

The Metropolis adjusted Langevin Algorithm for log-concave probability measures in high dimensions

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1 INTRODUCTION

$$U(x) = \frac{1}{2}|x|^2 + V(x), \quad x \in \mathbb{R}^d, \quad V \in C^4(\mathbb{R}^d),$$

$$\mu(dx) = \frac{1}{Z} e^{-U(x)} \lambda^d(dx) = \frac{(2\pi)^{d/2}}{Z} e^{-V(x)} \gamma^d(dx),$$

$\gamma_d = N(0, I_d)$ standard normal distribution in \mathbb{R}^d .

AIM :

- Approximate Sampling from μ .
- Rigorous error and complexity estimates, $d \rightarrow \infty$.

RUNNING EXAMPLE: TRANSITION PATH SAMPLING

$$dY_t = dB_t - \nabla H(Y_t) dt, \quad Y_0 = y_0 \in \mathbb{R}^n,$$

μ = conditional distribution on $C([0, T], \mathbb{R}^n)$ of $(Y_t)_{t \in [0, T]}$ given $Y_T = y_T$.

By Girsanov's Theorem:

$$\mu(dy) = Z^{-1} \exp(-V(y)) \gamma(dy),$$

γ = distribution of Brownian bridge from y_0 to y_T ,

$$V(y) = \int_0^T \left(\frac{1}{2} \Delta H(y_t) + |\nabla H(y_t)|^2 \right) dt.$$

Finite dimensional approximation via Karhunen-Loève expansion:

$$\gamma(dy) \rightarrow \gamma^d(dx), \quad V(y) \rightarrow V_d(x) \quad \rightsquigarrow \text{setup above}$$

MARKOV CHAIN MONTE CARLO APPROACH

- Simulate an ergodic Markov process (X_n) with stationary distribution μ .
- n large: $P \circ X_n^{-1} \approx \mu$
- Continuous time: *(over-damped) Langevin diffusion*

$$dX_t = -\frac{1}{2}X_t dt - \frac{1}{2}\nabla V(X_t) dt + dB_t$$

- Discrete time: *Metropolis-Hastings Algorithms, Gibbs Samplers*

METROPOLIS-HASTINGS ALGORITHM

(Metropolis et al 1953, Hastings 1970)

$\mu(x) := Z^{-1} \exp(-U(x))$ density of μ w.r.t. λ^d ,

$p(x, y)$ stochastic kernel on \mathbb{R}^d proposal density, > 0 ,

ALGORITHM

1. Choose an initial state X_0 .

2. For $n := 0, 1, 2, \dots$ do

- Sample $Y_n \sim p(X_n, y)dy$, $U_n \sim \text{Unif}(0, 1)$ independently.
- If $U_n < \alpha(X_n, Y_n)$ then accept the proposal and set $X_{n+1} := Y_n$; else reject the proposal and set $X_{n+1} := X_n$.

METROPOLIS-HASTINGS ACCEPTANCE PROBABILITY

$$\alpha(x, y) = \min \left(\frac{\mu(y)p(y, x)}{\mu(x)p(x, y)}, 1 \right) = \exp(-G(x, y)^+), \quad x, y \in \mathbb{R}^d,$$

$$G(x, y) = \log \frac{\mu(x)p(x, y)}{\mu(y)p(y, x)} = U(y) - U(x) + \log \frac{p(x, y)}{p(y, x)} = V(y) - V(x) + \log \frac{\gamma^d(x)p(x, y)}{\gamma^d(y)p(y, x)}$$

- (X_n) is a time-homogeneous Markov chain with transition kernel

$$q(x, dy) = \alpha(x, y)p(x, y)dy + q(x)\delta_x(dy), \quad q(x) = 1 - q(x, \mathbb{R}^d \setminus \{x\}).$$

- *Detailed Balance:*

$$\mu(dx) q(x, dy) = \mu(dy) q(y, dx).$$

PROPOSAL DISTRIBUTIONS FOR METROPOLIS-HASTINGS

$x \mapsto Y_h(x)$ proposed move, $h > 0$ step size,

$p_h(x, dy) = P[Y_h(x) \in dy]$ proposal distribution,

$\alpha_h(x, y) = \exp(-G_h(x, y)^+)$ acceptance probability.

- **Random Walk Proposals** (\rightsquigarrow Random Walk Metropolis)

$$\begin{aligned} Y_h(x) &= x + \sqrt{h} \cdot Z, & Z &\sim \gamma^d, \\ p_h(x, dy) &= N(x, h \cdot I_d), \\ G_h(x, y) &= U(y) - U(x). \end{aligned}$$

- **Ornstein-Uhlenbeck Proposals**

$$\begin{aligned} Y_h(x) &= \left(1 - \frac{h}{2}\right)x + \sqrt{h - \frac{h^2}{4}} \cdot Z, & Z &\sim \gamma^d, \\ p_h(x, dy) &= N\left(\left(1 - \frac{h}{2}\right)x, \left(h - \frac{h^2}{4}\right) \cdot I_d\right), & \text{det. balance w.r.t. } &\gamma^d \\ G_h(x, y) &= V(y) - V(x). \end{aligned}$$

- **Euler Proposals** (\rightsquigarrow **Metropolis Adjusted Langevin Algorithm**)

$$Y_h(x) = \left(1 - \frac{h}{2}\right)x - \frac{h}{2}\nabla V(x) + \sqrt{h} \cdot Z, \quad Z \sim \gamma^d.$$

(Euler step for Langevin equation $dX_t = -\frac{1}{2}X_t dt - \frac{1}{2}\nabla V(X_t) dt + dB_t$)

$$p_h(x, dy) = N\left(\left(1 - \frac{h}{2}\right)x - \frac{h}{2}\nabla V(x), h \cdot I_d\right),$$

$$G_h(x, y) = V(y) - V(x) - (y - x) \cdot (\nabla V(y) + \nabla V(x))/2 \\ + h(|\nabla U(y)|^2 - |\nabla U(x)|^2)/4.$$

REMARK. Even for $V \equiv 0$, γ^d is not a stationary distribution for p_h^{Euler} . Stationarity only holds asymptotically as $h \rightarrow 0$. This causes substantial problems in high dimensions.

- **Semi-implicit Euler Proposals** (\rightsquigarrow **Semi-implicit MALA**)

$$Y_h(x) = \left(1 - \frac{h}{2}\right)x - \frac{h}{2}\nabla V(x) + \sqrt{h - \frac{h^2}{4}} \cdot Z, \quad Z \sim \gamma^d,$$

$$p_h(x, dy) = N\left(\left(1 - \frac{h}{2}\right)x - \frac{h}{2}\nabla V(x), \left(h - \frac{h^2}{4}\right) \cdot I_d\right) \quad (= p_h^{OU} \text{ if } V \equiv 0)$$

$$G_h(x, y) = V(y) - V(x) - (y - x) \cdot (\nabla V(y) + \nabla V(x))/2 \\ + \frac{h}{8 - 2h} \left((y + x) \cdot (\nabla V(y) - \nabla V(x)) + |\nabla V(y)|^2 - |\nabla V(x)|^2 \right).$$

REMARK. Semi-implicit discretization of Langevin equation

$$dX_t = -\frac{1}{2}X_t dt - \frac{1}{2}\nabla V(X_t) dt + dB_t$$

$$X_{n+1} - X_n = -\frac{\varepsilon}{2} \frac{X_{n+1} + X_n}{2} - \frac{\varepsilon}{2}\nabla V(X_n) + \sqrt{\varepsilon}Z_{n+1}, \quad Z_i \text{ i.i.d. } \sim \gamma^d$$

Solve for X_n and substitute $h = \varepsilon/(1 + \varepsilon/4)$:

$$X_{n+1} = \left(1 - \frac{h}{2}\right) X_n - \frac{h}{2} \nabla V(X_n) + \sqrt{h - \frac{h^2}{4}} \cdot Z_{n+1}.$$

KNOWN RESULTS FOR METROPOLIS-HASTINGS IN HIGH DIMENSIONS

- Scaling of acceptance probabilities and mean square jumps as $d \rightarrow \infty$
- Diffusion limits as $d \rightarrow \infty$
- Ergodicity, Geometric Ergodicity
- Quantitative bounds for mixing times, rigorous complexity estimates

Optimal Scaling and diffusion limits

- *Roberts, Gelman, Gilks 1997*: Diffusion limit for RWM with product target, $h = O(d^{-1})$
- *Roberts, Rosenthal 1998*: Diffusion limit for MALA with product target, $h = O(d^{-1/3})$
- *Beskos, Roberts, Stuart, Voss 2008*: Semi-implicit MALA applied to Transition Path Sampling, Scaling $h = O(1)$
- *Beskos, Roberts, Stuart 2009*: Optimal Scaling for non-product targets
- *Mattingly, Pillai, Stuart 2010*: Diffusion limit for RWM with non-product target, $h = O(d^{-1})$
- *Pillai, Stuart, Thiéry 2011*: Diffusion limit for MALA with non-product target, $h = O(d^{-1/3})$

Geometric ergodicity for MALA

- *Roberts, Tweedie 1996*: Geometric convergence holds if ∇U is globally Lipschitz but fails in general
- *Bou Rabee, van den Eijnden 2009*: Strong accuracy for truncated MALA
- *Bou Rabee, Hairer, van den Eijnden 2010*: Convergence to equilibrium for MALA at exponential rate up to term exponentially small in time step size

BOUNDS FOR MIXING TIME, COMPLEXITY

Metropolis with ball walk proposals

- *Dyer, Frieze, Kannan 1991*: $\mu = \text{Unif}(K)$, $K \subset \mathbb{R}^d$ convex
 \Rightarrow Total variation mixing time is polynomial in d and $\text{diam}(K)$
- *Applegate, Kannan 1991, ... , Lovasz, Vempala 2006*: $U : K \rightarrow \mathbb{R}$ concave, $K \subset \mathbb{R}^d$ convex
 \Rightarrow Total variation mixing time is polynomial in d and $\text{diam}(K)$

Metropolis adjusted Langevin :

- No rigorous complexity estimates so far.
- Classical results for Langevin diffusions. In particular: If μ is strictly log-concave, i.e.,

$$\exists \kappa > 0 : \partial^2 U(x) \geq \kappa \cdot I_d \quad \forall x \in \mathbb{R}^d$$

then

$$d_K(\text{law}(X_t), \mu) \leq e^{-\kappa t} d_K(\text{law}(X_0), \mu).$$

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then

$$d_K(\text{law}(X_t), \mu) \leq e^{-\kappa t} d_K(\text{law}(X_0), \mu).$$

- Bound is independent of dimension, sharp !
- Under additional conditions, a corresponding result holds for the Euler discretization.
- This suggests that comparable bounds might hold for MALA, or even for Ornstein-Uhlenbeck proposals.

2 Main result and strategy of proof

Semi-implicit MALA:

$$Y_h(x) = \left(1 - \frac{h}{2}\right)x - \frac{h}{2}\nabla V(x) + \sqrt{h - \frac{h^2}{4}} \cdot Z, \quad Z \sim \gamma^d, h > 0,$$

Coupling of proposal distributions $p_h(x, dy)$, $x \in \mathbb{R}^d$,

$$W_h(x) = \begin{cases} Y_h(x) & \text{if } U \leq \alpha_h(x, Y_h(x)) \\ x & \text{if } U > \alpha(x, Y(x, \tilde{x})) \end{cases}, \quad U \sim \text{Unif}(0, 1) \text{ independent of } Z,$$

Coupling of MALA transition kernels $q_h(x, dy)$, $x \in \mathbb{R}^d$.

We fix a radius $R \in (0, \infty)$ and a norm $\|\cdot\|_-$ on \mathbb{R}^d such that $\|x\|_- \leq |x|$ for any $x \in \mathbb{R}^d$, and set

$$d(x, \tilde{x}) := \min(\|x - \tilde{x}\|_-, R), \quad B := \{x \in \mathbb{R}^d : \|x\|_- < R/2\}.$$

EXAMPLE: Transition Path Sampling

- $|x|_{\mathbb{R}^d}$ is finite dimensional projection of Cameron-Martin norm

$$|x|_{CM} = \left(\int_0^T \left| \frac{dx}{dt} \right|^2 dt \right)^{1/2}.$$

- $\|x\|_-$ is finite dimensional approximation of supremum or L^2 norm.

GOAL:

$$E [d(W_h(x), W_h(\tilde{x}))] \leq \left(1 - \kappa h + Ch^{3/2}\right) d(x, \tilde{x}) \quad \forall x, \tilde{x} \in B, h \in (0, 1)$$

with explicit constants $\kappa, C \in (0, \infty)$ that do depend on the dimension d only through the moments

$$m_k := \int_{\mathbb{R}^d} \|x\|_-^k \gamma^d(dx), \quad k \in \mathbb{N}.$$

CONSEQUENCE:

- Contractivity of MALA transition kernel q_h for small h w.r.t. Kantorovich-Wasserstein distance

$$d_K(\nu, \eta) = \sup_{X \sim \nu, Y \sim \eta} E[d(X, Y)], \quad \nu, \eta \in \text{Prob}(\mathbb{R}^d).$$

$$d_K(\nu q_h, \mu) \leq (1 - \kappa h + Ch^{3/2}) d_K(\nu, \mu) + R \cdot (\nu(B^c) + \mu(B^c)).$$

- Upper bound for mixing time

$$T_{mix}(\varepsilon) = \inf \{n \geq 0 : d_K(\nu q_h^n, \mu) < \varepsilon \text{ for any } \nu \in \text{Prob}(\mathbb{R}^d)\}.$$

EXAMPLE: Transition Path Sampling

Dimension-independent bounds hold under appropriate assumptions.

STRATEGY OF PROOF: Let

$$A(x) := \{U \leq \alpha_h(x, Y_h(x))\} \quad (\text{proposed move from } x \text{ is accepted})$$

Then

$$\begin{aligned} E[d(W_h(x), W_h(\tilde{x}))] &\leq E[d(Y_h(x), Y_h(\tilde{x})); A(x) \cap A(\tilde{x})] \\ &\quad + d(x, \tilde{x}) \cdot P[A(x)^C \cap A(\tilde{x})^C] \\ &\quad + R \cdot P[A(x) \Delta A(\tilde{x})]. \end{aligned}$$

We prove under appropriate assumptions:

1. $E[d(Y_h(x), Y_h(\tilde{x}))] \leq (1 - \kappa h) \cdot d(x, \tilde{x}),$
2. $P[A(x)^C] = E[1 - \alpha_h(x, Y_h(x))] \leq C_1 h^{3/2},$
3. $P[A(x) \Delta A(\tilde{x})] \leq E[|\alpha_h(x, Y_h(x)) - \alpha_h(\tilde{x}, Y_h(\tilde{x}))|] \leq C_2 h^{3/2} \|x - \tilde{x}\|_-,$

with explicit constants $\kappa, C_1, C_2 \in (0, \infty)$.

3 Contractivity of proposal step

PROPOSITION. Suppose there exists a constant $\alpha \in (0, 1)$ such that

$$\|\nabla^2 V(x) \cdot \eta\|_- \leq \alpha \|\eta\|_- \quad \forall x \in B, \eta \in \mathbb{R}^d. \quad (1)$$

Then

$$\|Y_h(x) - Y_h(\tilde{x})\|_- \leq \left(1 - \frac{1-\alpha}{2}h\right) \|x - \tilde{x}\|_- \quad \forall x, \tilde{x} \in B, h > 0.$$

Proof.

$$\begin{aligned} \|Y_h(x) - Y_h(\tilde{x})\|_- &\leq \int_0^1 \|\partial_{x-\tilde{x}} Y_h(tx + (1-t)\tilde{x})\|_- dt \\ &= \int_0^1 \left\| \left(1 - \frac{h}{2}\right)(x - \tilde{x}) - \frac{h}{2} \nabla^2 V(tx + (1-t)\tilde{x}) \cdot (x - \tilde{x}) \right\|_- dt \\ &\leq \left(1 - \frac{h}{2}\right) \|x - \tilde{x}\|_- + \frac{h}{2} \alpha \|x - \tilde{x}\|_- \quad \square \end{aligned}$$

REMARK.

The assumption (1) implies strict convexity of $U(x) = \frac{1}{2}|x|^2 + V(x)$.

EXAMPLE.

For Transition Path Sampling, (A1) holds for small T with α independent of the dimension.

4 Bounds for MALA rejection probabilities

$\alpha_h(x, y) = \exp(-G_h(x, y)^+)$ Acceptance probability for semi-implicit MALA,

$$G_h(x, y) = V(y) - V(x) - (y - x) \cdot (\nabla V(y) + \nabla V(x))/2 \\ + \frac{h}{8 - 2h} ((y + x) \cdot (\nabla V(y) - \nabla V(x)) + |\nabla V(y)|^2 - |\nabla V(x)|^2).$$

ASSUMPTION. There exist finite constants $C_n, p_n \in [0, \infty)$ such that

$$|(\partial_{\xi_1, \dots, \xi_n}^n V)(x)| \leq C_n \max(1, \|x\|_-)^{p_n} \|\xi_1\|_- \cdots \|\xi_n\|_-$$

for any $x \in \mathbb{R}^d$, $\xi_1, \dots, \xi_n \in \mathbb{R}^d$, and $n = 2, 3, 4$.

THEOREM. If the assumption above is satisfied then there exists a polynomial $\mathcal{P} : \mathbb{R}^2 \rightarrow \mathbb{R}_+$ of degree $\max(p_3 + 3, 2p_2 + 2)$ such that

$$E[1 - \alpha_h(x, Y_h(x))] \leq E[G_h(x, Y_h(x))^+] \leq \mathcal{P}(\|x\|_-, \|\nabla U(x)\|_-) \cdot h^{3/2}$$

for all $x \in \mathbb{R}^d$, $h \in (0, 2)$.

REMARK.

- The polynomial \mathcal{P} is explicit. It depends only on the values C_2, C_3, p_2, p_3 and on the moments

$$m_k = E[\|Z\|_-^k], \quad 0 \leq k \leq \max(p_3 + 3, 2p_2 + 2)$$

but it does not depend on the dimension d .

- For MALA with explicit Euler proposals, a corresponding estimate holds with m_k replaced by $\tilde{m}_k = E[\|Z\|^k]$. Note, however, that $\tilde{m}_k \rightarrow \infty$ as $d \rightarrow \infty$.

Proof.

$$\begin{aligned}
& |V(y) - V(x) - (y - x) \cdot (\nabla V(y) + \nabla V(x))/2| \tag{2} \\
&= \left| \frac{1}{2} \int_0^1 t(1-t) \partial_{y-x}^3 V(x + t(y-x)) dt \right| \\
&\leq \frac{1}{12} \|y - x\|_-^3 \cdot \sup\{\partial_\eta^3 V(z) : z \in [x, y], \|\eta\|_- \leq 1\}
\end{aligned}$$

$$E [\|Y_h(x) - x\|_-^3] \leq \text{const.} \cdot h^{3/2} \tag{3}$$

$$\begin{aligned}
& |(y + x) \cdot (\nabla V(y) - \nabla V(x))| \tag{4} \\
&\leq \|y + x\|_- \cdot \sup_{\|\xi\|_- \leq 1} |\partial_\xi V(y) - \partial_\xi V(x)| \\
&\leq \|y + x\|_- \cdot \|y - x\|_- \cdot \sup\{\partial_{\xi\eta}^2 V(z) : z \in [x, y], \|\xi\|_-, \|\eta\|_- \leq 1\}
\end{aligned}$$

5 Dependence of rejection on current state

THEOREM. If the assumption above is satisfied then there exists a polynomial $Q : \mathbb{R}^2 \rightarrow \mathbb{R}_+$ of degree $\max(p_4 + 2, p_3 + p_2 + 2, 3p_2 + 1)$ such that

$$E [\|\nabla_x G_h(x, Y_h(x))\|_+] \leq Q(\|x\|_-, \|\nabla U(x)\|_-) \cdot h^{3/2}$$

for all $x \in \mathbb{R}^d$, $h \in (0, 2)$, where

$$\|\eta\|_+ := \sup\{\xi \cdot \eta : \|\xi\|_- \leq 1\}.$$

CONSEQUENCE.

$$\begin{aligned} P[\text{Accept}(x) \triangle \text{Accept}(\tilde{x})] &\leq E[|\alpha_h(x, Y_h(x)) - \alpha_h(\tilde{x}, Y_h(\tilde{x}))|] \\ &\leq E[|G_h(x, Y_h(x)) - G_h(\tilde{x}, Y_h(\tilde{x}))|] \\ &\leq \|x - \tilde{x}\|_- \cdot \sup_{z \in [x, \tilde{x}]} \|\nabla_z G_h(z, Y_h(z))\|_+ \\ &\leq h^{3/2} \|x - \tilde{x}\|_- \sup_{z \in [x, \tilde{x}]} Q(\|x\|_-, \|\nabla U(x)\|_-) \end{aligned}$$