Sampling through Optimization of Divergences

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Joint work with many people cited on the flow.

Outline

Why sampling?

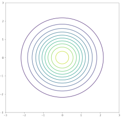
Suppose you are interested in some target probability distribution on $\mathbb{R}^d$, denoted μ^*, and you have access only to partial information, e.g.:

1. its unnormalized density (as in Bayesian inference)
2. a discrete approximation $\frac{1}{m}\sum_{k=1}^m \delta_{x_i} \approx \mu^*$ (e.g. i.i.d. samples, iterates of MCMC algorithms...)

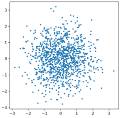
Problem: approximate $\mu^* \in \mathcal{P}(\mathbb{R}^d)$ by a finite set of n points $x_1, \ldots, x_n$, e.g. to compute functionals $\int_{\mathbb{R}^d} f(x) d\mu^*(x)$.

The quality of the set can be measured by the integral error:

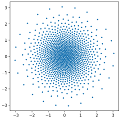
$$\left| \frac{1}{n} \sum_{i=1}^n f(x_i) - \int_{\mathbb{R}^d} f(x) d\mu^*(x) \right|.$$



a Gaussian density



I.i.d. samples.



Particle scheme (SVGD).

Example 1: Bayesian inference

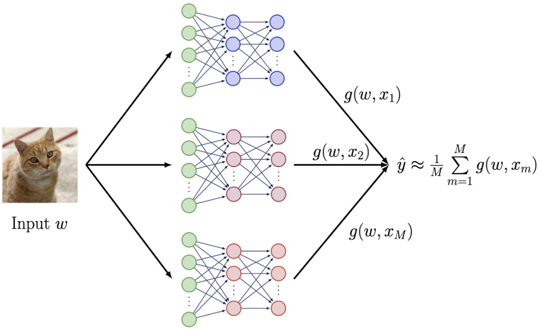
We want to sample from

$$\mu^*(x) \propto \exp\left(-V(x)\right), \quad V(\theta) = \underbrace{\sum_{i=1}^{m} \|y_i - g(w_i, x)\|^2}_{\text{loss on labeled data } (w_i, y_i)_{i=1}^m} + \frac{\|x\|^2}{2}.$$

Ensemble prediction for a new input w:

$$\hat{y} = \underbrace{\int_{\mathbb{R}^d} g(w, x) d\mu^*(x)}_{\text{"Bayesian model averaging"}}$$

Predictions of models parametrized by $x \in \mathbb{R}^d$ are reweighted by $\mu^*(x)$.

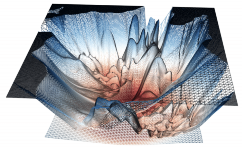


Difficult cases (in practice and in theory)

Recall that

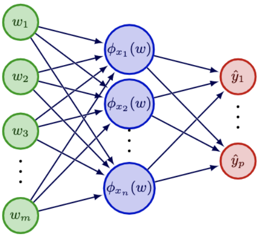
$$\mu^*(x) \propto \exp(-V(x)), \quad V(\theta) = \underbrace{\sum_{i=1}^{m} \|y_i - g(w_i, x)\|^2}_{\text{loss}} + \frac{\|x\|^2}{2}.$$

- if V is convex (e.g. $g(w,x) = \langle w, x\rangle$) many sampling methods (e.g. Langevin Monte Carlo) are known to work quite well [Durmus and Moulines, 2016, Vempala and Wibisono, 2019]
- but if its not (e.g. $g(w,x)$ is a neural network), the situation is much more delicate

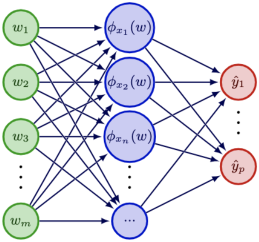


A highly nonconvex loss surface, as is common in deep neural nets. From https://www.telesens.co/2019/01/16/neural-network-loss-visualization.

Example 2 : Regression with infinite width NN



$$\xrightarrow[n\to\infty]{}$$



$$\min_{(x_i)_{i=1}^n \in \mathbb{R}^d} \mathbb{E}_{(w,y)\sim P_{data}} \left[\left\| y - \underbrace{\frac{1}{n}\sum_{i=1}^n \phi_{x_i}(w)}_{\hat{y}} \right\|^2 \right] \xrightarrow[n\to\infty]{} \min_{\mu\in\mathcal{P}(\mathbb{R}^d)} \underbrace{\mathbb{E}_{(w,y)\sim P_{data}}\left[\left\|y - \int_{\mathbb{R}^d}\phi_x(w)d\mu(x)\right\|^2\right]}_{\mathcal{F}(\mu)}$$

Define the target distribution $\mu^* \in \arg\min \mathcal{F}(\mu)$. Optimising the neural network $\iff$ approximating μ^* [Chizat and Bach, 2018, Mei et al., 2018].

If $y(w) = \frac{1}{m}\sum_{i=1}^m \phi_{x_i}(w)$ is generated by a neural network (as in the student-teacher network setting), then $\mu^* = \frac{1}{m}\sum_{i=1}^m \delta_{x_m}$ and $\mathcal{F}$ can be identified to an MMD [Arbel et al., 2019].

Outline

Sampling as optimization over probability distributions

Assume that $\mu^* \in \mathcal{P}_2(\mathbb{R}^d) = \left\{\mu \in \mathcal{P}(\mathbb{R}^d), \int \|x\|^2 d\mu(x) < \infty\right\}$.
The sampling task can be recast as an optimization problem:

$$\mu^* = \operatorname*{arg\,min}_{\mu \in \mathcal{P}_2(\mathbb{R}^d)} D(\mu|\mu^*) := \mathcal{F}(\mu),$$

where D is a **dissimilarity functional**, for instance:

- a f-divergence: $\int f\left(\frac{\mu}{\mu^*}\right) d\mu^*, \quad f$ convex, $f(1) = 0$
- an integral probability metric: $\sup_{f \in \mathcal{G}} \left|\int f d\mu - \int f d\mu^*\right|$
- an optimal transport distance...

Starting from an initial distribution $\mu_0 \in \mathcal{P}_2(\mathbb{R}^d)$, one can then consider the **Wasserstein-2* gradient flow** of $\mathcal{F}$ over $\mathcal{P}_2(\mathbb{R}^d)$ to transport μ_0 to μ^*.

* $W_2^2(\nu, \mu) = \inf_{s \in \Gamma(\nu,\mu)} \int_{\mathbb{R}^d \times \mathbb{R}^d} \|x - y\|^2 ds(x, y)$, where $\Gamma(\nu, \mu)$= couplings between ν, μ.

Wasserstein gradient flows (WGF) [Ambrosio et al., 2008]

The first variation of $\mu \mapsto \mathcal{F}(\mu)$ evaluated at $\mu \in \mathcal{P}(\mathbb{R}^d)$ is the unique function $\frac{\partial \mathcal{F}(\mu)}{\partial \mu} : \mathbb{R}^d \to \mathbb{R}$ s. t. for any $\mu, \nu \in \mathcal{P}(\mathbb{R}^d)$, $\nu - \mu \in \mathcal{P}(\mathbb{R}^d)$:

$$\lim_{\epsilon \to 0} \frac{1}{\epsilon}(\mathcal{F}(\mu + \epsilon(\nu - \mu)) - \mathcal{F}(\mu)) = \int_{\mathbb{R}^d} \frac{\partial \mathcal{F}(\mu)}{\partial \mu}(x)(d\nu - d\mu)(x).$$

The family $\mu : [0, \infty] \to \mathcal{P}_2(\mathbb{R}^d), t \mapsto \mu_t$ is a Wasserstein gradient flow of $\mathcal{F}$ if:

$$\boxed{\frac{\partial \mu_t}{\partial t} = \boldsymbol{\nabla} \cdot (\mu_t \nabla_{W_2} \mathcal{F}(\mu_t)),}$$

where $\nabla_{W_2} \mathcal{F}(\mu) := \nabla \frac{\partial \mathcal{F}(\mu)}{\partial \mu}$ denotes the Wasserstein gradient of $\mathcal{F}$.

It can be implemented by the deterministic process:

$$\boxed{\frac{dx_t}{dt} = -\nabla_{W_2} \mathcal{F}(\mu_t)(x_t), \quad \text{where } x_t \sim \mu_t}$$

Particle system/Gradient descent approximating the WGF

Space/time discretization : Introduce a particle system $x_0^1, \ldots, x_0^n \sim \mu_0$, a step-size γ, and at each step:

$$x_{l+1}^i = x_l^i - \gamma \nabla_{W_2} \mathcal{F}(\hat{\mu}_l)(x_l^i) \quad \text{for } i = 1, \ldots, n, \text{ where } \hat{\mu}_l = \frac{1}{n}\sum_{i=1}^{n} \delta_{x_l^i}$$

In particular, the algorithm above simply corresponds to gradient descent.

We consider several questions:

- what can we say as time goes to infinity ? (optimization error)
  $\implies$ heavily linked with the geometry (convexity, smoothness in the Wasserstein sense) of the loss
- (for minimizers) what can we say as the number of particles grow ? ("quantization" error)

Outline

Loss function for the unnormalized densities - the KL

Many possibilities for the choice of $\mathrm{D}(\cdot|\mu^*)$ among Wasserstein distances, f-divergences, Integral Probability Metrics...

For instance, D could be the Kullback-Leibler divergence:

$$\mathrm{KL}(\mu|\mu^*) = \begin{cases} \int_{\mathbb{R}^d} \log\left(\frac{\mu}{\mu^*}(x)\right) d\mu(x) & \text{if } \mu \ll \mu^* \\ +\infty & \text{otherwise.} \end{cases}$$

The KL as an objective is convenient when the unnormalized density of μ^* is known since it **does not depend on the normalization constant!**

Indeed writing $\mu^*(x) = e^{-V(x)}/Z$ we have:

$$\mathrm{KL}(\mu|\mu^*) = \int_{\mathbb{R}^d} \log\left(\frac{\mu}{e^{-V}}(x)\right) d\mu(x) + \log(Z).$$

But, it is not convenient when we have a discrete approximation of μ^*. Also, we cannot evaluate it for discrete μ.

KL Gradient flow in practice

- The gradient flow of the KL can be implemented via the Probability Flow (ODE):

$$d\tilde{x}_t = -\nabla \log \left(\frac{\mu_t}{\mu^*}\right)(\tilde{x}_t)dt \tag{1}$$

  or the Langevin diffusion (SDE):

$$dx_t = \nabla \log \mu^*(x_t)dt + \sqrt{2}dB_t \tag{2}$$

  (they share the same marginals $(\mu_t)_{t\geq 0}$)

- (2) can be discretized in time as Langevin Monte Carlo (LMC) [Roberts and Tweedie, 1996]

$$x_{m+1} = x_m + \gamma \nabla \log \mu^*(x_m) + \sqrt{2\gamma}\epsilon_m, \quad \epsilon_m \sim \mathcal{N}(0, \mathrm{Id}_{\mathbb{R}^d}).$$

- (1) can be approximated by a particle system (e.g. SVGD [Liu, 2017, He et al., 2022])
- however MCMC methods suffer an integral approximation error of order $\mathcal{O}(n^{-1/2})$ if we use $\mu_n = \frac{1}{n}\sum_{i=1}^n \delta_{x_i}$ (x_i iterates of MCMC) [Łatuszyński et al., 2013]

Another f-divergence?

- The chi-square divergence:

$$\chi^2(\mu \,\|\, \mu^*) := \begin{cases} \int \left(\frac{\mathrm{d}\mu}{\mathrm{d}\mu^*} - 1\right)^2 \mathrm{d}\mu^* & \mu \ll \mu^* \\ +\infty & \text{otherwise.} \end{cases}$$

  not convenient neither when μ^*'s unnormalized density is known, or if we have a discrete approximation.
- χ^2-gradient requires the normalizing constant of μ^*: $\nabla \frac{\mu}{\mu^*}$
- However, the GF of χ^2 has interesting properties (see [Chewi et al., 2020, Craig et al., 2022] for a discussion, results from [Matthes et al., 2009, Dolbeault et al., 2007])
  $\Longrightarrow$ distinguishing whether KL or χ^2 GF is more favorable is an active area of research

Losses for the discrete case

D could be the MMD (Maximum Mean Discrepancy):

$$\begin{aligned}
\mathrm{MMD}^2(\mu,\mu^*) &= \sup_{f\in\mathcal{H}_k,\|f\|_{\mathcal{H}_k}\le 1} \left| \int f d\mu - \int f d\mu^* \right| \\
&= \|m_\mu - m_{\mu^*}\|^2_{\mathcal{H}_k}, \quad \text{where } m_\mu = \int k(x,\cdot) d\mu(x) \\
&= \iint_{\mathbb{R}^d} k(x,y) d\mu(x) d\mu(y) \\
&\quad + \iint_{\mathbb{R}^d} k(x,y) d\mu^*(x) d\mu^*(y) - 2 \iint_{\mathbb{R}^d} k(x,y) d\mu(x) d\mu^*(y).
\end{aligned}$$

where $k : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is a p.s.d. kernel (e.g. $k(x,y) = e^{-\|x-y\|^2}$) and $\mathcal{H}_k$ is the RKHS associated to k.

It is convenient when we have a discrete approximation of μ^* (to approximate integrals).

Why we care about the loss

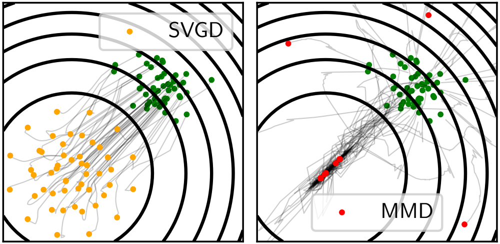


Figure: Toy example with 2D standard Gaussian. The green points represent the initial positions of the particles. The light grey curves correspond to their trajectories under the different v_{μ_t}.

Gradient flow of the KL to a Gaussian $\mu^*(x) \propto e^{-\frac{\|x\|^2}{2}}$ is well-behaved, but not the MMD.

A proposal†: Interpolate between MMD and χ^2

"De-Regularized MMD" leverages the variational formulation of χ^2:

$$\mathrm{DMMD}(\mu||\mu^*) = (1+\lambda)\Big\{\max_{h\in\mathcal{H}_k} \int h d\mu - \int h d\mu^* - \frac{1}{4}\int h^2 d\mu^* - \frac{1}{4}\lambda\|h\|^2_{\mathcal{H}_k}\Big\} \quad (3)$$

It is a divergence for any λ, recovers χ^2 for $\lambda = 0$ and MMD for $\lambda = +\infty$.

DMMD **and its gradient be written in closed-form, in particular if μ, μ^* are discrete** (depends on λ and kernel matrices over samples of μ, μ^*):

$$\mathrm{DMMD}(\mu||\mu^*) = (1+\lambda)\left\|(\Sigma_{\mu^*} + \lambda\,\mathrm{Id})^{-\frac{1}{2}}(m_\mu - m_{\mu^*})\right\|^2_{\mathcal{H}_k},$$

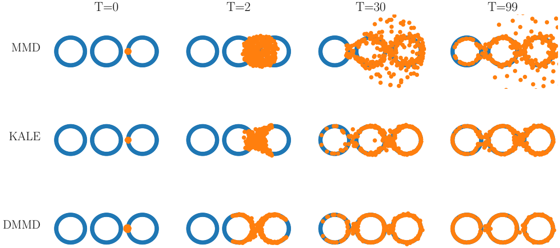
$$\nabla\,\mathrm{DMMD}(\mu||\mu^*) = \nabla h^*_{\mu,\mu^*}$$

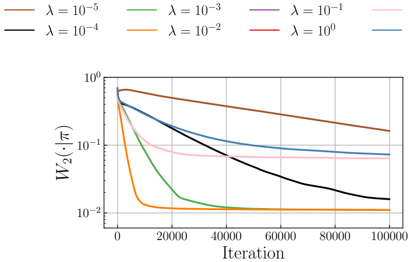
where $\Sigma_{\mu^*} = \int k(\cdot,x)\otimes k(\cdot,x)d\mu^*(x)$, where $(a\otimes b)c = \langle b,c\rangle_{\mathcal{H}_k} a$; and h^*_{μ,μ^*} solves (3).

A similar idea was proposed for the KL, yielding Kale divergence [Glaser et al., 2021] but was not closed-form.

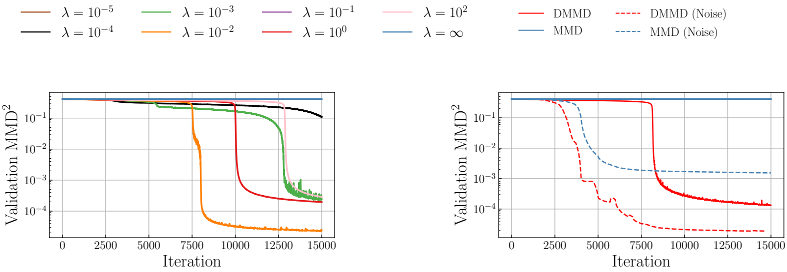
† with H. Chen, A. Gretton, P. Glaser (UCL), A. Mustafi, B. Sriperumbudur (CMU)

Ring Experiment





Student-teacher networks experiment[‡]



- the teacher network $w \mapsto \Psi_{\mu^*}(w)$ is given by M particles $(\xi_1, \ldots, \xi_M)$ which are fixed during training $\Longrightarrow \mu = \frac{1}{M}\sum_{j=1}^{M} \delta_{\xi_j}$
- the student network $w \mapsto \Psi_{\mu}(w)$ has n particles $(x_1, \ldots, x_n)$ that are initialized randomly $\Longrightarrow \mu = \frac{1}{n}\sum_{i=1}^{n} \delta_{x_j}$

$$\min_{\mu} \mathbb{E}_{w \sim P_{data}} \left[(\Psi_{\mu^*}(w) - \Psi_{\mu}(w)^2 \right]$$

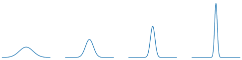
$$\Longleftrightarrow \min_{\mu} \mathrm{MMD}(\mu, \mu^*) \text{ with } k(x, x') = \mathbb{E}_{w \sim P_{data}}[\phi_{x'}(w)\phi_x(w)].$$

[‡]Same setting as [Arbel et al., 2019].

Another idea - "Mollified" discrepancies

Examples of mollifiers/kernels (Gaussian, Laplace, Riesz-s):

$$k_\epsilon^g(x) := \frac{\exp\left(-\frac{\|x\|_2^2}{2\epsilon^2}\right)}{Z^g(\epsilon)}, \quad k_\epsilon^g(x) := \frac{\exp\left(-\frac{\|x\|_2}{\epsilon}\right)}{Z^l(\epsilon)}, \quad k_\epsilon^s(x) := \frac{1}{(\|x\|_2^2 + \epsilon^2)^{s/2} Z^r(s,\epsilon)}$$



- Mollified chi-square [Li et al., 2022a, Craig et al., 2022]:

$$\mathcal{E}_\epsilon(\mu) = \int \left(k_\epsilon * \frac{\mu}{\sqrt{\mu^*}}\right)(x) \frac{\mu}{\sqrt{\mu^*}}(x)\,\mathrm{d}x \xrightarrow[\varepsilon \to 0]{} \chi^2(\mu|\mu^*) + 1$$

- Mollified KL[§] [Craig and Bertozzi, 2016]:

$$\mathrm{KL}(k_\epsilon \star \mu|\mu^*) \xrightarrow[\varepsilon \to 0]{} \mathrm{KL}(\mu|\mu^*)$$

[§] Also ongoing work with Tom Huix (CMAP).

Outline

Background on convexity and smoothness in $\mathbb{R}^d$

Recall that if $f : \mathbb{R}^d \to \mathbb{R}$ is twice differentiable,

- f is λ-convex

$$\forall x, y \in \mathbb{R}^d, t \in [0,1] :$$

$$f(tx + (1-t)y) \leq tf(x) + (1-t)f(y) - \frac{\lambda}{2} t(1-t)\|x-y\|^2$$
$$\iff v^T \nabla f(x) v \leq M\|v\|_2^2 \quad \forall x, v \in \mathbb{R}^d.$$

- f is M-smooth

$$\|\nabla f(x) - \nabla f(y)\| \leq M\|x-y\| \quad \forall x, y \in \mathbb{R}^d$$
$$\iff v^T \nabla f(x) v \leq M\|v\|_2^2 \quad \forall x, v \in \mathbb{R}^d.$$

(Geodesically)-convex and smooth losses

$\mathcal{F}$ is said to be λ-displacement convex if along W_2 geodesics $(\rho_t)_{t\in[0,1]}$:

$$\mathcal{F}(\rho_t) \leq (1-t)\mathcal{F}(\rho_0) + t\mathcal{F}(\rho_1) - \frac{\lambda}{2}t(1-t)W_2^2(\rho_0,\rho_1) \qquad \forall\, t \in [0,1].$$

The **Wasserstein Hessian** of a functional $\mathcal{F} : \mathcal{P}_2(\mathbb{R}^d) \to \mathbb{R}$ at μ is defined for any $\psi \in \mathcal{C}_c^\infty(\mathbb{R}^d)$ as:

$$\operatorname{Hess}_\mu \mathcal{F}(\psi,\psi) := \frac{\mathrm{d}^2}{\mathrm{d}t^2}\Big|_{t=0} \mathcal{F}(\mu_t)$$

where $(\mu_t, v_t)_{t\in[0,1]}$ is a Wasserstein geodesic with $\mu_0 = 0$, $v_0 = \nabla\psi$.

$$\boxed{\mathcal{F} \text{ is } \lambda\text{-displacement convex} \iff \operatorname{Hess}_\mu \mathcal{F}(\psi,\psi) \geq \lambda\|\nabla\psi\|^2_{L^2(\mu)}}$$

(See [Villani, 2009, Proposition 16.2]). In an analog manner we can define smooth functionals as functionals with upper bounded Hessians.

Guarantees for Wasserstein gradient descent

Consider Wasserstein gradient descent (Euler discretization of Wasserstein gradient flow)

$$\mu_{l+1} = (\mathrm{Id} - \gamma \nabla \mathcal{F}'(\mu_l))_{\#}\mu_l$$

Assume $\mathcal{F}$ is M-smooth. Then, we have a descent lemma:

$$\mathcal{F}(\mu_{l+1}) - \mathcal{F}(\mu_l) \leq -\gamma \left(1 - \frac{\gamma}{2} M\right) \|\nabla \mathcal{F}'(\mu_l)\|^2_{L^2(\mu_l)}.$$

Moreover, if $\mathcal{F}$ is λ-convex, we have the global rate

$$\mathcal{F}(\mu_L) \leq \frac{W_2^2(\mu_0, \mu^*)}{2\gamma L} - \frac{\lambda}{L} \sum_{l=0}^{L} W_2^2(\mu_l, \mu^*).$$

(so the barrier term degrades with λ).

Some examples

- Let $\mu^* \propto e^{-V}$, we have [Wibisono, 2018]

$$\mathrm{Hess}_\mu \, \mathrm{KL}(\psi,\psi) = \int \left[\langle \mathrm{H}_V(x) \nabla\psi(x), \nabla\psi(x) \rangle + \|\mathrm{H}\psi(x)\|_{HS}^2 \right] q(x) \, \mathrm{d}x.$$

  If V is m-strongly convex, then the KL is m-geo. convex; however it is not smooth (Hessian is unbounded). Similar story for χ^2-square [Ohta and Takatsu, 2011].

- For a M-smooth kernel k [Arbel et al., 2019]

$$\mathrm{Hess}_\mu \, \mathrm{MMD}^2(\psi,\psi) = \int \nabla\psi(x)^\top \nabla_1 \nabla_2 k(x,y) \nabla\psi(y) d\mu(x) d\mu(y) +$$

$$2 \int \nabla\psi(x)^\top \left(\int \mathrm{H}_1 k\,(x,z)\, d\mu(z) - \int \mathrm{H}_1 k\,(x,z)\, d\mu^*(z) \right) \nabla\psi(x) d\mu(x)$$

  It is M-smooth but not geodesically convex (Hessian lower bounded by a big negative constant)

Partial results for other discrepancies

- For DMMD (interpolating between χ^2 and MMD), for $\mu^* \propto e^{-V}$. If V is m-strongly convex, for λ small enough, we can lower bound $\mathrm{Hess}_\mu \, \mathrm{DMMD}(\mu||\mu^*)$ [¶].

$$\mathrm{Hess}_\mu \, \chi^2(\mu\|\mu^*) = \int \frac{\mu(x)^2}{\mu^*(x)}(L_{\mu^*}\psi(x))^2 dx$$
$$+ \int \frac{\rho(x)^2}{\mu^*(x)} \langle \mathrm{H}_V(x)\nabla\psi(x), \nabla\psi(x)\rangle \, dx + \int \frac{\mu(x)^2}{\mu^*(x)} \|\mathrm{H}\psi(x)\|^2_{HS} \, dx$$

where L_{μ^*} is the standard Langevin diffusion $L_{\mu^*}\psi = \langle \nabla V(x), \nabla\psi(x)\rangle - \Delta\psi(x)$.

- For mollified discrepancies
  - some asymptotic results for mollified χ^2 [Li et al., 2022a] (only at μ^*)
  - mollified $\mathrm{KL}(k_\epsilon \star \mu||\mu^*)$: we only get smoothness for discrete μ

¶ under strong regularity assumptions on μ and μ^*

Outline

What is known

What can we say on $\inf_{x_1,\ldots,x_n} D(\mu_n|\mu^*)$ where $\mu_n = \sum_{i=1}^n \delta_{x_i}$?

- Quantization rates for the Wasserstein distance [Kloeckner, 2012, Mérigot et al., 2021]

$$W_2(\mu_n, \mu^*) \sim O(n^{-\frac{1}{d}})$$

- Forward KL [Li and Barron, 1999]: for every $g_P = \int k_\epsilon(\cdot - w)dP(w)$,

$$\arg\min_{\mu_n} \mathrm{KL}(\mu^*|k_\epsilon \star \mu_n) \leq \mathrm{KL}(\mu^*|g_P) + \frac{C^2_{\mu^*,P}\gamma}{n}$$

where $C^2_{\mu^*,P} = \int \frac{\int k_\epsilon(x-m)^2 dP(m)}{(\int k_\epsilon(x-w)dP(w))^2} d\mu^*(x)$, and $\gamma = 4\log(3\sqrt{e}+a)$ is a constant depending on ϵ with $a = \sup_{z,z'\in\mathbb{R}^d} \log\left(k_\epsilon(x-z)/k_\epsilon(x-z')\right)$.

Recent results

- For smooth and bounded kernels in [Xu et al., 2022] and μ^* with exponential tails, we get using Koksma-Hlawka inequality

$$\min_{\mu_n} \mathrm{MMD}(\mu_n, \mu^*) \leq C_d \frac{(\log n)^{\frac{5d+1}{2}}}{n}.$$

This bounds the integral error for $f \in \mathcal{H}_k$ (by Cauchy-Schwartz):

$$\left| \int_{\mathbb{R}^d} f(x) d\mu^*(x) - \int_{\mathbb{R}^d} f(x) d\mu(x) \right| \leq \|f\|_{\mathcal{H}_k} \mathrm{MMD}(\mu, \pi).$$

- For the reverse KL (joint work with Tom Huix) we get (in the well-specified case) adapting the proof of [Li and Barron, 1999]:

$$\min_{\mu_n} \mathrm{KL}(k_\epsilon \star \mu | \mu^*) \leq C^2_{\mu^*} \frac{\log(n) + 1}{n}.$$

This bounds the integral error for measurable $f : \mathbb{R}^d \to [-1, 1]$ (by Pinsker inequality):

$$\left| \int f d(k_\epsilon \star \mu_n) - \int f d\mu^* \right| \leq \sqrt{\frac{C^2_{\mu^*}(\log(n) + 1)}{2n}}.$$

Outline

More ideas can be borrowed to optimization (but there are limitations)

- Sampling with inequality constraints [Liu et al., 2021, Li et al., 2022b]

$$\min_{\mu \in \mathcal{P}_2(\mathbb{R}^d)} \mathrm{KL}(\mu \| \mu^*)$$
$$\text{subject to } \mathbb{E}_{x\sim\mu}\left[g(x)\right] \leq 0$$

- Bilevel sampling ‖

$$\min_{\theta \in \mathbb{R}^p} \ell(\theta) := \min_{\theta \in \mathbb{R}^p} \mathcal{F}(\mu^*(\theta))$$

where for instance

  - $\mu^*(\theta)$ is a Gibbs distribution, minimizing the KL

$$\mu^*(\theta)[x] = \exp(-V(x,\theta))/Z_\theta \,.$$

  - $\mu^*(\theta)$ is the output of a Diffusion model parametrized by θ, this does not minimize a divergence on $\mathcal{P}(\mathbb{R}^d)$

‖ with P. Marion, Q. Berthet, P. Bartlett, M. Blondel, V. Bortoli, A. Doucet, F. Llinares-Lopez, C. Paquette

A numerical example from [Li et al., 2022a]

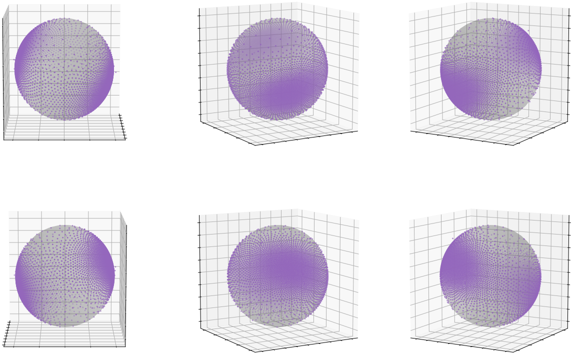
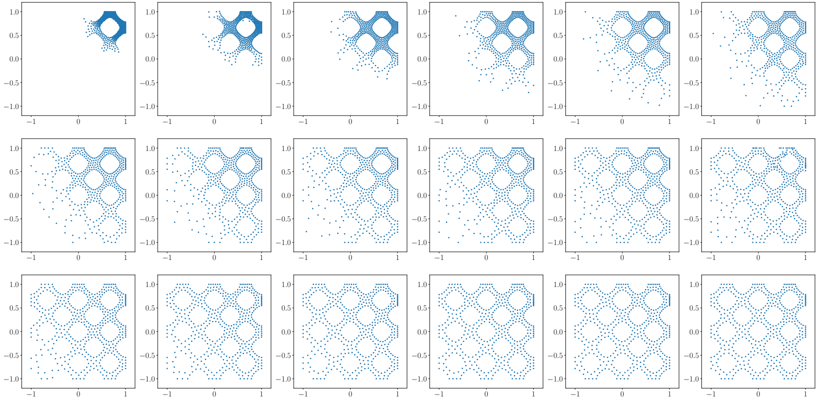


Figure: Sampling from the von Mises-Fisher distribution obtained by constraining a 3-dimensional Gaussian to the unit sphere. The unit-sphere constraint is enforced using the dynamic barrier method and the shown results are obtained using MIED with Riesz kernel and $s = 3$. The six plots are views from six evenly spaced angles.

A numerical example from [Li et al., 2022a]



Uniform sampling of the region $\{(x, y) \in [-1, 1]^2 : (\cos(3\pi x) + \cos(3\pi y))^2 < 0.3\}$ using MIED with a Riesz mollifier ($s = 3$) where the constraint is enforced using the dynamic barrier method.

Open questions, directions

- Finite-particle/quantization guarantees are still missing for many losses or in the non-well specified case

$$\mathrm{D}(\mu_n||\mu^*) \leq f(n, \mu^*)?$$

- How to improve the performance of the algorithms for highly non-log concave targets? e.g. through sequence of targets $(\mu^*)_{t\in[0,1]}$ interpolating between μ_0 and μ^*?
- Multimodal targets μ^*? choose a sequence of intermediate targets.
- Shape of the trajectories? change the underlying metric

Main references

(with code):

- Maximum Mean Discrepancy Gradient Flow. Arbel, M., Korba, A., Salim, A., and Gretton, A. (Neurips 2019).
- Accurate quantization of measures via interacting particle-based optimization. Xu, L., Korba, A., and Slepcev, D. (ICML 2022).
- Sampling with mollified interaction energy descent. Li, L., Liu, Q., Korba, A., Yurochkin, M., and Solomon, J. (ICLR 2023).

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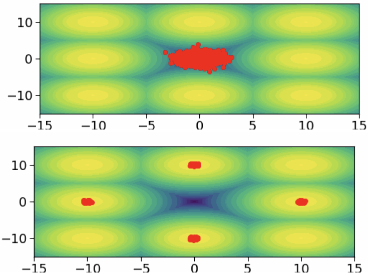
Mixture of Gaussians

Langevin Monte Carlo on a mixture of Gaussians does not manage to target all modes in reasonable time, even in low dimensions.



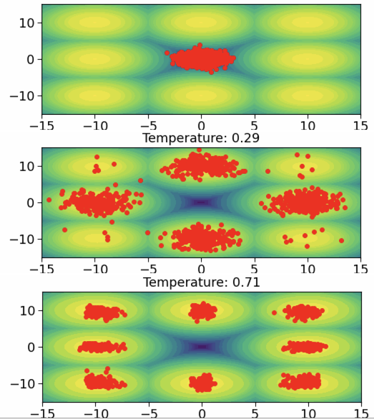
Picture from O. Chehab.

Annealing

One possible fix : sequence of tempered targets as:

$$\mu_\beta^* \propto \mu_0^\beta (\mu^*)^{1-\beta}, \quad \beta \in [0,1]$$

It is **discretized Fisher-Rao gradient flow** [Chopin et al., 2023].



Other tempered path

"Convolutional path" ($\beta \in [0, +\infty[$) frequently used in Diffusion Models

$$\mu_\beta^* = \frac{1}{\sqrt{1-\beta}}\mu_0\left(\frac{\cdot}{\sqrt{1-\beta}}\right) * \frac{1}{\sqrt{\beta}}\mu^*\left(\frac{\cdot}{\sqrt{\beta}}\right)$$

(vs "geometric path" $\mu_\beta^* \propto \mu_0^\beta (\mu^*)^{1-\beta}$)