# Geometry of Measure-Preserving Flows and Hamiltonian Monte Carlo

Alessandro Barp (with Girolami, Betancourt, Kennedy, Lelievre...)
July 27, 2020

Imperial College London, University of Cambridge, Alan Turing Institute

#### Plan

- 1. Sampling a Measure via Measure-preserving Continuous Flows
- Euclidean Measure-preserving Diffusions; Connections with Poisson mechanics
- 3. Inspire Geometry of Smooth Measures
- 4. Geometry of Measure-preserving Flows
- 5. Measure-preserving Flows Vs Mechanics
- 6. Hamiltonian Monte Carlo
- 7. Geometric Integration and Implementation of HMC

# Sampling Smooth Measures on Manifolds

#### Aim

Construct efficient sampling methods on manifolds for unnormalised smooth distributions using Measure-Preserving Flows

• Given a target  $P \propto p_{\infty} \mu_{\mathcal{M}} = e^{-V} \mu_{\mathcal{M}}$  on  $\mathcal{M}$ , we want to generate a "sample"  $(X_i)_{i=1}^N$  (e.g. MCMC), to approximate

$$P \approx P_N \equiv \frac{1}{N} \sum_{i=1}^N \delta_{X_i}$$

• Usually want a.s. narrow/weak\* convergence  $P_N \to P$  to approximate expectation

$$\mathbb{E}[f] \equiv \int f \mathrm{d}P \approx \frac{1}{N} \sum_{i=1}^{N} f(X_i)$$

- Build  $(X_i)$  using P-preserving flows (dynamics, mechanics, diffusions)
- Examples: Fisher-Bingham distributions on Stiefel manifolds for directional statistics/principal component analysis, canonical distributions in molecular dynamics on holonomic manifold, distributions on covariances and Hermitian positive matrices for learning spectral density matrix, discrete actions on gauge groups...

#### Monte Carlo Methods

Two standard strategy to build samplers:

• Suppose  $S: \mathcal{M} \to \mathcal{M}$  is a P-preserving, and  $\Psi_{\delta t}: \mathcal{M} \to \mathcal{M}$  is S-reversible:

$$\Psi_{\delta t}^{-1} = S \circ \Psi_{\delta t} \circ S^{-1}$$

MCMC: Given  $q^{\ell} \in \mathcal{M}$ :

- 1.  $q_* \leftarrow \Psi_{\delta t}(q^{\ell})$
- 2. set  $q^{\ell+1} \leftarrow q_*$  with probability min  $(1, |\mathcal{J}(P, \Psi_{\delta t})|(q^{\ell}))$ , else  $q^{\ell+1} \leftarrow \mathcal{S}(q^{\ell})$ ,

where 
$$|\mathcal{J}(P,\Psi_{\delta t})| \equiv \mathrm{d}\Psi_{\delta t}^* P/\mathrm{d}P$$

 Take a P-preserving diffusion and approximate it, or break it into tractable P-preserving components. For example, HMC

$$\underline{\mathrm{d}Q_t = G^{-1}P_t\mathrm{d}t, \qquad \mathrm{d}P_t = -\nabla V(Q_t)\mathrm{d}t - \gamma(Q_t)G^{-1}P_t\mathrm{d}t + \sigma(Q_t)\mathrm{d}W_t}$$
Hamiltonian Mechanics

OU heat bath

 Samplers are physics-inspired, but we do not "care" about physics (we care about ergodicity, rate of convergence...) • Under some  $L^1(dx)$ -integrability and uniqueness assumptions, a  $P \propto e^{-V} dx$  diffusion on  $\mathbb{R}^n$  has the form [Ma et al., 2015, Thm. 2]

$$dZ_t = -(Q\nabla V + D\nabla V) dt + \nabla \cdot (Q + D) dt + \sqrt{2D} dW_t, \qquad (1)$$

Q antisymmetric, D positive semi-definite (eg Langevin/metriplectic).

- Proof uses Fourier transforms to turn the question into a linear algebra problem in Fourier space.
- Not clear how to generalise this construction to manifolds.
- Intuitive generalisation to manifolds: start by replacing

$$dx \mapsto \mu_{\mathcal{M}}, \qquad Q\nabla V \mapsto X_V^{\mathcal{B}} \equiv \mathcal{B}^{\sharp}(dV),$$
$$\nabla \cdot Q \mapsto Y, \qquad \sqrt{2D} dW_t \mapsto Y_i \circ dW_t^i,$$

where  $\mathcal{B}^{\sharp} \in \text{Hom}(T^*\mathcal{M}, T\mathcal{M})$ .

## Measure Preserving Diffusions on Manifolds

• If  $dZ_t = Xdt + Y_i \circ dW_t^i$ , then

$$\mathcal{L}^*f = \mathsf{div}_{\mu_{\mathcal{M}}}\left(-\mathit{fX} + \tfrac{1}{2}\mathit{Y}_i(f)\mathit{Y}_i + \tfrac{1}{2}\mathit{f}\mathsf{div}_{\mu_{\mathcal{M}}}(\mathit{Y}_i)\mathit{Y}_i\right).$$

• Thus, to have  $\mathcal{L}^*e^{-V}=0$  when  $\mathcal{B}=0$ , we set

$$dZ_t = (X_V^{\mathcal{B}} + Y)dt + \left(-\frac{1}{2}Y_i(V)Y_i + \frac{1}{2}\operatorname{div}_{\mu_{\mathcal{M}}}(Y_i)Y_i\right)dt + Y_i \circ dW_t^i. \tag{2}$$

• The bracket diffusion (2) satisfies  $\mathcal{L}^*p_{\infty}=0$  if and only if Y satisfies

$$\operatorname{div}_{\mu_{\mathcal{M}}}(X_{p_{\infty}}^{\mathcal{B}} - p_{\infty}Y) = 0. \tag{3}$$

• This should hold for all  $p_{\infty}$ , so  $\operatorname{div}_{\mu_{M}}(Y) = 0$ , and

$$\operatorname{div}_{\mu_{\mathcal{M}}}(X_{p_{\infty}}^{\mathcal{B}}) = Y(p_{\infty}), \qquad \forall p_{\infty}. \tag{4}$$

- Y vector field, implies  $\mathcal{B} \equiv \mathcal{A}$  antisymmetric (as a rank two tensor)
- (4) is precisely the definition of the modular vector field  $Y \equiv X_{\mathcal{B}}^{\mu_{\mathcal{M}}}$  in Poisson mechanics [Dufour and Haraki, 1991, Weinstein, 1997]

$$\mathrm{d} Z_t = \underbrace{ \underbrace{ \underbrace{ \underbrace{ X_{\mathcal{N}}^{\mathcal{A}} \mathrm{d} t }_{e^{-V}\text{-preserving}} + \underbrace{ \beta^{-1} X_{\mathcal{A}}^{\mu_{\mathcal{M}}} \mathrm{d} t }_{\mu_{\mathcal{M}}\text{-preserving}} - \underbrace{ \underbrace{ \underbrace{ \underbrace{ \underbrace{ 2} \mathrm{div}_{\mu_{\mathcal{M}}} \mathrm{preserving} }_{\mu_{\mathcal{M}}\text{-preserving}} }^{e^{-\beta V} \mu_{\mathcal{M}}\text{-preserving}} }_{\mu_{\mathcal{M}}\text{-preserving}},$$

# **Canonical Geometry of Smooth Measures**

- $\bullet$  Is our generalisation complete? To answer we develop intrinsic geometry of target P
- Let P be smooth measure, locally  $P = f|\mathrm{d}x|$ . Denote by  $P^{\flat}$  the morphism  $P^{\flat}(X) \equiv i_X P$  on  $\mathfrak{X}^k(\mathcal{M})$ . If P positive, we have an inverse  $P^{\sharp}$  (R-N).
- The *P*-rotationnel of a *k*-vector field for some integer  $1 \le k \le n$  is defined as [Koszul, 1985]

$$\operatorname{\mathsf{curl}}_P \equiv P^\sharp \circ \operatorname{d} \circ P^\flat : \mathfrak{X}^k(\mathcal{M}) \to \mathfrak{X}^{k-1}(\mathcal{M}).$$

curl<sub>P</sub> ∘ curl<sub>P</sub> = 0, boundary operator. On vector fields, curl<sub>P</sub> = div<sub>P</sub>.
 Generalise

$$\nabla \cdot \nabla \times = 0, \qquad \delta = \star d \star.$$

- On bivectors: Modular field  $X_A^P = -\text{curl}_P(A)$ .
- ullet Canonical statistical calculus. Only depend on P up to normalisation.
- Smooth measure defines P-homology, which is isomorphic to the (twisted)
  de Rham cohomology 

  curl<sub>P</sub>-free fields can be represented as closed
  forms.

# Complete Recipe on Manifolds

• If  $dZ_t = Xdt + Y_i \circ dW_t^i$ , then

$$\mathcal{L}^*P = \mathsf{div}_P(\underbrace{\frac{1}{2}\mathsf{div}_P(Y_i)Y_i - X}_{\mathsf{Fokker-Plank \; current}})P,$$

so  $\mathcal{L}^*P = 0$  iff

$$\tfrac{1}{2}\mathsf{div}_P(Y_i)Y_i - X = \mathsf{curl}_P(\mathcal{A}) + P^\sharp(\gamma), \qquad \mathcal{A} \in \mathfrak{X}^2(\mathcal{M}), \gamma \in H^{n-1}_{dR}(\mathcal{M})$$

P-preserving diffusions

$$\mathrm{d}Z_t = \underbrace{-\mathsf{curl}_P(\mathcal{A})\mathrm{d}t}_{\mathsf{conservative}} + \underbrace{P^\sharp(\gamma)\mathrm{d}t}_{\mathsf{conservative}} + \underbrace{\frac{1}{2}\mathsf{div}_P(Y_i)Y_i\mathrm{d}t}_{\mathsf{dissipative}} + \underbrace{\frac{1}{2}\mathsf{div}_P(Y_i)Y_i\mathrm{d}t}_{\mathsf{dissipative}} + \underbrace{\frac{1}{2}\mathsf{div}_P(Y_i)Y_i\mathrm{d}t}_{\mathsf{Stratonovich noise}} + \underbrace{\frac{1}{2}\mathsf{div}_P(Y_i)Y_i\mathrm{d}t}_{\mathsf{dissipative}} + \underbrace{\frac{1}{2}\mathsf{div}_P(Y_i)Y_i\mathrm{d}t}_{\mathsf{Stratonovich noise}} + \underbrace{\frac$$

- Complete Recipe 

  ✓, canonical 

  ✓, no integrability assumption 

  ✓
- Compare with

$$dZ_t = -(Q\nabla V + D\nabla V) dt + \nabla \cdot (Q + D) dt + \sqrt{2D} dW_t.$$

## Measure Preserving Dynamics Vs Mechanics

Completeness is based on the fact that

$$\operatorname{\mathsf{ker}}\operatorname{\mathsf{div}}_P=\operatorname{\mathsf{curl}}_P(\mathfrak{X}^2(\mathcal{M}))\oplus P^\sharp(H^{\dim\mathcal{M}-1}_{dR}(\mathcal{M}))$$

 Potential Theory of Measures: P-preserving flow are "locally curled" correspond to a choice of "potential" A,

$$X = \text{curl}_P(A)$$
, just as  $F = -dV$ ,  $F = dA$ 

Many connections between P-flows and Hamiltonian mechanics

1. Locally,  $P \propto p_{\infty} |\mathrm{d}x|$ 

$$X|_U = \sum_{i < j} X_{\mathcal{A}^{ij}} + i_{\mathrm{d} \log \rho_{\infty}} \mathcal{A}$$

where 
$$X_{\mathcal{A}^{ij}} = \partial_j \mathcal{A}^{ij} \partial_i - \partial_i \mathcal{A}^{ij} \partial_j$$
.

2. If X, Y preserve P, then

$$[X,Y] = \operatorname{curl}_P(X \wedge Y),$$

just as symplectic vector fields.

## Measure Preserving Mechanics

In general we can decompose

$$\operatorname{curl}_{P}(\mathcal{A}) = \underbrace{\operatorname{curl}_{\mu_{\mathcal{M}}}(\mathcal{A})}_{\mu_{\mathcal{M}}\text{-preserving}} + \underbrace{i_{\operatorname{d}\log p_{\infty}}\mathcal{A}}_{p_{\infty}\text{-preserving}}.$$

- What potentials give rise to score-based P-preserving flows?
- Recall  $\operatorname{curl}_{\mu_{\mathcal{M}}}(\mathcal{A}) = -X_{\mathcal{A}}^{\mu_{\mathcal{M}}} : f \mapsto \operatorname{div}_{\mu_{\mathcal{M}}}(X_f^{\mathcal{A}}).$
- Thus  $\mu_{\mathcal{M}}$  is invariant measure for  $\mathcal{A}$ -mechanics

$$\{X_f^{\mathcal{A}} \equiv i_{\mathrm{d}f}\mathcal{A} : f \in C^{\infty}(\mathcal{M})\}$$

iff  $\operatorname{curl}_{\mu_{\mathcal{M}}}(\mathcal{A}) = 0$ ;  $\Longrightarrow$  space of  $\mu_{\mathcal{M}}$ -preserving  $\mathcal{A}$ -mechanics is  $\ker \operatorname{curl}_{\mu_{\mathcal{M}}}|_{\mathcal{X}^{2}(\mathcal{M})} = \operatorname{curl}_{\mu_{\mathcal{M}}}(\mathfrak{X}^{3}(\mathcal{M})) \oplus \mu_{\mathcal{M}}^{\sharp}(H_{dR}^{\dim \mathcal{M}-2}(\mathcal{M}))$ 

Machine Learning 2015 < Mathematical Physics 1887.

• Splitting Methods: if  $p_{\infty} = \prod_i e^{-V_j}$ 

$$\operatorname{curl}_{\rho_{\infty}\mu_{\mathcal{M}}}(\mathcal{A}) = i_{\operatorname{d}\log\rho_{\infty}}\mathcal{A} = -\sum_{i}i_{\operatorname{d}V_{j}}\mathcal{A},$$

no "Jacobian", MC is simply energy difference.

#### Hamiltonian Monte Carlo: Canonical Mechanics

• Given  $P=e^{-V}\mu_{\mathcal{M}}$ , where  $\mu_{\mathcal{M}}$  is Riemannian measure. Use mechanics to propose new sample by viewing V as a potential energy

$$\underbrace{m\ddot{q} = -\partial V}_{\text{Flat Newton}} \longrightarrow \underbrace{\frac{\nabla \dot{q}}{\mathrm{d}t} = -\nabla V}_{Riemannian \ Newton}$$

• 2<sup>nd</sup>-order, tangent bundle flow



Solution preserves

$$\mu_H \propto \mathrm{e}^{-H(q, \mathbf{v})} \omega_\flat^n \equiv \mathrm{e}^{-\frac{1}{2}\|\mathbf{v}\|_q^2 - V(q)} \omega_\flat^n, \quad \omega_\flat^n \text{ symplectic measure},$$
 on  $T\mathcal{M}$ , and

$$\mathsf{Proj}_*\mu_{\mathsf{H}} = \mathsf{P}.$$

ullet Flow of mechanics preserves  $\mu_H$ , projection of  $\mu_H$ -samples are P-samples

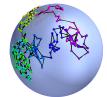
#### **Geodesic Integrators**

- A1: Hamiltonian Mechanics is a natural volume-preserving mechanics
- A2: velocity flip S(q, v) = (q, -v) preserves  $\mu_H$ , so if integrator  $\Psi_{\delta t}: T\mathcal{M} \to T\mathcal{M}$  is

S-reversible  $\Psi_{\delta t}^{-1} = S \circ \Psi_{\delta t} \circ S$ ; volume preserving  $(\Psi_{\delta t})_* \omega_{\flat}^n = \omega_{\flat}^n$ , then MDMC

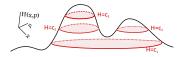
- Let  $z^* \equiv \Psi_{\delta t}(z^n)$
- accept  $z^*$  with probability min  $\left(1, e^{-(H(z^*)-H(z^n))}\right)$ . If accepted, then  $z^{n+1} \equiv z^*$ . Else  $z^{n+1} \equiv S(z^*)$ .
- A3: If we know geodesics of  $\mu_{\mathcal{M}}$ , can use geodesic integrators  $X_H = \frac{1}{2}X_V + X_T + \frac{1}{2}X_V$





#### Hamiltonian Monte Carlo

Ergodicity:  $\mathcal{A}$ -mechanics preserve energy, and we want small energy difference during numerical integration for good acceptance rate  $\longrightarrow$  but then we get stuck in level sets H=c

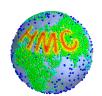


A4: We can simply add Gaussian heat bath to MDMC associated to lift

$$\mu_H = \pi^* P \wedge Gaussian.$$

and obtain

$$\mathsf{HMC} = \mathsf{MDMC} + \mathsf{heat} \; \mathsf{bath}$$



#### **Energy Conservation: Shadow Hamiltonian**

- Can use Mechanical Integrator: preserving energy, symmetries or  $\omega_{\flat}$  (cant have all three).
- A5: If symplectic:  $\Psi_{\delta t}^* \omega_{\flat} = \omega_{\flat}$ , using Hamilton-Jacobi theorem/Jacobi identity there exist nearby shadow Hamiltonian whose flow is  $\Psi_{\delta t} \implies$  acceptance-rate remains high
- Unlike "Theory of Numerical Integrators": we don't care about correct trajectories!
- A6: Theory of symplectic integrators:
  - Hamiltonian: splitting method:

$$H = \underbrace{ rac{1}{2} \| \cdot \|^2}_{ ext{geodesic flow}} + \underbrace{V}_{ ext{vertical gradient step}}, \qquad V = V_{ ext{hard}} + V_{ ext{easy}}$$

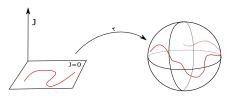
- ullet Lagrangian: discrete variational principle o symmetry for free
- Generating Functions and Hamilton-Jacobi PDE

$$F: T^*\mathcal{M} \to T^*\mathcal{M} \quad \text{is symplectic iff} \quad \mathrm{d}\iota_F^*\Xi = 0$$
 where  $\Xi \equiv \pi_1^*\Theta - \pi_2^*\Theta$ . Thus locally  $\iota_F^*\Xi = \mathrm{d}S$  
$$p = -\frac{\partial S}{\partial g}(q,Q), \qquad P = \frac{\partial S}{\partial Q}(q,Q).$$

ullet Shadow for Splitting + Invariant Measures  $\implies$  Unimodular Poisson

## Implementing HMC

- ullet Every potential on  $\mathcal{M}=\mathcal{G}/\mathcal{K}$  is a potential with symmetry on  $\mathcal{G}$
- Consider right action of  $\mathcal K$  on  $\mathcal G$ , momentum map  $J:\mathcal G imes \mathfrak g o \mathfrak k^*$
- If action is Hamiltonian and system K-invariant, reduced space is target space  $J^{-1}(0)/K \cong TM$



For geodesic orbit manifolds, all geodesics are homogeneous. For naturally reductive  $J^{-1}(0) = \mathcal{G} \times \mathfrak{p}$ , and HMC is straightforward [Barp et al., 2019].

- ullet For holonomic manifolds  $\mathcal{M}=f^{-1}(0)$ , can use RATTLE for kinetic step...
- ... but must add reversibility check! [Lelièvre et al., 2018]

Partition function of lattice QCD

$$Z = \int \prod_{x,\mu} dU_{\mu}(x) d\phi^{\dagger} d\phi e^{-S_{WG} - \phi^{\dagger}(DD^{\dagger})^{-1}\phi}.$$

Here  $U_{\mu}(x) \in \mathrm{SU}(3)$  is discretised gauge field,  $\mathrm{d}U_{\mu}(x)$  is Haar measure,  $\phi$  pseudofermions,  $S_{WG}$  is Wilson gauge action (discretisation of Yang-Mills action), D is Wilson-Dirac operator (discretised Dirac operator).

Introduce fictitious momenta on the links, to obtain

$$H = S_{WG} + \phi^\dagger (DD^\dagger)^{-1} \phi + \tfrac{1}{2} \sum_{\mathbf{x},\mu} \langle p_{\mathbf{x},\mu}, p_{\mathbf{x},\mu} \rangle_{\mathfrak{su}(3)} \,.$$

Need to construct mechanics on SU(3). Define

$$\omega \equiv -\mathrm{d}(p_i \pi^* \theta^i) = \underbrace{\pi^* \theta^i \wedge \mathrm{d} p_i}_{\text{usual "dx} \wedge \mathrm{d} p^\text{" term}} + \underbrace{\frac{1}{2} p_i c_{jk}^i \pi^* \theta^j \wedge \pi^* \theta^k}_{\text{additional non-abelian term}},$$

and use representations.

#### Riemannian Manifold HMC

• Target is posterior  $P = \rho_{post}(\theta|\omega)\mathrm{d}\theta$ . Want Riemannian metric on  $\mathcal M$  that locally matches Hessian of posterior

$$\Sigma_{post,\omega}( heta) \equiv -rac{\partial^2}{\partial heta^i \partial heta^j} \log 
ho_{post}( heta|\omega)$$

• Average over data (statistical manifold  $\phi(\theta) \equiv \rho(\omega|\theta) d\omega$ )

$$\int \Sigma_{post,\omega}(\theta) \rho(\omega|\theta) d\omega = \underbrace{\phi^* g^F}_{Fisher Matrix}(\theta) + \Sigma_{prior}(\theta)$$

• setting  $G(\theta) \equiv \phi^* g^F(\theta) + \Sigma_{\textit{prior}}$ , the target Hamiltonian of RMHMC is then

$$H(\theta, v) = -\log \rho_{post}(\theta|\omega) + \frac{1}{2}\log \det G(\theta) + \frac{1}{2}v^{\top}G(\theta)v.$$

- Fake reference measures... typically canonical (not necessarily geodesic)
- "Non-separable" Hamiltonian symmetry-break
- No manifold involved! Should be Statistical Model/Information Geometric HMC
- RM/Geodesic/Lagrangian Monte Carlo → just HMC

## **HMC** for Molecular Dynamics

- Typical Applications: Molecular constraints, Blue Moon Sampling, Thermodynamic Integration
- Molecular Constraints define holonomic manifolds: RATTLE/SHAKE but need reversibility check
- Blue Moon Sampling idea: microcanonical distribution  $(\mu_{mc,E})$

$$\mathbb{E}_{\mu_H}[f] = \frac{1}{\int_{\mathcal{F}} e^{-H} \omega^n} \int_{\mathbb{R}} \mathbb{E}_{\mu_{mc,E}}[f] e^{-E} \mathrm{d}(E) \mathrm{d}E.$$

• Thermodynamic Integration: Macroscopic states are often defined using reaction coordinates  $\xi: \mathcal{M} \to \mathbb{R}^m$ , with Free energy  $F: \mathbb{R}^m \to \mathbb{R}$ 

$$F \equiv -\frac{1}{\beta} \log \frac{\mathrm{d}(\pi^* \xi)_{\sharp} \mu_H}{\mathrm{d}(\mathrm{d} x)}.$$

Want to calculate energy difference

$$F(x_1) - F(x_0) = \int_0^1 \frac{\partial F}{\partial x^i} \big|_{\ell(t)} \frac{\mathrm{d} \ell^i}{\mathrm{d} t} \big|_t \mathrm{d} t, \qquad \frac{\partial F}{\partial x^i}(x) = \int_{\xi^{-1}(x)} \cdots$$



Barp, A., Kennedy, A., and Girolami, M. (2019).

Hamiltonian monte carlo on symmetric and homogeneous spaces via symplectic reduction.

arXiv preprint arXiv:1903.02699.



Dufour, J.-P. and Haraki, A. (1991).

Rotationnnels et structures de poisson quadratiques.

Comptes rendus de l'Académie des sciences. Série 1, Mathématique, 312(1):137–140.



Koszul, J.-L. (1985).

Crochet de schouten-nijenhuis et cohomologie.

Astérisque, 137:257-271.



Lelièvre, T., Rousset, M., and Stoltz, G. (2018).

Hybrid monte carlo methods for sampling probability measures on submanifolds.

arXiv preprint arXiv:1807.02356.



Ma, Y.-A., Chen, T., and Fox, E. (2015).

A complete recipe for stochastic gradient mcmc.

In Advances in Neural Information Processing Systems, pages 2917–2925.



Weinstein, A. (1997).

The modular automorphism group of a poisson manifold.

Journal of Geometry and Physics, 23(3-4):379–394.