Lecture 16:
3D Vision

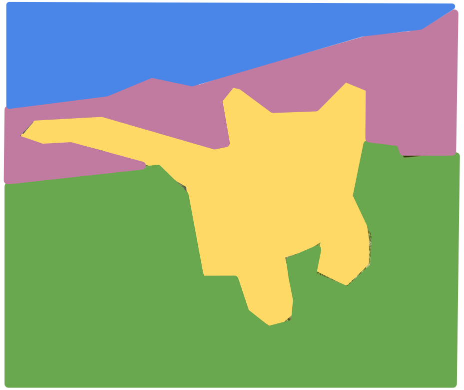
Slides credit: Justin Johnson

Recall: 2D Detection and Segmentation

Classification

CAT

Semantic Segmentation

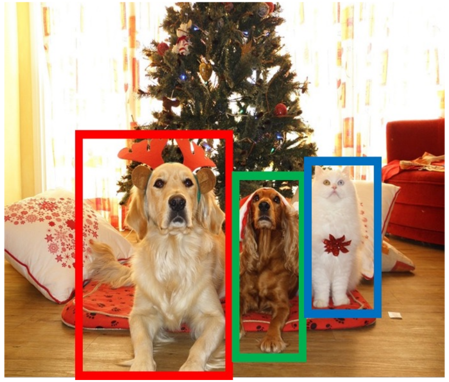


GRASS, CAT, TREE, SKY

No spatial extent

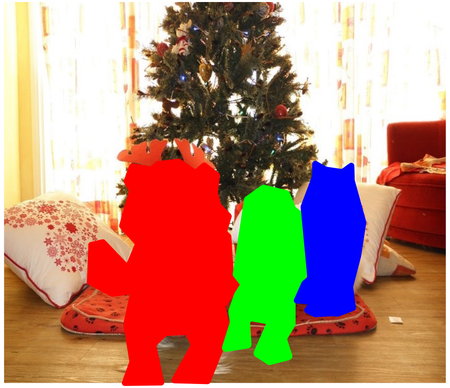
No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Objects

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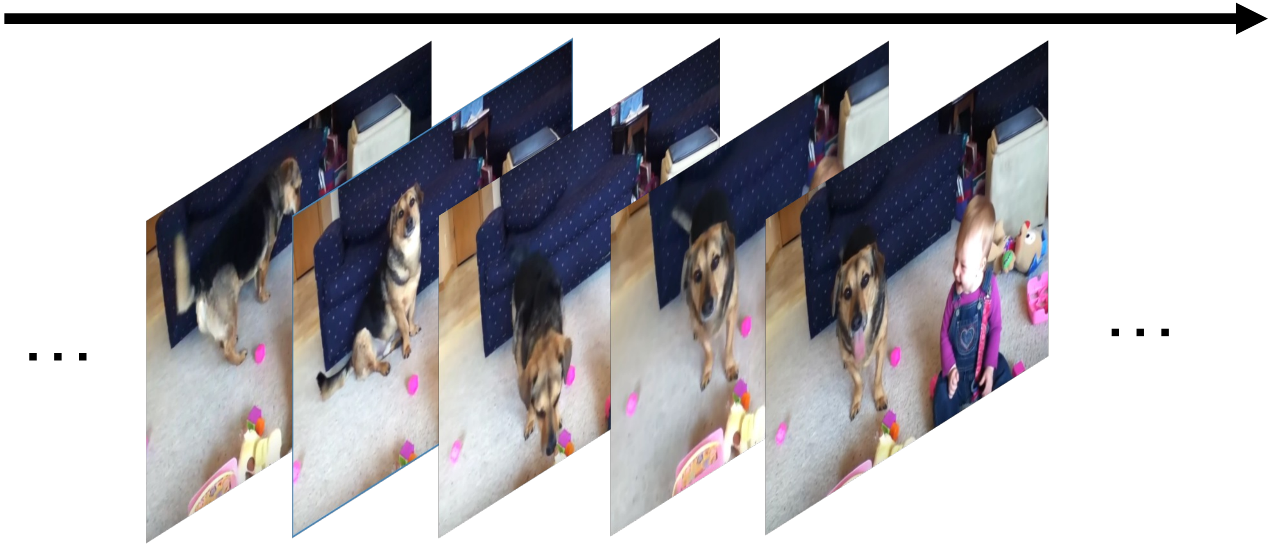
Recall: **Video** = 2D + Time

A video is a **sequence** of images
4D tensor: T x 3 x H x W
(or 3 x T x H x W)



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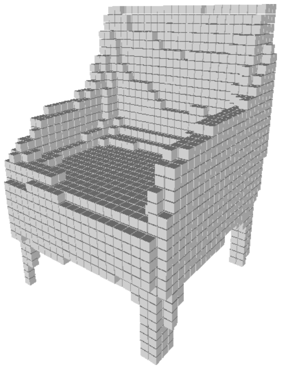
Focus on Two Problems today

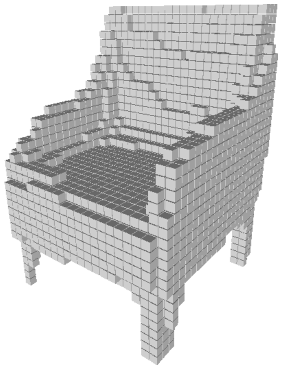
Predicting 3D Shapes from single image

Input Image



3D Shape

Processing 3D input data



3D Shape

Chair

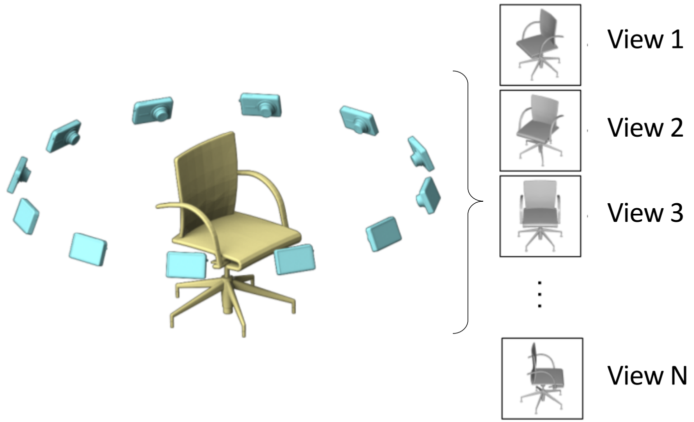
Many more topics in 3D Vision!

3D Representations
Computing Correspondences
Multi-view stereo
Structure from Motion
Simultaneous Localization and Mapping (SLAM)
View Synthesis
Differentiable Graphics
3D Sensors
……

Multi-View CNN

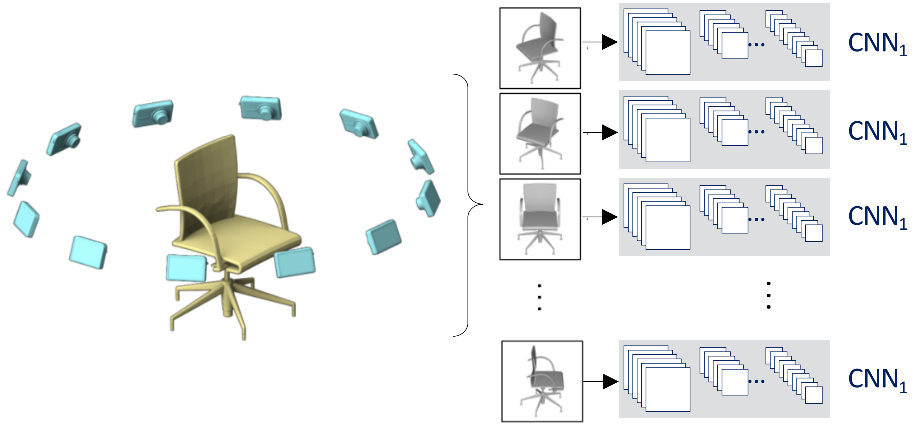
Su et al. ICCV 2015

Multi-View CNN



Su et al. ICCV 2015

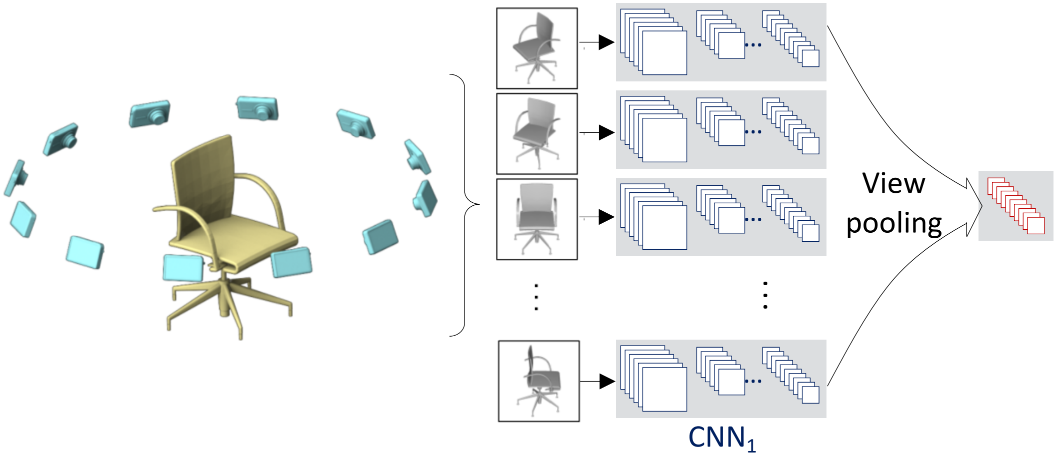
Multi-View CNN



CNN_1: a ConvNet extracting image features

Su et al. ICCV 2015

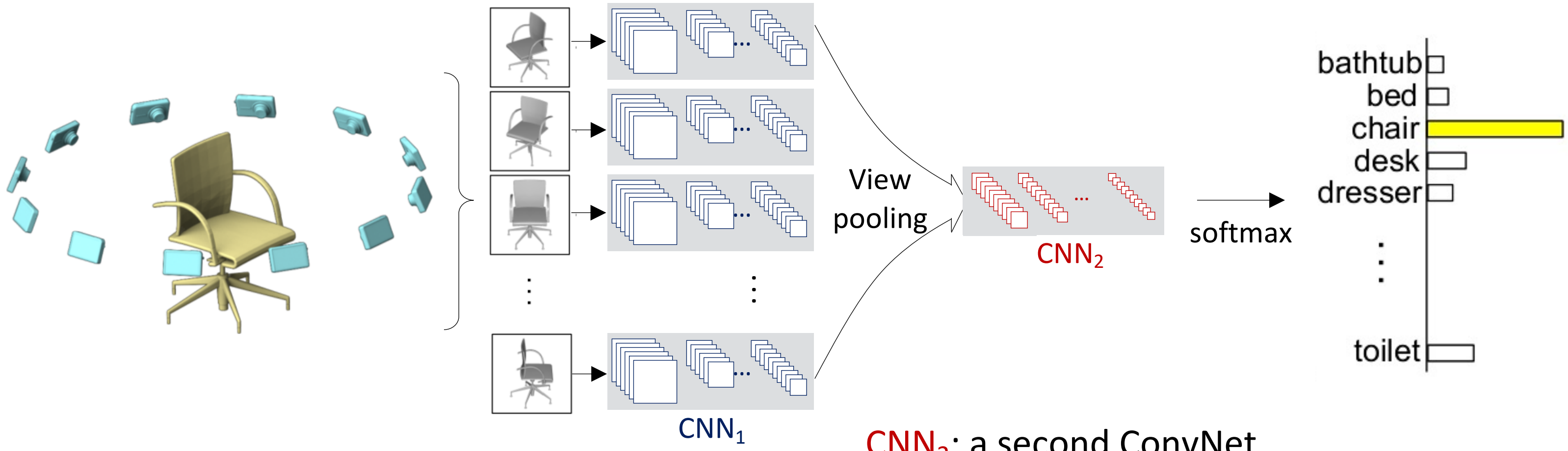
Multi-View CNN



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

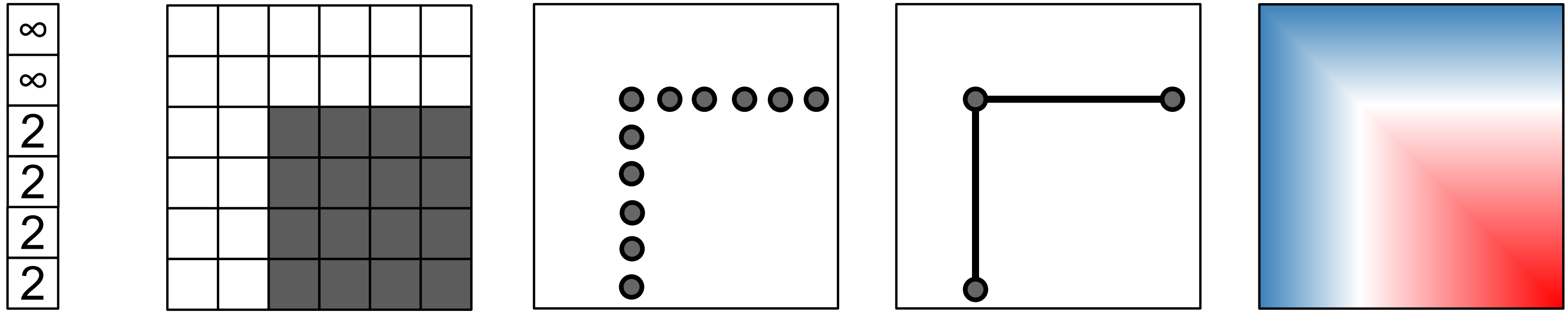
Experiments – Classification & Retrieval

	Method	Classification (Accuracy)	Retrieval (mAP)
Non-deep	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

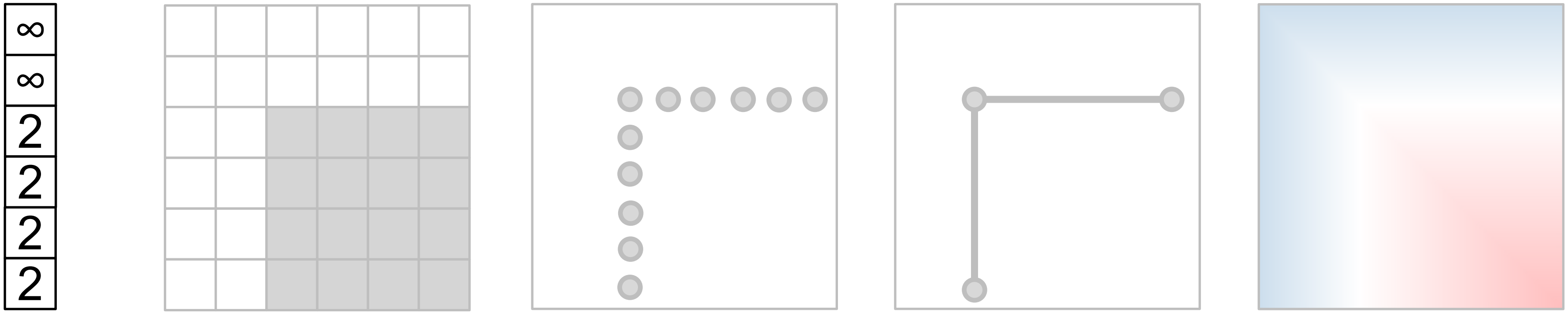
Su et al. ICCV 2015

3D Shape Representations



Depth Map | Voxel Grid | Pointcloud | Mesh | Implicit Surface

3D Shape Representations



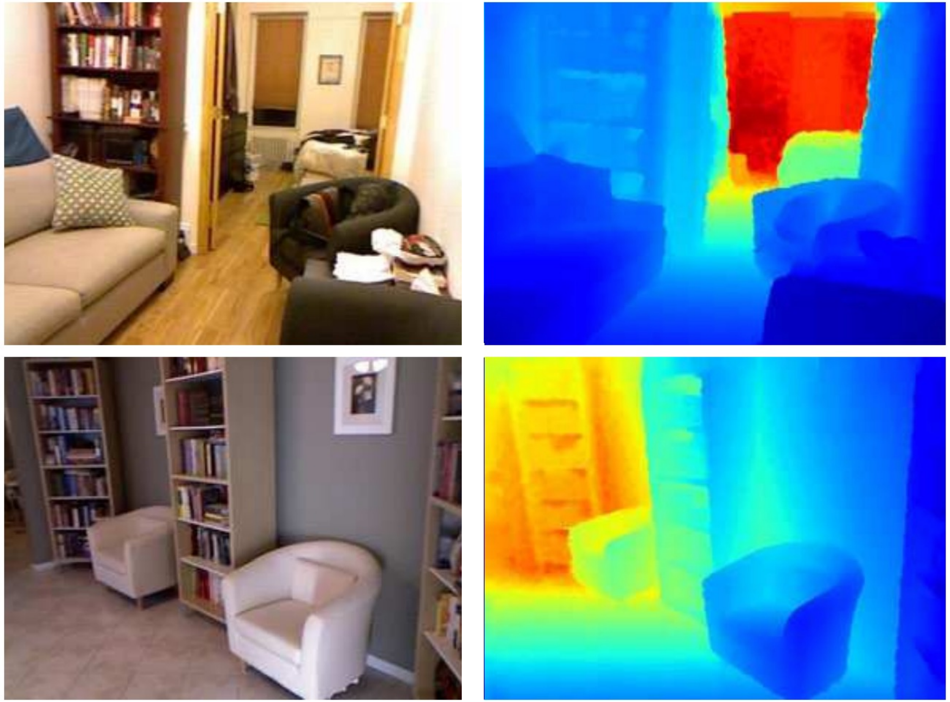
Depth Map | Voxel Grid | Pointcloud | Mesh | Implicit Surface

3D Shape Representations: Depth Map

For each pixel, **depth map** gives distance from the camera to the object in the world at that pixel

RGB image + Depth image
= RGB-D Image (2.5D)

This type of data can be recorded directly for some types of 3D sensors (e.g. Microsoft Kinect)

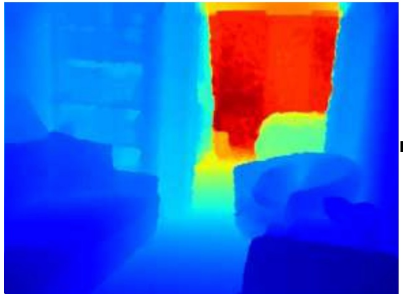


RGB Image: 3 x H x W Depth Map: H x W

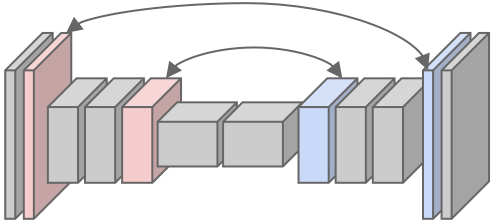
Eigen and Fergus, “Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture”, ICCV 2015

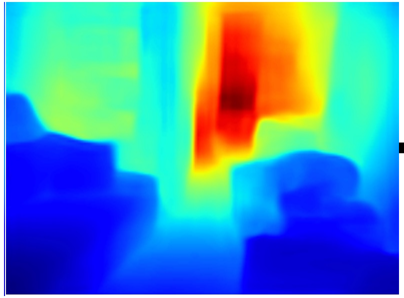
Predicting Depth Maps

Predicted Depth Image:
1 x H x W



Per-Pixel Loss
(L2 Distance)





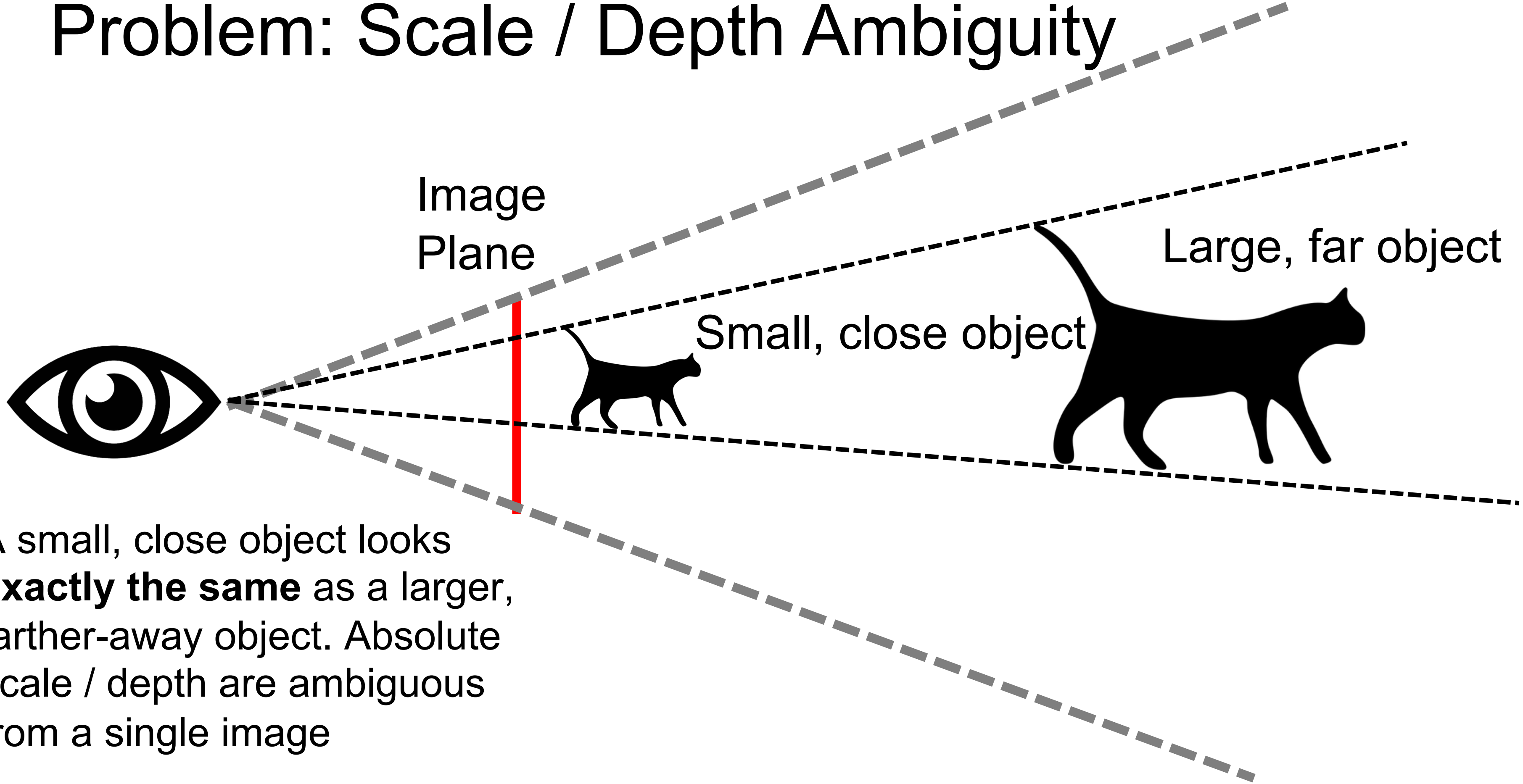
RGB Input Image:
3 x H x W

Fully Convolutional network

Predicted Depth Image:
1 x H x W

Eigen, Puhrsh, and Fergus, "Depth Map Prediction from a Single Image using a Multi-Scale Deep Network", NeurIPS 2014
Eigen and Fergus, "Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture", ICCV 2015

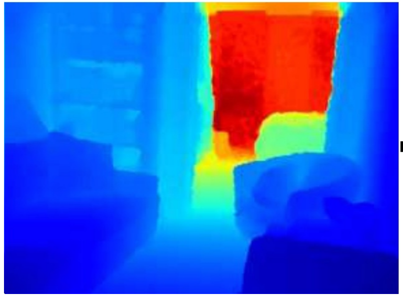
Problem: Scale / Depth Ambiguity



A small, close object looks **exactly the same** as a larger, farther-away object. Absolute scale / depth are ambiguous from a single image

Predicting Depth Maps

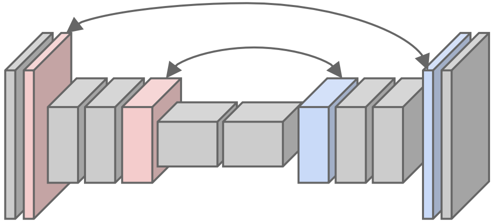
Predicted Depth Image:
1 x H x W

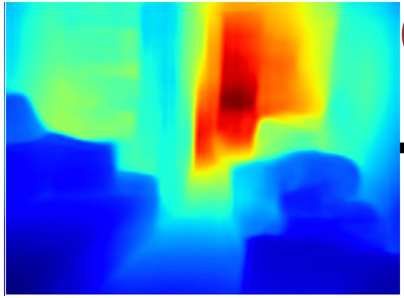


Scale invariant loss

$$
\begin{aligned}
D(y, y^*) &= \frac{1}{2n^2}\sum_{i,j}\left((\log y_i - \log y_j) - (\log y_i^* - \log y_j^*)\right)^2 \\
&= \frac{1}{n}\sum_i d_i^2 - \frac{1}{n^2}\sum_{i,j} d_i d_j \;=\; \frac{1}{n}\sum_i d_i^2 - \frac{1}{n^2}\left(\sum_i d_i\right)^2
\end{aligned}
$$

Per-Pixel Loss
(Scale invariant)





RGB Input Image:
3 x H x W

Fully Convolutional network

Predicted Depth Image:
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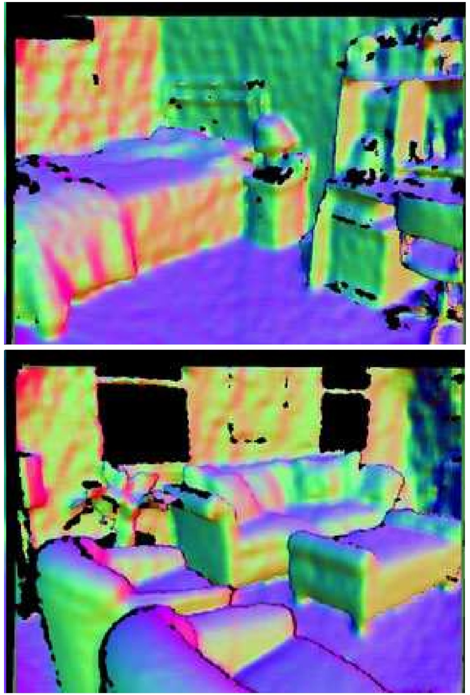
3D Shape Representations: Surface Normals

For each pixel, **surface normals** give a vector giving the normal vector to the object in the world for that pixel

RGB Image: 3 x H x W

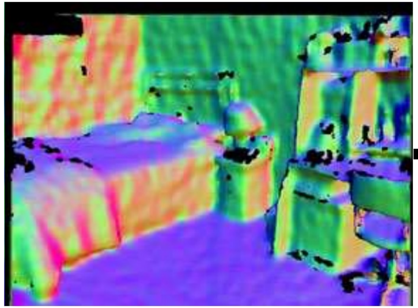


Normals: 3 x H x W

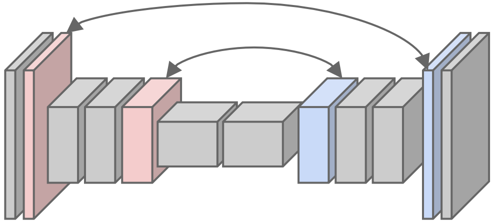
Eigen and Fergus, “Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture”, ICCV 2015

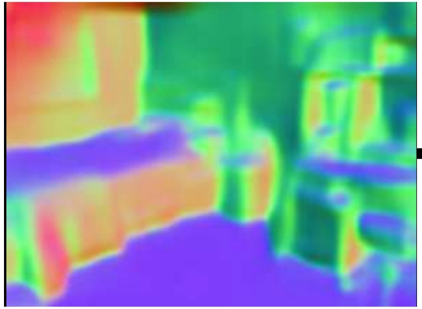
Predicting Normals

Ground-truth Normals:
3 x H x W



Per-Pixel Loss:
$(x \cdot y) / (|x||y|)$





RGB Input Image:
3 x H x W

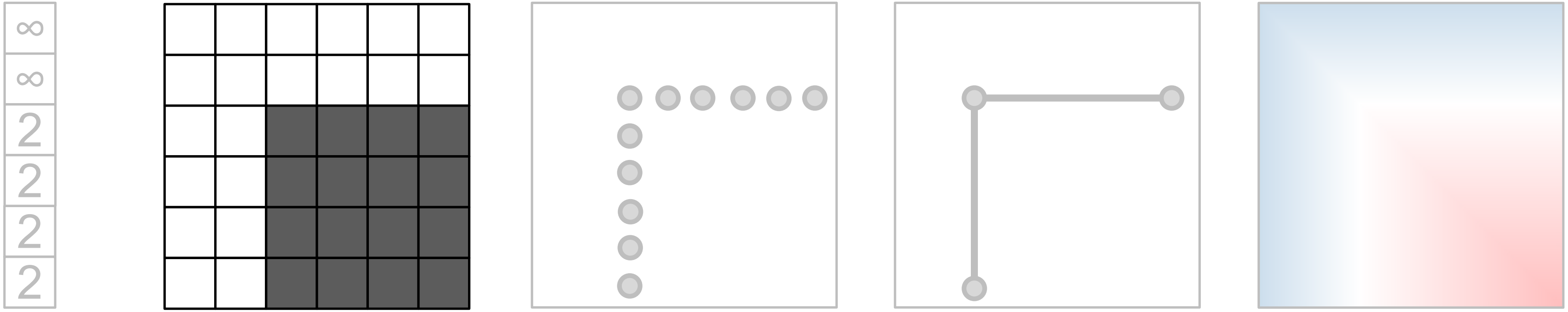
Fully Convolutional network

Predicted Normals:
3 x H x W

Recall:
$x \cdot y$
$= |x|\ |y| \cos \theta$

Eigen and Fergus, "Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture", ICCV 2015

3D Shape Representations



Depth Map

Voxel Grid

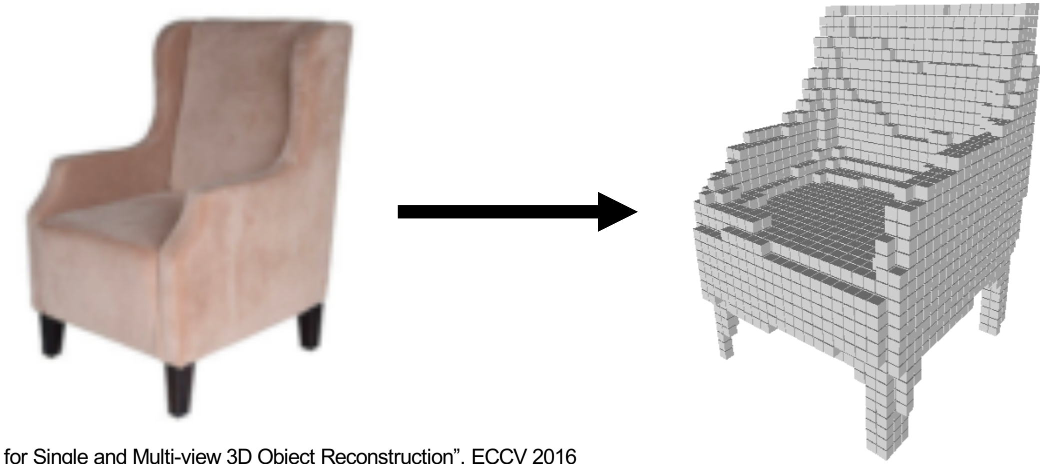
Pointcloud

Mesh

Implicit Surface

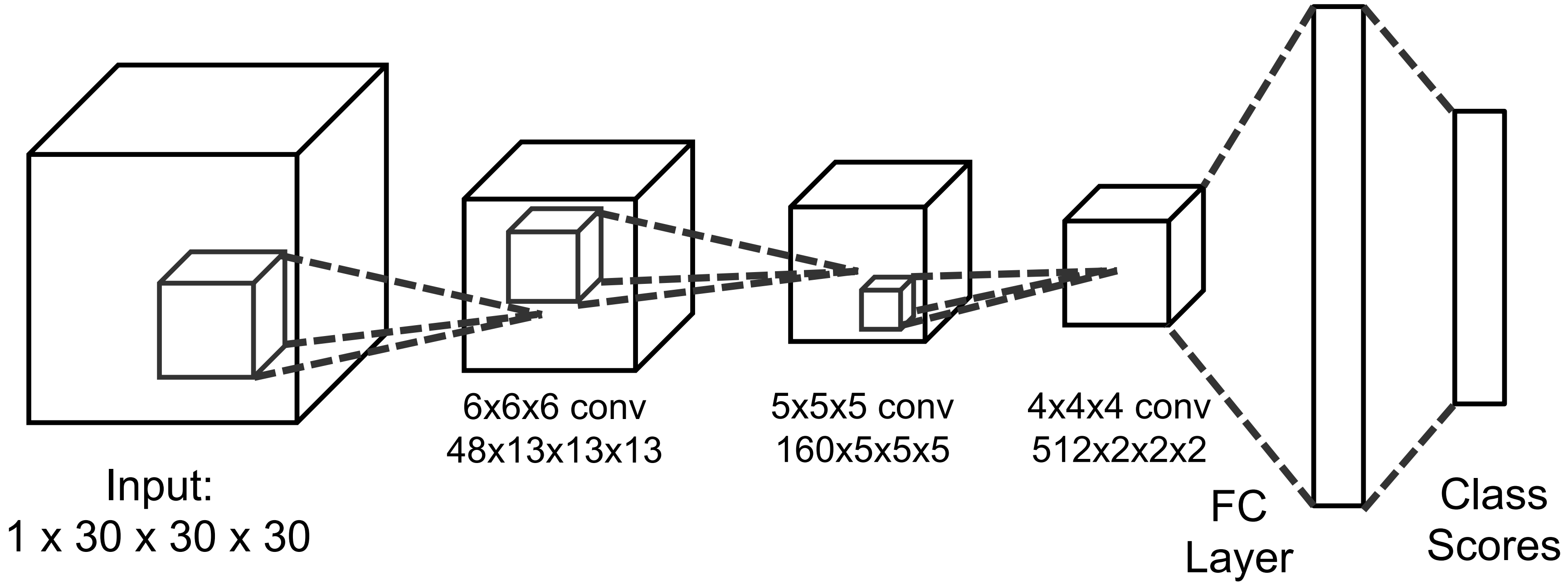
3D Shape Representations: Voxels

- Represent a shape with a V x V x V grid of occupancies
- Just like segmentation masks in Mask R-CNN, but in 3D!
- (+) Conceptually simple: just a 3D grid!
- (-) Need high spatial resolution to capture fine structures
- (-) Scaling to high resolutions is nontrivial!



Choy et al, “3D-R2N2: A Unified Approach for Single and Multi-view 3D Object Reconstruction”, ECCV 2016

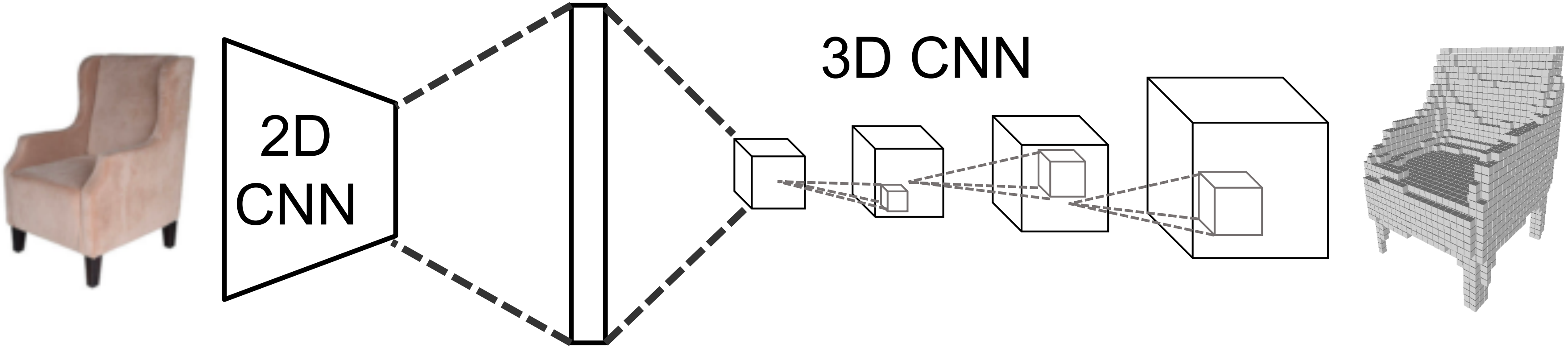
Processing Voxel Inputs: 3D Convolution



Train with classification loss

Wu et al, “3D ShapeNets: A Deep Representation for Volumetric Shapes”, CVPR 2015

Generating Voxel Shapes: 3D Convolution



Input image: 3 x 112 x 112

2D Features: C x H x W

3D Features: C' x D' x H' x W'

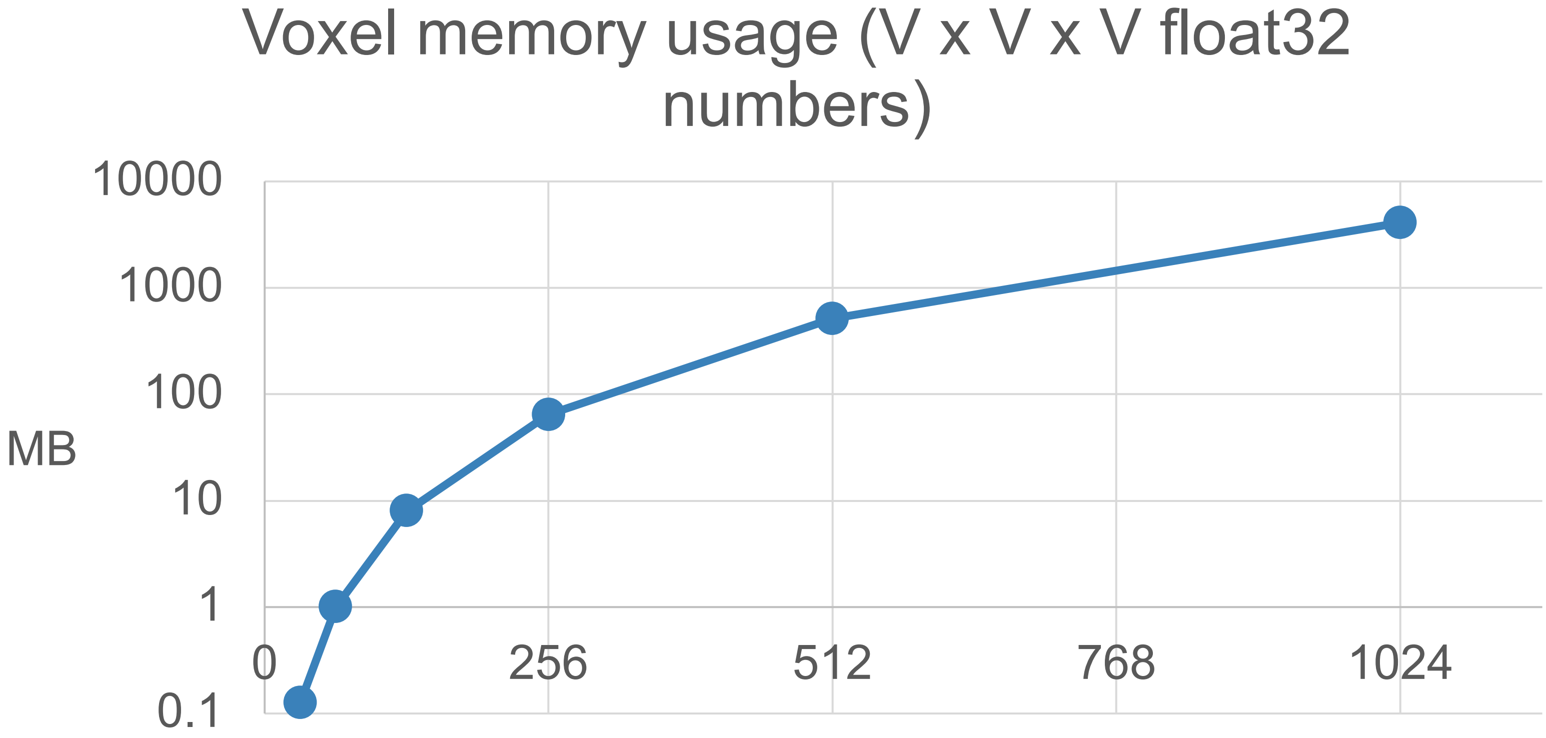
Voxels: 1 x V x V x V

Train with per-voxel cross-entropy loss

Choy et al, "3D-R2N2: A Unified Approach for Single and Multi-view 3D Object Reconstruction", ECCV 2016

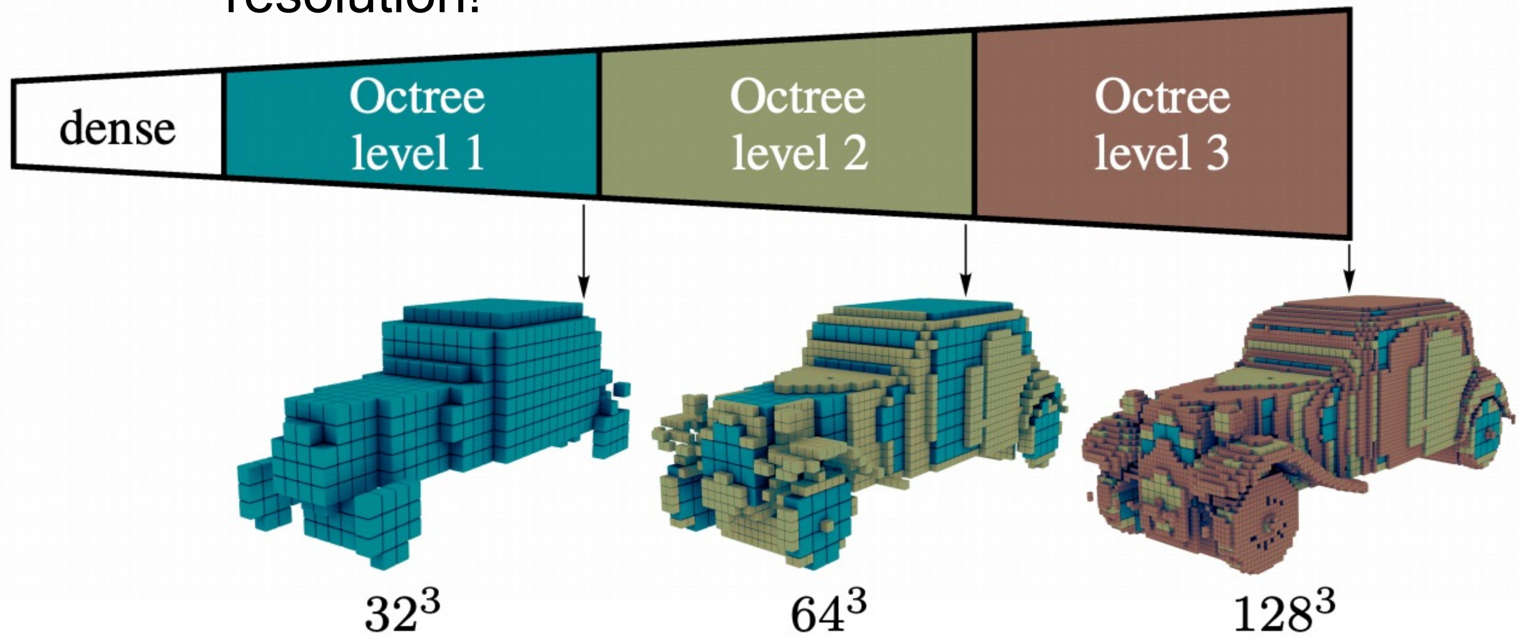
Voxel Problems: Memory Usage

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



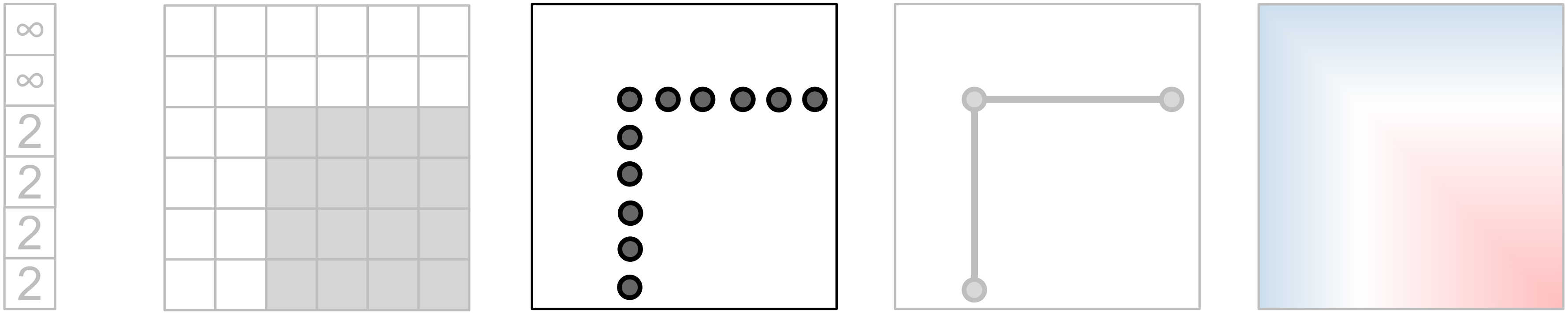
Scaling Voxels: Oct-Trees

Use voxel grids with heterogenous resolution!



Tatarchenko et al, "Octree Generating Networks: Efficient Convolutional Architectures for High-resolution 3D Outputs", ICCV 2017

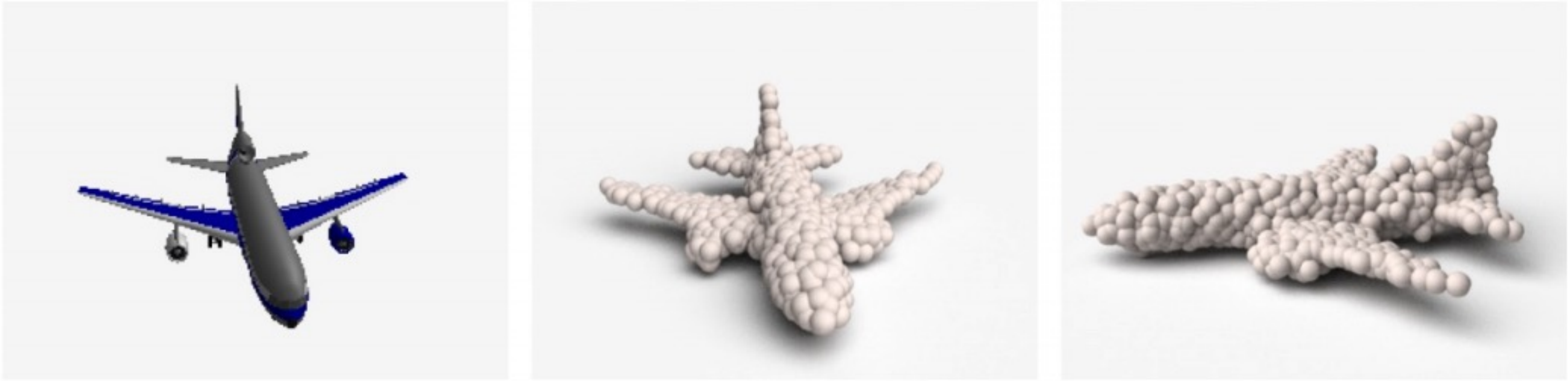
3D Shape Representations



Depth Map | Voxel Grid | **Pointcloud** | Mesh | Implicit Surface

3D Shape Representations: Point Cloud

- Represent shape as a set of P points in 3D space
- (+) Can represent fine structures without huge numbers of points
- ( ) Requires new architecture, losses, etc
- (-) Doesn't explicitly represent the surface of the shape: extracting a mesh for rendering or other applications requires post-processing



Fan et al, "A Point Set Generation Network for 3D Object Reconstruction from a Single Image", CVPR 2017

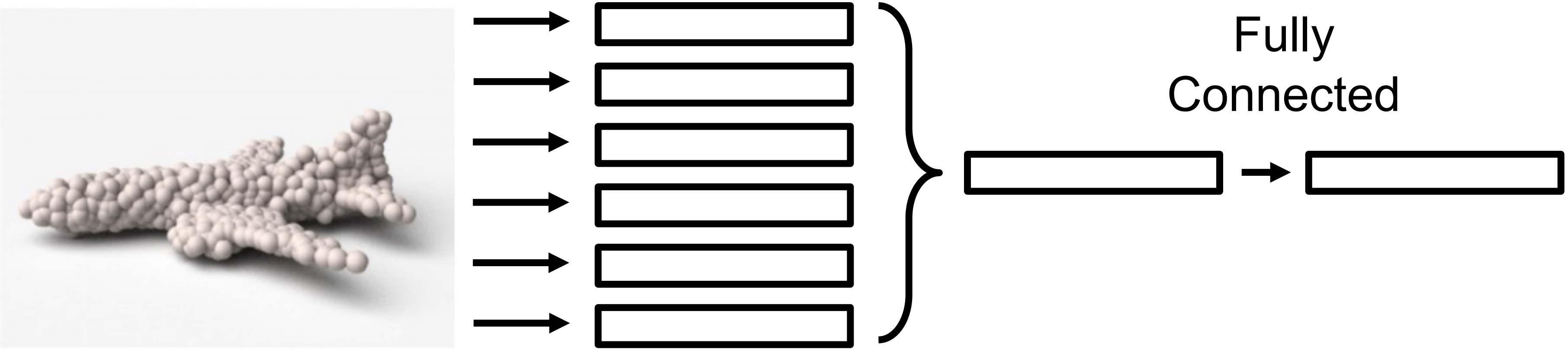
Processing Pointcloud Inputs: PointNet

Run MLP on each point

Max-Pool

Want to process pointclouds as **sets**: order should not matter

Fully Connected



Input pointcloud: P x 3

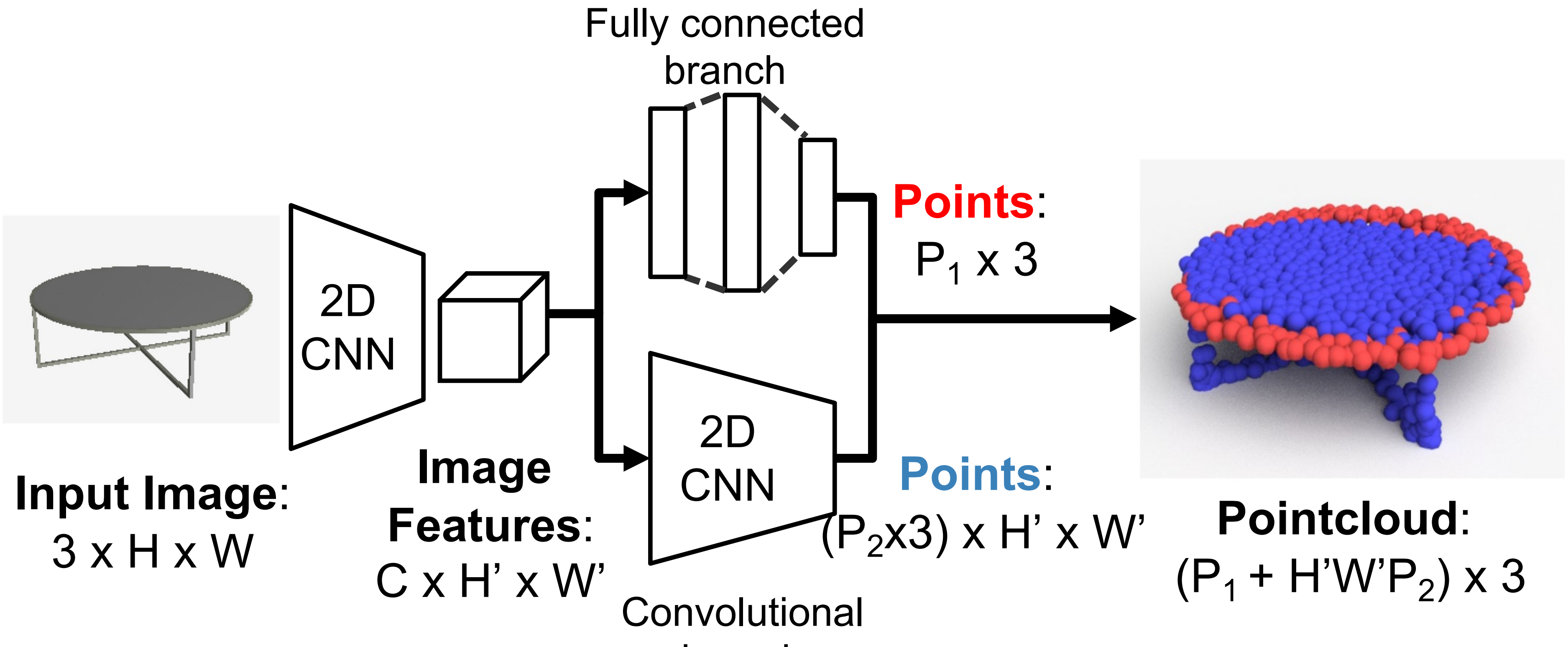
Point features: P x D

Pooled vector: D

Class score: C

Qi et al, "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation", CVPR 2017
Qi et al, "PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space", NeurIPS 2017

Generating Pointcloud Outputs



Fan et al, “A Point Set Generation Network for 3D Object Reconstruction from a Single Image”, CVPR 2017

Predicting Point Clouds: Loss Function

We need a (differentiable) way to compare pointclouds **as sets**!

Fan et al, "A Point Set Generation Network for 3D Object Reconstruction from a Single Image", CVPR 2017

Predicting Point Clouds: Loss Function

We need a (differentiable) way to compare pointclouds **as sets**!

Chamfer distance is the sum of L2 distance to each point's nearest neighbor in the other set

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2^2$$

Fan et al, "A Point Set Generation Network for 3D Object Reconstruction from a Single Image", CVPR 2017

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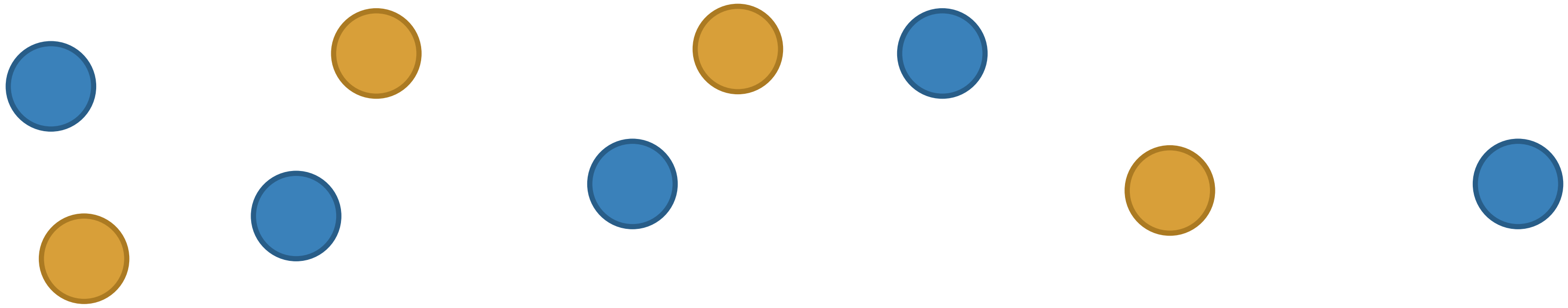

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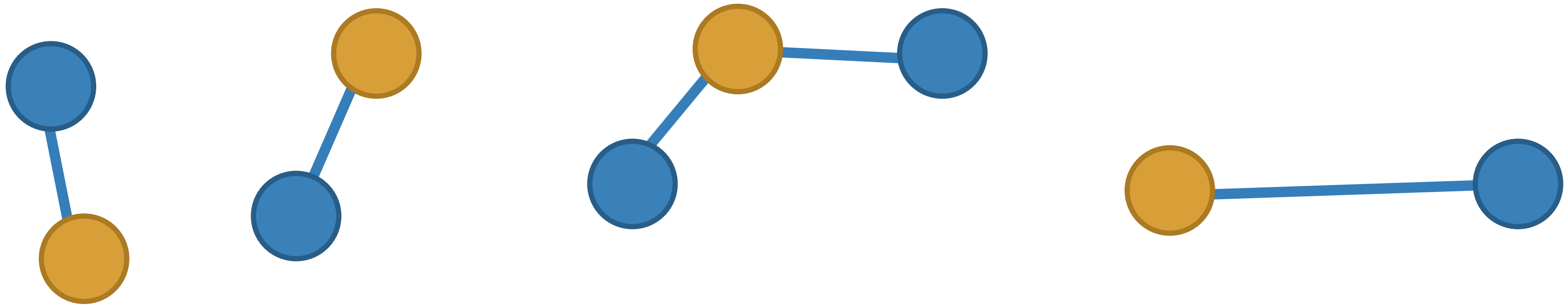

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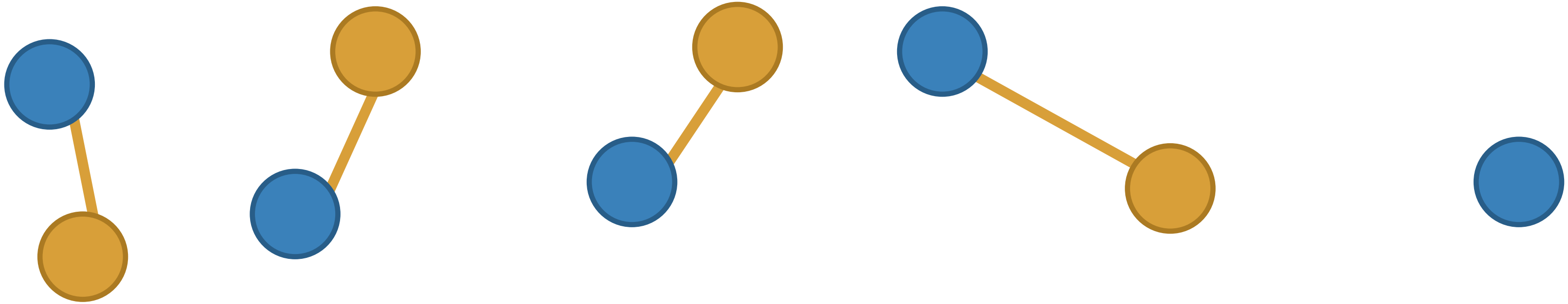
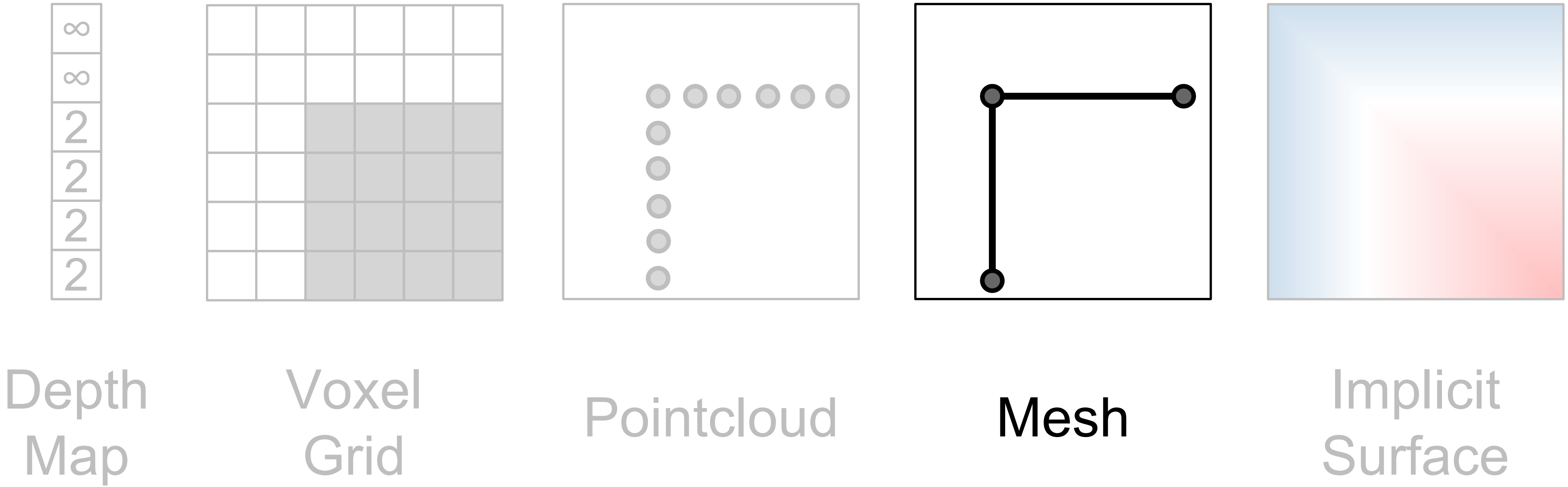


Fan et al, "A Point Set Generation Network for 3D Object Reconstruction from a Single Image", CVPR 2017

3D Shape Representations



3D Shape Representations: Triangle Mesh

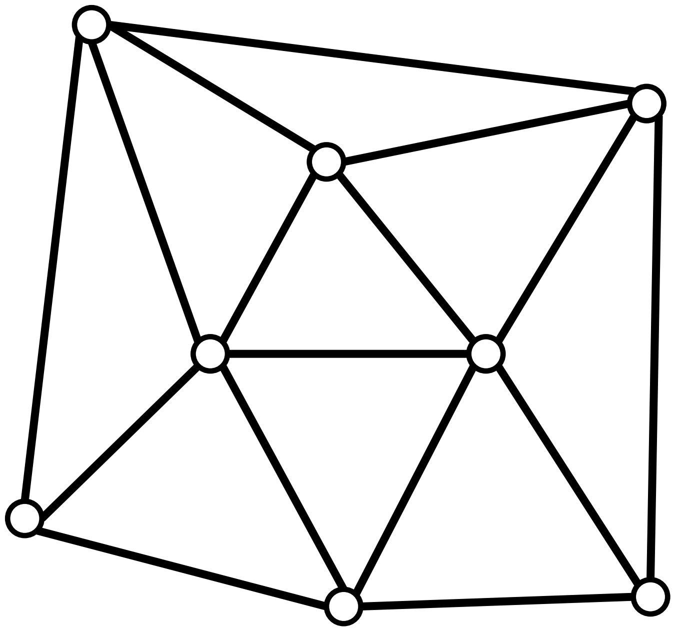
Represent a 3D shape as a set of triangles

Vertices: Set of V points in 3D space

Faces: Set of triangles over the vertices

(+) Standard representation for graphics

(+) Explicitly represents 3D shapes



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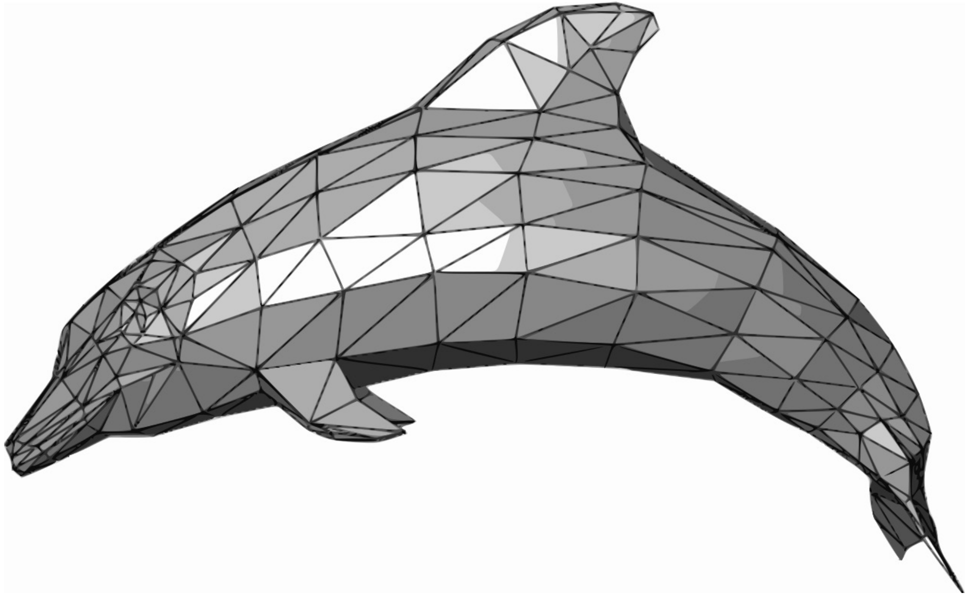
(+) Adaptive: Can represent flat surfaces very efficiently, can allocate more faces to areas with fine detail



Dolphin image is in the public domain

3D Shape Representations: Triangle Mesh

Represent a 3D shape as a set of triangles

Vertices: Set of V points in 3D space

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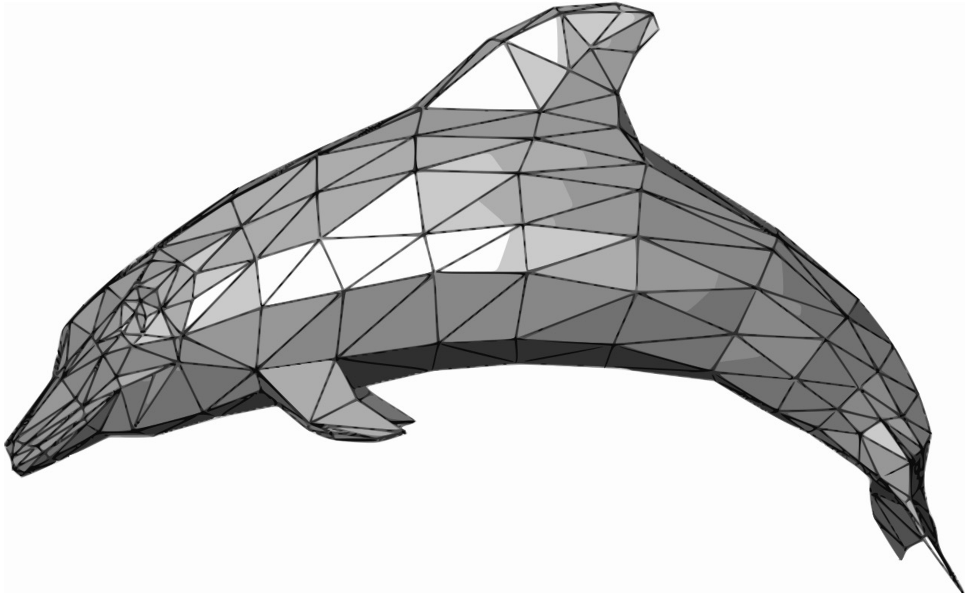
(+) Standard representation for graphics

(+) Explicitly represents 3D shapes

(+) Adaptive: Can represent flat surfaces very efficiently, can allocate more faces to areas with fine detail

(+) Can attach data on verts and interpolate over the whole surface: RGB colors, texture coordinates, normal vectors, etc.

(-) Nontrivial to process with neural networks

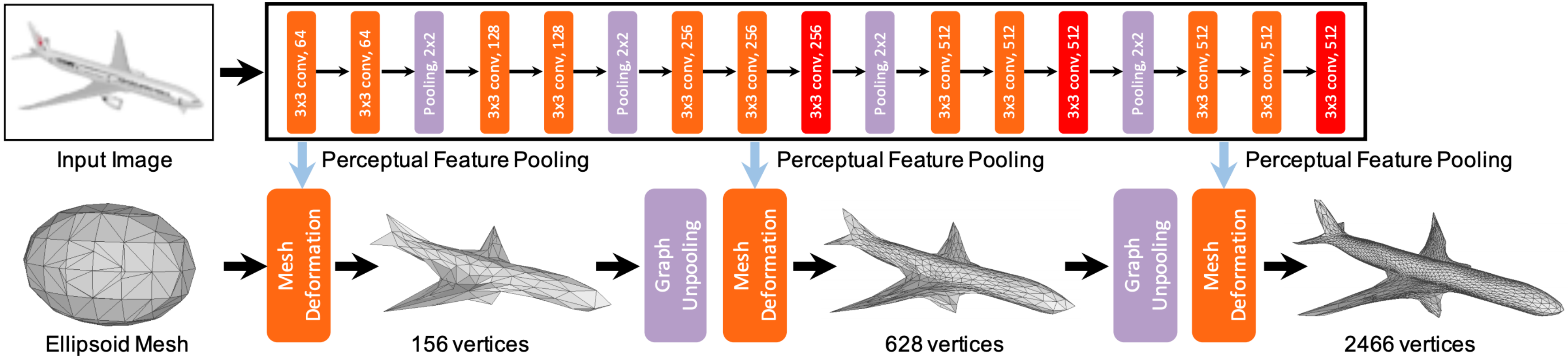


UV mapping figure is licensed under CC BY-SA 3.0. Figure slightly reorganized.

Predicting Meshes: Pixel2Mesh

Input: Single RGB Image of an object

Output: Triangle mesh for the object



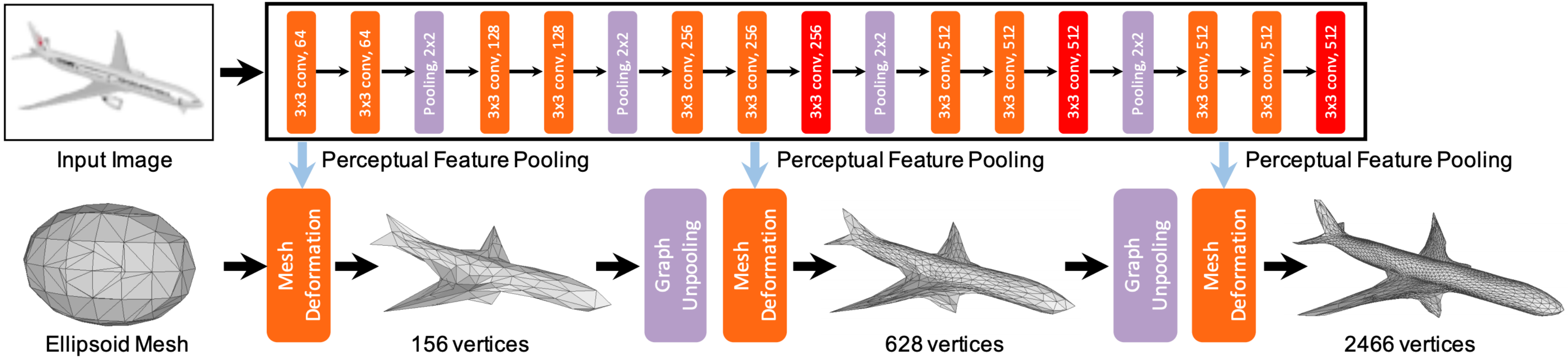
Wang et al, “Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images”, ECCV 2018

Predicting Meshes: Pixel2Mesh

Input: Single RGB Image of an object

Key ideas:
Iterative Refinement
Graph Convolution
Vertex Aligned-Features
Chamfer Loss Function

Output: Triangle mesh for the object



Wang et al, “Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images”, ECCV 2018

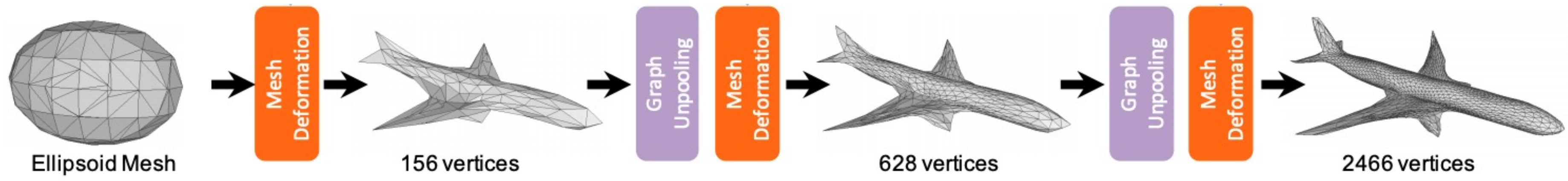
Predicting Triangle Meshes: Iterative Refinement

Idea #1: Iterative mesh refinement

Start from initial ellipsoid mesh

Network predicts offsets for each vertex

Repeat.



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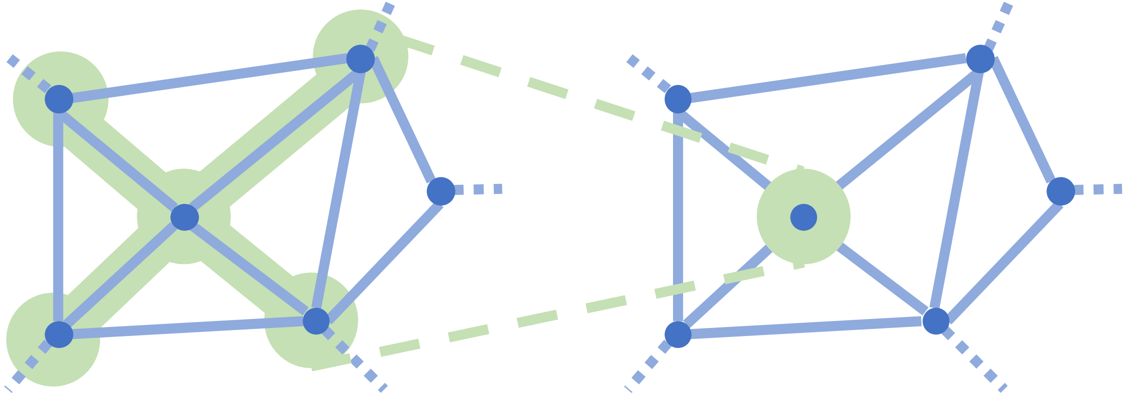
Predicting Triangle Meshes: Graph Convolution

$$f_i' = W_0 f_i + \sum_{j \in N(i)} W_1 f_j$$

Vertex v_i has feature f_i

New feature f_i' for vertex v_i depends on feature of neighboring vertices $N(i)$

Use same weights W_0 and W_1 to compute all outputs

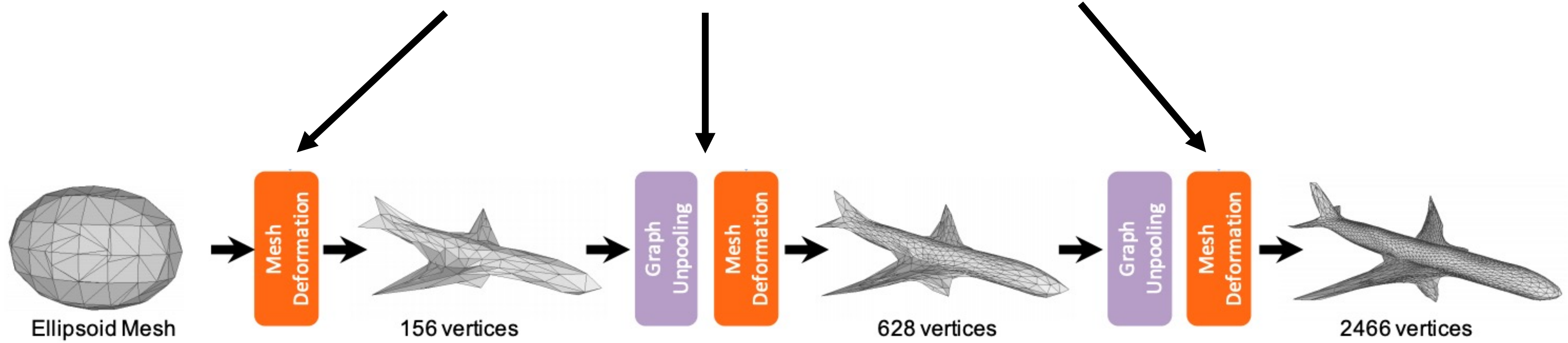


Input: Graph with a feature vector at each vertex

Output: New feature vector for each vertex

Predicting Triangle Meshes: Graph Convolution

Each of these blocks consists of a stack of **graph convolution layers** operating on edges of the mesh

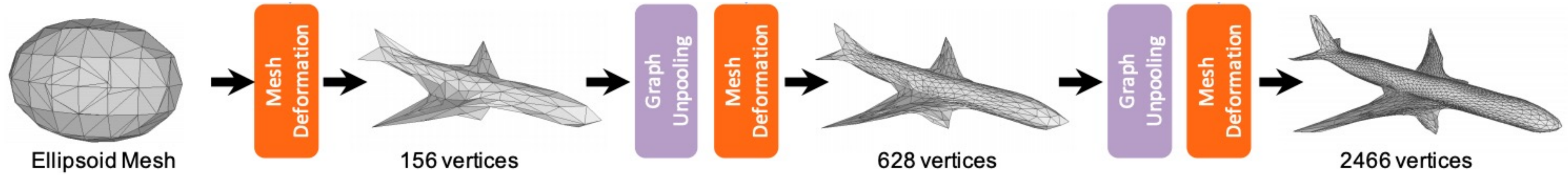


Wang et al, “Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images”, ECCV 2018

Predicting Triangle Meshes: Graph Convolution

Each of these blocks consists of a stack of **graph convolution layers** operating on edges of the mesh

Problem: How to incorporate image features?



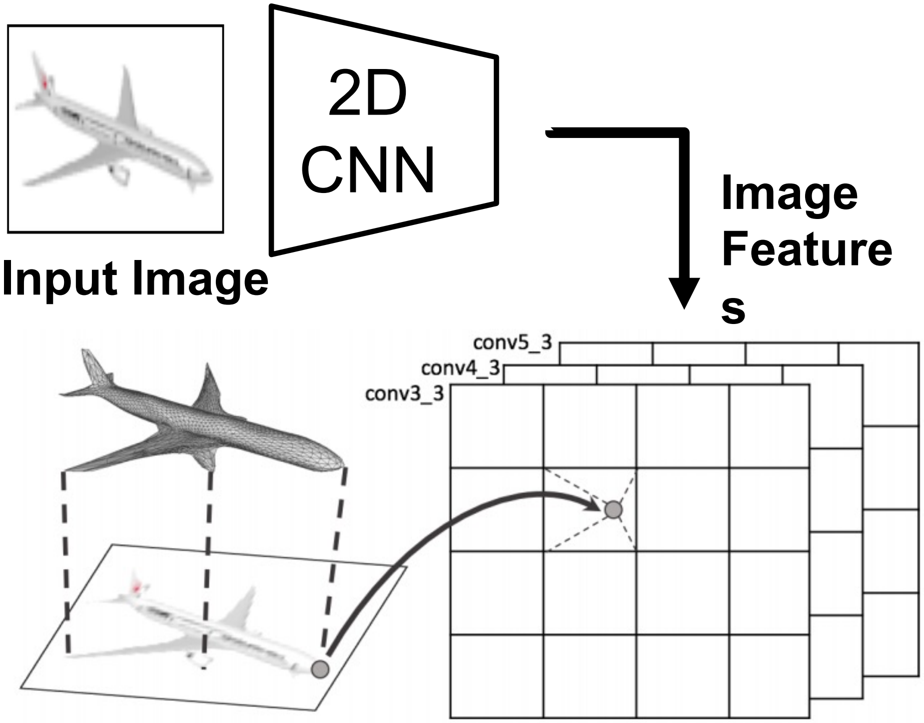
Wang et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images", ECCV 2018

Predicting Triangle Meshes: Vertex-Aligned Features

Idea #2: Aligned vertex features

For each vertex of the mesh:

- Use camera information to project onto image plane
- Use bilinear interpolation to sample a CNN feature



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Predicting Triangle Meshes: Vertex-Aligned Features

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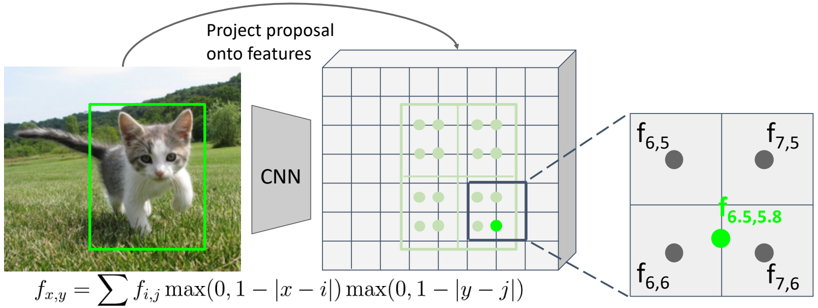
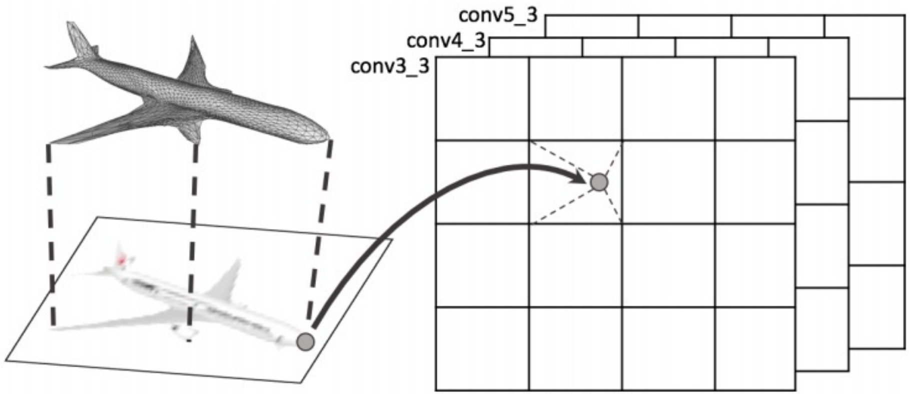
For each vertex of the mesh:

- Use camera information to project onto image plane
- Use bilinear interpolation to sample a CNN feature

Similar to RoI-Align operation from detection: maintains alignment between input image and feature vectors



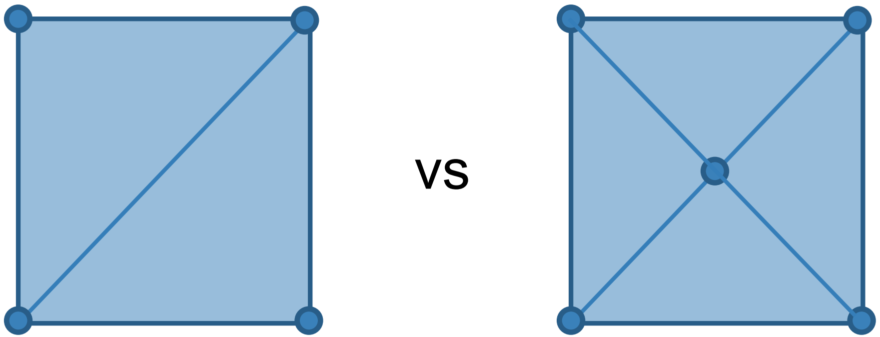
$$f_{x,y} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - i|) \max(0, 1 - |y - j|)$$



Wang et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images", ECCV 2018

Predicting Meshes: Loss Function

The same shape can be represented with different meshes – how can we define a loss between predicted and ground-truth mesh?



Prediction Ground-Truth

Wang et al, “Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images”, ECCV 2018

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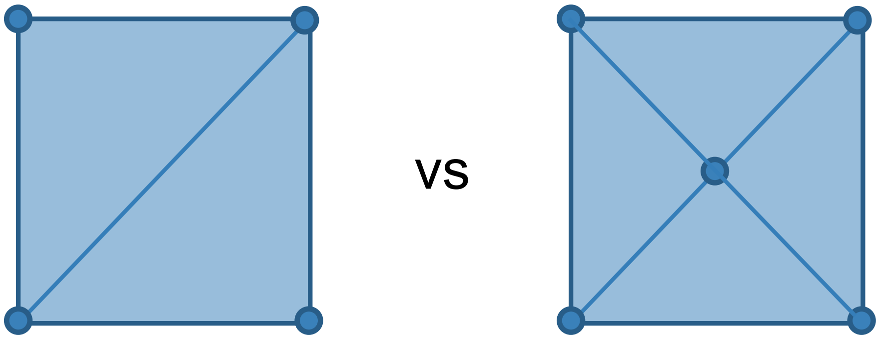
Idea: Convert meshes to pointclouds, then compute loss



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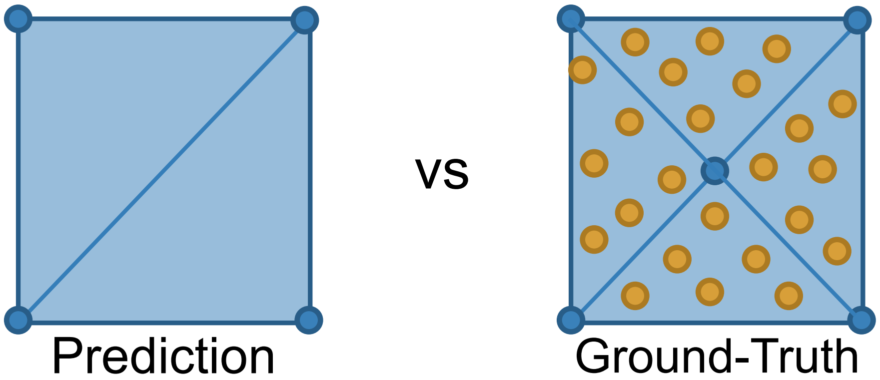


Sample points from the surface of the ground-truth mesh (offline)

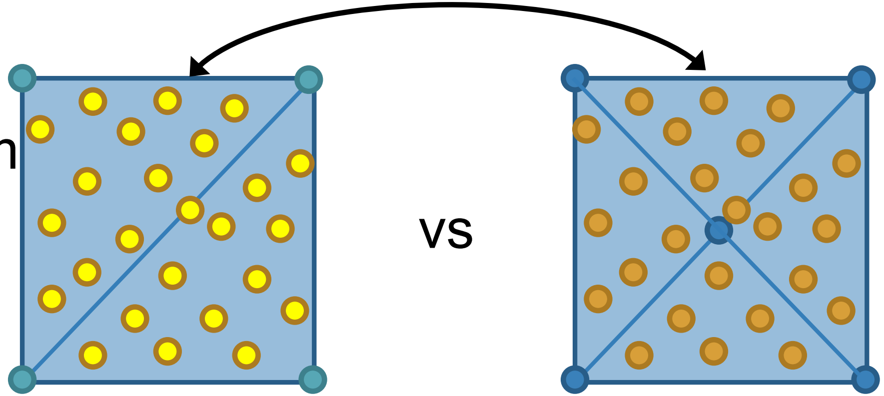
Wang et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images", ECCV 2018

Predicting Meshes: Loss Function

The same shape can be represented with different meshes – how can we define a loss between predicted and ground-truth mesh?

Loss = Chamfer distance between **predicted verts** and **ground-truth samples**

Sample points from the surface of the predicted mesh (online)



Prediction

Ground-Truth

Sample points from the surface of the ground-truth mesh (offline)

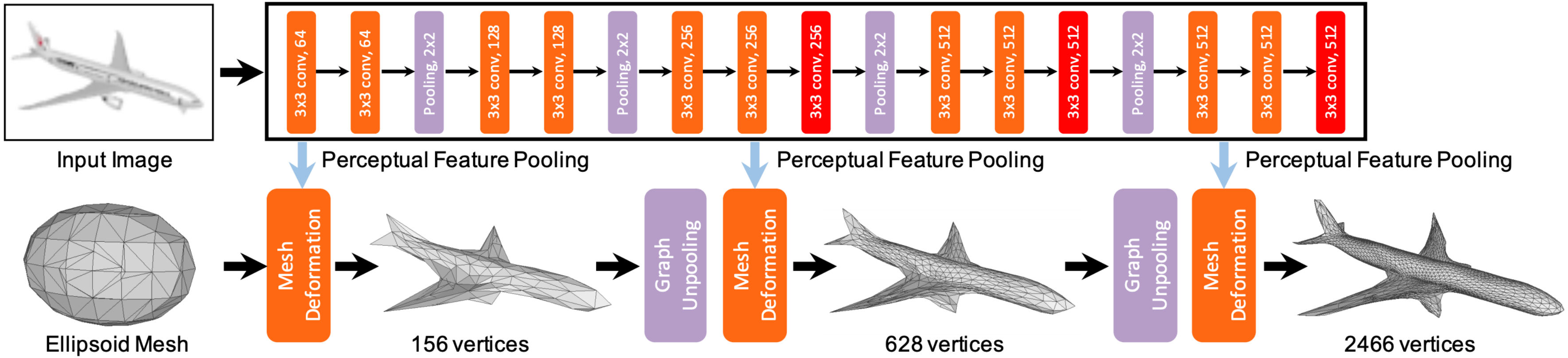
Wang et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images", ECCV 2018

Predicting Meshes: Pixel2Mesh

Input: Single RGB Image of an object

Key ideas:
Iterative Refinement
Graph Convolution
Vertex Aligned-Features
Chamfer Loss Function

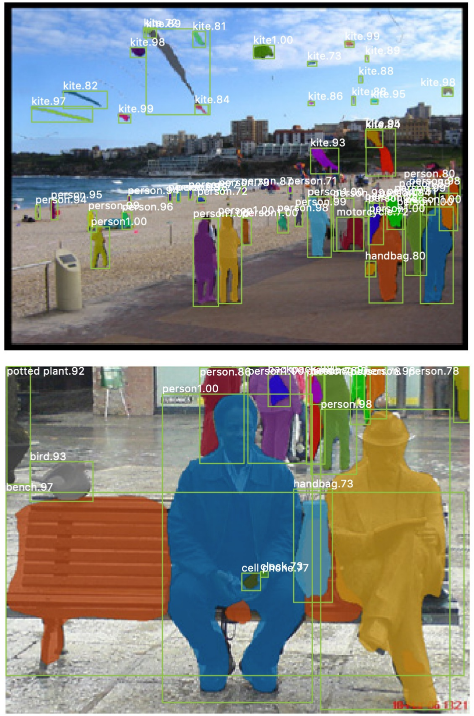
Output: Triangle mesh for the object



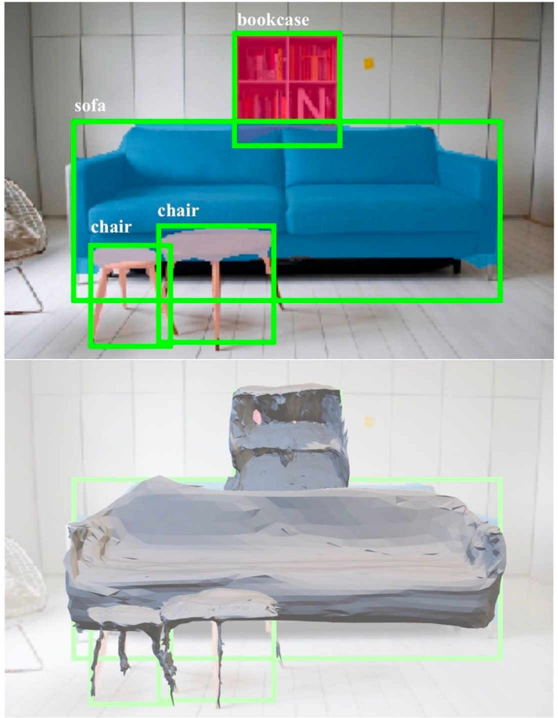
Wang et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images", ECCV 2018

3D Shape Prediction: Mesh R-CNN

Mask R-CNN:
2D Image -> 2D shapes



Mesh R-CNN:
2D Image -> **Triangle Meshes**



He, Gkioxari, Dollár, and Girshick, "Mask R-CNN", ICCV 2017

Gkioxari, Malik, and Johnson, "Mesh R-CNN", ICCV 2019

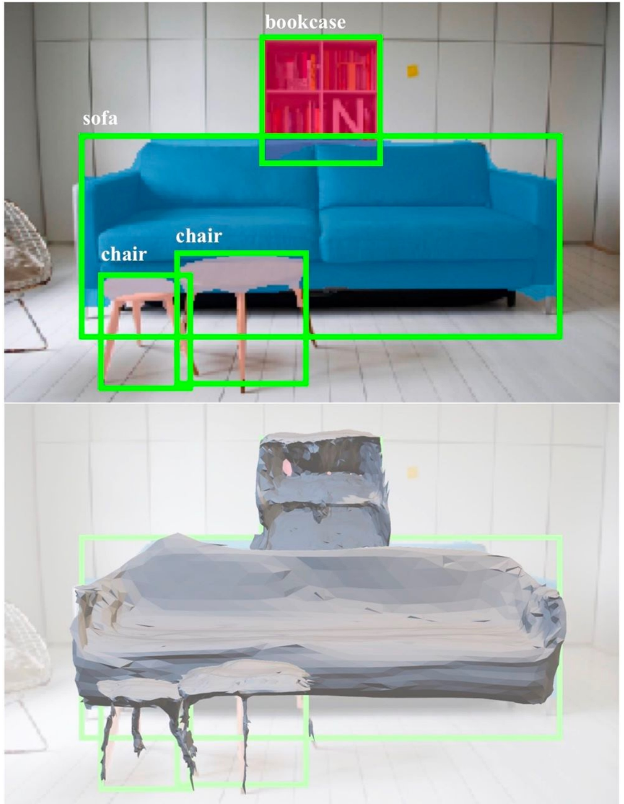
Mesh R-CNN: Task

Input: Single RGB image

Output:
A set of detected objects
For each object:
- Bounding box
- Category label
- Instance segmentation
- 3D triangle mesh

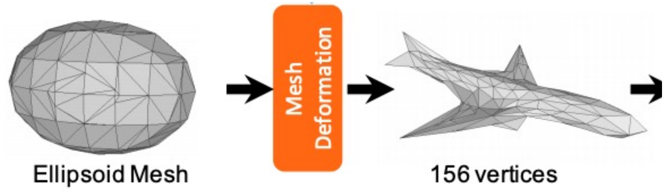
Mask R-CNN

Mesh head



Mesh R-CNN: Hybrid 3D shape representation

Mesh deformation gives good results, but the topology (verts, faces, genus, connected components) fixed by the initial mesh



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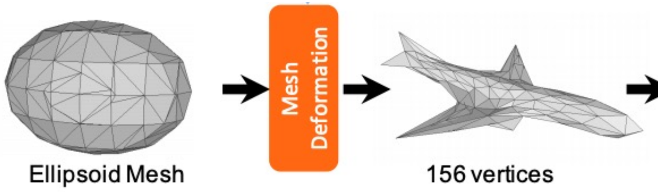
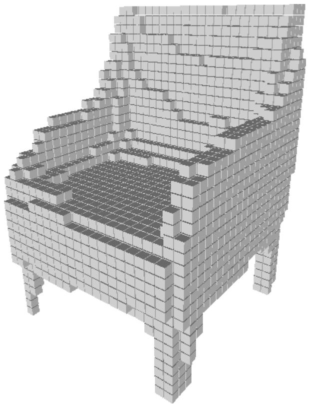


Mesh R-CNN: Use voxel predictions to create initial mesh prediction!



Mesh R-CNN Pipeline

Input image

Mesh R-CNN Pipeline

Input image

2D object recognition

Mesh R-CNN Pipeline

Input image

2D object recognition

3D object voxels

Mesh R-CNN Pipeline

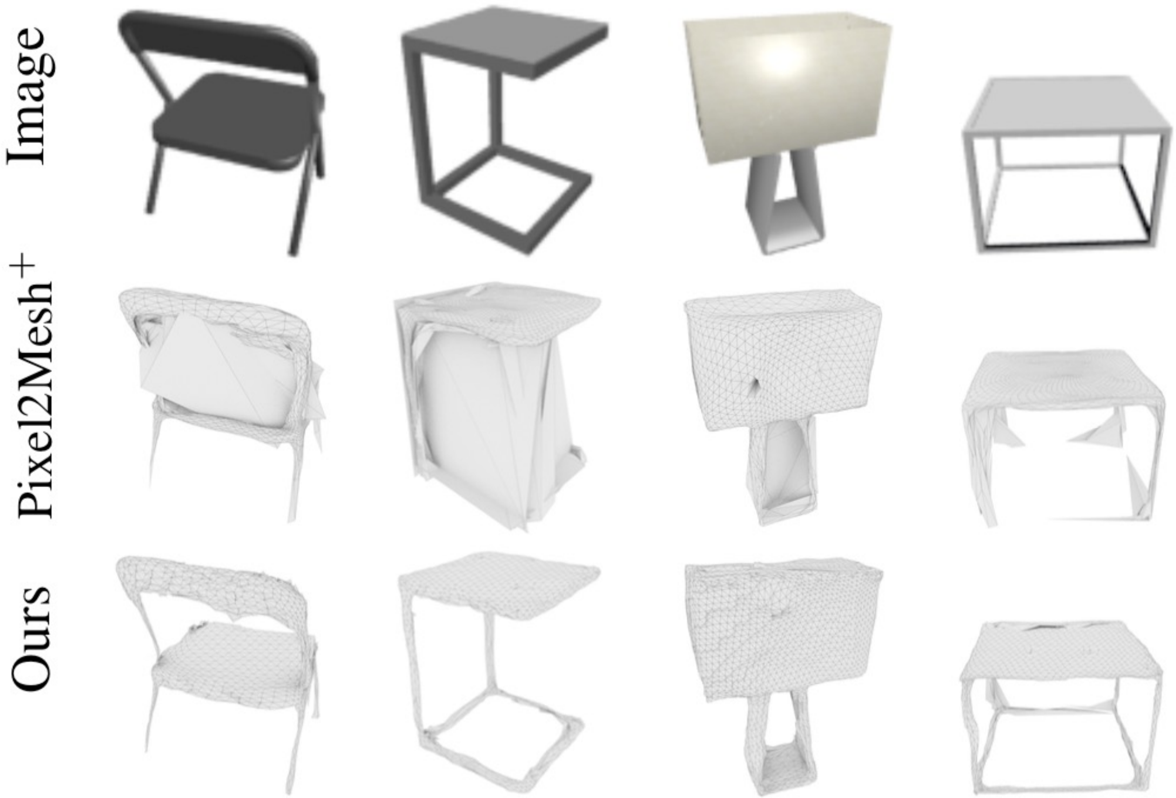
Input image

2D object recognition

3D object voxels

3D object meshes

Mesh R-CNN: ShapeNet Results

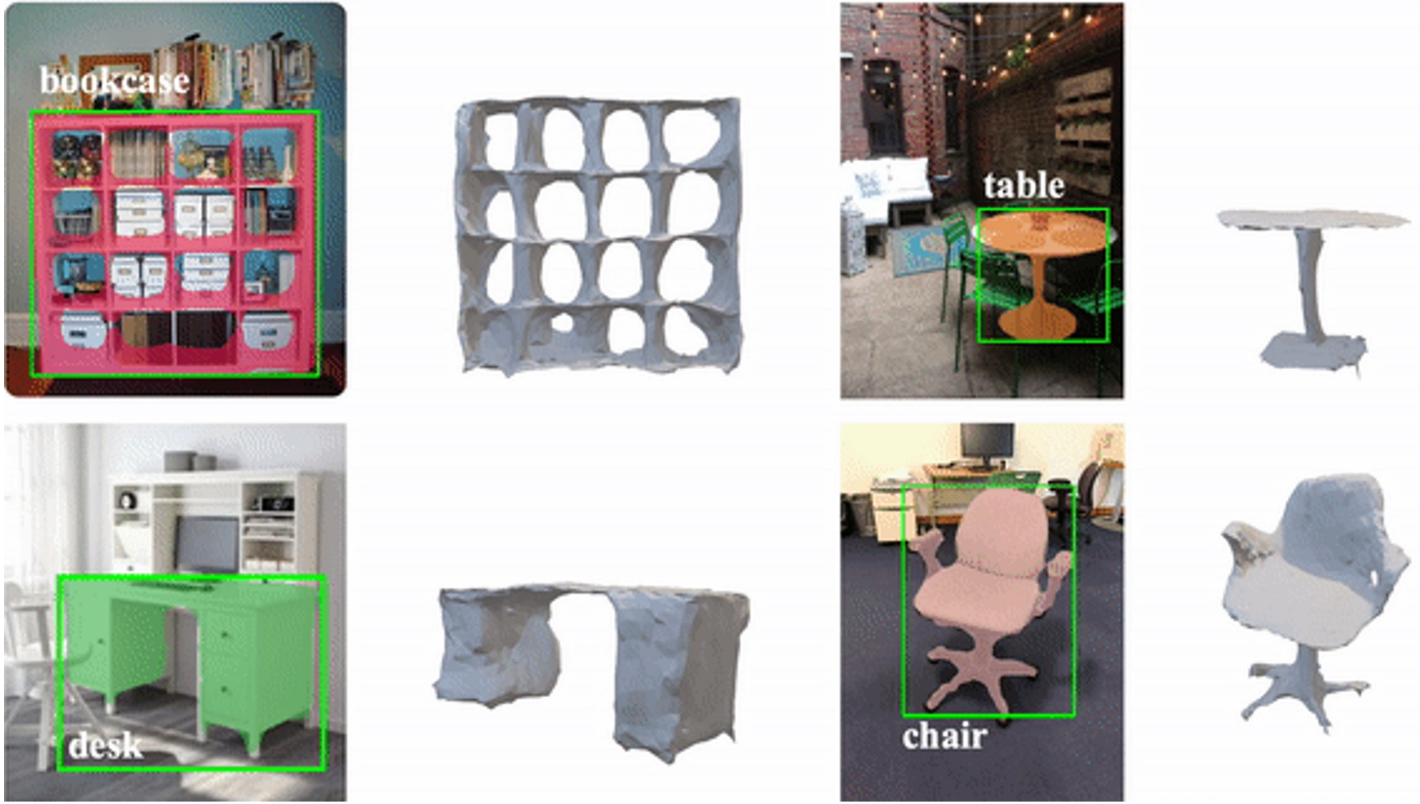


Datasets for 3D Objects

- 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

Mesh R-CNN: Pix3D Results



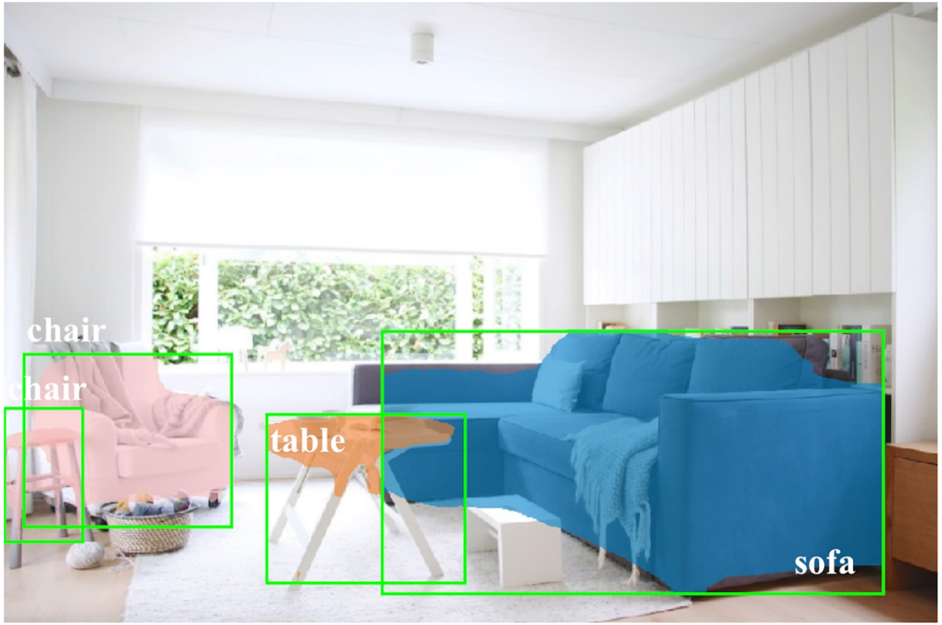
Pix3D

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

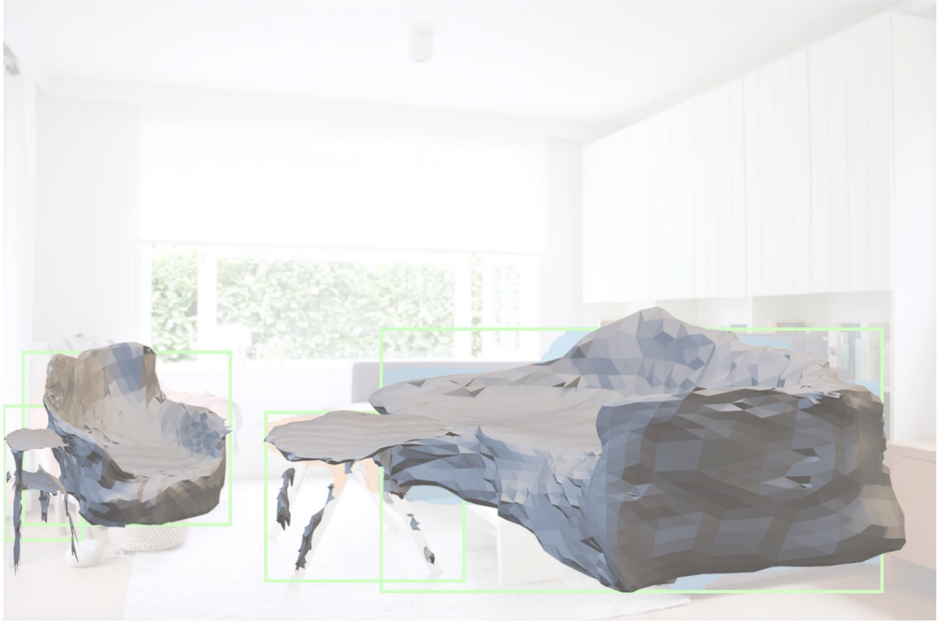
Sun et al. CVPR 2018, building upon Lim et al. ICCV 2013

Mesh R-CNN: Pix3D Results

Predicting many objects per scene



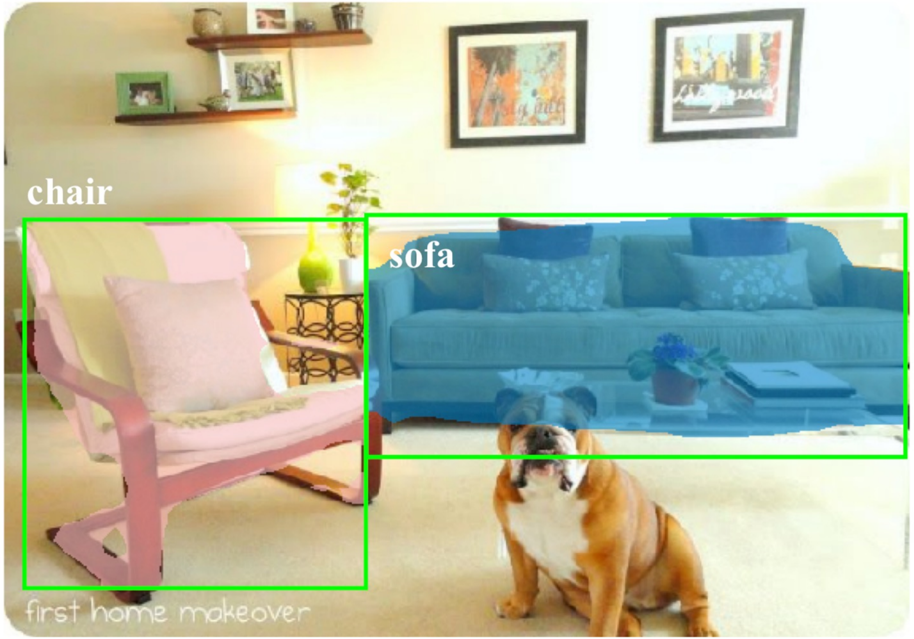
Box & Mask Predictions



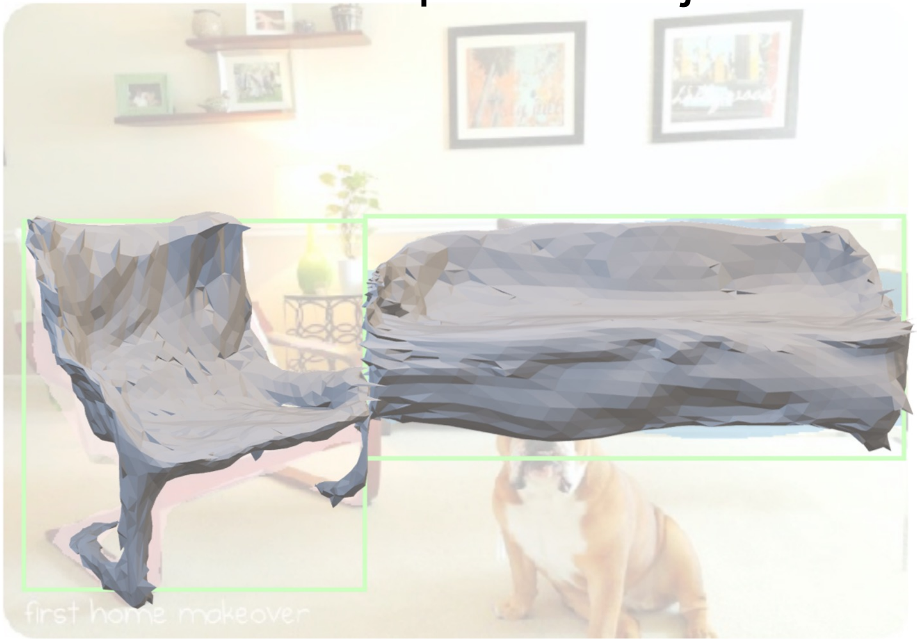
Mesh Predictions

Mesh R-CNN: Pix3D Results

Amodal completion: predict occluded parts of objects



Box & Mask Predictions



Mesh Predictions

Mesh R-CNN: Pix3D Results

Segmentation failures propagate to meshes

Box & Mask Predictions

Mesh Predictions

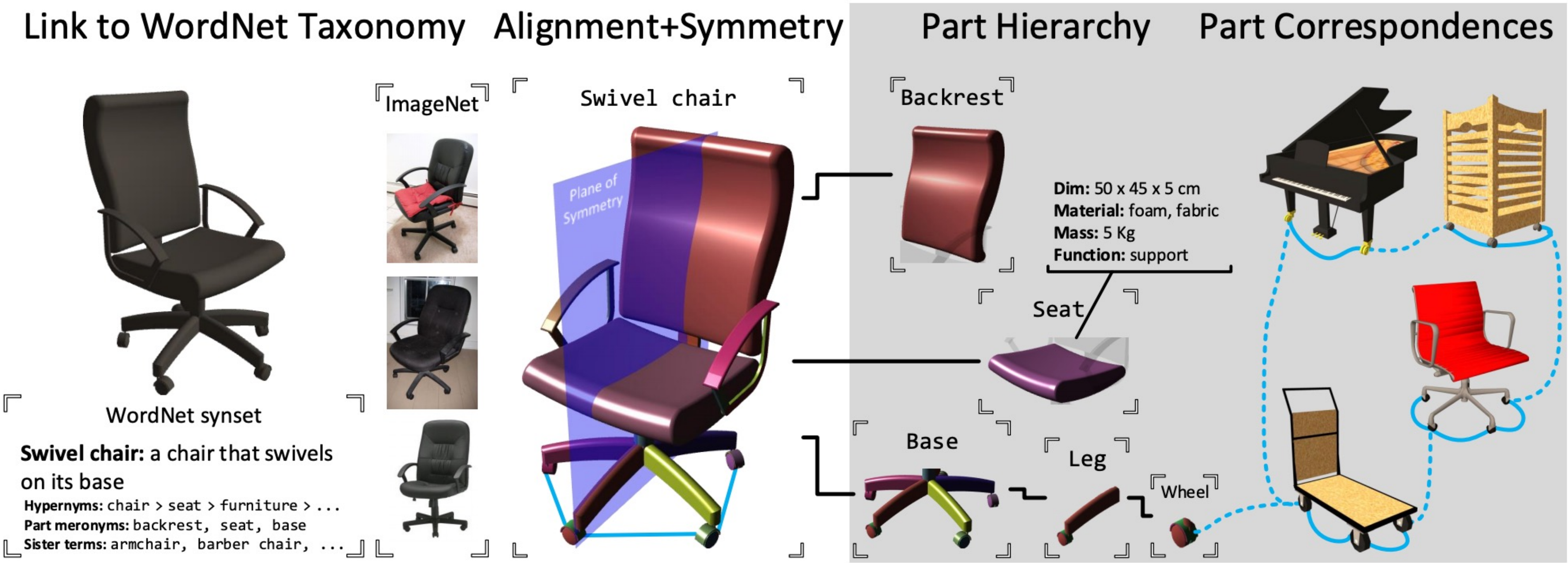
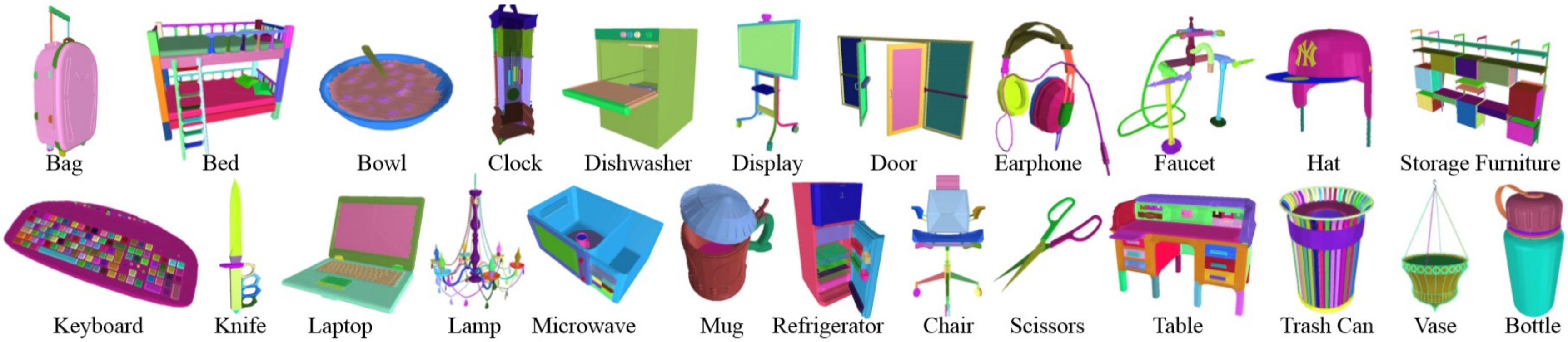


Figure from the ShapeNet paper, Chang et al. arXiv 2015

Datasets for 3D Object Parts

Fine-grained Parts: PartNet

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



Mo et al. CVPR 2019
Slide credit: Hao Su

Physical Interaction with Articulated Objects

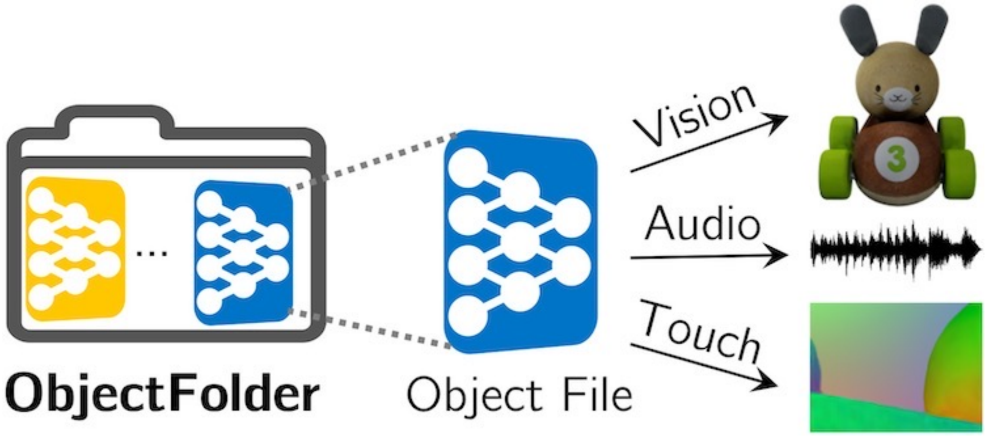
300+ door annotations

support articulated objects

(cabinets, doors, fridge, oven, window etc.)

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

ObjectFolder



Multisensory neural objects

Multisensory real objects

Gao et al. CVPR 2023. https://objectfolder.stanford.edu/

Visual Data in ObjectFolder Real

Gao et al. CVPR 2023. https://objectfolder.stanford.edu/

Acoustic Data in ObjectFolder Real

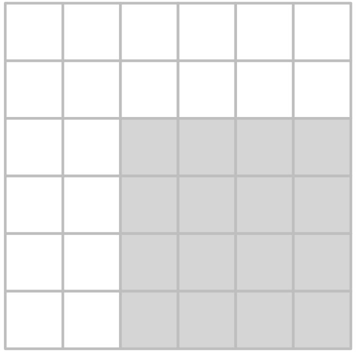
Gao et al. CVPR 2023. https://objectfolder.stanford.edu/

Tactile Data in ObjectFolder Real

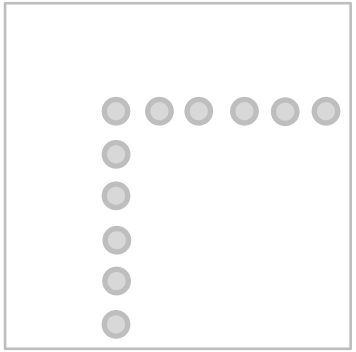
Gao et al. CVPR 2023. https://objectfolder.stanford.edu/

3D Shape Representations

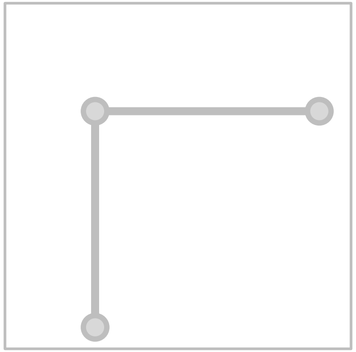
Depth Map



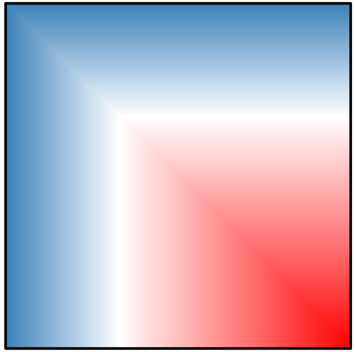
Voxel Grid



Pointcloud



Mesh

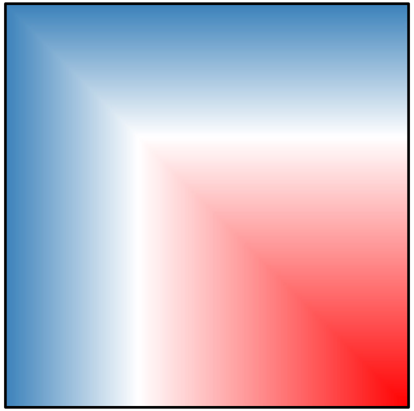


Implicit Surface

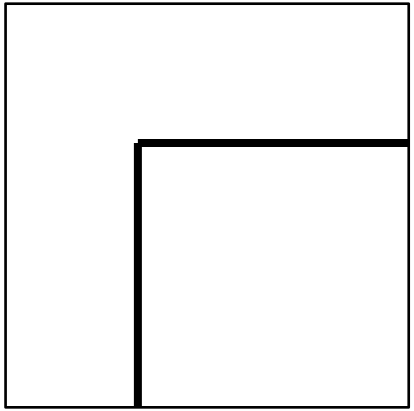
3D Shape Representations: Implicit Functions

Learn a function to classify arbitrary 3D points as inside / outside the shape $o : \mathbb{R}^3 \to \{0, 1\}$

The surface of the 3D object is the level set $\{x : o(x) = \frac{1}{2}\}$



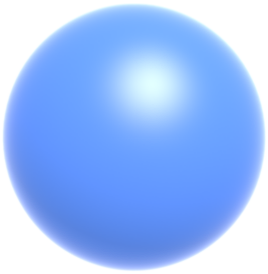
Implicit function



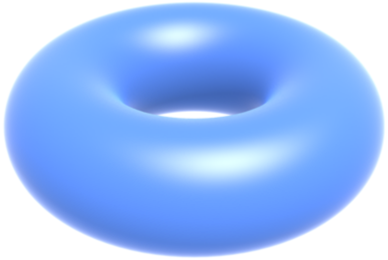
Explicit Shape

Algebraic Surfaces (Implicit)

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



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



$$(R-\sqrt{x^2+y^2})^2+z^2=r^2$$

$$\left(x^2+\frac{9y^2}{4}+z^2-1\right)^3 = x^2z^3+\frac{9y^2z^3}{80}$$

Slide credit: Ren Ng

Algebraic Surfaces (Implicit)

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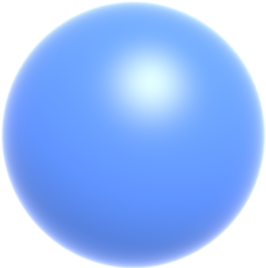

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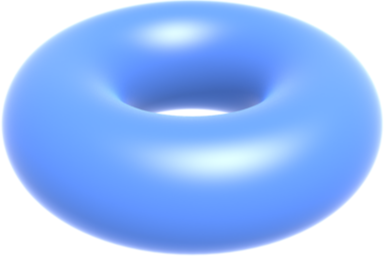

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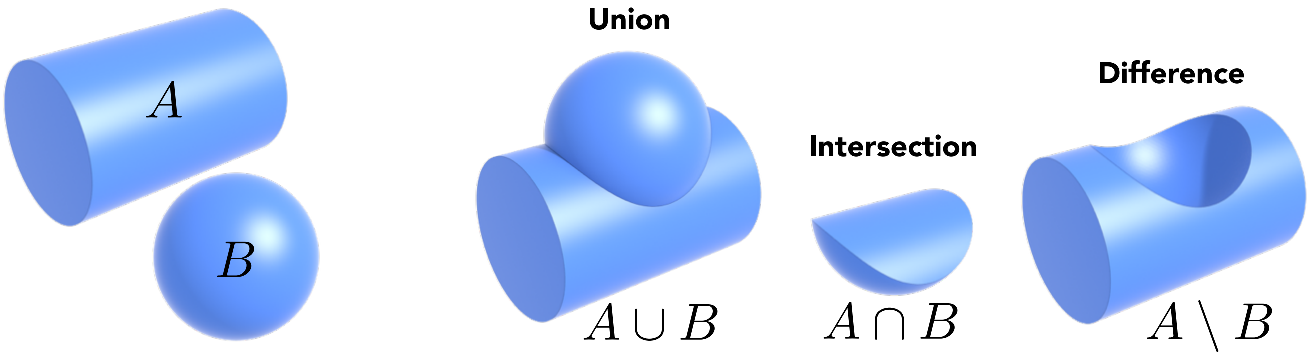
$$(x^2+\frac{9y^2}{4}+z^2-1)^3 = x^2z^3+\frac{9y^2z^3}{80}$$

More complex shapes?

Slide credit: Ren Ng

Constructive Solid Geometry (Implicit)

Combine implicit geometry via Boolean operations



Slide credit: Ren Ng

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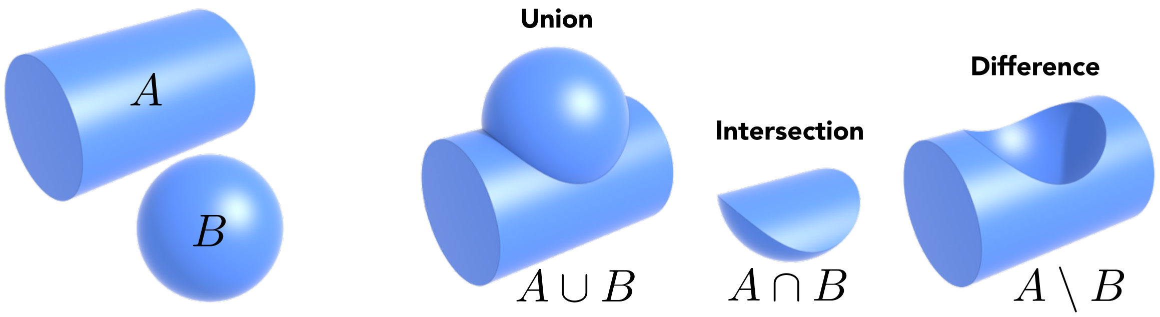
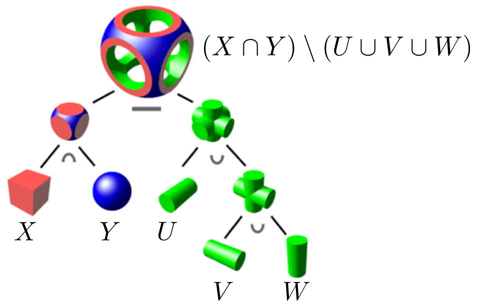


Boolean expressions:



CS184/284A

Ren Ng

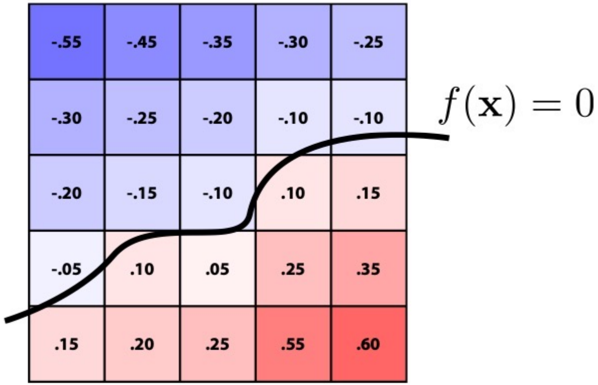
Slide credit: Ren Ng

Level Set Methods (Implicit)

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

But, hard to describe complex shapes in closed form

Alternative: store a grid of values approximating function



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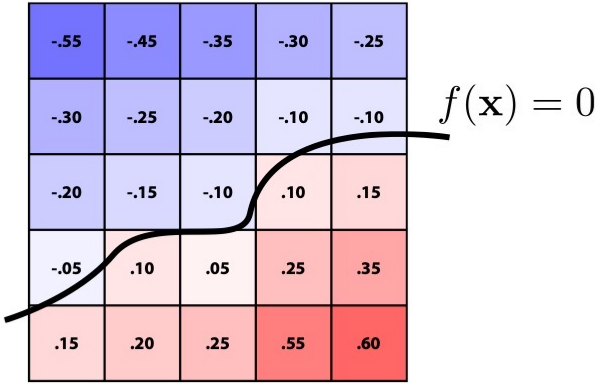
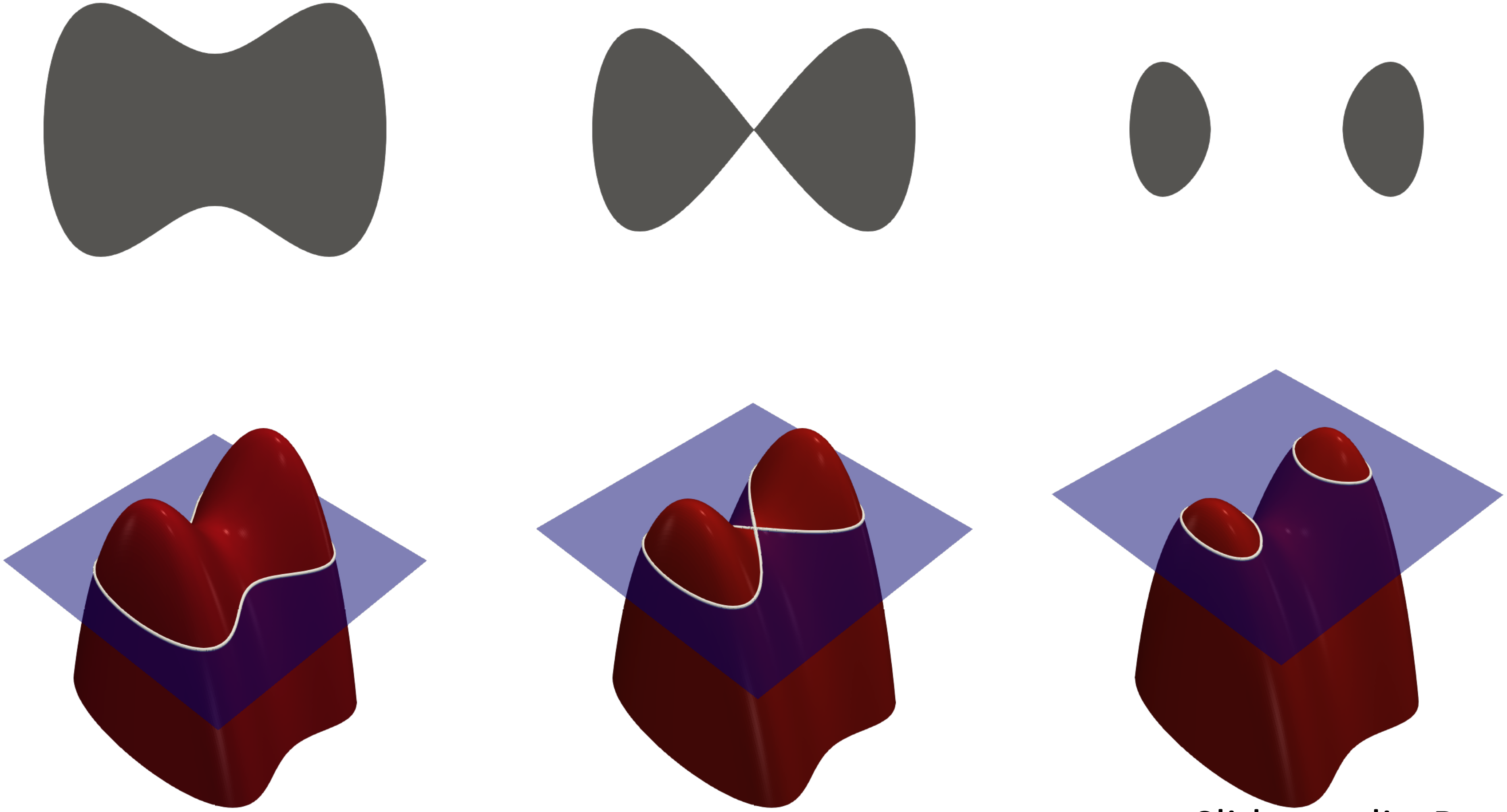


Surface is found where interpolated values equal zero

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

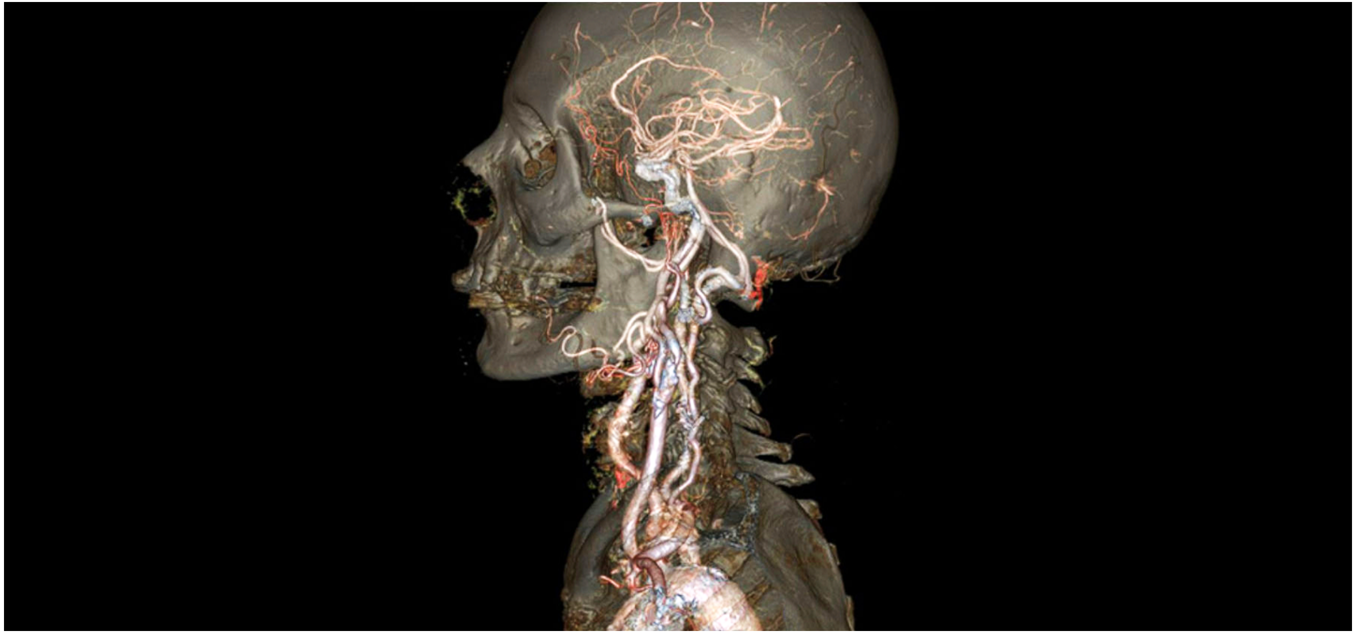
Slide credit: Ren Ng



Slide credit: Ren Ng

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

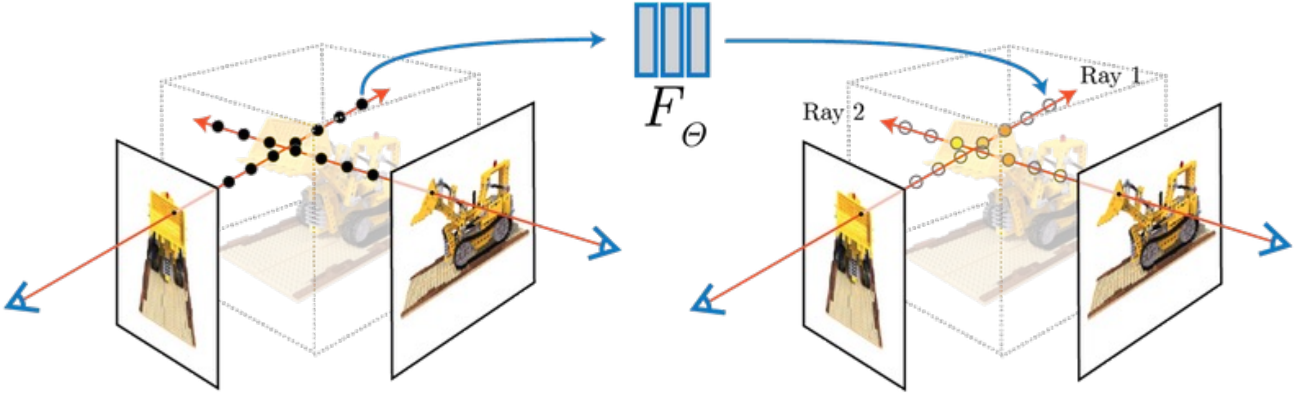
Level sets encode, e.g., constant tissue density



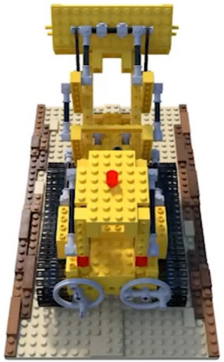
Slide credit: Ren Ng

Mildenhall et al, “Representing Scenes as Neural Radiance Fields for View Synthesis”, ECCV 2020

NeRF: Representing Scenes as Neural Radiance Fields



Novel view synthesis



$$\underbrace{(x, y, z,}_{\text{Scene location}} \underbrace{\theta, \phi)}_{\text{Viewing direction}} \rightarrow F_\theta \rightarrow \underbrace{(r, g, b,}_{\text{Output color}} \underbrace{\sigma)}_{\text{Output density}}$$

Mildenhall et al, “Representing Scenes as Neural Radiance Fields for View Synthesis”, ECCV 2020

Mildenhall et al, “Representing Scenes as Neural Radiance Fields for View Synthesis”, ECCV 2020

Mildenhall et al, “Representing Scenes as Neural Radiance Fields for View Synthesis”, ECCV 2020

Main Problem: Very slow!

Training: 1-2 days on a V100 GPU, for just a single scene!

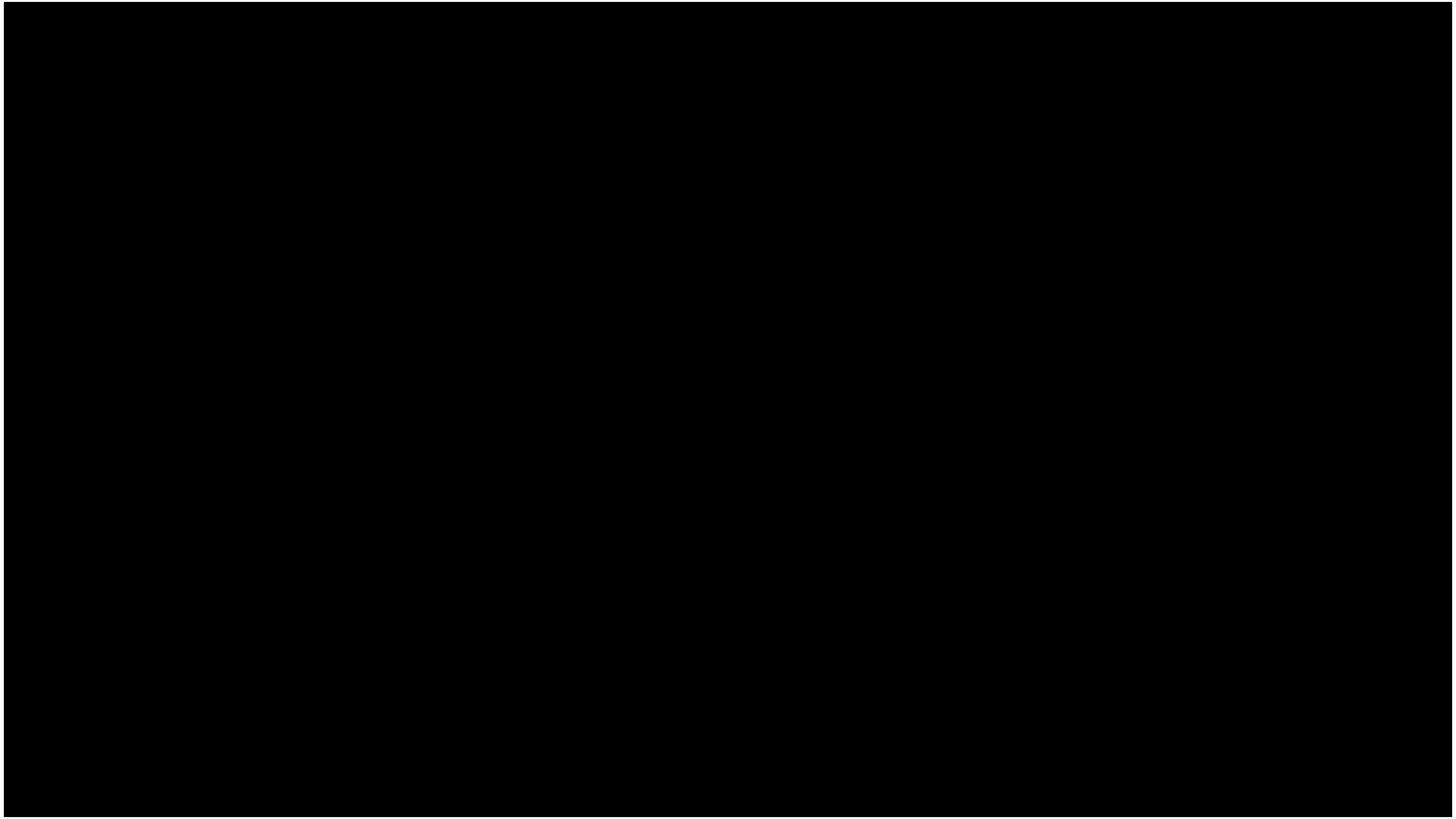
Inference: Sampling an image from a trained model:
(256 x 256 pixels) x (224 samples per pixel)
= 14.6M forward passes through MLP

Tons of follow-up work!

Mildenhall et al, “Representing Scenes as Neural Radiance Fields for View Synthesis”, ECCV 2020

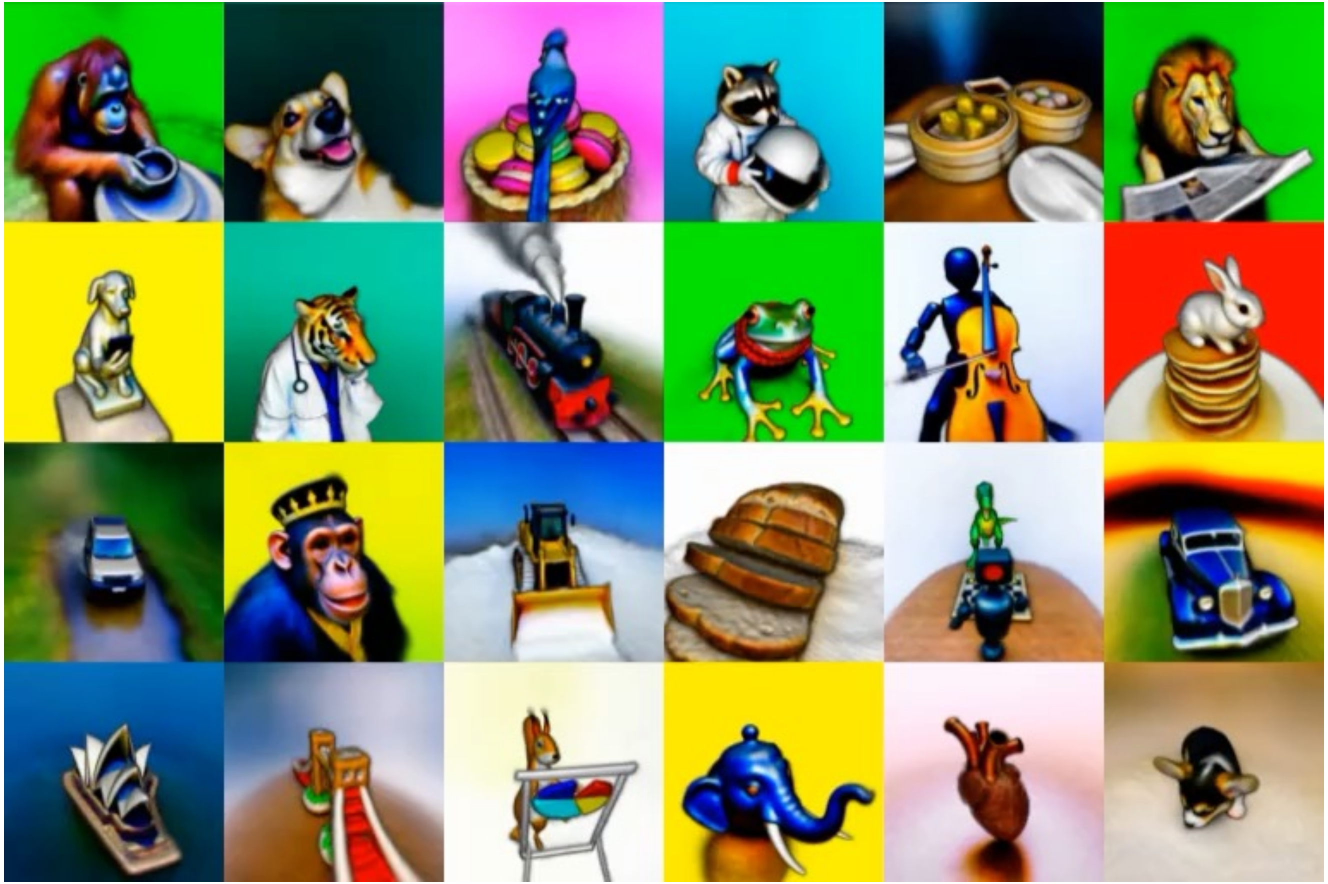
(a) Capture Process (b) Input (c) Nerfie (d) Nerfie Depth

Park et al, “Nerfies: Deformable Neural Radiance Fields”, ICCV 2021



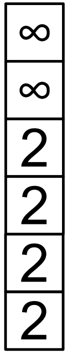
Mildenhall et al, “NeRF in the Dark: High Dynamic Range View Synthesis from Noisy Raw Images”, CVPR 2022

Tancik et al, “Block-NeRF: Scalable Large Scene Neural View Synthesis”, CVPR 2022

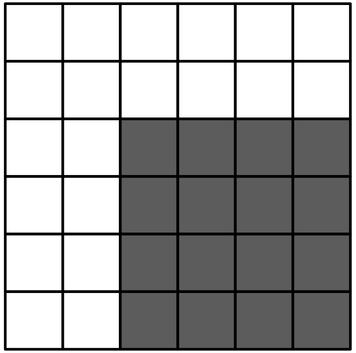


DreamFusion: Text-to-3D using 2D Diffusion, Ben et al., arXiv 2022

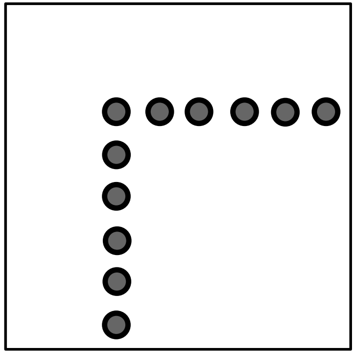
Summary: 3D Shape Representations



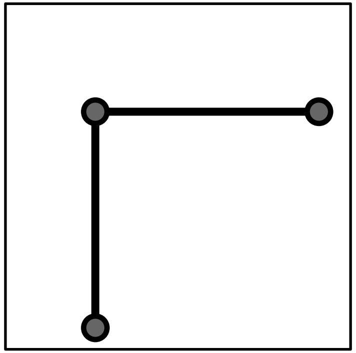
Depth Map



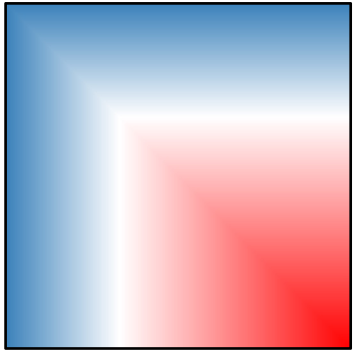
Voxel Grid



Pointcloud



Mesh



Implicit Surface

Next time:

Lecture 17: Human-Centered Artificial Intelligence

by Prof. Fei-Fei Li

Lecture 18 on 6/6:

Zoom Guest Lecture by Prof. Sara Beery