

Chapter 2

Doebelin's Theory for Markov Chains

In this chapter we begin in earnest our study of Markov processes. Like the random walks in Chap. 1, the processes with which we will be dealing here take only countably many values and have a discrete (as opposed to continuous) time parameter. In fact, in many ways, these processes are the simplest generalizations of random walks. To be precise, random walks proceed in such a way that the distribution of their increments are independent of everything that has happened before the increment takes place. The processes at which we will be looking now proceed in such a way that the distribution of their new position depends on where they are at the time when they move but not on where they were in the past. A process with this sort of dependence property is said to have the *Markov property* and is called a *Markov chain*.¹

The set \mathbb{S} in which a process takes its values is called its *state space*, and, as I said, our processes will have state spaces which are either finite or countably infinite. Thus, at least for theoretical purposes, there is no reason for us not to think of \mathbb{S} as the set $\{1, \dots, N\}$ or \mathbb{Z}^+ , depending on whether \mathbb{S} is finite or countably infinite. On the other hand, always taking \mathbb{S} to be one of these has the disadvantage that it may mask important properties. For example, it would have been a great mistake to describe the nearest neighbor random walk on \mathbb{Z}^2 after mapping \mathbb{Z}^2 isomorphically onto \mathbb{Z}^+ .

2.1 Some Generalities

Before getting started, there are a few general facts that we will need to know about Markov chains.

A *Markov chain* on a finite or countably infinite state space \mathbb{S} is a family of \mathbb{S} -valued random variables $\{X_n : n \geq 0\}$ with the property that, for all $n \geq 0$ and

¹The term “chain” is commonly applied to processes with a time discrete parameter.

$$(i_0, \dots, i_n, j) \in \mathbb{S}^{n+2},$$

$$\mathbb{P}(X_{n+1} = j \mid X_0 = i_0, \dots, X_n = i_n) = (\mathbf{P})_{i_n j}, \quad (2.1.1)$$

where \mathbf{P} is a matrix all of whose entries are non-negative and each of whose rows sums to 1. Equivalently (cf. Sect. 7.4.1)

$$\mathbb{P}(X_{n+1} = j \mid X_0, \dots, X_n) = (\mathbf{P})_{X_n j}. \quad (2.1.2)$$

It should be clear that (2.1.2) is a mathematically precise expression of the idea that, when a Markov chain jumps, the distribution of where it lands depends only on where it was at the time when it jumped and not on where it was in the past.

2.1.1 Existence of Markov Chains

For obvious reasons, a matrix whose entries are non-negative and each of whose rows sum to 1 is called a *transition probability matrix*: it gives the probability that the Markov chain will move to the state j at time $n + 1$ given that it is at state i at time n , independent of where it was prior to time n . Further, it is clear that only a transition probability matrix could appear on the right of (2.1.1). What may not be so immediate is that one can go in the opposite direction. Namely, let $\boldsymbol{\mu}$ be a *probability vector*² and \mathbf{P} a transition probability matrix. Then there exists a Markov chain $\{X_n : n \geq 0\}$ with *initial distribution* $\boldsymbol{\mu}$ and transition probability matrix \mathbf{P} . That is, $\mathbb{P}(X_0 = i) = (\boldsymbol{\mu})_i$ and (2.1.1) holds.

To prove the preceding existence statement, one can proceed as follows. Begin by assuming, without loss in generality, that \mathbb{S} is either $\{1, \dots, N\}$ or \mathbb{Z}^+ . Next, given $i \in \mathbb{S}$, set $\beta(i, 0) = 0$ and $\beta(i, j) = \sum_{k=1}^j (\mathbf{P})_{ik}$ for $j \geq 1$, and define $F : \mathbb{S} \times [0, 1) \rightarrow \mathbb{S}$ so that $F(i, u) = j$ if $\beta(i, j-1) \leq u < \beta(i, j)$. In addition, set $\alpha(0) = 0$ and $\alpha(i) = \sum_{k=1}^i (\boldsymbol{\mu})_k$ for $i \geq 1$, and define $f : [0, 1) \rightarrow \mathbb{S}$ so that $f(u) = i$ if $\alpha(i-1) \leq u < \alpha(i)$. Finally, let $\{U_n : n \geq 0\}$ be a sequence of mutually independent random variables (cf. Theorem 7.3.2) which are uniformly distributed on $[0, 1)$, and set

$$X_n = \begin{cases} f(U_0) & \text{if } n = 0 \\ F(X_{n-1}, U_n) & \text{if } n \geq 1. \end{cases} \quad (2.1.3)$$

We will now show that the sequence $\{X_n : n \geq 0\}$ in (2.1.3) is a Markov chain with the required properties. For this purpose, suppose that $(i_0, \dots, i_n) \in \mathbb{S}^{n+1}$, and

²A probability vector is a row vector whose coordinates are non-negative and sum to 1.

observe that

$$\begin{aligned}
 & \mathbb{P}(X_0 = i_0, \dots, X_n = i_n) \\
 &= \mathbb{P}(U_0 \in [\alpha(i_0 - 1), \alpha(i_0)) \\
 &\quad \& U_m \in [\beta(i_{m-1}, i_m - 1), \beta(i_{m-1}, i_m)) \text{ for } 1 \leq m \leq n) \\
 &= \mu_{i_0}(\mathbf{P})_{i_0 i_1} \cdots (\mathbf{P})_{i_{n-1} i_n} = \mathbb{P}(X_0 = i_0, \dots, X_{n-1} = i_{n-1}) \mathbf{P}_{i_{n-1}, j}.
 \end{aligned}$$

2.1.2 Transition Probabilities & Probability Vectors

Notice that the use of matrix notation here is clever. To wit, if μ is the row vector with i th entry $(\mu)_i = \mathbb{P}(X_0 = i)$, then μ is called the *initial distribution* of the chain and

$$(\mu \mathbf{P}^n)_j = \mathbb{P}(X_n = j), \quad n \geq 0 \text{ and } j \in \mathbb{S}, \quad (2.1.4)$$

where we have adopted the convention that \mathbf{P}^0 is the identity matrix and $\mathbf{P}^n = \mathbf{P} \mathbf{P}^{n-1}$ for $n \geq 1$.³ To check (2.1.4), let $n \geq 1$ be given, and note that, by (2.1.1) and induction,

$$\mathbb{P}(X_0 = i_0, \dots, X_{n-1} = i_{n-1}, X_n = j) = (\mu)_{i_0} (\mathbf{P})_{i_0 i_1} \cdots (\mathbf{P})_{i_{n-1} j}.$$

Hence (2.1.4) results after one sums with respect to (i_0, \dots, i_{n-1}) . Obviously, (2.1.4) is the statement that the row vector $\mu \mathbf{P}^n$ is the *distribution of the Markov chain at time n if μ is its initial distribution* (i.e., its distribution at time 0). Alternatively, \mathbf{P}^n is the n -step transition probability matrix: $(\mathbf{P}^n)_{ij}$ is the conditional probability that $X_{m+n} = j$ given that $X_m = i$.

For future reference, we will introduce here an appropriate way in which to measure the length of row vectors when they are being used to represent measures. Namely, given a row vector ρ , we set

$$\|\rho\|_v = \sum_{i \in \mathbb{S}} |(\rho)_i|, \quad (2.1.5)$$

where the subscript “v” is used in recognition that this is the notion of length which corresponds to the *variation norm* on the space of measures. The basic reason for our making this choice of norm is that

$$\|\rho \mathbf{P}\|_v \leq \|\rho\|_v, \quad (2.1.6)$$

since, by Theorem 7.1.15,

$$\|\rho \mathbf{P}\|_v = \sum_{j \in \mathbb{S}} \left| \sum_{i \in \mathbb{S}} (\rho)_i (\mathbf{P})_{ij} \right| \leq \sum_{i \in \mathbb{S}} \left(\sum_{j \in \mathbb{S}} |(\rho)_i| (\mathbf{P})_{ij} \right) = \|\rho\|_v.$$

³The reader should check for itself that \mathbf{P}^n is again a transition probability matrix for all $n \in \mathbb{N}$: all entries are non-negative and each row sums to 1.

Notice that this is a quite different way of measuring the length from the way Euclid would have: he would have used

$$\|\rho\|_2 = \left(\sum_{i \in \mathbb{S}} (\rho)_i^2 \right)^{\frac{1}{2}}.$$

When \mathbb{S} is finite, these two norms are comparable. Namely,

$$\|\rho\|_2 \leq \|\rho\|_v \leq \sqrt{\#\mathbb{S}} \|\rho\|_2, \quad \text{where } \#\mathbb{S} \text{ denotes the cardinality of } \mathbb{S}.$$

The first inequality is easily seen by squaring both sides, and the second is an application of Schwarz's inequality (cf. Exercise 1.3.1). However, when \mathbb{S} is infinite, they are not comparable. Nonetheless, $\|\cdot\|_v$ is a good *norm* (i.e., measure of length) in the sense that $\|\rho\|_v = 0$ if and only if $\rho = \mathbf{0}$ and that it satisfies the *triangle inequality*: $\|\rho + \rho'\|_v \leq \|\rho\|_v + \|\rho'\|_v$. Furthermore, Cauchy's convergence criterion holds for $\|\cdot\|_v$. That is, if $\{\rho_n\}_1^\infty$ is a sequence in $\mathbb{R}^\mathbb{S}$, then there exists $\rho \in \mathbb{R}^\mathbb{S}$ for which $\|\rho_n - \rho\|_v \rightarrow 0$ if and only if $\{\rho_n\}_1^\infty$ is *Cauchy convergent* in the sense that

$$\lim_{m \rightarrow \infty} \sup_{n > m} \|\rho_n - \rho_m\|_v = 0.$$

As usual, the “only if” direction is an easy application of the triangle inequality:

$$\|\rho_n - \rho_m\|_v \leq \|\rho_n - \rho\|_v + \|\rho - \rho_m\|_v.$$

To go the other direction, suppose that $\{\rho_n\}_1^\infty$ is Cauchy convergent, and observe that each coordinate of $\{\rho_n\}_1^\infty$ must be Cauchy convergent as real numbers. Hence, by Cauchy's criterion for real numbers, there exists a ρ to which $\{\rho_n\}_1^\infty$ converges in the sense that each coordinate of the ρ_n 's tends to the corresponding coordinate of ρ . Thus, by Fatou's lemma, Theorem 7.1.10, as $m \rightarrow \infty$,

$$\|\rho - \rho_m\|_v = \sum_{i \in \mathbb{S}} |(\rho)_i - (\rho_m)_i| \leq \lim_{n \rightarrow \infty} \sum_{i \in \mathbb{S}} |(\rho_n)_i - (\rho_m)_i| \rightarrow 0.$$

2.1.3 Transition Probabilities and Functions

As we saw in Sect. 2.1.2, the representation of the transition probability as a matrix and the initial distributions as a row vector facilitates the representation of the distribution at later times. In order to understand how to get the analogous benefit when computing expectation values of functions, think of a function f on the state space \mathbb{S} as the column vector \mathbf{f} whose j th coordinate is the value of the function f at j . Clearly, if μ is the row vector which represents the probability measure μ on \mathbb{S} and \mathbf{f} is the column vector which represents a function f which is either non-negative or bounded, then $\mu\mathbf{f} = \sum_{i \in \mathbb{S}} f(i)\mu(\{i\})$ is the expected value of f with respect to μ .

Similarly, the column vector $\mathbf{P}^n \mathbf{f}$ represents that function whose value at i is the conditional expectation value of $f(X_n)$ given that $X_0 = i$. Indeed,

$$\begin{aligned} \mathbb{E}[f(X_n) \mid X_0 = i] &= \sum_{j \in \mathbb{S}} f(j) \mathbb{P}(X_n = j \mid X_0 = i) \\ &= \sum_{j \in \mathbb{S}} (\mathbf{P}^n)_{ij} (\mathbf{f})_j = (\mathbf{P}^n \mathbf{f})_i. \end{aligned}$$

More generally, if f is either a non-negative or bounded function on \mathbb{S} and \mathbf{f} is the column vector which it determines, then, for $0 \leq m \leq n$,

$$\begin{aligned} \mathbb{E}[f(X_n) \mid X_0 = i_0, \dots, X_m = i_m] &= (\mathbf{P}^{n-m} \mathbf{f})_{i_m}, \quad \text{or, equivalently,} \\ \mathbb{E}[f(X_n) \mid X_0, \dots, X_m] &= (\mathbf{P}^{n-m} \mathbf{f})_{X_m} \end{aligned} \tag{2.1.7}$$

since

$$\begin{aligned} \mathbb{E}[f(X_n) \mid X_0 = i_0, \dots, X_m = i_m] &= \sum_{j \in \mathbb{S}} f(j) \mathbb{P}(X_n = j \mid X_0 = i_0, \dots, X_m = i_m) \\ &= \sum_{j \in \mathbb{S}} f(j) (\mathbf{P}^{n-m})_{i_m j} = (\mathbf{P}^{n-m} \mathbf{f})_{i_m}. \end{aligned}$$

In particular, if $\boldsymbol{\mu}$ is the initial distribution of $\{X_n : n \geq 0\}$, then

$$\mathbb{E}[f(X_n)] = \boldsymbol{\mu} \mathbf{P}^n \mathbf{f},$$

since $\mathbb{E}[f(X_n)] = \sum_i (\boldsymbol{\mu})_i \mathbb{E}[f(X_n) \mid X_0 = i]$.

Just as $\|\cdot\|_v$ was the appropriate way to measure the length of row vectors when we were using them to represent measures, the appropriate way to measure the length of column vectors which represent functions is with the *uniform norm* $\|\cdot\|_u$:

$$\|\mathbf{f}\|_u = \sup_{j \in \mathbb{S}} |(\mathbf{f})_j|. \tag{2.1.8}$$

The reason why $\|\cdot\|_u$ is the norm of choice here is that $\|\boldsymbol{\mu} \mathbf{f}\| \leq \|\boldsymbol{\mu}\|_v \|\mathbf{f}\|_u$, since

$$\|\boldsymbol{\mu} \mathbf{f}\| \leq \sum_{i \in \mathbb{S}} |(\boldsymbol{\mu})_i| |(\mathbf{f})_i| \leq \|\mathbf{f}\|_u \sum_{i \in \mathbb{S}} |(\boldsymbol{\mu})_i|.$$

In particular, we have the complement to (2.1.6):

$$\|\mathbf{P} \mathbf{f}\|_u \leq \|\mathbf{f}\|_u. \tag{2.1.9}$$

2.1.4 The Markov Property

By definition, if μ is the initial distribution of $\{X_n : n \geq 0\}$, then

$$\mathbb{P}(X_0 = i_0, \dots, X_n = i_n) = (\mu)_{i_0} (\mathbf{P})_{i_0 i_1} \cdots (\mathbf{P})_{i_{n-1} i_n}. \quad (2.1.10)$$

Hence, if $m, n \geq 1$ and $F : \mathbb{S}^{n+1} \rightarrow \mathbb{R}$ is either bounded or non-negative, then

$$\begin{aligned} & \mathbb{E}[F(X_m, \dots, X_{m+n}), X_0 = i_0, \dots, X_m = i_m] \\ &= \sum_{j_1, \dots, j_n \in \mathbb{S}} F(i_m, j_1, \dots, j_n) \mu_{i_0} (\mathbf{P})_{i_0 i_1} \cdots (\mathbf{P})_{i_{m-1} i_m} (\mathbf{P})_{i_m j_1} \cdots (\mathbf{P})_{j_{n-1} j_n} \\ &= \mathbb{E}[F(X_0, \dots, X_n) \mid X_0 = i_m] \mathbb{P}(X_0 = i_0, \dots, X_m = i_m). \end{aligned}$$

Equivalently, we have now proved the *Markov property* in the form

$$\begin{aligned} & \mathbb{E}[F(X_m, \dots, X_{m+n}) \mid X_0 = i_0, \dots, X_m = i_m] \\ &= \mathbb{E}[F(X_0, \dots, X_n) \mid X_0 = i_m]. \end{aligned} \quad (2.1.11)$$

2.2 Doeblin's Theory

In this section I will introduce an elementary but basic technique, due to Doeblin, which will allow us to study the long time distribution of a Markov chain, particularly ones on a finite state space.

2.2.1 Doeblin's Basic Theorem

For many purposes, what one wants to know about a Markov chain is its distribution after a long time, and, at least when the state space is finite, it is reasonable to think that the distribution of the chain will stabilize. To be more precise, if one is dealing with a chain which can go in a single step from any state i to some state j with positive probability, then that state j is going to be visited again and again, and so, after a while, the chain's initial distribution is going to get "forgotten." In other words, we are predicting for such a chain that $\mu \mathbf{P}^n$ will, for sufficiently large n , be nearly independent of μ . In particular, this would mean that $\mu \mathbf{P}^n = (\mu \mathbf{P}^{n-m}) \mathbf{P}^m$ is very nearly equal to $\mu \mathbf{P}^m$ when m is large and therefore, by Cauchy's convergence criterion, that $\pi = \lim_{n \rightarrow \infty} \mu \mathbf{P}^n$ exists. In addition, if this were the case, then we would have that $\pi = \lim_{n \rightarrow \infty} \mu \mathbf{P}^{n+1} = \lim_{n \rightarrow \infty} (\mu \mathbf{P}^n) \mathbf{P} = \pi \mathbf{P}$. That is, π would have to be a left eigenvector for \mathbf{P} with eigenvalue 1. A probability vector π is, for obvious reasons, called a *stationary probability* for the transition probability matrix \mathbf{P} if $\pi = \pi \mathbf{P}$.

Although a state j of the sort in the preceding discussion is most likely to exist when the state space is finite, there are situations in which these musings apply even to infinite state spaces. That is, if, no matter where the chain starts, it has a positive probability of immediately visiting some fixed state, then, as the following theorem shows, it will stabilize.

Theorem 2.2.1 (Doeblin's Theorem) *Let \mathbf{P} be a transition probability matrix with the property that, for some state $j_0 \in \mathbb{S}$ and $\epsilon > 0$, $(\mathbf{P})_{ij_0} \geq \epsilon$ for all $i \in \mathbb{S}$. Then \mathbf{P} has a unique stationary probability vector $\boldsymbol{\pi}$, $(\boldsymbol{\pi})_{j_0} \geq \epsilon$, and, for all initial distributions $\boldsymbol{\mu}$,*

$$\|\boldsymbol{\mu}\mathbf{P}^n - \boldsymbol{\pi}\|_{\mathbf{v}} \leq (1 - \epsilon)^n \|\boldsymbol{\mu} - \boldsymbol{\pi}\|_{\mathbf{v}} \leq 2(1 - \epsilon)^n, \quad n \geq 0.$$

Proof The key to the proof lies in the observations that if $\boldsymbol{\rho} \in \mathbb{R}^{\mathbb{S}}$ is a row vector with $\|\boldsymbol{\rho}\|_{\mathbf{v}} < \infty$, then

$$\begin{aligned} \sum_{j \in \mathbb{S}} (\boldsymbol{\rho}\mathbf{P})_j &= \sum_{i \in \mathbb{S}} (\boldsymbol{\rho})_i, \\ \text{and } \sum_{i \in \mathbb{S}} (\boldsymbol{\rho})_i &= 0 \implies \|\boldsymbol{\rho}\mathbf{P}^n\|_{\mathbf{v}} \leq (1 - \epsilon)^n \|\boldsymbol{\rho}\|_{\mathbf{v}} \quad \text{for } n \geq 1. \end{aligned} \tag{2.2.2}$$

The first of these is trivial, because, by Theorem 7.1.15,

$$\sum_{j \in \mathbb{S}} (\boldsymbol{\rho}\mathbf{P})_j = \sum_{j \in \mathbb{S}} \left(\sum_{i \in \mathbb{S}} (\boldsymbol{\rho})_i (\mathbf{P})_{ij} \right) = \sum_{i \in \mathbb{S}} \left(\sum_{j \in \mathbb{S}} (\boldsymbol{\rho})_i (\mathbf{P})_{ij} \right) = \sum_{i \in \mathbb{S}} (\boldsymbol{\rho})_i.$$

As for the second, note that, by an easy induction argument, it suffices to check it when $n = 1$. Next, suppose that $\sum_i (\boldsymbol{\rho})_i = 0$, and observe that

$$\begin{aligned} |(\boldsymbol{\rho}\mathbf{P})_j| &= \left| \sum_{i \in \mathbb{S}} (\boldsymbol{\rho})_i (\mathbf{P})_{ij} \right| \\ &= \left| \sum_{i \in \mathbb{S}} (\boldsymbol{\rho})_i ((\mathbf{P})_{ij} - \epsilon \delta_{j, j_0}) \right| \leq \sum_{i \in \mathbb{S}} |(\boldsymbol{\rho})_i| ((\mathbf{P})_{ij} - \epsilon \delta_{j, j_0}), \end{aligned}$$

and therefore that

$$\begin{aligned} \|\boldsymbol{\rho}\mathbf{P}\|_{\mathbf{v}} &\leq \sum_{j \in \mathbb{S}} \left(\sum_{i \in \mathbb{S}} |(\boldsymbol{\rho})_i| ((\mathbf{P})_{ij} - \epsilon \delta_{j, j_0}) \right) \\ &= \sum_{i \in \mathbb{S}} |(\boldsymbol{\rho})_i| \left(\sum_{j \in \mathbb{S}} ((\mathbf{P})_{ij} - \epsilon \delta_{j, j_0}) \right) = (1 - \epsilon) \|\boldsymbol{\rho}\|_{\mathbf{v}}. \end{aligned}$$

Now let $\boldsymbol{\mu}$ be a probability vector, and set $\boldsymbol{\mu}_n = \boldsymbol{\mu}\mathbf{P}^n$. Then, because $\boldsymbol{\mu}_n = \boldsymbol{\mu}_{n-m}\mathbf{P}^m$ and $\sum_i ((\boldsymbol{\mu}_{n-m})_i - \boldsymbol{\mu}_i) = 1 - 1 = 0$,

$$\|\boldsymbol{\mu}_n - \boldsymbol{\mu}_m\|_{\mathbf{v}} \leq (1 - \epsilon)^m \|\boldsymbol{\mu}_{n-m} - \boldsymbol{\mu}\|_{\mathbf{v}} \leq 2(1 - \epsilon)^m$$

for $1 \leq m < n$. Hence $\{\mu_n\}_1^\infty$ is Cauchy convergent, and therefore there exists a π for which $\|\mu_n - \pi\|_v \rightarrow 0$. Since each μ_n is a probability vector, it is clear that π must also be a probability vector. In addition, $\pi = \lim_{n \rightarrow \infty} \mu \mathbf{P}^{n+1} = \lim_{n \rightarrow \infty} (\mu \mathbf{P}^n) \mathbf{P} = \pi \mathbf{P}$, and so π is stationary. In particular,

$$(\pi)_{j_0} = \sum_{i \in \mathbb{S}} (\pi)_i (\mathbf{P})_{ij_0} \geq \epsilon \sum_{i \in \mathbb{S}} (\pi)_i = \epsilon.$$

Finally, if \mathbf{v} is any probability vector, then

$$\|\mathbf{v} \mathbf{P}^m - \pi\|_v = \|(\mathbf{v} - \pi) \mathbf{P}^m\|_v \leq (1 - \epsilon)^m \|\mu - \pi\|_v \leq 2(1 - \epsilon)^m,$$

which, of course, proves both the stated convergence result and the uniqueness of π as the only stationary probability vector for \mathbf{P} . \square

The condition in Doeblin's Theorem is called *Doeblin's condition*, and it is instructive to understand what his theorem says in the language of *spectral theory*. Namely, as an operator on the space of bounded functions (a.k.a. column vectors with finite uniform norm), \mathbf{P} has the function $\mathbf{1}$ as a right eigenfunction with eigenvalue 1: $\mathbf{P}\mathbf{1} = \mathbf{1}$. Thus, at least if \mathbb{S} is finite, general principles say that there must exist a row vector which is a left eigenvector of \mathbf{P} with eigenvalue 1. Moreover, because 1 and the entries of \mathbf{P} are real, this left eigenvector can be taken to have real components. Thus, from the spectral point of view, it is no surprise that there is a non-zero row vector $\mu \in \mathbb{R}^{\mathbb{S}}$ with the property that $\mu \mathbf{P} = \mu$. On the other hand, standard spectral theory would not predict that μ can be chosen to have non-negative components, and this is the first place where Doeblin's theorem gives information which is not readily available from standard spectral theory, even when \mathbb{S} is finite. To interpret the estimate in Doeblin's Theorem, let $M_1(\mathbb{S}; \mathbb{C})$ denote the space of row vectors $\mathbf{v} \in \mathbb{C}^{\mathbb{S}}$ with $\|\mathbf{v}\|_v = 1$. Then,

$$\|\mathbf{v} \mathbf{P}\|_v \leq 1 \quad \text{for all } \mathbf{v} \in M_1(\mathbb{S}; \mathbb{C}),$$

and so

$$\sup\{|\alpha| : \alpha \in \mathbb{C} \text{ \& \; } \exists \mathbf{v} \in M_1(\mathbb{S}; \mathbb{C}) \mathbf{v} \mathbf{P} = \alpha \mathbf{v}\} \leq 1.$$

Moreover, if $\mathbf{v} \mathbf{P} = \alpha \mathbf{v}$ for some $\alpha \neq 1$, then $\mathbf{v} \mathbf{1} = \mathbf{v}(\mathbf{P}\mathbf{1}) = (\mathbf{v} \mathbf{P})\mathbf{1} = \alpha \mathbf{v} \mathbf{1}$, and therefore $\mathbf{v} \mathbf{1} = 0$. Thus, the estimate in (2.2.2) says that all eigenvalues of \mathbf{P} which are different from 1 have absolute value dominated by $1 - \epsilon$. That is, the entire spectrum of \mathbf{P} lies in the complex unit disk, 1 is a simple eigenvalue, and all the other eigenvalues lie in the disk of radius $1 - \epsilon$. Finally, although general spectral theory fails to predict Doeblin's Theorem, it should be said that there is a spectral theory, the one initiated by Frobenius and developed further by Kakutani, that does cover Doeblin's results. The interested reader should consult Chap. VIII in [2].

2.2.2 A Couple of Extensions

An essentially trivial extension of Theorem 2.2.1 is provided by the observation that, for any $M \geq 1$ and $\epsilon > 0$,⁴

$$\begin{aligned} \sup_j \inf_i (\mathbf{P}^M)_{ij} &\geq \epsilon \\ \implies \|\mu \mathbf{P}^n - \pi\|_v &\leq (1 - \epsilon)^{\lfloor \frac{n}{M} \rfloor} \|\mu - \pi\|_v \leq 2(1 - \epsilon)^{\lfloor \frac{n}{M} \rfloor} \end{aligned} \quad (2.2.3)$$

for all probability vectors μ and a unique stationary probability vector π . To see this, let π be the stationary probability vector for \mathbf{P}^M , the one guaranteed by Theorem 2.2.1, and note that, for any probability vector μ , any $m \in \mathbb{N}$, and any $0 \leq r < M$,

$$\|\mu \mathbf{P}^{mM+r} - \pi\|_v = \|(\mu \mathbf{P}^r - \pi \mathbf{P}^r) \mathbf{P}^{mM}\|_v \leq (1 - \epsilon)^m \|\mu - \pi\|_v \leq 2(1 - \epsilon)^m.$$

Thus (2.2.3) has been proved, and from (2.2.3) the argument needed to show that π is the one and only stationary measure for \mathbf{P} is the same as the one given in the proof of Theorem 2.2.1.

The next extension is a little less trivial. In order to appreciate the point that it is addressing, one should keep in mind the following example. Consider the transition probability matrix

$$\mathbf{P} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad \text{on } \{1, 2\}.$$

Obviously, this two state chain goes in a single step from one state to the other. Thus, it certainly visits all its states. On the other hand, it does not satisfy the hypothesis in (2.2.3): $(\mathbf{P}^n)_{ij} = 0$ if either $i = j$ and n is odd or if $i \neq j$ and n is even. Thus, it should not be surprising that the conclusion in (2.2.3) fails to hold for this \mathbf{P} . Indeed, it is easy to check that although $(\frac{1}{2}, \frac{1}{2})$ is the one and only stationary probability vector for \mathbf{P} , $\|(1, 0)\mathbf{P}^n - (\frac{1}{2}, \frac{1}{2})\|_v = 1$ for all $n \geq 0$. As we will see later (cf. Sect. 3.1.3), the problems encountered here stem from the fact that $(\mathbf{P}^n)_{ii} > 0$ only if n is even.

In spite of the problems raised by the preceding example, one should expect that the chain corresponding to this \mathbf{P} does equilibrate in some sense. To describe what I have in mind, set

$$\mathbf{A}_n = \frac{1}{n} \sum_{m=0}^{n-1} \mathbf{P}^m. \quad (2.2.4)$$

Although the matrix \mathbf{A}_n is again a transition probability matrix, it is not describing transitions but instead it is giving the average amount of time that the chain will visit

⁴Here and elsewhere, we use $\lfloor s \rfloor$ to denote the *integer part* of s of $s \in \mathbb{R}$. That is, $\lfloor s \rfloor$ is the largest integer dominated by s .

states. To be precise, because

$$(\mathbf{A}_n)_{ij} = \frac{1}{n} \sum_{m=0}^{n-1} \mathbb{P}(X_m = j \mid X_0 = i) = \mathbb{E} \left[\frac{1}{n} \sum_{m=0}^{n-1} \mathbf{1}_{\{j\}}(X_m) \mid X_0 = i \right],$$

$(\mathbf{A}_n)_{ij}$ is the expected value of the average time spent at state j during the time interval $[0, n-1]$ given that i was the state from which the chain started. Experience teaches us that data becomes much more forgiving when it is averaged, and the present situation is no exception. Indeed, continuing with the example given above, observe that, for any probability vector μ ,

$$\left\| \mu \mathbf{A}_n - \left(\frac{1}{2}, \frac{1}{2} \right) \right\|_v \leq \frac{1}{n} \quad \text{for } n \geq 1.$$

What follows is a statement which shows that this sort of conclusion is quite general.

Theorem 2.2.5 *Suppose that \mathbf{P} is a transition probability matrix on \mathbb{S} . If for some $M \in \mathbb{Z}^+$, $j_0 \in \mathbb{S}$, and $\epsilon > 0$, $(\mathbf{A}_M)_{ij_0} \geq \epsilon$ for all $i \in \mathbb{S}$, then there is precisely one stationary probability vector π for \mathbf{P} , $(\pi)_{j_0} \geq \epsilon$, and*

$$\|\mu \mathbf{A}_n - \pi\|_v \leq \frac{M-1}{n\epsilon}$$

for any probability vector μ .

To get started, let π be the unique stationary probability that Theorem 2.2.3 guarantees for \mathbf{A}_M . Then, because any μ which is stationary for \mathbf{P} is certainly stationary for \mathbf{A}_M , it is clear that π is the only candidate for \mathbf{P} -stationarity. Moreover, to see that π is \mathbf{P} -stationary, observe that, because \mathbf{P} commutes with \mathbf{A}_M , $(\pi \mathbf{P}) \mathbf{A}_M = (\pi \mathbf{A}_M) \mathbf{P} = \pi \mathbf{P}$. Hence, $\pi \mathbf{P}$ is stationary for \mathbf{A}_M and therefore, by uniqueness, must be equal to π . That is, $\pi = \pi \mathbf{P}$.

In order to prove the asserted convergence result, we will need an elementary property of averaging procedures. Namely, for any probability vector μ ,

$$\|\mu \mathbf{A}_n \mathbf{A}_m - \mu \mathbf{A}_n\|_v \leq \frac{m-1}{n} \quad \text{for all } m, n \geq 1. \quad (2.2.6)$$

To check this, first note that, by the triangle inequality,

$$\begin{aligned} \|\mu \mathbf{A}_n \mathbf{A}_m - \mu \mathbf{A}_n\|_v &= \frac{1}{m} \left\| \sum_{k=0}^{m-1} (\mu \mathbf{A}_n \mathbf{P}^k - \mu \mathbf{A}_n) \right\|_v \\ &\leq \frac{1}{m} \sum_{k=0}^{m-1} \|\mu \mathbf{A}_n \mathbf{P}^k - \mu \mathbf{A}_n\|_v. \end{aligned}$$

Second, if $k \geq n$ then $\|\mu \mathbf{A}_n \mathbf{P}^k - \mu \mathbf{A}_n\|_v \leq 2 \leq \frac{2k}{n}$, and if $0 \leq k < n$ then

$$\mu \mathbf{A}_n \mathbf{P}^k - \mu \mathbf{A}_n = \frac{1}{n} \sum_{\ell=0}^{n-1} (\mu \mathbf{P}^{\ell+k} - \mu \mathbf{P}^\ell) = \frac{1}{n} \left(\sum_{\ell=k}^{n+k-1} \mu \mathbf{P}^\ell - \sum_{\ell=0}^{n-1} \mu \mathbf{P}^\ell \right),$$

and so $\|\mu \mathbf{P}^k \mathbf{A}_n - \mu \mathbf{A}_n\|_v \leq \frac{2k}{n}$ for all $n \geq 1$. Hence, after combining this with the first observation, we are lead to

$$\|\mu \mathbf{A}_n \mathbf{A}_m - \mu \mathbf{A}_n\|_v \leq \frac{2}{mn} \sum_{k=0}^{m-1} k = \frac{m-1}{n},$$

which is what we wanted.

To complete the proof of Theorem 2.2.5 from here, assume that $(\mathbf{A}_M)_{ij_0} \geq \epsilon$ for all i , and, as above, let π be the unique stationary probability vector for \mathbf{P} . Then, π is also the unique stationary probability vector for \mathbf{A}_M , and so, by the estimate in the second line of (2.2.2) applied to \mathbf{A}_M , $\|\mu \mathbf{A}_n \mathbf{A}_M - \pi\|_v = \|(\mu \mathbf{A}_n - \pi) \mathbf{A}_M\|_v \leq (1 - \epsilon) \|\mu \mathbf{A}_n - \pi\|_v$, which, in conjunction with (2.2.6), leads to

$$\begin{aligned} \|\mu \mathbf{A}_n - \pi\|_v &\leq \|\mu \mathbf{A}_n - \mu \mathbf{A}_n \mathbf{A}_M\|_v + \|\mu \mathbf{A}_n \mathbf{A}_M - \pi\|_v \\ &\leq \frac{M-1}{n} + (1 - \epsilon) \|\mu \mathbf{A}_n - \pi\|_v. \end{aligned}$$

Finally, after elementary rearrangement, this gives the required result.

2.3 Elements of Ergodic Theory

In the preceding section we saw that, under suitable conditions, either $\mu \mathbf{P}^n$ or $\mu \mathbf{A}_n$ converge and that the limit is the unique stationary probability vector π for \mathbf{P} . In the present section, we will provide a more probabilistically oriented interpretation of these results. In particular, we will give a probabilistic interpretation of π . This will be done again, by entirely different methods, in Chap. 4.

Before going further, it will be useful to have summarized our earlier results in the form (cf. (2.2.3) and remember that $\|\mu \mathbf{f}\| \leq \|\mu\|_v \|f\|_u$)⁵

$$\sup_j \inf_i (\mathbf{P}^M)_{ij} \geq \epsilon \quad \implies \quad \|\mathbf{P}^n \mathbf{f} - \pi \mathbf{f}\|_u \leq 2(1 - \epsilon)^{\lfloor \frac{n}{M} \rfloor} \|\mathbf{f}\|_u \quad (2.3.1)$$

and (cf. Theorem 2.2.5)

$$\sup_j \inf_i (\mathbf{A}_M)_{ij} \geq \epsilon \quad \implies \quad \|\mathbf{A}_n \mathbf{f} - \pi \mathbf{f}\|_u \leq \frac{M-1}{n\epsilon} \|\mathbf{f}\|_u \quad (2.3.2)$$

when \mathbf{f} is a bounded column vector.

⁵Here, and elsewhere, I abuse notation by using a constant to stand for the associated constant function.

2.3.1 The Mean Ergodic Theorem

Let $\{\mathbf{X}_n : n \geq 0\}$ be a Markov chain with transition probability \mathbf{P} . Obviously,

$$\bar{T}_j^{(n)} \equiv \frac{1}{n} \sum_{m=0}^{n-1} \mathbf{1}_{\{j\}}(X_m) \quad (2.3.3)$$

is the average amount of time that the chain spends at j before time n . Thus, if $\boldsymbol{\mu}$ is the initial distribution of the chain (i.e., $(\boldsymbol{\mu})_i = \mathbb{P}(X_0 = i)$), then $(\boldsymbol{\mu}\mathbf{A}_n)_j = \mathbb{E}[\bar{T}_j^{(n)}]$, and so, when it applies, Theorem 2.2.5 implies that $\mathbb{E}[\bar{T}_j^{(n)}] \rightarrow (\boldsymbol{\pi})_j$ as $n \rightarrow \infty$. Here we will be proving that the random variables $\bar{T}_j^{(n)}$ themselves, not just their expected values, tend to $(\boldsymbol{\pi})_j$ as $n \rightarrow \infty$. Such results come under the heading of *ergodic theory*. Ergodic theory is the mathematics of the principle, first enunciated by the physicist J.W. Gibbs in connection with the kinetic theory of gases, which asserts that the time-average over a particular trajectory of a dynamical system will approximate the equilibrium state of that system. Unfortunately, in spite of results, like those given here, confirming this principle, even now, nearly 150 years after Gibbs, there are embarrassingly few physically realistic situations in which Gibbs's principle has been mathematically confirmed.

Theorem 2.3.4 (Mean Ergodic Theorem) *Under the hypotheses in Theorem 2.2.5,*

$$\sup_{j \in \mathbb{S}} \mathbb{E}[(\bar{T}_j^{(n)} - (\boldsymbol{\pi})_j)^2] \leq \frac{2(M-1)}{n\epsilon} \quad \text{for all } n \geq 1.$$

(See (2.3.10) below for a more refined, less quantitative version.) More generally, for any bounded function f on \mathbb{S} and all $n \geq 1$:

$$\mathbb{E} \left[\left(\frac{1}{n} \sum_{m=0}^{n-1} f(X_m) - \boldsymbol{\pi}\mathbf{f} \right)^2 \right] \leq \frac{4(M-1)\|\mathbf{f}\|_{\mathbf{u}}^2}{n\epsilon},$$

where \mathbf{f} denotes the column vector determined by f .

Proof Let \bar{f} be the column vector determined by the function $\bar{f} = f - \boldsymbol{\pi}\mathbf{f}$. Obviously,

$$\frac{1}{n} \sum_{m=0}^{n-1} f(X_m) - \boldsymbol{\pi}\mathbf{f} = \frac{1}{n} \sum_{m=0}^{n-1} \bar{f}(X_m),$$

and so

$$\begin{aligned}
 \left(\frac{1}{n} \sum_{m=0}^{n-1} f(X_m) - \pi \mathbf{f} \right)^2 &= \frac{1}{n^2} \left(\sum_{m=0}^{n-1} \bar{f}(X_m) \right)^2 = \frac{1}{n^2} \sum_{k, \ell=0}^{n-1} \bar{f}(X_k) \bar{f}(X_\ell) \\
 &= \frac{2}{n^2} \sum_{0 \leq k \leq \ell < n} \bar{f}(X_k) \bar{f}(X_\ell) - \frac{1}{n^2} \sum_{k=0}^{n-1} \bar{f}(X_k)^2 \\
 &\leq \frac{2}{n^2} \sum_{0 \leq k \leq \ell < n} \bar{f}(X_k) \bar{f}(X_\ell).
 \end{aligned}$$

Hence,

$$\begin{aligned}
 \mathbb{E} \left[\left(\frac{1}{n} \sum_{m=0}^{n-1} f(X_m) - \pi \mathbf{f} \right)^2 \right] &\leq \frac{2}{n^2} \sum_{k=0}^{n-1} \mathbb{E} \left[\bar{f}(X_k) \sum_{\ell=0}^{n-k-1} \bar{f}(X_{k+\ell}) \right] \\
 &= \frac{2}{n^2} \sum_{k=0}^{n-1} \mathbb{E} \left[\bar{f}(X_k) \sum_{\ell=0}^{n-k-1} (\mathbf{P}^\ell \bar{\mathbf{f}})_{X_k} \right] \\
 &= \frac{2}{n^2} \sum_{k=0}^{n-1} (n-k) \mathbb{E} [\bar{f}(X_k) (\mathbf{A}_{n-k} \bar{\mathbf{f}})_{X_k}].
 \end{aligned}$$

But, by (2.3.2), $\|\mathbf{A}_{n-k} \bar{\mathbf{f}}\|_u \leq \frac{M-1}{(n-k)\epsilon} \|\bar{\mathbf{f}}\|_u$, and so, since $\|\bar{\mathbf{f}}\|_u \leq 2\|\mathbf{f}\|_u$,

$$(n-k) \mathbb{E} [\bar{f}(X_k) (\mathbf{A}_{n-k} \bar{\mathbf{f}})_{X_k}] \leq \frac{2(M-1)\|\mathbf{f}\|_u^2}{\epsilon}.$$

After plugging this into the preceding, we get the second result. To get the first, simply take $f = \mathbf{1}_{\{j\}}$ and observe that, in this case, $\|\bar{\mathbf{f}}\|_u \leq 1$. \square

2.3.2 Return Times

As the contents of Sects. 1.1 and 1.2 already indicate, return times ought to play an important role in the analysis of the long time behavior of Markov chains. In particular, if $\rho_j^{(0)} \equiv 0$ and, for $m \geq 1$, the *time of m th return* to j is defined so that $\rho_j^{(m)} = \infty$ if $\rho_j^{(m-1)} = \infty$ or $X_n \neq j$ for every $n > \rho_j^{(m-1)}$ and $\rho_j^{(m)} = \inf\{n > \rho_j^{(m-1)} : X_n = j\}$ otherwise, then we say that j is *recurrent* if $\mathbb{P}(\rho_j^{(1)} < \infty | X_0 = j) = 1$ and that it is *transient* if $\mathbb{P}(\rho_j^{(1)} < \infty | X_0 = j) < 1$; and we can hope that when j is recurrent, then the history of the chain breaks into epochs which are punctuated by the successive returns to j . In this subsection we will provide evidence which bolsters that hope.

Notice that $\rho_j \equiv \rho_j^{(1)} \geq 1$ and, for $n \geq 1$,

$$\begin{aligned} \mathbf{1}_{(n, \infty]}(\rho_j) &= F_{n,j}(X_0, \dots, X_n) \quad \text{where} \\ F_{n,j}(i_0, \dots, i_n) &= \begin{cases} 1 & \text{if } i_m \neq j \text{ for } 1 \leq m \leq n, \\ 0 & \text{otherwise.} \end{cases} \end{aligned} \quad (2.3.5)$$

In particular, this shows that the event $\{\rho_j > n\}$ is a measurable function of (X_0, \dots, X_n) . More generally, because

$$\mathbf{1}_{(n, \infty]}(\rho_j^{(m+1)}) = \mathbf{1}_{[n, \infty]}(\rho_j^{(m)}) + \sum_{\ell=1}^{n-1} \mathbf{1}_{\{\ell\}}(\rho_j^{(m)}) F_{n-\ell, j}(X_\ell, \dots, X_n),$$

an easy inductive argument shows that, for each $m \in \mathbb{N}$ and $n \in \mathbb{N}$, $\{\rho_j^{(m)} > n\}$ is a measurable function of (X_0, \dots, X_n) .

Theorem 2.3.6 For all $m \in \mathbb{Z}^+$ and $(i, j) \in \mathbb{S}^2$,

$$\mathbb{P}(\rho_j^{(m)} < \infty \mid X_0 = i) = \mathbb{P}(\rho_j < \infty \mid X_0 = i) \mathbb{P}(\rho_j < \infty \mid X_0 = j)^{m-1}.$$

In particular, if j is recurrent, then $\mathbb{P}(\rho_j^{(m)} < \infty \mid X_0 = j) = 1$ for all $m \in \mathbb{N}$. In fact, if j is recurrent, then, conditional on $X_0 = j$, $\{\rho_j^{(m)} - \rho_j^{(m-1)} : m \geq 1\}$ is a sequence of mutually independent random variables each of which has the same distribution as ρ_j .

Proof To prove the first statement, we apply (2.1.11) and the monotone convergence theorem, Theorem 7.1.9, to justify

$$\begin{aligned} &\mathbb{P}(\rho_j^{(m)} < \infty \mid X_0 = i) \\ &= \sum_{n=1}^{\infty} \mathbb{P}(\rho_j^{(m-1)} = n \text{ \& } \rho_j^{(m)} < \infty \mid X_0 = i) \\ &= \lim_{N \rightarrow \infty} \sum_{n=1}^{\infty} \mathbb{P}(\rho_j^{(m-1)} = n \text{ \& } \rho_j^{(m)} \leq N \mid X_0 = i) \\ &= \sum_{n=1}^{\infty} \lim_{N \rightarrow \infty} \mathbb{E}[1 - F_{N,j}(X_n, \dots, X_{n+N}), \rho_j^{(m-1)} = n \mid X_0 = i] \\ &= \sum_{n=1}^{\infty} \lim_{N \rightarrow \infty} \mathbb{E}[1 - F_{N,j}(X_0, \dots, X_N) \mid X_0 = j] \mathbb{P}(\rho_j^{(m-1)} = n \mid X_0 = i) \\ &= \sum_{n=1}^{\infty} \lim_{N \rightarrow \infty} \mathbb{P}(\rho_j \leq N \mid X_0 = j) \mathbb{P}(\rho_j^{(m-1)} = n \mid X_0 = i) \\ &= \mathbb{P}(\rho_j < \infty \mid X_0 = j) \mathbb{P}(\rho_j^{(m-1)} < \infty \mid X_0 = i). \end{aligned}$$

Turning to the second statement, note that it suffices for us prove that

$$\begin{aligned} \mathbb{P}(\rho_j^{(m+1)} > n + n_m \mid X_0 = j, \rho_j^{(1)} = n_1, \dots, \rho_j^{(m)} = n_m) \\ = \mathbb{P}(\rho_j > n \mid X_0 = j). \end{aligned}$$

But, again by (2.1.11), the expression on the left is equal to

$$\begin{aligned} \mathbb{E}[F_{n,j}(X_{n_m}, \dots, X_{n_m+n}) \mid X_0 = j, \rho_j^{(1)} = n_1, \dots, \rho_j^{(m)} = n_m] \\ = \mathbb{E}[F_{n,j}(X_0, \dots, X_n) \mid X_0 = j] = \mathbb{P}(\rho_j > n \mid X_0 = j). \quad \square \end{aligned}$$

Reasoning as we did in Sect. 1.2.2, we can derive from the first part of Theorem 2.3.6:

$$\begin{aligned} \mathbb{E}[T_j \mid X_0 = i] &= \delta_{i,j} + \frac{\mathbb{P}(\rho_j < \infty \mid X_0 = i)}{\mathbb{P}(\rho_j = \infty \mid X_0 = j)}, \\ \mathbb{E}[T_j \mid X_0 = j] &= \infty \iff \mathbb{P}(T_j = \infty \mid X_0 = j) = 1, \\ \mathbb{E}[T_j \mid X_0 = j] < \infty &\iff \mathbb{P}(T_j < \infty \mid X_0 = j) = 1, \end{aligned} \tag{2.3.7}$$

where $T_j = \sum_{m=0}^{\infty} \mathbf{1}_{\{j\}}(X_m)$ is the total time the chain spends in the state j . Indeed, because

$$\mathbb{P}(T_j > m \mid X_0 = i) = \begin{cases} \mathbb{P}(\rho_j^{(m)} < \infty \mid X_0 = j) & \text{if } i = j \\ \mathbb{P}(\rho_j^{(m+1)} < \infty \mid X_0 = i) & \text{if } i \neq j, \end{cases}$$

all three parts of (2.3.7) follow immediately from the first part of Theorem 2.3.6.

Of course, from (2.3.7) we know that

$$j \text{ is recurrent} \iff \mathbb{E}[T_j \mid X_0 = j] = \infty.$$

In particular, under the conditions in Theorem 2.2.5, this means that j_0 is recurrent since $(\mathbf{A}_n)_{j_0 j_0} \longrightarrow (\boldsymbol{\pi})_{j_0} > 0$ and therefore

$$\mathbb{E}[T_{j_0} \mid X_0 = j_0] = \sum_{m=0}^{\infty} (\mathbf{P}^m)_{j_0 j_0} = \lim_{n \rightarrow \infty} n(\mathbf{A}_n)_{j_0 j_0} = \infty.$$

To facilitate the statement of the next result, we will say that j is *accessible* from i and will write $i \rightarrow j$ if $(\mathbf{P}^n)_{ij} > 0$ for some $n \geq 0$. Equivalently, $i \rightarrow j$ if and only if $i = j$ or $i \neq j$ and $\mathbb{P}(\rho_j < \infty \mid X_0 = i) > 0$.

Theorem 2.3.8 *Assume that $\inf_k (\mathbf{A}_M)_{ki} \geq \epsilon$ for some $M \geq 1$, $i \in \mathbb{S}$, and $\epsilon > 0$. Then j is recurrent if and only if $i \rightarrow j$, in which case $\inf_k (\mathbf{A}_{M'})_{kj} > 0$ for some $M' > 0$. Moreover, if k is recurrent, then $\sup_{j \in \mathbb{S}} \mathbb{E}[\rho_k^p \mid X_0 = j] < \infty$ for all $p \in (0, \infty)$.*

Proof First suppose that $i \nrightarrow j$. Equivalently, $\mathbb{P}(\rho_j = \infty | X_0 = i) = 1$. At the same time, because $(\mathbf{A}_M)_{ji} \geq \epsilon$, there exists an $1 \leq m < M$ such that $(\mathbf{P}^m)_{ji} > 0$, and so (cf. (2.3.5))

$$\begin{aligned} \mathbb{P}(\rho_j = \infty | X_0 = j) &\geq \mathbb{P}(X_n \neq j \text{ for } n \geq m \text{ \& } X_m = i | X_0 = j) \\ &\geq \lim_{N \rightarrow \infty} \mathbb{E}[F_{N,j}(X_m, \dots, X_{m+N}), X_m = i | X_0 = j] \\ &= \lim_{N \rightarrow \infty} \mathbb{E}[F_{N,j}(X_0, \dots, X_N) | X_0 = i] \mathbb{P}(X_m = i | X_0 = j) \\ &= \mathbb{P}(\rho_j = \infty | X_0 = i) (\mathbf{P}^m)_{ji} > 0. \end{aligned}$$

Therefore j cannot be recurrent.

We next show that

$$i \rightarrow j \implies \inf_k (\mathbf{A}_{M'})_{kj} > 0 \quad \text{for some } M' \geq 1. \quad (*)$$

To this end, choose $m \in \mathbb{N}$ so that $(\mathbf{P}^m)_{ij} > 0$. Then, for all $k \in \mathbb{S}$,

$$\begin{aligned} (\mathbf{A}_{m+M})_{kj} &= \frac{1}{m+M} \sum_{\ell=0}^{M+m-1} (\mathbf{P}^\ell)_{kj} \geq \frac{1}{m+M} \sum_{\ell=0}^{M-1} (\mathbf{P}^\ell)_{ki} (\mathbf{P}^m)_{ij} \\ &= \frac{M}{m+M} (\mathbf{A}_M)_{ki} (\mathbf{P}^m)_{ij} \geq \frac{M\epsilon}{m+M} (\mathbf{P}^m)_{ij} > 0. \end{aligned}$$

In view of (*) and what we have already shown, it suffices to show that $\mathbb{E}[\rho_i^p | X_0 = j] < \infty$ for all $j \in \mathbb{S}$. For this purpose, set

$$u(n, k) = \mathbb{P}(\rho_i > nM | X_0 = k) \quad \text{for } n \in \mathbb{Z}^+ \text{ and } k \in \mathbb{S}.$$

Then, by (2.1.11),

$$\begin{aligned} u(n+1, k) &= \sum_{j \in \mathbb{S}} \mathbb{P}(\rho_i > (n+1)M \text{ \& } X_{nM} = j | X_0 = k) \\ &= \sum_{j \in \mathbb{S}} \mathbb{E}[F_{M,i}(X_{nM}, \dots, X_{(n+1)M}), \rho_i > nM \text{ \& } X_{nM} = j | X_0 = k] \\ &= \sum_{j \in \mathbb{S}} \mathbb{P}(\rho_i > M | X_0 = j) \mathbb{P}(\rho_i > nM \text{ \& } X_{nM} = j | X_0 = k) \\ &= \sum_{j \in \mathbb{S}} u(1, j) \mathbb{P}(\rho_i > nM \text{ \& } X_{nM} = j | X_0 = k). \end{aligned}$$

Hence, $u(n+1, k) \leq U u(n, k)$ where $U \equiv \max_{j \in \mathbb{S}} u(1, j)$. Finally, since $u(1, j) = 1 - \mathbb{P}(\rho_i \leq M | X_0 = j)$ and

$$\mathbb{P}(\rho_i \leq M | X_0 = j) \geq \max_{0 \leq m < M} (\mathbf{P}^m)_{ji} \geq (\mathbf{A}_M)_{ji} \geq \epsilon,$$

$U \leq 1 - \epsilon$. In particular, this means that $u(n+1, k) \leq (1 - \epsilon)u(n, k)$, and therefore that $\mathbb{P}(\rho_i > nM | X_0 = k) \leq (1 - \epsilon)^n$, from which

$$\begin{aligned} \mathbb{E}[\rho_i^p | X_0 = k] &= \sum_{n=1}^{\infty} n^p \mathbb{P}(\rho_i = n | X_0 = k) \\ &\leq \sum_{m=1}^{\infty} (mM)^p \sum_{n=(m-1)M+1}^{mM} \mathbb{P}(\rho_i = n | X_0 = k) \\ &\leq M^p \sum_{m=1}^{\infty} m^p \mathbb{P}(\rho_i > (m-1)M | X_0 = k) \\ &\leq M^p \sum_{m=1}^{\infty} m^p (1 - \epsilon)^{m-1} < \infty \end{aligned}$$

follows immediately. \square

2.3.3 Identification of π

Under the conditions in Theorem 2.2.5, we know that there is precisely one \mathbf{P} -stationary probability vector π . In this section, we will give a probabilistic interpretation of $(\pi)_j$. Namely, we will show that

$$\begin{aligned} \sup_{M \geq 1} \sup_{j \in \mathbb{S}} \inf_{i \in \mathbb{S}} (\mathbf{A}_M)_{ij} &> 0 \\ \implies (\pi)_j &= \frac{1}{\mathbb{E}[\rho_j | X_0 = j]} \quad (\equiv 0 \text{ if } j \text{ is transient}). \end{aligned} \quad (2.3.9)$$

The idea for the proof of (2.3.9) is that, on the one hand, (cf. (2.3.3))

$$\mathbb{E}[\overline{T}_j^{(n)} | X_0 = j] = (\mathbf{A}_n)_{jj} \longrightarrow (\pi)_j,$$

while, on the other hand,

$$X_0 = j \implies \overline{T}_j^{(\rho_j^{(m)})} = \frac{1}{\rho_j^{(m)}} \sum_{\ell=0}^{\rho_j^{(m)}-1} \mathbf{1}_{\{j\}}(X_\ell) = \frac{m}{\rho_j^{(m)}}.$$

Thus, since, at least when j is recurrent, Theorem 2.3.6 says that $\rho_j^{(m)}$ is the sum of m mutually independent copies of ρ_j , the preceding combined with the weak law of large numbers should lead

$$(\pi)_j = \lim_{m \rightarrow \infty} \mathbb{E}[\overline{T}_j^{(\rho_j^{(m)})} | X_0 = j] = \frac{1}{\mathbb{E}[\rho_j | X_0 = j]}.$$

To carry out the program suggested above, we will actually prove a stronger result. Namely, we will show that, for each $j \in \mathbb{S}$,⁶

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} \bar{T}_j^{(n)} = \frac{1}{\mathbb{E}[\rho_j | X_0 = j]} \mid X_0 = j\right) = 1. \quad (2.3.10)$$

In particular, because $0 \leq \bar{T}_j^{(n)} \leq 1$, Lebesgue's dominated convergence theorem, Theorem 7.1.11, says that

$$(\pi)_j = \lim_{n \rightarrow \infty} (\mathbf{A}_n)_{jj} = \lim_{n \rightarrow \infty} \mathbb{E}[\bar{T}_j^{(n)} \mid X_0 = j] = \frac{1}{\mathbb{E}[\rho_j \mid X_0 = j]}$$

follows from (2.3.10). Thus, we need only prove (2.3.10). To this end, choose j_0 , M , and $\epsilon > 0$ so that $(\mathbf{A}_M)_{ij_0} \geq \epsilon$ for all i . If $j_0 \nrightarrow j$, then, by Theorem 2.3.8, j is transient, and so, by (2.3.7), $\mathbb{P}(T_j < \infty \mid X_0 = j) = 1$. Hence, conditional on $X_0 = j$, $\bar{T}_j^{(n)} \leq \frac{1}{n} T_j \rightarrow 0$ with probability 1. At the same time, because j is transient, $\mathbb{P}(\rho_j = \infty \mid X_0 = j) > 0$, and so $\mathbb{E}[\rho_j \mid X_0 = j] = \infty$. Hence, we have proved (2.3.10) in the case when $j_0 \nrightarrow j$.

Next assume that $j_0 \rightarrow j$. Then, again by Theorem 2.3.8, $\mathbb{E}[\rho_j^4 \mid X_0 = j] < \infty$ and, conditional on $X_0 = j$, Theorem 2.3.6 says that the random variables $\rho_j^{(m)} - \rho_j^{(m-1)}$ are mutually independent random variables and have the same distribution as ρ_j . In particular, by the strong law of large numbers (cf. Exercise 1.3.4)

$$\mathbb{P}\left(\lim_{m \rightarrow \infty} \frac{\rho_j^{(m)}}{m} = r_j \mid X_0 = j\right) = 1 \quad \text{where } r_j \equiv \mathbb{E}[\rho_j \mid X_0 = j].$$

On the other hand, for any $m \geq 1$,

$$\left| \bar{T}_j^{(n)} - \frac{1}{r_j} \right| \leq \left| \bar{T}_j^{(n)} - \bar{T}_j^{(\rho_j^{(m)})} \right| + \left| \bar{T}_j^{(\rho_j^{(m)})} - \frac{1}{r_j} \right|,$$

and

$$\begin{aligned} \left| \bar{T}_j^{(n)} - \bar{T}_j^{(\rho_j^{(m)})} \right| &\leq \frac{|T_j^{(n)} - T_j^{(\rho_j^{(m)})}|}{n} + \left| 1 - \frac{\rho_j^{(m)}}{n} \right| \left| \bar{T}_j^{(\rho_j^{(m)})} \right| \\ &\leq 2 \left| 1 - \frac{\rho_j^{(m)}}{n} \right| \leq 2 \left| 1 - \frac{mr_j}{n} \right| + \frac{2m}{n} \left| \frac{\rho_j^{(m)}}{m} - r_j \right| \end{aligned}$$

⁶Statements like the one which follows are called *individual ergodic theorems* because they, as distinguished from the first part of Theorem 2.3.4, are about convergence with probability 1 as opposed to convergence in square mean. See Exercise 4.2.10 below for more information.

while, since $\overline{T}_j^{(\rho_j^{(m)})} = \frac{m}{\rho_j^{(m)}} \leq 1$,

$$\left| \overline{T}_j^{(\rho_j^{(m)})} - \frac{1}{r_j} \right| \leq \frac{1}{r_j} \left| \frac{\rho_j^{(m)}}{m} - r_j \right|.$$

Hence,

$$\left| \overline{T}_j^{(n)} - \frac{1}{r_j} \right| \leq 2 \left| 1 - \frac{mr_j}{n} \right| + \left(\frac{2m}{n} + \frac{1}{r_j} \right) \left| \frac{\rho_j^{(m)}}{m} - r_j \right|.$$

Finally, by taking $m_n = \lfloor \frac{n}{r_j} \rfloor$ we get

$$\left| \overline{T}_j^{(n)} - \frac{1}{r_j} \right| \leq \frac{2r_j}{n} + \frac{3}{r_j} \left| \frac{\rho_j^{(m_n)}}{m_n} - r_j \right| \longrightarrow 0 \quad \text{as } n \rightarrow \infty.$$

Notice that (2.3.10) is precisely the sort of statement for which Gibbs was looking. That is, it says that, with probability 1, when one observes an individual path, the average time that it spends in each state tends, as one observes for a longer and longer time, to the probability that the equilibrium (i.e., stationary) distribution assigns to that state.

2.4 Exercises

Exercise 2.4.1 In this exercise we will give a probabilistic interpretation of the *adjoint* of a transition probability matrix with respect to a stationary probability. To be precise, suppose that the transition probability matrix \mathbf{P} admits a stationary distribution $\boldsymbol{\pi}$, assume $(\boldsymbol{\pi})_i > 0$ for each $i \in \mathbb{S}$, and determine the matrix \mathbf{P}^\top by $(\mathbf{P}^\top)_{ij} = \frac{(\boldsymbol{\pi})_j}{(\boldsymbol{\pi})_i} (\mathbf{P})_{ji}$.

- Show that \mathbf{P}^\top is a transition probability matrix for which $\boldsymbol{\pi}$ is again a stationary probability.
- Use \mathbb{P} and \mathbb{P}^\top to denote probabilities computed for the chains determined, respectively, by \mathbf{P} and \mathbf{P}^\top with initial distribution $\boldsymbol{\pi}$, and show that these chains are the *reverse* of one another in the sense that, for each $n \geq 0$ the distribution of (X_0, \dots, X_n) under \mathbb{P}^\top is the same as the distribution of (X_n, \dots, X_0) under \mathbb{P} . That is,

$$\mathbb{P}^\top(X_0 = i_0, \dots, X_n = i_n) = \mathbb{P}(X_n = i_0, \dots, X_0 = i_n)$$

for all $n \geq 0$ and $(i_0, \dots, i_n) \in \mathbb{S}^{n+1}$.

Exercise 2.4.2 The Doeblin theory applies particularly well to chains on a finite state. For example, suppose that \mathbf{P} is a transition probability matrix on an N element state space \mathbb{S} , and show that there exists an $\epsilon > 0$ such that $(\mathbf{A}_N)_{ij_0} \geq \epsilon$ for all $i \in \mathbb{S}$

if and only if $i \rightarrow j_0$ for all $i \in \mathbb{S}$. In particular, if such a j_0 exists, conclude that, for all probability vectors μ ,

$$\|\mu \mathbf{A}_n - \pi\|_v \leq \frac{2(N-1)}{n\epsilon}, \quad n \geq 1,$$

where π is the unique stationary probability vector for \mathbf{P} .

Exercise 2.4.3 Here is a version of Doeblin's theorem that sometimes gives a slightly better estimate. Namely, assume that $(\mathbf{P})_{ij} \geq \epsilon_j$ for all (i, j) , and set $\epsilon = \sum_j \epsilon_j$. If $\epsilon > 0$, show that the conclusion of Theorem 2.2.1 holds with this ϵ and that $(\pi)_i \geq \epsilon_i$ for each $i \in \mathbb{S}$.

Exercise 2.4.4 Assume that \mathbf{P} is a transition probability matrix on the finite state space \mathbb{S} , and show that

$$j \in \mathbb{S} \text{ is recurrent} \quad \text{if and only if} \quad \mathbb{E}[\rho_j | X_0 = j] < \infty.$$

Of course, the “if” part is trivial and has nothing to do with the finiteness of the state space.

Exercise 2.4.5 Again assume that \mathbf{P} is a transition probability matrix on the finite state space \mathbb{S} . In addition, assume that \mathbf{P} is *doubly stochastic* in the sense that each of its columns as well as each of its rows sums to 1. Under the condition that every state is accessible from every other state, show that $\mathbb{E}[\rho_j | X_0 = j] = \#\mathbb{S}$ for each $j \in \mathbb{S}$.

Exercise 2.4.6 In order to test how good Doeblin's theorem is, consider the case when $\mathbb{S} = \{1, 2\}$ and

$$\mathbf{P} = \begin{pmatrix} 1 - \alpha & \alpha \\ \beta & 1 - \beta \end{pmatrix} \quad \text{for some } (\alpha, \beta) \in (0, 1).$$

Show that $\pi = (\alpha + \beta)^{-1}(\beta, \alpha)$ is a stationary probability for \mathbf{P} , that

$$\|v\mathbf{P} - \pi\|_v = |1 - \alpha - \beta| \|\mu - \pi\|_v \quad \text{for all probability vectors } \mu.$$

Hence, in this case, Doeblin's theorem gives the optimal result.

Exercise 2.4.7 One of the earliest examples of Markov processes are the *branching processes* introduced, around the end of the nineteenth century, by Galton and Watson to model demographics. In this model, $\mathbb{S} = \mathbb{N}$, the state $i \in \mathbb{N}$ representing the number of members in the population, and the process evolves so that, at each stage, every individual, independently of all other members of the population, dies and is replaced by a random number of offspring. Thus, 0 is an absorbing state, and, given that there are $i \geq 1$ individuals alive at a given time n , the number of

individuals alive at time $n + 1$ will be distributed like the sum of i mutually independent, \mathbb{N} -valued, identically distributed random variables. To be more precise, if $\boldsymbol{\mu} = (\mu_0, \dots, \mu_k, \dots)$ is the probability vector giving the number of offspring each individual produces, define the m -fold convolution power $\boldsymbol{\mu}^{\star m}$ so that $(\boldsymbol{\mu}^{\star 0})_j = \delta_{0,j}$ and, for $m \geq 1$,

$$(\boldsymbol{\mu}^{\star m})_j = \sum_{i=0}^j (\boldsymbol{\mu}^{\star (m-1)})_{j-i} \mu_i.$$

Then the transition probability matrix \mathbf{P} is given by $(\mathbf{P})_{ij} = (\boldsymbol{\mu}^{\star i})_j$.

The first interesting question which one should ask about this model is what it predicts will be the probability of eventual *extinction*. That is, what is $\lim_{n \rightarrow \infty} \mathbb{P}(X_n = 0)$? A naïve guess is that eventual extinction should occur or should not occur depending on whether the expected number $\gamma \equiv \sum_{k=0}^{\infty} k \mu_k$ of progeny is strictly less or strictly greater than 1, with the case when the expected number is precisely 1 being more ambiguous. In order to verify this guess and remove trivial special cases, we make the assumptions that $\mu_0 > 0$, $\mu_0 + \mu_1 < 1$, and $\gamma \equiv \sum_{k=0}^{\infty} k \mu_k < \infty$.

- (a) Set $f(s) = \sum_{k=0}^{\infty} s^k \mu_k$ for $s \in [0, 1]$, and define $f^{\circ n}(s)$ inductively so that $f^{\circ 0}(s) = s$ and $f^{\circ n} = f \circ f^{\circ (n-1)}$ for $n \geq 1$. Show that $\gamma = f'(1)$ and that

$$f^{\circ n}(s)^i = \mathbb{E}[s^{X_n} \mid X_0 = i] = \sum_{j=0}^{\infty} s^j (\mathbf{P}^n)_{ij} \quad \text{for } s \in [0, 1] \text{ and } i \geq 0.$$

Hint: Begin by showing that $f(s)^i = \sum_{j=0}^{\infty} s^j (\boldsymbol{\mu}^{\star i})_j$.

- (b) Observe that $s \in [0, 1] \mapsto f(s) - s$ is a continuous function which is positive at $s = 0$, zero at $s = 1$, and smooth and strictly convex (i.e., $f'' > 0$) on $(0, 1)$. Conclude that either $\gamma \leq 1$ and $f(s) > s$ for all $s \in [0, 1)$ or $\gamma > 1$ and there is exactly one $\alpha \in (0, 1)$ at which $f(\alpha) = \alpha$.
- (c) Referring to the preceding, show that

$$\gamma \leq 1 \implies \lim_{n \rightarrow \infty} \mathbb{E}[s^{X_n} \mid X_0 = i] = 1 \quad \text{for all } s \in (0, 1]$$

and that

$$\gamma > 1 \implies \lim_{n \rightarrow \infty} \mathbb{E}[s^{X_n} \mid X_0 = i] = \alpha^i \quad \text{for all } s \in (0, 1).$$

- (d) Based on (c), conclude that $\gamma \leq 1 \implies \mathbb{P}(X_n = 0 \mid X_0 = i) \longrightarrow 1$ and that $\gamma > 1 \implies \lim_{n \rightarrow \infty} \mathbb{P}(X_n = 0 \mid X_0 = i) = \alpha^i$ and

$$\lim_{n \rightarrow \infty} \mathbb{P}(1 \leq X_n \leq L \mid X_0 = i) = 0 \quad \text{for all } L \geq 1.$$

The last conclusion has the ominous implication that, when the expected number of progeny is larger than 1, then the population either becomes extinct or, what may be worse, grows indefinitely.

Exercise 2.4.8 Continue with the setting and notation in Exercise 2.4.7. We will to show in this exercise that there are significant differences between the cases when $\gamma < 1$ and $\gamma = 1$.

- (a) Show that $\mathbb{E}[X_n | X_0 = i] = i\gamma^n$. Hence, when $\gamma < 1$, the expected size of the population goes to 0 at an exponential rate. On the other hand, when $\gamma = 1$, the expected size remains constant, this in spite of the fact that as $n \rightarrow \infty$ $\mathbb{P}(X_n = 0 | X_0 = i) \rightarrow 1$. Thus, when $\gamma = 1$, we have a typical situation of the sort which demonstrates why Lebesgue had to make the hypotheses he did in his dominated convergence theorem, Theorem 7.1.11. In the present case, the explanation is simple: as $n \rightarrow \infty$, with large probability $X_n = 0$ but, nonetheless, with positive probability X_n is enormous.
- (b) Let ρ_0 be the time of first return to 0. Show that

$$\mathbb{P}(\rho_0 \leq n | X_0 = i) = \mathbb{P}(X_n = 0 | X_0 = i) = (f^{\circ(n-1)}(\mu_0))^i,$$

and use this to get the estimate

$$\mathbb{P}(\rho_0 > n | X_0 = i) \leq i\gamma^{n-1}(1 - \mu_0).$$

In particular, this shows that $\mathbb{E}[\rho_0^k | X_0 = i] < \infty$ for all $k \in \mathbb{Z}^+$ when $\gamma < 1$.

- (c) Now assume that $\gamma = 1$. Under the additional condition that $\beta \equiv f''(1) = \sum_{k \geq 2} k(k-1)\mu_k < \infty$, start from $\mathbb{P}(\rho_0 \leq n | X_0 = 1) = f^{\circ(n-1)}(\mu_0)$, and show that $\mathbb{E}[\rho_0 | X_0 = i] = \infty$ for all $i \geq 1$.

Hint: Begin by showing that

$$1 - f^{\circ n}(\mu_0) \geq \left(\prod_{\ell=m}^{n-1} (1 - \beta(1 - f^{\circ \ell}(\mu_0))) \right) (1 - f^{\circ m}(\mu_0))$$

for $n > m$. Next, use this to show that

$$\infty > \mathbb{E}[\rho_0 | X_0 = 1] = 1 + \sum_0^{\infty} (1 - f^{\circ n}(\mu_0))$$

would lead to a contradiction.

- (d) Here we show that the conclusion in (c) will, in general, be false without the finiteness condition on the second derivative. To see this, let $\theta \in (0, 1)$ be given, and check that $f(s) \equiv s + \frac{(1-s)^{1+\theta}}{1+\theta} = \sum_{k=0}^{\infty} s^k \mu_k$, for some probability vector $\mu = (\mu_0, \dots, \mu_k, \dots)$ with $\mu_k > 0$ unless $k = 1$. Now use this choice of μ to see that, when the second derivative condition in (c) fails, $\mathbb{E}[\rho_0 | X_0 = 1]$ can be finite even though $\gamma = 1$.

Hint: Set $a_n = 1 - f^{\circ n}(\mu_0)$, note that $a_n - a_{n+1} = \mu_0 a_n^{1+\theta}$, and use this first to see that $\frac{a_{n+1}}{a_n} \rightarrow 1$ and then that there exist $0 < c_2 < c_1 < \infty$ such that $c_1 \leq a_{n+1}^{-\theta} - a_n^{-\theta} \leq c_2$ for all $n \geq 1$. Conclude that $\mathbb{P}(\rho_0 > n | X_0 = 1)$ tends to 0 like $n^{-\frac{1}{\theta}}$.

Exercise 2.4.9 The idea underlying this exercise was introduced by J.L. Doob and is called⁷ *Doob's h-transformation*. Let \mathbf{P} is a transition probability matrix on the state space \mathbb{S} . Next, let $\emptyset \neq \Gamma \subsetneq \mathbb{S}$ be given, set

$$\rho_\Gamma = \inf\{n \geq 1 : X_n \in \Gamma\},$$

and assume that

$$h(i) \equiv \mathbb{P}(\rho_\Gamma = \infty \mid X_0 = i) > 0 \quad \text{for all } i \in \hat{\mathbb{S}} \equiv \mathbb{S} \setminus \Gamma.$$

- (a) Show that $h(i) = \sum_{j \in \hat{\mathbb{S}}} (\mathbf{P})_{ij} h(j)$ for all $i \in \hat{\mathbb{S}}$, and conclude that the matrix $\hat{\mathbf{P}}$ given by $(\hat{\mathbf{P}})_{ij} = \frac{1}{h(i)} (\mathbf{P})_{ij} h(j)$ for $(i, j) \in (\hat{\mathbb{S}})^2$ is a transition probability matrix on $\hat{\mathbb{S}}$.
- (b) For all $n \in \mathbb{N}$ and $(j_0, \dots, j_n) \in (\hat{\mathbb{S}})^{n+1}$, show that, for each $i \in \hat{\mathbb{S}}$,

$$\begin{aligned} \hat{\mathbb{P}}(X_0 = j_0, \dots, X_n = j_n \mid X_0 = i) \\ = \mathbb{P}(X_0 = j_0, \dots, X_n = j_n \mid \rho_\Gamma = \infty \text{ \& } X_0 = i), \end{aligned}$$

where $\hat{\mathbb{P}}$ is used here to denote probabilities computed for the Markov chain on $\hat{\mathbb{S}}$ whose transition probability matrix is $\hat{\mathbf{P}}$. That is, the Markov chain determined by $\hat{\mathbf{P}}$ is the Markov chain determined by \mathbf{P} conditioned to never hit Γ .

Exercise 2.4.10 Here is another example of an h -transform. Assume that $j_0 \in \mathbb{S}$ is transient but that $i \rightarrow j_0$ for all $i \in \mathbb{S}$.⁸ Set

$$h(j_0) = 1 \quad \text{and} \quad h(i) = \mathbb{P}(\rho_{j_0} < \infty \mid X_0 = i) \quad \text{for } i \neq j_0.$$

- (a) After checking that $h(i) > 0$ for all $i \in \mathbb{S}$, define $\hat{\mathbf{P}}$ so that

$$(\hat{\mathbf{P}})_{ij} = \begin{cases} (\mathbf{P})_{j_0 j} & \text{if } i = j_0 \\ h(i)^{-1} (\mathbf{P})_{ij} h(j) & \text{if } i \neq j_0. \end{cases}$$

Show that $\hat{\mathbf{P}}$ is again a transition probability matrix.

- (b) Using $\hat{\mathbb{P}}$ to denote probabilities computed relative to the chain determined by $\hat{\mathbf{P}}$, show that

$$\hat{\mathbb{P}}(\rho_{j_0} > n \mid X_0 = i) = \frac{1}{h(i)} \mathbb{P}(n < \rho_{j_0} < \infty \mid X_0 = i)$$

for all $n \in \mathbb{N}$ and $i \neq j_0$.

- (c) Starting from the result in (b), show that j_0 is recurrent for the chain determined by $\hat{\mathbf{P}}$.

⁷The “ h ” comes from the connection with harmonic functions.

⁸By Exercise 2.4.2, this is possible only if \mathbb{S} is infinite.



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