

Homology inference

Goal: infer the homology groups of a topological space from a finite set of points.

(cf. slides: pages 0-1)

① Distance functions:

Let $X \subset \mathbb{R}^d$ be compact.

Def: The distance function d_X is defined by:

$$d_X : \begin{cases} \mathbb{R}^d \rightarrow \mathbb{R} \\ z \mapsto \min_{x \in X} \|z - x\|_2. \end{cases}$$

Note: distance functions are closely related to the Hausdorff distance d_H , which is the "right" metric between compact sets in \mathbb{R}^d :

$$\text{Def: } d_H(X, Y) := \max \left\{ \max_{x \in X} d_Y(x); \max_{y \in Y} d_X(y) \right\}$$

$$\text{Prop: } d_H(X, Y) = \|d_X - d_Y\|_\infty = \sup_{z \in \mathbb{R}^d} |d_X(z) - d_Y(z)|$$

→ proof: By definition, $\|d_X - d_Y\|_\infty \geq \begin{cases} \max_{x \in X} |d_Y(x) - 0| \\ \max_{y \in Y} |d_X(y) - 0| \end{cases}$
 $\Rightarrow \|d_X - d_Y\|_\infty \geq d_H(X, Y)$

Now, given $z \in \mathbb{R}^d$, let $x \in X$ be one of its nearest

neighbors in X , and let $y \in Y$ be a nearest neighbor of x on Y .

$$\Rightarrow d_Y(y) - d_X(y) \leq \|y - z\| - \|x - z\|$$

$$\leq \|x - y\| = d_Y(x) \leq \max_X d_Y$$

Symmetrically, $d_X(y) - d_Y(y) \leq \max_Y d_X$.

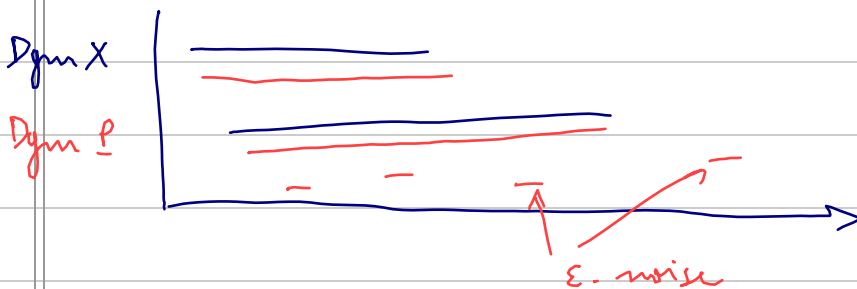
$$\Rightarrow |d_Y(y) - d_X(y)| \leq d_H(X, Y)$$

$$\Rightarrow \|d_Y - d_X\|_\infty \leq d_H(X, Y). \quad \square$$

Corollary: (Prop. + stability thm)

Given P finite s.t. $d_H(P, X) \leq \epsilon$ for some (unknown) compact set X :

$$d_b(\text{Dym } d_P, \text{Dym } d_X) \leq \epsilon.$$



Questions:

a) when and how does $\text{Dym } d_X$ reflect the homology of X ?

sweet range

(cf. slides: page 1)

b) how to compute $\text{Dym } d_P$ in practice?

② Medial axis and reach:

let $X \subset \mathbb{R}^d$ be compact.

Def: Given $z \in \mathbb{R}^d$, let $\tilde{\Pi}_X(z) := \underset{x \in X}{\operatorname{argmin}} \|z - x\|$.
(projection set)

Notes:

- $\tilde{\Pi}_X(z) \neq \emptyset$ (because X is compact)
- when $\#\tilde{\Pi}_X(z) = 1$, one calls "projection of z " the unique point of $\tilde{\Pi}_X(z)$, denoted by $\pi_X(z)$.

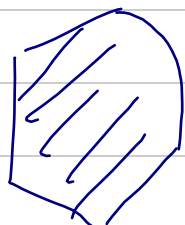
Def: The medial axis of X is:

$$\mathcal{M}(X) := \{z \in \mathbb{R}^d \mid \#\tilde{\Pi}_X(z) > 1\}.$$

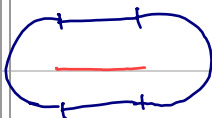
Note: the projection map π_X is defined outside $\mathcal{M}(X)$:
 $\pi_X: \mathbb{R}^d \setminus \mathcal{M}(X) \rightarrow X$.

Def: The reach of X is: $\operatorname{rch}(X) := \inf_{\substack{x \in X \\ y \in \mathcal{M}(X)}} \|x - y\|$.

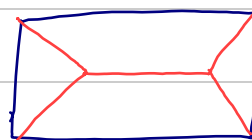
Examples:



$\mathcal{M}(X) = \emptyset$ ($\Leftrightarrow X$ convex)
($\operatorname{rch}(X) = +\infty$)



X compact $C^{1,1}$ -continuous manifold in $\mathbb{R}^d \Rightarrow \operatorname{rch}(X) > 0$



$\mathcal{M}(X)$ is neither open nor closed

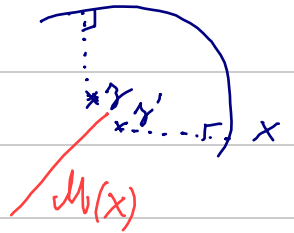


$\mathcal{M}(X)$ is not bounded

Lemma: [Federer 1959]

Π_x is continuous over $\mathbb{R}^d \setminus \mathcal{M}(x)$.

Note: Π_x is not Lipschitz continuous over $\mathbb{R}^d \setminus \mathcal{M}(x)$,
 however it is outside every offset of $\mathcal{M}(x)$
 (and the Lipschitz constant depends of the
 offset parameter).



Thm: Let $X \subset \mathbb{R}^d$ compact be such that $\text{rch}(X)$.

Then: $\forall t \in [0, \text{rch}(X))$, the t -offset of X
 is homotopy equivalent to X :

$$X \underset{\text{(homotopy)}}{\simeq} X^t := \bigcup_{x \in X} B(x, t) = d_X^{-1}([-\infty, t])$$

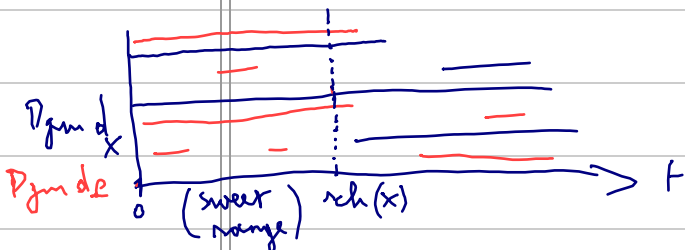
→ proof: Note that $X \subseteq X^t$.

$$\hookrightarrow \text{Take } \begin{cases} i: X \hookrightarrow X^t \text{ (inclusion)} \\ \Pi_x: X^t \rightarrow X \text{ (projection)} \end{cases}$$

Since $t < \text{rch}(X)$, we have $X^t \cap \mathcal{M}(X) = \emptyset$ and
 so Π_x is well-defined over X^t .

$$\hookrightarrow \begin{cases} \Pi_x \circ i = \text{id}_X \\ i \circ \Pi_x = \Pi_x \end{cases}$$

which is homotopic to id_{X^t}
homotopy: $F: [0, 1] \times X^t \rightarrow X^t$
 $(s, y) \mapsto (1-s)y + s\Pi_x(y)$



\Rightarrow when $d_{\text{H}}(P, X) \rightarrow 0$, the signal-to-noise ratio in the sweet range goes to ∞ .

③ Computing Dgm d_P :

(In practice, offsets filtrations are replaced by "equivalent" simplicial filtrations built on P using metric information.

(cf. slide 2)

* Classical choices:

Def: Čech (or Nerve) filtration $\mathcal{C}(P) = (C(P, t))_{t \in \mathbb{R}}$:

$$\left[\sigma = \{p_0, \dots, p_n\} \subseteq P \in C(P, t) \Leftrightarrow \bigcap_{i=0}^n B(p_i, t) \neq \emptyset \right.$$

Def: (Vietoris-) Rips filtration $\mathcal{R}(P) = (R(P, t))_{t \in \mathbb{R}}$:

$$\left[\sigma = \{p_0, \dots, p_n\} \subseteq P \in R(P, t) \Leftrightarrow \begin{array}{l} \text{diam } \sigma \leq t \\ \text{"} \\ \max_{i,j} \|p_i - p_j\| \end{array} \right.$$

* Sparsified filtrations:

(cf. slides 3-4)

- Sparse Voronoi Refinement filtration: $\begin{bmatrix} O(d^2) \\ 2 \\ n \end{bmatrix}$
[Hudson, Miller, O., Sheehy 2010]
- Sparse Rips filtration: $\begin{bmatrix} O(m^2) \\ 2 \\ n \end{bmatrix}$ where m is the intrinsic dimension.
[Sheehy 2012]
- Rips zigzags: $\begin{bmatrix} O(m^2) \\ 2 \\ n \end{bmatrix}$ with improved constant
[O., Sheehy 2013] the big-O.