Deep Marching Cubes: Learning Explicit Surface Representations

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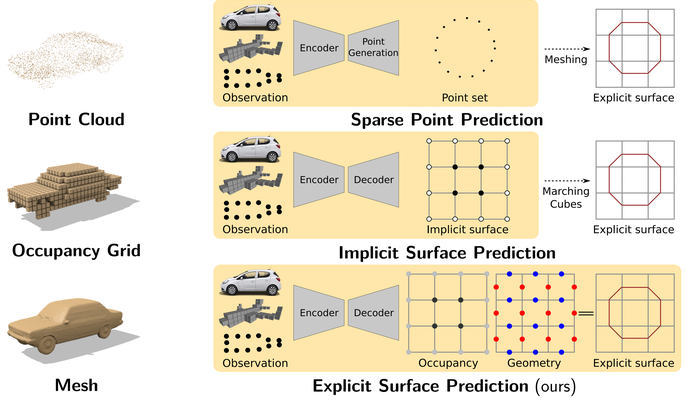
Motivation

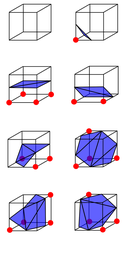
Goal: Reconstruct a 3D model from sparse and incomplete observations.



Contributions:

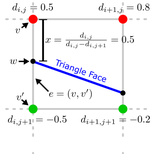
- Differentiable formulation of Marching Cubes Algorithm
- End-to-end surface prediction trained from unstructured point clouds

Differentiable Marching Cubes



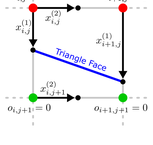
Marching Cubes:

- $x = d/(d - d')$ singular at $d = d'$
- Observations affect only grid cells in immediate vicinity

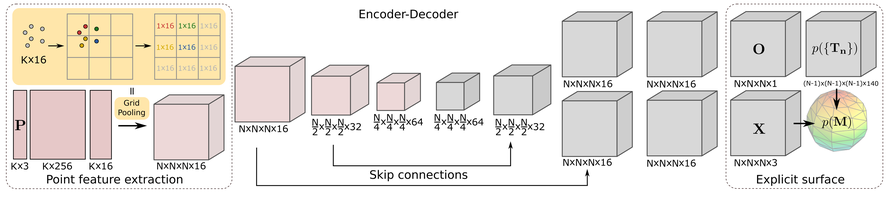


Differentiable Marching Cubes:

- Predict a vertex displacement field $\mathbf{X}$
- $p_{\mathbf{n}}(\mathbf{T}) = \prod_{\mathbf{m}} (o_{\mathbf{n}+\mathbf{m}})^{t_{\mathbf{m}}} (1 - o_{\mathbf{n}+\mathbf{m}})^{1-t_{\mathbf{m}}}$



Network Architecture and Loss Function



- **Point to Mesh Loss:**

$$\mathcal{L}^{\text{mesh}} = \sum_{\mathbf{n}} \mathbb{E}_{p_{\mathbf{n}}(\mathbf{T}|\boldsymbol{\theta})} \left[\sum_{\mathbf{y} \in \mathbf{Y}_{\mathbf{n}}} \Delta(\mathbf{M}_{\mathbf{n}}(\mathbf{T}, \mathbf{X}(\boldsymbol{\theta})), \mathbf{y}) \right]$$

- **Occupancy Loss:**

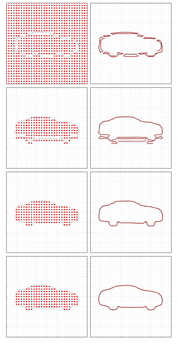
$$\mathcal{L}^{\text{occ}} = \frac{1}{|\Gamma|} \sum_{\mathbf{n} \in \Gamma} o_{\mathbf{n}}(\boldsymbol{\theta}) + w\left(1 - \frac{1}{|\Omega|} \sum_{\mathbf{n} \in \Omega} o_{\mathbf{n}}(\boldsymbol{\theta})\right)$$

- **Smoothness Loss:**

$$\mathcal{L}^{\text{smooth}} = \sum_{\mathbf{n} \sim \mathbf{m}} |o_{\mathbf{n}}(\boldsymbol{\theta}) - o_{\mathbf{m}}(\boldsymbol{\theta})|$$

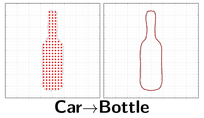
- **Curvature Loss:**

$$\mathcal{L}^{\text{curve}} = \sum_{\mathbf{n} \sim \mathbf{m}} \mathbb{E}_{p_{\mathbf{n},\mathbf{m}}(\mathbf{T},\mathbf{T}'|\boldsymbol{\theta})} \left[\varphi_{\mathbf{n},\mathbf{m}}(\mathbf{T}, \mathbf{T}', \mathbf{X}(\boldsymbol{\theta})) \right]$$

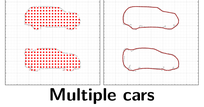


Experiments on ShapeNet 2D

Generalization:



Car→Bottle



Multiple cars

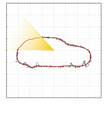
Robustness:

	Chamfer	Accuracy	Complete.
$\sigma = 0.00$	0.245	0.219	0.272
$\sigma = 0.15$	0.246	0.219	0.273
$\sigma = 0.30$	0.296	0.267	0.325

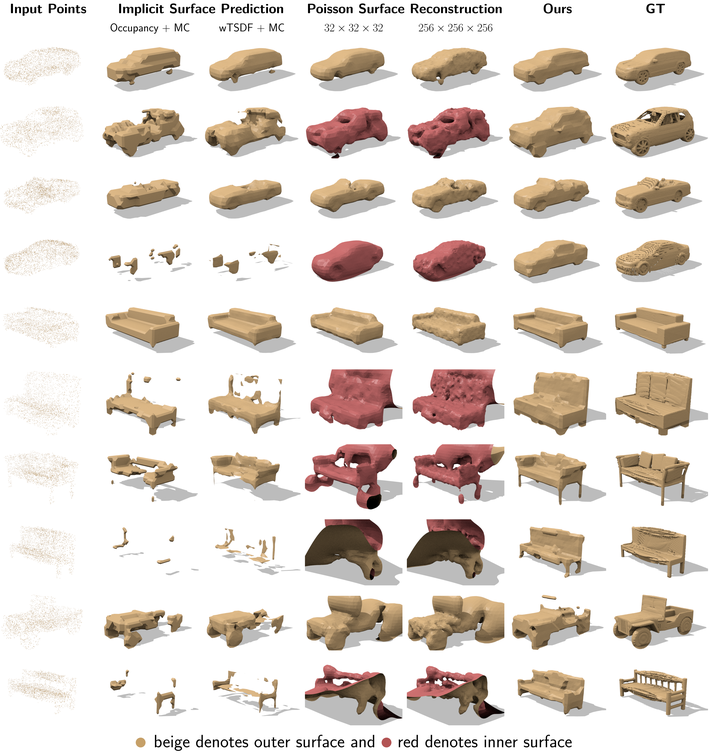
Noisy ground truth

	Chamfer	Accuracy	Complete.
$\theta = 15°$	0.234	0.210	0.257
$\theta = 30°$	0.250	0.227	0.273
$\theta = 45°$	0.308	0.261	0.354

Incomplete ground truth



Experiments on ShapeNet 3D



● beige denotes outer surface and ● red denotes inner surface

Resolution	Method	Chamfer	Accuracy	Complete.
$32 \times 32 \times 32$	Occupancy + MC	0.407	0.246	0.567
	TSDF + MC	0.412	0.236	0.588
	wTSDF + MC	0.354	0.219	0.489
	Poisson Surface Reconstruction	0.352	0.405	0.298
	Ours	**0.218**	**0.182**	**0.254**
$256 \times 256 \times 256$	Poisson Surface Reconstruction	0.198	0.196	0.200