

# Coupling Explicit and Implicit Surface Representations for Generative 3D Modeling

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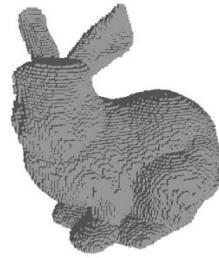


# Representing 3D Shapes

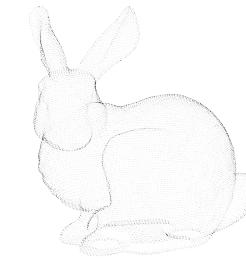
## Discretized representations

- ❑ Fixed sampling density

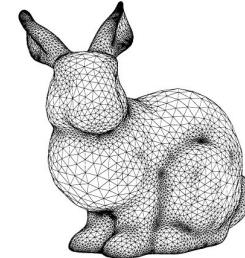
### Voxel grid



### Point Cloud



### Mesh



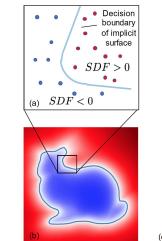
## Continuous representations

- ❑ Arbitrary resolution

### Surface Atlas

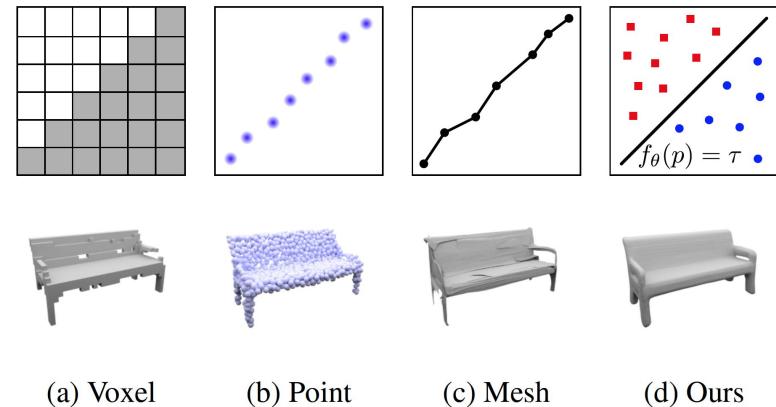
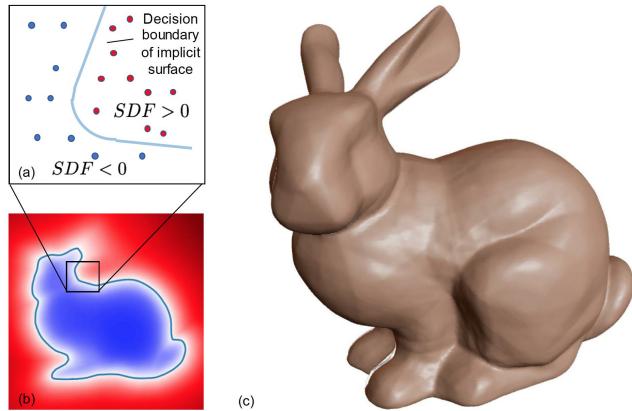


### Implicit Function



# Implicit Functions

Map each 3D point to inside/outside the shape



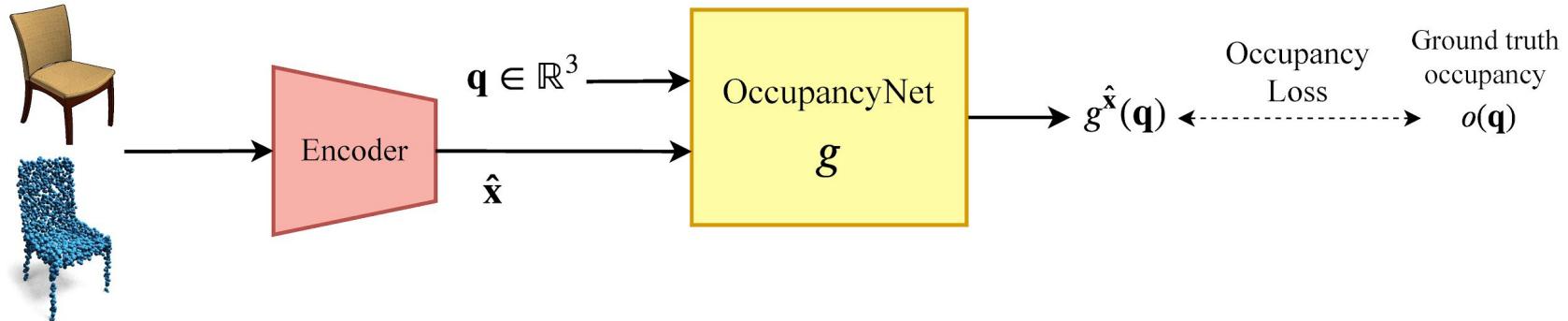
DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, Park et al., CVPR 2019

Occupancy Networks: Learning 3D Reconstruction in Function Space, Mescheder et al., CVPR 2019

Coupling Explicit and Implicit Surface Representations for Generative 3D Modeling, Poursaeed et al., ECCV 2020

# Implicit Functions

**OccupancyNet:**  $g^{\hat{x}} : \mathbb{R}^3 \rightarrow [0, 1]$  (Occupancy Probability)

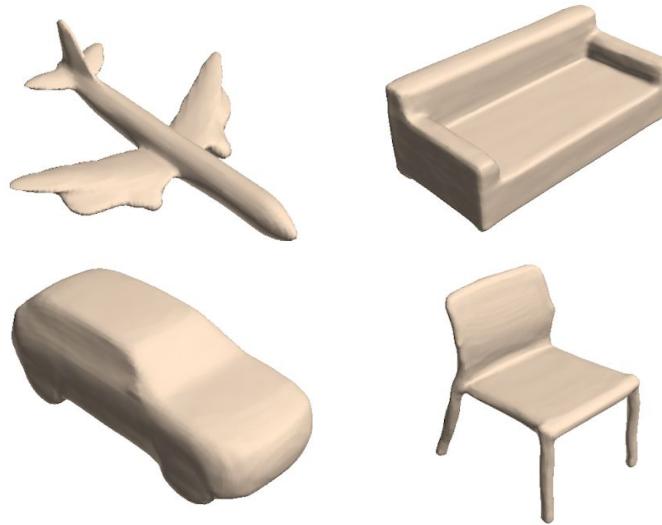


$\tau$  : Surface threshold

# Implicit Functions

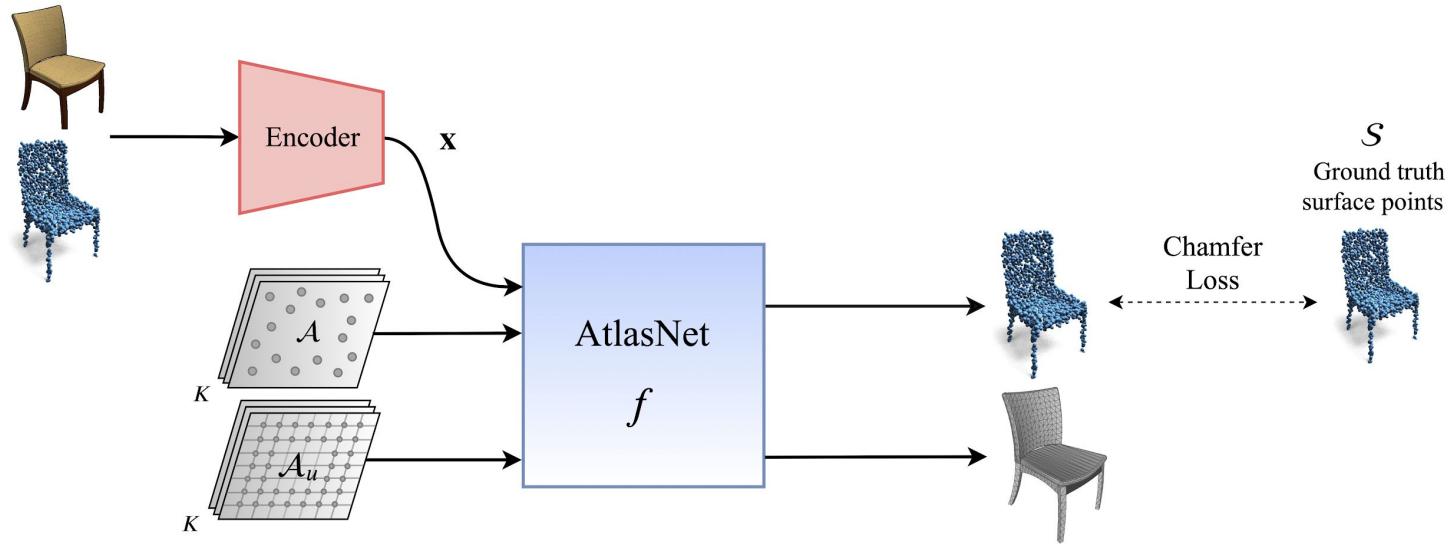
OccupancyNet results

- + Smooth
- Fail to capture details
- Slow rendering (Marching Cubes)



# Surface Atlas

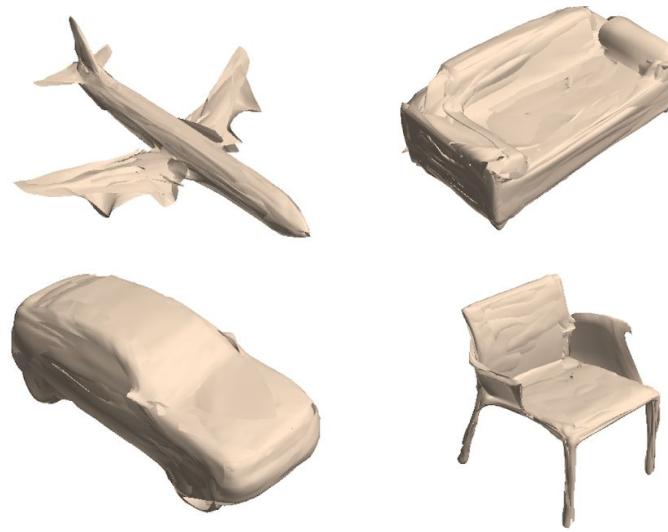
**AtlasNet:** maps points on 2D patches to the surface  $f_i^{\mathbf{x}} : [0, 1]^2 \rightarrow \mathbb{R}^3$



# Surface Atlas

## AtlasNet results

- + Fast rendering
- + Easy to store textures
- Non-smooth
- Artifacts at boundaries of patches



# Hybrid Explicit / Implicit Model

Hybrid Approach:

- Aligning the **surface** generated by AtlasNet to the level-set of the implicit function

$$g^{\hat{\mathbf{x}}} (f_i^{\mathbf{x}}(\mathbf{p})) = \tau$$

- Aligning AtlasNet and OccupancyNet **normals**

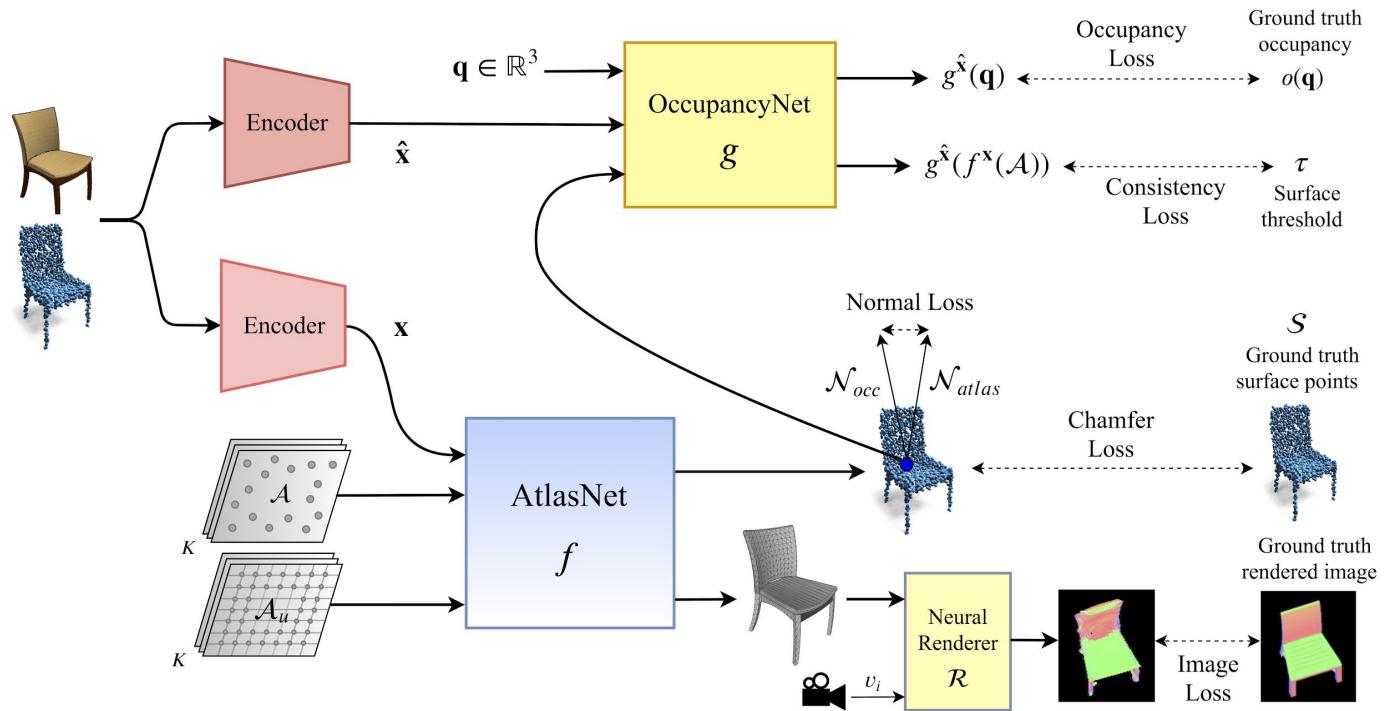
$$\mathcal{N}_{\text{occ}} = \mathcal{N}_{\text{atlas}}$$

$$\mathcal{N}_{\text{atlas}} = \frac{\partial f_i^{\mathbf{x}}}{\partial u} \times \frac{\partial f_i^{\mathbf{x}}}{\partial v} \Big|_{\mathbf{p}}$$

$$\mathcal{N}_{\text{occ}} = \nabla_{\mathbf{q}} g^{\hat{\mathbf{x}}}(\mathbf{q})$$

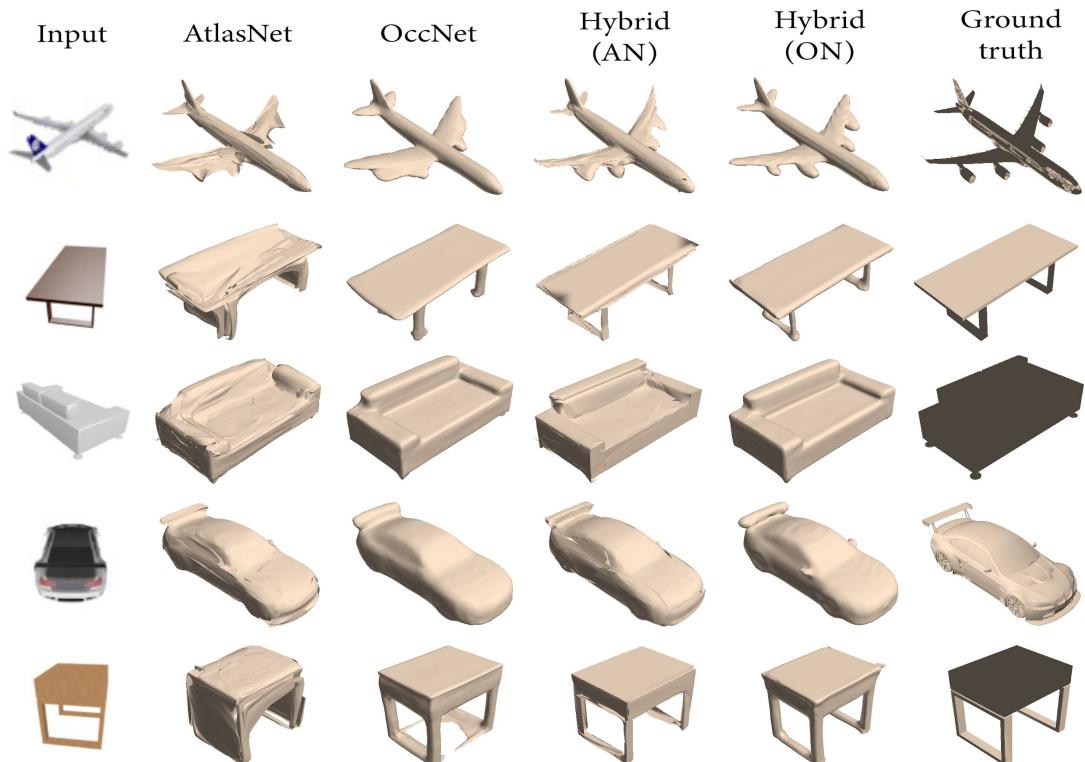
# Hybrid Explicit / Implicit Model

Architecture:



# Results

## Single-view reconstruction



# Results

## Single-view reconstruction

Metric	Chamfer- $L_1(\times 10^{-1})$													
	Model		AN		ON		Hybrid		No $\mathcal{L}_{\text{img}}$		No $\mathcal{L}_{\text{norm}}$		No $\mathcal{L}_{\text{img}}, \mathcal{L}_{\text{norm}}$	
Branch			AN	ON	AN	ON	AN	ON	AN	ON	AN	ON	AN	ON
airplane	1.05	1.34	<b>0.91</b>	1.03	0.96	1.10	0.95	1.08	1.01	1.17				
bench	1.38	1.50	<b>1.23</b>	1.26	1.27	1.31	1.26	1.29	1.32	1.38				
cabinet	1.75	1.53	1.53	<b>1.47</b>	1.57	1.49	1.55	1.49	1.61	1.50				
car	1.41	1.49	<b>1.28</b>	1.31	1.33	1.37	1.33	1.36	1.37	1.42				
chair	2.09	2.06	1.96	<b>1.95</b>	2.02	2.01	1.99	1.99	2.04	2.03				
display	1.98	2.58	<b>1.89</b>	2.14	1.92	2.24	1.90	2.19	1.94	2.29				
lamp	3.05	3.68	<b>2.91</b>	3.02	2.93	3.09	2.91	3.06	2.99	3.21				
sofa	1.77	1.81	<b>1.56</b>	1.58	1.61	1.63	1.59	1.61	1.68	1.71				
table	1.90	1.82	1.73	<b>1.72</b>	1.80	1.78	1.78	1.76	1.83	1.79				
telephone	1.28	1.27	<b>1.17</b>	1.18	1.22	1.21	1.19	1.19	1.24	1.24				
vessel	1.51	2.01	<b>1.42</b>	1.53	1.46	1.60	1.46	1.58	1.48	1.69				
mean	1.74	1.92	<b>1.60</b>	1.65	1.64	1.71	1.63	1.69	1.68	1.77				

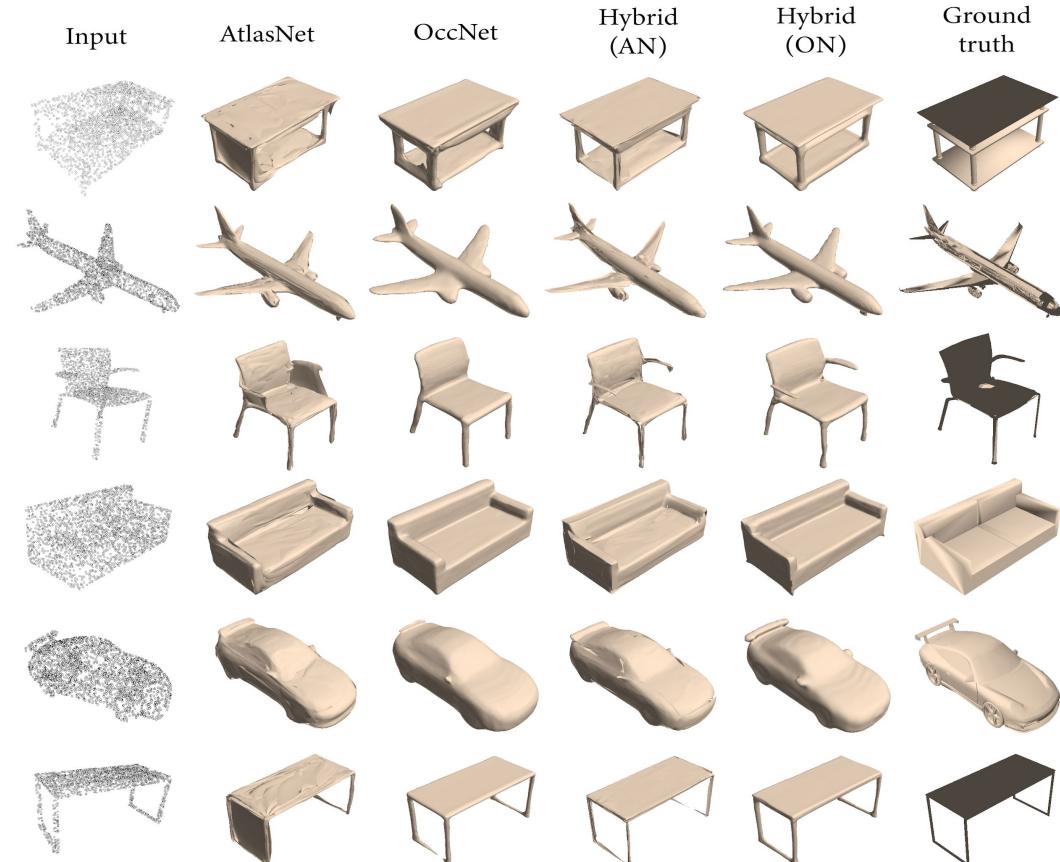
# Results

## Single-view reconstruction

Metric	Normal Consistency ( $\times 10^{-2}$ )												
	Model		AN		ON		Hybrid		No $\mathcal{L}_{\text{img}}$		No $\mathcal{L}_{\text{norm}}$		No $\mathcal{L}_{\text{img}}, \mathcal{L}_{\text{norm}}$
Branch		AN	ON	AN	ON	AN	ON	AN	ON	AN	ON	AN	ON
airplane		83.6	84.5	85.5	<b>85.7</b>	85.3	85.6	84.8	85.3	84.3	85.0		
bench		77.9	81.4	81.4	<b>82.5</b>	80.9	82.2	80.4	81.9	79.9	81.7		
cabinet		85.0	88.4	88.3	<b>89.1</b>	88.1	89.0	87.2	88.7	86.8	88.6		
car		83.6	85.2	86.2	<b>86.8</b>	85.8	86.5	85.3	86.0	84.9	85.8		
chair		79.1	82.9	83.5	<b>84.0</b>	83.1	83.7	82.4	83.4	82.0	83.2		
display		85.8	85.7	<b>87.0</b>	86.9	86.7	86.6	86.3	86.1	86.0	85.9		
lamp		69.4	75.1	74.9	<b>76.0</b>	74.7	75.9	73.3	75.6	72.8	75.4		
sofa		84.0	86.7	87.2	<b>87.5</b>	86.9	87.4	86.4	87.1	85.9	86.9		
table		83.2	85.8	86.3	<b>87.4</b>	86.0	87.1	85.3	86.4	84.9	86.1		
telephone		92.3	93.9	94.0	<b>94.5</b>	93.8	94.4	93.6	94.2	93.3	94.1		
vessel		75.6	79.7	79.2	<b>80.6</b>	78.9	80.4	77.7	80.0	77.4	79.9		
mean		81.8	84.5	84.9	<b>85.5</b>	84.6	85.4	83.9	85.0	83.5	84.8		

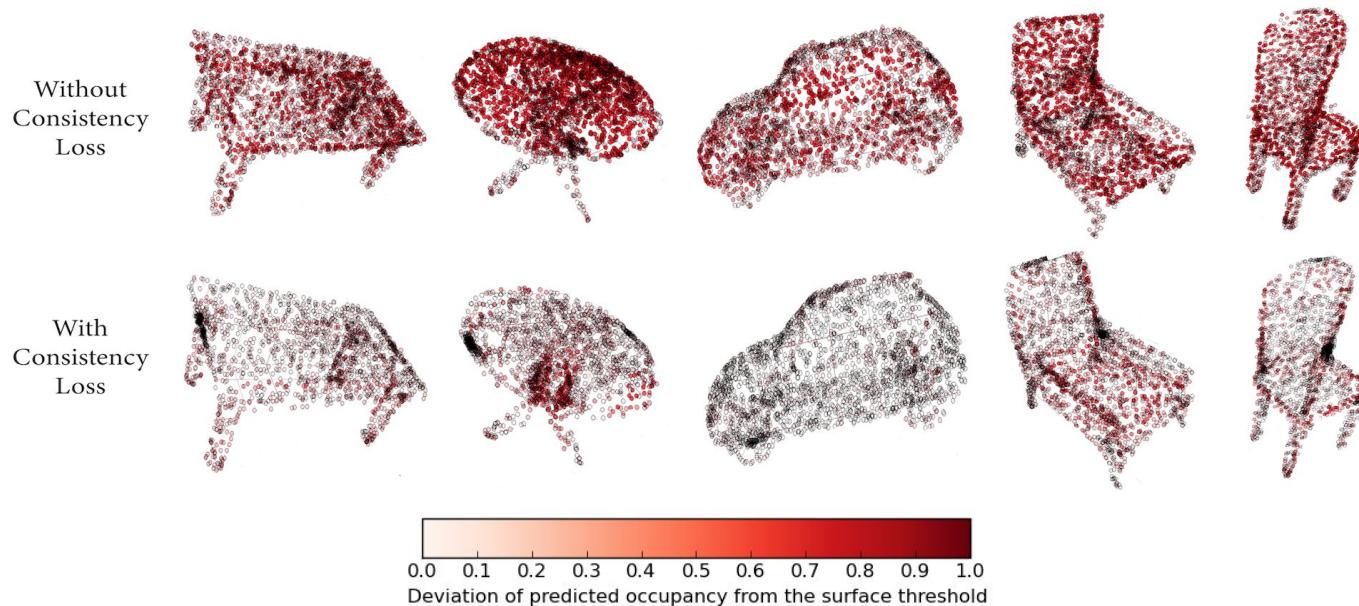
# Results

Auto-encoding point clouds



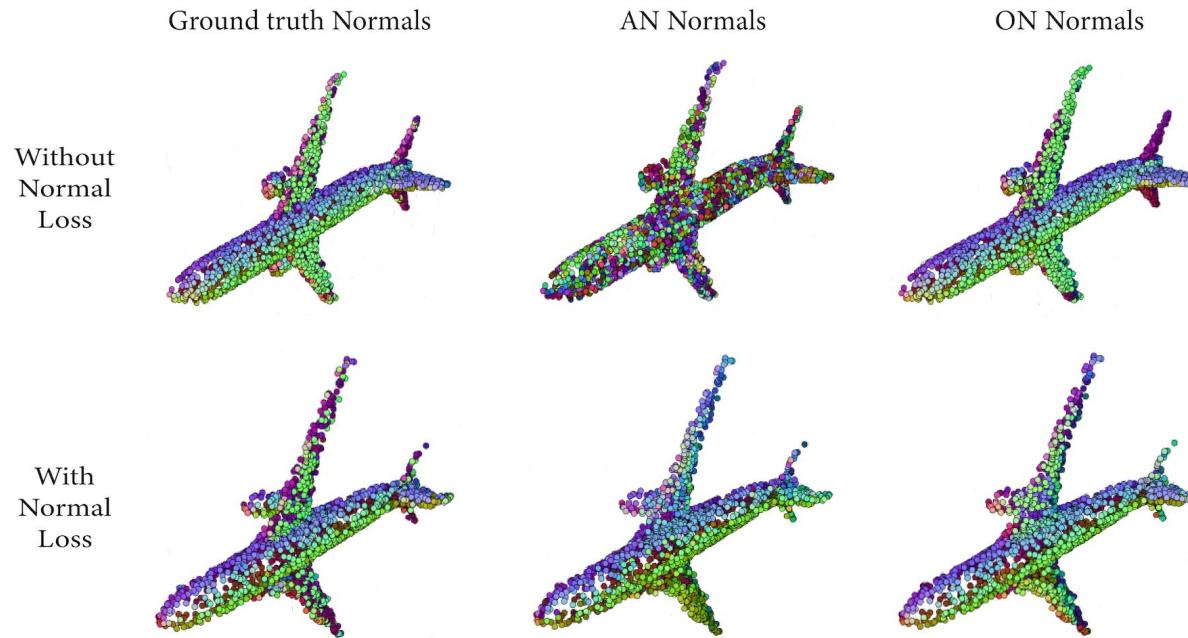
# Impact of Loss Components

## Consistency Loss



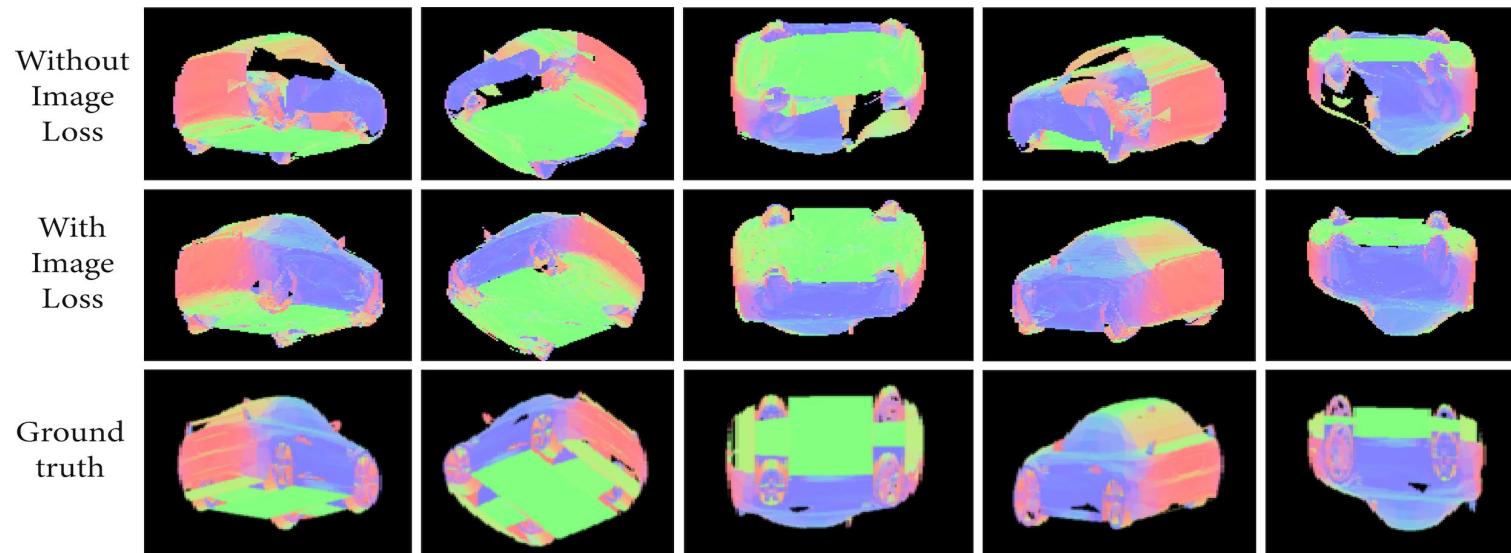
# Impact of Loss Components

## Normal Loss



# Impact of Loss Components

## Image loss



# Summary: Hybrid Approach

Advantages:

- Learning smoother surface
- Accurate normals
- Accurate surface: small chamfer distance to ground truth
- Faster inference

