

# Studying behavior before absorption in stochastic epidemic models: Quasi-stationary and Ratio of Expectations distributions

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MPDE, Aix-Marseille, 5th - 9th September 2016

# Talk Schedule

1. Introduction
2. Quasi-stationarity
3. RE-distribution
4. Application to epidemic stochastic models
5. Conclusions and References

# 1. Introduction

We deal with continuous time Markov chains  $\{X(t); t \geq 0\}$  (CTMC) with state space

$$S = S_A \cup S_T,$$

where  $S_T$  is a set of transient states and  $S_A$  is a set of absorbing states (e.g.  $S_A = \{0\}$ ).

The stationary distribution is degenerate so the fundamental problem is:

*There exist a need for probabilistic measures of the system behavior before absorption. Analogues of the stationary distribution of the irreducible case should be considered and compared.*

In the spirit of the seminal work by Darroch and Seneta (1967), we will consider two possibilities:

- Quasi-stationary distribution.
- Ratio of expectations (RE) distribution.

A comparison between both distributions is justified only if the convergence to quasi-stationary regime is relatively fast.

## 2. Quasi-stationarity

The starting point is the conditional probability

$$u_i(t) = P\{X(t) = i \mid T > t\}, \quad i \in S_T,$$

where  $T = \sup\{t \geq 0 \mid X(t) \in S_T\}$  denotes the absorption time.

**Definition 1.** Suppose that the chain starts with the initial distribution  $a_i = P\{X(0) = i\}$ ,  $i \in S_T$ . If there exists a starting distribution  $a_i = u_i$  such that

$$P\{X(t) = i \mid T > t\} = u_i, \quad i \in S_T,$$

for all  $t \geq 0$ , then  $\mathbf{u} = \{u_i; i \in S_T\}$  is called a quasi-stationary distribution.

There also exists a limiting interpretation which states that

$$\lim_{t \rightarrow \infty} P\{X(t) = i \mid T > t\} = u_i, \quad i \in S_T,$$

independently of the initial distribution  $\{a_i; i \in S_T\}$ .

The above limiting result shows that the quasi-stationary distribution is a good measure of the system dynamics before absorption, but restricting only to those realizations in which the time to absorption is sufficiently large.

The existence and computation of the quasi-stationary distribution becomes difficult when  $S_T$  is infinite.

A.  $S_T$  is finite and irreducible

There exists a unique quasi-stationary distribution, but an analytical (explicit form) solution only exists in a few special cases.

**Example 1.** If  $\{X(t); t \geq 0\}$  is a birth and death process with  $S_A = \{0\}$ , then

$$(1 - \delta_{iN})\mu_{i+1}u_{i+1} - (\lambda_i + \mu_i)u_i + \lambda_{i-1}u_{i-1} = -\mu_1u_1u_i, \quad 1 \leq i \leq N,$$

where  $S = \{0, \dots, N\}$  and  $\lambda_0 = 0$ .

The above non-linear equation also holds when  $S = \mathbb{N}$ .

## Computation, approximations and recursive methods

- The power method provides an iterative procedure for computing  $\mathbf{u}$  and  $-\alpha$  (associate eigenvalue).
- Several approximations and recursive methods are available for the birth and death process on  $S = \{0, \dots, N\}$ , with  $S_A = \{0\}$ . A first approximation uses a birth and death process,  $X^{(0)}(t)$ , with the same rates except  $\mu_1^{(0)} = 0$ .
- A second approximation is based on the birth and death process,  $X^{(1)}(t)$ , with shifted death rates  $\mu_i^{(1)} = \mu_{i-1}$ ,  $1 \leq i \leq N$ .
- A recursive scheme is based on the following formula:

$$u_i = u_1 \pi_i \sum_{k=1}^i \frac{1 - (1 - \delta_{k1}) \sum_{j=1}^{k-1} u_j}{\tau_k}, \quad 2 \leq i \leq N.$$



B.  $S_T$  is finite but reducible (van Doorn and Pollett, 2008)

Suppose that  $S_T$  consists of  $L$  communicating classes  $S_k$ , for  $1 \leq k \leq L$ . A partial order on  $\{S_k; 1 \leq k \leq L\}$  is defined by writing  $S_i \prec S_j$  when class  $S_i$  is accessible from  $S_j$ . Let  $-\alpha_k$  be the (negative) eigenvalue with maximal real part of the sub-generator  $Q_k$  corresponding to the states in  $S_k$ . Then, the eigenvalue of  $Q_{S_T}$  with maximal real part is obtained as  $-\alpha$ , where  $\alpha = \min_{1 \leq k \leq L} \alpha_k$ . We also define  $I(\alpha) = \{k : \alpha_k = \alpha\}$  and  $a(\alpha) = \min I(\alpha)$ .

**Theorem 1.** If  $-\alpha$  has a geometric multiplicity one, then the Markov chain has a unique quasi-stationary distribution  $\{u_i; i \in S_T\}$  from which  $S_{a(\alpha)}$  is accessible. The  $j$ th component of  $\{u_i; i \in S_T\}$  is positive if and only if state  $j$  is accessible from  $S_{a(\alpha)}$ . A simple necessary and sufficient condition for establishing that  $-\alpha$  has geometric multiplicity one is that  $\{S_k; k \in I(\alpha)\}$  is linearly ordered, that is,  $S_i \prec S_j \iff i \leq j$ , for all  $i, j \in I(\alpha)$ .

### 3. RE-distribution

Let  $T_j$  be the time that the CTMC spends in state  $j \in S_T$  before absorption.

**Definition 2.** Given that  $X(0) = i \in S_T$ , we define the RE-distribution,  $\mathbf{P}_i = (P_i(j))$ , as follows

$$P_i(j) = \frac{E_i[T_j]}{E_i[T]}, \quad i, j \in S_T.$$

The ratio of means distribution (Darroch and Seneta, 1967) corresponds with the unconditional version:

$$P(j) = \frac{\sum_{i \in S_T} a_i E_i[T_j]}{\sum_{i \in S_T} a_i E_i[T]}, \quad j \in S_T.$$

## Remarks and computation

- The RE-distribution always exists provided that the expected time to absorption  $E_i [T] < \infty$ .
- The RE-distribution assigns positive probability to all state  $j$  accessible from the initial state  $i$ .
- Let us construct the ideal replicated model obtained by assuming that at each extinction the biological model restarts in the same initial state  $i \in S_T$ . The stationary distribution of this replicated (regenerative) model amounts to the RE-distribution  $\mathbf{P}_i$ .

For a fixed  $j \in S_T$ , a first-step argument yields

$$E_i [T_j] = \frac{\delta_{ij}}{q_i} + \sum_{\substack{k \in S_T \\ k \neq i}} \frac{q_{ik}}{q_i} E_k [T_j], \quad i \in S_T.$$

## 4. Application to the SIS stochastic model

- Closed population model of  $N$  individuals.
  - Classified either as susceptible or infective individual.
- Susceptible can be infected, then they recover and return to the susceptible pool.
- Evolution of the epidemic:
  - Birth and death process  $\{I(t); t \geq 0\}$ .
  - $I(t)$  : number of infective individuals at time  $t$ .
  - $S = \{0, 1, \dots, N\}$  (0 is an absorbing state).

- Classical SIS rates
  - Infection rate  $\lambda_i = \frac{\beta}{N}i(N - i)$ .
  - Recovery rate  $\mu_i = \gamma i$ .
- $R_0 = \frac{\beta}{\gamma}$  denotes the transmission factor.

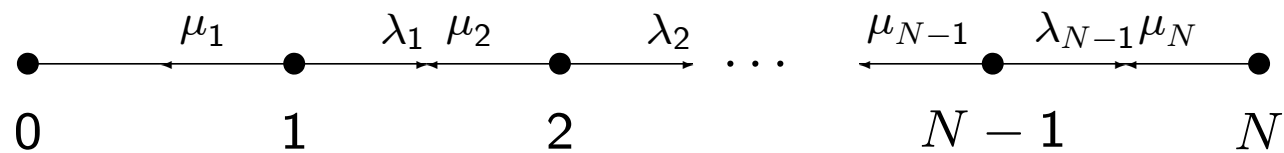


Figure 1. States and transitions of the birth and death model

In the case of a birth and death process, we have

$$\begin{aligned}
 E_0 [T_j] &= 0, \\
 (\lambda_i + \mu_i)E_i [T_j] &= \mu_i E_{i-1} [T_j] + \lambda_i E_{i+1} [T_j], \quad i \neq j, \quad 1 \leq i \leq N, \\
 (\lambda_j + \mu_j)E_j [T_j] &= \mu_j E_{j-1} [T_j] + \lambda_j E_{j+1} [T_j] + 1.
 \end{aligned}$$

**Theorem 2.** For the SIS epidemic model, the RE-distribution reduces to

$$P_i(j) = \frac{\frac{1}{j} \sum_{k=1}^{\min(i,j)} \left(\frac{R_0}{N}\right)^{j-k} \frac{(N-k)!}{(N-j)!}}{\sum_{j=1}^N \frac{1}{j} \sum_{k=1}^{\min(i,j)} \left(\frac{R_0}{N}\right)^{j-k} \frac{(N-k)!}{(N-j)!}}, \quad 1 \leq j \leq N.$$

## Stochastic ordering relationships

- For a birth and death process with  $S = \{0, \dots, N\}$  and  $S_A = \{0\}$ :

$$\mathbf{P}_1 = \mathbf{p}^{(0)},$$

$$\mathbf{p}^{(0)} \leq_{st} \mathbf{u},$$

$$\mathbf{P}_1 \leq_{st} \mathbf{u} \leq_{st} \mathbf{P}_N,$$

$$\mathbf{P}_i \leq_{st} \mathbf{P}_{i'}, \quad 1 \leq i \leq i' \leq N,$$

where  $X \leq_{st} Y \Leftrightarrow F_X(x) \geq F_Y(x)$ , for all  $x \in \mathbb{R}$ .

- For the SIS model:

$$\mathbf{u} \leq_{st} \mathbf{p}^{(1)},$$

$\mathbf{P}_N \leq_{st} \mathbf{p}^{(1)}$ , for  $N$  fixed and  $R_0$  sufficiently large,

$\mathbf{p}^{(1)} \leq_{st} \mathbf{P}_N$ , for  $N$  fixed and  $R_0$  sufficiently small.



## Numerical example

$N = 100$ ,  $\gamma = 1$  and several choices of  $R_0 = \beta$ .

$R_u < 1 \Rightarrow$  to use  $\mathbf{u}$  is meaningful.

$\hat{\mathbf{P}}$  and  $\tilde{\mathbf{P}}$  are mixtures of the RE-distributions.

$$|\mathbf{p}^{(1)} - \mathbf{u}| = \max_{1 \leq j \leq N} |p_j^{(1)} - u_j| \text{ (maximum pointwise distance).}$$

$R_0$	0.5	0.9	1.0	1.3	1.5	2.0
$ \mathbf{p}^{(1)} - \mathbf{u} $	0.00440	0.05091	0.08746	0.16147	0.11150	0.05890
$ \mathbf{P}_1 - \mathbf{u} $	0.21231	0.30368	0.30295	0.07878	0.00357	$4.267 \times 10^{-8}$
$ \mathbf{P}_N - \mathbf{u} $	0.58829	0.37515	0.28886	0.03260	0.00107	$1.038 \times 10^{-8}$
$ \hat{\mathbf{P}} - \mathbf{u} $	0.05134	0.09190	0.06356	0.00546	$1.485 \times 10^{-4}$	$9.214 \times 10^{-10}$
$ \tilde{\mathbf{P}} - \mathbf{u} $	0.05508	0.08627	0.06453	0.00232	$5.591 \times 10^{-6}$	$9.020 \times 10^{-16}$

Table 1. Distributions distances with respect to  $\mathbf{u}$

## Application to the SIR stochastic model

- Classical SIR rates:  $\lambda_{ij} = \frac{\beta}{N}ij$  (infection rate) and  $\mu_i = \gamma i$  (recovery rate).

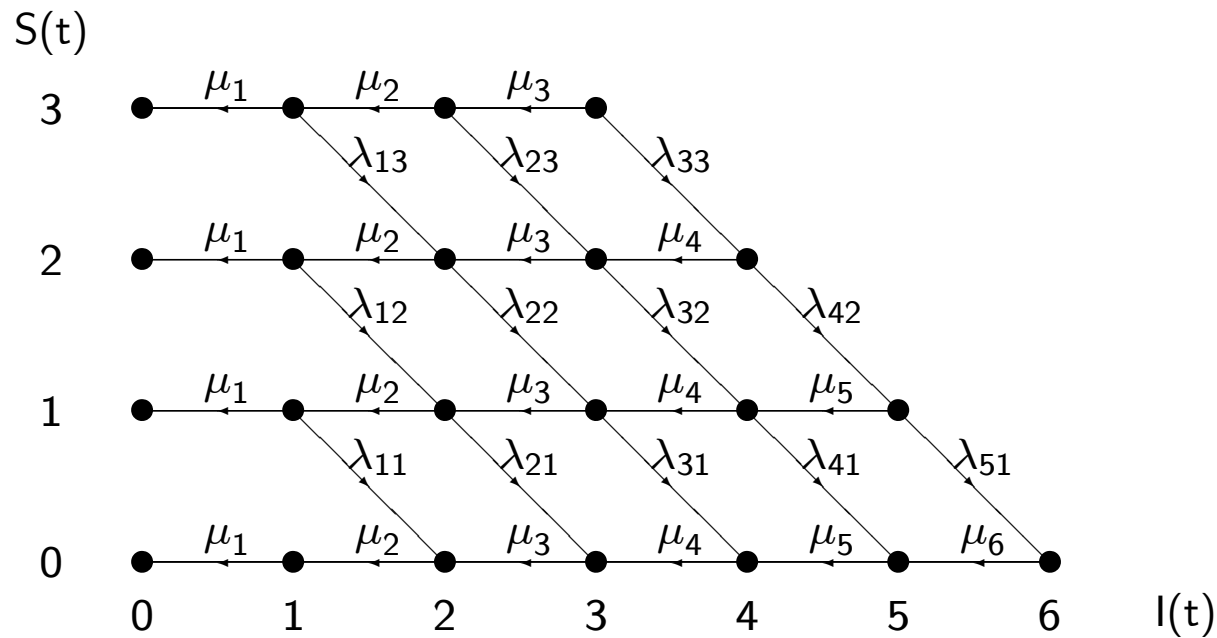


Figure 2. States and transitions of the SIR epidemic model

The quasi-stationary probabilities are

$$u_{(i,j)} = \delta_{(1,0)}(i,j), \quad 0 \leq j \leq n, \quad 1 \leq i \leq m+n-j,$$

because  $\min_{(i,j) \in S_T} (\lambda_{ij} + \mu_i) = \lambda_{10} + \mu_1 = \gamma$ , for  $\mu_i = \gamma i$ , and  $1 \leq i \leq m+n$ .

The RE-distribution of the SIR epidemic model is given by

$$P_{(m,n)}(i,j) = \frac{\frac{A_{ij}}{\lambda_{ij} + \mu_i}}{\sum_{j=0}^n \sum_{i=1}^{m+n-j} \frac{A_{ij}}{\lambda_{ij} + \mu_i}}, \quad (i,j) \in S_T,$$

where  $A_{ij}$  is the probability of reaching the state  $(i,j) \in S$  starting from  $(m,n)$  before the extinction occurs.

## Application to the SEIR stochastic model

- Classical SEIR rates:  $\lambda_{ij} = \frac{\beta}{N}ij$  (infection rate),  $\sigma_e = \sigma e$  ( $\sigma$  rate at which exposed an individual becomes infective) and  $\mu_i = \gamma i$  (recovery rate).
- Quasi-stationary distribution is almost degenerate: The quasi-stationary distribution assigns all its probability mass to one or two states.  
To state  $(0,0,1)$ , i.e., 1 infective individuals and  $N-1$  recovered, for  $\gamma \leq \sigma$ .  
To states  $(0,1,0)$  and  $(0,0,1)$ ; i.e, 1 exposed or infective individual and  $N-1$  recovered, for  $\gamma > \sigma$ .

The RE-distribution of the SEIR  $\mathbf{p}^{RE} = (p_{sei}^{RE} : (s, e, i) \in S_T)$  is given by

$$p_{sei}^{RE} = \frac{\frac{\theta_{sei}}{\beta_{si} + \sigma_e + \gamma_i}}{\sum_{(s', e', i') \in S_T} \frac{\theta_{s'e'i'}}{\beta_{s'i'} + \sigma_{e'} + \gamma_{i'}}}, \quad (s, e, i) \in S_T,$$

where  $\theta_{sei}$  is the probability of having a finite first passage time to state  $(s, e, i)$ , for  $(s, e, i) \in S_T$ .

The expected values corresponding to the RE-distributions of the number of individuals  $E_{RE}$  and  $I_{RE}$  in the  $E$  and  $I$  classes quantify intuitively the mean number of exposed and infected individuals during an outbreak of the epidemic. They are related to the expected values of the final size  $R(\infty)$  and the extinction time  $L(\infty)$  through the relationships

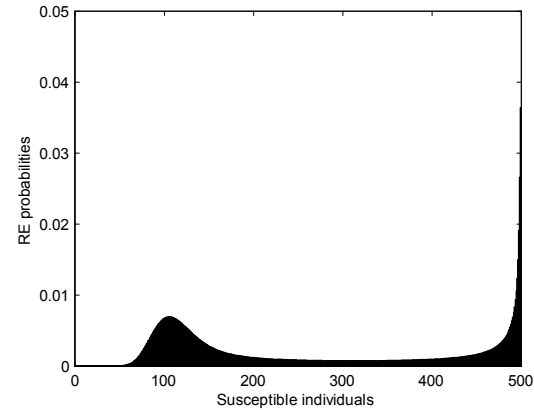
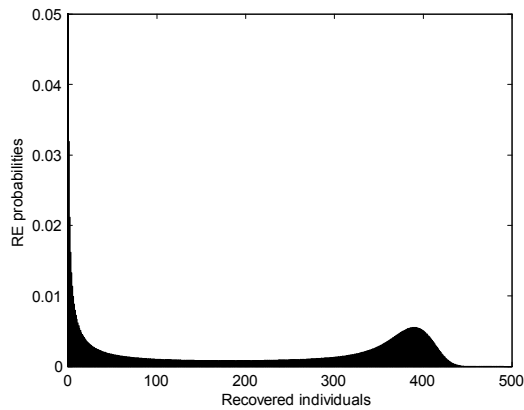
$$E_{(s_0, e_0, i_0)}[E_{RE}] = \frac{E_{(s_0, e_0, i_0)}[R(\infty)] - i_0}{E_{(s_0, e_0, i_0)}[L(\infty)]} \times \frac{1}{\sigma},$$

$$E_{(s_0, e_0, i_0)}[I_{RE}] = \frac{E_{(s_0, e_0, i_0)}[R(\infty)]}{E_{(s_0, e_0, i_0)}[L(\infty)]} \times \frac{1}{\gamma}.$$

## Numerical example

$N = 500$ ,  $\gamma = 1$ ,  $\beta = 2.0$ . Starting from a single infective individual: initial state  $(499, 0, 1)$ .

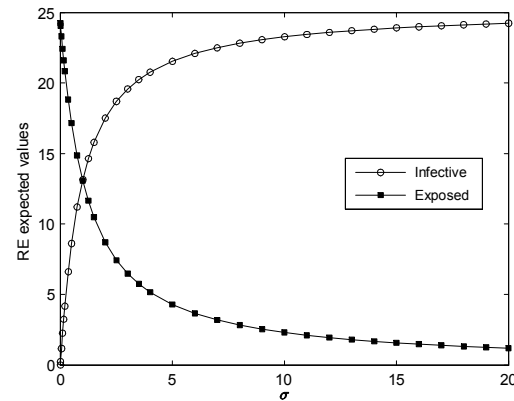
- Mass functions for the  $R$  (recovered) and  $S$  (susceptible) classes,  $\sigma = 5.0$



## Numerical example

$N = 500$ ,  $\gamma = 1$ ,  $\beta = 2.0$ . Starting from a single infective individual: initial state (499,0,1).

- Mean values of the RE distributions for the  $E$  and  $I$  classes versus  $\sigma$



## 5. Conclusions and References

The talk has a two-fold objective: *i*) to consider the quasi-stationarity and the ratio of expectations as two conceptually different approaches for measuring the behavior of a biological system before reaching the absorbing states, and *ii*) to evaluate the possibility of using the RE-distribution as an approximation to the quasi-stationary distribution provided that the quasi-stationary regime has already been reached.

- The quasi-stationary distribution gives an excellent measure of the long-term behavior of the system. Due to the non-linear structure of the quasi-stationary equations, it is usually impossible to obtain explicit expressions. However, there exists a number of helpful results including recursive methods, approximations and asymptotic analysis.
- The RE-distribution gives an alternative to measure the system dynamics before absorption, despite of how long the absorption time is. Since the RE-distribution is governed by linear equations, it can typically be evaluated more simply. The RE-distribution assigns positive mass to all transient states. The main problem concerns the difficulties for managing info about the initial state.



## Main references

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