Computing Optimal Transport Barycentres

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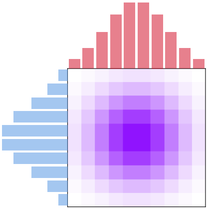
21st November 2025

Comparing Measures with Optimal Transport

Discrete OT cost:

$\mu := \sum_{i=1}^{n} a_i \delta_{x_i}, \ \nu := \sum_{j=1}^{m} b_j \delta_{y_j},$

$$\mathcal{T}_c(\mu, \nu) := \min_{\substack{P \in \mathbb{R}_+^{n \times m} \\ P\mathbf{1} = a \\ P^\top \mathbf{1} = b}} \sum_{i=1}^{n} \sum_{j=1}^{m} c(x_i, y_j) P_{i,j}.$$



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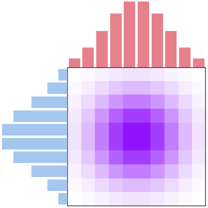
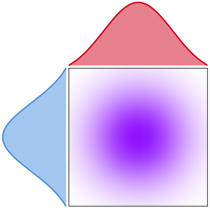


OT cost: $\mu \in \mathcal{P}(\mathcal{X}), \; \nu \in \mathcal{P}(\mathcal{Y}),$

$$\mathcal{T}_c(\mu, \nu) := \inf_{\substack{\pi \in \mathcal{P}(\mathcal{X}\times\mathcal{Y}) \\ \pi_{\mathcal{X}} = \mu \\ \pi_{\mathcal{Y}} = \nu}} \int_{\mathcal{X}\times\mathcal{Y}} c(x, y) \mathrm{d}\pi(x, y).$$



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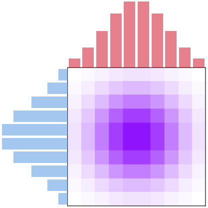

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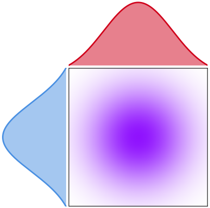

p-Wasserstein distance: $\mathcal{X} = \mathcal{Y}$ and $c(x, y) = d_{\mathcal{X}}(x, y)^p$.

Random variable formulation: $\mathcal{T}_c(\mu, \nu) = \inf_{(X,Y):\ X\sim\mu, Y\sim\nu} \mathbb{E}\left[c(X, Y)\right].$

Euclidean 2-Wasserstein Distance and Gaussian Case

$$\mathrm{W}_2^2(\mu, \nu) = \inf_{\pi \in \Pi(\mu,\nu)} \int_{\mathbb{R}^d \times \mathbb{R}^d} \|x - y\|_2^2 \mathrm{d}\pi(x, y).$$

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Bures-Wasserstein

$$\mathrm{W}_2^2(\mathcal{N}(m_1, S_1), \mathcal{N}(m_2, S_2))$$
$$= \|m_1 - m_2\|_2^2$$
$$+\mathrm{Tr}\left(S_1 + S_2 - 2(S_1^{1/2} S_2 S_1^{1/2})^{1/2}\right)$$

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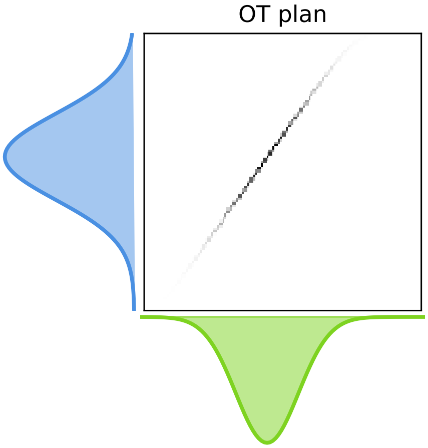
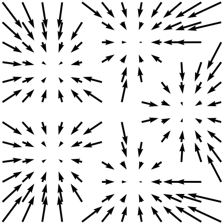
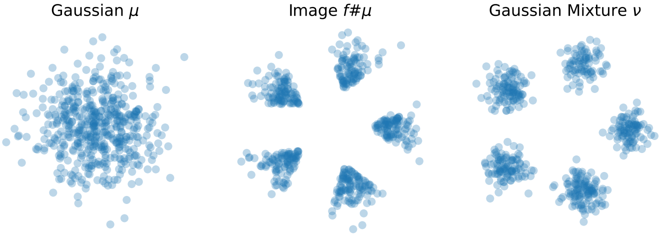


Push-forward measures and OT maps

Image Measure: $f\#\mu := \mathrm{Law}_{X\sim\mu}[f(X)]$





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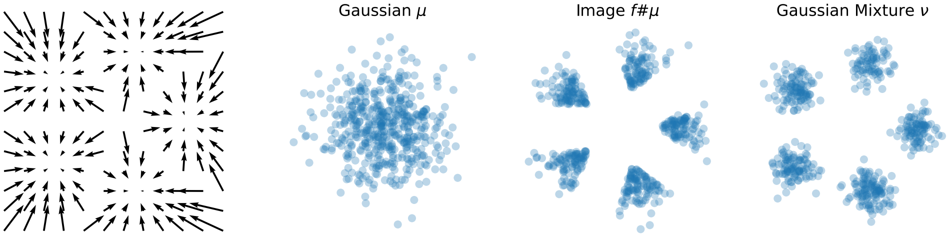

Brenier's Theorem

If $c(x,y) = \|x-y\|_2^2$, and $\mu \ll \mathscr{L}^d$, then unique solution $\pi^* = (I, \nabla\varphi)\#\mu$, with φ convex.

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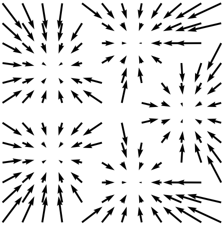

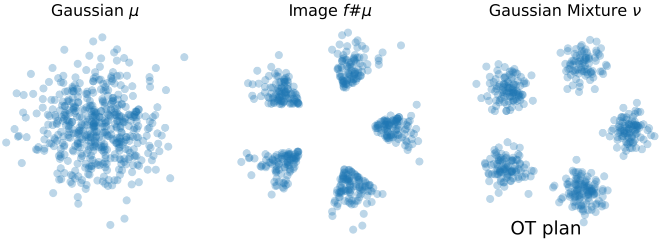

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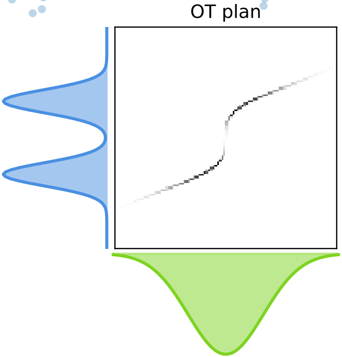


1. Optimal Transport

2. Wasserstein Barycentres

3. OT Barycentres

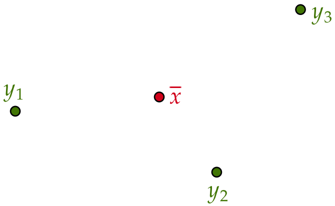
4. Discrete Case and Numerics

5. Application to GMMs

From Euclidean Combinations to Fréchet Means

$$\overline{x} = \sum_{k=1}^{K} \lambda_k y_k$$

$$\overline{x} = \underset{x \in \mathbb{R}^d}{\operatorname{argmin}} \sum_{k=1}^{K} \lambda_k \|x - y_k\|_2^2$$



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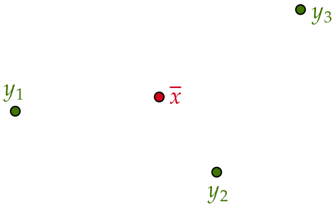
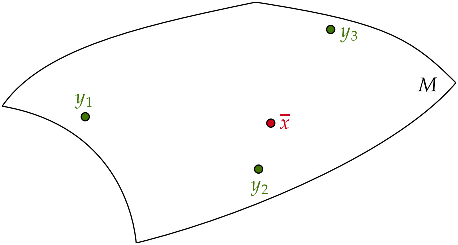


$$\overline{x} = \underset{x \in \mathbb{R}^d}{\operatorname{argmin}} \sum_{k=1}^{K} \lambda_k \|x - y_k\|_2^2$$

Fréchet mean:

$$\overline{x} \in \underset{x \in \mathcal{X}}{\operatorname{argmin}} \sum_{k=1}^{K} \lambda_k d(x, y_k)^2.$$



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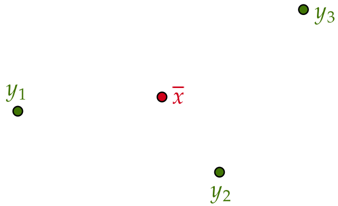

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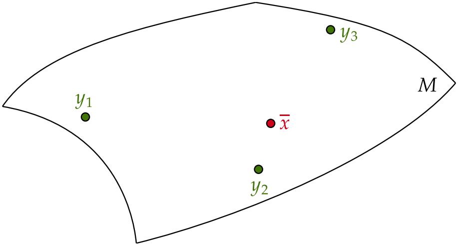
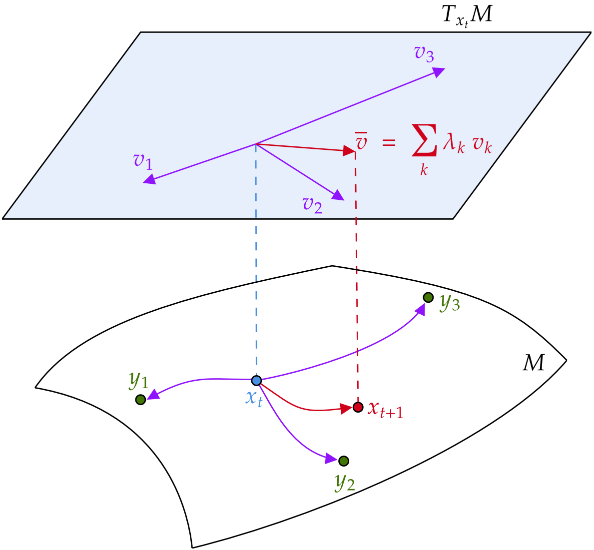


Generalisation: $\overline{x} \in \underset{x \in \mathcal{X}}{\operatorname{argmin}} \sum_{k=1}^{K} c_k(x, y_k)$.

Fixed-Point Algorithm for Fréchet Means on Manifolds



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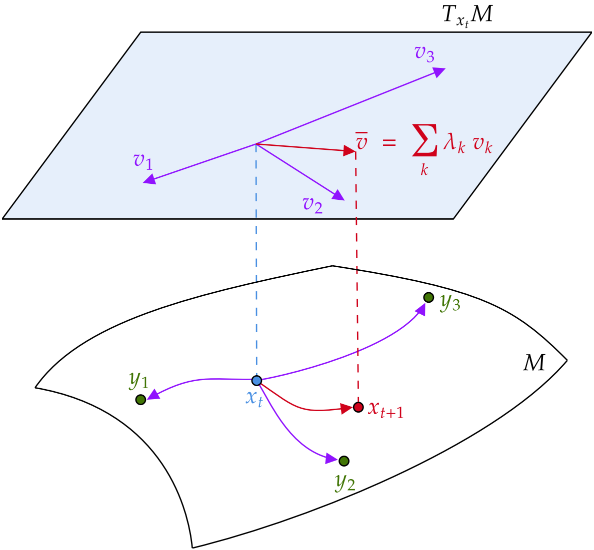


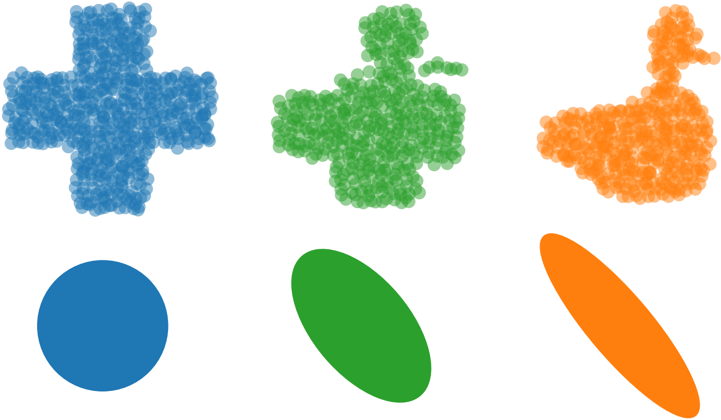
$$V(x) = \sum_{k=1}^{K} \lambda_k d(x, y_k)^2.$$

$$\nabla V(x) = -2 \sum_{k=1}^{K} \lambda_k \mathrm{Log}_x(y_k).$$

$$x_{t+1} = \mathrm{Exp}_{x_t}\left(-\frac{1}{2}\nabla V(x_t)\right).$$

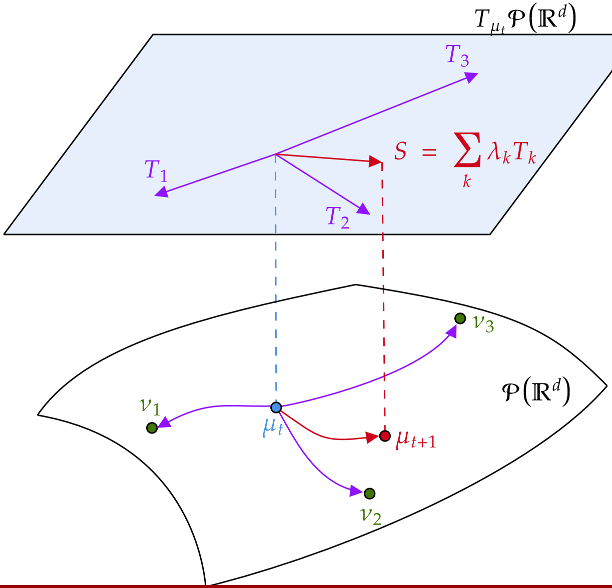
2-Wasserstein Barycentres (Agueh & Carlier 2011 [1])

$$\underset{\mu \in \mathcal{P}(\mathbb{R}^d)}{\operatorname{argmin}} \sum_{k=1}^{K} \lambda_k \mathrm{W}_2^2(\mu, \nu_k).$$



Fixed-Point Method (Alvarez-Esteban et al. 2016 [3])

Assumptions: $c(x, y) = \|x - y\|_2^2$, AC measures on $\mathbb{R}^d$.



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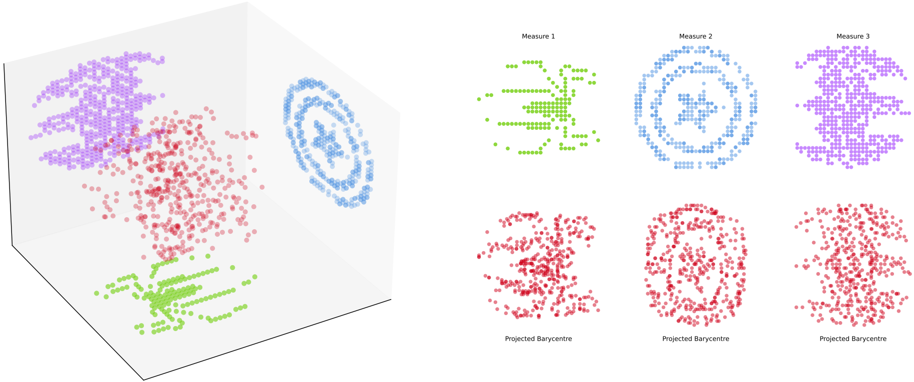
Motivation for OT barycenters with generic costs

$$\mathrm{W}_1(\mu,\nu) := \inf_{\pi\in\Pi(\mu,\nu)} \int \|x-y\|_2 \mathrm{d}\pi(x,y).$$

Find $\mu \in \mathcal{P}(\mathbb{R}^3)$ minimising $\sum_k \frac{1}{3}\mathrm{W}_1(P_k\#\mu, \nu_k)$ where $\nu_k \in \mathcal{P}(\mathbb{R}^2)$.



Generalises Delon et al. 2021 [5] where $c_k(x,y) = \|P_k(x) - y\|_2^2$.

Generalising Wasserstein Barycentres

Setting:

- $(\mathcal{X}, d_{\mathcal{X}})$ compact metric space for barycentres μ.
- $(\mathcal{Y}_k, d_{\mathcal{Y}_k})$ compact metric spaces for measures ν_k.
- $c_k : \mathcal{X} \times \mathcal{Y}_k \longrightarrow \mathbb{R}_+$ continuous cost functions.

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$$\underset{\mu \in \mathcal{P}(\mathcal{X})}{\operatorname{argmin}}\ V(\mu), \quad V(\mu) := \sum_{k=1}^{K} \mathcal{T}_{c_k}(\mu, \nu_k).$$

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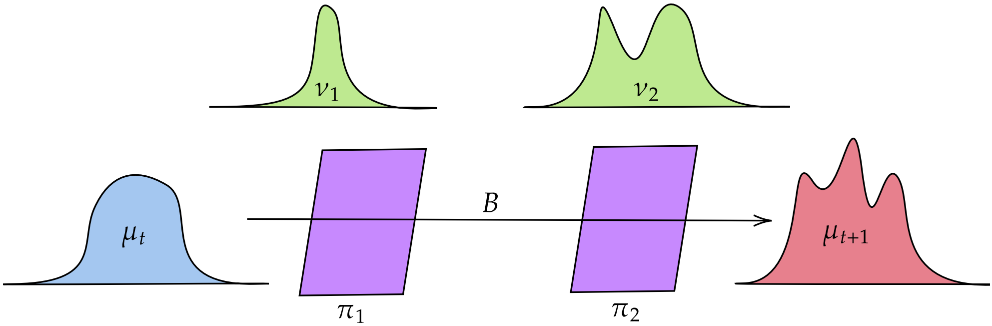
$$\underset{\mu \in \mathcal{P}(\mathcal{X})}{\operatorname{argmin}} V(\mu), \quad V(\mu) := \sum_{k=1}^{K} \mathcal{T}_{c_k}(\mu, \nu_k).$$

Assumption: The ground barycenter function

$$B(y_1, \cdots, y_k) := \underset{x \in \mathcal{X}}{\operatorname{argmin}} \sum_{k=1}^{K} c_k(x, y_k)$$

is well-defined.

Fixed-point Algorithm



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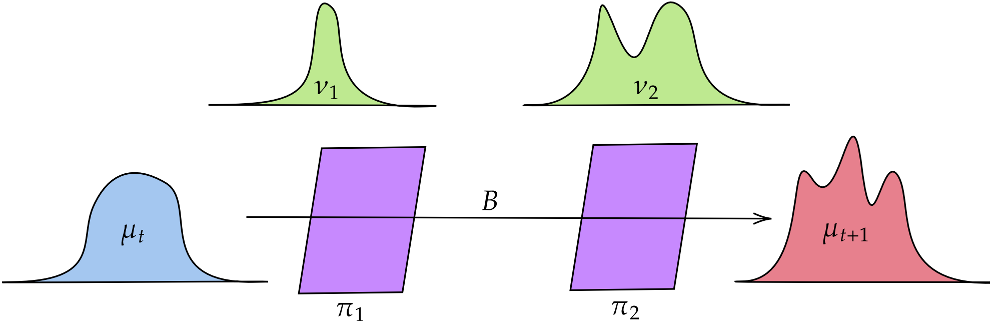


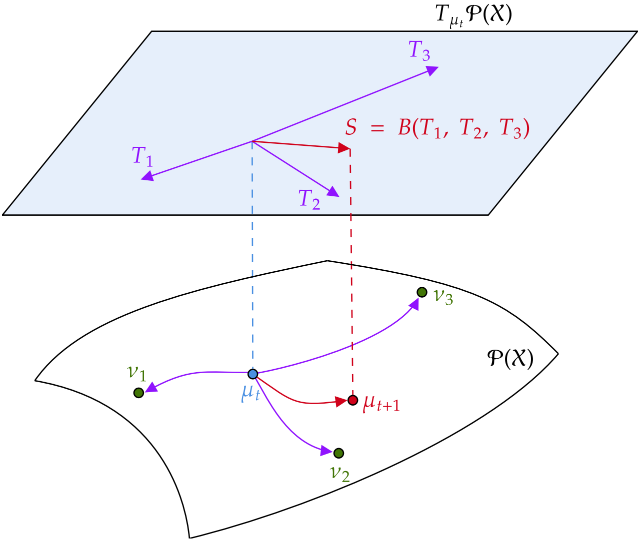
$$\Gamma(\mu) := \left\{(X, Y_1, \cdots, Y_K) \ : \ (X, Y_k) \in \Pi^*_{c_k}(\mu, \nu_k)\right\},$$

$$G := \begin{cases} \mathcal{P}(\mathcal{X}) & \rightrightarrows & \mathcal{P}(\mathcal{X}) \\ \mu & \mapsto & \{\mathrm{Law}\,[B(Y_1, \cdots, Y_K)] \ : (X, Y_1, \cdots, Y_K) \in \Gamma(\mu)\} \end{cases}.$$

$$\boxed{\mu_{t+1} \in G(\mu_t).}$$

Relation to Alvarez-Esteban et al. 2016 [3]

Dream case: $\mathcal{X} = \mathcal{Y}_1 = \cdots = \mathcal{Y}_K$ and maps exist.



Reality:

$$\gamma : \gamma_{0,k} \in \Pi^*_{c_k}(\mu_t, \nu_k),$$

$$\mu_{t+1} = B\#\gamma.$$

Algorithm Convergence

Ground Barycentre Inequality [6, Lemma 3.8]

$$\sum_k c_k(x, y_k) \geq \sum_k c_k(\overline{x}, y_k) + \delta(x, \overline{x}), \quad \overline{x} := B(y_1, \cdots, y_K).$$

Case $\|x - y\|_2^2$: simply $\sum_k \lambda_k \|x - y_k\|_2^2 = \sum_k \|\overline{x} - y_k\|_2^2 + \|x - \overline{x}\|_2^2$.

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Decrease Property [6, Proposition 3.9]

$$\forall \overline{\mu} \in G(\mu),\ V(\mu) \geq V(\overline{\mu}) + \mathcal{T}_\delta(\mu, \overline{\mu}).$$

If μ^* is a barycentre then $G(\mu^*) = \{\mu^*\}$.

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Convergence [6, Theorem 3.10]

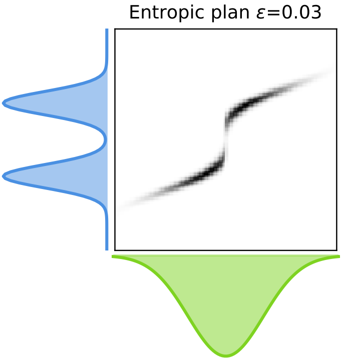
If μ is a subsequential limit of (μ_t) then $\mu \in G(\mu)$.

Entropic Barycentres

$$\mathcal{T}_{c,\varepsilon}(\mu, \nu) := \inf_{\pi \in \Pi(\mu,\nu)} \int_{\mathcal{X}\times\mathcal{Y}} c\mathrm{d}\pi + \varepsilon \, \mathrm{KL}(\pi | \mu \otimes \nu).$$

$$V_\varepsilon(\mu) := \sum_{k=1}^{K} \mathcal{T}_{c,\varepsilon}(\mu, \nu_k).$$

$G_\varepsilon(\mu) := B\#\gamma,$ with $\gamma_{0,k} = \Pi^*_{c_k,\varepsilon}(\mu, \nu_k).$



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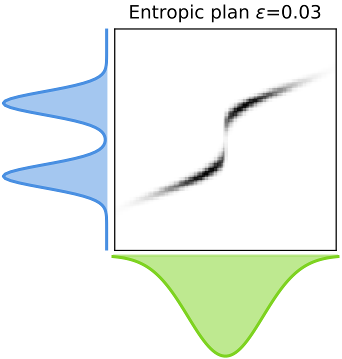


Decrease Property

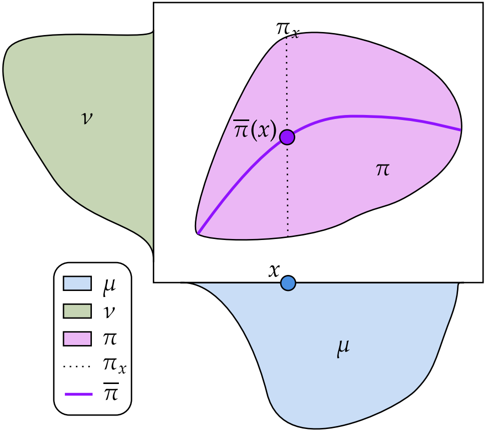
$V_\varepsilon(\mu) \geq V_\varepsilon(G_\varepsilon(\mu)) + \mathcal{T}_\delta(\mu, G_\varepsilon(\mu))$. If μ^* barycentre, $G_\varepsilon(\mu^*) = \mu^*$.

Convergence

If μ is a subsequential limit of (μ_t) then $\mu = G_\varepsilon(\mu)$.

Barycentric Projections

Replace a coupling π with a map $\overline{\pi}$.



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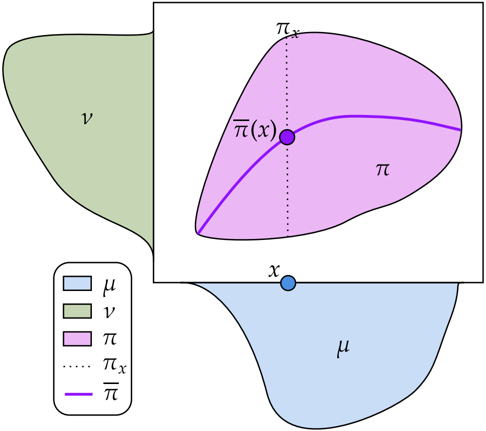

$$\overline{\pi}(x) = \int y \mathrm{d}\pi_x(y).$$

$$\overline{\pi}(x) = \mathbb{E}_{(X,Y)\sim\pi}[Y|X = x].$$

$$\overline{\pi} = \underset{f\in L^2(\mu)}{\operatorname{argmin}} \int \|f(x) - y\|_2^2 \mathrm{d}\pi(x, y).$$

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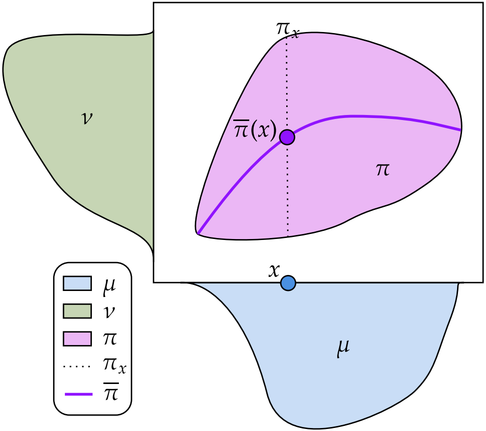

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$$H(\mu) = \left\{ B(\overline{\pi_1}, \cdots, \overline{\pi_K})\#\mu,\ \pi_k \in \Pi^*_{c_k}(\mu, \nu_k) \right\}.$$

No guarantees.

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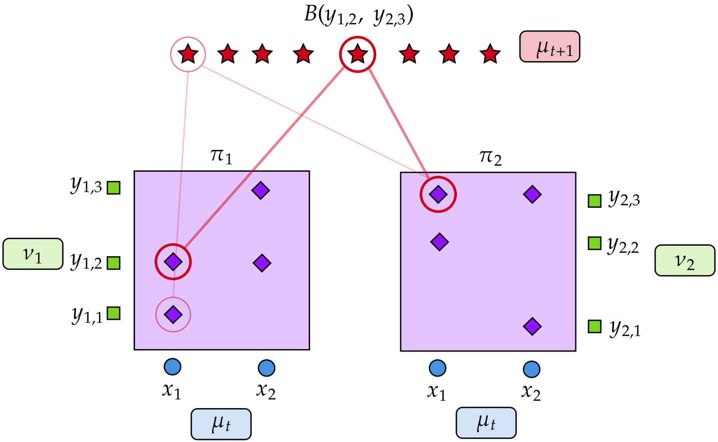
4. **Discrete Case and Numerics**
5. Application to GMMs

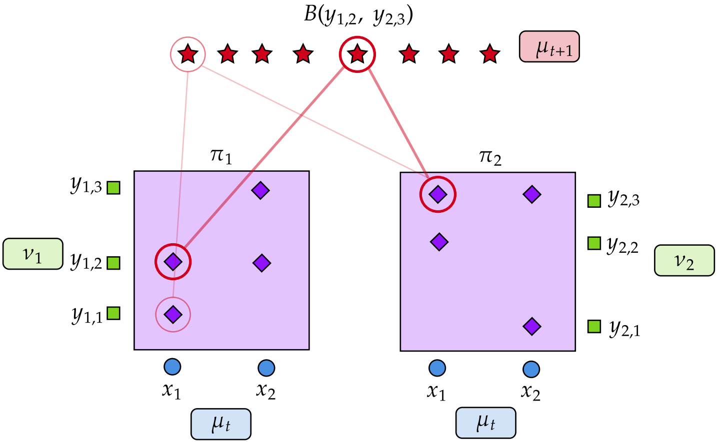
Discrete G



$$\mu = \sum_{i=1}^{n} a_i \delta_{x_i}$$

$$\nu_k = \sum_{j=1}^{n_k} b_{k,j} \delta_{y_{k,j}}$$

Discrete G



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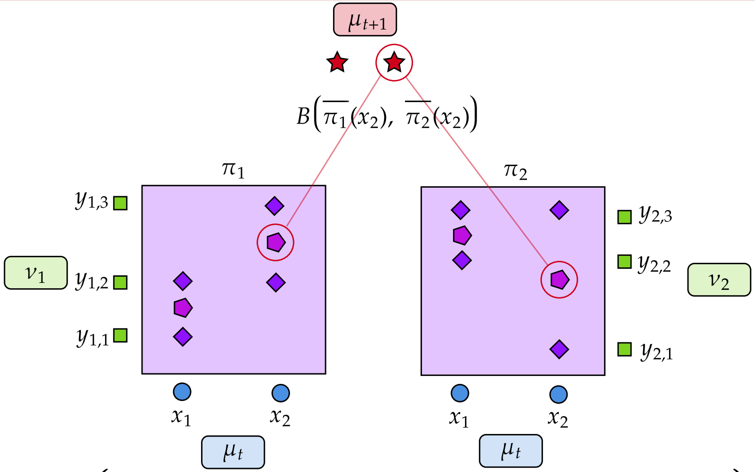
$$\nu_k = \sum_{j=1}^{n_k} b_{k,j} \delta_{y_{k,j}}$$

$$G(\mu) = \left\{ \sum_{i,j_1,\cdots,j_K} \gamma_{i,j_1,\cdots,j_K} \delta\Big(B(y_{1,j_1},\cdots,y_{K,j_K})\Big),\ \gamma^{(k)} \in \Pi^*_{c_k}(\mu,\nu_k) \right\}.$$

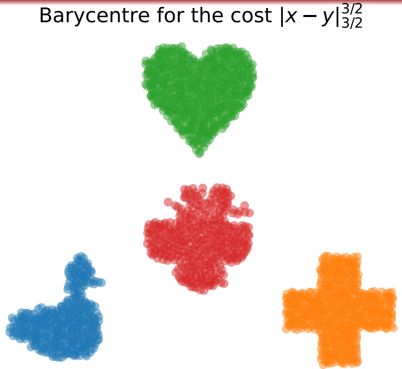
Discrete H (Generalises Cuturi & Doucet 2014 [4])

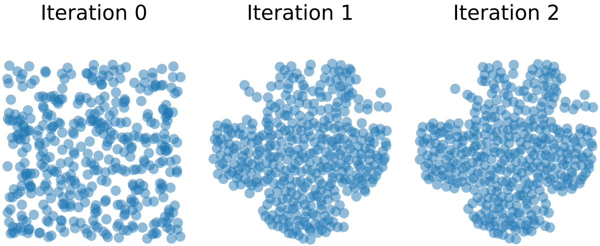


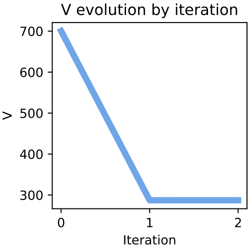
$$H(\mu) = \left\{ \sum_{i=1}^{n} a_i \delta\Big(B\left(\overline{\pi}_1(x_i), \cdots, \overline{\pi}_K(x_i)\right)\Big),\ \pi_k \in \Pi^*_{c_k}(\mu, \nu_k) \right\},$$

$$\overline{\pi}_k(x_i) = \frac{1}{a_i} \sum_{j=1}^{n_1} \pi^{(k)}_{i,j} y_{k,j}.$$

Illustration for $c(x, y) = \|x - y\|_{1.5}^{1.5}$

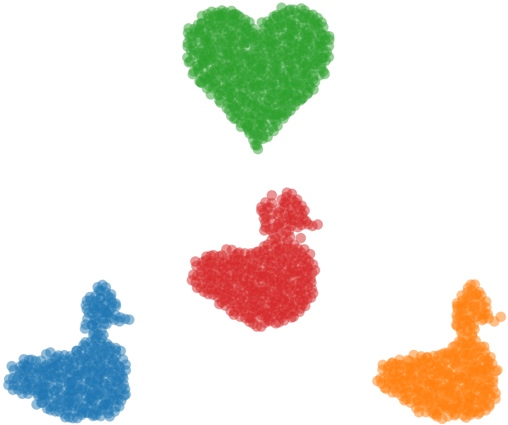




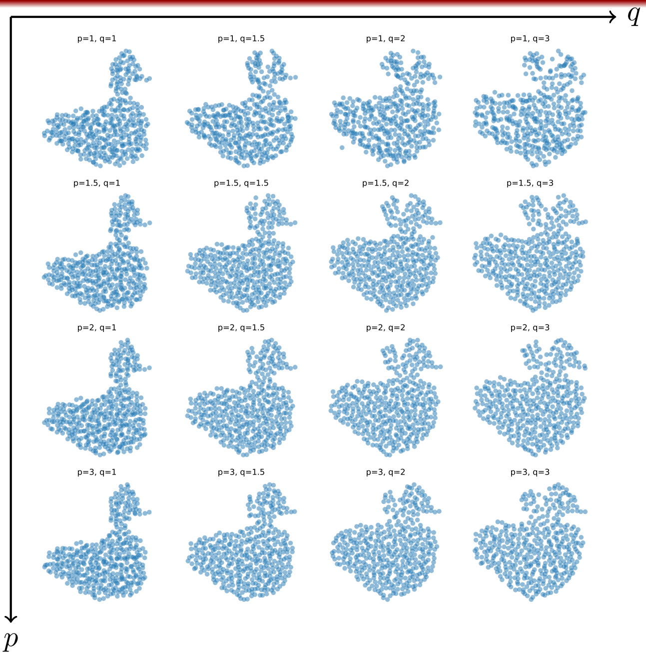


Application: Barycentres for p-norms with power q

Cost: $c(x, y) = \|x - y\|_p^q$.

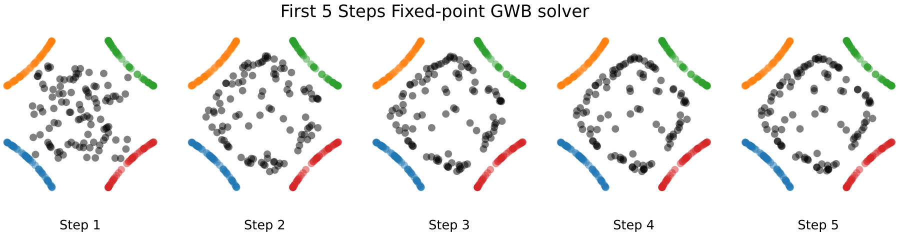


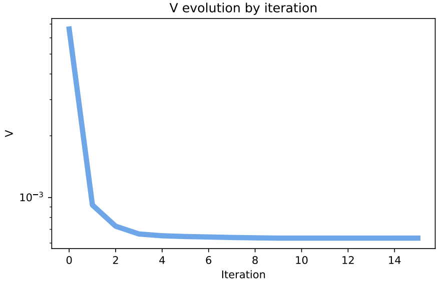
Application: Barycentres for p-norms with power q



Non-linear Generalised Wasserstein Barycentre

$\operatorname{argmin}_\mu \sum_{k=1}^4 \frac{1}{4}\mathrm{W}_2^2(P_k\#\mu, \nu_k)$ where P_k is the projection onto circle k.





OT between GMMs

$$\mathrm{W}_2^2(\mathcal{N}(m_1, S_1), \mathcal{N}(m_2, S_2)) = \|m_1 - m_2\|_2^2 + \underbrace{\mathrm{Tr}\left(S_1 + S_2 - 2(S_1^{1/2} S_2 S_1^{1/2})^{1/2}\right)}_{d_{\mathrm{BW}}^2(S_1, S_2) :=}.$$

OT between GMMs

$$\mathrm{W}_2^2(\mathcal{N}(m_1, S_1), \mathcal{N}(m_2, S_2)) = \|m_1 - m_2\|_2^2 + \underbrace{\mathrm{Tr}\left(S_1 + S_2 - 2(S_1^{1/2} S_2 S_1^{1/2})^{1/2}\right)}_{d_{\mathrm{BW}}^2(S_1, S_2) :=}.$$

Ground space: $(\mathcal{X}, d) = (\mathcal{Y}_k, d_{\mathcal{Y}_k}) = (\mathcal{N}, \mathrm{W}_2)$ with ground cost $c = \mathrm{W}_2^2$.

$$\mu = \sum_{i=1}^{n} a_i \delta_{\mathcal{N}(m_i, S_i)}, \ \nu = \sum_{j=1}^{m} b_j \delta_{\mathcal{N}(m_j', S_j')} \in \mathcal{P}(\mathcal{N});$$

$$\mathcal{T}_{\mathrm{W}_2^2}(\mu, \nu) = \min_{\pi \in \Pi(a, b)} \sum_{i,j} \left(\|m_i - m_j'\|_2^2 + d_{\mathrm{BW}}^2(S_i, S_j')\right) \pi_{i,j}.$$

Ground Barycentre Between Gaussians

Gaussian barycentres (Agueh & Carlier 2011 [1]).

$$B(\mathcal{N}(m_1, S_1), \cdots, \mathcal{N}(m_K, S_K)) = \mathcal{N}(\overline{m}, \overline{S}),$$

$$\overline{m} := \sum_{k=1}^{K} \lambda_k m_k, \quad \overline{S} := \underset{S \in S_d^{++}(\mathbb{R})}{\operatorname{argmin}} \sum_{k=1}^{K} \lambda_k d_{\mathrm{BW}}^2(S, S_k).$$

Fixed-point computation for $\overline{S}$:

$$G_{\mathcal{N}}(S) = S^{-1/2} \left(\sum_{k=1}^{K} \lambda_k (S^{1/2} S_k S^{1/2})^{1/2} \right)^2 S^{-1/2}.$$

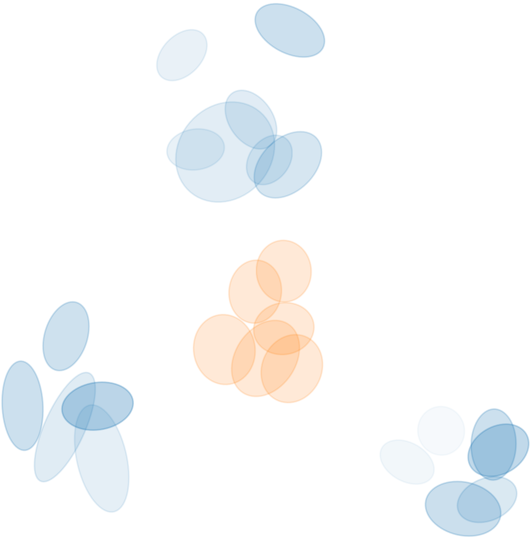
Riemannian gradient descent interpretation by Altschuler et al. 2021 [2].

GMM Barycentre

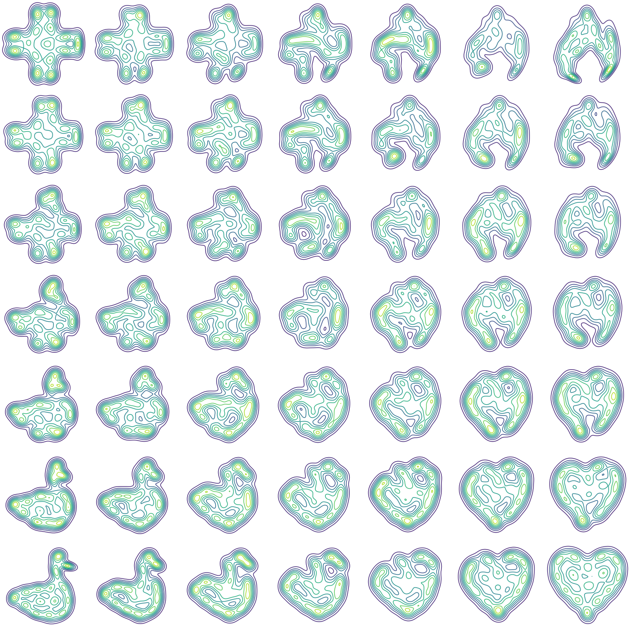
$$\mu = \sum_{i=1}^{n} a_i \delta_{\mathcal{N}(m_i, S_i)},$$

$$\nu_k = \sum_{j=1}^{n_k} b_{k,j} \delta_{\mathcal{N}(m_{k,j}, S_{k,j})},$$

$$V(\mu) = \sum_{k=1}^{K} \lambda_k \mathcal{T}_{\mathrm{W}_2^2}(\mu, \nu_k).$$



GMM Barycentre Example



- Talk based on [6] *ET, Julie Delon and Nathaël Gozlan (2024): Computing Barycentres of Measures for Generic Transport Costs*. arXiv preprint 2501.04016.
- All code at `https://github.com/eloitanguy/ot_bar`
- Functions released on `https://pythonot.github.io/`
- Slides at `https://eloitanguy.github.io/publications/`

Thanks!

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Computing barycentres of measures for generic transport costs, 2024.