

# Towards an Optimal Bound for the Interleaving Distance on Mapper Graphs

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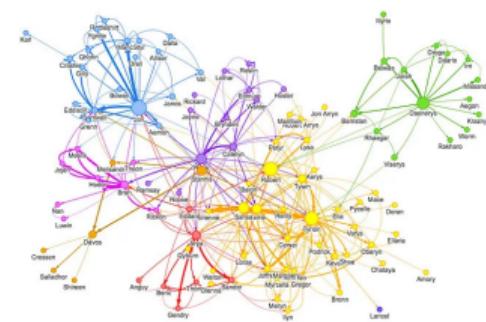
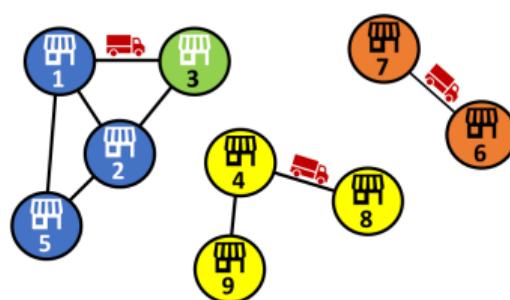
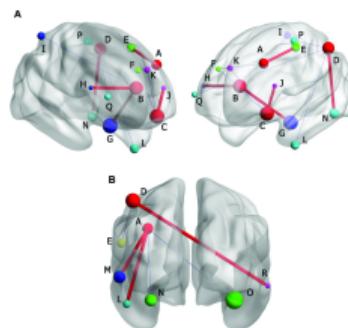
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# Graphs in the Wild

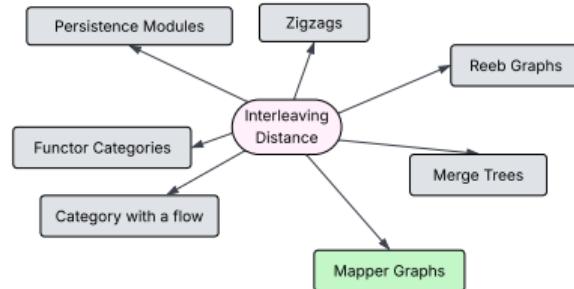
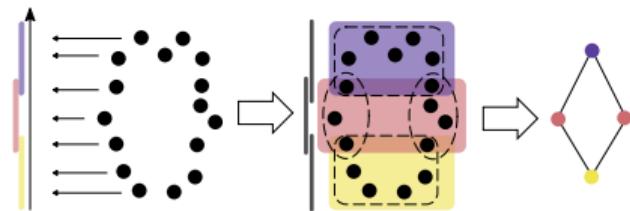
- Graphs with functions show up everywhere.
- We want to cluster and compare them.
- Need a meaningful and computable distance.
- But it's expensive to compute.



Real-world examples: brain activity, traffic flow, and social networks

# Key Problem

- Study graph-based topological signatures.
- Focus on Mapper graphs.
- Use interleaving distance.
- Computation is NP-hard.
- Loss function to upper bound.
- How to get the best upper bound?



We make Mapper graphs ML-friendly  
by  
optimizing a loss that bounds interleaving distance.

$$d_I(\text{Graph 1}, \text{Graph 2}) \leq n + Loss(\varphi, \psi)$$

# Mapper Graphs: Categorical Framework

**Goal:** Express mappers as cosheaves.

- Given:
  - Data  $\mathbb{X}$  with function  $f : \mathbb{X} \rightarrow \mathbb{R}$
  - Cover  $\mathcal{U} = \{U_\alpha\}$  of  $\mathbb{R}$
- Preserves connected components of  $f^{-1}(U_\alpha)$
- Discretize using a grid on  $\mathbb{R}$
- Represent  $f$  in cosheaf form
- Encoded as functor:  $F : \mathbf{Open}(\mathcal{U}) \rightarrow \mathbf{Set}$
- Components stored in  $\pi_0(f^{-1}(U))$ .

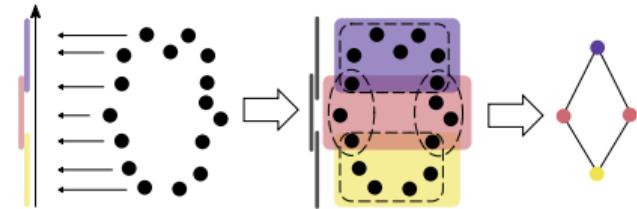
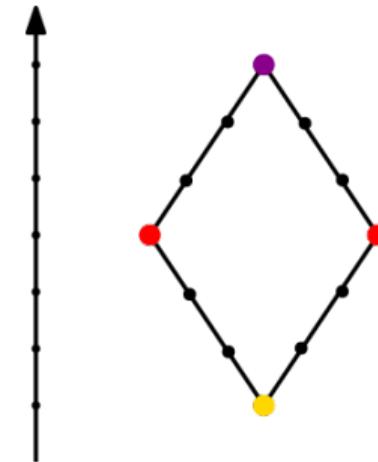


Image credit: Percival et al., 2024

# Mapper Graphs: Categorical Framework

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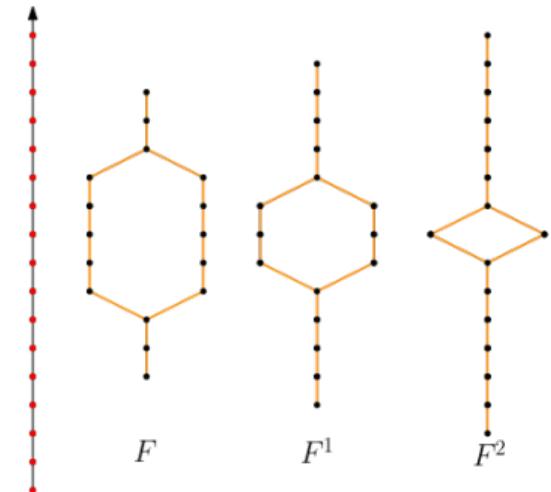
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# Distance Between Mappers: Interleaving Distance

**Goal:** to compare  $F, G : \mathbf{Open}(\mathcal{U}) \rightarrow \mathbf{Set}$ .

- Define  $n$ -thickening of open sets.
  - Geometrically,  $(i\delta, j\delta) \rightarrow ((i - n)\delta, (j + n)\delta)$
- Thickening of functor  $F^n := F \circ (-)^n$ 
  - Means,  $F^n(S) = F(S^n)$
- $n$ -interleaving is  $\varphi : F \Rightarrow G^n$  and  $\psi : G \Rightarrow F^n$ .
- Must satisfy diagram commutativity.



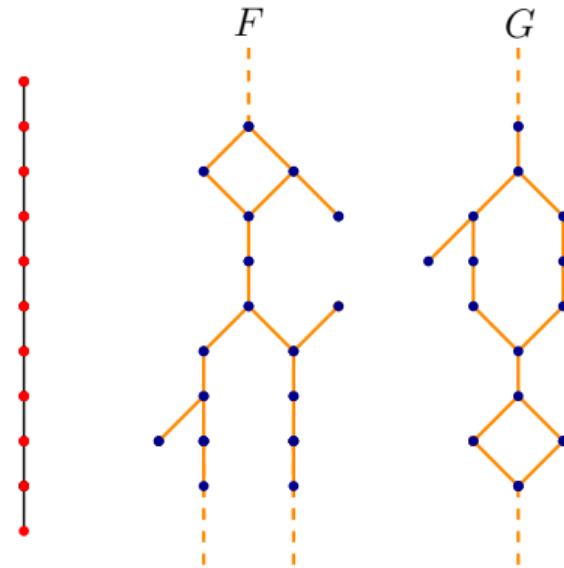
# Distance Between Mappers: Interleaving Distance

- Diagrams to commute:

$$\begin{array}{ccc} F(S) & \xrightarrow{F[S \subseteq S^{2n}]} & F(S^{2n}) \\ & \searrow \varphi_S & \nearrow \psi_{S^n} \\ & G(S^n) & \end{array}$$

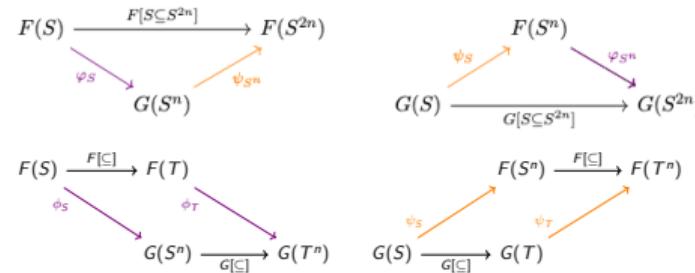
$$\begin{array}{ccc} & & F(S^n) \\ & \swarrow \psi_S & \downarrow \varphi_{S^n} \\ G(S) & \xrightarrow{G[S \subseteq S^{2n}]} & G(S^{2n}) \end{array}$$

- Smallest  $n$  is the interleaving distance.
- NP hard.



# Bounding Interleaving Distance: Assignment

- Assignment  $(\varphi, \psi)$ : Natural transformation like maps without commutativity.
- Diagrams:
  - Triangle: Looks like interleaving
  - Parallelogram: Looks like natural transformation



# Bounding Interleaving Distance: Loss Function

- Given  $n$ , how much to thicken ( $k$ ), so that the diagrams commute for  $n + k$ ?

$$\begin{array}{ccc} F(S) & \xrightarrow{F[\subseteq]} & F(S^{2n}) \longrightarrow F(S^{2(n+k)}) \\ & \varphi_S \searrow & \nearrow \psi_{S^n} \\ & G(S^n) & \end{array} \qquad \begin{array}{ccc} F(S) & \xrightarrow{F[\subseteq]} & F(T) \\ \varphi_S \searrow & & \swarrow \varphi_T \\ G(S^n) & \xrightarrow[G[\subseteq]} & G(T^n) \longrightarrow G(T^{n+k}) \end{array}$$

- Diagram loss  $L_{\square}, L_{\square}, L_{\triangle}, L_{\nabla}$  is a quality measure.
- Basic loss  $L_B(\varphi, \psi)$ : Measures how far from commuting.

$$L_B(\varphi, \psi) = \max_{\substack{\sigma < \tau \in K \\ \rho \in K}} \left\{ L_{\square}^{S_\tau, S_\sigma}, L_{\square}^{S_\tau, S_\sigma}, L_{\square}^{S_\rho, S_\rho^n}, L_{\square}^{S_\rho, S_\rho^n}, L_{\triangle}^{S_\rho}, L_{\nabla}^{S_\rho} \right\}$$

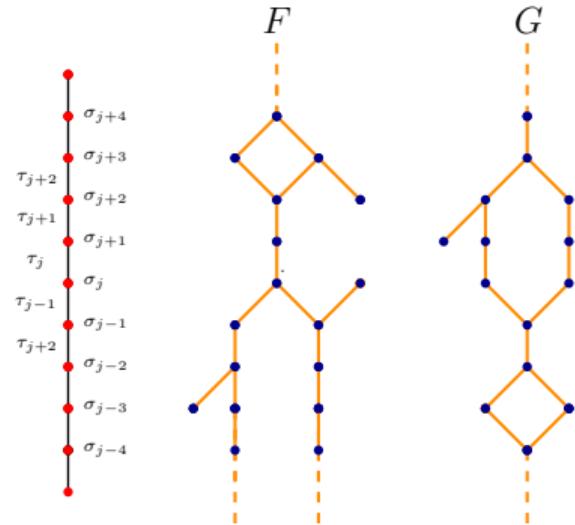
Theorem ( Chambers et al. (2023))

For an  $n$ -assignment,  $\varphi : F \Rightarrow G^n$  and  $\psi : G \Rightarrow F^n$ ,

$$d_I(F, G) \leq n + L_B(\varphi, \psi).$$

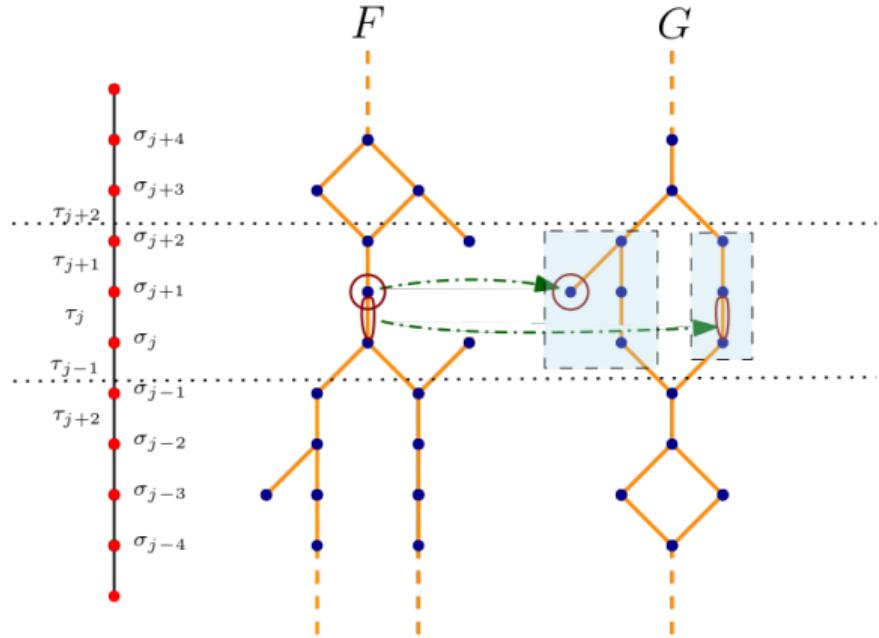
# Data Structure: Mapper as Graphs

- Store  $F : \mathbf{Open}(\mathcal{U}) \rightarrow \mathbf{Set}$  as graph  $F \sim (V_F, E_F)$ .
- Use grid structure on  $\mathbb{R}$ .
- Vertices: stored with height.
- Assignment: vertex and edge maps.
- Diagram commutes  $\sim$  same connected component.



# Commutativity and Connected Components

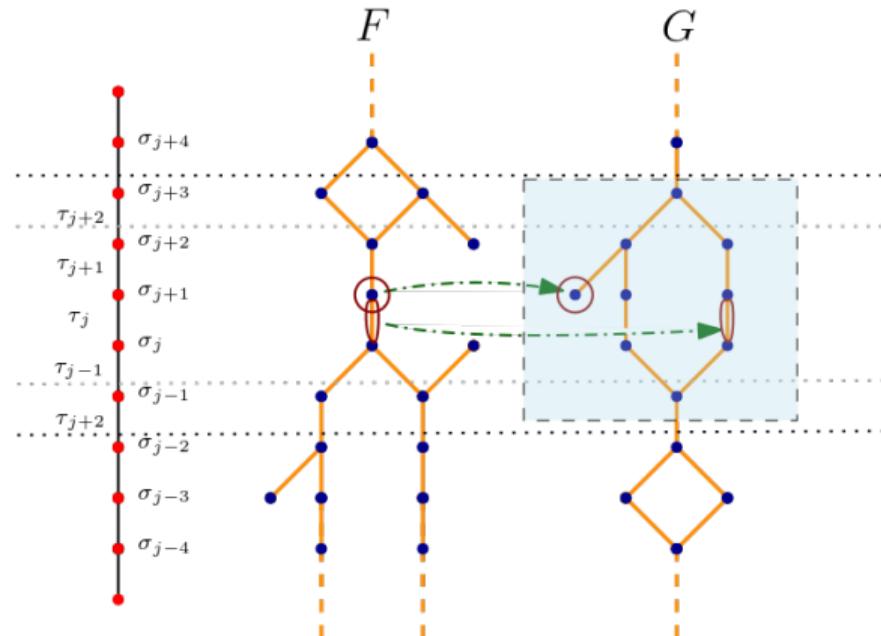
$$\begin{array}{ccccc}
 F(S_\tau) & \xrightarrow{F[\subseteq]} & F(S_\sigma) & & \\
 \searrow \varphi_{S_\tau} & & \searrow \varphi_{S_\sigma} & & \\
 G^n(S_\tau) & \xrightarrow[G[\subseteq]} & G^n(S_\sigma) & & \\
 \\[10pt]
 e & \xrightarrow{\hspace{1cm}} & v & & \\
 & \swarrow & \uparrow & & \\
 & [e'] & \xrightarrow{\hspace{1cm}} & [w] & \\
 & \uparrow & & \uparrow & \\
 & [e'] & \xrightarrow{\hspace{1cm}} & [w] &
 \end{array}$$



# Commutativity and Connected Components

$$\begin{array}{ccccc}
 F(S_\tau) & \xrightarrow{F[\subseteq]} & F(S_\sigma) & & \\
 \varphi_{S_\tau} \searrow & & \swarrow \varphi_{S_\sigma} & & \\
 G^n(S_\tau) & \xrightarrow{G[\subseteq]} & G^n(S_\sigma) & \longrightarrow & G(S_{\sigma_\ell}^{n+k})
 \end{array}$$
  

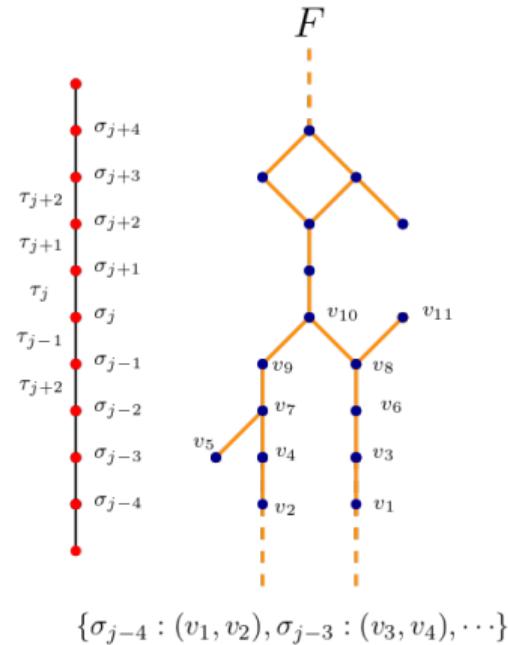
$$\begin{array}{ccccc}
 e & \xrightarrow{\quad} & v & & \\
 & \nwarrow & \swarrow & & \\
 & [e'] & \xrightarrow{\quad} & [w] & \xrightleftharpoons{\quad} [w] \\
 & & \xrightarrow{\quad} & [e'] &
 \end{array}$$



# Data Structure: Maps as Matrices

**Goal:** Express diagram commutativity as matrix multiplication.

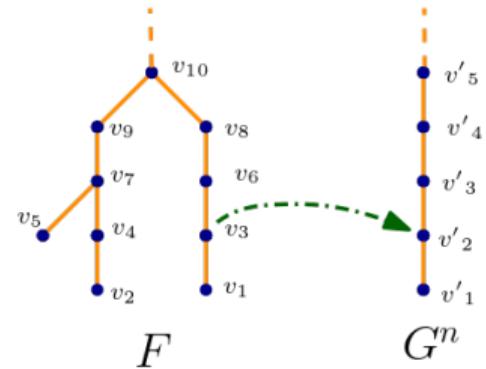
- Order vertices by increasing function values.
- Same for edges (lower vertex).
- Assignment: vertex and edge maps.
- Matrix whose rows and columns are these.
- Block Structure.



# Assignment Matrices

- Store maps like  $\varphi : F \rightarrow G^n$ .
- Place 1 if  $\varphi(v) = v'$ , 0 otherwise.
- For a valid map: only one 1 for each column.

$$\begin{matrix} & & F \\ & & v_1 & v_2 & v_3 & v_4 & \dots \\ v'_1 & \left[ \begin{array}{cccc} & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \end{array} \right] \\ v'_2 \\ v'_3 \\ v'_4 \\ \vdots \end{matrix}$$



- To have lower loss, need better assignment.

# Loss Terms as Matrix Multiplication

- Diagram:

$$\begin{array}{ccc} F(S_\tau) & \xrightarrow{F[\subseteq]} & F(S_\sigma) \\ \varphi_{S_\tau} \searrow & & \swarrow \varphi_{S_\sigma} \\ G^n(S_\tau) & \xrightarrow[G[\subseteq]} & G^n(S_\sigma) \end{array}$$
$$\begin{array}{ccccc} & & e & \xrightarrow{\quad} & v \\ & \swarrow & & \nearrow & \\ & & [e'] & \xrightarrow{\quad} & [w] \end{array}$$

- Top-right:  $M_\phi^V \cdot B_F^\downarrow$
- Left-Down:  $B_{G^n}^\downarrow \cdot M_\phi^E$
- In matrix terms:

$$\max_i L_{\square}^{S_{\tau_i}, S_{\sigma_i}} = \max \left\{ x \mid x \in D_{G^n}^V \left( M_\phi^V \cdot B_F^\downarrow - B_{G^n}^\downarrow \cdot M_\phi^E \right) \right\}$$

- computing loss  $\rightarrow$  finding largest matrix element.

# Loss in Matrix Terms

	Loss Term	Diagram	Matrix Multiplication	Eval.
Edge-vertex Parallelogram	$L_{\square}^{S_\tau, S_\sigma}$	$\begin{array}{ccc} F(S_\tau) & \xrightarrow{F[\subseteq]} & F(S_\sigma) \\ & \searrow \varphi_{S_\tau} & \swarrow \varphi_{S_\sigma} \\ G^n(S_\tau) & \xrightarrow[G[\subseteq]]{} & G^n(S_\sigma) \end{array}$	$D_{G^n}^V \left( M_\varphi^V \cdot B_F^\uparrow - B_{G^n}^\uparrow \cdot M_\varphi^E \right)$ $D_{G^n}^E \left( M_\varphi^V \cdot B_F^\downarrow - B_{G^n}^\downarrow \cdot M_\varphi^E \right)$	$\max_{x_{ij} \in A} x_{ij}$
	$L_{\square}^{S_\tau, S_\sigma}$	$\begin{array}{ccc} F^n(S_\tau) & \xrightarrow{F[\subseteq]} & F^n(S_\sigma) \\ & \nearrow \psi_{S_\tau} & \nearrow \psi_{S_\sigma} \\ G(S_\tau) & \xrightarrow[G[\subseteq]]{} & G(S_\sigma) \end{array}$	$D_{F^n}^V \left( M_\psi^V \cdot B_G^\uparrow - B_{F^n}^\uparrow \cdot M_\psi^E \right)$ $D_{F^n}^E \left( M_\psi^V \cdot B_G^\downarrow - B_{F^n}^\downarrow \cdot M_\psi^E \right)$	
	$L_{\square}^{S_\rho, S_\rho^n}$	$\begin{array}{ccc} F(S_\rho) & \xrightarrow{F[\subseteq]} & F^n(S_\rho) \\ & \searrow \varphi_{S_\rho^n} & \swarrow \varphi_{S_\rho^n} \\ G^n(S_\rho) & \xrightarrow[G[\subseteq]]{} & G^{2n}(S_\rho) \end{array}$	$D_{G^n}^V \left( M_{\varphi^n}^V \cdot I_F^V - I_{G^n}^V \cdot M_\varphi^V \right)$ $D_{G^n}^E \left( M_{\varphi^n}^E \cdot I_F^E - I_{G^n}^E \cdot M_\varphi^E \right)$	
	$L_{\square}^{S_\rho, S_\rho^n}$	$\begin{array}{ccc} F^n(S_\rho) & \xrightarrow{F[\subseteq]} & F^{2n}(S_\rho) \\ & \nearrow \psi_{S_\rho^n} & \nearrow \psi_{S_\rho^n} \\ G(S_\rho) & \xrightarrow[G[\subseteq]]{} & G(S_\rho^n) \end{array}$	$D_{F^n}^V \left( M_{\psi^n}^V \cdot I_G^V - I_{F^n}^V \cdot M_\psi^V \right)$ $D_{F^n}^E \left( M_{\psi^n}^E \cdot I_G^E - I_{F^n}^E \cdot M_\psi^E \right)$	
Thickening Parallelogram	$L_{\nabla}^{S_\rho}$	$\begin{array}{ccc} F(S_\rho) & \xrightarrow{F[\subseteq]} & F^{2n}(S_\rho) \\ & \searrow \varphi_{S_\rho} & \nearrow \psi_{S_\rho^n} \\ G^n(S_\rho) & & \end{array}$	$D_{F^{2n}}^V \left( I_{F^n}^V \cdot I_F^V - M_{\psi^n}^V \cdot M_\varphi^V \right)$ $D_{F^{2n}}^E \left( I_{F^n}^E \cdot I_F^E - M_{\psi^n}^E \cdot M_\varphi^E \right)$	$\max_{x_{ij} \in A} \left[ \frac{x_{ij}}{2} \right]$
	$L_{\Delta}^{S_\rho}$	$\begin{array}{ccc} F^n(S_\rho) & & \\ \nearrow \psi_{S_\rho} & \searrow \varphi_{S_\rho} & \\ G(S_\rho) & \xrightarrow[G[\subseteq]]{} & G^{2n}(S_\rho) \end{array}$	$D_{G^{2n}}^V \left( I_{E^n}^V \cdot I_G^V - M_{\varphi^n}^V \cdot M_\psi^V \right)$ $D_{G^{2n}}^E \left( I_{E^n}^E \cdot I_G^E - M_{\varphi^n}^E \cdot M_\psi^E \right)$	

# Implement Loss Optimization

- Question: Can we formulate loss optimization as a linear program?
  - Yes! Both the objective function and constraints can be linearized.
- Discretized setup calls for integer linear programming.
- ILP is formulated as follows:

Minimize  $\ell$

Subject to  $\ell \geq x_{ij}^{F,\uparrow} \quad \forall x_{ij}^{F,\uparrow} \in D_{G^n}^V \left( M_\varphi^V \cdot B_F^\uparrow - B_{G^n}^\uparrow \cdot M_\varphi^E \right)$

$\sum_i x_{ij}^{\eta,A} = 1 \quad \forall x_{ij}^{\eta,A} \in M_\eta^A, \eta \in \{\phi, \phi^n, \psi, \psi^n\}, A \in \{V, E\}$

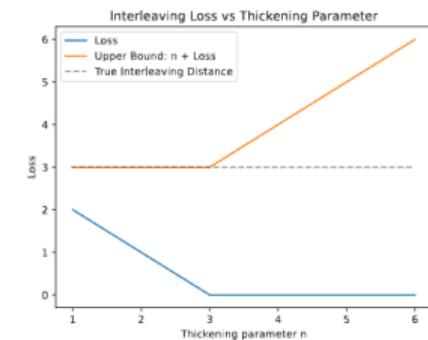
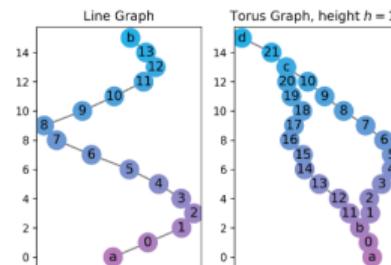
$$x_{ij} \geq 0$$

⋮ (more constraints)

- Nonlinearity in triangles (e.g.,  $M_{\psi^n}^V \cdot M_\varphi^V$ ) is linearized with additional variables.

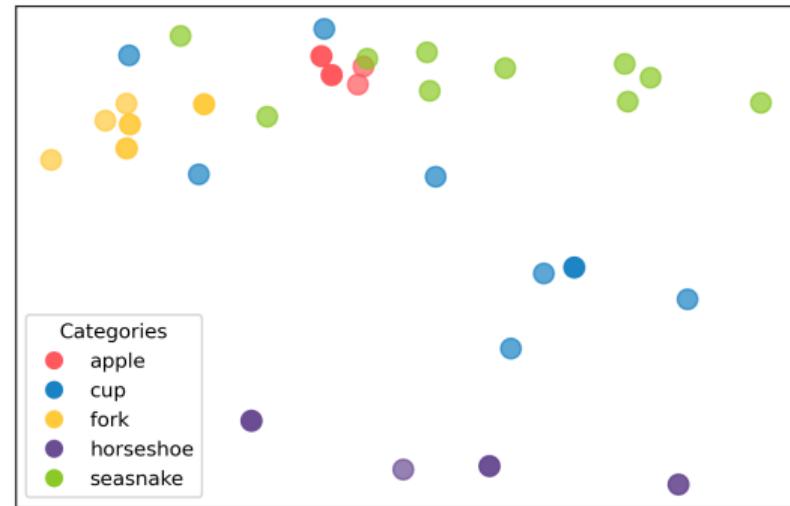
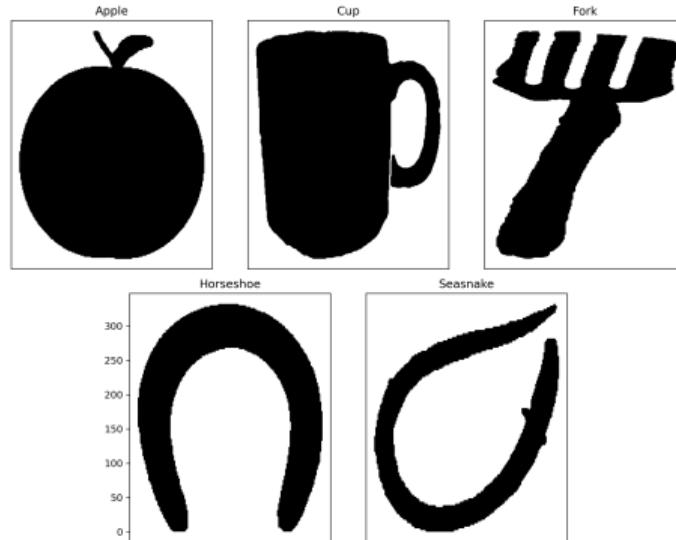
# Experiments with Small Mappers

- Small mappers where interleaving distance can be computed.
- Line mapper: One vertex at every height.
- Torus mapper: A loop in the middle.
- Interleaving distance is  $\lceil \frac{h}{4} \rceil$ .



# Experiments with Images

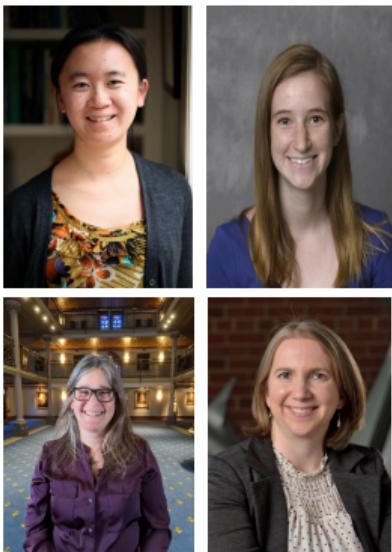
- Mappers of images from the MPEG7 image dataset.
- Pairwise distance with the optimized mapper loss.
- MDS to preserve pairwise dissimilarities.



## Summary and Future Work

- First available method to compute a bound for the interleaving distance.
- Mapper as graphs, maps as matrices.
- Loss optimization using ILP.
- Initial experiments support the approach.
- Future: test on more datasets, improve efficiency.
- Explore mapper construction and parameter selection.
- Integrate into ML pipelines.

# Thank You!



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MunchLab, Spring 2025

