# Topology for Data Science 2: Learning from the shape of data

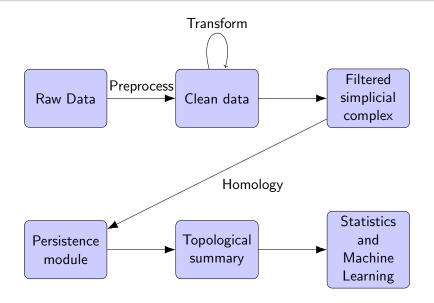
#### Peter Bubenik

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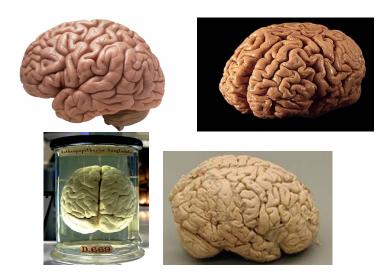
January 24, 2017

Tercera Escuela de Análisis Topológico de Datos y Topología Estocástica ABACUS, Estado de México

## Topological Data Analysis



## Brains



## BRAINS!!!







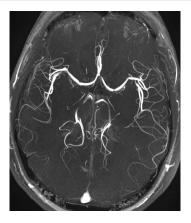


eometry and algebra

# Magnetic Resonance Imaging (MRI)

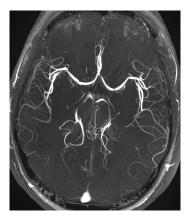


#### **Brain** arteries



Paul Bendich, J.S. Marron, Ezra Miller, Alex Pieloch, Sean Skwerer, Ann. Appl. Stat. **10** (2016) no. 1, 198–218 (presented here with changes by me)

#### **Brain** arteries

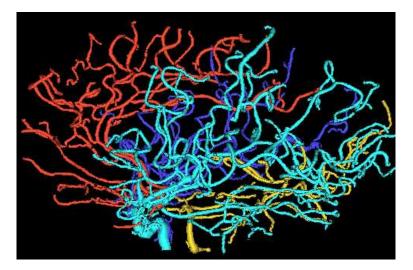


Want to:

- understand normal changes with respect to age
- detect and locate pathology (tumors)
- predict stroke risk

# Brain arterial data

#### Bullitt and Aylward (2002) MRA $\rightarrow$ Tubes



#### Mathematical viewpoint

#### Graph X with (x, y, z, r) for each vertex.

#### Mathematical viewpoint

Graph X with (x, y, z, r) for each vertex.

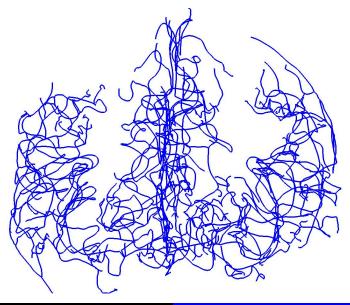
 $X_t$  is the full subgraph on the vertices with  $z \leq t$ .

$$\emptyset = X_0 \subseteq X_1 \subseteq X_2 \subseteq \cdots \subseteq X_m = X$$

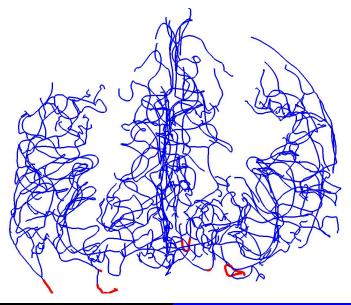
Apply  $H_0$ .

$$H_0(X_0) \rightarrow H_0(X_1) \rightarrow H_0(X_2) \rightarrow \cdots \rightarrow H_0(H_m)$$

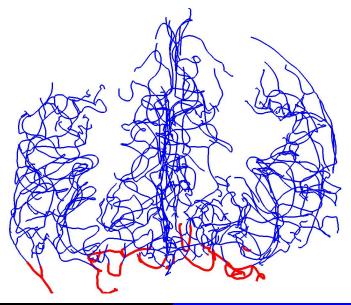
Geometry and algebra



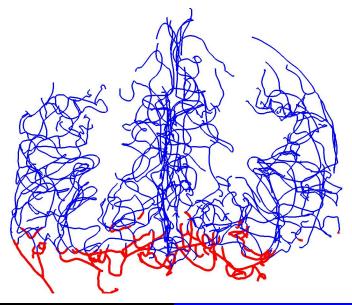
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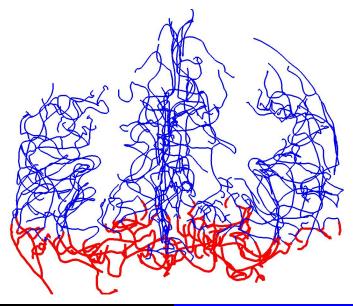
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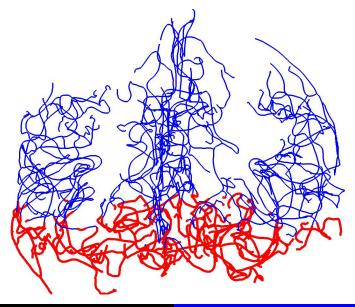
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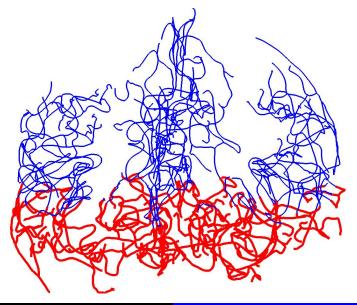
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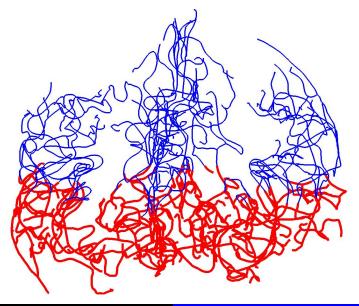
Geometry and algebra



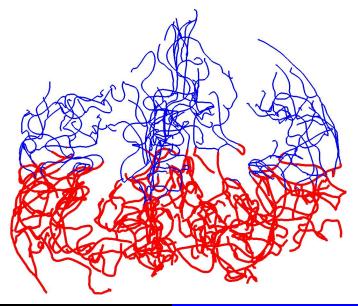
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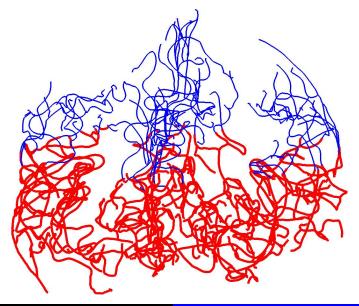
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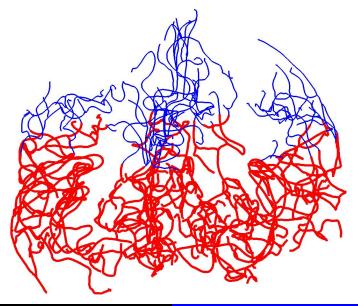
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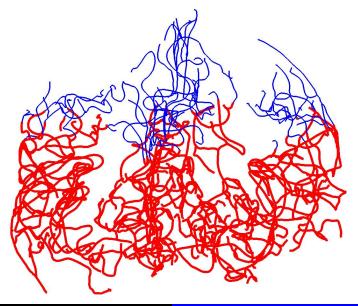
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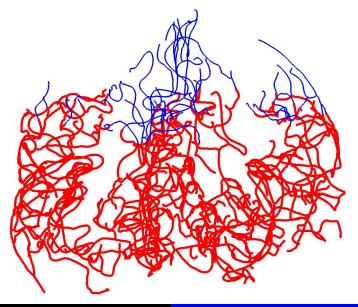
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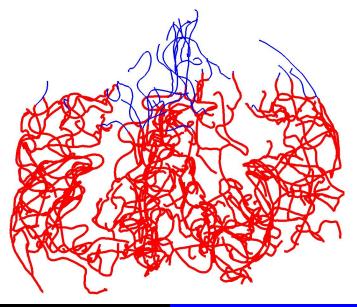
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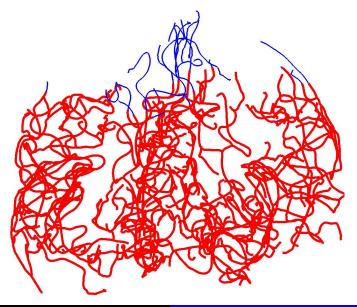
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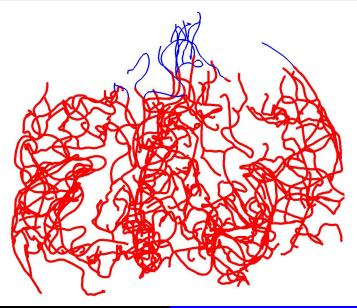
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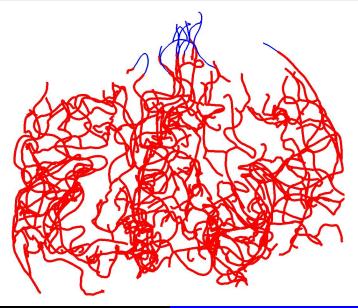
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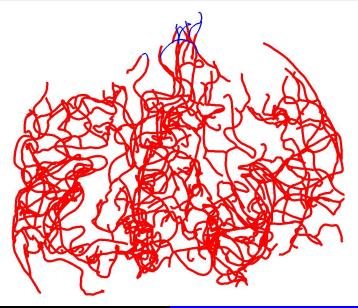
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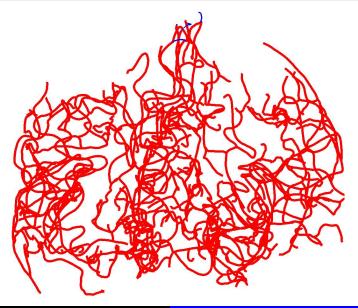
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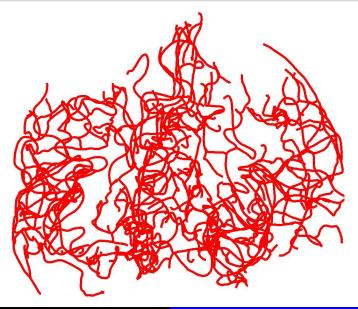
Geometry and algebra



Geometry and algebra



Geometry and algebra



## Mathematical encoding

We have an increasing sequence of simplicial complexes

$$X_0 \subseteq X_1 \subseteq X_2 \subseteq \cdots \subseteq X_m$$

called a filtered simplicial complex.

Apply  $H_k(-; \mathbb{F})$ .

We get a sequence of vector spaces and linear maps

$$V_0 \rightarrow V_1 \rightarrow V_2 \rightarrow \cdots \rightarrow V_m$$

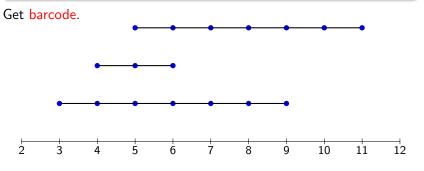
called a persistence module.

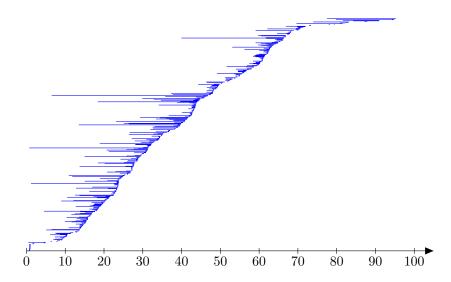
#### Summaries of persistence modules

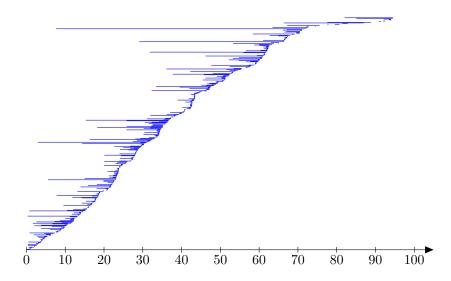
$$V_0 \rightarrow V_1 \rightarrow V_2 \rightarrow V_3 \rightarrow V_4 \rightarrow V_5 \rightarrow V_6 \rightarrow V_7 \rightarrow \cdots \rightarrow V_m$$

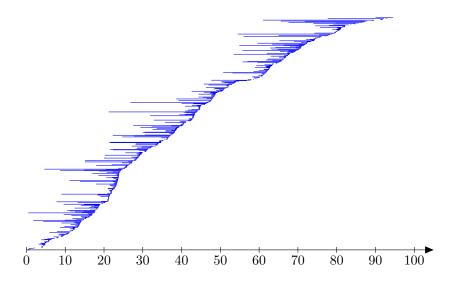
#### Fundamental Theorem of Persistent Homology

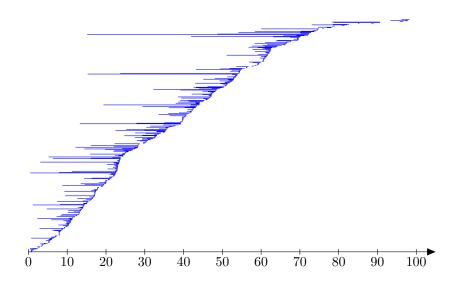
There exists a choice of bases for the vector spaces  $V_i$  such that each map is determined by a bipartite matching of basis vectors.

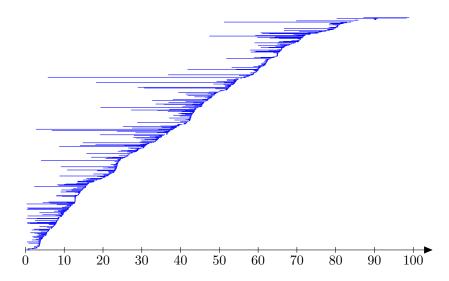












## Challenges



We want to:

- calculate averages
- understand variances
- test hypotheses
- cluster and classify

We can only do a few of these using barcodes.

# Making life easier



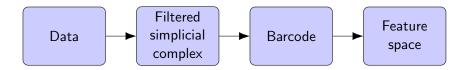
The feature space is a Hilbert space.

What is great about a Hilbert space?

- it is a vector space (easy to measure distances, averages)
- it has an inner product (easy to measure angles)
- it is complete (good for studying convergence)

#### Feature maps and kernels

Feature map  $\Phi : \mathcal{X} \to \mathcal{H}$ 



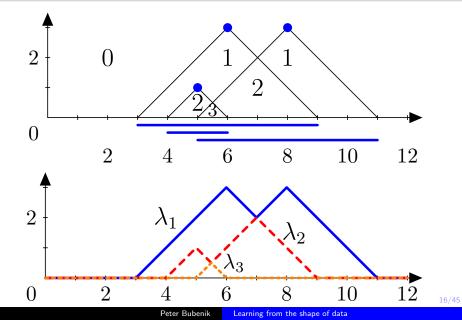
 $\text{Kernel } \mathcal{K}: \mathcal{X} \times \mathcal{X} \to \mathbb{R}, \quad \mathcal{K}(x,y) = \langle \Phi(x), \Phi(y) \rangle_{\mathcal{H}}.$ 

With a kernel, we can

• measure distance  $d(x, y) = K(x - y, x - y)^{1/2}$ 

• measure angles:  $\angle(x,y) = \arccos \frac{K(x,y)}{K(x,x)^{1/2}K(y,y)^{1/2}}$ 

## Constructing a persistence landscape



# Constructing a persistence landscape

