Fixed Support Tree-Sliced Wasserstein Barycenter

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1. Background

Wasserstein Distance

- Powerful tool to measure the distance between distributions.
- High computational cost. (e.g., Sinkhorn algorithm requires $O(M^2)$)

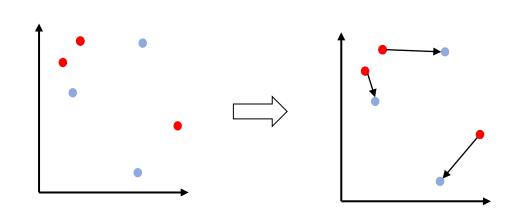


Fig.1

Wasserstein Barycenter

- $\{a_1, a_2, ..., a_N \mid a_i \in \mathbb{R}^M\}$: a set of probability distributions.
- A: simplex.

$$\operatorname{argmin}_{\mathbf{a} \in A} \frac{1}{N} \sum_{i=1}^{N} W_d(\mathbf{a}_i, \mathbf{a})$$

Application:

- Topic Modeling [Xu+ 18]
- Generative Model [Simon+ 20]



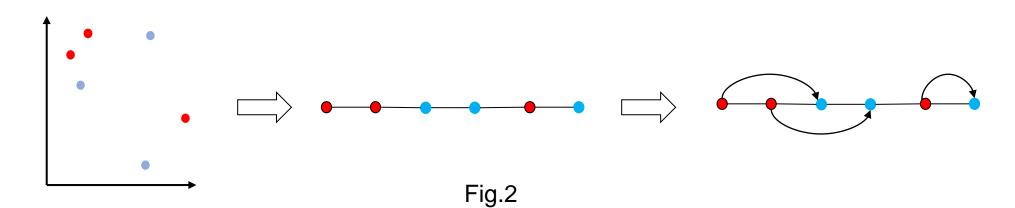
Fig.4: [Simon+ 20]

Algorithm: Iterative Bregman Projection (IBP) [Benamou+15]

- Time Complexity: $O(NM^2)$ (N: #samples, M: #supports)
- The reason of this high computational cost is the computation of the Wasserstein distance itself requires $O(M^2)$.

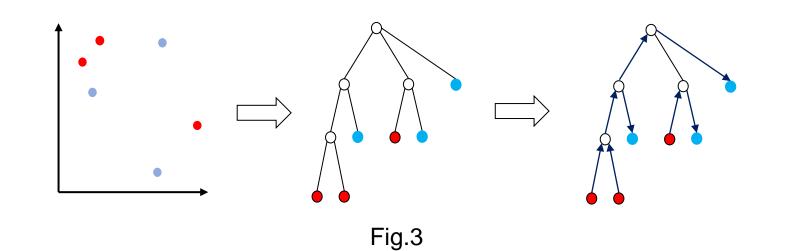
Sliced-Wasserstein Distance

Closed-form solution.



Tree-Sliced Wasserstein Distance

- Closed-form solution, which in linear time.
- Generalization of the sliced-Wasserstein distance.



2. Contribution Summary

To compute the Wasserstein barycenter fast, we propose the Fixed Support Tree-Sliced Wasserstein Barycenter (FS-TSWB), the Wasserstein barycenter on the tree metric.

Proposed Algorithm:

	Time Complexity
FS-WB (IBP [Benamou+15])	$O(NM^2)$
FS-TSWB (PSD)	$O(T(\log M + N + D)M)$
FS-TSWB (FastPSD)	$O(T(\log M + \log N + D)M)$

Experimental Results:

- The FS-TSWB can be solved 2-order magnitude faster than the FS-WB.
- The FS-TSWB can better approximate the FS-WB than the Fixed Support Sliced-Wasserstein Barycenter (FS-SWB)

N: the number of samples, M: the number of supports, D: the depth of a tree.

3. FS-TSWB

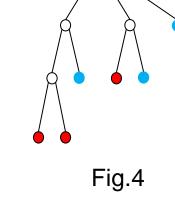
Matrix-Form Formulation of Tree Wasserstein Distance [Takezawa+ 21]

$$W_{d_T}(\mathbf{a}_i, \mathbf{a}_j) = \|\mathbf{B}(\mathbf{a}_i - \mathbf{a}_j)\|_1$$

Problem Formulation of FS-TSWB:

- $\{a_1, a_2, ..., a_N \mid a_i \in \mathbb{R}^M\}$: a set of probability distributions.
- A: simplex.

$$\operatorname{argmin}_{\mathbf{a} \in A} \frac{1}{N} \sum_{i=1}^{N} \|\mathbf{B}(\mathbf{a} - \mathbf{a}_i)\|_{1}$$



- Convex optimization.
- Projected Subgradient Descent (PSD) is applicable.

4. Algorithm: PSD

1. Compute subgradient.

$$\mathbf{g}^{(k)} = \frac{1}{N} \mathbf{B}^{\mathsf{T}} \left(\sum_{i} \operatorname{sign} (\mathbf{B} \mathbf{a}^{(k)} - \mathbf{B} \mathbf{a}_{i}) \right) \qquad O((N + D)M)$$

2. Update barycenter.

$$\mathbf{a}^{(k+1)} = \operatorname{argmin}_{\mathbf{a} \in A} \|\mathbf{a} - (\mathbf{a}^{(k)} - \gamma \mathbf{g}^{(k)})\|^{2} \qquad O(M \log(M))$$

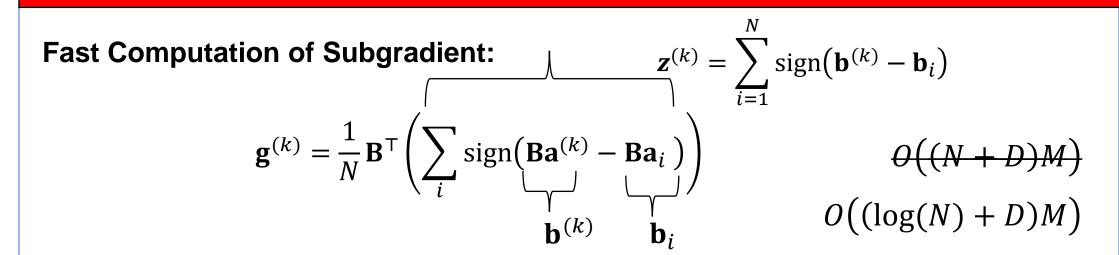
3. Compute loss. $\frac{1}{N} \sum_{i=1}^{N} \left\| \mathbf{B} \mathbf{a}^{(k+1)} - \mathbf{B} \mathbf{a}_{i} \right\|_{1}$ O(NM)

Time Complexity: $O(T(\log M + N + D)M)$

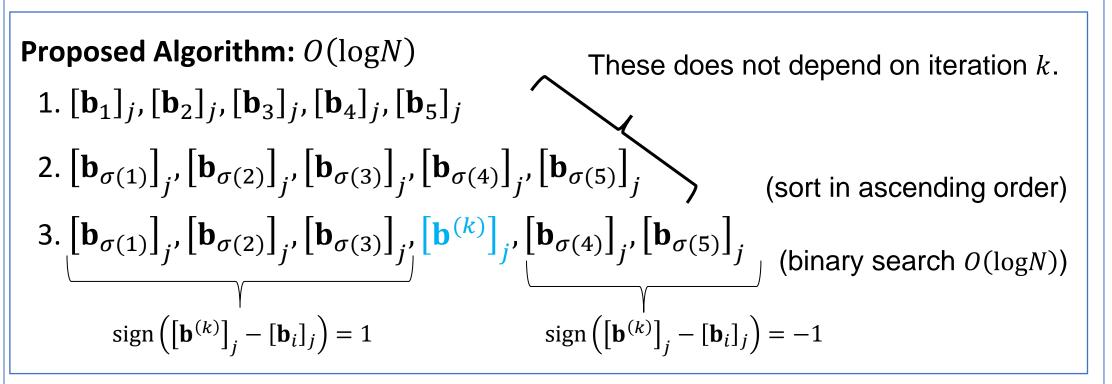
The PSD is faster than the IBP.

N: the number of samples, M: the number of supports, D: the depth of a tree.

5. Algorithm: FastPSD



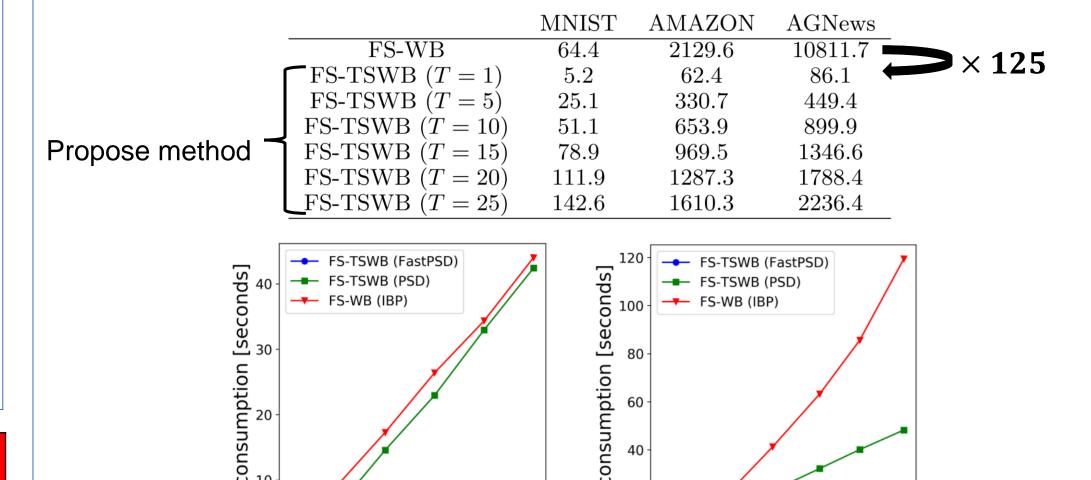
Naively, to compute $[\mathbf{z}^{(k)}]_i = \sum_{i=1}^N \operatorname{sign}\left([\mathbf{b}^{(k)}]_i - [\mathbf{b}_i]_i\right)$ requires O(N).



6. Experimental Results

Time Consumption: Table 1: Time consumption [seconds].

number of samples



Visualization:

FS-Sliced-Wasserstein Barycenter

361784 1521 2304 3136 3844 4624

number of supports

FS-Wasserstein Barycenter

FS-WB

FS-Tree-Sliced Wasserstein Barycenter

FS-SWB (T=5) FS-SWB (T=10) FS-SWB (T=25)

FS-TSWB (T=1) FS-TSWB (T=5) FS-TSWB (T=10) FS-TSWB (T=25)