Application #1: 3D Modeling

Deep neural network predicts the **next best part** to add and its **position** to enable non-expert users to create novel shapes.

[Sung et al. 2017]

Application #2: Image Understanding

- Joint multi-modal understanding

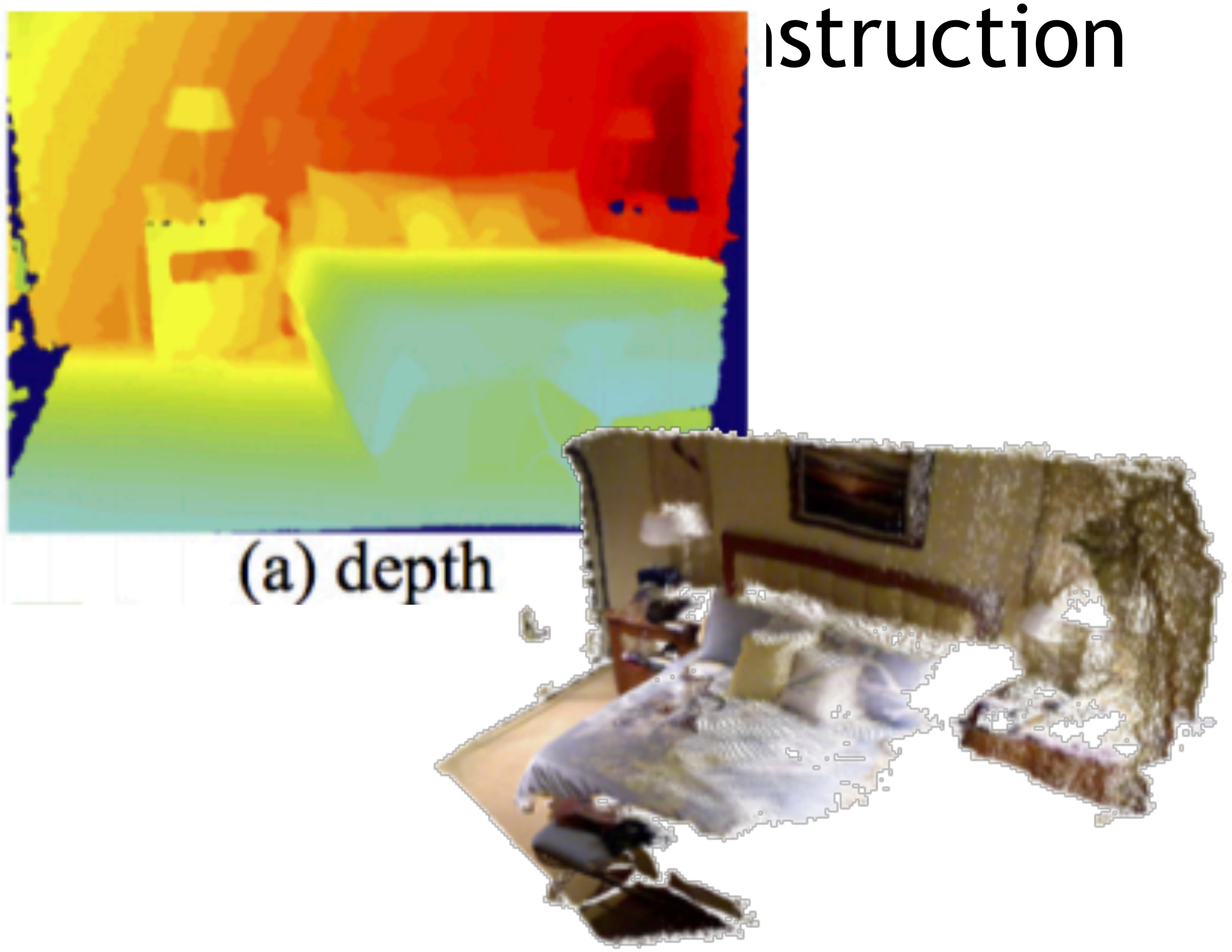
understanding 3D shapes can benefit image understanding

Physically based Rendering

[Zhang et al. 2017]

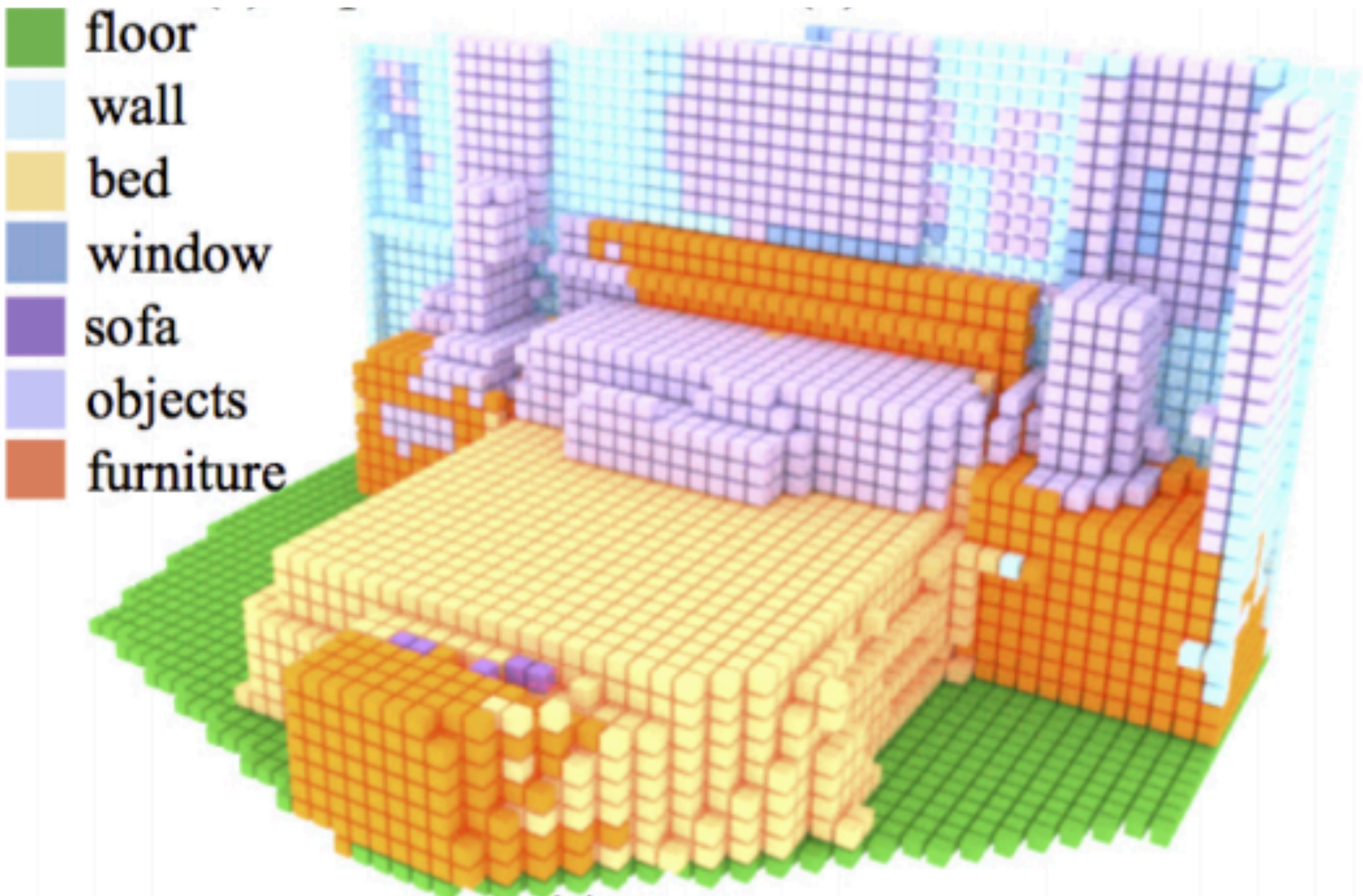
Application #3: Semantic Scene Understanding

ıstruction



(a) depth

(b) visible surface



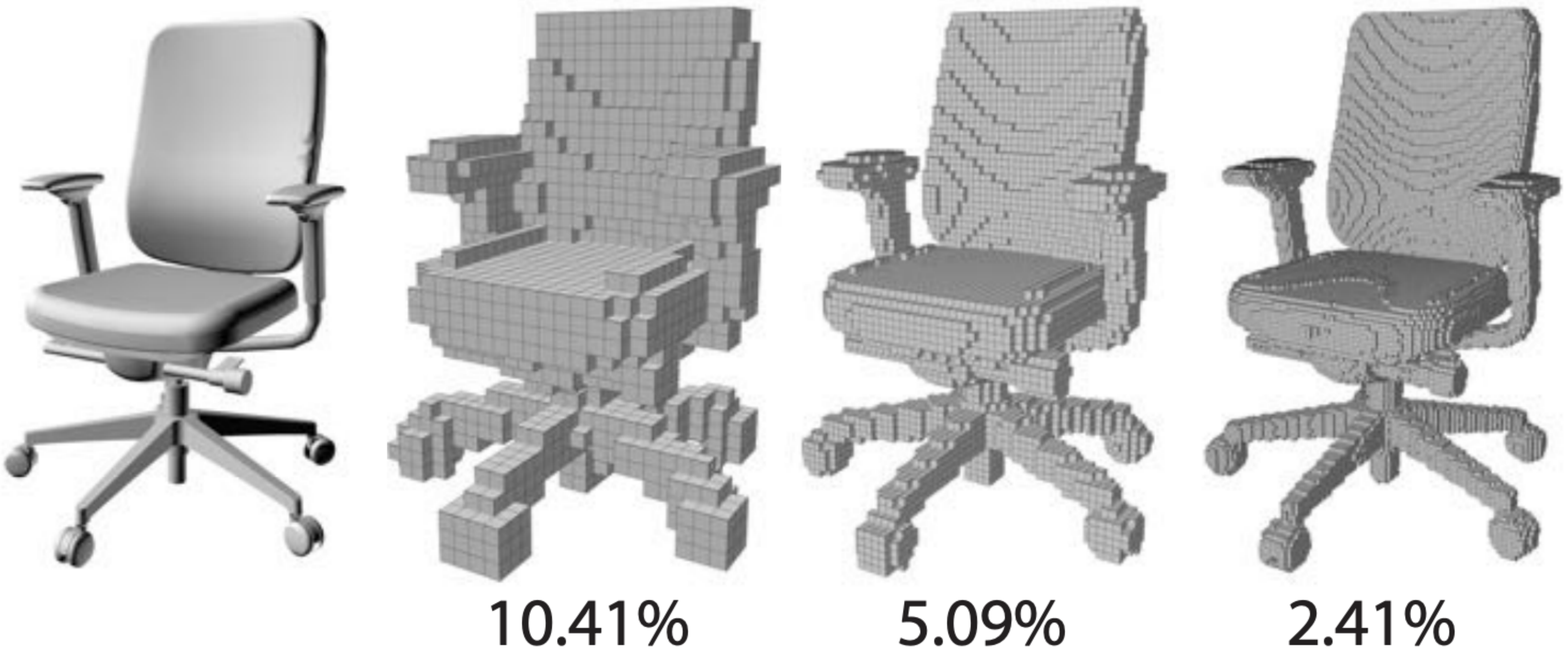
(c) output

[Song et al. 2017]

Application #4: 3D Asset Creation

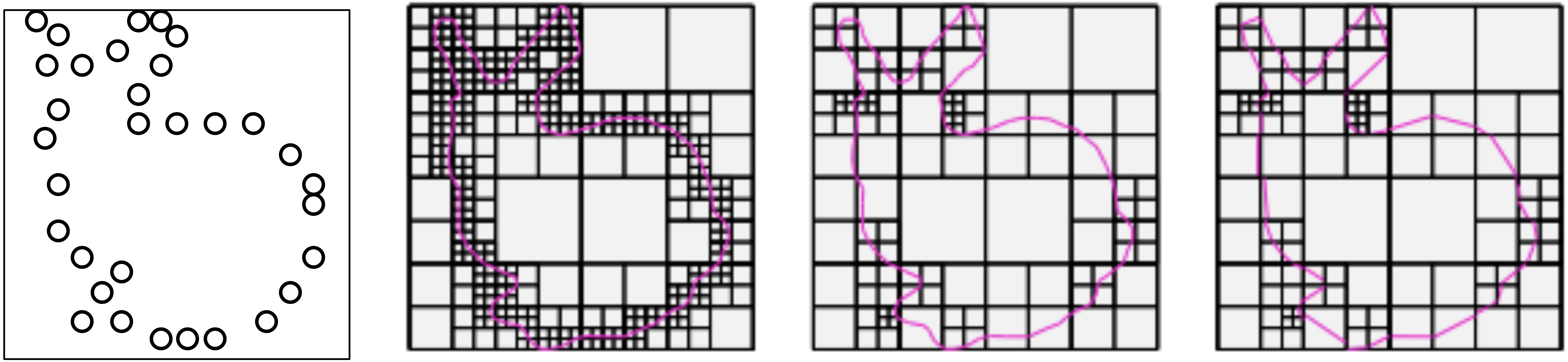
What’s Different in 3D?

- Number of Voxels grows as $\mathcal{O}(n^3)$ versus occupied surface $\mathcal{O}(n^2)$



Data Representation .. Many Possibilities!

AO-CNN STRUCTURE



points voxels cells patches

Challenges

1. Representation

2. Neighborhood information
   - who are the neighbouring elements
   - how are the elements ordered

3. Extrinsic versus intrinsic representation

4. Simplicity versus memory/runtime tradeoff

Representation for 3D

- Image-based
- Volumetric
- Surface-based
- Point-based

Representation for 3D

- **Image-based**
- Volumetric
- Surface-based
- Point-based

Representation for 3D: Multi-view CNN

- **Image-based**

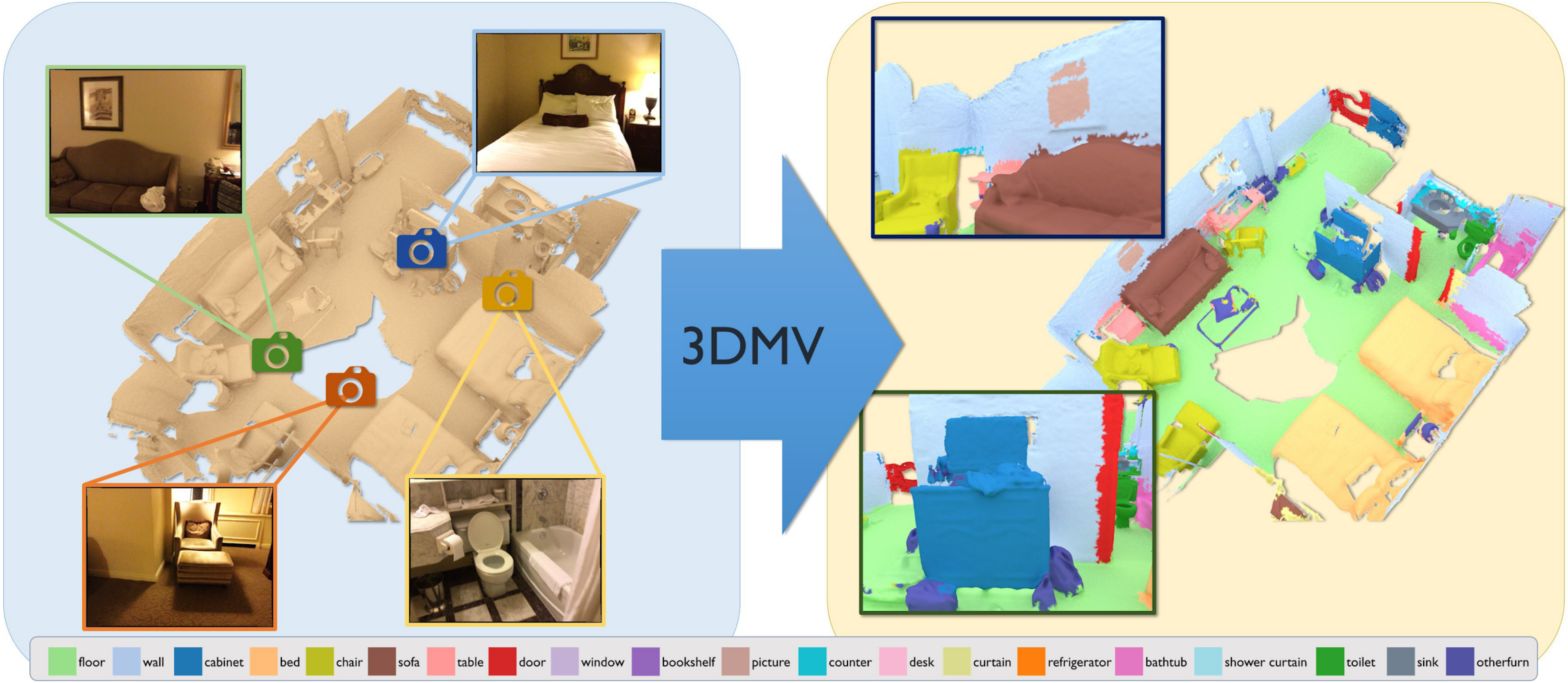
regular image analysis networks

3D shape model
rendered with
different virtual cameras

[Kalogerakis et al. 2015]

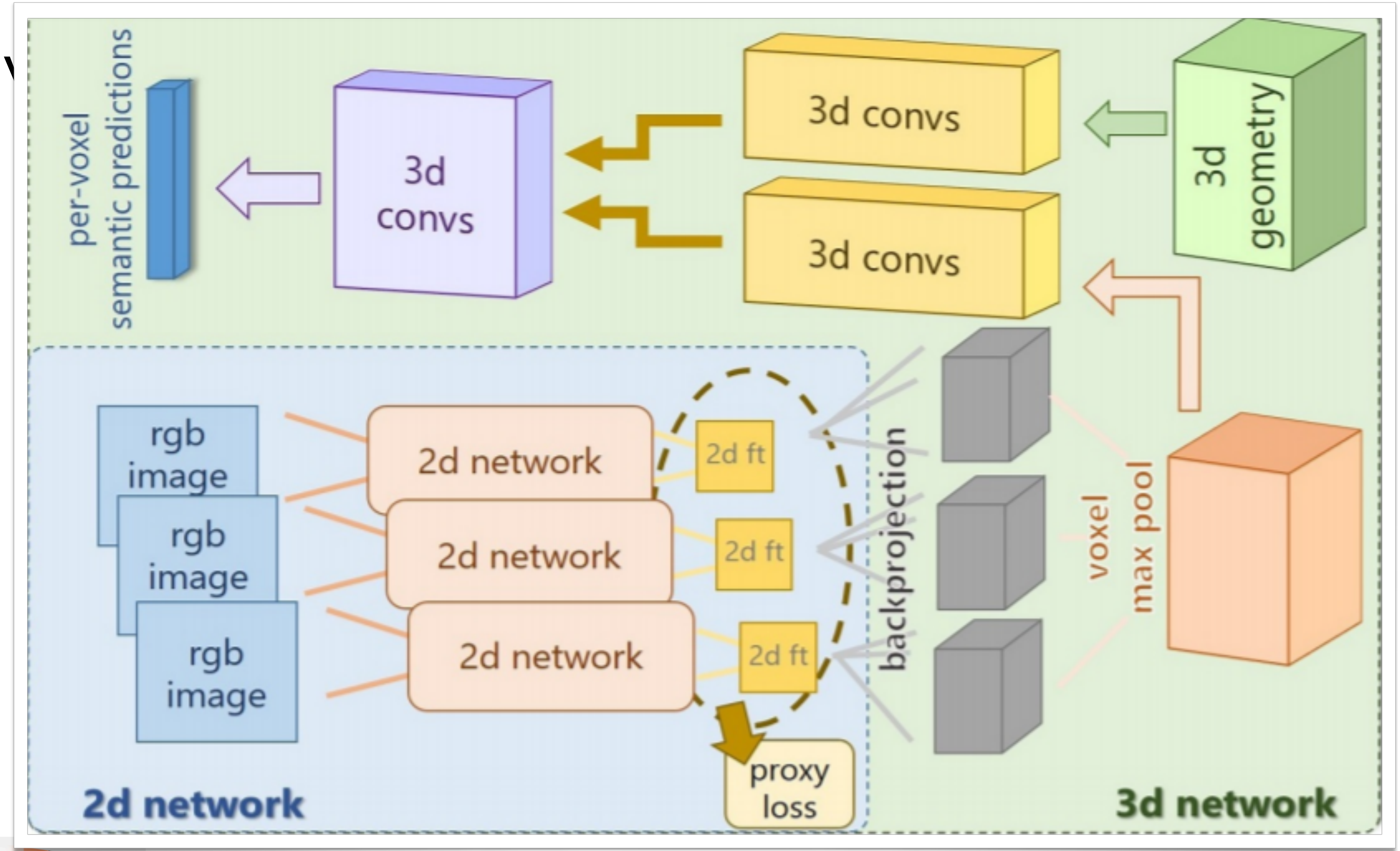
3DMV: Joint 3D-Multi-View Prediction for 3D Semantic Scene Segmentation

3DMV: Joint 3D-Multi-View Prediction for 3D Semantic Scene Segmentation



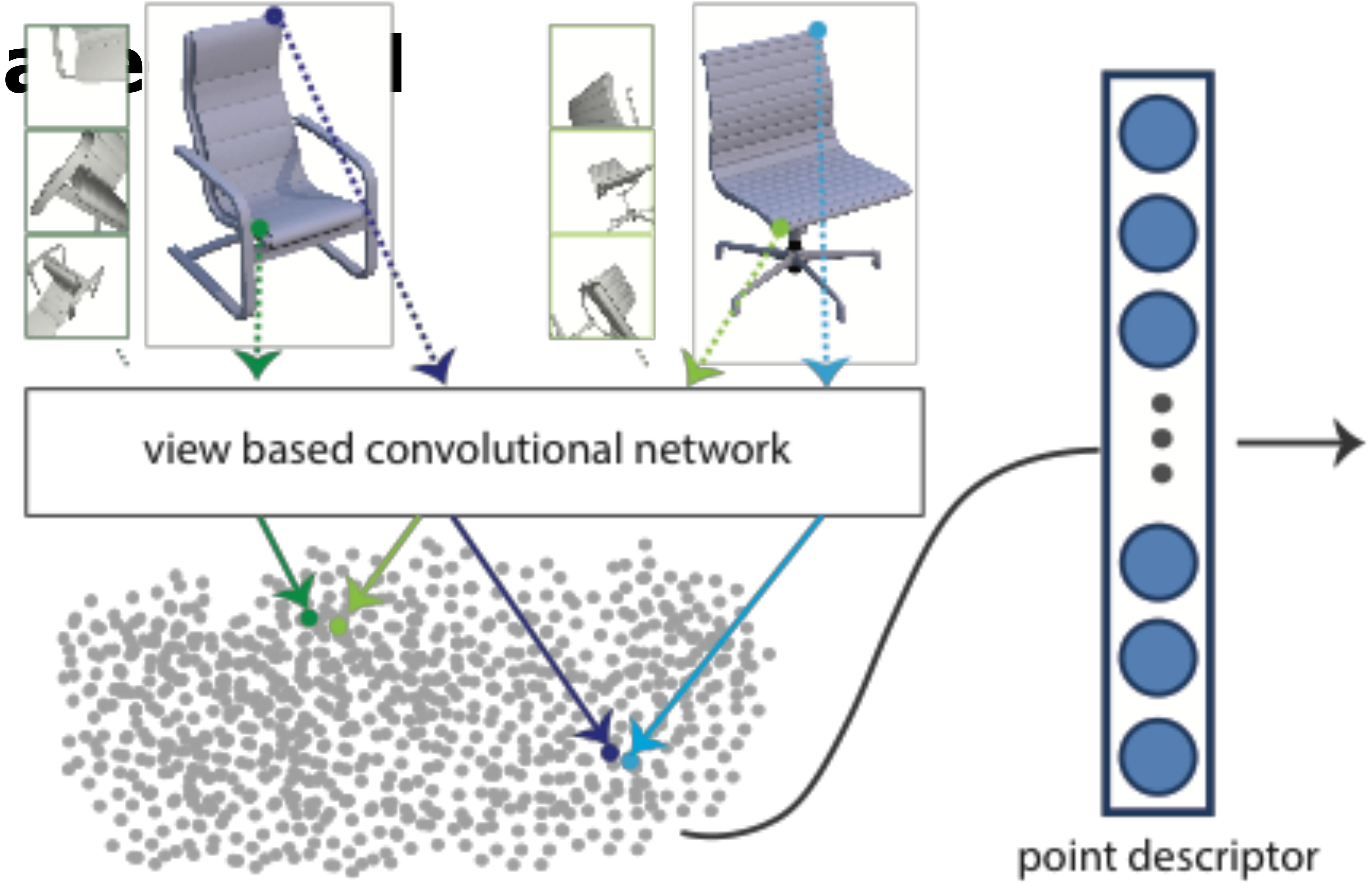
Integrating View Information

Multi-v



Representation for 3D: Local Multi-view CNN

- **Ima e l**

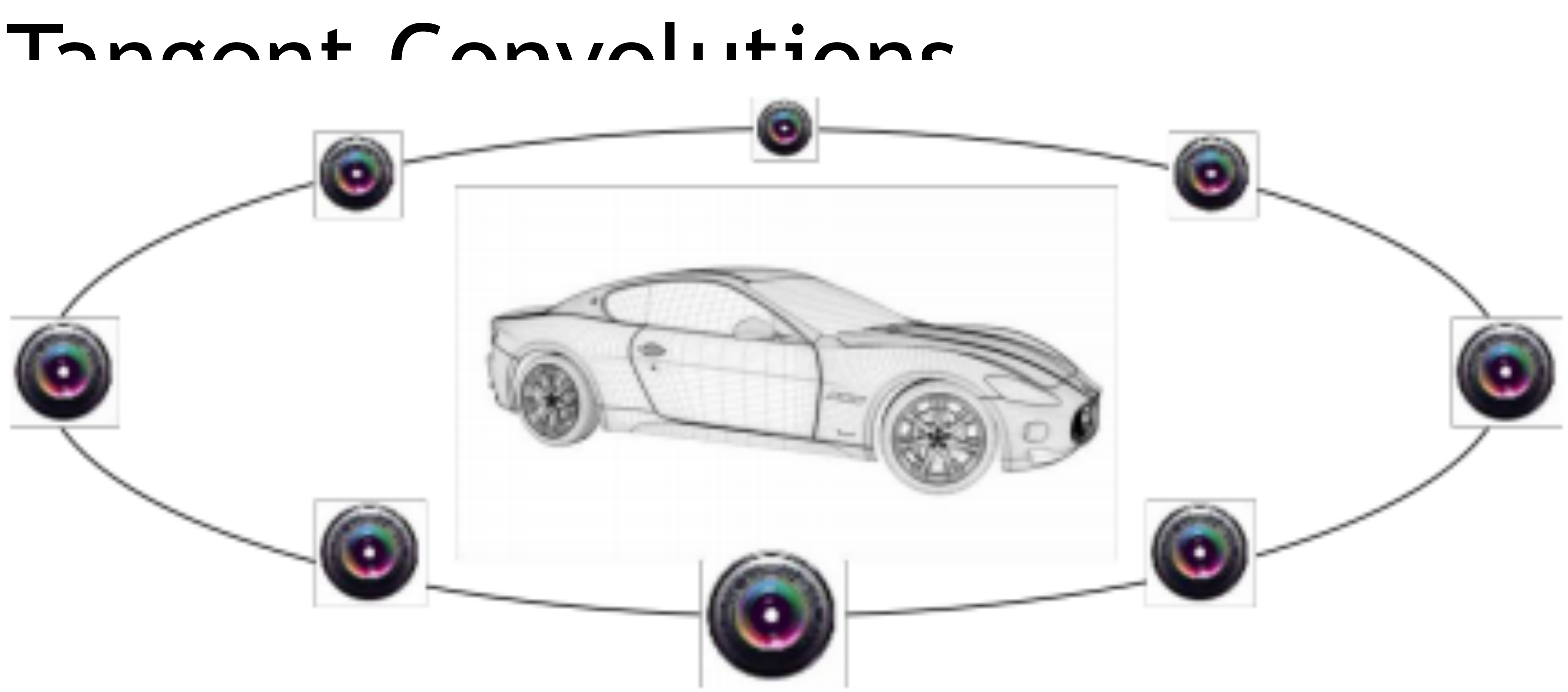


Segmentation
Correspondence
Feature matching
Predicting semantic functions

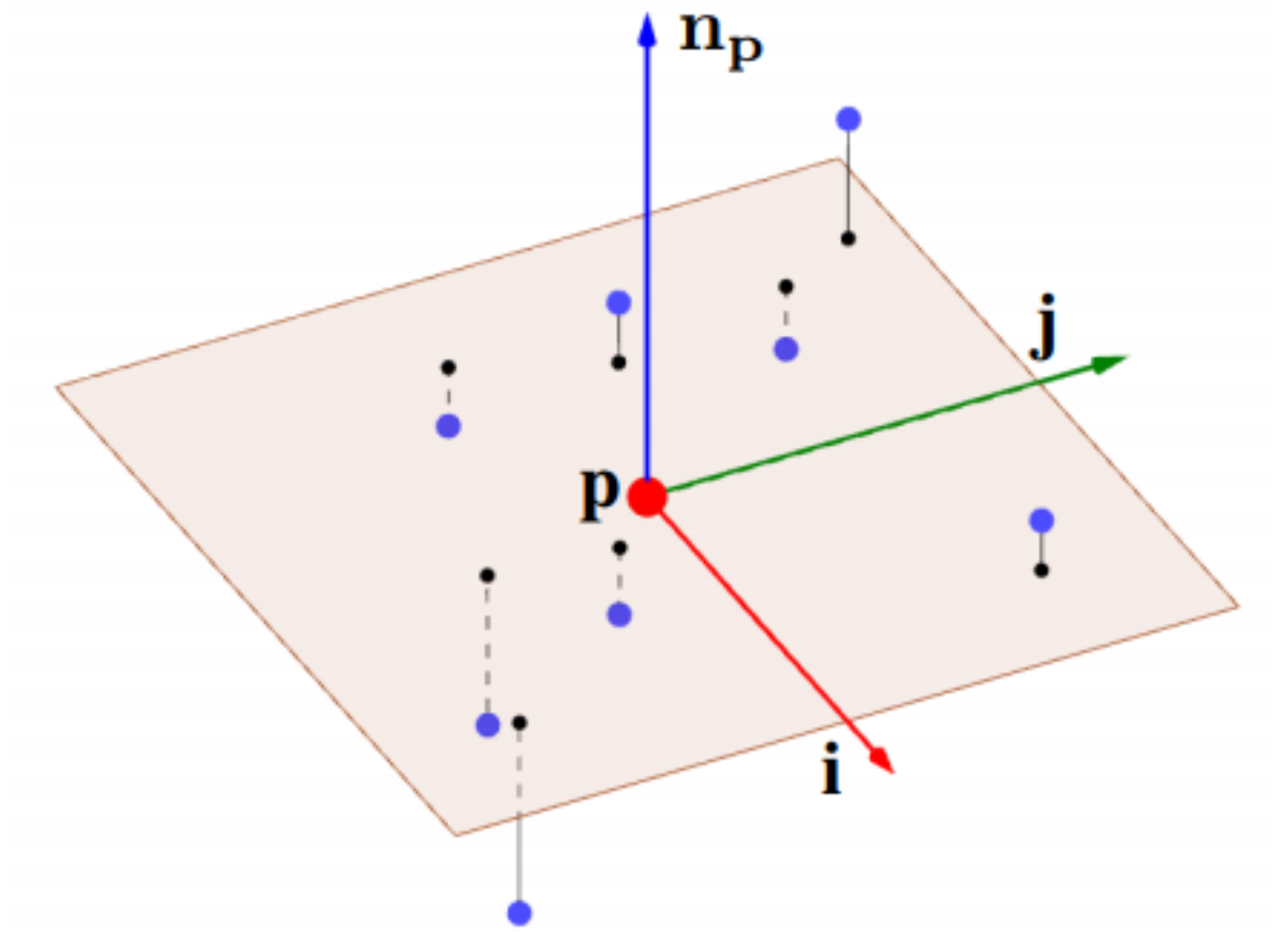
localized renderings for point-wise features

[Huang et al. 2018]

Tangent Convolutions



loses information due to occlusion

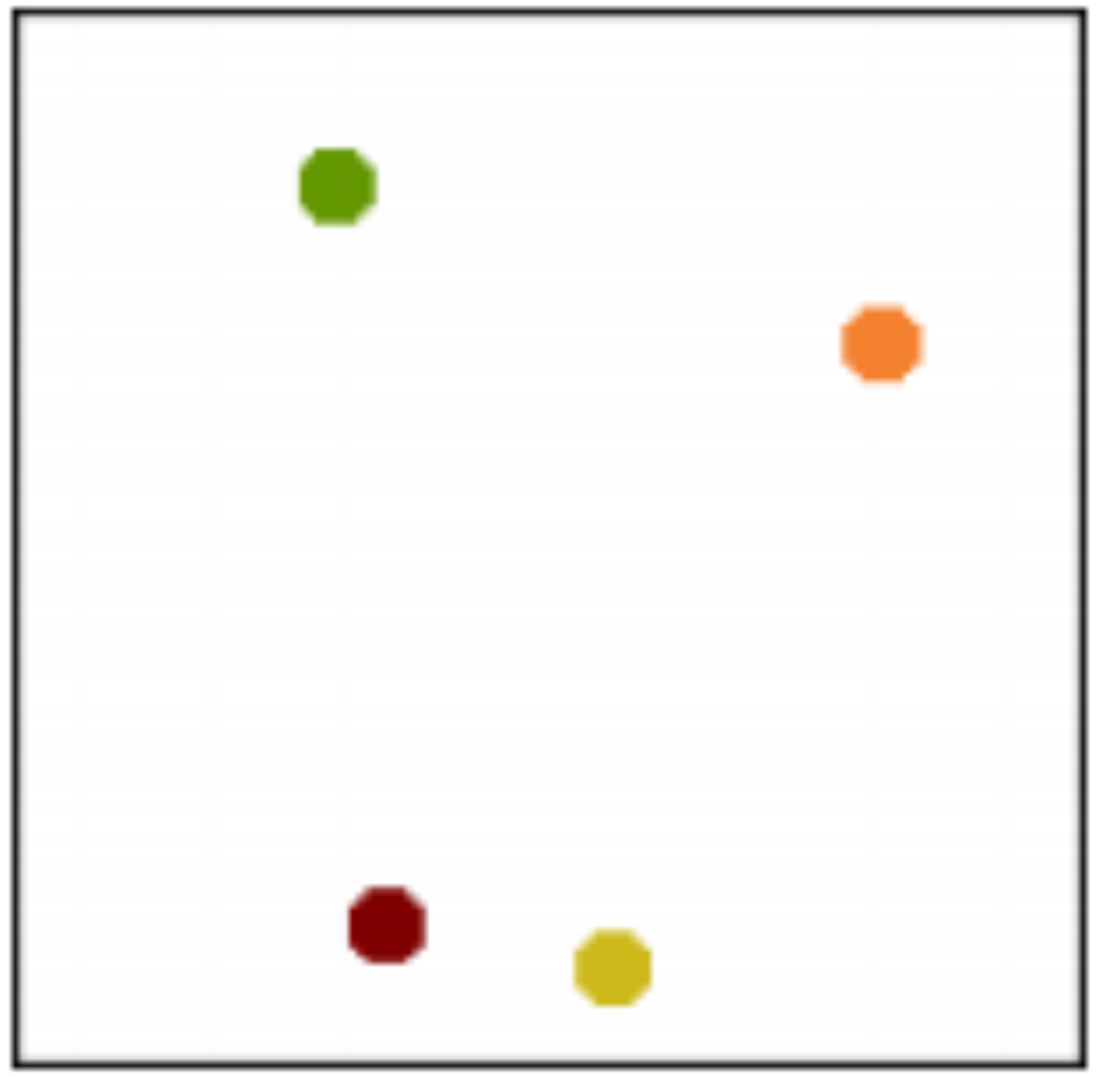


project to local patches
(contrast with PCPNet construction)

[Tatarchenko et al. 2018]

Dealing with Sparse Points

Signal Interpolation



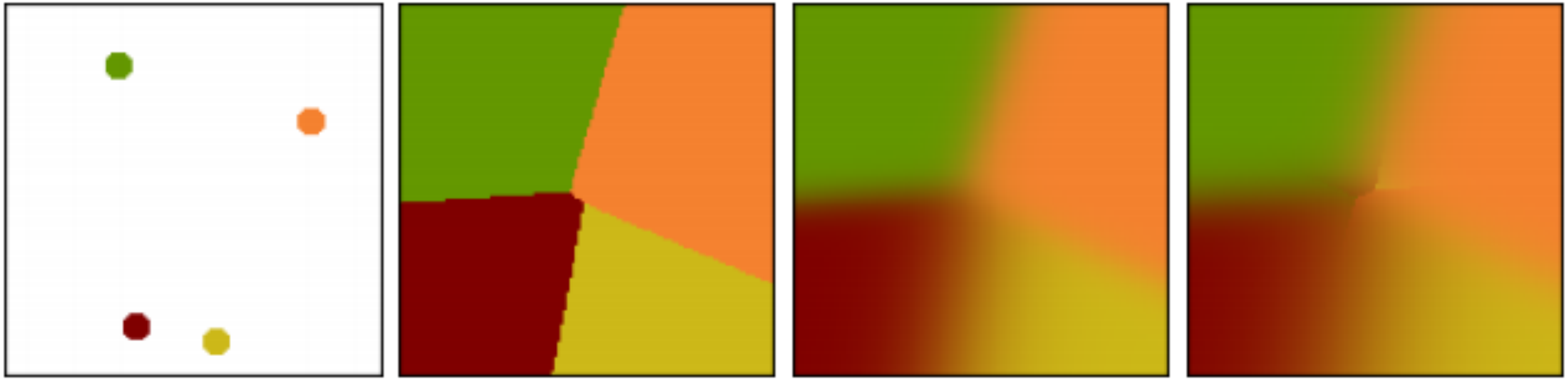
(a)

r or Gaussian mixture based methods for interpolation.

re dense

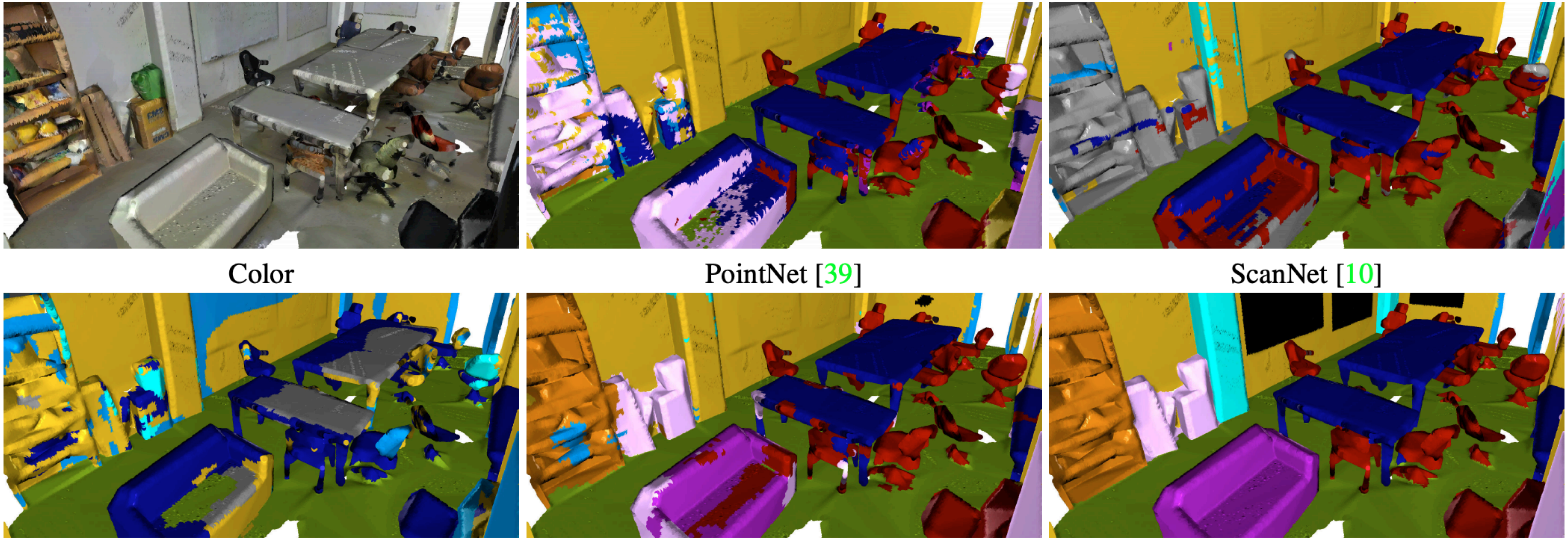
Dealing with Sparse Points

Signal Interpolation



(a) (b) (c) (d)

Improved Performance



Color | PointNet [39] | ScanNet [10]

OctNet [43] | Ours (DHNRGB) | Ground truth

Representation for 3D

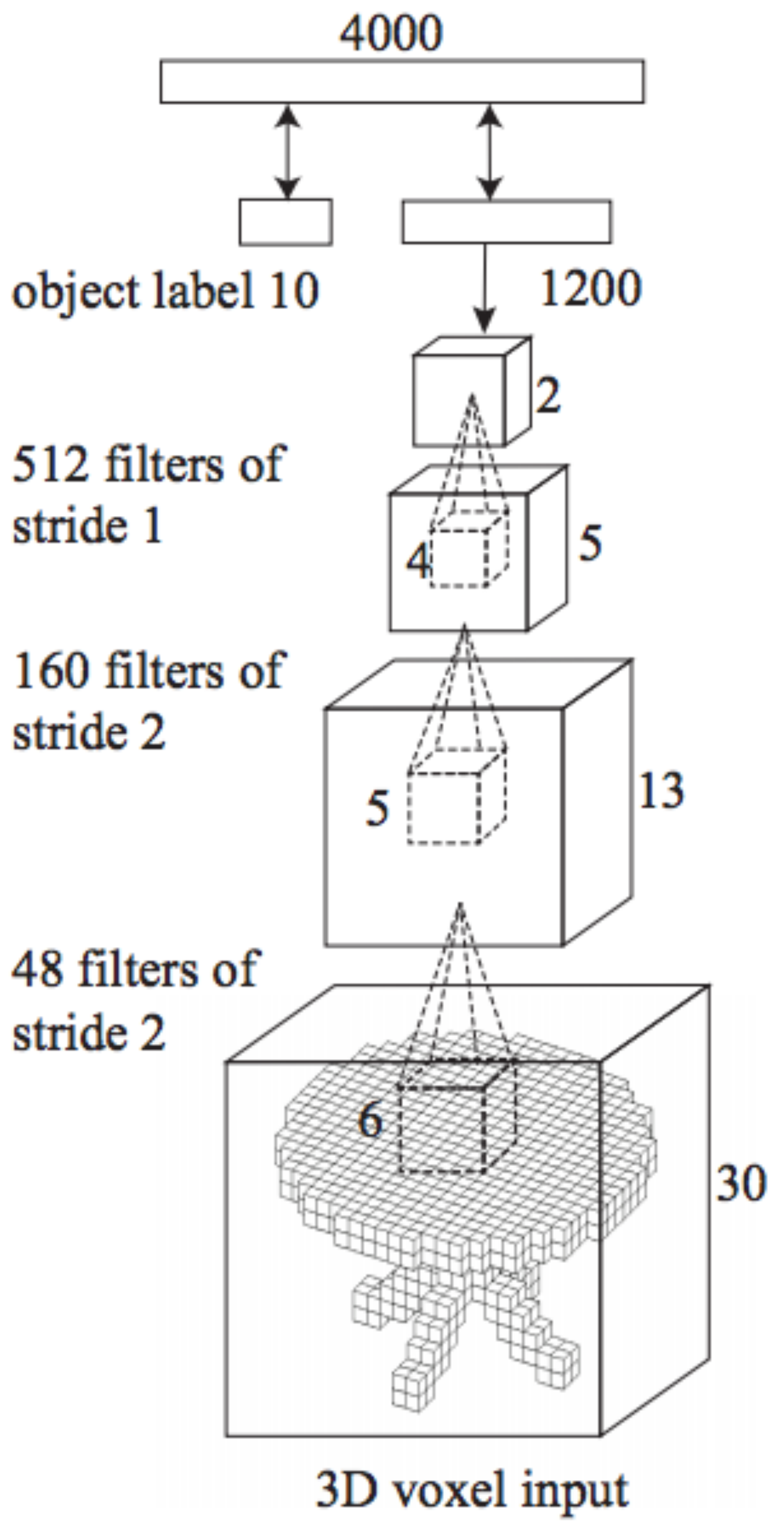
- **Image-based**
  - **PROS**: directly use image networks, good performance
  - **CONS**: rendering is slow and memory-heavy, not very geometric
- Volumetric
- Point-based
- Surface-based

Representation for 3D

- Image-based
- **Volumetric**
- Surface-based
- Point-based

3D CNNs : Direct Approach

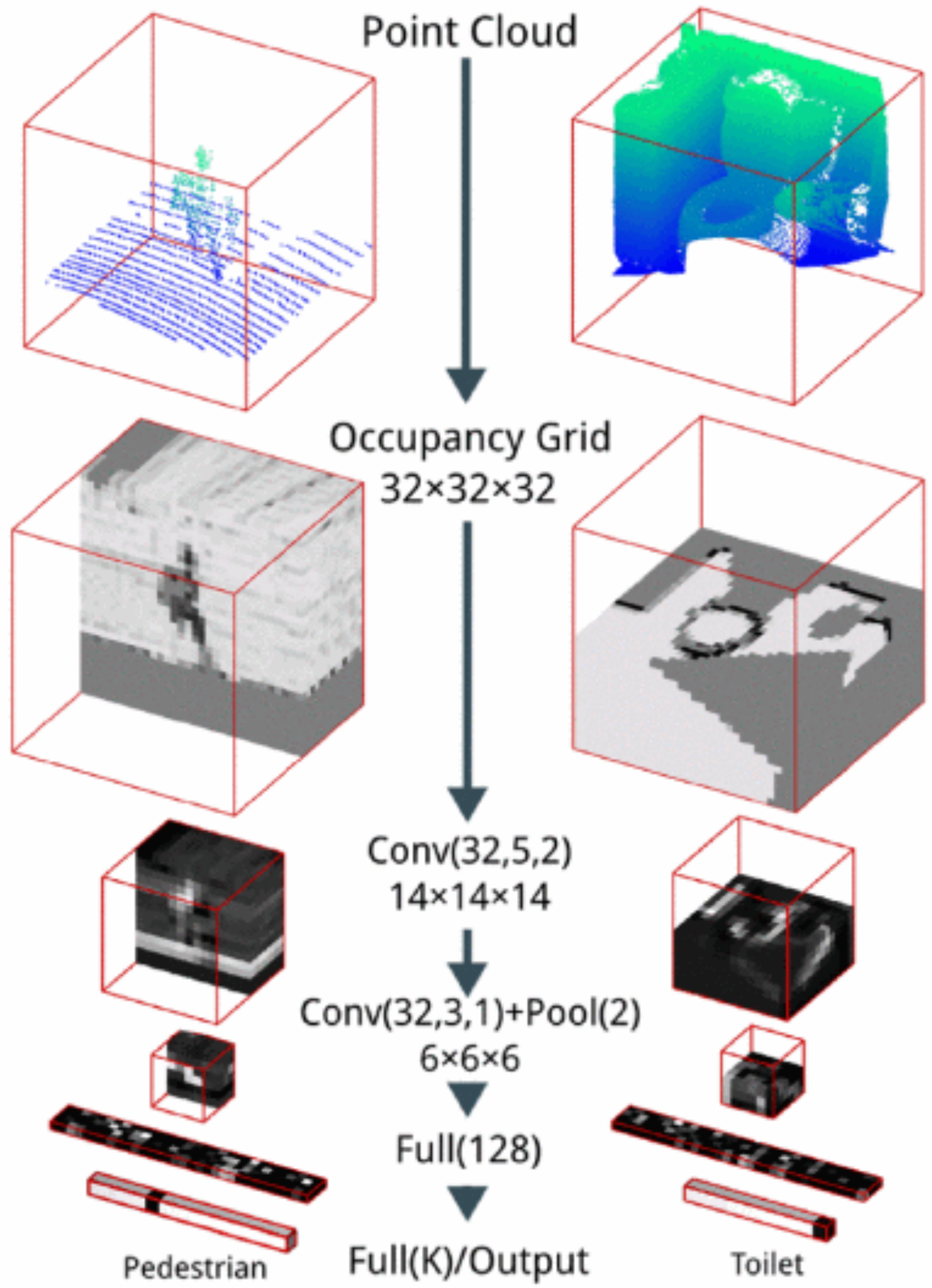
- **Volumetric**



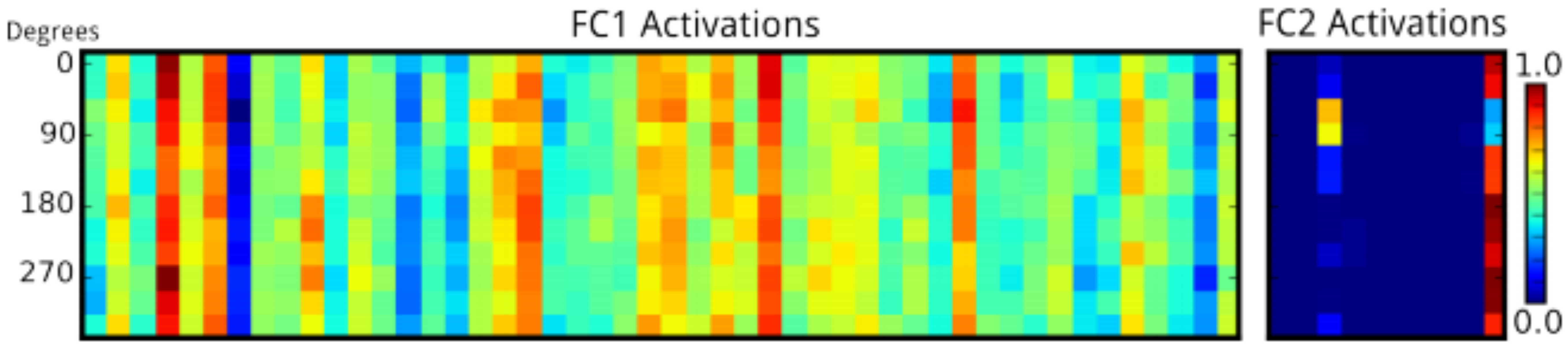
[Xiao et al. 2014]

VoxNet [Maturana et al. 15]

- *) VOXNET: A 3D CONVOLUTIONAL NEURAL NET
  OBJECT RECOGNITION [MATURANA ET AL. 2015
- Binary occupancy, density grid, etc.



rotational invariance

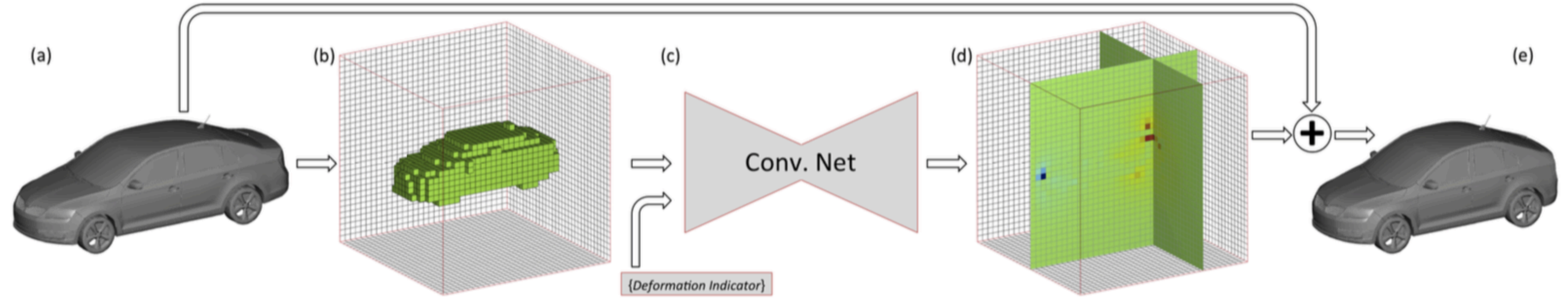


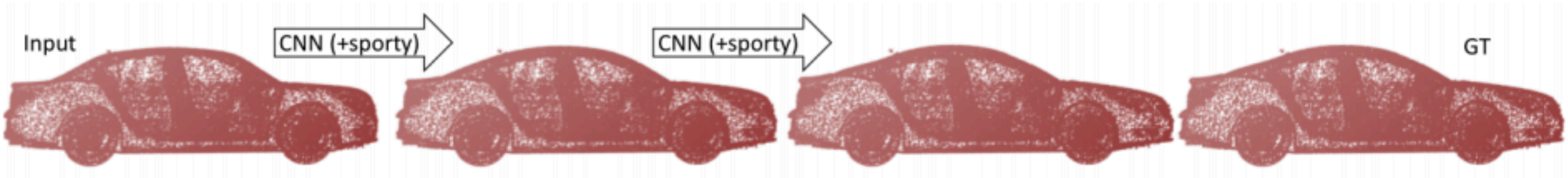
Visualization of First Level Filters

VISUALISATION OF FIRST LAYER FILTERS

Representation for 3D: Volumetric Deformation

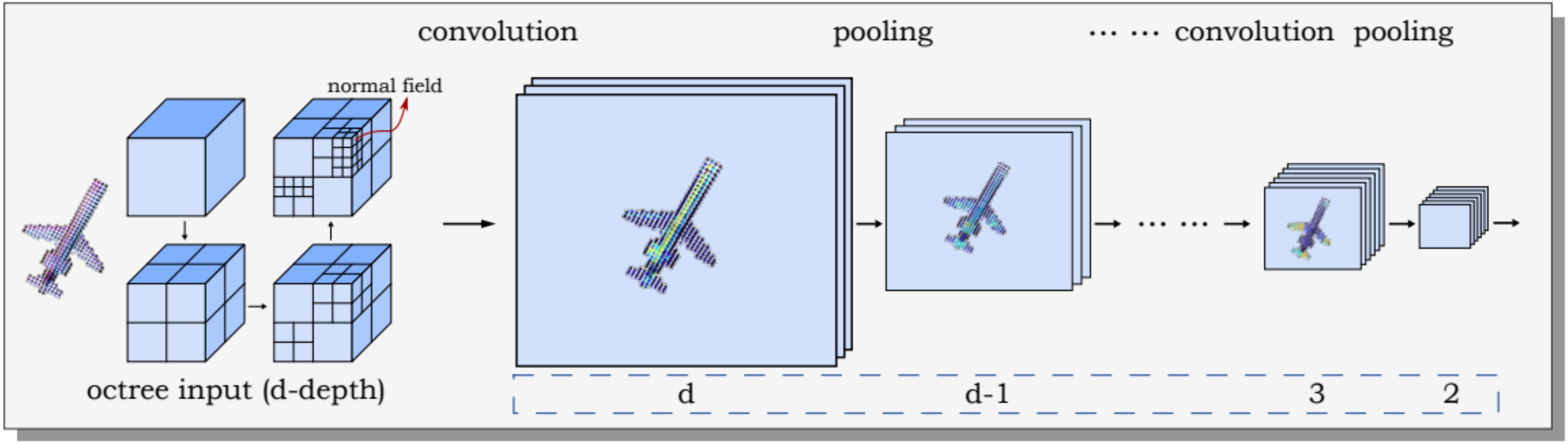
• \





[Yumer and Mitra 2016]

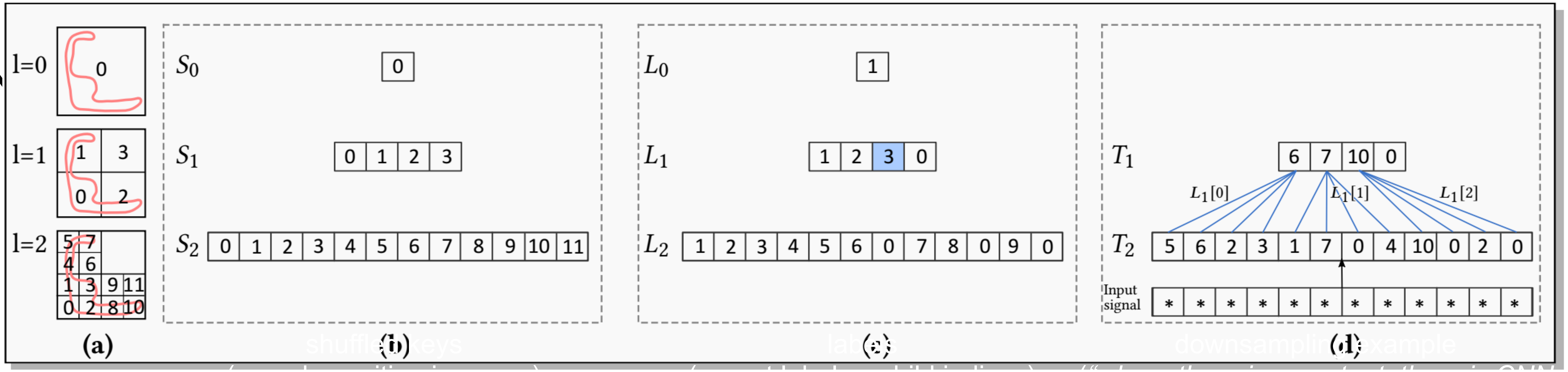
Efficient Volumetric Datastructures

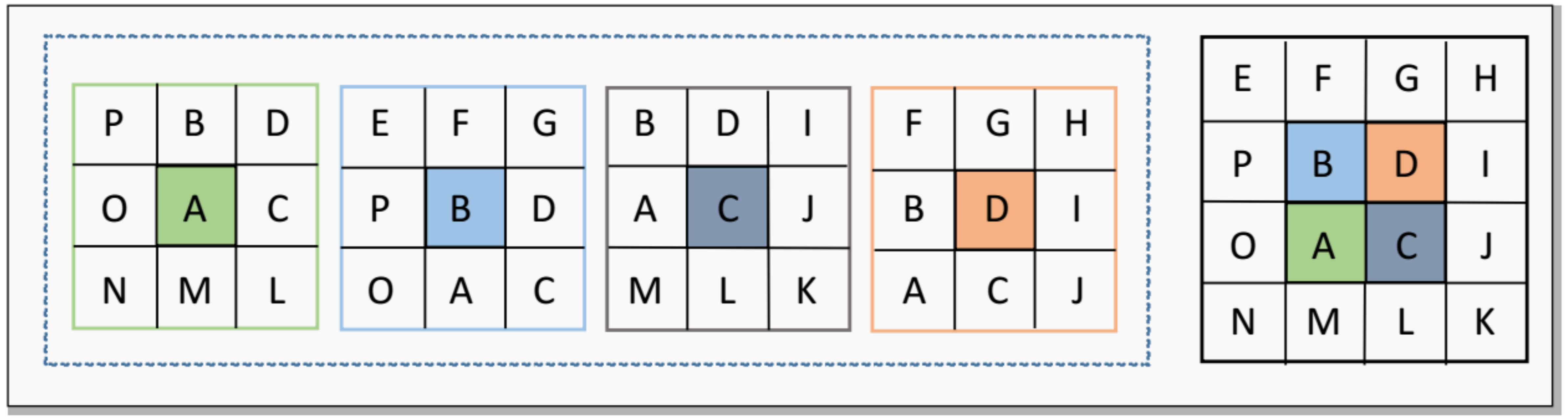


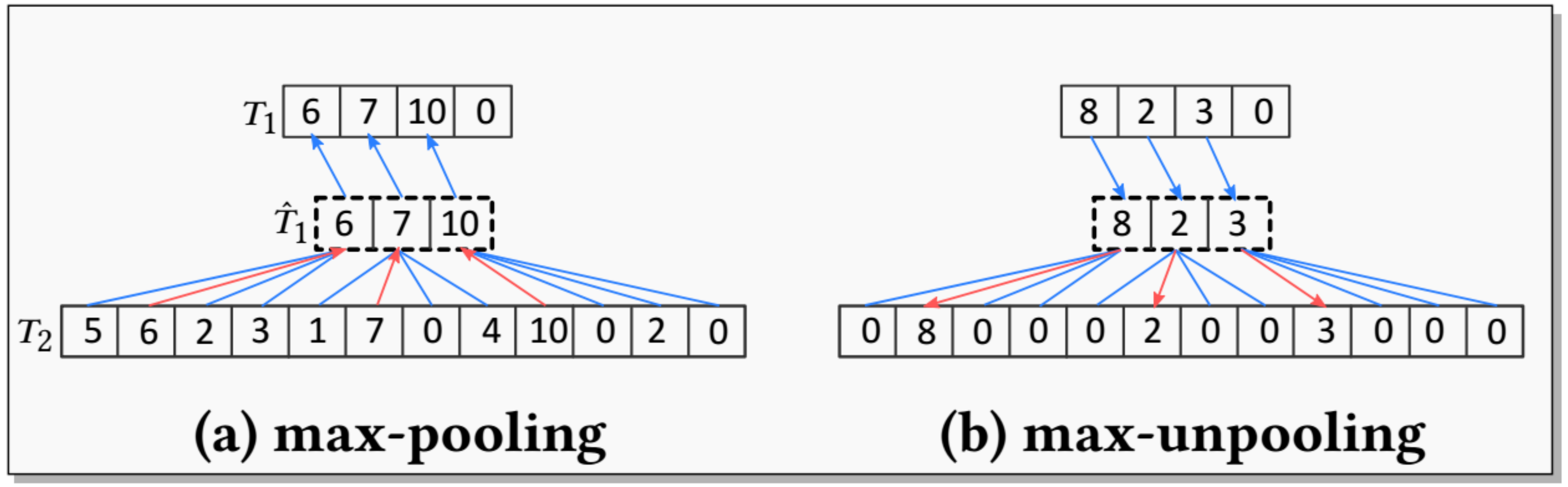
[Wang et al. 2017]

Data Structure and CNN Operations

O-CNN

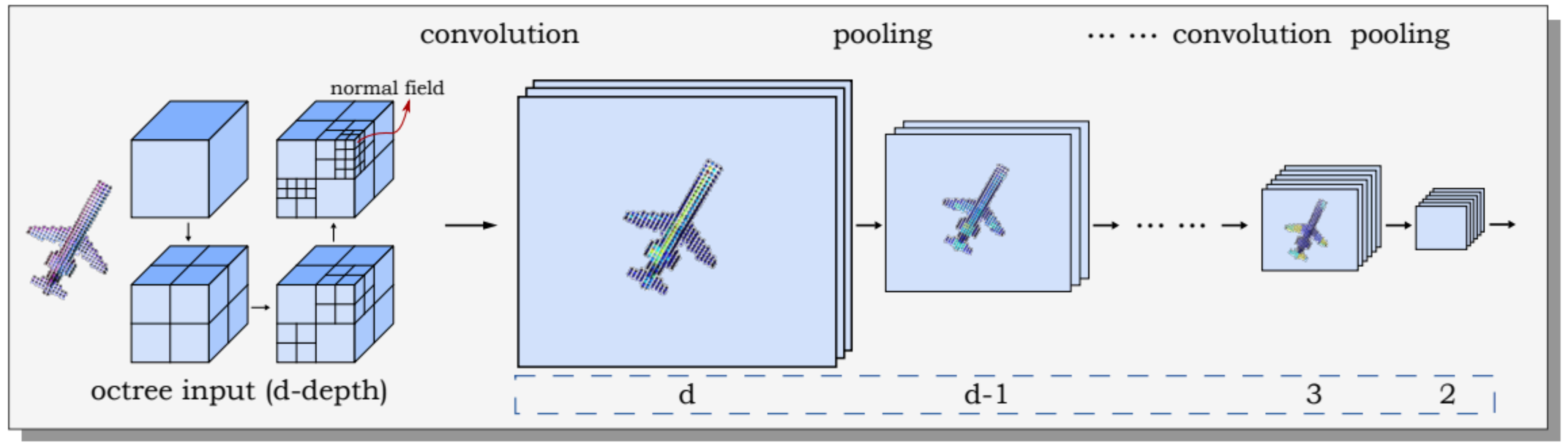






Efficient Volumetric Datastructures

Encoder



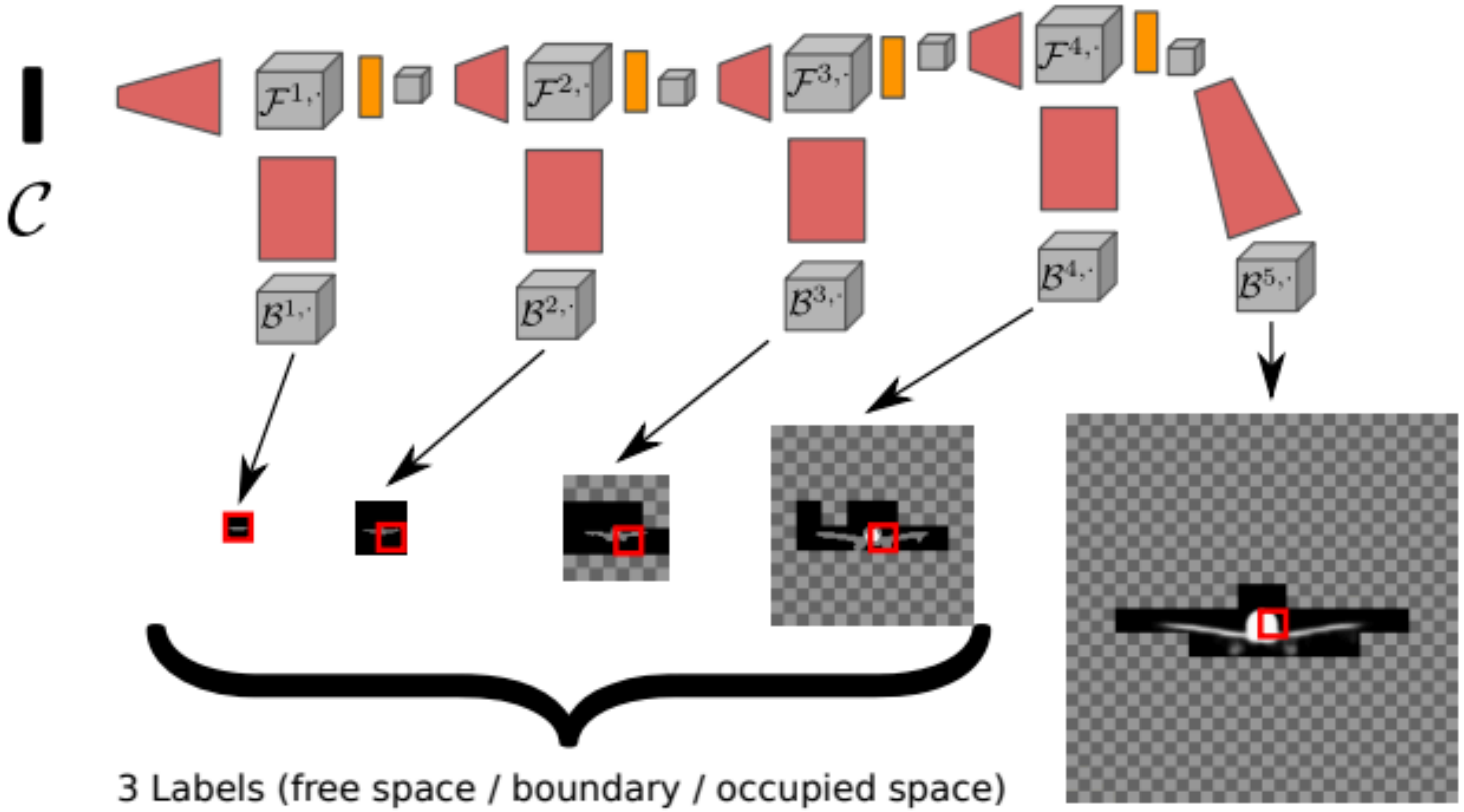
Wang et al. 2017

only generate non-empty voxels

Decoder/generator

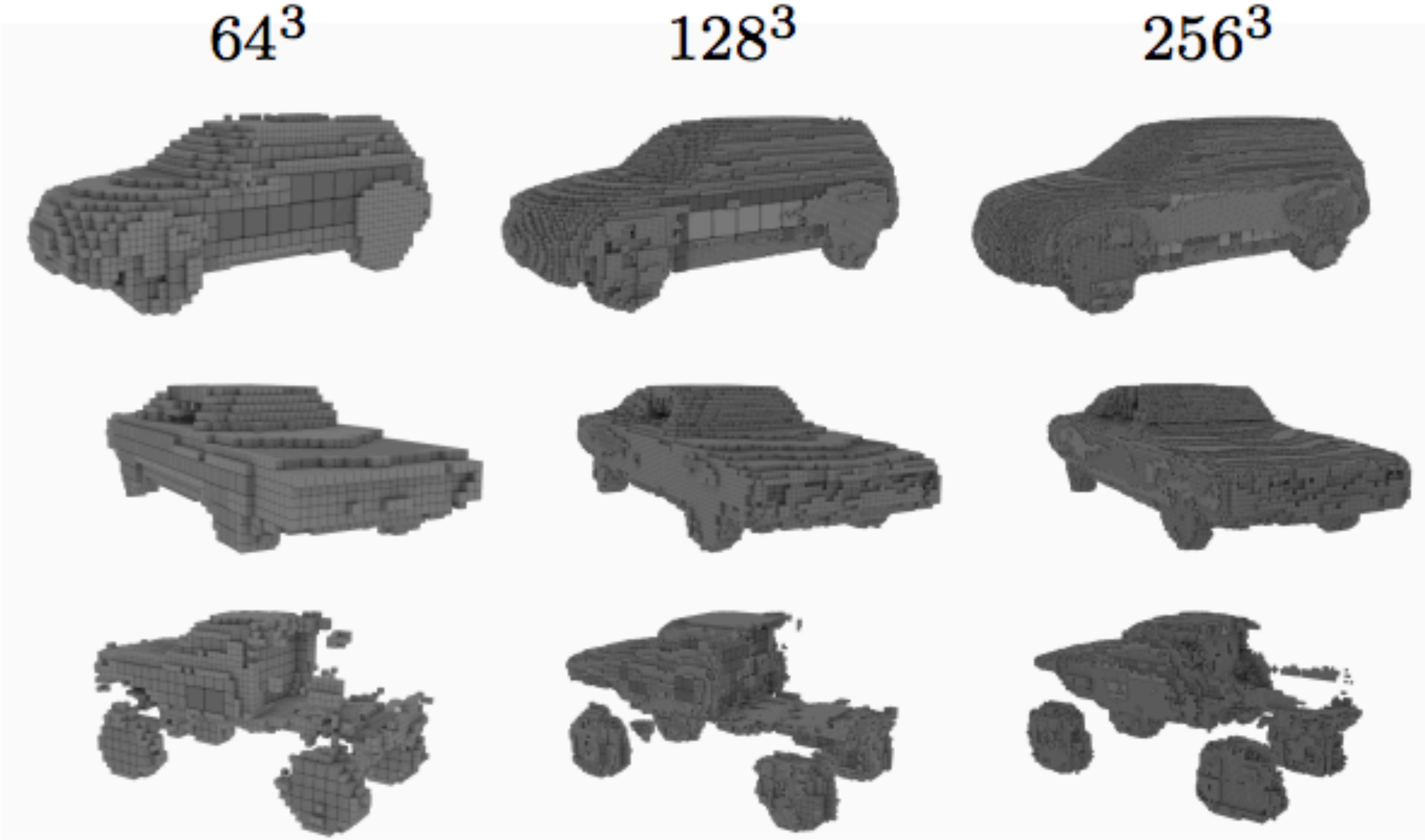
Volumetric (Up-) Convolutions

Cropping



[Hane et al. 2018]

Efficient Volumetric Datastructures



[Hane et al. 2018]

Lower Memory Footprint

O-CN

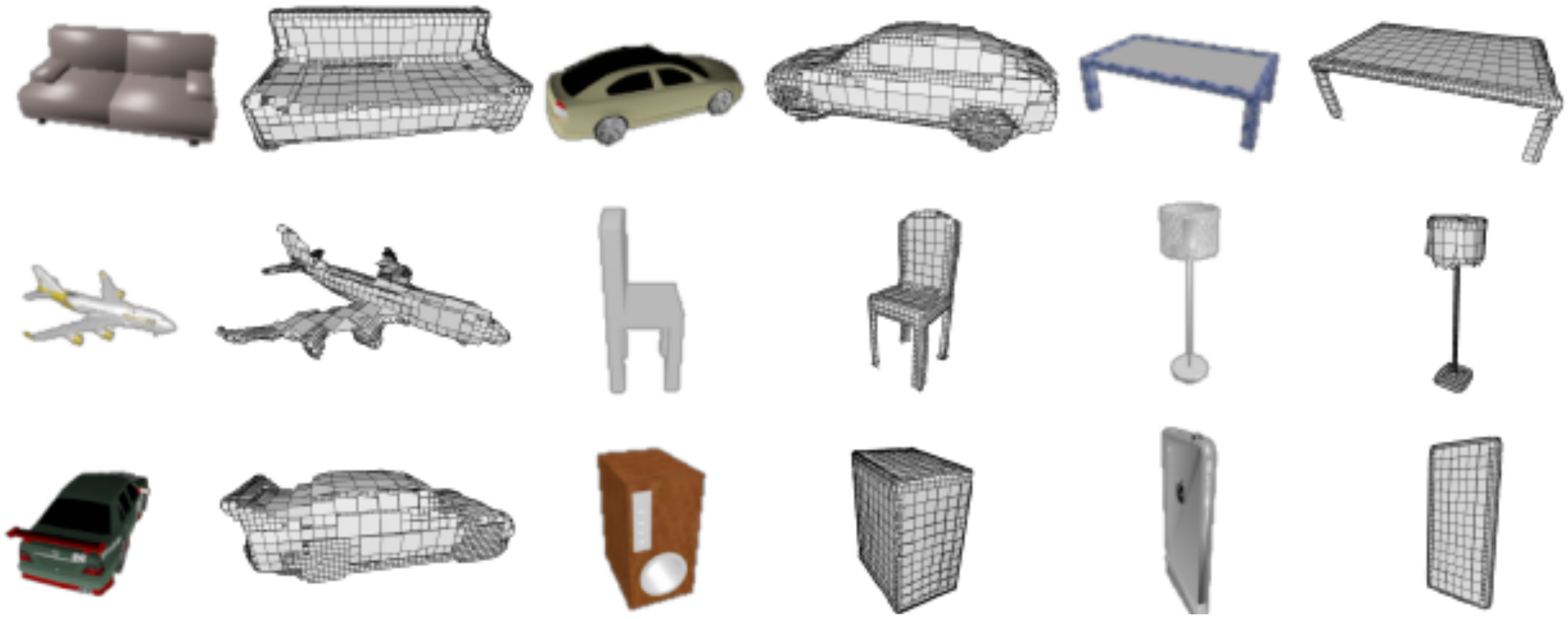
Method	16^3	32^3	64^3	128^3	256^3
O-CNN	0.32GB	0.58GB	1.1GB	2.7GB	6.4GB
full voxel+binary	0.23GB	0.71GB	3.7GB	Out of memory	Out of memory
full voxel+normal	0.27GB	1.20GB	4.3GB	Out of memory	Out of memory

Table 3. Comparisons on GPU-memory consumption. The batch size is 32.

Method	16^3	32^3	64^3	128^3	256^3
O-CNN	17ms	33ms	90ms	327ms	1265ms
full voxel+binary	59ms	425ms	1648ms	-	-
full voxel+normal	75ms	510ms	4654ms	-	-

Table 4. Timings of one backward and forward operation in milliseconds. The batch size is 32.

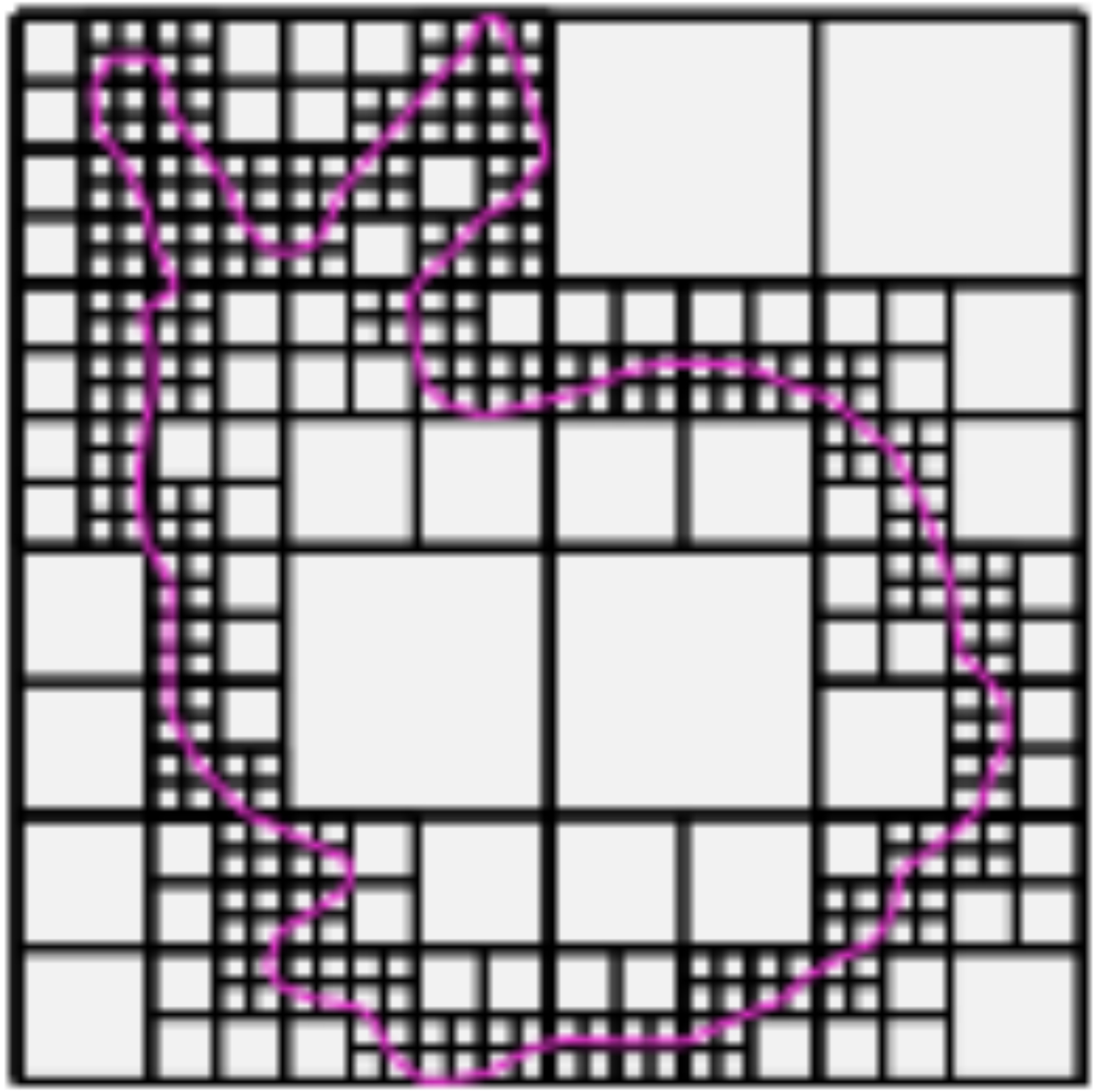
Adaptive O-CNN



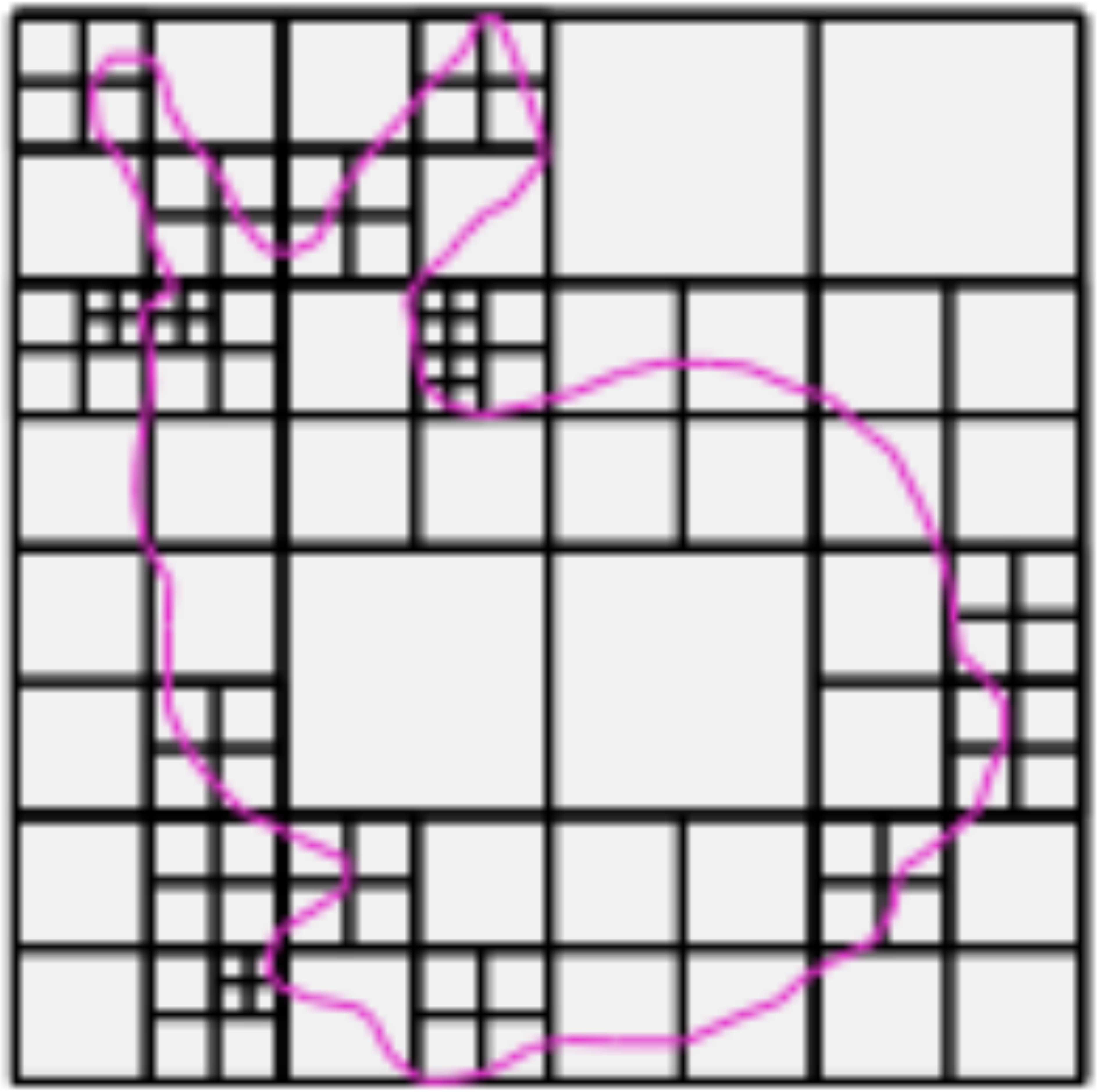
[Wang et al. 2018]

image to planar patch-based shapes

First-order Patches



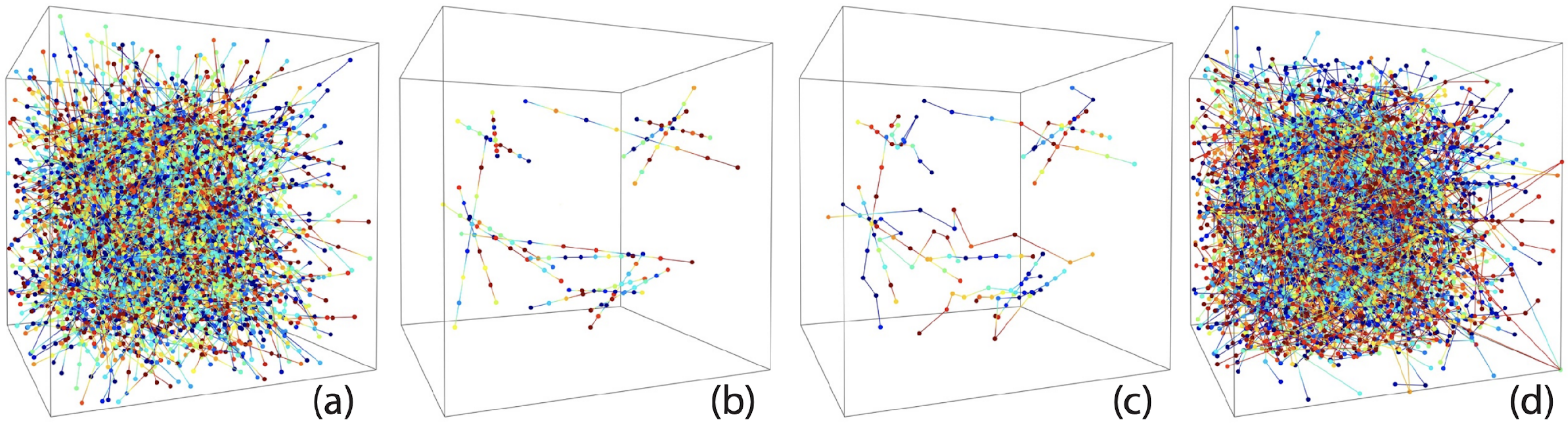
OCNN



Adaptive OCNN

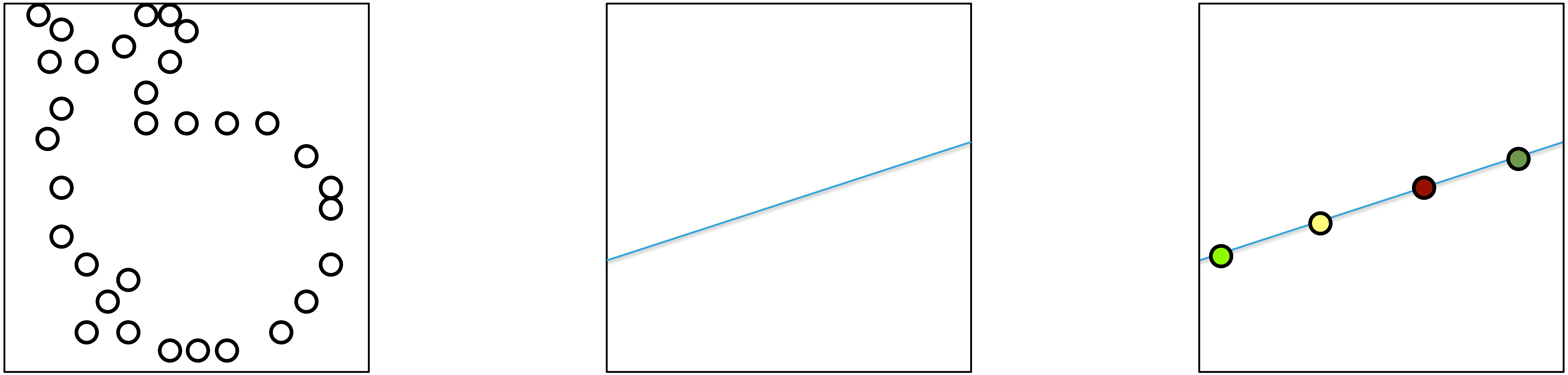
Field Probing Neural Networks for 3D Data

*)

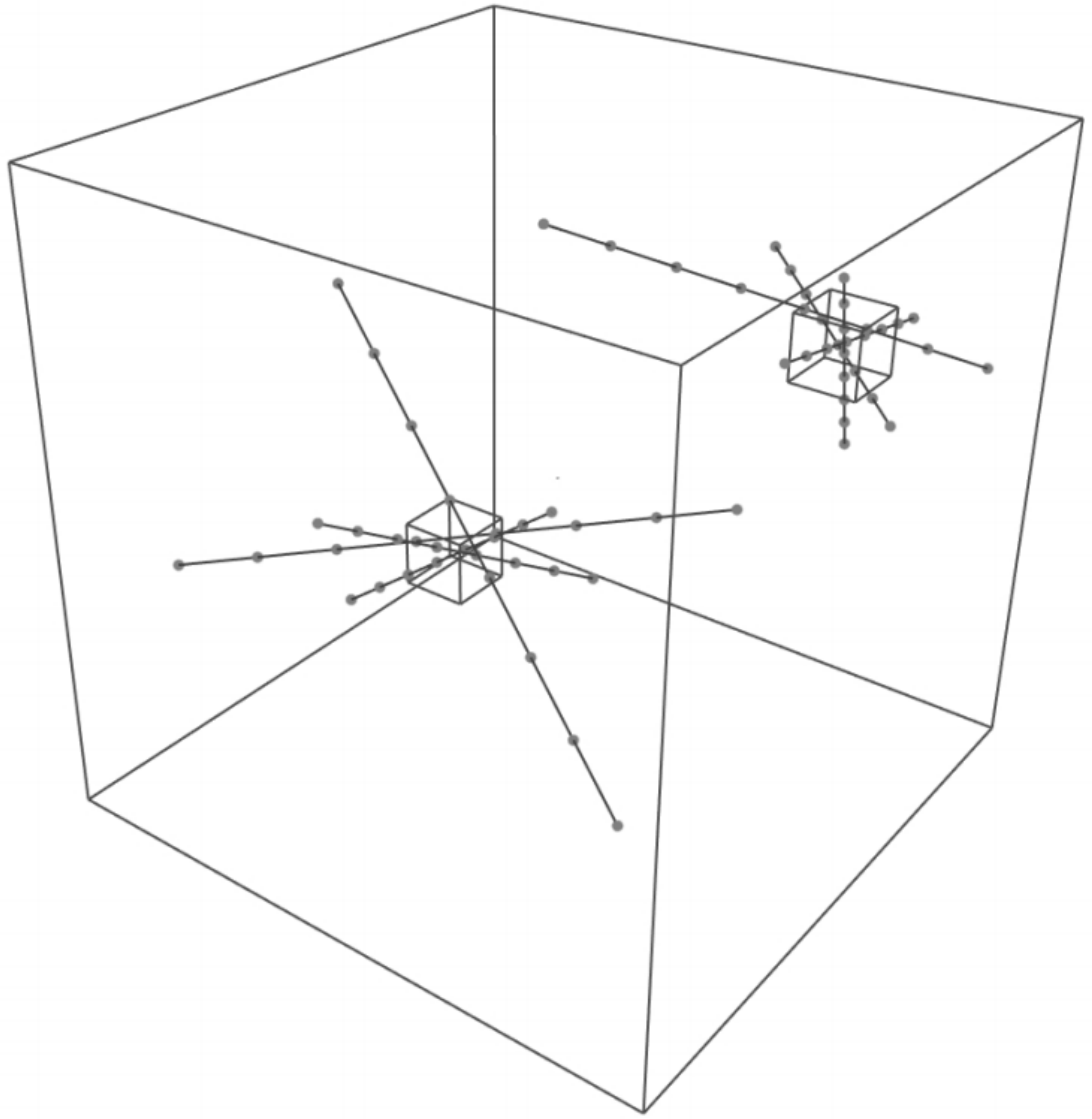


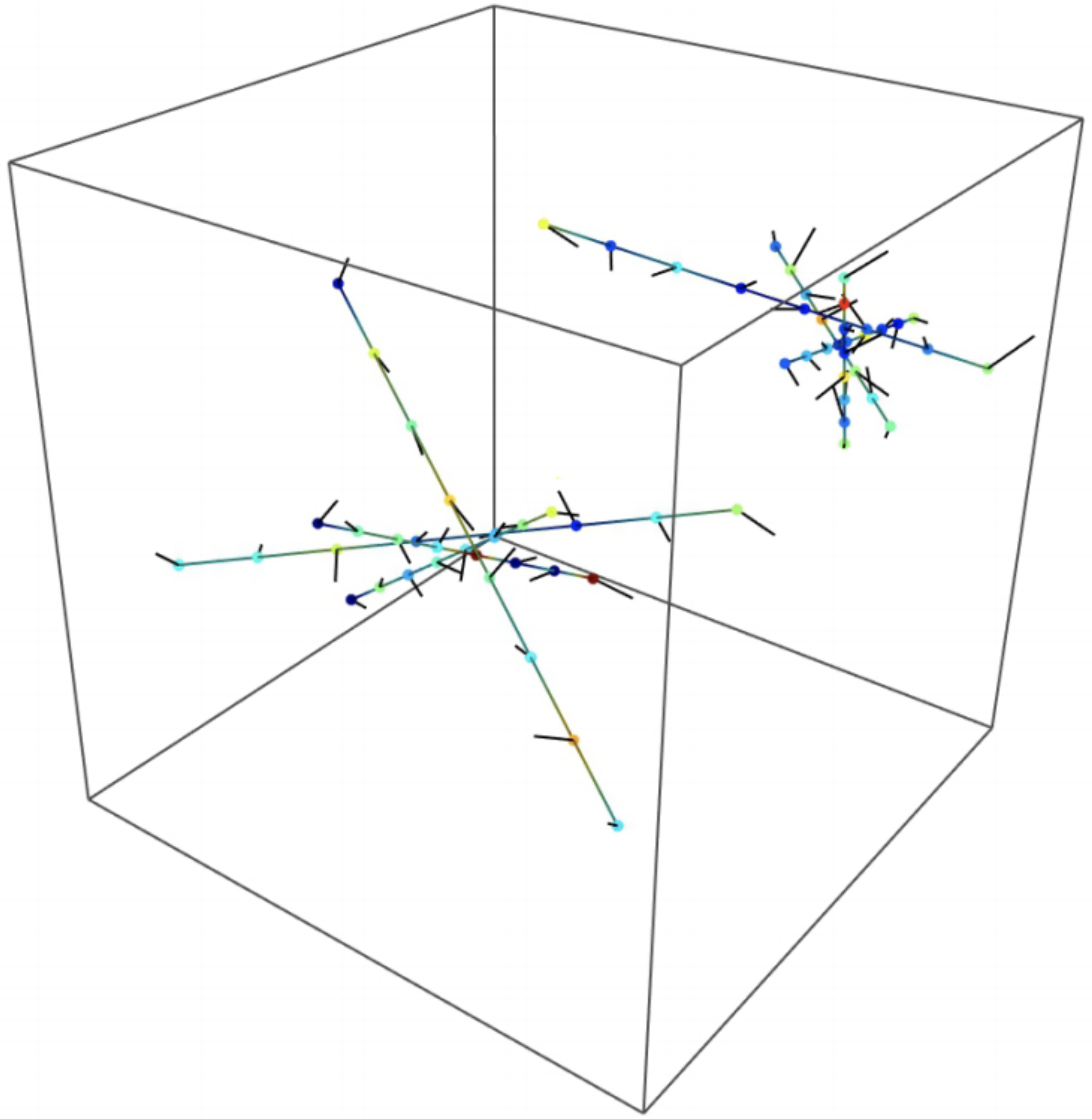
[Li et al. 2016]

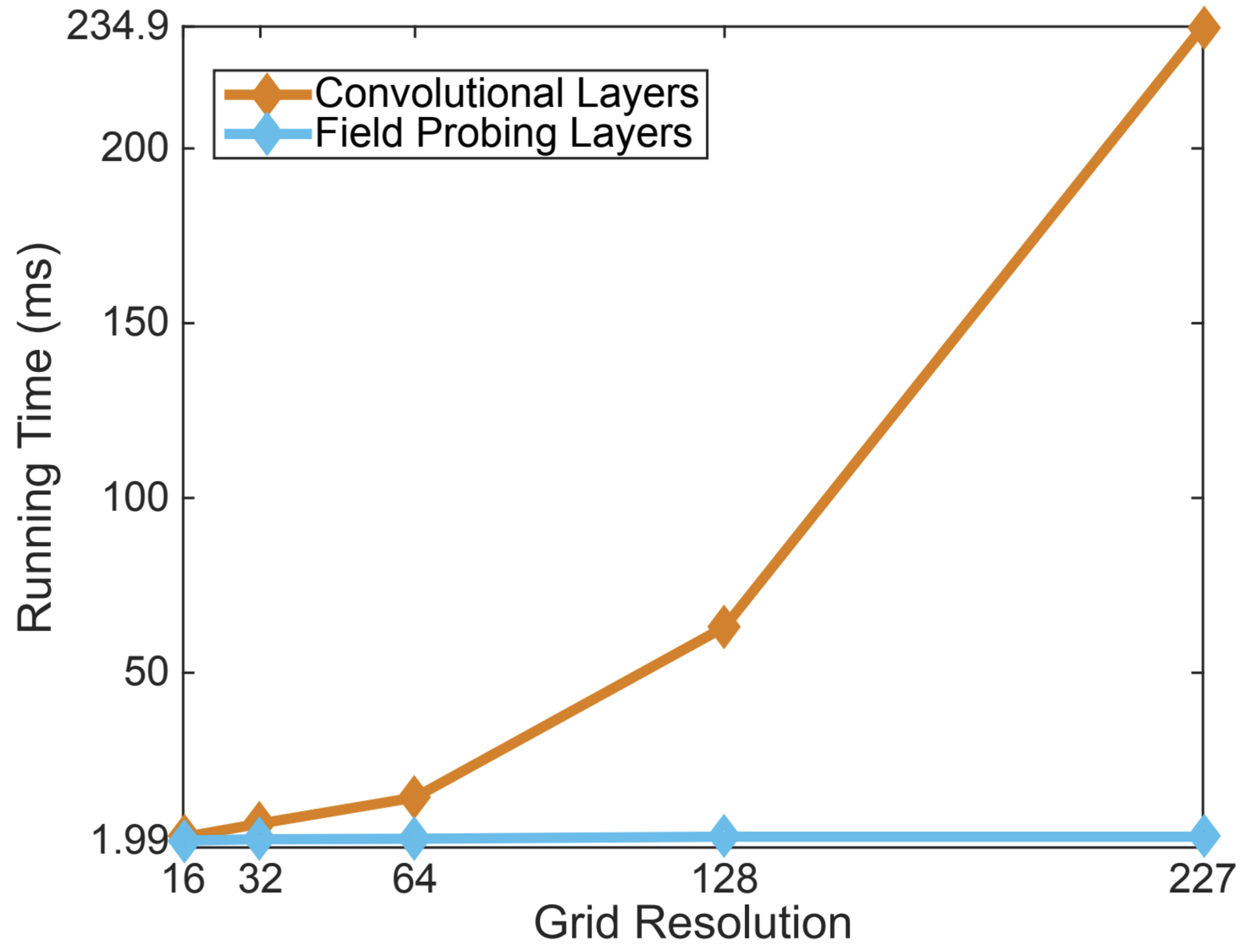
Spatial Probes



Method Details







$$v_c = v(\{p_{c,i,j}\},\{w_{c,i,j}\}) = \sum_{\substack{i=1,\ldots,N\\ j=1,\ldots,T}} p_{c,i,j} \times w_{c,i,j}$$

Representation for 3D

- Image-based

- Volumetric
  - PROS: adaptations of image networks
  - CONS: special layers for hierarchical datastructures, still too coarse

- Surface-based

- Point-based

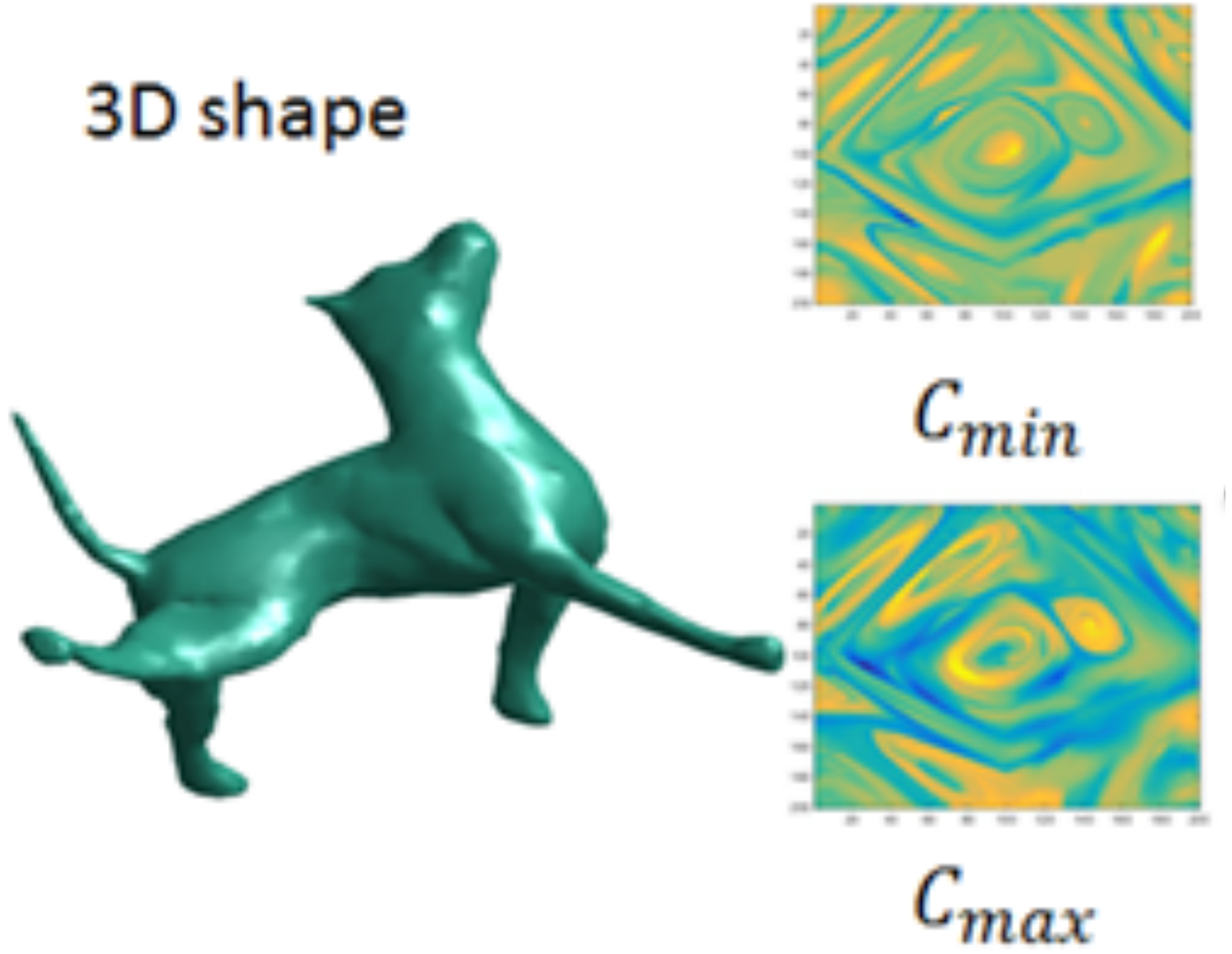
Representation for 3D

- Image-based
- Volumetric
- **Surface-based**
- Point-based

Local/Global Parameterizations

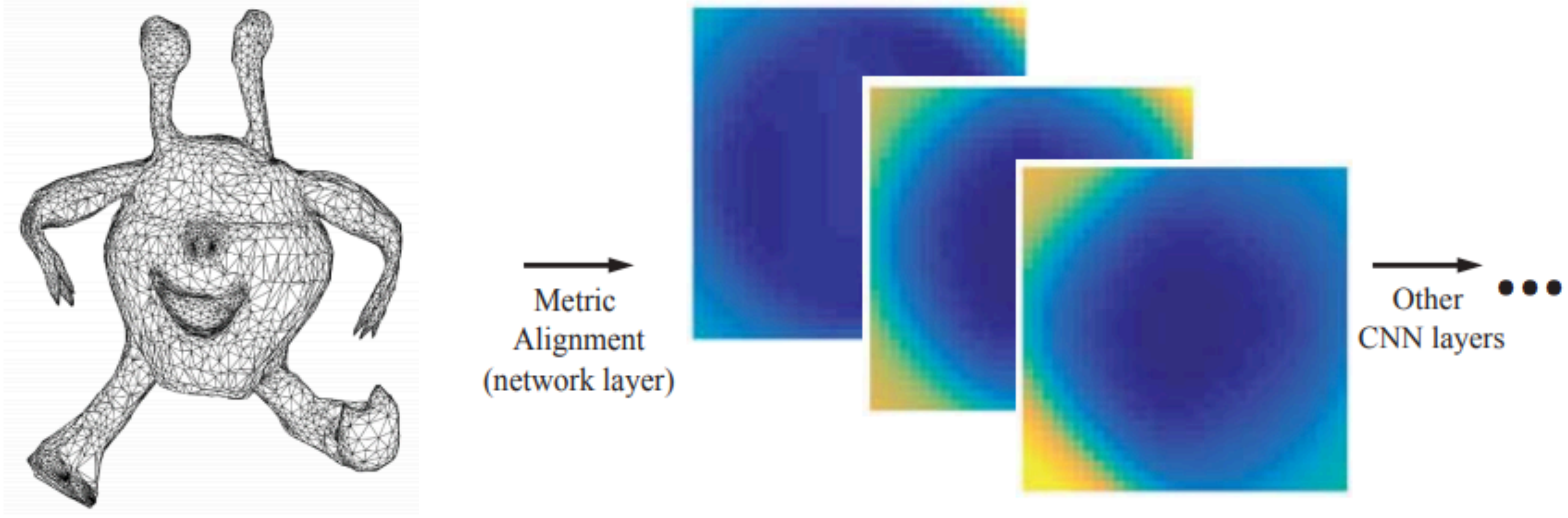
- Many different ways to parameterize a surface:

Geometry Image



[Sinha et al. 2016]

Metric Alignment (GWCNN)

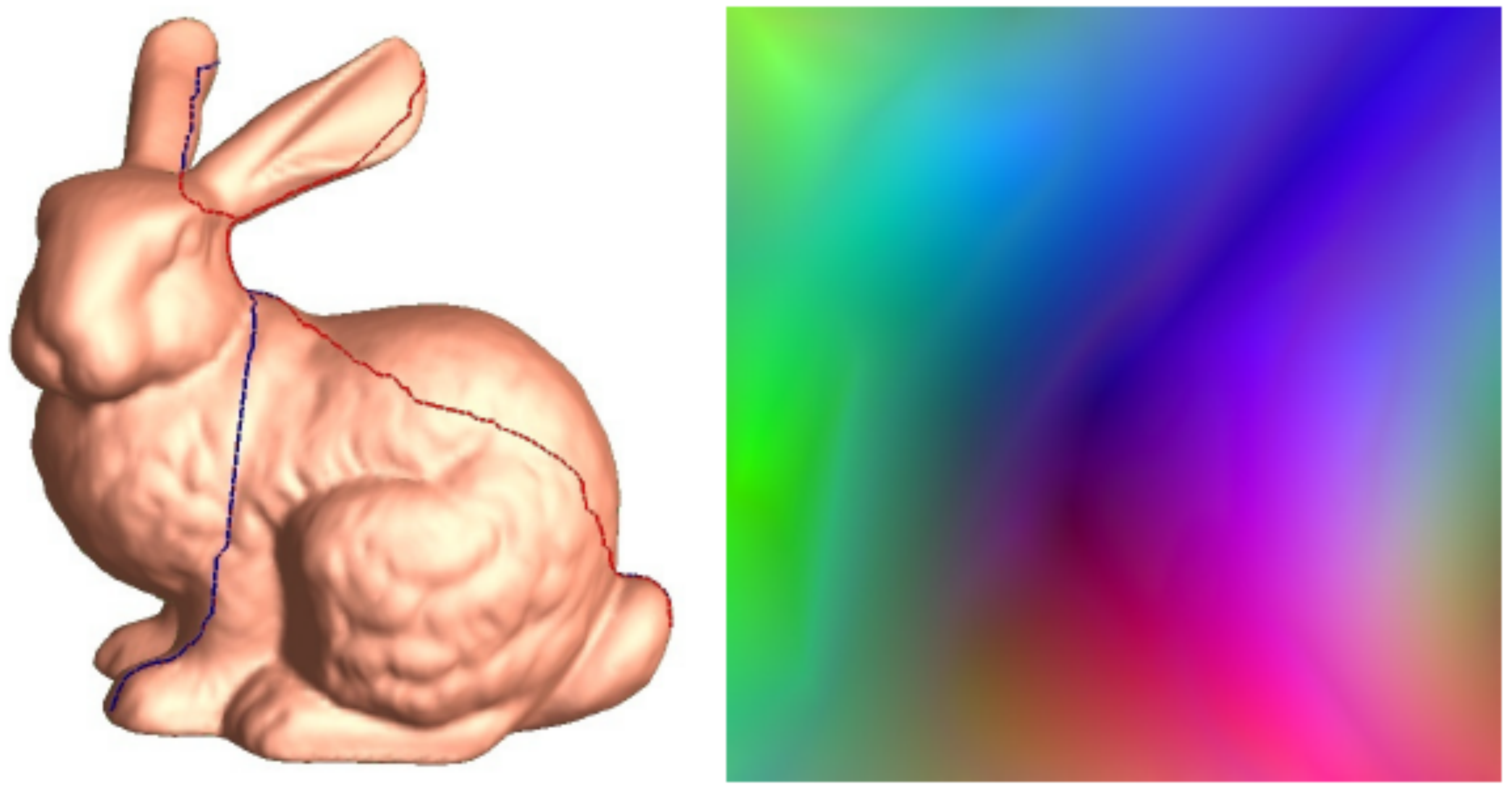


[Ezuz et al. 2017]

Shape Surfaces using Geometry Images

*) DEEP L
[SINHA E

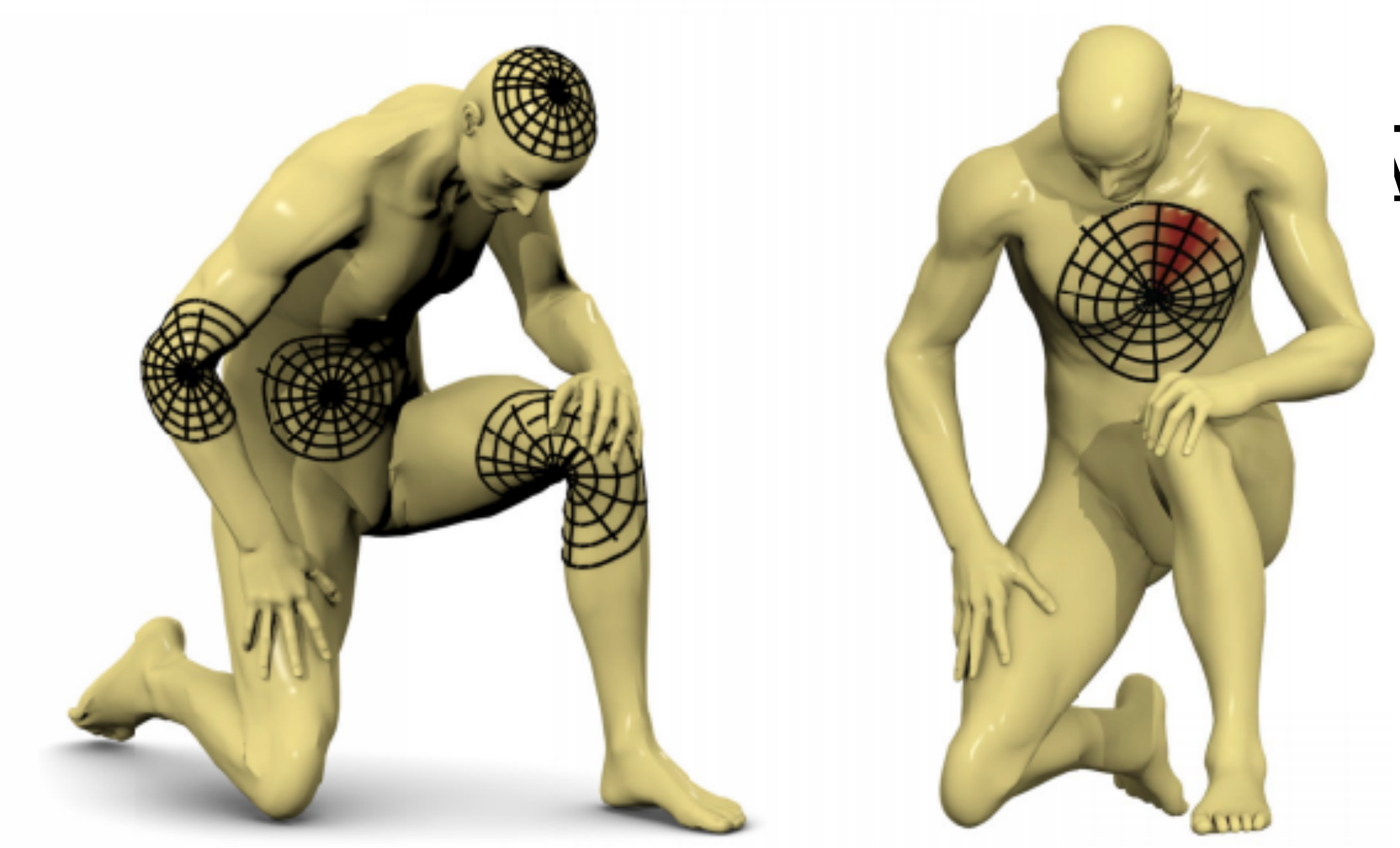
IAGES



(a) Original mesh with cut
70K faces; genus 0

(b) Geometry image 257×257
(b∗) Compr. to 1.5KB (not shown)

Using Geodesic Patches: GCNN

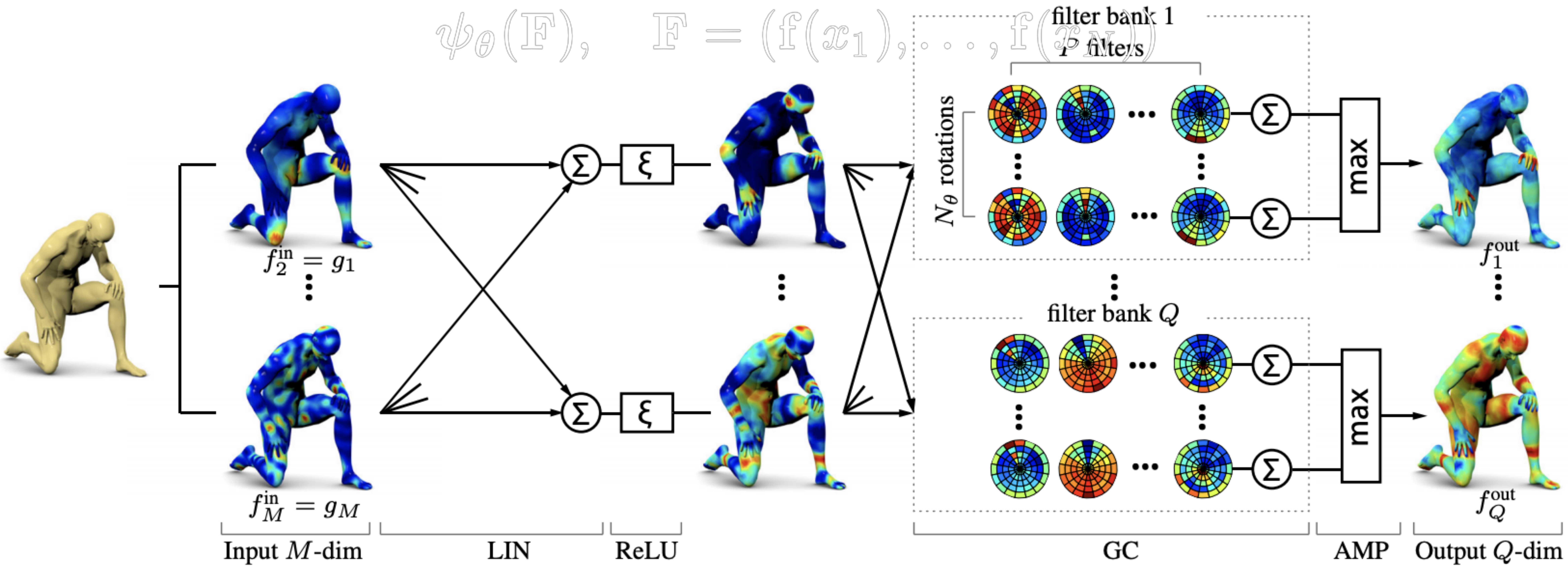


NETWORKS ON RIEMANNIAN
TED VERSION]

$$(f \star a)(x) := \sum_{\theta, r} a(\theta + \Delta\theta, r)(D(x)f)(r, \theta)$$

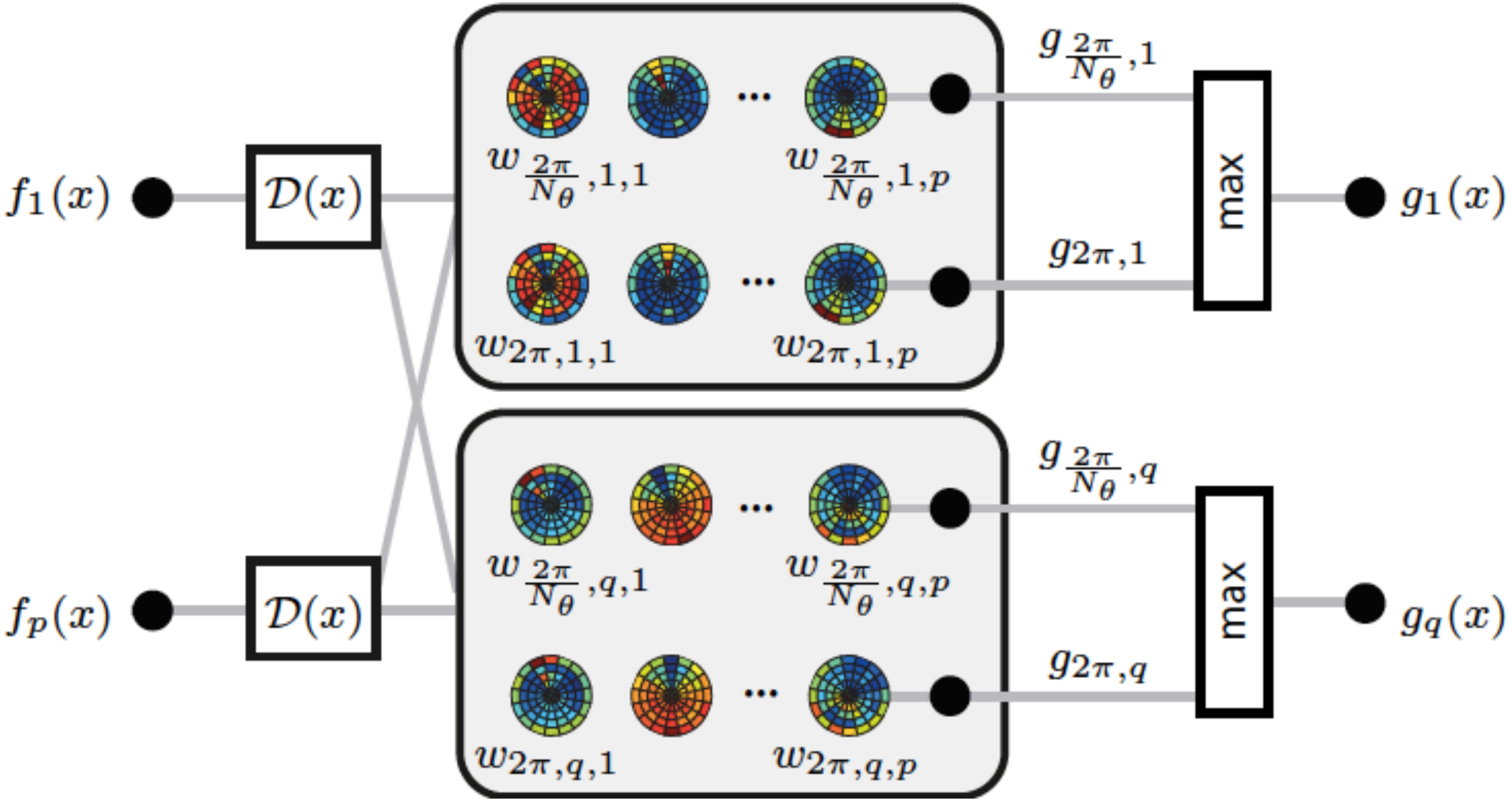
[Masci et al. 2015]

GCNN Architecture



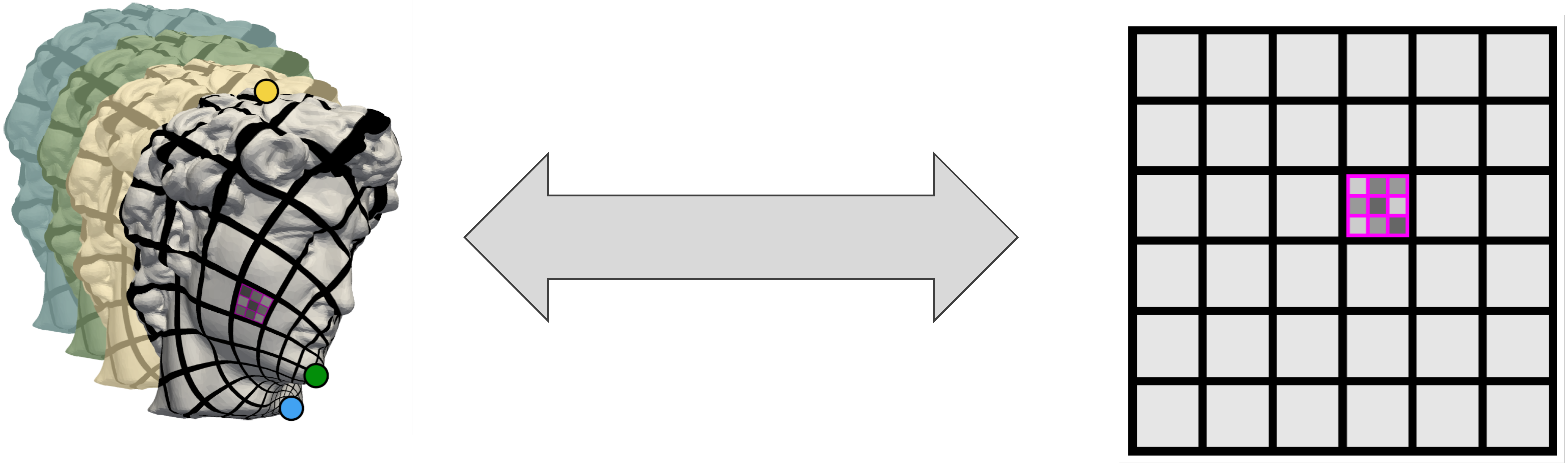
Handling Rotational Ambiguity

- Para



Parameterization for Surface Analysis

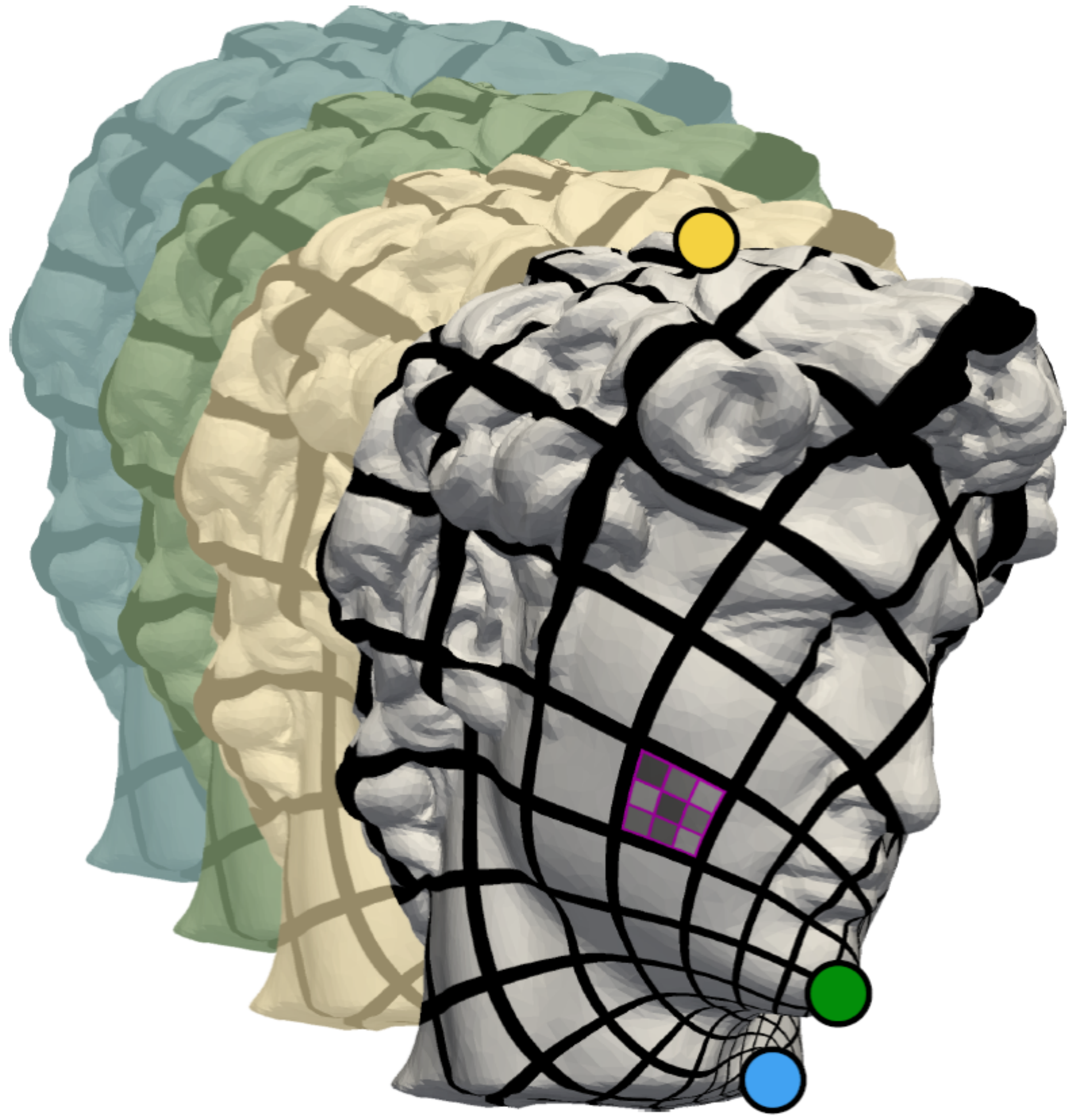
map 3D surface to 2D domain

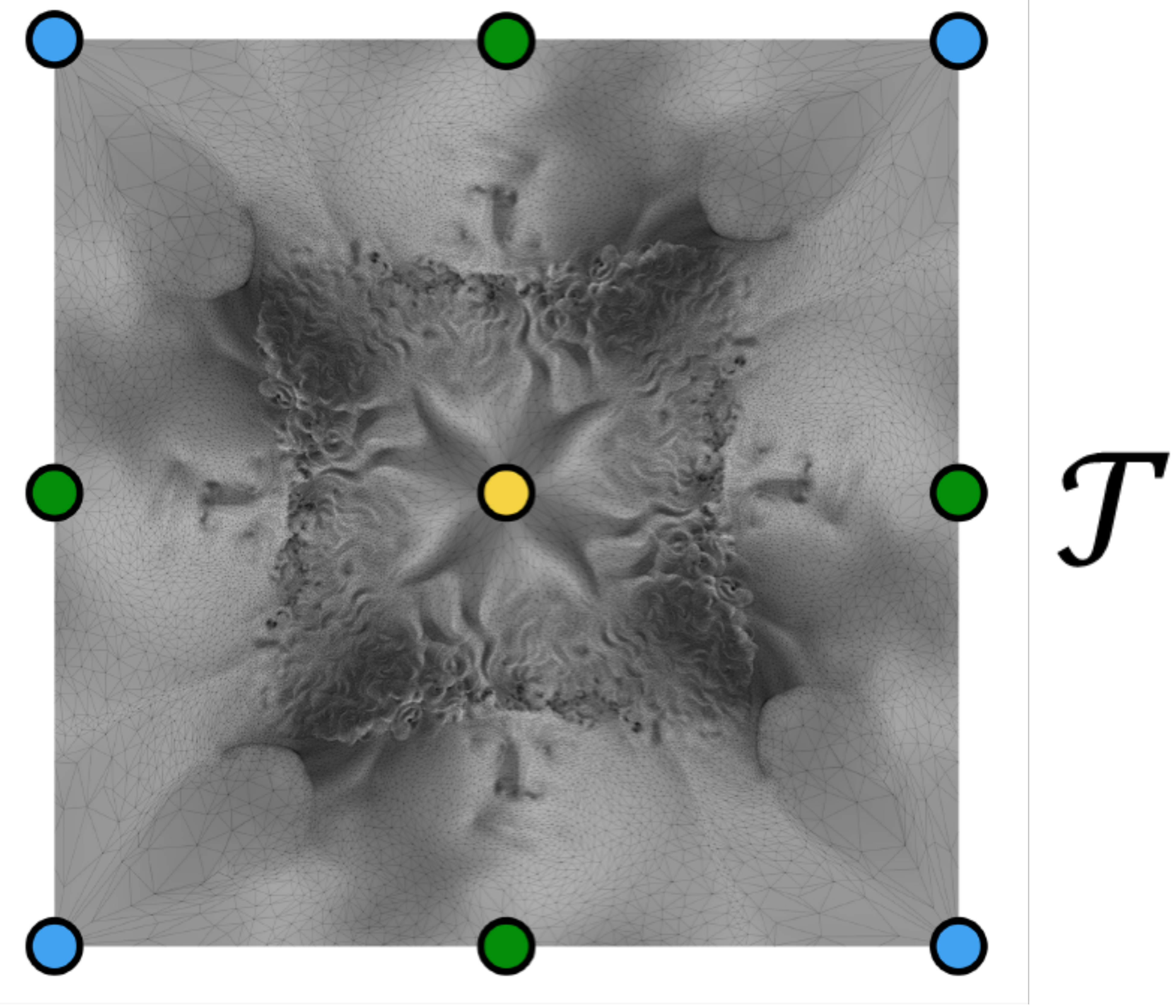


[Maron et al. 2017]

Parameterization for Surface Analysis

map 3D surface to 2D domain





[Maron et al. 2017]

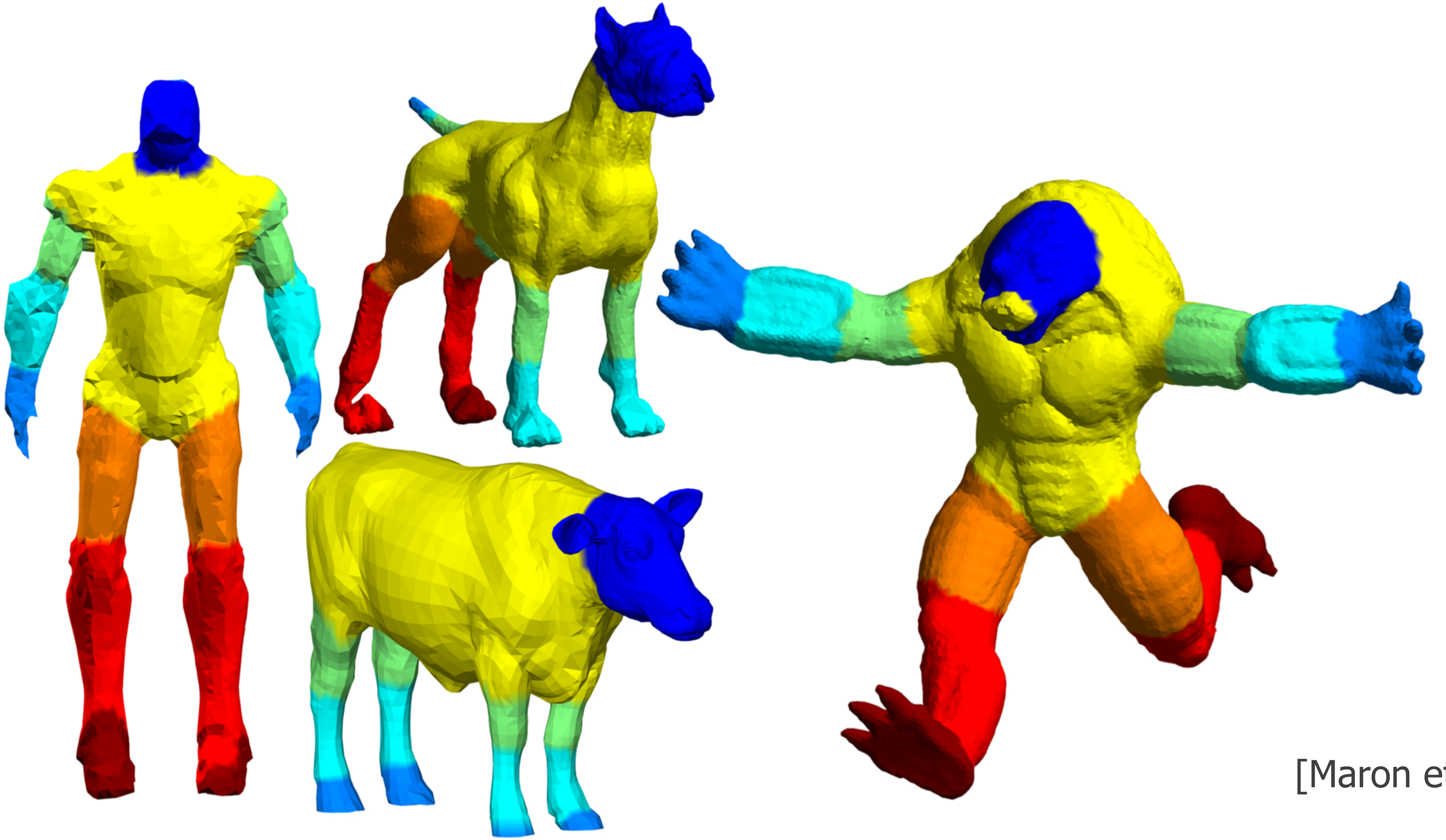
Parameterization for Surface Analysis

- Map 3D surface to 2D domain
  - One such mapping: **flat torus** (seamless => translation-invariant)
  - Many mappings exists: sample a few and average result
  - Which functions to map?
    XYZ, normals, curvature, …

[Maron et al. 2017]

Parameterization for Surface Analysis

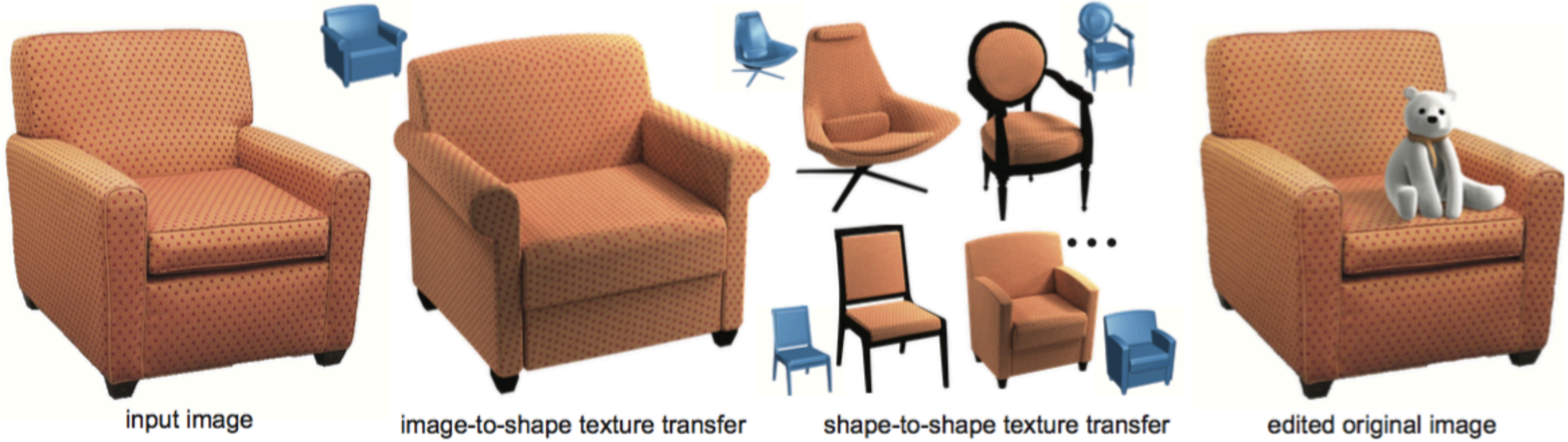
• Teste



[Maron et al. 2017]

Texture Transfer (Parameterization + Alignment)

- Condition decoded points on 2D patches

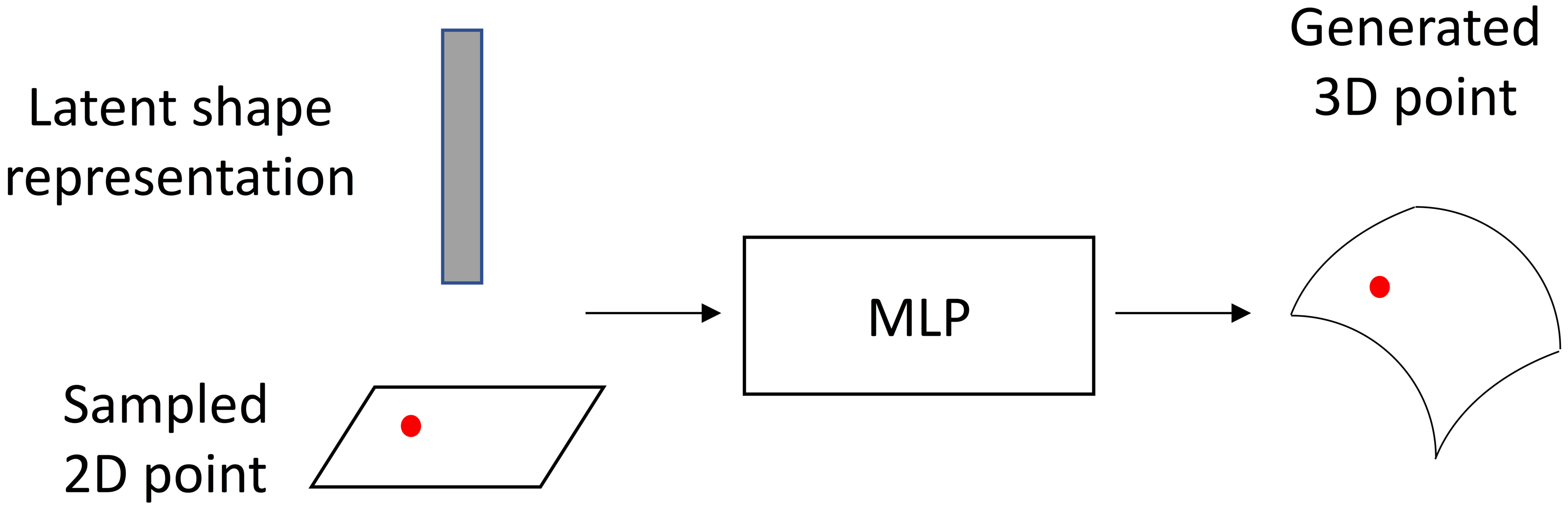


[Wang et al. 2016]

AtlasNet for Surface Generation

- Condition decoded points on 2D patches

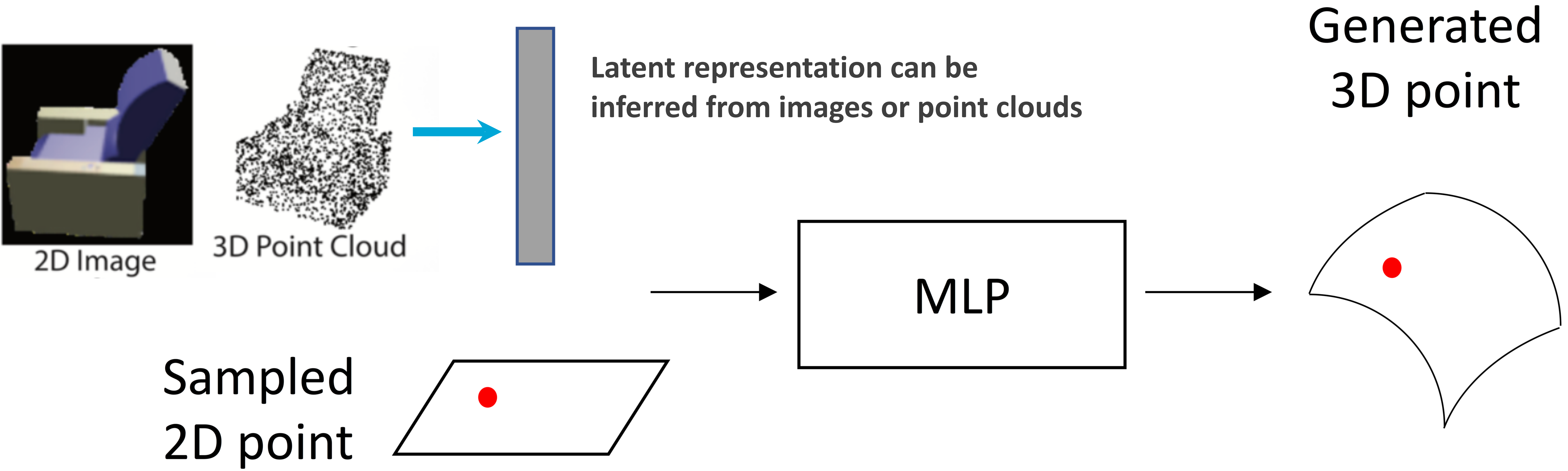
condition decoded points on 2D patches



[Groueix et al. 2018]

AtlasNet for Surface Generation

- Condition decoded points on 2D patches



[Groueix et al. 2018]

AtlasNet for Surface Generation

- Condition decoded points on 2D patches

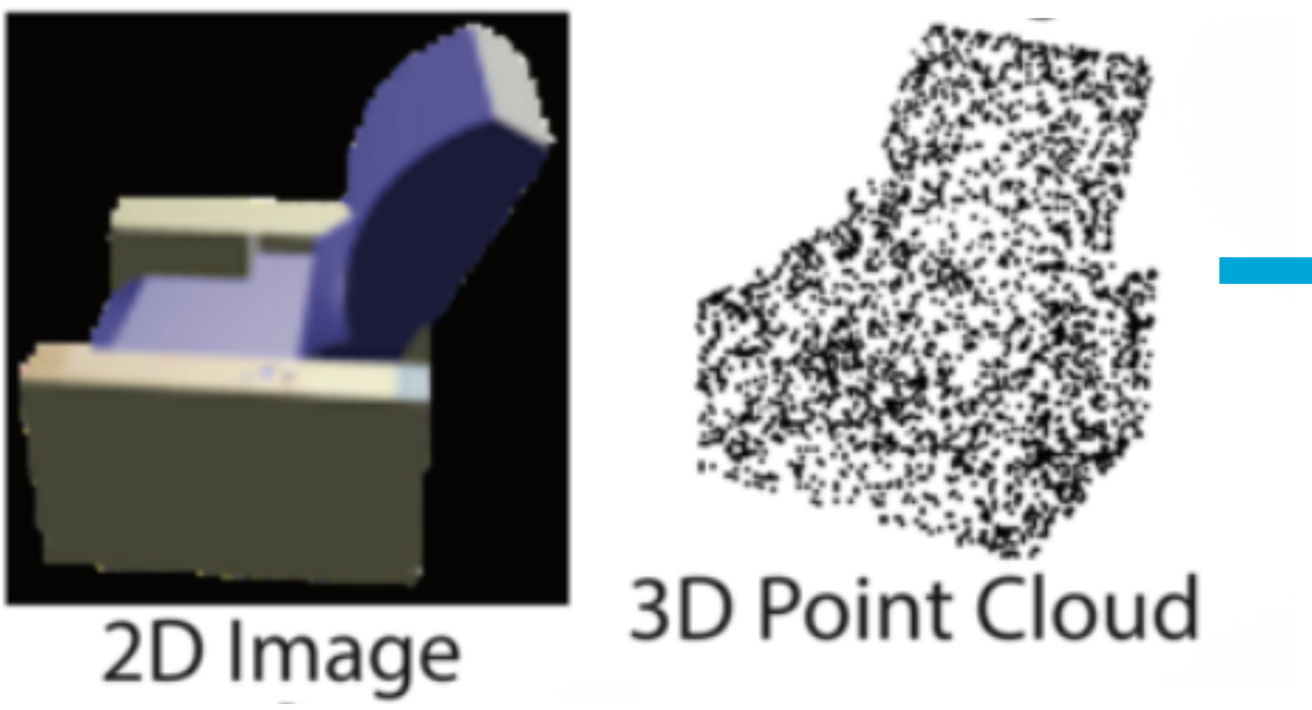
Quad Mesh is generated by mapping a regular grid in 2D domain to 3D points

[Groueix et al. 2018]

AtlasNet for Surface Generation

texture coordinates come for free!!

- Condition decoded points on 2D patches



Latent representation can be inferred from images or point clouds

MLP

Sampled 2D point

Representation for 3D

- Image-based
- Volumetric
- Surface-based
  - PROS: parameterize + image networks (instrinsic representation)
  - CONS: suffers from parameterisation artefacts (local versus global distortion), requires good quality mesh
- Point-based

Representation for 3D

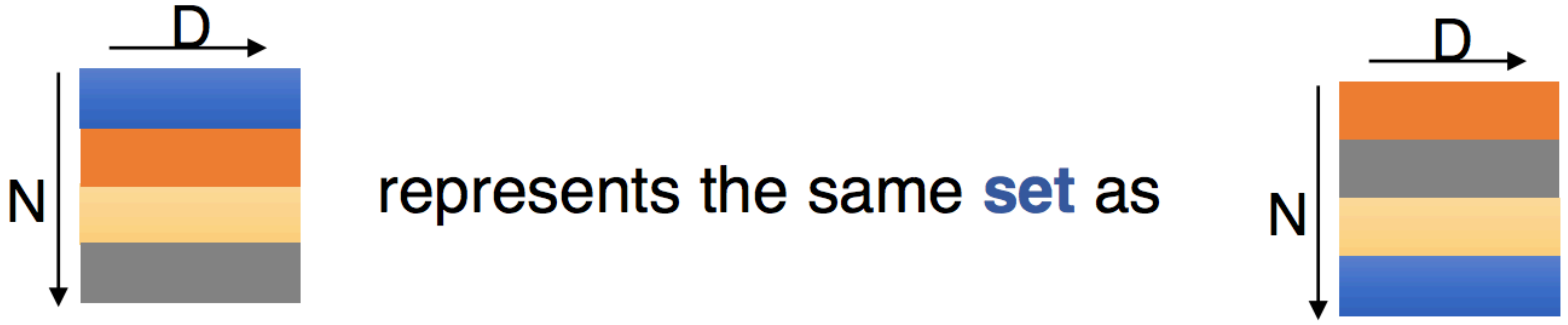
- Image-based
- Volumetric
- Surface-based
- **Point-based**

Representation for 3D: Point-based

- Common representation: native representation
- Easy to obtain from meshes, depth scans, laser scai

In Original Representation

- Common representation
- Easy to obtain from meshes, depth scans, laser scans
- **Unstructured** (e.g., any permutation of points gives same shape!)



2D array representation

[Qi et al. 2017]

PointNet for Point Cloud Analysis

- Permutation-invariant functions

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n}), \quad x_i \in \mathbb{R}^D$$

permutation-invariant functions

[Qi et al. 2017]

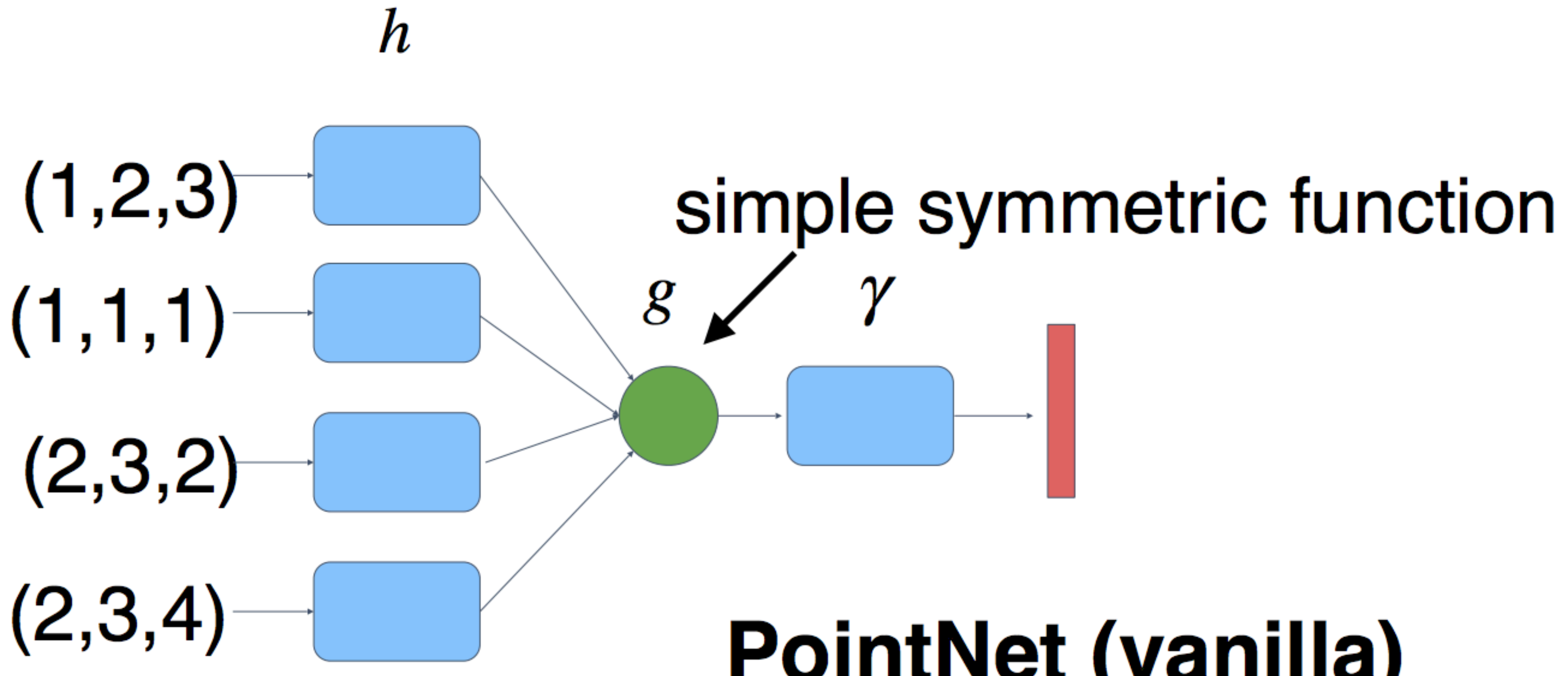
PointNet for Point Cloud Analysis

- Permutation-invariant functions
  - Use **MLPs** (h) and **max-pooling** (g) as simple symmetric functions

Use MLPs (h) and max-pooling (g) as simple symmetric functions

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n}), \quad x_i \in \mathbb{R}^D$$

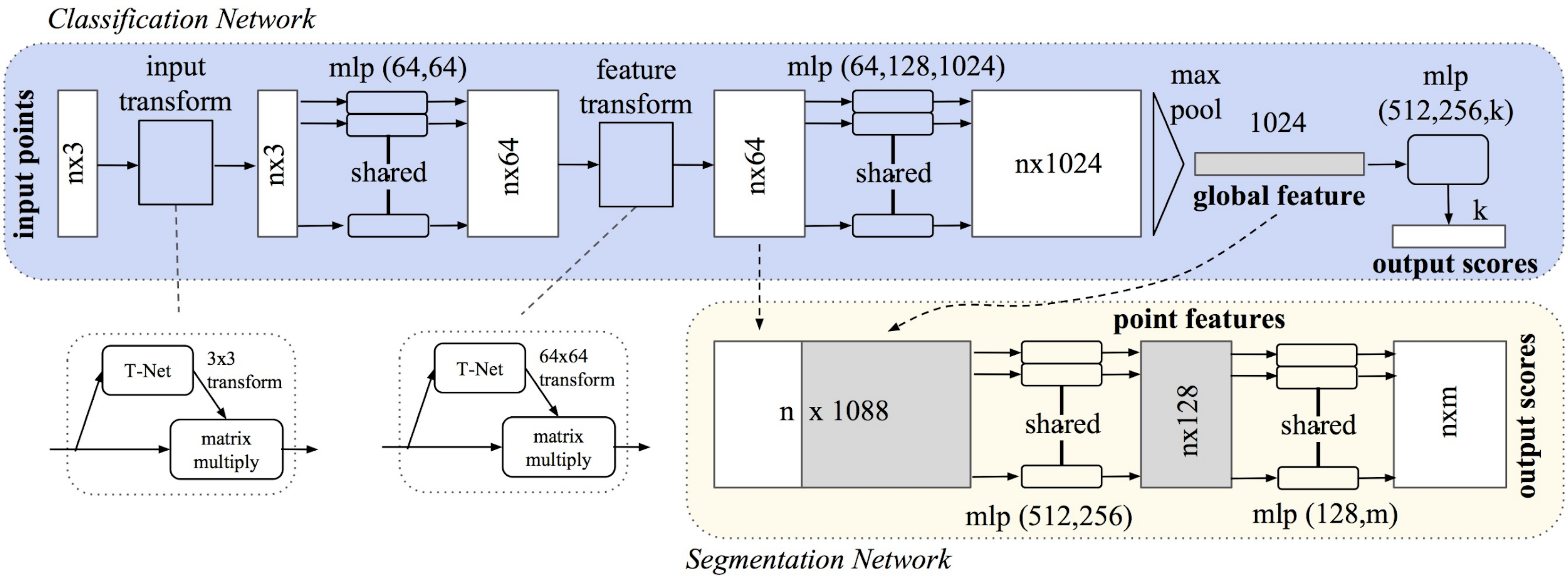
$$f(x_1, x_2, \ldots, x_n) = \gamma \circ g(h(x_1), \ldots, h(x_n))$$



PointNet (vanilla)

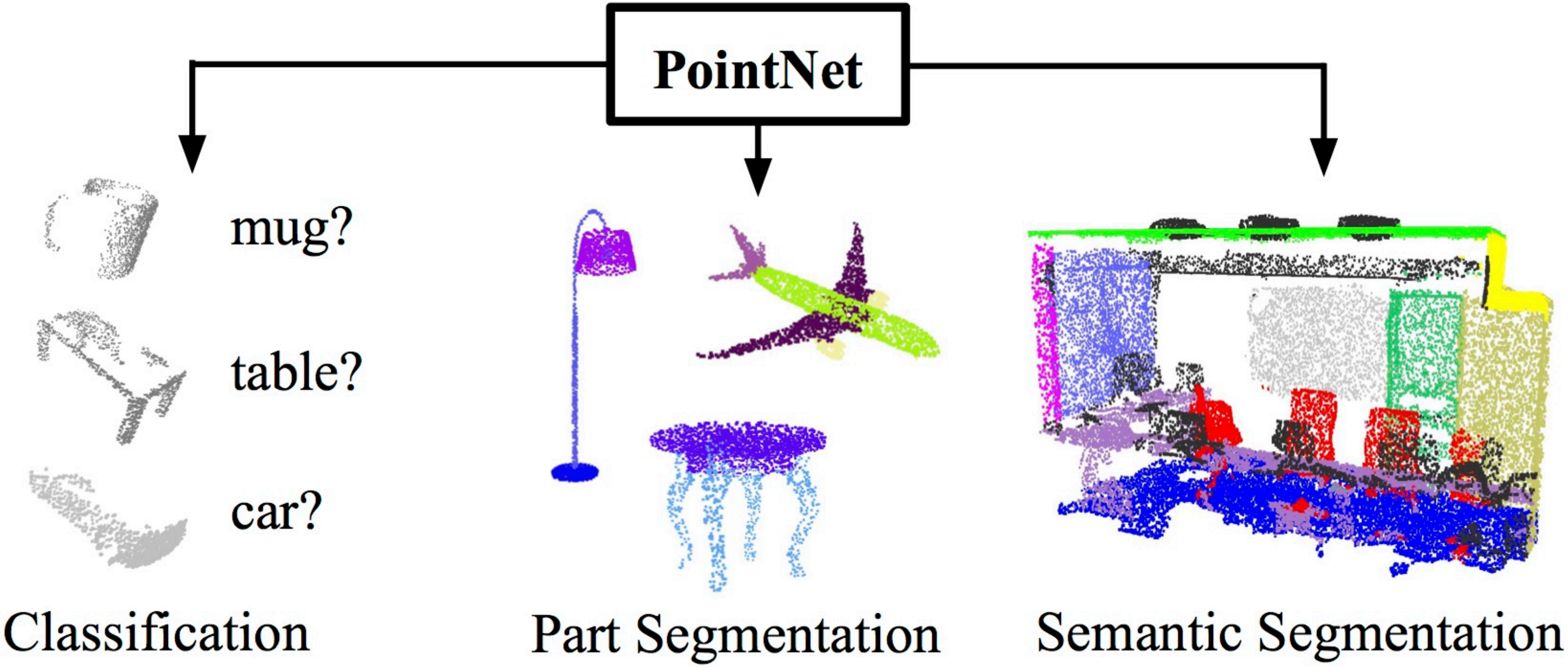
[Qi et al. 2017]

PointNet Architecture

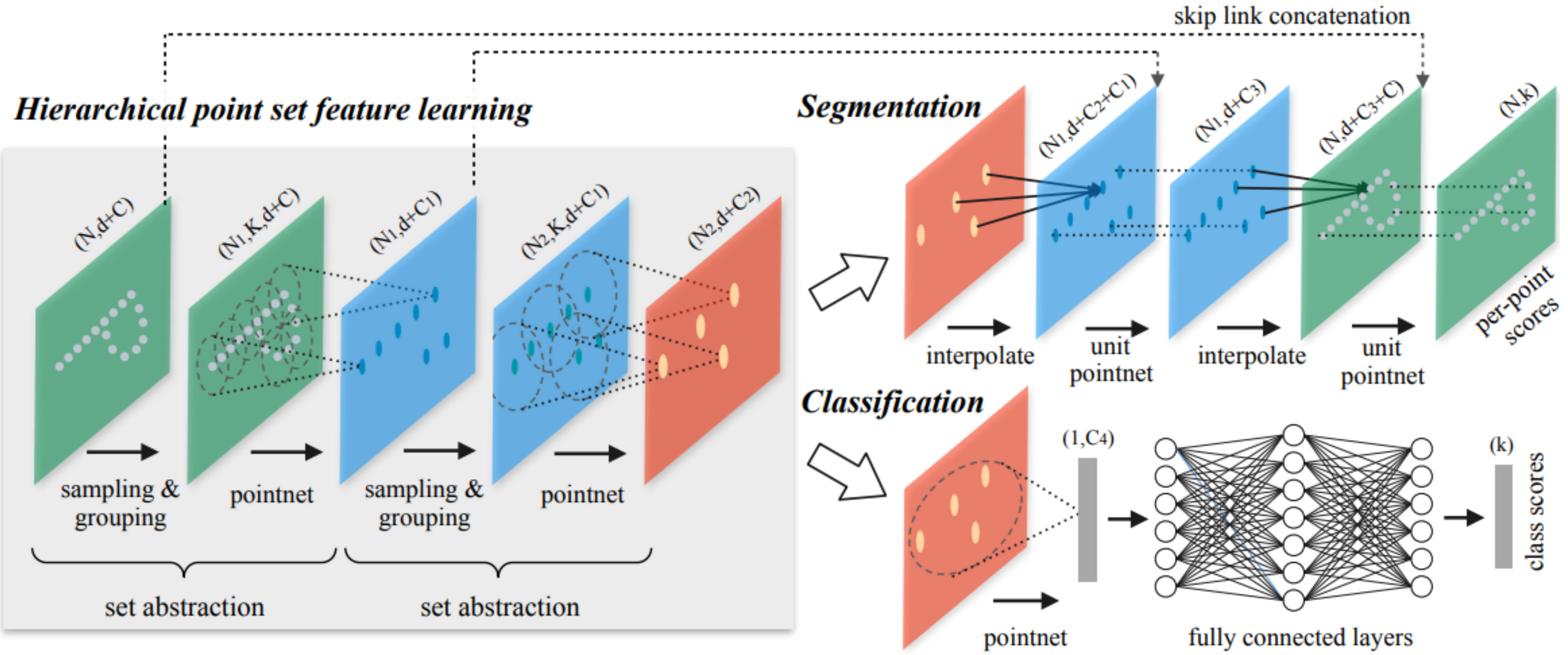


[Qi et al. 2017]

PointNet for Point Cloud Analysis



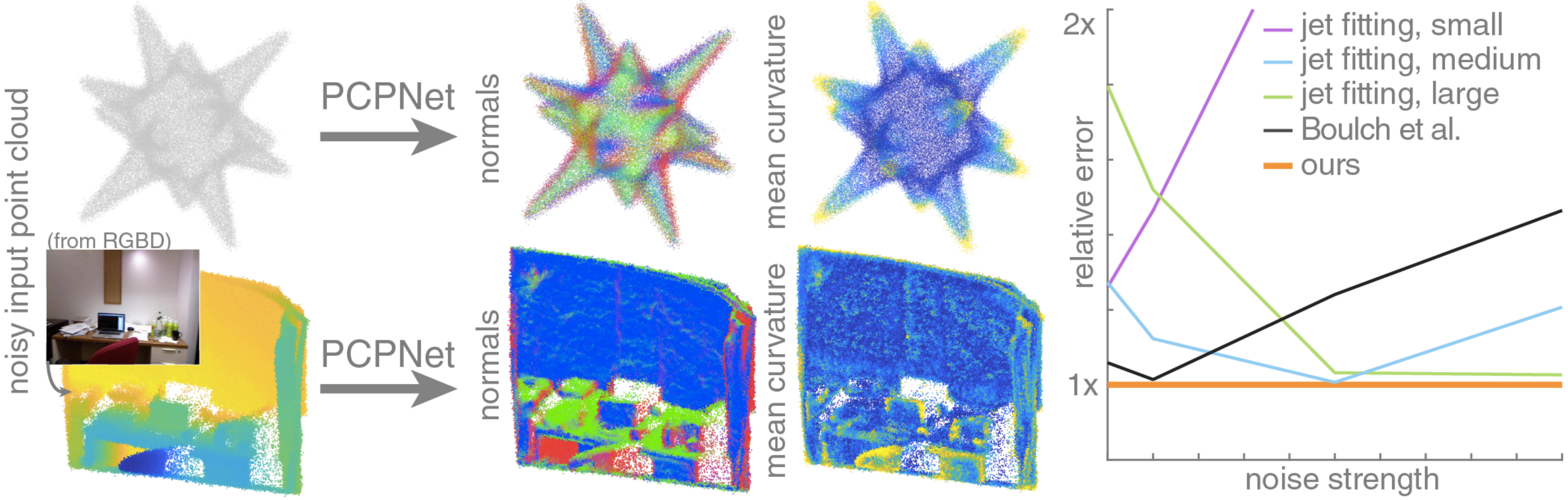
PointNet++



[Qi et al. 2018]

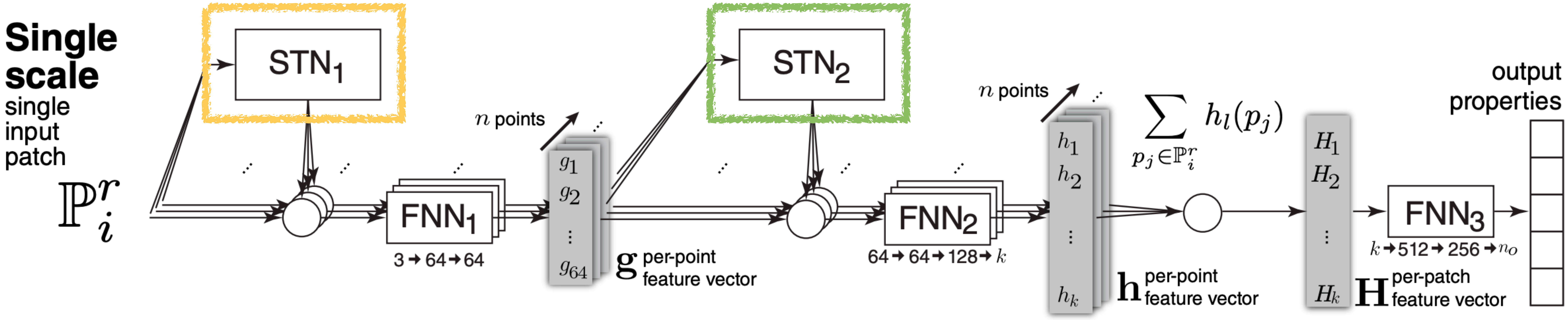
PCPNet for Local Point Cloud Analysis

- Multi-scale version



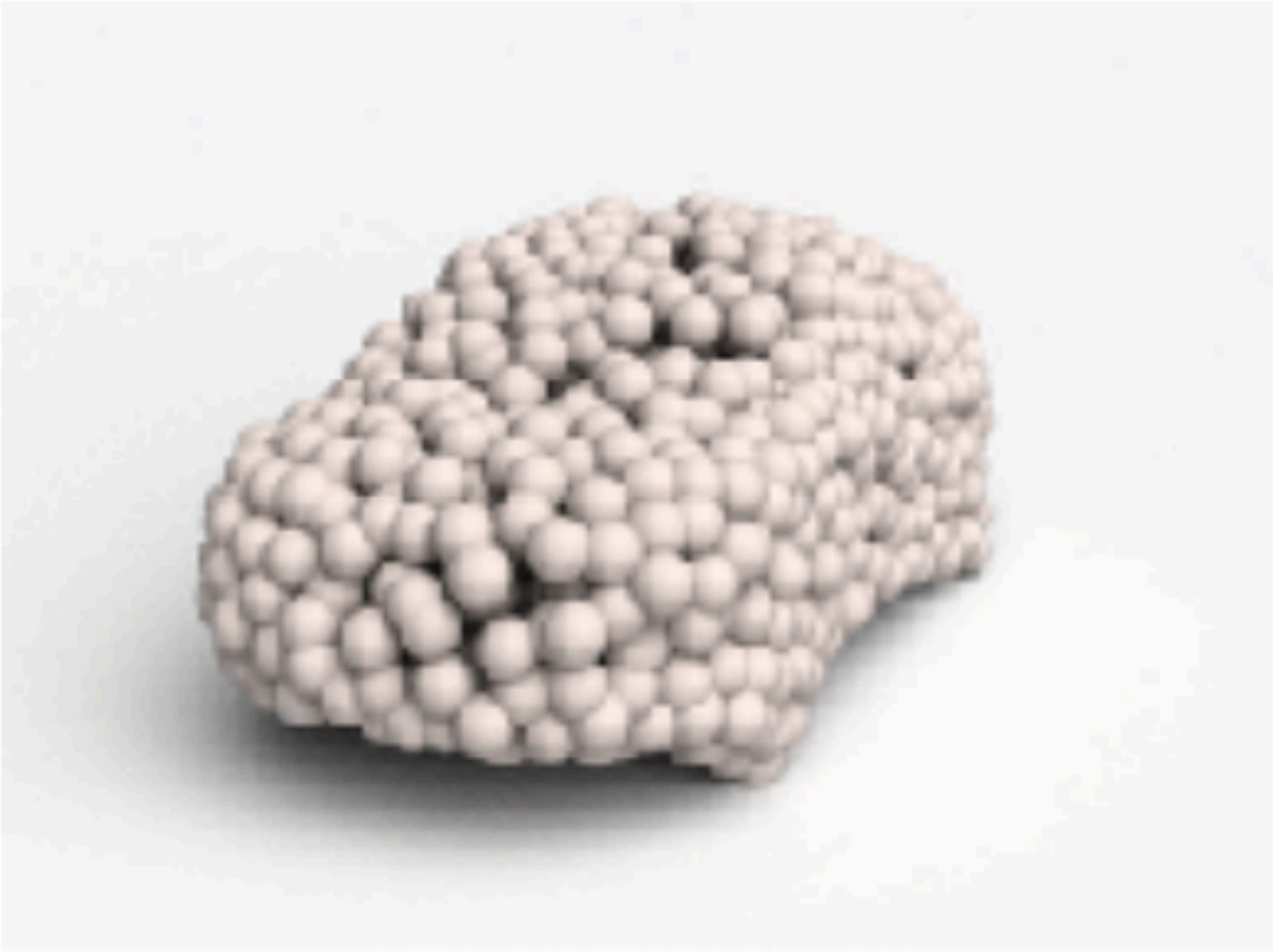
[Guerrero et al. 2018]

PCPNet Architecture



PointNet for Point Cloud Synthesis

- Oft e



Earth Mover Distance as loss function

$$d_{EMD}(S_1, S_2) = \min_{\phi: S_1 \to S_2} \sum_{x \in S_1} \|x - \phi(x)\|_2$$

[Su et al. 2017]