

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

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Representing 3d shapes

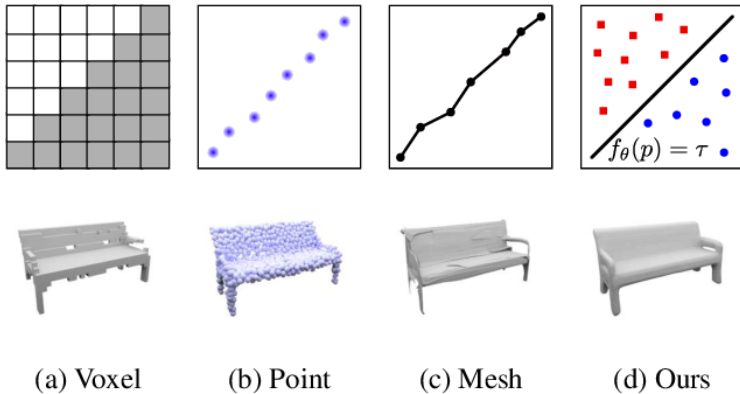
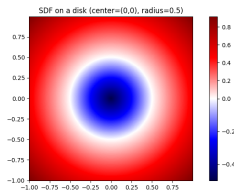


Figure 1: Various methods to store shapes

Continuous representations

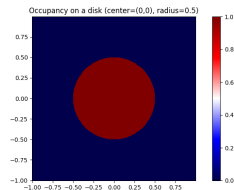
SDF

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



Occupancy

$$f(x) = \begin{cases} 1 & x \in \Omega \\ 0 & x \notin \Omega \end{cases}$$

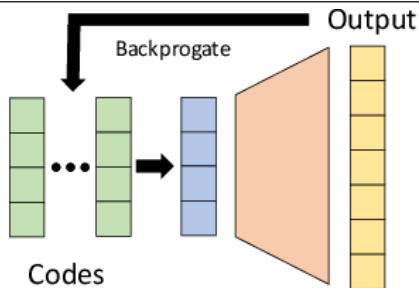


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- ▶ Can be approximated with neural networks
 - ▶ Mesh can easily be reconstructed with marching cubes

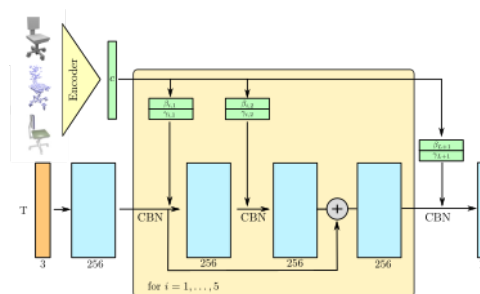
Neural networks approaches

- 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

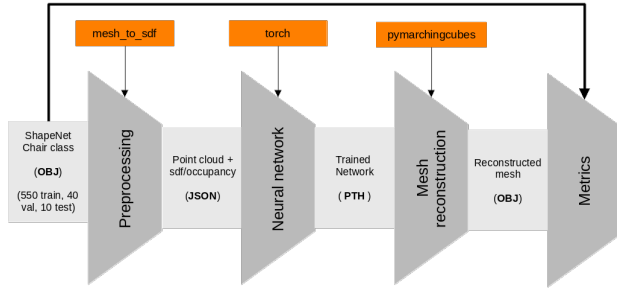


Figure 2: Training pipeline

- ▶ 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

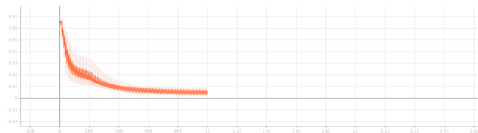


Figure 3: DeepSDF training loss



Figure 4: ONet training loss

	Chamfer	precision	recall
DeepSDF	0.09	0.77	0.64
ONet	0.1 (0.079 in original paper)	0.75	0.67

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

Bibliography

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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