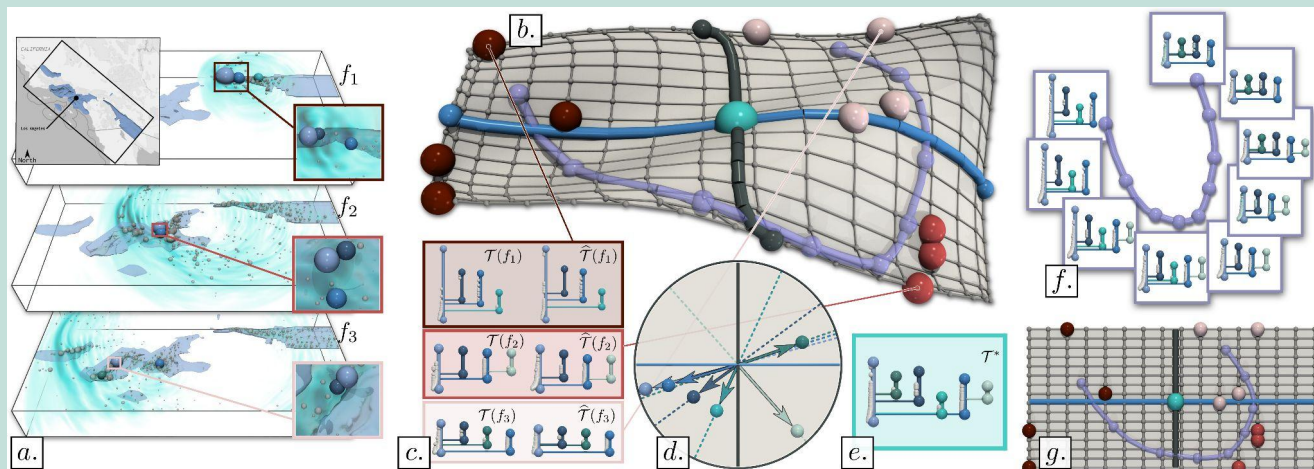


Principal Geodesic Analysis of Merge Trees (and Persistence Diagrams)

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MATHÉMATIQUES
VISION
APPRENTISSAGE

Ensemble datasets

Challenge : Several datasets for one phenomenon

- > Each dataset is called an ensemble member**
- > Each ensemble member is represented by a Merge Tree**

Merge Tree and BDT

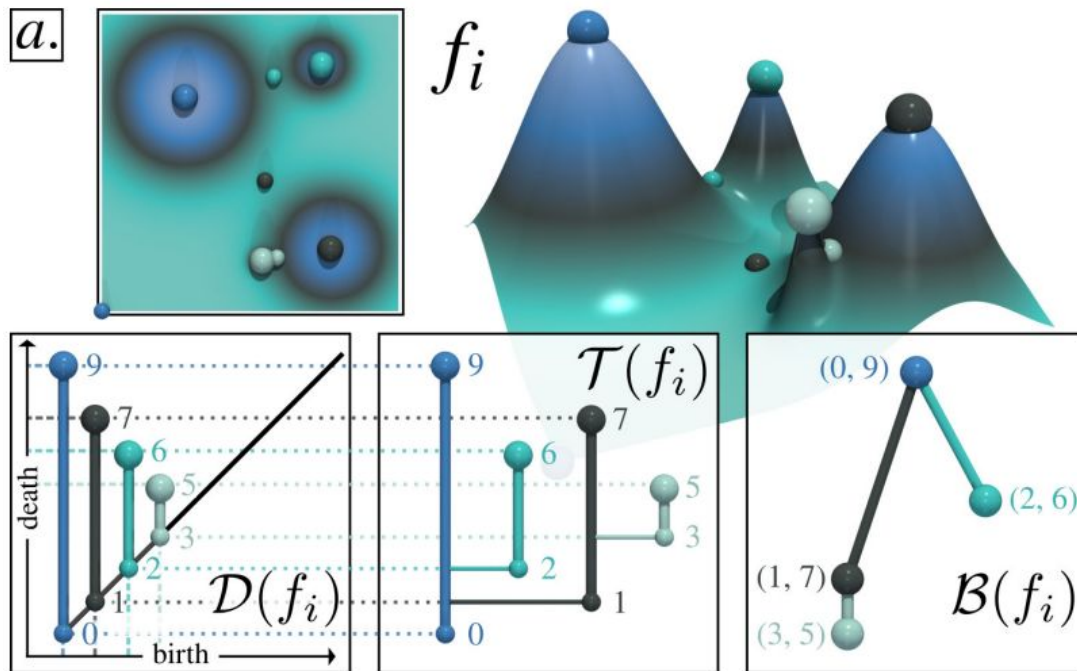
We consider a manifold and a Piecewise Linear scalar function on it

$$f : \mathcal{M} \rightarrow \mathbb{R}$$

Merge tree = \mathcal{M}/\sim where $p_1 \sim p_2$ if $f(p_1) = f(p_2)$ and p_1, p_2 in the same connected component of the sublevel (or superlevel) set of f at $f(p_1)$.

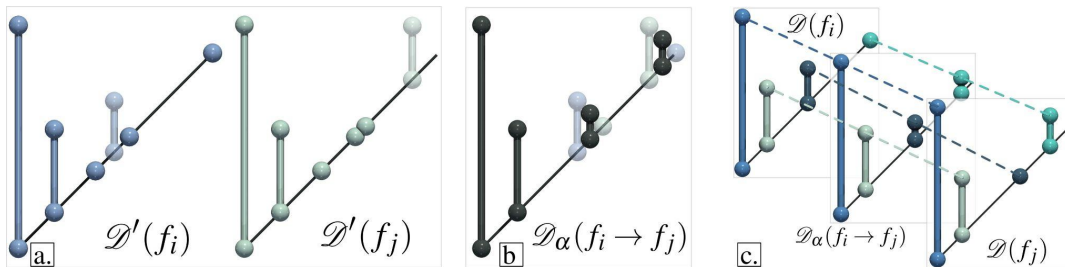
Branch Decomposition Tree (BDT) : A tree with nodes as the persistence branches and edges between adjacent branches.

Merge Tree and BDT



Wasserstein distance on persistence diagrams

- Partial assignment between
 - Off-diagonal points
 - Subset P_i
 - Complement $\overline{P_i}$
 - Bijection $\phi : P_i \rightarrow P_j$
 - Partial assignment $(\phi, \overline{P_i}, \overline{P_j}) \in \Phi$



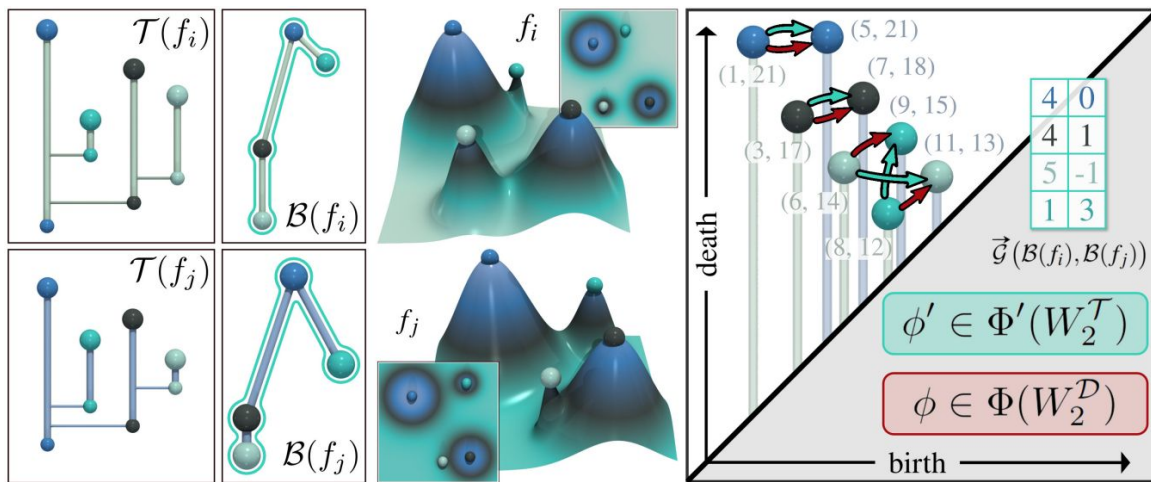
$$\begin{aligned}
 W_q(\mathcal{D}(f_i), \mathcal{D}(f_j)) = & \min_{(\phi, \overline{P_i}, \overline{P_j}) \in \Phi} \left(\sum_{p_i \in P_i} d_q(p_i, \phi(p_i))^q \right. \\
 & + \sum_{p_i \in \overline{P_i}} d_q(p_i, \Delta(p_i))^q \\
 & \left. + \sum_{p_j \in \overline{P_j}} d_q(\Delta(p_j), p_j)^q \right)^{1/q}
 \end{aligned}$$

Wasserstein distance on Merge trees

- Same, for $q = 2$ but $\phi : P_i \rightarrow P_j$ must be a partial rooted isomorphism

Partial isomorphism : Operates only on a subset P_i - no difference

Rooted isomorphism : Conserves adjacency relationship.

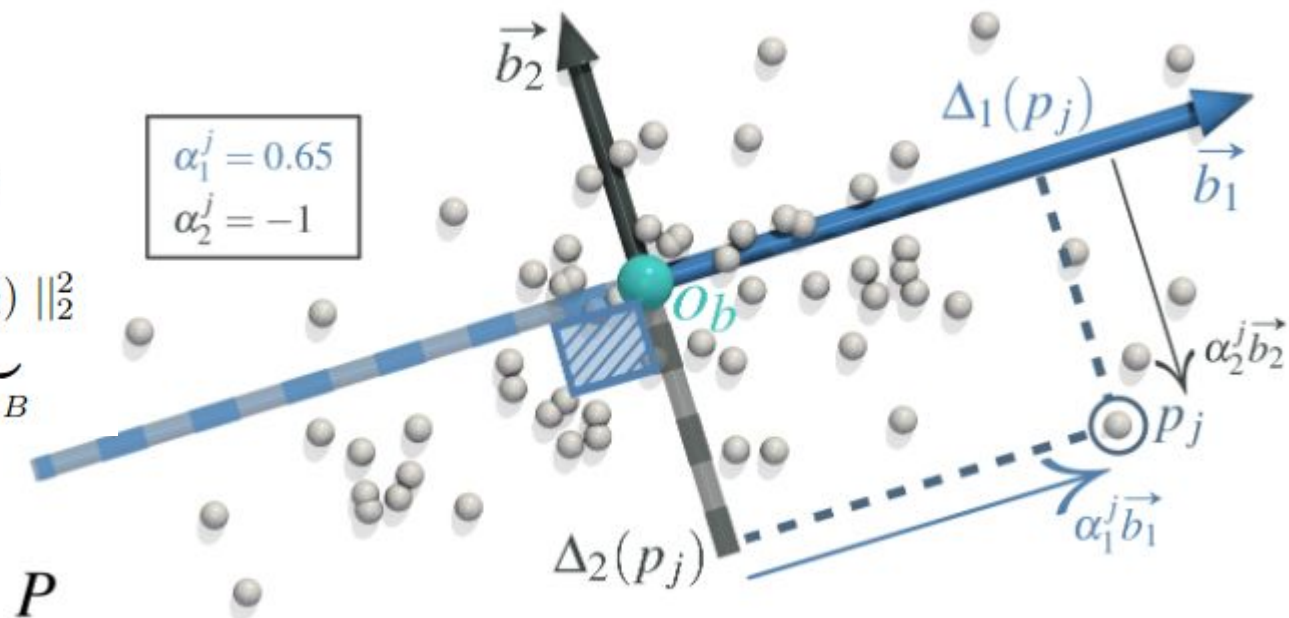


Recall PCA in \mathbb{R}^d

$$P = \{p_1, \dots, p_N\}, p_j \in \mathbb{R}^d, \forall j$$

$$B = \{v_1, \dots, v_q\}, v_i \cdot v_j = 0, \forall i \neq j$$

$$E_{L_2}(B) = \sum_{j=1}^N \left\| p_j - \underbrace{\left(\mathbf{o} + \sum_{i=1}^q \alpha_i^j v_i \right)}_{\text{Proj. of } p_j \text{ onto } B} \right\|_2^2$$



From PCA to MT-PGA

A **geodesic** is a shortest path between two MT $\mathcal{G}(\mathcal{E}, \mathcal{E}') = \operatorname{argmin}_{\phi' \in \Phi'} W_q^T(\mathcal{E}, \mathcal{E}')$

Geodesic dot product:

- Share extremity point
- Cartesian dot product in $\mathbb{R}^{2 \times |\mathcal{E}|}$

Orthogonal $\rightarrow \mathcal{G}(\mathcal{E}, \mathcal{E}') \cdot \mathcal{G}(\mathcal{E}, \mathcal{E}'') = 0$

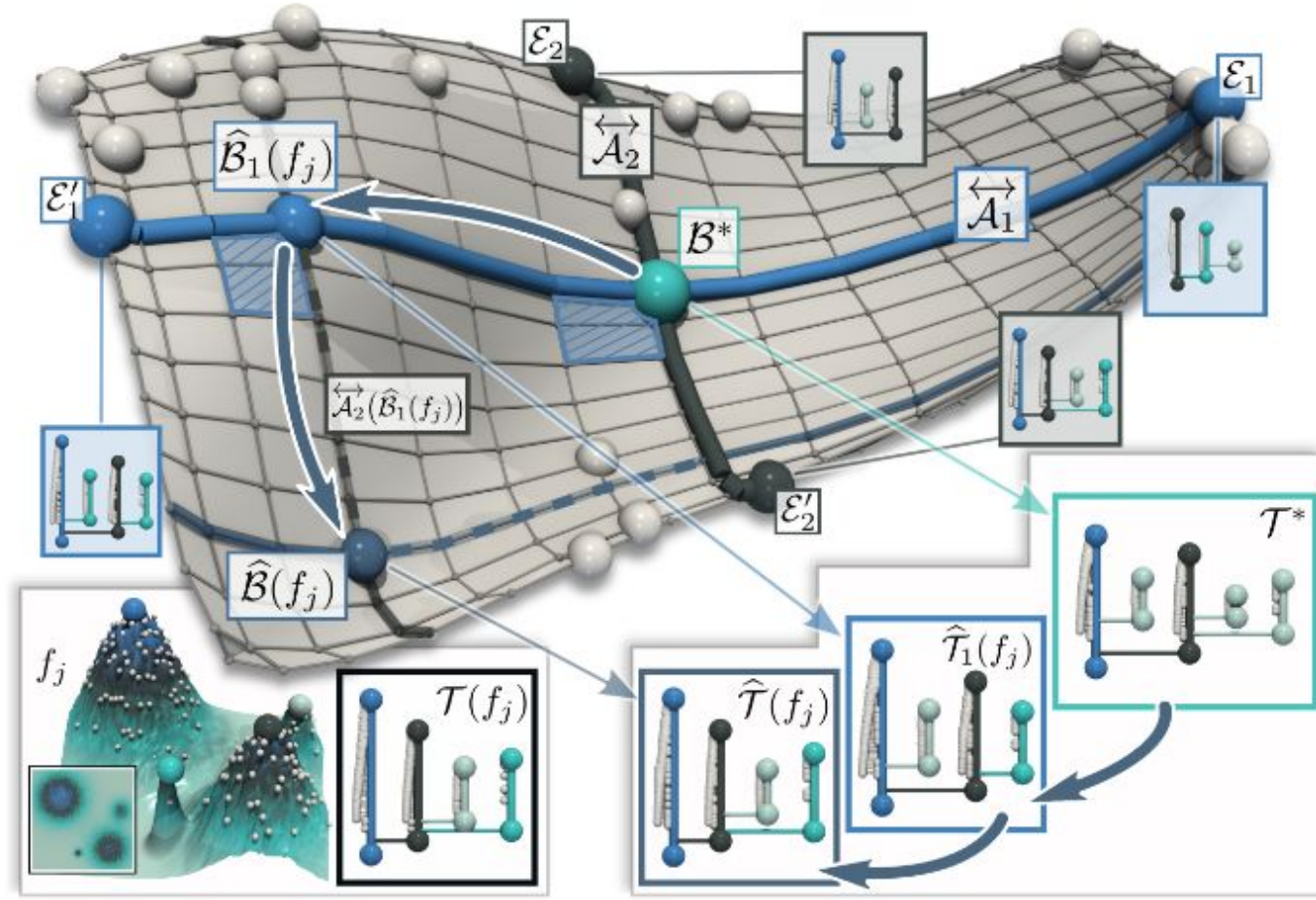
Collinear $\rightarrow \mathcal{G}(\mathcal{E}, \mathcal{E}') = \lambda \mathcal{G}(\mathcal{E}, \mathcal{E}'')$

Geodesic axis is a pair of negatively collinear geodesics through the origin \mathcal{E}_o



It's a geodesic and defines a direction vector $\mathcal{V}_i = \mathcal{G}(\mathcal{E}_i, \mathcal{E}'_i)$ Between the extremities

From PCA to MT-PGA



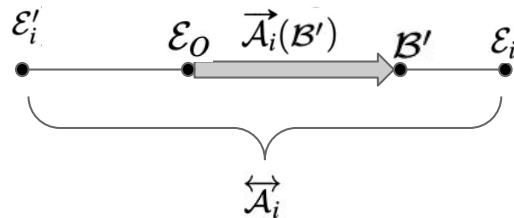
From PCA to MT-PGA

- BDT(\mathcal{B}) geodesic axis ($\overleftrightarrow{\mathcal{A}}_i$) projection

$$\mathcal{B}_{\overleftrightarrow{\mathcal{A}}_i} = \arg \min_{\mathcal{B}' \in \overleftrightarrow{\mathcal{A}}_i} (w_2^T(\mathcal{B}, \mathcal{B}'))$$

- BDT($\mathcal{B}' \in \overleftrightarrow{\mathcal{A}}_i$) geodesic axis arc-length parametrization $\vec{\mathcal{G}}'_i = \vec{\mathcal{G}}(\varepsilon_0, \varepsilon'_i)$ $\vec{\mathcal{G}}_i = \vec{\mathcal{G}}(\varepsilon_0, \varepsilon_i)$

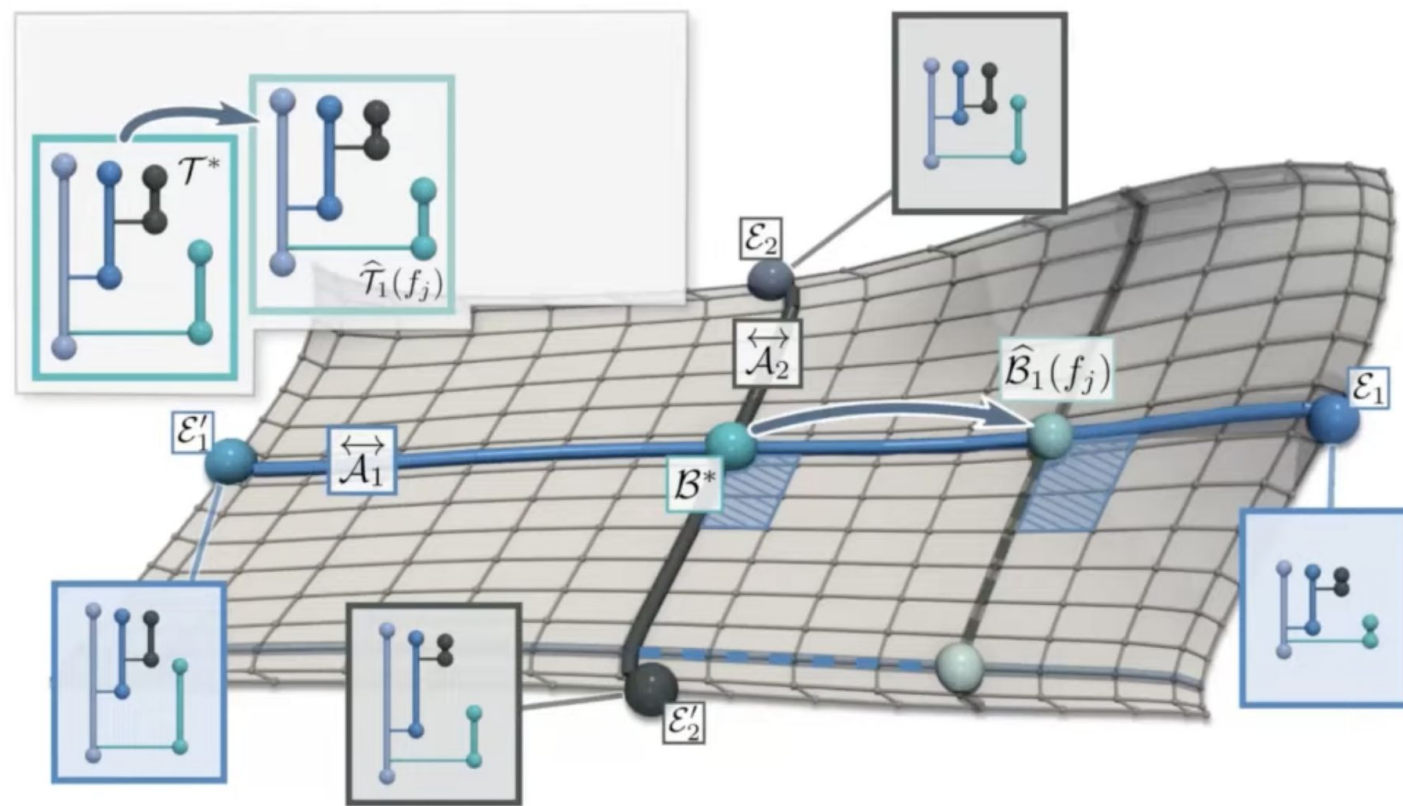
$$\mathcal{B}' = \varepsilon_0 + \overrightarrow{\mathcal{A}}_i(\mathcal{B}') = \varepsilon_0 + \alpha_i \times \vec{\mathcal{G}}_i + (1 - \alpha_i) \times \vec{\mathcal{G}}'_i.$$



- BDT(\mathcal{B}) geodesic axis ($\overleftrightarrow{\mathcal{A}}_i$) projection

$$\mathcal{B}_{\overleftrightarrow{\mathcal{A}}_i} = \arg \min_{\mathcal{B}' \in \overleftrightarrow{\mathcal{A}}_i} (w_2^T(\mathcal{B}, \varepsilon_0 + \overrightarrow{\mathcal{A}}_i(\mathcal{B}')))$$

- BDT axis translation: $\overleftrightarrow{\mathcal{A}}_j(\mathcal{B}) = ((\mathcal{B}, \mathcal{B} + \vec{g}_j), (\mathcal{B}, \mathcal{B} + \vec{g}'_j))$



From PCA to MT-PGA

- **BDT geodesic orthogonal basis**

Orthogonal basis of d' geodesic axes $\vec{B}_{\mathbb{B}} = \{\vec{\mathcal{A}}_1, \vec{\mathcal{A}}_2, \dots, \vec{\mathcal{A}}_{d'}\}$ with origine $\underline{\mathcal{E}_O}$.

Project an arbitrary BDT \mathcal{B} on $\vec{\mathcal{A}}_1$: $\hat{\mathcal{B}}_1 = \mathcal{B}_{\vec{\mathcal{A}}_1} = \mathcal{B}_{\vec{\mathcal{A}}_1}(\mathcal{E}_O)$

Recursively: $\hat{\mathcal{B}}_{d'} = \mathcal{B}_{\vec{\mathcal{A}}_{d'}(\hat{\mathcal{B}}_{d'-1})} \longrightarrow \hat{\mathcal{B}}_{d'} = \mathcal{E}_O + \sum_{i=1}^{d'} \vec{\mathcal{A}}_i(\hat{\mathcal{B}}_i)$

- **MT-PGA formulation: distance to the constructed basis of BDT**

\mathcal{B}^* : Wasserstein barycenter

$$E_{W_2^T}(\mathcal{B}_{\mathbb{B}}) = \sum_{j=1}^N w_j^T \left(\mathcal{B}(f_j), \mathcal{B}^* + \sum_{i=1}^{d'} \vec{\mathcal{A}}_i(\hat{\mathcal{B}}_i(f_j)) \right)^2$$

Algorithm

Finding an orthogonal basis of principal geodesics in the Wasserstein metric space of MTs



Constrained optimization problem

$$\min_{B_{\mathbb{B}} = \{\overrightarrow{\mathcal{A}}_1, \overrightarrow{\mathcal{A}}_2, \dots, \overrightarrow{\mathcal{A}}_{2 \times |\mathcal{B}^*|}\}} E_{W_2^{\mathcal{T}}}(B_{\mathbb{B}}) = \sum_{j=1}^N W_2^{\mathcal{T}} \left(\mathcal{B}(f_j), \mathcal{B}^* + \sum_{i=1}^{d'} \overrightarrow{\mathcal{A}}_i (\widehat{\mathcal{B}}_i(f_j)) \right)^2$$

subject to

- geodesics
- negative collinearity
- orthogonality

Algorithm

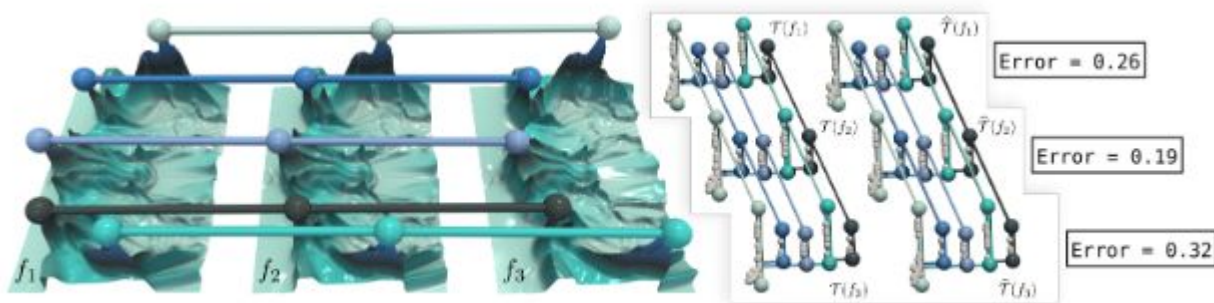
- For d' in $\{1, \dots, d_{\max}\}$
 - While $E_{W_2\mathcal{T}}(B_{\mathbb{B}})$ decreases
 - Find $A_{d'}$ such that it minimizes $E_{W_2\mathcal{T}}(B_{\mathbb{B}})$
 - enforce the 3 constraints on $A_{d'}$

As constraint enforcements are not necessarily compatible together -> while loop until convergence:

```
while  $\overleftrightarrow{\mathcal{A}}_{d'}$  evolves do  
     $\overleftrightarrow{\mathcal{A}}_{d'} \leftarrow \text{EnforceGeodesics}(\mathcal{B}^*, \overleftrightarrow{\mathcal{A}}_{d'});$   
     $\overleftrightarrow{\mathcal{A}}_{d'} \leftarrow \text{EnforceNegativeCollinearity}(\overleftrightarrow{\mathcal{A}}_{d'});$   
     $\overleftrightarrow{\mathcal{A}}_{d'} \leftarrow \text{EnforceOrthogonality}(B_{\mathbb{B}}, \overleftrightarrow{\mathcal{A}}_{d'});$ 
```

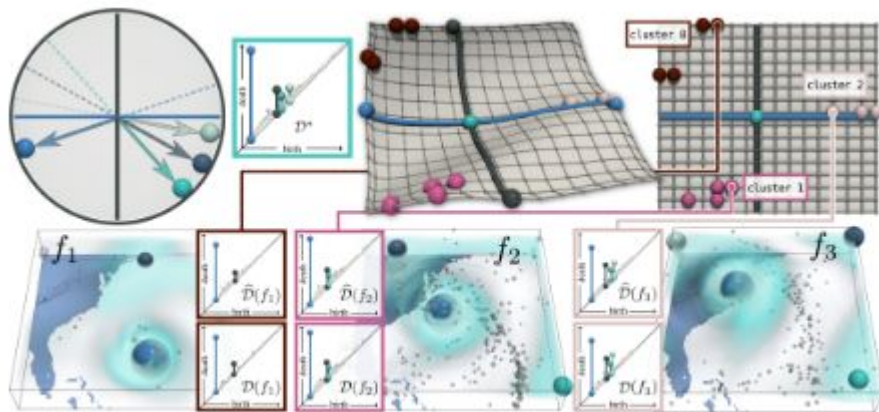
Applications

1. Data reduction → Lossy compression



2. Dimensionality reduction

3. Clustering



Thank you!