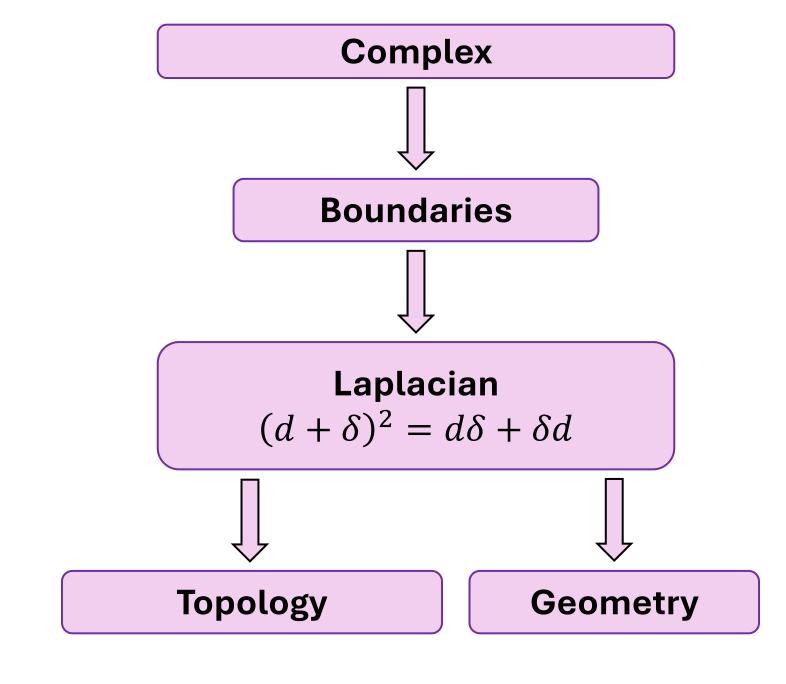
Computing Persistent Laplacians

Toward Broader Applications in TDA

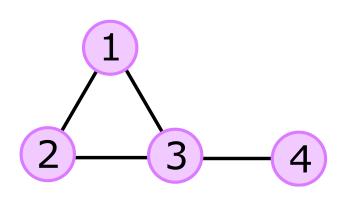
Ben Jones Michigan State University

> ComPer 2025 SUNY Albany

Laplacians



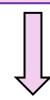
Graph Laplacian







Boundary: *B*



Graph Laplacian

$$L = BB^T$$





Topology: $H_0(G; \mathbb{R})$

Geometry: λ_0

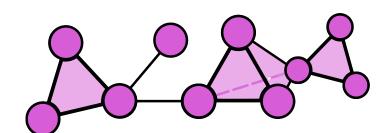
Combinatorial Laplacian

Simplicial Complex: K



Boundaries: d_n





Combinatorial Laplacian

$$\Delta_n = d_{n+1} d_{n+1}^* + d_n^* d_n$$

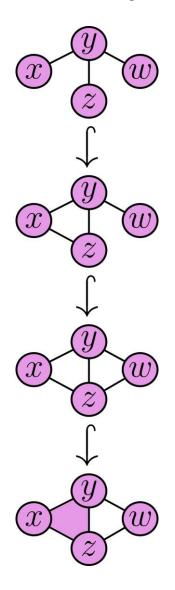




Topology: $H_n(K; \mathbb{R})$

Geometry: λ_n

Persistent Laplacian







Boundaries: d_n^a , d_n^b



Persistent Laplacian

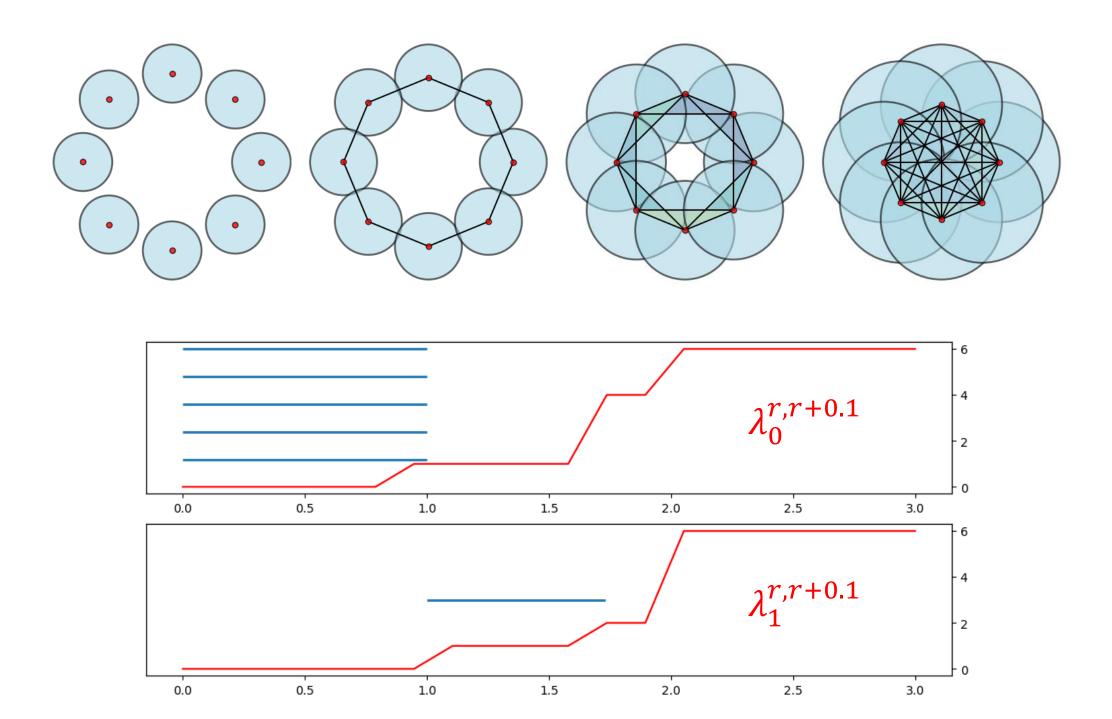
$$\Delta_n = d_{n+1}^{a,b} (d_{n+1}^{a,b})^* + (d_n^a)^* d_n^a$$





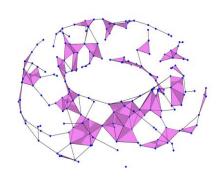
Topology: $H_n^{a,b}(K; \mathbb{R})$

Geometry: $\lambda_n^{a,b}$



Persistent Laplacian Pipeline

Multiscale Data

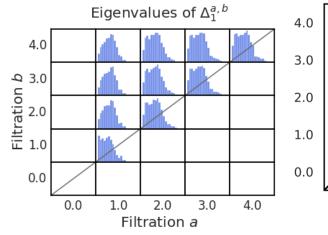


Persistent Laplacians

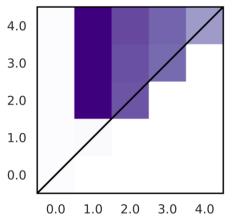
$$\{\Delta_n^{a,b} \mid a \le b\}$$

PSD matrices

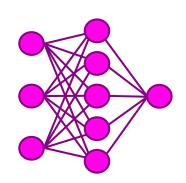
Eigenvalues



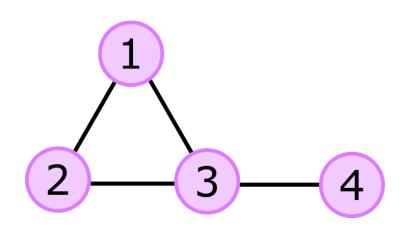
Summaries



Analysis



Graph Laplacian



$$B = egin{array}{ccccc} & e_{12} & e_{13} & e_{23} & e_{34} \ & v_1 & -1 & -1 & 0 & 0 \ & 1 & 0 & -1 & 0 \ & v_2 & 0 & 1 & 1 & -1 \ & v_4 & 0 & 0 & 0 & 1 \ \end{pmatrix}$$

$$L = BB^{T} = egin{array}{ccccc} v_{1} & v_{2} & v_{3} & v_{4} \\ v_{1} & v_{2} & v_{3} & v_{4} \\ v_{2} & -1 & -1 & 0 \\ -1 & 2 & -1 & 0 \\ -1 & -1 & 3 & -1 \\ v_{4} & 0 & 0 & -1 & 1 \\ \end{array}$$

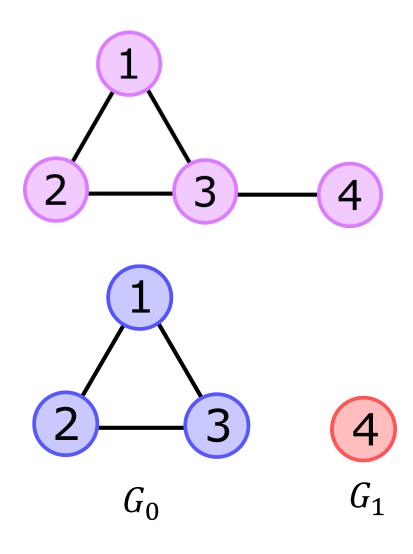
Graph Laplacian

Eigenvalues: $\{0, 1, 3, 4\}$

Topological Information:

Multiplicity of 0 = # components

Spectral Clustering



Eigenvector partition

$$L\begin{pmatrix} 1\\1\\0\\-2 \end{pmatrix} = 1\begin{pmatrix} 1\\1\\0\\-2 \end{pmatrix} v_1 v_2 v_i \in G_0 \text{ if } \ge 0 v_3 v_i \in G_1 \text{ if } < 0$$

Gives min-cut partition

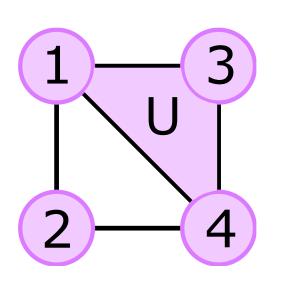
Eigenvalues: $\{0, 1, 3, 4\}$

Geometric Information:

$$\lambda = \min\{\lambda_i > 0\}$$

Algebraic Connectivity

Combinatorial Laplacian



$$d_1 = \begin{matrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{matrix} \begin{pmatrix} e_{12} & e_{13} & e_{14} & e_{24} & e_{34} \\ -1 & -1 & -1 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & -1 \\ v_4 & 0 & 0 & 1 & 1 & 1 \end{pmatrix} \quad d_2 = \begin{matrix} e_{12} \\ e_{13} \\ e_{13} \\ e_{14} \\ e_{24} \\ e_{34} \end{matrix} \begin{pmatrix} 0 \\ 1 \\ -1 \\ 0 \\ 1 \end{pmatrix}$$

Eigenvalues:
$$\{0, 2, 3, 3, 4\}$$

$$\beta_1$$

$$= \begin{pmatrix} 2 & 1 & 1 & -1 & 0 \\ 1 & 3 & 0 & 0 & 0 \\ 1 & 0 & 3 & 1 & 0 \\ -1 & 0 & 1 & 2 & 1 \\ 0 & 0 & 0 & 1 & 3 \end{pmatrix}$$

 $\Delta_1 = d_2 \circ d_2^* + d_1^* \circ d_1$

Combinatorial Laplacian

$$C_{n+1}(K;\mathbb{R}) \xrightarrow{d_{n+1}} C_n(K;\mathbb{R}) \xrightarrow{d_n} C_{n-1}(K;\mathbb{R})$$
Inner product: $\langle \sigma_i, \sigma_j \rangle = \begin{cases} 1 \text{ if } i = j \\ 0 \text{ if } i \neq j \end{cases}$

$$Implies C_n \cong C^n$$

$$C_{n+1}(K;\mathbb{R}) \xrightarrow{d_{n+1}} C_n(K;\mathbb{R}) \xrightarrow{d_n} C_{n-1}(K;\mathbb{R})$$

$$\Delta_n^{\text{up}} = d_{n+1} \circ d_{n+1}^* \longrightarrow C_n(K) \longrightarrow \Delta_n^{\text{down}} = d_n^* \circ d_n$$

$$\Delta_n = d_{n+1} d_{n+1}^* + d_n^* d_n$$

$$= \Delta_n^{\text{up}} + \Delta_n^{\text{down}}$$

Properties $\Delta_n = d_{n+1} \circ d_{n+1}^* + d_n^* \circ d_n$

Hodge Decomposition:

$$\ker \Delta_n \cong H_n(K; \mathbb{R})$$

 $C_n(K; \mathbb{R}) \cong \operatorname{Im} d_n^* \oplus H_n(K) \oplus \operatorname{Im} d_{n+1}$

Self-adjoint:
$$(\Delta_n)^* = \Delta_n$$

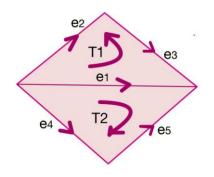
Eigenvalues
$$\geq 0: \{\lambda_n^0, \lambda_n^1, \dots, \lambda_n^i\}$$

Multiplicity of 0: dim $ker\Delta_n = \beta_n$

Spectral gap:
$$\lambda_n = \min\{\lambda_n^i > 0\}$$

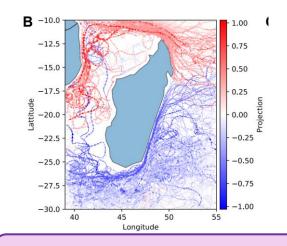
de Rham Hodge Decomposition: $\Omega^{n}(M) \cong \operatorname{Im} d^{n-1} \oplus \mathcal{H}^{n}_{\Lambda}(M) \oplus \operatorname{Im} \delta^{n+1}$

In practice



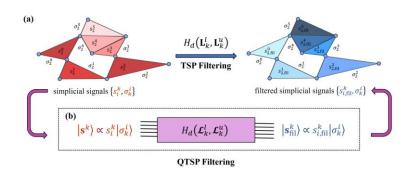
Random walks

Eidi and Mukherjee 2023



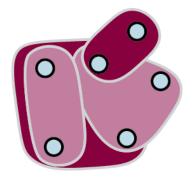
Trajectory embeddings

Schaub et al., 2019



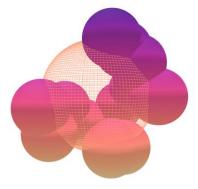
Quantum Computing

Leditto et al., 2024



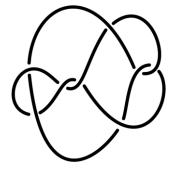
TopoNetX

Hajij et al., 2024



OAT

Henselman-Petrusek et al., 2023



Knot Theory

Jones and Wei, 2024



Topological Clustering

Ebli and Spreemann 2019

Persistent Laplacian $\Delta_n^{a,b}: C_n^a \to C_n^a$

$$C_{n+1}^{a} \xrightarrow{d_{n+1}^{a}} C_{n}^{a} \xrightarrow{d_{n}^{a}} C_{n-1}^{a}$$

$$\downarrow i_{n+1}^{a,b} C_{n+1}^{a,b} \downarrow i_{n}^{a,b} \downarrow i_{n}^{a,b} \downarrow i_{n-1}^{a,b}$$

$$C_{n+1}^{b} \xrightarrow{d_{n+1}^{b}} C_{n}^{b} \xrightarrow{d_{n}^{b}} C_{n-1}^{b}$$

Subspace: $C_{n+1}^{a,b} = \{ \sigma \in C_{n+1}^b | d_{n+1}^b(\sigma) \in i_n^{a,b}(C_n^a) \}$

Peristent Laplacian: $\Delta_n^{a,b} = d_{n+1}^{a,b} \circ (d_{n+1}^{a,b})^* + (d_n^a)^* \circ d_n^a$

Combinatorial Laplacian

$$\Delta_n \colon C_n \to C_n$$

$$\Delta_n = d_{n+1} \circ d_{n+1}^* + d_n^* \circ d_n$$

Hodge Decomposition:

$$\ker \Delta_n \cong H_n(K; \mathbb{R})$$

 $C_n(K; \mathbb{R}) \cong \operatorname{Im} d_n^* \oplus H_n(K) \oplus \operatorname{Im} d_{n+1}$

Self-adjoint:
$$(\Delta_n)^* = \Delta_n$$

Eigenvalues
$$\geq 0: \{\lambda_n^0, \lambda_n^1, ..., \lambda_n^k\}$$

Multiplicity of 0: dim
$$ker \Delta_n = \beta_n$$

Spectral gap:
$$\lambda_n = \min\{\lambda_n^i > 0\}$$

Persistent Laplacian

$$\Delta_n^{a,b}: C_n^a \to C_n^a \Delta_n^{a,b}: d_{n+1}^a \circ (d_{n+1}^{a,b})^* + (d_n^a)^* \circ d_n^a$$

Hodge Decomposition:

$$\ker \Delta_n^{a,b} \cong H_{n+1}^{a,b}(K;\mathbb{R})$$

$$C_n^a(K;\mathbb{R}) \cong \operatorname{Im}(d_n^a)^* \oplus H_n^{a,b}(K) \oplus \operatorname{Im} d_{n+1}^{a,b}$$

Self-adjoint:
$$(\Delta_n^{a,b})^* = \Delta_n^{a,b}$$

$$\mathsf{Eigenvalues} \geq 0: \{ \left(\lambda_n^{a,b} \right)_0, \left(\lambda_n^{a,b} \right)_1, \dots, \left(\lambda_n^{a,b} \right)_k \}$$

Multiplicity of 0: dim $\ker \Delta_n^{a,b} = \beta_n^{a,b}$

Spectral gap:
$$\lambda_n^{a,b} = \min\{(\lambda_n^{a,b})_i > 0\}$$

PL Example

$$K_a$$
 $\begin{bmatrix} 1 & 3 \\ U & 4 \end{bmatrix}$

$$\Delta_{1,\mathbf{down}}^{a,b} = \begin{pmatrix} 2 & 1 & 1 & -1 & 0 \\ 1 & 2 & 1 & 0 & -1 \\ 1 & 1 & 2 & 1 & 1 \\ -1 & 0 & 1 & 2 & 1 \\ 0 & -1 & 1 & 1 & 2 \end{pmatrix}$$

$$\Delta_{1,\mathbf{up}}^{a,b} = \begin{pmatrix} 1 & 0 & -1 & 1 & 0 \\ 0 & 1 & -1 & 0 & 1 \\ -1 & -1 & 2 & -1 & -1 \\ 1 & 0 & -1 & 1 & 0 \\ 0 & 1 & -1 & 0 & 1 \end{pmatrix}$$

Combinatorial Laplacian Eigenvalues: {0, 2, 3, 4, 4}

$$K_b$$
 $\begin{bmatrix} 1 & 3 \\ U & 1 \\ 2 & 4 \end{bmatrix}$

$$\Delta_1^{a,b} = \begin{pmatrix} 3 & 1 & 0 & 0 & 0 \\ 1 & 3 & 0 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 \\ 0 & 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 & 3 \end{pmatrix}$$

Persistent Laplacian Eigenvalues: $\{2, 2, 4, 4, 4\}$ Multiplicity of $0 = \beta_n^{a,b}$

How many 0-eigenvalues should we expect?

What is this "geometric information"?

- Short answer: we don't know
- Medium answer: analogies and machine learning
- Long answer: Cheeger-type inequalities
 - Manifolds

$$\frac{h_M^2}{4} \le \lambda_M$$

Graphs

$$\frac{h_G^2}{2\max_{v\in V}\deg(v)} \le \lambda_G \le 2h_G$$

• Non-branching filtered simplicial complexes (Botnan & Dong, 2025)

$$\min_{j \le h+r} \frac{\widehat{\mathbf{A}}(P_j)}{\mathbf{V}(P_j)} \le \lambda_{\min}^{\mathcal{K}, \mathcal{L}} \le \min_{j \le h+r} \frac{\mathbf{A}(P_j)}{\mathbf{V}(P_j)}$$

Algorithms

- Projection R. Wang et al., 2019
- Reduction Mémoli, Wan, Y. Wang 2020
- Schur Complement MWW 2020
- Non-branching Dong 2024

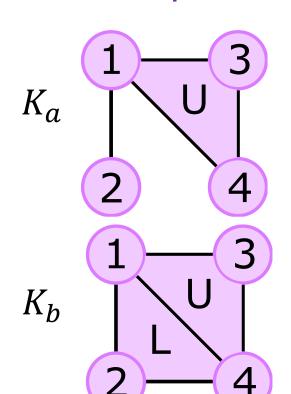
$$\Delta_{n,\mathbf{up}}^{b} = \begin{pmatrix} A & B \\ C & D \end{pmatrix}$$

$$n_{n}^{a} & n_{n}^{b} - n_{n}^{a} \\ b & A & B & D \end{pmatrix}$$

 n_n^b

$$\Delta_n^{a,b} = \Delta_{n,\mathbf{up}}^b / \Delta_{n,\mathbf{up}}^b (I_a^b, I_a^b) = A - BD^{-1}C$$
$$= O\left(\left(n_n^b\right)^3\right)$$

PL Example 2



$$\Delta_{1,\mathbf{up}}^{b} = \begin{pmatrix} 1 & 0 & -1 & 0 & 1\\ 0 & 1 & -1 & 1 & 0\\ -1 & -1 & 2 & -1 & -1\\ 0 & 1 & -1 & 1 & 0\\ \hline 1 & 0 & -1 & 0 & 1 \end{pmatrix}$$

$$\Delta_{1,\text{down}}^{a} = \begin{pmatrix} 2 & 1 & 1 & 0 \\ 1 & 2 & 1 & -1 \\ 1 & 1 & 2 & 1 \\ 0 & -1 & 1 & 2 \end{pmatrix}$$
Eigenvalues: $\{0, 1, 3, 4\}$

$$\Delta_{n,\mathrm{up}}^b/\Delta_{n,\mathrm{up}}^b(I_a^b,I_a^b)=A-BD^{-1}C$$

$$= \begin{pmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & -1 & 1 \\ -1 & -1 & 2 & -1 \\ 0 & 1 & -1 & 1 \end{pmatrix} - \begin{pmatrix} 1 \\ 0 \\ -1 \\ 0 \end{pmatrix} (1)^{-1} (1 \quad 0 \quad -1 \quad 0)$$

$$= \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 1 \\ 0 & -1 & 1 & -1 \\ 0 & 1 & -1 & 1 \end{pmatrix}$$
Eigenvalues: $\{0, 0, 0, 3\}$

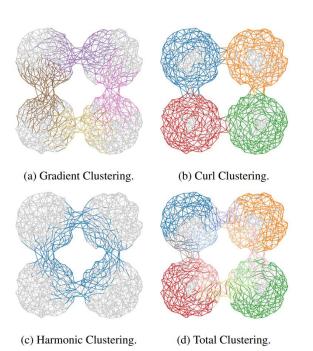
Persistent Laplacian:
$$\Delta_1^{a,b} = \begin{pmatrix} 2 & 1 & 1 & 0 \\ 1 & 3 & 0 & 0 \\ 1 & 0 & 3 & 0 \\ 0 & 0 & 0 & 3 \end{pmatrix}$$

Eigenvalues: {1, 3, 3, 4}

Applications

Topological Spectral Clustering

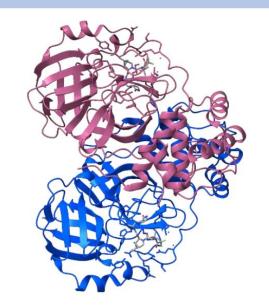
(Grande and Schaub, 2024)



Drug Resistance

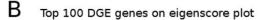
(Chen, Liu, Du, <u>Jones</u>, Wee, Wang, Chen, Shen, Wei, 2025)

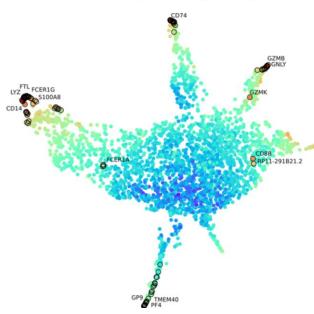
SARC-CoV Mpro - PAXLOVID



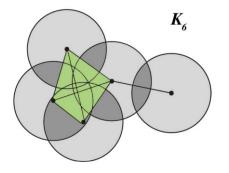
Single-cell Differential Gene Expression

(R. Hoekzema, et al., 2022)



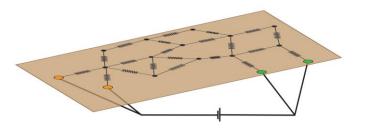


Variants



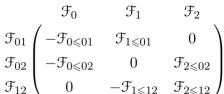
Simplicial Complexes

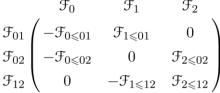
R. Wang, D.-D. Nguyen, and G.-W. Wei 2019

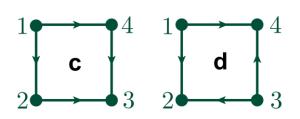


Weighted **Simplicial Complexes**

F. Mémoli, Z. Wan, Y. Wang 2020





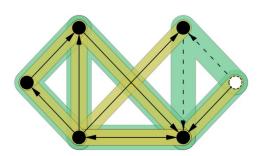


Cellular sheaves

X. Wei and G.-W. Wei 2021

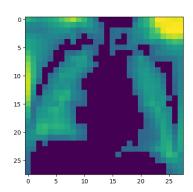
Path complexes

R. Wang and G.-W. Wei 2022



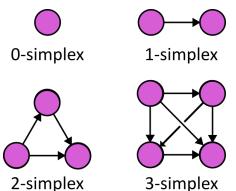
Directed hypergraphs

D. Chen, J. Liu, J. Wu, G.-W. Wei 2023



Cubical complexes

R. Dong 2024

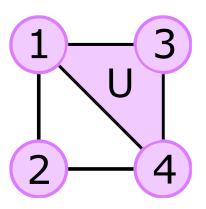


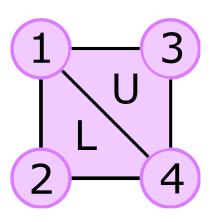
Directed flag complexes

Jones and G.-W. Wei 2024

PETLS: PErsistent Topological Laplacian Software

[2. 2. 4. 4. 4.]



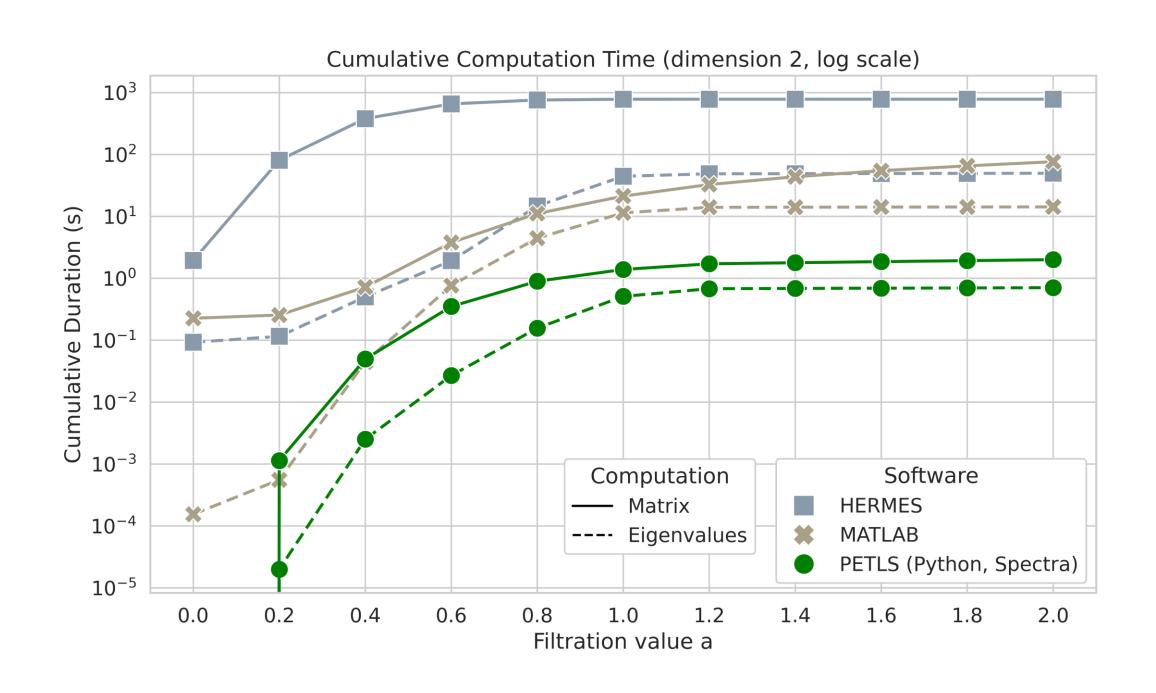


```
from gudhi import SimplexTree
  from petls import Complex
  stree = SimplexTree()
  stree.insert([1,3,4], filtration=0.0)
  stree.insert([1,2], filtration=0.0)
  stree.insert([2,4], filtration=0.0)
  stree.insert([1,2,4], filtration=1.0)
  complex = Complex(simplex_tree=stree)
  print(complex.spectra(dim=1,a=0,b=1))
✓ 0.0s
```

Highlights

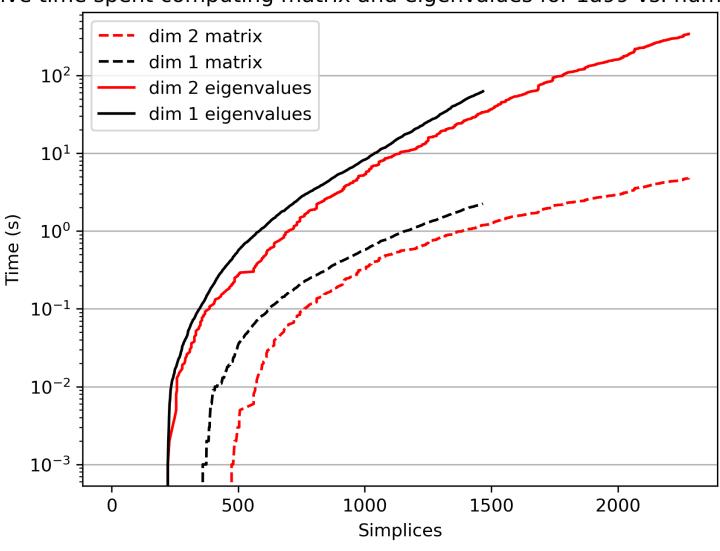
- C++ backend (fast)
- Python frontend (easy)
- Modular algorithms for
 - Up-Laplacian
 - Eigenvalues

... or any filtered boundary matrices

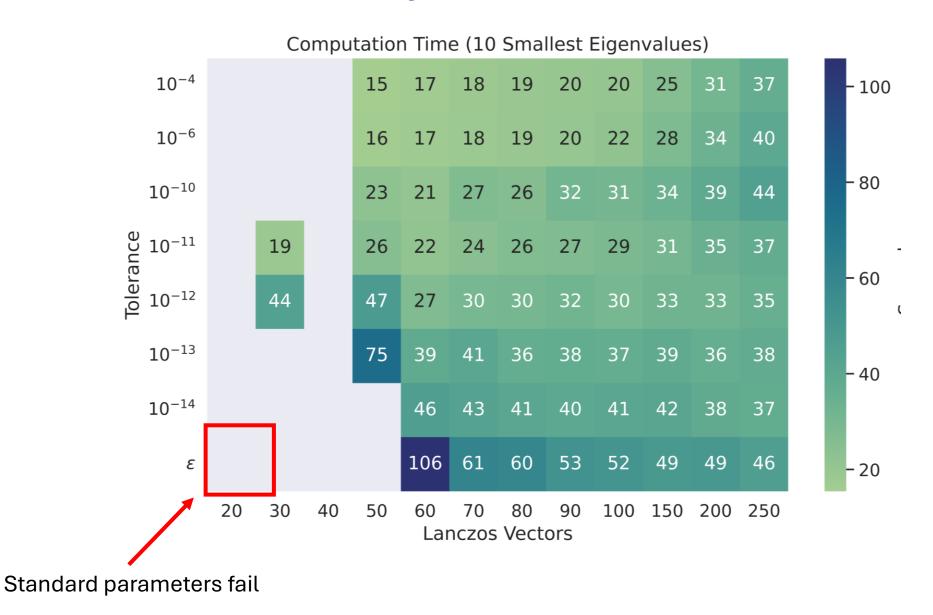


An Unexpected Problem: Eigenvalues

Cumulative time spent computing matrix and eigenvalues for 1a99 vs. number of simplices



Iterative Methods Don't Always Work



Reduction by Persistent Homology

$$\Delta_n^{a,b}$$
 = PH + "non-harmonic"

"non-harmonic" =
$$\Delta_n^{a,b}$$
 - PH

PH representatives as columns of

$$N = [\alpha_1 \dots \alpha_n]$$
 = basis for ker $\Delta_n^{a,b}$

Let X =basis for im $\Delta_n^{a,b}$ (e.g. random)

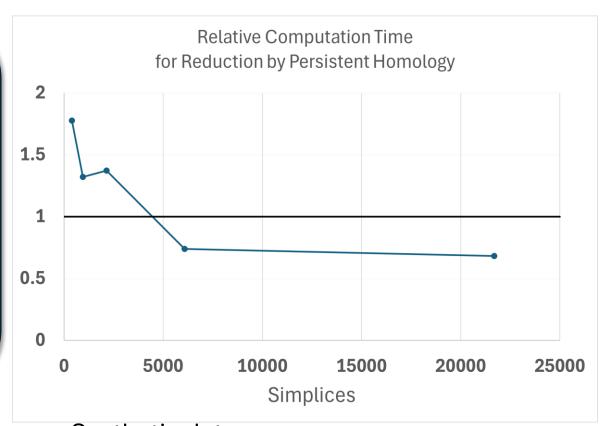
$$S = [X \quad N]$$

$$L = S^{-1} \Delta_n^{a,b} S = [S^{-1} L X \quad 0]$$

Let $A = \text{Top left } (\dim C_n^a - \beta_n^{a,b})$ square of L_A

Properties of *A***:**

- 1) Same nonzero eigenvalues as $\Delta_n^{a,b}$
- 2) Smaller than $\Delta_n^{a,b}$
- 3) Positive <u>definite</u> (no zero-eigenvalues)



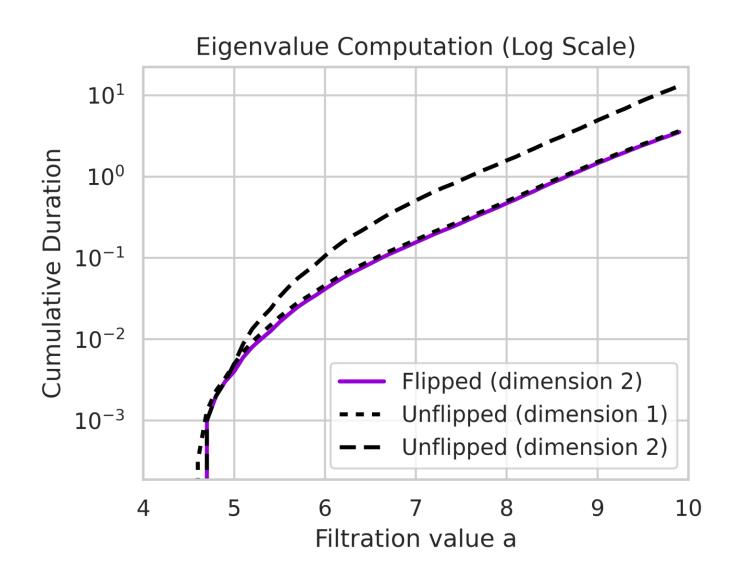
Synthetic data, without optimization, saves ~20% computation time

Faster via (standard) linear algebra

Nonzero eigenvalues(XY) = Nonzero eigenvalues(YX)

Apply to
$$\Delta_N^{a,b} = (B_N^a)^T B_N^a$$

Saves 70% of computation time



Recommended Resources

- "Persistent Spectral Graph" R. Wang, et al. (2020)
- "Persistent Laplacians: properties, algorithms, and implications" Mémoli, Wan, Y. Wang (2022)
- "Persistent sheaf Laplacians" X. Wei and G.-W. Wei (2025)
- "PETLS: PErsistent Topological Laplacian Software" Jones and Wei (2025)
- "Disentangling the Spectral Properties of the Hodge Laplacian: Not All Small Eigenvalues Are Equal" Grande and Schaub (2024)

Thank you!

Ben Jones
Michigan State University
jones657@msu.edu

BenJones-Math.com/software/PETLS/github.com/bdjones13

> pip install petls

