

~~Quiz 7: tonight~~

HW 4 → 2 weeks

Quiz 8: ~~next Wed~~, conjugate Bayesian

Hamiltonian MCMC

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default sampler
for many ppls
stan, numpyro
highly automated

Review: Metropolis-Hastings

P

- ▶ Given: probability density $P(\mathbf{x})$, $\mathbf{x} \in \mathbb{R}^d$
- ▶ Goal: generate sample $\mathbf{x} \sim P$

Metropolis-Hastings

- ▶ Initialize $\mathbf{x}^{(0)}$ arbitrarily
- ▶ Given $\mathbf{x}^{(t)} = \mathbf{x}$, propose

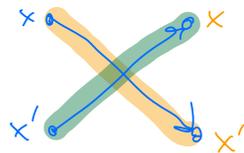
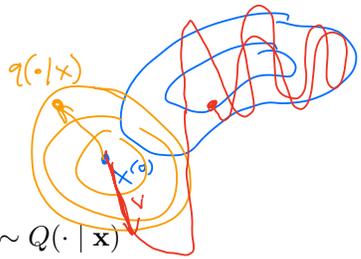
$$\mathbf{x}' \sim Q(\cdot | \mathbf{x})$$

- ▶ Accept and set $\mathbf{x}^{(t+1)} = \mathbf{x}'$ with probability $\min(a, 1)$

$$a = \frac{P(\mathbf{x}') \cdot Q(\mathbf{x} | \mathbf{x}')}{P(\mathbf{x}) \cdot Q(\mathbf{x}' | \mathbf{x})}$$

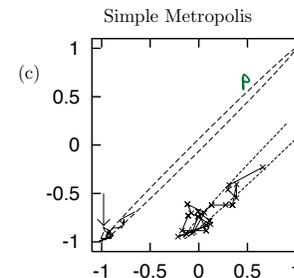
- ▶ Else reject and set $\mathbf{x}^{(t+1)} = \mathbf{x}^{(t)}$

For large enough T , have $\mathbf{x}^{(T)} \sim P$



Problem: random walk

Slow mixing due to “random walk” behavior



Why? Typical proposal is a random *displacement*

- ▶ Spherical Gaussian → Brownian motion-like
- ▶ Ignores density surface

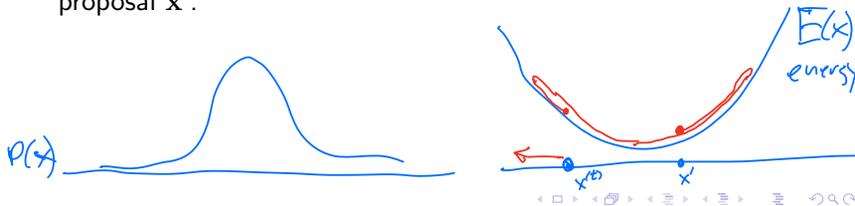
dist after n
steps is order \sqrt{n}

Main Idea

- ▶ Idea: use density to guide proposals
- ▶ Select random **velocity** $\mathbf{p}/m \in \mathbb{R}^d$
 - ▶ \mathbf{p} = momentum, m = mass
- ▶ Simulate motion on energy surface

$$\{(\mathbf{x}, E(\mathbf{x})) : \mathbf{x} \in \mathbb{R}^d\} \subseteq \mathbb{R}^{d+1}, \quad E(\mathbf{x}) = -\log P(\mathbf{x})$$

with initial velocity \mathbf{p}/m for some amount of time to get proposal \mathbf{x}' .



Main Idea

Demo: $P(x)$, $E(x)$, motion in 1D

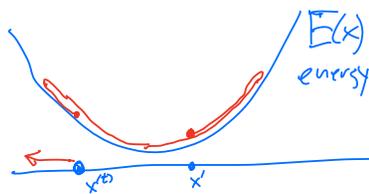
Hamiltonian Mechanics

- ▶ Position $\mathbf{x} \in \mathbb{R}^d$
- ▶ Velocity $\mathbf{p}/m \in \mathbb{R}^d$
- ▶ Potential energy $E(\mathbf{x})$ (= height)
- ▶ Temporal dynamics

$$\frac{d\mathbf{x}}{dt} = \frac{\mathbf{p}}{m} \leftarrow \text{vel.}$$

$$\frac{d\mathbf{p}}{dt} = -\frac{\partial E(\mathbf{x})}{\partial \mathbf{x}} = -E'(\mathbf{x})$$

Puck of mass m sliding on frictionless surface with velocity \mathbf{p}/m , height at \mathbf{x} equal to $E(\mathbf{x})$ (and thus "incline" $\partial E(\mathbf{x})/\partial \mathbf{x}$).



Generalization: Kinetic Energy

scalar $\frac{d}{dp} \frac{p^2}{2m} = \frac{p}{m}$

vector $\frac{d}{dp} \frac{\mathbf{p}^T \mathbf{p}}{2m} = \frac{\mathbf{p}}{m}$

Define $K(\mathbf{p}) = \frac{\mathbf{p}^T \mathbf{p}}{2m}$

kinetic energy

$$\frac{d\mathbf{x}}{dt} = \frac{\mathbf{p}}{m}$$

$$\frac{d\mathbf{p}}{dt} = -\frac{\partial E(\mathbf{x})}{\partial \mathbf{x}}$$

\implies

$$\frac{d\mathbf{x}}{dt} = \frac{\partial K(\mathbf{p})}{\partial \mathbf{p}}$$

$$\frac{d\mathbf{p}}{dt} = -\frac{\partial E(\mathbf{x})}{\partial \mathbf{x}}$$

Generalization: The Hamiltonian

$$\frac{\partial}{\partial p} (E(x) + K(p)) = \frac{\partial}{\partial p} K(p)$$

Define $H(x, p) = E(x) + K(p)$ $\frac{\partial}{\partial x} (E(x) + K(p)) = \frac{\partial}{\partial x} E(x)$

Hamiltonian or total energy

$$\begin{aligned} \frac{dx}{dt} &= \frac{\partial K(p)}{\partial p} = \frac{p}{m} \\ \frac{dp}{dt} &= -\frac{\partial E(x)}{\partial x} \end{aligned} \Rightarrow \begin{aligned} \frac{dx}{dt} &= \frac{\partial H(x, p)}{\partial p} \\ \frac{dp}{dt} &= -\frac{\partial H(x, p)}{\partial x} \end{aligned}$$

Simulating Hamiltonian Mechanics

$$\begin{aligned} x(t) &\mapsto x(t+\epsilon) \\ p(t) &\mapsto p(t+\epsilon) \end{aligned}$$

Euler's method

$$\begin{aligned} x(t+\epsilon) &= x(t) + \epsilon \frac{p(t)}{m} \\ p(t+\epsilon) &= p(t) - \epsilon \frac{\partial E(x(t))}{\partial x} \end{aligned}$$

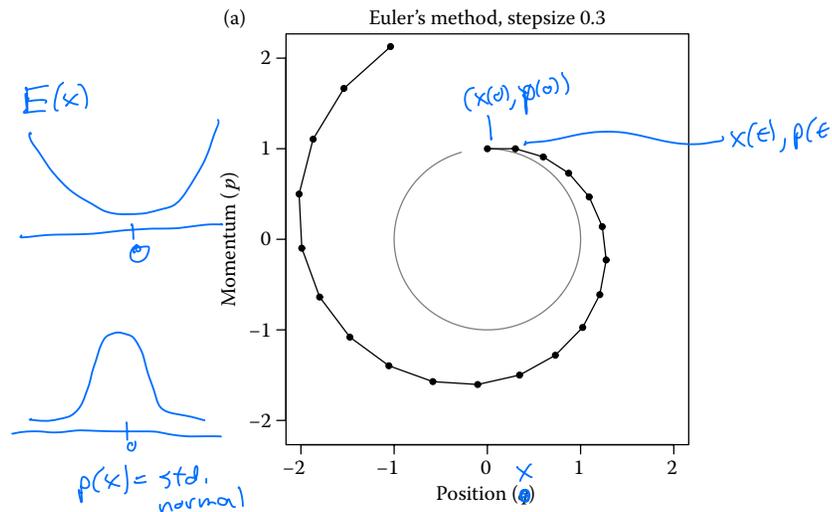
Problem: numerically unstable

$$\begin{aligned} \frac{dx}{dt} &= \frac{p}{m} \\ \frac{dp}{dt} &= -\frac{\partial E(x)}{\partial x} \end{aligned}$$

Euler's Method

$$E(x) = \frac{x^2}{2} \quad K(p) = \frac{p^2}{2}$$

$$\text{total energy} = H(x, p) = \frac{x^2}{2} + \frac{p^2}{2} = \text{const}$$



Leapfrog Method

Leapfrog

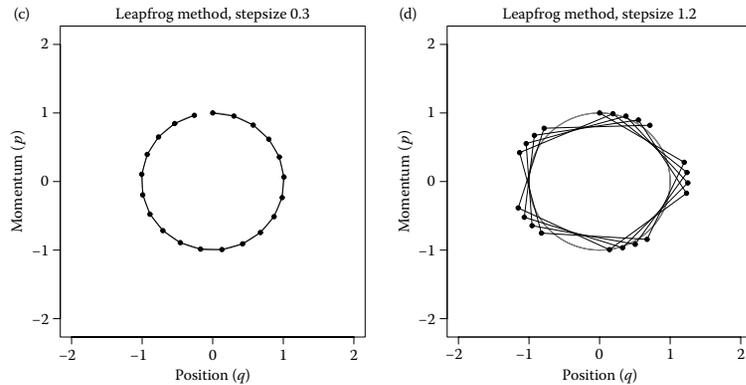
Euler: $\begin{aligned} x(t) &\mapsto x(t+\epsilon) \\ p(t) &\mapsto p(t+\epsilon) \end{aligned}$

- ① $p(t) \mapsto p(t + \frac{\epsilon}{2})$ "half step"
- ② $x(t) \mapsto x(t + \epsilon)$ "full step"
- ③ $p(t + \frac{\epsilon}{2}) \mapsto p(t + \epsilon)$ "half step"

More accurate and stable method

$$\begin{aligned} p(t + \epsilon/2) &= p(t) - (\epsilon/2) \frac{\partial E(x(t))}{\partial x} \\ x(t + \epsilon) &= x(t) + \epsilon \frac{p(t + \epsilon/2)}{m} \\ p(t + \epsilon) &= p(t + \epsilon/2) - (\epsilon/2) \frac{\partial E(x(t + \epsilon))}{\partial x} \end{aligned}$$

Leapfrog Method

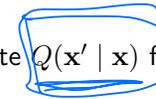


Hamiltonian MCMC

Random velocity/momentum instead of random displacement

- ▶ Start at \mathbf{x}
- ▶ Choose random momentum $\mathbf{p} \sim \exp(-\mathbf{p}^T \mathbf{p} / 2m)$
- ▶ Simulate Hamiltonian mechanics for s time units
→ end at \mathbf{x}'
- ▶ Propose \mathbf{x}'

Problem: how to compute $Q(\mathbf{x}' | \mathbf{x})$ for acceptance probability?



Auxilliary Variables

pos → \mathbf{x} mom. → \mathbf{p}

Sample both \mathbf{x} and \mathbf{p} from

$P(\mathbf{x}, \mathbf{p}) \propto \exp(-H(\mathbf{x}, \mathbf{p}))$

$\propto \underbrace{\exp(-E(\mathbf{x}))}_{P(\mathbf{x})} \underbrace{\exp(-K(\mathbf{p}))}_{\text{"prior over p"}}$

when done, discard \mathbf{p} values

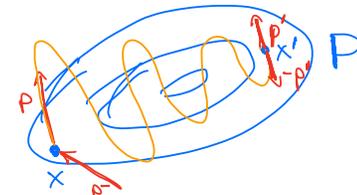
Note: \mathbf{x} and \mathbf{p} are independent

Given: $P(\mathbf{x}) \xrightarrow{\text{augment}} P(\mathbf{x}, \mathbf{p}) = P(\mathbf{x}) \cdot \exp(-K(\mathbf{p}))$

$x^{(1)}, p^{(1)}$
 $x^{(2)}, p^{(2)}$
 $x^{(3)}, p^{(3)}$
 \vdots

Hamiltonian MCMC

$$\alpha = \frac{P(\mathbf{x}', \mathbf{p}') Q(\mathbf{x}, \mathbf{p} | \mathbf{x}', \mathbf{p}')}{P(\mathbf{x}, \mathbf{p}) G(\mathbf{x}', \mathbf{p}' | \mathbf{x}, \mathbf{p})}$$



Gibbs step

- ▶ Start at $(\mathbf{x}, \mathbf{p}^-)$
- ▶ Choose random momentum $\mathbf{p} \sim \exp(-\mathbf{p}^T \mathbf{p} / 2m)$
- ▶ End at (\mathbf{x}, \mathbf{p})

$$E(\mathbf{x}) = -\log P(\mathbf{x})$$

Metropolis-Hastings step

- ▶ Start at (\mathbf{x}, \mathbf{p})
- ▶ Simulate Hamiltonian mechanics → end at $(\mathbf{x}', \mathbf{p}')$
- ▶ Propose $(\mathbf{x}', -\mathbf{p}')$

Acceptance Probability?

$$P(\mathbf{x}, \mathbf{p}) = \exp(-E(\mathbf{x})) \exp(-K(\mathbf{p})) \\ = \exp(-E(\mathbf{x}) - K(\mathbf{p}))$$

$$a = \frac{P(\mathbf{x}', -\mathbf{p}')}{P(\mathbf{x}, \mathbf{p})} \cdot \frac{Q(\mathbf{x}, \mathbf{p} | \mathbf{x}', -\mathbf{p}')}{Q(\mathbf{x}', -\mathbf{p}' | \mathbf{x}, \mathbf{p})}$$

$$= \frac{P(\mathbf{x}', -\mathbf{p}')}{P(\mathbf{x}, \mathbf{p})} \quad (\text{reversibility, volume preservation})$$

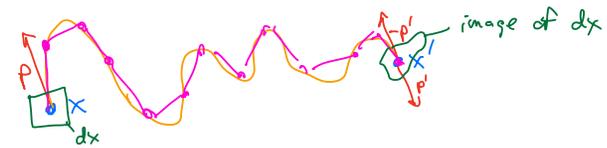
$$= \exp(E(\mathbf{x}) - E(\mathbf{x}') + K(\mathbf{p}) - K(\mathbf{p}')) \quad (K(\mathbf{p}') = K(-\mathbf{p}'))$$

$$\approx 1 \quad (\text{conservation of energy})$$

Reversibility

Let $T_{L,\varepsilon} : \mathbb{R}^{2d} \rightarrow \mathbb{R}^{2d}$ be simulation mapping with L steps at time increment ε

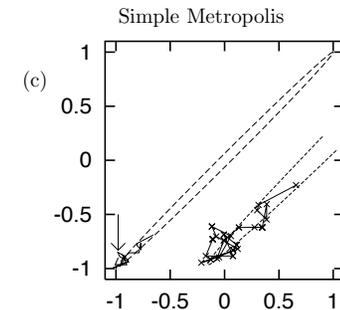
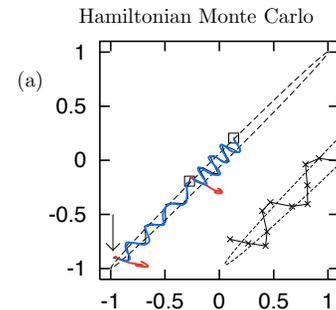
$$T_{L,\varepsilon}(\mathbf{x}, \mathbf{p}) = (\mathbf{x}', \mathbf{p}') \implies T_{L,\varepsilon}(\mathbf{x}', -\mathbf{p}') = (\mathbf{x}, -\mathbf{p})$$



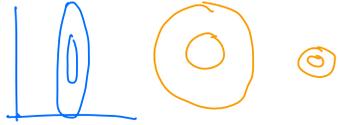
Demo

Demo with sampling

Example



Example



Setup: 100D Gaussian, standard deviations in different dimensions are 0.01, 0.02, ..., 1.00

