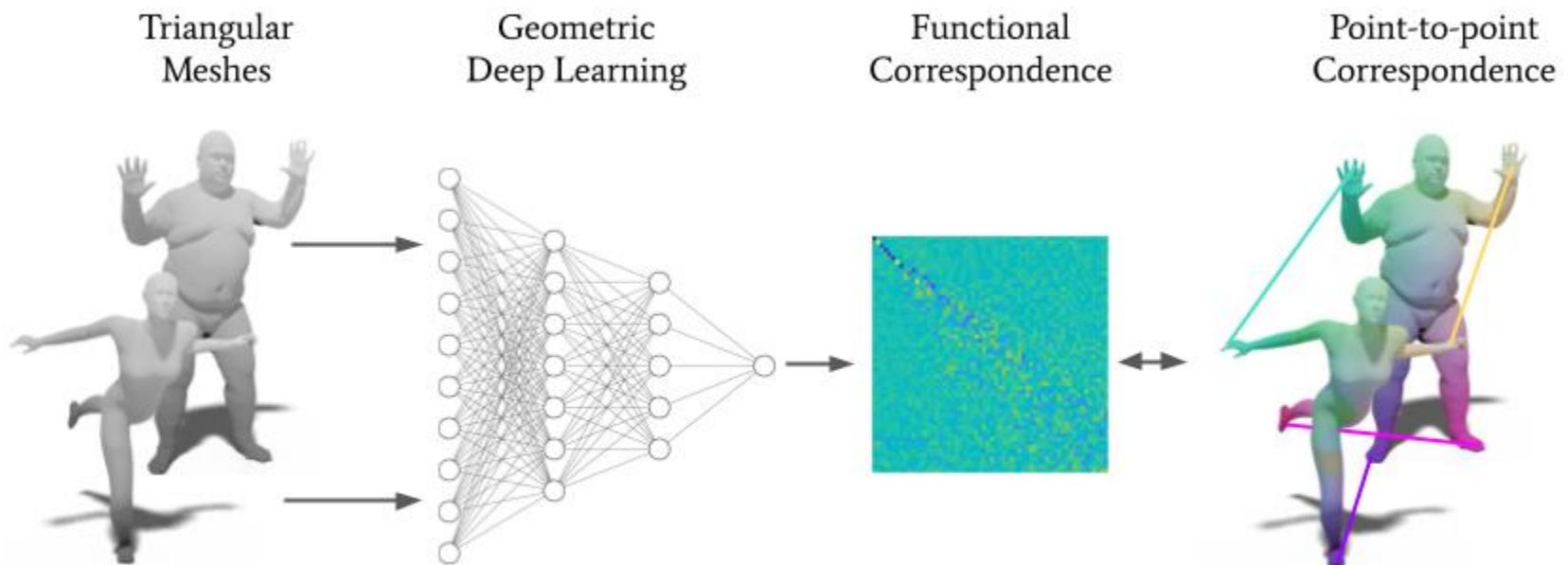


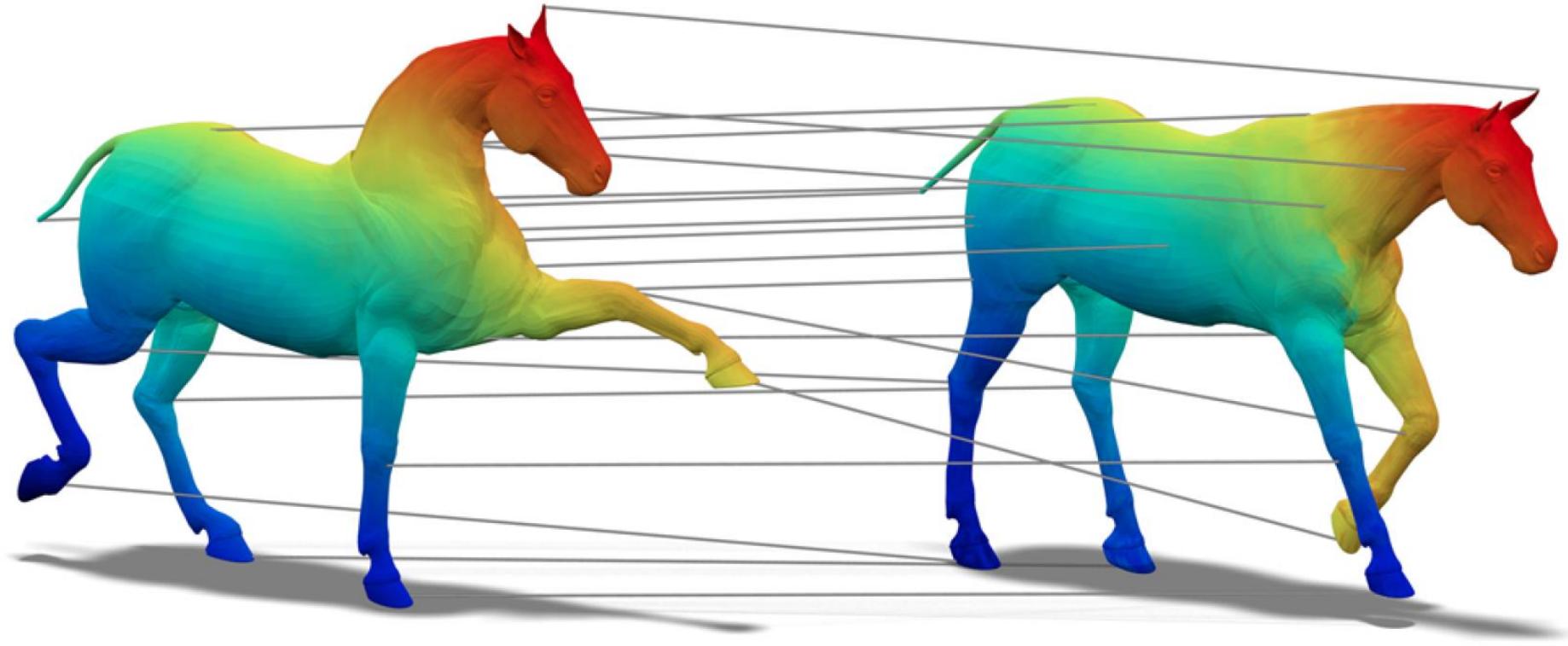
Functional Correspondence from Discrete Geometry to Learning

Riccardo Marin, Emanuele Rodolà

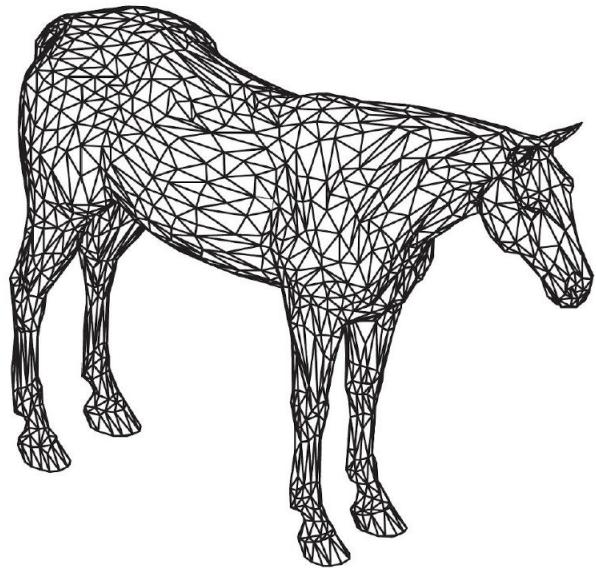




Task: Given a set of objects, find a correspondence between them



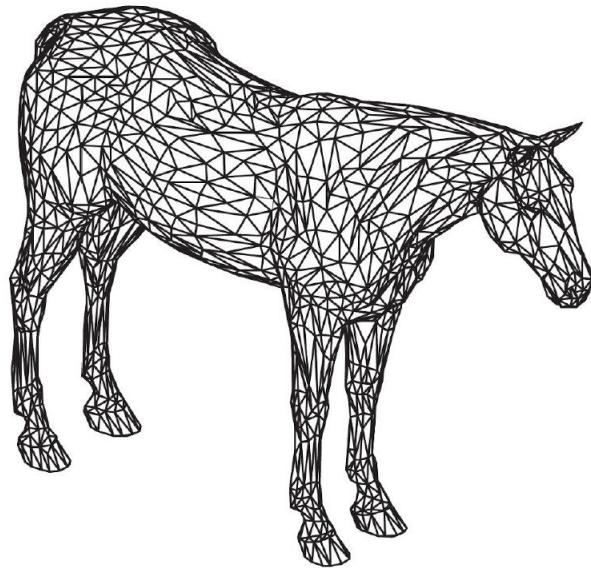
Huge permutation matrix
Can we make it more compact?



graph

Vertices $\mathcal{V} = \{1, \dots, n\}$

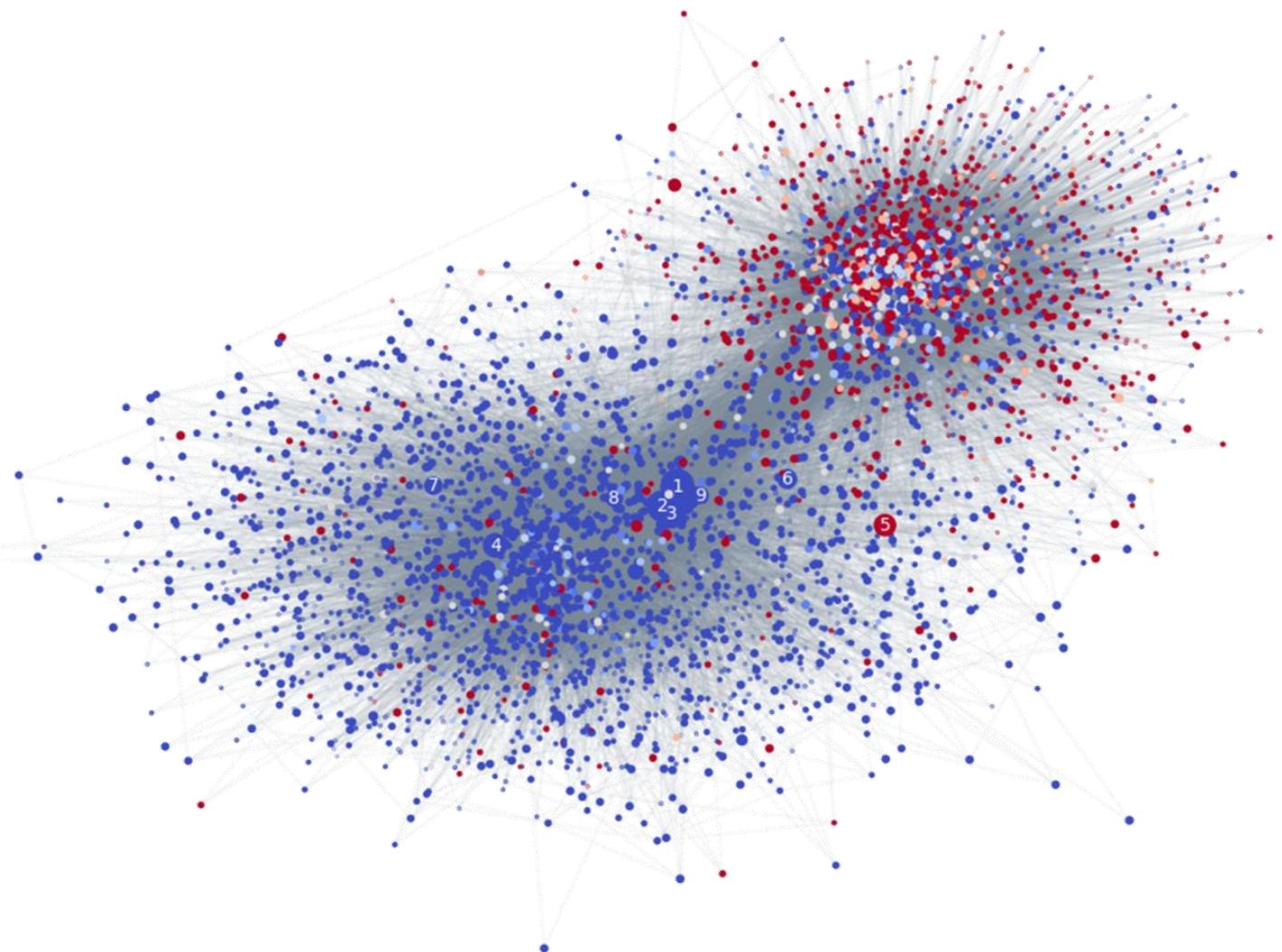
Edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$

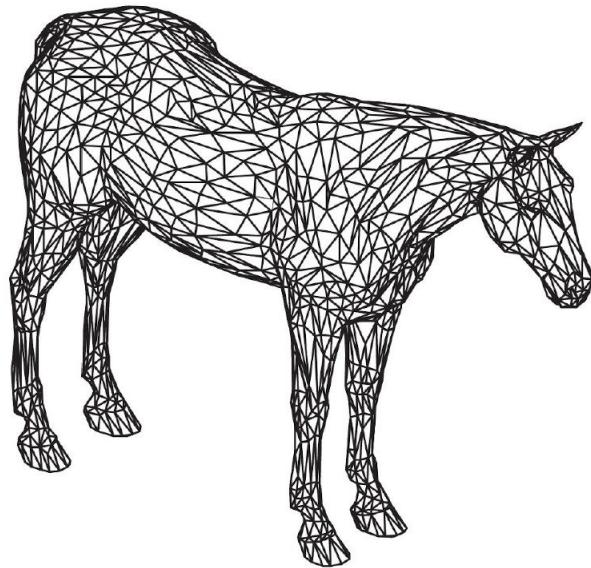


graph

Vertices $\mathcal{V} = \{1, \dots, n\}$

Edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$



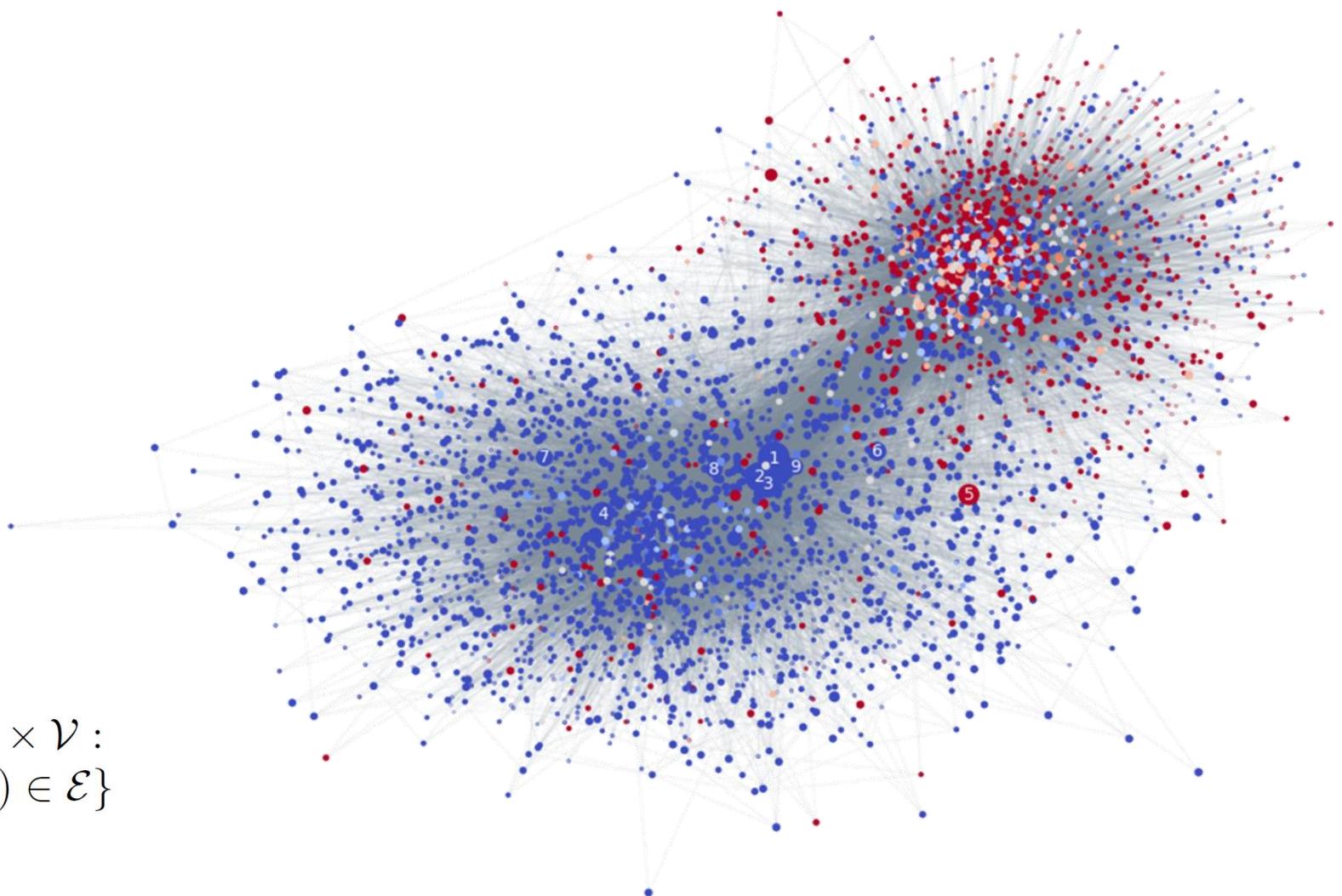


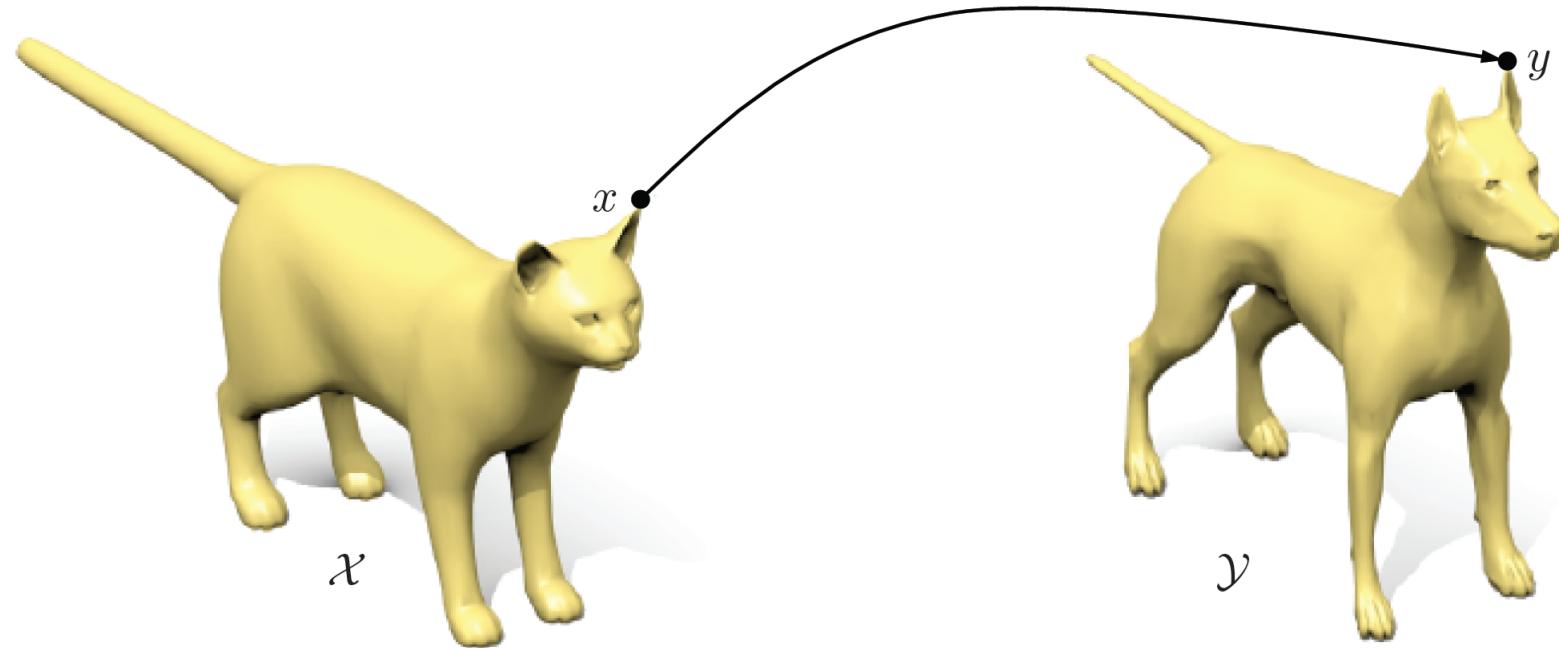
Triangular mesh

Vertices $\mathcal{V} = \{1, \dots, n\}$

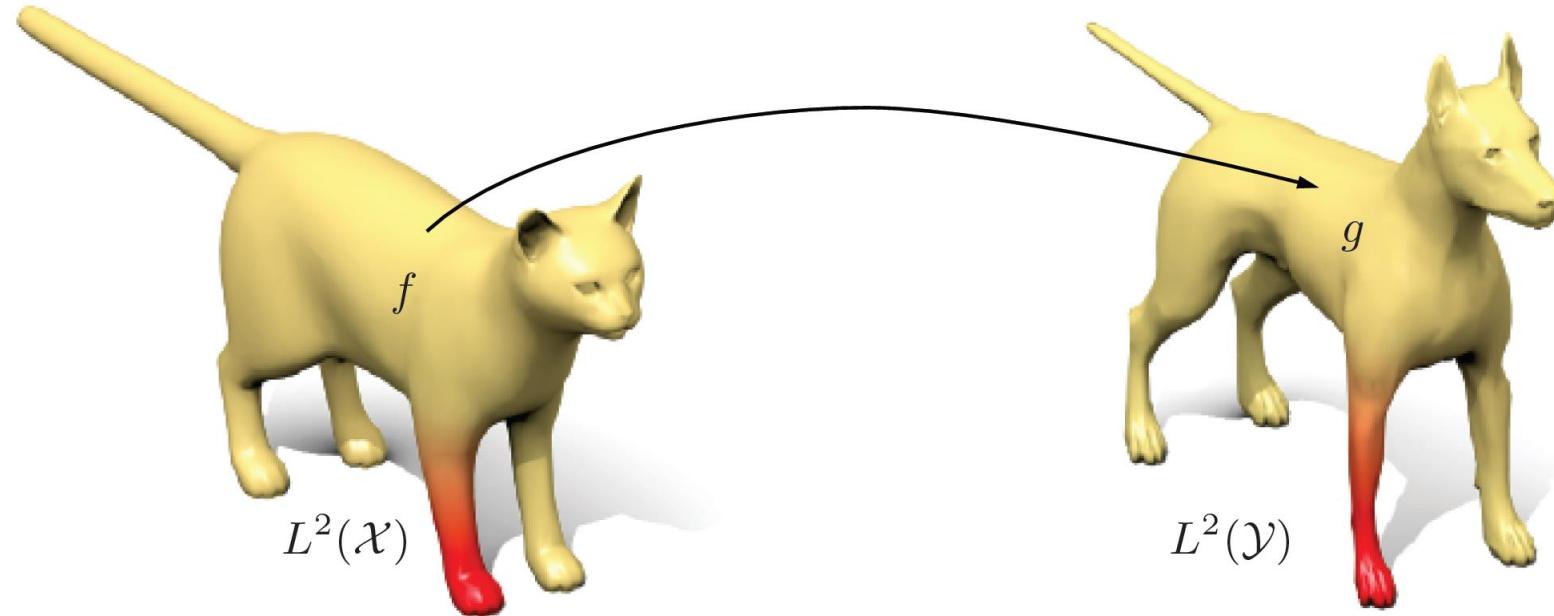
Edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$

Faces $\mathcal{F} = \{(i, j, k) \in \mathcal{V} \times \mathcal{V} \times \mathcal{V} : (i, j), (j, k), (k, i) \in \mathcal{E}\}$

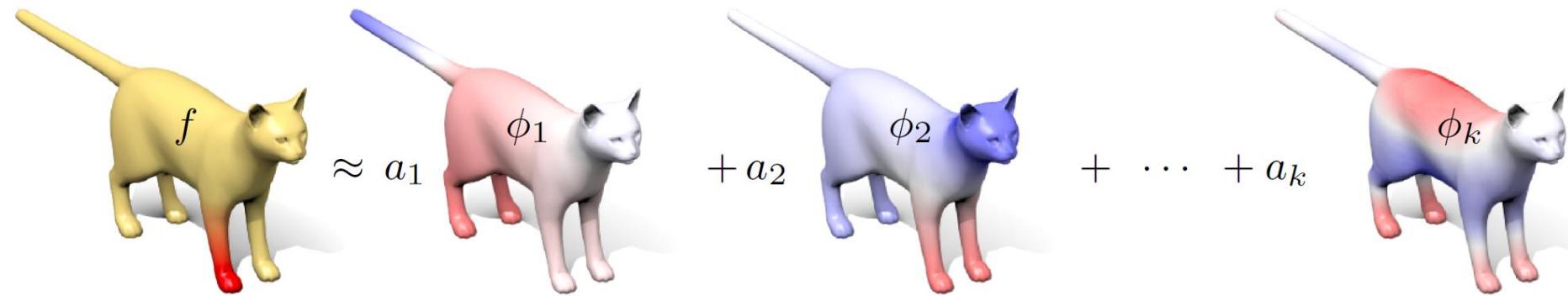


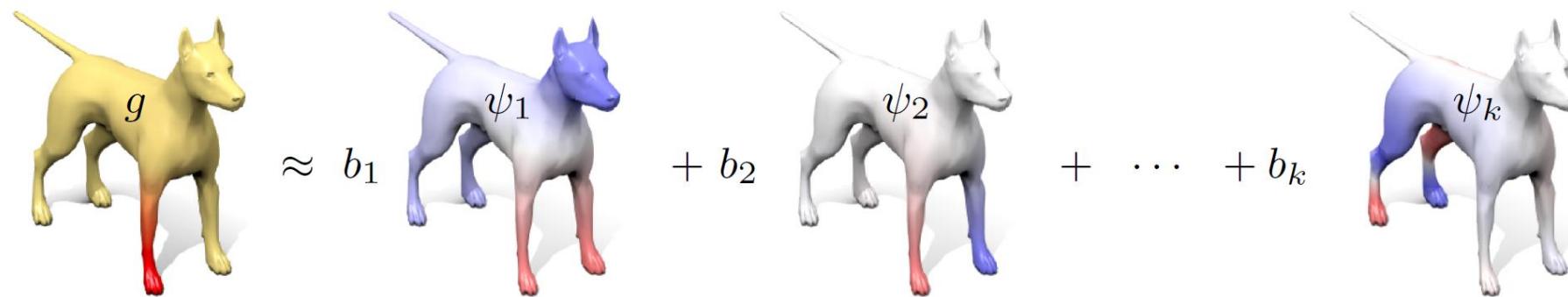
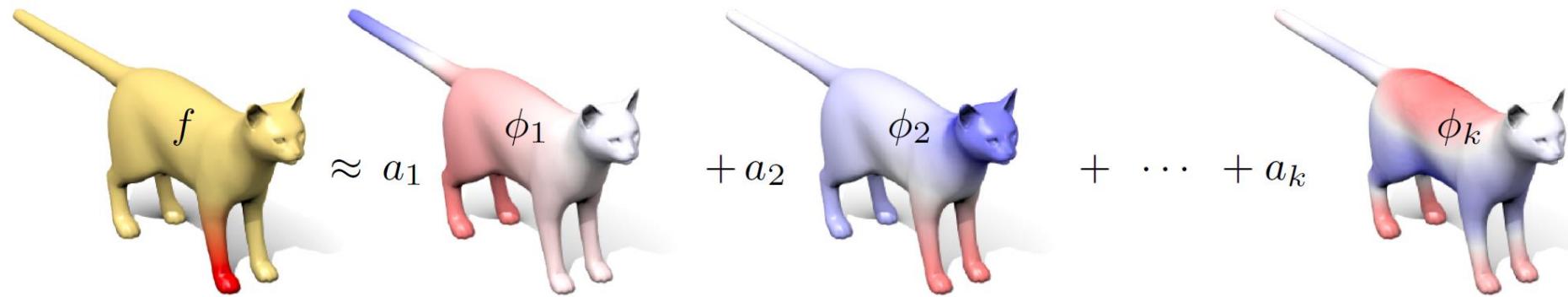


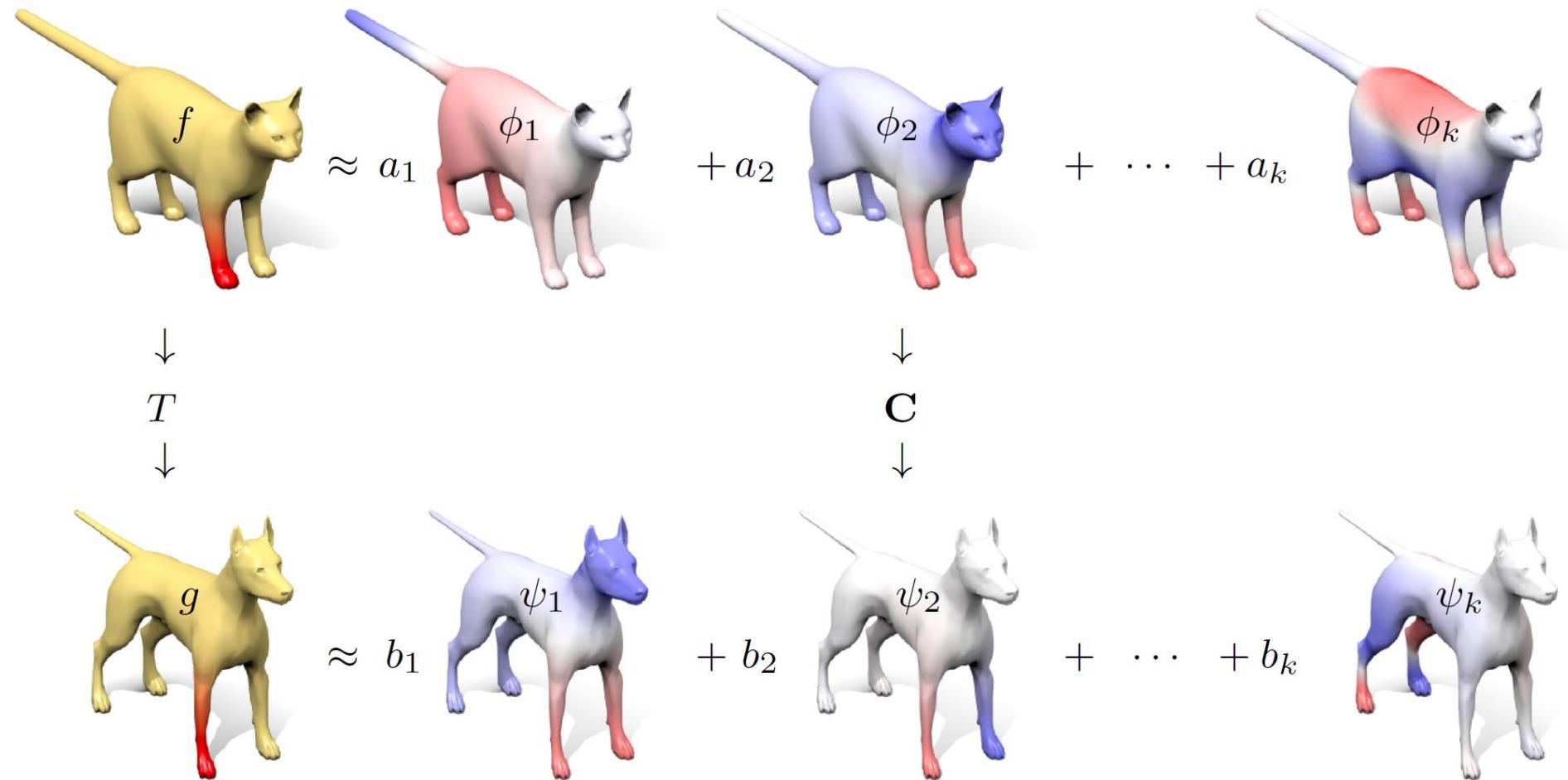
Point-wise map $t: \mathcal{X} \rightarrow \mathcal{Y}$

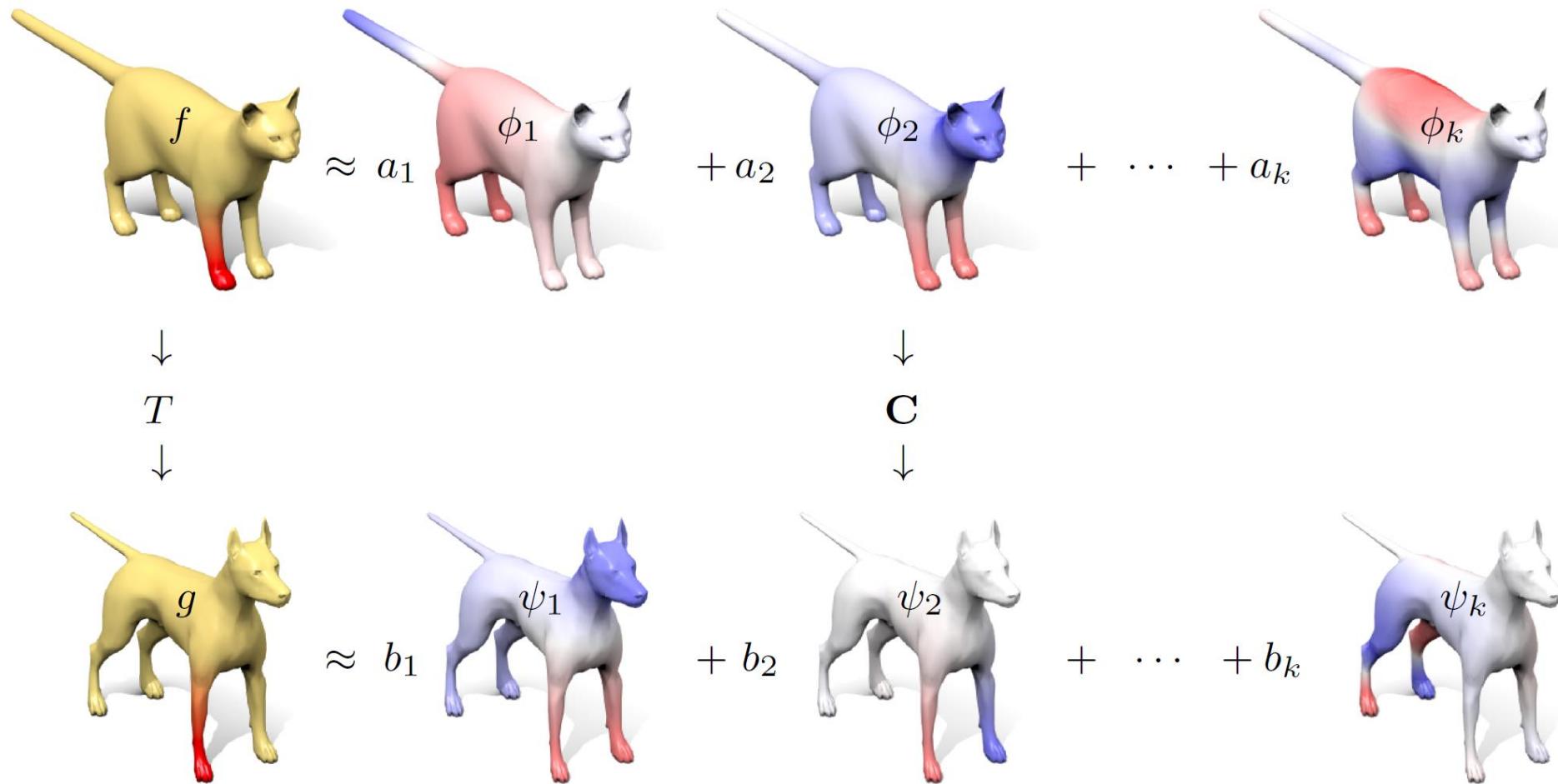


Functional map $T: L^2(\mathcal{X}) \rightarrow L^2(\mathcal{Y})$
 $Tf = f \circ t^{-1}$



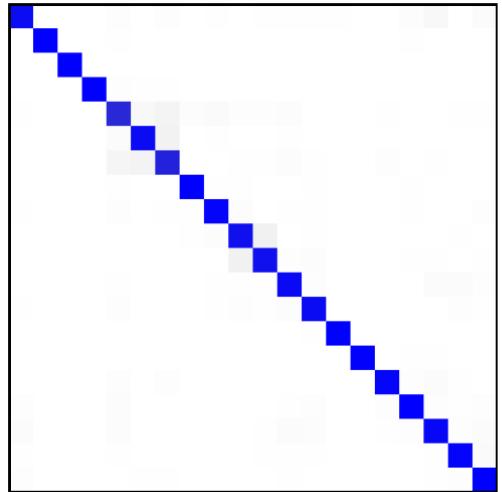
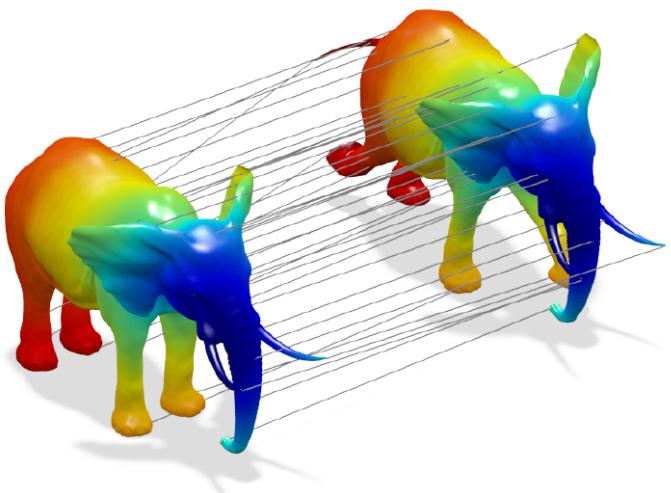




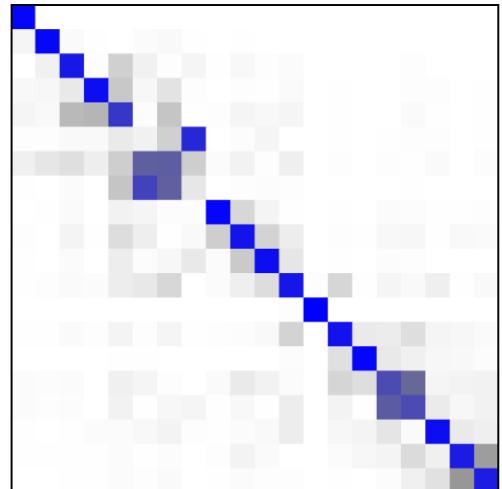
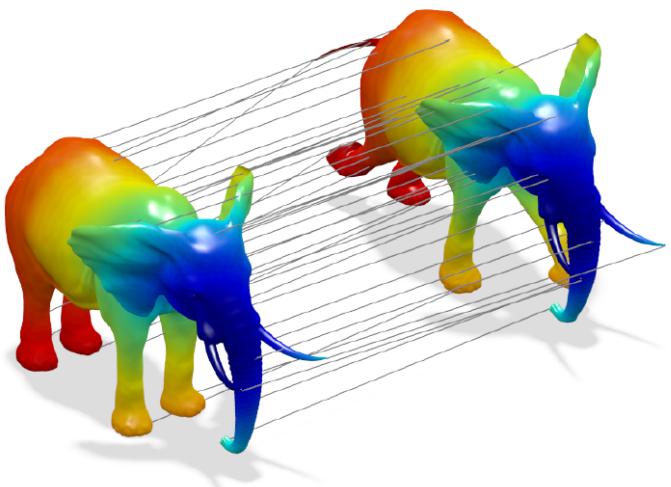


Functional correspondence boils down to a [linear equation](#) w.r.t. \mathbf{C}

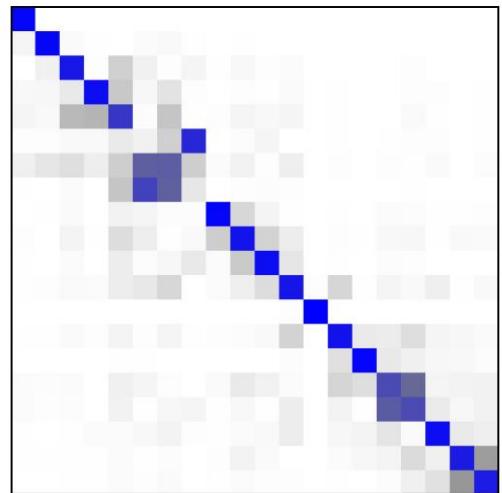
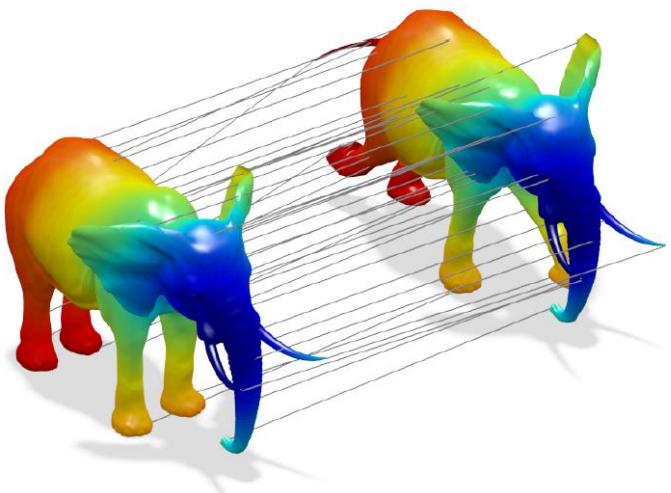
$$g = Tf \iff \mathbf{b} = \mathbf{Ca}$$



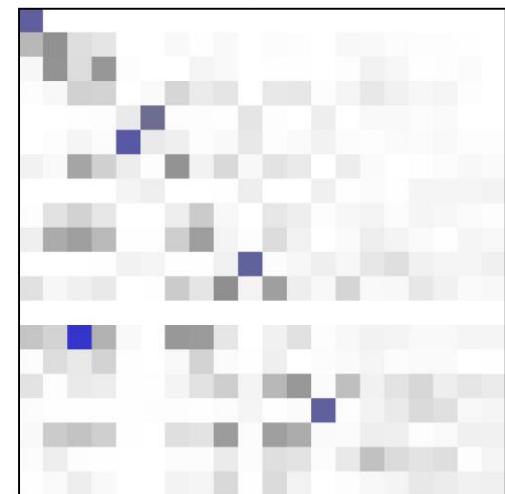
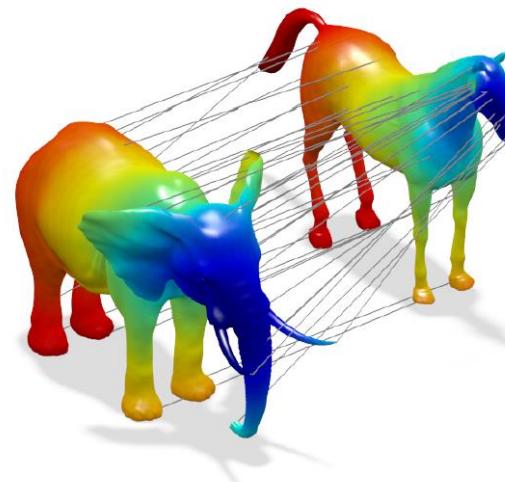
Isometric
 $C \approx I$



Isometric
 $C \approx I$



Isometric
 $C \approx I$

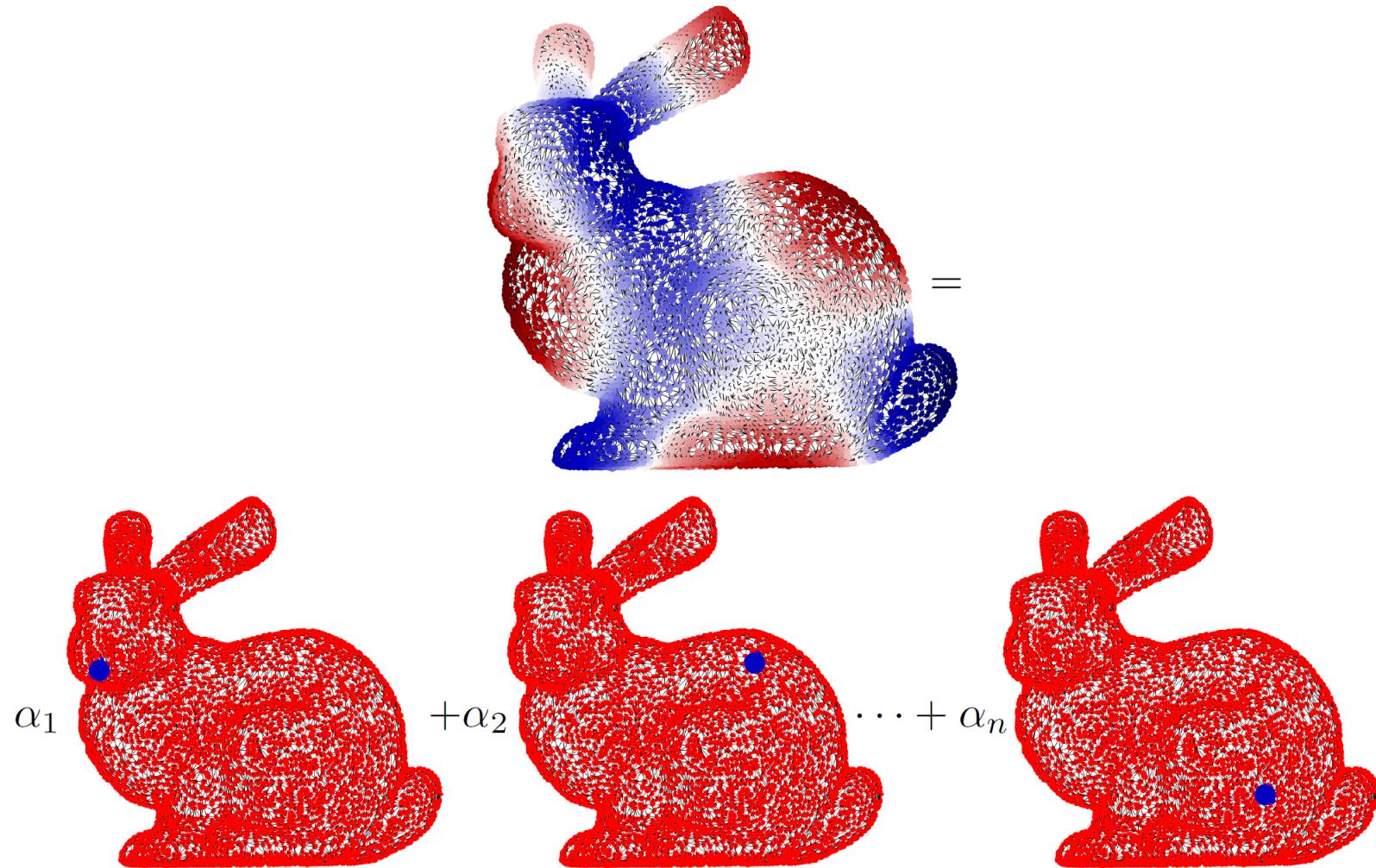


Non-isometric

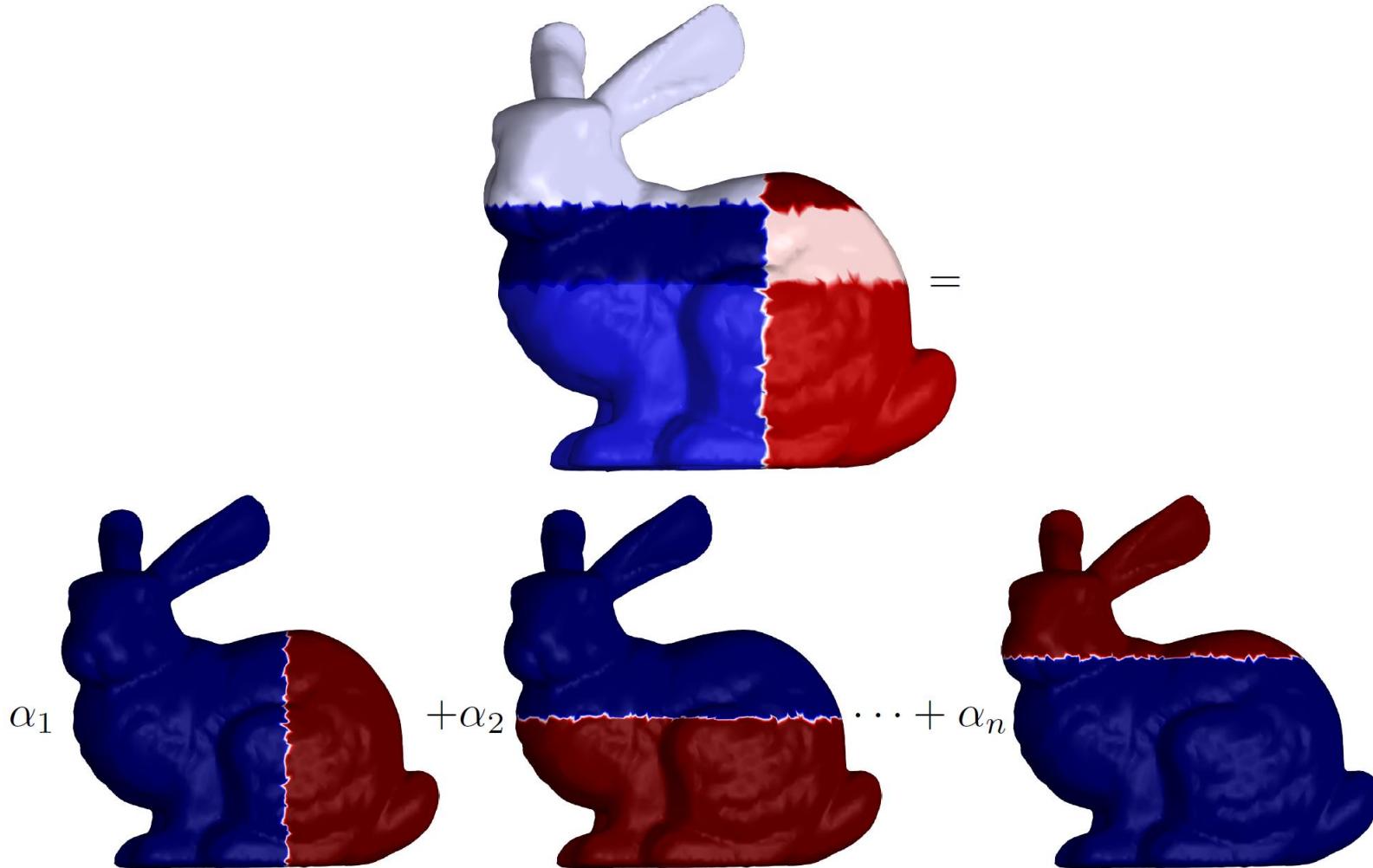
Where do we get a basis?

- Can be computed directly on a given shape
- Can be optimized on a given set of shapes
- Can be learned
- Combination of the above

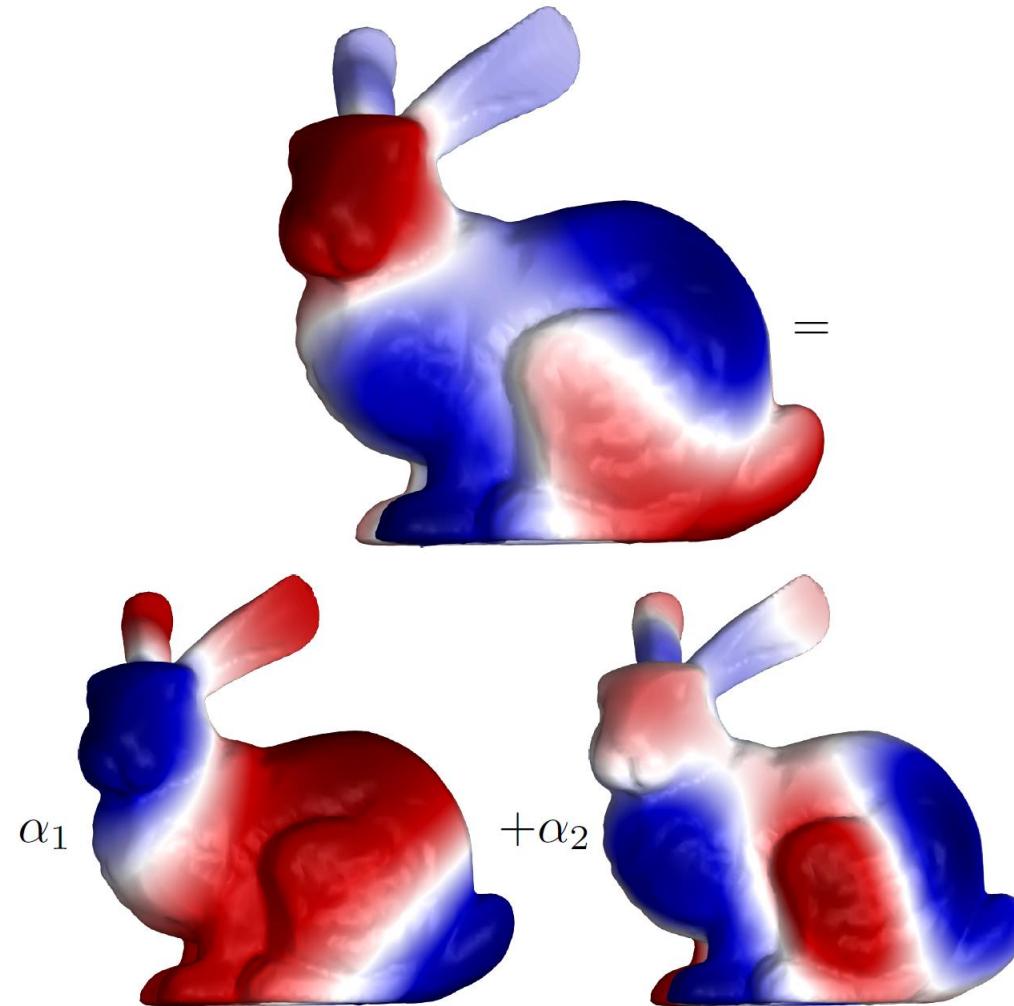
Basis vectors are indicator functions at all vertices in the mesh



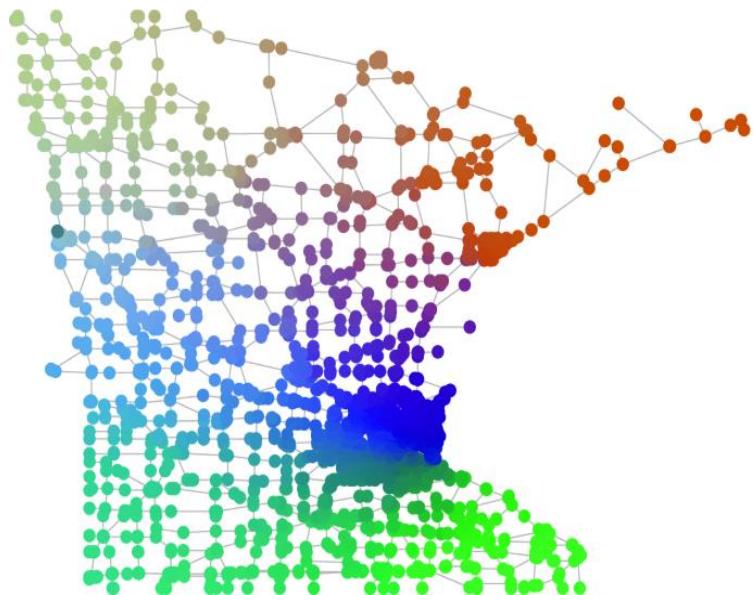
Basis vectors are some piecewise-constant functions on the mesh



Basis vectors are two random smooth functions



$$g(v_i) = f(v_i) - \frac{1}{d_i} \sum_{j:(i,j)\in E} f(v_j)$$

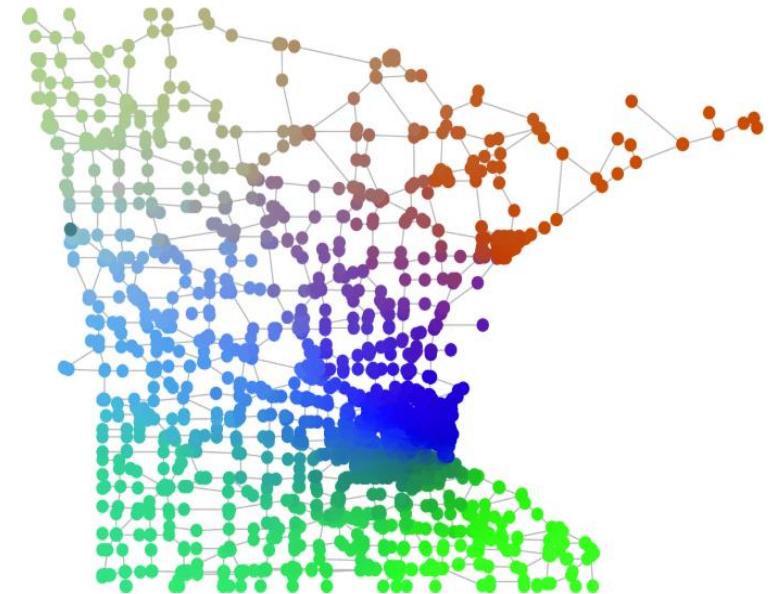


$$g(v_i) = f(v_i) - \frac{1}{d_i} \sum_{j:(i,j) \in E} f(v_j)$$

In matrix notation, we define the $n \times n$ matrix \mathbf{L} as:

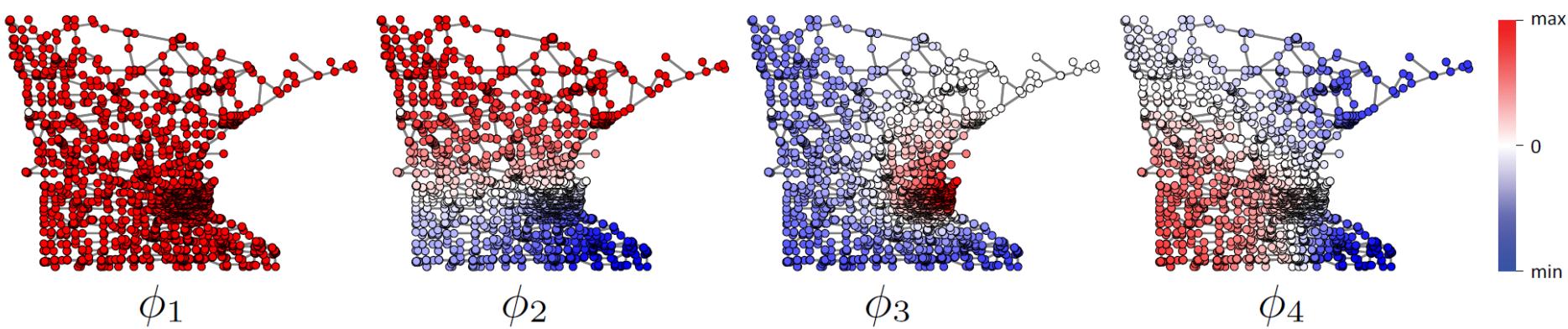
$$L_{ij} = \begin{cases} 1 & \text{if } i = j \\ -\frac{1}{d_i} & \text{if } e_{ij} \in E \\ 0 & \text{otherwise} \end{cases}$$

also known as the [graph Laplacian](#) of G .



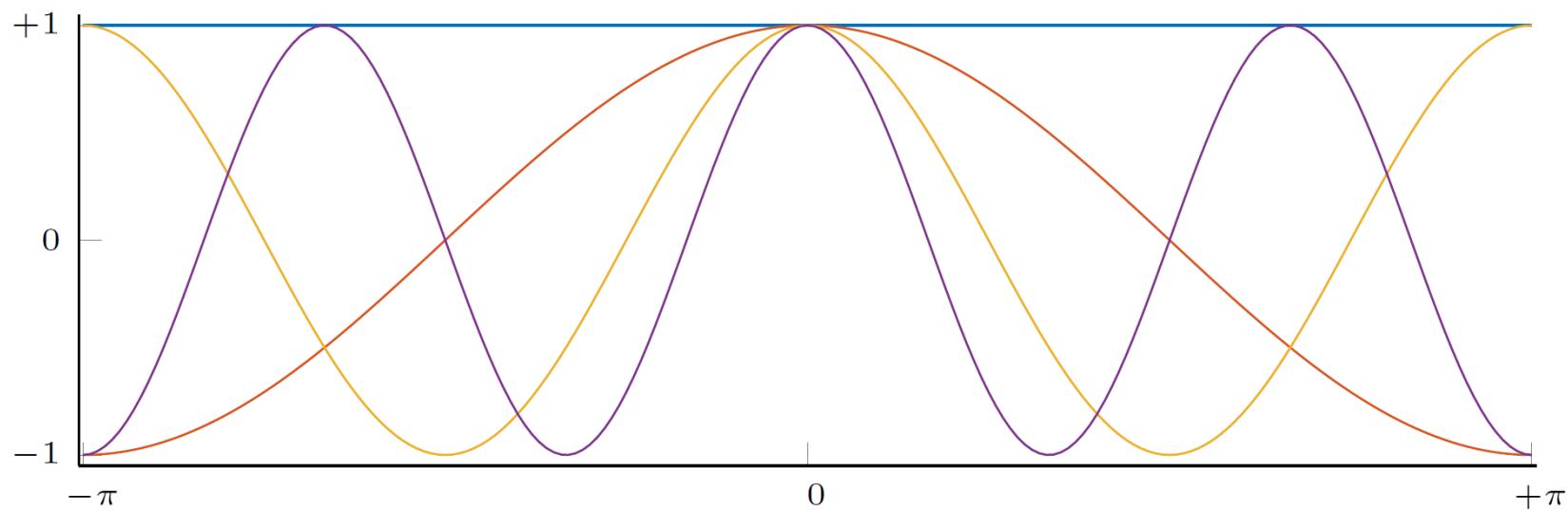
Variants with different properties exist (e.g. normalized Laplacian, random walk Laplacian, etc.).

Theorem: The eigenfunctions $\{\phi_i\}$ of \mathbf{L} form an orthonormal basis of $\mathcal{F}(G)$



First eigenfunctions of a graph Laplacian
(ordered by corresponding eigenvalue)

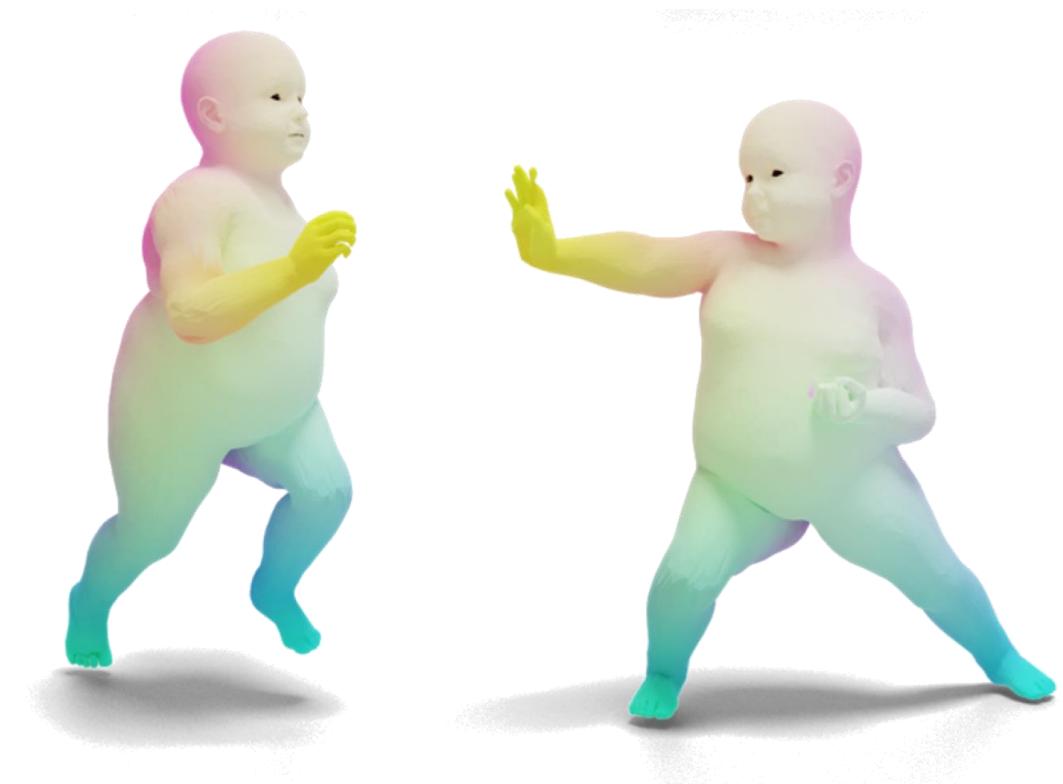
Theorem: The eigenfunctions $\{\phi_i\}$ of \mathbf{L} form an orthonormal basis of $\mathcal{F}(G)$



First eigenfunctions of 1D Euclidean Laplacian = standard Fourier basis

1. Compute bases Φ, Ψ
2. Compute corresponding functions \mathbf{F}, \mathbf{G}
3. Represent \mathbf{F} in Φ , and \mathbf{G} in Ψ , obtaining coefficients \mathbf{A} and \mathbf{B}
4. Solve:

$$\min_{\mathbf{C}} \|\mathbf{CA} - \mathbf{B}\| + \rho(\mathbf{C})$$

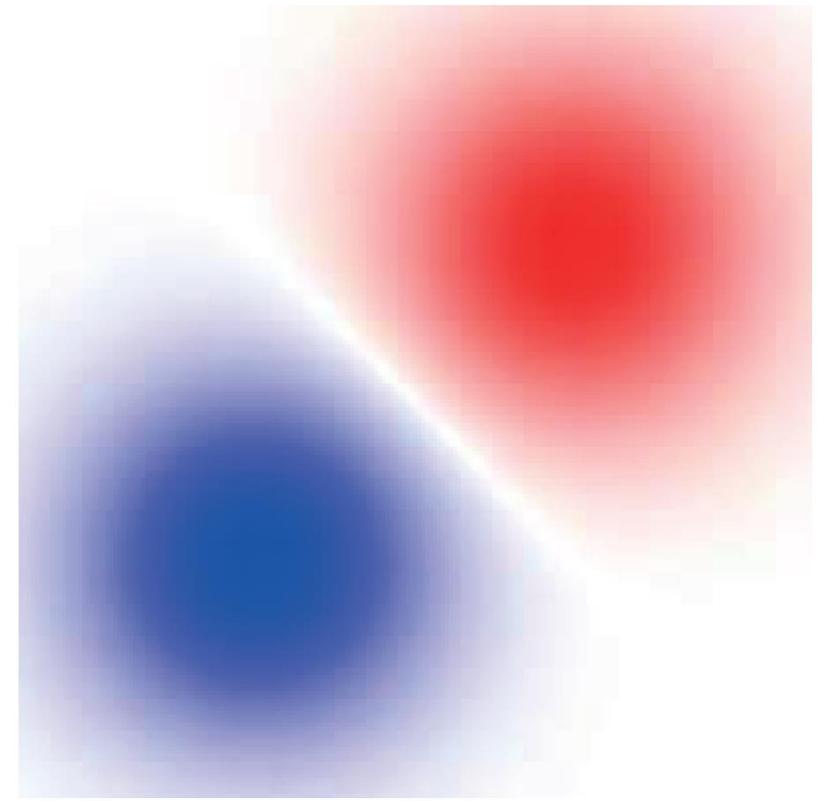


5. Use the optimized \mathbf{C} ...or...

Convert \mathbf{C} to point-to-point



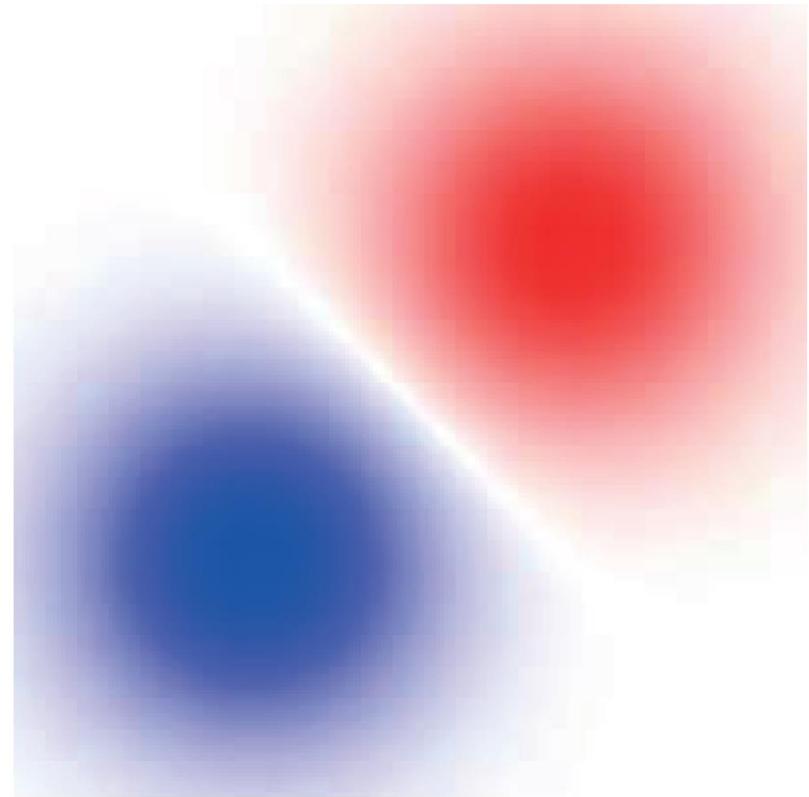
$$f : \mathcal{M} \rightarrow \mathbb{R}^3$$



Smooth scalar field f

Gradient $\nabla f(x)$

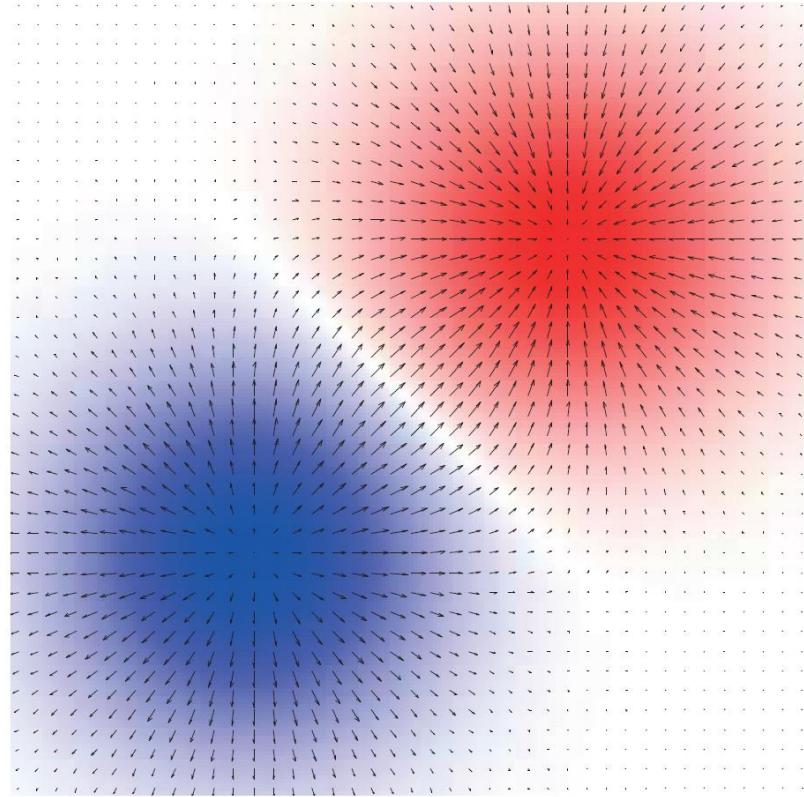
'direction of the steepest increase
of f at x '



Smooth scalar field f

Gradient $\nabla f(x)$

'direction of the steepest increase
of f at x'



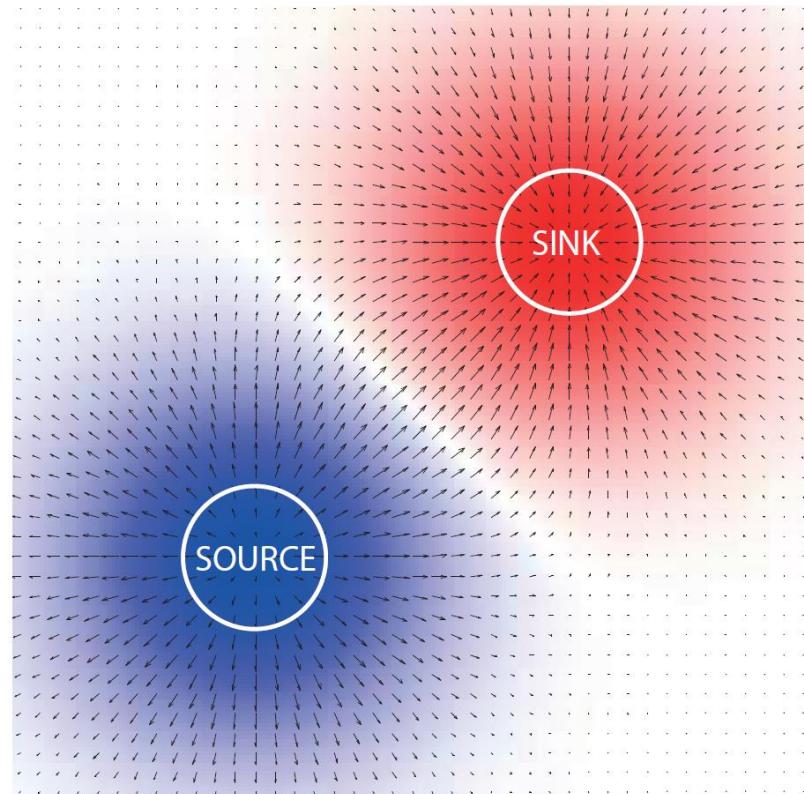
Smooth vector field F

Gradient $\nabla f(x)$

'direction of the steepest increase
of f at x'

Divergence $\operatorname{div}(F(x))$

'scalar density of an outward flux of
 F from an infinitesimal volume
around x'



Smooth **vector field** F

Gradient $\nabla f(x)$

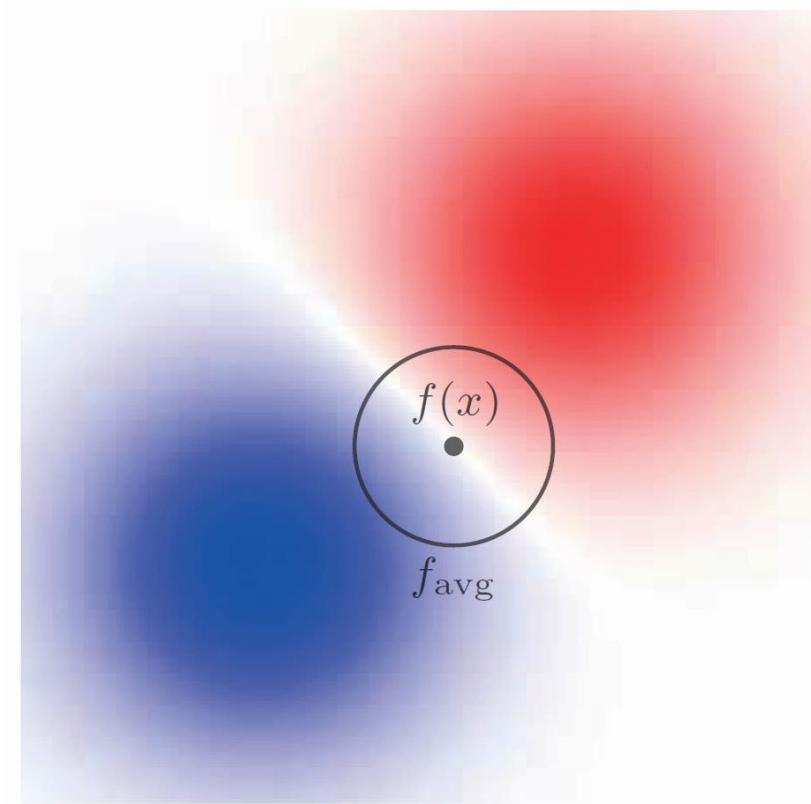
'direction of the steepest increase
of f at x'

Divergence $\operatorname{div}(F(x))$

'scalar density of an outward flux of
 F from an infinitesimal volume
around x'

Laplacian $\Delta f(x) = -\operatorname{div}(\nabla f(x))$

'scalar difference between $f(x)$ and
the average of f on an infinitesimal
sphere around x'



Smooth scalar field f

$$L_{ij} = \begin{cases} 1 & \text{if } i = j \\ -\frac{1}{d_i} & \text{if } e_{ij} \in E \\ 0 & \text{otherwise} \end{cases} \quad \text{graph Laplacian of } G$$

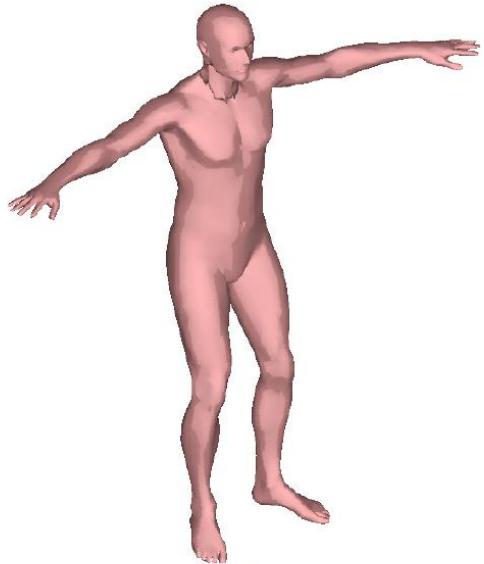
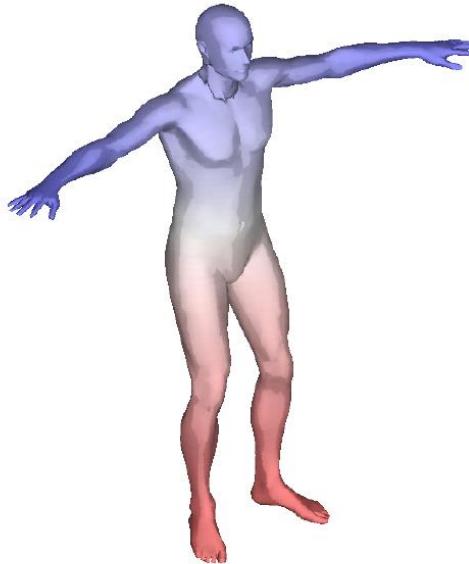
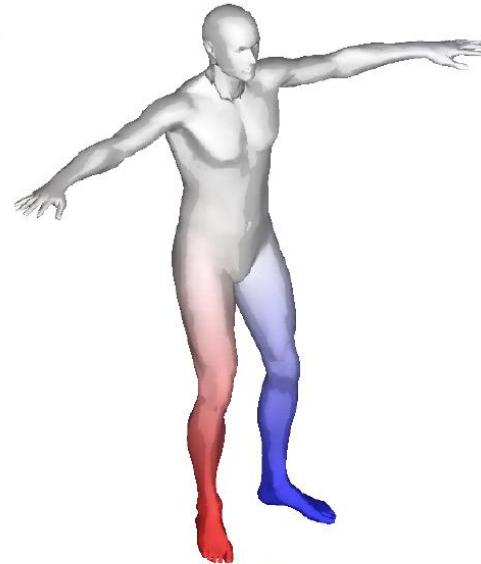
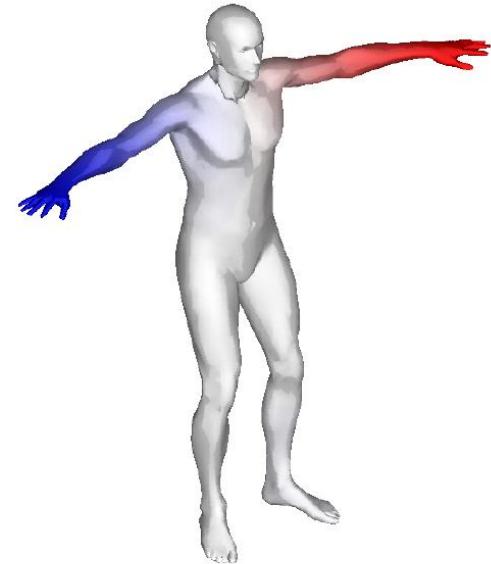
The discrete Laplace operator on a mesh is the $n \times n$ matrix:

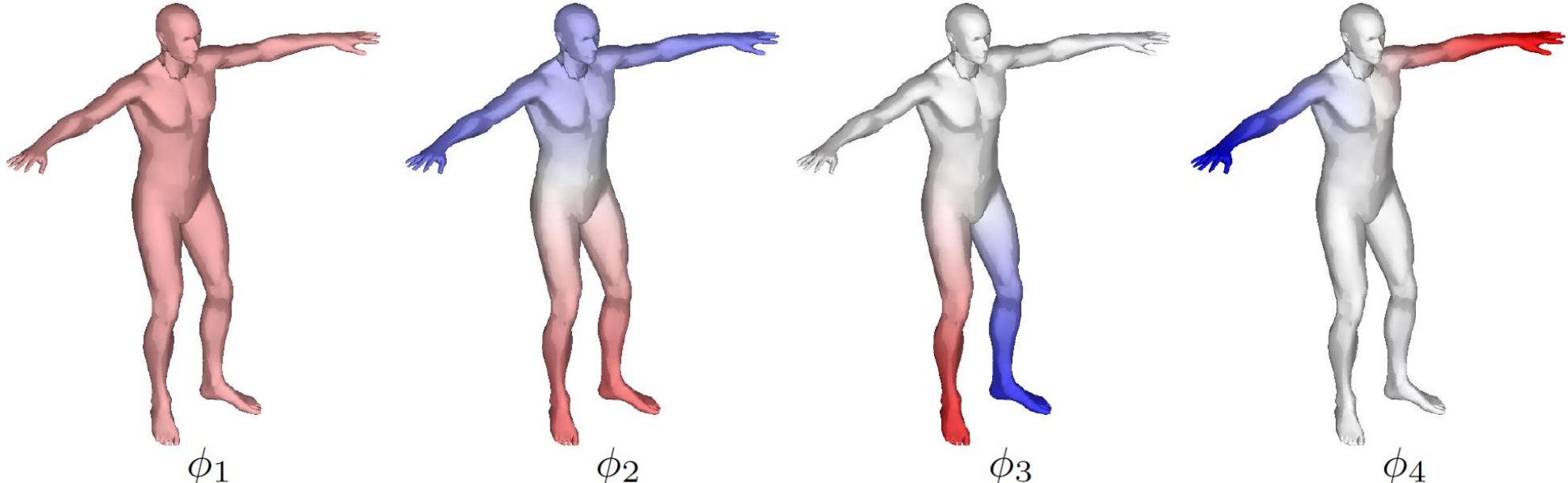
$$\mathbf{L} = \mathbf{A}^{-1} \mathbf{S}$$

where

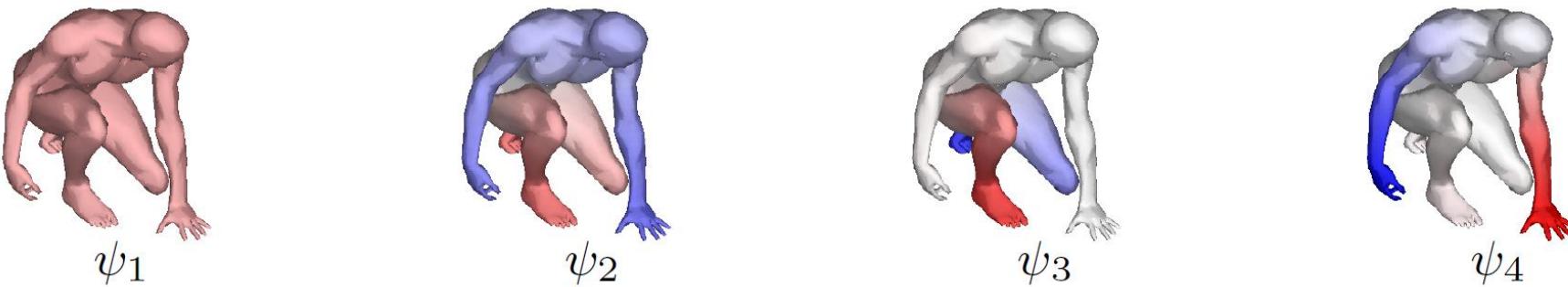
$$s_{ij} = \begin{cases} -\frac{1}{2}(\cot\alpha_{ij} + \cot\beta_{ij}) & \text{if } e_{ij} \in E \\ -\sum_{k \neq i} s_{ik} & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

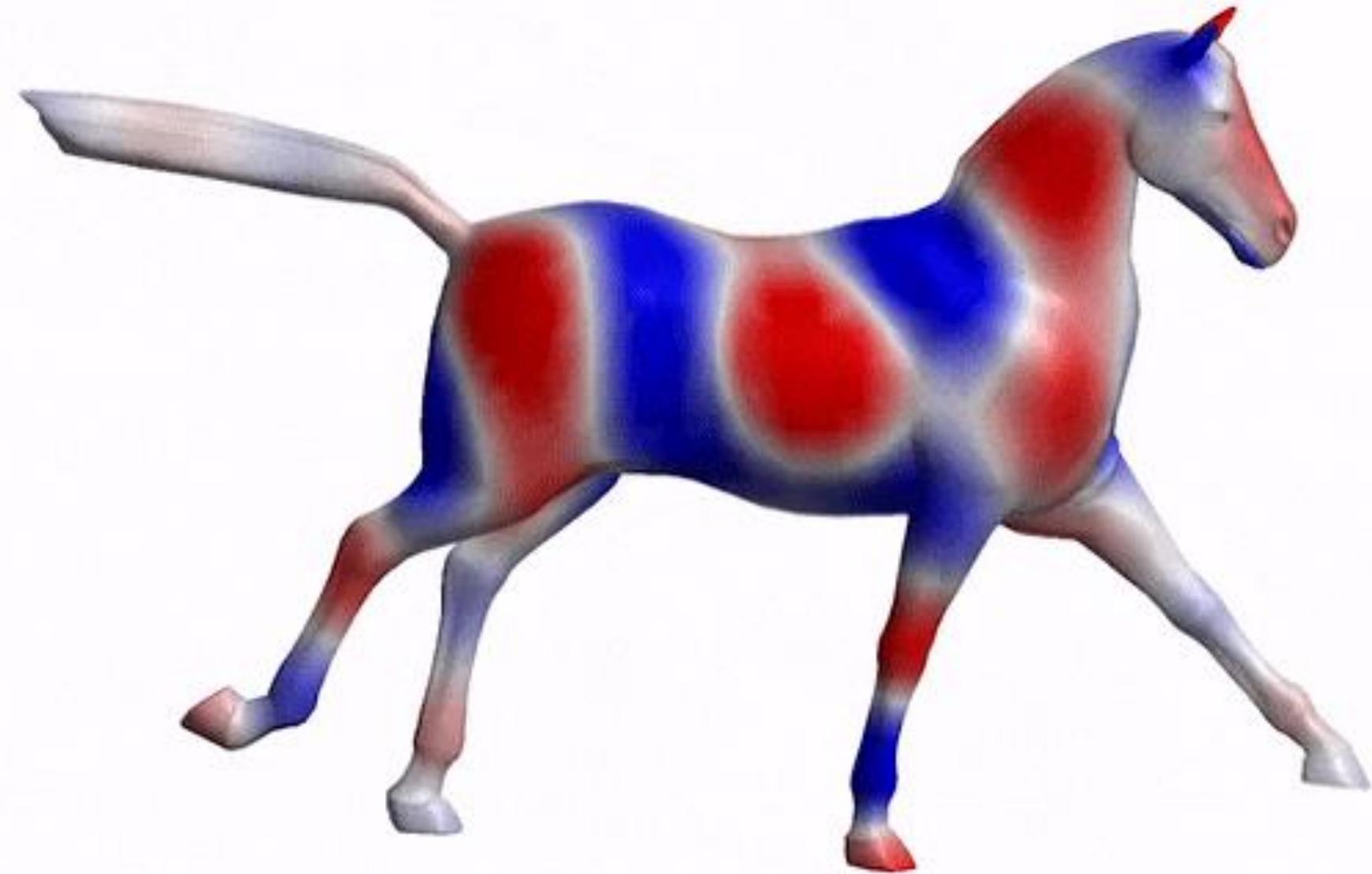
$$a_{ij} = \begin{cases} \frac{1}{12}(A(T_{jii'}) + A(T_{ji''i})) & \text{if } e_{ij} \in E \\ \frac{1}{6} \sum_{k \in \mathcal{N}(i)} A(T_k) & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

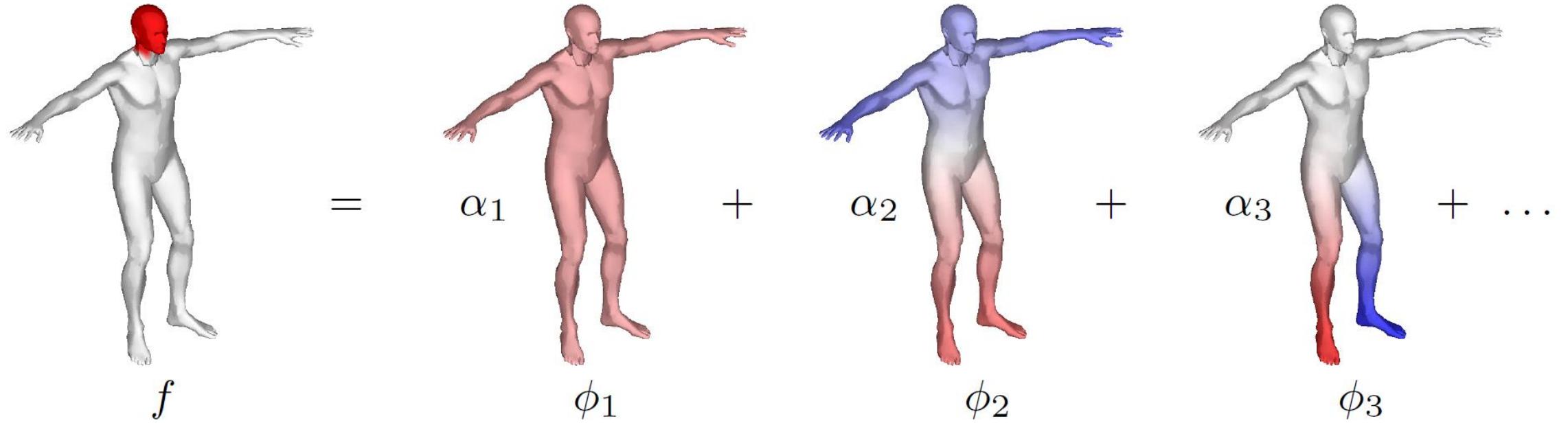
 ϕ_1  ϕ_2  ϕ_3  ϕ_4



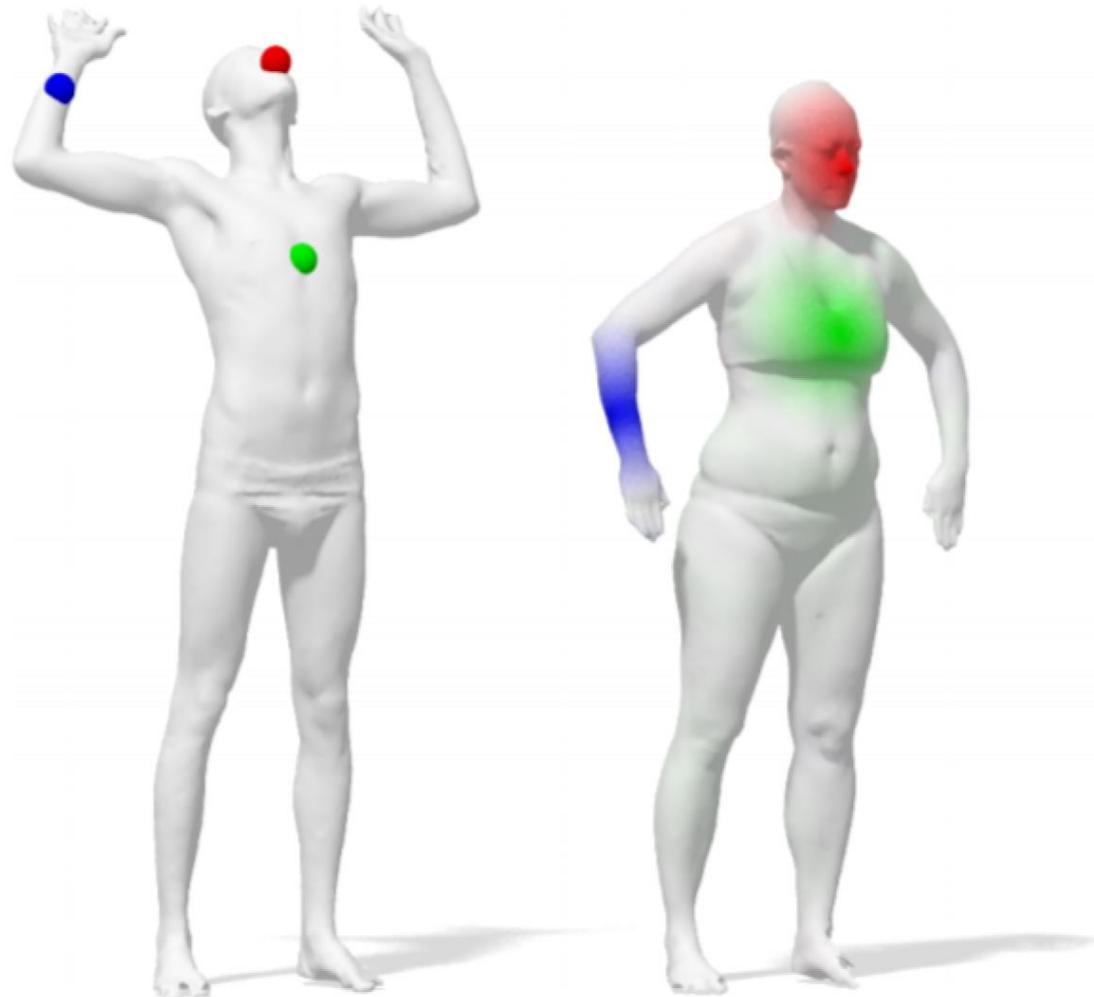
For shapes with simple spectrum, Laplacian eigenfunctions are invariant
(up to sign) to isometric deformations, $\psi_i = \pm T\phi_i$



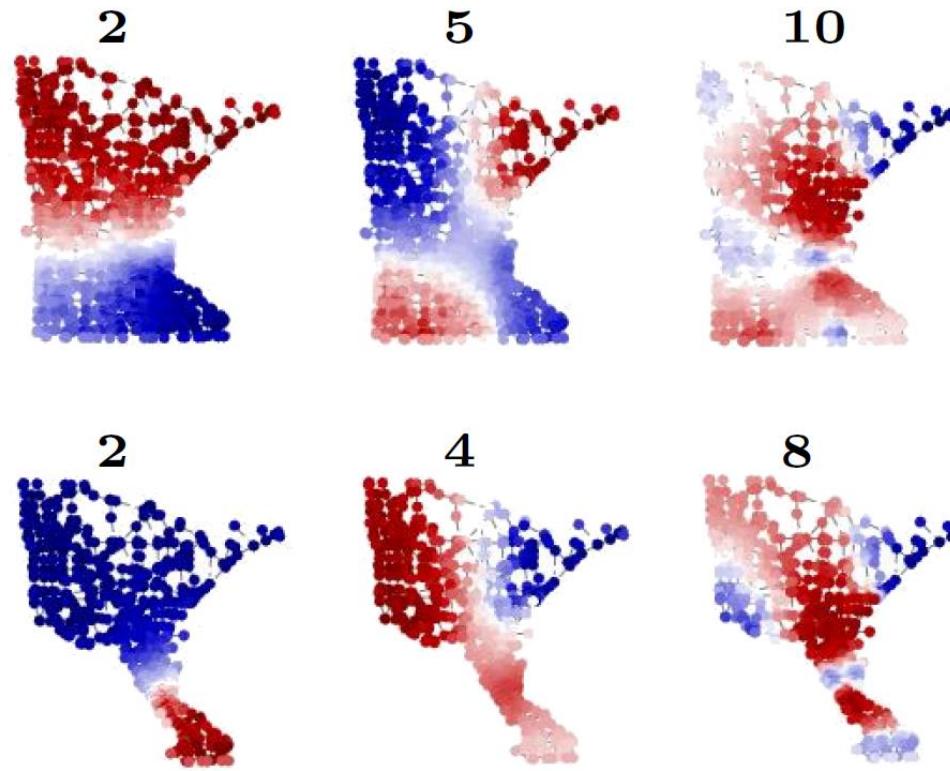




With coefficients $\langle f, \phi_k \rangle$



Truncating the sum to the first few terms has a smoothing effect



Eigenvectors of the graph Laplacian



full graph



(i) isomorphic

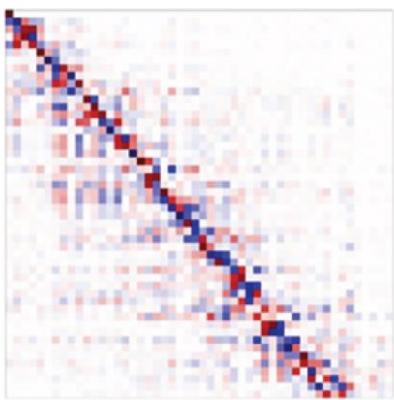




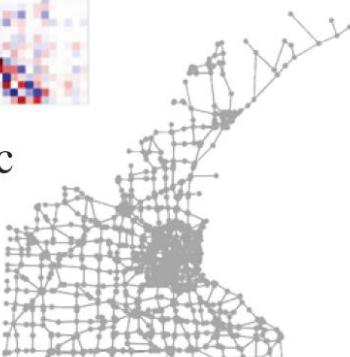
full graph



(i) isomorphic

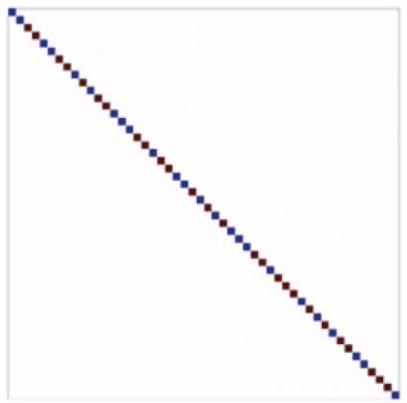


(ii) isomorphic
subgraph

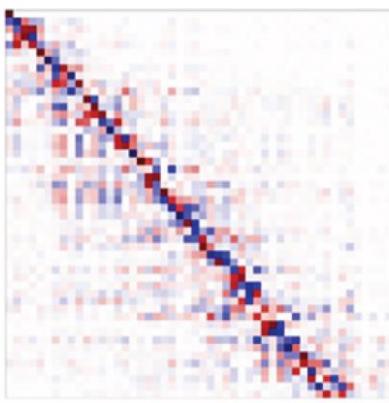




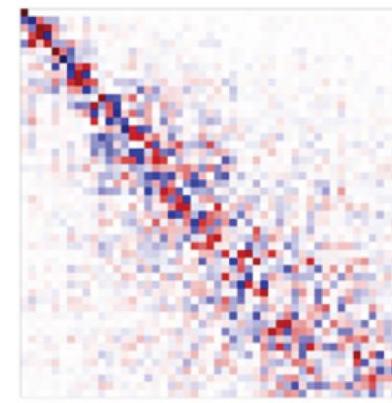
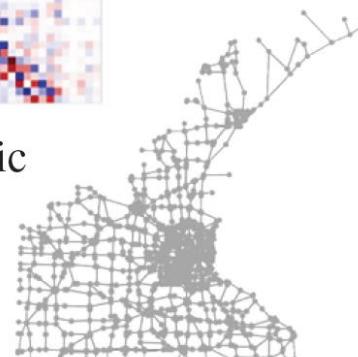
full graph



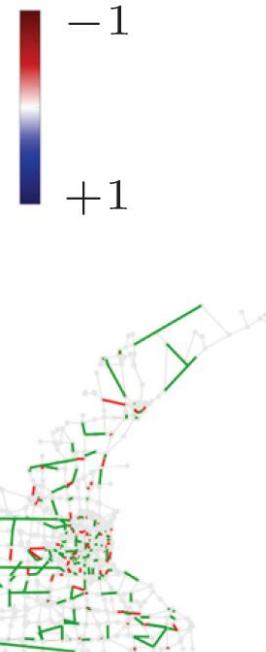
(i) isomorphic



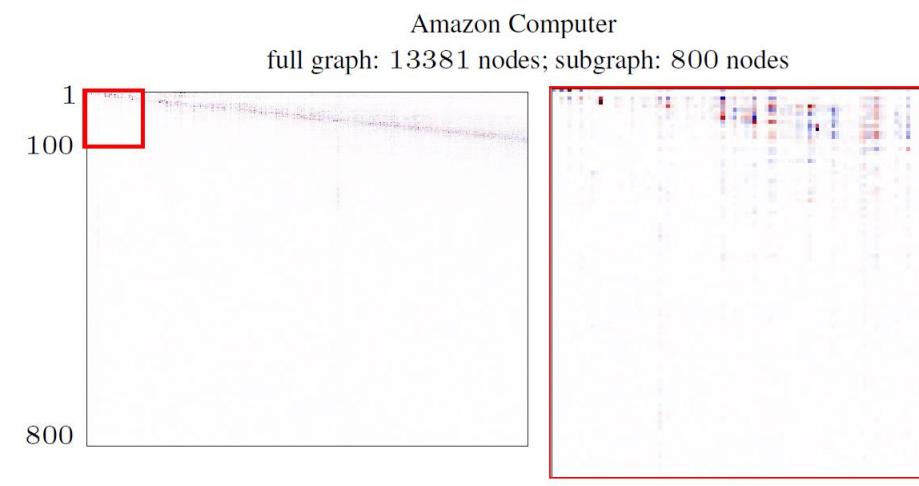
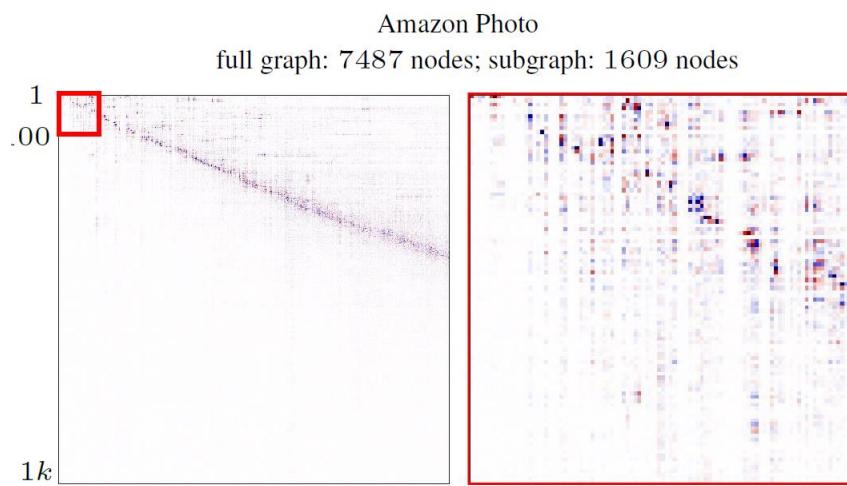
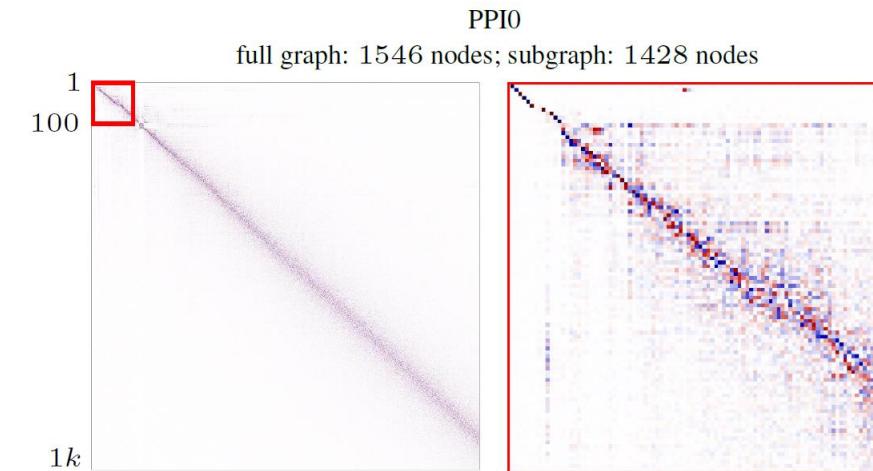
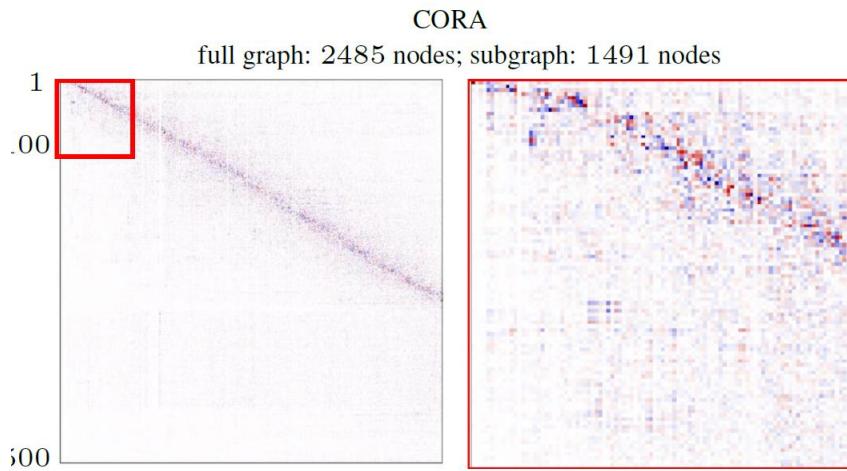
(ii) isomorphic
subgraph

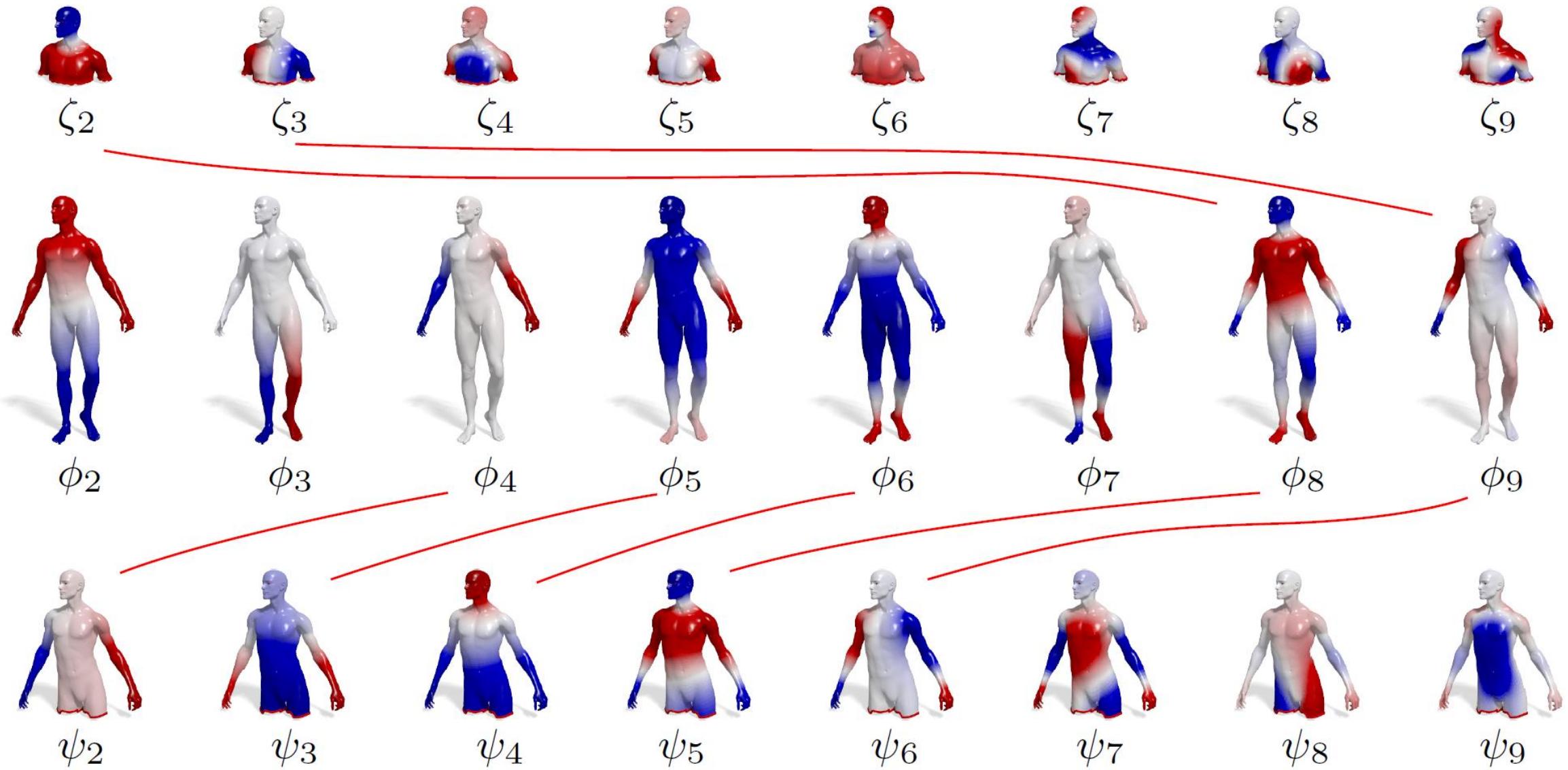


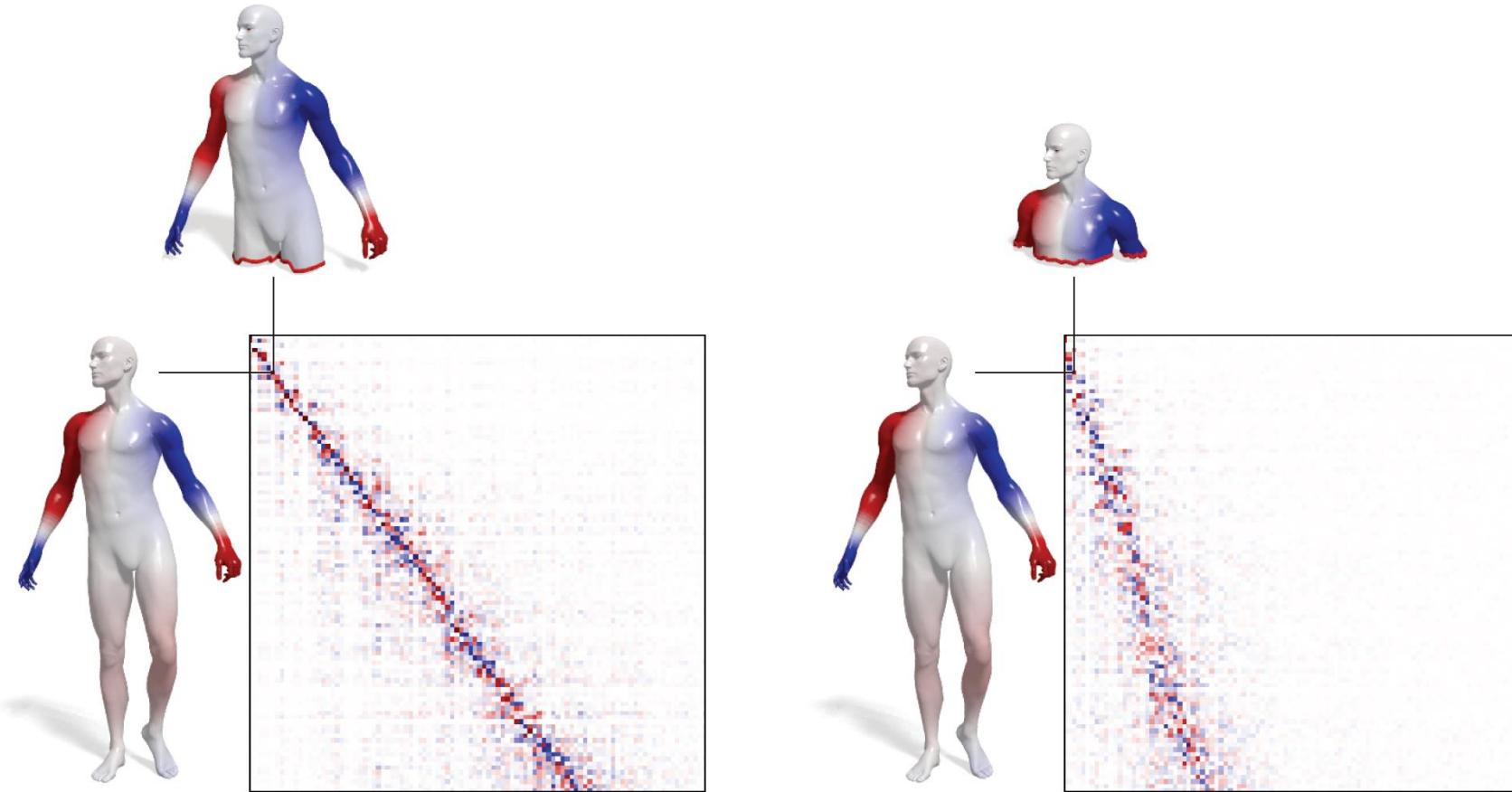
(iii) non-isomorphic
subgraph



-1
+1







Functional correspondence matrix \mathbf{C}

Slope angle depends on the areas ratio $\frac{|\mathcal{X}|}{|\mathcal{Y}|}$

