

HMC

Given $\pi(x) = \frac{e^{-u(x)}}{Z}$ $u(\cdot)$ smooth

Idea: Define $H(p, x) = \frac{1}{2} \underbrace{\bar{p}^T \bar{L}^{-1} p}_{\text{psd}} + u(x)$

Algo: Given $x^{(i)}$:

- $p \sim N(0, c)$
- $(p', x') = S_L(p, x^{(i)})$
- Set $x^{(i+1)} = \begin{cases} x' & \text{Min}[1, \exp(\#(p, x) - \#(p', x')) \\ x^{(i)} & \text{o.w.} \end{cases}$

where $S : \mathbb{R}^{2d} \mapsto \mathbb{R}^{2d}$ is the Leap frog map when

$$(p, x) \mapsto (p', x') \quad \begin{cases} \bar{p} = p - \frac{\varepsilon}{2} \nabla u(x) \\ x' = x + \varepsilon \bar{L}^{-1} \bar{p} \\ \bar{p} + \frac{\varepsilon}{2} \nabla u(x') \end{cases}$$

$$S_L = \underbrace{S \circ \dots \circ S}_{L\text{-times}}$$

We sometimes replace $\nabla u(x)$ for computational speedup.

Ex: $\pi(x) \propto \exp\left(\sum_{i=1}^n u_i(x)\right)$

If $\mathbb{E}[\hat{\pi}(x)] = \pi(x)$ then we can do MCMC based on

1. Pseudo-MCMC

Still unsure what to do with $\mathbb{E}[\hat{u}(x)] = u(x)$

* get $(\hat{u}^{(i)})_{i=1}^J$ s.t. $\mathbb{E}[\hat{u}^{(i)}(x)] = u(x)$

then $\hat{\pi}^{(i)}(x) \propto \exp(-\hat{u}^{(i)}(x))$ and then combine these estimated posteriors

Useful when we think about splitting our the dataset.



Two Properties

1. S_L is symplectic $\nabla S(p, x) J \nabla S(p, x)^T = J$

$$J = \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix}$$

2. $S_L^{-1}(p, x) = F \circ S_L \circ F(p, x) = F \circ S_L(-p, x)$

$$= (-S_{L,1}(-p, x), S_{L,2}(p, x))$$

Rmk: These properties still hold when $u' \in \mathbb{C}^2$ replaces u

Langevin MCMC

Define $T(x) = x - \epsilon \nabla U(x)$

Then for $X^{(i)} = x$

$$\bar{x} = T^L(x) + z$$

$$X^{(i+1)} = \begin{cases} \bar{x} & \text{w.p.} \\ X^{(i)} & \text{w.p.} \end{cases}$$

Similar to the Hamiltonian MCMC

→ Controlled convergence to the mode

→ A little worse

Prop: In the HMC sampler given, if $X_0 \sim \pi$ then $X_1 \sim \pi$

Proof:
$$\begin{aligned} \mathbb{P}(X_1 \in A) &= \int \pi(x) \mathbb{P}(X_1 \in A | X_0 = x) dx \\ &= \int \pi(x) \int q_c(p) \mathbb{P}(X_1 \in A | X_0 = x, p) dp dx \\ &= \int \pi(x) \int q_c(p) \left[\min(1, e^{-(H(p,x) - H(S_L(p,x)))}) \mathbb{1}_A(S_L(p,x)) \right. \\ &\quad \left. + (1 - \min(1, e^{-(H(p,x) - H(S_L(p,x)))}) \mathbb{1}_A(x)) \right] dx dp \\ &= \int_A \pi(x) dx + \frac{1}{2} \iint \min \left[e^{-H(p,x)}, e^{-H(S_L(p,x))} \right] \mathbb{1}_A(S_L(p,x)) dx dp \end{aligned}$$

$$- \frac{1}{2} \iint \min(e^{-H(p,x)}, e^{-H(S_L(p,x))}) \mathbb{1}_A(x) dx dp \quad \text{WTS}$$

Looking at this last term we do the change of variable given by

$$(p', x) \mapsto S_L(p, x) \quad \text{or} \quad S_L^{-1}(p', x) = (p, x)$$

$$S_L \text{ symplectic} \implies |\det \nabla S_L^{-1}(p, x)| = 1$$

$$\implies \iint \min(e^{-H(S_L^{-1}(p', x'))}, e^{-H(p', x')}) \mathbb{1}_A(x') dx' dp'$$

$$\implies H(S_L^{-1}(p', x')) = H(S_L(-p', x')) \quad \text{by symmetry of } H(\cdot, x)$$

Plugging back in gives

$$= \iint_A \min(e^{-H(S_L(-p, x))}, e^{-H(p, x)}) dp dx$$

$p \mapsto -p$ gives

$$\iint_A \min(e^{-H(S_L(p, x))}, e^{-H(p, x)}) dp dx$$

∴
Therefore these terms cancel and we get

$$P(X_1 \in A) = \int_A \pi(x_0) dx_0 = P(x_0 \in A).$$



Rmk. Proof didn't rely on $U(\cdot)$ so we can
have some flexibility in choice of $U(\cdot)$.