

# Dual Octree Graph Networks for Learning Adaptive Volumetric Shape Representations

**Peng-Shuai Wang**

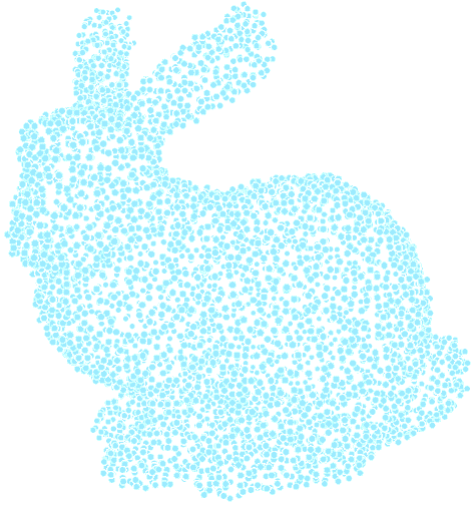
Yang Liu

Xin Tong

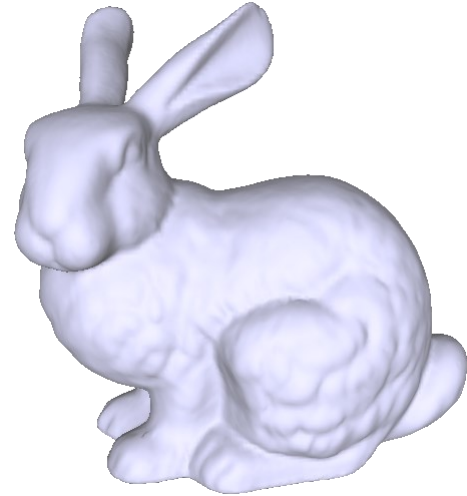
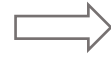
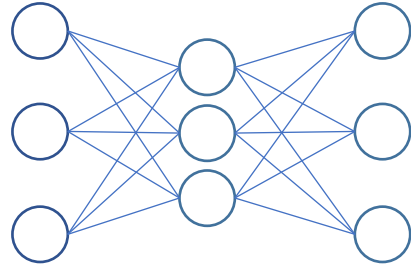
Microsoft Research Asia

ACM Transactions on Graphics (SIGGRAPH), 2022

# Learning to Reconstruct Continuous Surfaces



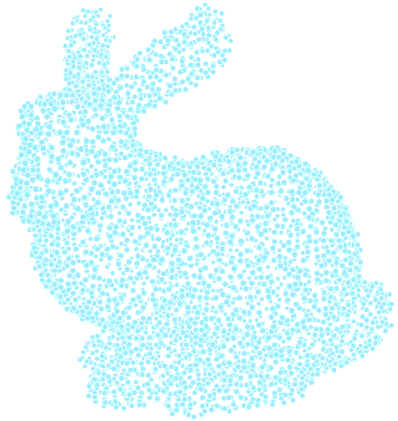
Point cloud



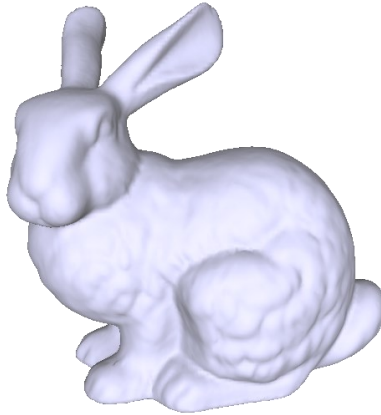
Mesh

# Key Challenges

- Shape representation  
Discrete  $\leftrightarrow$  Continuous

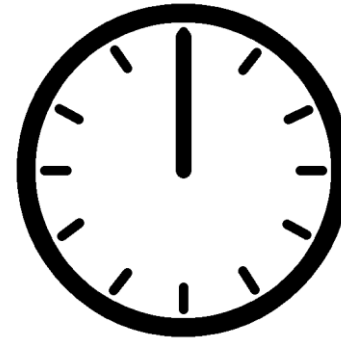


Point cloud



Mesh

- Network  
Efficient & Effective



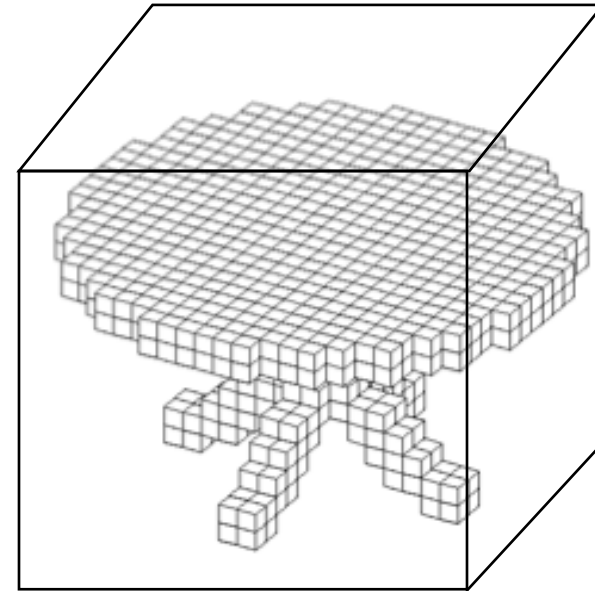
Time cost



Performance

# Full-Voxel-based CNNs

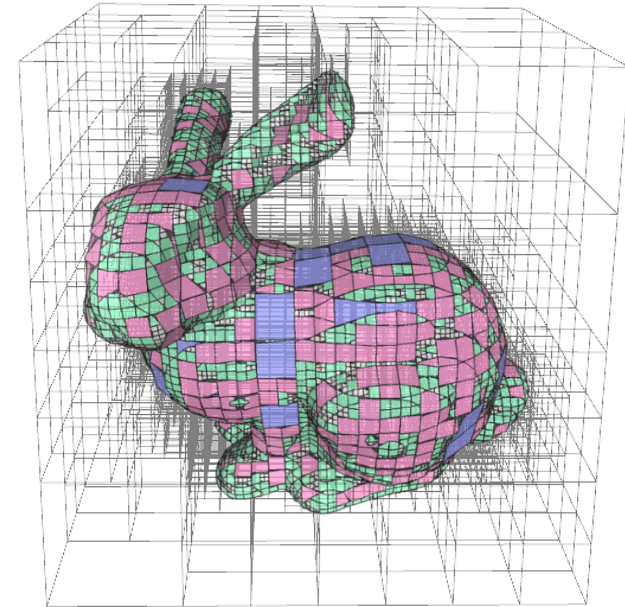
- Related work: [Wu et al. 2016; Choy et al. 2016; Dai et al. 2017]
- ✓ Natural extension of 2D CNNs
- ✗ Low efficiency



3D ShapeNet  
[Wu et al. 2015]

# Sparse-Voxel-based CNNs

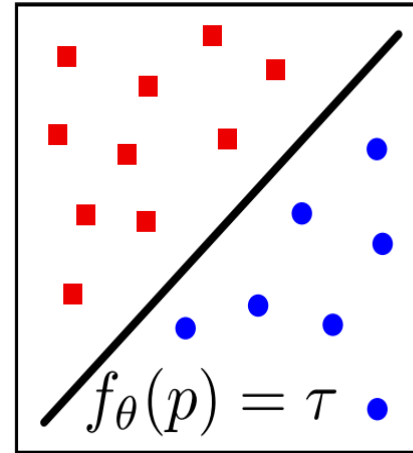
- Related work: [Wang et al. 2017; Graham et al. 2018; Shao et al. 2018;]
- ✓ High efficiency
- ✗ Hard to produce continuous surfaces



Adaptive O-CNN  
[Wang et al. 2018]

# Coordinate-based MLPs

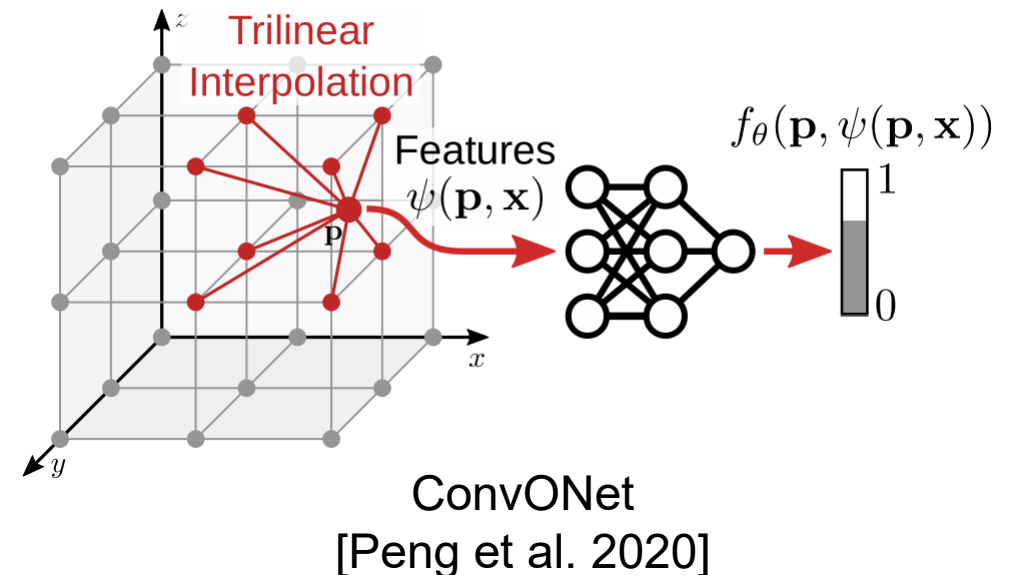
- Related work: [Chen et al. 2019; Mescheder et al. 2019; Park et al. 2019]
- ✓ A compact and continuous shape representation
- ✗ Hard to design encoding networks with MLPs



Occupancy Networks  
[Mescheder et al. 2019]

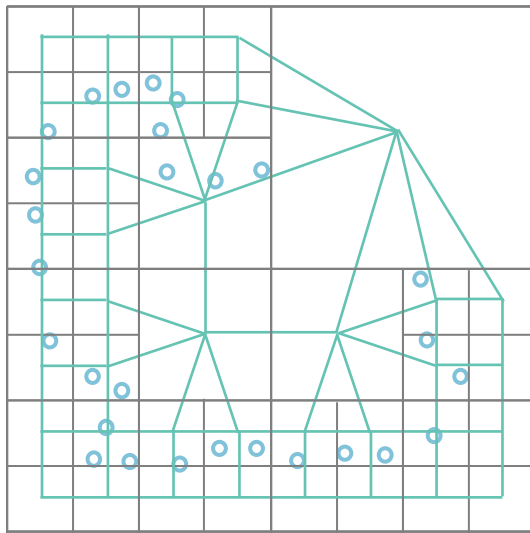
# Hybrid Methods

- Related works: [Peng et al. 2020; Martel et al. 2021; Takikawa et al. 2021]
- ✓ Partially overcome limitations of MLP-based methods
- ✗ Low resolution feature volume (ConvONet [Peng et al. 2020])
- ✗ No encoder networks (ACORN & NGLOD [Martel et al. 2021; Takikawa et al. 2021])

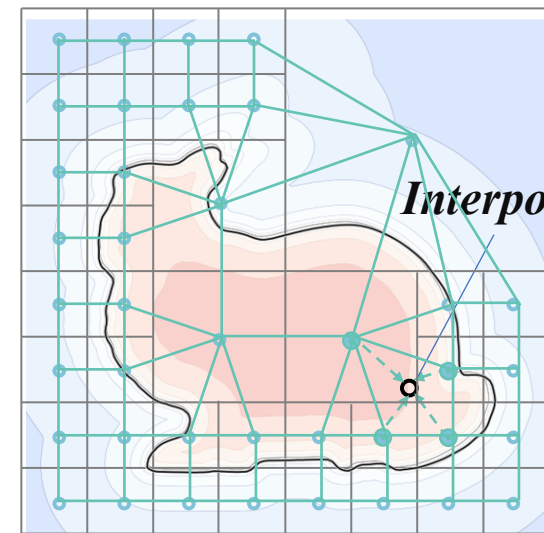
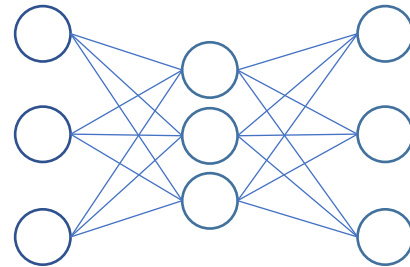


# Key Idea

- Represent both volumetric fields and point clouds with **Octrees**
- Learn features with **graph networks** on **dual Octrees**



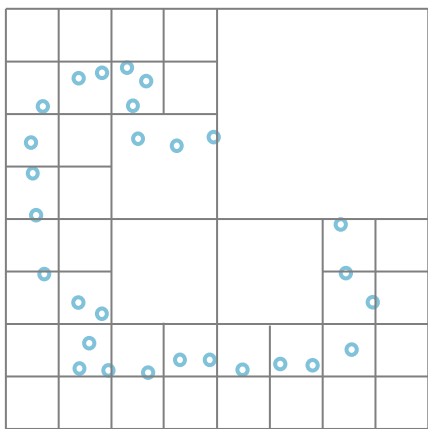
Dual Octree Graph



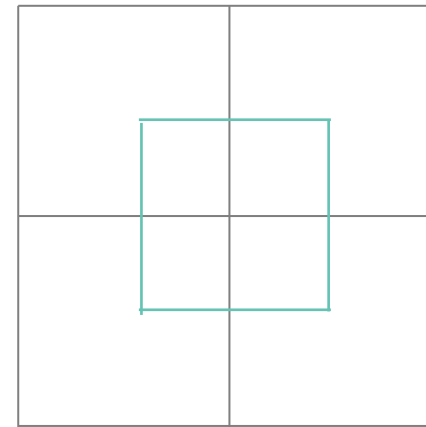
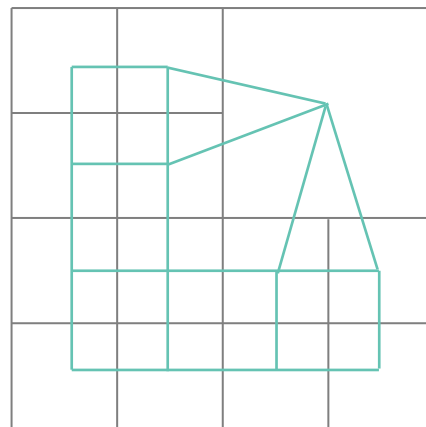
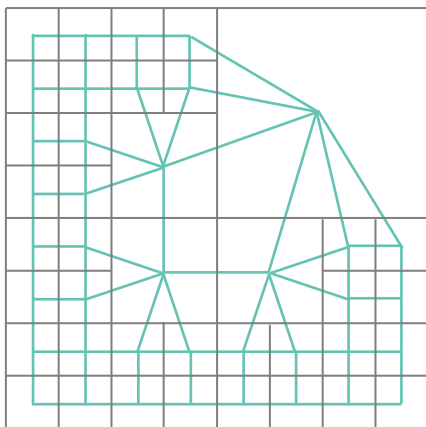
Adaptive Features



# Dual Octree Graphs



Octree

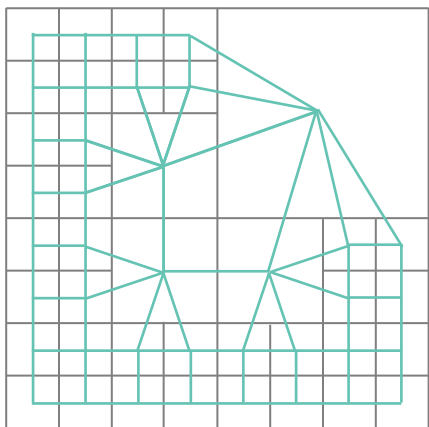


Encoder

Decoder

Multi-Resolution Dual Octree Graphs

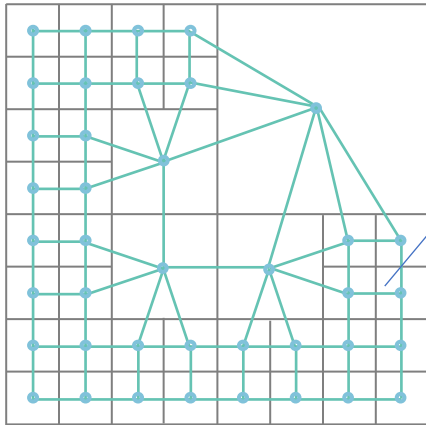
# Graph Convolution on Dual Octrees



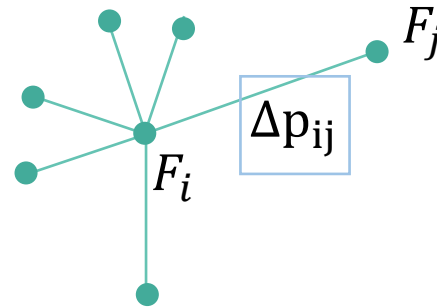
## Message passing:

$$F_i = \sum_{j \in N_i} W(\Delta p_{ij}) \times F_j$$

# Graph Convolution on Dual Octrees



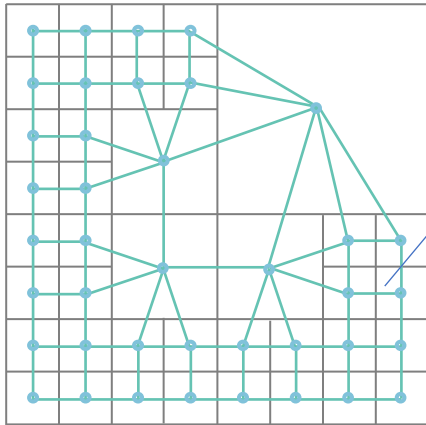
$\Delta p_{ij}$  has finite number of values:



Message passing:

$$F_i = \sum_{j \in N_i} W(\Delta p_{ij}) \times F_j$$

# Graph Convolution on Dual Octrees



$\Delta p_{ij}$  has finite number of values:

$$F_i = \sum_{j \in N_i} W_{I(\Delta p_{ij})} \times F_j \quad \Leftarrow$$

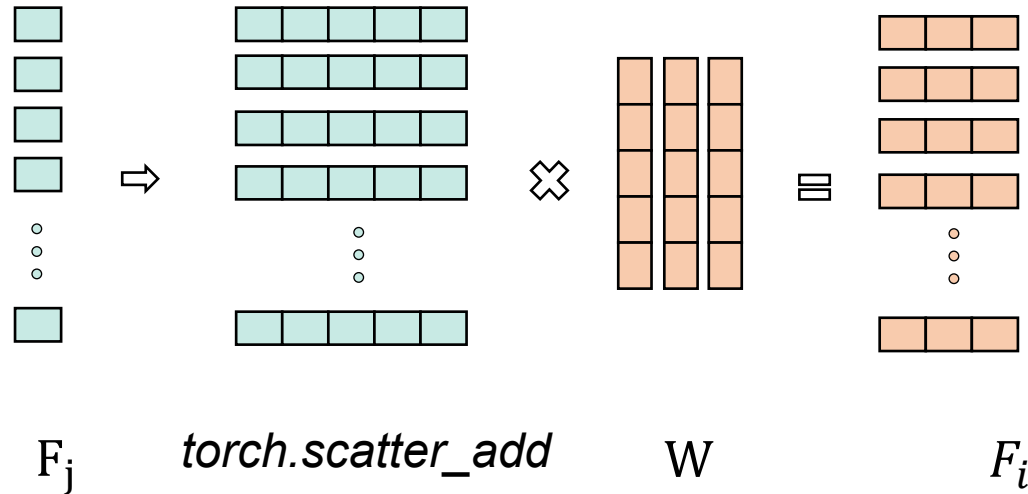
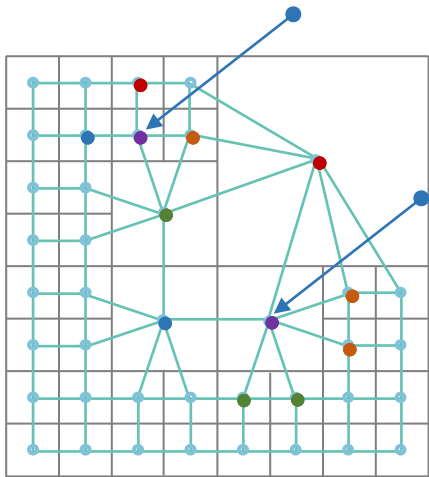
where  $I(p_{ij}) \in \{0, 1, 2, \dots, 7\}$

Message passing:

$$F_i = \sum_{j \in N_i} W(\Delta p_{ij}) \times F_j$$

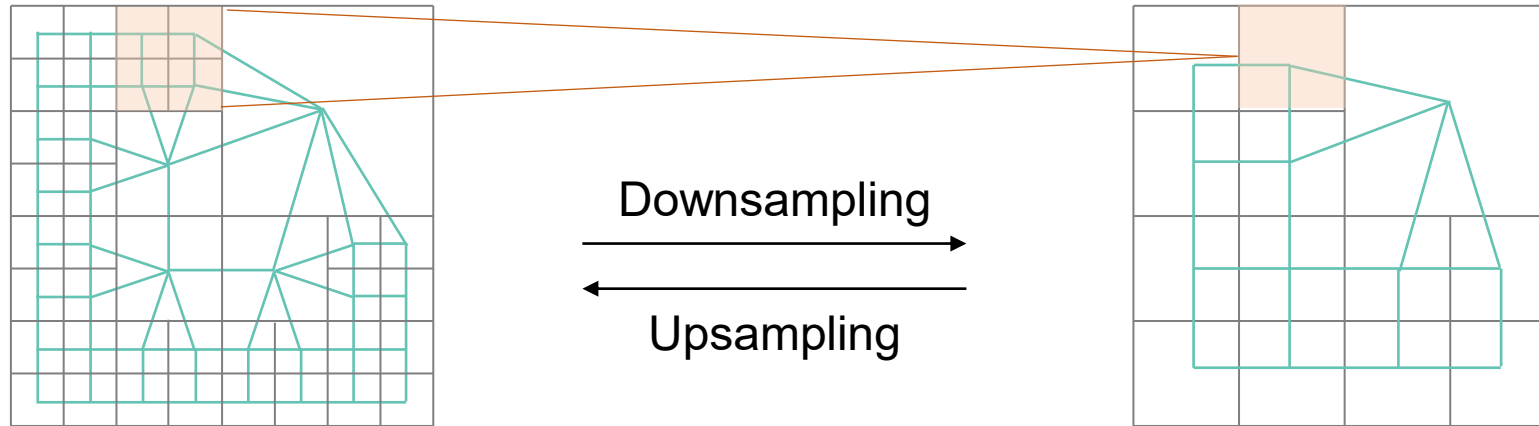
# Graph Convolution on Dual Octrees

- ✓ 5 times faster than previous graph convolutions

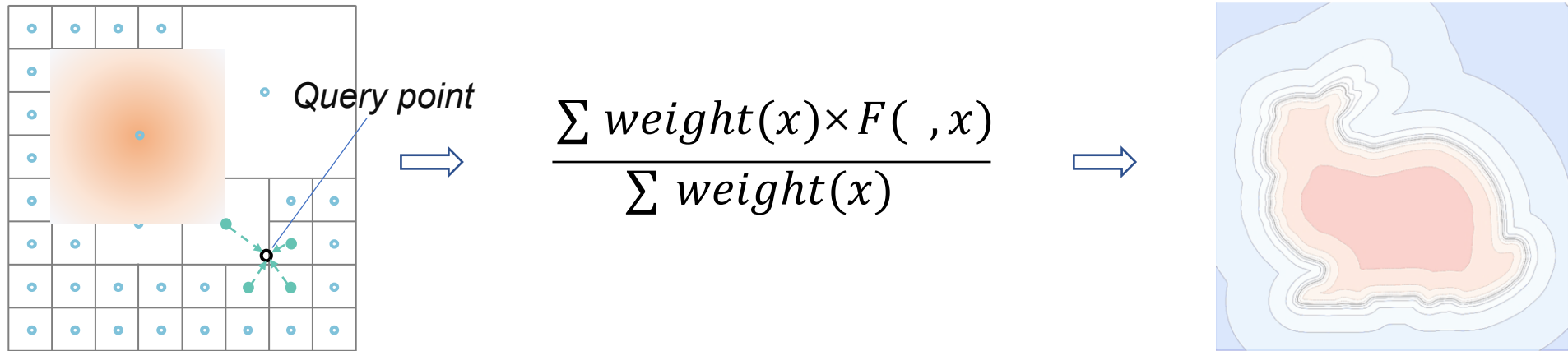


$$F_i = \sum_{j \in N_i} W_{I(\Delta p_{ij})} \times F_j$$

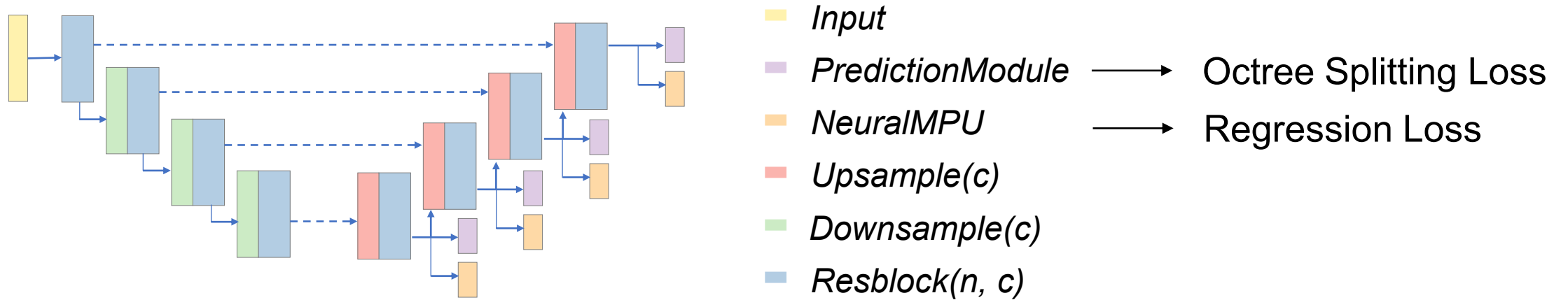
# Graph Downsampling and Upsampling



# Neural Multi-level Partition of Unity (MPU)



# Network and Loss Functions



$$\mathcal{L}_{octree} = \sum_d \frac{1}{N_d} \sum_{o \in O_d} \text{CrossEntropy}(o, o_{gt})$$

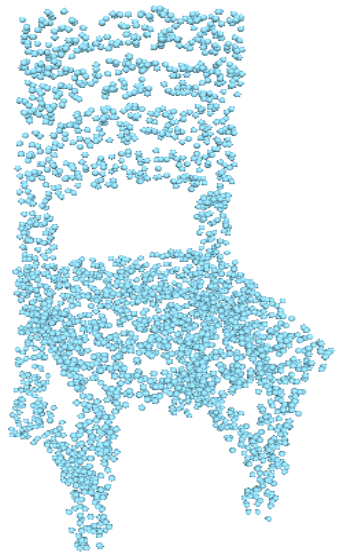
$$\mathcal{L}_{regress} = \sum_d \frac{1}{N_{\mathcal{P}}} \sum_{x \in \mathcal{P}} \left( \lambda_v \|F(x) - G(x)\|_2^2 + \|\nabla F(x) - \nabla G(x)\|_2^2 \right)$$

$$\mathcal{L}_{grad} = \sum_d \left\{ \frac{1}{N_S} \sum_{x \in S} \left( \lambda_v \|F(x)\|_2^2 + \|\nabla F(x) - \mathcal{N}(x)\|_2^2 \right) + \frac{1}{N_Q} \sum_{x \in Q} \lambda_g \|\nabla F(x)\|_2^2 \right\}$$

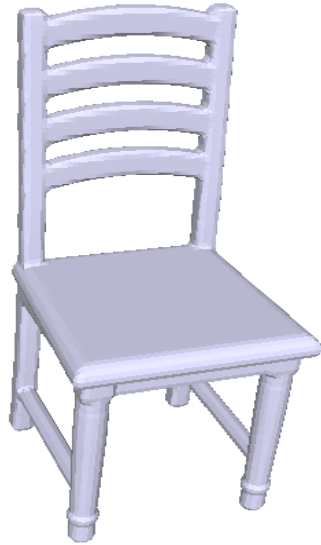


# Shape Reconstruction from Point Clouds

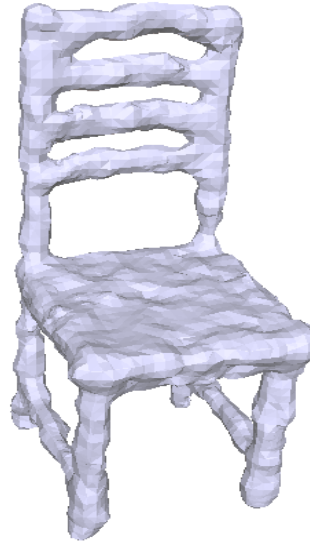
- Dataset: 13 categories from ShapeNet



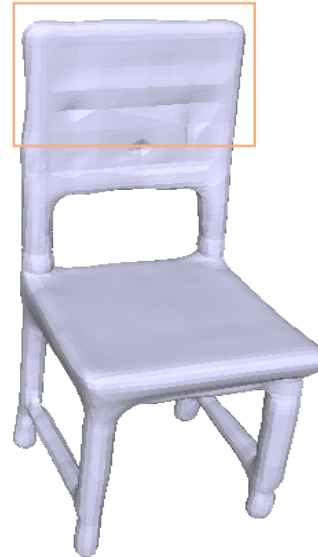
Input (3k)



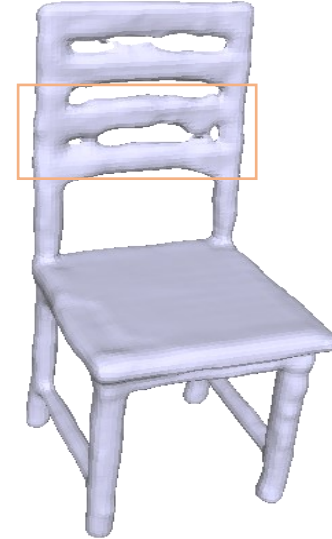
GT



PSR



ConvONet



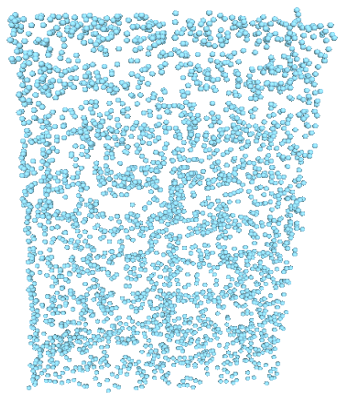
DeepMLS



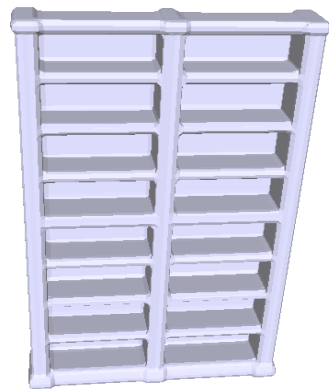
Ours

# Shape Reconstruction from Point Clouds

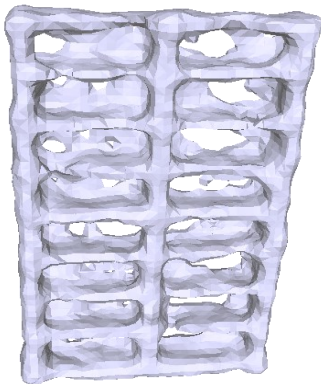
- 13 categories from ShapeNet



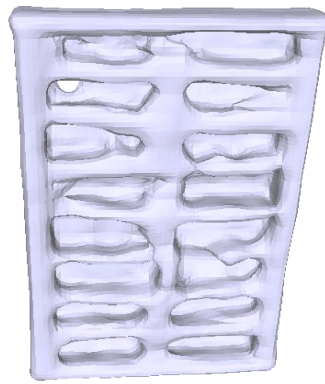
Input (3k)



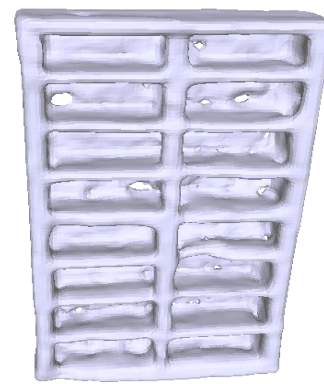
GT



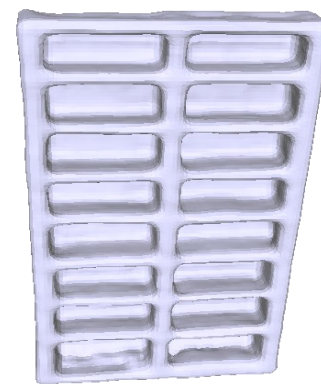
PSR



ConvONet

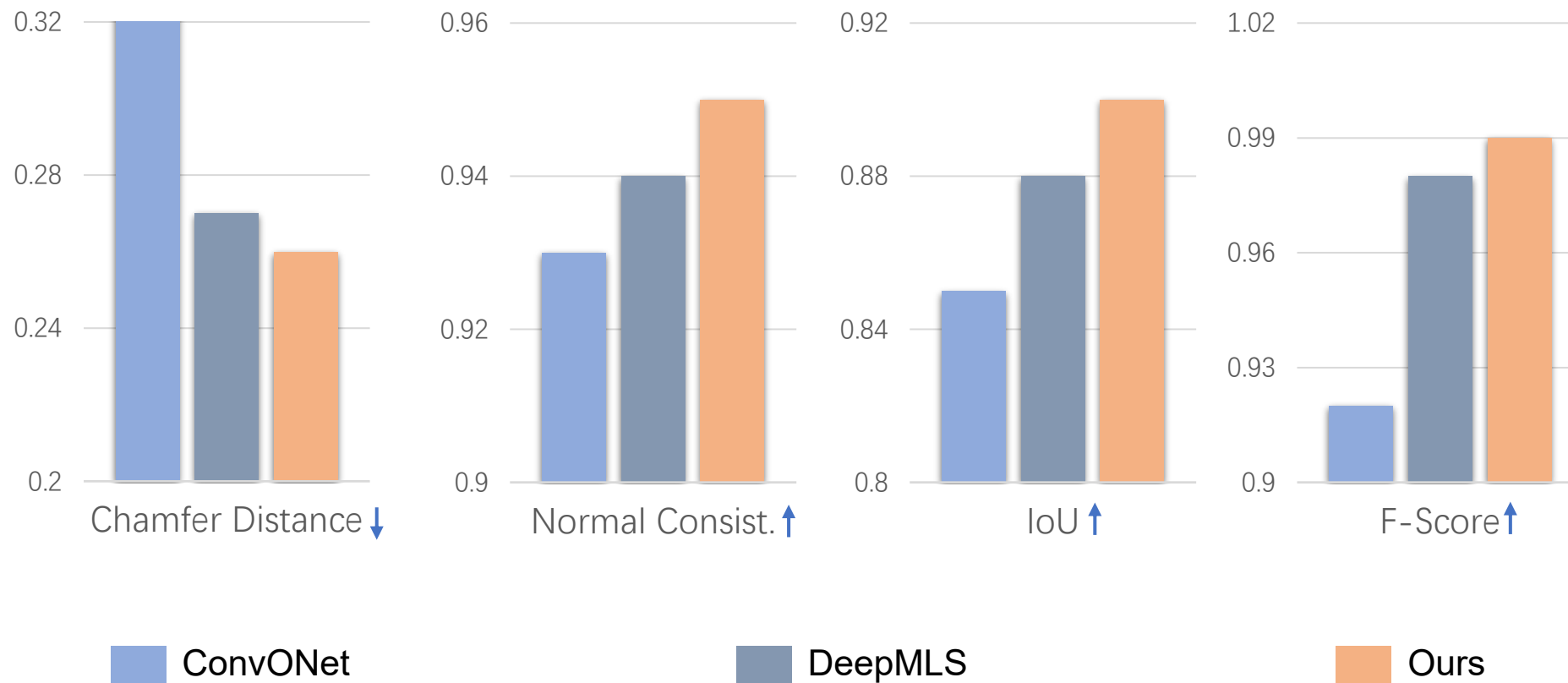


DeepMLS



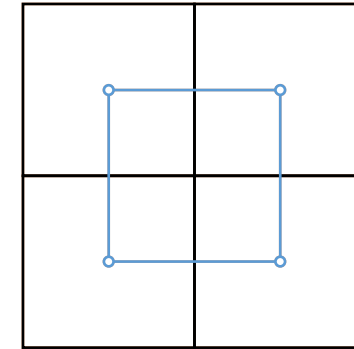
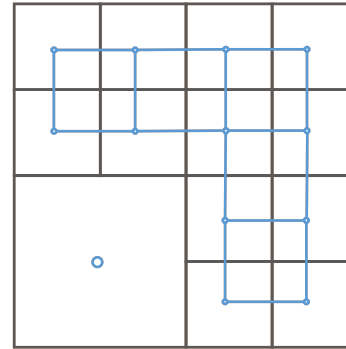
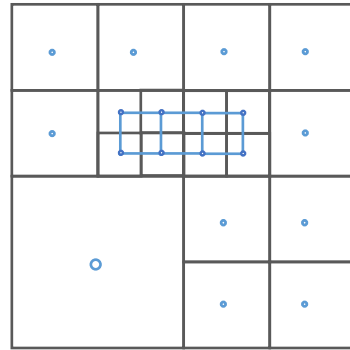
Ours

# Shape Reconstruction from Point Clouds

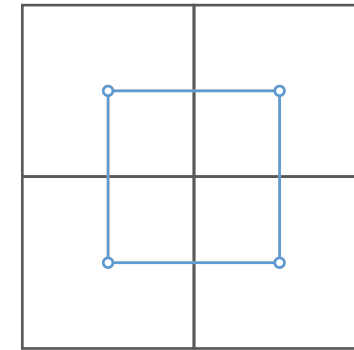
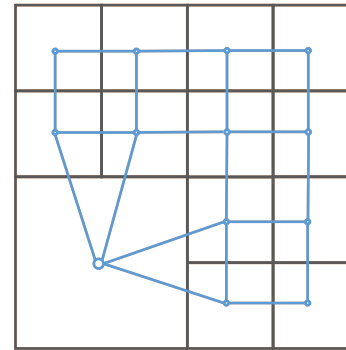
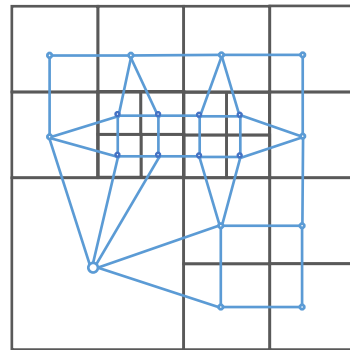


# Effectiveness: Multiscale Features in Convolutions

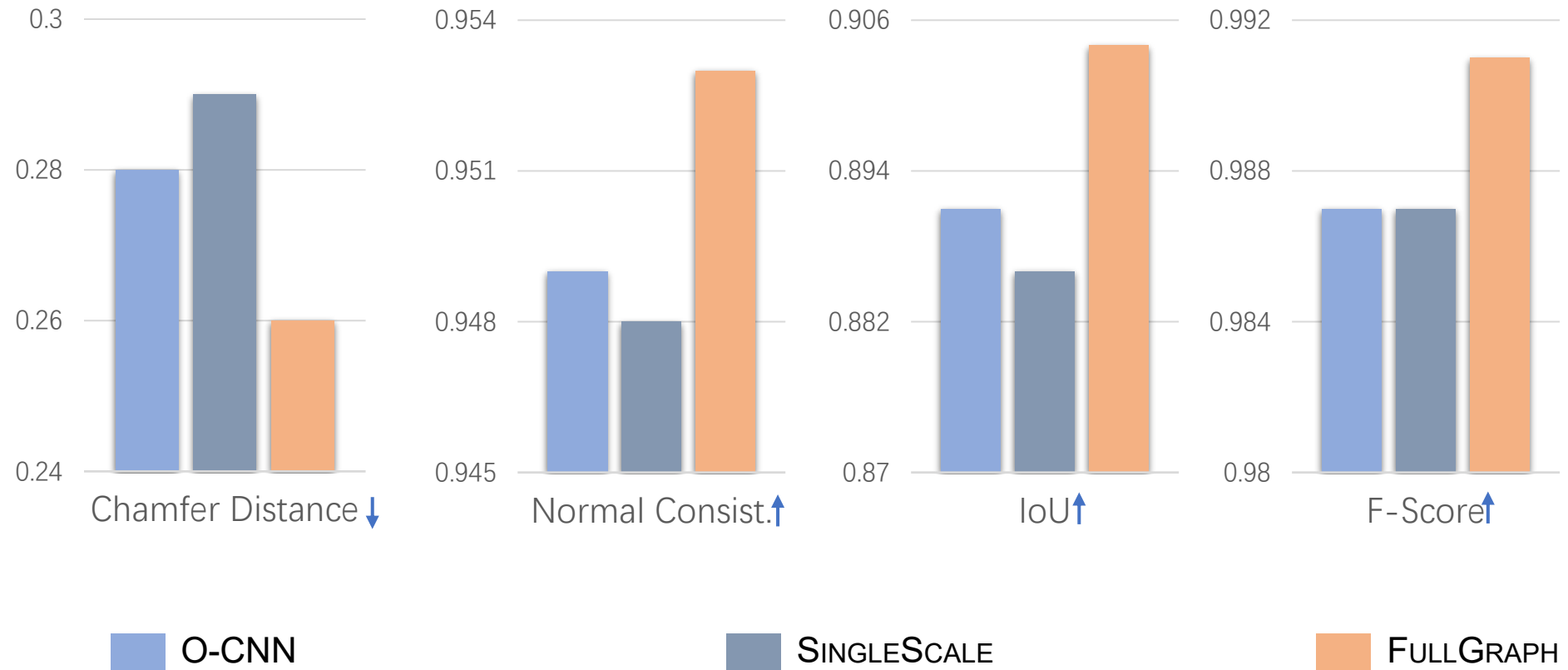
O-CNN



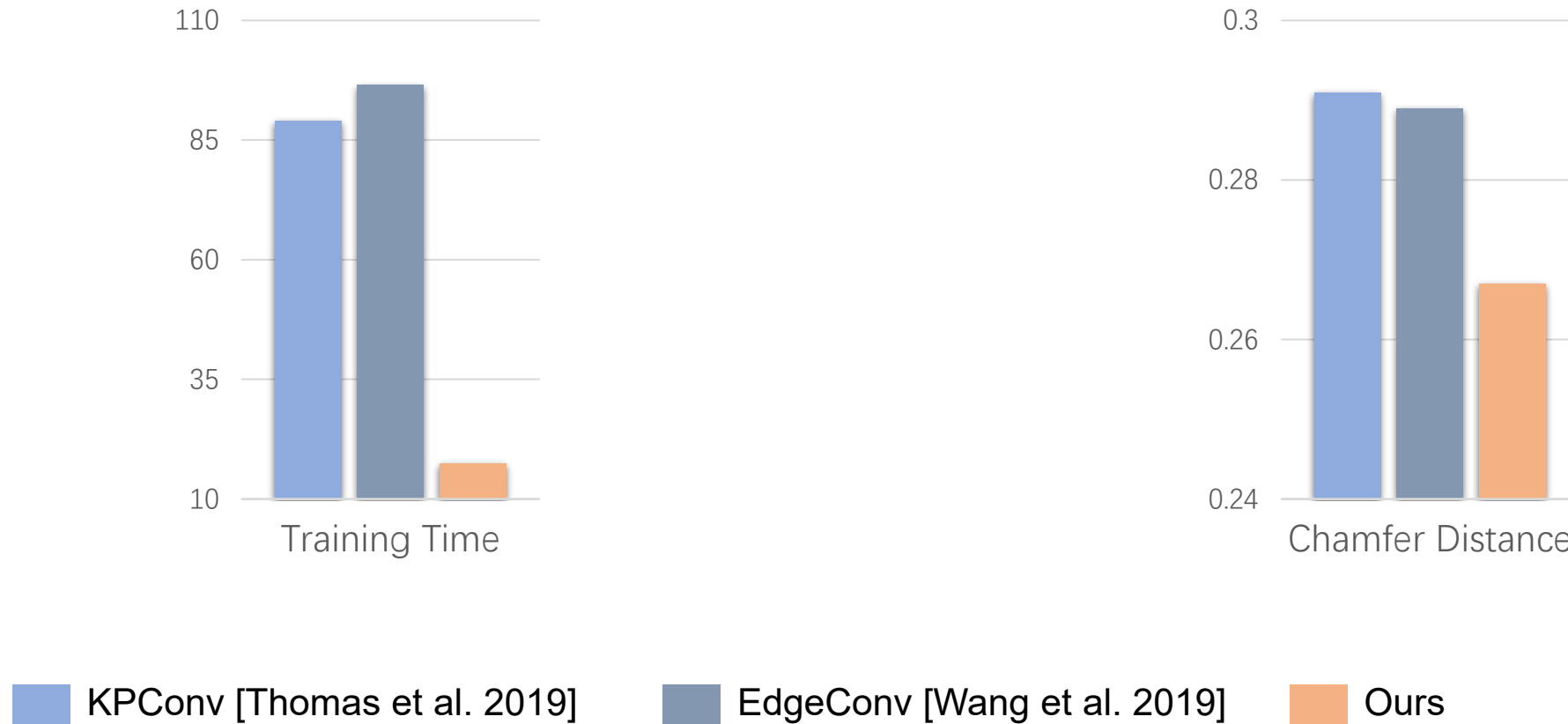
Dual  
Octree GNNs



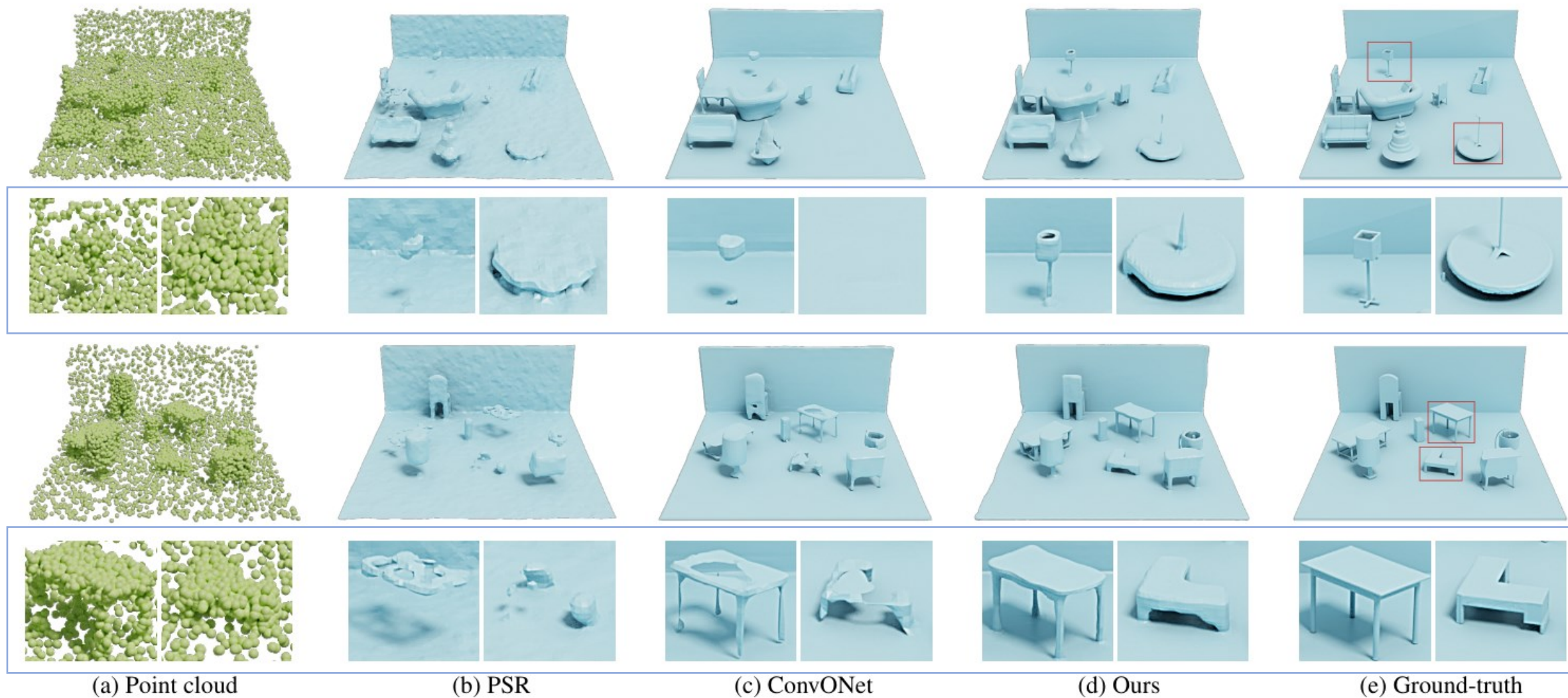
# Effectiveness: Multiscale Features in Convolutions



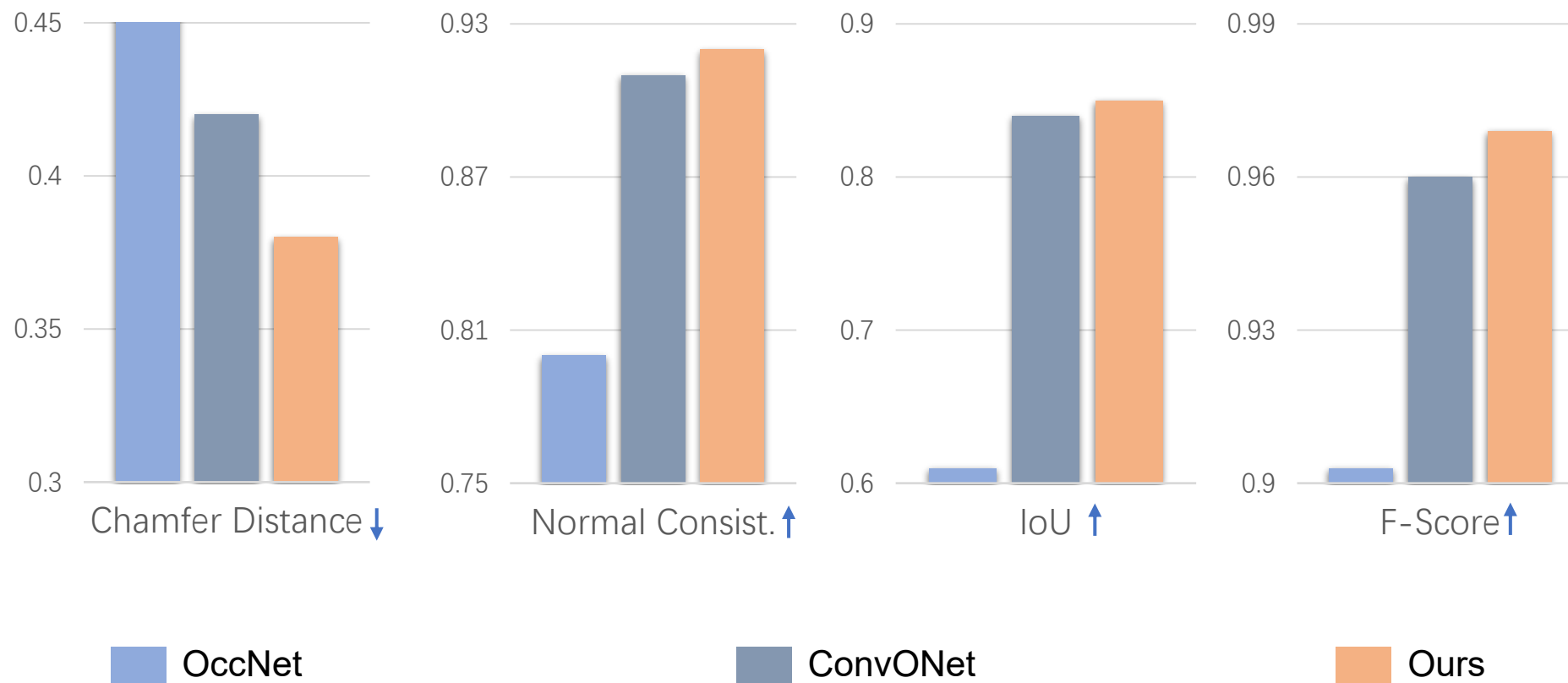
# Efficiency: Faster than Other Graph Convolutions



# Scene Reconstruction from Point Clouds

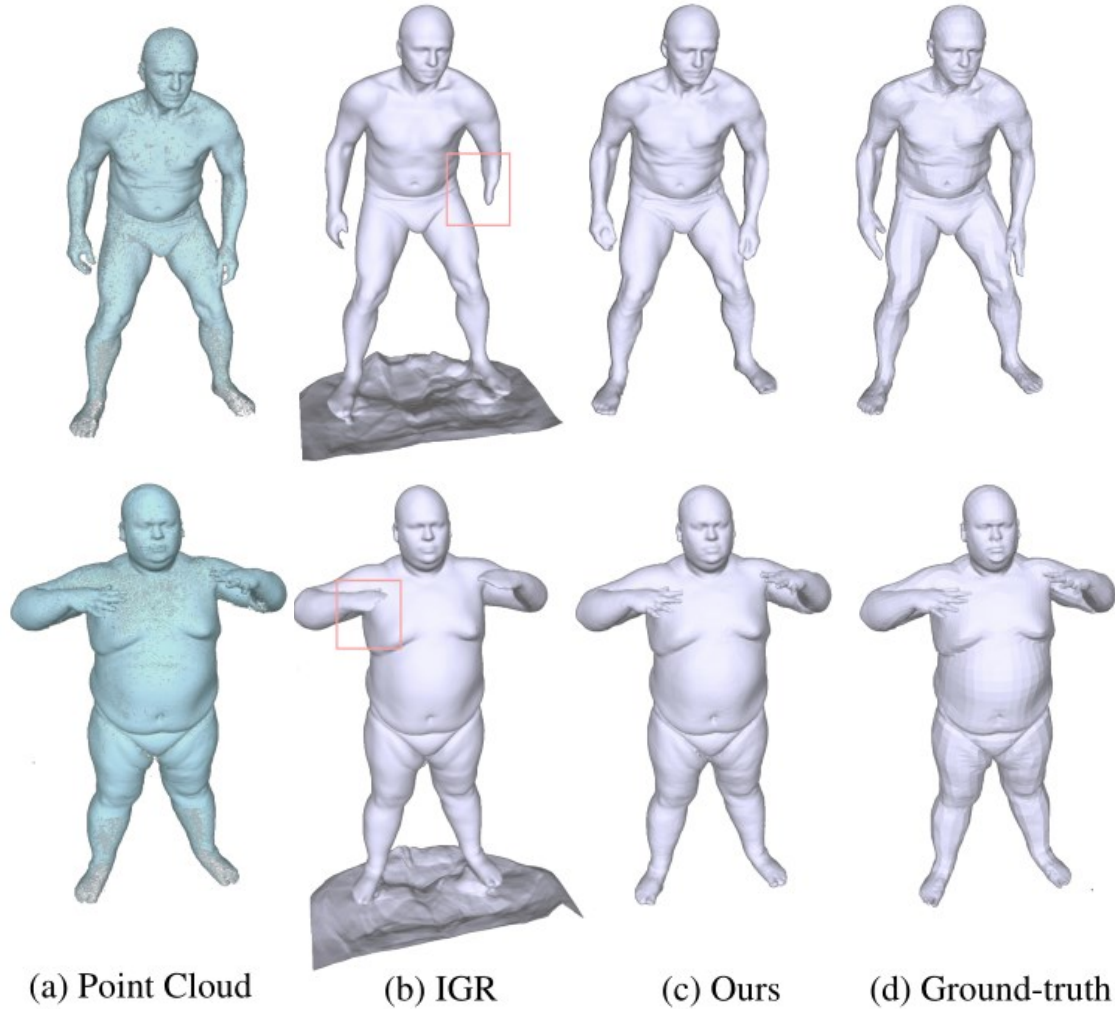


# Scene Reconstruction from Point Clouds

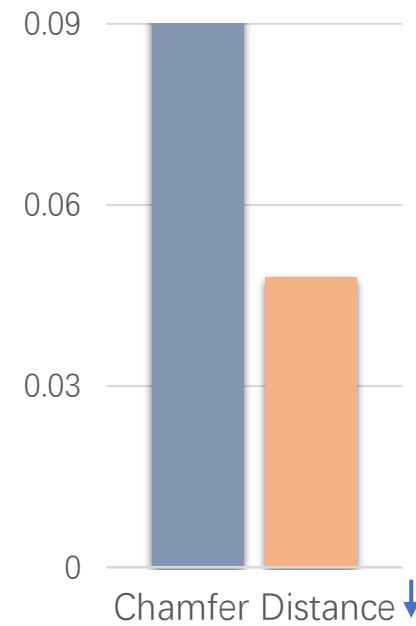




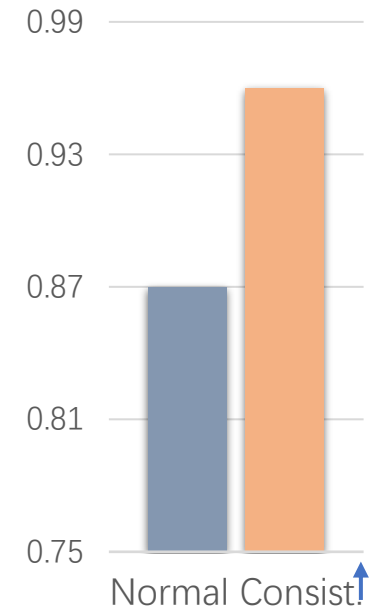
# Surface Reconstruction from Point Clouds



-  390 TIMES FASTER!



IGR



Ours

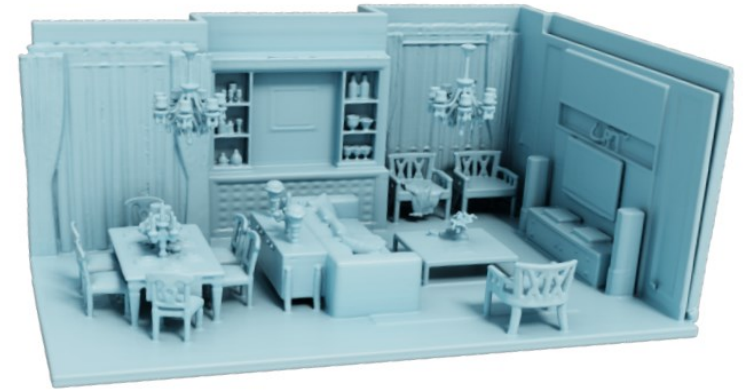
# Generalization Ability

- The network trained on human bodies can be applied to general shapes



# Summary

- Learning to predict adaptive volumetric fields
  - Dual octree graph networks
  - Neural MPU
  - Produce high-quality continuous surfaces
- General for more applications
  - Superior performances for shape autoencoding
  - Promising performance for shape analysis
- Future work
  - Shape generation, like Diffusion Models



Reconstruct a complex scene in 478ms



Code and data are available online