## Efficient Sampling on Riemannian Manifolds via Langevin MCMC ampling on Riemannian Manifolds<br>via Langevin MCMC<br><sub>Xiang Cheng, Jingzhao Zhang, Suvrit Sra</sub>

#### Sampling over Riemannian Manifolds

Given manifold  $(M, g)$ , sample from  $\boldsymbol{dp}(\pmb{x}) = \ \pmb{e}^{-\boldsymbol{U}(\pmb{x})}\boldsymbol{dvol}_{\boldsymbol{g}}(\pmb{x})$ 

- $U(x)$ :  $M \to \mathbb{R}$  is a potential function (e.g. negative-log-posterior)
- $dvol_{g}(x)$  is manifold volume, in coordinates, it is  $\sqrt{\det(g)}$ .

The Riemannian Langevin Diffusion (RLD):

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dx(t) = -\text{grad } U\big(x(t)\big)dt + dB_t^g
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- grad U denotes the manifold gradient, and  $dB_t^g$  denotes the manifold Brownian motion
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#### Riemannian Langevin MCMC

Based on the geometric Euler Murayama Discretization of RLD:

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x_{(k+1)\delta} = Exp_{x_{k\delta}}(-\delta \text{ grad } U(x_{k\delta}) + \sqrt{\delta} \xi_k)
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where  $\xi_k$  is "standard Gaussian" wrt an orthonormal basis at  $T_{x_k}M$ <br> **Exponential** 

#### Exponential maps can be approximated to high accuracy efficiently

# RLMCMC can be much faster than Euclidean Langevin MCMC **EXEMC CALTA COMPLANE COMPTE CONTROLL CONDUCT:**<br>• Given: unobserved ( $\mu = 0, \sigma = 10$ ), observe samples  $x_1 ... x_{100} \sim \mathcal{N}(\mu, \sigma^2)$ .<br>• Task: sample from the posterior distribution  $p(\mu, \sigma | x_1 ... x_{100}) \propto \exp\left(\sum_l \frac{||x_l - \mu||^2}{2$  $\frac{1}{\sigma^2}$ <br>  $\frac{1}{\mu} \frac{||x_i - \mu||^2}{2\sigma^2} - N \log \sigma$

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#### Key Assumptions

- Assume  $(M, g)$  satisfies
	- Ricci curvature lower bounded by  $-L_{ric}$
	- Absolute value of sectional curvature upper bounded by  $L_{sec}$
- Assume  $-U$  satisfies
	- (gradient Lipschitz)  $\textbf{Hess}(U)[v,v] \leq L_U ||v||^2$ , for all  $x \in M$ ,  $v \in T_xM$
	- (distant dissipativity)  $\left(\Gamma_X^{\mathcal{Y}}\right)$  grad  $U(y)$  grad  $U(x)$ ,  $\chi^-(y)$   $\geq m$  dist $(x, y)$ ,  $\vert u^{-1}(y) \vert > m$  dist(x y)<sup>2</sup>  $\overline{\phantom{a}}$ for all dist(x, y) > R and some  $m$  >  $-L_{Ric}$



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## Main Theoretical Result

- Assume  $(M, g)$  satisfies
	- Ricci curvature lower bounded by  $-L_{ric}$ , for some  $L_{Ric} > 0$
	- Absolute value of sectional curvature upper bounded by  $L_{sec}$
- Assume  $-U$  satisfies
	- (gradient Lipschitz)  $\textbf{Hess}(U)[v,v] \leq L_U ||v||^2$ , for all  $x \in M$ ,  $v \in T_xM$
	- (distant dissipativity)  $\left(\Gamma_{x}^{y}\right)$  grad  $U(y)$  grad  $U(x)$ ,  $\chi$  (*y*)  $\ell$  *m* dist(*x*, *y*),  $^{-1}(v)$  > m dist(x v)<sup>2</sup>  $\overline{\phantom{a}}$ for all dist(x, y) > R and some  $m > L_{Ric}$

#### Theorem 1

Let  $x_{k\delta}$  be iterates of RLMCMC, and let  $y(t)$  denote RLD, then  $\mathbb{E}[\text{dist}(x_{K\delta}, y(K\delta))] \leq \epsilon$ 

for  $K = \text{poly}\left(e^{(L_U + L_{ric})R^2}, L_{sec}, L_U, d, \frac{1}{m_U - 1}\right) \cdot 1/\epsilon^2$  $\int$ sec,  $L$ U,  $\left(u,\frac{m-1}{m-1}\right)$ .  $1/\epsilon$ <sup>-</sup>  $1 \quad 112$  $m-L_{Ric}$ ,  $\left( \begin{array}{c} 1 \end{array} \right)$ ଶ