

Topological Perspectives On Stratification Learning

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Stratification learning driven by computation:

- What is stratification learning?
- Stratification in statistics and machine learning
- Stratification learning using geometry
- Stratification learning based on homology and cohomology
- Sheaf-theoretic stratification learning (Brown and Wang (2018))
- Discrete stratified Morse theory (Knudson and Wang (2018))
- Challenges and opportunities

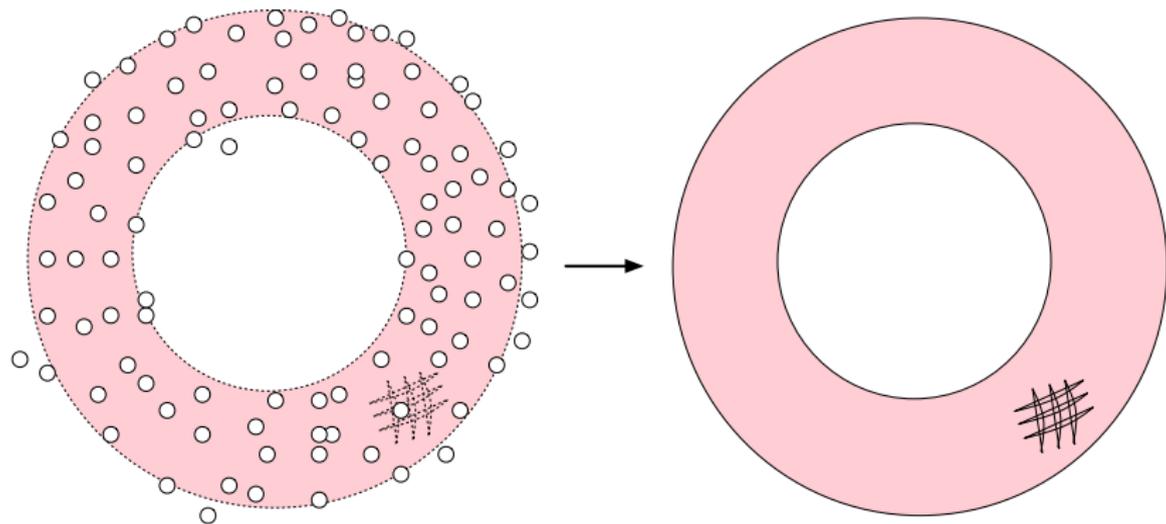
Acknowledgement

- NSF IIS-1513616
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- Collaborators: Sayan Mukherjee, Paul Bendich, Adam Brown, Kevin Knudson, Yulong Liang

What is Stratification Learning?

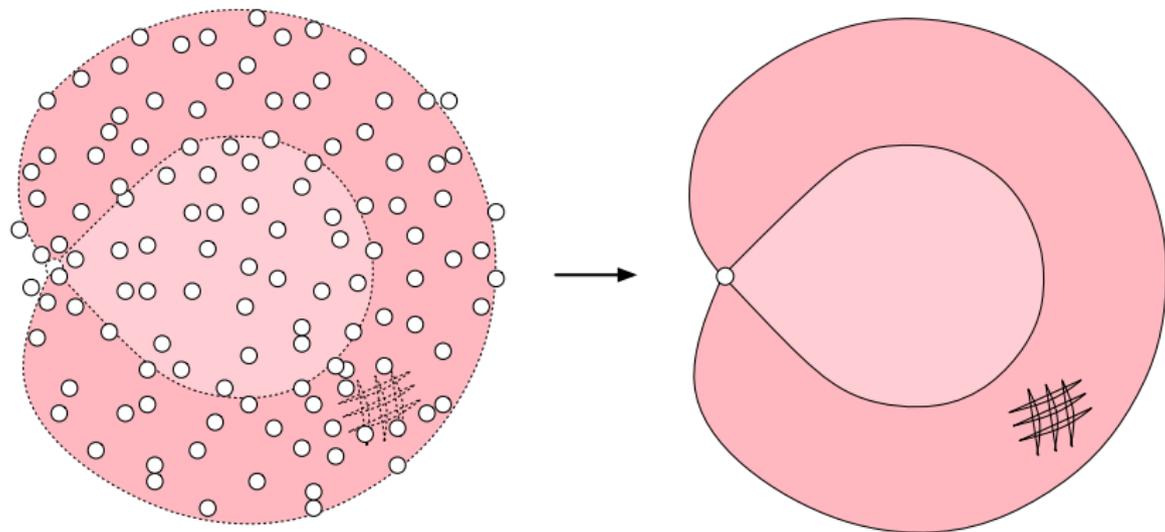
Manifold Learning

Assumption: data is sampled from some unknown manifold



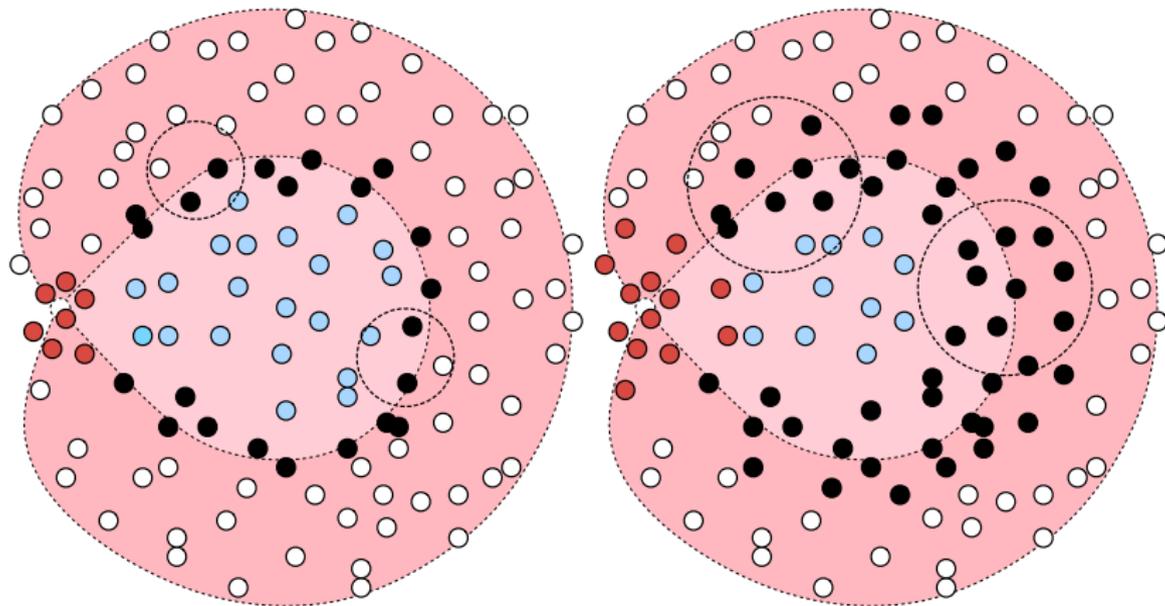
Stratification Learning

Assumption: data is sampled from some unknown underlying space with mixed dimensionality and singularities (beyond manifold)



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Topological Stratifications

Definition

A topological stratification of a topological space X is a filtration by closed subsets

$$\emptyset = X_{-1} \subset X_0 \subset X_1 \subset \cdots \subset X_n = X$$

such that $X_i - X_{i-1}$ is an i -dimensional (topological) manifold.

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+ conditions on how the strata fit together.

Topological Stratification

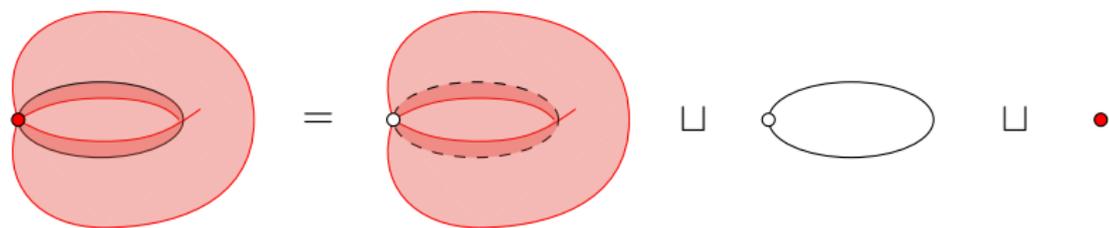


Figure: Example of a topological stratification of a *pinched torus*.

Computing Stratifications

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Instead: Using only the tools practically available to us, how can we partition our space into strata so that our tools can be used to distinguish two different strata, but can not distinguish two points in the same stratum?

Available tools: Statistics, geometry, homology, cohomology.

Stratification Learning

We use the word *stratification learning* loosely to mean:

An *unsupervised, exploratory, clustering* process that infers a decomposition of data into disjoint subsets that capture recognizable and meaningful structural information.

Goal: better understand the complexity of the data.

Stratification in Statistics and Machine Learning

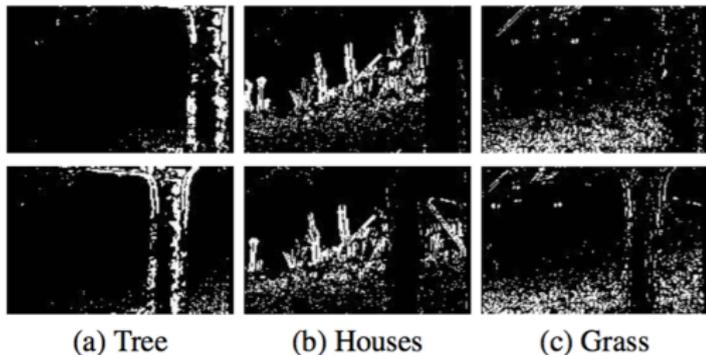
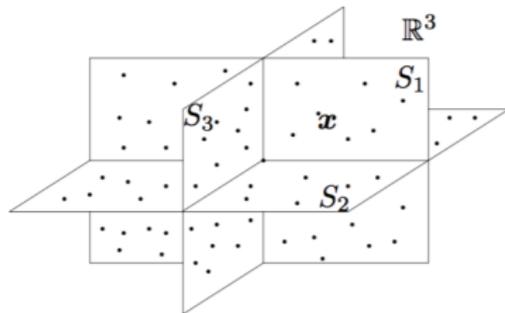
Statistical Approaches

- Inferences of mixture models
- (Local) dimensionality estimation
- With or without linearity assumptions
- Vidal et al. (2005); Haro et al. (2005); Lerman and Zhang (2010)
- Challenges: How to handle complex (nonlinear) singularities?
- Opportunities: Can we combine statistical methods with topological ones?

Generalized Principal Component Analysis (GPCA)

Vidal et al. (2005)

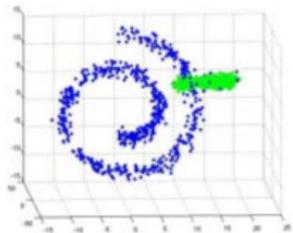
- Estimating a mixture of linear subspaces from sample data points.
- A constrained nonlinear least squares problem.
- Minimizes the error between the noisy points and their projections onto the linear subspaces.
- Examples: estimating a mixture of motion models from 2D imagery.



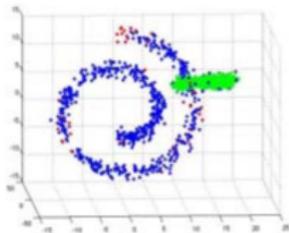
Detecting Mixed Density and Dimensionality

Haro et al. (2005)

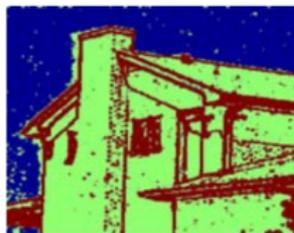
- Simultaneously soft clustering and estimating the mixed dimensionality and density.
- No assumption on linear subspaces.
- Maximum likelihood estimation of a Poisson mixture model (PMM).
- Cluster the data according to the complexity (dimensionality) of the underlying possible multiple manifolds.



(d) PMM ($J = 2$)



(e) PMM ($J = 3$)



Probabilistic Recovery of Multiple Linear Subspaces

Lerman and Zhang (2010)

- l_p energy minimization for modeling data by multiple subspaces.
- Simultaneous recover a number of K fixed subspaces by minimizing the l_p -averaged distances of the sampled data points from any subspace.
- $0 < p \leq 1$: all underlying subspaces can be precisely recovered by l_p minimization with overwhelming probability.
- $K > 1$ and $p > 1$: the underlying subspaces cannot be recovered or even nearly recovered by l_p minimization.

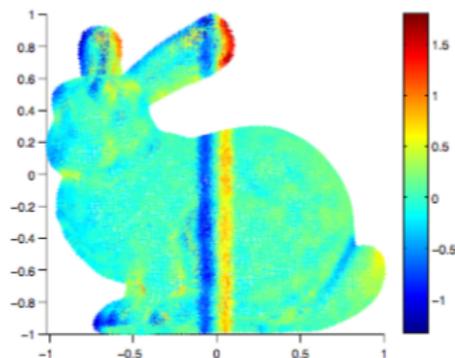
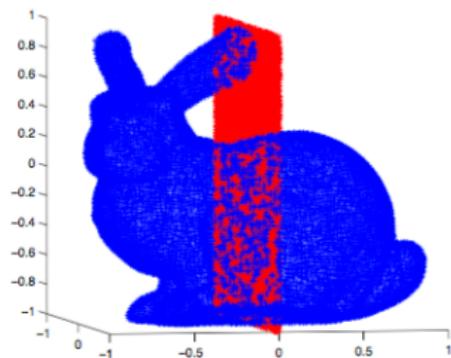
$$e_{l_p}(\mathcal{X}, L_1, \dots, L_K) = \sum_{\mathbf{x} \in \mathcal{X}} \text{dist}^p \left(\mathbf{x}, \bigcup_{i=1}^K L_i \right)$$

Stratification Learning Using Geometry

Graph Laplacians on Singular Manifolds

Belkin et al. (2012)

- Singularities: *Intersections* (where different manifolds come together) and *sharp edges* (where a manifold sharply changes direction).
- The behavior of graph Laplacian near singularities is quite different from that in the interior of the manifolds.
- In the interior of the manifold: graph Laplacian converges to the Laplace-Beltrami operator.
- Near singularities: graph Laplacian tends to a first-order differential operator.



Stratification Learning based on (Co)Homology

Homological Stratification

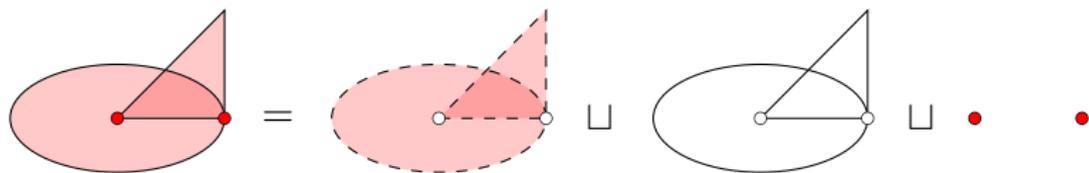


Figure: Example of a homological stratification of a *sundial*.

Homological Stratification: An Incomplete Review

- Rourke and Sanderson (1999): *Homology stratifications and intersection homology*.
- Goresky and MacPherson (1983): *Intersection homology II*.
- Bendich et al. (2007): *Inferring local homology from sampled stratified spaces*.
- Bendich and Harer (2011): *Persistent intersection homology*.
- Bendich et al. (2012): *Local homology transfer and stratification learning*.
- Skraba and Wang (2014): *Approximating Local Homology from Samples*.
- Nanda (2017): *Local cohomology and stratification*.
- Brown and Wang (2018): *Sheaf-theoretic stratification learning*.
- Challenges: One step closer to (certain) topological stratification?
- Opportunities: Beyond (co)homological stratification.

Local Homology

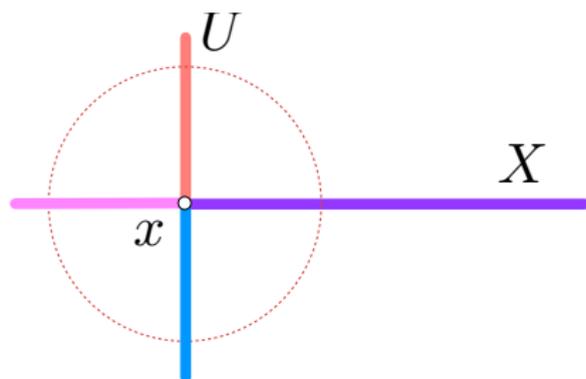
The local homology of a point $x \in X$ is defined as

$$H_{\bullet}(X, X - x) := \varinjlim_{U \ni x} H_{\bullet}(X, X - U)$$

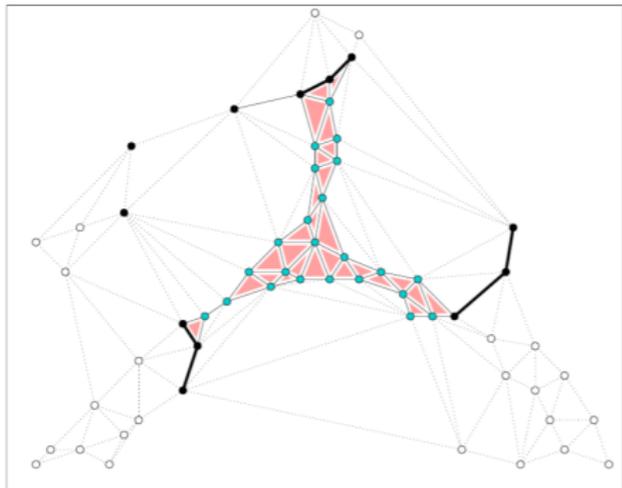
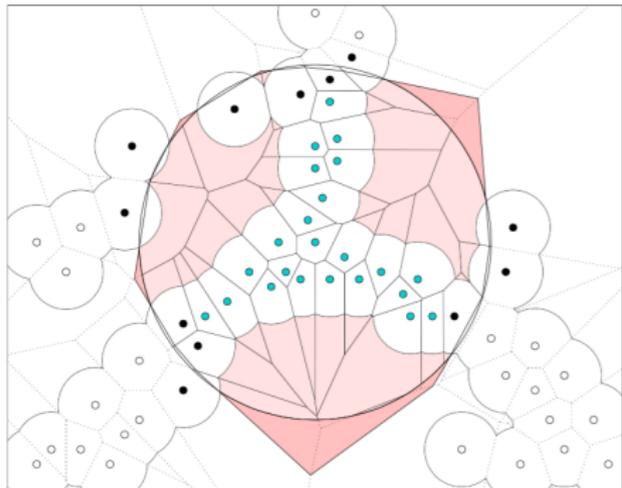
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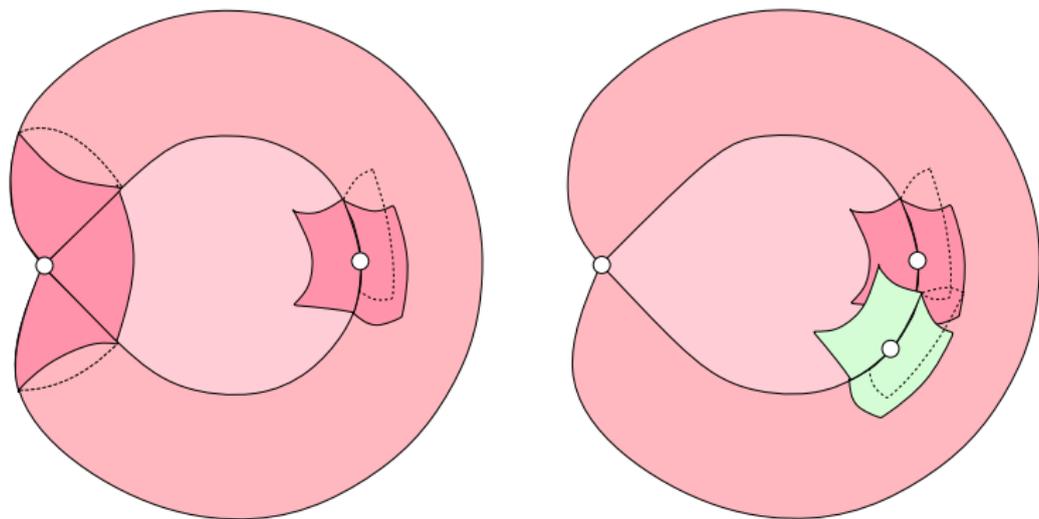
Infer Local Homology from Samples



Bendich et al. (2007)

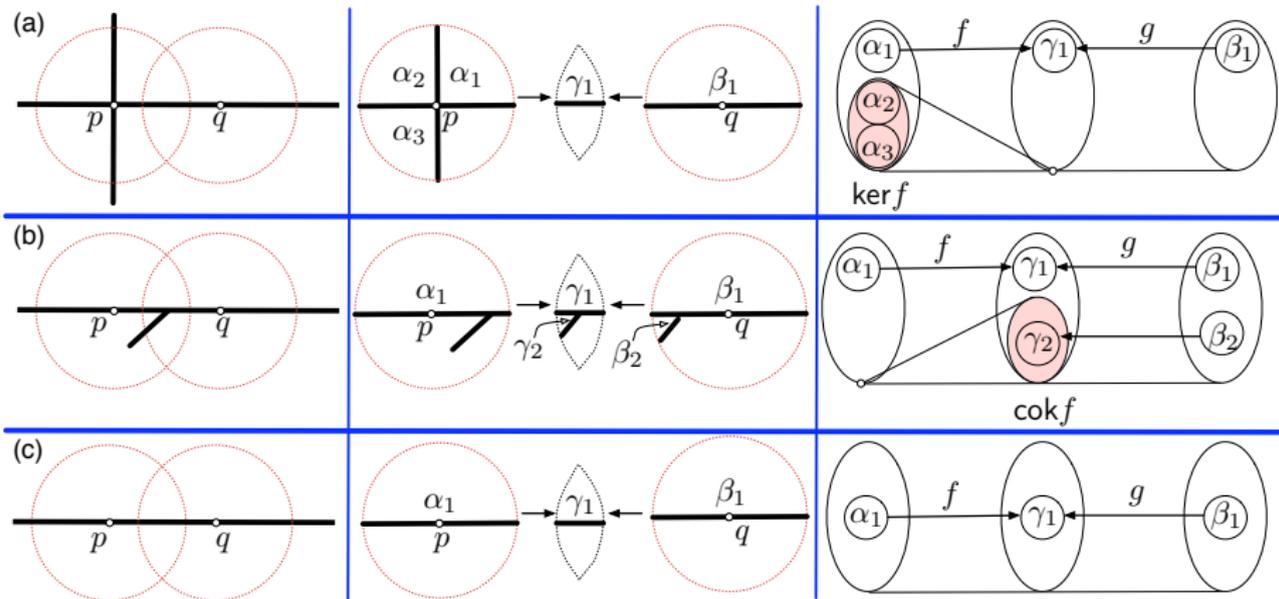
Local Homology Transfer

Local homology may have the same rank but with different structure.



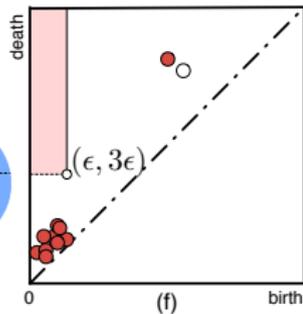
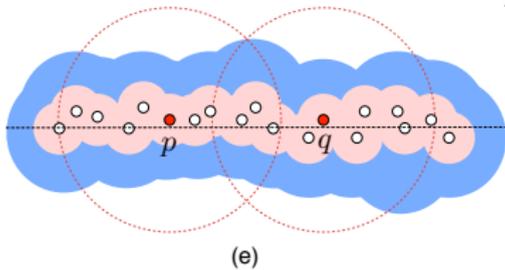
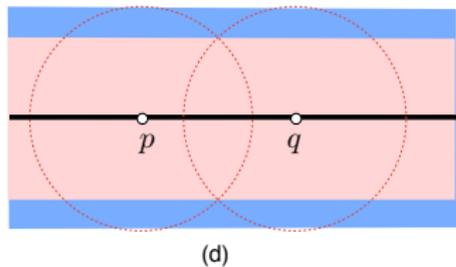
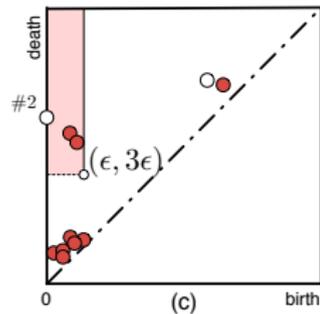
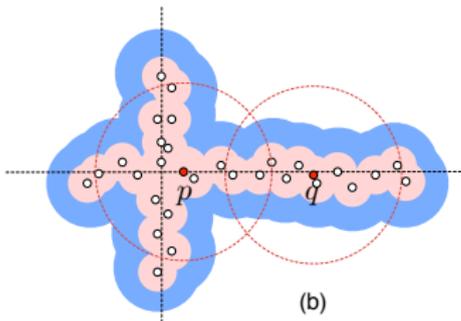
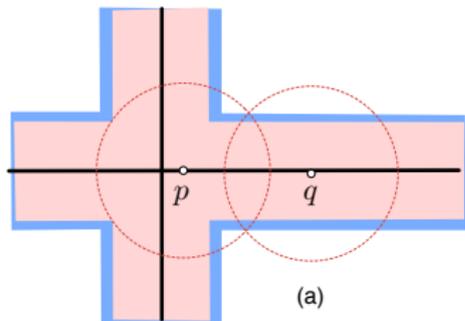
Bendich, Wang, Mukherjee (2012)

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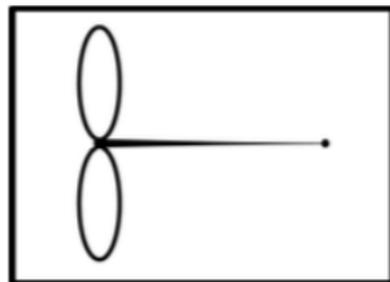
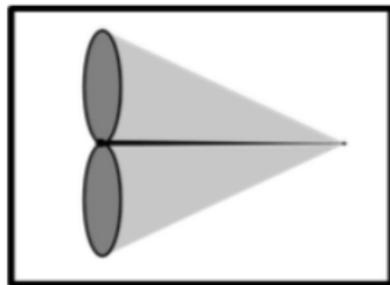


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Local Cohomology and Stratification

Nanda (2017)

- Recover the canonical (or, coarsest) stratification of a given regular CW complex into cohomology manifolds, each of which is a union of cells.
- Cosheaves: capture variations in cohomology of cellular neighborhoods across the underlying complex.
- Efficient distributed computation.



Sheaf-Theoretic Stratification Learning

Key Idea

- Use the language of sheaf theory to generalize existing algorithms, e.g. homological stratification.
- Aim to investigate stratifications which can be computed using homological methods and beyond.

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such that there are some nice properties:

- 1 $\mathcal{F}(\emptyset) = 0$;
- 2 $\mathcal{F}(U \subset U) = \text{id}_U$.
- 3 If $U \subset V \subset W$, then $\mathcal{F}(U \subset W) = \mathcal{F}(U \subset V) \circ \mathcal{F}(V \subset W)$.
- 4 If $\{V_i\}$ is an open cover of U , and $s_i \in \mathcal{F}(V_i)$ has the property that $\forall i, j, \mathcal{F}((V_i \cap V_j) \subset V_i)(s_i) = \mathcal{F}((V_j \cap V_i) \subset V_j)(s_j)$, then there exists a unique $s \in \mathcal{F}(U)$ such that $\forall i, \mathcal{F}(V_i \subset U)(s) = s_i$.

Local Homology

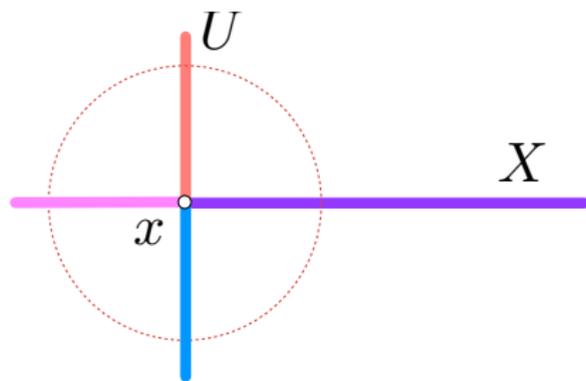
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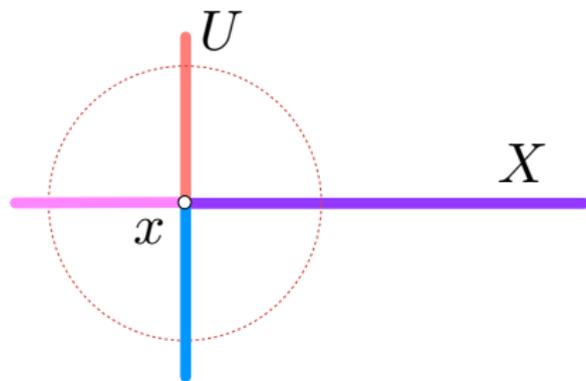
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Local Homology Sheaf

Local homology can be viewed as a sheaf on X :

$$\mathcal{L}(U) = H_{\bullet}(X, X - U)$$



\mathcal{F} -Stratifications

Suppose \mathcal{F} is a sheaf on a topological space X .

Definition

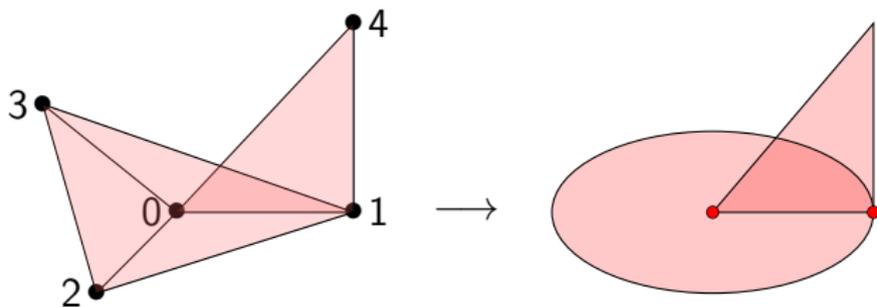
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such that \mathcal{F} is locally constant ^a when restricted to $X_i - X_{i-1}$, for each i .

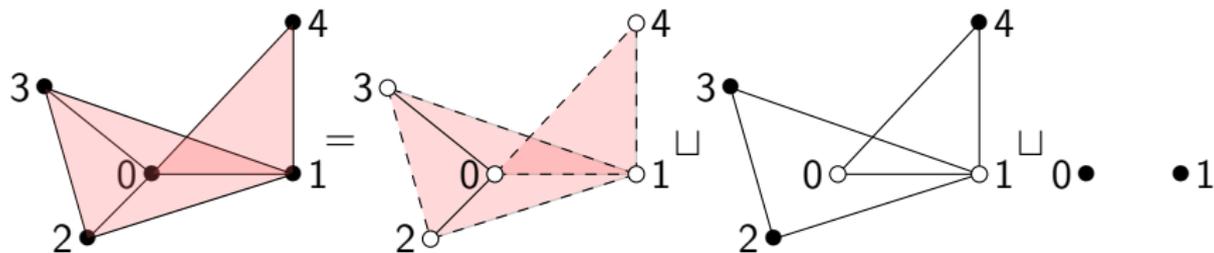
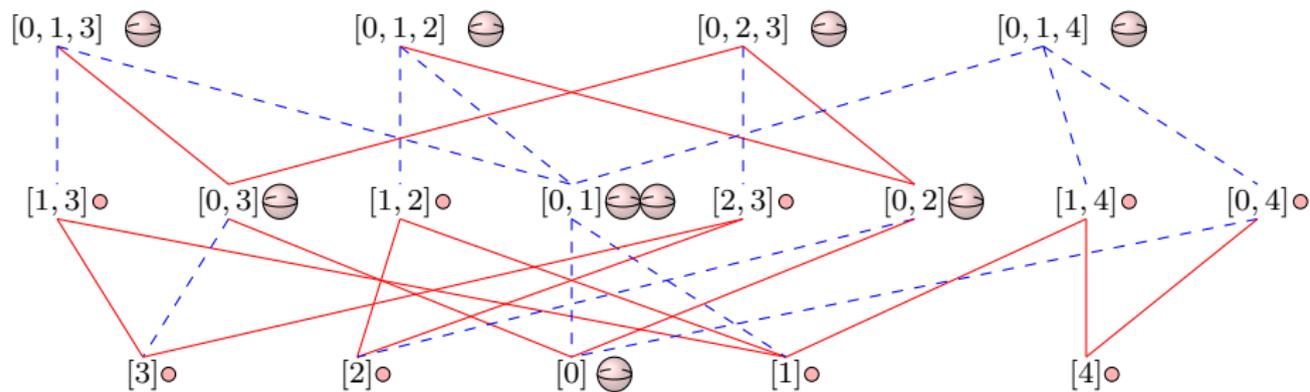
^aA sheaf \mathcal{F} is a *constant sheaf* if \mathcal{F} is isomorphic to the pull back of a sheaf \mathcal{G} on a single point space $\{x\}$, along the projection map $p: X \rightarrow x$. A sheaf \mathcal{F} is *locally constant* if for all $x \in X$, there is a neighborhood U of x such that $\mathcal{F}|_U$ (the restriction of \mathcal{F} to U), is a constant sheaf.

Triangulation of the Sundial

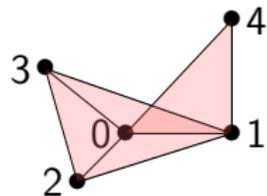
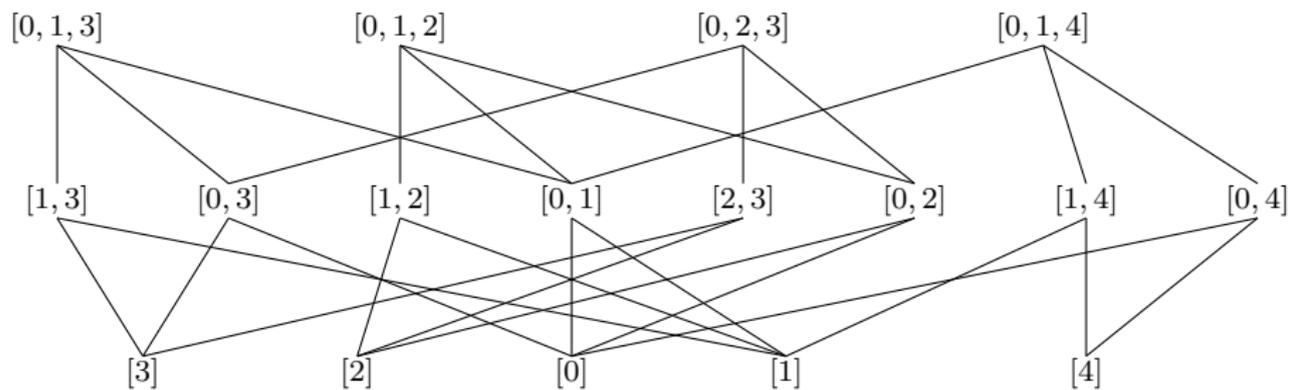


Sheaf-Theoretic Stratifications by Example

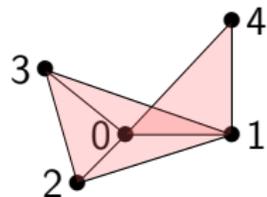
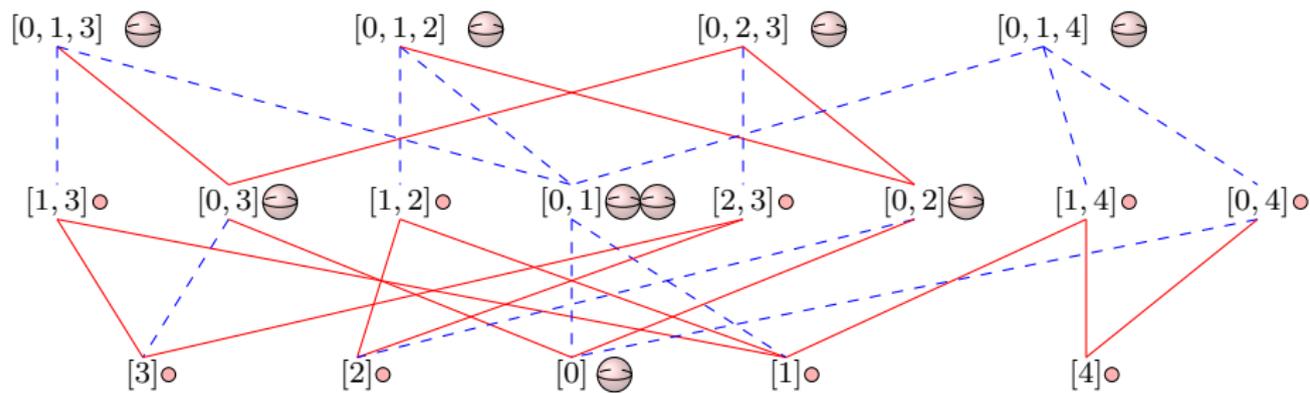
Using labeled Hasse diagram:



Hasse Diagram



Labeled Hasse Diagram



Inductively defined stratification

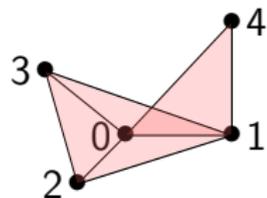
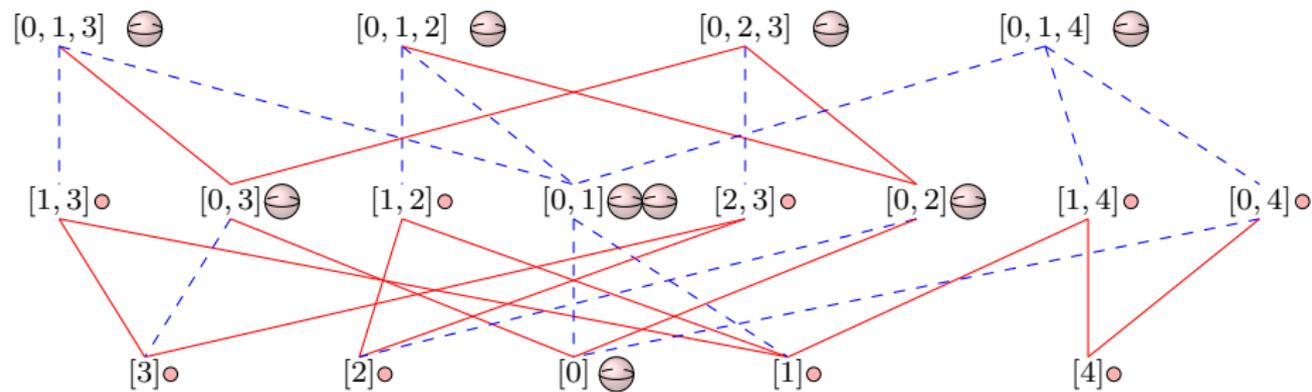
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Inductively defined stratification

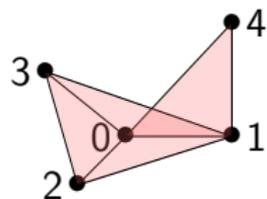
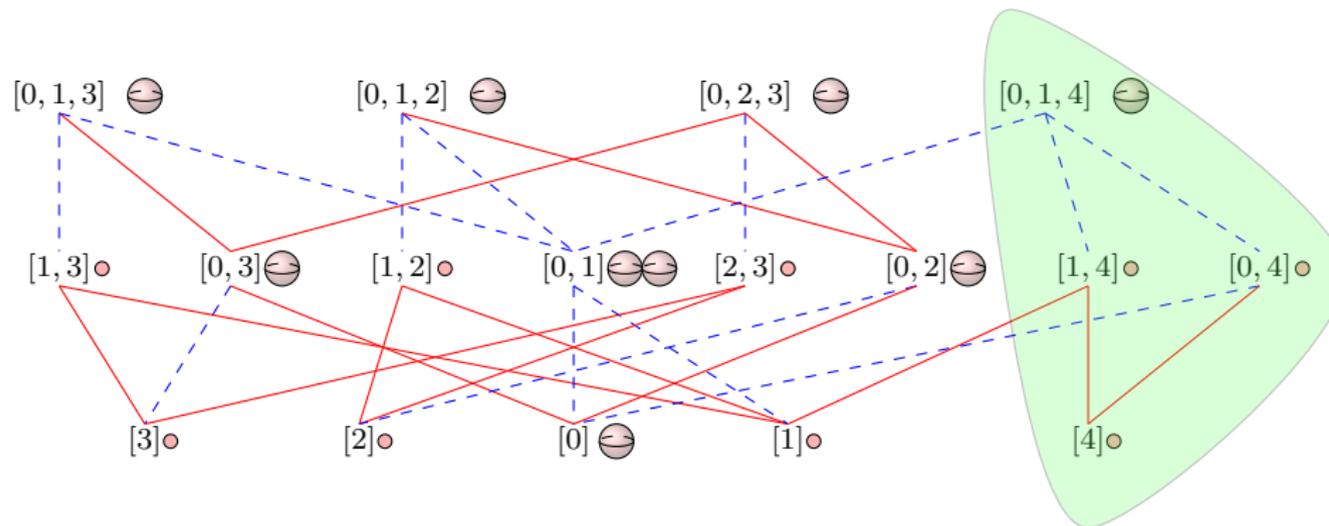
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$$S_n = \{\sigma \in X : \mathcal{L}|_{\text{St}\sigma} \text{ is constant}\}$$

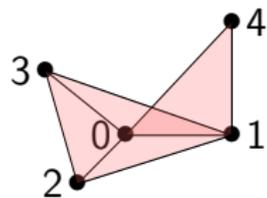
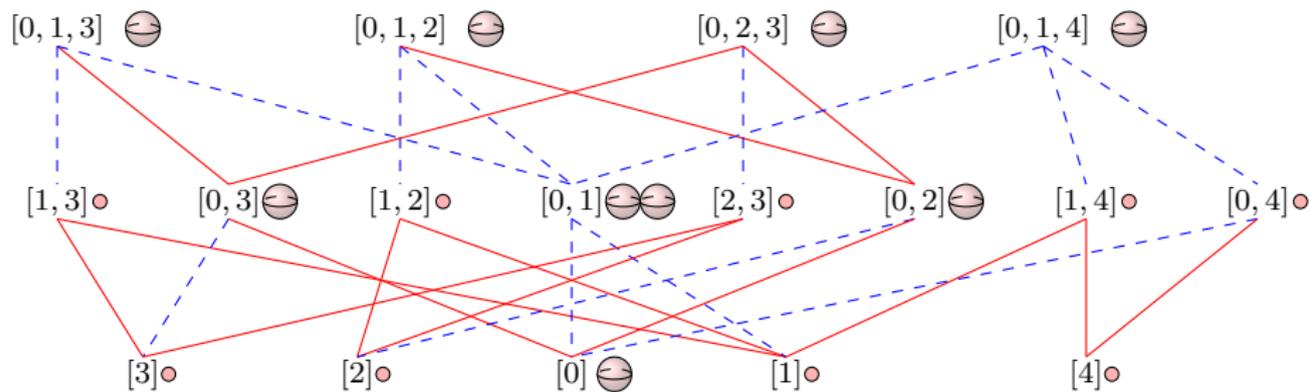
Labeled Hasse Diagram, $St[4]$



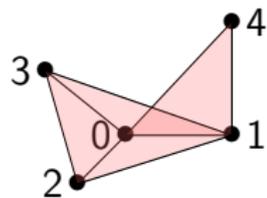
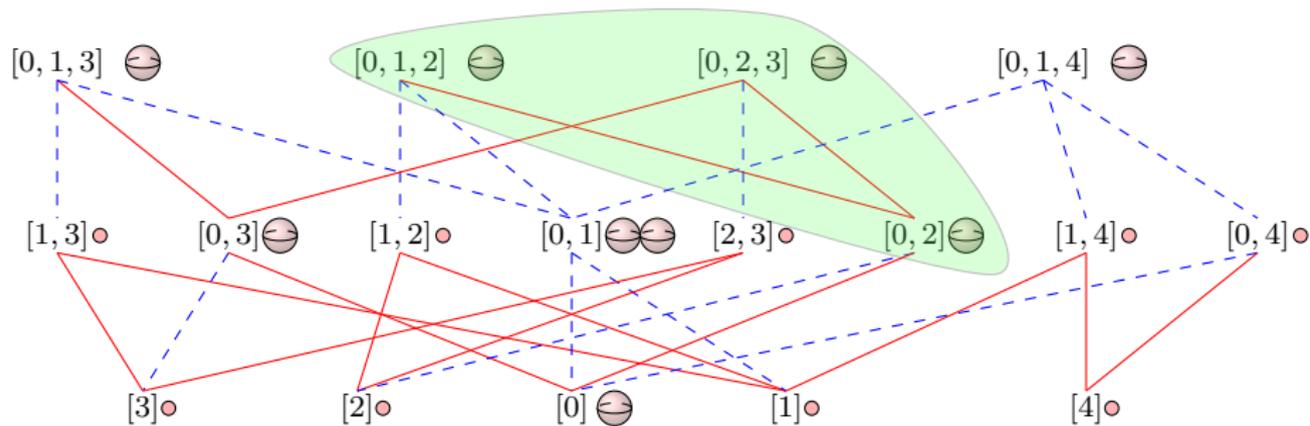
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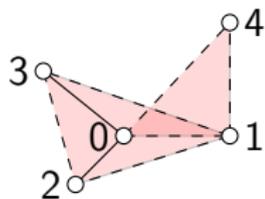
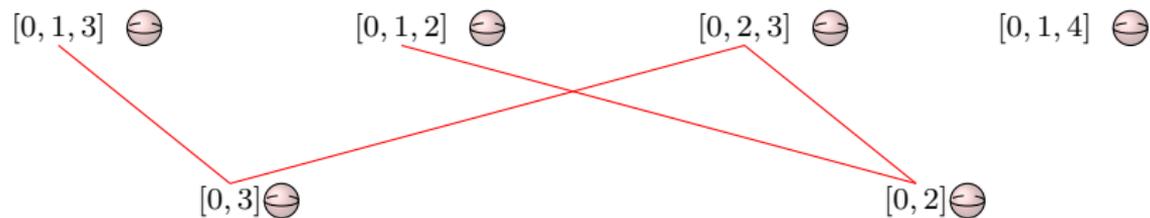
Labeled Hasse Diagram, $\text{St}[0, 2]$



Labeled Hasse Diagram, $\text{St}[0, 2]$



Labeled Hasse Diagram of S_2



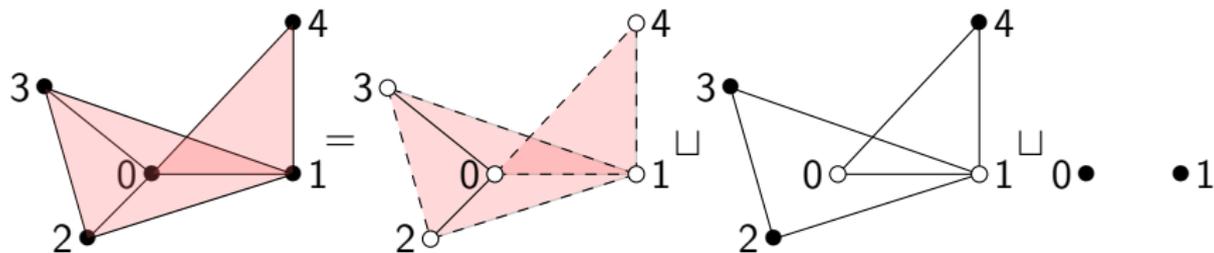
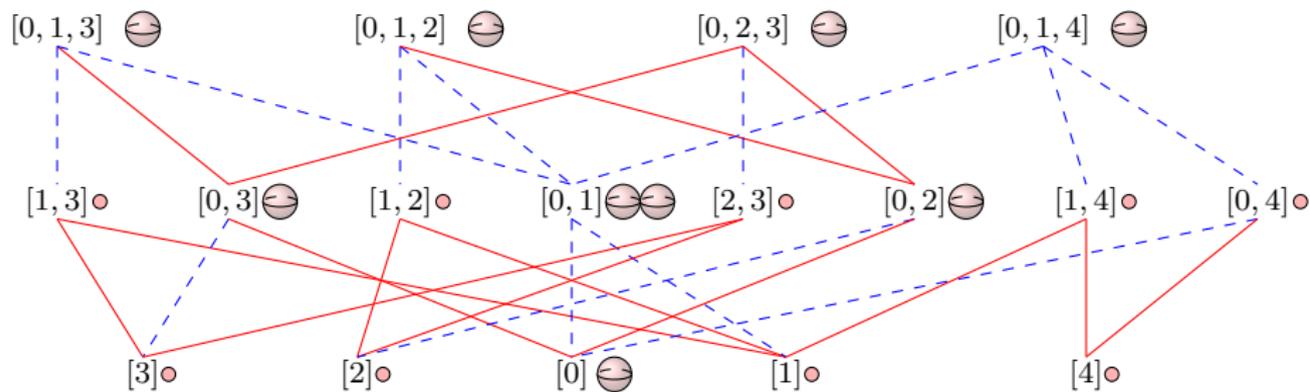
Inductively defined stratification

Inductive step: Restrict the local homology sheaf from X to the complement of S_n and repeat:

$$S_{n-1} = \{\sigma \in X - S_n : \mathcal{L}|_{\text{St}_{(X-S_n)}\sigma} \text{ is constant}\}$$

Sheaf-Theoretic Stratifications by Example

Using labeled Hasse diagram:



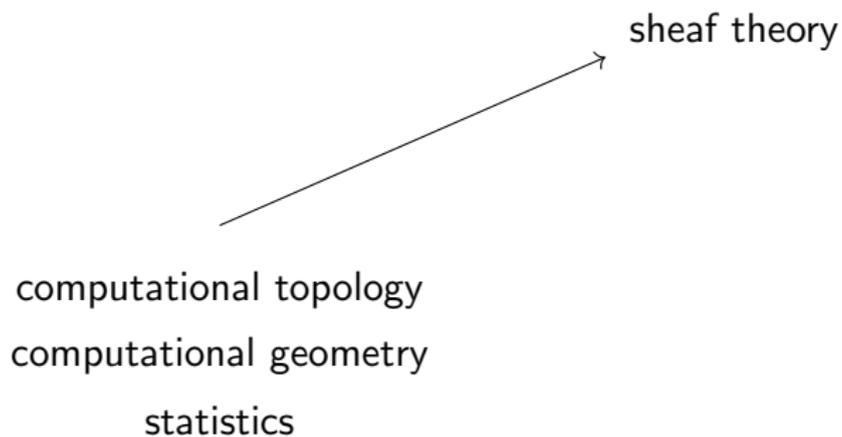
Highlight

computational topology

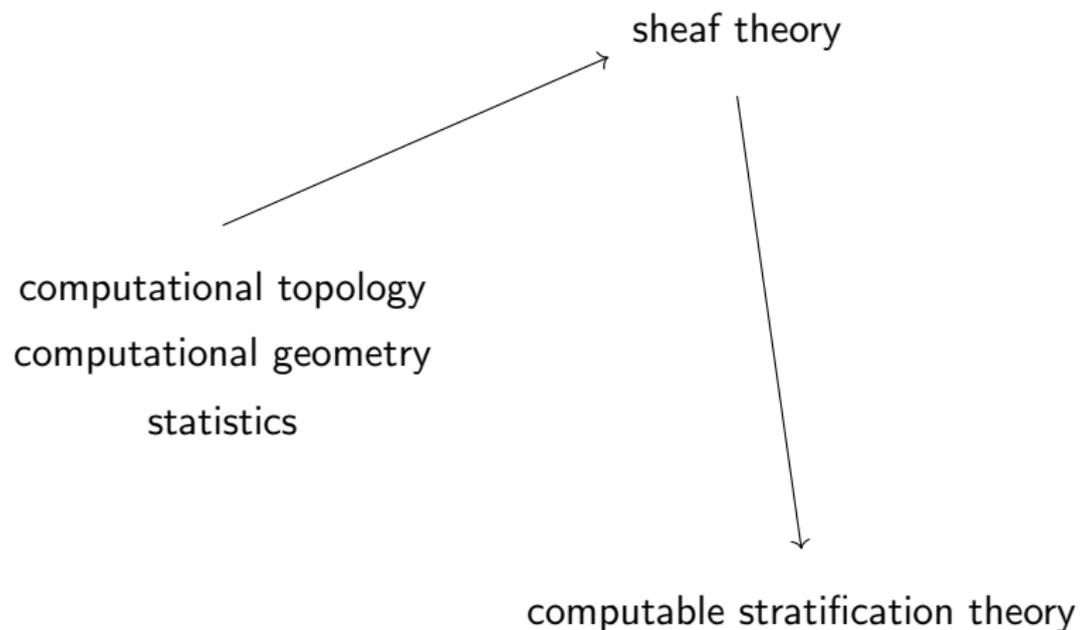
computational geometry

statistics

Highlight



Highlight

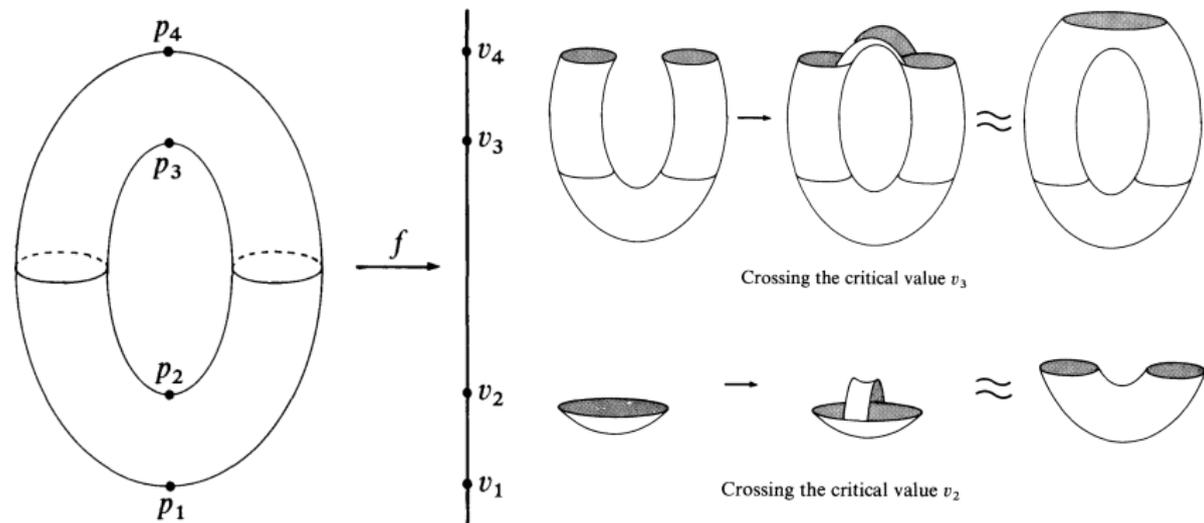


Discrete Stratified Morse Theory for Stratification Learning

Key Ideas

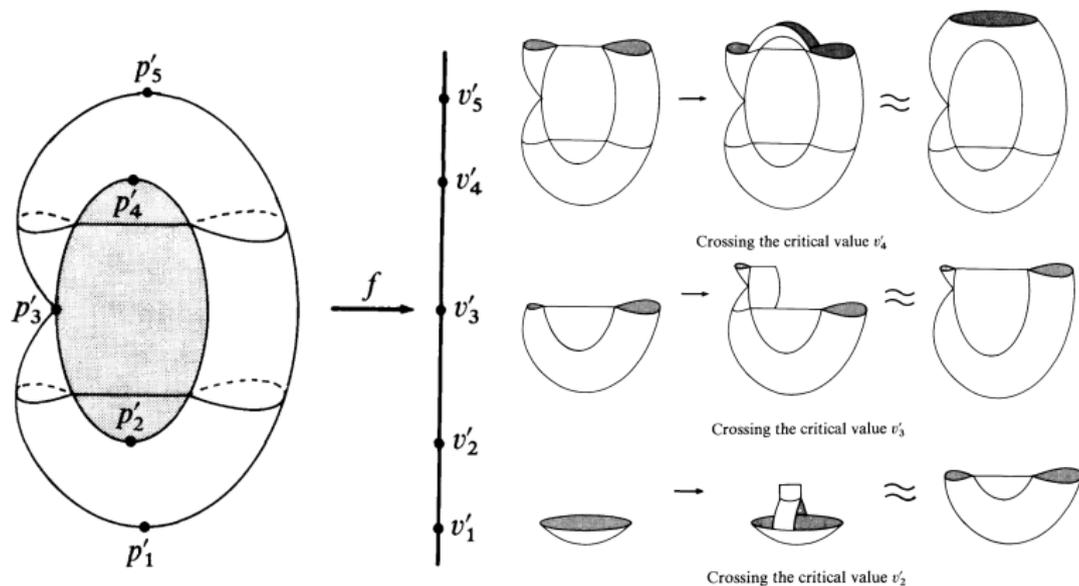
- Data as a simplicial complex equipped with an arbitrary function
- When the function is not a discrete Morse function, we can introduce a *stratification* so that the function restricted to each strata is a discrete Morse function.
- Data simplification and compression

Classic Morse Theory by Picture



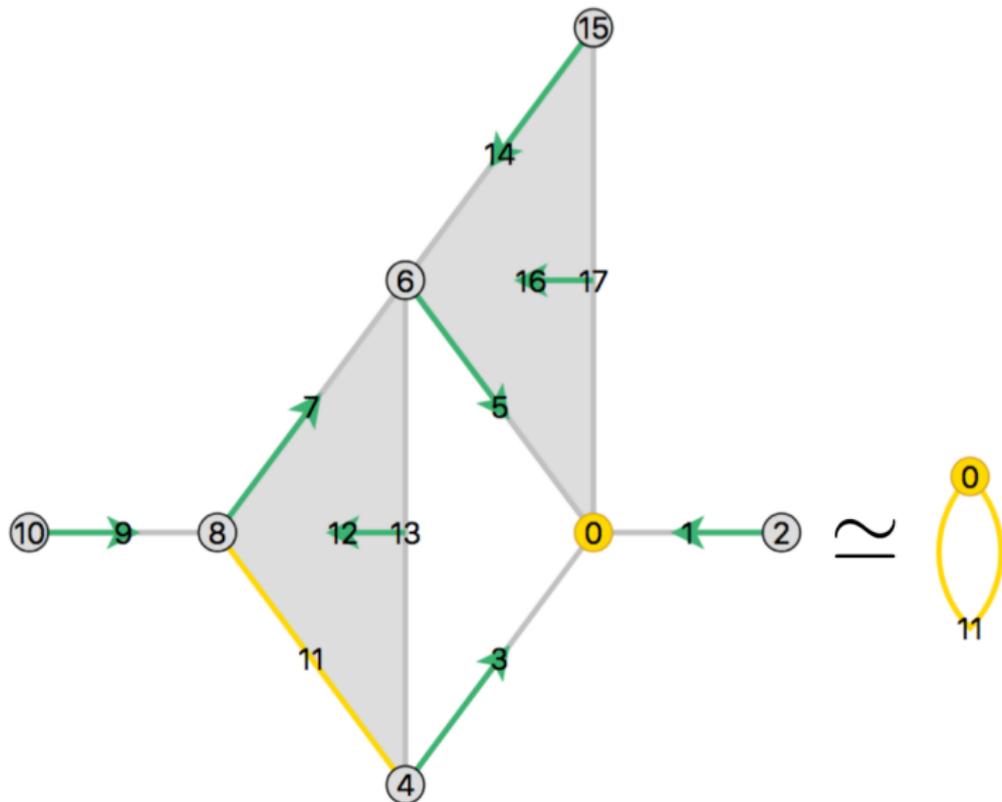
Goresky and MacPherson (1988)

Stratified Morse Theory by Picture



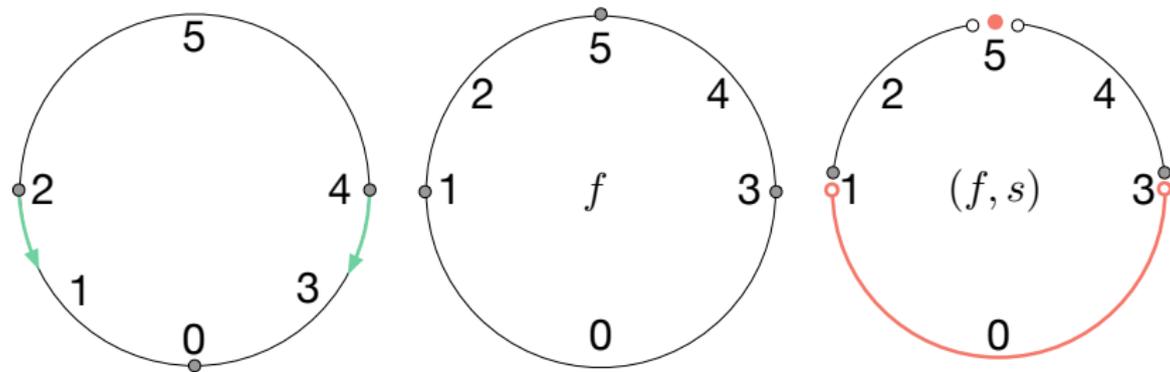
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Discrete Morse Theory by Picture

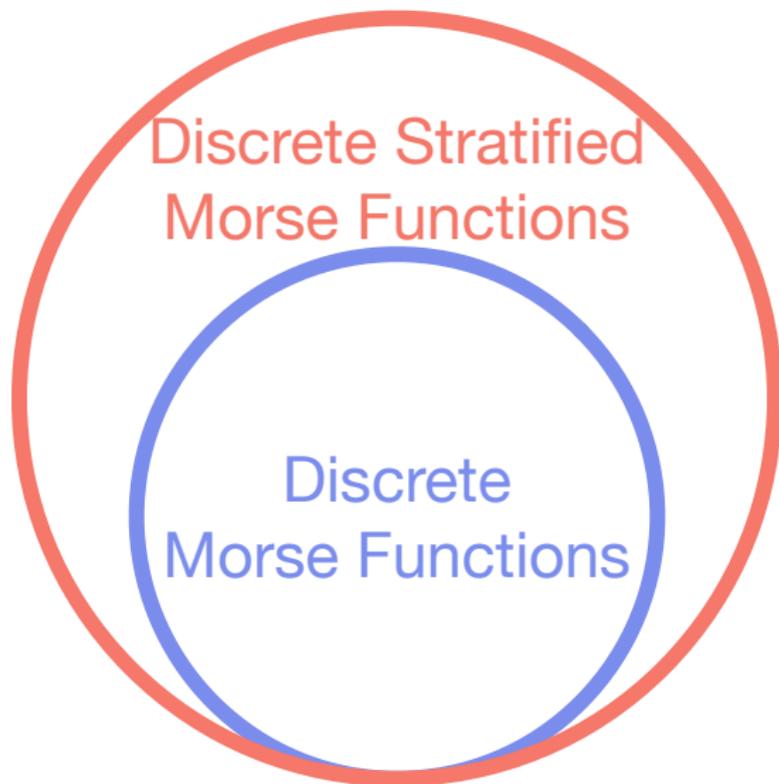


Discrete Stratified Morse Theory by Picture

When the function is not a discrete Morse function, we can introduce a *stratification* so that the function restricted to each strata is a discrete Morse function.



Highlight: Space of Functions



A Combinatorial Adaptation of Stratified Morse Theory

- Data: A simplicial complex K equipped with an arbitrary, real-valued function $f : K \rightarrow \mathbb{R}$.

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- Applications: data reduction and simplification; parallel computation; imaging and visualization.

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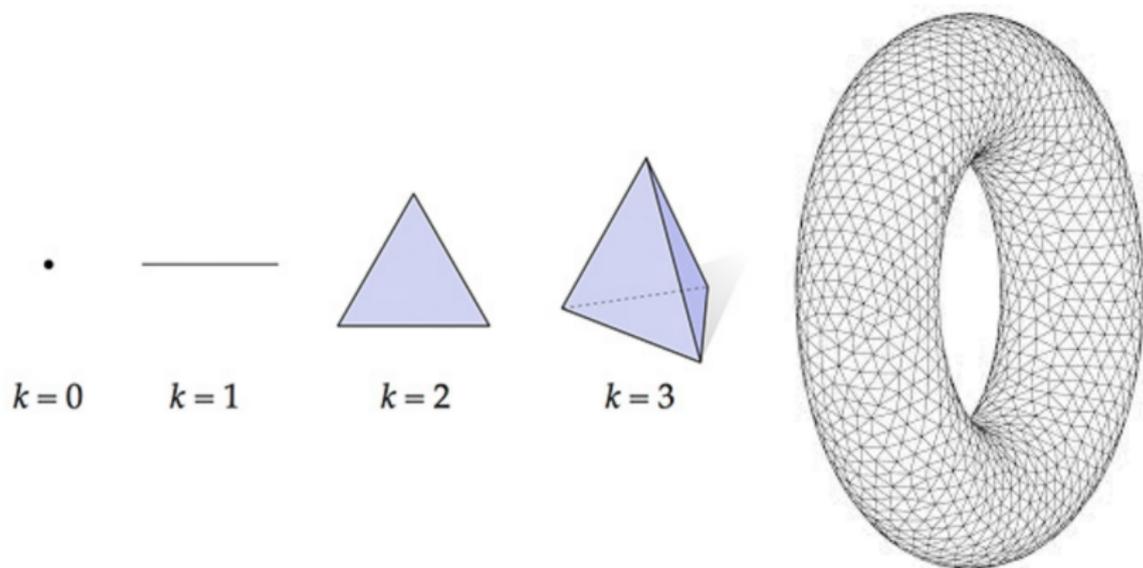
- Data: A simplicial complex K equipped with an arbitrary, real-valued function $f : K \rightarrow \mathbb{R}$.
- Goal: Construct a *discrete stratified Morse function* (DSMF) on the data by introducing a stratification.
- Key point: A function is a stratified Morse function iff it is a Morse function when restricted to each stratum in the classical sense (roughly speaking).
- Applications: data reduction and simplification; parallel computation; imaging and visualization.
- Relevant references: Goresky and MacPherson (1988), Matsumoto (1997), Forman (1998), Forman (2002),...

High-Level Results

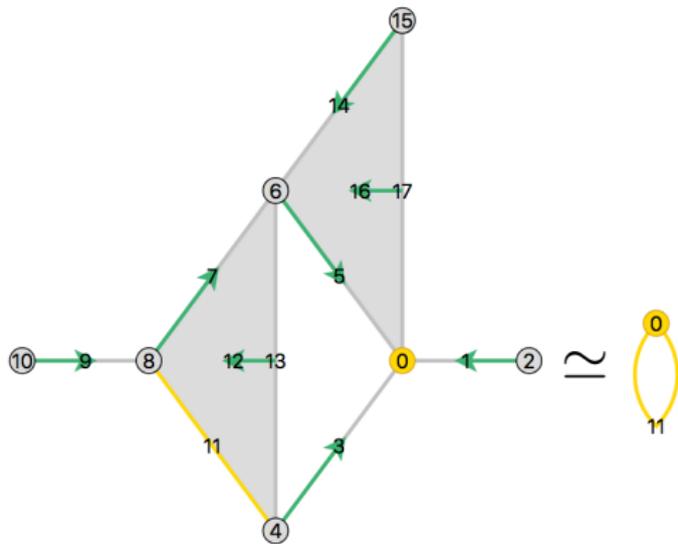
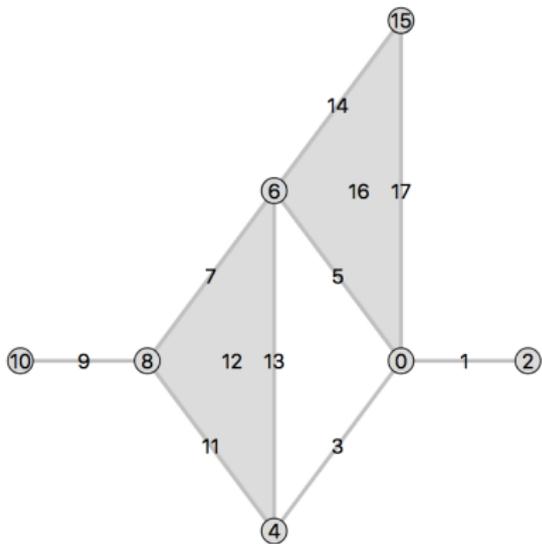
- Relate the *topology* of a finite simplicial complex with the *critical simplices* of a discrete stratified Morse function (DSMF) defined on the complex.
- Provide an algorithm that constructs a DSMF on any finite simplicial complex equipped with a real-valued function.

Discrete Morse Theory (DMT)

Data as a function on a simplicial complex



DMT: an example



Key Definitions

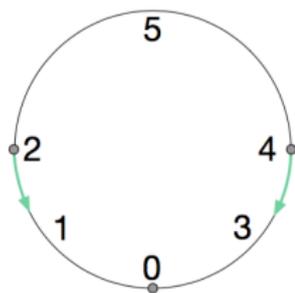
- $U(\alpha) = \{\beta^{(p+1)} > \alpha \mid f(\beta) \leq f(\alpha)\}$
- $L(\alpha) = \{\gamma^{(p-1)} < \alpha \mid f(\gamma) \geq f(\alpha)\}$

Definition

A function $f : K \rightarrow \mathbb{R}$ is a *discrete Morse function* if for every $\alpha^{(p)} \in K$,
(i) $|U(\alpha)| \leq 1$ and (ii) $|L(\alpha)| \leq 1$.

Definition

A simplex $\alpha^{(p)}$ is *critical* if (i) $|U(\alpha)| = 0$ and (ii) $|L(\alpha)| = 0$.



$$\alpha = f^{-1}(0) : U(\alpha) = L(\alpha) = \emptyset$$

$$\alpha = f^{-1}(1) : U(\alpha) = \emptyset, L(\alpha) = \{f^{-1}(2)\}$$

$$\alpha = f^{-1}(2) : U(\alpha) = \{f^{-1}(1)\}, L(\alpha) = \emptyset$$

Level subcomplex

- Given $c \in \mathbb{R}$, we have the *level subcomplex*

$$K_c = \cup_{f(\alpha) \leq c} \cup_{\beta \leq \alpha} \beta.$$

- K_c contains all simplices α of K such that $f(\alpha) \leq c$ along with all of their faces.

Two fundamental results of DMT

Theorem (DMT-A, Forman (1998))

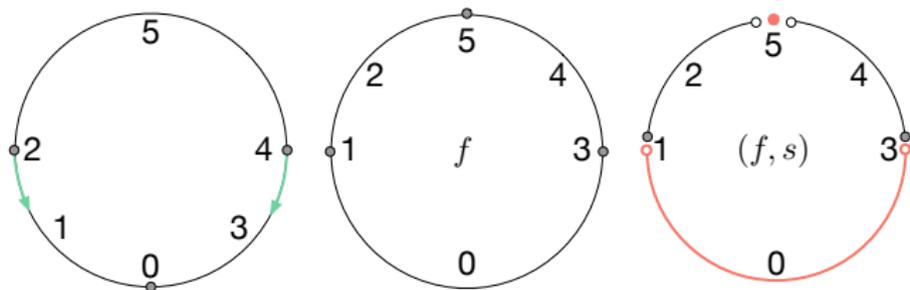
Suppose the interval $[a, b]$ contains no critical value of f . Then K_b is homotopy equivalent to K_a . In fact, K_a is a deformation retract of K_b and moreover, K_b simplicially collapses onto K_a .

Theorem (DMT-B, Forman (1998))

Suppose $\sigma^{(p)}$ is a critical simplex with $f(\sigma) \in (a, b]$, and there are no other critical simplices with values in $(a, b]$. Then K_b is homotopy equivalent to attaching a p -cell $e^{(p)}$ along its entire boundary; that is,

$$K_b = K_a \cup_{e^{(p)}} e^{(p)}.$$

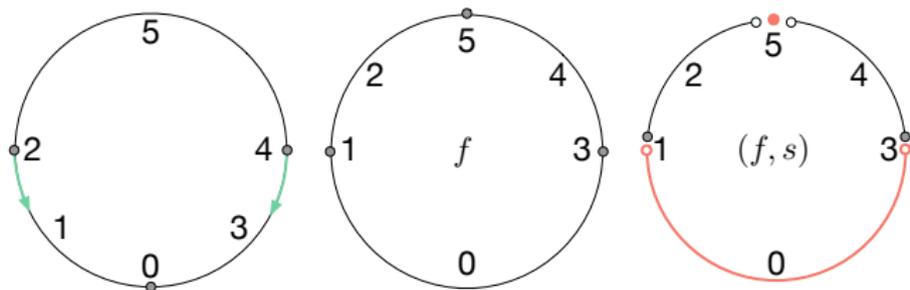
When DMT is not applicable (middle picture)



$$\alpha = f^{-1}(0) : U(\alpha) = \emptyset, L(\alpha) = \{f^{-1}(1), f^{-1}(3)\}$$

- $f : K \rightarrow \mathbb{R}$ is not a DMF (not well behaved)

When DMT is not applicable (middle picture)

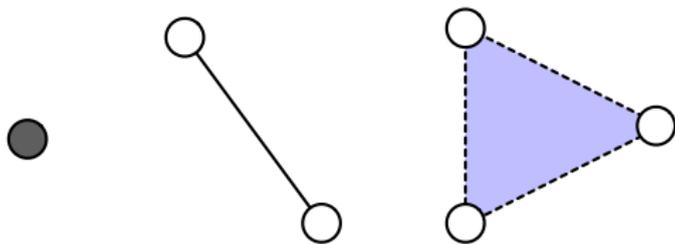


$$\alpha = f^{-1}(0) : U(\alpha) = \emptyset, L(\alpha) = \{f^{-1}(1), f^{-1}(3)\}$$

- $f : K \rightarrow \mathbb{R}$ is not a DMF (not well behaved)
- **Solution:** Introduce a stratification s of K such that f restricted to each stratum is a DMF

Discrete Stratified Morse Theory

Open simplices



Stratified simplicial complex

Definition

A *stratification* of a simplicial complex K is a finite filtration

$$\emptyset = K^0 \subset K^1 \subset \dots \subset K^m = K,$$

such that K^1 is a subcomplex of K , and for each i , $K^i - K^{i-1}$ is a locally closed subset of K ^a.

^aA subset $L \subset K$ is locally closed if it is the intersection of an open and a closed set in K .

- A simplicial complex K equipped with a stratification is referred to as a *stratified simplicial complex*.
- A connected component of the space $K^i - K^{i-1}$ is a *stratum*; and the collection of all strata is denoted by $\mathcal{S} = \{S_j\}$.
- A stratification is an assignment from K to the set \mathcal{S} , denoted $s : K \rightarrow \mathcal{S}$.

Key Definitions

- Given a simplicial complex K equipped with a stratification $s : K \rightarrow \mathcal{S}$, and a function $f : K \rightarrow \mathbb{R}$,

$$U_s(\alpha) = \{\beta^{(p+1)} > \alpha \mid s(\beta) = s(\alpha) \text{ and } f(\beta) \leq f(\alpha)\},$$

$$L_s(\alpha) = \{\gamma^{(p-1)} < \alpha \mid s(\gamma) = s(\alpha) \text{ and } f(\gamma) \geq f(\alpha)\}.$$

Definition

A function $f : K \rightarrow \mathbb{R}$ (equipped with s) is a *discrete stratified Morse function* if for every $\alpha^{(p)} \in K$, (i) $|U_s(\alpha)| \leq 1$ and (ii) $|L_s(\alpha)| \leq 1$.

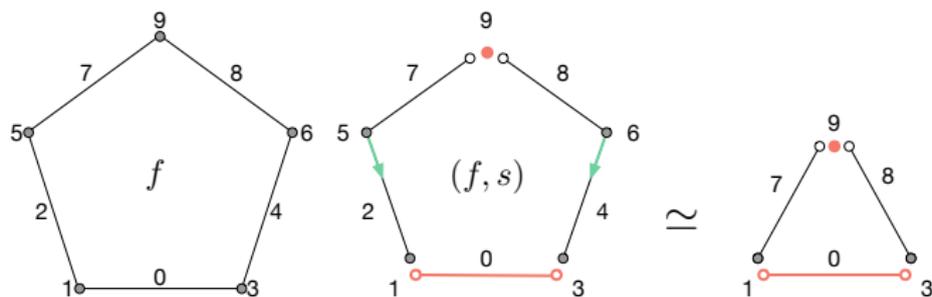
Definition

A simplex $\alpha^{(p)}$ is *critical* if (i) $|U_s(\alpha)| = 0$ and (ii) $|L_s(\alpha)| = 0$.

Violators

Definition

A simplex $\alpha^{(p)}$ is a *violator* (of the conditions associated with a discrete Morse function) if one of these conditions hold: (i) $|U(\alpha)| \geq 2$; (ii) $|L(\alpha)| \geq 2$; (iii) $|U(\alpha)| = 1$ and $|L(\alpha)| = 1$.



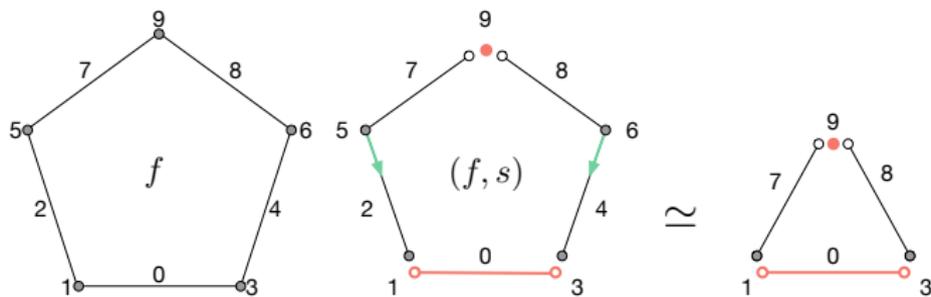
Violator $\alpha = f^{-1}(0)$, $L(\alpha) = \{f^{-1}(1), f^{-1}(3)\}$

Critical $\alpha = f^{-1}(7)$, $L(\alpha) = \{f^{-1}(9)\}$, $L_s(\alpha) = \emptyset$

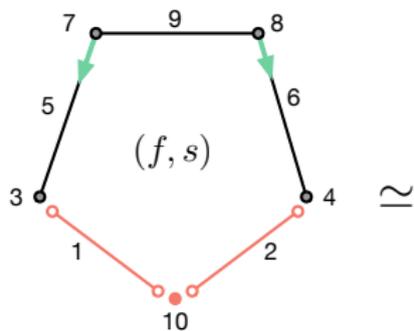
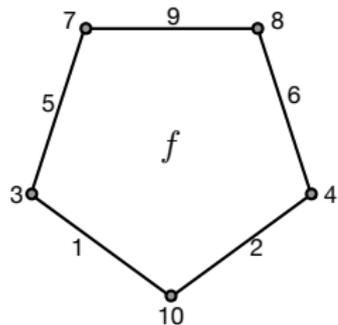
Algorithm

- (Lazy) Make every violator its own stratum; the connected components of the remaining pieces are the other strata.
- (Aggressive) Remove violators one at a time by increasing dimension, and after each removal, check to see if what remains is a discrete Morse function globally.

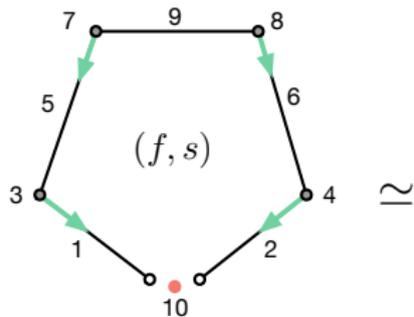
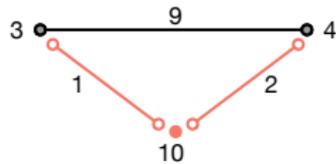
Demo: <https://leong1016.github.io/dsmt/>



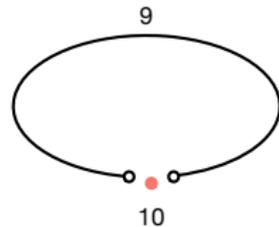
Algorithm: Upside-down pentagon



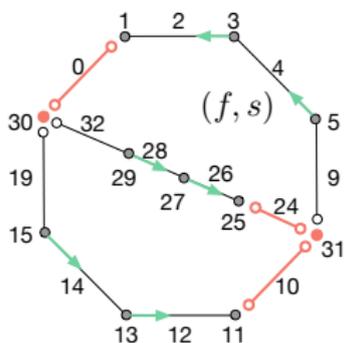
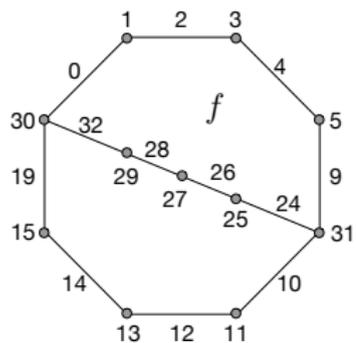
\approx



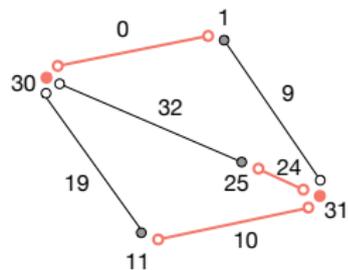
\approx



Algorithm: Split Octagon



\approx



Sublevel set

- *Sublevel set* of an open simplicial complex K : $\forall c \in \mathbb{R}$,

$$K_c = \cup_{f(\alpha) \leq c} \alpha.$$

- K_c contains all open simplices α of K such that $f(\alpha) \leq c$.
- Suppose that K is a simplicial complex equipped with a stratification s and a discrete stratified Morse function $f : K \rightarrow \mathbb{R}$.

Two fundamental results of DSMT

A map between two stratified sets $f : \mathbb{X} \rightarrow \mathbb{Y}$ is strata-preserving if it maps each stratum in \mathbb{X} bijectively onto some stratum in \mathbb{Y} .

Theorem (DSMT-A, Knudson and Wang (2018))

Suppose the interval $(a, b]$ contains no critical value of f . Then K_b is strata-preserving homotopy equivalent to K_a .

Theorem (DSMT-B, Knudson and Wang (2018))

Suppose $\sigma^{(p)}$ is a critical simplex with $f(\sigma) \in (a, b]$, and there are no other critical simplices with values in $(a, b]$. Then K_b is homotopy equivalent to attaching a p -cell $e^{(p)}$ along its boundary in K_a ; that is,

$$K_b = K_a \cup_{e^{(p)}|_{K_a}} e^{(p)}.$$

Challenges and Opportunities

Stratification Learning with Computational Topology

- Combining statistics with topological methods?
- Combining geometric with topological approaches?
- What are other sheaves that could be used in the sheaf-theoretic framework for stratification learning? We are currently considering geometric ones.
- What about sheaves beyond homology/cohomology?
- Computability?
- Unifying DSTM and sheaf-theoretic framework for stratification learning?

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