

## Continuous-time Markov chains (continued)

### Transition Probability Function

Let  $P_{ij}(t) = P(X_{t+s} = j \mid X_s = i)$  denote the probability that a process presently in state  $i$  will be in state  $j$  an amount of time  $t$  later.

$\Rightarrow$  These are the transition probabilities of the CTMC.

(In discrete-time MCs, transition probabilities  $P_{ij}$  is the probability of jumping from  $i$  to  $j$  in 1 step.)

In continuous time, there's no first time  $t > 0$  so we use the above definition of  $P_{ij}(t)$  for each  $t > 0$ .)

We can explicitly determine  $P_{ij}(t)$  in certain cases.

Example:  $\{N(t) : t \geq 0\}$  is a Poisson process with rate  $\lambda$ .

Let  $Y_n$  be a discrete-time MC with transition probabilities  $u_{ij}$ . Then  $\{X_t = Y_{N(t)}\}$  is a CTMC that takes 1 jump according to  $u_{ij}$  at each arrival of  $\{N(t)\}$ .

In this example,  $N(t)$  has a Poisson number of jumps with rate  $\lambda t$ . Hence,  
(=mean).

$$P_{ij}(t) = \sum_{n=0}^{\infty} e^{-\lambda t} \frac{(\lambda t)^n}{n!} u_{ij}^n$$

↑  
Transition Probability  
for CTMC  $\{X_t: t \geq 0\}$

↑  
where  $u_{ij}^n$  is the  $n^{\text{th}}$   
power of the discrete-time  
MC  $Y_n$ 's transition  
prob.  $u_{ij}$

Recall: Chapman-Kolmogorov Equation

$$\sum_k P_{ik}(s) P_{kj}(t) = P_{ij}(s+t)$$

Note: Transition Probabilities  $P_{ij}(t)$  can be determined from their derivatives at 0:

$$q_{ij} = \lim_{h \rightarrow 0} \frac{P_{ij}(h)}{h} \quad \text{for } j \neq i$$

If this limit exists (it will for all cases we consider), we call  $q_{ij}$  the jump rate from  $i$  to  $j$ .

\* In most cases, it is simpler to describe a CTMC by describing its transition RATES  $q_{ij}$  for  $i \neq j$  rather than first figuring out  $P_{ij}(t)$ .

Recall: The rate at which the chain leaves state  $i$  is denoted by  $\nu_i$  s.t.

$$\nu_i = \sum_{j \neq i} q_{ij}$$

def: The generator of the CTMC is the matrix  $Q$  such that

$$Q_{ij} = \begin{cases} q_{ij} & \text{if } i \neq j \\ -\nu_i & \text{if } i = j \end{cases}$$

← aka  
Instantaneous  
Transition Rate  
Matrix

def: State  $i$  is absorbing if  $\nu_i = 0$ .

def: State  $i$  is stable if  $0 < \nu_i < \infty$ .

(If  $\nu_i = \infty$ , then the chain will leave  $i$  immediately so we will always assume  $\nu_i < \infty$ ).

## Kolmogorov's Equations

Q. How to obtain transition probabilities from the transition rates?

Theorem: Assume  $\nu_i < \infty \forall i$  in the state space. Then the transition probabilities are differentiable (in  $t$ ), and for any pair of states  $i \neq j$

$$\frac{dP_{ij}(t)}{dt} = \sum_{k \neq i} q_{ik} P_{kj}(t) - \nu_i P_{ij}(t) \quad \text{Backward Equation}$$

$$\frac{dP_{ij}(t)}{dt} = \sum_{k \neq j} q_{kj} P_{ik}(t) - \nu_j P_{ij}(t) \quad \text{Forward Equation}$$

$$\left[ \begin{array}{l} \text{In Matrix notation,} \\ P'(t) = Q P(t) \quad \text{Backward Eqn} \\ P'(t) = P(t) Q \quad \text{Forward Eqn} \\ \Leftrightarrow \text{Boundary Condition } P(0) = I \end{array} \right]$$

\* Rate matrix  $Q$  gives us everything we need to construct a CTMC, if we only had  $P$  we couldn't infer  $Q$ .

Example: Backward Eqns for Pure Birth Process

$$P'_{ij}(t) = \lambda_i P_{i+1,j}(t) - \lambda_i P_{ij}(t)$$

Stationary Distribution

Similar to discrete-time MC case,  $\pi$  is said to be the stationary distribution if

$$\pi P = \pi.$$

def: Let  $\{X_t : t \geq 0\}$  be a CTMC with generator  $Q$ . <sup>(rate matrix)</sup>

Then  $\pi$  is a stationary distribution if

$$\pi Q = 0.$$

OR, equivalently, for each  $j \in S$  the following equations hold:

$$\sum_{i \neq j} \pi(i) q_{ij} = \nu_j \pi(j)$$

def: We say  $\pi$  satisfies detailed balance for the CTMC if for each  $i \neq j$

$$\pi(i) q_{ij} = \pi(j) q_{ji}$$

Thm: If  $\pi$  satisfies detailed balance, then  $\pi$  is a stationary distribution.

# Gillespie's Stochastic Simulation Algorithm

Lec 21

Procedure for simulating sample paths of CTMCs.

Reactions: single instantaneous events changing at least 1 of the populations cause the system to change over time.

e.g. birth, death, movement, infection, etc.

Stochastic simulation algorithm (SSA):

samples the time  $\tau$  to the next reaction

& updates the system accordingly.

Each reaction  $R_j$  is characterized by 2 quantities:

- state change vector  $v_j$

$v_j = (v_{1j}, \dots, v_{nj})$  where  $v_{ij}$  is the change in # of indivs in pop.  $i$  caused by 1 reaction of type  $j$

- propensity function  $a_j(x)$

i.e. prob. that reaction  $R_j$  will occur in  $[t, t+dt]$  is  $a_j(x) dt$

$\frac{\text{rate } q_j}{\sum \text{all rates}}$

— this is the correct probability