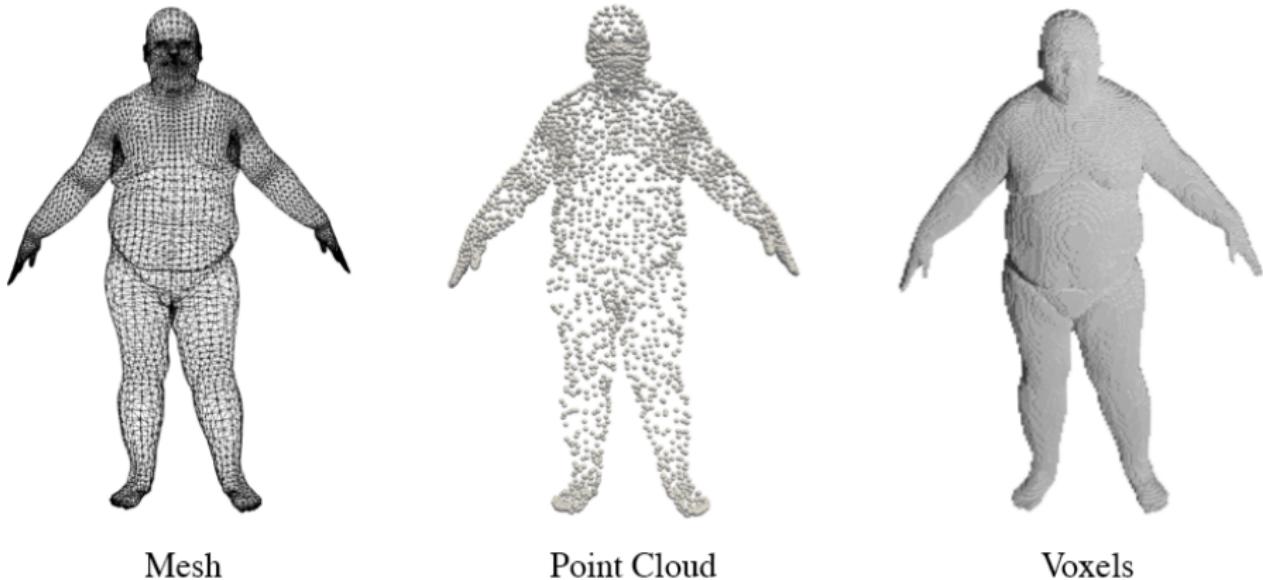


Sign Agnostic Learning with Derivatives of 3D Geometry from Raw Data

Debabrata Ghosh

Representations of 3D shapes



Mesh

Point Cloud

Voxels

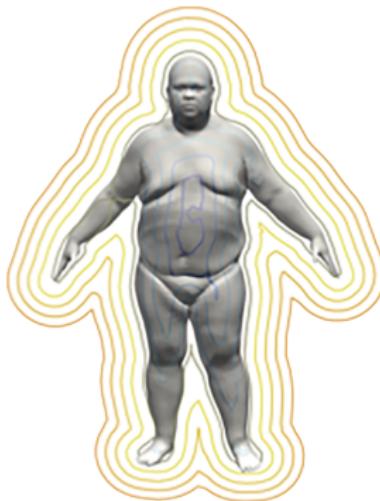
Discrete Representation of 3D Shape [1]

Representations of 3D shapes

Surface represented as zero level-set: $\mathcal{S} = \{x \in \mathbb{R}^3 \mid f(x) = 0\}$

Representations of 3D shapes

Surface represented as zero level-set: $\mathcal{S} = \{x \in \mathbb{R}^3 \mid f(x) = 0\}$



Continuous (Implicit) Representation of 3D Shape [1]

Implicit Neural Representation

Why Neural Networks

- flexibility and approximation power [4]

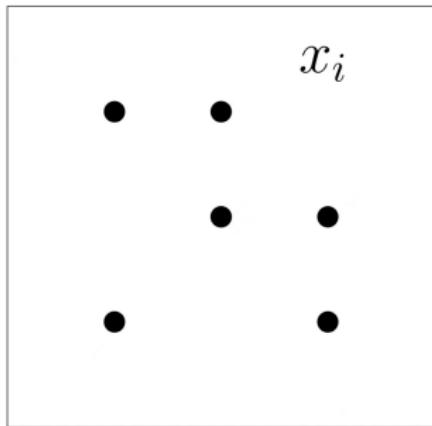
Implicit Neural Representation

Why Neural Networks

- flexibility and approximation power [4]
- optimization and generalization properties

Learning Implicit Neural Representation

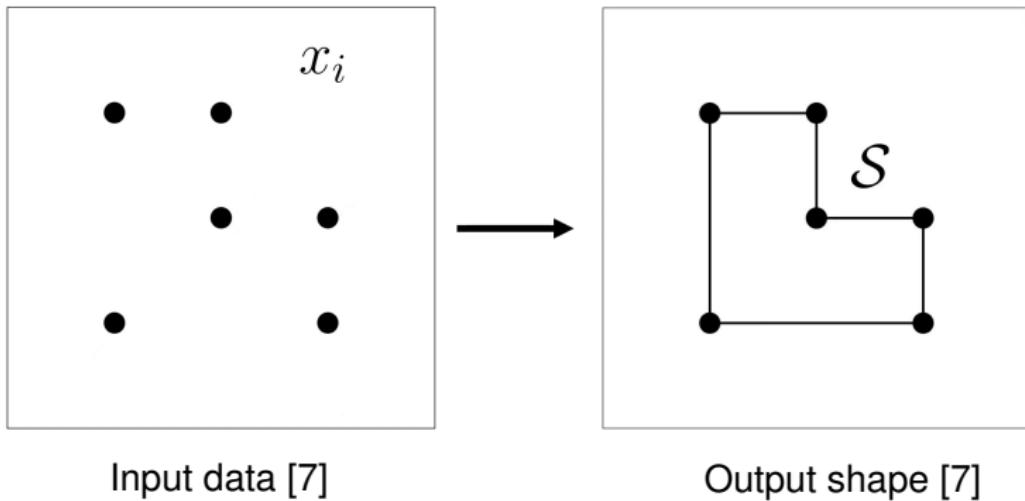
Methods



Input data [7]

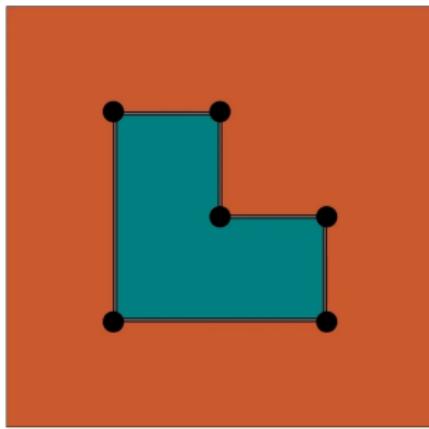
Learning Implicit Neural Representation

Methods



Learning Implicit Neural Representation

Methods



Occupancy function

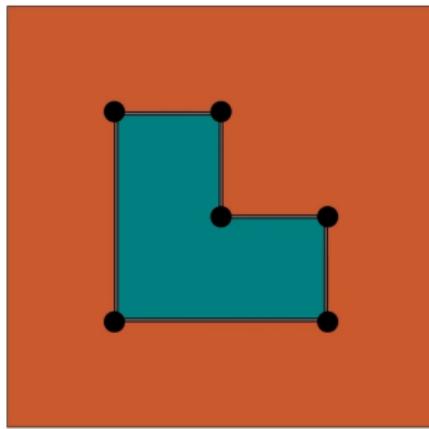
$$\Phi_{ind}(x) = \begin{cases} 0 & x \text{ outside} \\ 1 & x \text{ inside} \end{cases} [7]$$

3

Debabrata Ghosh
Sign Agnostic Learning with Derivatives
May 23, 2023

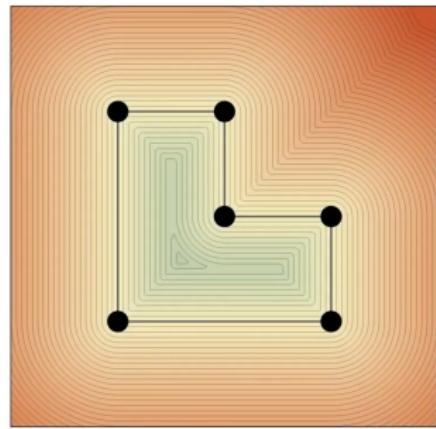
Learning Implicit Neural Representation

Methods



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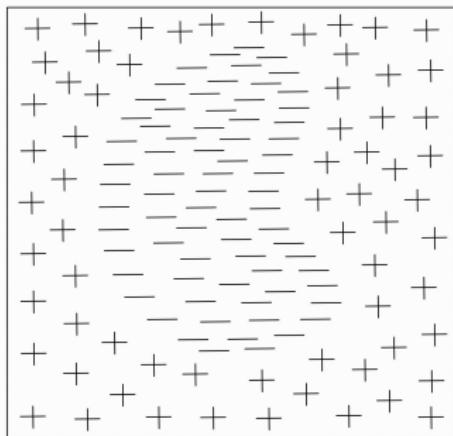


Signed distance function

$$\Phi_{sdf}(x) = (-1)^{\Phi_{ind}(x)} \min_{z \in \mathcal{X}} \|x - z\|_2 [7]$$

Learning Implicit Neural Representation

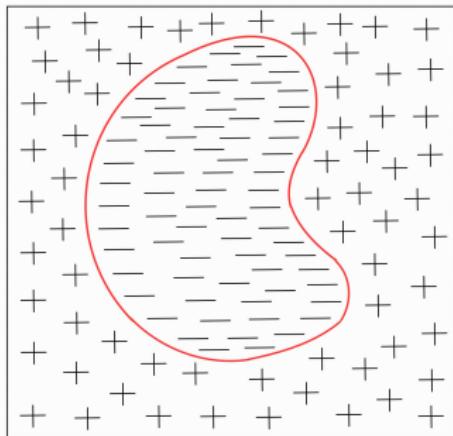
Challenges



Data available for supervised
learning [2]

Learning Implicit Neural Representation

Challenges



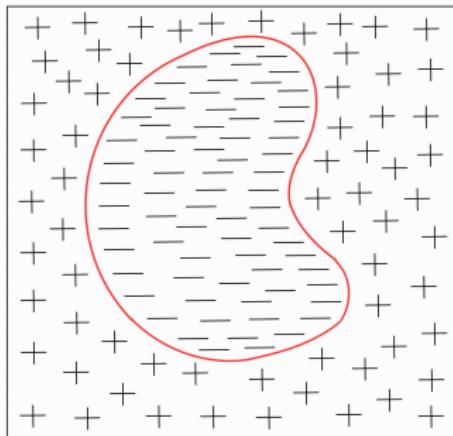
Data available for supervised learning [2]

4

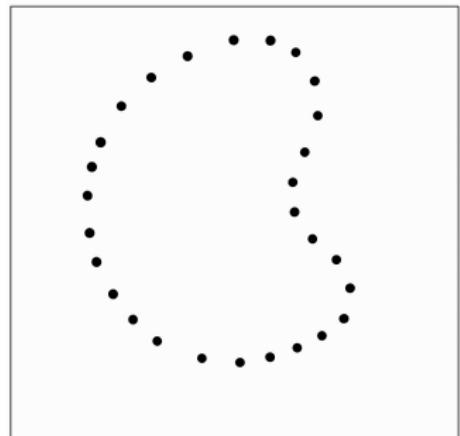
Debabrata Ghosh
Sign Agnostic Learning with Derivatives
May 23, 2023

Learning Implicit Neural Representation

Challenges



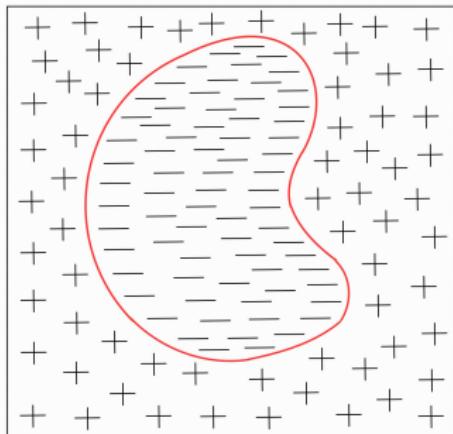
Data available for supervised learning [2]



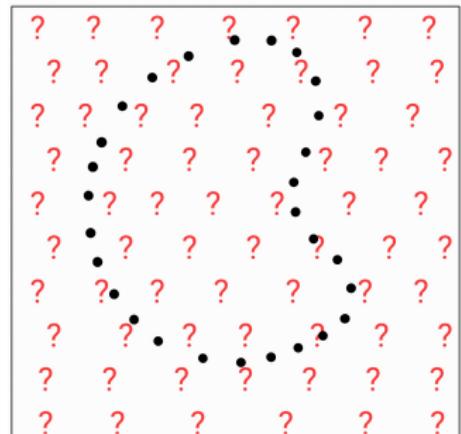
Raw data [2]

Learning Implicit Neural Representation

Challenges



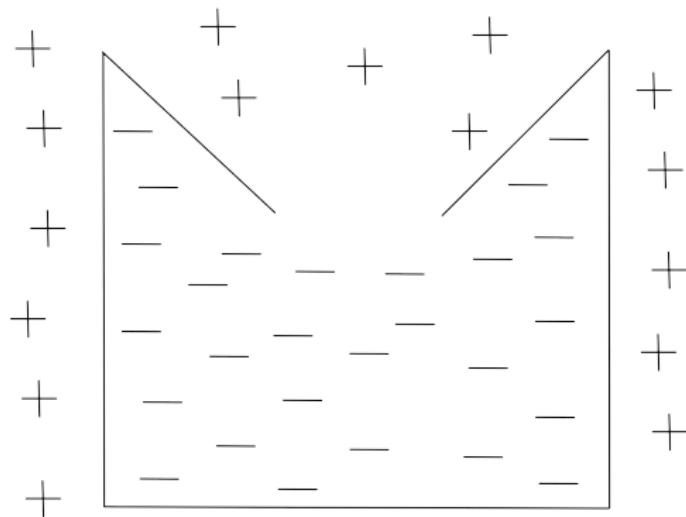
Data available for supervised learning [2]



Raw data [2]

Learning Implicit Neural Representation

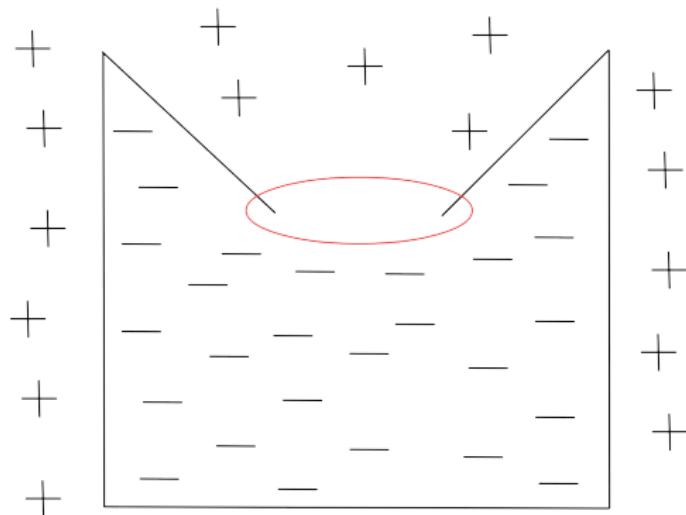
Challenges



Learning missing parts [2]

Learning Implicit Neural Representation

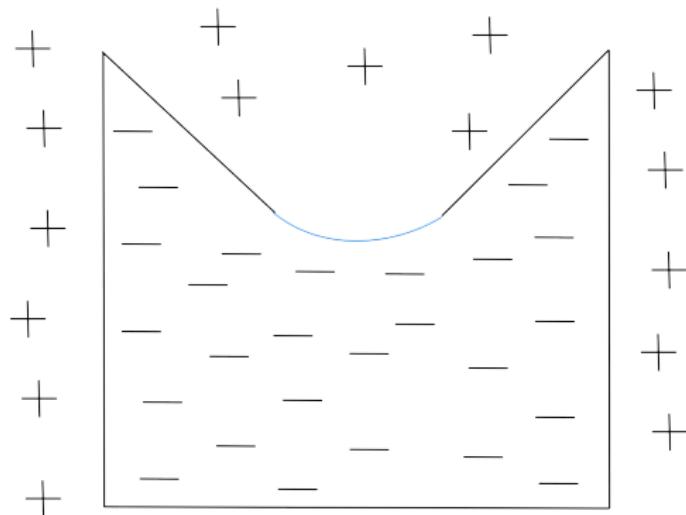
Challenges



Learning missing parts [2]

Learning Implicit Neural Representation

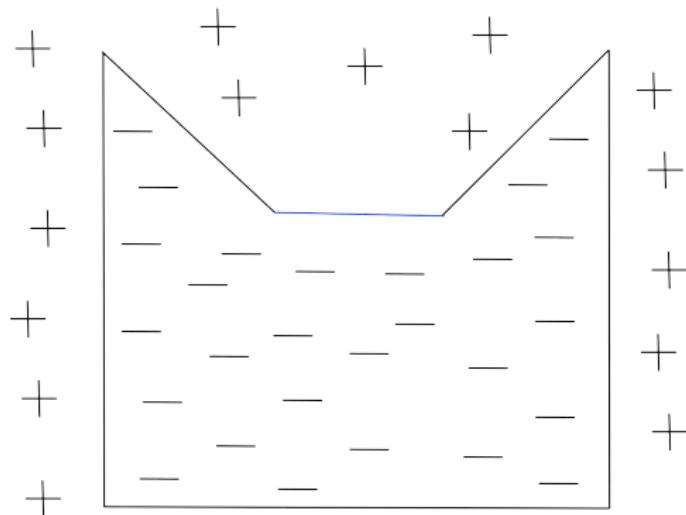
Challenges



Learning missing parts [2]

Learning Implicit Neural Representation

Challenges



Learning missing parts [2]

Background: Sign Agnostic Learning (SAL)

Unsigned Distance Function



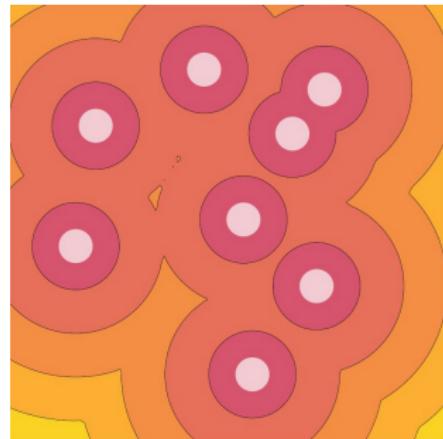
$$L^0 \text{ distance, } h_0(z) = \begin{cases} 0 & z \in \mathcal{X} \\ 1 & z \notin \mathcal{X} \end{cases} [2]$$

Background: Sign Agnostic Learning (SAL)

Unsigned Distance Function



$$L^0 \text{ distance}, h_0(z) = \begin{cases} 0 & z \in \mathcal{X} \\ 1 & z \notin \mathcal{X} \end{cases} [2]$$



$$L^2 \text{ (Euclidean) distance}, h_2(z) = \min_{x \in \mathcal{X}} \|z - x\|_2 [2]$$

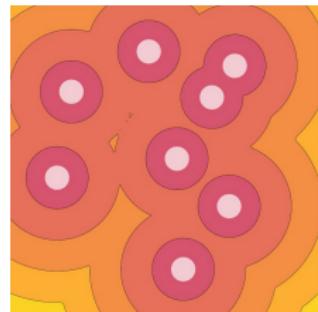
Background: Sign Agnostic Learning (SAL)

SAL Loss Function

$$\text{loss}(\theta) = \mathbb{E}_x \ell(f(x; \theta), h(x))$$

Loss function

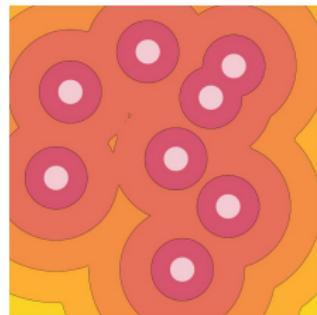
Unsigned distance



Background: Sign Agnostic Learning (SAL)

SAL Loss Function

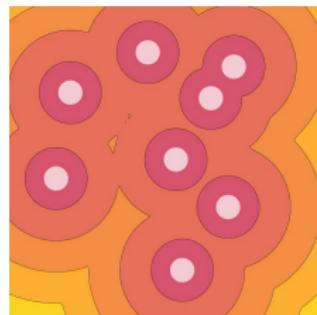
$$\text{loss}(\theta) = \mathbb{E}_{\mathbf{x}} |f(\mathbf{x}; \theta), h(\mathbf{x})|$$
$$\text{loss}(\theta) = \mathbb{E}_{\mathbf{x}} (f(\mathbf{x}; \theta), h(\mathbf{x}))^2$$



Background: Sign Agnostic Learning (SAL)

SAL Loss Function

$$\text{loss}(\theta) = \mathbb{E}_{\mathbf{x}} |f(\mathbf{x}; \theta), h(\mathbf{x})| \quad \times$$
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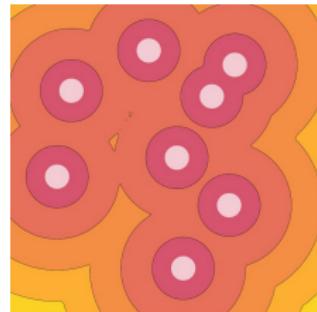
Background: Sign Agnostic Learning (SAL)

SAL Loss Function

$$\text{loss}(\theta) = \mathbb{E}_{\mathbf{x}} \tau(f(\mathbf{x}; \theta), h(\mathbf{x}))$$



Sign agnostic dissimilarity



Background: Sign Agnostic Learning (SAL)

SAL Loss Function

$$\text{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{x}} \tau(f(\mathbf{x}; \boldsymbol{\theta}), h(\mathbf{x}))$$



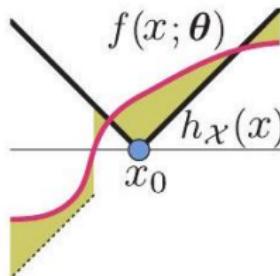
Sign agnostic dissimilarity

$$\tau(a, b) = ||a| - b|$$

Background: Sign Agnostic Learning (SAL)

SAL Loss Function

$$\text{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{x}} \tau(f(\mathbf{x}; \boldsymbol{\theta}), h(\mathbf{x}))$$
$$\tau(a, b) = ||a - b|| \quad h(x) = |x - x_0|$$



Sign agnostic learning in 1-D case [2]

Background: Sobolev Training

Adding Derivatives

- Target function: $f(x; \theta) = \max\{ax, bx\} + c$ [8]

Background: Sobolev Training

Adding Derivatives

- Target function: $f(x; \theta) = \max\{ax, bx\} + c$ [8]
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Background: Sobolev Training

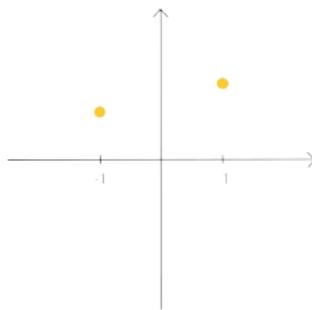
Adding Derivatives

- Target function: $f(x; \theta) = \max\{ax, bx\} + c$ [8]
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Background: Sobolev Training

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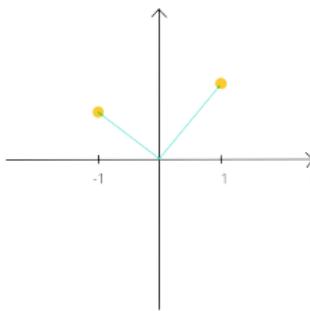
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Background: Sobolev Training

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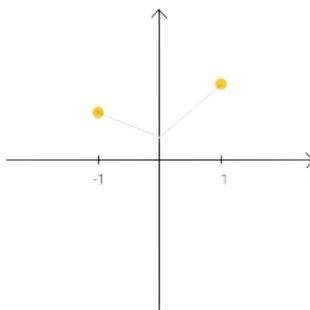
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Background: Sobolev Training

Adding Derivatives

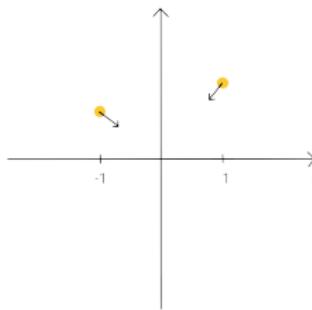
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Background: Sobolev Training

Adding Derivatives

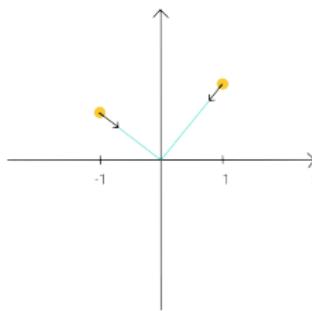
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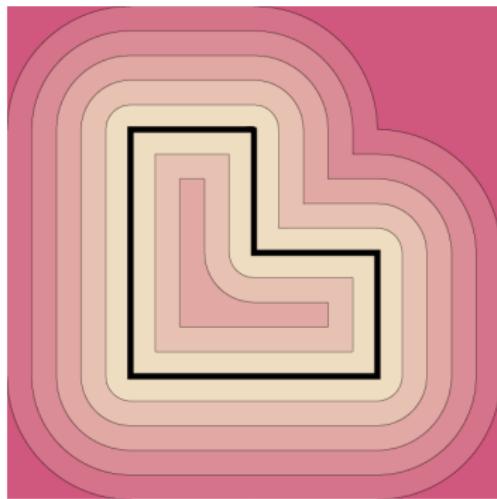
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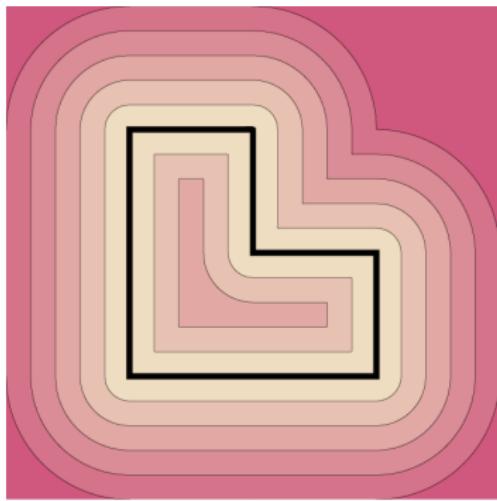


Limitations of SAL

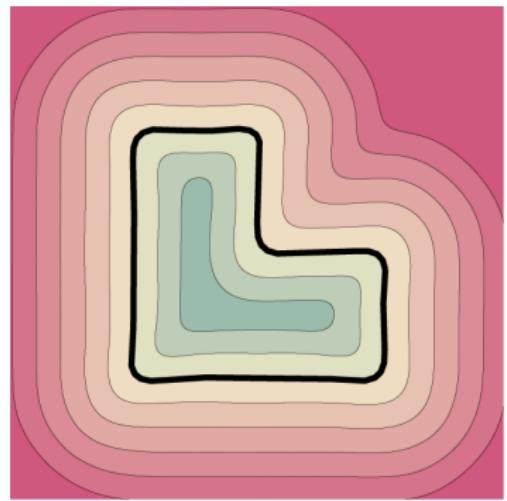


Unsigned distance [3]

Limitations of SAL

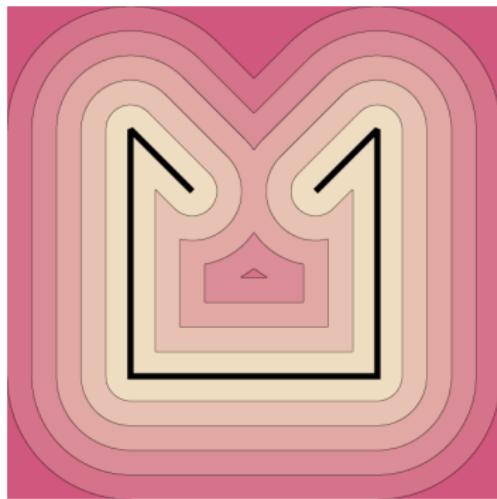


Unsigned distance [3]



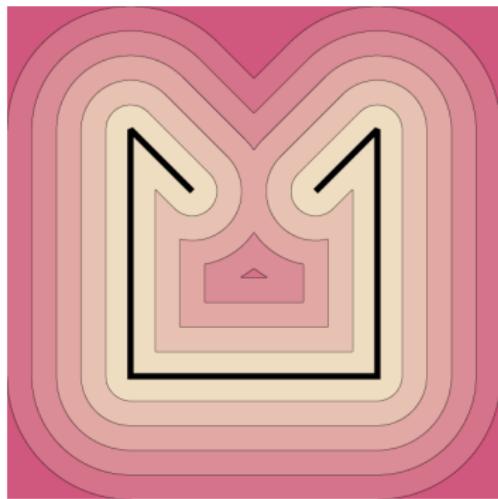
Level sets after SAL training [3]

Limitations of SAL

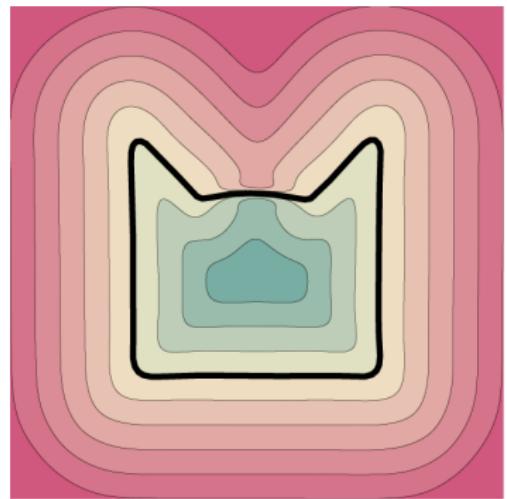


Unsigned distance [3]

Limitations of SAL



Unsigned distance [3]



Level sets after SAL training [3]

Sign Agnostic Learning with Derivatives (SALD)

Extension of SAL Loss

$$\text{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{x}} \tau(f(\mathbf{x}; \boldsymbol{\theta}), h(\mathbf{x}))$$

Sign Agnostic Learning with Derivatives (SALD)

Extension of SAL Loss

$$\text{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{x}} \textcolor{teal}{T}(f(\mathbf{x}; \boldsymbol{\theta}), \textcolor{orange}{h}(\mathbf{x})) + \mathbb{E}_{\mathbf{x}} \textcolor{teal}{T}(\nabla_{\mathbf{x}} f(\mathbf{x}; \boldsymbol{\theta}), \nabla_{\mathbf{x}} \textcolor{orange}{h}(\mathbf{x}))$$

Sign Agnostic Learning with Derivatives (SALD)

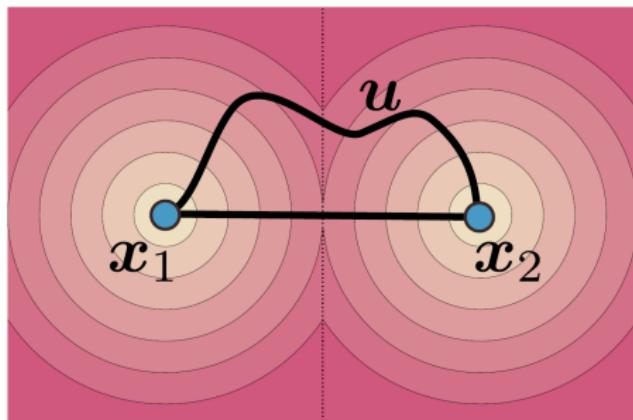
Minimal Surface Property

Minimizes the surface area of missing parts [13, 3].

Sign Agnostic Learning with Derivatives (SALD)

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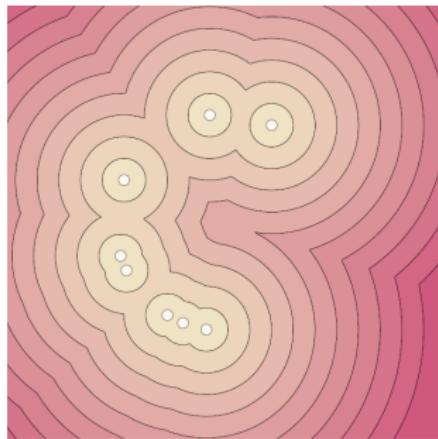


Minimal Surface Property in 2D [3]

Sign Agnostic Learning with Derivatives (SALD)

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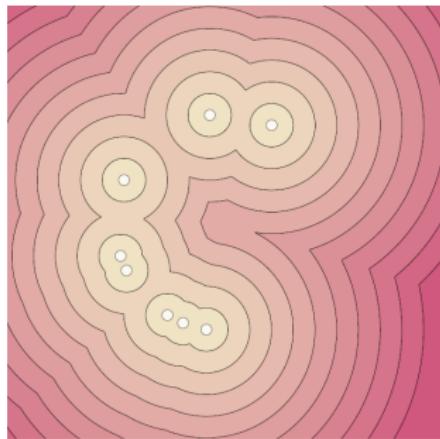


Unsigned distance [3]

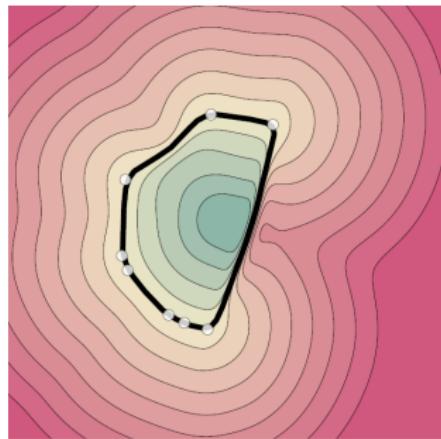
Sign Agnostic Learning with Derivatives (SALD)

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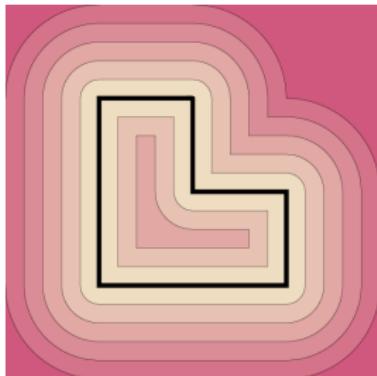
Unsigned distance [3]



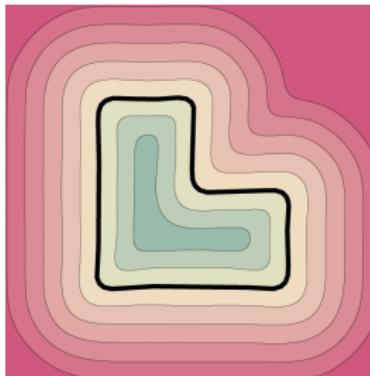
Level sets after SALD training [3]

Sign Agnostic Learning with Derivatives (SALD)

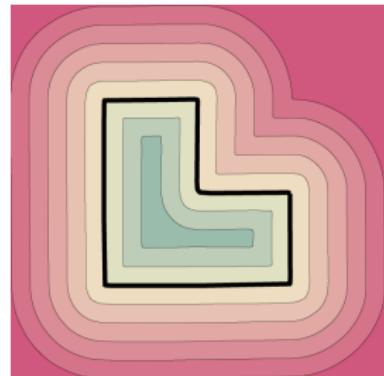
Results in 2D



Unsigned distance [3]



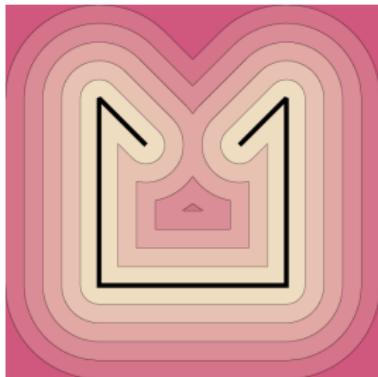
Level sets after SAL
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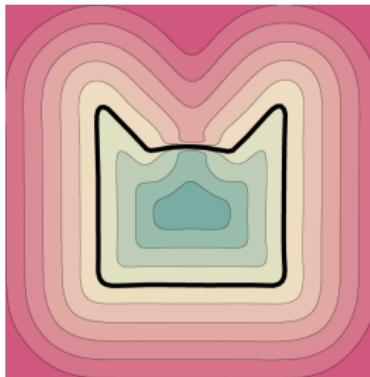
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Sign Agnostic Learning with Derivatives (SALD)

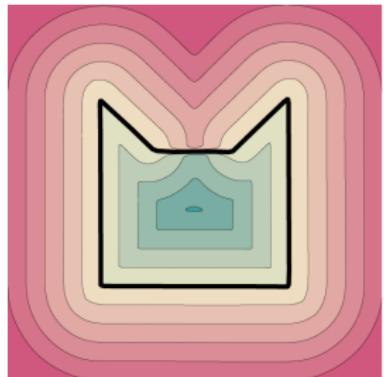
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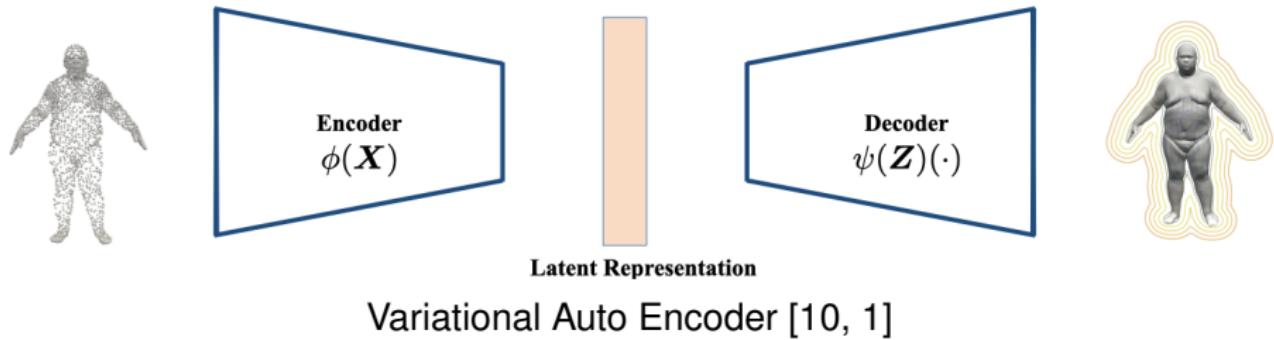


Level sets after SAL
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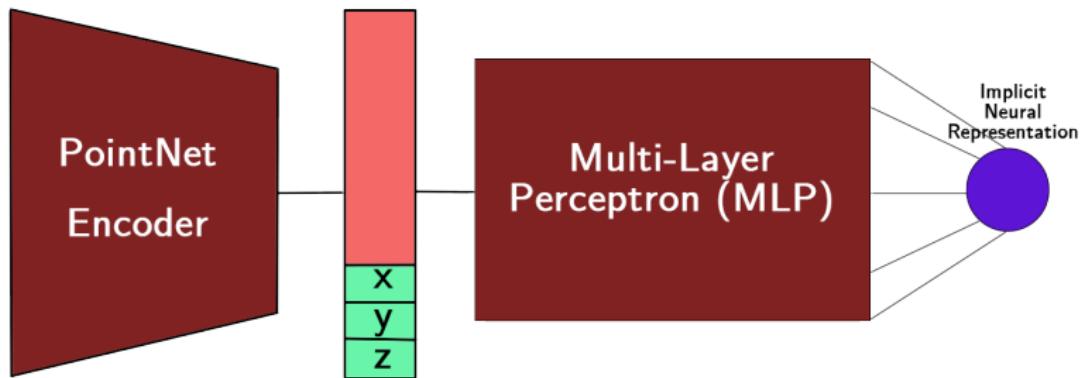


Level sets after SALD
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Neural Network Architecture

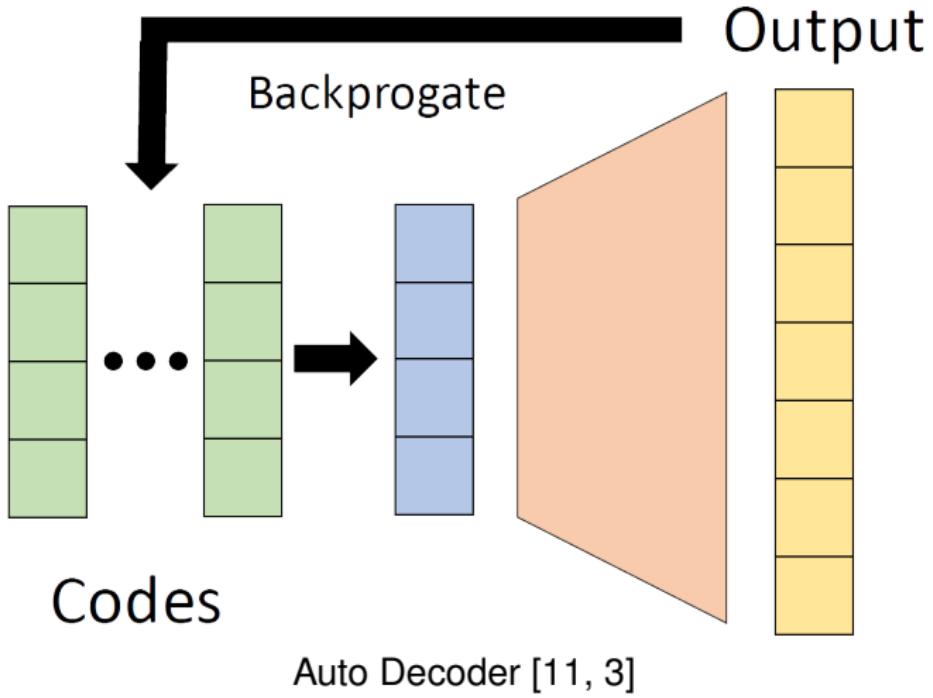


Neural Network Architecture



Variational Auto Encoder with PointNet Encoder [10, 6]

Neural Network Architecture



Experiments and Results

Evaluation Metrics

Chamfer distance: $d_C(\mathcal{X}_1, \mathcal{X}_2) = \frac{1}{2} (d_C^{\rightarrow}(\mathcal{X}_1, \mathcal{X}_2) + d_C^{\rightarrow}(\mathcal{X}_2, \mathcal{X}_1))$,

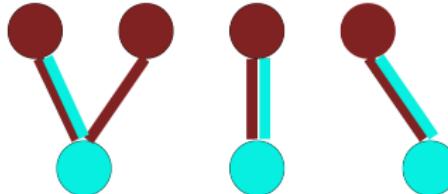
$$d_C^{\rightarrow}(\mathcal{X}_1, \mathcal{X}_2) = \frac{1}{|\mathcal{X}_1|} \sum_{\mathbf{x}_1 \in \mathcal{X}_1} \min_{\mathbf{x}_2 \in \mathcal{X}_2} \|\mathbf{x}_1 - \mathbf{x}_2\|$$

Experiments and Results

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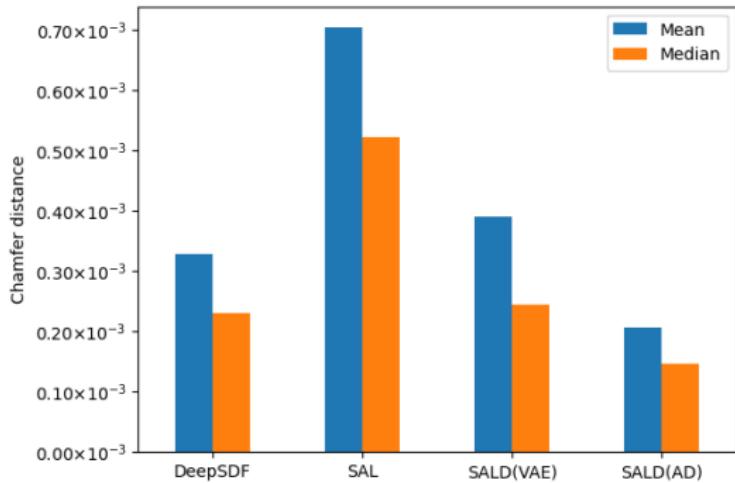
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Chamfer distance between 2 point clouds

Experiments and Results

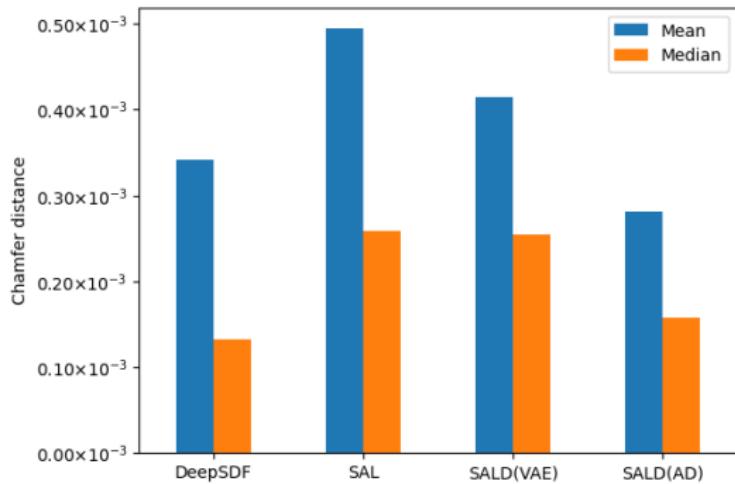
ShapeNet



ShapeNet quantitative results [3]

Experiments and Results

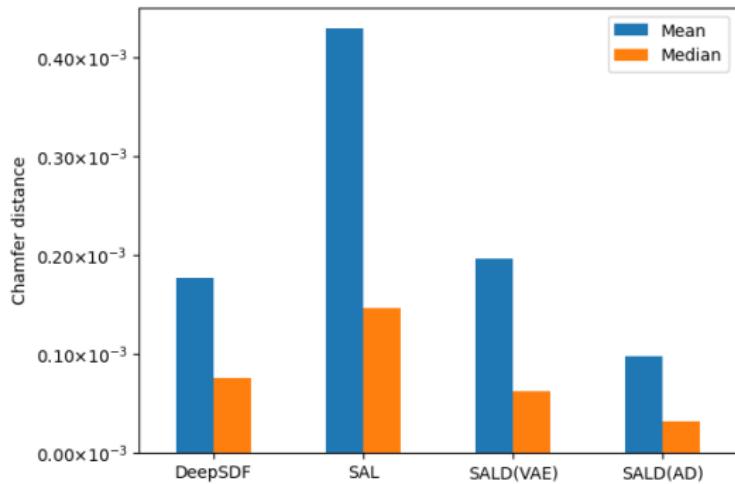
ShapeNet



ShapeNet quantitative results [3]

Experiments and Results

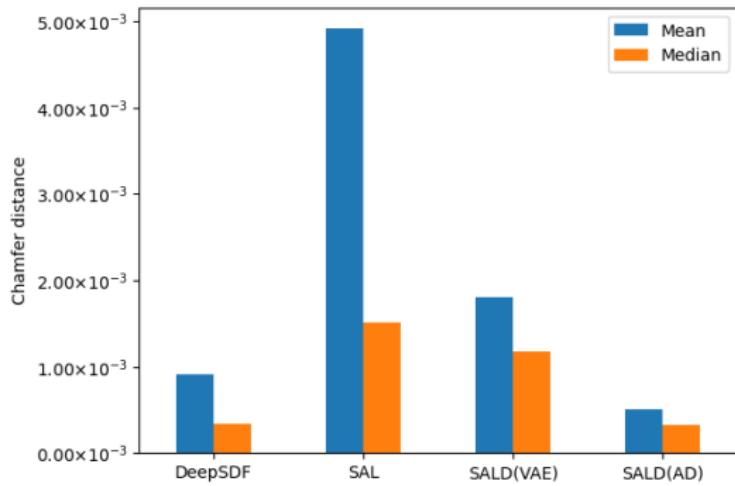
ShapeNet



ShapeNet quantitative results [3]

Experiments and Results

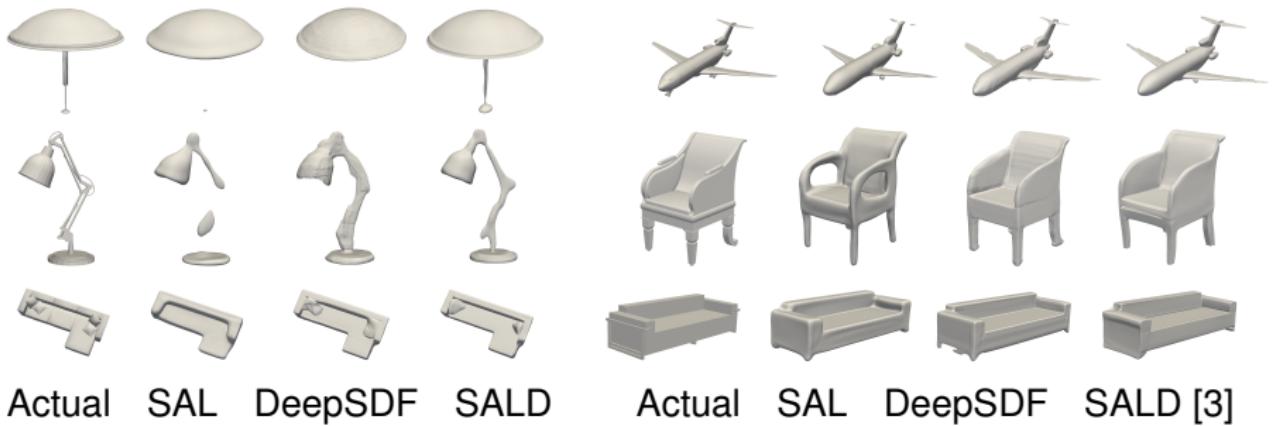
ShapeNet



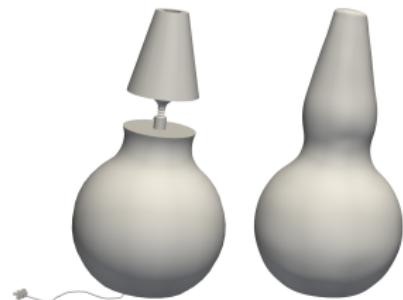
ShapeNet quantitative results [3]

Experiments and Results

ShapeNet



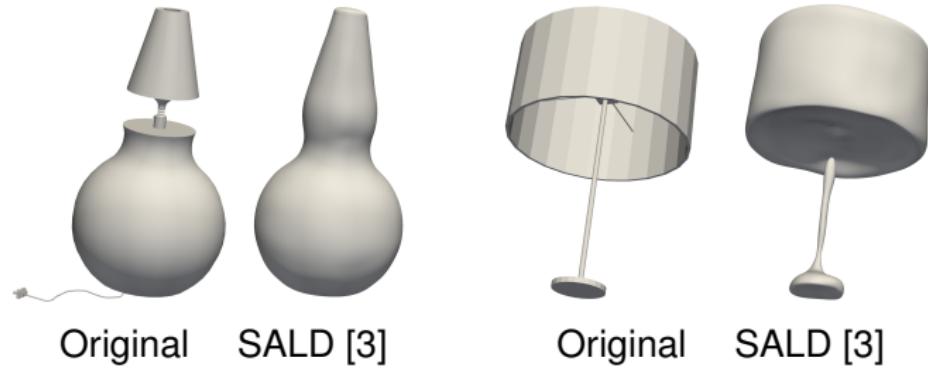
Shortcomings



Original

SALD [3]

Shortcomings



Shortcomings



Conclusion and Further Works

- Adding derivatives can improve learned 3D geometry significantly

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- Sharp features in the reconstructed shapes

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- Adding derivatives can improve learned 3D geometry significantly
- Sharp features in the reconstructed shapes
- Favourable minimal surface property

Conclusion and Further Works



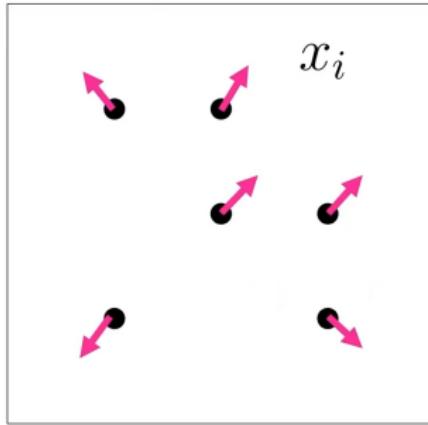
SAL

Model efficiency: point-cloud reconstruction after 500 training epochs [5]



LightSAL

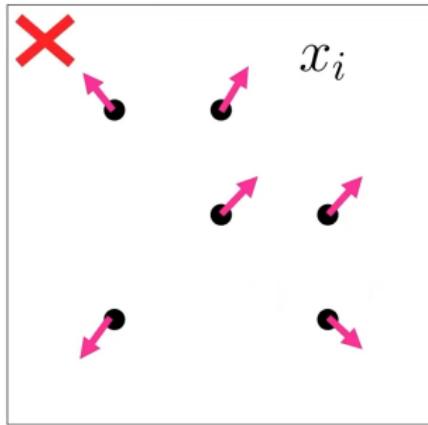
Conclusion and Further Works



Input data [7]

DiGS: Divergence guided shape implicit neural representation for unoriented point clouds

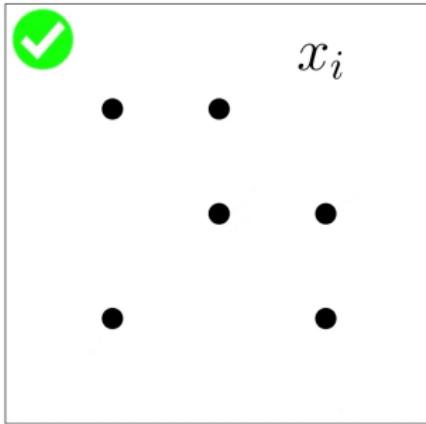
Conclusion and Further Works



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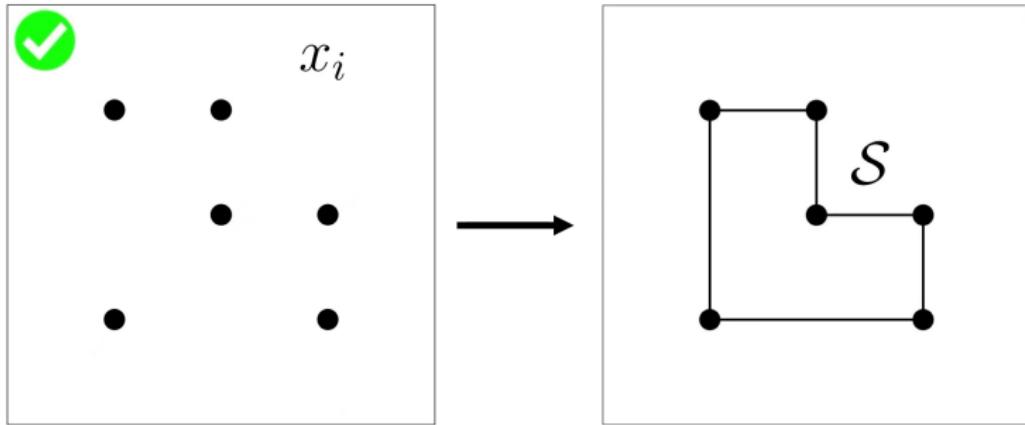
Conclusion and Further Works



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Conclusion and Further Works



Input data [7]

Output shape [7]

DiGS: Divergence guided shape implicit neural representation for unoriented point clouds

Conclusion and Further Works

- Combining sign agnostic learning with positional encoding (Fourier features) [3, 12]

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- Combining sign agnostic learning with positional encoding (Fourier features) [3, 12]
- Combining the sign-agnostic loss with gradient regularization [3, 9]

Feedback

Questions?

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