

Performance Evaluation

Second Part

Lecture 3

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Outline

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

Heterogeneous Networks

- Denote $P(d)$ the probability that a node has degree d
- If the degree does not change much, we can replace d with $\langle d \rangle$
 - what we have done for ER graphs (N,p)
 - Binomial with parameters $(N-1,p)$
- How should we proceed (more) correctly?
 - Split the nodes in degree classes
 - Write an equation for each class
- Remark: following derivation will not be as rigorous as previous ones

Heterogeneous Networks

- N_d number of nodes with degree d ($=N \cdot P(d)$)
- I_d : number of infected nodes with degree d
- Given node i with degree d and a link e_{ij} , what is the prob. that j has degree d' ?
 - $P(d')$? NO
- and if degrees are uncorrelated? i.e. Prob(neighbour has degree d' | node has a degree d) independent from d ,
 - $P(d')$? NO
 - Is equal to $d' / \langle d \rangle P(d')$

Heterogeneous Networks

- Given node i with degree d and a link e_{ij}
- Prob. that j has degree d' is
 - $d' / \langle d \rangle P(d')$
- Prob. that j has degree d' and is infected
 - $d' / \langle d \rangle P(d') I_{d'} / N_{d'}$
 - more correct $(d'-1) / \langle d \rangle P(d') I_{d'} / N_{d'}$
- Prob. that i is infected through link e_{ij} is
 - $p = p_g \sum_{d'} (d'-1) / \langle d \rangle P(d') I_{d'} / N_{d'}$
- Prob. that i is infected through one link
 - $1 - (1-p)^d$

Heterogeneous Networks

$$\square E[(I_d(k+1) - I_d(k) | \mathbf{I}(k) = \mathbf{I})] = (N_d - I_d)(1 - (1-p)^d)$$

$$- p = p_g \sum_{d'} (d'-1) / \langle d \rangle P(d') I_{d'} / N_{d'}$$

$$\square f_d^{(N)}(i) = (1 - i_d)(1 - (1-p)^d)$$

$$- i_d = I_d / N_d$$

$$- \text{if we choose } p_g = p_{g0} / N$$

$$- f_d(i) = (1 - i_d) p_{g0} d \underbrace{\sum_{d'} (d'-1) / \langle d \rangle P(d') i_{d'}}_{\Theta}$$

Θ

$$\square di_d(t)/dt = f_d(i(t)) = p_{g0} (1 - i_d(t)) \Theta(t)$$

Heterogeneous Networks

- $di_d(t)/dt = f_d(i(t)) = p_{g0} (1 - i_d(t)) d \Theta(t)$,
 - for $d=1,2,\dots$
 - $\Theta(t) = \sum_{d'} (d'-1) / \langle d \rangle P(d') i_{d'}(t)$
 - $i_d(0) = i_{d0}$, for $d=1,2,\dots$
- If $i_d(0) \ll 1$, for *small* t
 - $di_d(t)/dt \approx p_{g0} d \Theta(t)$
 - $d\Theta(t)/dt = \sum_{d'} (d'-1) / \langle d \rangle P(d') di_{d'}(t)/dt$
 $\approx p_{g0} \sum_{d'} (d'-1) / \langle d \rangle P(d') d' \Theta(t) =$
 $= p_{g0} (\langle d^2 \rangle - \langle d \rangle) / \langle d \rangle \Theta(t)$

Heterogeneous Networks

- $d\Theta(t)/dt \approx p_{g_0}(\langle d^2 \rangle - \langle d \rangle) / \langle d \rangle \Theta(t)$
 - Outbreak time: $\langle d \rangle / ((\langle d^2 \rangle - \langle d \rangle) p_{g_0})$
 - For ER $\langle d^2 \rangle = \langle d \rangle (\langle d \rangle + 1)$, we find the previous result, $1 / (\langle d \rangle p_{g_0})$
 - What about for Power-law graphs, $P(d) \sim d^{-\gamma}$?
- For the SIS model:
 - $d\Theta(t)/d \approx p_{g_0}(\langle d^2 \rangle - \langle d \rangle) / \langle d \rangle \Theta(t) - r_0 \Theta(t)$
 - Epidemic threshold: $p_{g_0} (\langle d^2 \rangle - \langle d \rangle) / (\langle d \rangle r_0)$

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Outline and references

Introduction to epidemic routing

Markovian models

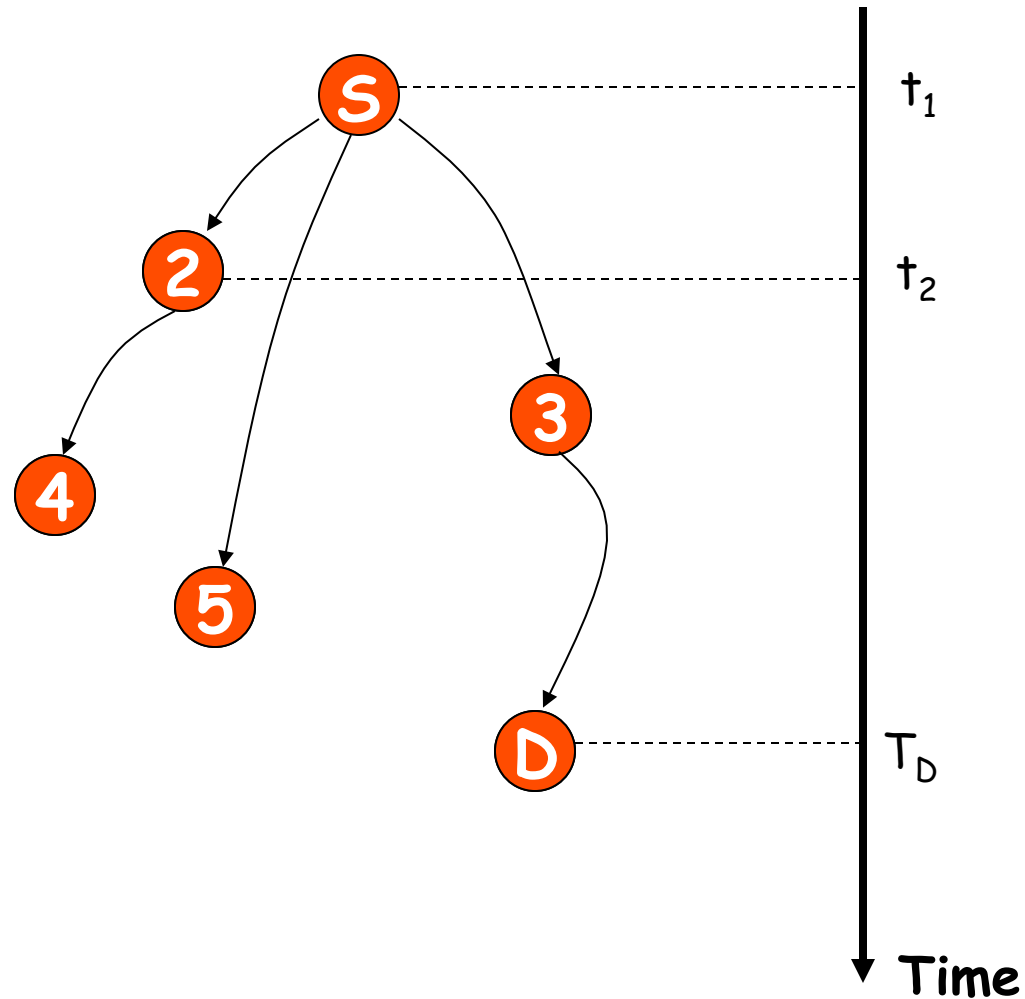
Message Delay in Mobile Ad Hoc Networks, R. Groenevelt, G. Koole, and P. Nain, Performance, Juan-les-Pins, October 2005

Impact of Mobility on the Performance of Relaying in Ad Hoc Networks, A. Al-Hanbali, A.A. Kherani, R. Groenevelt, P. Nain, and E. Altman, IEEE Infocom 2006, Barcelona, April 2006

Fluid models

Performance Modeling of Epidemic Routing, X. Zhang, G. Neglia, J. Kurose, D. Towsley, Elsevier Computer Networks, Volume 51, Issue 10, July 2007, Pages 2867-2891

Standard Epidemic Routing



Epidemic Style Routing

Epidemic Routing [Vahdat&Becker00]

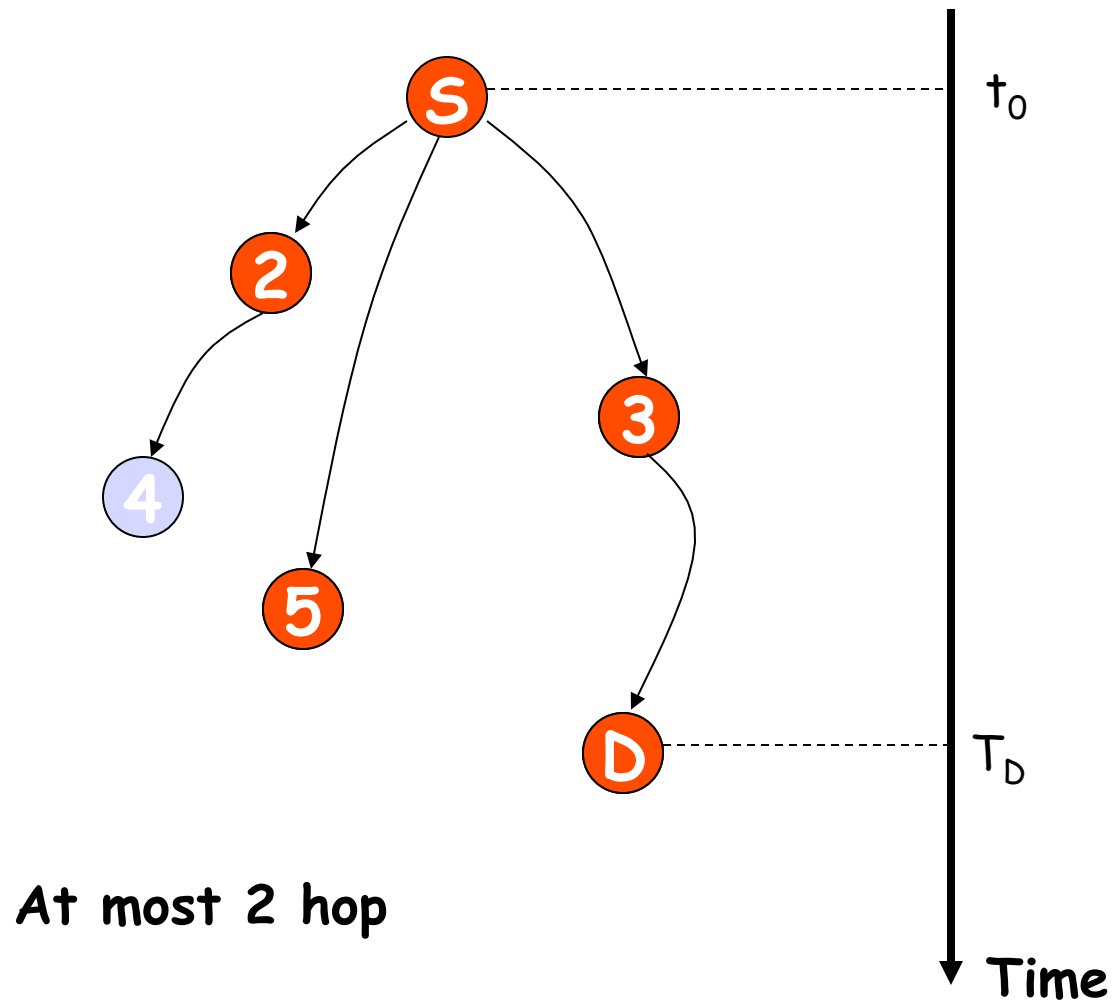
Propagation of a pkt -> Disease Spread

achieve min. delay, at the cost of transm. power,
storage

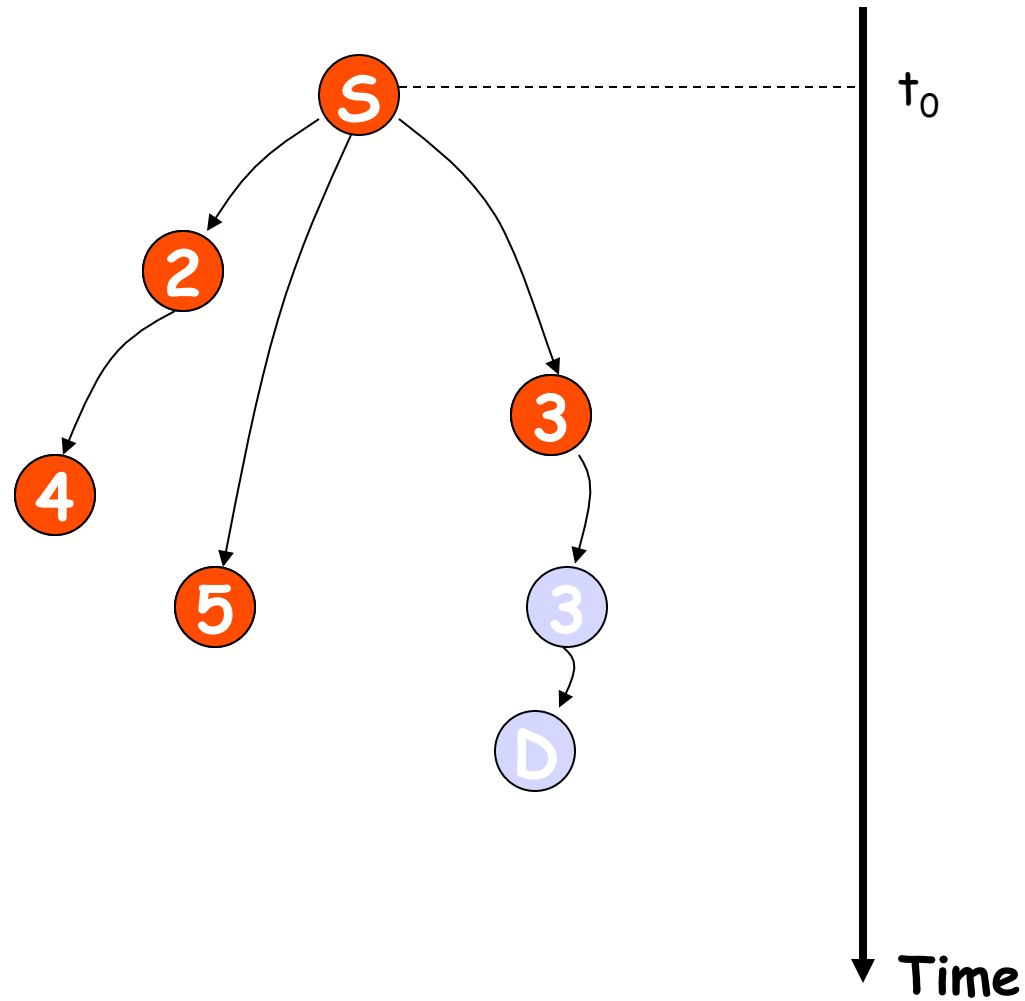
trade-off delay for resources

K-hop forwarding, probabilistic forwarding,
limited-time forwarding, spray and wait...

2-Hop Forwarding



Limited Time Forwarding



Epidemic Style Routing

Epidemic Routing [Vahdat&Becker00]

Propagation of a pkt -> Disease Spread
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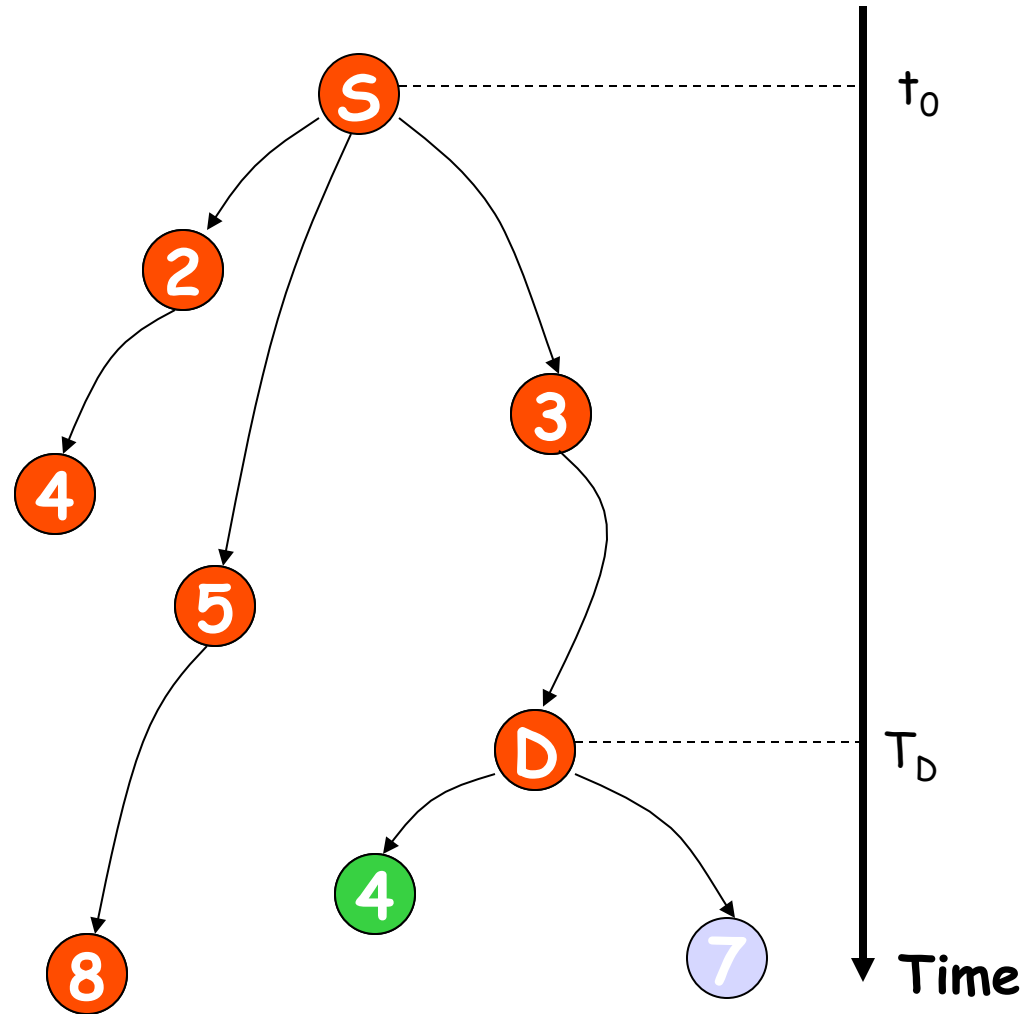
Recovery: deletion of obsolete copies after
delivery to dest., e.g.,

TIMERS: when time expires all the copies are
erased

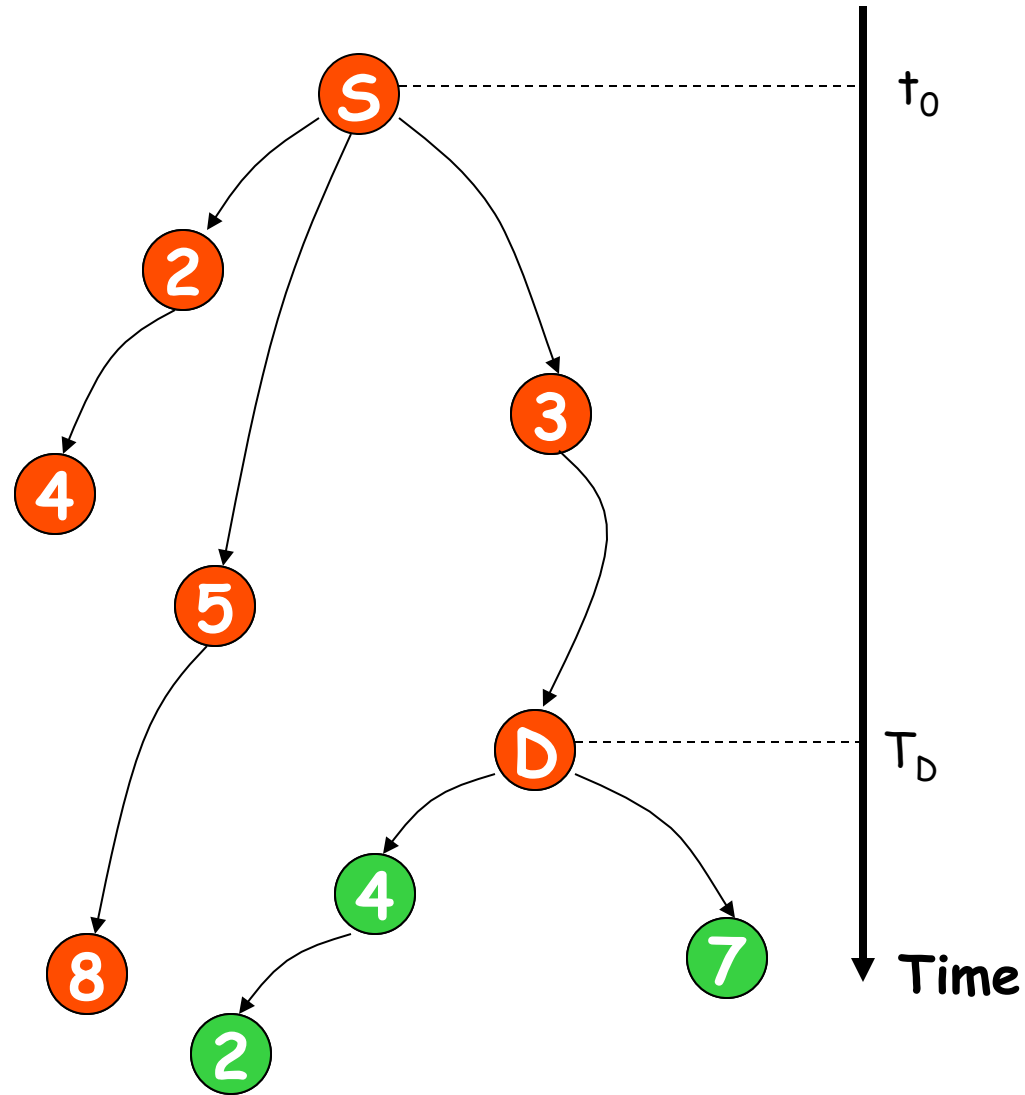
IMMUNE: dest. cures infected nodes

VACCINE: on pkt delivery, dest propagates anti-
pkt through network

IMMUNE Recovery



VACCINE Recovery



Outline

Introduction to Epidemic Routing

Markovian models

- the key to Markov model

- Markovian analysis of epidemic routing

Fluid models

The setting we consider

$N+1$ nodes

moving independently in an finite area A

with a fixed transmission range r and no interference

1 source, 1 destination

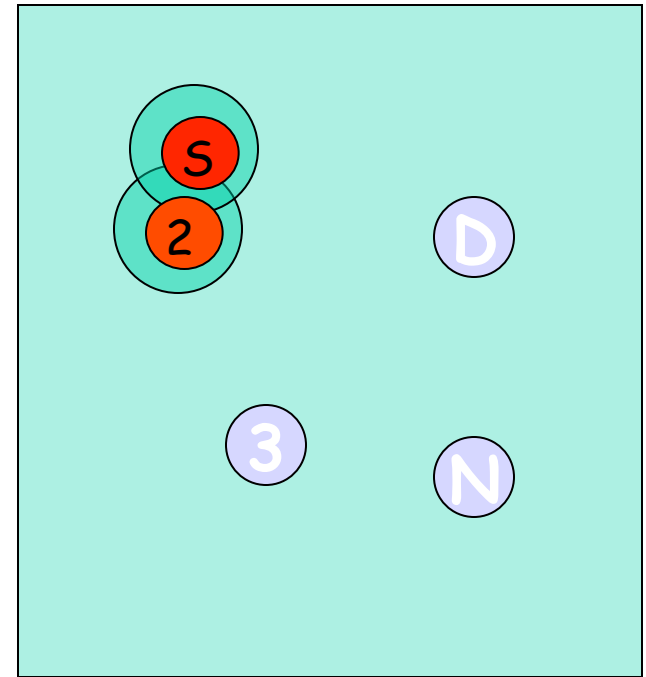
Performance metrics:

Delivery delay T_d

Avg. num. of copies at delivery C

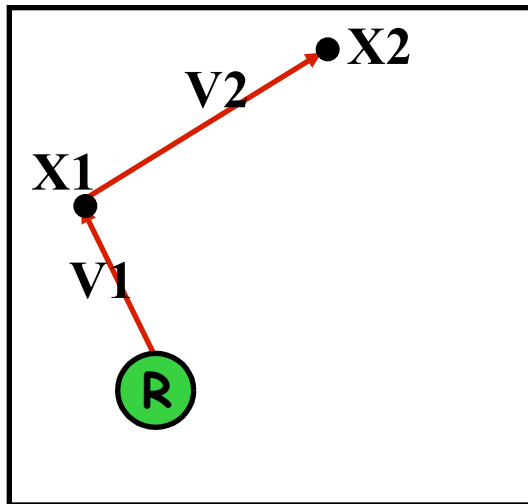
Avg. total num. of copies made G

Avg. buffer occupancy



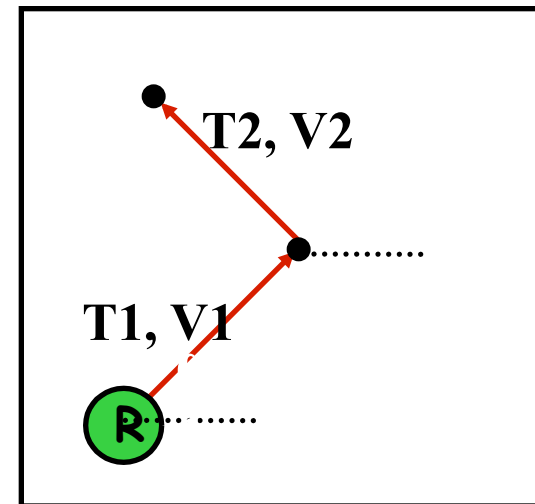
Standard random mobility models

Random Waypoint model (RWP)



- Next positions (X_i)s are uniformly distributed
- Speeds (V_i)s are uniformly distributed (V_{min}, V_{max})

Random Direction model (RD)



- Directions (α_i) are uniformly distributed ($0, 2\pi$)
- Speeds (V_i) are uniformly distributed (V_{min}, V_{max})
- Travel times (T_i) are exponentially / generally distributed

The key to Markov model

[Groenevelt05]

if nodes move according to standard random mobility model (random waypoint, random direction) with average relative speed $E[V^*]$,

and if Nr^2 is small in comparison to A

pairwise meeting processes are *almost* independent Poisson processes with rate:

$$\lambda \approx \frac{2wrV^*}{A}$$

w : mobility specific constant

Intuitive explanation

Exponential distribution finds its roots in the independence assumptions of each mobility model:

- Nodes move independently of each other
- **Random waypoint**: future locations of a node are independent of past locations of that node.
- **Random direction**: future speeds and directions of a node are independent of past speeds and directions of that node.

There is some probability q that two nodes will meet before the next change of direction. At the next change of direction the process repeats itself, **almost** independently.

Why “almost”?

pairwise meeting processes are *almost* independent Poisson processes with rate:

$$\lambda \approx \frac{2wrV^*}{A} \quad w: \text{mobility specific constant}$$

1. inter-meeting times are not exponential

if N1 and N2 have met in the near past they are more likely to meet (they are close to each other)

the more the bigger it is r^2 in comparison to A

2. meeting processes are not independent

if in $[t, t+\tau]$ N1 meets N2 and N2 meets N3, it is more likely that N1 meets N3 in the same interval

the more the bigger it is r^2 in comparison to A

moreover if Nr^2 is comparable with A (dense network) a lot of meeting happen at the same time.

Examples

Nodes move on a square of size $4 \times 4 \text{ km}^2$ ($L=4 \text{ km}$)
Different transmission radii ($R=50,100,250 \text{ m}$)

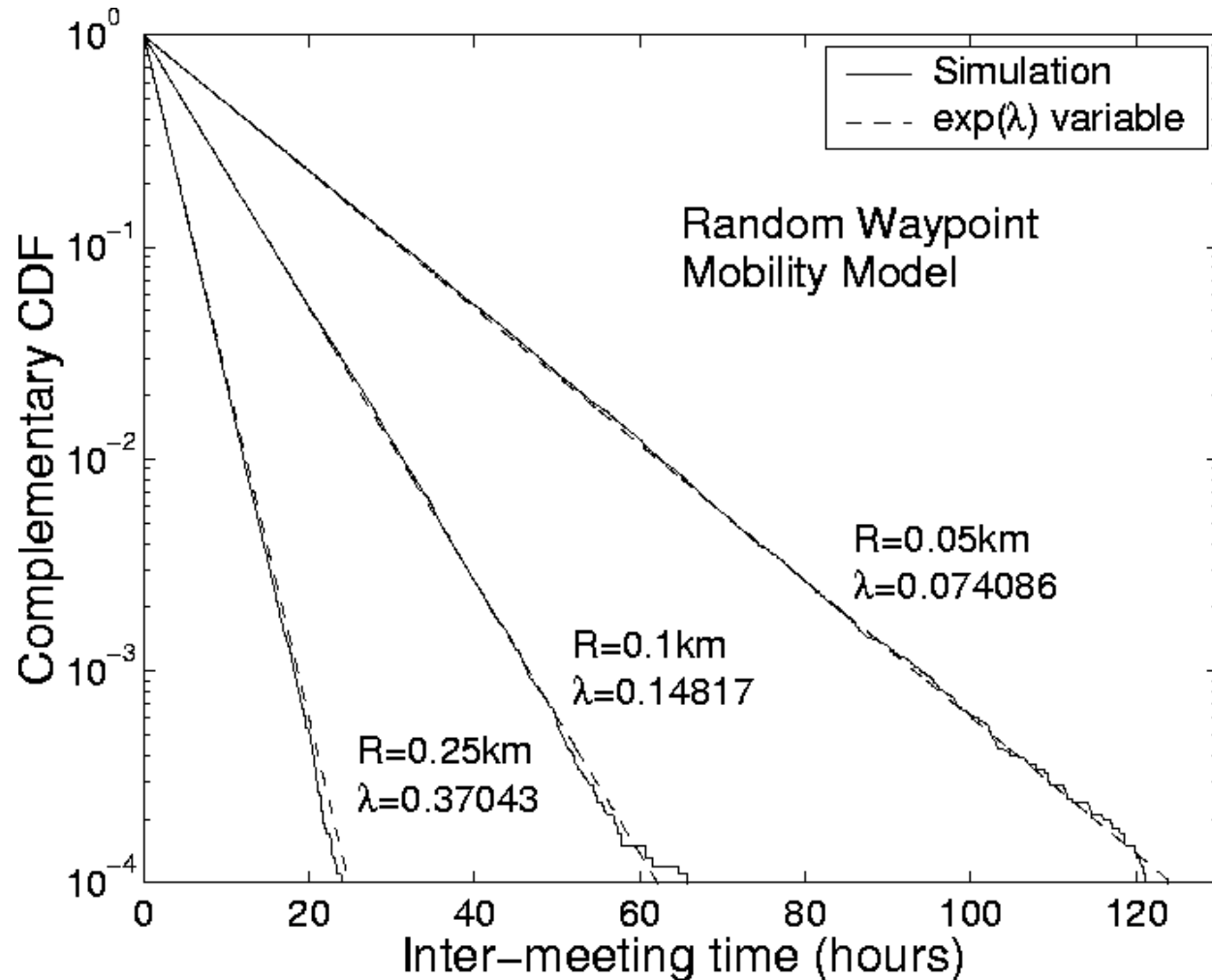
Random waypoint and random direction:

no pause time

$[v_{\min}, v_{\max}] = [4, 10] \text{ km/hour}$

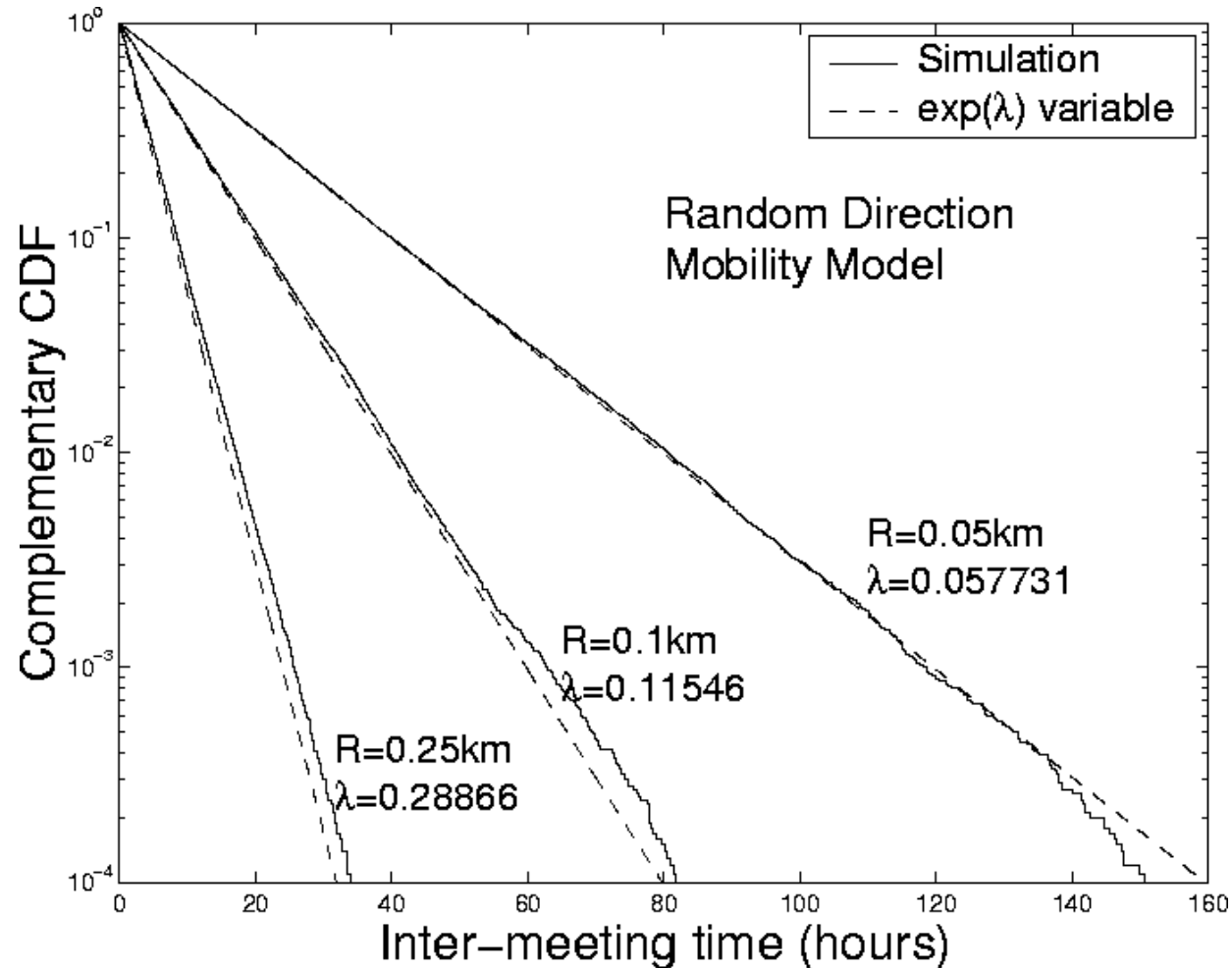
Random direction: travel time $\sim \exp(4)$

Pairwise Inter-meeting time



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

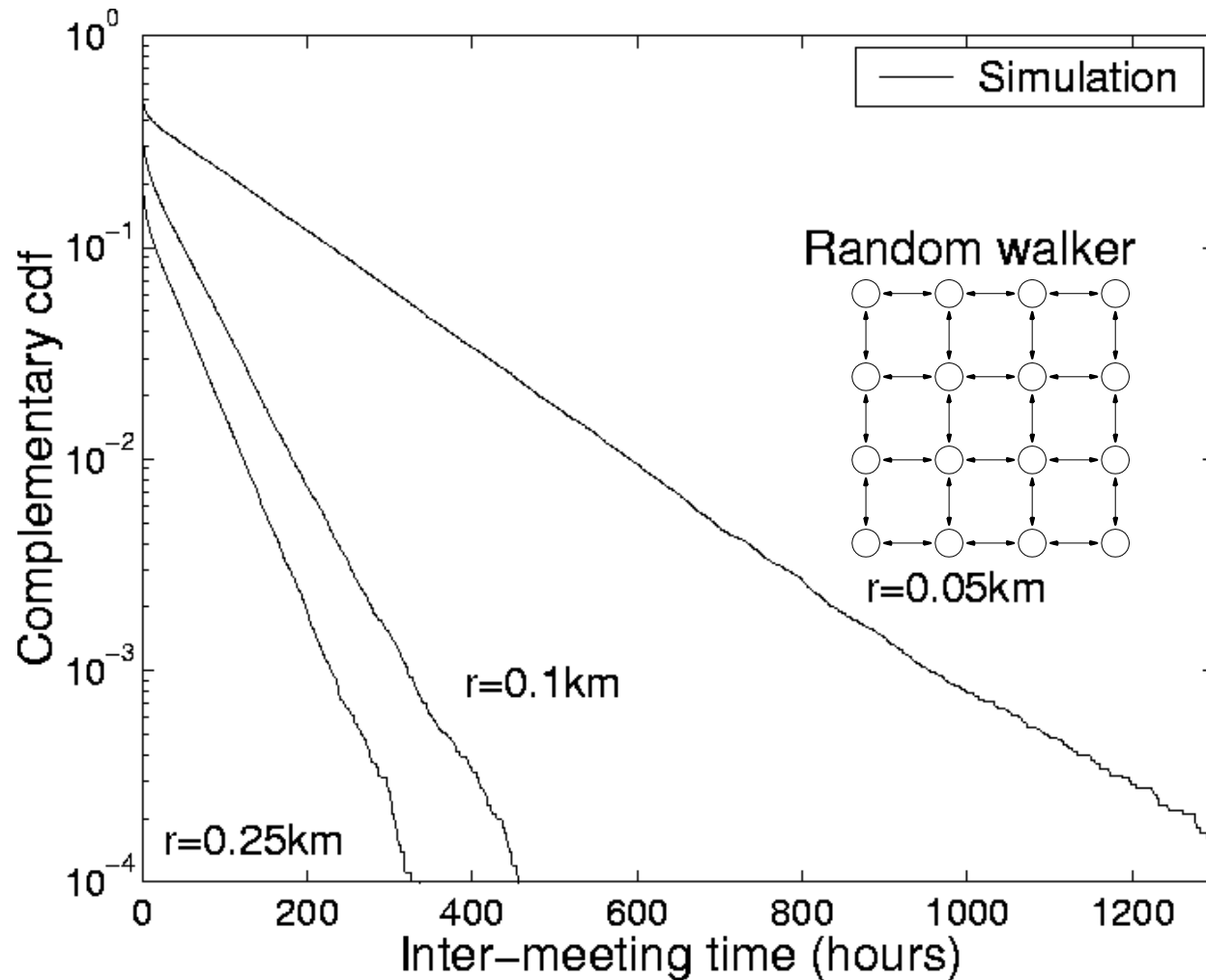
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Pairwise Inter-meeting time



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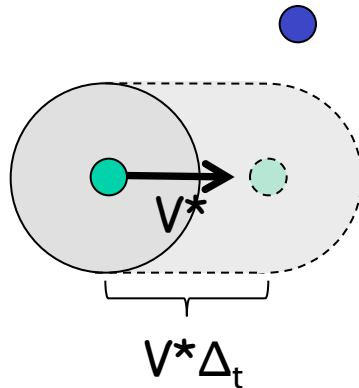
$$\log P(T > t) = -\lambda t$$

The derivation of λ

Assume a node in position (x_1, y_1) moves in a straight line with speed V_1 .

Position of the other node comes from steady-state distribution with pdf $\pi(x, y)$.

Look at the area A covered in Δ_t time:



The derivation of λ

Probability that nodes meet given by

$$P_{x_1, y_1} = \iint_A \pi(x, y) dx dy.$$

For small r the points in $\pi(x, y)$ in A can be approximated by $\pi(x_1, y_1)$ to give

$$P_{x_1, y_1} \approx 2r \cdot V_1^* \cdot \Delta_t \cdot \pi(x_1, y_1).$$

Unconditioning on (x_1, y_1) gives

$$\begin{aligned} p &= \int_0^L \int_0^L P_{x_1, y_1} \cdot \pi(x_1, y_1) dx_1 y_1 \\ &\approx 2r \cdot V_1^* \cdot \Delta_t \cdot \int_0^L \int_0^L \pi^2(x_1, y_1) dx_1 y_1 \end{aligned}$$

The derivation of λ

Proposition: Let $r \ll L$. The inter-meeting time for the random direction and the random waypoint mobility models is approximately exponentially distributed with parameter

$$\lambda \approx 2 r \cdot E[V^*] \cdot \int_0^L \int_0^L \pi^2(x,y) dx dy,$$

Here $E[V^*]$ is the average relative speed between two nodes and $\pi(x,y)$ is the pdf in the point (x,y) .

The derivation of λ

Proposition: Let $r \ll L$. The inter-meeting time for the random direction and the random waypoint mobility models is approximately exponentially distributed with parameter

$$\lambda_{RD} \approx \frac{2rE[V^*]}{L^2}, \quad \lambda_{RW} \approx \frac{2r\omega E[V^*]}{L^2}.$$

Here $E[V^*]$ is the average relative speed between two nodes and $\omega \approx 1.3683$ is the Waypoint constant.

If speeds of the nodes are constant and equal to v ,

$$\lambda_{RD} \approx \frac{8rv}{\pi L^2}, \quad \lambda_{RW} \approx \frac{8\omega rv}{\pi L^2}.$$

Summary up to now

First steps of this research

- a good intuition

- some simulations validating the intuition for a reasonable range of parameters

What could have been done more

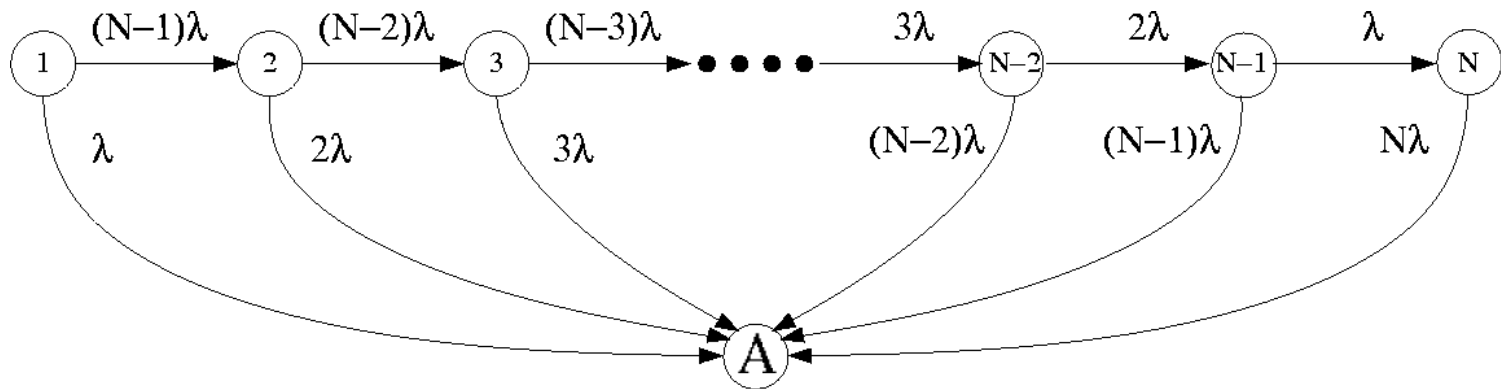
- prove that the results is asymptotically ($r \rightarrow 0$) true “in some sense”

What can be built on top of this?

- Markovian models for routing in DTNs

2-hop routing

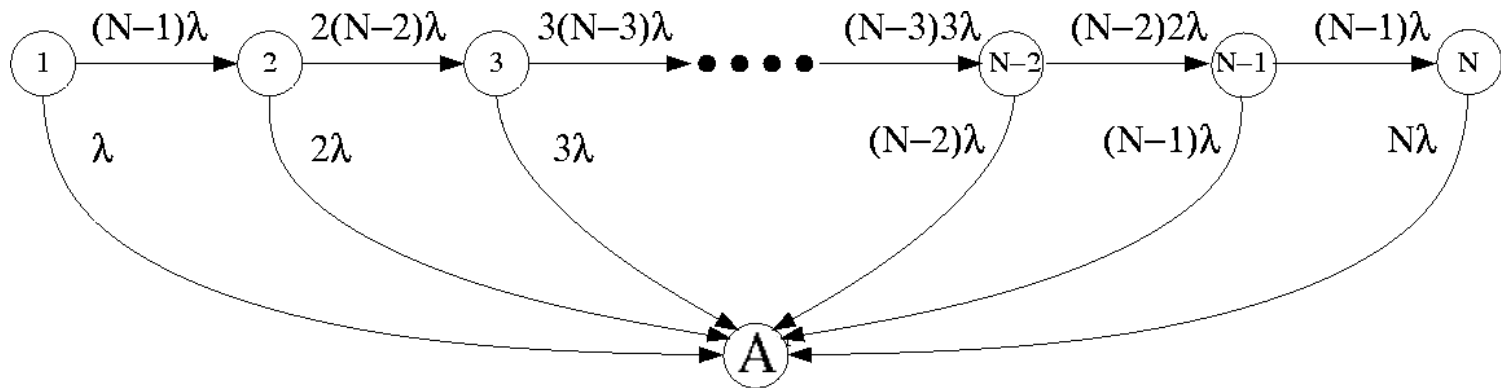
Model the number of occurrences of the message as an absorbing Continuous Time Markov Chain (CTMC):



- 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:



- 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.