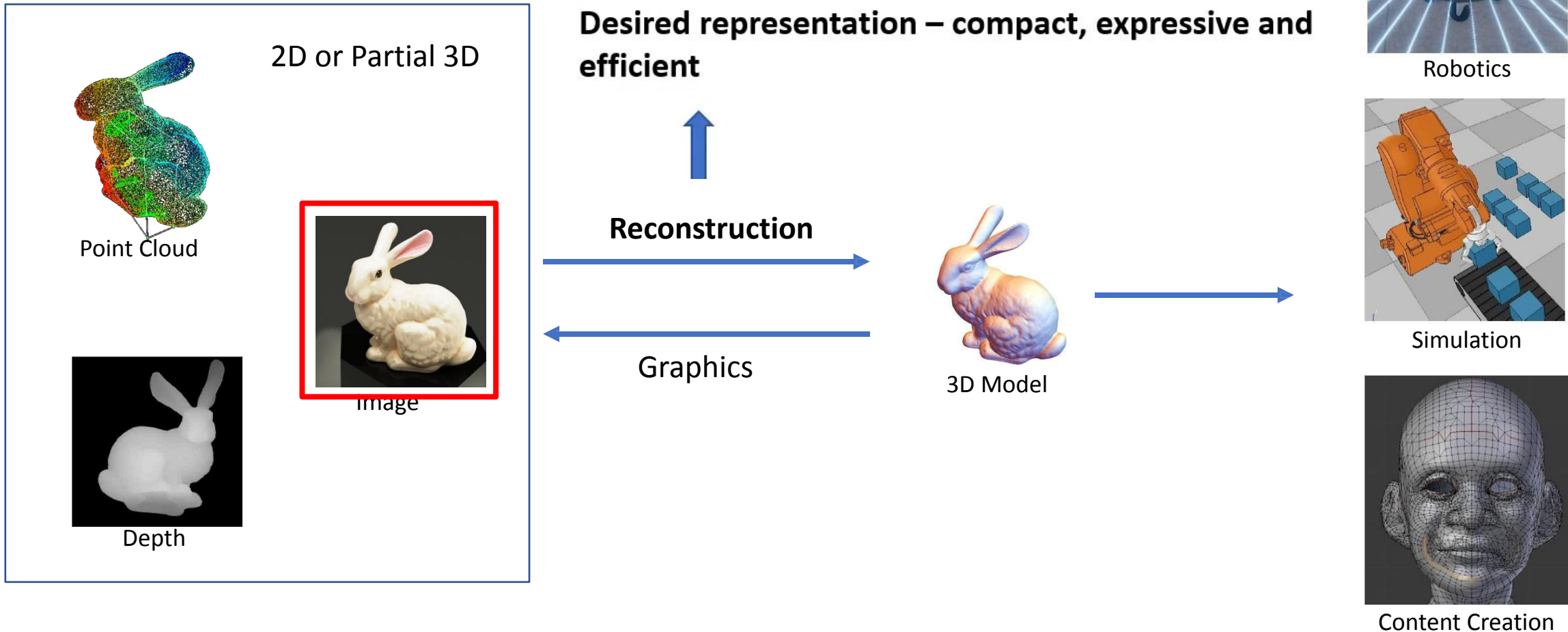


DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation

Date: 28.04.2023

Presenter: Prakash Naikade

Motivation and Main Problem



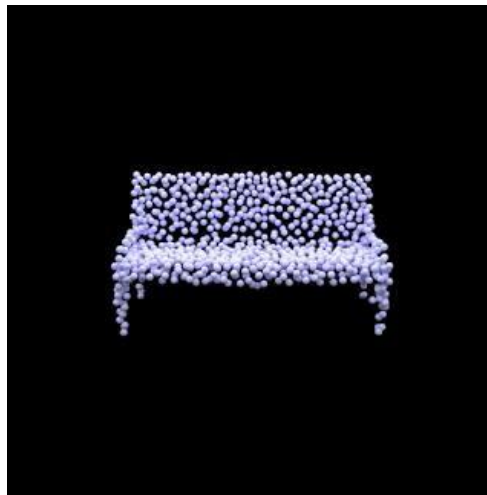
Motivation and Main Problem

3D Representations prior to DeepSDF



Voxel (Choy et al. 2016)

Cubically growing compute and memory requirements



Point Cloud (Fan et al. 2017)

Do not describe surface



Mesh (Groueix et al. 2017)

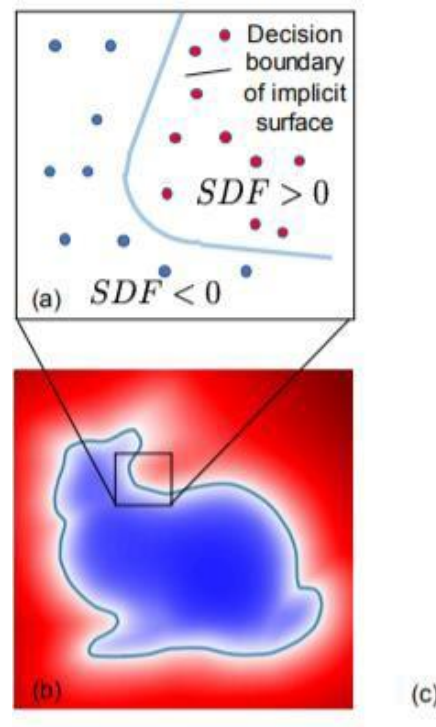
Limited to the typology of the template

Motivation and Main Problem

Key insight

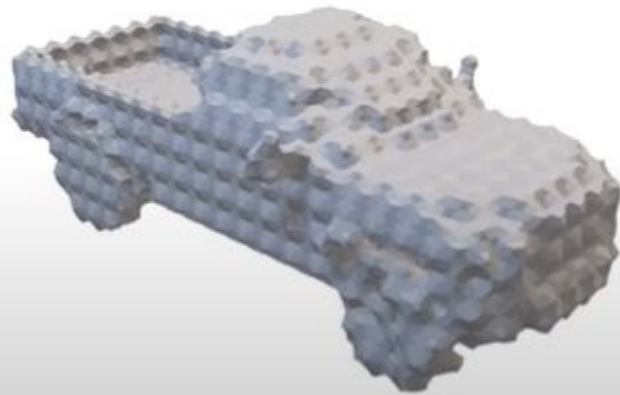
- Directly regress SDF
- The surface is implicitly represented by the zero-level set

$$f_{\theta}(x, y, z) \approx SDF(x, y, z)$$

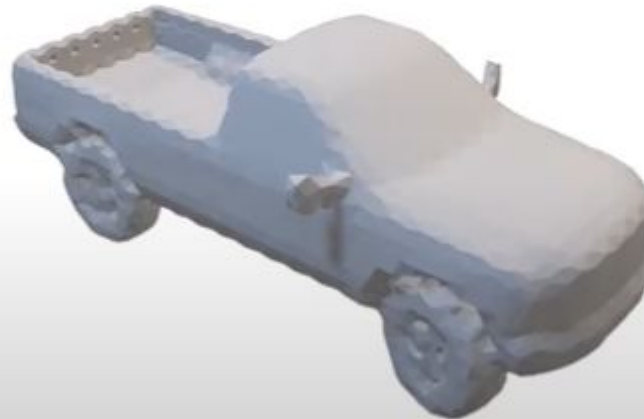


Motivation and Main Problem

Marching Tetrahedron with grid size = 100



With only occupancy value



With SDF



GT

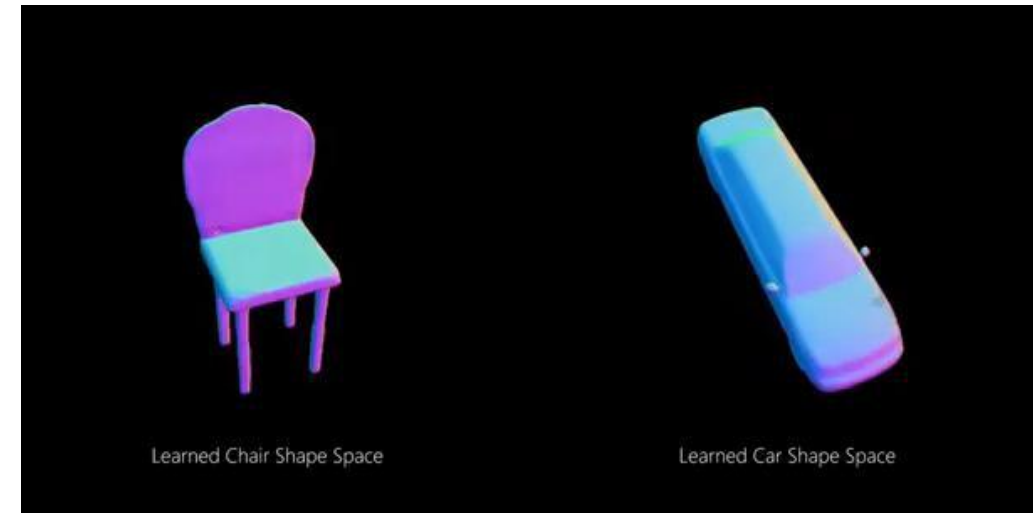
Contribution

Prior work of 3D representations lacks the ability of representing fine surface details.

In this paper, the authors proposed

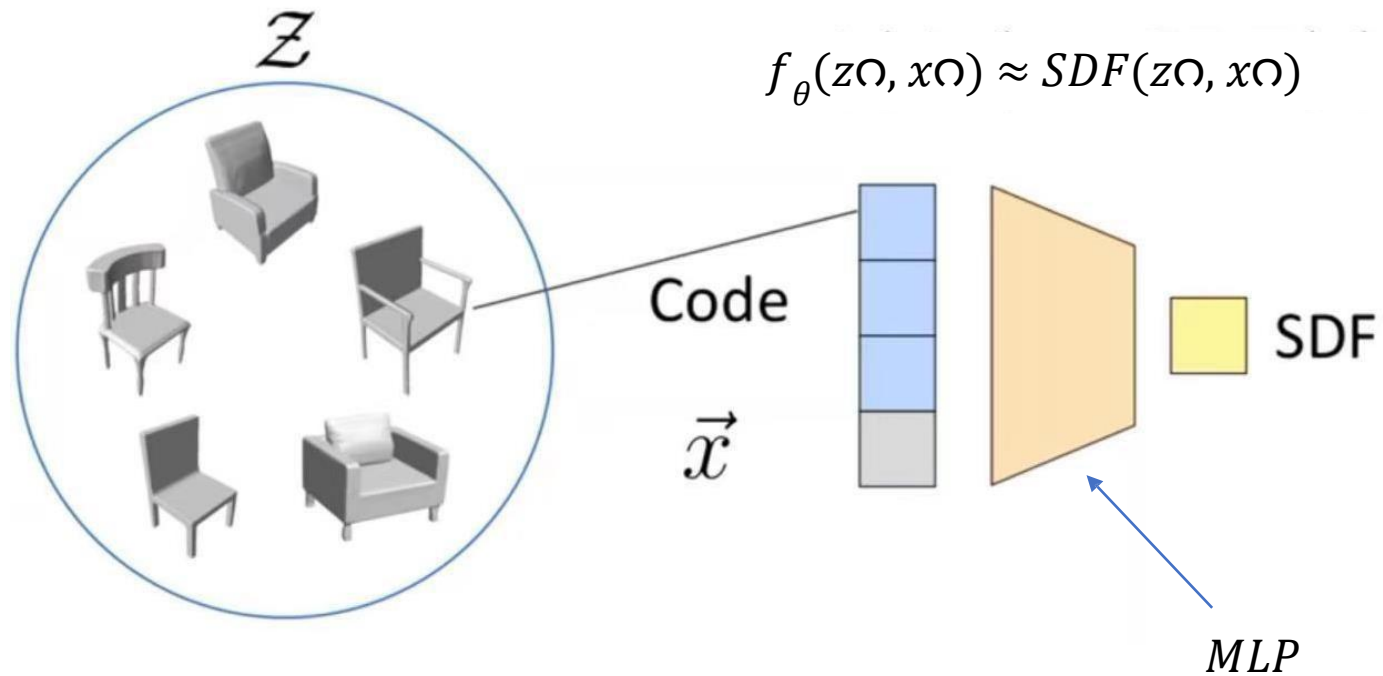
- a new 3D representation that is efficient, expressive and continuous.
- a learning method for 3D shapes based on a probabilistic auto-decoder

Further, they demonstrate the application of their formulation by obtaining SOTA results on shape reconstruction and completion

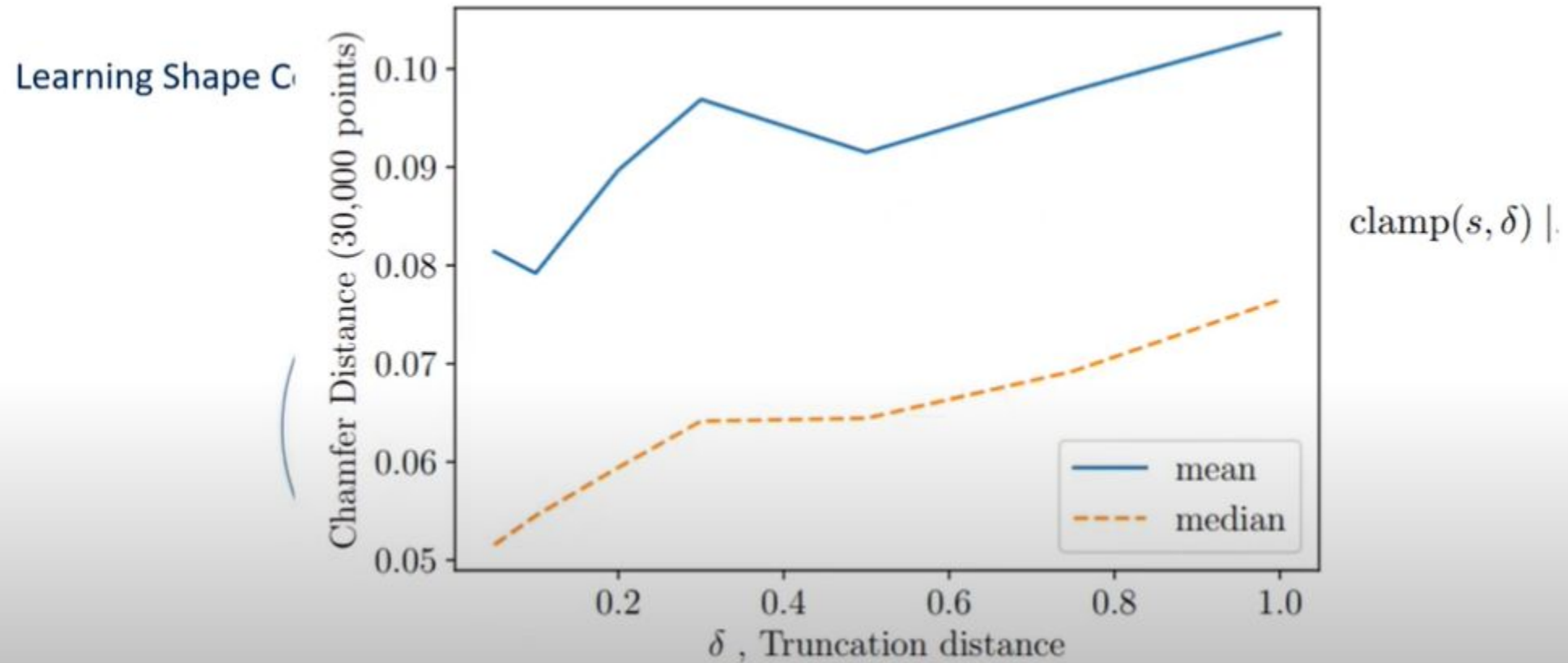


Problem Setting

Learning Shape Conditioned Reconstruction with a Continuous Implicit Surface

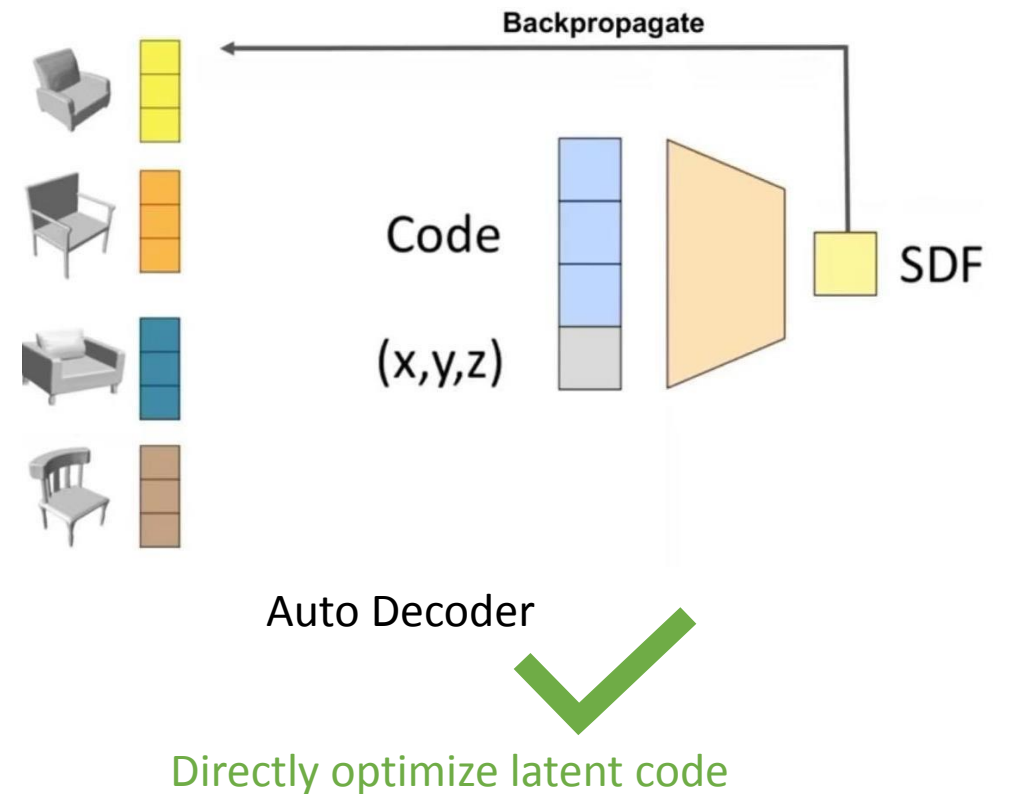
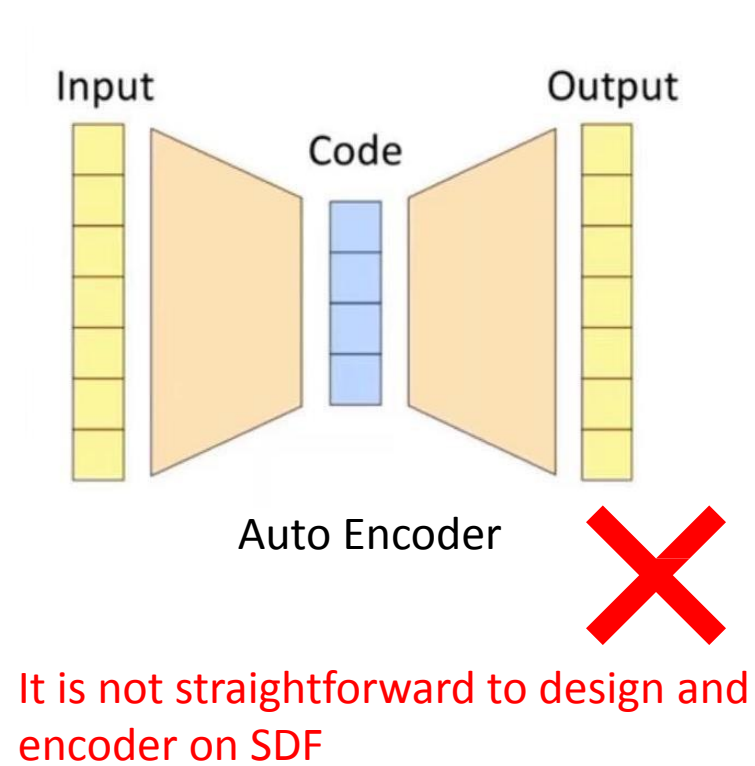


Problem Setting

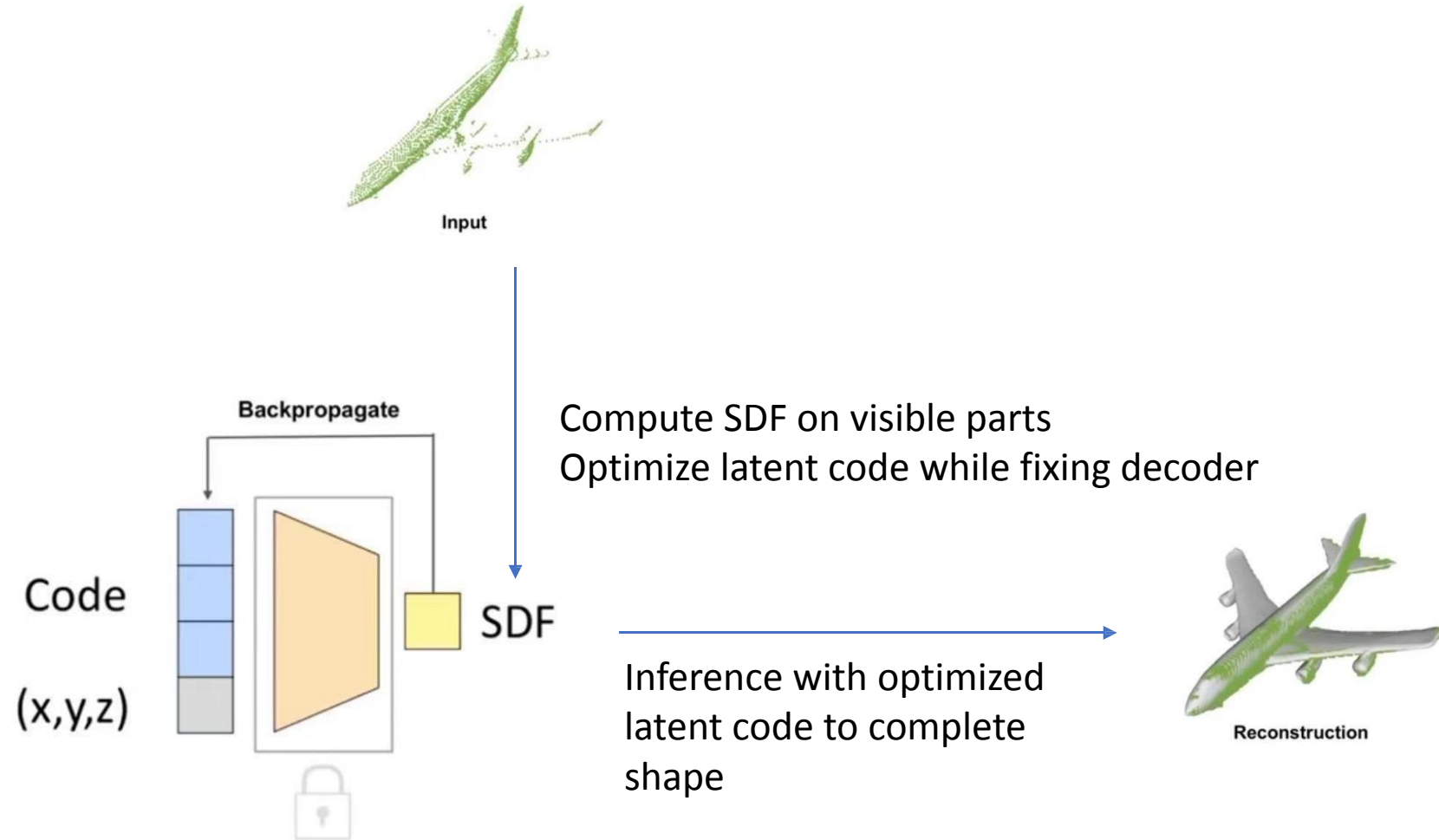


Learning

Coding Multiple Shapes with Auto Decoder

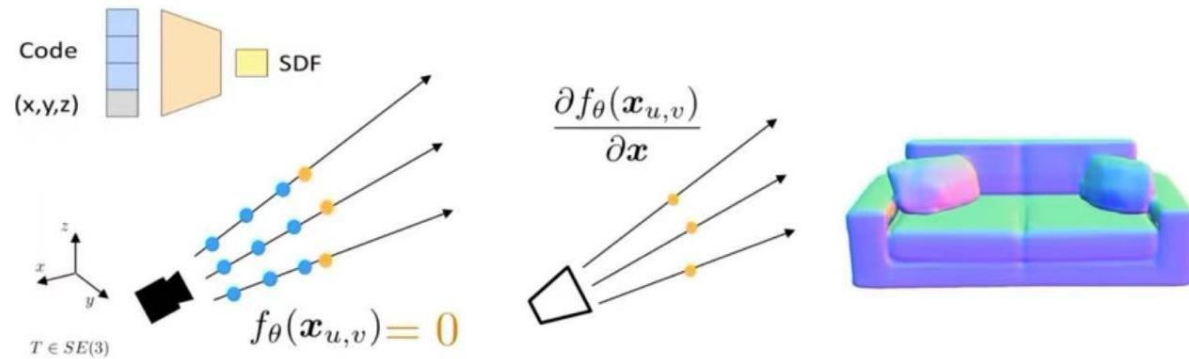


Inference



Surface Extraction

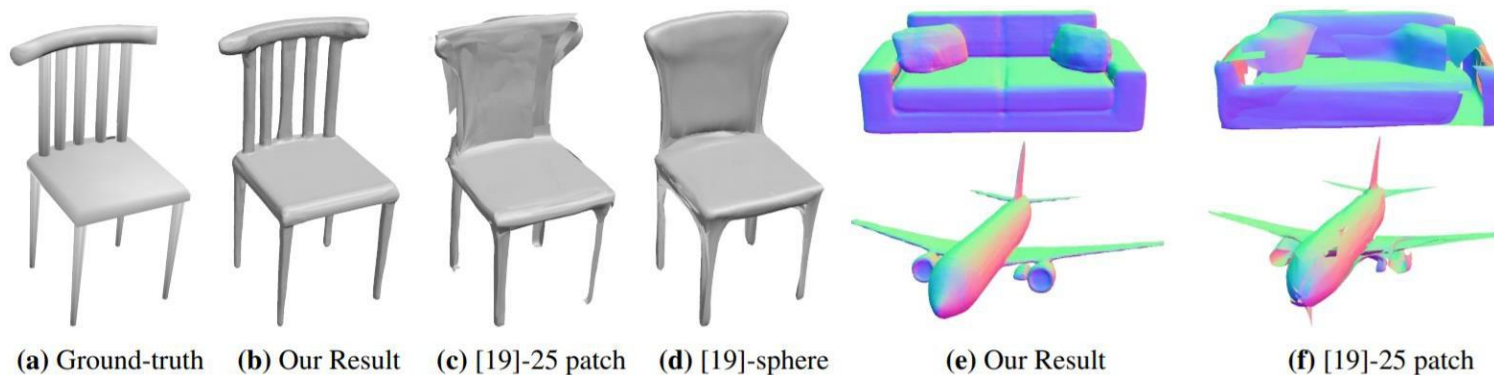
1. Ray casting



2. Marching Cubes – faster, however imposes quantization error due to fixed grid size

Results and Discussion

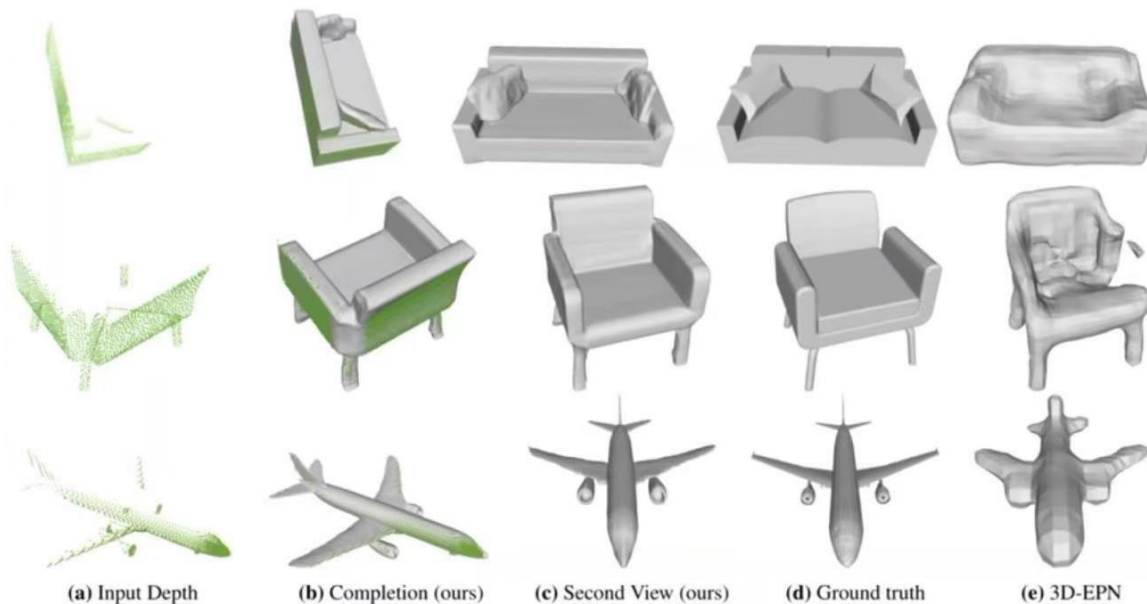
- Representing unknown shapes



CD, mean	chair	plane	table	lamp	sofa
AtlasNet-Sph.	0.752	0.188	0.725	2.381	0.445
AtlasNet-25	0.368	0.216	0.328	1.182	0.411
DeepSDF	0.204	0.143	0.553	0.832	0.132
CD, median					
AtlasNet-Sph.	0.511	0.079	0.389	2.180	0.330
AtlasNet-25	0.276	0.065	0.195	0.993	0.311
DeepSDF	0.072	0.036	0.068	0.219	0.088
EMD, mean					
AtlasNet-Sph.	0.071	0.038	0.060	0.085	0.050
AtlasNet-25	0.064	0.041	0.073	0.062	0.063
DeepSDF	0.049	0.033	0.050	0.059	0.047
Mesh acc., mean					
AtlasNet-Sph.	0.033	0.013	0.032	0.054	0.017
AtlasNet-25	0.018	0.013	0.014	0.042	0.017
DeepSDF	0.009	0.004	0.012	0.013	0.004

Results and Discussion

- Shape completion from partial range scans
 - Notice that, the same trained model can be applied to different reconstruction tasks, unlike Octnet.



Method \ Metric	<i>lower is better</i>				<i>higher is better</i>	
	CD, med.	CD, mean	EMD	Mesh acc.	Mesh comp.	Cos sim.
chair						
3D-EPN	2.25	2.83	0.084	0.059	0.209	0.752
DeepSDF	1.28	2.11	0.071	0.049	0.500	0.766
plane						
3D-EPN	1.63	2.19	0.063	0.040	0.165	0.710
DeepSDF	0.37	1.16	0.049	0.032	0.722	0.823
sofa						
3D-EPN	2.03	2.18	0.071	0.049	0.254	0.742
DeepSDF	0.82	1.59	0.059	0.041	0.541	0.810

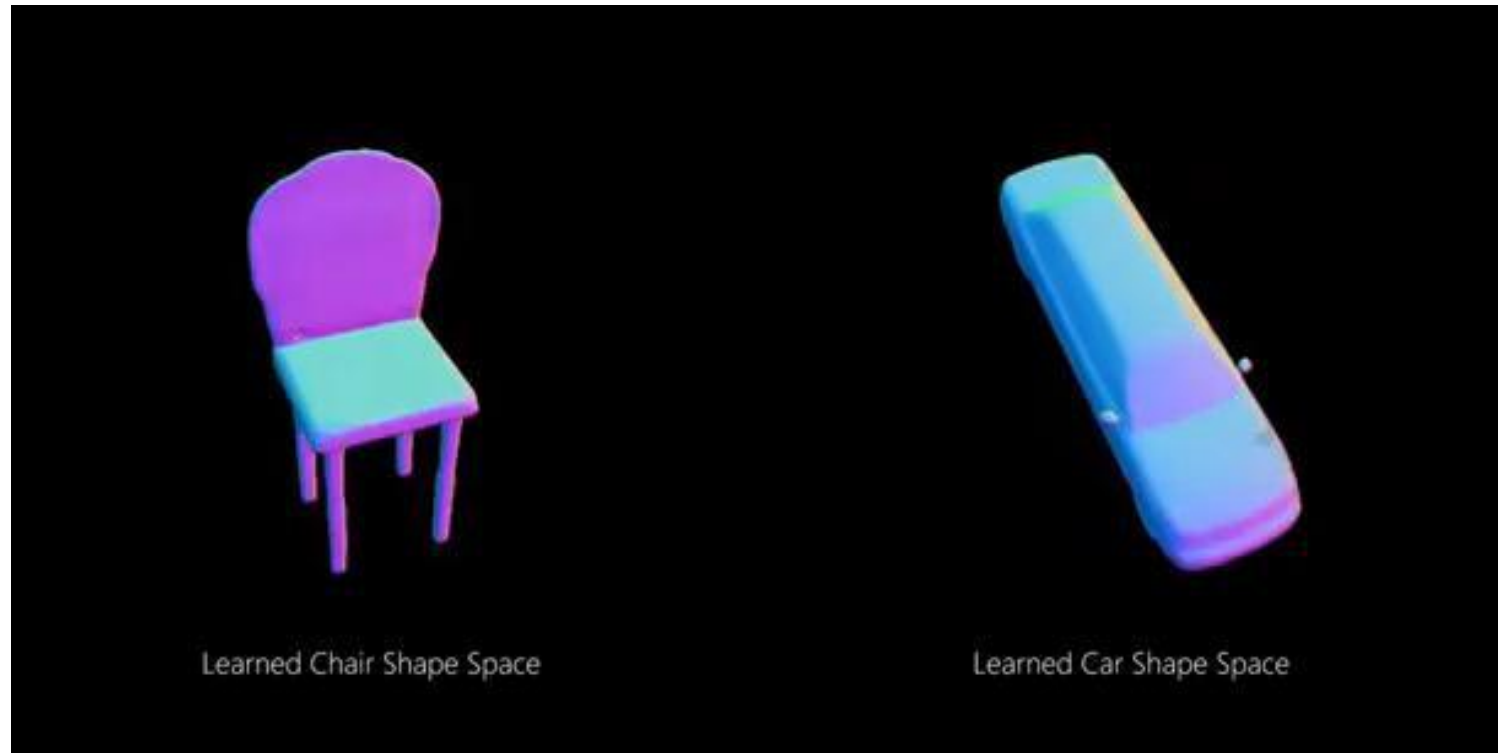
Results and Discussion

- Overview of the benchmarked methods

Method	Type	Discretization	Complex topologies	Closed surfaces	Surface normals	Model size (GB)	Inf. time (s)	Eval. tasks
3D-EPN [15]	Voxel SDF	32^3 voxels	✓	✓	✓	0.42	-	C
OGN [49]	Octree	256^3 voxels	✓	✓		0.54	0.32	K
AtlasNet-Sphere [19]	Parametric mesh	1 patch		✓		0.015	0.01	K, U
AtlasNet-25 [19]	Parametric mesh	25 patches	✓			0.172	0.32	K, U
DeepSDF (ours)	Continuous SDF	none	✓	✓	✓	0.0074	9.72	K, U, C

Results and Discussion

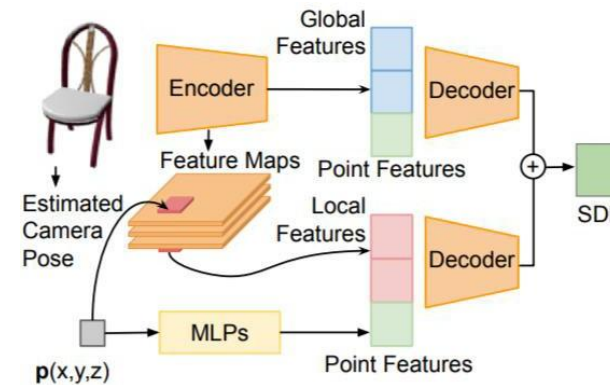
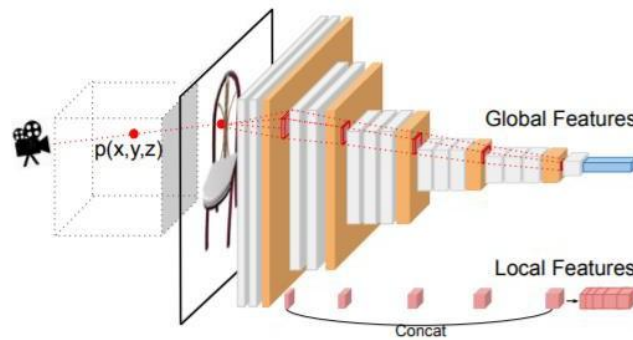
- Feature Space Interpolation



Limitation

S

- Inference need optimizing latent code with SDF -> not applicable to 2D observation.
 - DISN (Wang et al. 2019) addressed this problem with a novel image encoder.



- The inference time is slow even assuming models are in their canonical pose.

Contribution

Prior work of 3D representations lacks the ability of representing fine surface details.

In this paper, the authors proposed

- A formulation of generative shape modeling with SDF in continuous space that is efficient, expressive and continuous
- a learning method for 3D shapes based on a probabilistic auto-decoder

Further, they demonstrate the application of their formulation by obtaining SOTA results on shape reconstruction and completion