Foundations of Geometric Methods in Data Analysis

Instructors:

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Class outline (each class is 50% lecture 50% practical session)

- 1. Computational Topology (I): Simplicial Complexes
- 2. Nearest Neighbors in Euclidean and metric spaces (I): Data Structures and Algorithms
- 3. Nearest Neighbors in Euclidean and metric spaces (II): Analysis
- 4. Comparing Samplings, Distributions, Clusterings
- 5. Computational Topology (II): Persistence Theory
- 6. Topological Machine Learning (I): An Introduction
- 7. Topological Machine Learning (II): Advanced Topics
- 8. Dimensionality Reduction Algorithms

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Practical sessions are based on:

ਗੂਫੀ GUDHI Structural Bioinformatics Library

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Topological Data Analysis (TDA)

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Question: What is topology?

A: Roughly speaking, the topology of a space X is its number of 'holes'. More formally, it is the class of spaces that can be obtained by continuous deformations of X.

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Topological Data Analysis (TDA)

Goal: Study geometric data sets with techniques coming from *topology*.

Question: What is topology?

[*Elements of Algebraic Topology*, Munkres, CRC Press, 1984]

[*Algebraic Topology*, Hatcher, Cambridge University Press, 2002]

[*Computational Topology: an introduc-tion*, Edelsbrunner, Harer, AMS, 2010]



We will see how to build new topological features from data sets...

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...but why is that interesting?



Data often come as (sampling of) metric spaces or sets/spaces endowed with a similarity measure with, possibly complex, topological/geometric structure.

Data carrying geometric information is usually high dimensional.



Features from Topological Data Analysis allow to:

- infer relevant topological and geometric features of these spaces.
- take advantage of topol./geom. information for further processing of data (classification, recognition, learning, clustering, parametrization...).



Pros of topology:

• **Coordinate invariance:** topological features/invariants do not rely on any coordinate system so no need to have data with coordinates, or to embed data in spaces with coordinates... but the metric (distance/similarity between data points) is important.

• **Deformation invariance:** topological features are invariant under homeomorphism and reparameterization.

• **Compressed representation:** topology offers a set of tools to summarize the data in compact ways while preserving its topological structure.

Problem: how to define the *topology* of a data set?



Cons of topology:

- No direct access to topological/geometric information: need of intermediate constructions with *simplicial complexes*.
- Distinguish topological "signal" from noise.
- Topological information may be multiscale.
- Statistical analysis of topological information.



- **1. Simplicial Complexes**
 - 2. Nerve Theorem
 - 3. Homology Groups

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Pbm: How to encode topological spaces for computational purposes?

Simplicial Complexes
Nerve Theorem
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Pbm: How to encode topological spaces for computational purposes?

A: Using spaces made of small convex bricks, namely the *simplicial complexes* made of *simplices*.



0-simplex: vertex

1-simplex: edge

2-simplex: triangle

3-simplex: tetrahedron

etc...



Def: Given a set $P = \{p_0, \ldots, p_k\} \subset \mathbb{R}^d$ of k+1 affinely independent points, the k-dimensional simplex σ (or k-simplex for short) spanned by P is the set of convex combinations

$$\sum_{i=0}^{k} \lambda_i p_i, \quad \text{with} \quad \sum_{i=0}^{k} \lambda_i = 1 \quad \text{and} \quad \lambda_i \ge 0.$$

The points p_0, \ldots, p_k are called the vertices of σ .

Def: A simplicial complex K in \mathbb{R}^d is a collection of simplices s.t.:

- (i) any face of a simplex of K is a simplex of K,
- (ii) the intersection of any two simplices of K is either empty or a common face of both.

The underlying space of K, written $|K| \subseteq \mathbb{R}^d$, is the union of its simplices. The k-skeleton of K, written $\operatorname{Skel}_k(K)$, is the smaller complex made of the simplices of K of dimension up to k: $\operatorname{Skel}_k(K) = \{\sigma \in K : \dim(\sigma) \leq k\}$.



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Remark: Simplicial complexes can be seen at the same time as geometric/topological spaces (good for geometrical/topological inference) and as combinatorial objects (good for computations).

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Q: Triangulate



Def: Let $P = \{p_1, \dots, p_n\}$ be a (finite) set of vertices (*not necessarily embedded in* \mathbb{R}^d). An abstract simplicial complex K with vertex set P is a set of subsets of P satisfying the two conditions:

- (i) the elements of P belong to K,
- (ii) if $\tau \in K$ and $\sigma \subseteq \tau$, then $\sigma \in K$.

The elements of K are the simplices.



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Remark: It is possible to define abstract simplicial complexes out of point clouds embedded in \mathbb{R}^d —in this case, the dimension of the complex is not necessarily d, see for instance Rips complexes later.

Def: A realization of an abstract simplicial complex K is a geometric simplicial complex K' who is isomorphic to K, i.e., there exists a bijection

 $f: \operatorname{vert}(K) \to \operatorname{vert}(K'),$

such that $\sigma \in K \iff f(\sigma) \in K'$.

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Q: Prove that any simplicial complex with n vertices can be realized in \mathbb{R}^n .

Čech and (Vietoris)-Rips complexes

Def: Given a point cloud $P = \{P_1, \ldots, P_n\} \subset \mathbb{R}^d$, its Čech complex of radius r > 0 is the abstract simplicial complex C(P, r) s.t. vert(C(P, r)) = P and

 $\sigma = [P_{i_0}, P_{i_1}, \dots, P_{i_k}] \in C(P, r) \quad \text{iif} \quad \cap_{j=0}^k B(P_{i_j}, r) \neq \emptyset.$
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Pbm: Čech complexes can be quite hard to compute.

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$$\sigma = [P_{i_0}, P_{i_1}, \dots, P_{i_k}] \in R(P, r) \text{ iif } \|P_{i_j} - P_{i_{j'}}\| \le 2r, \forall 1 \le j, j' \le k.$$

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Remark: The 1-skeleton $\text{Skel}_1(R(P, r))$ of a Rips complex of radius r is also called the *r*-neighborhood graph of P.

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Good news is that Rips and Čech complexes are related:

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Good news is that Rips and Čech complexes are related:

Prop: $R(P, r/2) \subseteq C(P, r) \subseteq R(P, r)$.

Q: Prove it.

[*The Simplex Tree: An Efficient Data Structure for General Simplicial Complexes*, Boissonnat, Maria, Algorithmica, 2014]

We want to store simplicial complexes with a data structure that allows to perform standard operations (insertion of a simplex, checking if a simplex is present, etc) in a fast and easy way.

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Idea: store sorted simplices in a prefix tree (also called *trie*).



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It allows to store all simplices explicitly without storing all adjacency relations, while maintaining low complexity for basic operations.

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A: The *Nerve Theorem* ensures that appropriate complexes have the right topology.

Introduction

Topology is the art of deformation. It was introduced by Poincaré as a way to classify topological spaces: 'two topological spaces are in the same class if one can deform it into the other'.



The Nerve Theorem provides conditions under which a simplicial complex can be deformed into the topological space it was computed from.

Introduction

Idea: work with cover complexes.

- Group data points in local clusters.
- Summarize the data through the combinatorial/topological structure of the intersection patterns of these local clusters.



Def: An open cover of a topological space X is a collection $\mathcal{U} = (U_i)_{i \in I}$ of open subsets $U_i \subseteq X$, $i \in I$ where I is a set, such that $X \subseteq \bigcup_{i \in I} U_i$.



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Def: Given a cover of a topological space X, $\mathcal{U} = (U_i)_{i \in I}$, its nerve is the abstract simplicial complex $C(\mathcal{U})$ whose vertex set is \mathcal{U} and s.t.

 $\sigma = [U_{i_0}, U_{i_1}, \dots, U_{i_k}] \in C(\mathcal{U}) \text{ if and only if } \cap_{j=0}^k U_{i_j} \neq \emptyset.$



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[On the imbedding of systems of compacta in simplicial complexes, Borsuk, Fund. Math., 1948]



The Nerve Theorem: Let $\mathcal{U} = (U_i)_{i \in I}$ be a finite open cover of a subset X of \mathbb{R}^d such that any intersection of the U_i 's is either empty or convex. Then there are continuous deformations $X \to C(\mathcal{U})$ and $C(\mathcal{U}) \to X$.

Remark: More formally, one say they are homotopy equivalent.

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Two maps $f_0: X \to Y$ and $f_1: X \to Y$ are homotopic if \exists a continuous map F: $[0,1] \times X \to Y$ s.t. $\forall x \in X, F(0,x) =$ $f_0(x)$ and $F_1(1,x) = f_1(x)$. The spaces X and Y are homotopy equivalent if \exists continuous maps $f: X \to$ Y and $g: Y \to X$ s.t. $g \circ f$ is homotopic to id_X and $f \circ g$ is homotopic to id_Y.



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Ex: There are continuous deformations between the Čech complex C(P, r) and the union of balls $\bigcup_{p \in P} B(p, r)$.

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- 1. Using a function (lens) defined on the data:
- \rightarrow the Mapper algorithm
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2. Covering data by balls:

 \rightarrow distance functions frameworks, persistence-based signatures,...

 \rightarrow geometric inference, provide a framework to establish various theoretical results in TDA.



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 \rightarrow geometric inference, provide a framework to establish various theoretical results in TDA.











Input:

- topological space \boldsymbol{X}
- continuous function $f: X \to Y$ (99% of the time $Y = \mathbb{R}^D$)
- cover ${\mathcal I}$ of $\operatorname{im}(f)$ by open intervals: $\operatorname{im}(f) \subseteq \bigcup_{I \in {\mathcal I}} I$

Method:

- Compute *pullback cover* \mathcal{U} of X: $\mathcal{U} = \{f^{-1}(I)\}_{I \in \mathcal{I}}$
- \bullet Refine ${\mathcal U}$ by separating each of its elements into its various connected components in $X\to$ connected cover ${\mathcal V}$
- The Mapper is the *nerve* of \mathcal{V} :
 - 1 vertex per element $V \in \mathcal{V}$
 - 1 edge per intersection $V \cap V' \neq \emptyset$, $V,V' \in \mathcal{V}$
 - 1 k-simplex per (k+1)-fold intersection $\bigcap_{i=0}^{k} V_i \neq \emptyset, V_0, \cdots, V_k \in \mathcal{V}$

Mapper in practice

Input:

- point cloud $P \subseteq X$ with metric d_P
- continuous function $f: \textbf{\textit{P}} \rightarrow \mathbb{R}$
- cover ${\mathcal I}$ of $\operatorname{im}(f)$ by open intervals: $\operatorname{im} f \subseteq \bigcup_{I \in {\mathcal I}} I$

Method:

- Compute *pullback cover* \mathcal{U} of P: $\mathcal{U} = \{f^{-1}(I)\}_{I \in \mathcal{I}}$
- Refine \mathcal{U} by separating each of its elements into its various clusters, as identified by a clustering algorithm \rightarrow connected cover \mathcal{V}
- The Mapper is the *nerve* of \mathcal{V} : intersections are assessed by the
 - 1 vertex per element $V \in \mathcal{V}$
- presence of common data points
- 1 edge per intersection $V \cap V' \neq \emptyset$, $V,V' \in \mathcal{V}$
- 1 k-simplex per (k + 1)-fold intersection $\bigcap_{i=0}^{k} V_i \neq \emptyset$, $V_0, \cdots, V_k \in \mathcal{V}$

Mapper in practice

Parameters:

- function $f:P\to \mathbb{R}$
- cover ${\mathcal I}$ of $\operatorname{im}(f)$ by open intervals
- clustering algorithm $\ensuremath{\mathcal{C}}$

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- function $f: P \to \mathbb{R}$
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Classical choices:

- density estimates
- centrality $f(x) = \sum_{y \in X} d(x, y)$
- eccentricity $f(x) = \max_{y \in X} d(x, y)$
- PCA coordinates

- Eigenfunctions of graph laplacians.
- Functions detecting outliers.
- Distance to a root point.
- Prior knowledge


Parameters:

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range scale

Uniform cover:

- resolution / granularity: r (diameter of intervals)
- gain: g (percentage of overlap)



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Intuition:

- small $r \rightarrow$ finer resolution, more nodes.
- large $r \rightarrow$ rougher resolution, less nodes.
- small $g \rightarrow$ less connectivity, nerve dimension small.
- large $g \rightarrow$ more connectivity, nerve dimension large.

 \mathcal{I} q = 30%

Parameters:

- function $f:P\to \mathbb{R}$
- cover ${\mathcal I}$ of $\operatorname{im}(f)$ by open intervals
- clustering algorithm $\ensuremath{\mathcal{C}}$

Classical choices:

- any clustering algorithm works
- different clustering algorithms/parameters for each preimage
- for theoretical reasons, we prefer to work with

hierarchical clustering with (predefined) neighborhood size δ

geometric scale

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Build a neighboring graph (kNN,...)



Take the connected components of the subgraph spanned by the vertices in the preimage $f^{-1}(U)$.



Applications



3D shape classification



Genomic analysis of spinal cord



Breast cancer subtype identification

Computational Topology (I): Simplicial Complexes and Homology

- 1. Simplicial Complexes
 - 2. Nerve Theorem
 - 3. Homology Groups

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 Nerve Theorem
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Pbm: Looking for homotopy equivalences is extremely difficult. Are there mathematical quantities that are invariant to homotopy equivalences **and** easy to compute?

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A: The *holes*, encoded in the *homology groups* H_k , $k \in \mathbb{N}$.

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But what about higher dimensional holes (like the inside of a tetrahedron)?





A: A hole in dimension d is a simplicial complex in which each (d-1)-simplex appears an even number of times.

Def: A *d*-chain *C* is a formal sum of *d*-simplices with coefficients in $\mathbb{Z}/2\mathbb{Z}$: $C = \sum_{\dim(\sigma)=d} \alpha_{\sigma} \delta_{\sigma}, \text{ where } \delta_{\sigma} : \tau \mapsto \begin{cases} 1 & \text{if } \tau = \sigma \\ 0 & \text{otherwise} \end{cases}, \quad \alpha_{\sigma} \in \mathbb{Z}/2\mathbb{Z}$

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Def: The *boundary* ∂_d of a *d*-simplex is the (d-1)-chain:

$$\partial_d[v_1, \dots, v_{d+1}] = \sum_{i=1}^{d+1} [v_1, \dots, v_{i-1}, v_{i+1}, \dots, v_{d+1}]$$

It extends linearly to *d*-chains.

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Ex: Let $C = [v_0, v_1] + [v_1, v_2] + [v_2, v_3] + [v_3, v_4] + [v_4, v_5] + [v_5, v_0].$ $\partial_1 C = \partial_1 [v_0, v_1] + \partial_1 [v_1, v_2] + \partial_1 [v_2, v_3] + \partial_1 [v_3, v_4] + \partial_1 [v_4, v_5] + \partial_1 [v_5, v_0]$

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Def: A *d*-cycle is a *d*-chain C s.t. $\partial_d C = 0$.

Pb: Different cycles can represent the same hole.



Lemma:
$$\partial_{n-1} \circ \partial_n = 0.$$

Q: Prove it.

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Def: Two *d*-cycles are homologous if 'their combination is in $\operatorname{im}(\partial_{d+1})$ ': $C \sim C' \iff C + C' \in \operatorname{im}(\partial_{d+1})$

Prop: The space of *d*-chains $C_d(K)$ is a vector space with basis $\{\sigma \in K : \dim(\sigma) = d\}.$

The space of d-cycles $Z_d(K)$ is a linear subspace of $C_d(K)$.

The boundary operator $\partial_{d+1} : C_{d+1}(K) \to C_d(K)$ is linear and $\operatorname{im}(\partial_{d+1})$ is a linear subspace of $C_d(K)$.

Def: Given a vector space V, and a linear subspace $W \subseteq V$, their quotient is the vector space: $V/W := \{[v] = \{v + w : w \in W\} : v \in V\}.$

Remark: v_1 and v_2 are mapped to the same element of V/W iif $v_1 + v_2 \in W$.

Lemma: $\partial_{n-1} \circ \partial_n = 0.$

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 H_d is a vector space in which each element is an equivalence class of cycles associated to the same hole.

Def: The dimension of H_d is called the *Betti number* β_d .

Minimum number of (classes of) cyles needed to create a basis, i.e., to be able to write *any* cycle as a linear combination of cycles in the basis.

 β_0 counts the connected components, β_1 counts the loops, β_2 counts the cavities, and so on...

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The whole point of homology groups and Betti numbers is that they satisfy:

 $H_d(X) \neq H_d(Y) \Longrightarrow X, Y$ are not homotopy equivalent.

Summary

In this class, I introduced the basic bricks of Topological Data Analysis.

We have seen how to encode data sets as topological spaces using combinatorial models called simplicial complexes.

We have seen simplicial complex constructions, e.g., Mapper, that are based on the Nerve Theorem which guarantees that the topology is correct.

We have seen how to quantify topology in simplicial complexes with homology groups and Betti numbers.

Next week, we will see an extension of homology groups, called persistent homology, that allows to create richer descriptors for data science, called persistence diagrams, out of simplicial complexes.