



DENSITY-BASED PERSISTENT HOMOLOGY

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joint work with E. Borghini, P. Groisman and G. Mindlin

2ND WORKSHOP ON TOPOLOGICAL METHODS IN DATA ANALYSIS

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*EPSRC Centre for Topological Data Analysis



Durham
University

The problem

Homology inference

$\mathbb{X}_n = \{x_1, x_2, \dots, x_n\} \subseteq \mathbb{R}^D$ a finite **sample**.

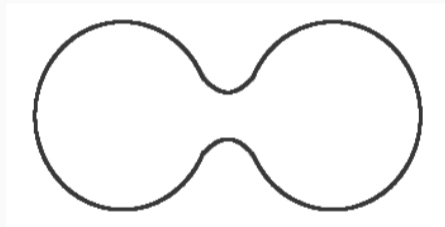


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$\mathbb{X}_n \subseteq \mathcal{M}$ a **d -dimensional Riemannian manifold**.

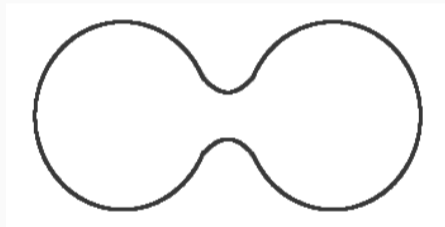


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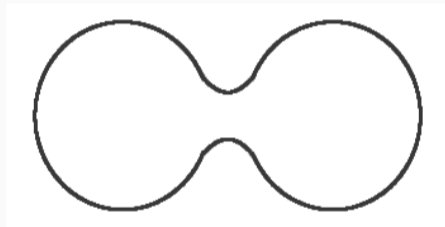
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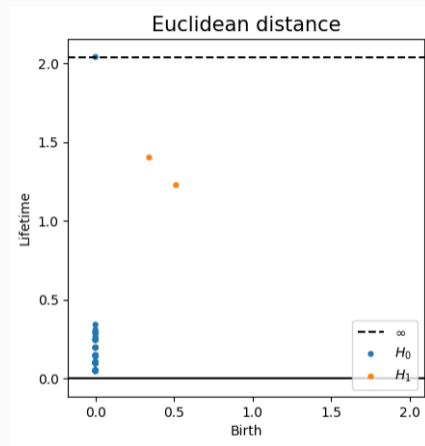
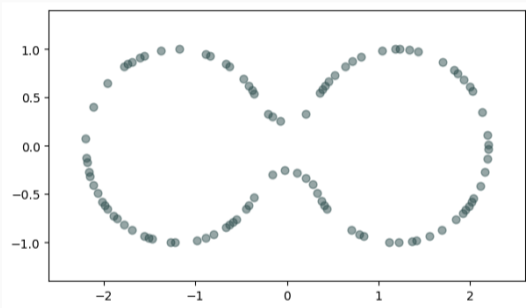
A: Compute **persistent homology** of \mathbb{X}_n .

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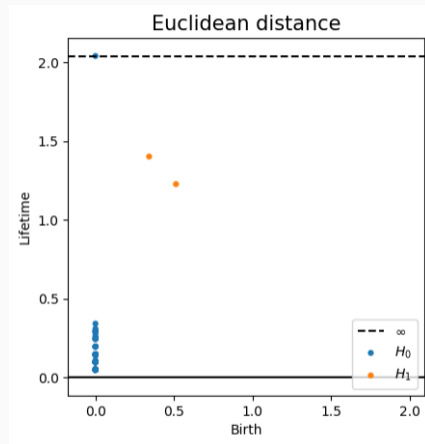
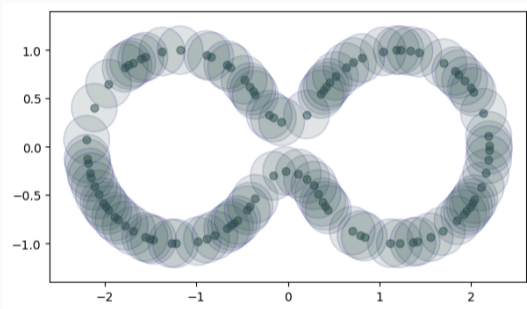


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Ambient persistent homology

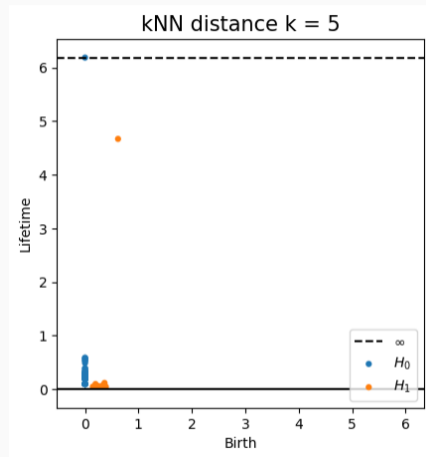
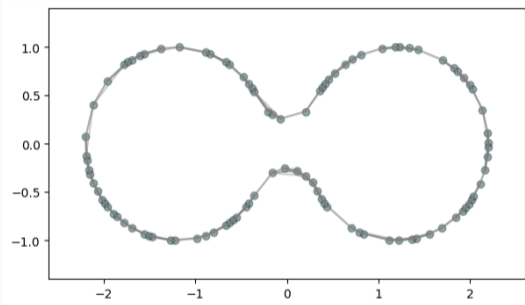


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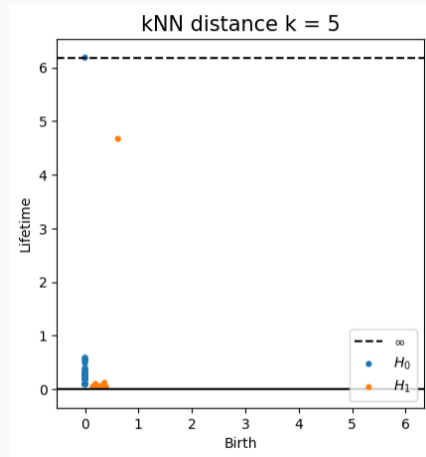
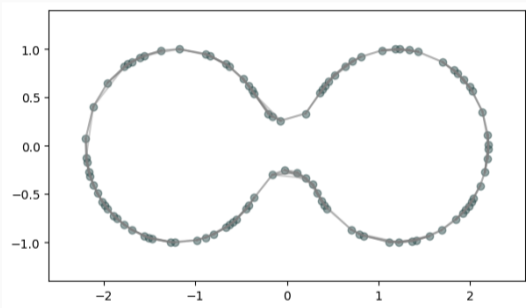
- $\text{Rips}_\epsilon(\mathcal{M}, d_E) \simeq \mathcal{M}$ for $\epsilon < 2\text{rch}(\mathcal{M})$

Intrinsic persistent homology



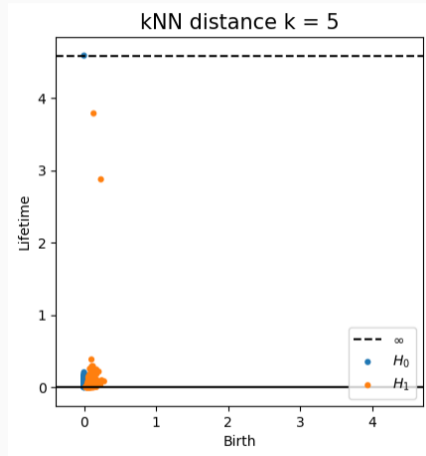
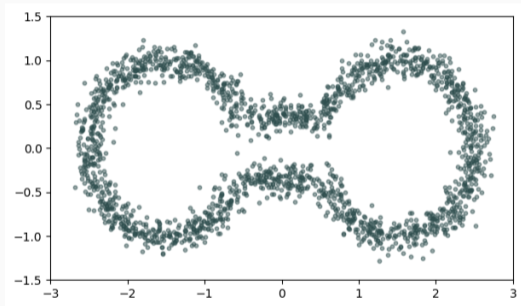
$$d_{kNN}(x, y) = \inf_{\gamma: x \rightarrow y} \sum |x_i - x_{i+1}| \sim d_{\mathcal{M}}(x, y)$$

Intrinsic persistent homology

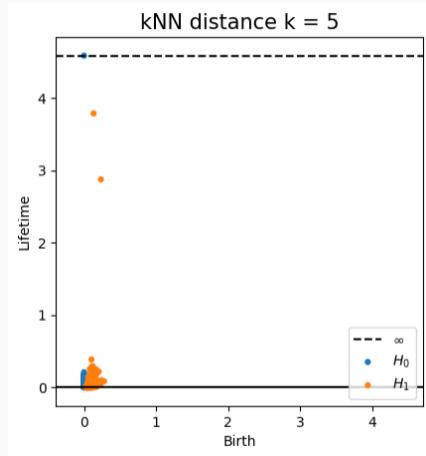
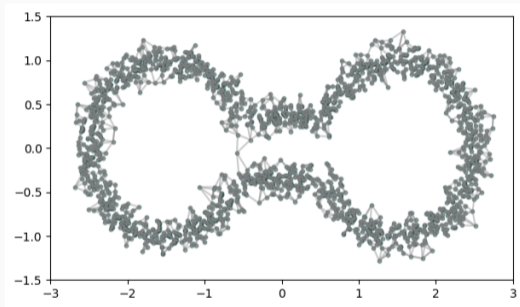


- $\text{Rips}_\epsilon(\mathcal{M}, d_{\mathcal{M}}) \simeq \mathcal{M}$ for $\epsilon < \text{conv}(\mathcal{M}, d_{\mathcal{M}})$

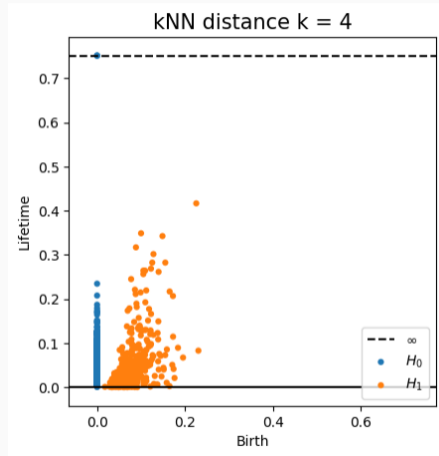
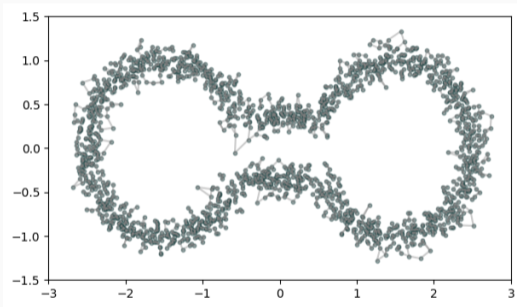
The problem of noise



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Density-based manifold learning

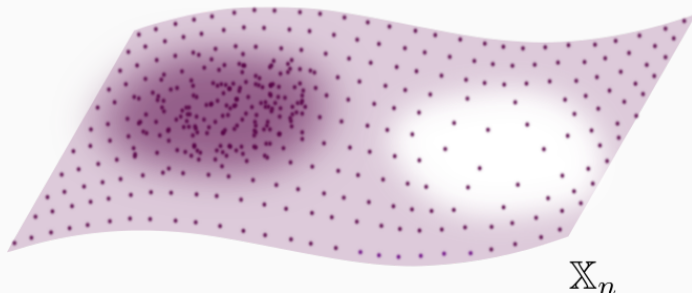
Fermat distance

Let $\mathbb{X}_n \subseteq \mathbb{R}^D$ a **sample** of points.

For $p > 1$, the **Fermat distance** between $x, y \in \mathbb{R}^D$ is defined by

$$d_{\mathbb{X}_n, p}(x, y) = \inf_{\gamma} \sum_{i=0}^r |x_{i+1} - x_i|^p$$

over all paths $\gamma = (x_0, \dots, x_{r+1})$ of finite length with $x_0 = x$, $x_{r+1} = y$ and $\{x_1, x_2, \dots, x_r\} \subseteq \mathbb{X}_n$.



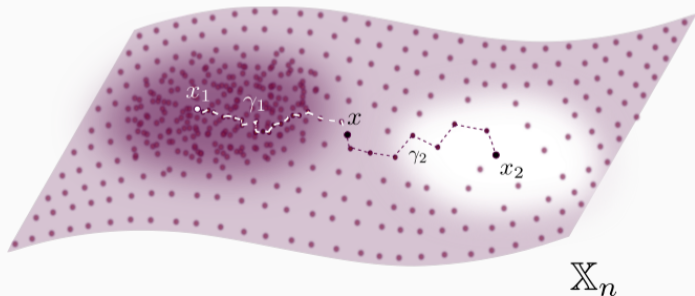
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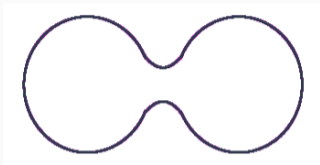
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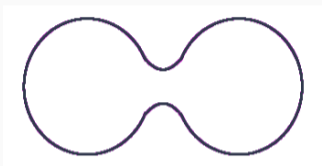
Example

Manifold

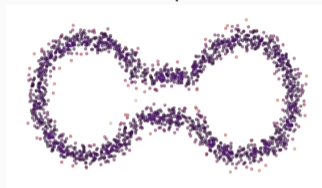


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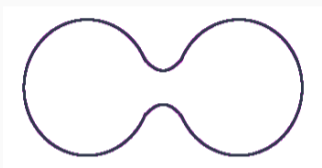


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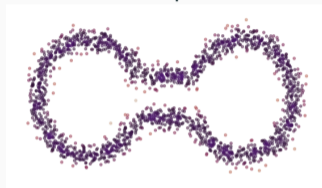


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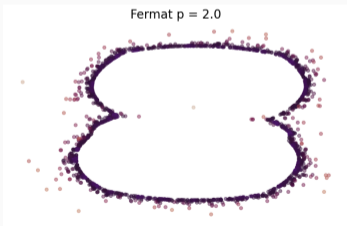
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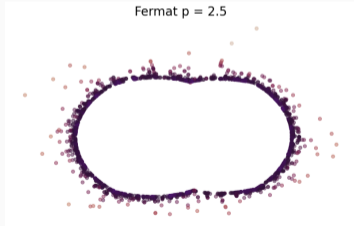
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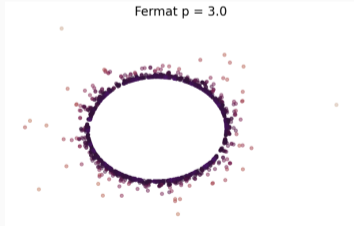
Fermat $p = 2.0$



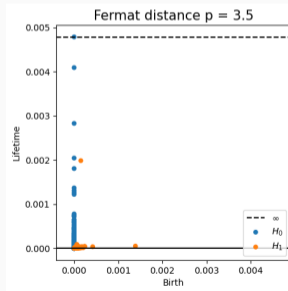
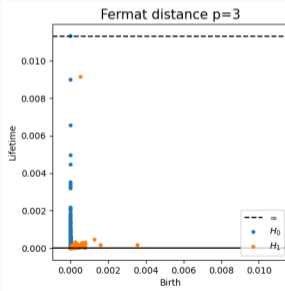
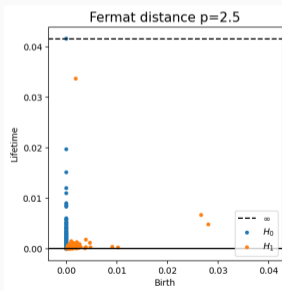
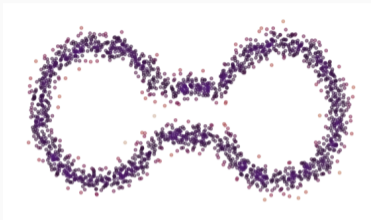
Fermat $p = 2.5$



Fermat $p = 3.0$



Example



Properties of Fermat distance

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$f : \mathcal{M} \rightarrow \mathbb{R}$ a density function.

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- Convergence of metric spaces:

$$\boxed{(\mathbb{X}_n, C(n, p, d) d_{\mathbb{X}_n, p}) \xrightarrow[n \rightarrow \infty]{GH} (\mathcal{M}, d_{\mathcal{M}, f, p})}$$

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- Convergence of persistence diagrams:

$$\boxed{\text{dgm}\left(\text{Rips}\left(\mathbb{X}_n, C(n, p, d) d_{\mathbb{X}_n, p}\right)\right) \xrightarrow[n \rightarrow \infty]{B} \text{dgm}\left(\text{Rips}\left(\mathcal{M}, d_{\mathcal{M}, f, p}\right)\right)}$$

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- **Robustness to outliers:** $\mathbb{X}_n \subseteq \mathcal{M}$ sample, $Y \subseteq \mathbb{R}^D \setminus \mathcal{M}$ outliers.



$$\text{dgm}_k\left(\text{Rips}_{< \delta^p}\left(\mathbb{X}_n \cup Y, d_{\mathbb{X}_n \cup Y, p}\right)\right) = \text{dgm}_k\left(\text{Rips}_{< \delta^p}\left(\mathbb{X}_n, d_{\mathbb{X}_n, p}\right)\right)$$

for some $\delta > 0^*$ and all degree $k > 0$.

* Here, for p large enough $\delta^p > \text{diam}(\mathbb{X}_n, d_{\mathbb{X}_n, p})$.

- **Preprint:** X. Fernandez, E. Borghini, G. Mindlin, P. Groisman. *Intrinsic persistent homology via density-based metric learning*. arXiv:2012.07621 (2020)
- **Code:**  <https://github.com/ximenafernandez/intrinsicPH>
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THANKS FOR YOUR ATTENTION!