

# Sampling probability measures on submanifolds

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## Objective

Let us be given a submanifold of  $\mathbb{R}^d$ :

$$\mathcal{M} = \left\{ q \in \mathbb{R}^d, \xi(q) = 0 \right\}$$

where  $\xi : \mathbb{R}^d \rightarrow \mathbb{R}^m$  is a given smooth function (with  $m < d$ ) such that

$$G(q) = [\nabla \xi(q)]^T \nabla \xi(q) \in \mathbb{R}^{m \times m}$$

is an invertible matrix for all  $q$  in a neighborhood of  $\mathcal{M}$ . The objective is to sample the probability measure:

$$\nu(dq) = Z_\nu^{-1} e^{-V(q)} \sigma_{\mathcal{M}}(dq), \quad Z_\nu = \int_{\mathcal{M}} e^{-V(q)} \sigma_{\mathcal{M}}(dq) < \infty,$$

where  $\sigma_{\mathcal{M}}(dq)$  is the Riemannian measure on  $\mathcal{M}$  induced by the scalar product  $\langle \cdot, \cdot \rangle$  defined in the ambient space  $\mathbb{R}^d$ .

## Motivation

Such problems arise in many contexts: constrained mechanical systems with noise, statistics, ...

One example is computational statistical physics: **free energy calculations**. If  $X \sim \rho$  where  $\rho(dq) = Z^{-1}e^{-V(q)} dq$ , then  $\xi(X) \sim \xi_{\#}\rho$ . Let us define  $A : \mathbb{R}^m \rightarrow \mathbb{R}$  by:

$$e^{-A(z)} dz = \xi_{\#}\rho(dz).$$

Then, using the co-area formula,

$$\nabla A(0) = \mathbb{E}_{\rho}(f(X) | \xi(X) = 0) = \int_{\mathcal{M}} f(q) \tilde{\nu}(dq)$$

where  $f = G^{-1}\nabla\xi \cdot \nabla V - \operatorname{div}(G^{-1}\nabla\xi)$  and

$$\tilde{\nu}(dq) = Z_{\tilde{\nu}}^{-1} e^{-\tilde{V}(q)} \sigma_{\mathcal{M}}(dq)$$

where  $\tilde{V}(q) = V(q) + \frac{\ln \det G(q)}{2}$ .

→ Thermodynamic integration.

# Plan

The constrained overdamped Langevin dynamics

The constrained Langevin dynamics

The reverse projection check

Beyond reverse projection check

## Step 1: the overdamped Langevin dynamics (1/3)

The constrained overdamped Langevin dynamics ( $W_t$  is a  $d$ -dimensional Brownian motion):

$$\begin{cases} dq_t = -\nabla V(q_t) dt + \sqrt{2}dW_t + \nabla \xi(q_t)d\lambda_t \\ d\lambda_t \in \mathbb{R}^m \text{ such that } \xi(q_t) = 0 \end{cases}$$

is ergodic with respect to  $\nu$ . It can indeed be rewritten as:

$$dq_t = \Pi(q_t) \circ (-\nabla V(q_t) dt + \sqrt{2}dW_t)$$

where  $\circ$  denotes the Stratonovitch product and

$$\Pi(q) = \text{Id} - \nabla \xi(q) G^{-1}(q) [\nabla \xi(q)]^T$$

is the orthogonal projector from  $\mathbb{R}^d$  to  $T_q\mathcal{M}$ . One can then use the divergence theorem on manifolds to prove that its unique invariant measure is  $\nu$  [Ciccotti, TL, Vanden-Einijden, 2008].

## Step 1: the overdamped Langevin dynamics (2/3)

Discretization of the constrained overdamped Langevin dynamics:

$$\begin{cases} q^{n+1} = q^n - \nabla V(q^n)\Delta t + \sqrt{2\Delta t}G_n + \nabla\xi(q_n)\lambda^n \\ \lambda^n \in \mathbb{R}^m \text{ such that } \xi(q^{n+1}) = 0 \end{cases}$$

where  $G_n \sim \mathcal{N}(0, \text{Id})$ .

*Remark:* By choosing  $V = \tilde{V}$ , an approximation of  $\nabla A(0)$  is given by the average of the Lagrange multipliers:

$$\lim_{T \rightarrow \infty} \lim_{\Delta t \rightarrow 0} \frac{1}{T} \sum_{n=1}^{T/\Delta t} \lambda^n = \nabla A(0).$$

## Step 1: the overdamped Langevin dynamics (3/3)

Time discretization implies a bias, which is of order  $\Delta t$ . Let  $\nu_{\Delta t}$  be the invariant measure for  $(q^n)_{n \geq 0}$ , then [Faou, TL, 2010]: for all smooth function  $\varphi : \mathcal{M} \rightarrow \mathbb{R}$ ,  $\exists C$ , for small  $\Delta t$ ,

$$\left| \int_{\mathcal{M}} \varphi d\nu_{\Delta t} - \int_{\mathcal{M}} \varphi d\nu \right| \leq C\Delta t.$$

The proof is based on expansions à la Talay-Tubaro.

How to eliminate the bias?

Metropolis-Hastings is not easy to apply since the probability to go from  $q^n$  to  $q^{n+1}$  does not have a simple analytical expression.

Idea: lift the problem to phase space in order to use the symmetry up to momentum reversal of the constrained Hamiltonian dynamics.

## Step 2: the Langevin dynamics (1/8)

Extended measure in phase space:

$$\mu(dq dp) = Z_{\mu}^{-1} e^{-H(q,p)} \sigma_{T^* \mathcal{M}}(dq dp)$$

where  $H(q, p) = V(q) + \frac{|p|^2}{2}$  and  $\sigma_{T^* \mathcal{M}}(dq dp)$  is the phase space Liouville measure on

$$T^* \mathcal{M} = \left\{ (q, p) \in \mathbb{R}^d \times \mathbb{R}^d, \xi(q) = 0 \text{ and } [\nabla \xi(q)]^T p = 0 \right\}.$$

The marginal of  $\mu$  in  $q$  is  $\nu$ . Indeed, the measure  $\mu$  rewrites:

$$\mu(dq dp) = \nu(dq) \kappa_q(dp)$$

where

$$\kappa_q(dp) = (2\pi)^{\frac{m-d}{2}} e^{-\frac{|p|^2}{2}} \sigma_{T_q^* \mathcal{M}}(dp)$$

with  $T_q^* \mathcal{M} = \left\{ p \in \mathbb{R}^d, [\nabla \xi(q)]^T p = 0 \right\} \subset \mathbb{R}^d$ .

*Remark:* Here and in the following, we assume for simplicity that the mass tensor  $M = \text{Id}$ . It is easy to generalize the algorithm and the analysis to the case  $M \neq \text{Id}$ .



## Step 2: the Langevin dynamics (2/8)

The constrained Langevin dynamics ( $\gamma > 0$  is the friction parameter)

$$\begin{cases} dq_t = p_t dt \\ dp_t = -\nabla V(q_t) dt - \gamma p_t dt + \sqrt{2\gamma} dW_t + \nabla \xi(q_t) d\lambda_t \\ \xi(q_t) = 0 \end{cases}$$

is ergodic with respect to  $\mu$ . Notice that  $[\nabla \xi(q_t)]^T p_t = 0$ .

It can be seen as the composition of two dynamics:

- the constrained Hamiltonian dynamics:

$$\begin{cases} dq_t = p_t dt \\ dp_t = -\nabla V(q_t) dt + \nabla \xi(q_t) d\lambda_t \\ \xi(q_t) = 0. \end{cases}$$

- the Ornstein-Uhlenbeck process on momenta:

$$\begin{cases} dq_t = 0 \\ dp_t = -\gamma p_t dt + \sqrt{2\gamma} dW_t + \nabla \xi(q_t) d\lambda_t \\ [\nabla \xi(q_t)]^T p_t = 0. \end{cases}$$

## Step 2: the Langevin dynamics (3/8)

Discretization of the Ornstein-Uhlenbeck process on momenta:  
**midpoint Euler** leaves the measure  $\kappa_{q^n}$  and thus  $\mu$  invariant:

$$\begin{cases} p^{n+1} = p^n - \frac{\Delta t}{2} \gamma (p^n + p^{n+1}) + \sqrt{2\gamma \Delta t} G^n + \nabla \xi(q^n) \lambda^n, \\ \nabla \xi(q^n)^T p^{n+1} = 0, \end{cases}$$

In the following, we denote one step of this dynamics by  
 $\Psi_{\Delta t}^{OU} : T^*\mathcal{M} \rightarrow T^*\mathcal{M}$ :

$$\Psi_{\Delta t}^{OU}(q^n, p^n) = (q^n, p^{n+1}).$$

*Remark:* The projection is always well defined, and easy to implement:

$$p^{n+1} = \Pi^*(q^n) \left( \frac{(1 - \Delta t \gamma / 2) p^n + \sqrt{2\gamma \Delta t} G^n}{1 + \Delta t \gamma / 2} \right)$$

where  $\Pi^*(q) = \text{Id} - \nabla \xi(q) G^{-1}(q) [\nabla \xi(q)]^T$  is the orthogonal projector from  $\mathbb{R}^d$  to  $T_q^*\mathcal{M}$ .

## Step 2: the Langevin dynamics (4/8)

Discretization of the constrained Hamiltonian dynamics (RATTLE):

$$\left\{ \begin{array}{l} p^{n+1/2} = p^n - \frac{\Delta t}{2} \nabla V(q^n) + \nabla \xi(q^n) \lambda^{n+1/2}, \\ q^{n+1} = q^n + \Delta t p^{n+1/2}, \\ \xi(q^{n+1}) = 0, \end{array} \right. \quad (C_q)$$

$$\left\{ \begin{array}{l} p^{n+1} = p^{n+1/2} - \frac{\Delta t}{2} \nabla V(q^{n+1}) + \nabla \xi(q^{n+1}) \lambda^{n+1}, \\ [\nabla \xi(q^{n+1})]^T p^{n+1} = 0, \end{array} \right. \quad (C_p)$$

where  $\lambda^{n+1/2} \in \mathbb{R}^m$  are the Lagrange multipliers associated with the position constraints  $(C_q)$ , and  $\lambda^{n+1} \in \mathbb{R}^m$  are the Lagrange multipliers associated with the velocity constraints  $(C_p)$ .

In the following, we denote one step of the RATTLE dynamics by  $\Psi_{\Delta t}^{\text{RATTLE}} : T^*\mathcal{M} \rightarrow T^*\mathcal{M}$ :

$$\Psi_{\Delta t}^{\text{RATTLE}}(q^n, p^n) = (q^{n+1}, p^{n+1}).$$

## Step 2: the Langevin dynamics (5/8)

Discretization of the constrained Langevin dynamics (Strang splitting):

$$\begin{cases} (q^n, p^{n+1/4}) = \Psi_{\Delta t/2}^{OU}(q^n, p^n) \\ (q^{n+1}, p^{n+3/4}) = \Psi_{\Delta t}^{RATTLE}(q^n, p^{n+1/4}) \\ (q^{n+1}, p^{n+1}) = \Psi_{\Delta t/2}^{OU}(q^{n+1}, p^{n+3/4}) \end{cases}$$

But there is still a bias due to time discretization...

## Step 2: the Langevin dynamics (6/8)

Let us denote by

$$S(q, p) = (q, -p)$$

the momentum reversal map and

$$\Psi_{\Delta t}(q, p) = S \left( \Psi_{\Delta t}^{\text{RATTLE}}(q, p) \right).$$

Fundamental properties of RATTLE: for  $\Delta t$  small enough,

- $\Psi_{\Delta t}(\Psi_{\Delta t}(q, p)) = (q, p)$
- $\Psi_{\Delta t}$  is a **symplectic map**, which thus **preserves**  $\sigma_{T^*\mathcal{M}}$

[Hairer, Lubich, Wanner, 2006] [Leimkuhler, Reich, 2004] [Leimkuhler, Skeel, 1994].

One can thus add a Metropolis Hastings rejection step to get unbiased samples: if  $(q', p') = \Psi_{\Delta t}(q, p)$ , the MH ratio writes:

$$\frac{\delta_{\Psi_{\Delta t}(q', p')}(dq dp) e^{-H(q', p')} \sigma_{T^*\mathcal{M}}(dq' dp')}{\delta_{\Psi_{\Delta t}(q, p)}(dq' dp') e^{-H(q, p)} \sigma_{T^*\mathcal{M}}(dq dp)} = e^{-H(q', p') + H(q, p)}.$$

## Step 2: the Langevin dynamics (7/8)

Constrained Generalized Hybrid Monte Carlo algorithm ([TL, Rousset,

Stoltz 2012], constrained version of [Horowitz 1991]):

$$\left\{ \begin{array}{l} (q^n, p^{n+1/4}) = \Psi_{\Delta t/2}^{OU}(q^n, p^n) \\ (\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) = \Psi_{\Delta t}(q^n, p^{n+1/4}) \\ \text{If } U^n \leq e^{-H(\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) + H(q^n, p^{n+1/4})} \\ \quad \text{accept the proposal: } (q^{n+1}, p^{n+3/4}) = (\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) \\ \quad \text{else reject the proposal: } (q^{n+1}, p^{n+3/4}) = (q^n, p^{n+1/4}) \\ \tilde{p}^{n+1} = -p^{n+3/4} \\ (q^{n+1}, p^{n+1}) = \Psi_{\Delta t/2}^{OU}(q^{n+1}, \tilde{p}^{n+1}) \end{array} \right.$$

where  $U^n \sim \mathcal{U}(0, 1)$ .

*Remark:* If  $\Delta t \gamma / 4 = 1$ , then  $p^{n+1/4} = \Pi^*(q^n)(G^n) \sim \kappa_{q^n}$ . One thus obtains a constrained HMC algorithm, consistent with the constrained overdamped Langevin (constrained MALA).

## Step 2: the Langevin dynamics (8/8)

Problem: RATTLE is only well defined and reversible for **locally small timesteps**. Three possible difficulties:

- $\Psi_{\Delta t}(q, p)$  may not be defined;
- If  $\Psi_{\Delta t}(q, p)$  is well defined,  $\Psi_{\Delta t}(\Psi_{\Delta t}(q, p))$  may not be defined;
- If  $\Psi_{\Delta t}(q, p)$  and  $\Psi_{\Delta t}(\Psi_{\Delta t}(q, p))$  are well defined, one may have  $\Psi_{\Delta t}(\Psi_{\Delta t}(q, p)) \neq (q, p)$ .

## Step 3: the reverse projection check (1/9)

In order to introduce the the set of positions and momenta from which RATTLE is well defined, let us rewrite the RATTLE dynamics as follows:

$$\begin{cases} q^{n+1} = q^n + \Delta t \left[ p^n - \frac{\Delta t}{2} \nabla V(q^n) \right] + \Delta t \nabla \xi(q^n) \lambda^{n+1/2} \\ p^{n+1} = \Pi^*(q^n) \left( p^n - \frac{\Delta t}{2} (\nabla V(q^n) + \nabla V(q^{n+1})) + \nabla \xi(q^n) \lambda^{n+1/2} \right) \end{cases}$$

where

$$\Delta t \lambda^{n+1/2} = \Lambda \left( q^n, q^n + \Delta t \left[ p^n - \frac{\Delta t}{2} \nabla V(q^n) \right] \right).$$

The function  $\Lambda : \mathcal{D} \rightarrow \mathbb{R}^m$ , where  $\mathcal{D}$  is an open set of  $\mathcal{M} \times \mathbb{R}^d$  is the **Lagrange multiplier function** which satisfies:

$$\forall (q, \tilde{q}) \in \mathcal{D}, \tilde{q} + \nabla \xi(q) \Lambda(q, \tilde{q}) \in \mathcal{M}.$$

We will discuss later how to rigorously build such a Lagrange multiplier function.



## Step 3: the reverse projection check (2/9)

The function  $\Lambda$  is only defined on  $\mathcal{D}$  and thus  $\Psi_{\Delta t}^{RATTLE}$  is only defined on the open set:

$$A = \left\{ (q, p) \in T^*\mathcal{M}, \left( q, q + \Delta t M^{-1} \left[ p - \frac{\Delta t}{2} \nabla V(q) \right] \right) \in \mathcal{D} \right\}$$

and likewise,  $\Psi_{\Delta t} = S \circ \Psi_{\Delta t}^{RATTLE}$  is defined on  $A$ .

**Proposition ([TL, Rousset, Stoltz 2018])**

*If  $\Lambda$  is  $C^1$ , then  $\Psi_{\Delta t} : A \rightarrow T^*\mathcal{M}$  is a  $C^1$  local diffeomorphism, locally preserving the phase-space measure  $\sigma_{T^*\mathcal{M}}(dq dp)$ .*

### Step 3: the reverse projection check (3/9)

Let us now introduce the **RATTLE dynamics with momentum reversal and reverse projection check**: for any  $(q, p) \in T^*\mathcal{M}$ ,

$$\Psi_{\Delta t}^{\text{rev}}(q, p) = \Psi_{\Delta t}(q, p)1_{\{(q,p) \in B\}} + (q, p)1_{\{(q,p) \notin B\}}$$

where the set  $B \subset A \subset T^*\mathcal{M}$  is defined by

$$B = \left\{ (q, p) \in A, \Psi_{\Delta t}(q, p) \in A \text{ and } \Psi_{\Delta t} \circ \Psi_{\Delta t}(q, p) = (q, p) \right\}.$$

**Proposition ([TL, Rousset, Stoltz 2018])**

*Let us assume that  $\Lambda$  is  $C^1$  and satisfies the non-tangential condition:  $\forall (q, \tilde{q}) \in \mathcal{D}$ ,*

$$[\nabla \xi(\tilde{q} + \nabla \xi(q)\Lambda(q, \tilde{q}))]^T \nabla \xi(q) \in \mathbb{R}^{m \times m} \text{ is invertible.}$$

*Then, the set  $B$  is the union of path connected components of the open set  $A \cap \Psi_{\Delta t}^{-1}(A)$ . It is thus an open set of  $T^*\mathcal{M}$ . Moreover,  $\Psi_{\Delta t}^{\text{rev}} : T^*\mathcal{M} \rightarrow T^*\mathcal{M}$  is **globally well defined, preserves globally the measure  $\sigma_{T^*\mathcal{M}}(dq dp)$  and satisfies  $\Psi_{\Delta t}^{\text{rev}} \circ \Psi_{\Delta t}^{\text{rev}} = \text{Id}$ .***

## Step 3: the reverse projection check (4/9)

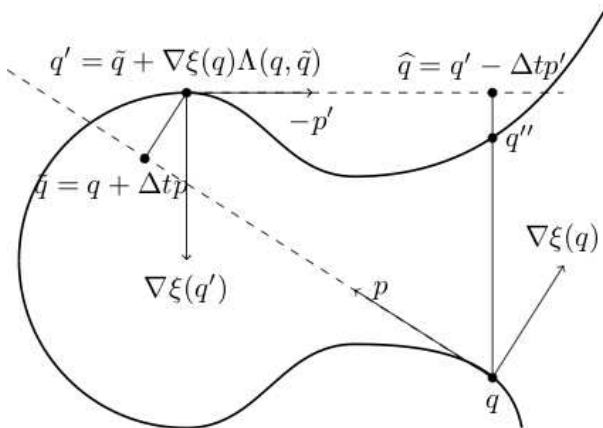
Practically,  $\Psi_{\Delta t}^{\text{rev}}(q, p)$  is obtained from  $(q, p) \in T^*\mathcal{M}$  by the following procedure:

- (1) check if  $(q, p)$  is in  $A$ ; if not return  $(q, p)$ ;
- (2) when  $(q, p) \in A$ , compute the configuration  $(q^1, p^1)$  obtained by one step of the RATTLE scheme;
- (3) check if  $(q^1, -p^1)$  is in  $A$ ; if not, return  $(q, p)$ ;
- (4) compute the configuration  $(q^2, -p^2)$  obtained by one step of the RATTLE scheme starting from  $(q^1, -p^1)$ ;
- (5) if  $(q^2, -p^2) = (q, p)$ , return  $(q^1, -p^1)$ ; otherwise return  $(q, p)$ .

The steps (3)-(4)-(5) correspond to the *reverse projection check* [Goodman, Holmes-Cerfon, Zappa, 2017].

## Step 3: the reverse projection check (5/9)

The reverse projection check is useful!



Here,  $V = 0$  and the projection is defined as the closest point to  $\mathcal{M}$ . Notice that  $q'' \neq q$ !

## Step 3: the reverse projection check (6/9)

Assume for simplicity that  $\exists \alpha > 0$ ,  $\{q \in \mathbb{R}^d, \|\xi(q)\| \leq \alpha\}$  is compact. How to build admissible Lagrange multiplier functions?

Theoretically, one can use the **implicit function theorem** to build a function  $\Lambda : \mathcal{D}_{\text{imp}} \rightarrow \mathbb{R}^m$  where  $\mathcal{D}_{\text{imp}}$  is an open subset of  $\mathcal{M} \times \mathbb{R}^d$  such that

$$\{(q, \tilde{q}) \in \mathcal{M} \times \mathcal{M}, [\nabla \xi(q)]^T \nabla \xi(\tilde{q}) \text{ is invertible}\} \subset \mathcal{D}_{\text{imp}}$$

This defines  $\Lambda(q, \tilde{q})$  for  $\tilde{q}$  in a neighborhood of  $\mathcal{M}$ .

*Remarks:*

- There exists a non increasing function  $\delta$  such that:

$$\|\xi(\tilde{q})\| < \delta \left( \|([\nabla \xi(q)]^T \nabla \xi(\tilde{q}))^{-1}\| \right) \Rightarrow (q, \tilde{q}) \in \mathcal{D}_{\text{imp}}.$$

- For a fixed  $(q, p) \in T^*\mathcal{M}$ , for a sufficiently small timestep  $\Delta t$ ,  $\Psi_{\Delta t}(q, p) \in A_{\text{imp}}$  and  $\Psi_{\Delta t} \circ \Psi_{\Delta t}(q, p) = (q, p)$ . Thus,  $B_{\text{imp}}$  is non empty!

## Step 3: the reverse projection check (7/9)

Numerically, one can use the [Newton algorithm](#) to extend this local construction and compute the Lagrange multipliers for  $\tilde{q}$  far from  $\mathcal{M}$ : perform a fixed number of iterations of the Newton algorithm to solve

$$\text{find } \lambda \in \mathbb{R}^m, \xi(\tilde{q} + \nabla\xi(q)\lambda) = 0$$

and check if one gets into  $\mathcal{D}_{\text{imp}}$ .

In practice, the set  $\mathcal{D}_{\text{newt}}$  is defined as the configurations for which convergence to a point in  $\mathcal{M}$  is observed (up to numerical error).

## Step 3: the reverse projection check (8/9)

The constrained GHMC algorithm writes:

$$\left\{ \begin{array}{l} (q^n, p^{n+1/4}) = \Psi_{\Delta t/2}^{OU}(q^n, p^n) \\ (\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) = \Psi_{\Delta t}^{rev}(q^n, p^{n+1/4}) \\ \text{If } U^n \leq e^{-H(\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) + H(q^n, p^{n+1/4})} \\ \quad \text{accept the proposal: } (q^{n+1}, p^{n+3/4}) = (\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) \\ \quad \text{else reject the proposal: } (q^{n+1}, p^{n+3/4}) = (q^n, p^{n+1/4}) \\ \tilde{p}^{n+1} = -p^{n+3/4} \\ (q^{n+1}, p^{n+1}) = \Psi_{\Delta t/2}^{OU}(q^{n+1}, \tilde{p}^{n+1}) \end{array} \right.$$

where  $U^n \sim \mathcal{U}(0, 1)$ .

**Proposition** ([TL, Rousset, Stoltz 2018])

*The Markov chain  $(q^n, p^n)_{n \geq 0}$  admits  $\mu$  as an invariant measure.*

To prove ergodicity, it remains to check irreducibility [Hartmann, 2008].

## Step 3: the reverse projection check (9/9)

### Remarks:

- In  $\Psi_{\Delta t}^{rev}$ , one can use any potential  $V$ ! Choosing the potential  $V$  of the target measure  $d\nu = Z_\nu^{-1} e^{-V} d\sigma_{\mathcal{M}}$  is good to increase the acceptance probability.
- If  $\Delta t \gamma / 4 = 1$ , one obtains a HMC (or MALA) algorithm. If  $\Delta t \gamma / 4 = 1$  and  $V = 0$  in  $\Psi_{\Delta t}^{rev}$ , this is a constrained random walk MH algorithm [Goodman, Holmes-Cerfon, Zappa, 2017].
- In practice, one can use  $K$  steps of RATTLE within  $\Psi^{rev}$  to get less correlated samples. [Bou-Rabee, Sanz Serna]
- If  $\Psi_{\Delta t}^{rev}(q^n, p^{n+1/4}) = \Psi_{\Delta t}(q^n, p^{n+1/4})$  (reverse projection check OK), one obtains a consistent discretization of the constrained Langevin dynamics.
- Similar ideas can be used to enforce inequality constraints.
- It may be interesting for numerical purposes to consider non identity mass matrices.

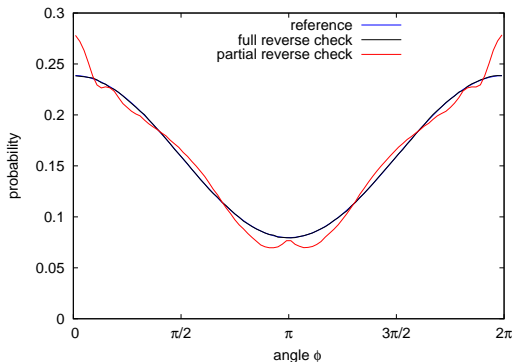


## Numerical experiments (1/3)

Let  $\mathcal{M}$  be the three-dimensional torus  $\mathcal{M} = \{q \in \mathbb{R}^3, \xi(q) = 0\}$  where

$$\xi(q) = \left(R - \sqrt{x^2 + y^2}\right)^2 + z^2 - r^2,$$

with  $0 < r < R$ . Let us consider for  $\nu = \sigma_{T^*\mathcal{M}}$  the uniform measure on  $\mathcal{M}$ .

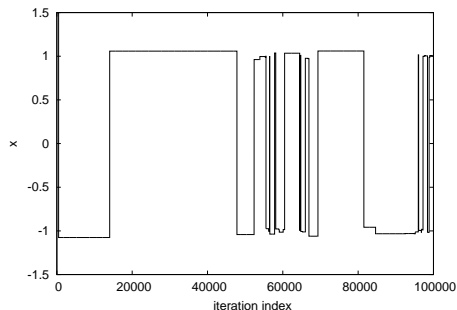
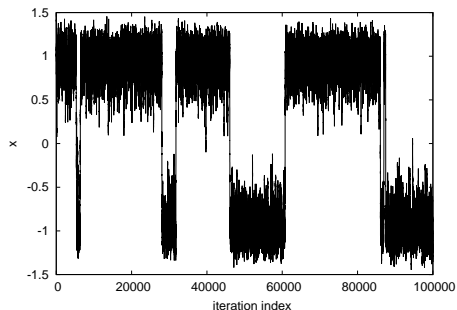


“partial reverse check” = do not check  $(\Psi_{\Delta t} \circ \Psi_{\Delta t} = \text{Id}) \Rightarrow \text{BIAS!}$

## Numerical experiments (2/3)

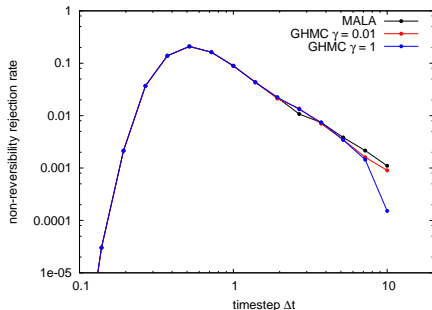
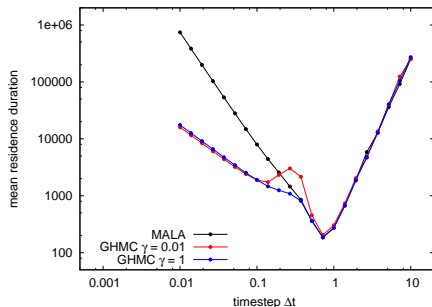
Let us now consider a double well case:  $\nu = e^{-V} \sigma_{T^* \mathcal{M}}$  where  $V(x, y, z) = k(x^2 - R^2)^2$ .

Typical trajectories for the GHMC dynamics (left  $\Delta t = 0.05$ , right  $\Delta t = 3$ ):



## Numerical experiments (3/3)

Analysis of the efficiency (left: mean residence duration, right: non-reversibility rejection rate)



The optimal timestep is of the order of 0.7. For such timesteps, the rejections due to the non reversibility condition  $(q^n, p^n) \neq \Psi_{\Delta t} \circ \Psi_{\Delta t}(q^n, p^n)$  are of the order of 15-20%, the total rejection rate being about 90%.

→ reverse projection check is useful to get efficient algorithms.

## Beyond reverse projection check

In collaboration with G. Stoltz and W. Zhang...  
... following discussions with P. Breiding

In many situations, one is able to compute if not all, **many solutions to the problem**: for  $(q, \tilde{q}) \in \mathcal{M} \times \mathbb{R}^d$ ,

$$\text{find } \Lambda(q, \tilde{q}) \in \mathbb{R}^m \text{ s.t. } \tilde{q} + \nabla \xi(q) \Lambda(q, \tilde{q}) \in \mathcal{M}.$$

Let us assume that there exists  $\mathcal{D} \subset \mathcal{M} \times \mathbb{R}^d$  such that for all  $(q, \tilde{q}) \in \mathcal{D}$ , there exists  $n(q, \tilde{q}) \in \mathbb{N}$  which is locally constant, and  $n(q, \tilde{q})$   $C^1$  functions  $(\Lambda^i(q, \tilde{q}) : \mathcal{D} \rightarrow \mathbb{R}^m)_{1 \leq i \leq n(q, \tilde{q})}$  such that

$$\forall (q, \tilde{q}) \in \mathcal{D}, \tilde{q} + \nabla \xi(q) \Lambda^i(q, \tilde{q}) \in \mathcal{M}.$$

How to use this additional information ?

## Examples

We have two situations in mind:

- All the solutions to  $\xi(\tilde{q} + \nabla\xi(q)\lambda) = 0$  can be analytically computed
- Many solutions to  $\xi(\tilde{q} + \nabla\xi(q)\lambda) = 0$  can be numerically computed

This is typically the case for **algebraic** submanifolds, i.e. when  $\xi$  is a polynomial function. See for example the Julia packages *PolynomialRoots* [J. Skowron, A. Gould] and *HomotopyContinuation* [P. Breiding, S. Timme].

## Generalized algorithm (1/2)

Let us assign a probability  $\pi^i(q, \tilde{q})$  to each of the solutions  $(\Lambda^i(q, \tilde{q}))_{1 \leq i \leq n(q, \tilde{q})}$ :

$$\pi^i(q, \tilde{q}) \geq 0 \text{ and } \sum_{i=1}^{n(q, \tilde{q})} \pi^i(q, \tilde{q}) = 1.$$

For example,  $\pi^i(q, \tilde{q}) = \frac{1}{n(q, \tilde{q})}$ .

Then choose one of the solution at random, and adapt the constrained GHMC algorithm.

## Generalized algorithm (2/2)

1. Update momenta:  $(q^n, p^{n+1/4}) = \Psi_{\Delta t/2}^{OU}(q^n, p^n)$
2. Compute the Lagrange multipliers  $(\Lambda^i(q^n, \tilde{q}^n))_{1 \leq i \leq n(q^n, \tilde{q}^n)}$ , where  $\tilde{q}^n = q^n + \Delta t [p^{n+1/4} - \frac{\Delta t}{2} \nabla V(q^n)]$ . Choose index  $i^n \in \{1, \dots, n(q^n, \tilde{q}^n)\}$  with probability  $\pi^{i^n}(q^n, \tilde{q}^n)$ .
3. Compute the move  $(\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) = \Psi_{\Delta t}(q^n, p^{n+1/4})$ , where  $\Psi_{\Delta t}$  uses in the RATTLE step the Lagrange multiplier  $\Lambda^{i^n}$ .
4. Check if one of the Lagrange multipliers (denoted by  $\Lambda^{j^n}$ )  $(\Lambda^j(\tilde{q}^{n+1}, \bar{q}^{n+1}))_{1 \leq j \leq n(q^{n+1}, \bar{q}^{n+1})}$  brings back to  $(q^n, -p^{n+1/4})$ , where  $\bar{q}^{n+1} = \tilde{q}^{n+1} + \Delta t [\tilde{p}^{n+3/4} - \frac{\Delta t}{2} \nabla V(\tilde{q}^{n+1})]$ . If not, set  $(q^{n+1}, p^{n+3/4}) = (q^n, p^{n+1/4})$ , and go to Step 6.
5. Accept the move  $(q^{n+1}, p^{n+3/4}) = (\tilde{q}^{n+1}, \tilde{p}^{n+3/4})$  with probability

$$1 \wedge \left( \frac{\pi^{j^n}(\tilde{q}^{n+1}, \bar{q}^{n+1})}{\pi^{i^n}(q^n, \tilde{q}^n)} e^{-H(\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) + H(q^n, p^{n+1/4})} \right)$$

else reject  $(q^{n+1}, p^{n+3/4}) = (q^n, p^{n+1/4})$ .

6.  $\tilde{p}^{n+1} = -p^{n+3/4}$  and  $(q^{n+1}, p^{n+1}) = \Psi_{\Delta t/2}^{OU}(q^{n+1}, \tilde{p}^{n+1})$

## No need of a reverse projection check (1/2)

- If all the solutions to  $\xi(\tilde{q} + \nabla\xi(q)\lambda) = 0$  can be computed, one knows in Step 4 that one of the Lagrange multipliers  $(\Lambda^j(\tilde{q}^{n+1}, \bar{q}^{n+1}))_{1 \leq j \leq n(q^{n+1}, \bar{q}^{n+1})}$  brings back to  $(q^n, -p^{n+1/4}) \rightarrow$  no rejection in Step 4.
- If, in addition, one chooses  $\pi^i(q, \tilde{q}) = \frac{1}{n(q, \tilde{q})}$ , no need to identify the Lagrange multiplier  $\Lambda^j$  which brings back to  $(q^n, -p^{n+1/4})$  in Step 4.

Under these two assumptions (all Lagrange multipliers can be computed, and uniform probability on the Lagrange multipliers), the algorithm is the following:



## No need of a reverse projection check (2/2)

1. Update momenta:  $(q^n, p^{n+1/4}) = \Psi_{\Delta t/2}^{OU}(q^n, p^n)$
2. Compute the Lagrange multipliers  $(\Lambda^i(q^n, \tilde{q}^n))_{1 \leq i \leq n(q^n, \tilde{q}^n)}$ , where  $\tilde{q}^n = q^n + \Delta t [p^{n+1/4} - \frac{\Delta t}{2} \nabla V(q^n)]$ . Choose index  $i^n \in \{1, \dots, n(q^n, \tilde{q}^n)\}$  with probability  $1/n(q^n, \tilde{q}^n)$ .
3. Compute the move  $(\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) = \Psi_{\Delta t}(q^n, p^{n+1/4})$ , where  $\Psi_{\Delta t}$  uses in the RATTLE step the Lagrange multiplier  $\Lambda^{i^n}$ .
4. Compute the number of Lagrange multipliers  $n(q^{n+1}, \bar{q}^{n+1})$  for the backward move, where  $\bar{q}^{n+1} = \tilde{q}^{n+1} + \Delta t [\tilde{p}^{n+3/4} - \frac{\Delta t}{2} \nabla V(\tilde{q}^{n+1})]$ .
5. Accept the move  $((q^{n+1}, p^{n+3/4}) = (\tilde{q}^{n+1}, \tilde{p}^{n+3/4}))$  with probability

$$1 \wedge \left( \frac{n(q^n, \tilde{q}^n)}{n(\tilde{q}^{n+1}, \bar{q}^{n+1})} e^{-H(\tilde{q}^{n+1}, \tilde{p}^{n+3/4}) + H(q^n, p^{n+1/4})} \right)$$

else reject  $((q^{n+1}, p^{n+3/4}) = (q^n, p^{n+1/4}))$ .

6.  $\tilde{p}^{n+1} = -p^{n+3/4}$  and  $(q^{n+1}, p^{n+1}) = \Psi_{\Delta t/2}^{OU}(q^{n+1}, \tilde{p}^{n+1})$

## Theoretical results

One can adapt the arguments of the work [TL, Rousset, Stoltz 2018] to show that

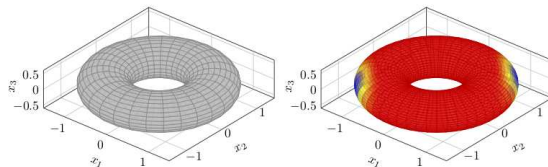
Proposition ([TL, Stoltz, Zhang 2019])

*The Markov chain  $(q^n, p^n)_{n \geq 0}$  admits  $\mu$  as an invariant measure.*

Same remarks as before apply: change  $V$  or the number of steps in  $\Psi_{\Delta t}$ , MALA version if  $\Delta t \gamma / 4 = 1$ , inequality constraints, change the mass matrix, ...

## Numerical experiments

Two measures on the torus.

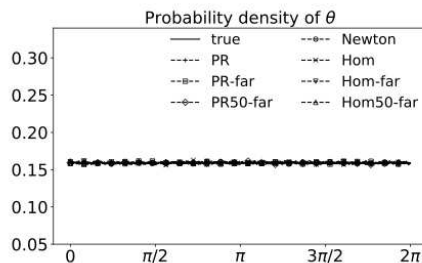
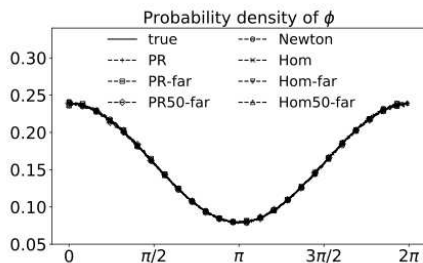


Compare, over  $10^7$  iterations:

- Newton
- PolynomialRoots (PR) or HomotopyContinuation (Hom) with uniform law on the Lagrange multipliers
- PolynomialRoots (PR-far) or HomotopyContinuation (Hom-far) with non-uniform law on the Lagrange multipliers (favor large jumps)
- Use PR-far and Hom-far every 50 Newton steps: PR50-far and Hom50-far

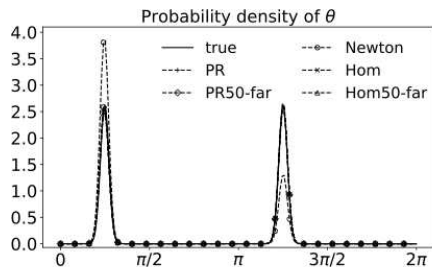
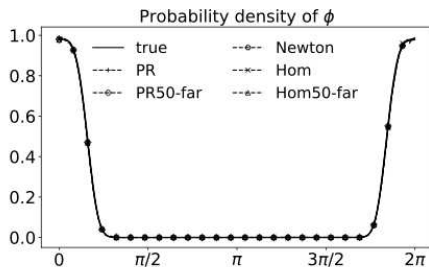
## Numerical experiments

For the uniform law on the torus, results are indeed unbiased:



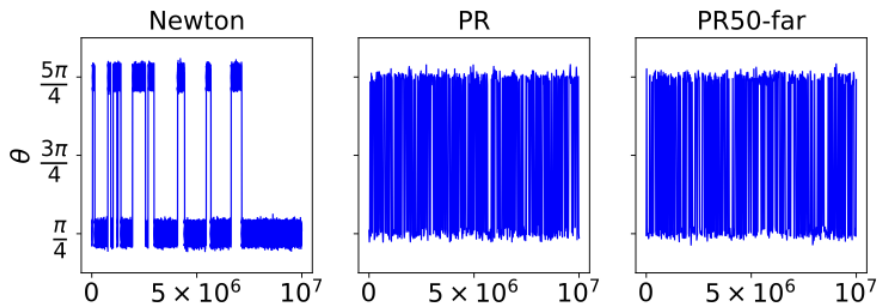
## Numerical experiments

For the bimodal distribution on the torus, Newton exhibits metastability:



## Numerical experiments

For the bimodal distribution on the torus, Newton exhibits metastability:



## Numerical experiments

Quantitative comparisons for the bimodal distribution on the torus:

Scheme	No. of solutions in forward					No. of solutions in backward				
	0	1	2	3	4	0	1	2	3	4
Newton	7.9%	92.1%	0.0%	0.0%	0.0%	0.1%	99.9%	0.0%	0.0%	0.0%
PR	2.1%	0.0%	51.8%	0.0%	46.1%	0.0%	0.0%	75.2%	0.0%	24.8%
PR50-far	2.2%	95.8%	1.0%	0.0%	0.9%	0.0%	98.0%	1.5%	0.0%	0.5%
Hom	2.1%	0.0%	51.8%	0.0%	46.1%	0.0%	0.0%	75.2%	0.0%	24.8%
Hom50-far	2.2%	95.8%	1.0%	0.0%	0.9%	0.0%	98.0%	1.5%	0.0%	0.5%

Scheme	FSR	BSR	Jump rate	Large jump rate	Time (s)
Newton	0.92	1.00	0.38	$1.8 \times 10^{-6}$	$1.7 \times 10^3$
PR	0.98	1.00	0.22	$4.1 \times 10^{-3}$	$1.0 \times 10^4$
PR50-far	0.98	1.00	0.60 (0.18)	$7.3 \times 10^{-5}$	$2.0 \times 10^3$
Hom	0.98	1.00	0.22	$4.1 \times 10^{-3}$	$1.2 \times 10^4$
Hom50-far	0.98	1.00	0.60 (0.18)	$6.4 \times 10^{-5}$	$2.1 \times 10^3$

## References

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- TL, M. Rousset and G. Stoltz, *Hybrid Monte Carlo methods for sampling probability measures on submanifolds*, Numerische Mathematik 143(2), 2019.
- TL, G. Stoltz and W. Zhang, *Multiple projection MCMC algorithms on submanifolds*, <https://arxiv.org/abs/2003.09402>
- E. Zappa, M. Holmes-Cerfon and J. Goodman, *Monte Carlo on manifolds: sampling densities and integrating functions*, CPAM 71(12), 2018.



# References

## Implementations:

- <https://github.com/zwpku/Constrained-HMC>
- <https://github.com/matt-graham/mici>