## EMAp Summer Course

## Topological Data Analysis with Persistent Homology

https://raphaeltinarrage.github.io/EMAp.html

## Lesson 8: Datasets have topology

## Introduction

## Oudot in 2015

## Persistence Theory: From Quiver Representations to Data Analysis

Steve Y. Oudot

Applications. This richness is also reflected in the diversity of the applications, whose list has been ever growing since the early developments of the theory. The following excerpt 5 illustrates the variety of the topics addressed:

- analysis of random, modular and non-modular scale-free networks and networks with exponential connectivity distribution [158],
- analysis of social and spatial networks, including neurons, genes, online messages, air passengers, Twitter, face-to-face contact, co-authorship 210],
- coverage and hole detection in wireless sensor fields 98, 136],
- multiple hypothesis tracking on urban vehicular data [23],
- analysis of the statistics of high-contrast image patches [54],
- image segmentation 70, 209],
- 1d signal denoising 212],
- 3d shape classification [58],
- clustering of protein conformations 70],
- measurement of protein compressibility [135],
- classification of hepatic lesions 1],
- identification of breast cancer subtypes [205],
- analysis of activity patterns in the primary visual cortex 224],
- discrimination of electroencephalogram signals recorded before and during epileptic seizures [237],
- analysis of 2 d cortical thickness data 82],
- statistical analysis of orthodontic data [134, 155],
- measurement of structural changes during lipid vesicle fusion 169],
- characterization of the frequency and scale of lateral gene transfer in pathogenic bacteria [125],
- pattern detection in gene expression data [105],
- study of plant root systems [115, §IX.4],
- study of the cosmic web and its filamentary structure 226, 227],
- analysis of force networks in granular matter 171],
- analysis of regimes in dynamical systems 25].

In most of these applications, the use of persistence resulted in the definition of new descriptors for the considered data, which revealed previously hidden structural information and allowed the authors to draw original conclusions.

## I - Some examples

II - Betti curves
(III - Tutorial)

## Configurations of cyclo-octane

Shawn Martin, Aidan Thompson, Evangelos A Coutsias, and Jean- Paul Watson. Topology of cyclo-octane energy landscape. The journal of chemical physics, 2010. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3188624/

The cyclo-octane molecule $\mathrm{C}_{8} \mathrm{H}_{16}$ admits several stable configurations, i.e., several spatial arrangements of its atoms.


## Configurations of cyclo-octane

Shawn Martin, Aidan Thompson, Evangelos A Coutsias, and Jean- Paul Watson. Topology of cyclo-octane energy landscape. The journal of chemical physics, 2010. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3188624/

The cyclo-octane molecule $\mathrm{C}_{8} \mathrm{H}_{16}$ admits several stable configurations, i.e., several spatial arrangements of its atoms.


The configuration of such a molecule can be represented by 72 variables-the 3D coordinates of each of its 24 atoms-, or equivalently, by a point in $\mathbb{R}^{72}$.

## Configurations of cyclo-octane

The configuration of such a molecule can be represented by 72 variables-the 3D coordinates of each of its 24 atoms-, or equivalently, by a point in $\mathbb{R}^{72}$.

By analyzing many of these molecules, the authors obtain a point cloud in $\mathbb{R}^{72}$.


## Configurations of cyclo-octane

The configuration of such a molecule can be represented by 72 variables-the 3D coordinates of each of its 24 atoms-, or equivalently, by a point in $\mathbb{R}^{72}$.

By analyzing many of these molecules, the authors obtain a point cloud in $\mathbb{R}^{72}$.


## Natural images

Gunnar Carlsson, Tigran Ishkhanov, Vin De Silva, and Afra Zomorodian. On the local behavior of spaces of natural images. International journal of computer vision, 2008. https://www.researchgate.net/publication/2206593470ntheLocalBehaviorof SpacesofNaturalImages

From a large collection of natural images, the authors extract $3 \times 3$ patches.


## Natural images

Gunnar Carlsson, Tigran Ishkhanov, Vin De Silva, and Afra Zomorodian. On the local behavior of spaces of natural images. International journal of computer vision, 2008. https://www.researchgate.net/publication/2206593470ntheLocalBehaviorof SpacesofNaturalImages

From a large collection of natural images, the authors extract $3 \times 3$ patches.


Since it consists of 9 pixels, each of these patches can be seen as point in $\mathbb{R}^{9}$, and the whole set as a point cloud in $\mathbb{R}^{9}$.

## Natural images

Gunnar Carlsson, Tigran Ishkhanov, Vin De Silva, and Afra Zomorodian. On the local behavior of spaces of natural images. International journal of computer vision, 2008. https://www.researchgate.net/publication/2206593470ntheLocalBehaviorof SpacesofNaturalImages
From a large collection of natural images, the authors extract $3 \times 3$ patches.


Since it consists of 9 pixels, each of these patches can be seen as point ih $\mathbb{R}^{9}$, and the whole set as a point cloud in $\mathbb{R}^{9}$.
this dataset concentrates near a Klein bottle


## Breast cancer

Monica Nicolau, Arnold J Levine, and Gunnar Carlsson. Topology based data analysis identifies a subgroup of breast cancers with a unique mutational profile and excellent survival. Proceedings of the National Academy of Sciences, 2011.
https://www.pnas.org/content/108/17/7265

Tissues of patients infected with breast cancer has been analyzed, resulting in 262 genomic variables per patients.

$$
\left(x_{1}, x_{2}, \ldots, x_{262}\right)
$$



## Breast cancer

Monica Nicolau, Arnold J Levine, and Gunnar Carlsson. Topology based data analysis identifies a subgroup of breast cancers with a unique mutational profile and excellent survival. Proceedings of the National Academy of Sciences, 2011.
https://www.pnas.org/content/108/17/7265

Tissues of patients infected with breast cancer has been analyzed, resulting in 262 genomic variables per patients.

$$
\left(x_{1}, x_{2}, \ldots, x_{262}\right)
$$

Gathering these data yields a point cloud in $\mathbb{R}^{262}$

## Breast cancer

Monica Nicolau, Arnold J Levine, and Gunnar Carlsson. Topology based data analysis identifies a subgroup of breast cancers with a unique mutational profile and excellent survival. Proceedings of the National Academy of Sciences, 2011.
https://www.pnas.org/content/108/17/7265

Tissues of patients infected with breast cancer has been analyzed, resulting in 262 genomic variables per patients.

$$
\left(x_{1}, x_{2}, \ldots, x_{262}\right)
$$

Gathering these data yields a point cloud in $\mathbb{R}^{262}$
The result is a graph composed of three distinct branches.

## Breast cancer

Monica Nicolau, Arnold J Levine, and Gunnar Carlsson. Topology based data analysis identifies a subgroup of breast cancers with a unique mutational profile and excellent survival. Proceedings of the National Academy of Sciences, 2011.
https://www.pnas.org/content/108/17/7265

Tissues of patients infected with breast cancer has been analyzed, resulting in 262 genomic variables per patients.

$$
\left(x_{1}, x_{2}, \ldots, x_{262}\right)
$$

Gathering these data yields a point cloud in $\mathbb{R}^{262}$
The result is a graph composed of three distinct branches.

Designation of new type of breast cancer ( $c-\mathrm{MYB}^{+}$) - 100\%
survival, and no metastasis.


## I - Some examples

## II - Betti curves

(III - Tutorial)

## Reminder of yesterday

Let $\mathcal{M} \subset \mathbb{R}^{n}$ be a bounded subset.
Suppose that we are given a finite sample $X \subset \mathcal{M}$.
Estimate the homology groups of $\mathcal{M}$ from $X$.

Definition: For every $t \geq 0$, the $t$-thickening of the set $X$, denoted $X^{t}$, is the set of points of the ambient space with distance at most $t$ from $X$ :

$$
X^{t}=\bigcup_{x \in X} \overline{\mathcal{B}}(x, t)
$$

Definition: The Čech complex of $X$ at time $t$ is the nerve of the cover

$$
\mathcal{V}^{t}=\{\overline{\mathcal{B}}(x, t), x \in X\}
$$

Definition: The Rips complex of $X$ at time $t$ is the clique complex of the graph $G^{t}$ defined as: its vertex set is $\{1, \ldots, N\}$, and its edges are the pairs $(i, j)$ such that $\left\|x_{i}-x_{j}\right\| \leq 2 t$.

## Betti numbers

We can compute the Betti numbers for each value of $t$ :


## Betti curves

Definition: Let $X \subset \mathbb{R}^{n}$ and $i \geq 0$. The $i^{\text {th }}$ Betti curve of $X$ is the map

$$
\begin{aligned}
\beta_{i}(t): \mathbb{R}^{+} & \longrightarrow \mathbb{N} \\
t & \longmapsto \beta_{i}\left(X^{t}\right)
\end{aligned}
$$

In our context, this will be

$$
\begin{aligned}
\beta_{i}(t): \mathbb{R}^{+} & \longrightarrow \mathbb{N} \\
t & \longmapsto \beta_{i}\left(\operatorname{Rips}^{t}(X)\right)
\end{aligned}
$$

Exercise: For $i=0$, show that $t \mapsto \beta_{0}(t)$ is non-increasing.

## I - Some examples

II - Betti curves
(III - Tutorial)

## Link of the notebook

https://github.com/raphaeltinarrage/EMAp/blob/main /Tutorial2.ipynb

## Conclusion

We tried to find topology in datasets.
We studied it via the Betti curves.
We are ready for Persistent Homology :)

Homework: não

## Conclusion

We tried to find topology in datasets.
We studied it via the Betti curves.
We are ready for Persistent Homology :)

Homework: não

