Geometry Understanding in Higher Dimensions Collège de France, June 2017

# Topological Graphs for Data Analysis Structure, Stability, and Statistics

Steve Oudot



# Graph Structures in the Data Sciences



- Input: proteins, social networks, galaxies, etc.
- Statistical proxy: dendrograms, cluster trees, spanning trees, etc.
- Geometric proxy: neighborhood graphs, k-NN graphs, etc.
- Topological proxy: Reeb graphs, Joint Contour Nets, Mappers, etc.

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principle: summarize the topological structure of a map  $f: X \to \mathbb{R}$  through a graph

#### Reeb Graph

 $x \sim y \iff [f(x) = f(y) \text{ and } x, y \text{ belong to same cc of } f^{-1}(\{f(x)\})]$  $R_f(X) := X/ \sim$ 



## Applications of Reeb graphs

- Scientific visualization
- Skeletonization, parametrization



• Data comparison, segmentation, matching, property transfer, ...





**Def:**  $d_f(x, y) := \inf_{\gamma: x \rightsquigarrow y} \max f \circ \gamma - \min f \circ \gamma$ 



Gromov-Hausdorff distance:

**Def:**  $d_{GH}(R_f, R_g) := \inf_{\nu_f, \nu_g} d_H(\nu_f(R_f), \nu_g(R_g))$ 

Note:  $d_H(X, Y) = \inf \{ \varepsilon \mid Y \subseteq \bigcup_{x \in X} B(x, \varepsilon) \text{ and } X \subseteq \bigcup_{y \in Y} B(y, \varepsilon) \}$ 



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Gromov-Hausdorff distance:

variants and simplifications:

- correspondences in product space [Gromov]
- correspondences from continuous maps
   [Bauer et al.]
- edit distances [di Fabio, Landi]
- interleaving distances
  [Morozov et al.] [de Silva et al.]
- descriptor distances

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- use *homological algebra* to encode the evolution of the topology of the family



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Theorem (stability): [Bauer, Ge, Wang 2014]

 $d_B(\operatorname{Dg} \mathcal{R}_f, \operatorname{Dg} \mathcal{R}_g) \le 6 d_{\operatorname{GH}}(\mathcal{R}_f, \mathcal{R}_g)$ 



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 $d_B(\operatorname{Dg} \mathbf{R}_f, \operatorname{Dg} \mathbf{R}_g) \le 6 d_{\operatorname{GH}}(\mathbf{R}_f, \mathbf{R}_g)$ 







**Note:**  $d_B(Dg \cdot, Dg \cdot)$  is only a pseudometric on Reeb graphs **Thm:** [Carrière, O. 2017]  $d_B(Dg \cdot, Dg \cdot)$  is *locally* a metric equivalent to  $d_{GH}$ 



## Computing Reeb graphs

**Procedure** given a point cloud P and a filter  $f: P \to \mathbb{R}$ :

- 1. build a (possibly non-manifold) 2-d simplicial complex X on top of P
- 2. compute the Reeb graph of  $(X,\bar{f}),$  where  $\bar{f}$  is the PL interpolation of f
# Computing Reeb graphs

**Procedure** given a point cloud P and a filter  $f: P \to \mathbb{R}$ :

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**Complexity:** O(nm) for n points and m simplices

**Q:** convergence?

**Thm:** [Dey, Wang 2013] For P an  $\varepsilon$ -sample of M a sufficiently regular manifold, and for X a Rips complex on P of appropriate parameter r,  $d_B(Dg R_{\bar{f}}(X), Dg R_f(M)) \leq cr$ .

# Approximations to Reeb graphs

- $\alpha$ -Reeb graphs [Chazal, Huang, Sun 2015]
- Joint Contour Nets [Carr, Duke 2014]
- Mappers [Singh, Mémoli, Carlsson 2007]
- etc.

### Reeb Graph vs. Mapper

 $x \sim y \iff [f(x) = f(y) \text{ and } x, y \text{ belong to same cc of } f^{-1}(\{f(x)\})]$  $R_f(X) := X/\sim$ 



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## Mapper in practice



# Mapper in applications

Two types of applications:

- clustering
- feature selection

principle: identify statistically relevant subpopulations through patterns (flares, loops)







 $\rightarrow$  in practice: trial-and-error

high-dimensional data sets<sup>40,48</sup>. This is performed automatically within the software, by deploying an ensemble machine learning algorithm that iterates through overlapping subject bins of different sizes that resample the metric space (with replacement), thereby using a combination of the metric location and similarity of subjects in the network topology. After performing millions of iterations, the algorithm returns the most stable, consensus vote for the resulting 'golden network' (Reeb graph), representing the multidimensional data shape<sup>12,40</sup>.

Nielson et al.: Topological Data Analysis for Discovery in Preclinical Spinal Cord Injury and Traumatic Brain Injury, Nature, 2015

Example:  $P \subset \mathbb{R}^2$  sampled from a known probability distribution









 $f = f_x$   $\delta = 1\%$   $\delta = 10\%$  $\delta = 25\%$ 

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#### **Recent contributions:**

- $\rightarrow$  clarify the roles of r and g in the continuous setting
- $\rightarrow$  introduce metrics between mappers
- $\rightarrow$  establish stability and convergence results for Mappers
- $\rightarrow$  relate discrete and continuous Mappers under conditions on  $\delta$

2 approaches:

connection to topological persistence and representation theory
 [Carrière, O. 2016] < [Bauer, Ge, Wang 2013] [Cohen-Steiner, Edelsbrunner, Harer 2009]</li>

 $\bullet$  connection to constructible cosheaves in Sets and stratification theory [Munch, Wang 2016] < [de Silva, Munch, Patel 2016]

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Reminder: mapper  $\equiv$  *pixelized* Reeb graph



**Def:** Given 
$$X, f, \mathcal{I}$$
:  
 $\operatorname{Dg} M_f := \left(\operatorname{Ord} R_f \setminus Q_{\mathcal{I}}^{\operatorname{Ord}}\right) \cup \left(\operatorname{Rel} R_f \setminus Q_{\mathcal{I}}^{\operatorname{Rel}}\right) \cup \left(\operatorname{Ext} R_f \setminus Q_{\mathcal{I}}^{\operatorname{Ext}}\right)$ 





















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$$d_{\mathcal{I}}(\mathrm{Dg}\,\mathrm{M}_f, \mathrm{Dg}\,\mathrm{M}_g) := \inf_m \mathrm{cost}_{\mathcal{I}}(\mathrm{m})$$



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**Thm:** [Carrière, O. 2016] For any Morse-type functions  $f, g : X \to \mathbb{R}$ :

 $d_{\mathcal{I}}(\operatorname{Dg} M_f(X, \mathcal{I}), \ \operatorname{Dg} M_g(X, \mathcal{I})) \le ||f - g||_{\infty}$ 



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Extensions to:

- perturbations of X
- perturbations of  ${\mathcal I}$



 $m: \operatorname{Dg} \operatorname{M}_{f} \longleftrightarrow \operatorname{Dg} \operatorname{M}_{g}$ 



#### **Questions:**

- Statistical properties of the estimator  $M_f(\widehat{X}_n, \delta_n, \mathcal{I}(g_n, r_n))$  ?
- Convergence to the ground truth  $R_f(X)$  in  $d_B$ ? Deviation bounds?



 $V_n(\delta_n) := \max\{f(X_i) - f(X_j) \mid ||X_i - X_j|| \le \delta_n\}$ 

**Theorem** [Carrière, Michel, O. 2017]: If  $\mu$  is (a, b)-standard, then for  $g \in (0, \frac{1}{2})$ ,  $\delta_n = 8\left(\frac{2\log n}{an}\right)^{1/b}$ ,  $r_n = \frac{V_n(\delta_n)}{g}$ :

$$\sup_{\mu \in \mathcal{P}} \mathbb{E} \left[ \mathrm{d}_B \left( \mathrm{Dg} \, \mathrm{R}_f(X) \right), \, \mathrm{Dg} \, \mathrm{M}_f(\widehat{X}_n, \delta_n, \mathcal{I}(g, r_n)) \right] \leq C \, \omega(\delta_n),$$

where  $\omega$  is the modulus of continuity of f and C depends only on a, b. Moreover, the estimator  $Dg M_f(\widehat{X}_n, \delta_n, \mathcal{I}(g, r_n))$  is minimax optimal (up to  $\log n$  factors).



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 $\rightarrow$  subsampling to tune  $\delta_n$ : let  $\beta > 0$  and take  $s(n) = \frac{n}{\log(n)^{1+\beta}}$ 

 $\delta_n := d_H(\hat{X}_n^{s(n)}, \hat{X}_n)$  where  $\hat{X}_n^{s(n)}$  is a subset of  $\hat{X}_n$  of size s(n)



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# Experiments

### confidence level: 85%



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## References

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