

Cochains are all you need

A summary of work from the thesis of

Kelly Maggs



Structure of the talk

- 1) What are cochains and what do they encode?
- 2) Cochains in signal processing
- 3) Cochains in machine learning
- 4) Cochains in computational biology

What are cochains?

And what do they encode?

Chain complexes of \mathbb{R} -vector spaces

\mathbb{R} -linear
transformation

$$C_* = C_0 \xleftarrow{d_1} C_1 \xleftarrow{d_2} C_2 \xleftarrow{\dots} \xleftarrow{d_n} C_n \xleftarrow{d_{n+1}} C_{n+1} \xleftarrow{\dots}$$

$$d_n \circ d_{n+1} = 0 \quad f_n$$

Chain complexes of \mathbb{R} -vector spaces

\mathbb{R} -linear
transformation

$$\begin{array}{ccccccccc} C_* = C_0 & \xleftarrow{d_1} & C_1 & \xleftarrow{d_2} & C_2 & \leftarrow \cdots & \leftarrow C_n & \xleftarrow{d_{n+1}} & C_{n+1} \leftarrow \cdots \\ f_* \downarrow & f_0 \downarrow & \downarrow f_1 & \downarrow f_2 & & & \downarrow f_n & \downarrow f_{n+1} & \\ C'_* = C'_0 & \xleftarrow{d'_1} & C'_1 & \xleftarrow{d'_2} & C'_2 & \leftarrow \cdots & \leftarrow C'_n & \xleftarrow{d'_{n+1}} & C'_{n+1} \leftarrow \cdots \end{array}$$

Chain complexes of \mathbb{R} -vector spaces

$$\begin{array}{ccccccccc} C_* = C_0 & \xleftarrow{d_1} & C_1 & \xleftarrow{d_2} & C_2 & \leftarrow \cdots & \leftarrow C_n & \xleftarrow{d_{n+1}} & C_{n+1} \leftarrow \cdots \\ f_* \downarrow & f_0 \downarrow & \downarrow f_1 & \downarrow f_2 & & & \downarrow f_n & \downarrow f_{n+1} & \\ C'_* = C'_0 & \xleftarrow{d'_1} & C'_1 & \xleftarrow{d'_2} & C'_2 & \leftarrow \cdots & \leftarrow C'_n & \xleftarrow{d'_{n+1}} & C'_{n+1} \leftarrow \cdots \end{array}$$

$$\text{Im } d_{n+1} \subseteq \ker d_n \quad \text{if } n$$

$$H_n(C_*) = \ker d_n / \text{Im } d_{n+1}$$

Chain complexes of \mathbb{R} -vector spaces

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$$H_n(C_*) = \ker d_n / \text{Im } d_{n+1}$$

$$f_* : C_* \rightarrow C'_*$$

$$H_n(f_*) : H_n(C_*) \rightarrow H_n(C'_*)$$

Cochain complexes of \mathbb{R} -vector spaces

$$C^* = C^0 \xrightarrow{d^0} C^1 \xrightarrow{d^1} C^2 \rightarrow \dots \rightarrow C^n \xrightarrow{d^{n+1}} C^{n+1} \rightarrow \dots$$
$$f^0 \downarrow \quad \downarrow f^1 \quad \downarrow f^2 \quad \downarrow f^n \quad \downarrow f^{n+1}$$
$$C'^0 \xrightarrow{d'^0} C'^1 \xrightarrow{d'^1} C'^2 \rightarrow \dots \rightarrow C'^n \xrightarrow{d'^{n+1}} C'^{n+1} \rightarrow \dots$$

$$\text{Im } d^n \subseteq \ker d^{n+1} \quad \forall n$$
$$f^*: C^* \rightarrow C'^*$$

$$H^n(C^*) = \ker d^{n+1} / \text{Im } d^n$$
$$H^n(f^*): H^n(C^*) \rightarrow H^n(C'^*)$$
$$\Downarrow$$

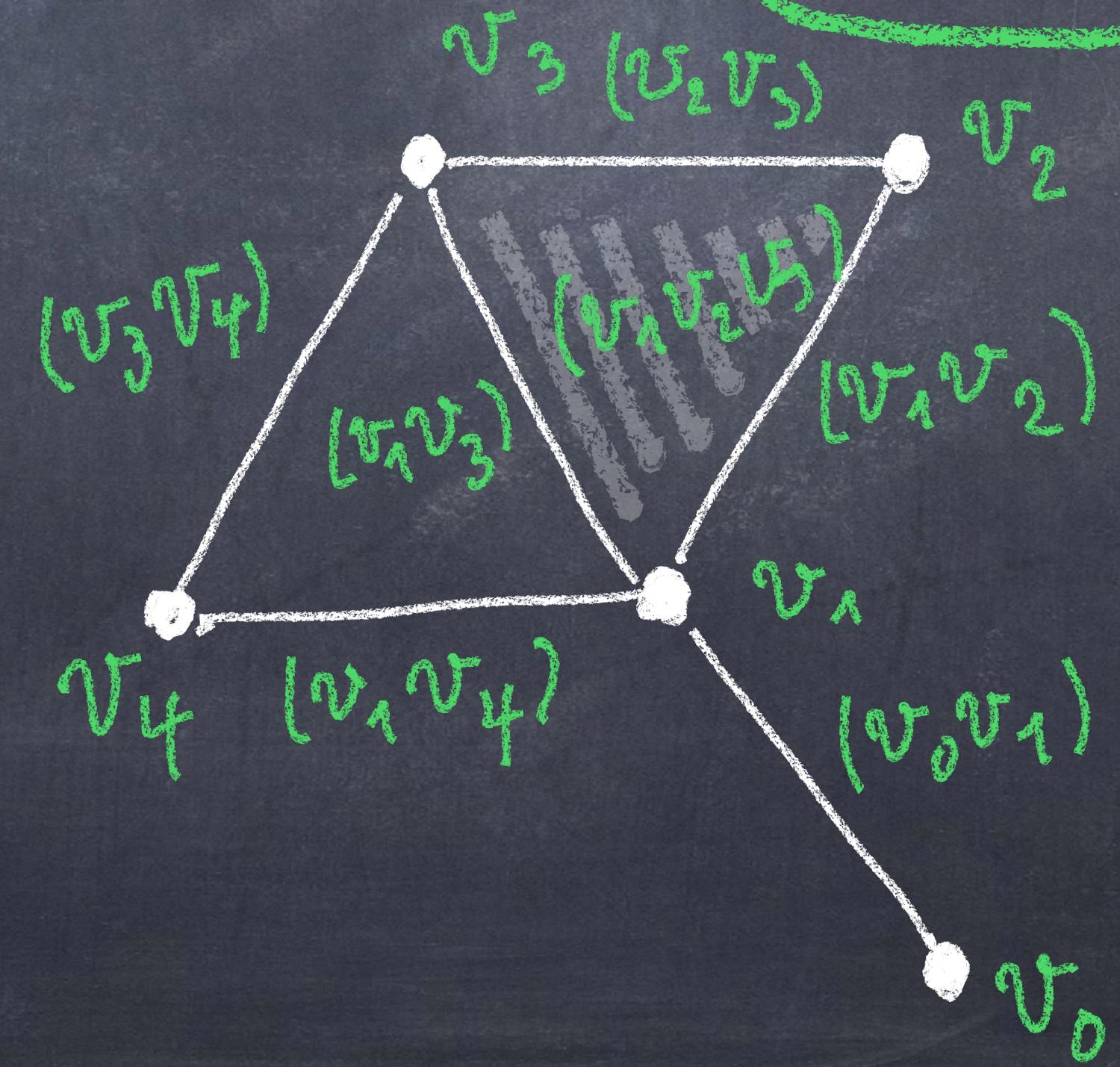
Example ①

Let \mathcal{K} be a simplicial complex on a vertex set V ,

i.e., $\mathcal{K} \subseteq \wp(V)$ satisfying

$$S \subseteq T \subseteq V \quad \text{and} \quad T \in \mathcal{K} \Rightarrow S \in \mathcal{K}.$$

Generalization
of graphs.

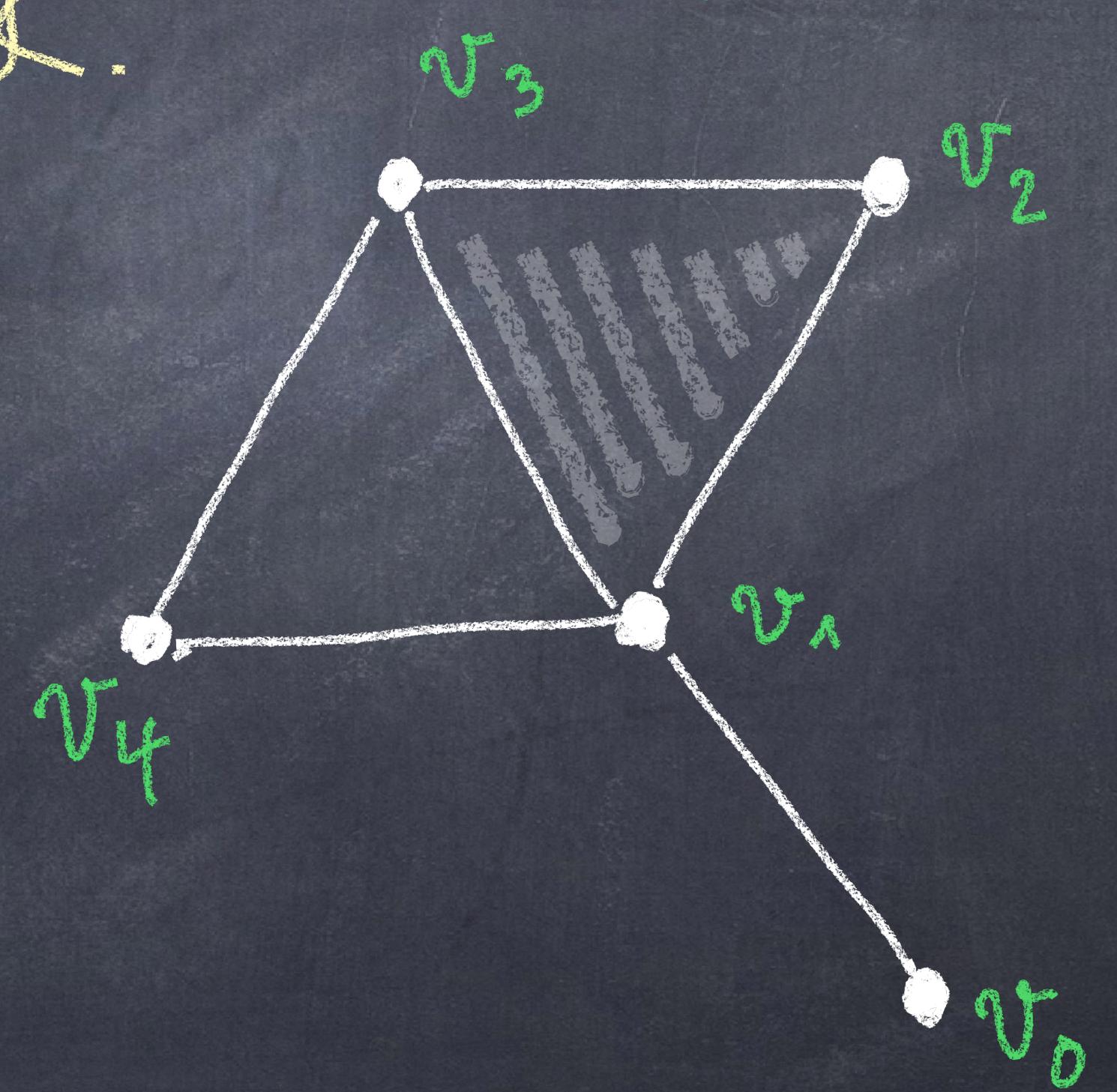


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$$\mathcal{K}_n = \{T \in \mathcal{K} \mid \#T = n+1\}$$



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$$\mathcal{K}_n = \{\tau \in \mathcal{K} \mid |\tau| = n+1\}$$

Choose a total order \prec on V .

Example ①

Let \mathcal{K} be a simplicial complex on a vertex set V .

The chain complex $C_*(\mathcal{K}, \mathbb{R})$:

- $C_n(\mathcal{K}, \mathbb{R}) = \text{Span}_{\mathbb{R}}(\mathcal{K}_n)$

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- $C_n(\mathcal{K}, \mathbb{K}) = \text{Span}_{\mathbb{R}}(\mathcal{K}_n)$
- $d_n : C_n(\mathcal{K}, \mathbb{K}) \rightarrow C_{n-1}(\mathcal{K}, \mathbb{K})$
 $(v_0, \dots, v_n) \mapsto \sum_{i=0}^n (-1)^i (v_0, \dots, \hat{v}_i, \dots, v_n)$

Example ①

Let \mathcal{K} be a simplicial complex on a vertex set V .

The chain complex $C_*(\mathcal{K}, \angle)$:

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- $d_n : C_n(\mathcal{K}, \angle) \rightarrow C_{n-1}(\mathcal{K}, \angle)$

$$(v_0, \dots, v_n) \mapsto \sum_{i=0}^n (-1)^i (v_0, \dots, \hat{v}_i, \dots, v_n)$$

$$H_n(\mathcal{K}) = H_n(C_*(\mathcal{K}, \angle))$$

NB: \angle often dropped
from the notation

Example ①

Let \mathcal{K} be a simplicial complex on a vertex set V ,

The cochain complex $C^*(\mathcal{K}, \angle)$:

$$\cdot C^n(\mathcal{K}, \angle) = \text{Fun}(\mathcal{K}_n, \mathbb{R})$$

$$\cdot d^n : C^{n-1}(\mathcal{K}, \angle) \rightarrow C^n(\mathcal{K}, \angle)$$

$$f \mapsto d^n f : \mathcal{K}_n \rightarrow \mathbb{R}$$

$$(v_0, \dots, v_n) \mapsto \sum_{i=0}^n (-1)^i f(v_0, \dots, \hat{v_i}, \dots, v_n).$$

$$H^n(\mathcal{K}) = H^n(C^*(\mathcal{K}, \angle)).$$

NB: \angle often dropped from the notation

Example ①

Let \mathcal{K} be a simplicial complex on a vertex set V ,

The cochain complex $C^*(\mathcal{K}, \mathbb{Z})$:

- $C^n(\mathcal{K}, \mathbb{Z}) = \text{Fun}(\mathcal{K}_n, \mathbb{R})$
- $d^n : C^{n-1}(\mathcal{K}, \mathbb{Z}) \rightarrow C^n(\mathcal{K}, \mathbb{Z})$
 $f \quad \mapsto \quad d^n f : \mathcal{K}_n \rightarrow \mathbb{R}$

$H^n(\mathcal{K}) = H^n(C^*(\mathcal{K}, \mathbb{Z}))$. — detects non-trivial maps of \mathcal{K} into spaces of interest

Example ①

Let \mathcal{K} be a simplicial complex on a finite vertex set V .

$$\cdot C^n(\mathcal{K}, \mathbb{Z}) \cong C_n(\mathcal{K}, \mathbb{Z}) \text{ if } n$$

$$\cdot H^n(\mathcal{K}) \cong H_n(\mathcal{K}) \text{ if } n$$

Example ②

The de Rham complex of \mathbb{R}^n is a cochain complex

$$\Omega^*(\mathbb{R}^n) = C^\infty(\mathbb{R}^n) \otimes \Lambda(dx_1, \dots, dx_n)$$

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$$\cdot \Omega^k(\mathbb{R}^n) = \left\{ \sum_{t \in T} f_t \cdot dx_{i_{t,1}} \wedge \dots \wedge dx_{i_{t,k}} \mid \begin{array}{l} i_{t,1} < \dots < i_{t,k} \\ f_t \in C^\infty(\mathbb{R}^n) \end{array} \right\}$$

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$$\cdot d^{k+1}: \Omega^k(\mathbb{R}^n) \longrightarrow \Omega^{k+1}(\mathbb{R}^n)$$

$$f dx_{i_1} \wedge \dots \wedge dx_{i_k} \mapsto \sum_{j=1}^n \pm \frac{\partial f}{\partial x_j} dx_{i_1} \wedge \dots \wedge \hat{dx_{i_j}} \wedge \dots \wedge dx_{i_k}$$

Example ②

Given $g: \Delta^k \rightarrow \mathbb{R}^n$, $\omega = f dy_{i_1} \wedge \dots \wedge dy_{i_k} \in \Omega^k(\mathbb{R}^n)$ ↗ affine embeddings

- $g^* \omega = \sum (f \circ g) dg_{i_1} \wedge \dots \wedge dg_{i_k}$

where $dg_i = \sum_{j=1}^k \frac{\partial g_i}{\partial x_j} dx_j$.

- Makes sense therefore to compute $\int_{\Delta^k} g^* \omega \in \mathbb{R}$.

Relation between the examples

- The deRham complex generalizes to $\Omega^*(M)$ for M a smooth n -manifold, by gluing together copies of $\Omega^*(\mathbb{R}^n)$ according to an atlas.

Relation between the examples

- The deRham complex generalizes to $\Omega^*(M)$ for M a smooth n -manifold, by gluing together copies of $\Omega^*(\mathbb{R}^n)$ according to an atlas.
- If a simplicial complex K is a triangulation of M , then $H^*(\Omega^*(M)) \cong H^*(C^*(K))$, mediated by integration.

Incorporating geometry

If M is a Riemannian manifold, each $\Omega^k(M)$ is equipped with an inner product $\langle \cdot, \cdot \rangle$.

Thus \exists :

$$\Omega^{k-1}(M) \xrightarrow{d^k} \Omega^k(M) \xrightarrow{d^{k+1}} \Omega^{k+1}(M)$$
$$\xleftarrow{(d^k)^+}$$
$$(d^{k+1})^+$$

Incorporating geometry

If M is a Riemannian manifold, each $\Omega^k(M)$ is equipped with an inner product $\langle \cdot, \cdot \rangle$.

Thus \exists :

$$\begin{array}{ccccc} & d^k & & d^{k+1} & \\ \Omega^{k-1}(M) & \xrightarrow{\quad} & \Omega^k(M) & \xrightarrow{\quad} & \Omega^{k+1}(M) \\ (d^k)^+ & & & & (d^{k+1})^+ \end{array}$$

$$\Delta^k = d^k (d^k)^+ + (d^{k+1})^+ d^{k+1}: \Omega^k(M) \rightarrow \Omega^k(M)$$

- the Hodge - Laplacian

Hodge's Theorem

If M is a compact Riemannian manifold, then

- $(\ker \Delta^*, 0) \hookrightarrow \Omega^*(M)$ is a map of cochain complexes inducing $\ker \Delta^* \cong H^*(M)$.

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If M is a compact Riemannian manifold, then

- $(\ker \Delta^*, 0) \hookrightarrow \Omega^*(M)$ is a map of cochain complexes inducing $\ker \Delta^* \cong H^*(M)$.

- $\Omega^k(M) \cong \text{Im } d^k \oplus \ker \Delta^k \oplus \text{Im } (d^{k+1})^+$

Harmonic classes

- orthogonal decomposition

Each cohomology class has a unique harmonic representative.

Cochains in signal processing

Ebli-Hacker-Maggs
J. App Comp Top 2024

Goal

Generalize signal processing on graphs
to simplicial complexes, in particular
to better understand signal compression
and reconstruction.

Signals on simplicial complexes

Informally : example of a signal on
2-simplices of \mathcal{K}



Signals on simplicial complexes

Formally: for K a simplicial complex,

a signal on the n -simplices of K
can be viewed as either

$$s \in C_n(K) \quad \text{or} \quad s \in C^n(K).$$

$$s: K_n \rightarrow \mathbb{R}$$

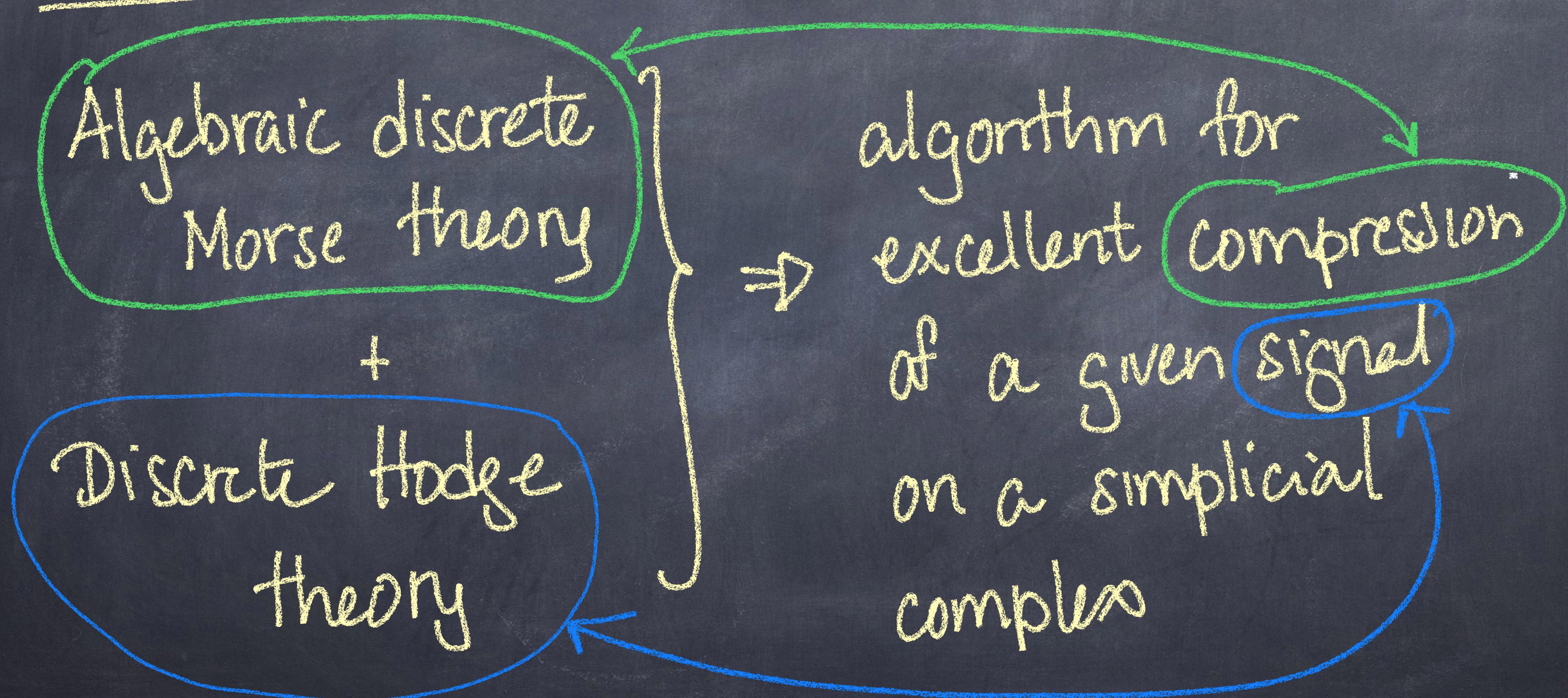
Motivating question

How to compress or sparsify a
signal on a simplicial complex
while minimizing loss?

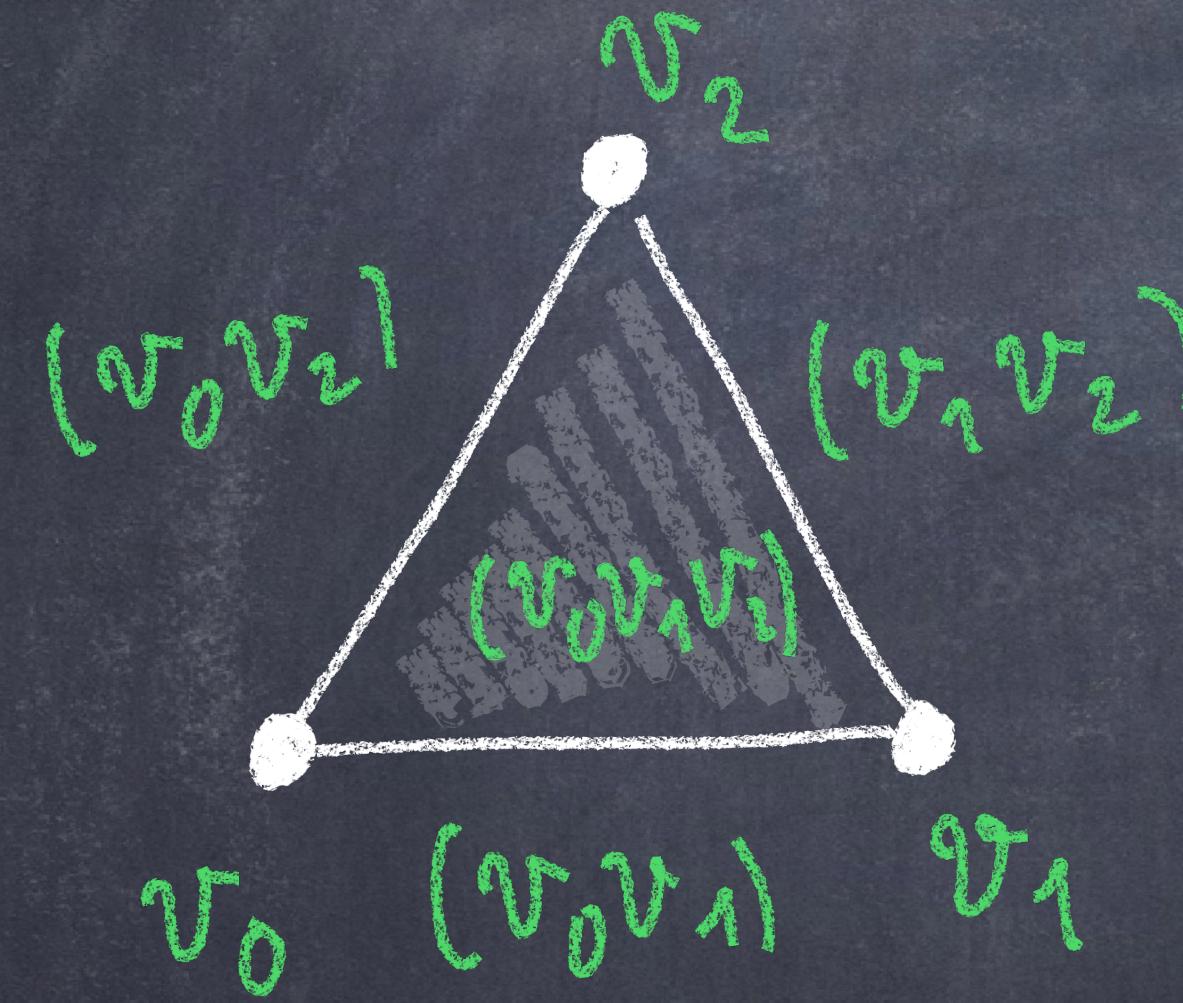
The approach of Eblí - Haker - Maggs

Algebraic discrete Morse theory } + Discrete Hodge theory } \Rightarrow algorithm for excellent compression of a given signal on a simplicial complex

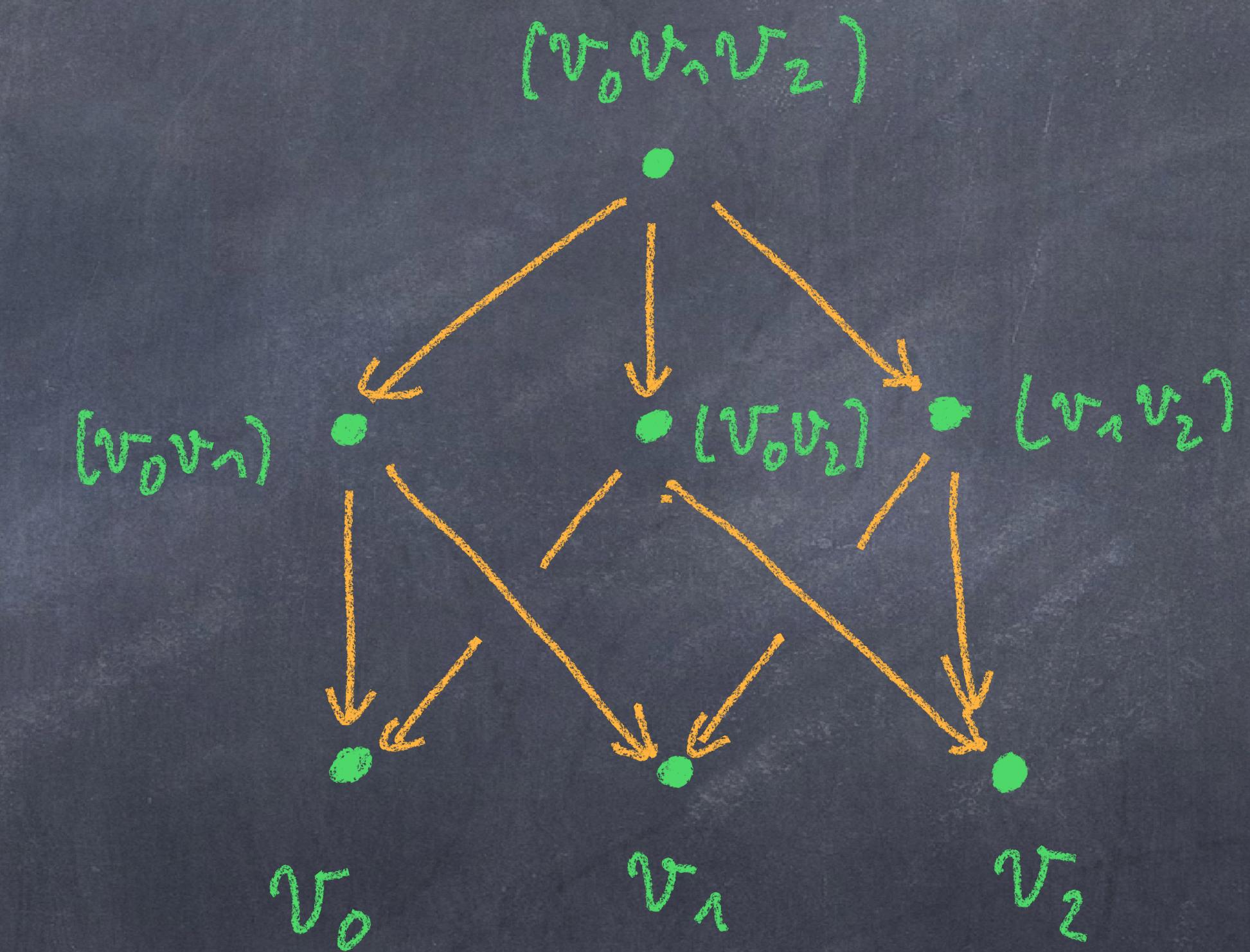
The approach of Eblí - Haker - Maggs



Essential mathematical notions



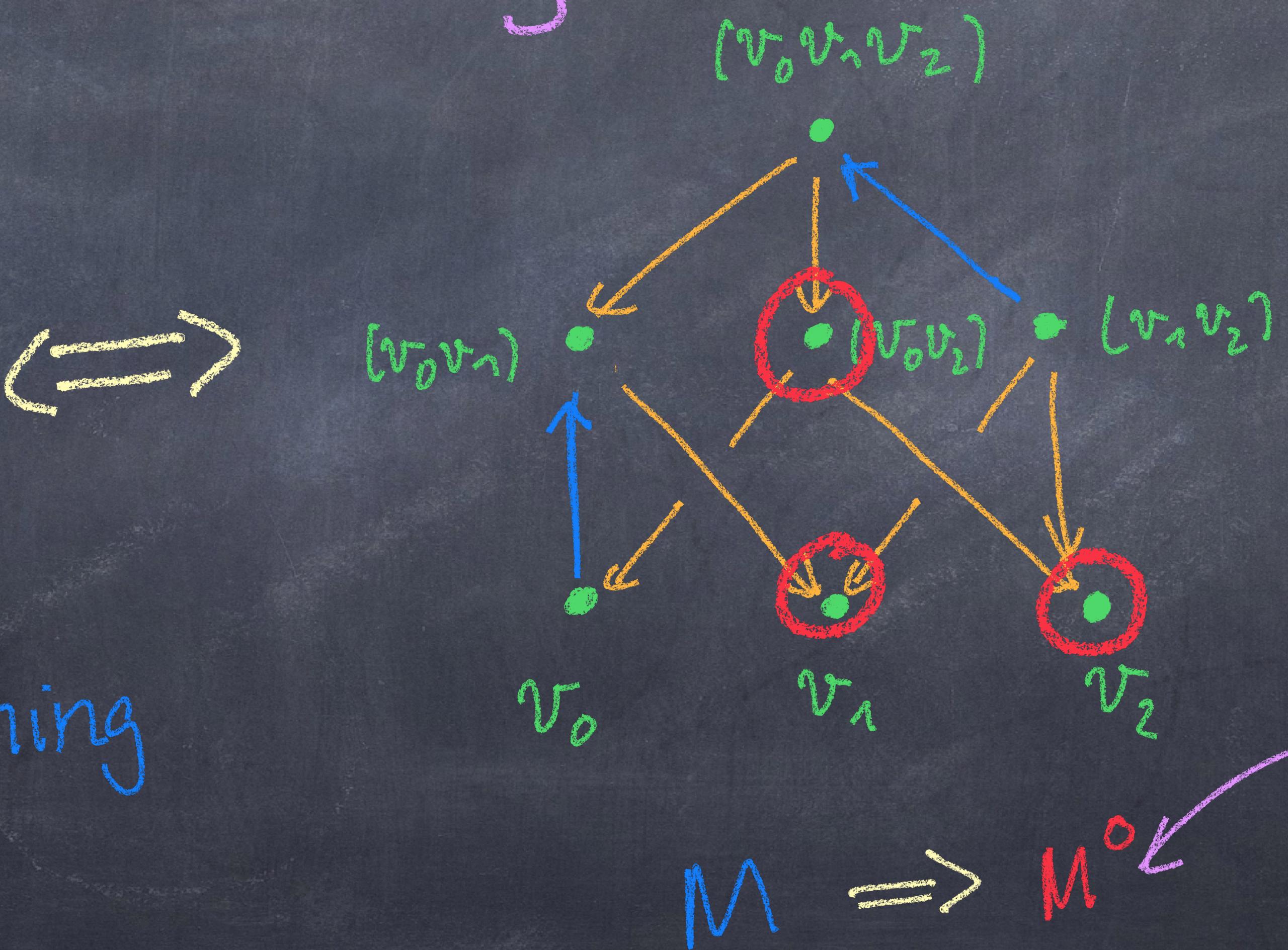
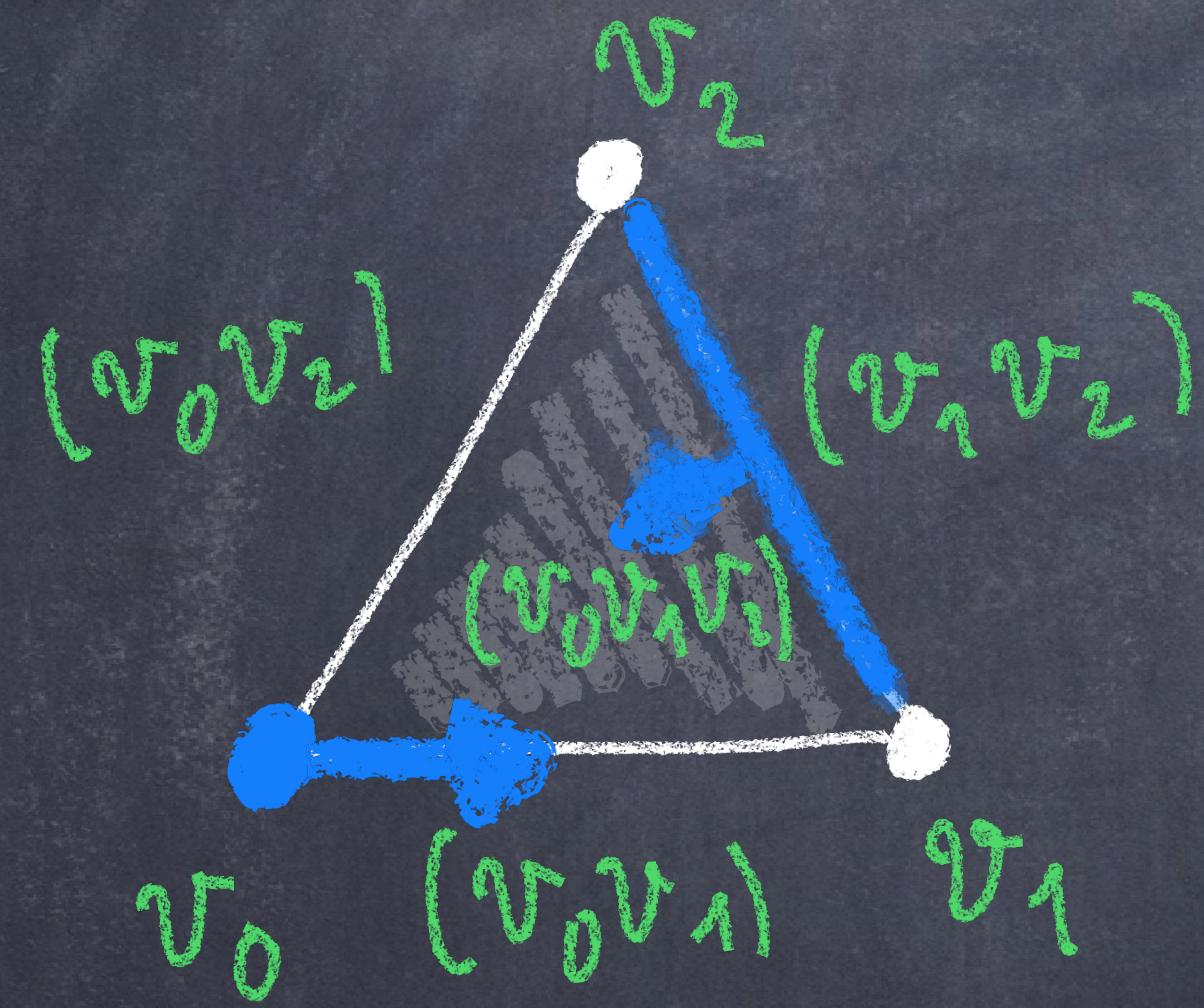
\iff



Hasse diagram of X

Essential mathematical notation

Morse matching



Fundamental Thm of ADMT [Sköldberg]

For every Morse matching M on a chain complex C , \exists deformation retract

$$\rho^M \gamma^M = \text{Id}_C$$

$$\gamma^M \rho^M \cong \text{Id}_C$$

$$C^M \xrightarrow{\gamma^M} CQh^M \xleftarrow{\rho^M}$$

← Explicit formulas!

where

$$C_n^M = \text{Span}_{\mathbb{R}} \{ \text{critical } n\text{-cells} \}.$$

Discrete Hodge theory

(C, ∂) = finite-type chain complex of real
inner product spaces

$$\partial_n : C_n \rightarrow C_{n-1} \Rightarrow \partial_n^t : C_{n-1} \rightarrow C_n$$

(adjoint)

$$f_{n \geq 1}$$

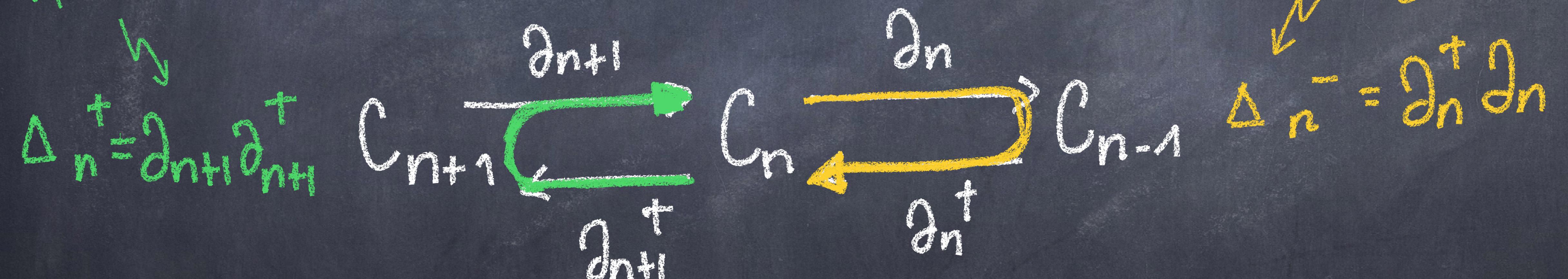
Discrete Hodge theory

(C, ∂) = finite type chain complex of real inner product spaces

Up Laplacian

product spaces

Down Laplacian



Discrete Hodge theory

(C, ∂) = finite type chain complex of real inner product spaces

$$\Delta_n^+ = \partial_{n+1} \partial_{n+1}^+ \quad C_{n+1} \xrightarrow{\partial_{n+1}} C_n \xrightarrow{\partial_n} C_{n-1}$$
$$\Delta_n^- = \partial_n^+ \partial_n \quad \Delta_n = \Delta_n^+ + \Delta_n^-$$

The diagram illustrates the boundary operators ∂_{n+1} and ∂_n between the spaces C_{n+1} , C_n , and C_{n-1} . The operator ∂_{n+1} maps C_{n+1} to C_n , and the operator ∂_n maps C_n to C_{n-1} . A green arrow also points from C_{n-1} back to C_n , labeled ∂_n^+ .

$$\Delta_n = \Delta_n^+ + \Delta_n^- : C_n \longrightarrow C_n \quad \text{The combinatorial Laplacian}$$

Fundamental Thm of DHT [Eckmann]

For (C, δ) any finite-type chain complex of real inner product spaces:

- $H_n(C, \delta) \cong \ker \Delta_n$

and

- $C_n \cong \text{Im } \mathcal{I}_{n+1} \oplus \ker \Delta_n \oplus \text{Im } \mathcal{J}_n^+,$
 $\text{if } n \geq 0.$

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Diagram illustrating the decomposition of C_n into three components:

- The first component, $\text{Im } \mathcal{I}_{n+1}$, is circled in green and labeled "curl-like".
- The second component, $\ker \Delta_n$, is circled in green and labeled "harmonics".
- The third component, $\text{Im } \mathcal{J}_n$, is circled in green and labeled "gradient-like".

Fundamental Thm of DHT [Eckmann]

For (C, δ) any finite-type chain complex of real inner product spaces:

$$C_n \cong \overbrace{\text{Im } \delta_{n+1}}^{\exists \text{ ON basis}} \oplus \ker \Delta_n \oplus \overbrace{\text{Im } \delta_n}^{\exists \text{ ON basis}},$$

\exists ON basis

of eigenvectors

of Δ_n^+

+

\exists ON basis

of eigenvectors

of $\bar{\Delta}_n$

\Rightarrow

Hodge basis
of (C, δ)

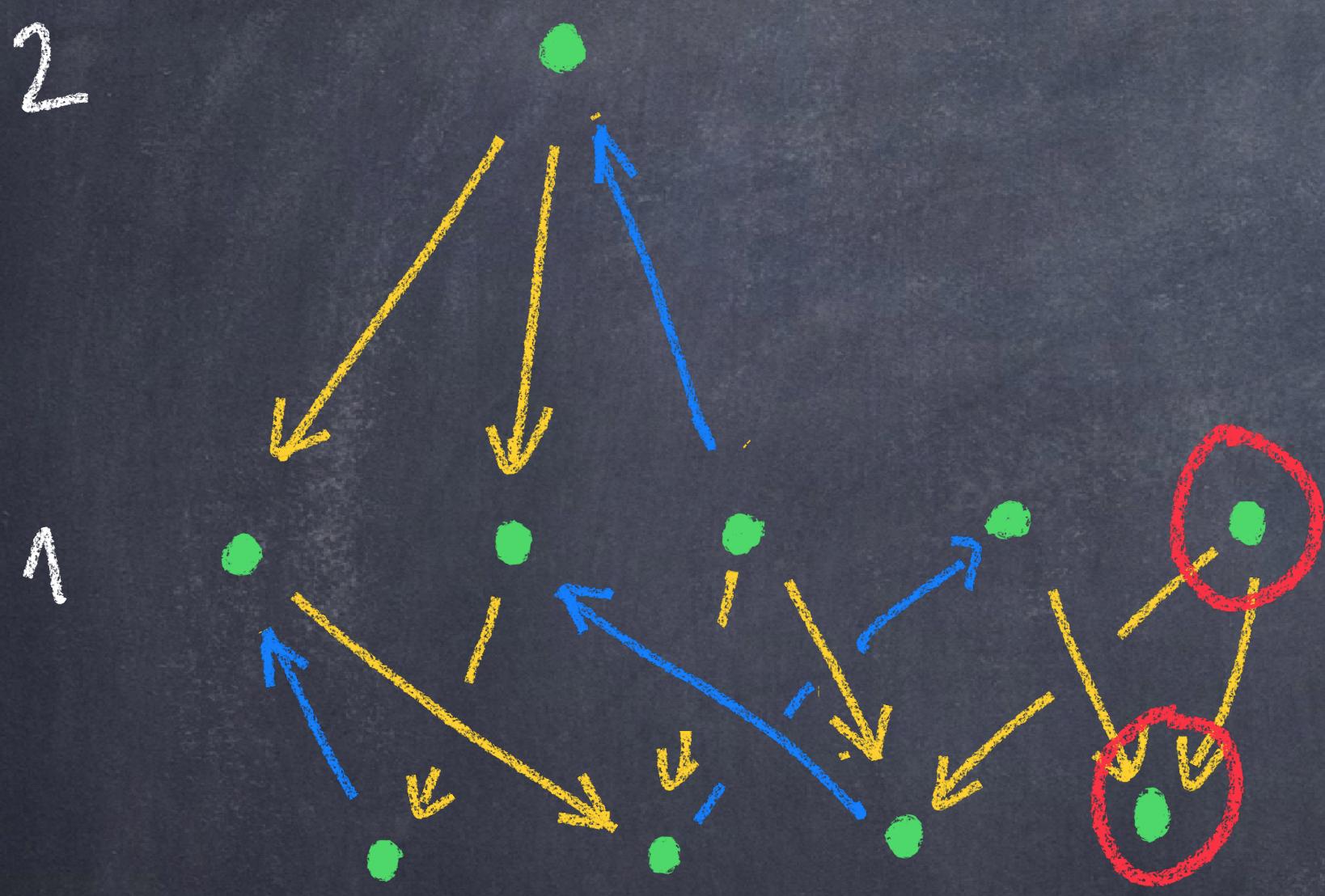
The Hodge Matching Thm [EHM '22]

Given (C, ∂) as above, the Hodge basis gives rise to a Moore matching with associated deformation retract

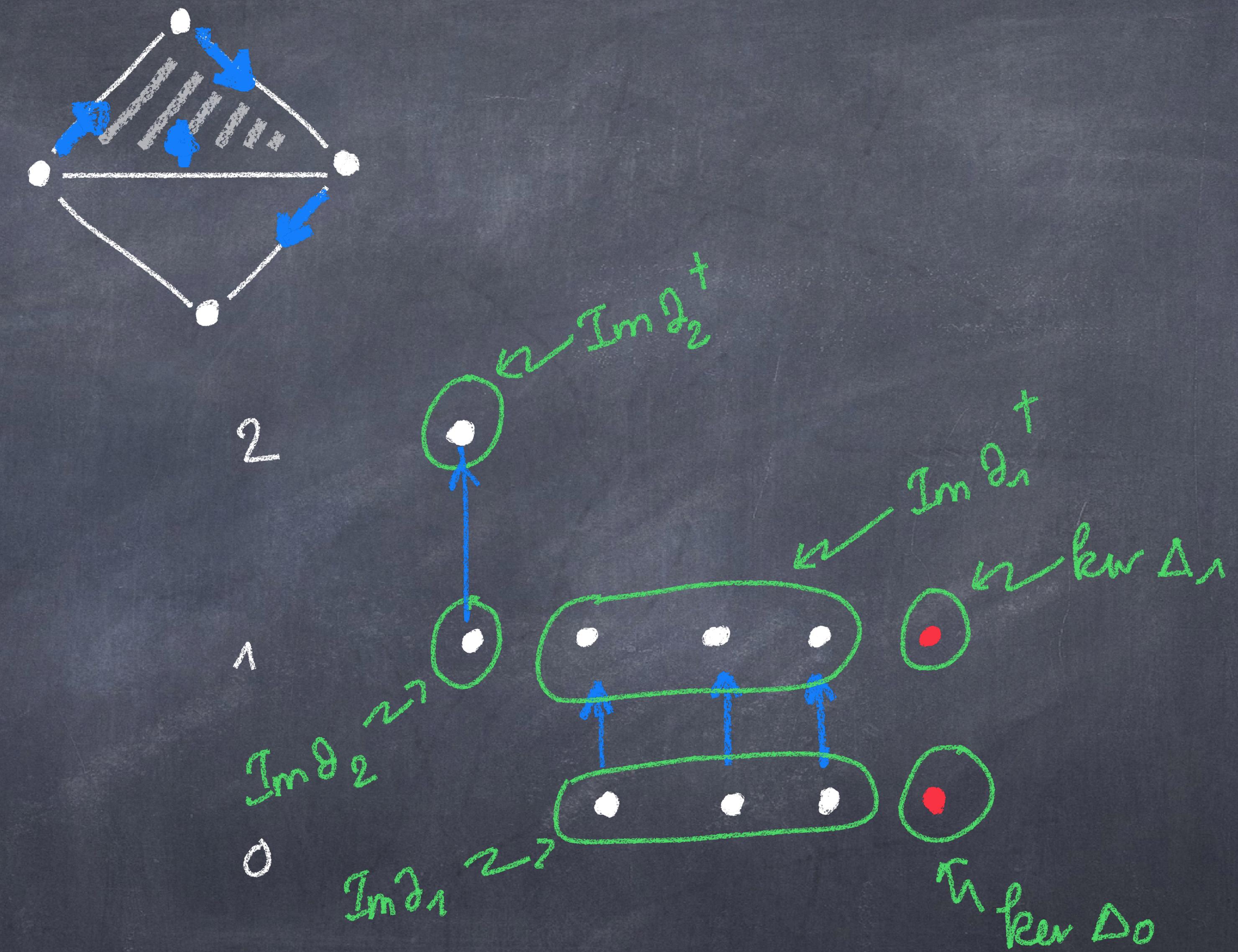
$$(\ker \Delta, 0) \begin{array}{c} \xrightarrow{\quad} \\[-1ex] \xleftarrow{\quad} \end{array} (C, \partial) \text{ wr}^\Delta.$$

- the Hodge retraction

Example



Geometric Morse matching



Algebraic Morse matching

An autoencoder problem

Given a deformation retract

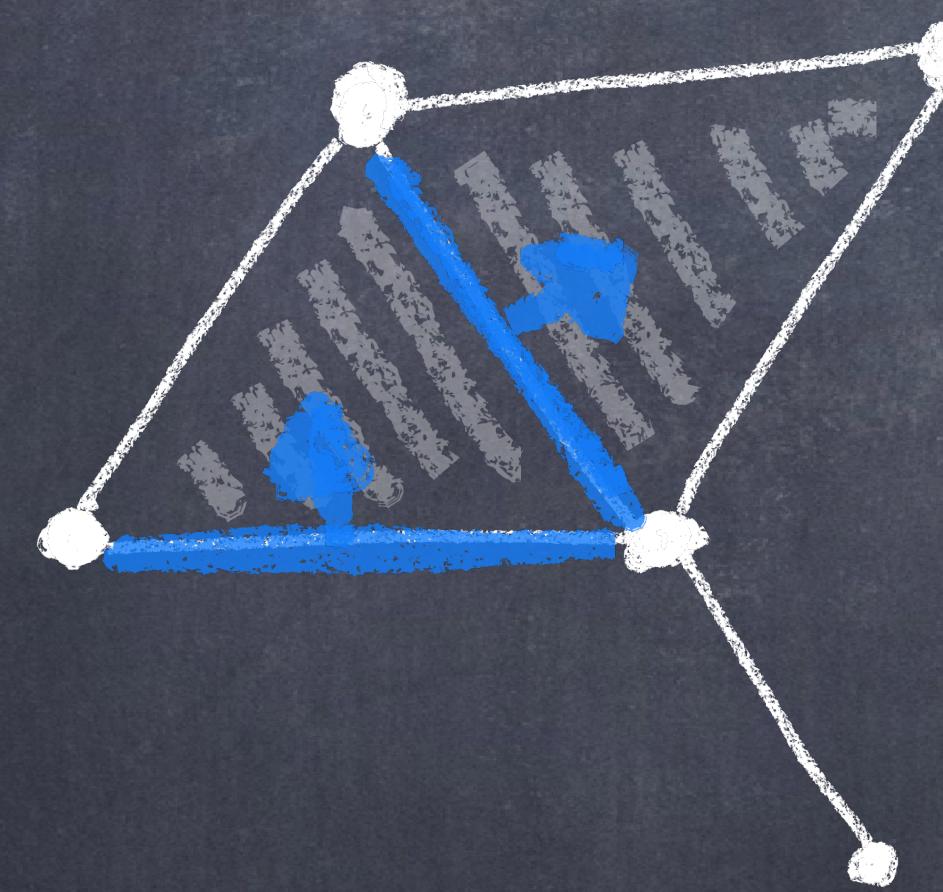
$$(C, g) \xrightarrow{r} (C, g) \circ h \xleftarrow{P}$$

reconstruction
compression

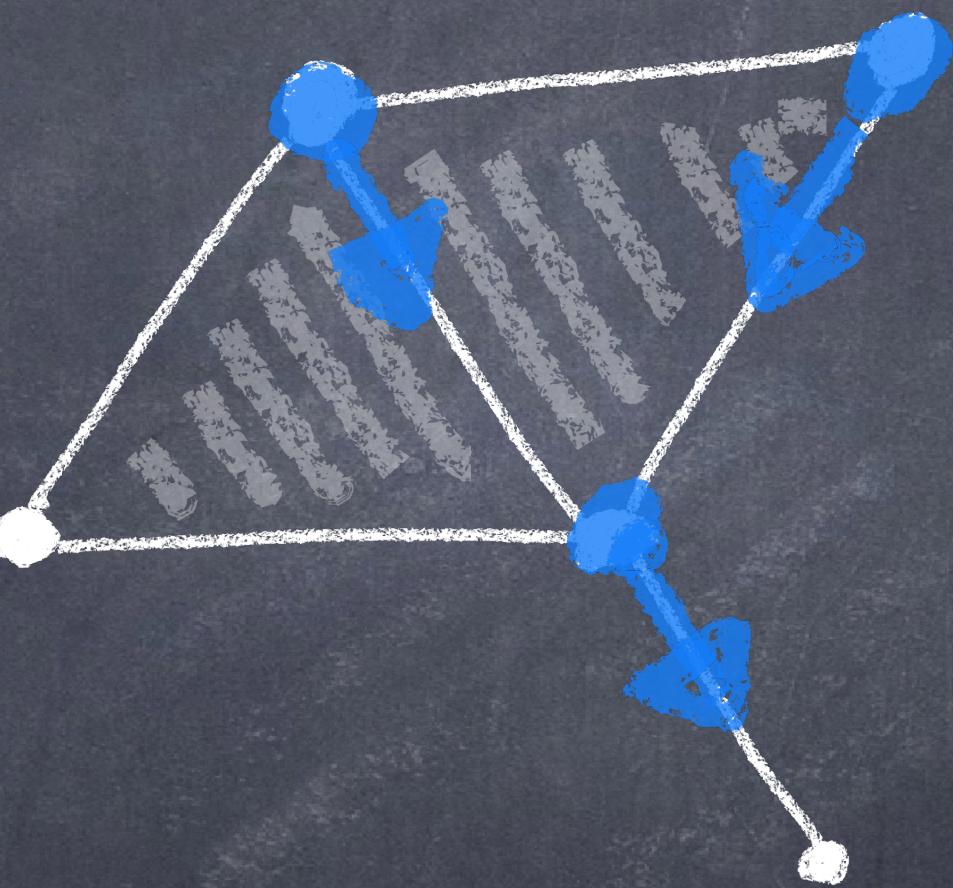
and a "signal" $s \in C$, what can we say about $s - r(s)$?

$(n, n-1)$ free Morse matchings

No $(n-1)$ -simplex matched to an n -simplex



$(1,0)$ -free



$(2,1)$ -free

Adjoint decompositions

Let (C, ∂) be a chain complex of f-dim'l real inner product spaces.

$$\begin{array}{ccccc} & \partial_{n+1} & & \partial_n & \\ C_{n+1} & \xrightarrow{\quad} & C_n & \xrightarrow{\quad} & C_{n-1} \\ & \downarrow \partial_n^t & & \downarrow \partial_{n-1}^t & \\ & \partial_{n+1} & & & \end{array}$$

$$\Rightarrow \ker \partial_n \oplus \text{Im } \partial_n^t \cong C_n \cong \text{Im } \partial_{n+1} \oplus \ker \partial_{n+1}^t$$

Reconstruction Theorem [EHM '22]

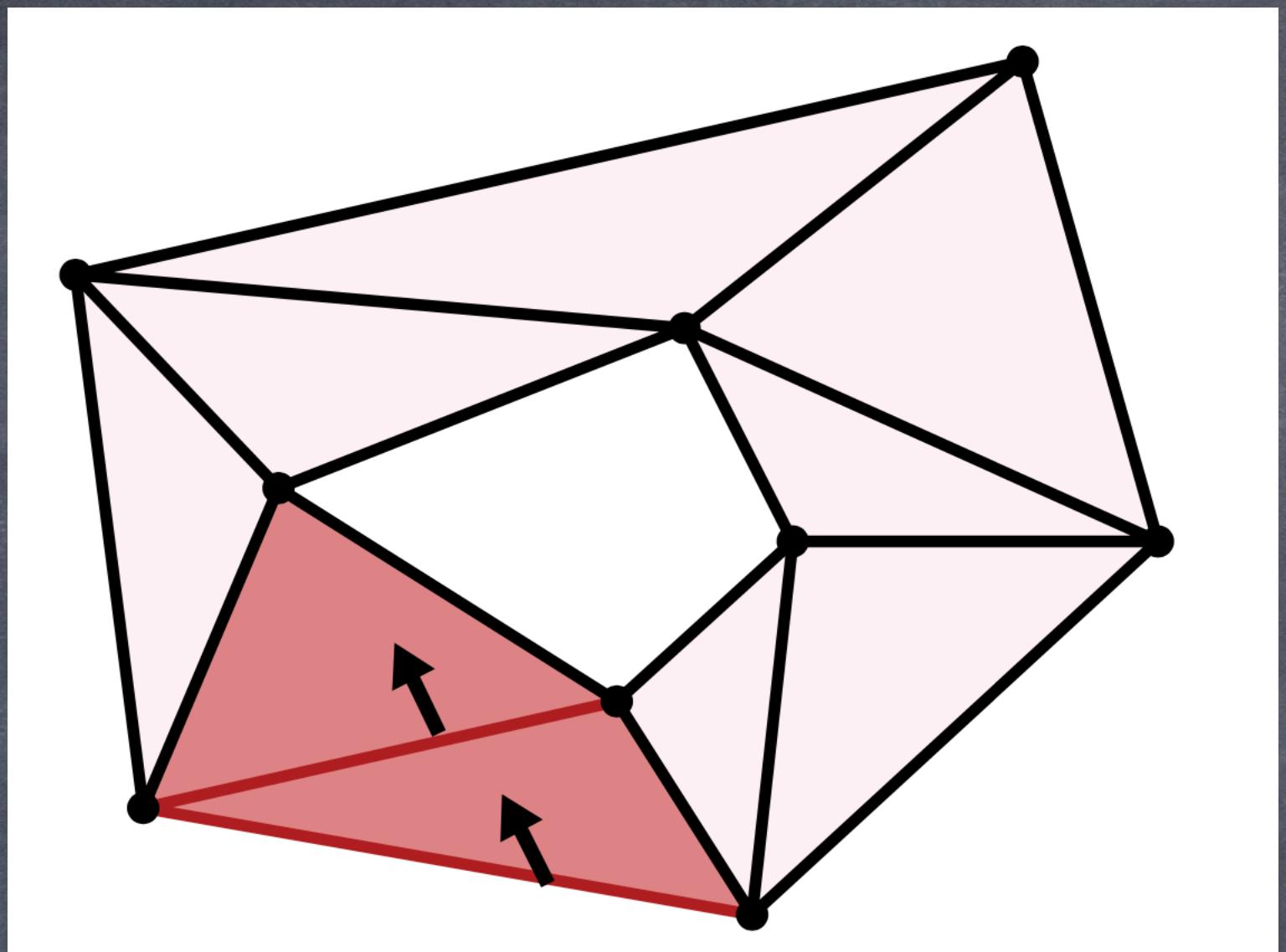
Let M be a $(n, n-1)$ -free Morse matching on (C, ∂) chain complex of f-dim'l inner product spaces.

Consider $(C, \partial)^M \xrightarrow{\varphi^M} (C, \partial) 2^{h^M}$.

Then: $\text{Proj}_{\ker D_{n+1}} + (s - \varphi^M p^M(s)) = 0 \quad \forall s \in C_n$

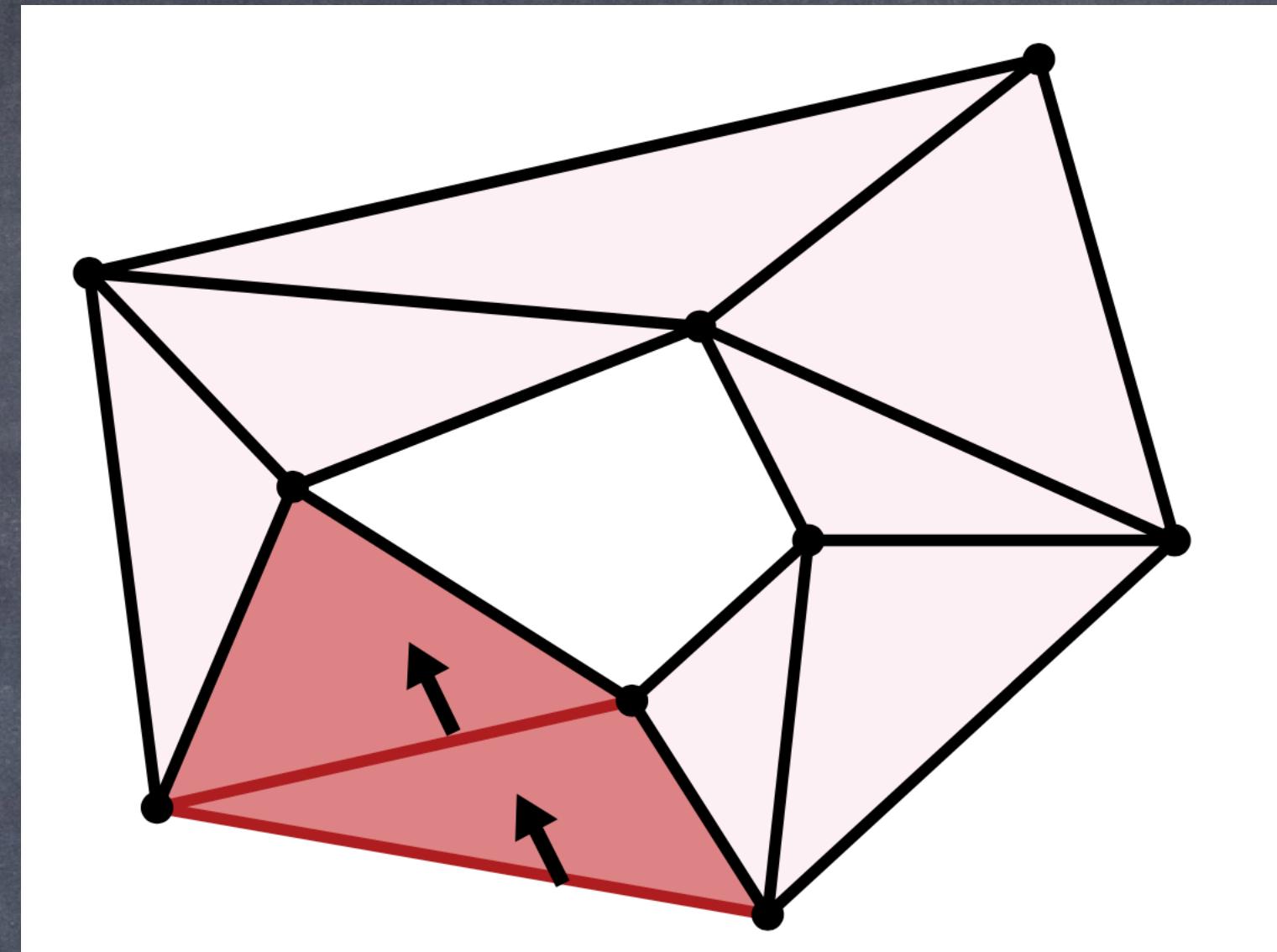
- the error lies uniquely in $\text{Im } D_{n+1}^\perp$!

Example

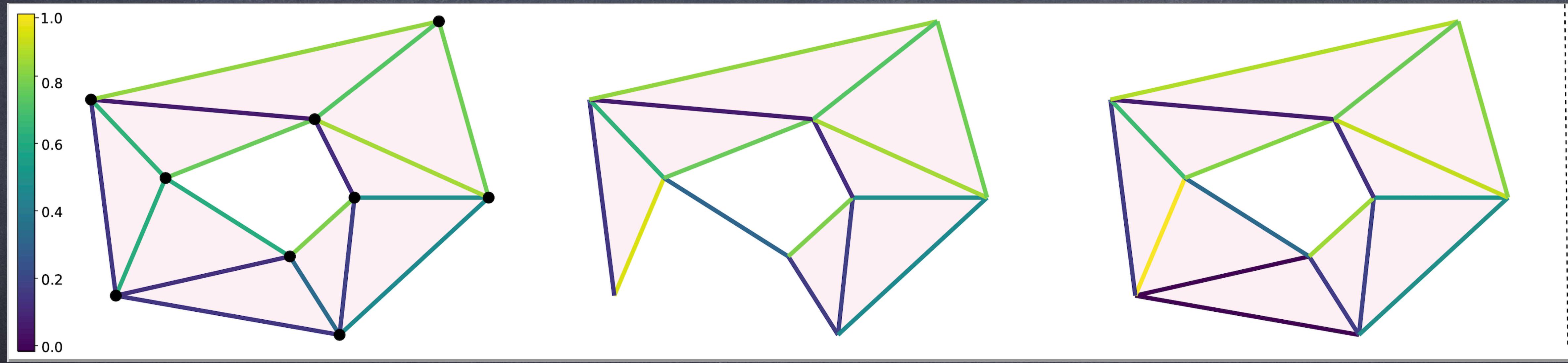


$(1,0)$ - free
Morse matching

Example

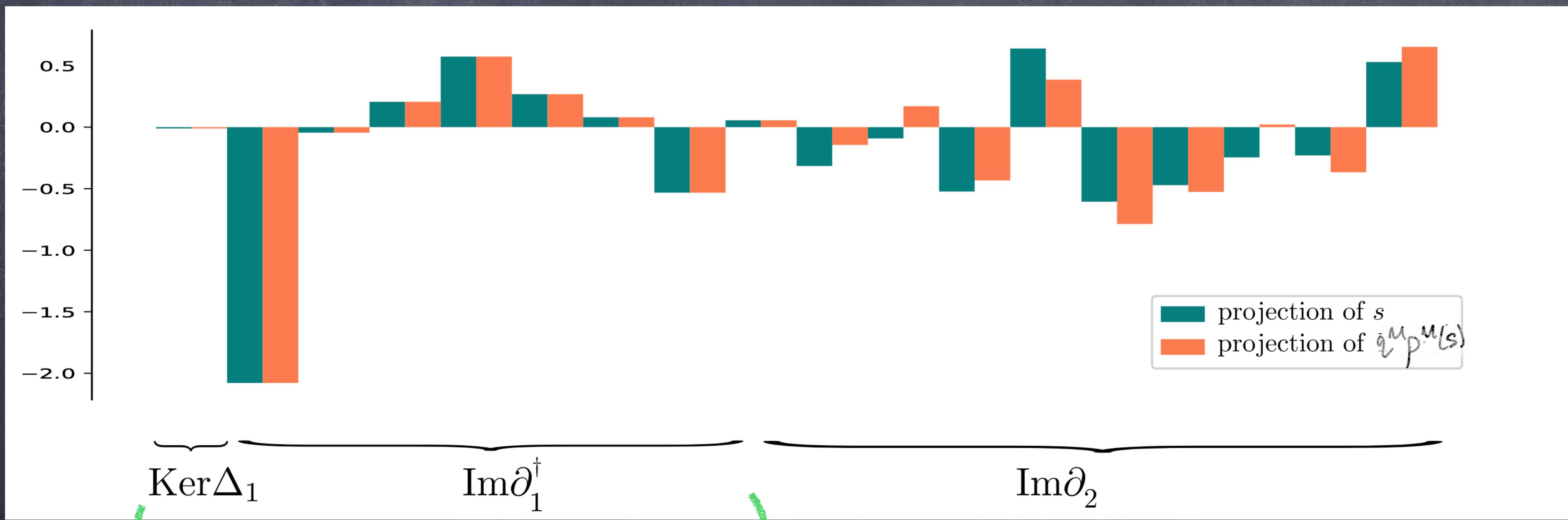
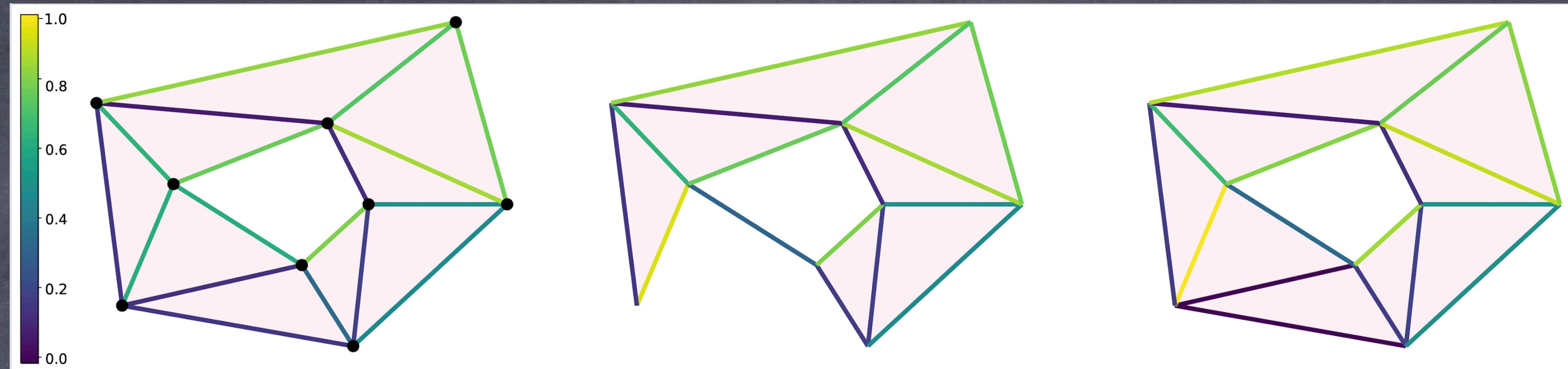


(1,0)- free
Morse matching



$$s \in C_n(k) \xrightarrow{\quad} p^M(s) \in C_1(k)^M \xrightarrow{\quad} q^M p^M(s) \in C_1(k)$$

Example



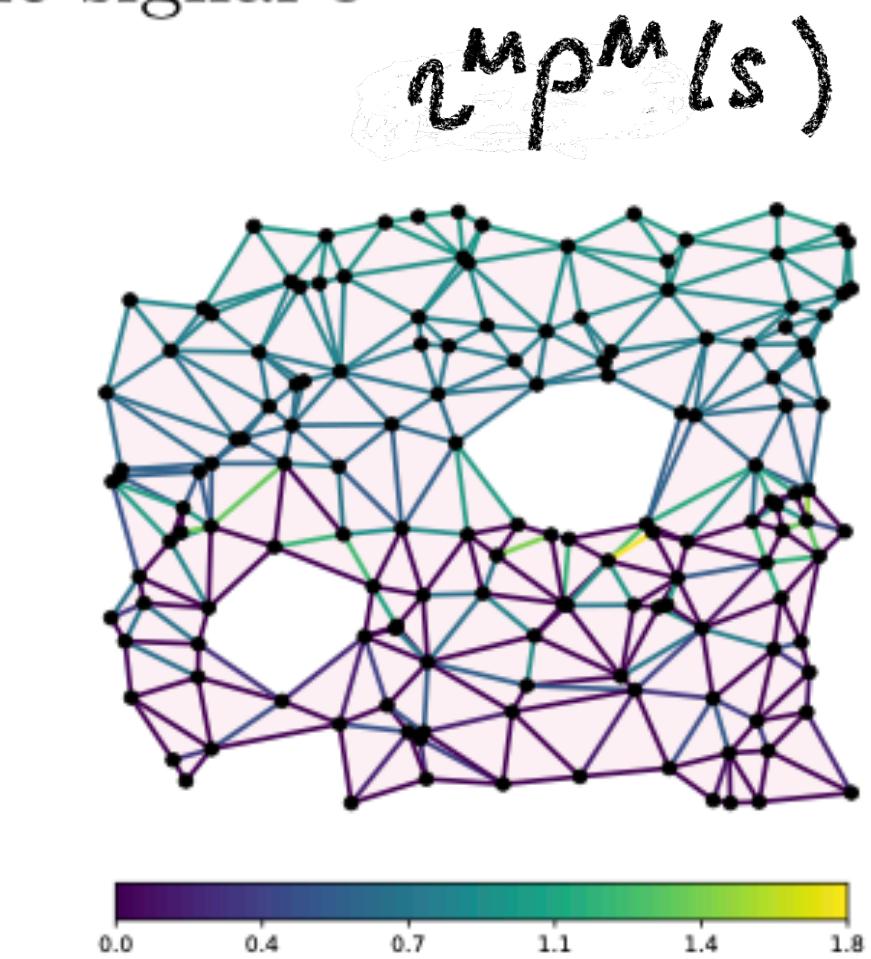
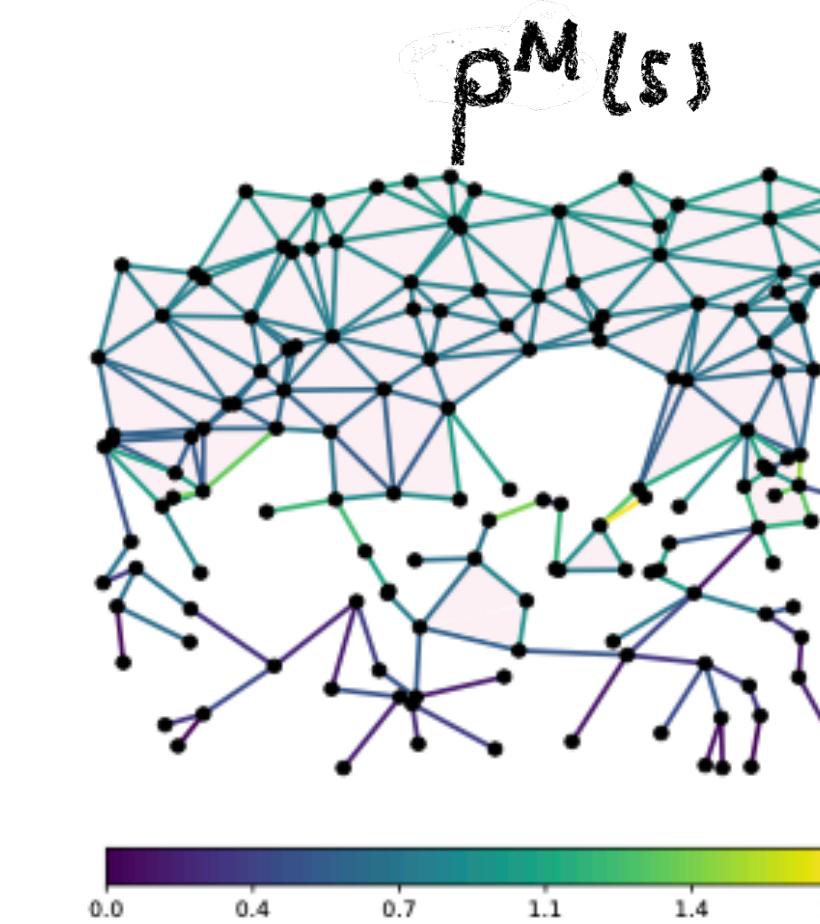
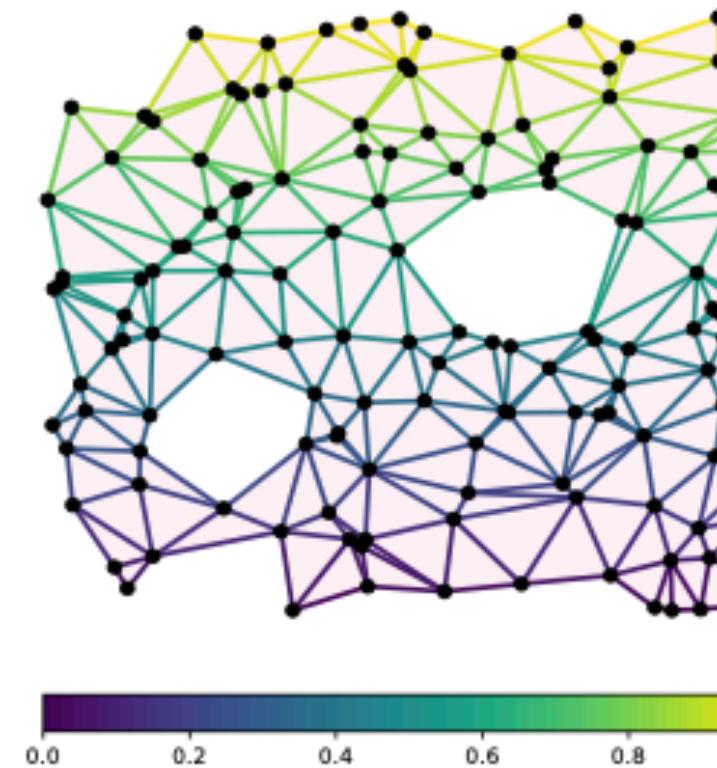
$\overbrace{\quad\quad\quad}^{\text{Ker}\Delta_1} \quad \overbrace{\quad\quad\quad}^{\text{Im}\partial_1^\dagger} \quad \overbrace{\quad\quad\quad}^{\text{Im}\partial_2}$

$= \ker \partial_2^\dagger$

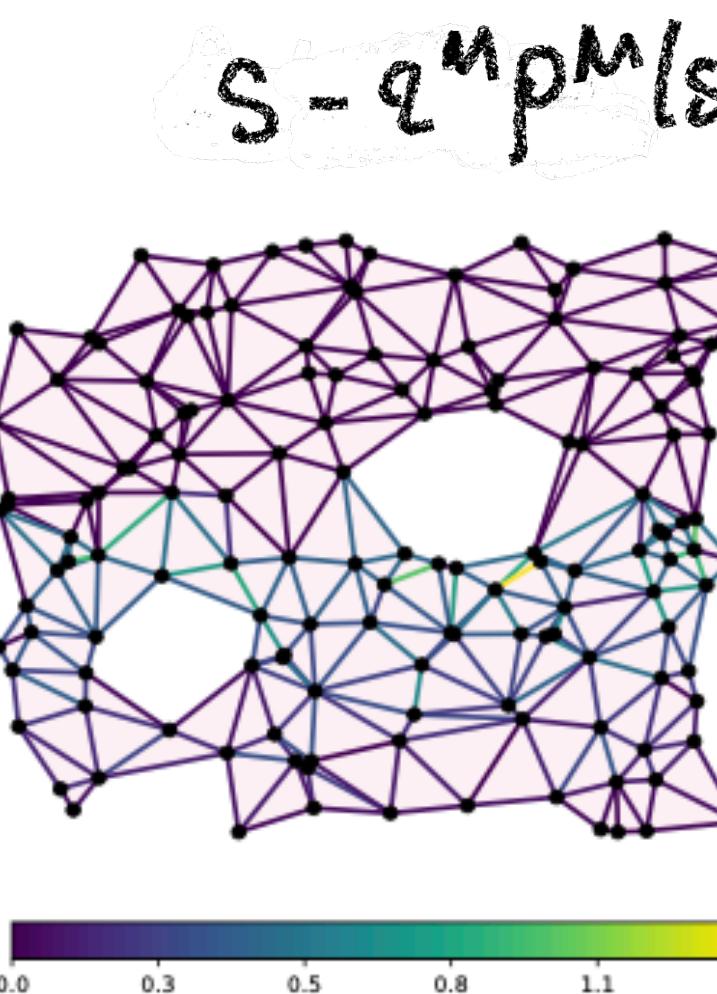
Experiments

A Sequence of optimal pairings and reconstruction of the signal s

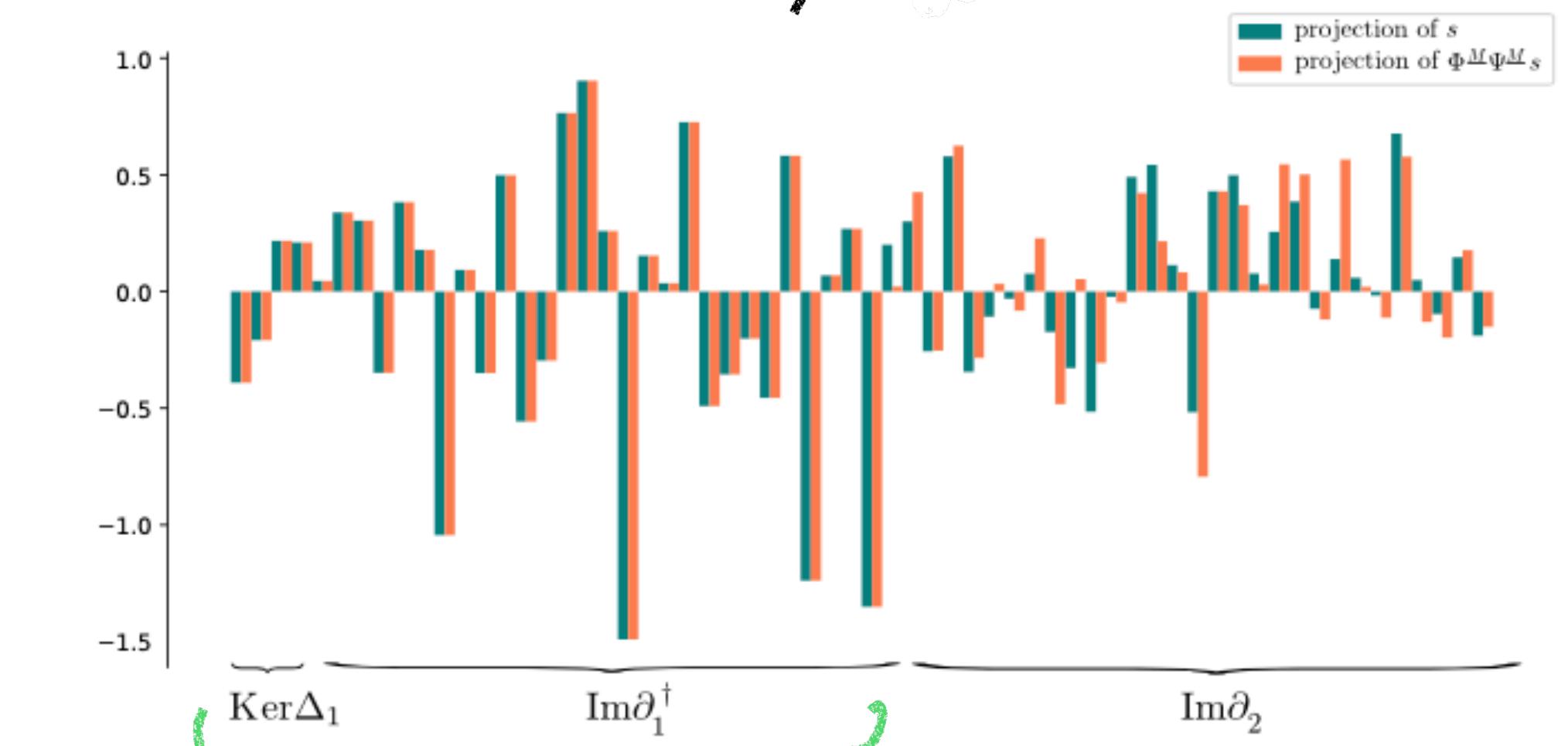
s = height function



B Reconstruction error

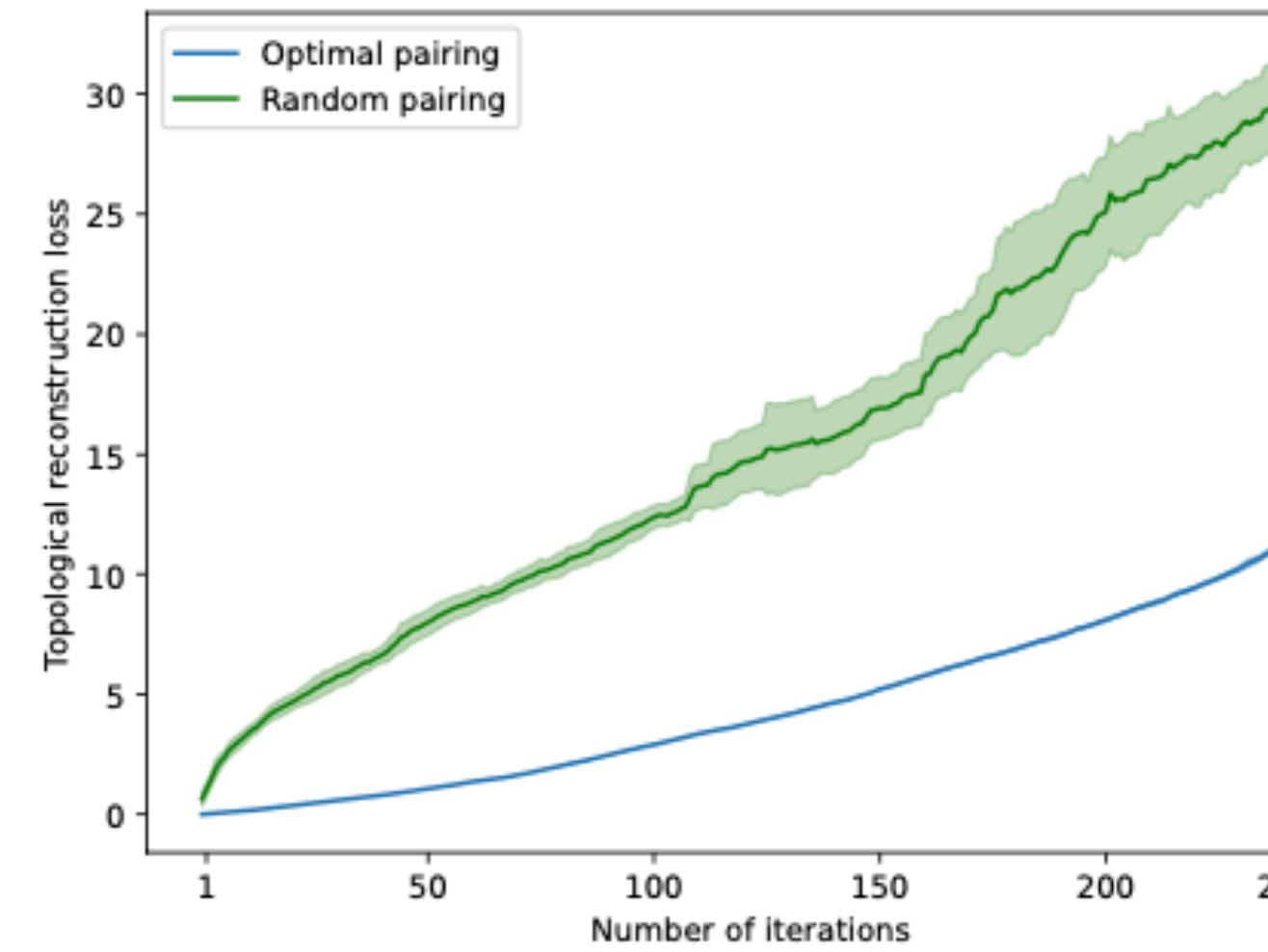


C Projection of s and $q^M p^M(s)$ on the Hodge basis

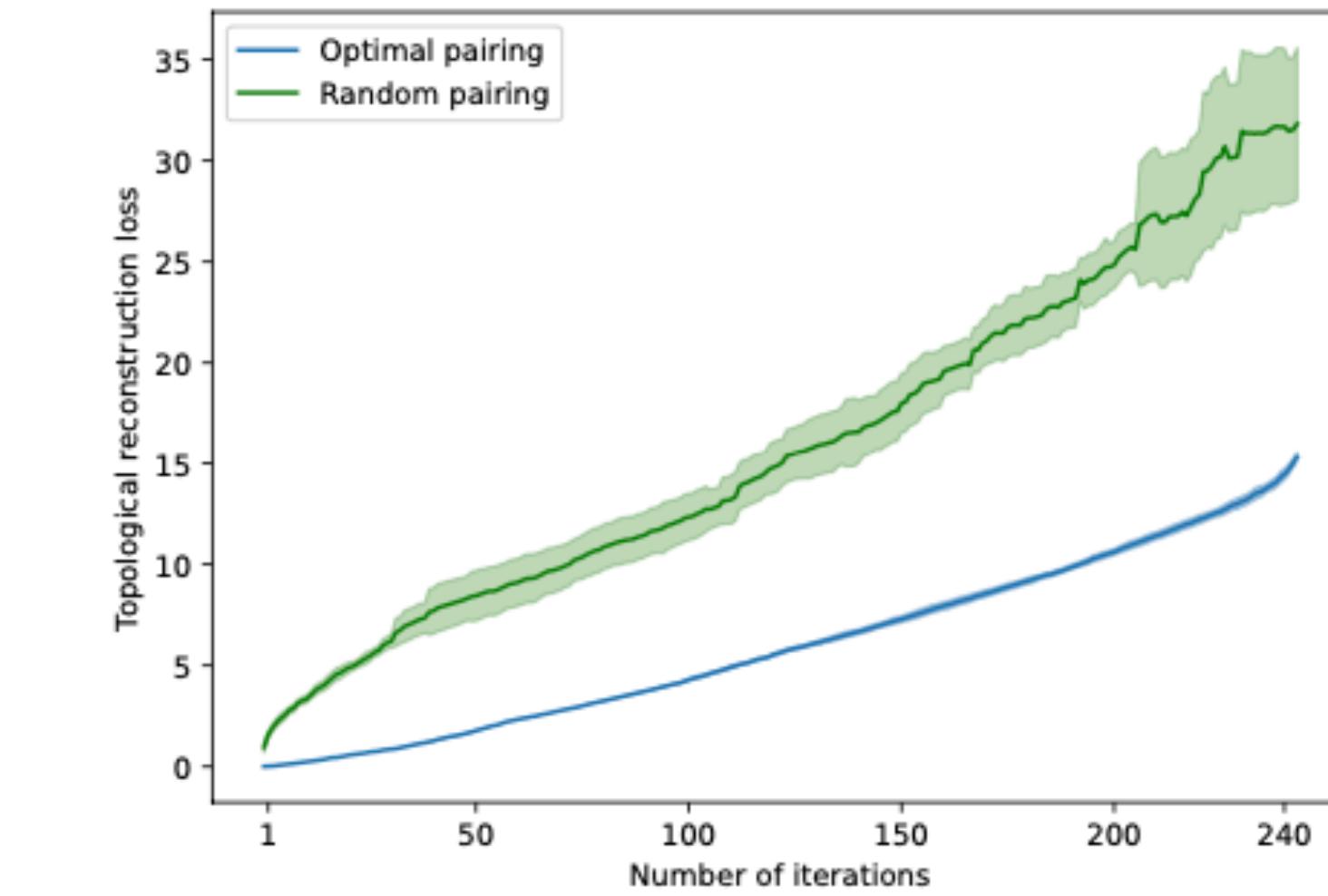


Experiments

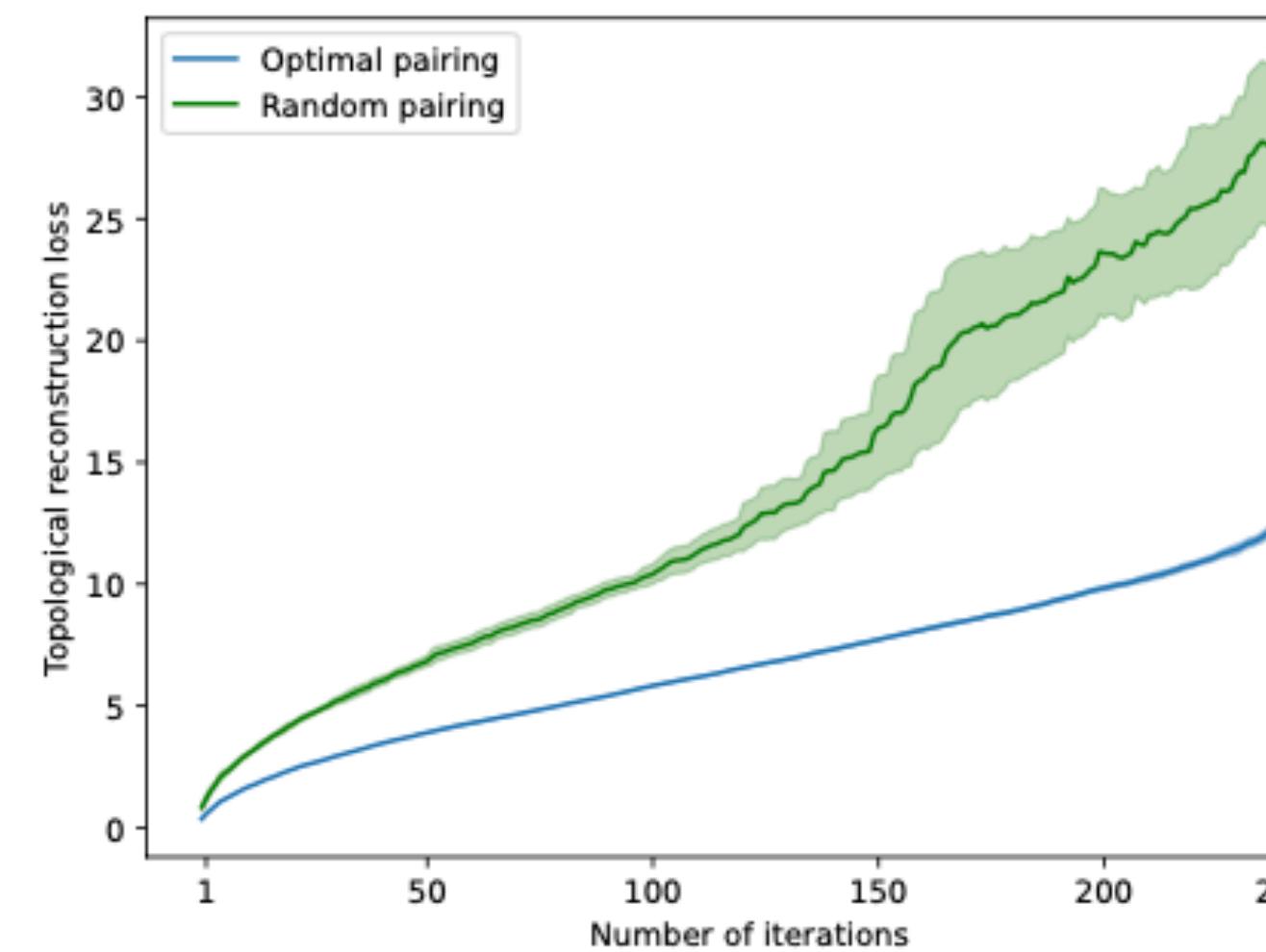
A Signal sampled from a uniform distribution



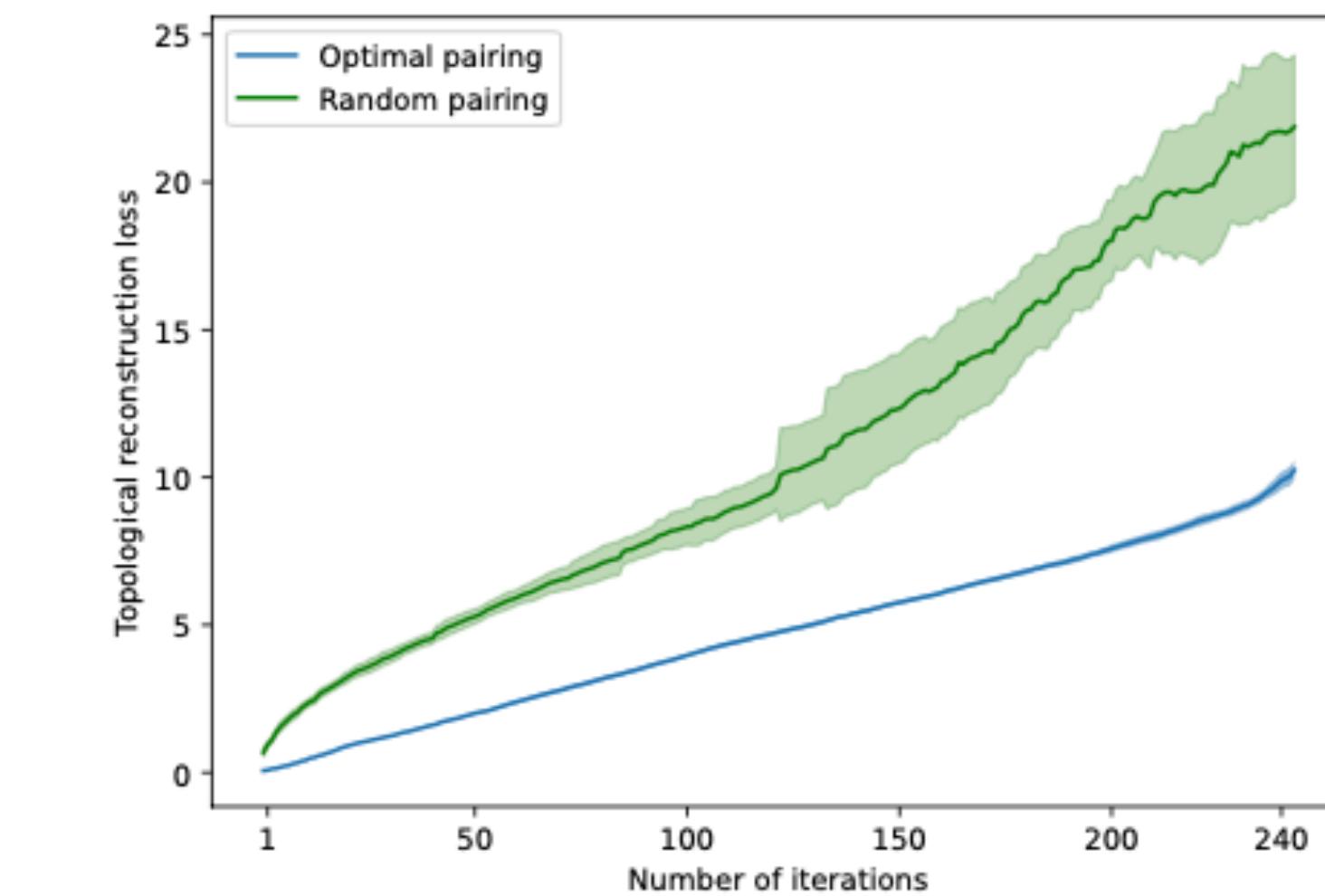
B Signal given by the height function



C Signal sampled from a normal distribution



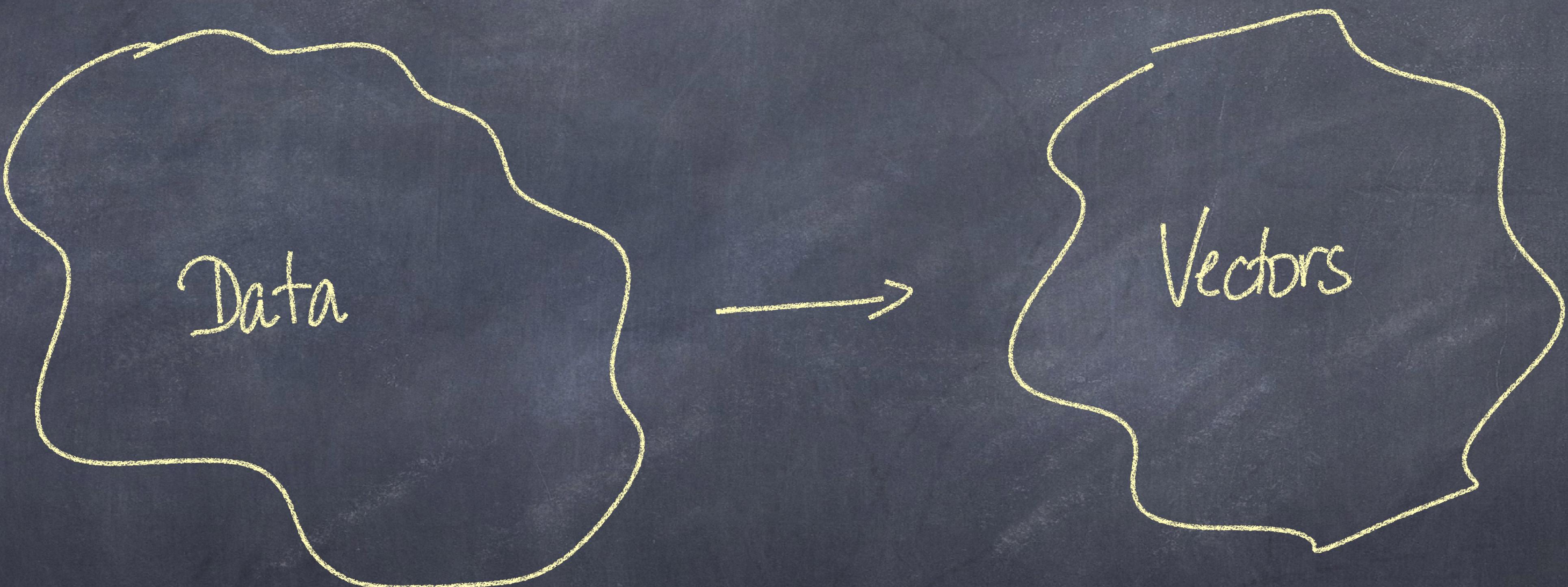
D Signal given by the distance from the center



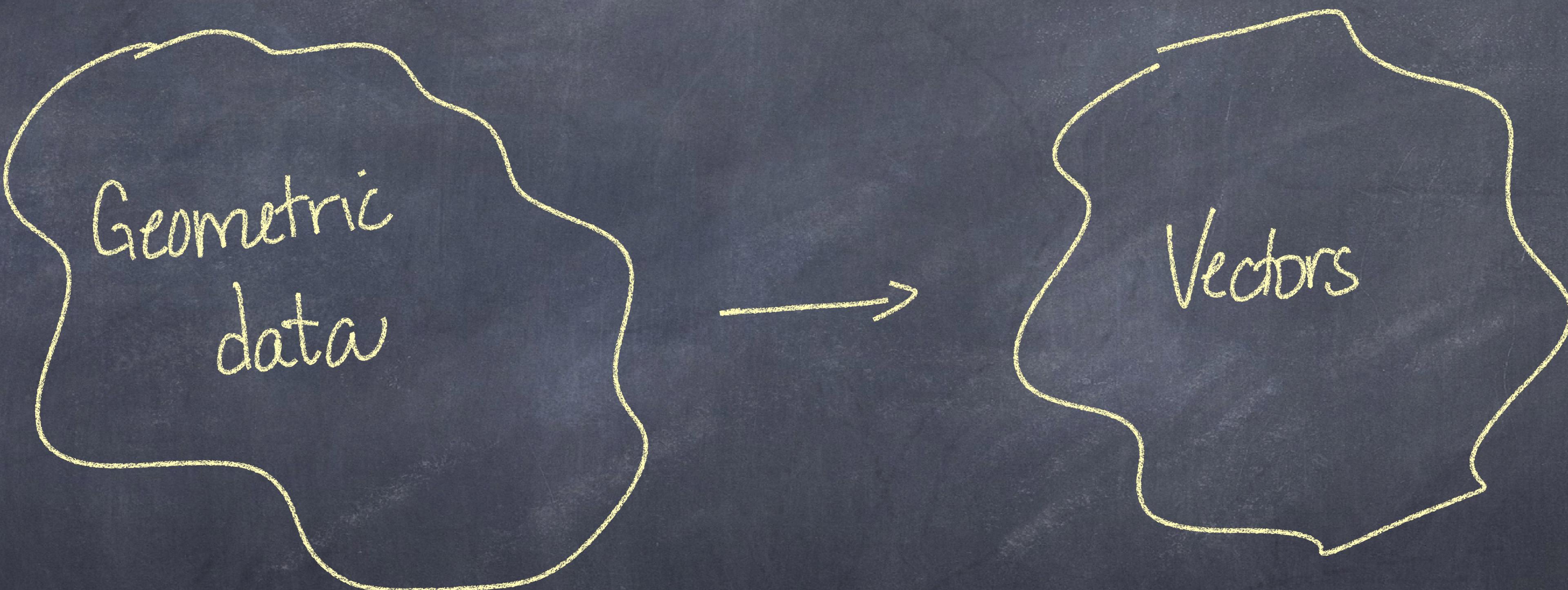
Cochains in machine learning

Maggs - Hader - Rieck
ICLR 2024

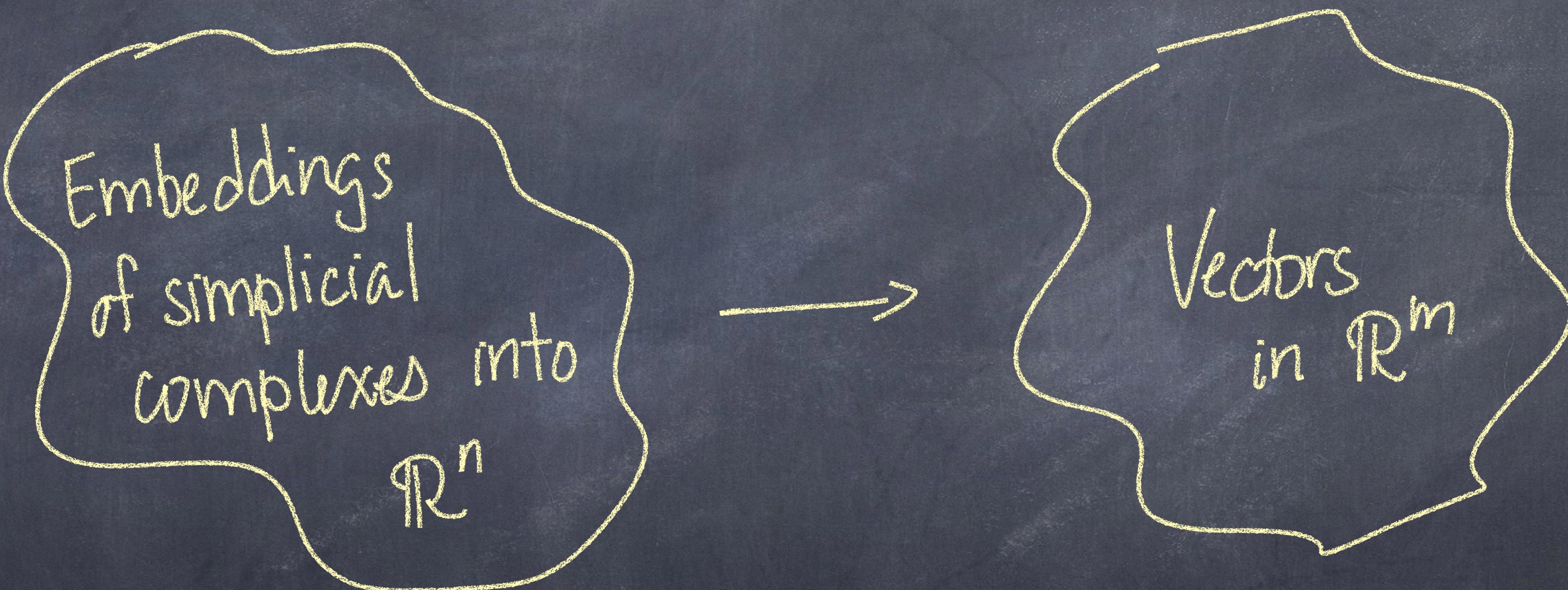
Representation learning



Geometric representation learning

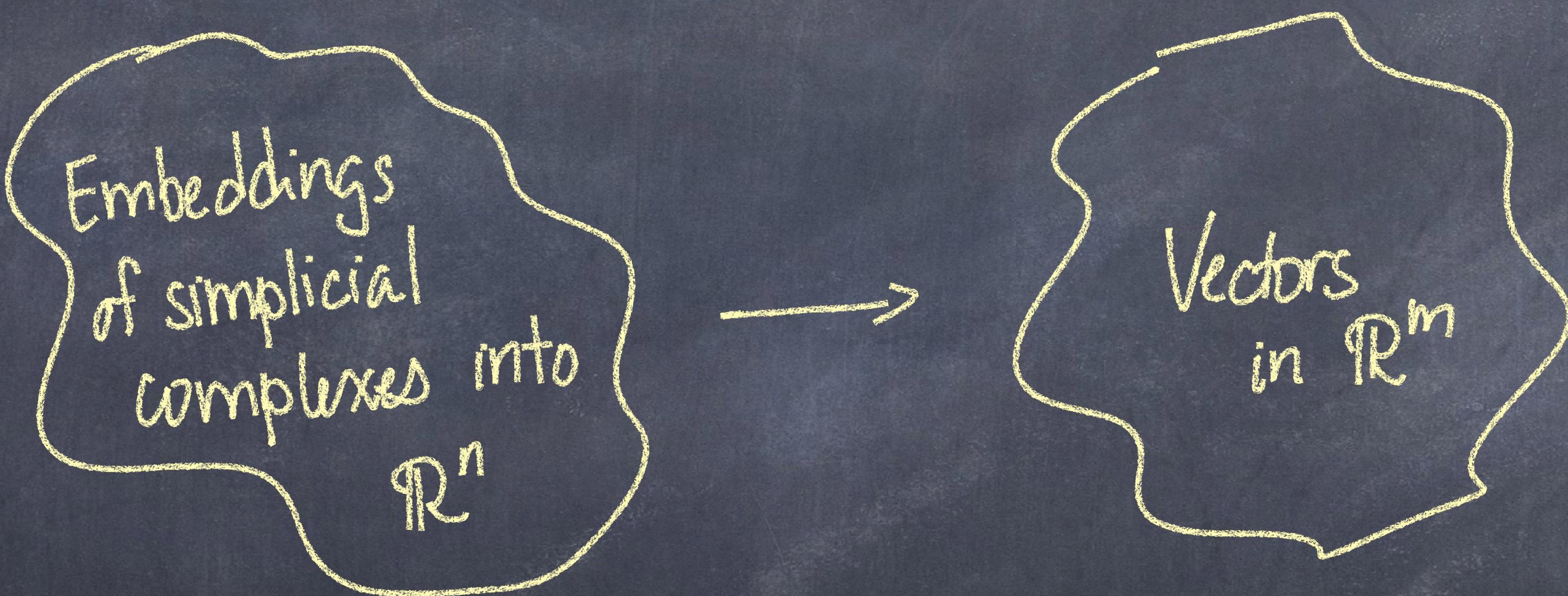


Simplicial representation learning



From k -forms to simplicial representations

Let $\omega_1, \dots, \omega_m \in \Omega^k(\mathbb{R}^n)$.



Slogan: k -forms
are feature maps
on the space of
embedded
 k -simplices.

$$\Delta^k \xrightarrow{\varphi} \mathbb{R}^n \quad \mapsto \quad (\int_{\Delta^k} \varphi^* \omega_1, \dots, \int_{\Delta^k} \varphi^* \omega_m)$$

Making it learnable

Recall: $\Omega^*(\mathbb{R}^n) = C^\infty(\mathbb{R}^n) \otimes \Lambda(dx_1, \dots, dx_n)$

- not appropriate for learning

Making it learnable

Recall: $\Omega^*(\mathbb{R}^n) = C^\infty(\mathbb{R}^n) \otimes \Lambda(dx_1, \dots, dx_n)$

- not appropriate for learning

The fix: $\Omega_{\text{neu}}^*(\mathbb{R}^n) = \text{MLP}(\mathbb{R}^n) \otimes \Lambda(dx_1, \dots, dx_n)$

- neural k-forms

Neural k-forms generalize MLP's

Object	$f \in \text{MLP}(\mathbb{R}^n)$
Input	$* \xrightarrow{\psi} \mathbb{R}^n$
Output	$f(\psi) \in \mathbb{R}$

Neural k-forms generalize MLP's

Object	$f \in \text{MLP}(\mathbb{R}^n)$	$\omega \in \Omega_{\text{neur}}^k(\mathbb{R}^n)$
Input	$* \xrightarrow{\psi} \mathbb{R}^n$	$\Delta^k \xrightarrow{f} \mathbb{R}^n$
Output	$f(w) \in \mathbb{R}$	$\int_{\Delta^k} f^* \omega \in \mathbb{R}$

Universal Approximation Theorem [M-H-R, 24]

Compactly supported k -forms on \mathbb{R}^n can be arbitrarily well approximated by neural k -forms with coefficients in MLP's with one hidden layer.

Architecture

• Input: $(\vec{\phi}, \vec{\beta}) = \{(\mathcal{K} \xrightarrow{\phi_t} \mathbb{R}^n, \beta_t \in C_k(\mathcal{K}_t)^{\oplus m_t}) \mid t \in T\}$

simplicial
complex

affine
embedding

m_t -tuple of
data k -chains

index
set
 \downarrow

Architecture

- Input: $(\vec{g}, \vec{\beta}) = \{(\mathcal{K} \xrightarrow{g_t} \mathbb{R}^n, \beta_t \in C_k(\mathcal{K}_2)^{\oplus m_t}) \mid t \in T\}$
- Initiation: $\vec{\omega} = (\omega_1, \dots, \omega_l) \in \Omega_{\text{neur}}^k(\mathbb{R}^n)^{\oplus l}$
 \Rightarrow matrices $M_{\vec{g}, \vec{\beta}}^t(\vec{\omega}) \in \mathbb{R}^{m_t, l}$
$$(M_{\vec{g}, \vec{\beta}}^t(\vec{\omega}))_{i,j} = \sum_{\beta_{t,i}} g_t^*(\omega_j)$$

admits finite approx.
appropriately
differentiable

Architecture

- Input: $(\vec{\phi}, \vec{\beta}) = \{(\mathcal{K} \xrightarrow{\phi_t} \mathbb{R}^n, \beta_t \in C_k(\mathcal{K}_2)^{\oplus m_t}) \mid t \in T\}$
- Initiation: $\vec{\omega} = (\omega_1, \dots, \omega_e) \in \Omega_{\text{neur}}^k (\mathbb{R}^n)^{\oplus l}$
 \Rightarrow matrices $M_{\vec{\phi}, \vec{\beta}}^t(\vec{\omega}) \in \mathbb{R}^{m_{t,l}}$
- Readout: $\Phi: \mathbb{R}^{m_{t,l}} \rightarrow \mathbb{R}^l$ (Ex: summing columns,
taking norms of columns.)

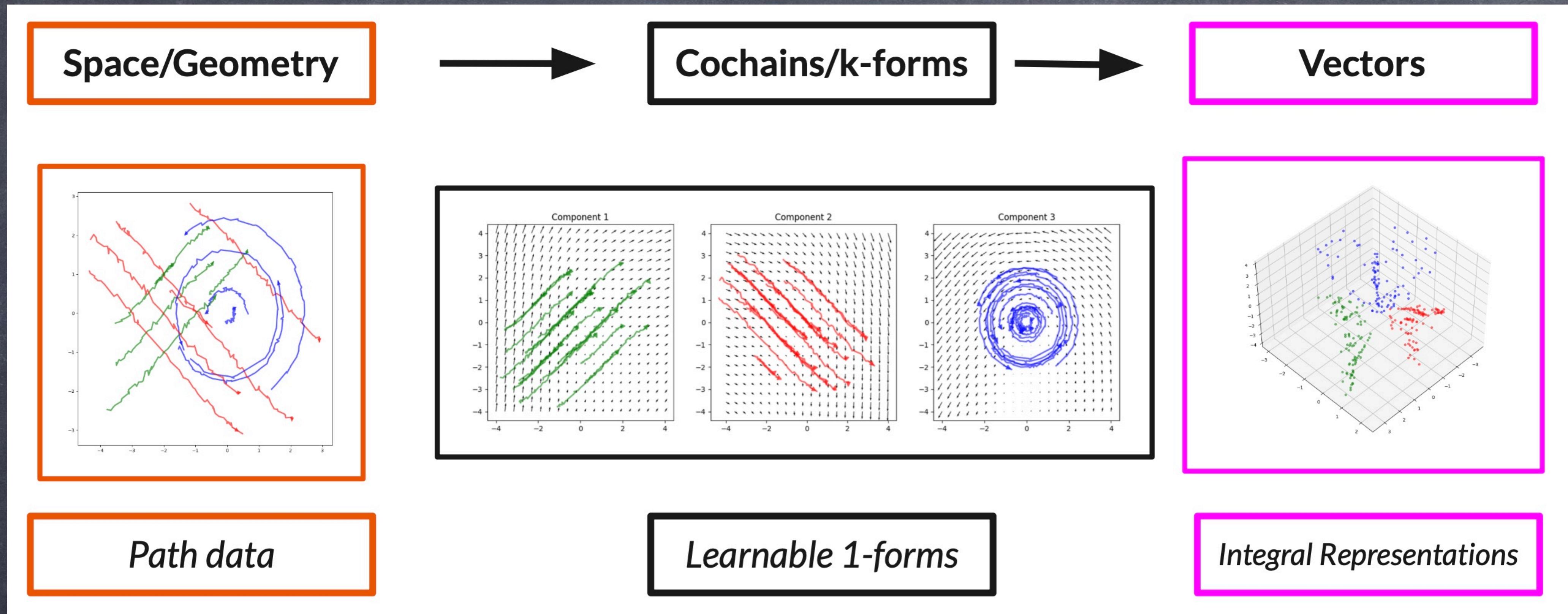
Architecture

- Input: $(\vec{\phi}, \vec{\beta}) = \{(\mathcal{K} \xrightarrow{\phi_t} \mathbb{R}^n, \beta_t \in C_k(\mathcal{K}_2)^{\oplus m_t}) \mid t \in T\}$
- Initiation: $\vec{\omega} = (\omega_1, \dots, \omega_l) \in \Omega_{\text{neur}}^k(\mathbb{R}^n)^{\oplus l}$
 \Rightarrow matrices $M_{\vec{\phi}, \vec{\beta}}^t(\vec{\omega}) \in \mathbb{R}^{m_{t,l}}$
- Readout: $\Phi: \mathbb{R}^{m_{t,l}} \rightarrow \mathbb{R}^l$
- Classify and evaluate against a loss function

Remarks

- ① Realizable by any deep learning framework appropriate for training MLP's.
- ② No message passing involved.

Experiment ①



Objective function : maximize path integrals within
classes, minimize else

Experiment ②

AUROC \pm std. deviation of 5 runs

	Params.	BACE	BBBP	HIV
GAT [Vel+18]	135K	69.52 ± 17.52	76.51 ± 3.36	56.38 ± 4.41
GCN [KW17]	133K	66.79 ± 1.56	73.77 ± 3.30	68.70 ± 1.67
GIN [Xu+19]	282K	42.91 ± 18.56	61.66 ± 19.47	55.28 ± 17.49
NkF (ours)	9K	83.50 ± 0.55	86.41 ± 3.64	76.70 ± 2.17

Benchmark datasets from the MoleculeNet database, reporting only best results for GNNs.

Cochains in computational biology

Maggs-Youssef-Nguyen-Pulver

In progress

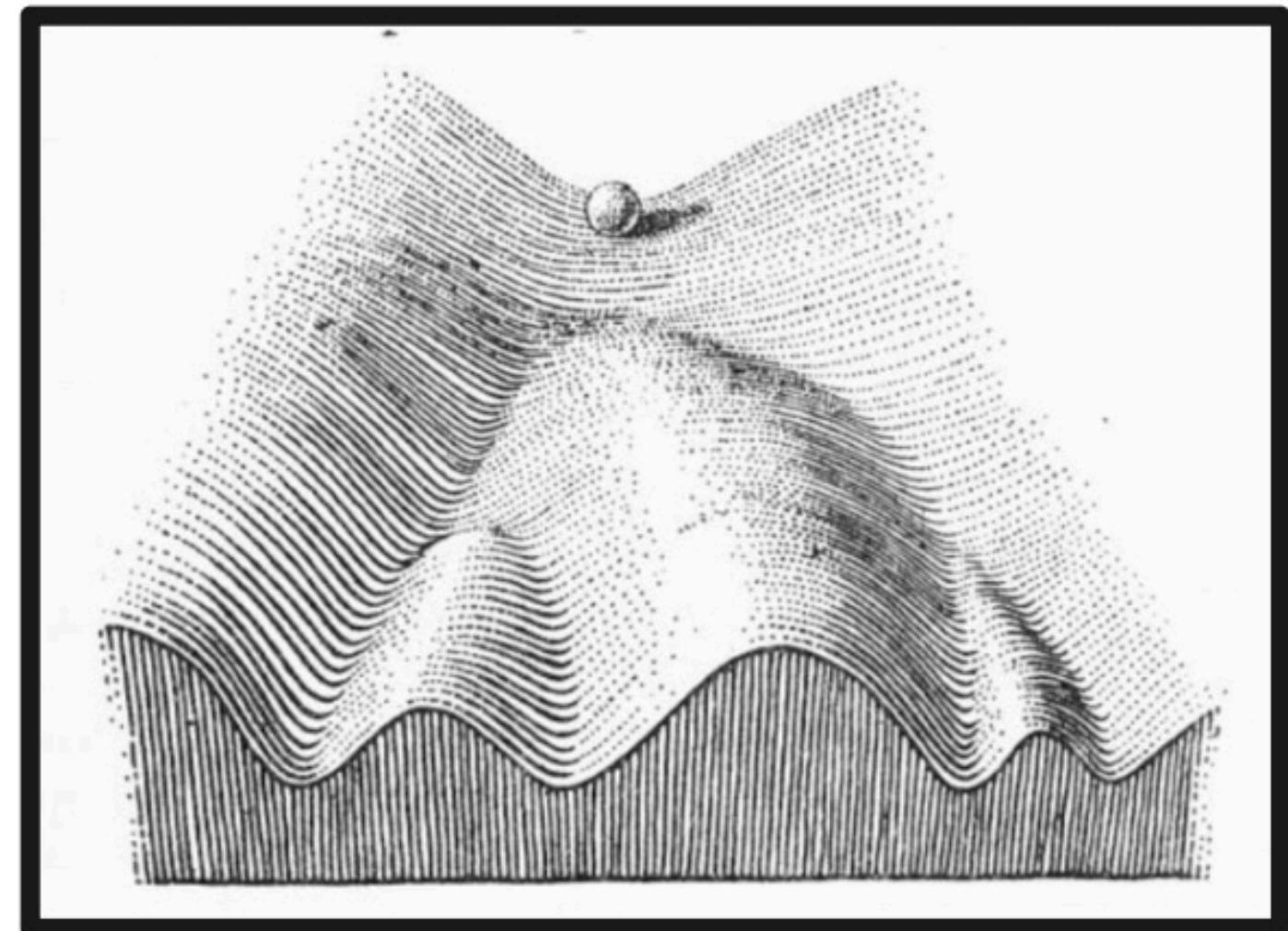
The geometry of biology

Space/Geometry

Biology

Gradient Descent

Cell Development

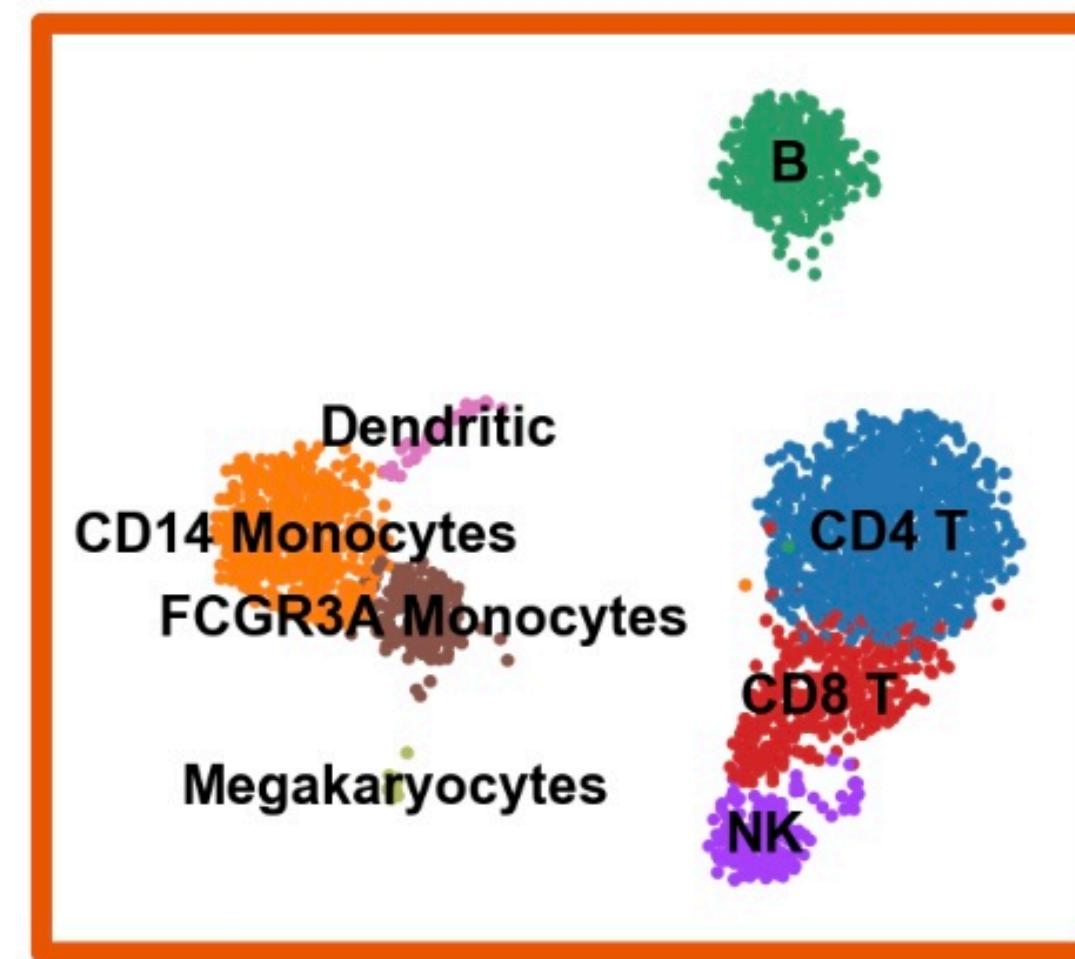


The Epigenetic Landscape

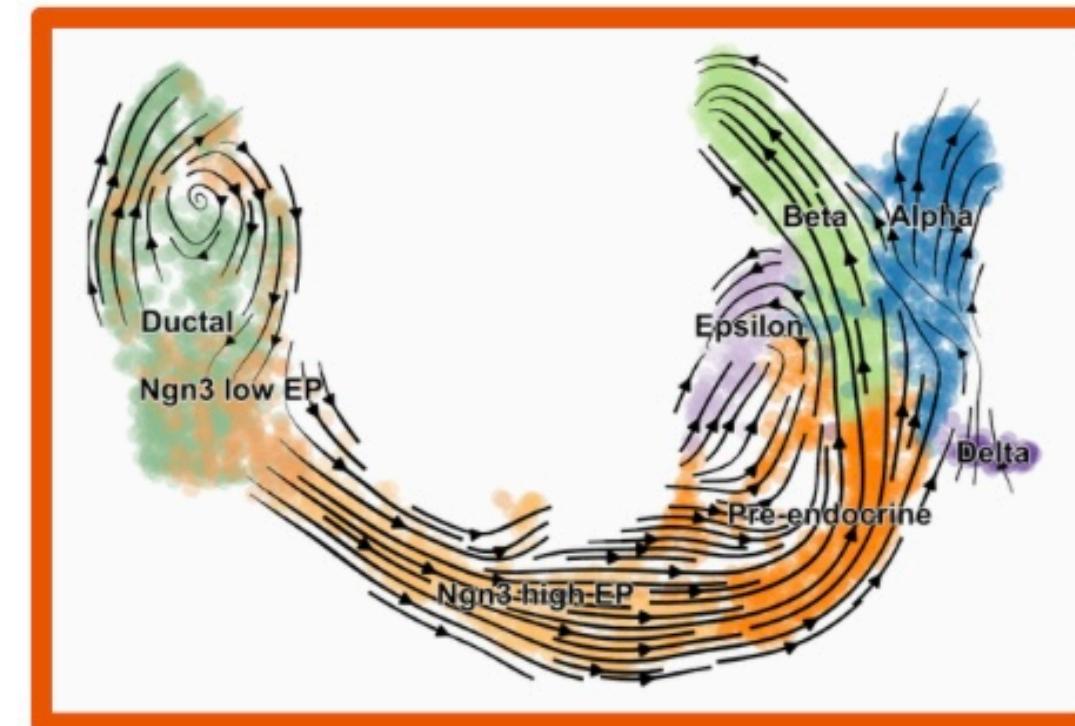
C.H. Waddington. *The Strategy of the Genes*. Routledge. (1957)

The phase space of single-cell data

Space/Geometry



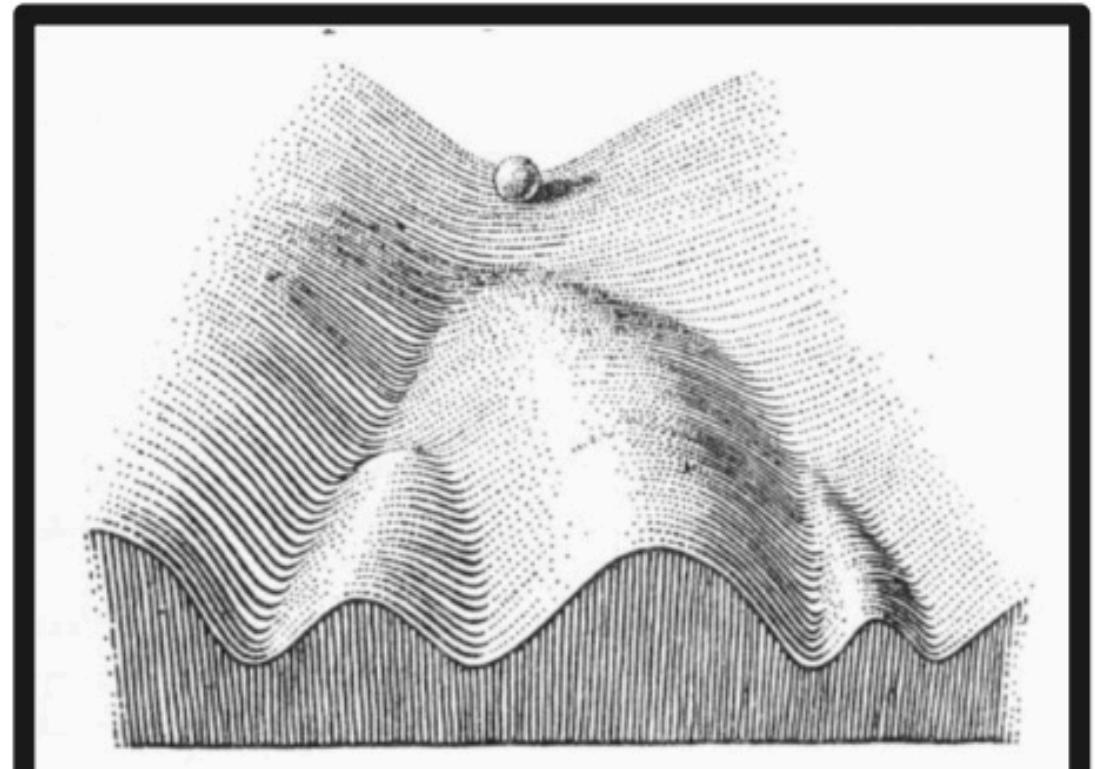
Gene x Cell Matrix



Cell Type

Biology

Differentiation



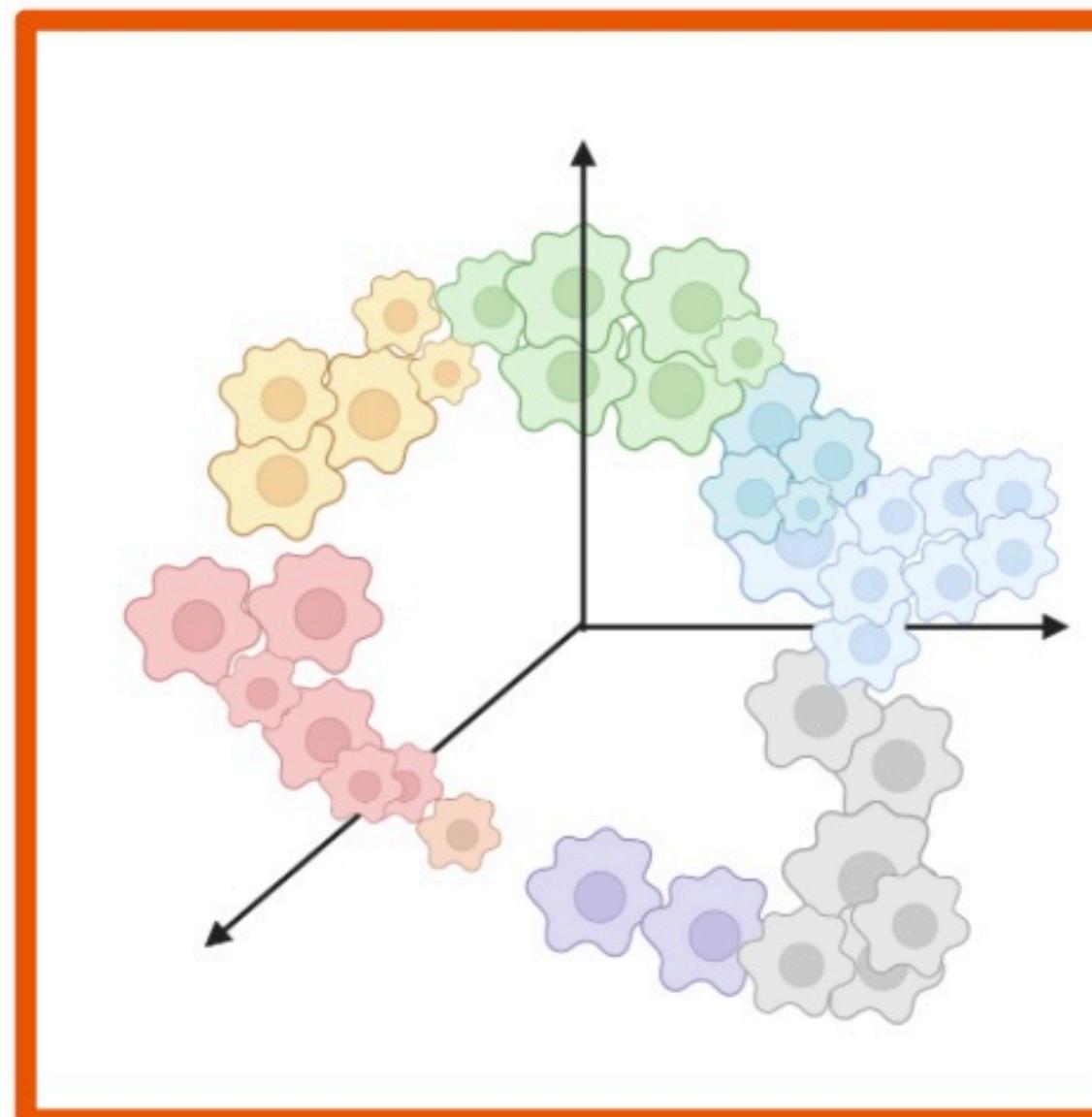
Bergen, V et al. Generalizing RNA velocity to transient cell states through dynamical modeling. *Nat Biotechnol* 38, 1408–1414 (2020).

From circular structure to gene cascades

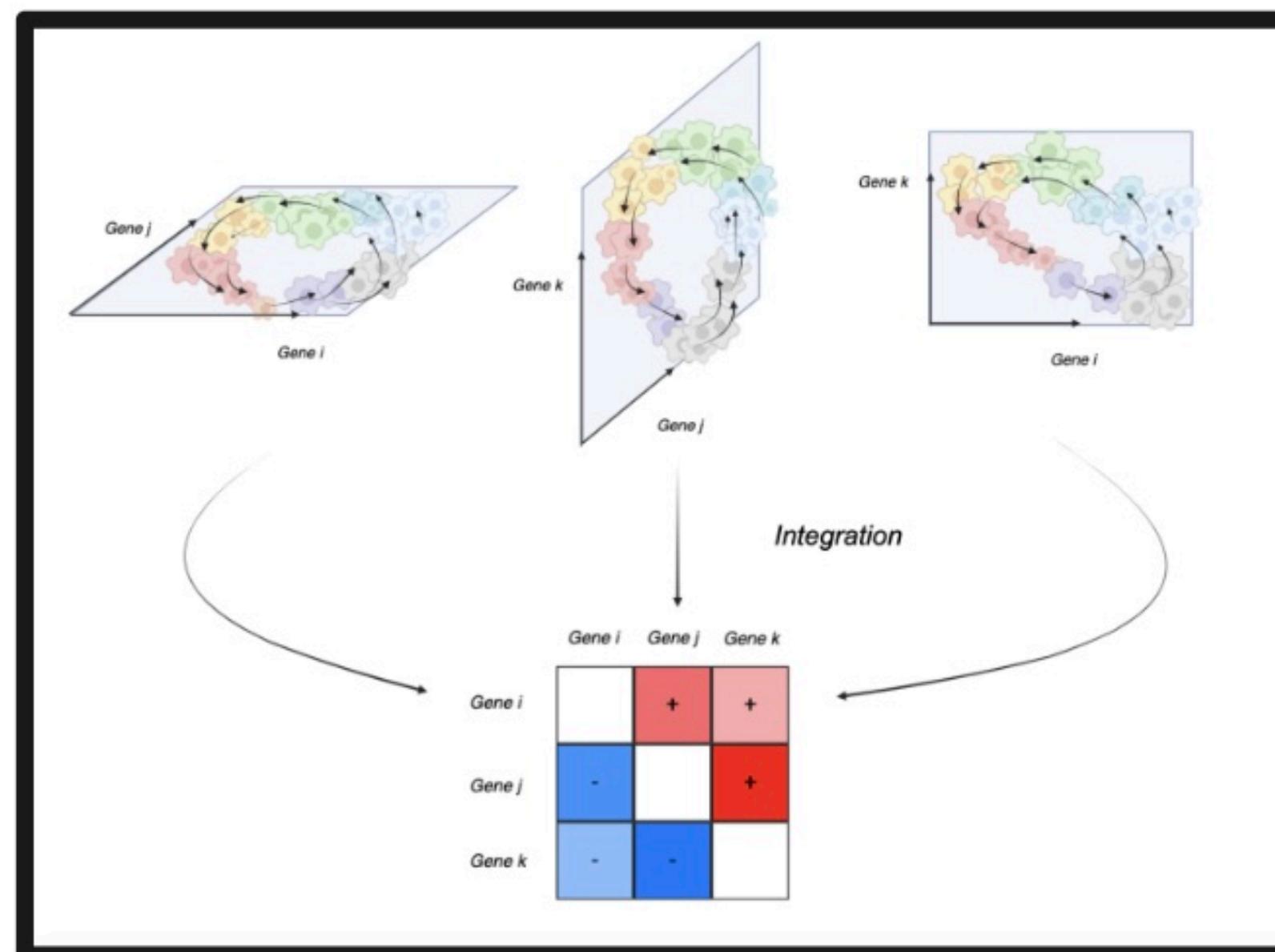
Space/Geometry

Cochains/k-forms

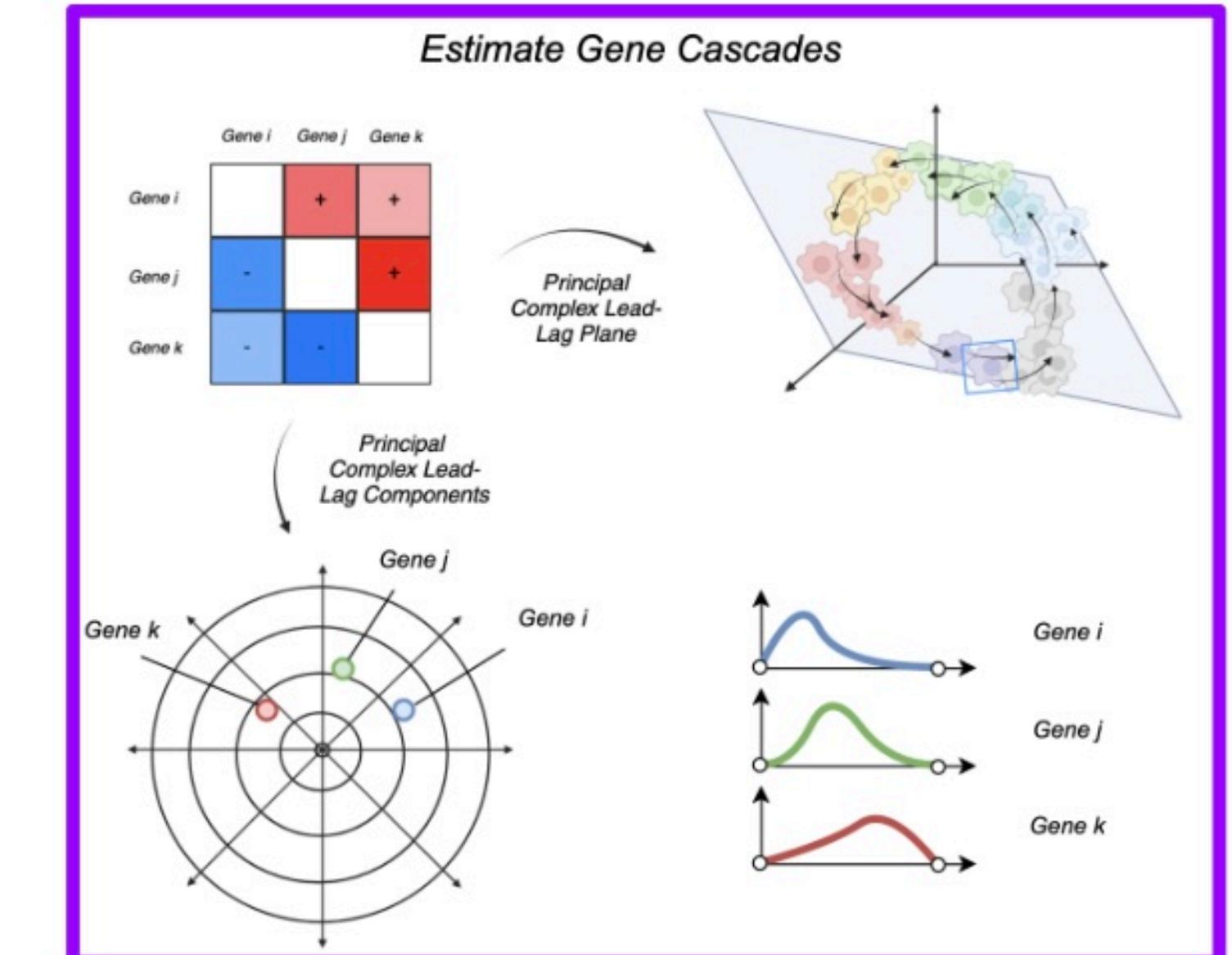
Biology



Structural: cohomology class

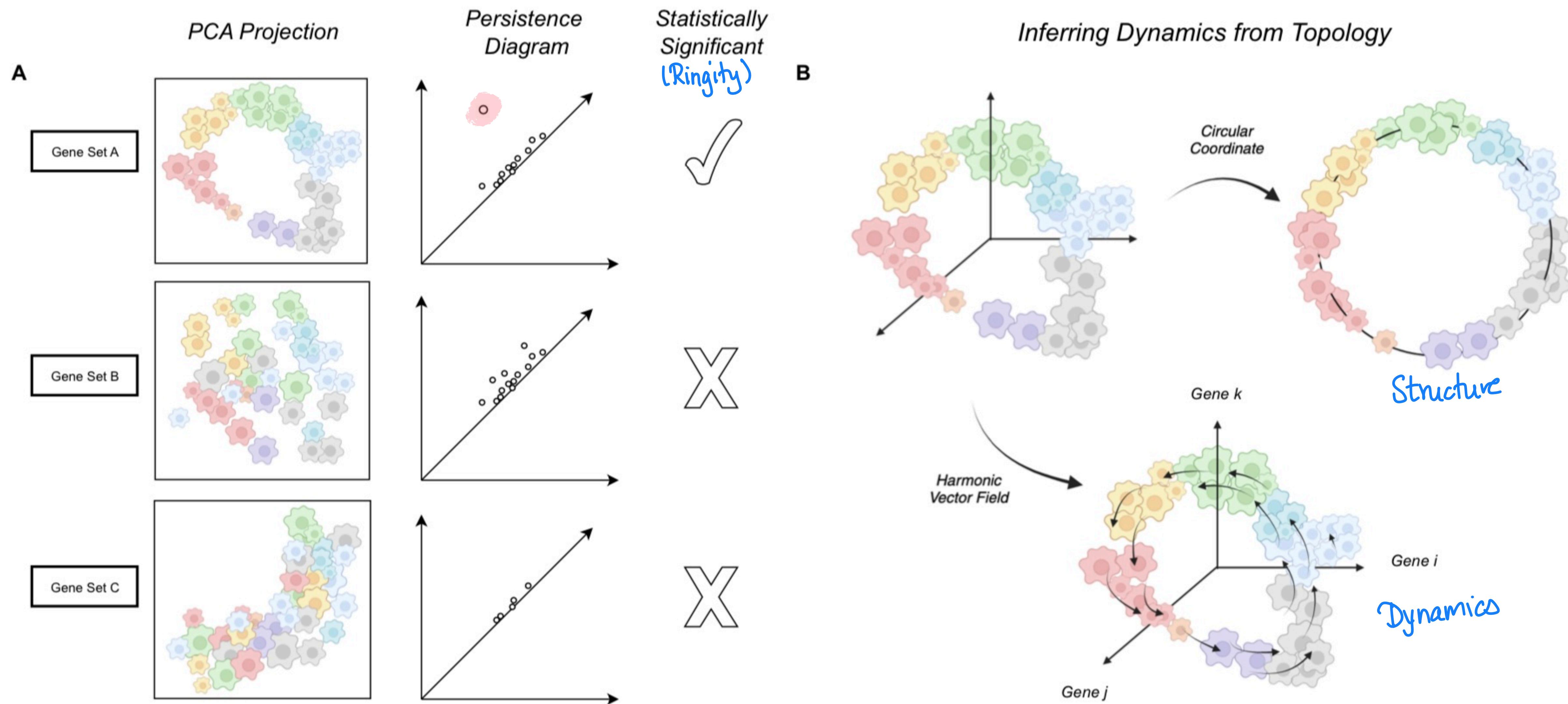


Dynamical



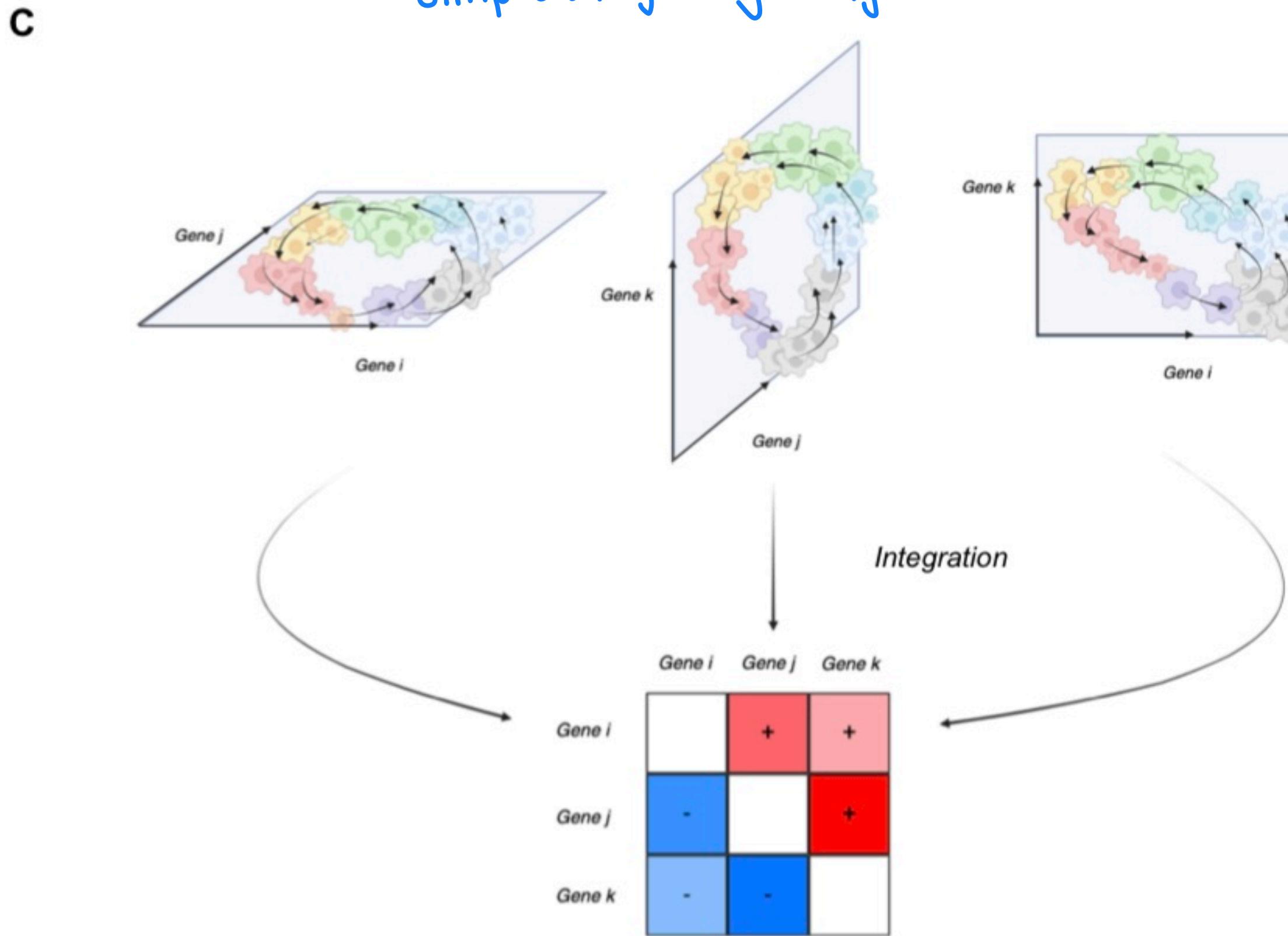
Estimate gene cascades

The pipeline

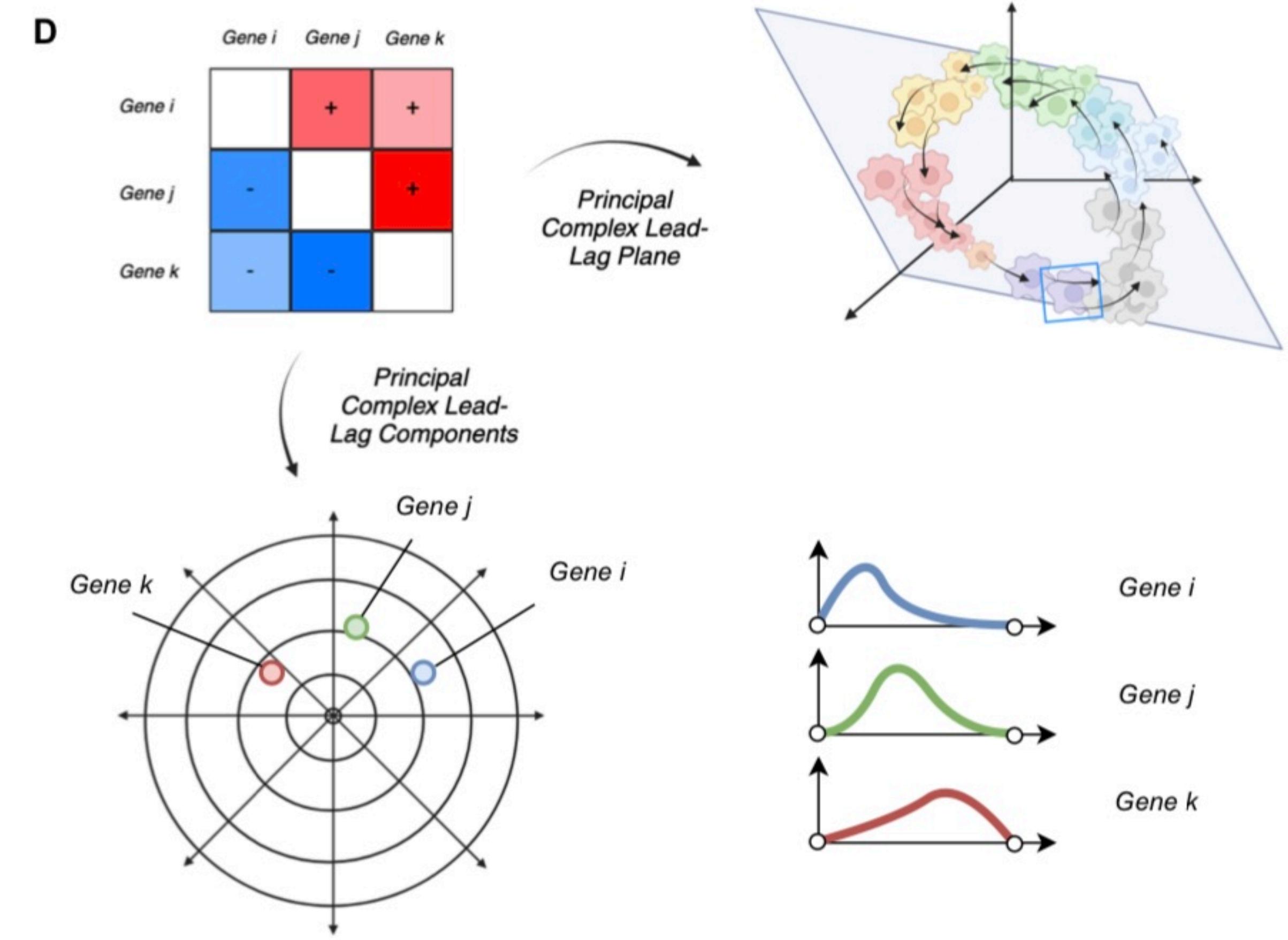


The pipeline

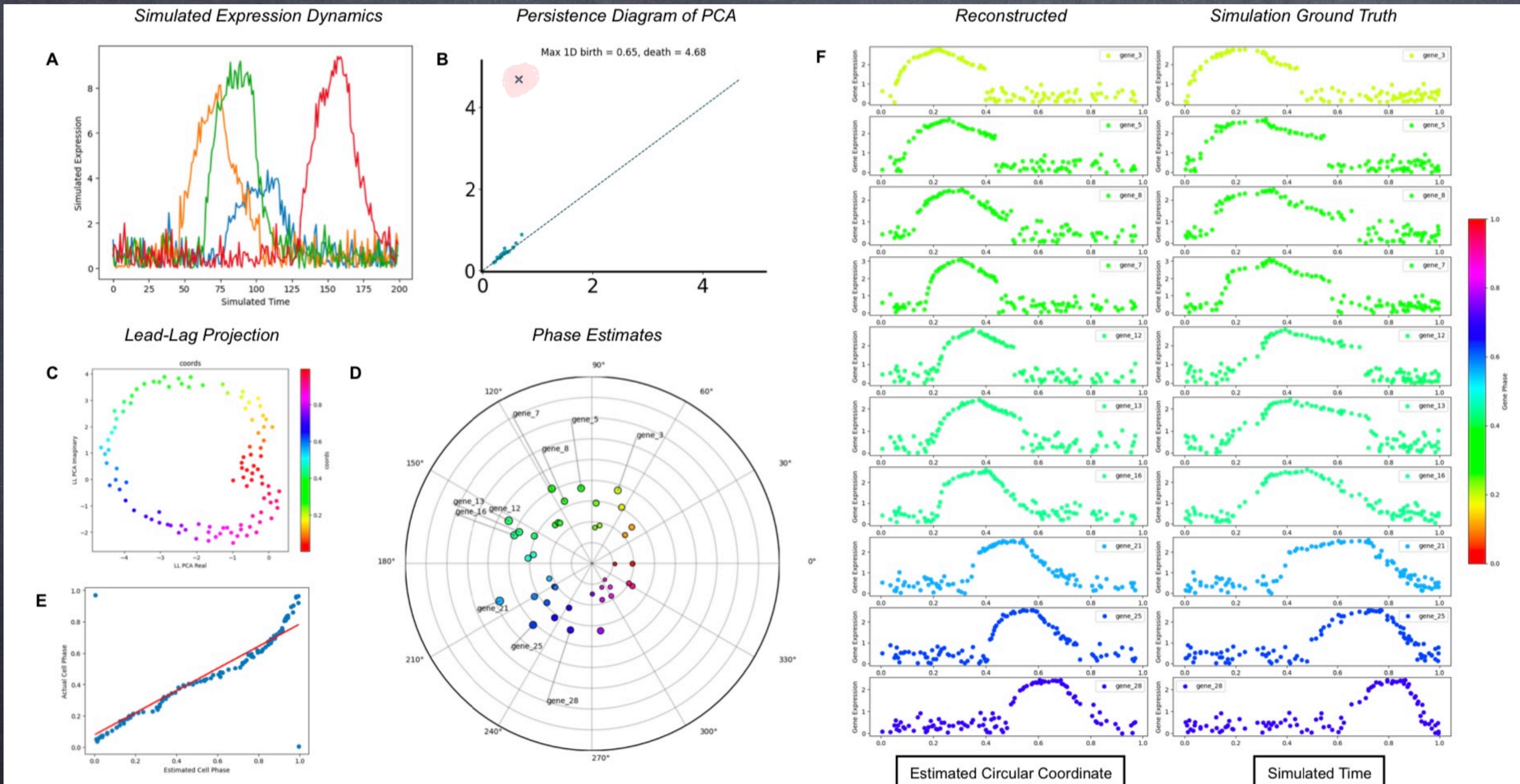
Integral-based Harmonic Lead-Lag Matrix Simplicial cyclicity analysis



Estimate Gene Cascades



Testing the Pipeline (synthetic data)



Thank you!

