MAI4CAREU Master programmes in Artificial Intelligence 4 Careers in Europe

University of Cyprus

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MAI645 - Machine Learning for Graphics and Computer Vision

Marios Loizou, PhD candidate

Spring Semester 2023

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3D Vision

These notes are mainly based on the following works:

- Fei-Fei Li, Jiajun Wu, Ruohan Gao, **CS231n - Deep Learning for Computer Vision**, Stanford University
- Hao Su, Jiayuan Gu, Minghua Liu, **Tutorial on 3D Deep Learning**, University of California San Diego
- Evangelos Kalogerakis, **Deep learning architectures for 3D shape analysis and synthesis**, University of Massachusetts Amherst

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3D Vision

Notes have been prepared by **Mr. Marios Loizou**

Research Associate at Visual Computing Group at CYENS Centre of Excellence

Visual Computing Group

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Today's Agenda

- Who are we?
- What is 3D Vision
- 3D shape representations
- 3D shape datasets
- 3D Deep Learning architectures
- What we do

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Who are we?

Visual Computing Group at CYENS Centre of Excellence

Melinos Averkiou

MRG Leader

Yiangos Georgiou

Research Associate

Marios Loizou

Research Associate

Yeshwanth Kumar Adimoolam

Research Associate

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What is 3D Vision: *Overview*

- **Teaching** the computer (**learning**) to **understand the 3D world** around it
- In 3D Vision the input data lie in the **3D space**, rather the 2D domain as in the case of images (2D Vision)
- Deep Learning algorithms and architectures are specifically designed to process this type of data

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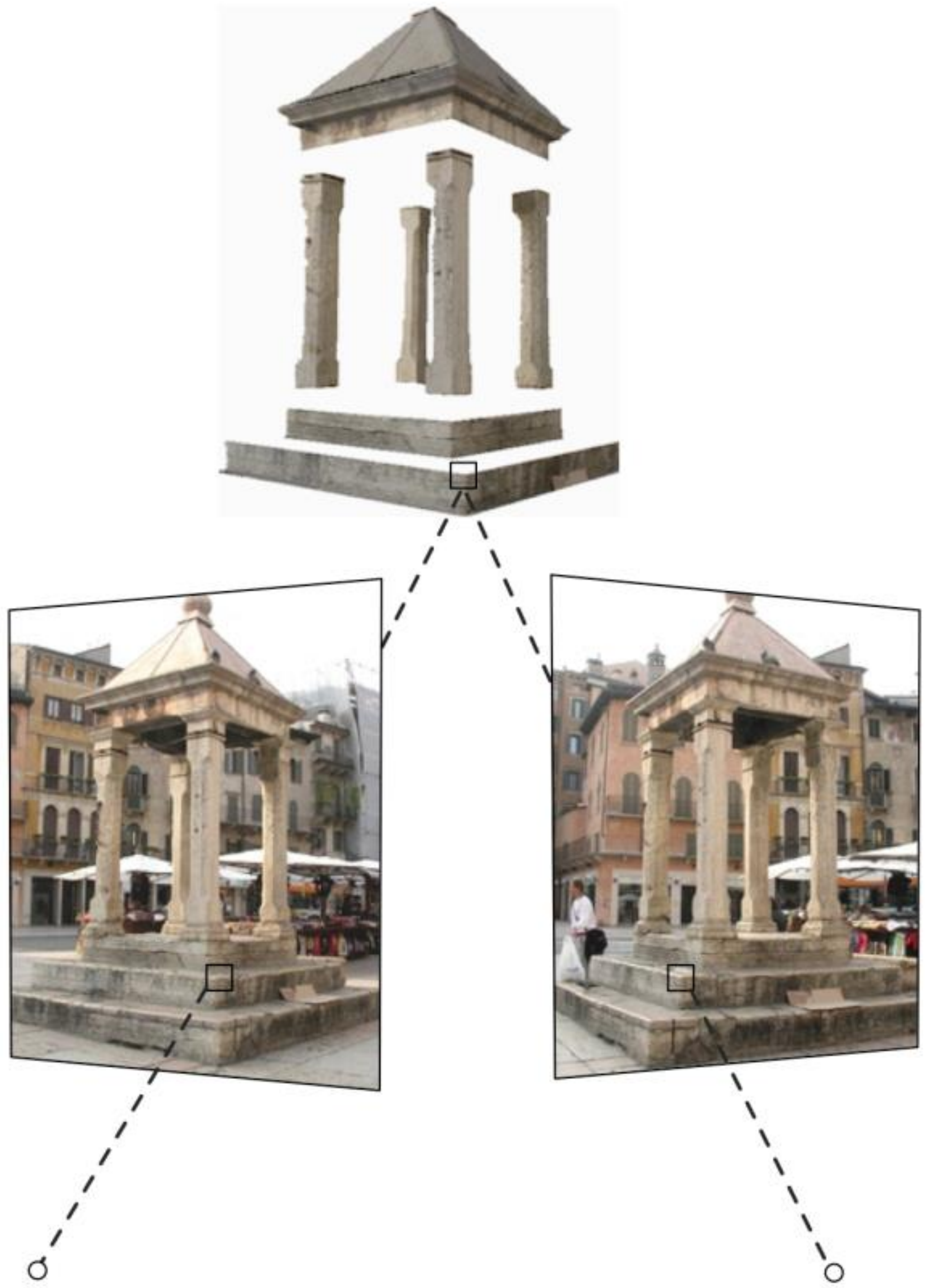
What is 3D Vision: *Overview*

Traditional 3D Vision

- Multi-view Geometry: Structure from Motion (SfM)



Hao Su et al.

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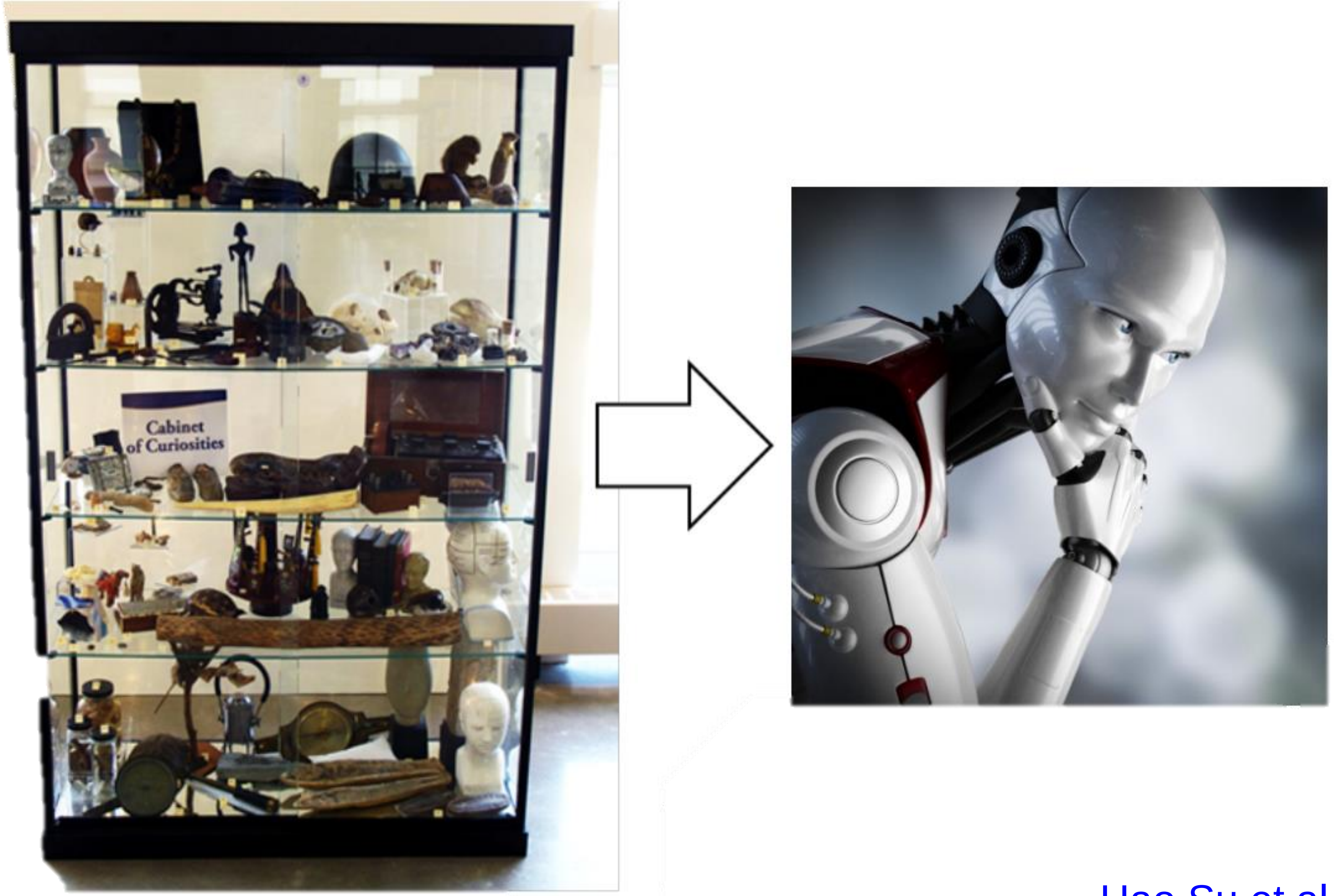
What is 3D Vision: *Overview*

Now

- Acquire knowledge of the 3D world by **Learning**



Hao Su et al.

What is 3D Vision: *Tasks (a very small subset)*

Object Classification

ShapeNetCore, Chang et al.

What is 3D Vision: *Tasks (a very small subset)*

Indoor Scene Segmentation

ScanNet,
Angela Dai et al.

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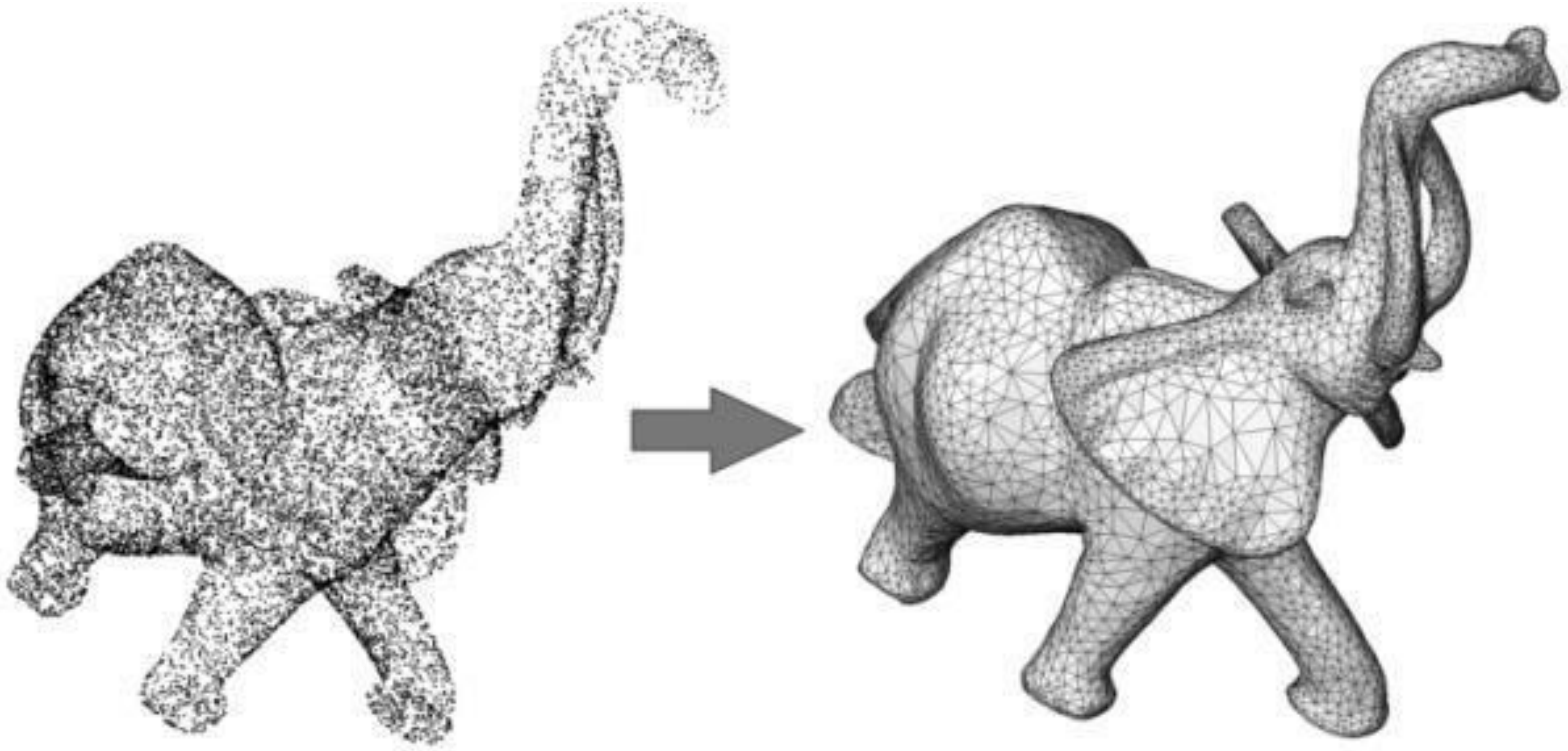
What is 3D Vision: *Tasks (a very small subset)*

Surface reconstruction



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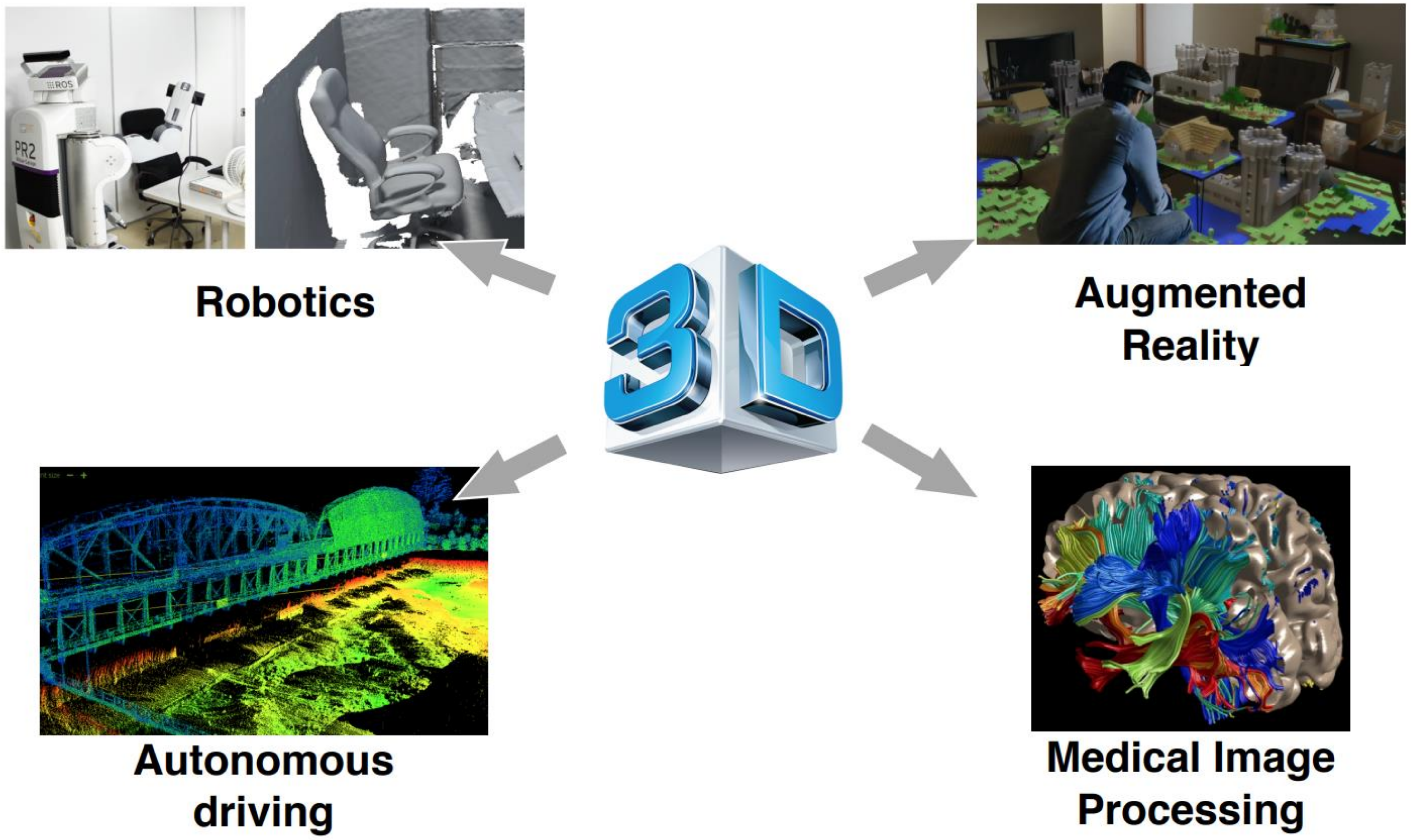
What is 3D Vision: *Applications*



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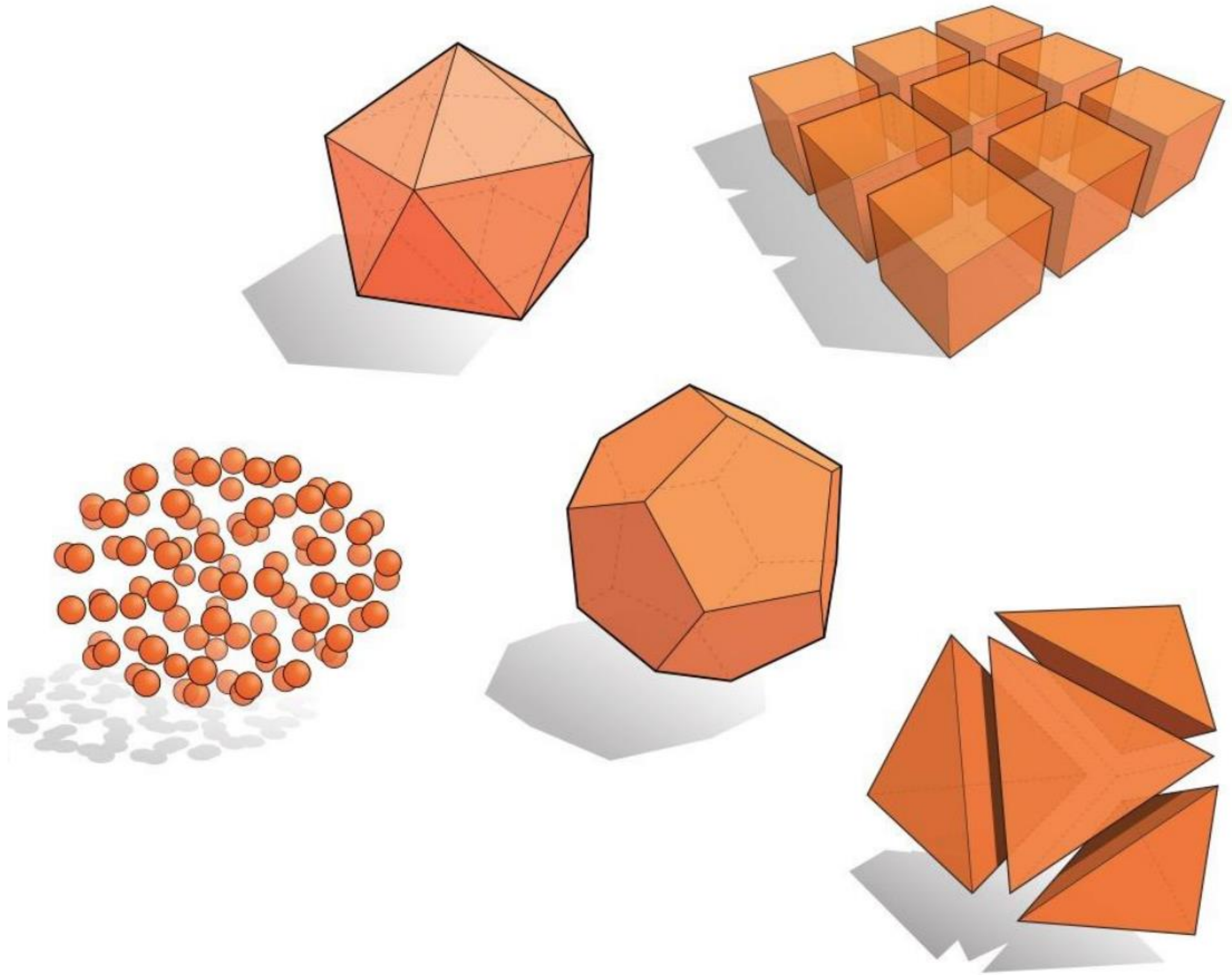
3D shape representations: *Many ways to represent geometry*

Explicit
- point cloud
- polygon mesh
- …

Implicit
- level sets
- distance functions
- …

- Voxels



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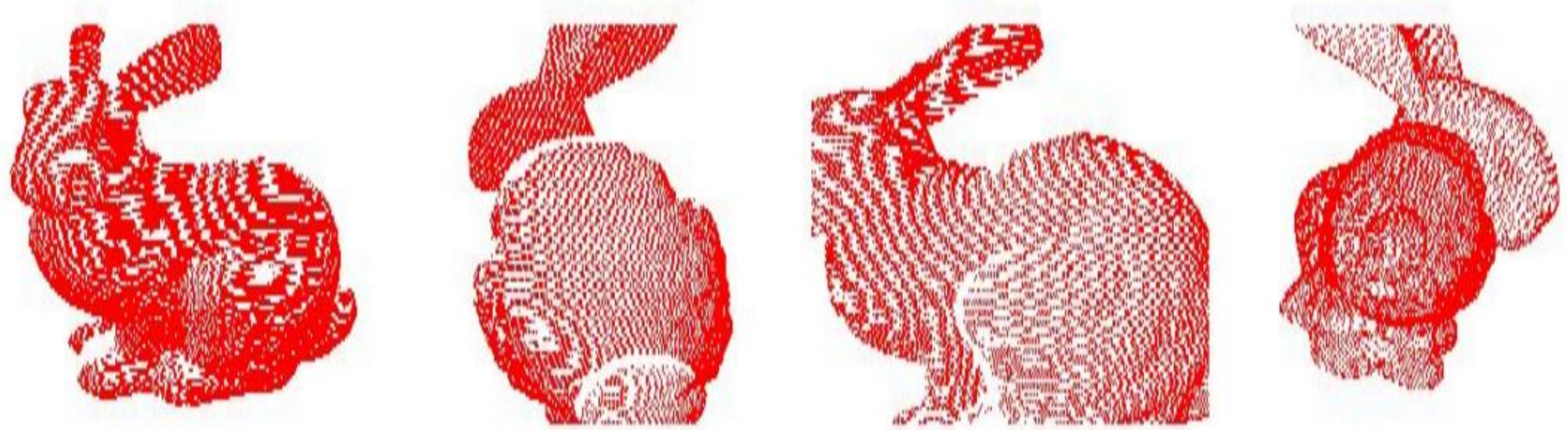
3D shape representations: *Point clouds*

- Simplest representation: **only points**, no connectivity



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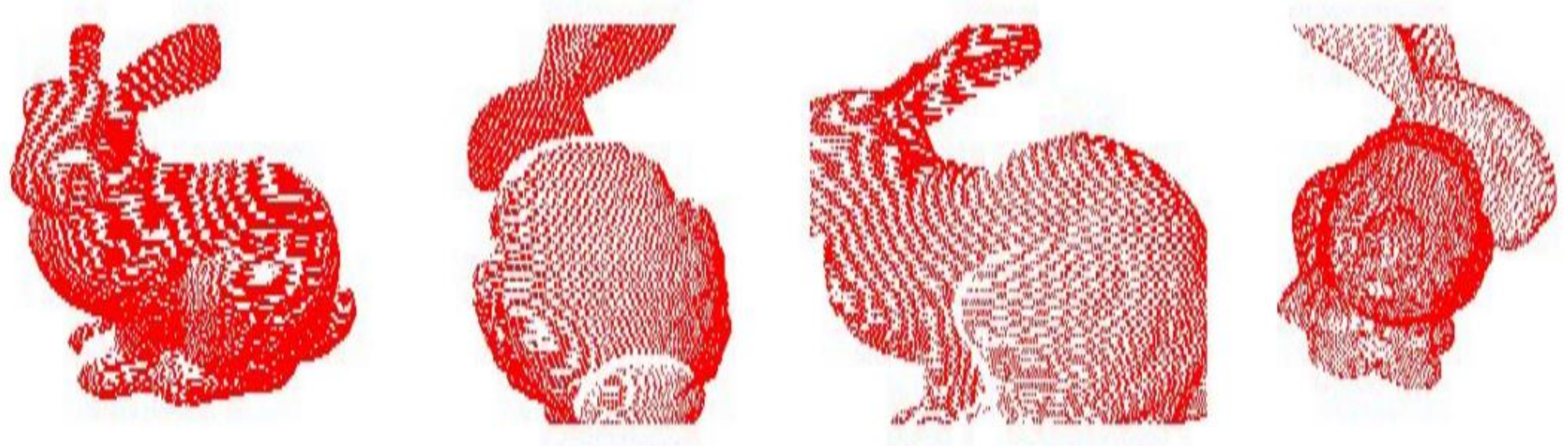
3D shape representations: *Point clouds*

- Simplest representation: **only points**, no connectivity

- Collection of (x, y, z) coordinates, possibly with **normal** (perpendicular to the underlying surface)



List of N **unordered** points

$$\left\{\begin{array}{l|l} p_1 & x_1, y_1, z_1, n_{x_1}, n_{y_1}, n_{z_1} \\ p_2 & x_2, y_2, z_2, n_{x_2}, n_{y_2}, n_{z_2} \\ p_3 & x_3, y_3, z_3, n_{x_3}, n_{y_3}, n_{z_3} \\ \vdots & \vdots \\ p_N & x_N, y_N, z_N, n_{x_N}, n_{y_N}, n_{z_N} \end{array}\right.$$

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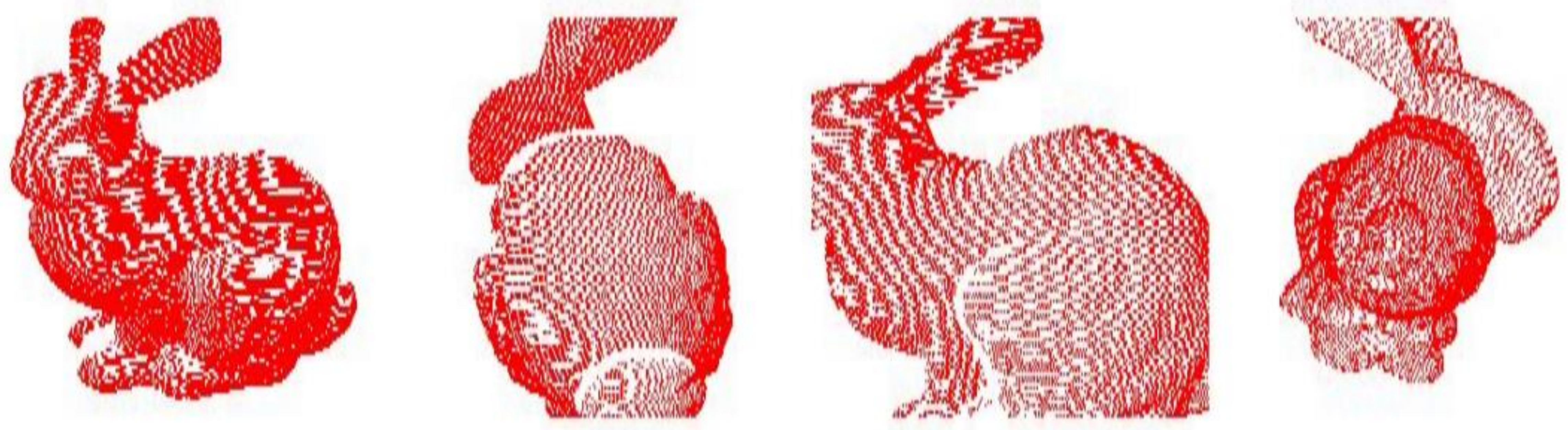
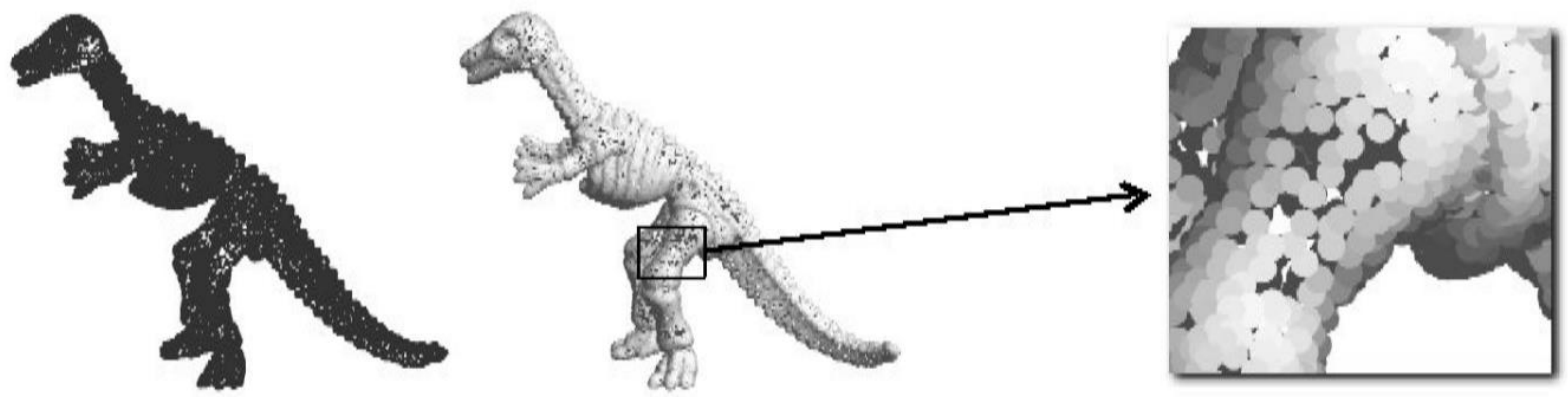
3D shape representations: *Point clouds*

- Simplest representation: **only points**, no connectivity

- Collection of (x, y, z) coordinates, possibly with **normal** (perpendicular to the underlying surface)

- Points with orientation (normal) are called **surfels**





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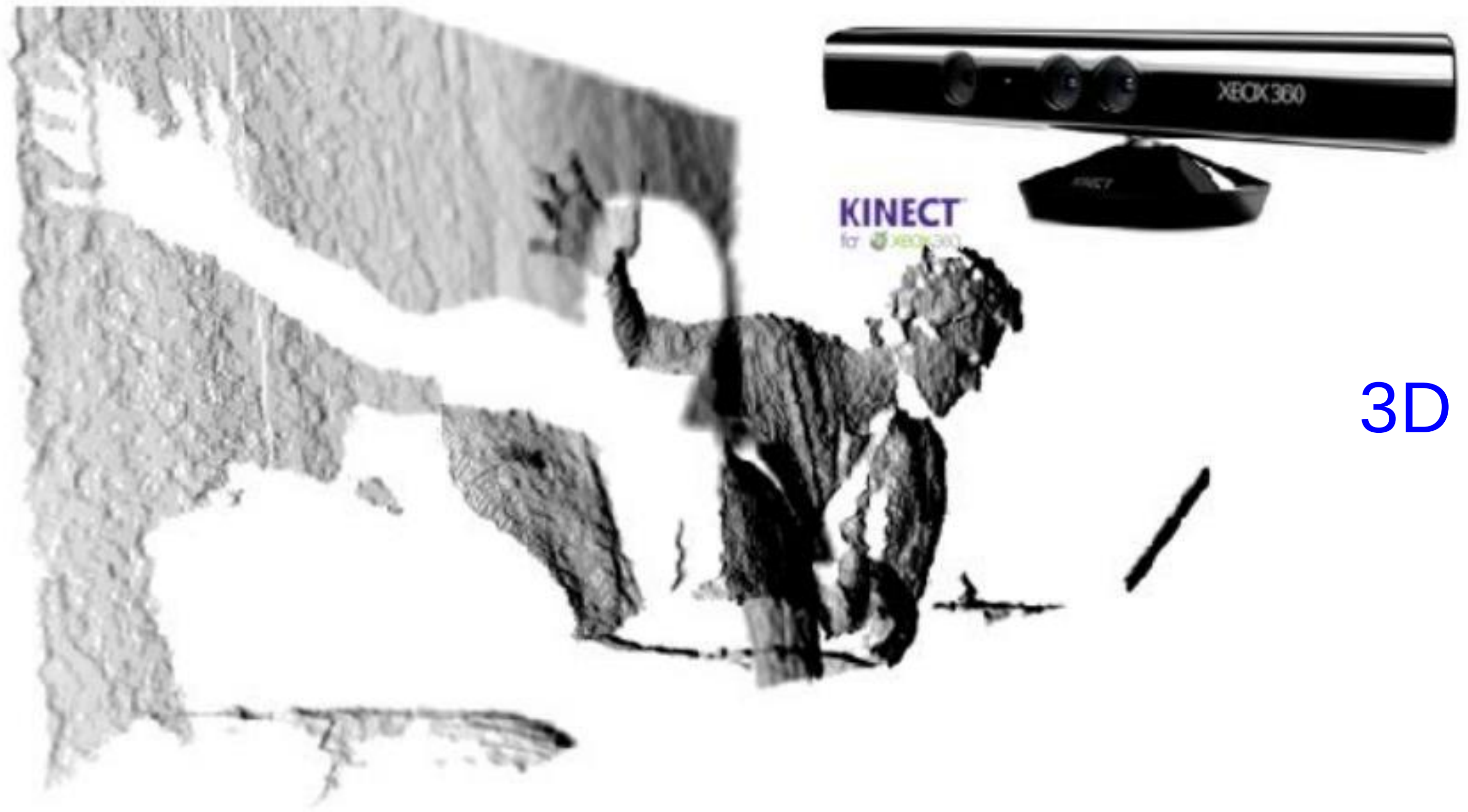
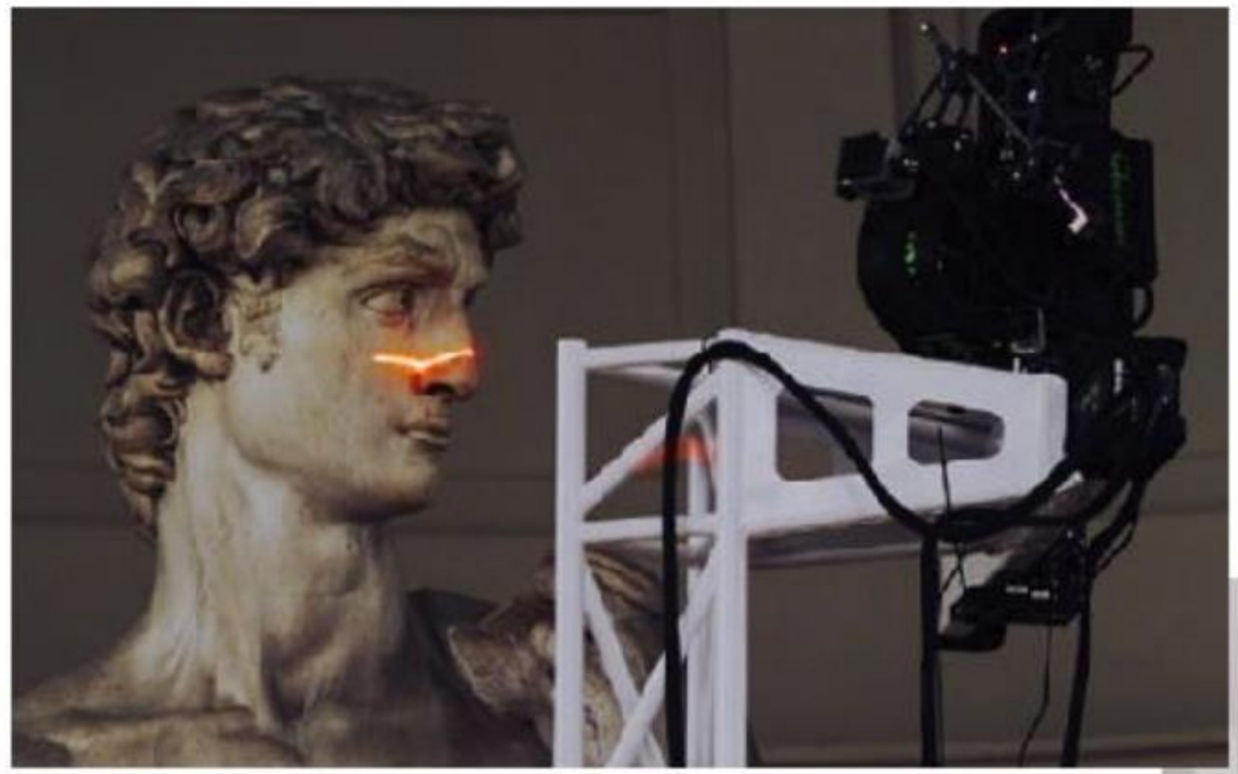
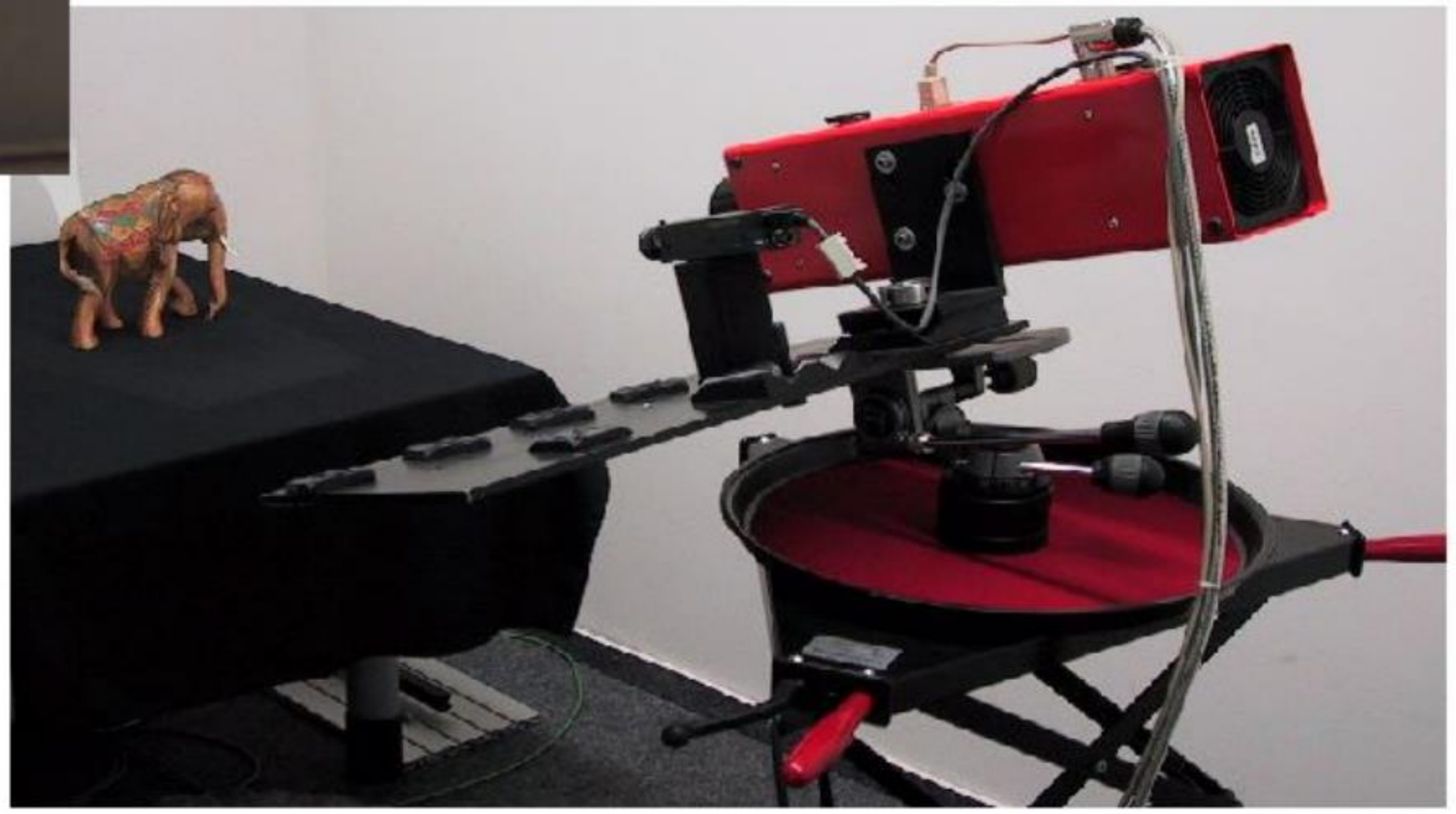
3D shape representations: *Point clouds acquisition*



3D Depth sensor

Laser triangulation rangefinder





3D Laser scanner

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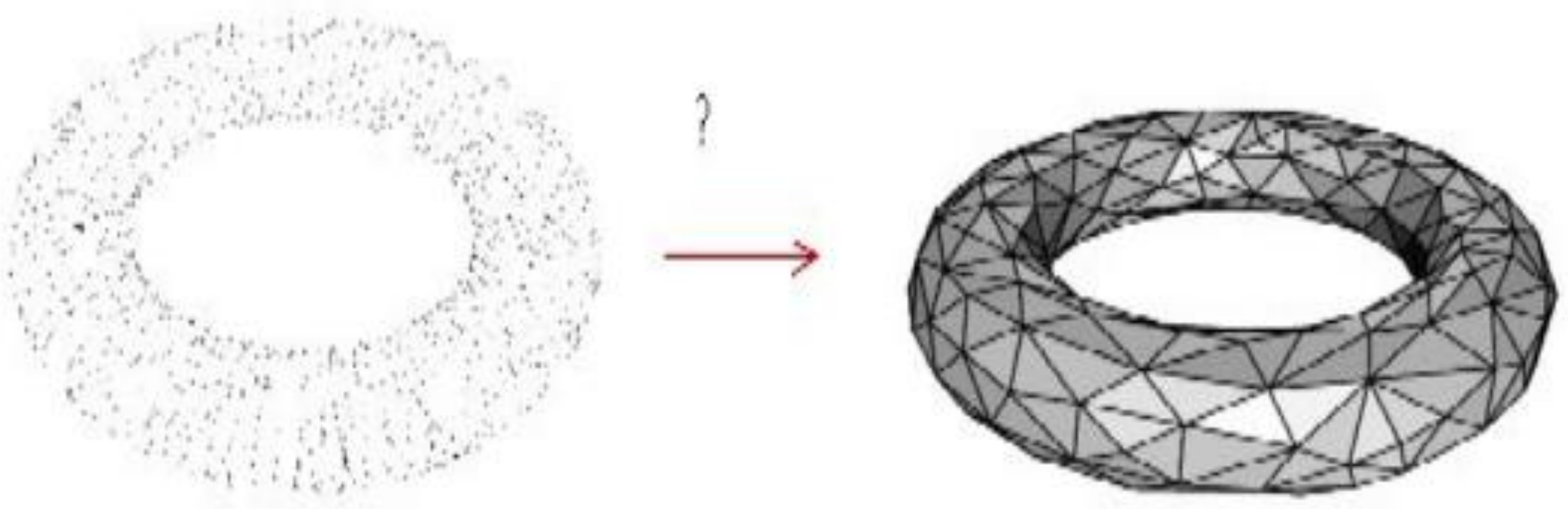
3D shape representations: *Point clouds pros & cons*

- Pros:
  - ✓ Easily represents any kind of geometry
  - ✓ Useful for large datasets

- Cons
  - x Incomplete/noisy point clouds
  - x No topological information

Incomplete scans



No topology

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3D shape representations: *Polygonal Meshes*

- A 3D polygonal mesh is the **structural build** of a **3D model** consisting of **polygons**
- **Boundary representation** of objects

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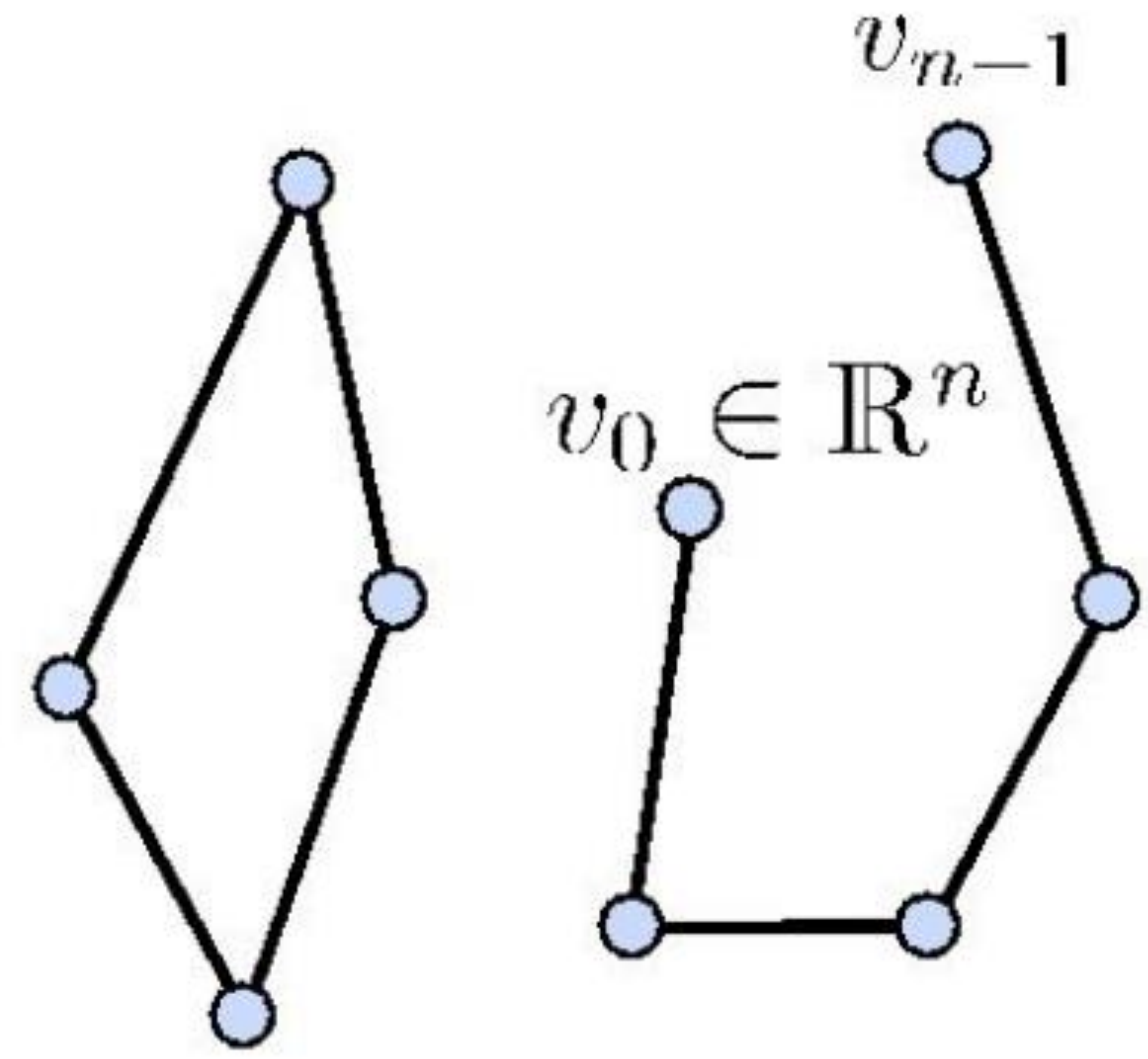
3D shape representations: *Polygonal Meshes*

- Polygon:
  - **Vertices**: $v_0, v_1, \cdots, v_{n-1}$
  - **Edges**: $\{(v_0, v_1), \cdots, (v_{n-2}, v_{n-1})\}$

- Types of polygons:
  - **Closed**: $v_0 = v_{n-1}$
  - **Planar**: all vertices on a plane
  - **Simple**: not self-intersecting



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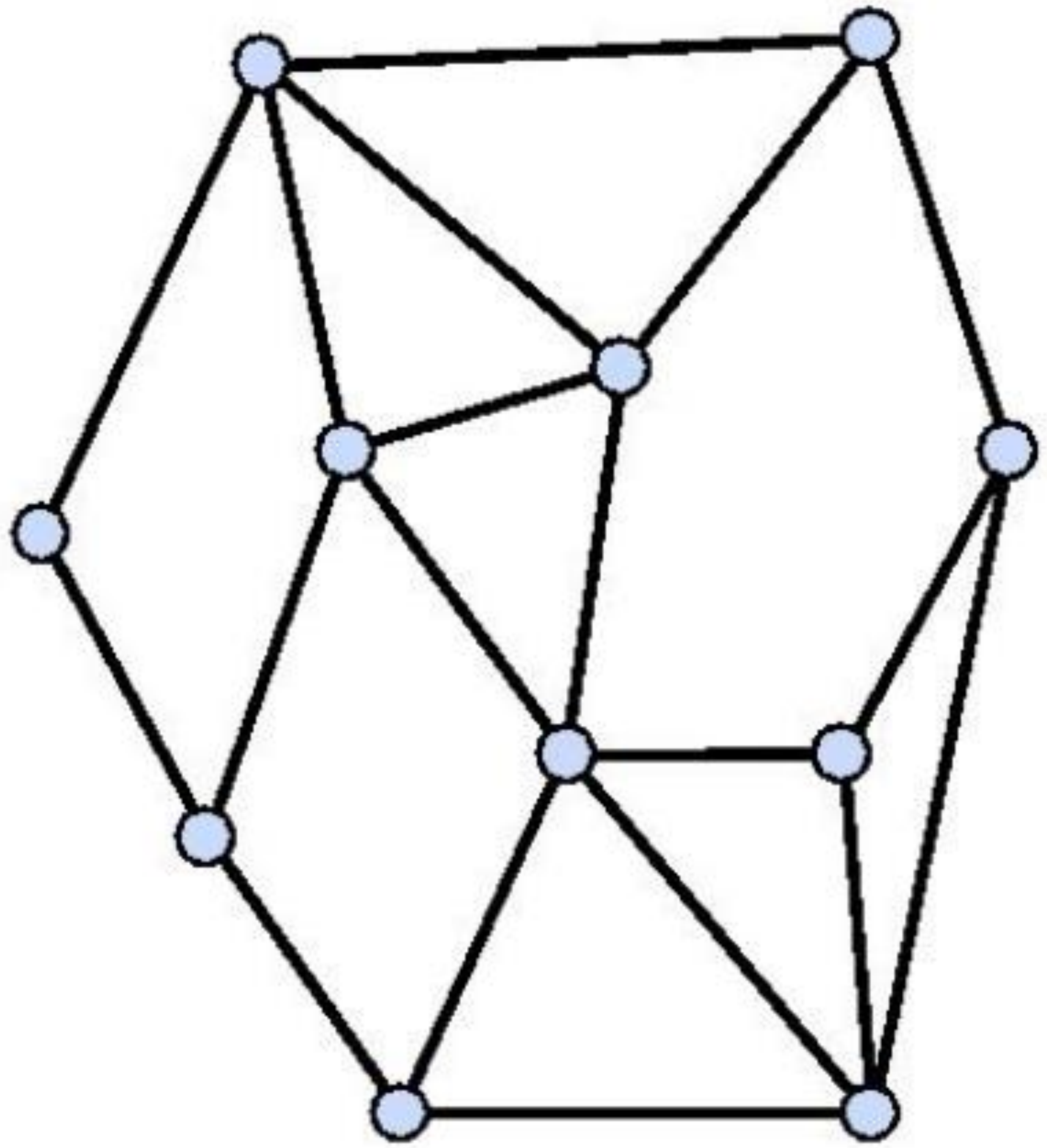
3D shape representations: *Polygonal Meshes*

- Polygonal Mesh:
  - A finite set M of **closed, simple** polygons Q_i

$$\boldsymbol{M} = \langle \boldsymbol{V}, \boldsymbol{E}, \boldsymbol{F} \rangle$$

$\boldsymbol{V}$ = set of vertices
$\boldsymbol{E}$ = set of edges
$\boldsymbol{F}$ = set of faces



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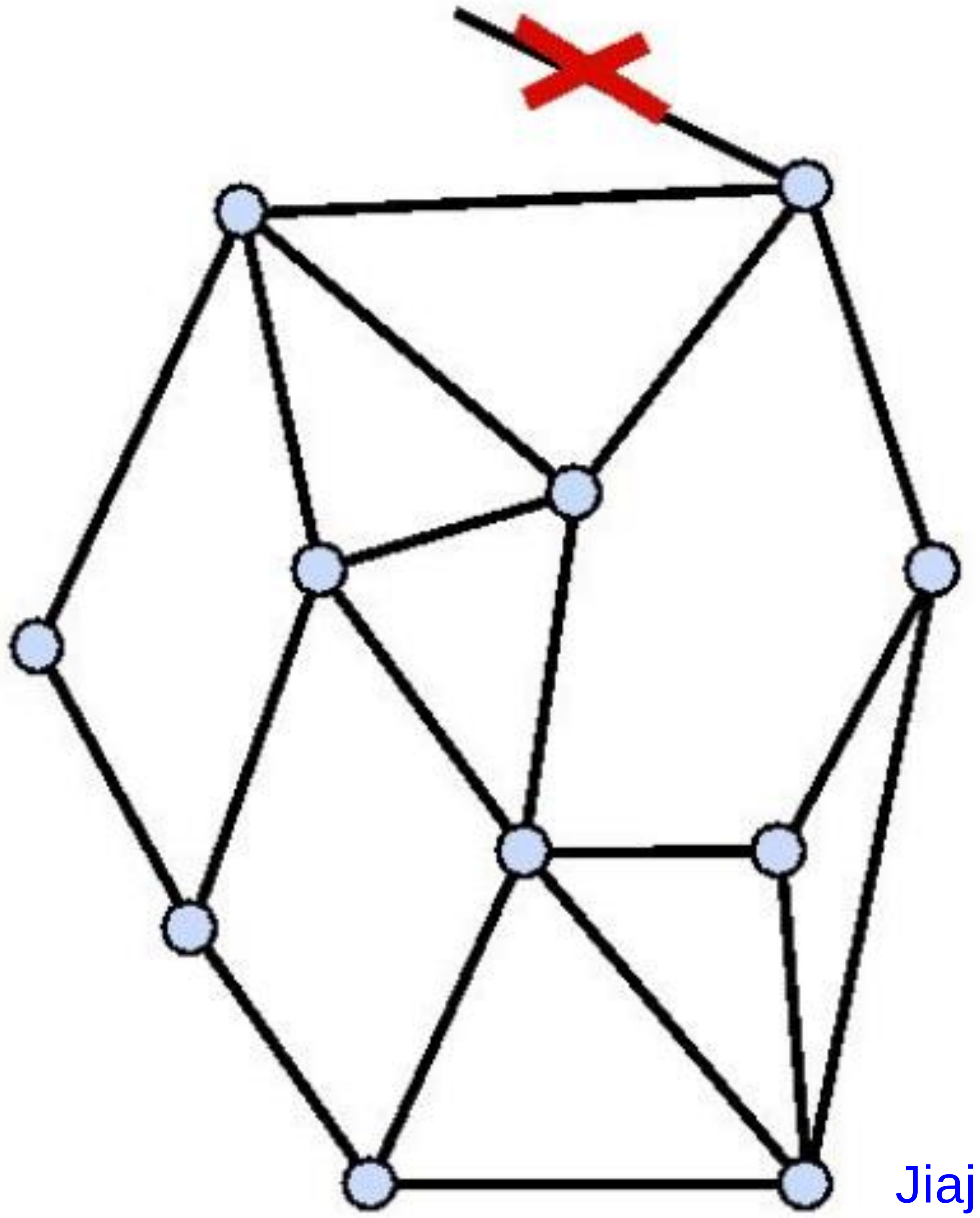
3D shape representations: *Polygonal Meshes*

- Polygonal Mesh:
  - A finite set M of **closed, simple** polygons Q_i
  - Every **edge** belongs to **at least one polygon**



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3D shape representations: *Polygonal Meshes*

- Polygonal Mesh:
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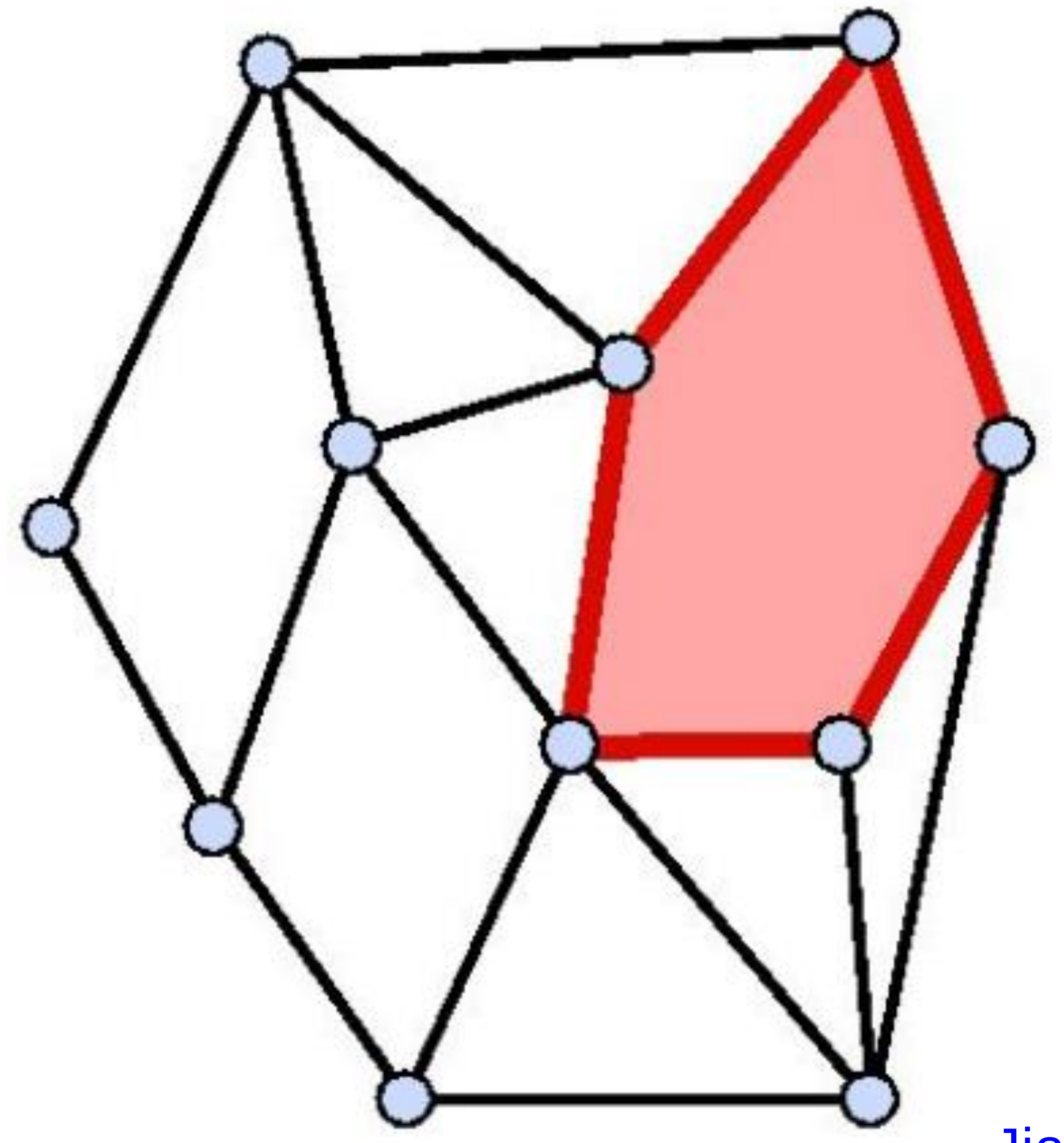
  - Every **edge** belongs to **at least one polygon**
  - Each Q_i defines a **face** of the polygonal mesh



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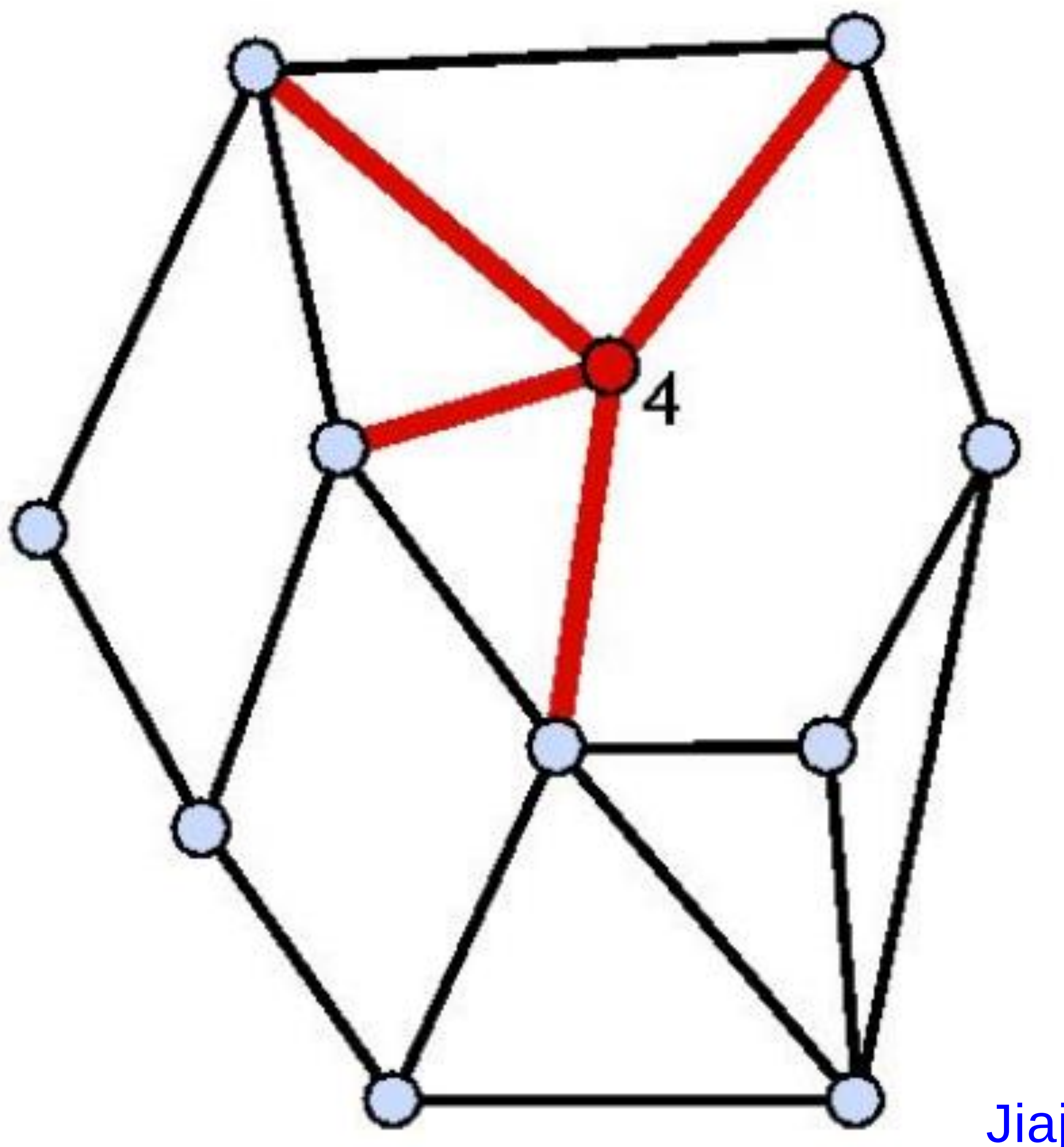
3D shape representations: *Polygonal Meshes*

- Polygonal Mesh:
  - A finite set M of **closed, simple** polygons Q_i
  - Every **edge** belongs to **at least one polygon**
  - Each Q_i defines a **face** of the polygonal mesh
  - Vertex **degree** or **valance** = number of incident edges



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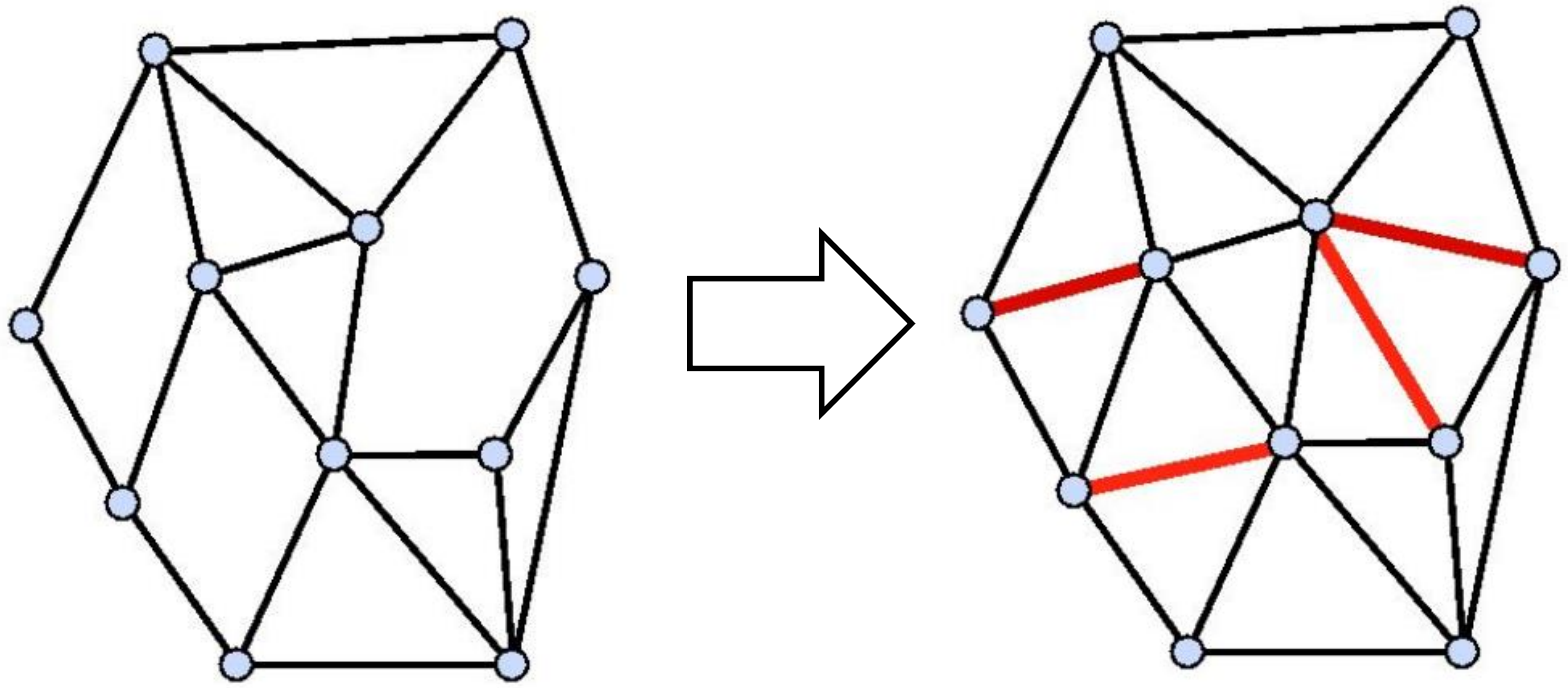
3D shape representations: *Polygonal Meshes*

- Polygonal Mesh **Triangulation**:
  - Polygonal mesh where every face is a triangle → **triangular mesh**
  - Simplifies data structures
  - Simplifies rendering
  - Simplifies algorithms
  - Each face is planar and convex
  - Any polygon can be triangulated



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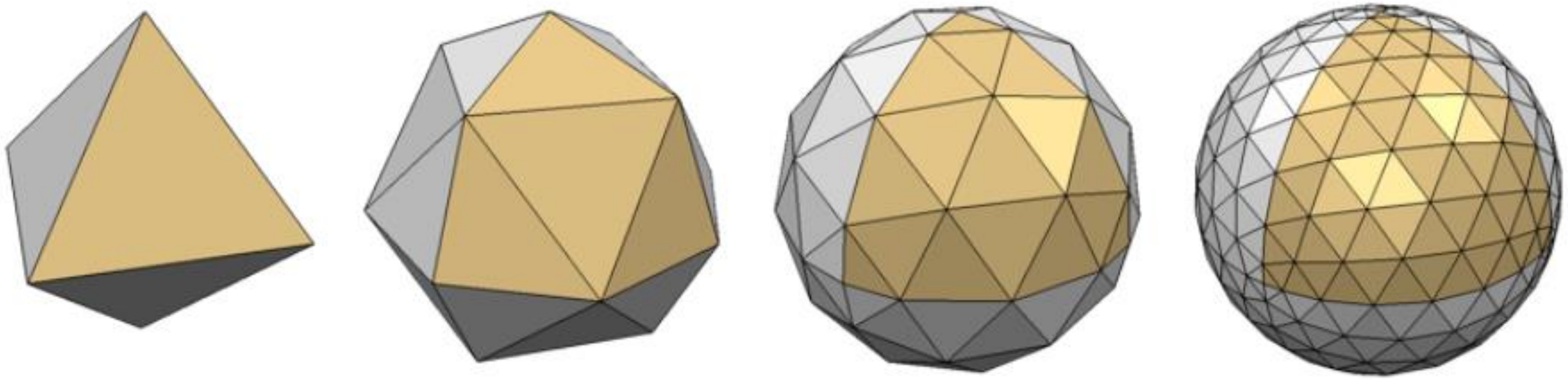

- A polygonal mesh consists of **three kinds** of **mesh elements**: **vertices**, **edges** and **faces**
- **Mesh connectivity** or **topology**: describes the incidence relation amongst mesh elements
- **Mesh geometry**: specifies the position and other geometric characteristics of each vertex

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3D shape representations: *Polygonal Meshes*

- **Data Structures**:
  - What should be stored?
    - **Geometry**: 3D coordinates
    - **Connectivity**: Adjacency relationships
    - **Attributes**:
      - Normal, color, texture coordinates
      - Per vertex, face, edge

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3D shape representations: *Polygonal Meshes*

- **Indexed Face Set**
  - Used in formats like OBJ and OFF
  - Storage
    - Vertex: position
    - Face: vertex indices
  - No explicit neighborhood info

Vertices			
v0	x0	y0	z0
v1	x1	x1	z1
v2	x2	y2	z2
v3	x3	y3	z3
v4	x4	y4	z4
v5	x5	y5	z5
v6	x6	y6	z6
...	...	...	...

Triangles			
t0	v0	v1	v2
t1	v0	v1	v3
t2	v2	v4	v3
t3	v5	v2	v6
...	...	...	...

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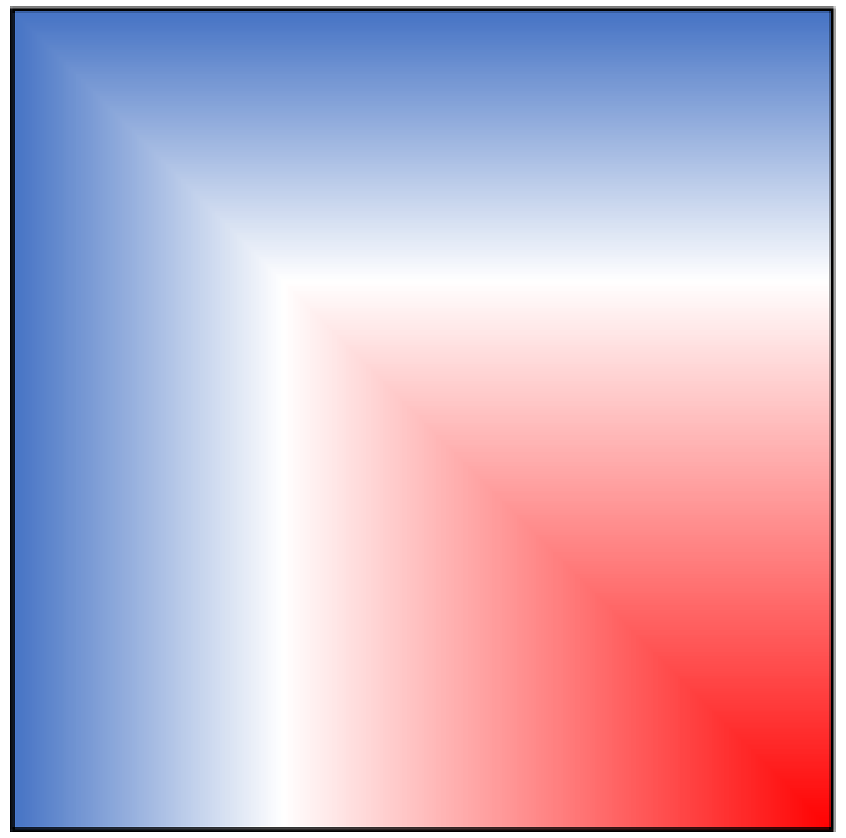
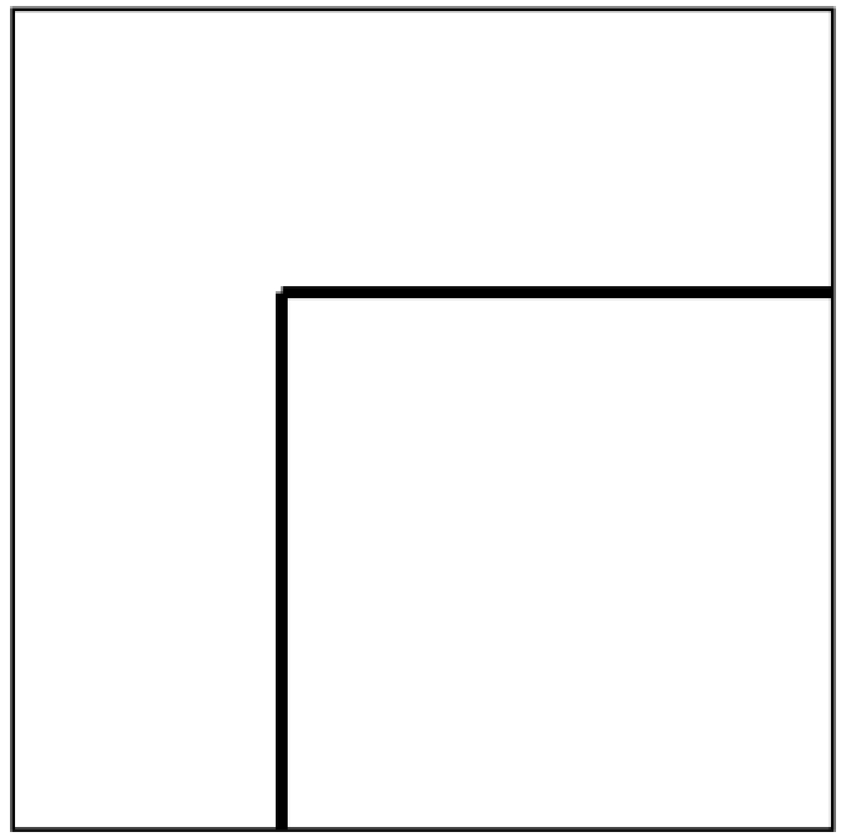
3D shape representations: *Implicit Functions*

- **Implicit function**
  - Classifies arbitrary $3D$ points as inside / outside the shape



Implicit function



Explicit Shape

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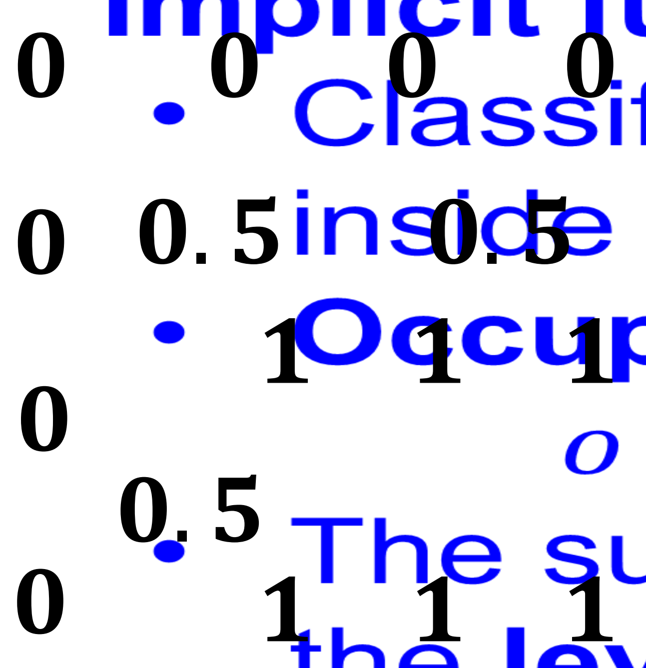
3D shape representations: *Implicit Functions*

- **Implicit function**
  - Classifies arbitrary $3D$ points as inside / outside the shape
  - **Occupancy function**:

    $$o : \mathbb{R}^3 \rightarrow \{0,1\}$$

  - The surface of the 3D object is the **level set**:

    $$\{x : \boldsymbol{o}(x) = \frac{1}{2}\}$$



- **Implicit function**
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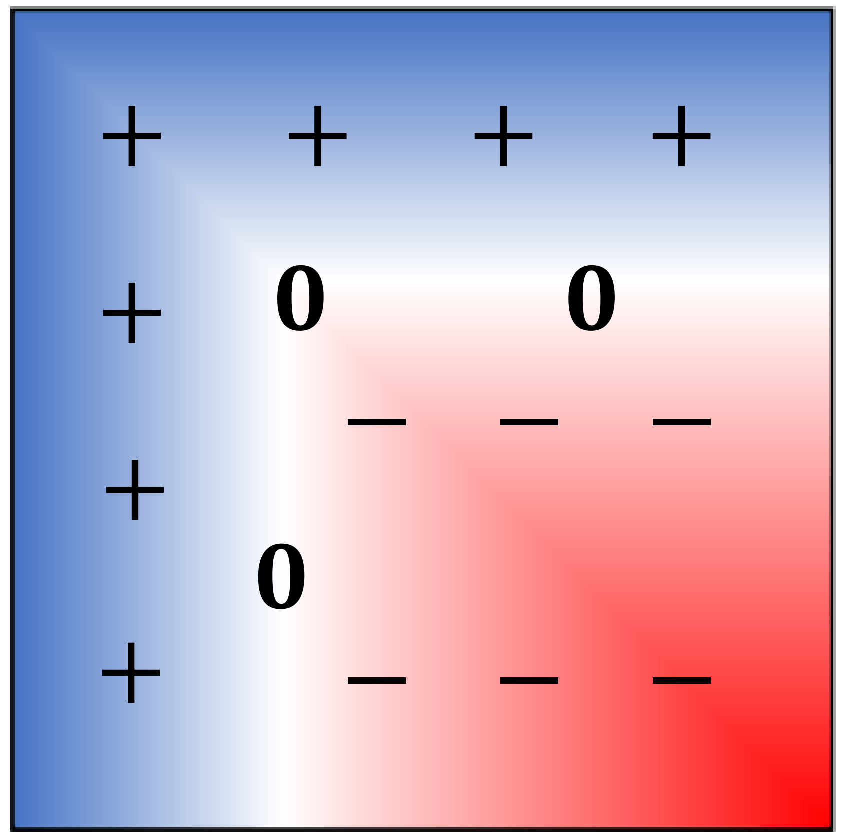
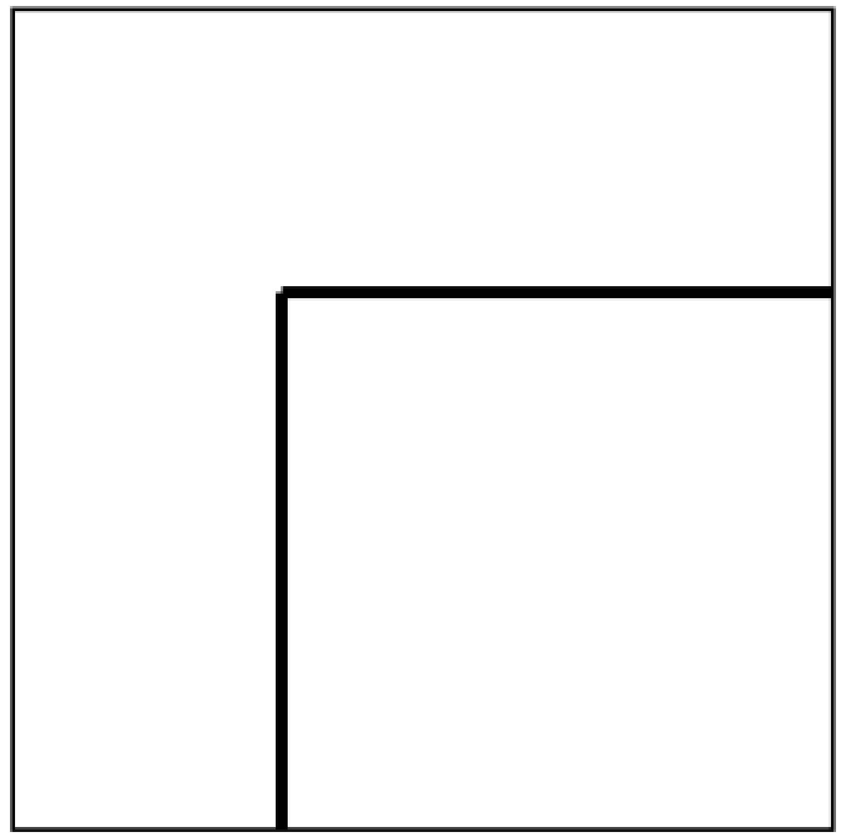
3D shape representations: *Implicit Functions*

- **Implicit function**
  - Classifies arbitrary $3D$ points as inside / outside the shape
  - **Signed Distance Function:** Euclidean distance to the surface of shape; sign gives inside / outside
  - The surface of the 3D object is the **level set**:

$$\{x: \boldsymbol{SDF}(x) = 0\}$$



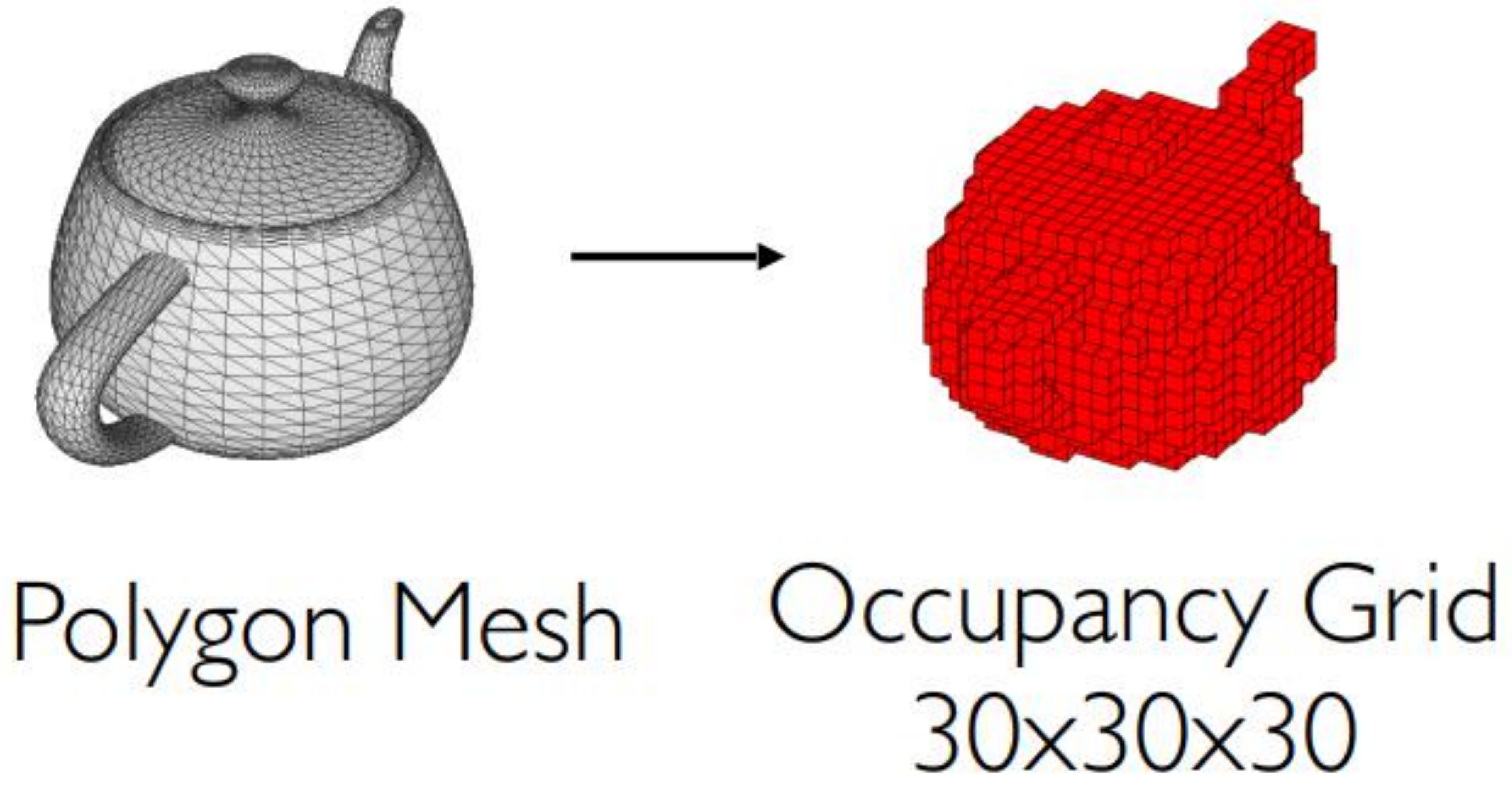
Implicit function


Explicit Shape

Justin Solomon

3D shape representations: *Volumetric Grid*

- **Volumetric Grid**
  - Represent a shape with a $V \times V \times V$ grid of occupancies or SDFs
  - Conceptually simple → just a 3D **regular Euclidean** grid
  - Like an image
    - Pixels –> Voxels
  - Straightforward to apply 3D convolutions



Hao Su et al.

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3D shape datasets: *Datasets for 3D Objects*

- **Princeton Shape Benchmark**
  - # Models: 1,814
  - # Categories: 182

Shilane et al., 2004

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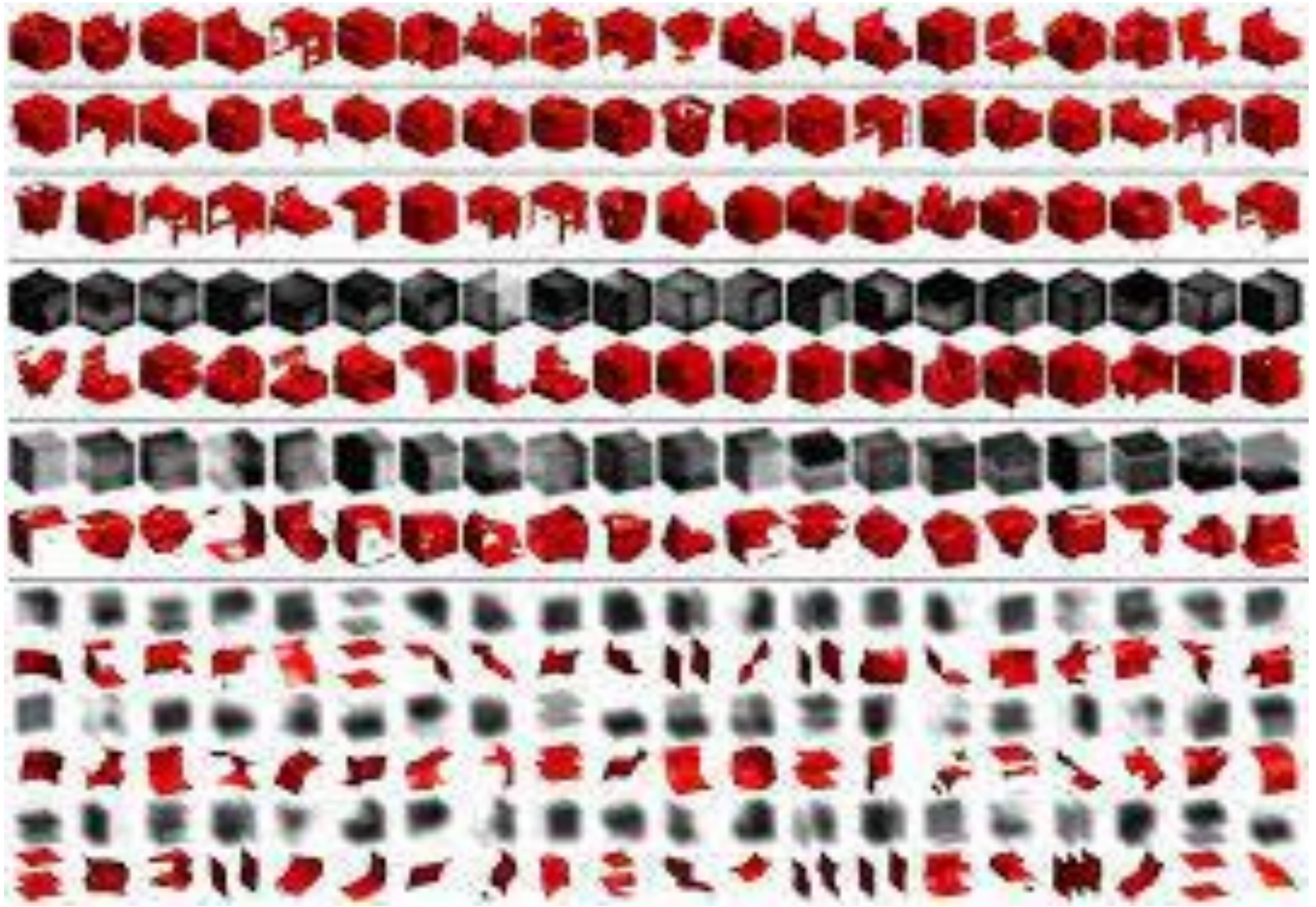
3D shape datasets: *Datasets for 3D Objects*

- **ModelNet40 and ModelNet40**
  - # Models: 12,311
  - # Categories: 40

- **ModelNet10** (subset of ModelNet10)
  - # Models: 4,899
  - # Categories: 10



Z. Wu et al., 2015

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3D shape datasets: *Datasets for 3D Objects*

- **ShapeNet**
  - # Models: 3M (not publicly available)
- **ShapeNetCore** (subset of ShapeNet)
  - # Models: 51,300
  - # Categories: 55

Change et al., 2015

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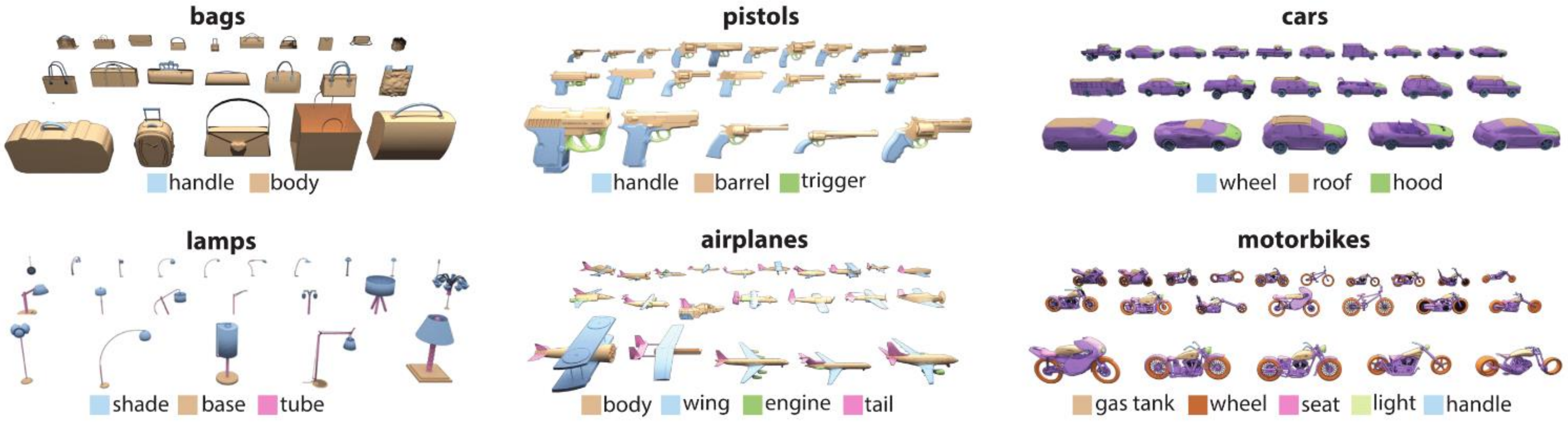
3D shape datasets: *Datasets for 3D Objects*

- **Pix3D**
  - # Images: 10,069
  - # Models: 395 (2D-3D aligned)

Sun et al., 2018

3D shape datasets: *Datasets for 3D Objects Parts*

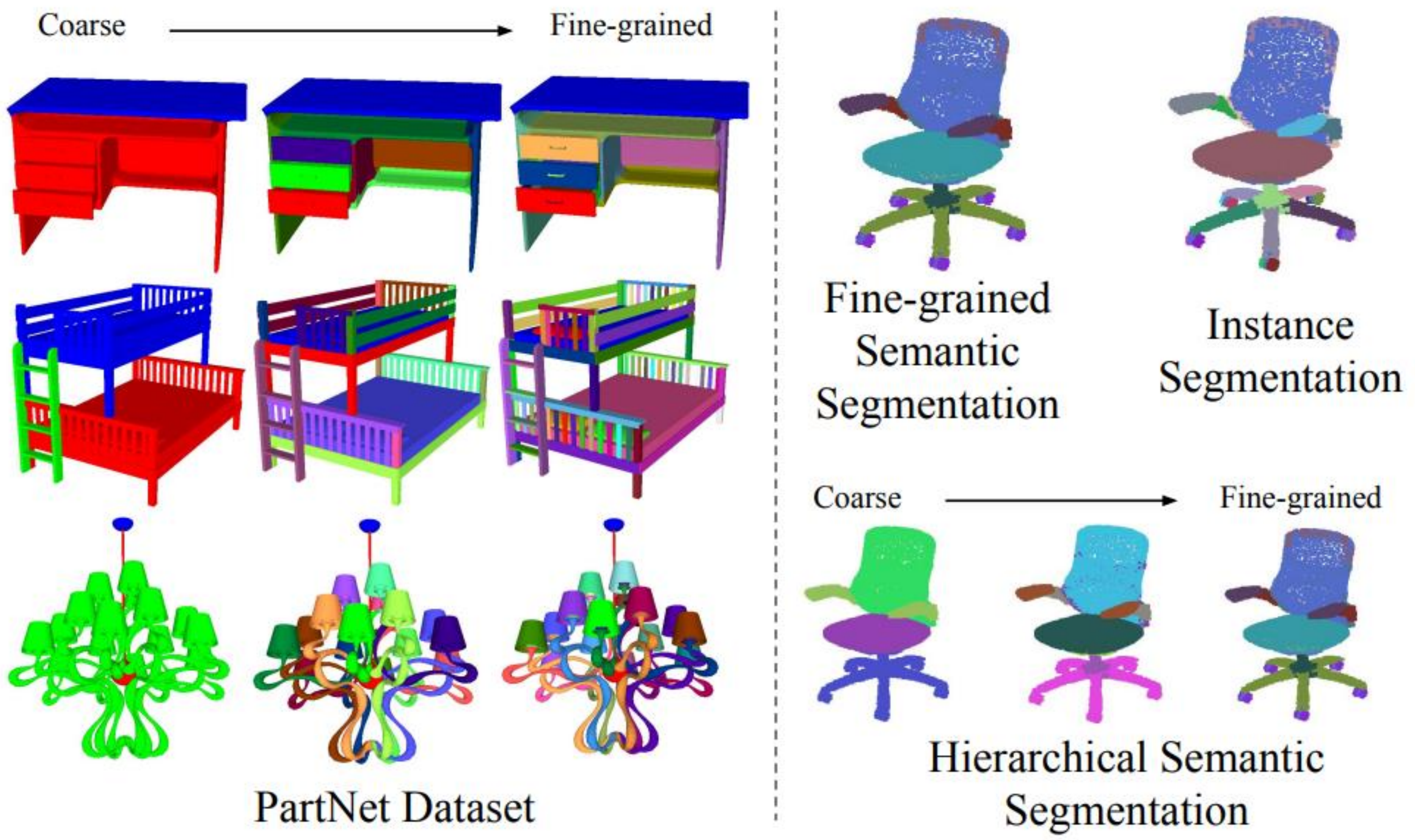
- **ShapeNet-Part** (subset of ShapeNet)
  - # Models: 16,881
  - # Categories: 16
  - # Semantic parts: 50



Yi et al., 2016

3D shape datasets: *Datasets for 3D Objects Parts*

- **PartNet** (subset of ShapeNet)
    - # Models: 26,671
    - # Categories: 24
    - # Part instances: 573,585
    - # Semantic parts: 480
    - Fine-grained
    - Hierarchical



Mo et al., 2019

3D shape datasets: *Datasets for Indoor 3D Scenes*

- **Large-scale Scanned Real Scenes: ScanNet**
  - # Views: 2.5M
  - # RGBD scans: 1,500
  - 3D camera poses
  - Surface reconstruction
  - Instance-level semantic segmentations

Dai et al., 2017

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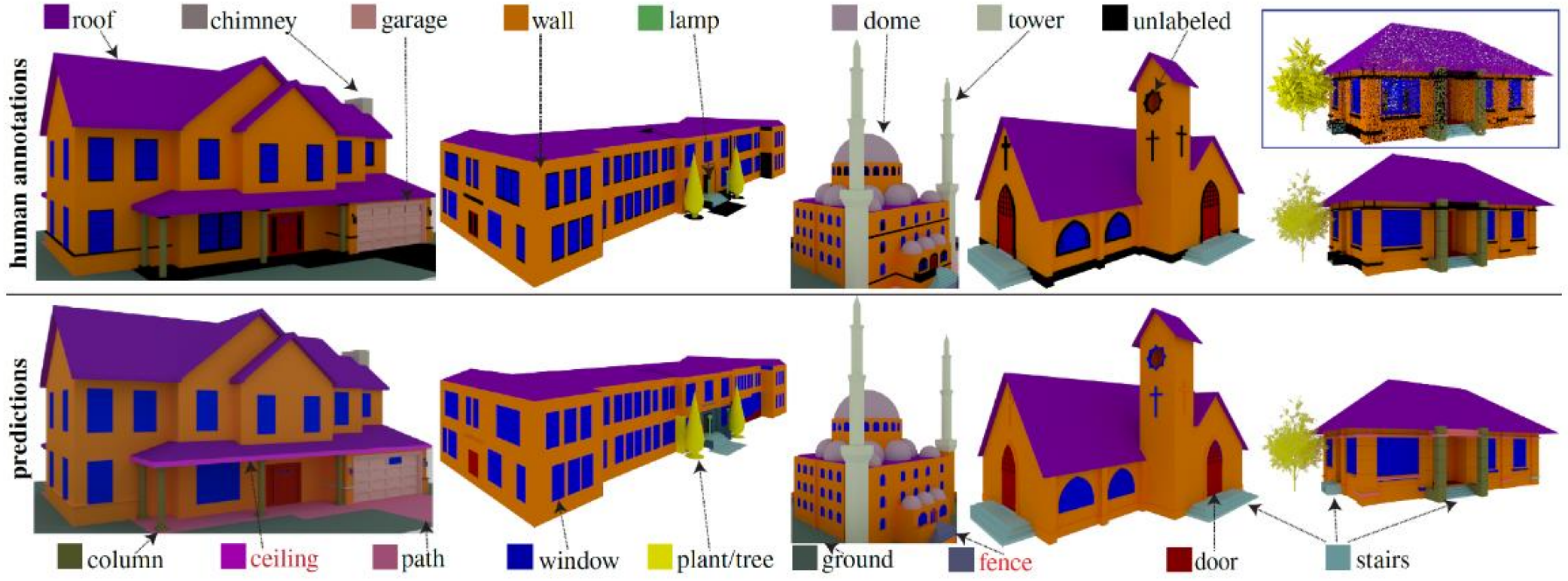
3D shape datasets: *Datasets for 3D Buildings*

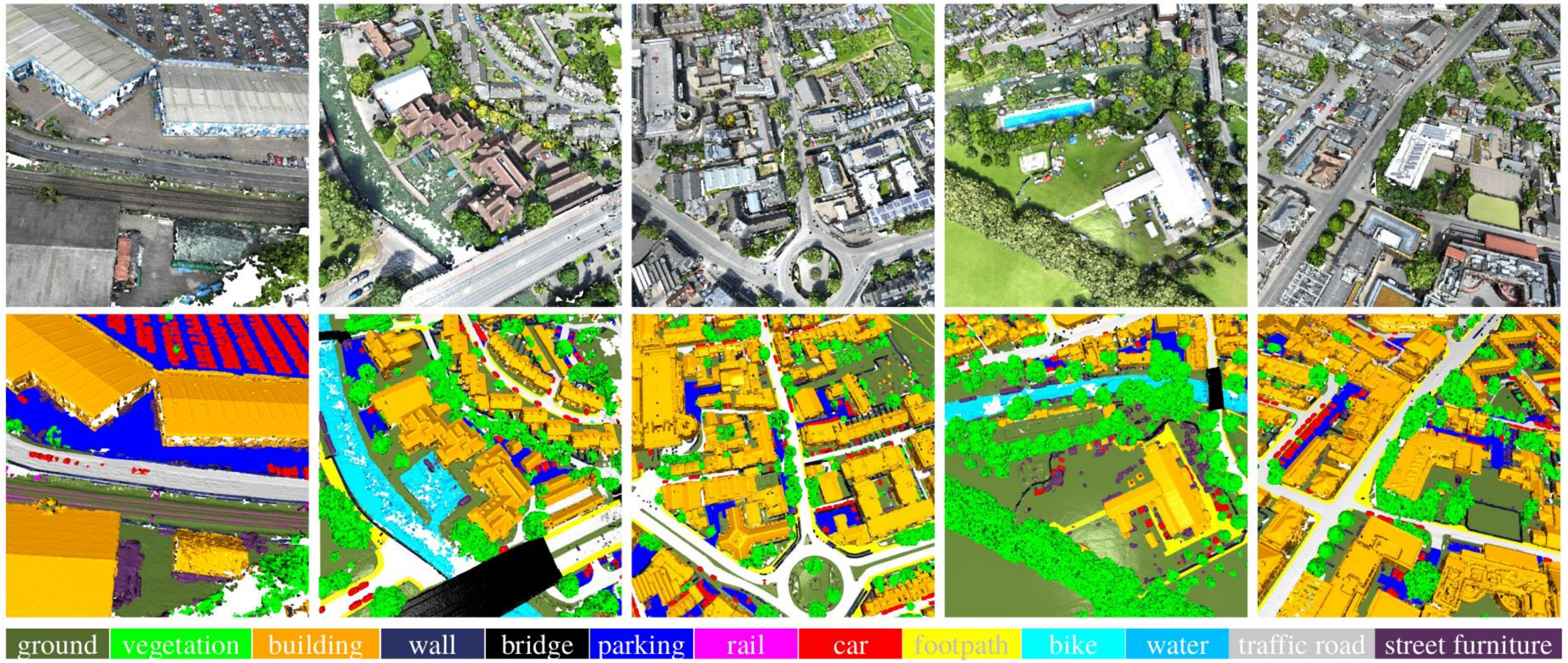
- **BuildingNet**
  - # Models: 2,000
  - # Semantic Components: 292K
  - # Semantic Parts: 31
  - Semantic segmentation
  - Surface reconstruction



Selvaraju et al., 2021

3D shape datasets: *Datasets for Urban Areas*

- **SensatUrban**
  - # Points: 3B
  - # Semantic Classes: 13



Qingyong et al., 2022

Figure 3: Examples of our SensatUrban dataset. Different semantic classes are labeled by different colors.

Today’s Agenda

- Who are we?
- What is 3D Vision
- 3D shape representations
- 3D shape datasets
- 3D Deep Learning architectures
- What we do

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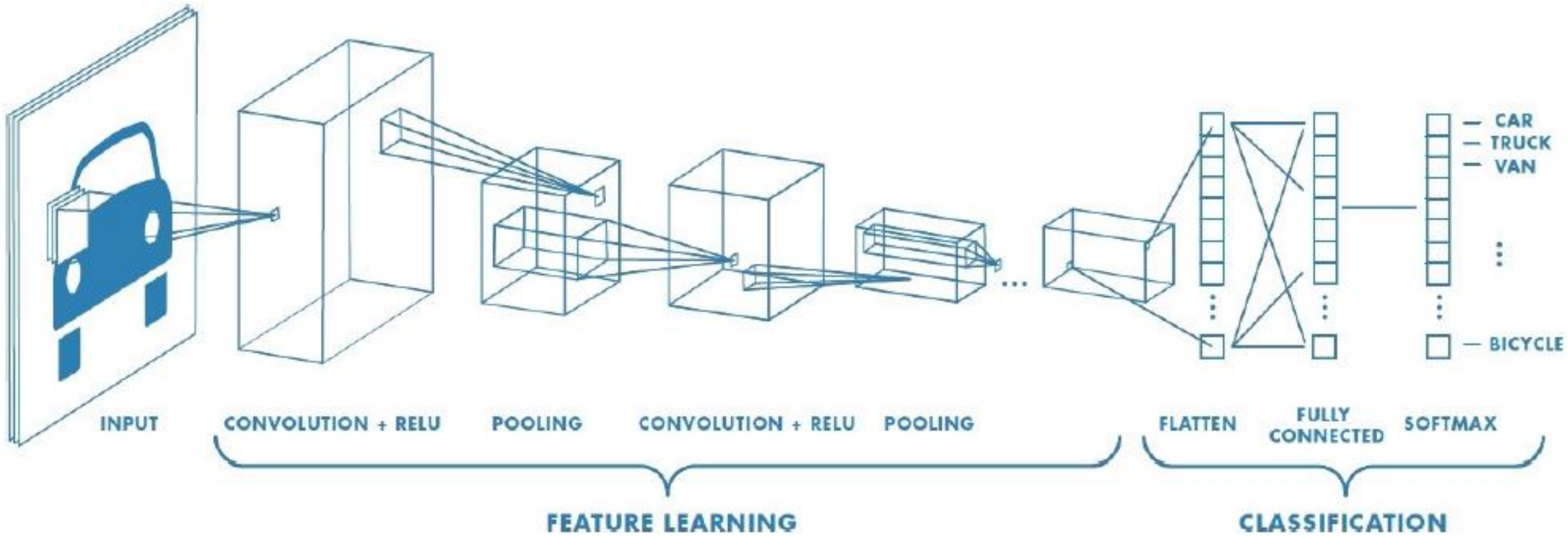
3D DL architectures: *2D architectures “success story”*

Layers of **convolutional filters** trained to extract descriptors + **learned functions** that map descriptors to high-level concepts



Kalogerakis E.

3D DL architectures: *2D architectures "success story"*

Can capture various **low-level** and **high-level** features through hierarchical representation learning. **Very good performance** in 2D vision tasks (class., seg., obj. det….)

Kalogerakis E.

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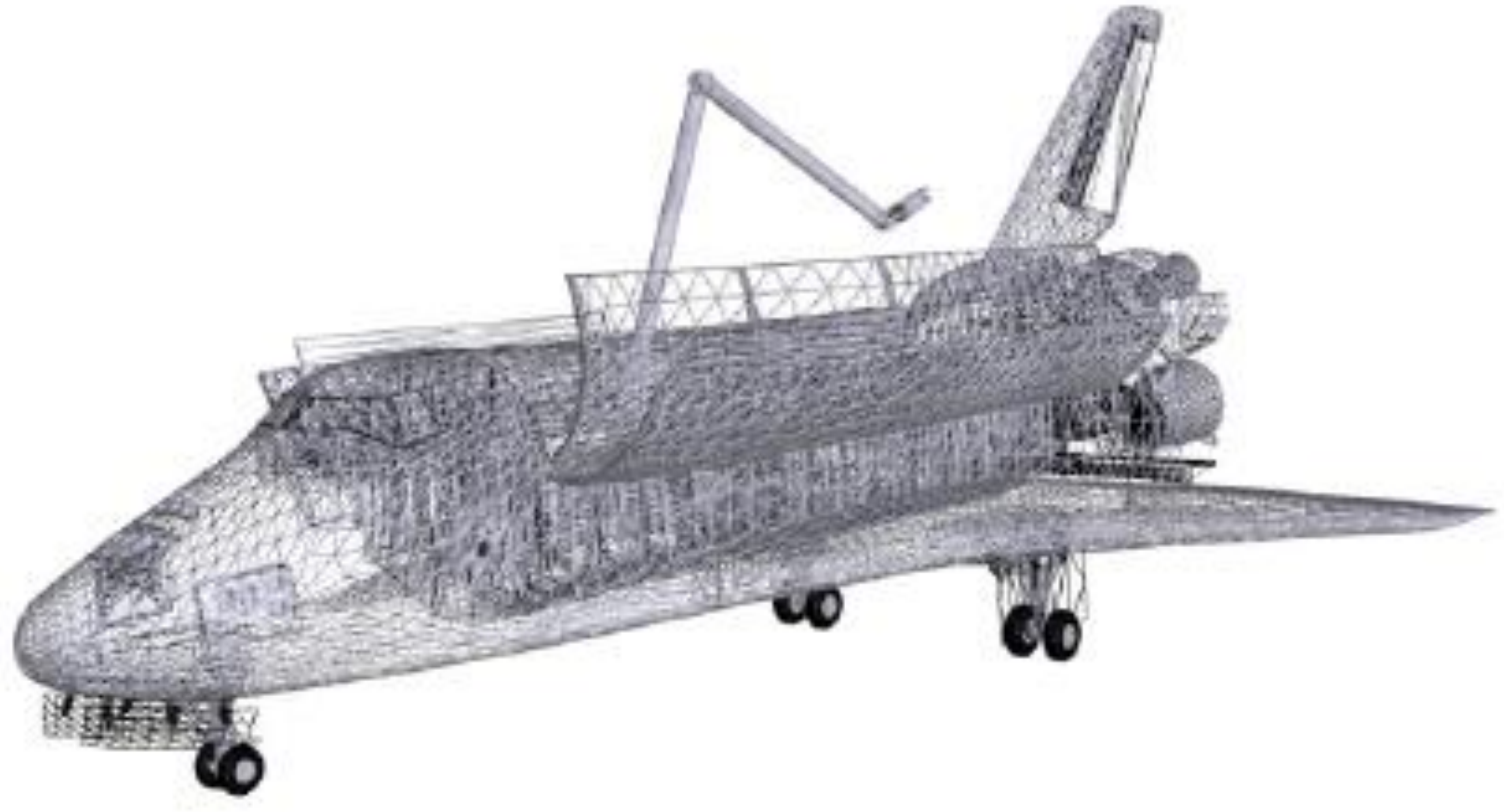
3D DL architectures: *Challenges – How do we apply convnets in 3D shapes*

Geometric representations are **irregular** and **unordered**: arbitrary point order, different #points, different #neighbor per point etc.



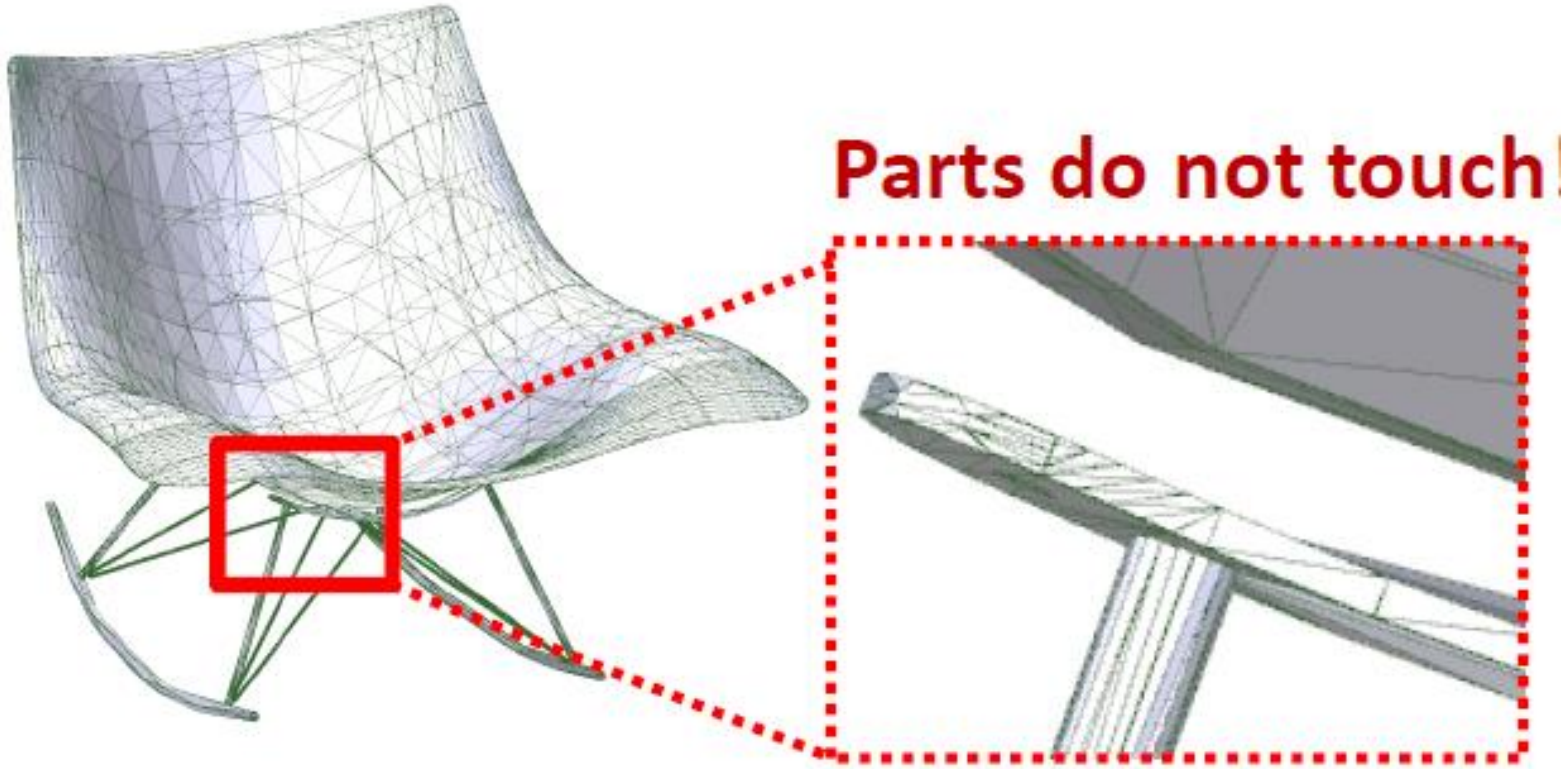
Polygon mesh

Point clouds

Kalogerakis E.

3D DL architectures: *Challenges – Artifacts*

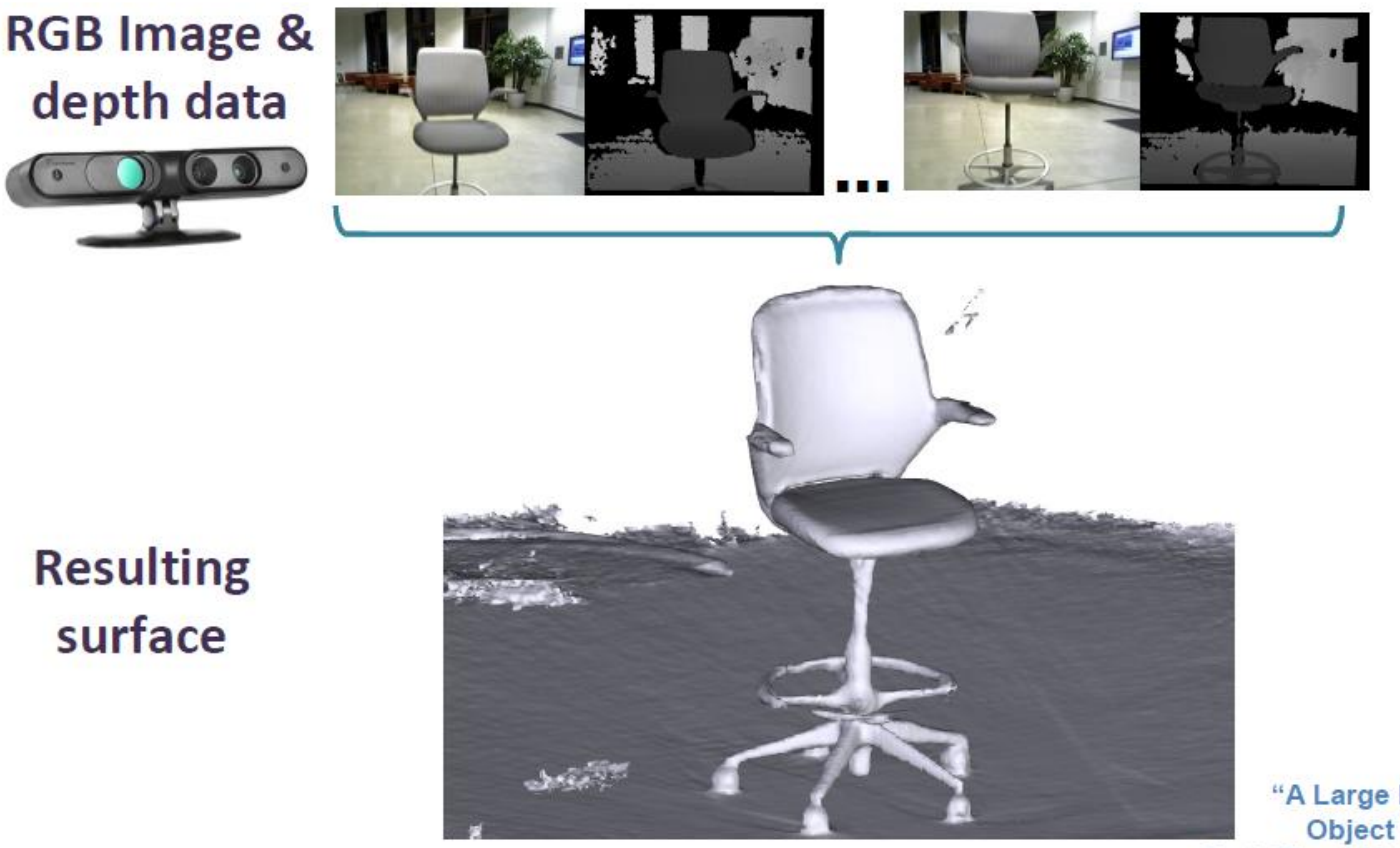
3D models can have several **artifacts**



Kalogerakis E.

3D DL architectures: *Challenges – Noise*

Scanned surfaces have **noisy** and **missing parts**



"A Large Dataset of Object Scans"
Choi, Zhou, Miller, Koltun 2016

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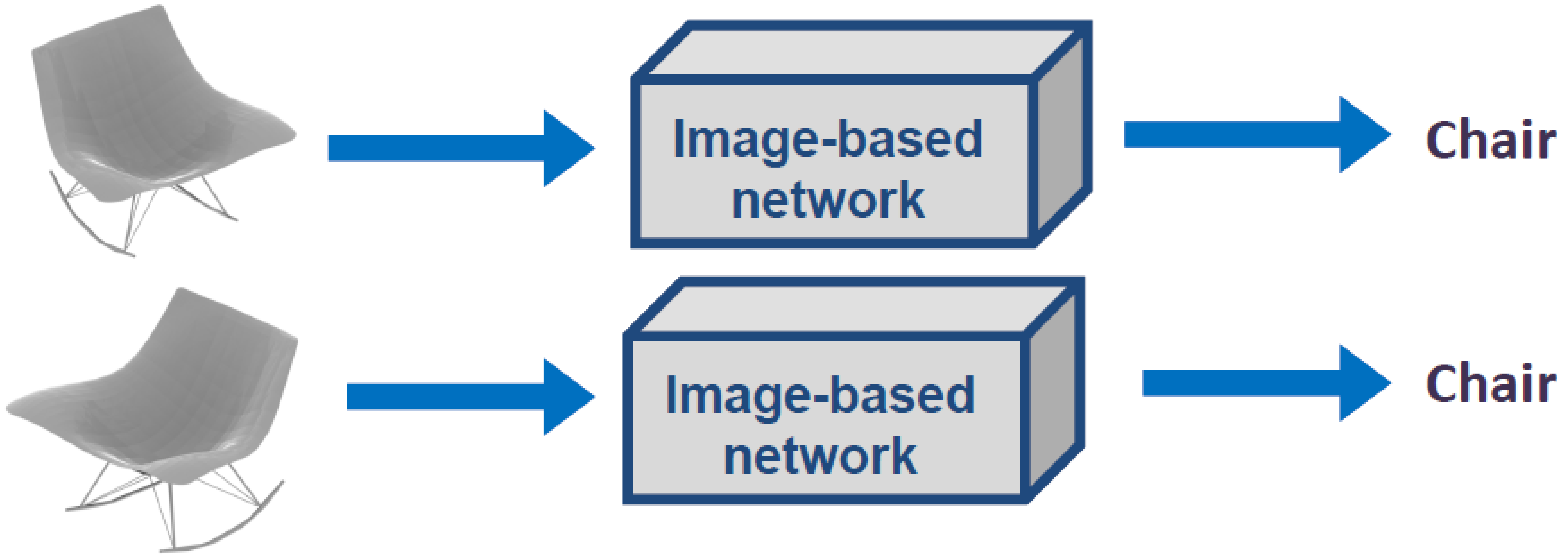
3D DL architectures: *Multi-view approach*

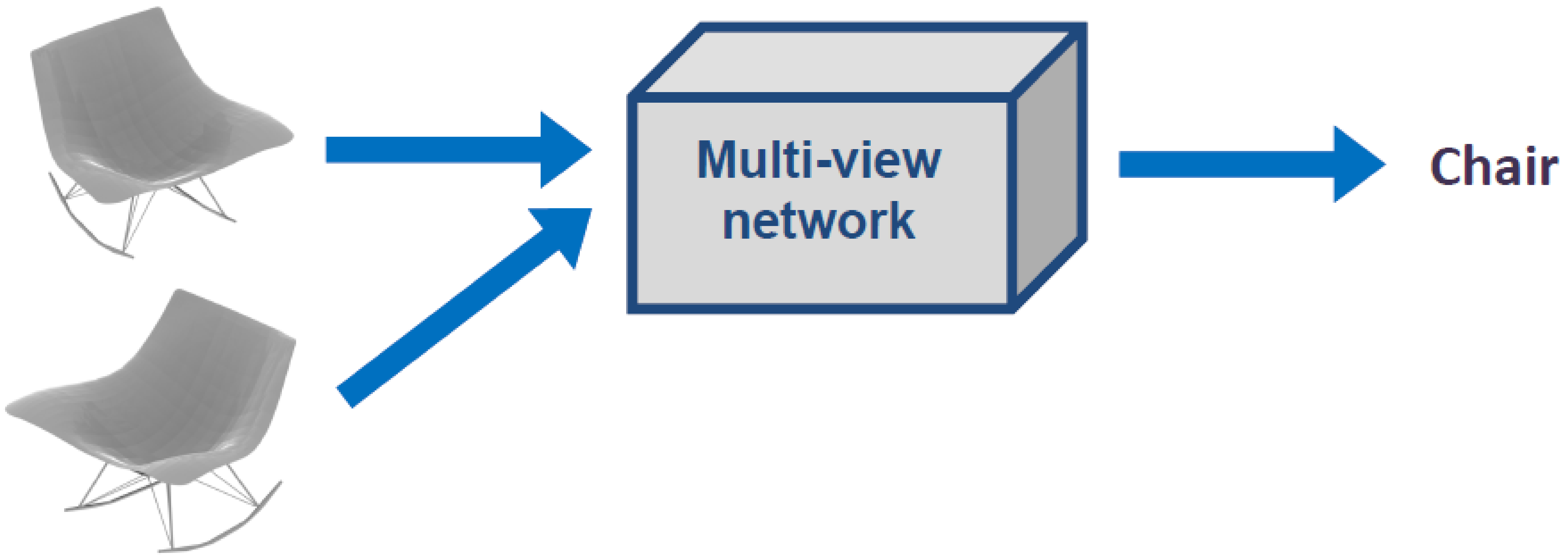
Image-based networks can process individual shape renderings



Kalogerakis E.

3D DL architectures: *Multi-view approach*

Image-based networks can process individual shape renderings



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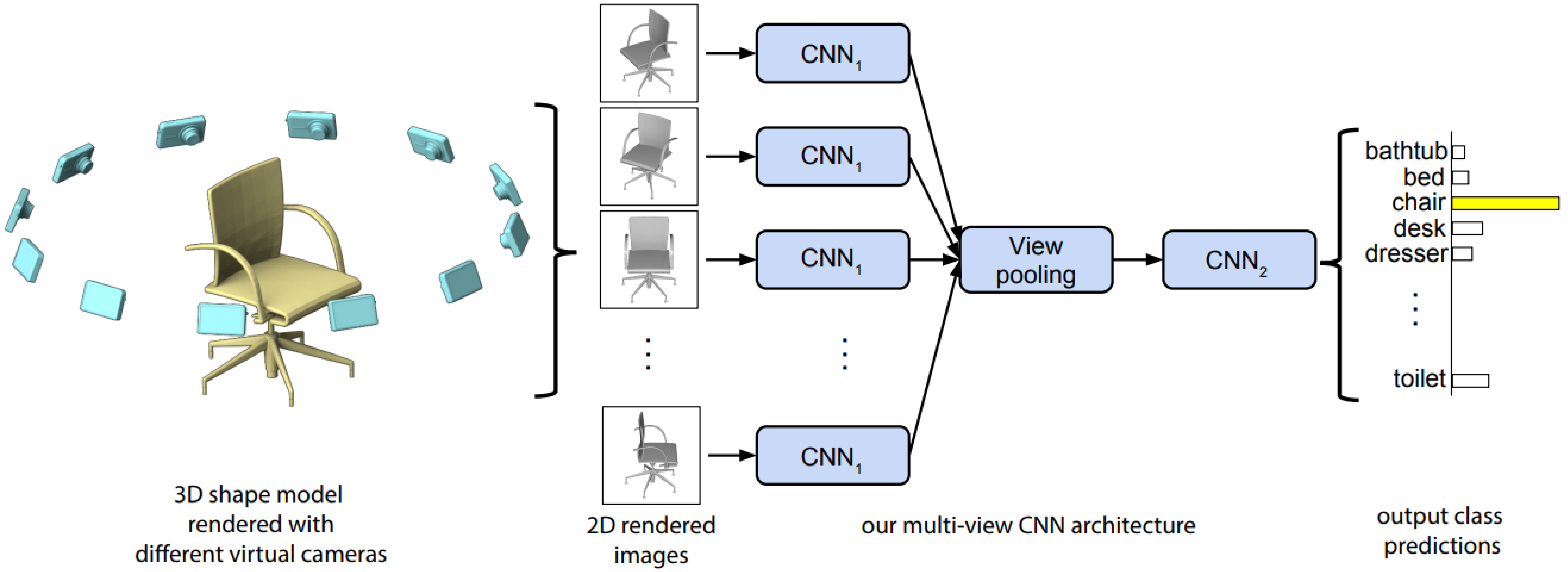
3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition



Hang Su et al.
ICCV 2015

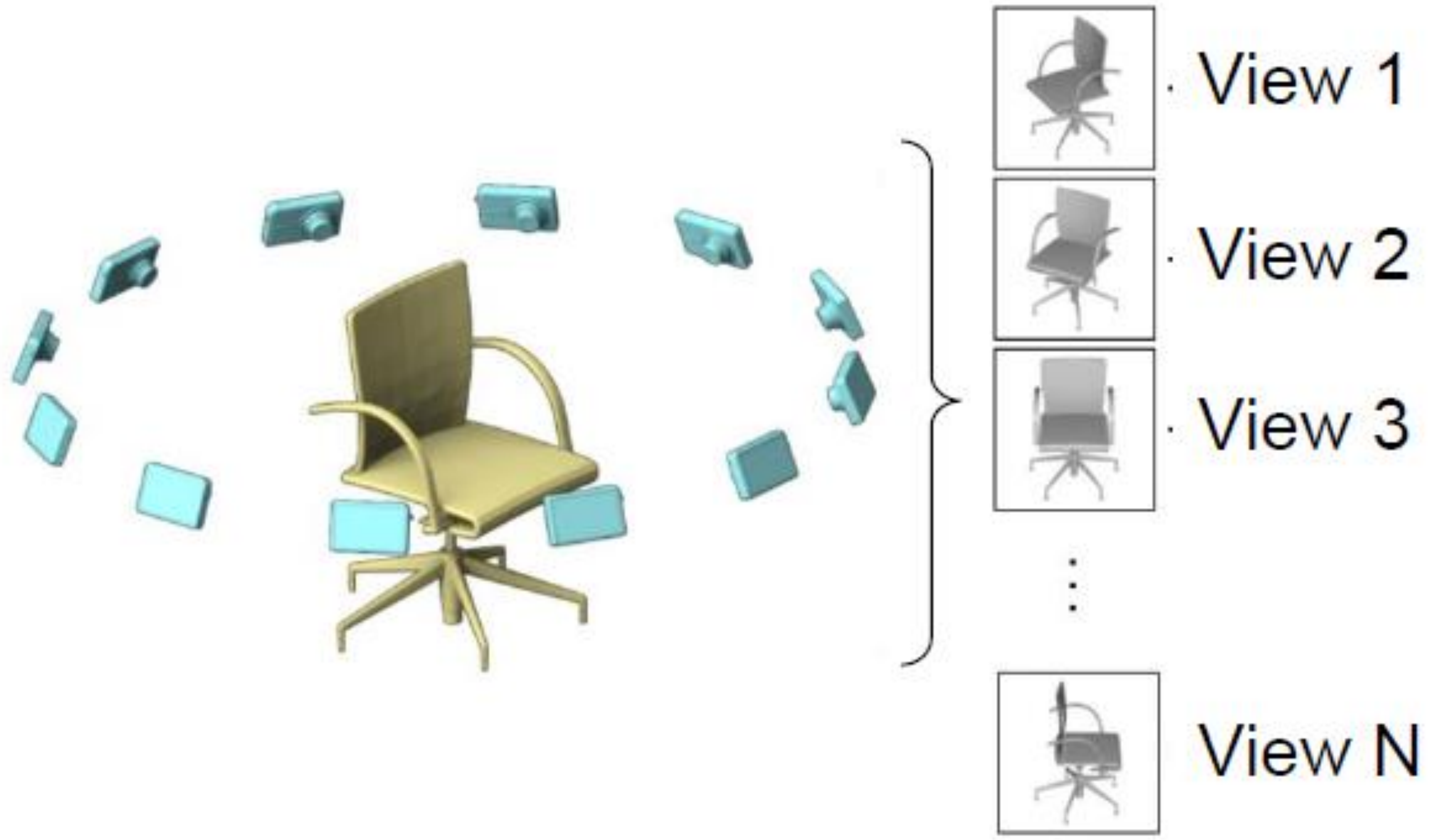
3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition

Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

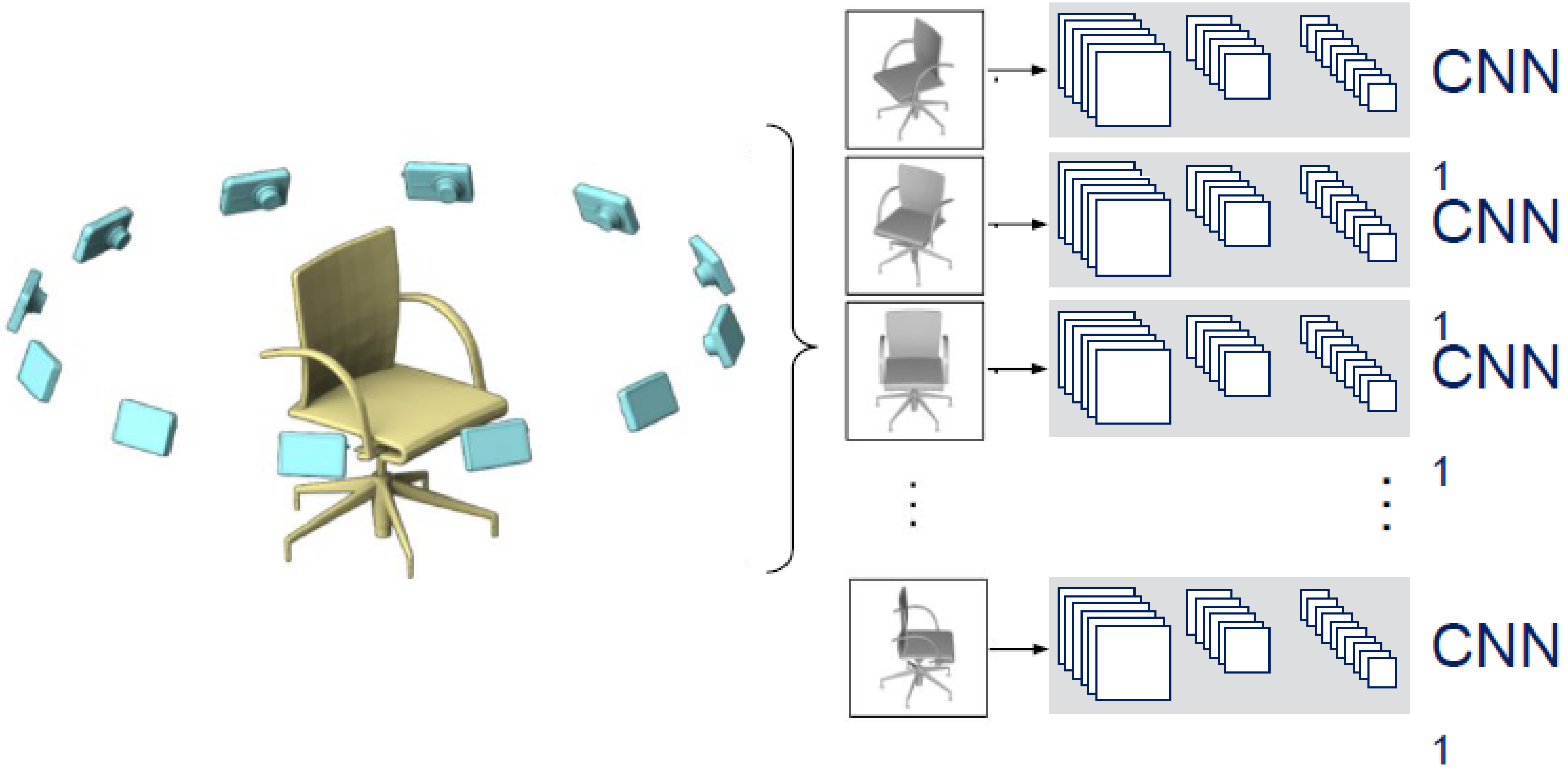
Multi-view Convolutional Neural Networks for 3D Shape Recognition



Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition

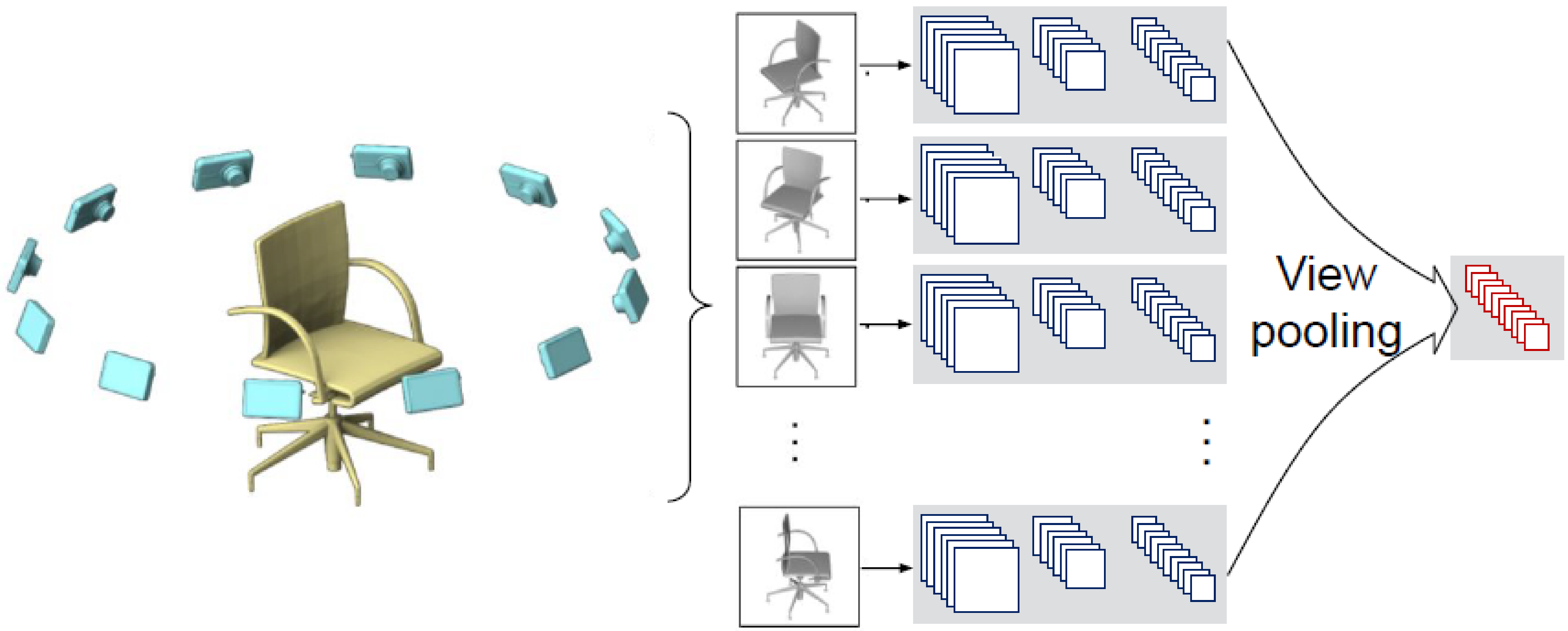


CNN_1: a ConvNet extracting image features

Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition

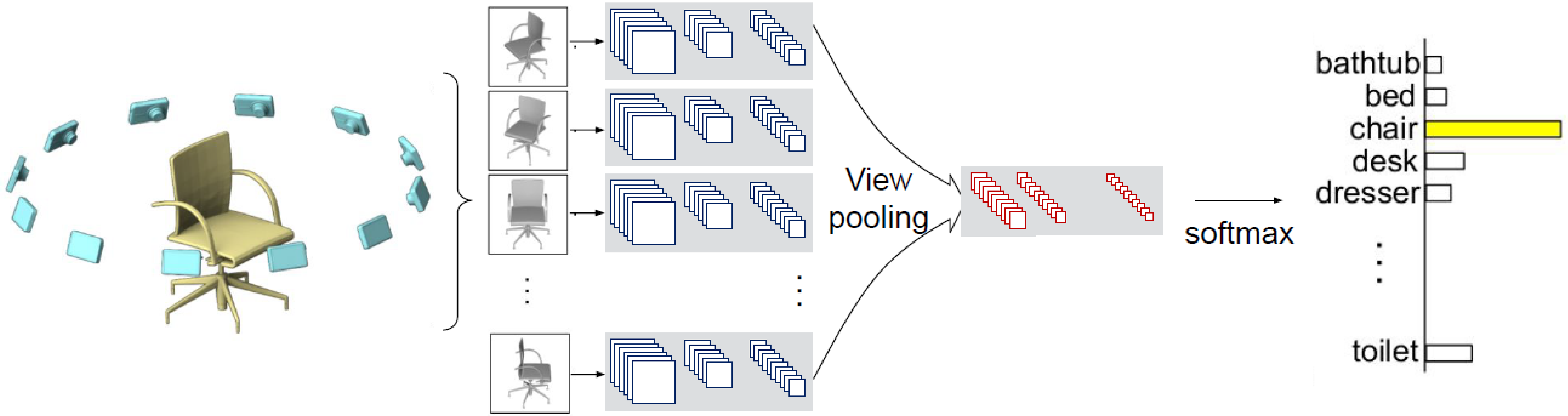


View pooling: element-wise
max-pooling across all views

Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition



CNN$_2$: a second ConvNet producing shape descriptors

Hang Su et al. ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition

ModelNet40: Classification & Retrieval

Method	Classification (Accuracy)
Spherical Harmonics [Kazhdan et al.]	68.2%
LightField [Chen et al.]	75.5%
Volumetric Net [Wu et al.]	77.3%
ImageNet-trained CNN (VGG-M, 1 view)	83.0%
Multi-view convnet (MVCNN)	**90.1%**

Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Networks

- Pros:
  - ✓ Good performance
  - ✓ Can leverage vast literature of image classification
  - ✓ Can use pretrained features
- Cons
  - x Need projection
  - x Issue with noisy and/or incomplete input, e.g., point cloud

Jiajun Wu

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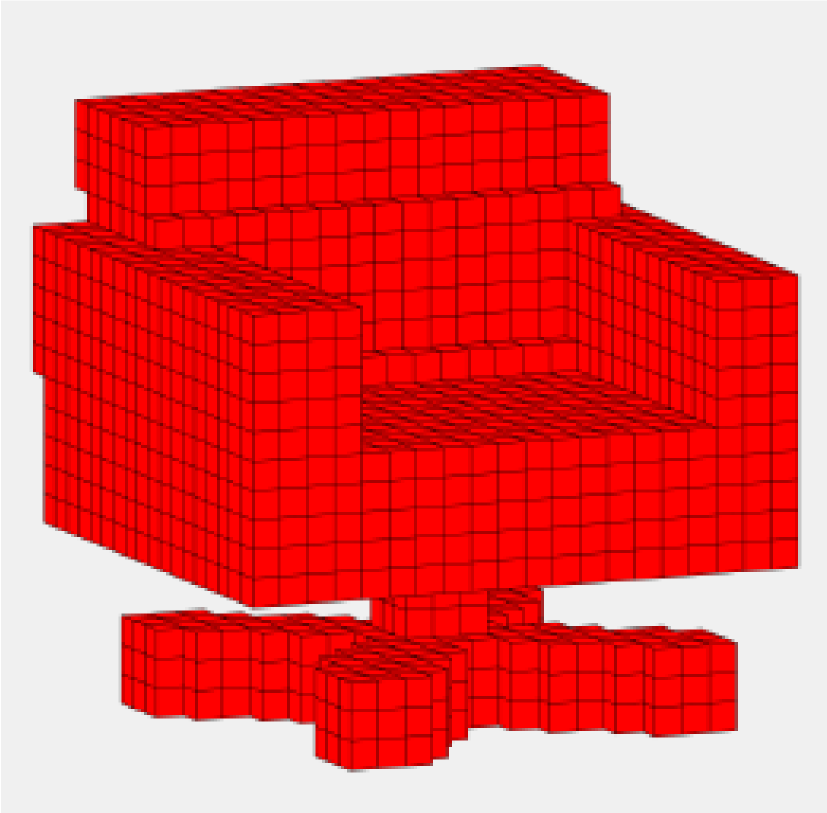
3D DL architectures: *Volumetric approach*

Voxelization: Convert shape to 3D regular volumetric grid

3D polygon mesh



Voxels

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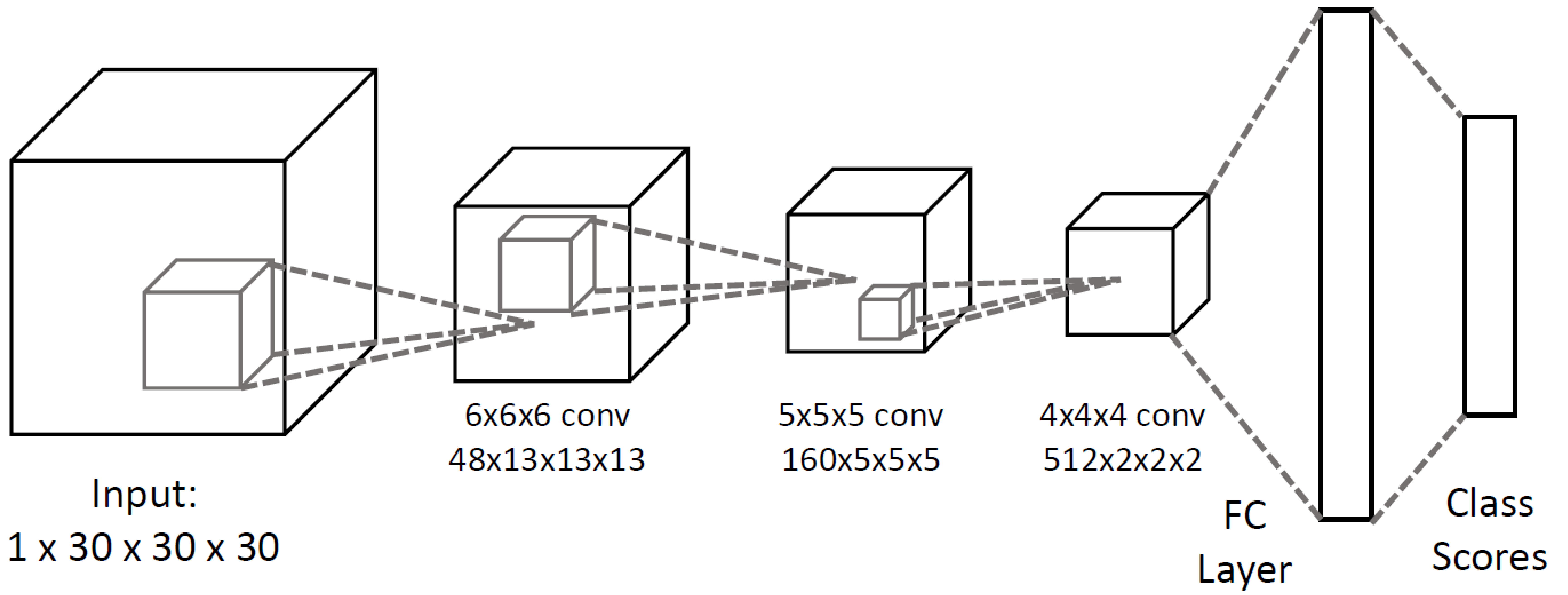
3D DL architectures: *Volumetric approach*

Processing Voxel Inputs –> **3D Convolution**

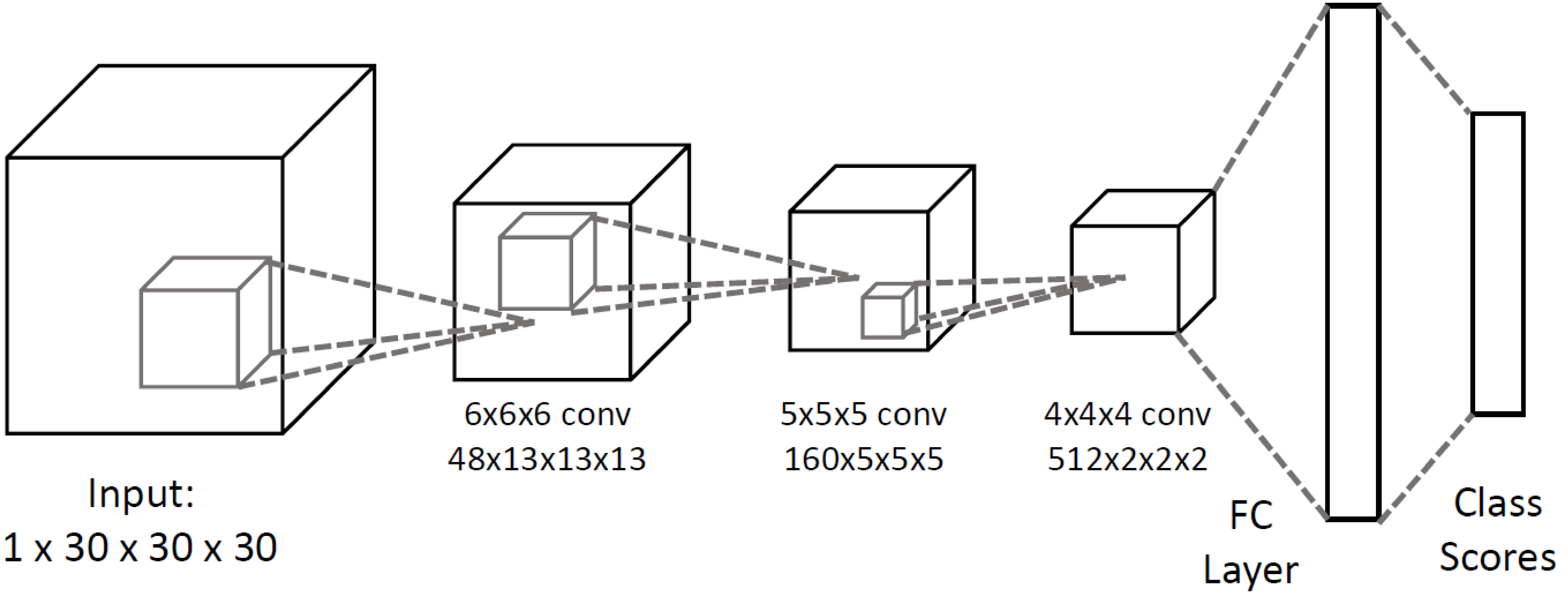


"3D ShapeNet",
Wu et al., CVPR 2015

3D DL architectures: *Volumetric approach*

Processing Voxel Inputs –> **3D Convolution**

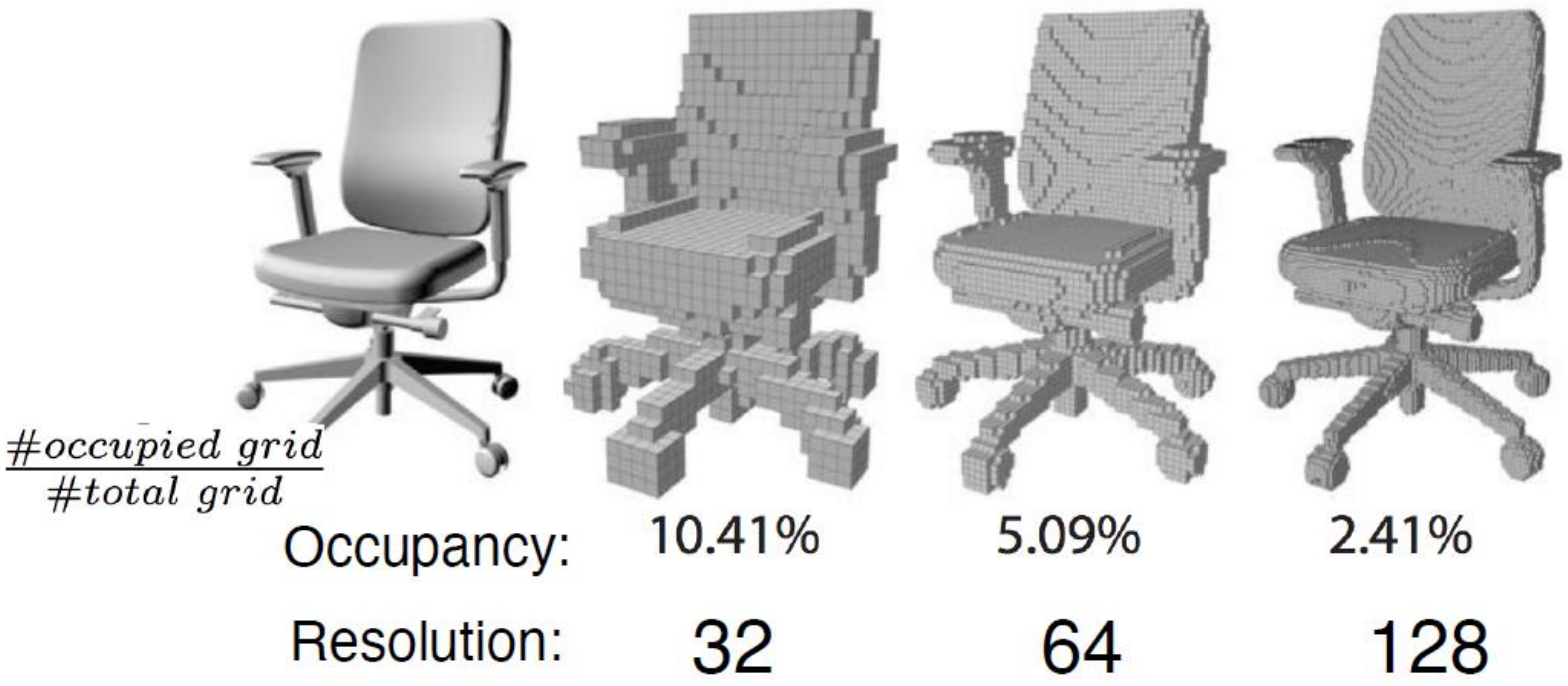
Computationally and memory expensive! Requires low-res input



"3D ShapeNet", Wu et al., CVPR 2015

3D DL architectures: *Volumetric approach*

Sparsity of 3D data

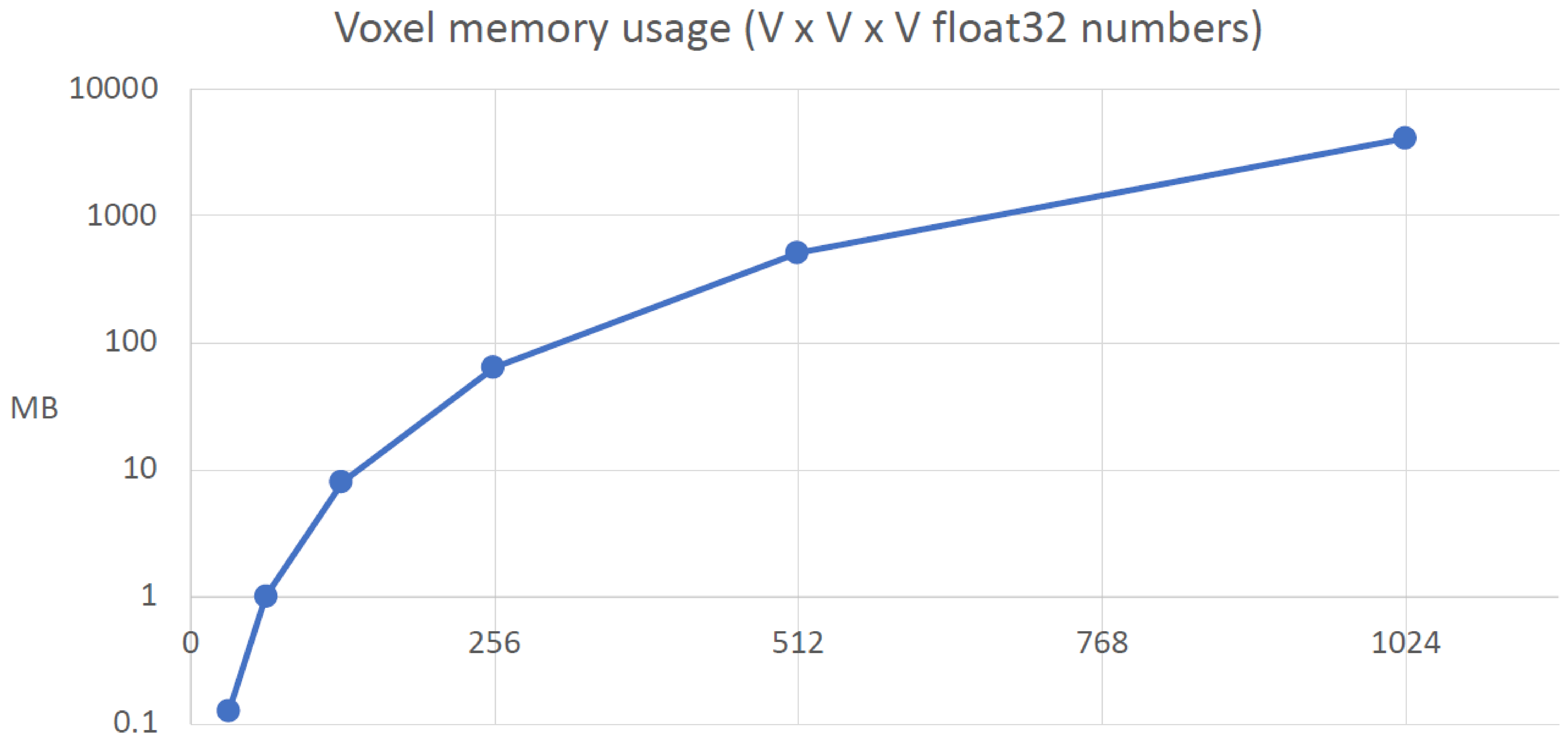


Running convolution on so much empty space is wasteful!

Hao Su et al.

3D DL architectures: *Volumetric approach*

Memory usage



Storing 1024^3 voxel grid takes 4GB of memory!

Justin Solomon

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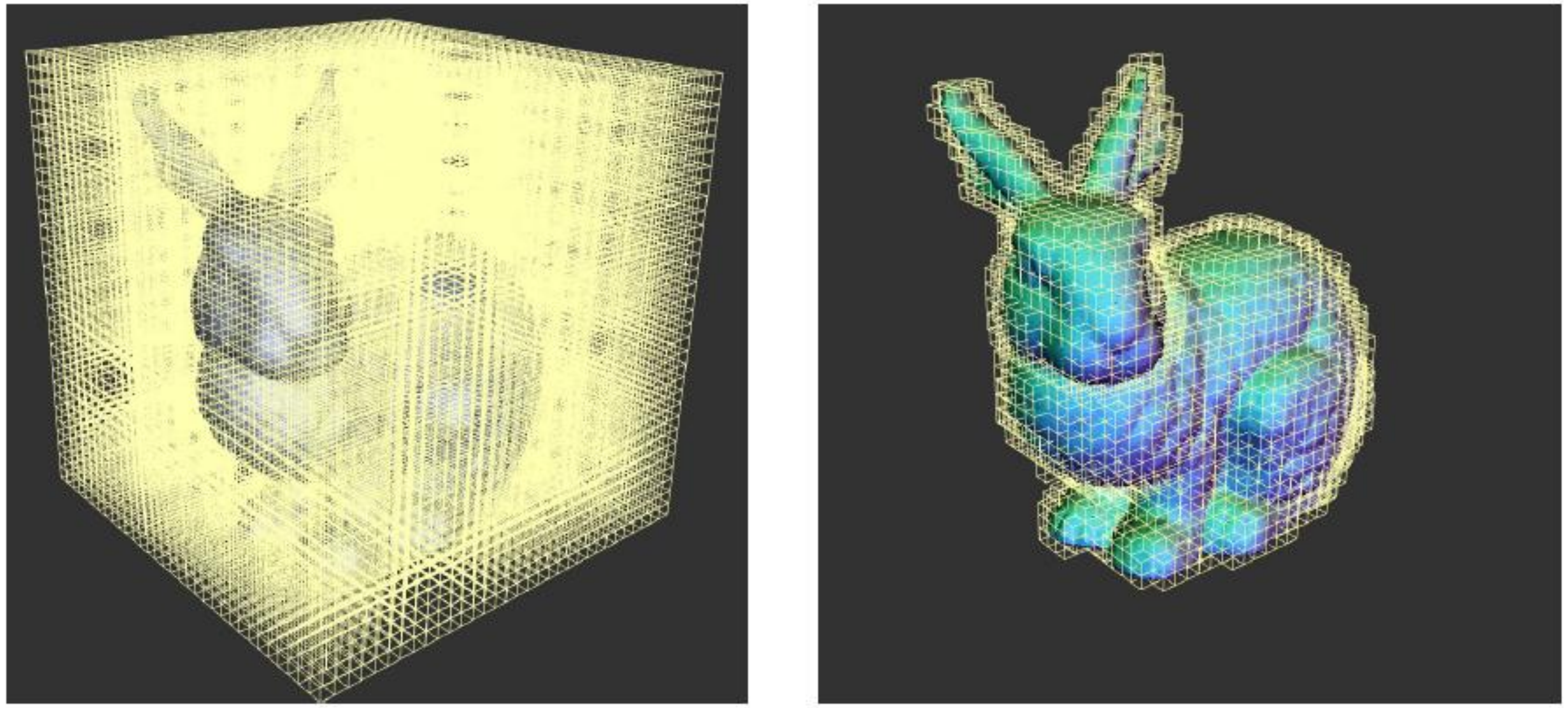
3D DL architectures: *Volumetric approach*

Solution –> **Octave Tree Representations**

- Store the sparse surface signals
- Constrain the computation near the surface



Hao Su et al.

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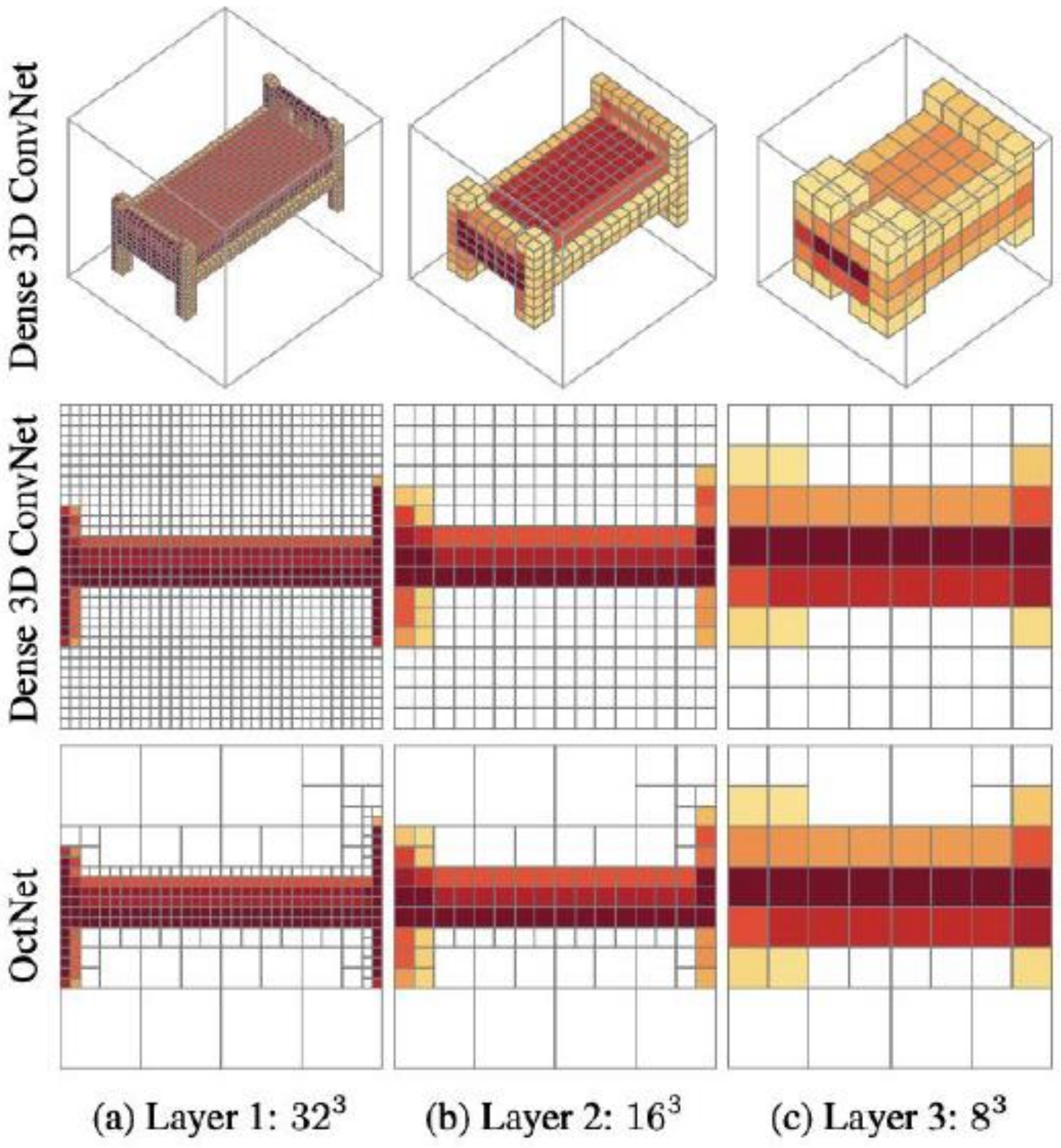
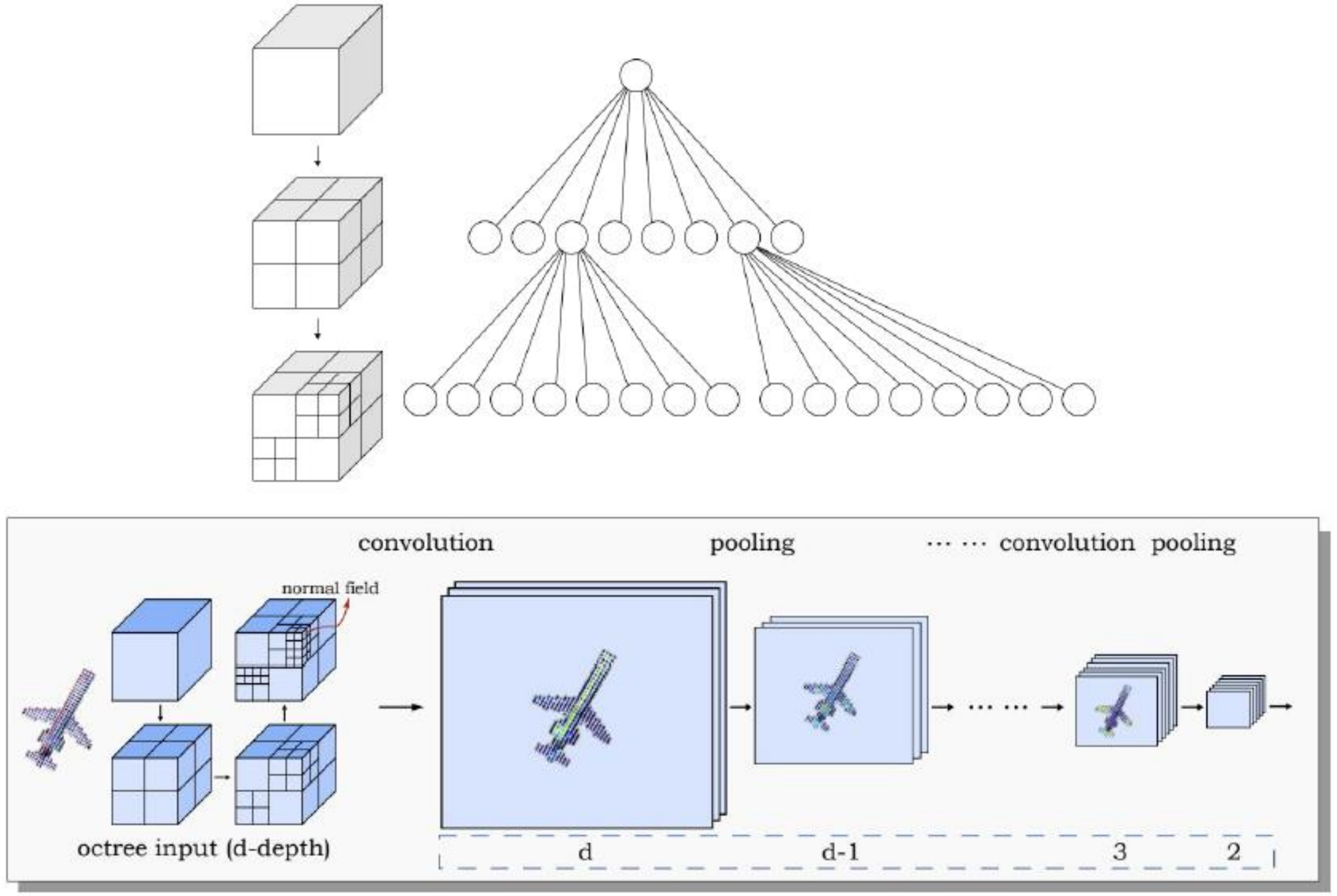
3D DL architectures: *Volumetric approach*

Octree: Recursively Partition the Space



Riegler et al. OctNet. CVPR 2017

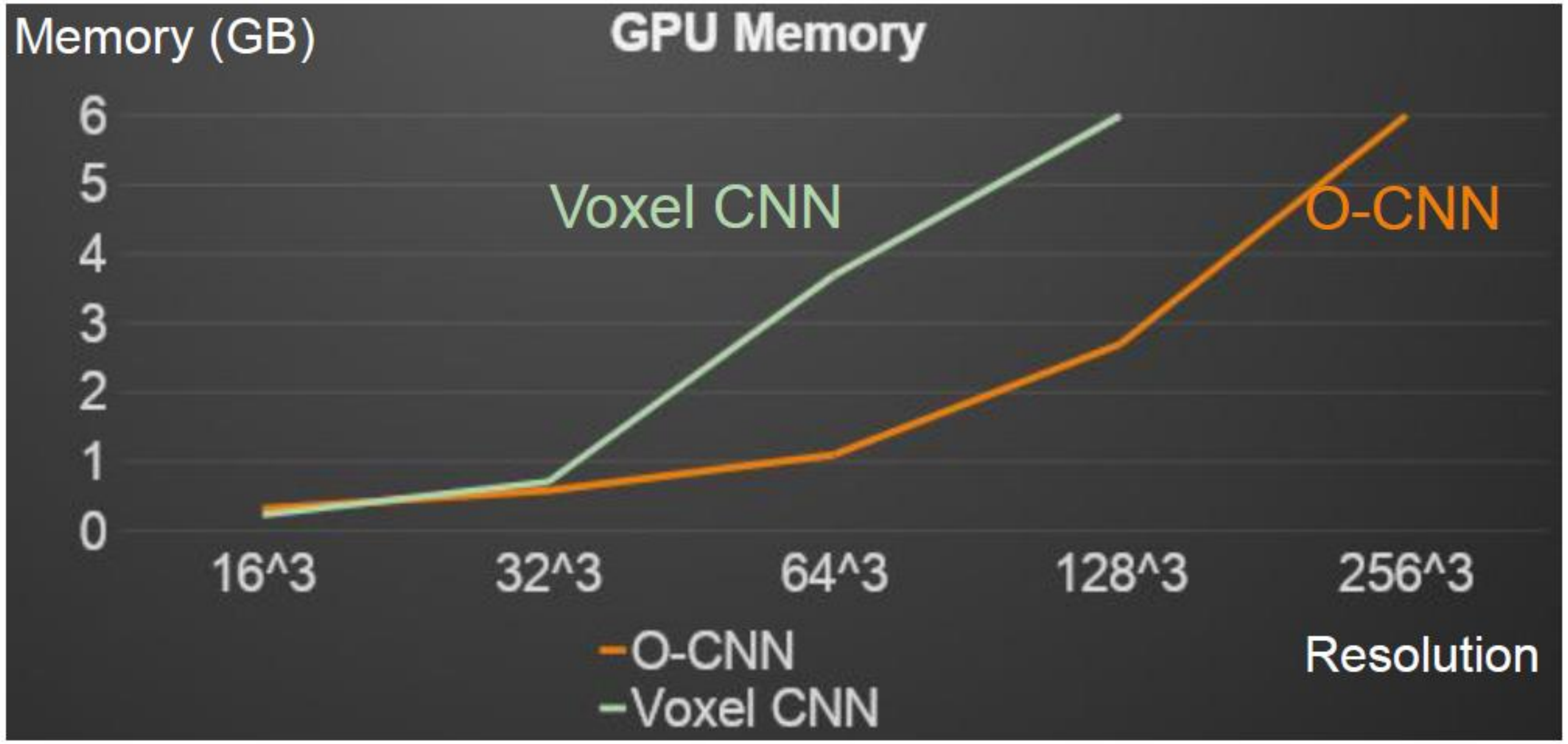


Wang et al. O-CNN. SIGGRAPH 2017

Hao Su et al.

3D DL architectures: *Volumetric approach*

Memory Efficiency

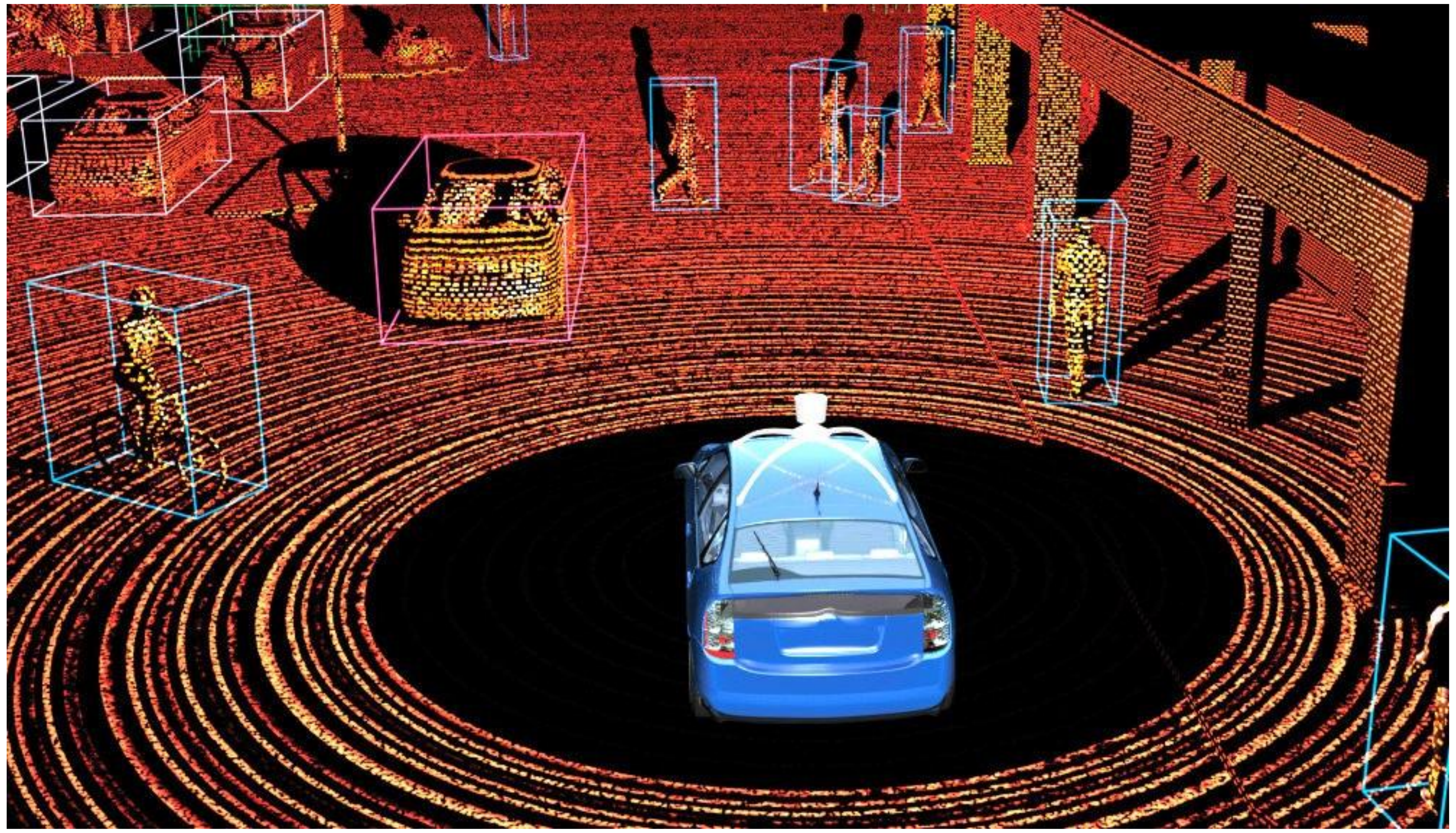


Hao Su et al.

3D DL architectures: *Point-based approach*

Motivation:

- Lots of **scanned data** are raw 3D point clouds
- **Process raw input**, i.e., point cloud, without any preprocessing



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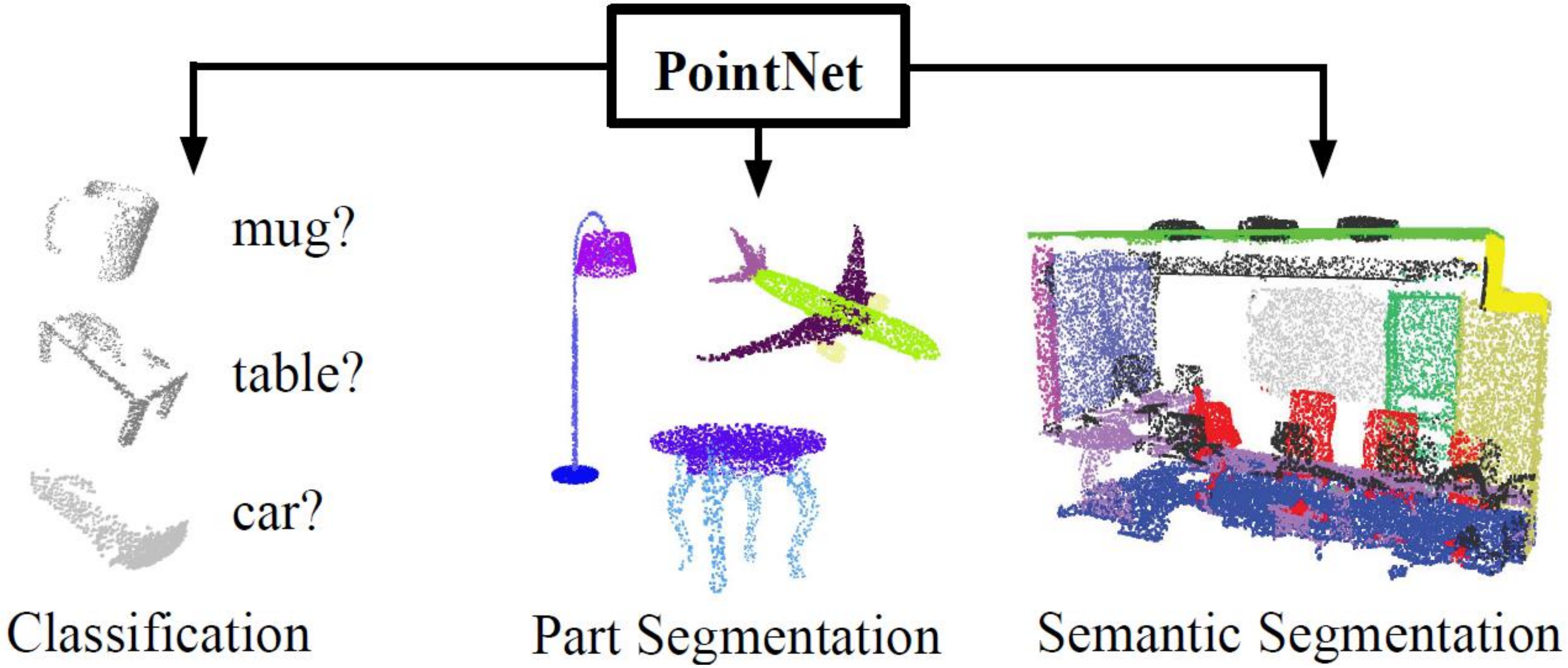
3D DL architectures: *Point-based approach*

PointNet: (Qi et al., CVPR 2017)

- Processes input point clouds for various tasks

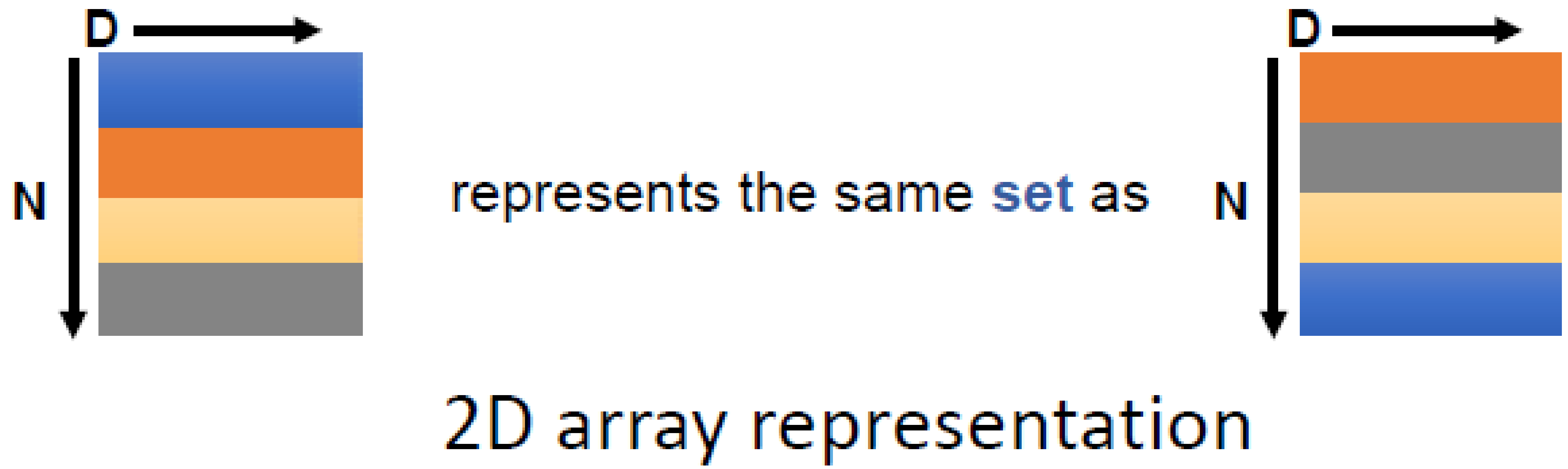


Hao Su

3D DL architectures: *Point-based approach*

Desired Properties of PointNet:

- **Permutation invariance**



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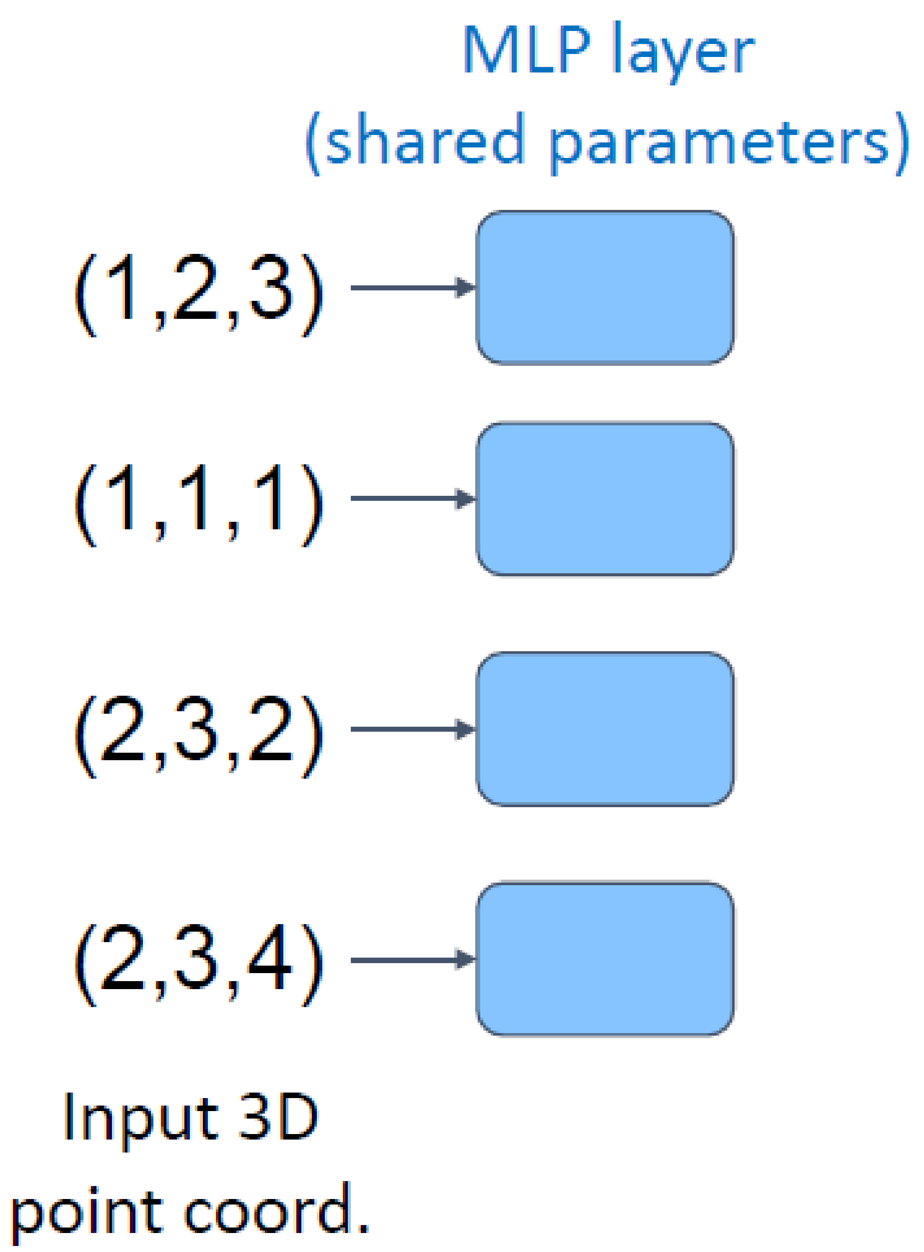
3D DL architectures: *Point-based approach*

PointNet architecture:



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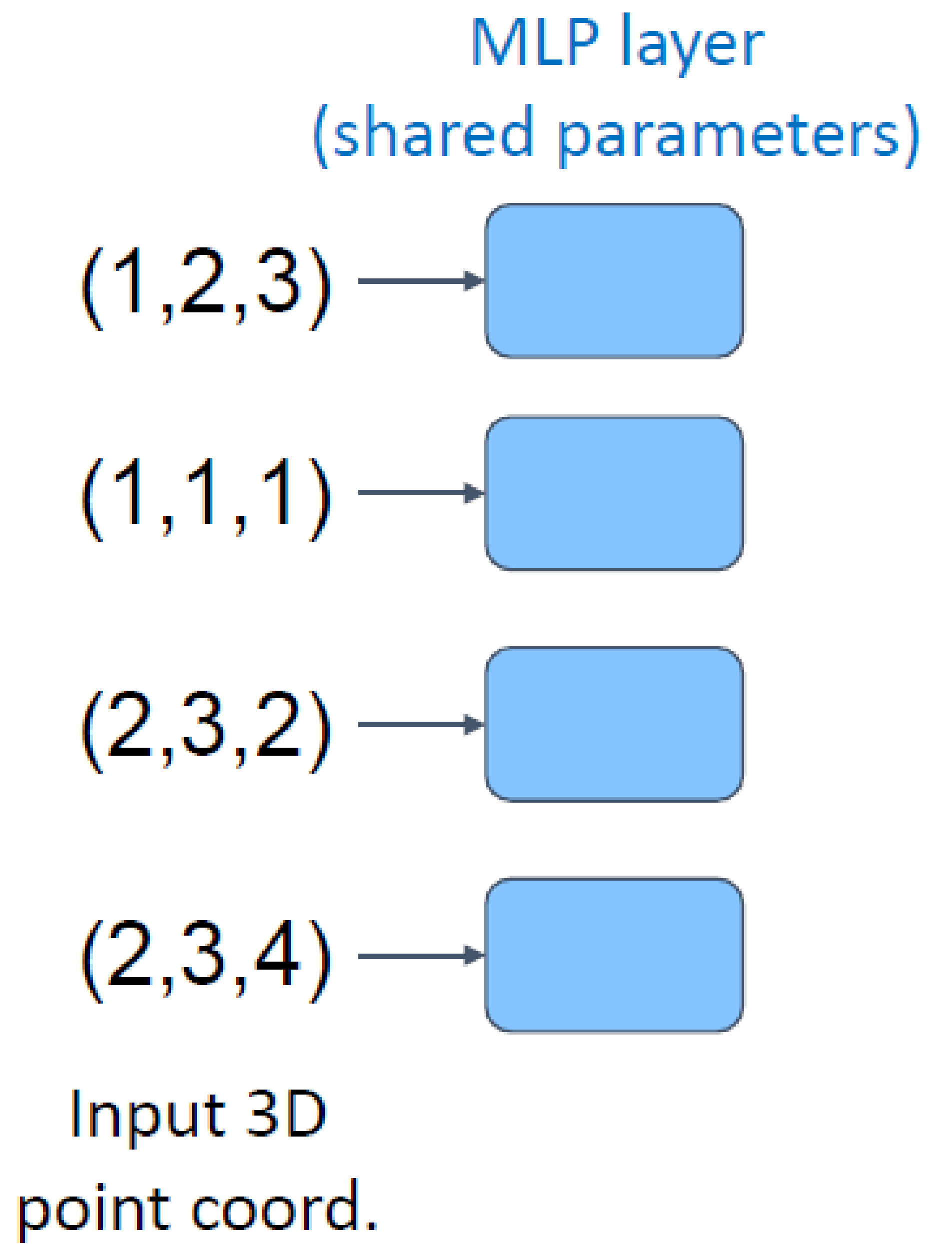
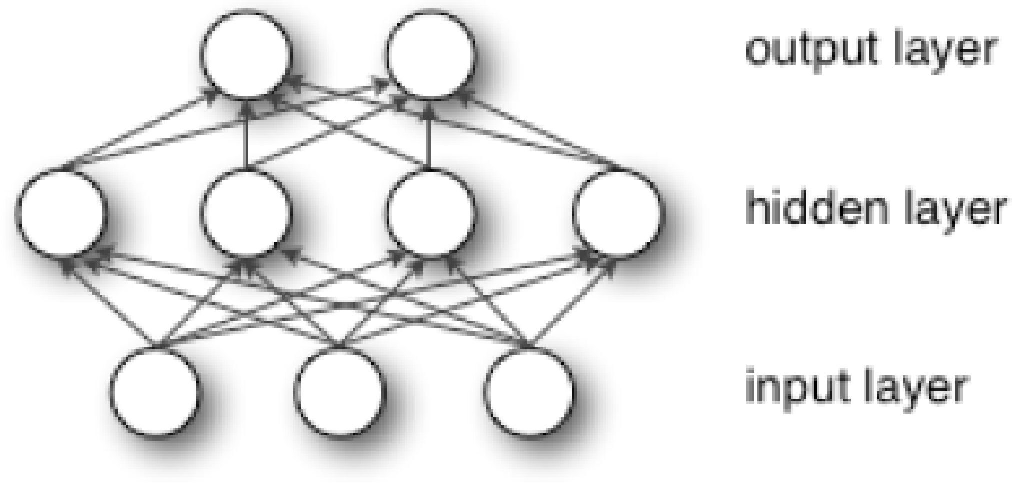
3D DL architectures: *Point-based approach*

PointNet architecture:





Simply a fully connected NN
with one hidden layer,
3 inputs for 3D points, and T
outputs (T is layer parameter)

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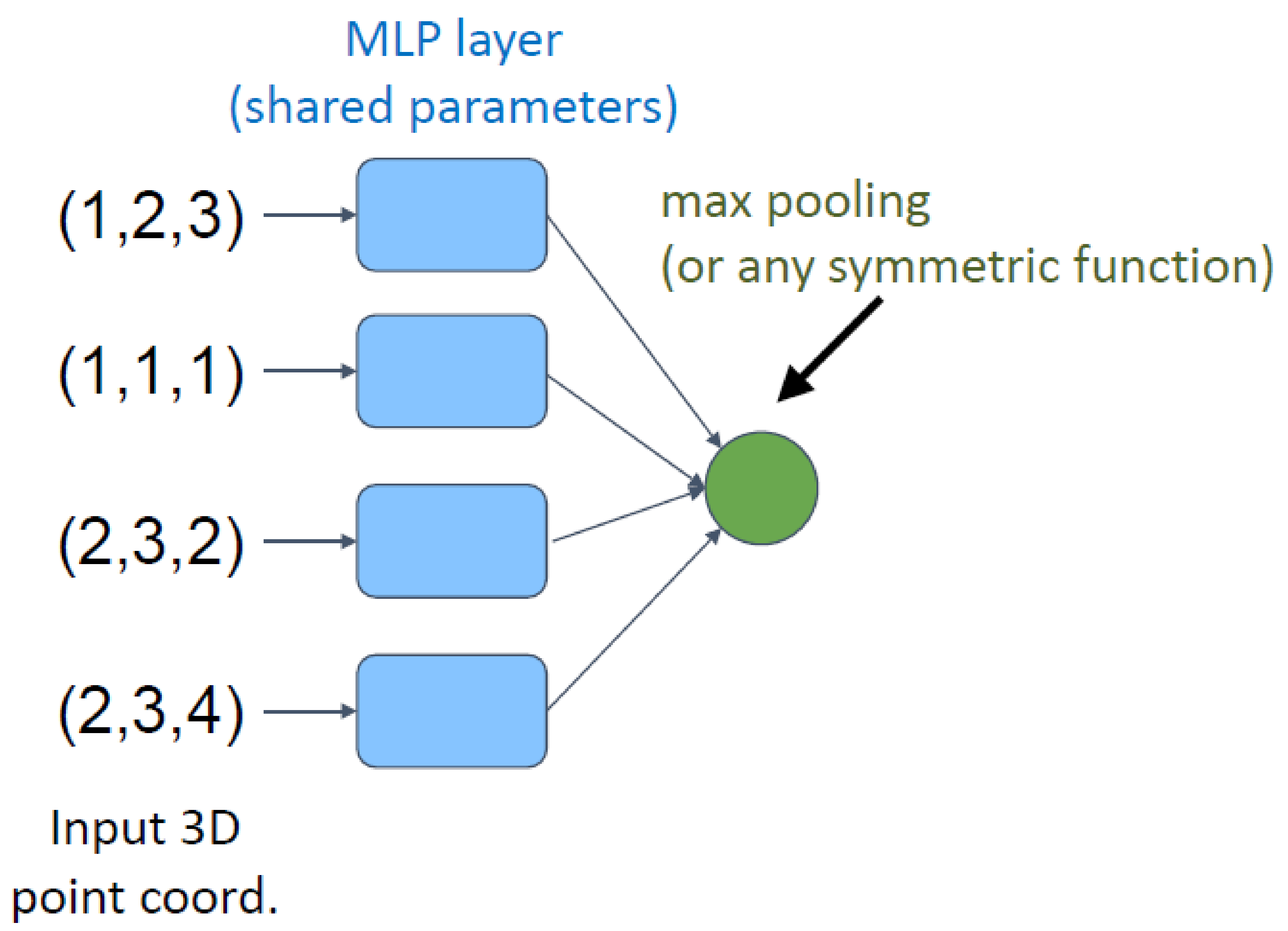
3D DL architectures: *Point-based approach*

PointNet architecture:



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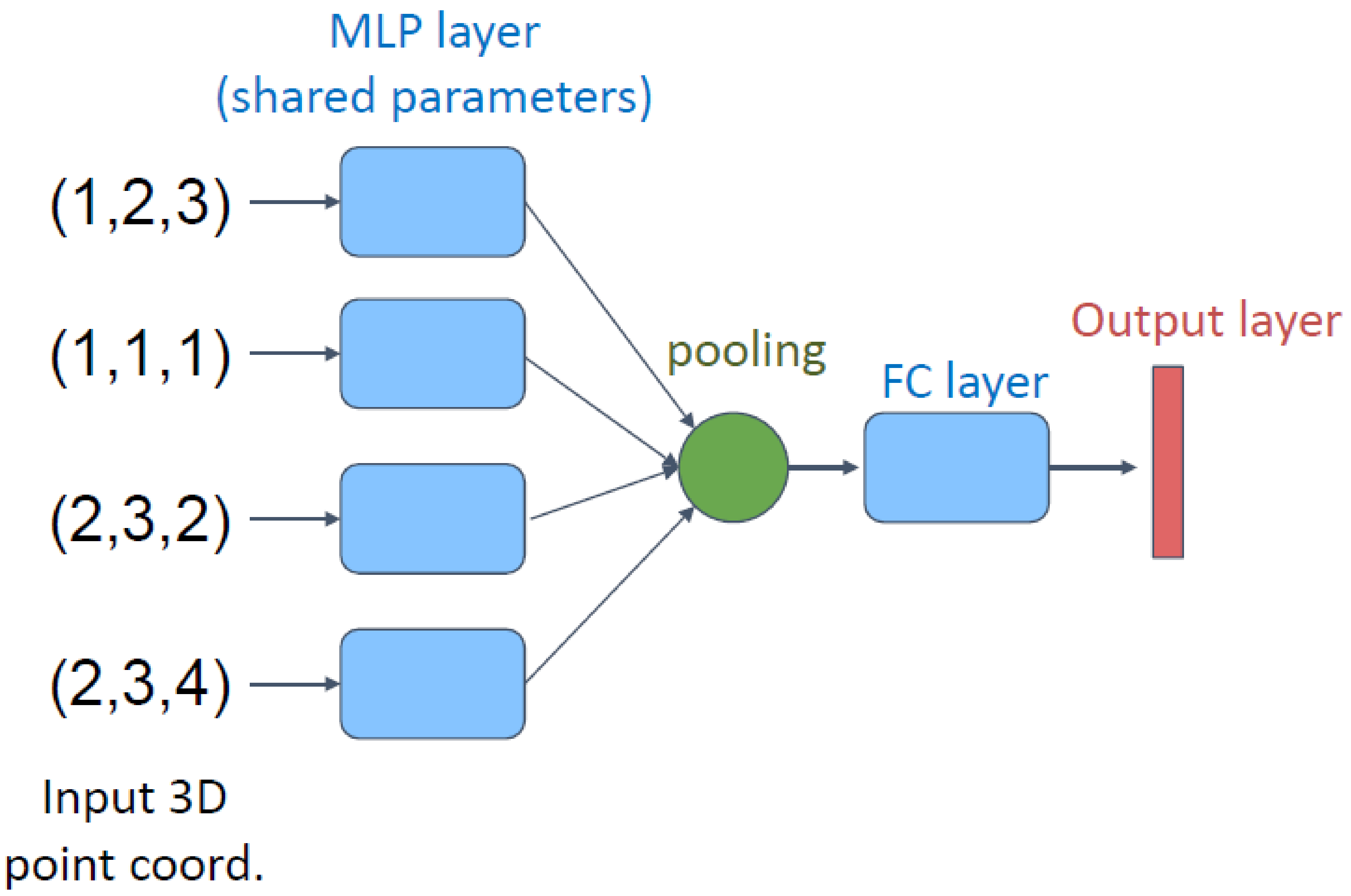
3D DL architectures: *Point-based approach*

PointNet architecture:



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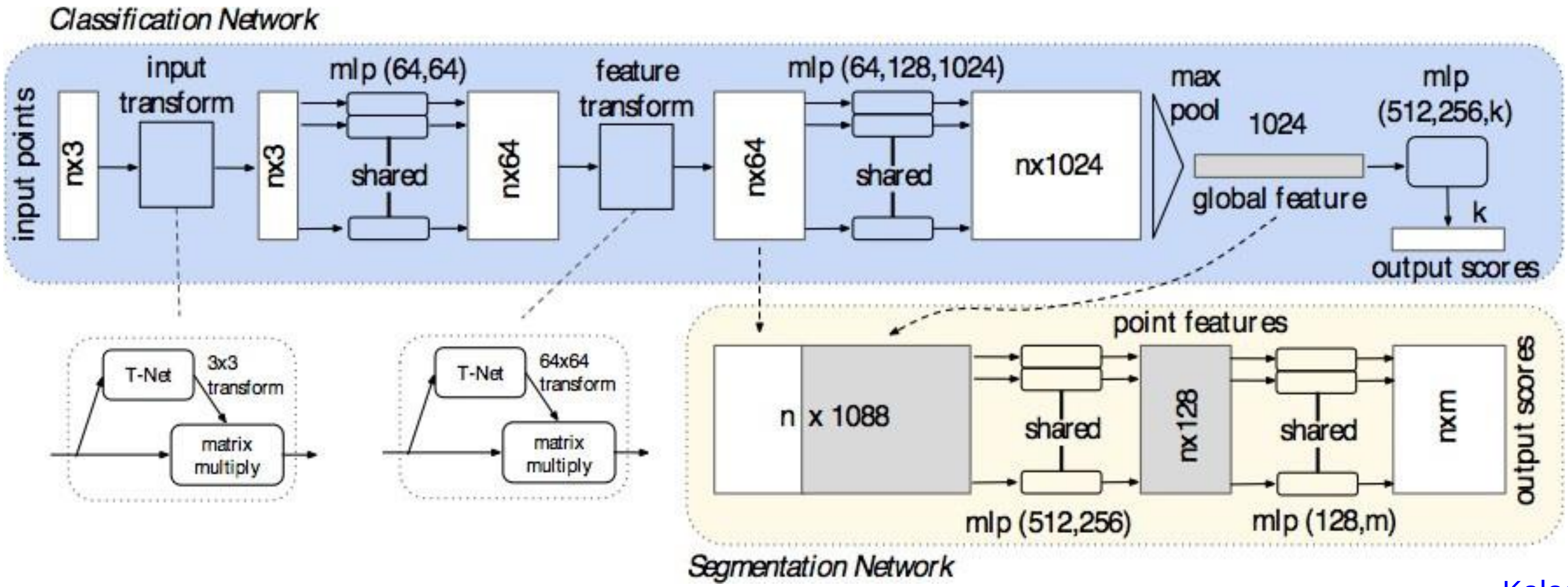
3D DL architectures: *Point-based approach*

PointNet architecture:



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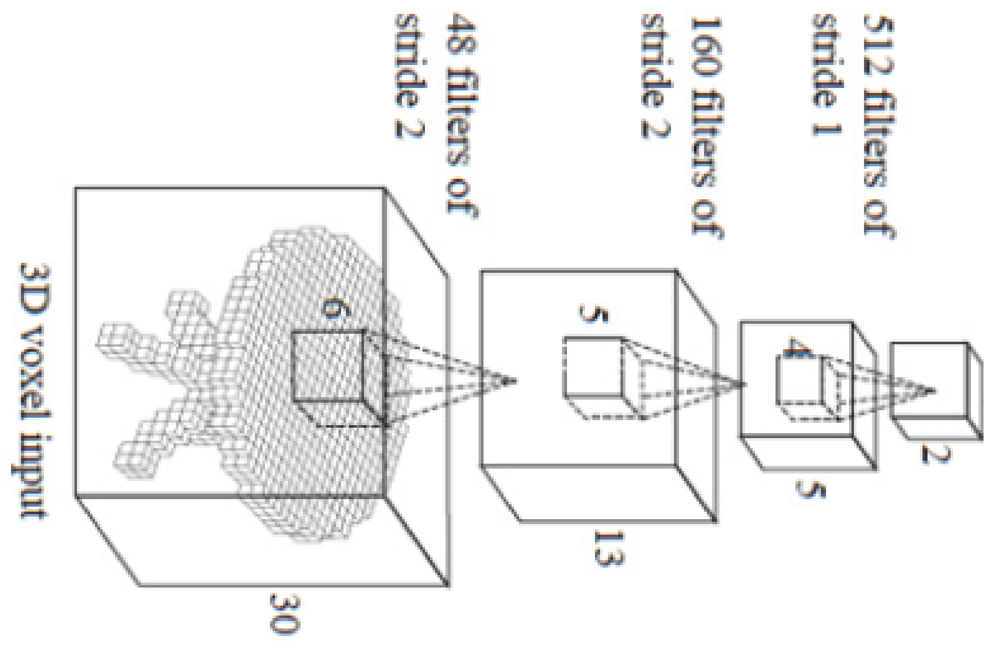
3D DL architectures: *Point-based approach*

Limitations of PointNet

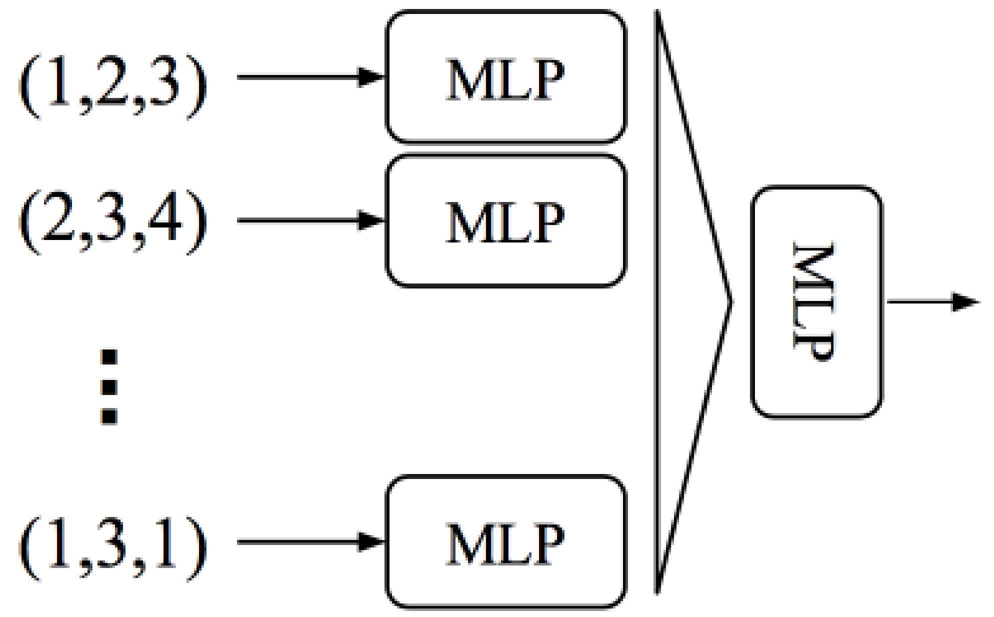
Hierarchical feature learning
Multiple levels of abstraction

v.s.

Global feature learning
Either one point or all points



3D CNN (Wu et al.)



PointNet (vanilla) (Qi et al.)

No local context for each point!

Hao Su et al.

3D DL architectures: *Point-based approach*

Points in Metric Space

- Learn “kernels” in 3D space and conduct convolution
- Kernels have compact spatial support
- For convolution, we need to find neighboring points
- Possible strategies for range query
  - Ball query (results in more stable features)
  - k-NN query (faster)

Hao Su et al.

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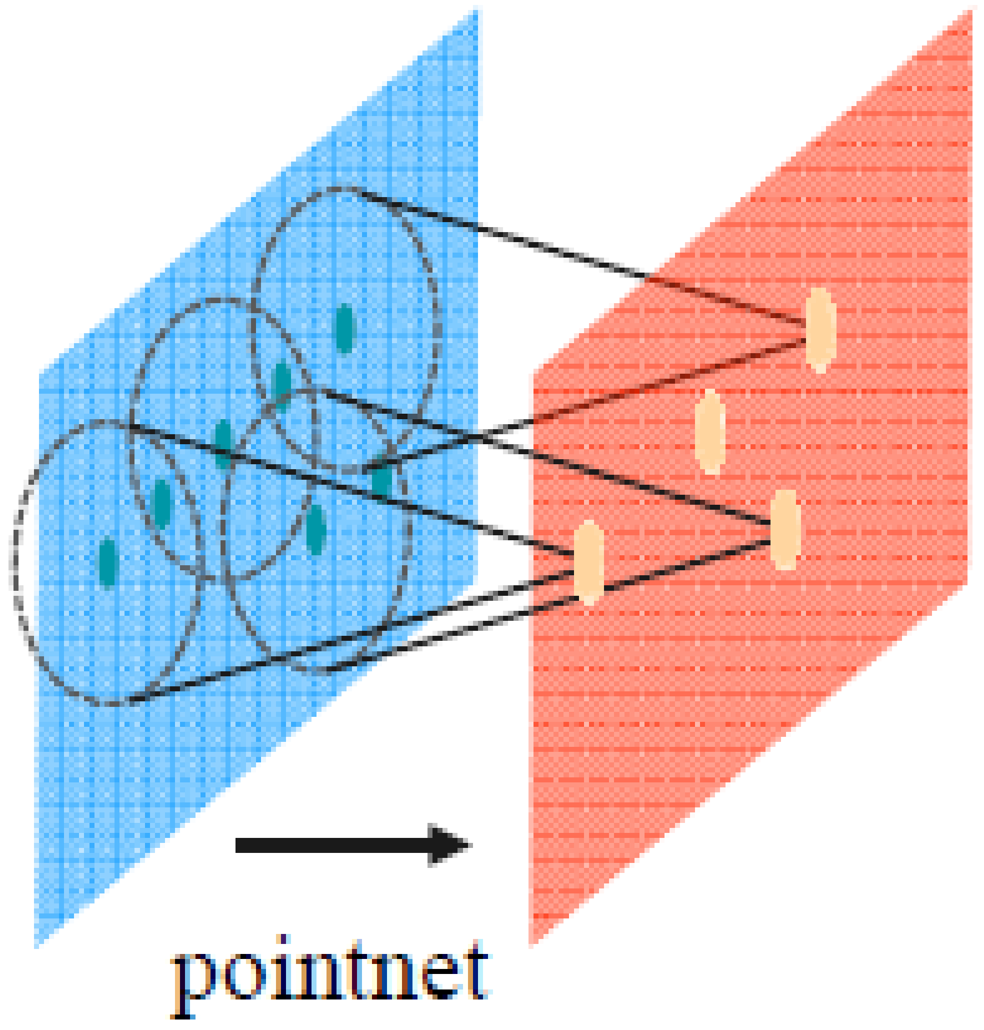
3D DL architectures: *Point-based approach*

PointNet++: (Qi et al., NIPS 2017)

- Use PointNet in local regions
- Aggregate local features by PointNet again

–> **Hierarchical feature learning**



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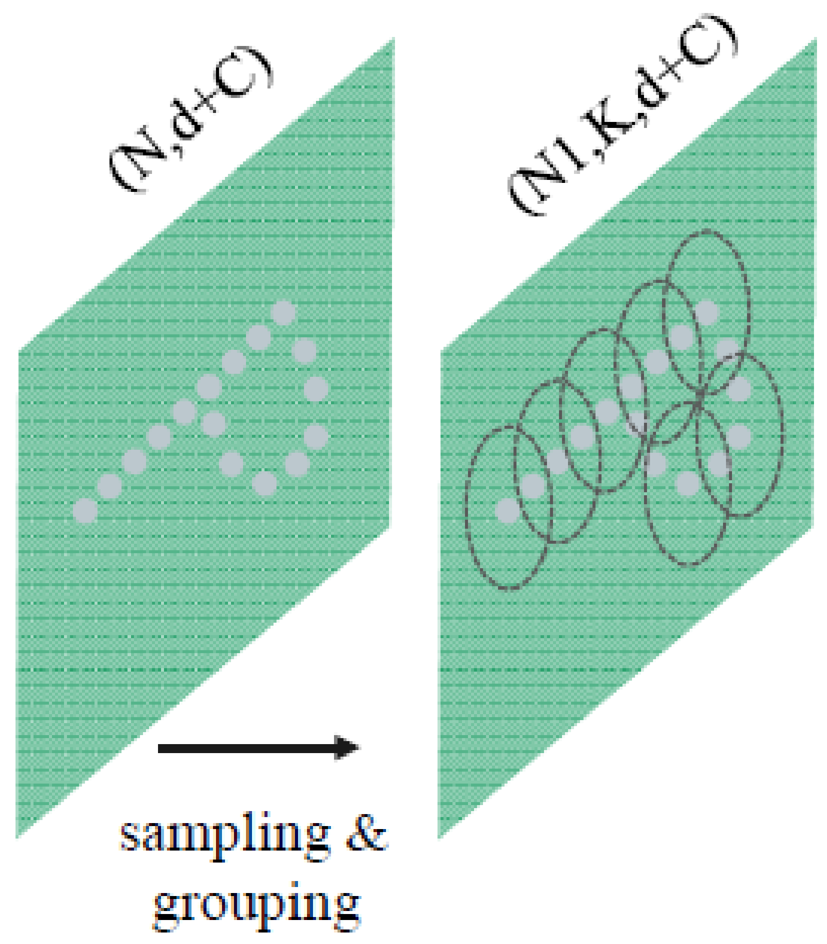
3D DL architectures: *Point-based approach*

PointNet++:

- **Sampling**: Farthest Point Sampling (FPS)
- **Grouping**: Radius-based ball query



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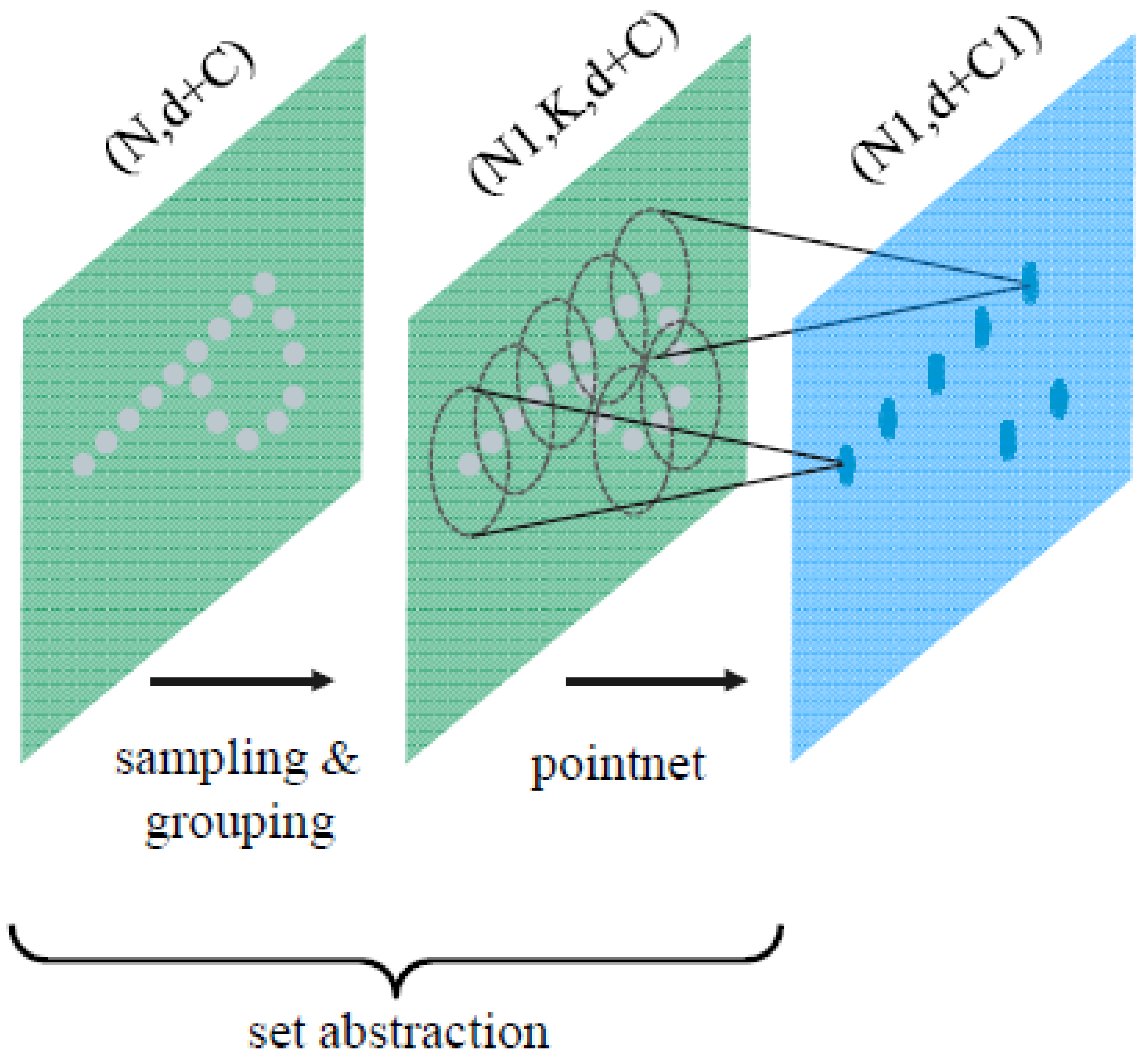
3D DL architectures: *Point-based approach*

PointNet++:

- Shared PointNet applied in each local region using local coordinates

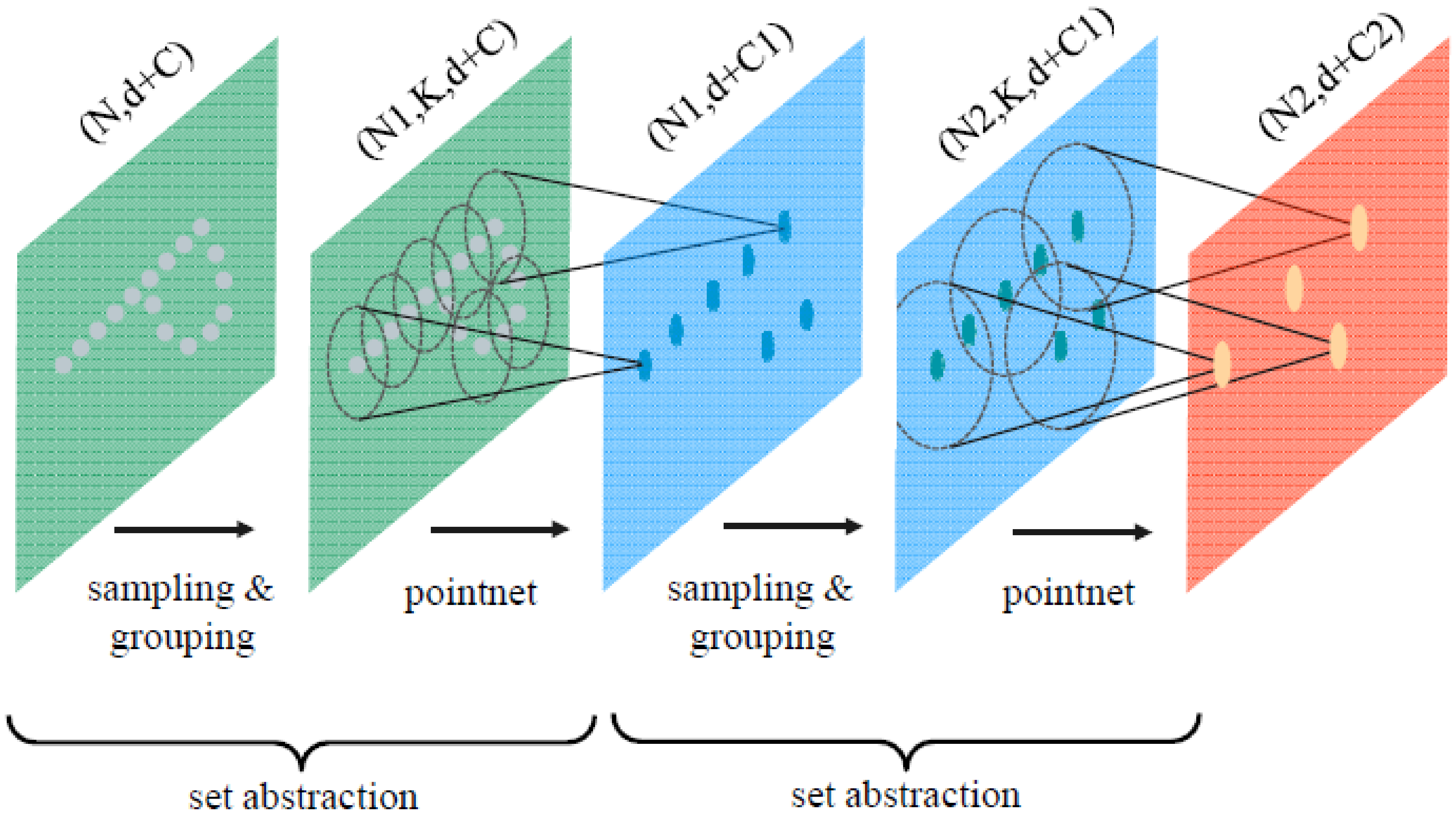


Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet++:

- Shared PointNet applied in each local region using local coordinates



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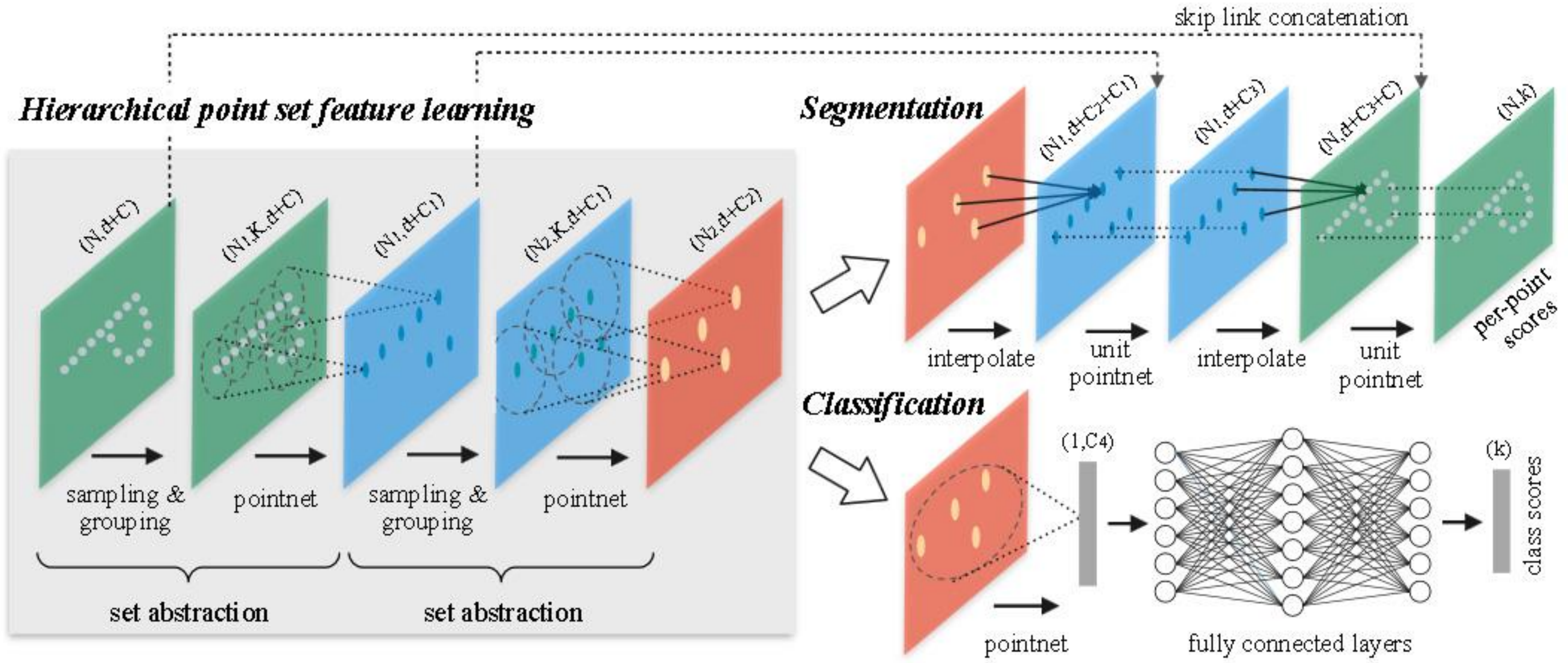
3D DL architectures: *Point-based approach*

PointNet++ architecture

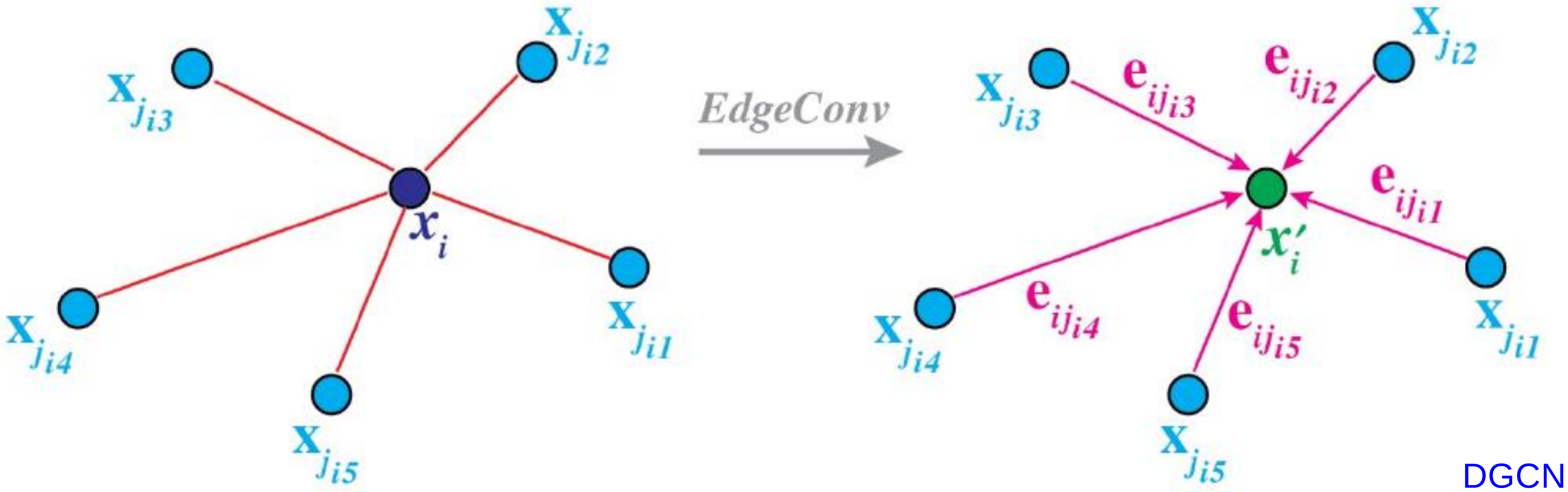


Qi et al., NIPS 2017

3D DL architectures: *Point-based approach*

Point Convolution as Graph Convolution: **Dynamic Graph CNN**

- Points –> Nodes
- Neighborhood –> Edges
- Graph CNN for point cloud processing

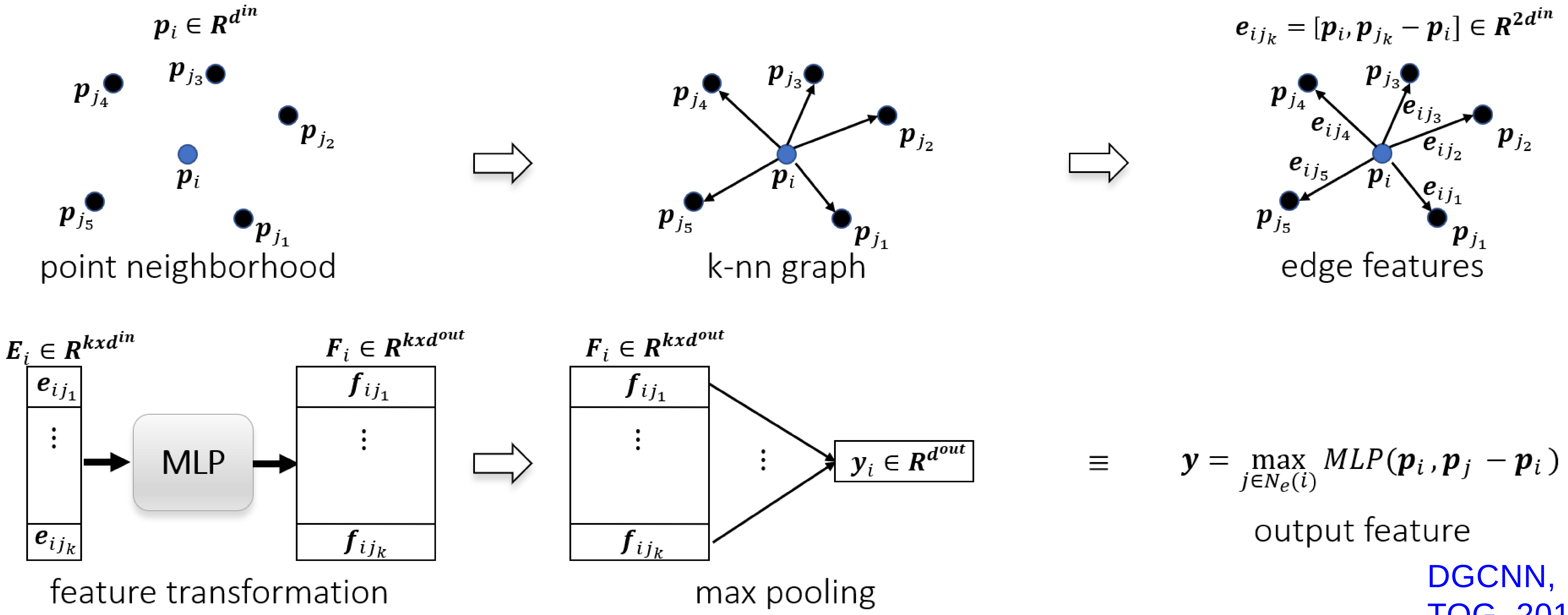


DGCNN, Wang et al., TOG, 2019

3D DL architectures: *Point-based approach*

Dynamic Graph CNN

- **EdgeConv Layer**

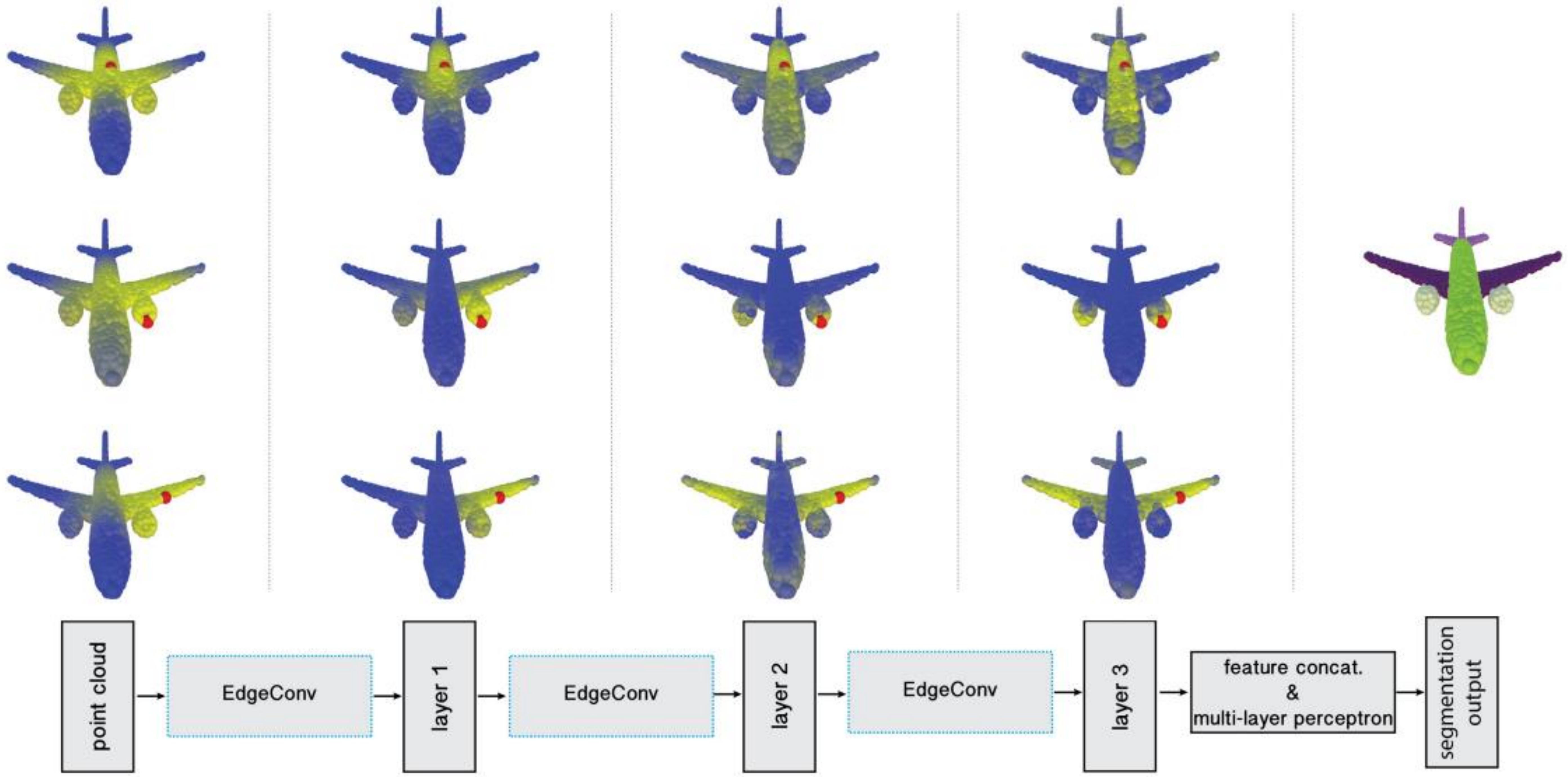


DGCNN, Wang et al., TOG, 2019

3D DL architectures: *Point-based approach*

Dynamic Graph CNN:

- At each layer, each local graph is rebuilt upon the feature space of the previous EdgeConv layer



DGCNN, Wang et al., TOG, 2019

3D DL architectures: *Point-based approach*

Standard GCNs are not Geometry Aware:

- Note that points are **sampled** from surfaces
- Ideally, features describe the geometry of the underlying surface
- Should be **sample invariant**
- But GCNs lack design to address sample invariance
- **Solution**: Estimate the continuous kernel and point density for continuous convolution

Hao Su et al.

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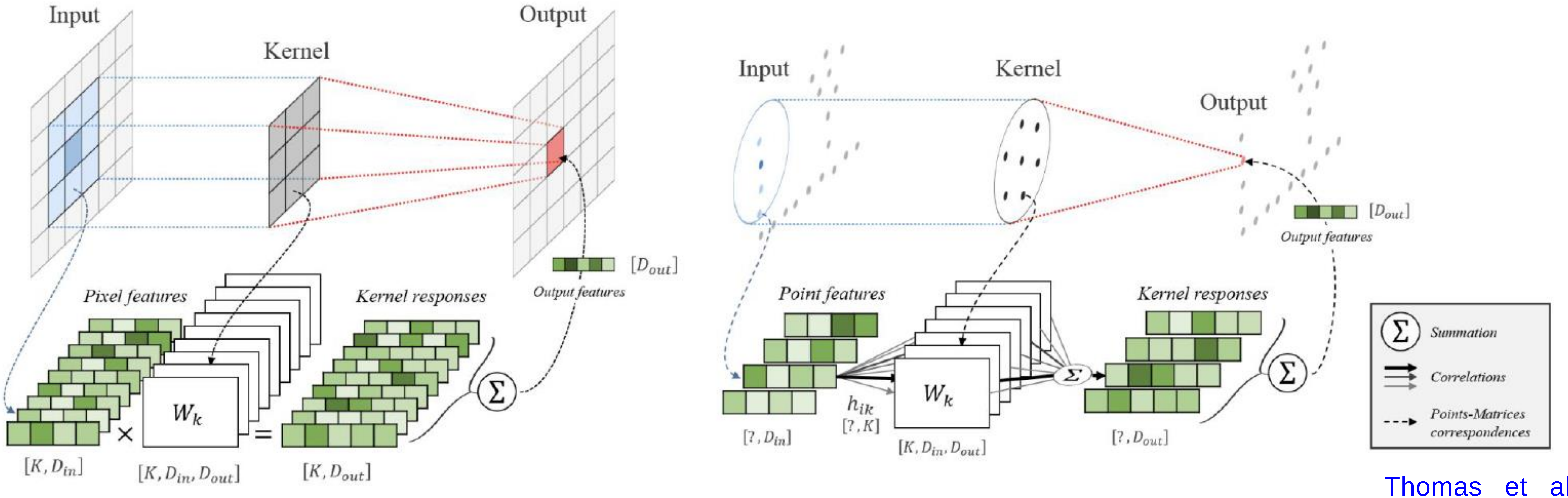
3D DL architectures: *Point-based approach*

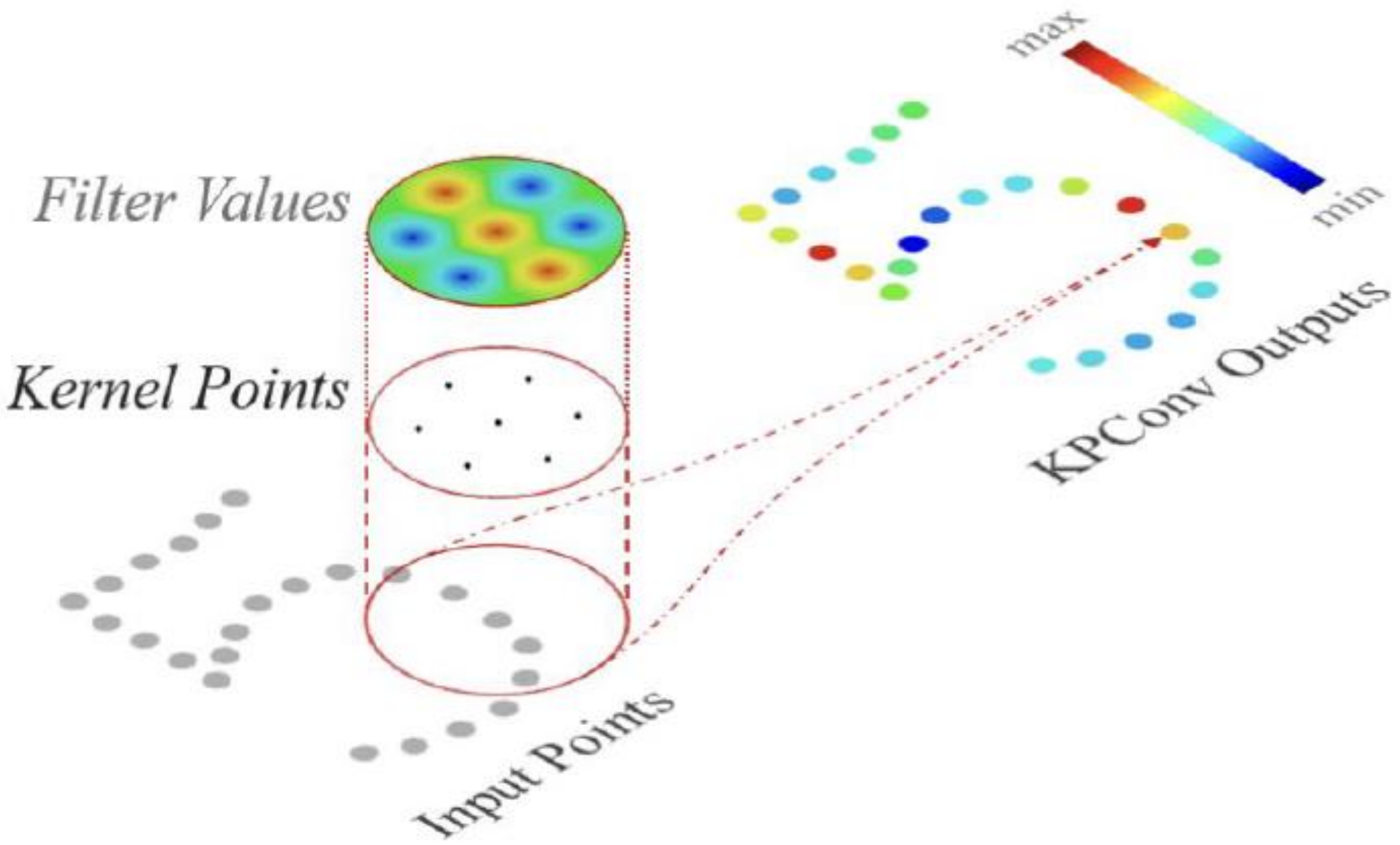
Kernel Point Convolution (KPConv)



Thomas et al., ICCV, 2019

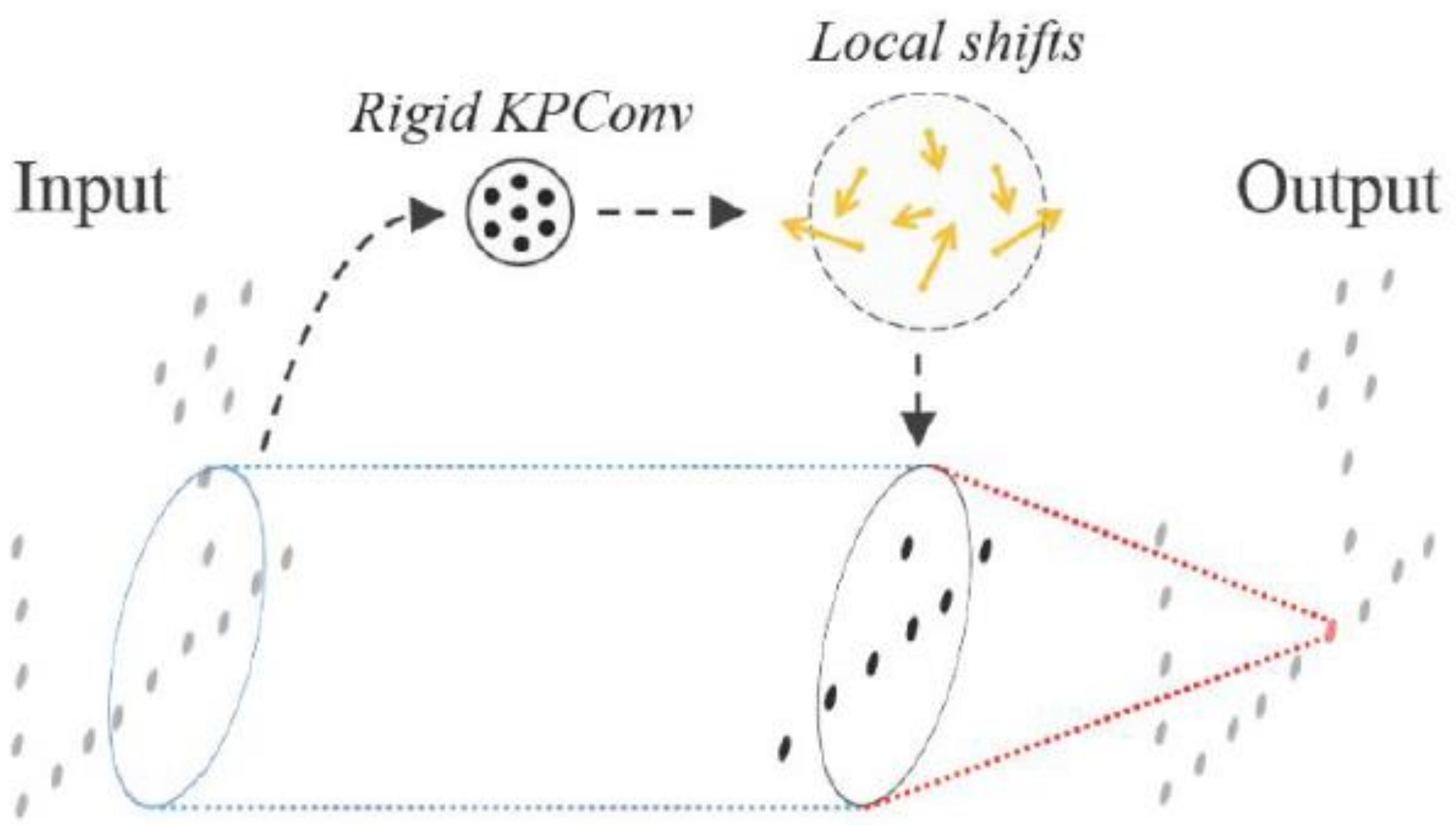
3D DL architectures: *Point-based approach*

Kernel Point Convolution (KPConv)



Deformable point-based kernel

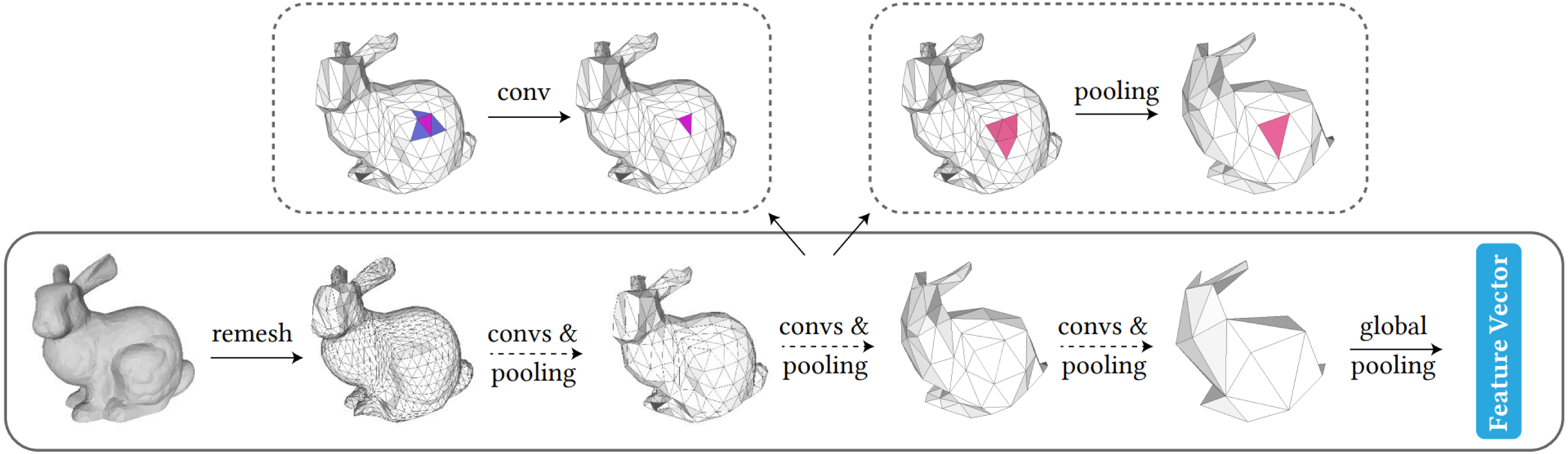
- 3D version of 2D deformable convolution



Hao Su et al.

3D DL architectures: *Mesh-based approach*

Subdivision-Based Mesh Convolution Networks (SubdivNet)

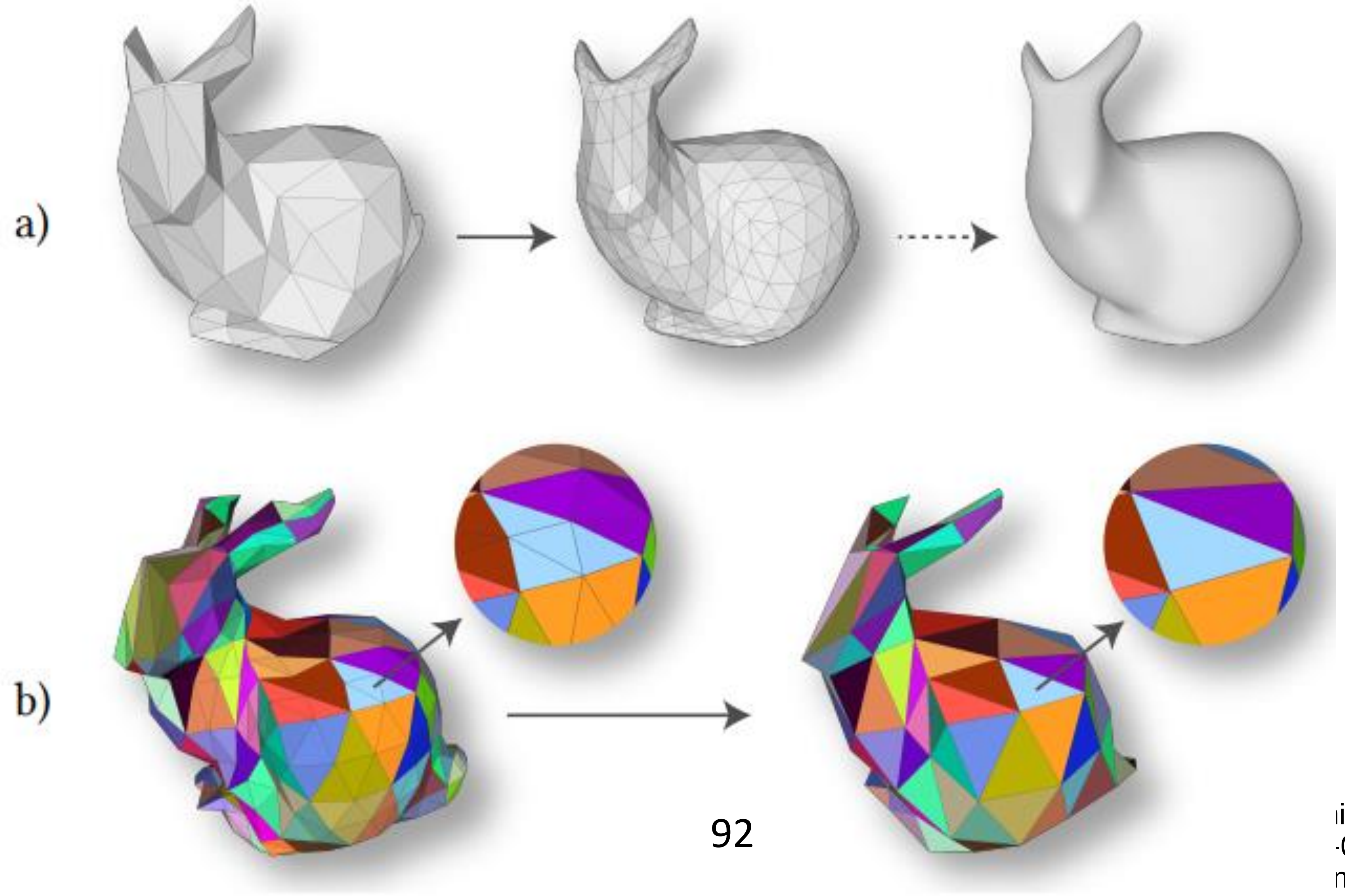


Shi-Min Hu et al., TOG, 2021

3D DL architectures: *Mesh-based approach*

SubdivNet:

- A **subdivision surface** provides a h**ierarchical multi-resolution structure**, in which **each face** in a **closed triangle** mesh is exactly **adjacent to three faces**



Shi-Min Hu et al., TOG, 2021

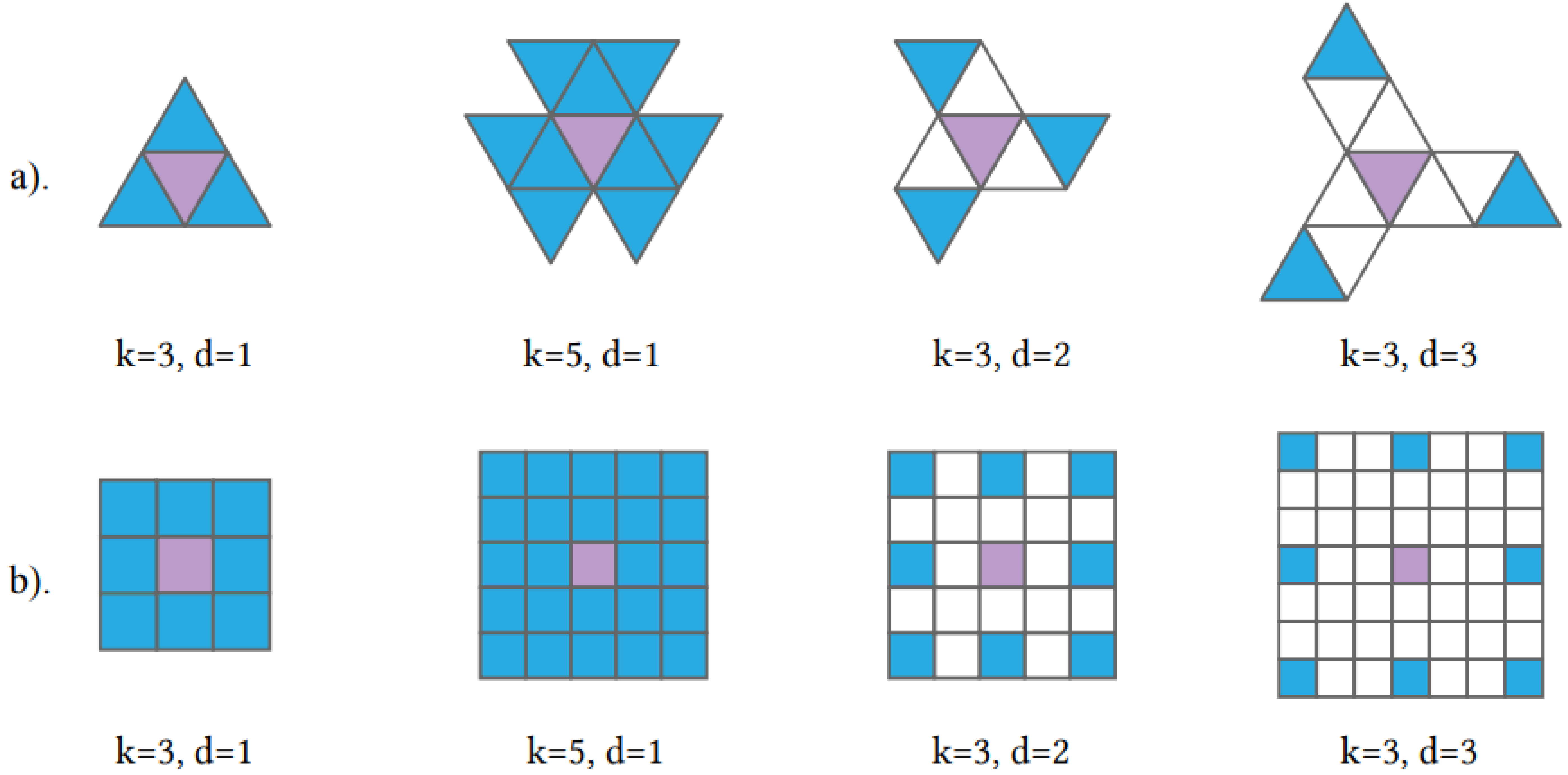
3D DL architectures: *Mesh-based approach*

SubdivNet:

- Can support **mesh convolution**

Mesh conv. kernels

2D conv. kernels

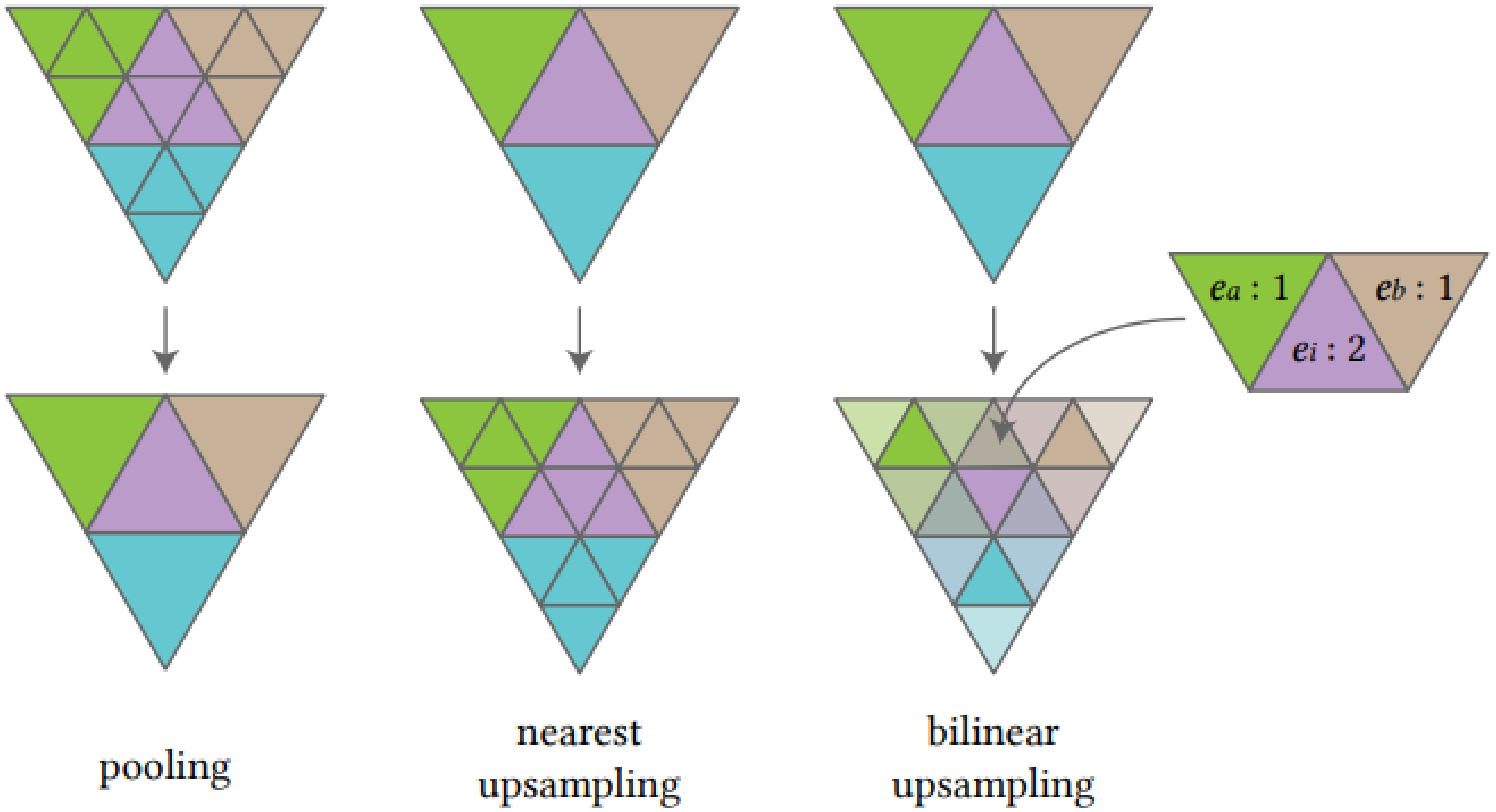


Shi-Min Hu et al., TOG, 2021

3D DL architectures: *Mesh-based approach*

SubdivNet:

- Can support **pooling** and **upsampling**



Shi-Min Hu et al., TOG, 2021

Today's Agenda

- Who are we?
- What is 3D Vision
- 3D shape representations
- 3D shape datasets
- 3D Deep Learning architectures
- What we do

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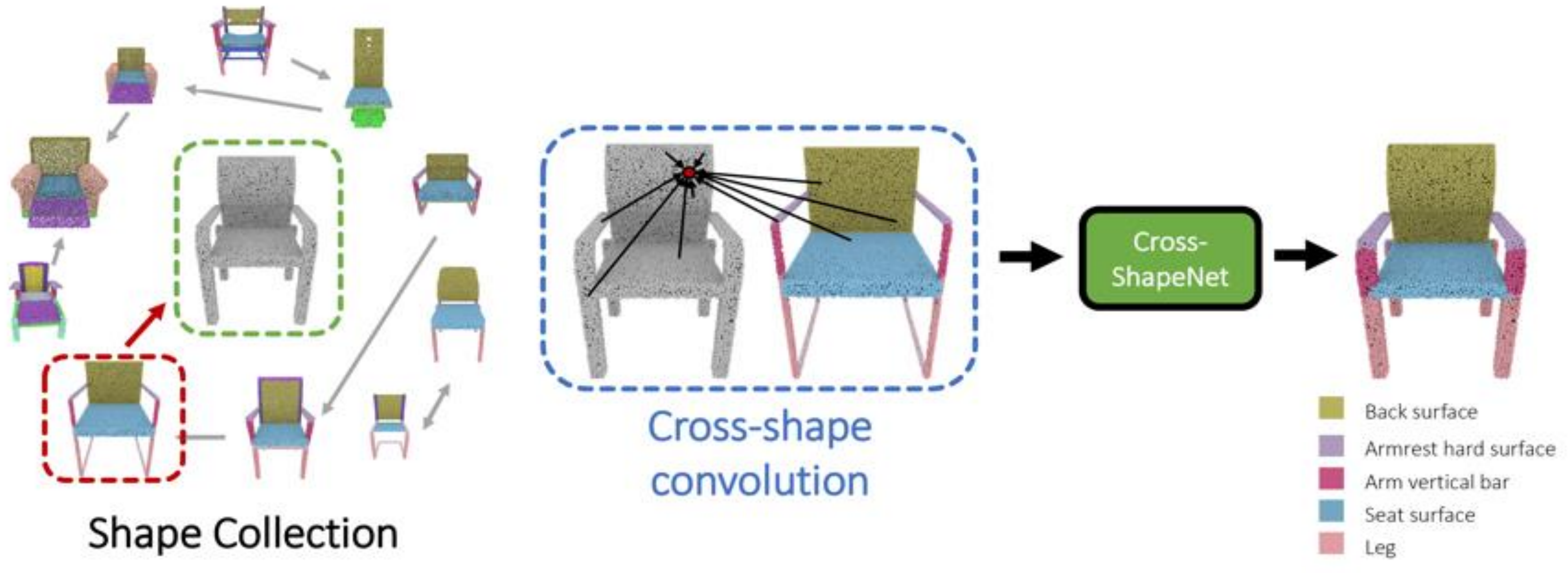
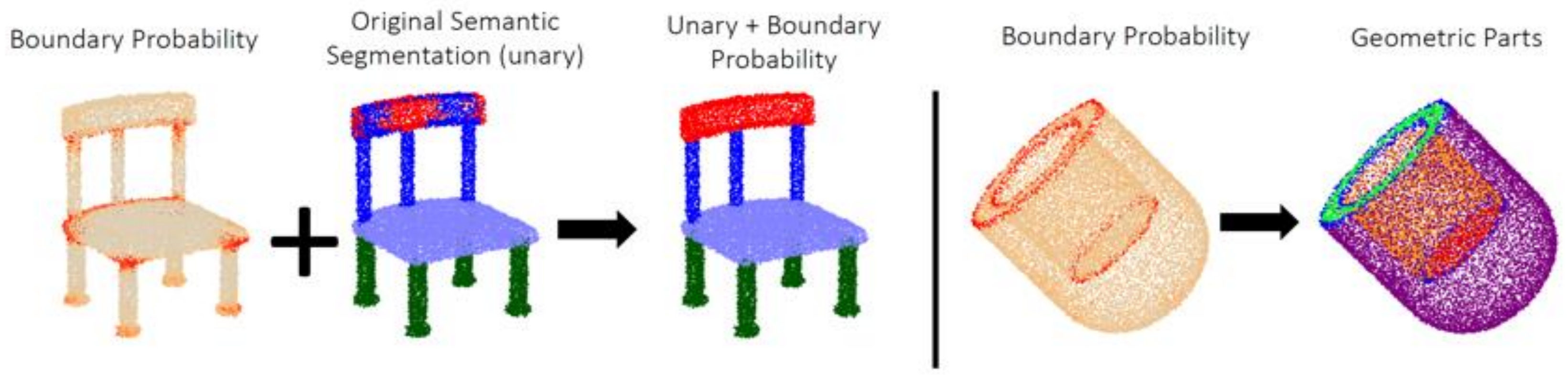
What we do: *3D shape understanding*

3D Building Semantic Understanding

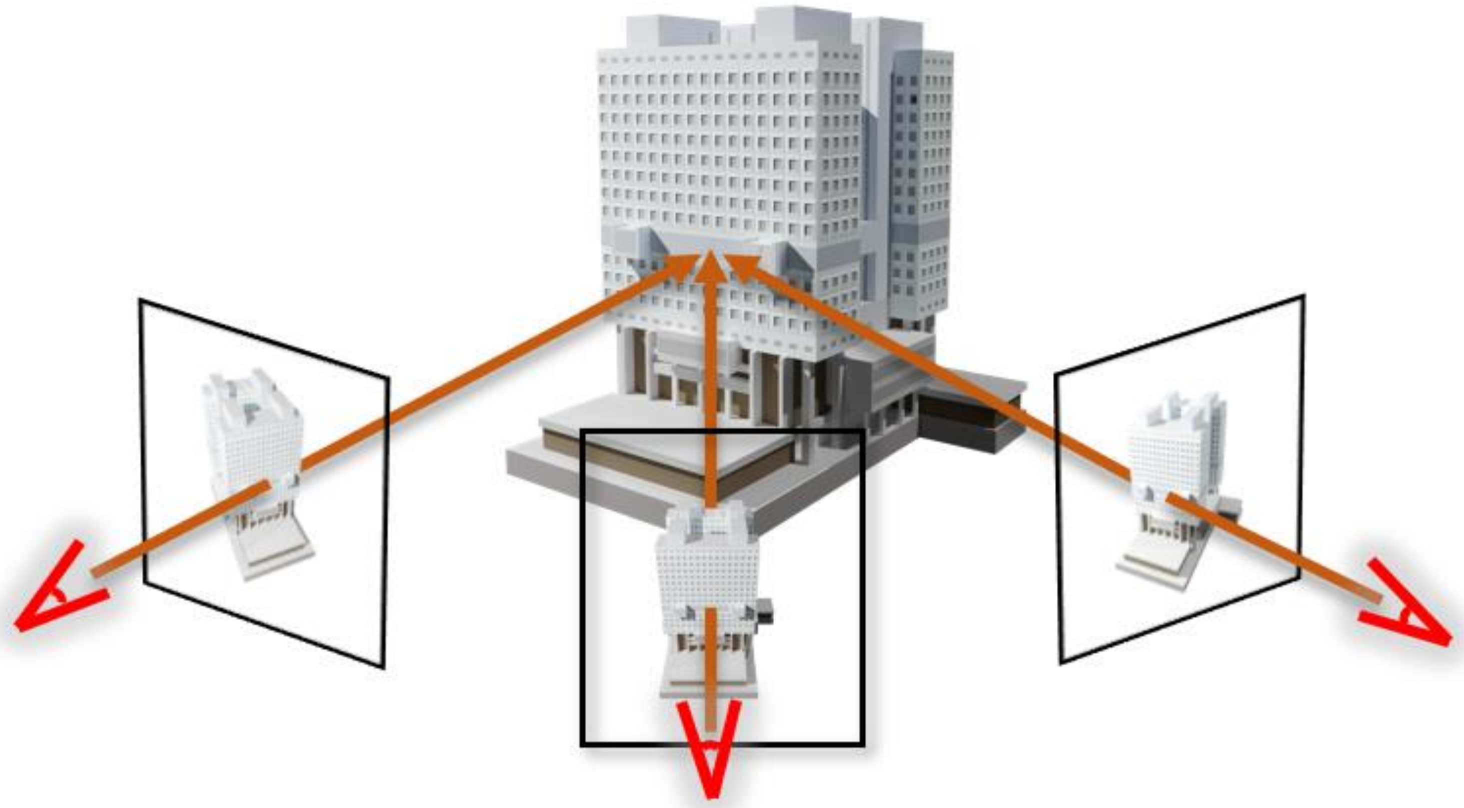
Cross-shape semantic segmentation



Geometric/Semantic Decomposition

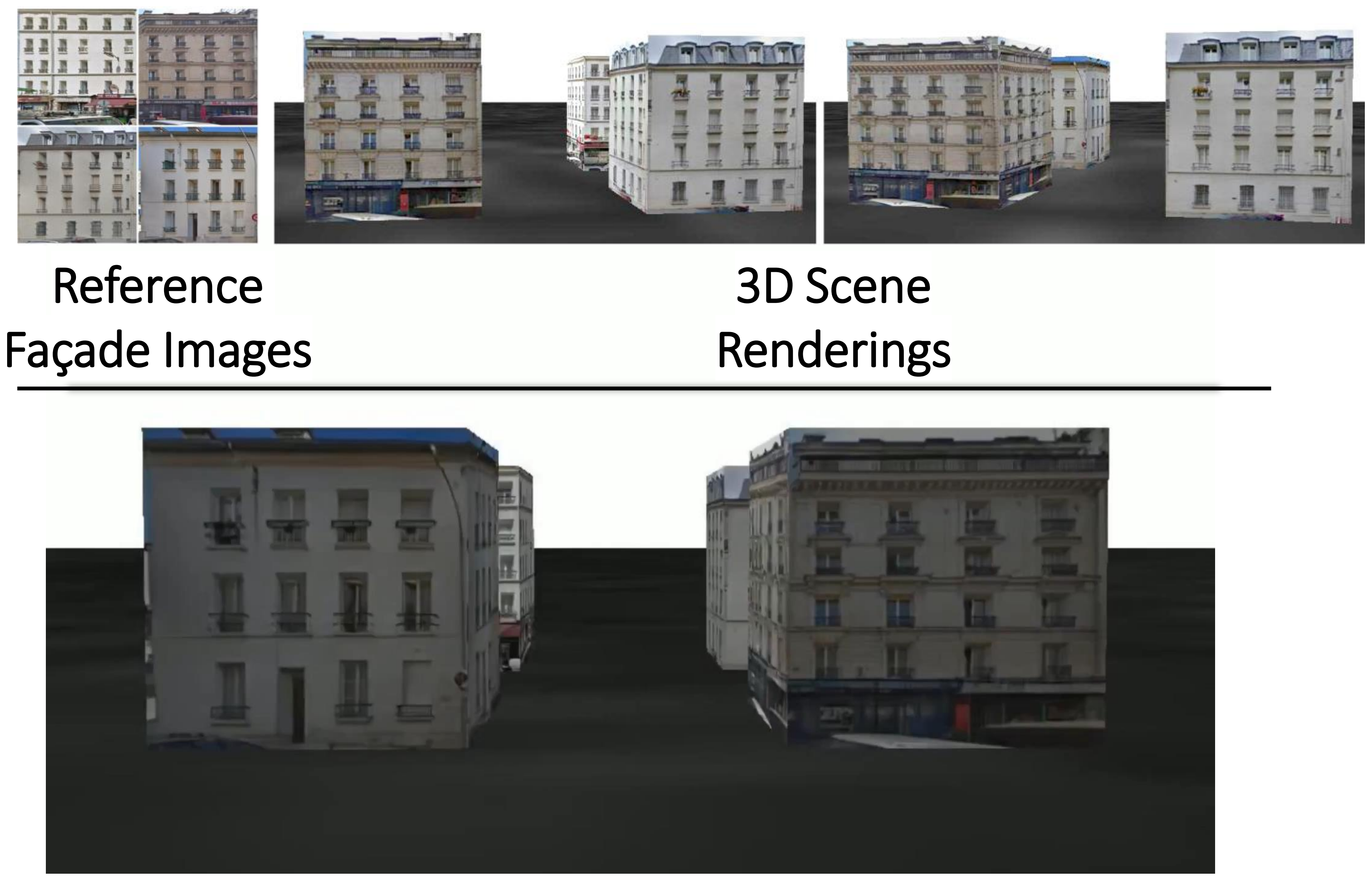


Neural 3D Reconstruction

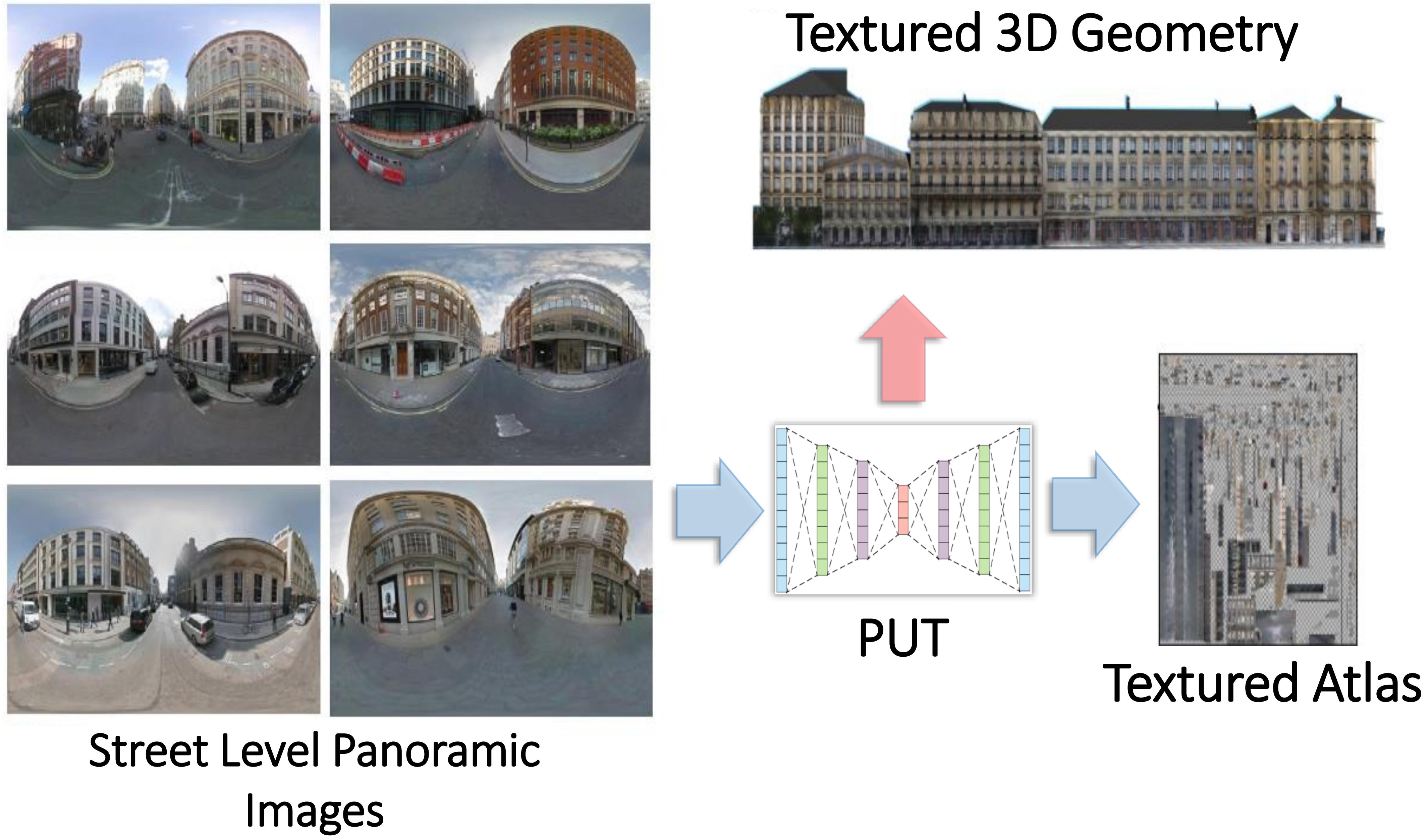


What we do: *Texture Generation for 3D Data*

Single-View Guided Façade Synthesis

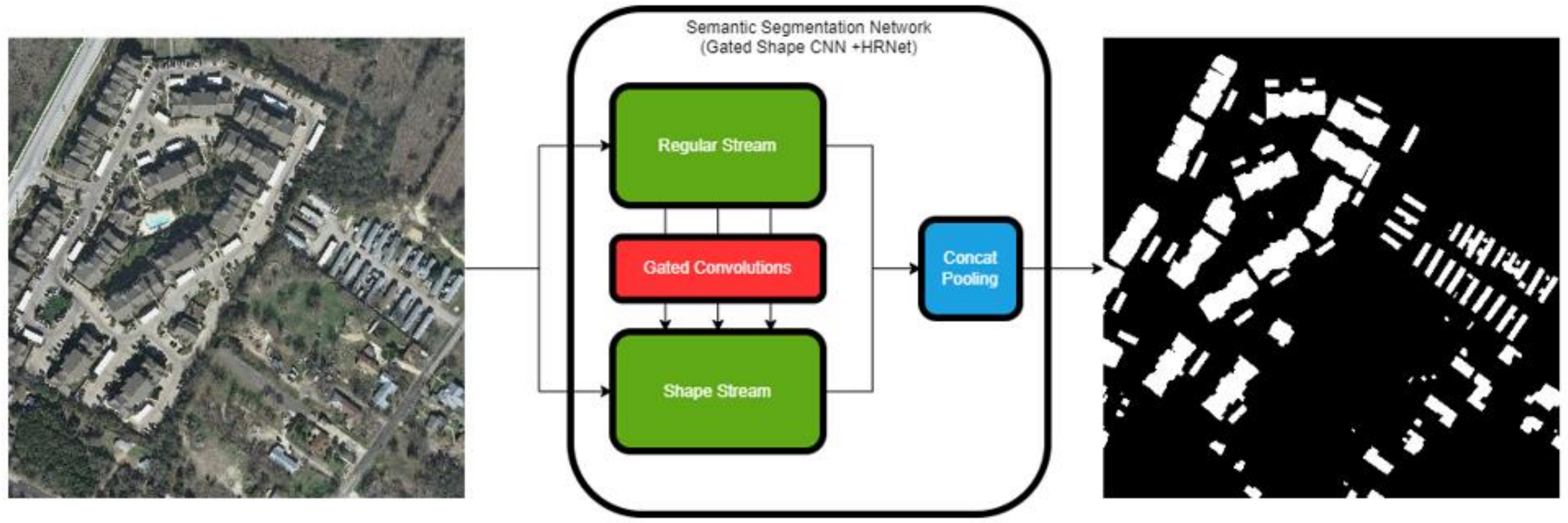


Projective Urban Texturing

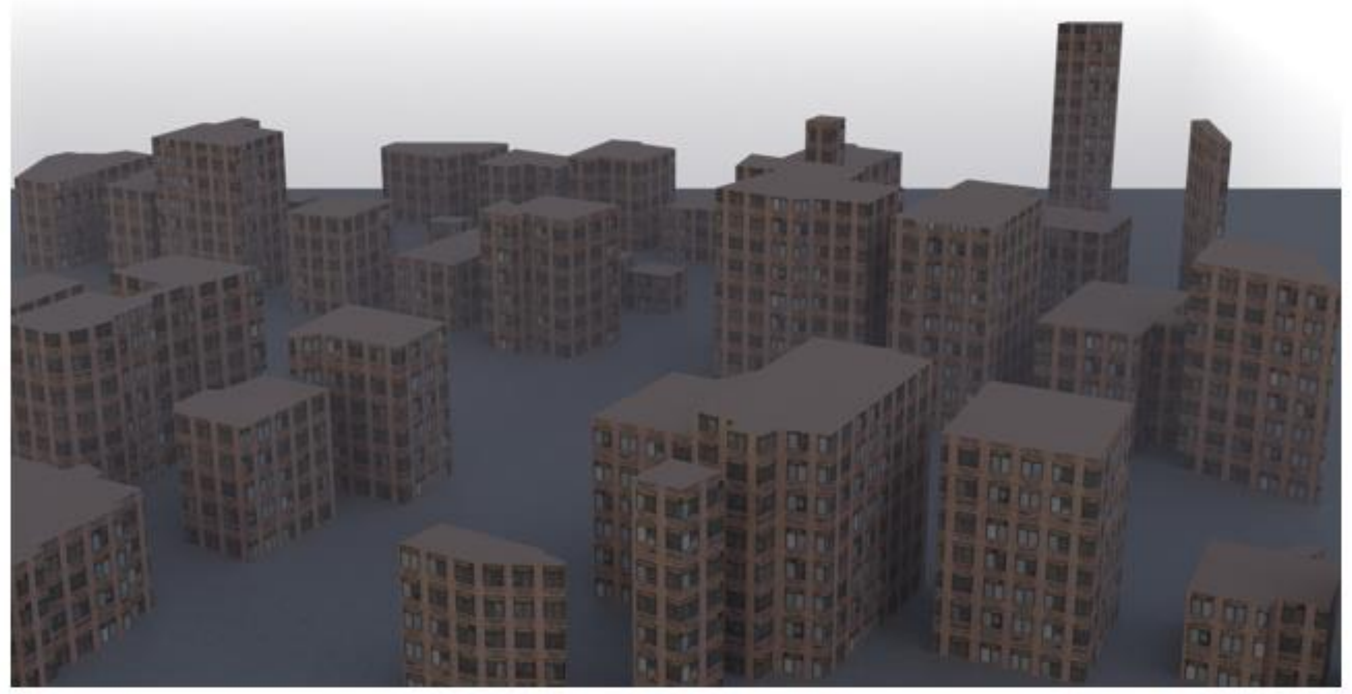


What we do: *Urban Semantic Understanding from Remote Sensing Data Sources*

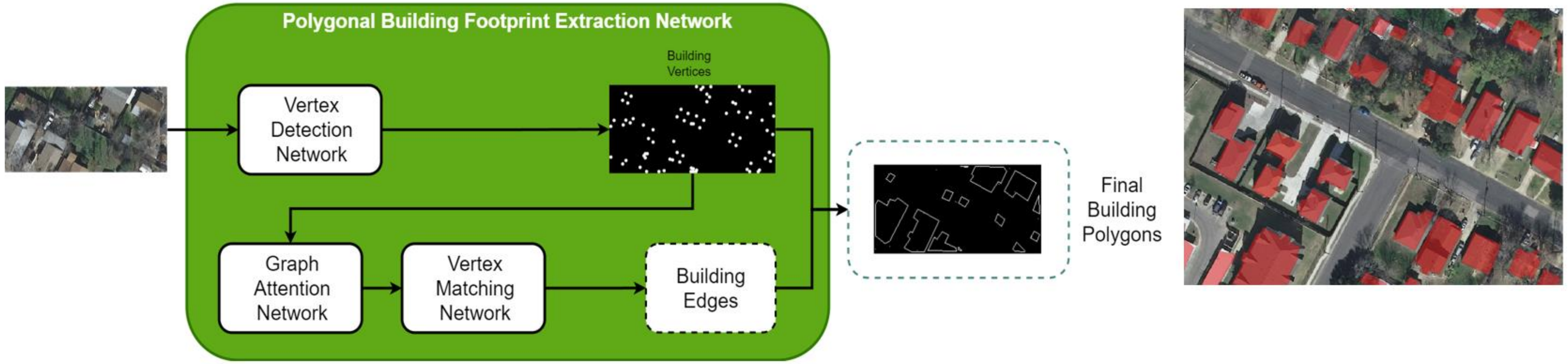
Semantic Segmentation of Buildings



Urban 3D Reconstruction



Building Footprint Extraction



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Research in Visual Computing

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VCG

CYENS
CENTRE OF EXCELLENCE

Research Interests:

Geometry processing, acquisition, understanding and modeling of 3D geometry, deep learning for 3D objects, including part segmentation, material identification and style detection.

https://www.cyens.org.cy/en-gb/research/pillars-groups/visual-sciences/deep-camera/people/alessandro-artusi/

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Thank you!

See you next week

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