CS 231N Lecture 16:
3D Vision

Slide credit: Ren Ng, Hao Su, Leo Guibas


NATIONAL GEOGRAPHIC
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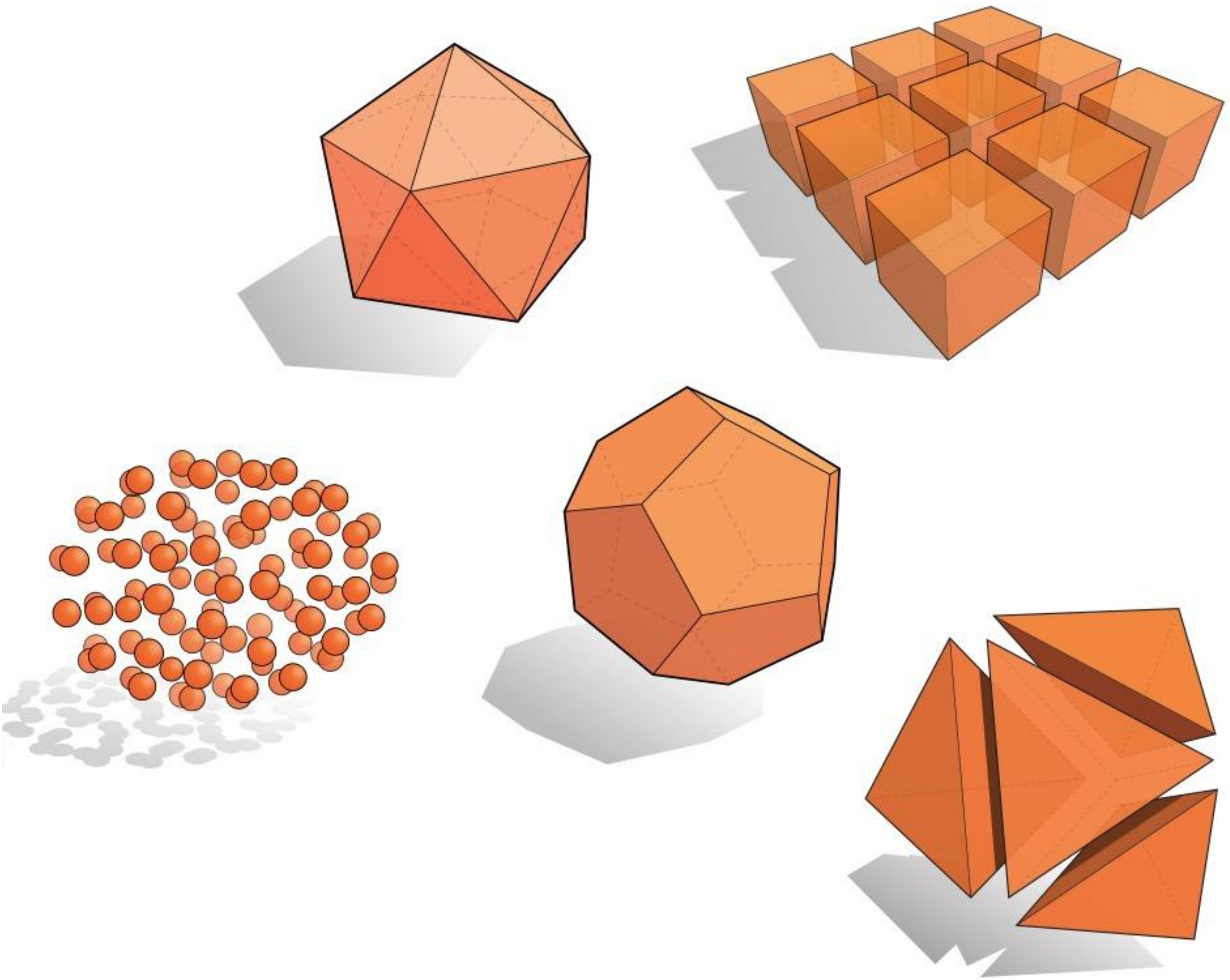
Many Ways to Represent Geometry

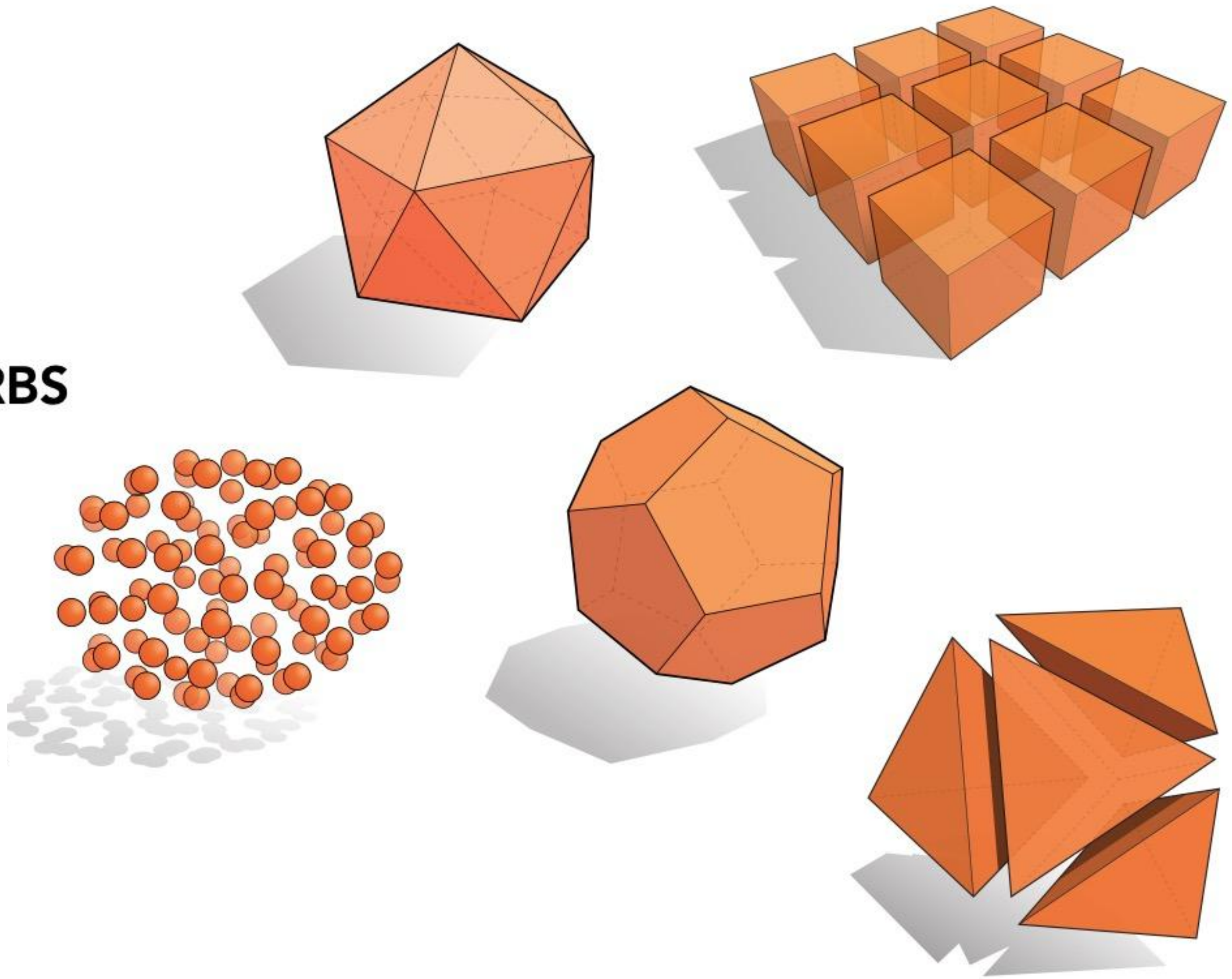


Slide credit: Ren Ng

Many Ways to Represent Geometry

Explicit

- point cloud
- polygon mesh
- subdivision, NURBS
- ...



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Many Ways to Represent Geometry

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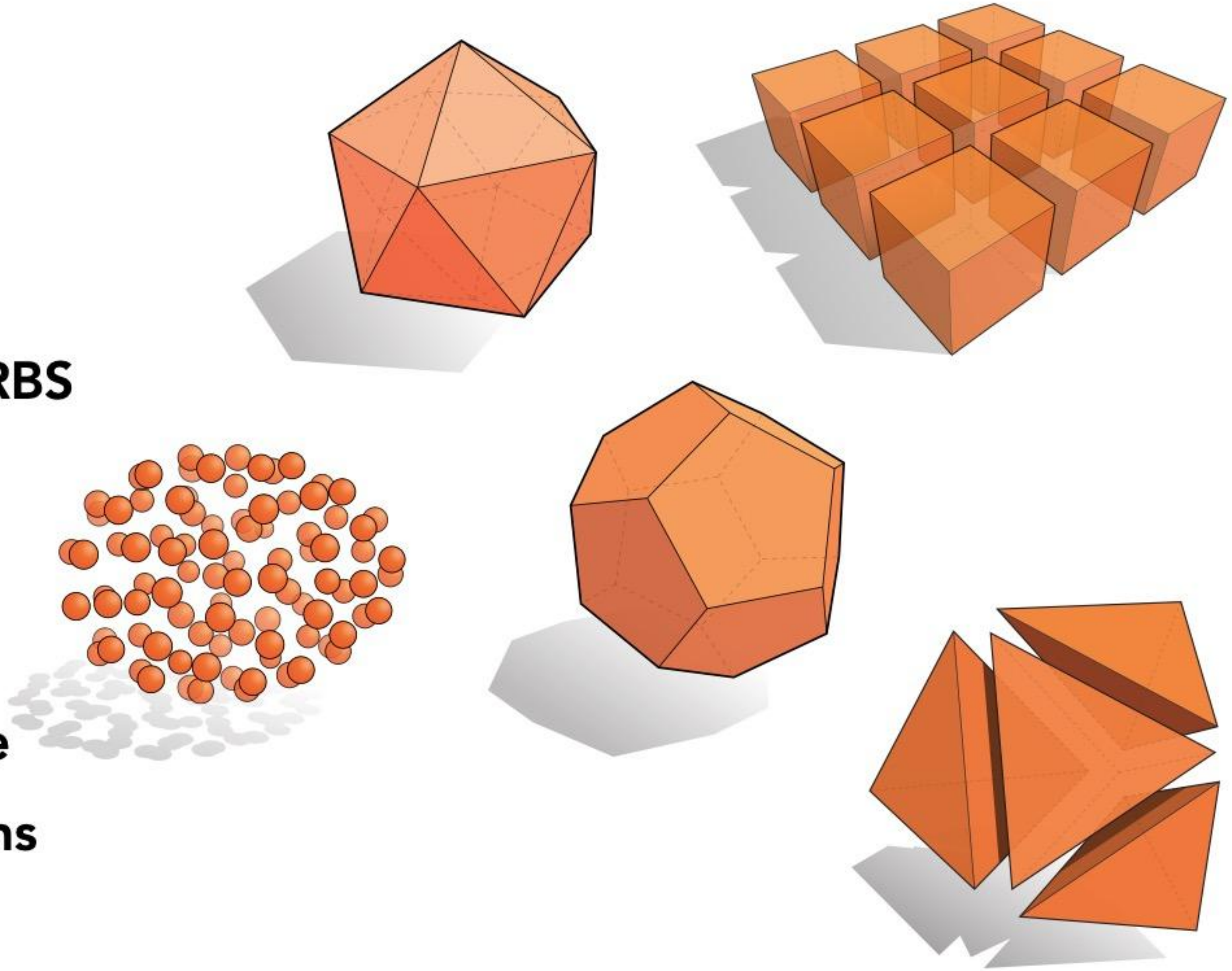
Implicit

- level sets
- algebraic surface
- distance functions
- ...



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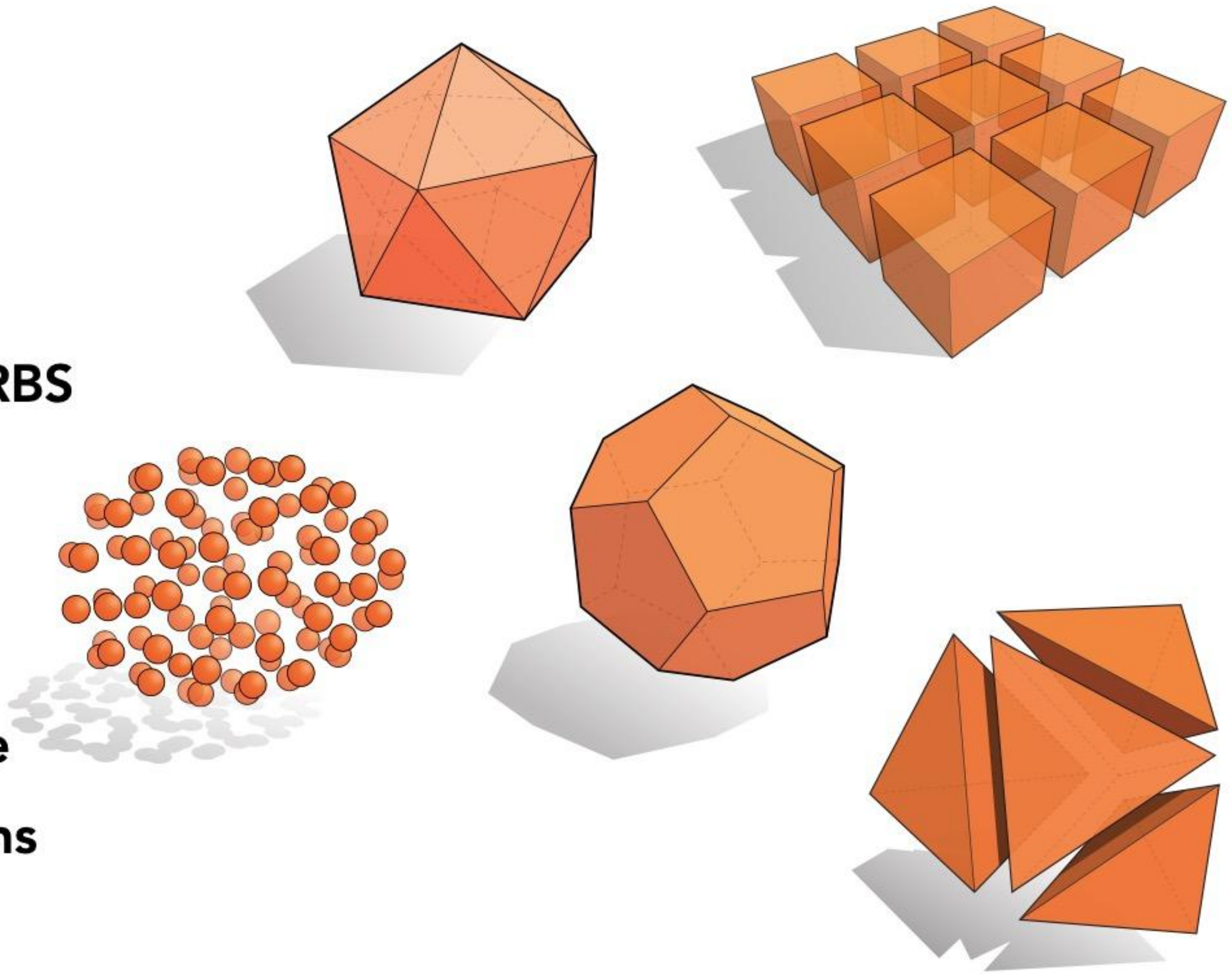
Many Ways to Represent Geometry



Explicit

- point cloud
- polygon mesh
- subdivision, NURBS
- ...

Implicit

- level sets
- algebraic surface
- distance functions
- ...

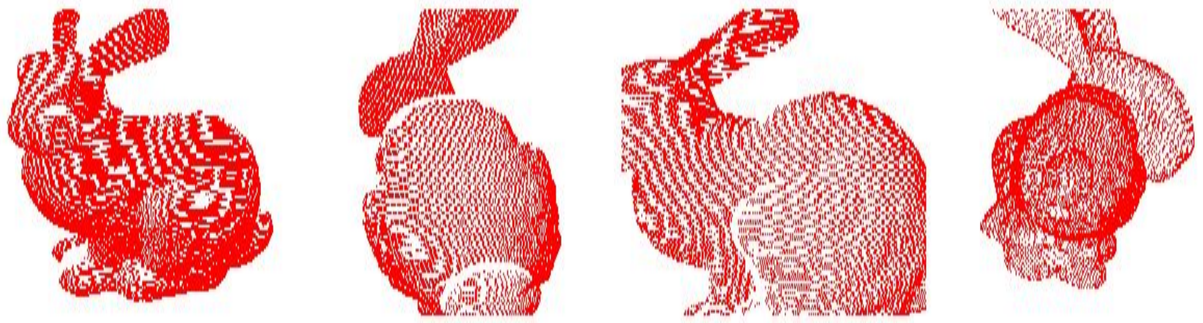
Each choice best suited to a different task/type of geometry

Slide credit: Ren Ng

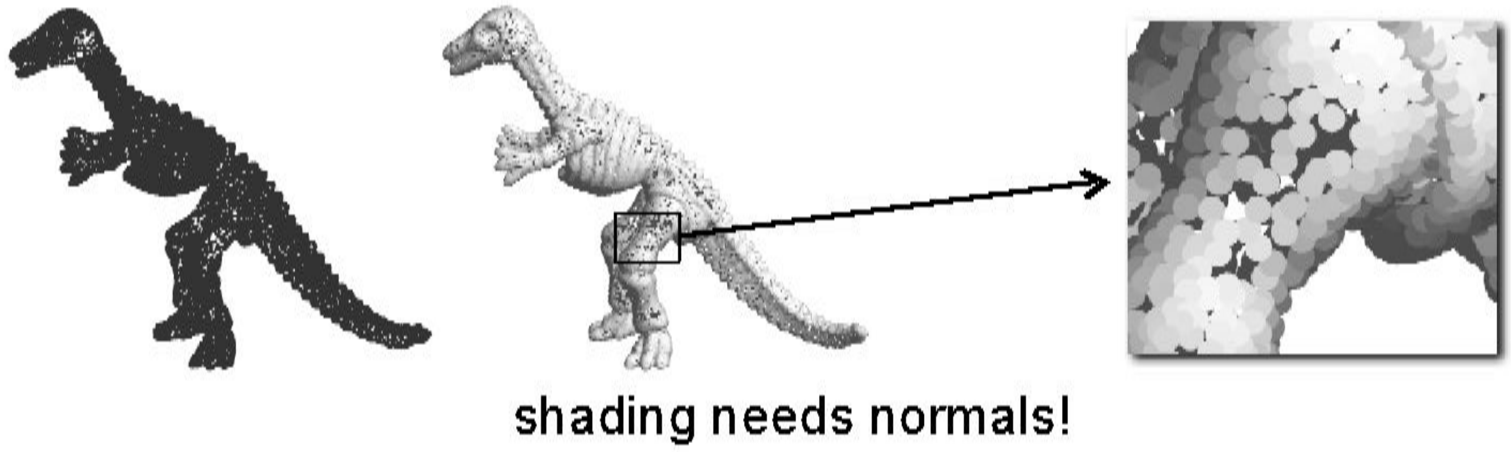
Representation Considerations

- Needs to be stored in the computer
- Creation of new shapes
    - Input metaphors, interfaces…
- Operations
    - Editing, simplification, smoothing, filtering, repairing…
- Rendering
    - Rasterization, ray tracing…
- Animation

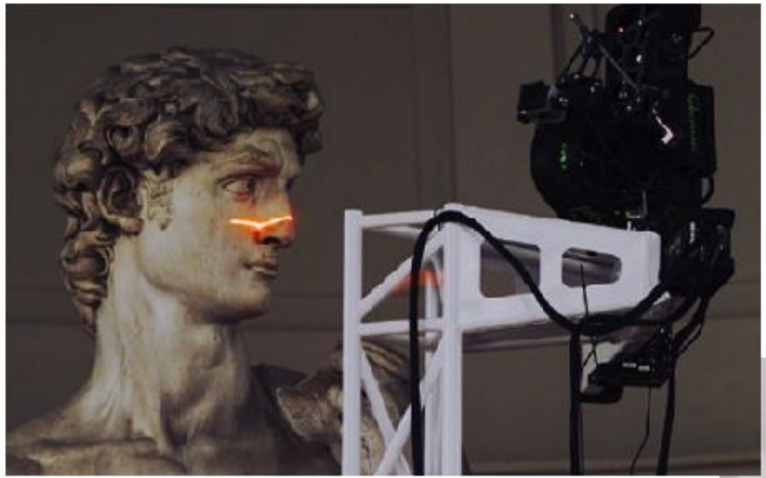
Point Clouds

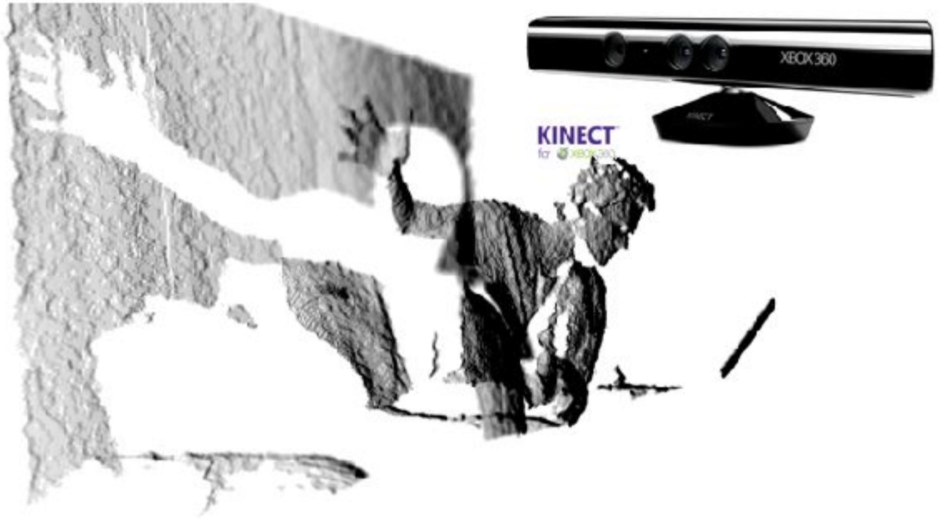


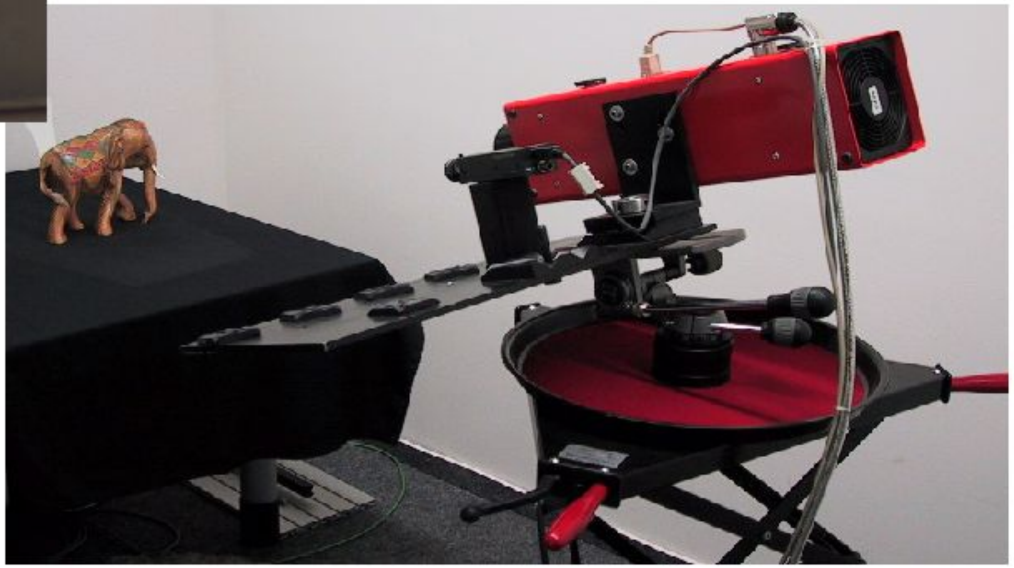
- Simplest representation: **only points**, no connectivity
- Collection of (x,y,z) coordinates, possibly with normal
- Points with orientation are called **surfels**



Output of Acquisition







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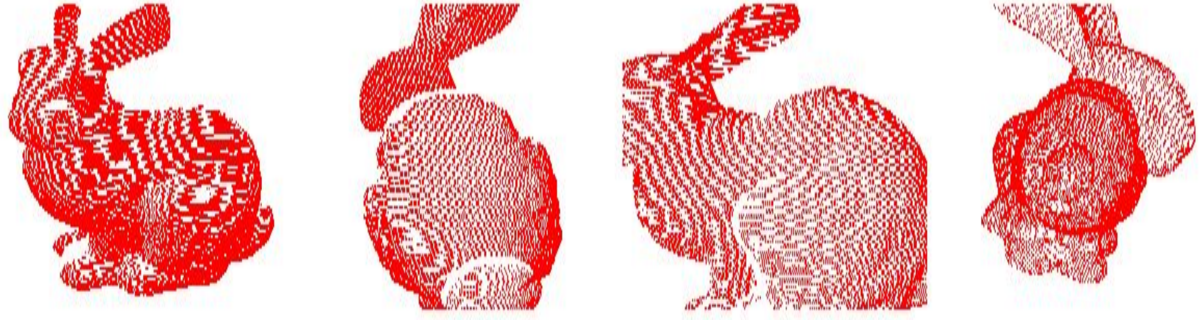
Point Clouds

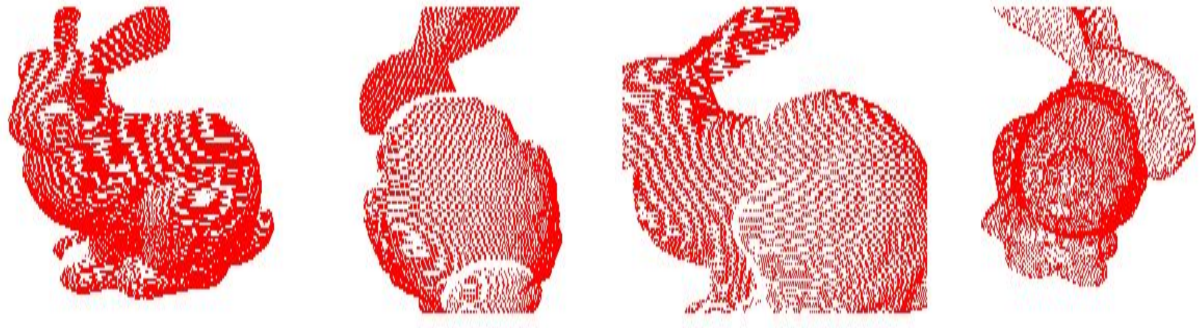


- Simplest representation: **only points**, no connectivity
- Collection of (x,y,z) coordinates, possibly with normal
- Points with orientation are called **surfels**

- Often results from scanners
- Potentially noisy
- Registration of multiple images

set of raw scans

Point Clouds

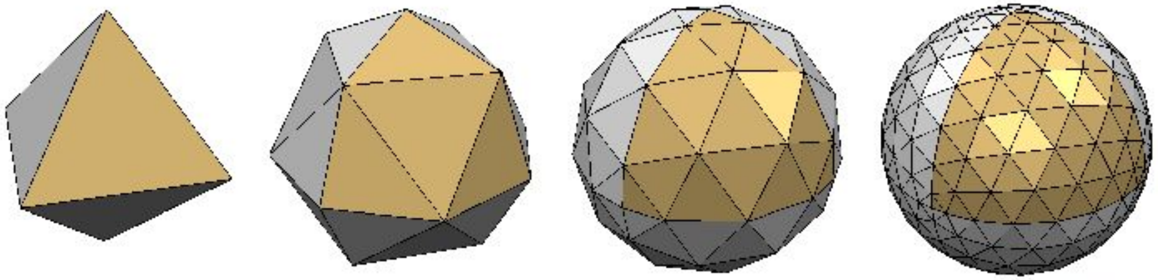


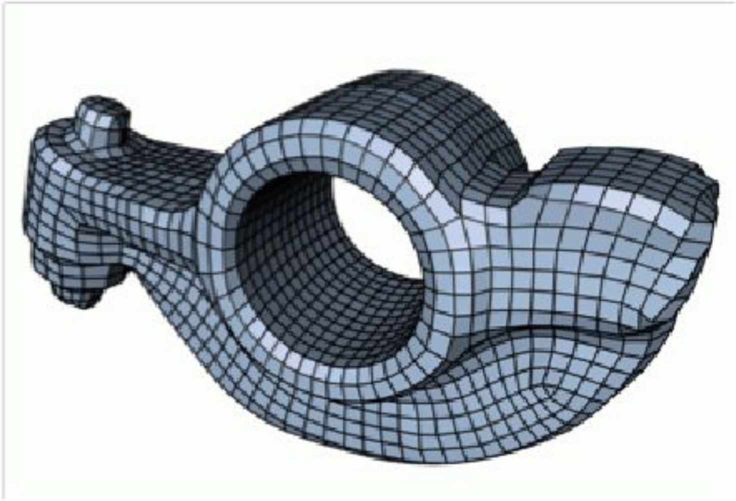
- Easily represent any kind of geometry
- Useful for large datasets
- Difficult to draw in undersampled regions

- Other limitations:
  - No simplification or subdivision
  - No direction smooth rendering
  - No topological information

Polygonal Meshes

- Boundary representations of objects





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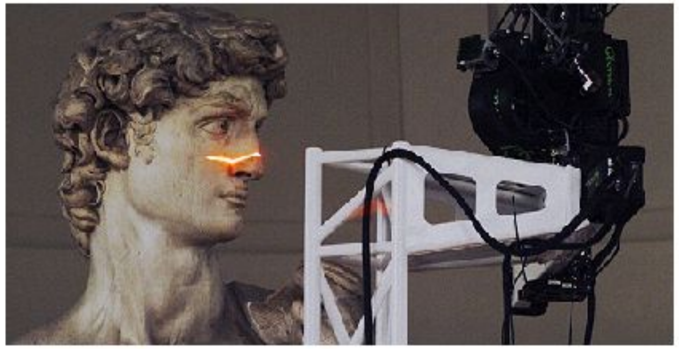
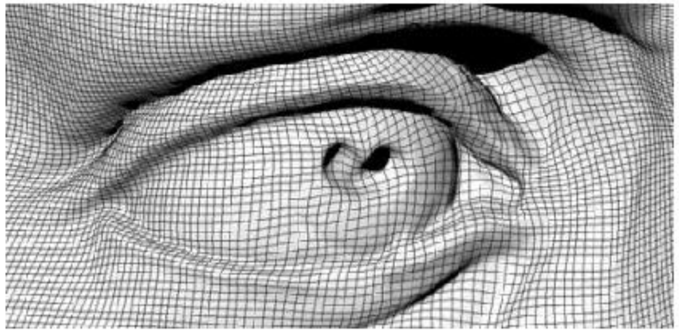
A Large Triangle Mesh

David

Digital Michelangelo Project
28,184,526 vertices
56,230,343 triangles





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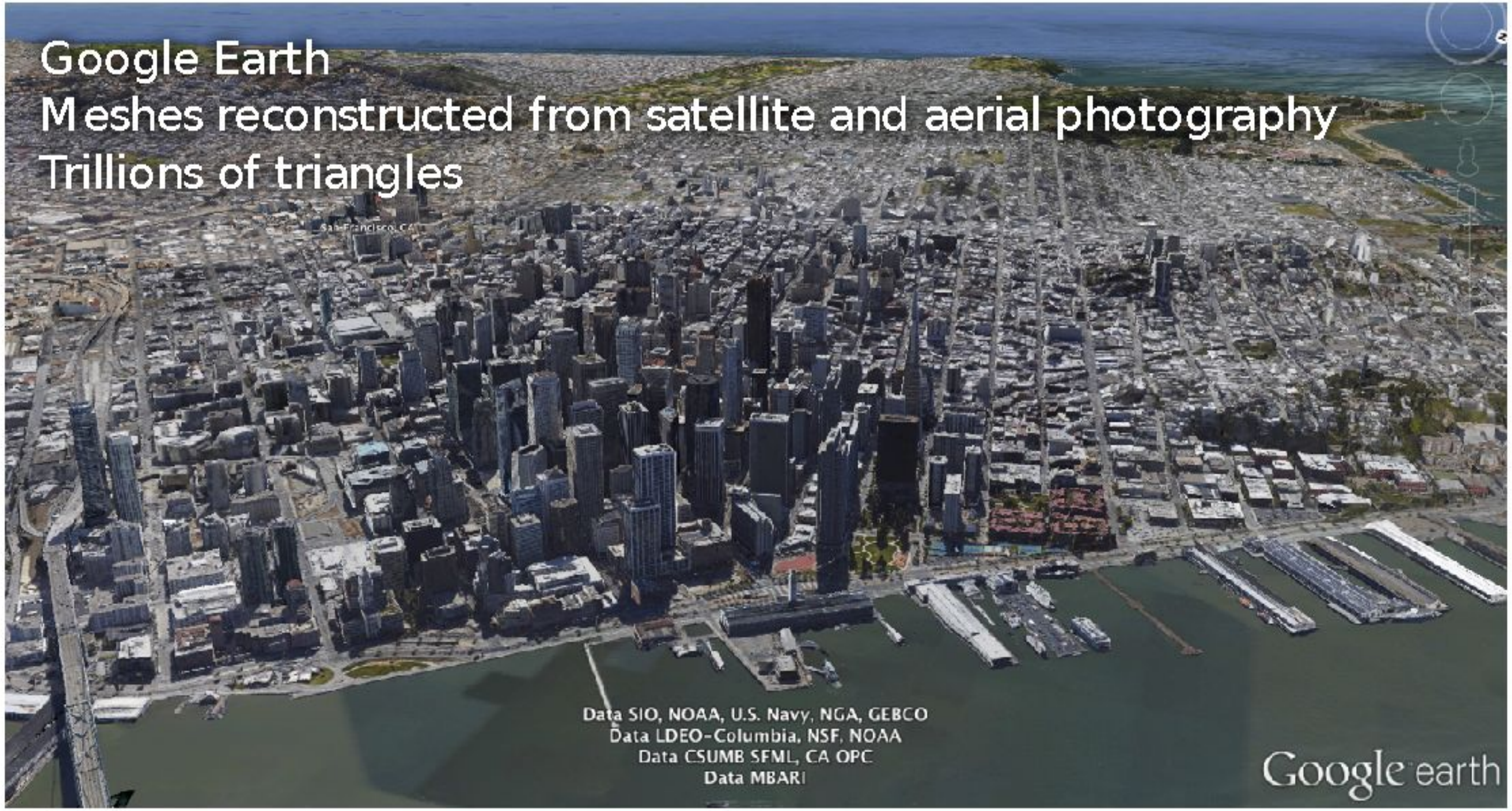
A Very Large Triangle Mesh



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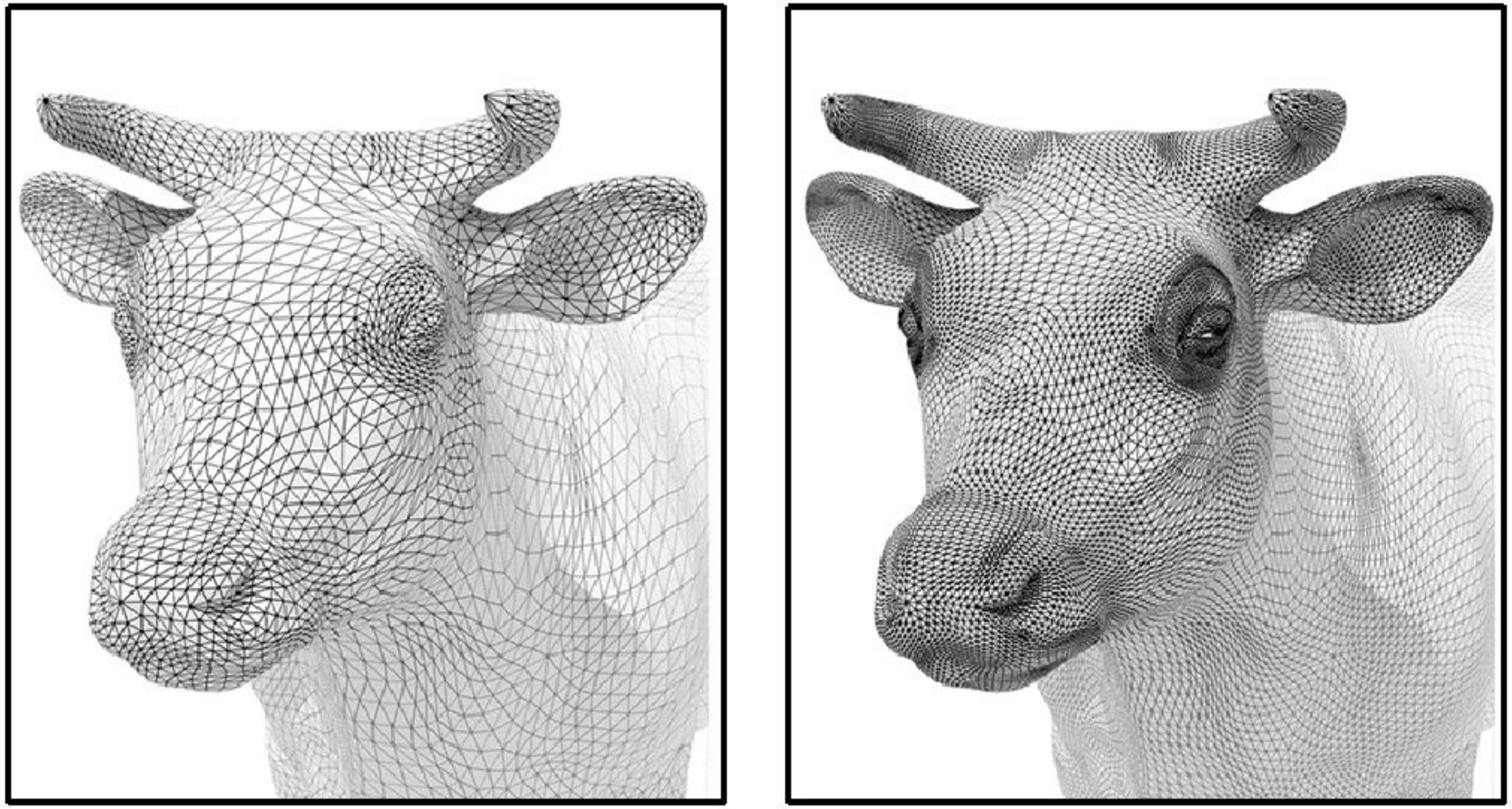
Mesh Upsampling – Subdivision



Increase resolution via interpolation

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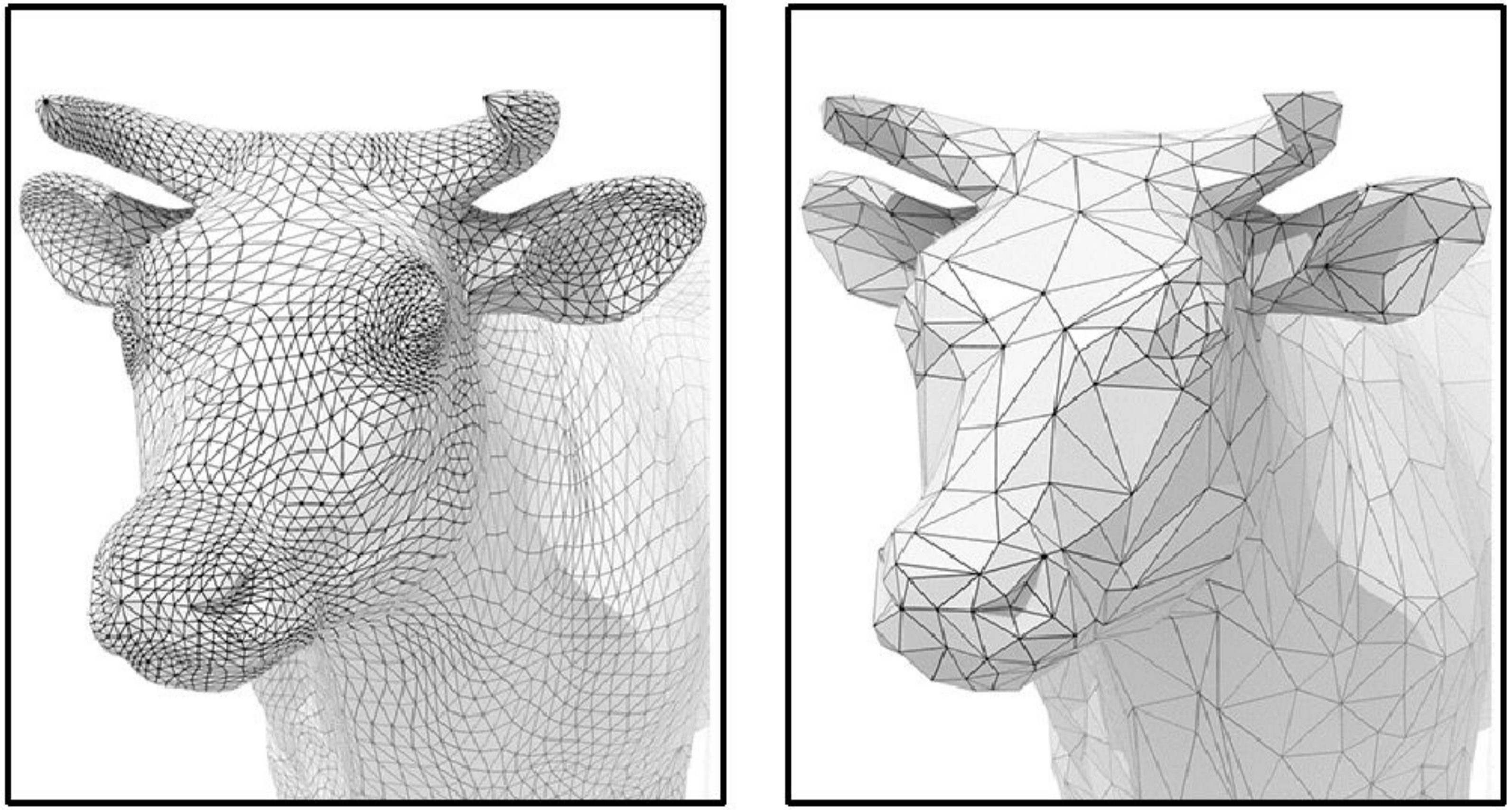
Mesh Downsampling – Simplification



Decrease resolution; try to preserve shape/appearance

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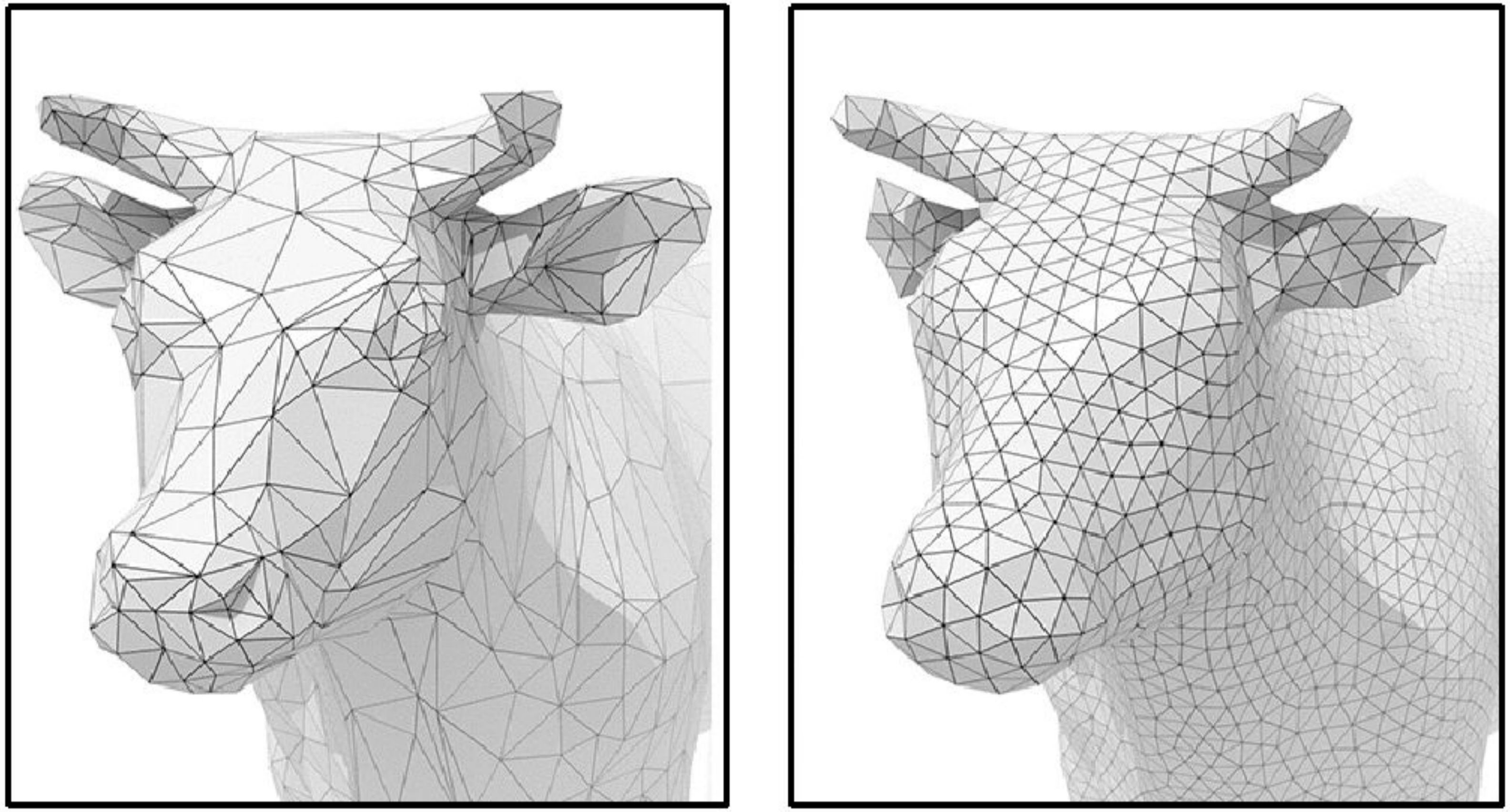
Mesh Regularization

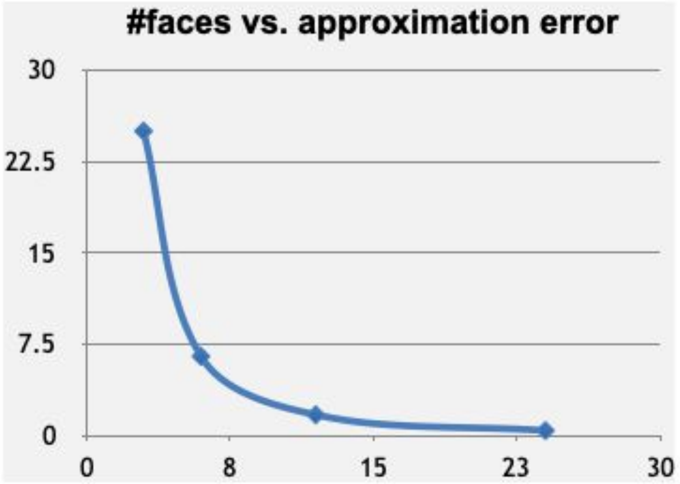


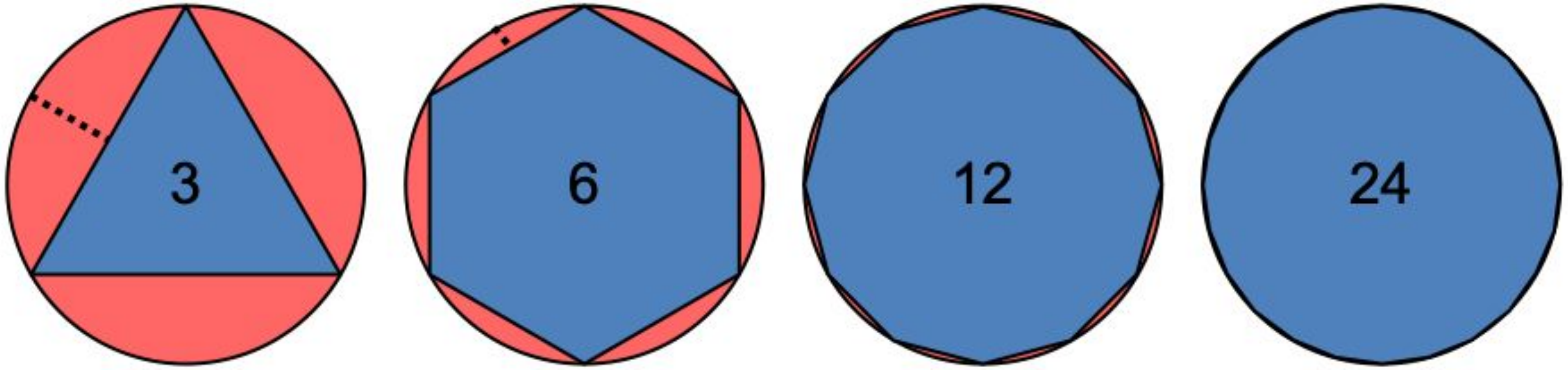
Modify sample distribution to improve quality

Slide credit: Ren Ng

Meshes as Approximations of Smooth Surfaces

- Piecewise linear approximation
  - Error is $O(h^2)$





25% 6.5% 1.7% 0.4%

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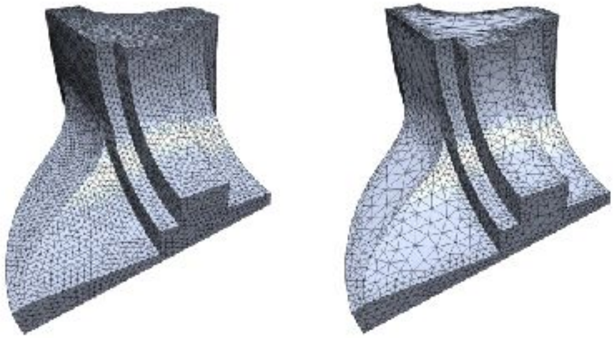
Polygonal Meshes

- Polygonal meshes are a good representation
  - approximation $O(h^2)$
  - arbitrary topology
  - adaptive refinement
  - efficient rendering



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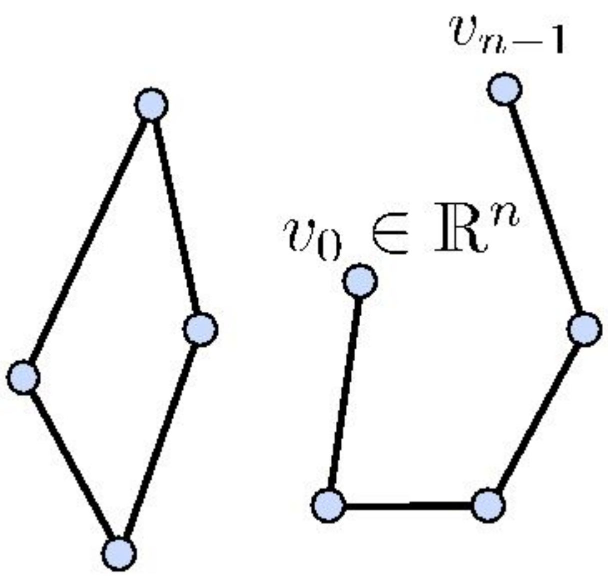
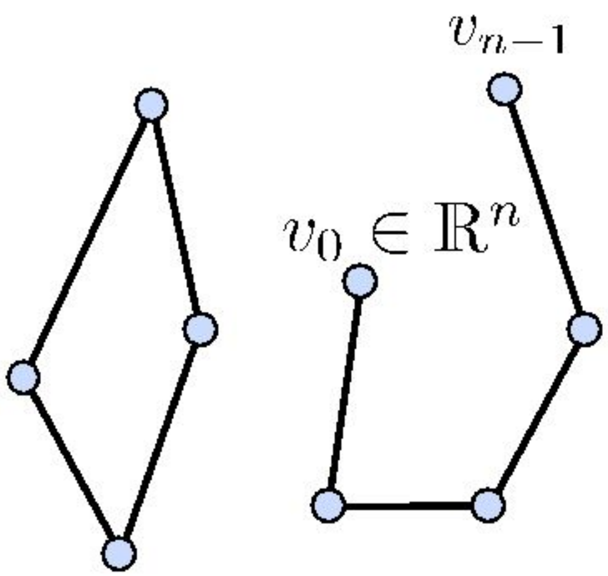
Polygon



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

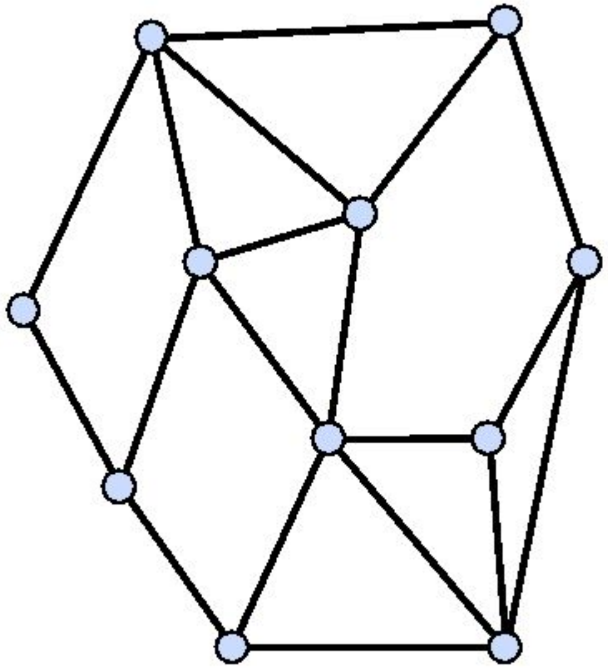
Polygon



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

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

Polygonal Mesh



- A finite set *M* of closed, simple polygons Q_i is a polygonal mesh
- The intersection of two polygons in *M* is either empty, a vertex, or an edge

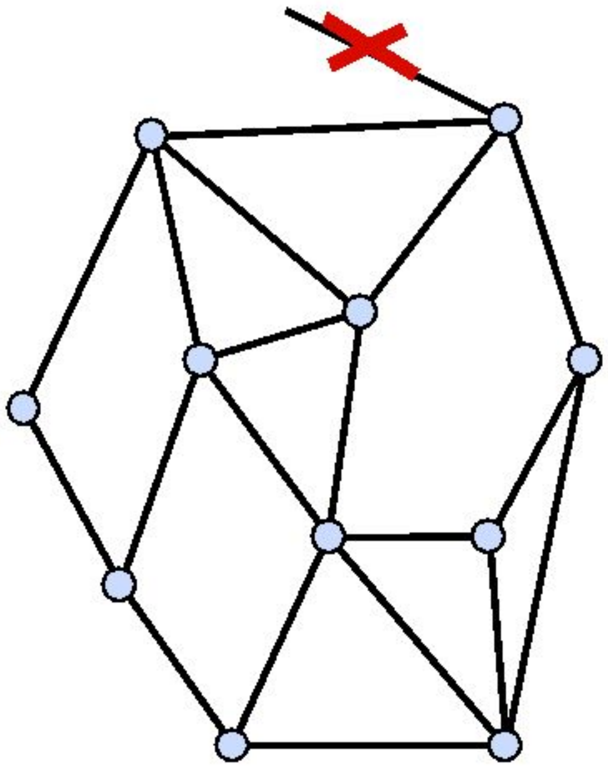
$$M = \langle V, E, F \rangle$$

vertices

edges

faces

Polygonal Mesh



- A finite set M of closed, simple polygons Q_i is a polygonal mesh
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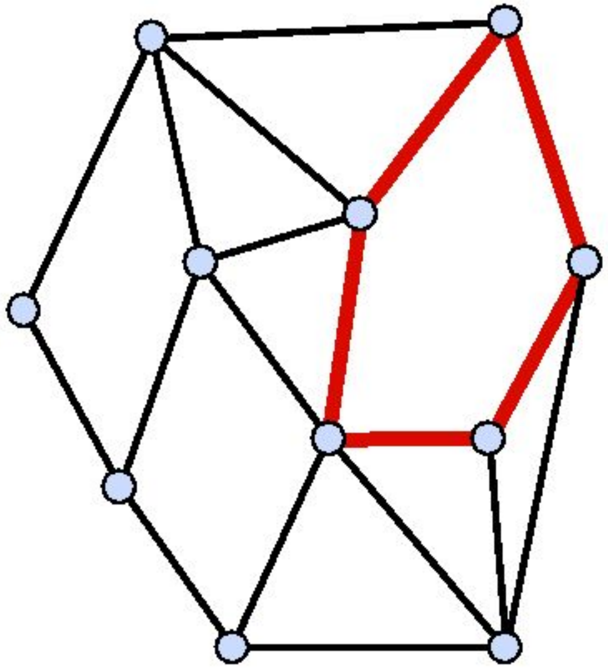
- Every edge belongs to at least one polygon

Polygonal Mesh



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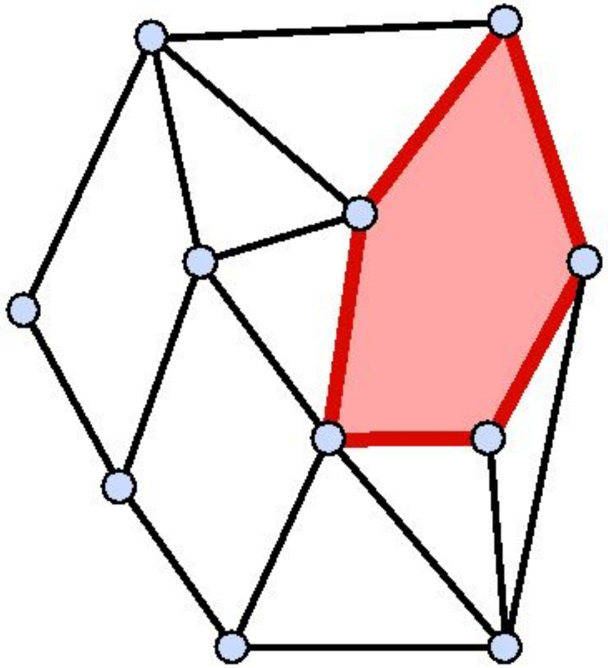
- Each Q_i defines a **face** of the polygonal mesh

Polygonal Mesh



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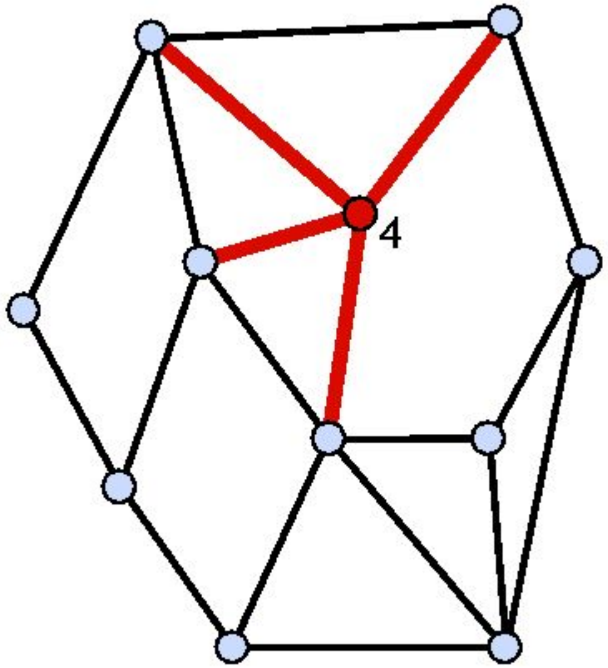
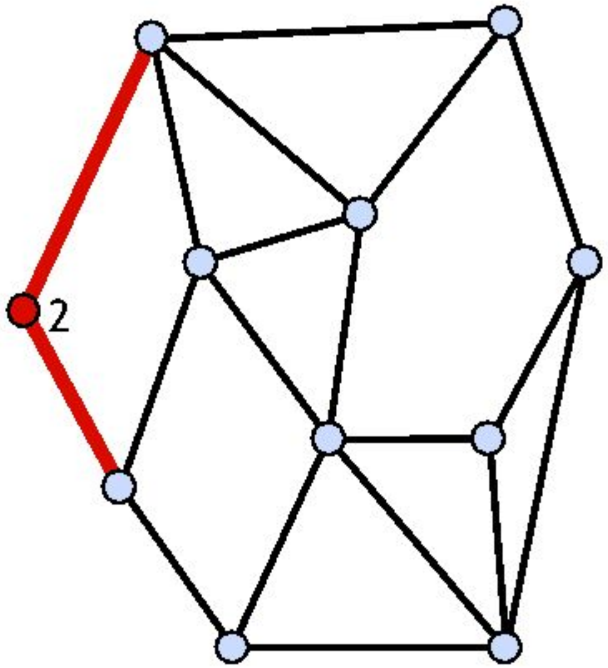


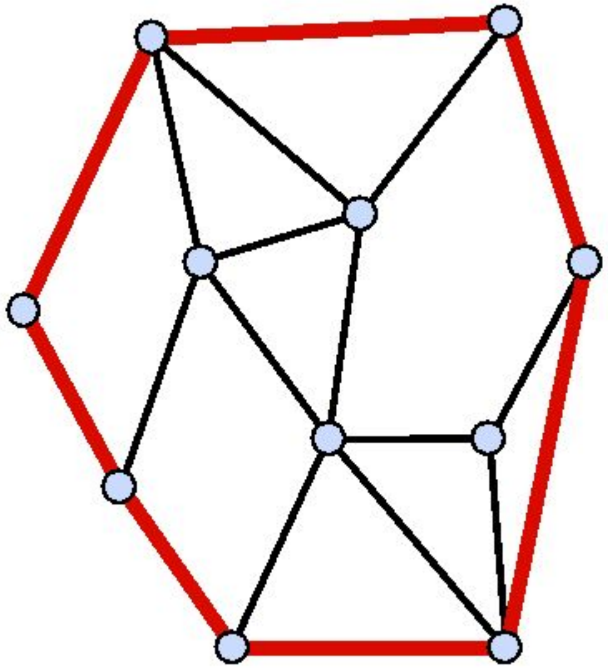
- Vertex **degree** or **valence** = number of incident edges

Polygonal Mesh

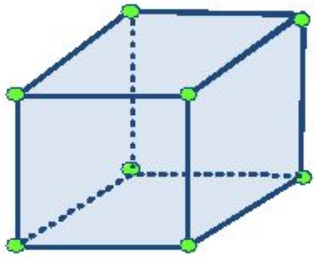
- Vertex degree or valence = number of incident edges



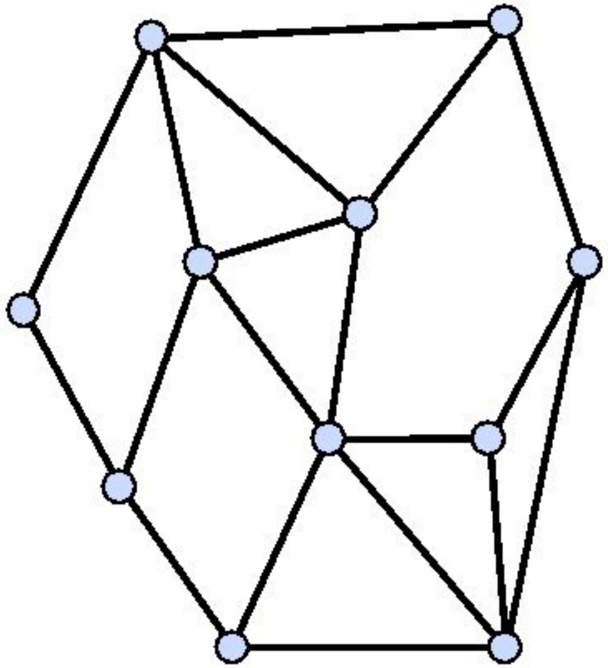
Polygonal Mesh



- Boundary: the set of all edges that belong to only one polygon
  - Either empty or forms closed loops
  - If empty, then the polygonal mesh is closed

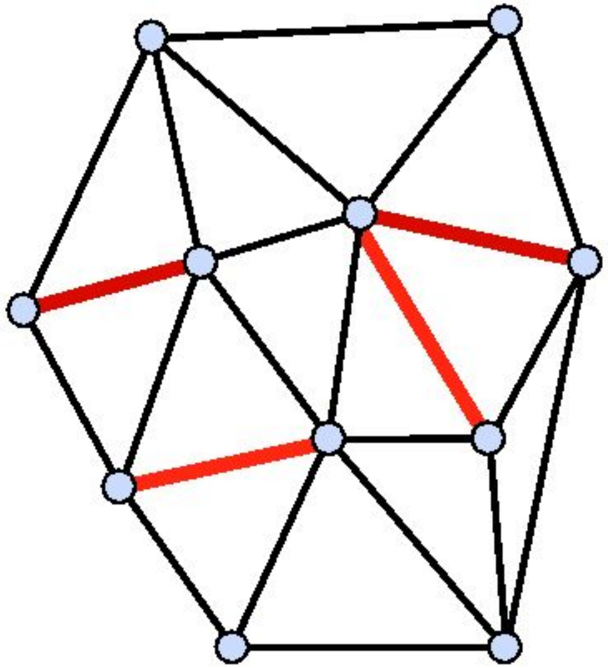


Triangulation



- Polygonal mesh where every face is a triangle

Triangulation



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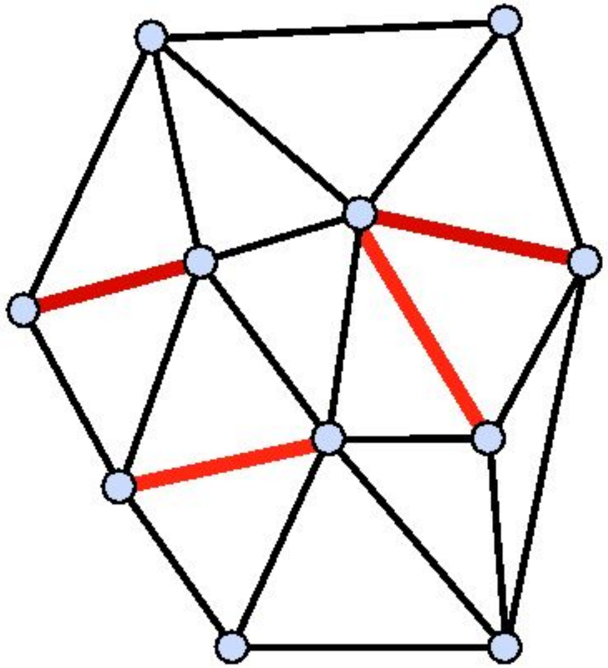
Triangulation



- Polygonal mesh where every face is a triangle

- Simplifies data structures
- Simplifies rendering
- Simplifies algorithms
- Each face planar and convex
- Any polygon can be triangulated

Data Structures

- What should be stored?
  - Geometry: 3D coordinates

Data Structures

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  - Geometry: 3D coordinates
  - Connectivity
    - Adjacency relationships

Data Structures

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

Simple Data Structures:Indexed Face Set

- Used in formats
- OBJ , OFF, WRL
- Storage
  - Vertex: position
  - Face: vertex indices
  - 12 bytes per vertex
  - 12 bytes per face
  - 36*v bytes for the mesh
- No explicit neighborhood info

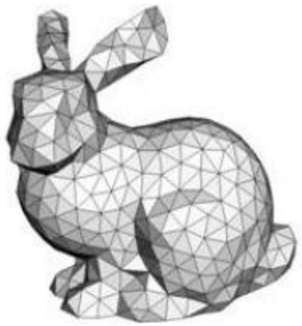
Vertices			
v0	x0	y0	z0
v1	x1	x1	z1
v2	x2	y2	z2
v3	x3	y3	z3
v4	x4	y4	z4
v5	x5	y5	z5
v6	x6	y6	z6
...	...	...	...

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

Shape Representations

Non-parametric

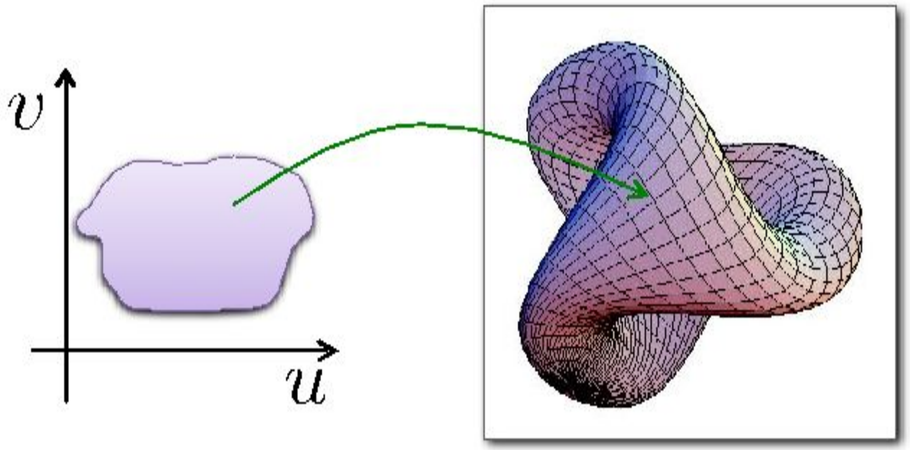
Points



Meshes

Parametric Representation

- Range of a function $f : X \to Y, X \subseteq \mathbb{R}^m, Y \subseteq \mathbb{R}^n$
  - Surface in 3D: $m = 2, n = 3$



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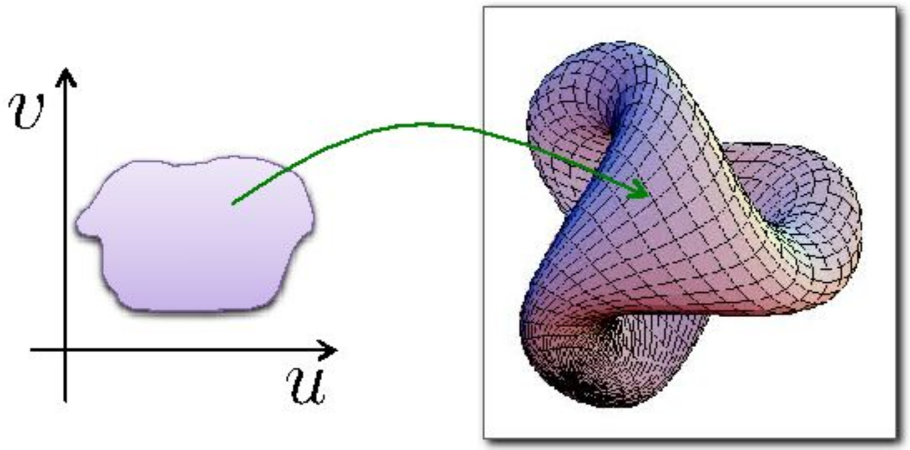


$$s(u, v) = (x(u, v), y(u, v), z(u, v))$$

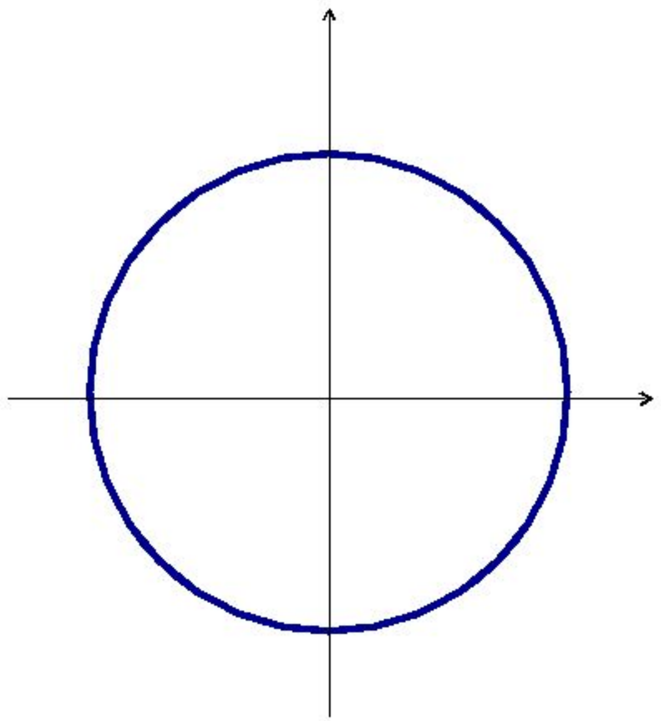
Slide credit: Hao Su

Parametric Curves

- Example: Explicit curve/circle in 2D

$$\mathbf{p} : \mathbb{R} \to \mathbb{R}^2$$

$$t \mapsto \mathbf{p}(t) = (x(t), y(t))$$



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Parametric Curves

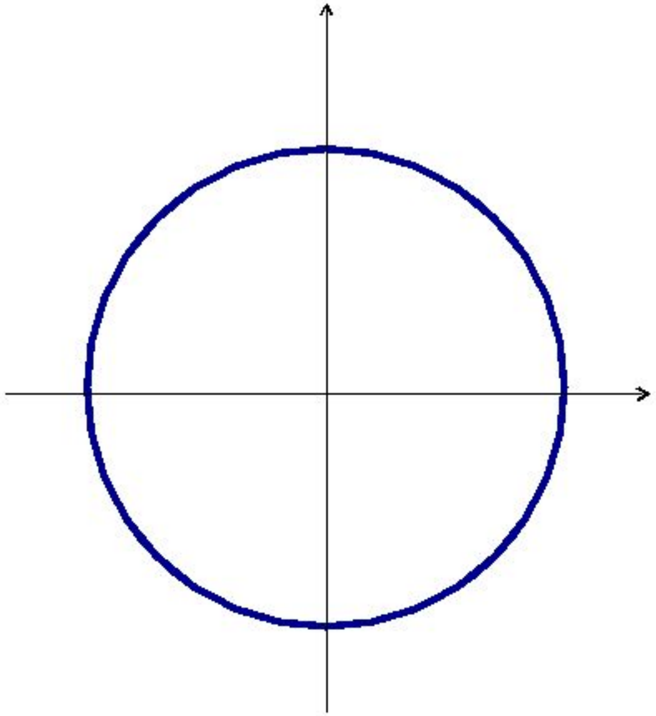
- Example: Explicit curve/circle in 2D

$$\mathbf{p} : \mathbb{R} \to \mathbb{R}^2$$

$$t \mapsto \mathbf{p}(t) = (x(t), y(t))$$

$$\mathbf{p}(t) = r\,(\cos(t), \sin(t))$$

$$t \in [0, 2\pi)$$



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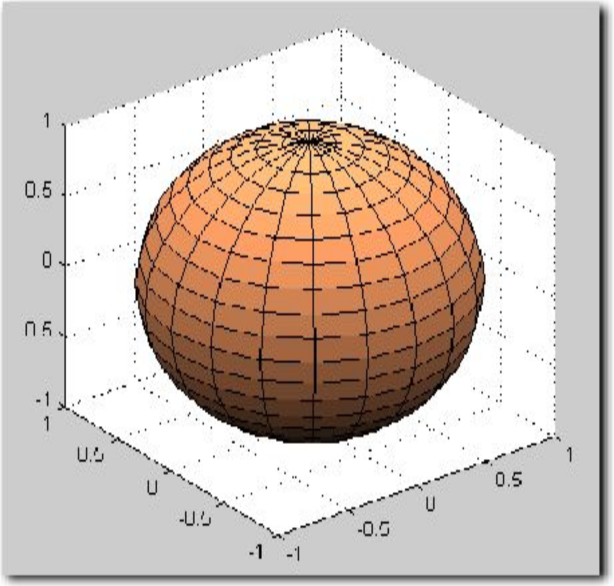
Parametric Surfaces

- Sphere in 3D

$$s : \mathbb{R}^2 \rightarrow \mathbb{R}^3$$



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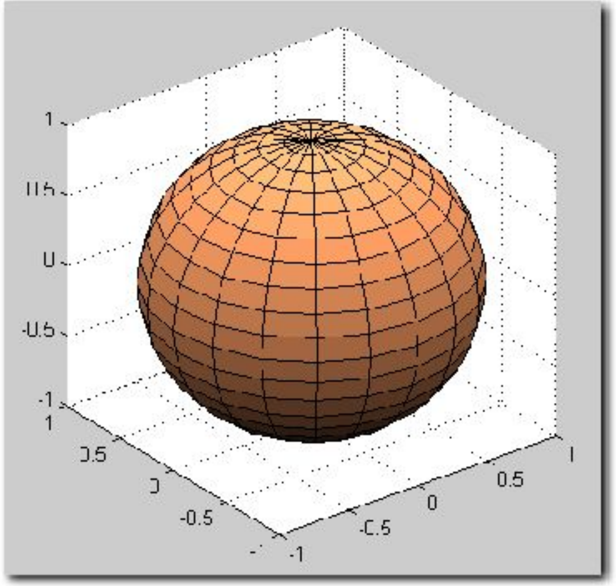
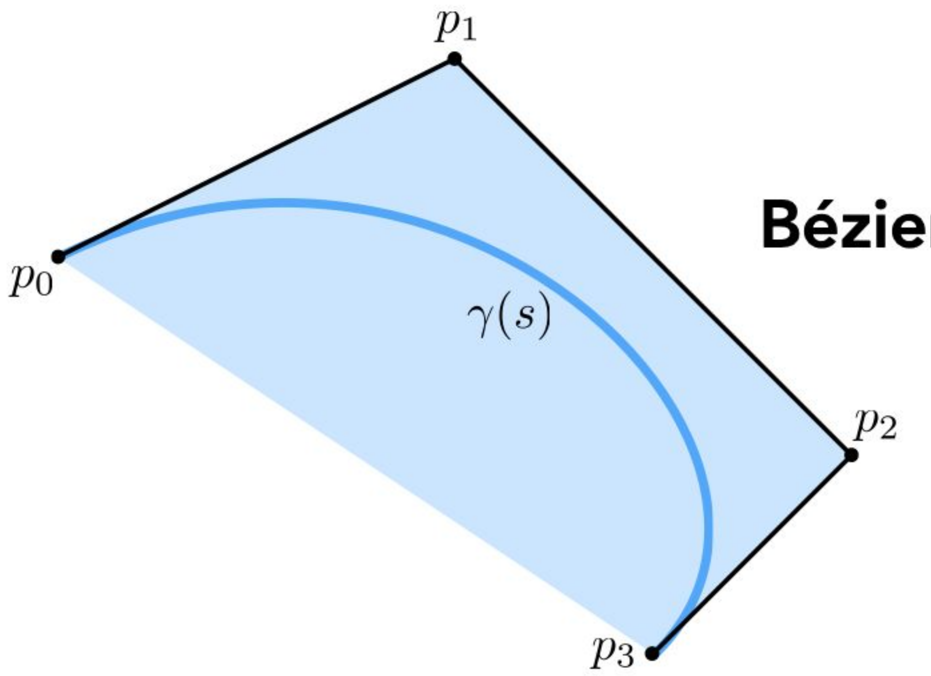


$$s(u, v) = r\left(\cos(u)\cos(v), \sin(u)\cos(v), \sin(v)\right)$$

$$(u, v) \in [0, 2\pi) \times [-\pi/2, \pi/2]$$

Slide credit: Hao Su

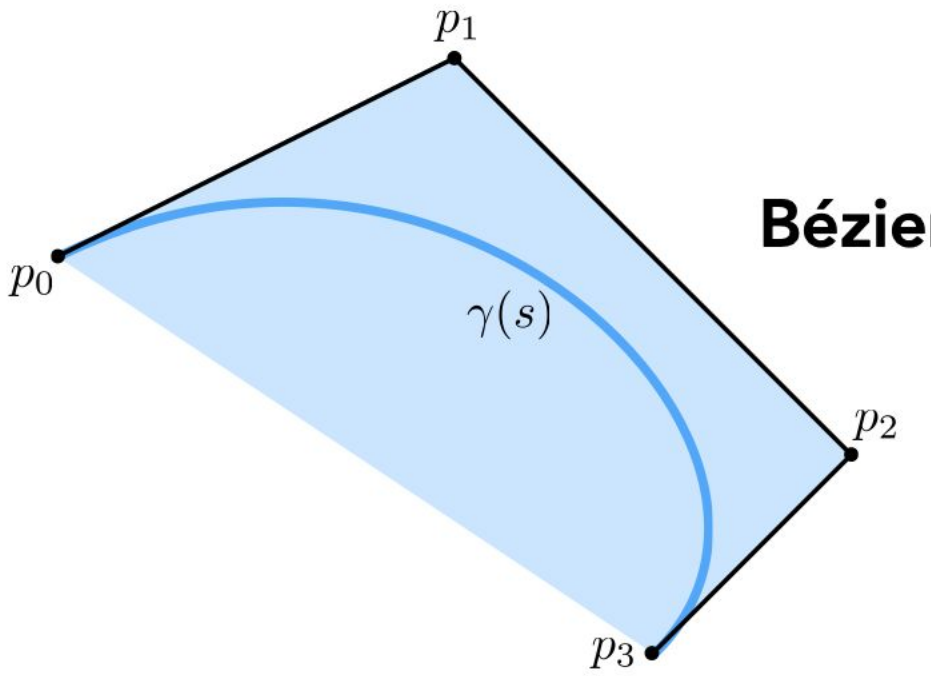
Bézier Curves



Bézier curves

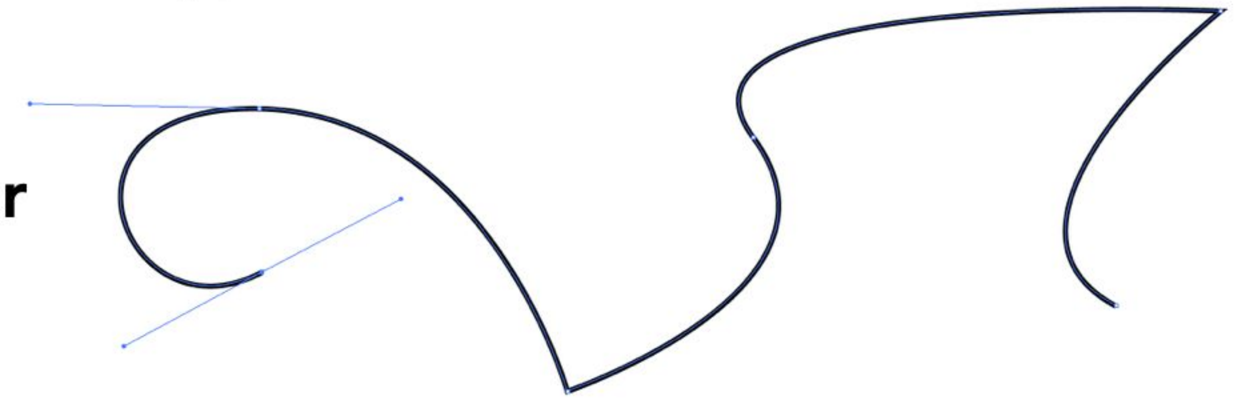
Slide credit: Ren Ng

Bézier Curves



Bézier curves

Piecewise Bézier



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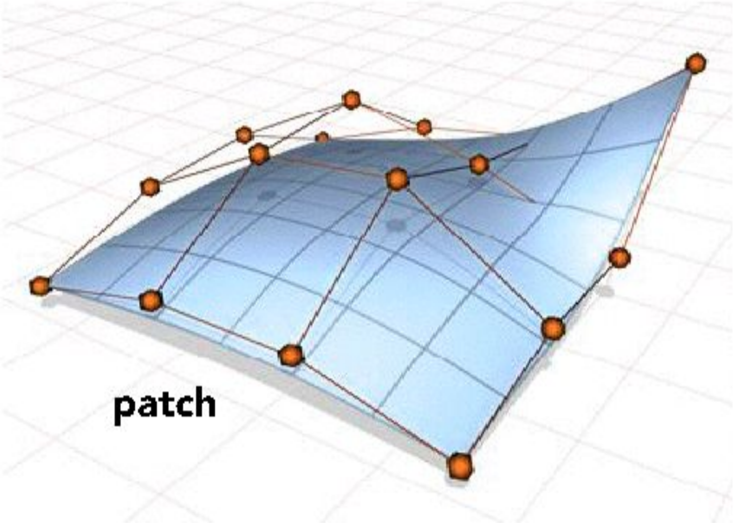
Bézier Surfaces

Use tensor product of Bézier curves to get a patch:



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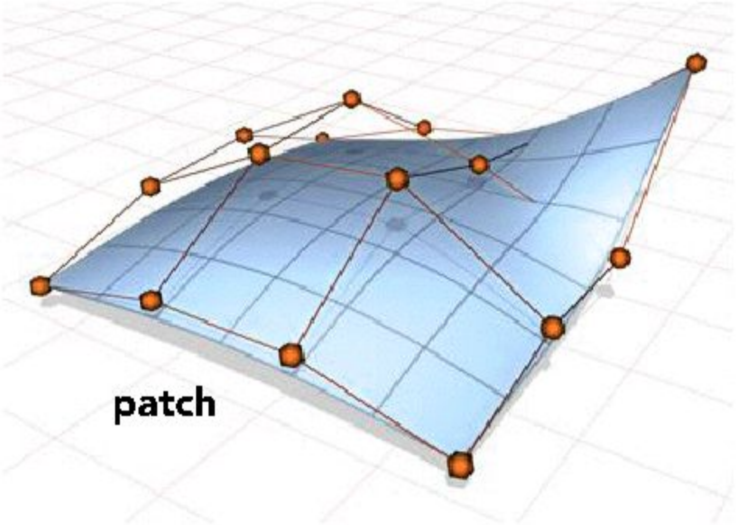
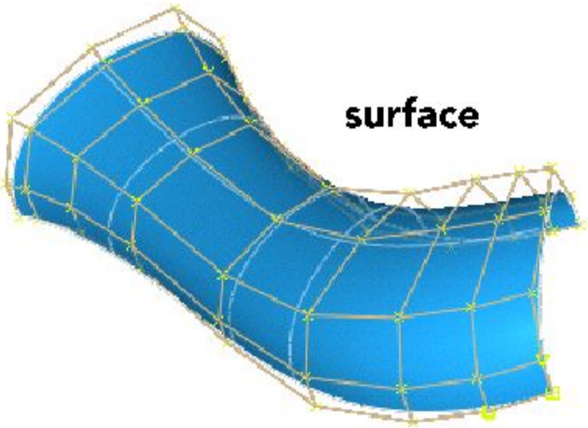




Multiple Bézier patches form a surface

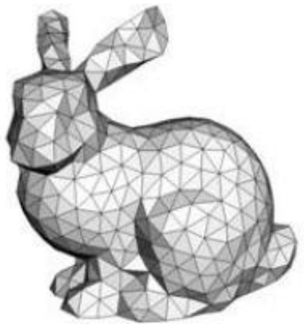
Slide credit: Ren Ng

Shape Representations

Explicit

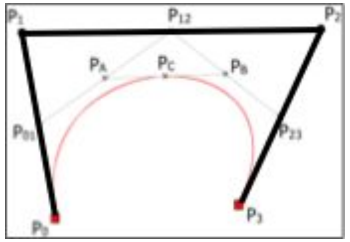
Non-parametric

Points

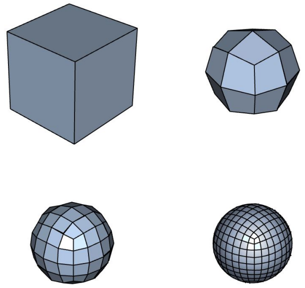


Meshes

Parametric



Splines



Subdivision Surfaces

“Explicit” Representations of Geometry

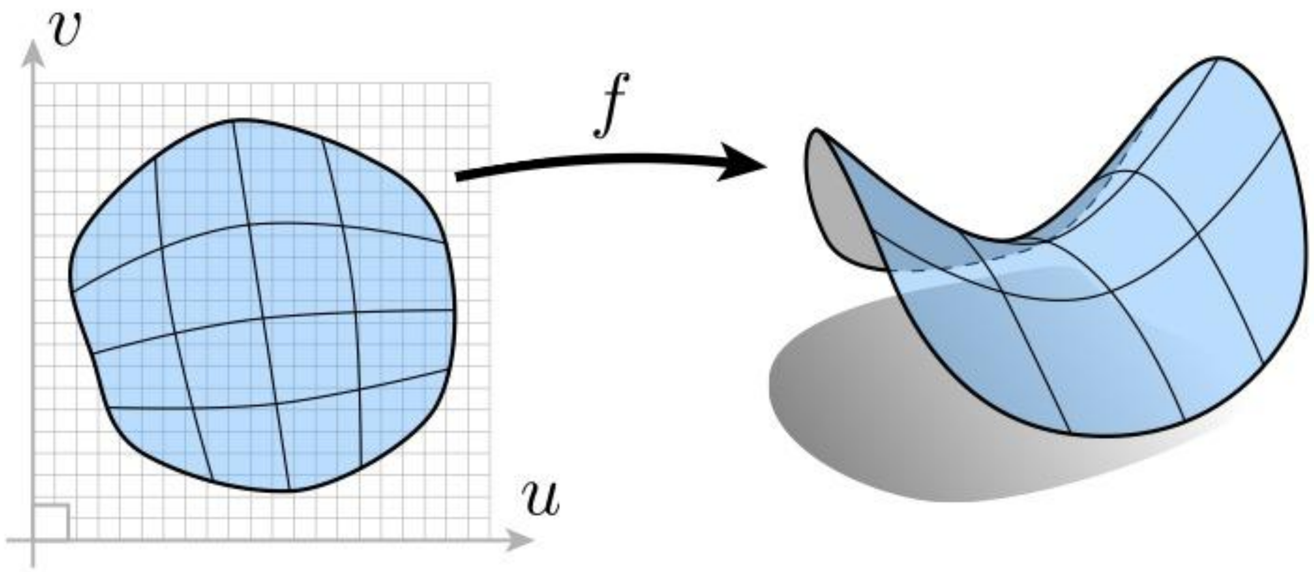
All points are given directly

Slide credit: Ren Ng

"Explicit" Representations of Geometry

All points are given directly

Generally: $f : \mathbb{R}^2 \to \mathbb{R}^3; (u, v) \mapsto (x, y, z)$



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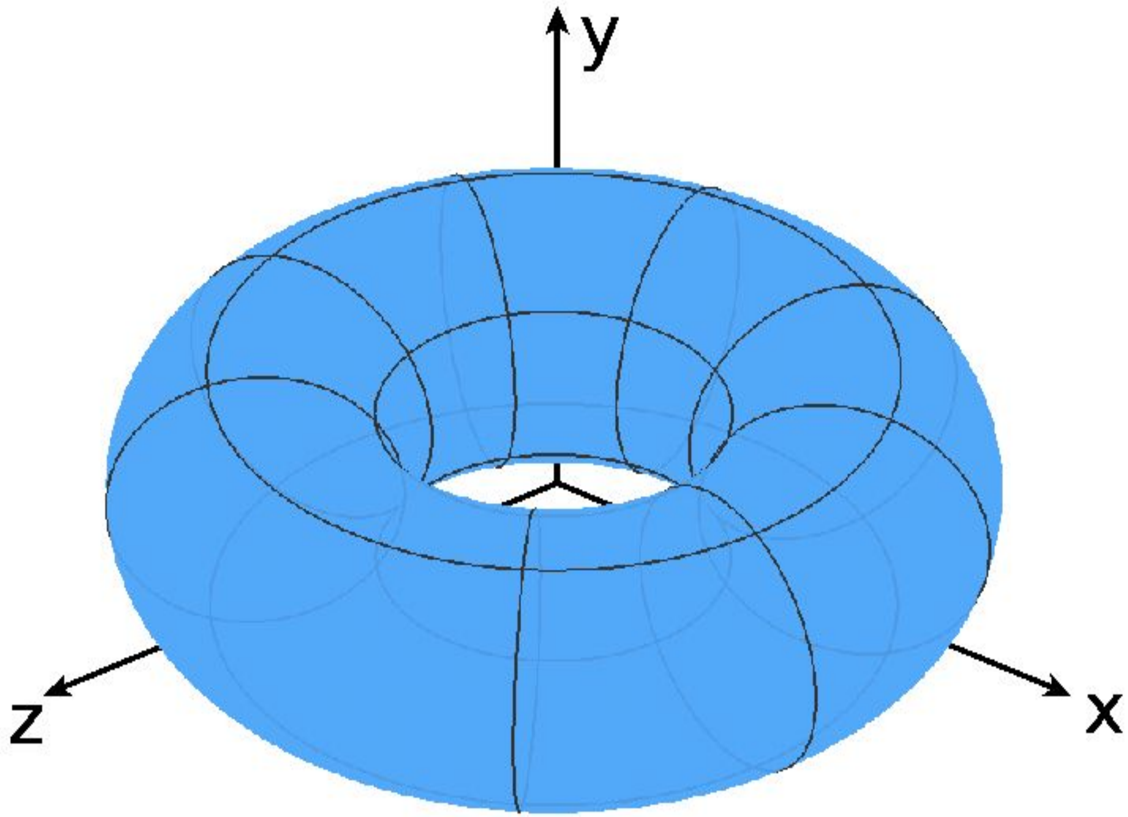
Explicit Surface – Sampling Is Easy

$f(u, v) = ((2 + \cos u)\cos v, (2 + \cos u)\sin v, \sin u)$



Explicit Surface – Sampling Is Easy

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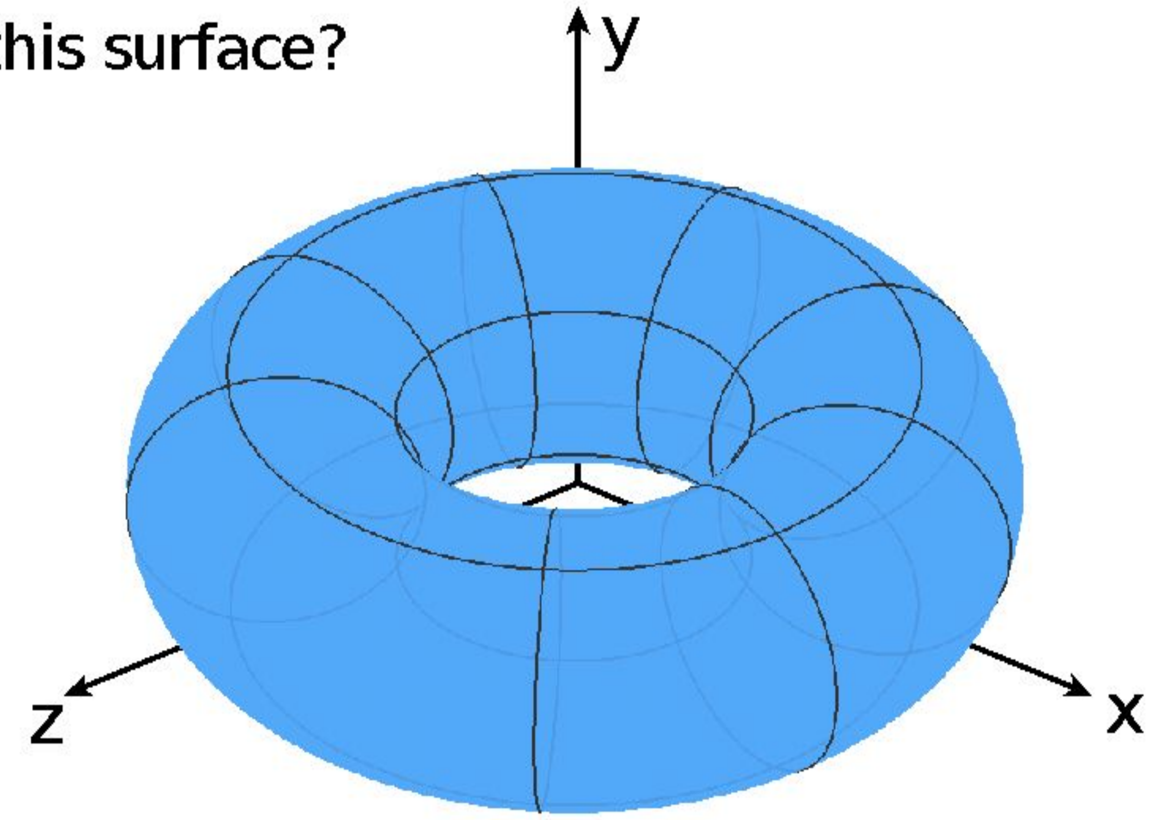
What points lie on this surface?



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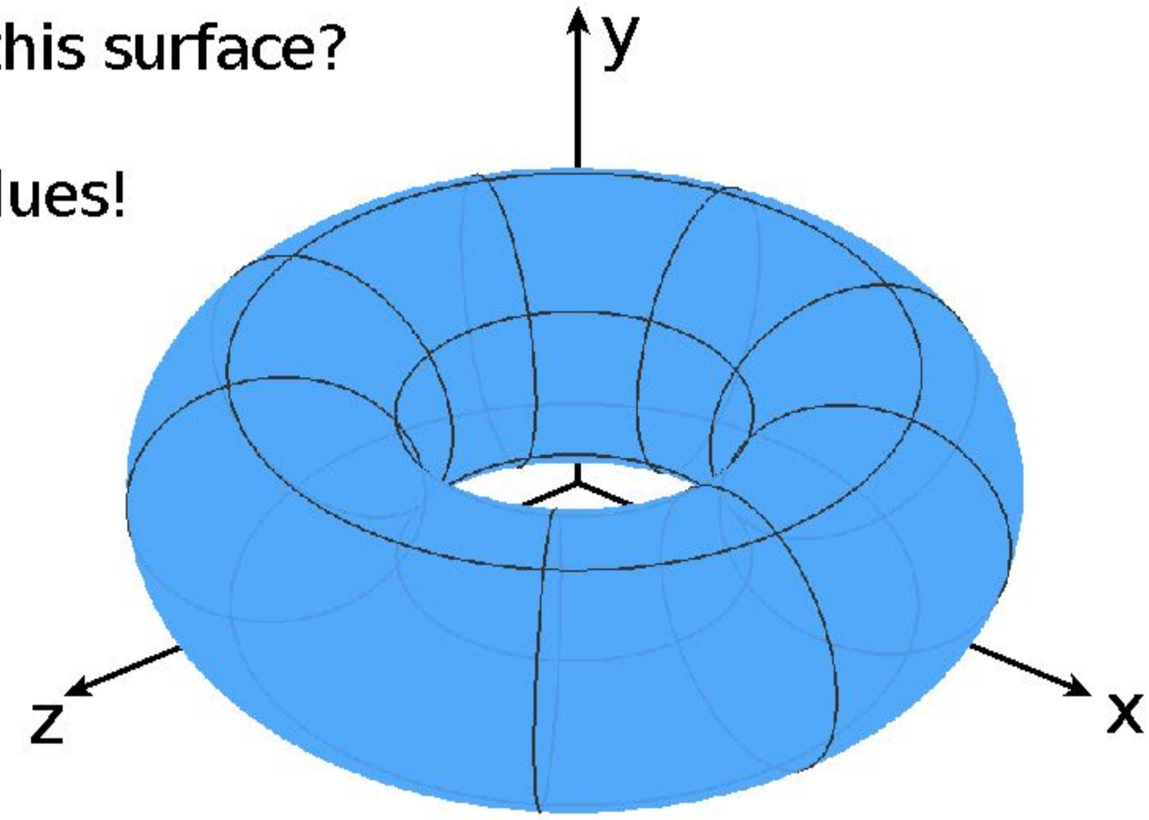
Just plug in (u,v) values!



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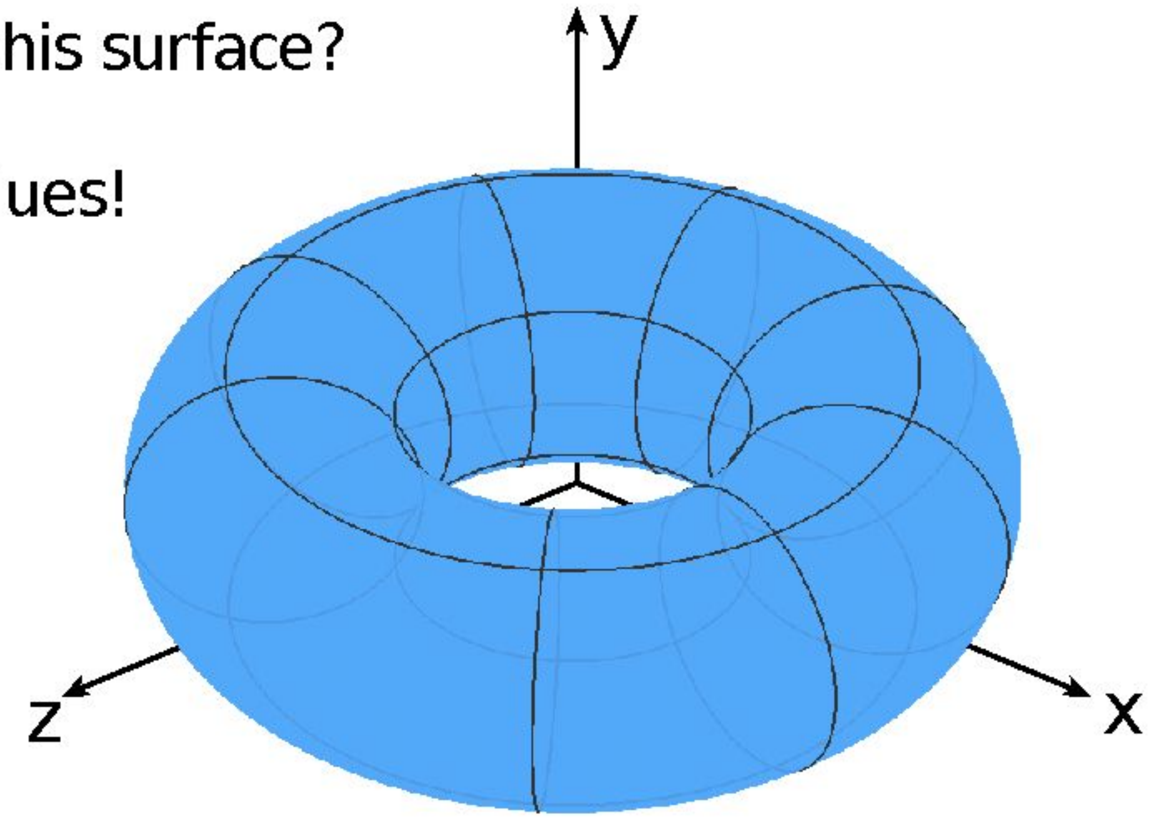
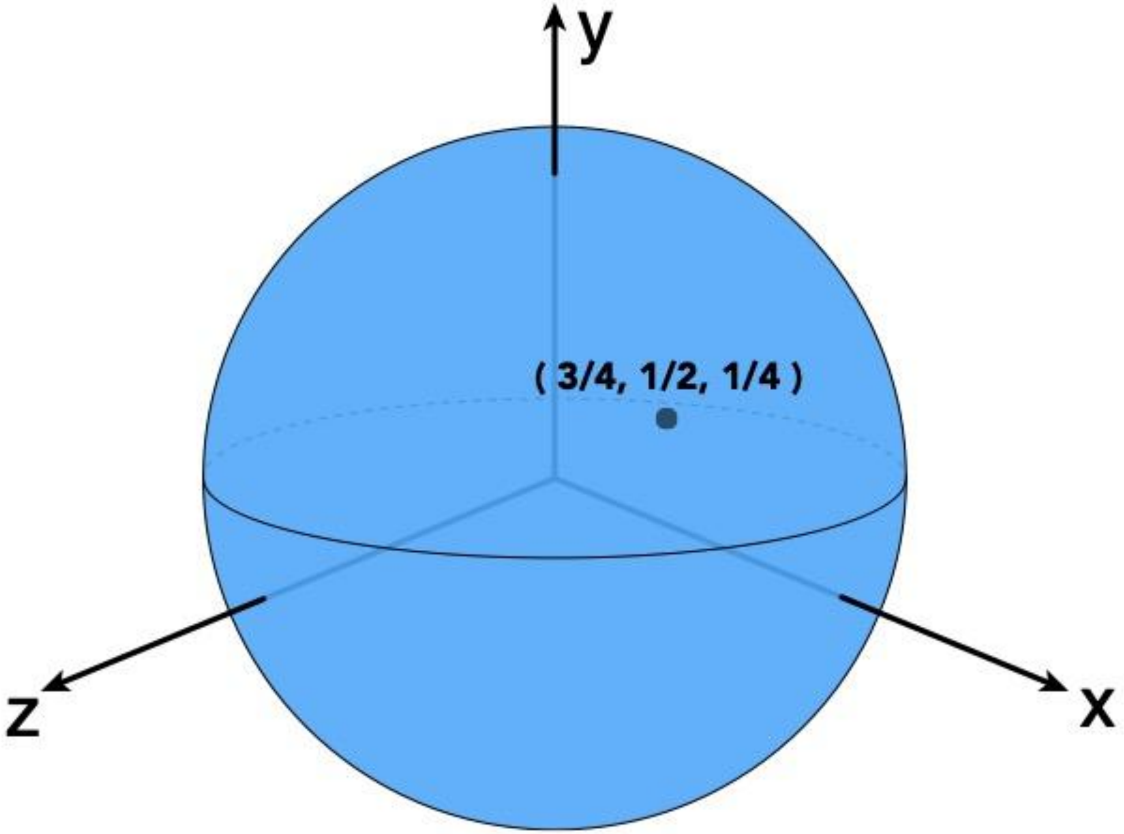


Explicit representations make some tasks easy

Explicit Surface – Inside/Outside Test Hard

$$f(u,v) = (\cos u \, \sin v, \sin u \, \sin v, \cos v)$$



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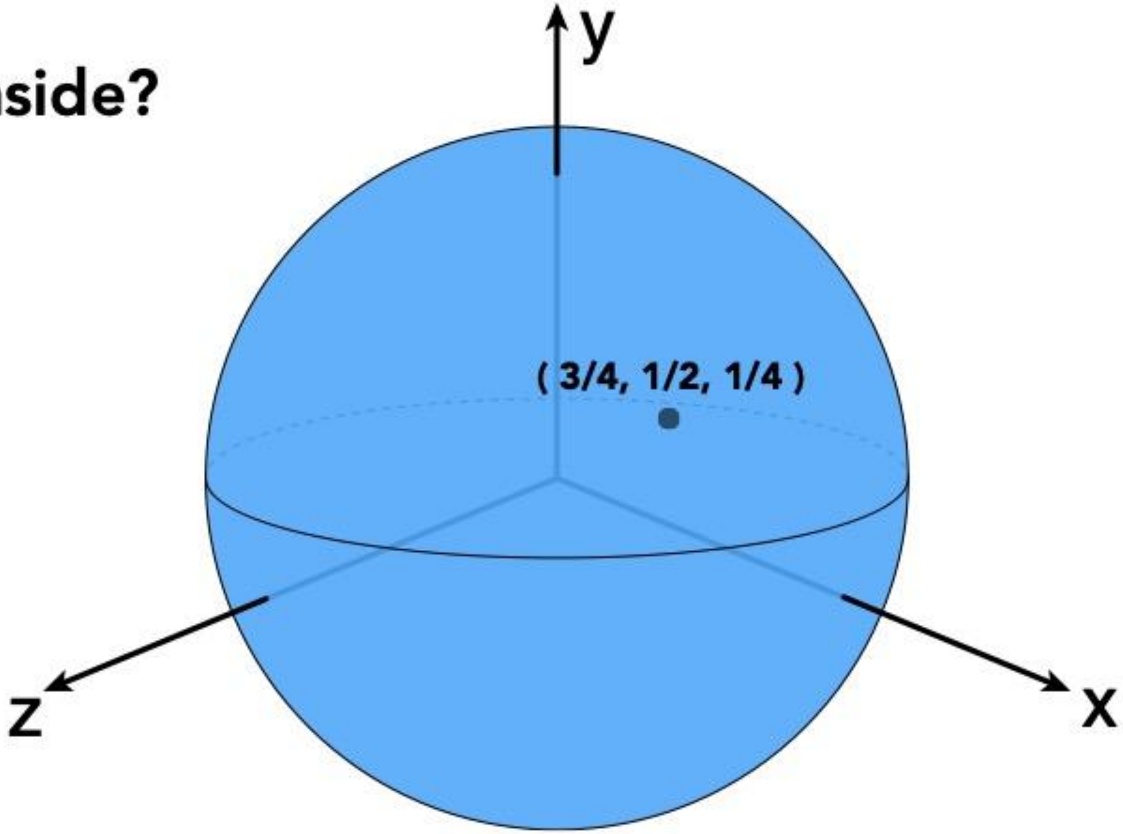
Is (3/4, 1/2, 1/4) inside?



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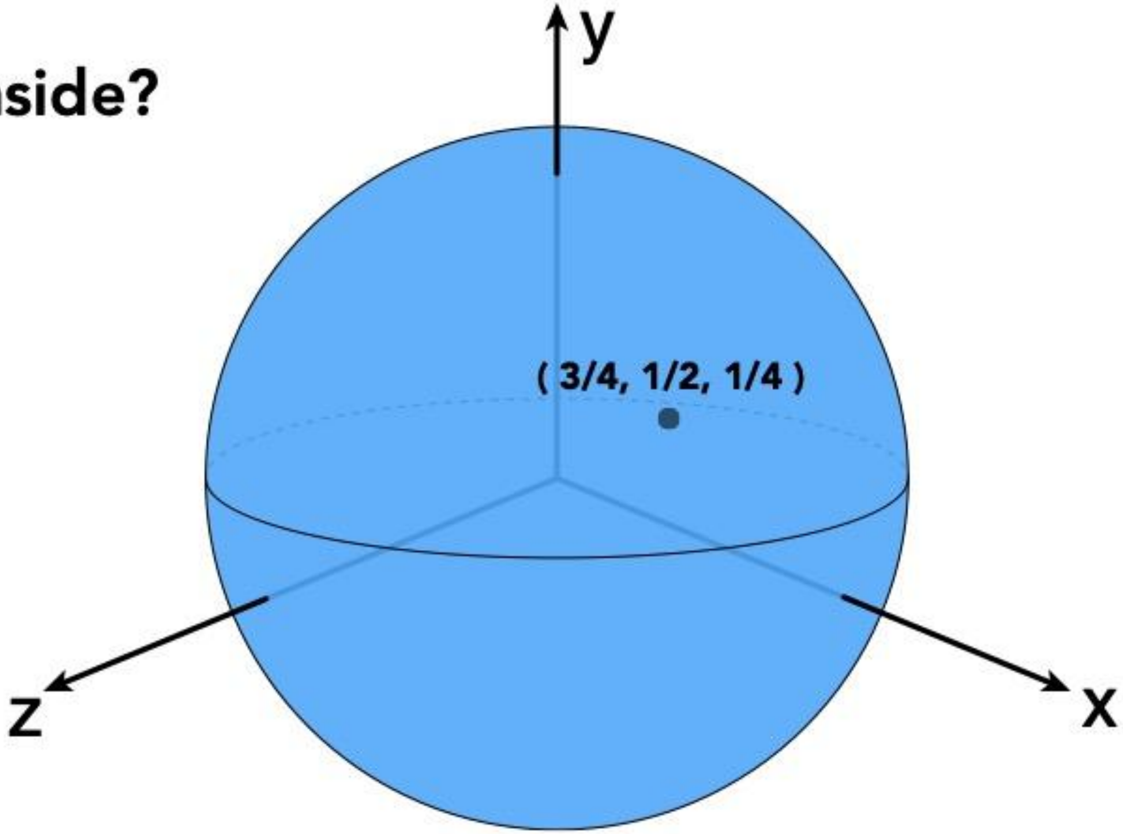

Some tasks are hard with explicit representations

“Implicit” Representations of Geometry

Based on classifying points

- Points satisfy some specified relationship

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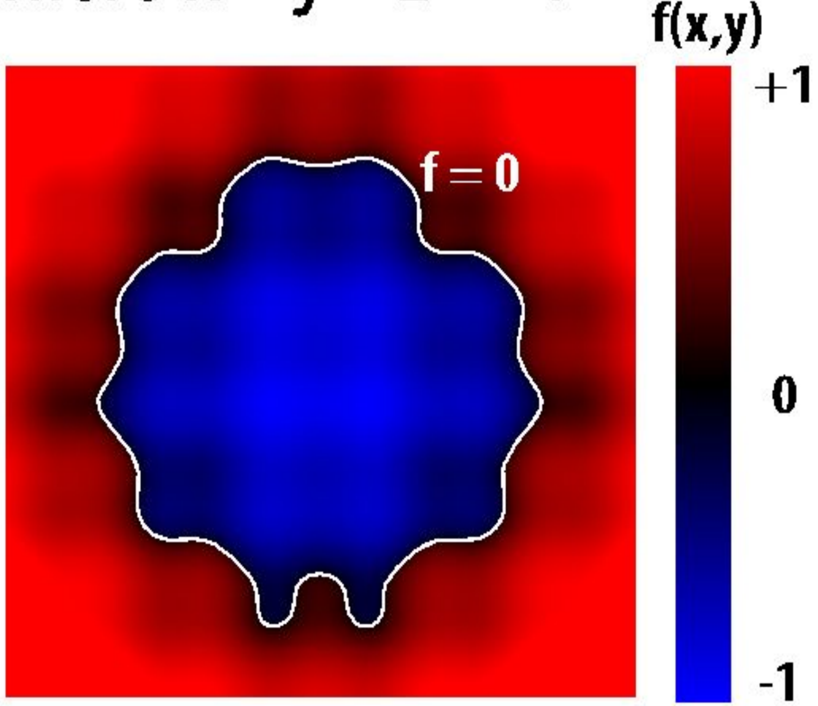
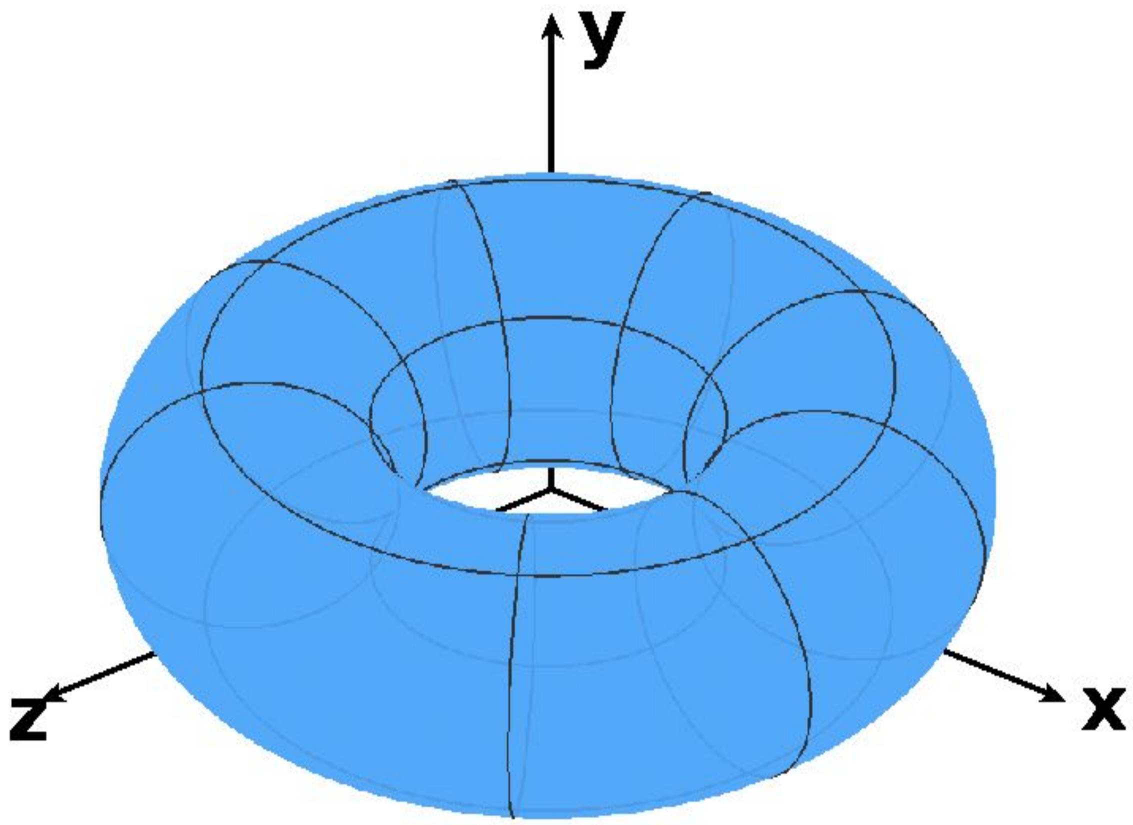
E.g. sphere: all points in 3D, where $x^2+y^2+z^2 = 1$

More generally, $f(x,y,z) = 0$



Implicit Surface – Sampling Can Be Hard

$$f(x, y, z) = (2 - \sqrt{x^2 + y^2})^2 + z^2 - 1$$



Implicit Surface – Sampling Can Be Hard

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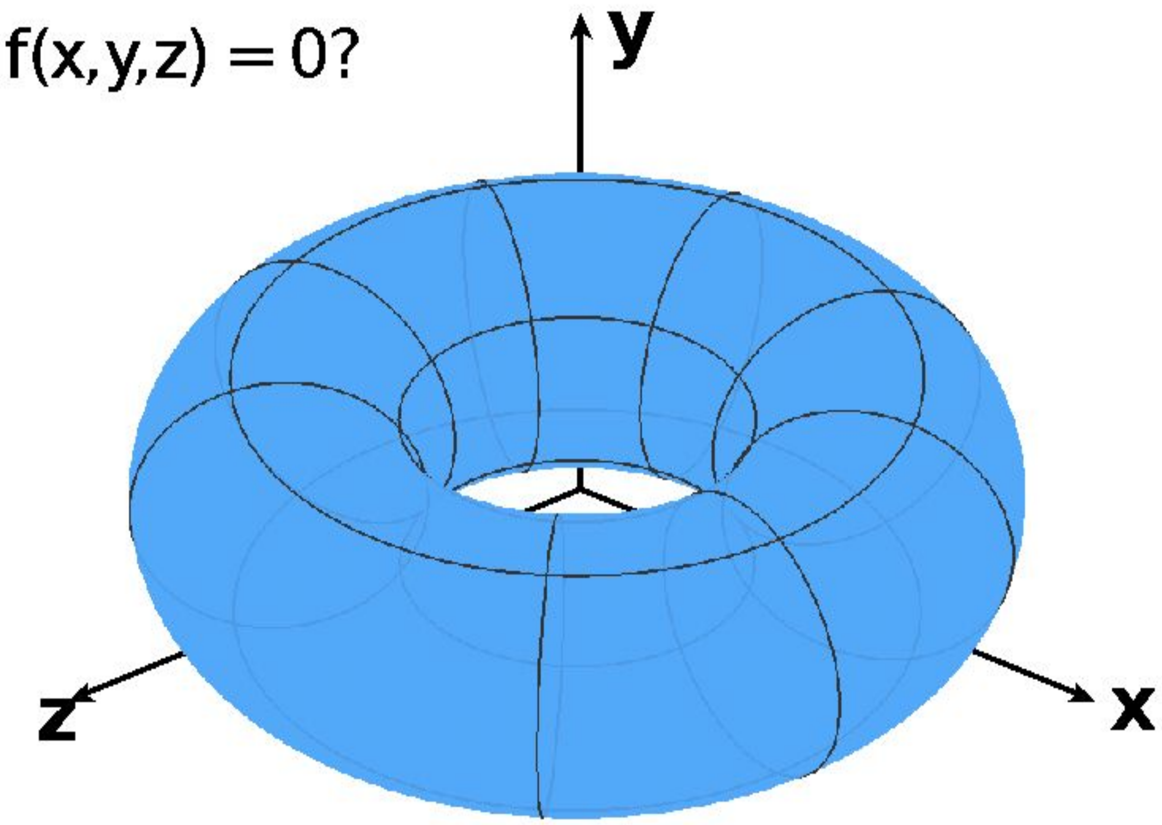
What points lie on f(x,y,z) = 0?



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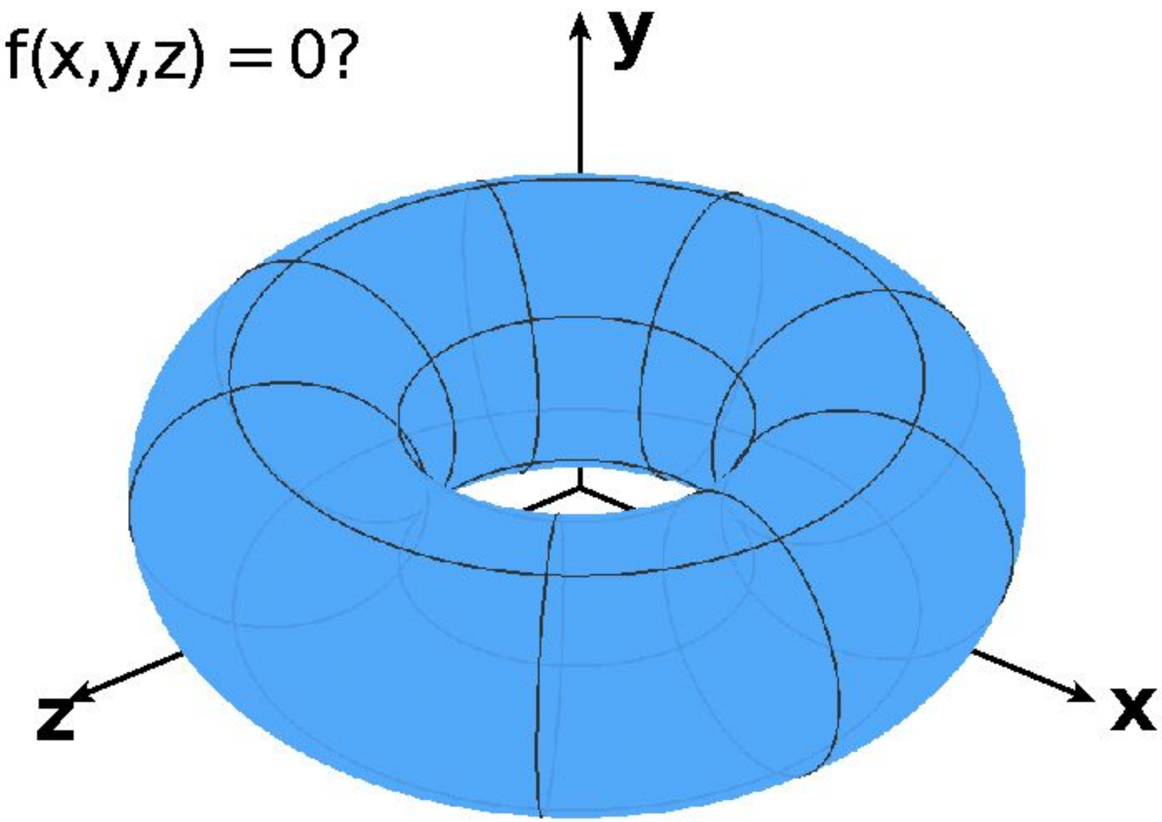

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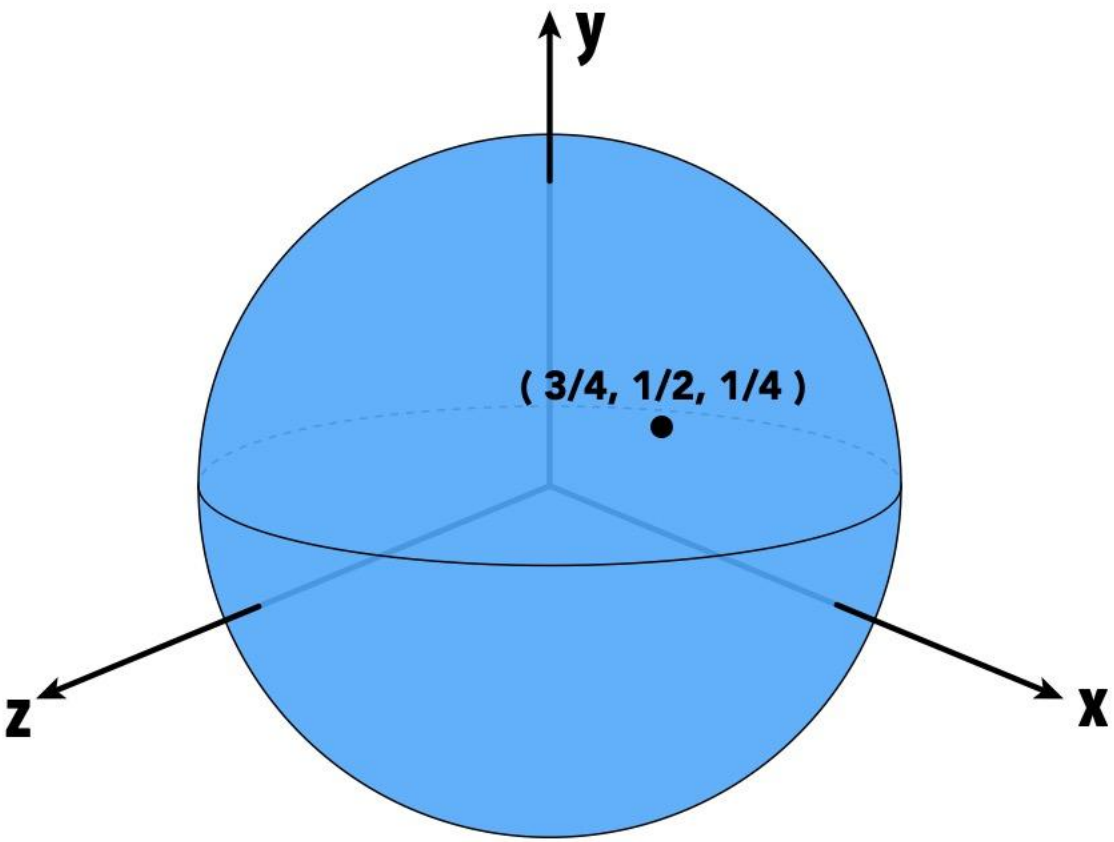

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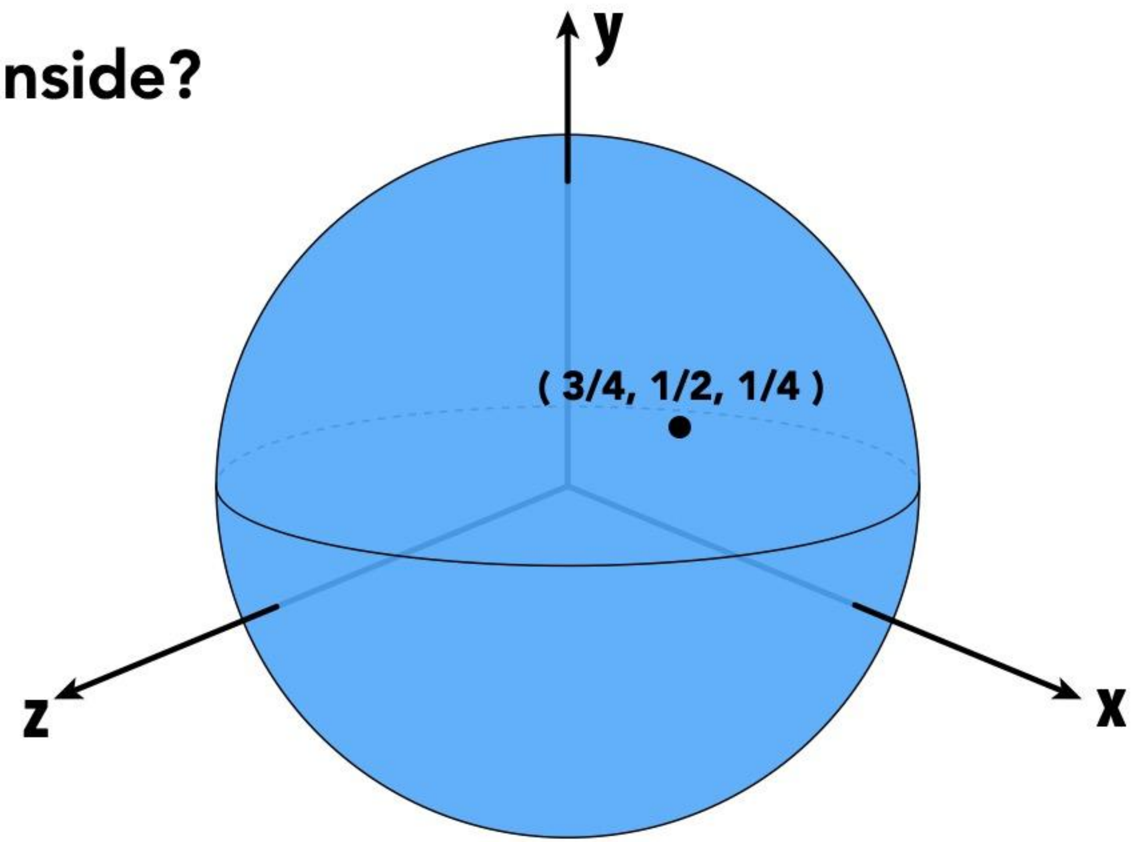

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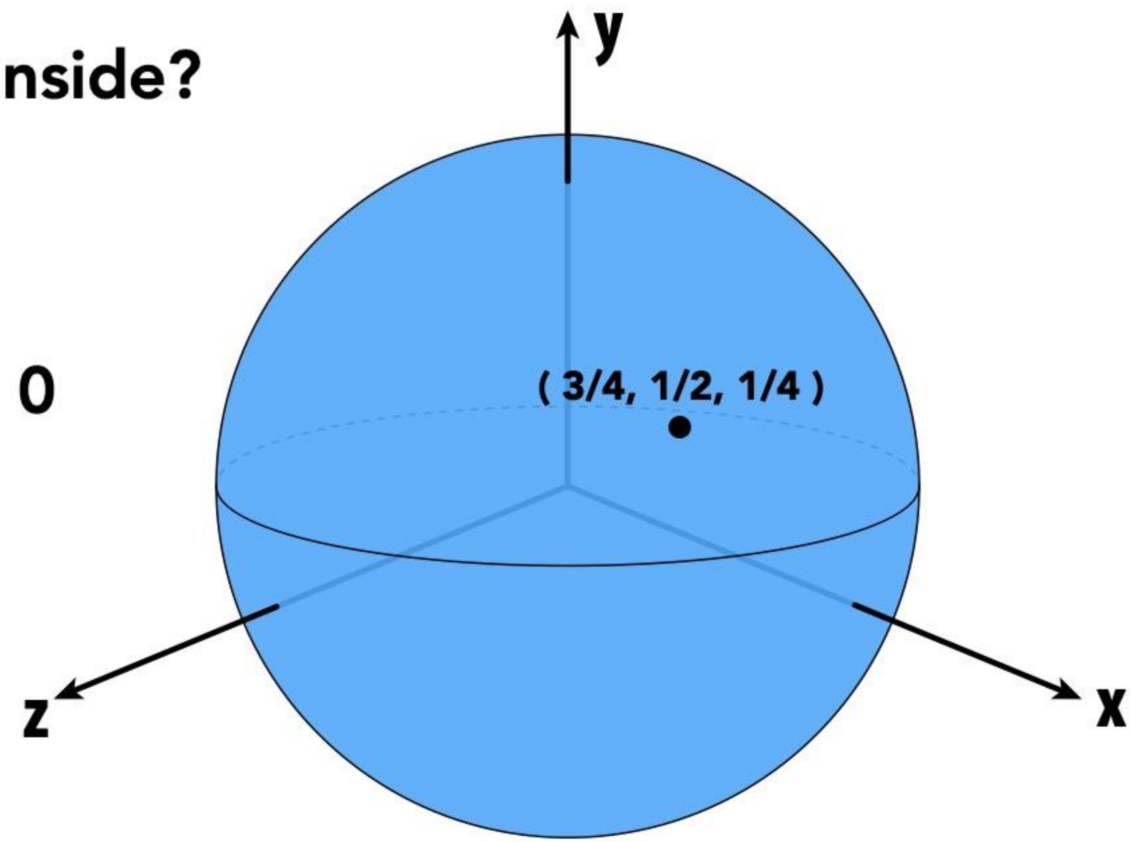
Just plug it in:

$f(x,y,z) = -1/8 < 0$

Yes, inside.



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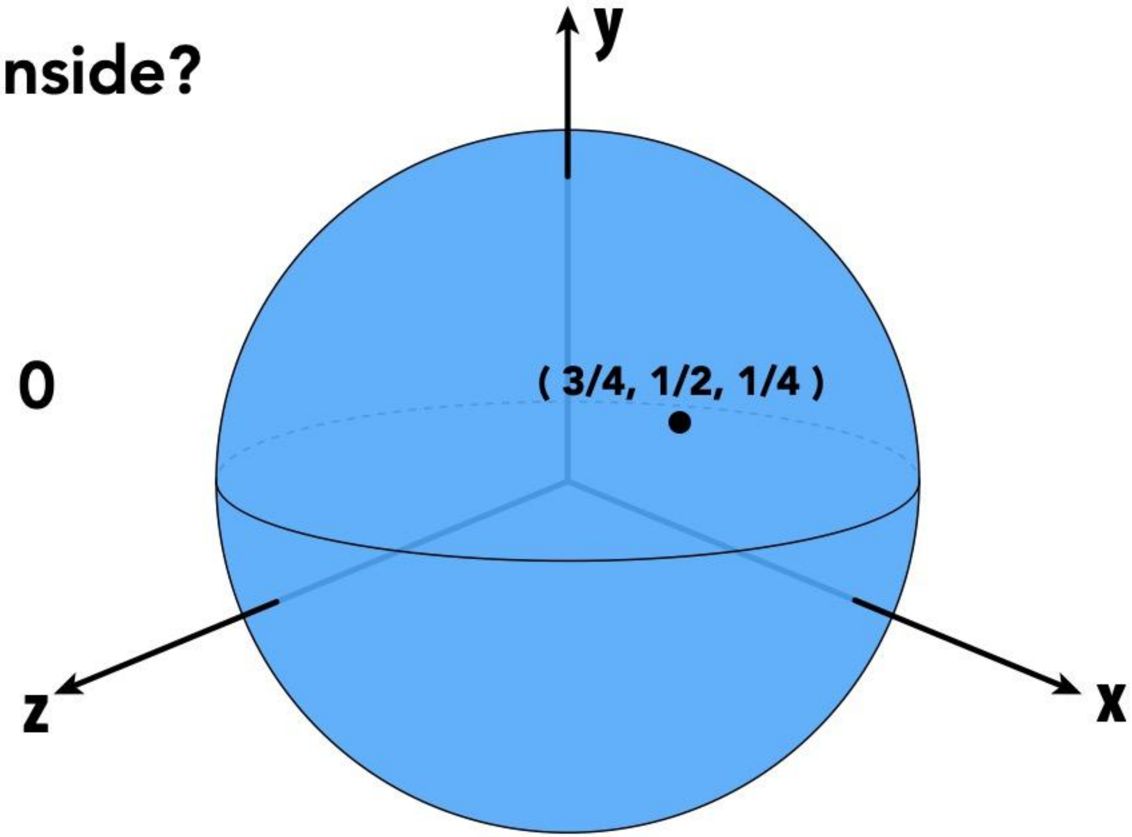

Implicit representations make some tasks easy

Algebraic Surfaces (Implicit)

Surface is zero set of a polynomial in x, y, z

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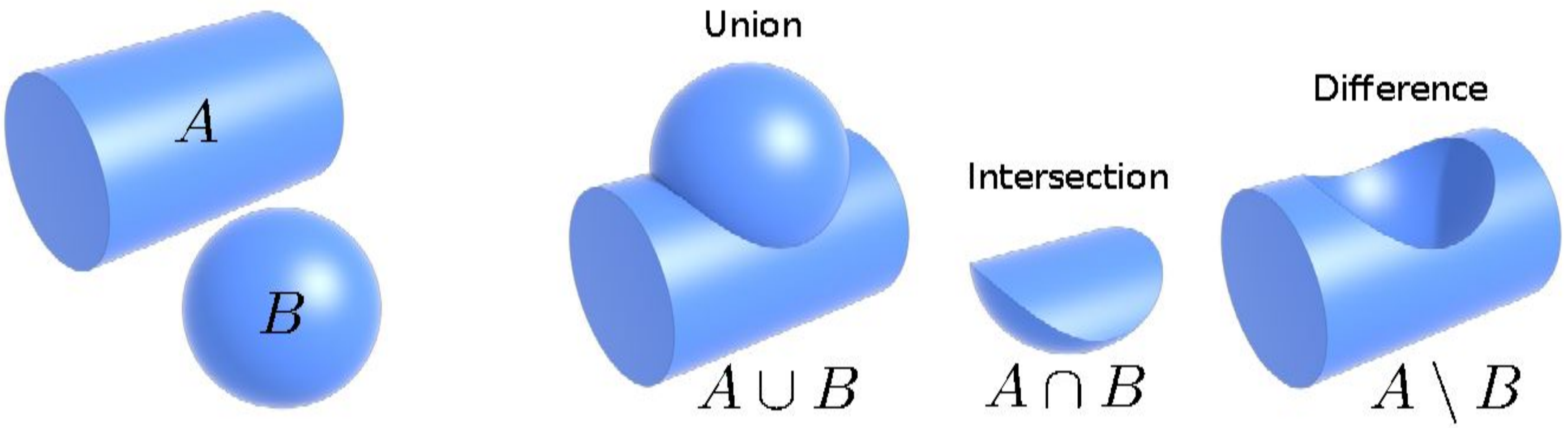
More complex shapes?

Constructive Solid Geometry (Implicit)

Combine implicit geometry via Boolean operations



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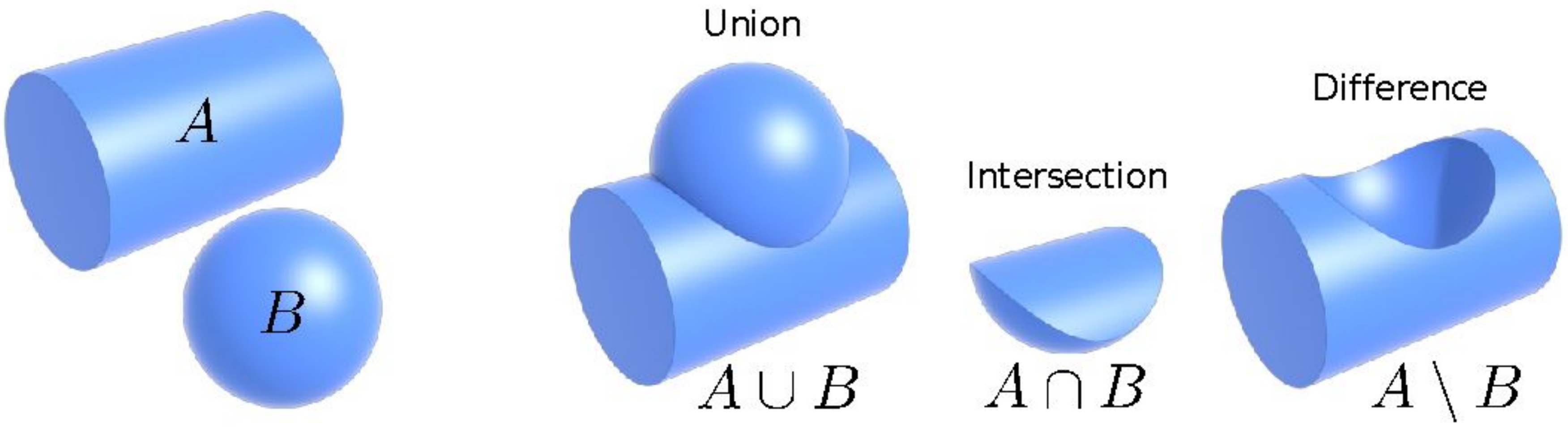
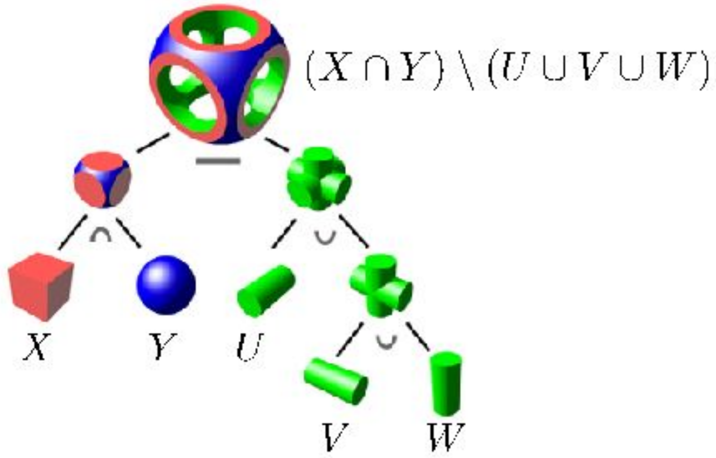


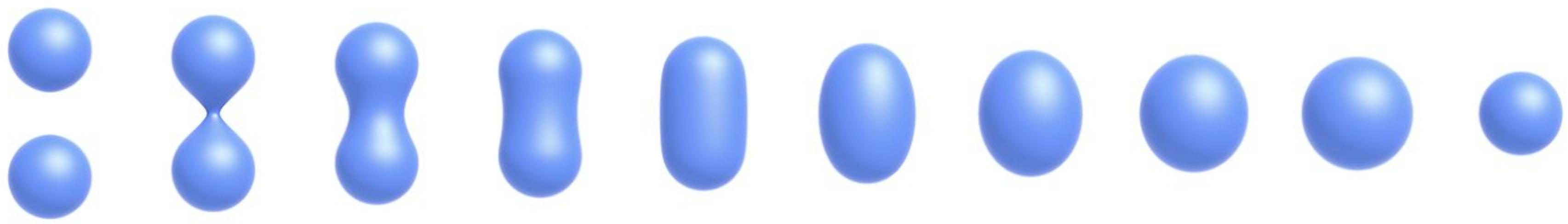
Boolean expressions:



Distance Functions (Implicit)

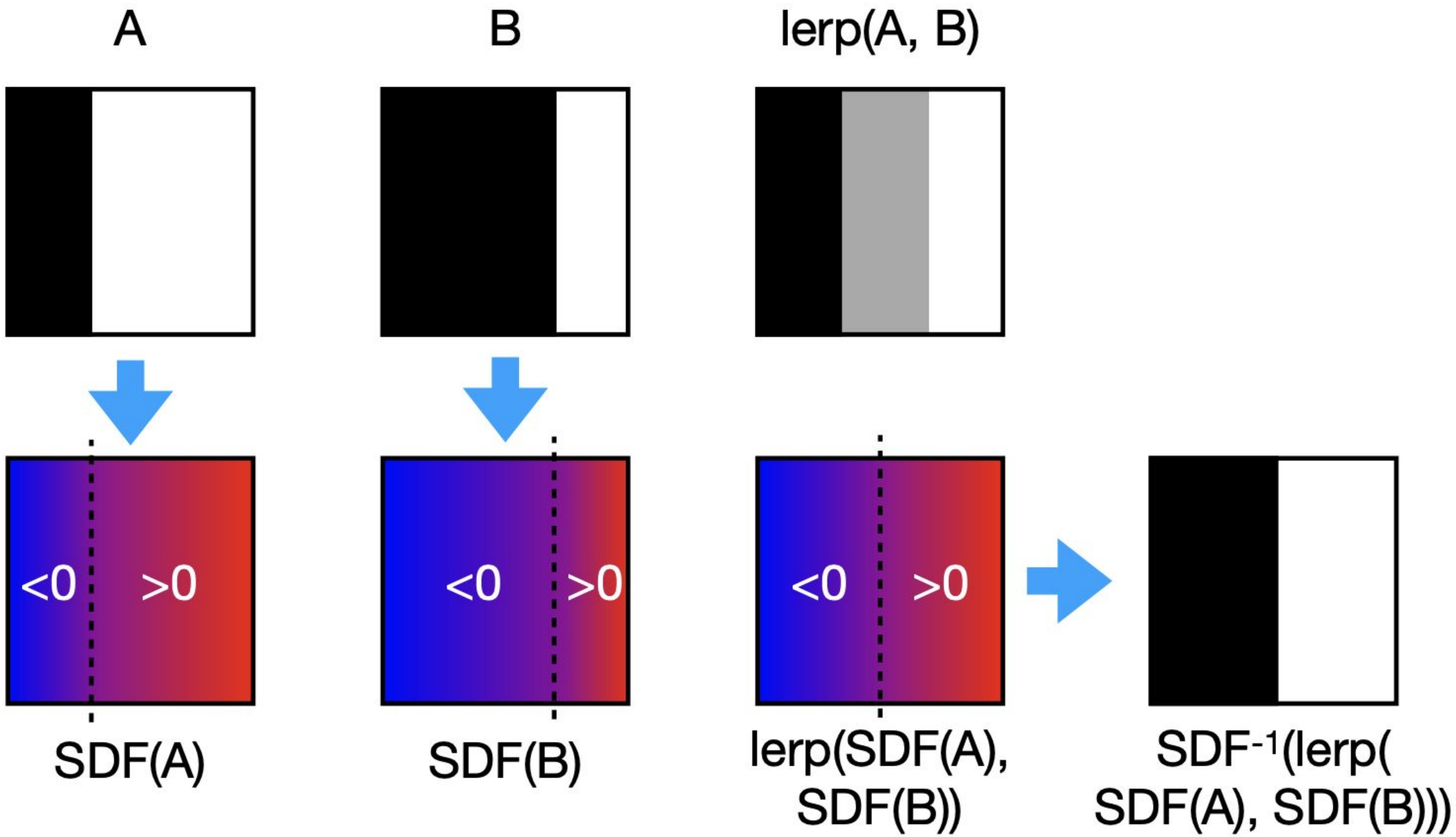
Instead of Booleans, gradually blend surfaces together using

Distance functions:
giving minimum distance (could be **signed** distance)
from anywhere to object



Distance Functions (Implicit)

An Example: Blending (linear interp.) a moving boundary



Scene of Pure Distance Functions (Not Easy!)

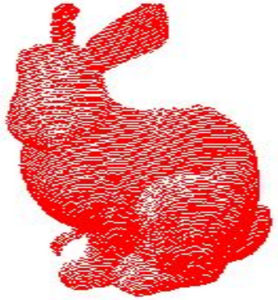
See http://iquilezles.org/www/material/nvscene2008/nvscene2008.htm

Shape Representations

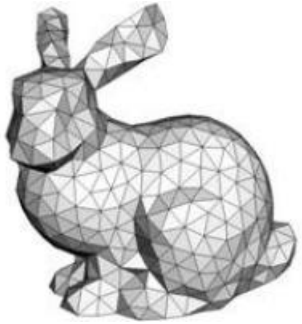
Explicit

Implicit

Non-parametric

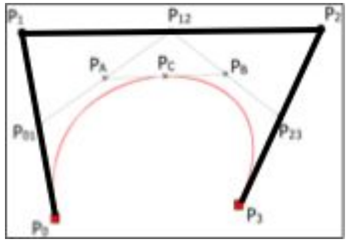


Points

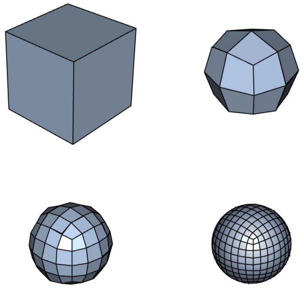


Meshes

Parametric



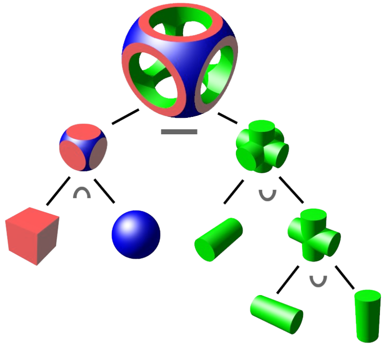
Splines



Subdivision Surfaces

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

Algebraic Surfaces



Constructive Solid Geometry

Level Set Methods (Implicit)

Implicit surfaces have some nice features (e.g., merging/splitting)

But, hard to describe complex shapes in closed form

Slide credit: Ren Ng

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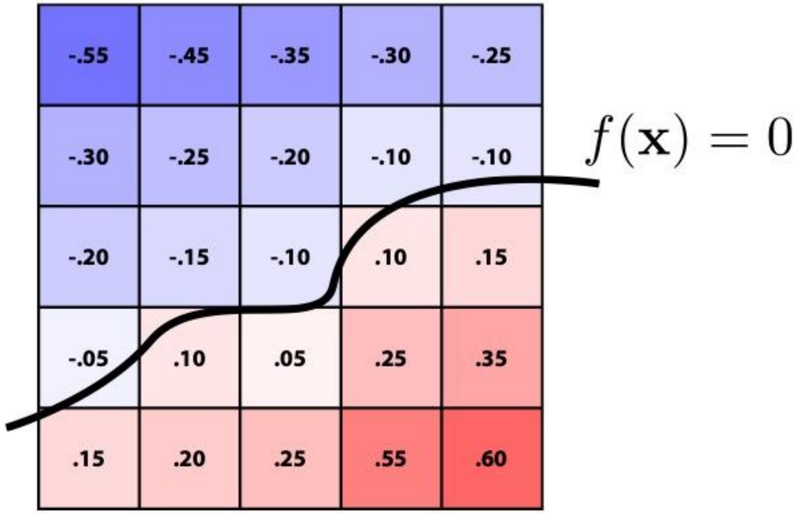
Alternative: store a grid of values approximating function



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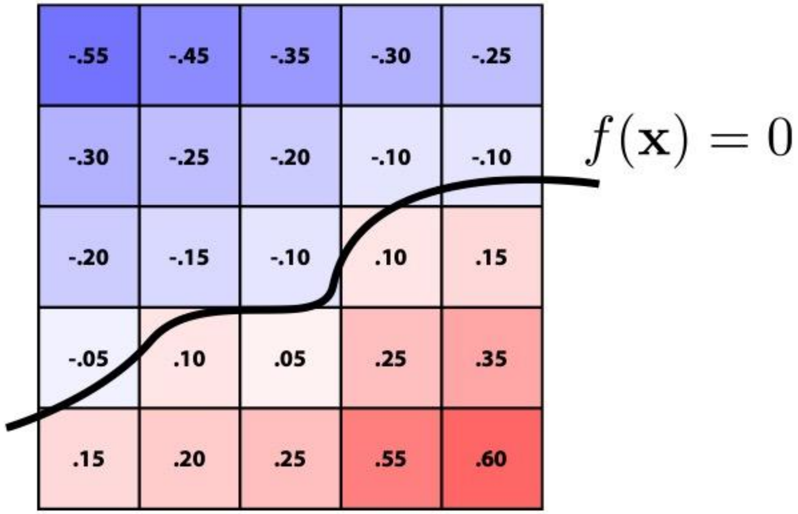
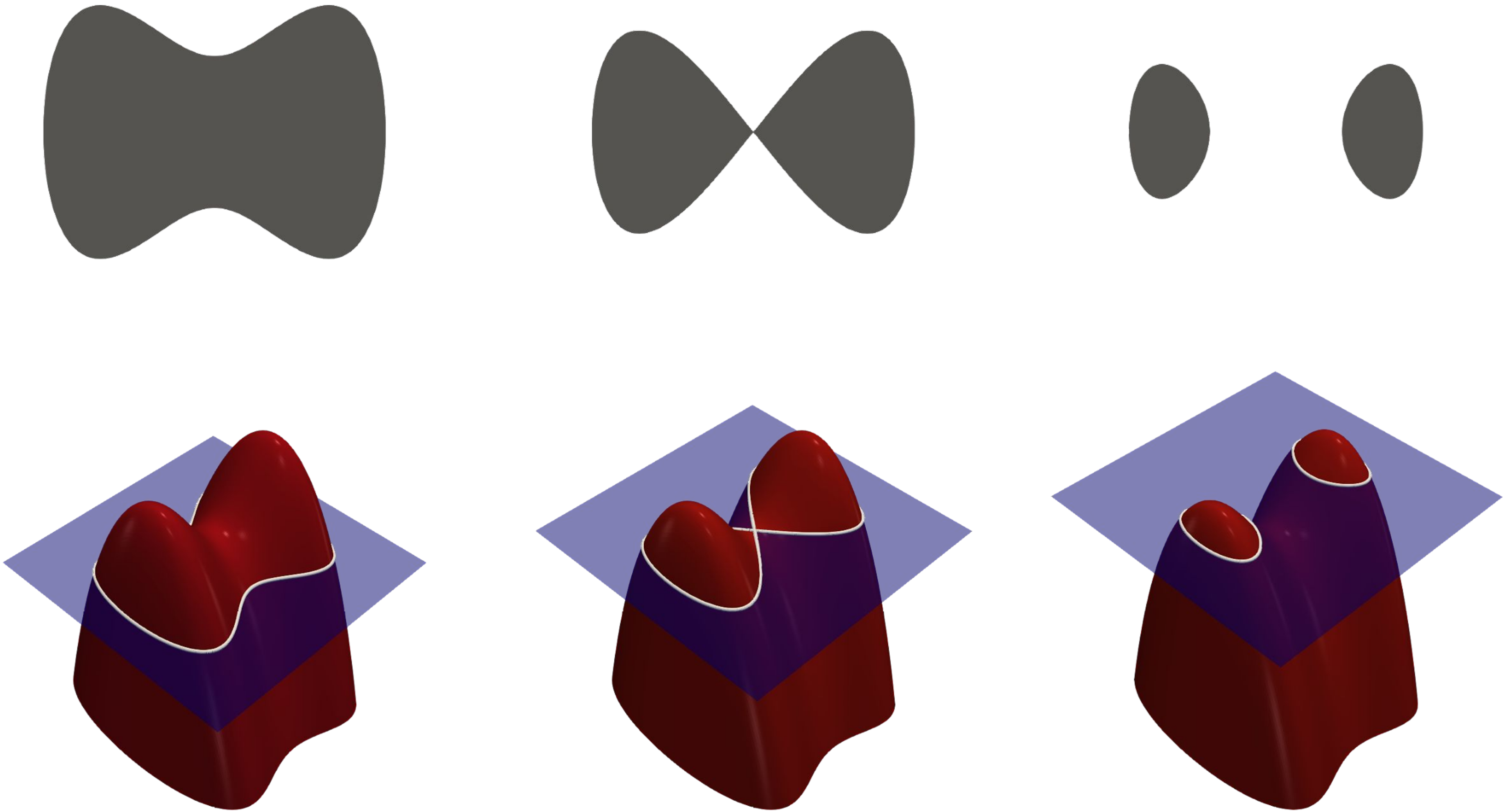


Surface is found where interpolated values equal zero

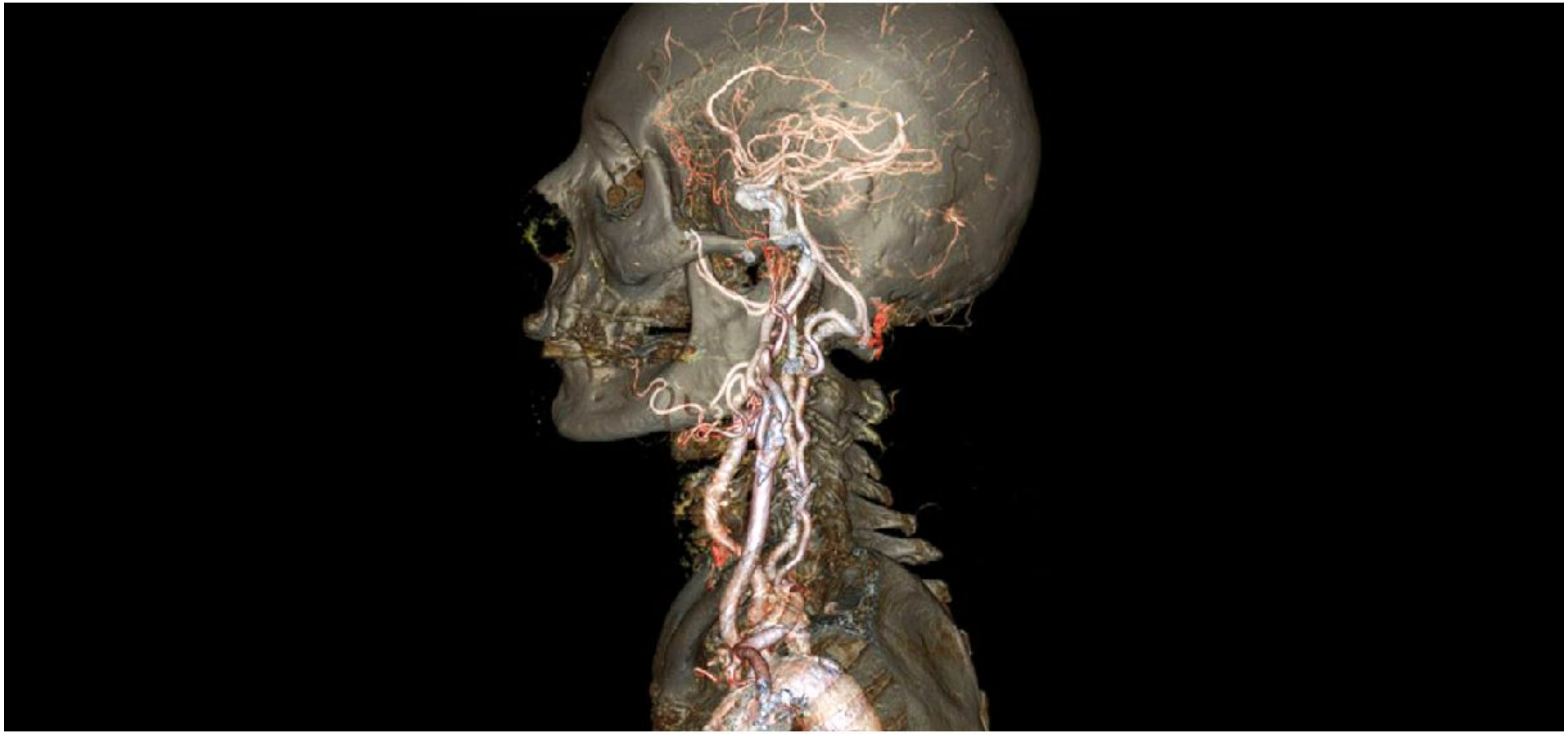
Provides much more explicit control over shape (like a texture)

Slide credit: Ren Ng



Level Sets from Medical Data (CT, MRI, etc.)

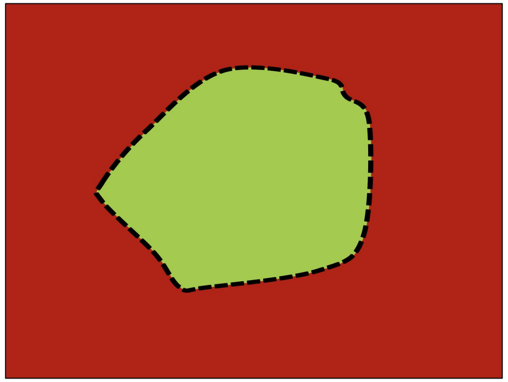
Level sets encode, e.g., constant tissue density

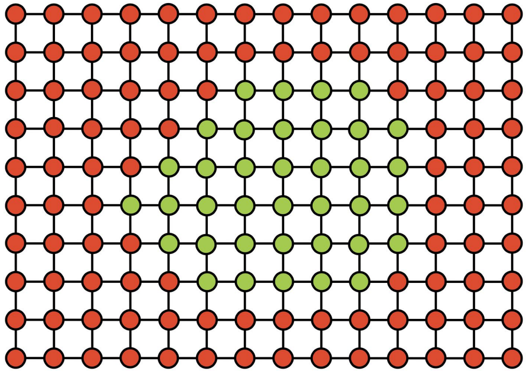


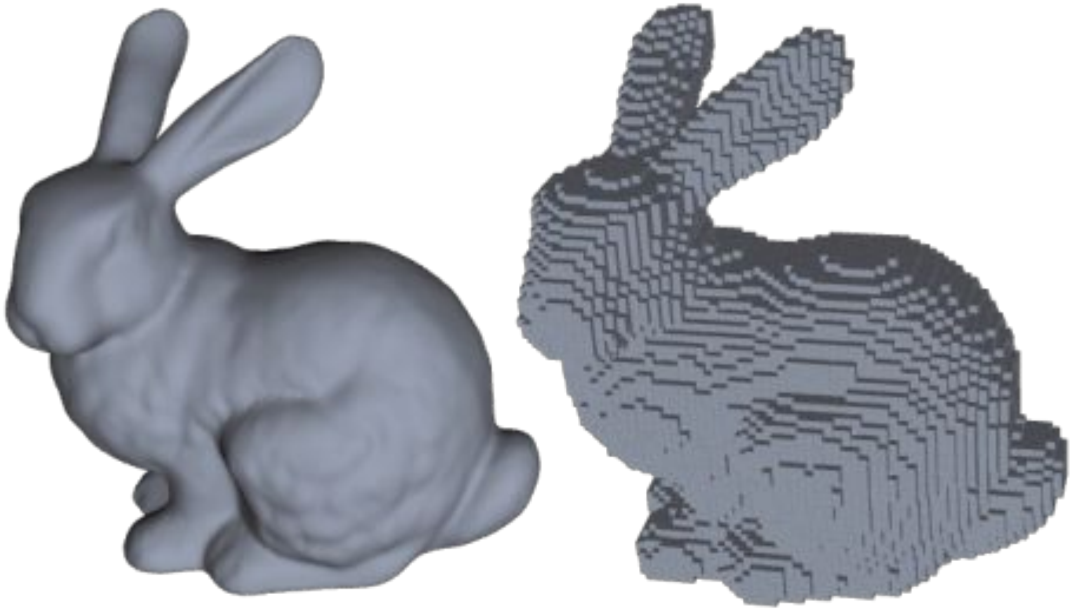
Slide credit: Ren Ng

Related Representation: Voxels

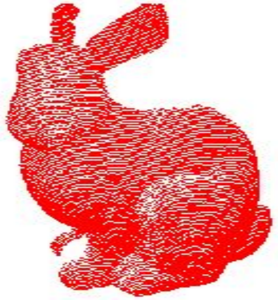
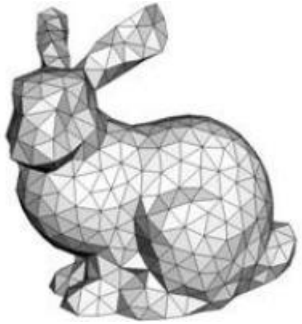
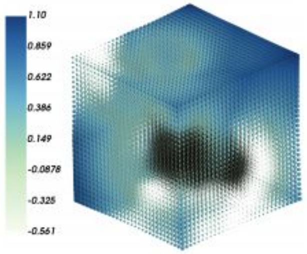
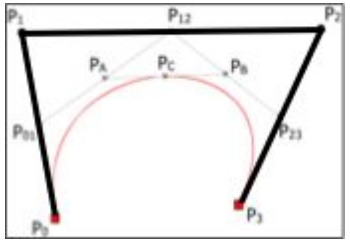
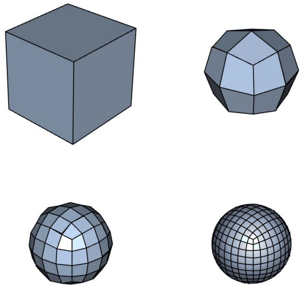
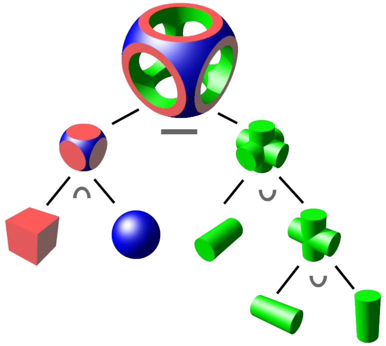
- Binary thresholding the volumetric grid







Shape Representations

	Explicit		Implicit (Eulerian)	
Non-parametric	 Points	 Meshes	 Voxels	 Level Sets
Parametric	 Splines	 Subdivision Surfaces	 $x^2+y^2+z^2=1$ Algebraic Surfaces	 Constructive Solid Geometry

AI + Shapes

- In 3D …

Princeton Shape Benchmark

- 1814 Models
- 182 Categories

Shilane et al, 2004

Datasets Prior to 2014

Benchmarks	Types	# models	# classes	Avg # models per class
SHREC14LSGTB	Generic	8,987	171	53
PSB	Generic	907+907 (train+test)	90+92 (train+test)	10+10 (train+test)
SHREC12GTB	Generic	1200	60	20
TSB	Generic	10,000	352	28
CCCC	Generic	473	55	9
WMB	Watertight (articulated)	400	20	20
MSB	Articulated	457	19	24
BAB	Architecture	2257	183+180 (function+form)	12+13 (function+form)
ESB	CAD	867	45	19

Table 1. Source datasets from SHREC 2014: *Princeton Shape Benchmark (PSB)* [27], *SHREC 2012 generic Shape Benchmark (SHREC12GTB)* [16], *Toyohashi Shape Benchmark (TSB)* [29], *Konstanz 3D Model Benchmark (CCCC)* [32], *Watertight Model Benchmark (WMB)* [31], *McGill 3D Shape Benchmark (MSB)* [37], *Bonn Architecture Benchmark (BAB)* [33], *Purdue Engineering Shape Benchmark (ESB)* [9].

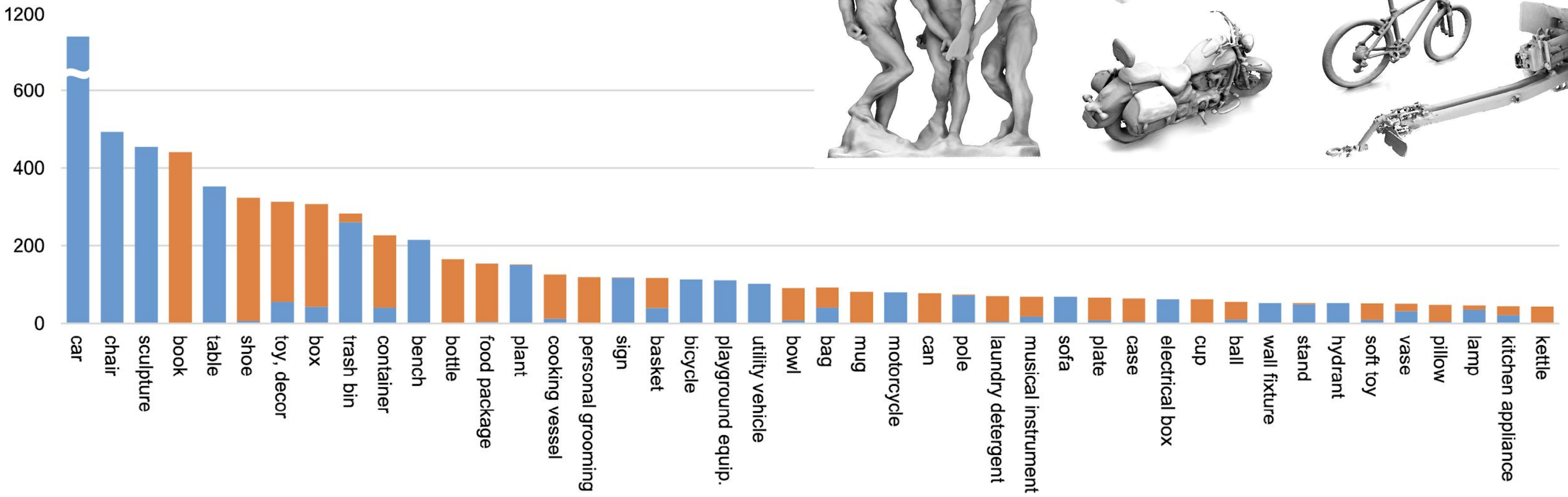
Datasets for 3D Objects

- Large-scale Synthetic Objects: ShapeNet, 3M models
- ModelNet: absorbed by ShapeNet
- ShapeNetCore: 51.3K models in 55 categories

Chang et al. ShapeNet. arXiv 2015
Wu et al. 3D ShapeNets. CVPR 2015

Object Scan

- 10,933 RGBD scans
- 441 models



Choi et al, arXiv 2016

Pascal 3D+

- Retrieve a nearest-neighbor 3D model for objects in real images
- 8,505 PASCAL images (13,898 instances) + 22,394 ImageNet images
- 12 rigid categories, 3,000+ instances per category on average

Xiang et al, WACV 2014

Pix3D

- 10,069 images
- 395 shapes (IKEA furniture + 3D scan)

Sun et al. CVPR 2018, building upon Lim et al. ICCV 2013

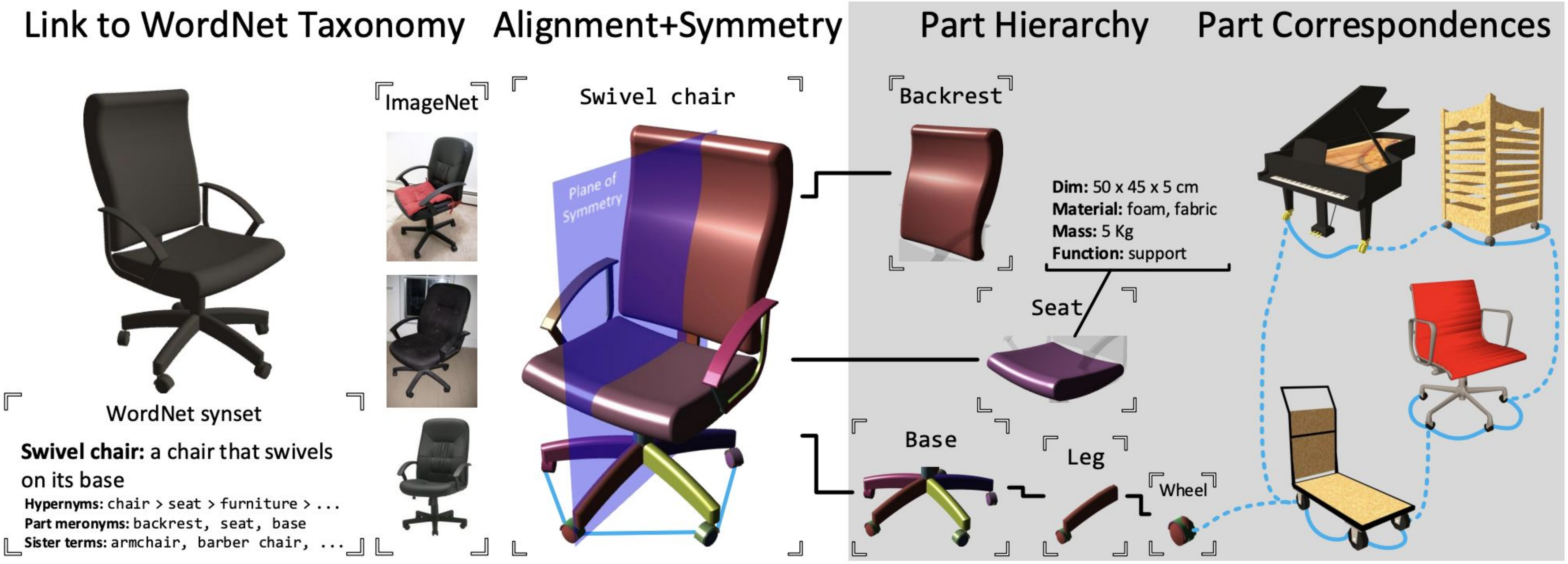
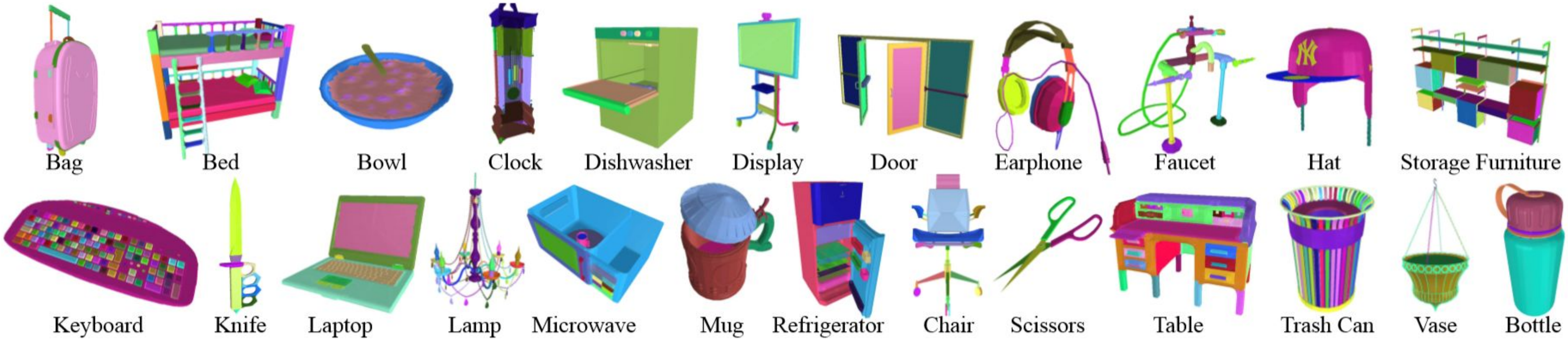


Figure from the ShapeNet paper, Chang et al. arXiv 2015

Datasets for 3D Object Parts

Fine-grained Parts: PartNet

- Fine-grained (+mobility)
- Instance-level
- Hierarchical

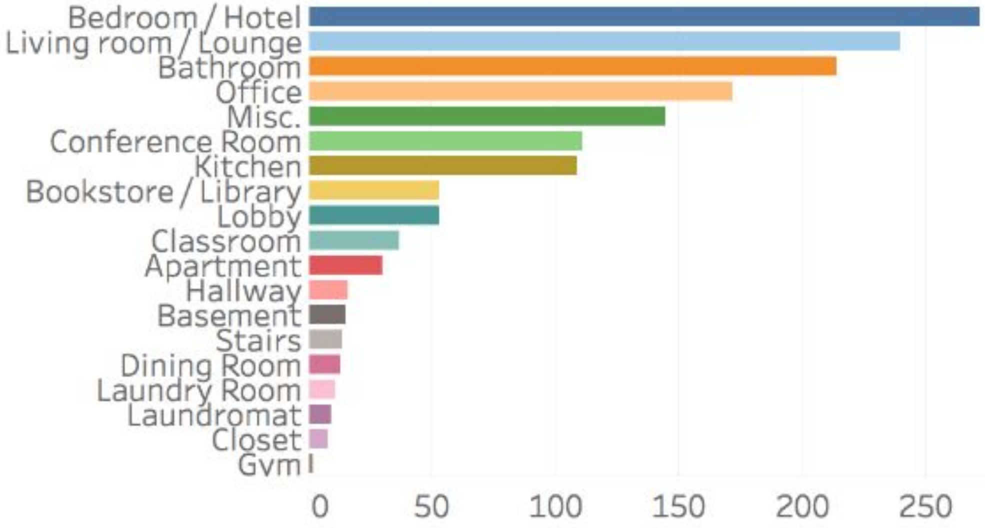


Mo et al. CVPR 2019
Slide credit: Hao Su

Datasets for Indoor 3D Scenes

Large-scale Scanned Real Scenes: ScanNet

- 2.5M Views in 1,500 RGBD scans
- 3D camera poses
- Surface reconstructions
- Instance-level semantic segmentations



Dai et al. CVPR 2017. Slide credit: Hao Su

Physical Interaction with Articulated Objects

300+ door annotations

support articulated objects
(cabinets, doors, fridge, oven, window etc.)

http://svl.stanford.edu/igibson/

AI + Geometry

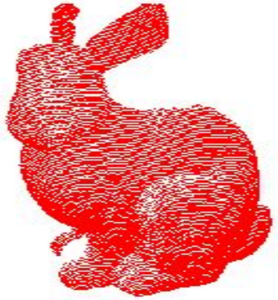
- P(S) or P(S|c) --- Generative models
  - Learning (conditional) shape priors
  - Shape generation, completion, & geometry data processing
- P(c|S) --- Discriminative models
  - Learning shape descriptors
  - Shape classification, segmentation, view estimation, etc.
- Joint modeling of 3D and 2D data
  - Large-scale 2D datasets & very good pretrained models
  - Differentiable projection/back-projection & differentiable/neural rendering

Which Shape Representation?

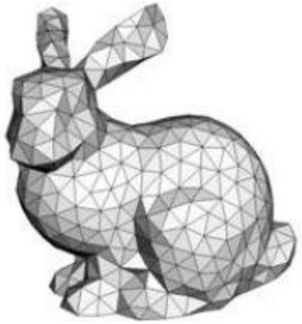
Explicit

Implicit (Eulerian)

Non-parametric

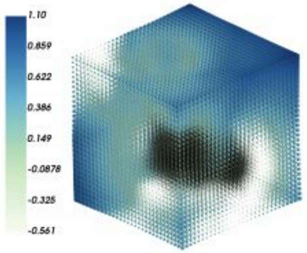


Points



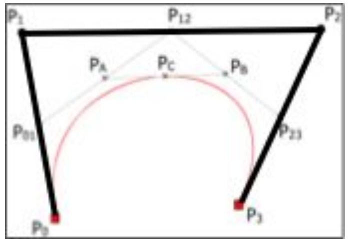
Meshes

Voxels

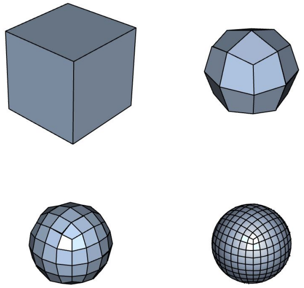


Level Sets

Parametric



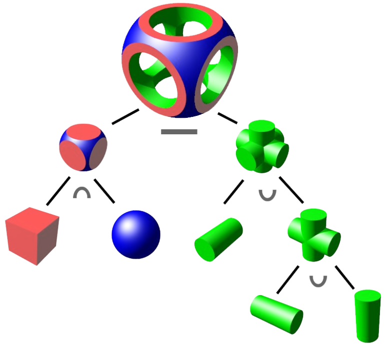
Splines



Subdivision Surfaces

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

Algebraic Surfaces

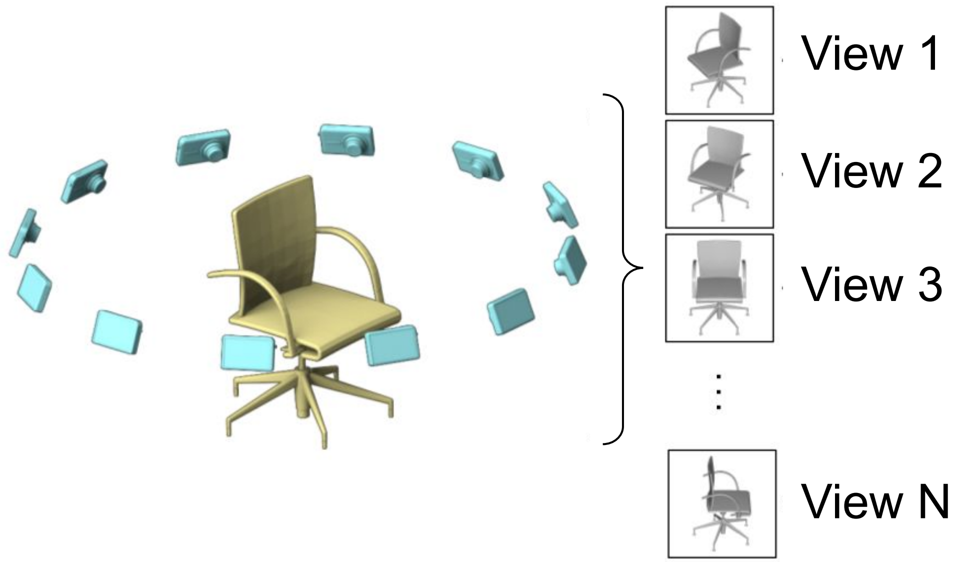


Constructive Solid Geometry

Multi-View CNN

Su et al. ICCV 2015

Multi-View CNN



Su et al. ICCV 2015

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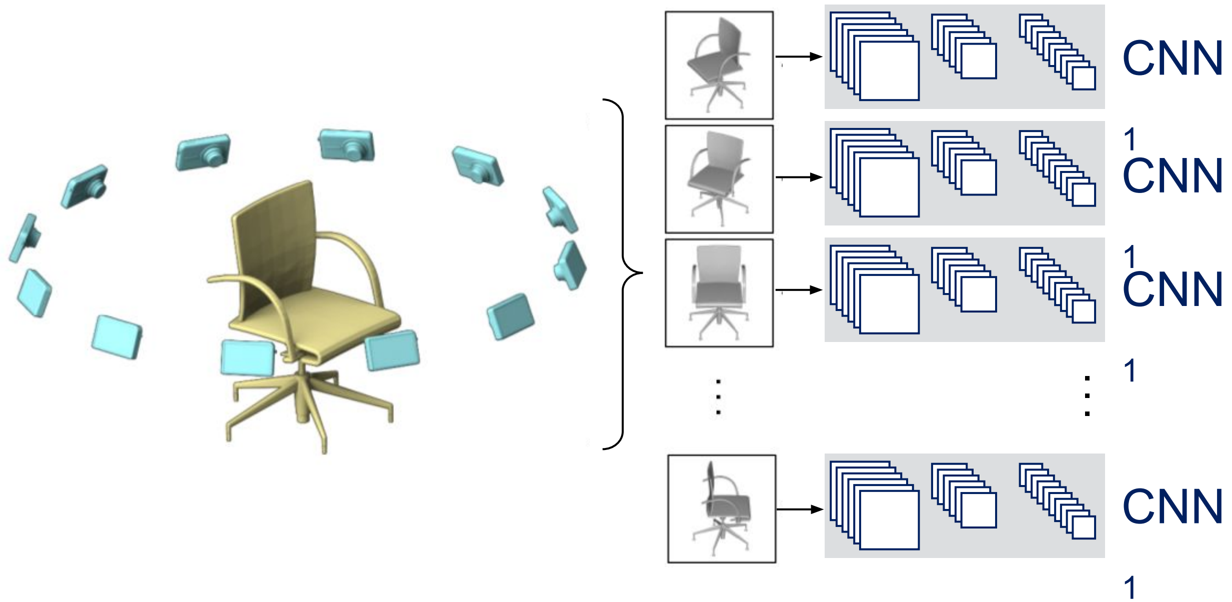
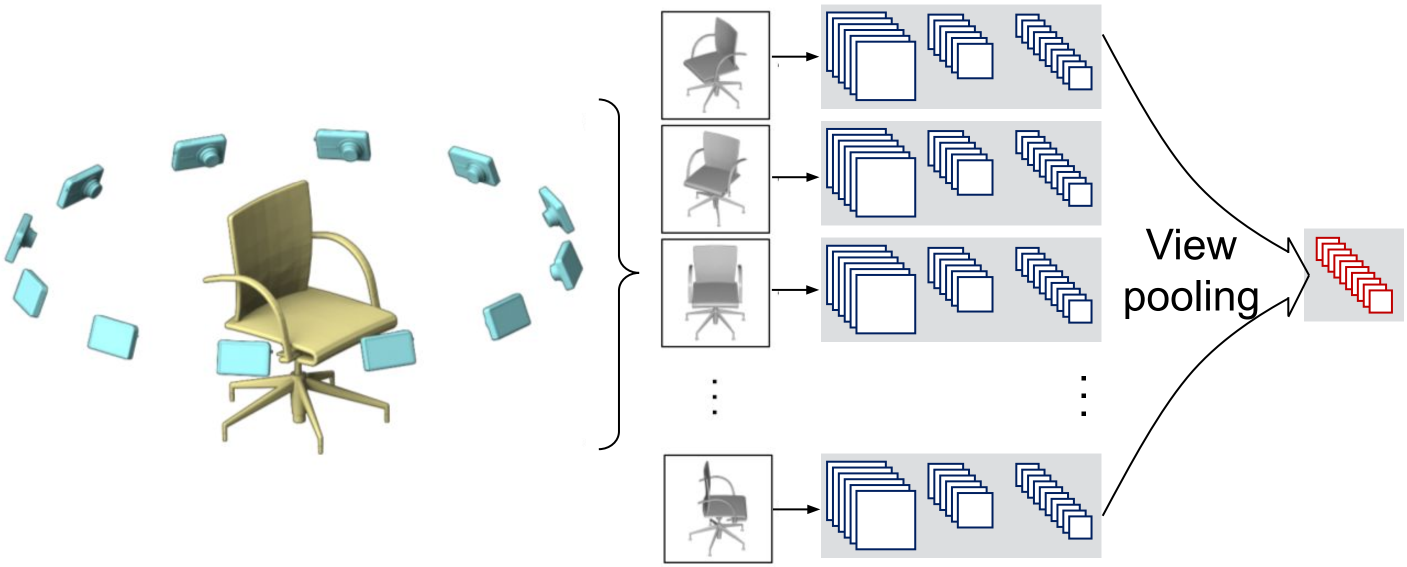


CNN$_1$: a ConvNet extracting image features

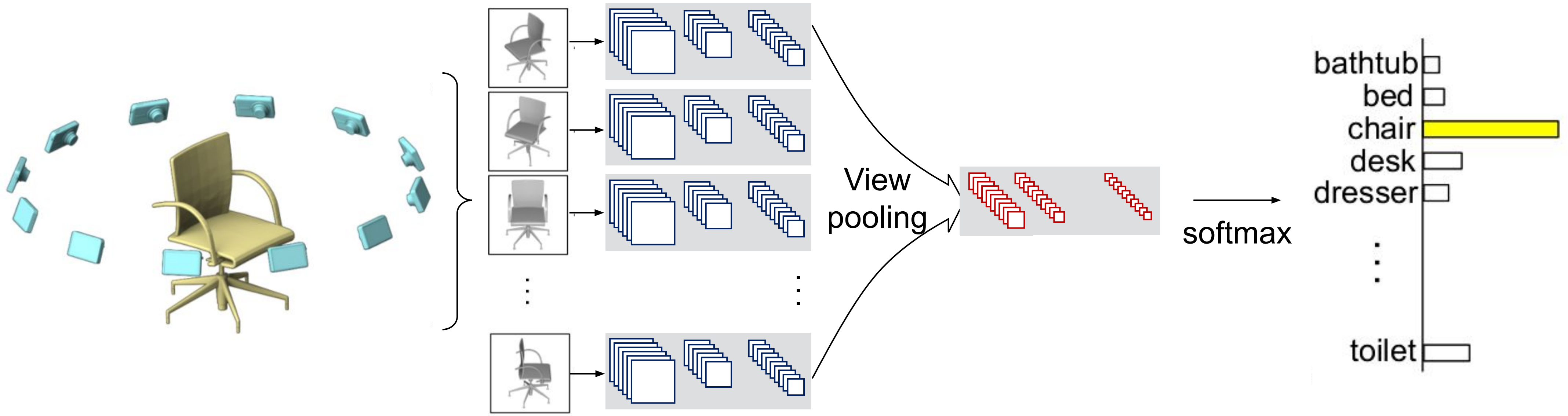
Multi-View CNN



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

Su et al. ICCV 2015

Multi-View CNN



CNN$_2$: a second ConvNet producing shape descriptors

Su et al. ICCV 2015

Experiments – Classification & Retrieval

Non-dee
p {

Method	Classificatio n (Accuracy)	Retrieval (mAP)
SPH	68.2%	33.3%
LFD	75.5%	40.9%
3D ShapeNets	77.3%	49.2%
FV, 12 views	84.8%	43.9%
CNN, 12 views	88.6%	62.8%
MVCNN, 12 views	**89.9%**	70.1%
MVCNN+metric, 12 views	89.5%	**80.2%**
MVCNN, 80 views	90.1%	70.4%
MVCNN+metric, 80 views	**90.1%**	**79.5%**

On ModelNet
40

Su et al. ICCV 2015

Multi-View Representations

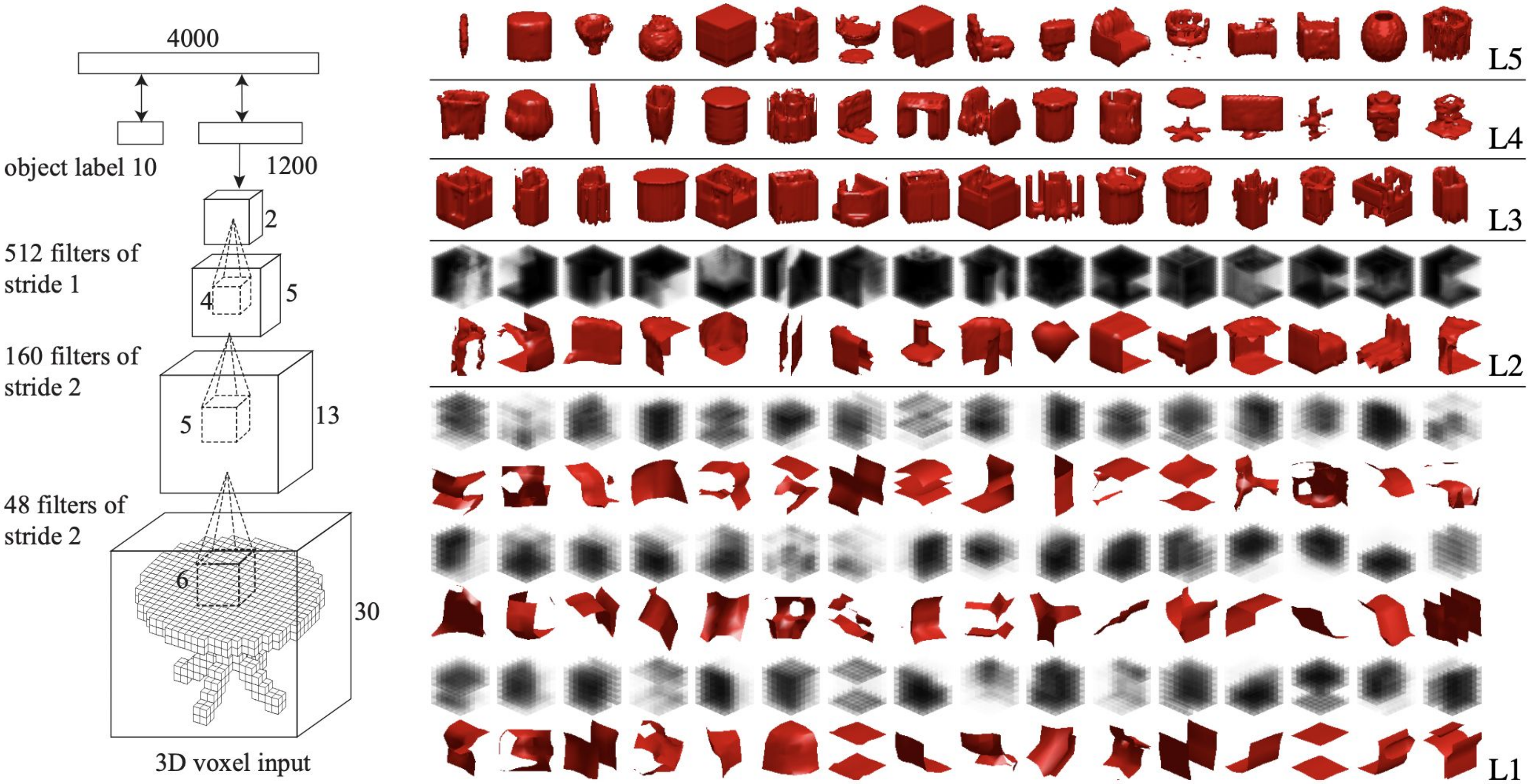
- Indeed gives good performance
- Can leverage vast literature of image classification
- Can use pertained features

- Need projection
- What if the input is noisy and/or incomplete? e.g., point cloud

Slide Credit: Hao Su

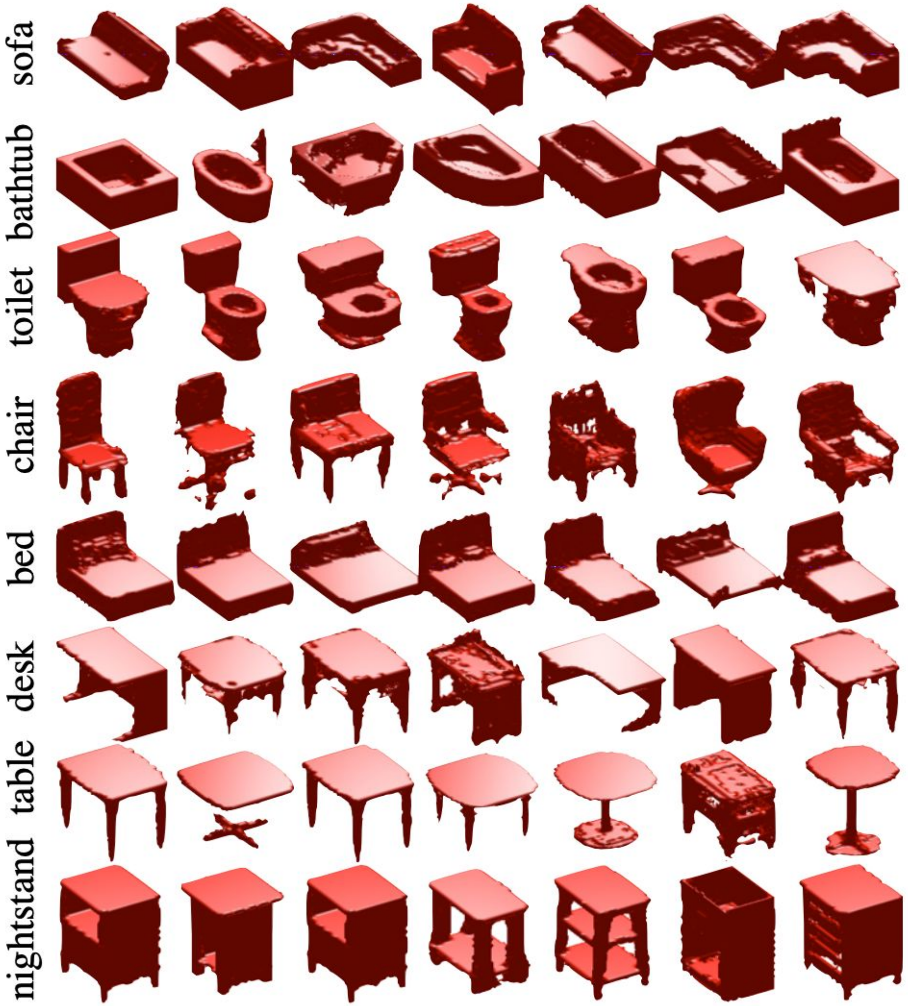
Pixels -> Voxels

- 3D Conv Deep Belief Networks (CDBN)



Wu et al. CVPR 2015

Generative Modeling

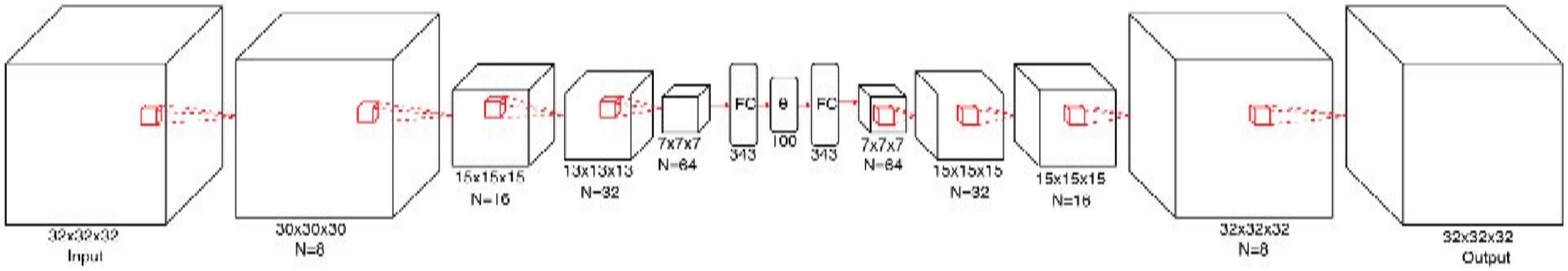


10 classes	SPH [18]	LFD [8]	Ours
classification	79.79 %	79.87 %	**83.54%**
retrieval AUC	45.97%	51.70%	**69.28%**
retrieval MAP	44.05%	49.82%	**68.26%**
40 classes	SPH [18]	LFD [8]	Ours
classification	68.23%	75.47%	**77.32%**
retrieval AUC	34.47%	42.04%	**49.94%**
retrieval MAP	33.26%	40.91%	**49.23%**

Table 1: **Shape Classification and Retrieval Results.**

Wu et al. CVPR 2015

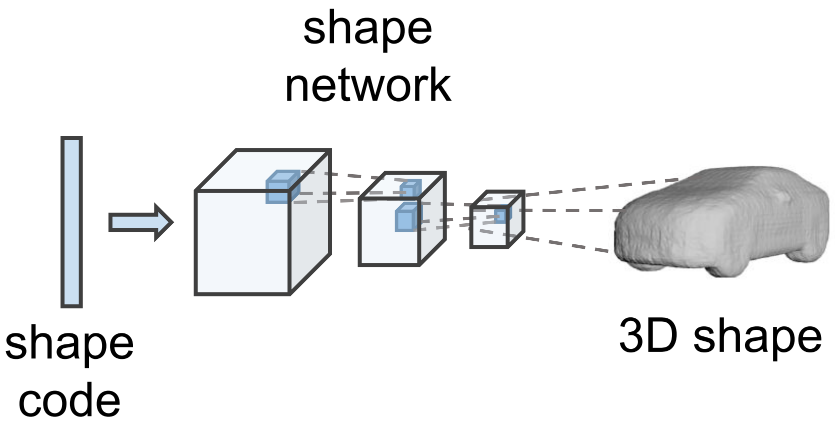
Volumetric Autoencoders



Binary Cross-Entropy Loss: $\mathcal{L} = -t \log(o) - (1-t)\log(1-o)$

Brock et al. NeurIPS Workshop 2016

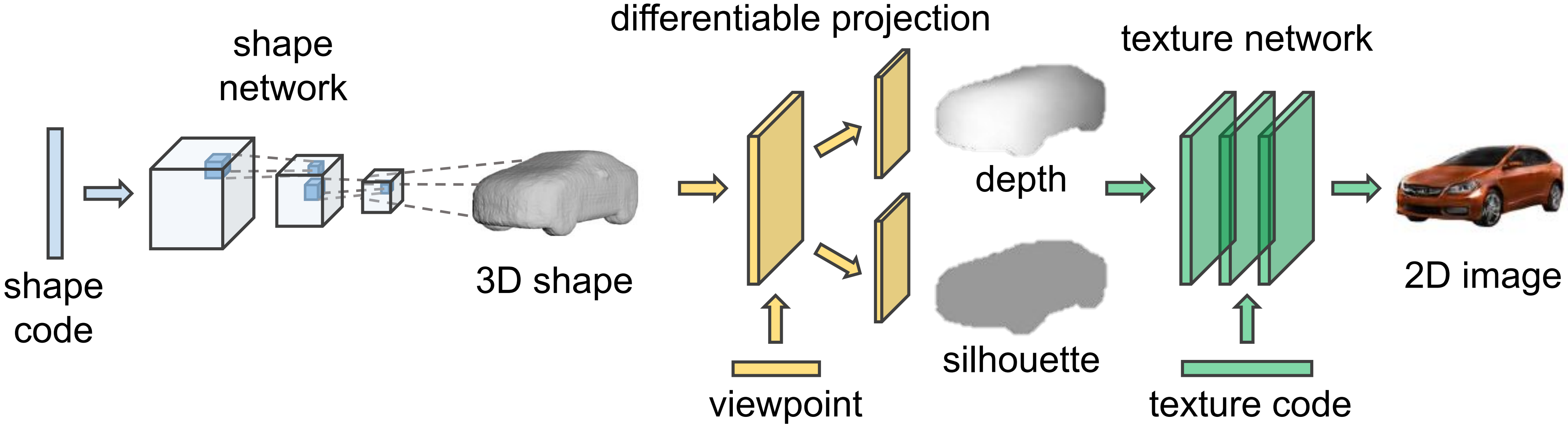
3D-GANs



3
D

Wu et al. NeurIPS 2016

Visual Object Networks



3
D

2
D

Wu et al. NeurIPS 2016

Zhu et al. NeurIPS 2018

Editing viewpoint, shape, and texture

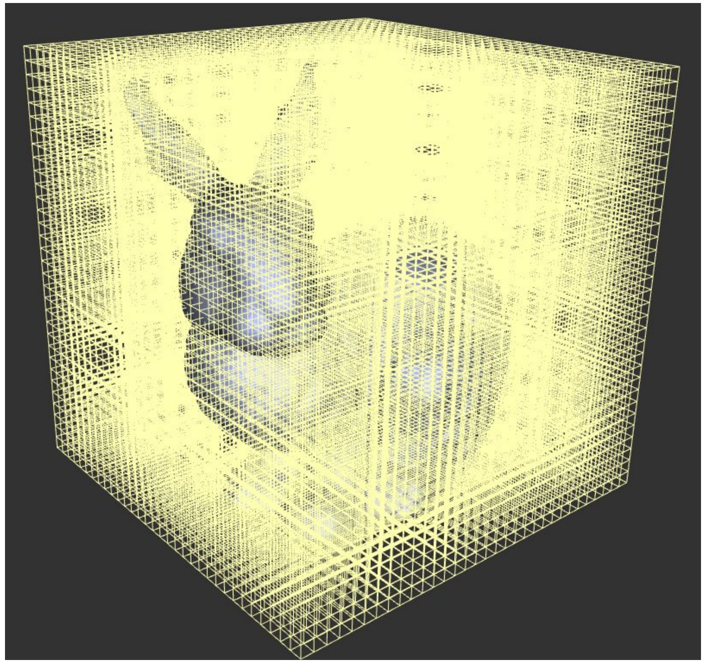
Interpolation in the latent space

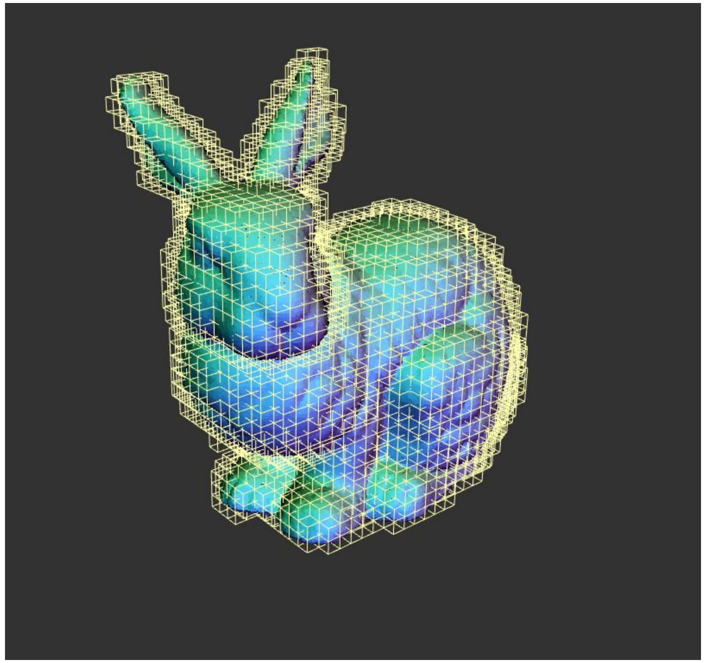
Transferring shape and texture

Zhu et al. NeurIPS 2018

Octave Tree Representations

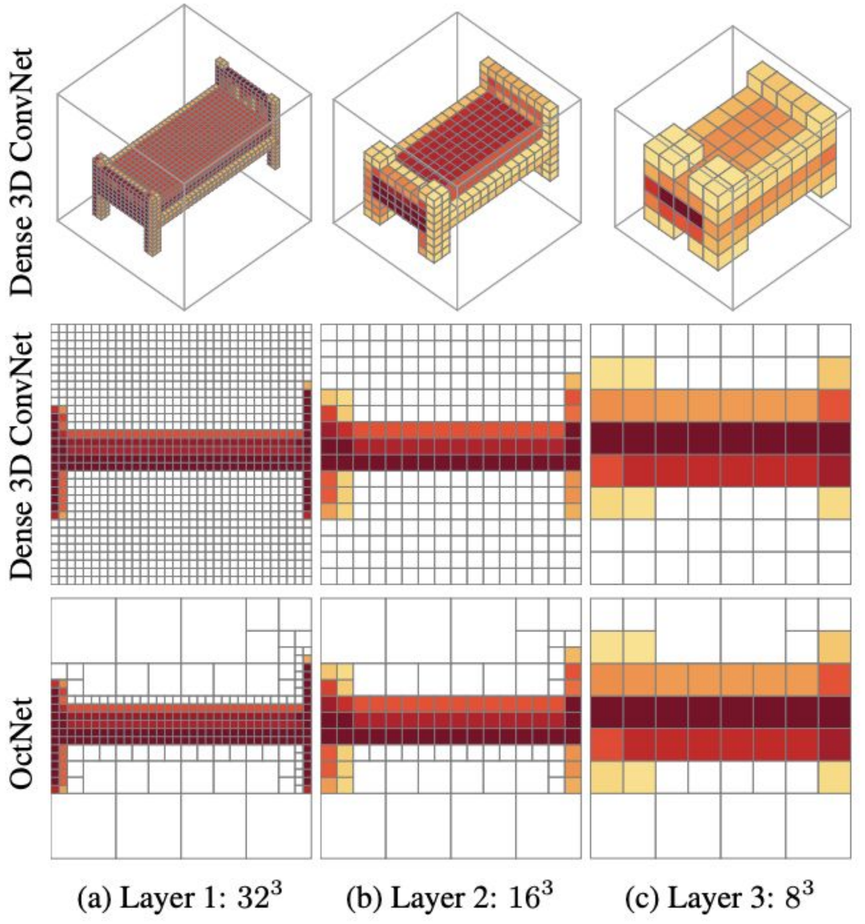
- Store the sparse surface signals
- Constrain the computation near the surface



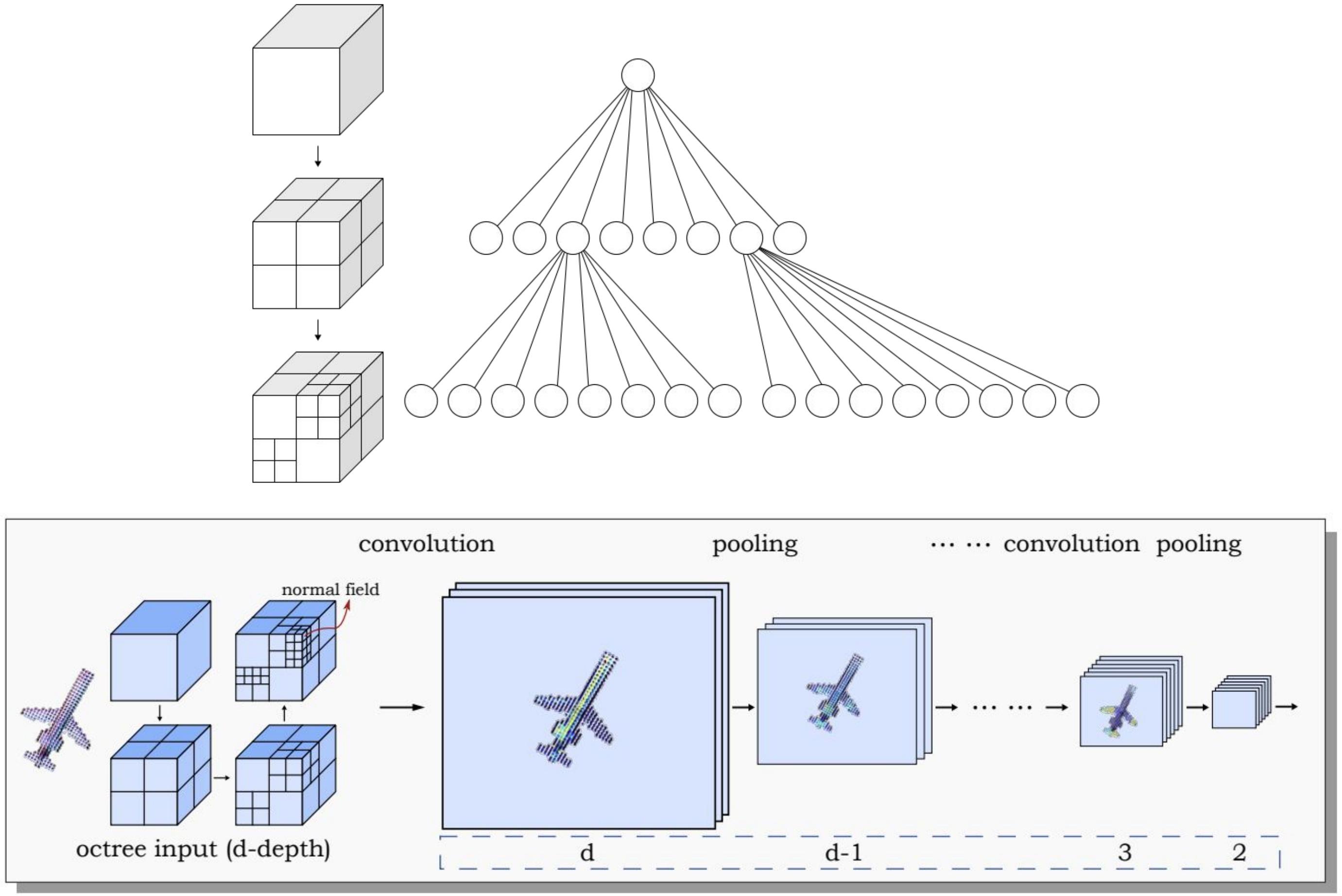


Slide Credit: Hao Su

Octree: Recursively Partition the Space

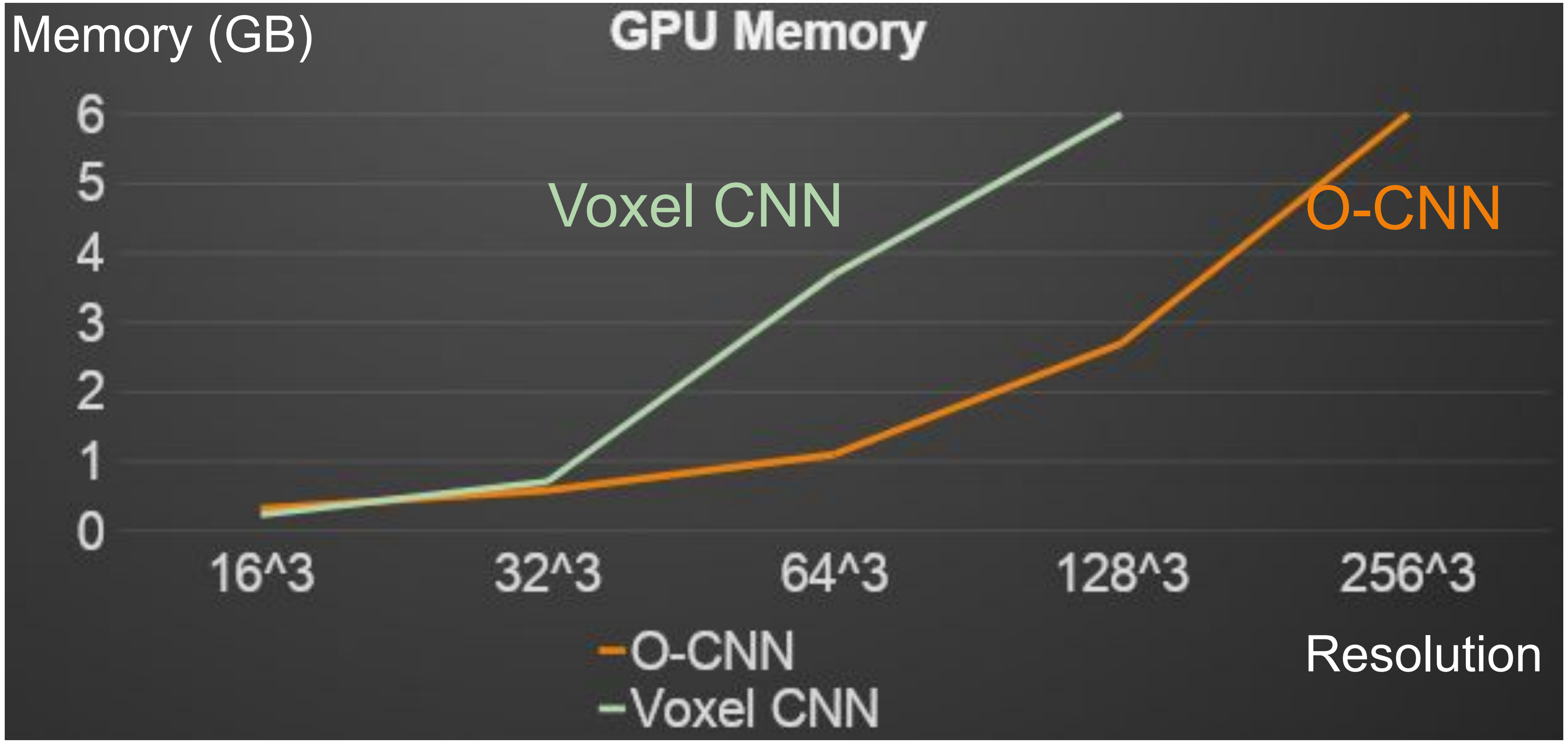


Riegler et al. OctNet. CVPR 2017



Wang et al. O-CNN. SIGGRAPH 2017

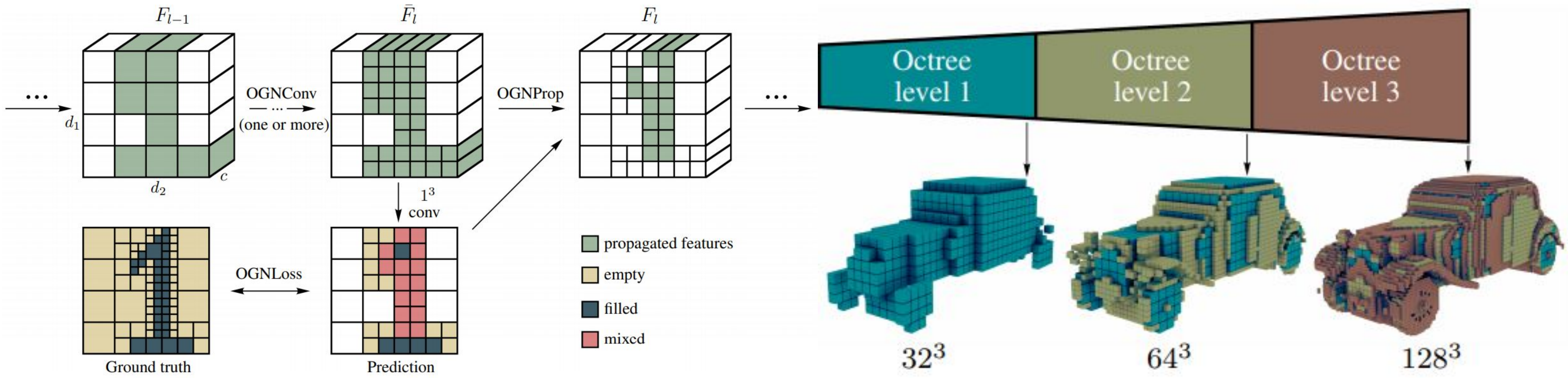
Memory Efficiency



Slide Credit: Hao Su

Octree Generating Networks

•



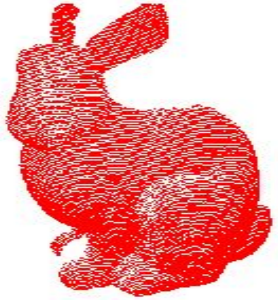
Tatarchenko et al. ICCV 2017
Slide Credit: Hao Su

Eulerian -> Lagrangian

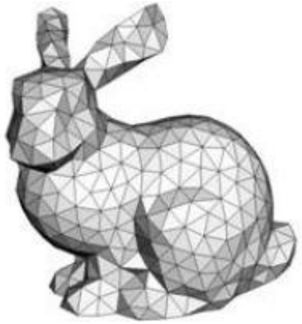
Explicit

Implicit (Eulerian)

Non-parametric

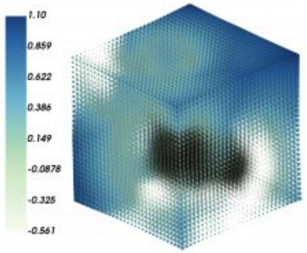


Points



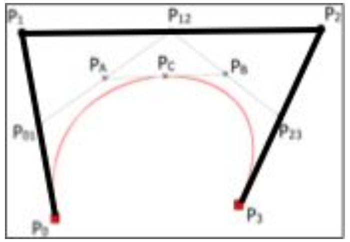
Meshes

Voxels

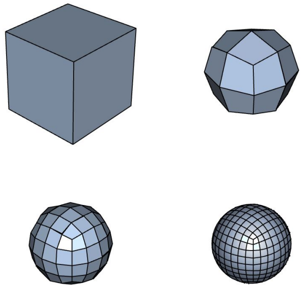


Level Sets

Parametric



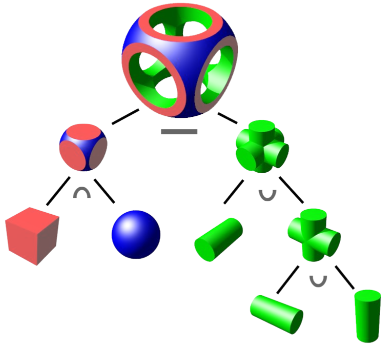
Splines



Subdivision Surfaces

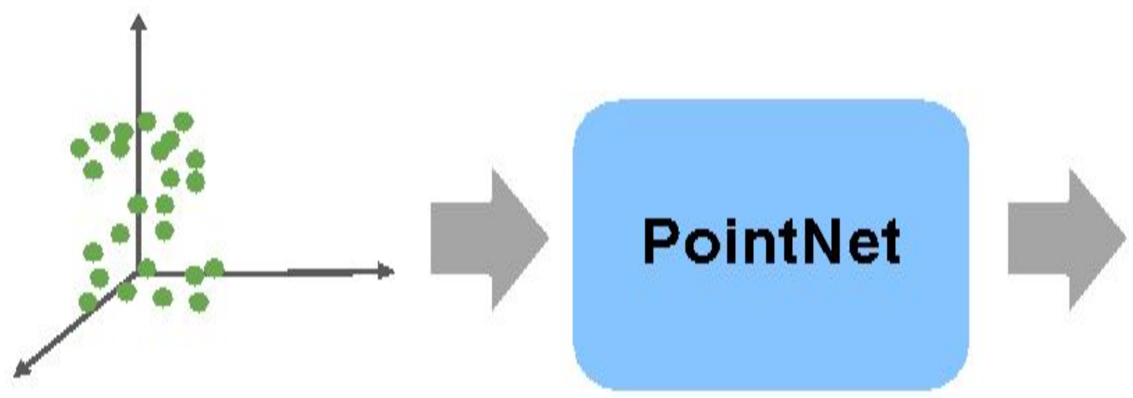
$x^2+y^2+z^2=1$

Algebraic Surfaces



Constructive Solid Geometry

PointNet: First Learning Tool for Point Clouds

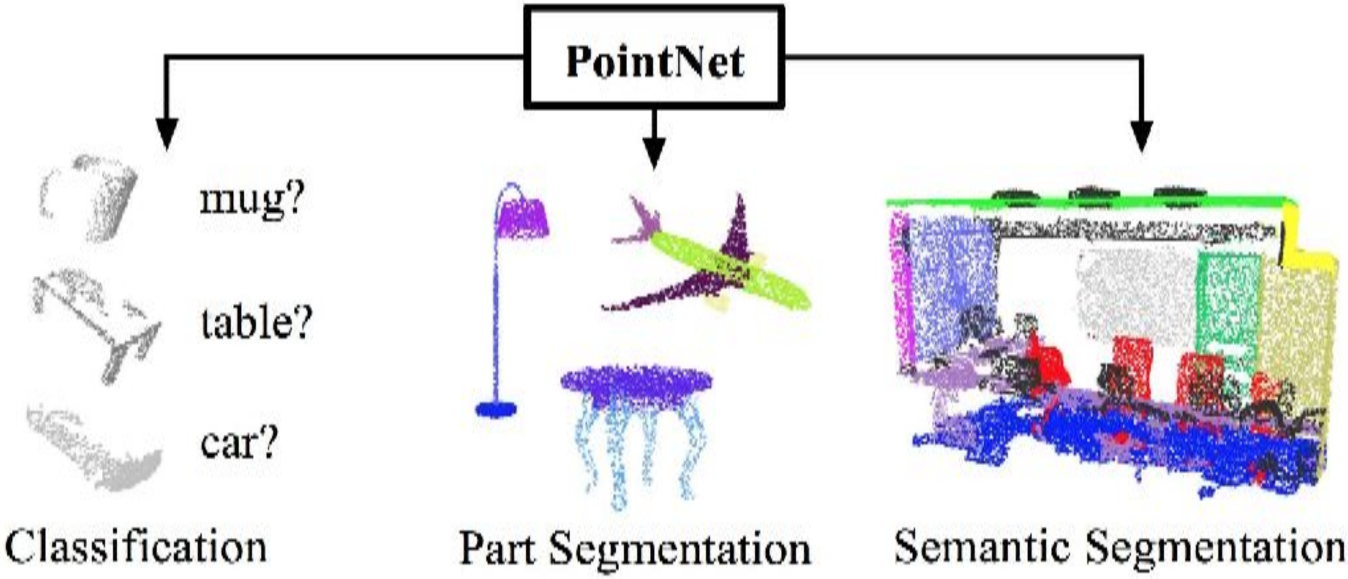


Object Classification

Object Part Segmentation

Semantic Scene Parsing

...



End-to-end learning for irregular point data

Unified framework for various tasks

Charles R. Qi, Hao Su, Kaichun Mo, Leonidas J. Guibas. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. (CVPR'17)

Slide credit: He Wang

Invariances

The model has to respect key desiderata for point clouds:

Point Permutation Invariance

Point cloud is a set of unordered points

Sampling Invariance

Output a function of the underlying geometry and not the sampling

Slide credit: He Wang

Permutation Invariance: Symmetric Functions

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

Examples:

$$f(x_1, x_2, \ldots, x_n) = \max\{x_1, x_2, \ldots, x_n\}$$

$$f(x_1, x_2, \ldots, x_n) = x_1 + x_2 + \ldots + x_n$$

...

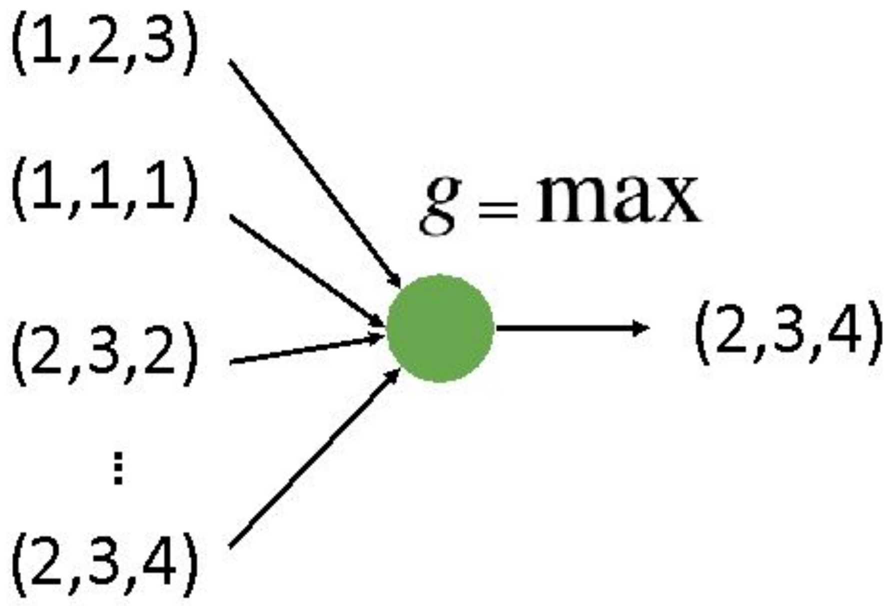
How can we construct a universal family of symmetric functions by neural networks?

Slide credit: He Wang

Construct Symmetric Functions by Neural Networks

Simplest form: directly aggregate all points with a symmetric operator g

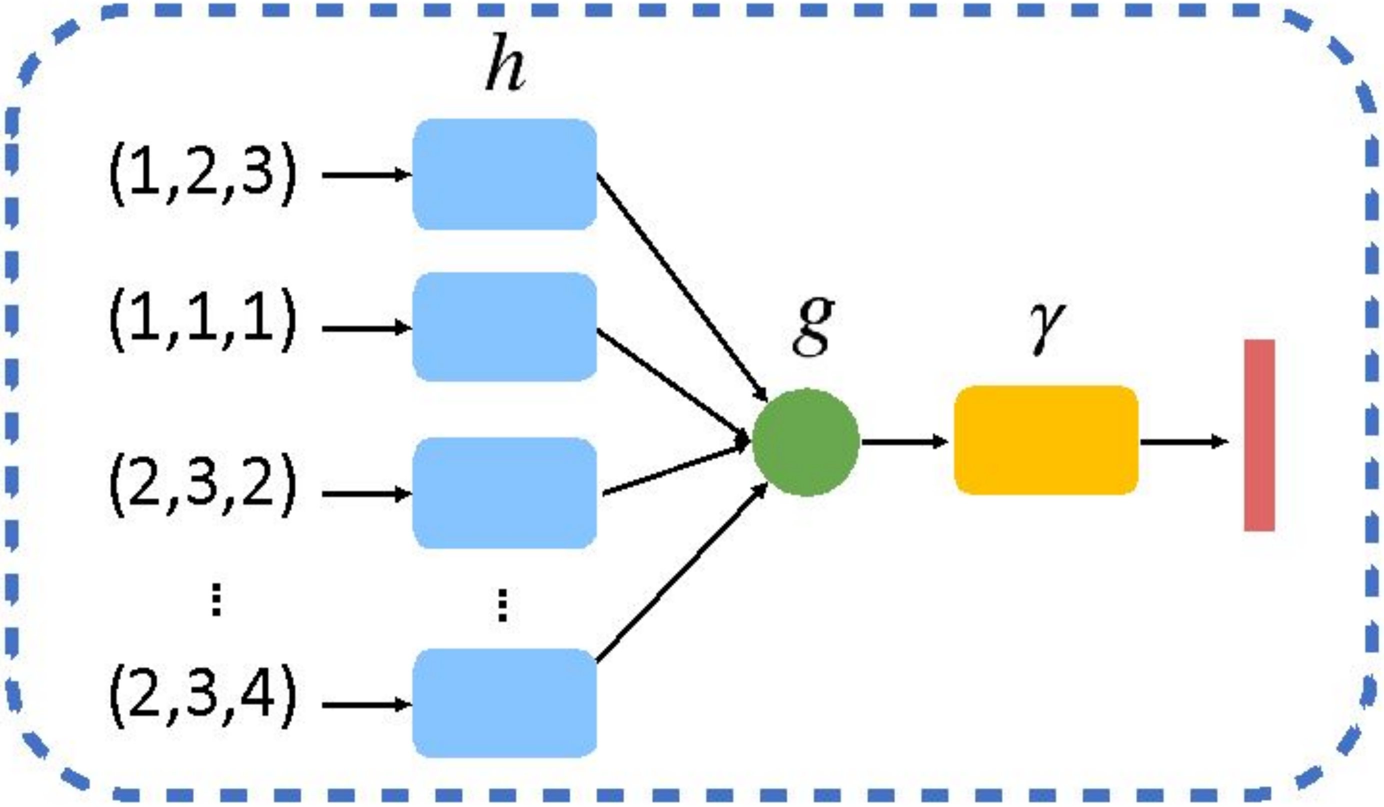
Just discovers simple extreme/aggregate properties of the geometry.



Slide credit: He Wang

Construct Symmetric Functions by Neural Networks

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



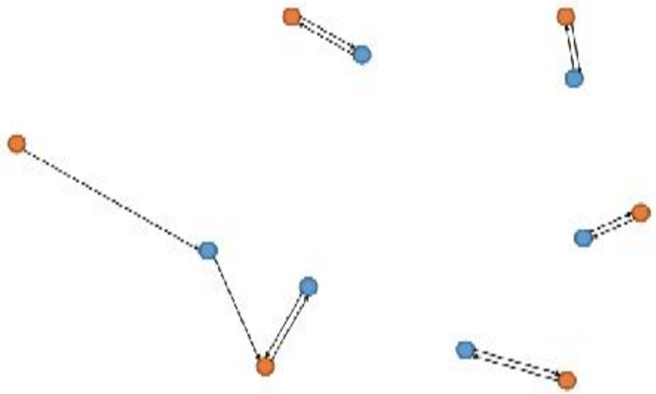
PointNet (vanilla)

Slide credit: He Wang

Distance Metrics for Point Cloud

Chamfer distance We define the Chamfer distance between $S_1, S_2 \subseteq \mathbb{R}^3$ as:

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2$$



Slide credit: He Wang

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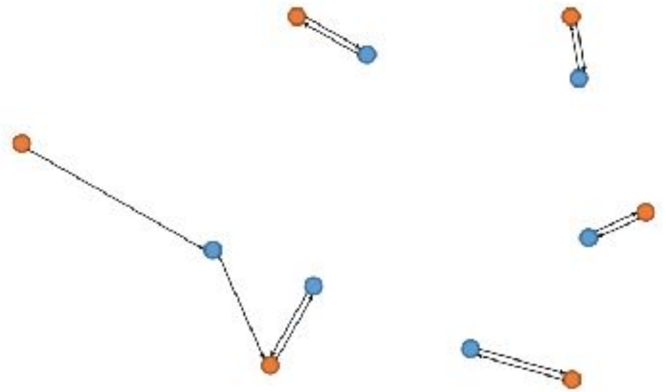
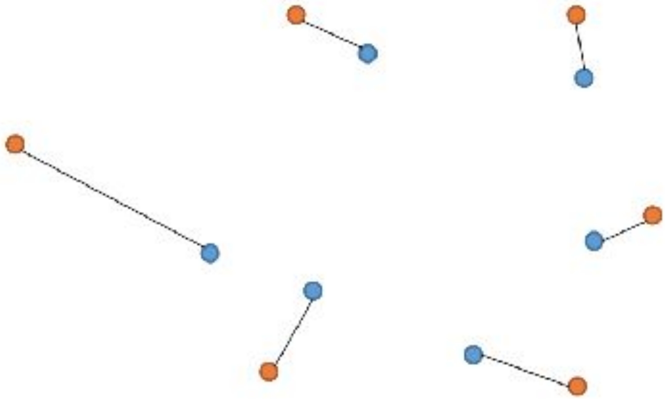
Earth Mover's distance Consider $S_1, S_2 \subseteq \mathbb{R}^3$ of equal size $s = |S_1| = |S_2|$. The EMD between A and B is defined as:

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

where $\phi : S_1 \to S_2$ is a bijection.





A Point Set Generation Network for 3D Object Reconstruction from a Single Image, CVPR 2016

Slide credit: He Wang

Distance Metrics for Point Cloud

Chamfer distance We define the Chamfer distance between $S_1, S_2 \subseteq \mathbb{R}^3$ as:

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2$$

Sum of closest distances

Insensitive to sampling (only relatively)

Earth Mover's distance Consider $S_1, S_2 \subseteq \mathbb{R}^3$ of equal size $s = |S_1| = |S_2|$. The EMD between A and B is defined as:

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

where $\phi : S_1 \rightarrow S_2$ is a bijection.

Sum of matched closest distances

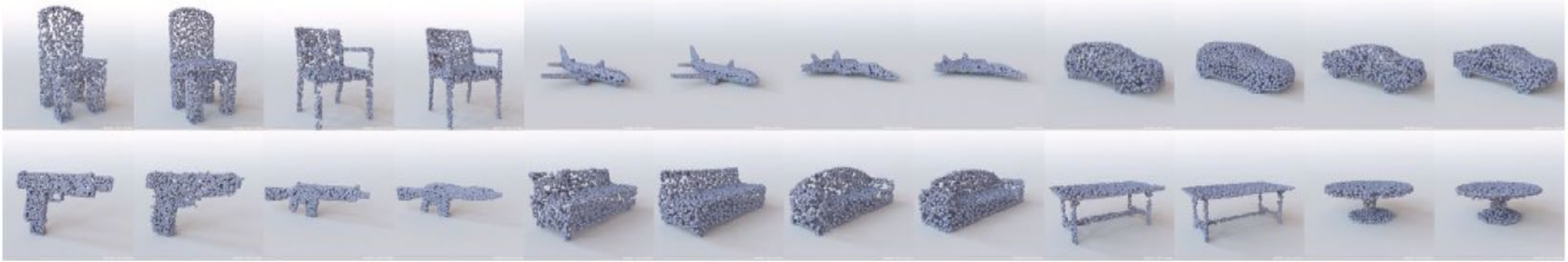
Sensitive to sampling

Slide credit: He Wang

Point Cloud AE

Encoder: PointNet

Decoder: MLP

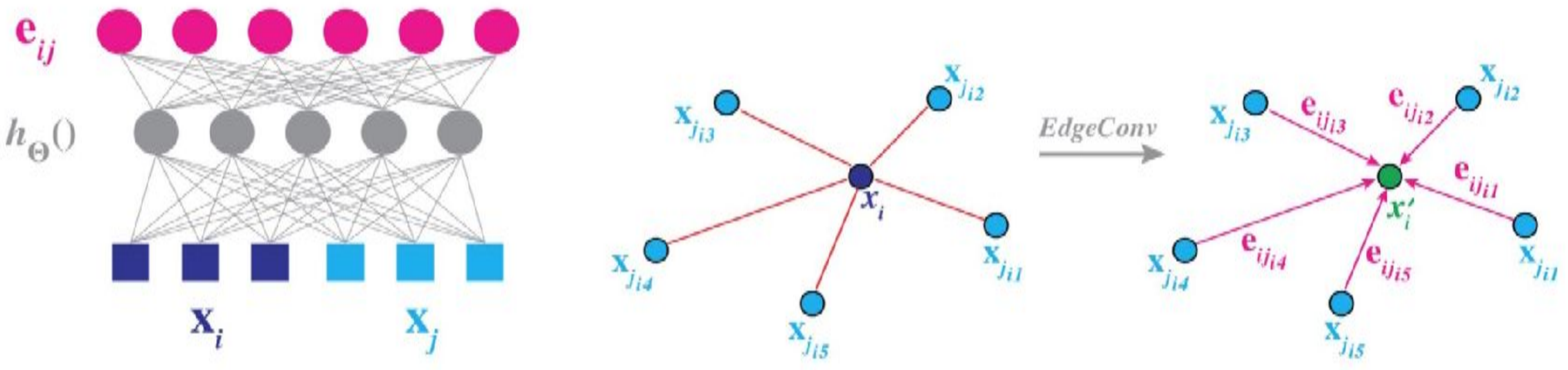


ICML, 2018, Learning Representations and Generative Models for 3D Point Clouds, Panos Achlioptas, et. al.

Slide credit: He Wang

Graph NNs on Point Clouds

- Points -> Nodes
- Neighborhood -> Edges
- Graph NNs for point cloud processing



Wang et al. TOG 2019

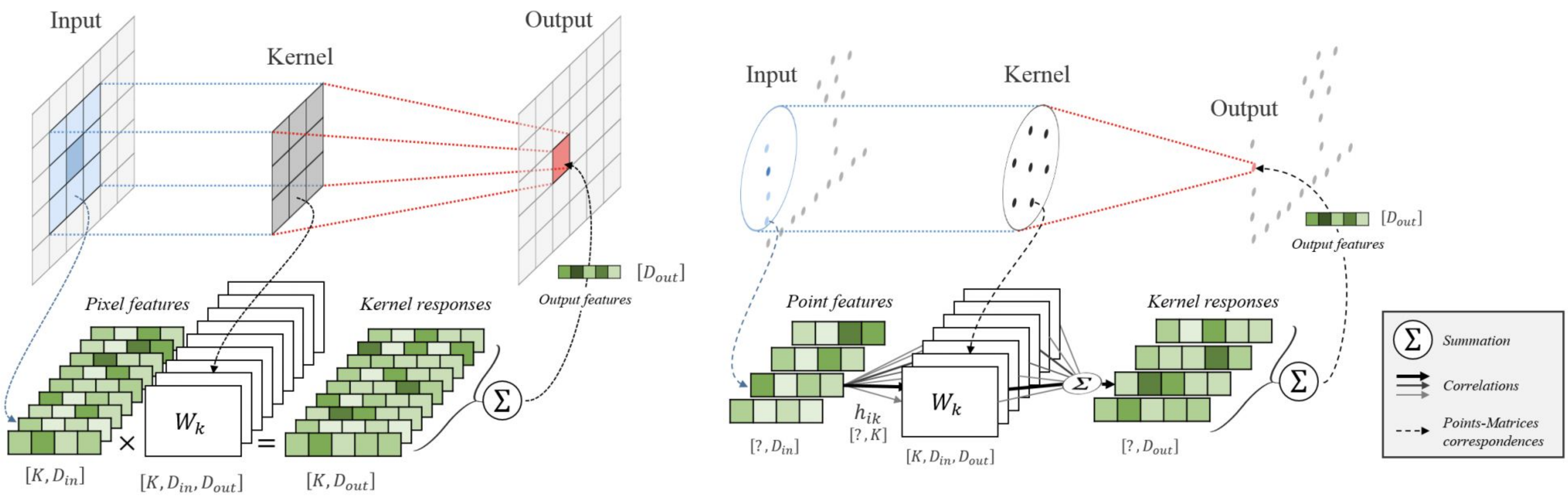
Message-Passing GNNs are not Geometry-Aware

- Points are **sampled** from surfaces.
- Ideally, features describe the geometry of underlying surface. They should be sample invariant.
- Message-passing GNNs do not address sample invariance.

- **Solution**: Estimate the continuous kernel and point density for continuous convolution (KPConv)

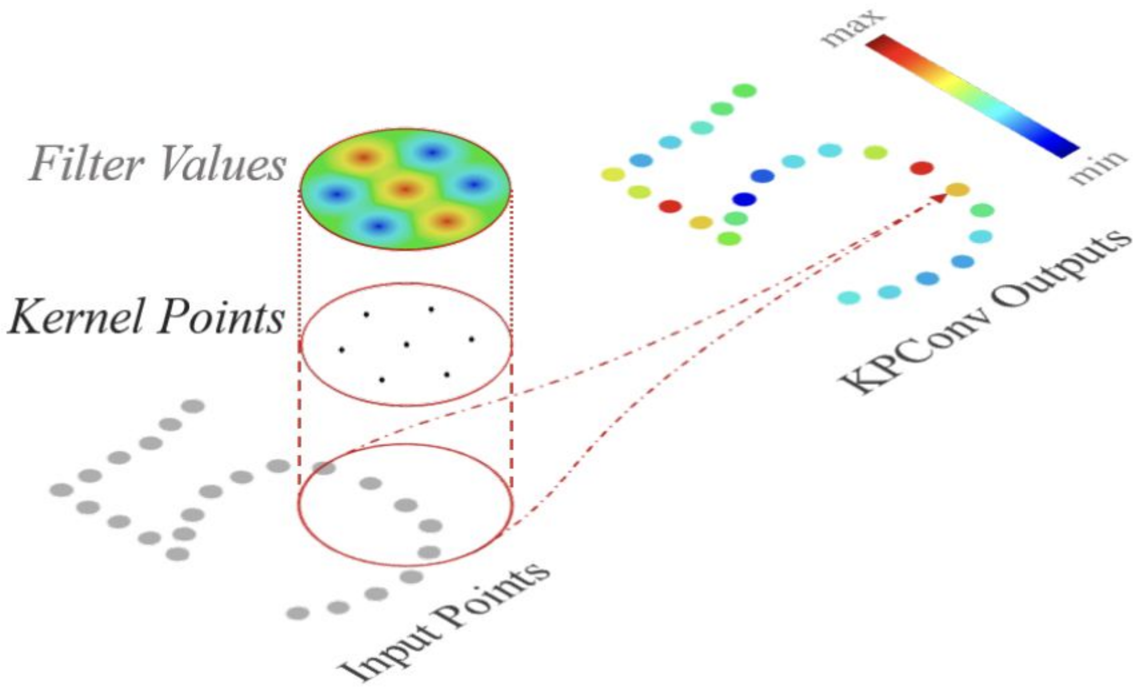
Slide Credit: Hao Su

Kernel Point Convolution (KPConv)



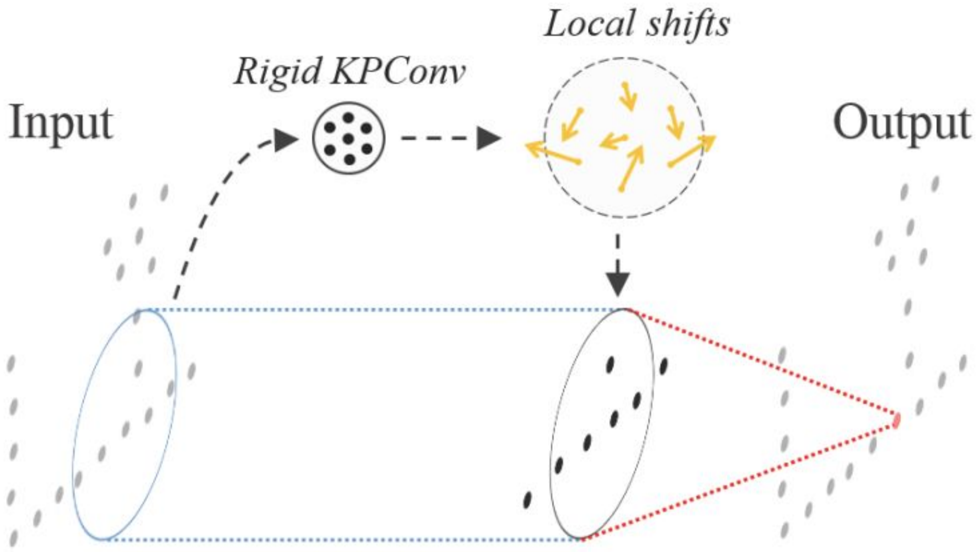
Thomas et al. ICCV 2019

Deformable Kernel for Deformable Objects



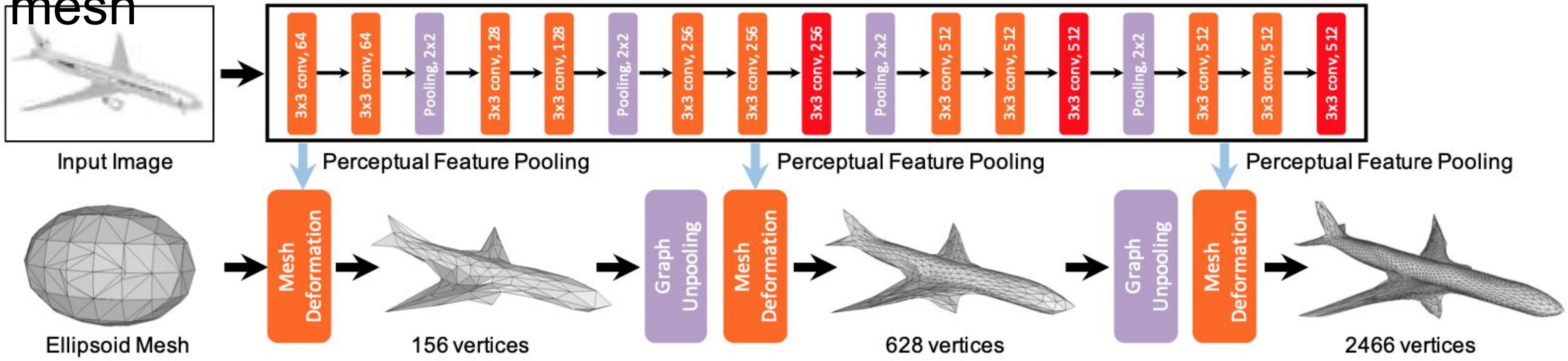
Deformable point-based kernel

- 3D version of 2D deformable convolution

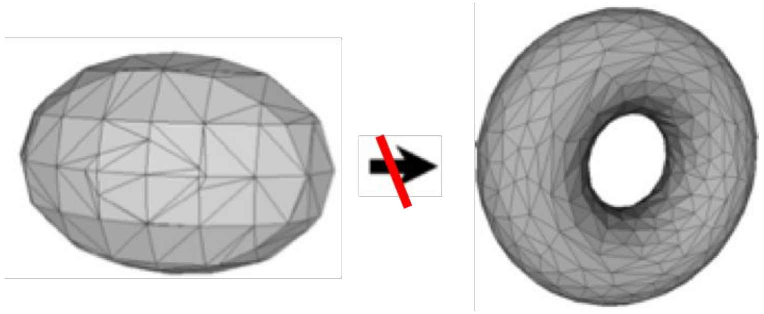


Pixel2Mesh

Learn to deform a template mesh



Cannot change the topology of the template mesh



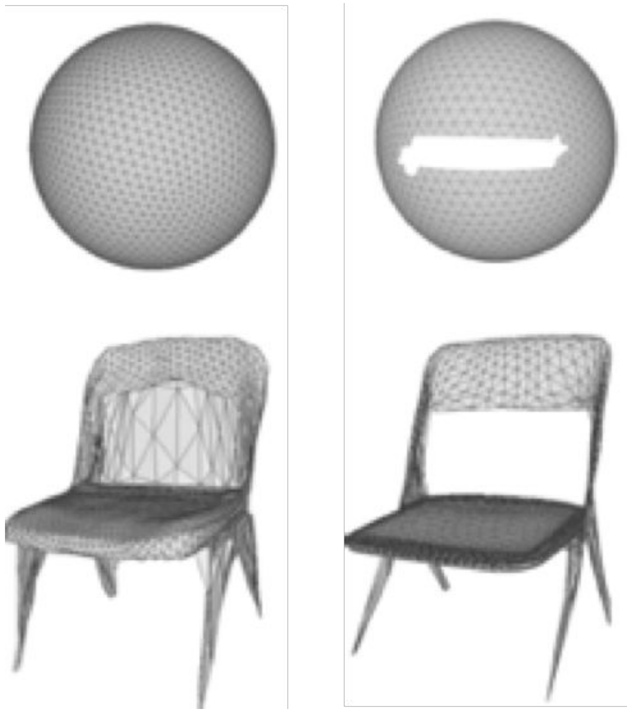
Wang et al. Pixel2Mesh. ECCV 2018

More on Mesh Deformation

Part-level deformation

Gao et al. SDM-NET: Deep generative network for structured deformable mesh. SIGGRAPH Asia 2019

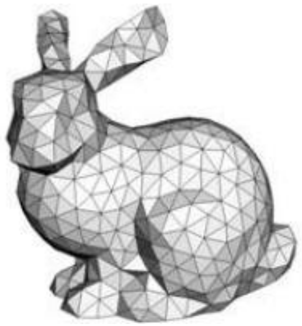
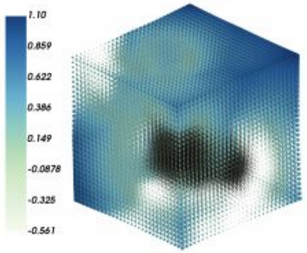
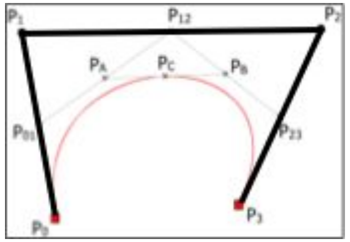
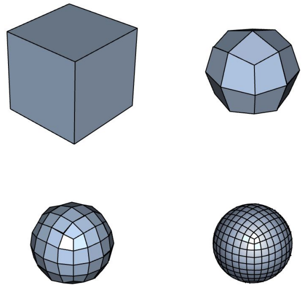
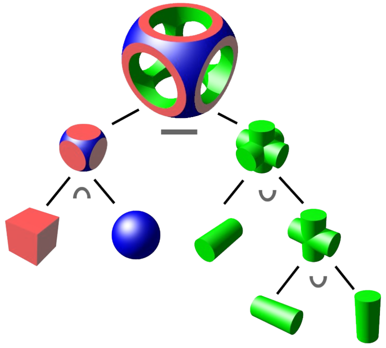
Modify the topology of the template mesh



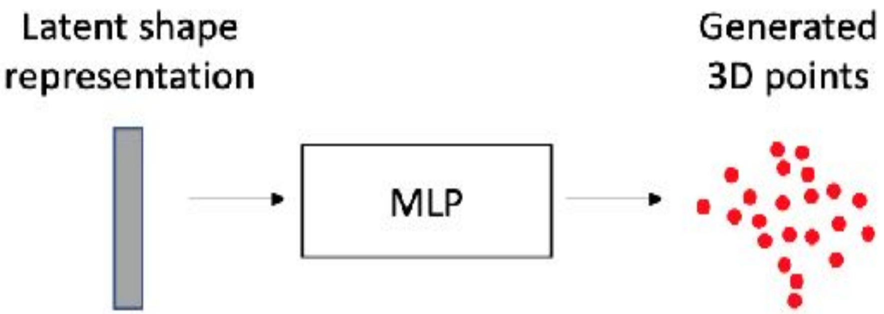
Pan et al., Deep Mesh Reconstruction from Single RGB Images via Topology Modification Networks. ICCV 2019

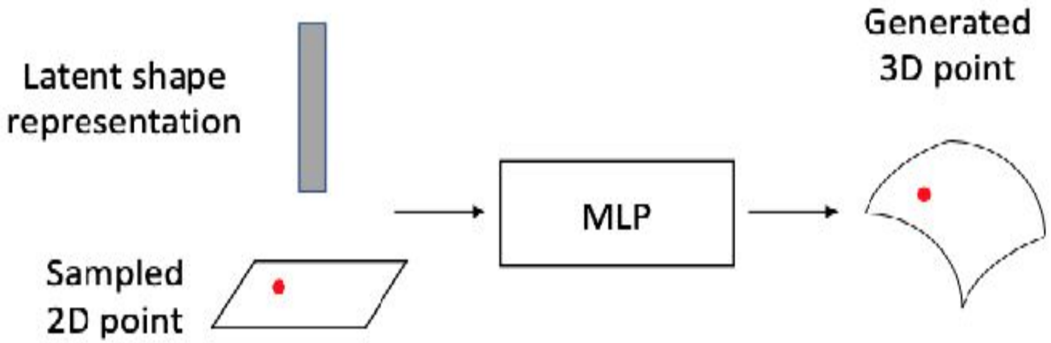
Slide: Hao Su

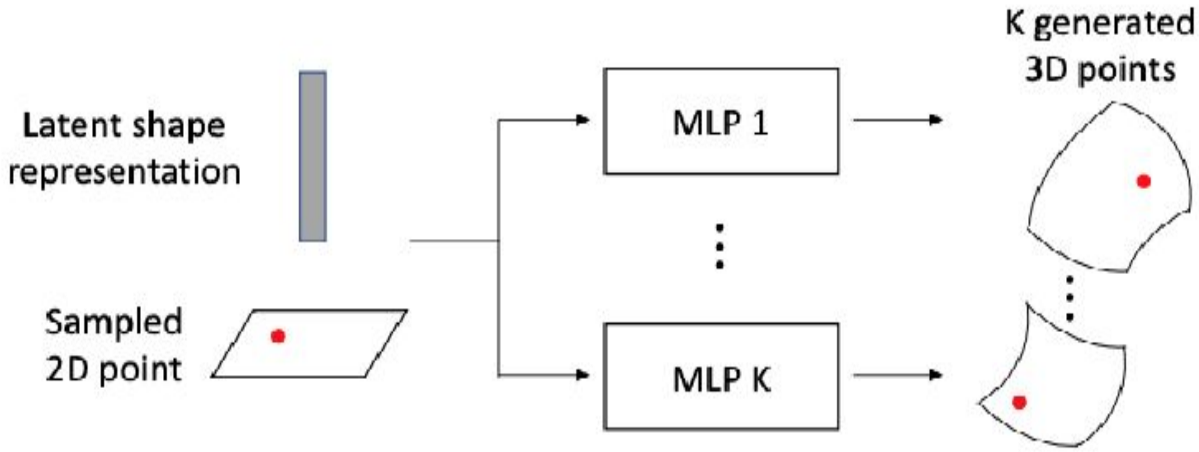
Non-Parametric -> Parametric

	Explicit		Implicit (Eulerian)	
Non-parametric	 Points	 Meshes	 Voxels	 Level Sets
Parametric	 Splines	 Subdivision Surfaces	 $x^2+y^2+z^2=1$ Algebraic Surfaces	 Constructive Solid Geometry

Parametric Decoder: AtlasNet





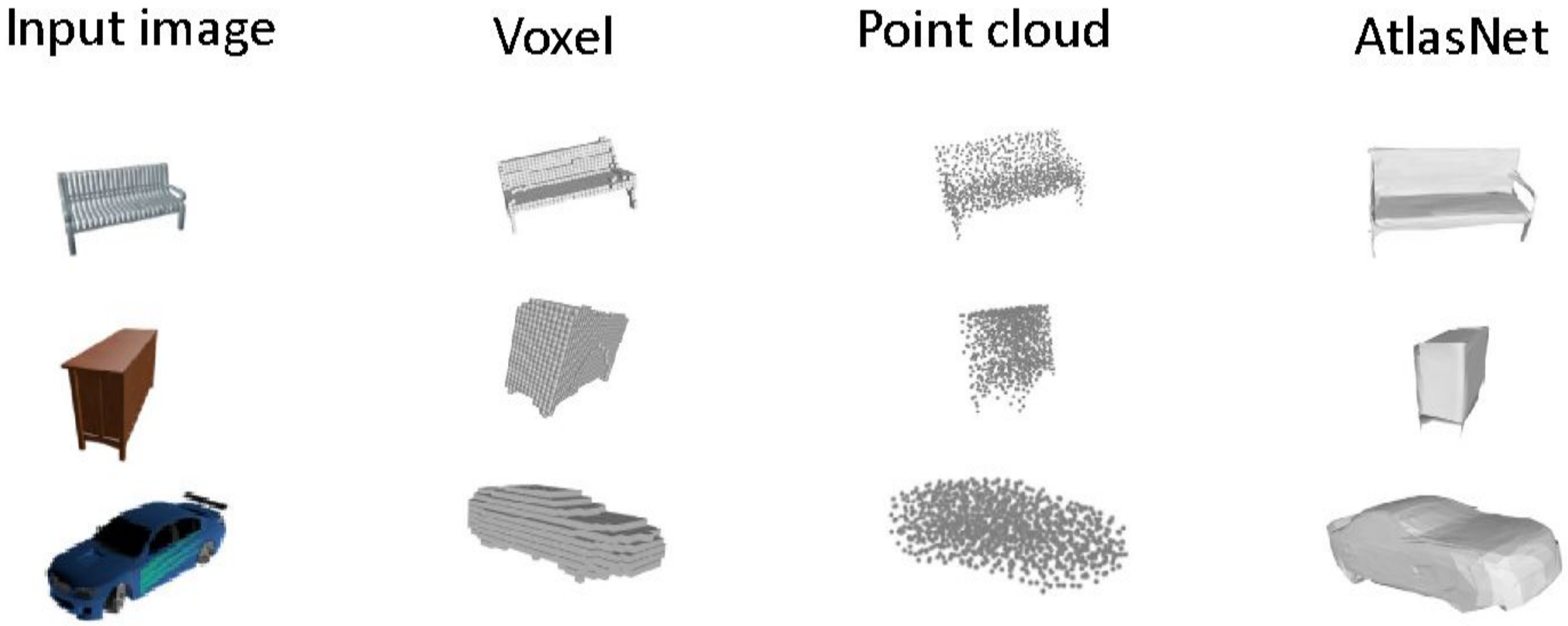


Given the output points form a smooth surface, enforce such a parametrization as input.

MLP(z, u, v) -> point

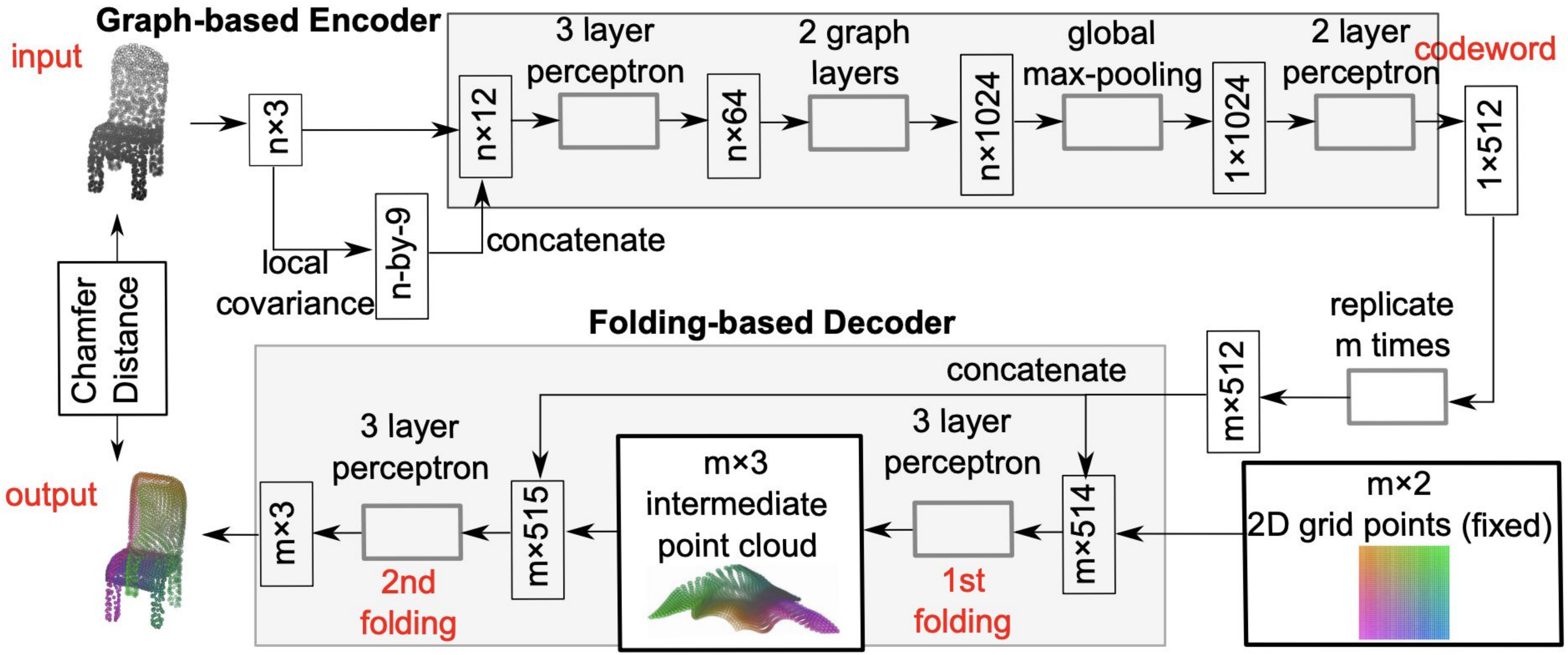
Groueix et al. CVPR 2018

Results



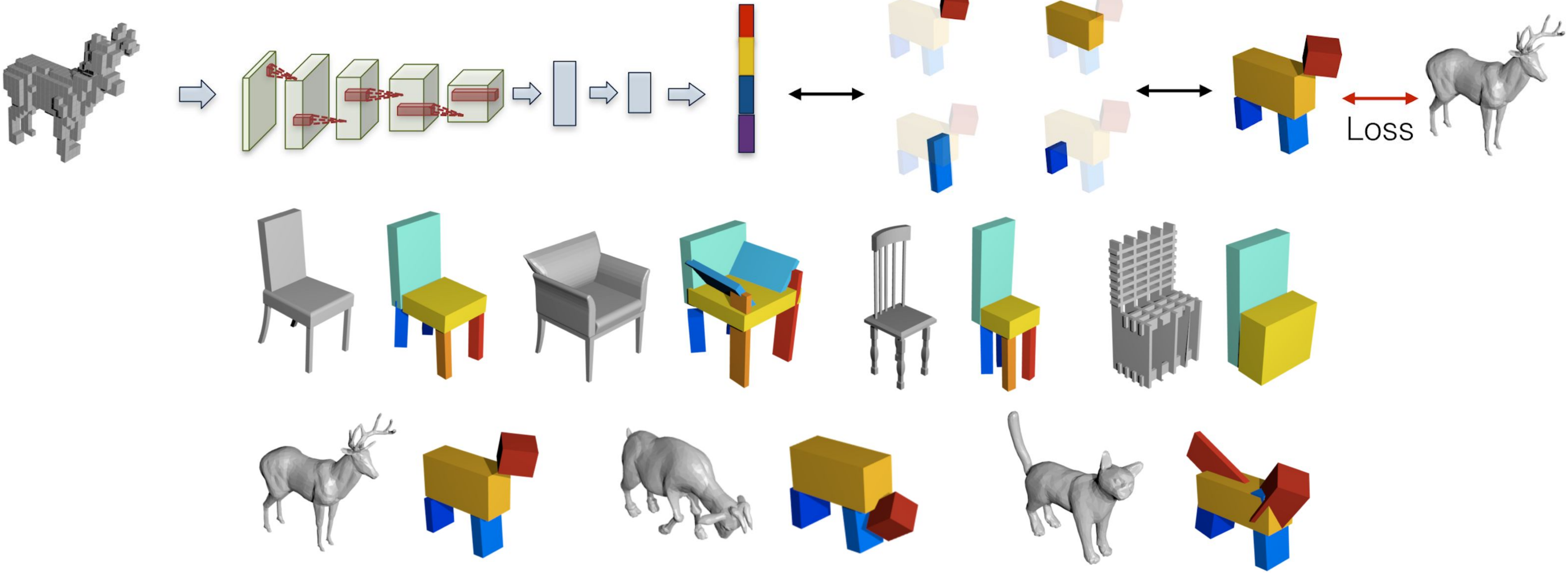
Groueix et al. CVPR 2018

FoldingNet



Yang et al. CVPR 2018

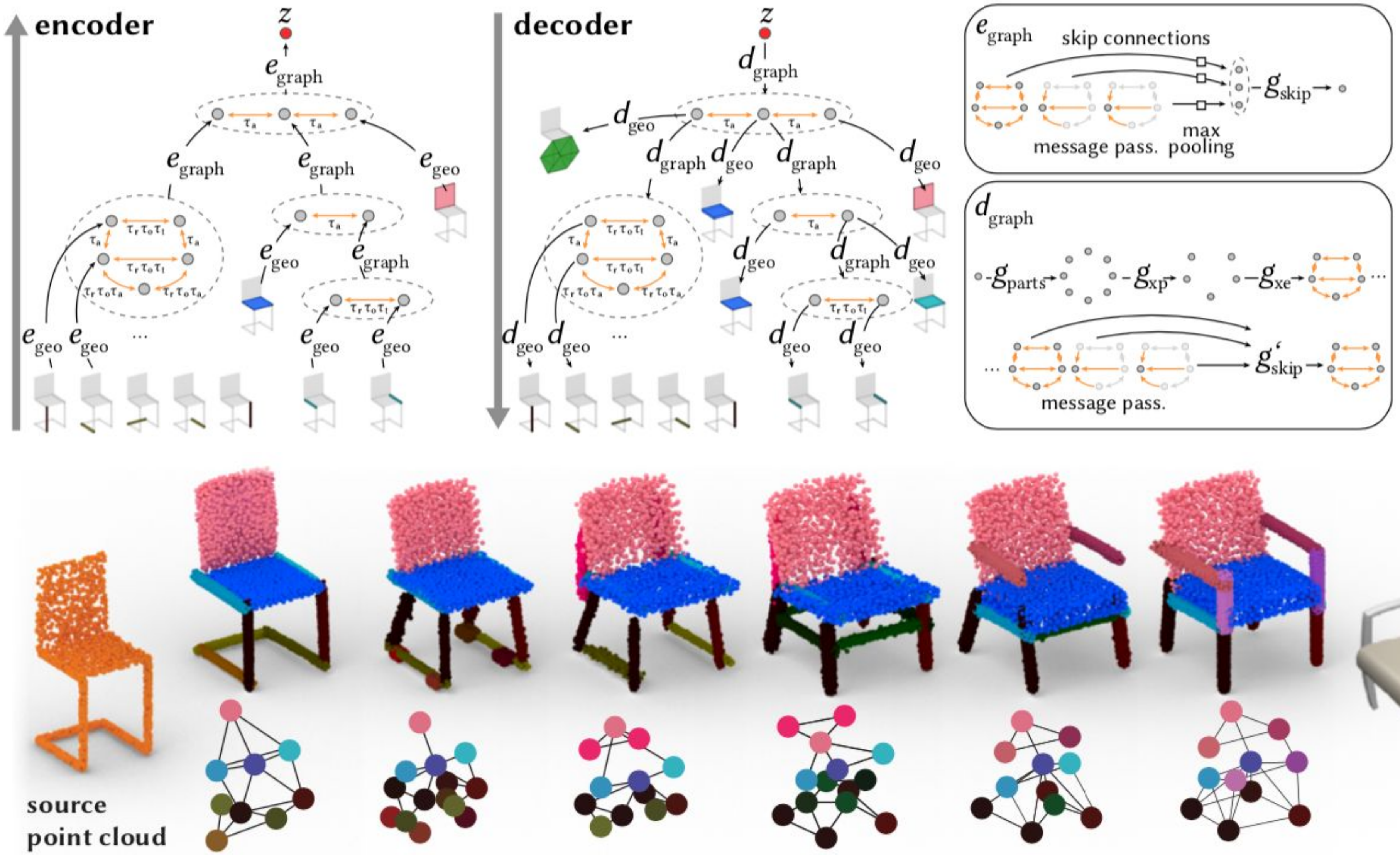
Assembling Volumetric Primitives



Tulsiani et al. CVPR 2017

Incorporating Shape Structure

StructureNet

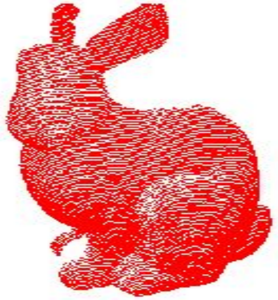


Graph convnets encode/decode variable-degree nodes

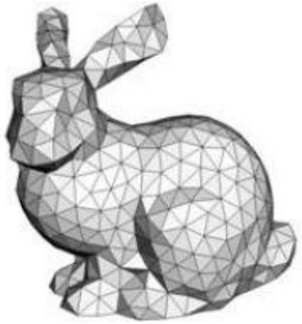
Explicit -> Implicit

Explicit | Implicit (Eulerian)

Non-parametric

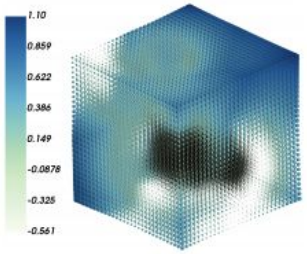


Points



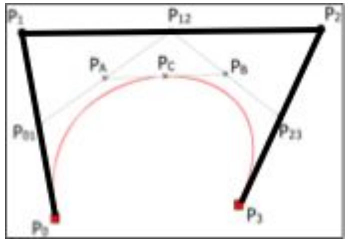
Meshes

Voxels

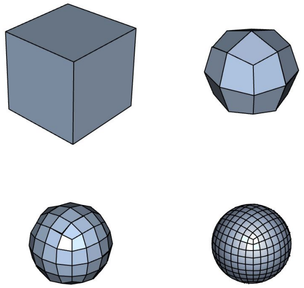


Level Sets

Parametric



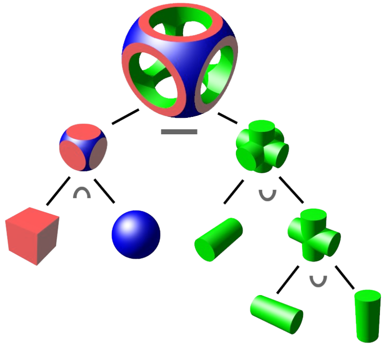
Splines



Subdivision Surfaces

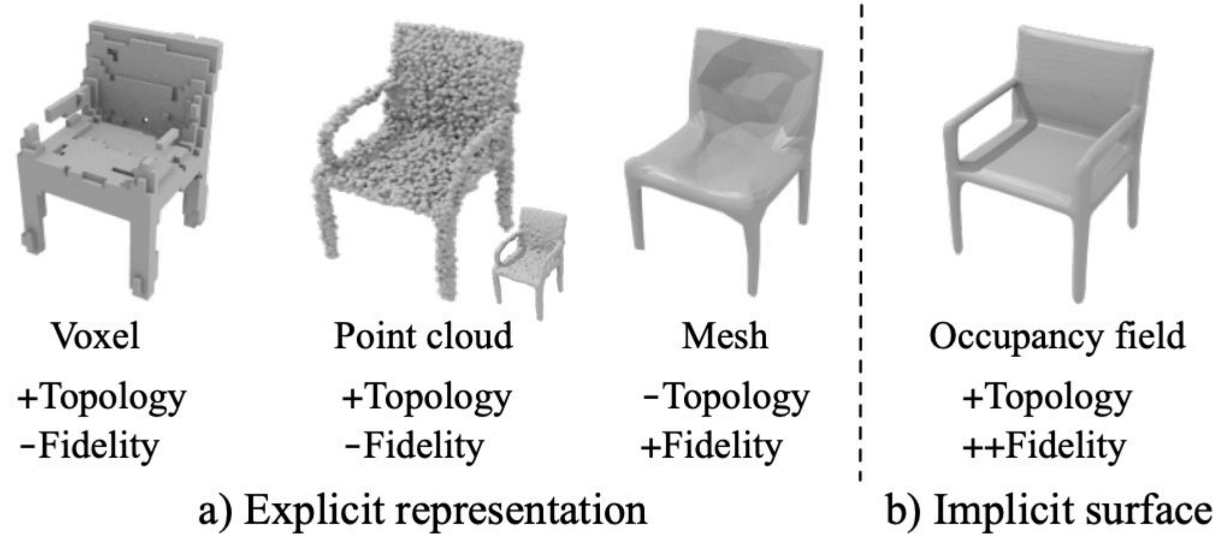
$x^2+y^2+z^2=1$

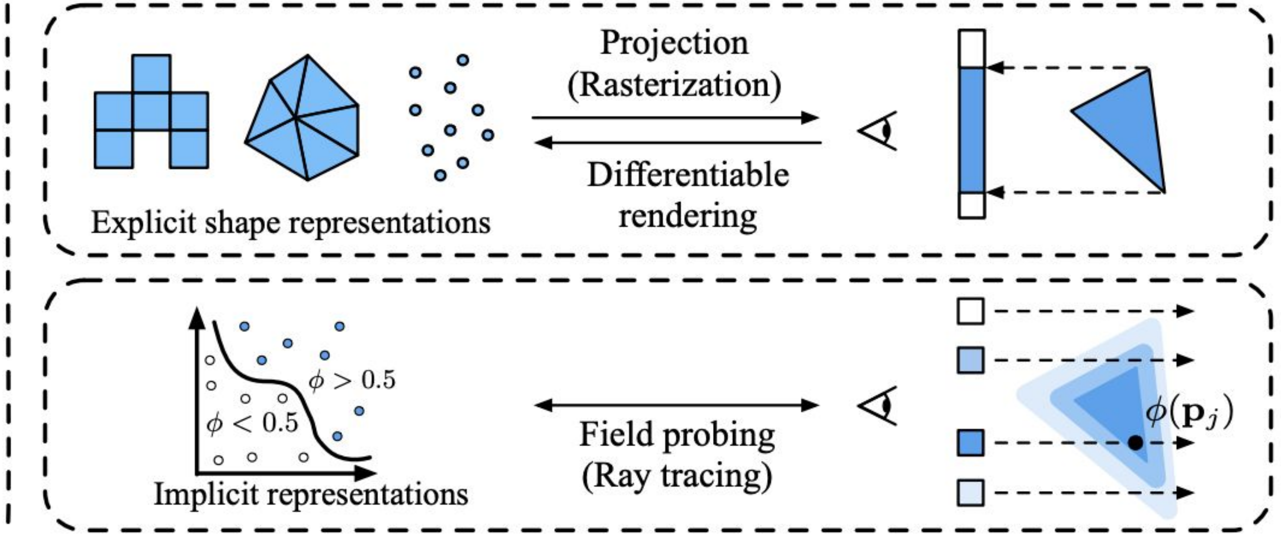
Algebraic Surfaces



Constructive Solid Geometry

Deep Implicit Functions





Liu et al. Learning to Infer Implicit Surfaces without 3D Supervision. NeurIPS 2019

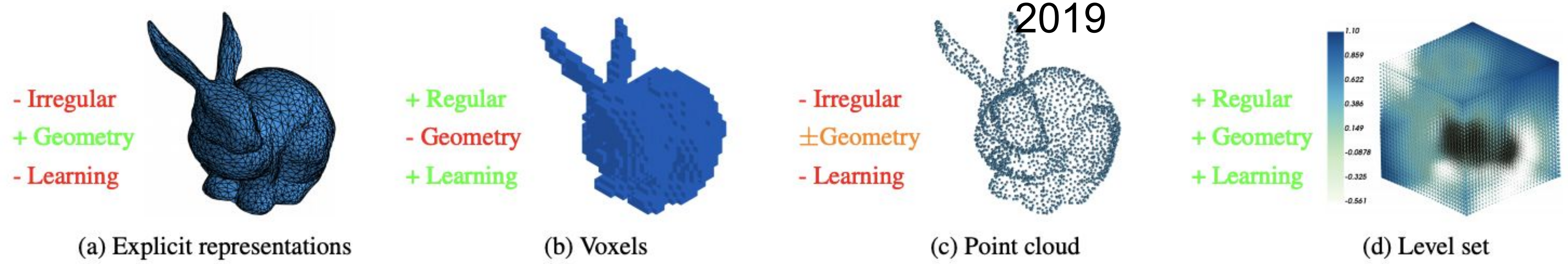
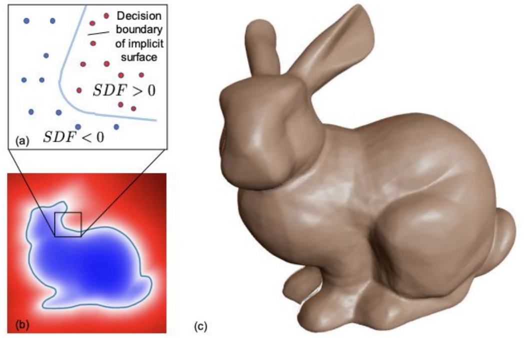
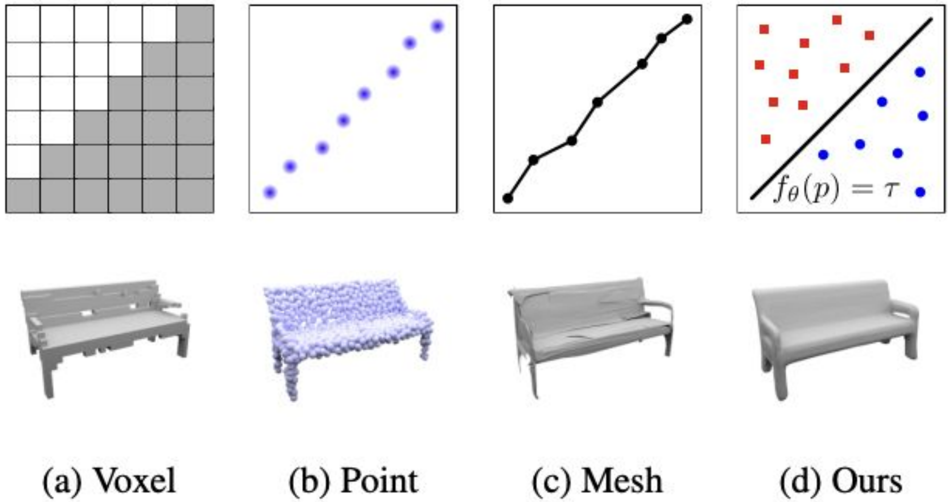


Figure 2. Four common representations of 3D shape along with their advantages and disadvantages.

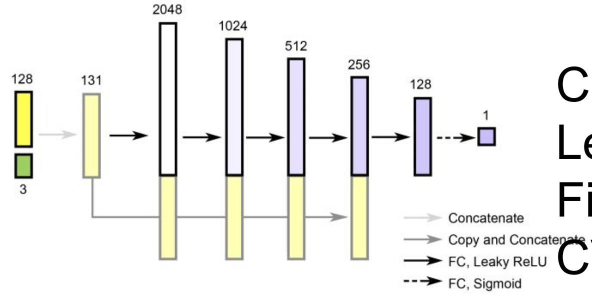


Deep Level Sets: Implicit Surface Representations for 3D Shape Inference. 2019

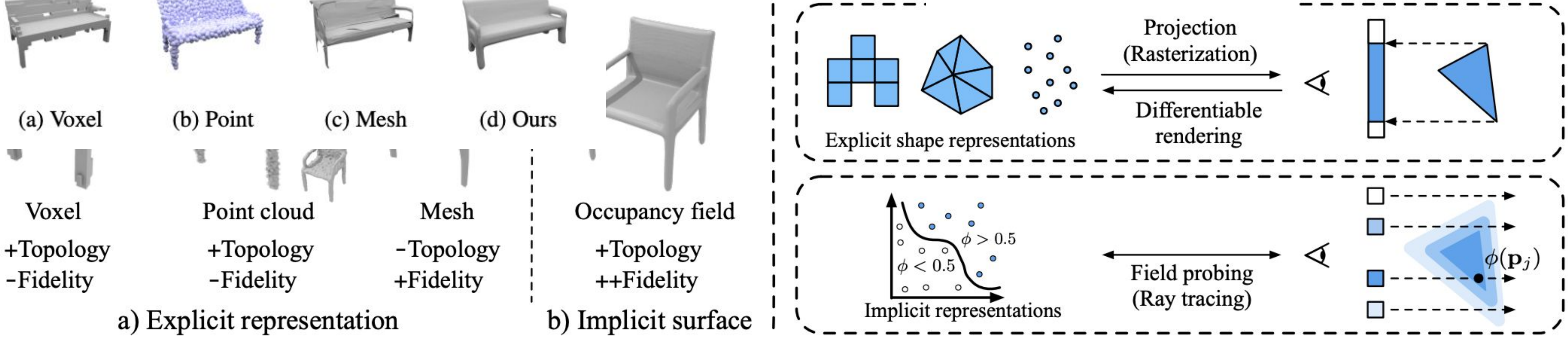
DeepSDF. CVPR 2019



Occupancy Networks CVPR 2019



Chen and Zhang. Learning Implicit Fields CVPR 2019



Liu et al. Learning to Infer Implicit Surfaces without 3D Supervision. NeurIPS 2019

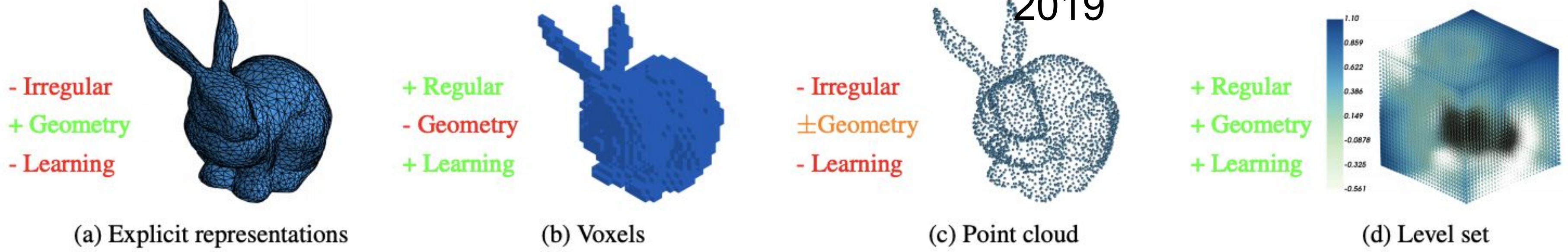
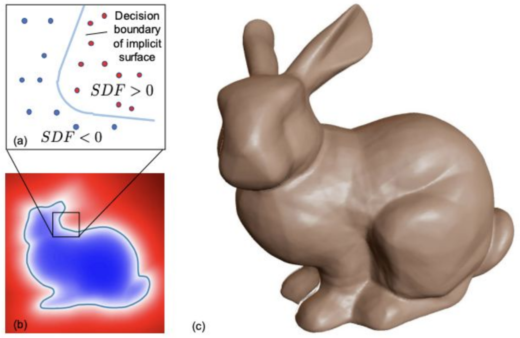


Figure 2. Four common representations of 3D shape along with their advantages and disadvantages.

Deep Level Sets: Implicit Surface Representations for 3D Shape Inference. 2019



DeepSDF. CVPR 2019

Neural Radiance Fields (NeRF) for View Synthesis

Input: Many images of the same scene
(with known camera parameters)

Output: Images showing the scene from novel viewpoints

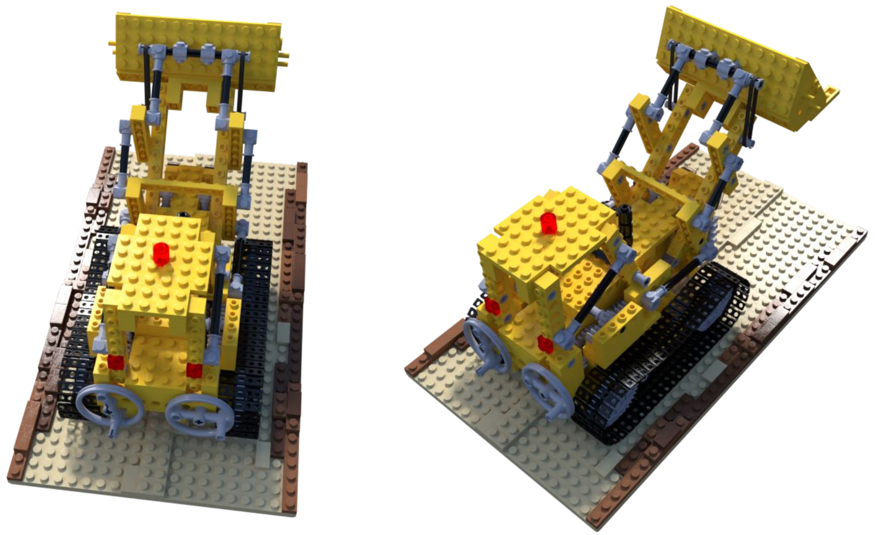


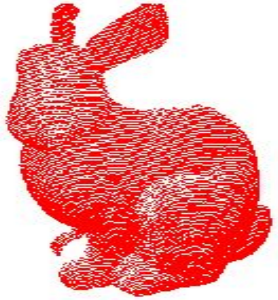
Image source: Mildenhall et al, "Representing Scenes as Neural Radiance Fields for View Synthesis", ECCV

Shape Representations

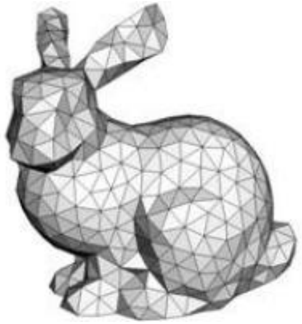
Explicit

Implicit (Eulerian)

Non-parametric

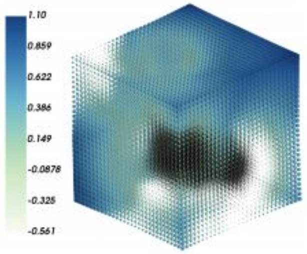


Points



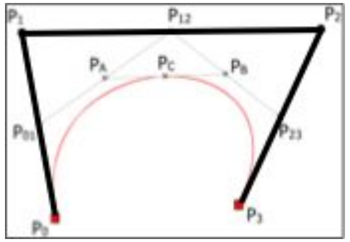
Meshes

Voxels

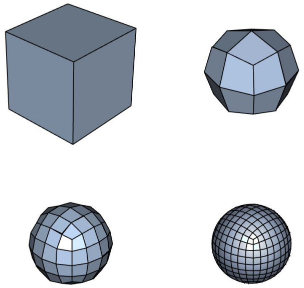


Level Sets

Parametric



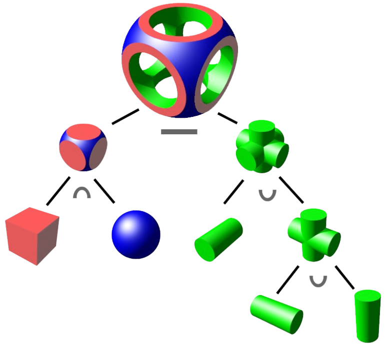
Splines



Subdivision Surfaces

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

Algebraic Surfaces



Constructive Solid Geometry

Next:
Human-Centered Artificial Intelligence