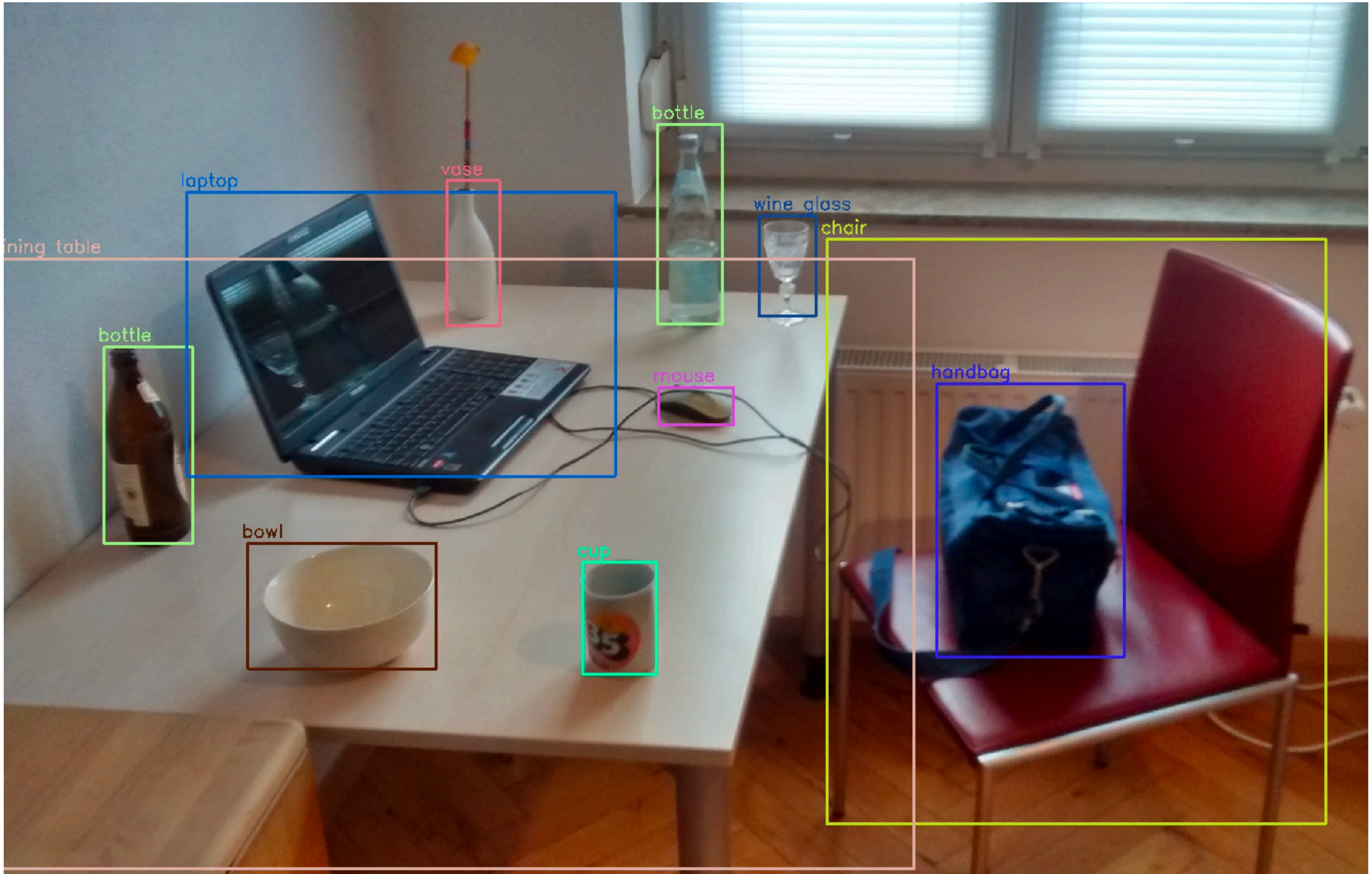
3D Perception: PointNet and NERFs

Sanjiban Choudhury

Cornell Bowers CIS
Computer Science

Last Class: How does a robot identify objects?



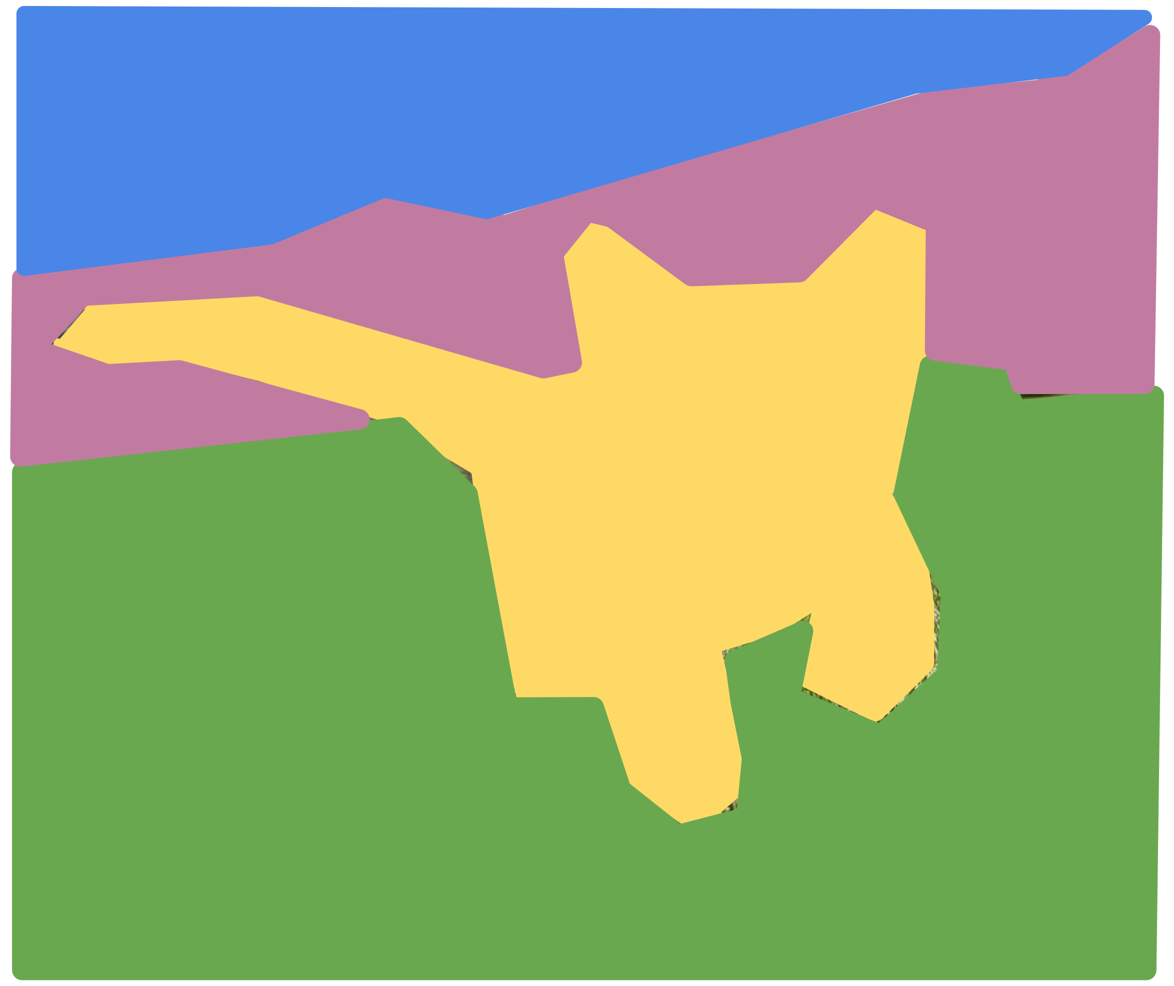
Last Class: How does a robot identify objects?

Classification

CAT

No spatial extent

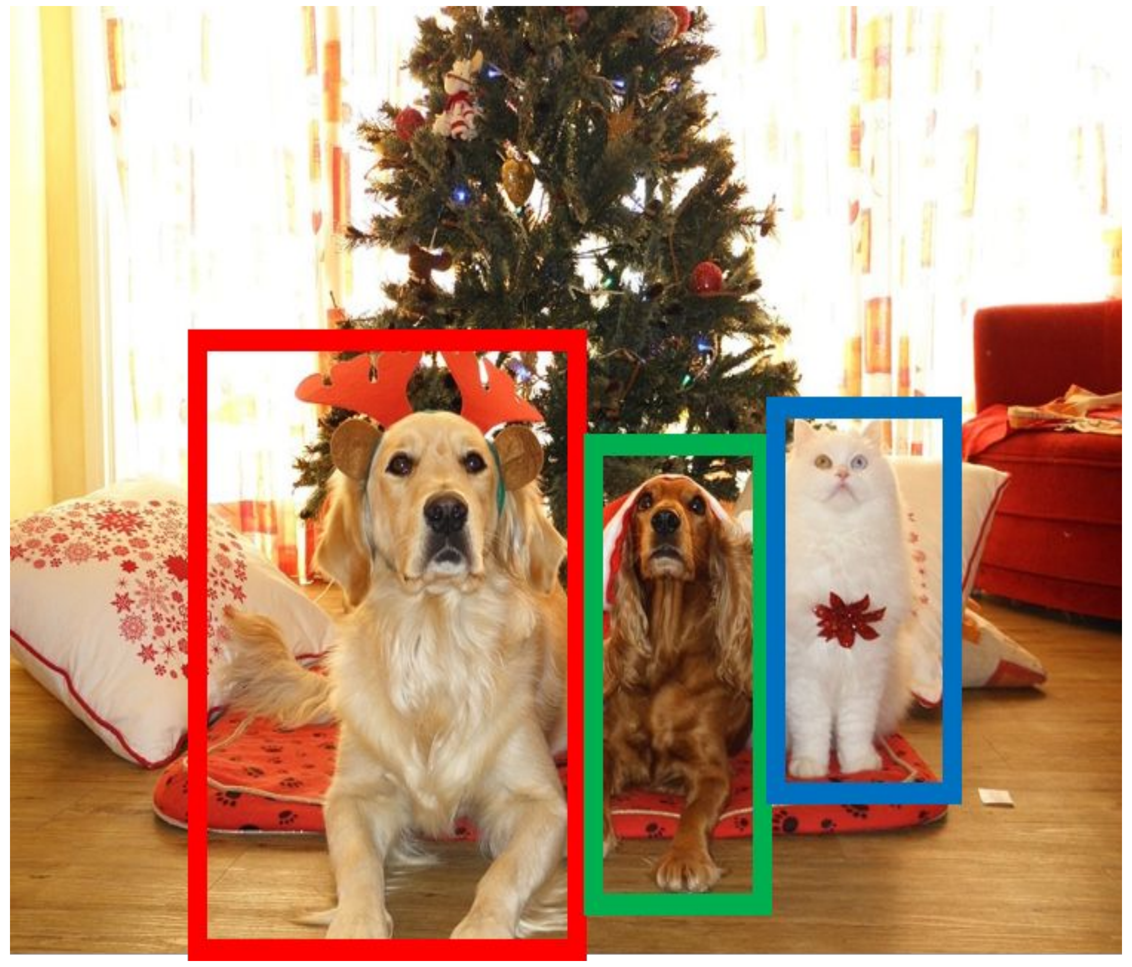
Semantic Segmentation



GRASS, CAT, TREE, SKY

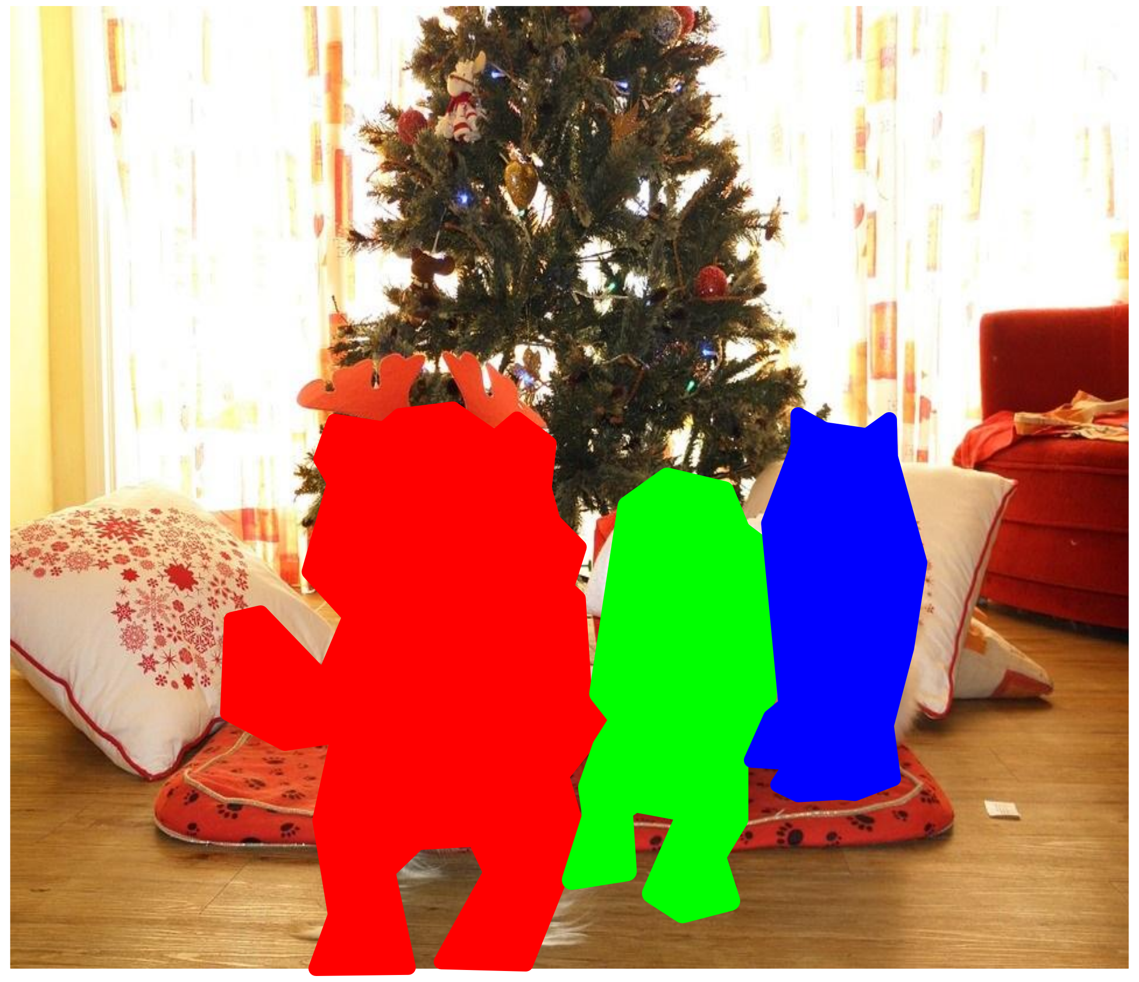
No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

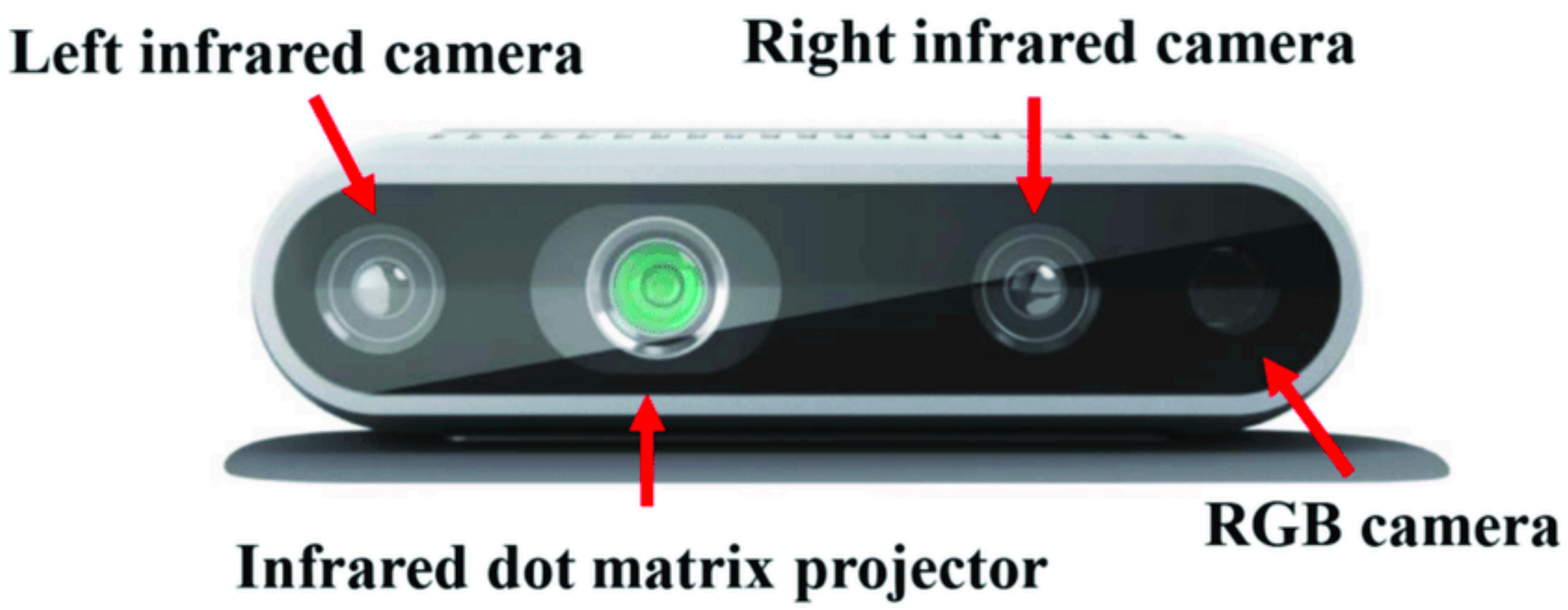
Multiple Object

Slides from Stanford CS231N: Object Detection and Image Segmentation

But manipulating objects require 3D reasoning!

What sensors can we use to get 3D information?

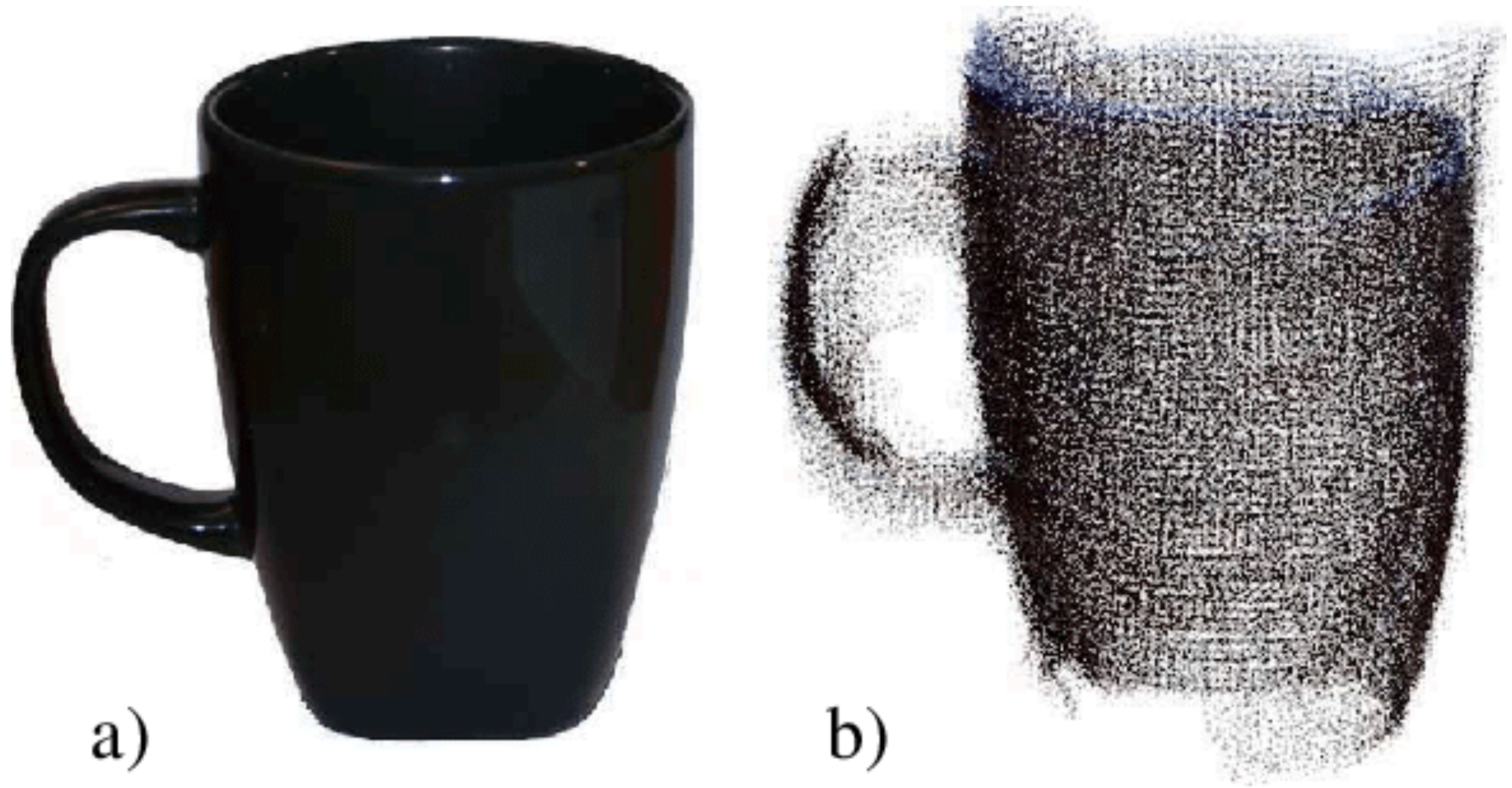
Depth cameras give us 3D information!




Add Source
2D
3D
Intel RealSense D435I
3.2
File: "20210622_173905.bag"
Speed: x1
0:00:03
0:00:26
Pause
Reset
Lock
Source
Texture
Shading
Measure
Export
Stereo Module
on
Resolution: 848 x 480
Frame Rate (FPS): 30
Infrared 2 Y8
Infrared 1 Y8
Depth Z16
Visual Preset:
0
Emitter Enabled:
1
Enable Auto Exposure:
1
Controls
Depth Visualization
Post-Processing
RGB Camera
on
Resolution: 1280 x 720
Frame Rate (FPS): 30
Color RGB8
Enable Auto Exposure:
1
Controls
Post-Processing
Motion Module
on
Gyro stream:
Format: MOTION_XYZ32F
Frame Rate (FPS): 200
Accel stream:
Format: MOTION_XYZ32F
Frame Rate (FPS): 63
Controls

What data structure represents 3D information?

Masked Depth Image -> Point Cloud



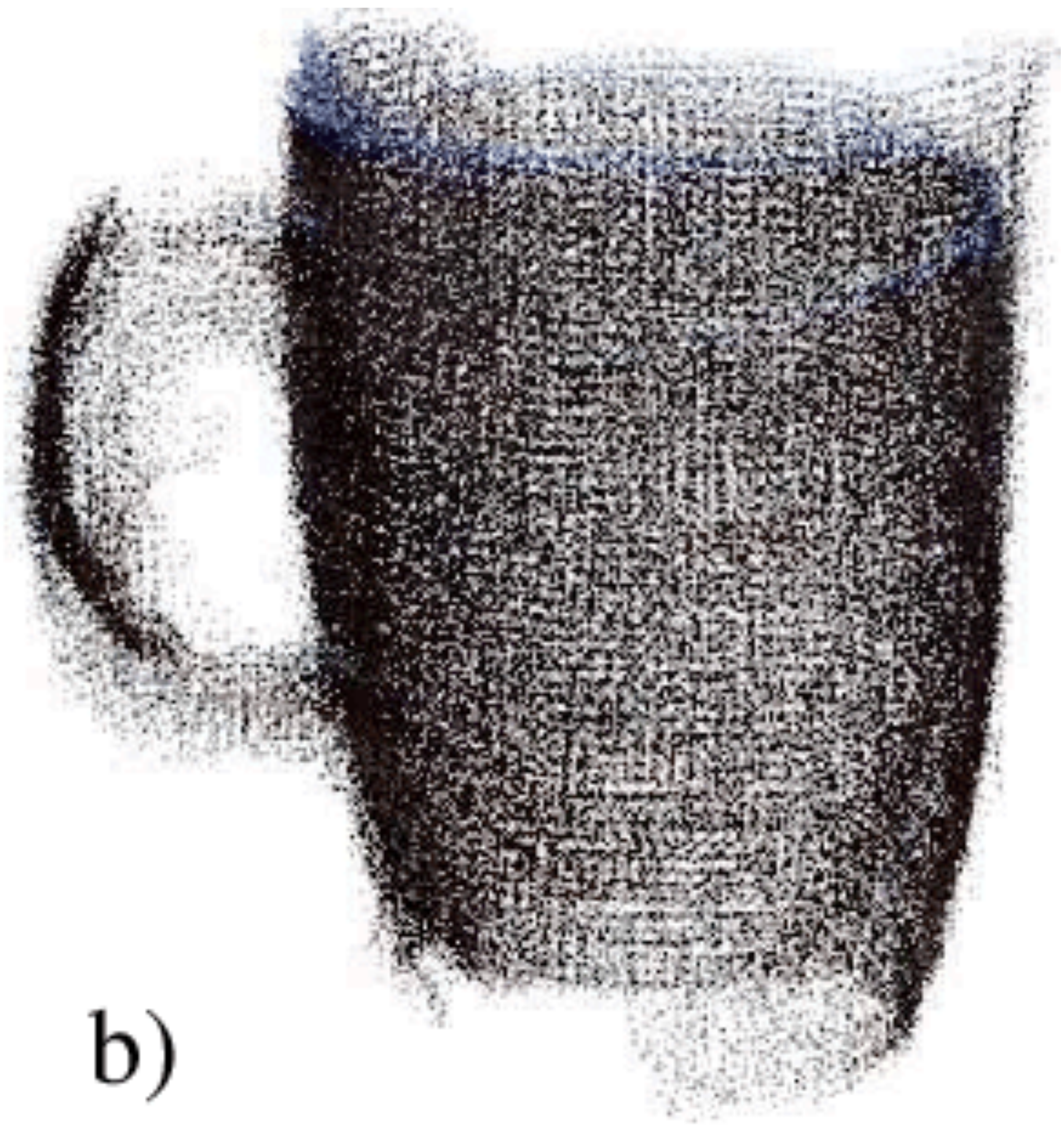
Think-Pair-Share

Think-Pair-Share!

Think (30 sec): Given a point cloud of an object, how would you learn where to grasp it? What are some informative features?

Pair: Find a partner

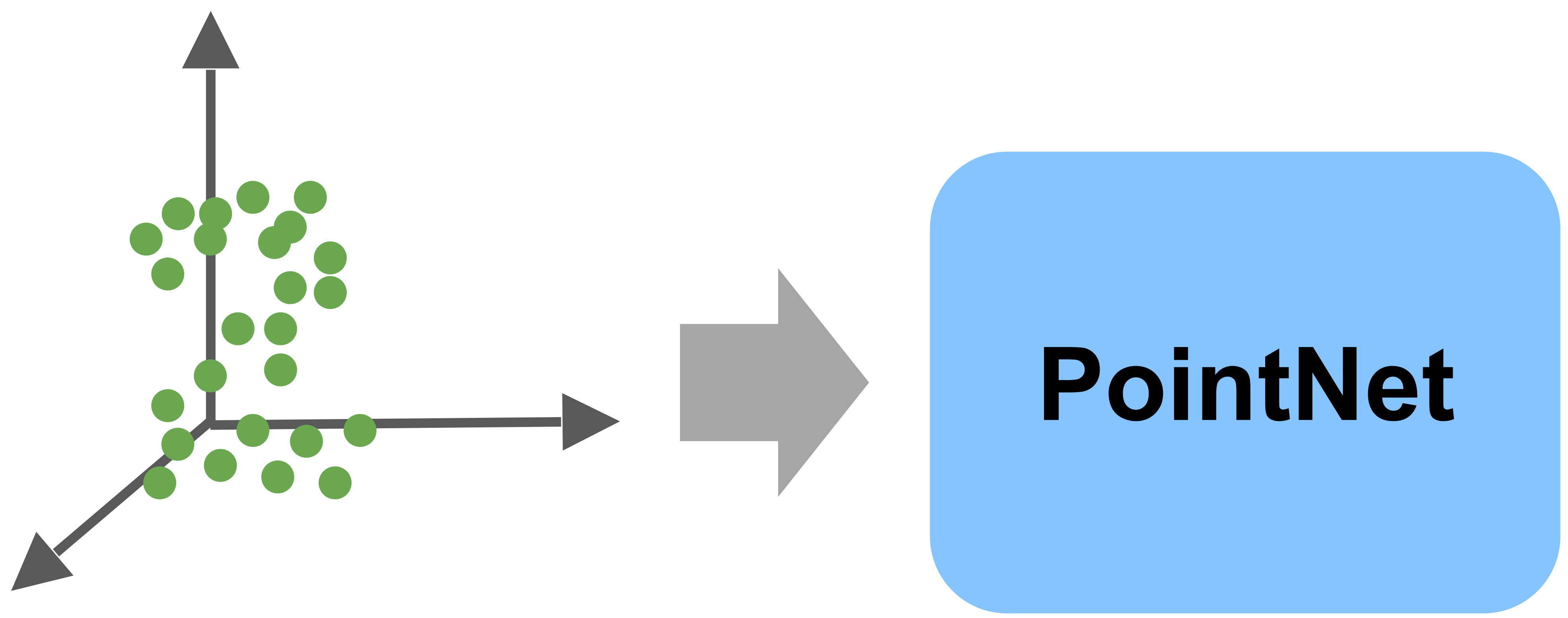
Share (45 sec): Partners exchange ideas


b)

Part 1: PointNet

PointNet

End-to-end learning for **scattered, unordered** point data

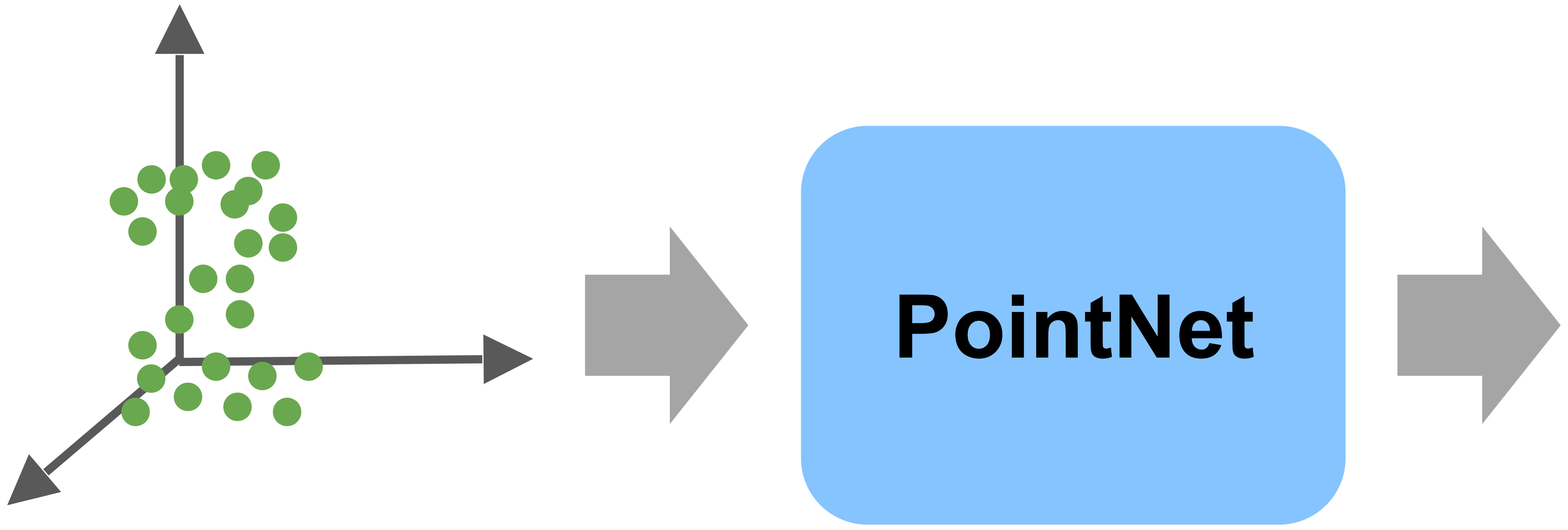


Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

PointNet

End-to-end learning for **scattered, unordered** point data

Unified framework for various tasks



Object Classification

Object Part Segmentation

Semantic Scene Parsing

...

Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

PointNet

End-to-end learning for **scattered, unordered** point data

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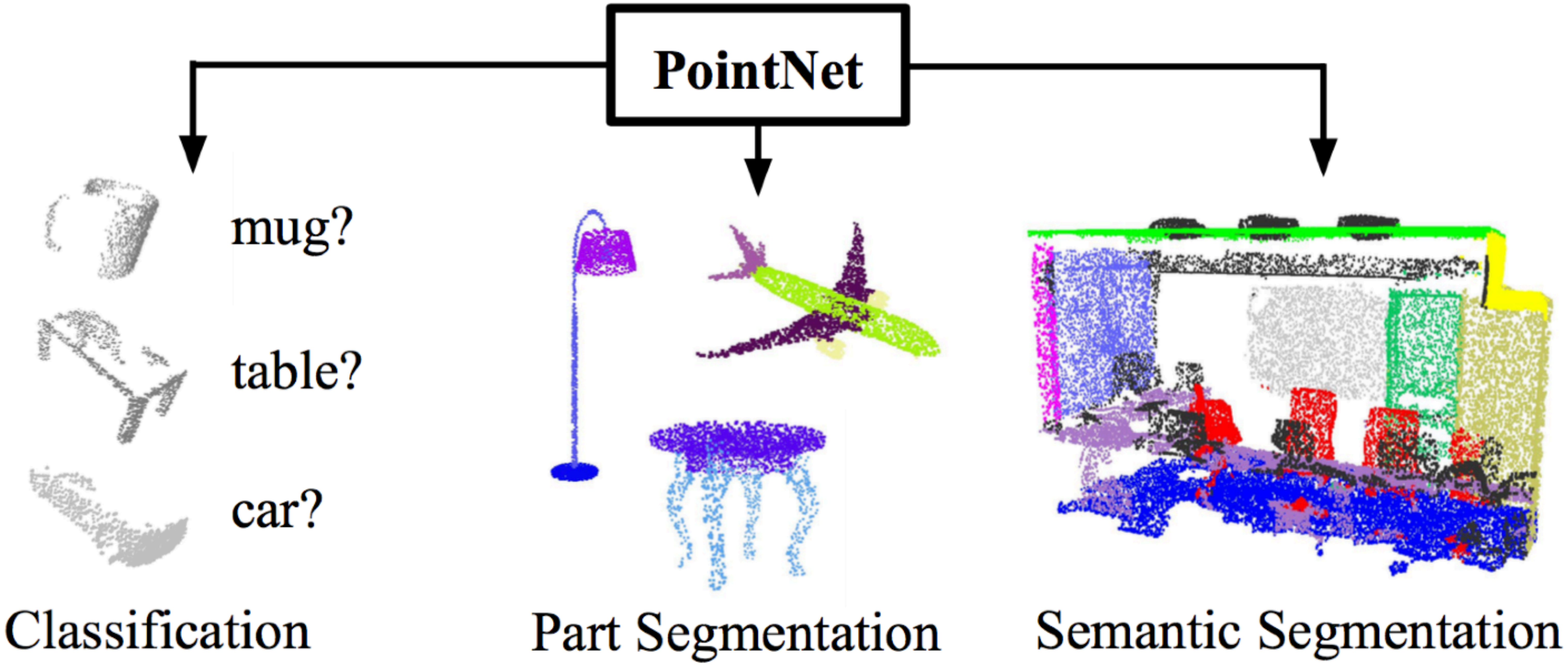

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Challenges with point clouds

Two Challenges

Challenge 1: **Unordered** point set as input

Model needs to be invariant to N! permutation

Challenge 2: Invariance under **geometric** transformations

Point cloud rotation should not alter classification results

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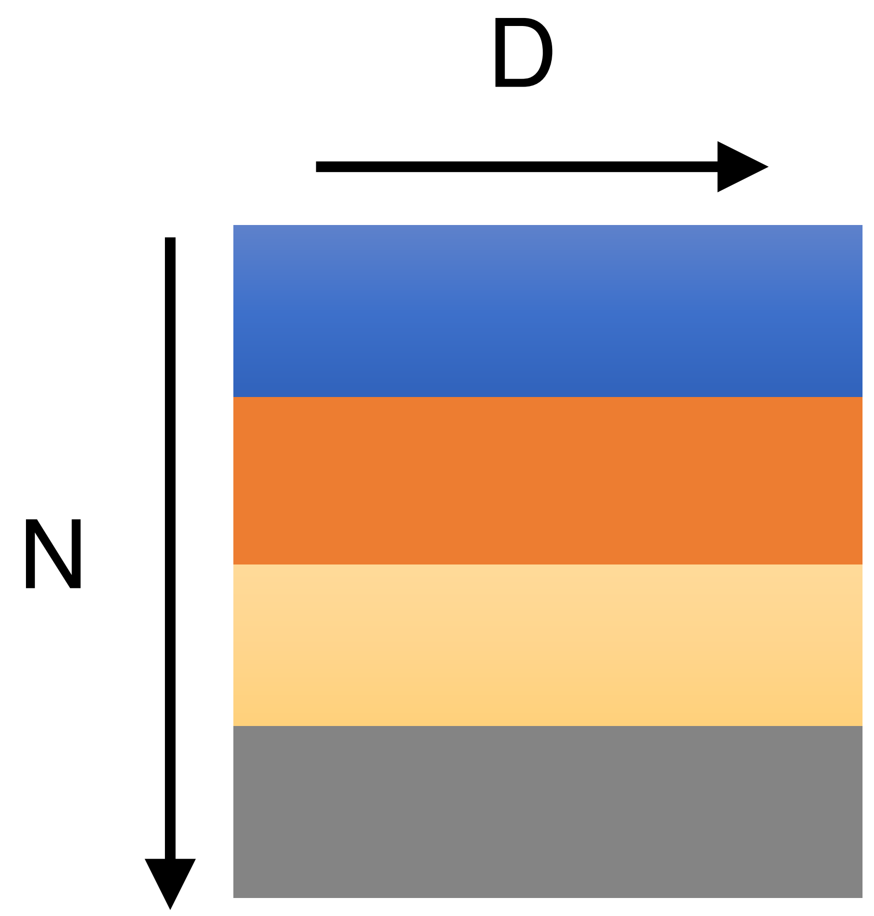
Unordered Input

Point cloud: N **orderless** points, each represented by a D dim vector



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Unordered Input

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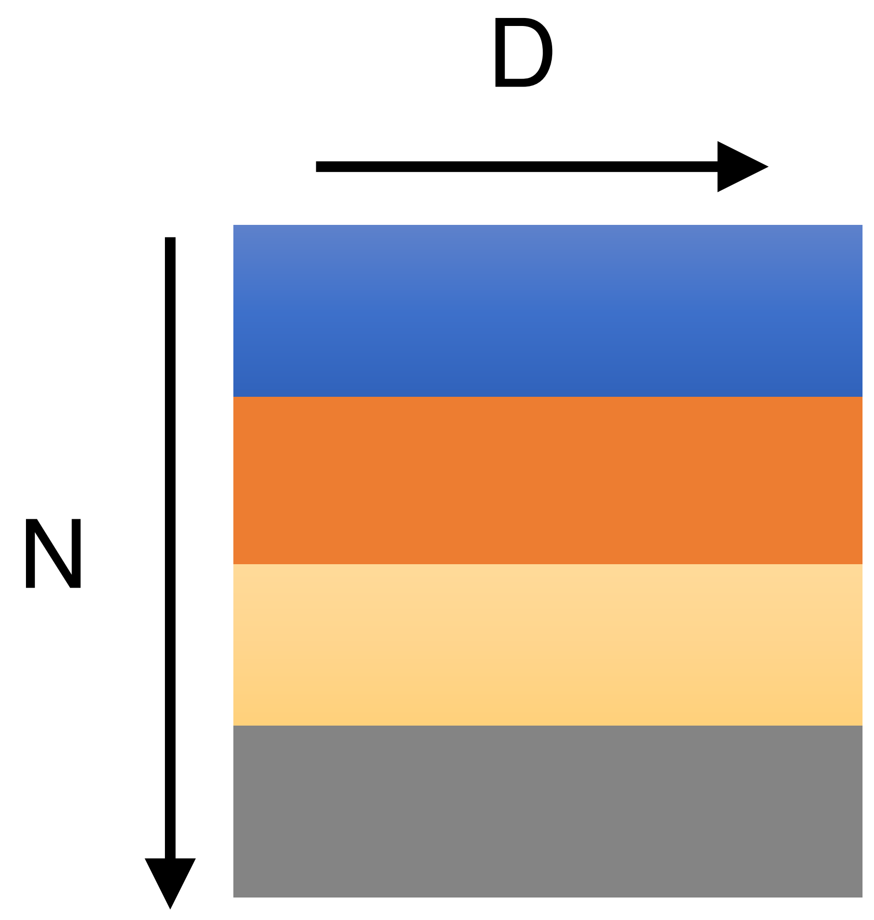
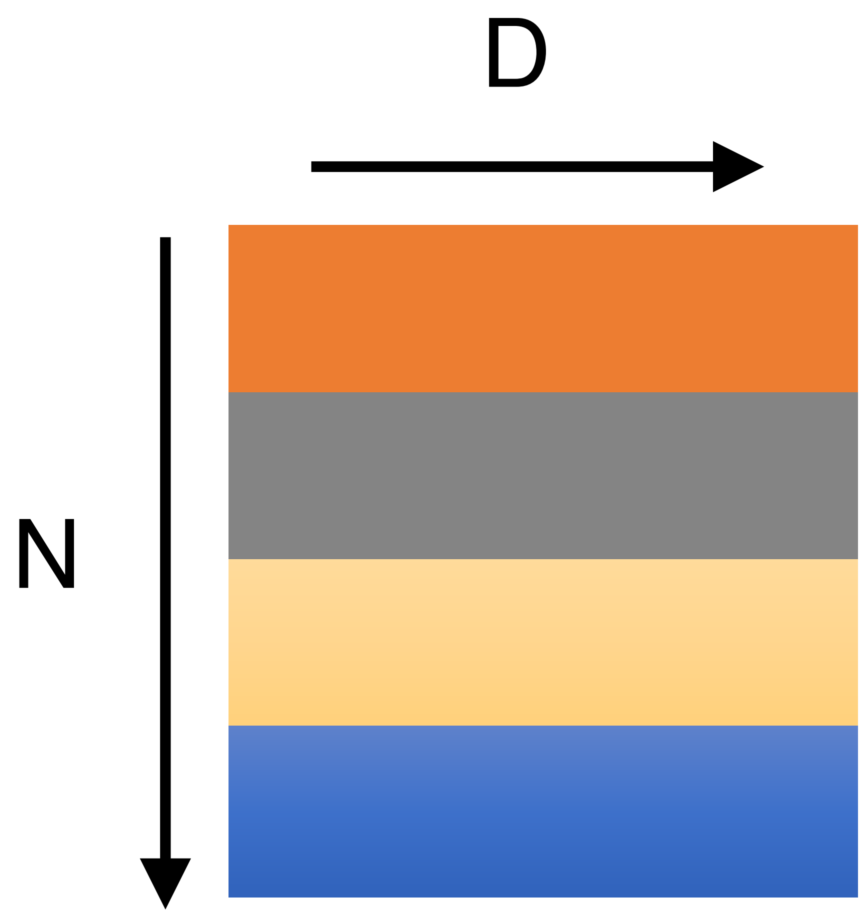


represents the same **set** as



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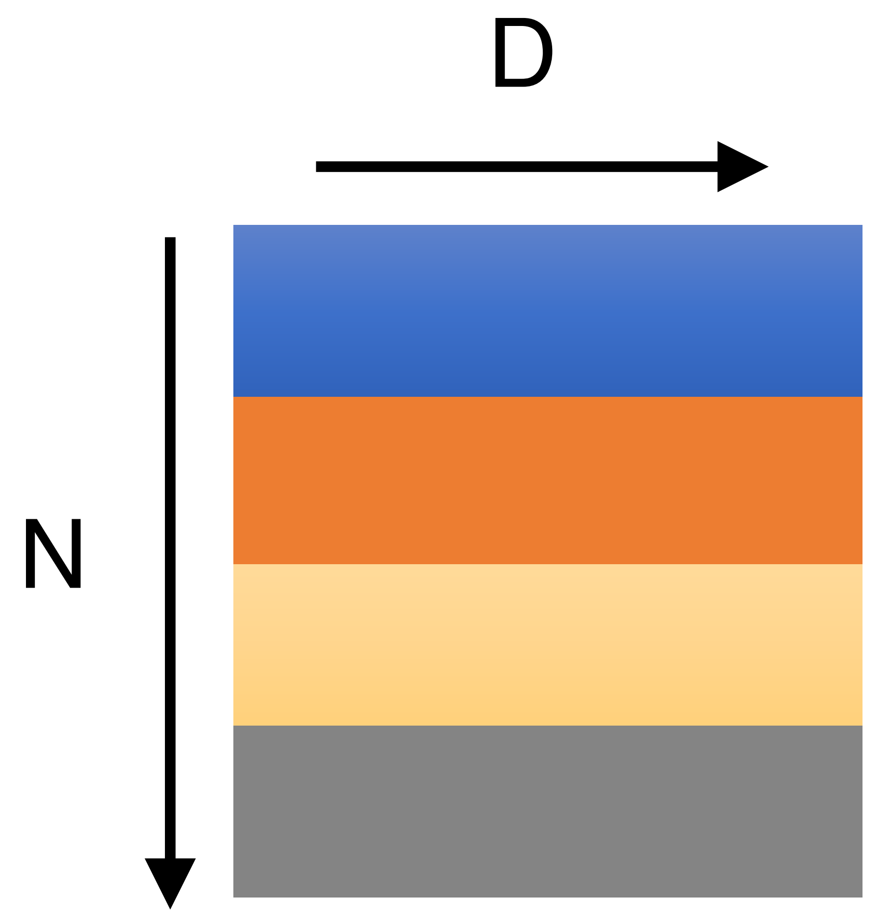

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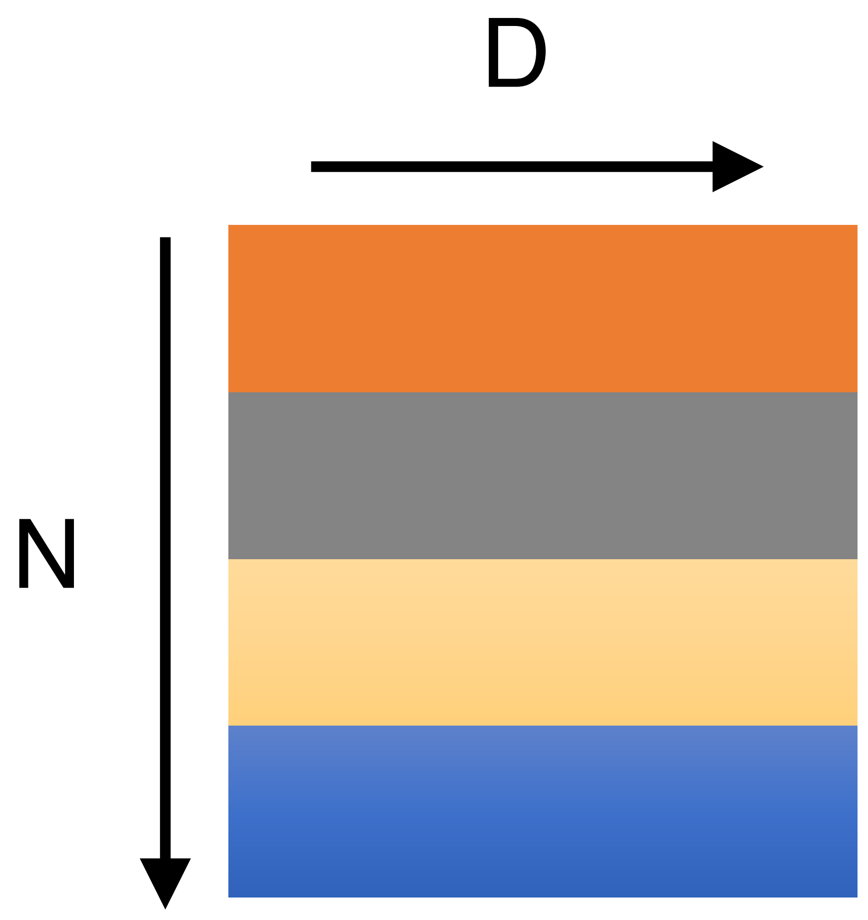

Model needs to be invariant to N! permutations

Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

Permutation Invariance: Symmetric Function

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

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Examples:

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

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

…

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$\ldots$

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

Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

Permutation Invariance: Symmetric Function

Observe:

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

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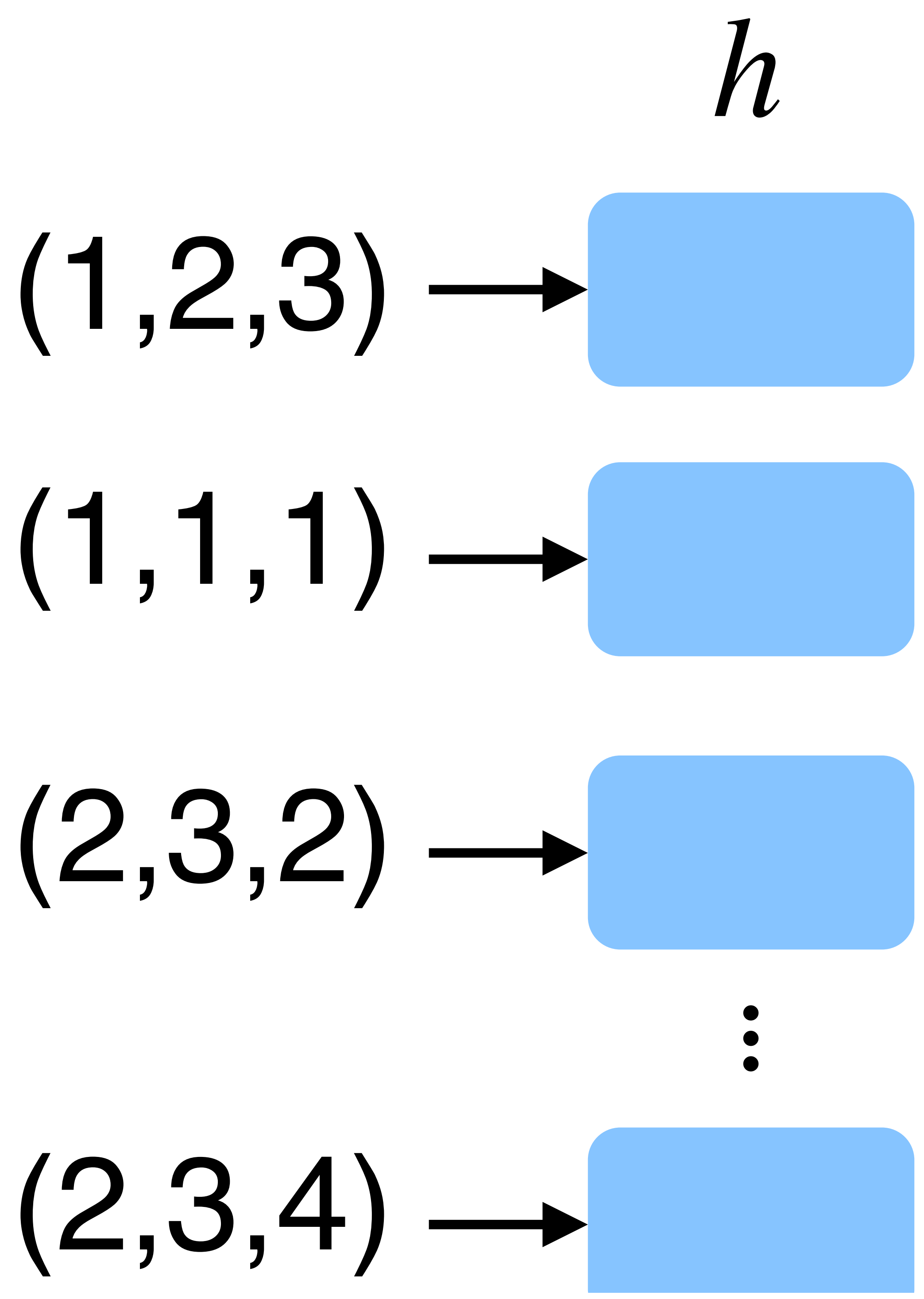

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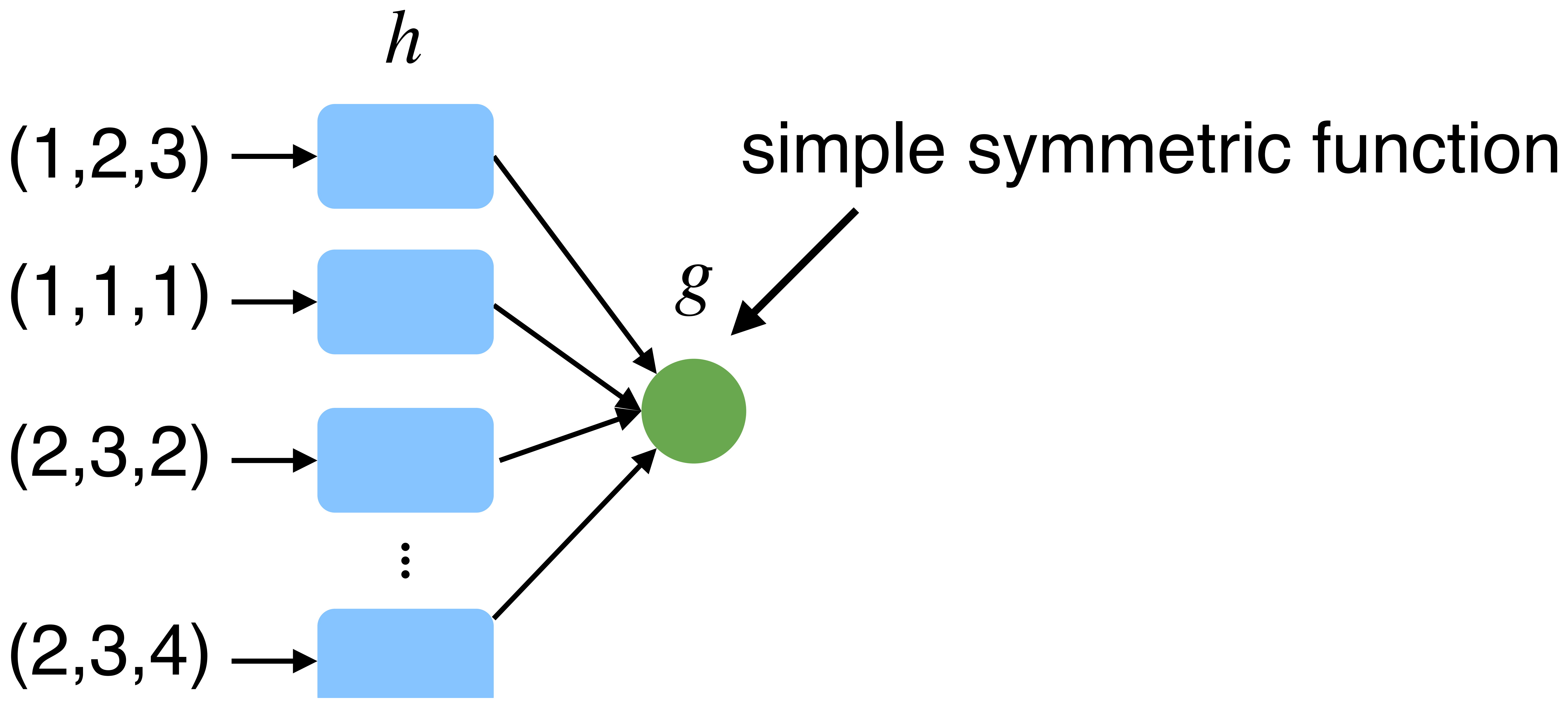

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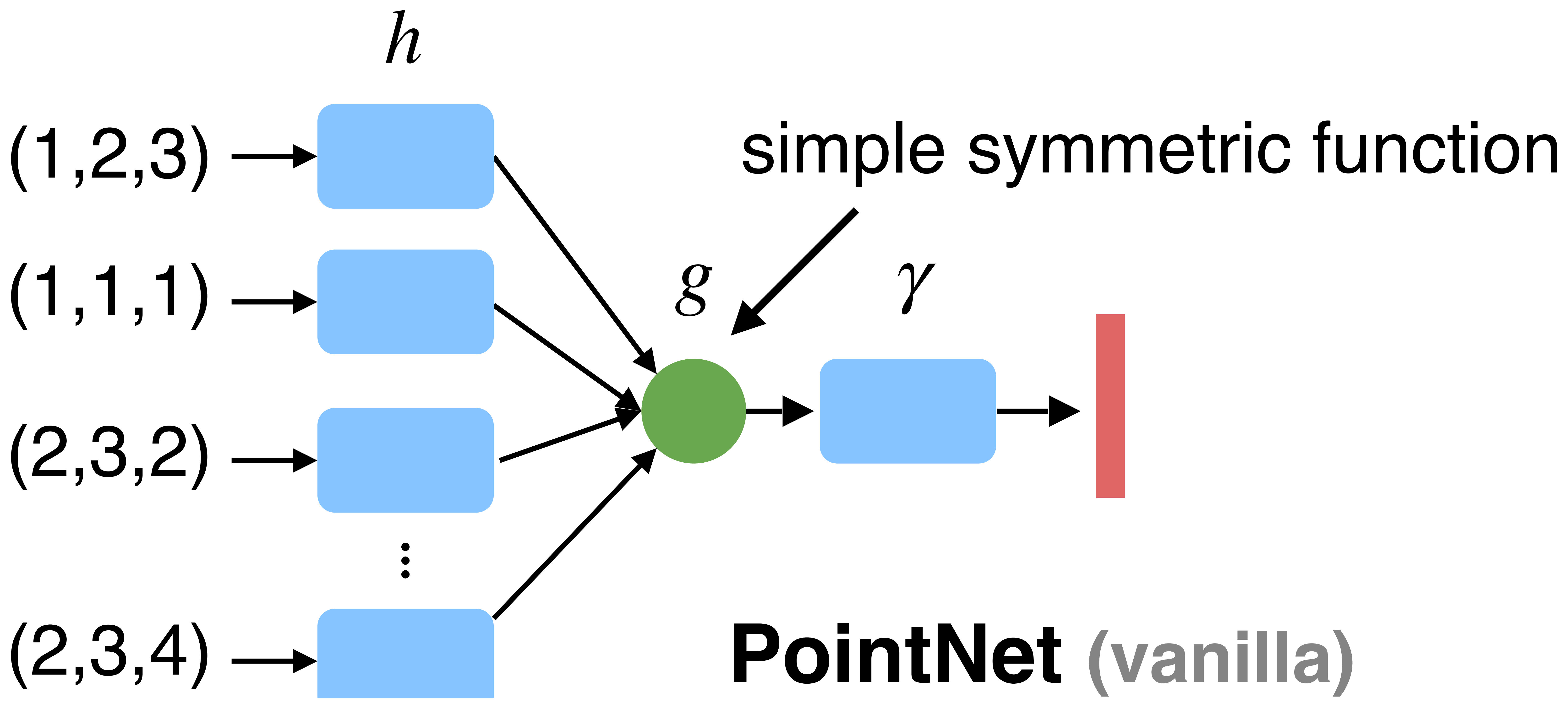
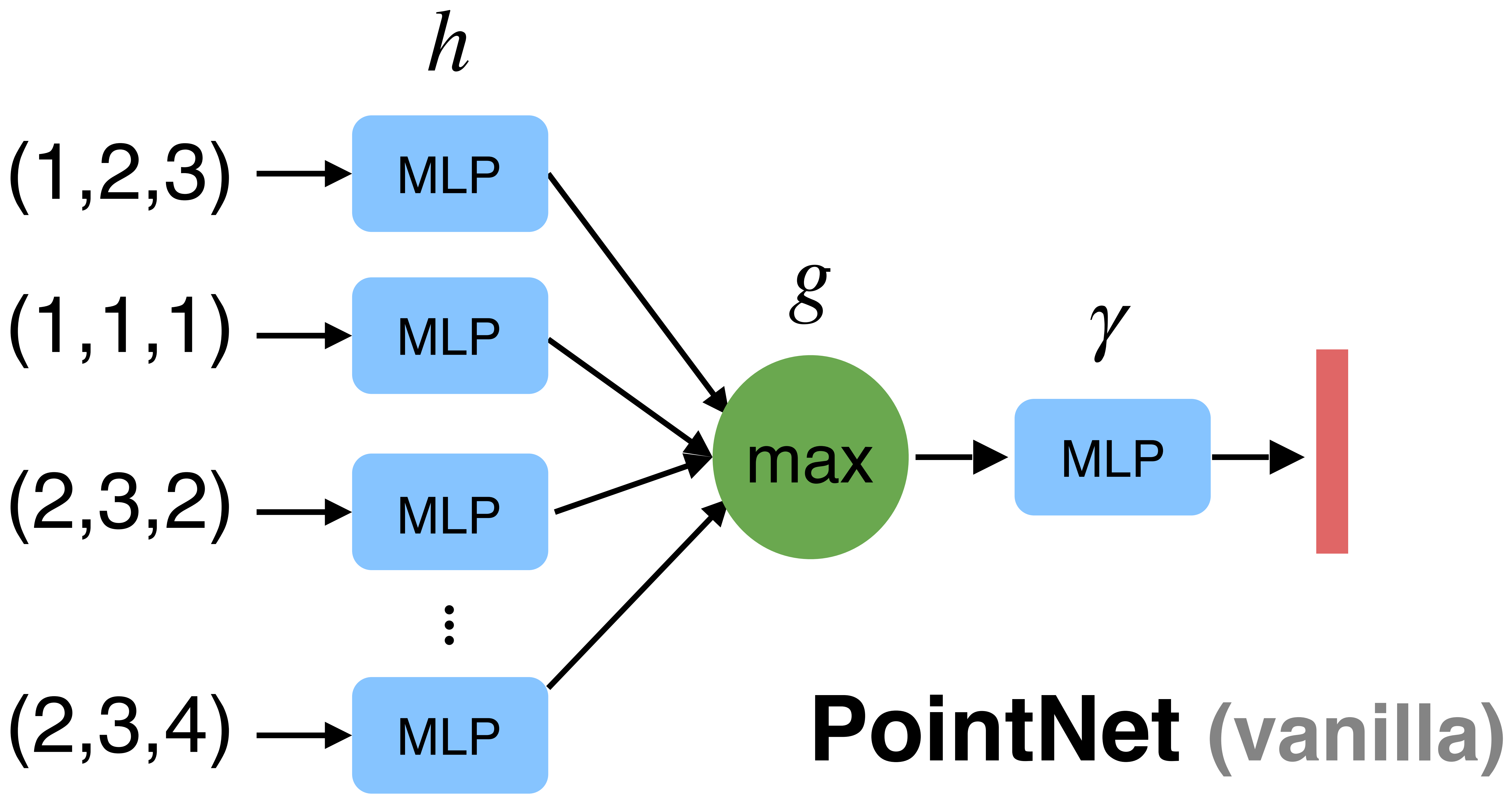


PointNet **(vanilla)**

Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

Basic PointNet Architecture

Empirically, we use **multi-layer perceptron (MLP)** and **max pooling**:



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Two Challenges

Challenge 1: **Unordered** point set as input

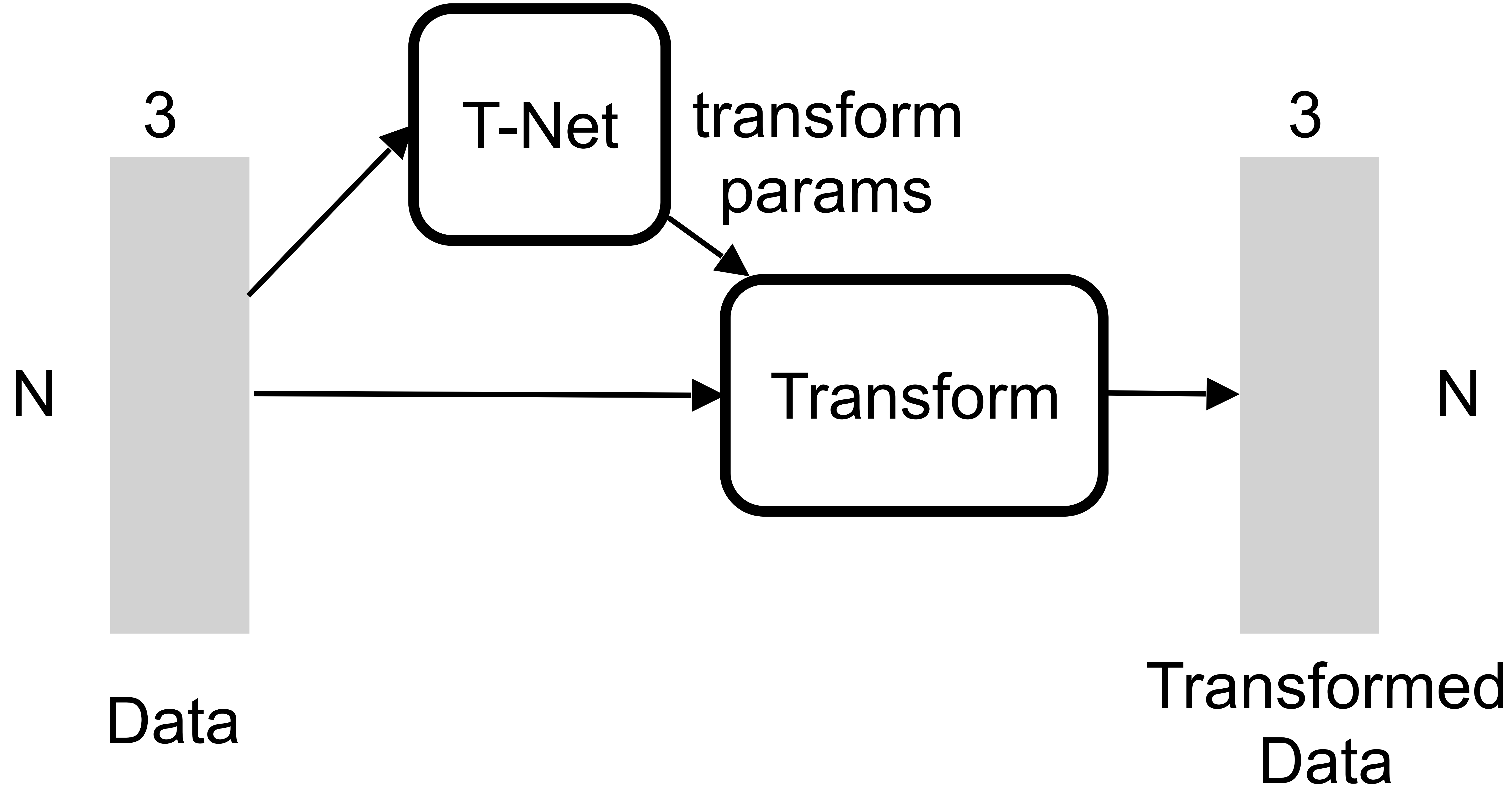
Model needs to be invariant to N! permutation

Challenge 2: Invariance under **geometric** transformations

Point cloud rotation should not alter classification results

Input Alignment by Transformer Network

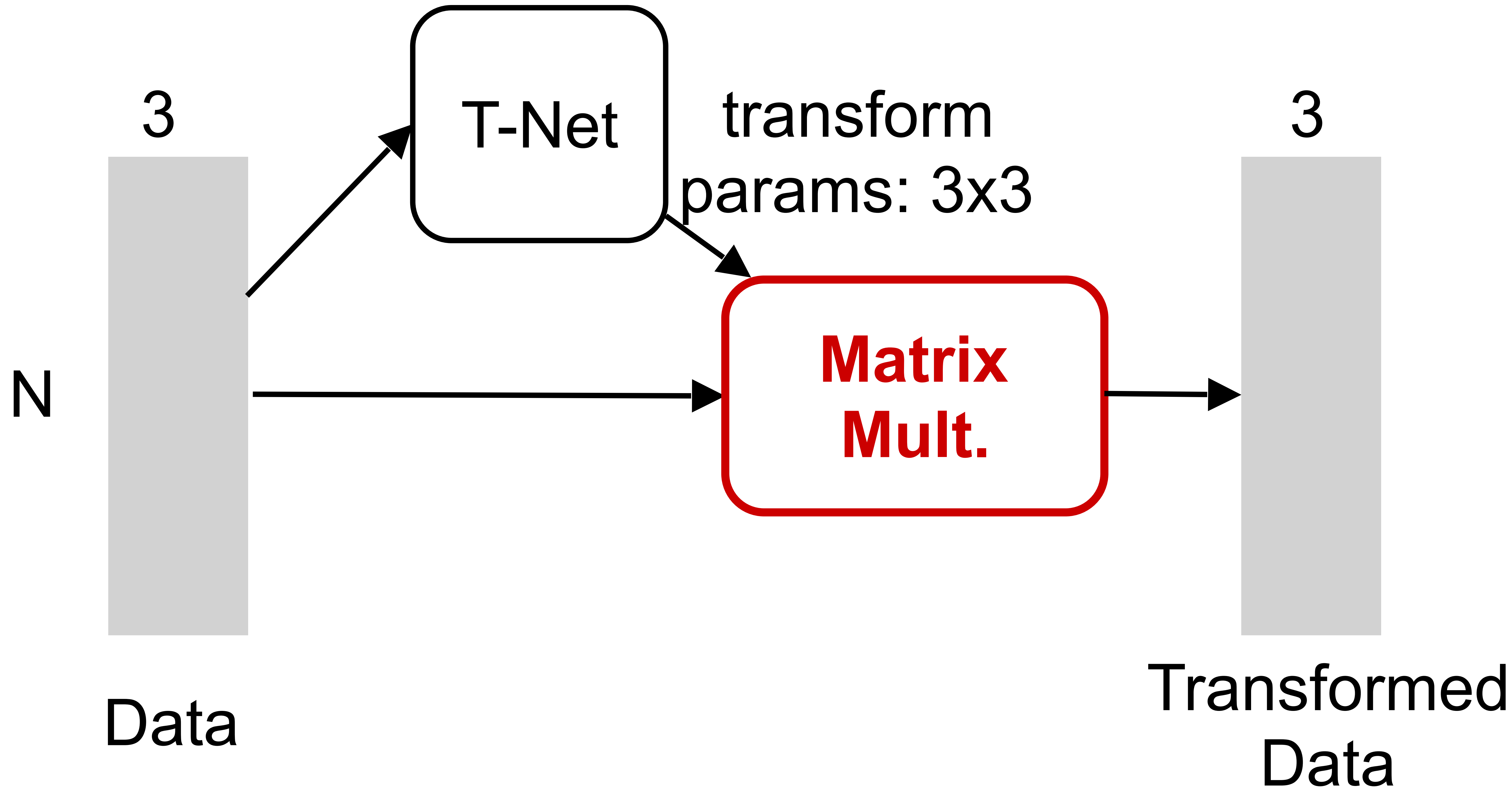
Idea: Data dependent transformation for automatic alignment



Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

Input Alignment by Transformer Network

The transformation is just matrix multiplication!



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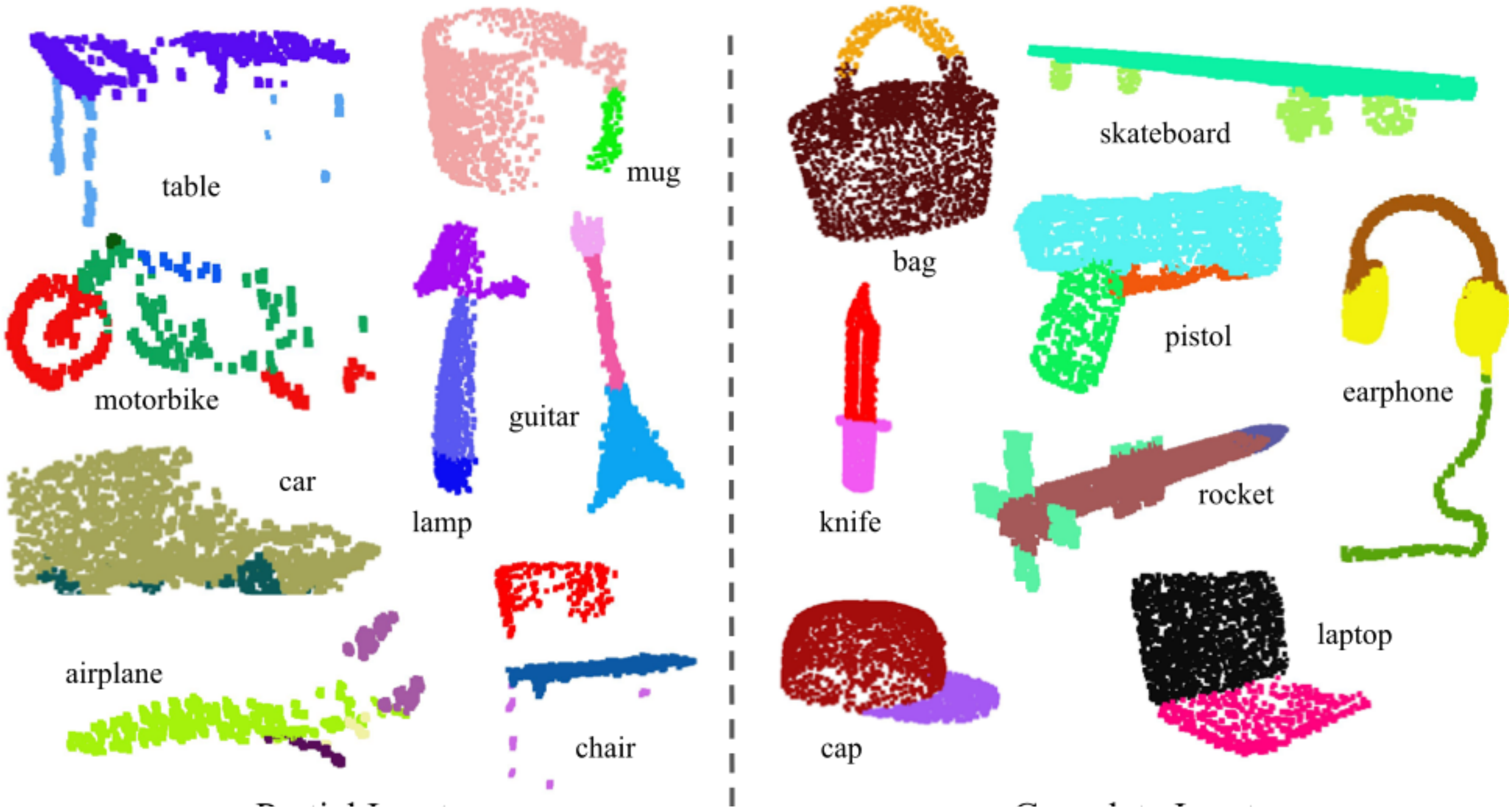
Results on Object Part Segmentation



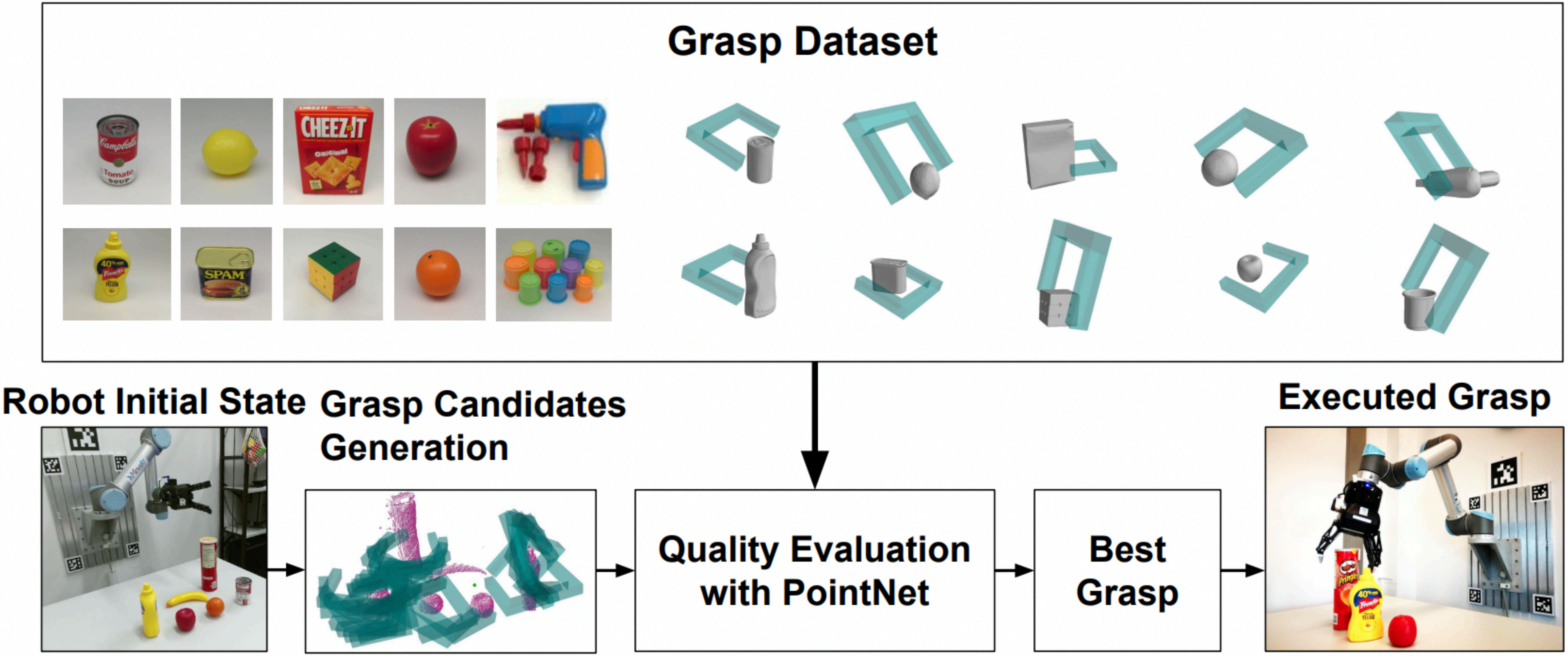
Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

Results on Semantic Scene Parsing

Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

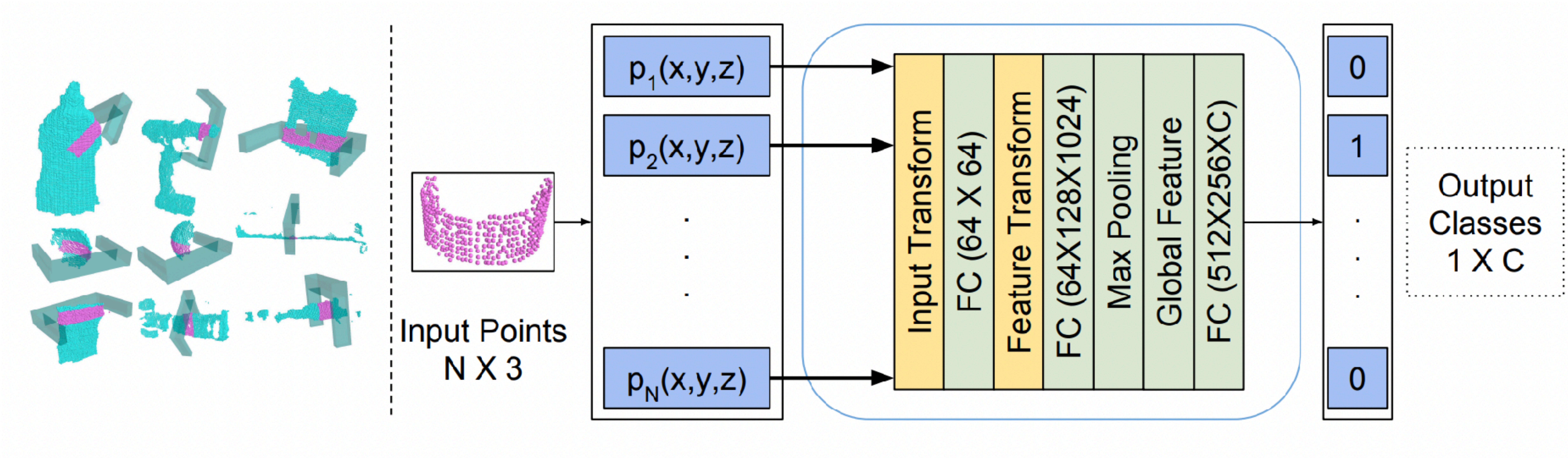
How do we use this for learning grasping?

PointNetGPD: Detecting Grasp Configurations from Point Sets



Liang et al.

PointNetGPD: Detecting Grasp Configurations from Point Sets



Liang et al.

What if we don't have good depth information?

Poll

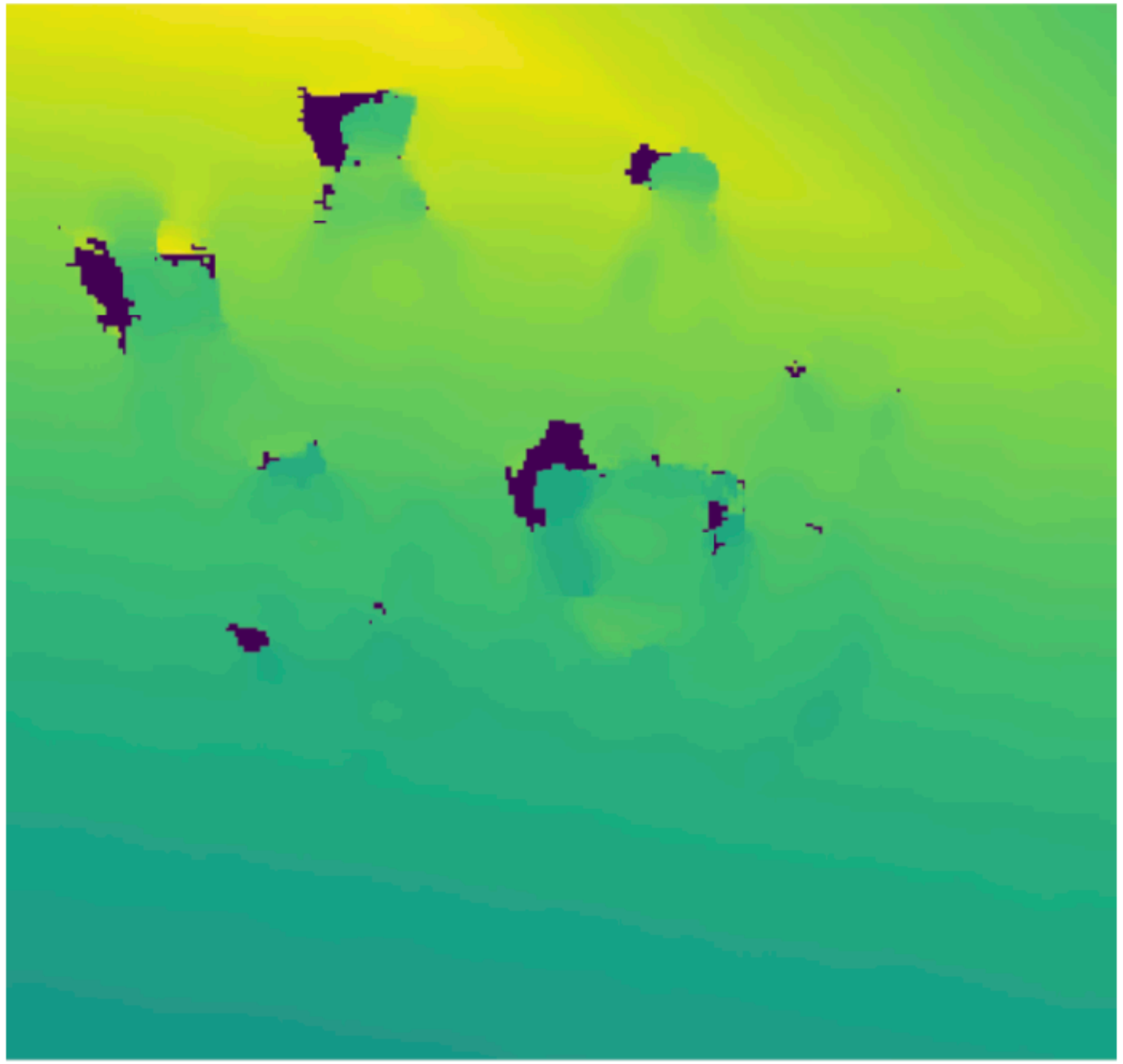
What are the limits of depth camera?

When poll is active respond at **PollEv.com/sc2582**

Send **sc2582** to **22333**

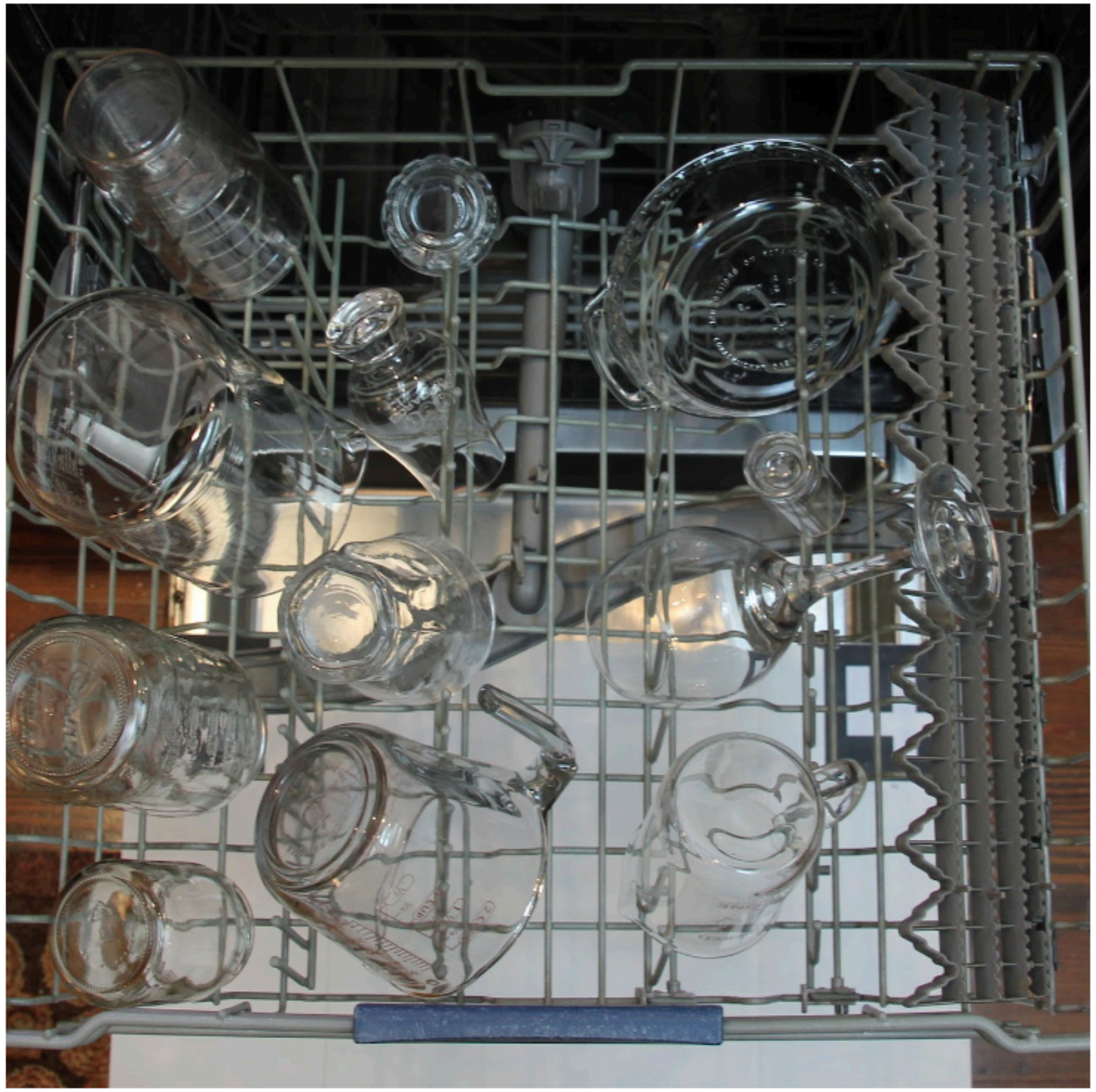
Completely fails for transparent / reflective objects!

Real-world Scene

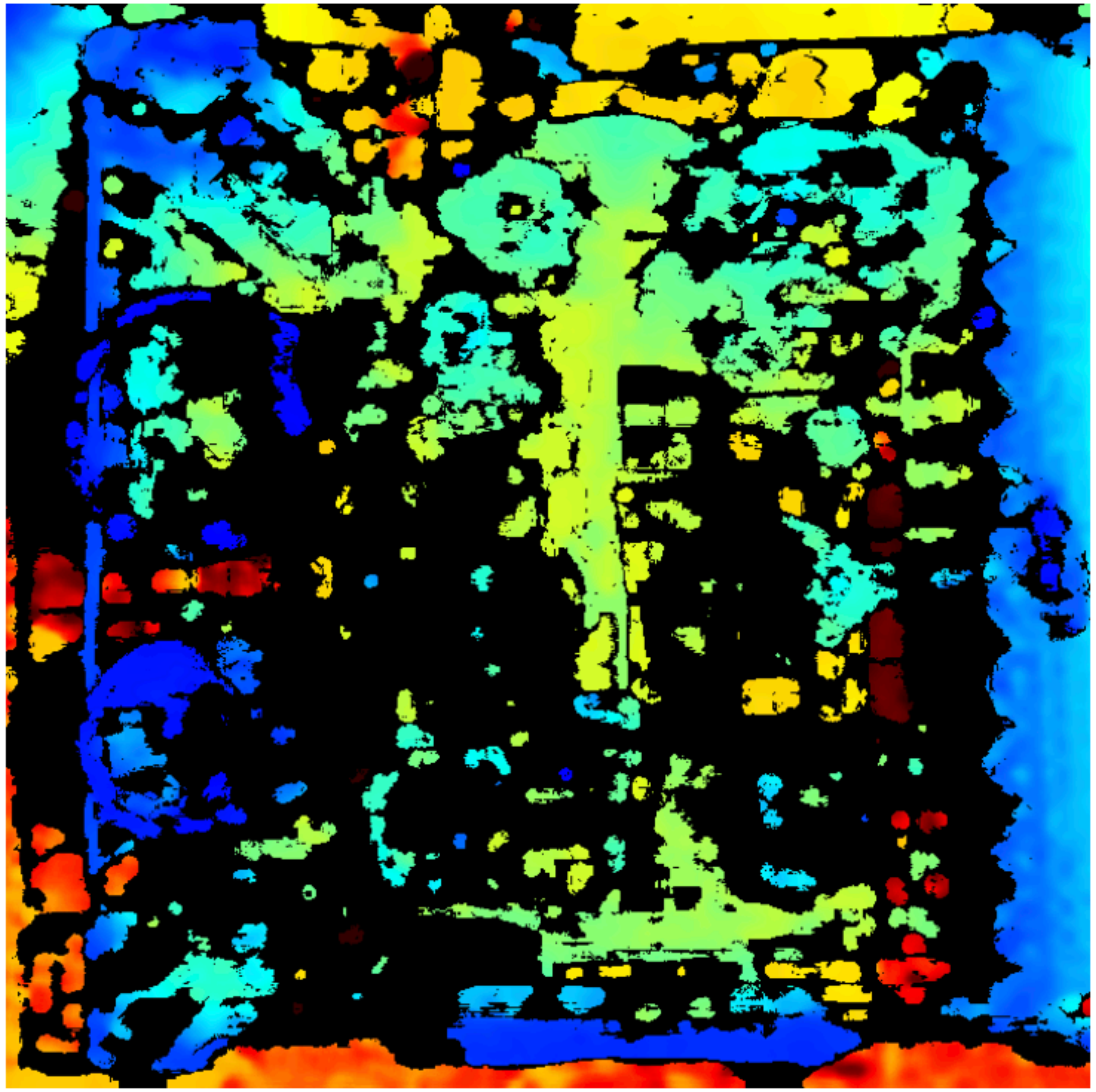


RealSense D410 Depth Image

Completely fails for transparent / reflective objects!



Dishwasher Real-world Scene



RealSense D410 Depth Image

Part 2:

Neural Radiance Fields (NeRFs)

Let's say I just have a set of images & camera poses

$x_1, y_1, z_1, \theta_1, \phi_1$

$x_2, y_2, z_2, \theta_2, \phi_2$

$x_3, y_3, z_3, \theta_3, \phi_3$

How do we predict a 3D structure?

2D images

Camera Poses

$x_1, y_1, z_1, \theta_1, \phi_1$ $x_2, y_2, z_2, \theta_2, \phi_2$ $x_3, y_3, z_3, \theta_3, \phi_3$

3D structure

If you can predict how the object will look

from a *novel viewpoint*,

you have *implicitly* modeled the

3D structure

Let's setup a learning problem

x, y, z, θ, ϕ

Novel viewpoint

Neural Network

Predicted

Let's setup a learning problem

x, y, z, θ, ϕ

Novel viewpoint

Neural Network

Predicted

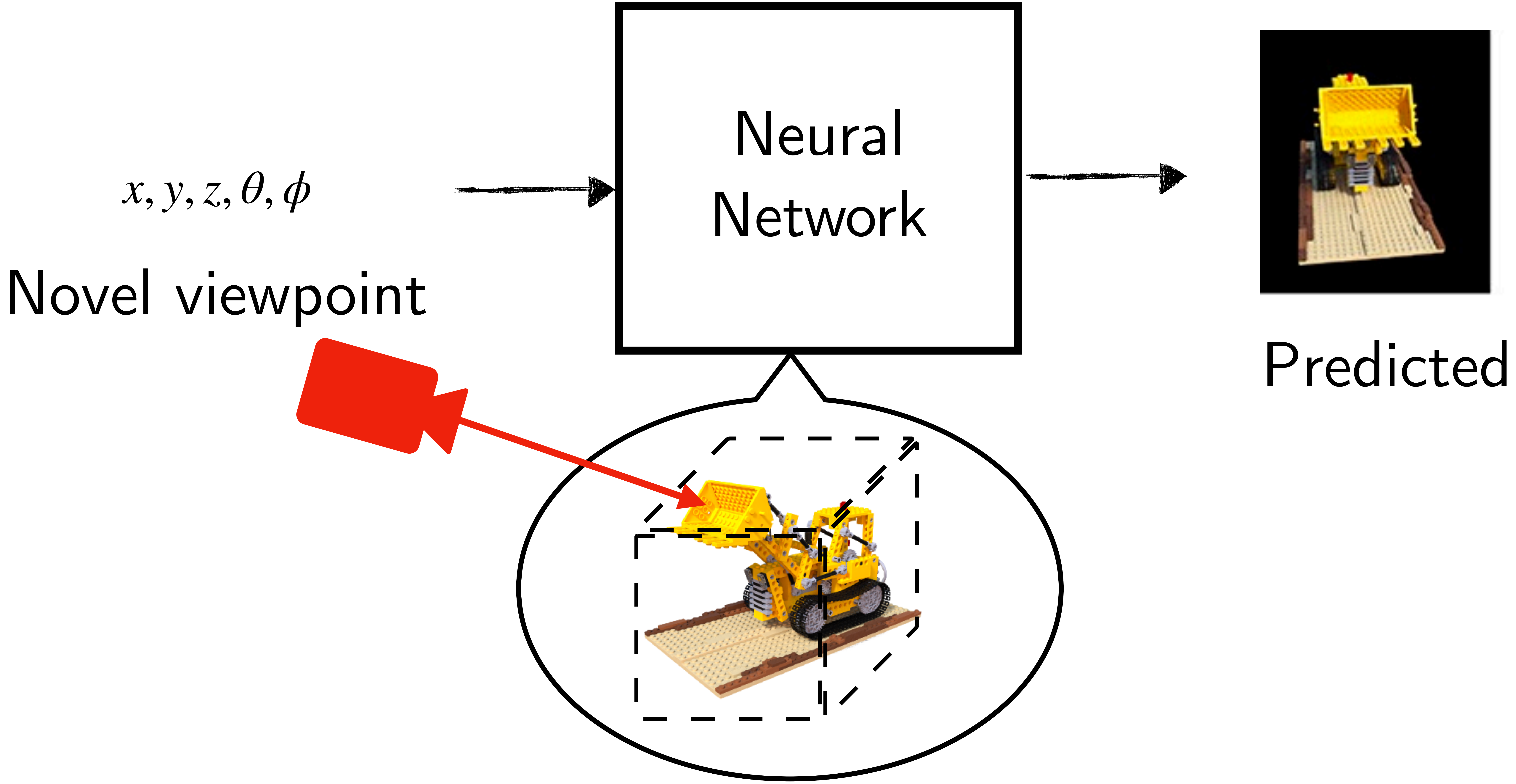
—

Ground Truth

Simple idea:

Can't we just make the neural network predict a 3D voxel grid of RGB values?

Predict a 3D grid, render image from viewpoint

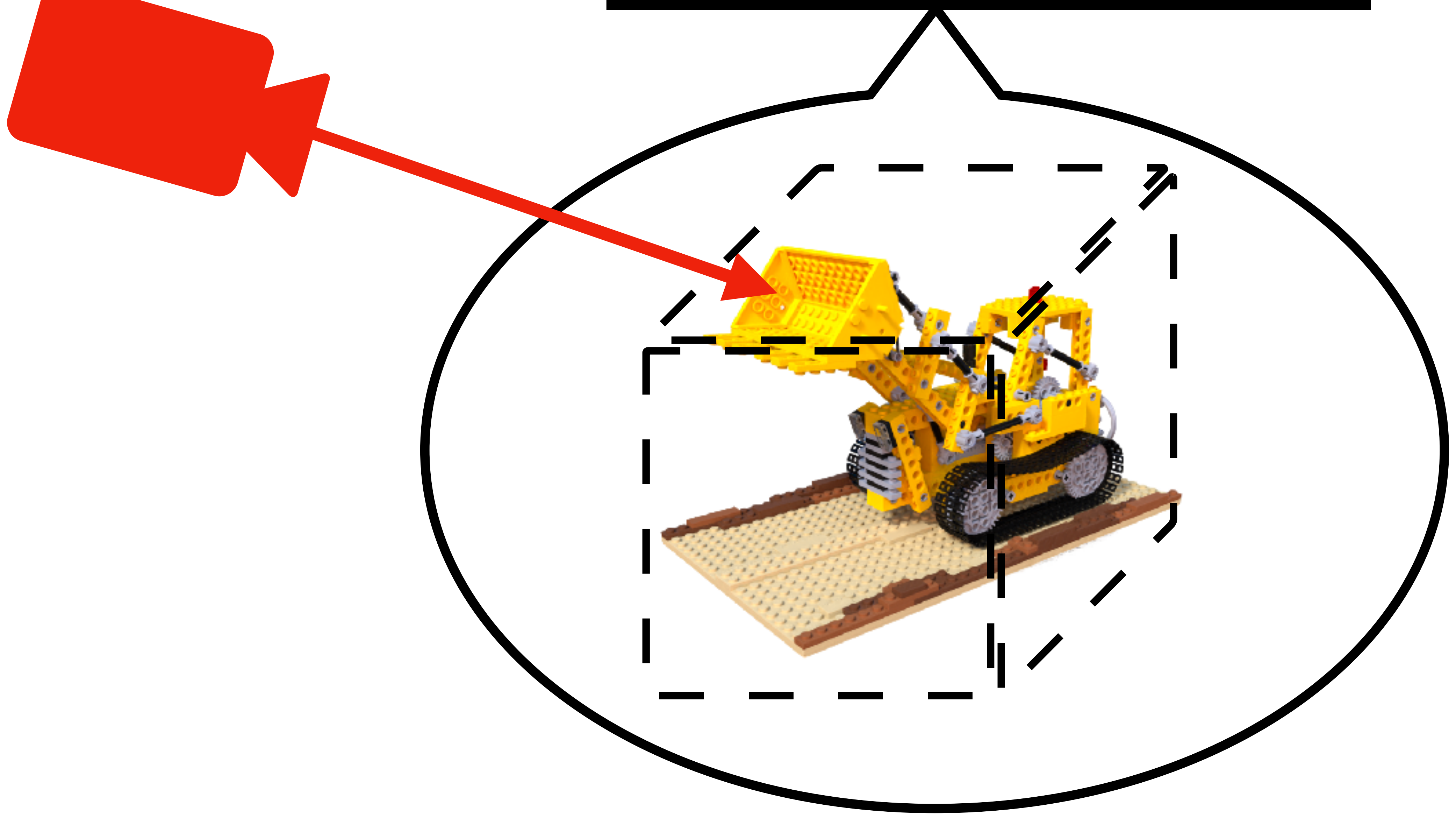


Predict a 3D grid, render image from viewpoint

x, y, z, θ, ϕ

Novel viewpoint

Neural Network



Predicted

What are challenges with this approach?

Challenges

Discretization loses information!

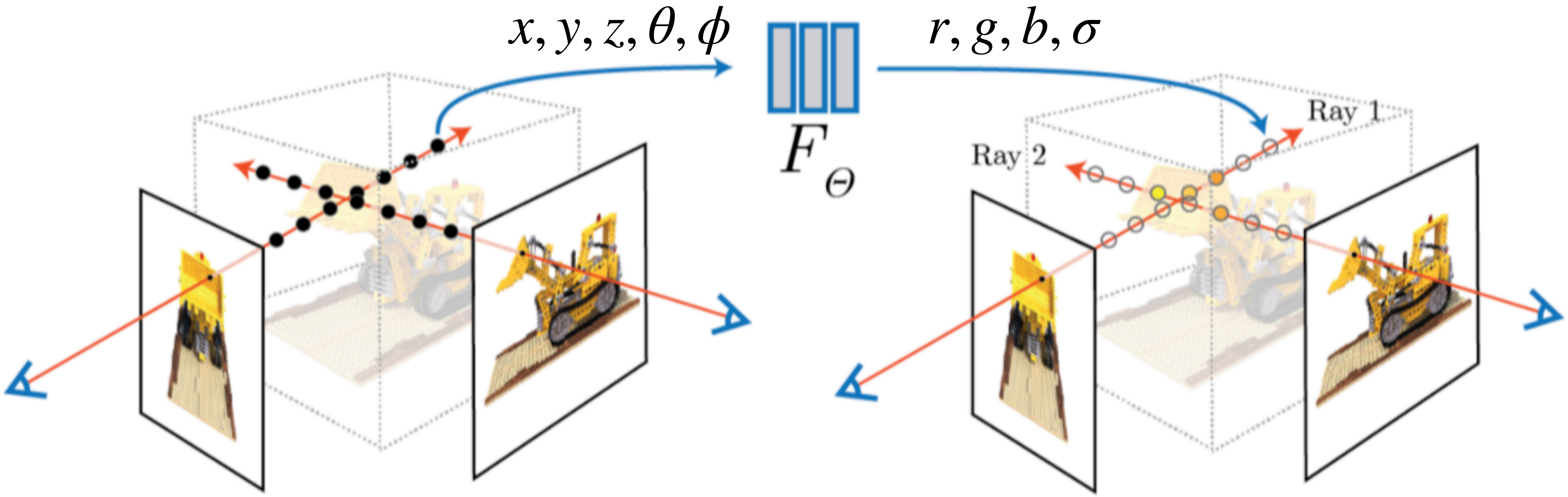
Memory Inefficient!

Not differentiable! (Not a continuous projection)

NERF to the rescue!

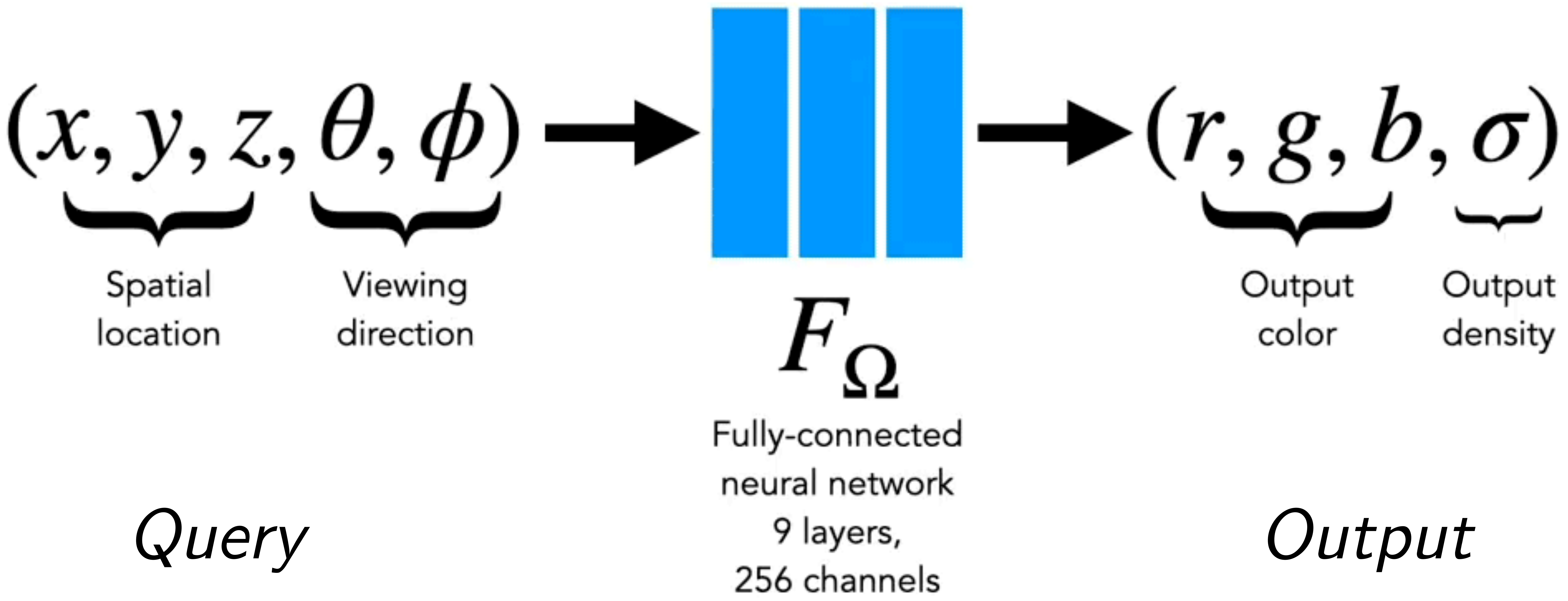
What are Neural Radiance Fields (NeRFs)?

Idea: Use a neural network to *implicitly* represent 3D volume!

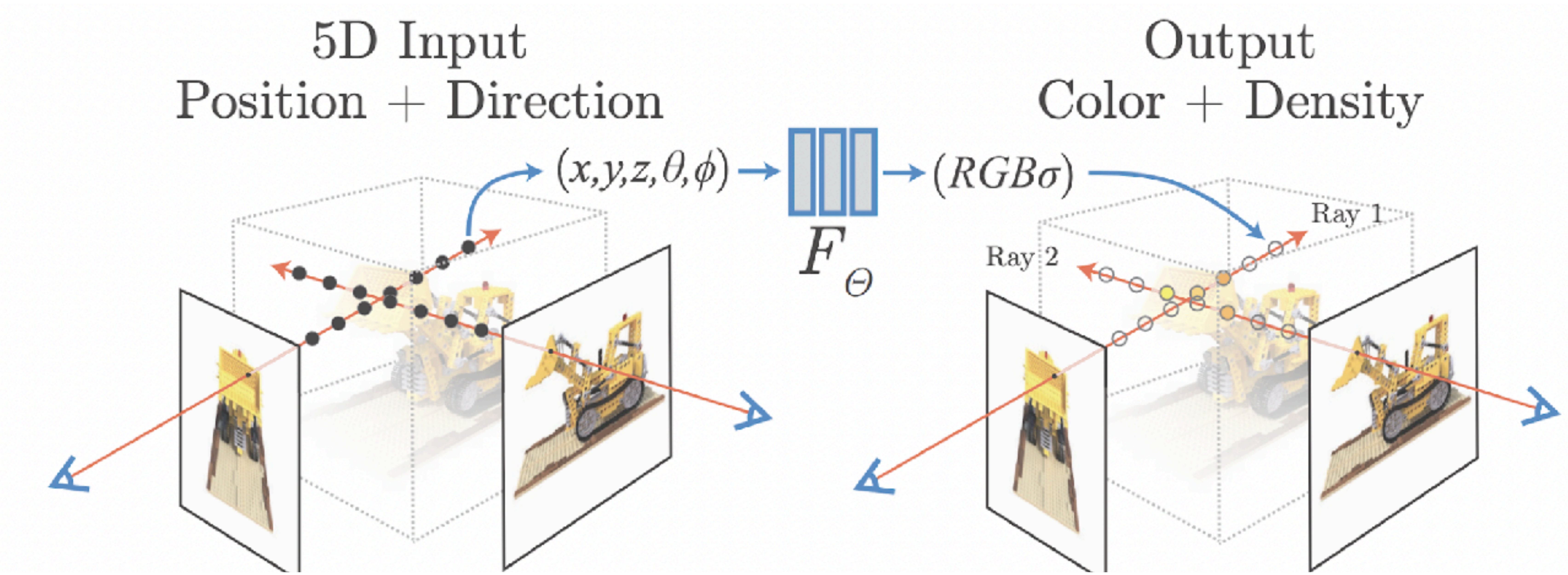


✓ No Discretization ✓ Compressible ✓ Differentiable

How does a NERF *implicitly* represent 3D scene?



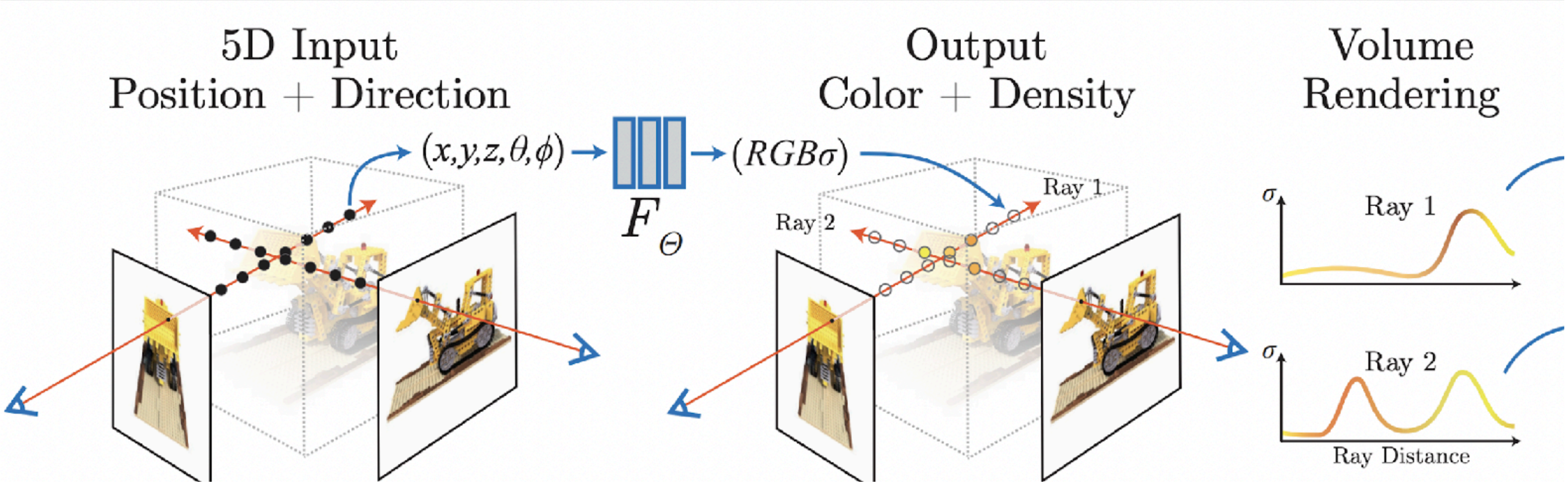
Differentiable Loss Function



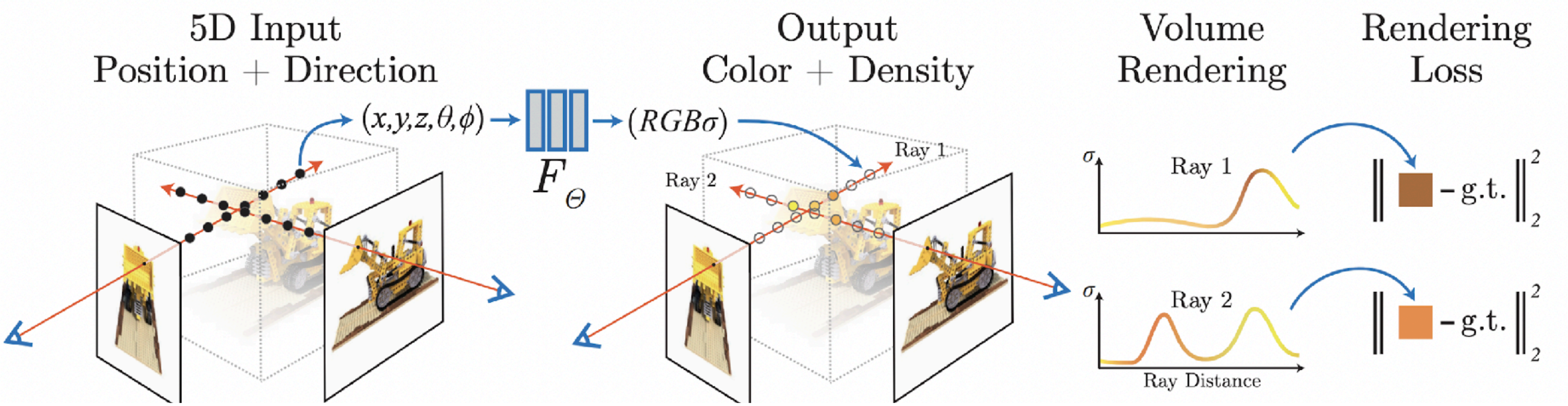
$$\min_{\Theta} \sum_i ||\mathbf{render}_i(F_\Theta) - I_i^{gt}||^2$$

What is the render() function?
How is it differentiable?

NeRF scene: Generate views



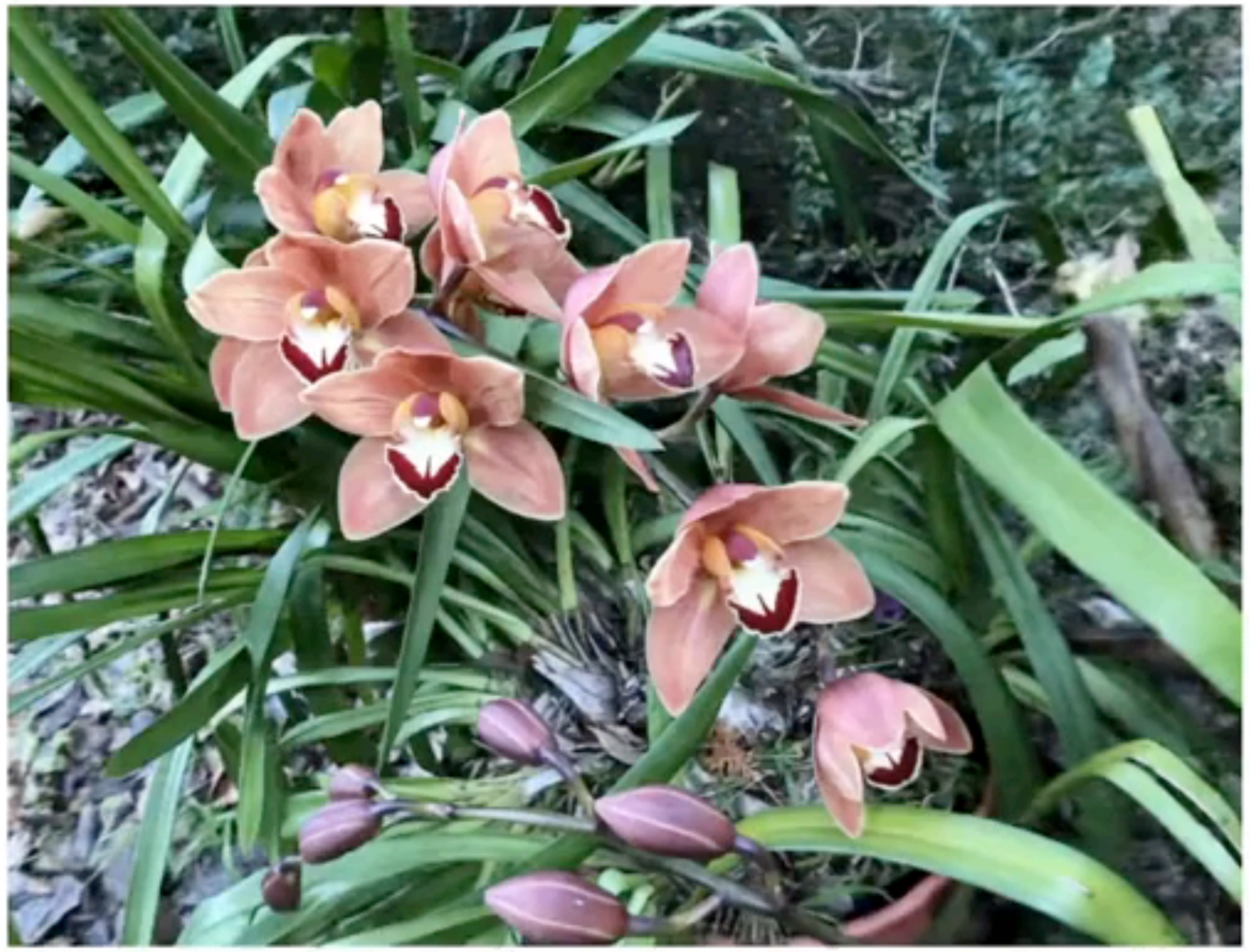
NeRF scene: Generate views



Results

Novel View Synthesis

Inputs: sparsely sampled images of scene



Outputs: *new* views of same scene
(rendered by our method)

More detailed and consistent than prior work that represents scene as discrete voxel grid

Neural Volumes [Lombardi 2019]

NeRF

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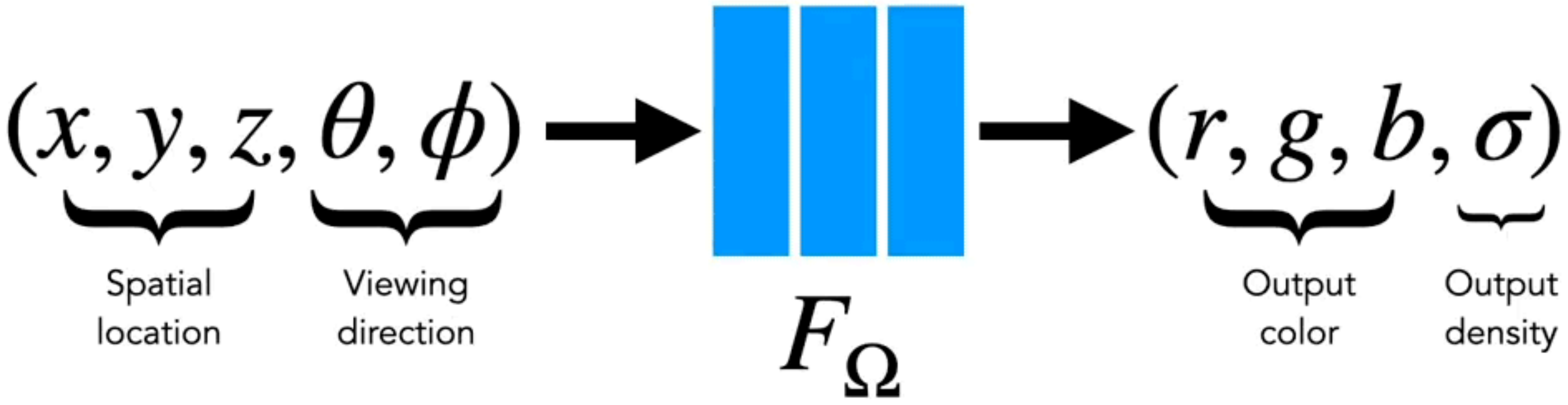
One key trick to make it work ...

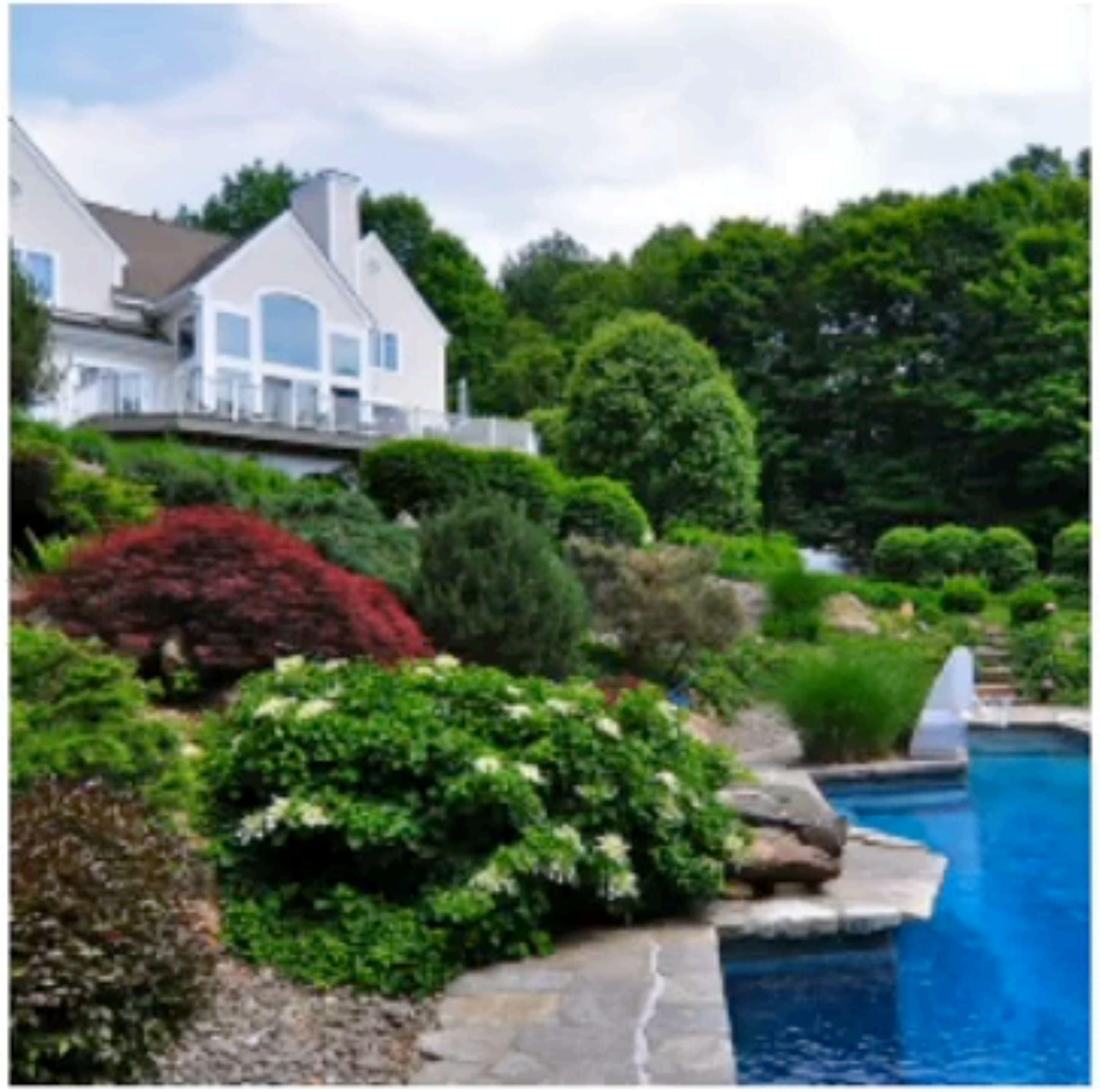
Naively passing in position creates blurry images!



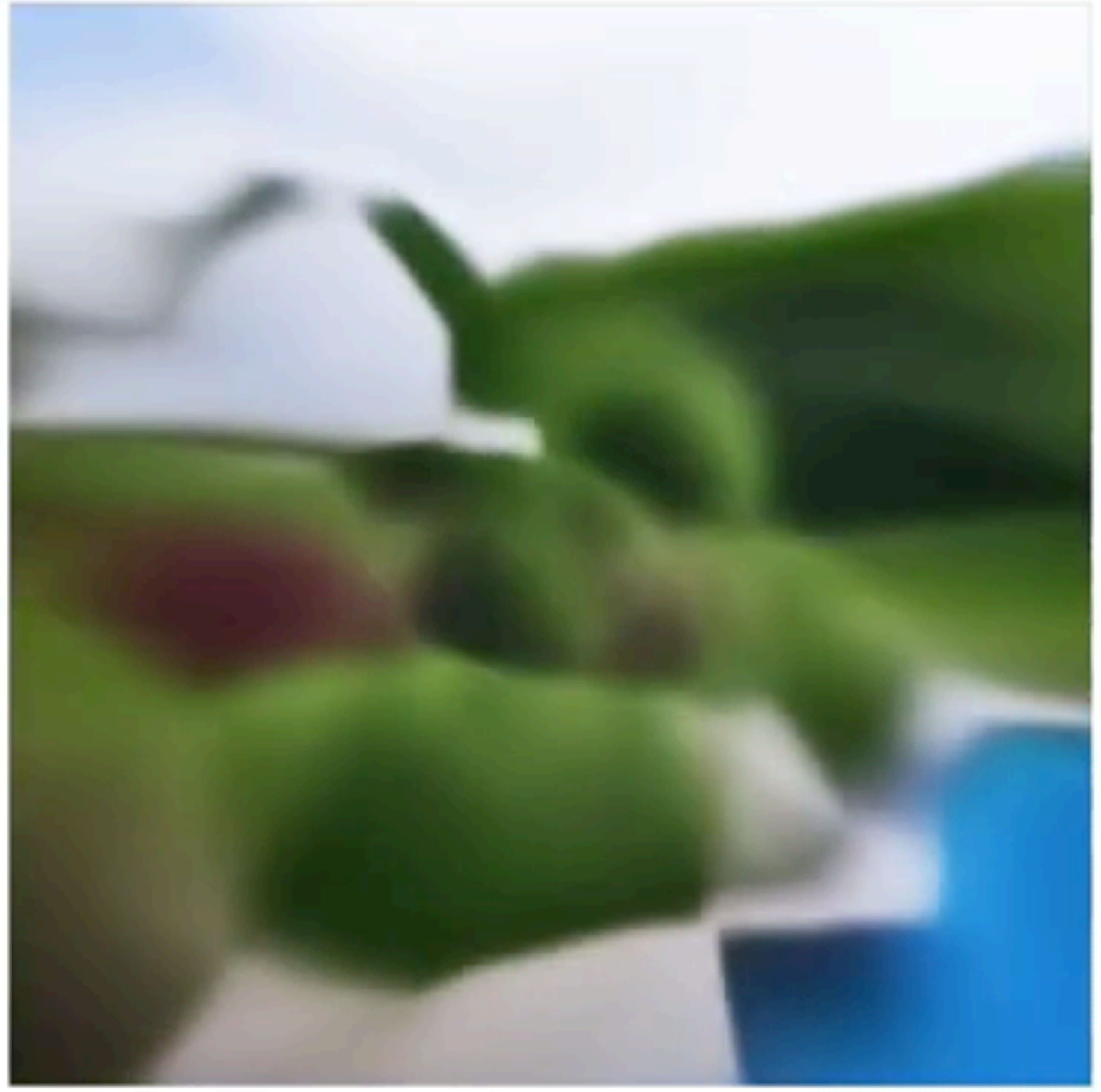
Why?

Let's say we train a network to memorize an image

Ground truth image



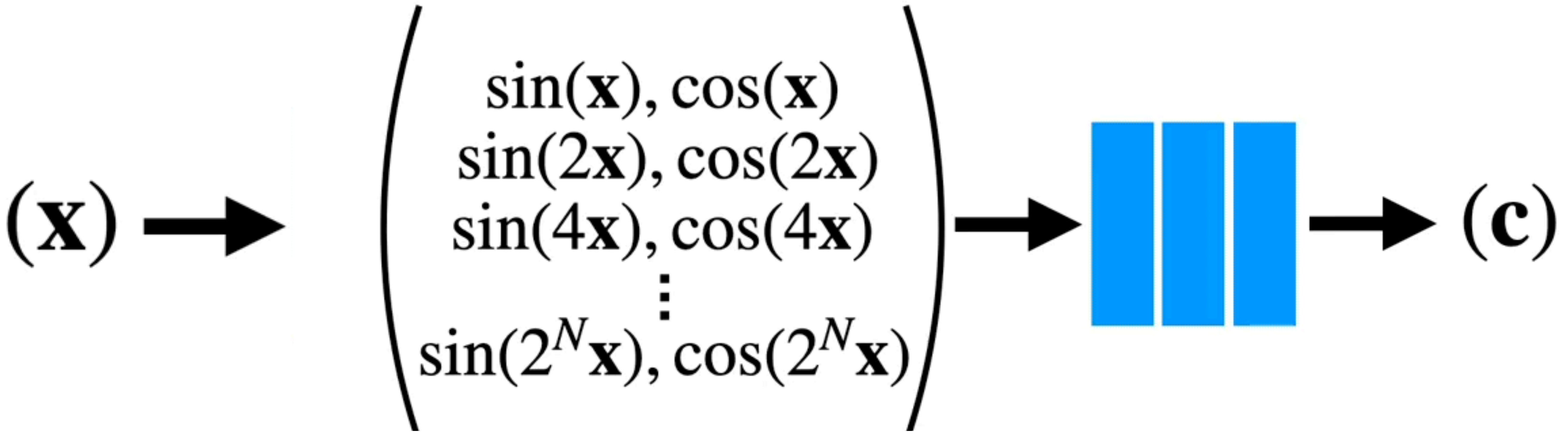
Standard fully-connected net



How do we make the image look sharper?

Idea: Encode low-dim coordinates to high-dim features

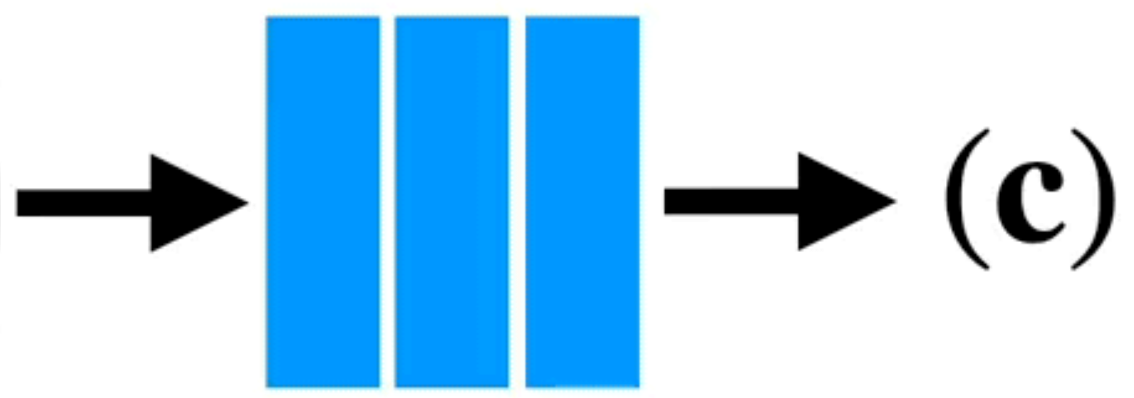
High-frequency embedding of input coordinates



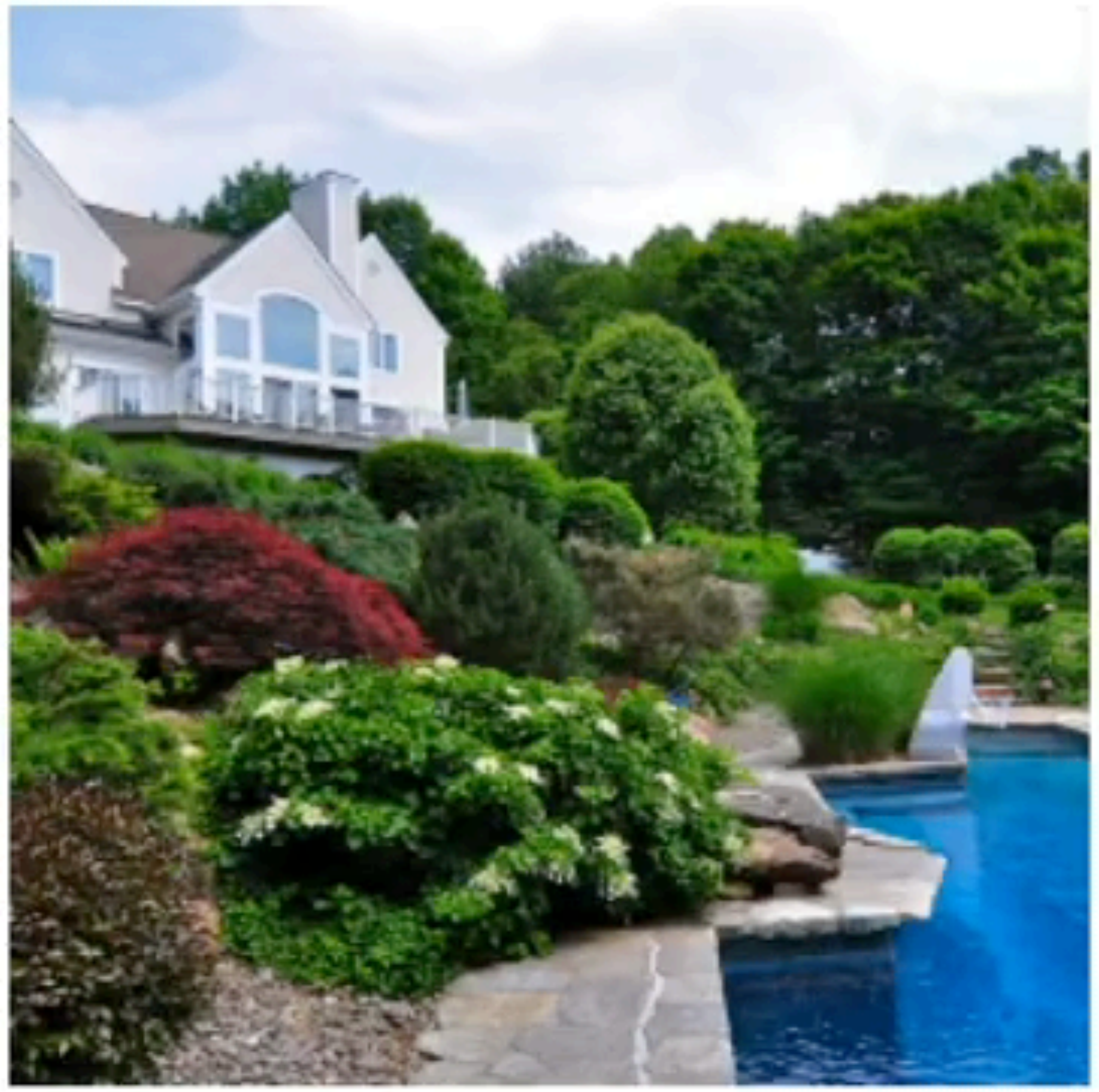
[Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains, Tancik et al.]

Use positional encoding

$$\begin{pmatrix} \sin(\mathbf{x}), \cos(\mathbf{x}) \\ \sin(2\mathbf{x}), \cos(2\mathbf{x}) \\ \sin(4\mathbf{x}), \cos(4\mathbf{x}) \\ \vdots \\ \sin(2^N\mathbf{x}), \cos(2^N\mathbf{x}) \end{pmatrix}$$



Ground truth image



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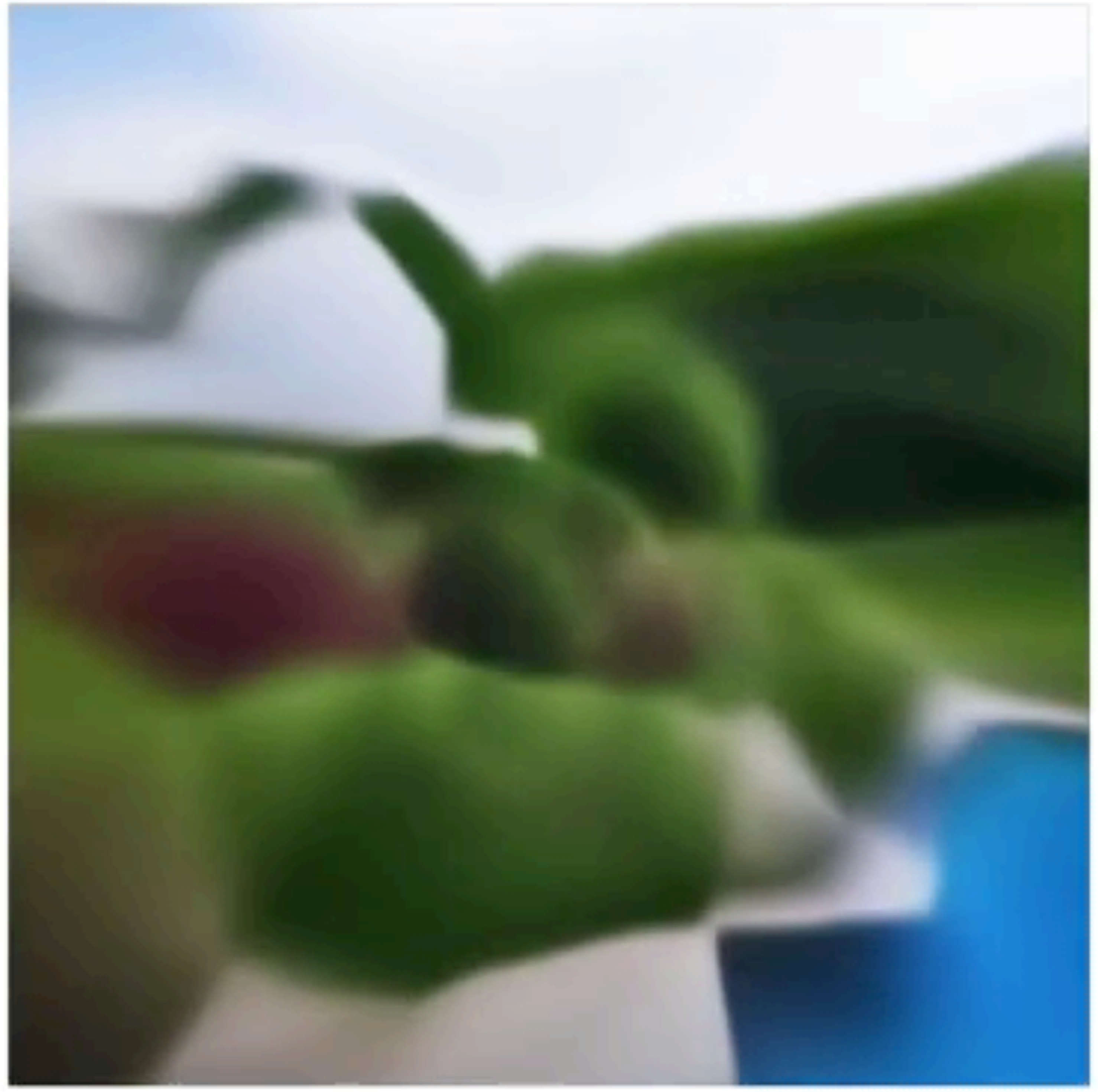
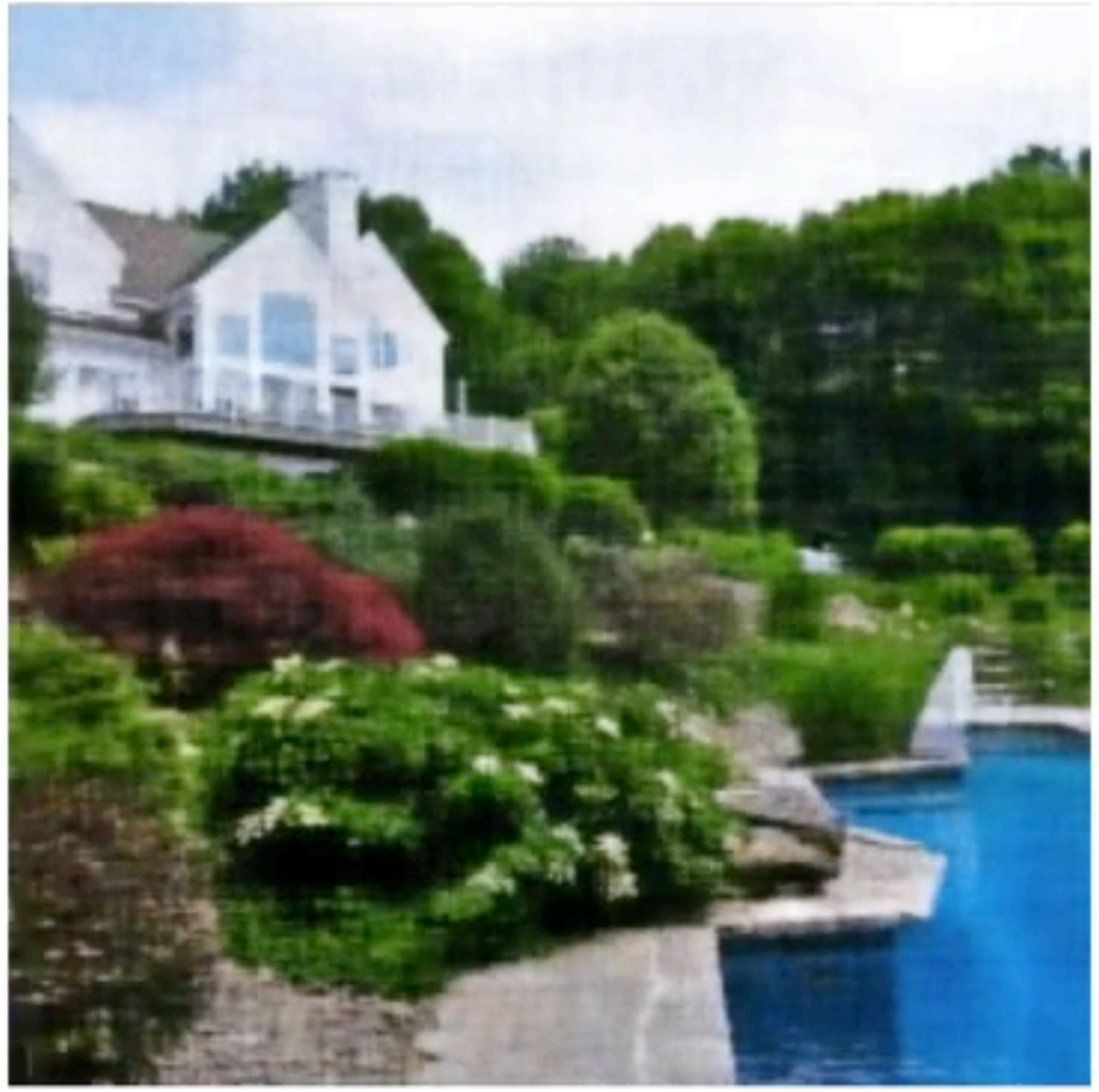
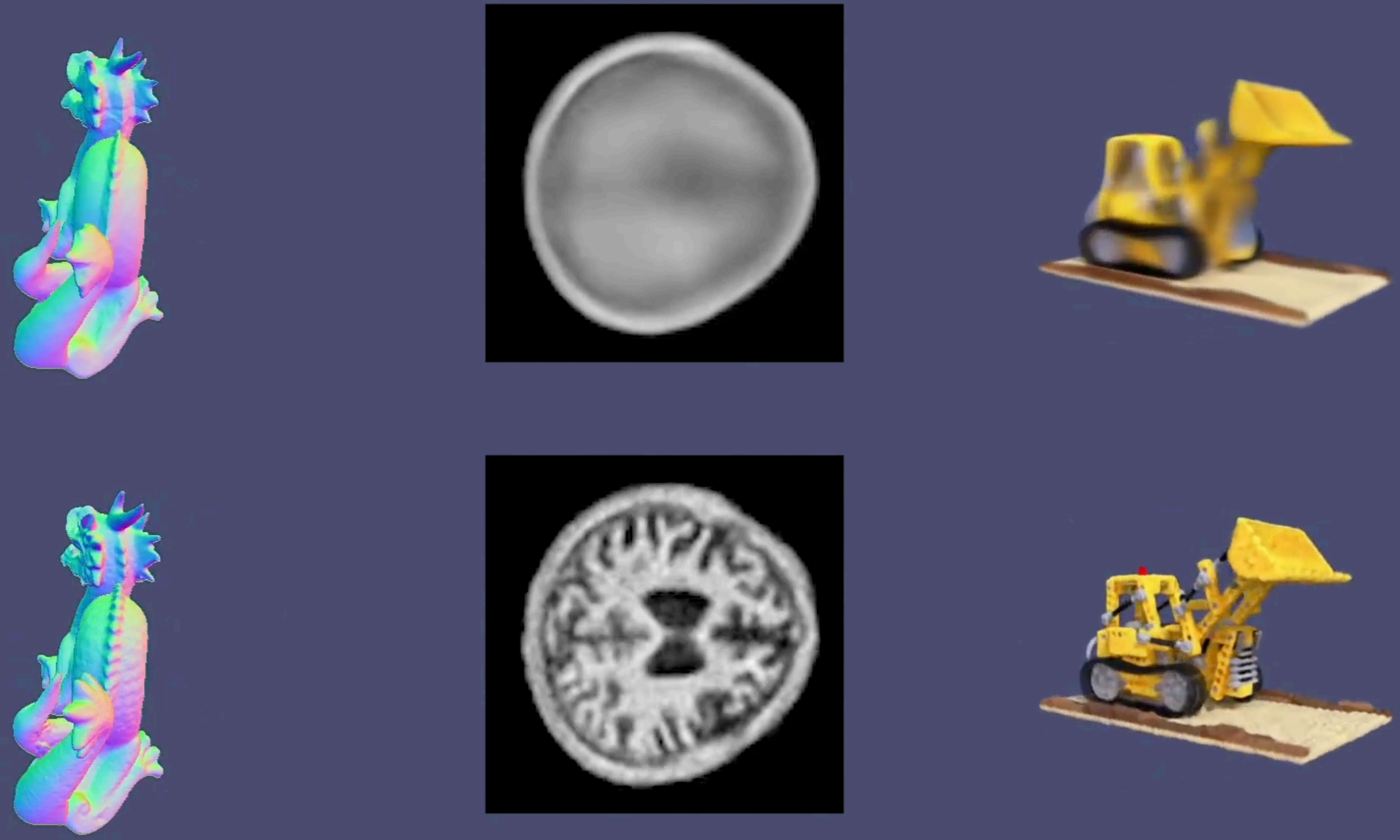


With "positional encoding"

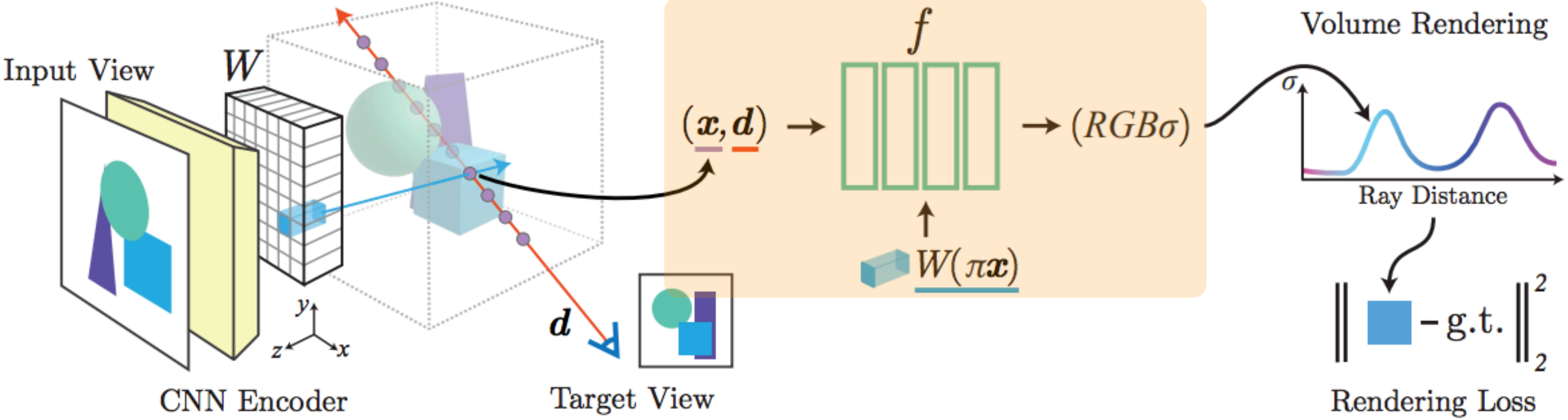



Standard input
Fourier feature input
3D Shape
3D MRI
3D NeRF

Lots of extension and applications!

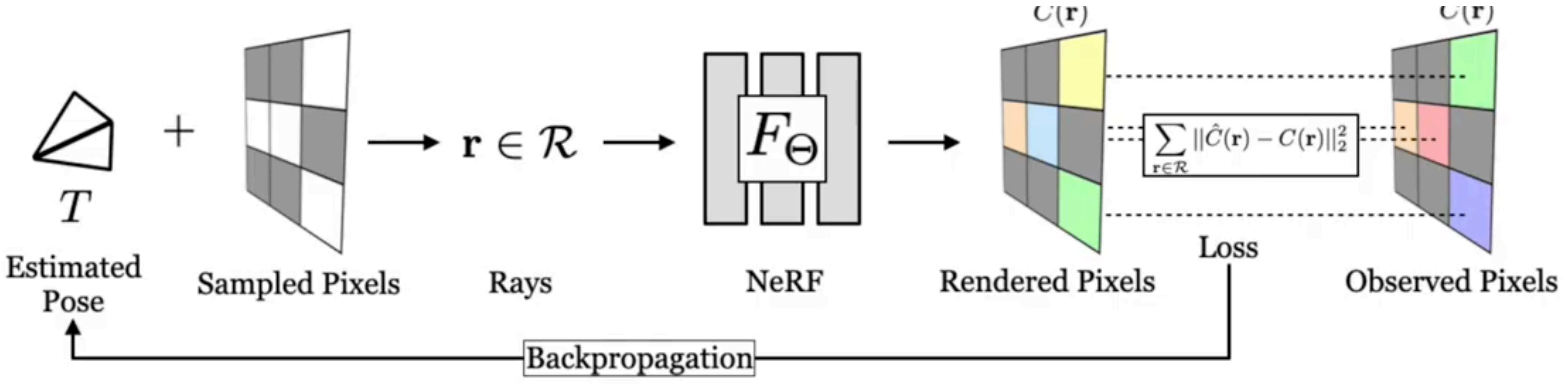
Generalization

Goal: Train a NeRF for arbitrary new scenes with fewer images



Unknown camera poses

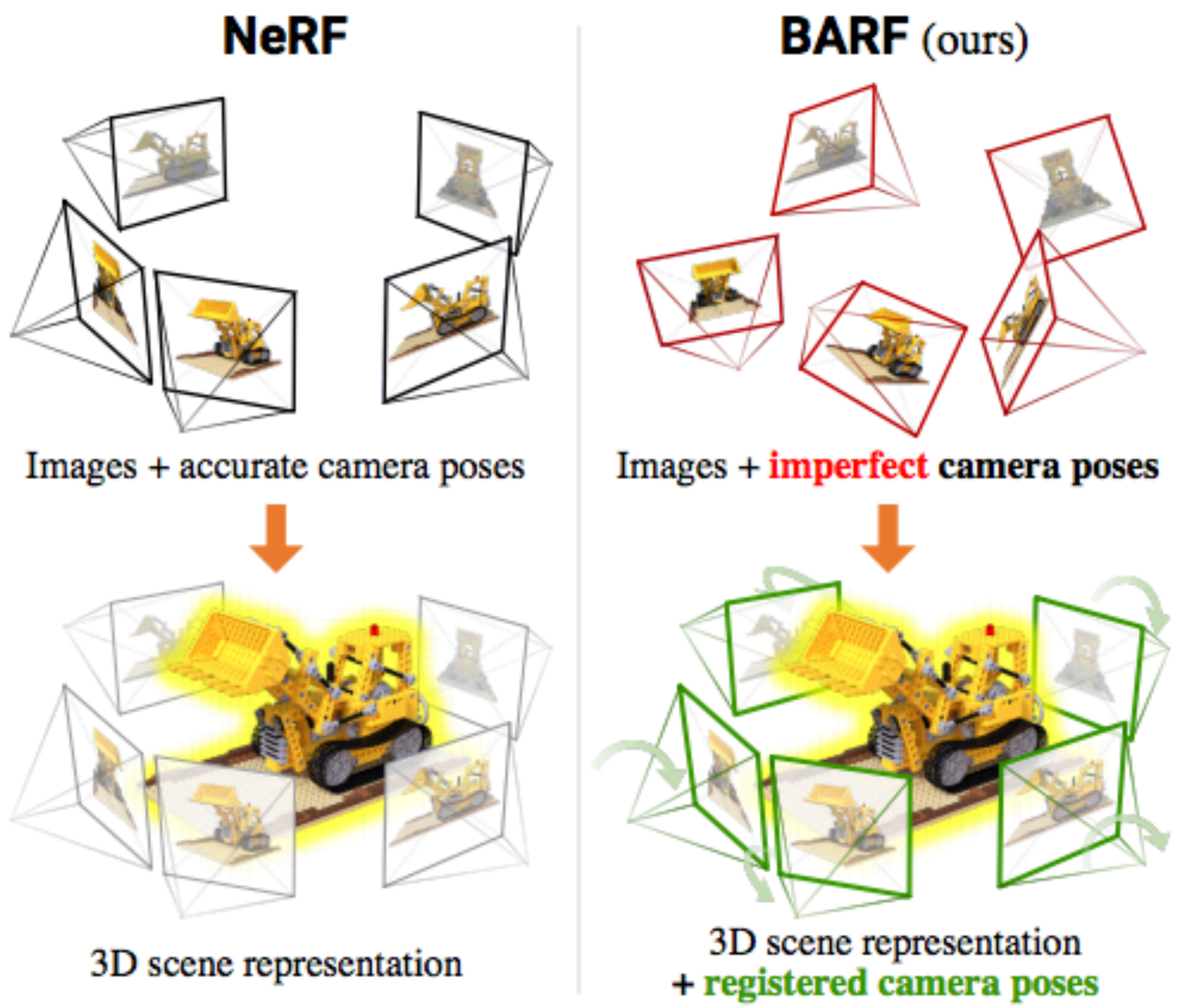
Goal: Estimate poses given a trained NeRF

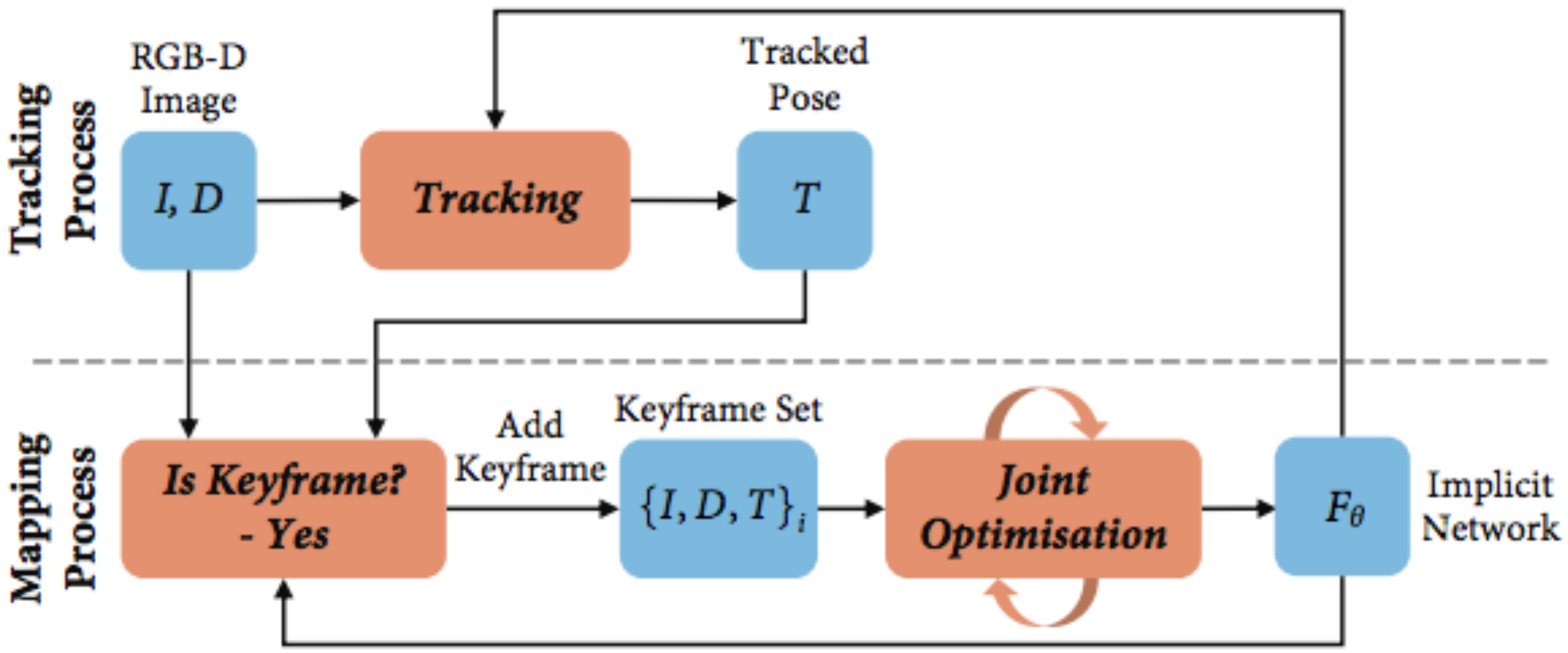


[iNeRF: Inverting Neural Radiance Fields for Pose Estimation]

Unknown camera poses + Scene

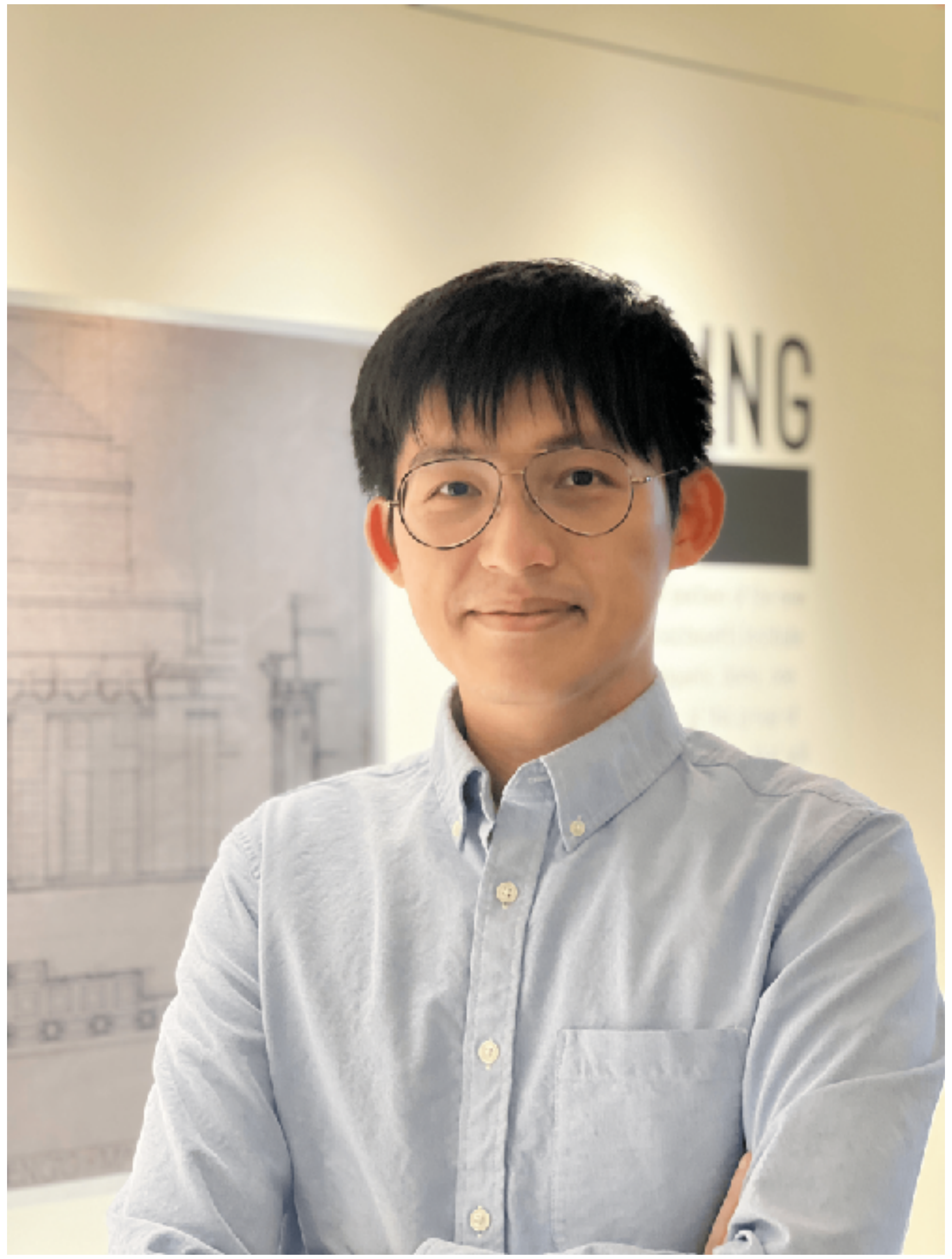
Goal: Simultaneously estimate pose and scene representation





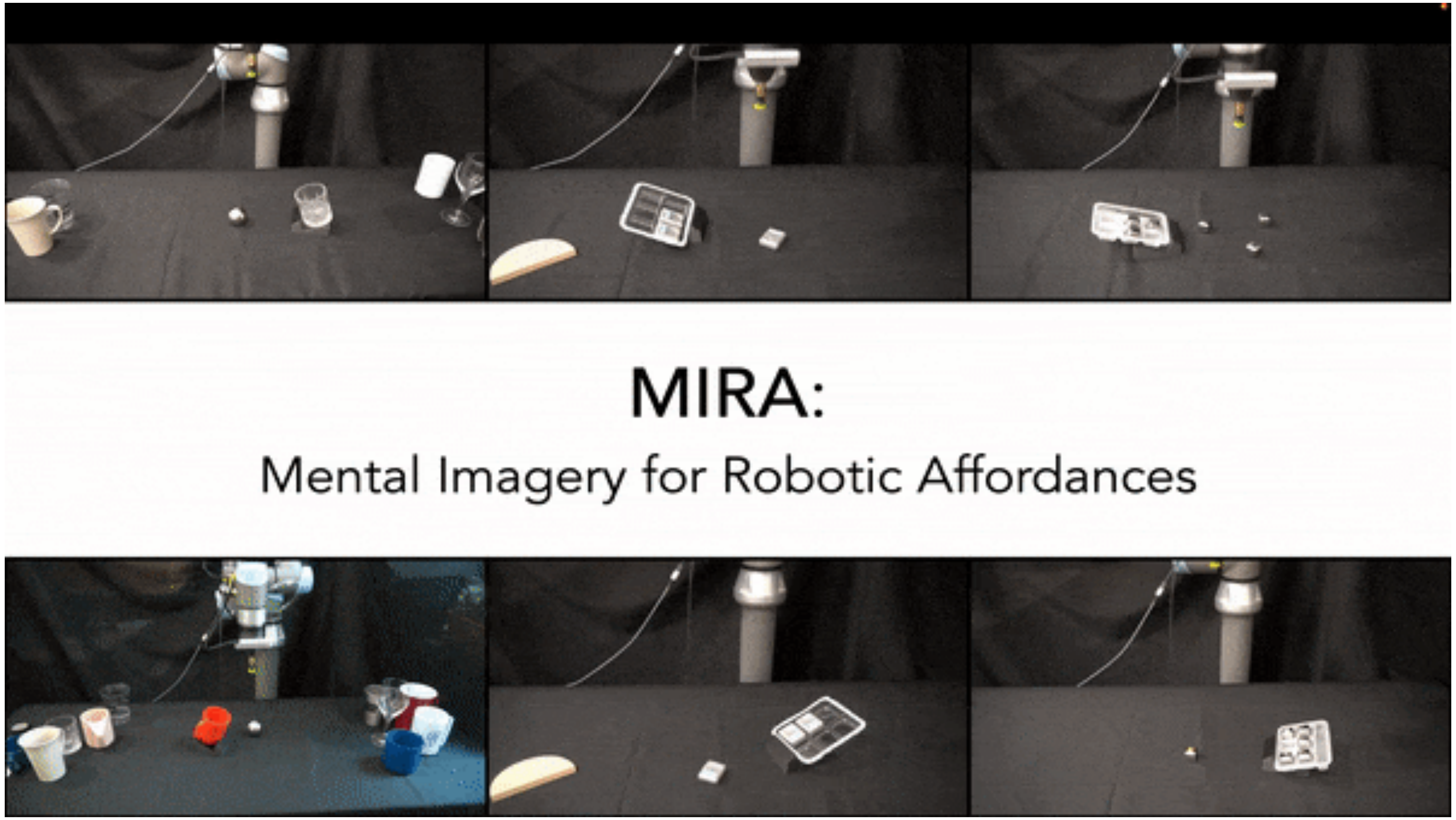
BARF : Bundle-Adjusting Neural Radiance Fields

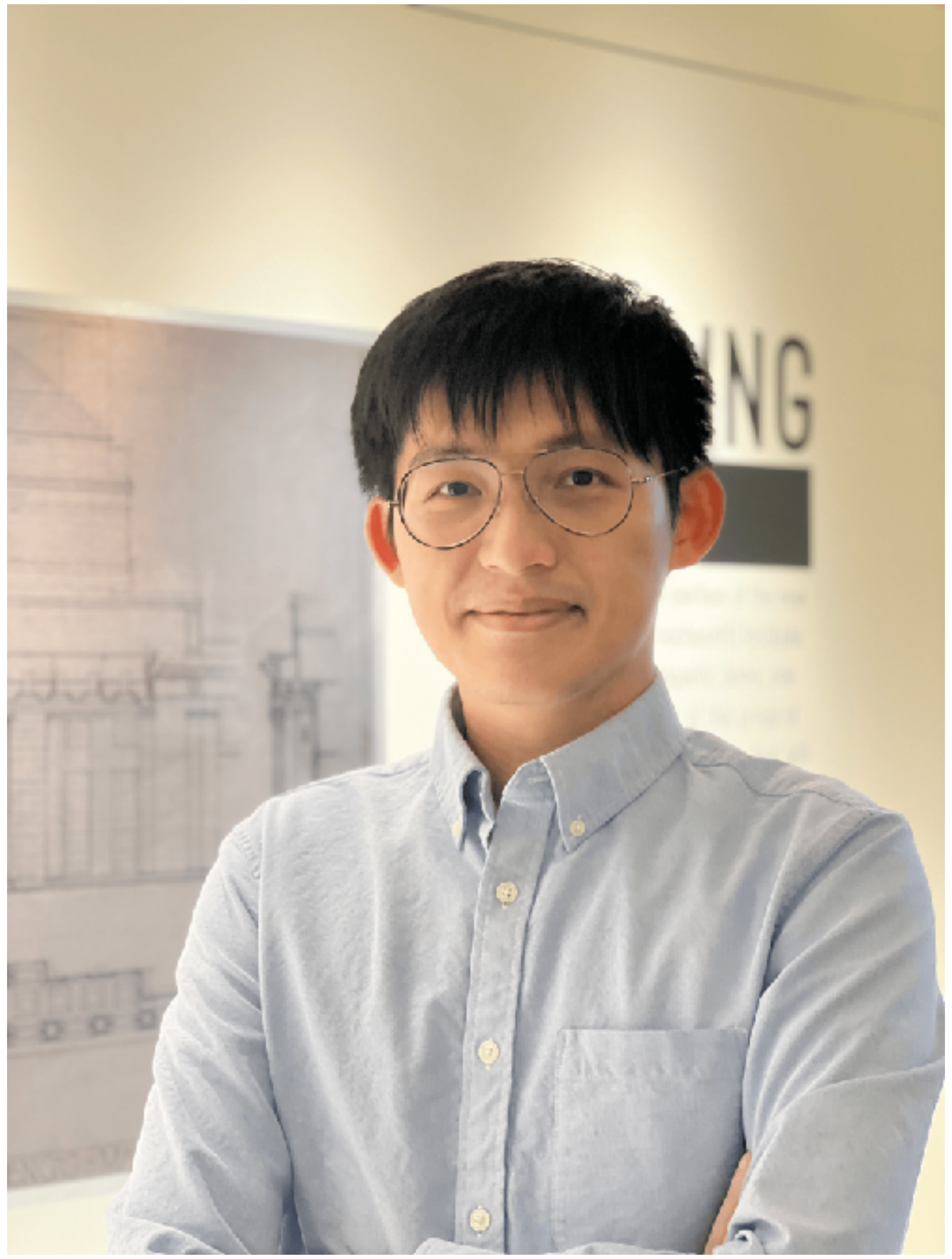
iMAP: Implicit Mapping and Positioning in Real-Time



Prof. Wei Chiu Ma
(Joining Fall 2024!)

CS6672 3D Vision





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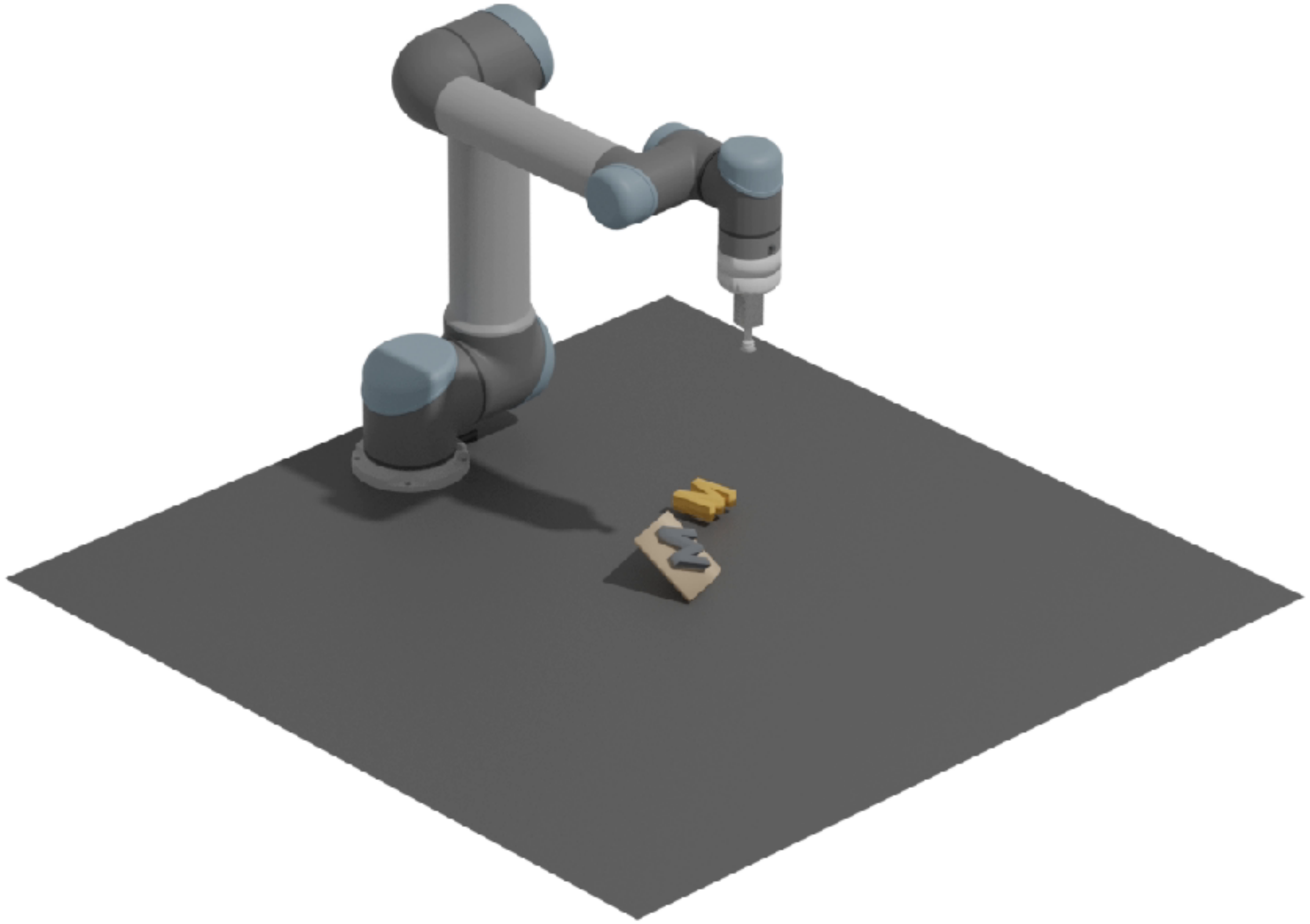
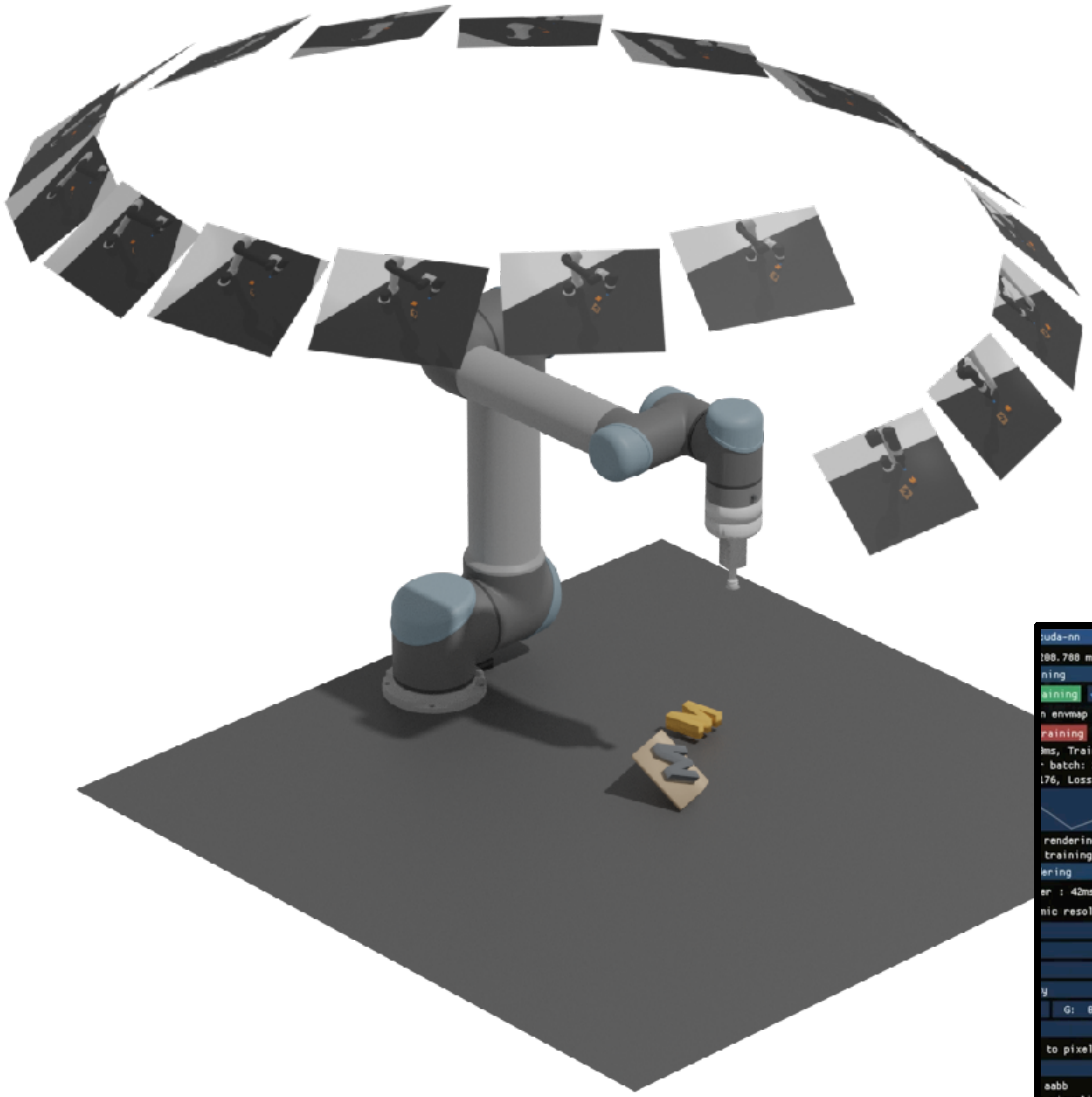
CS6672 3D Vision

MIRA represents the scene with a Neural Radiance Field (NeRF) and hence requires RGB-only inputs.



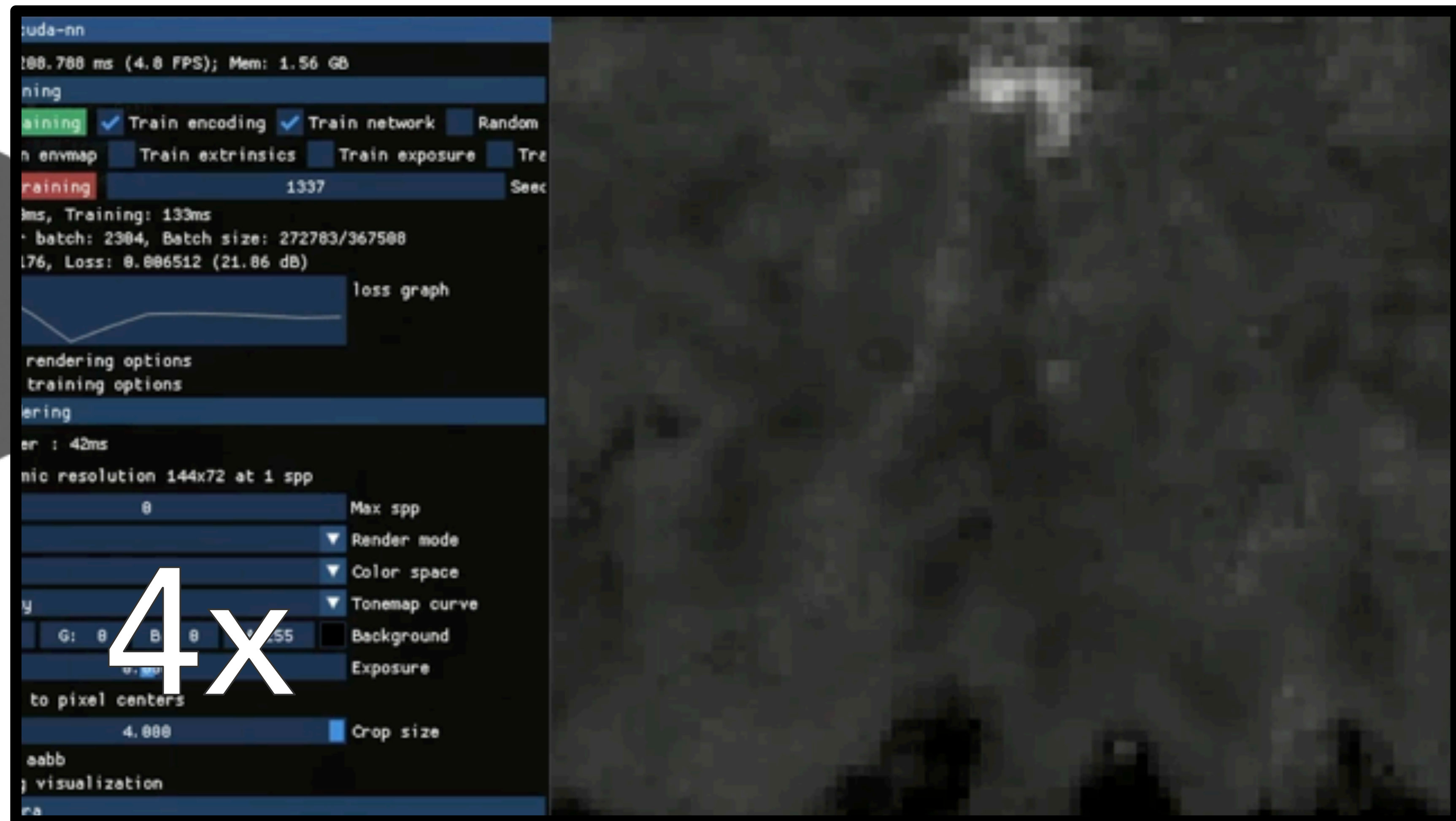
Before each action, it takes multi-view RGB images as inputs to optimize a NeRF of the scene.



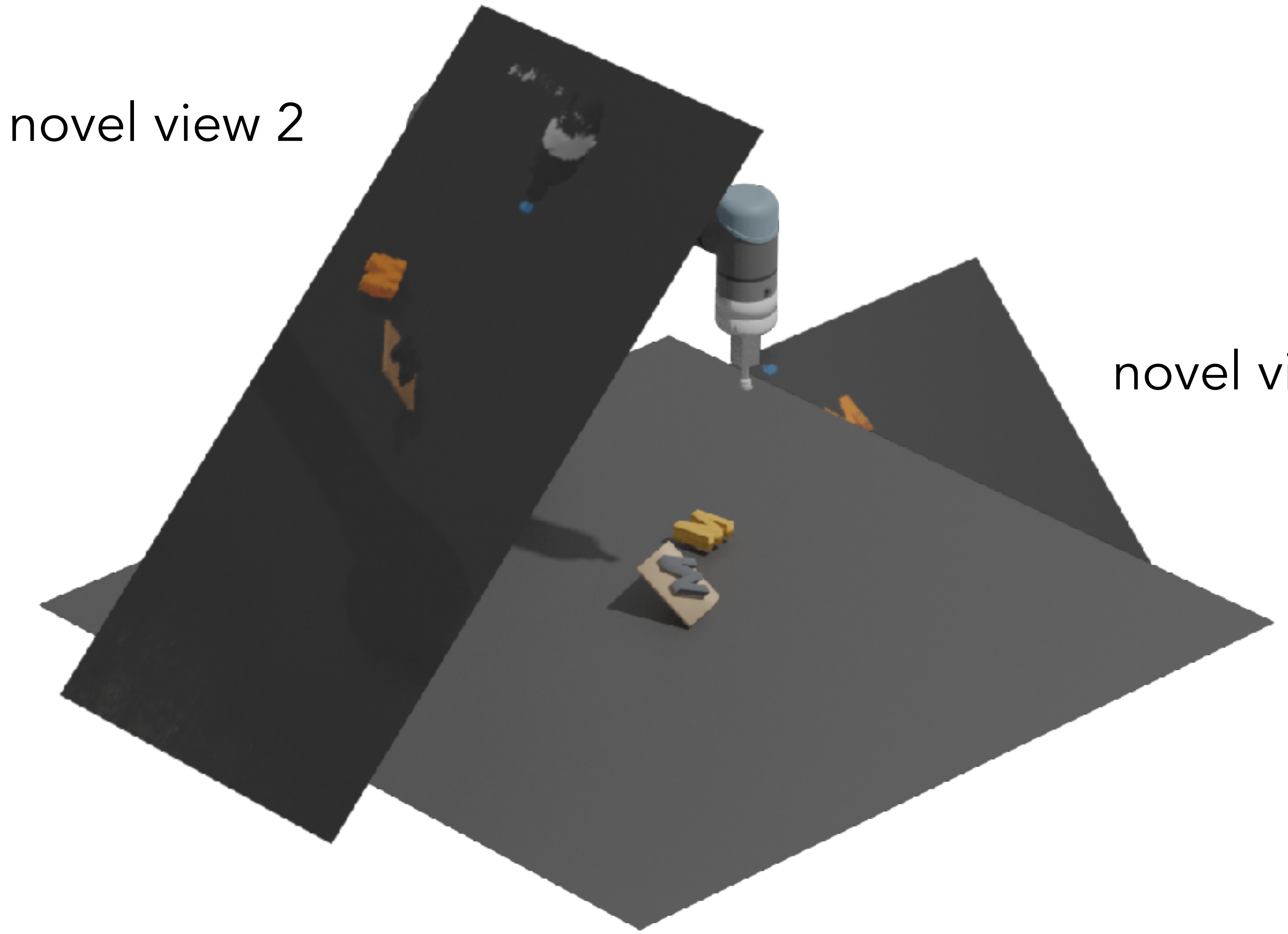
Input: 30 images

Optimization: ~10s

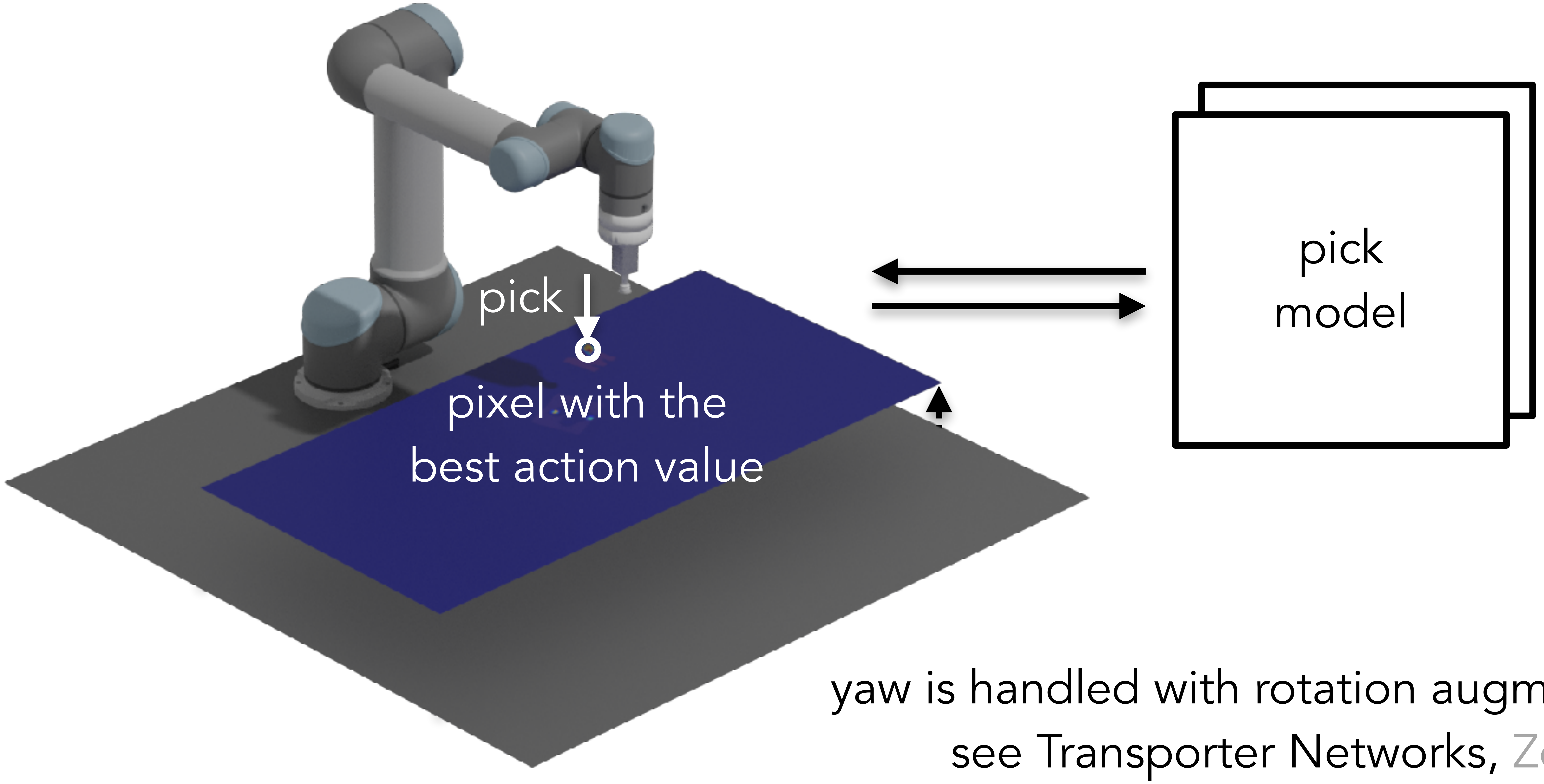
Rendering: 60fps



Given a NeRF, MIRA uses orthographic ray casting to render novel views densely. We show 2 views for illustration.

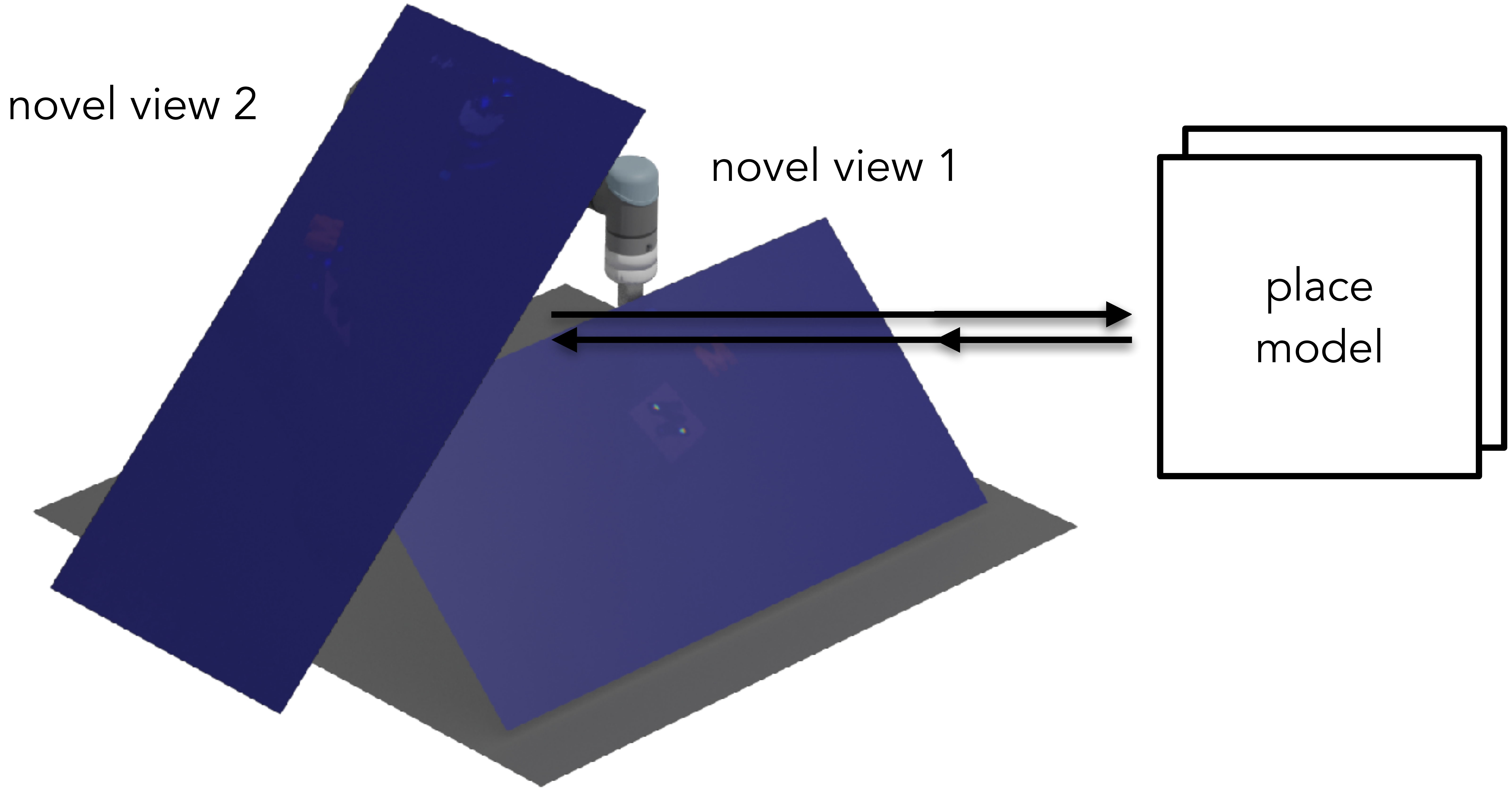


Existing action-centric methods predict 3-DoF action (x, y, yaw) from a top-down image.



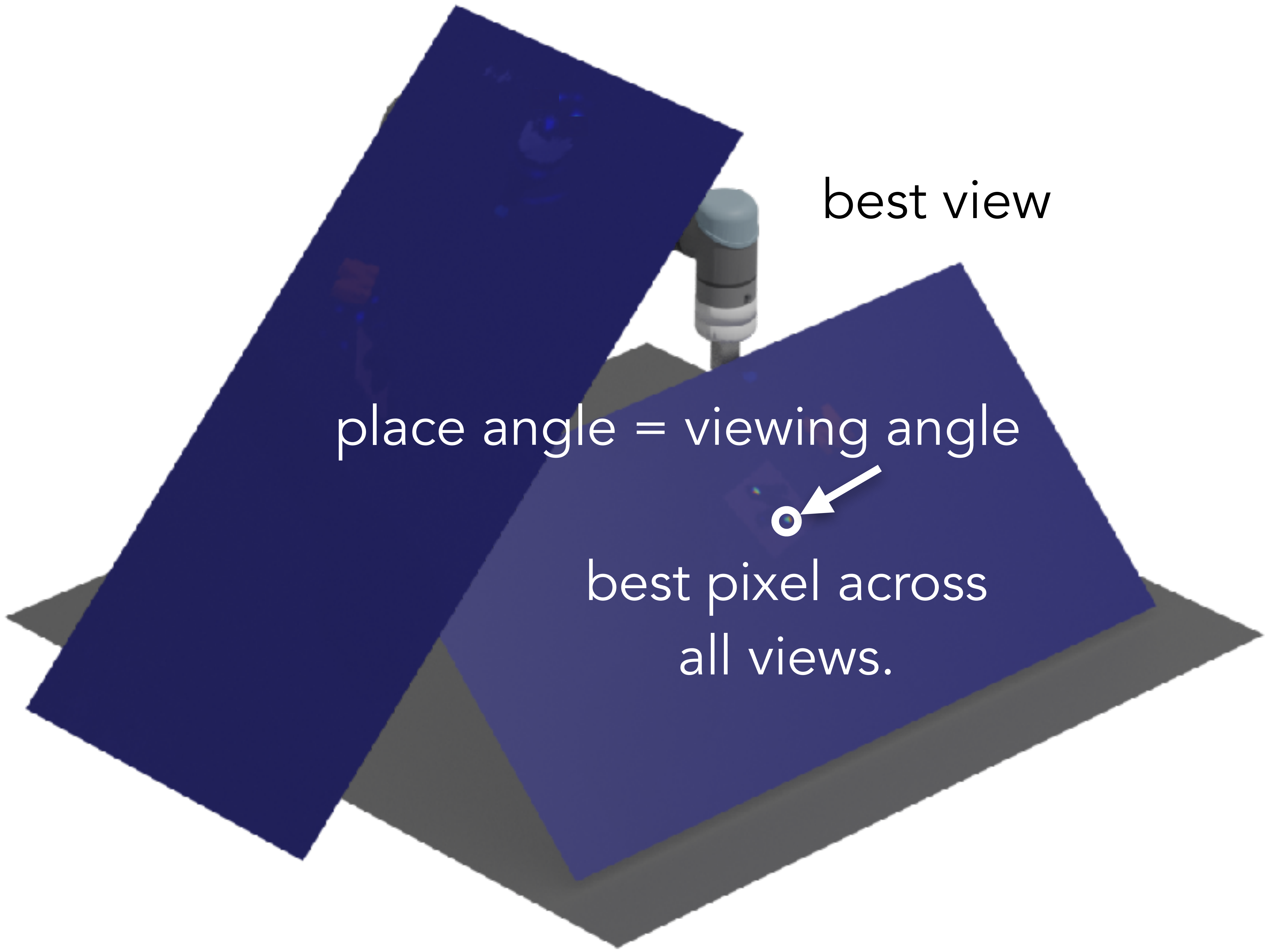
yaw is handled with rotation augmentation,
see Transporter Networks, Zeng et al.

MIRA generalizes this idea to predict 6-DoF actions using images synthesized by NeRF.

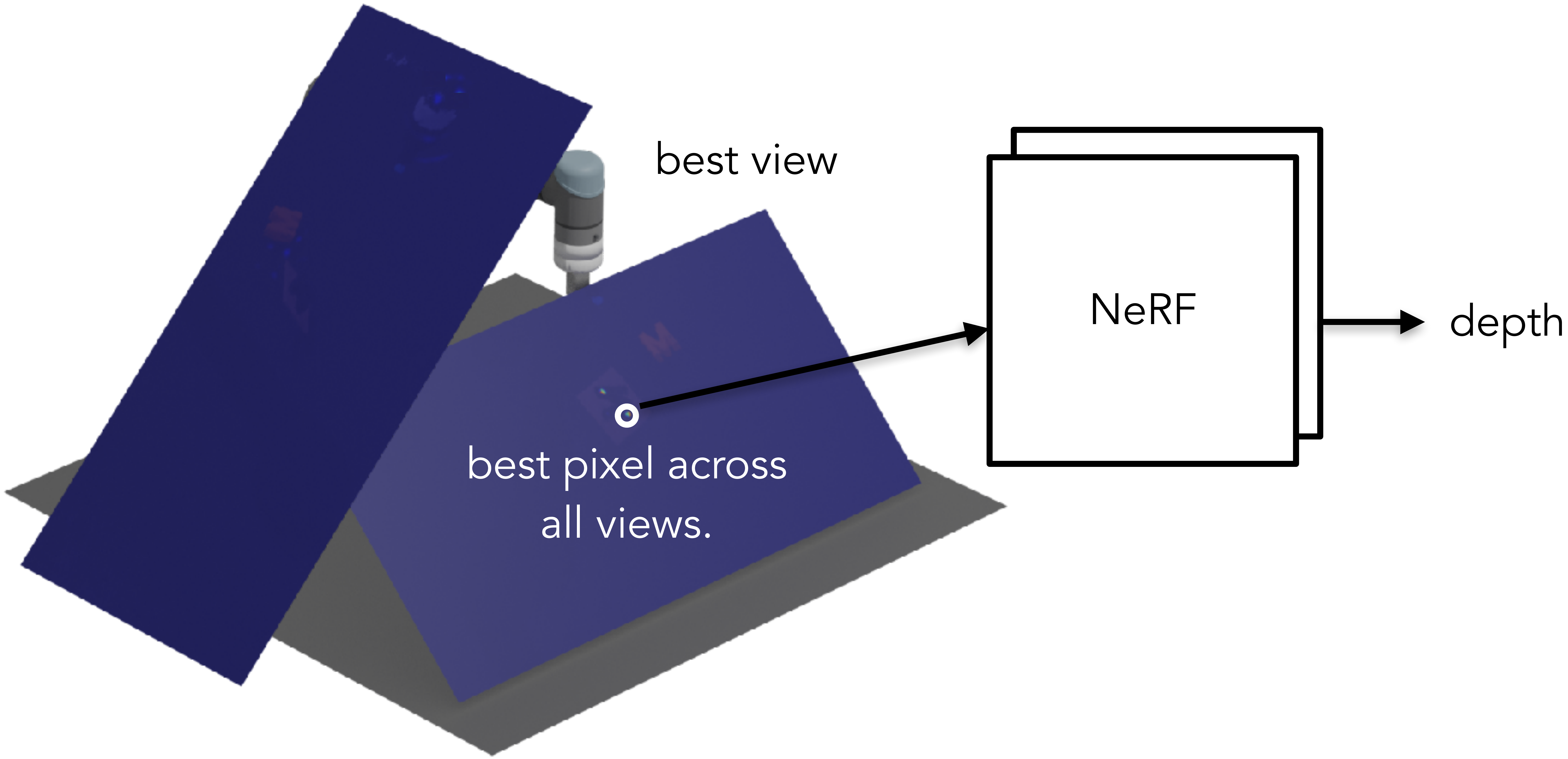


It compares each novel view's best action value to decide the best pixel & the best view.

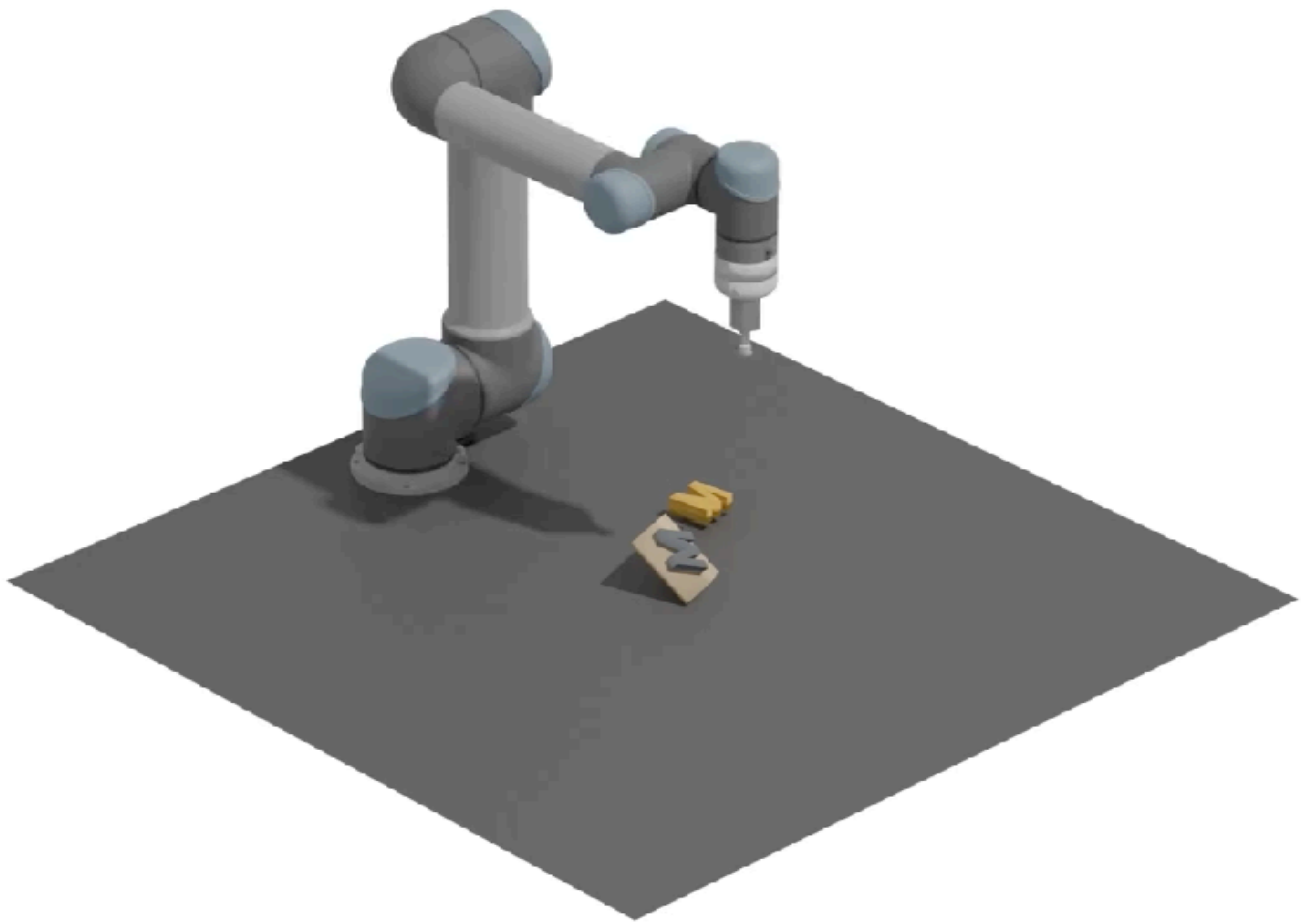
It then uses the best view's viewing angle to parameterize the 6-DoF action's (roll, pitch).



To determine the output action's z, MIRA uses NeRF to predict the best pixel's depth.



We show the result of executing 6-DoF actions predicted by MIRA.




Failed!

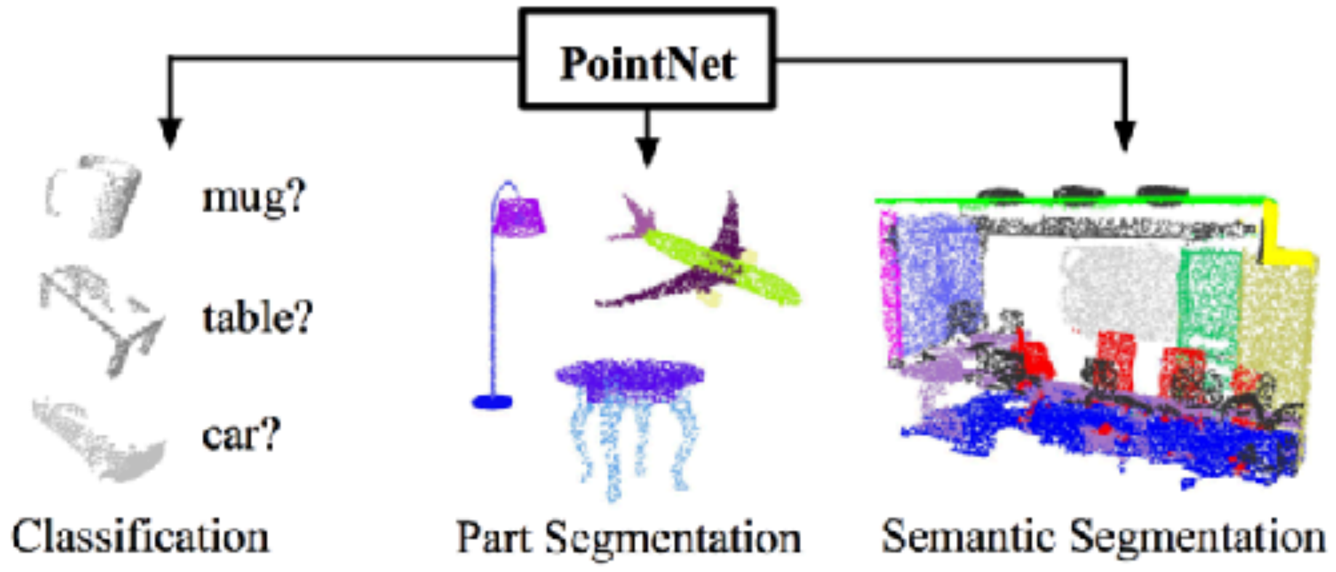
tl;dr

But manipulating objects require 3D reasoning!

PointNet

End-to-end learning for **scattered, unordered** point data

Unified framework for various tasks



Slides from Qi et al, CVP 2017 http://stanford.edu/~rqi/pointnet/docs/cvpr17_pointnet_slides.pdf

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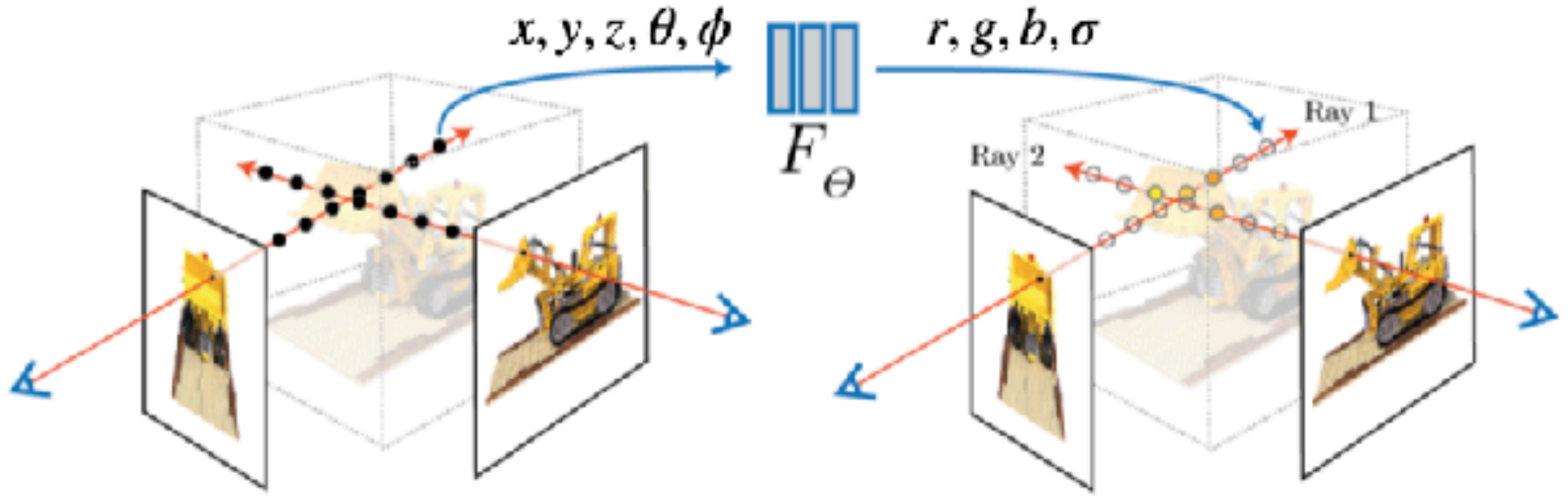
What are Neural Radiance Fields (NeRFs)?

Idea: Use a neural network to *implicitly* represent 3D volume!



✓ No Discretization ✓ Compressible ✓ Differentiable

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