

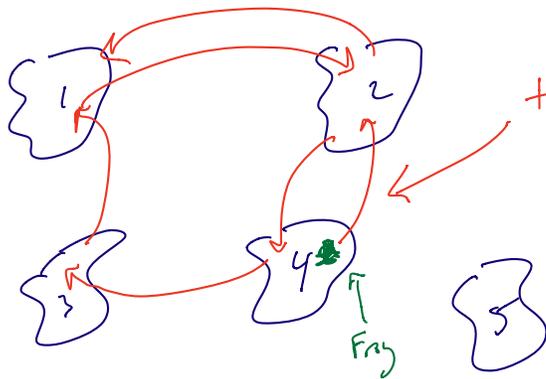
Markov Chains:

Stochastic Process  $\{X_t : t \in T\}$  (assume that  $T = \{1, 2, 3, \dots\}$ )  
with the property that  $f(x_t | x_{t-1}) = f(x_t | x_{t-2}, \dots, x_1)$

$\Rightarrow f(x_1, x_2, \dots, x_t) = f(x_1) f(x_2 | x_1) f(x_3 | x_2) \dots f(x_t | x_{t-1})$ .

State space:  $\mathcal{X}$  (discrete for now)

"states":  $1, 2, \dots$



transition probabilities

$P_{ij} = P(X_{n+1} = j | X_n = i)$

If  $P_{ij}$  does not depend on  $n$  for all  $i, j$ , the

Markov chain is homogeneous.

The matrix  $P$  of transition probabilities is the transition matrix.  $P_{ij} = p_{ij}$ .

Two properties

①  $P_{ij} \geq 0$

②  $\sum_j P_{ij} = 1$  (Typo in book.)

↑ each row in  $P$  is a probability mass function.

n-step transition probability:  $P(X_{m+n} = j \mid X_m = i) = p_{ij}(n)$

Theorem (Chapman-Kolmogorov) The n-step transition probabilities satisfy:

$$p_{ij}(m+n) = \sum_k p_{ik}(m) p_{kj}(n) = (P(m) P(n))_{ij}$$

$$\Rightarrow P(2) = P \cdot P = P^2$$

$$\Rightarrow P(3) = P^3$$

$$\Rightarrow P(n) = P^n$$

This means that if at time 0, my probability of being in state  $i$  is  $\mu_i$ , and define

$$\mu^{(0)} = (\mu_1^{(0)}, \mu_2^{(0)}, \dots, \mu_N^{(0)})$$

$$\Rightarrow \mu^{(1)} = \mu^{(0)} P,$$

$$\Rightarrow \mu^{(n)} = \mu^{(0)} P^n \quad \leftarrow \text{matrix vector multiplication.}$$

Question: As  $n \rightarrow \infty$ , is  $\mu_i^{(n)} > 0$ ? Or is  $p_{ij} > 0$  for all  $i$ ?

Def: state  $i$  reaches state  $j$  ( $j$  is accessible from  $i$ ) if  $p_{ij}(n) > 0$  for some  $n$

$$\Rightarrow i \rightarrow j$$

$$\Rightarrow \text{if } i \rightarrow j \text{ and } j \rightarrow i, \text{ then } i \leftrightarrow j \text{ "communicate"}$$

Thm

①  $i \leftrightarrow i$

②  $i \leftrightarrow j \Rightarrow j \leftrightarrow i$

③  $i \leftrightarrow j$  and  $j \leftrightarrow k$  then  $i \leftrightarrow k$ .

④ The state space  $\mathcal{X}$  can be written as a disjoint union of classes  $\mathcal{X} = \mathcal{X}_1 \cup \mathcal{X}_2 \cup \dots$  where  $i, j$  communicate iff  $i, j \in \mathcal{X}_k$ .

Def: If all states communicate, then the chain is irreducible,

Closed: set of states is closed if the chain enters but never leaves.

Closed set with a single state: an absorbing state.

Recurrent/persistent state:  $P(X_n = i \text{ for some } n \geq 1 \mid X_0 = i) = 1$

Transient: else.

Stationarity  $\pi$  is a stationary (or invariant) distribution if  $\pi = \pi P$ .

$\Rightarrow \pi$  is a row eigenvector of  $P$

$\Rightarrow P^T \pi^T = \pi^T$

$\Rightarrow$  with eigenvalue 1.

Idea: Draw  $X_0$  from  $\pi$ , a stationary distribution of  $P$ .

Next, draw  $X_1 \sim \pi P$ .

Notationally:  $X_1 \sim \mu_1 = \mu_0 P = \pi P = \pi$

$\Rightarrow$  If  $X_2 \sim \mu_2 = \mu_1 P = \mu_0 P^2 = \pi P = \pi$

$\Rightarrow$  that  $X_2 \sim \pi$

When a chain has distribution  $\pi$ , it will forever.

Def A Markov Chain has limiting distribution  $\pi$

if  $P^n \rightarrow \begin{pmatrix} \pi \\ \pi \\ \vdots \\ \pi \end{pmatrix} = \begin{pmatrix} \pi_1 & \pi_2 & \dots & \pi_N \\ \vdots & \vdots & & \vdots \\ \pi_1 & \pi_2 & \dots & \pi_N \end{pmatrix}$

$\Rightarrow \mu_0 P^n = \pi$

$$(\mu_1 \dots \mu_N) \begin{pmatrix} \pi_1 & \dots & \pi_N \\ \pi_1 & & \pi_N \\ \vdots & & \vdots \\ \pi_1 & & \pi_N \end{pmatrix} = \begin{pmatrix} \pi_1 \sum \mu_j & \pi_2 \sum \mu_j & \dots \end{pmatrix} \\ = (\pi_1 \pi_2 \dots \pi_N).$$

Detailed Balance  $\pi$  satisfies detailed balance if

for all  $i, j$

$$\pi_i P_{ij} = P_{ji} \pi_j$$

$\swarrow \quad \downarrow \quad \searrow$

$$\underbrace{P(X_n = i) P(X_{n+1} = j | X_n = i)}_{P(X_{n+1} = j, X_n = i)} \quad P(X_{n+1} = i, X_n = j)$$

Thm If  $\pi$  satisfies detailed balance, then  $\pi$  is a stationary distribution.

Proof: Detailed balance says  $\pi_i p_{ij} = p_{ji} \pi_j$

We need to show that  $\pi P = \pi$ . The  $j$ th element of  $\pi P = (\pi P)_j = \sum_{k=1}^N \pi_k p_{kj} = \sum_{k=1}^N p_{jk} \pi_j = \pi_j \sum_{k=1}^N p_{jk} = \pi_j$ . ✓

## Markov Chain Monte Carlo (MCMC)

Goal: Estimate an integral  $E(h(X)) = \int h(x) f(x) dx$ .

Idea: Construct a Markov Chain  $X_1, X_2, \dots$  whose stationary distribution is  $f$

$\Rightarrow X_n \sim F = \int f$  | We're specifying  $\pi$ , and trying to find  $P$  such that  $\pi = \pi P$ .

If this can be done, then under certain assumptions

$$\frac{1}{N} \sum_{i=1}^N h(X_i) \xrightarrow{P} E(h(X)).$$

For example: Draw from posterior in Bayesian

calculator:  $f(\theta|x) = \frac{\mathcal{L}(\theta) f(\theta)}{C}$ ,  $\int \mathcal{L}(\theta) f(\theta) d\theta$

## Specific Algorithm Metropolis - Hastings.

Listed as one of top 10 algorithms of 20<sup>th</sup> century.  
(along with FFT, FMM, QR, Fortran)

Goal: Draw samples from  $X$  with density  $f$ .

### M-H Algorithm

① Choose  $X_0$  arbitrarily. Assuming that we have generated  $X_0, \dots, X_i$ :

① Generate  $Y$  from density  $q(y|X_i)$

proposal or candidate value

$\uparrow$   $q$  is a density that is easy to draw from: proposal distribution

Ex:  $q(y|x) \sim N(x, \sigma^2)$ .

② Evaluate  $r = r(X_i, Y)$  where

$$r(x, y) = \min \left\{ \frac{f(y) q(x|y)}{f(x) q(y|x)}, 1 \right\}$$

③ Set  $X_{i+1} = \begin{cases} Y & \text{with probability } r \\ X_i & \text{with probability } 1-r \end{cases}$

Completely opaque algorithm, look at specific example first before understanding why it works.

Ex: Draw from Cauchy distribution  $f(x) = \frac{1}{\pi} \frac{1}{1+x^2}$ .

$$\text{Take } q(y|x) = \frac{1}{\sqrt{2\pi}b} e^{-\frac{(y-x)^2}{2b^2}}.$$

$$\text{So then } r(x,y) = \min \left\{ \frac{f(y)}{f(x)} \frac{q(x|y)}{q(y|x)}, 1 \right\}$$

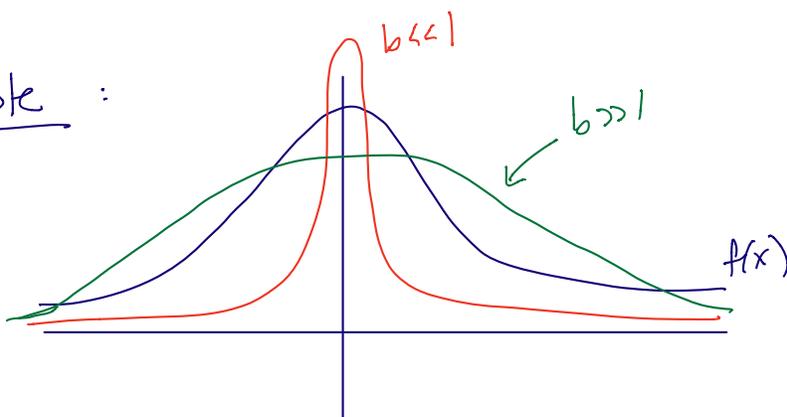
$$= \min \left\{ \frac{1+x^2}{1+y^2} \frac{e^{-\frac{(x-y)^2}{2b^2}}}{e^{-\frac{(y-x)^2}{2b^2}}}, 1 \right\}$$

$$= \min \left\{ \frac{1+x^2}{1+y^2}, 1 \right\}$$

So the algorithm reduces to following:

$$X_{i+1} = \begin{cases} Y \sim N(x_i, b^2) & \text{with probability } r(x_i, Y) \\ X_i & \text{with prob. } 1 - r(x_i, Y) \end{cases}$$

Note :



Why does this algorithm work at all?

Short answer: We enforce detailed balance in the chain, therefore guaranteeing the existence of a stationary distribution.

Recall:  $p_{ij}\pi_i = p_{ji}\pi_j$

Continuous version of detailed balance:

$$p_{ij} \rightarrow p(x,y) \approx \mathbb{P}(X_{n+1}=y | X_n=x)$$

$$\pi_i \rightarrow f(x) \approx \mathbb{P}(X_n \approx x).$$

The function  $f$  is a stationary distribution if

$$f(y) = \int p(x,y) f(x) dx$$

$\Rightarrow$  Detailed Balance then means that

$$f(x) p(x,y) = f(y) p(y,x)$$

If this equation holds, then just integrate each side to show that  $f$  is a stationary distribution.

Using the construction of the M-H algorithm, show that detailed balance is satisfied, and therefore  $f$  is the stationary distribution.

Consider  $x,y$  (i.e.  $x=X_i$ , and  $y=Y$ , the proposal value).

$$\text{Either } f(x) q(y|x) < f(y) q(x|y)$$

$$\text{or } f(x) q(y|x) > f(y) q(x|y) \quad (*)$$

Without loss of generality, assume that (\*) holds.

and we then have:

$$\frac{f(y) q(x|y)}{f(x) q(y|x)} \geq 1$$

and therefore  $r(x,y) = \frac{f(y) q(x|y)}{f(x) q(y|x)}$ .

( And obviously  $r(y,x) = \min \left\{ \frac{f(x) q(y|x)}{f(y) q(x|y)}, 1 \right\} = 1$  . )

Next, compute the transition probabilities:

$p(x,y) = P(x \rightarrow y)$  and requires that

(i) generate  $y$

(ii) accept  $y$

$$\begin{aligned} \Rightarrow p(x,y) &= q(y|x) \cdot r(x,y) = \cancel{q(y|x)} \cdot \frac{f(y)}{f(x)} \frac{q(x|y)}{\cancel{q(y|x)}} \\ &= \frac{f(y)}{f(x)} q(x|y) \end{aligned}$$

$$\Rightarrow f(x) p(x,y) = f(y) q(x|y)$$

On the other hand,  $p(y,x) = P(y \rightarrow x)$  and requires:

(i) generate  $x$

(ii) accept  $x$

$$\Rightarrow p(y,x) = q(x|y) r(y,x) = q(x|y)$$

And therefore  $f(x) p(x,y) = f(y) p(y,x)$ , ✓

This is detailed balance.

---

Monte Carlo methods:

$$= \int h(x) f(x) dx \approx \underbrace{\frac{1}{N} \sum_{j=1}^N h(X_j)}_{\mathbb{I}} \quad \text{when } X_j \sim \text{samps from } f$$

$$E(\mathbb{I}) = \int h f$$

$$\text{Var}(\mathbb{I}) \propto \frac{1}{N} \Rightarrow \text{std}(\mathbb{I}) \sim \frac{1}{\sqrt{N}}$$