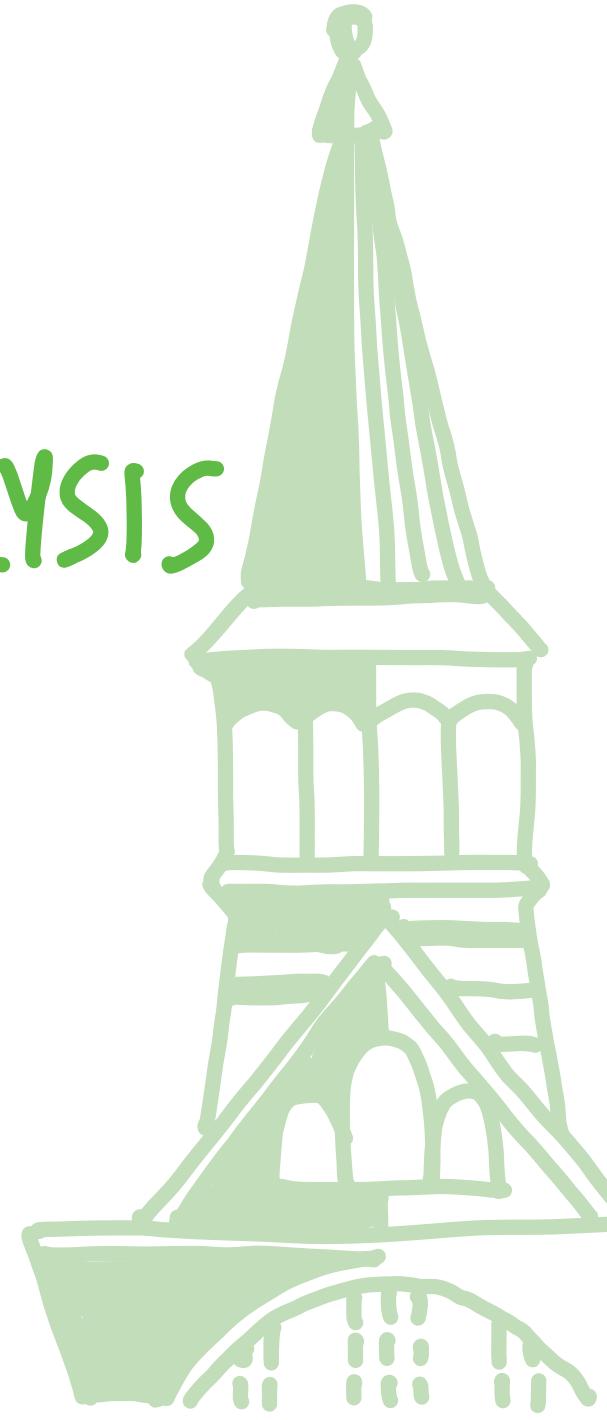


Introduction to TOPOLOGICAL DATA ANALYSIS

Alice Patania PhD

ASSISTANT RESEARCH PROFESSOR
DEPT. OF MATHEMATICS and STATISTICS
VERMONT COMPLEX SYSTEMS CENTER

February 11th 2022



The theory

data

complexes

filtrations

structure

persistence modules

homology and barcodes

function

sheaves

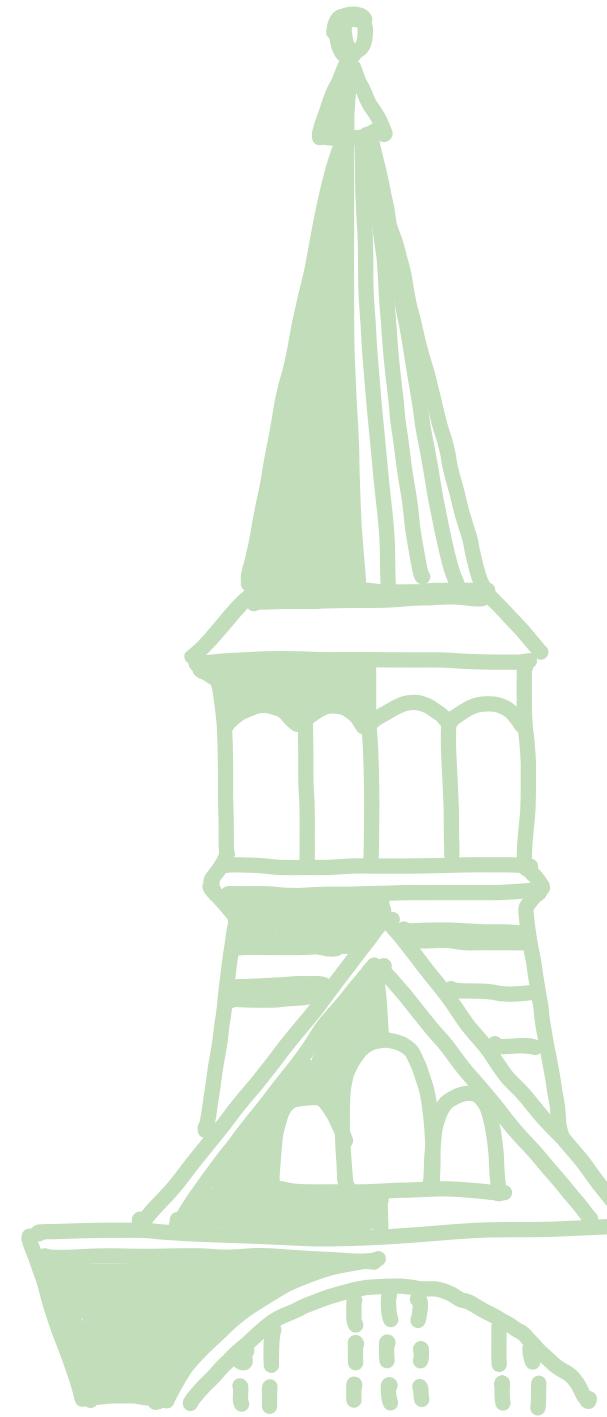
sheaf cohomology

The application

brain data

Alzheimer disease

brain dynamics



What is data?

Let X be a topological space

X is unknown, we want to study it, but we can only collect discrete random samples

What is data?

Let X be a topological space

X is unknown, we want to study it, but we can only collect discrete random samples

data set $D \subseteq X$

What can we learn about X from D ?
and how can do we do it without bias?

What do I mean about Bias?

When the theoretical model is unknown, coordinates are not necessarily meaningful

Similarly, metrics in data sets are not always justified

choosing a parameter gives a partial view

Topology is the cure to all evil !

(IRONY)

When the theoretical model is unknown, coordinates are not necessarily meaningful
coordinate-free method

Similarly, metrics in data sets are not always justified
ignore the quantitative values of distance function
and get information only the nearness of points

choosing a parameter gives a partial view

Construct summaries of information over whole domains of parameters

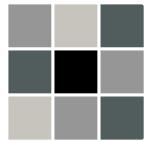
On the local behaviour of spaces of natural images

G. Carlsson, T. Ishkhanov, V. de Silva, A. Zomorodian (2008)

Data: 3x3 patches from images

They can be seen as points in 9-dimensional space

normalized to have average = "gray"
 $\text{norm} = 1$



On the local behaviour of spaces of natural images

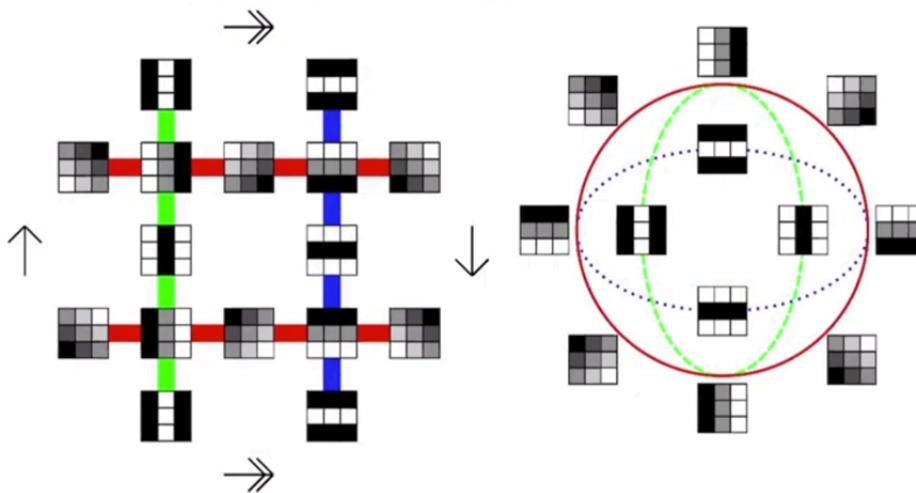
G. Carlsson, T. Ishkhanov, V. de Silva, A. Zomorodian (2008)

Data: 3x3 patches from images

They can be seen as points in 9-dimensional space

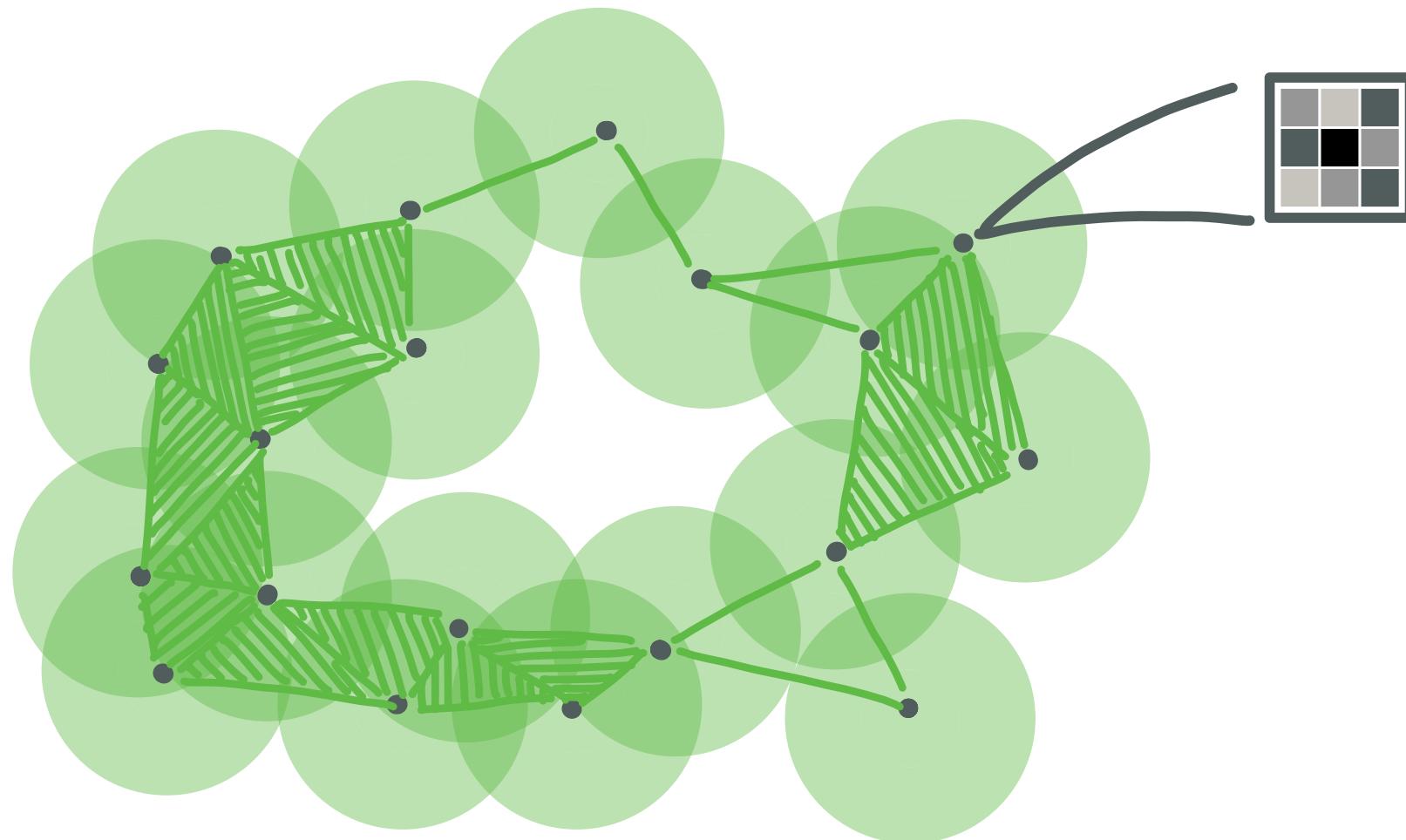
normalized to have average = "gray"
 $\text{norm} = 1$ } \Rightarrow the points lay on a 7-sphere

using topological data analysis they were able to
find out that the subspace the data comes from has
the same homology type as the **KLEIN BOTTLE**



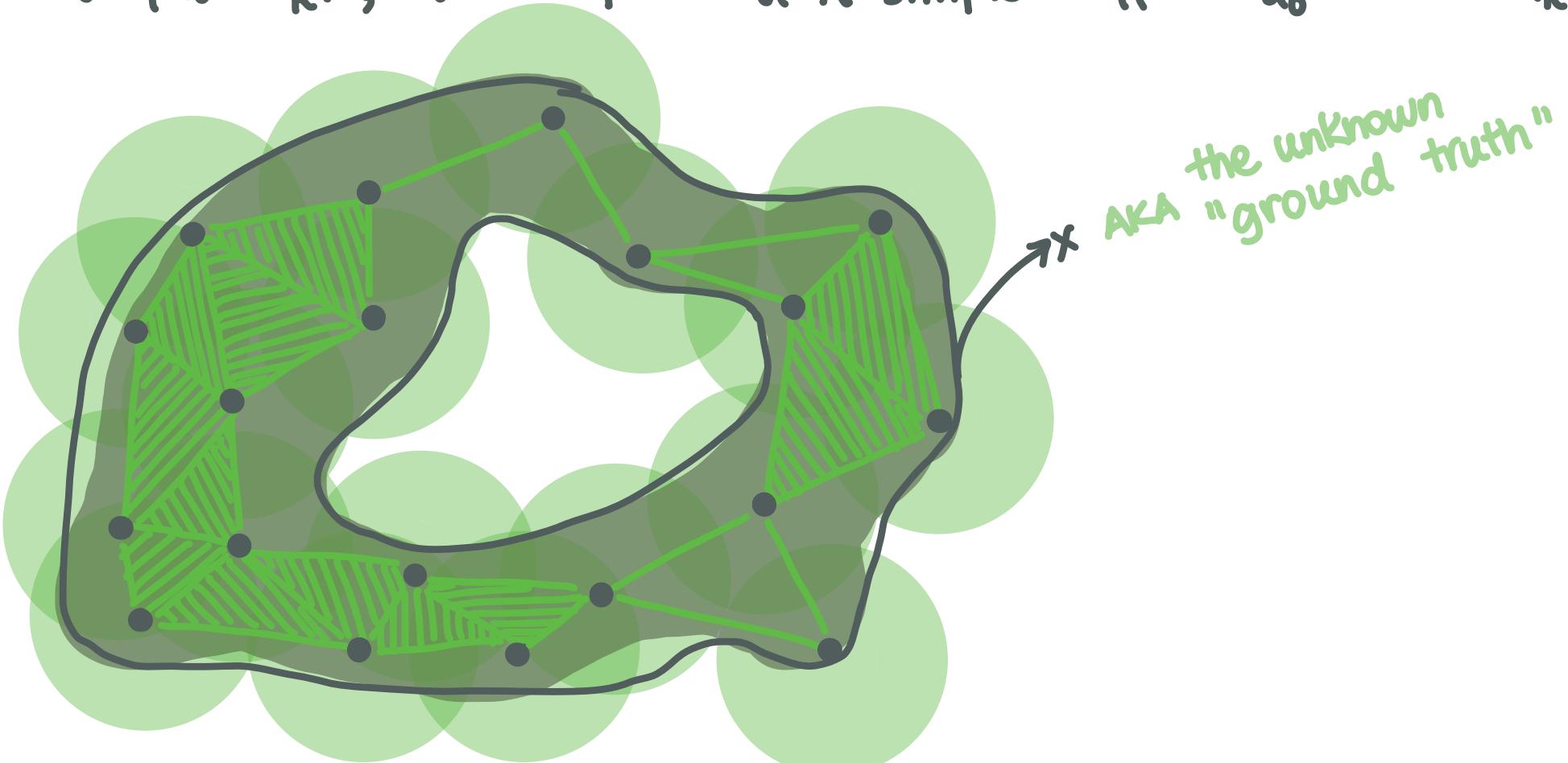
How to go from data to a structure ?

In this case the data set comes with an intrinsic metric
then we can construct a simplicial complex from it.



Nerve

let X be a topological space and $\mathcal{U} = \{U_\alpha\}_{\alpha \in A}$ a covering of X .
The **nerve** of \mathcal{U} is an abstract simplicial complex with vertex set A .
 $\sigma = \{a_0, \dots, a_k\}$, $a_i \in A$ spans a k -simplex iff $U_{a_0} \cap \dots \cap U_{a_k} \neq \emptyset$



Nerve

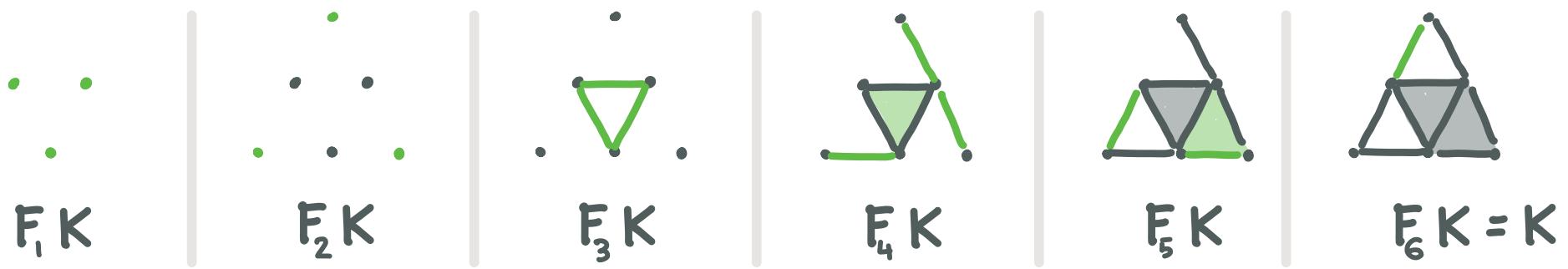
Let X be a topological space and $\mathcal{U} = \{U_\alpha\}_{\alpha \in A}$ a covering of X .
The **nerve** of \mathcal{U} is an abstract simplicial complex with vertex set A .
 $\sigma = \{a_0, \dots, a_k\}$, $a_i \in A$ spans a k -simplex iff $U_{a_0} \cap \dots \cap U_{a_k} \neq \emptyset$

Theorem

Let X be a topological space, $\mathcal{U} = \{U_\alpha\}_{\alpha \in A}$ a countable open covering of X s.t. $\forall S \subseteq A$ with $S \neq \emptyset$ $\bigcap_{s \in S} U_s$ is either contractible or empty

Then $N(\mathcal{U})$ is homotopy equivalent to X .

Let K be a simplicial complex. A **filtration** F is a nested sequence of strictly increasing subcomplexes of K $F_1K \subsetneq F_2K \subsetneq \dots \subsetneq F_nK = K$

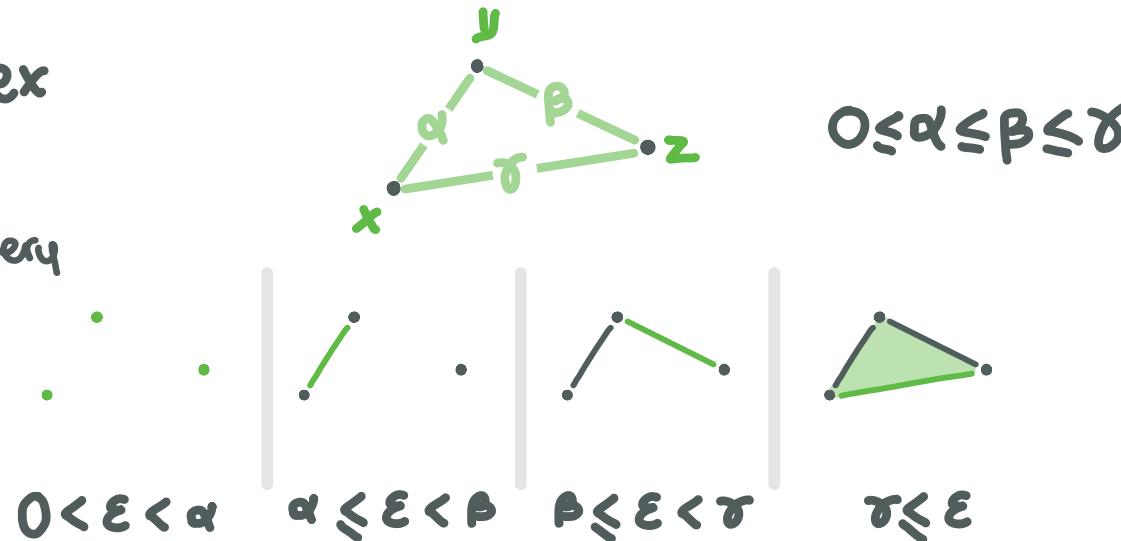


Vietoris-Rips filtration

$VR(X, \varepsilon)$ is a simplicial complex

$$\sigma = \{a_0, \dots, a_K\}, a_i \in A$$

$\sigma \in K$ iff the distance between every pair of points in σ is at most ε



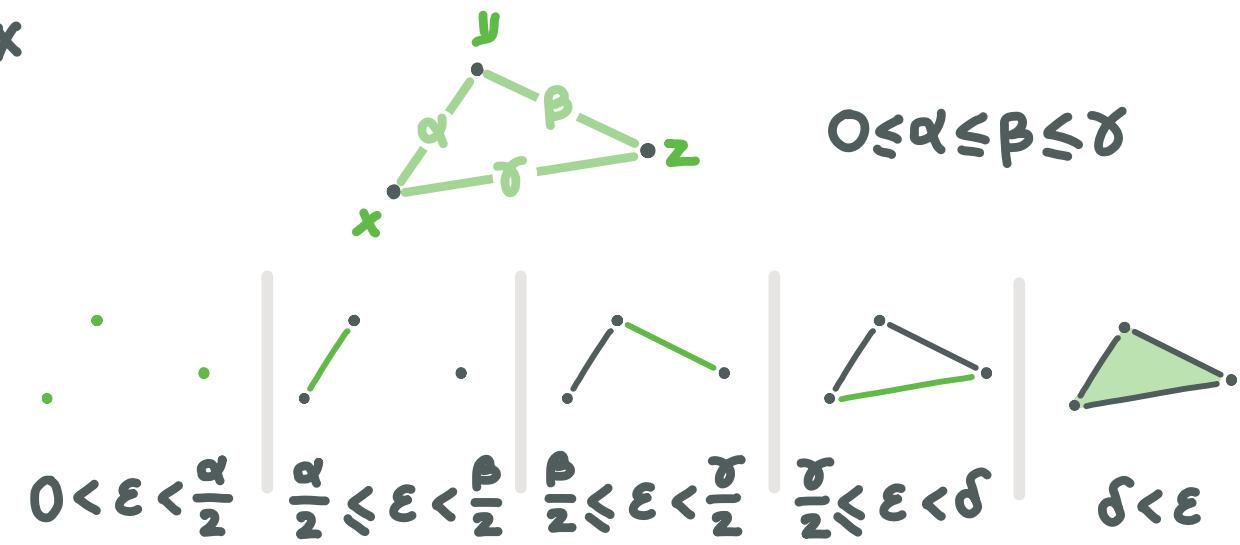
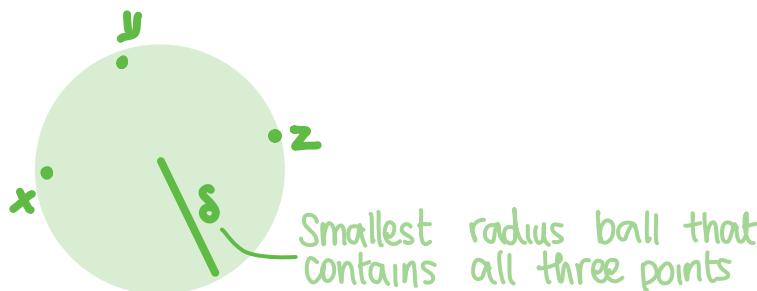
Čech filtration

$\check{C}(X, \varepsilon)$ is a simplicial complex

$$\sigma = \{a_0, \dots, a_K\}, a_i \in A$$

$\sigma \in K$ iff $B_{a_0}^{(\varepsilon)} \cap \dots \cap B_{a_K}^{(\varepsilon)} \neq \emptyset$

$B_x^{(\varepsilon)}$ = ball centered in x of radius ε



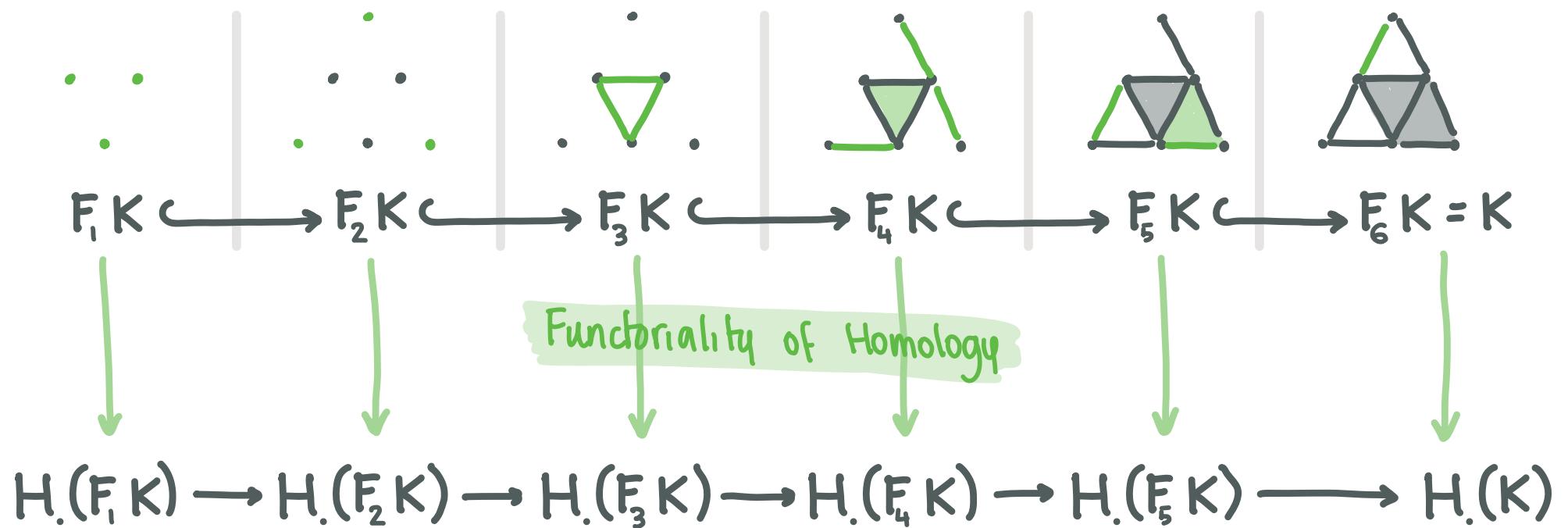
Let K be a simplicial complex. A **filtration** F is a nested sequence of strictly increasing subcomplexes of K $F_1K \subset F_2K \subset \dots \subset F_nK = K$



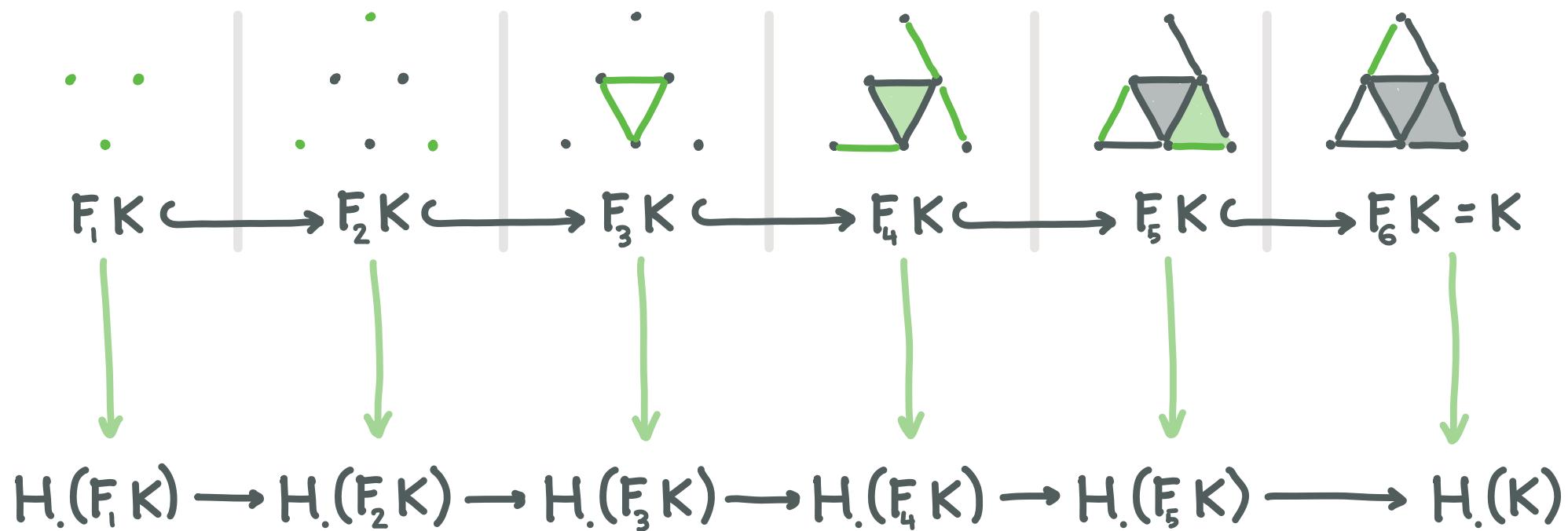
Functoriality of Homology

- If $f: K \rightarrow L$ and $g: L \rightarrow M$ simplicial maps then $C.(g \circ f) = C.(g) \circ C(f)$
- If $\varphi: (C, d) \rightarrow (C', d')$ and $\psi: (C', d') \rightarrow (C'', d'')$ chain maps then
 $H_*(\psi \circ \varphi) = H_*(\psi) \circ H_*(\varphi)$

Let K be a simplicial complex. A **filtration** F is a nested sequence of strictly increasing subcomplexes of K $F_1 K \subset F_2 K \subset \dots \subset F_n K = K$

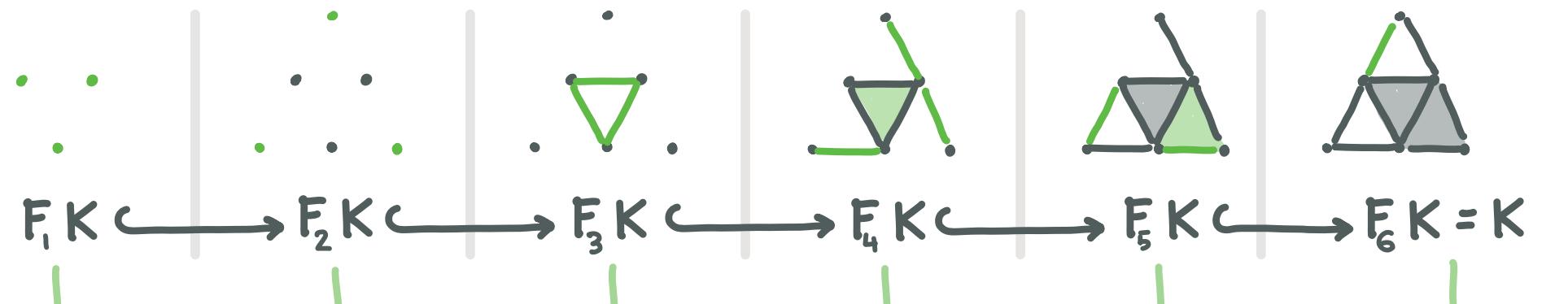


Let K be a simplicial complex. A **filtration** F is a nested sequence of strictly increasing subcomplexes of K $F_1K \subset F_2K \subset \dots \subset F_nK = K$



PERSISTENT HOMOLOGY

Let K be a simplicial complex. A **filtration** F is a nested sequence of strictly increasing subcomplexes of K $F_1 K \subsetneq F_2 K \subsetneq \dots \subsetneq F_n K = K$



$$H_*(F_1 K) \rightarrow H_*(F_2 K) \rightarrow H_*(F_3 K) \rightarrow H_*(F_4 K) \rightarrow H_*(F_5 K) \rightarrow H_*(K)$$

PERSISTENT HOMOLOGY

persistence homology module

A (discrete) **persistence module** is a pair (V, a) of vector spaces $\{V_i : i \in \mathbb{N}\}$ and linear maps $a_i : V_i \rightarrow V_{i+1}$

$$V_0 \longrightarrow V_1 \longrightarrow \dots \longrightarrow V_i \longrightarrow V_{i+1} \longrightarrow \dots$$

Warning! This is not necessarily a complex (i.e. $a_i \circ a_{i+1}$ is not always =0)

A (discrete) **persistence module** is a pair (V, a) of vector spaces $\{V_i : i \in \mathbb{N}\}$ and linear maps $a_i : V_i \rightarrow V_{i+1}$

$$V_0 \longrightarrow V_1 \longrightarrow \dots \longrightarrow V_i \longrightarrow V_{i+1} \longrightarrow \dots$$

Persistence modules form a category!

A morphism of persistence modules $\varphi : (V, a) \longrightarrow (W, b)$

$$\begin{array}{ccccccc} V_0 & \xrightarrow{a_0} & V_1 & \xrightarrow{a_1} & \dots & \longrightarrow & V_i & \xrightarrow{a_i} & V_{i+1} & \longrightarrow & \dots \\ \varphi_0 \downarrow & & \varphi_1 \downarrow & & & & \varphi_i \downarrow & & \varphi_{i+1} \downarrow & & & \\ W_0 & \xrightarrow{b_0} & W_1 & \xrightarrow{b_1} & \dots & \longrightarrow & W_i & \xrightarrow{b_i} & W_{i+1} & \longrightarrow & \dots \end{array}$$

If $\forall i \quad \varphi_i$ is invertible, then φ is an **isomorphism**

The **direct sum** of persistence modules $(V, a) \oplus (W, b) = (V \oplus W, a \oplus b)$

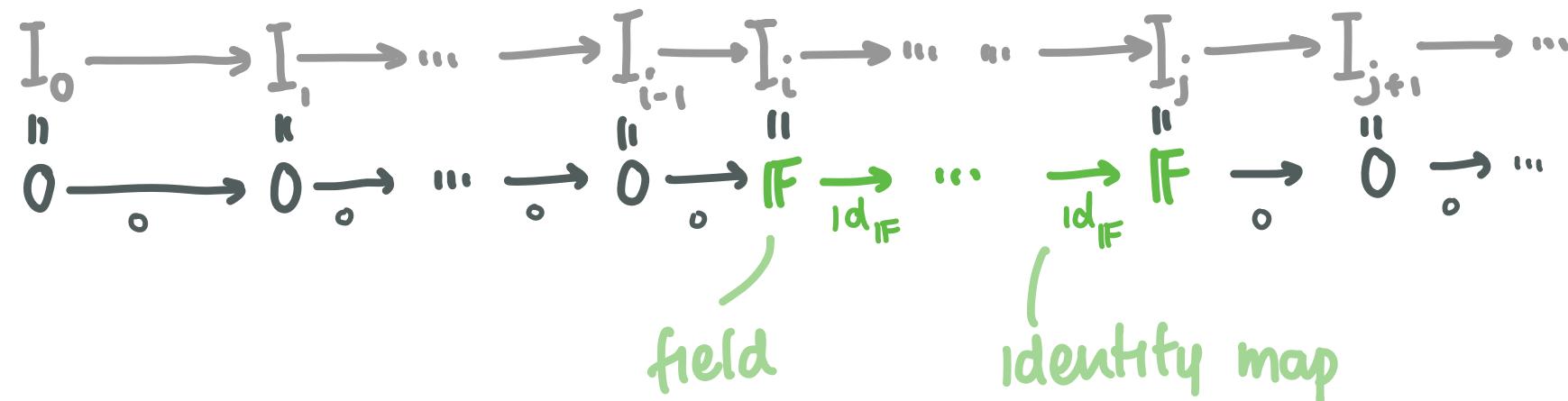
$$V_0 \oplus W_0 \xrightarrow{a_0 \oplus b_0} V_1 \oplus W_1 \xrightarrow{a_1 \oplus b_1} \dots \longrightarrow V_i \oplus W_i \xrightarrow{a_i \oplus b_i} \dots$$

A persistence module is indecomposable if it admits no interesting direct sum decomposition

$$\text{if } (I, c) \underset{\text{isomorphism}}{\simeq} (V, a) \oplus (W, b) \quad \text{then} \quad \begin{cases} (V, a) \simeq (I, c) \\ (W, b) \simeq (0, 0) \end{cases}$$

Property

Persistence modules of the following type are indecomposable
for $i \leq j$ with $i, j \in \mathbb{N}$

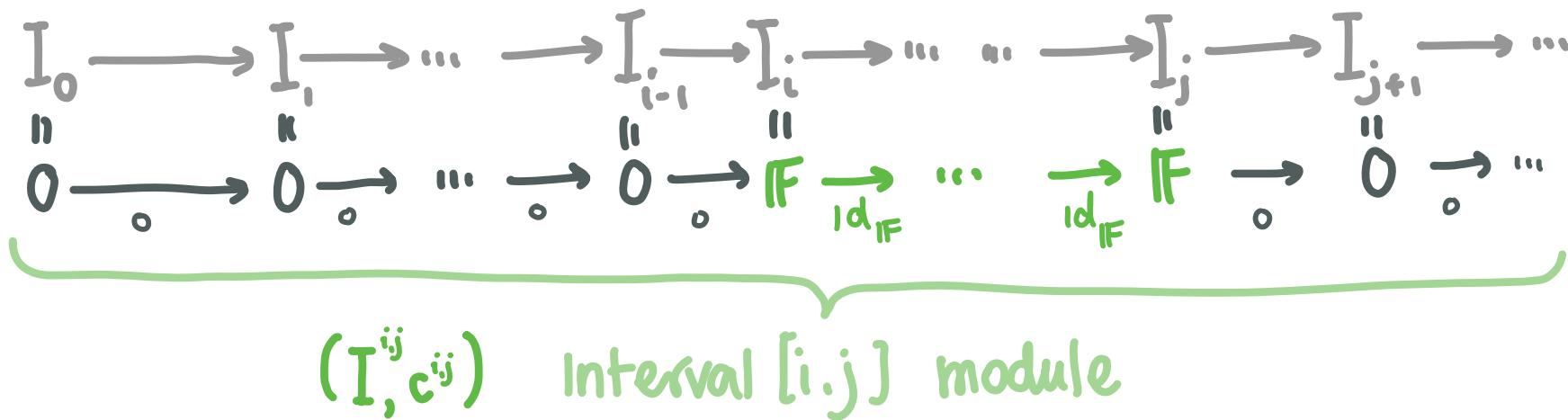


A persistence module is indecomposable if it admits no interesting direct sum decomposition

$$\text{if } (I, c) \underset{\text{isomorphism}}{\simeq} (V, a) \oplus (W, b) \quad \text{then} \quad \begin{cases} (V, a) \simeq (I, c) \\ (W, b) \simeq (0, 0) \end{cases}$$

Property

Persistence modules of the following type are indecomposable
for $i \leq j$ with $i, j \in \mathbb{N}$



Decomposition Theorem

$\forall i \dim V_i < \infty$ and $a_i : V_i \rightarrow V_{i+1}$
 a_i is isomorphism $\forall j > 0$

Let (V, a) be a finite type persistence module then exists a finite set of intervals $\text{Bar}(V, a) = \{[i, j] \mid i \in \mathbb{N}, j \in \mathbb{N} \cup \{\infty\}, j \geq i\}$ and a multiplicity $\mu : \text{Bar}(V, a) \longrightarrow \mathbb{N}$ so that:

$$(V, a) \simeq \bigoplus_{[i, j] \in \text{Bar}(V, a)} (I^{ij}, c^{ij})^{\mu[i, j]}$$

Barcode decomposition

(idea)

PROOF uses the classification of freely generated $\mathbb{F}[t]$ -modules into a free and torsion part. Because there is a lemma saying that we can always represent a persistence tame module as a graded module over $\mathbb{F}[t]$

Decomposition Theorem

(or tame)

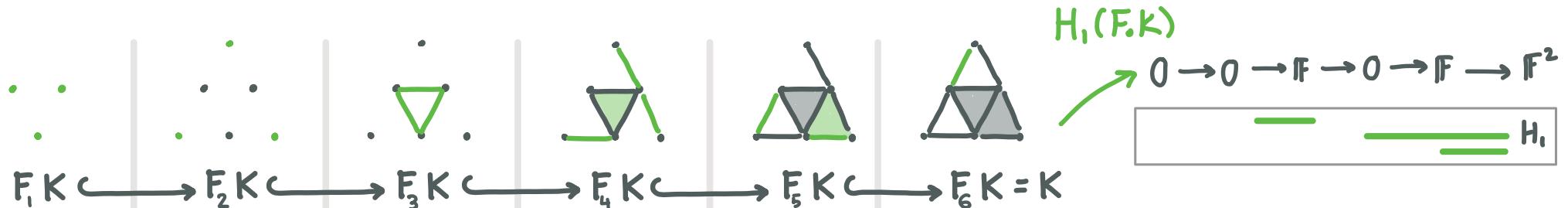
$\forall i \dim V_i < \infty$ and $a_i : V_i \rightarrow V_{i+1}$
 a_i is isomorphism $\forall j > 0$

Let (V, a) be a finite type persistence module then exists a finite set of intervals $\text{Bar}(V, a) = \{[i, j] \mid i \in \mathbb{N}, j \in \mathbb{N} \cup \{\infty\}, j \geq i\}$ and a multiplicity $\mu : \text{Bar}(V, a) \longrightarrow \mathbb{N}$ so that:

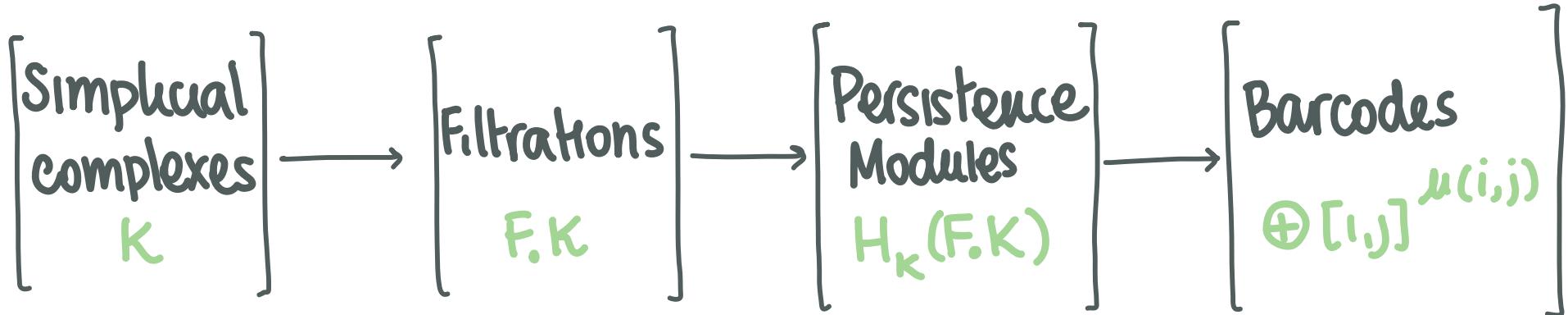
$$(V, a) \simeq \bigoplus_{[i, j] \in \text{Bar}(V, a)} (I^{ij}, c^{ij})^{\mu[i, j]}$$

Barcode decomposition

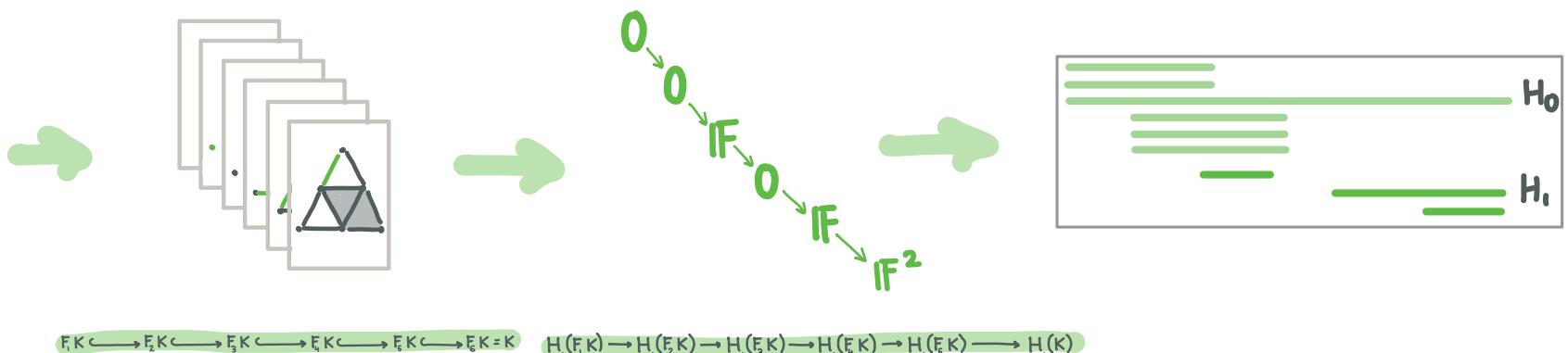
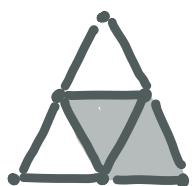
The Barcode decomposition is unique up to reordering of factors



Persistent Homology



example



The theory

data

complexes

filtrations

structure

persistence modules

homology and barcodes

function

sheaves

sheaf cohomology

The application

brain data

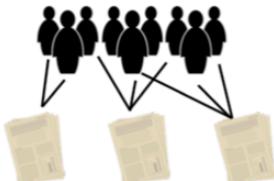
Alzheimer disease

brain dynamics

YOU ARE HERE!



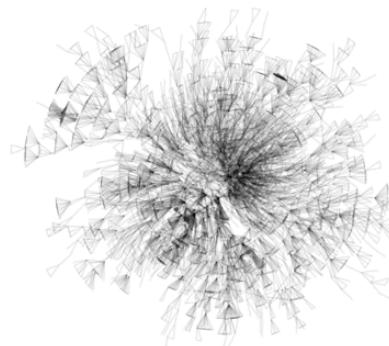
Applications



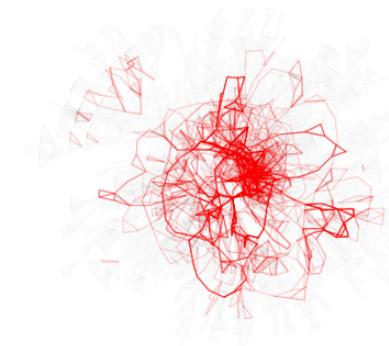
collaboration networks



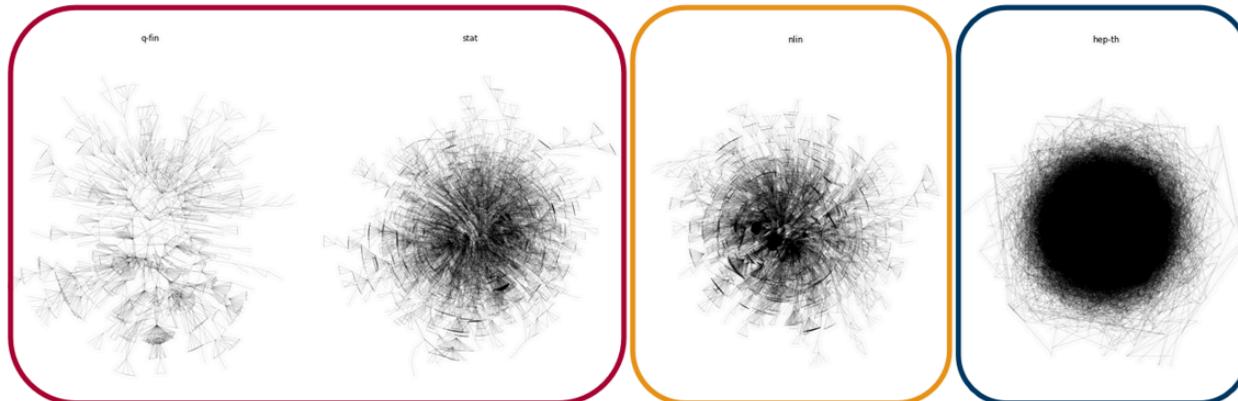
math-ph



math-ph



Examples for the biggest connected component for each group.

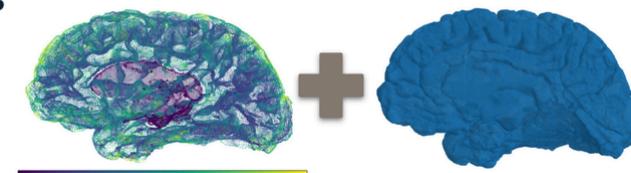


The shape of collaboration

A Patania, F Vaccarino, G Petri - EPJ Data Science (2017)

Applications

Cortical thickness



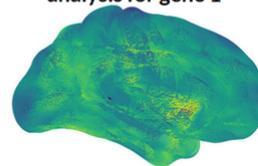
327684 vertices
thickness

155 participants

3000 genes expression from plasma of peripheral blood

155 participants

Beta coefficients of regression analysis for gene 1



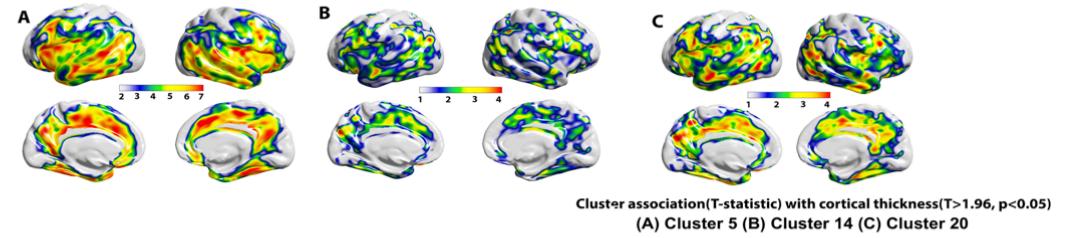
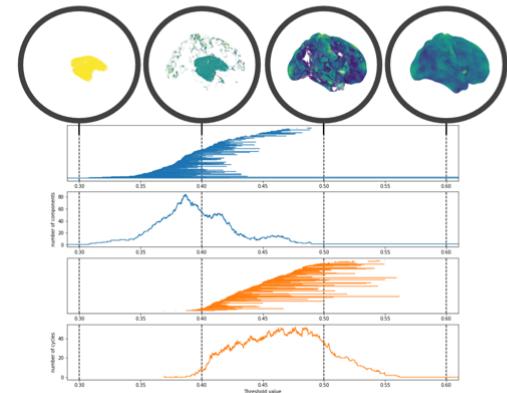
National Institutes of Health



R21 - Integrative Predictive Modeling of Alzheimer's Disease

NIH Exploratory/Developmental Research Grant

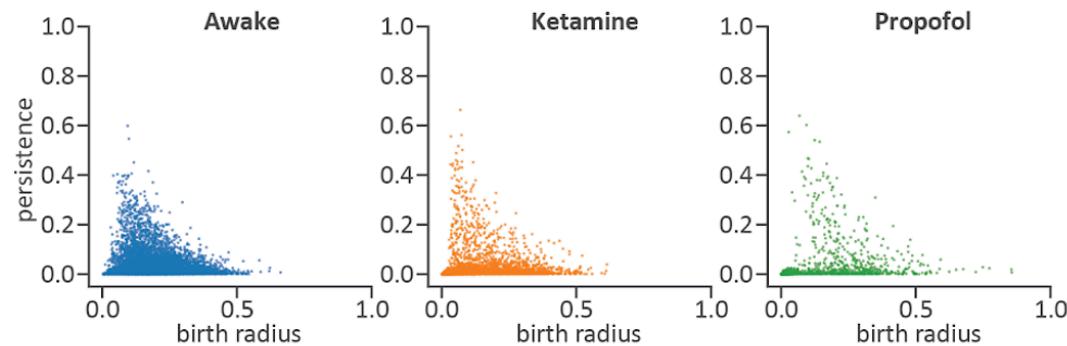
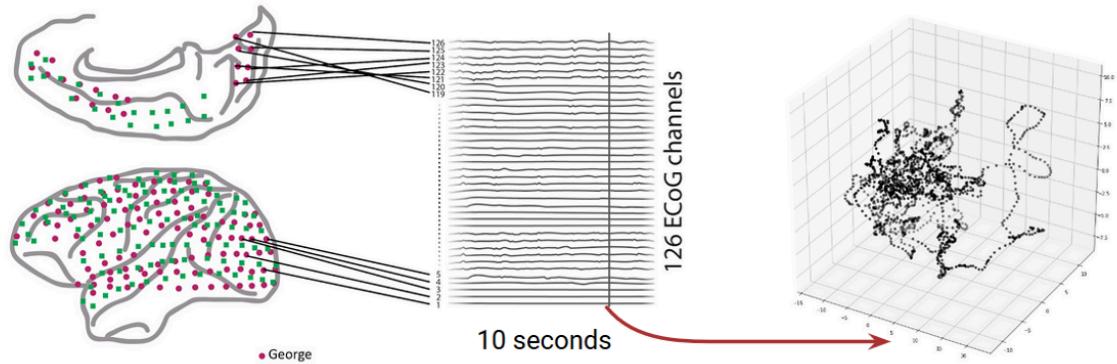
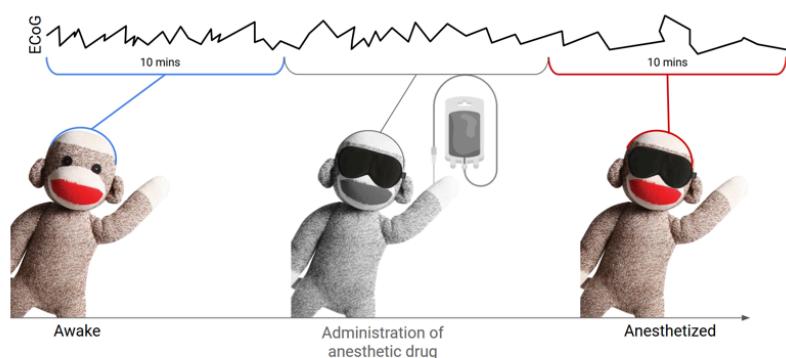
Persistent Homology



Characterization of genetic expression patterns in Mild Cognitive Impairment using a multiomics approach and neuroimaging endophenotypes
A Bharthur Sanjay, A Patania, X Yan, D Svaldi, T Duran, N Shah, E Chen, LG Apostolova (2021)

Applications

Neurotycho - The experiment



Topological Analysis of Differential Effects of Ketamine and Propofol Anesthesia on Brain Dynamics

T F. Varley, V Denny, O Sporns, A Patania (2021) in submission Open Science ([bioarxiv- https://doi.org/10.1101/2020.04.04.025437](https://doi.org/10.1101/2020.04.04.025437))

A simplicial map $f: K \rightarrow L$

$$\begin{array}{ccc} & f: K \longrightarrow L \\ \sigma & \longmapsto & f(\sigma) \end{array}$$

where $f(\sigma)$ is a simplex of L such that $\dim f(\sigma) \leq \dim(\sigma)$ and if $\dim \sigma = 0$, $\dim f(\sigma) = 0$

Let $f: K \rightarrow L$ simplicial map, the fiber of $\tau \in L$ is the set $\tau_{/f}$
 $\tau_{/f} = \{a \in K \mid f(a) \subseteq \tau\}$ these are the simplices of K that end up being faces of the simplex τ

Proposition

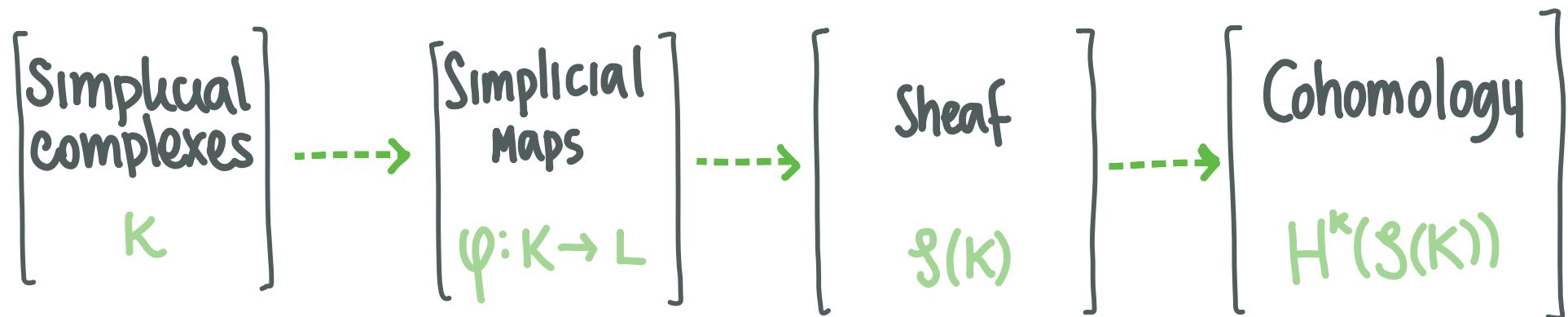
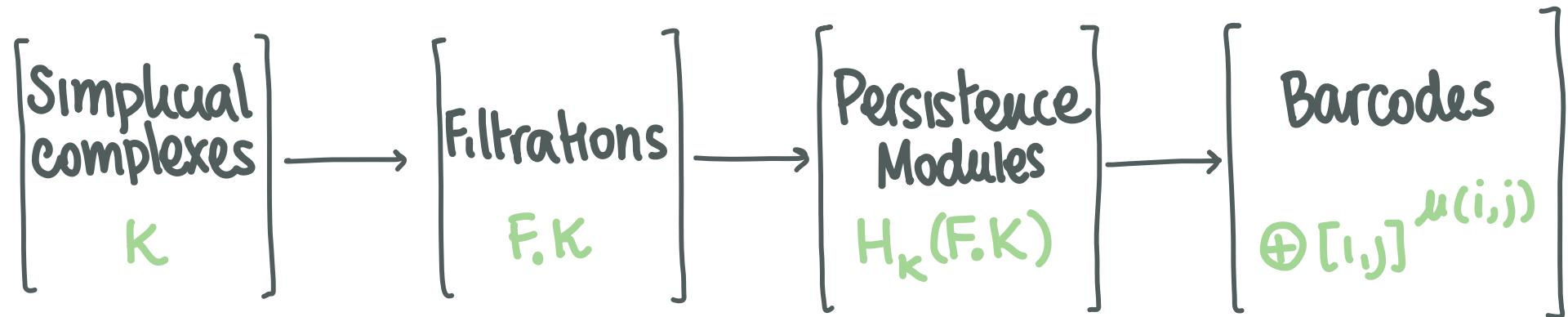
- i) $\tau_{/f}$ is a subcomplex of K
- ii) $\tau_{/f} \subseteq \tau'_{/f}$ inclusion of simplicial complexes

Homology is a functor then $\forall \tau \in L$

$$\begin{aligned} \tau &\mapsto H_K(\tau_{/f}) \\ \tau \subseteq \tau' &\mapsto H_K(\tau_{/f} \hookrightarrow \tau'_{/f}) \end{aligned}$$

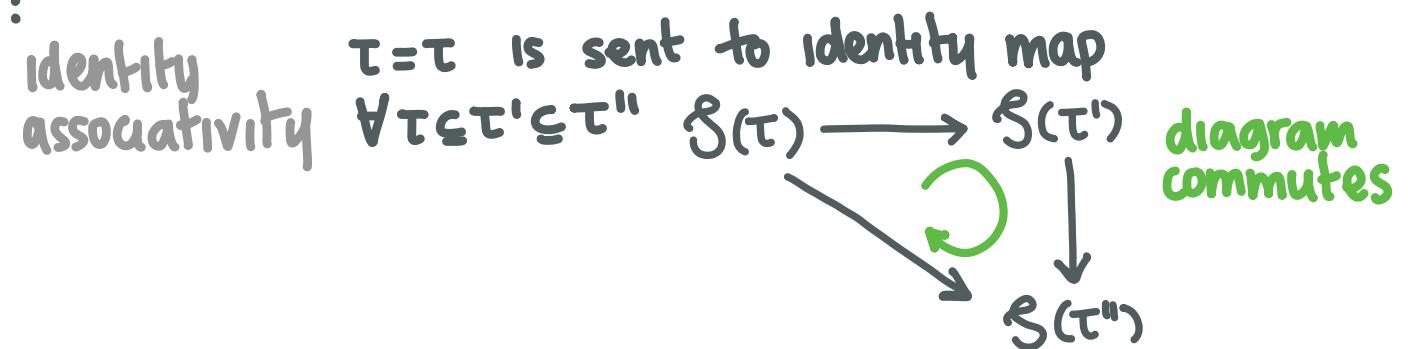
This is a well known construction in topology: a sheaf!

Sheaves



L as a poset is a category
 $\mathcal{S}: (L, \leq) \rightarrow \text{Vect}_{\mathbb{F}}$
 ↗ category of vector spaces over a field
 A sheaf on a simplicial complex is a functor
 \mathcal{S} assigns to each simplex $\tau \in L$ a vector space $\mathcal{S}(\tau)$ called the stalk of \mathcal{S} over τ
 inclusion $\tau' \subseteq \tau$ a linear map $\mathcal{S}(\tau' \subseteq \tau): \mathcal{S}(\tau') \rightarrow \mathcal{S}(\tau)$ restriction map

such that the following hold:

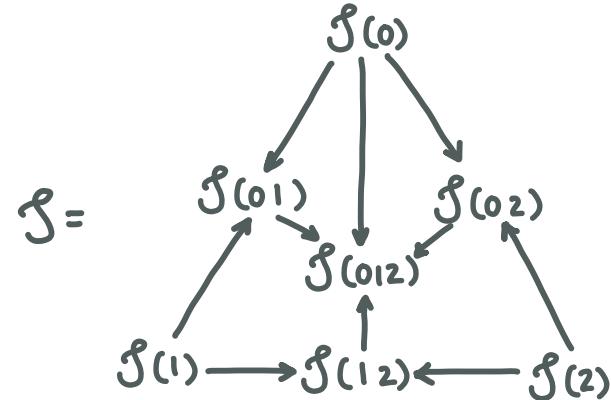
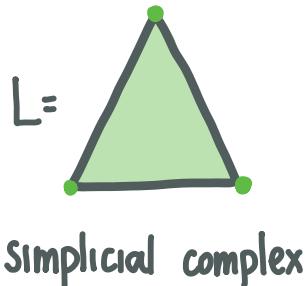


L as a poset is a category
 $\mathcal{S}: (L, \leq) \rightarrow \text{Vect}_{\mathbb{F}}$
 ↗ category of vector spaces over a field

A sheaf on a simplicial complex is a functor $\mathcal{S}: (L, \leq) \rightarrow \text{Vect}_{\mathbb{F}}$
 \mathcal{S} assigns to each simplex $\tau \in L$ a vector space $\mathcal{S}(\tau)$ called the stalk of \mathcal{S} over τ
 inclusion $\tau' \subseteq \tau$ a linear map $\mathcal{S}(\tau' \subseteq \tau): \mathcal{S}(\tau') \rightarrow \mathcal{S}(\tau)$ restriction map

such that the following hold:
 identity $\tau = \tau$ is sent to identity map
 associativity $\forall \tau \subseteq \tau' \subseteq \tau'' \quad \mathcal{S}(\tau) \rightarrow \mathcal{S}(\tau') \rightarrow \mathcal{S}(\tau'')$
 diagram commutes

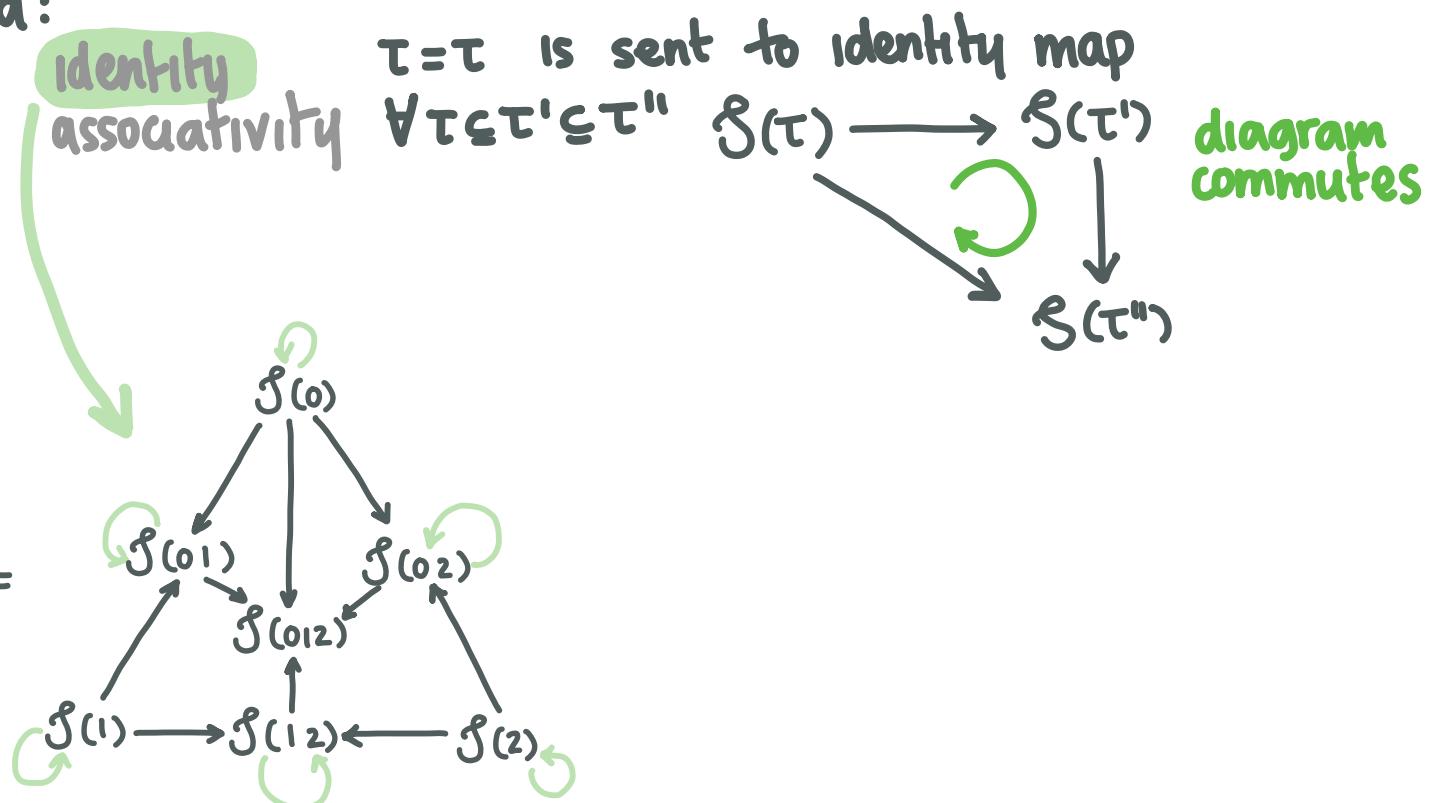
small example



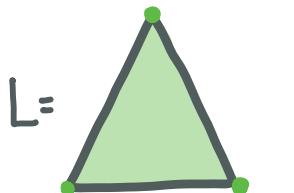
L as a poset is a category
 $\mathcal{S}: (L, \leq) \rightarrow \text{Vect}_{\mathbb{F}}$
 \uparrow category of vector spaces over a field

\mathcal{S} assigns to each simplex $\tau \in L$ a vector space $\mathcal{S}(\tau)$ called the stalk of \mathcal{S} over τ
 inclusion $\tau' \subseteq \tau$ a linear map $\mathcal{S}(\tau' \subseteq \tau): \mathcal{S}(\tau') \rightarrow \mathcal{S}(\tau)$ restriction map

such that the following hold:



small example

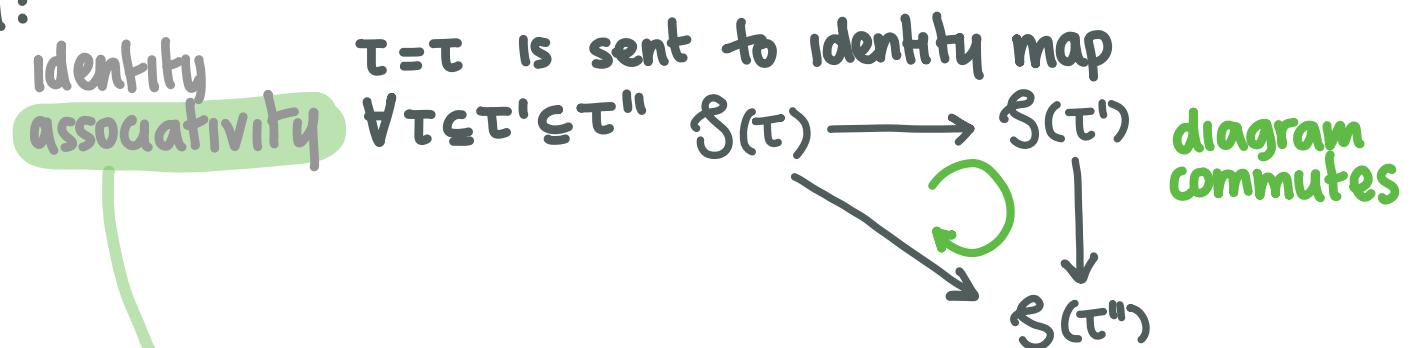


simplicial complex

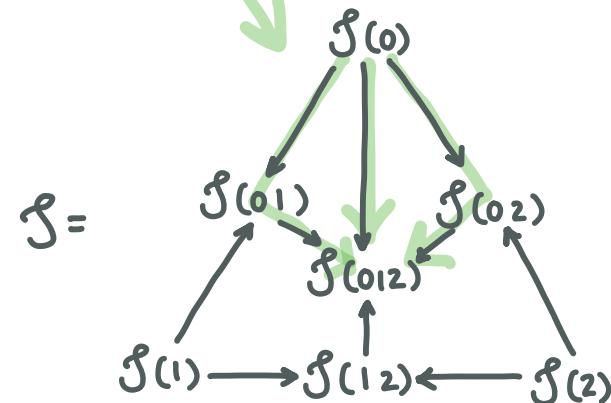
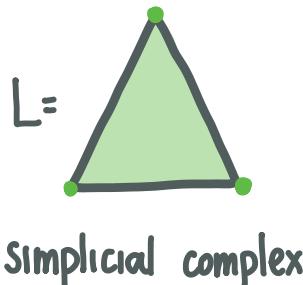
L as a poset is a category
 $\mathcal{S}: (L, \leq) \rightarrow \text{Vect}_{\mathbb{F}}$
 category of vector spaces over a field

\mathcal{S} assigns to each simplex $\tau \in L$ a vector space $\mathcal{S}(\tau)$ called the stalk of \mathcal{S} over τ
 inclusion $\tau' \subseteq \tau$ a linear map $\mathcal{S}(\tau' \subseteq \tau): \mathcal{S}(\tau') \rightarrow \mathcal{S}(\tau)$ restriction map

such that the following hold:

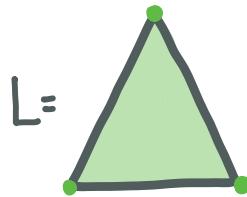


small example

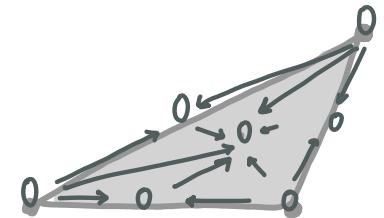
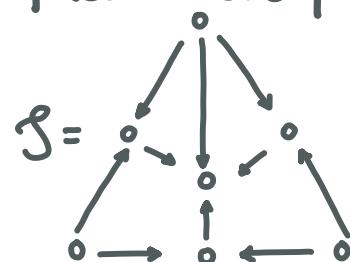


Meaningful sheaves

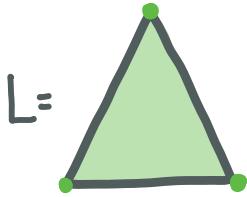
zero sheaf assigns the 0 vector space to every $\tau \in L$ and all inclusions to 0 map



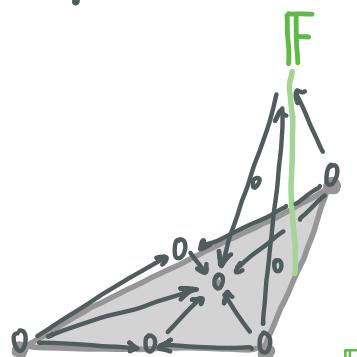
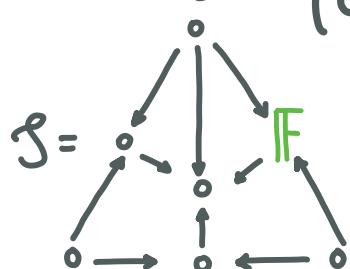
Simplicial complex



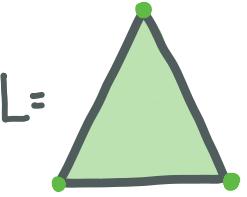
skyscraper sheaf fix a simplex $\tau \in L$, assigns $\begin{cases} \mathbb{F} & \text{to } \tau \\ 0 & \text{to } \tau' \neq \tau \end{cases}$, all inclusions to 0 map



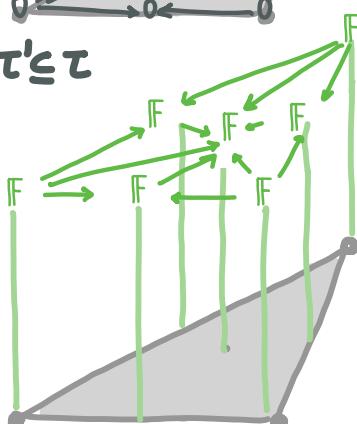
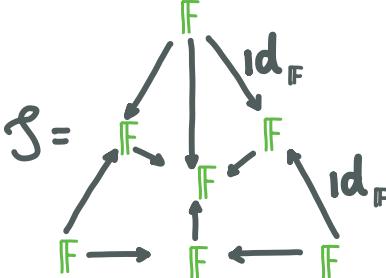
Simplicial complex



constant sheaf \mathbb{F}_c assigns \mathbb{F} to every simplex $\tau \in L$ and $\text{id}_{\mathbb{F}}$ to every inclusion $\tau' \subseteq \tau$



Simplicial complex



Sheaf Cohomology

To define a cohomology, we need to define a cochain complex.

For that we need cochain groups and coboundary maps

cochain group of L with coefficients in the sheaf \mathcal{S} is the vector space

$$C^k(L; \mathcal{S}) = \prod_{\dim \tau = k} \mathcal{S}(\tau)$$

coboundary map $\partial_s^k: C^k(L; \mathcal{S}) \longrightarrow C^{k+1}(L; \mathcal{S})$ is the linear combination $\sum (-1)^i \mathcal{S}(\tau \subseteq \tau')$

$\dim k$ $\dim k+1$

Proposition

The sequence $0 \longrightarrow C^0(L; \mathcal{S}) \xrightarrow{\partial_0^0} C^1(L; \mathcal{S}) \xrightarrow{\partial_1^0} \dots$ is a co-chain complex

We can define the sheaf cohomology of L with coefficients in \mathcal{S} as $H^k(L; \mathcal{S}) = \frac{\text{Ker } \partial^k}{\text{Im } \partial^{k-1}}$

Sheaf Cohomology

To define a cohomology, we need to define a cochain complex.

For that we need cochain groups and coboundary maps

cochain group of L with coefficients in the sheaf \mathcal{S} is the vector space

$$C^k(L; \mathcal{S}) = \prod_{\dim \tau = k} \mathcal{S}(\tau)$$

coboundary map $\partial_s^k: C^k(L; \mathcal{S}) \longrightarrow C^{k+1}(L; \mathcal{S})$ is the linear combination $\sum (-1)^i \mathcal{S}(\tau \subseteq \tau')$

$\dim k$ $\dim k+1$

Proposition

The sequence $0 \longrightarrow C^0(L; \mathcal{S}) \xrightarrow{\partial_0^0} C^1(L; \mathcal{S}) \xrightarrow{\partial_1^0} \dots$ is a co-chain complex

We can define the sheaf cohomology of L with coefficients in \mathcal{S} as $H^k(L; \mathcal{S}) = \frac{\text{Ker } \partial^k}{\text{Im } \partial^{k-1}}$

NOTE

When $\mathcal{S} = \mathbb{F}_L$ is the constant sheaf, the sheaf cohomology is the classical simplicial cohomology

Sheaves in the wild

In practice, sheaves can be considered as way to encode very complex data structures without having to build overly complex, overfitted models.

Sheaves are good, for example, to represent time-series, images, and videos.

v-sampling sheaf $\dots \leftarrow V \rightarrow O \leftarrow V \rightarrow O \leftarrow \dots$ where V a vector space

(for discrete sampling)

supported on a subset A of L is a sheaf whose stalks are V in each cell in A and O everywhere else

H^0 sheaf cohomology can be interpreted as the number of connected solutions / global sections of the system defined by the linear transformations + the simplicial structure

Some interesting applications

opinion dynamics / spectral theory

topological filters for signal processing

Robert Ghrist, Jakob Hansen

Georg Essl, Michael Robinson

Sheaves in the wild

In practice, sheaves can be considered as way to encode very complex data structures without having to build overly complex, overfitted models.

Sheaves are good, for example, to represent time-series, images, and videos.

v-sampling sheaf $\dots \leftarrow V \rightarrow O \leftarrow V \rightarrow O \leftarrow \dots$ where V a vector space

(for discrete sampling)

supported on a subset A of L is a sheaf whose stalks are V in each cell in A and O everywhere else

H^0 sheaf cohomology can be interpreted as the number of connected solutions / global sections of the system defined by the linear transformations + the simplicial structure

Some interesting applications

opinion dynamics / spectral theory

topological filters for signal processing

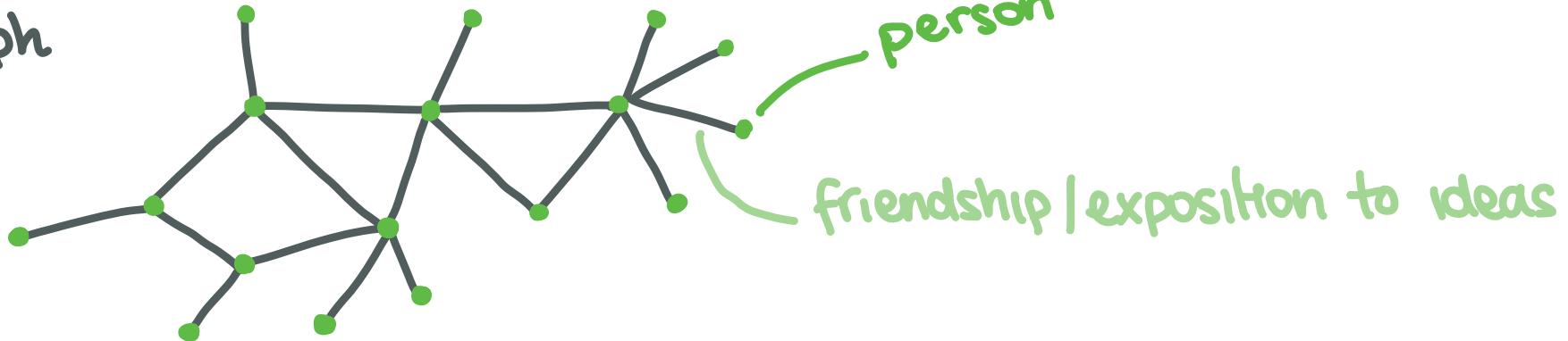
Robert Ghrist, Jakob Hansen

Georg Essl, Michael Robinson

Opinion Dynamics on sheaves

Jakob Hansen, Robert Ghrist

K is a graph



$C^0(K; \mathcal{S})$

0-chains

private opinion distribution

$C^1(K; \mathcal{S})$

1-chains

pairwise discussion

$\partial^0: C^0 \rightarrow C^1$

coboundary

aggregate of public disagreement

$L(C^0(K; \mathcal{S}))$

laplacian

"average" of private disagreement

$H^0(K; \mathcal{S})$

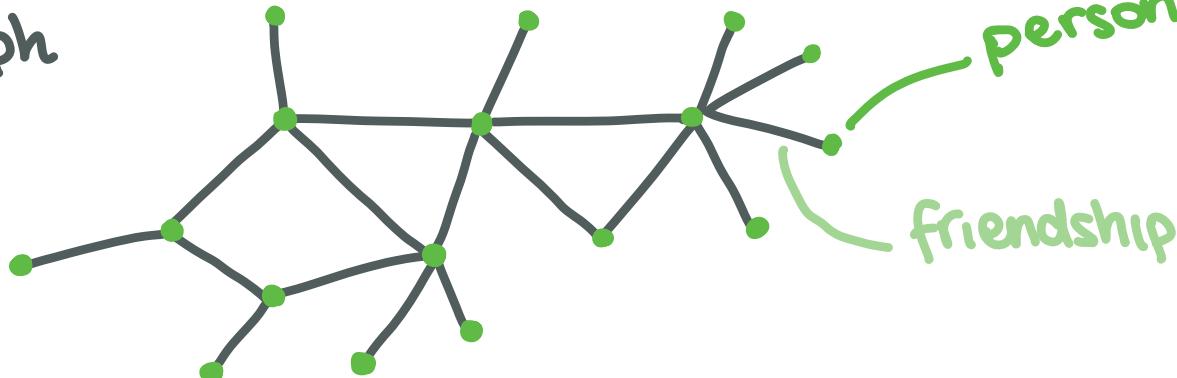
global sections

harmonic opinions

Opinion Dynamics on sheaves

Jakob Hansen, Robert Ghrist

K is a graph



$C^0(K; \mathcal{S})$

0-chains

private opinion distribution

$C^1(K; \mathcal{S})$

1-chains

pairwise discussion

$\partial^0: C^0 \rightarrow C^1$

coboundary

aggregate of public disagreement

$L(C^0(K; \mathcal{S}))$

laplacian

"average" of private disagreement

$H^0(K; \mathcal{S})$

global sections

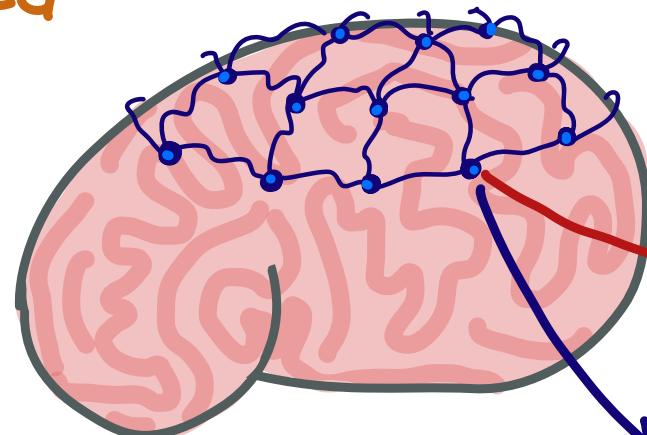
harmonic opinions

public agreement

My research

TOPOLOGY + BRAIN FUNCTION

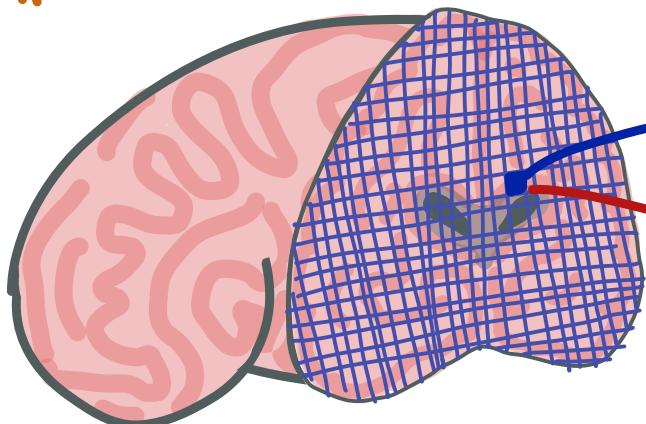
EEG



electrical current $ee \in \mathbb{R} \times \text{time} \in \mathbb{N}$

relative position in space $(x,y) \in \mathbb{R}^2$

MRI



relative position in space $(x,y,z) \in \mathbb{R}^3$

color $cc \in \mathbb{R} \times \text{time} \in \mathbb{N}$

Topological Data Analysis : getting started

ARTICLES

- Persistent Homology - Theory & Practice H. Edelsbrunner and D. Morozov
Barcodes: the persistent topology of data R. Ghrist
Topology and data G. Carlsson
High-dimensional Topological Data Analysis F. Chazal
Persistence theory: from quiver representations to data analysis S. Oudot

BOOKS

- Elementary Applied Topology R. Ghrist
Computational Topology: an introduction H. Edelsbrunner and J.L. Harer
Topology for computing A.J. Zomorodian
Topological Signal Processing M. Robinson

Topological Data Analysis : the Community

Applied algebraic topology network Youtube channel + weekly seminar series

WinCompTop - Women in computational topology Google group + newsletter

The conferences

ATMCS = Algebraic Topology : Methods, Computations and Science every 2 years

SOCG = Symposium on Computational Geometry every year

The journals

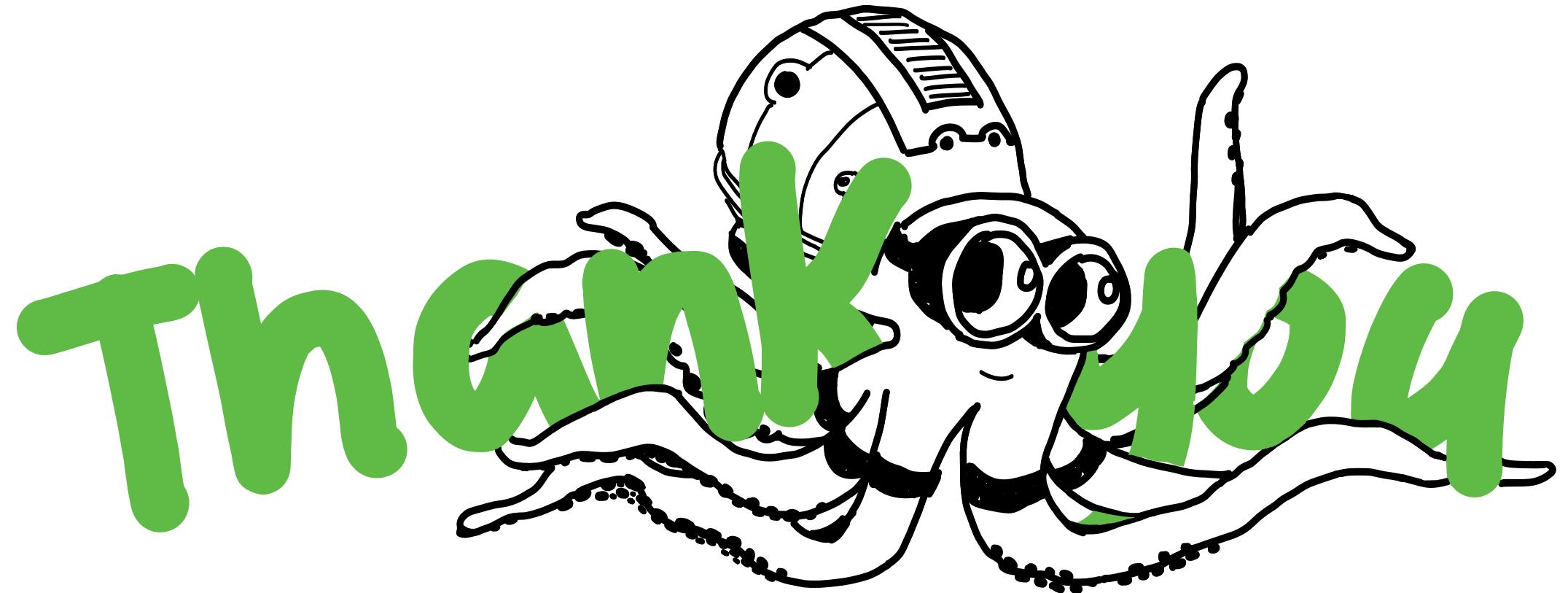
Journal of Applied and computational topology

Homotopy, Homology and Applications

SIAM Journal of Applied Algebra and Geometry

Discrete and Computational Geometry

Foundations of computational Mathematics



my e-mail: apatania@uvm.edu
my office: Innovation E442