

Topological Adventures in Machine Learning

Applied Machine Learning Days
28 January 2020

A word cloud centered around the word "topology". The word "topology" is the largest and most prominent, written in a light blue color. Other large words include "shape" (white, vertical), "connectivity" (blue, horizontal), "algebra" (blue, horizontal), and "geometry" (yellow, vertical). Smaller words include "deformation" (orange), "path" (blue), "classification" (orange), "invariants" (orange), "cavity" (orange), "open" (blue), "homology" (white), "equivalence" (orange, vertical), "closed" (blue), "continuity" (blue), "complex" (blue), "mug" (orange), "connected" (orange), "simplex" (orange), "donut" (white), "proximity" (blue), and "continuous" (blue).

deformation
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geometry

DATA ANALYSIS
~~PSYCHIATRIC~~
HELP 5¢



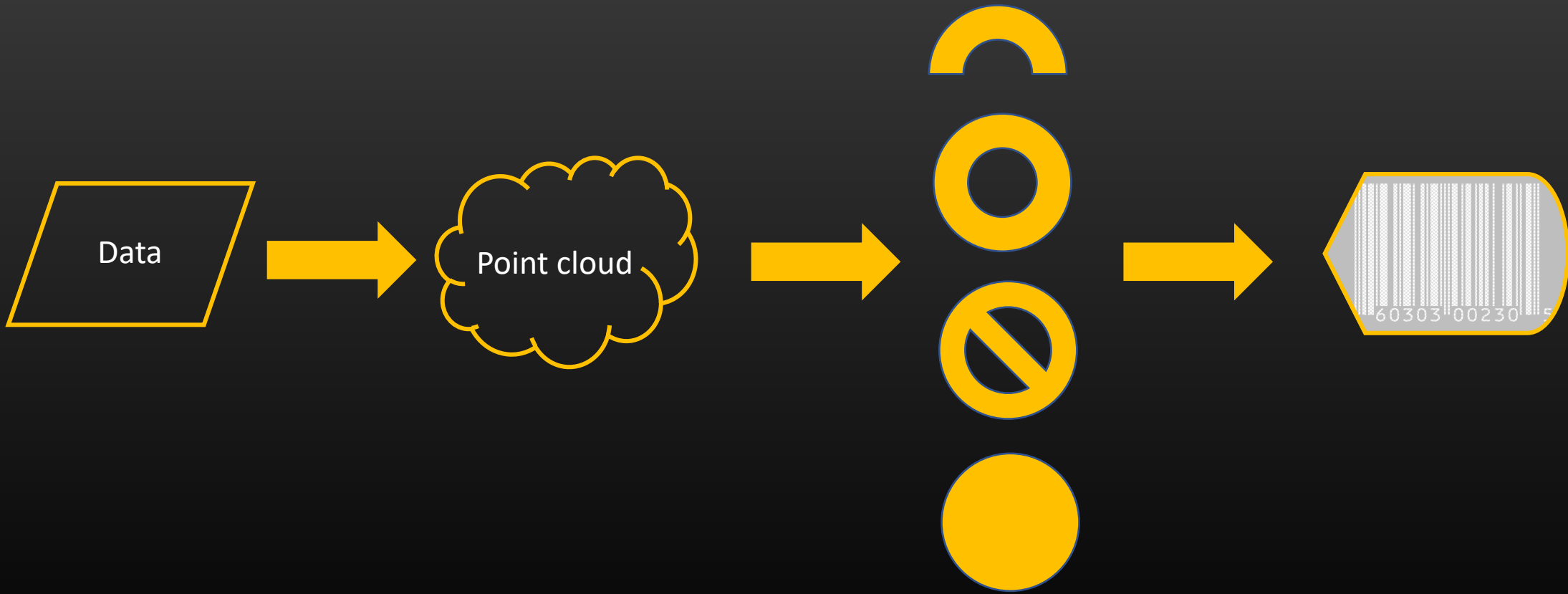
TOPOLOGIST
THE ~~DOCTOR~~
IS IN

Topological Data Analysis (TDA)

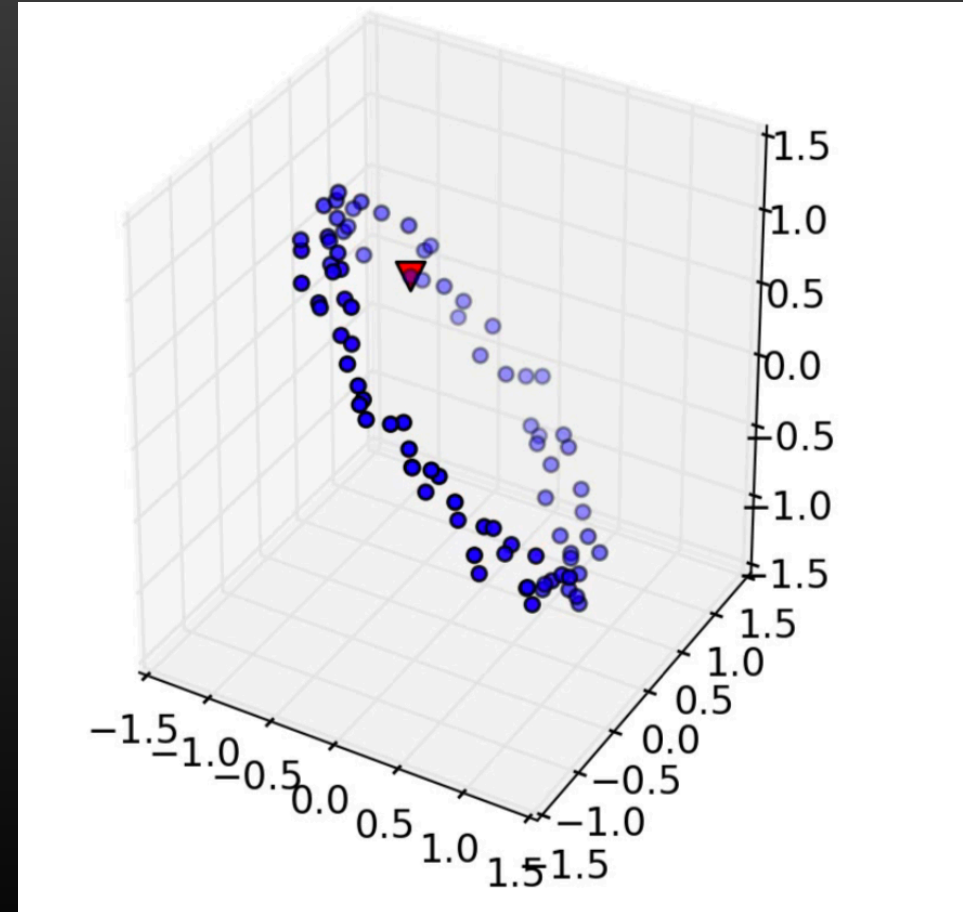
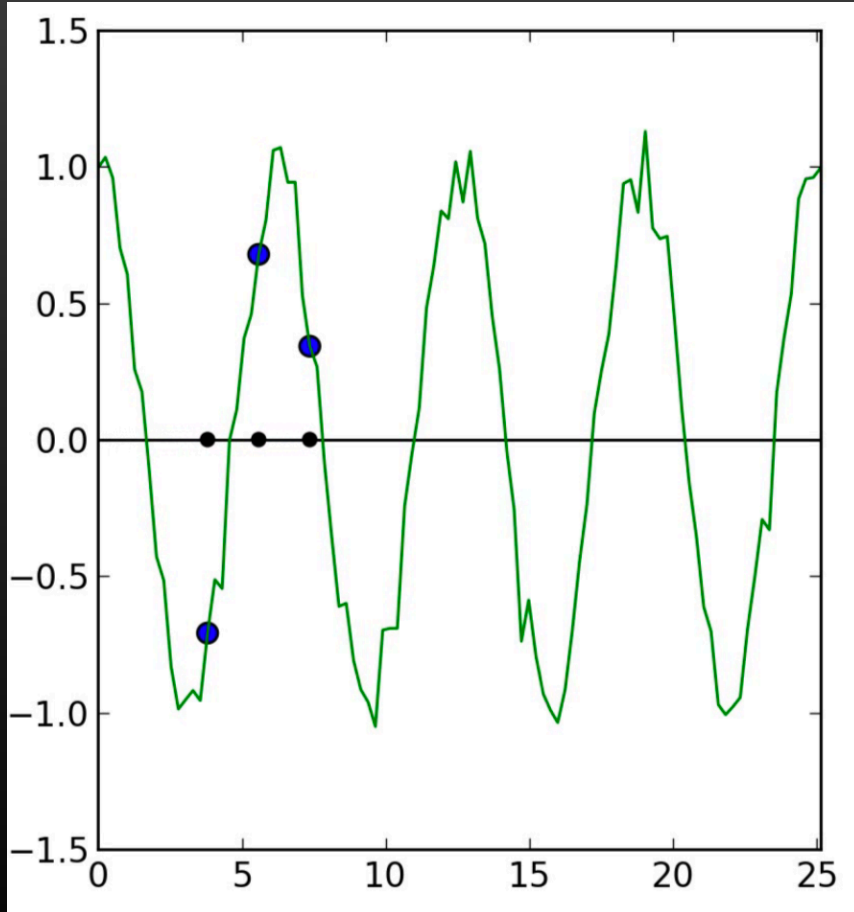
Guiding philosophy of TDA

The **shape** of a data set, encoded by a **topological signature**, should reveal important relations among the data points with the help of machine learning.

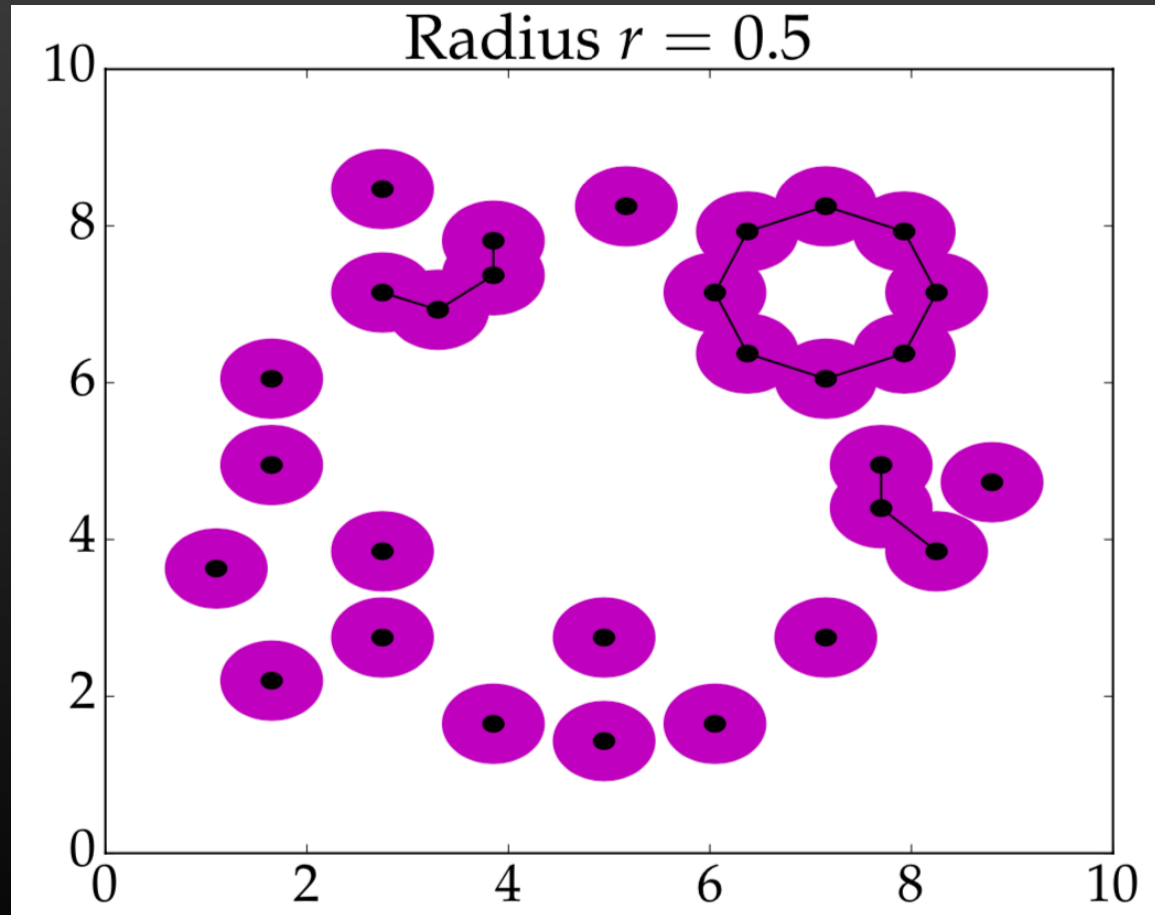
The usual TDA workflow



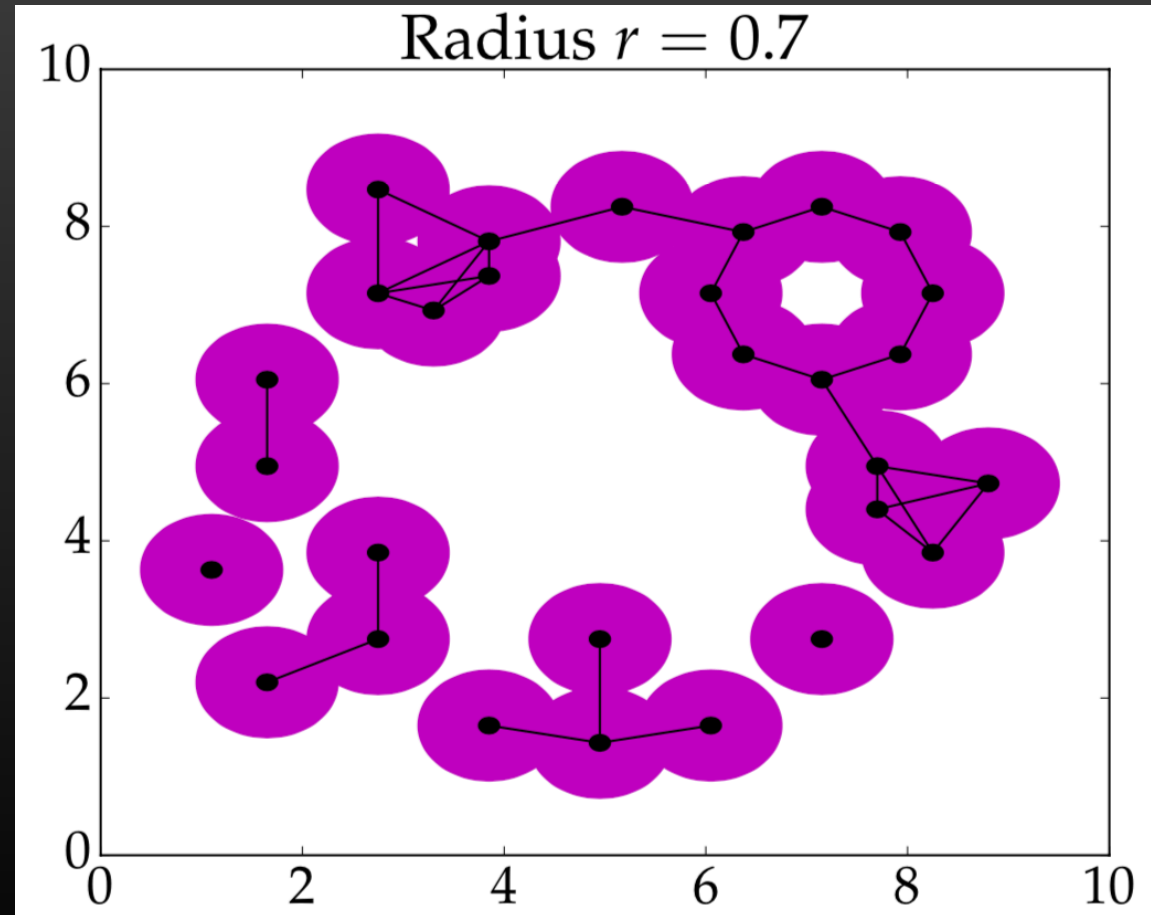
Step 1: Data to Point Cloud



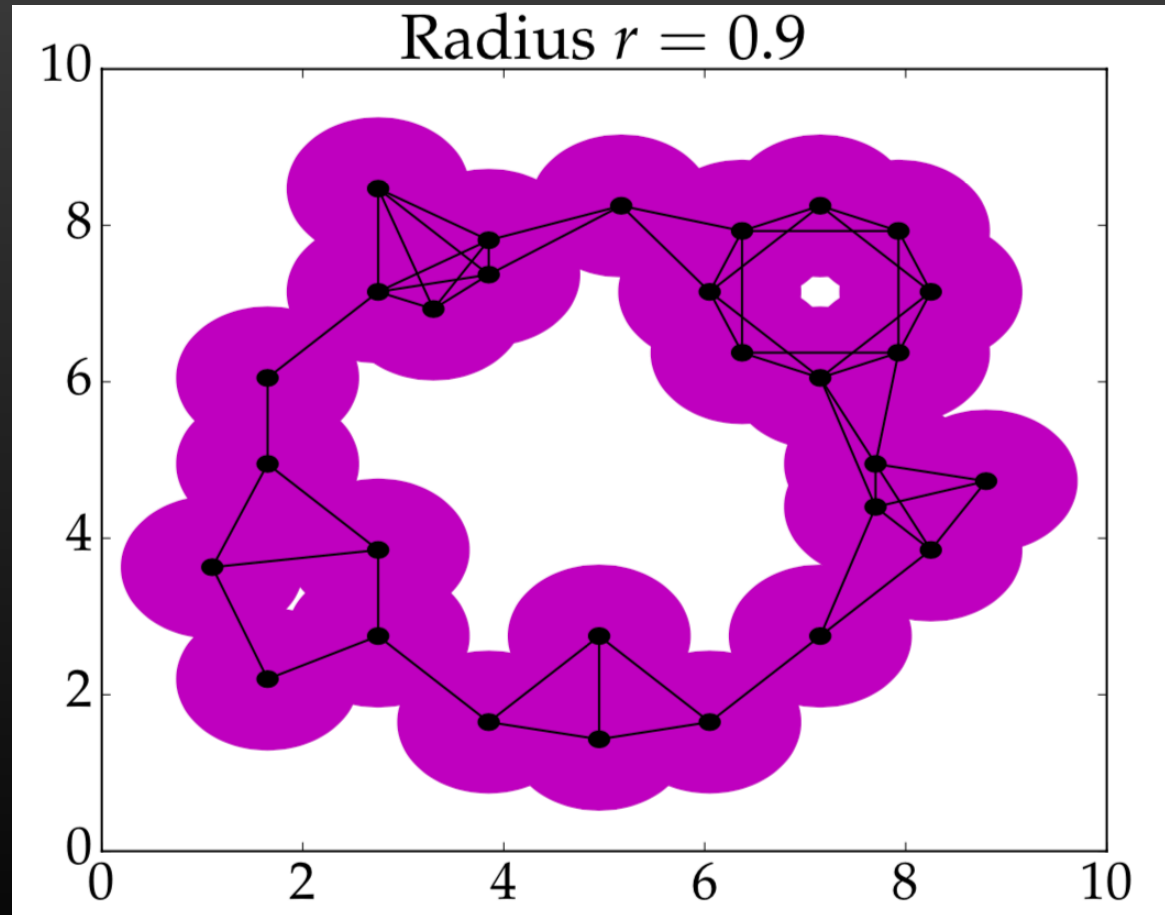
Step 2: Point cloud to nested complexes



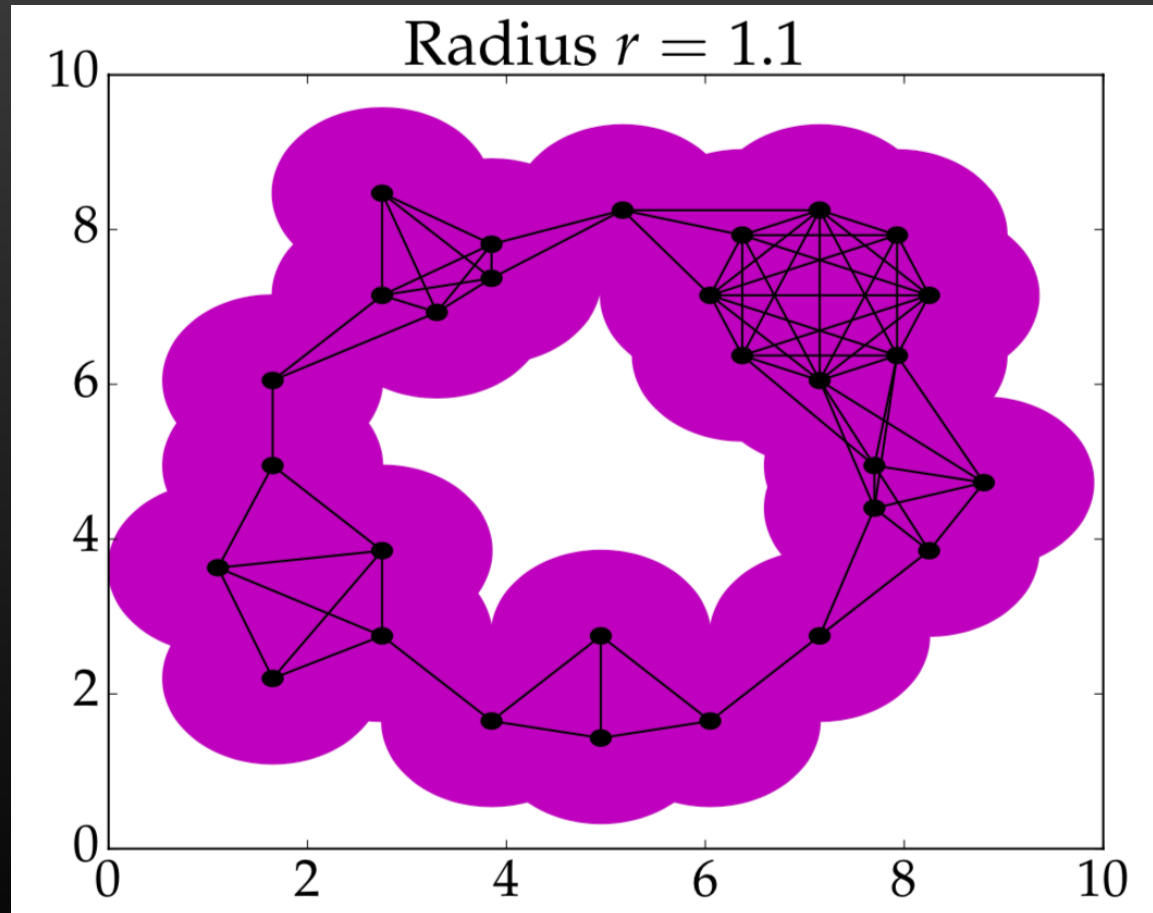
Step 2: Point cloud to nested complexes



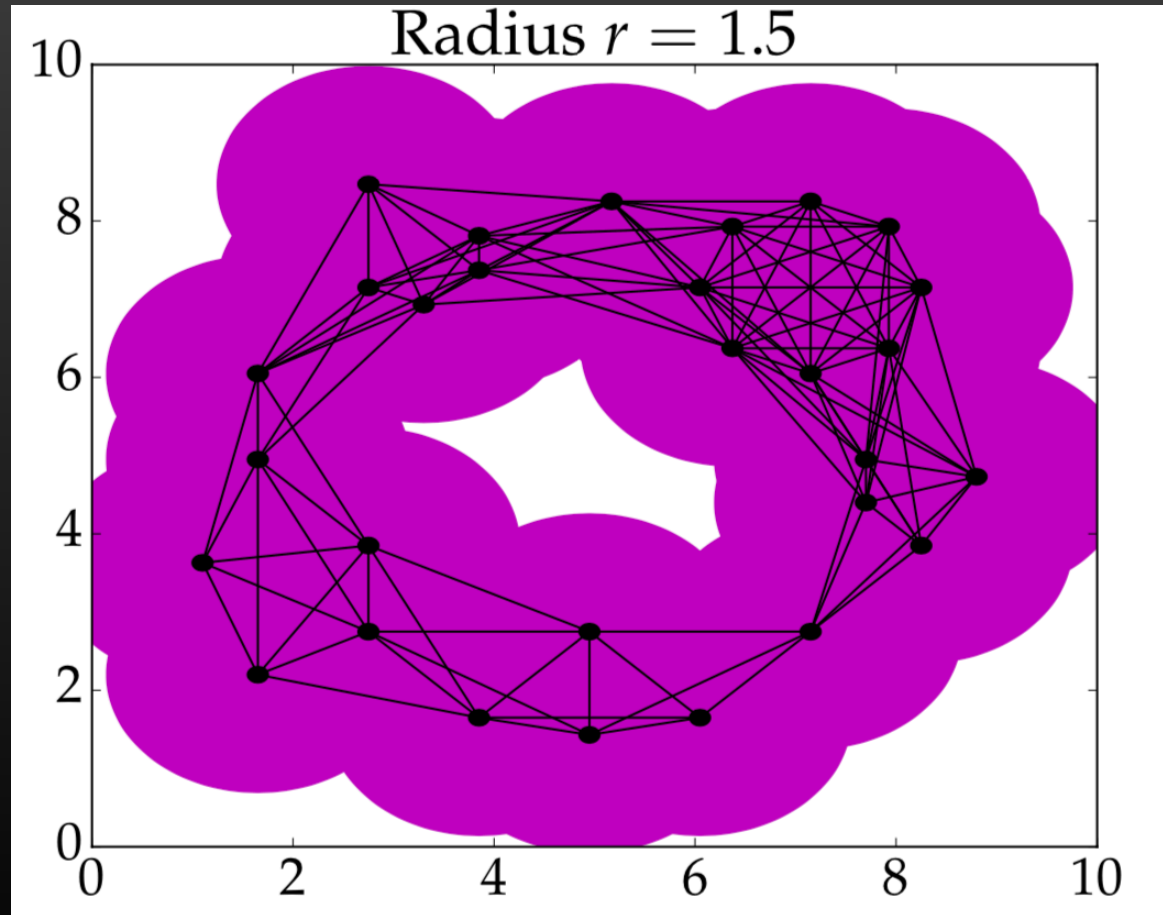
Step 2: Point cloud to nested complexes



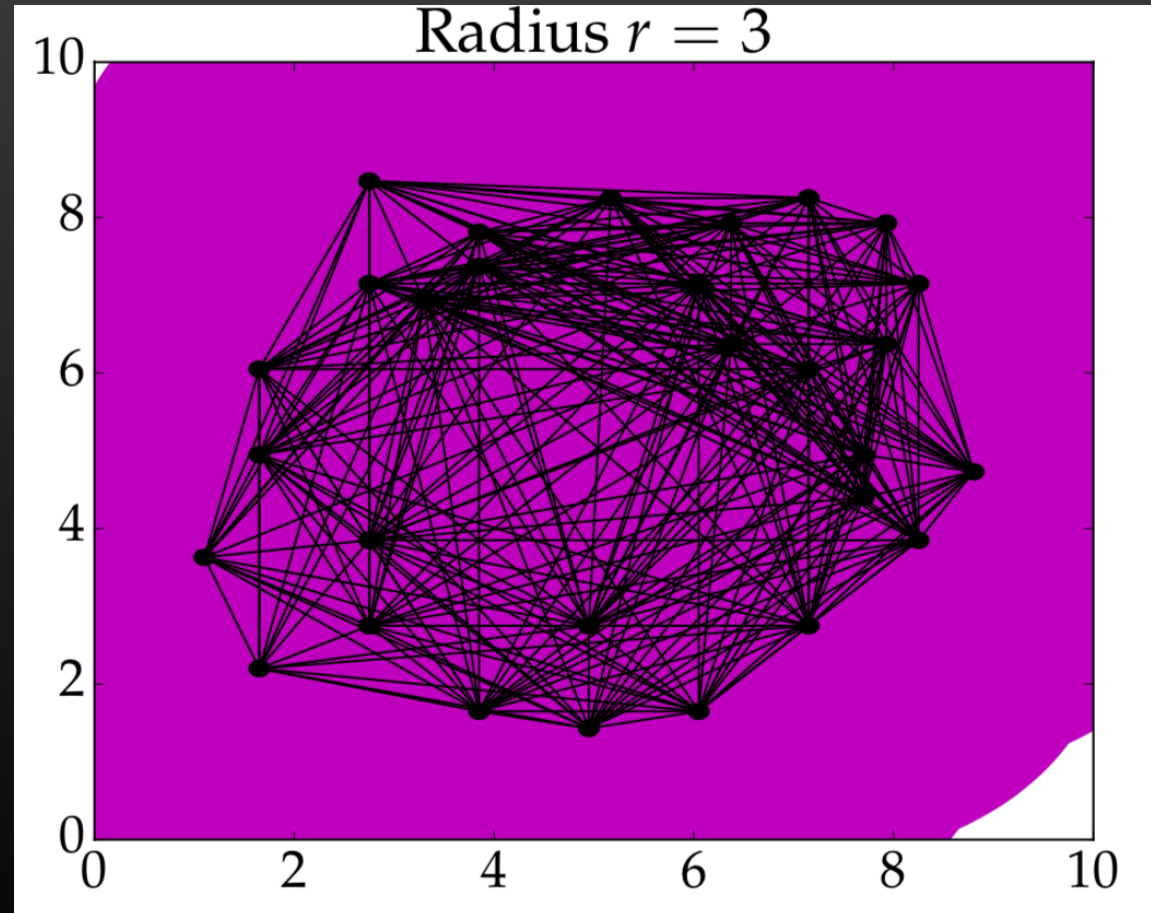
Step 2: Point cloud to nested complexes



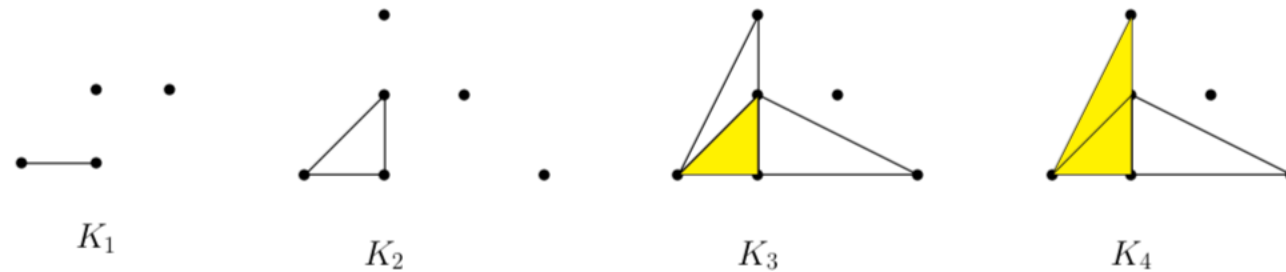
Step 2: Point cloud to nested complexes



Step 2: Point cloud to nested complexes



Step 3: Nested complexes to barcode



$$\beta_0(K_1) = 3$$

$$\beta_1(K_1) = 0$$

$$\beta_0(K_2) = 4$$

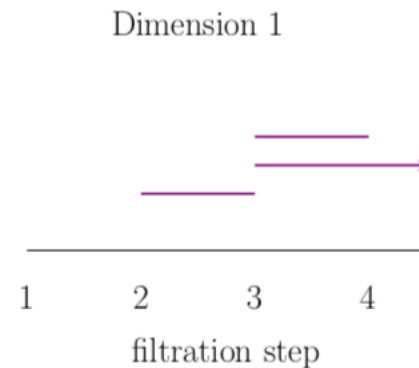
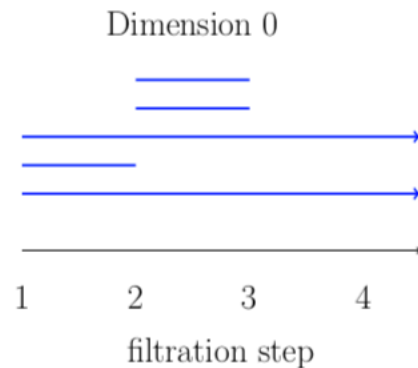
$$\beta_1(K_2) = 1$$

$$\beta_0(K_3) = 2$$

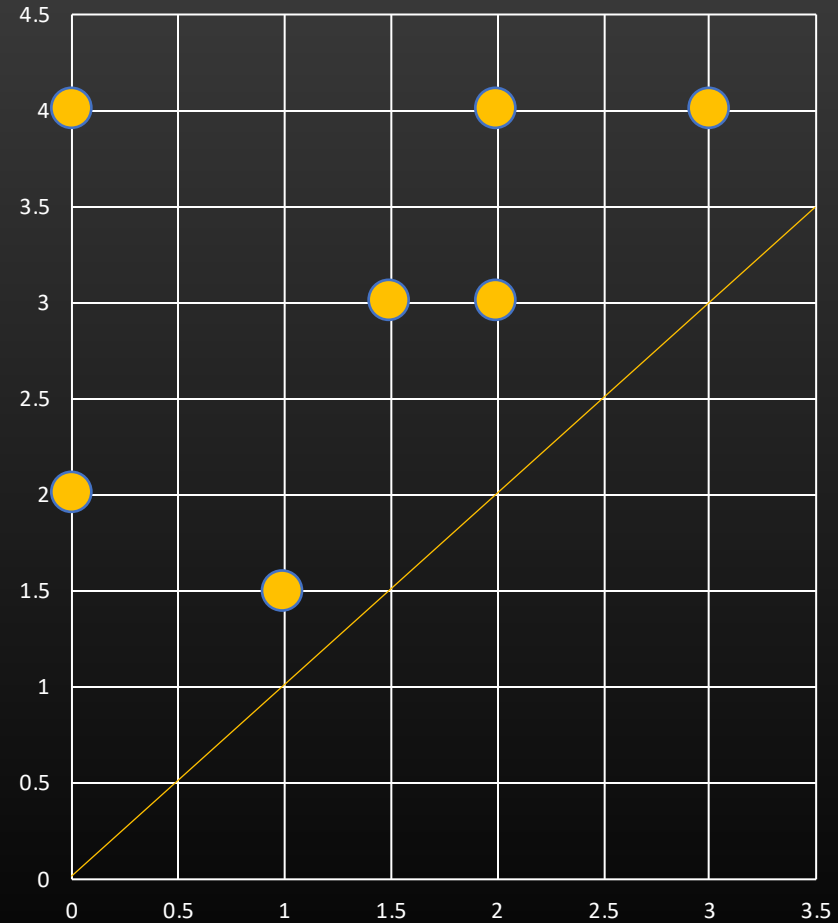
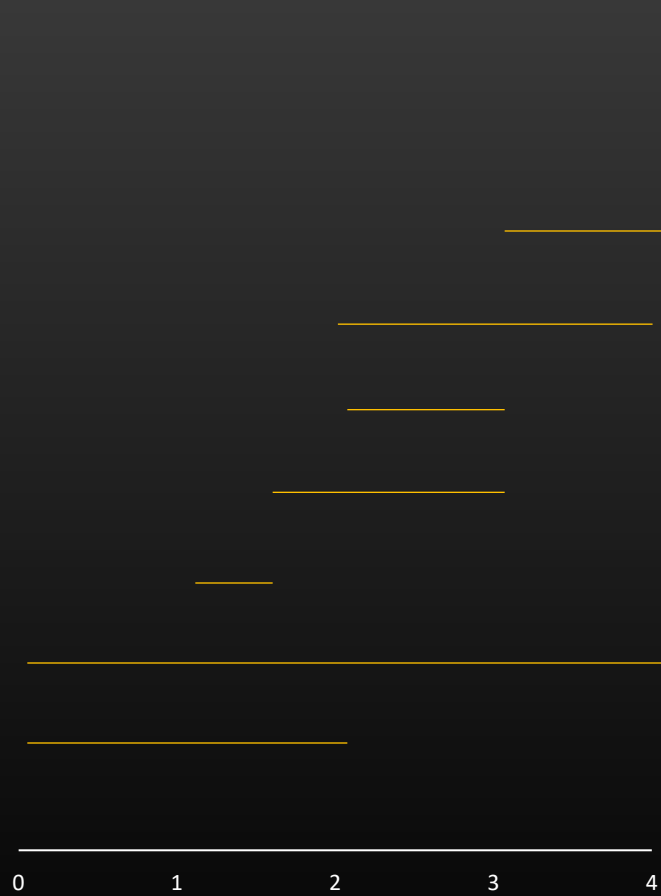
$$\beta_1(K_3) = 2$$

$$\beta_0(K_4) = 2$$

$$\beta_1(K_4) = 1$$



Barcodes vs persistence diagrams



Stability

- The set of barcodes/persistence diagrams can be equipped with a variety of **earthmover-type distances**: the Wasserstein distances of L_p -type and the bottleneck distance of L_∞ -type.
- Most reasonable known instantiations of the TDA pipeline are **Lipschitz continuous** with respect to Hausdorff distance on point clouds and bottleneck distance on persistence diagrams.

Practicalities

- There are extensive **libraries of software**, mostly open source, for TDA computations (e.g., GUDHI, Ripser, Flagser, Giotto,...).
- There exist **“inverse analysis” tools** for interpreting results of TDA computations (e.g., work of Hiraoka et al.).

From TDA to ML

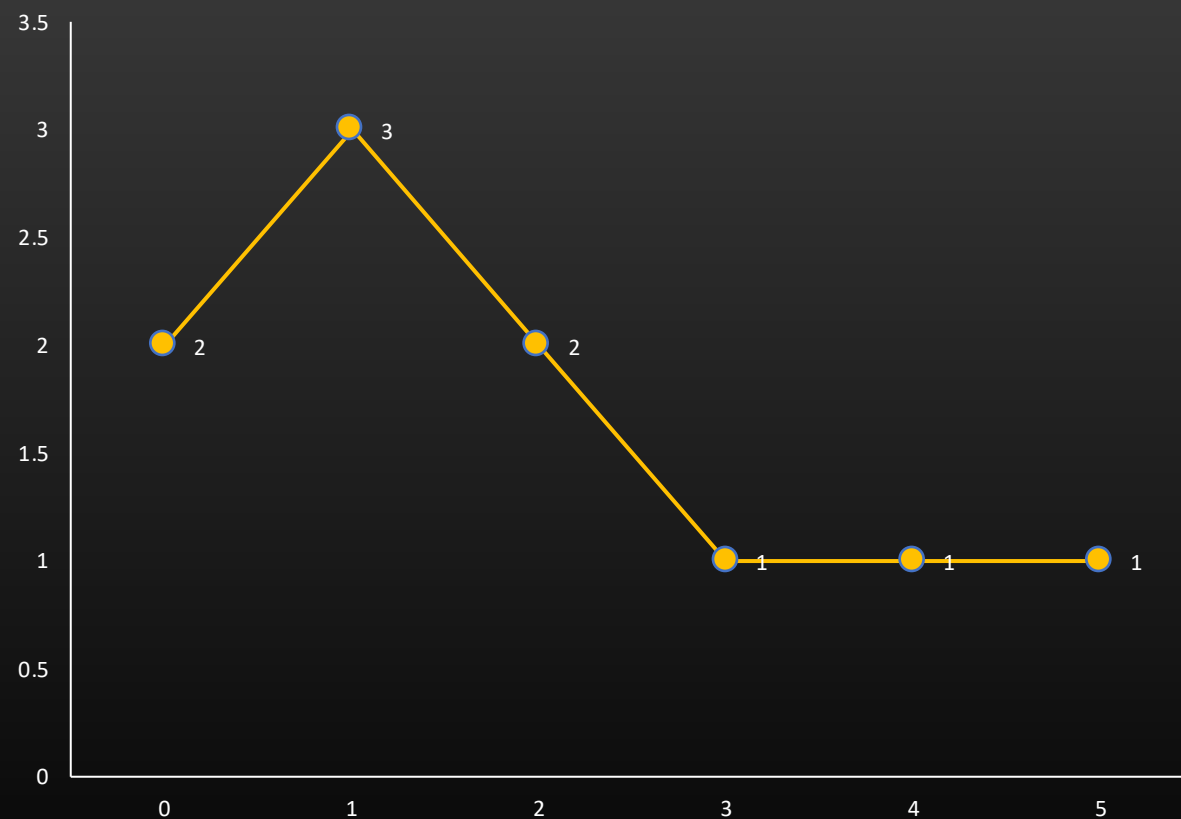
Strategies for featurization

- **Problem:** Cannot compute statistics in the space of barcodes or the space of persistence diagrams.
- **Solution:**
 - Define a Lipschitz-continuous mapping from the space of barcodes/persistence diagrams to a vector space \mathcal{V} equipped with an inner product.
 - Compute statistics in \mathcal{V} !
 - [Leygonie-Oudot-Tillmann, 2019] New **differentiable approach**, enabling the use of gradient descent.

Betti curves

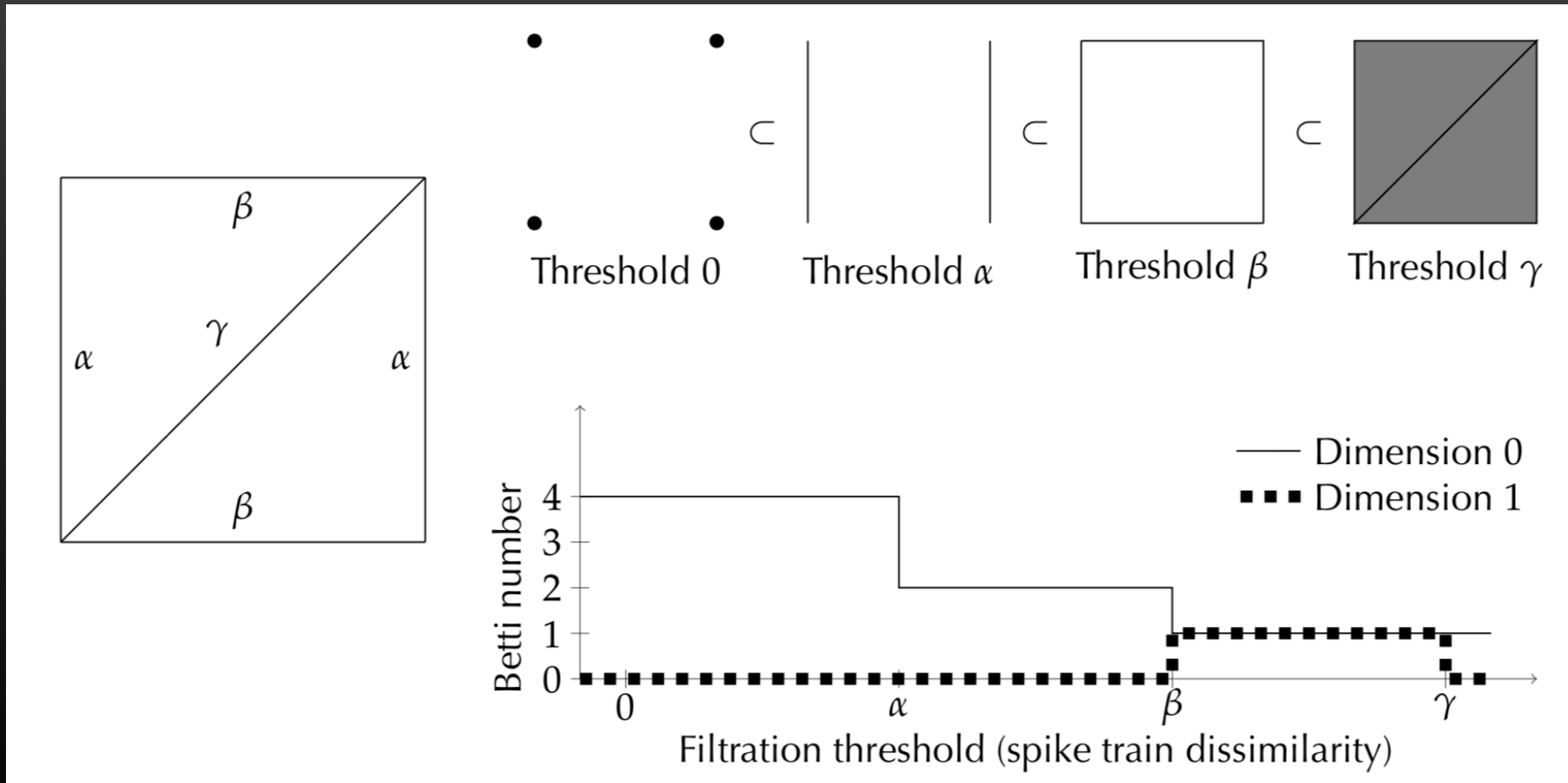


Bar code for cavities of dimension k

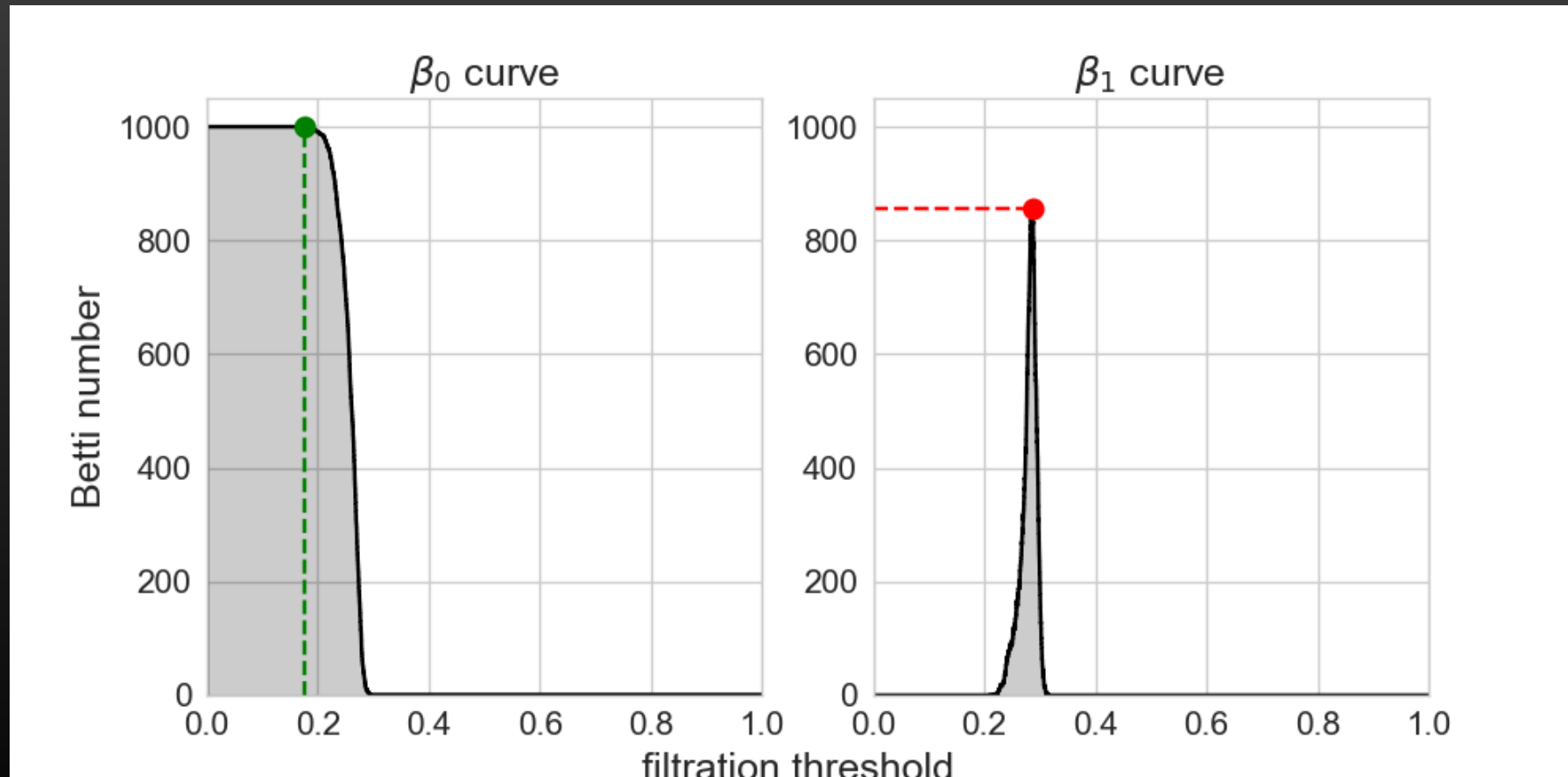


Betti_k curve

Nested complex to Betti curve

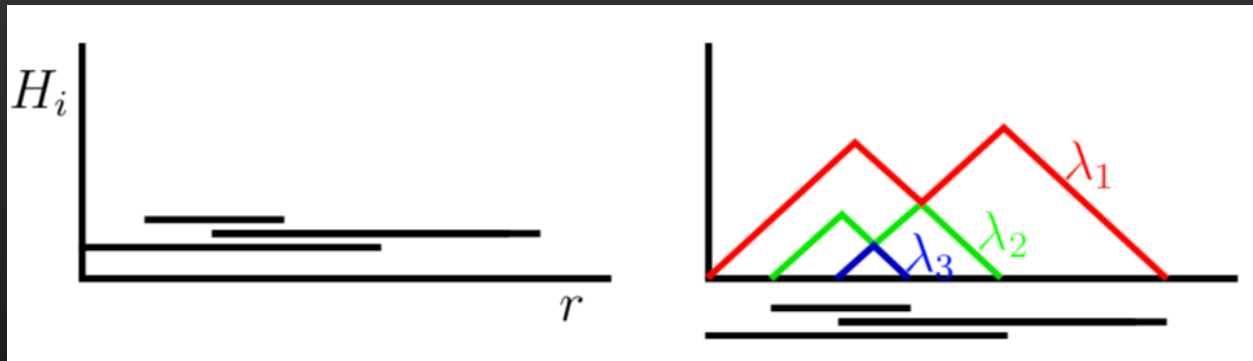


Extracting numerical features



Persistence landscapes

- Barcodes also give rise to *persistence landscapes*.



$$\lambda = \{ \lambda_k : \mathbb{R} \rightarrow \mathbb{R} \cup \{ \infty \} \mid k \in \mathbb{N} \}$$

- The *L2-landscape distance* between barcodes B and B' with associated landscapes λ and λ' :

$$\Lambda(B, B') = \|\lambda - \lambda'\|_2 = \sum_{k=1}^{\infty} \left(\int |\lambda_k(t) - \lambda'_k(t)|^2 dt \right)^{\frac{1}{2}}$$

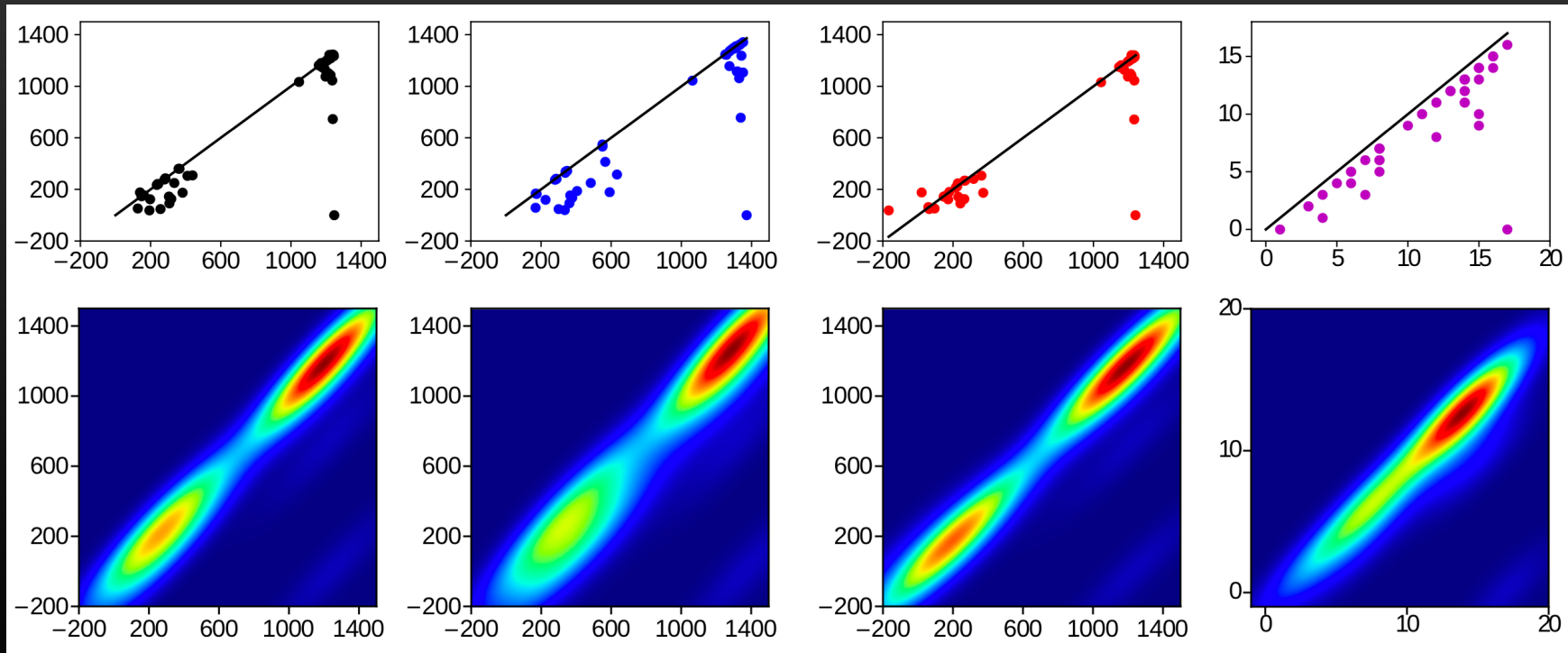
Persistence curves

Name	Notation	$\psi(b, d, t)$	T
Betti	$\beta(D)$	1	sum
Midlife	$\mathbf{ml}(D)$	$(b + d)/2$	sum
Life	$\ell(D)$	$d - b$	sum
Multiplicative Life	$\mathbf{mul}(D)$	d/b	sum
Life Entropy [2]	$\mathbf{le}(D)$	$-\frac{d-b}{\sum(d-b)} \log \frac{d-b}{\sum(d-b)}$	sum
Midlife Entropy	$\mathbf{mle}(D)$	$-\frac{d+b}{\sum(d+b)} \log \frac{d+b}{\sum(d+b)}$	sum
Mult. Life Entropy	$\mathbf{mule}(D)$	$-\frac{d/b}{\sum(d/b)} \log \frac{d/b}{\sum(d/b)}$	sum
k -th Landscape [5]	$\lambda_k(D)$	$\min\{t - b, d - t\}$	\max_k

Simultaneous generalization of Betti curves and persistence landscapes

Persistence images

- Smooth the PD: replace each point by a Gaussian kernel, then sum
- Discretize



ML methods applied to featurized TDA

- Decision tree
- Random forest
- Support Vector Machine
- CNN
- Graph CNN

Examples

- Topological characterization of neuron morphologies
- Automated classification of dynamic regimes in networks of neurons
- High-throughput screening of nanoporous materials



Thank you!