

# Continuous Time Markov Chain Basics

## 1 The Transition Matrix

As earlier, we presume a set of states  $S$  that is either finite or countably infinite. We have a set of random variables  $\{X_t, t \geq 0\}$  satisfying the Markov Property, namely for every non-negative integer  $k$ ,  $0 \leq t_0 < t_1 < \dots < t_k < t$  and  $h > 0$  we have

$$\Pr(X_{t+h} = y | X_t = x, X_{t_k} = x_k, \dots, X_{t_0} = x_0) = \Pr(X_{t+h} = y | X_t = x) =: P_t(x, y).$$

Just as in the discrete time case, we have the Chapman-Kolmogorov equations, which in matrix form say

$$P_{t+s} = P_t P_s.$$

We assume that the time elapsed between transitions to new states are independent exponential random variables, each with a rate depending on the state currently occupied. We then have

$$\Pr(X_{t+h} = x | X_t = x) = 1 - \lambda_x h + o_{x,x}(h)$$

while for  $y \neq x$  we have

$$\Pr(X_{t+h} = y | X_t = x) = p_{x,y} \lambda_x h + o_{x,y}(h)$$

In matrix form we have

$$P_h = I + h\Lambda + A_h$$

with

$$\Lambda(x, y) = \begin{cases} -\lambda_x & \text{if } y = x \\ p_{x,y} \lambda_x & \text{if } y \neq x \end{cases}$$

and

$$A_h(x, y) = o_{x,y}(h).$$

If  $M$  is a matrix we define

$$\|M\| = \max\left\{\sum_{y \in S} |M(x, y)|, x \in S\right\}$$

and we assume that  $\|A_h\|$  is  $o(h)$  and  $\|\Lambda\| < \infty$ . (This is not an additional assumption if  $S$  is finite.)

If this is the case then it can be shown that since  $P_t = (P_{t/n})^n$  for every  $n$  that

$$\begin{aligned} P_t &= \lim_{n \rightarrow \infty} (P_{t/n})^n \\ &= \lim_{n \rightarrow \infty} (I + (t/n)\Lambda + A_{t/n})^n \\ &= \lim_{n \rightarrow \infty} (I + (t/n)\Lambda)^n \\ &= \exp(t\Lambda). \end{aligned}$$

The matrix  $\Lambda$  is called the rate matrix for the Markov Chain.

## 2 Stationary Probabilities

We should like to solve  $\vec{\pi} = \vec{\pi}P_t$  independent of  $t$ . However, since

$$\exp(t\Lambda) = I + \sum_{k=1}^{\infty} \frac{t^k}{k!} \Lambda^k$$

$\vec{\pi} = \vec{\pi}P_t$  is the same as

$$\vec{0} = \sum_{k=1}^{\infty} \frac{t^k}{k!} \pi \Lambda^k$$

If we divide both sides of this equation by  $t$  and let  $t \rightarrow 0^+$  we see that we must have  $\vec{0} = \vec{\pi}\Lambda$ , while if this is the case then we will have  $\vec{\pi} = \vec{\pi}P_t$  for any  $t \geq 0$ .

The equation  $\vec{\pi}\Lambda = \vec{0}$  is called the rate balancing equation.

## 3 Birth and Death Models

Suppose now that  $S = \{0, 1, \dots\}$ . If  $p_{x,y} = 0$  for  $|x - y| \neq 1$  the Markov Chain is called a Birth and Death Model. In such models it is usual to redefine  $p_{x,x+1}\lambda_x$  to be  $\lambda_x$ ,  $p_{x,x-1}\lambda_x$  to be  $\delta_x$  and  $\lambda_x$  is replaced by  $\lambda_x + \delta_x$ .  $\delta_0 = 0$ . This means that  $\Lambda$  takes the form

$$\begin{bmatrix} -\lambda_0 & \lambda_0 & 0 & \dots & & & & \\ \delta_1 & -\delta_1 - \lambda_1 & \lambda_1 & 0 & 0 & \dots & & \\ 0 & \delta_2 & -\delta_2 - \lambda_2 & \lambda_2 & 0 & 0 & \dots & \\ 0 & 0 & \delta_3 & -\delta_3 - \lambda_3 & \lambda_3 & 0 & 0 & \dots \\ \vdots & \vdots & \dots & & & & & \end{bmatrix}$$

If we write out the rate balancing equations we see that

$$\begin{aligned} -\lambda_0\pi_0 + \delta_1\pi_1 &= 0 \\ \lambda_0\pi_0 - (\lambda_1 + \delta_1)\pi_1 + \delta_2\pi_2 &= 0 \\ \lambda_1\pi_1 - (\lambda_2 + \delta_2)\pi_2 + \delta_3\pi_3 &= 0 \\ \lambda_{x-1}\pi_{x-1} - (\lambda_x + \delta_x)\pi_x + \delta_{x+1}\pi_{x+1} &= 0 \end{aligned}$$

By sequentially adding each equation to the following equation we come to

$$\begin{aligned} \delta_1\pi_1 - \lambda_0\pi_0 &= 0 \\ \delta_2\pi_2 - \lambda_1\pi_1 &= 0 \\ \delta_3\pi_3 - \lambda_2\pi_2 &= 0 \\ \delta_{x+1}\pi_{x+1} - \lambda_x\pi_x &= 0 \end{aligned}$$

which means that if  $\delta_x > 0$  for  $x \geq 1$  that

$$\pi_{x+1} = \frac{\lambda_x}{\delta_{x+1}}\pi_x = \prod_{k=0}^x \frac{\lambda_k}{\delta_{k+1}}\pi_0$$

### 3.1 The M|M|1 Queuing System

Here is the simplest example:  $\delta_x = \delta$ ,  $\lambda_x = \lambda$ . Then

$$\pi_x = \left(\frac{\lambda}{\delta}\right)^x \pi_0.$$

If  $\delta > \lambda$  we can sum both sides from 0 to  $\infty$  to get

$$1 = \frac{\delta}{\delta - \lambda} \pi_0$$

so

$$\pi_x = \left(1 - \frac{\lambda}{\delta}\right) \left(\frac{\lambda}{\delta}\right)^x,$$

a geometric distribution.