

Recall: We want to conduct a MC simulation using P but it is hard to sample from P

Idea: Build MC X_t with stat. dist. P .

Then by Ergodic Theory

$$X_1, \dots, X_t, \dots \sim MC$$

$$\frac{1}{T} \sum_{t=1}^T f(X_t) \longrightarrow \mathbb{E}_P(f(X))$$

$X \sim P$

We build the chain using Metropolis-Hastings

We need

- P - Proposal: $Q(x_i | f_i)$

- Acceptance Ratio

$$R(\mathbf{x}^*, \mathbf{x}^{(t)}) = \frac{P(\mathbf{x}^*) Q(\mathbf{x}^{(t)} | \mathbf{x}^*)}{P(\mathbf{x}^{(t)}) Q(\mathbf{x}^* | \mathbf{x}^{(t)})}$$

Alg:

1. Start. arb. $\mathbf{x}^{(t)}$

2. For $i=1, 2, \dots$ until convergence

(i) Sample $\mathbf{x}^* \sim Q(\cdot | \mathbf{x}^{(t)})$

(ii) $\mathbf{x}^{(t+1)} = \mathbf{x}^*$ with prob
 $\min\{1, R(\mathbf{x}^*, \mathbf{x}^{(t)})\}$

$\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)}$ o.w.

How to choose Q

Independent Chain M.H.

$$Q(\mathcal{F}_1 | \mathcal{F}_2) = Q(\mathcal{F}_1)$$

then

$$R(\mathcal{F}^*, \mathcal{F}^{(t)}) = \frac{P(\mathcal{F}^*) / Q(\mathcal{F}^{(*)})}{P(\mathcal{F}^{(t)}) / Q(\mathcal{F}^{(t)})}$$

If $Q(\cdot) \equiv P$ then $R \equiv 1$

Ex: Bayesian Inference

$$\begin{array}{cc} P(\theta | x) & Q \equiv P(\theta) \\ \text{posterior} & \text{prior} \end{array}$$

$$R(\theta^*, \theta^{(t)}) = \frac{P(\theta^*) / Q(\theta^*)}{P(\theta^{(t)}) / Q(\theta^{(t)})}$$

$$= \frac{P(\theta^* | x) / P(\theta^*)}{P(\theta^{(t)} | x) / P(\theta^{(t)})}$$

$$\begin{aligned}
 & \mathbb{P}(\theta^{(t)} | x) / \mathbb{P}(\theta^{(t)}) \\
 &= \frac{\mathbb{P}(x | \theta^*) / \mathbb{P}(x)}{\mathbb{P}(x | \theta^{(t)}) / \mathbb{P}(x)} \\
 &= \frac{\mathbb{P}(x | \theta^*)}{\mathbb{P}(x | \theta^{(t)})} \quad \begin{array}{l} \text{likelihood} \\ \text{ratio} \end{array}
 \end{aligned}$$

Ex: θ = prob of heads

X = # heads of n coin flips

$$\theta \sim \text{Beta}(\alpha, \beta)$$

$$X | \theta \sim \text{Binomial}(n, \theta)$$

$$\mathbb{R}(\theta^*, \theta^{(t)}) = \frac{\binom{n}{x} (\theta^*)^x (1 - \theta^*)^{1-x}}{\binom{n}{x} (\theta^{(t)})^x (1 - \theta^{(t)})^{1-x}}$$

$$= \left(\frac{\Theta^*}{\Theta^{(t)}} \right)^x \left(\frac{1 - \Theta^*}{1 - \Theta^{(t)}} \right)^{1-x}$$

Random Walk MH

Proposal $\mathcal{S}^* = \mathcal{S}^{(t)} + \delta$ $\delta \sim q(\cdot | \mathcal{S}^{(t)})$
 \uparrow perturbation

$$Q(\mathcal{S}^* | \mathcal{S}^{(t)}) = q(d(\mathcal{S}^*, \mathcal{S}^{(t)}) | \mathcal{S}^{(t)})$$

If $\delta \sim q(\cdot)$ "location independent"

$$R(\mathcal{S}^*, \mathcal{S}^{(t)}) = \frac{P(\mathcal{S}^*) q(d(\mathcal{S}^{(t)}, \mathcal{S}^*))}{P(\mathcal{S}^{(t)}) q(d(\mathcal{S}^*, \mathcal{S}^{(t)}))}$$

$$= \frac{P(\mathcal{S}^*)}{P(\mathcal{S}^{(t)})} \quad \text{"Metropolis's Algorithm"}$$

$$\underline{\text{Ex:}} \quad \theta^* = \theta^{(t)} + \delta \quad \delta \sim \text{Unif}(-s, s)$$

Issues: Hard to tune how large the perturbations should be.

Gibbs Sampling

MH with a proposal Q s.t.

$$R(s^*, s^*) = 1$$

Suppose $X = (x_1, \dots, x_n)$

Alg:

1. Start at $s^{(1)}$ arbitrarily

2. For $i = 1, 2, \dots$ UNTIL Con

(i) Sample $\mathbf{z}_1^{(t+1)} \sim P(X_1 | \mathbf{z}_2^{(t)}, \dots, \mathbf{z}_n^{(t)})$

$$\mathbf{z}_2^{(t+1)} \sim P(X_2 | \mathbf{z}_1^{(t+1)}, \dots, \mathbf{z}_n^{(t)})$$

Cycle
through.

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$$\mathbf{z}_n^{(t+1)} \sim P(X_n | \mathbf{z}_1^{(t+1)}, \dots, \mathbf{z}_{n-1}^{(t+1)})$$