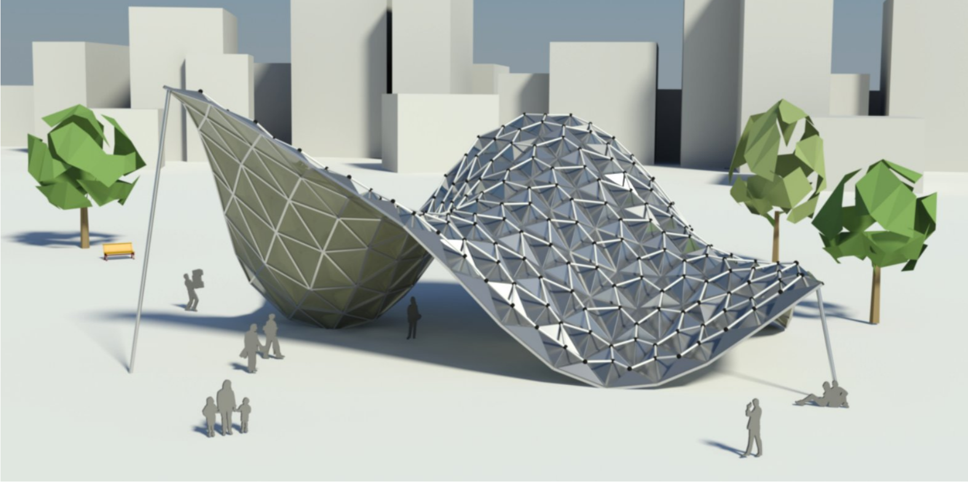

Sign Agnostic Learning with Derivatives of 3D Geometry from Raw Data

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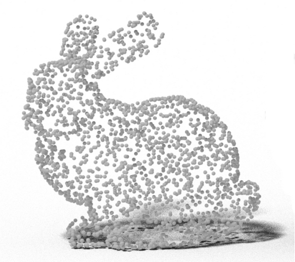
Representations of 3D shapes

Discrete Representations



Point Cloud

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Representations of 3D shapes

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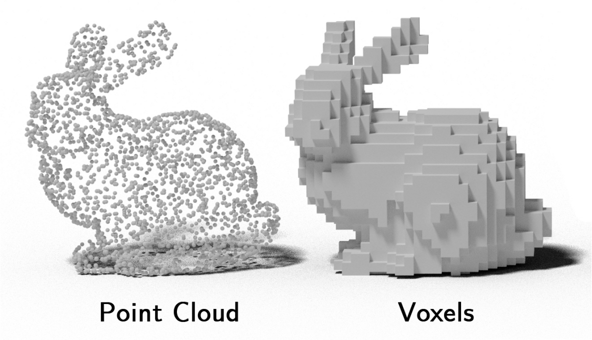

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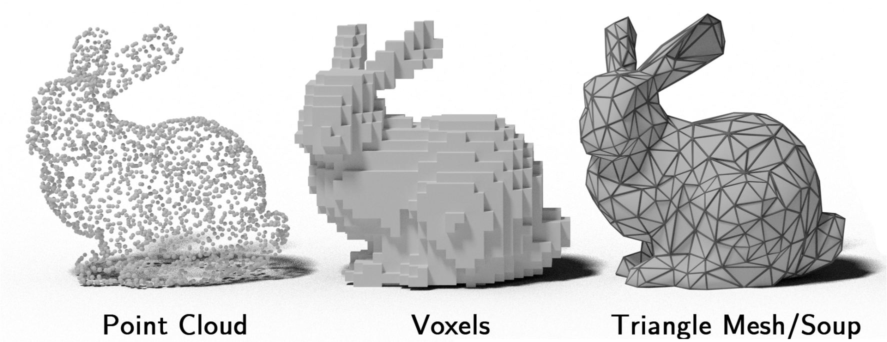

Representations of 3D shapes

Continuous Representations

- Parametric Representation

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  - Surface represented as zero level-set: $\mathcal{S} = \{\boldsymbol{x} \in \mathbb{R}^3 \mid f(\boldsymbol{x}) = 0\}$
  - We refer to such representation as Implicit Neural Representation (INR)

Implicit Neural Representation

... why Neural Networks?

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Current works to learn INR show a recent trend of using Neural networks (NN) to model and reconstruct 3D surfaces. This stems from

- flexibility and approximation power of NNs [3]
- optimization and generalization properties of NNs

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Training Implicit Neural Representation

Methods and Challenges

Given raw geometric data as input, $\mathcal{X} \subset \mathbb{R}^3$, the idea is to try optimizing the weights $\boldsymbol{\theta} \in \mathbb{R}^m$ of a network $f(\boldsymbol{x}; \boldsymbol{\theta})$, where $f : \mathbb{R}^3 \times \mathbb{R}^m \to \mathbb{R}$, so that zero level-set of f represents the surface approximating $\mathcal{X}$.

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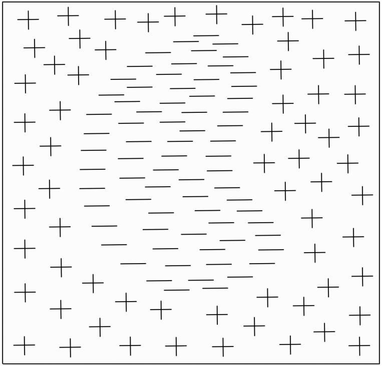
Training Implicit Neural Representation

Methods and Challenges



Data for supervised learning

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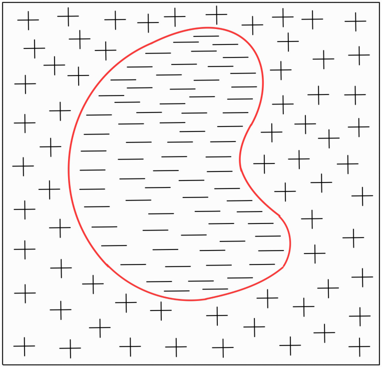
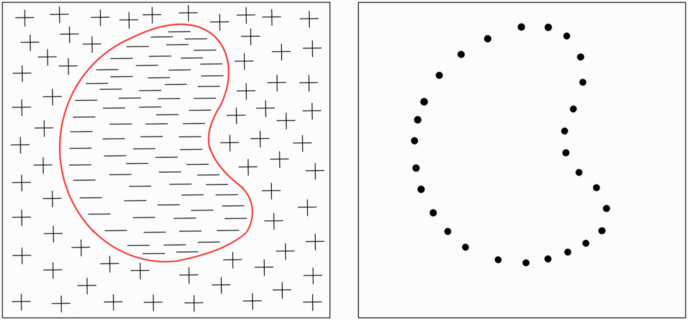
Methods and Challenges



Data for supervised learning

Training Implicit Neural Representation

Methods and Challenges



Data for supervised learning

Raw Data

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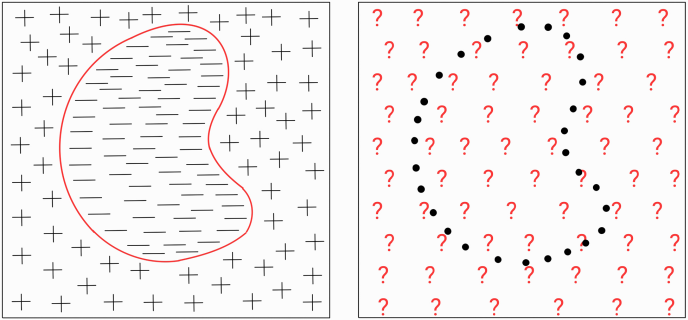
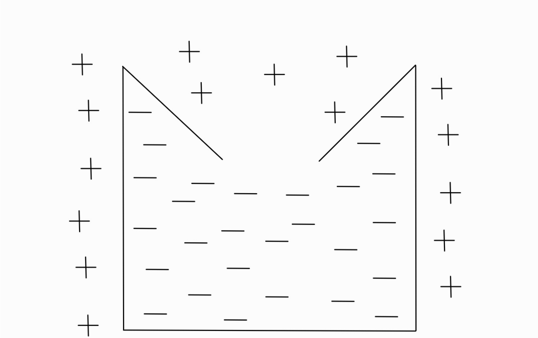
Methods and Challenges



Data for supervised learning | Raw Data

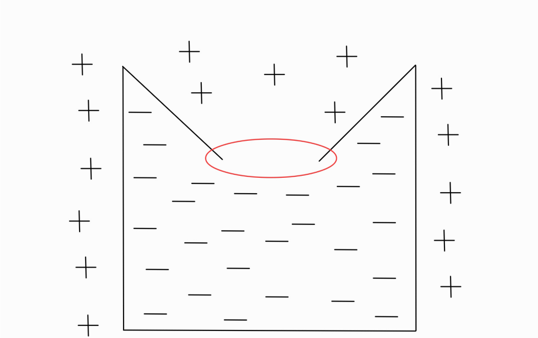
Methods and Challenges



How to learn missing parts?

Training Implicit Neural Representation

Methods and Challenges



How to learn missing parts?

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Training Implicit Neural Representation

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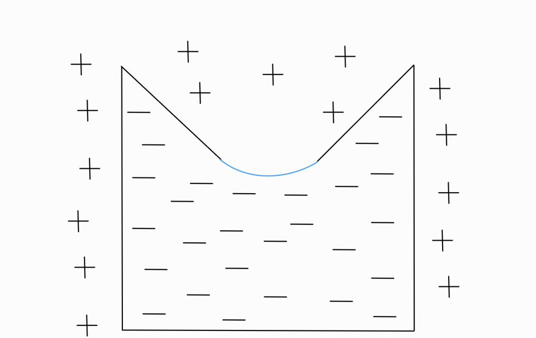

How to learn missing parts?

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Training Implicit Neural Representation

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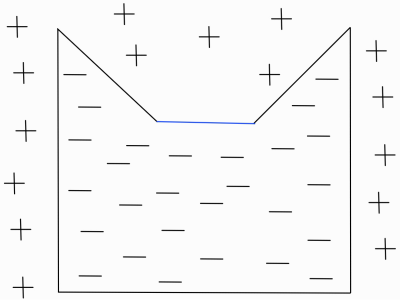

How to learn missing parts?

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Previous Work

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Previous Work

Parametric Representation

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Previous Work

Parametric Representation

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- Williams et al. improved this construction by introducing better transitions between charts [17].

Previous Work

Implicit Representation

Previous Work

Implicit Representation

- Convolutional neural network predicting scalar values over a predefined fixed volumetric structure (e.g., grid or octree) in space [16, 18].

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Previous Work

Implicit Representation

- Convolutional neural network predicting scalar values over a predefined fixed volumetric structure (e.g., grid or octree) in space [16, 18].
- Multilayer Perceptron of the form $f : \mathbb{R}^3 \rightarrow \mathbb{R}$ defining a continuous volumetric function [15, 14, 10].

Sign Agnostic Learning (SAL): Motivation

- A method for learning implicit neural representations of surfaces directly from raw $3\mathrm{D}$ data.

Background

Sign Agnostic Learning (SAL): Motivation

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- By learning directly from raw data, e.g., inconsistently oriented point clouds or triangle soups [8] and raw scans [6] the need to obtain a ground truth signed distance representation of surfaces to be learned can be avoided.

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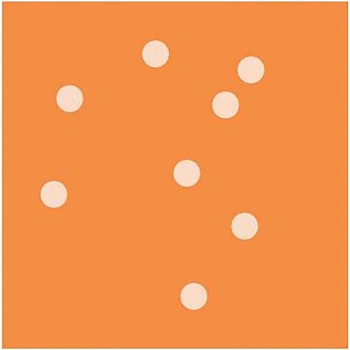
- By learning directly from raw data, e.g., inconsistently oriented point clouds or triangle soups [8] and raw scans [6] the need to obtain a ground truth signed distance representation of surfaces to be learned can be avoided.
- Working with complex models with inconsistent normals and/or missing parts becomes easier.

Sign Agnostic Learning (SAL): Method

Unsigned Distance Function

- Given raw geometric data, $\mathcal{X} \subset \mathbb{R}^3$, unsigned distance function can be formulated as either of:
  - standard L^2 (Euclidean) distance, $h_2(\boldsymbol{z}) = \min_{\boldsymbol{x} \in \mathcal{X}} \|\boldsymbol{z} - \boldsymbol{x}\|_2$
  - L^0 distance, $h_0(\boldsymbol{z}) = \begin{cases} 0 & \boldsymbol{z} \in \mathcal{X} \\ 1 & \boldsymbol{z} \notin \mathcal{X} \end{cases}$.

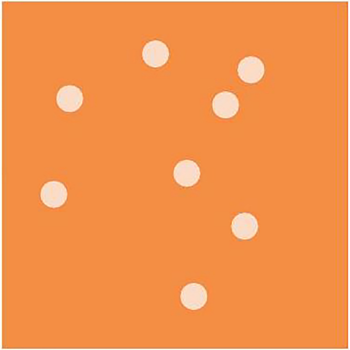
Sign Agnostic Learning (SAL): Method



Unsigned L^0 distance (2D point cloud in gray)

Background

Sign Agnostic Learning (SAL): Method



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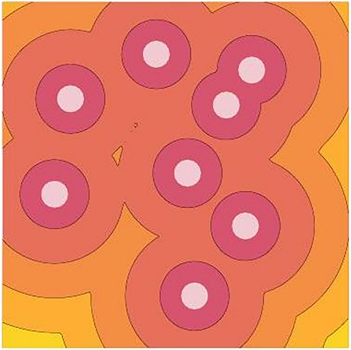

Unsigned L^2 Distance

(2D point cloud in gray)

Background

Sign Agnostic Learning (SAL): Method

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Unsigned Similarity Function

- $\tau : \mathbb{R} \times \mathbb{R}_+ \to \mathbb{R}$ is a differentiable unsigned similarity function defined by the following properties:
  1. Sign agnostic: $\tau(-a, b) = \tau(a, b), \forall a \in \mathbb{R}, b \in \mathbb{R}_+$.
  2. Monotonic: $\frac{\partial \tau}{\partial a}(a, b) = g(a - b), \forall a, b \in \mathbb{R}_+$, where $g : \mathbb{R} \to \mathbb{R}$ is a monotonically increasing function with $g(0) = 0$ [1].

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- e.g. $\tau_\ell(a, b) = ||a| - b|^\ell$ where $\ell \geq 1$
  - τ_ℓ satisfies sign-agnostic property due to the symmetry of $|\cdot|$.
  - Since $\frac{\partial \tau}{\partial a} = \ell||a| - b|^{\ell-1}\operatorname{sign}(a - b\operatorname{sign}(a))$ it satisfies monotonicity as well.

Background

Sign Agnostic Learning (SAL): Method

SAL Loss Function

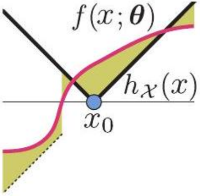
$$\mathrm{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\boldsymbol{x}\sim\mathcal{D}}\tau\left(f(\boldsymbol{x};\boldsymbol{\theta}), h_{\mathcal{X}}(\boldsymbol{x})\right),$$

where $\mathcal{D}$ is a probability distribution defined by the input data $\mathcal{X}$; $h_{\mathcal{X}}(\boldsymbol{x})$ is some unsigned distance measure to $\mathcal{X}$; and τ is a differentiable unsigned similarity function.

Sign Agnostic Learning (SAL): Method

SAL Loss Function

- Illustrating one dimensional case: $\mathcal{X} = \{x_0\}$, $h_{\mathcal{X}}(x) = |x - x_0|$, and $\tau(a, b) = ||a| - b|$.
- When the network parameters $\boldsymbol{\theta} = \boldsymbol{\theta}^0$ are initialized properly, the minimizer $\boldsymbol{\theta}^*$ of loss defines an implicit function $f(x; \boldsymbol{\theta}^*)$ that realizes a signed version of $h_{\mathcal{X}}$; in this case $f(x; \boldsymbol{\theta}^*) = x - x_0$.



Sobolev Training

Consider a NN with one-hidden layer and the target function $f\left(x;\boldsymbol{\theta}\right)=\max\{ax,bx\}+c$ with data given for $x=\{-1,1\}$:

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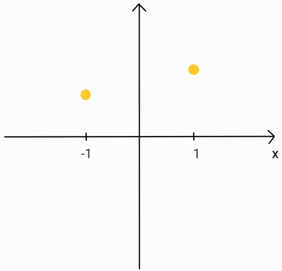

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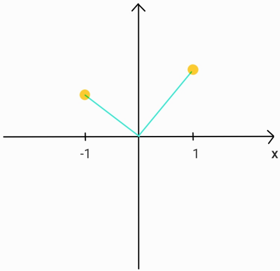

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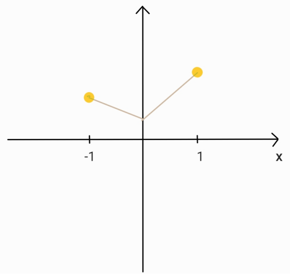

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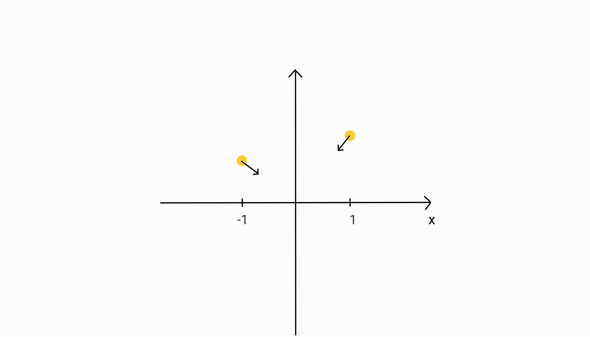

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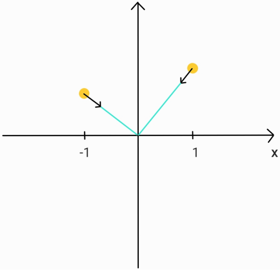
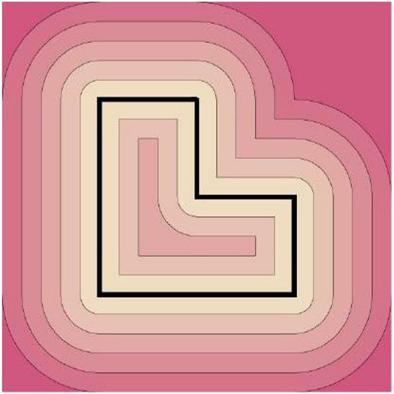


Limitations of SAL



Unsigned distance

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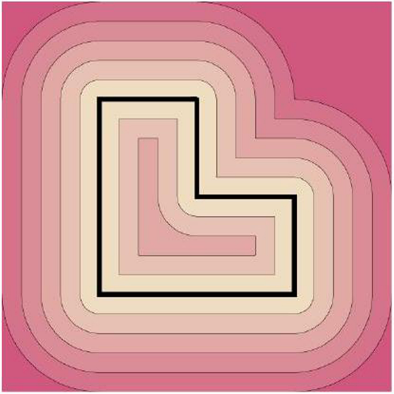

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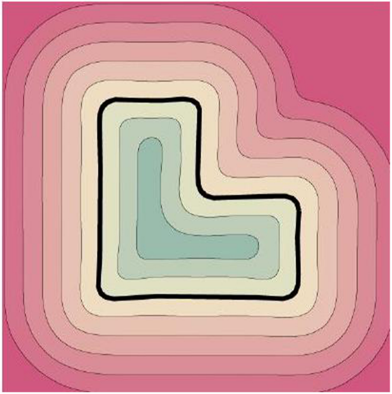

Learned from SAL

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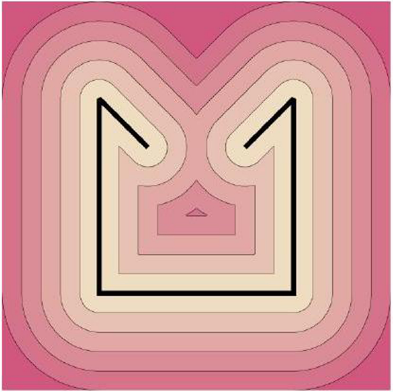

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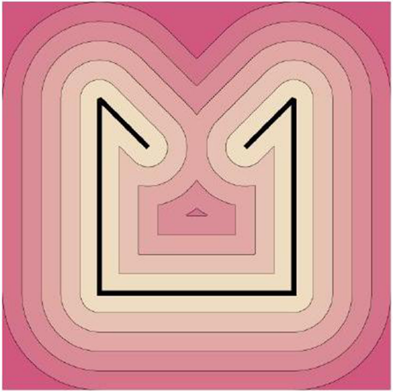

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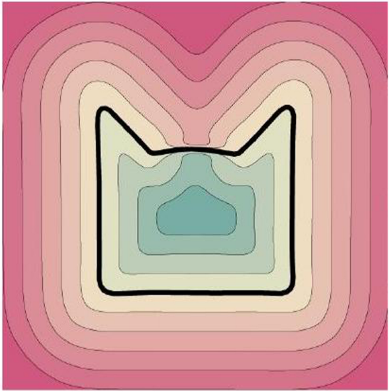

Learned from SAL

Sign Agnostic Learning with Derivatives (SALD)

Extension of SAL Loss

$$\text{loss}(\boldsymbol{\theta}) = \mathbb{E}_{\boldsymbol{x}\sim\mathcal{D}}\tau(f(\boldsymbol{x};\boldsymbol{\theta}), h_{\mathcal{X}}(\boldsymbol{x})) + \lambda\mathbb{E}_{\boldsymbol{x}\sim\mathcal{D}'}\tau\left(\nabla_{\boldsymbol{x}} f(\boldsymbol{x};\boldsymbol{\theta}), \nabla_{\boldsymbol{x}} h_{\mathcal{X}}(\boldsymbol{x})\right)$$

where $\lambda > 0$ is a parameter, $\mathcal{D}'$ is a probability distribution, and $\nabla_{\boldsymbol{x}} f(\boldsymbol{x};\boldsymbol{\theta}), \nabla_{\boldsymbol{x}} h_{\mathcal{X}}(\boldsymbol{x})$ are the gradients of f, h (resp.) with respect to their input $\boldsymbol{x}$.

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May 6, 2023

Sign Agnostic Learning with Derivatives (SALD)

Minimal Surface Property

SALD loss possesses a minimal surface property [19] meaning the learning process using SALD loss tries to minimize the surface area of missing parts.

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For two points $x_1, x_2 \in \mathbb{R}^2$, between them a straight line is the strict global minimizer when using SALD loss.

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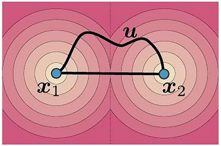
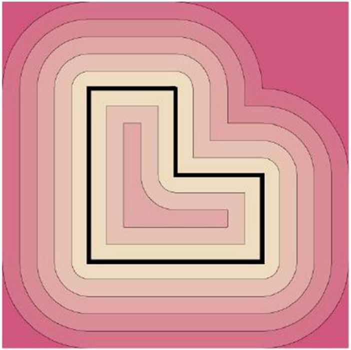


Sign Agnostic Learning with Derivatives (SALD)

Results in 2D



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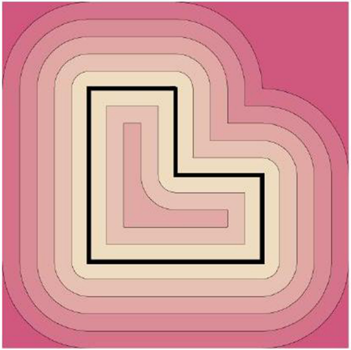

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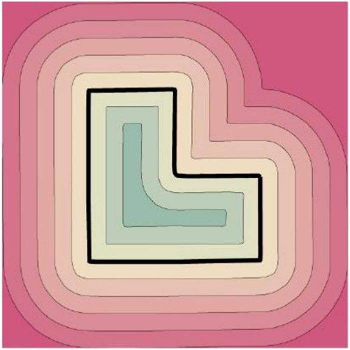

Learned from SALD

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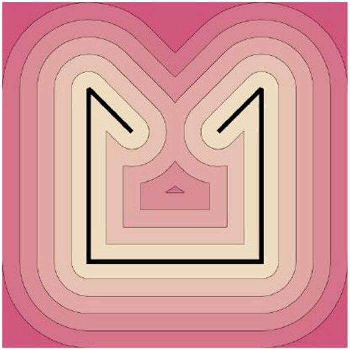

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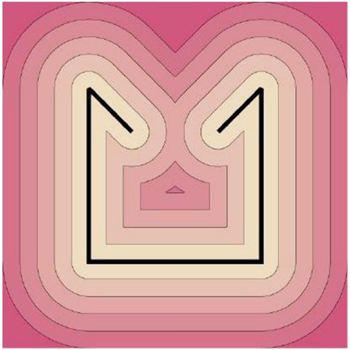

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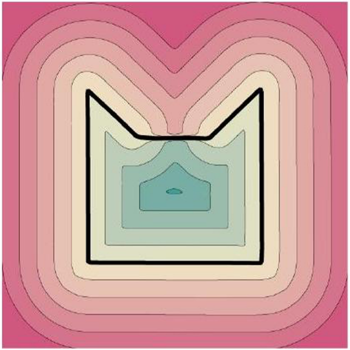
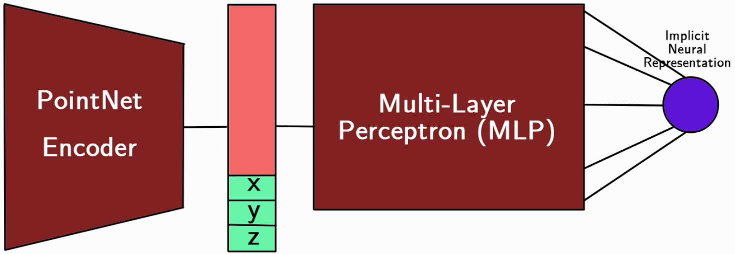


Learned from SALD

Neural Network Architecture



Variational Auto-Encoder

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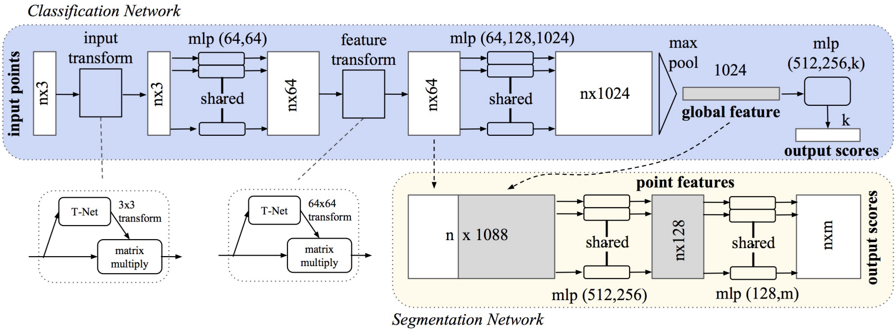
Neural Network Architecture



PointNet Architecture

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Neural Network Architecture

- A modified variational encoder-decoder [13] used, where the encoder $(\boldsymbol{\mu}, \boldsymbol{\eta}) = g\left(\boldsymbol{X}; \boldsymbol{\theta}_1\right)$ is taken to be PointNet [9], $\boldsymbol{X} \in \mathbb{R}^{n \times 3}$ is an input point cloud ($n = 128^2$), $\boldsymbol{\mu} \in \mathbb{R}^{256}$ is the latent vector, and $\boldsymbol{\eta} \in \mathbb{R}^{256}$ represents a diagonal covariance matrix $\boldsymbol{\Sigma} = \mathrm{diag}(e^{\boldsymbol{\eta}})$.

Neural Network Architecture

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- The network f is taken to be an 8-layer Multi-layer Perceptron (MLP).

Experiments and Results

Evaluation Metrics

Chamfer distance metrics to measure similarity between shapes:

$$\mathrm{d_C}\left(\mathcal{X}_1, \mathcal{X}_2\right) = \frac{1}{2}\left(\mathrm{d_{\vec{C}}}\left(\mathcal{X}_1, \mathcal{X}_2\right) + \mathrm{d_{\vec{C}}}\left(\mathcal{X}_2, \mathcal{X}_1\right)\right)$$

where

$$\mathrm{d_{\vec{C}}}\left(\mathcal{X}_1, \mathcal{X}_2\right) = \frac{1}{|\mathcal{X}_1|} \sum_{\boldsymbol{x}_1 \in \mathcal{X}_1} \min_{\boldsymbol{x}_2 \in \mathcal{X}_2} \|\boldsymbol{x}_1 - \boldsymbol{x}_2\|$$

and the sets $\mathcal{X}_i$ are either point clouds or triangle soups.

Evaluation Metrics

Also, to measure similarity of the normals of triangle soups $\mathcal{T}_1, \mathcal{T}_2$, define:

$$\mathrm{d_N}\left(\mathcal{T}_1, \mathcal{T}_2\right) = \frac{1}{2}\left(\ \mathrm{d}_{\mathrm{N}}^{\rightarrow}\left(\mathcal{T}_1, \mathcal{T}_2\right) + \mathrm{d_N}\left(\mathcal{T}_2, \mathcal{T}_1\right)\right)$$

where

$$\mathrm{d}_{\mathrm{N}}^{\vec{T}}\left(\mathcal{T}_1, \mathcal{T}_2\right) = \frac{1}{\left|\mathcal{T}_1\right|} \sum_{\boldsymbol{x}_1 \in \mathcal{T}_1} \angle\left(\boldsymbol{n}\left(\boldsymbol{x}_1\right), \boldsymbol{n}\left(\hat{\boldsymbol{x}}_1\right)\right)$$

where $\angle(\boldsymbol{a}, \boldsymbol{b})$ is the positive angle between vectors $\boldsymbol{a}, \boldsymbol{b} \in \mathbb{R}^3$, $\boldsymbol{n}\left(\boldsymbol{x}_1\right)$ denotes the face normal of a point $\boldsymbol{x}_1$ in triangle soup $\mathcal{T}_1$, and $\hat{\boldsymbol{x}}_1$ is the projection of $\boldsymbol{x}_1$ on $\mathcal{T}_2$.

Baseline

- DeepSDF [15] is chosen as a representative out of the methods that require pre-computed implicit representation for training.

Experiments and Results

Baseline

- DeepSDF [15] is chosen as a representative out of the methods that require pre-computed implicit representation for training.
- For methods that train directly on raw 3D data, comparisons were done versus SAL [1] and IGR [11].

Experiments and Results

ShapeNet

Category	Sofas		Chairs		Tables		Planes		Lamps	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
DeepSDF	**0.329**	**0.230**	**0.341**	**0.133**	0.839	**0.149**	**0.177**	0.076	**0.909**	**0.344**
SAL	0.704	0.523	0.494	0.259	**0.543**	**0.231**	0.429	0.146	4.913	1.515
SALD(VAE)	0.391	0.244	0.415	0.255	0.679	0.279	0.197	**0.062**	1.808	1.172
SALD(AD)	**0.207**	**0.147**	**0.281**	**0.157**	**0.408**	0.25	**0.098**	**0.032**	**0.506**	**0.327**

Figure: ShapeNet quantitative results with the mean and median of the Chamfer distances $(\mathrm{d_C})$ between the reconstructed $3\mathrm{D}$ surfaces and the ground truth meshes. Numbers are reported $\times 10^3$. [2]

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Experiments and Results

ShapeNet

Figure: ShapeNet qualitative test results. Each quadruple shows (columns from left to right): ground truth model, SAL-reconstruction, DeepSDF reconstruction, SALD reconstruction. [2]

D-Faust

	$\mathrm{d}_{\mathrm{C}}^{\rightarrow}$ (reg., recon.)		d_{N} (reg., recon.)		$\mathrm{d}_{\mathrm{C}}^{\rightarrow}$ (recon., reg.)		$\mathrm{d}_{\mathrm{N}}^{\rightarrow}$ (recon., reg.)		$\mathrm{d}_{\mathrm{C}}^{\rightarrow}$ (scan, recon.)		d_{N} (scan, recon.)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
SAL	0.418	0.328	13.21	12.459	0.344	0.256	11.354	**10.522**	0.429	0.246	10.096	9.096
IGR	0.276	0.187	10.328	9.822	3.806	3.627	17.124	17.902	0.241	0.11	5.829	5.295
SALD	0.428	0.346	11.67	11.07	0.489	0.362	11.035	10.371	0.397	0.279	7.884	7.227

Table: D-Faust quantitative results with mean and median of the one-sided Chamfer and normal distances between registration meshes (reg), reconstructions (recon) and raw input scans (scan). The d_{C} numbers are reported $\times 10^2$. [2]

Experiments and Results

D-Faust

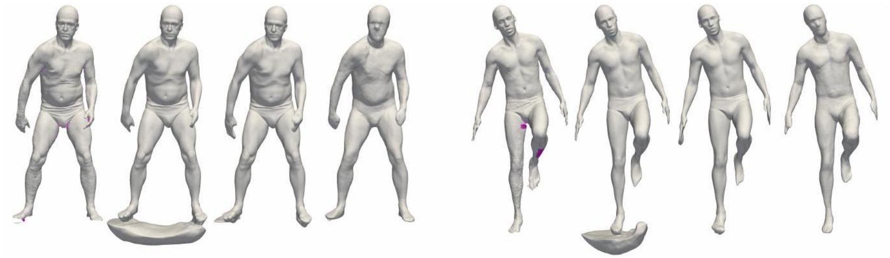

Figure: D-Faust qualitative results on test examples. Each quadruple shows (columns from left to right): raw scans (magenta depict back-faces), IGR, SALD, and SAL. [2]

Further Improvements

Shortcomings of SALD

When looking at the qualitative results of SALD we can observe some shortcomings that can be further attempted to improve.

Further Improvements

Shortcomings of SALD

Figure: Left one of each pair is the original surface and the right one is reconstructed using SALD. [2]

Further Improvements

Network Improvements

LightSAL, a novel deep convolutional architecture for learning 3D shapes based on the same technique as SAL, concentrates on efficiency in network training time and resulting model size [4].

Further Improvements

Technical Improvements

- Existing INRs require point coordinates to learn the implicit level sets of the shape and if a normal vector is available for each point, a higher fidelity representation can be learned.

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- Existing INRs require point coordinates to learn the implicit level sets of the shape and if a normal vector is available for each point, a higher fidelity representation can be learned.
- However, normal vectors are often not provided as raw data.
- In DiGS, the authors propose a divergence-guided shape representation learning approach that does not require normal vectors as input [5].
- Incorporating a soft constraint on the divergence of the distance function leads to smooth solutions that reliably orient gradients to match the unknown normal at each point, sometimes even better than approaches that use ground truth normal vectors directly [5].

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