

# Application: Manifold Learning.

Last time: Stability of persistence

$\varepsilon$ -interleaving  $\Rightarrow$   $\varepsilon$ -bottleneck distance between diagrams

Viewpoint 1: if we perturb the input, the change in output is controlled

Viewpoint 2: if 2 diagrams are more than  $\varepsilon$ -apart then no  $\varepsilon$ -interleaving exists (ie a lower bound on the distance between the input)

## Problem Definition

Given a manifold  $M$  and a random sample  $P$ , can we "reconstruct"  $M$ ?

Reconstruction can mean:

diffeomorphism

homeomorphism

up to homotopy

\* homologically equivalent (isomorphism of homology groups)

\* We will focus on this:

$$H_c(\underbrace{X(P)}_{\substack{\downarrow \\ \text{some} \\ \text{construction} \\ \text{on } P}}) \cong H_c(M)$$

\* We will also focus on  $M$  embedded in  $\mathbb{R}^d$  ;  $P$  either on  $M$  or near  $M$ .

# Building a Simplicial Approximation

## Construction 1: Čech complex

We are given a (finite) set of points  $P$  and define the open ball of radius  $r$  around each point  $p \in P$ . This is denoted  $B_r(p)$ .

We will first consider a different space:

Let  $\bigcup_{p \in P} B_r(p)$  be the union of balls of radius  $r$  centered at the points  $p$ .

Note: If we consider the balls open, the above space is not compact. In most cases we assume that taking the closure does not change the topology. However, one needs to check this.

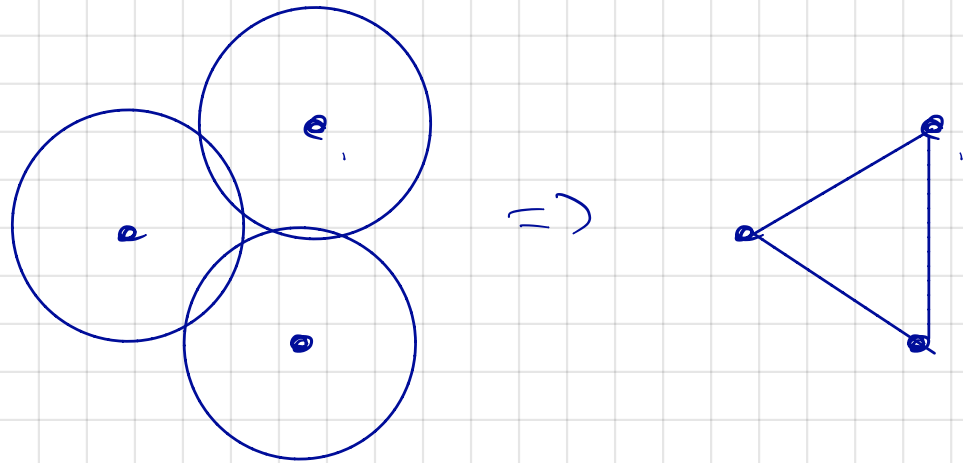
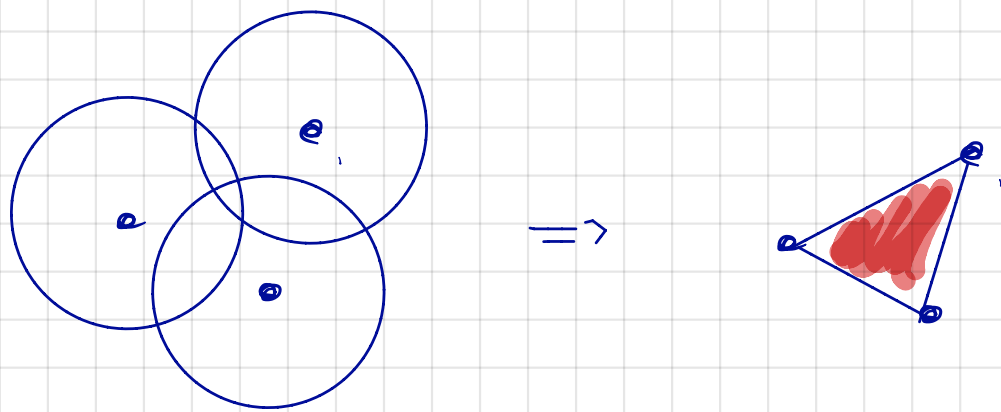
## Nerve construction

We now represent  $\bigcup_{p \in P} B_r(p)$  by an equivalent simplicial complex.

For each ball, add a vertex (or equivalently for each point). Insert a  $k$ -simplex

$\sigma = [v_1, \dots, v_n]$  if the corresponding balls have a nonzero intersection.

# Examples



in the first example there is a triple intersection so the triangle is in the nerve, whereas it is absent in the second example.

We denote the nerve  $N(B_r(P))$

"Nerve Thm": For  $P \subset \mathbb{R}^d$  the nerve is homologically equivalent to the union of balls.

Note: Something stronger is true, the spaces are homotopic, but we will not go into this further here.

Note: In a bit we will describe the real Nerve Theorem. § see why the above holds.

More generally

Def: A cover  $\mathcal{U}$  of  $X$  is a collection of **open sets** such that

$$\bigcup_i U_i = X$$

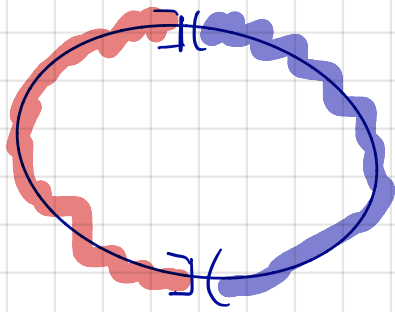
Def: A good cover of  $X$  is a cover of  $X$  such that every (finite) non-empty intersection has the topology of a point.

Note: Usually topology of a point is considered to be contractible (to a point) but in our case we can consider  $\beta_0 = 1, \beta_k = 0 \quad k > 0$  (ie 1 component, no holes of any dimension)

Nerve Theorem: If  $\mathcal{U}$  is a good cover of  $X$  then

$$H_k(X) \cong H_k(N(\mathcal{U}))$$


Note: Often one can make this work with closed sets but one should never mix



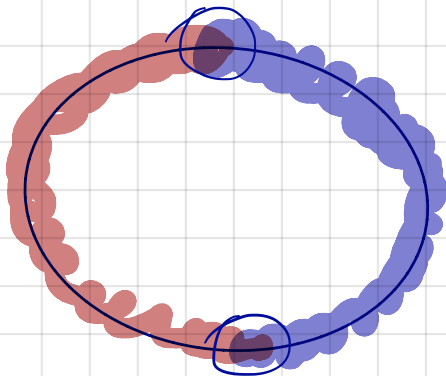
A cover of the circle

$$\left[ \frac{\pi}{2}, \frac{3\pi}{2} \right] \cup \left( -\frac{\pi}{2}, \frac{\pi}{2} \right)$$

This is a cover, both intervals are contractible as is the intersection (empty). The nerve is

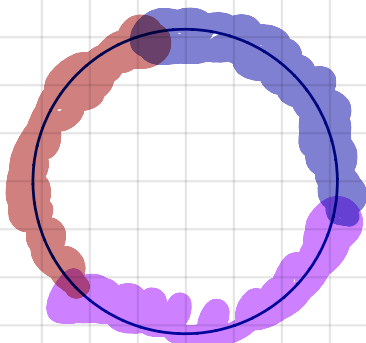
 which has  $\beta_1 = 0$  but the circle has  $\beta_1 = 1$ .

Ex 2

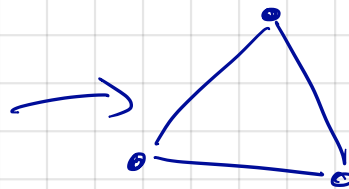


Not a good cover, the intersection is 2 points (rather than 1)

Ex 3



A good cover



## Back to $\bigcup_p B_r(p)$

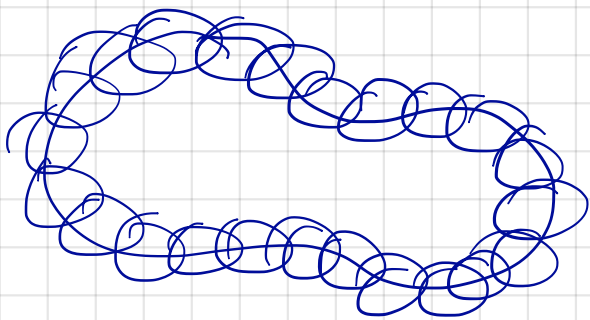
$\bigcup B_r(p)$  is a cover of the union of balls.  
in Euclidean space ( $\mathbb{R}^d$ ) each  $B_r(p)$  is convex  
{ the intersection of convex sets is convex (so all non-empty intersections are convex)

Convex sets always have the topology of a point  $\Rightarrow$  so the Nerve theorem applies.

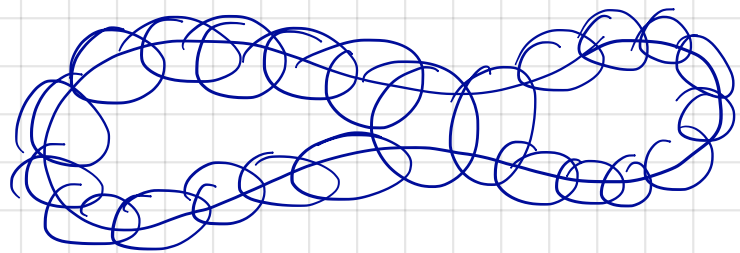
### More interesting case

$\bigcup B_r(p)$  is a cover of  $X \Rightarrow$  we must show that for each  $\bigcap_p B_r(p) \cap X$  that is non-empty, it must have the topology of a point

### Examples

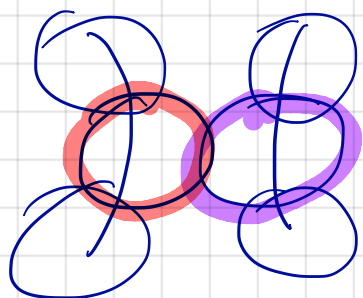


Good cover



Not good cover

## One more example



This is a good cover because although the two highlighted elements intersect the intersection is empty with respect to the space

Often we use the balls as a proxy as we cannot access the intersection with the space directly. In this case, one needs to show that the union of balls is a good approximation of the space (the above example is where it is not)

To show this we need to introduce geometry.

# Reach

One way to measure local "niceness" of a space

$$\rho(X) = \sup_r \left\{ \forall x \in \mathbb{R}^d \setminus X \text{ with } d(x, X) < r \text{ there exists a unique closest point } u \in X \text{ s.t. } d(x, u) = d(x, X) \right\}$$

That is, it is the largest ball which is tangent to a unique point in  $X$

Can be  $\infty$


•

$$\rho(\text{one point}) = \infty$$

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$$\rho(\text{line}) = \infty$$

or ○


$$\rho(\text{corner}) = 0$$

if its differentiable (no corners) can be arbitrarily small.

Theorem: if  $r < \frac{1}{2} \rho$  then  $UB_r(p)$  is equivalent to  $X$  (or alternatively  $UB_r(p)$  is a good cover)

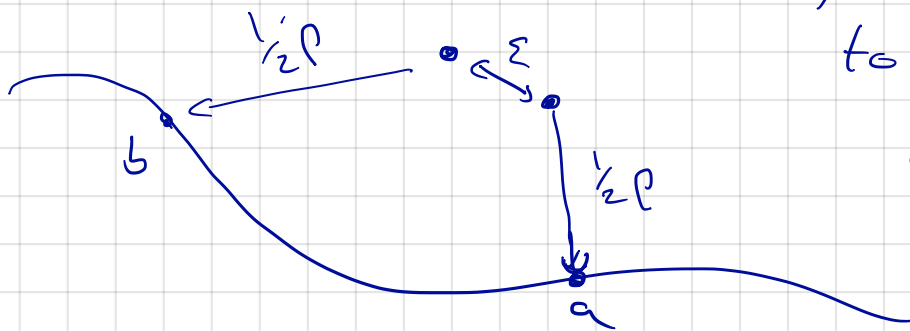


The first statement is easier to prove  
by constructing a homotopy

(a continuous map from  $\bigcup_p B_\rho(p)$  to  $X$ )

Proof: For each point in  $\bigcup_p B_\rho(p)$  project  
to the unique point in  $X$ . This can be  
verified to be continuous (since if it was  
not continuous it would imply the existence  
of a smaller ball which is tangent to 2  
points in  $X$ )

there must exist a  
point which is tangent  
to  $X$  at both  $a$  &  $b$   
w/ distance less  
than  $\rho$ .



There are many other measures

curvature,

condition number of a manifold

homotopical/homological critical value

injectivity radius ...

Each was designed for a specific purpose.

Back to manifold reconstruction...

Case 1:  $\mathcal{P}$  lies on  $X$

Theorem 1: if we have an  $\varepsilon$ -sample then  
for any  $\varepsilon < r < \rho/2$ , we have

$$H_c(X) \cong H_c(\cup B_r(p)) \cong H_c(N(\cup B_r(p)))$$

Def: An  $\varepsilon$ -sample of  $X$  is a set such  
that for every  $x \in X$ , the distance to the  
nearest element of the  $\varepsilon$ -sample is at most  
 $\varepsilon$ .

Random construction

Fix a cover  $\mathcal{U}$  with radius  $\varepsilon/2$ . If each  
element of the cover contains at least 1 point,  
the result is an  $\varepsilon$ -sample.

How many points do we need?

Coupon collector problem  $\Rightarrow |\mathcal{U}| \log |\mathcal{U}|$

with high probability.

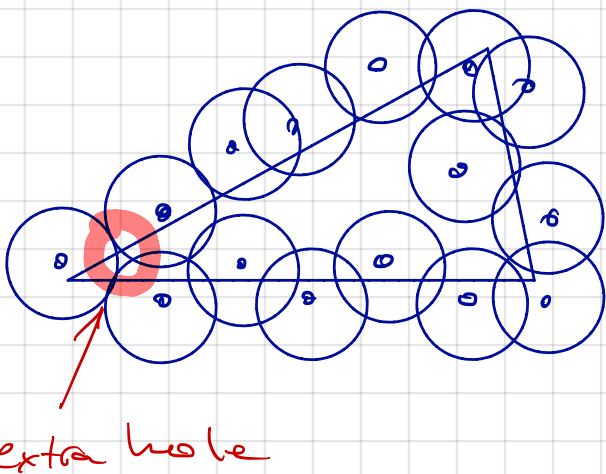
$\uparrow$   
# of elements  
in cover

In this case, there exists a  $r$  such that  $UB_r(p)$  has the correct homology (true reconstruction)

If points can lie near  $X$  then the situation is more complicated

Bad Case : Charal-Oudot

Towards Persistence-Based Reconstruction in Euclidean Spaces



No one radius is correct  
 $\Rightarrow$  there are always extra nontrivial cycles

Persistent homology is correct

$$\text{im} \left( H_k(N(\mathcal{U}_r)) \rightarrow H_k(N(\mathcal{U}_{r'})) \right)$$

↑  
cover  
at radius  
r

Key idea: Interleave offset filtration and Čech filtration (ie union of balls)

Def: offset filtration is

$$X_\delta = \{x \in \mathbb{R}^d \text{ st. } d(x, X) < \delta\}$$

Let  $P$  be an  $\varepsilon$ -cover (this is a simplification from lecture)

$$P \subset X_\varepsilon \quad ; \quad X \subset B_\varepsilon(P)$$

Observe via triangle inequality

$$X \subset B_\varepsilon(P) \subset X_{2\varepsilon} \subset B_{3\varepsilon}(P)$$

Assume  $2\varepsilon < \frac{1}{2} \rho$ , notice  $H_k(X) \cong H_k(X_{2\varepsilon})$ .

does not imply  $H_k(X) \cong H_k(B_\varepsilon(P))$

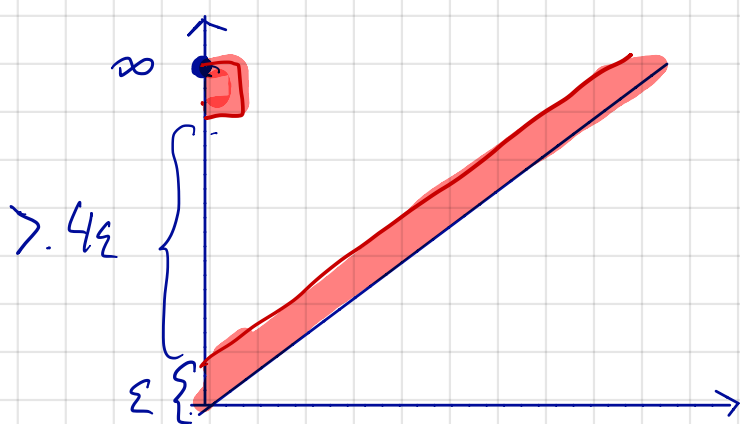
However  $H_k(B_\varepsilon(P))$  is an upper bound for  $H_k(X)$  (ie it may contain spurious features)

## Persistence viewpoint

$$X \subset B_\varepsilon(p) \subset X_{2\varepsilon} \subset B_{3\varepsilon}(p)$$

implies that  $X_r \cap B_r(p)$  are  $\varepsilon$ -interleaved

So if  $H_k(X_r) \cong H_k(X)$  for all  $r < \rho/2$



• points corresponding to  $X$

• area where points corresponding to  $B_r(p)$  can be

all spurious features are here so

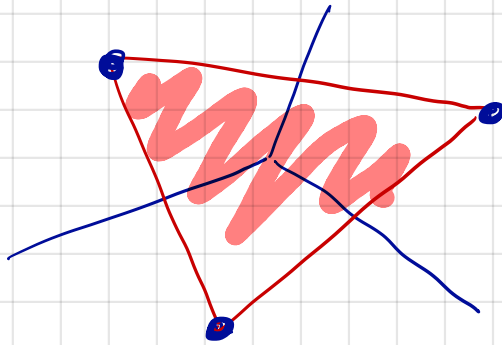
$$\lim H_k(B_\varepsilon(p)) \rightarrow H_k(B_{3\varepsilon}(p)) \cong H_k(X)$$

# Alternative constructions

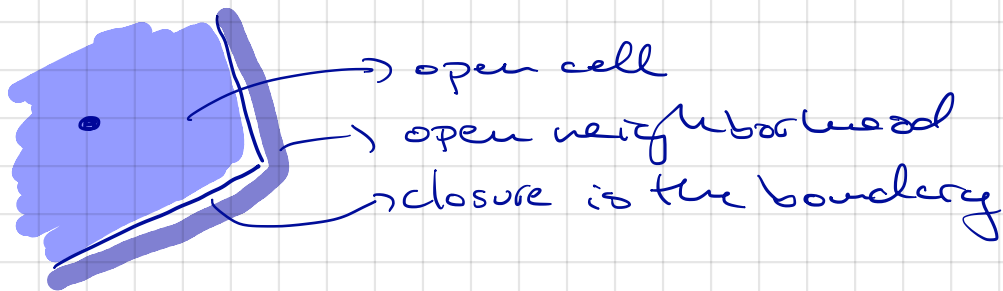
Delanay /  $\alpha$ -complex

Given a set of points  $P$ , build Voronoi diagram

Delanay / Delone triangulation is dual



Alternative viewpoint: Build a cover by taking the neighborhood of the closure of each Voronoi cell



To compute  $\alpha$ -filtration, intersect  $B_r(p)$  with the corresponding Voronoi cell of  $p$ .

Fact: This is equivalent to the Čech filtration (but smaller)

# Vietoris-Rips

Build a graph on a pointset

$$(x, y) \in \Delta_1 \text{ if } d(x, y) < r$$

↑  
1-skeleton

The graph is a 1-dimension complex

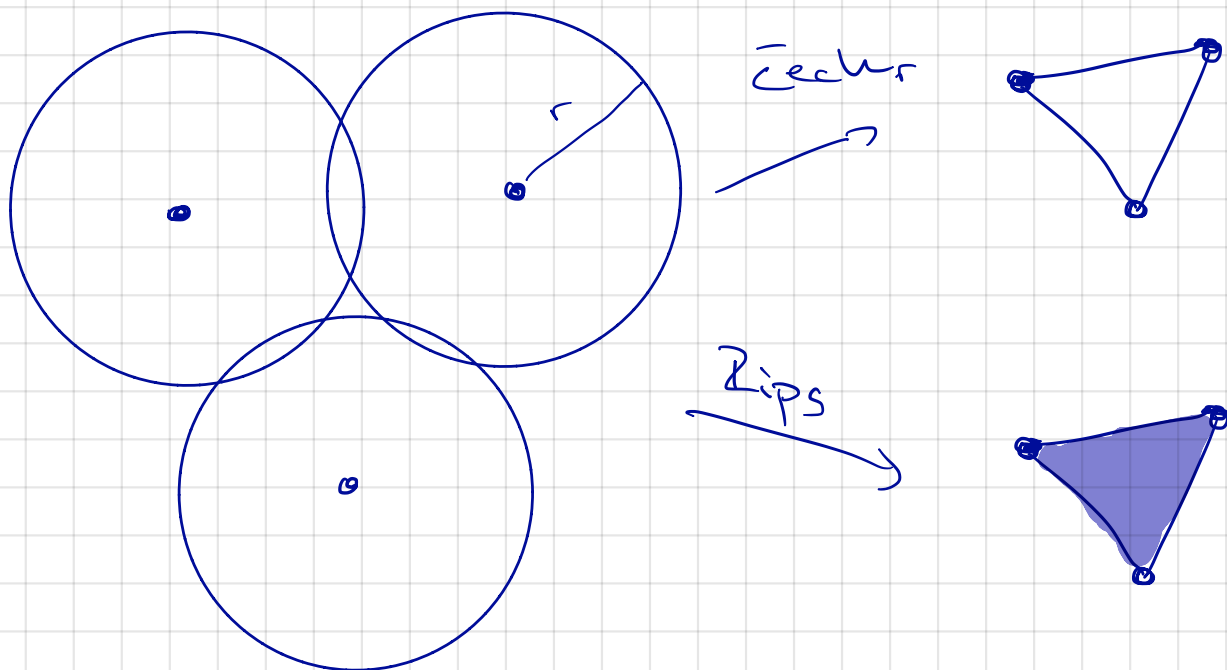
Clique complex: put in all possible simplices  
(if all edges are present)

There is a correspondence

$$k\text{-simplex} \iff (k+1)\text{-clique}$$

(complete graph on  $k+1$  vertices)

## Difference w/ Čech complex



$$\text{Observe: } C_1(\bar{C}_r) = C_1(\sqrt{2}r/2)$$

$\bar{C}_r$  ← each      ← Vietoris-rips  
 $\sqrt{2}r/2$

The 1-dimensional skeletons are the same with a rescaling of 2 (if two balls of radius  $r$  intersect, the distance between the centers  $< 2r$ )

This implies

$$C_k(\bar{C}_r) \subseteq C_k(\sqrt{2}r) \subseteq C_k(\bar{C}_{2r})$$

Note in Euclidean space, this can be improved.

This is called a 2-interleaving. It is a multiplicative interleaving not additive as we saw before. We can transform this to additive by reparameterizing and taking the logarithm.



There are many other possible constructions

- Witness complexes
- Sparse Lips complexes
- graph-induced complexes

## Estimating functions

Assume we have a  $c$ -Lipschitz function  $f: X \rightarrow \mathbb{R}$

$$f(x) - f(y) \leq c \cdot d(x, y)$$

! we have an  $\varepsilon$ -sample of  $X$  (and we only know  $f$  at the sample points)

$$f^{-1}(-\infty, \alpha] \subseteq \bigcup_{f(p) < \alpha + c\varepsilon} B_\varepsilon(p) \subseteq f^{-1}(-\infty, \alpha + 2c\varepsilon]$$

$\Rightarrow$  again we have interleaving.

## Relevant reading list

NSW 08 - Niyogi - Smale - Weinberger - Finding the Homology of Submanifolds with High Confidence from Random Samples DCG, 08

CO - Chazal - Oudot - Towards Persistence Based Reconstruction in Euclidean Spaces 2007

BM - Bobrowski - Mukherjee - The Topology of Probability Distributions on Manifolds 2013

CGOS - Chazal - Guibas - Oudot - Skraba  
Scalar Field Analysis over Point Cloud Data 2011

Not an exhaustive list...many more