## INF 556: Topological Data Analysis

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Lecture 6: Homology Inference

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#### Disclaimer:

Some typo and errors may remain. Please mention them at theo.lacombe@polytechnique.edu. Use these notes with caution, especially during the exam (we decline all responsibility linked with the use of these notes during the exam session).

**Reminder:** These notes are a concise summary of the lectures. They do not intend in any case to substitute to your personal notes and are just an additional support in order to clarify or insist on some points.

**Goal:** Infer the homology group of (unknown) topological space X from a finite set of points P (roughly approximating X).

# 6.1 Distance functions

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

**Definition 1** (Distance function). The distance function  $d_X$  is defined by:

$$d_X : \mathbb{R}^d \to \mathbb{R}_+$$
$$z \mapsto \min_{x \in X} \|z - x\|_2$$

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

### Definition 2.

$$d_H(X,Y) := \max\{\max_{x \in X} d_Y(x), \max_{y \in Y} d_X(y)\}$$

## Proposition 1.

$$d_H(X,Y) = \|d_X - d_Y\|_{\infty} = \sup_{z \in \mathbb{R}^d} |d_X(z) - d_Y(z)|$$
(6.1)

*Proof.* By definition,

$$\|d_X - d_Y\|_{\infty} \ge \begin{cases} \max_{x \in X} |d_Y(x) - 0| \\ \max_{y \in Y} |d_X(y) - 0| \end{cases}$$
$$\Rightarrow \|d_X - d_Y\|_{\infty} \ge d_H(X, Y)$$

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. We have:

$$d_Y(z) - d_X(z) \le ||y - z|| - ||x - z||$$
  
 $\le ||x - y|| = d_Y(x) \le \max_X d_Y$ 

Symmetrically,  $d_X(z) - d_Y(z) \leq \max_X d_Y$ . Therefore,

$$\begin{aligned} \forall z, |d_Y(z) - d_X(z)| &\leq d_H(X, Y) \\ \Rightarrow ||d_X - d_Y||_\infty &\leq d_H(X, Y) \end{aligned}$$

**Corollary 1** (Prop + stability theorem). Given P finite such that  $d_H(P,X) \leq \varepsilon$  for some (unknown) compact set X,

$$d_B(\operatorname{Dgm}(d_P), \operatorname{Dgm}(d_X)) \leqslant \varepsilon$$
 (6.2)

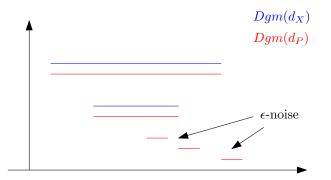


Figure 6.1: Illustration of the corollary ?? : approximating X with a point cloud P lead to an  $\varepsilon$ -close barcode (in bottleneck distance).

#### Questions:

- When and how does  $Dgm(d_X)$  reflect the homology of X?
- How to compute Dgm(P) in practice?

# 6.2 Medial axis and reach

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

**Definition 3.** Given  $z \in \mathbb{R}^d$ , let  $\Pi_X(z) := \arg \min_{x \in X} ||z - x||$ , which is called the projection set of z on X.

## Notes:

- $Pi_X(z) \neq \emptyset$  since X is compact.
- When  $\#\Pi_X(z) = 1$ , one calls "projection of z on X" the unique point of  $\Pi_X(z)$ , denoted by  $\pi_X(z)$ .

**Definition 4** (Medial axis). The medial axis of X is:

$$\mathcal{M}(X) := \left\{ z \in \mathbb{R}^d | \# \Pi_X(z) > 1 \right\}$$

**Note:** The projection map  $\pi_X$  is defined outside  $\mathcal{M}(X)$ :

$$\pi_X: \mathbb{R}^d \backslash \mathcal{M}(X) \to X$$

**Definition 5** (Reach). The reach of X is:

$$rch(X) := \inf_{x \in X, z \in \mathcal{M}(X)} ||x - z|$$

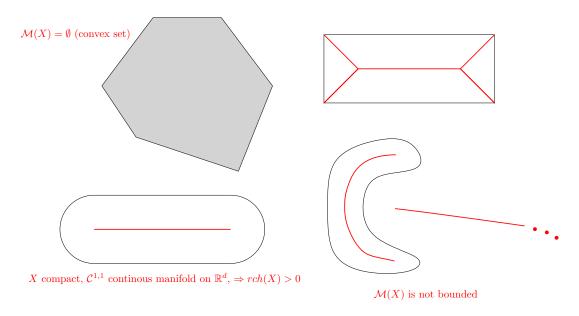


Figure 6.2: Different example of medial axis for different compact sets.

**Lemma 1** (Federer 1959).  $\pi_X$  is continuous over  $\mathbb{R}^d \setminus \mathcal{M}(X)$  (admitted).

**Theorem 1.** Let  $X \subset \mathbb{R}^d$  compact be such that rch(X) > 0. Then:  $\forall t \in [0, rch(X))$ , the t-offset of X is homotopy equivalent to X:

$$X \simeq X_t := \bigcup_{x \in X} B(x, t) = d_X^{-1}((-\infty, t])$$
(6.3)

*Proof.* Note that  $X \subset X_r$  for all r > 0. So one can consider:

$$i: X \to X_t$$
 natural inclusion  
 $\pi_X: X_t \to X$  projection

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

We have that:

$$\begin{aligned} \pi_X \circ i &= id_X \\ i \circ \pi_X &= \pi_X \\ F &: [0,1] \times X_t \to X_t \\ (s,z) \mapsto (1-s)z + s\pi_X(z) \end{aligned}$$

# 6.3 Computing $Dgm(d_P)$

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

**Classical choices:** 

**Definition 6** (Čech (or nerve) filtration).

$$\mathcal{C}(P) = (C(P,t))_{t \in \mathbb{R}}$$
$$\sigma = \{p_0 \dots p_r\} \subset P \in C(P,t) \Leftrightarrow \bigcap_{i=0}^r B(p_i,t) \neq \emptyset$$

**Theorem 2** (Nerve).  $\forall t \in \mathbb{R}, C(P, t)$  is homotopy equivalent to  $P_t := \bigcup_{p \in P} B(p, t)$ 

**Lemma 2** (Persistent nerve, Chazal, O, 2008). Moreover,  $\forall s \leq t \in \mathbb{R}$ , the following diagram commutes:

$$H_r(P_s) \xrightarrow{\subseteq} H_r(P_t)$$

$$\simeq \downarrow \qquad \qquad \downarrow \simeq$$

$$H_r(C(P,s)) \xrightarrow{\subseteq} H_r(C(P,t))$$

$$\Rightarrow \operatorname{Dgm}(P_t)_{t \in \mathbb{R}} = \operatorname{Dgm}(\mathcal{C}(P))$$

**Definition 7** (Vietoris-Rips filtration).

$$\mathcal{R}(P) := (R(P,t))_{t \in \mathbb{R}}$$
$$\sigma = \{p_0 \dots p_r\} \in R(P,t) \Leftrightarrow \underbrace{\max_{\substack{p_i, p_j \in \sigma \\ diam(\sigma)}} \|p_i - p_j\|}_{diam(\sigma)} \leqslant t$$

Proposition 2.

$$\forall t \in \mathbb{R}, R(P, t) \subseteq C(P, t) \subseteq R(P, 2t)$$

Proof.

$$\bigcap_{i=0}^{r} B(p_i, t) \neq \emptyset \Rightarrow \forall i, ||p_i - p_0|| \leq 2t$$
$$\Rightarrow diam(\{p_0 \dots p_r\}) \leq 2t$$
$$\Rightarrow C(P, t) \subseteq R(P, 2t)$$

Conversely,

$$diam(\{p_0 \dots p_r\}) \leqslant t \Rightarrow p_0 \in \bigcap_{i=0}^r B(p_i, t) \neq \emptyset$$
$$\Rightarrow R(P, t) \subseteq C(P, t)$$

Note:  $C(P,t) = R(P,2t), \forall t \in \mathbb{R}$ , when  $P \subset (\mathbb{R}^n, l^\infty)$ .

Proof. Exercise

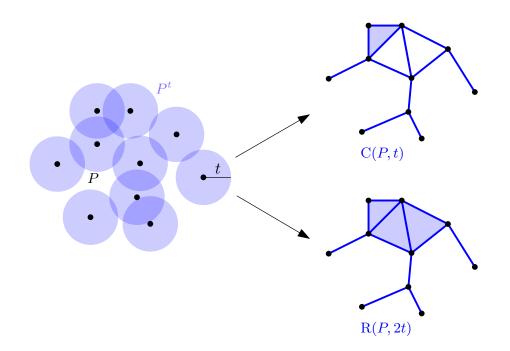


Figure 6.3: Example of  $\tilde{C}ech$  and Rips filtrations.

**Remark:** These filtrations can be computationally costly to compute: size grows with scale  $2^n$  in general, where n is the number of points in P. Finding sparsified filtrations (i.e. better than Rips or Čech in terms of complexity while preserving good homological properties regarding the unknown underlying space X). This is a current research topic, some recent progress are:

- Sparse Voronoi Refinement filtration
- Sparse Rips filtrations
- Rips zigzags