = \sum_h h f(x, h)$

Kurtz's theorem determines when $\{X_N(t)\}$ are *close*
to the solution of the differential equation:

$$\frac{\partial x(s)}{\partial s} = F(x(s)),$$

The formal result [Kurtz1970]

Theorem. Suppose there is an open set E in \mathbb{R}^m and a constant M such that

$$|F(x) - F(y)| < M|x - y|, \quad x, y \text{ in } E$$

$$\sup_{x \text{ in } E} \sum_h |h| f(x, h) < \infty,$$

$$\lim_{d \rightarrow \infty} \sup_{x \text{ in } E} \sum_{|h| > d} |h| f(x, h) = 0$$

Consider the set of processes in $\{X_N(t)\}$ such that

$$\lim_{N \rightarrow \infty} 1/N X_N(0) = x_0 \text{ in } E$$

and a solution of the differential equation

$$\frac{\partial x(s)}{\partial s} = F(x(s)), \quad x(0) = x_0$$

such that $x(s)$ is in E for $0 \leq s \leq t$, then for each $\delta > 0$

$$\lim_{N \rightarrow \infty} \Pr \left\{ \sup_{0 \leq s \leq t} \left| \frac{1}{N} X_N(s) - x(s) \right| > \delta \right\} = 0$$

Application to epidemic routing

$$r_N(n_I) = \lambda n_I (N - n_I) = N (\lambda N) (n_I/N) (1 - n_I/N)$$

assuming $\beta = \lambda N$ keeps constant (e.g. node density is constant)

$$f(x, h) = f(x) = x(1 - x), \quad F(x) = f(x)$$

as $N \rightarrow \infty$, $n_I/N \rightarrow i(t)$, s.t.

$$i'(t) = \beta i(t)(1 - i(t))$$

with initial condition

$$i(0) = \lim_{N \rightarrow \infty} n_I(0) / N$$

Application to epidemic routing

$$i'(t) = \beta i(t)(1 - i(t)), \quad i(0) = \lim_{N \rightarrow \infty} n_I(0) / N$$

The solution is

$$i(t) = \frac{1}{1 + \left(\frac{1}{i(0)} - 1 \right) e^{-\beta t}}$$

And for the Markov system we expect

$$n_I(t) \approx Ni(t) = \frac{N}{1 + \left(\frac{N}{n_I(0)} - 1 \right) e^{-N\lambda t}}$$