

# From Geometry to Topology : Inverse Theorems for Distributed Persistence - Solomon, Wagner, Bendich

- Given a statistic  $\lambda$  of a finite pt cloud  $X \subset \mathbb{R}^d$ , what does computing  $\lambda$  on Subsets of  $X$  tell us?

Definition • For  $k \in \mathbb{N}$  we define

$$\lambda_k := \{(S, \lambda(S)) \mid S \subseteq X, |S| = k\}$$

- we say  $\lambda$  is  $k$ -distributed if  $\lambda_k(X)$  determines  $\lambda(X)$  for any  $|X| \geq k$ .

Example

Consider  $\lambda(S) := \text{diameter}(S)$

$$= \max_{x,y \in S} d(x, y)$$

then we see that  $\lambda$  is  $k$ -distributed for any  $k \geq 2$ :

$$\lambda(X) = \max \lambda_k(X)$$

Moreover,  $\lambda_k$  may contain more information — here  $\lambda_2$  is the entire distance matrix.

- ① Are any TDA statistics  $\lambda$   $k$ -distributed?
- ② Does  $\lambda_k$  contain more geometric information than  $\lambda$ ?
- ③ Do we really need to compute  $\lambda$  on all subsets of size  $k$ ?

They consider

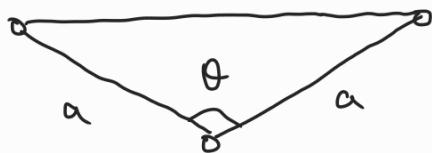
$$\begin{aligned}\lambda &= \text{VR persistence (RP)} \\ &\quad \text{VR Euler curve (RE)} \\ &\quad \text{Cech Persistence (CP)} \\ &\quad \text{Cech Euler curve (CE)}.\end{aligned}$$

proposition • Each of these  $\lambda$  is  $\mathbb{Z}$ -distributed.

Moreover,  $\lambda_2(X)$  determines the distance matrix of  $X$  and thus  $X$  up to isometry.

°  $\lambda_3$  does not determine  $X$  up to isometry.

proof:



RP



RP

$\lambda_2$  contains more geometric information

than ever  $\lambda_3$ . Can we quantify  
the change from increasing  $k$ ?

Definition °  $\lambda$  is  $(k_1, \dots, k_r)$ -distributed

if  $\lambda_{k_1}, \dots, \lambda_{k_r}$  determine  $\lambda$ .

For any of the four  $\lambda$  considered, let

$\lambda^m(X)$  denote  $\lambda$  ( $m$ -skeleton of  $X$ ).

### Theorem

For any of the four  $\lambda$  we have  
that  $\lambda^m$  is  $(k, k-1, \dots, k-m-1)$  —  
distributed for all  $k \geq m+1 \geq 2$ .

Moreover,  $\{\lambda_k^m(x), \dots, \lambda_{k-m}^m(x)\}$   
determine  $x$  up to isometry.

If the  $\lambda_k^m(x)$  are 'close' to  $\lambda_k^m(y)$

does that mean the geometry of  $x$  is  
'close' to that of  $y$ ?

### Definition • $\phi: (X, d_X) \rightarrow (Y, d_Y)$ is

an  $\varepsilon$ -quasi isometry if we have

that

$$|d_X(x_1, x_2) - d_Y(\phi(x_1), \phi(x_2))| \leq \varepsilon$$

for all  $x_1, x_2 \in X$ .

## Theorem

Let  $\lambda = RP$  or  $CP$  and take  $k > m > 0$ .

Let  $\phi: X \rightarrow Y$  be a bijection s.t.

$\forall S \subseteq X$  with  $|S| \in \{k, k-1, \dots, k-m-1\}$

we have

$$d_{Bottleneck}(\lambda^m(S), \lambda^m(\phi(S))) \leq \varepsilon.$$

Then

$$\phi \text{ is a } \begin{cases} 112k^2\varepsilon - QI & \text{if } \lambda = RP \\ 224S(k,m)k^{m+1}\varepsilon - QI & \text{if } \lambda = CP \end{cases}$$

$$\text{where } S(k,m) = \binom{k}{2} + \binom{k}{3} + \dots + \binom{k}{m+1}.$$

So increasing  $k$  interpolates between capturing geometric info and capturing topological info.

In fact, a tighter bound linear in  $k$  is available by considering  $\omega'(\lambda'(x), \lambda'(\phi(x)))$ .

This seems expensive. Do we need to compute  $\lambda$  on every subset?

Proposition The conditions of the previous

theorem can be weakened. It suffices that

$$d_B(\lambda^m(s), \lambda^m(\phi(s))) \leq \varepsilon$$

for all  $s \in C$ , where  $C$  is any collection of subsets of  $X$  satisfying:

- (convexity)

$\forall \sigma \subseteq X$  with  $|\sigma| \leq 2 \exists s \in C, |s|=k$   
s.t.  $\sigma \subseteq s$ .

- (closure)

$\forall s \in C$  s.t.  $|s|=k$  we have that

$\forall s' \subseteq s$  with  $|s'| \geq k-m-1$ , then  $s' \in C$ .

Moreover, we can bound the probability that randomly sampled subsets will satisfy

the covering property. (we can just fill in the necessary subsets to satisfy closure).

Proposition Let  $|X| = n$  and choose  $M$

Subsets  $S_1, \dots, S_M$  of size  $k$  by uniform sampling without replacement.

Let  $A_2$  be the event that every pair of points  $(x_1, x_2)$  is contained in at least one  $S_i$  (i.e.  $S_1, \dots, S_M$  cover),

then

$$P(A_2) \geq 1 - \binom{n}{2} \left[ 1 - \left( \frac{k-1}{n-1} \right)^2 \right]^M.$$

In particular, given  $p \in (0, 1)$  then

Setting

$$M \geq \left[ 2 \log\left(\frac{n}{2}\right) - \log(1-p) \right] \left( \frac{n-1}{k-1} \right)^2$$

ensures  $P(A_2) \geq p$ .