Object recognition and computer vision - Single view 3D object reconstruction

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Representing 3d shapes

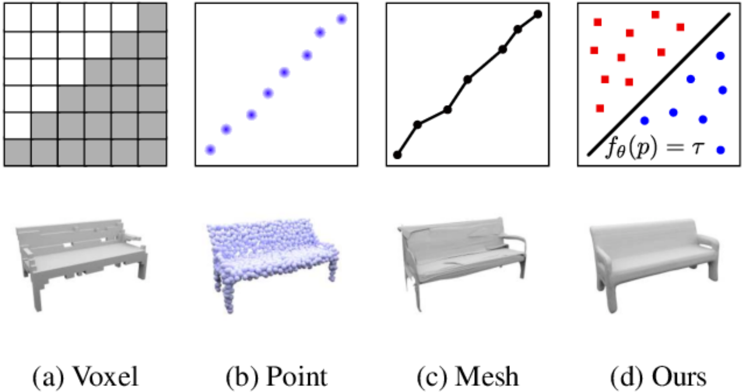
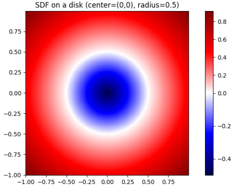
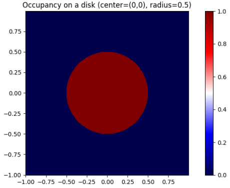


Figure 1: Various methods to store shapes

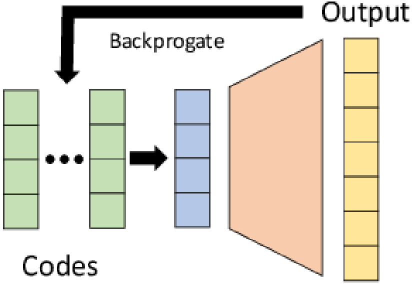
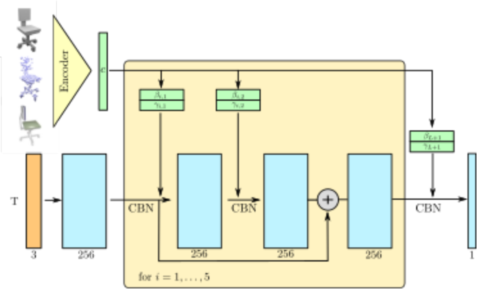
Continuous representations

SDF	Occupancy
$f(x) = \begin{cases} d(x, \partial\Omega) & x \in \Omega \\ -d(x, \partial\Omega) & x \notin \Omega \end{cases}$	$f(x) = \begin{cases} 1 & x \in \Omega \\ 0 & x \notin \Omega \end{cases}$
	

- Can be approximated with neural networks
- Mesh can easily be reconstructed with marching cubes

Neural networks approaches

- Idea: learn a shape representation in a latent space, and use it to compute SDF/Occupancy map on every point of the space

Auto-decoder (DeepSDF)	Auto-encoder (ONet)
	

Training setup

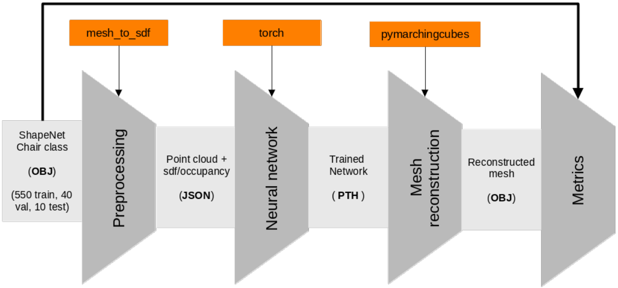


Figure 2: Training pipepline

- For SDF: clamped L_1 loss: $\mathcal{L}(f_\theta(x), s) = |\text{clamp}(f_\theta(x), \delta), \text{clamp}(f_\theta(x), \delta)|$
- Regularization on latent space (autodecoder): $\frac{1}{\sigma^2}||z||_2^2$
- For Occupancy: Binary cross entropy loss

Results

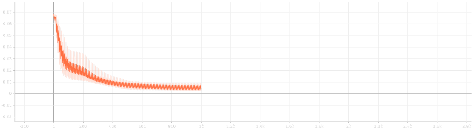


Figure 3: DeepSDF training loss

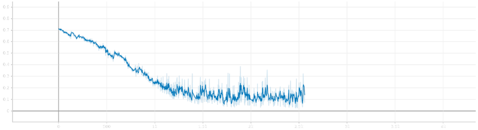


Figure 4: ONet training loss

	Chamfer	precision	recall
DeepSDF	0.09	0.82	0.81
ONet	0.1 (0.079 in original paper)	0.75	0.87

Visuals (point cloud completion)

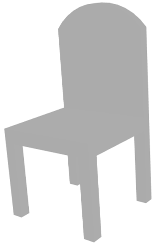


Figure 5: Original mesh

Figure 6: DeepSDF

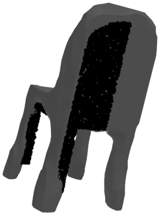


Figure 7: ONet

Conclusions

- Train on a bigger dataset
- Try other encoder architectures (for single view reconstruction in particular)
- Train autoencoder on SDF and autodecoder on occupancy

Biliography

[1]
Park J J, Florence P, Straub J, Newcombe R and Lovegrove S 2019 DeepSDF: Learning continuous signed distance functions for shape representation

[2]
Mescheder L, Oechsle M, Niemeyer M, Nowozin S and Geiger A 2019 Occupancy networks: Learning 3D reconstruction in function space

[3]
Chen Z and Zhang H 2019 Learning implicit fields for generative shape modeling