CONICET DUDF: Differentiable Unsigned Distance Fields with hyperbolic scaling



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Motivation & Challenges

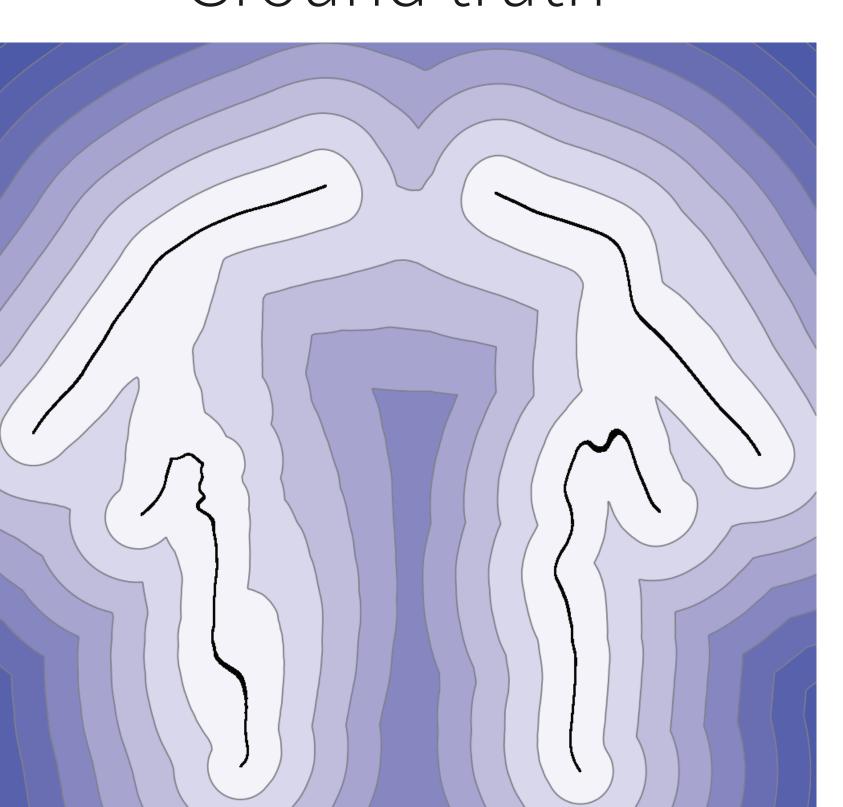
- Implicit Neural Representations (INRs) have achieved high-quality results for modeling closed surfaces.
- State-of-the-art methods for open surfaces often suffer from a lack of detail and frequent topological errors, such as incorrectly closing holes.

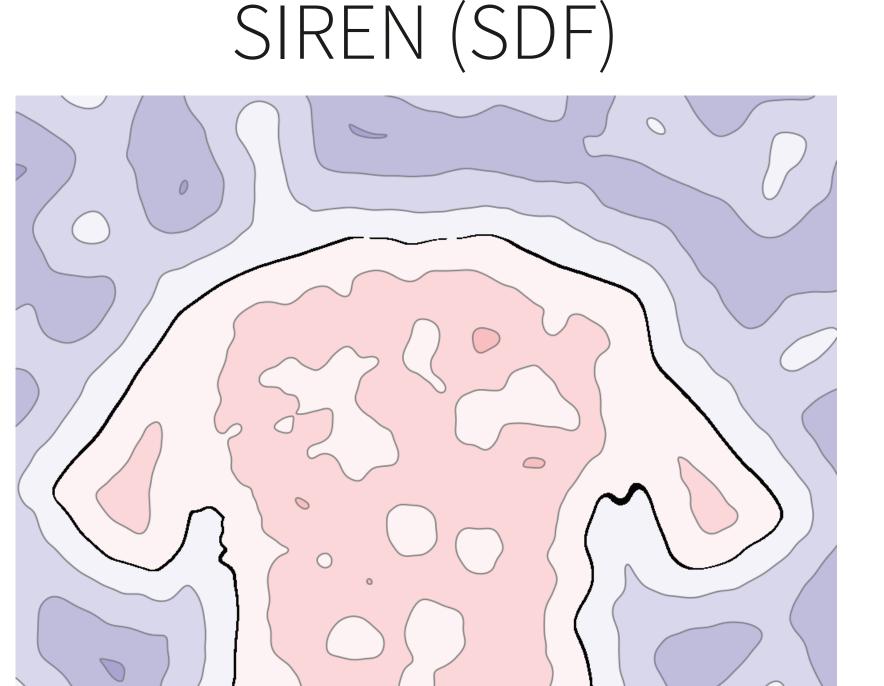
Proposed Method: We introduce a novel approach tailored for open surface implicit representation based on differentiable neural networks (SIREN) to achieve greater accuracy.

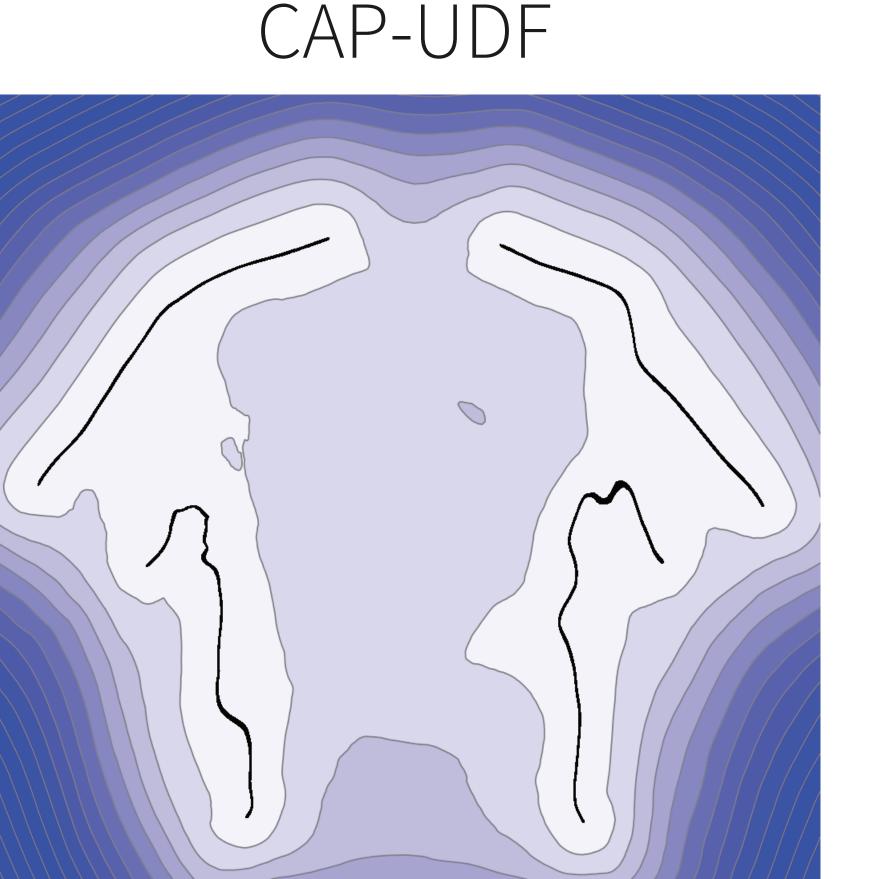
Results

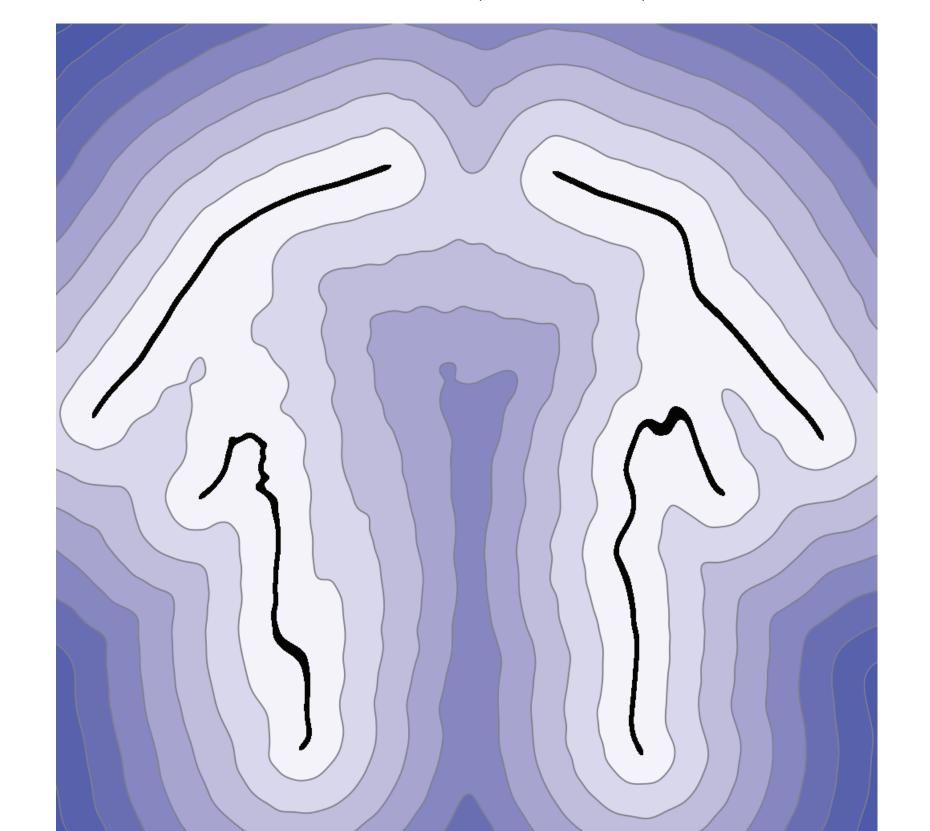
• DUDF shows better performance than SOTA on both, open and closed surfaces.

Ground truth





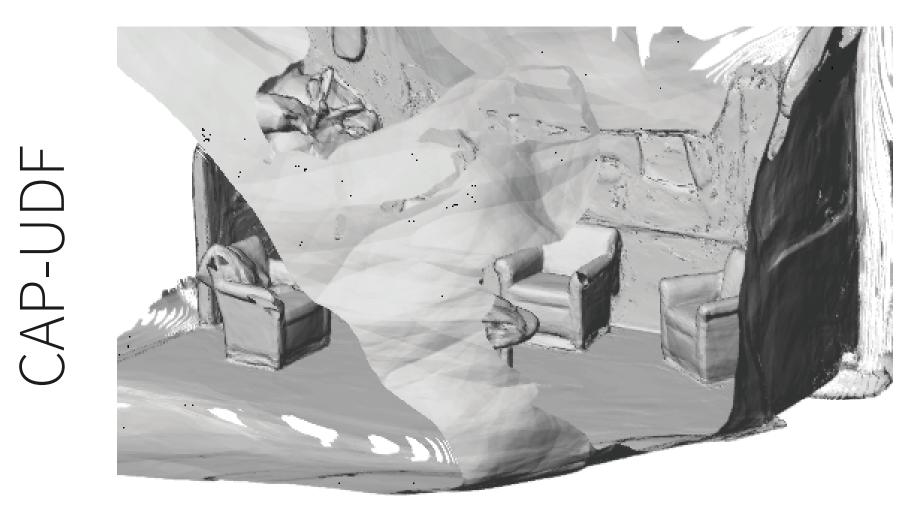


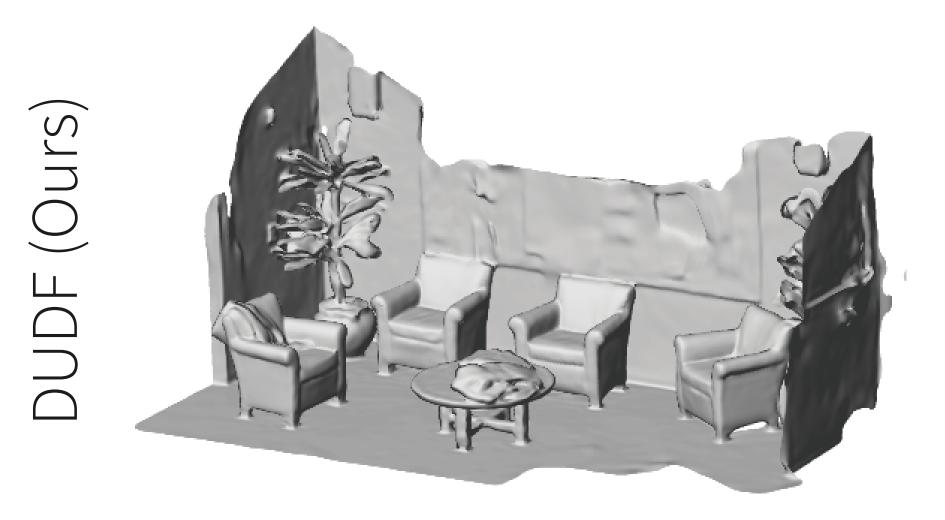


DUDF (Ours)

Rendering

- Our representations precisely approximate the distance field, enhancing compatibility with sphere tracing rendering algorithms.
- DUDF's ability to compute the normal field enables the of illumination techniques, which was not possible with earlier methods.





Method

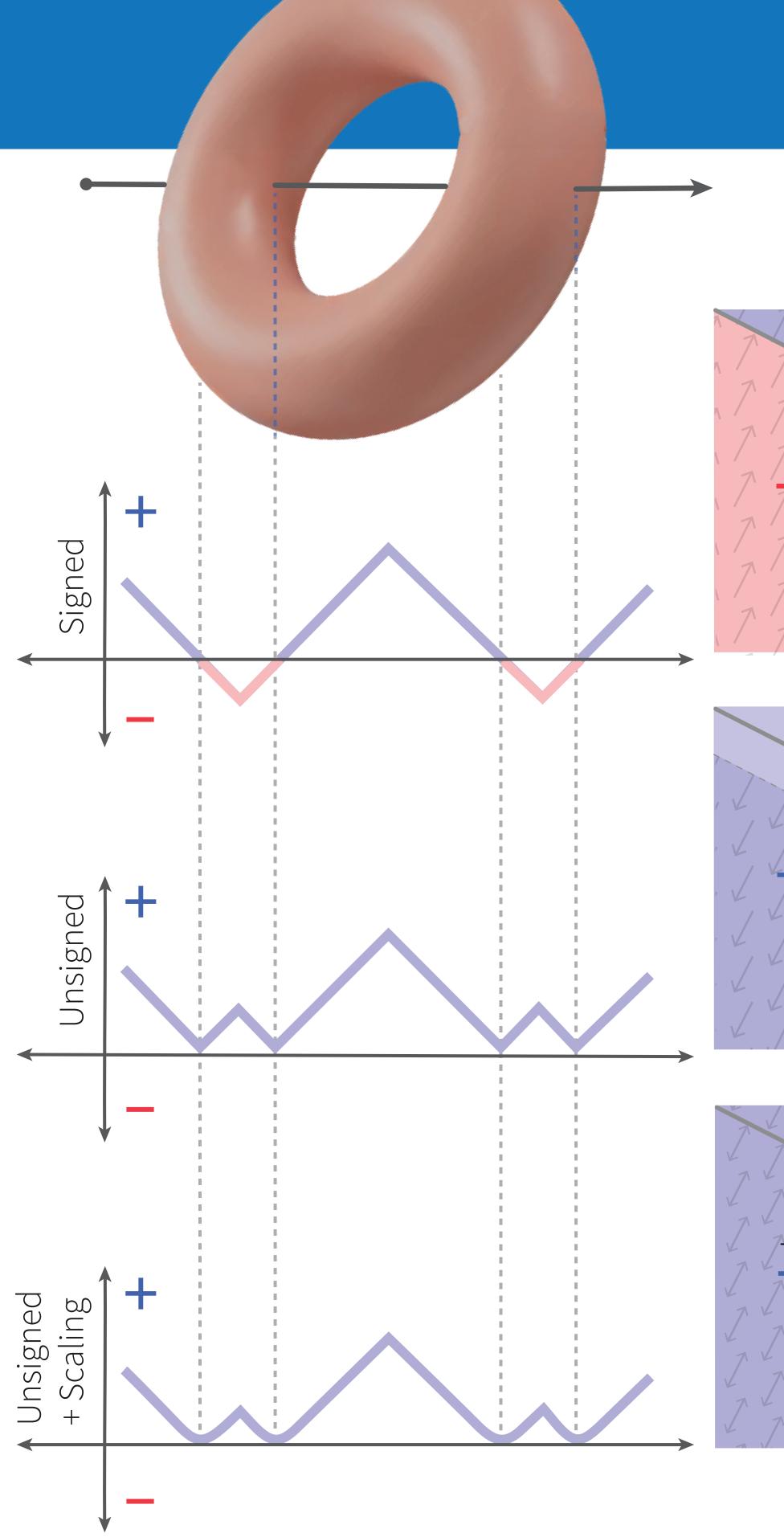
- ullet Unsigned distance function $\,d_{\mathcal{S}}\,$ is not differentiable at the isosurface \mathcal{S} , hence it cannot be approximated with differentiable NNs.
- Instead, we approximate:

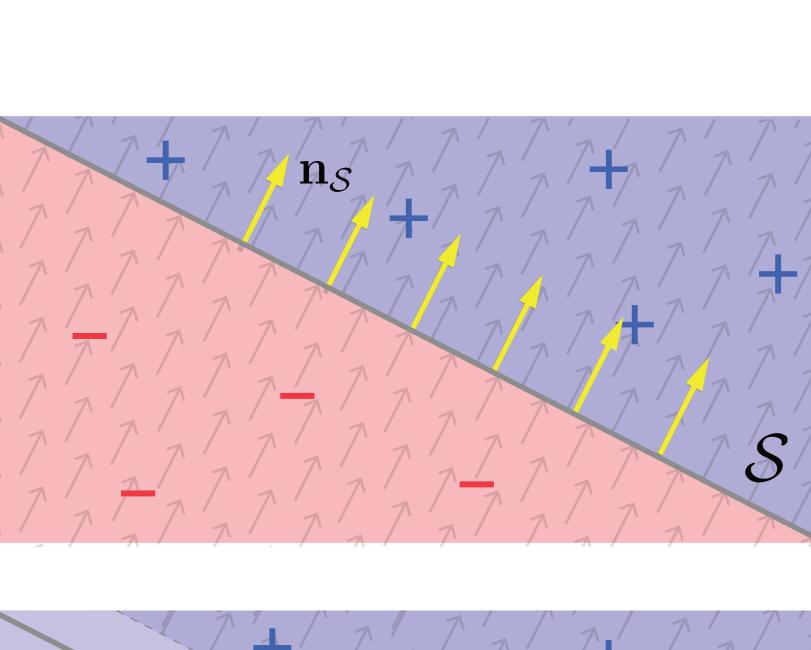
$$t_{\mathcal{S}}(\mathbf{x}) = d_{\mathcal{S}}(\mathbf{x}) anh(lpha d_{\mathcal{S}}(\mathbf{x}))$$

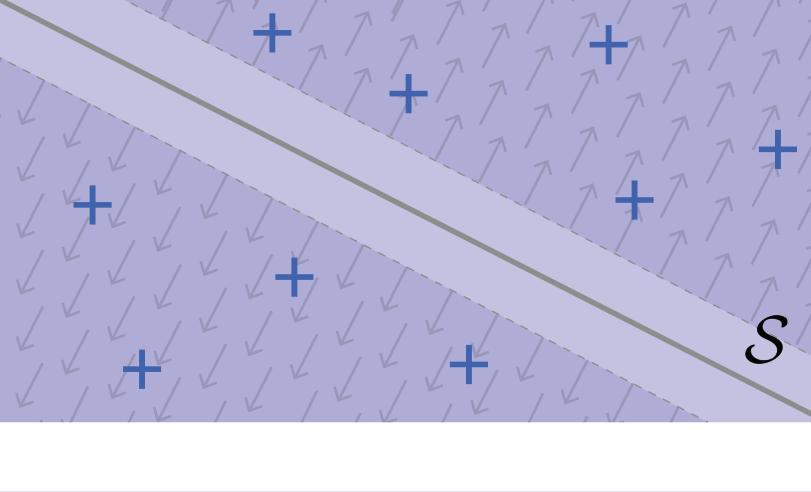
which is solution of the Eikonal problem:

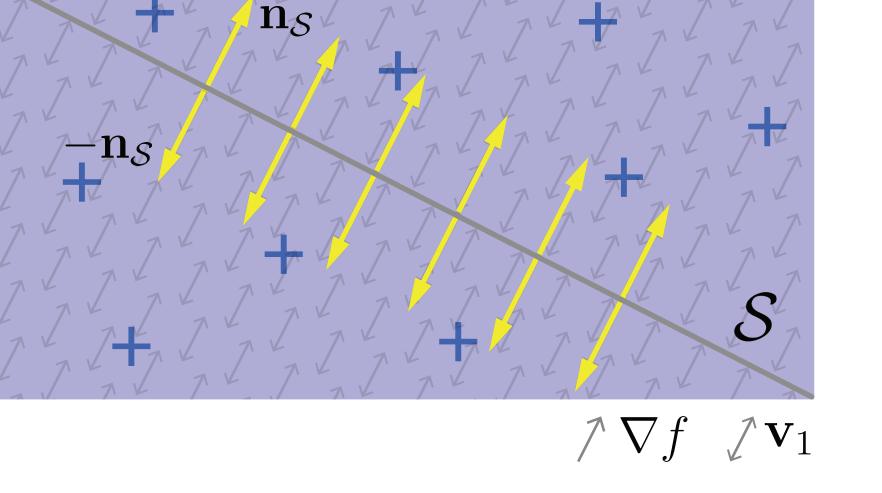
$$egin{cases} \|
abla f\| &= anh(lpha d_{\mathcal{S}}) + lpha d_{\mathcal{S}}ig(1 - anh^2(lpha d_{\mathcal{S}})ig). \ f_{|_{\mathcal{S}}} &= 0 \
abla f_{|_{\mathcal{S}}} &= \mathbf{0} \ \mathbf{v_1}ig(f_{|_{\mathcal{S}}}ig) &= \pm \mathbf{n}_{\mathcal{S}} \end{cases}$$

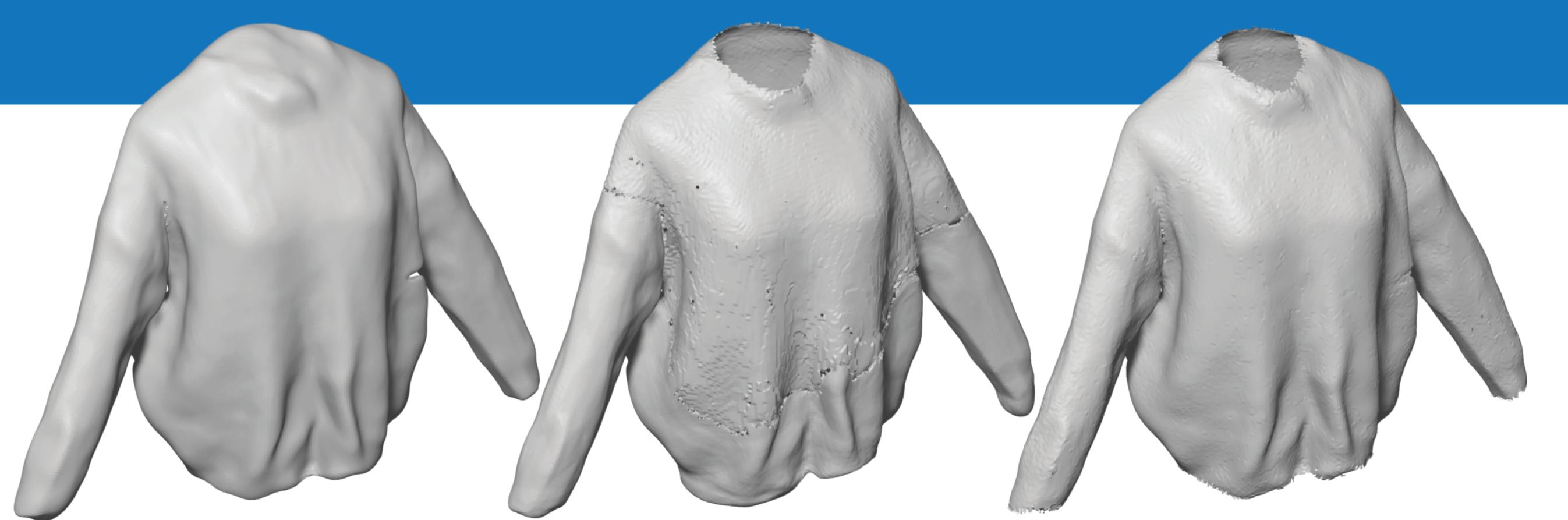
 We align the field's maximum principal curvature $\mathbf{v_1}$ with the surface normals $\mathbf{n}_{\mathcal{S}}$ for better reconstruction and computation of topological properties.











Conditioning

• We condition our differentiable neural networks to satisfy the Eikonal problem:

$$\mathcal{L} = \lambda_e \mathcal{L}_{\mathrm{Eikonal}} + \lambda_d \mathcal{L}_{\mathrm{Dirichlet}} + \lambda_n \mathcal{L}_{\mathrm{Neumann}} + \lambda_g \mathcal{L}_{M \; \mathrm{Curv}}$$

$$egin{aligned} \mathcal{L}_{ ext{Eikonal}} &= \int_{\mathcal{C}} |\|
abla f_{ heta}(\mathbf{x}) \| - \phi(\mathbf{x}) | d\mathbf{x} \end{aligned} \qquad egin{aligned} \mathcal{L}_{ ext{Neumann}} &= \int_{\mathcal{S}} \|
abla f_{ heta}(\mathbf{x}) \| d\mathbf{x} \end{aligned} \qquad \mathcal{L}_{ ext{Dirichlet}} &= \int_{\mathcal{S}} |f_{ heta}(\mathbf{x})| d\mathbf{x} \end{aligned} \qquad egin{aligned} \mathcal{L}_{ ext{MCurv}} &= \int_{\mathcal{S}} 1 - |\mathbf{v_1}(\mathbf{x}) \cdot \mathbf{n_{\mathcal{S}}}(\mathbf{x}) | d\mathbf{x} \end{aligned}$$

Curvatures

 From the computed normal field we can extract high order surface properties such as mean and gaussian curvature using automatic differentiation methods. Unaivalable with earlier methods.

