

# Geometric Convergence of HMC on Complete Riemannian Manifolds

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Daily work:                    sampling from  $\tilde{\mu}$  on  $\mathcal{M}$  using algorithm  $\mathcal{P}$ .

Our aim:                    conditions on  $\mathcal{P} \implies$  converge exponentially towards  $\tilde{\mu}$ .

Assuming sampling space  $\mathcal{M}$  is a complete Riemannian manifold, we prove

- If  $\mathcal{M}$  is compact, HMC converges.
- If  $\mathcal{M}$  is non-compact, after mixed with a radial Metropolis(provided there is radial direction), HMC converges.

- 1 Background: Harris' theorem
- 2 Convergence proof for HMC

# Convergence of Markov chains

What do we mean by convergence?

## Banach fixed-point theorem

If  $(X, d)$  is a complete metric space and the transition  $\mathcal{P} : X \rightarrow X$  is a contraction mapping,

$$d(\mathcal{P}\mu, \mathcal{P}\nu) \leq a \cdot d(\mu, \nu)$$

for some  $a \in [0, 1)$  and  $\forall \mu, \nu \in X$ , then there is a unique fixed-point  $\tilde{\mu}$  such that  $\lim_{n \rightarrow \infty} \mathcal{P}^n \mu = \tilde{\mu} \quad \forall \mu \in X$ .

So one has to prepare

- a metric on the space of probability measures.
- show  $\mathcal{P}$  is a contraction on it.

# Compact spaces: Doeblin's condition

A sufficient condition for convergence on compact spaces is

## Doeblin's condition

If  $\exists \alpha \in (0, 1)$  and a probability measure  $\nu$  such that

$$\mathcal{P}(x, \cdot) \geq \alpha \nu(\cdot) \quad \forall x \in \mathcal{M}$$

then the Markov chain converges geometrically.

- Total Variation (TV) metric:

$$d(\mu, \nu) \equiv \|\mu - \nu\|_{\text{TV}} = \sup_{A \in \mathcal{B}(\mathcal{M})} |\mu(A) - \nu(A)|.$$

- It may be shown that  $\forall \mu, \nu \in \mathcal{X}$ :

$$\|\mathcal{P}\mu - \mathcal{P}\nu\|_{\text{TV}} \leq (1 - \alpha) \cdot \|\mu - \nu\|_{\text{TV}}$$

Not able to construct Doeblin's condition on the whole non-compact  $\mathcal{M}$  since

$$1 = \int_{\mathcal{M}} \mathcal{P}(x, \mathcal{M}) \cdot \mu_V(dx) \geq \alpha \nu(\mathcal{M}) \cdot \mu_V(\mathcal{M})$$

and the volume  $\mu_V(\mathcal{M})$  can be infinite.

# Harris' theorem

Hairer and Mattingly gave an elegant simplification of Harris theorem<sup>1</sup>.

## Geometric Drift Condition (GDC)

There is a Lyapunov function  $L : \mathcal{M} \rightarrow [0, \infty)$ ,  $\gamma \in (0, 1)$ , and  $K \geq 0$  such that  $\forall x \in \mathcal{M}$  we have

$$(\mathcal{P}L)(x) \leq \gamma \cdot L(x) + K.$$

- if  $\gamma \in [0, 1]$ , we say **weak GDC**.

## Doebelin's Condition (DC)

$\exists \alpha \in (0, 1)$ , a probability measure  $\nu$ , and a *small set*  $\mathcal{C} = \{x \in \mathcal{M} : L(x) \leq R\}$

where  $R > \frac{2K}{1-\gamma}$ , such that

$$\inf_{x \in \mathcal{C}} \mathcal{P}(x, \cdot) \geq \alpha \nu(\cdot).$$

- use a more simple condition:

$$\inf_{x, y \in \mathcal{C}} P(x \rightarrow y) \geq \alpha.$$

<sup>1</sup>Martin Hairer and Jonathan C. Mattingly (2011). "Yet Another Look at Harris' Ergodic Theorem for Markov Chains". In: *Seminar on Stochastic Analysis, Random Fields and Applications VI*. ed. by Robert Dalang, Marco Dozzi, and Francesco Russo. Basel: Springer, pp. 109–117. ISBN: 978-3-0348-0021-1.

- 1 Background: Harris' theorem
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# Introduction

HMC assigns each degree of freedom a fictitious momentum:

$$q \in \mathcal{M} \longrightarrow (q, p) \in T^*\mathcal{M}$$

The cotangent bundle  $T^*\mathcal{M}$  admits a symplectic structure because

- $\exists$  Liouville one-form:  $\exists \theta \in \Lambda^1(T^*\mathcal{M})$  with  $\beta^*\theta = \beta$ ,  $\forall \beta \in \Lambda^1(\mathcal{M})$ .
- $\exists$  a closed, non-singular fundamental two-form  $\omega$ :

$$\omega \equiv -d\theta, \quad d\omega = 0, \quad \det \omega \neq 0.$$

Then for every smooth function  $F$ , there is a unique Hamiltonian vector field  $\hat{F}$  such that

$$\omega(\hat{F}, \cdot) = -dF.$$

Trajectories, denoted as  $\sigma_{\hat{F}}$ , are local flows tangential to  $\hat{F}$ .

# Doebelin's condition for probability density

## Probability Densities

A probability density is usually just the Radon–Nikodym derivative of the transition probability, but sometimes this needs to be extended to a distribution (generalized function).

Measure of  $T^*\mathcal{M}$  is the volume form of the phase space:

$$\text{Vol} \equiv \omega^n.$$

Define probability densities:

$$P(x \rightarrow y) \equiv \frac{d\mathcal{P}(x, \cdot)}{d\text{Vol}}(y), \quad Q(y) \equiv \frac{d\nu}{d\text{Vol}}(y).$$

Then  $\forall x, y \in \mathcal{C}$ :

$$P(x \rightarrow y) \geq c > 0 \iff P(x \rightarrow y) \geq \alpha Q(y) \iff \mathcal{P}(x, \cdot) \geq \alpha \nu.$$

# Doebelin's condition for probability density

It is convenient to use on  $T^*\mathcal{M}$  and  $\mathcal{M}$  that are invariant under transition:

- symplectomorphisms (canonical transformations) preserve the volume form:

$$\mathcal{L}_{\hat{V}, \hat{T}} \text{Vol} = 0.$$

- $\hat{T}$  is an isometry: Riemannian measure  $\mu_g$  is preserved.

As a result, the extended target distribution

$$\int_{\text{Vol}} e^{-H} = \int_{\text{Vol}} e^{-(V+T)}$$

has well-defined state density  $e^{-H}$ , and after integration over momentum:

$$\int_{\text{Vol}} e^{-(T+V)} \Rightarrow \int_{\mu_g} e^{-V}$$

also has well-defined  $e^{-V}$ .

The algorithm we use:

① (Partial) Momentum Refreshment

$$S_{\text{MR}} : (q, p) \mapsto (q', p') = p \cdot \cos \theta + \eta \cdot \sin \theta, \quad \eta \sim \mu_G.$$

② Molecular Dynamics Monte Carlo ( $S_{\text{MDMC}}$ ) Which is made up of

- A Hamiltonian trajectory

$$S_{\text{MD}} : (q, p) \mapsto (q', p') = \sigma(t).$$

- A Metropolis accept/reject test  $S_{\text{MC}}$ .
- A momentum flip if rejected:

$$S_{\text{Flip}} : (q, p) \mapsto (q, -p).$$

# Algorithm

We use the Leapfrog (Verlet, Störmer) integrator  $S_{\text{LF}}$  to approximate Hamiltonian dynamics  $S_{\text{MD}}$ ; given a step size  $\tau$ , it is

$$S_{\text{MD}} = S_{\text{LF}} \equiv \sigma_{\hat{V}} \left( \frac{\tau}{2} \right) \circ \sigma_{\hat{T}} (\tau) \circ \sigma_{\hat{V}} \left( \frac{\tau}{2} \right).$$

Kinetic energy  $T$  is naturally defined by the inverse Riemannian metric

$$T(q, p) \equiv \frac{1}{2} g_q^{-1}(p, p).$$

Thus the Gibbs sampler of  $S_{\text{MR}}$  is the distribution

$$\mu_G(A) \propto \int_A e^{-T(q, \eta)} d\eta.$$

# Leapfrog on the cotangent bundle

Levi-Civita connection  $\nabla$ :

$$\begin{aligned} \nabla g &= 0. \\ \nabla_X Y - \nabla_Y X - [X, Y] &= 0, \quad \forall X, Y \in \mathfrak{X}(\mathcal{M}). \end{aligned}$$

$\nabla$  is an Ehresmann connection:

$$T_x T^* \mathcal{M} = \mathcal{V}_x \oplus \mathcal{H}_x.$$

Denote  $\sharp$  the musical isomorphism of  $g$ , we have:

- $\hat{V}$  is vertical:

$$\hat{V} = (0, -dV) \quad \sigma_{\hat{V}}(t) : (q, p) \mapsto (q, p - t \cdot dV_q).$$

- $\hat{T}$  is horizontal:

$$\hat{T} = (p^\sharp, 0) \quad \sigma_{\hat{T}}(t) : (q, p) \mapsto (\exp_q(t \cdot p^\sharp), p'), \quad T(x) = T(x').$$

# Doebelin's condition for HMC

So, An update is:

$$(q_0, p_0) \xrightarrow{S_{MR}} (q_0, p_1) \xrightarrow{\sigma_{\hat{v}}} (q_0, p_2) \xrightarrow{\sigma_{\hat{t}}} (q_1, p_3) \xrightarrow{\sigma_{\hat{v}}} (q_1, p_4) \xrightarrow{S_{MR}} (q_1, p_5)$$

The step  $S_{MC} \circ S_{Flip}$  after  $(q_1, p_4)$  is not shown explicitly.

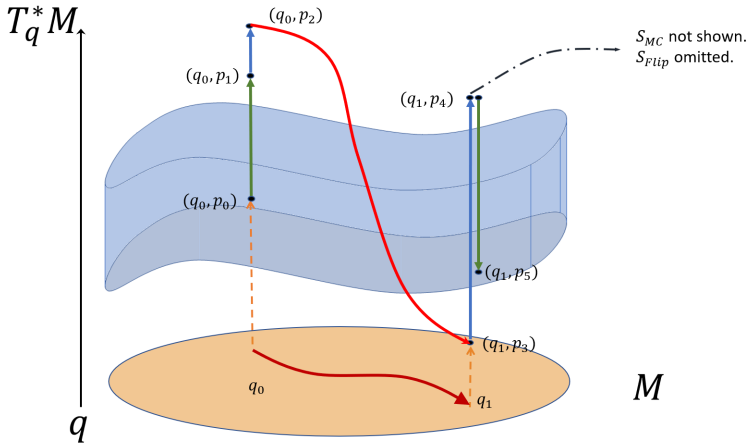
## small set

The Lyapunov function is chosen to be Hamiltonian:  $L \equiv H$ .

The small set is:

$$\mathcal{C} = \{x \in T^*\mathcal{M} \mid H(x) \leq V_R\}$$

# Doebelin's condition for HMC





① We have

- $|V(q_1) - V(q_0)| \leq V_R \Rightarrow |q_1 - q_0| \leq R.$
- $|dV_{q_0}| \leq M_1$

②  $\sigma_{\hat{\tau}}$  exists:

By Hopf-Rinow theorem, there is a geodesic connecting any two points on  $\mathcal{M}$ ,  $\sigma_{\hat{\tau}}$  is the unique horizontal lift of it.

③  $T(q_0, p_2) = T(q_1, p_3)$  is bounded, since

$$T = d(q_0, q_1)^2 / 2\tau^2$$

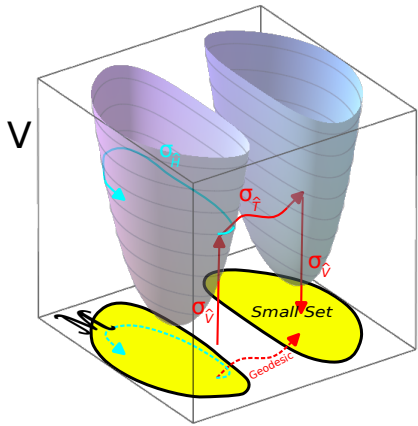
④  $p_2 = p_0 \cos \theta + \eta \sin \theta - \frac{\tau}{2} dV_{q_0} \Rightarrow T(\eta)$  and  $e^{-T(\eta)}$  bounded.

⑤ As a result, the probability density is bounded by

$$P(x \rightarrow y) \geq c = \exp \left\{ \frac{-2}{\sin^2 \theta} \left[ \frac{R^2}{2\tau^2} + \cos^2 \theta V_R + \frac{\tau^2}{4} M_1^2 \right] \right\} \cdot e^{-2V_R},$$

the multiplication of probability densities from two  $S_{MR}$  and a Metropolis test.

# Leapfrog integrator



Reasons for using a single Leapfrog step:

- When  $\mathcal{C}$  disconnected,  $\sigma_{\hat{T}}$  can join state between subsets.  
This will not work if use exact integrator  $\sigma_{\hat{H}}$ .
- A trajectory consists of a random number of Leapfrog steps, and there is a positive probability of taking a single step.
- This depends on ability of the algorithm to cross a potential barrier, HMC was not designed to deal with such barriers.

# Geometric drift condition: Compact $\mathcal{M}$

- No need for Harris' theorem if total momentum refreshment.
- However in general we must consider the non-compact phase space  $T^*\mathcal{M}$  as the state space; e.g., when partial momentum refreshment is used.

## Lyapunov function $L$

Choose the Lyapunov function to be the Hamiltonian,  $L = H$ . In general it is always minus the logarithm of the target distribution.

The strategy of our proof is

- ① Momentum Refreshment satisfies the **strong GDC**.
- ② Molecular Dynamics satisfies **weak GDC**.
- ③ Thus combining them HMC satisfies **strong GDC** on compact  $\mathcal{M}$ .

# Generalized Drift Condition for compact $\mathcal{M}$

$\mathcal{M}$  is compact and  $V$  is smooth, so must be bounded  $V \leq V_{\max}$ .

- 1 Partial momentum refreshment ( $\mathcal{P}_{\text{MR}}$ ) satisfies the **strong GDC**

$$\begin{aligned}
 (\mathcal{P}_{\text{MR}}H)(q, p) &= \langle H(q, p) \rangle_{\eta} \\
 &\propto \int_{\Omega} [T(q, S_{\text{MR}}(p)) + V(q)] e^{-T(\eta)} d\eta \\
 &= V(q) + (\cos \theta)^2 T(q, p) + (\sin \theta)^2 \\
 &= (\cos \theta)^2 H(q, p) + (\sin \theta)^2 (1 + V(q)) \\
 &\leq (\cos \theta)^2 H(q, p) + (\sin \theta)^2 (1 + V_{\max}).
 \end{aligned}$$

This also works for pseudofermions, since they are generated using a Gibbs sampler (heatbath) from a distribution with exponentially small tails.

# Generalized Drift Condition for compact $\mathcal{M}$

- ②  $\mathcal{P}_{\text{MD}}$  satisfies **weak GDC**.

## Weak Generalized Drift Condition for the Metropolis Algorithm

In general any Metropolis algorithm satisfies the **weak GDC** with minus log probability as the Lyapunov function.

Let  $\tilde{x} = (\tilde{q}, \tilde{p}) = S_{\text{MD}}(x)$ , then the acceptance rate is

$$\mathcal{A}(x, \tilde{x}) = \min \left( 1, e^{-H(\tilde{x})+H(x)} \right) = \min \left( 1, e^{-\delta H} \right).$$

Thus we have

$$\begin{aligned} (\mathcal{P}_{\text{MD}}H)(x) &= \mathcal{A} \cdot H(\tilde{x}) + (1 - \mathcal{A}) \cdot H(x) \\ &= H(x) + \mathcal{A} \cdot \delta H. \end{aligned}$$

The term  $\mathcal{A} \cdot \delta H$  is bounded from above since

- If  $\delta H \leq 0$  then  $\mathcal{A} \cdot \delta H = \delta H \leq 0$ .
- If  $\delta H > 0$  then  $\mathcal{A} \cdot \delta H = e^{-\delta H} \delta H \leq 1/e$ , the maximum value being attained at  $\delta H = 1$ .

# Generalized Drift Condition for compact $\mathcal{M}$

- 3 The combination of steps satisfy the **strong GDC**.  
If a bounded number of transitions  $\{\mathcal{P}_i\}$  with  $i = 1, \dots, n$  all satisfy the **weak GDC**, and furthermore one of them  $\mathcal{P}_k$  satisfies the **strong GDC**, then the composite transition satisfies the **strong GDC** whose parameters are

$$\gamma = \gamma_k, \quad K = \sum_i K_i.$$

Thus HMC on a compact Riemannian manifold satisfies the **strong GDC**.

# Drift Condition on non-compact $\mathcal{M}$

What goes wrong in the non-compact case?

- Doeblin's Condition is fine.
- previous results, such as **weak GDC** for Metropolis still hold.
- $V$  is no longer bounded thus  $S_{\text{MR}}$  merely satisfies the **weak GDC**

$$\begin{aligned}(\mathcal{P}_{\text{MR}}H)(q, p) &= V(q) + (\cos \theta)^2 T(p) + (\sin \theta)^2 \\ &= H(q, p) + \sin^2 \theta (1 - T(p)),\end{aligned}$$

We fix this by introducing a new Markov step that has the desired fixed-point distribution and satisfies the **strong GDC** by construction. It is a Metropolis algorithm in the radial direction.

# Radial Metropolis Algorithm

The algorithm is on the base manifold  $\mathcal{M}$ . With a reference point  $q_0$  as the origin, the radius is defined as the distance  $r_q \equiv d(q, q_0)$ , the complementary angular direction is denoted by  $\theta \in \Omega_\theta$ , so we have the parameterization  $q = (r, \theta)$ .

Define a forward step  $f : r \rightarrow f(r) = R_f$  and the corresponding backward step  $b : r \rightarrow g(r) = R_b$  such that  $b = f^{-1}$ . Then, the algorithm works as follows

- 1  $r \rightarrow R_f$  or  $r \rightarrow R_b$  with equal probability  $= \frac{1}{2}$ .
- 2 Apply a Metropolis test with the acceptance rate  $\mathcal{A} = \min(1, e^{-\delta V})$ .



# GDC for Radial Metropolis

At angle  $\theta_0$ . Denote the acceptance rate  $\mathcal{A}_x(r \rightarrow R_x) = \min(1, e^{-V(R_x)+V(r)} J(R_x, r))$ , transition on  $V$  is:

$$(\mathcal{P}_r V)(r) = \frac{1}{2} \sum_{x \in \{f, b\}} \{V(R_x) \mathcal{A}_x + V(r) (1 - \mathcal{A}_x)\}$$

Three conditions sufficient for Radial Metropolis to satisfy **strong GDC**:

- 1  $\exists \tilde{R}$  such that  $e^{-V(R_f)+V(r)} J(R_f, r) \leq 1 \leq e^{-V(R_b)+V(r)} J(R_b, r)$  for all  $r > \tilde{R}$ .
- 2 Backward step shrinks  $V$ :  $\exists \rho \in (0, 1)$  such that  $\forall r \geq \tilde{R}$  one has  $V(R_b) \leq \rho V(r) + N$ .
- 3  $\exists M \geq 0$  such that  $J(R_f, r) \delta V \cdot e^{-\delta V} \leq M$ .

Under these requirements

$$\begin{aligned}(\mathcal{P}_r V)(r) &= \frac{1}{2} \sum_{x \in \{f, b\}} \{V(R_x) \mathcal{A}_x + V(r) (1 - \mathcal{A}_x)\} \\ &= \frac{1}{2} \left\{ J(R_f, r) \delta V e^{-\delta V} + V(r) + V(R_b) \right\} \\ &\leq \frac{1 + \rho}{2} V(r) + M + N \\ &= \gamma V(r) + K.\end{aligned}$$

We now provide a choice of forward/backward steps that meet these requirements.

# Radial Metropolis: polynomial potential

Case 1:  $V(r) = kr^\alpha + o(r^\alpha)$ .

- Forward step:  $r \rightarrow R_f = (1 + \epsilon)r$ ,
- Backward step:  $r \rightarrow R_b = r/(1 + \epsilon)$ .

All three conditions met, with parameters:

- 1  $\tilde{R} \geq \left\{ \frac{\log(1 + \epsilon)}{k(1 - (1 + \epsilon)^{-\alpha})} \right\}^{1/\alpha}$ .
- 2  $\gamma = \frac{1}{(1 + \epsilon)^\alpha}$ .
- 3  $K = (1 + \epsilon)/e$ .

# Example: $\phi^4$

Consider the lattice action with volume  $N$  and  $n$  dimension of  $\phi$  (thus  $\mathcal{M} = \mathbb{R}^{N \times n}$ ):

$$S = \sum_{x,i} \frac{1}{2} |\nabla_\mu \phi_{x,i}|^2 + \frac{1}{2} m^2 |\phi_{x,i}|^2 + \frac{\lambda}{4!} (|\phi_{x,i}|^2)^2.$$

Set a basis  $(\theta, r) \in \mathbb{R}^{N \times n}$  such that  $\phi_{x,i} = f_{x,i}(\theta)r$  and  $\sum_{x,i} |f_{x,i}(\theta)|^2 = 1$ , so:

$$S = k_1(\theta)r^4 + k_2(\theta)r^2.$$

# Radial Metropolis: logarithmic potential

Case 2:  $V(r) = \beta \log r + o(\log r)$ .

$\beta \geq D - 1 \geq 0$  for normalization

- Forward step:  $R_f = r(1 + \epsilon \cdot r)^\delta$ ,
- Backward step:  $r = R_b(1 + \epsilon \cdot R_b)^\delta$ .

All three conditions are met, with parameters:

- 1  $\tilde{R}_b \geq \frac{1}{\epsilon} \left\{ \left( (1 + \delta)^{\frac{1}{\beta-1}} - 1 \right)^{1/\delta} \right\}$
- 2  $\gamma = \frac{1}{\delta}$ .
- 3  $K = \frac{\beta(1+\delta)}{(\beta-1)e}$ .

# Radial Metropolis: uniform GDC

What we have done so far: **strong GDC** in any direction  $\theta_0$  by radial Metropolis.

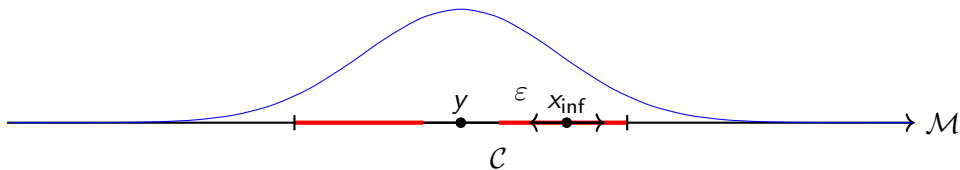
What we need: **strong GDC** of the whole space.

It requires combine the GDCs for all angular directions and obtain one single GDC bound. Fortunately  $\Omega_\theta$  is compact, at least in finite dimensional spaces, so we have the following:

For a family of strong drift conditions along radial directions with  $\gamma(\theta) \in (0, 1)$  and  $K(\theta) > 0$  are continuous functions of  $\theta \in \Omega_\theta$  for a compact state subspace  $\Omega$ , there exist a constant  $\gamma \in [0, 1)$  and a constant  $K > 0$  such that they are maxima of the corresponding functions at some  $\theta$ , hence the family of the **strong GDCs** yields uniformly a strong drift condition with  $\gamma$  and  $K$ :

$$(\mathcal{P}_r L)(r, \theta) \leq \gamma L(r, \theta) + K.$$

Thank you !



If the  $\mathcal{C}$  chosen by GDC has  $R > \varepsilon$ ,  $\inf_{x,y} P(x \rightarrow y)$  vanishes, if  $R \leq \varepsilon$  it is fine.