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# Introduction to Topological Data Analysis

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- Topology
- 2 Algebraic Topology toolbox
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- The scikit-tda
- 6 Hands-on

### **Topology**

- Topology is concerned with the study of the shape of objects up to homeomorphisms, as well as its holes and connections.
- Practical examples of homeomorphisms are (no intersecting is allowed!)
  - Stretching
  - Twisting
- Looks for distinct global features, e.g homologies.

Algebraic Topology is therefore capable of categorizing topological object and characterize their properties. The Euler characteristic is a topological invariant.



### **Topology**

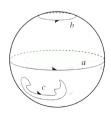
"Algebraic Topology offers a mature set of tools for counting and collating holes." 1

<sup>&</sup>lt;sup>1</sup>Robert Ghrist, Barcodes: A persistent Topology of Data.

#### Homology

Association of algebraic objects to topological spaces. Homology groups which characterize topological spaces can also be express as linear operators.

"Intuitively, two curves in a plane or other two-dimensional surface are homologous if together they bound a region—thereby distinguishing between an inside and an outside."

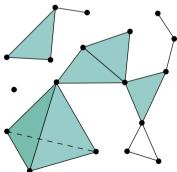


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#### Simplicial Complex

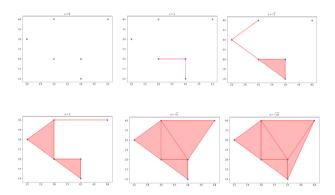
A non-empty set G with a collection of non-empty subsets F where, for  $x \in F \ \forall x \in G$ , if  $a \in F$  and  $b \subseteq a$ , then  $b \in G$ .

The elements of a simplicial complex are known as simplices. In practise those are a set of points, lines, faces, and their n-dimensional counterparts.



#### Alpha Complex

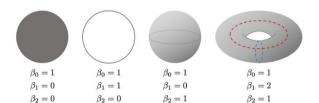
Simplicial Complex constructed based on the Delaunay triangulation of point cloud data.<sup>2</sup>



Felipe Nathan deOliveira-Lopes (IPP)

#### Betti numbers

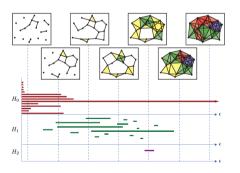
Counts the number of n-dimensional holes on a given topological object via the connectivity of n-dimensional simplicial complexes. It is directly associated with the objects nth dimensional homology group.  $b_0 \rightarrow$  connected components,  $b_1 \rightarrow$  tunnels,  $b_2 \rightarrow$  voids, etc.



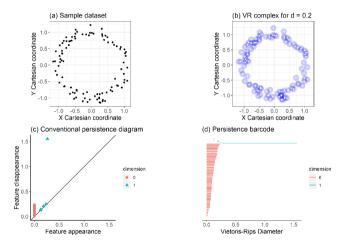
<sup>&</sup>lt;sup>1</sup>Image: Omer Bobrowski, Primoz Skraba. "Homological Percolation and the Euler Characteristic"

#### Persistence Diagram and barcodes

Graphical representation of Homology groups of a given data set under a family of Vietoris–Rips complex varying according to some parameter  $\epsilon$ .



<sup>&</sup>lt;sup>3</sup>Robert Ghrist, Barcodes: A persistent Topology of Data.



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Raoul R. et al. "A flat persistence diagram for improved visualization of persistent homology." arXiv: Applications (2018) 🗇 🕟 🖎 📜 🔻 🔾 🔾 🕒

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# Analysis of Kolmogorov flow and Rayleigh-Bénard convection using persistent homology



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- Far-from-equilibrium systems such as flow of field patterns for two important numerical simulations
  - Kolgomorov flow
  - Rayleigh–Bénard convection
- First persistence diagram computed from images of flow
- Second persistence diagram computed from times series of the dynamics of the flow

#### Kolgomorov flow

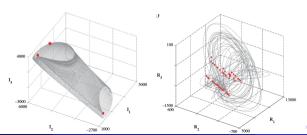
2-D Navier-Stokes equations with a monochromatic force assumed stationary

$$\frac{\partial u}{\partial t} + \beta u \cdot \nabla u = \frac{1}{\rho} \nabla p + \nu \nabla^2 u - \alpha u + f \& \nabla \cdot u = 0,$$

$$\nabla \cdot u = 0$$

which can be written as

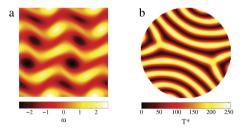
$$\frac{\partial \omega}{\partial t} + \beta \mathbf{u} \cdot \omega = \nu \nabla^2 \omega - \alpha \omega + \chi \kappa \cos(\kappa \mathbf{y})$$



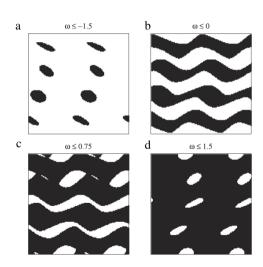
#### Rayleigh-Bénard convection

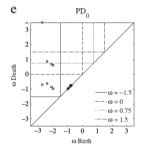
Canonical pattern forming system occurring in upward heating system constrained by downwards gravity. Governed by the Boussinesq equations.

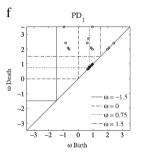
$$Pr^{-1} \left( \frac{\partial u}{\partial t} + u \cdot \nabla u \right) = -\nabla p + \nabla^2 u + RaT\hat{z},$$
  
$$\frac{\partial T}{\partial t} + u \cdot \nabla T = \nabla^2 T,$$
  
$$\nabla \cdot u = 0$$



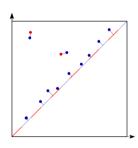
**Fig. 2.** (a) A snapshot of the *z*-component of the vorticity field  $\omega$  for Kolmogorov flow from the stable relative periodic orbit found at Re = 25.43, (b) A snapshot of the renormalized 8-bit mid-plane temperature field  $T^*$  for Rayleigh-Bénard convection from the stable almost-periodic orbit found at Ra = 3000 and Pr = 1.

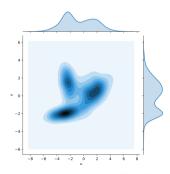




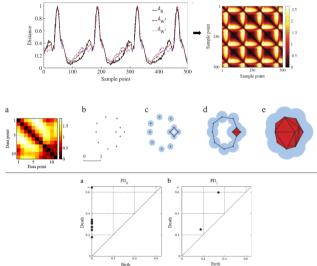


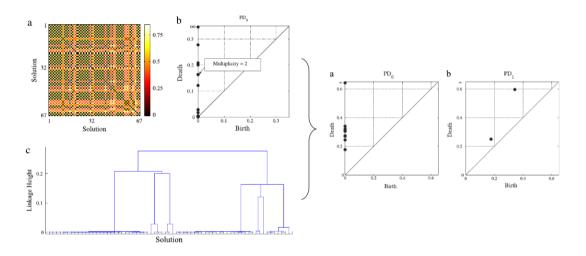
PD are tightly way to express properties of the geometry of scalar functions. It allow us to represent the state of a dynamic system at given points in time. The dynamics is encoded in the relationship between a family of PDs. A metric to analyze this is to construct a pair-wise correspondence between points in different PDs through a the computation of a bottleneck or a p-Wasserstein distance.





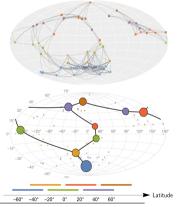
<sup>&</sup>lt;sup>2</sup>Image: GUDHI, MIT (GPL v3). & Lambdabadger - Own work, CC BY-SA 4.0

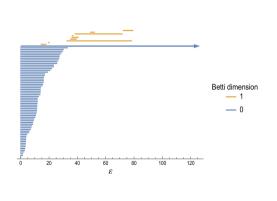




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#### TDA and Fast Radio Busters<sup>5</sup>





 $<sup>^{5}</sup>$ An Introduction to Topological Data Analysis for Physicists: From LGM to FRBs - arXiv:1904.11044

Found Comput Math (2015) 15:799–838 DOI 10.1007/s10208-014-9206-z

# FOUNDATIONS OF COMPUTATIONAL MATHEMATICS

The Journal of the Society for the Foundations of Computational Mathematics



# Sliding Windows and Persistence: An Application of Topological Methods to Signal Analysis

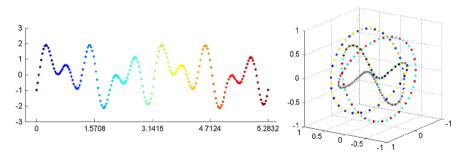
Jose A. Perea · John Harer

For a given function f(t) defined on  $\mathcal{R}$ , the sliding-window function embedding defines a point and is given by

$$SW_{M, au}f(t) = egin{bmatrix} f(t) \ f(t+ au) \ ... \ f(t+M au) \end{bmatrix}$$
 ,

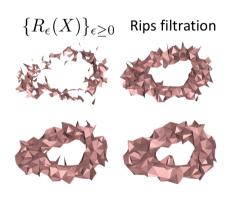
Where N is the integer and  $\tau$  is a real value, both greater than zero, which together for the window size  $M\tau$ . For different values of t, the function generates a sliding window point cloud for f.

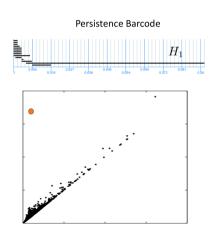
Projection of the time series onto a point cloud data embedded on a higher dimensional space



$$PH_n(\mathcal{R}(\mathbb{SW}_{M,\tau}f); \mathbb{F})$$

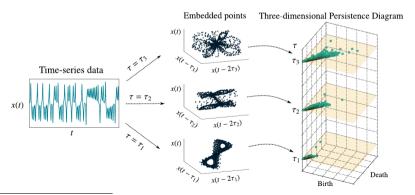
From the point cloud data, we already know how to use the Vietoris–Rips complex in order to generate the persistence barcode and the persistence diagram.





#### Topological time-series analysis with delay-variant embedding<sup>6</sup>

Through a change on the delay parameter, one could better understand multiple-timescale patterns and the overall dynamics of the system.



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For real time series data, the model is tested for the classification of different heartbeat-signal patters based on six electrocardiogram data sets. <sup>7</sup>

Data	Delay	Single		NN	NN	NN		
Data	variant	delay	(E)	(D)	(AC)	(PS)	$_{ m EE}$	$_{\rm LS}$
ECG200	90.0	87.0	88.0	88.0	82.0	86.0	88.0	88.0
ECG5000	93.6	92.1	92.5	92.5	91.0	93.6	93.9	93.2
Thorax1	91.8	78.2	82.9	82.9	72.1	87.5	84.6	25.9
Thorax2	93.0	83.6	88.0	87.0	75.2	88.4	91.4	77.0
FiveDays	99.9	92.0	79.7	79.7	98.1	100.0	82.0	100.0
TwoLead	99.4	94.0	74.7	86.8	80.4	96.1	97.1	99.6
Worms	83.1	83.1	61.0	58.4	76.6	81.8	68.8	72.7
FordB	90.8	78.2	60.6	59.9	78.0	79.0	66.2	91.7

The goal is to classify the *Caenorhabditis elegans* roundworms from EigenWorms as either wild or mutant based on their movements.

<sup>&</sup>lt;sup>7</sup>Y. Chen, et al., The UCR Time Series Classification Archive (2015).

Multiple time-scale behaviour can be studied with a delay-variant method followed by a principal components projections  $^8$ . Consider the synthetic noisy time series obtained from a frequency-modulated model.

$$s_m(t) = A_m sin(2\pi f_m t),$$

with a carrier signal

$$s_c(t) = A_c \sin(2\pi f_c t).$$

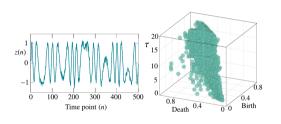
The modulated signal is then

$$s(t) = A_c sin[2\pi f_c t + A_m sin(2\pi f_m t)], t \in [0, 0.1].$$

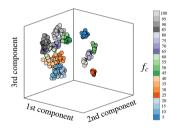
For each value of  $f_c$ , 20 noisy discrete time series  $z_l(n) = s(0.0002n) + w_l(n)$  are generated, where  $w_l(n)$  is the Gaussian white noise with a variance of 0.1.

<sup>&</sup>lt;sup>8</sup>Y. Chen, et al., The UCR Time Series Classification Archive (2015).

# Time series and three dimensional persistence diagram



# Principal component projection from kernel space



#### The scikit-tda

 "Scikit-TDA is a home for Topological Data Analysis Python libraries intended for non-topologists"

#### https://github.com/scikit-tda



#### Audeant Facere

In lieu of more slides... hands on!