

HodgeRank

A ranking method based on Hodge-Helmholtz decomposition

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Hodge Decomposition Described in the Language of Linear Algebra

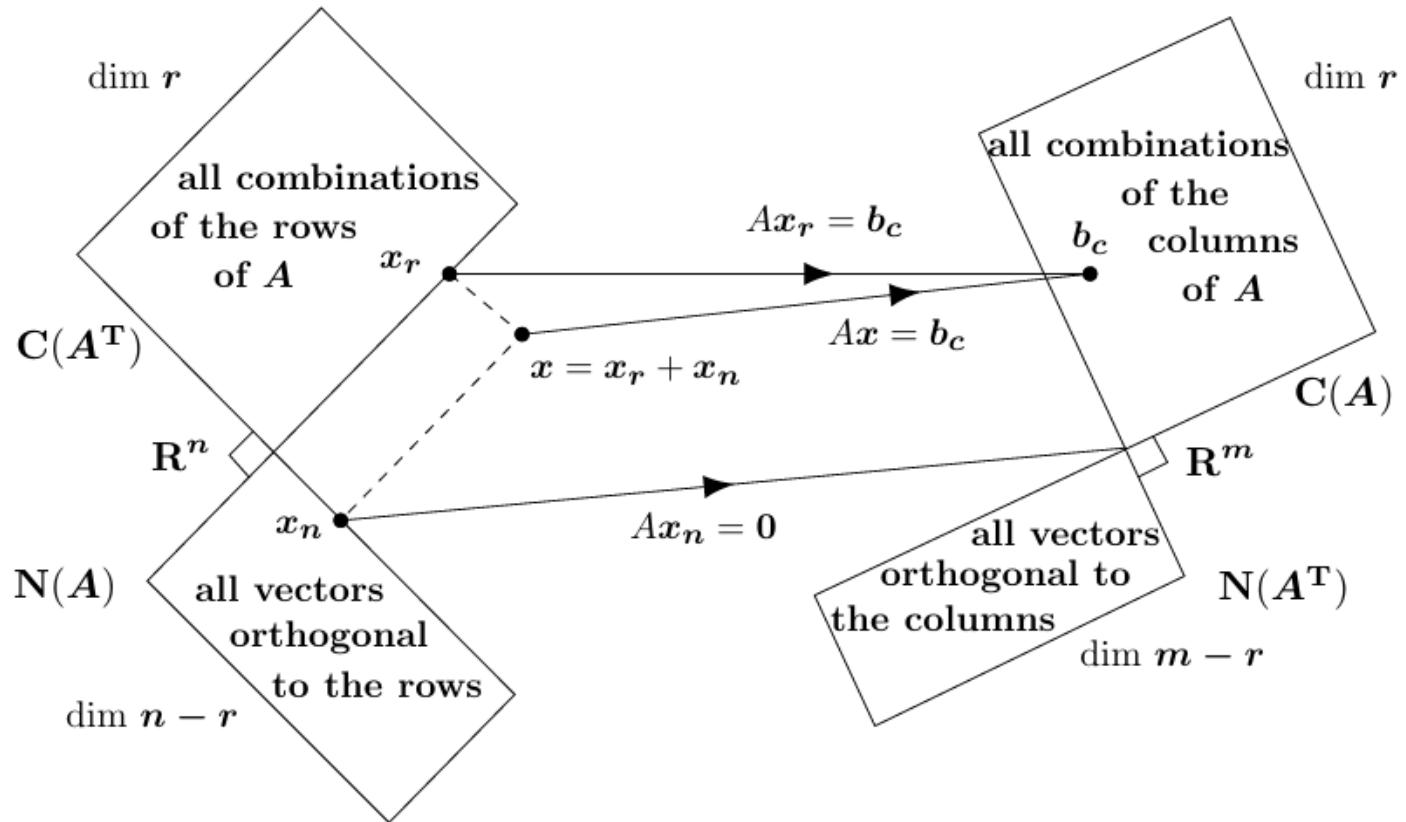
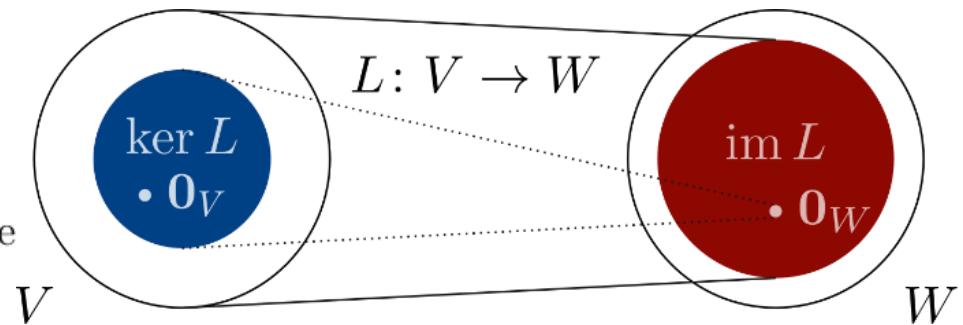


Figure 1: $Ax_r = b$ is in the column space of A and $Ax_n = \mathbf{0}$. The complete solution to $Ax = b$ is $x = \text{one } x_r + \text{any } x_n$.

$$\begin{aligned}
 A_{m \times n} & \\
 \text{im}(A_{m \times n}) \oplus \ker(A_{m \times n}^T) &= \mathbb{R}^m \\
 \text{im}(A_{m \times n}^T) \oplus \ker(A_{m \times n}) &= \mathbb{R}^n
 \end{aligned}$$

$$\begin{aligned}
 B_{n \times p} & \\
 \text{im}(B_{n \times p}) \oplus \ker(B_{n \times p}^T) &= \mathbb{R}^n \\
 \text{im}(B_{n \times p}^T) \oplus \ker(B_{n \times p}) &= \mathbb{R}^p
 \end{aligned}$$



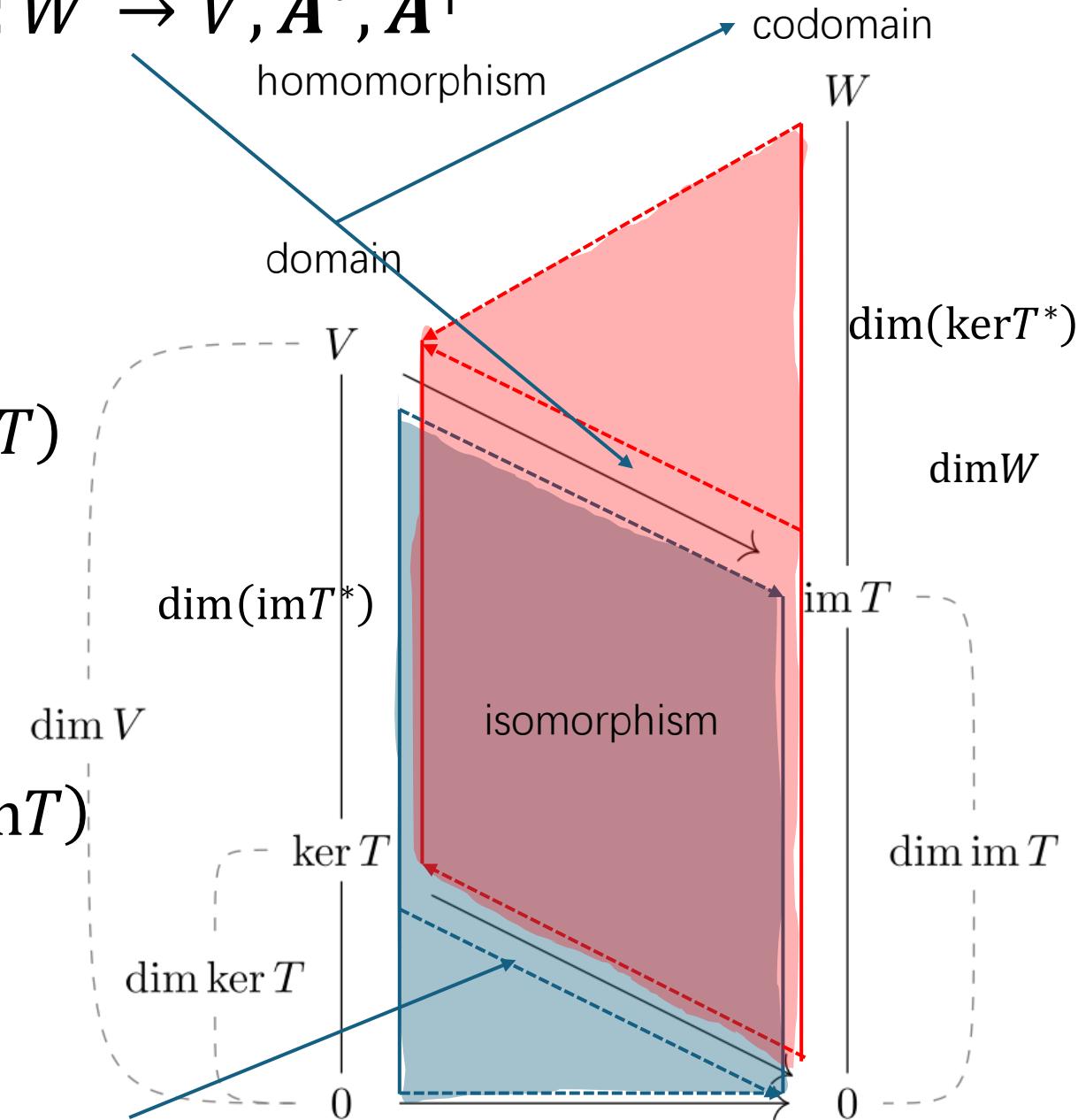
$$A_{m \times n} B_{n \times p} = \mathbf{0}_{m \times p} \Leftrightarrow B_{n \times p}^T A_{m \times n}^T = \mathbf{0}_{p \times m}$$

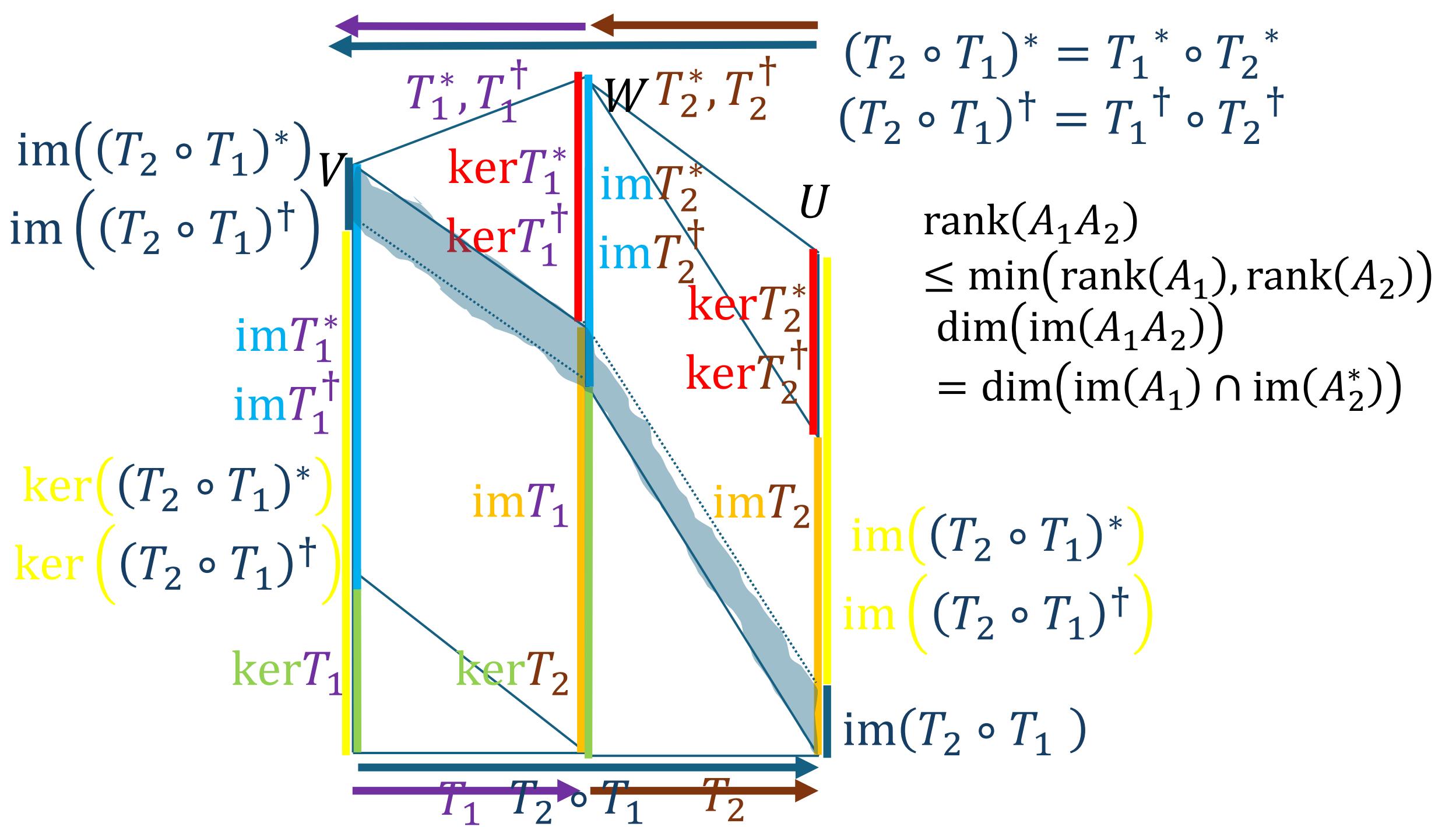
$$\text{im}(B_{n \times p}) \subseteq \ker(A_{m \times n}) \Leftrightarrow \text{im}(A_{m \times n}^T) \subseteq \ker(B_{n \times p}^T)$$

$$T^*, T^\dagger: W \rightarrow V, A^*, A^\dagger$$

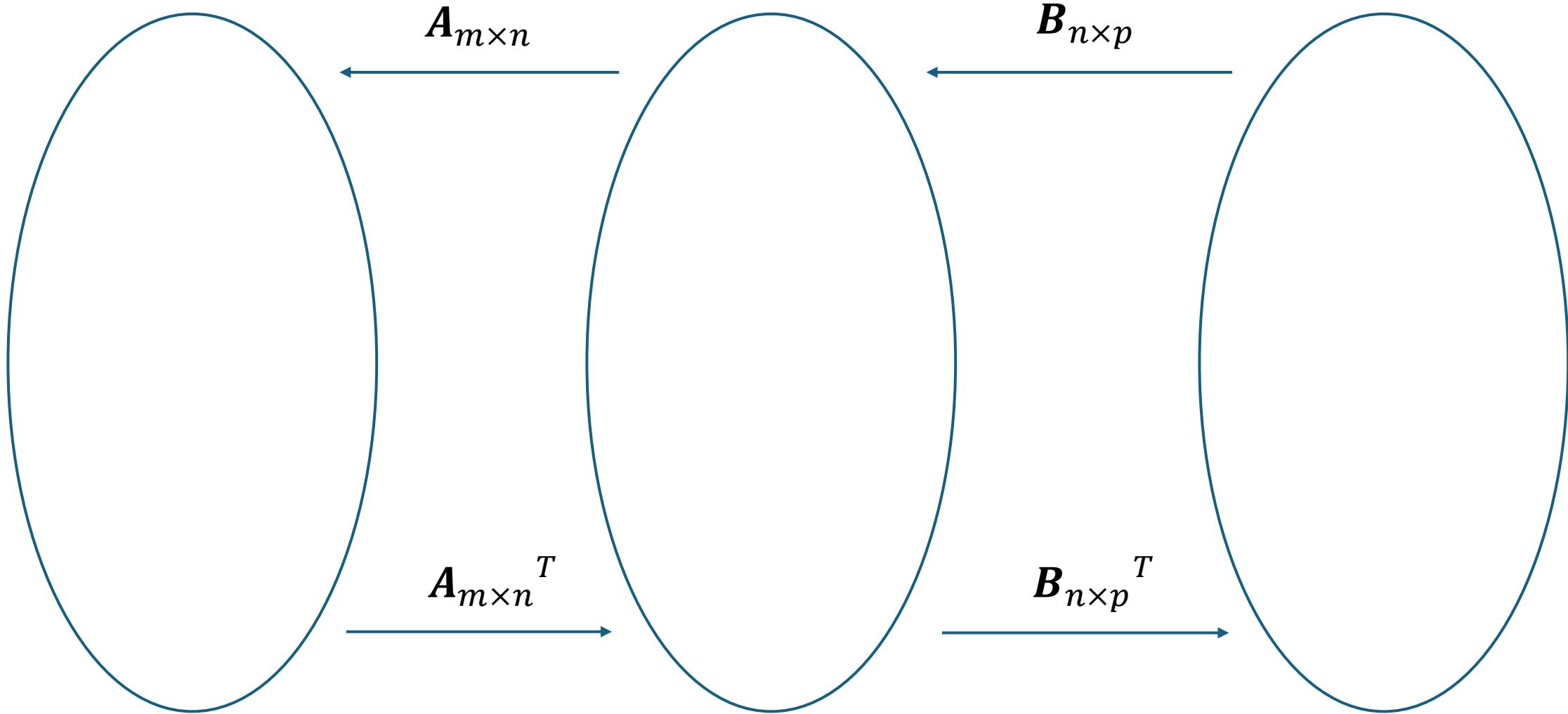
- Rank-nullity theorem:
- $T: V \rightarrow W$
- $\text{rank}(T) + \text{nullity}(T) = \dim(V)$
- $\dim(\text{im } T) + \dim(\ker T) = \dim(\text{domain } T)$
- $\text{im } T \oplus \ker T \cong V$
- $T^*: W \rightarrow V$
- $\text{rank}(T^*) + \text{nullity}(T) = \dim(V)$
- $\dim(\text{im } T^*) + \dim(\ker T) = \dim(\text{domain } T)$
- $\text{im } T^* \oplus \ker T \cong V$
- $\text{rank}(T^*) = \text{rank}(T)$
- $\dim(\text{im } T^*) = \dim(\text{im } T)$

$$T: V \rightarrow W, A$$

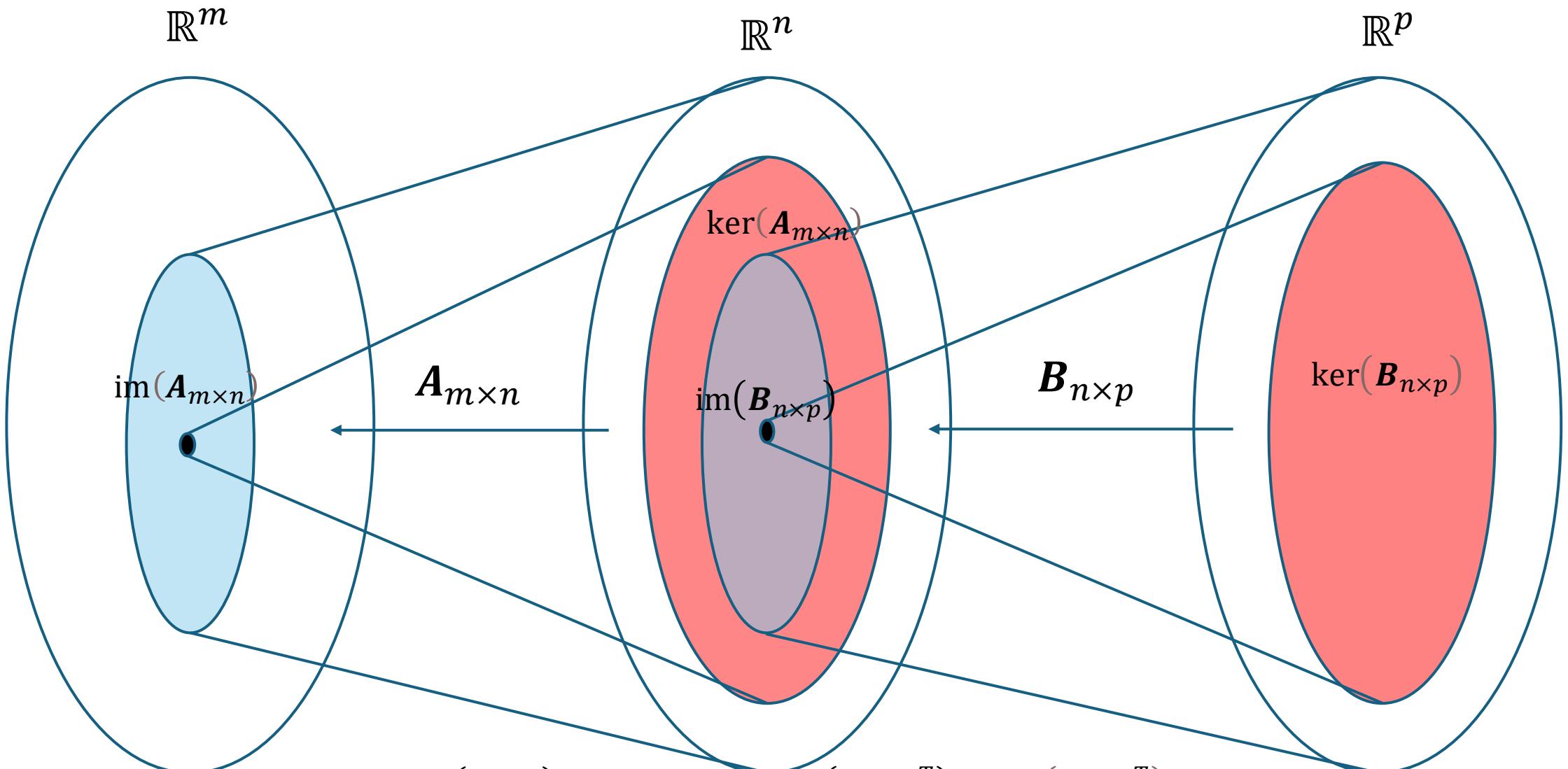




$$\begin{array}{c} \mathbb{R}^m \quad \text{im}(\mathbf{B}_{n \times p}) \subseteq \ker(\mathbf{A}_{m \times n}) \Leftrightarrow \mathbf{B}_{n \times p}^T \mathbf{A}_{m \times n}^T = \mathbf{0}_{p \times m} \\ \mathbb{R}^n \quad \text{im}(\mathbf{A}_{m \times n}^T) \subseteq \ker(\mathbf{B}_{n \times p}^T) \\ \mathbb{R}^p \end{array}$$



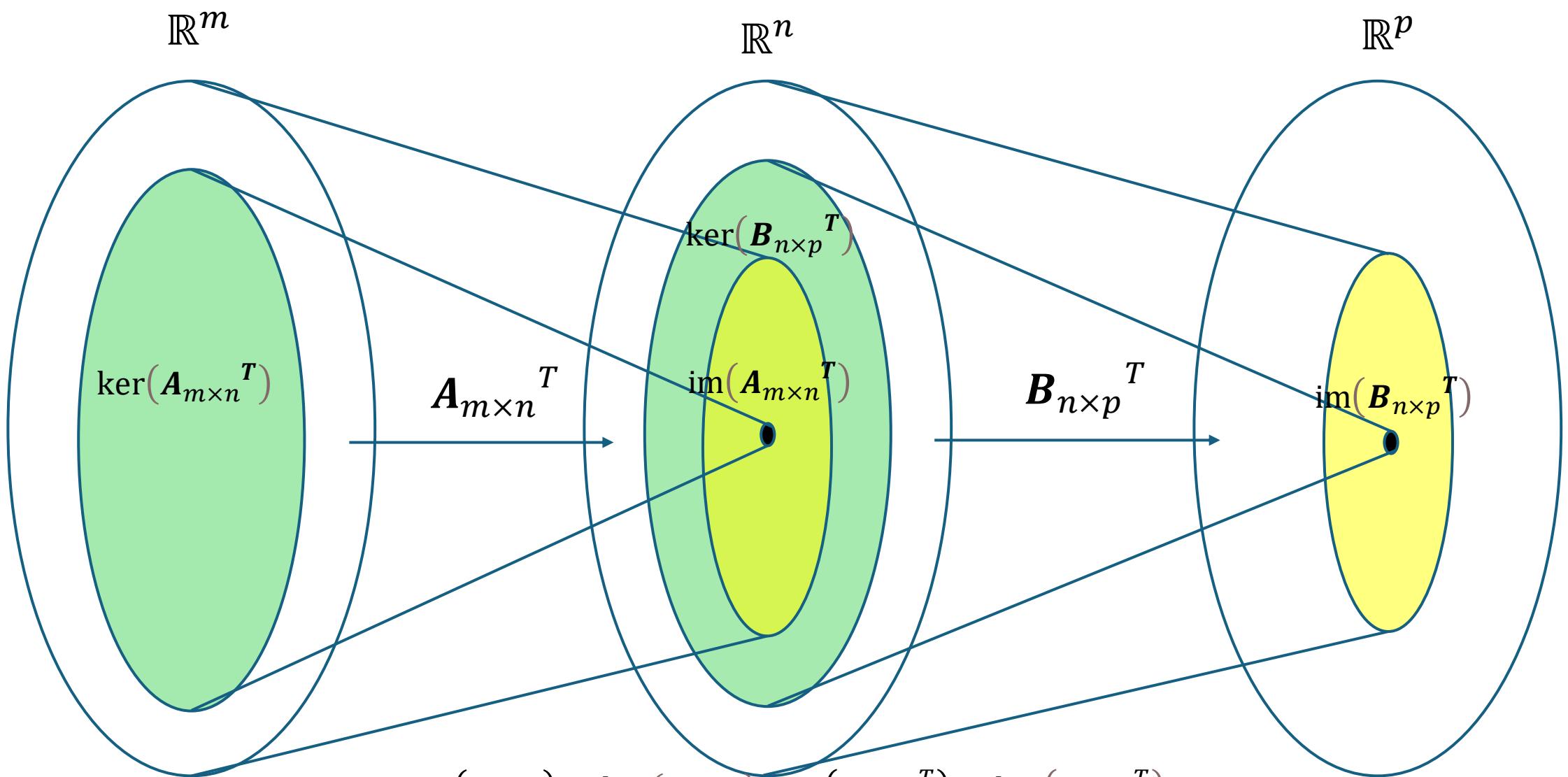
$$\begin{aligned} \text{im}(\mathbf{A}_{m \times n}) \oplus \ker(\mathbf{A}_{m \times n}^T) &= \mathbb{R}^m \text{im}(\mathbf{A}_{m \times n}^T) \oplus \ker(\mathbf{A}_{m \times n}^T) = \mathbb{R}^n \\ \text{im}(\mathbf{B}_{n \times p}) \oplus \ker(\mathbf{B}_{n \times p}^T) &= \mathbb{R}^n \text{im}(\mathbf{B}_{n \times p}^T) \oplus \ker(\mathbf{B}_{n \times p}^T) = \mathbb{R}^p \end{aligned}$$



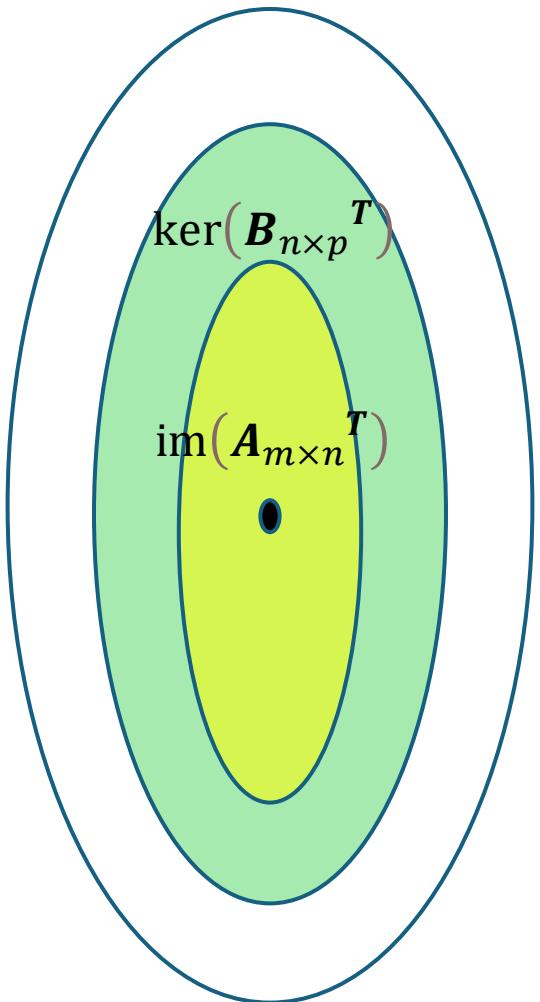
$$\text{im}(B_{n \times p}) \subseteq \ker(A_{m \times n}) \quad \text{im}(A_{m \times n}^T) \subseteq \ker(B_{n \times p}^T)$$

$$\text{im}(A_{m \times n}^T) \oplus \ker(A_{m \times n}) = \mathbb{R}^n$$

$$\text{im}(B_{n \times p}) \oplus \ker(B_{n \times p}^T) = \mathbb{R}^n$$



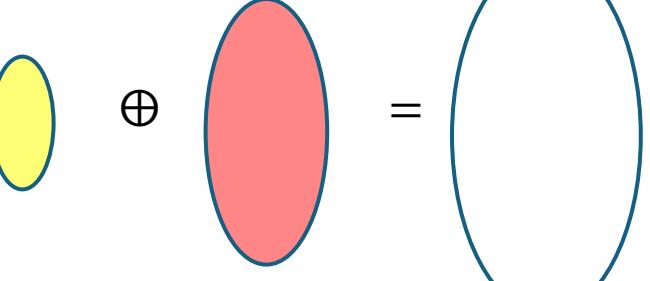
$$\begin{aligned}\text{im}(B_{n \times p}) &\subseteq \ker(A_{m \times n}) \\ \text{im}(A_{m \times n}^T) &\subseteq \ker(B_{n \times p}^T) \\ \text{im}(A_{m \times n}^T) \oplus \ker(A_{m \times n}) &= \mathbb{R}^n \\ \text{im}(B_{n \times p}) \oplus \ker(B_{n \times p}^T) &= \mathbb{R}^n\end{aligned}$$

\mathbb{R}^n 

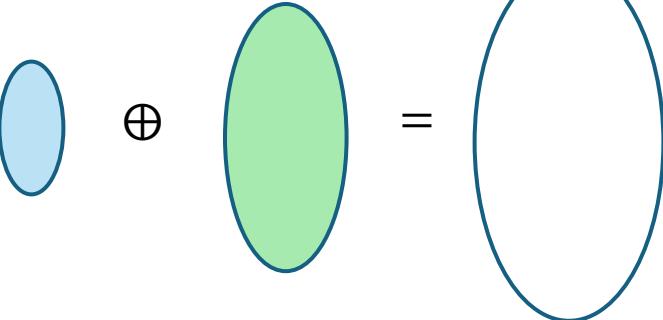
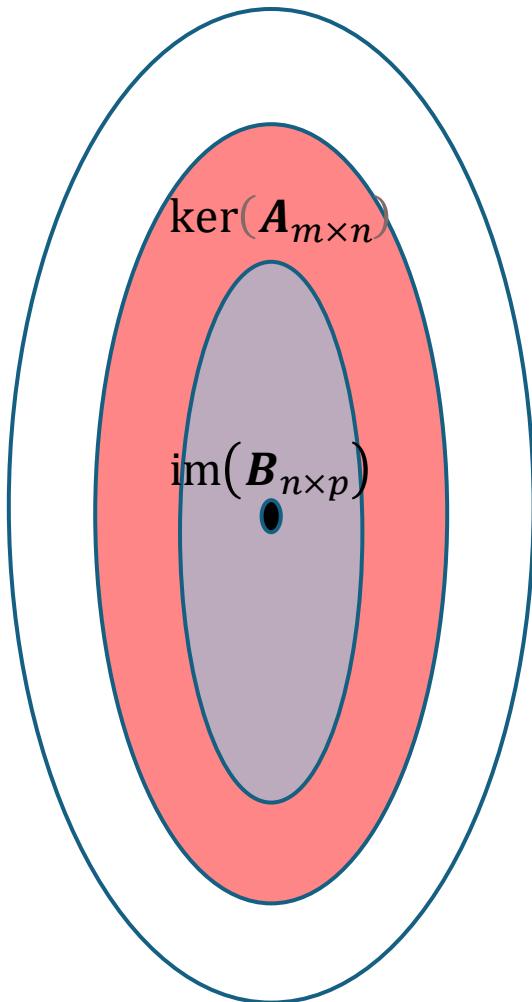
$$\text{im}(B_{n \times p}) \subseteq \ker(A_{m \times n})$$



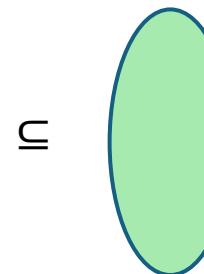
$$\text{im}(A_{m \times n}^T) \oplus \ker(A_{m \times n}) = \mathbb{R}^n$$

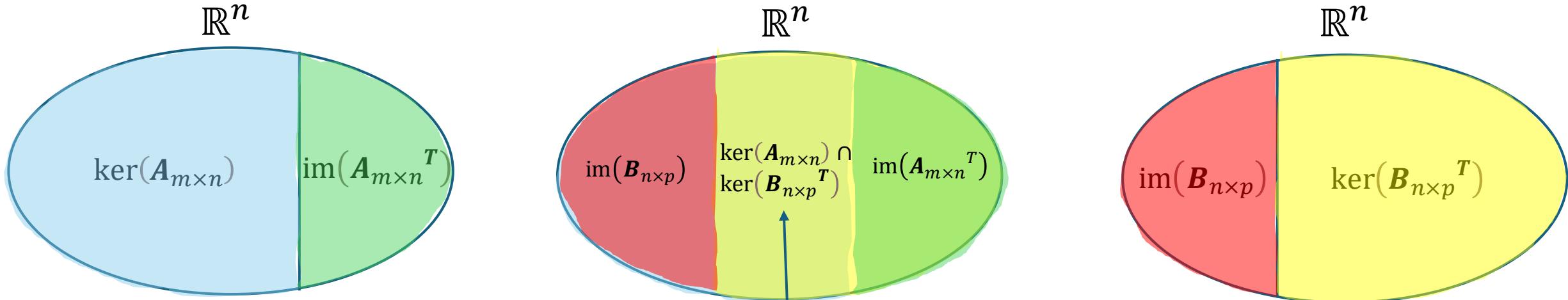


$$\text{im}(B_{n \times p}) \oplus \ker(B_{n \times p}^T) = \mathbb{R}^n$$

 \mathbb{R}^n 

$$\text{im}(A_{m \times n}^T) \subseteq \ker(B_{n \times p}^T)$$





$$\text{im}({A_{m x n}}^T) \oplus \ker(A_{m x n}) = \mathbb{R}^n$$

$$\subseteq$$

$$\text{im}(B_{n x p}) \subseteq \ker(A_{m x n})$$

$$\begin{aligned} & \ker(A_{m x n}) \cap \ker({B_{n x p}}^T) \\ &= \ker(A_{m x n}) / \text{im}(B_{n x p}) \\ &= \ker({B_{n x p}}^T) / \text{im}({A_{m x n}}^T) \\ &= \ker({A_{m x n}}^T A_{m x n} + B_{n x p} {B_{n x p}}^T) \end{aligned}$$

$$\text{im}(B_{n x p}) \oplus \ker({B_{n x p}}^T) = \mathbb{R}^n$$

$$\subseteq$$

$$\text{im}({A_{m x n}}^T) \subseteq \ker({B_{n x p}}^T)$$

$$\mathbb{R}^n = \text{im}(B_{n x p}) \oplus (\ker(A_{m x n}) \cap \ker({B_{n x p}}^T)) \oplus \text{im}({A_{m x n}}^T)$$

$$\mathbb{R}^n = \text{im}(B_{n x p}) \oplus \ker({A_{m x n}}^T A_{m x n} + B_{n x p} {B_{n x p}}^T) \oplus \text{im}({A_{m x n}}^T)$$

$$x \in \mathbb{R}^n, \quad ({A_{m x n}}^T A_{m x n} + B_{n x p} {B_{n x p}}^T)x_H = \mathbf{0}, \quad v \in \mathbb{R}^p, \quad w \in \mathbb{R}^m$$

$$x = {A_{m x n}}^T w + x_H + B_{n x p} v, \quad \langle {A_{m x n}}^T w, x_H \rangle = \langle B_{n x p} v, x_H \rangle = \langle {A_{m x n}}^T w, B_{n x p} v \rangle = \mathbf{0}$$

$$x_{n \times 1} \in \ker(A_{m \times n}) \Rightarrow A_{m \times n} x_{n \times 1} = \mathbf{0}_{m \times 1} \Rightarrow A_{m \times n}^T A_{m \times n} x_{n \times 1} = \mathbf{0}_{n \times 1}$$

$$x_{n \times 1} \in \ker(B_{n \times p}^T) \Rightarrow B_{n \times p}^T x_{n \times 1} = \mathbf{0}_{p \times 1} \Rightarrow B_{n \times p} B_{n \times p}^T x_{n \times 1} = \mathbf{0}_{n \times 1}$$

$$\Rightarrow (A_{m \times n}^T A_{m \times n} + B_{n \times p} B_{n \times p}^T) x_{n \times 1} = \mathbf{0}_{n \times 1} \Rightarrow x_{n \times 1} \in \ker(A_{m \times n}^T A_{m \times n} + B_{n \times p} B_{n \times p}^T)$$

$$x_{n \times 1} \in \ker(A_{m \times n}^T A_{m \times n} + B_{n \times p} B_{n \times p}^T) \Rightarrow (A_{m \times n}^T A_{m \times n} + B_{n \times p} B_{n \times p}^T) x_{n \times 1} = \mathbf{0}_{n \times 1}$$

$$\Rightarrow A_{m \times n}^T A_{m \times n} x_{n \times 1} = -B_{n \times p} B_{n \times p}^T x_{n \times 1}$$

$$A_{m \times n} A_{m \times n}^T A_{m \times n} x_{n \times 1} = -A_{m \times n} B_{n \times p} B_{n \times p}^T x_{n \times 1} \Rightarrow A_{m \times n} A_{m \times n}^T A_{m \times n} x_{n \times 1} = \mathbf{0}_{n \times 1}$$

$$\Rightarrow A_{m \times n}^T A_{m \times n} x_{n \times 1} \in \ker(A_{m \times n})$$

$$A_{m \times n}^T A_{m \times n} x_{n \times 1} \in \text{im}(A_{m \times n}^T) = \ker(A_{m \times n})^\perp$$

$$\Rightarrow A_{m \times n}^T A_{m \times n} x_{n \times 1} = \mathbf{0} \Rightarrow x_{n \times 1} \in \ker(A_{m \times n}^T A_{m \times n}) = \ker(A_{m \times n})$$

$$B_{n \times p}^T A_{m \times n}^T A_{m \times n} x_{n \times 1} = -B_{n \times p}^T B_{n \times p} B_{n \times p}^T x_{n \times 1} \Rightarrow B_{n \times p}^T B_{n \times p} B_{n \times p}^T x_{n \times 1} = \mathbf{0}_{n \times 1}$$

$$\Rightarrow B_{n \times p} B_{n \times p}^T x_{n \times 1} \in \ker(B_{n \times p}^T)$$

$$B_{n \times p} B_{n \times p}^T x_{n \times 1} \in \text{im}(B_{n \times p}) = \ker(B_{n \times p}^T)^\perp$$

$$\Rightarrow B_{n \times p} B_{n \times p}^T x_{n \times 1} = \mathbf{0} \Rightarrow x_{n \times 1} \in \ker(B_{n \times p} B_{n \times p}^T) = \ker(B_{n \times p}^T)$$

$A_{m \times n}^T A_{m \times n} + B_{n \times p} B_{n \times p}^T$ is a sum of Gram matrices, symmetric, positive semi-definite

$$\mathbf{A}_{m \times n} \mathbf{B}_{n \times p} = \mathbf{0}_{m \times p} \Rightarrow$$

$$\mathbf{A}_{m \times n} \mathbf{B}_{n \times p} = \mathbf{0}_{m \times p} \Leftrightarrow \mathbf{B}_{n \times p}^T \mathbf{A}_{m \times n}^T = \mathbf{0}_{p \times m}$$

$$\text{im}(\mathbf{B}_{n \times p}) \subseteq \ker(\mathbf{A}_{m \times n}) \Leftrightarrow \text{im}(\mathbf{A}_{m \times n}^T) \subseteq \ker(\mathbf{B}_{n \times p}^T)$$

$$\begin{array}{ll} \mathbf{A}_{m \times n} & \text{im}(\mathbf{A}_{m \times n}) \oplus \ker(\mathbf{A}_{m \times n}^T) = \mathbb{R}^m \\ & \text{im}(\mathbf{A}_{m \times n}^T) \oplus \ker(\mathbf{A}_{m \times n}) = \mathbb{R}^n \end{array}$$

$$\begin{array}{ll} \mathbf{B}_{n \times p} & \text{im}(\mathbf{B}_{n \times p}) \oplus \ker(\mathbf{B}_{n \times p}^T) = \mathbb{R}^n \\ & \text{im}(\mathbf{B}_{n \times p}^T) \oplus \ker(\mathbf{B}_{n \times p}) = \mathbb{R}^p \end{array}$$

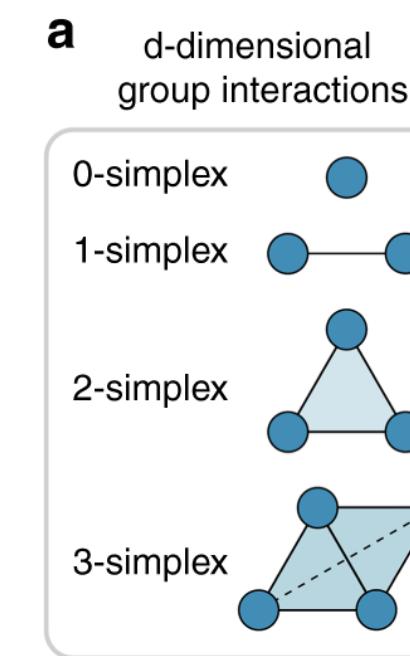
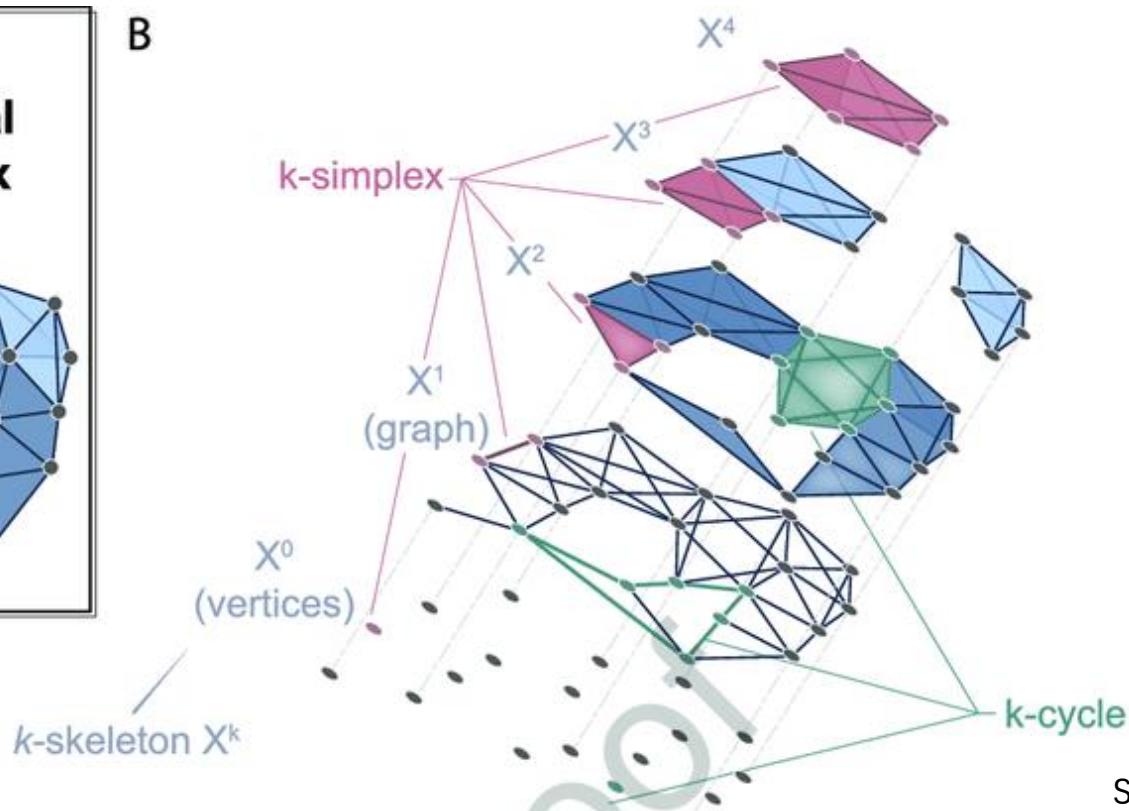
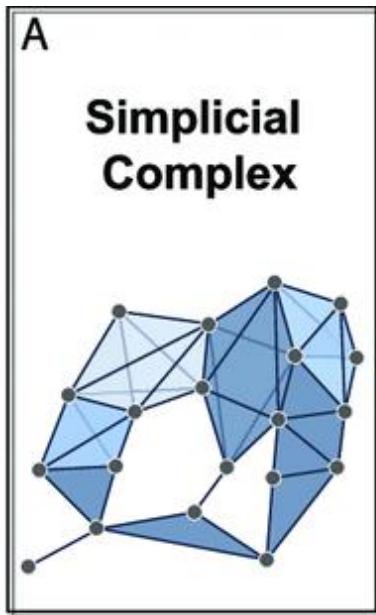
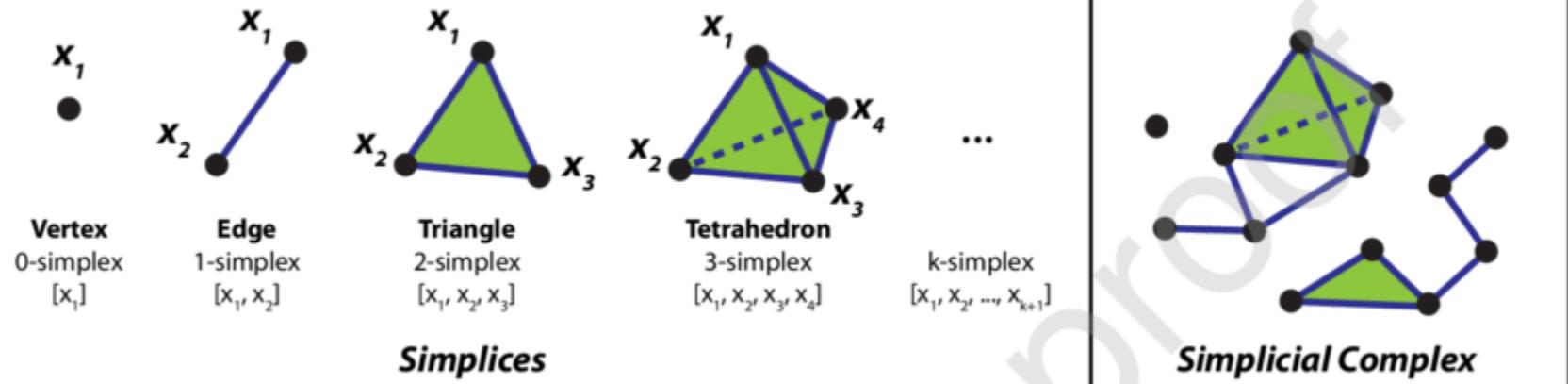
$$\Rightarrow \mathbb{R}^n = \text{im}(\mathbf{B}_{n \times p}) \oplus \ker(\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T) \oplus \text{im}(\mathbf{A}_{m \times n}^T)$$

$$\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T: \text{Hodge Laplacian} \quad \begin{cases} \text{Graph Laplacian} \\ \text{Graph Helmholtzian} \\ \text{and more} \end{cases}$$

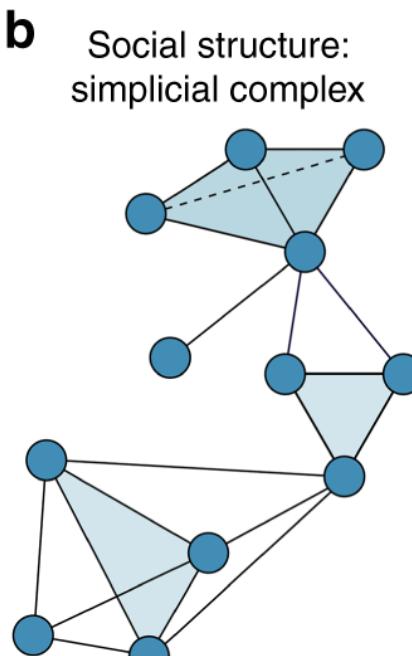
$$\ker(\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T): \text{Harmonic function}$$

Some Concepts in Algebraic Topology

Simplex and Simplicial Complex



K-simplex: filled $K+1$ cliques
simplicial complex: family of subsets of vertices



- k-simplex (oriented) $\sigma^k: [i_0, \dots, i_k]: i_0 < \dots < i_k$
- Simplicial complex X : a set of simplices that satisfies every face of a simplex from X is also in X
- Chain: linear combination of simplices (simplices as bases)

$$C_k(X) = \left\{ \sum_i a_i \sigma^k_i \right\}$$

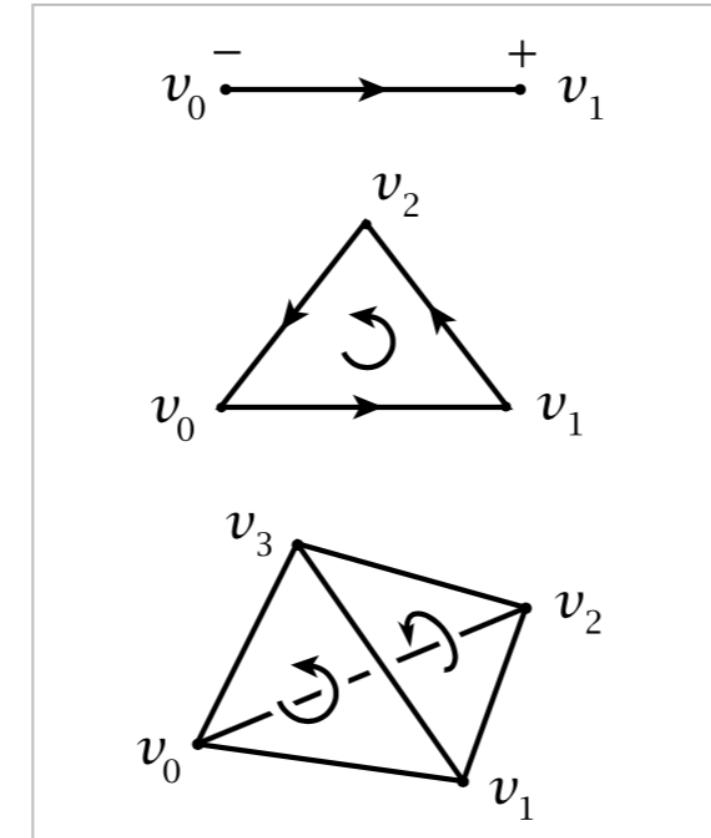
- Cochain: function on simplices $X \rightarrow \mathbb{R}$, can be represented as a vector $\mathbb{R}^{|V|}, \mathbb{R}^{|E|}, \mathbb{R}^{|T|}$, etc.

$$f([i_{p(0)}, \dots, i_{p(k)}]) = \text{sign}(p)f([i_0, \dots, i_k])$$

$i_{p(0)}, \dots, i_{p(k)}$ is a permutation of i_0, \dots, i_k ,

Odd permutation $\text{sign}(p) = -1$, $f([1,2]) = -f([2,1]), f([1,2,3]) = -f([2,1,3])$

Even permutation $\text{sign}(p) = 1$, $f([1,2,3]) = f([3,1,2])$



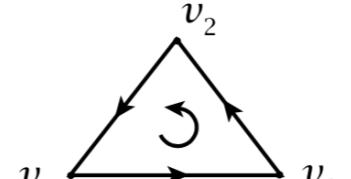
k th boundary operator $\partial_k : C_k(X) \rightarrow C_{k-1}(X)$ is the linear map that takes a k -chain $\in C_k$ to a $(\underline{k-1})$ -chain $\in C_{k-1}$ defined by

$(\partial_k)_k[i_0, i_1, \dots, i_k]$:

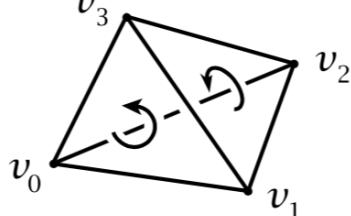
$$= \sum_{j=0} (-1)^j [i_0, \dots, i_{j-1}, i_{j+1}, \dots, i_k]$$



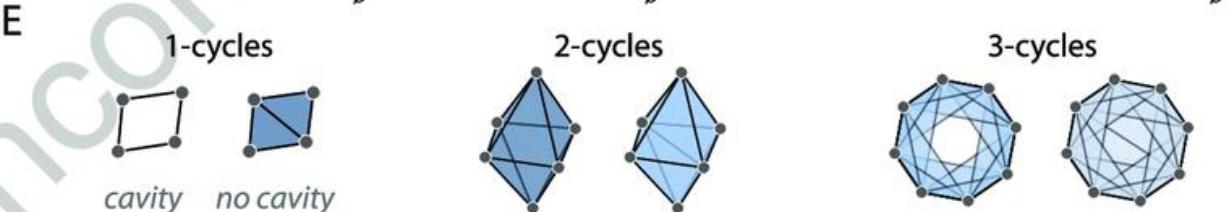
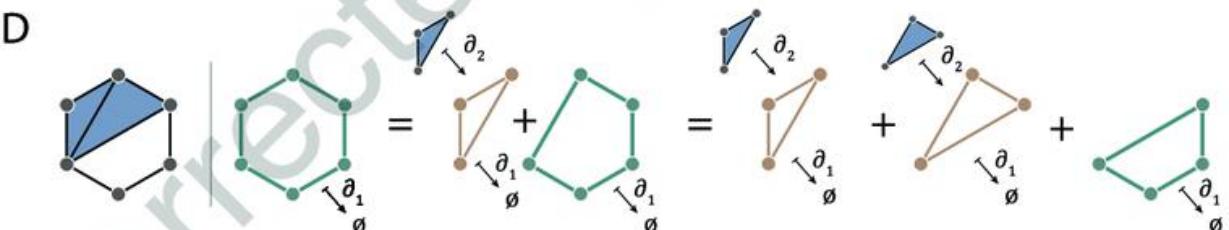
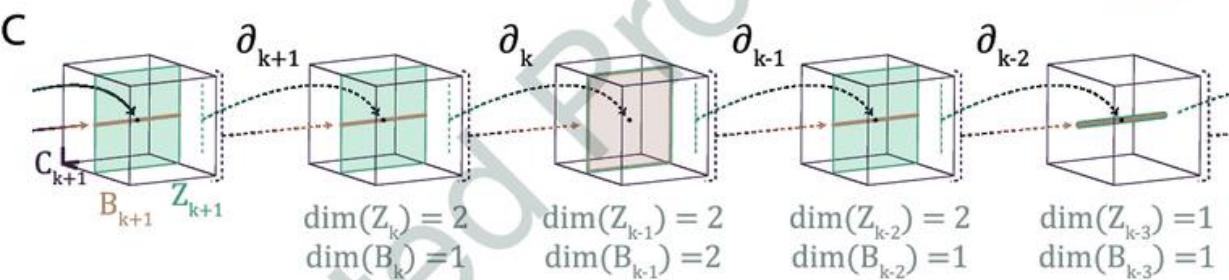
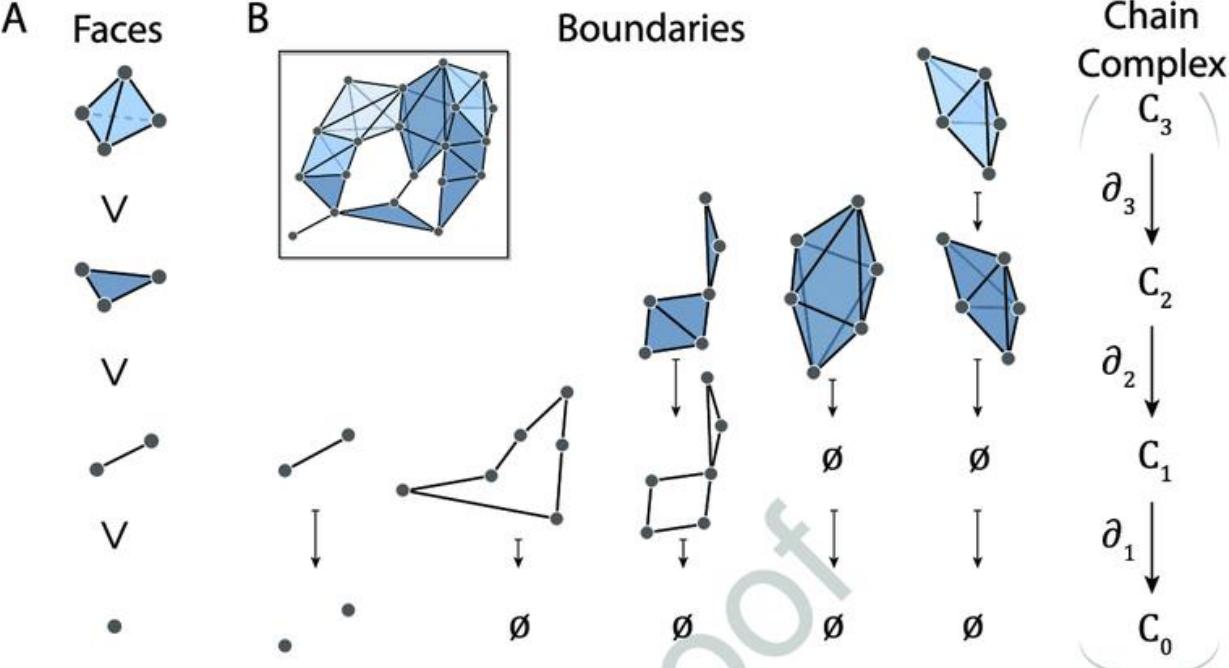
$$\partial[v_0, v_1] = [v_1] - [v_0]$$



$$\partial[v_0, v_1, v_2] = [v_1, v_2] - [v_0, v_2] + [v_0, v_1]$$



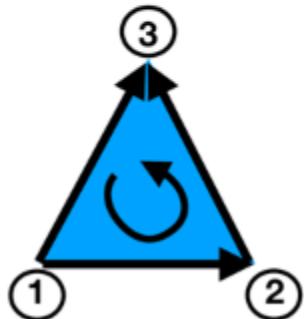
$$\partial[v_0, v_1, v_2, v_3] = [v_1, v_2, v_3] - [v_0, v_2, v_3] \\ + [v_0, v_1, v_3] - [v_0, v_1, v_2]$$



Boundary operator

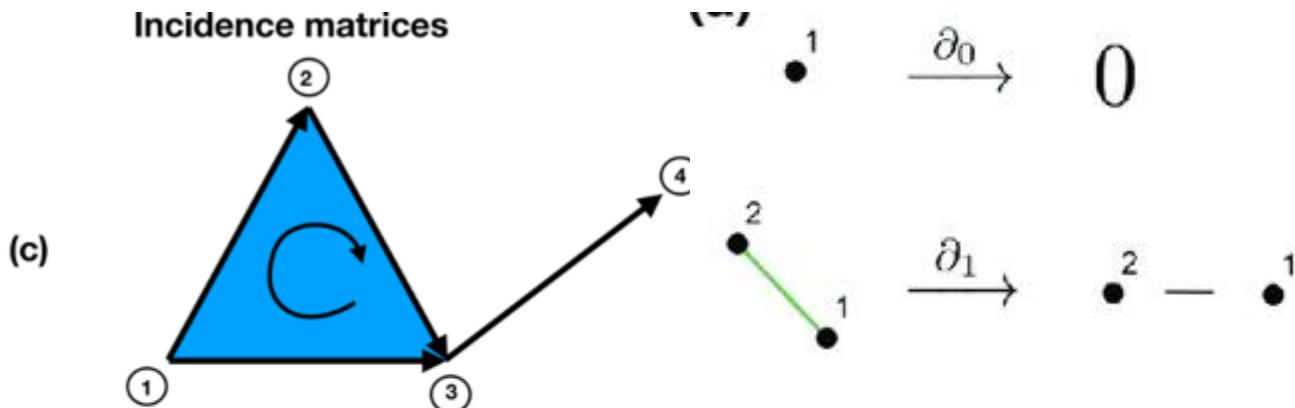
(a) $\textcircled{1} \longrightarrow \textcircled{2}$

$$\partial_1[1,2] = [2] - [1].$$



$$\partial_2[1,2,3] = [2,3] - [1,3] + [1,2].$$

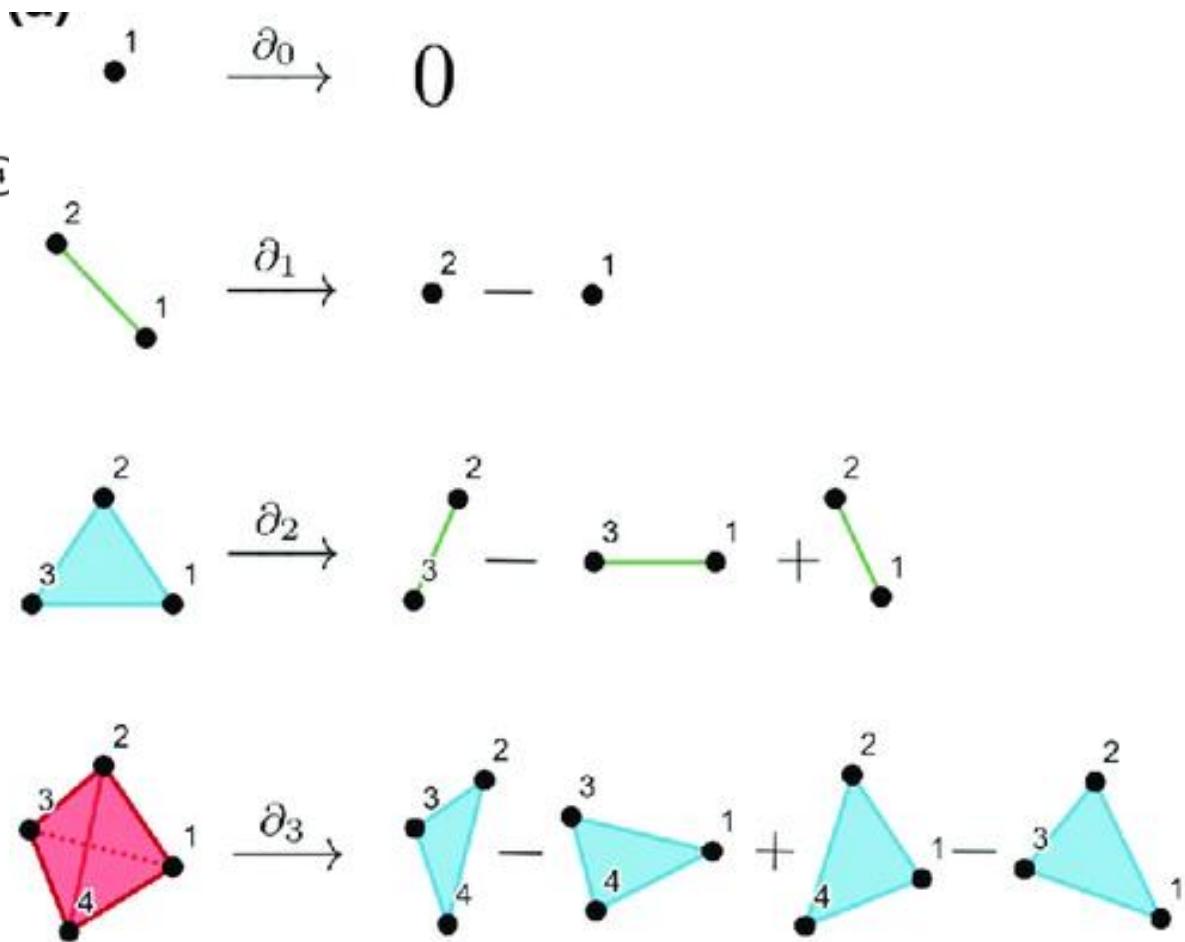
Incidence matrices



(d)

$$\mathbf{B}_{[1]} = \begin{bmatrix} [1,2] & [1,3] & [2,3] & [3,4] \\ [1] & -1 & -1 & 0 & 0 \\ [2] & 1 & 0 & -1 & 0 \\ [3] & 0 & 1 & 1 & -1 \\ [4] & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{B}_{[2]} = \begin{bmatrix} [1,2,3] \\ [1,2] & 1 \\ [1,3] & -1 \\ [2,3] & 1 \\ [3,4] & 0 \end{bmatrix}.$$



- Chain complex (A_\bullet, d_\bullet) : a sequence of abelian groups or modules (chains) $\dots, A_0, A_1, A_2, A_3, A_4, \dots$ connected by homomorphism (boundary operators) $d_n: A_n \rightarrow A_{n-1}$ (decrease dimension) ($d_n \circ d_{n+1} = 0$)

$$\dots \xleftarrow{d_0} A_0 \xleftarrow{d_1} A_1 \xleftarrow{d_2} A_2 \xleftarrow{d_3} A_3 \xleftarrow{d_4} A_4 \xleftarrow{d_5} \dots$$

- Cochain complex (A^\bullet, d^\bullet) : a sequence of abelian groups or modules (cochains) $\dots, A^0, A^1, A^2, A^3, A^4, \dots$ connected by homomorphism $d^n : A^n \rightarrow A^{n+1}$ (increase dimension) ($d^{n+1} \circ d^n = 0$)

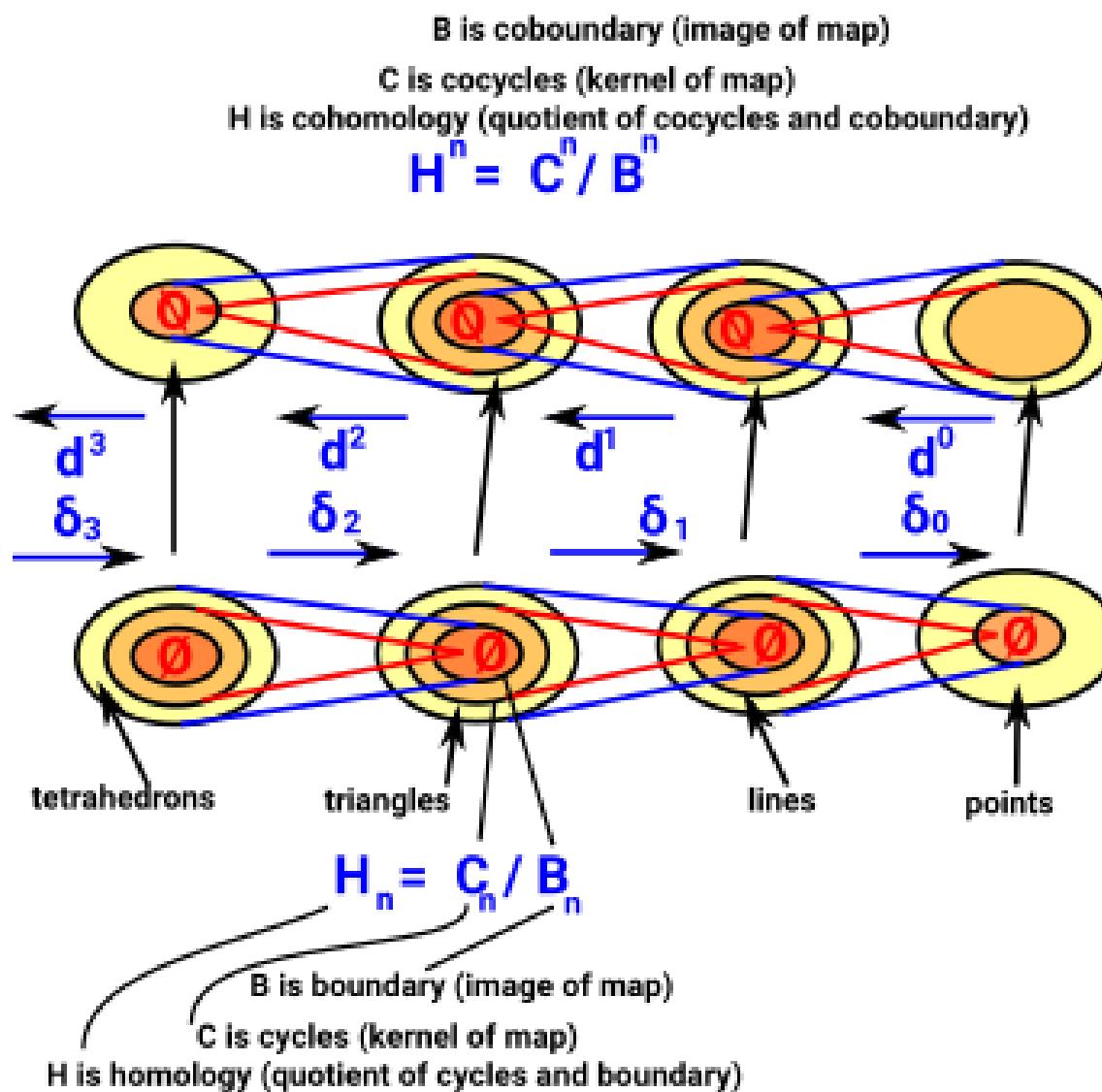
$$\dots \xrightarrow{d^{-1}} A^0 \xrightarrow{d^0} A^1 \xrightarrow{d^1} A^2 \xrightarrow{d^2} A^3 \xrightarrow{d^3} A^4 \xrightarrow{d^4} \dots$$

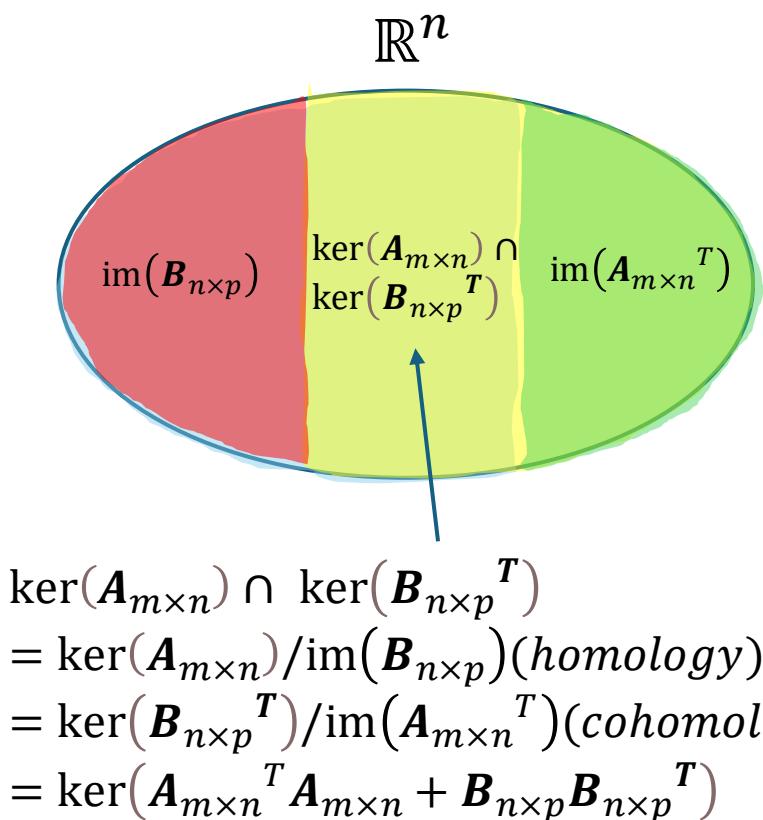
The boundary of a boundary is 0.

- n Boundary operator: d_n
- n Boundaries $B_n : \text{im}(d_n)$
- n Cycles $C_n : \ker(d_{n-1})$
- n homology group:

$$H_n = C_n / B_n = : \ker(d_{n-1}) / \text{im}(d_n)$$
- n Coboundary operator: d^n
- n Coboundaries $B^n : \text{im}(d^{n-1})$
- n Cocycles $C^n : \ker(d^n)$
- n cohomology group:

$$H^n = C^n / B^n = : \ker(d^n) / \text{im}(d^{n-1})$$





$$A_{n-1} \xleftarrow{d_{n-1}} A_n \xleftarrow{d_n} A_{n+1}$$

$$A^{n-1} \xrightarrow{d^{n-1}} A^n \xrightarrow{d^n} A^{n+1}$$

- n Boundary operator: d_n
- n Boundaries $B_n : \text{im}(d_n)$
- n Cycles $C_n : \ker(d_{n-1})$
- n homology group:

$$H_n = C_n / B_n = : \ker(d_{n-1}) / \text{im}(d_n)$$

- n Coboundary operator: d^n
- n Coboundaries $B^n : \text{im}(d^{n-1})$
- n Cocycles $C^n : \ker(d^n)$
- n cohomology group:

$$H^n = C^n / B^n = : \ker(d^n) / \text{im}(d^{n-1})$$

$$\mathbb{R}^n = \text{im}(\mathbf{B}_{n \times p}) \oplus (\ker(\mathbf{A}_{m \times n}) \cap \ker(\mathbf{B}_{n \times p}^T)) \oplus \text{im}(\mathbf{A}_{m \times n}^T)$$

$$\mathbb{R}^n = \text{im}(\mathbf{B}_{n \times p}) \oplus \ker(\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T) \oplus \text{im}(\mathbf{A}_{m \times n}^T)$$

$$\mathbb{R}_n^k = n \text{ boundaries} \oplus (n \text{ homology/cohomology group}) \oplus n \text{ coboundaries}$$

$$C_{k-1} \xleftarrow{\mathbf{A}_{m \times n}} C_k \xleftarrow{\mathbf{B}_{n \times p}} C_{k+1}$$

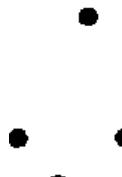
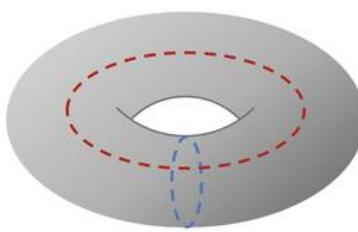
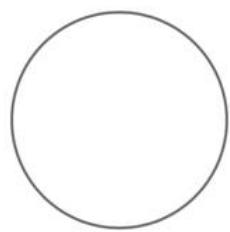
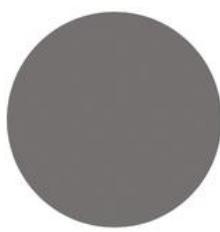
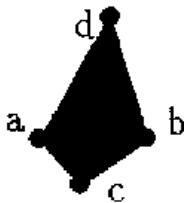
- A hole is a chain with zero boundary (a cycle) but not the boundary of anything else (this cycle is not filled) = $\ker(\mathbf{A}_{m \times n})/\text{im}(\mathbf{B}_{n \times p})$
- kth homology = $H_k(X) = \ker(\mathbf{A}_{m \times n}) \cap \ker(\mathbf{B}_{n \times p}^T) = \ker(\mathbf{A}_{m \times n})/\text{im}(\mathbf{B}_{n \times p}) = \ker(\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T)$
- $\dim(\ker(\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T))$ = Betti number = number of k dimensional holes
- $H_0(X) = \ker(d_0^T d_0 + d_1 d_1^T) = \ker(d_1 d_1^T) = \ker(\mathbf{L})$ = connected components (both continuous and discrete/in graphs)

L : Graph Laplacian

- $H_1(X) = \ker(d_1^T d_1 + d_2 d_2^T) = \ker(\mathbf{H})$ = non – contractable cycles (in graphs: cycles longer than 3, cycles of length 3 are the boundaries of those triangles encircled by them, cycles longer than 3 are not boundaries of anything)

H : Graph Helmholtzian

- $H_2(X) = \ker(d_2^T d_2 + d_3 d_3^T) = 3 - \text{dimensional voids}$ (in graphs: closed surface made up of more than four triangles, can not encircle a tetrahedron)

 $\mathcal{K}^{(0)}$  $\mathcal{K}^{(1)}$  $\mathcal{K}^{(2)}$  $\mathcal{K}^{(3)}$

$\beta_0 = 1$

$\beta_0 = 1$

$\beta_0 = 1$

$\beta_1 = 0$

$\beta_1 = 1$

$\beta_1 = 0$

$\beta_2 = 0$

$\beta_2 = 0$

$\beta_2 = 1$

$\beta_0 = 1$

$\beta_1 = 2$

$\beta_2 = 1$

$\beta_0 = 4$

$\beta_1 = 0$

$\beta_2 = 0$

$\beta_0 = 1$

$\beta_1 = 3$

$\beta_2 = 0$

$\beta_0 = 1$

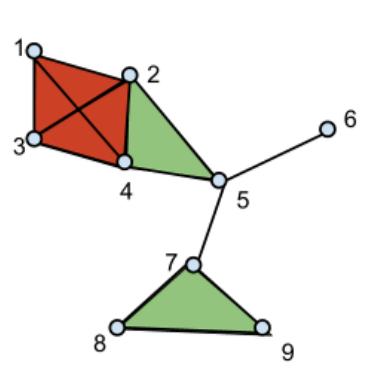
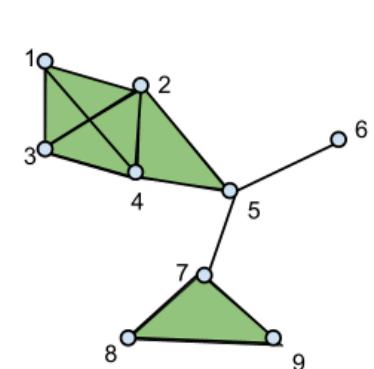
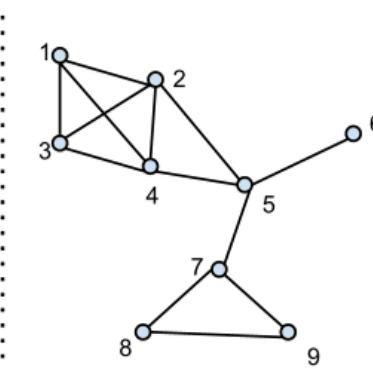
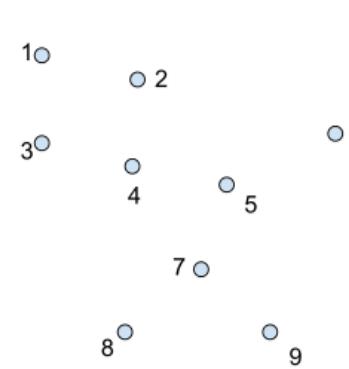
$\beta_1 = 0$

$\beta_2 = 1$

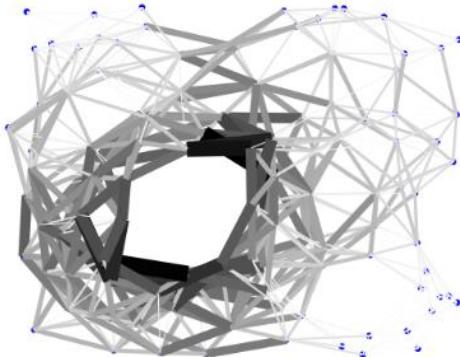
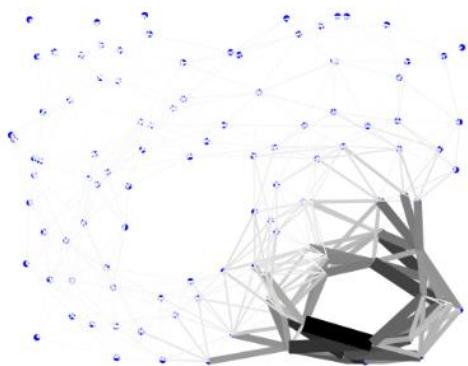
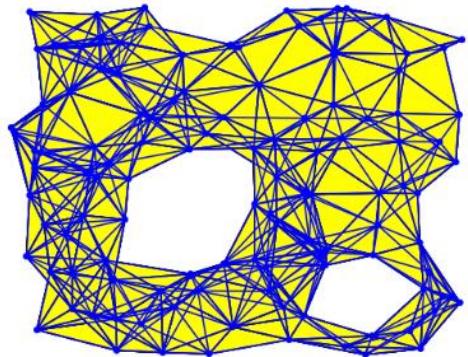
$\beta_0 = 1$

$\beta_1 = 0$

$\beta_2 = 0$



β_2	0	0	1	0
β_1	0	5	0	0
β_0	9	1	1	1



$\dim \left(\ker(d_k^T d_k + d_k d_k^T) \right)$ = number of k dim holes
 $\ker(d_k^T d_k + d_k d_k^T)$ = nullspace =
eigenvectors corresponding to 0 eigenvalues
eigenvectors corresponding to small but non – zero eigenvalues indicate what parts of the complex are close to becoming holes. fragilities of a simplicial complex.

Spectral clustering: looking for the eigenvectors corresponding to the smallest k eigenvalues of the graph Laplacian (detect the different almost connected components)

Hodge Decomposition in Graphs

Divergence, Gradient, Curl

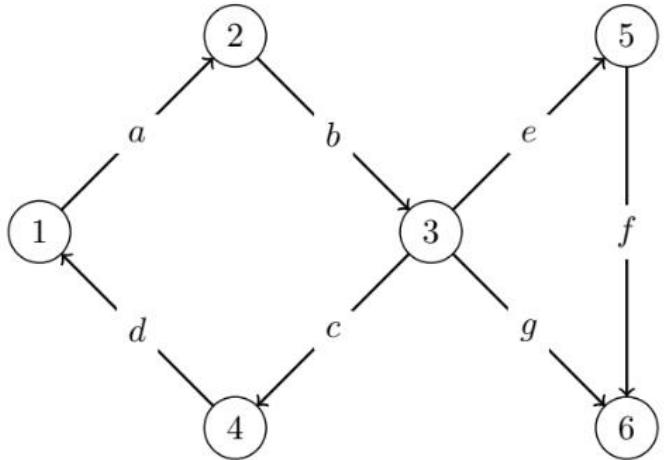
- $\text{grad} \boldsymbol{v}_{(i,j)} = v_j - v_i, \quad \text{grad} \boldsymbol{f}_1|_{V \times 1} = \boldsymbol{g}_2|_{E \times 1}$
- $\text{curl} \boldsymbol{e}_{(i,j,k)} = e_{(i,j)} + e_{(j,k)} + e_{(k,i)}, \quad \text{curl} \boldsymbol{f}_2|_{E \times 1} = \boldsymbol{g}_3|_{T \times 1}$
- $\text{div} \boldsymbol{e}_{(i)} = \sum e_{(i,j)}, \quad \text{div} \boldsymbol{f}_2|_{E \times 1} = \boldsymbol{g}_1|_{V \times 1}$
- $\text{curl} \circ \text{grad} = 0 \Leftrightarrow -\text{div} \circ \text{curl}^* = 0$
- $-\text{div} \circ \text{grad} = \text{graph Laplacian}$

Continuous calculus in vector field \Rightarrow Discrete calculus in a graph

$\boldsymbol{f}_1|_{V \times 1}$: potential function on nodes (0-simplices)

$\boldsymbol{f}_2|_{E \times 1}$: flow function on edges (1-simplices)

$\boldsymbol{f}_3|_{T \times 1}$: local curl function on triangles (2-simplices)



Edge-vertex incident matrix = grad $A_1 =$
 $-\text{div} = \text{grad}^* = \mathbf{A}_1^T$
 (Very sparse)

$$\begin{matrix} & 1 & 2 & 3 & 4 & 5 & 6 \\ a & -1 & 1 & 0 & 0 & 0 & 0 \\ b & 0 & -1 & 1 & 0 & 0 & 0 \\ c & 0 & 0 & -1 & 1 & 0 & 0 \\ d & 1 & 0 & 0 & -1 & 0 & 0 \\ e & 0 & 0 & -1 & 0 & 1 & 0 \\ f & 0 & 0 & 0 & 0 & -1 & 1 \\ g & 0 & 0 & -1 & 0 & 0 & 1 \end{matrix}$$

Graph Laplacian $L_1 = A_1^* A_1 =$
 $-\text{div} \circ \text{grad}$
 (Very sparse)

$$\begin{matrix} & 1 & 2 & 3 & 4 & 5 & 6 \\ 1 & 2 & -1 & 0 & -1 & 0 & 0 \\ 2 & -1 & 2 & -1 & 0 & 0 & 0 \\ 3 & 0 & -1 & 4 & -1 & -1 & -1 \\ 4 & -1 & 0 & -1 & 2 & 0 & 0 \\ 5 & 0 & 0 & -1 & 0 & 2 & -1 \\ 6 & 0 & 0 & -1 & 0 & -1 & 2 \end{matrix}$$

Triangle-edge incident matrix = curl $B_1 = T \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 1 & -1 \end{bmatrix}$
 $\text{curl}^* = \mathbf{B}_1^T$
 (Very sparse)

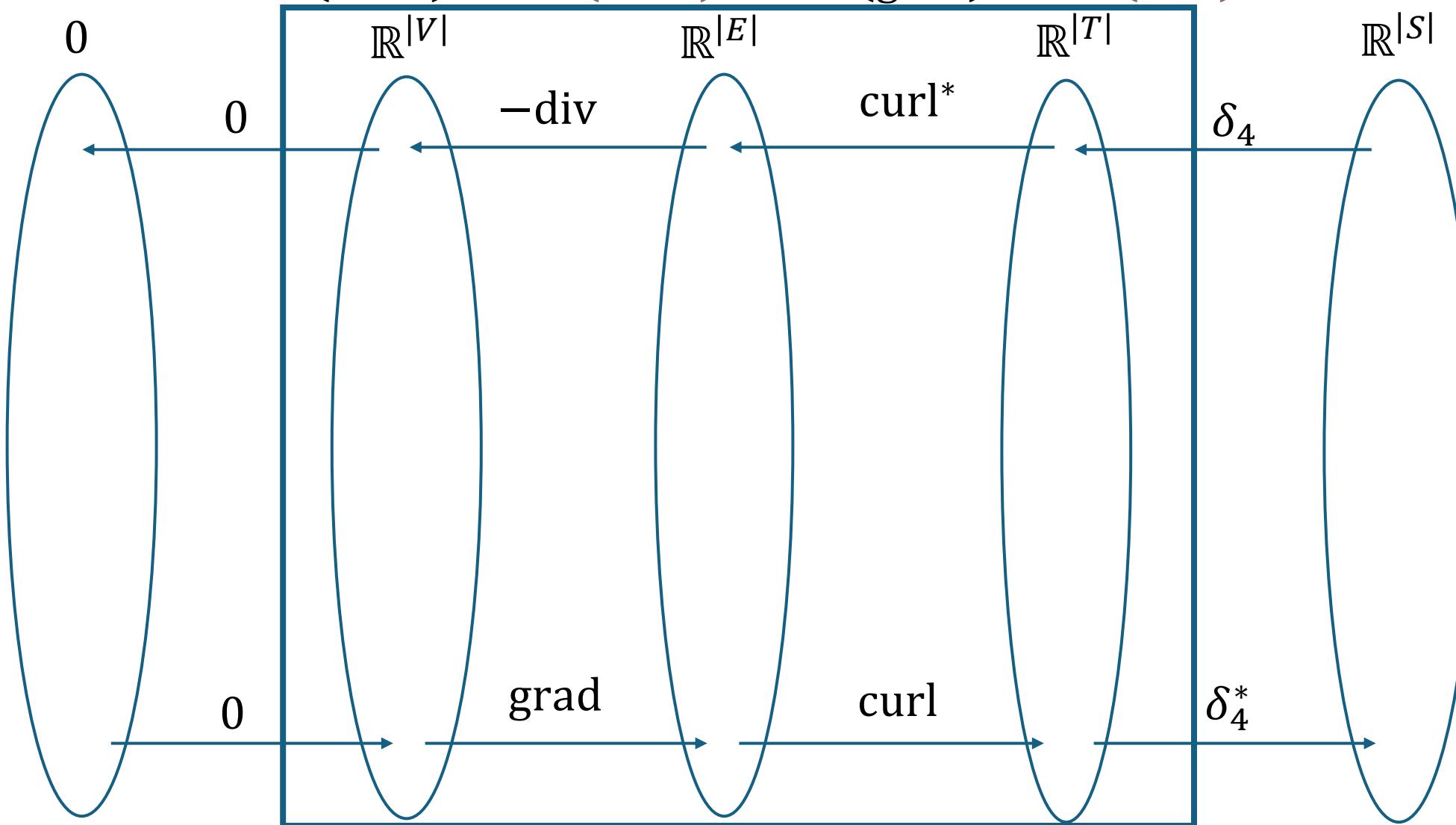
$$\begin{matrix} & a & b & c & d & d & e & f \\ a & 2 & -1 & 0 & -1 & 0 & 0 & 0 \\ b & -1 & 2 & -1 & 0 & -1 & 0 & -1 \\ c & 0 & -1 & 2 & -1 & 1 & 0 & 1 \\ d & -1 & 0 & -1 & 2 & 0 & 0 & 0 \\ e & 0 & -1 & 1 & 0 & 3 & 0 & 0 \\ f & 0 & 0 & 0 & 0 & 0 & 3 & 0 \\ g & 0 & -1 & 1 & 0 & 0 & 0 & 3 \end{matrix}$$

Graph Helmholtzian $H_1 = A_1 A_1^* + B_1^* B_1 =$
 $-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}$
 (Very sparse)

$$T \begin{bmatrix} a & b & c & d & d & e & f \\ 0 & 0 & 0 & 0 & 1 & 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ a & -1 & 1 & 0 & 0 & 0 \\ b & 0 & -1 & 1 & 0 & 0 \\ c & 0 & 0 & -1 & 1 & 0 \\ d & 1 & 0 & 0 & -1 & 0 \\ e & 0 & 0 & -1 & 0 & 1 \\ f & 0 & 0 & 0 & 0 & -1 \\ g & 0 & 0 & -1 & 0 & 0 \end{bmatrix} = [0 \ 0 \ 0 \ 0 \ 0 \ 0]$$

$$-\operatorname{div} \circ \operatorname{curl}^* = 0 \Leftrightarrow \operatorname{curl} \circ \operatorname{grad} = 0$$

$$\operatorname{im}(\operatorname{curl}^*) \subseteq \ker(-\operatorname{div}) \Leftrightarrow \operatorname{im}(\operatorname{grad}) \subseteq \ker(\operatorname{curl})$$



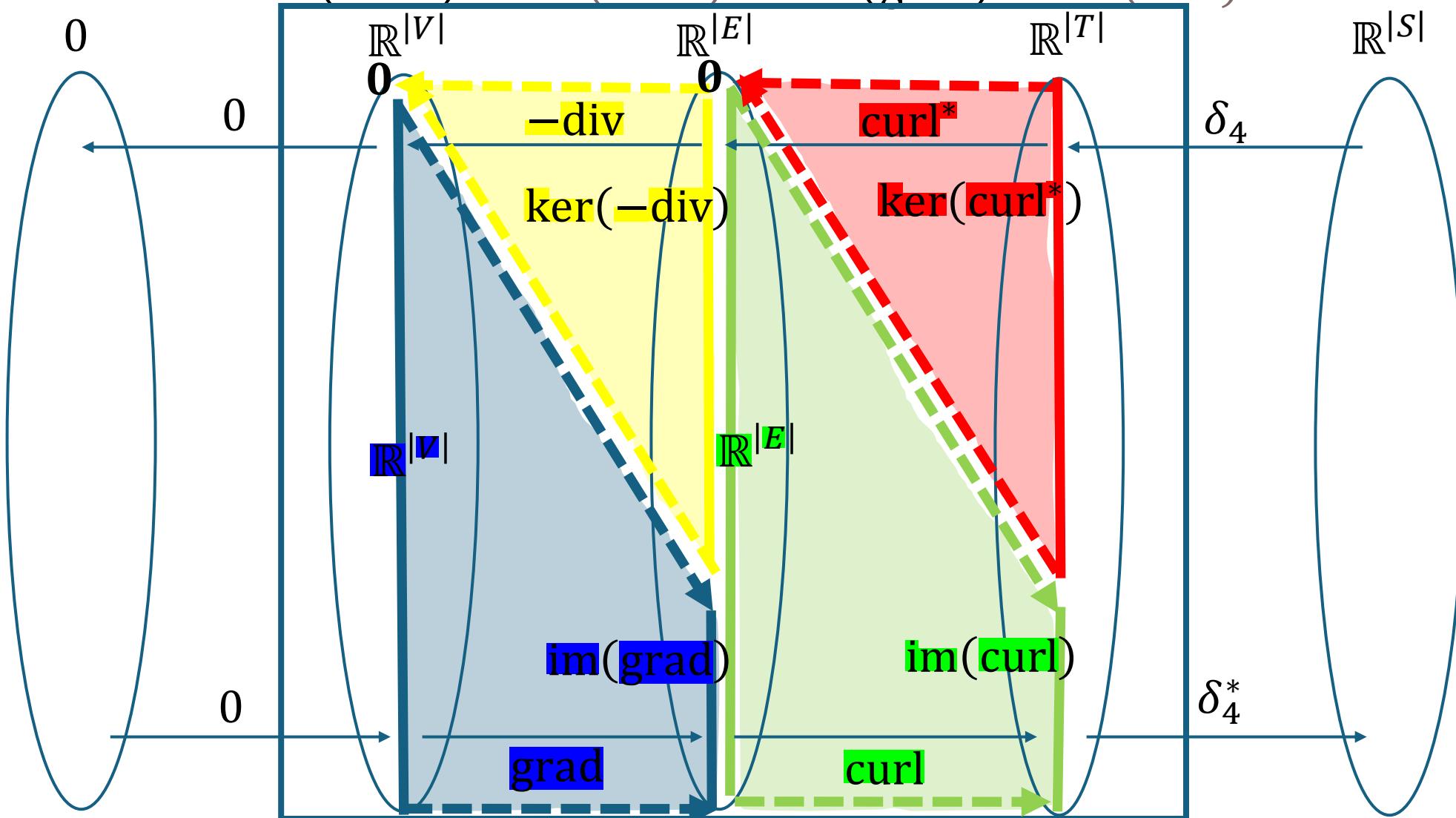
$$\operatorname{im}(-\operatorname{div}) \oplus \ker(\operatorname{grad}) = \mathbb{R}^{|V|}$$

$$\begin{aligned}\operatorname{im}(\operatorname{grad}) \oplus \ker(-\operatorname{div}) &= \mathbb{R}^{|E|} \\ \operatorname{im}(\operatorname{curl}^*) \oplus \ker(\operatorname{curl}) &= \mathbb{R}^{|E|}\end{aligned}$$

$$\operatorname{im}(\operatorname{curl}) \oplus \ker(\operatorname{curl}^*) = \mathbb{R}^{|T|}$$

$$-\operatorname{div} \circ \operatorname{curl}^* = 0 \Leftrightarrow \operatorname{curl} \circ \operatorname{grad} = 0$$

$$\operatorname{im}(\operatorname{curl}^*) \subseteq \ker(-\operatorname{div}) \Leftrightarrow \operatorname{im}(\operatorname{grad}) \subseteq \ker(\operatorname{curl})$$



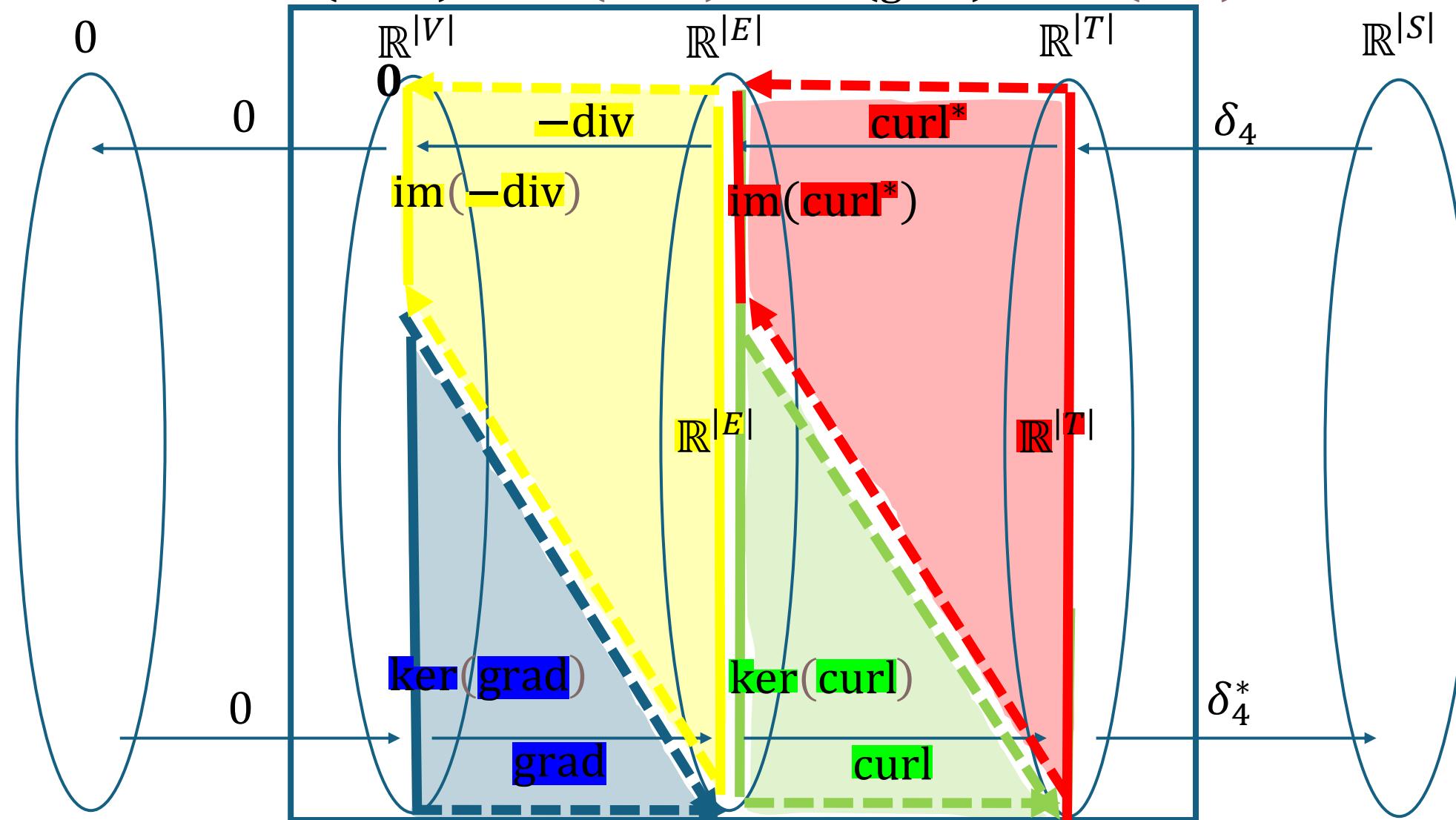
$$\operatorname{im}(-\operatorname{div}) \oplus \operatorname{ker}(\operatorname{grad}) = \mathbb{R}^{|V|}$$

$$\begin{aligned}\operatorname{im}(\operatorname{grad}) \oplus \operatorname{ker}(-\operatorname{div}) &= \mathbb{R}^{|E|} \\ \operatorname{im}(\operatorname{curl}^*) \oplus \operatorname{ker}(\operatorname{curl}) &= \mathbb{R}^{|E|}\end{aligned}$$

$$\operatorname{im}(\operatorname{curl}) \oplus \operatorname{ker}(\operatorname{curl}^*) = \mathbb{R}^{|T|}$$

$$-\operatorname{div} \circ \operatorname{curl}^* = 0 \Leftrightarrow \operatorname{curl} \circ \operatorname{grad} = 0$$

$$\operatorname{im}(\operatorname{curl}^*) \subseteq \ker(-\operatorname{div}) \Leftrightarrow \operatorname{im}(\operatorname{grad}) \subseteq \ker(\operatorname{curl})$$



$$\text{im}(\text{-div}) \oplus \text{ker}(\text{grad}) = \mathbb{R}^{|V|}$$

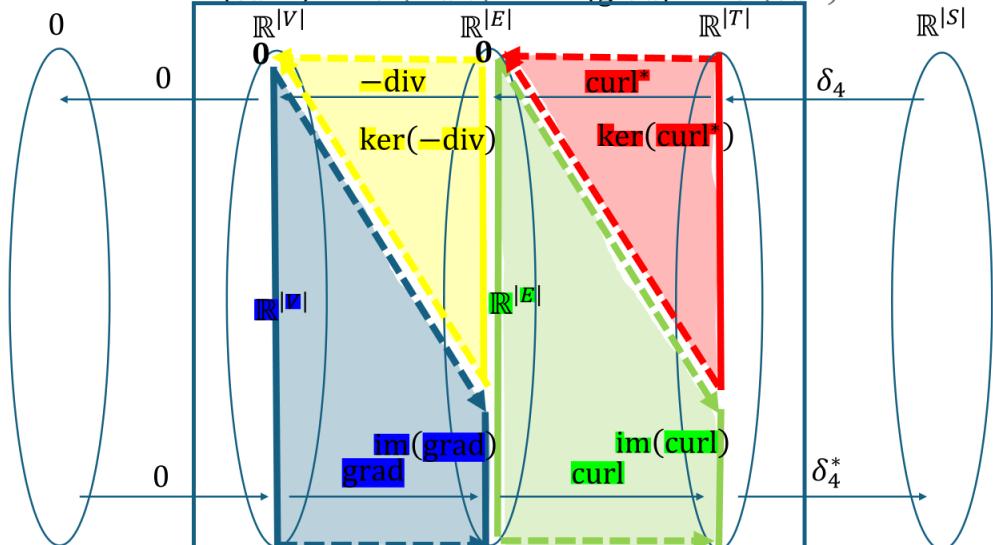
$$\text{im}(\text{grad}) \oplus \text{ker}(\text{-div}) = \mathbb{R}^{|E|}$$

$$\text{im}(\text{curl}^*) \oplus \text{ker}(\text{curl}) = \mathbb{R}^{|E|}$$

$$\text{im}(\text{curl}) \oplus \text{ker}(\text{curl}^*) = \mathbb{R}^{|T|}$$

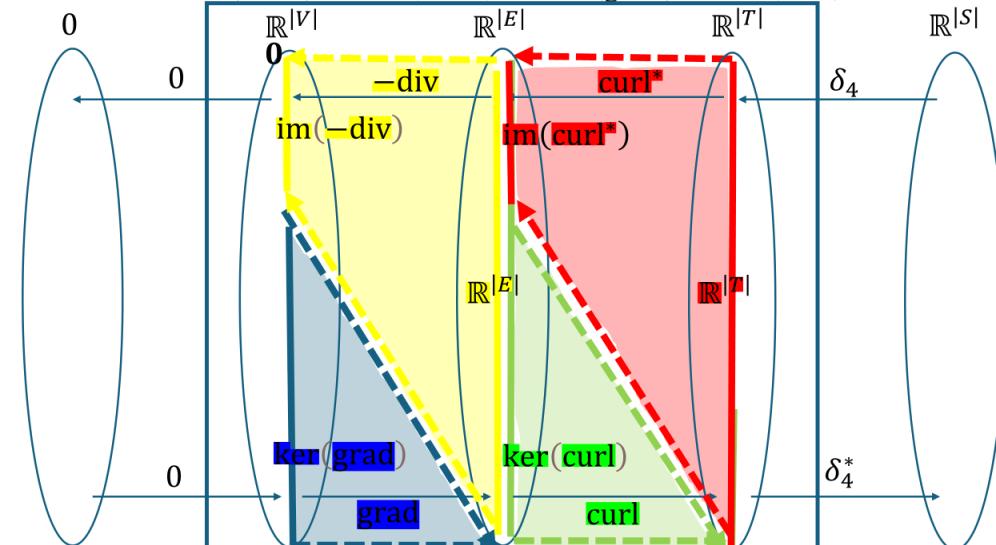
$$-\text{div} \circ \text{curl}^* = 0 \Leftrightarrow \text{curl} \circ \text{grad} = 0$$

$$\text{im}(\text{curl}^*) \subseteq \ker(-\text{div}) \Leftrightarrow \text{im}(\text{grad}) \subseteq \ker(\text{curl})$$



$$-\text{div} \circ \text{curl}^* = 0 \Leftrightarrow \text{curl} \circ \text{grad} = 0$$

$$\text{im}(\text{curl}^*) \subseteq \ker(-\text{div}) \Leftrightarrow \text{im}(\text{grad}) \subseteq \ker(\text{curl})$$

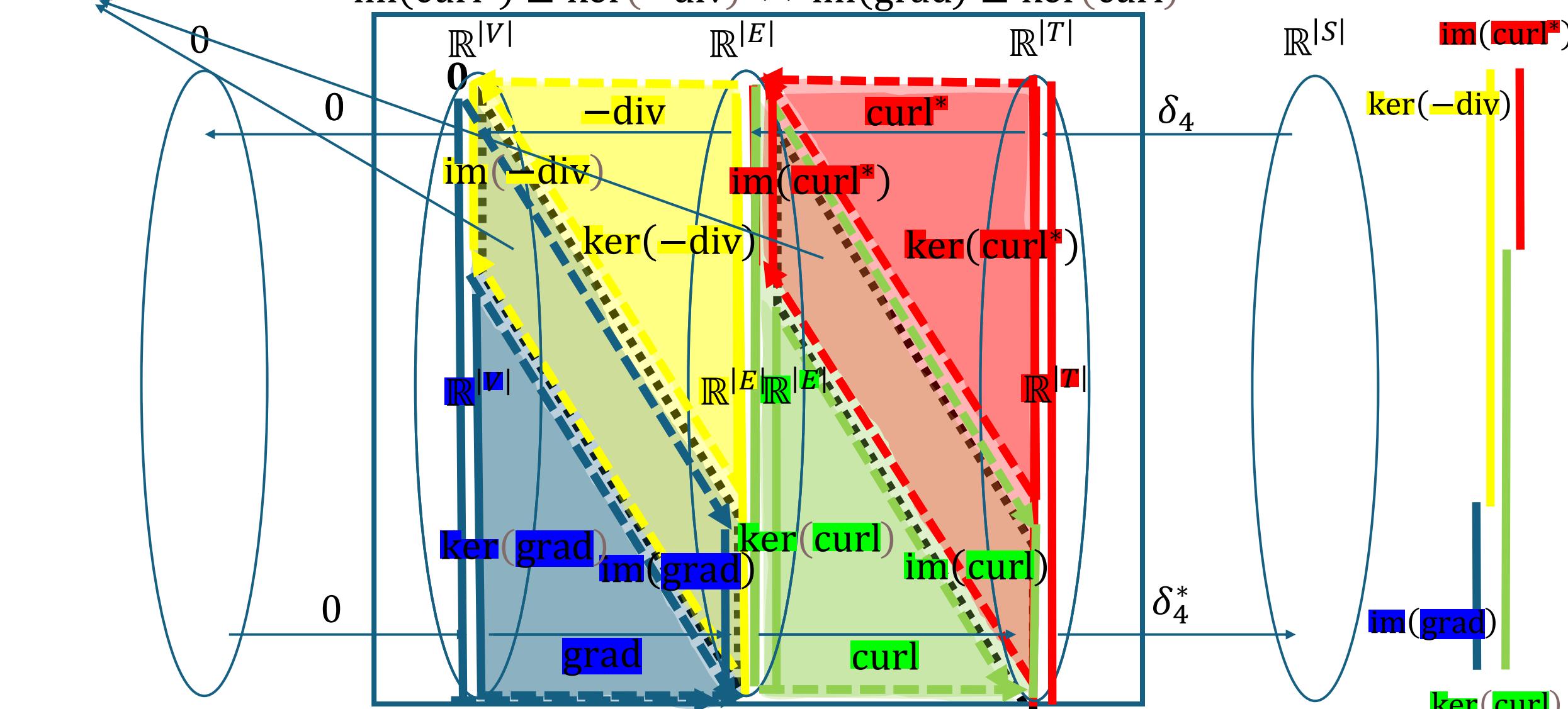


Bijective
isomorphism

$$-\operatorname{div} \circ \operatorname{curl}^* = 0 \Leftrightarrow \operatorname{curl} \circ \operatorname{grad} = 0$$

$$\operatorname{im}(\operatorname{curl}^*) \subseteq \ker(-\operatorname{div}) \Leftrightarrow \operatorname{im}(\operatorname{grad}) \subseteq \ker(\operatorname{curl})$$

$\mathbb{R}^{|E|}$



$$\operatorname{im}(-\operatorname{div}) \oplus \operatorname{ker}(\operatorname{grad}) = \mathbb{R}^{|V|}$$

$$\operatorname{im}(\operatorname{grad}) \oplus \operatorname{ker}(-\operatorname{div}) = \mathbb{R}^{|E|}$$

$$\operatorname{im}(\operatorname{curl}^*) \oplus \operatorname{ker}(\operatorname{curl}) = \mathbb{R}^{|E|}$$

$$\operatorname{im}(\operatorname{curl}) \oplus \operatorname{ker}(\operatorname{curl}^*) = \mathbb{R}^{|T|}$$

$\operatorname{ker}(\operatorname{curl})$

$\operatorname{im}(\operatorname{grad})$

$\operatorname{im}(\operatorname{curl}^*)$

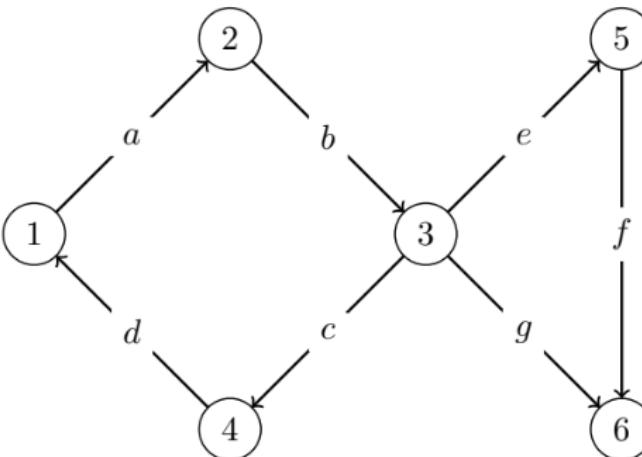
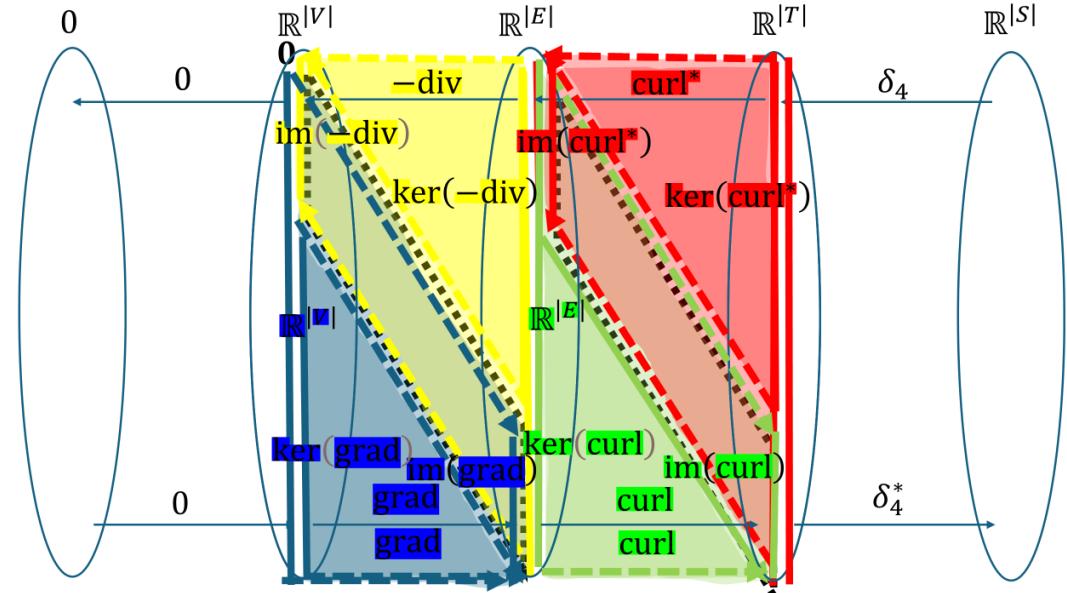
$\operatorname{ker}(-\operatorname{div})$

δ_4

δ_4^*

$\mathbb{R}^{|S|}$

$\mathbb{R}^{|E|}$



$$\ker(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}) = \ker(-\text{div}) \cap \ker(\text{curl})$$

$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus \ker(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}) \oplus \text{im}(\text{grad})$$

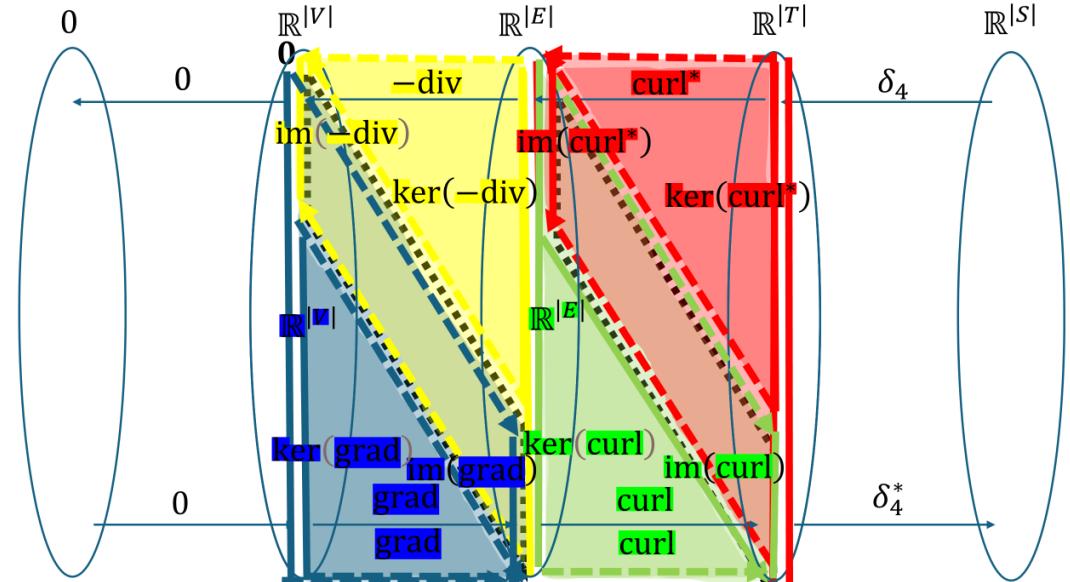
im(grad) = conservative =

$$a \begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & -1 & 1 \\ 0 & 0 & -1 & 0 & 0 & 1 \end{bmatrix} \mathbf{f}_{|V| \times 1}$$

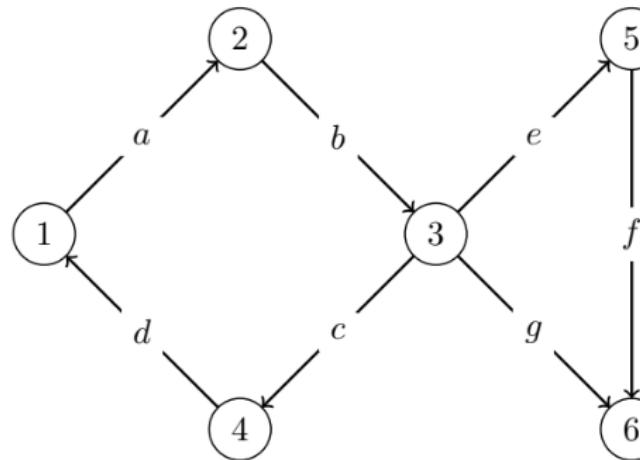
(The value on every edge is the directed difference between the two end nodes)

$$\text{im}(\text{curl}^*) = \text{vorticity} = T \begin{bmatrix} a & b & c & d & d & e & f \end{bmatrix}^T \mathbf{f}_{|T| \times 1}$$

(The values on edges in a triad are the same)



$\ker(-\text{div}) = \text{divergence-free}$



$$\ker(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}) = \ker(-\text{div}) \cap \ker(\text{curl})$$

$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus (\ker(-\text{div}) \cap \ker(\text{curl})) \oplus \text{im}(\text{grad})$$

$$T = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ a & -1 & 1 & 0 & 0 & 0 & 0 \\ b & 0 & -1 & 1 & 0 & 0 & 0 \\ c & 0 & 0 & -1 & 1 & 0 & 0 \\ d & 1 & 0 & 0 & -1 & 0 & 0 \\ e & 0 & 0 & -1 & 0 & 1 & 0 \\ f & 0 & 0 & 0 & 0 & -1 & 1 \\ g & 0 & 0 & -1 & 0 & 0 & 1 \end{bmatrix}$$

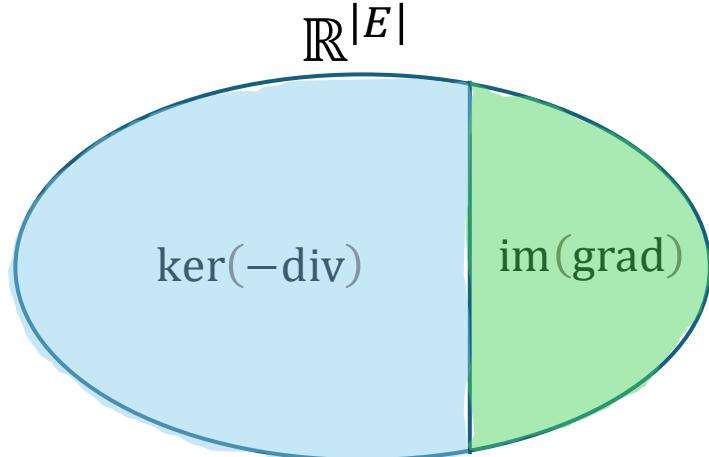
$$\ker(-\text{div}) = \mathbf{0}$$

(The flow into a node is equal to the flow out of a node)

$$\ker(\text{curl}) = \text{curl-free} \quad T \quad \begin{bmatrix} a & b & c & d & d & e & f \\ 0 & 0 & 0 & 0 & 1 & 1 & -1 \end{bmatrix} \quad \ker(\text{curl}) = \mathbf{0}$$

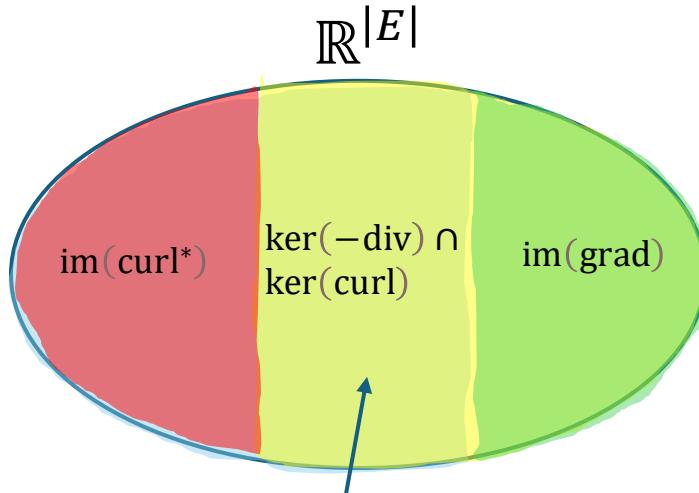
(The directed flows on edges in a triad must be added to 0)

$\ker(-\text{div}) \cap \ker(\text{curl}) = \text{divergence-free and curl-free}$

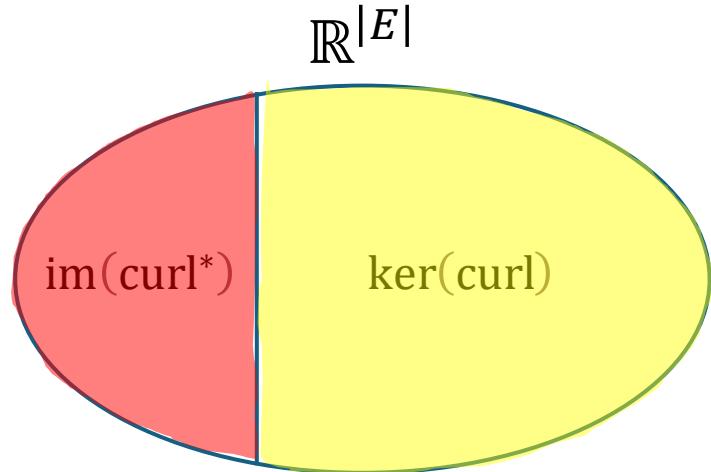


$$\text{im}(\text{grad}) \oplus \ker(-\text{div}) = \mathbb{R}^{|E|}$$

$$\text{im}(\text{curl}^*) \subseteq \ker(-\text{div})$$



$$\begin{aligned} \ker(-\text{div}) \cap \ker(\text{curl}) \\ = \ker(-\text{div}) / \text{im}(\text{curl}^*) \\ = \ker(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}) \end{aligned}$$



$$\text{im}(\text{curl}^*) \oplus \ker(\text{curl}) = \mathbb{R}^{|E|}$$

$$\text{im}(\text{grad}) \subseteq \ker(\text{curl})$$

$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus (\ker(-\text{div}) \cap \ker(\text{curl})) \oplus \text{im}(\text{grad})$$

$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus \ker(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}) \oplus \text{im}(\text{grad})$$

$$x \in \mathbb{R}^{|E|}, \quad (-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl})x_H = \mathbf{0}, \quad v \in \mathbb{R}^{|T|}, \quad w \in \mathbb{R}^{|V|}$$

$$x = \text{grad}w + x_H + \text{curl}^*v, \quad \langle \text{grad}w, x_H \rangle = \langle \text{curl}^*v, x_H \rangle = \langle \text{grad}w, \text{curl}^*v \rangle = \mathbf{0}$$

$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus (\ker(-\text{div}) \cap \ker(\text{curl})) \oplus \text{im}(\text{grad})$$

$$\mathbb{R}^{|E|} = \text{vorticity} \oplus (\text{solenoidal and irrotational}) \oplus \text{conservative}$$

$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus \ker \left(\underbrace{-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}}_{\text{Graph Helmholtzian}} \right) \oplus \text{im}(\text{grad})$$

$$L^2_\wedge(E) = \overbrace{\text{im}(\text{curl}^*) \oplus \ker(\Delta_1)}^{\ker(\text{div})} \oplus \overbrace{\text{im}(\text{grad})}^{\ker(\text{curl})}, \quad \ker(\Delta_1) = \ker(\text{curl}) \cap \ker(\text{div}), \\ \text{im}(\Delta_1) = \text{im}(\text{curl}^*) \oplus \text{im}(\text{grad}).$$

$$\text{Edge Flow} = \text{vorticity} \oplus \underbrace{\text{solenoidal} \quad \text{irrotational}}_{\text{solenoidal irrotational}} \oplus \text{conservative}$$

$$\text{Edge Flow} = \underbrace{\text{divergence - free}}_{\text{divergence - free but not curl - free}} \oplus \underbrace{\text{divergence - free and curl - free}}_{\text{curl - free}} \oplus \underbrace{\text{curl - free but not divergence - free}}_{\text{curl - free}}$$

$$\text{Hodge Decomposition} \quad \mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus \ker(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}) \oplus \text{im}(\text{grad})$$

Graph Helmholtzian

$$\text{Edge Flow} = \underbrace{\text{solenoidal}}_{\text{vorticity}} \oplus \underbrace{\text{solenoidal irrotational}}_{\text{irrotational}} \oplus \boxed{\text{conservative}}$$

$$\text{Edge Flow} = \underbrace{\text{divergence - free}}_{\substack{\text{divergence - free but} \\ \text{not curl - free}}} \oplus \underbrace{\text{divergence - free and curl - free}}_{\text{curl - free}} \oplus \boxed{\text{curl - free but} \\ \text{not divergence - free}}$$

Helmholtz Decomposition

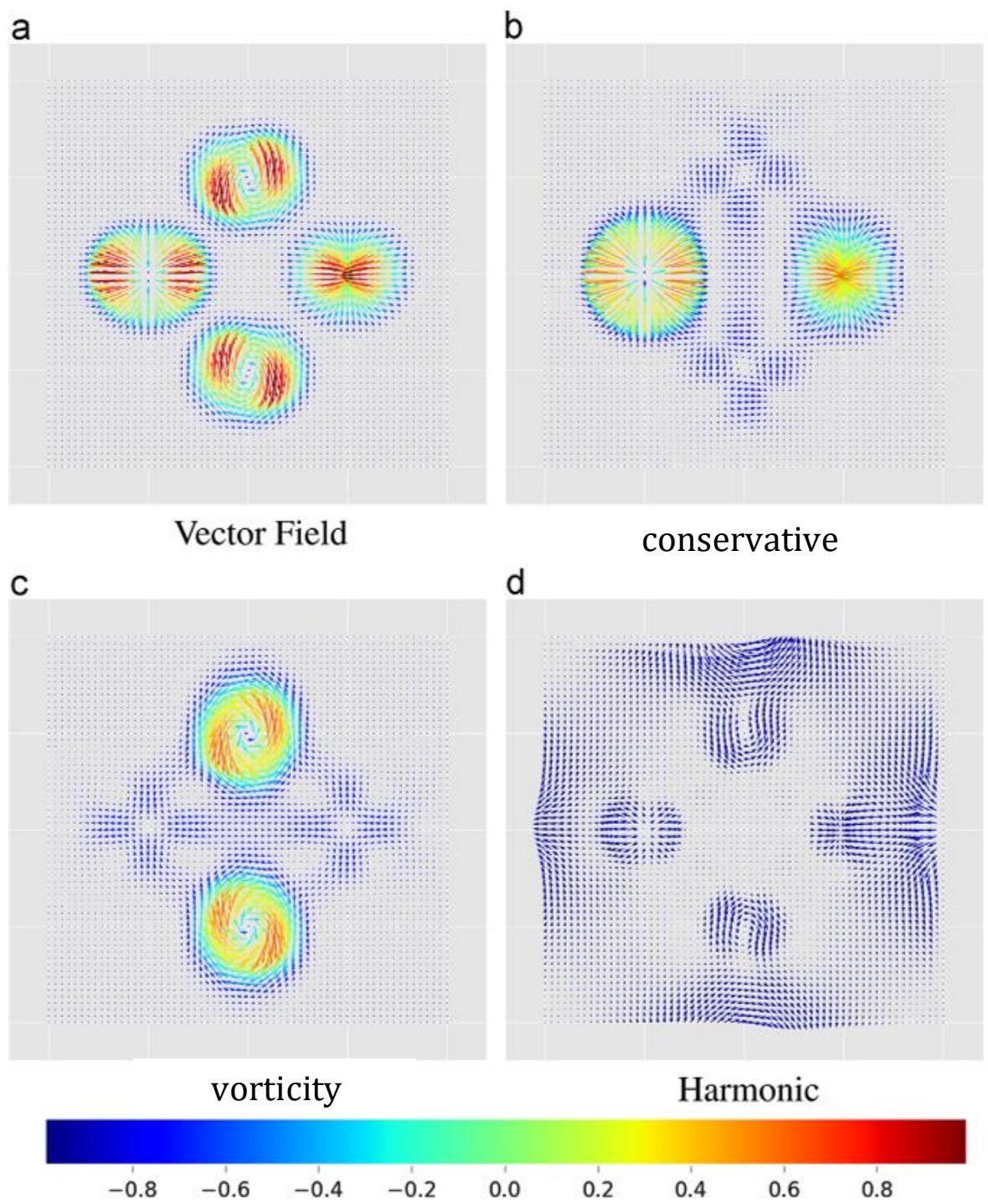
For a vector field $\mathbf{F} \in C^1(V, \mathbb{R}^n)$ defined on a domain $V \subseteq \mathbb{R}^n$, there exists a pair of vector field $\mathbf{G} \in C^1(V, \mathbb{R}^n)$ and $\mathbf{R} \in C^1(V, \mathbb{R}^n)$ such that

$$\mathbf{F}(\mathbf{r}) = \mathbf{G}(\mathbf{r}) + \mathbf{R}(\mathbf{r})$$

$$\mathbf{G}(\mathbf{r}) = -\nabla\Phi(\mathbf{r}) \quad \text{gradient field}$$

$$\nabla \cdot \mathbf{R}(\mathbf{r}) = 0 \quad \text{divergence-free}$$

Helmholtz Decomposition



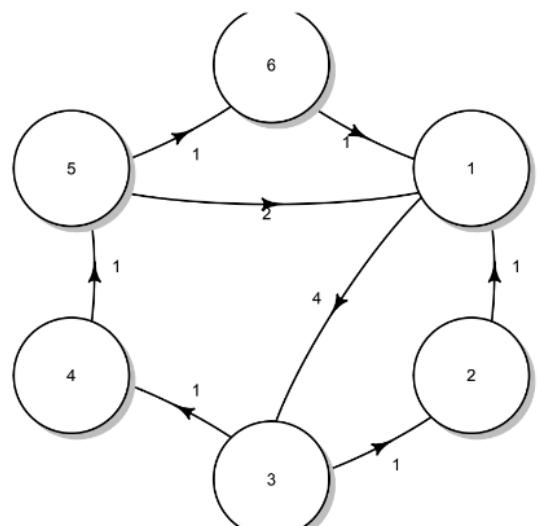
Hodge Decomposition

$$\text{Edge Flow} = \underbrace{\text{vorticity}}_{\text{solenoidal}} \oplus \underbrace{\text{solenoidal irrotational}}_{\text{irrotational}} \oplus \underbrace{\text{conservative}}_{\text{irrotational}}$$

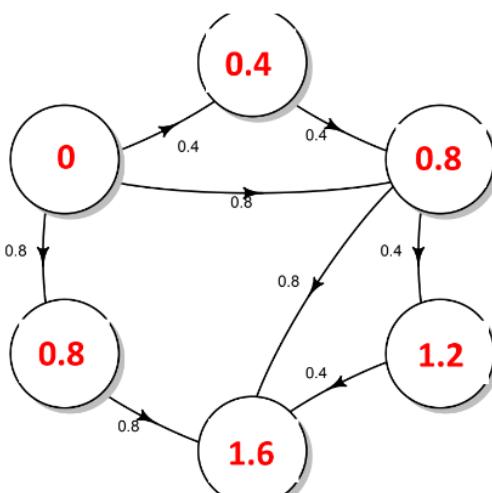
$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus \ker \left(\underbrace{-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl}}_{\text{Graph Helmholtzian}} \right) \oplus \text{im}(\text{grad})$$

Edge Flow = locally cyclic flow + globally cyclic flow + gradient flow

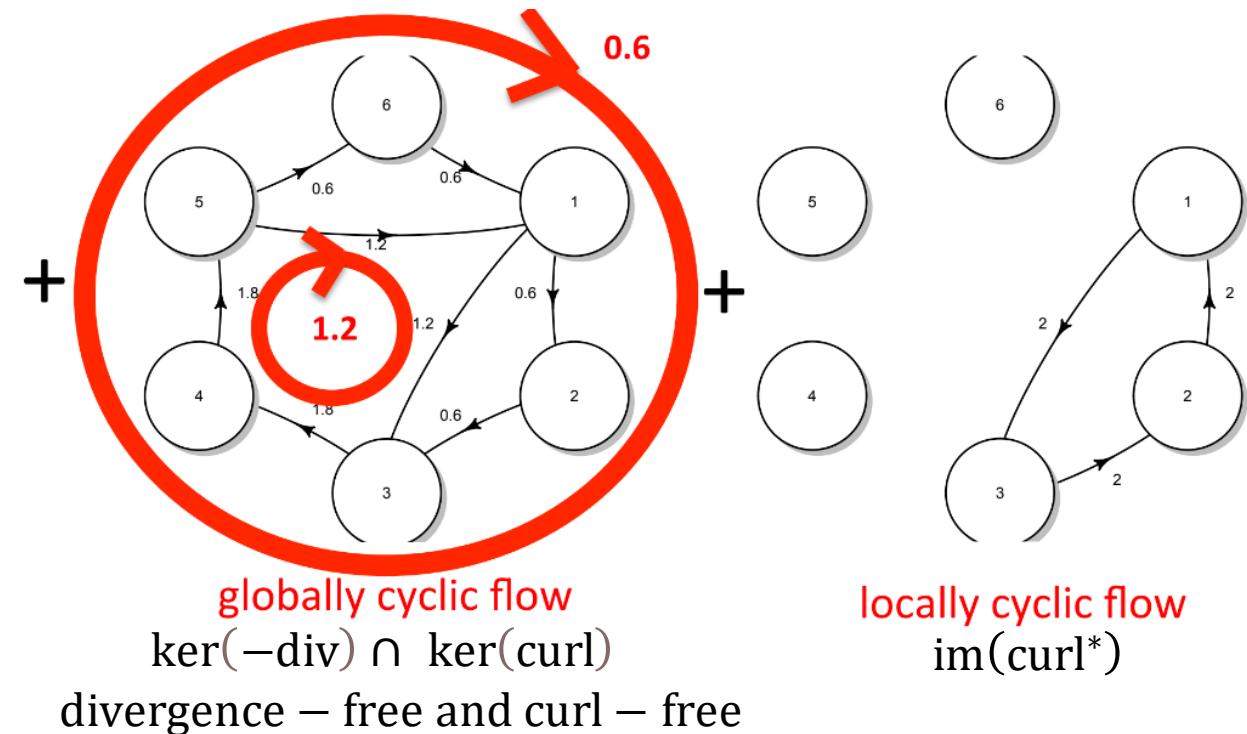
$$\text{Edge Flow} = \underbrace{\text{divergence - free}}_{\text{divergence - free but not curl - free}} \oplus \underbrace{\text{curl - free}}_{\text{divergence - free and curl - free} \oplus \text{curl - free but not divergence - free}}$$



=



gradient flow
im(grad)



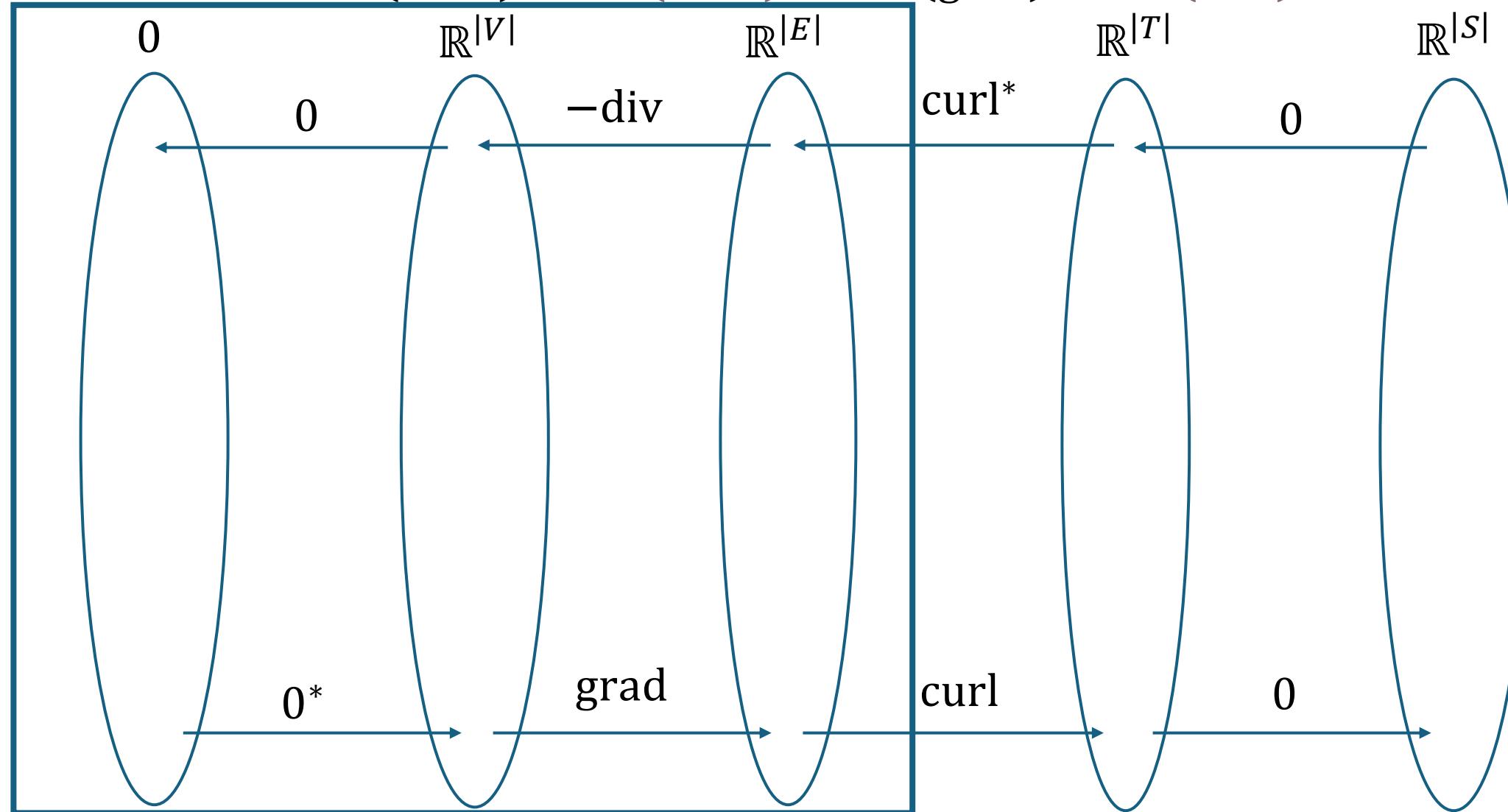
globally cyclic flow
 $\ker(-\text{div}) \cap \ker(\text{curl})$

divergence - free and curl - free

locally cyclic flow
im(curl*)

$$-\operatorname{div} \circ \operatorname{curl}^* = 0 \Leftrightarrow \operatorname{curl} \circ \operatorname{grad} = 0$$

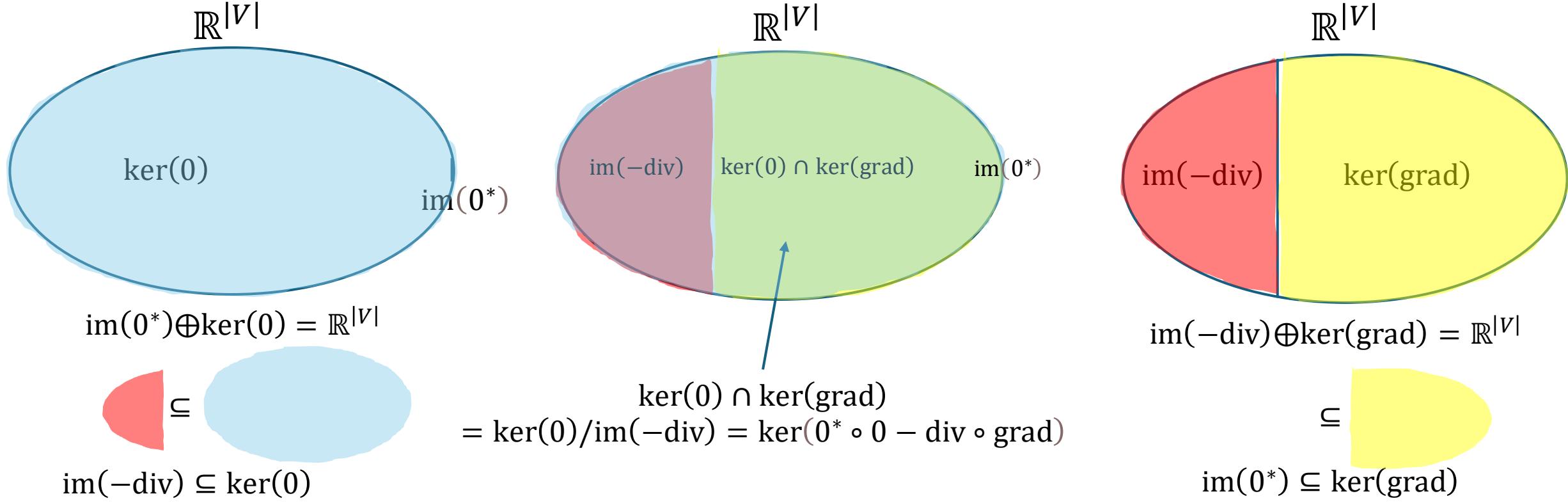
$$\operatorname{im}(\operatorname{curl}^*) \subseteq \ker(-\operatorname{div}) \Leftrightarrow \operatorname{im}(\operatorname{grad}) \subseteq \ker(\operatorname{curl})$$



$$\operatorname{im}(-\operatorname{div}) \oplus \ker(\operatorname{grad}) = \mathbb{R}^{|V|}$$

$$\begin{aligned}\operatorname{im}(\operatorname{grad}) \oplus \ker(-\operatorname{div}) &= \mathbb{R}^{|E|} \\ \operatorname{im}(\operatorname{curl}^*) \oplus \ker(\operatorname{curl}) &= \mathbb{R}^{|E|}\end{aligned}$$

$$\operatorname{im}(\operatorname{curl}^*) \oplus \ker(\operatorname{curl}) = \mathbb{R}^{|T|}$$



$$\mathbb{R}^{|V|} = \text{im}(-\text{div}) \oplus (\ker(0) \cap \ker(\text{grad})) \oplus \text{im}(0^*)$$

$$\mathbb{R}^{|V|} = \text{im}(\text{div}) \oplus \ker(\text{grad})$$

$$x \in \mathbb{R}^{|V|}, \quad \text{grad}x_H = \mathbf{0}, \quad v \in \mathbb{R}^{|E|}$$

$$x = x_H + \text{div}v, \quad \langle \text{div}v, x_H \rangle = \mathbf{0}$$

x_H is a multiple of all 1s vector

$$\mathbb{R}^{|V|} = \text{im}(\text{div}) \oplus \ker(\text{grad}) = \text{im}(\text{div}) \oplus \ker(\text{grad}^* \circ \text{grad}) = \text{im}(\text{div}) \oplus \ker \left(\underbrace{-\text{div} \circ \text{grad}}_{\text{Graph Laplacian}} \right)$$

$$\mathbb{R}^{|V|} = \text{divergence} \oplus \text{gradient - free} = \text{divergence} + \text{Const} \mathbf{1}$$

HodgeRank

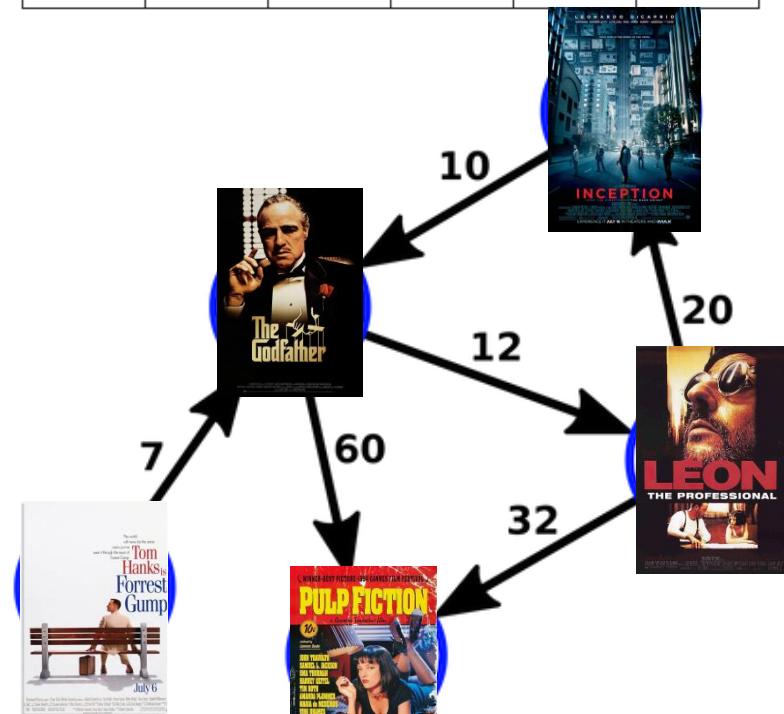
Rank movies based on a graph

- Most viewers only watched a small portion of movies in the database—user-item matrix is very sparse
- However, building a weighted directed graph with movies as vertices and average score differences as edges does not involve sparsity
- Edge weights represent the number of viewers coviewing the two movies
- Average score differences between two movies are the averages of the viewers' scoring differences

Items

User-item Interaction matrix

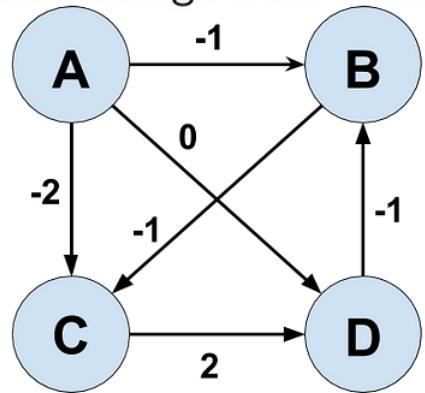
	Items					
	THE GODFATHER	INCEPTION	LEON	FORREST GUMP	PULP FICTION	THE JUNGLE BOOK
Users	10	-1	8	10	9	4
	8	9	10	-1	-1	8
	10	5	4	9	-1	-1
	9	10	-1	-1	-1	3
	6	-1	-1	-1	8	10



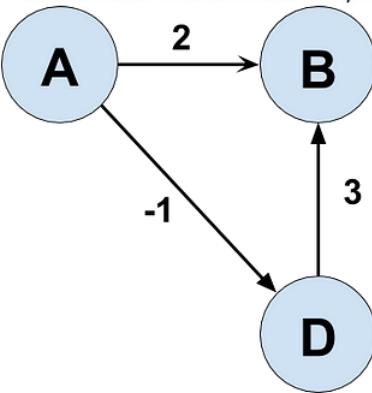
	A	B	C	D
α	5	4	3	5
β	3	5	-	2

$$(\partial_1)_{ij} = \begin{cases} -1, & v_i \text{ is the source node in } e_j \\ +1, & v_i \text{ is the sink node in } e_j \\ 0, & \text{else} \end{cases}$$

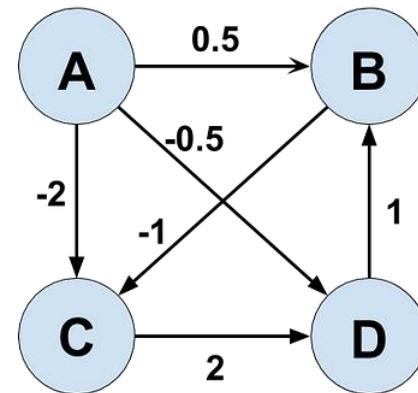
Table: Ratings from voters α, β to alternatives A,B,C,D



α



β



$\alpha+\beta$

	A	B	C	D
α	5	4	3	5
β	3	5	-	2
r	r_A	r_B	r_C	r_D

$f \in \mathbb{R}^{|E|}$ takes the average of all the votes between each pair of alternatives.

$$f = \begin{pmatrix} [(5-4) + (3-5)]/2 \\ (5-3)/1 \\ (4-3)/1 \\ [(3-2) + (5-5)]/2 \\ [(4-5) + (5-2)]/2 \\ (3-5)/1 \end{pmatrix} = \begin{pmatrix} -0.5 \\ 2 \\ 1 \\ 0.5 \\ 1 \\ -2 \end{pmatrix} \in \mathbb{R}^{|E|}$$

$\mathbf{f} \in \mathbb{R}^{|E|}$ takes the average of all the votes between each pair of alternatives.

$$\mathbf{f} = \begin{pmatrix} [(5-4) + (3-5)]/2 \\ (5-3)/1 \\ (4-3)/1 \\ [(3-2) + (5-5)]/2 \\ [(4-5) + (5-2)]/2 \\ (3-5)/1 \end{pmatrix} = \begin{pmatrix} -0.5 \\ 2 \\ 1 \\ 0.5 \\ 1 \\ -2 \end{pmatrix} \in \mathbb{R}^{|E|}$$

Define $\mathbf{r} \in \mathbb{R}^{|V|} = \begin{pmatrix} r_A \\ r_B \\ r_C \\ r_D \end{pmatrix}$ and notice

$$\partial_1^T \mathbf{r} = \begin{pmatrix} 1 & -1 & 0 & 0 \\ 1 & 0 & -1 & 0 \\ 0 & 1 & -1 & 0 \\ 1 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & -1 \end{pmatrix} \begin{pmatrix} r_A \\ r_B \\ r_C \\ r_D \end{pmatrix} = \begin{pmatrix} r_A - r_B \\ r_A - r_C \\ r_B - r_C \\ r_A - r_D \\ r_B - r_D \\ r_C - r_D \end{pmatrix}$$

Very sparse incidence matrix

$$\partial_1^T \mathbf{r} = \begin{pmatrix} r_A - r_B \\ r_A - r_C \\ r_B - r_C \\ r_A - r_D \\ r_B - r_D \\ r_C - r_D \end{pmatrix} \longleftrightarrow \mathbf{f} = \begin{pmatrix} -0.5 \\ 2 \\ 1 \\ 0.5 \\ 1 \\ -2 \end{pmatrix}$$

$$\min_{\mathbf{r} \in \mathbb{R}^{|V|}} \|\mathbf{f} - \partial_1^T \mathbf{r}\|_W^2,$$

$$W = \text{diag}([2, 1, 1, 2, 2, 1])$$

$$\partial_1 W \partial_1^T \mathbf{r} = \partial_1 W \mathbf{f}.$$

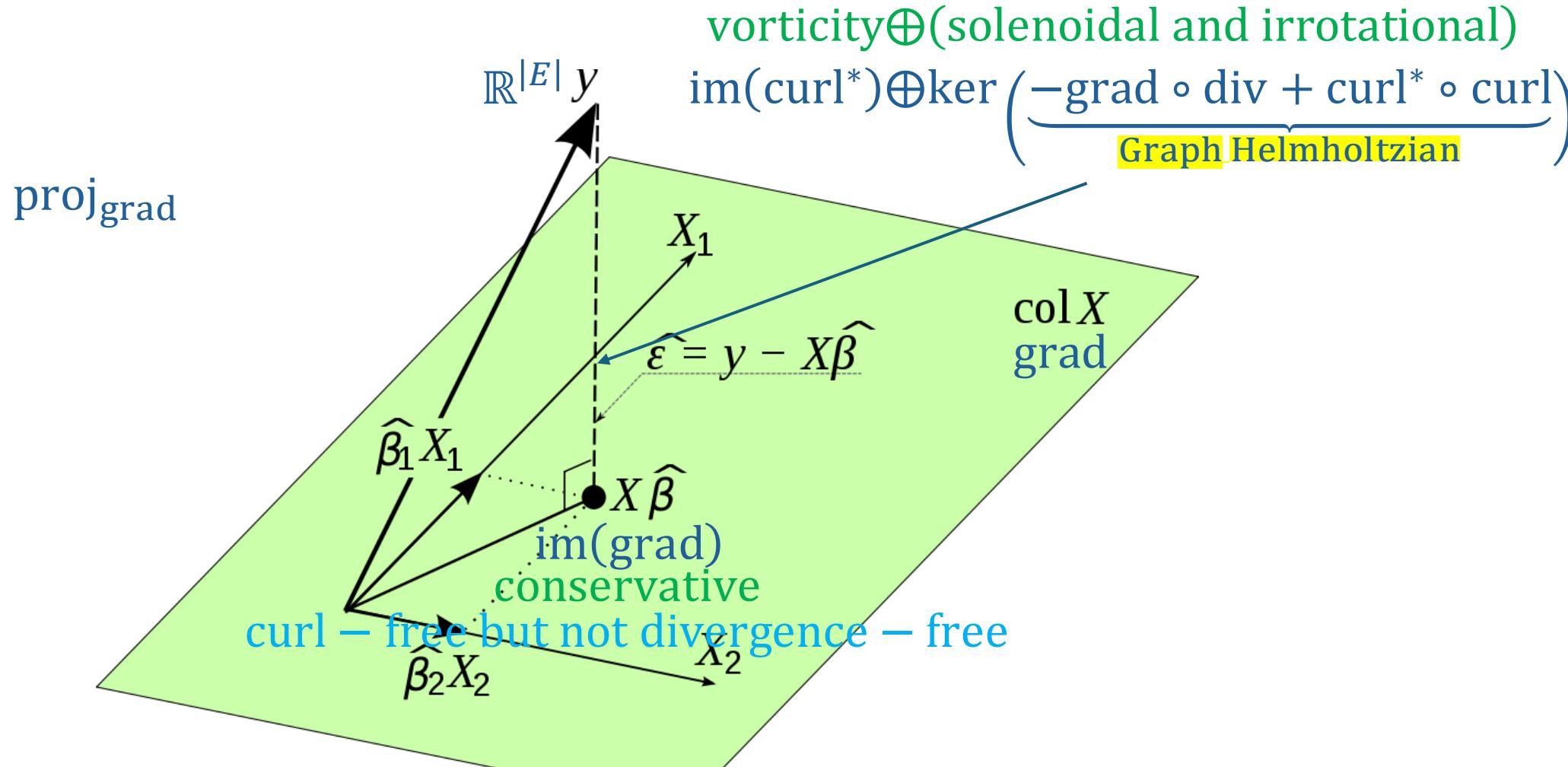
The normal equation can also be written as

$$L\mathbf{r} = \mathbf{b}$$

for weighted graph Laplacian defined as $L = \partial_1 W \partial_1^T$, $\mathbf{b} = \partial_1 W \mathbf{f}$.

- Weighted least squares

divergence – free but not curl – free \oplus (divergence – free and curl – free)



$$\mathbb{R}^n = \text{im}(\mathbf{B}_{n \times p}) \oplus \ker(\mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T) \oplus \text{im}(\mathbf{A}_{m \times n}^T)$$

$$\partial_1 = \mathbf{A}_{m \times n}, \quad \mathbf{r} = \text{proj}_{\mathbf{A}_{m \times n}^T}(\mathbf{x})$$

$$\min_{\mathbf{r} \in \mathbb{R}^{|V|}} \|\mathbf{f} - \partial_1^T \mathbf{r}\|_W^2$$

Normal equation

$$\begin{aligned} \partial_1 \mathbf{W} \partial_1^T \mathbf{r} &= \partial_1 \mathbf{W} \mathbf{f} \\ \partial_1 \mathbf{W}^{\frac{1}{2}} \mathbf{W}^{\frac{1}{2}T} \partial_1^T \mathbf{r} &= \partial_1 \mathbf{W}^{\frac{1}{2}} \mathbf{W}^{\frac{1}{2}T} \mathbf{f} \\ (\partial_1 \mathbf{W}^{\frac{1}{2}}) (\partial_1 \mathbf{W}^{\frac{1}{2}})^T \mathbf{r} &= (\partial_1 \mathbf{W}^{\frac{1}{2}}) (\mathbf{W}^{\frac{1}{2}} \mathbf{f}) \end{aligned}$$

∂_1 is not full rank, $\partial_1 \mathbf{W} \partial_1^T$ is not full rank, non-invertible

Infinite solution (potential function additive invariant)

$$\mathbf{r} = (\partial_1 \mathbf{W}^{\frac{1}{2}})^{T^\dagger} \mathbf{W}^{\frac{1}{2}} \mathbf{f} + \left(\mathbf{I} - (\partial_1 \mathbf{W}^{\frac{1}{2}})^{T^\dagger} (\partial_1 \mathbf{W}^{\frac{1}{2}})^T \right) \mathbf{w}$$

Infinite solution (potential function additive invariant)

$$\mathbf{r} = \left(\partial_1 \mathbf{W}^{\frac{1}{2}} \right)^T \mathbf{W}^{\frac{1}{2}} \mathbf{f} + \left(\mathbf{I} - \left(\partial_1 \mathbf{W}^{\frac{1}{2}} \right)^T \left(\partial_1 \mathbf{W}^{\frac{1}{2}} \right)^T \right) \mathbf{w}$$

SVD of ∂_1, ∂_1^T :

$$\partial_1 = \mathbf{U} \Sigma \mathbf{V}^T = \mathbf{U} [S \quad \mathbf{0}] \mathbf{V}^T$$

$$\partial_1 = \mathbf{U} \Sigma \mathbf{V}^T = \mathbf{U} \begin{bmatrix} S \\ \mathbf{0} \end{bmatrix} \mathbf{V}^T$$

$$\partial_1^T = \mathbf{V} \Sigma^T \mathbf{U}^T = \mathbf{V} \begin{bmatrix} S^T \\ \mathbf{0}^T \end{bmatrix} \mathbf{U}^T$$

$$\partial_1^T = \mathbf{V} \Sigma^T \mathbf{U}^T = \mathbf{V} [S^T \quad \mathbf{0}^T] \mathbf{U}^T$$

Moore-Penrose pseudoinverse of ∂_1, ∂_1^T :

$$\partial_1^\dagger = (\mathbf{U} \Sigma \mathbf{V}^T)^\dagger = \mathbf{V} \begin{bmatrix} S^{-T} \\ \mathbf{0}^T \end{bmatrix} \mathbf{U}^T$$

$$\partial_1^\dagger = (\mathbf{U} \Sigma \mathbf{V}^T)^\dagger = \mathbf{V} [S^{-T} \quad \mathbf{0}^T] \mathbf{U}^T$$

$$\partial_1^{T\dagger} = (\mathbf{V} \Sigma^T \mathbf{U}^T)^\dagger = \mathbf{U} [S^{-1} \quad \mathbf{0}] \mathbf{V}^T$$

$$\partial_1^{T\dagger} = (\mathbf{V} \Sigma^T \mathbf{U}^T)^\dagger = \mathbf{U} \begin{bmatrix} S^{-1} \\ \mathbf{0} \end{bmatrix} \mathbf{V}^T$$

$$\partial_1 \partial_1^\dagger = \mathbf{U} [S \quad \mathbf{0}] \mathbf{V}^T \mathbf{V} \begin{bmatrix} S^{-T} \\ \mathbf{0}^T \end{bmatrix} \mathbf{U}^T = \mathbf{U} \mathbf{U}^T = \mathbf{I}$$

$$\partial_1 \partial_1^\dagger = \mathbf{U} \begin{bmatrix} S \\ \mathbf{0} \end{bmatrix} \mathbf{V}^T \mathbf{V} [S^{-T} \quad \mathbf{0}^T] \mathbf{U}^T = \mathbf{U} \begin{bmatrix} \mathbf{I} & \mathbf{0}^T \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{U}^T$$

$$\partial_1^\dagger \partial_1 = \mathbf{V} \begin{bmatrix} S^{-T} \\ \mathbf{0}^T \end{bmatrix} \mathbf{U}^T \mathbf{U} [S \quad \mathbf{0}] \mathbf{V}^T = \mathbf{V} \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0}^T & \mathbf{0} \end{bmatrix} \mathbf{V}^T$$

$$\partial_1^\dagger \partial_1 = \mathbf{V} [S^{-T} \quad \mathbf{0}^T] \mathbf{U}^T \mathbf{U} \begin{bmatrix} S \\ \mathbf{0} \end{bmatrix} \mathbf{V}^T = \mathbf{V} \mathbf{V}^T = \mathbf{I}$$

\Leftrightarrow	\Leftrightarrow	A full row rank \Leftrightarrow	A not full row rank \Leftrightarrow								
\Leftrightarrow	\Leftrightarrow	<p>A full row rank $\Leftrightarrow A'$ column rank is $m \Leftrightarrow$ A can span the whole m dimensional space \Leftrightarrow any b is in the column space of $A \Leftrightarrow Ax = b$ always has solution \Leftrightarrow</p>	<p>A not full row rank $\Leftrightarrow A'$ column rank is less than $m \Leftrightarrow$ A can not span the whole m dimensional space \Leftrightarrow not any b is in the column space of $A \Leftrightarrow Ax = b$ does not always have solution \Leftrightarrow</p>								
$A \Leftrightarrow$ full column rank \Leftrightarrow	<p>A full column rank $\Leftrightarrow Ax = 0$ only one solution (only zero) $\Leftrightarrow Ax = b$ only one solution (when has solution) \Leftrightarrow</p>	<p>example (A is squared matrix and full rank) \Leftrightarrow dimension of space does not change before and after the transformation \Leftrightarrow</p> <table border="1" style="margin-left: auto; margin-right: auto;"> <tr> <td>$Ax = b \Leftrightarrow$</td><td>$Ax = 0 \Leftrightarrow$</td></tr> <tr> <td>$Ax = b$ has unique solutions x for any $b \Leftrightarrow$</td><td>$Ax = 0$ has unique solutions $x = 0 \Leftrightarrow$ $\text{rank}(A_{m \times n}) = m = n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = 0 \Leftrightarrow$</td></tr> </table>	$Ax = b \Leftrightarrow$	$Ax = 0 \Leftrightarrow$	$Ax = b$ has unique solutions x for any $b \Leftrightarrow$	$Ax = 0$ has unique solutions $x = 0 \Leftrightarrow$ $\text{rank}(A_{m \times n}) = m = n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = 0 \Leftrightarrow$	<p>example (tall and slim A full column rank) \Leftrightarrow dimension of space increases seemingly after transformation (in reality does not really increase) \Leftrightarrow</p> <table border="1" style="margin-left: auto; margin-right: auto;"> <tr> <td>$Ax = b \Leftrightarrow$</td><td>$Ax = 0 \Leftrightarrow$</td></tr> <tr> <td>$Ax = b$ does not unique solution x for any b (approximation solution using projection is unique) \Leftrightarrow has unique solution x for some $b \Leftrightarrow$ does not have solution x for some $b \Leftrightarrow$</td><td>$Ax = 0$ has unique solution $x = 0 \Leftrightarrow$ $\text{rank}(A_{m \times n}) = n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = 0 \Leftrightarrow$</td></tr> </table>	$Ax = b \Leftrightarrow$	$Ax = 0 \Leftrightarrow$	$Ax = b$ does not unique solution x for any b (approximation solution using projection is unique) \Leftrightarrow has unique solution x for some $b \Leftrightarrow$ does not have solution x for some $b \Leftrightarrow$	$Ax = 0$ has unique solution $x = 0 \Leftrightarrow$ $\text{rank}(A_{m \times n}) = n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = 0 \Leftrightarrow$
$Ax = b \Leftrightarrow$	$Ax = 0 \Leftrightarrow$										
$Ax = b$ has unique solutions x for any $b \Leftrightarrow$	$Ax = 0$ has unique solutions $x = 0 \Leftrightarrow$ $\text{rank}(A_{m \times n}) = m = n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = 0 \Leftrightarrow$										
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$A \Leftrightarrow$ not full column rank \Leftrightarrow	<p>A not full column rank $\Leftrightarrow Ax = 0$ infinite solutions (non-zero solutions exist) $\Leftrightarrow Ax = b$ infinite solution (when has solution) \Leftrightarrow</p>	<p>example (short and fat A full row rank) \Leftrightarrow dimension of space decreases after transformation (indeed decreases) \Leftrightarrow</p> <table border="1" style="margin-left: auto; margin-right: auto;"> <tr> <td>$Ax = b \Leftrightarrow$</td><td>$Ax = 0 \Leftrightarrow$</td></tr> <tr> <td>$Ax = b$ has infinite solutions for any $b \Leftrightarrow$</td><td>$Ax = 0$ has infinite solutions $\text{rank}(A_{m \times n}) = m < n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = n - m > 0 \Leftrightarrow$</td></tr> </table>	$Ax = b \Leftrightarrow$	$Ax = 0 \Leftrightarrow$	$Ax = b$ has infinite solutions for any $b \Leftrightarrow$	$Ax = 0$ has infinite solutions $\text{rank}(A_{m \times n}) = m < n \Leftrightarrow$ $\text{nullity}(A_{m \times n}) = n - m > 0 \Leftrightarrow$	<p>example (A is squared matrix and not full rank) \Leftrightarrow example (short and fat A not full row rank) \Leftrightarrow example (tall and slim A not full column rank) \Leftrightarrow dimension of space decreases after transformation (indeed decreases), but can not span the whole target space \Leftrightarrow</p> <table border="1" style="margin-left: auto; margin-right: auto;"> <tr> <td>$Ax = b \Leftrightarrow$</td><td>$Ax = 0 \Leftrightarrow$</td></tr> <tr> <td>$Ax = b$ does not infinite solutions x for any b (approximation solution using projection is infinite) \Leftrightarrow has infinite solutions x for some $b \Leftrightarrow$ does not have solution x for some $b \Leftrightarrow$</td><td>$Ax = 0$ has infinite solutions $x \Leftrightarrow$ $\text{rank}(A_{m \times n}) < n \Leftrightarrow$ $\text{rank}(A_{m \times n}) < m \Leftrightarrow$ $\text{nullity}(A_{m \times n}) > 0 \Leftrightarrow$</td></tr> </table>	$Ax = b \Leftrightarrow$	$Ax = 0 \Leftrightarrow$	$Ax = b$ does not infinite solutions x for any b (approximation solution using projection is infinite) \Leftrightarrow has infinite solutions x for some $b \Leftrightarrow$ does not have solution x for some $b \Leftrightarrow$	$Ax = 0$ has infinite solutions $x \Leftrightarrow$ $\text{rank}(A_{m \times n}) < n \Leftrightarrow$ $\text{rank}(A_{m \times n}) < m \Leftrightarrow$ $\text{nullity}(A_{m \times n}) > 0 \Leftrightarrow$
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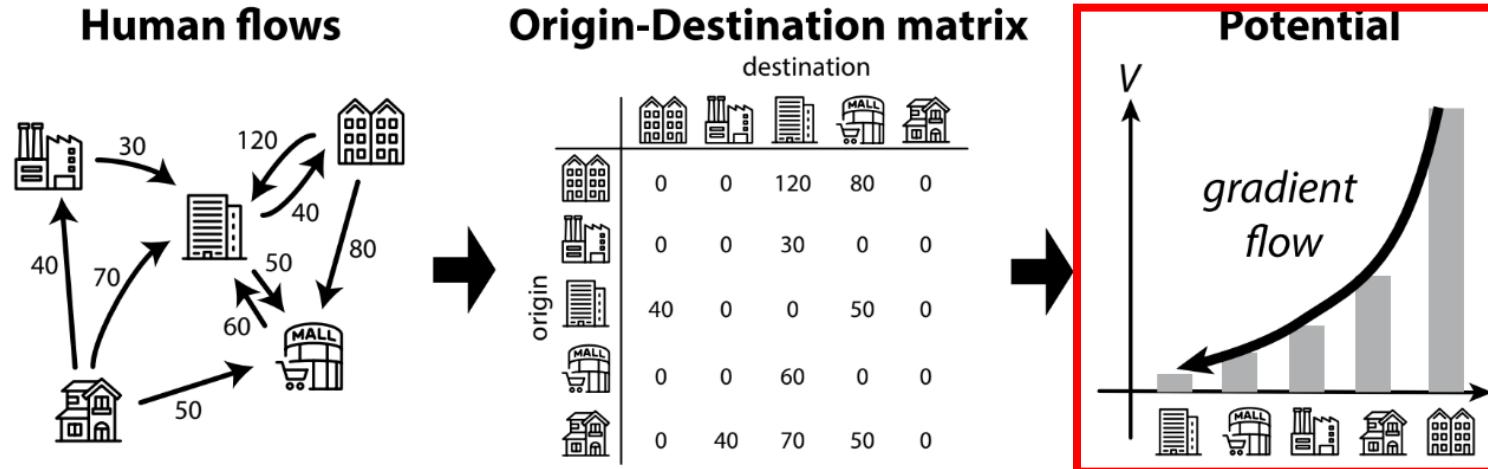
$$\begin{aligned}
& \mathbb{R}^n = \text{im}(\mathbf{B}_{n \times p}) \oplus \ker(\Delta) \oplus \text{im}(\mathbf{A}_{m \times n}^T) \\
& \Delta = \mathbf{A}_{m \times n}^T \mathbf{A}_{m \times n} + \mathbf{B}_{n \times p} \mathbf{B}_{n \times p}^T \\
& \mathbf{x} \in \mathbb{R}^n, \quad \mathbf{x} = \text{proj}_{\mathbf{B}_{n \times p}}(\mathbf{x}) \oplus \text{proj}_{\Delta^T \perp}(\mathbf{x}) \oplus \text{proj}_{\mathbf{A}_{m \times n}^T}(\mathbf{x}) \\
& \text{proj}_X = \mathbf{X}\mathbf{X}^\dagger, \quad \text{proj}_X(\mathbf{y}) = \mathbf{X}\mathbf{X}^\dagger \mathbf{y} + \mathbf{X}(\mathbf{I} - \mathbf{X}^\dagger \mathbf{X})\mathbf{w} \\
& \Delta^{T \perp} = \mathbf{I} - \Delta^T, \quad \text{proj}_{\Delta^T \perp} = \mathbf{I} - \text{proj}_{\Delta^T} = \mathbf{I} - \Delta^T \Delta^{T \dagger} = \mathbf{I} - \Delta \Delta^\dagger, \quad \text{proj}_{\Delta^T \perp}(\mathbf{y}) = (\mathbf{I} - \Delta \Delta^\dagger)\mathbf{y} \\
& \Delta^T = \Delta, \quad \Delta = \mathbf{U}\mathbf{S}\mathbf{V}^T, \quad \Delta^\dagger = (\mathbf{U}\mathbf{S}\mathbf{V}^T)^\dagger = \mathbf{V}\mathbf{S}^{-T}\mathbf{U}^T, \\
& \Delta^\dagger \Delta = \mathbf{V} \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{V}^T, \quad \Delta \Delta^\dagger = \mathbf{U} \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \mathbf{U}^T \\
& \Delta \text{ is a symmetric square matrix, } \mathbf{U}, \mathbf{V} \text{ same dimension, } \mathbf{U} = \mathbf{V} \\
& \Delta^\dagger \Delta = \Delta \Delta^\dagger, \quad \mathbf{U}^T \mathbf{U} = \mathbf{U} \mathbf{U}^T = \mathbf{V}^T \mathbf{V} = \mathbf{V} \mathbf{V}^T = \mathbf{I}
\end{aligned}$$

$$\begin{aligned}
& \left\langle \text{proj}_{B_{n \times p}}(x), \text{proj}_{A_{m \times n}^T}(x) \right\rangle = \left\langle B_{n \times p} y_{1_{p \times 1}}, A_{m \times n}^T y_{2_{m \times 1}} \right\rangle \\
&= \left(B_{n \times p} y_{1_{p \times 1}} \right)^T A_{m \times n}^T y_{2_{m \times 1}} = y_{1_{p \times 1}}^T B_{n \times p}^T A_{m \times n}^T y_{2_{m \times 1}} \\
&= y_{1_{p \times 1}}^T (A_{m \times n} B_{n \times p})^T y_{2_{m \times 1}} = y_{1_{p \times 1}}^T \mathbf{0}_{p \times m} y_{2_{m \times 1}} = 0
\end{aligned}$$

$$\Delta x_{3_{n \times 1}} = (A_{m \times n}^T A_{m \times n} + B_{n \times p} B_{n \times p}^T) x_{3_{n \times 1}} = \mathbf{0} \Rightarrow \begin{cases} A_{m \times n} x_{3_{n \times 1}} = \mathbf{0} \\ B_{n \times p}^T x_{3_{n \times 1}} = \mathbf{0} \end{cases}$$

$$\begin{aligned}
& \left\langle \text{proj}_{B_{n \times p}}(x), x_{3_{n \times 1}} \right\rangle = \left\langle B_{n \times p} y_{1_{p \times 1}}, x_{3_{n \times 1}} \right\rangle = y_{1_{p \times 1}}^T B_{n \times p}^T x_{3_{n \times 1}} = 0 \\
& \left\langle \text{proj}_{A_{m \times n}^T}(x), x_{3_{n \times 1}} \right\rangle = \left\langle A_{m \times n}^T y_{2_{m \times 1}}, x_{3_{n \times 1}} \right\rangle = y_{2_{m \times 1}}^T A_{m \times n} x_{3_{n \times 1}} = 0
\end{aligned}$$

Get potentials of nodes in a flow network



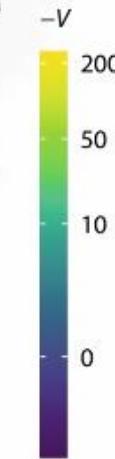
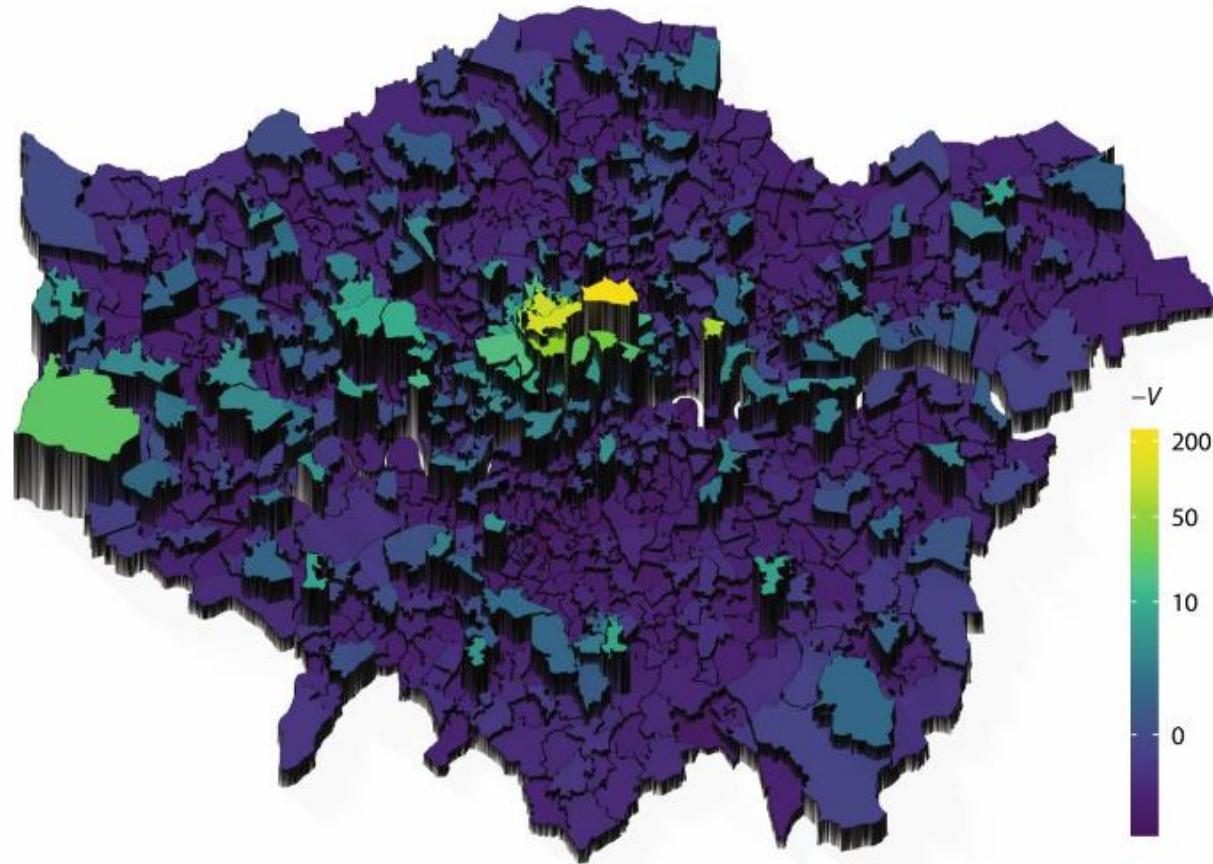
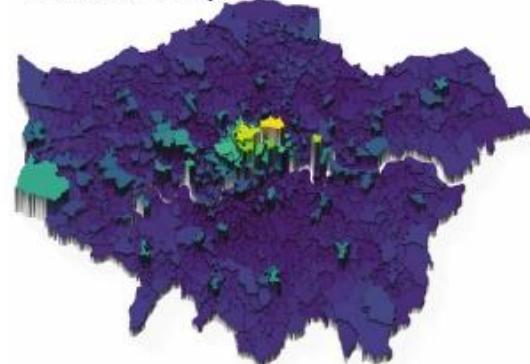
$$\mathbb{R}^{|E|} = \text{im}(\text{curl}^*) \oplus \ker \underbrace{\left(-\text{grad} \circ \text{div} + \text{curl}^* \circ \text{curl} \right)}_{\text{Graph Helmholtzian}} \oplus \text{im}(\text{grad})$$

$$\text{Edge Flow} = \text{solenoidal} \quad \text{vorticity} \quad \oplus \quad \text{solenoidal irrotational} \quad \oplus \quad \text{irrotational}$$

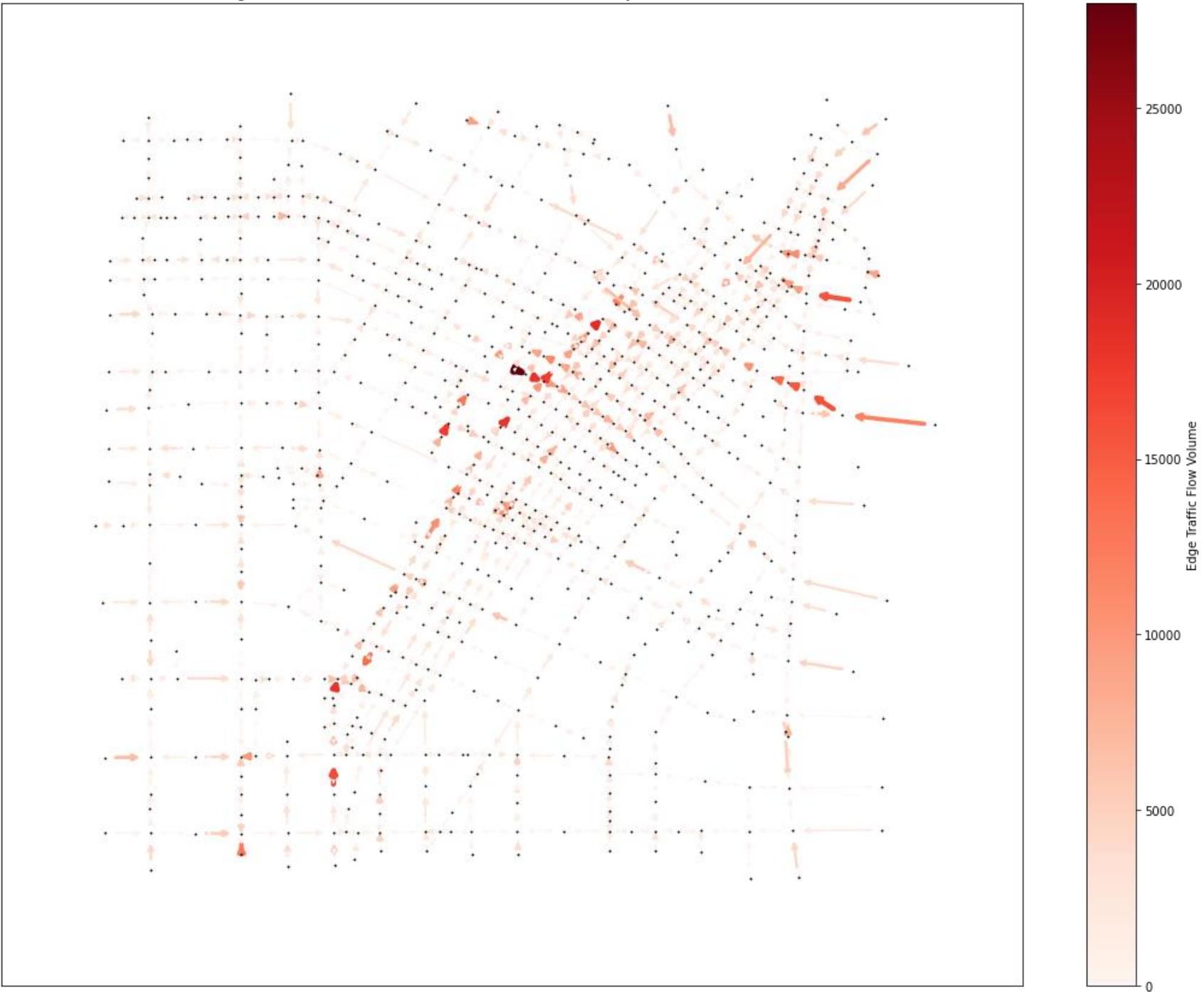
$$\text{Edge Flow} = \text{divergence - free} \quad \text{divergence - free but not curl - free} \quad \oplus \quad \text{divergence - free and curl - free} \quad \oplus \quad \text{curl - free but not divergence - free}$$

Red part denotes the gradient flow, which is used as a ranking of nodes in the flow network.

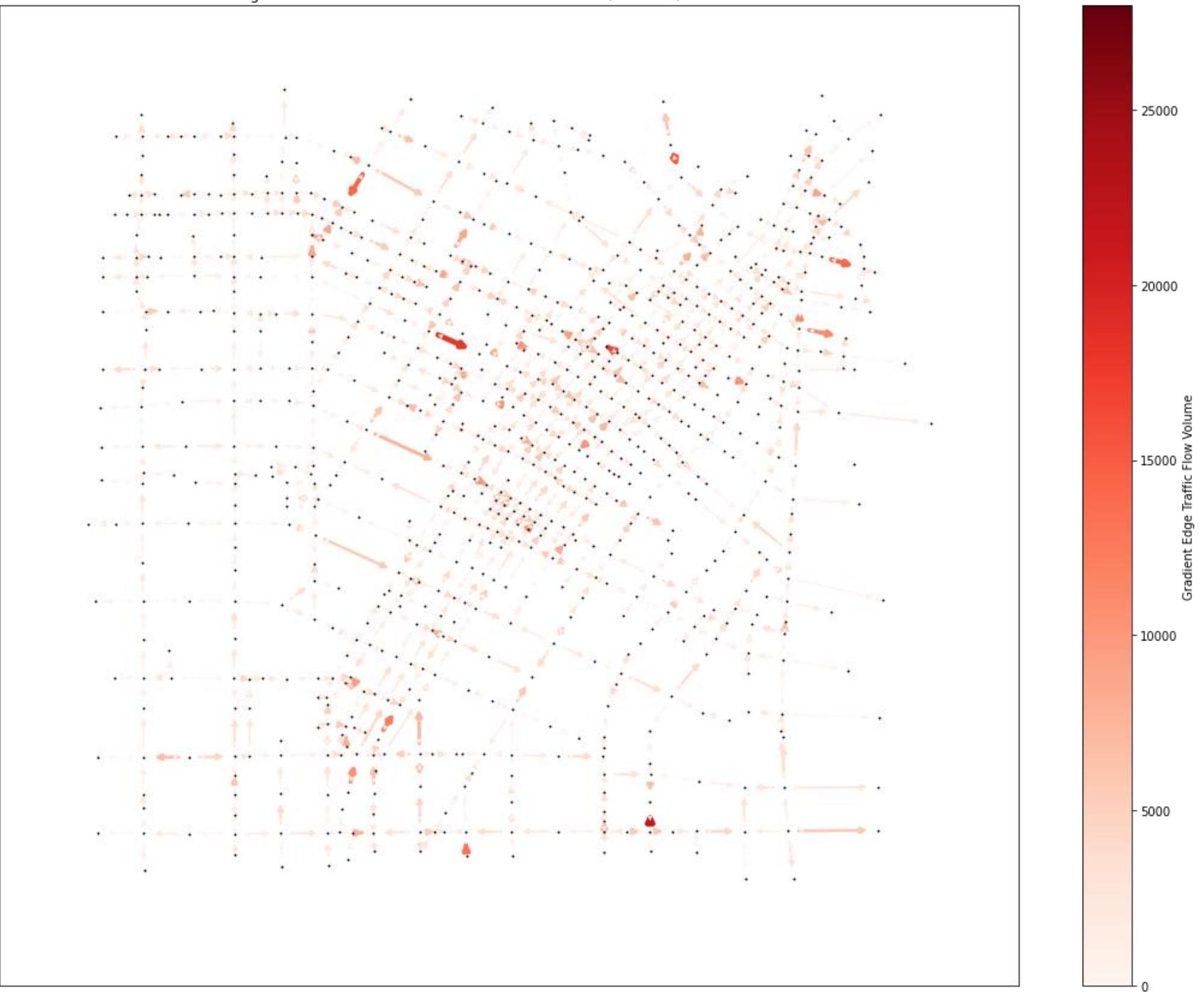
Blue part orthogonal to the gradient flow is used as inconsistency measurements. A larger blue component means this flow graph is more unrankable.

a**b** Public transport**c** Private car

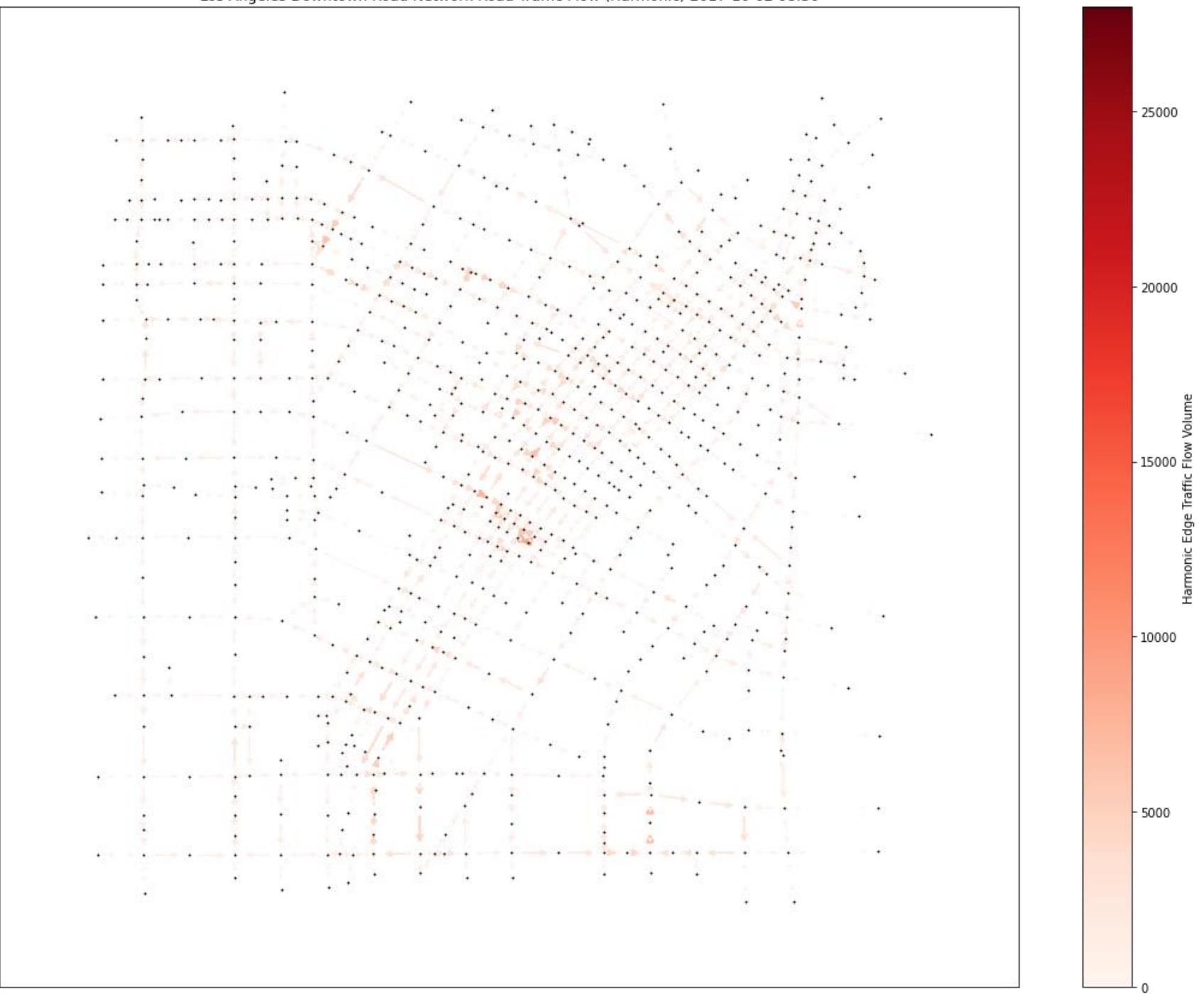
Los Angeles Downtown Road Network Road Traffic Flow (Assymmetric) 2017-10-02 08:30



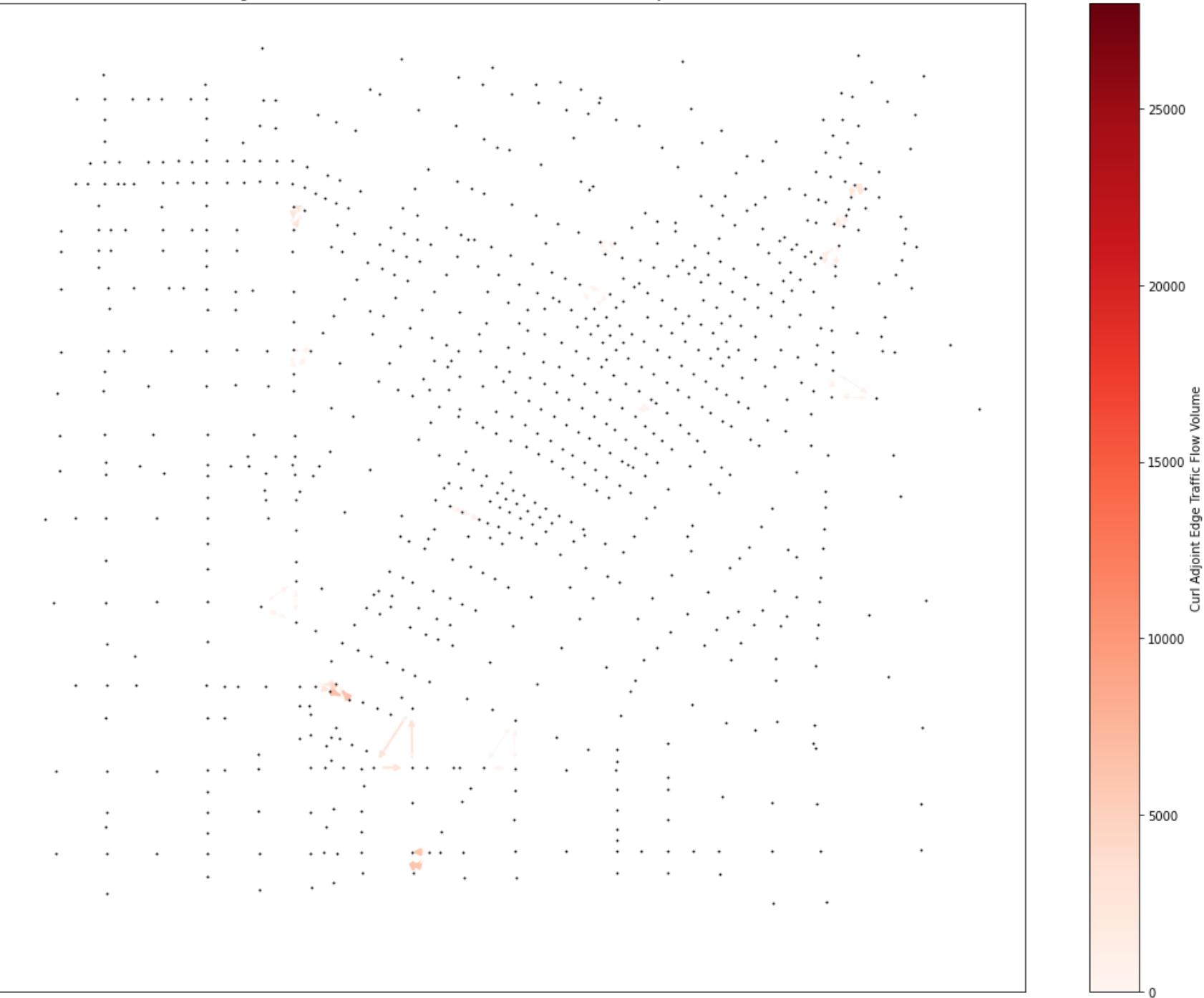
Los Angeles Downtown Road Network Road Traffic Flow (Gradient) 2017-10-02 08:30



Los Angeles Downtown Road Network Road Traffic Flow (Harmonic) 2017-10-02 08:30



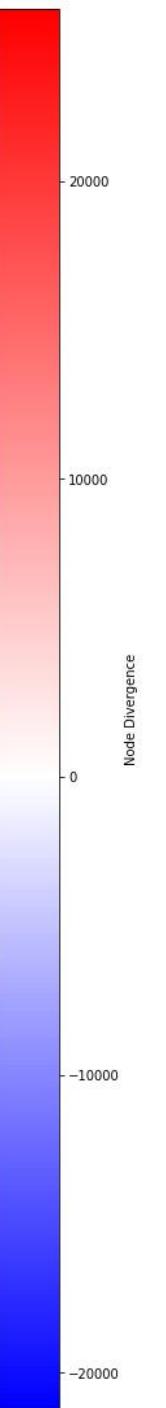
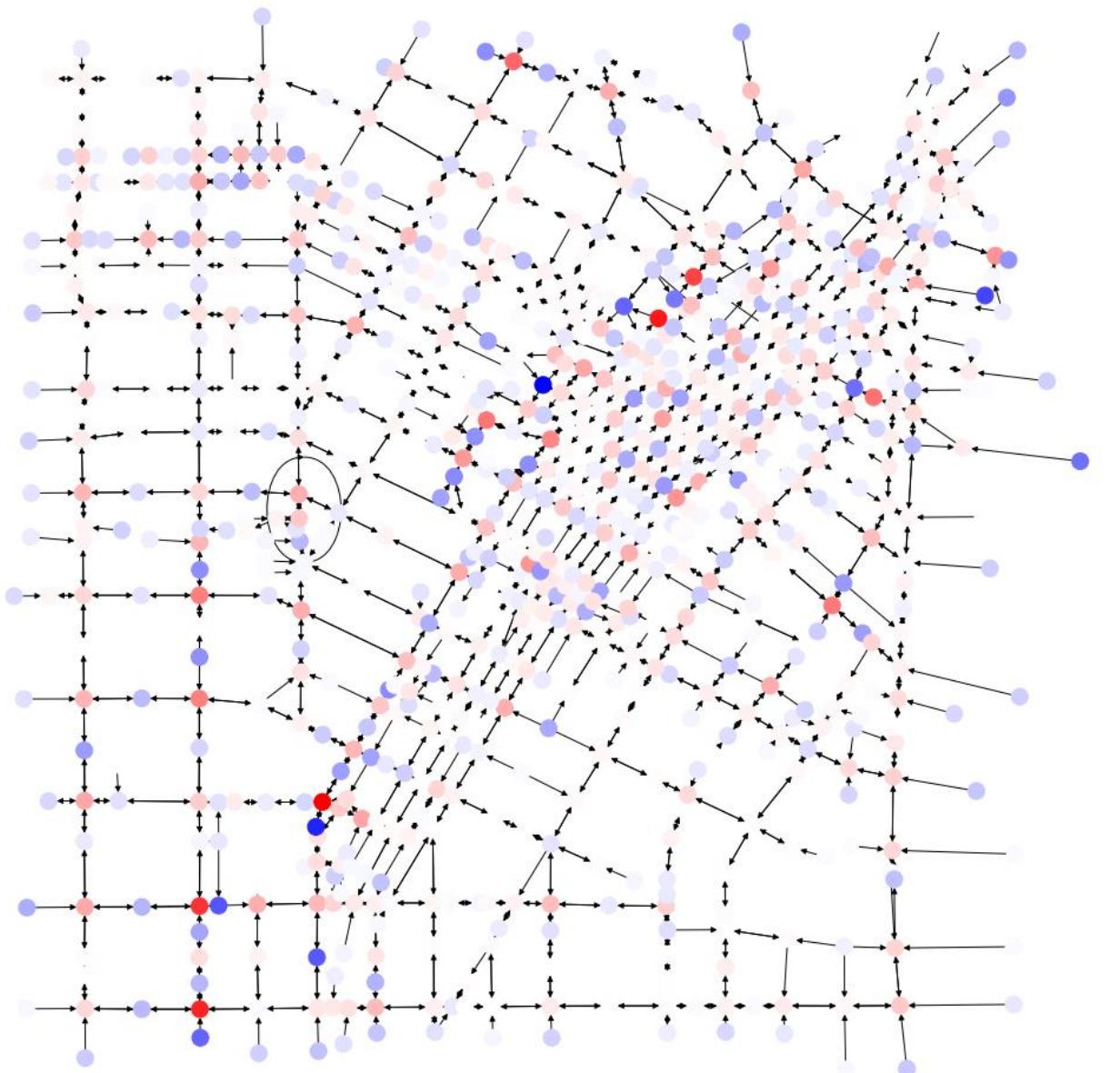
Los Angeles Downtown Road Network Road Traffic Flow (Curl Adjoint) 2017-10-02 08:30



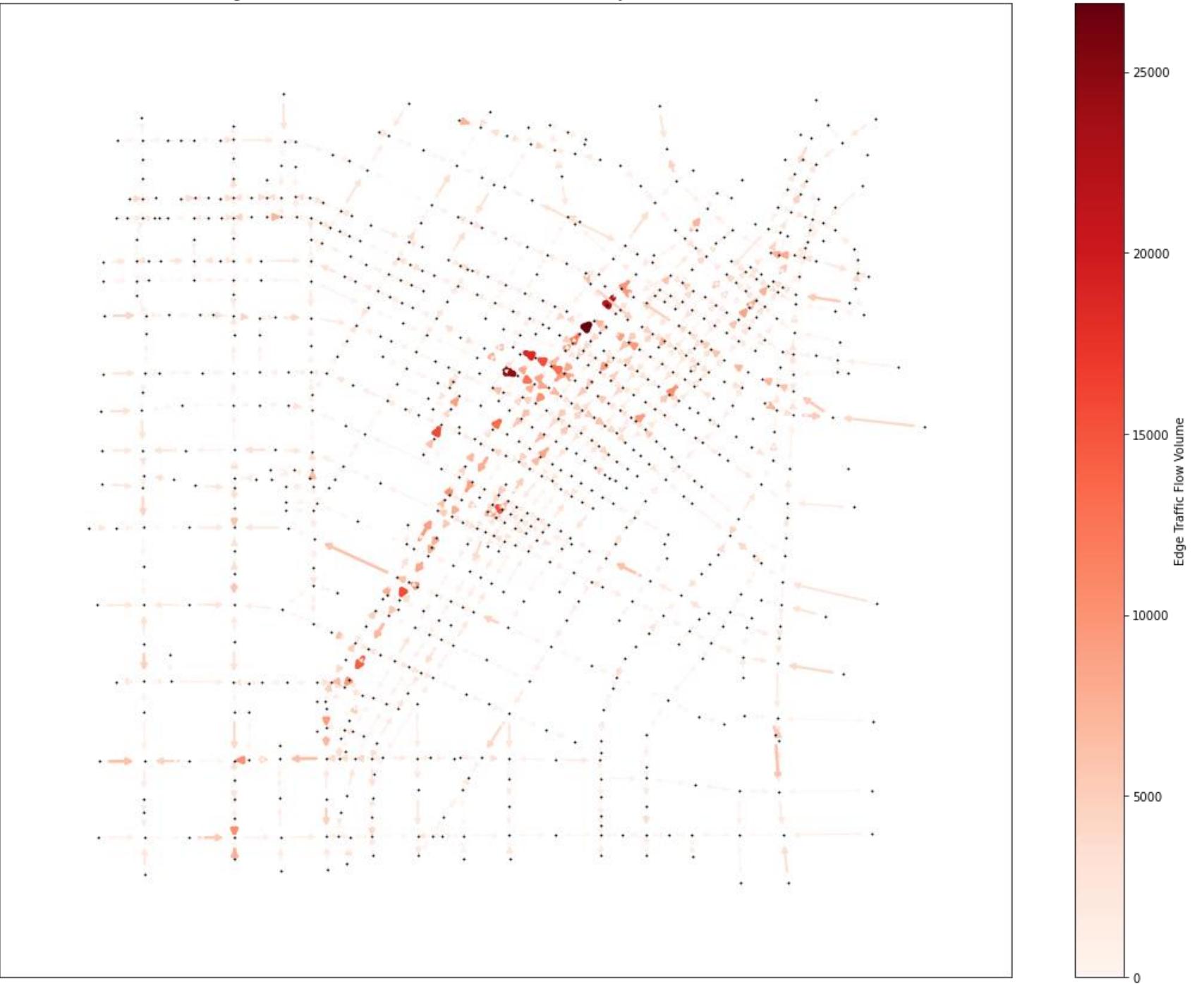
Los Angeles Downtown Road Network Negative Potential 2017-10-02 08:30



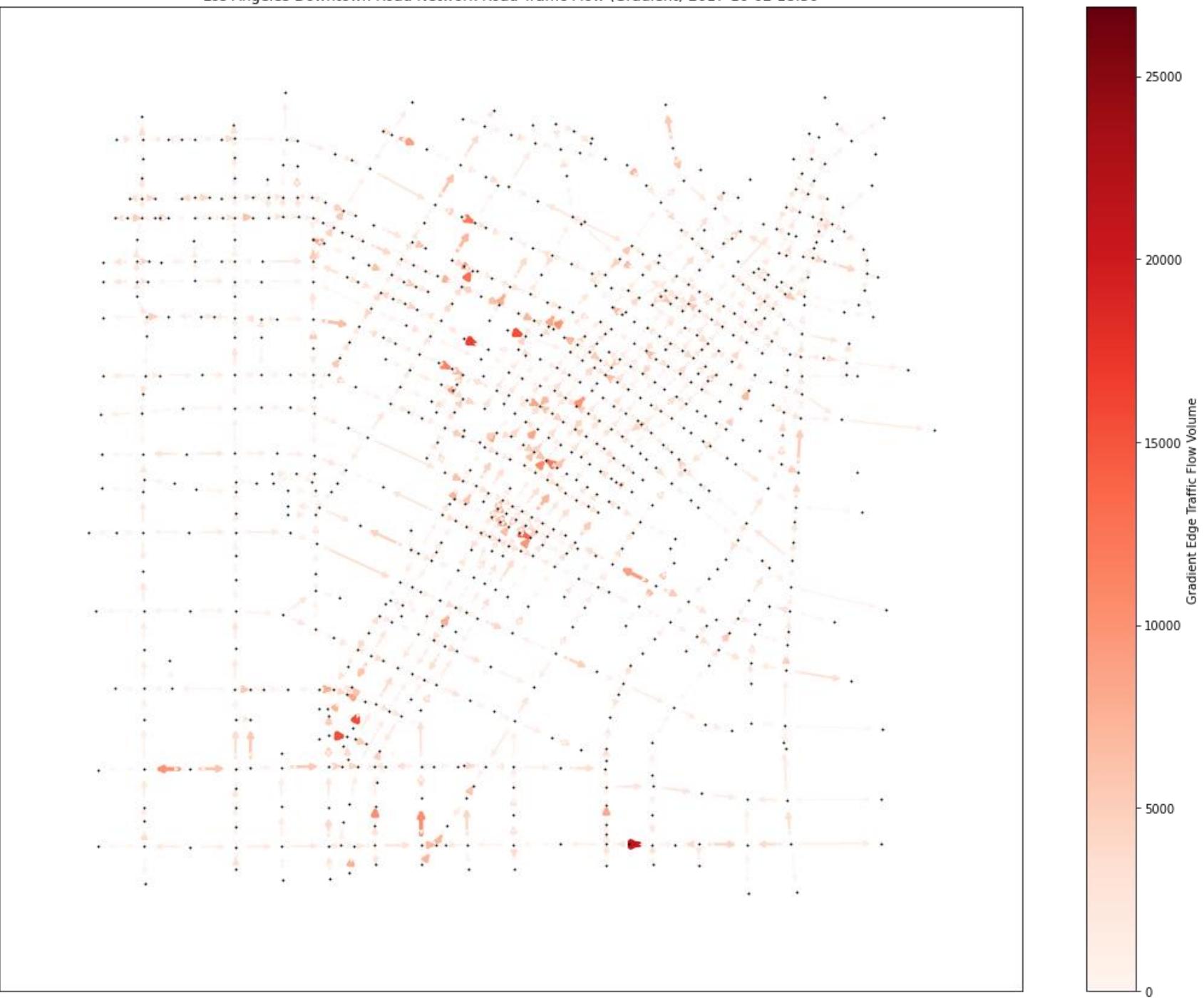
Los Angeles Downtown Road Network Divergence 2017-10-02 08:30



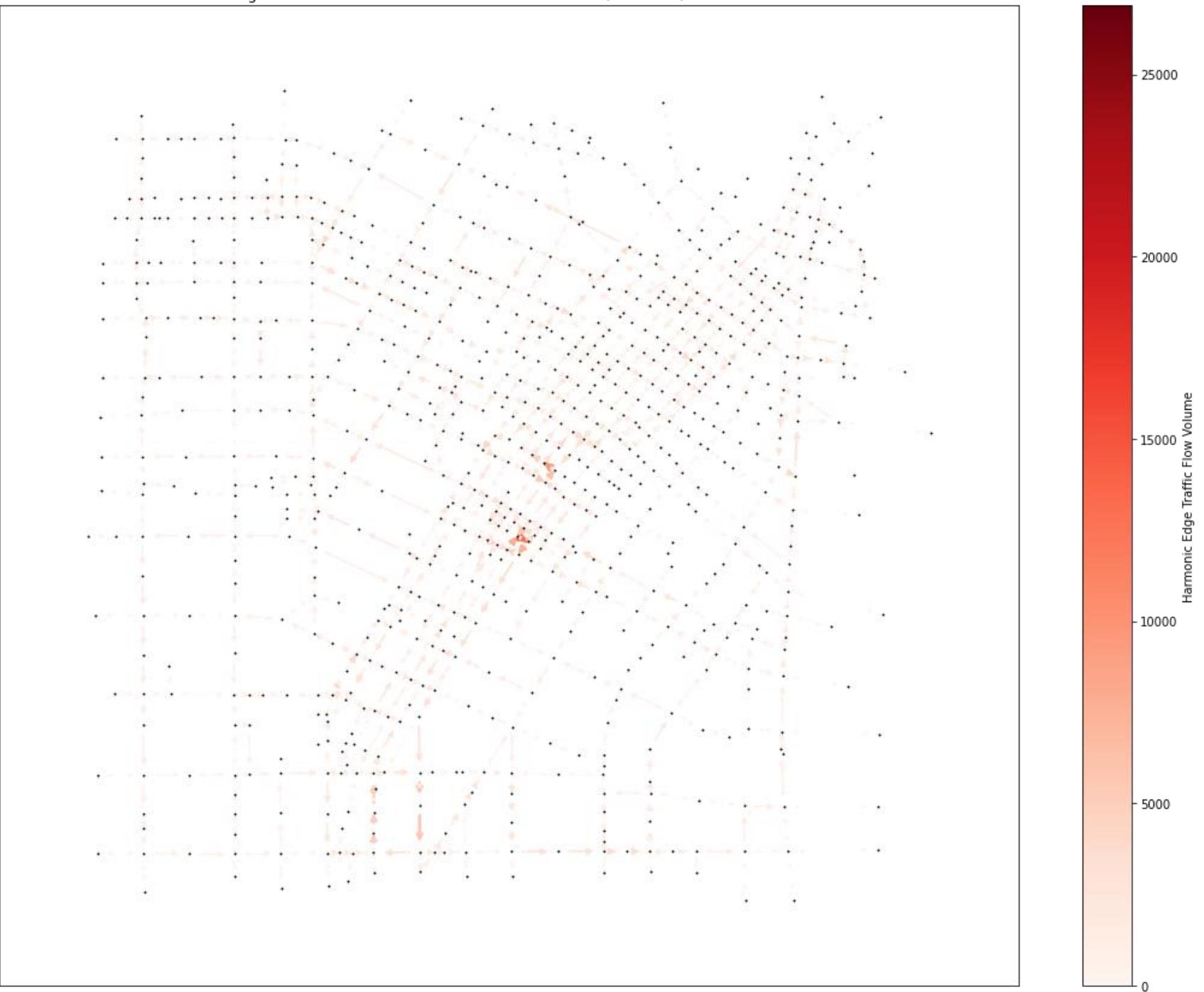
Los Angeles Downtown Road Network Road Traffic Flow (Assymmetric) 2017-10-02 18:30



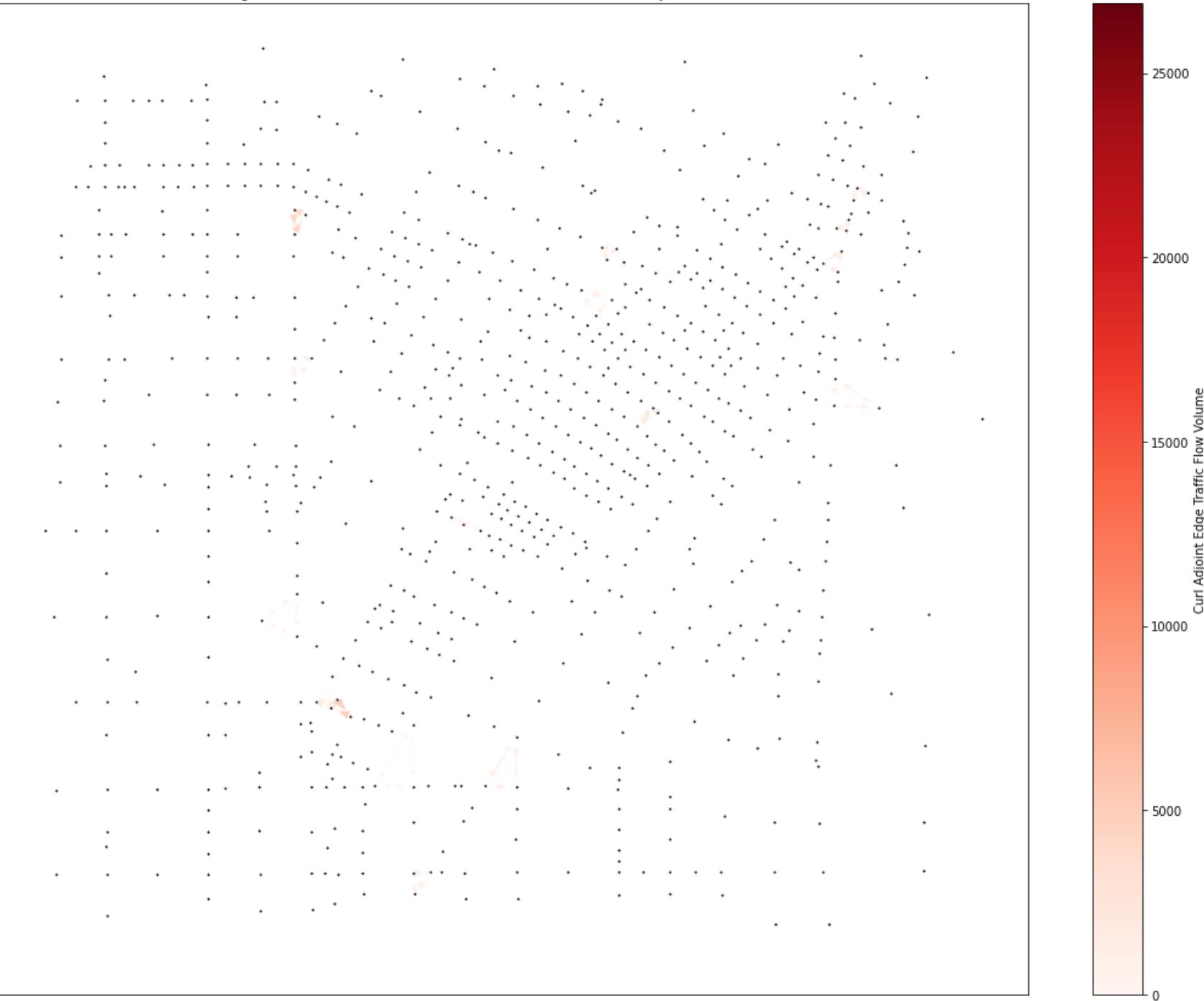
Los Angeles Downtown Road Network Road Traffic Flow (Gradient) 2017-10-02 18:30



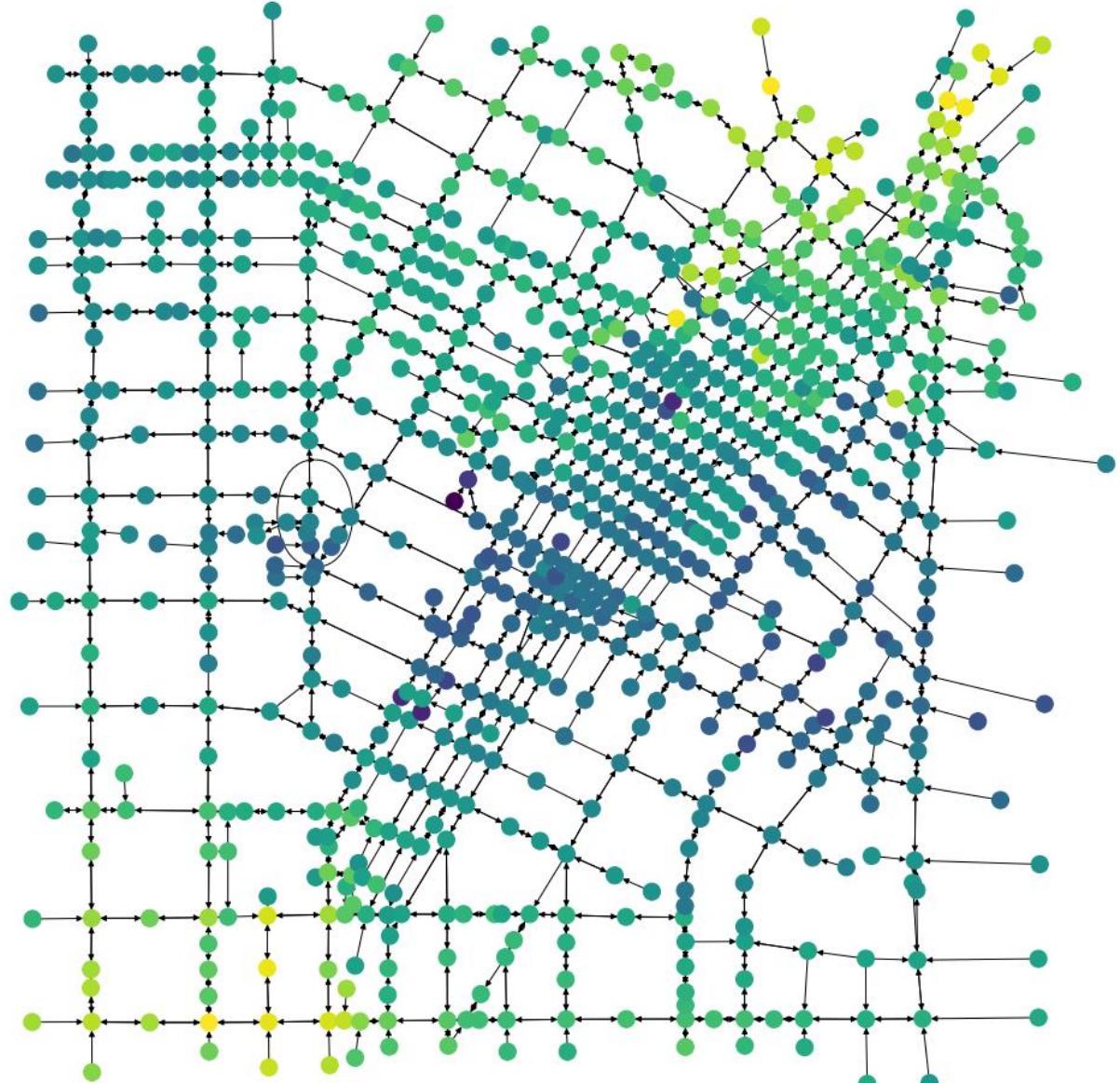
Los Angeles Downtown Road Network Road Traffic Flow (Harmonic) 2017-10-02 18:30



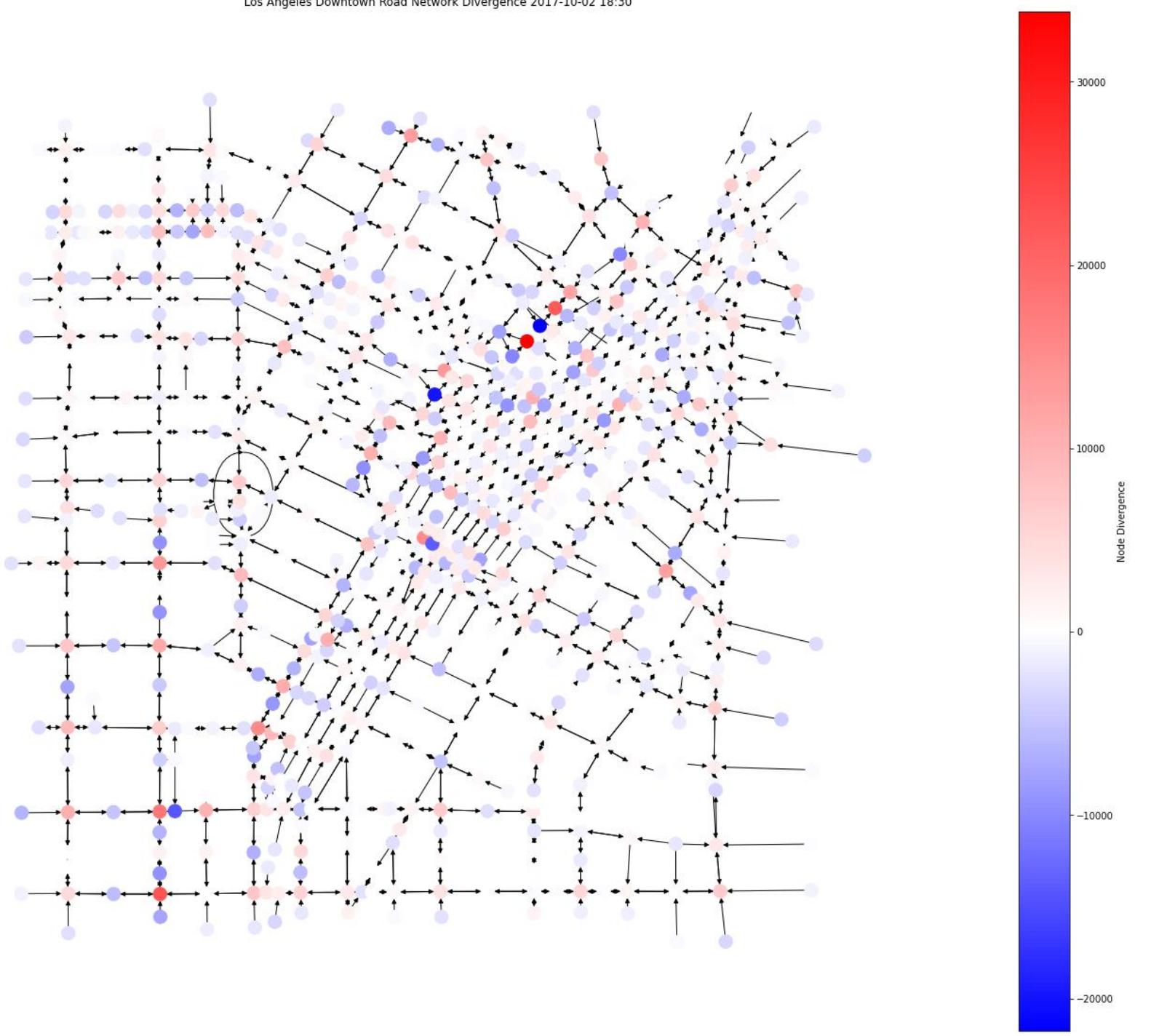
Los Angeles Downtown Road Network Road Traffic Flow (Curl Adjoint) 2017-10-02 18:30



Los Angeles Downtown Road Network Negative Potential 2017-10-02 18:30



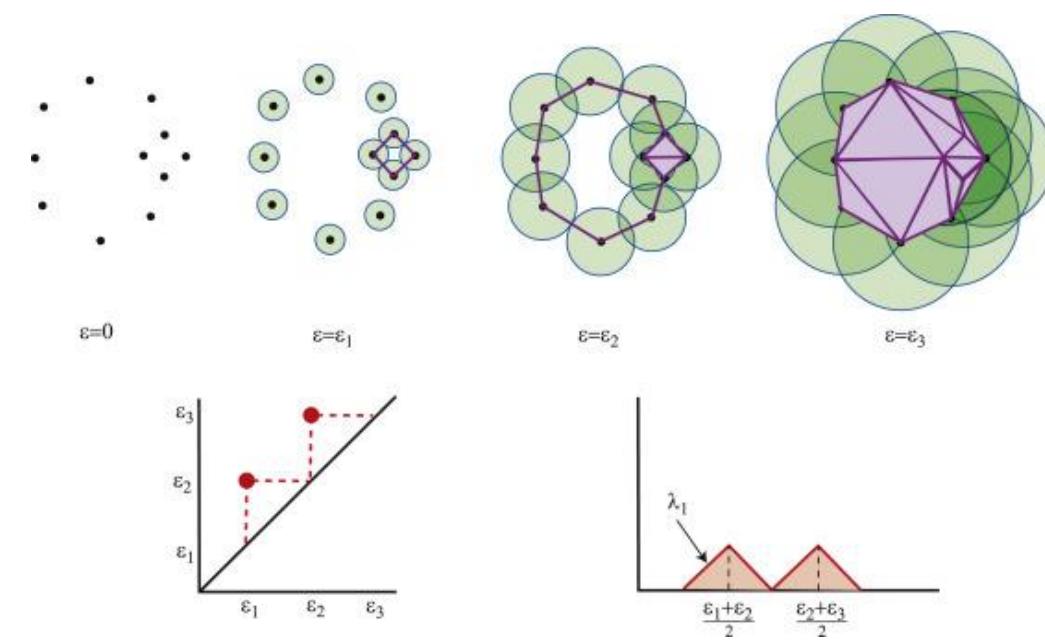
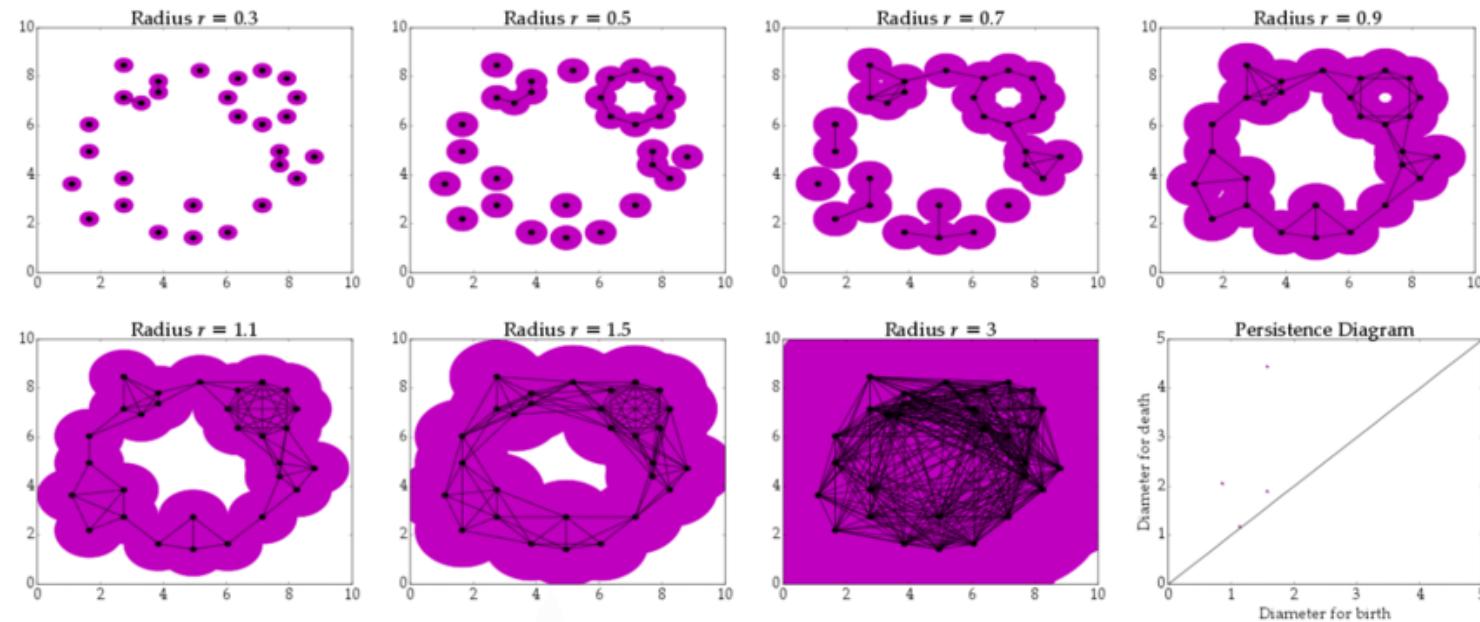
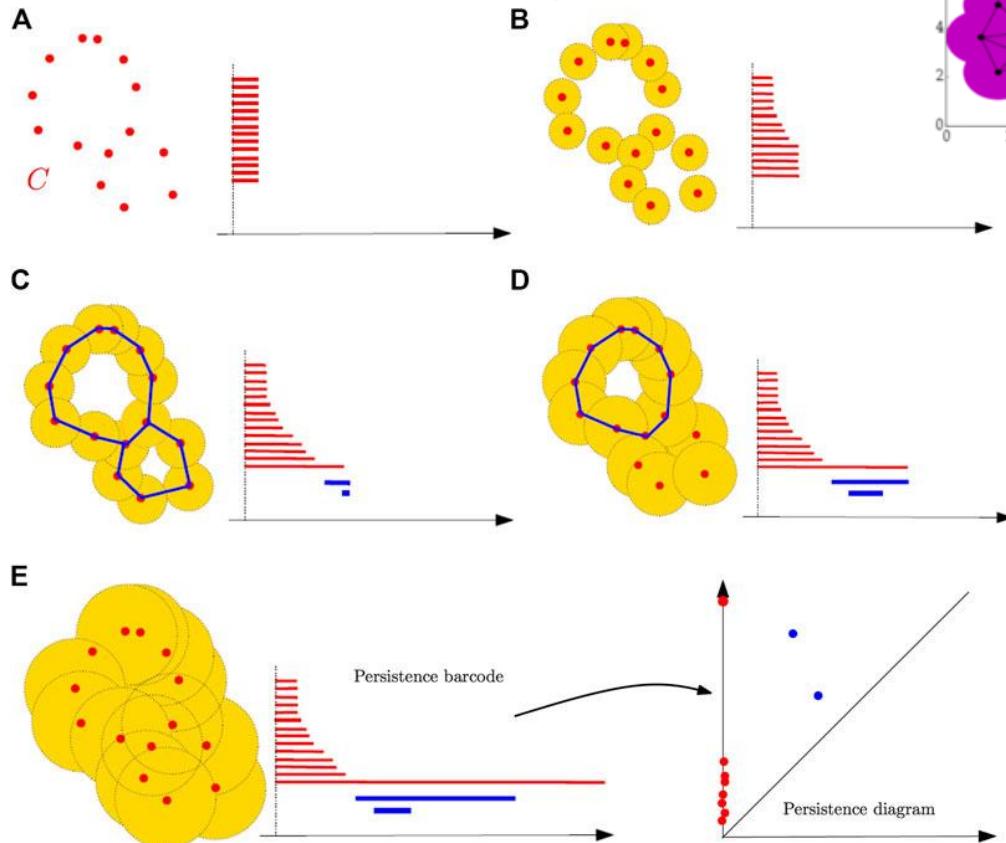
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Related topics

- Topological data analysis

Persistent homology



Other applications

- (i) ranking
- (ii) graphics and imaging
- (iii) games and traffic flows
- (iv) brain networks
- (v) data representations
- (vi) deep learning
- (vii) denoising
- (viii) dimension reduction
- (ix) link prediction
- (x) object synchronization
- (xi) sensor network coverage
- (xii) cryo-electron microscopy
- (xiii) generalizing effective resistance to simplicial complexes
- (xiv) modeling biological interactions between a set of molecules or communication systems with group messages

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