



Stochastic Processes

Ergodic Theorem, Markov Chain Monte Carlo Methods

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- If x is transient, then

$$\lim_{n \rightarrow \infty} P_{x,x}^n = 0, \quad \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n P_{x,x}^k = 0.$$

- If x is recurrent, then

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n P_{x,x}^k = \frac{1}{\mu_{xx}}.$$

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In addition, if x is aperiodic, then

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- For an irreducible Markov chain,

Unique stationary distribution exists \iff Markov chain is positive recurrent.

Furthermore, in this case, $\pi(x) = \frac{1}{\mu_{xx}} > 0$ for all x .

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In addition, if y is positive recurrent, then

$$\lim_{n \rightarrow \infty} P_{x,y}^n = \frac{1}{\mu_{yy}} = \pi(y).$$

Ergodicity and Convergence to Stationary Distribution

Theorem (Ergodicity and Convergence to Stationary Distribution)

Consider a time-homogeneous DTMC $\{X_n\}_{n=0}^{\infty}$ on a discrete state space \mathcal{X} with TPM P . Assume that $X_0 = x$, and for each $n \in \mathbb{N}$, let π_n denote the PMF of X_n .

If P is ergodic with associated stationary distribution π , then

$$\lim_{n \rightarrow \infty} d_{\text{TV}}(\pi_n, \pi) = \lim_{n \rightarrow \infty} \frac{1}{2} \|\pi_n - \pi\|_1 = 0,$$

where d_{TV} denotes the **total variation distance**.

Ergodic Theorem

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Theorem (Ergodic Theorem)

For an ergodic Markov chain $\{X_n\}_{n=0}^\infty$ on a finite state space \mathcal{X} with TPM P , stationary distribution π , and **any starting state** $X_0 = x \in \mathcal{X}$,

$$\frac{N_y(n)}{n} \xrightarrow{\text{a.s.}} \pi(y) \quad \forall y \in \mathcal{X},$$

where $N_y(n)$ is the number of times the Markov chain visits state y up to time n .

More generally, for any bounded, continuous function $f : \mathcal{X} \rightarrow \mathbb{R}$ and for **any starting state** $X_0 = x \in \mathcal{X}$,

$$\frac{1}{n} \sum_{k=1}^n f(X_k) \xrightarrow{\text{a.s.}} \sum_{y \in \mathcal{X}} f(y) \pi(y).$$



Proof of Theorem

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- To prove the second part of the theorem, observe that

$$\frac{1}{n} \sum_{k=1}^n f(X_k) = \sum_{y \in \mathcal{X}} f(x) \frac{N_y(n)}{n}$$

The result then follows from part 1

Markov Chain Monte Carlo Methods

Objective

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To evaluate a sum of the form

$$I = \sum_{x \in \mathcal{X}} f(x) \pi(x),$$

for given functions $f, \pi : \mathcal{X} \rightarrow \mathbb{R}$, where π is a probability distribution on \mathcal{X} .
Here, $\mathcal{X} \subseteq \mathbb{R}^d$ for some d .

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Difficulties:

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- High dimensionality: d may be large (e.g., 10000)
- h and/or π may have complex expressions, making it difficult to compute the sum

Metropolis–Hastings Algorithm



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- The method also applies when \mathcal{X} is countable or uncountable

Construction of Markov Chain

- Let Q be any row-stochastic matrix on $\mathcal{X} \times \mathcal{X}$, i.e.,

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- Let $A = [A_{x,y}]_{x,y \in \mathcal{X}}$ be defined via

$$A_{x,y} = \frac{S_{x,y}}{1 + \frac{\pi(x) Q_{x,y}}{\pi(y) Q_{y,x}}}.$$

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- A is called the **acceptance matrix**



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- **Claim:** The TPM of $\{X_n\}_{n=0}^{\infty}$ will have π as the unique stationary distribution!

Proof of Claim

- For any $x, y \in \mathcal{X}$, we have

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- It then follows that for all $x, y \in \mathcal{X}$,

$$\pi(x) P_{x,y} = \left(\pi(x) Q_{x,y} \pi(y) Q_{y,x} \right) \cdot \frac{S_{x,y}}{\pi(x) Q_{x,y} + \pi(y) Q_{y,x}} = \pi(y) P_{y,x}.$$

- Therefore, $\pi(x) = \sum_y \pi(y) P_{x,y}$ for all x , thus proving that π is a stationary distribution

References



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