Understanding MCMC Dynamics as Flows on the Wasserstein Space

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INTRODUCTION

Known before: Langevin Dynamics (LD) = gradient flow of KL on the Wasserstein space (Jordan *et al.*, 1998).

This work: general MCMC = fGH flow of KL on the Wasserstein space of an fRP manifold,

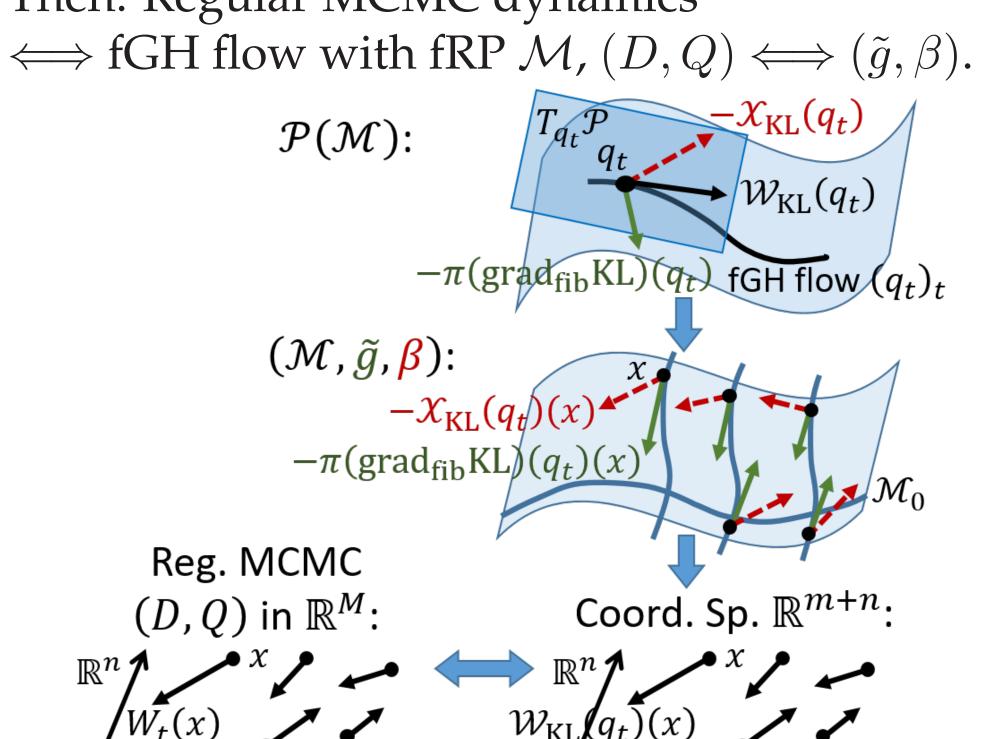
- so the behavior of a general MCMC is clear;
- so more MCMCs could inspire more ParVIs.

MCMC AS FGH FLOW

Theorem 5. (The unified framework) Fiber-Riemannian Poisson (fRP) manifold: $(\mathcal{M}, \tilde{g}, \beta)$. Fiber-Grad. Hamiltonian (fGH) flow on $\mathcal{P}(\mathcal{M})$:

$$\mathcal{W}_{\mathrm{KL}_p} := -\pi(\operatorname{grad}_{\mathrm{fib}} \mathrm{KL}_p) - \mathcal{X}_{\mathrm{KL}_p},$$
$$\left(\mathcal{W}_{\mathrm{KL}_p}(q)\right)^i = \pi_q\left((\tilde{g}^{ij} + \beta^{ij})\partial_j \log(p/q)\right).$$

Then: Regular MCMC dynamics



PRELIMINARY

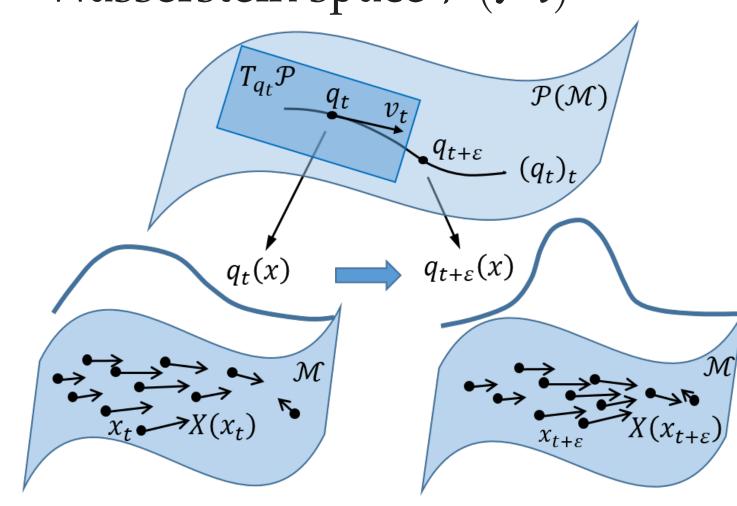
• The complete recipe of general MCMC dynamics on \mathbb{R}^M (Ma et al., 2015)

$$dx = V(x) dt + \sqrt{2D(x)} dB_t(x),$$

$$V^{i}(x) = \frac{1}{p(x)} \partial_{j} \left(p(x) \left(D^{ij}(x) + Q^{ij}(x) \right) \right), \tag{1}$$

 $D_{M\times M}$: pos. semi-def.; $Q_{M\times M}$: skewsymm.

• Wasserstein space $\mathcal{P}(\mathcal{M})$



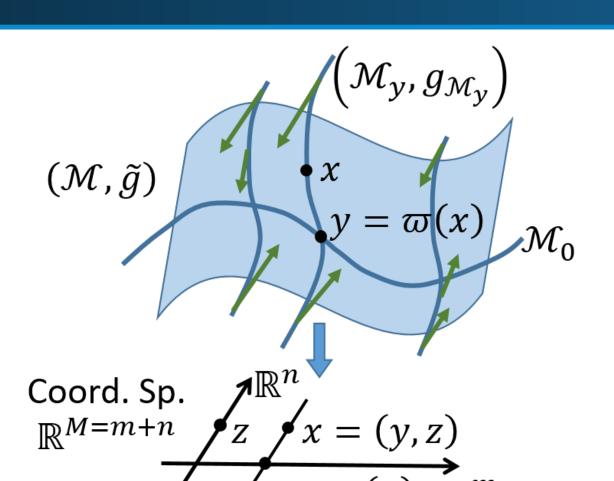
Tangent vector $v \Leftrightarrow \text{vector field } X \text{ on } \mathcal{M}$.

- Gradient flow on $\mathcal{P}(\mathcal{M})$
- Riemannian structure: $\langle X, Y \rangle_{T_{\alpha}\mathcal{P}} = \mathbb{E}_{q(x)}[\langle X(x), Y(x) \rangle_{T_x\mathcal{M}}],$ $\langle u,v\rangle_{T_x\mathcal{M}}=g_{ij}(x)u^iv^j$, (g_{ij}) : pos. def.
- Ortho. proj. $\pi_q: \mathcal{L}_q^2 \to T_q \mathcal{P}$ preserves distribution evolution.
- $\operatorname{grad}_{\mathcal{P}(\mathcal{M})} \operatorname{KL}_p(q) = \operatorname{grad}_{\mathcal{M}} \log(q/p) = g^{ij} \partial_j \log(q/p) \partial_i$.
- Hamiltonian flow on $\mathcal{P}(\mathcal{M})$
- Poisson structure: $\{F_f, F_h\}_{\mathcal{P}(\mathcal{M})} := F_{\{f,h\}_{\mathcal{M}}}$ $\{f,h\}_{\mathcal{M}} = \beta(\mathrm{d}f,\mathrm{d}h) = \beta^{ij}\partial_i f\partial_j h, F_f[q] := \mathbb{E}_q[f].$ (β^{ij}) : skew-symm., Jacobi identity.
- Hamiltonian flow: $\mathcal{X}_F(q) = \pi_q(X_f) = \pi_q(\beta^{ij}\partial_j f\partial_i)$.

TECHNICAL DEVELOPMENTS

Lemma 1. MCMC dynamics Eq. (1) with symm. D is equiv. to $dx = W_t(x)dt$, $(W_t)^i(x) = D^{ij}(x) \partial_j \log(p(x)/q_t(x)) +$ $Q^{ij}(x) \partial_j \log p(x) + \partial_j Q^{ij}(x)$.

Lemma 2. $\mathcal{X}_{\mathrm{KL}_p}(q) = \pi_q(X_{\log(q/p)})$, where $(X_{\log(q/p)}(x))^{i} = \beta^{ij}(x) \partial_{j} \log(q(x)/p(x)).$



Def. 3. Fiber-Riemannian manifold: a fiber bundle with a Riemannian structure $g_{\mathcal{M}_y}$ on each fiber \mathcal{M}_y .

• Fiber-gradient $(\operatorname{grad}_{\operatorname{fib}} f(x))^i = \tilde{g}^{ij}(x) \, \partial_j f(x), \quad 1 \leq i, j \leq M,$

$$(\tilde{g}^{ij}(x)) := \begin{pmatrix} 0_{m \times m} & 0_{m \times n} \\ 0_{n \times m} & ((g_{\mathcal{M}_{\varpi(x)}}(z))^{ab})_{n \times n} \end{pmatrix}.$$

• Fiber-gradient on $\mathcal{P}(\mathcal{M})$: $\left(\operatorname{grad}_{\operatorname{fib}} \operatorname{KL}_{p}(q)(x)\right)_{M} = \left(\tilde{g}^{ij}(x) \partial_{j} \log \left(q(x)/p(x)\right)\right)_{M}.$

MCMCs under the Framework

Type 1: D is non-singular (m = 0).

- \mathcal{M}_0 degenerates, \mathcal{M} is the unique fiber.
- fGH flow = grad. flow + Ham. flow, grad. flow: min. KL_p on $\mathcal{P}(\mathcal{M})$. Ham. flow: conserves KL_p on $\mathcal{P}(\mathcal{M})$. • Robust to stochastic gradient (SG).
- $\mathcal{M}_0 = \mathcal{M}$, fibers degenerate.
 - fGH flow = Ham. flow.

Type 2: D = 0 (n = 0).

• Fragile against SG: no stablizing forces (fiber-gradient flows)

Type 3: $D \neq 0$ and D is singular $(m, n \geq 1)$.

- Non-degenerate \mathcal{M}_0 and \mathcal{M}_y .
- fGH = fib. grad. + Ham., fib. grad.: min. $\mathrm{KL}_{p(\cdot|y)}(q(\cdot|y))$ on each fiber $\mathcal{P}(\mathcal{M}_y)$. Ham.: conserves KL_p on $\mathcal{P}(\mathcal{M})$ and helps mixing/exploration.
- Robust to SG (SG appears on each fiber).

SIMULATION AS PARVIS

Samples from $q_t \in \mathbb{R}^m$

Deterministic dynamics of SGHMC: By Lemma 1 (pSGHMC-det):

$$\begin{cases} \frac{\mathrm{d}\theta}{\mathrm{d}t} = \Sigma^{-1}r, \\ \frac{\mathrm{d}r}{\mathrm{d}t} = \nabla_{\theta}\log p(\theta) - C\Sigma^{-1}r - C\nabla_{r}\log q(r). \end{cases}$$

By Theorem 5 (pSGHMC-fGH):

$$\begin{cases} \frac{\mathrm{d}\theta}{\mathrm{d}t} = \Sigma^{-1}r + \nabla_r \log q(r), \\ \frac{\mathrm{d}r}{\mathrm{d}t} = \nabla_\theta \log p(\theta) - C\Sigma^{-1}r - C\nabla_r \log q(r) - \nabla_\theta \log q(\theta). \end{cases}$$

Estimate $\nabla \log q$ using ParVI techniques, e.g., Blob (Chen et al., 2018).

EXPERIMENTS

