

MAI4CAREU

Master programmes in Artificial
Intelligence 4 Careers in Europe



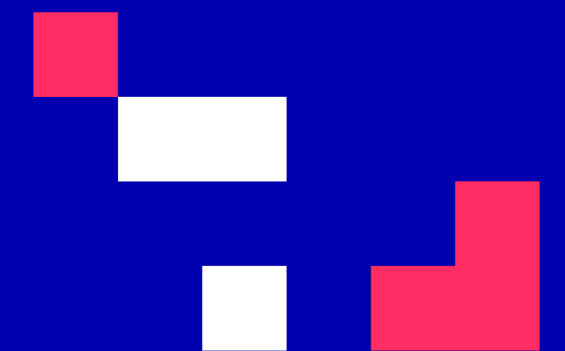
University
of Cyprus

University of Cyprus

MAI645 - Machine Learning for Graphics and Computer Vision

Marios Loizou, PhD

Spring Semester 2025



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

3D Vision

Notes have been prepared by **Dr. Marios Loizou**
Research Associate at Visual Computing Group at
CYENS Centre of Excellence





Today's Agenda

- Who are we?
- What is 3D Vision
- Geometry
- 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



Today's Agenda

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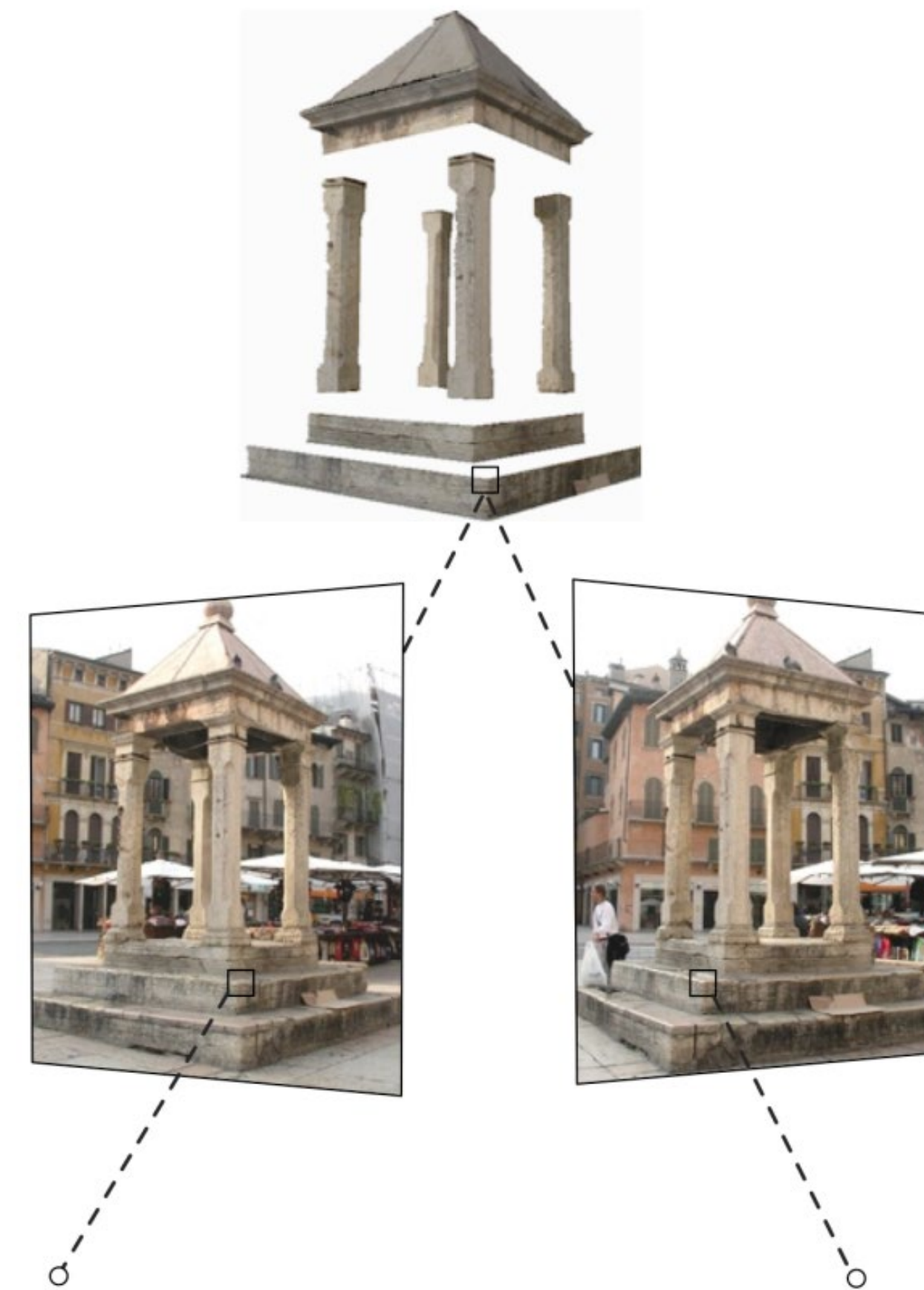
What is 3D Vision: *Overview*

- **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

What is 3D Vision: *Overview*

Traditional 3D Vision

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

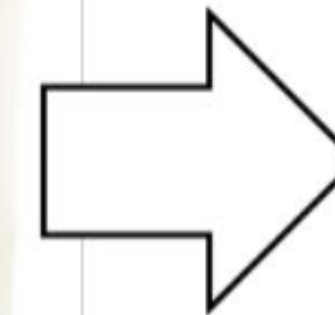


Hao Su et al.

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)*

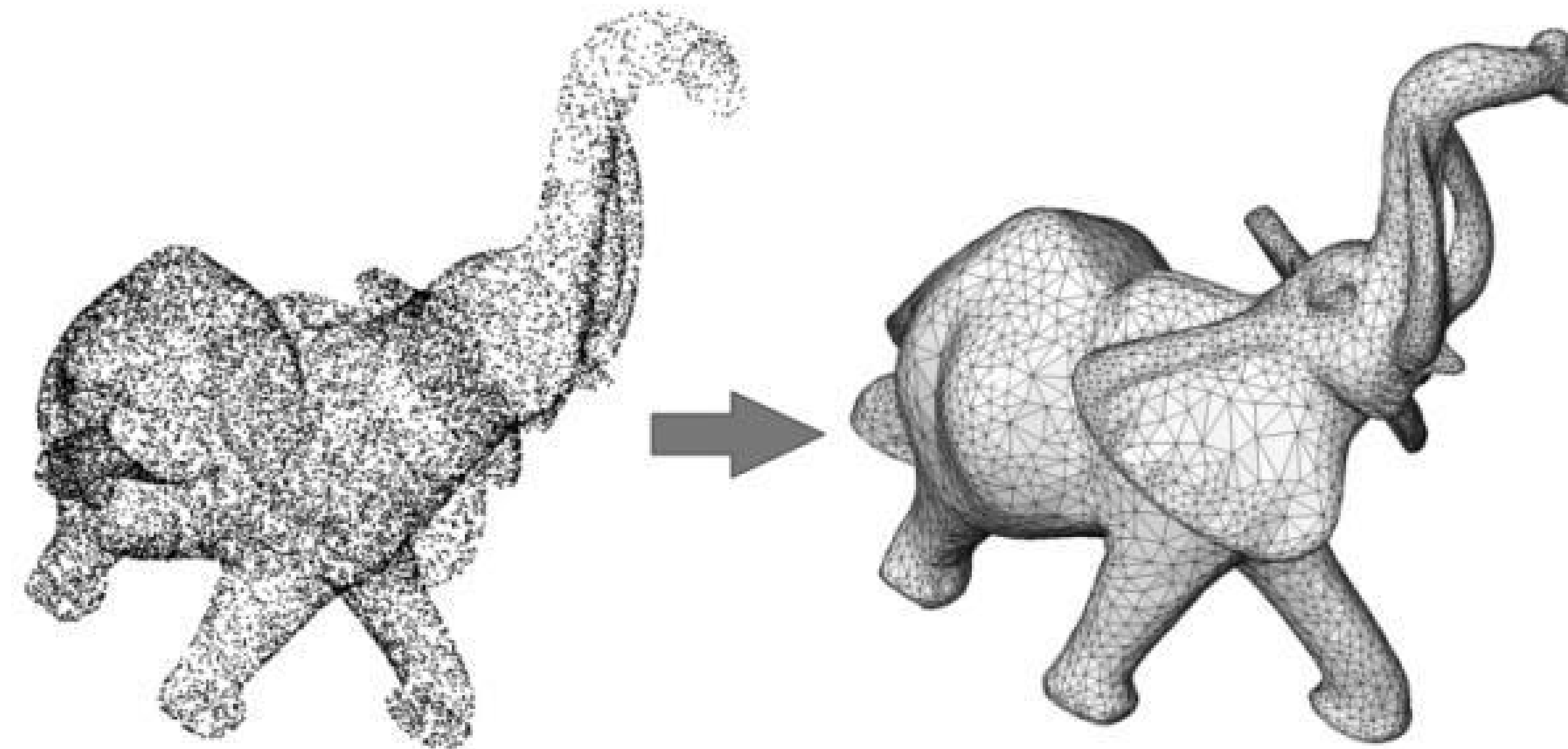
Indoor Scene Segmentation



ScanNet,
Angela Dai et al.

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

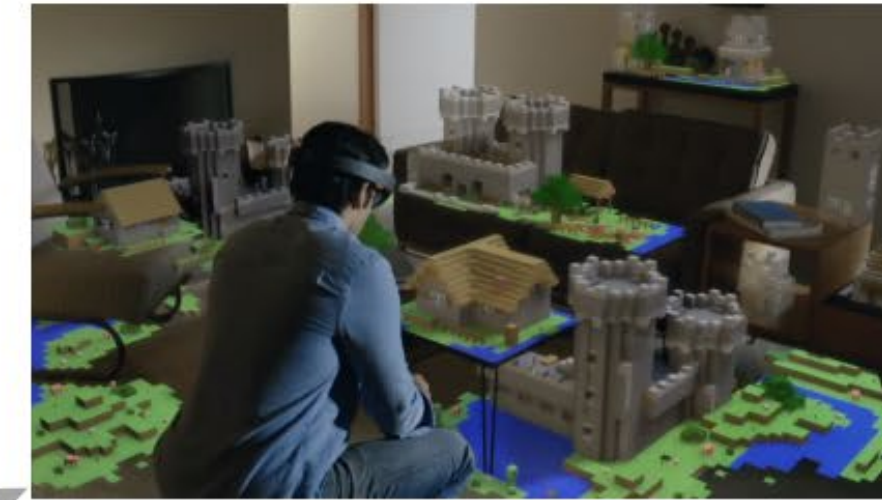
Surface reconstruction



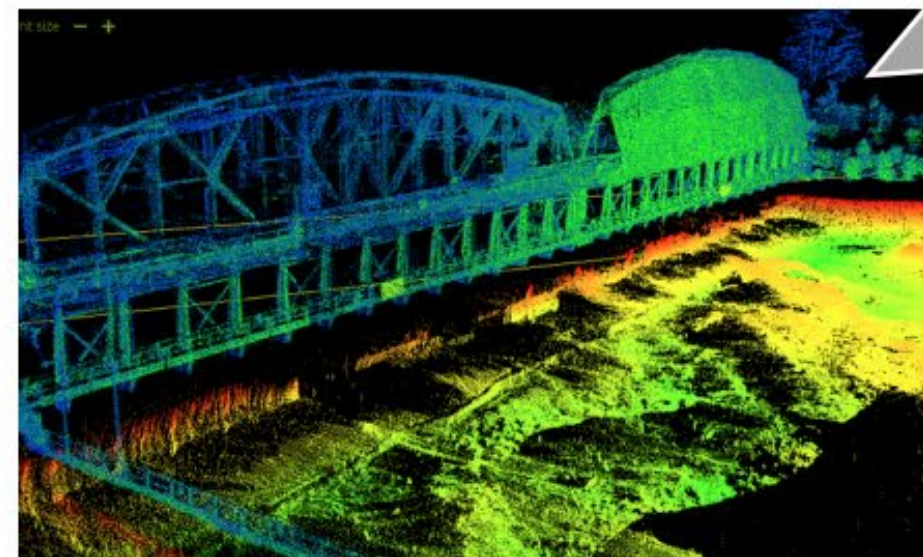
What is 3D Vision: *Applications*



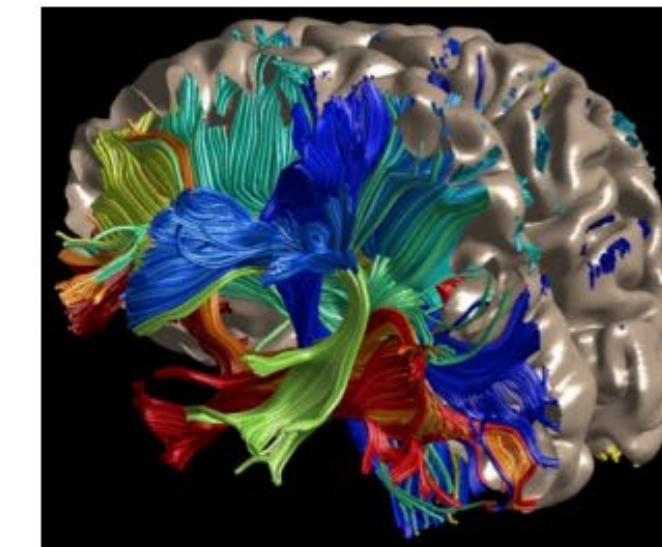
Robotics



Augmented Reality



Autonomous driving



Medical Image Processing

Hao Su et al.



Today's Agenda

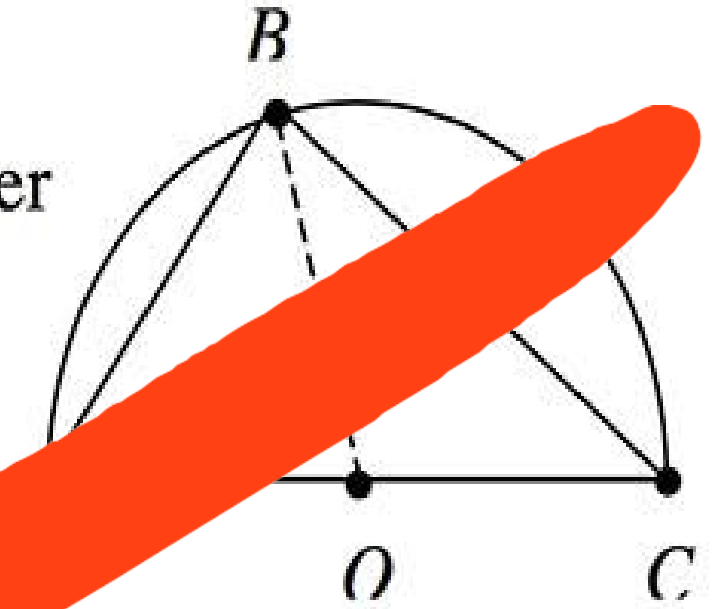
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Geometry: Definition

Geometry is the study of two-column proofs

THEOREM 9.5. Let ΔABC be inscribed in a semicircle with diameter \overline{AC} . Then $\angle ABC$ is a right angle.



Proof:

Ceci n'est pas géométrie!

Statement

1. Draw radius OB . Then $OB = OC = OA$
2. $m\angle OBC = m\angle BCA$
 $m\angle OBA = m\angle BAC$
3. $m\angle ABC = m\angle OBA + m\angle OBC$
4. $m\angle ABC + m\angle BCA + m\angle BAC = 180$
5. $m\angle ABC + m\angle OBA + m\angle OBC = 180$
6. $2m\angle ABC = 180$
7. $m\angle ABC = 90$
8. $\angle ABC$ is a right angle

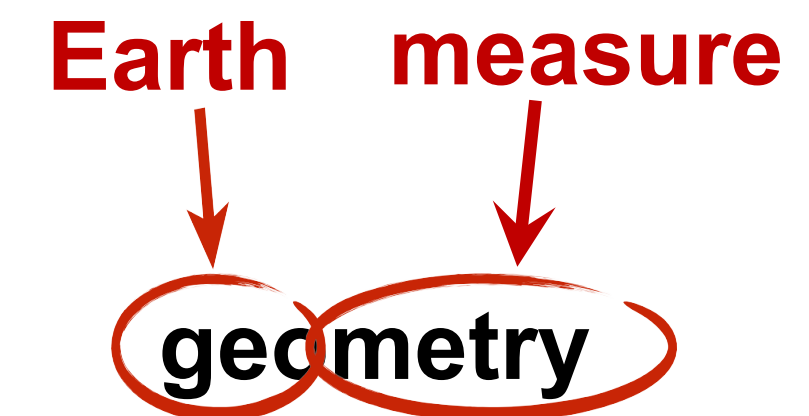
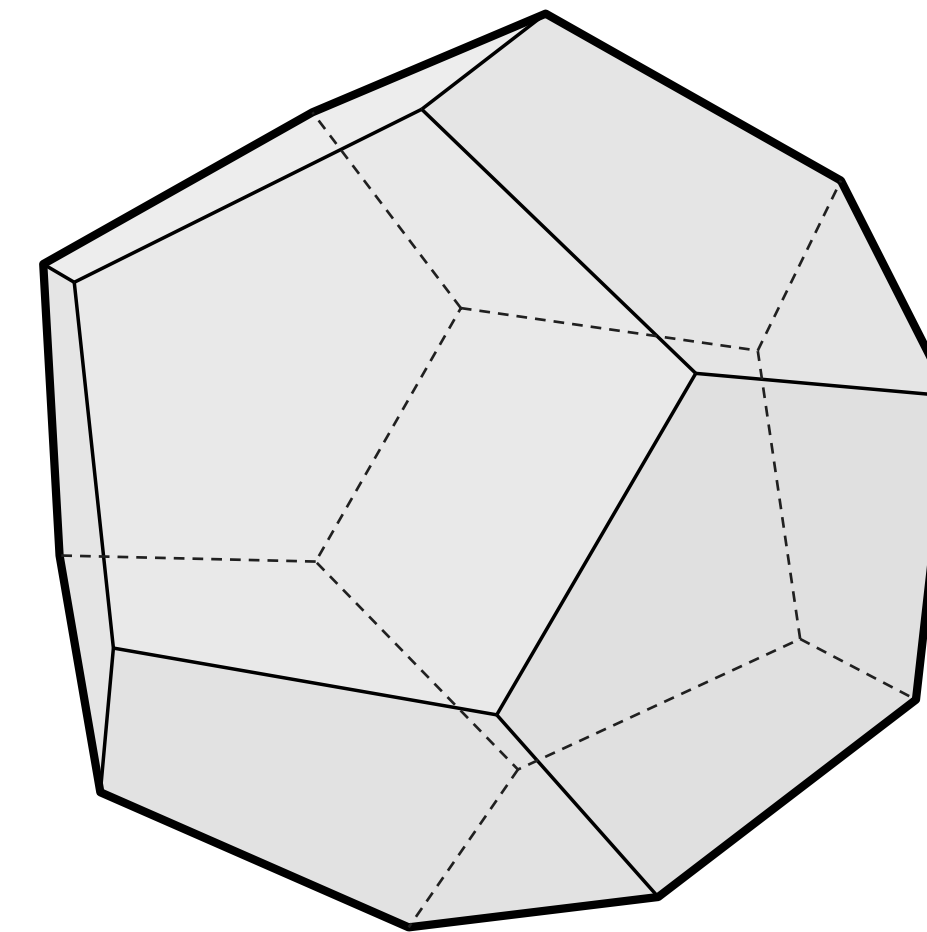
Reason

1. Given
2. Isosceles Triangle Theorem
3. Angle Addition Postulate
4. The sum of the angles of a triangle is 180
5. Substitution (line 2)
6. Substitution (line 3)
7. Division Property of Equality
8. Definition of Right Angle

Keenan Crane

Geometry: *Definition*

1. The study of **shapes**, sizes, patterns and positions
2. The study of **spaces** where some quantity can be measured



Plato «... the earth is in appearance like one of those balls which have leather coverings in twelve pieces...»

Keenan Crane

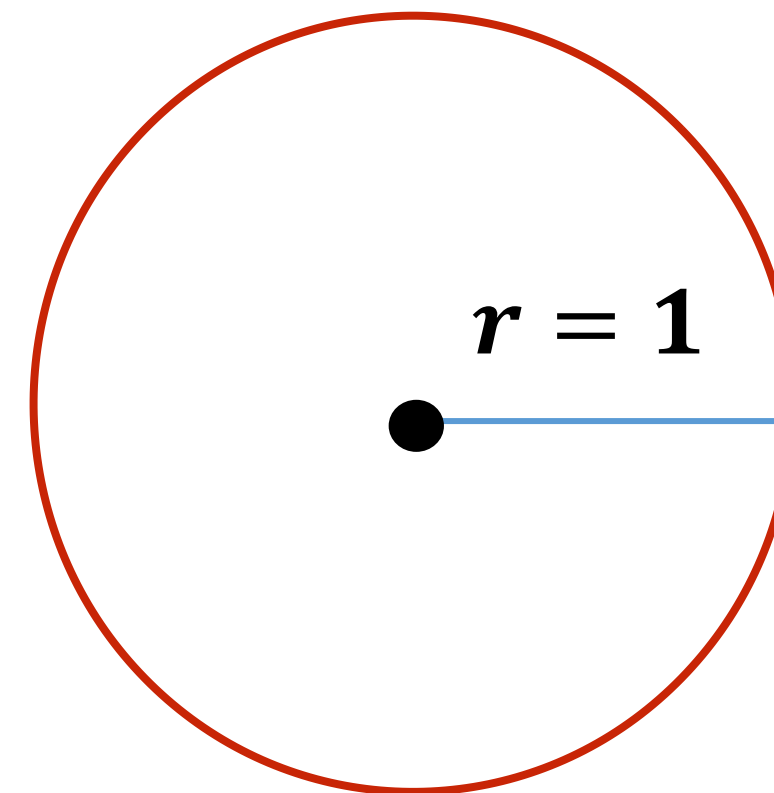
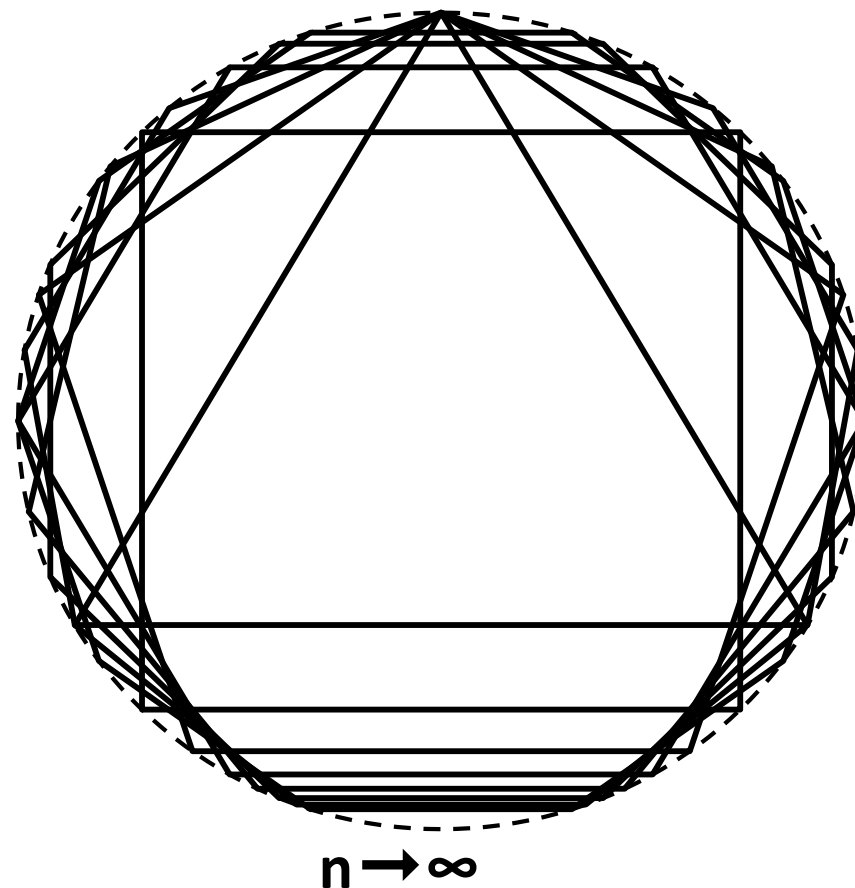
Geometry: *How to encode geometry?*

IMPLICIT
 $x^2 + y^2 = 1$

LINGUISTIC
 "unit circle"

EXPLICIT
 $(\cos\theta, \sin\theta)$

DISCRETE



Given all these options, what's the **best** way to encode geometry on a computer?

Keenan Crane

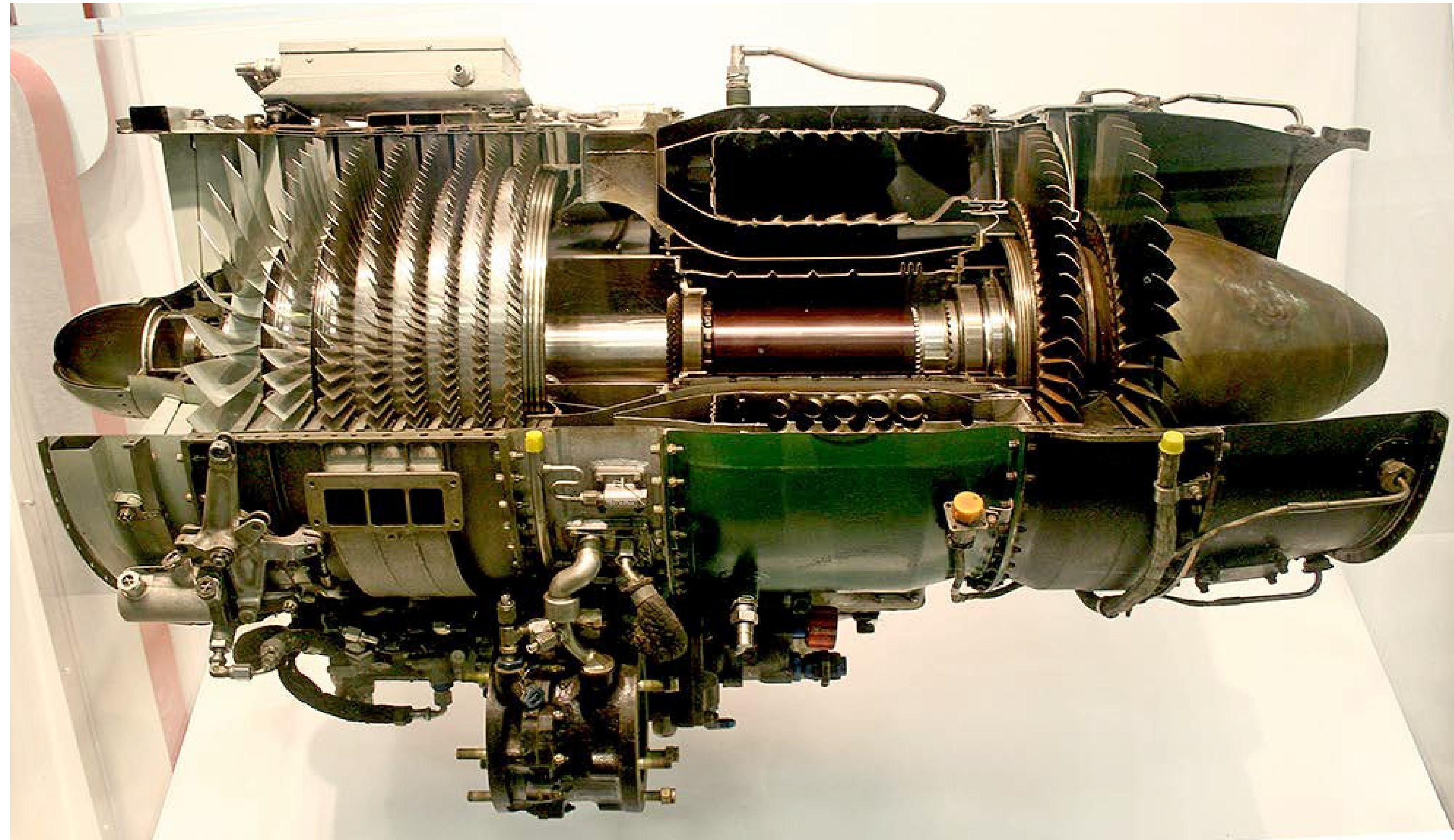


Geometry: *Examples*



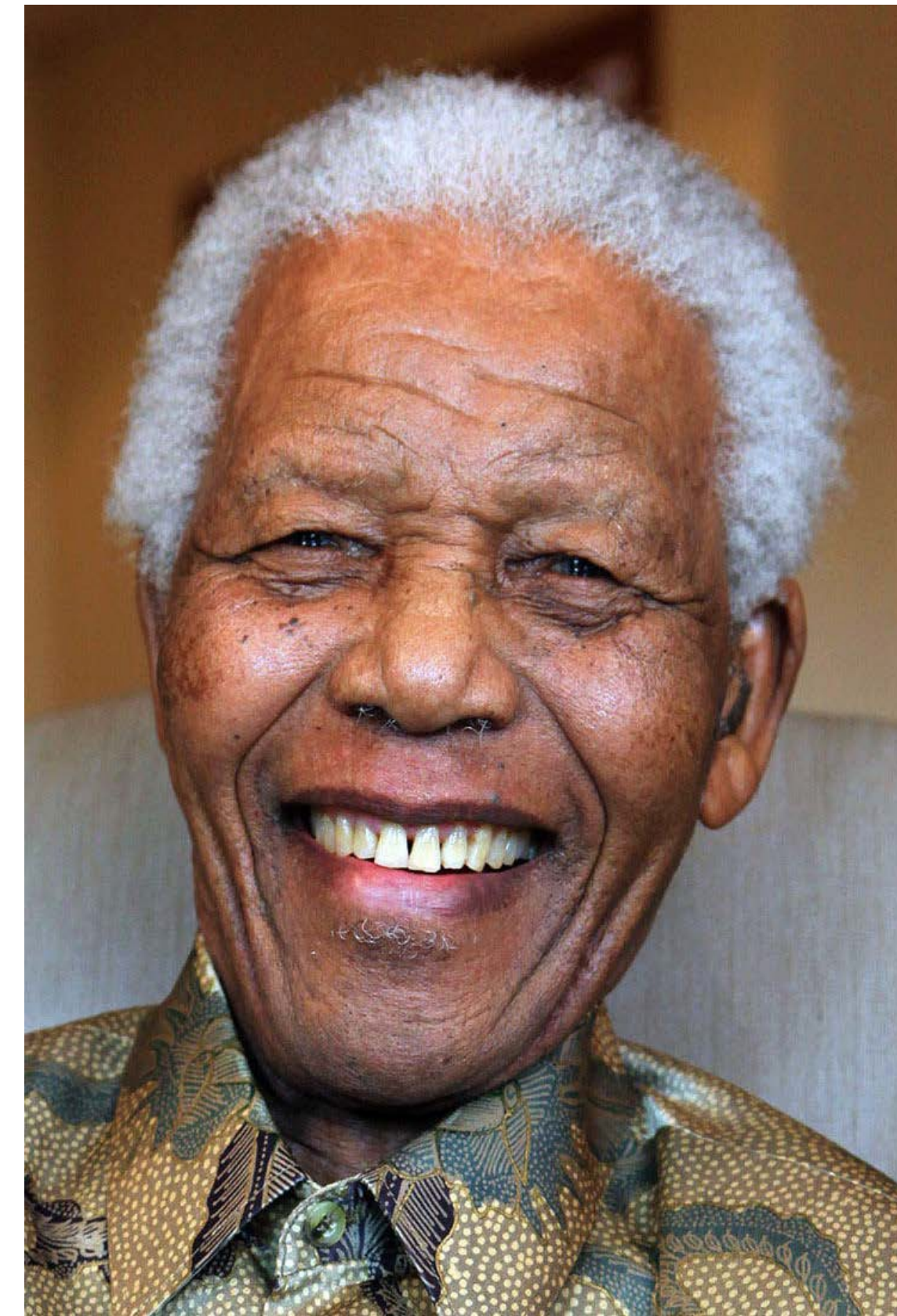
Keenan Crane

Geometry: *Examples*



Keenan Crane

Geometry: *Examples*



Keenan Crane

Geometry: *Examples*



Keenan Crane

Geometry: *Examples*



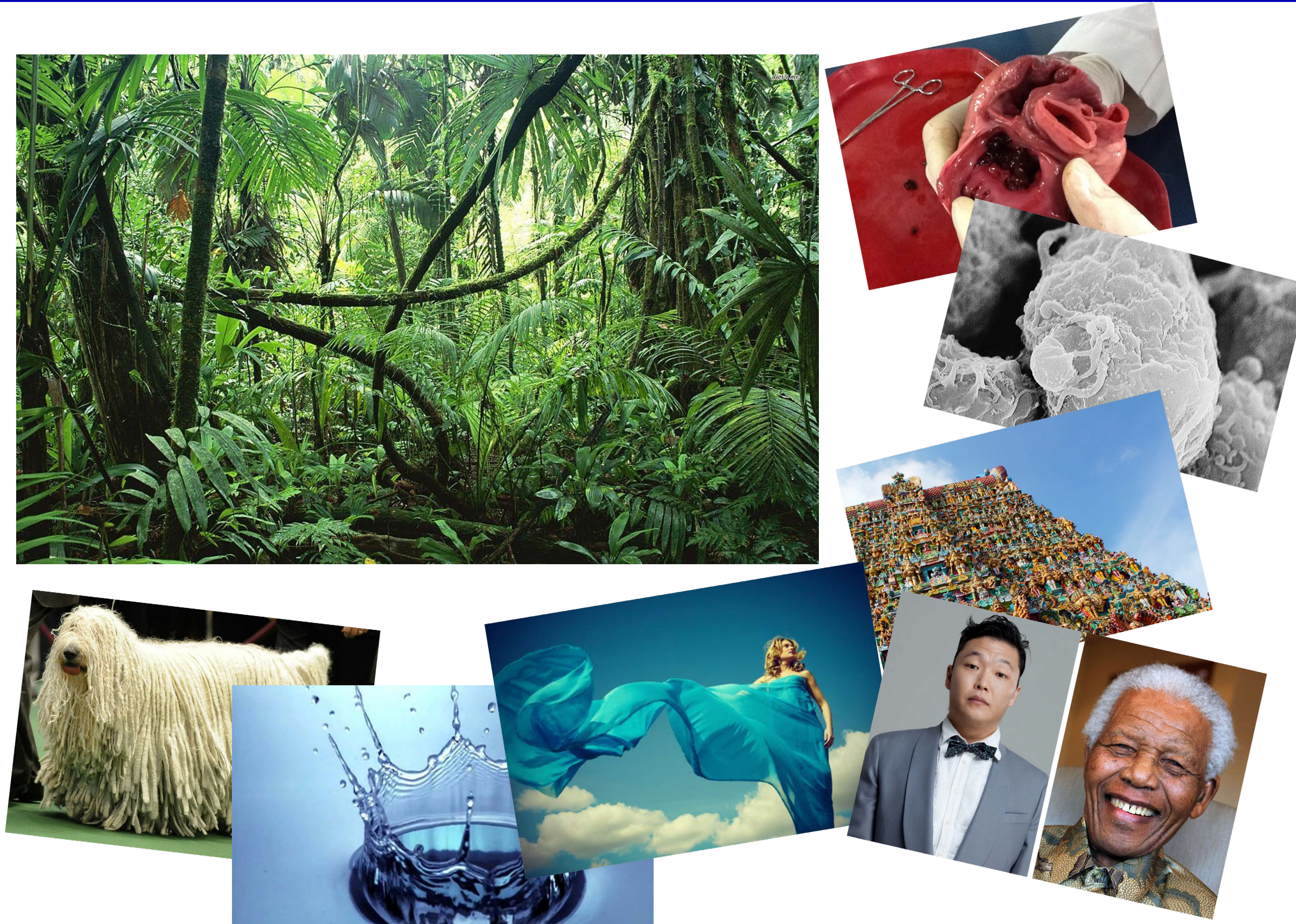
Keenan Crane

Geometry: *Examples*



Keenan Crane

Geometry: *Examples*





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

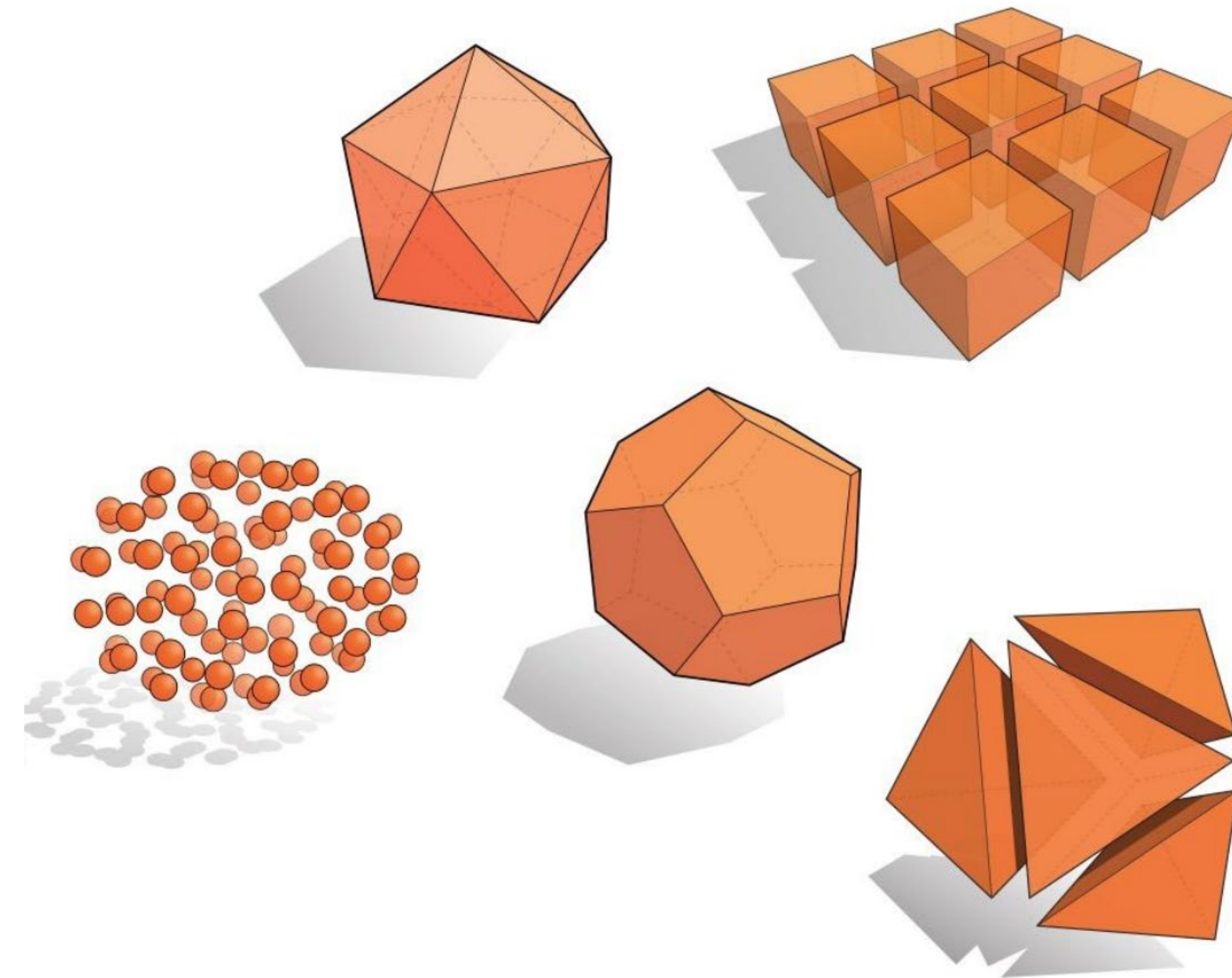
Explicit

- point cloud
- polygon mesh
- ...

Implicit

- level sets
- distance functions
- ...

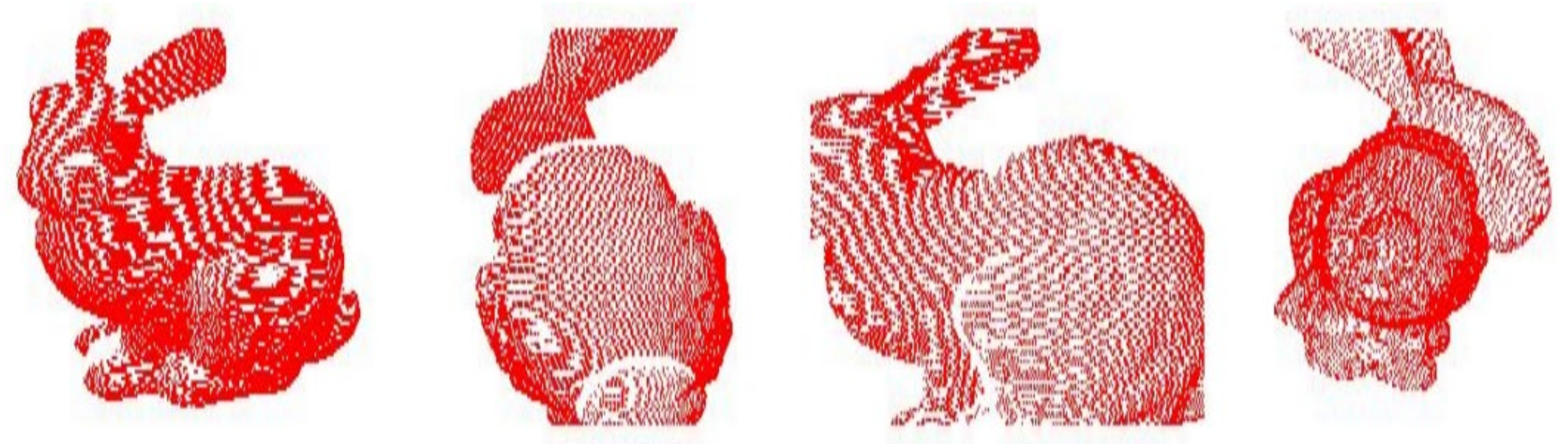
- Voxels



Jiajun Wu

3D shape representations: *Point clouds*

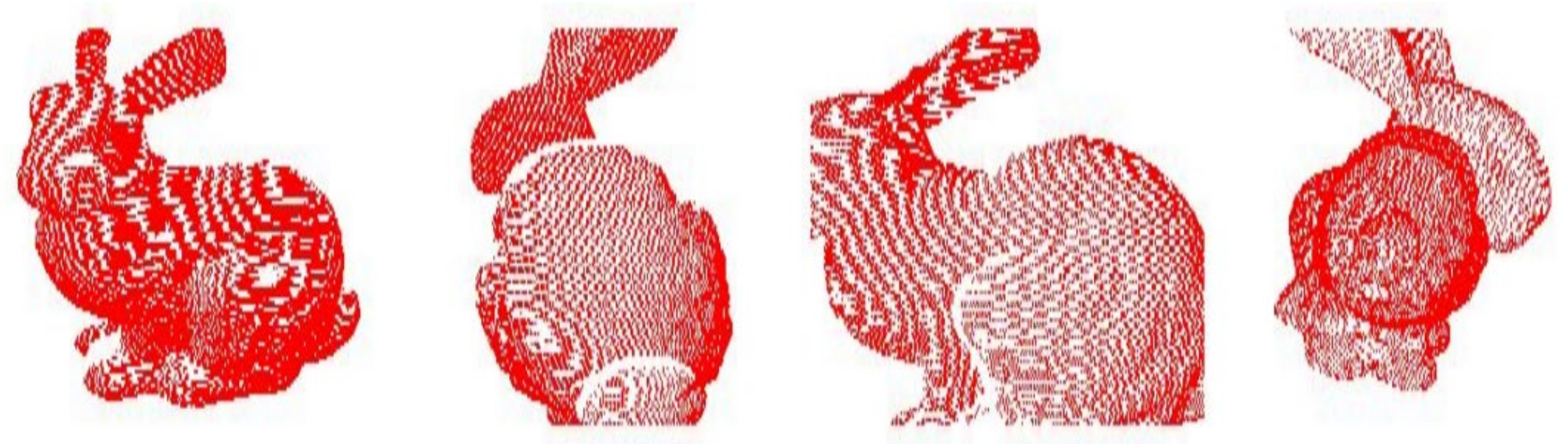
- Simplest representation: **only points**, no connectivity



Jiajun Wu

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)



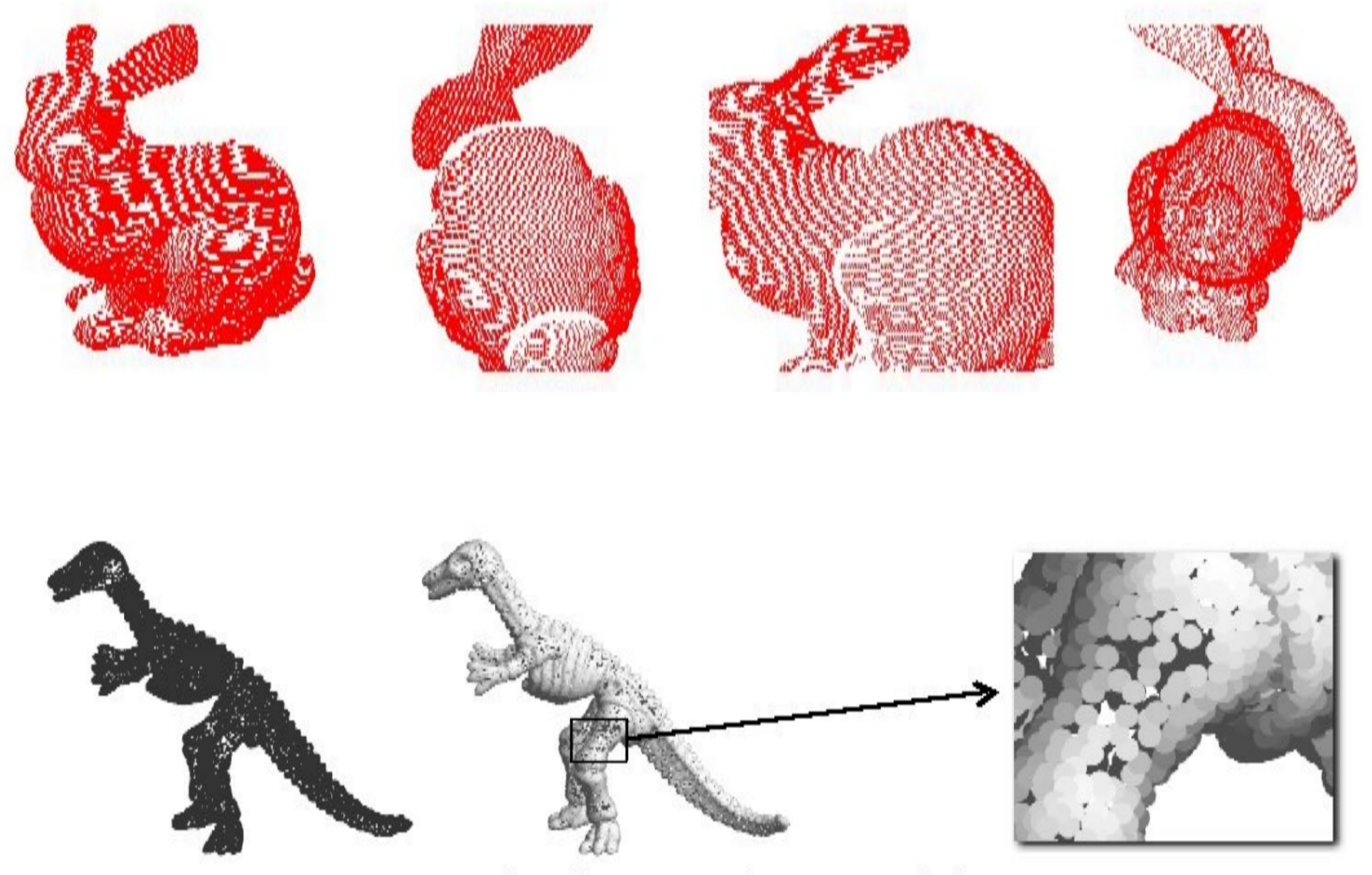
List of N
unordered
points

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

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3D shape representations: *Point clouds*

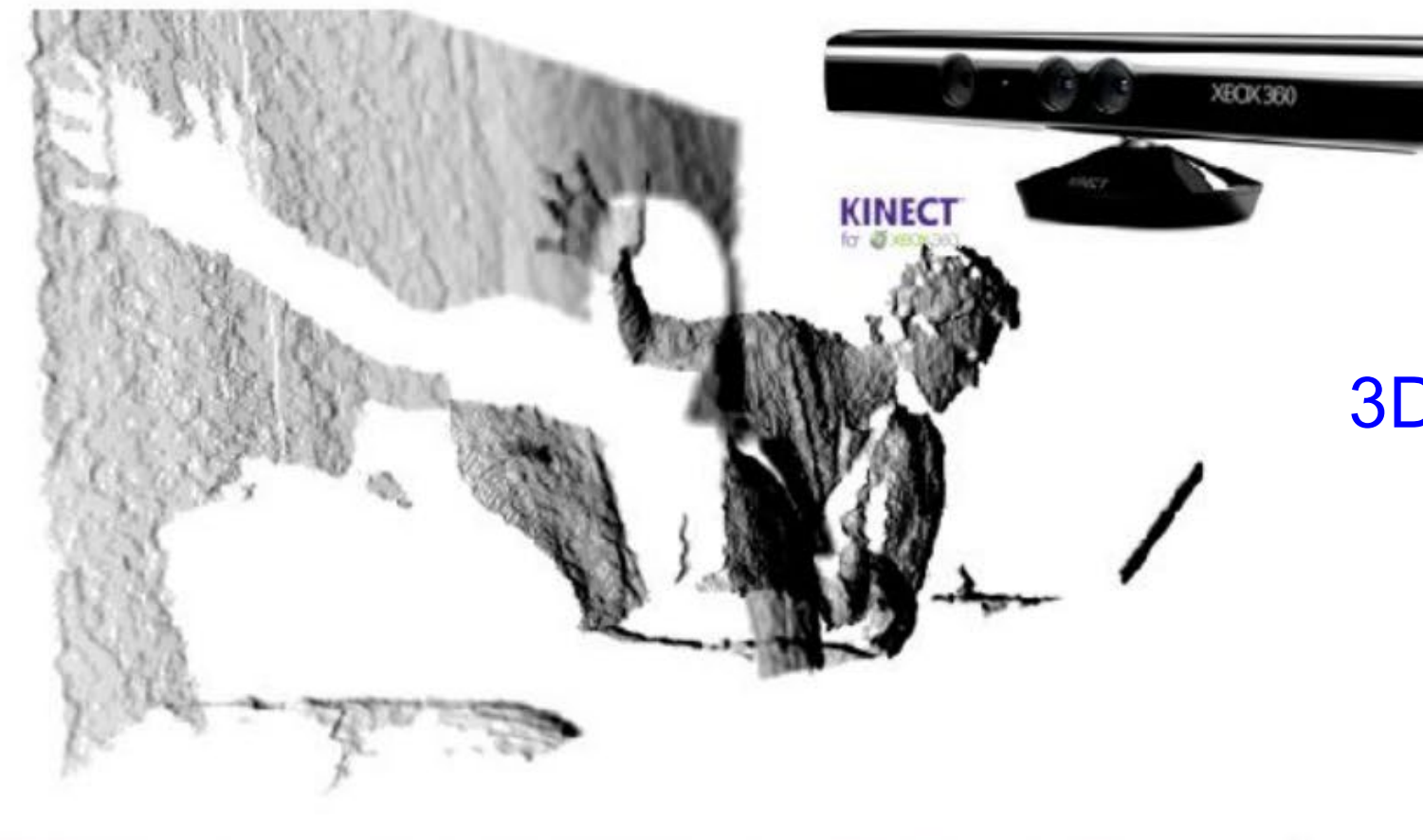
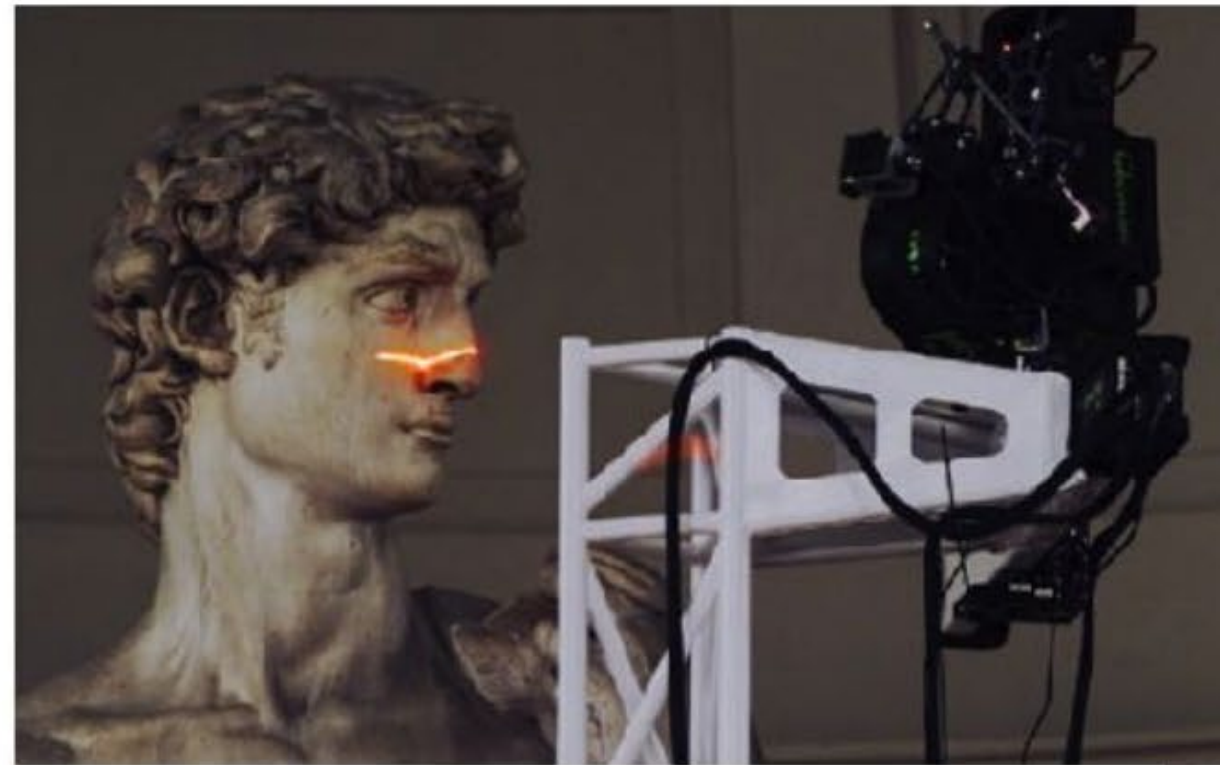
- Simplest representation: **only points**, no connectivity
- Collection of (x, y, z) coordinates, possibly with **normal** (perpendicular to the underlying surface)
- Points with orientation (normal) are called **surfels**



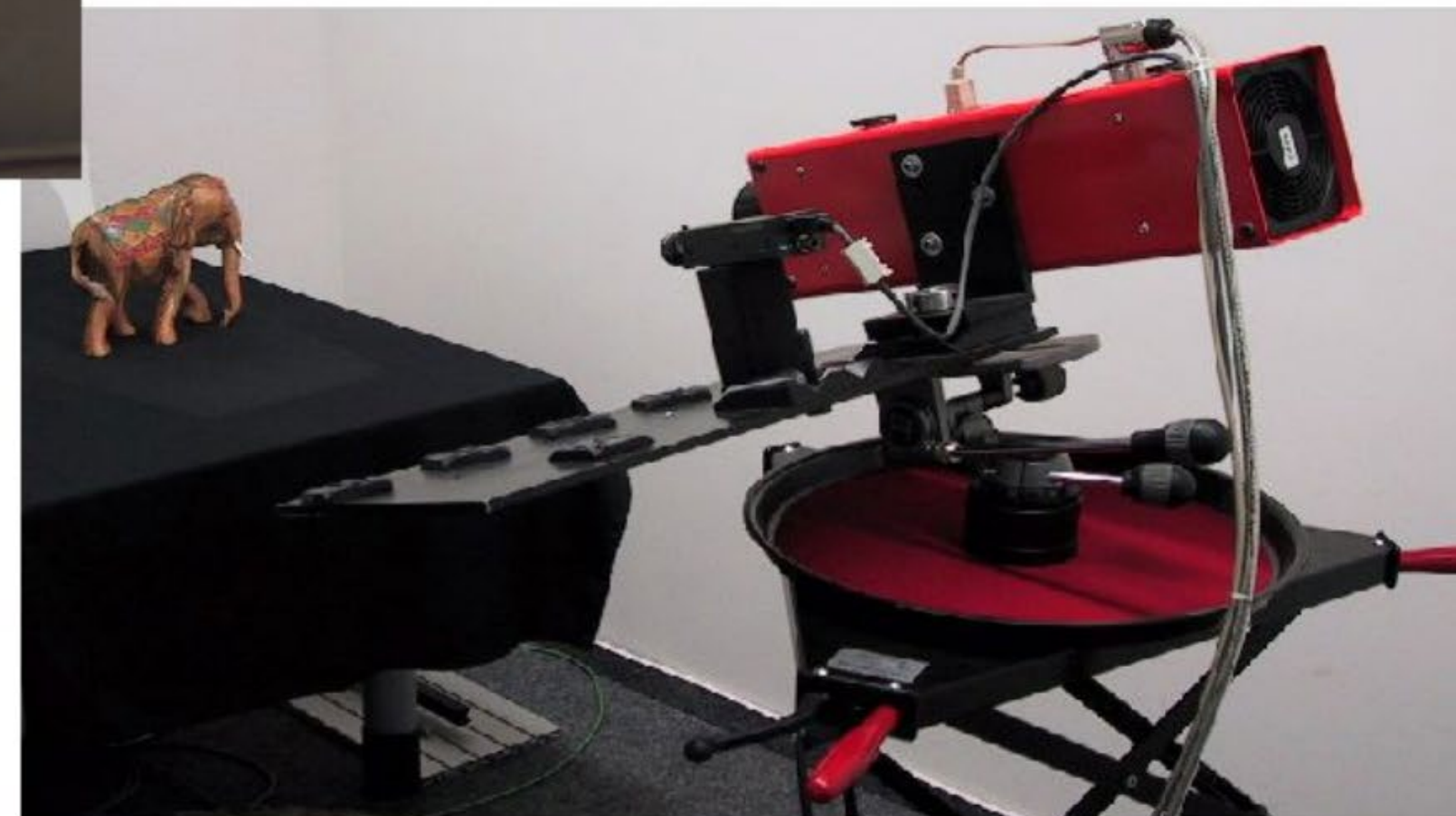
Jiajun Wu

3D shape representations: *Point clouds acquisition*

Laser triangulation rangefinder



3D Depth sensor



3D Laser scanner

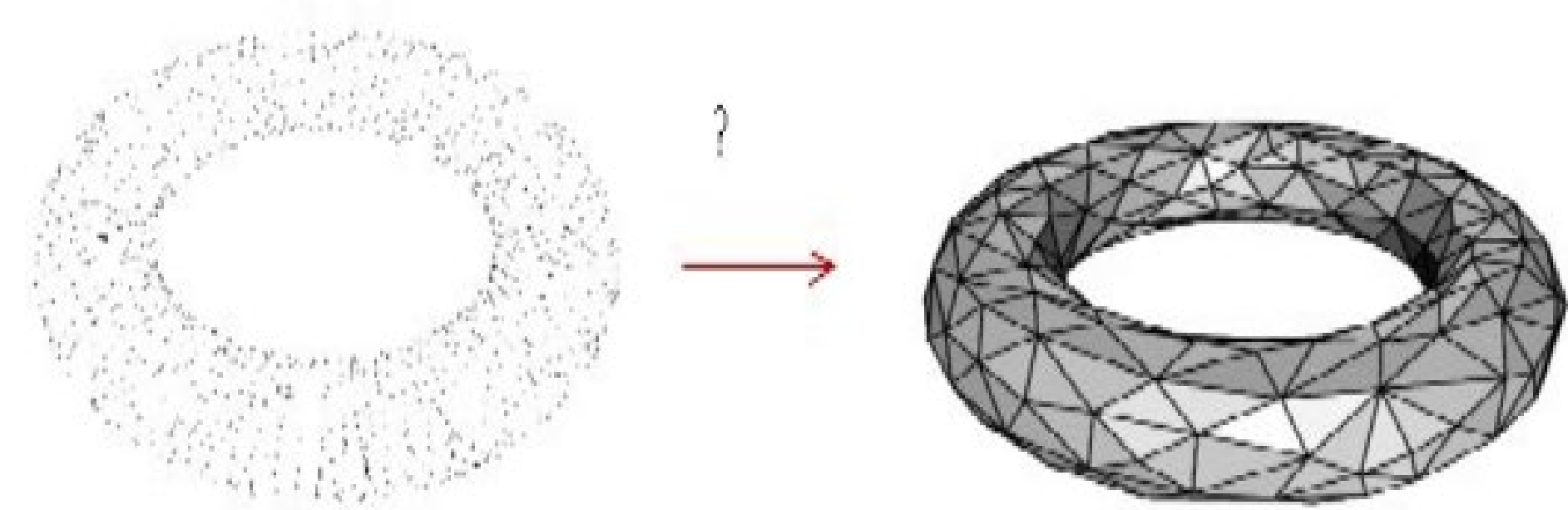
Jiajun Wu

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

- Pros:
 - ✓ Easily represents any kind of geometry
 - ✓ Useful for large datasets
- Cons
 - × Incomplete/noisy point clouds
 - × No topological information



Incomplete scans



No topology

Jiajun Wu

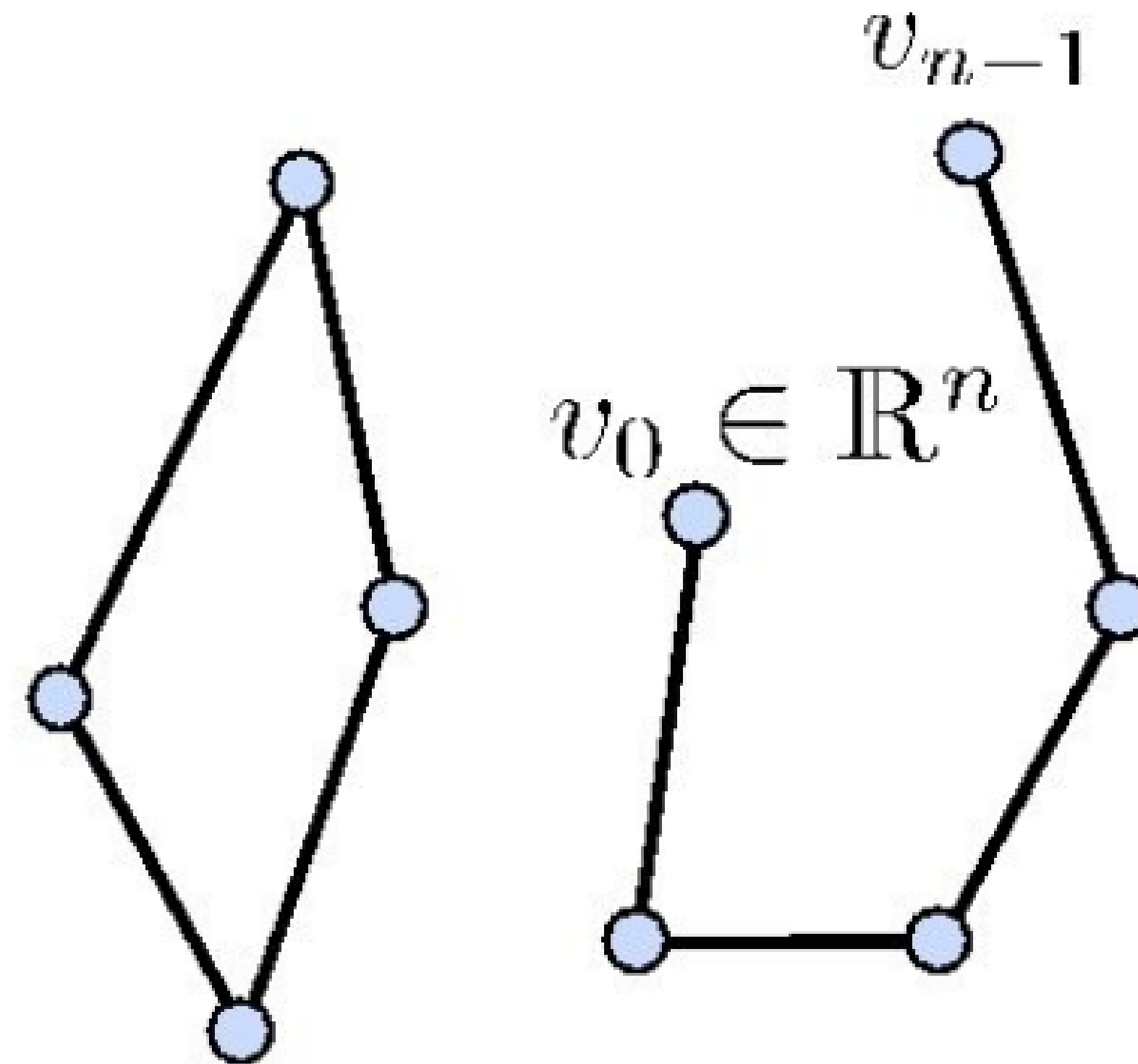
3D shape representations: *Polygonal Meshes*



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

3D shape representations: *Polygonal Meshes*

- Polygon:
 - **Vertices:** v_0, v_1, \dots, v_{n-1}
 - **Edges:** $\{(v_0, v_1), \dots, (v_{n-2}, v_{n-1})\}$
- Types of polygons:
 - **Closed:** $v_0 = v_{n-1}$
 - **Planar:** all vertices on a plane
 - **Simple:** not self-intersecting



Jiajun Wu

3D shape representations: *Polygonal Meshes*

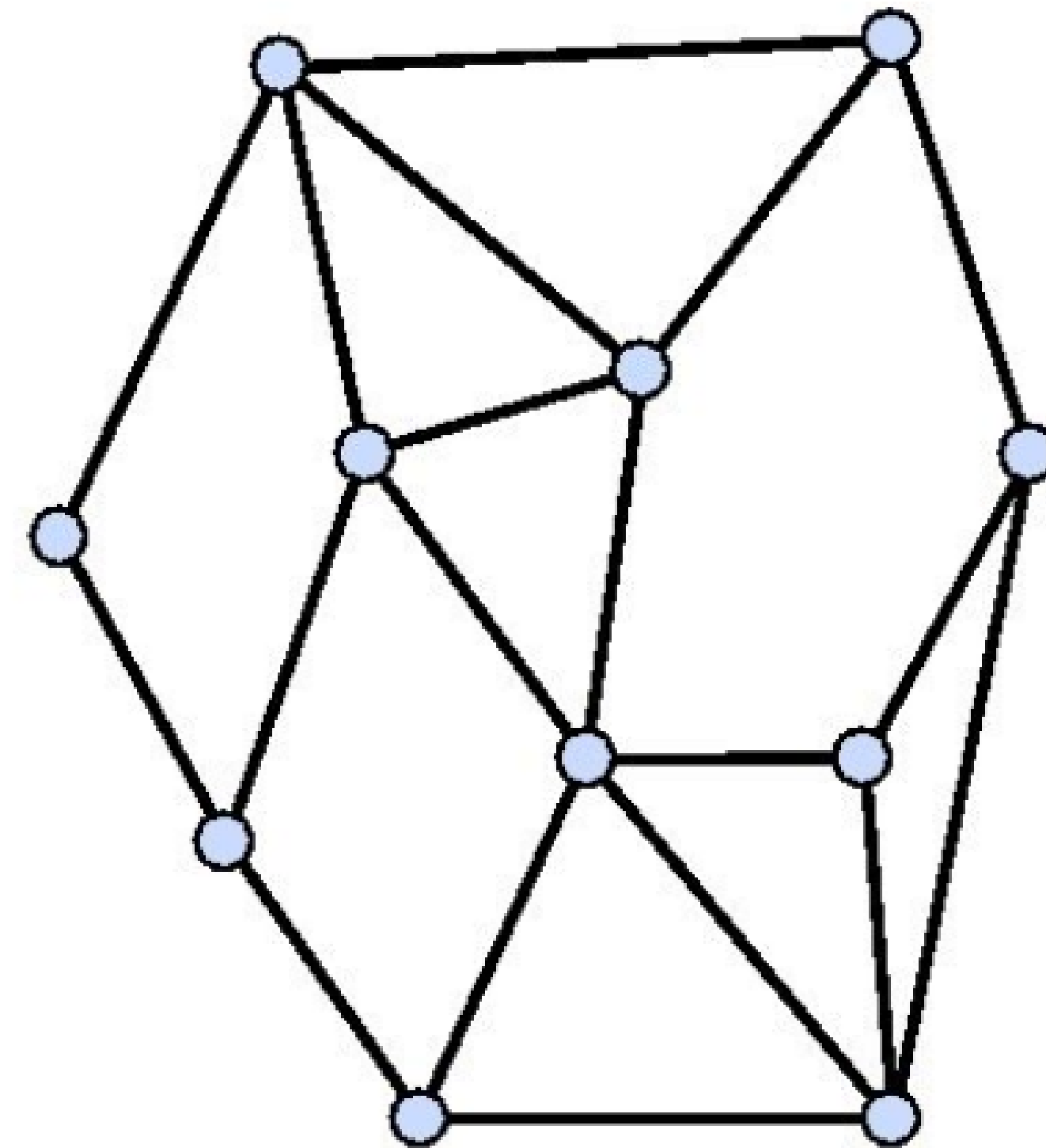
- Polygonal Mesh:
 - A finite set M of **closed, simple** polygons Q_i

$$M = \langle V, E, F \rangle$$

V = set of vertices

E = set of edges

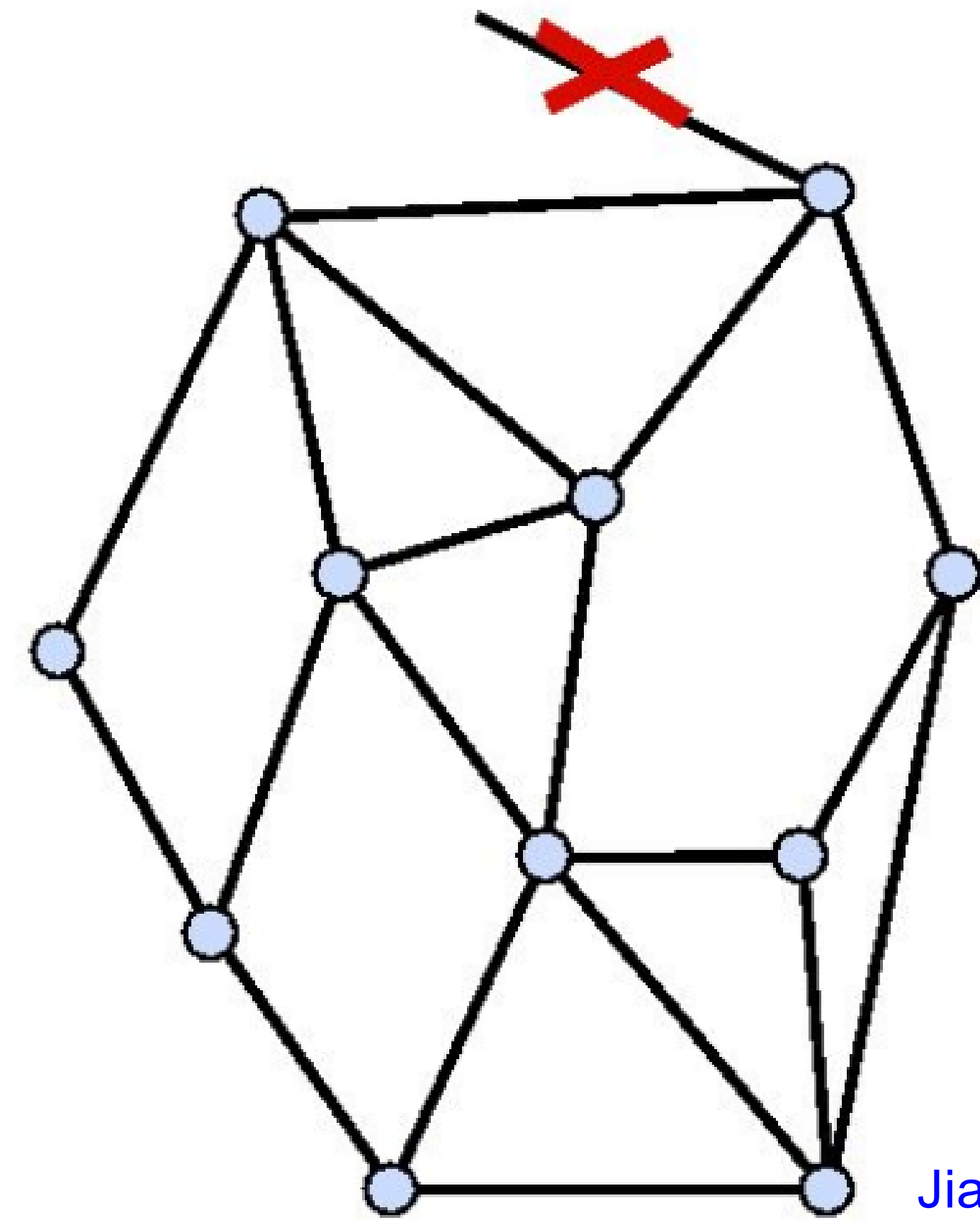
F = set of faces



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3D shape representations: *Polygonal Meshes*

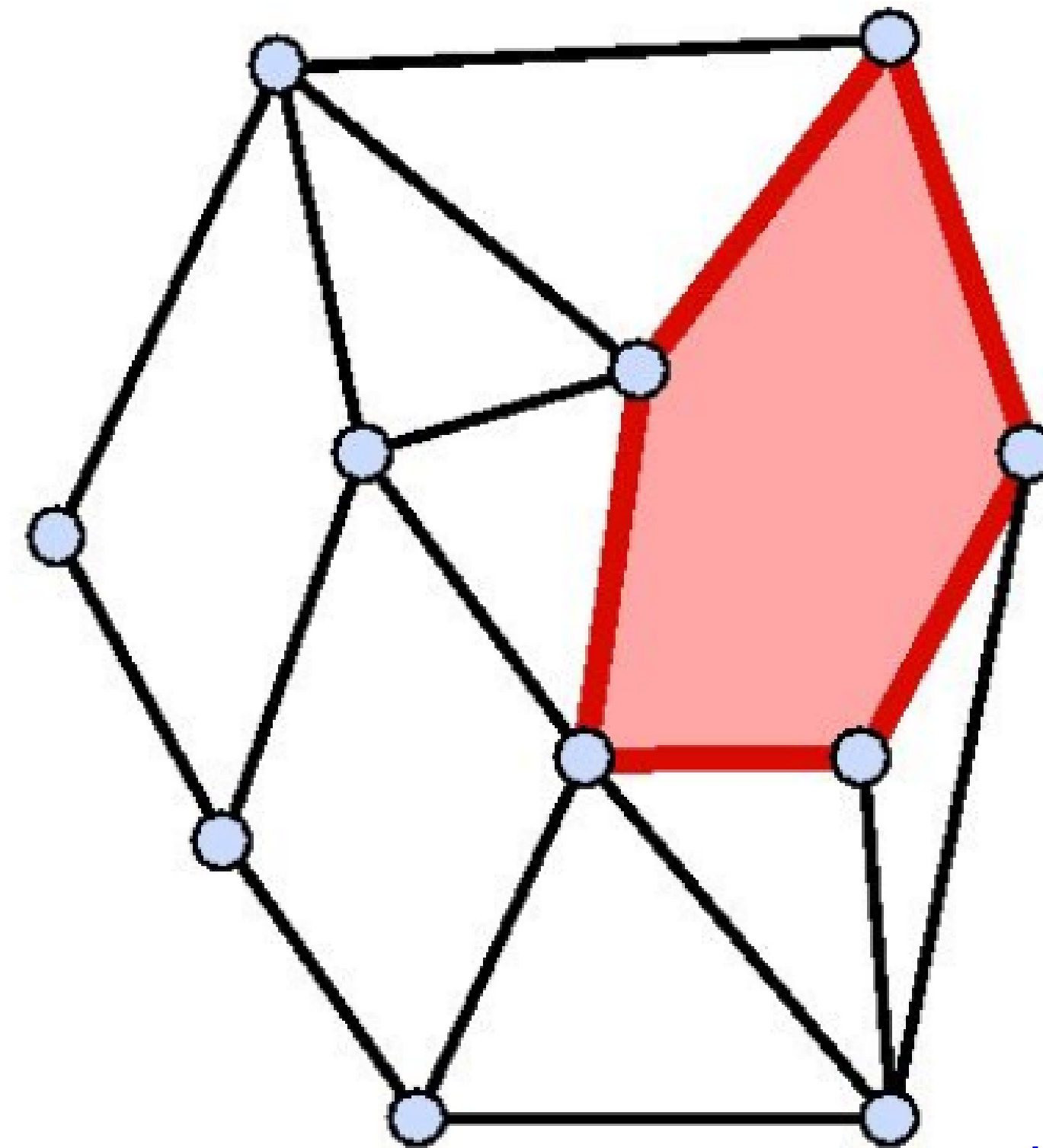
- Polygonal Mesh:
 - A finite set M of **closed, simple** polygons Q_i
 - Every **edge** belongs to **at least one polygon**



Jiajun Wu

3D shape representations: *Polygonal Meshes*

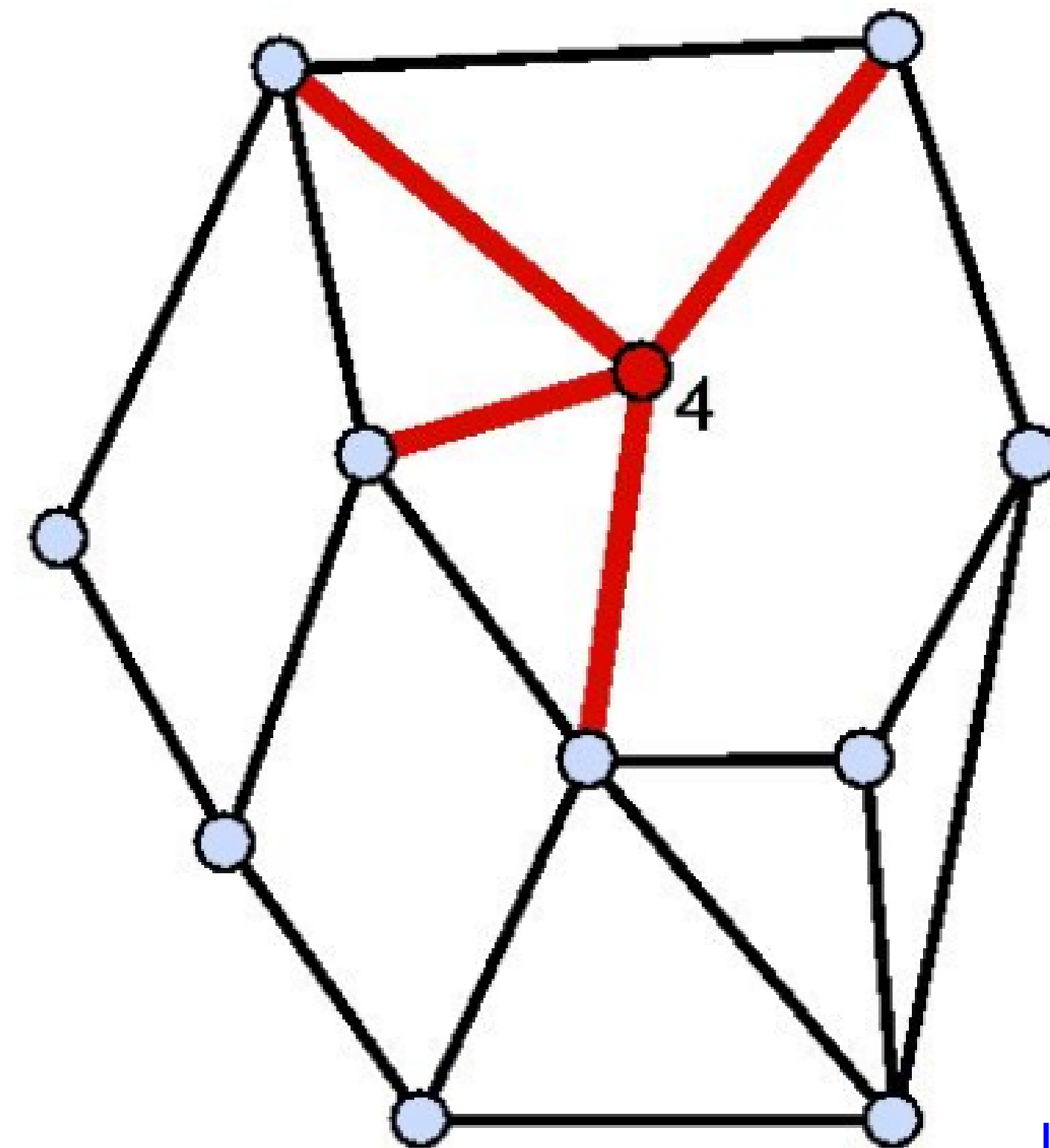
- Polygonal Mesh:
 - A finite set M of **closed, simple** polygons Q_i
 - Every **edge** belongs to **at least one polygon**
 - Each Q_i defines a **face** of the polygonal mesh



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3D shape representations: *Polygonal Meshes*

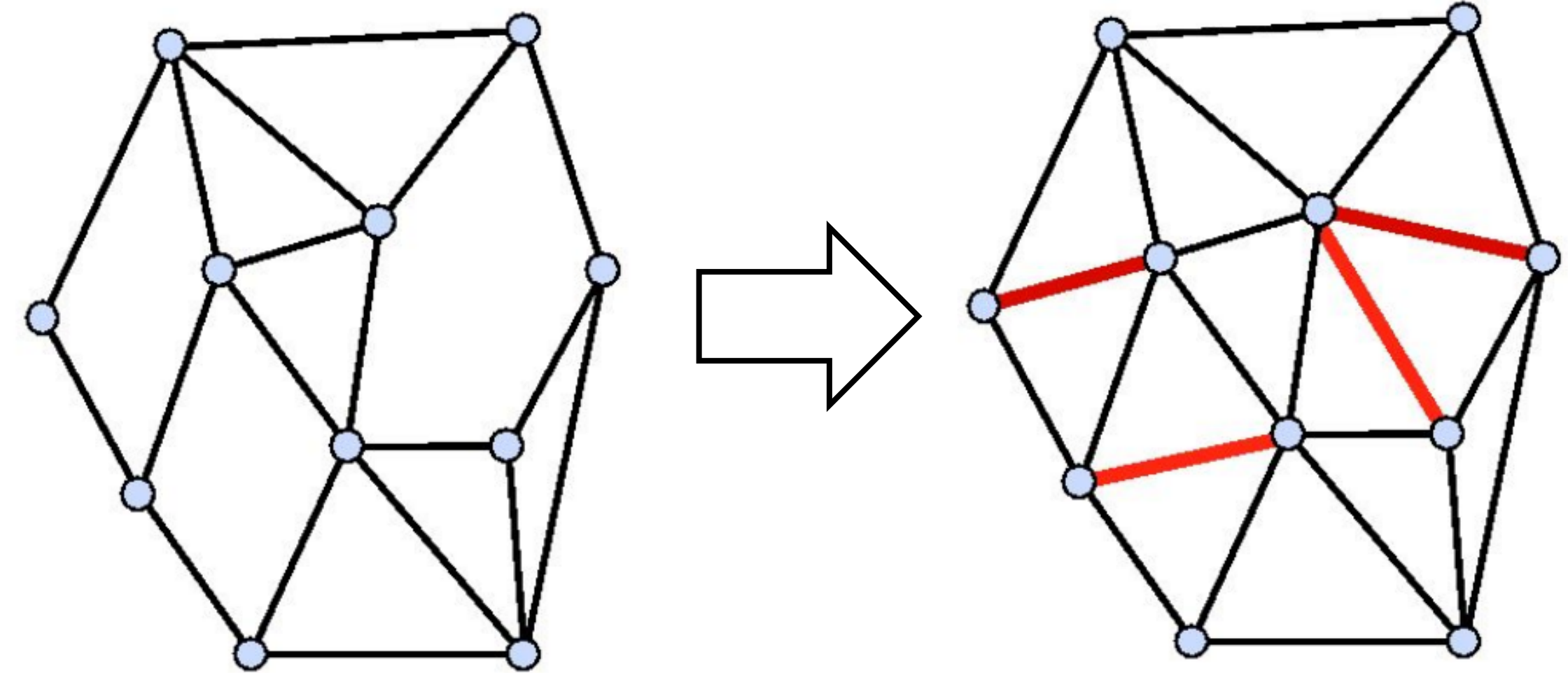
- Polygonal Mesh:
 - A finite set M of **closed, simple** polygons Q_i
 - Every **edge** belongs to **at least one polygon**
 - Each Q_i defines a **face** of the polygonal mesh
 - Vertex **degree** or **valance** = number of incident edges



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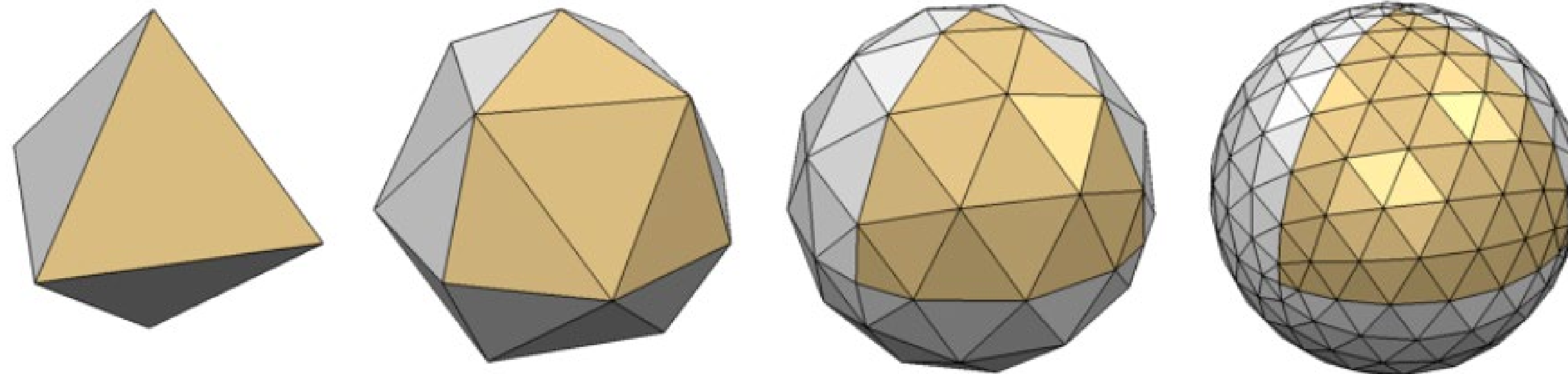
3D shape representations: *Polygonal Meshes*

- 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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3D shape representations: *Polygonal Meshes*



- 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

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

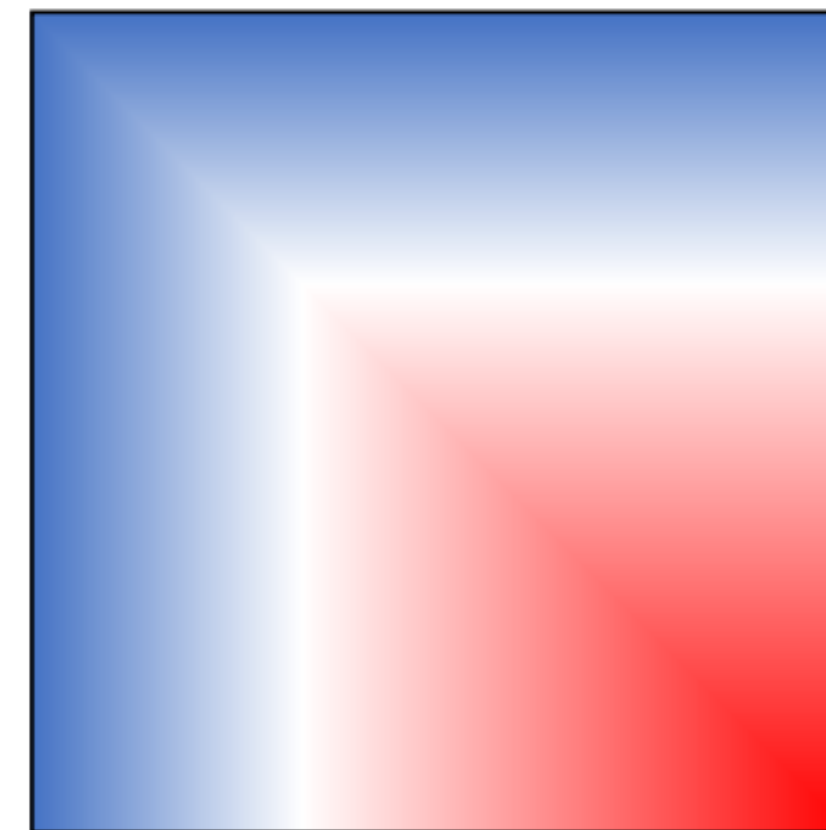
Vertices			
v0	x0	y0	z0
v1	x1	y1	z1
v2	x2	y2	z2
v3	x3	y3	z3
v4	x4	y4	z4
v5	x5	y5	z5
v6	x6	y6	z6
...

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

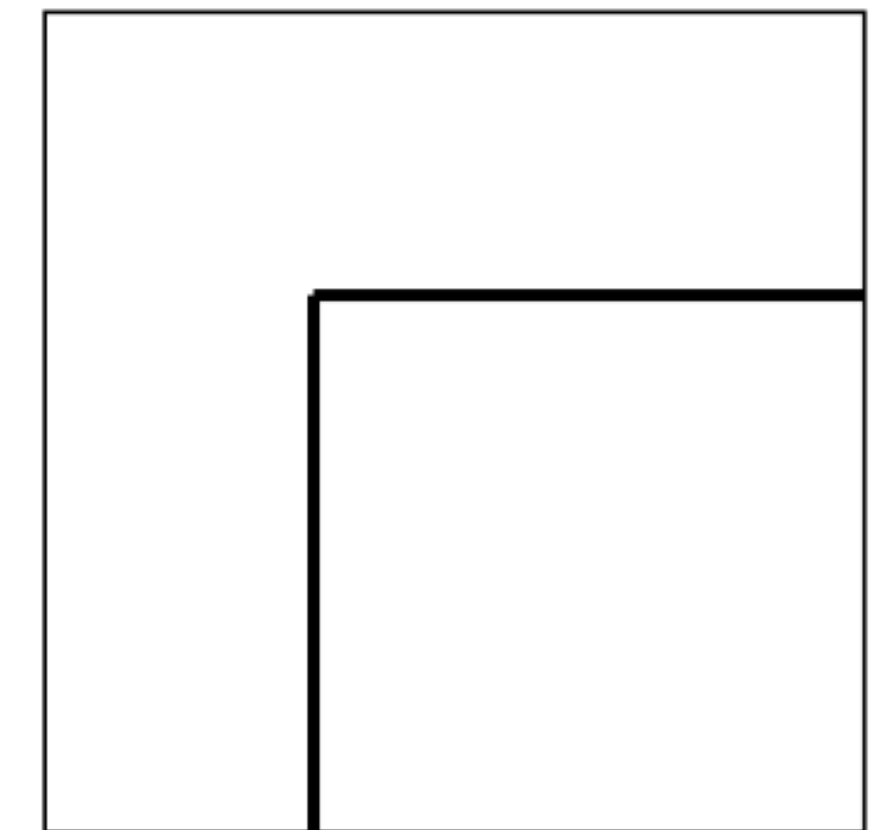
Jiajun Wu

3D shape representations: *Implicit Functions*

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



Implicit function



Explicit Shape

Justin Solomon

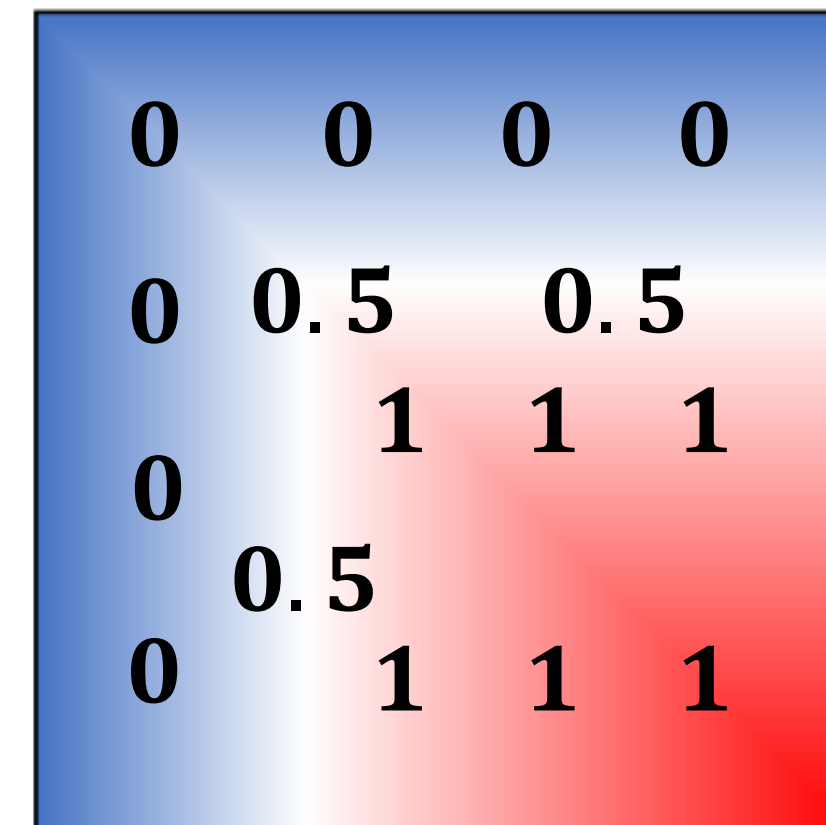
3D shape representations: *Implicit Functions*

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

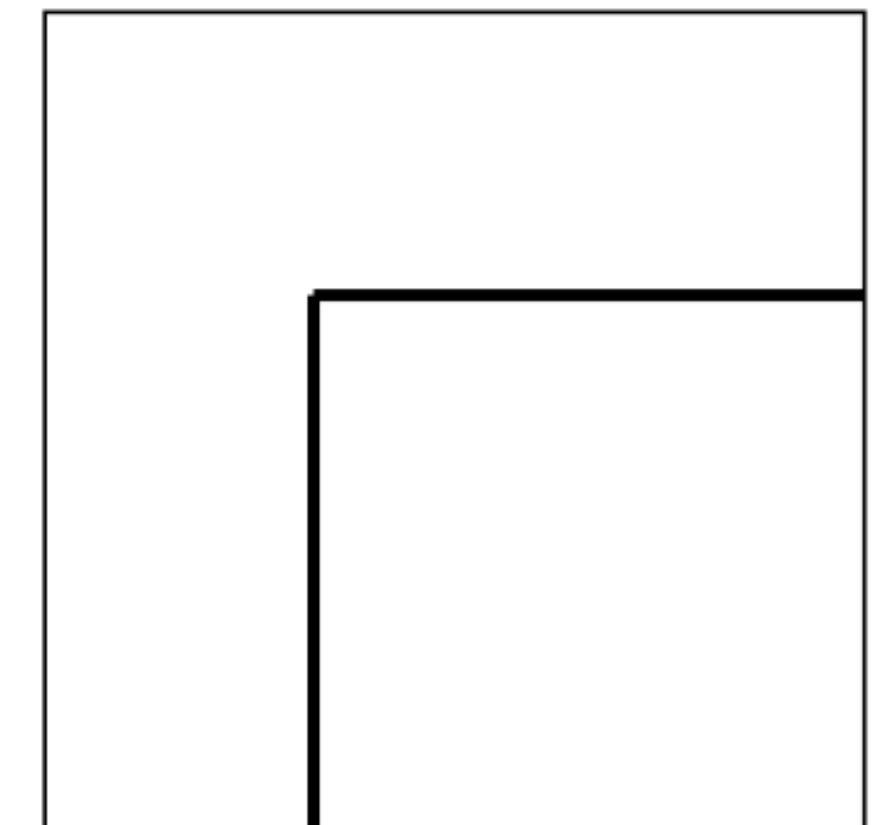
$$o : \mathbb{R}^3 \rightarrow \{0,1\}$$

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

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



Implicit function



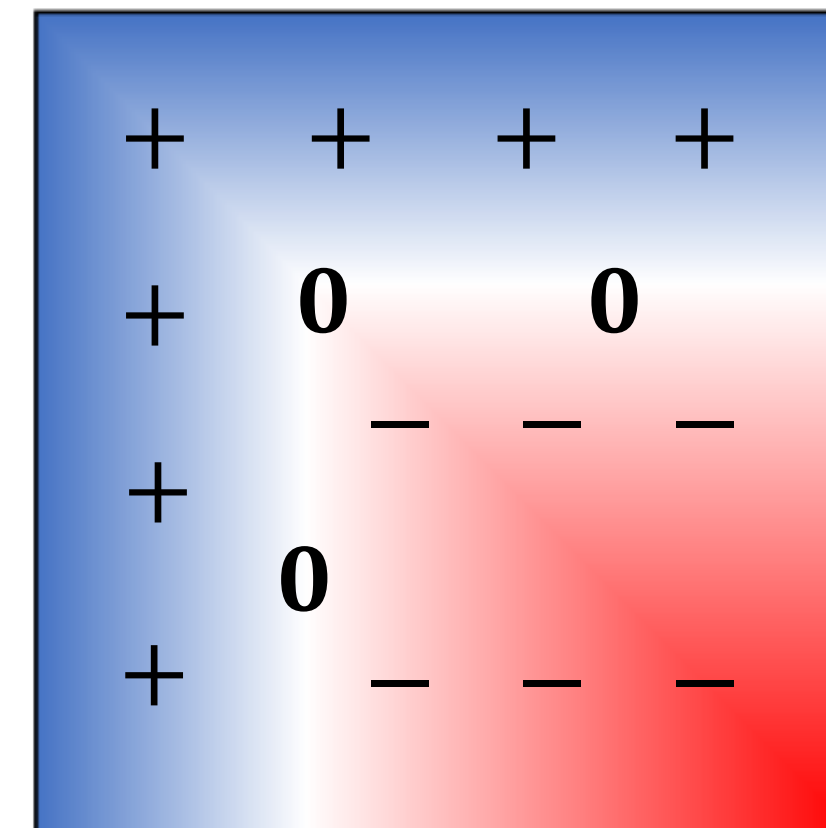
Explicit Shape

Justin Solomon

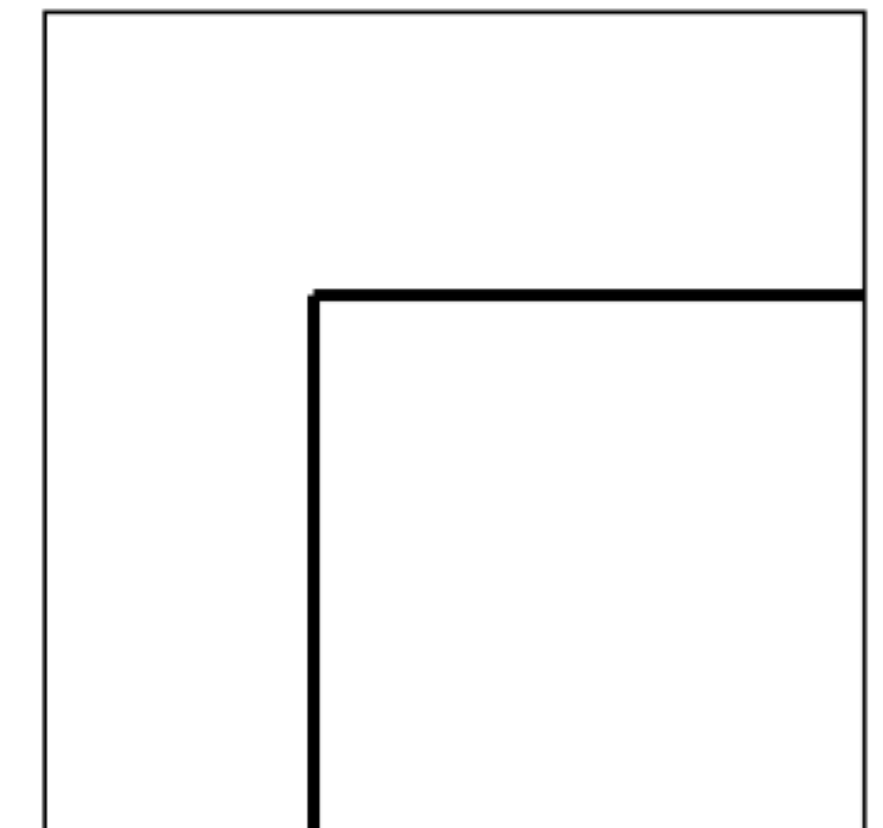
3D shape representations: *Implicit Functions*

- **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:**

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



Implicit function



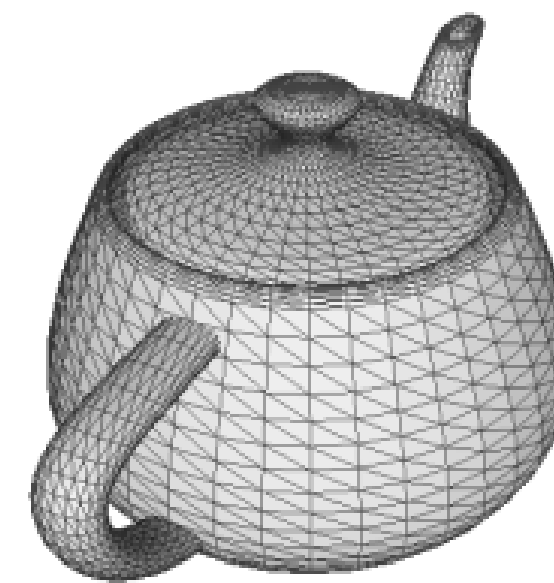
Explicit Shape

Justin Solomon

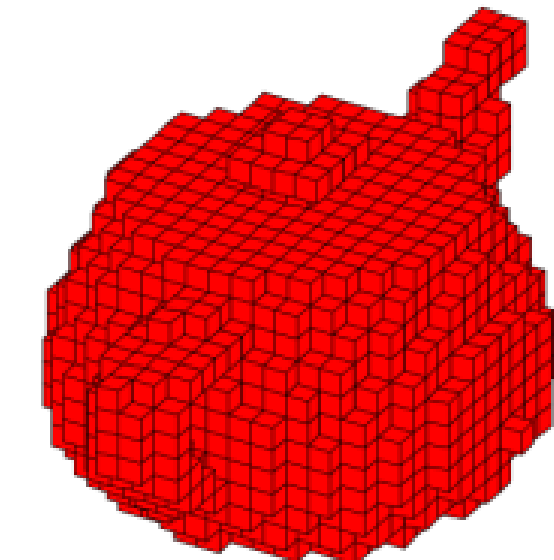


3D shape representations: *Volumetric Grid*

- **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



Polygon Mesh



Occupancy Grid
30x30x30

Hao Su et al.



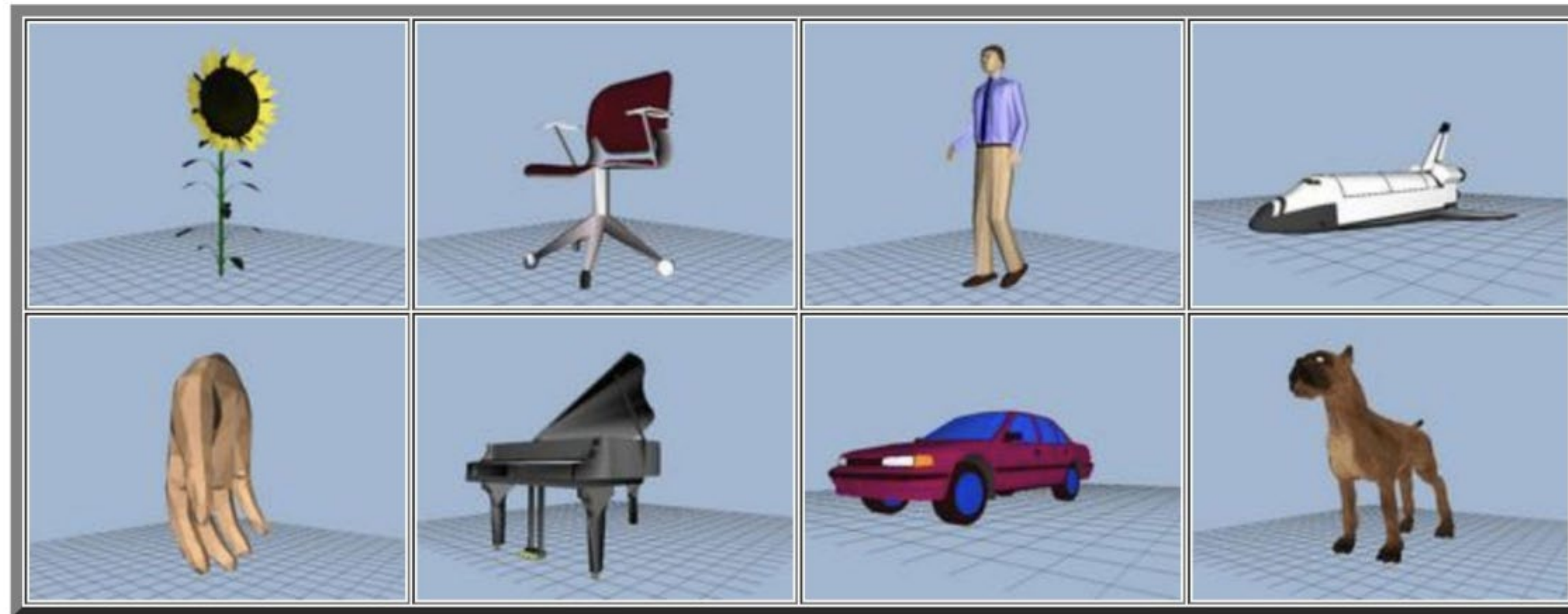
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- **3D shape datasets**
- 3D Deep Learning architectures
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3D shape datasets: *Datasets for 3D Objects*

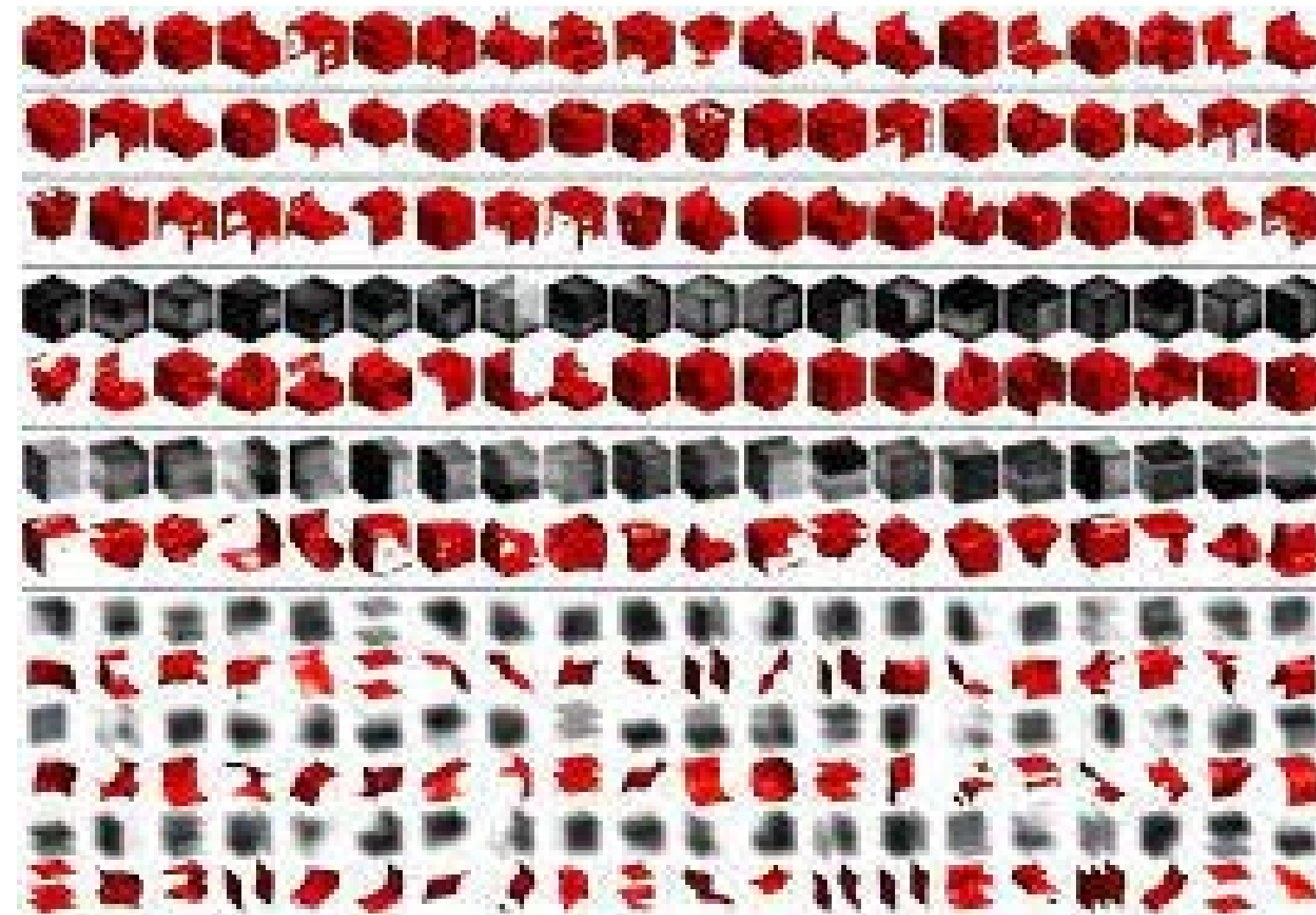
- **Princeton Shape Benchmark**
 - # Models: 1,814
 - # Categories: 182



Shilane et al., 2004

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

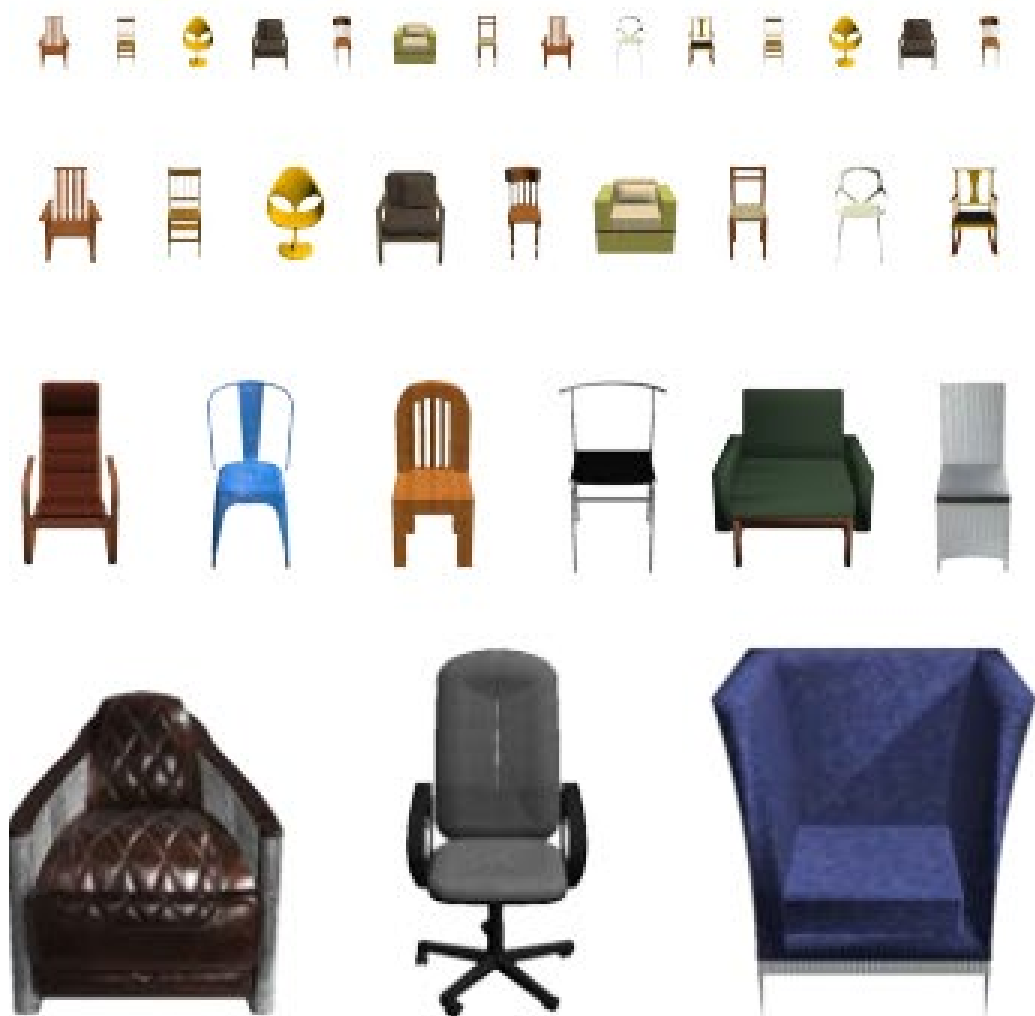
3D shape datasets: *Datasets for 3D Objects*

- **ShapeNet**

- # Models: 3M (not publicly available)

- **ShapeNetCore** (subset of ShapeNet)

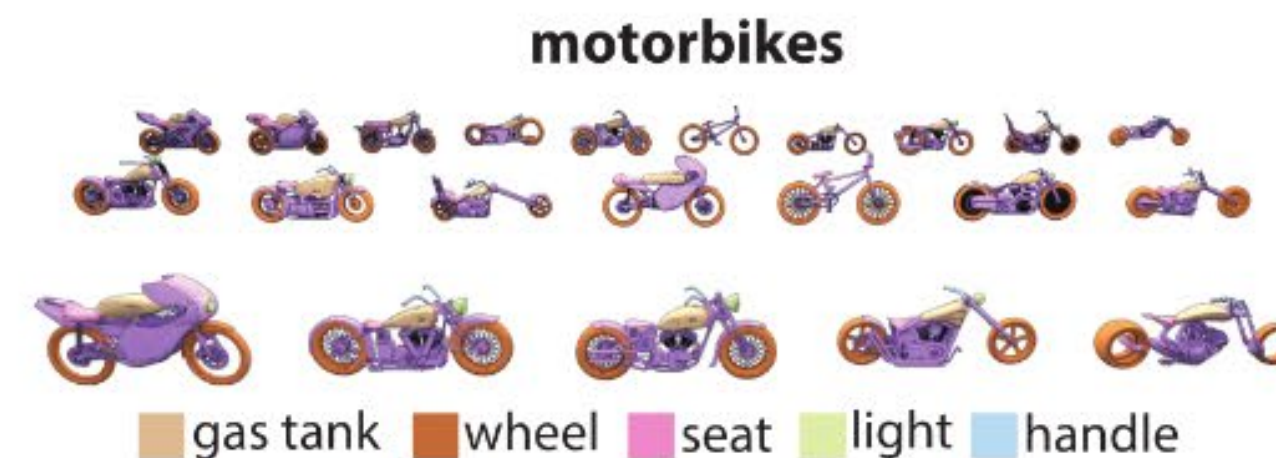
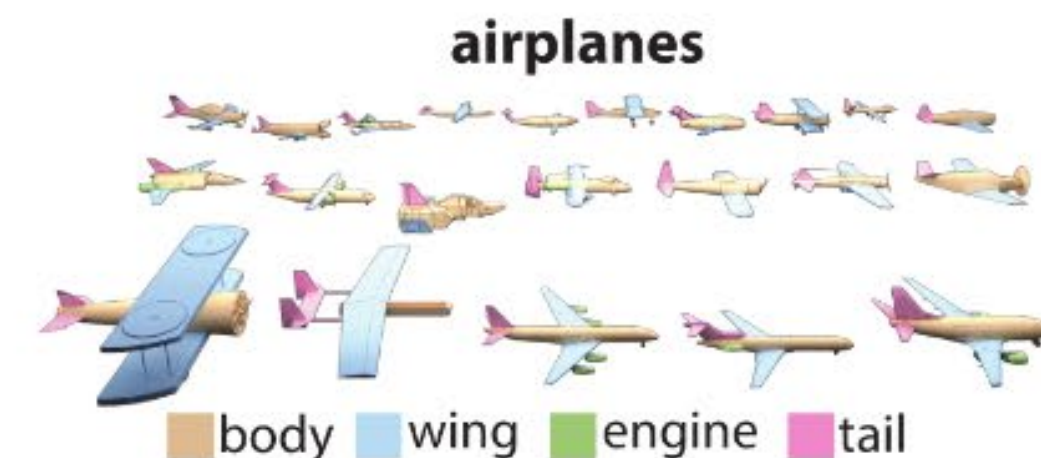
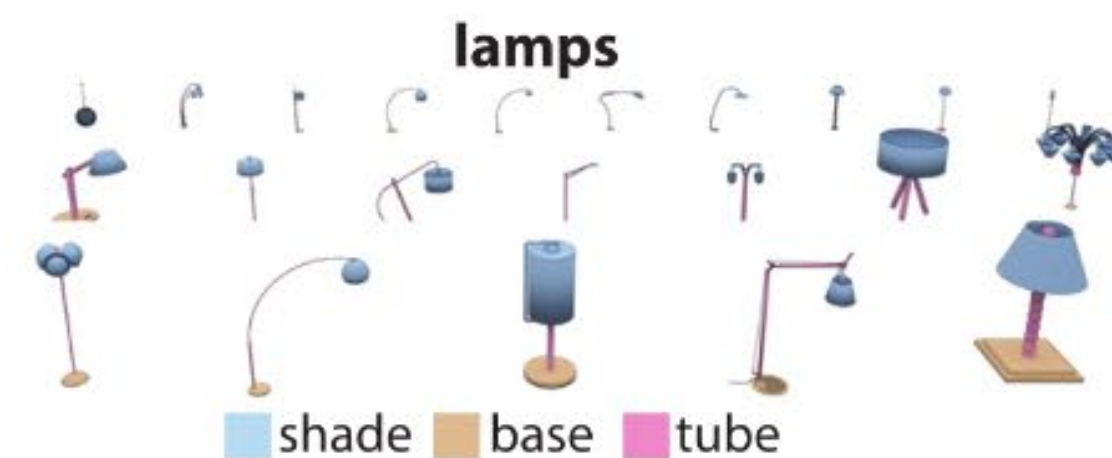
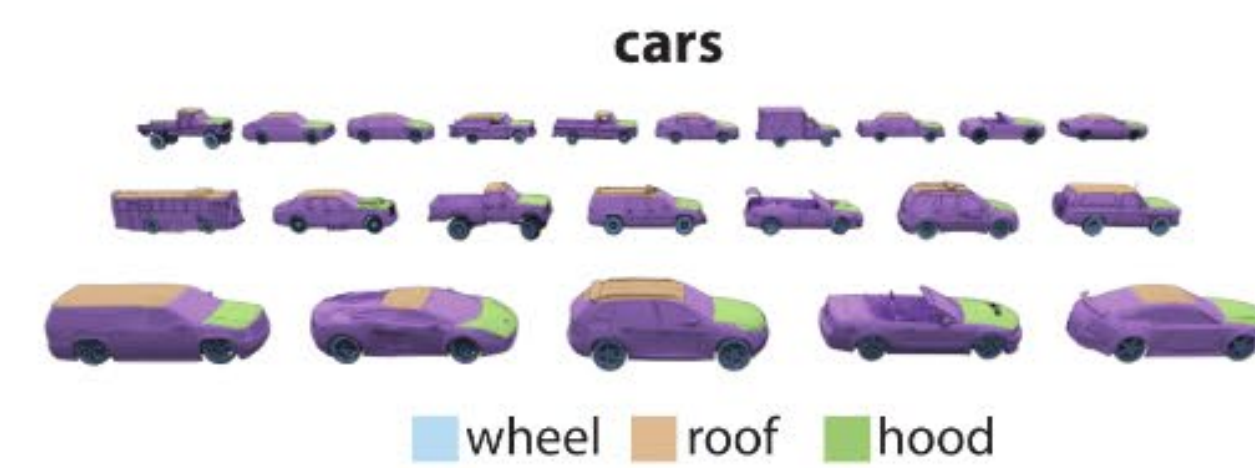
- # Models: 51,300
- # Categories: 55



Change et al., 2015

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

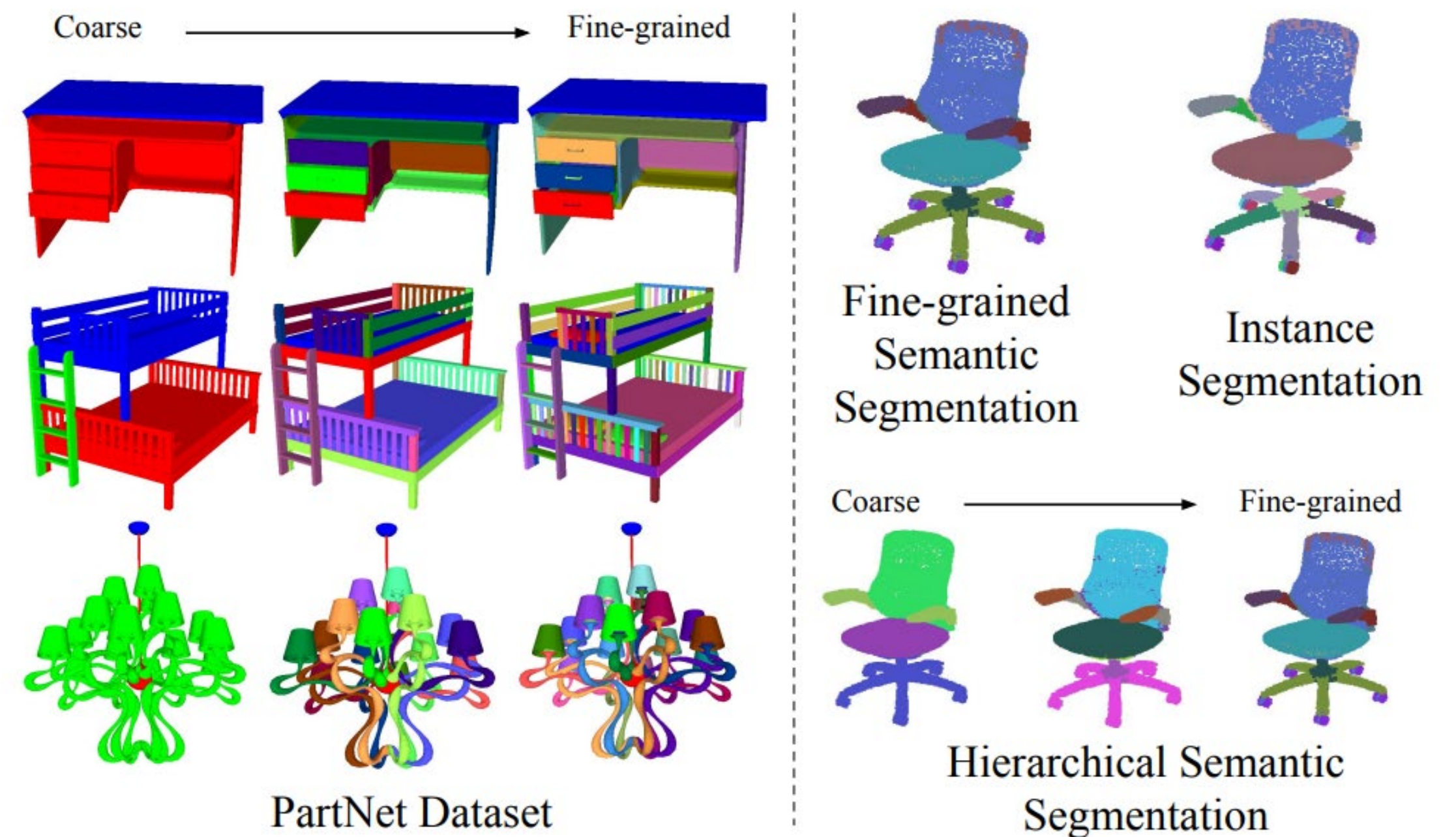
- **ShapeNet-Part** (subset of ShapeNet)
 - # Models: 16,881
 - # Categories: 16
 - # Semantic parts: 50



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 3D Objects*

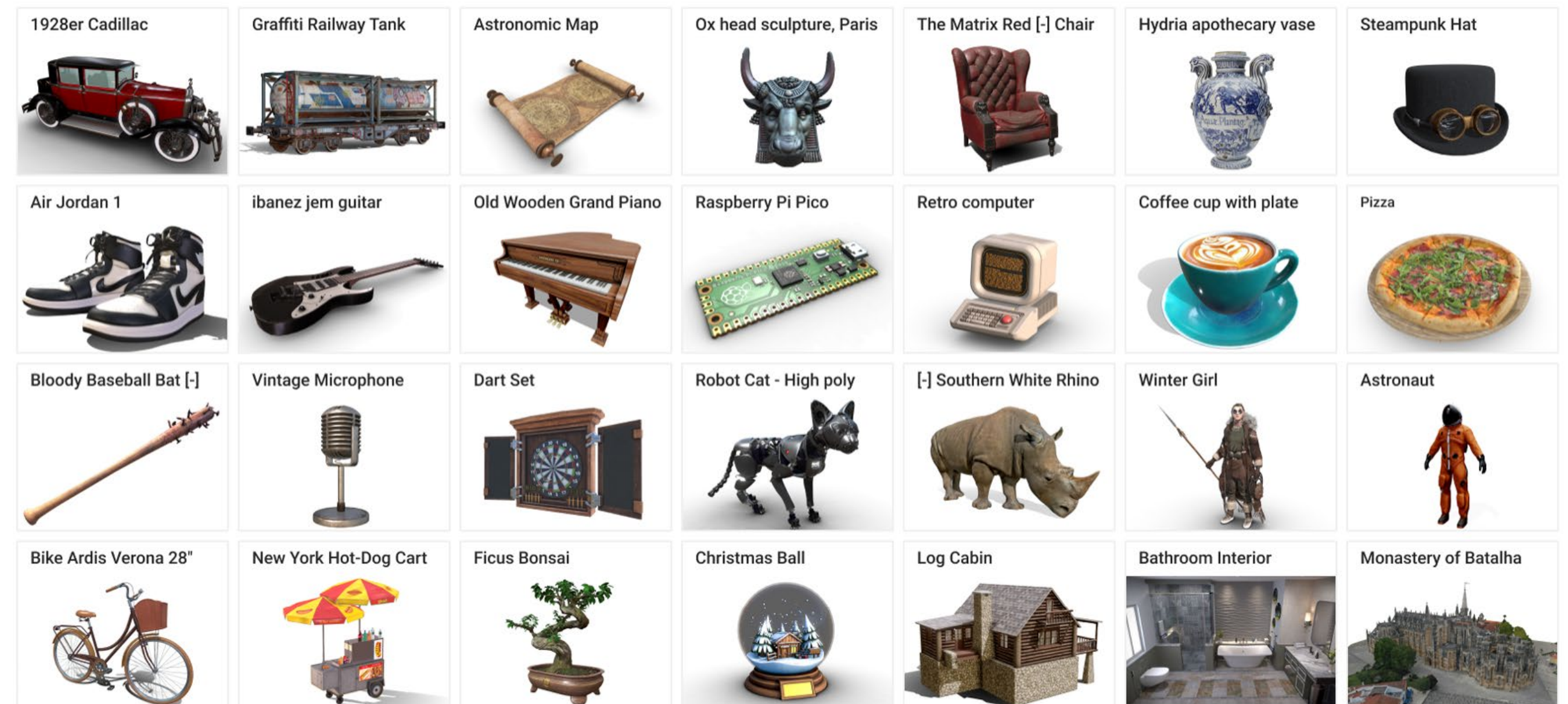
- **Pix3D**
 - # Images: 10,069
 - # Models: 395 (2D-3D aligned)



Sun et al., 2018

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

- **Objaverse 1.0**
 - # Models: 800,000+
 - # Categories: 21,000
 - Captions
 - Tags
 - Animations



Deitke et al., 2022

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

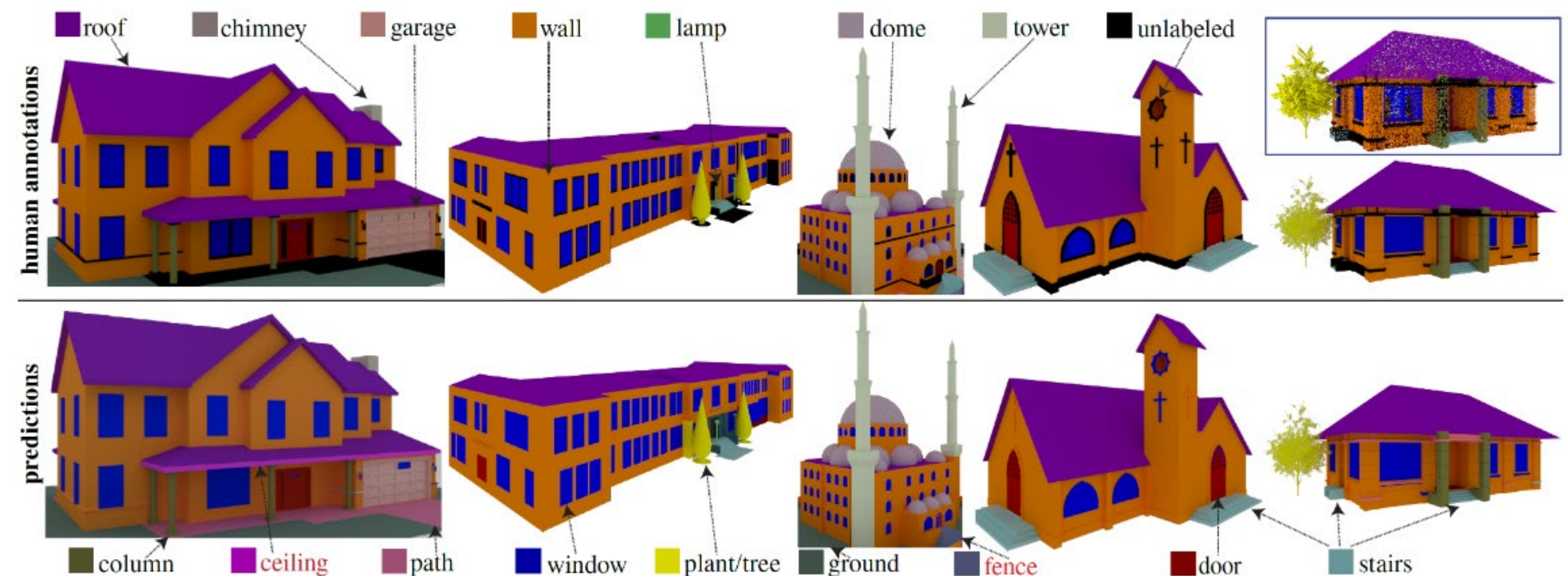
- **Large-scale Scanned Real Scenes: ScanNet**
 - # Views: 2.5M
 - # RGBD scans: 1,500
 - 3D camera poses
 - Surface reconstruction
 - Instance-level semantic segmentations



Dai et al., 2017

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

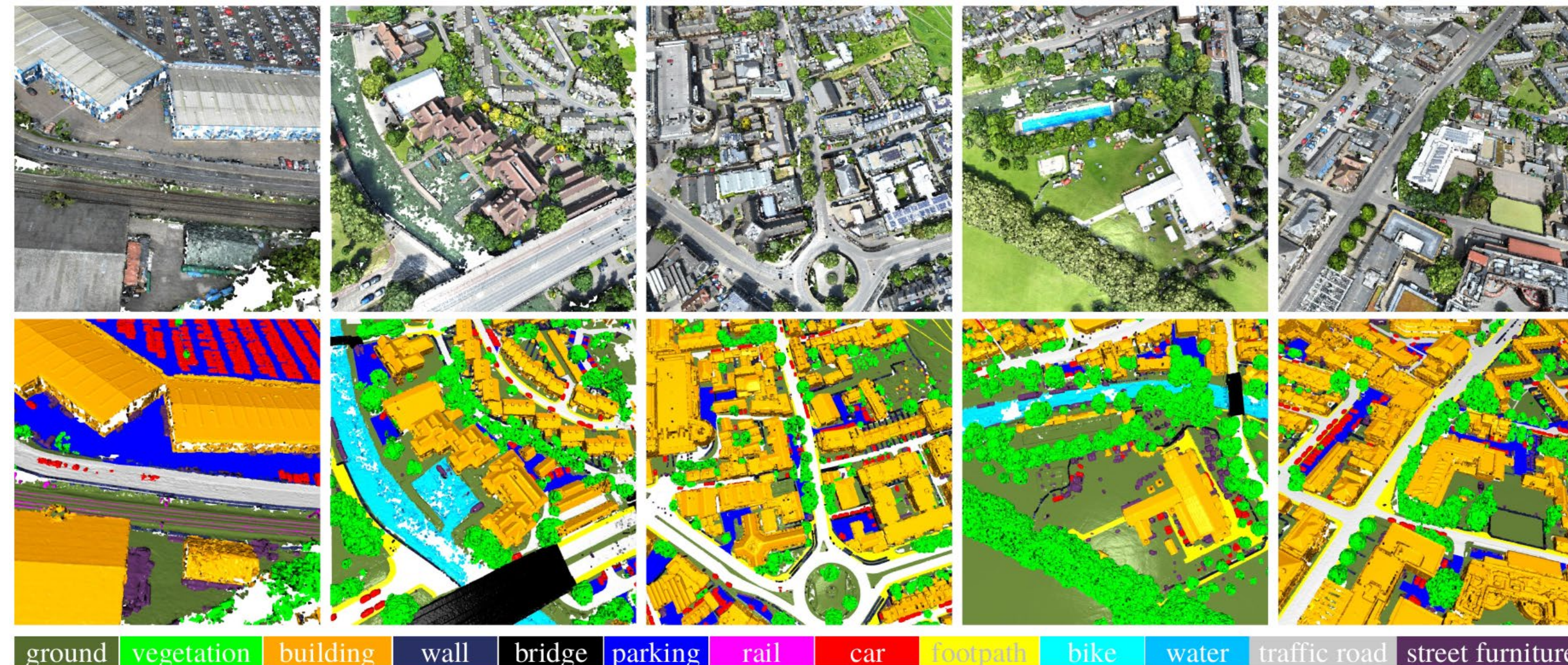
- **BuildingNet**
 - # Models: 2,000
 - # Semantic Components: 292K
 - # Semantic Parts: 31
 - Semantic segmentation
 - Surface reconstruction



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.



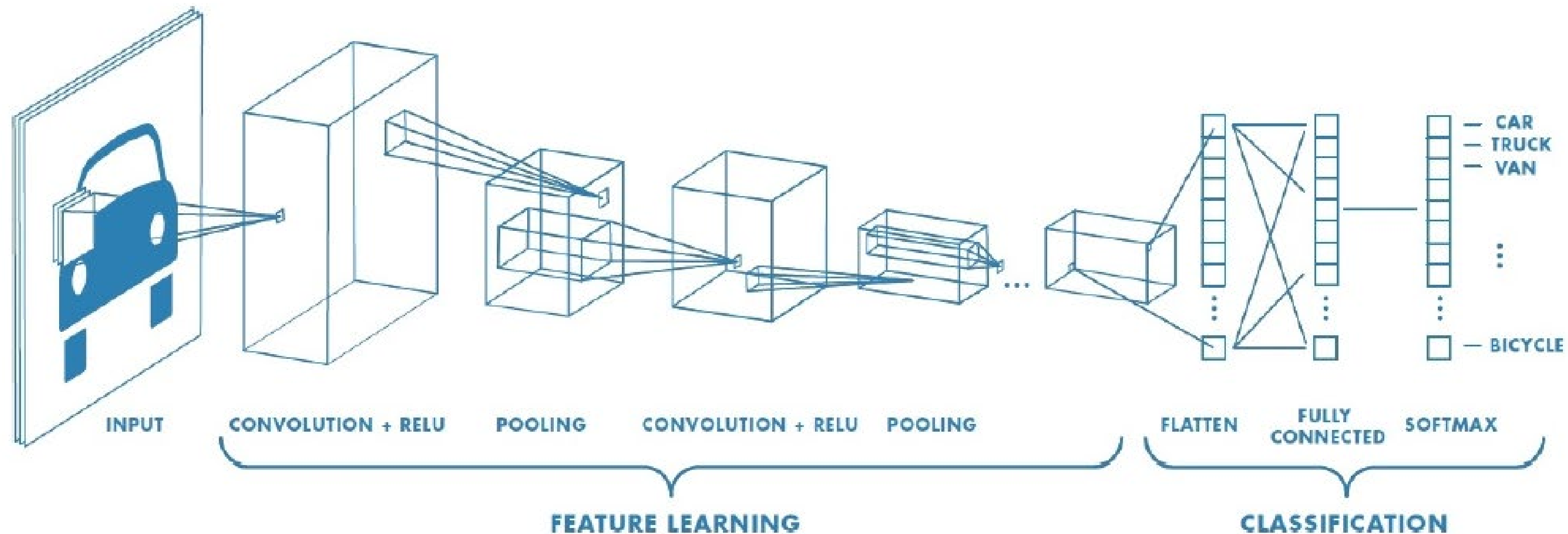
Today's Agenda

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



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

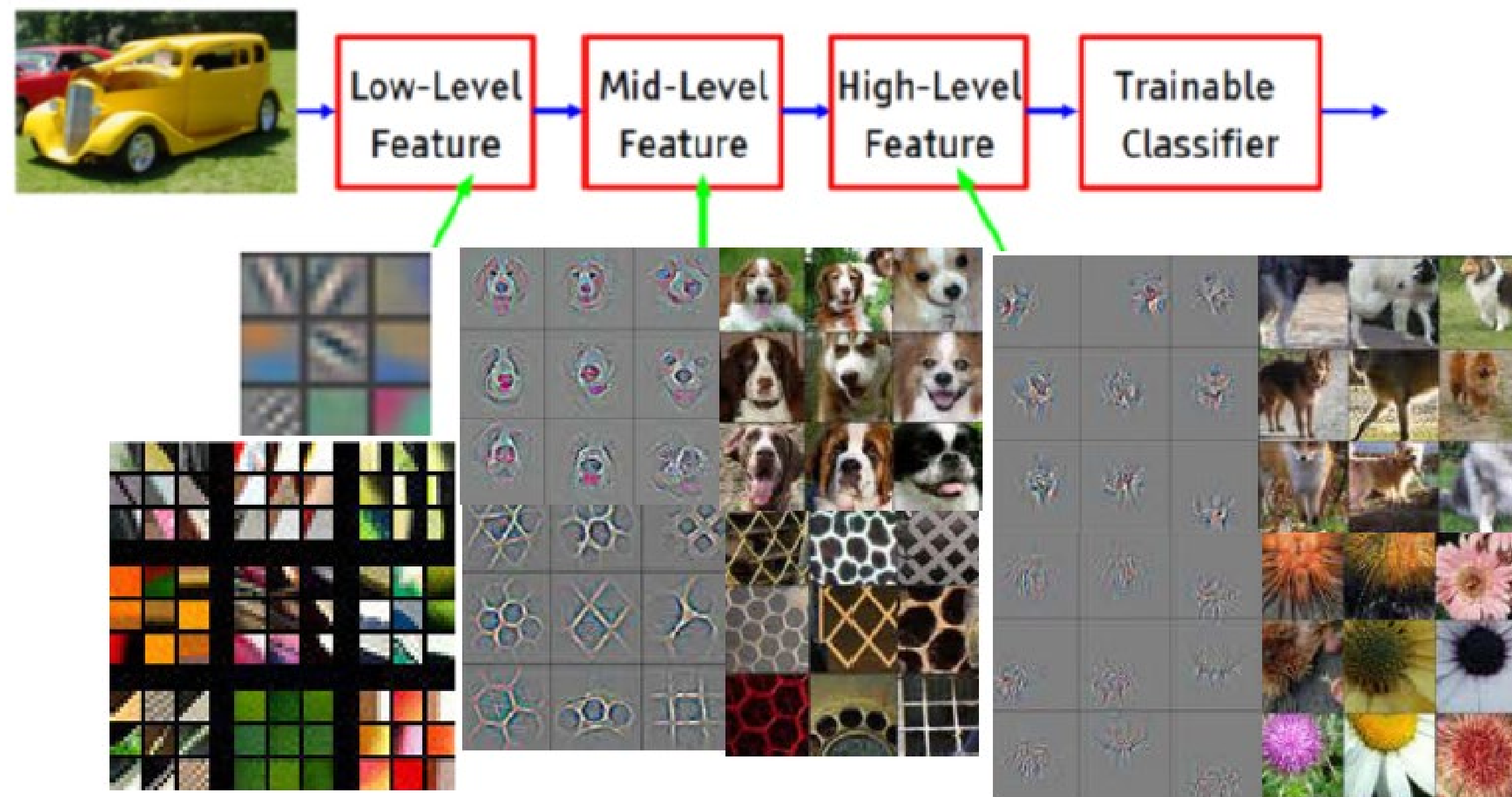
Layers of **convolutional filters** trained to extract descriptors + **learned functions** that map descriptors to high-level concepts



Kalogerakis E.

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

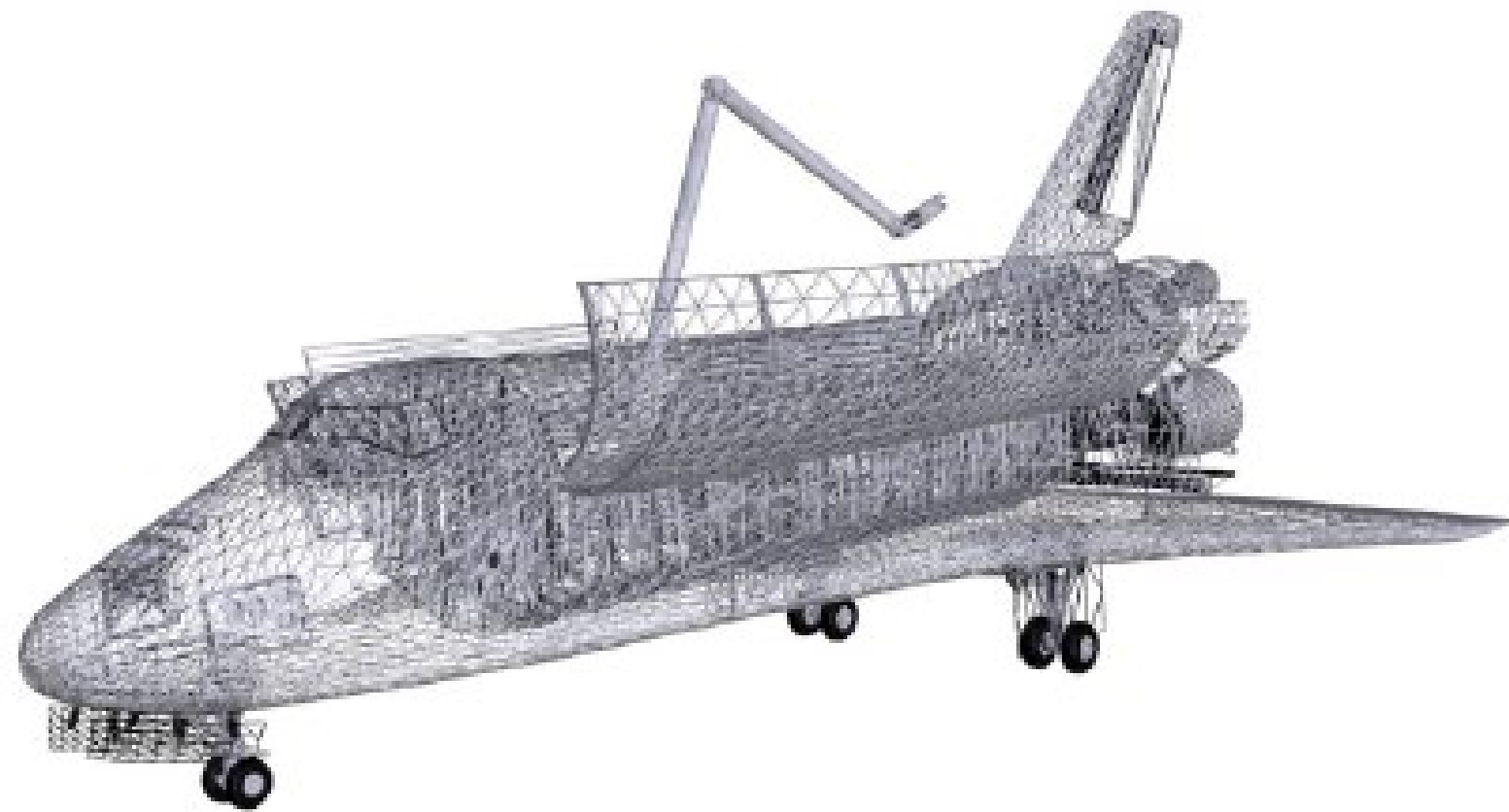
Can capture various **low-level** and **high-level** features through hierarchical representation learning. **Very good performance** in 2D vision tasks (class., seg., obj. det....)



Kalogerakis E.

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

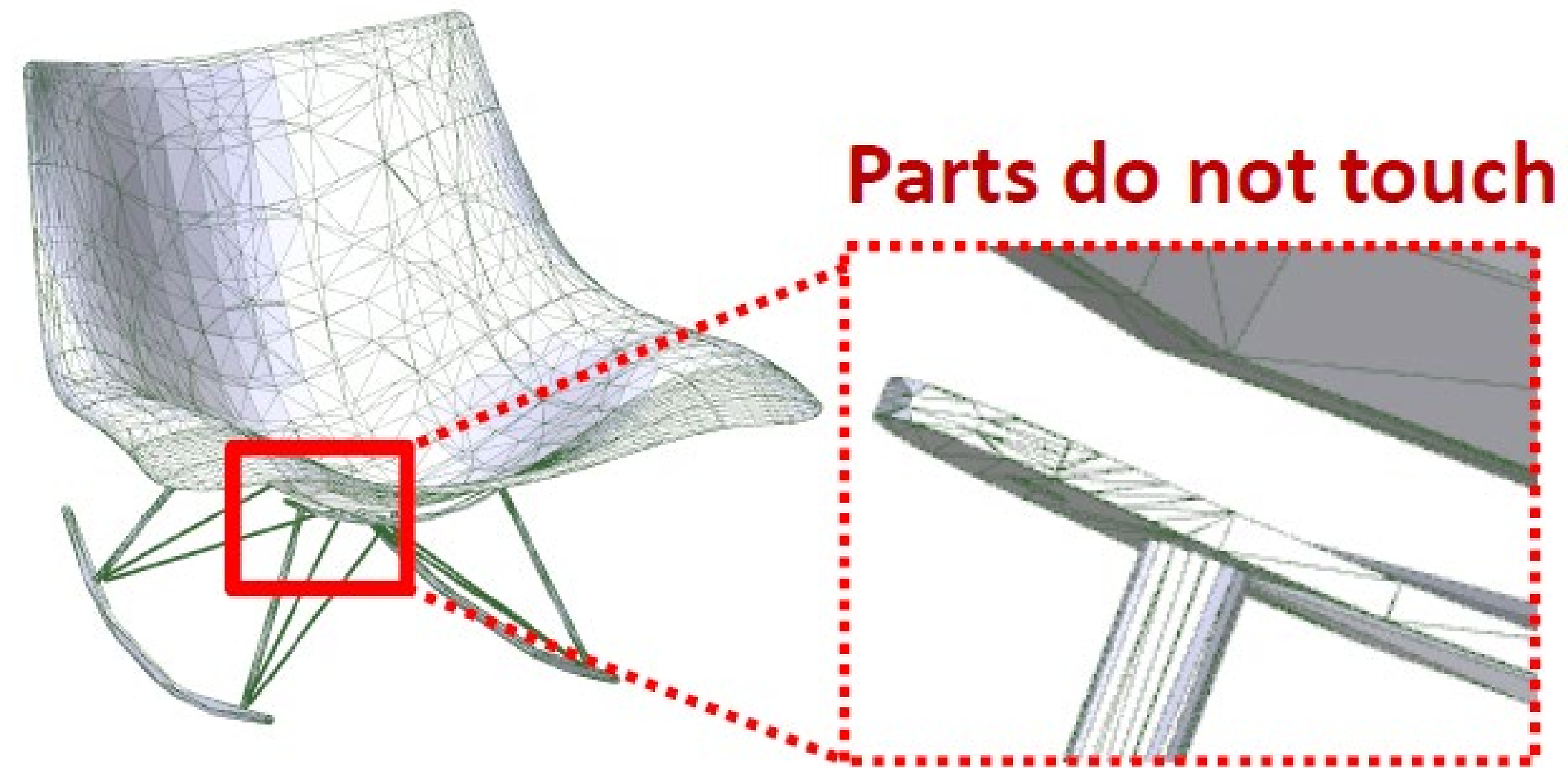


Point clouds

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**

RGB Image & depth data



Resulting surface

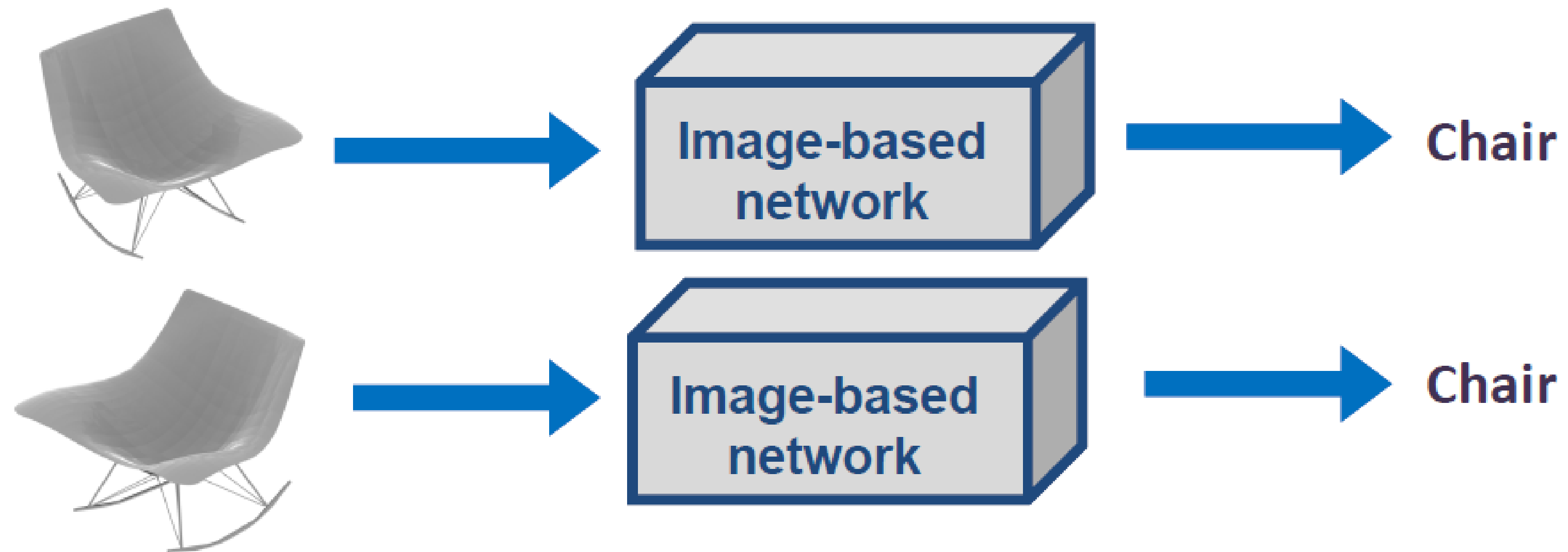


“A Large Dataset of Object Scans”

Choi, Zhou, Miller, Koltun 2016

3D DL architectures: *Multi-view approach*

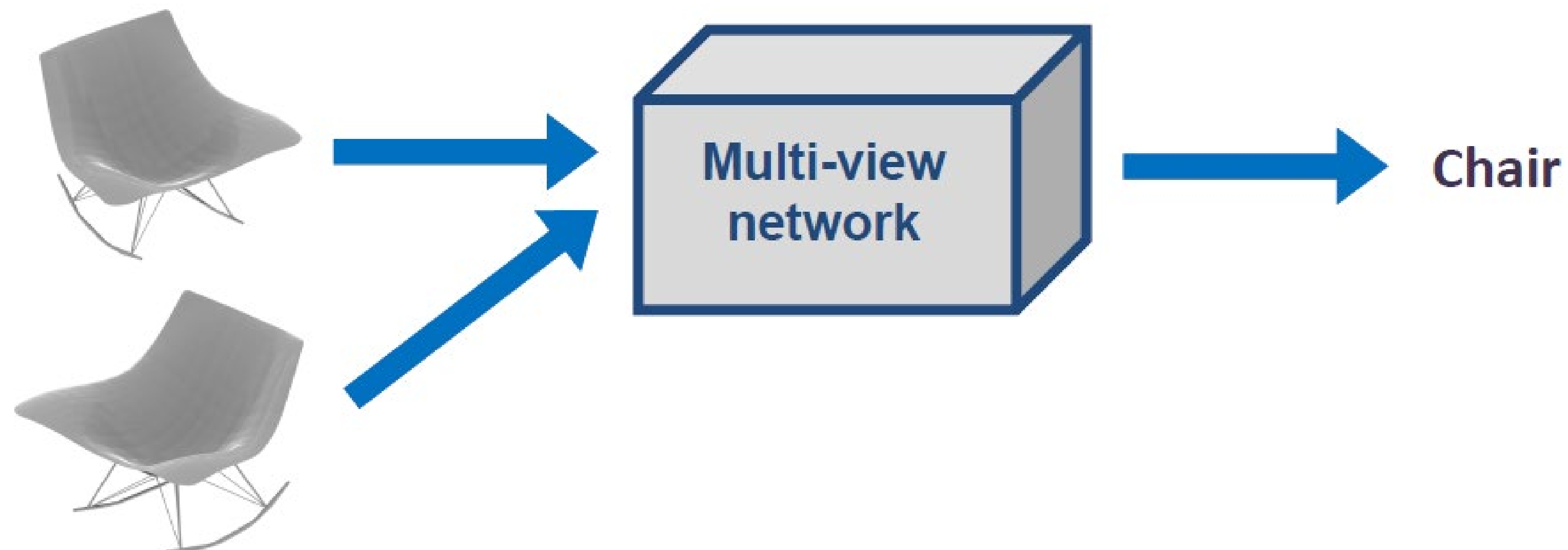
Image-based networks can process individual shape renderings



Kalogerakis E.

3D DL architectures: *Multi-view approach*

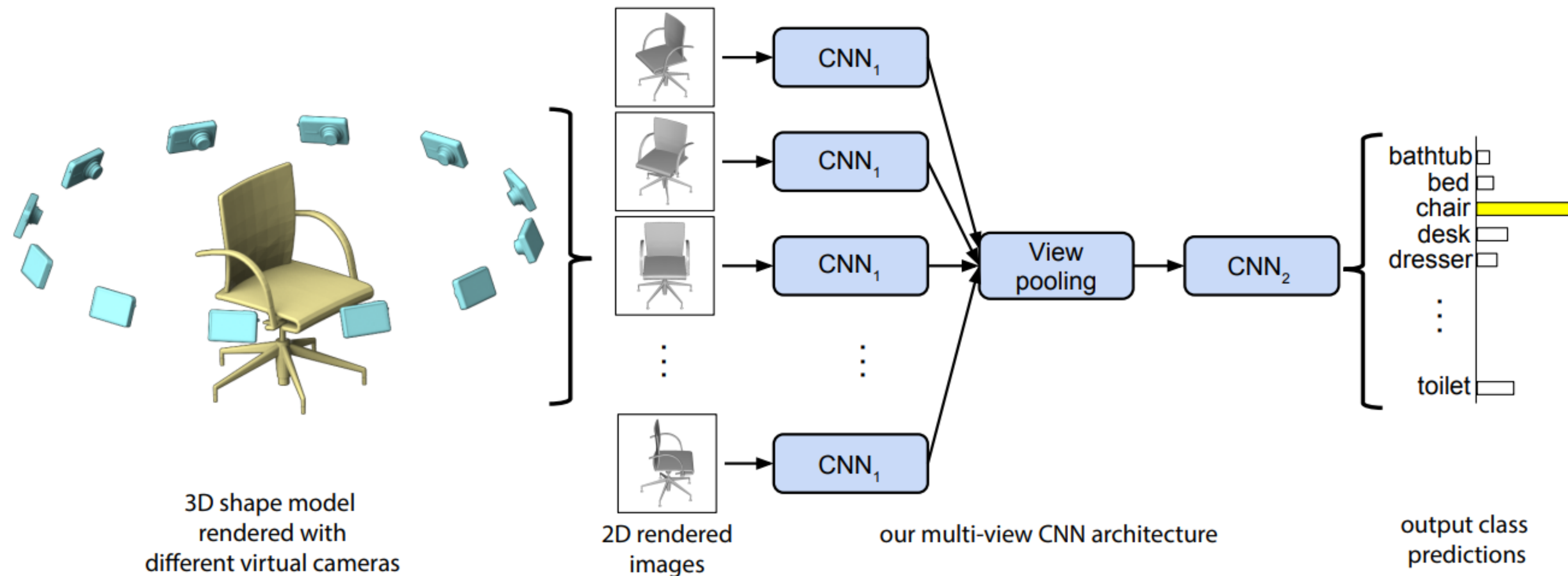
Image-based networks can process individual shape renderings



Kalogerakis E.

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*

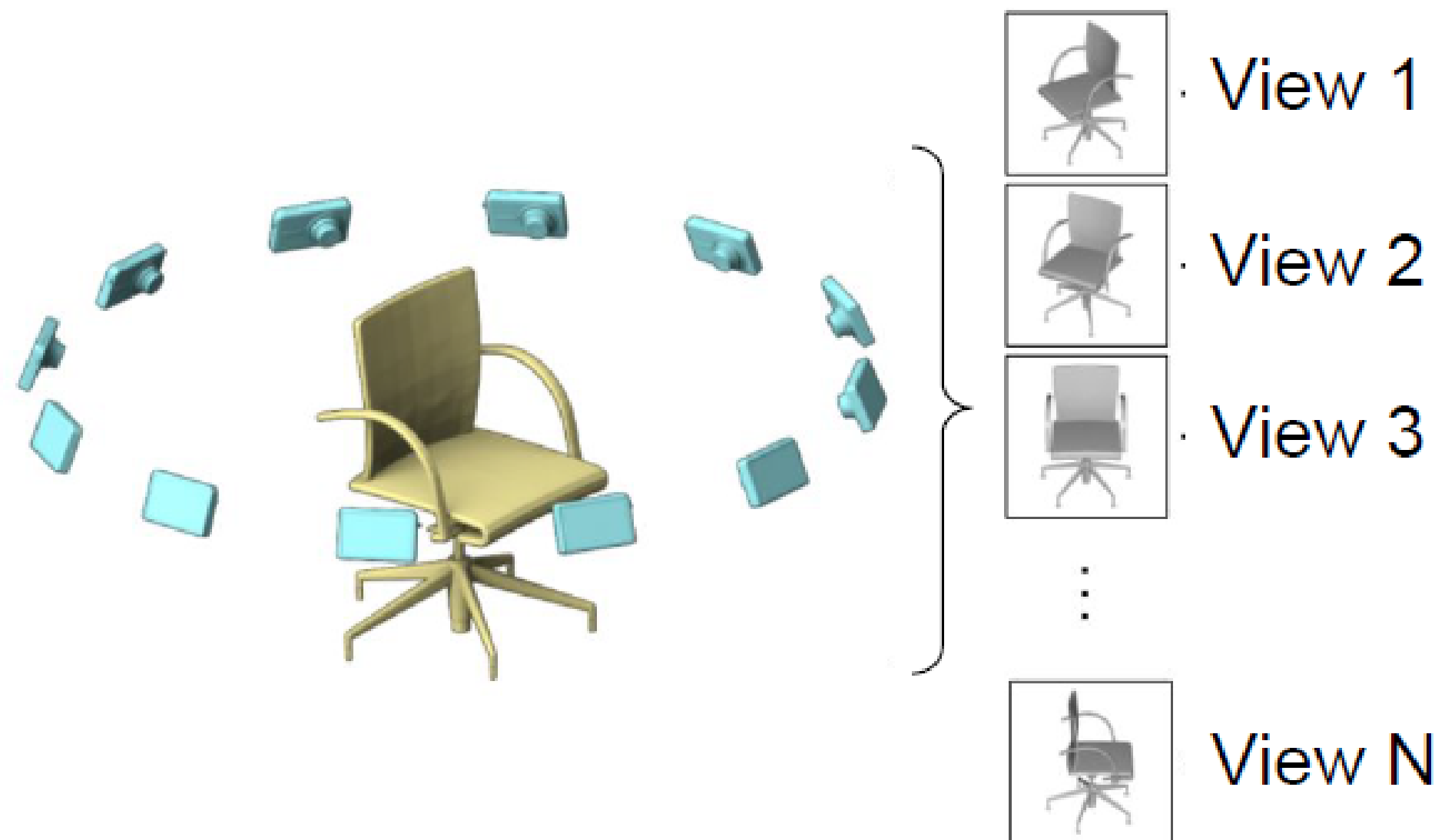
Multi-view Convolutional Neural Networks for 3D Shape Recognition



Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

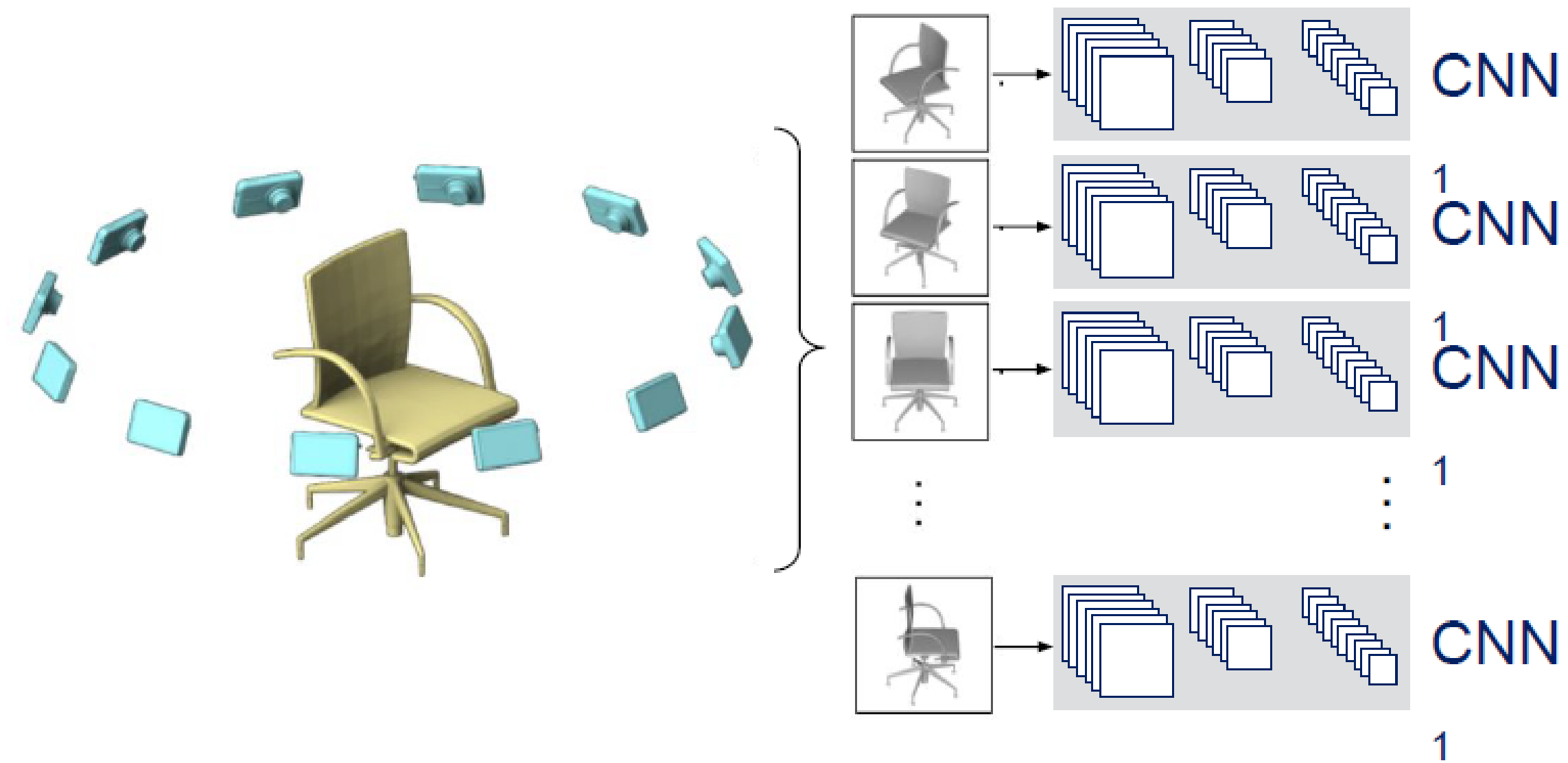
Multi-view Convolutional Neural Networks for 3D Shape Recognition



Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition

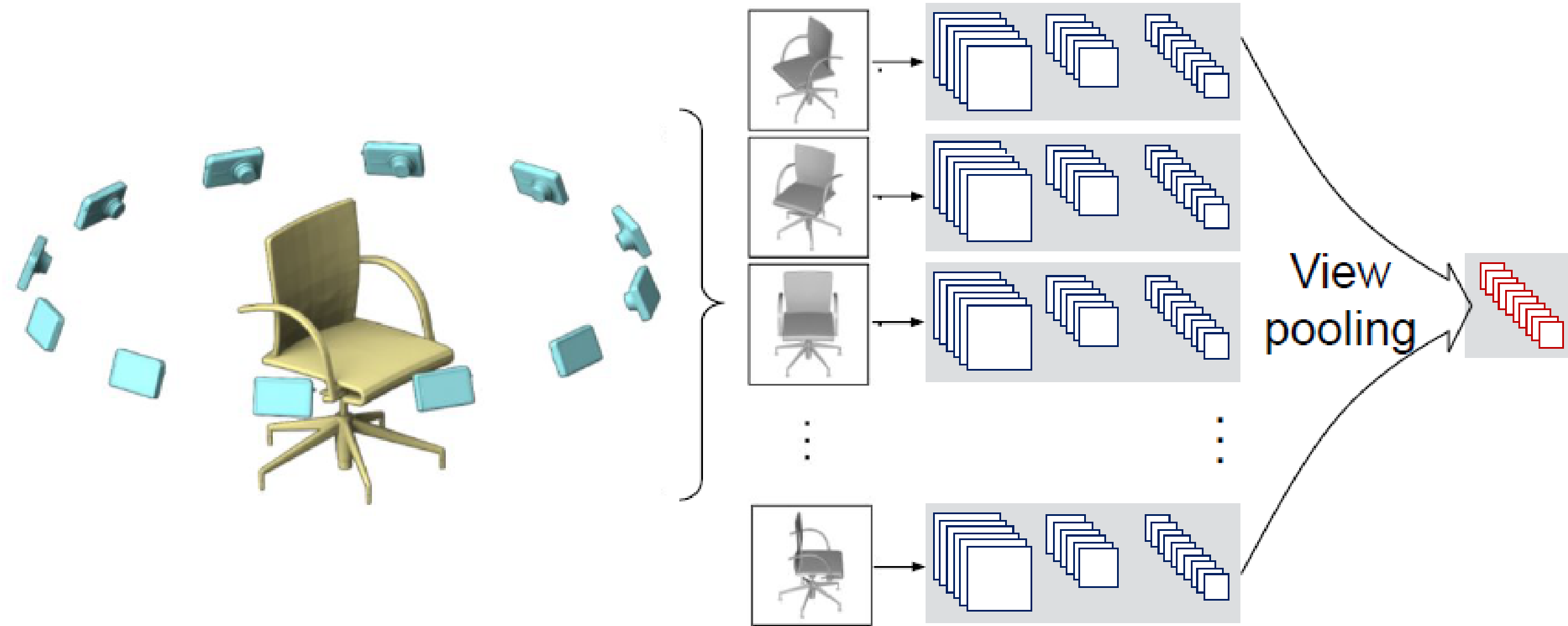


CNN_1 : a ConvNet extracting image features

Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition

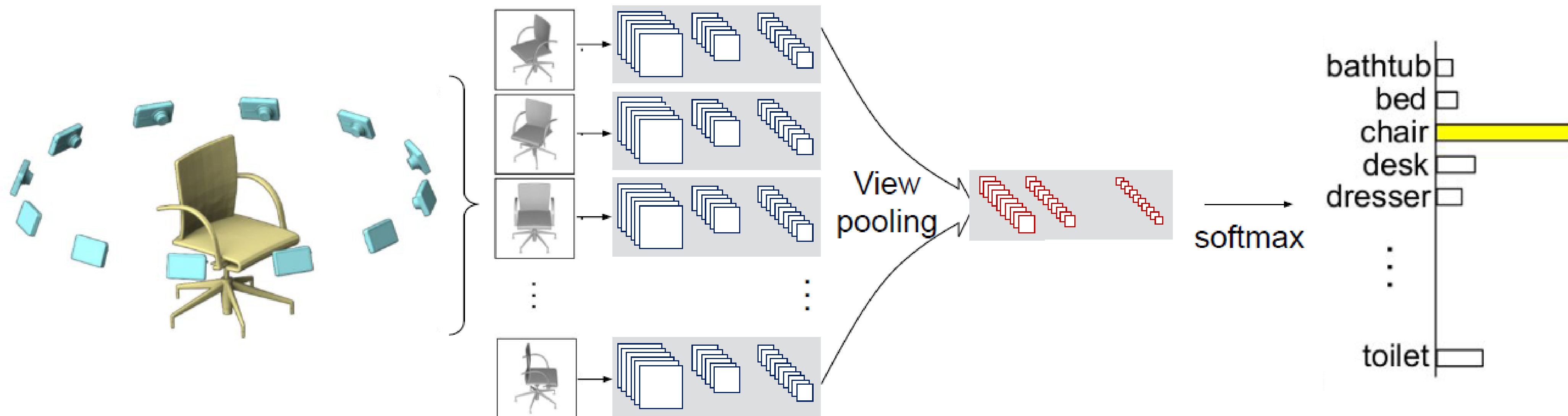


View pooling: element-wise max-pooling across all views

Hang Su et al.
ICCV 2015

3D DL architectures: *Multi-view approach*

Multi-view Convolutional Neural Networks for 3D Shape Recognition



CNN₂: 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
 - × Need projection
 - × Issue with noisy and/or incomplete input, e.g., point cloud

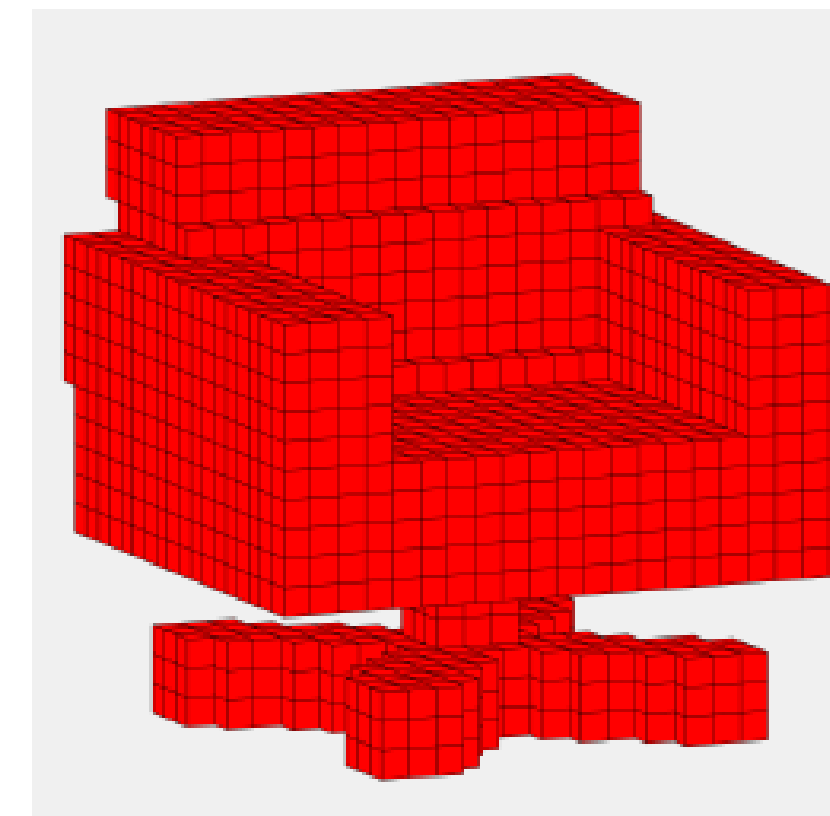
Jiajun Wu

3D DL architectures: *Volumetric approach*

Voxelization: Convert shape to 3D regular volumetric grid



3D polygon mesh

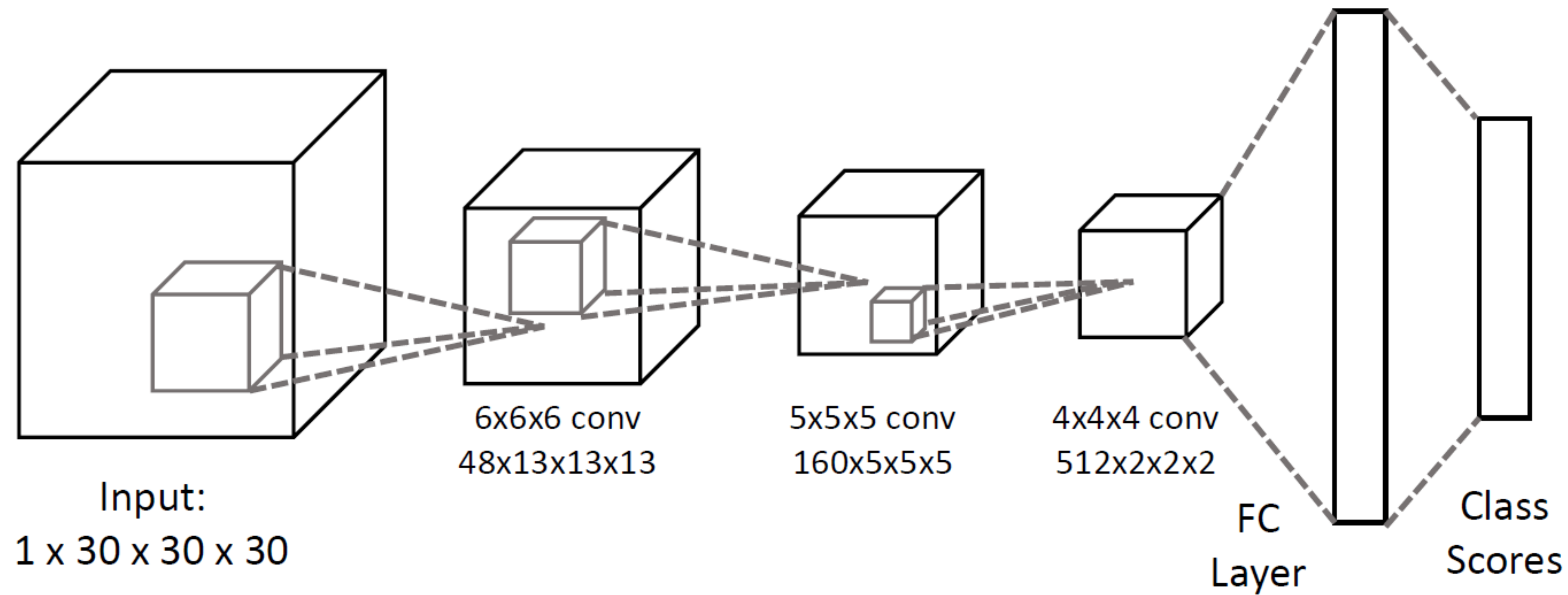


Voxels

Kalogerakis E.

3D DL architectures: *Volumetric approach*

Processing Voxel Inputs \rightarrow 3D Convolution

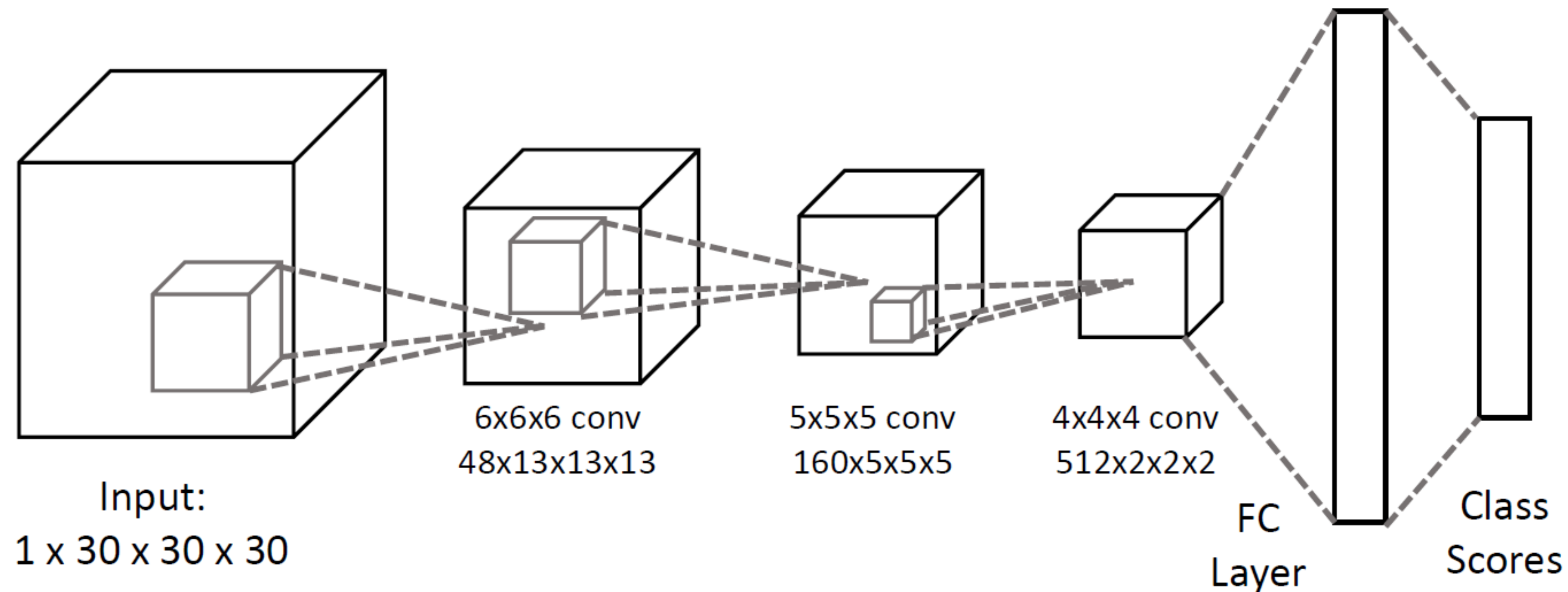


“3D ShapeNet”,
Wu et al., CVPR 2015

3D DL architectures: *Volumetric approach*

Processing Voxel Inputs → 3D Convolution

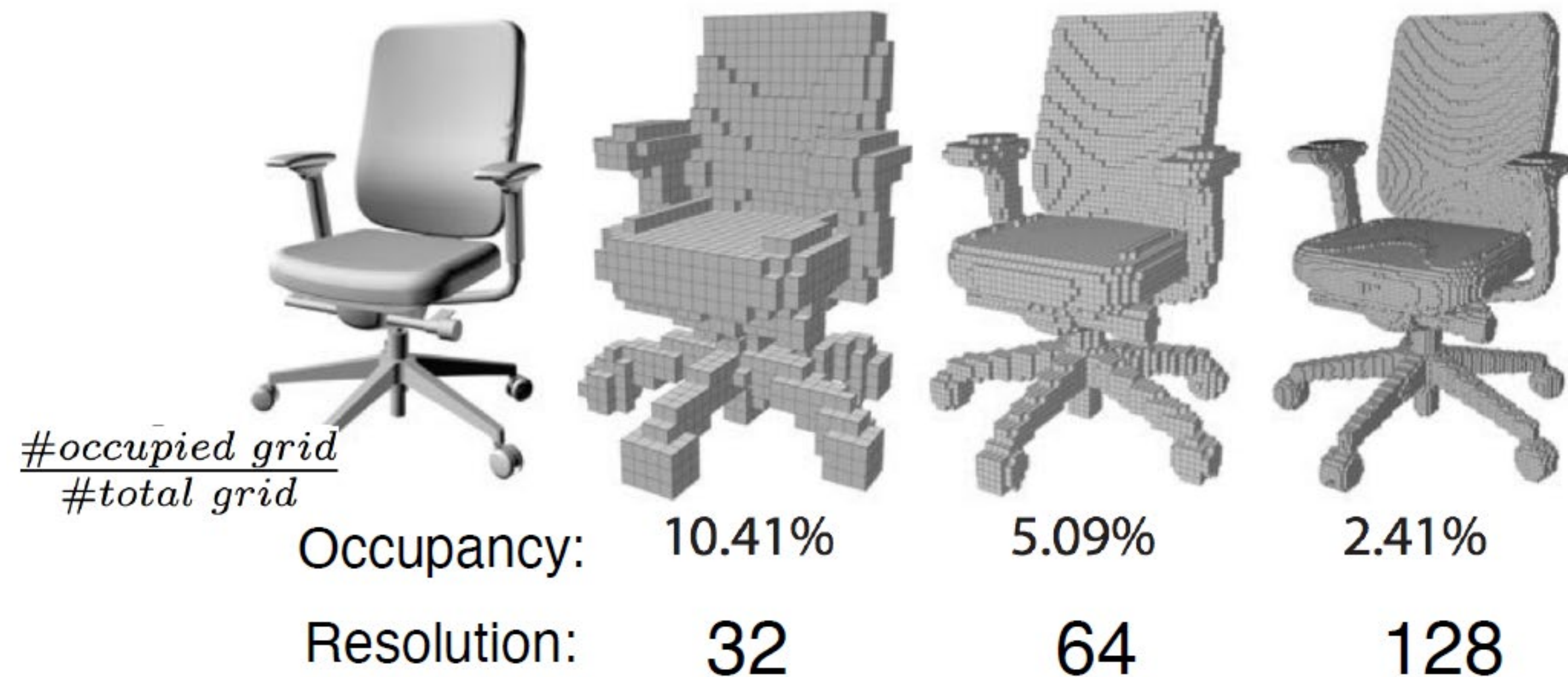
Computationally and memory expensive! Requires low-res input



“3D ShapeNet”,
Wu et al., CVPR 2015

3D DL architectures: *Volumetric approach*

Sparsity of 3D data

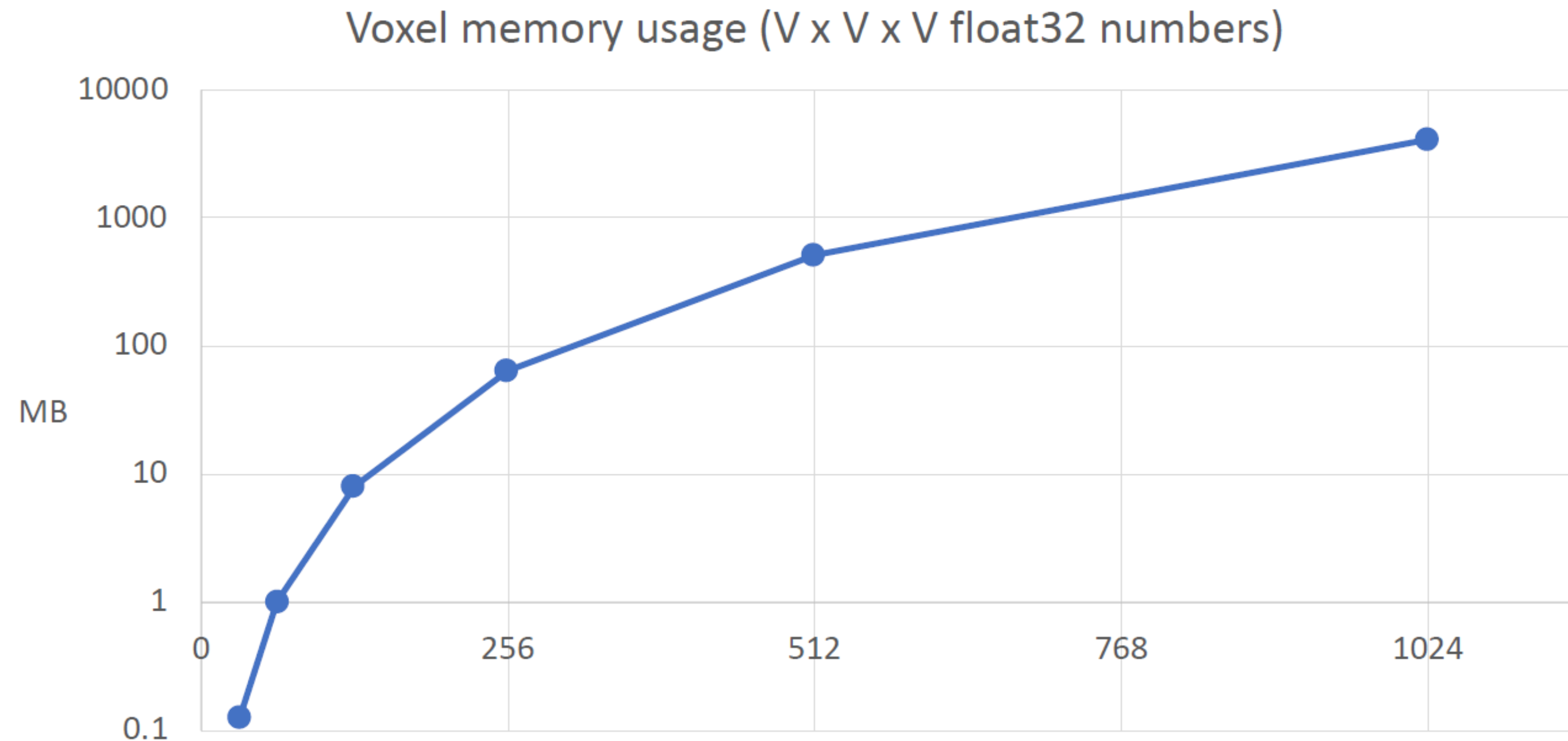


Running convolution on so much empty space is wasteful!

Hao Su et al.

3D DL architectures: *Volumetric approach*

Memory usage



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

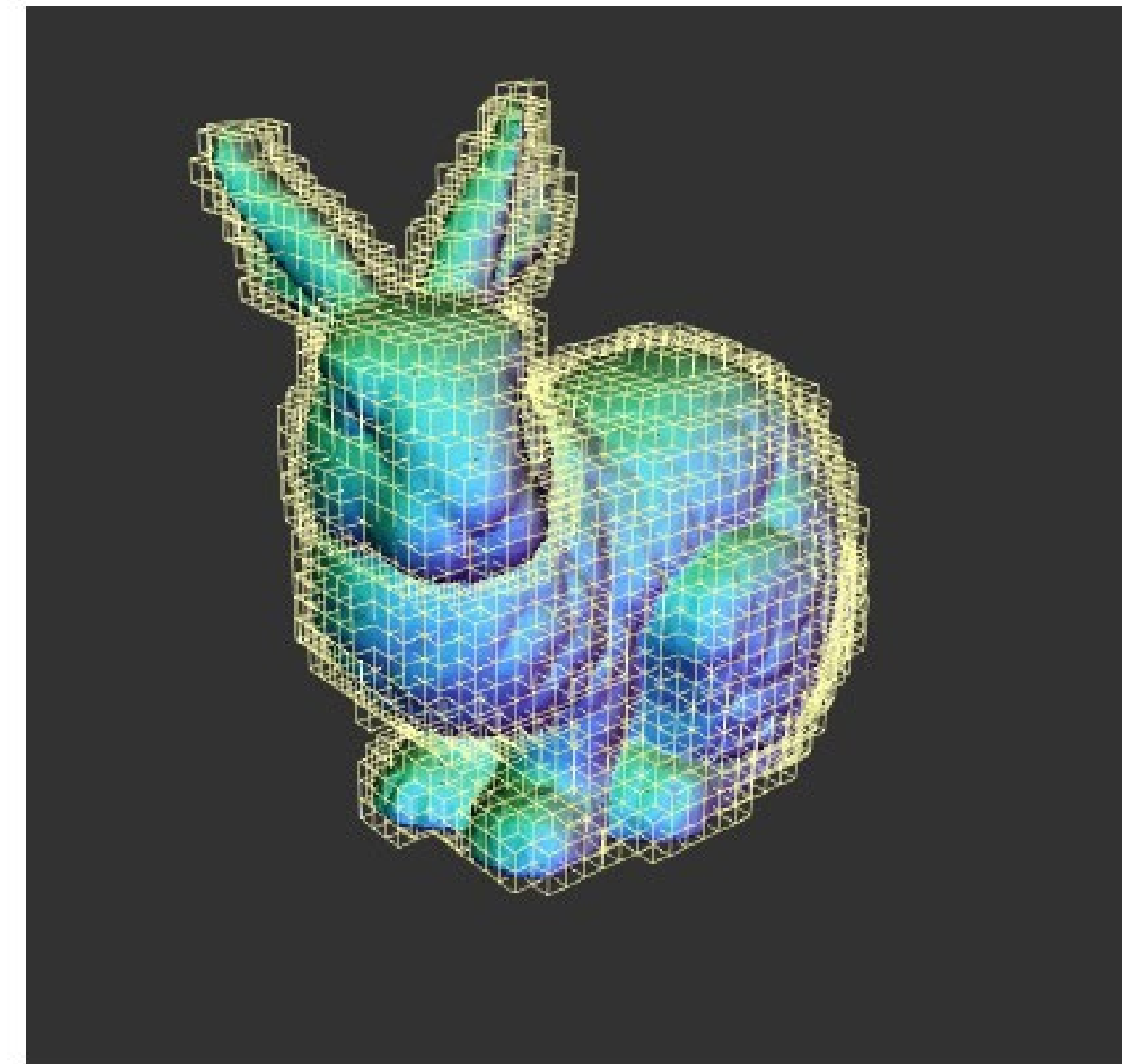
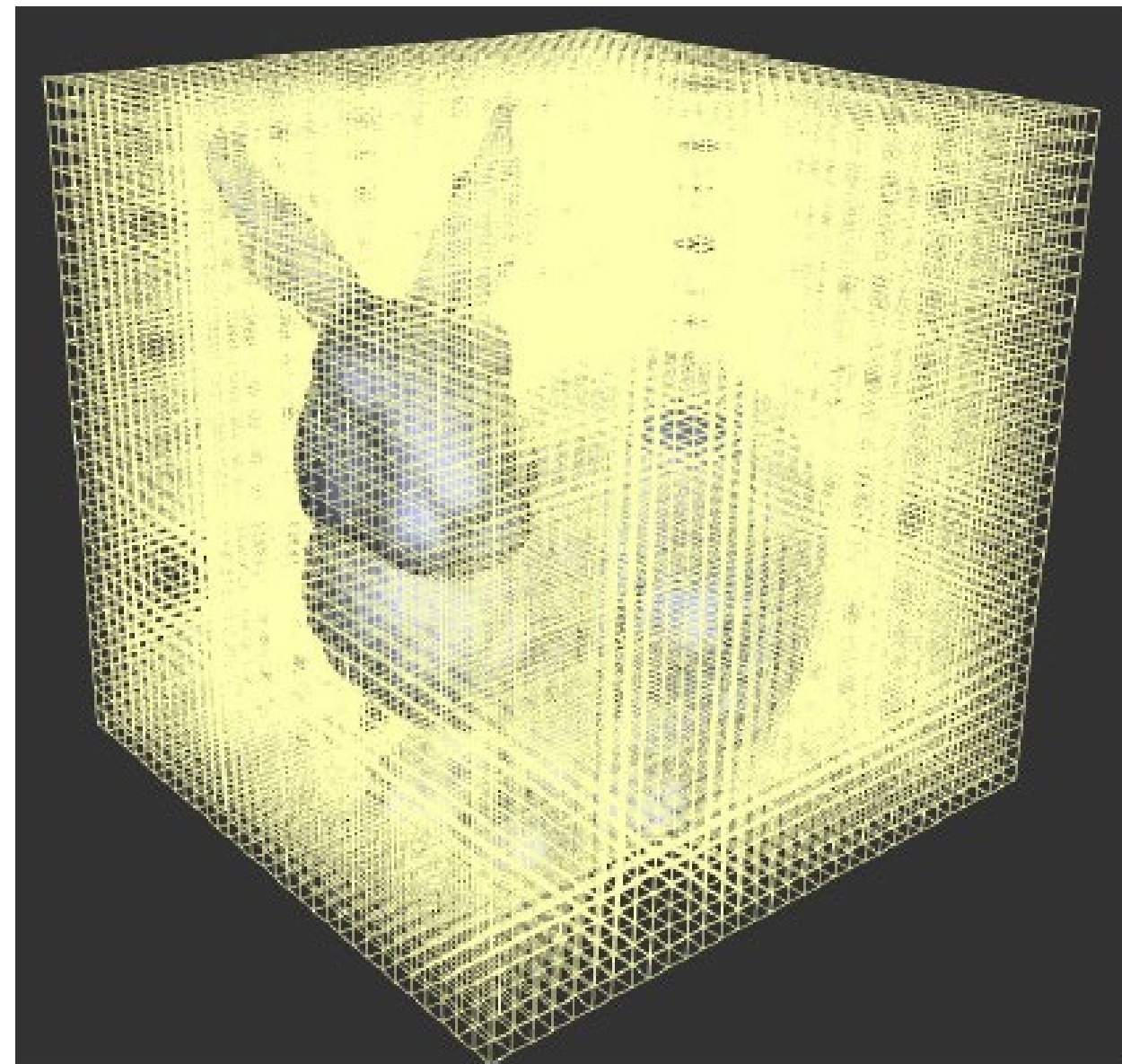
Justin Solomon



3D DL architectures: *Volumetric approach*

Solution → **Octave Tree Representations**

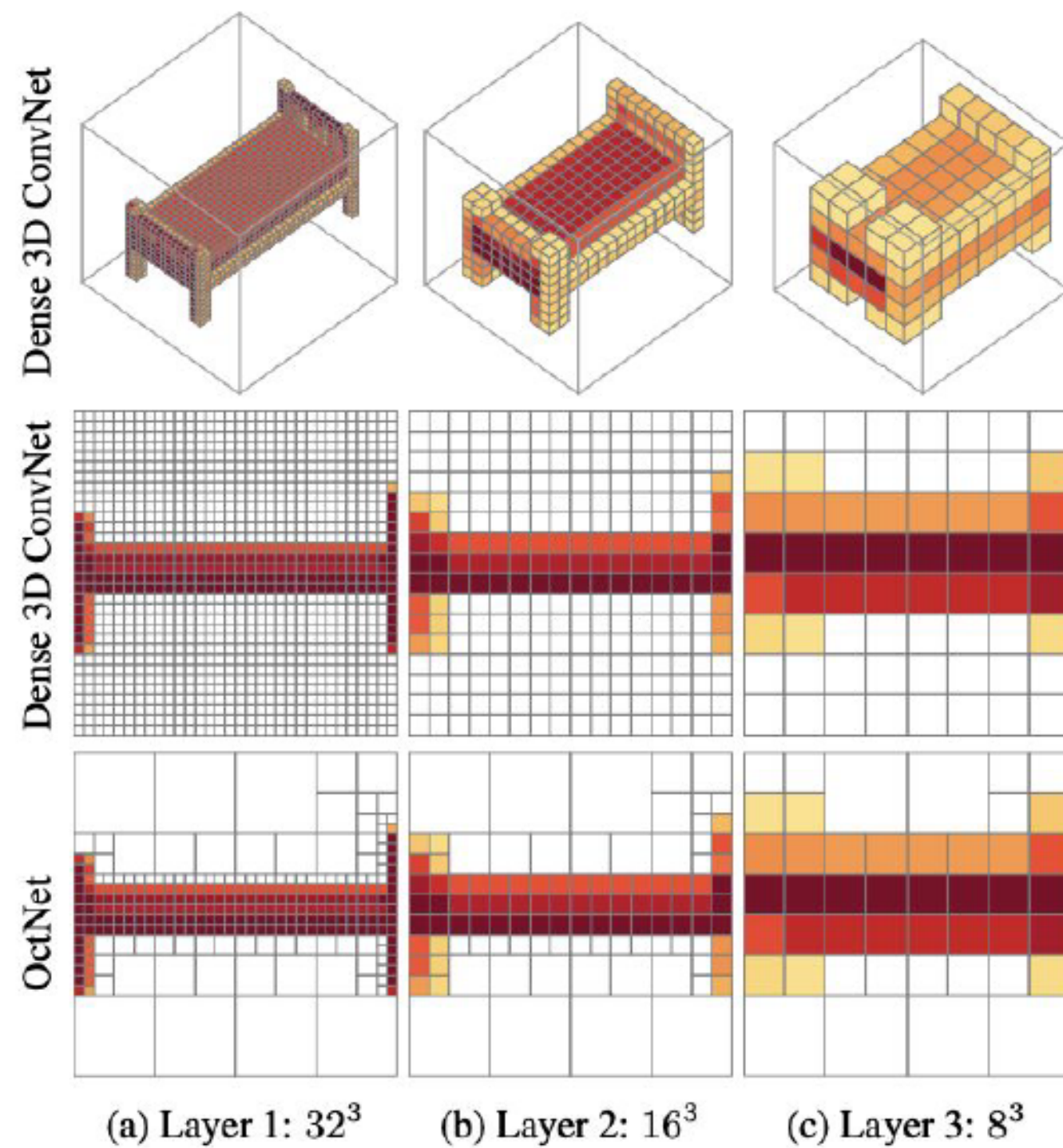
- Store the sparse surface signals
- Constrain the computation near the surface



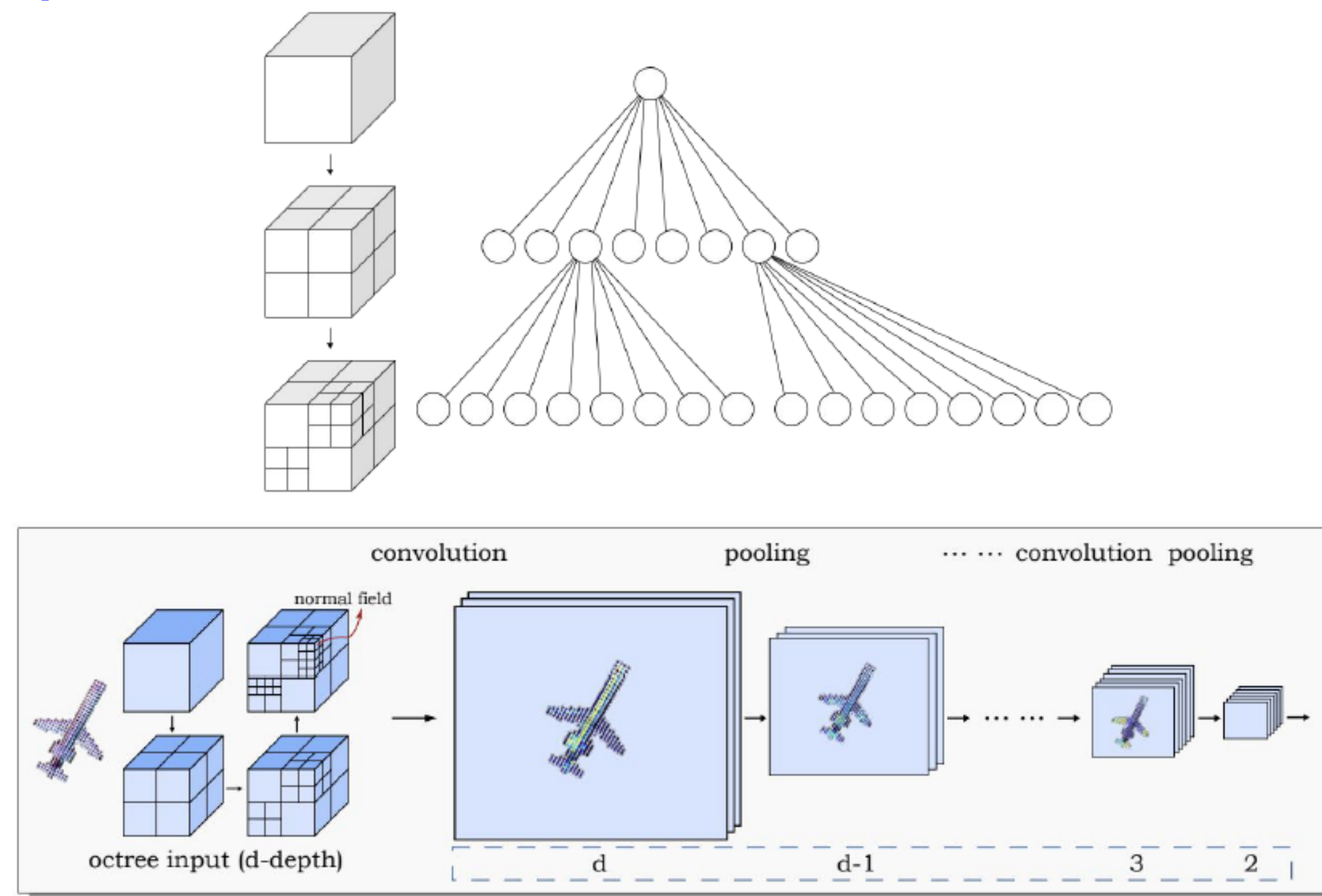
Hao Su et al.

3D DL architectures: Volumetric approach

Octree: Recursively Partition the Space



Riegler et al. OctNet. CVPR 2017

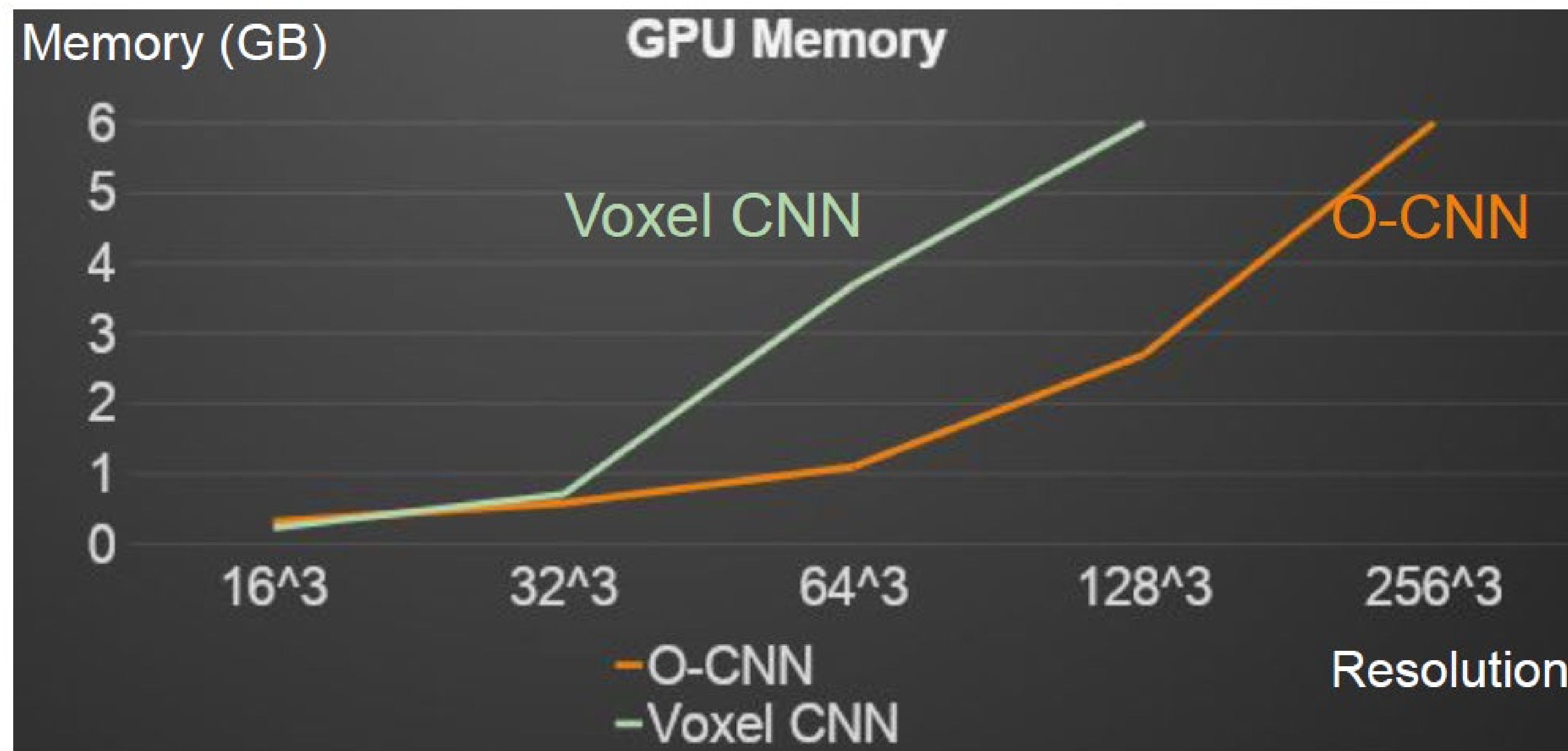


Wang et al. O-CNN. SIGGRAPH 2017

Hao Su et al.

3D DL architectures: *Volumetric approach*

Memory Efficiency



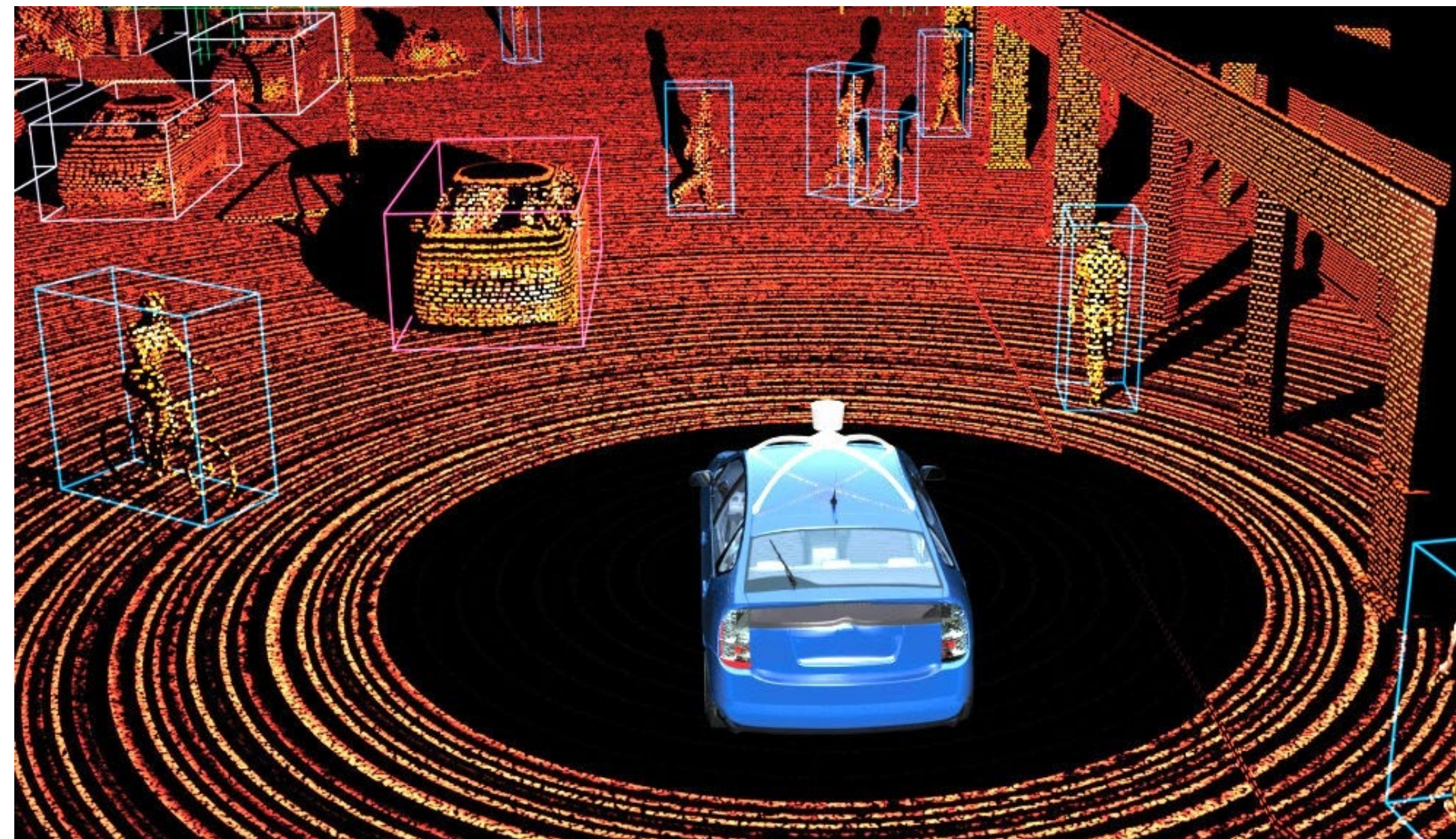
Hao Su et al.



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

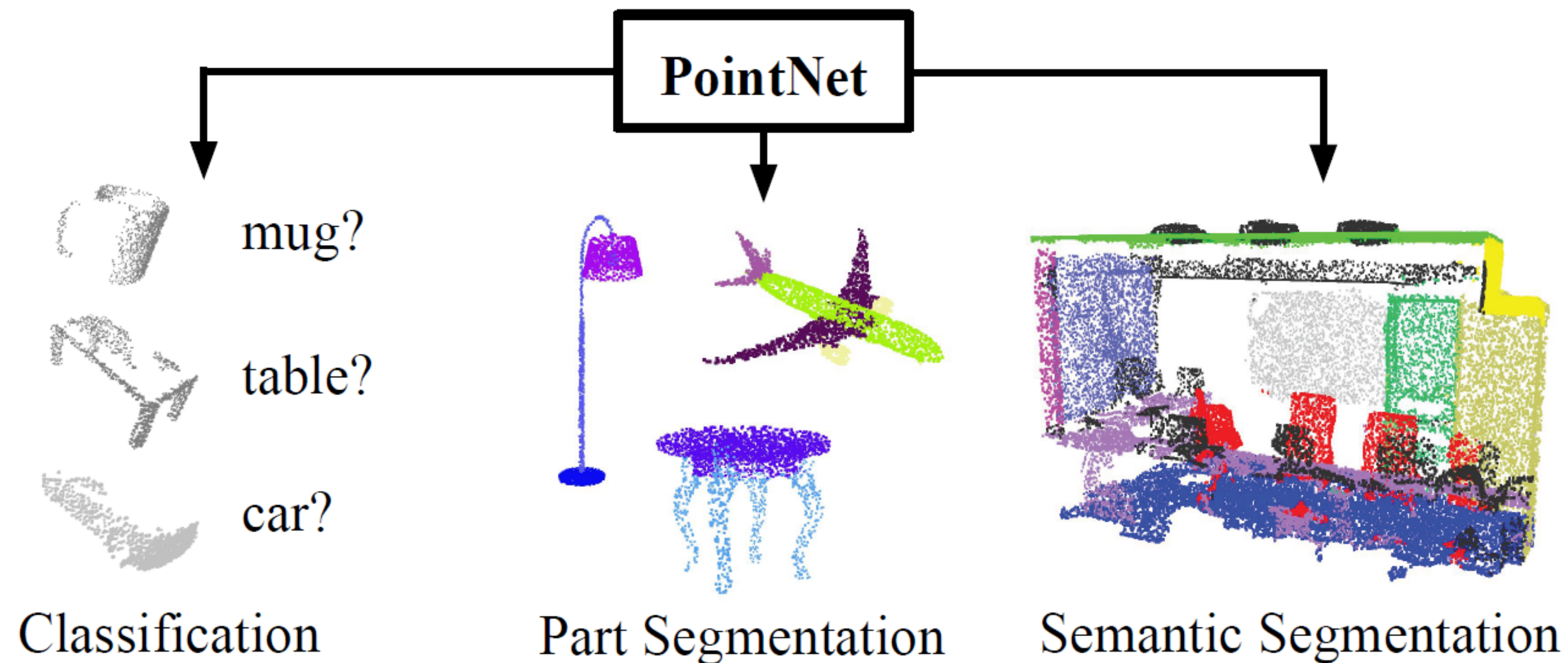


Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet: (Qi et al., CVPR 2017)

- Processes input point clouds for various tasks

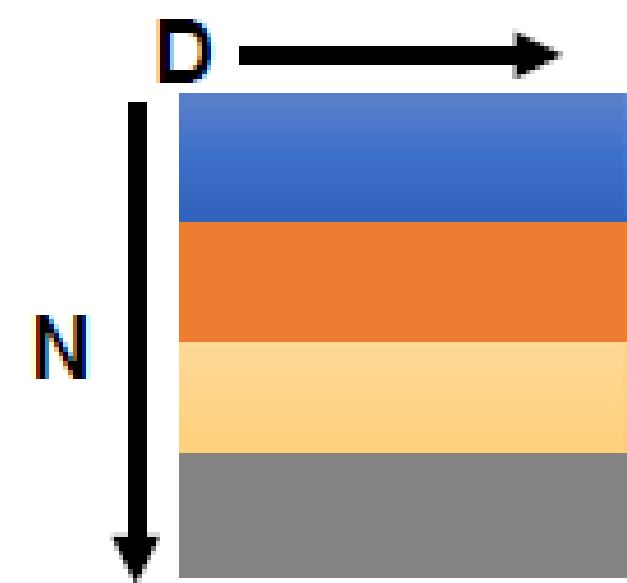


Hao Su

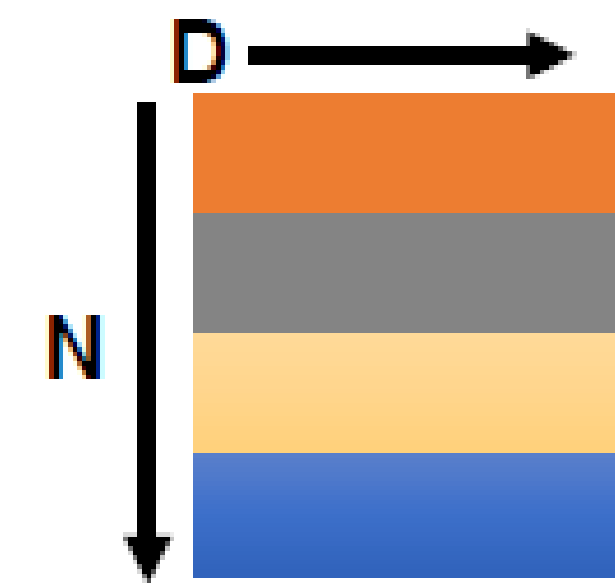
3D DL architectures: *Point-based approach*

Desired Properties of PointNet:

- **Permutation invariance**



represents the same set as

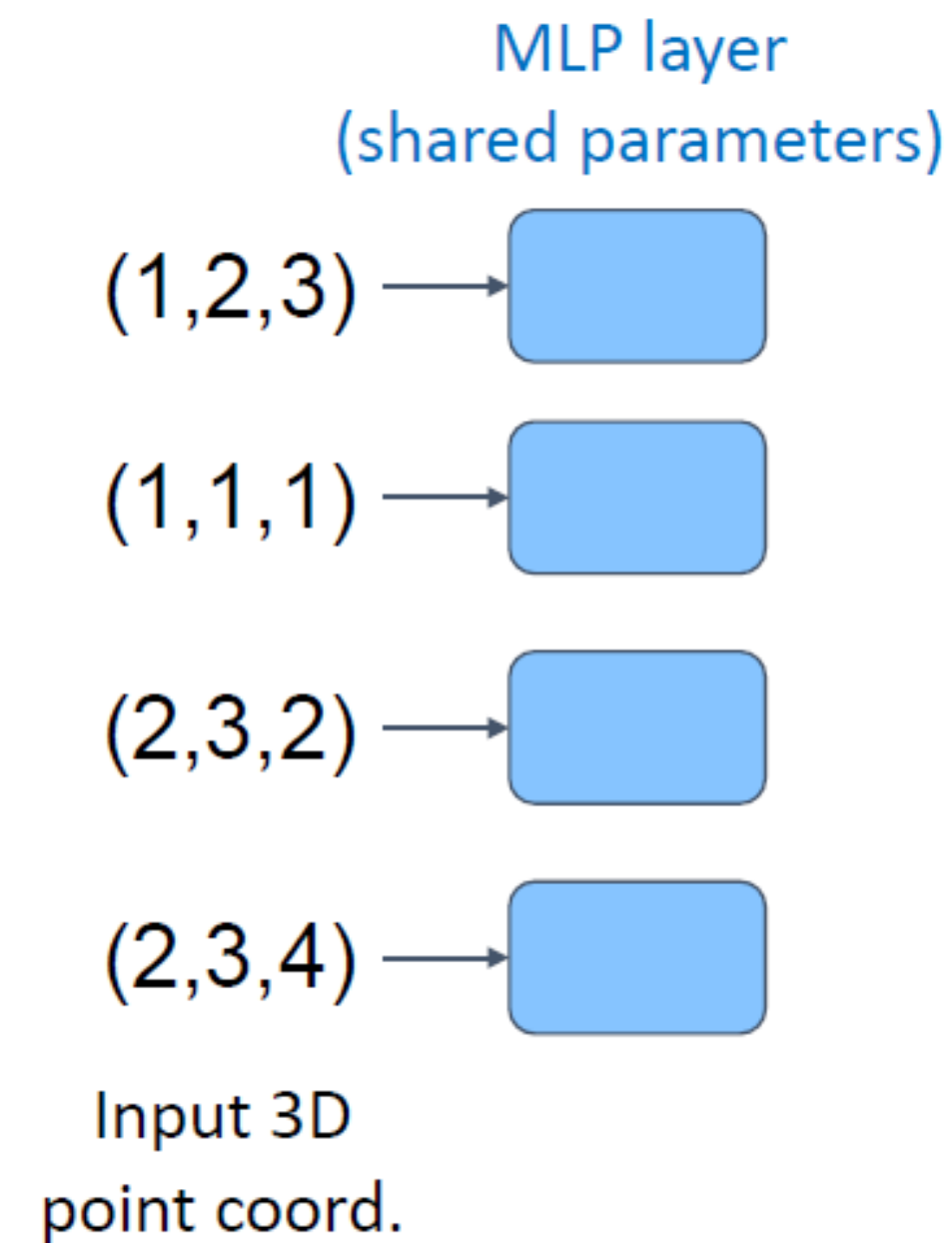


2D array representation

Kalogerakis E.

3D DL architectures: *Point-based approach*

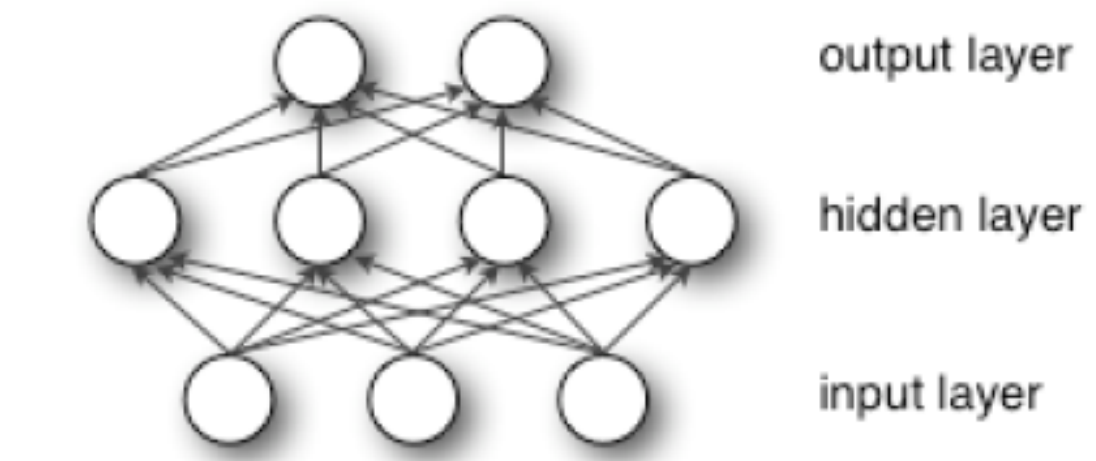
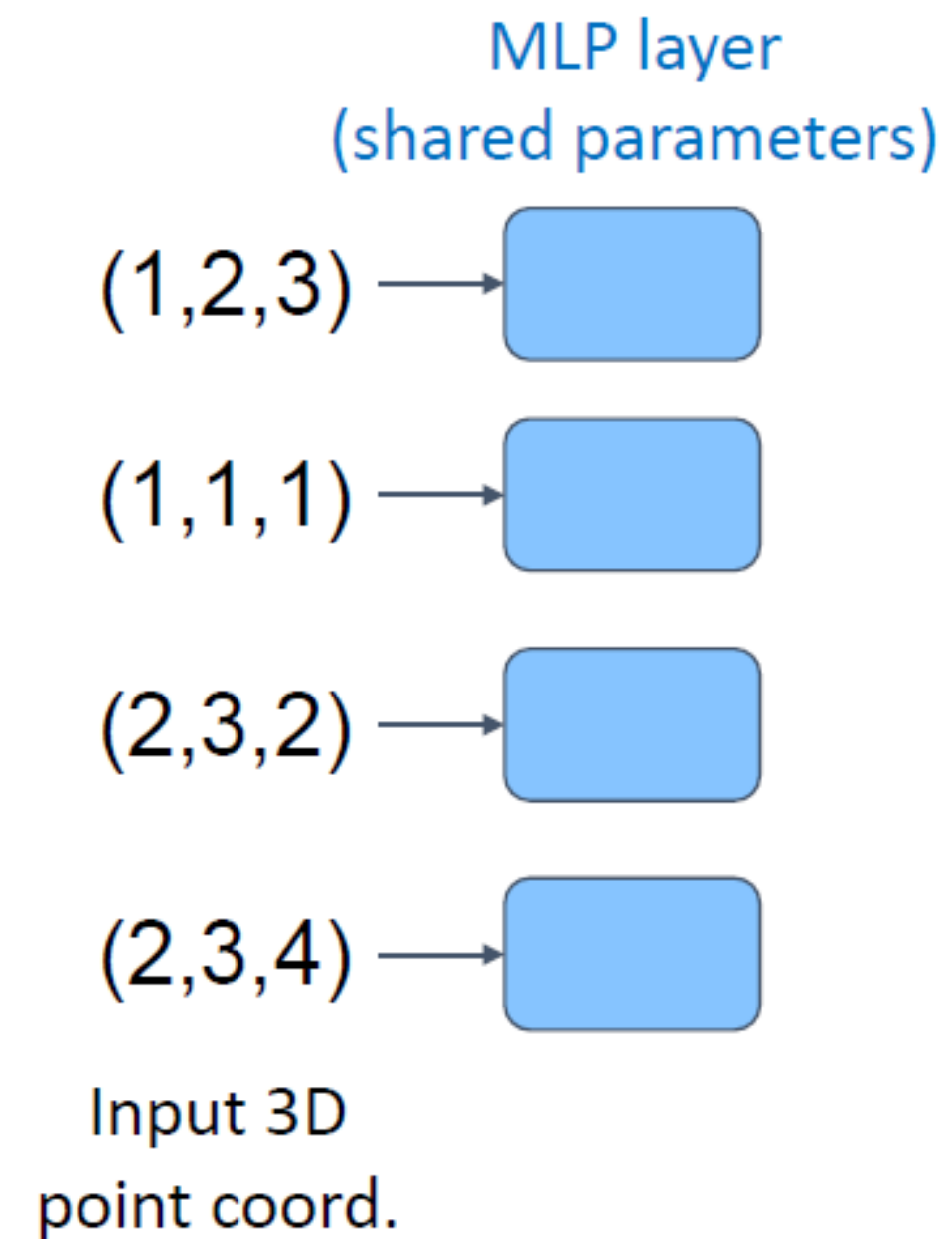
PointNet architecture:



Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet architecture:

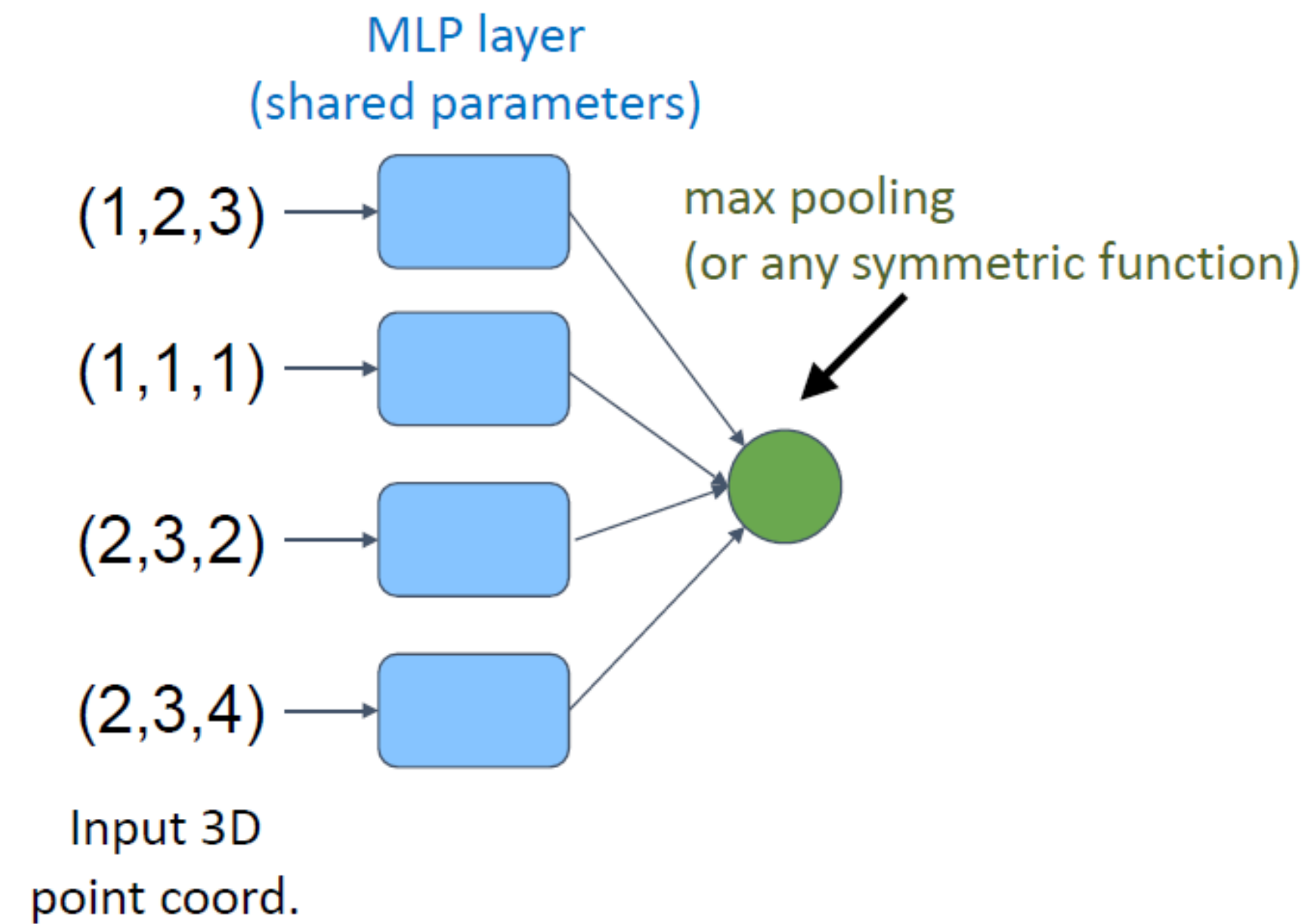


Simply a fully connected NN
with one hidden layer,
3 inputs for 3D points, and T
outputs (T is layer parameter)

Kalogerakis E.

3D DL architectures: *Point-based approach*

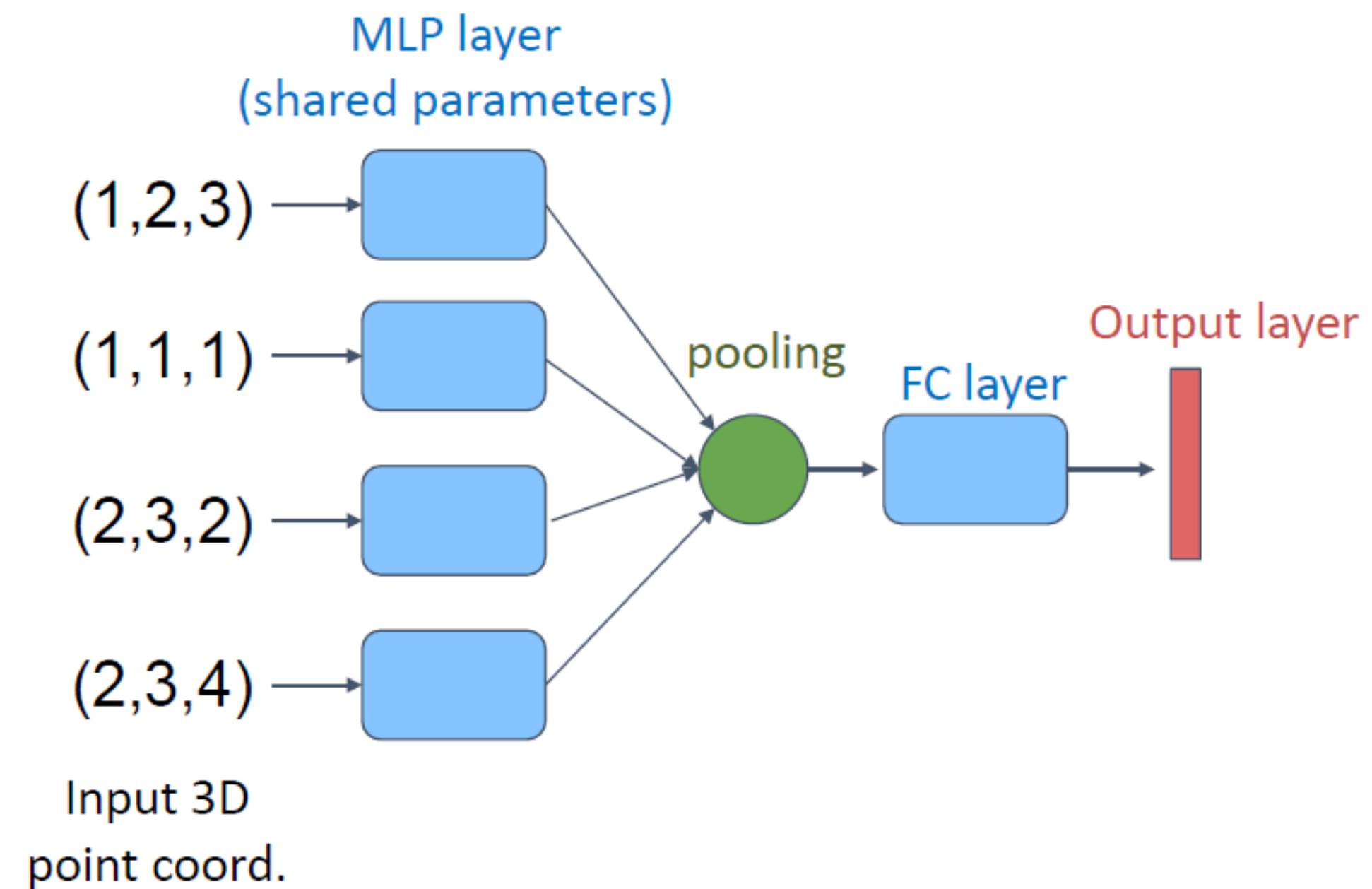
PointNet architecture:



Kalogerakis E.

3D DL architectures: *Point-based approach*

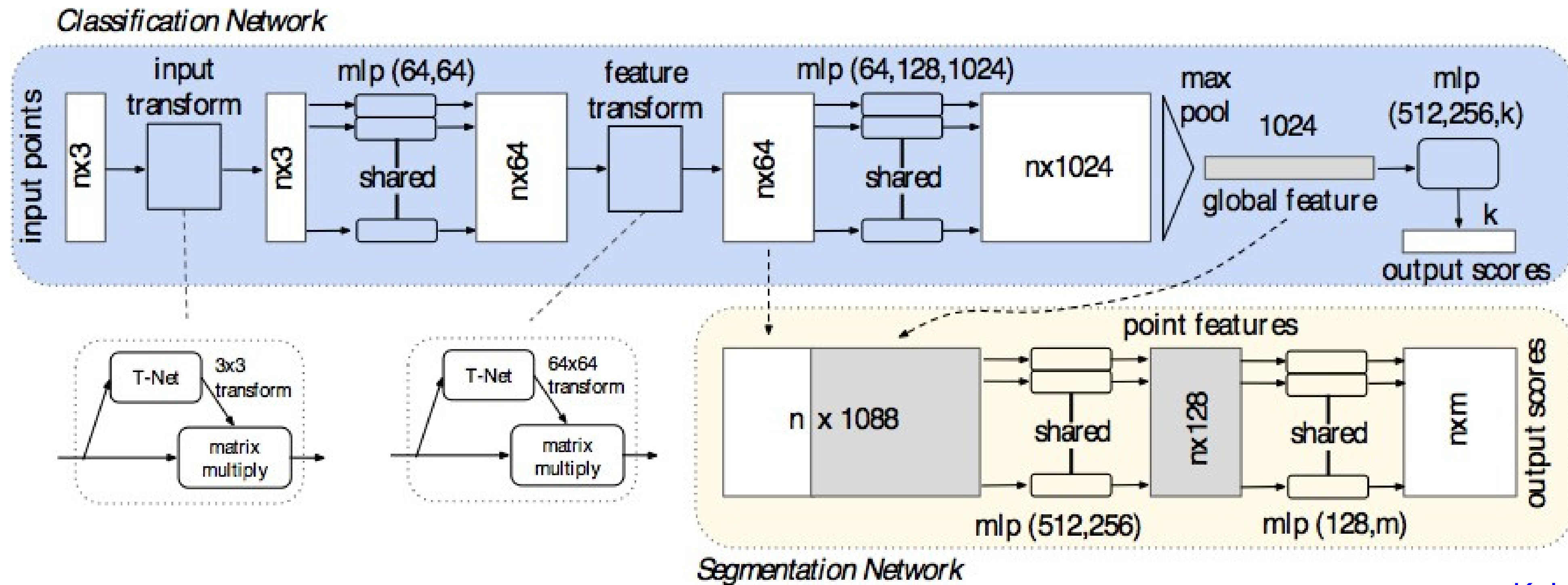
PointNet architecture:



Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet architecture:

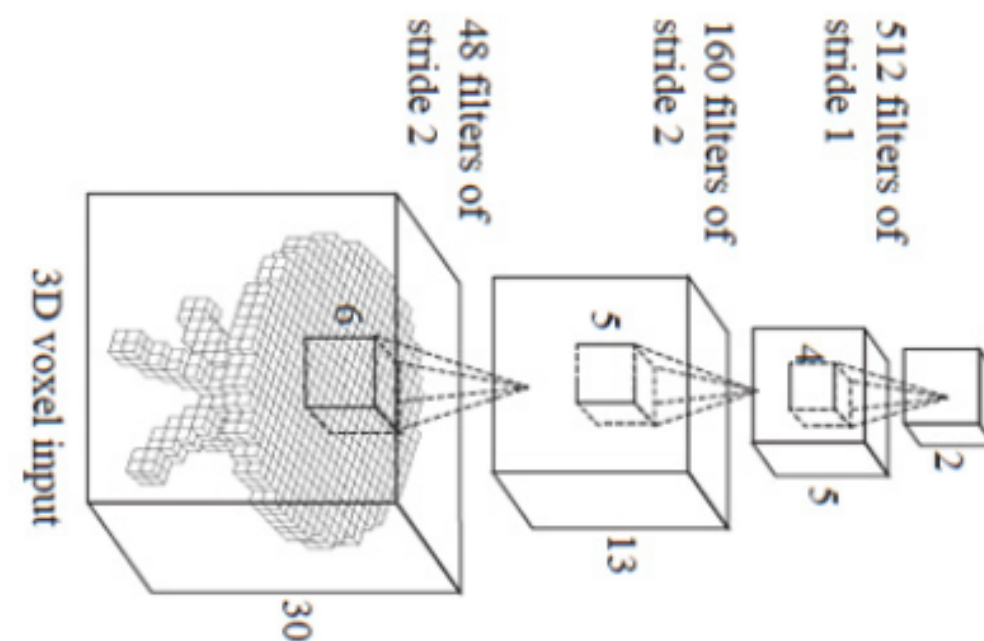


Kalogerakis E.

3D DL architectures: *Point-based approach*

Limitations of PointNet

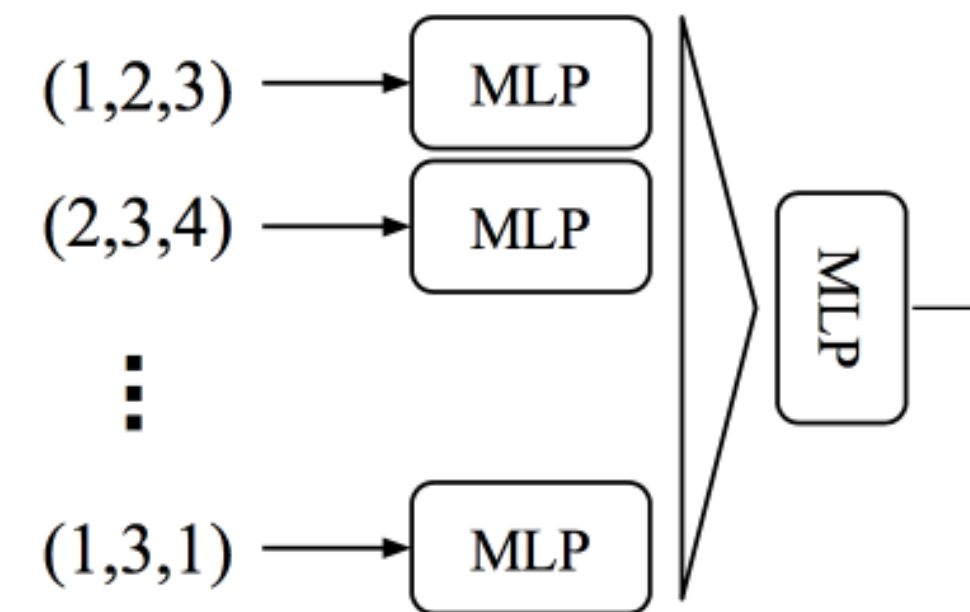
Hierarchical feature learning
Multiple levels of abstraction



3D CNN (Wu et al.)

v.s.

Global feature learning
Either one point or all points



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

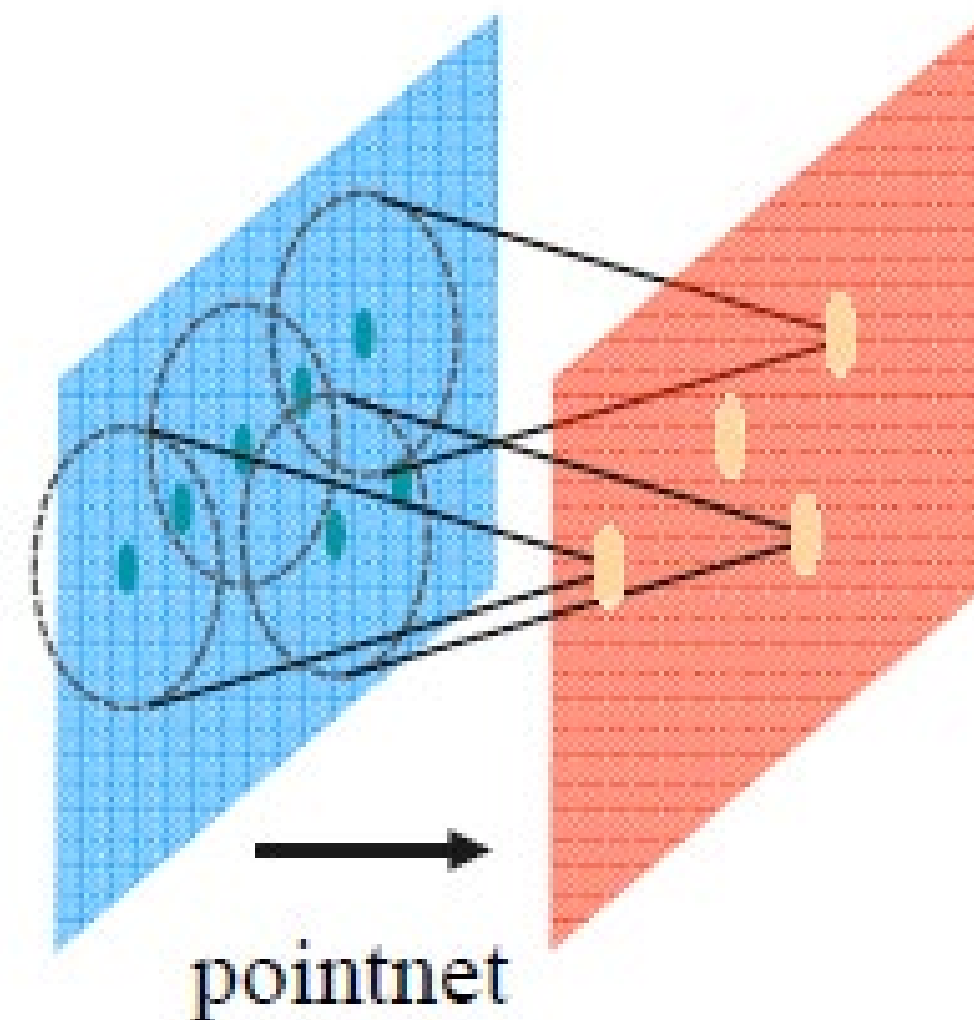
- Learn “**kernels**” in 3D space and conduct convolution
- Kernels have **compact spatial support**
- For convolution, we need to **find neighboring points**
- Possible strategies for range query
 - Ball query (results in more stable features)
 - k-NN query (faster)

Hao Su et al.

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**

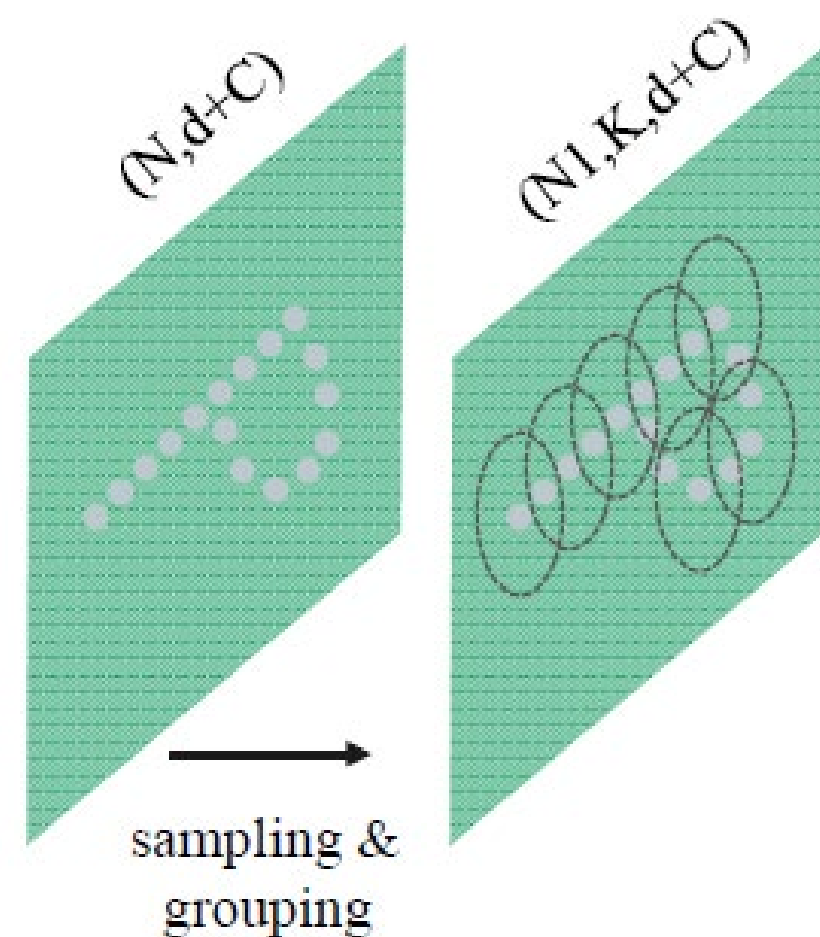


Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet++:

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

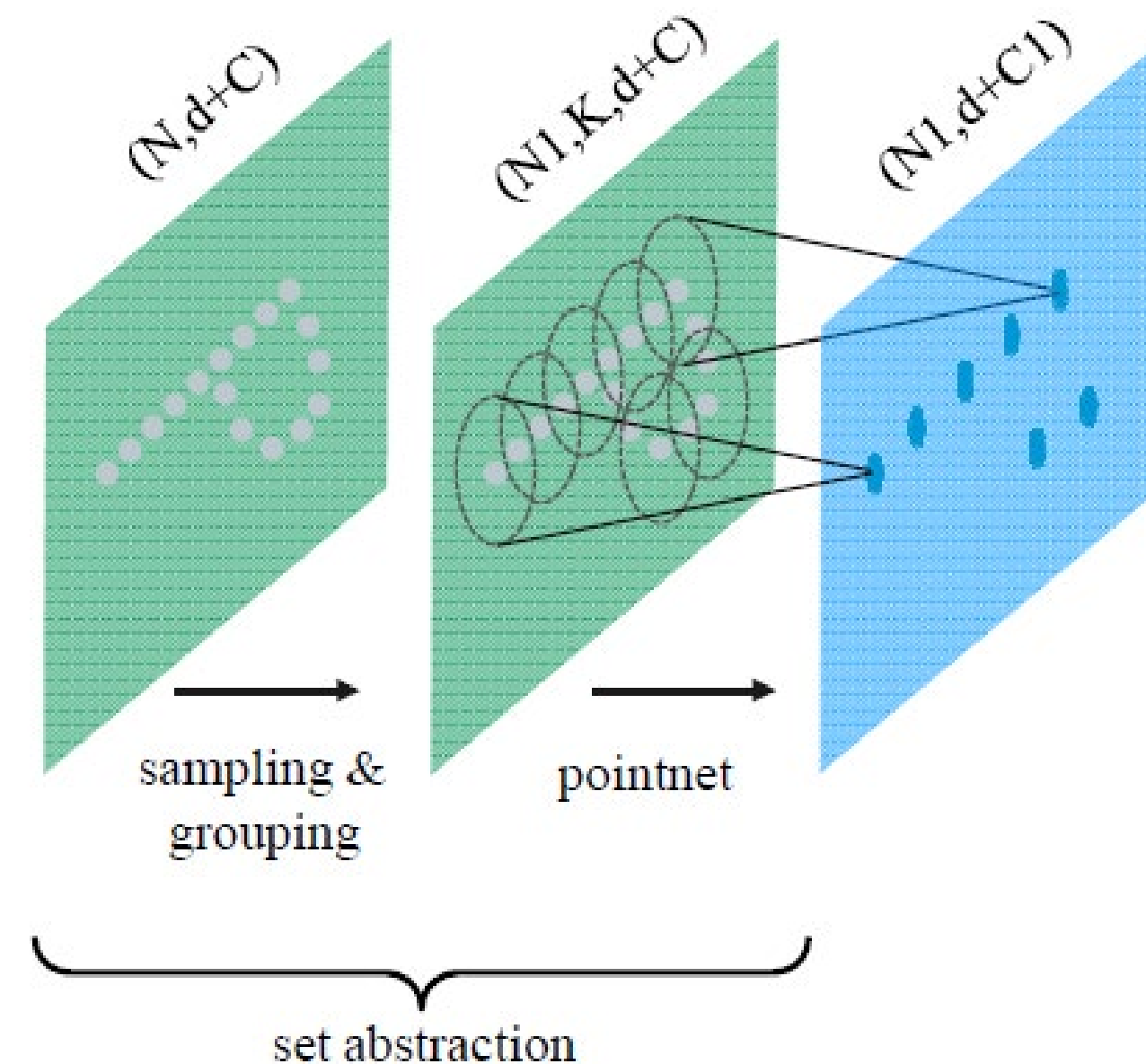


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3D DL architectures: *Point-based approach*

PointNet++:

- Shared PointNet applied in each local region using local coordinates

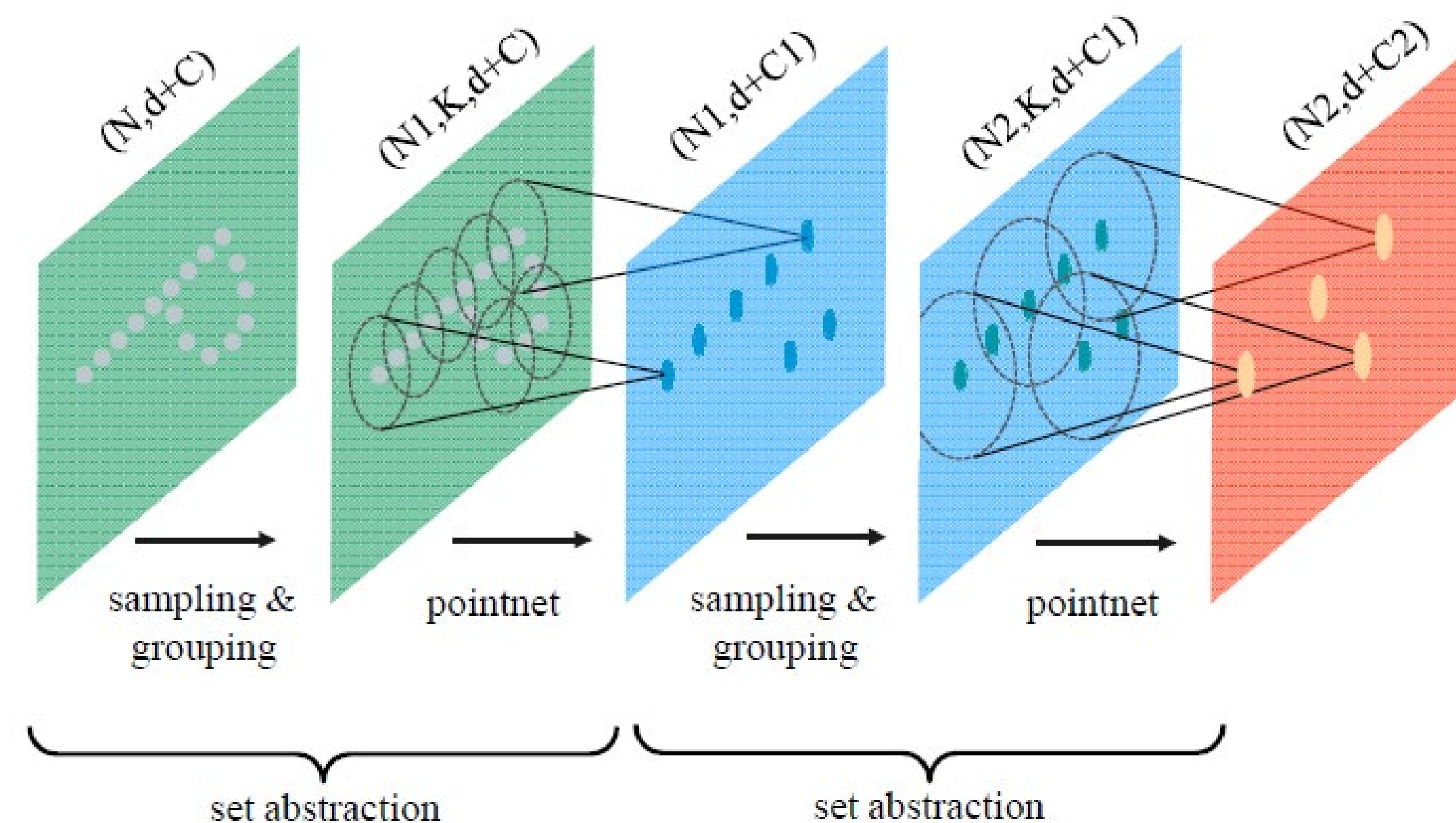


Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet++:

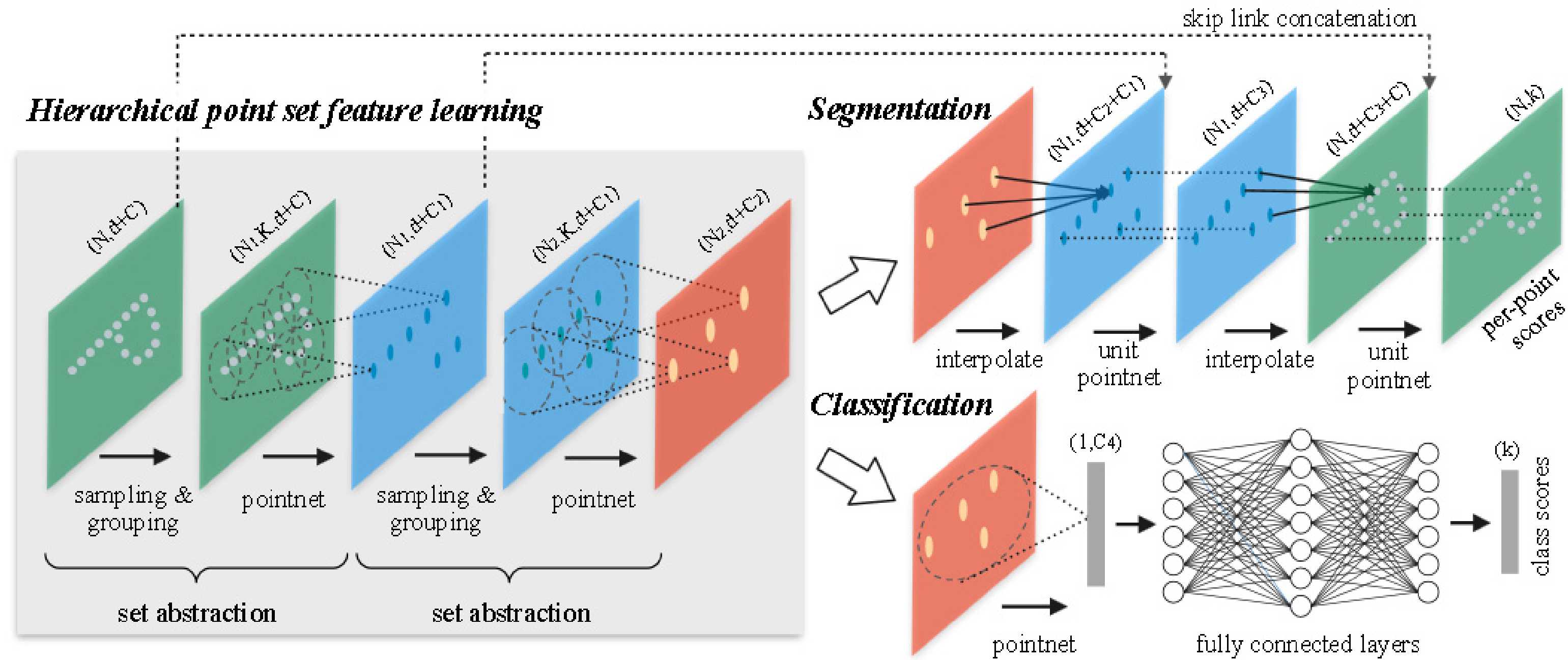
- Shared PointNet applied in each local region using local coordinates



Kalogerakis E.

3D DL architectures: *Point-based approach*

PointNet++ architecture

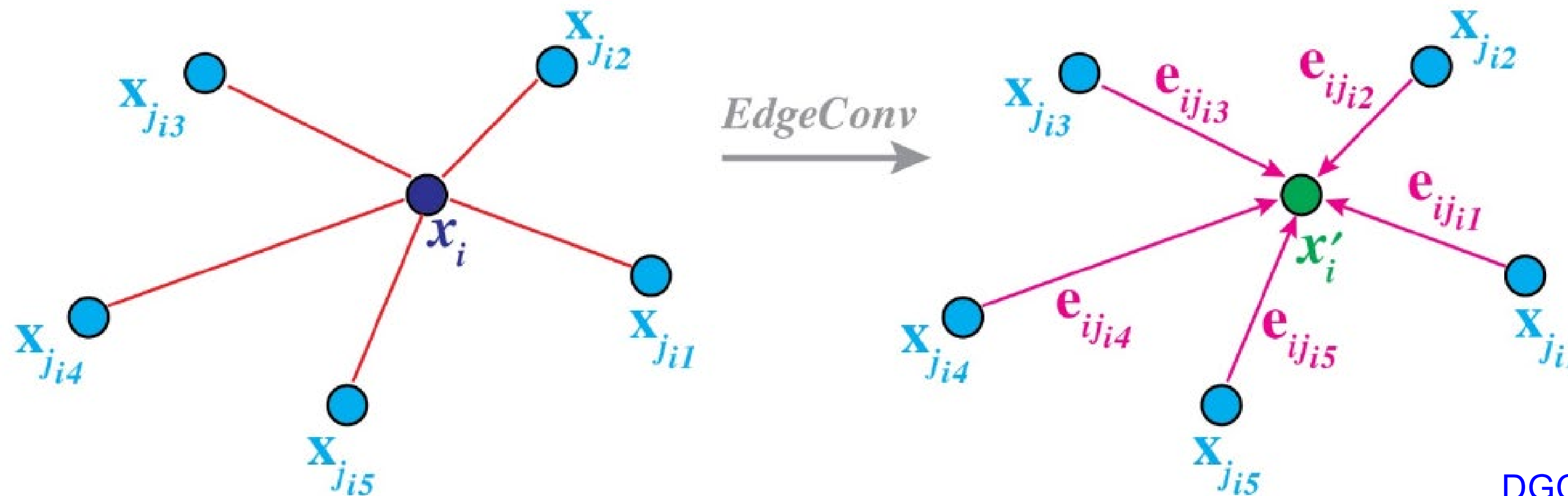


Qi et al., NIPS 2017

3D DL architectures: Point-based approach

Point Convolution as Graph Convolution: Dynamic Graph CNN

- Points \rightarrow Nodes
- Neighborhood \rightarrow Edges
- Graph CNN for point cloud processing



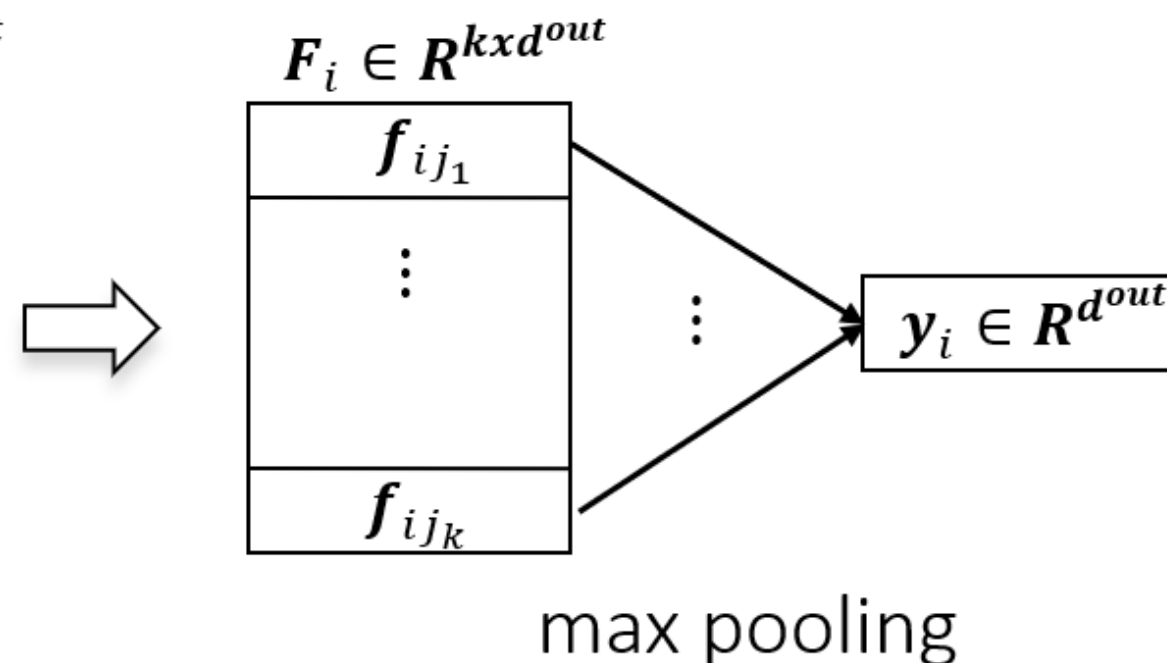
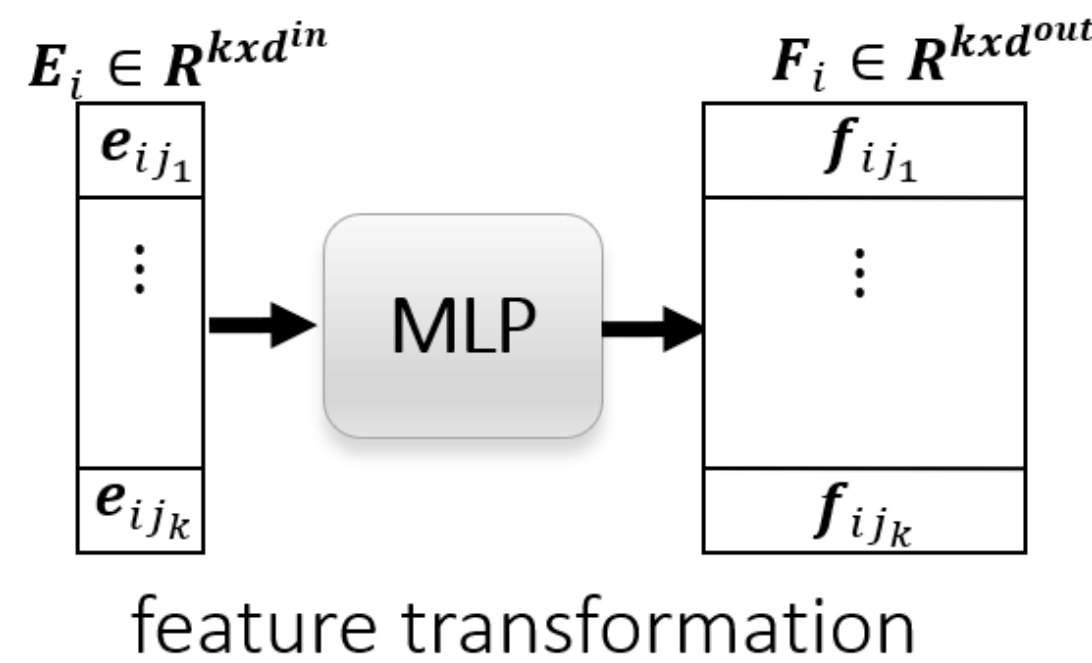
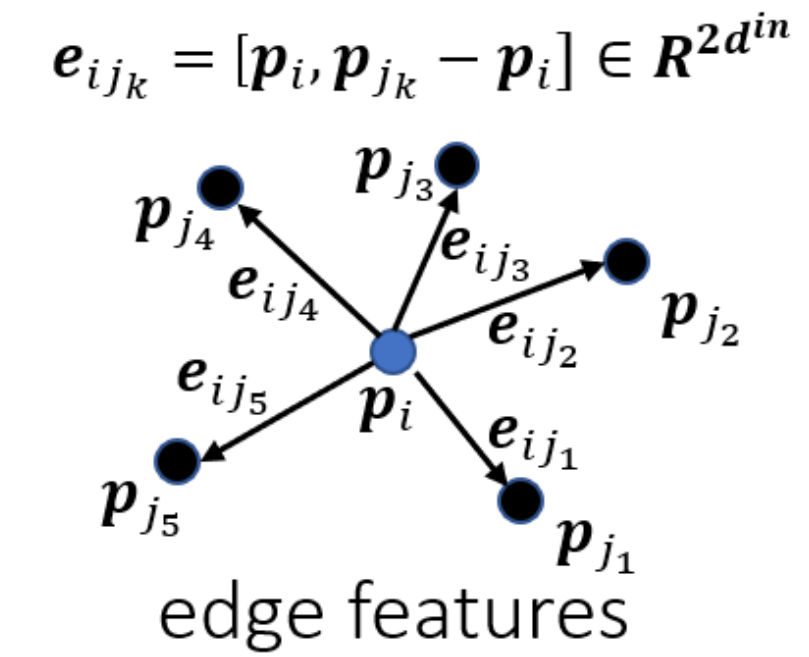
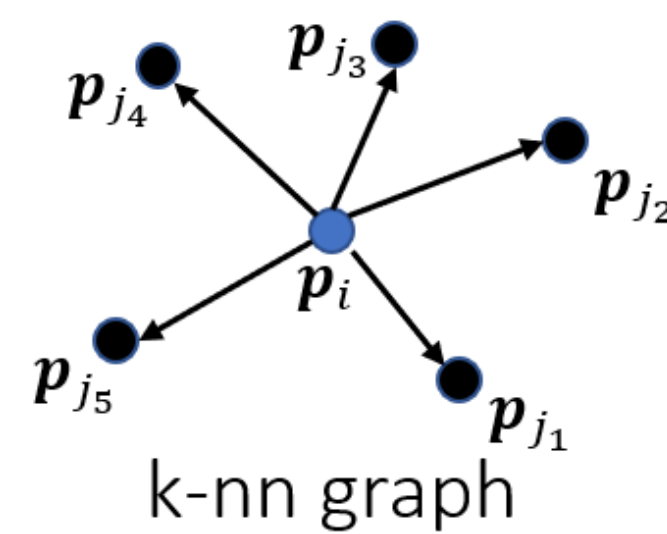
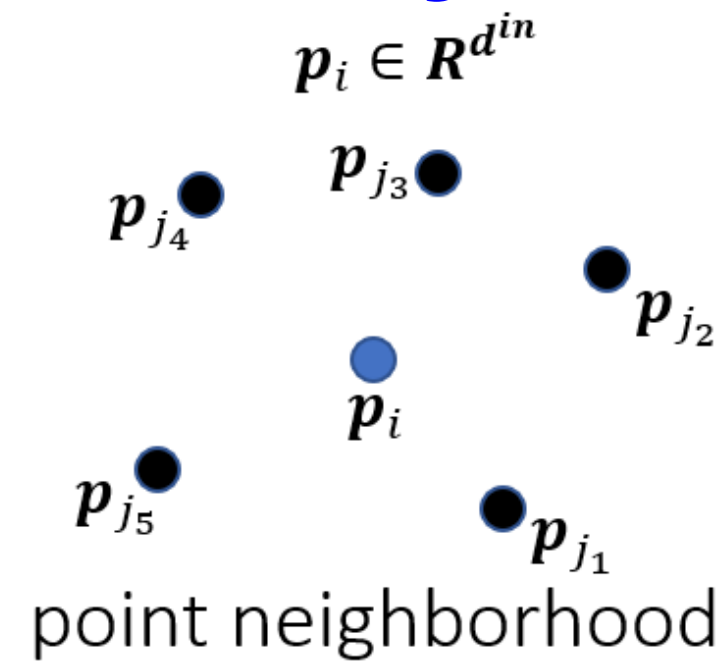
DGCNN, Wang et al., TOG, 2019



3D DL architectures: Point-based approach

Dynamic Graph CNN

- **EdgeConv Layer**



$$\equiv \mathbf{y} = \max_{j \in N_e(i)} MLP(\mathbf{p}_i, \mathbf{p}_j - \mathbf{p}_i)$$

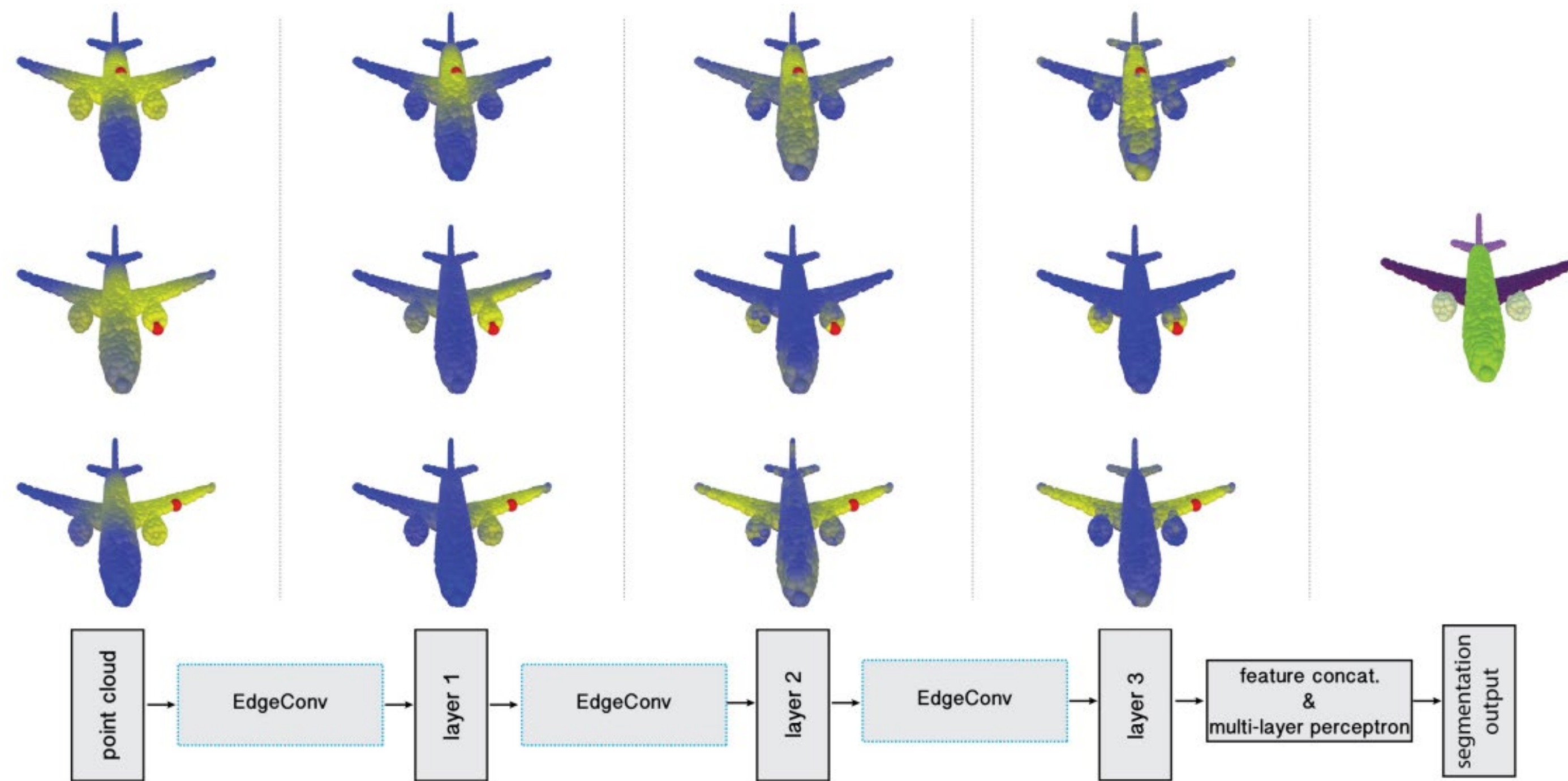
output feature

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*

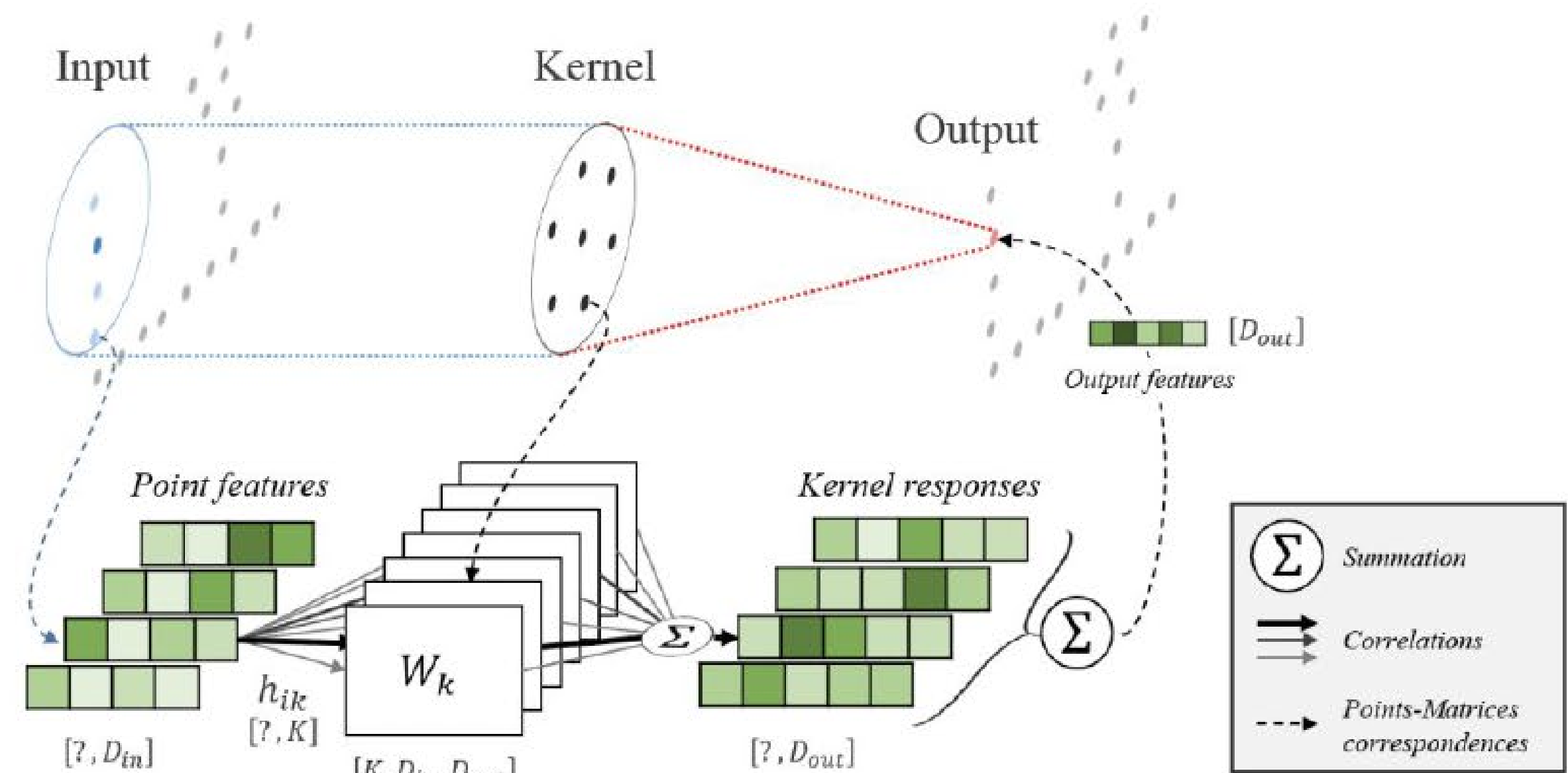
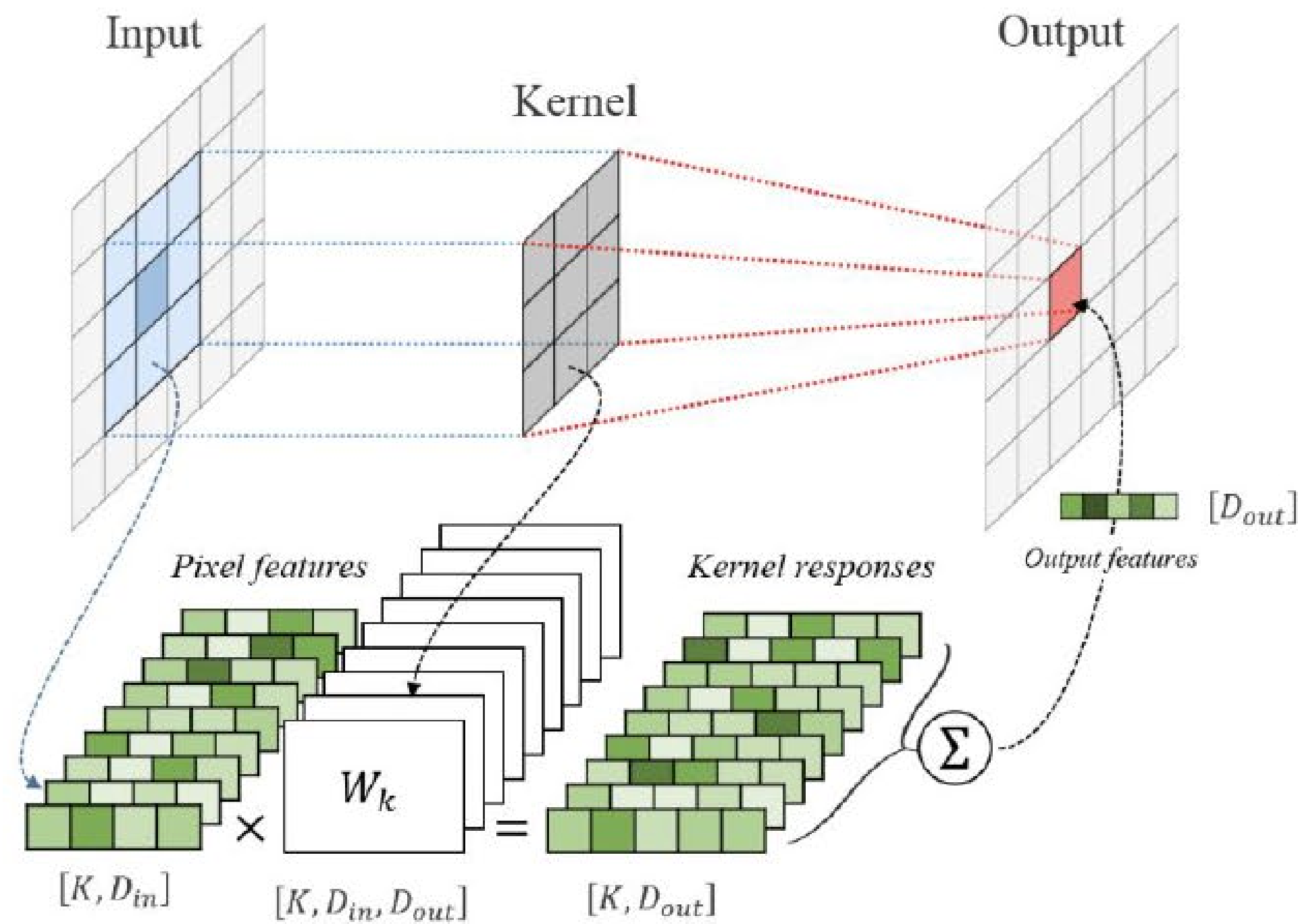
Standard GCNs are not Geometry Aware:

- 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.

3D DL architectures: *Point-based approach*

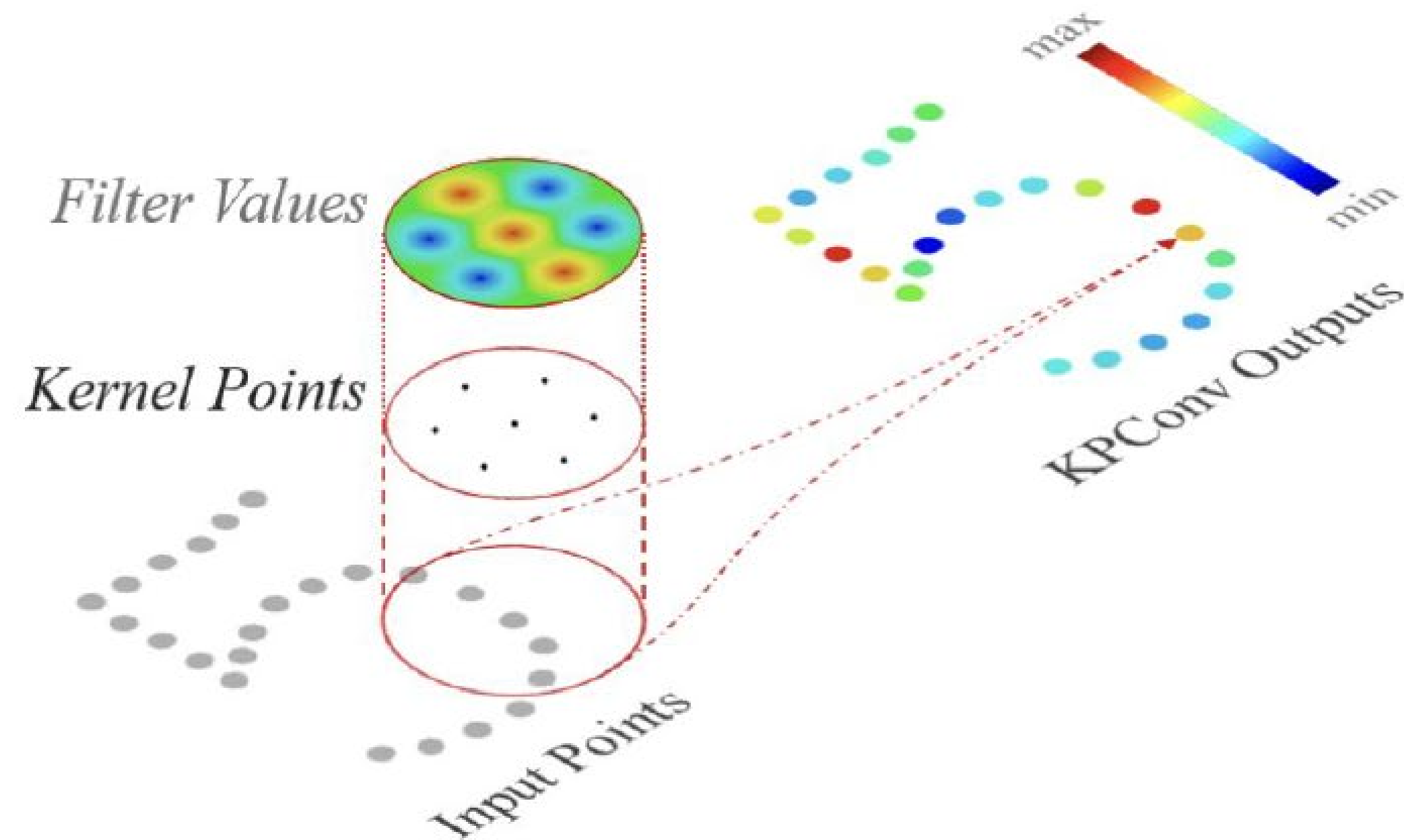
Kernel Point Convolution (KPCConv)



Thomas et al.,
ICCV, 2019

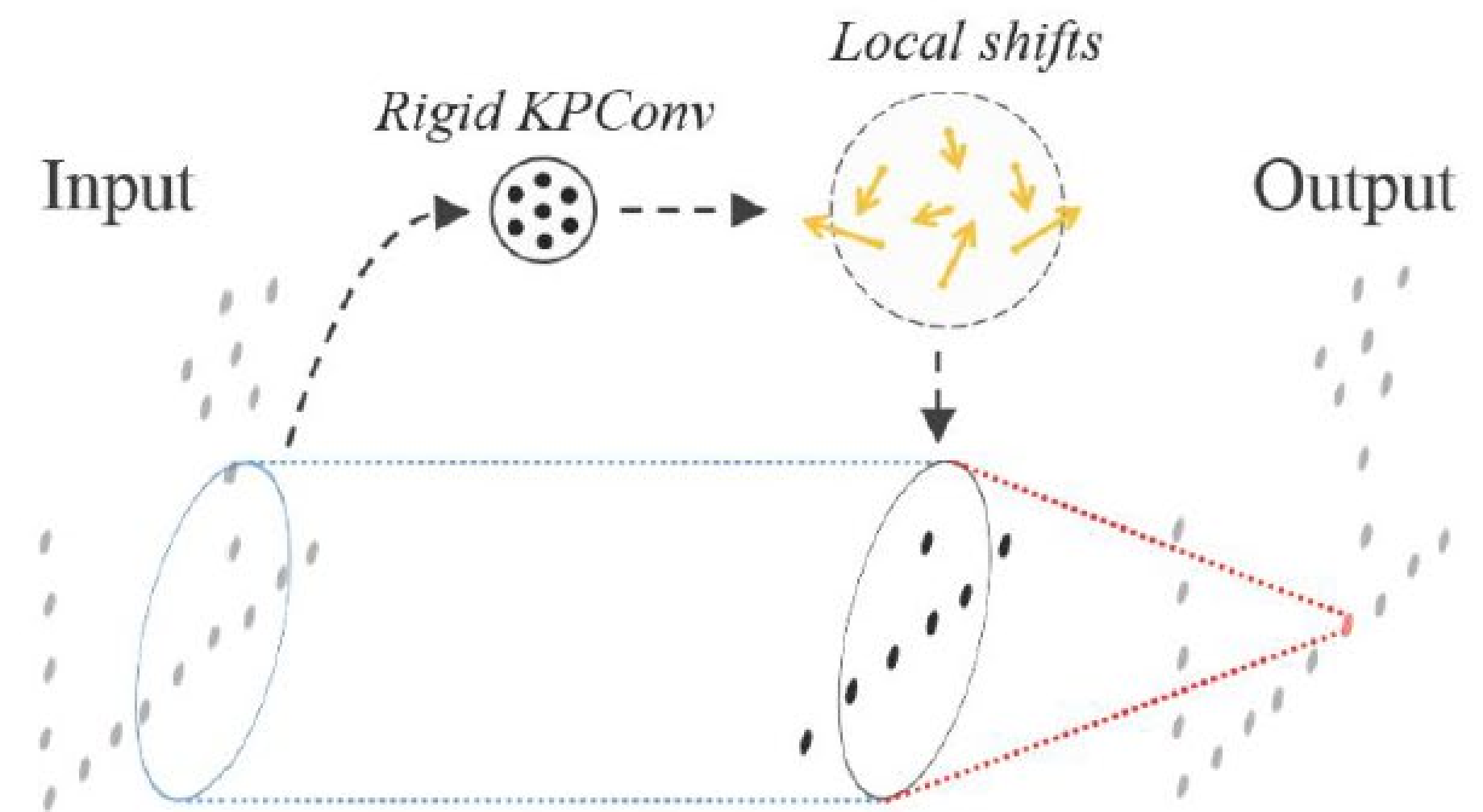
3D DL architectures: *Point-based approach*

Kernel Point Convolution (KPConv)



Deformable point-based kernel

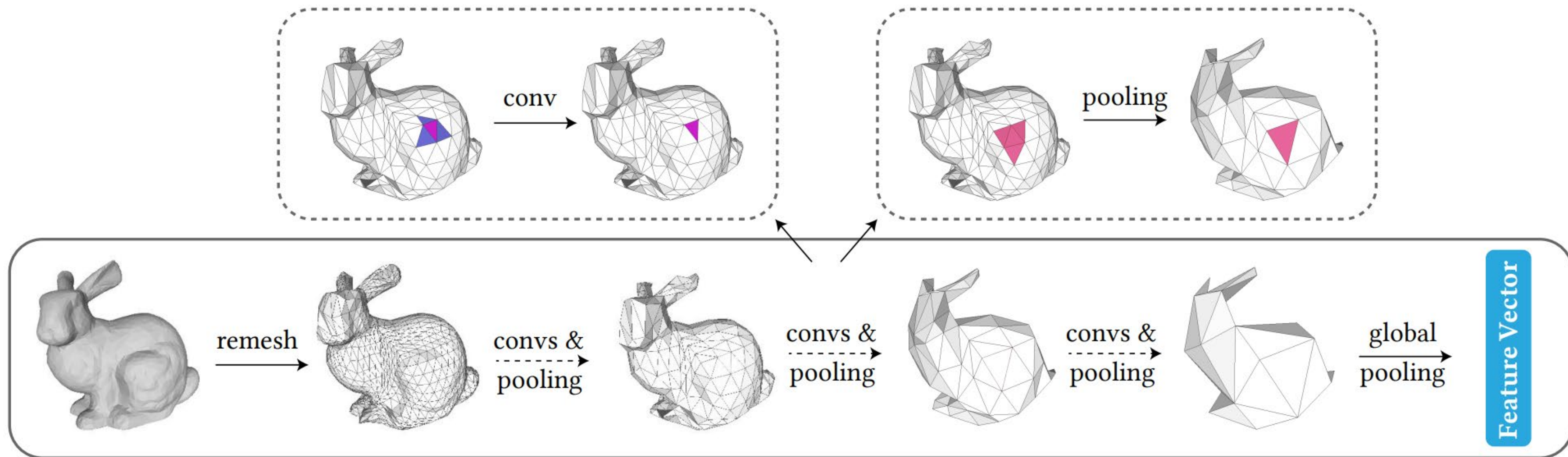
- 3D version of 2D deformable convolution



Hao Su et al.

3D DL architectures: *Mesh-based approach*

Subdivision-Based Mesh Convolution Networks (SubdivNet)

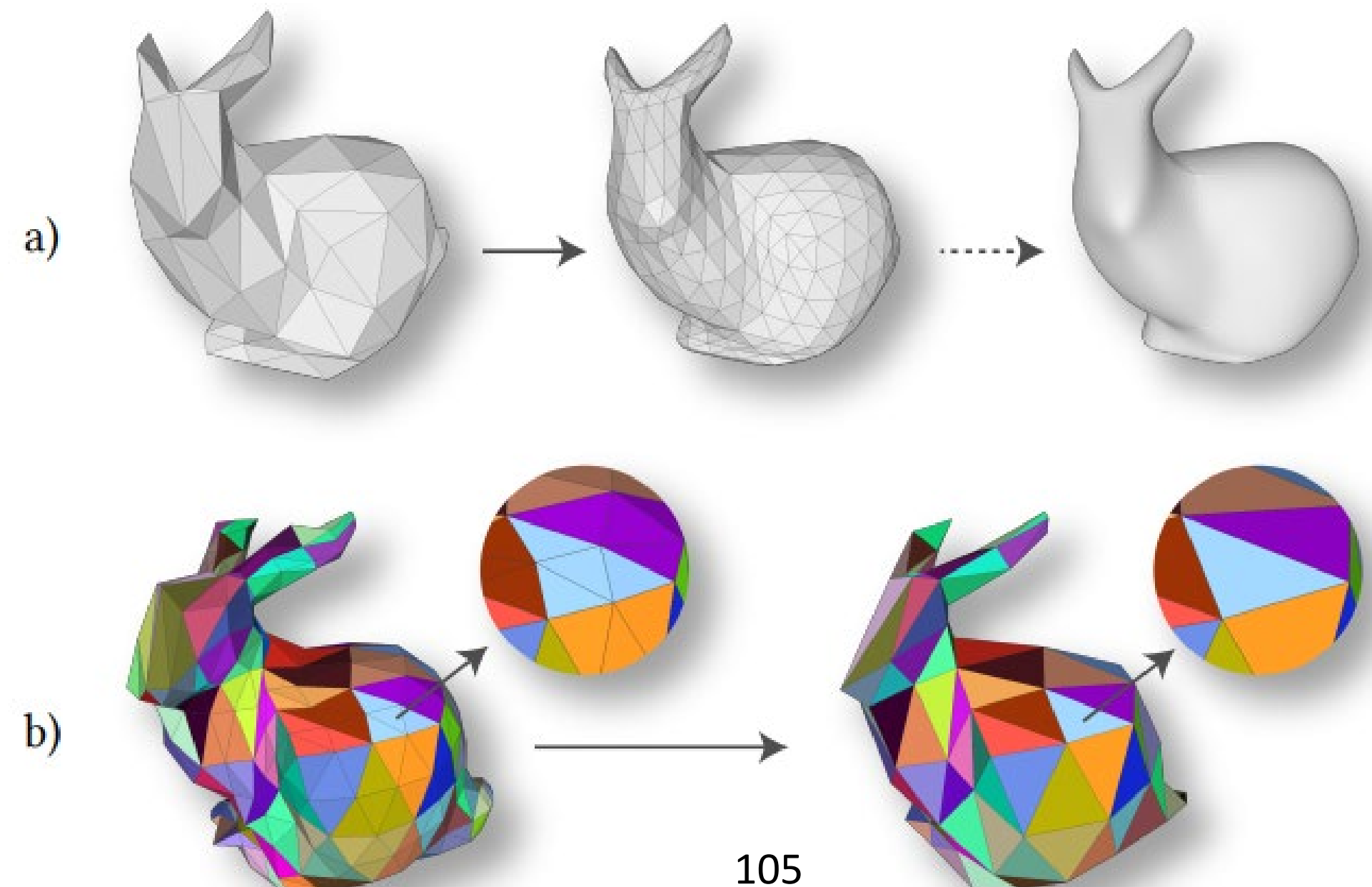


Shi-Min Hu et al., TOG, 2021

3D DL architectures: *Mesh-based approach*

SubdivNet:

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



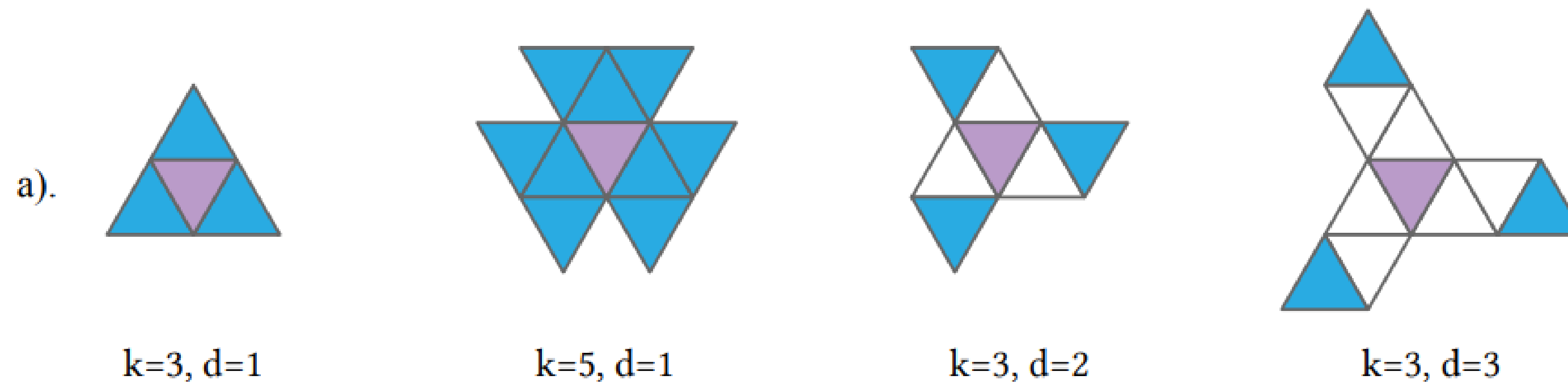
Shi-Min Hu et al., TOG, 2021

3D DL architectures: *Mesh-based approach*

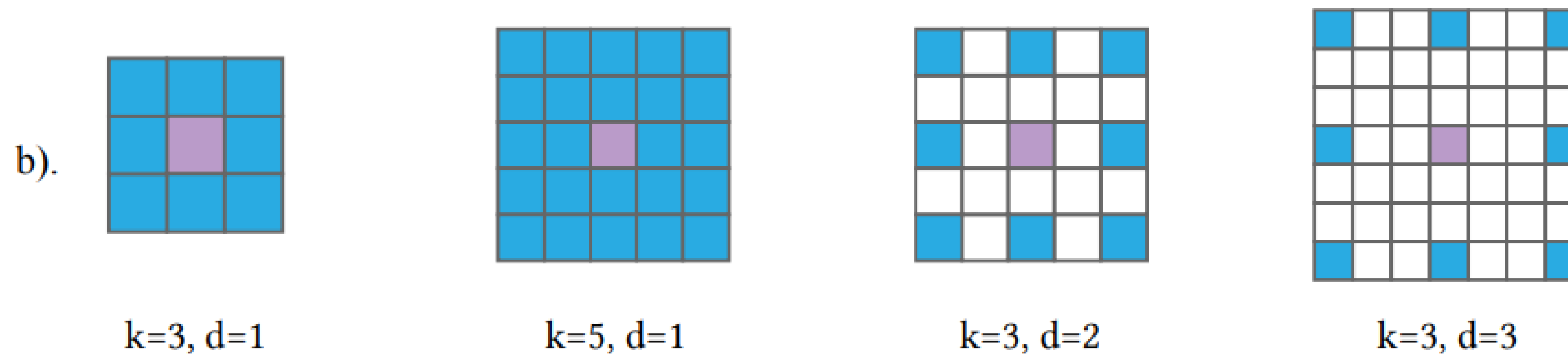
SubdivNet:

- Can support **mesh convolution**

Mesh conv. kernels



2D conv. kernels

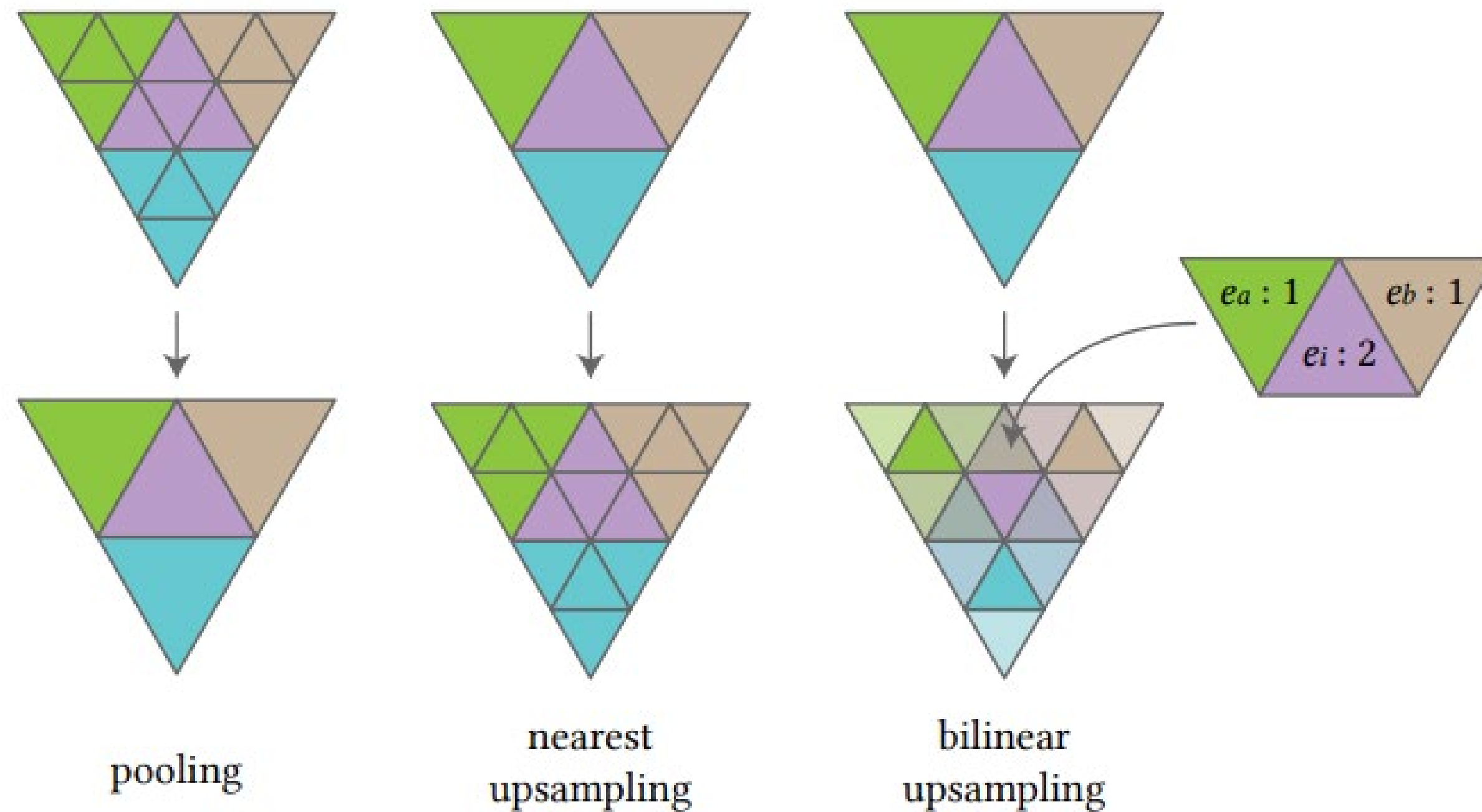


Shi-Min Hu et al., TOG, 2021

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
- Geometry
- 3D shape representations
- 3D shape datasets
- 3D Deep Learning architectures
- What we do

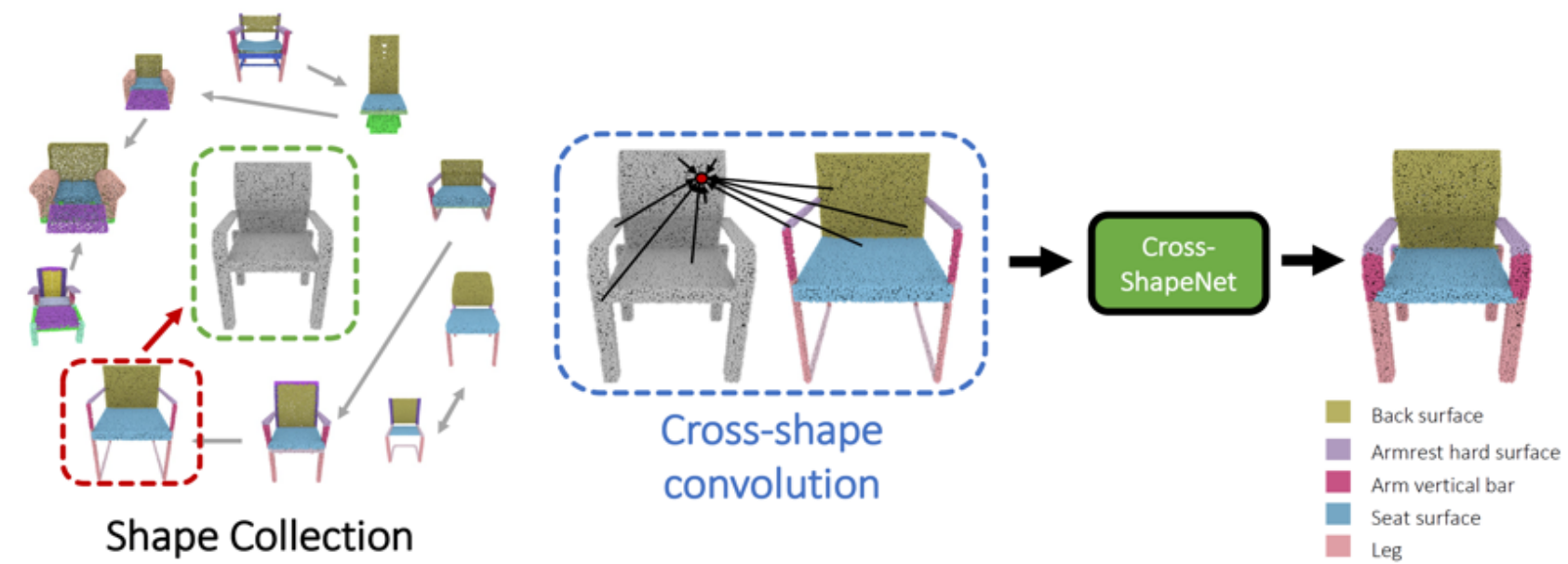


What we do: 3D shape understanding

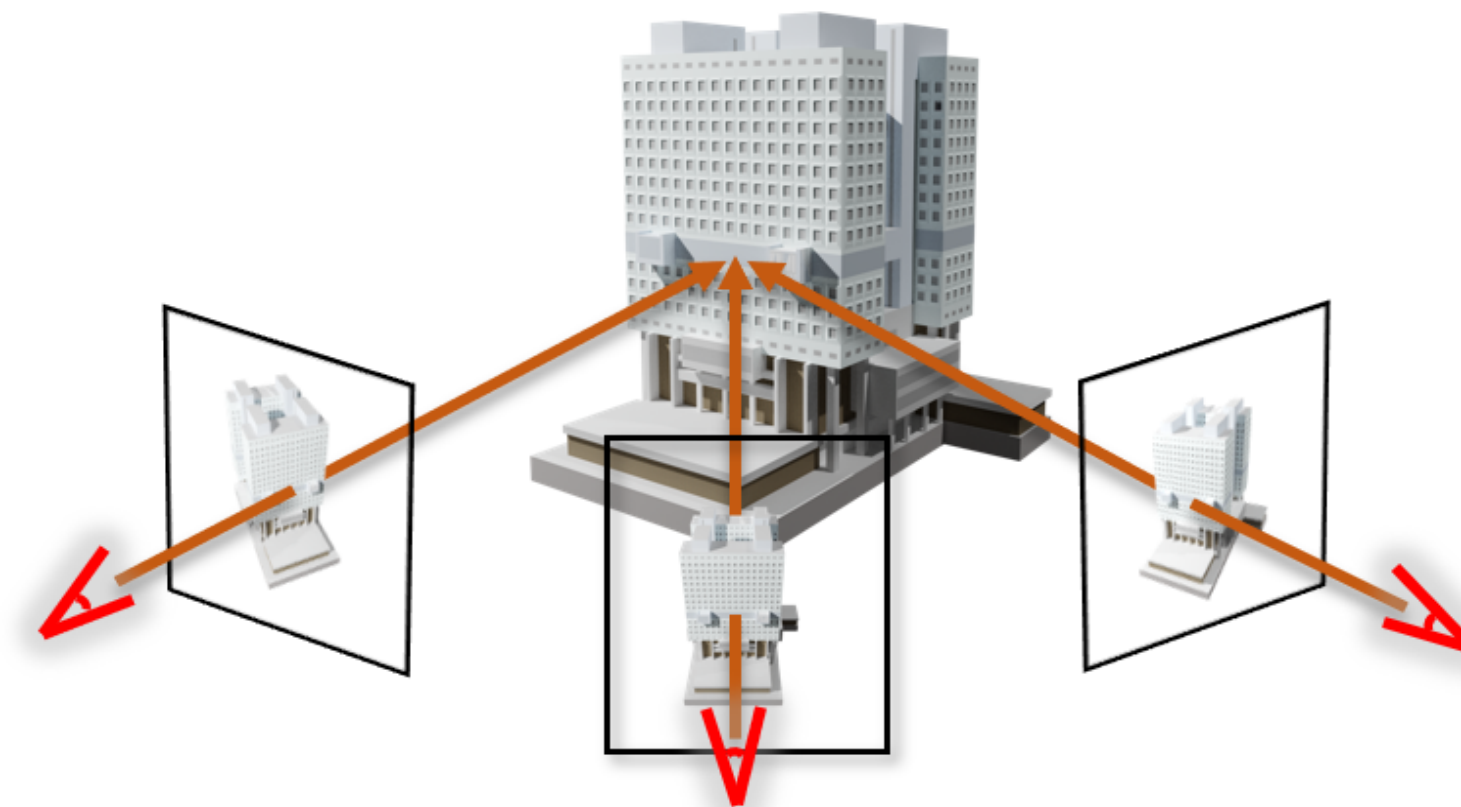
3D Building Semantic Understanding



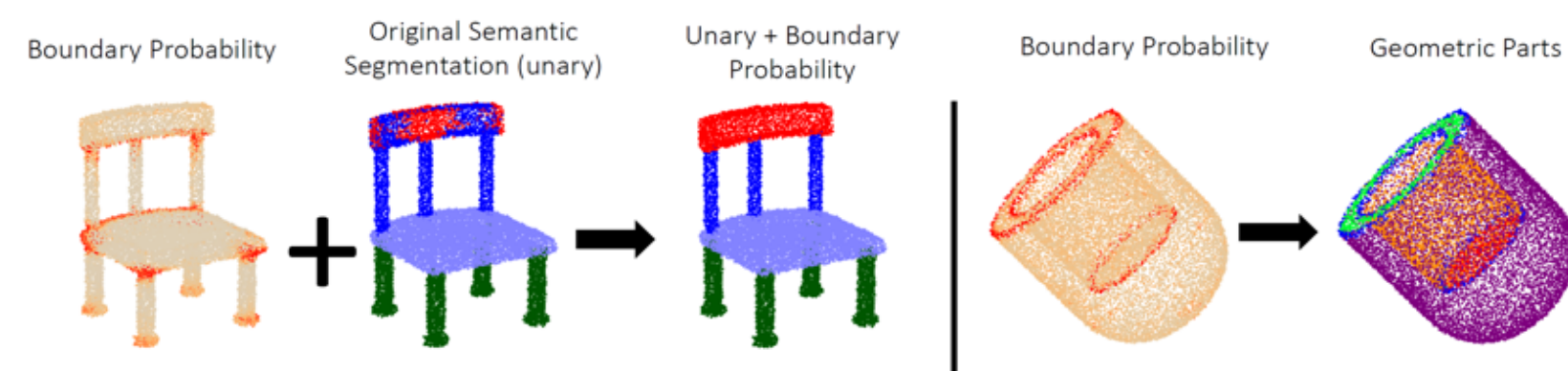
Cross-shape semantic segmentation



Neural 3D Reconstruction



Geometric/Semantic Decomposition



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

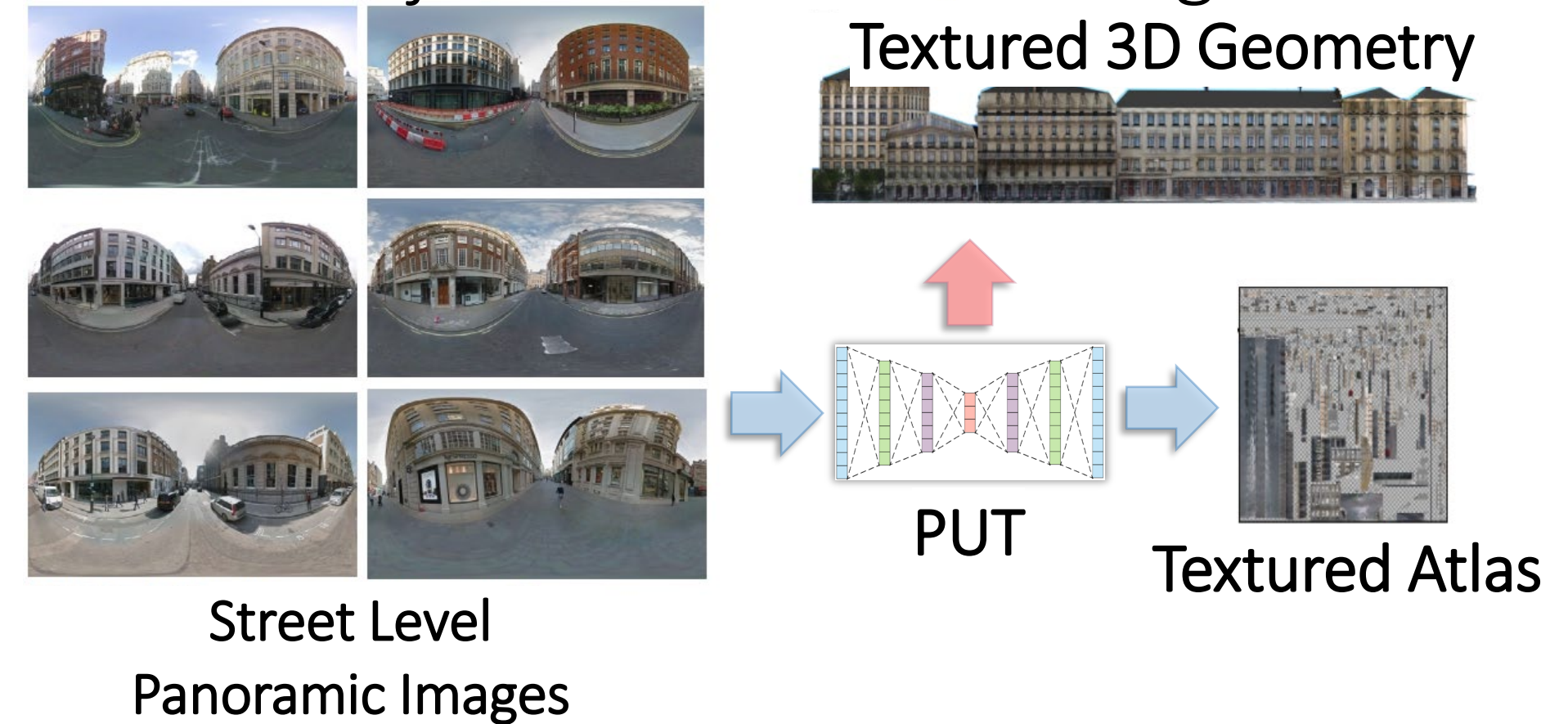
Single-View Guided Façade Synthesis



Re
Faça



Projective Urban Texturing

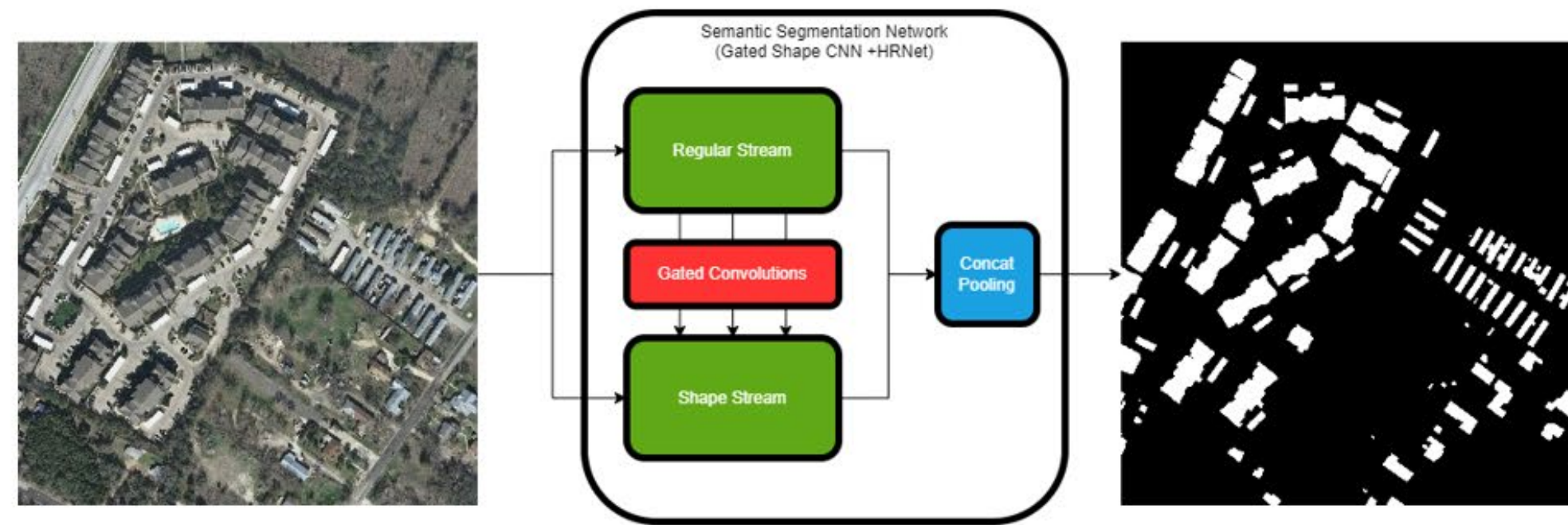


Surface Texture Generation via T2I Diffusion Models

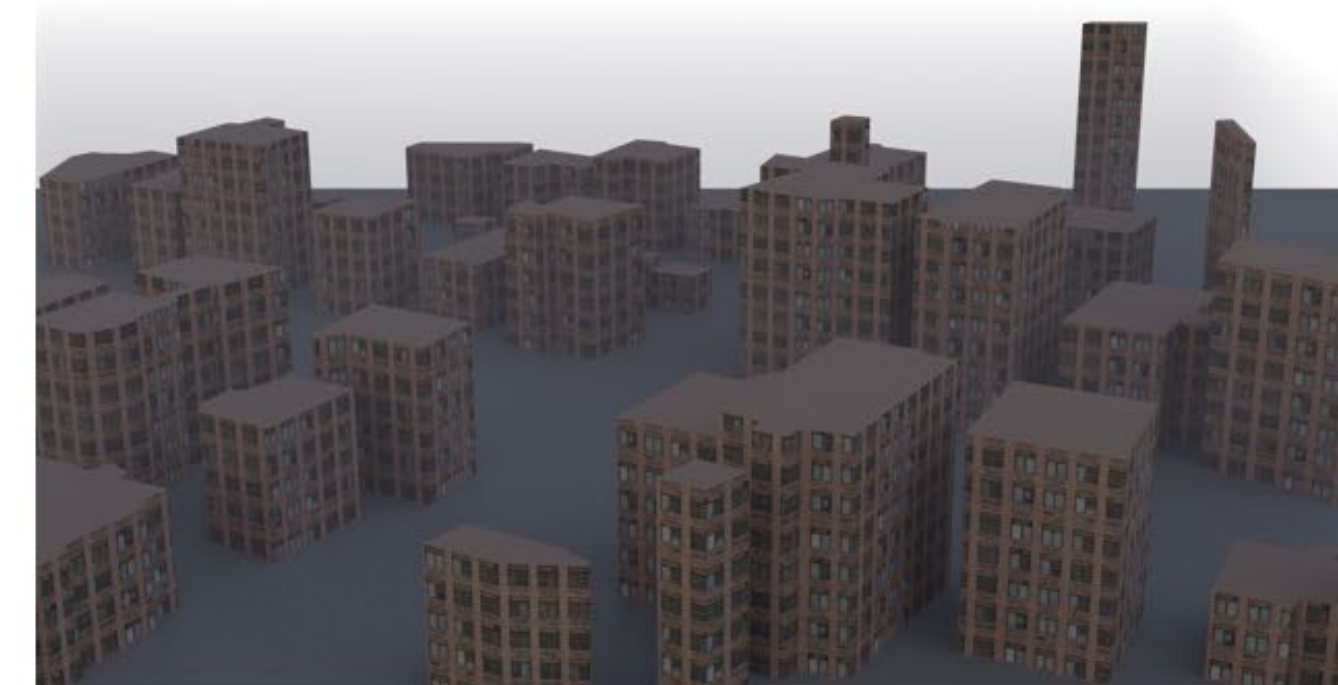


What we do: *Urban Semantic Understanding from Remote Sensing Data Sources*

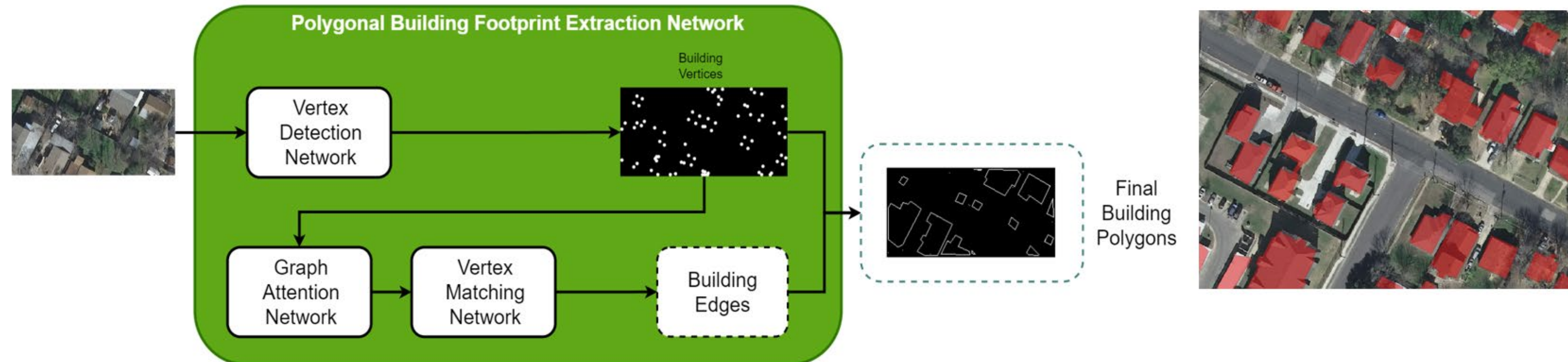
Semantic Segmentation of Buildings



Urban 3D Reconstruction



Building Footprint Extraction



Research in Visual Computing



Melinos Averkiou
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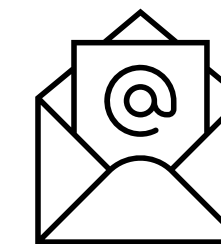
Research Interests:

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

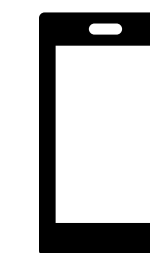
<https://www.cyens.org.cy/en-gb/research/pillars-groups/visual-sciences/deep-camera/people/alessandro-artusi/>



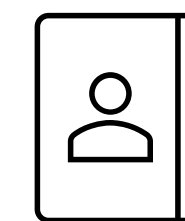
<https://vcg.cyens.org.cy/>



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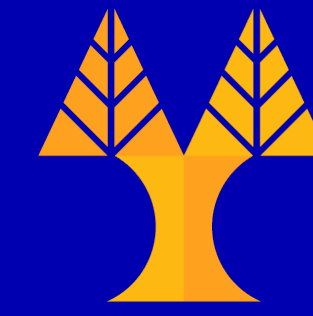


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Thank you!

