

## LECTURE NOTES

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**0.1 Lemma** Let  $\tau_+ = \inf\{t \geq 0 \mid X_t \neq X_0\}$  be the time of the first jump. Suppose  $\mathbb{P}\{\tau_+ > 0\} > 0$ . Then  $\tau_+ \sim \text{Exp}(\lambda)$  for some  $\lambda > 0$ .

*Proof.* Let  $F(t) = \mathbb{P}\{\tau_+ > t\}$  be the distribution function for  $\tau_+$ . By the Markov property on  $X_t$ , we have

$$\mathbb{P}\{\tau_+ > t + s \mid \tau_+ > t\} = \mathbb{P}\{\tau_+ > s\} = F(s).$$

Unraveling the conditional probability on the left, we find

$$F(s) = \frac{\mathbb{P}\{\tau_+ > t + s \text{ and } \tau_+ > t\}}{\mathbb{P}\{\tau_+ > t\}} = \frac{F(t+s)}{F(t)}.$$

We then have that  $F(t+s) = F(t)F(s)$ , and the only continuous solution to this equation is  $F(t) = e^{-\lambda t}$  for some  $\lambda > 0$ . □

To solve our problem with splitting and dying cells, we model it with a continuous time Markov chain with state space  $\{1, 2, \dots, N\}$  and generator  $G$  given by

$$G = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \mu & -\mu - \lambda & \lambda & 0 & 0 & \dots & 0 \\ 0 & 2\mu & -2\mu - 2\lambda & 2\lambda & 0 & \dots & 0 \\ 0 & 0 & 3\mu & -3\mu - 3\lambda & 3\lambda & \dots & 0 \\ \vdots & & & & & & \vdots \end{pmatrix}$$

Let  $h(x) = \mathbb{P}^x\{\tau_N < \tau_0\}$  be the hitting probability. From the theorem on hitting probabilities, we know that

$$\begin{aligned} h(0) &= 0 \\ h(N) &= 1 \\ Gh(x) &= 0 \quad \forall x \neq 0, N. \end{aligned}$$

The last of these equations says

$$x\lambda(h(x+1) - h(x)) + x\mu(h(x-1) - h(x)) = 0$$

which rearranges into

$$h(x+1) - h(x) = \frac{\mu}{\lambda}(h(x) - h(x-1)).$$

Since  $h(1) - h(0) = h(1)$  by our boundary condition we can use this as the seed for this recurrence relation. We get

$$h(x+1) - h(x) = \left(\frac{\mu}{\lambda}\right)^x h(1),$$

so

$$\begin{aligned} h(x) &= h(1) + \sum_{y=1}^{x-1} h(y+1) - h(y) \\ &= h(1) \left\{ 1 + \sum_{y=1}^{x-1} \left( \frac{\mu}{\lambda} \right)^y \right\} \\ &= h(1) \left( \frac{1 - \left( \frac{\mu}{\lambda} \right)^x}{1 - \frac{\mu}{\lambda}} \right). \end{aligned}$$

Next we use the other boundary condition:

$$1 = h(N) = h(1) \left( \frac{1 - \left( \frac{\mu}{\lambda} \right)^N}{1 - \frac{\mu}{\lambda}} \right)$$

which gives

$$h(1) = \left\{ \frac{1 - \left( \frac{\mu}{\lambda} \right)^N}{1 - \frac{\mu}{\lambda}} \right\}^{-1},$$

and

$$h(x) = \frac{1 - \left( \frac{\mu}{\lambda} \right)^x}{1 - \left( \frac{\mu}{\lambda} \right)^N}.$$

This gives us the answer to our first question: what is the probability that a single mutation “grows?” This is answered by the value

$$h(1) = \frac{1 - \left( \frac{\mu}{\lambda} \right)}{1 - \left( \frac{\mu}{\lambda} \right)^N} \approx 1 - \frac{\mu}{\lambda} \text{ for large } N.$$

## Stationary Distributions

**0.2 Proposition** Let  $(X_t)_{t \geq 0}$  be a continuous time Markov chain with generator  $G$  on state space  $\mathcal{X}$ . Suppose that  $G^T \pi = 0$  for some probability distribution  $\pi$  on  $\mathcal{X}$ . Then

$$\mathbb{P}^\pi \{X_t = y\} = \pi(y).$$

The conditions on  $\pi$  above mean

$$\sum_{y \in \mathcal{X}} \pi(y) = 1, \quad \pi(y) \geq 0, \quad \sum_{y \in \mathcal{X}} \pi(y) G_{yx} = 0.$$

The notation  $\mathbb{P}^\pi$  means

$$\mathbb{P}^\pi \{X_t = y\} = \sum_{x \in \mathcal{X}} \pi(x) \mathbb{P}^x \{X_t = y\}.$$

Such a distribution  $\pi$  is called a *stationary distribution*.

*Proof.* Let  $f : \mathcal{X} \rightarrow \mathbb{R}$  be a function (thought of as a column vector) with  $\sum_y \pi(y) f(y) < \infty$  (if we wished to generalize to a countable state space). Recall that

$$\mathbb{E}_{f(X_t)}^x = P_t f(x) = e^{tG} f(x).$$

Since  $\pi G = 0$ ,

$$\pi P_t = \pi e^{tG} = \pi \sum_{n \geq 0} \frac{t^n}{n!} G^n = \pi.$$

So,

$$\mathbb{E}_{f(X_t)}^\pi = \pi P_t f = \pi f = \sum_x \pi(x) f(x).$$

The statement of the proposition now follows from taking  $f$  to be the indicator of  $y$ :

$$f(x) = \begin{cases} 1 & x = y \\ 0 & x \neq y. \end{cases}$$

□

**Fact.** If  $\pi$  is unique, then  $P_t \rightarrow \pi$  as  $t \rightarrow \infty$ . That is, for all  $f, x$ ,

$$\mathbb{E}_{f(X_t)}^x \rightarrow \sum_y \pi(y) f(y) \quad \text{as } t \rightarrow \infty.$$

This can also be phrased as saying that  $X_t$  converges in distribution to  $\pi$ .