Informal Introduction to Topological Data Analysis

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Overview

Motivation:

- Topological Data Analysis (TDA) is a new field at the intersection of several mathematical fields.
- · Various approaches depending on your scientific field.
- Many new concepts: Topology, Homology, Persistence, Quiver, cycle, Reeb graph, mapper, Morse Theory ...
- Require background in field traditionally unknown by most statisticians.

Aim of this talk:

- · To provide the basic concepts and vocabulary appearing in TDA.
- · To provide an introduction to Anne Marie's talk.

TDA – History and Showcases

The theory and main objects can be trace back to the 90s:

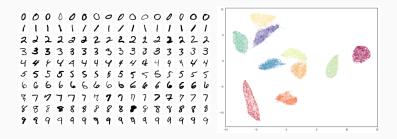
- Early concept of persistence, Frosini (1992)
- New descriptor: Persistent Betti numbers, Robins (1999)
- The currently most used object: Persistence Diagram, Edelsbrunner et al. (2000)

Other approaches have been developed since then

- Mapper: Singh et al. (2007)
- UMAP Uniform Manifold APproximation: McInnes et al. (2018)

All of them have been used for different applications.

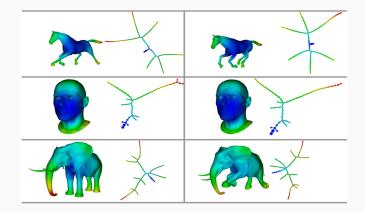
Applications – Dimension reduction



Encoding of each image:

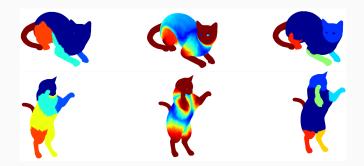
- a vector of dimension 28x28 "the number of pixels".
- The value on each coordinate is the gray level of the pixel.

Applications – Shape Classification



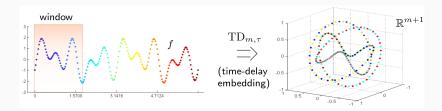
Motivation: Since topology is invariant by continuous deformation, then the same shape in different position will be well identified, Singh et al. (2007).

Applications – Image Segmentation



Skraba et al. (2010)

Data have shapes and their topology can be used as a descriptor.



TDA – What is topology?

Definition (Topology)

A topological space is a set E equipped with a family of subsets ${\cal O}$ such that, and such that

- $\emptyset, E \in \mathcal{O}$,
- \mathcal{O} is stable under union,
- \mathcal{O} is stable under finite intersection.

Warning: This is the first error actually.

In TDA: we do algebraic topology, not general topology.

- Roughly, this is the study of invariant quantities via continuous deformation of a shape, i.e. no tearing.
- Example: from an "algebraic topologist" point of view, a mug is a donut.



Topogical features: Every feature that is invariant under continuous deformation.

- The (path) connected components 0-dimensional features
- The loops 1-dimensional features
- The voids 2-dimensional features
- In higher dimension, *n*-dimensional holes.

Example: The torus has

- 1 connected component,
- 1 loop,
- 1 void the inside of the donut.

TDA – Persistent Homology – What is it?

Original motivation

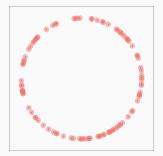
- We observe points sampled on an (unobserved) shape.
- Original motivation: How can we find the original shape only from the points?



Here comes Topological Data Analysis (TDA).

Topology of Points?

- We replace each point with a ball of radius r > 0.
- For a r large enough, we find indeed the loop.

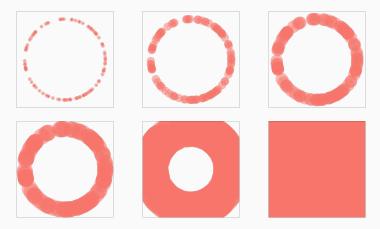




How to choose r?

Here comes Persistence

We let r growing from 0 up to ∞ .

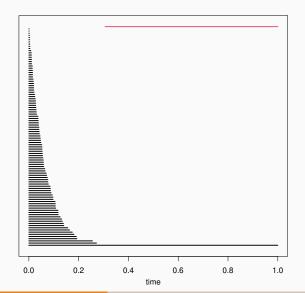


Original Idea: Important features will be the ones that "persist" a long "time" when r increases.

- We record each "radius/time" where change in the topology of the union of balls happens.
- Each time two balls connect: one connected component disappear it dies.
- When a loop appears for a radius *r*_{loop} we say it is the birth time of the loop.

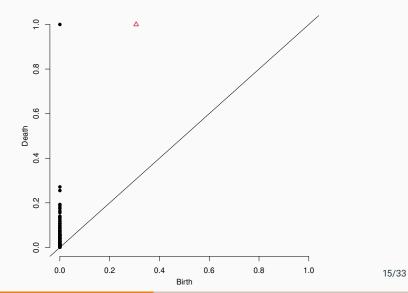


- When the loop is completely covered we say it is its death.
- There is two common ways to display this information.



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Persistent Diagram



- This is the most standard way in which TDA is performed.
- This is the so-called persistent homology approach
- Although these two representations are equivalents, the persistence diagrams appears to be the most used for applications.

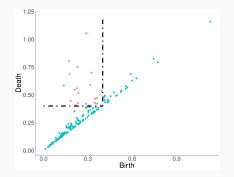
From this "mathematically complicated" object, we define other statistics.

Betti Numbers

Definition: Let b, d > 0 with b < d and D be a PD. The persistent Betti number is

$$\beta_{b,d}^D = \#\{(x,y) \in D, \ x \le b, y \ge d\}.$$

Example: The number of point in red is $\beta_{0.4,0.4}^D$.

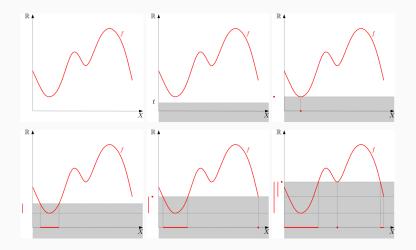


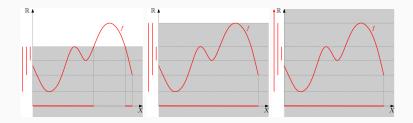
Important: The knowledge of $\beta_{b,d}^D$ for all b, d defines completely D.

But, even within the persistent homology approach, there may be some variations.

- · You do not need the balls.
- Building the union of balls \rightarrow constructing an increasing sequence of topological spaces called a **filtration**.
- Analytically the union of balls corresponds to the sublevel sets of the distance function to the data points.
- Any sublevel sets of a function (smooth enough) actually works and may be used for analysis.

Example





- The union of balls is just the interpretation
- The true mathematical objects are the distance function to the set of data points *X*:

$$d_X(u) := d(u, X) = \min\{|u - x|, x \in X\}$$

• and its level sets at level r > 0:

$$\{u \in \mathbb{R}^d, \ d_X(u) \le r\} = \bigcup_{x \in X} B(x, r).$$

The space of persistence diagram is a metric space: the Bottleneck distance on persistence diagram d_B .

Theorem (Stability, Cohen-Steiner et al. (2005))

Let *X* and *Y* be two sets of points in \mathbb{R}^d with d_X and d_Y being the distance function to *X* and *Y*, respectively. Let further PD(X), PD(Y) be the persistence diagrams obtained from the points *X* and *Y*, respectively. Then

$$d_B(PD(X), PD(Y)) \le |d_X - d_Y|_{\infty}.$$

Main idea: If I perturb my data X by ϵ to get Y, $|d_X - d_Y|_{\infty}$ is small and the persistence diagrams are similar.

- · There exists others stability theorems
- For example, assume the points *X* to be sampled on a manifold *M*.
- There is stability theorem to bound the Bottleneck distance $d_B(PD(X), PD(M))$ in function of the number of points.
- This is useful for shape analysis, to prove that you can recover the topology of the shape from points sampled on it.

What about PD computations? - Simplices

On the union of balls:

- We do not know how to define and compute easily the connected components, loops and other topological features of higher dimensions.
- Solution Using another mathematical objects easier to work with:

Simplicial Complexes

Definition (*k***-simplex)**

Given a set of k + 1 points $\{x_0, \ldots, x_k\} \subset \mathbb{R}^d$, the *k*-dimensional simplex $[x_0, \ldots, x_k]$ is the convex hull of the k + 1 points.

<u>Remark:</u> the dimension depends on the number of points, not the dimension of the space.



A simplicial complex is a (valid) union of simplices.

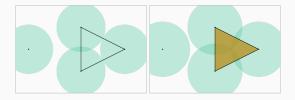
They can be build from the data in many ways:

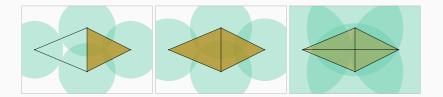
- Vietoris-Rips complexes
- Cech complexes
- α-complexes.
- Cubical complexes (suitable for images)

- Let's us consider the point pattern: $\mathbf{x} = \{x_1, \dots, x_n\}.$
- The Cech complex at radius r > 0 of x is an union of simplices noted $C_r(\mathbf{x})$.
- For $k \in \mathbb{N}$, a k-simplex $[y_0, \ldots, y_k]$ belongs to $C_r(\mathbf{x})$ if and only if $\{y_0, \ldots, y_k\} \subset \mathbf{x}$ and

 $\bigcap_{j=0}^{k} B(y_j, r) \neq \emptyset.$

Cech complex – Toy example

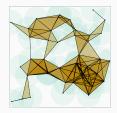


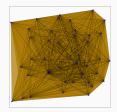


Cech complex – Poisson









Pros:

- · From a theoretical point of view: easy to study
- It verifies a Nerve Lemma: at each radius r, $C_r(\mathbf{x})$ is homotopic to the union of balls of radius r.
- Main message: Nerve Lemma ⇒ Studying the union of balls or simplicial complexes is the same

Cons:

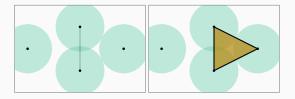
- · Contains simplices of very high dimensions.
- · Computationally hard to handle when lot of points.
- · Slow to compute.

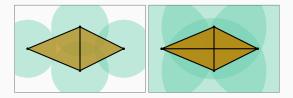
- Let's us consider the point pattern: $\mathbf{x} = \{x_1, \dots, x_n\}$.
- The (Vietoris-)Rips complex at radius r > 0 of x is an union of simplices noted R_r(x).
- For $k \in \mathbb{N}$, a k-dimensional simplex $[y_0, \ldots, y_k]$ belongs to $R_r(\mathbf{x})$ if and only if $\{y_0, \ldots, y_k\} \subset \mathbf{x}$ and for all $i, j \in \{0, \ldots, k\}$:

 $B(y_i, r) \cap B(y_j, r) \neq \emptyset.$

To compare with the Cech complex: $\bigcap_{j=0}^{k} B(y_j, r) \neq \emptyset$.

Rips complex – Toy example





- Cech complex: good but slow and hard to compute.
- Vietoris-Rips complex: the quickest to compute but no Nerve Lemma.
- However, it the persistence diagram is still a good approximation in some sense.

In conclusion: For applications, no major differences.

The End – Thank you