# Markov Chains

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1 MARKOV CHAIN

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## 1 Markov Chain

The notes taken during the first lecture was unfortunately lost.

**Theorem.** (Extended Markov Property) Let X be a Markov chain, and  $n \geq 0$ . Let H be an event defined in terms of  $X_0, ..., X_{n-1}$  (the history), and let F be an event defined in terms of  $X_{n+1}, X_{n+2}, ...$  (the future). Then

$$\mathbb{P}\left(F|H,X_{n}=i\right)=\mathbb{P}\left(F|X_{n}=i\right)$$

### 2 Transition Probabilities

We've known that  $p_{i,j}$  is the one-step transition probability,

$$\mathbb{P}(X_{n+1} = j | X_n = i) = \mathbb{P}(X_1 = j | X_0 = i)$$

Now it's natural to discuss the n-step transition probabilities

$$\mathbb{P}\left(X_{n}=j|X_{0}=i\right)=p_{i,j}\left(n\right)$$

**Theorem.** (Chapman-Kolmogorov Equations)

$$p_{i,j}\left(m+n\right) = \sum_{k \in S} p_{i,k}\left(m\right) p_{k,j}\left(n\right)$$

Proof.

$$p_{i,j}(m+n) = \sum_{k \in S} \mathbb{P}\left(X_{m+n} = j | X_m = k\right) \mathbb{P}\left(X_m = k\right)$$
$$= \sum_{k \in S} p_{k,j}(n) p_{i,k}(m)$$

Now let  $P(1) = P = p_{i,j}$ ,  $P(n) = p_{i,j}(n)$ . Then this is just matrix multiplication:  $P(n) = P^n$ . To find P(n) we can diagonalize the matrix. (or matrix mult + qpower!)

**Example.** Let  $S = \{1, 2\},\$ 

$$P = \begin{pmatrix} 1 - \alpha & \alpha \\ \beta & 1 - \beta \end{pmatrix}$$

ans assume that  $0 < \alpha, \beta < 1$  (non-trivial).

Then solve  $|P - \kappa I| = 0$ , we get  $\kappa = 1$  or  $\kappa = 1 - \alpha - \beta$ . So

$$P^{n} = U^{-1} \begin{pmatrix} 1^{n} & 0 \\ 0 & (1 - \alpha - \beta)^{n} \end{pmatrix} U$$

for some invertible U. Then

$$p_{1,1}(n) = A \cdot 1^n + B(1 - \alpha - \beta)^n$$

for some A, B. We know that  $p_{1,1}(1) = 1 - \alpha$ ,  $p_{1,1}(0) = 1$ . Then we can solve for A and B and get

$$A = \frac{\beta}{\alpha + \beta}, B = \frac{\alpha}{\alpha + \beta}$$

By symmetry we can get

$$P^{n} = \frac{1}{\alpha + \beta} \begin{pmatrix} \beta + \alpha (1 - \alpha - \beta)^{n} & \alpha - \alpha (1 - \alpha - \beta)^{n} \\ \beta - \beta (1 - \alpha - \beta)^{n} & \alpha + \beta (1 - \alpha - \beta)^{n} \end{pmatrix}$$

Another method is to use difference equations:

$$\begin{aligned} p_{1,1}\left(n+1\right) &= \mathbb{P}\left(X_{n+1} = 1 | X_0 = 1\right) \\ &= \mathbb{P}\left(X_{n+1} = 1 | X_n = 1, X_0 = 1\right) \mathbb{P}\left(X_n = 1 | X_0 = 1\right) + \\ \mathbb{P}\left(X_{n+1} = 1 | X_n = 2, X_0 = 1\right) \mathbb{P}\left(X_n = 2 | X_0 = 1\right) \\ &= \left(1 - \alpha\right) P_{1,1}\left(n\right) + \beta p_{1,2}\left(n\right) \end{aligned}$$

which is a difference equation for the sequence for  $(p_{1,1}(n))$  (note  $p_{1,2}(n) = 1 - p_{1,1}(n)$ ) solved in the normal way, subject to boundary conditions.

The distributions of a Markov chain is somewhat related to linear algebra. Let  $\lambda$  be the initial distribution of  $X_0$ , i.e.  $\lambda_i = \mathbb{P}(X_0 = i)$ . Then

$$\mathbb{P}\left(X_1 = j\right) = \sum_{i} \lambda_i p_{i,j}$$

So the distribution of  $X_1$  is  $\lambda P$ , and similarly  $X_n$  has distribution  $\lambda P^n$ .

#### 3 Class Structure

We write "i leads to j", or  $i \to j$ , if there exists  $n \ge 0$  s.t.  $p_{i,j}(n) > 0$ . Write  $i \leftrightarrow j$  if  $i \to j$  and  $j \to i$ , and say that i and j communicate.

**Proposition.**  $\leftrightarrow$  is an equivalence relation.

*Proof.* •  $i \leftrightarrow i$  since  $p_{i,i}(0) = 1 > 0$ .

- $i \leftrightarrow j \rightarrow j \leftrightarrow i$  is trivial.
- If  $i \leftrightarrow j$  and  $j \leftrightarrow i$ , in particular  $i \to j$  and  $j \to k$ . Then there exists m, k such that  $p_{i,j}(m) > 0$  and  $p_{j,k}(n) > 0$ . Then

$$p_{i,k}(m+n) \ge p_{i,j}(m) p_{j,k}(n) > 0$$

By C-K equation (since each term in the sum is non-negative). So  $i \to k$ . Similarly  $k \to i$ . So  $i \leftrightarrow k$ .

**Definition.** Now S, the set of all states, has equivalence classes under  $\leftrightarrow$ . We call them *communicating classes*, and define

$$C_i = \{j \in S : i \leftrightarrow j\}$$

The space S, or the chain X, is called *irreducible* if there exists a unique communicating class (which is S).

 $C \subset S$  is called closed if

$$i \in C, i \to j \implies j \to C$$

if  $\{i\}$  is closed, then i is called absorbing.

**Proposition.** A set C is closed if and only if  $p_{i,j} = 0$  for all  $i \in C, j \notin C$ .

*Proof.* Suppose the above condition does not hold. Then  $\exists i \in C, j \notin C$  with  $p_{i,j} > 0$ . But then C is not closed by definition since  $i \to j$ .

Now suppose the above condition hold. Let  $i \in C, i \to j$ . There exists several  $k_0 = i, k_1, ..., k_n = j$  such that

$$p_{k_0,k_1}p_{k_1,k_2}...p_{k_{n-1},k_n} > 0$$

which requires  $i=k_0\to k_1,\ k_1\to k_2,\ ...\ k_{n-1}\to k_n=j.$  Then  $k_1\in C,k_2\in C,...k_n=j\in C.$  So C is closed.  $\square$ 

**Example.** Let  $S = \{1, 2, ..., 6\}$ , and

$$P = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0\\ 0 & 0 & 1 & 0 & 0 & 0\\ \frac{1}{3} & 0 & 0 & \frac{1}{3} & \frac{1}{3} & 0\\ 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0\\ 0 & 0 & 0 & 0 & 0 & 1\\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

Here  $\{1, 2, 3\}$ ,  $\{4\}$ ,  $\{5, 6\}$  are communicating classes.

#### 4 Recurrence and Transience

We write  $\mathbb{P}\left(\cdot|X_0=i\right) = \mathbb{P}_i\left(\cdot\right)$ , and similarly for expectation.

**Definition.** The first-passage time of  $j \in S$  is

$$T_i = \inf \{ n \ge 1 : X_n = j \}$$

The first-passage probabilities are

$$f_{i,j}(n) = \mathbb{P}_i(T_i = n)$$

**Definition.** The state  $i \in S$  is recurrent (or persistent) if  $\mathbb{P}_i(T_i < \infty) = 1$ , and transient otherwise.

**Theorem.** The state i is recurrent if and only if

$$\sum_{n} p_{ii}\left(n\right) \to \infty.$$

Proof. We have

$$p_{ij}(n) = \mathbb{P}_i(x_n = j) = \sum_{m} \mathbb{P}_i(x_n = j | T_j = m) \, \mathbb{P}_i(T_j = m)$$
$$= \sum_{m \le n} \mathbb{P}_i(x_n = j | x_m = j) \, \mathbb{P}_i(T_j = m)$$
$$= \sum_{m=1}^{n} f_{i,j}(m) \, p_{jj}(n - m)$$

(which looks like a *convolution* of  $f_{i,j}$  and  $p_{jj}$ ).

Now consider generating sequences

$$F_{ij}(s) = \sum_{n=0}^{\infty} f_{ij}(n) s^n$$
$$P_{ij}(s) = \sum_{n=0}^{\infty} p_{ij}(n) s^n$$

with  $f_{ij}(0) = 0, p_{ij}(0) = \delta_{ij}$ .

Then

$$\sum_{n\geq 1} p_{ij}(n) s^n = \sum_{n\geq 1} \sum_{m=1}^n f_{ij}(m) s^m p_{jj}(n-m) s^{n-m}$$

So by reversing the order of the sums,

$$P_{ij}(s) - \delta_{ij} = \sum_{m=0}^{\infty} f_{ij}(m) s^m \sum_{n=m}^{\infty} p_{jj}(n-m) s^{n-m} = F_{ij}(s) P_{jj}(s)$$

So we've derived

**Theorem.**  $P_{ij}(s) = \delta_{ij} + F_{ij}(s) P_{jj}(s)$ .  $(1 < s \le 1, \text{ since we need the series to converge})$ 

When i = j,

$$P_{ii}\left(s\right) = \frac{1}{1 - F_{ii}\left(s\right)}$$

if  $0 \le s < 1$ .

Now let  $s \to 1$ , then

$$F_{ii}\left(s\right) \to \sum_{n} f_{ii}\left(n\right) = \mathbb{P}_{i}\left(T_{i} < \infty\right),$$

$$P_{ii}\left(s\right) \to \sum_{n} p_{ii}\left(n\right)$$

Therefore i is recurrent iff  $F_{ij}(s) = 1$ , i.e.  $\sum_{n} p_{ii}(n) \to \infty$ .

**Theorem.** Let C be a communicating class.

(a) For  $i, j \in C$ , either both of them are recurrent, or both are transient (i.e. recurrence is a class property).

(b) If  $i \in C$  is recurrent, then C is closed (i.e. a recurrent communicating class is closed).

*Proof.* (a) Let  $i \leftrightarrow j$ . Then

$$p_{ii}\left(m+k+n\right) \ge p_{ij}\left(m\right)p_{jj}\left(k\right)p_{ji}\left(n\right)$$

Pick m s.t.  $p_{ij}(m) > 0$ , and n s.t.  $p_{ji}(n) > 0$ . Then

$$\sum_{k} p_{ii} (m + k + n) \ge \alpha \sum_{k} p_{jj} (k)$$

for  $\alpha > 0$ .

Then if j is recurrent, then  $\sum_{k} p_{jj}(k) \to \infty$ , and hence  $\sum_{k} p_{ii}(k) \to \infty$ , i.e. i is recurrent, and vice versa.

(b) Suppose C is not closed. So  $\exists j \in C, k \notin C$  with  $p_{jk} > 0$ . If i is recurrent, so is j by (a). Then

$$1 - \mathbb{P}_i (T_i < \infty) = \mathbb{P}_i \text{ (no return to } j) \ge p_{ik}$$

Since  $k \notin C$ . However that implies  $p_{jk} \leq 1 - 1 = 0$ . Contradiction.

**Proposition.** Let  $i, j \in S$ . If j is transient, then  $p_{ij}(n) \to 0$  as  $n \to \infty$ .

*Proof.*  $P_{ij}\left(s\right) = \delta_{ij} + F_{ij}\left(s\right) P_{jj}\left(s\right)$  for -1 < s < 1. Now let  $i \neq j$ , and  $s \rightarrow 1$ . Then

$$P_{ij}(1) = F_{ij}(1) P_{jj}(1)$$

Since j is transient,  $F_{ij}(1) < \infty$  and  $P_{jj}(1) < \infty$ . So  $P_{ij}(n) < \infty$ , and hence  $p_{ij}(n) \to 0$  as  $n \to \infty$ . The argument is similar when i = j. **Theorem.** If S is finite, then there exists at least one recurrent state. Therefore, if the chain is irreducible, every state is recurrent.

 ${\it Proof.}$  Suppose otherwise, that every j is transient. Then we have

$$1 = \sum_{j \in S} p_{ij} \left( n \right) \to 0$$

as  $n \to \infty$ . Contradiction.

## 5 Random walks on $\mathbb{Z}^d$ with $d \geq 1$

We consider random walks on

$$\mathbb{Z}^d = \{(x_1, ..., x_d) : x_i \in \mathbb{Z}\}$$

Define two points  $x, y \in \mathbb{Z}^d$ :  $x = (x_1, ..., x_d), y = (y_1, ..., y_d)$  to be adjacent if

$$\sum_{i=1}^{d} |x_i - y_i| = 1$$

The Random walk on  $\mathbb{Z}^d$  is a Markov chain with state space  $\mathbb{Z}^d$ ; a walker lives at  $X_n$  at time n, with

$$\mathbb{P}\left(X_{n+1}=y\right)|X_{n}=x,X_{0}=x\left(0\right),...,X_{n-1}=x\left(n-1\right)=\left\{\begin{array}{ll}0&x,y\text{ are not adjacent}\\\frac{1}{2d}&x,y\text{ are adjacent}\end{array}\right.$$

Clearly RW is irreducible and has an infinite state space.

**Theorem.** The random walk is recurrent if d = 1, 2, and transient if  $d \ge 3$ .

*Proof.* • d=1:  $p_{0,0}\left(2n\right)=\left(\frac{1}{2}\right)^{2n}\binom{2n}{n}=\left(\frac{1}{2}\right)^{2n}\frac{2n!}{(n!)^2}\sim\frac{1}{\sqrt{\pi n}}$  by Stirling formula. Hence  $\sum_{n}p_{0,0}\left(n\right)\rightarrow\infty$ , i.e. 0 is recurrent.

• d=2: Suppose we walked m steps towards L/R, and n-m steps towards U/D.

$$p_{0,0}(2n) = \sum_{m=0}^{n} \left(\frac{1}{4}\right)^{2n} \frac{(2n)!}{m!m!(n-m)!(n-m)!}$$

$$= \left(\frac{1}{4}\right)^{2n} \binom{2n}{n} \sum_{m=0}^{n} \binom{n}{m}^{2}$$

$$= \left(\frac{1}{4}\right)^{2n} \binom{2n}{n}$$

$$\sim \frac{1}{\pi n}$$

So (0,0) is recurrent.

• d = 3 (and similarly  $d \ge 3$ ):

$$p_{0,0}(2n) = \sum_{i+j+k=n} \left(\frac{1}{6}\right)^{2n} \frac{(2n)!}{(i!j!k!)^2}$$

$$\leq \left(\frac{1}{2}\right)^{2n} \binom{2n}{n} \sum_{i+j+k=n} \left(\frac{n!}{3^n i! j! k!}\right)^2$$

$$\leq \left(\frac{1}{2}\right)^{2n} \binom{2n}{n} M_n \sum_{i+j+k=n} \frac{n!}{3^n i! k! l!}$$

where

$$M_n = \max\left\{\frac{n!}{3^n i! j! k!} | i + j + k = n\right\}$$

The sum in the last line is 1, since each term in the sum is the probability of n balls goes in to 3 boxes, with i, j, k balls in each box.

We see that  $M_n$  is achieved when i, j, k are 'as equal as possible. Then

$$p_{0,0}(2n) \le \left(\frac{1}{2}\right)^2 n \binom{2n}{n} \frac{n!}{3^n \left(\lfloor n/3 \rfloor!\right)^3}$$
$$\sim \frac{c}{n^{3/2}}$$

But this sum now converges. So (0,0,0) is transient.

### 6 Hitting probabilities

#### 6.1 Gambler's Ruin

What is the hitting probability for gambler's ruin,  $h_i = h_i^{\{0\}}$ ?

$$h_0 = 1, h_i = ph_{i+1} + qh_{i-1} \text{ for } i \ge 1.$$

Then guess a solution  $h_i = \theta^i$ , so  $\theta = q/p, 1$ . So the general solution is

$$h_i = A + B \left( q/p \right)^i$$

for all i.

Since  $h_0 = 1$ , A + B = 1.

If p < q: since the  $h_i$  are probability, B = 0, A = 1. So  $h_i = 1 - (q/p)^i$  for all i.

If p > q, since  $h_i \ge 0$  for all i, we have  $A \ge 0$ . By minimality of  $(h_i)$ , A = 0. So  $h_i = (q/p)^i$ .

When p = q: by the above arguments,  $h_i \equiv 1$ .

Extension: let  $p_i = 1 - q_i \in (0, 1)$ .

So  $h_0 = 1$ ,  $(p_i + q_i) h_i = p_i h_{i+1} + q_i h_{i-1}$ .  $p_i (h_{i+1} - h_i) = q_i (h_i - h_{i-1})$ .

Let  $u_i = h_{i-1} - h_i$ . Then  $p_i u_{i+1} = q_i u_i$ . So  $u_{i+1} = (q_i/p_i) u_i$ .

Therefore  $u_{i+1}\gamma_i u_1$ , where

$$\gamma_i = \frac{q_1 q_2 \dots q_i}{p_1 p_2 \dots p_i}$$

for  $i \ge 1$ , and  $\gamma_0 = 1$ . Then

$$u_1 + u_2 + \dots + u_i = (h_0 - h_i)$$
  
$$h_i = 1 - (u_1 + \dots + u_i) = 1 - u_1 (\gamma_0 + \gamma_1 + \dots + \gamma_{i-1})$$

Let  $S = \sum_{i=0}^{\infty} \gamma_i$ . If  $S = \infty$ , since  $h_1 \ge 0$  we have  $u_1 = 0$ , and hence  $h_i \equiv 1$ .

If  $S < \infty$ ,  $u_1$  is maximised when  $1 - u_1 S = 0$ , i.e.  $u_1 = 1/S$ .

### 7 Stopping times

Consider Markov chain X.

**Definition.** A random variable T taking values in  $\{0, 1, 2, ..., \} \cup \{\infty\}$  is a stopping time (for X) if for  $n \ge 0$ , the event  $\{T = n\}$  is given 'in terms of'  $X_0$ ,  $X_1, ..., X_n$  only.

Hitting times are stopping times:  $\{H^A = n\} = \{X_n \in A\} \cap (\bigcap_{0 \le m < n} \{x_m \notin A\}).$ 

 $H^A + 1$  is a stopping times is a stopping time,  $H^A - 1$  is not in general a stopping time.

**Definition.** (Strong Markov Property) Let X be a Markov chain with transition matrix P, and let T be a stopping time for X. Given  $T < \infty$  and  $X_T = i$ , then  $Y = (X_T, X_{T+1}, ...)$  is a Markov chain with transition matrix P and initial state  $Y_0 = i$ , and Y is independent of  $(X_0, ..., X_{T-1})$ .

**Example.** Consider a random walk with an absorbing wall at 0, with probability p going right and q = 1 - p going left. Assume particle starts at 1, and let H be the hitting time of 0. What is the mass function and mean of H?

Let

$$G(s) = \mathbb{E}_1(s^H) = \sum_{n=0}^{\infty} s^n \mathbb{P}_1(H=n)$$

if |s| < 1.

By assuming |s| < 1 (and using Abel's lemma when needed) we include the possibility  $\mathbb{P}_1(H = \infty) > 0$ . Then

$$G(s) = \mathbb{E}_{1}(s^{H})$$

$$= \mathbb{E}_{1}(s^{H}|X_{1} = 2) p + \mathbb{E}_{1}(s^{H}|X_{1} = 0) q$$

$$= p\mathbb{E}_{1}(s^{1+H_{1}+H_{0}}) + qs$$

$$= psG(s)^{2}(= \mathbb{E}_{1}(s^{H_{1}}) \mathbb{E}_{1}(s^{H_{2}})) + qs$$

where  $H_i$  is the time to go from i + 1 to i.

So

$$G\left(s\right) = \frac{1 \pm \sqrt{1 - 4pqs^2}}{2ps}$$

for |s| < 1.

Since G is continuous, the  $\pm$  sign is the same for all s. Since G has to remain regular at s=0, the  $\pm$  sign has to be - for all s. So

$$G\left(s\right) = \frac{1 - \sqrt{1 - 4pqs^2}}{2ps}$$

So

$$\mathbb{P}_1 (H = 2k - 1) = \frac{(2k - 2)!}{k!(k - 1)!} \frac{(pq)^k}{p}$$

where  $k \geq 1$ .

We can also get

$$\begin{split} P\left(H<\infty\right) &= \lim_{s\to 1} G\left(s\right) \\ &= \frac{1-\sqrt{1-4pq}}{2p} \\ &= \frac{1-|q-p|}{2p} \\ &= \left\{ \begin{array}{ll} 1 & p \leq q \\ q/p & p > q \end{array} \right. \end{split}$$

Now let  $p \leq q$ . We want to find  $\mathbb{E}_1(H)$ . Differentiate G,

$$G' = pG^{2} + 2psGG' + q$$

$$\implies G'(s) = \frac{pG^{2} + q}{1 - 2psG}$$

Take the limit  $s \to 1$ ,

$$G'(s) \to \begin{cases} \infty & p = q \\ \frac{1}{q-p} & p < q \end{cases}$$

### 8 Classification of states

**Definition.** (a) The mean recurrence time of  $i \in S$  is

$$\mu_{i} = \mathbb{E}_{i} (T_{i})$$

$$= \begin{cases} \infty & i \text{ is transient} \\ \sum_{n \geq 1} n f_{i,i} (n) & i \text{ is recurrent} \end{cases}$$

- (b) We call i null if  $\mu_i = \infty$ , and non-null or positive if  $\mu_i < \infty$ .
- (c) The period  $d_i$  of  $i \in S$  is  $d_i = \gcd\{n \ge 1 : p_{i,i}(n) > 0\}$ . We call i aperiodic if  $d_i = 1$ .
- (d) A state  $i \in S$  ie *ergodic* if it is aperiodic and non-null recurrent.

**Theorem.** If  $i \leftrightarrow j$  then

- (a) they have the same period;
- (b) if one is recurrent, so is the other;
- (c) if one is positive recurrent, so is the other;
- (d) if one is ergodic, so is the other.