

## Required Problems

1. (Strang 8.2.15)

- (a) What matrix  $M$  transforms  $(1, 0)$  and  $(0, 1)$  into  $(r, t)$  and  $(s, u)$ ?
- (b) What matrix  $N$  transforms  $(a, c)$  and  $(b, d)$  into  $(1, 0)$  and  $(0, 1)$ ?
- (c) What conditions on  $a, b, c, d$  will make part (b) impossible?

*Solution:*

(a)  $M \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} r & s \\ t & u \end{bmatrix}$

$$N = \begin{bmatrix} r & s \\ t & u \end{bmatrix}$$

(b)  $N \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

$$N = \begin{bmatrix} r & s \\ t & u \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

- (c) if  $ad-bc = 0$ , then part (b) will be impossible

2. (Strang 10.3.5) Every year 2% of young people become old and 3% of old people become dead. (No births.) Find the steady state for

$$\begin{bmatrix} \text{young} \\ \text{old} \\ \text{dead} \end{bmatrix}_{k+1} = \begin{bmatrix} .98 & .00 & 0 \\ .02 & .97 & 0 \\ .00 & .03 & 1 \end{bmatrix} \begin{bmatrix} \text{young} \\ \text{old} \\ \text{dead} \end{bmatrix}_k$$

*Solution:*

To find steady state, the eigenvector with a corresponding eigenvalue of 1 must be found.

$$N(A - I\lambda) = N(A - I(1)) = N\left(\begin{bmatrix} .98 - 1 & .00 & 0 \\ .02 & .97 - 1 & 0 \\ .00 & .03 & 1 - 1 \end{bmatrix}\right) = N\left(\begin{bmatrix} -0.02 & .00 & 0 \\ .02 & -0.03 & 0 \\ .00 & .03 & 0 \end{bmatrix}\right)$$

Now that we have the matrix, we can row reduce in jbox to find the Null space:

$$N\left(\begin{bmatrix} -0.02 & .00 & 0 \\ .02 & -0.03 & 0 \\ .00 & .03 & 0 \end{bmatrix}\right) = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} \text{ and } \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

However, since the steady state cannot contain negative values, the steady state must be:

$$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Where everybody is dead

3. Roots of a diagonalizable matrix. Suppose  $A$  is diagonalizable with nonnegative eigenvalues ( $A = X\Lambda X^{-1}$ ), and let  $\sqrt{\Lambda}$  be the matrix each of whose entries is the square root of the corresponding entry in  $\Lambda$ . Let  $B = X\sqrt{\Lambda}X^{-1}$ .

(a) Show that  $B^2 = A$ .

(b) Diagonalize the matrix  $C = \begin{bmatrix} 51 & -21 \\ 70 & -26 \end{bmatrix}$ .

(c) Find a matrix  $D$  such that  $D^2 = C$ .

*Solution:*

(a)  $B^2 = BB = (X\sqrt{\Lambda}X^{-1})(X\sqrt{\Lambda}X^{-1})$

$$= X\sqrt{\Lambda}X^{-1}X\sqrt{\Lambda}X^{-1}$$

$$= X\sqrt{\Lambda}I\sqrt{\Lambda}X^{-1}$$

$$= X\sqrt{\Lambda}\sqrt{\Lambda}X^{-1}$$

$$\text{Claim: } \sqrt{\Lambda}\sqrt{\Lambda} = \Lambda$$

let  $a_{ij}$  be an element in  $\Lambda$ , and  $\sqrt{a_{ij}}$  be the corresponding element in  $\sqrt{\Lambda}$

We know:

$$a_{ij} = \sum_{k=1}^n a'_{kj}a'_{ik}$$

We also know that since  $\Lambda$  is a diagonal, the only non-zero entries are where  $i = j$ . This now yields:

$$a_{ii} = a'_{ii}a'_{ii} = \sqrt{a_{ij}}\sqrt{a_{ij}} = a_{ii}$$

We can now see that:  $\sqrt{\Lambda}\sqrt{\Lambda} = \Lambda$

With this information, we see that:

$$B^2 = X\Lambda X^{-1} = A$$

And we are done

- (b) To diagonalize  $C$ , we must find the eigenvalues and eigenvectors for it. We begin by solving  $\det(A - I\lambda) = 0$

$$A - I\lambda = \begin{bmatrix} 51 - \lambda & -21 \\ 70 & -26 - \lambda \end{bmatrix}$$

After jbox does the work of solving the characteristic polynomial, We see that the eigenvalues are  $\lambda_1 = 9$  and  $\lambda_2 = 16$ . We now solve  $N(A - I\lambda)$  to get the eigenvectors, which turn out to be:

$$\begin{bmatrix} 0.5 \\ 1 \end{bmatrix} \text{ and } \begin{bmatrix} 0.6 \\ 1 \end{bmatrix}$$

Now, with these values, we can now say:

$$X = \begin{bmatrix} 0.5 & 0.6 \\ 1 & 1 \end{bmatrix}, X^{-1} = \begin{bmatrix} -10 & 6 \\ 10 & -5 \end{bmatrix}, \Lambda = \begin{bmatrix} 9 & 0 \\ 0 & -16 \end{bmatrix}$$

Combining these, we get that:

$$A = X^{-1} = \begin{bmatrix} 0.5 & 0.6 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 9 & 0 \\ 0 & 16 \end{bmatrix} \begin{bmatrix} -10 & 6 \\ 10 & -5 \end{bmatrix}$$

(c) From part (a) we can easily find D:

$$D = X\sqrt{\Lambda}X^{-1} = \begin{bmatrix} 0.5 & 0.6 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 3 & 0 \\ 0 & 4 \end{bmatrix} \begin{bmatrix} -10 & 6 \\ 10 & -5 \end{bmatrix}$$

4. Consider the permutation matrix

$$P = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix}.$$

- (a) Find the characteristic polynomial for  $P$ . [Hint: You can do this easily by looking at how many ways there are to choose a nonzero entry from each row and column of  $P - \lambda I$ . Alternatively you could use the Row 4 cofactor formula on  $P - \lambda I$  and then use the fact that the determinant of a triangular matrix is the product of the entries on the diagonal.]
- (b) Find the steady state vector  $\mathbf{v}$  corresponding to the eigenvalue  $\lambda = 1$ .
- (c) Let  $\mathbf{u}_0 = (1, 0, 0, 0)$ . If  $\mathbf{u}_{k+1} = P\mathbf{u}_k$ , what are  $\mathbf{u}_1$ ,  $\mathbf{u}_2$ ,  $\mathbf{u}_3$ , and  $\mathbf{u}_4$ ? Does the sequence  $\{\mathbf{u}_k\}$  converge to  $\mathbf{v}$ ?
- (d) What are the four eigenvalues for  $P$ ?

*Solution:*

(a)

$$\det(P - \lambda I) = \det \begin{pmatrix} -\lambda & 1 & 0 & 0 \\ 0 & -\lambda & 1 & 0 \\ 0 & 0 & -\lambda & 1 \\ 1 & 0 & 0 & -\lambda \end{pmatrix}$$

The only ways that a non-zero entry can be chosen in each row and column is when:

$$\begin{bmatrix} -\lambda & 0 & 0 & 0 \\ 0 & -\lambda & 0 & 0 \\ 0 & 0 & -\lambda & 0 \\ 0 & 0 & 0 & -\lambda \end{bmatrix}, \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

So, the characteristic polynomial will be:

$$\det \begin{bmatrix} -\lambda & 0 & 0 & 0 \\ 0 & -\lambda & 0 & 0 \\ 0 & 0 & -\lambda & 0 \\ 0 & 0 & 0 & -\lambda \end{bmatrix} + \det \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} = (-\lambda)^4 - 1 = \lambda^4 - 1$$

- (b) To calculate the eigenvector corresponding to 1, we can solve  $N(A - I)$  with jbox, yielding:

$$\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

(c)

$$\mathbf{u}_1 = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

using similar logic, we can see that:

$$\mathbf{u}_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \mathbf{u}_3 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \mathbf{u}_4 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

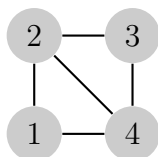
From these results, it appears that the sequence will not converge to P

(d) We can find the eigenvalues by solving  $\lambda^4 - 1 = 0$  and see that:

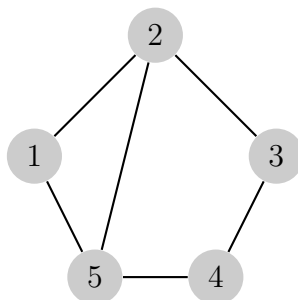
$$\lambda_1 = 1, \lambda_2 = -1, \lambda_3 = i, \lambda_4 = -i$$

5. A random walk on a graph. Suppose a person walks from node to node on a graph, at each time step choosing randomly to move to a neighboring node, each with equal probability. For each of the graphs below, what Markov matrix describes the transition probabilities for the random walk? [For grading purposes, please let Row  $i$  and column  $i$  correspond to node  $i$ , as labeled.] What proportion of the time would we expect to find the random walker at each node?

(a)



(b)



Do you notice any similarity between the steady states for the graphs?

*Solution:*

- (a) Disclaimer: I know  $.33 \neq \frac{1}{3}$ , but the second is annoying to type.

We can see that the markov matrix for the first one is:

$$\begin{bmatrix} 0 & 0.33 & 0 & 0.33 \\ 0.5 & 0 & 0.5 & 0.33 \\ 0 & 0.33 & 0 & 0.33 \\ 0.5 & 0.33 & 0.5 & 0 \end{bmatrix}$$

Using jbox to solve  $N(A - I)$  to find the eigenvector for 1, we get:

$$\mathbf{v}_1 = \begin{bmatrix} \frac{2}{3} \\ \frac{1}{3} \\ \frac{2}{3} \\ 1 \end{bmatrix}$$

However, since the sum of these is greater than 1, we can divide by the sum to obtain the true probabilities to see that :

$$probabilities = \begin{bmatrix} 0.2 \\ 0.3 \\ 0.2 \\ 0.3 \end{bmatrix} \implies Prob_1 = 0.2, Prob_2 = 0.3, Prob_3 = 0.2, Prob_4 = 0.3$$

(b) We can see that the markov matrix for the first one is:

$$\begin{bmatrix} 0 & 0.33 & 0 & 0 & 0.33 \\ 0.5 & 0 & 0.5 & 0 & 0.33 \\ 0 & 0.33 & 0 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 & 0.33 \\ 0.5 & 0.33 & 0 & 0.5 & 0 \end{bmatrix}$$

Using jbox to solve  $N(A - I)$  to find the eigenvector for 1, we get:

$$\mathbf{v}_1 = \begin{bmatrix} \frac{2}{3} \\ 1 \\ \frac{2}{3} \\ \frac{2}{3} \\ 1 \end{bmatrix}$$

However, since the sum of these is greater than 1, we can divide by the sum to obtain the true probabilities to see that :

$$probabilities = \begin{bmatrix} \frac{1}{6} \\ 0.25 \\ \frac{1}{6} \\ \frac{1}{6} \\ 0.25 \end{bmatrix} \Rightarrow Prob_1 = \frac{1}{6}, Prob_2 = 0.25, Prob_3 = \frac{1}{6}, Prob_4 = \frac{1}{6}, Prob_5 = 0.25$$

(c) After seeing the two steady states, the similarities lie in the presence of the  $\frac{2}{3}$ . It appears that nodes with an edge connecting them to nodes that are not 1 above or below them have a higher chance of being arrived at. This makes sense, as having an extra edge does not affect the chances of leaving a node, but increase the likelihood of others coming to that node.



6. In this problem we will see how calculating powers of (non-Markov) matrices can help understand recurrence relations. We will use the Fibonacci numbers as an example. The Fibonacci numbers are defined recursively as  $F_0 = 0$ ,  $F_1 = 1$ , and for  $n \geq 2$ ,  $F_n = F_{n-1} + F_{n-2}$ .
- Let  $A = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$  and  $\mathbf{u}_0 = (1, 0)$ . Note that  $\mathbf{u}_0 = (F_1, F_0)$ . Prove that  $A^k \mathbf{u}_0 = (F_{k+1}, F_k)$ .
  - Verify that the eigenvalues of  $A$  are  $\lambda_1 = (1 + \sqrt{5})/2$  and  $\lambda_2 = (1 - \sqrt{5})/2$ , with corresponding eigenvectors  $\mathbf{x}_1 = (\lambda_1, 1)$  and  $\mathbf{x}_2 = (\lambda_2, 1)$ .
  - Verify that  $\mathbf{u}_0 = \frac{1}{\lambda_1 - \lambda_2}(\mathbf{x}_1 - \mathbf{x}_2)$ . [Note you have expressed  $\mathbf{u}_0$  in the basis of eigenvectors.]
  - Write a simple expression for  $\mathbf{u}_k = A^k \mathbf{u}_0$  in terms of  $\mathbf{x}_1$  and  $\mathbf{x}_2$ . [Hint: Use the expression for  $\mathbf{u}_0$  in Part (c).]
  - Since  $F_k$  is the second component of  $\mathbf{u}_k$  and the second components of  $\mathbf{x}_1$  and  $\mathbf{x}_2$  are 1, write a simple expression for  $F_k$  in terms of  $\lambda_1$  and  $\lambda_2$ .
  - Explain why  $F_{100}$  is extremely close to  $\frac{1}{\sqrt{5}}\lambda_1^{100}$ . (Note that  $\lambda_1 - \lambda_2 = \sqrt{5}$ ),

*Solution:*

- Prove using induction:

Base case:  $k = 0$

$$A^0 \mathbf{u}_0 = I \mathbf{u}_0 = (F_1, F_0)$$

Induction Step: Assume  $\forall 0 \leq k \leq n$ .

W.T.S:

$$A^{k+1} \mathbf{u}_0 = (F_{k+2}, F_{k+1})$$

We know by algebra that:

$$A^{k+1} \mathbf{u}_0 = A A^k \mathbf{u}_0$$

We can now invoke our induction hypothesis to see that:

$$A A^k \mathbf{u}_0 = A \begin{bmatrix} F_{k+1} \\ F_k \end{bmatrix}$$

Multiplying these two yields:

$$\begin{bmatrix} F_{k+1} + F_k \\ F_{k+1} \end{bmatrix}$$

We can then use the definition of fibonacci numbers to see that:

$$\begin{bmatrix} F_{k+1} + F_k \\ F_{k+1} \end{bmatrix} = (F_{k+2}, F_{k+1})$$

Which is what we wanted. By the induction hypothesis, we are done

- (b) To find the eigenvalues, we will solve:  $\det(A - I\lambda) = 0$  Plugging these into jbox, we see that the eigenvalues are indeed:

$$\lambda_1 = \frac{1}{2}(1 + \sqrt{5}), \lambda_2 = \frac{1}{2}(1 - \sqrt{5})$$

and that the Solutions to  $N(A - \lambda I)$  are:

$$\mathbf{x}_1 = \begin{bmatrix} \frac{1}{2}(1 + \sqrt{5}) \\ 1 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} \frac{1}{2}(1 - \sqrt{5}) \\ 1 \end{bmatrix}$$

Which are in the form:  $(\lambda_1, 1)$  and  $(\lambda_2, 1)$

(c)

$$\begin{aligned} \frac{1}{\lambda_1 - \lambda_2}(\mathbf{x}_1 - \mathbf{x}_2) &= \frac{1}{\frac{1}{2}(1 + \sqrt{5}) - \frac{1}{2}(1 - \sqrt{5})} \begin{bmatrix} \frac{1}{2}(1 + \sqrt{5}) - \frac{1}{2}(1 - \sqrt{5}) \\ 1 - 1 \end{bmatrix} \\ &= \frac{1}{2(\frac{\sqrt{5}}{2})} \begin{bmatrix} 2(\frac{\sqrt{5}}{2}) \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \mathbf{u}_0 \end{aligned}$$

$$(d) \mathbf{u}_k = A^k \mathbf{u}_0 = A^k \frac{1}{\lambda_1 - \lambda_2}(\mathbf{x}_1 - \mathbf{x}_2) = A^k \frac{1}{\lambda_1 - \lambda_2} \mathbf{x}_1 - A^k \frac{1}{\lambda_1 - \lambda_2} \mathbf{x}_2$$

$$\begin{aligned} &= \frac{1}{\lambda_1 - \lambda_2} A^k \mathbf{x}_1 - \frac{1}{\lambda_1 - \lambda_2} A^k \mathbf{x}_2 \\ &= \frac{1}{\lambda_1 - \lambda_2} \lambda_1^k \mathbf{x}_1 - \frac{1}{\lambda_1 - \lambda_2} \lambda_2^k \mathbf{x}_2 \\ &= \frac{\lambda_1^k}{\lambda_1 - \lambda_2} \mathbf{x}_1 - \frac{\lambda_2^k}{\lambda_1 - \lambda_2} \mathbf{x}_2 \end{aligned}$$

(e)

$$\begin{aligned} F_k &= \frac{\lambda_1^k}{\lambda_1 - \lambda_2} - \frac{\lambda_2^k}{\lambda_1 - \lambda_2} \\ &= \frac{1}{\lambda_1 - \lambda_2} (\lambda_1^k - \lambda_2^k) \end{aligned}$$

- (f) From before, we know that  $F_k = \frac{(\frac{1}{2}(1+\sqrt{5}))^k}{\sqrt{5}} - \frac{(\frac{1}{2}(1-\sqrt{5}))^k}{\sqrt{5}}$  The expression on the left,

$$\frac{(\frac{1}{2}(1 + \sqrt{5}))^k}{\sqrt{5}}$$

Will not go to 0, as the numerator  $> 1$ . On the other hand, the expression on the right,

$$\frac{(\frac{1}{2}(1 - \sqrt{5}))^k}{\sqrt{5}}$$

Approaches 0, as  $|\frac{1}{2}(1 - \sqrt{5})| < 1$ . So, since 100 is large, our original expression gets close to:

$$\frac{1}{\sqrt{5}} \lambda_1^{100} - 0$$

7. Let  $M$  be an  $n \times n$  positive Markov matrix, with  $n$  independent eigenvectors  $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ , and  $n$  eigenvalues  $\{\lambda_1, \lambda_2, \dots, \lambda_n\}$ , where  $\lambda_1 = 1$  and  $|\lambda_i| < 1$  when  $i \geq 2$ .
- Verify that  $\mathbf{1} = (1, 1, \dots, 1)$  is in the left nullspace of  $M - I$ .
  - Verify that  $\mathbf{x}_i$  is in the column space of  $M - I$  if  $i \geq 2$ .
  - Fill in the blank: Since the column space of  $(M - I)$  is \_\_\_\_\_ the left nullspace of  $(M - I)$ ,  $\mathbf{x}_i$  is \_\_\_\_\_  $(1, 1, \dots, 1)$  if  $i \geq 2$ .
  - If  $i \geq 2$ , explain why the components of  $\mathbf{x}_i$  sum to zero. [Hint: Use Part (c) and the definition of orthogonal.]
  - For any  $\mathbf{v} \in \mathbb{R}^n$ , let  $\mathbf{v} = c_1\mathbf{x}_1 + \dots + c_n\mathbf{x}_n$ . Explain why the coefficient  $c_1$  is the same for all vectors  $\mathbf{v}$  whose components have a given sum.

*Solution:*

- Since the columns of a markov matrix  $M$  sum to 1, this means that the rows of  $M^T$  sum to 1. This means that  $(M^T - I^T)\mathbf{1} = 0$  and therefore  $(M - I)^T\mathbf{1} = 0$ , which means that  $\mathbf{1}$  is in  $LN(M^T)$
- Since we know that  $\lambda_i, i \geq 2$ , we know that the only nonzero vector in  $N(M - I)$  is associated with  $\lambda_1 = 1$ . Since  $\mathbf{1}$  must be  $> 1$ , the eigenvector must be different. That being said, since  $M - I$  and  $(M - I)^T$  share the same eigenvalues, the only nonzero vector in  $N(M - I)^T$  must be associated with  $\lambda_1$ . Thus, since it is not associated with  $\lambda_i$ , the vector  $\mathbf{x}_i$  is not in the left null space and therefore in the column space.
- first blank: is orthogonal, second blank: is also orthogonal
- Since the left Null space and column space are orthogonal, the dot product of a vector in the column space and a vector in the null space has to be 0. Thus, since we saw in part(a) that  $\mathbf{1}$  was in the left null space, and we proved in part(b) that  $\mathbf{x}_i$  was in the column space,  $\mathbf{1} \cdot \mathbf{x}_i = 0$ . The only way this is true is if the components of  $\mathbf{x}_i$  sum to 0.
- if:

$$\mathbf{v} = c_1\mathbf{x}_1 + \dots + c_n\mathbf{x}_n$$

Then

$$\mathbf{1} \cdot \mathbf{v} = \mathbf{1} \cdot (c_1\mathbf{x}_1 + \dots + c_n\mathbf{x}_n)$$

And

$$\mathbf{1} \cdot \mathbf{v} = \mathbf{1} \cdot c_1\mathbf{x}_1 + \dots + \mathbf{1} \cdot c_n\mathbf{x}_n$$

But from the previous problem, we know that the components of  $x_2, \dots, x_n$  sum to 0. This means that:

$$\mathbf{1} \cdot \mathbf{v} = \mathbf{1} \cdot c_1\mathbf{x}_1 + \dots + 0 + 0 + 0 \cdot c_n\mathbf{x}_n$$

Which means that

$$\mathbf{1} \cdot \mathbf{v} = \mathbf{1} \cdot c_1\mathbf{x}_1$$

But since  $\mathbf{x}_1$  is *fixed* We can say:

$$\mathbf{1} \cdot \mathbf{v} = \mathbf{1} \cdot c_1 \mathbf{x}_1$$

Which means that for a given sum of coefficients, there is only one possible  $c_1$  that will satisfy the above equation.

## Optional Problems

8. Prove that if  $M$  is a Markov matrix, then the sum of the components of a vector  $\mathbf{v}$  is the same as the sum of the components of  $M\mathbf{v}$ .
9. Prove that if  $M$  is a positive Markov matrix, the columns of  $M^k$  converge to the eigenvector  $\mathbf{x}_1$  with eigenvalue 1, whose components sum to 1.
10. Consider a random walk on the integers from 1 to  $n$ , where a random walker on  $i$  moves to  $i + 1$  or  $i - 1$  with equal probability unless they are at 1 or  $n$ , in which case they move to 2 or  $n - 1$  with probability 1. Find the stationary distribution for various values of  $n$ . Can you make a conjecture for the form of the stationary distribution for large values of  $n$ ?