

Computational Optimal Transport

Stochastic Wasserstein Barycenters

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JAN 19, 2024

1. Problem statement
2. Proposed Method
 - Ascent step
 - Snap step
 - Theoretical and Empirical Convergence
3. Experiments and Numerical Analysis
4. Conclusion and Perspectives



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Problem statement

Article : Clatici, Chien, and Solomon 2018, *Stochastic Wasserstein Barycenters*

- Compute the Wasserstein barycenter ν of a set of any probability measures $\{\mu_j\}_{j=1}^J$ defined of a metric space (\mathcal{X}, d) with $\mathcal{X} \subset \mathcal{R}^D$
- Primal problem

$$\min_{\nu} \frac{1}{J} \sum_{j=1}^J W_2^2(\mu_j, \nu) \quad (1)$$



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$$\min_{\nu} \frac{1}{J} \sum_{j=1}^J W_2^2(\mu_j, \nu) \quad (1)$$

- Approximation of the barycenter

$$\hat{\nu} = \frac{1}{M} \sum_{i=1}^M \delta_{x_i}$$

with optimized support $\Sigma = \{x_i\}_{i=1}^M$

- **Problem.** Find a minimizer of (1) with $\Sigma \subset \mathcal{X}$ and $|\Sigma| = M$



Related Work and Applications ?



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- Dual problem

$$F \left(\{\phi_j\}_{j=1}^J, \{x_i\}_{i=1}^M \right) = \frac{1}{J} \sum_{j=1}^J F_{dual} \left(\phi_j, \{x_i\}_{i=1}^M \right)$$

$$\begin{aligned} F_{dual} \left(\phi_j, \{x_i\}_{i=1}^M \right) &= \int_{\mathcal{X}} \phi_j(x) d\nu(x) + \int_{\mathcal{X}} \bar{\phi}_j(y) d\mu_j(y) \\ &= \frac{1}{M} \sum_{i=1}^M \phi_j(x_i) + \int_{\mathcal{X}} \bar{\phi}_j(y) d\mu_j(y) \end{aligned}$$

- **Stochastic Gradient Ascent** to optimize the potentials $\{\phi_j\}_{j=1}^J$ (*ascent step*)
- **Fixed point iteration** to optimize the positions $\{x_i\}_{i=1}^M$ (*snap step*)



Gradient $\frac{\partial F}{\partial \phi_j}$ depend on the terms

$$a_j^i = \int_{V_{\phi_j}^i} d\mu_j(y)$$

$$= \mathbb{E}_{y \sim \mu_j} \left[\mathbf{1}_{y \in V_{\phi_j}^i} \right]$$

$$b_j^i = \int_{V_{\phi_j}^i} y d\mu_j(y)$$

$$= \mathbb{E}_{y \sim \mu_j} \left[y \cdot \mathbf{1}_{y \in V_{\phi_j}^i} \right]$$

where $\mathbf{1}$ is the indicator function and the *power cell* $V_{\phi_j}^i$ of point x_i is

$$V_{\phi}^i = \{x \in \mathcal{X}, d(x, x_i)^2 - \phi_i \leq d(x, x_{i'})^2 - \phi_{i'}, \forall i'\}$$

where $d(x, y)^2 = \|x - y\|_2^2$.



Algorithm Ascent step

```
1: for  $j = 1, \dots, J$  do
2:    $z^{(0)} \leftarrow 0$ 
3:   while  $\left\| \widehat{\frac{\partial F}{\partial \phi_j}} \right\|_2^2 > \epsilon_{\text{ascent}}$  do
4:     Compute  $\hat{a}_j^i$  by Monte Carlo approximation
5:      $z^{l+1} \leftarrow \beta z^{(l)} + \widehat{\partial_{\phi_j} F}(\phi_j)$  {Nesterov acceleration}
6:      $\phi_j^{(l+1)} \leftarrow \phi_j^{(l)} + \alpha z^{(l+1)}$ 
7:   end while
8: end for
```

We will use $\epsilon_{\text{ascent}} = 10^{-4}$ and set a maximum number of iterations for the while loop to $T_{\max} = 1500$

And fix $\alpha = 0.05$ and $\beta = 0.99$ like in (Claici, Chien, and Solomon 2018)



The update of the point $\{x_i\}$ is given by

$$\frac{\partial F}{\partial x_i} = 0 \implies x_i = \frac{\sum_{j=1}^J b_j^i}{\sum_{j=1}^J a_j^i}$$

Intuition :

$$\frac{\partial F_{dual}}{\partial \phi_j^i} = \frac{1}{M} - \int_{V_{\phi_j^i}} d\mu_j(y) = 0$$

- Each cell V_{ϕ}^i contains as much mass as its associated source point x_i
- the fixed point iteration moves each point to the center of its power cell.



Algorithm Ascent and Snap algorithm for computing Stochastic Wasserstein Barycenters

```
1: for  $t = 1, \dots, T$  do
2:   Update  $\{\phi_j\}$  with algorithm {Ascent step}
3:   Compute  $\hat{b}_j^i$  by Monte Carlo approximation
4:   for  $x_i \in \Sigma$  do
5:      $x_i \leftarrow \frac{\sum_{j=1}^J \hat{b}_j^i}{\sum_{j=1}^J \hat{a}_j^i}$  {Snap step}
6:   end for
7: end for
8: return Optimized barycenter support  $\Sigma^* = \{x_i\}_{i=1}^M$ 
```



Assumptions

- At least one of the input distribution μ_j is absolutely continuous with respect to the Lebesgue measure.
- The domain \mathcal{X} is a compact subset of the Euclidean space \mathbb{R}^d .

Guarantees

- The global minimizer of (1) efficiently approximate the true barycenter as $M \rightarrow \infty$
- No guarantee of convergence toward ν_M^*
- The ascent snap algorithm converges to a local minimum
- Algorithm monotonically $\searrow F_{\text{primal}}(1)$
- The support of the estimated barycenter is empirically demonstrated to be contained within the support of the true barycenter
- Empirical evidences \implies convergence even in cases where these assumptions are not met



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Experiment 1



Experiment 2



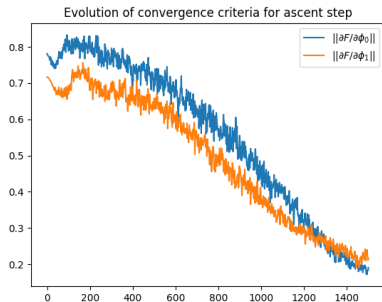
Computation time

Experiment	McCann	Iterative Bregman	POT support	free	Ascent Snap
1D skewnorm	0.02 ± 0.01	0.22 ± 0.02	0.74 ± 0.28		7814.27 ± 0.37
2D discrete	-	2.18 ± 0.34	0.38 ± 0.30		16351.66 ± 0.23

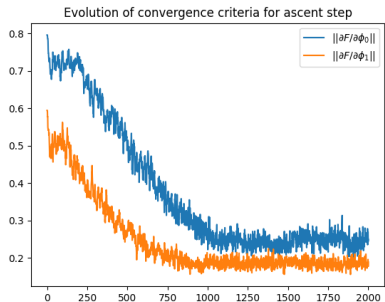
Table: Computation time (in seconds) for the different methods



Ascent step convergence



(a) Two 1D continuous distributions



(b) Two 2D discrete distributions

Figure: Evolution of $\left\| \frac{\partial F}{\partial \phi_j} \right\|$ during the ascent step for each experiment. In the x-axis, is the number of iterations of the while loop.



Experiment	Ascent step	Snap step
1D skewnorm	8309.44 ± 0.33	5.28 ± 0.23
2D discrete	11938.70 ± 0.34	9.81 ± 0.34

Table: Computation time (in seconds) for each step of the Algorithm **??**. The experiences are repeated 3 times.



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Claici, Sebastian, Edward Chien, and Justin Solomon (June 6, 2018).
Stochastic Wasserstein Barycenters. arXiv:
1802.05757 [cs,math,stat]. URL:
<http://arxiv.org/abs/1802.05757> (visited on 12/21/2023).

