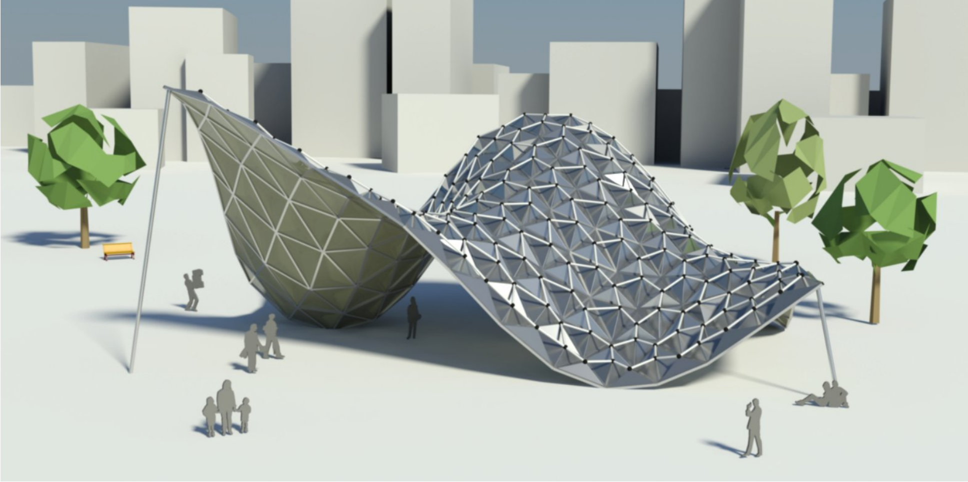

Sign Agnostic Learning with Derivatives of 3D Geometry from Raw Data

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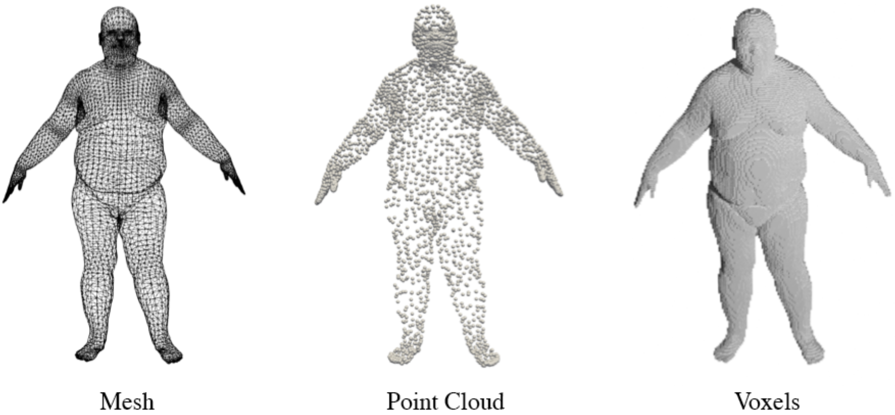
Representations of 3D shapes



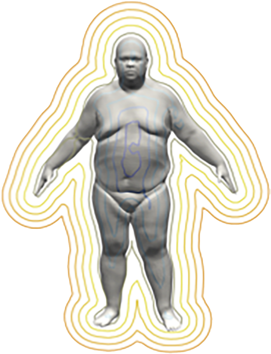
Discrete Representation of 3D Shape [1]

Representations of 3D shapes

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

Representations of 3D shapes

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



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

Why Neural Networks

- flexibility and approximation power [4]

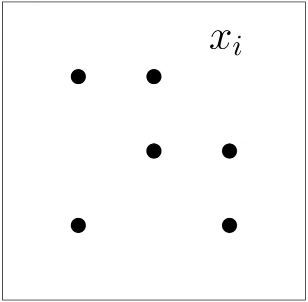
Implicit Neural Representation

Why Neural Networks

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

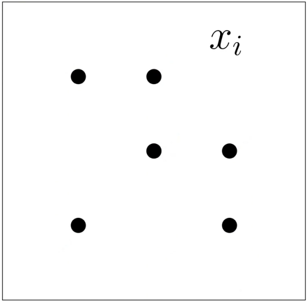
Learning Implicit Neural Representation

Methods

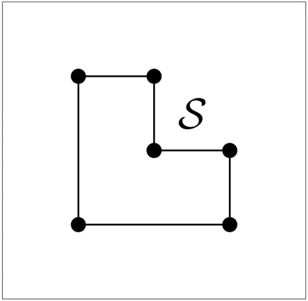


Input data [7]

Methods



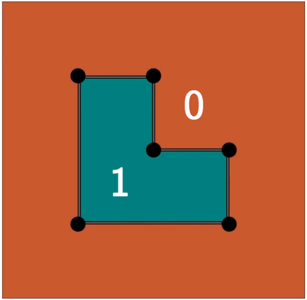
Input data [7]



Output shape [7]

Learning Implicit Neural Representation

Methods

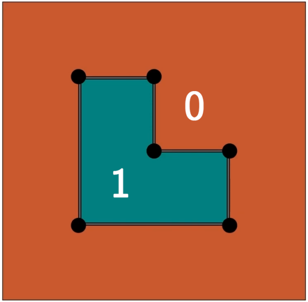


Occupancy function [7]

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

Learning Implicit Neural Representation

Methods



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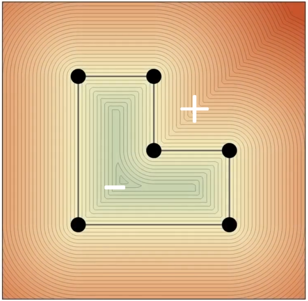
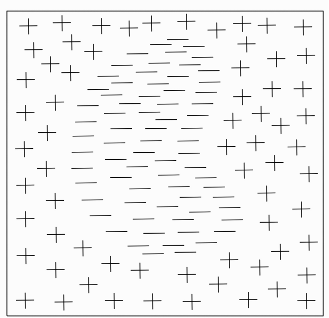


Signed distance function [7]

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

Learning Implicit Neural Representation

Challenges



Data available for supervised learning [2]

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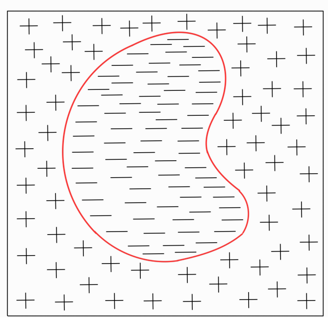
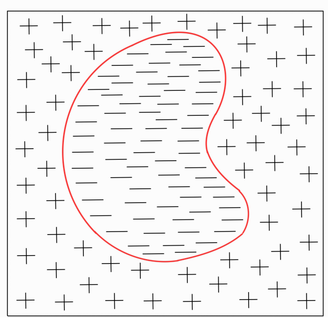
Challenges



Data available for supervised learning [2]

Learning Implicit Neural Representation

Challenges



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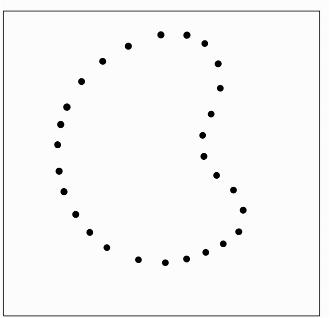
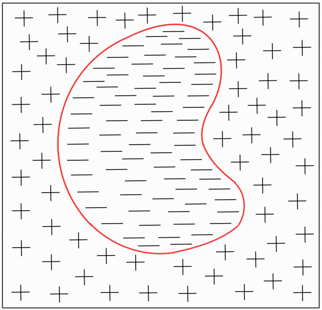


Raw data [2]

Learning Implicit Neural Representation

Challenges



Data available for supervised learning [2]

Raw data [2]

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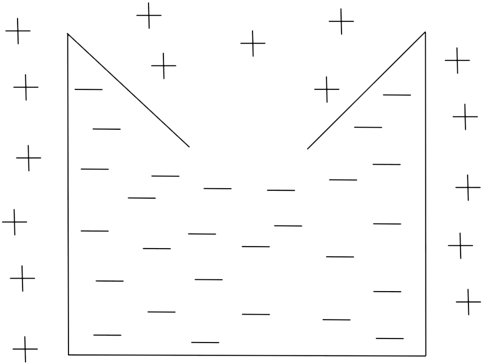
Learning Implicit Neural Representation

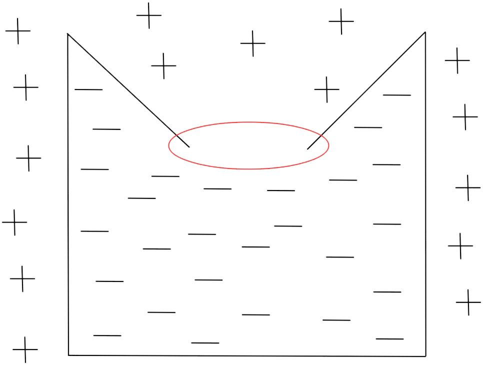
Challenges



Learning missing parts [2]

Learning Implicit Neural Representation

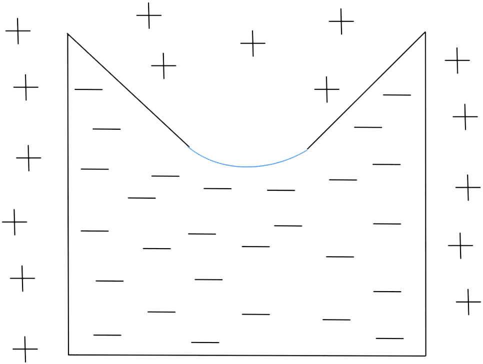
Challenges



Learning missing parts [2]

Learning Implicit Neural Representation

Challenges



Learning missing parts [2]

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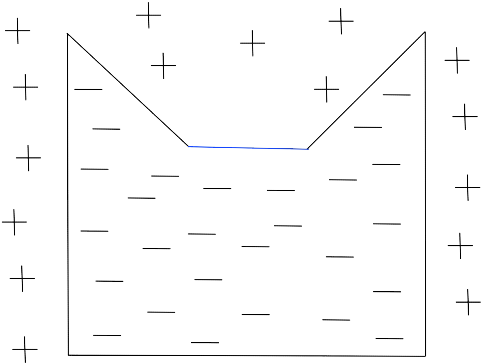
Learning Implicit Neural Representation

Challenges



Learning missing parts [2]

Background: Sign Agnostic Learning (SAL)

Unsigned Distance Function

L^0 distance [2]

$$h_0(\boldsymbol{z}) = \begin{cases} 0 & \boldsymbol{z} \in \mathcal{X} \\ 1 & \boldsymbol{z} \notin \mathcal{X} \end{cases}$$

Background: Sign Agnostic Learning (SAL)

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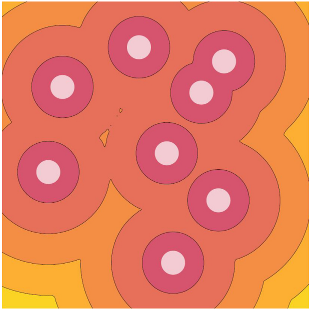


L^2 (Euclidean) distance [2]

$$h_2(\boldsymbol{z}) = \min_{\boldsymbol{x} \in \mathcal{X}} \|\boldsymbol{z} - \boldsymbol{x}\|_2$$

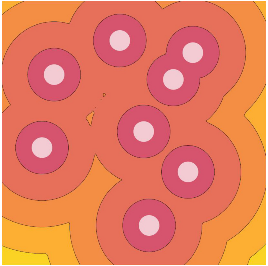
Background: Sign Agnostic Learning (SAL)

SAL Loss Function

$$\mathrm{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\boldsymbol{x}} \ell \left(f(\boldsymbol{x}; \boldsymbol{\theta}), h(\boldsymbol{x}) \right)$$

Loss function

Unsigned distance



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$$\mathrm{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\boldsymbol{x}} \left| f(\boldsymbol{x};\boldsymbol{\theta}), h(\boldsymbol{x}) \right|$$
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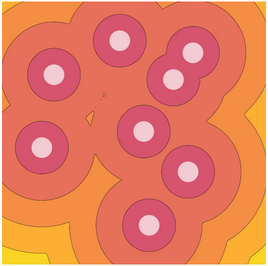

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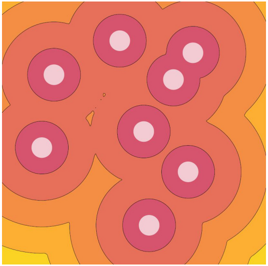

Background: Sign Agnostic Learning (SAL)

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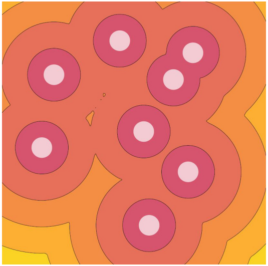
Sign agnostic dissimilarity



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$$\downarrow$$

Sign agnostic dissimilarity

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

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Background: Sign Agnostic Learning (SAL)

SAL Loss Function

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

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Sign agnostic learning in 1-D case [2]

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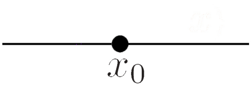

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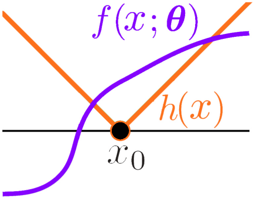

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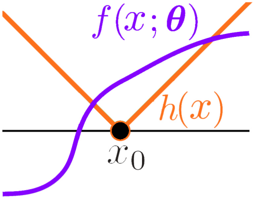

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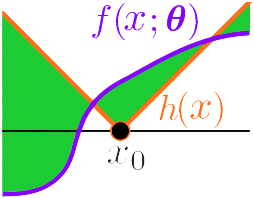
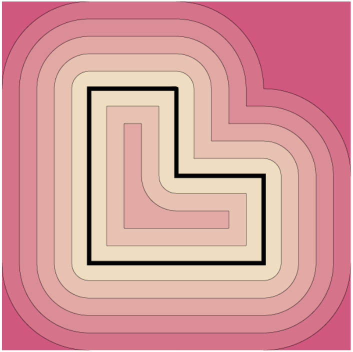


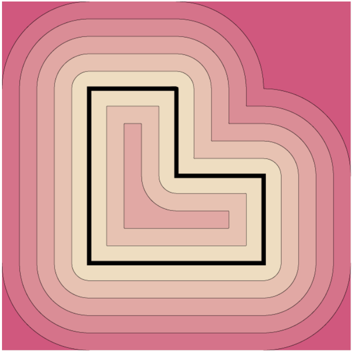
Sign agnostic learning in 1-D case [2]

Background: Limitations of SAL



Unsigned distance [3]

Background: Limitations of SAL



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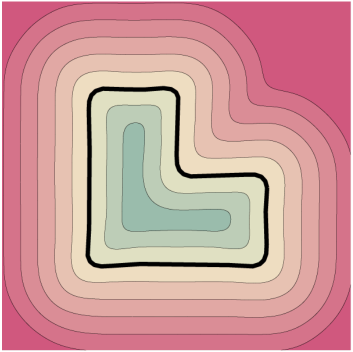
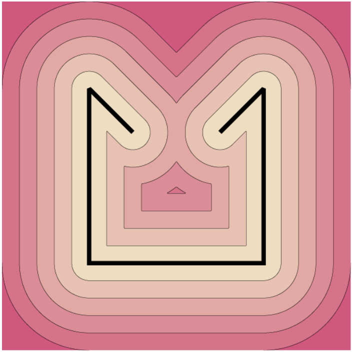


Level sets after SAL training [3]

Background: Limitations of SAL



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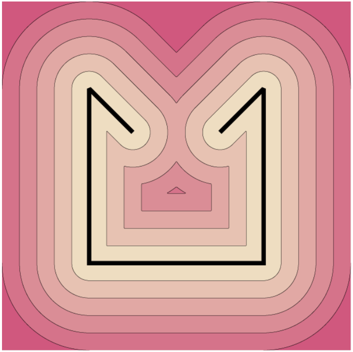

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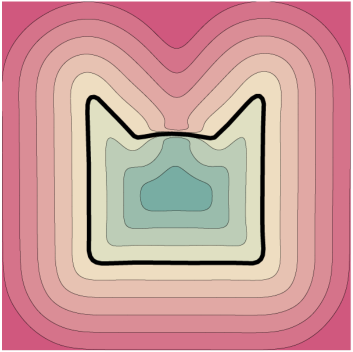

Level sets after SAL training [3]

Background: Sobolev Training

Adding Derivatives

- Encode additional information about the target function [8]

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Background: Sobolev Training

Adding Derivatives

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- Improve the prediction and generalization quality [8]

Background: Sobolev Training

Adding Derivatives

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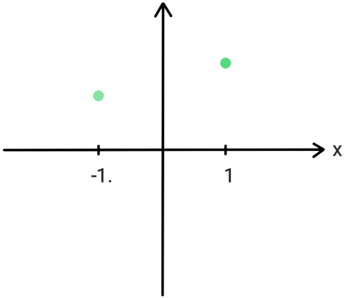

Background: Sobolev Training

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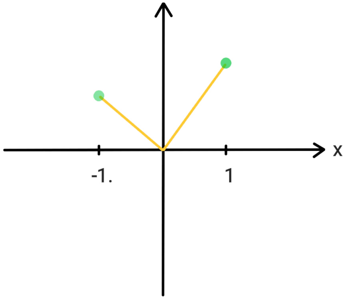

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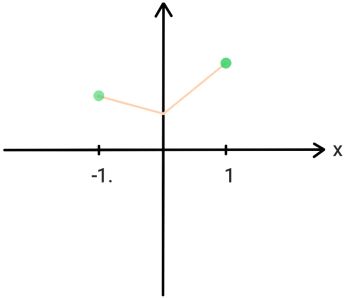

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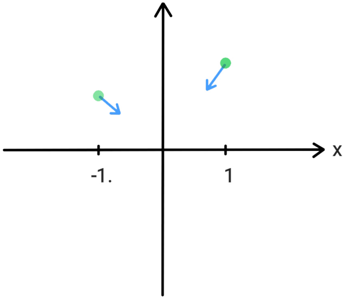

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Sign Agnostic Learning with Derivatives (SALD)

Extension of SAL Loss

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

Sign Agnostic Learning with Derivatives (SALD)

Extension of SAL Loss

$$\mathrm{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\boldsymbol{x}} \tau \left(f(\boldsymbol{x};\boldsymbol{\theta}), \quad h(\boldsymbol{x}) \right) + \\ \mathbb{E}_{\boldsymbol{x}} \tau \left(\nabla_{\boldsymbol{x}} f(\boldsymbol{x};\boldsymbol{\theta}), \nabla_{\boldsymbol{x}} h(\boldsymbol{x}) \right)$$ [3]

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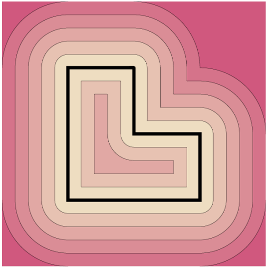
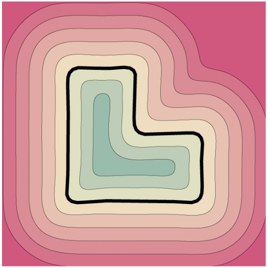
Sign Agnostic Learning with Derivatives (SALD)

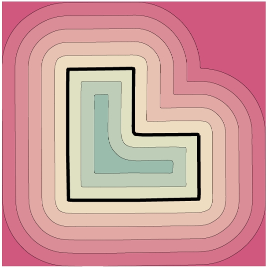
Results in 2D



Unsigned distance [3]



Level sets after SAL training [3]



Level sets after SALD training [3]

Sign Agnostic Learning with Derivatives (SALD)

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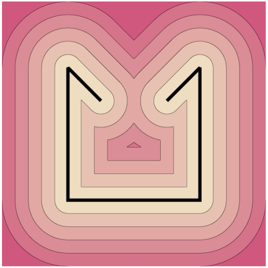

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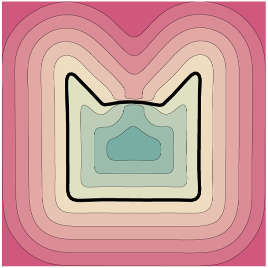
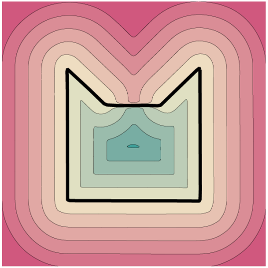


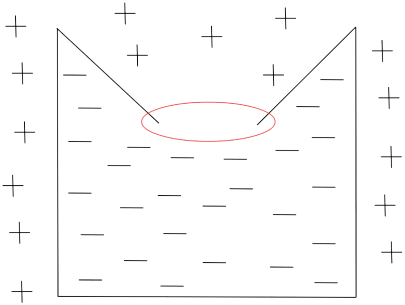
Level sets after SAL training [3]



Level sets after SALD training [3]

Sign Agnostic Learning with Derivatives (SALD)

Minimal Surface Property



Learning missing parts [2]

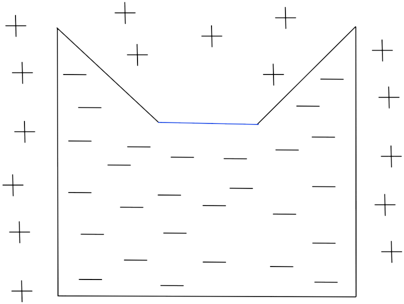
Minimal Surface Property

Minimizes the surface area of missing parts [9, 3]

Sign Agnostic Learning with Derivatives (SALD)

Minimal Surface Property

Minimizes the surface area of missing parts [9, 3]



Learning missing parts [2]

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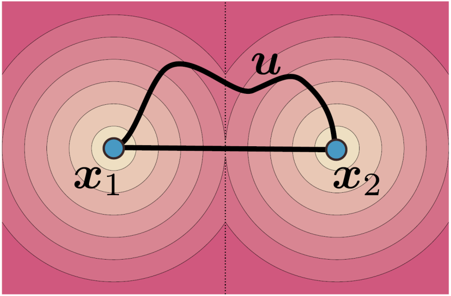
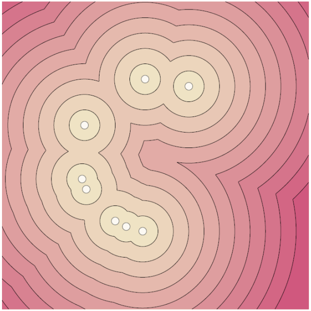
Minimal Surface Property



Minimal Surface Property in 2D [3]

Sign Agnostic Learning with Derivatives (SALD)

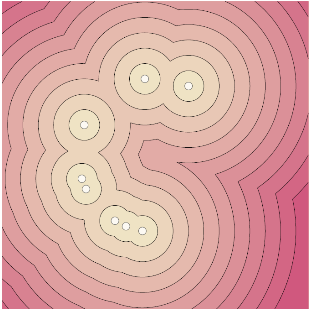
Minimal Surface Property



Unsigned distance [3]

Sign Agnostic Learning with Derivatives (SALD)

Minimal Surface Property



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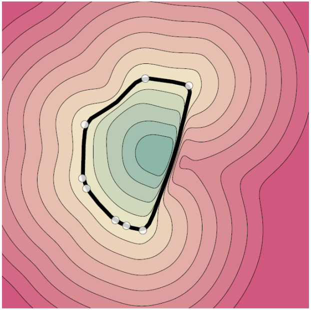
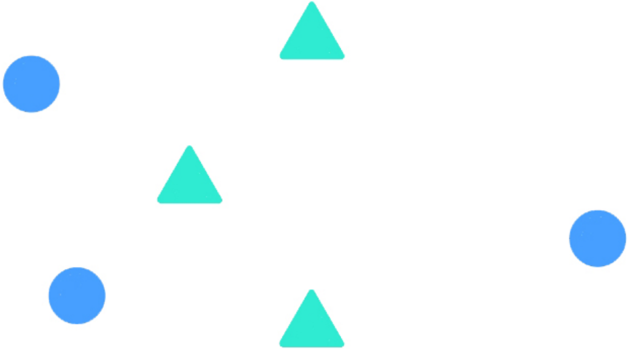


Level sets after SALD training [3]

Experiments and Results

Evaluation Metrics

Chamfer distance



Experiments and Results

Evaluation Metrics

Chamfer distance

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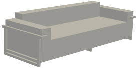
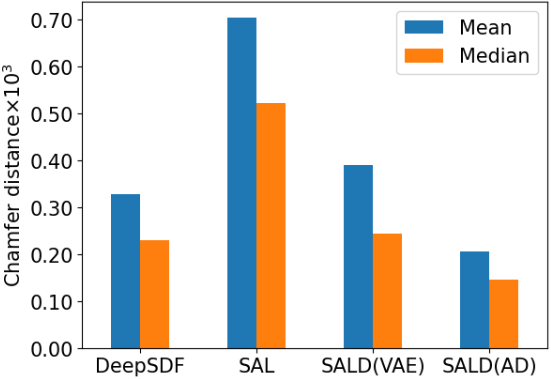
Experiments and Results

ShapeNet

Sofa Class



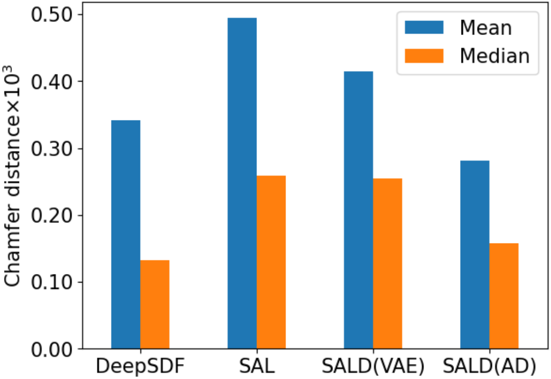


ShapeNet quantitative results [3]

Experiments and Results

ShapeNet

Chair Class

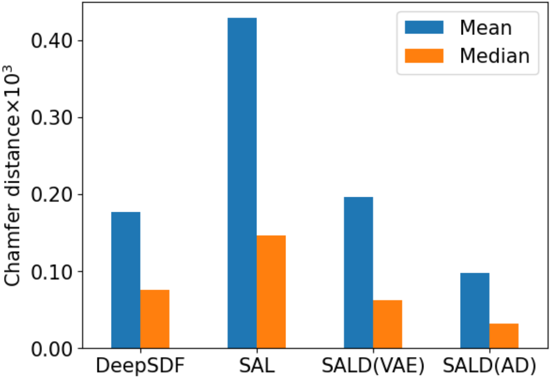


ShapeNet quantitative results [3]

Experiments and Results

ShapeNet

Plane Class

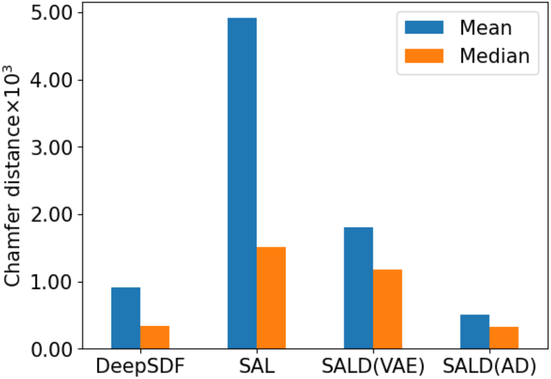


ShapeNet quantitative results [3]

Experiments and Results

ShapeNet

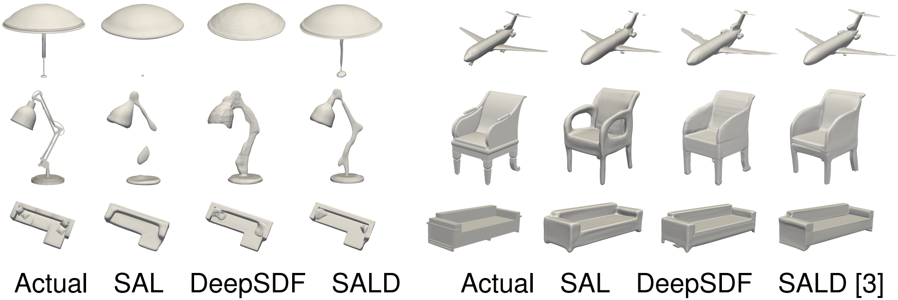
Lamp Class



ShapeNet quantitative results [3]

Experiments and Results

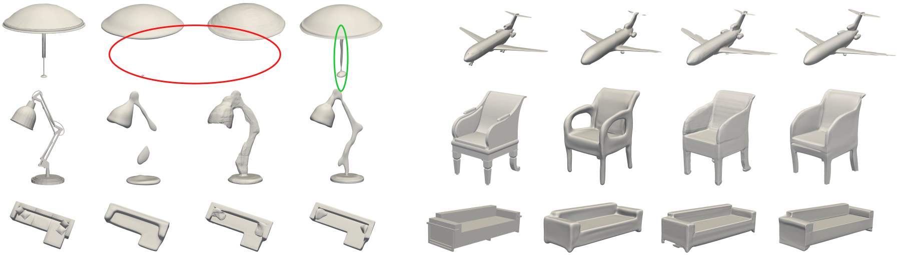
ShapeNet



ShapeNet qualitative results

Experiments and Results

ShapeNet



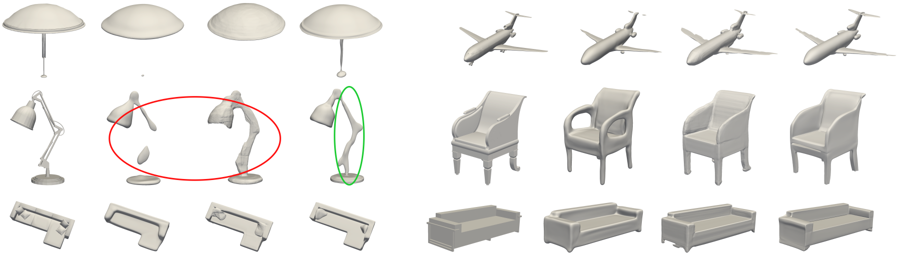
Actual SAL DeepSDF SALD Actual SAL DeepSDF SALD [3]

ShapeNet qualitative results

Visual Computing Institute

Experiments and Results

ShapeNet



Actual SAL DeepSDF SALD Actual SAL DeepSDF SALD [3]

ShapeNet qualitative results

Experiments and Results

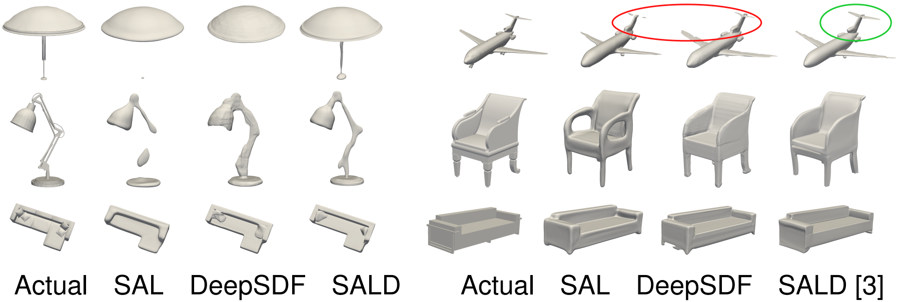
ShapeNet

Actual SAL DeepSDF SALD Actual SAL DeepSDF SALD [3]

ShapeNet qualitative results

Experiments and Results

ShapeNet



ShapeNet qualitative results

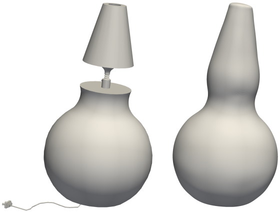
Experiments and Results

ShapeNet

Actual SAL DeepSDF SALD Actual SAL DeepSDF SALD [3]

ShapeNet qualitative results

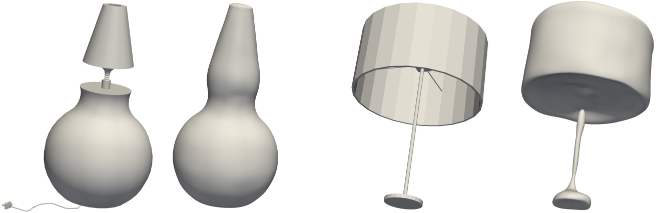
Shortcomings



Original SALD [3]

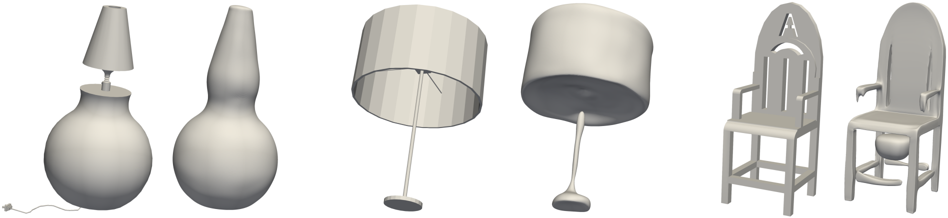
Debabrata Ghosh

Shortcomings



Original SALD [3] Original SALD [3]

Shortcomings

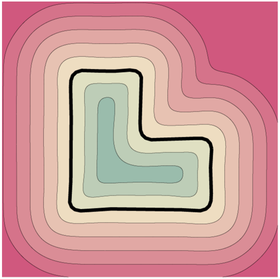


Original SALD [3] Original SALD [3] Original SALD [3]

Conclusion and Further Works

Conclusion

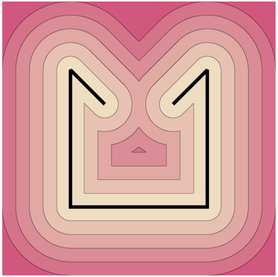
- Adding derivatives can improve learned 3D geometry significantly



Conclusion and Further Works

Conclusion

- Adding derivatives can improve learned 3D geometry significantly
- Reconstruction shows minimal surface property



Conclusion and Further Works

Further Works

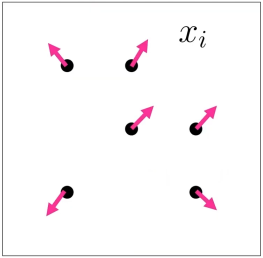
SAL [5]

LightSAL [5]

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

Conclusion and Further Works

Further Works



Input data [7]

Output shape [7]

DiGS: Divergence guided shape implicit neural representation for unoriented point clouds [6]

Conclusion and Further Works

- **Conclusion**
  - Adding derivatives can improve learned 3D geometry significantly [3]
  - Reconstruction shows minimal surface property [3]
- **Further Works**
  - More efficient network architecture for faster learning and inference [5]
  - Implicit neural representation for un-oriented point clouds [6]

References

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