

Continuous-Time Markov Chains

Karlin & Taylor, *A First Course in Stochastic Processes*, pp 145–152

**Return to Zero for Birth/Death Processes**

The probability  $F_i(t)$  of return to state 0 at or before time  $t$ , starting from  $X_0 = i$ , can also be studied by differential equation methods:

$$F_i(t + \epsilon) = \epsilon\lambda_i F_{i+1}(t) + \epsilon\mu_i F_{i-1}(t) + [1 - \epsilon(\lambda_i + \mu_i)]F_i(t) + o(\epsilon)$$

$$F_i'(t) = \lambda_i F_{i+1}(t) + \mu_i F_{i-1}(t) - (\lambda_i + \mu_i)F_i(t)$$

In the limit as  $t \rightarrow \infty$ , the probability  $F_i$  of *ever* returning to zero satisfies

$$0 = -\lambda_i[F_i - F_{i+1}] + \mu_i[F_{i-1} - F_i]$$

$$[F_i - F_{i+1}] = [F_{i-1} - F_i]\left(\frac{\mu_i}{\lambda_i}\right) = [1 - F_1]\left(\frac{\mu_1\mu_2\cdots\mu_i}{\lambda_1\lambda_2\cdots\lambda_i}\right)$$

$$1 - F_j = \sum_{i=0}^{j-1} [F_i - F_{i+1}] = [1 - F_1] \sum_{i=0}^{j-1} \left(\frac{\mu_1\mu_2\cdots\mu_i}{\lambda_1\lambda_2\cdots\lambda_i}\right).$$

If  $\sum_{i=0}^{\infty} \rho_i = \infty$ , where  $\rho_i \equiv \left(\frac{\mu_1\mu_2\cdots\mu_i}{\lambda_1\lambda_2\cdots\lambda_i}\right)$ , then  $[1 - F_1] = 0$  and  $F_j \equiv 1$ ; if the  $\rho_i$  are summable, then

$$F_j = \frac{\sum_{i=j}^{\infty} \rho_i}{\sum_{i=0}^{\infty} \rho_i}$$

For the linear birth/death process  $\rho_i = \left(\frac{\delta}{\beta}\right)^i$ ,  $\sum_{i=j}^{\infty} \rho_i = \frac{(\frac{\delta}{\beta})^j}{1 - \frac{\delta}{\beta}}$ , and so

$$F_j = \begin{cases} \left(\frac{\delta}{\beta}\right)^j & \text{if } \delta < \beta \\ 1 & \text{if } \delta \geq \beta. \end{cases}$$

In case  $\sum_{i=0}^{\infty} \rho_i = \infty$  the process is certain to return to zero, but when? The expectation of the first hitting-time of zero,  $G_i = \mathbb{E}[T_0 | X_0 = i]$ , satisfies  $G_0 = 0$  and, for  $i > 0$ ,

$$G_i = \frac{1}{\lambda_i + \mu_i} + \left(\frac{\lambda_i}{\lambda_i + \mu_i}\right)G_{i+1} + \left(\frac{\mu_i}{\lambda_i + \mu_i}\right)G_{i-1},$$

$$\lambda_i[G_{i+1} - G_i] = \mu_i[G_i - G_{i-1}] - 1$$

$$[G_{i+1} - G_i] = \frac{\mu_i}{\lambda_i}[G_i - G_{i-1}] - \frac{1}{\lambda_i}$$

$$= \frac{\mu_i\mu_{i-1}\cdots\mu_1}{\lambda_i\lambda_{i-1}\cdots\lambda_1}[G_1 - G_0] - \left[\frac{1}{\lambda_i} + \frac{\mu_i}{\lambda_i\lambda_{i-1}} + \cdots + \frac{\mu_i\cdots\mu_2}{\lambda_i\cdots\lambda_1}\right]$$

$$= \rho_i G_1 - \sum_{k=1}^i \frac{\rho_i}{\lambda_k \rho_k} \quad (\text{recall } \rho_i \equiv \left(\frac{\mu_1\mu_2\cdots\mu_i}{\lambda_1\lambda_2\cdots\lambda_i}\right)), \text{ so}$$

$$\frac{G_{i+1} - G_i}{\rho_i} = G_1 - \sum_{k=1}^i \frac{1}{\lambda_k \rho_k} \rightarrow 0. \quad \text{Thus}$$

$$G_1 = \sum_{k=1}^{\infty} \frac{1}{\lambda_k \rho_k}, \quad \text{and, more generally,}$$

$$G_j = \sum_{i=1}^j \sum_{k=i}^{\infty} \frac{\rho_{i-1}}{\lambda_k \rho_k}.$$

For the linear birth/death process with immigration,  $\frac{\rho_{i-1}}{\lambda_k \rho_k} = \frac{\lambda_i \lambda_{i+1} \cdots \lambda_{k-1}}{\mu_i \mu_{i+1} \cdots \mu_k} = \frac{\Gamma(\frac{a}{\beta} + k) (i-1)!}{a \Gamma(\frac{a}{\beta}) k!} \left(\frac{\beta}{\delta}\right)^{k-i+1}$ , so

$$G_1 = \sum_{k=1}^{\infty} \frac{\Gamma(\frac{a}{\beta} + k)}{a \Gamma(\frac{a}{\beta}) k!} \left(\frac{\beta}{\delta}\right)^k$$

$$\begin{aligned}
 &= \frac{1}{a} \left( \left(1 - \frac{\beta}{\delta}\right)^{-a/\beta} - 1 \right) && \text{(the Neg. Binom. sum)} \\
 &\rightarrow \frac{-1}{\beta} \log \left(1 - \frac{\beta}{\delta}\right) \text{ as } a \rightarrow 0. && \text{(the text's answer for } a = 0.)
 \end{aligned}$$

**Finite State Markov Chains**

The study of continuous-time Markov chains with finite state space  $\mathcal{S} = \{0, \dots, N\}$  is in some ways easier than the general case, because the tools of linear algebra can be brought to bear. It is also important in applications.

Let  $P_{ij}(t)$  be the transition function for a finite-state Markov chain and  $Q_{ij} = P'_{ij}(0)$  the infinitesimal transition matrix, so

$$P_{ij}(\epsilon) = \begin{cases} \epsilon Q_{ij} + o(\epsilon) & \text{if } i \neq j \\ 1 - \epsilon \sum_{k \neq i} Q_{ik} + o(\epsilon) & \text{if } i = j. \end{cases}$$

For the finite-state case, the Kolmogorov Backward and Forward equations are:

$$P'_{ij}(t) = \sum_{k=0}^N Q_{ik} P_{kj}(t) \tag{BE}$$

$$= \sum_{k=0}^N P_{ik}(t) Q_{kj}; \tag{FE}$$

recall that

$$Q_{ij} = P'_{ij}(0)$$

is just the rate of jumping from state  $i$  to  $j$ , if  $i \neq j$ . Since  $1 = \sum_j P_{ij}(t)$  for all  $t$ ,  $0 = \sum_j P'_{ij}(t)$  for any  $t$  and in particular for  $t = 0$ , so  $-Q_{ii} = \sum_{k \neq i} Q_{ik}$  is just the total rate of jumping away from state  $i$ .

Any  $(N + 1) \times (N + 1)$  matrix  $Q$  has  $N + 1$  real or complex eigenvalues  $\lambda_i$ , the  $N + 1$  solutions of the polynomial equation  $p(\lambda) = \det[Q - \lambda I] = 0$ . If the  $\lambda_i$  are all distinct, and often, even if they are not,  $Q$  can be put in the Jordan canonical form:

$$Q = U \Lambda U^{-1} \tag{JCF}$$

where  $U$  is an  $(N + 1) \times (N + 1)$  matrix whose columns  $u^i$  are (right) eigenvectors for  $Q$ ,  $V = U^{-1}$  is the matrix inverse of  $U$  whose rows  $v^j$  are left eigenvectors for  $Q$ , and  $\Lambda$  is a diagonal matrix of eigenvalues  $\lambda_i = \Lambda_{ii}$  of  $Q$ . Some matrices cannot *quite* be put into form (JCF), if the  $\{\lambda_i\}$  are not distinct; even in that case the Jordan canonical form can still be used, but we must allow the possibility that  $\Lambda_{i,j} = 1$  for some  $i, j$  such that  $\lambda_i = \lambda_j$  and  $|i - j| = 1$ . We will ignore that possibility in the sequel.

The Kolmogorov Forward Equation (FE) with initial condition  $P_{ij}(0) = \delta_{ij}$  can be solved for  $P_{ij}(t)$ . Formally the solution to the matrix equation  $P'(t) = P(t)Q$  is the familiar  $P(t) = P(0) \exp(tQ)$ ; when  $\mathcal{S}$  is finite we can make sense of that prescription in at least two different ways:

$$\begin{aligned}
 P(t) &= \sum_{n=0}^{\infty} \frac{t^n Q^n}{n!} && \text{(power-series)} \\
 &= e^{tQ} \\
 &= [U e^{t\Lambda} V]_{ij} && \text{(recall } V = U^{-1}) \\
 &= \sum_{k=0}^N e^{t\lambda_k} u_k v'_k && \text{(eigen-series)}
 \end{aligned}$$

either in an infinite series or in an eigen-vector expansion. Note that it is the matrix product  $Q^n$  appearing in the infinite series, defined recursively by  $Q^n_{ij} = \sum_{k=0}^N Q_{ik}^{n-1} Q_{kj}$ . When  $\mathcal{S}$  is infinite the power series expansion might not converge and the eigenvalue analysis of transition functions is more subtle.