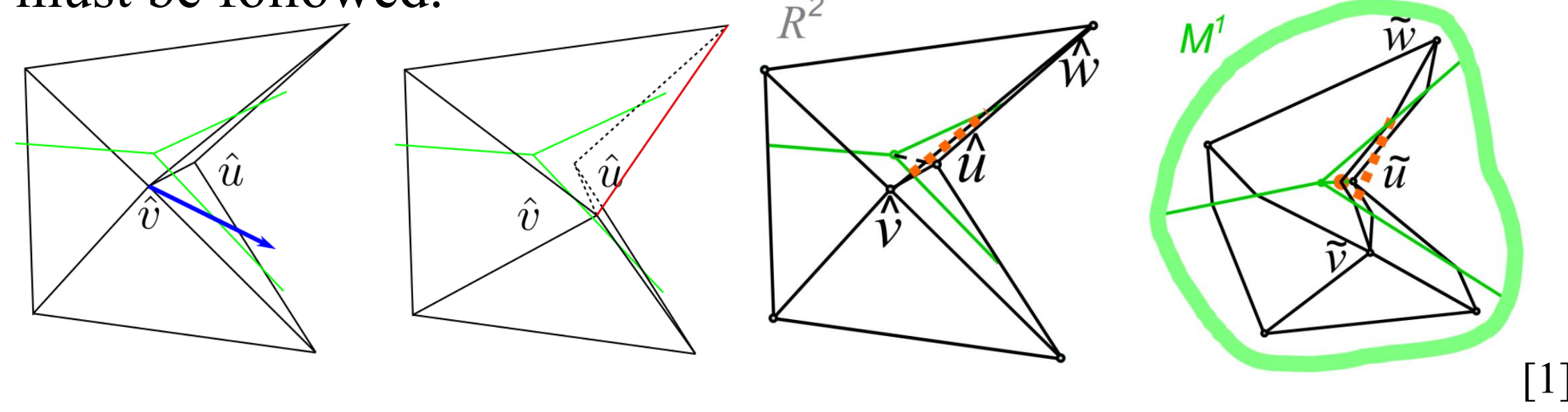


Motivation:

Meshes are the de-facto surface representation.
 Manipulation is non-trivial due to discreteness and combinatorial nature.
 Intricate rules must be followed.



Method:

We propose to encode surface maps with neural networks.

Why? Neural networks:

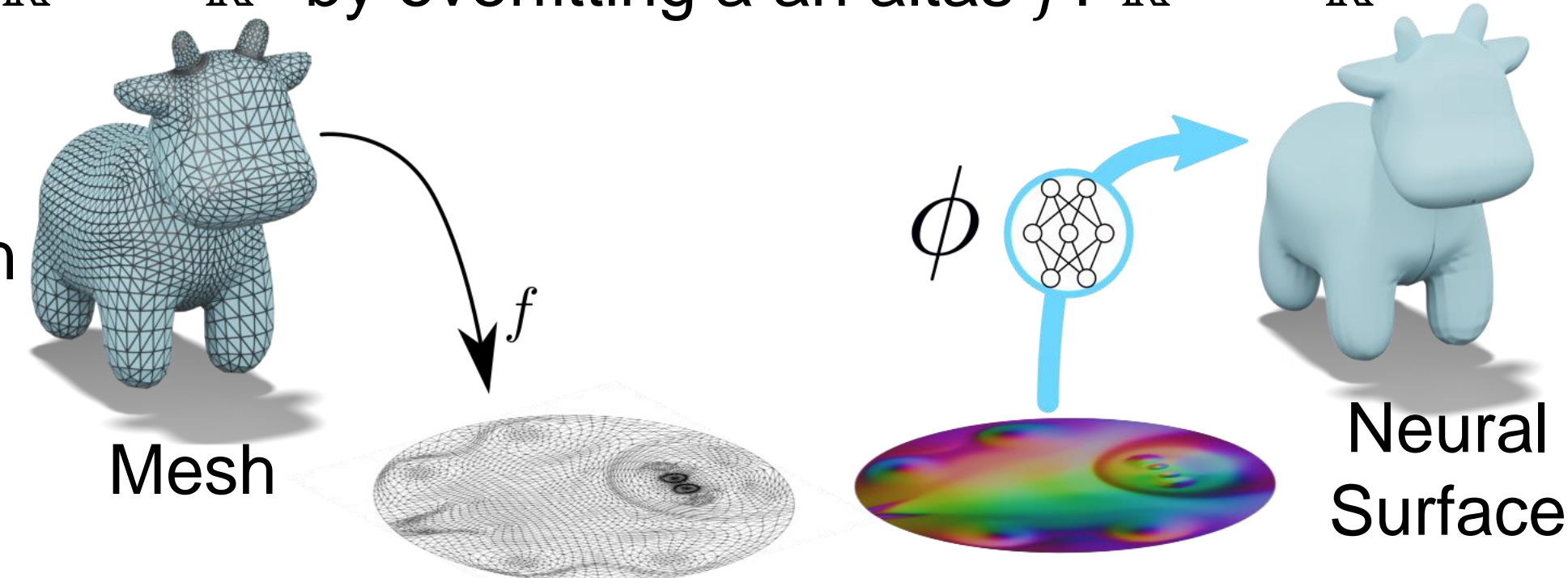
- are continuous and differentiable
- can be composed on one another

We define surfaces via atlases.

Neural Surface $\phi: \mathbb{R}^2 \rightarrow \mathbb{R}^3$ by overfitting a atlas $f: \mathbb{R}^3 \rightarrow \mathbb{R}^2$

Minimize:

- surface deviation
- normals deviation



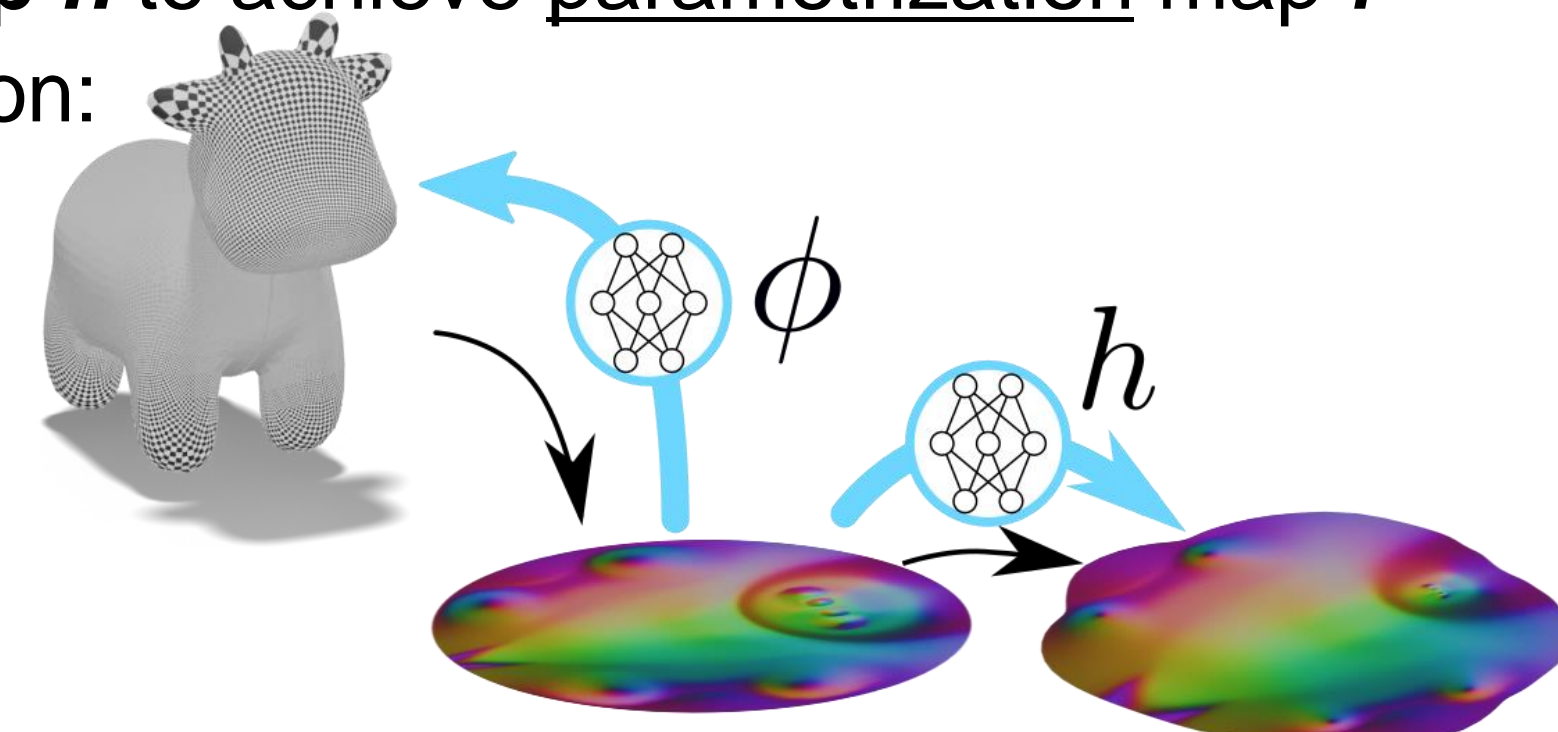
Differentiable objectives relating surfaces, e.g., distortion, can be optimized in trivial manner.

This simplifies a range of geometry processing tasks.

Compose ϕ with **neural map** h to achieve parametrization map f

Optimize end-to-end distortion:

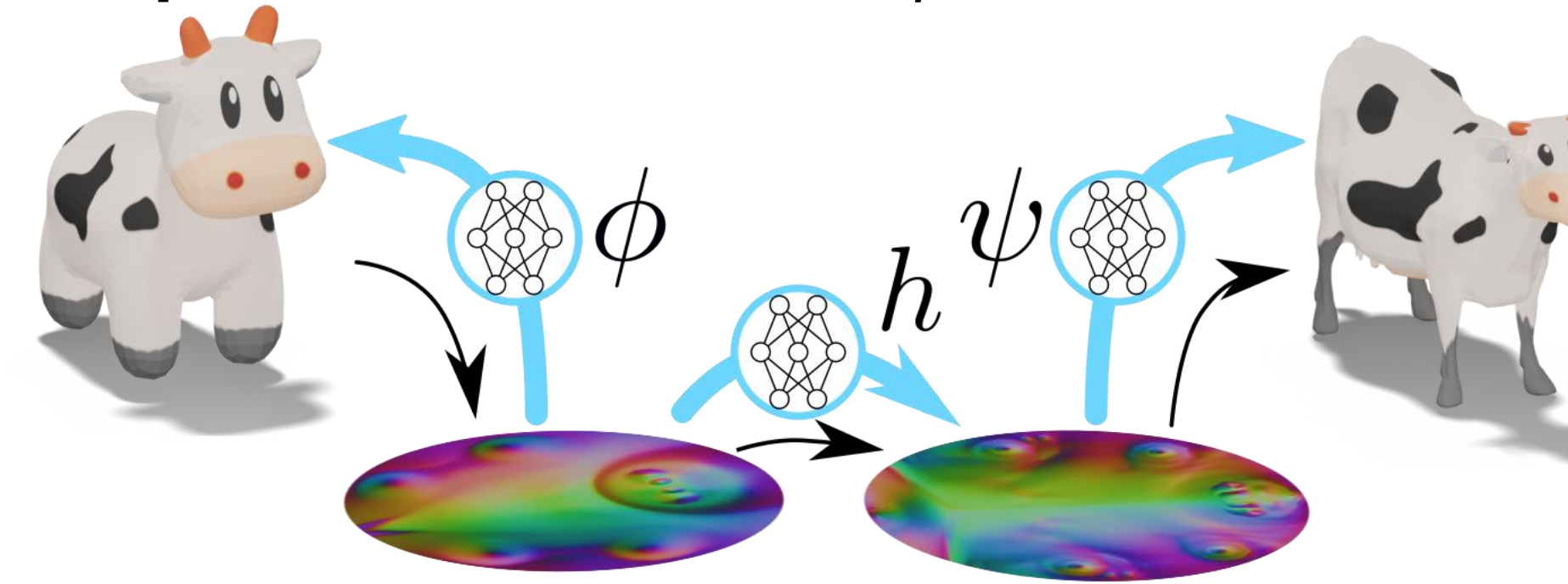
- Symmetric Dirichlet
- or
- Conformal distortion



Compose ϕ with **neural map** h and neural surface ψ for inter-surface map f

Optimize:

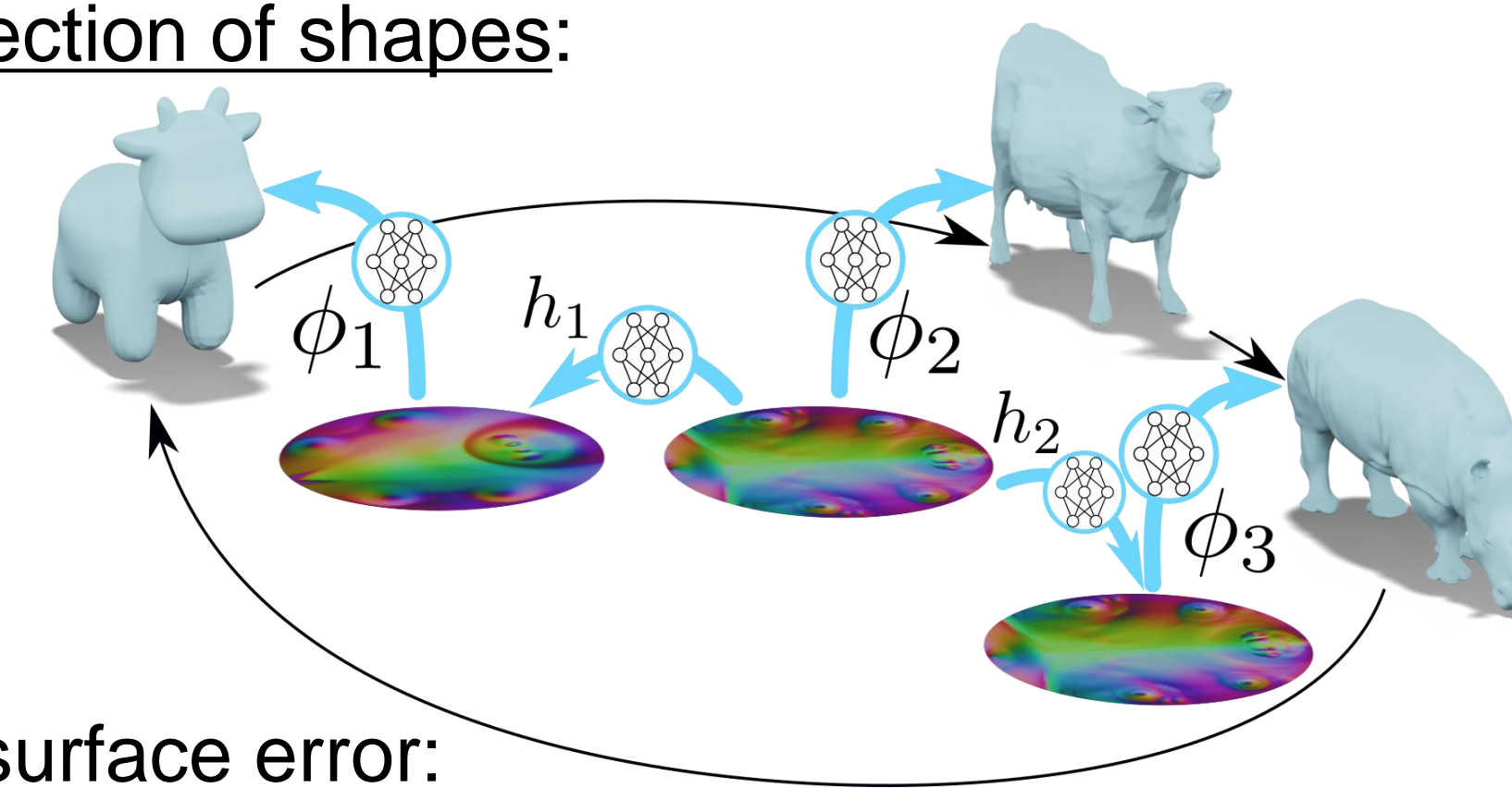
- distortion
- injectivity constraint
- domain constraints



Naturally extends to a collection of shapes:

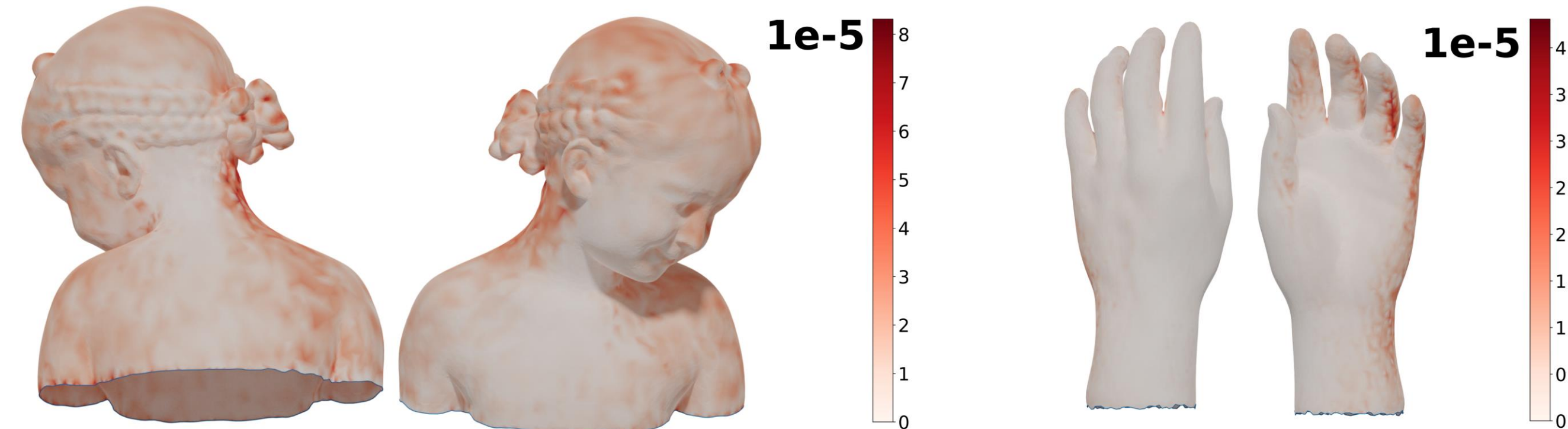
Optimize:

- distortion
- injectivity constraint
- domain constraint

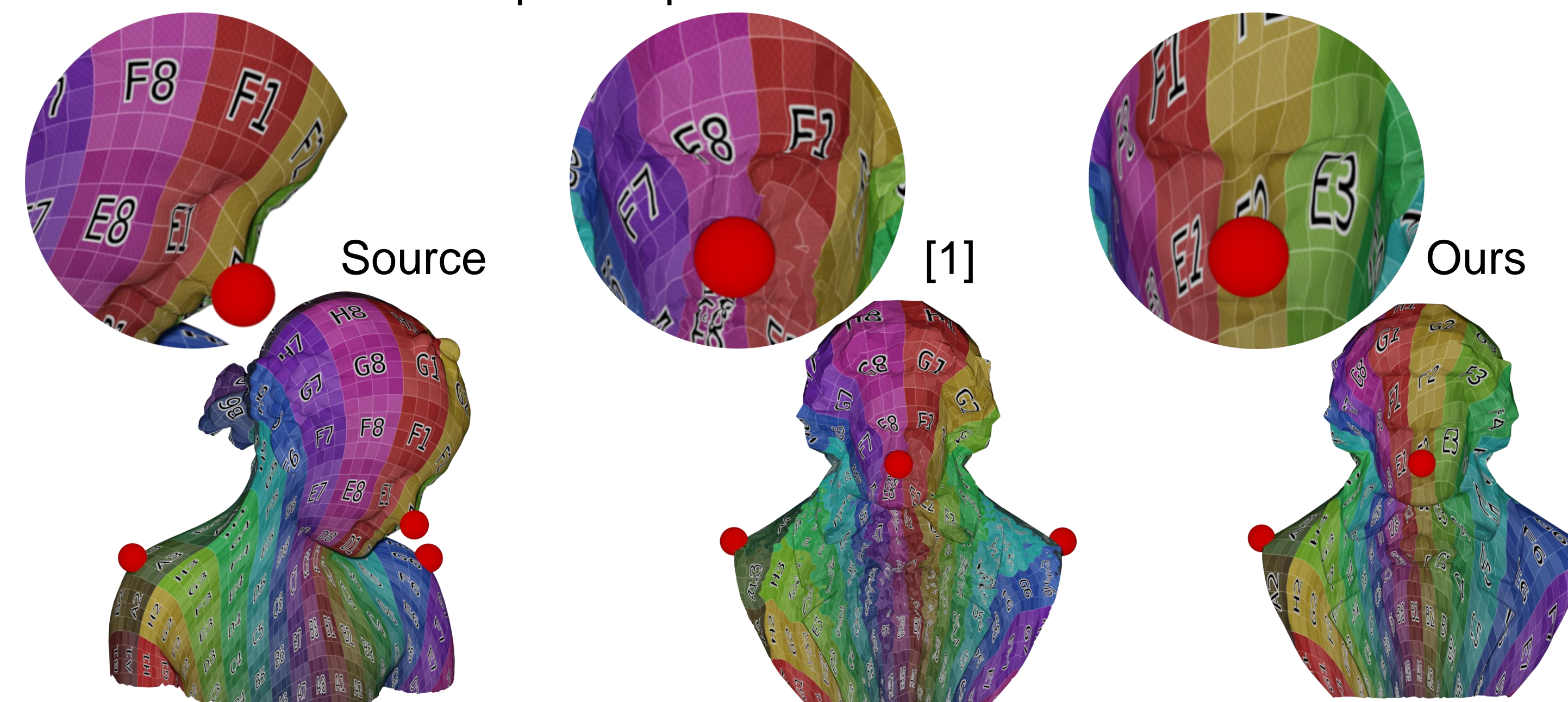


Results:

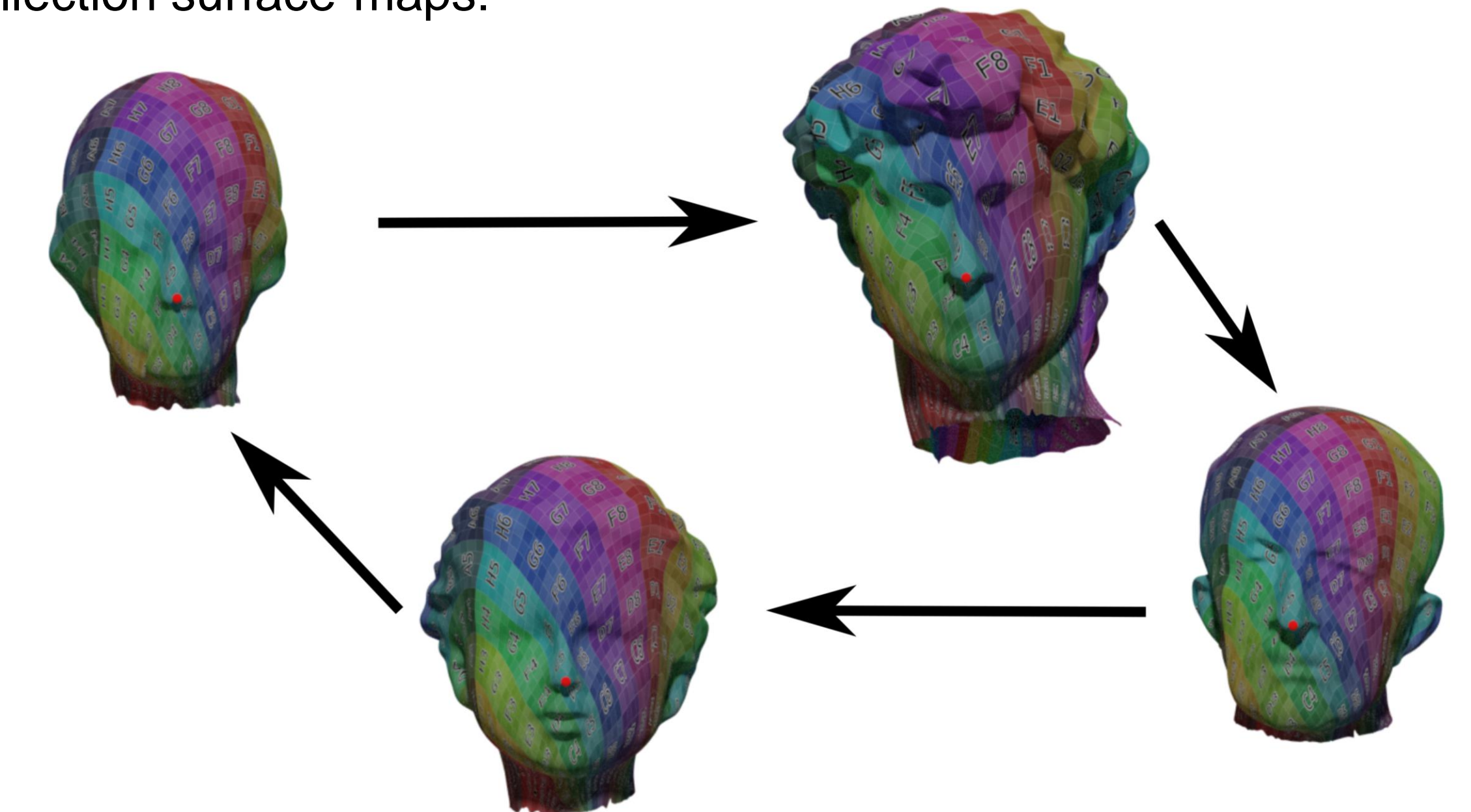
Neural Surfaces highlighting surface error:



Surface-to-surface maps comparison:



Collection surface-maps:



Surface-to-Surface map properties:

| | Continuous | Injective | End-to-end optimization |
|---------------------|------------|-----------|-------------------------|
| Functional Maps[2] | ✗ | ✗ | ✓ |
| Common Domain | ✓ | ✓ | ✗ |
| Neural Surface Maps | ✓ | ✓ | ✓ |

Conclusion:

- Novel surface representation
- Natural composition with maps

- Limited to disk topology and no partial cases
- Unable to handle partial maps
- Do not scale to large datasets

References:

- [1] Schreiner et al. - Inter-surface mapping - 2004
 [2] Ovsjanikov et al. - Functional Maps - 2012

Links:

[Project page](#)



[Code](#)

