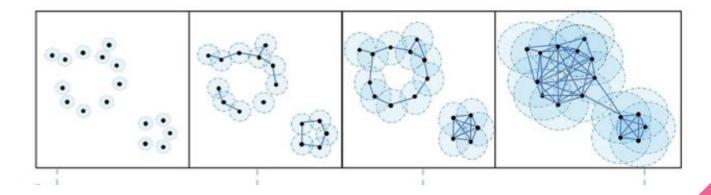
# An Exploration of Topological Data Analysis (TDA) for Arrhythmia Detection

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# **Topological Data Analysis**

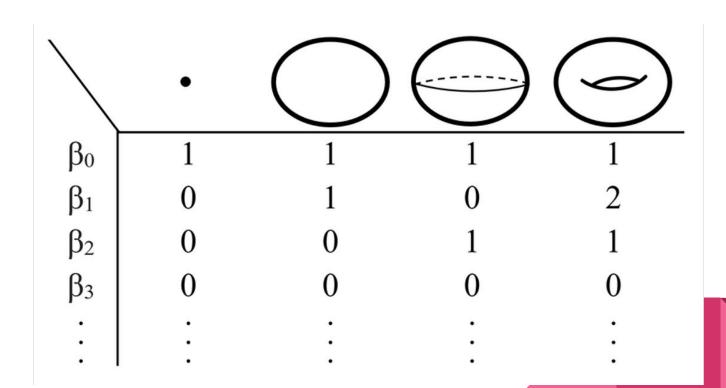
- Characterization of data using its geometric structure
- Persistent Homology: specifically looks at the structure of holes
- Relevance to machine learning



# Persistent Homology

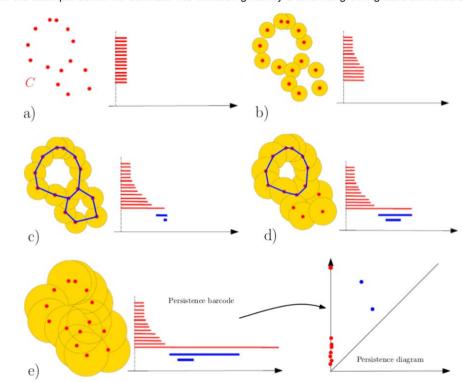
- In a given nested sequence X1 ⊆ X2 ⊆ . . . ⊆ Xn, the inclusion Xi ⊆ Xi' for i ≤ i' produces a linear map  $Hk(Xi) \rightarrow Hk(Xi')$  on the corresponding k-th homology. As the time parameter *i* increases, persistent homology tracks elements of Hk(Xi), most often represented with a persistence diagram (PD) in the Cartesian plane  $R^2$ .
- Each point (x, y) in a PD corresponds to a feature appearing at scale x (birth) and disappearing at scale y (death), and has a persistence value of (y x).

# **Betti Numbers**



# Persistence Diagrams and Barcodes

In the example below we consider the filtration given by a union of growing balls centered on the finite set of points C.

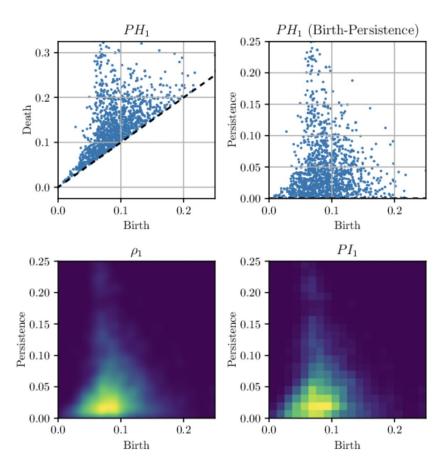


# Persistence Diagram → Persistence Image

- Need a vector representation in order to perform machine learning methods such as SVM, logistic regression, etc – Persistence Images provide this
  - Involves a linear transformation of the PD, B, from birth-death coordinates to birth-persistence coordinates:  $T: \mathbb{R}^2 \to \mathbb{R}^2$  defined as T(x, y) = (x, y x)
  - Center the points usually using a Gaussian distribution function:
  - $\circ$  Fix a nonnegative weighting function  $f: \mathbb{R}^2 \to \mathbb{R}$  to produce the corresponding persistence surface and ensure a stable transformation:

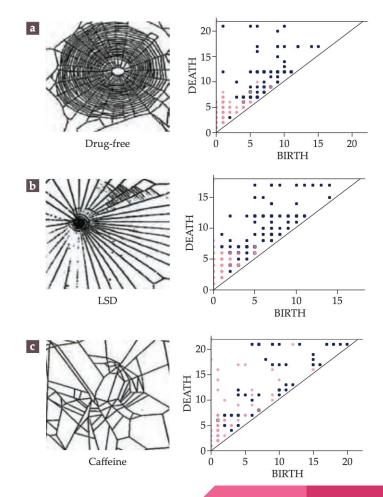
$$\rho_{\scriptscriptstyle B}(z)=\Sigma_{\scriptscriptstyle U\;\in\;T(B)}^{}\,f(u)\phi_{\scriptscriptstyle U}(z)$$

 Reduce the surface to a finite-dimension vector by overlaying it on a grid and integrating over each pixel to get the PI.

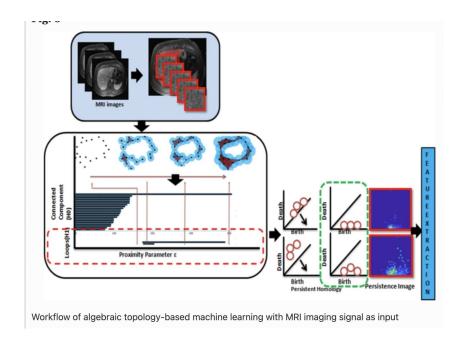


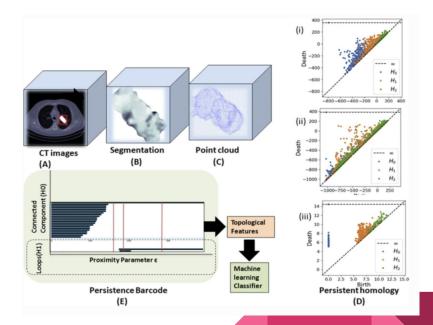
# **Applications of TDA**

- Shape extraction
- Medical image processing
  - High-dimensional MRIs and CT scans
  - Tumor detection
- Time-series analysis
  - ECGs
- Physics and dynamical systems
- Literature reviews
- Machine learning
  - Similarities to CNNs



### TDA and Healthcare





# **Heart Arrhythmia Detection**

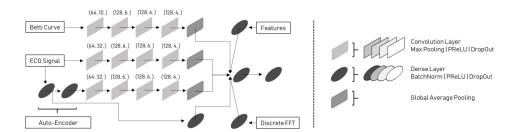
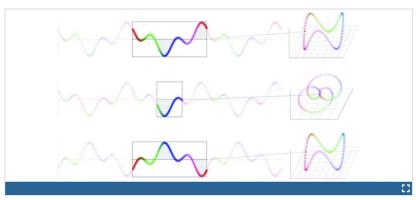


Figure 4: General Overview of Deep-Learning Architecture



**Fig. 2.** Multi-dimensional scaling to  $R^3$  of the high-dimensional point clouds generated from delay embeddings with varying window sizes (respectively 100, 35, and 100 time units). Here, the embedding dimensions are set equal to the window sizes and the delay parameter  $\tau$  is set to 1. Projection to  $R^3$  is only used for visualization.

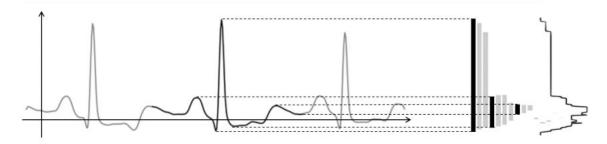
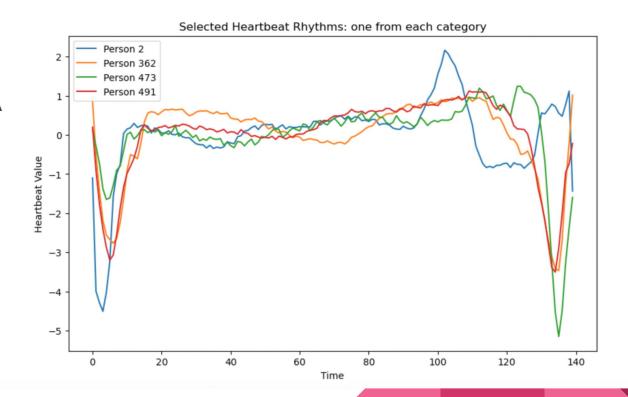


Figure 1: From three Consecutive Heartbeats to their corresponding persistence barcode and Betti curve

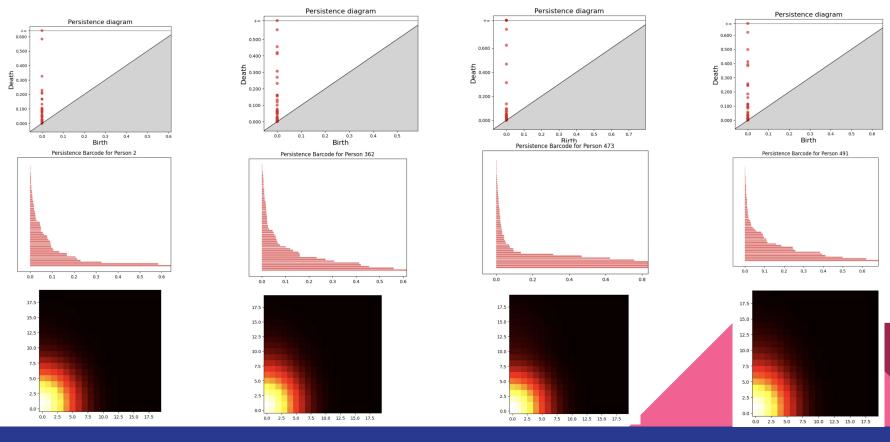
### ECG 5000 Dataset

Goal: Classify 4 classes of arrhythmias using TDA

- Persistence Diagrams
- 2. Persistence Images
- 3. Classification
  - a. Regression
  - b. LDA
  - c. DTC



### PDs and PIs



# **Classification Results**

	TDA: Binary (full set)	TDA: Binary (modified set)	TDA: Multi Class (full set)	TDA: Multi Class (modified set)	Non TDA (full dataset only)
Logistic regression	89.7%	97.4%	80.0%	88.8%	94.0%
DTC		97.0%		88.0%	94.0%
LDA		100%		88.8%	92.7%

### **Future Research**

- Non-aligned or multi-beat arrhythmias
- Tuning the persistence images
  - Weight functions
  - Resolution
- Multi-dimensional analysis