

04/05/04 : HW3 due date extended

04/14 at 5 PM

- PK: no OH on 04/13

How long (in terms of time variable t)
does a new request have to wait
before it is met by the server.

Let this random quantity be T .

$$T = \sum_{j=0}^N T_j \quad \text{where } N = \# \text{ demands in the queue upon arrival of new request}$$

T_j = random time to fulfill request
of j th "customer"
 $j=0$: new demand

$\{T_j\}$ are i.i.d so T
is a random sum of i.i.d r.v.s

Use generating function for T :

$$\mathcal{L}_T(\theta) \equiv \mathbb{E} e^{-\theta T} = \int_0^{\infty} e^{-\theta t} p_T(t) dt$$

\uparrow
 p_T for T

(Laplace transform for p_T ; works
basically same way as other versions
of gen fn)

$$\begin{aligned}
 \mathcal{L}_T(\theta) &= \mathbb{E} e^{-\theta \sum_{j=0}^N T_j} = \langle e^{-\theta \sum_{j=0}^N T_j} \rangle \\
 &= \langle \langle e^{-\theta \sum_{j=0}^N T_j} \rangle_T \rangle_N \\
 &= \langle (\mathcal{L}_{T_1}(\theta))^{N+1} \rangle
 \end{aligned}$$

$$\begin{aligned}
 \text{where } \mathcal{L}_{T_1}(\theta) &= \langle e^{-\theta T_1} \rangle \\
 &= G_N(\mathcal{L}_{T_1}(\theta)) \mathcal{L}_{T_1}(\theta) \\
 \text{where } G_N(s) &= \langle S^N \rangle
 \end{aligned}$$

$$p_{T_1}(t) = \mu e^{-\mu t} \quad \text{for } t \geq 0$$

$$\begin{aligned}
 \mathcal{L}_{T_1}(\theta) &= \int_0^{\infty} \mu e^{-\mu t} e^{-\theta t} dt \\
 &= \frac{\mu}{\mu + \theta}
 \end{aligned}$$

Assume system has settled down to
stat dist., (with $\lambda < \mu$)

$$\begin{aligned}
 G_N(s) = \langle S^N \rangle &= \sum_{j=0}^{\infty} \pi_j s^j = \sum_{j=0}^{\infty} \left(1 - \frac{\lambda}{\mu}\right) \left(\frac{\lambda}{\mu}\right)^j s^j \\
 &= \frac{1 - \frac{\lambda}{\mu}}{1 - \frac{\lambda s}{\mu}}
 \end{aligned}$$

$$\mathcal{L}_T(\theta) = \frac{\left(1 - \frac{\lambda}{\mu}\right) \frac{\mu}{\mu + \theta}}{1 - \frac{\lambda}{\mu} \left(\frac{\mu}{\mu + \theta}\right)} = \frac{\left(1 - \frac{\lambda}{\mu}\right) \frac{\mu}{\mu + \theta}}{1 - \frac{\lambda}{\mu + \theta}}$$

$$= \frac{\mu - \lambda}{\mu + \theta - \lambda} = \frac{\mu - \lambda}{\mu - \lambda + \theta}$$

which is Laplace xform of exp dist.

T has pdf

$$p_T(t) = (\mu - \lambda) e^{-(\mu - \lambda)t}$$

exp. dist. with mean $\frac{1}{\mu - \lambda}$.

Stochastic Models for Epidemics

Standard deterministic model for contagious person-to-person disease (Hethcote, SIAM Review 2000)

S = susceptible

I = infected

R = recovered (immune)

Kermack-McKendrick model:

$$\frac{dS}{dt} = - \frac{\lambda SI}{N}$$

λ = per capita contact rate

$$N = S + I + R$$

$$\frac{dI}{dt} = \frac{\lambda SI}{N} - \gamma I$$

γ = rate of recovery

$$\frac{dR}{dt} = \gamma I$$

Often in a highly contagious disease, there can be a wide variety of outcomes from given initial data.

- slight variations in initial progress disease can amplify to large changes

Simple stochastic model:

Reed-Frost model:

Andersson-Britton
Sec. 1.2

Discrete-time MC model for (S, I)

$$R = N - S - I$$

At each epoch, each infected person has probability p of infecting each susceptible person, $\frac{1}{\delta}$ = mean time of infection

$$p \approx 1 - e^{-\lambda/\delta N}$$

(Prob no infection from the I during time t)
$$\approx e^{-\lambda t/N}$$

At each epoch, all the infected people recover.

(Each epoch corresponds to a "generation" of the disease spread. $q = 1 - p$)

$$\text{Prob}(S_{n+1} = s_{n+1}, I_{n+1} = i_{n+1} | S_n = s_n, I_n = i_n) = \binom{s_n}{i_{n+1}} (1 - q^{i_n})^{i_{n+1}} (q^{i_n})^{s_n - i_{n+1}}$$

if $s_{n+1} + i_{n+1} = s_n$ → Prob a given S does not get sick
= 0 otherwise

Th_{1,3} is used a bit but
continuous-time stochastic models for
epidemics also of interest
for more flexibility in handling
extra complexity

- variability in recovery time
- when introduce other effects
like vaccination, death, immigration,
etc., these superpose simply
in instantaneous sense but
not simply over finite time
intervals.

Continuous-time stochastic SIR model

Andersson - Britton Ch. 2

Each infected person communicates disease
to each susceptible person according
to a Poisson process w/ rate $\frac{\lambda}{n+m}$

λ = per capita contact rate

n = # susceptibles initially

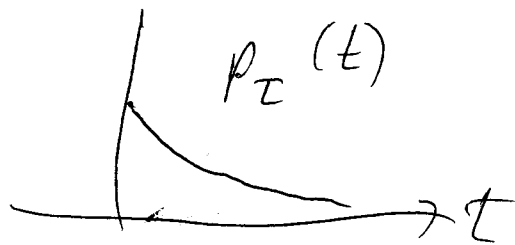
m = # infected initially

$N = n + m$

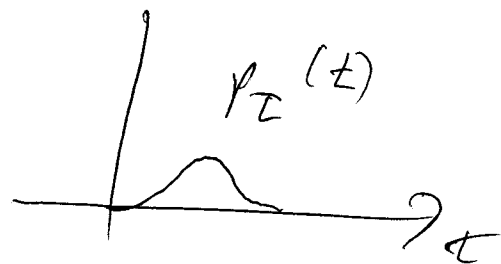
All interactions between people occur independently.

Each infected person remains infective for a random time τ , which is i.i.d for different infections.

Is this a continuous-time MC?
- only if τ has exp. dist.



- other distributions of interest to better match data



- τ deterministic \Rightarrow Reed-Frost model

For Markovian case (~~if τ is exp~~ $p_\tau(t) = \delta e^{-\delta t}$)

Transition rates: $(s, i) \rightarrow (s-1, i+1) \quad \frac{\lambda s i}{n+m}$

$(s, i) \rightarrow (s, i-1) \quad \delta i$

Sellke construction for stochastic SIR model

- works for non-Markovian case

Define an infection pressure:

$$\Phi(t) = \frac{\lambda}{n+m} \int_0^t I(s) ds$$

Each initially susceptible person (label them $1, \dots, n$)

has an infection threshold Q_j

which is random. In particular, the Q_j are i.i.d. rvs with pdf

$$p_Q(z) = e^{-z}$$

Susceptible # j becomes infected at the time t when $\Phi(t) = Q_j$

Each person, when infected, remains infective for random time T_i .

Let $Q_{(j)}$ be the threshold of the j th weakest susceptible. (order statistics)

Why is this equivalent to the stochastic SIR model,
Recovery correct so just need to check
infection process,

Need to show that, under the Sellke
construction, the probability that
a given susceptible person becomes
infected during time interval $[t, t + \Delta t]$
with probability $\frac{\lambda}{n+m} I(t) \Delta t + o(\Delta t)$
↑
higher order

(check: According to Sellke construction,
Prob (Susceptible #j becomes infected during $[t, t + \Delta t]$ |
j still susceptible at time t)

$$= \text{Prob}(\Phi(t + \Delta t) > Q_j \mid \Phi(t) < Q_j)$$

$$= 1 - \text{Prob}(Q_j > \bar{\Phi}(t + \Delta t) - \Phi(t)) \text{ because}$$

an exp. dist. variable Q has
the property $\text{Prob}(Q > b \mid Q > a)$
 $= \text{Prob}(Q > b - a)$

$$= 1 - e^{-(\Phi(t+\Delta t) - \Phi(t))}$$

$$\approx 1 - (1 - \Phi'(t) \Delta t + o(\Delta t))$$

$$= \Phi'(t) \Delta t + o(\Delta t)$$

$$= \frac{\lambda}{n+m} I(t) \Delta t + o(\Delta t) \quad \checkmark$$

Key question: How many people are infected before the epidemic dies out? Let Z be this random variable.

$$Z = \min \left\{ i : Q_{(i+1)} > \frac{\lambda}{n} \sum_{j=-i}^i I_j \right\}$$

~~Key are~~

I_j are the infective times for person # (j)

$(j) \in 1, \dots, n$: initial susceptibles

$(j) \in -i, \dots, 0$: initial infected

How do we calculate statistics of Z ?

(Clever recursive argument.)

Relate epidemic statistics for a given population to those of a population with a smaller # of initial susceptibles.

Let $Z^{n'}$, $\Phi^{n'}$ be the total epidemic size and infection pressure with n' initial susceptibles

but always normalize infection rate by $\frac{1}{n+m}$

↑ not n'

$$\Phi^{n'} = \frac{\lambda}{n+m} \int_0^{\infty} I^n(s) ds$$

$$S^{n'}(0) = n'$$