STA447: Stochastic Processes

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1 Markov Chain Probabilities

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Definition 1.1. A discrete-time, discrete-space, and time-homogenous Markov chain is a triple of (S, v, p) in which

- (i) S represents the state space, which is nonempty and countable;
- (ii) initial probability v, which is a distribution on S;
- (iii) and transition probability p_{ij} .

Definition 1.2. A Markov chain satisfies the **time-homogenous property** if

$$P(X_{n+1} = j | X_n = i) = P(X_1 = j | X_0 = i) = p_{ij} \quad \forall n \in \mathbb{N}$$
(1.1)

Definition 1.3. A Markov chain satisfies the **Markov property** if

$$P(X_{n+1} = j | X_n = i_n, X_{n-1} = i_{n-1}, \cdots, X_0 = i_0) = P(X_{n+1} = j | X_n = i_n)$$
(1.2)

That is, the chain is memoryless.

Proposition 1.1 (Multistep Arrival Probability). Let m = |S| and $\mu_i^{(n)} := P(X_n = i)$ denote the probability that the state ends up at i after n step. By the law of total expectation,

$$P(X_n = i) = \sum_{j \in S} P(X_n = i, X_{n-1} = j)$$
(1.3)

$$= \sum_{i \in S} P(X_n = i | X_{n-1} = j) P(X_{n-1} = j)$$
(1.4)

$$= \sum_{j \in S} P(X_{n-1} = j) p_{ij} \tag{1.5}$$

$$=\sum_{i\in S}\mu_j^{(n)}p_{ij}\tag{1.6}$$

Let $\mu^{(n)} := \left[\mu_1^{(n)}, \mu_2^{(n)}, \cdots, \mu_m^{(n)}\right] \in \mathbb{R}^{1 \times m}$ and $P = [p_{ij}] \in \mathbb{R}^{m \times m}$. In matrix notation:

$$\mu^{(n)} = \mu^{(n-1)} P \tag{1.7}$$

where $\mu^{(0)} = v = [v_1, v_2, \dots, v_m]$. Define $P^0 = I_m$, then

$$\mu^{(n)} = vP^n \tag{1.8}$$

Proposition 1.2 (Multistep Transition Probability). Define $p_{ij}^{(n)} := P(X_{m+n} = j | X_m = i)$ to be the probability of arriving state j after n steps, starting from state i. By the time-homogenous property,

$$p_{ij}^{(n)} = P(X_{m+n} = j | X_m = i) \quad \forall m \in \mathbb{N}$$

$$(1.9)$$

Let $P^{(n)} := [p_{ij}^{(n)}] \in \mathbb{R}^{m \times m}$.

Initial Step: for n = 1, $P^{(1)} = P$ by definition.

Inductive Step: for $n \in \mathbb{N}$,

$$p_{ij}^{(n+1)} = P(X_{n+1} = j | X_0 = i)$$
(1.10)

$$= \sum_{k \in S} P(X_{n+1} = j | X_n = k, X_0 = i) P(X_n = k | X_0 = i)$$
(1.11)

$$= \sum_{k \in S} P(X_{n+1} = j | X_n = k) p_{ik}^{(n)}$$
(1.12)

$$= \sum_{k \in S} p_{ik}^{(n)} p_{kj} \tag{1.13}$$

$$= [P^{(n)}P]_{ij} (1.14)$$

Therefore,

$$P^{(n+1)} = P^{(n)}P (1.15)$$

and

$$P^{(n)} = P^n \tag{1.16}$$

Theorem 1.1 (Chapman-Kolmogorov Equations). Let $n = (n_1, n_2, \dots, n_k)$ be a multi-set of non-negative integers, then

$$P^{(\sum_{i=1}^{k} n_i)} = \prod_{i=1}^{k} P^{(n_i)} \quad (\dagger)$$
 (1.17)

Proof. Prove by induction on the size of multi-set:

Base case is trivial for k = 1.

Inductive step for k > 1, suppose (†) holds for every set of length k, consider another multi-set with length k + 1: $n' = (n_1, n_2, \dots, n_k, n_{k+1})$. Let $\delta := \sum_{i=1}^k n_i$.

$$P_{ij}^{(\delta+n_{k+1})} = P(X_{\delta+n_{k+1}} = j|X_0 = i)$$
(1.18)

$$= \sum_{k \in S} P(X_{\delta + n_{k+1}} = j | X_{\delta} = k, X_0 = i) P(X_{\delta} | X_0 = i)$$
(1.19)

$$= \sum_{k \in S} P(X_{\delta + n_{k+1}} = j | X_{\delta} = k) P(X_{\delta} | X_0 = i)$$
(1.20)

$$= \sum_{k \in S} P(X_{n_{k+1}} = j | X_0 = k) P(X_{\delta} = k | X_0 = i)$$
(1.21)

$$= \sum_{k \in S} p_{kj}^{n_{k+1}} p_{ik}^{(\delta)} \tag{1.22}$$

$$= [P^{(\delta)}P^{(n_{k+1})}]_{ij} \tag{1.23}$$

$$\Rightarrow P^{(\delta+n_{k+1})} = P^{(\delta)}P^{(n_{k+1})} \tag{1.24}$$

Corollary 1.1 (Chapman-Kolmogorov Inequality). For every $k \in S$,

$$p_{ij}^{(m+n)} \ge p_{ik}^{(m)} p_{kj}^{(n)} \tag{1.25}$$

For $k, \ell \in S$,

$$p_{ij}^{(m+s+n)} \ge p_{ik}^{(m)} p_{k\ell}^{(s)} p_{\ell j}^{(n)} \tag{1.26}$$

Notation 1.1. Let $N(i) := |\{n \ge 1 : X_n = i\}|$ denote the number of arrivals to state i of the chain.

Definition 1.4. Define the **return probability** from state i to j, f_{ij} , as the probability of arriving state j starting from state i. That is,

$$f_{ij} = P(\exists n \ge 1 \ s.t. \ X_n = j | X_0 = i)$$
 (1.27)

$$= P(N(j) \ge 1 | X_0 = i) \tag{1.28}$$

Proposition 1.3. The probability of firstly arriving j, then arriving k (denoted as event E) starting from i equals

$$P(E|X_0 = i) = f_{ij}f_{jk} (1.29)$$

Proof. The proof follows the time-homogenous property.

Corollary 1.2.

$$P(N(i) \ge k | X_0 = i) = (f_{ii})^k \tag{1.30}$$

$$P(N(j) \ge k|X_0 = i) = f_{ij}(f_{ij})^{k-1} \tag{1.31}$$

Definition 1.5. A state i in a Markov chain is **recurrent** if $f_{ii} = 1$. Otherwise, this state is **transient**.

Theorem 1.2 (Recurrent State Theorem). The following statements are equivalent:

- (i) State *i* is recurrent;
- (ii) $P(N(i) = \infty | X_0 = i) = 1$, that is, state i will be visited infinitely often;
- (iii) $\sum_{n=1}^{\infty} p_{ii}^{(n)} = \infty.$

The following statements are equivalent:

- (a) State *i* is transient;
- (b) $P(N(i) = \infty | X_0 = i) = 0$, that is, state i will only be visited finitely many times;
- (c) $\sum_{n=1}^{\infty} p_{ii}^{(n)} < \infty$.

Proof. We only show the equivalence of $(i) \sim (iii)$, $(a) \sim (c)$ are simply the negation of previous statements. $(i) \iff (ii)$:

$$P(N(i) = \infty | X_0 = i) = P(\lim_{k \to \infty} N(i) \ge k | X_0 = i)$$
 (1.32)

$$= \lim_{k \to \infty} P(N(i) \ge k | X_0 = i) \tag{1.33}$$

$$= \lim_{k \to \infty} (f_{ii})^k = 1 \text{ if and only if } f_{ii} = 1$$
(1.34)

 $(i) \iff (iii)$:

$$\sum_{n=1}^{\infty} p_{ii}^{(n)} = \sum_{n=1}^{\infty} P(X_n = i | X_0 = i)$$
(1.35)

$$= \sum_{n=1}^{\infty} \mathbb{E}(1_{X_n=i}|X_0=i)$$
 (1.36)

$$= \mathbb{E}\left(\sum_{n=1}^{\infty} 1_{X_n=i} \middle| X_0 = i\right) \tag{1.37}$$

$$= \mathbb{E}(N(i)|X_0 = i) \tag{1.38}$$

$$= \sum_{n=k}^{\infty} kP(N(i) = k|X_0 = i)$$
 (1.39)

$$= \sum_{n=k}^{\infty} P(N(i) \ge k | X_0 = i)$$
 (1.40)

$$=\sum_{n=k}^{\infty} (f_{ii})^k \tag{1.41}$$

$$=\infty$$
 if and only if $f_{ii}=1$ (1.42)