

**Exercise 1** (Exercise 4.1.). A six-sided die is rolled repeatedly. Which of the following are Markov chains? For those that are, find the one-step transition matrix. (a)  $X_n$  is the largest number rolled up to the  $n$ th roll. (b)  $X_n$  is the number of sixes rolled in the first  $n$  rolls. (c) At time  $n$ ,  $X_n$  is the time since the last six was rolled. (d) At time  $n$ ,  $X_n$  is the time until the next six is rolled.

**Solution 1.** (a) Since  $X_n$  is the largest number rolled up to the  $n$ -th roll, we have that

$$X_{n+1} = \max\{X_n, Y_{n+1}\},$$

where  $Y_{n+1}$  is the  $(n+1)$ -th roll. As this only depends on the most recent value of  $X$ , this is a Markov chain. Since each roll of the six-sided die is independent, we have that  $Y_{n+1}$  has uniform distribution on  $\{1, 2, 3, 4, 5, 6\}$ . It follows that the probability that  $X_{n+1} = X_n$  is given by

$$\mathbb{P}(X_{n+1} = X_n \mid X_n = i) = \mathbb{P}(Y_{n+1} \geq i) = \frac{i}{6}.$$

and for each  $6 \geq j > i \geq 1$ , we have

$$\mathbb{P}(X_{n+1} = j \mid X_n = i) = \frac{1}{6}.$$

For any  $i < X_n$ , we have additionally that  $\mathbb{P}(X_{n+1} = i \mid X_n) = 0$  as the maximum is non-decreasing. We can write these probabilities in the one step transition matrix as

$$\mathbf{P} = \begin{pmatrix} 1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\ 0 & 2/6 & 1/6 & 1/6 & 1/6 & 1/6 \\ 0 & 0 & 3/6 & 1/6 & 1/6 & 1/6 \\ 0 & 0 & 0 & 4/6 & 1/6 & 1/6 \\ 0 & 0 & 0 & 0 & 5/6 & 1/6 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

or more compactly as

$$p_{ij} = \mathbb{P}(X_{n+1} = j \mid X_n = i) = \begin{cases} 1/6 & \text{if } j > i \\ i/6 & \text{if } j = i \\ 0 & \text{if } j < i. \end{cases}$$

(b) Setting  $X_n$  to be the number of sixes in the first  $n$  rolls, we have that

$$X_{n+1} = X_n + 1 + Y_{n+1},$$

where  $Y_{n+1}$  is the indicator variable for whether the  $n + 1$ -th roll was a six or not. This follows because

$$X_{n+1} = X_n + Y_{n+1}$$

For  $i, j \in \mathbb{N}_0$ , we have that

$$p_{ij} = \mathbb{P}(X_{n+1} = j \mid X_n = i) = \begin{cases} 5/6 & \text{if } j = i \\ 1/6 & \text{if } j = i + 1 \\ 0 & \text{otherwise,} \end{cases}$$

since  $Y_{n+1}$  is 1 with probability  $1/6$  and 0 otherwise. This shows that  $X$  is a Markov chain with transition matrix  $\mathbf{P} = (p_{ij})_{i,j \in \mathbb{N}_0}$

(c) If we define  $X_n$  to be the number of rolls since the last six, we see that

$$X_{n+1} = X_n(1 - Y_{n+1}) + 1,$$

where  $Y_{n+1}$  is 1 if the  $(n+1)$ th roll is a six and 0 otherwise. It follows that for  $i, j \in \mathbb{N}$ , we have

$$p_{ij} = \mathbb{P}(X_{n+1} = j \mid X_n = i) = \begin{cases} 5/6 & \text{if } j = i + 1 \\ 1/6 & \text{if } j = 1 \\ 0 & \text{otherwise,} \end{cases}$$

since the count will reset to 1 if  $Y_{n+1}$  is a six which occurs with probability  $1/6$  and will increase by one otherwise.

(d) If the time to the next roll of a six is known as  $X_n$ , then there are two options either  $X_n > 1$ , in which case  $X_{n+1} = X_n - 1$  as the countdown simply ticks down once. Otherwise, we have  $X_n = 1$ , in which case the next roll is certainly a six and the time to the next six is not deterministic. Assuming that each roll is independent, we can calculate the probability of the time to the next six for  $X_{n+1}$  given  $X_n = 1$  as being geometrically distributed with rate  $1/6$  since this is the probability that one rolls a six, so that

$$p_{ij} = \mathbb{P}(X_{n+1} = j \mid X_n = i) = \begin{cases} 1 & \text{if } j = i - 1 \text{ and } i \geq 2 \\ \frac{1}{6} \left(1 - \frac{1}{6}\right)^{j-1} & \text{if } i = 1 \text{ and } j \geq 1 \\ 0 & \text{otherwise .} \end{cases}$$

**Exercise 2** (Exercise 4.2). Let  $Y_n = X_{2n}$ . Compute the transition matrix for  $Y$  when (a)  $X$  is a simple random walk and (b)  $X$  is a branching process with generating function  $G$  for its offspring distribution.

**Solution 2.** (a) Notice that each step of our random walk  $X$  is given by  $X_{n+1} = X_n + \xi_{n+1}$ , where

$$\xi_n = \begin{cases} 1 & \text{with prob } p \\ -1 & \text{with prob } q \end{cases}$$

This shows that for

$$Y_{n+1} - Y_n = X_{2n+2} - X_{2n} = \xi_{2n+1} + \xi_{2n+2}$$

From this, we see that  $Y_{n+1} = Y_n + \xi_{2n+1} + \xi_{2n+2}$  where

$$\xi_{2n+1} + \xi_{2n+2} = \begin{cases} 2 & \text{with prob } p^2 \\ 0 & \text{with prob } 2pq \\ -2 & \text{with prob } q^2 \end{cases}$$

This means that for integers  $i$  and  $j$

$$p_{ij} = \mathbb{P}(Y_{n+1} = j \mid Y_n = i) = \begin{cases} p^2 & \text{if } j = i + 2 \\ 2pq & \text{if } j = i \\ q^2 & \text{if } j = i - 2 \\ 0 & \text{otherwise.} \end{cases}$$

(b) Fixing  $Y_n = X_{2n} = i$ , we see that for

$$X_{2n+1} = \sum_{k=1}^i \xi_k,$$

where  $\xi_k$  are i.i.d draws with common generating function  $G$ . Since  $i$  is fixed, we can compute the generating function at the next time step as

$$G_{X_{2n+1}}(s) = G(s)^i. \quad (1)$$

For the next time step, we have that

$$Y_{n+1} = X_{2n+2} = \sum_{k=0}^{X_{2n+1}} \xi_k.$$

Since  $X_{2n+1}$  is independent of the  $\xi_k$ , we have that

$$G_{Y_{n+1}}(s) = G_{X_{2n+1}}(G(s)) = G(G(s))^i.$$

With this generating function, we can compute the probability of having  $j$  offspring given  $Y_n = i$  as

$$p_{ij} = \mathbb{P}(Y_{n+1} = j \mid Y_n = i) = \frac{1}{j!} \left[ \frac{d^j}{dt^j} G_{Y_{n+1}}(t) \right]_{t=0} = \frac{1}{j!} \left[ \frac{d^j}{dt^j} G(G(t))^i \right]_{t=0},$$

where we have used that for a random variable  $X$  with generating function  $G_X(s)$

$$\mathbb{P}(X = j) = \frac{1}{j!} \left[ \frac{d^j}{dt^j} G_X(t) \right]_{t=0}$$

**Exercise 3** (Exercise 4.3). Let  $X$  be a Markov chain with state space  $S$  and absorbing state  $k$ . Suppose that  $j \rightarrow k$  for all  $k \in S$ . Show that all states other than  $k$  are transient.

**Solution 3.** Fix a state  $j \neq k$ . Since  $j \rightarrow k$ , we know there exists an integer  $n$  so that  $p_n(j, k) > 0$ . As  $k$  is an absorbing state, we have that  $p(k, i) = 0$  for any state  $i$ . This means that for all  $m \geq 1$ ,  $p_m(k, j) = 0$ . Therefore, if  $X_0 = j$  and  $X_n = k$  with probability  $p_n(j, k) > 0$ , then  $X$  cannot return to state  $j$  as  $p_m(k, j) = 0$  for all  $m \geq 1$ . This means that the state  $j \neq k$  cannot be recurrent and is therefore transient.

**Exercise 4** (Exercise 4.4). Suppose that two distinct states  $i, j$  satisfy

$$\mathbb{P}(\tau_j < \tau_i \mid X_0 = i) = \mathbb{P}(\tau_i < \tau_j \mid X_0 = j),$$

where  $\tau_j = \inf\{n \geq 1 \mid X_n = j\}$ . Show that if  $X_0 = i$ , the expected number of visits to  $j$  prior to re-visiting  $i$  is one.

**Solution 4.** Let  $Z$  be the random variable describing the number of visits to state  $j$  before re-visiting  $i$ . To start, we define

$$\begin{aligned} p &= \mathbb{P}(\tau_j < \tau_i \mid X_0 = i) = \mathbb{P}(\tau_i < \tau_j \mid X_0 = j) \\ 1 - p &= \mathbb{P}(\tau_i \leq \tau_j \mid X_0 = i) = \mathbb{P}(\tau_j \leq \tau_i \mid X_0 = j) \end{aligned}$$

In this way, we can define the probability that we start at  $X_0 = i$  and reach state  $j$  without first returning to  $i$  as  $p$ . Once we are at  $j$ , the probability of returning to  $j$  without first reaching state  $i$  is then  $1 - p$ . Starting at  $X_0 = i$ , we see that the probability of returning to  $i$  only after  $k$  visits is

$$\mathbb{P}(Z = 0) = 1 - p, \quad \mathbb{P}(Z = k) = p^2(1 - p)^{k-1}, k > 0.$$

We can compute this expectation directly as

$$\begin{aligned} \mathbb{E}[Z] &= \sum_{k=0}^{\infty} k \mathbb{P}(Z = k) \\ &= p \sum_{k=1}^{\infty} k p (1 - p)^{k-1} \\ &= p \mathbb{E}[\text{Geom}(p)] \\ &= 1 \end{aligned}$$



**Exercise 5** (Exercise 4.5). Let  $X$  be a Markov chain with transition matrix

$$\mathbf{P} = \begin{pmatrix} 1-2p & 2p & 0 \\ p & 1-2p & p \\ 0 & 2p & 1-2p \end{pmatrix}$$

Find the invariant distribution  $\pi$ , and the mean-recurrence times  $\bar{\tau}_j$  for  $j = 1, 2, 3$ .

**Solution 5.** Supposing the invariant distribution exists, we have that

$$\pi_1 = (1-2p)\pi_1 + p\pi_2$$

$$\pi_2 = 2p\pi_1 + (1-2p)\pi_2 + 2p\pi_3$$

$$\pi_3 = p\pi_2 + (1-2p)\pi_3$$

The first equation implies that  $2\pi_1 = \pi_2$ . The second implies  $2\pi_3 = \pi_2$ . Using that  $1 = \pi_1 + \pi_2 + \pi_3$ , this shows that

$$\pi = (1/4, 1/2, 1/4), \quad \bar{\tau} = (4, 2, 4)$$

since  $\mathbf{P}$  is irreducible and  $\pi_i = 1/\bar{\tau}_i$ .