

STAT253/317 Lecture 4: 4.4 Limiting Distribution I

Stationary Distribution

Define $\pi_i^{(n)} = P(X_n = i)$, $i \in \mathfrak{X}$ to be the marginal distribution of X_n , $n = 1, 2, \dots$, and let $\pi^{(n)}$ be the row vector

$$\pi^{(n)} = (\pi_0^{(n)}, \pi_1^{(n)}, \pi_2^{(n)}, \dots),$$

From Chapman-Kolmogorov Equation, we know that

$$\pi^{(n)} = \pi^{(n-1)}\mathbb{P} \quad \text{i.e.} \quad \pi_j^{(n)} = \sum_{i \in \mathfrak{X}} \pi_i^{(n-1)} P_{ij} \quad \text{for all } j \in \mathfrak{X},$$

If π is a distribution on \mathfrak{X} satisfying

$$\pi\mathbb{P} = \pi \quad \text{i.e.} \quad \pi_j = \sum_{i \in \mathfrak{X}} \pi_i P_{ij} \quad \text{for all } j \in \mathfrak{X},$$

then $\pi^{(0)} = \pi$ implies $\pi^{(n)} = \pi$ for all n .

We say π is a **stationary distribution** of the Markov chain.

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Example 1: 2-state Markov Chain

$$\mathfrak{X} = \{0, 1\}, \quad \mathbb{P} = \begin{matrix} & \begin{matrix} 0 & 1 \end{matrix} \\ \begin{matrix} 0 \\ 1 \end{matrix} & \begin{pmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{pmatrix} \end{matrix}$$

$$\begin{aligned} \pi\mathbb{P} = \pi &\Rightarrow \begin{cases} \pi_0 = (1-\alpha)\pi_0 + \beta\pi_1 \\ \pi_1 = \alpha\pi_0 + (1-\beta)\pi_1 \end{cases} \\ &\Rightarrow \begin{cases} \alpha\pi_0 = \beta\pi_1 \\ \beta\pi_1 = \alpha\pi_0 \end{cases} \end{aligned}$$

Need one more constraint: $\pi_0 + \pi_1 = 1$

$$\Rightarrow \pi = (\pi_0, \pi_1) = \left(\frac{\beta}{\alpha + \beta}, \frac{\alpha}{\alpha + \beta} \right)$$

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Example 2: Ehrenfest Diffusion Model

$$P_{ij} = \begin{cases} \frac{i}{2a} & \text{if } j = i - 1 \\ \frac{2a - i}{2a} & \text{if } j = i + 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\pi_0 = \pi_1 P_{10} = \frac{1}{2a} \pi_1 \Rightarrow \pi_1 = 2a\pi_0 = \binom{2a}{1} \pi_0$$

$$\pi_1 = \pi_0 P_{01} + \pi_2 P_{21} = \pi_0 + \frac{2}{2a} \pi_2 \Rightarrow \pi_2 = \frac{2a(2a-1)}{2} \pi_0 = \binom{2a}{2} \pi_0$$

$$\pi_2 = \pi_1 P_{12} + \pi_3 P_{32} = \frac{2a-1}{2a} \pi_1 + \frac{3}{2a} \pi_3 \Rightarrow \pi_3 = \frac{2a(2a-1)(2a-2)}{6} \pi_0 = \binom{2a}{3} \pi_0$$

\vdots \dots

In general,

$$\pi_i = \binom{2a}{i} \left(\frac{1}{2} \right)^{2a} \quad \text{for } i = 0, 1, 2, \dots, 2a$$

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Stationary Distribution May Not Be Unique

Consider a Markov chain with transition matrix \mathbb{P} of the form

$$\mathbb{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{pmatrix} * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ 0 & 0 & * & * & * \\ 0 & 0 & * & * & * \\ 0 & 0 & * & * & * \end{pmatrix} = \begin{pmatrix} \mathbb{P}_x & 0 \\ 0 & \mathbb{P}_y \end{pmatrix}$$

This Markov chain has 2 classes $\{0, 1\}$ and $\{2, 3, 4\}$, both closed and recurrent. So this Markov chain can be reduced to two sub-Markov chains, one with state space $\{0, 1\}$ and the other $\{2, 3, 4\}$. Their transition matrices are respectively \mathbb{P}_x and \mathbb{P}_y .

Say $\pi_x = (\pi_0, \pi_1)$ and $\pi_y = (\pi_2, \pi_3, \pi_4)$ be respectively the stationary distributions of the two sub-Markov chains, i.e.,

$$\pi_x \mathbb{P}_x = \pi_x, \quad \pi_y \mathbb{P}_y = \pi_y$$

Verify that $\pi = (c\pi_0, c\pi_1, (1-c)\pi_2, (1-c)\pi_3, (1-c)\pi_4)$ is a stationary distribution of $\{X_n\}$ for any c between 0 and 1.

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Not All Markov Chains Have a Stationary Distribution

For one-dimensional symmetric random walk, the transition probabilities are

$$P_{i,i+1} = P_{i,i-1} = 1/2$$

Try to solve for the stationary distribution

$$\pi_j = \sum_{i \in \mathfrak{X}} \pi_i P_{ij} = \frac{1}{2} \pi_{j-1} + \frac{1}{2} \pi_{j+1}$$

π_j must be of the form

$$\pi_j = a + bj, \quad \text{for all integer } j \text{ and some constants } a, b$$

To make $\pi_j \geq 0$ for all integer j , $\Rightarrow b = 0$. Thus

$$\pi_j = a \quad \text{for all integer } j$$

Impossible to make $\sum_{j=-\infty}^{\infty} \pi_j = 1$.

Conclusion: 1-dim symmetric random walk does not have a stationary distribution.

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Limiting Distribution

A Markov chain is said to have a **limiting distribution** if for all $i, j \in \mathfrak{X}$, $\pi_j = \lim_{n \rightarrow \infty} P_{ij}^n$ exists, independent of the initial state X_0 , and π_j 's satisfy $\sum_{j \in \mathfrak{X}} \pi_j = 1$.

$$\text{i.e.,} \quad \lim_{n \rightarrow \infty} \mathbb{P}^n = \begin{pmatrix} \pi_0 & \pi_1 & \pi_2 & \pi_3 & \dots \\ \pi_0 & \pi_1 & \pi_2 & \pi_3 & \dots \\ \pi_0 & \pi_1 & \pi_2 & \pi_3 & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

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Limiting Distribution is a Stationary Distribution

The limiting distribution of a Markov chain is a stationary distribution of the Markov chain.

Proof (not rigorous). By Chapman Kolmogorov Equation,

$$P_{ij}^{(n+1)} = \sum_{k \in \mathfrak{X}} P_{ik}^{(n)} P_{kj}$$

Letting $n \rightarrow \infty$, we get

$$\begin{aligned} \pi_j &= \lim_{n \rightarrow \infty} P_{ij}^{(n+1)} = \lim_{n \rightarrow \infty} \sum_{k \in \mathfrak{X}} P_{ik}^{(n)} P_{kj} \\ &= \sum_{k \in \mathfrak{X}} \lim_{n \rightarrow \infty} P_{ik}^{(n)} P_{kj} \quad (\text{needs justification}) \\ &= \sum_{k \in \mathfrak{X}} \pi_k P_{kj} \end{aligned}$$

Thus the limiting distribution π_j 's satisfies the equations $\pi_j = \sum_{k \in \mathfrak{X}} \pi_k P_{kj}$ for all $j \in \mathfrak{X}$ and is a stationary distribution.

See Karlin & Taylor (1975), Theorem 1.3 on p.85-86 for a rigorous proof.

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Limiting Distribution is Unique

If a Markov chain has a limiting distribution π , then

$$\lim_{n \rightarrow \infty} \pi_j^{(n)} = \pi_j \text{ for all } j \in \mathfrak{X}, \text{ whatever } \pi^{(0)} \text{ is}$$

Proof (not rigorous). Since

$$\pi_j^{(n)} = \sum_{k \in \mathfrak{X}} \pi_k^{(0)} P_{kj}^{(n)}$$

Letting $n \rightarrow \infty$, we get

$$\begin{aligned} \lim_{n \rightarrow \infty} \pi_j^{(n)} &= \lim_{n \rightarrow \infty} \sum_{k \in \mathfrak{X}} \pi_k^{(0)} P_{kj}^{(n)} \\ &= \sum_{k \in \mathfrak{X}} \pi_k^{(0)} \lim_{n \rightarrow \infty} P_{kj}^{(n)} \quad (\text{needs justification}) \\ &= \sum_{k \in \mathfrak{X}} \underbrace{\pi_k^{(0)}}_{=1} \pi_j = \pi_j \end{aligned}$$

i.e., if a limiting distribution exists, it is the unique stationary distribution.

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Example: Two-State Markov Chain

$$\mathfrak{X} = \{0, 1\}, \quad \mathbb{P} = \begin{matrix} & \begin{matrix} 0 & 1 \end{matrix} \\ \begin{matrix} 0 \\ 1 \end{matrix} & \begin{pmatrix} 1-\alpha & \alpha \\ \beta & 1-\beta \end{pmatrix} \end{matrix}$$

By induction, one can show that

$$\begin{aligned} \mathbb{P}^n &= \begin{pmatrix} \frac{\beta}{\alpha+\beta} + \frac{\alpha}{\alpha+\beta}(1-\alpha-\beta)^n & \frac{\alpha}{\alpha+\beta} - \frac{\alpha}{\alpha+\beta}(1-\alpha-\beta)^n \\ \frac{\beta}{\alpha+\beta} + \frac{\beta}{\alpha+\beta}(1-\alpha-\beta)^n & \frac{\alpha}{\alpha+\beta} - \frac{\beta}{\alpha+\beta}(1-\alpha-\beta)^n \end{pmatrix} \\ &\rightarrow \begin{pmatrix} \frac{\beta}{\alpha+\beta} & \frac{\alpha}{\alpha+\beta} \\ \frac{\beta}{\alpha+\beta} & \frac{\alpha}{\alpha+\beta} \end{pmatrix} \text{ as } n \rightarrow \infty \end{aligned}$$

The limiting distribution π is $(\frac{\beta}{\alpha+\beta}, \frac{\alpha}{\alpha+\beta})$.

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Not All Markov Chains Have Limiting Distributions I

Consider simple random walk on $\{0, 1, 2, 3, 4\}$ with absorbing boundary.

$$\mathbb{P} = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \end{matrix}$$

Classes: $\{0\}$, $\{1,2,3\}$, $\{4\}$. One can show that

$$\mathbb{P}^n \rightarrow \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 3/4 & 0 & 0 & 0 & 1/4 \\ 2/4 & 0 & 0 & 0 & 2/4 \\ 1/4 & 0 & 0 & 0 & 3/4 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \text{ as } n \rightarrow \infty \end{matrix}$$

This Markov chain has no limiting distribution since $\lim_{n \rightarrow \infty} P_{ij}^n$ depends on the initial state i .

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Not All Markov Chains Have Limiting Distributions II

For example, in the Ehrenfest diffusion model,

$$\begin{aligned} \mathbb{P}^{2n} &= \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots & 2a \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ \vdots \\ 2a \end{matrix} & \begin{pmatrix} * & 0 & * & 0 & \dots & * \\ 0 & * & 0 & * & \dots & 0 \\ * & 0 & * & 0 & \dots & * \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ * & 0 & * & 0 & \dots & * \end{pmatrix} \end{matrix} \quad \text{In fact, as } n \rightarrow \infty, \\ & \quad P_{ij}^{2n} \rightarrow \begin{cases} 2 \binom{2a}{j} (\frac{1}{2})^{2a} & \text{if } i+j \text{ is even} \\ 0 & \text{if } i+j \text{ is odd} \end{cases} \\ & \quad P_{ij}^{2n+1} \rightarrow \begin{cases} 0 & \text{if } i+j \text{ is even} \\ 2 \binom{2a}{j} (\frac{1}{2})^{2a} & \text{if } i+j \text{ is odd} \end{cases} \\ \mathbb{P}^{2n+1} &= \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots & 2a \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ \vdots \\ 2a \end{matrix} & \begin{pmatrix} 0 & * & 0 & * & \dots & 0 \\ * & 0 & * & 0 & \dots & * \\ 0 & * & 0 & * & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & * & 0 & * & \dots & 0 \end{pmatrix} \end{matrix} \quad \lim_{n \rightarrow \infty} P_{ij}^n \text{ doesn't exist} \\ & \quad \text{for all } i, j \in \mathfrak{X} \end{aligned}$$

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Periodicity

A state of a Markov chain is said to have **period** d if

$$P_{ii}^n = 0, \quad \text{whenever } n \text{ is not a multiple of } d$$

In other words, d is the *greatest common divisor* of all the n 's such that

$$P_{ii}^n > 0$$

We say a state is **aperiodic** if $d = 1$, and **periodic** if $d > 1$.

For the Ehrenfest diffusion model, all states are of period $d = 2$.

Fact: Periodicity is a class property.

That is, all states in the same class have the same period.

For a proof, see Problem 2&3 on p.77 of Karlin & Taylor (1975).

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