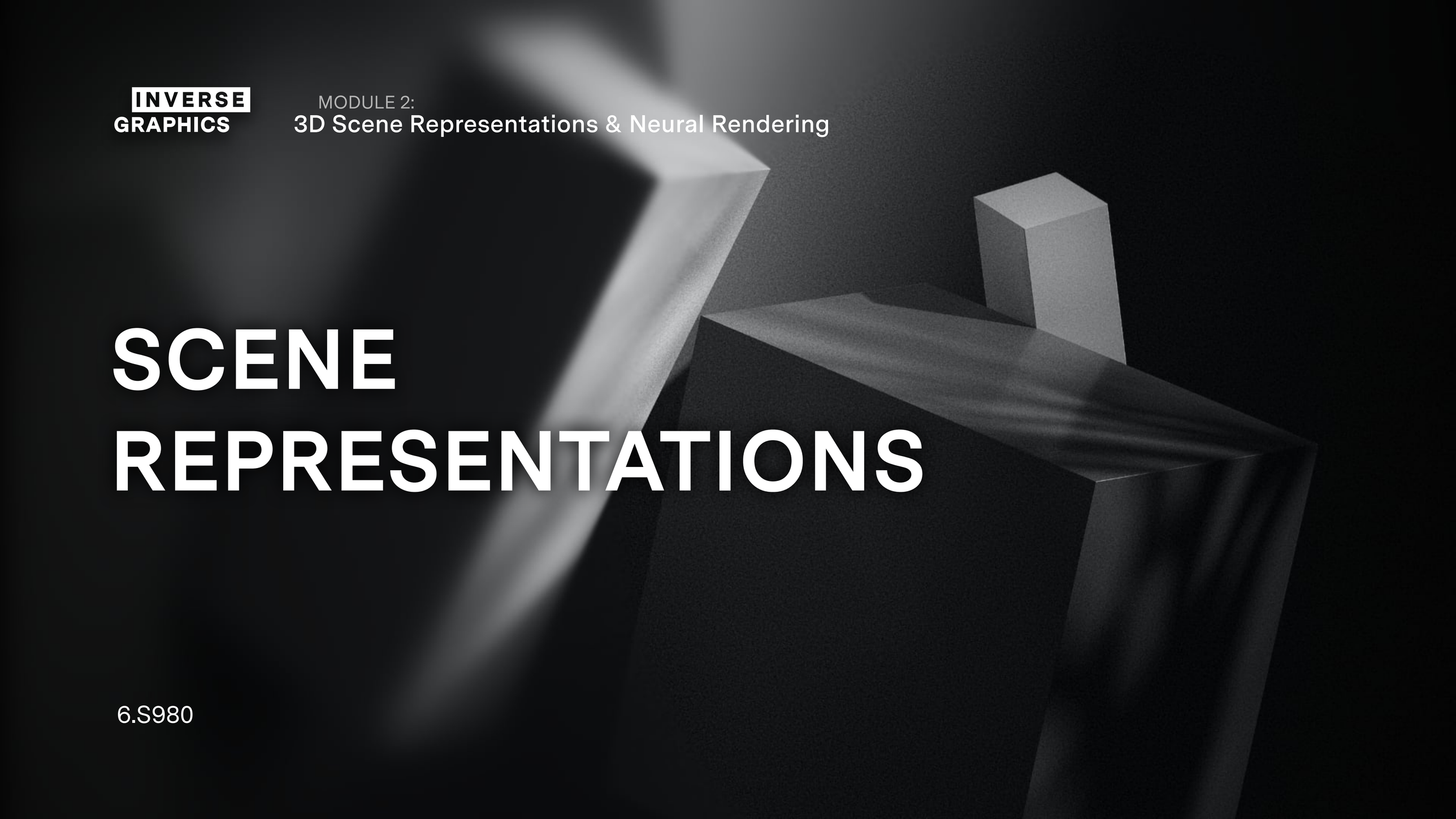
INVERSE GRAPHICS

MODULE 2:
3D Scene Representations & Neural Rendering



SCENE REPRESENTATIONS

6.S980

International Conference on 3D Vision
@3DVconf

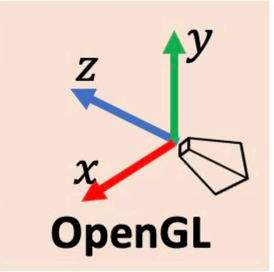
3DV Trivia Time!

Can you solve the 3DV CAPTCHAs? 🧐

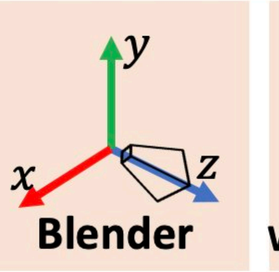
Select all squares with the correct

3D coordinate systems

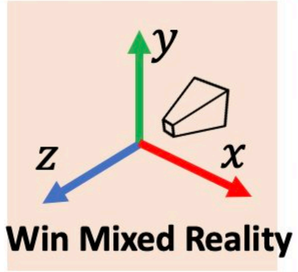
If there are none, click skip.



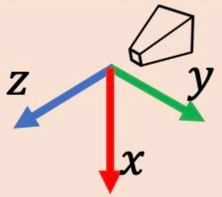
OpenGL



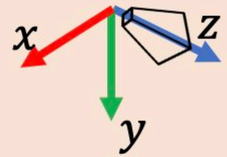
Blender



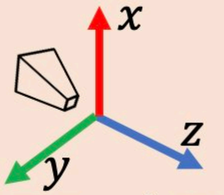
Win Mixed Reality



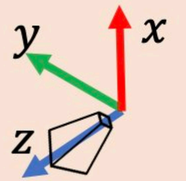
OpenGL



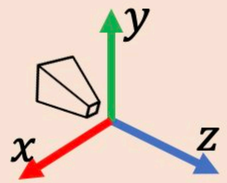
Unity



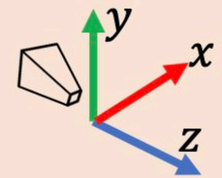
PyTorch3D



OpenCV



COLMAP



LLFF



SKIP

Unsupervised Depth Prediction!

Frame at time t_1

...

Frame at time t_2

Goal: Learn Depth and Ego-Motion (relative camera pose) just from video!

Unsupervised Depth Prediction!

Frame at time t_1

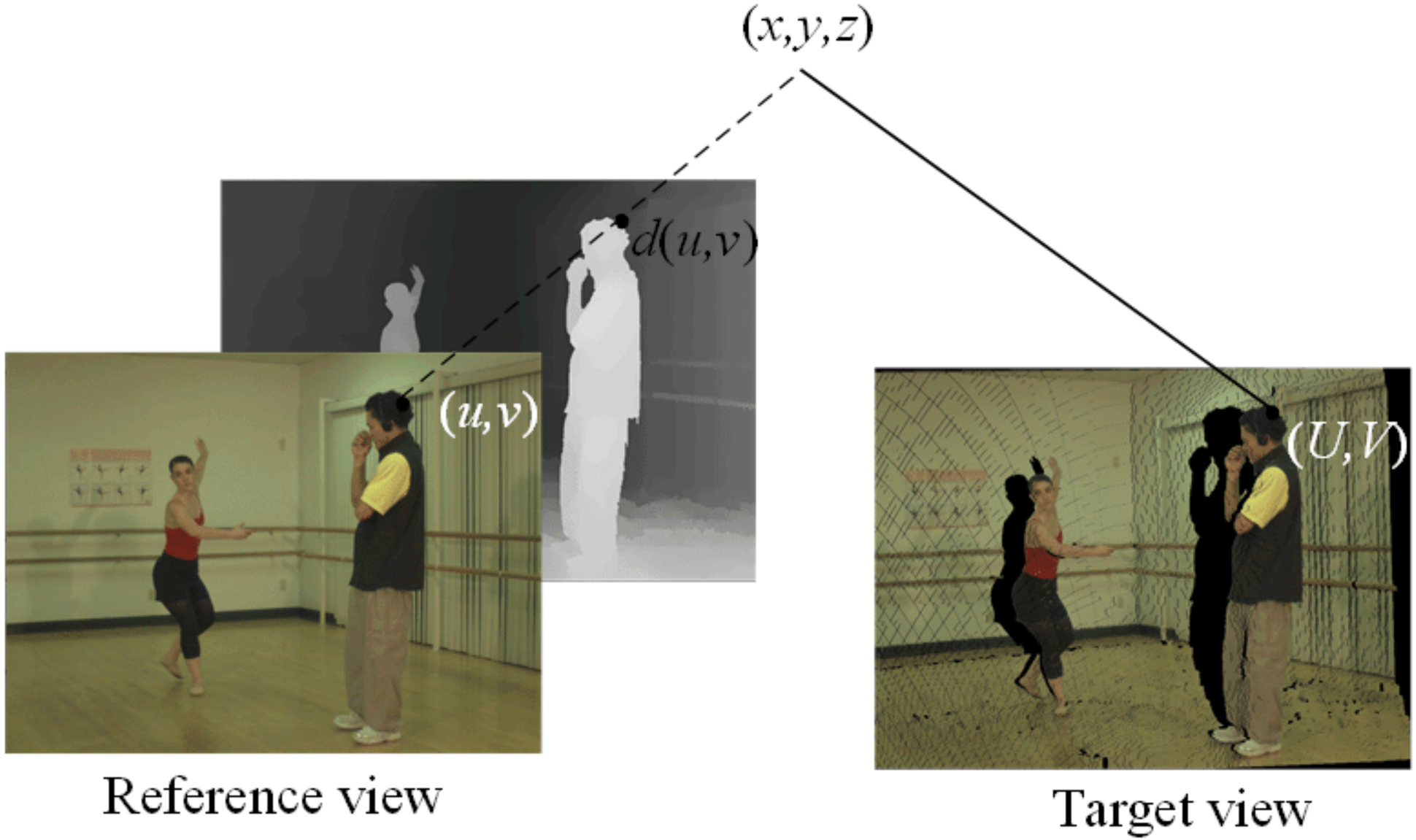
...

Frame at time t_2

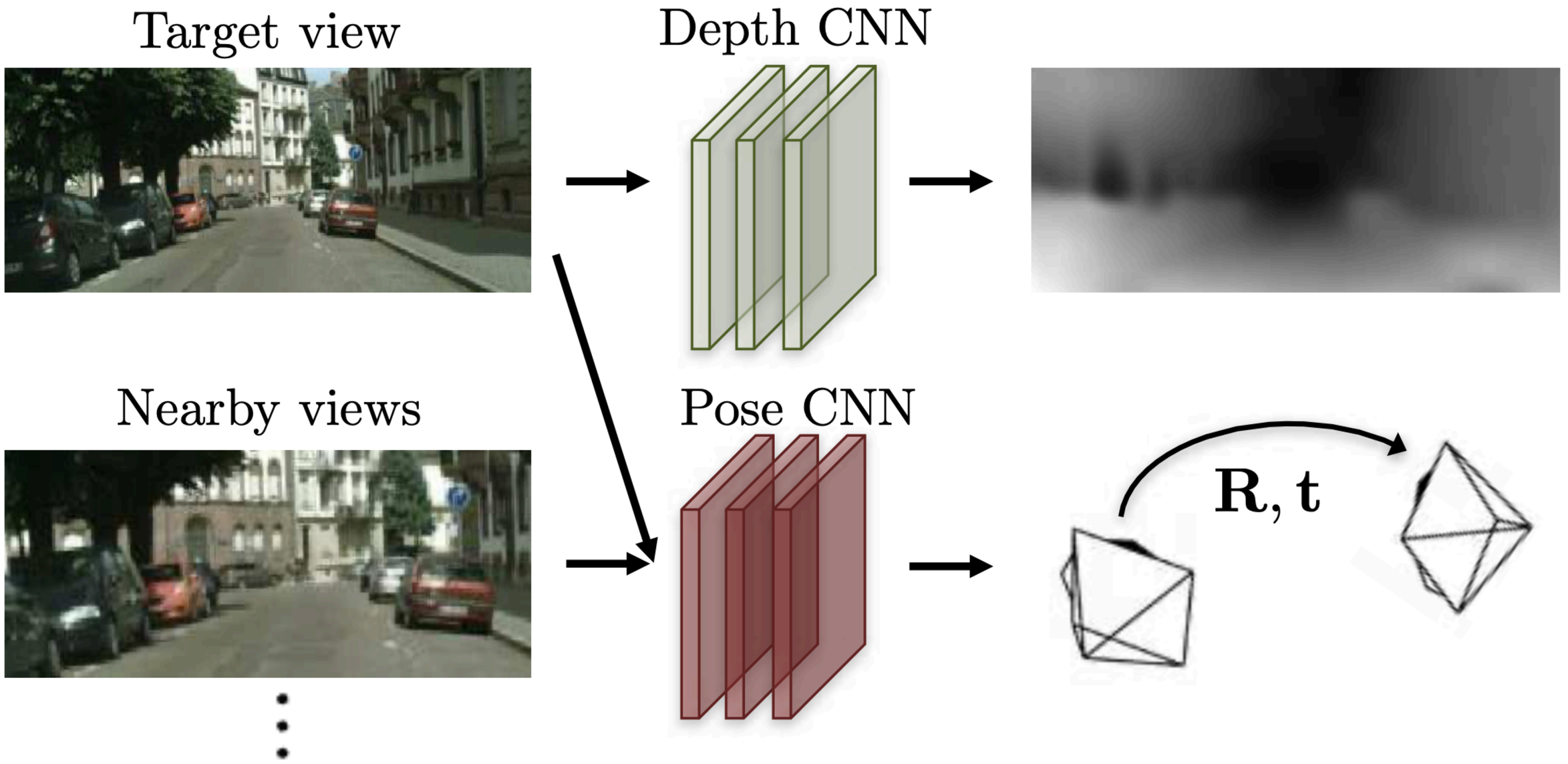
Goal: Learn Depth and Ego-Motion (relative camera pose) just from video!

How?

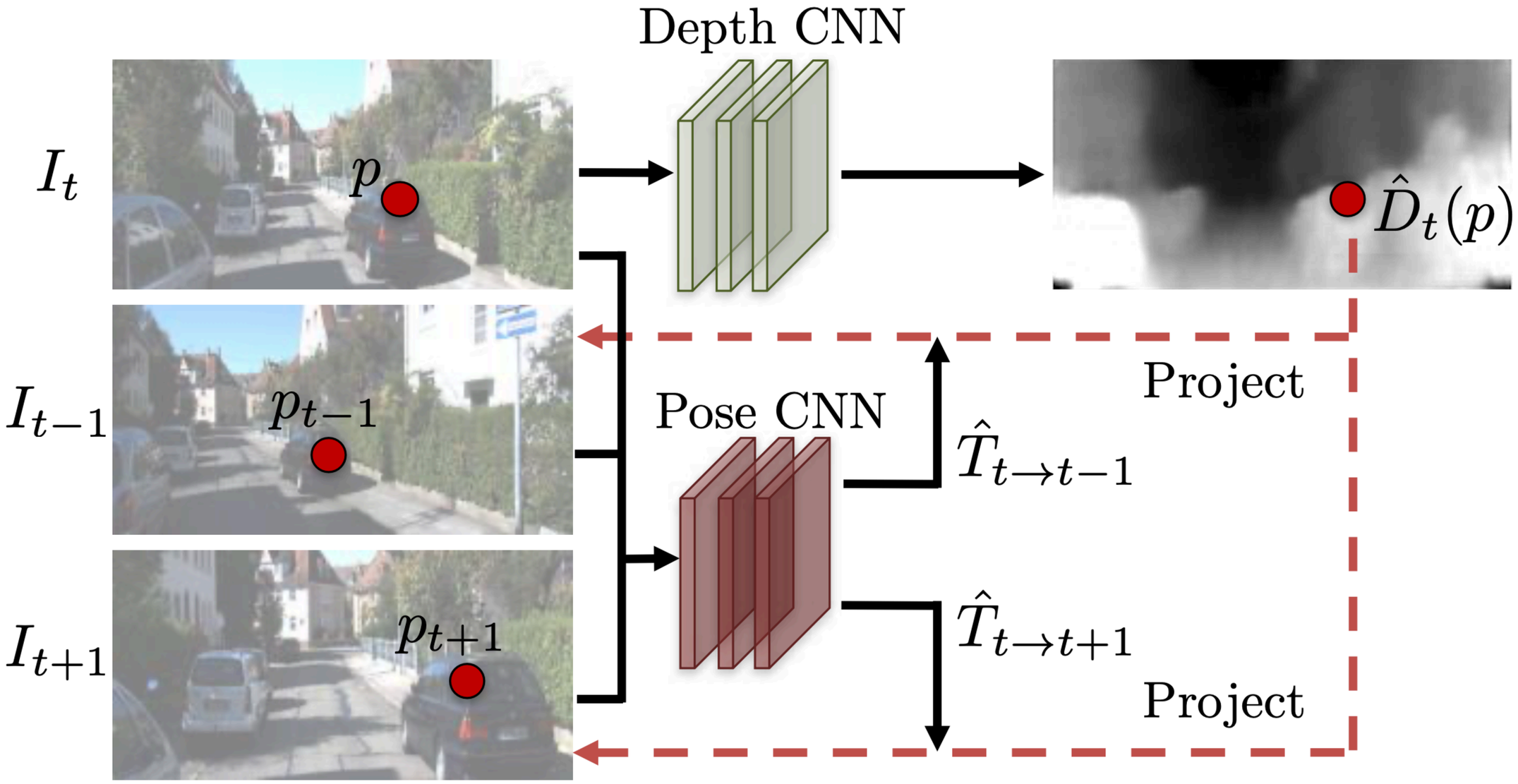
View Synthesis with Depth Maps (Depth Warping)

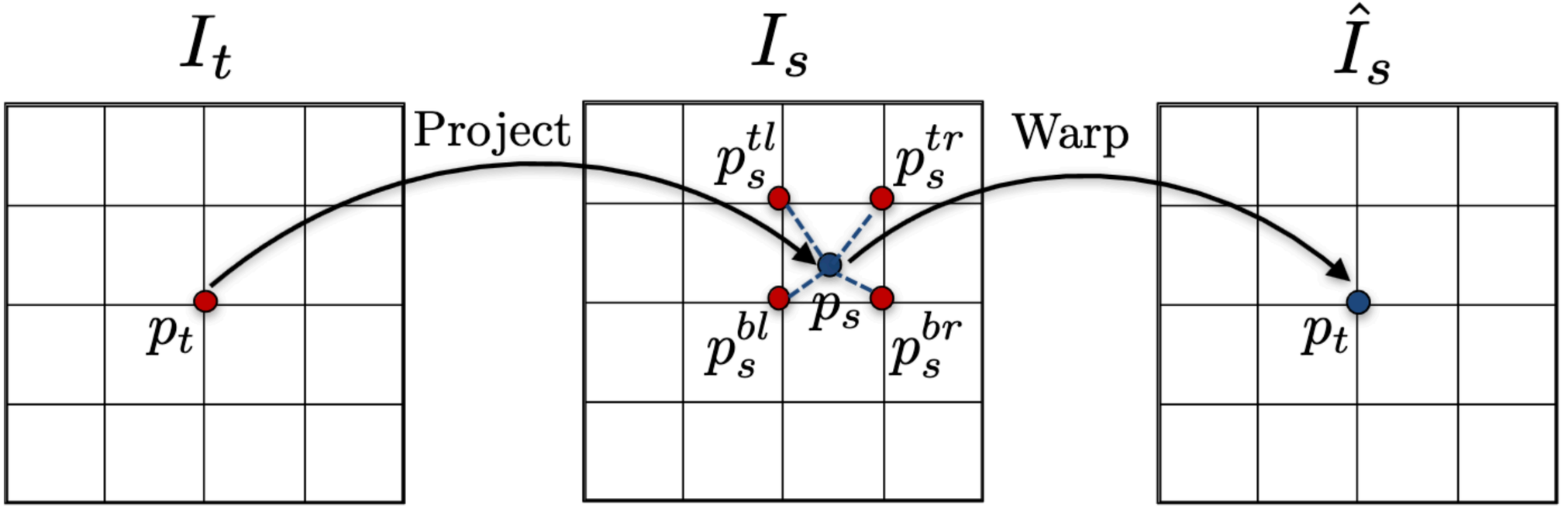


Unsupervised Depth and Ego-Motion from Video (Zhou et al. 2017)

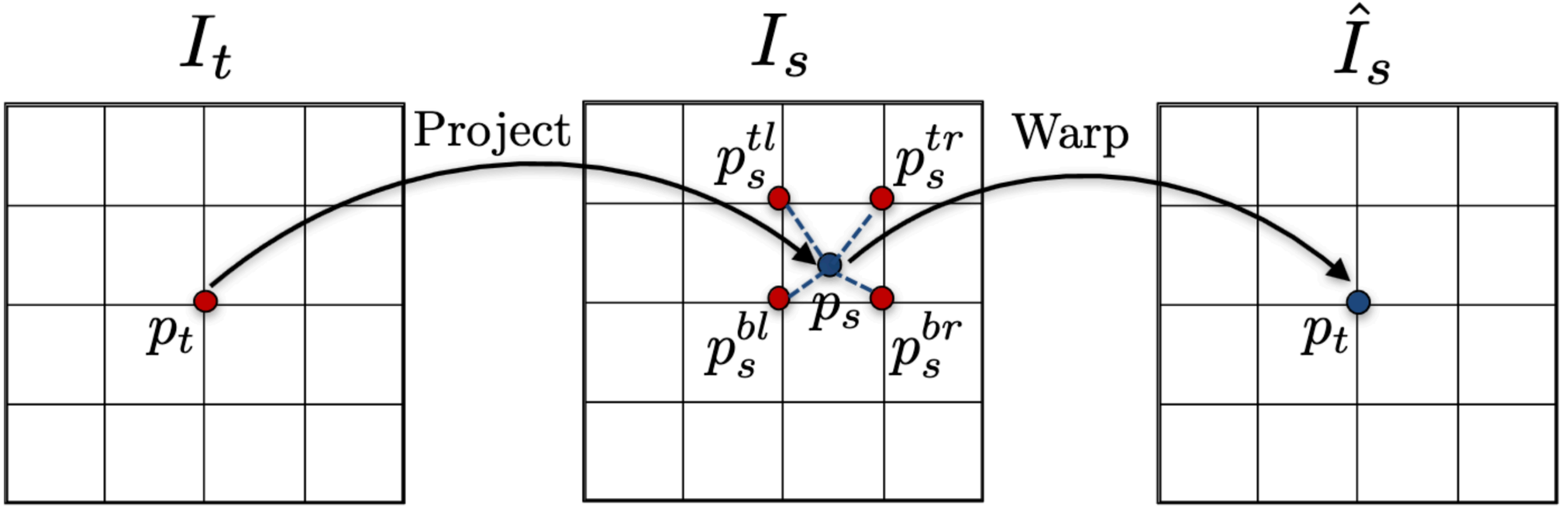


Unsupervised Depth and Ego-Motion from Video (Zhou et al. 2017)



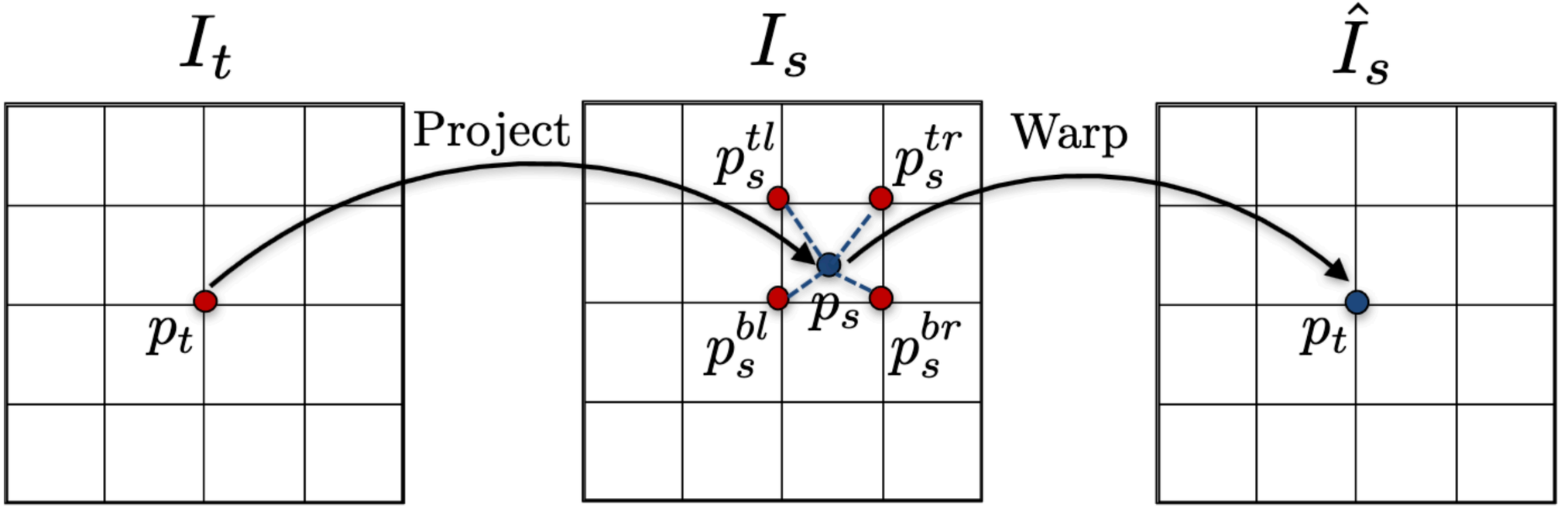


$$p_s \sim K\hat{T}_{t\to s}\hat{D}_t(p_t)K^{-1}p_t$$



$$p_s \sim K\hat{T}_{t\to s}\hat{D}_t(p_t)K^{-1}p_t$$

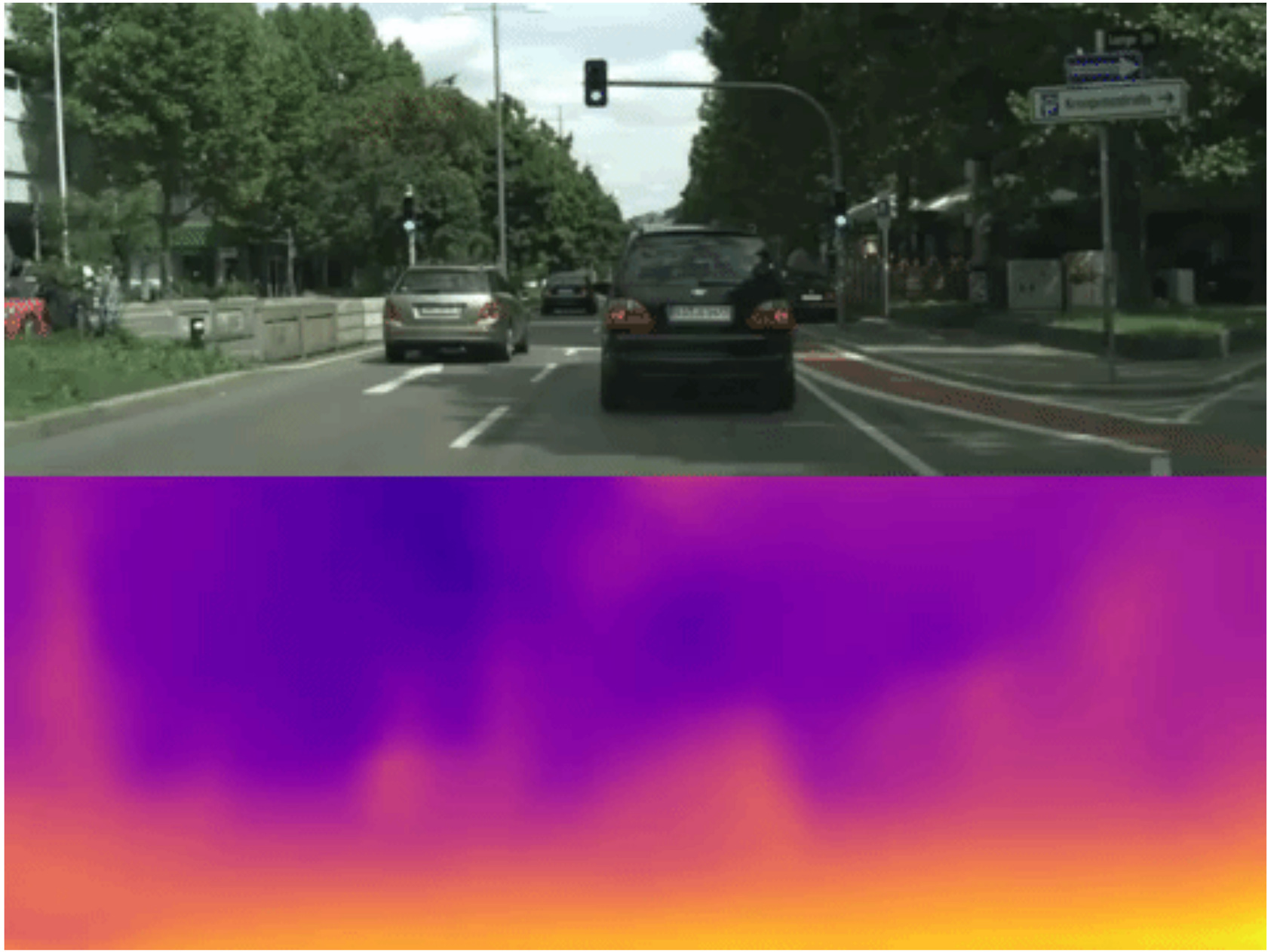
$$\hat{I}_s(p_t) = I_s(p_s) = \sum_{i\in\{t,b\},j\in\{l,r\}} w^{ij} I_s(p_s^{ij})$$



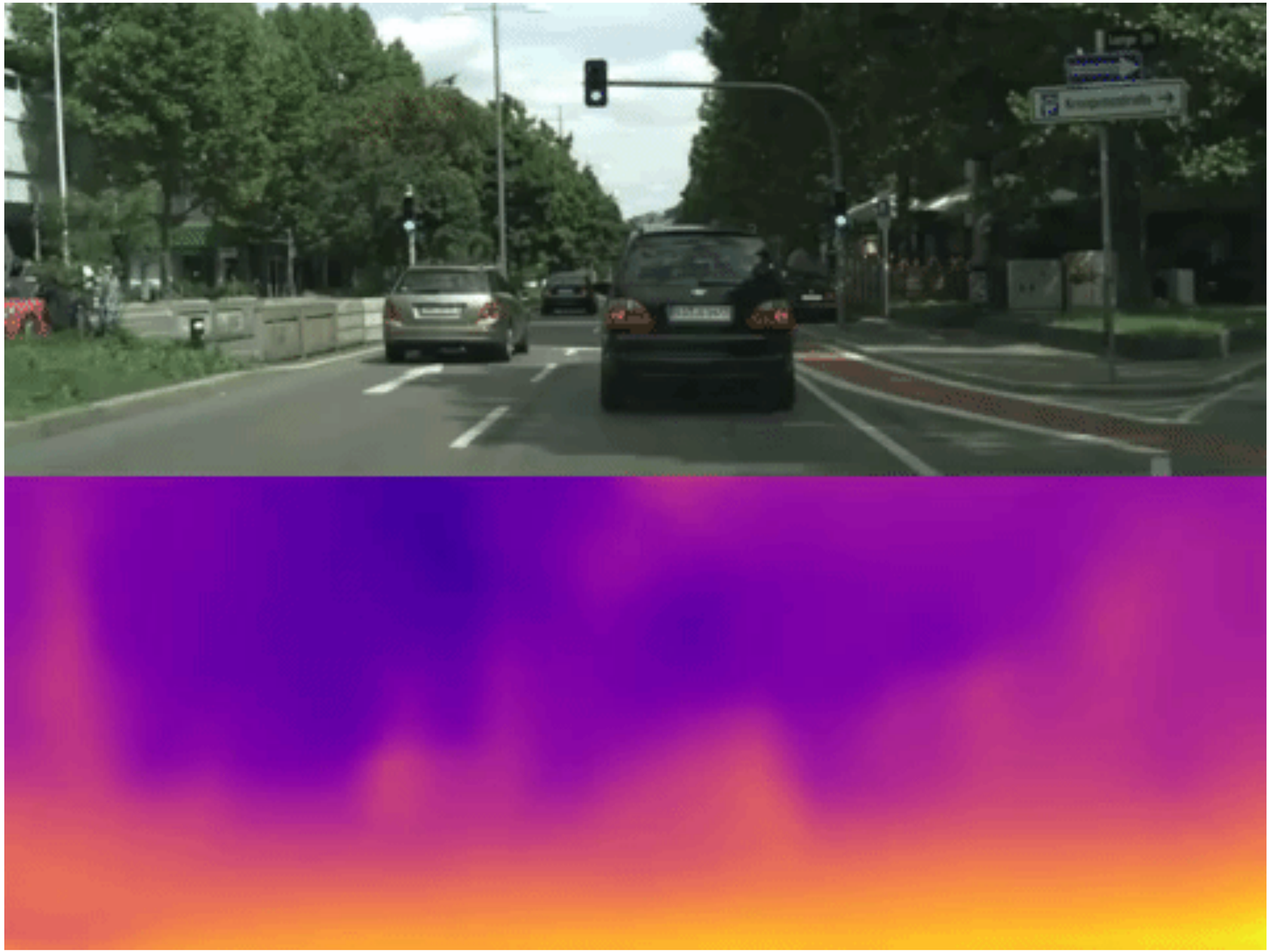
$$p_s \sim K\hat{T}_{t\to s}\hat{D}_t(p_t)K^{-1}p_t$$

$$\hat{I}_s(p_t) = I_s(p_s) = \sum_{i\in\{t,b\},j\in\{l,r\}} w^{ij} I_s(p_s^{ij})$$

$$\mathcal{L}_{vs} = \sum_s \sum_p |I_t(p) - \hat{I}_s(p)|$$



Unsupervised Depth and Ego-Motion from Video, Zhou et al. 2017

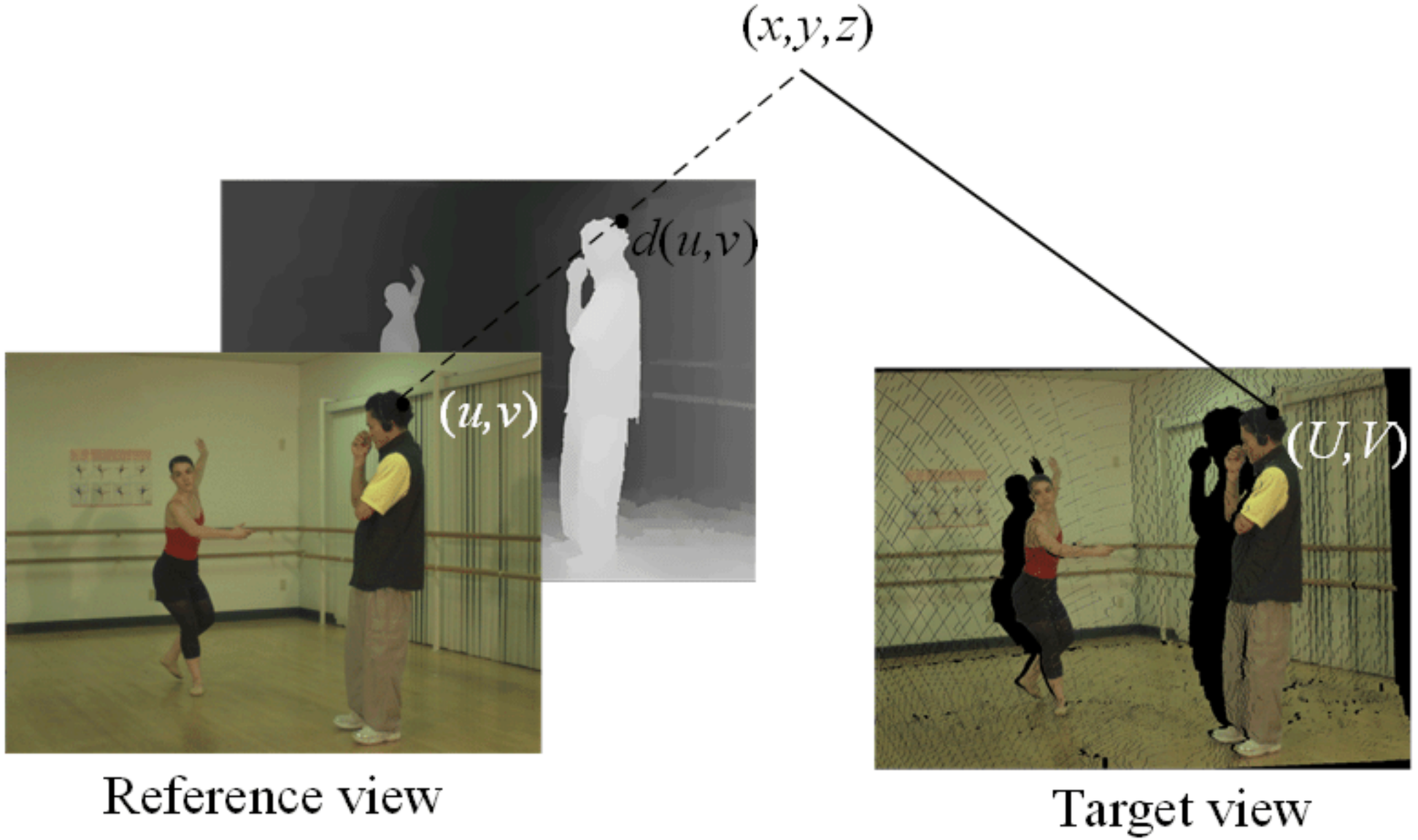


Unsupervised Depth and Ego-Motion from Video, Zhou et al. 2017

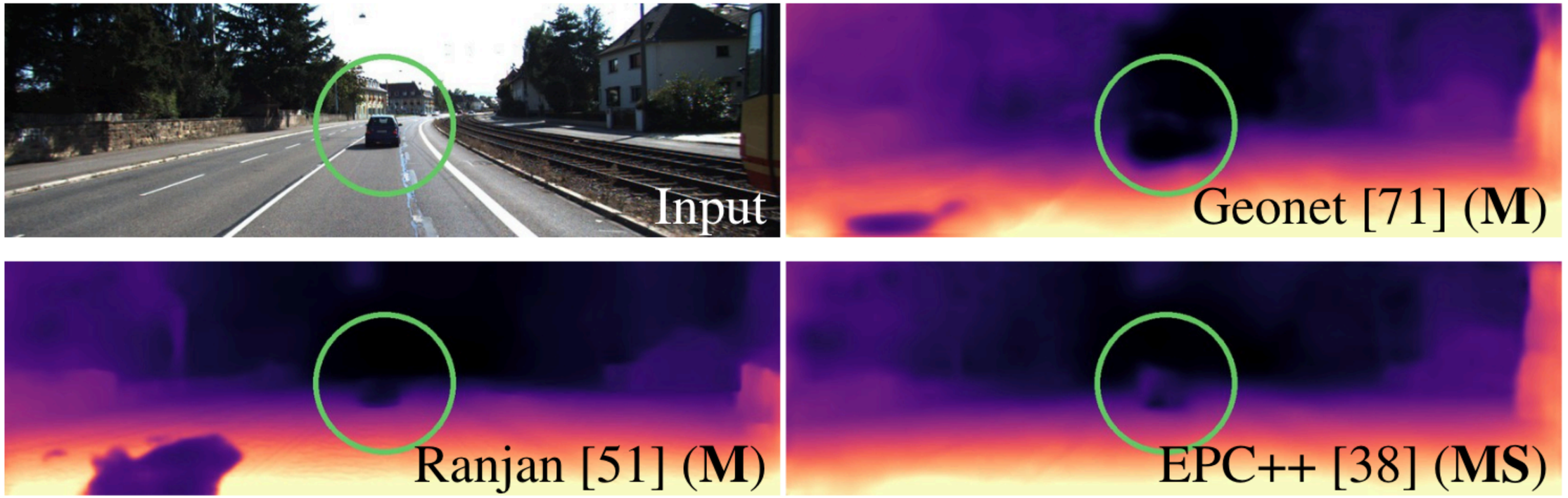
Self-supervised Learning of Depth and Pose from Video
Guizilini et al. 2021

Self-supervised Learning of Depth and Pose from Video
Guizilini et al. 2021

Can’t deal with occlusions / disocclusions



Assumes *static* scenes



Digging Into Self-Supervised Monocular Depth Estimation, Godard et al. 2018

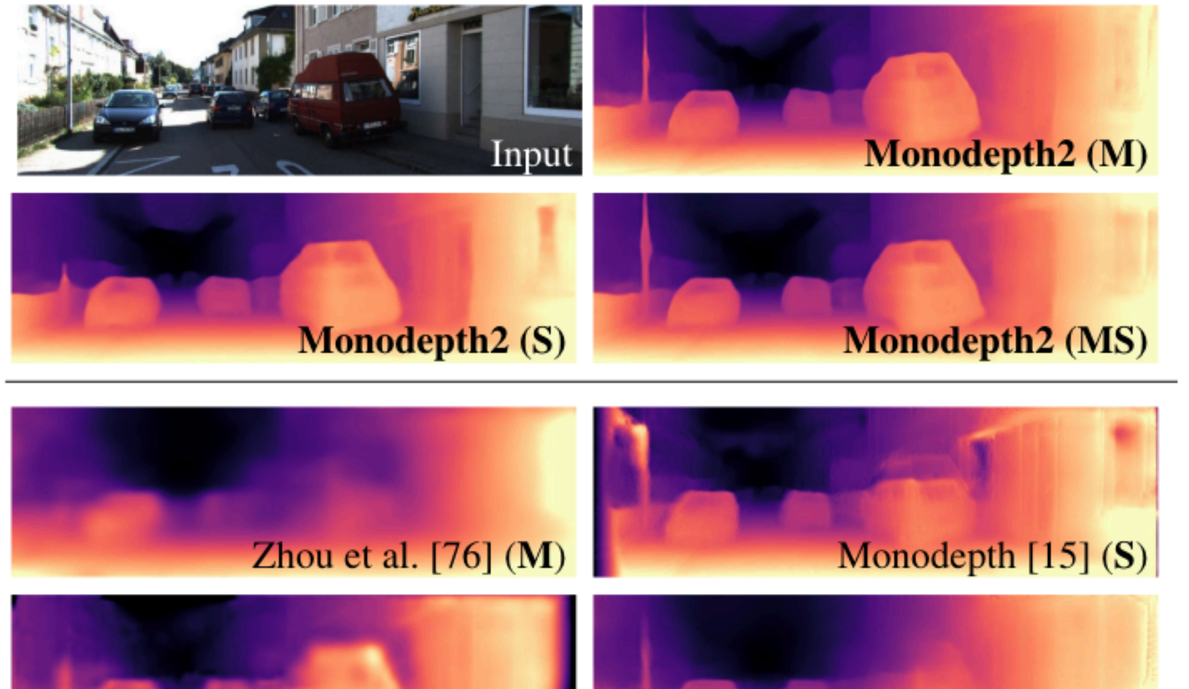
Digging Into Self-Supervised Monocular Depth Estimation

Clément Godard[1] Oisin Mac Aodha[2] Michael Firman[3] Gabriel Brostow[3,1]
[1]UCL [2]Caltech [3]Niantic
www.github.com/nianticlabs/monodepth2

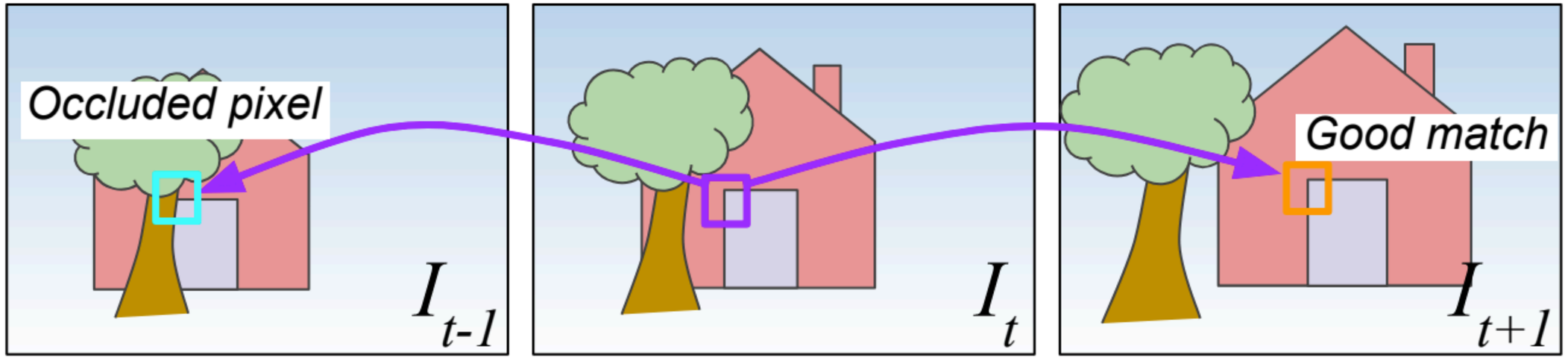
Abstract

Per-pixel ground-truth depth data is challenging to acquire at scale. To overcome this limitation, self-supervised learning has emerged as a promising alternative for training models to perform monocular depth estimation. In this paper, we propose a set of improvements, which together result in both quantitatively and qualitatively improved depth maps compared to competing self-supervised methods.

Research on self-supervised monocular training usually explores increasingly complex architectures, loss functions, and image formation models, all of which have recently



Dealing with Occlusions / Disocclusions



$pe($, $)$ = error

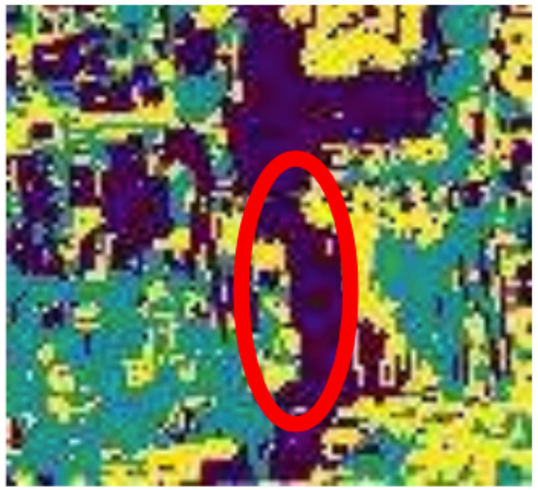
$pe($, $)$ = error

Baseline: $avg($, $)$ =

Ours: $min($, $)$ =

Digging into Self-Supervised Monocular Depth Estimation, Godard et al. 2018

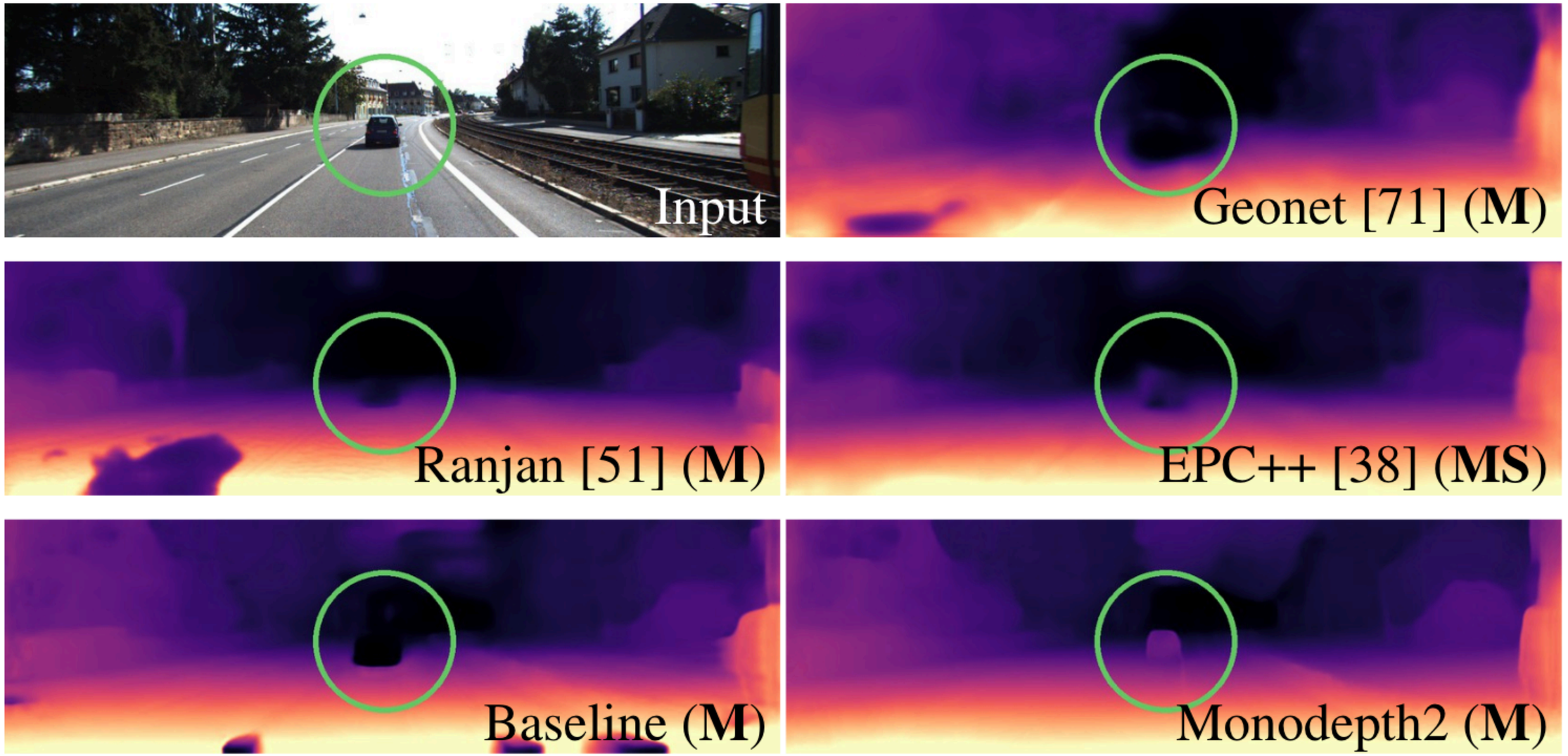
Dealing with Occlusions / Disocclusions



Colors here show which source frame each pixel in L is matched to.

Digging into Self-Supervised Monocular Depth Estimation, Godard et al. 2018

Dealing with moving objects



Dealing with moving objects: Predict per-pixel mask μ

We observe that pixels which remain the same between adjacent frames in the sequence often indicate a static camera, an object moving at equivalent relative translation to the camera, or a low texture region. We therefore set μ to only include the loss of pixels where the reprojection error of the warped image $I_{t' \to t}$ is lower than that of the original, unwarped source image I'_t, *i.e.*

$$\mu = \left[\min_{t'} pe(I_t, I_{t' \to t}) < \min_{t'} pe(I_t, I_{t'}) \right], \qquad (5)$$

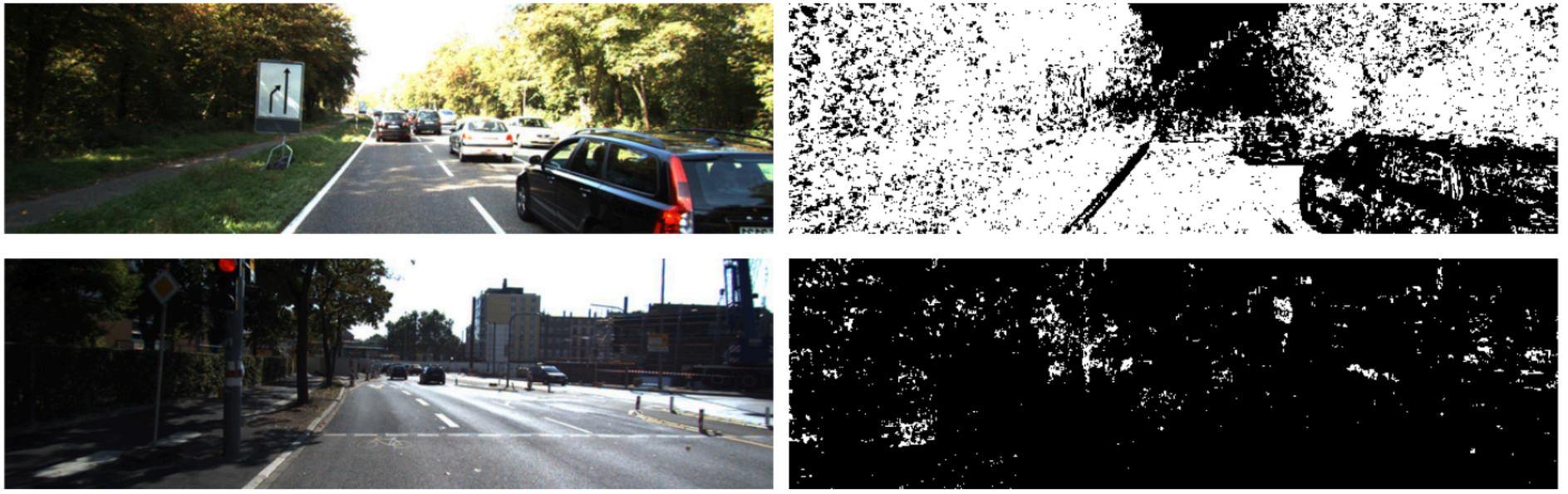
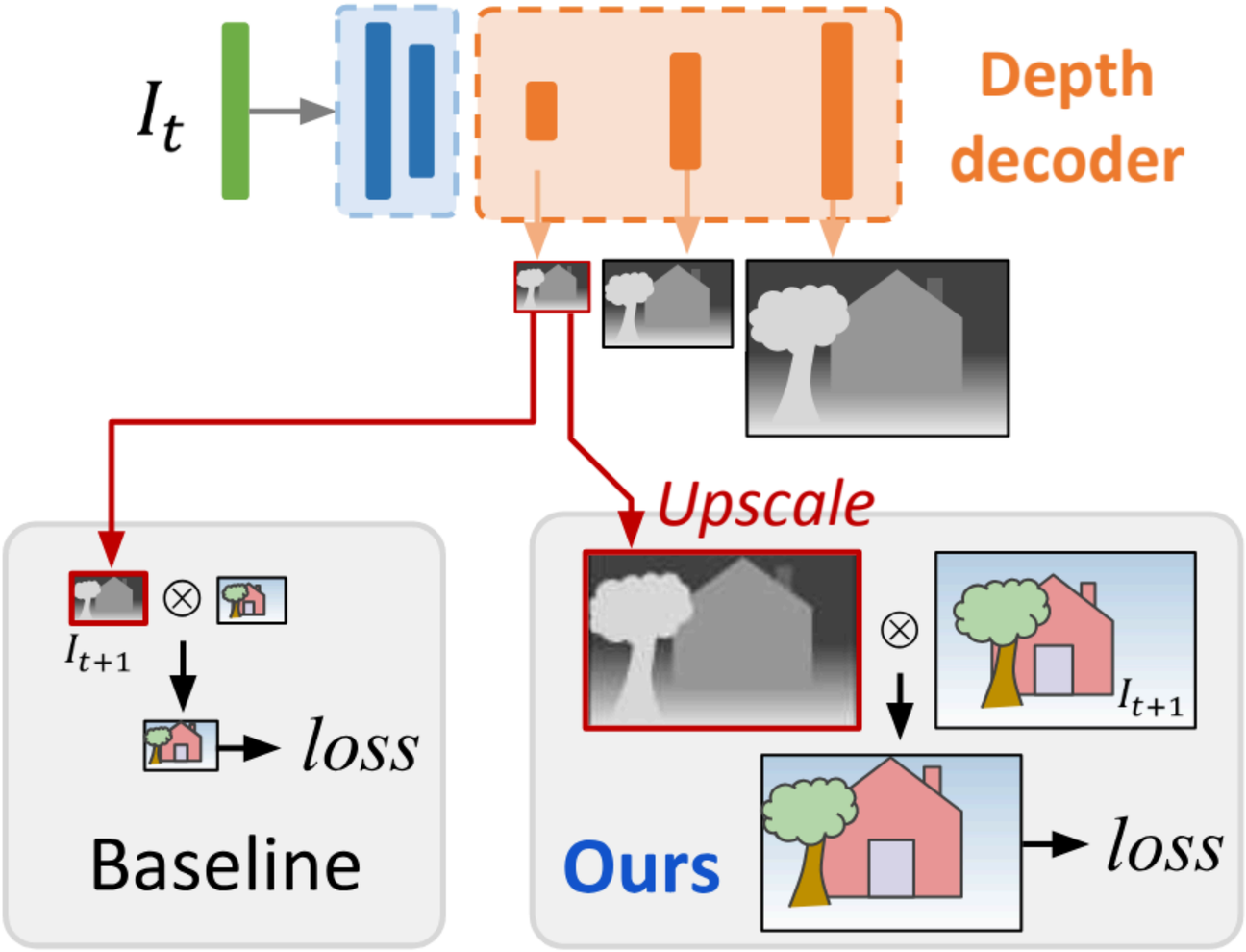


Figure 5. **Auto-masking.** We show auto-masks computed after one epoch, where black pixels are removed from the loss (*i.e.* $\mu = 0$). The mask prevents objects moving at similar speeds to the camera (top) and whole frames where the camera is static (bottom) from contaminating the loss. The mask is computed from the input frames and network predictions using Eqn. 5.

Better multi-scale loss



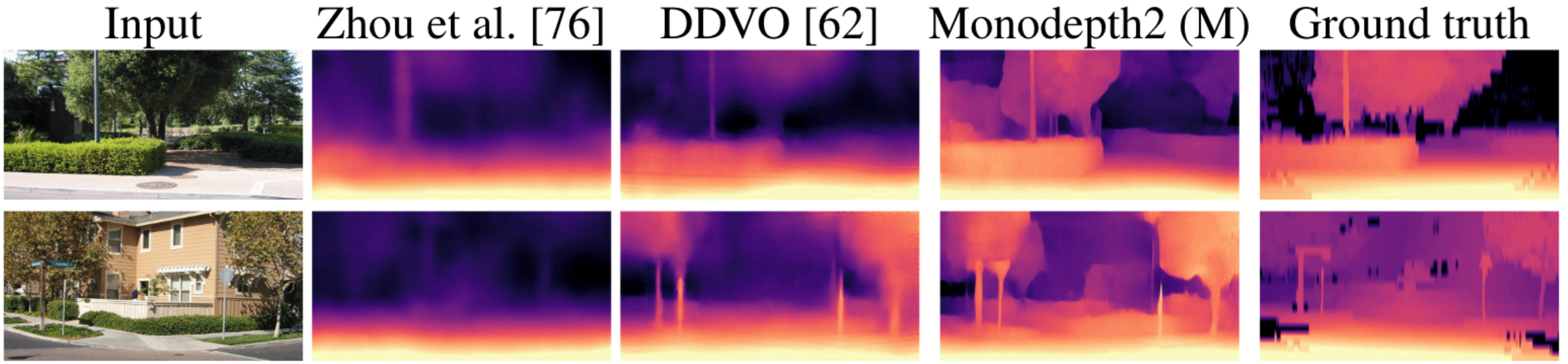


Figure 6. **Qualitative Make3D results.** All methods were trained on KITTI using monocular supervision.

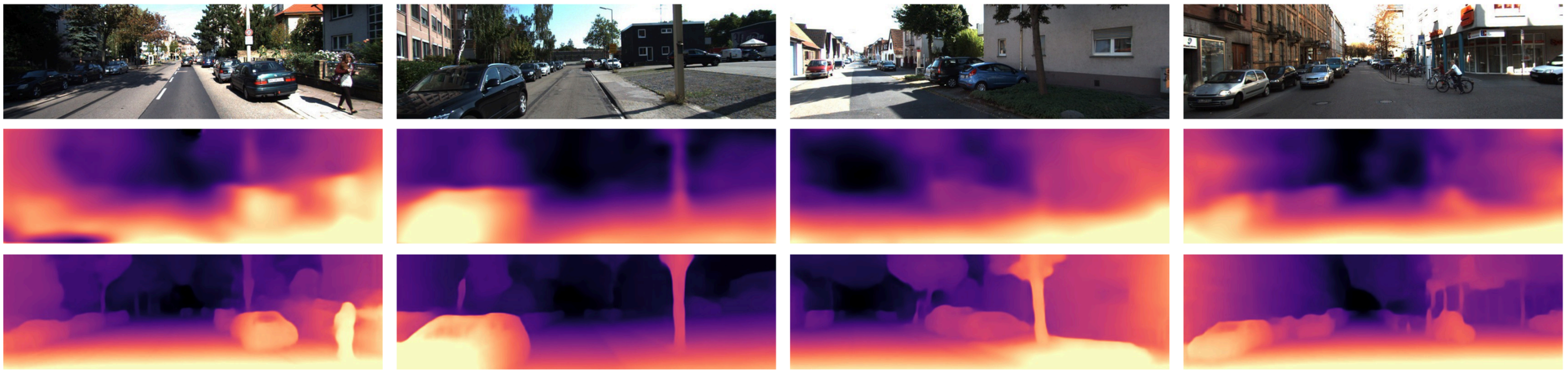
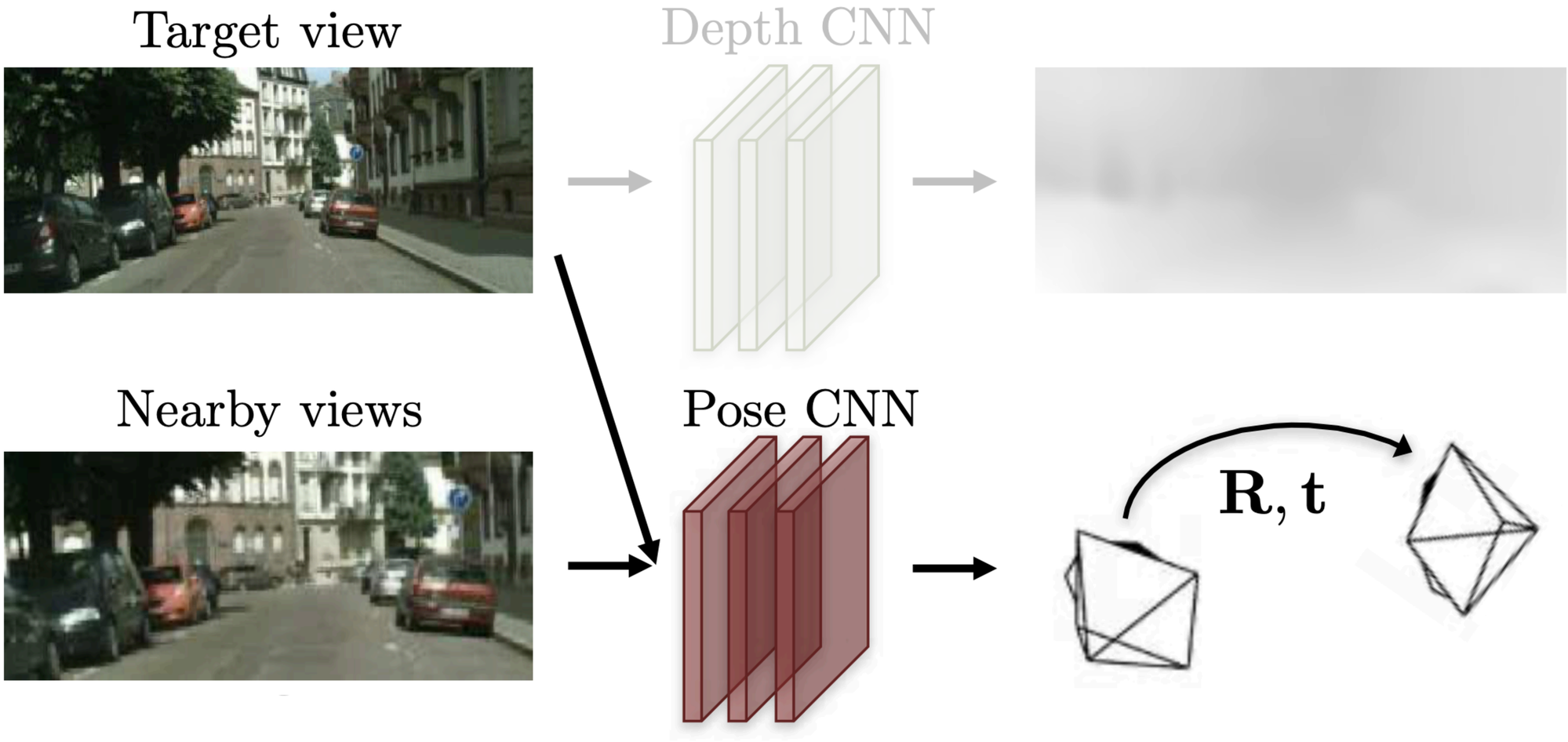

Input
Zhou et al. [76]
MD2 MS

Figure 8. **Failure cases. Top:** Our self-supervised loss fails to learn good depths for distorted, reflective and color-saturated regions. **Bottom:** We can fail to accurately delineate objects where boundaries are ambiguous (left) or shapes are intricate (right).

Problem: Only works for “simple” camera trajectories :/



CNNs are bad at predicting poses: no single pixel neighborhood informs completely about pose…

3D Scene

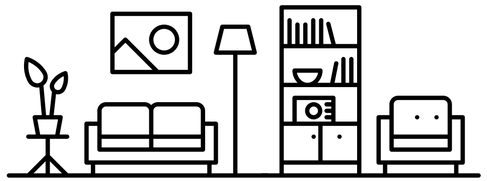


Image Formation

Graphics

3D Scene

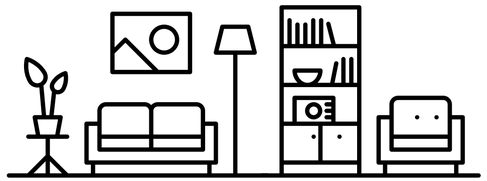


Image Formation

Neural Scene Representation

Graphics

3D Scene

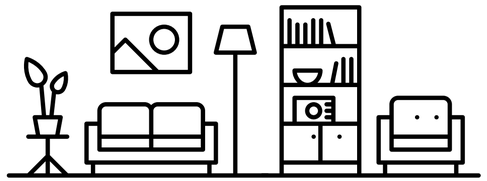


Image Formation

Inference

Neural Scene Representation

Graphics

3D Scene

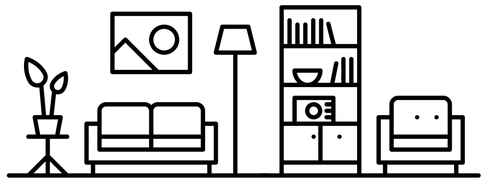


Image Formation

Inference

Neural Scene Representation

Graphics

“inverse graphics”…?

3D Scene

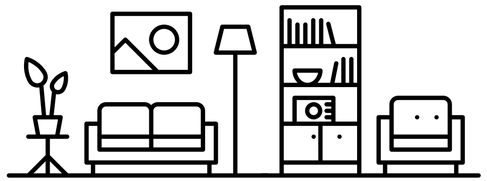


Image Formation

Inference

Neural Scene Representation

Downstream Tasks

Graphics

“inverse graphics”…?

Today: How to computationally represent 3D scenes.

3D Scene

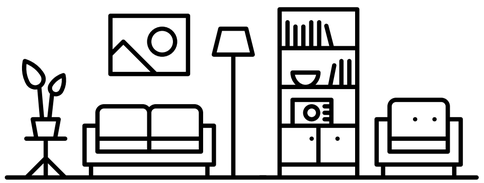


Image Formation

Inference

Neural Scene Representation

Downstream Tasks

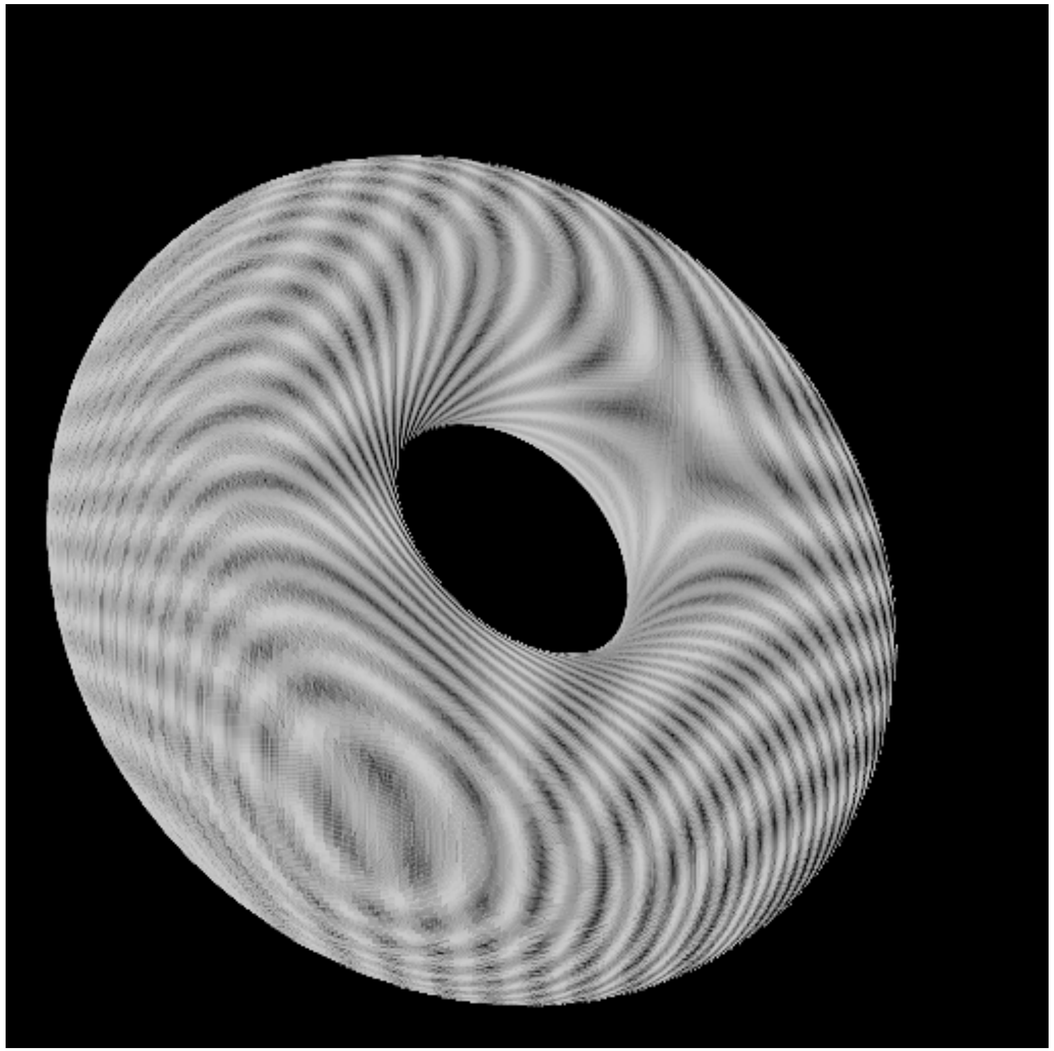
Why?	At the end of the day, we want to make predictions about 3D scenes. For that, we need to know how we can represent 3D scenes computationally.
What you'll learn.	Surface-based representations, volumetric representations, discrete representations, continuous representations.

Some Slides adapted from…

CMU 16-889: Learning for 3D Vision

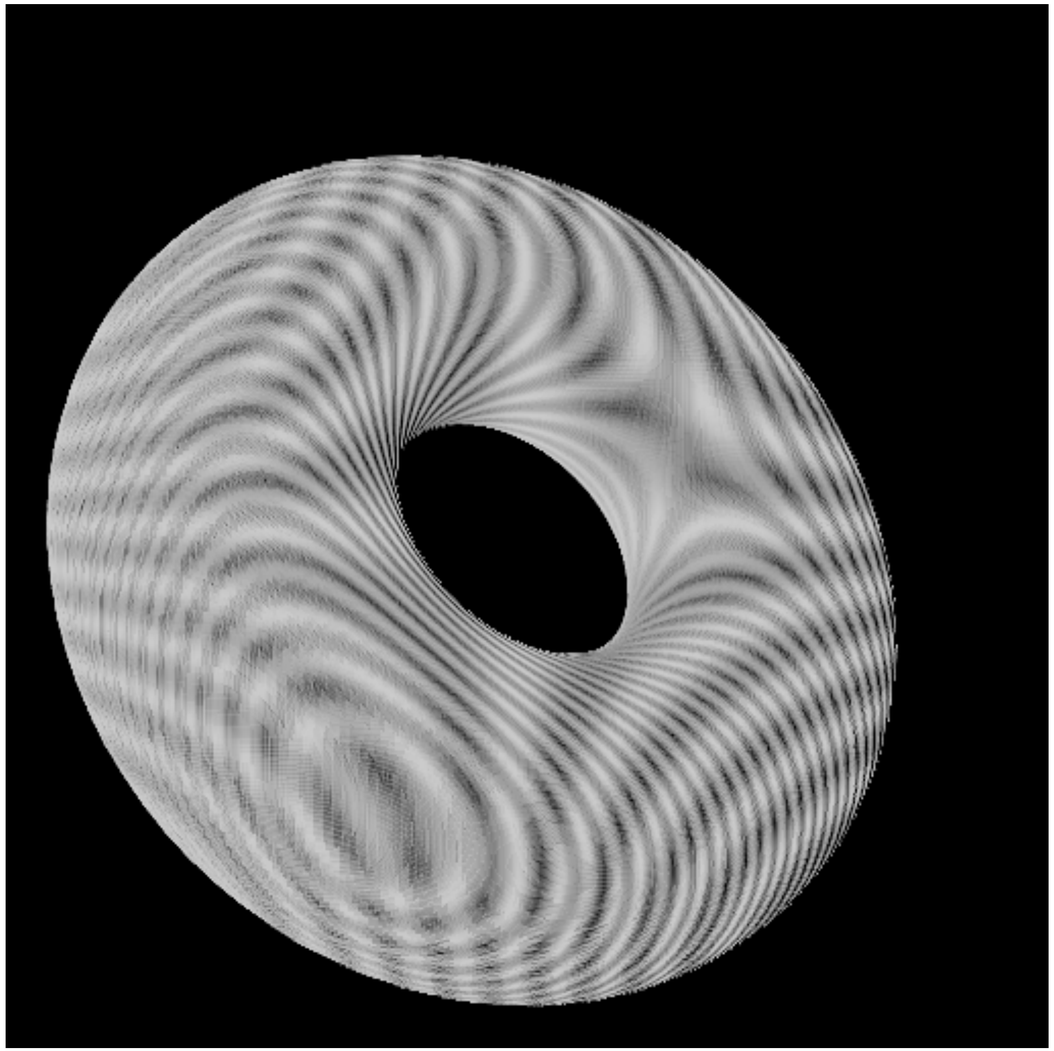
Prof. Shubham Tulsiani

Depth Maps — Representing the Visible



Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

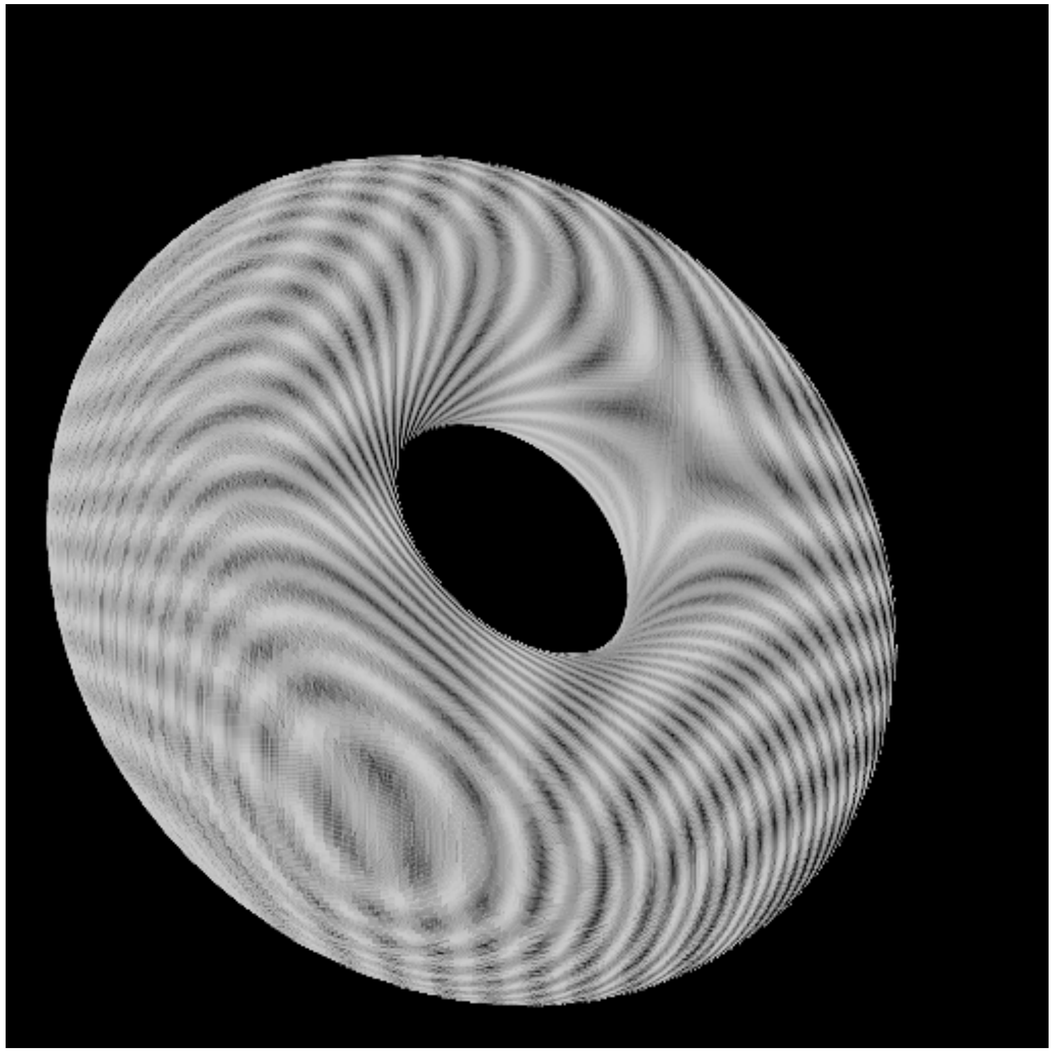
Depth Maps — Representing the Visible



Does not capture the ‘full’ 3D structure

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Depth Maps — Representing the Visible

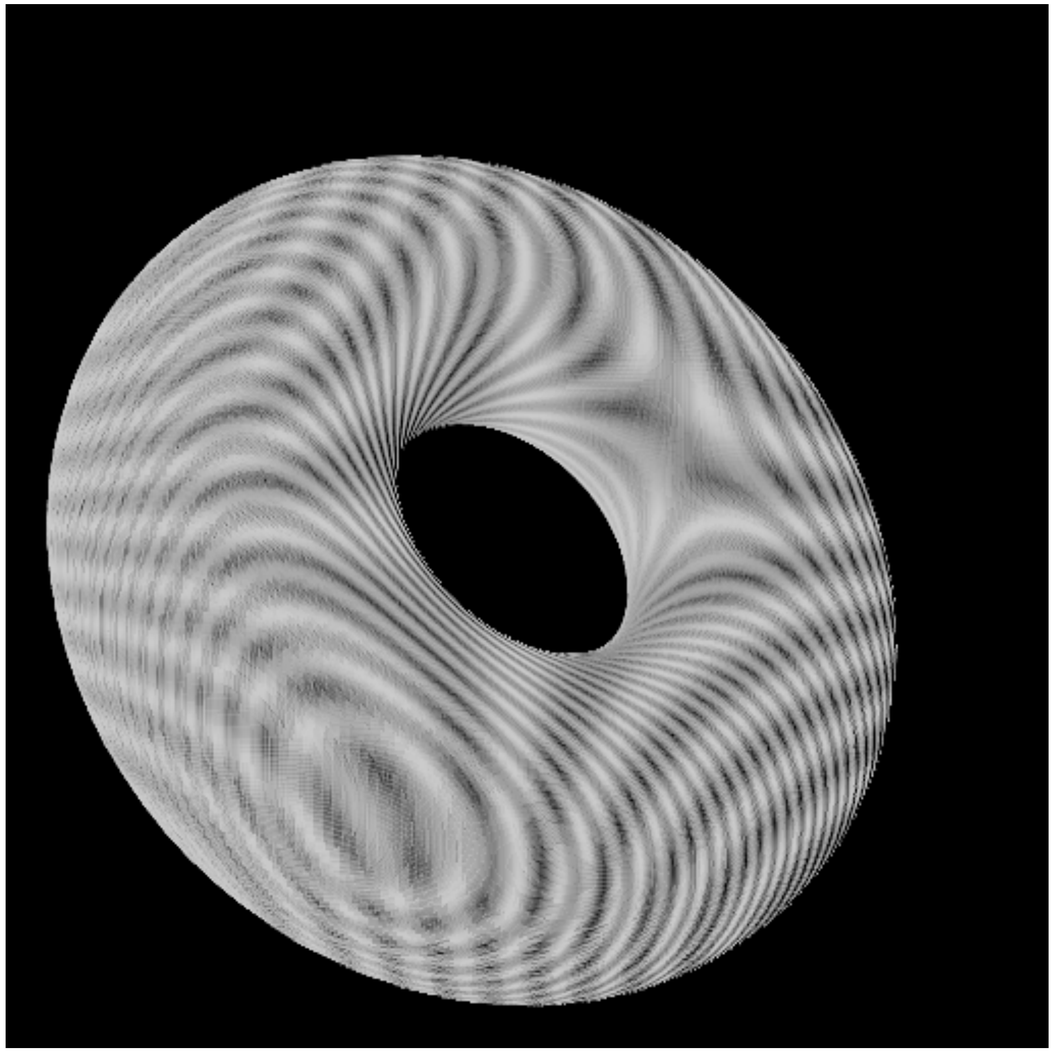


‘2.5D’ representation — properties associated to image pixels

Does not capture the ‘full’ 3D structure

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Depth Maps — Representing the Visible



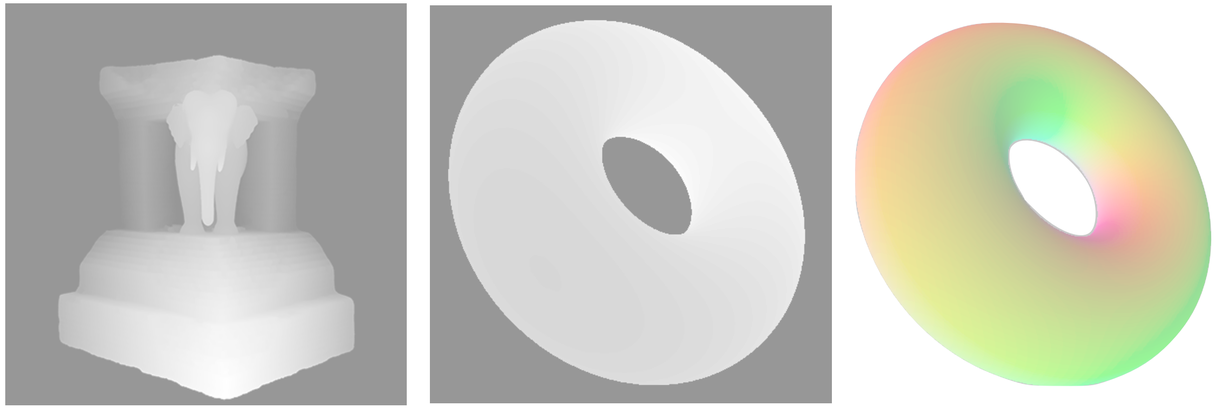
‘2.5D’ representation — properties associated to image pixels

Does not capture the ‘full’ 3D structure

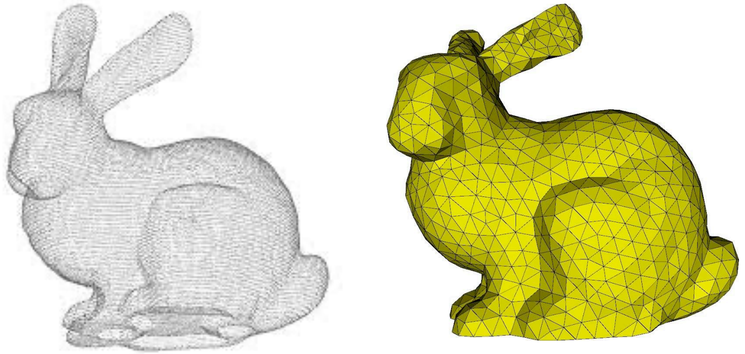
can we relax this ‘image-dependence’ constraint?

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

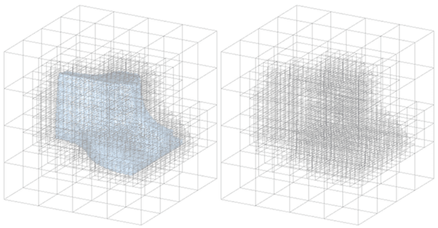
2.5D Representations

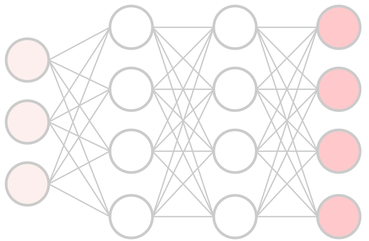


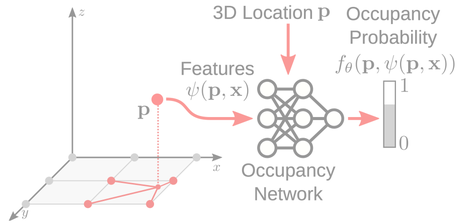
Surface Representations

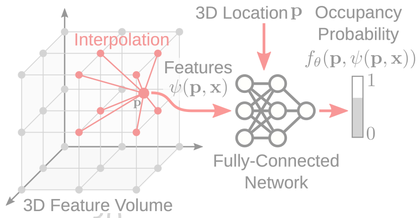


Field Parameterizations

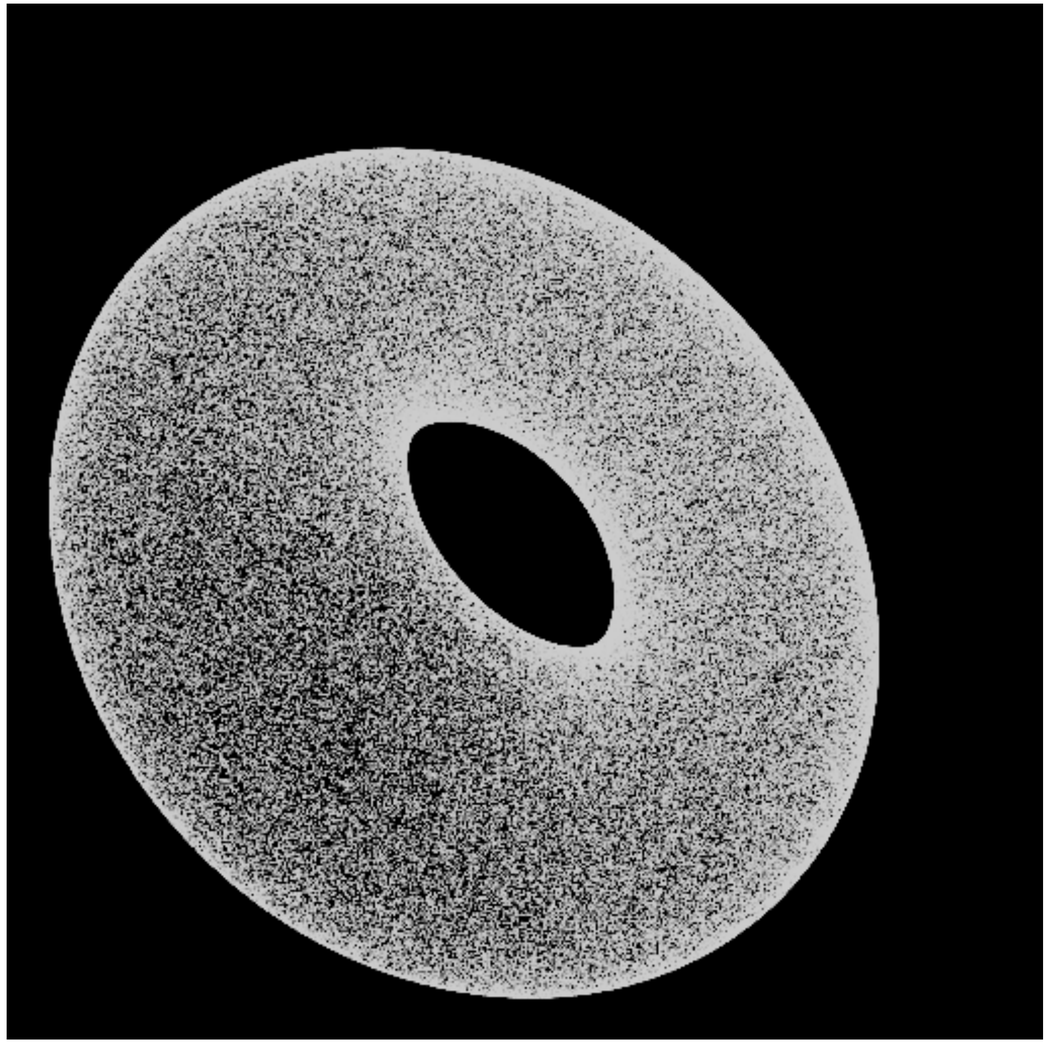








Point Clouds



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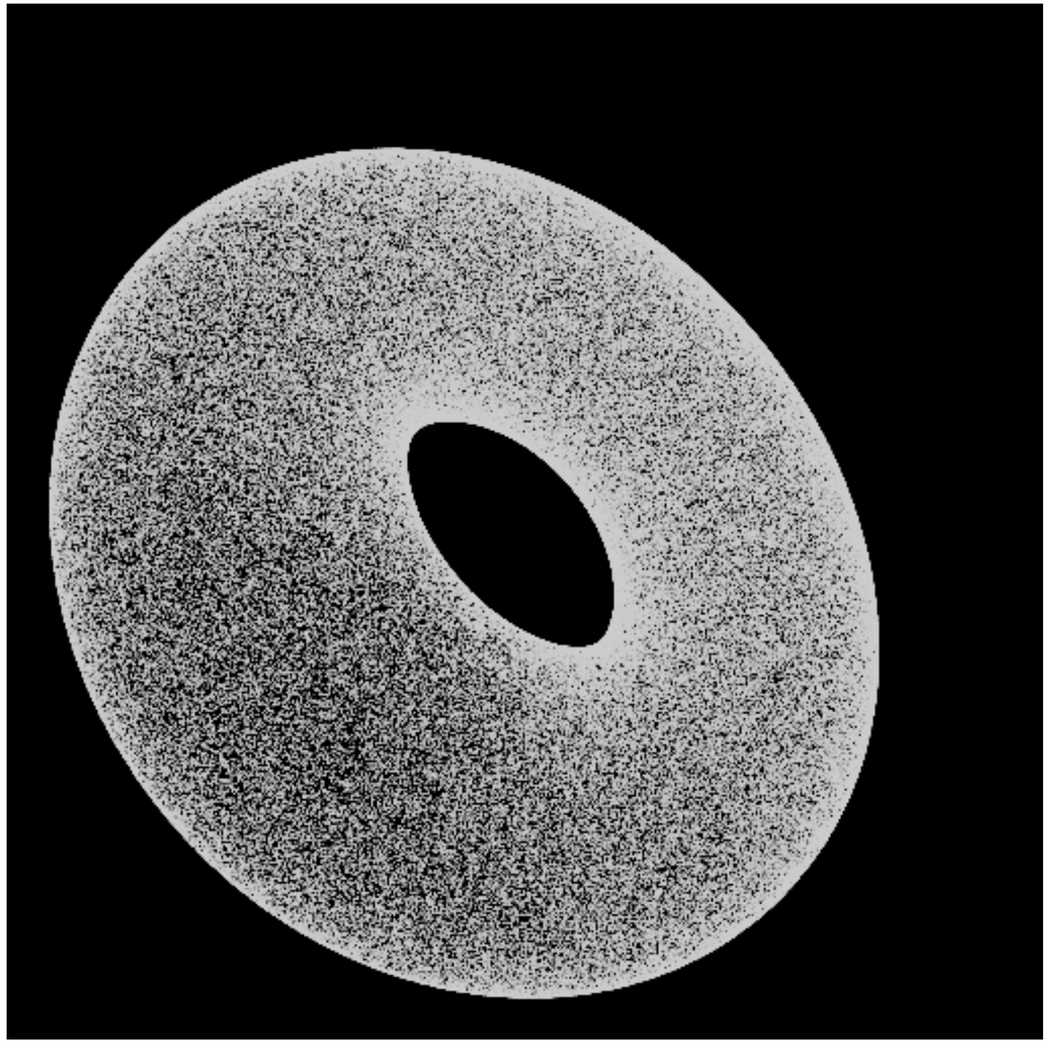
Point Clouds



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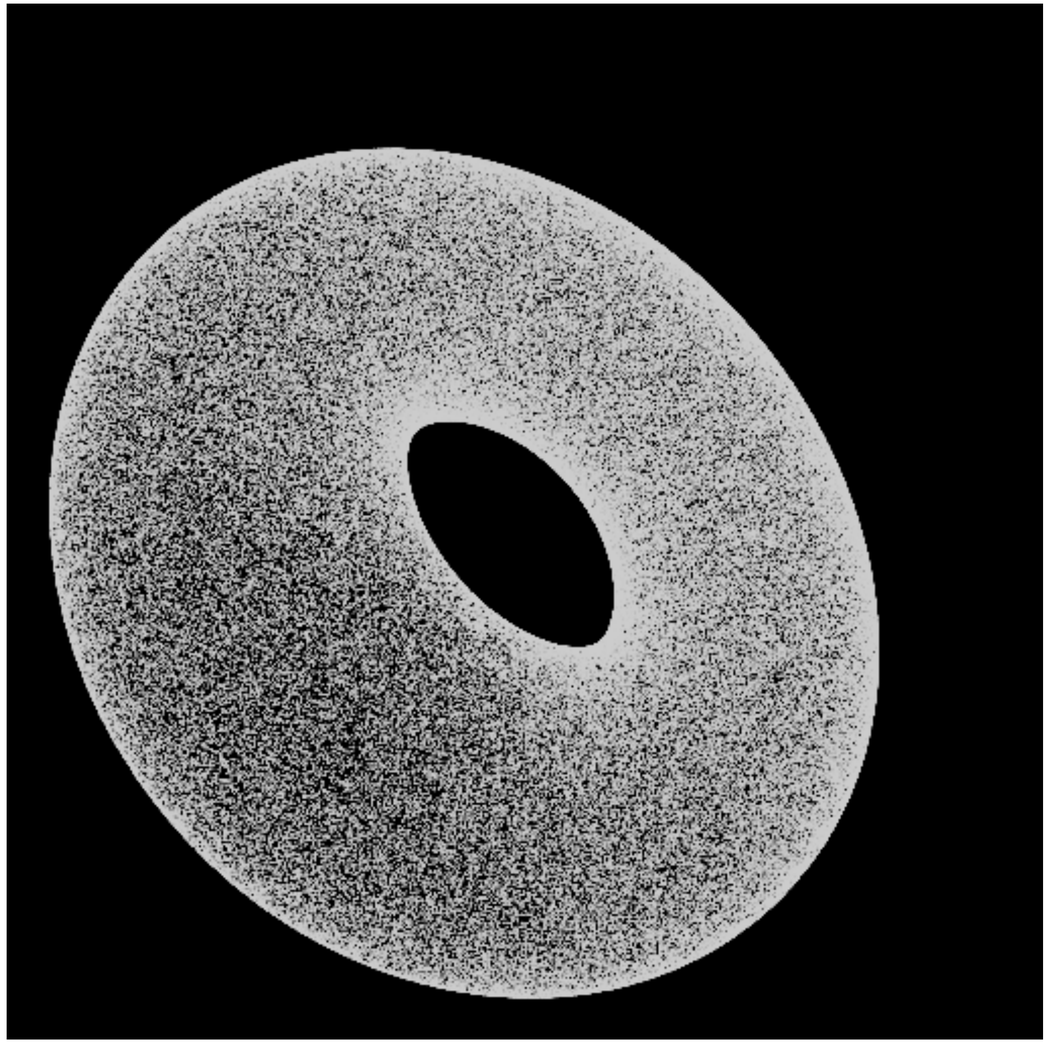

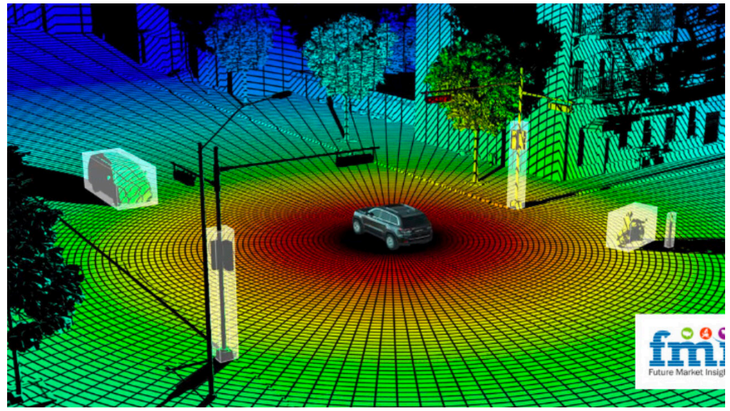

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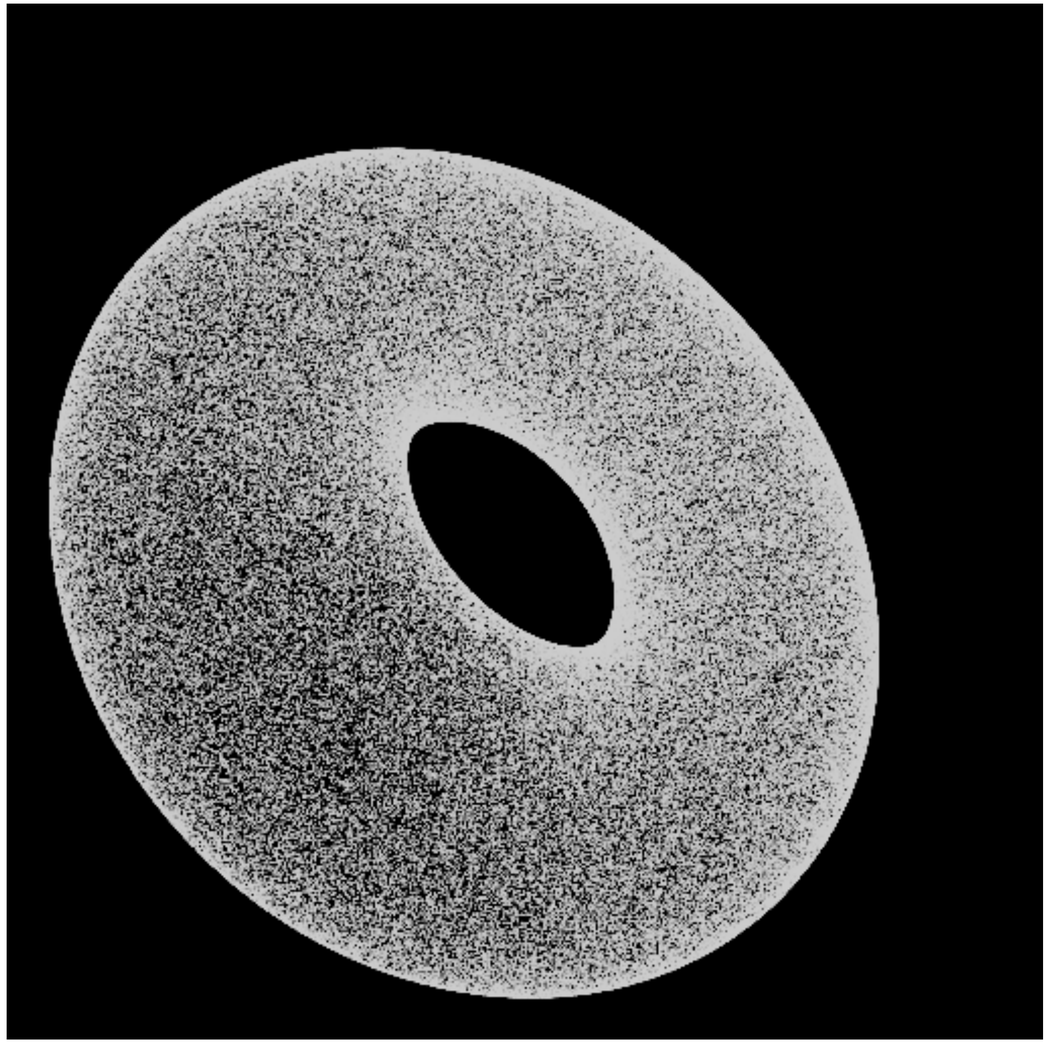
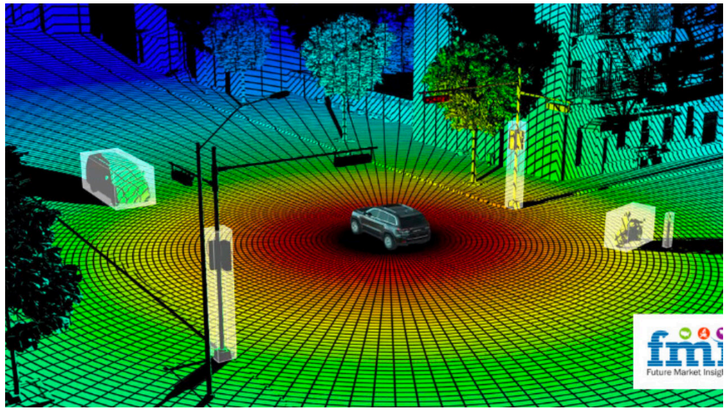
Point Clouds





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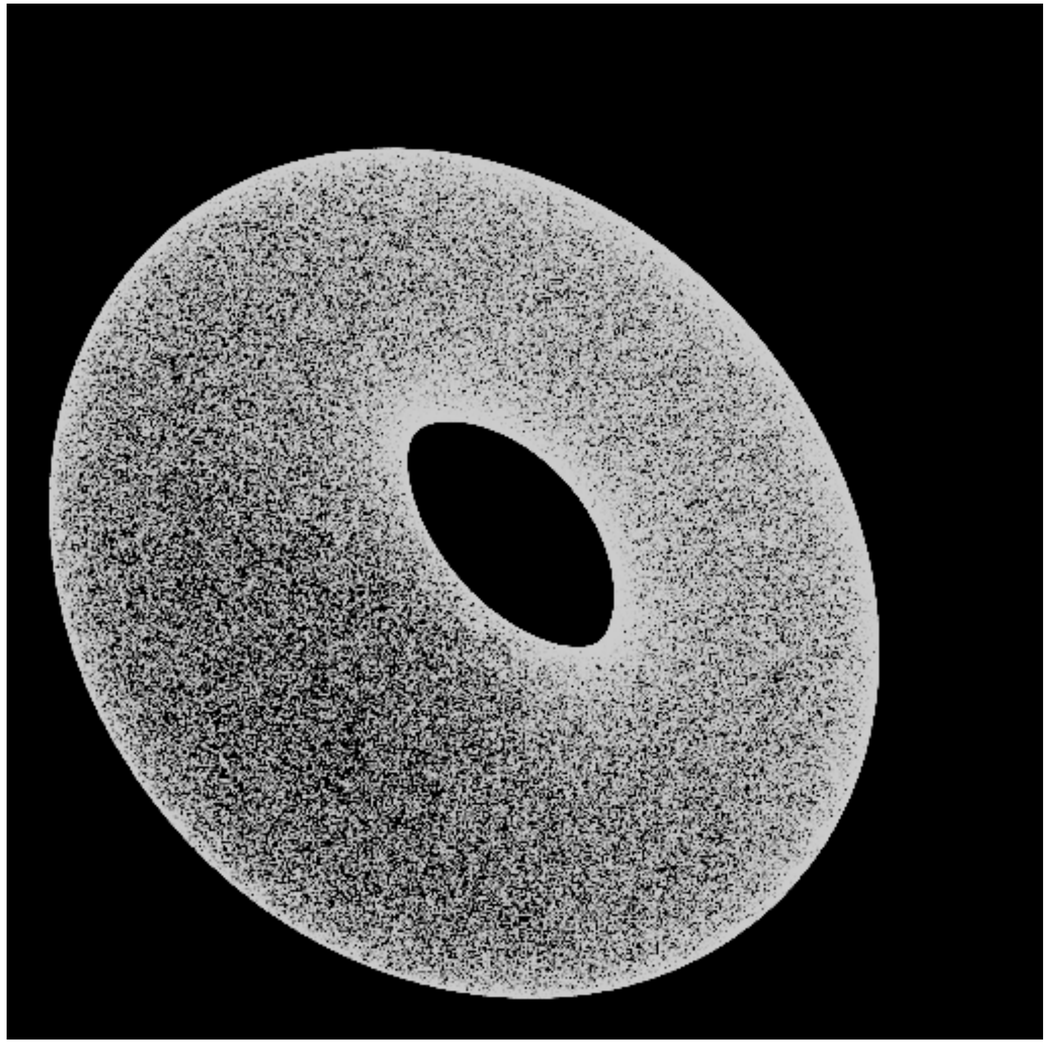
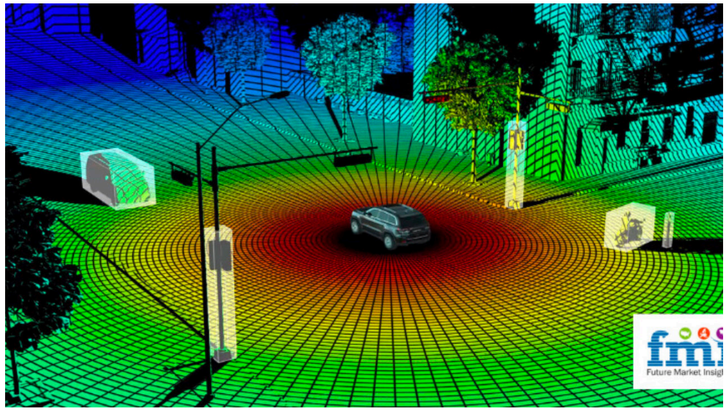
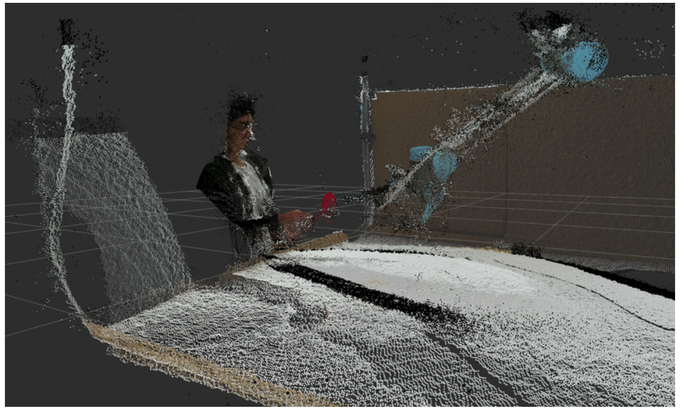
Point Clouds







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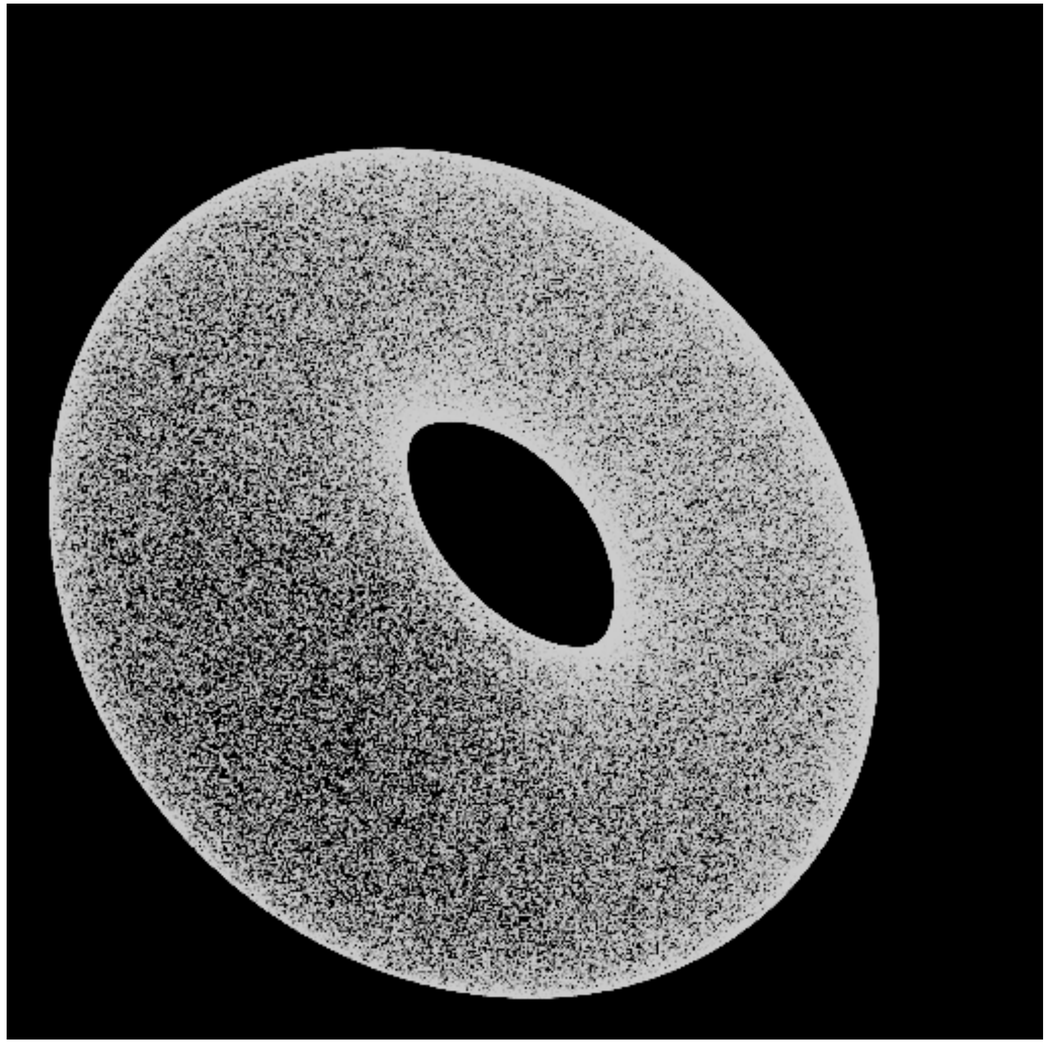
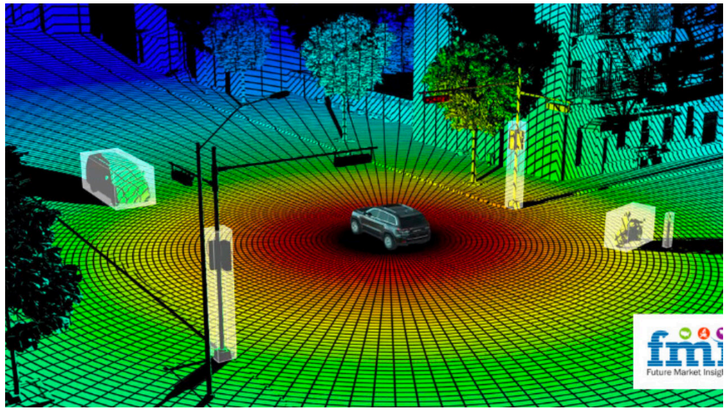
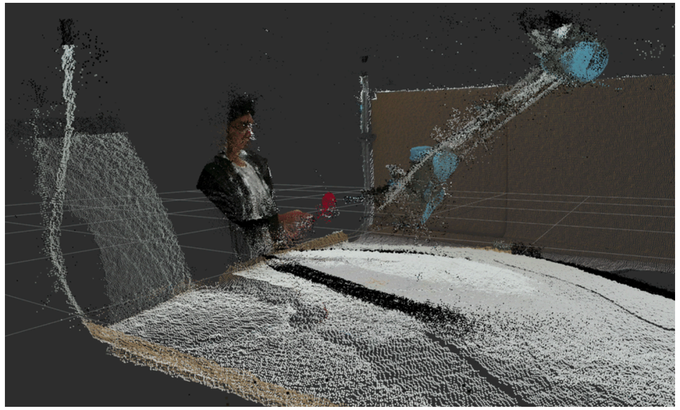
Point Clouds







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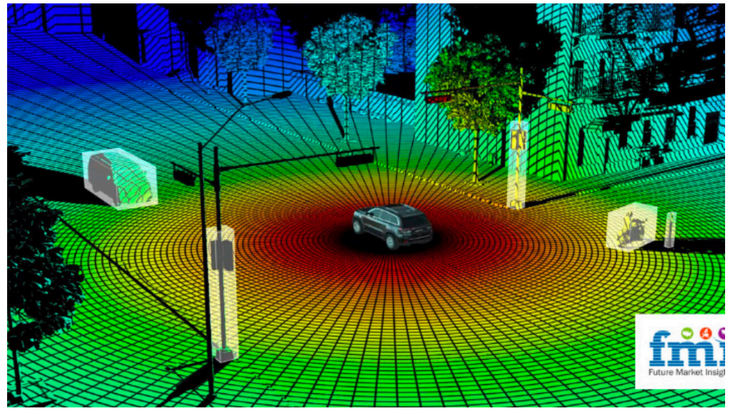
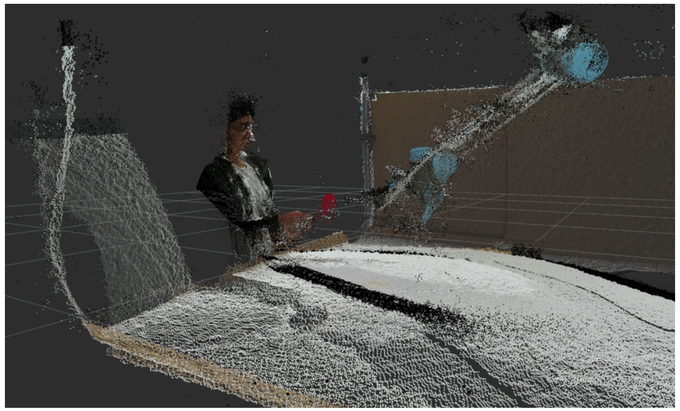
Point Clouds





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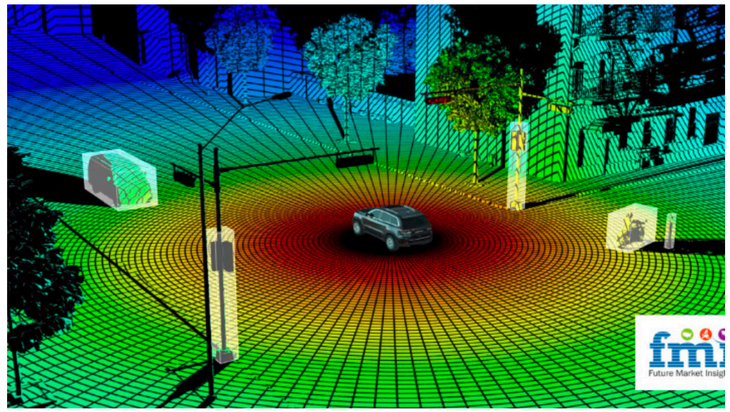
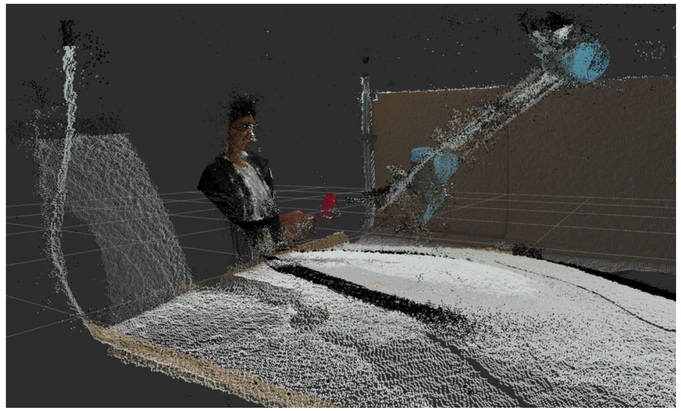
Point Clouds

Often acquired in an image-like manner from sensors but can be useful to ‘forget’ this





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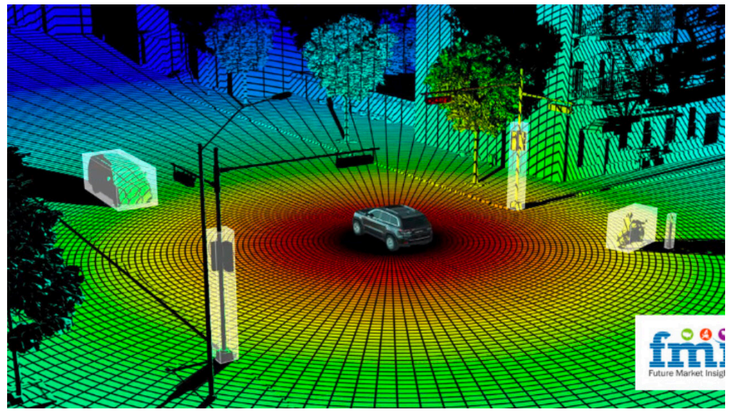
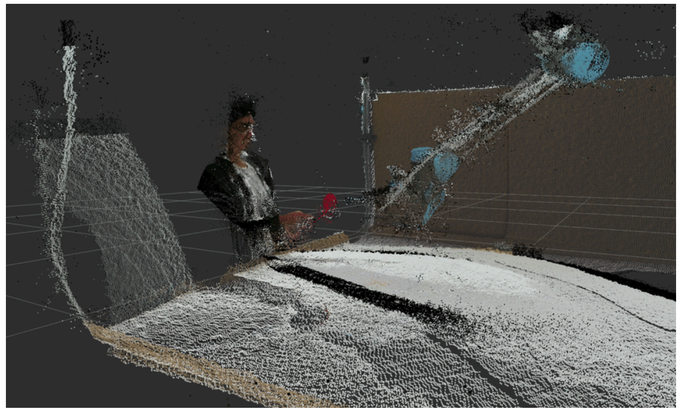
Point Clouds

Often acquired in an image-like manner from sensors but can be useful to ‘forget’ this

e.g. point clouds from multiple views can make a single point cloud





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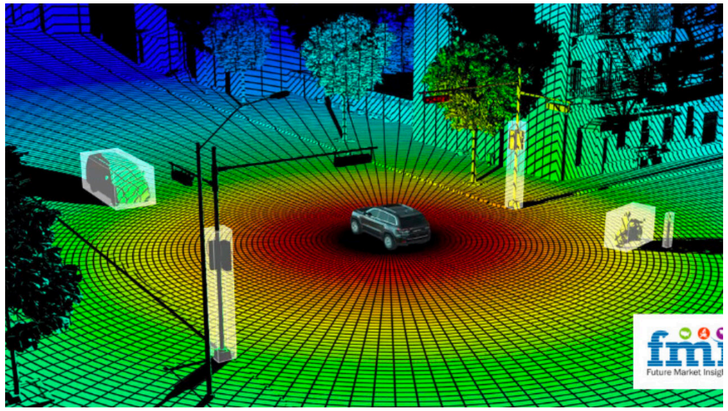
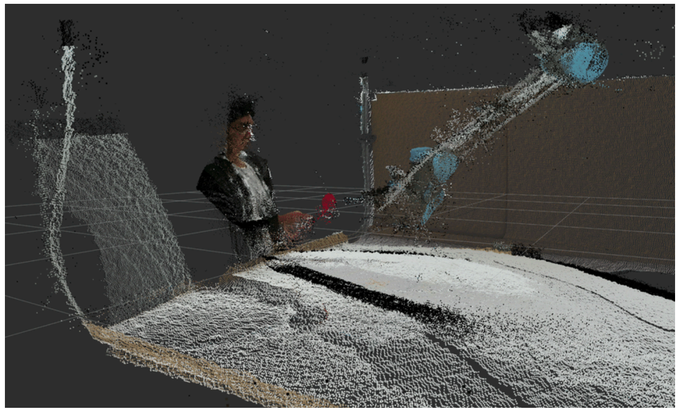
Point Clouds

Often acquired in an image-like manner from sensors but can be useful to ‘forget’ this

e.g. point clouds from multiple views can make a single point cloud

can help unify approaches independent of sensing modality





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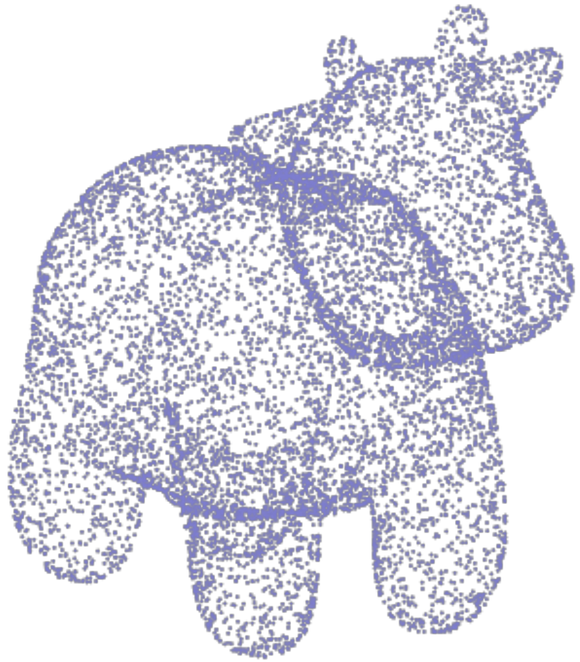
Point Clouds



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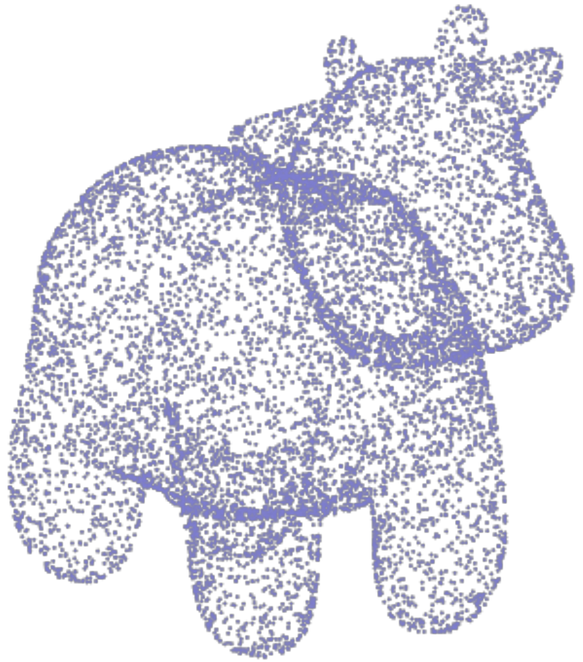
Point Clouds



$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

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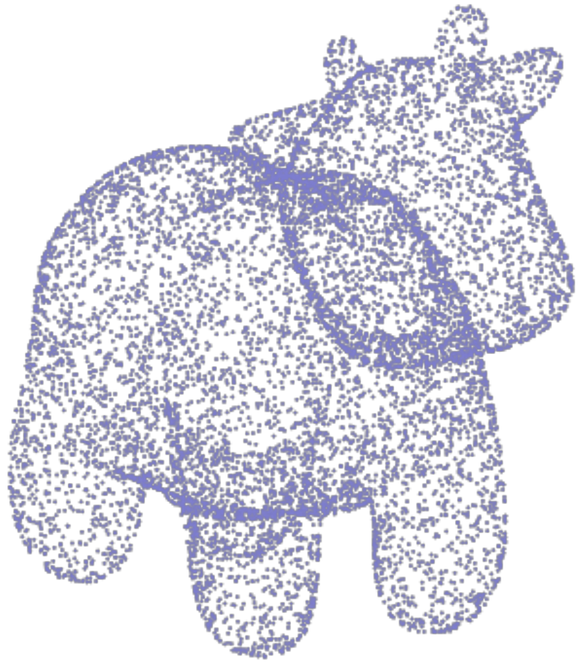
Point Clouds



Permutation σ

$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

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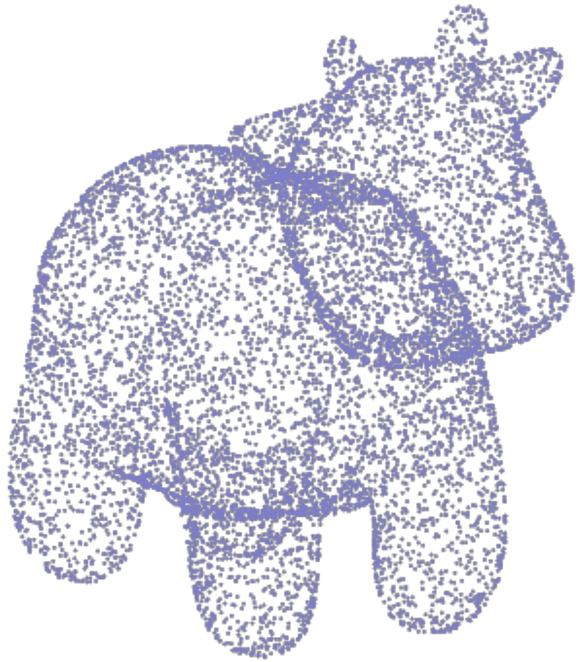
Point Clouds



Permutation σ

$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

$$\{\mathbf{p}_{\sigma(1)}, \mathbf{p}_{\sigma(2)}, \cdots, \mathbf{p}_{\sigma(N)}\}$$

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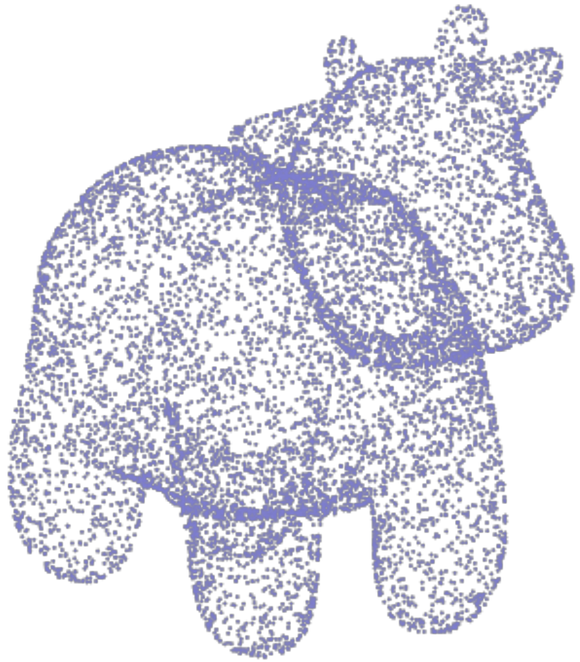
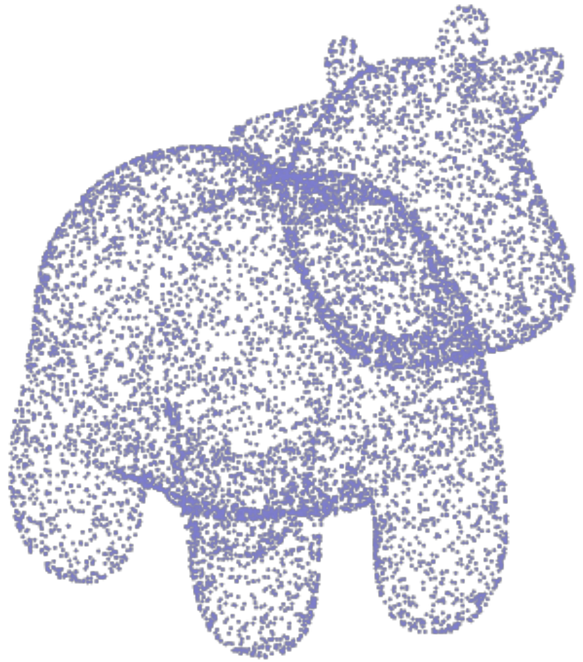
Point Clouds



Permutation σ



$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

$$\{\mathbf{p}_{\sigma(1)}, \mathbf{p}_{\sigma(2)}, \cdots, \mathbf{p}_{\sigma(N)}\}$$

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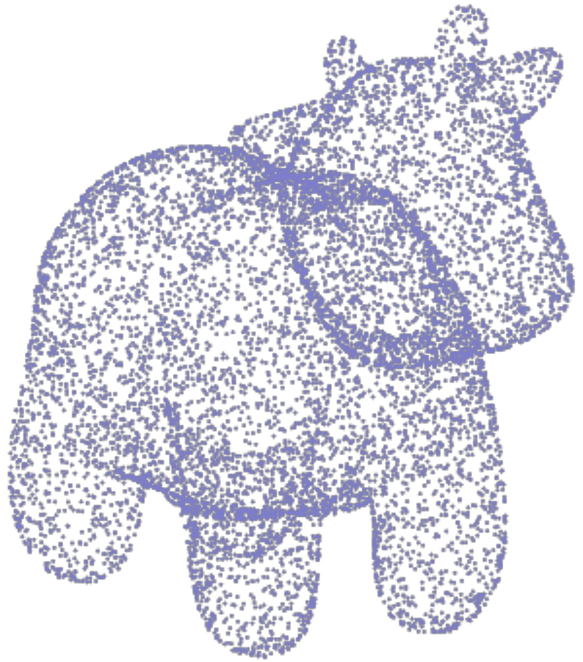
Point Clouds



$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

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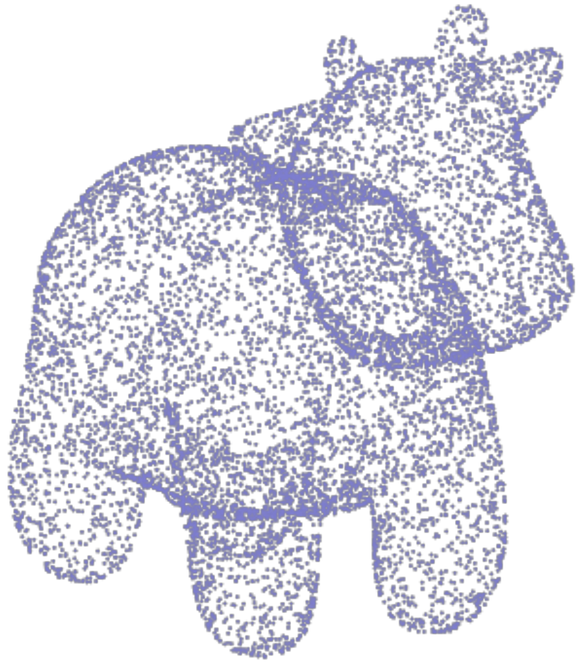
Point Clouds



$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

Unordered set of points

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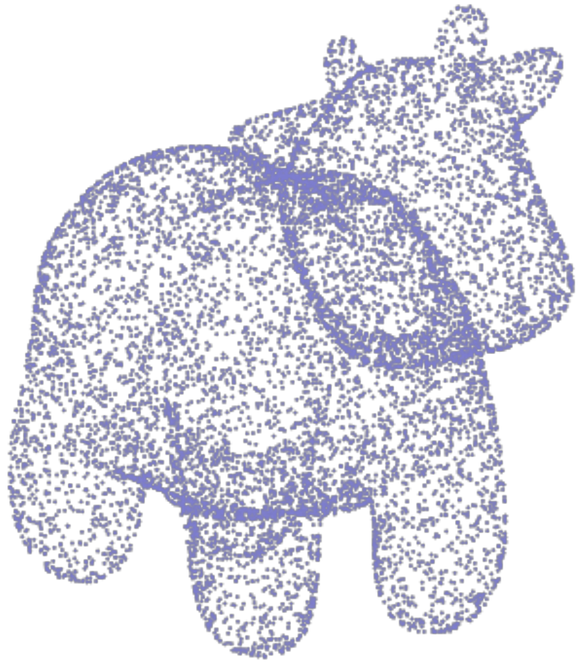
Point Clouds



x1,y1,z1
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$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

Unordered set of points

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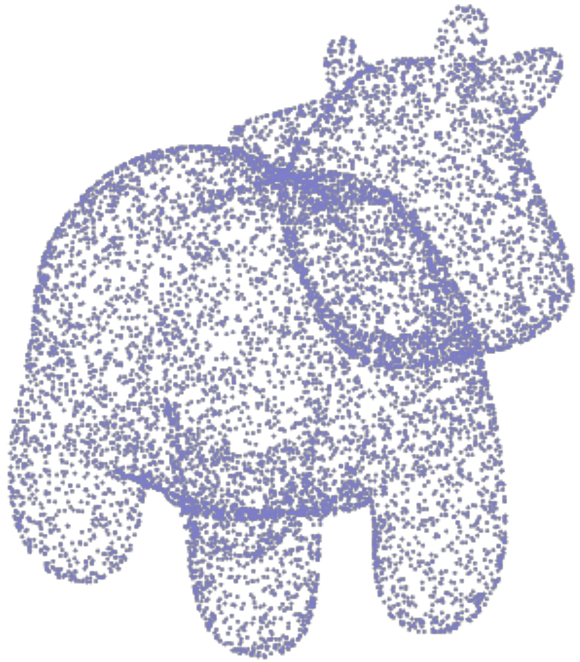
Point Clouds



x1,y1,z1
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Often represented as a NX3 array, but ordering does **not** matter (unlike images)

$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

Unordered set of points

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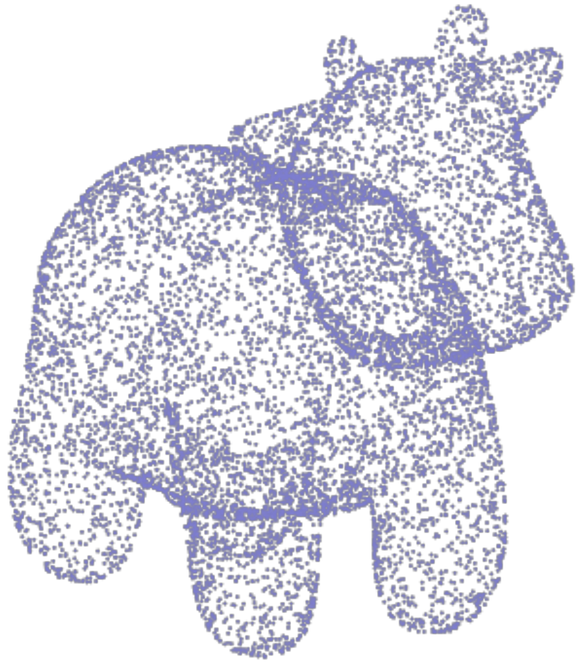
Point Clouds



x1,y1,z1
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Often represented as a NX3 array, but ordering does **not** matter (unlike images)

Need processing/generation methods that are permutation invariant (e.g. fully connected layer will not work)

$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

Unordered set of points

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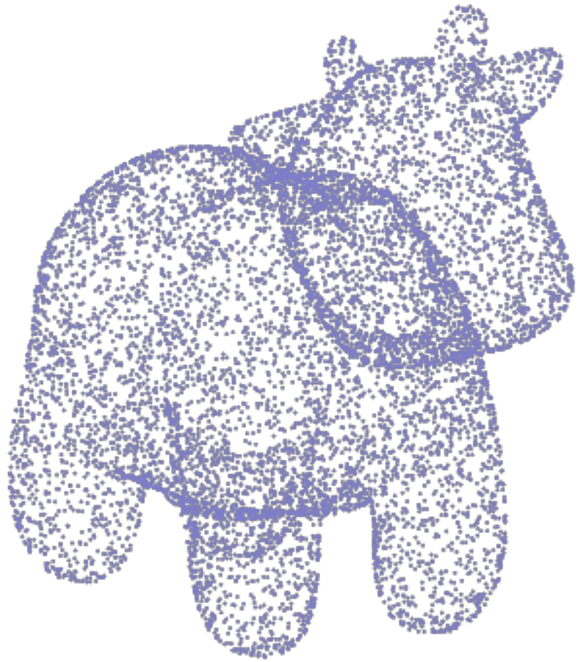
Point Clouds



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Unordered set of points

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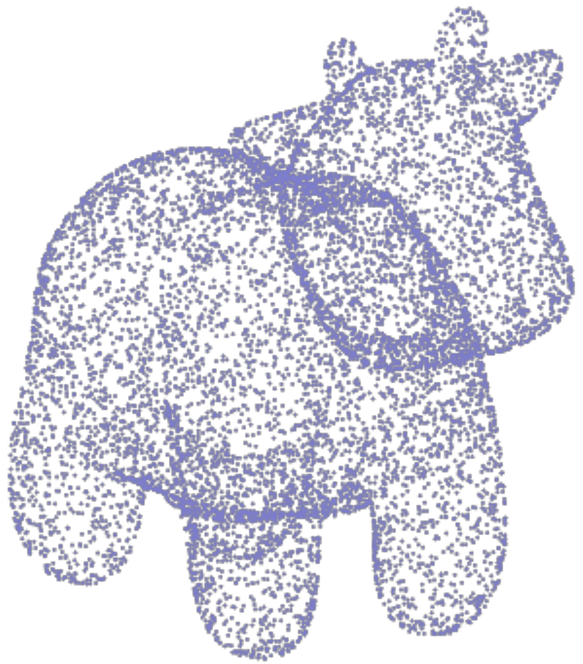
Point Clouds



No explicit ‘connectivity’ information

$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

Unordered set of points

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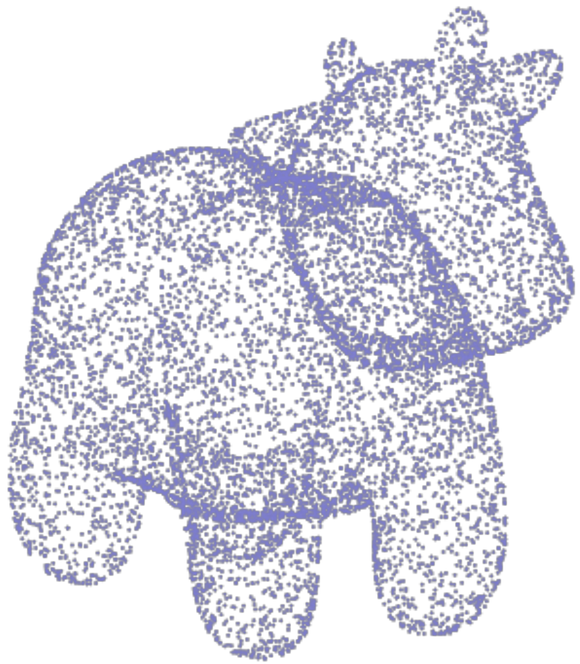
Point Clouds



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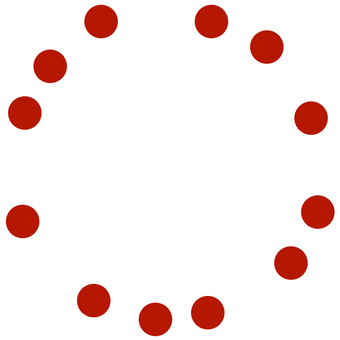

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Unordered set of points

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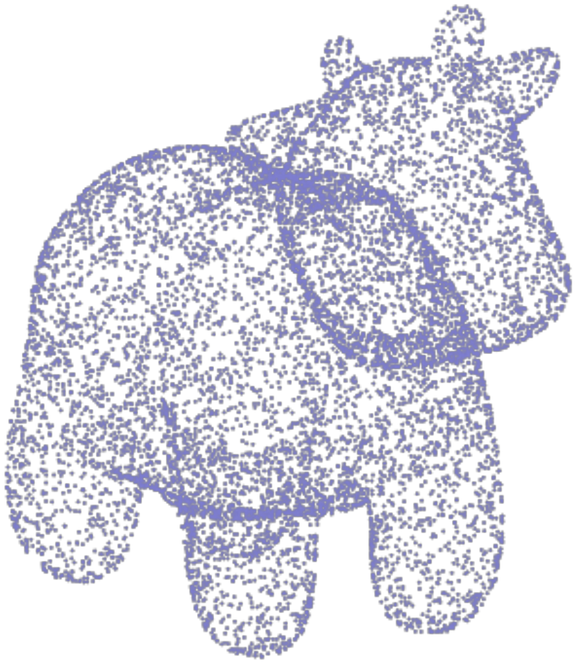
Point Clouds



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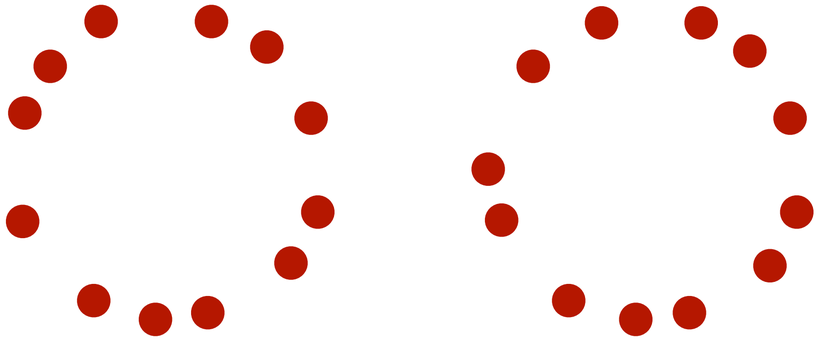

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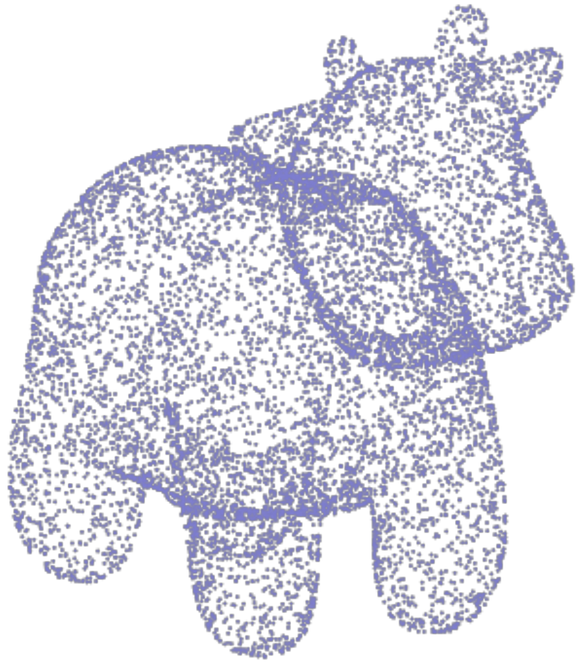

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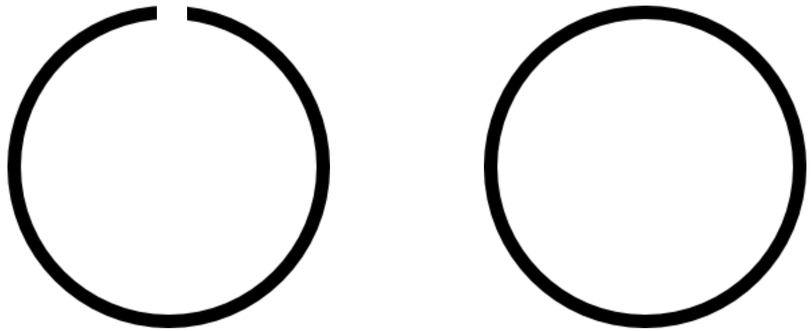

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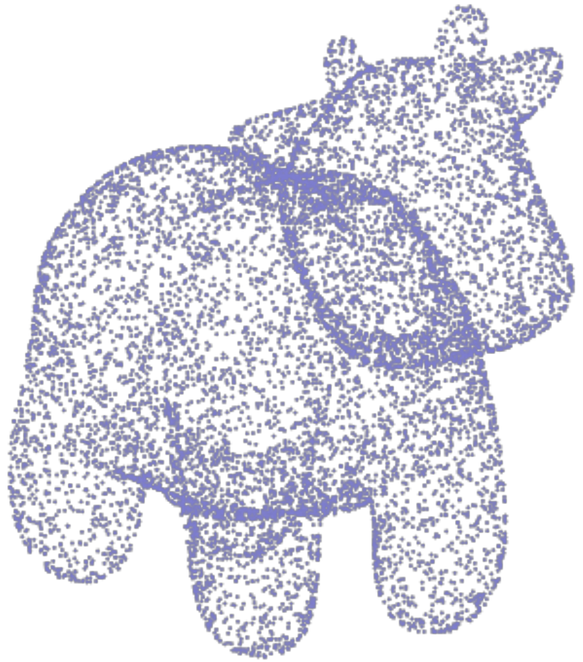
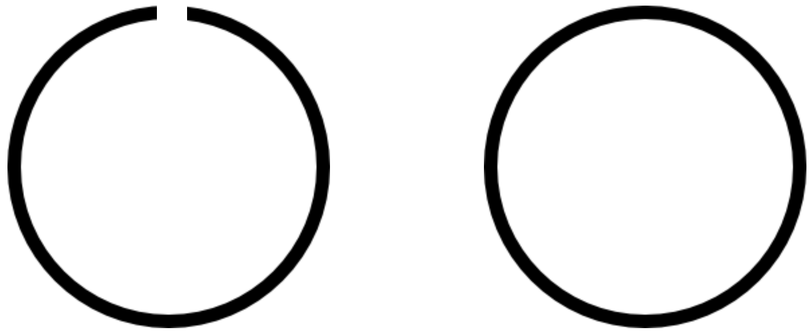
Point Clouds



$$\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N\}$$

Unordered set of points

No explicit ‘connectivity’ information



(yes, we can sample more - but more efficient to add edges)

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Meshes

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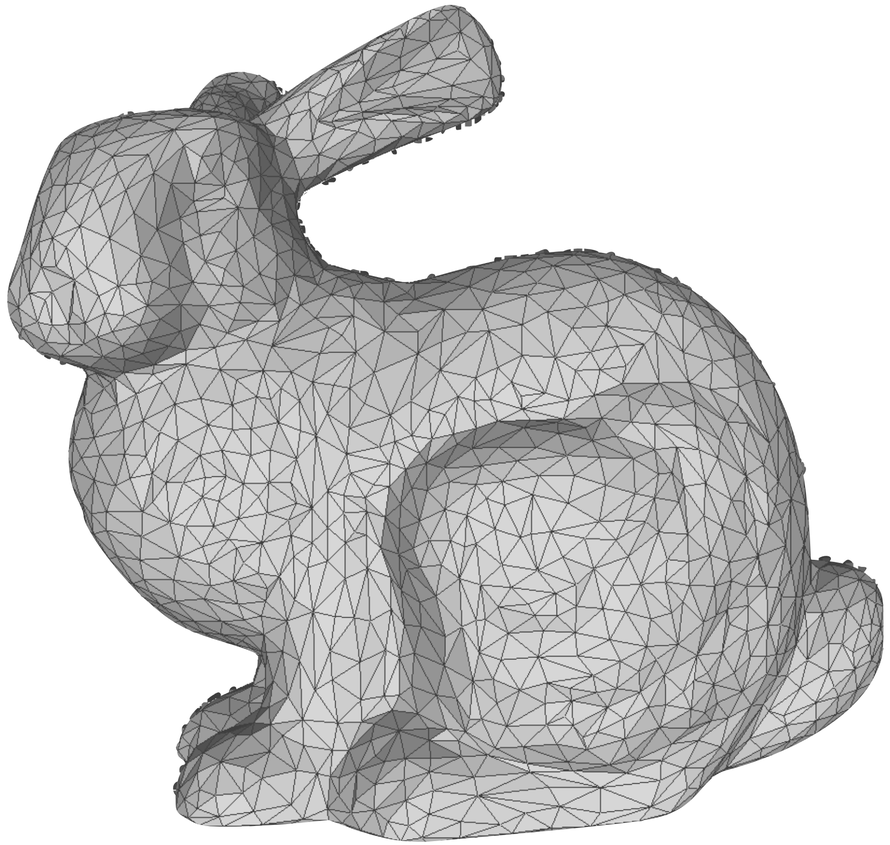
Meshes



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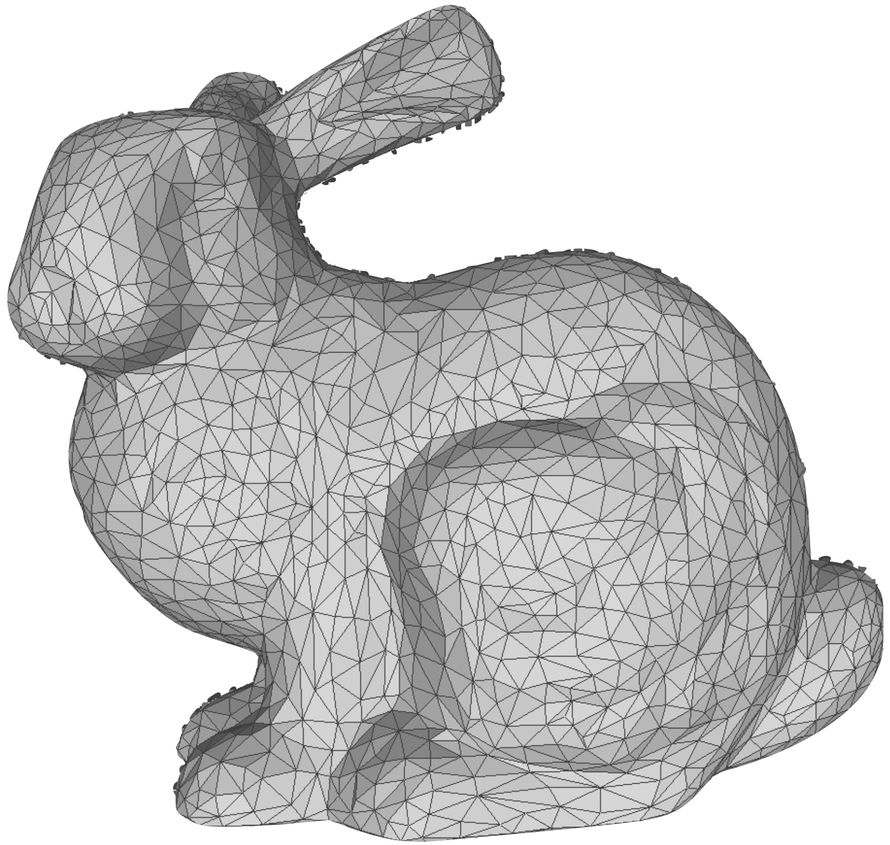
Meshes



Vertices + Faces

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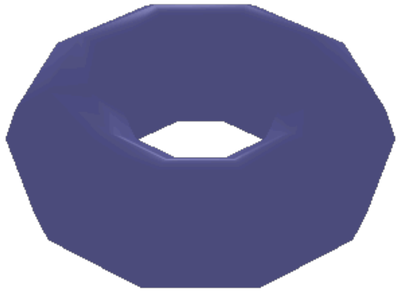
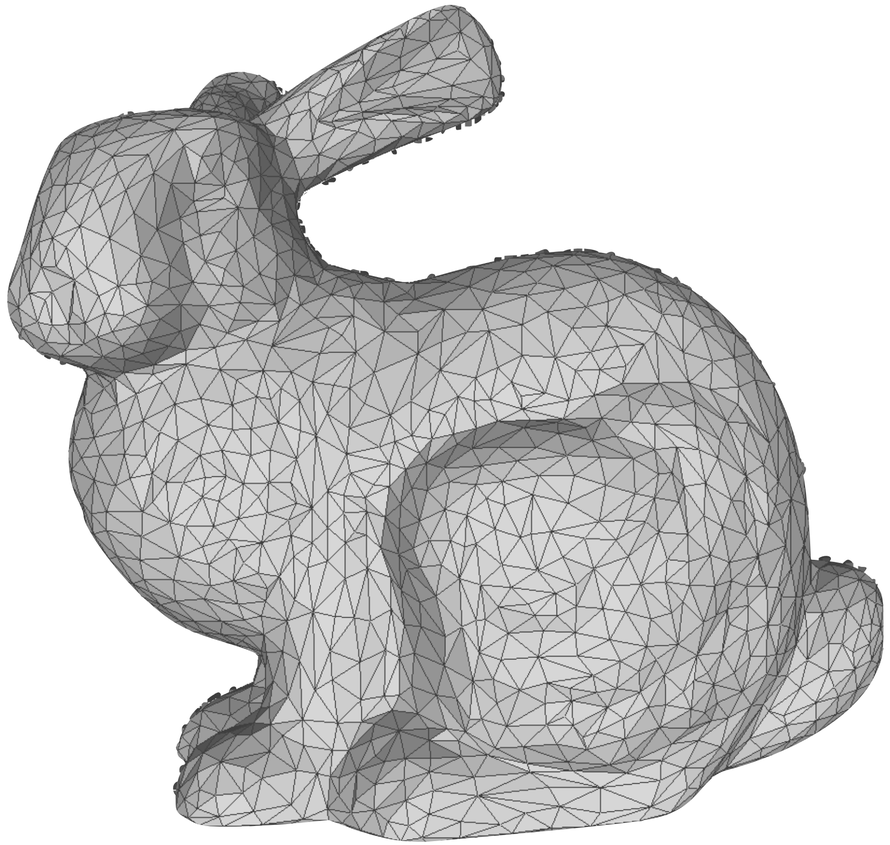
Meshes





Vertices + Faces

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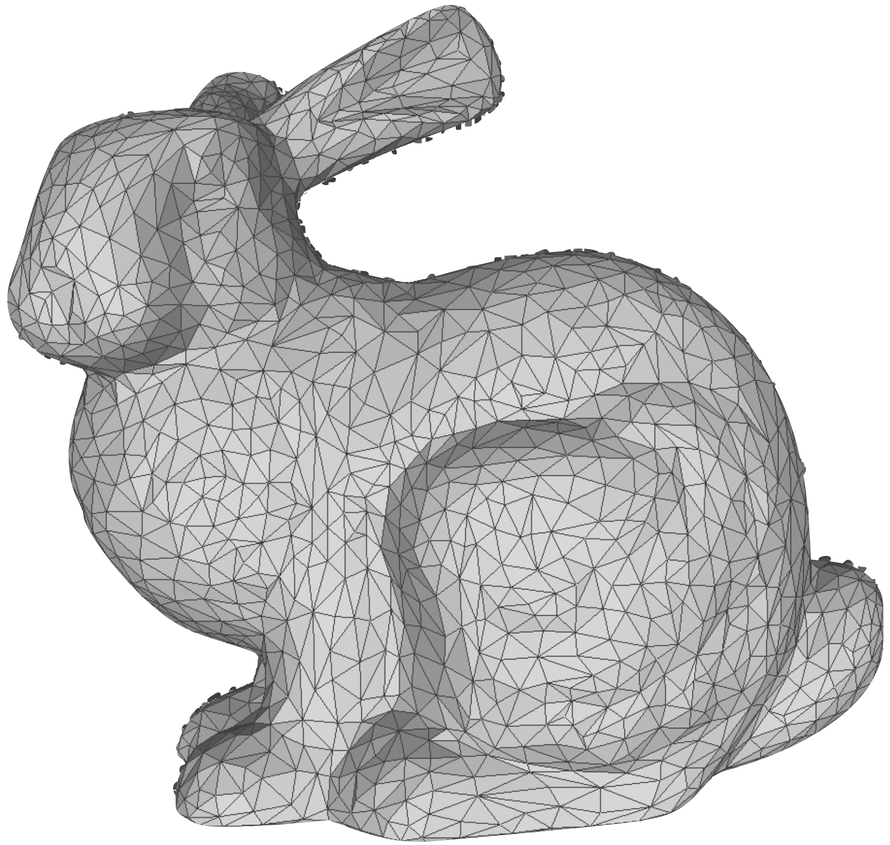
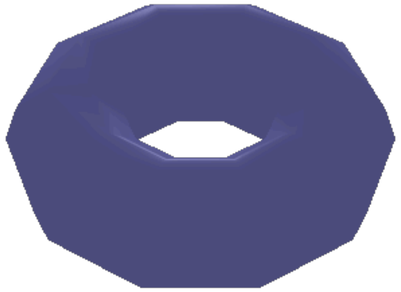
Meshes



Vertices + Faces



Piecewise linear approximations of underlying surface

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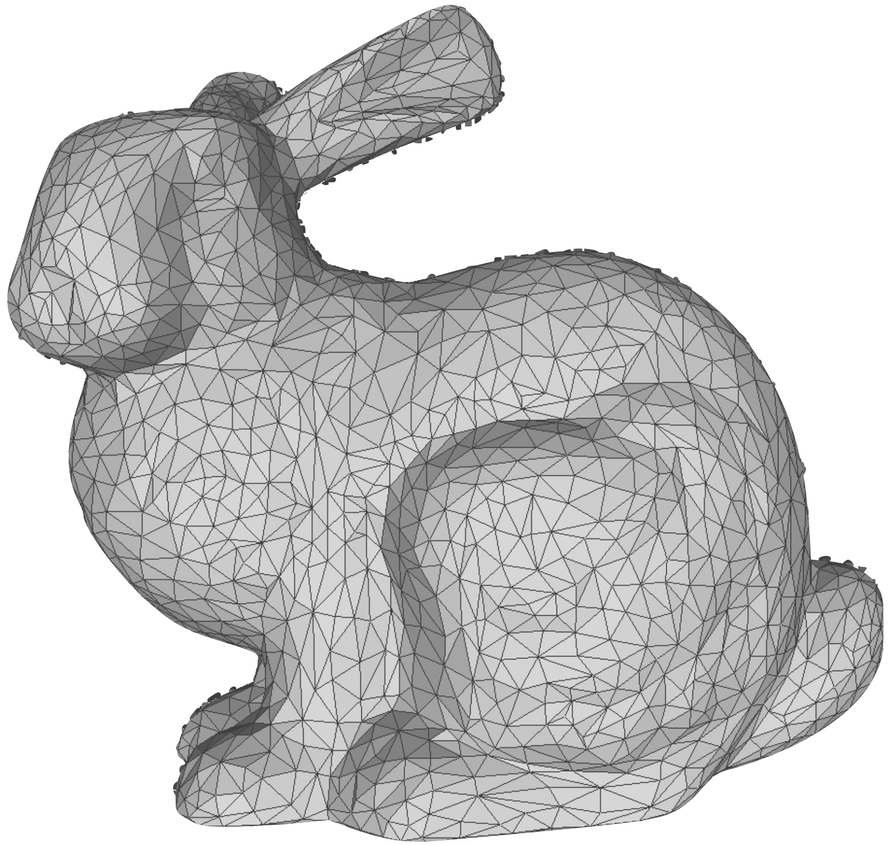
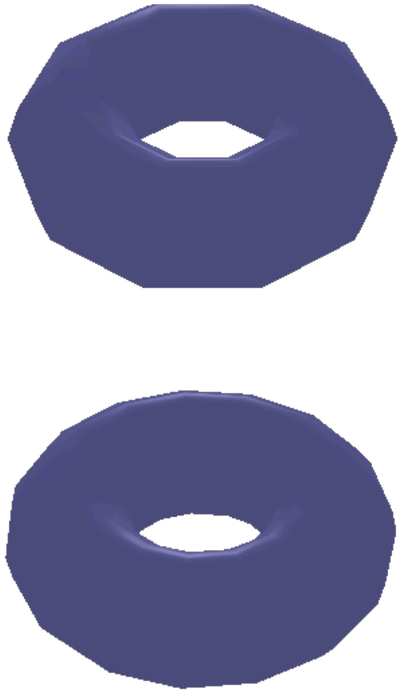
Meshes



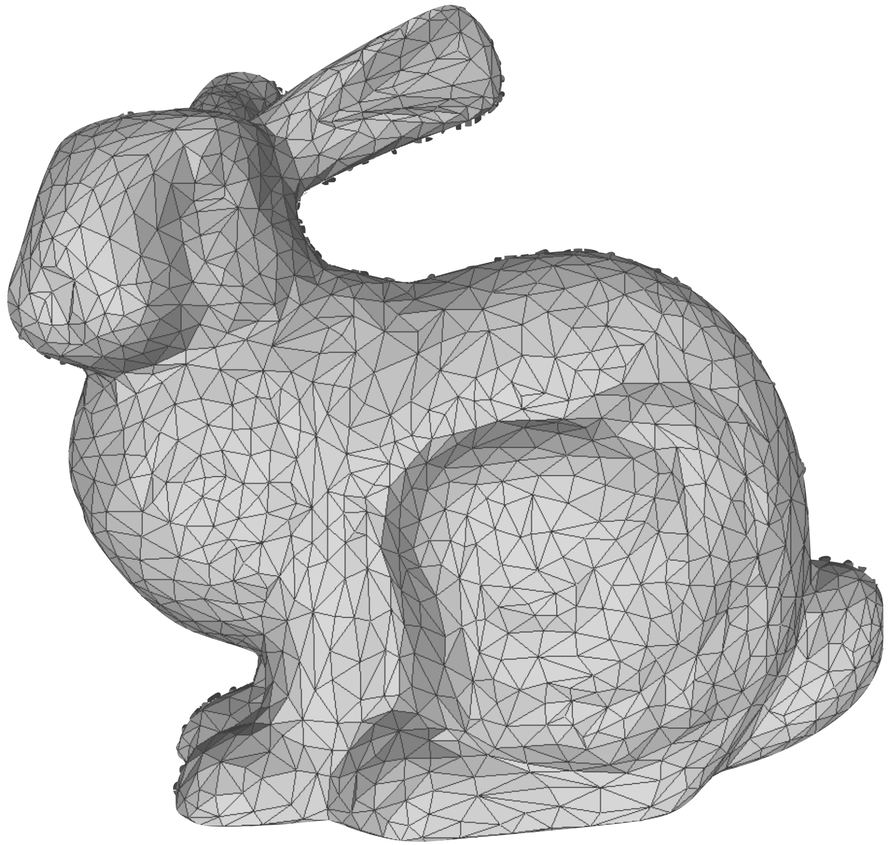
Vertices + Faces



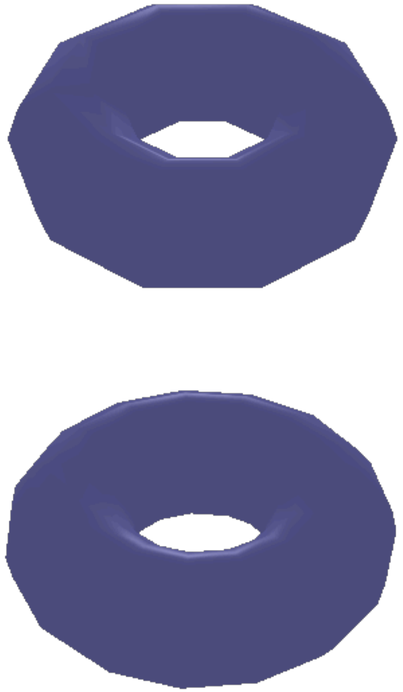
Piecewise linear approximations of underlying surface

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Meshes



Vertices + Faces

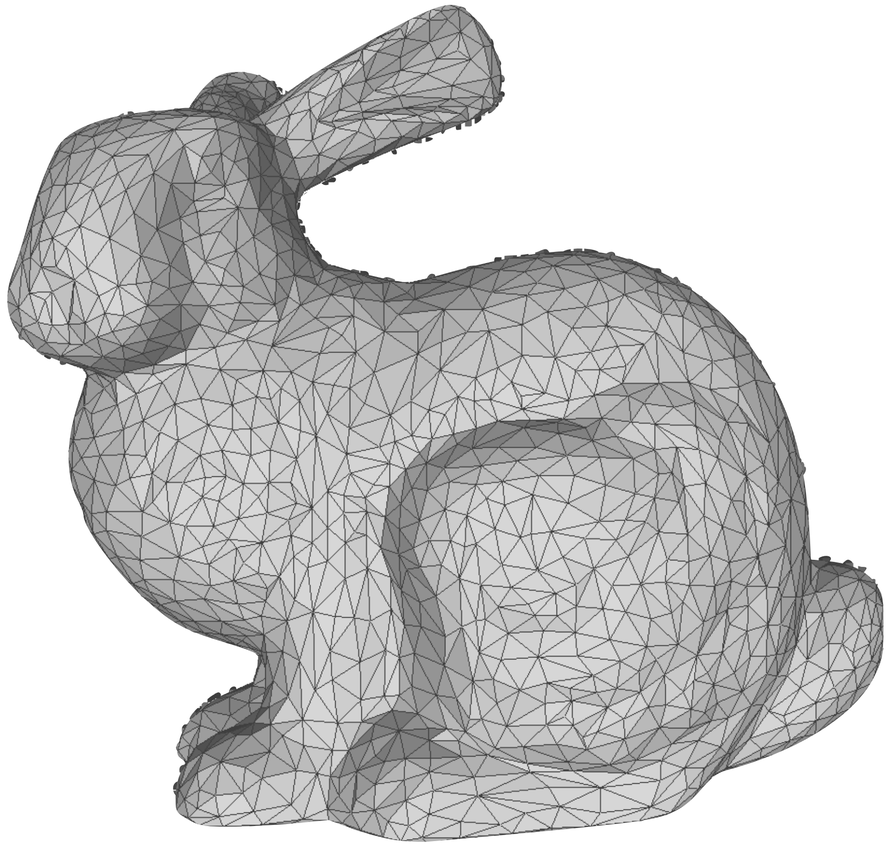


Piecewise linear approximations of underlying surface

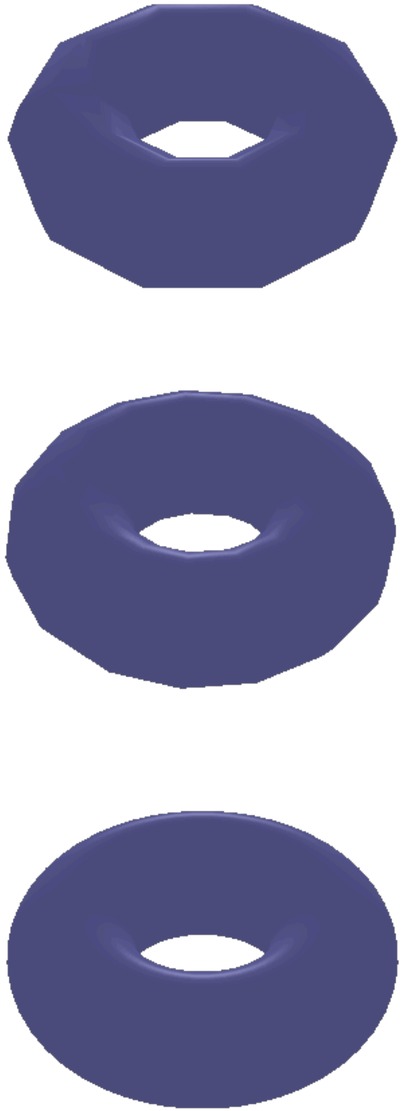
More elements allow better approximation

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Meshes



Vertices + Faces



Piecewise linear approximations of underlying surface

More elements allow better approximation

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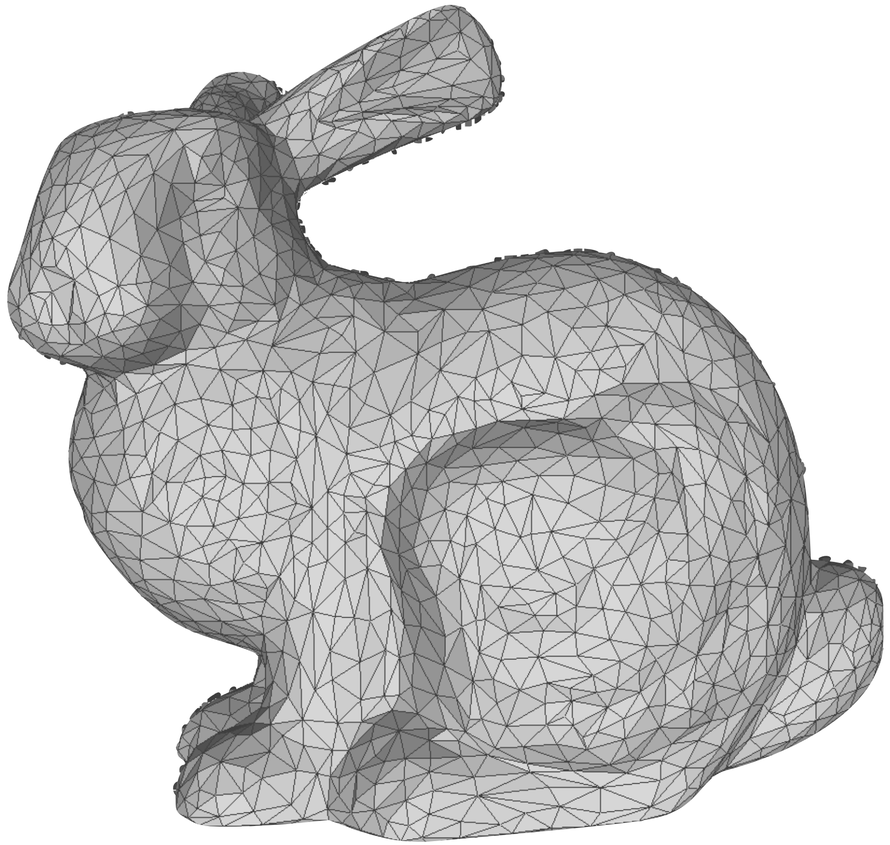
Meshes



Vertices + Faces

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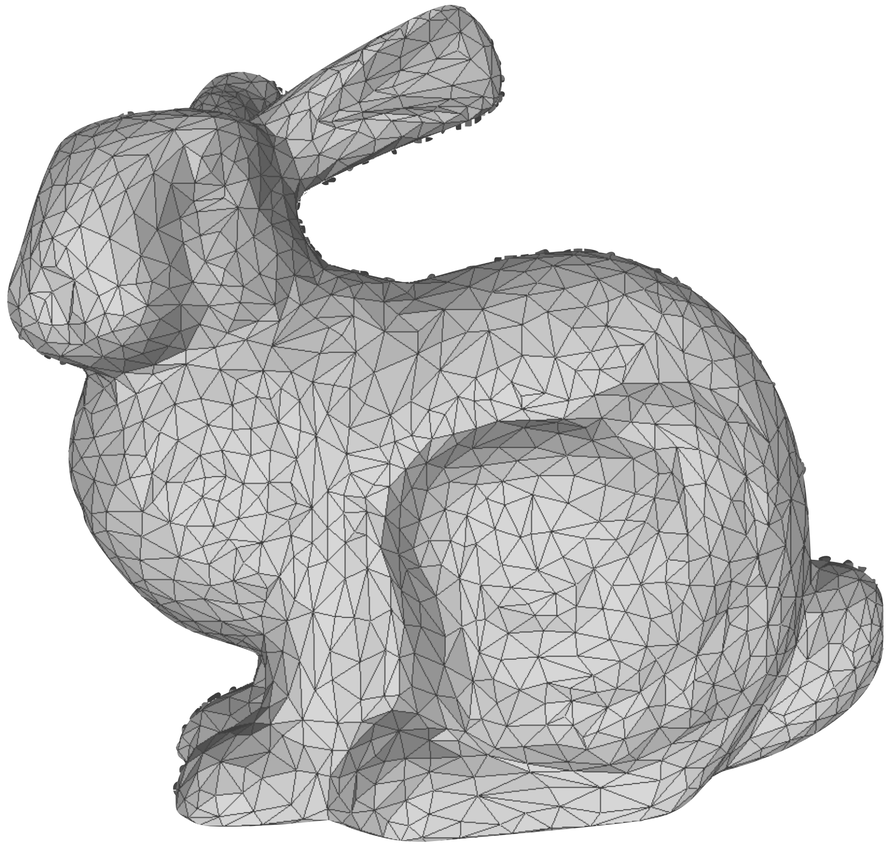
Meshes



Vertices + Faces

Vertices

x1,y1,z1
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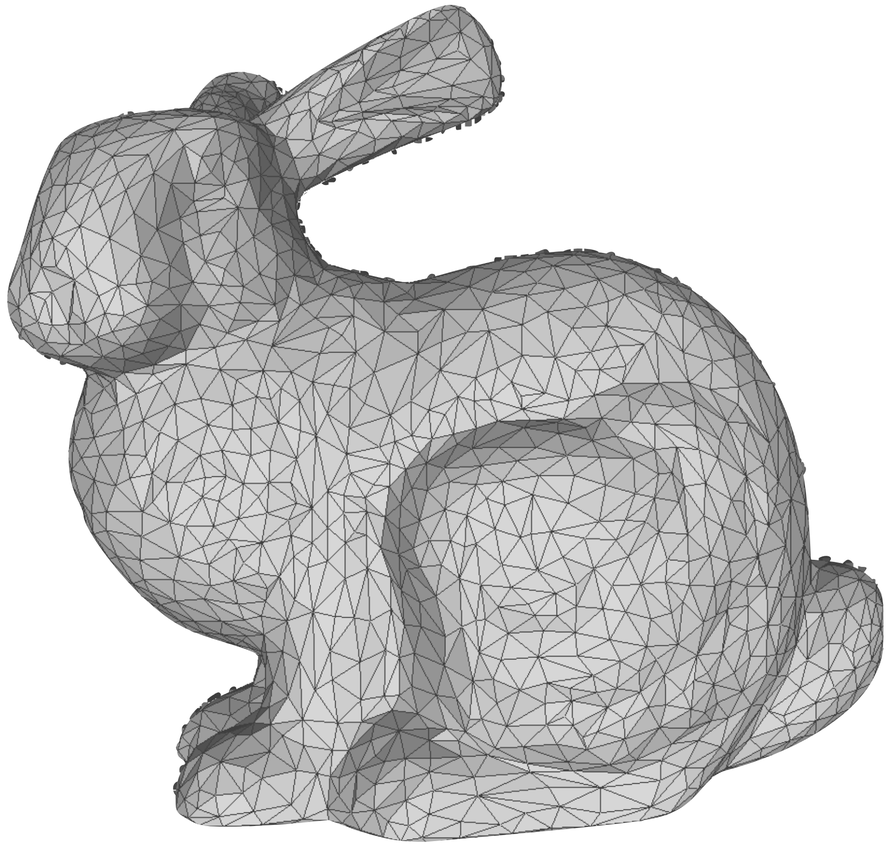
Meshes



Vertices + Faces

Vertices

x1,y1,z1
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Positions of Vertices

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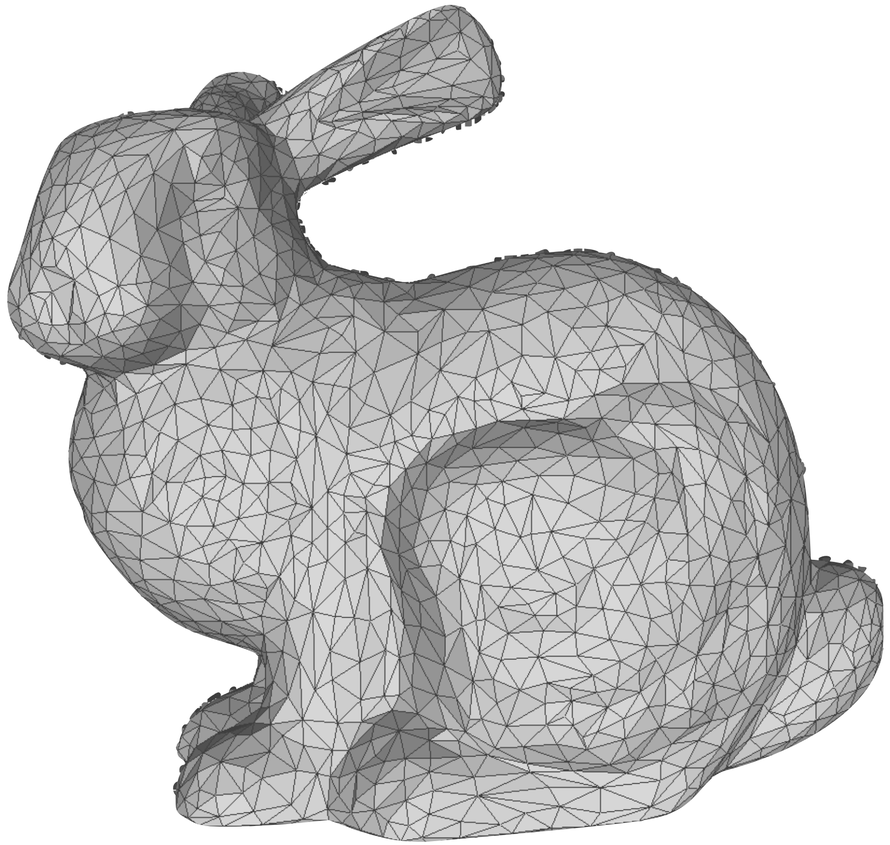
Meshes



Vertices + Faces

Vertices

x1,y1,z1
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Positions of Vertices

Faces

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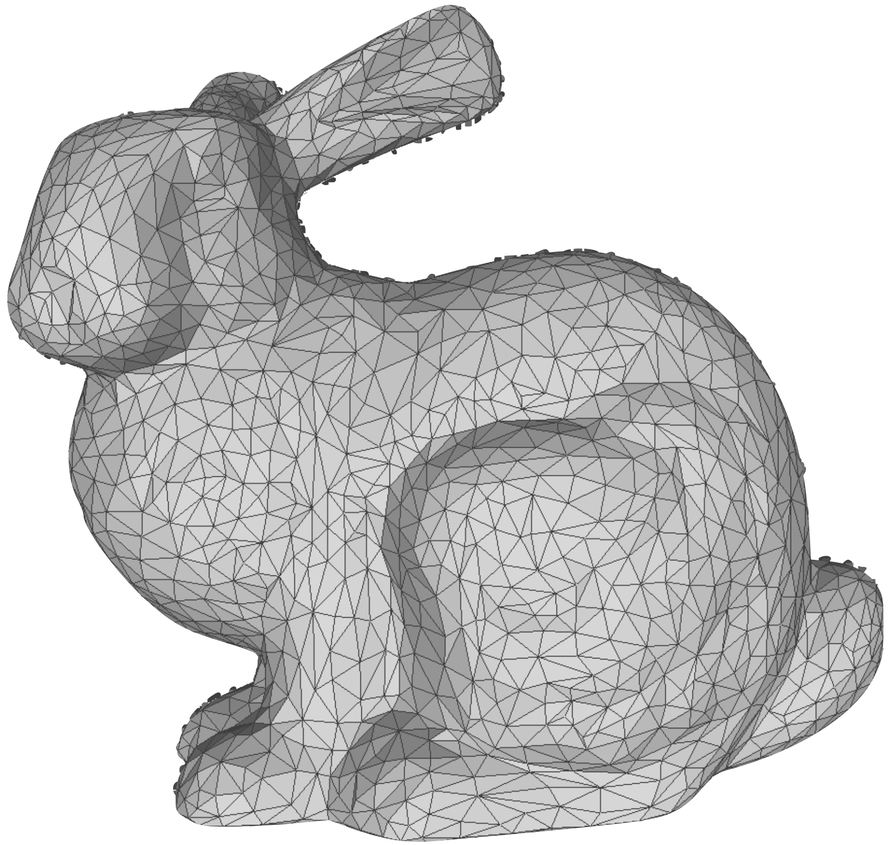
Meshes



Vertices + Faces

Vertices

x1,y1,z1
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Positions of Vertices

Faces

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Connectivity
(indices of vertices
that make a ‘face’)

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Meshes

Vertices + Faces

Vertices

x1,y1,z1
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Positions of Vertices

Faces

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Connectivity (indices of vertices that make a 'face')

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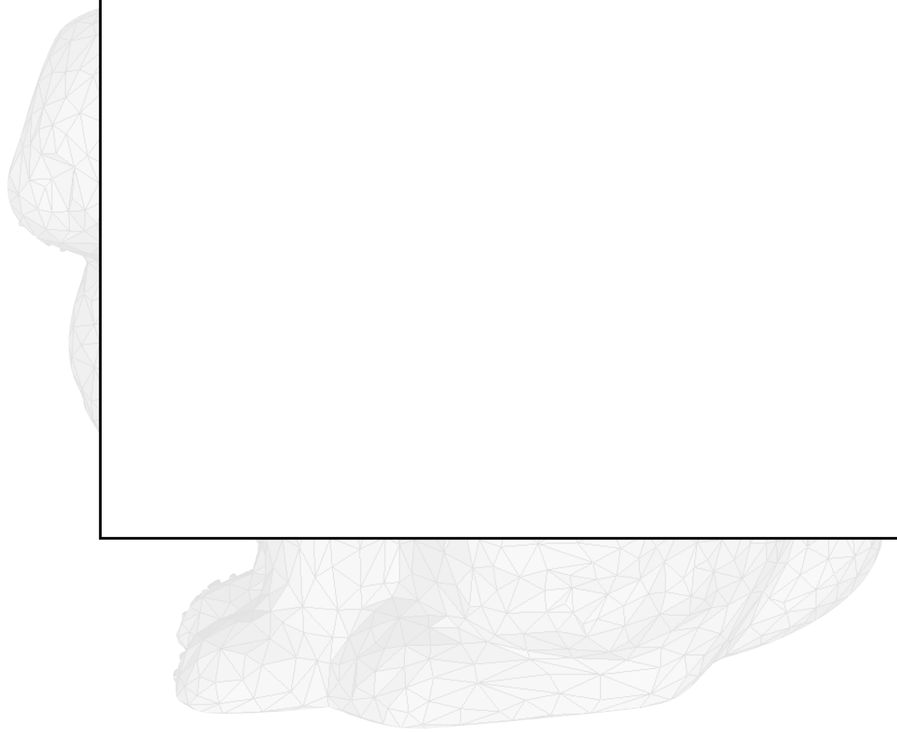
Meshes

Faces

Vertices

i,j,k

Ordering Matters in Face Indices



Vertices + Faces

Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

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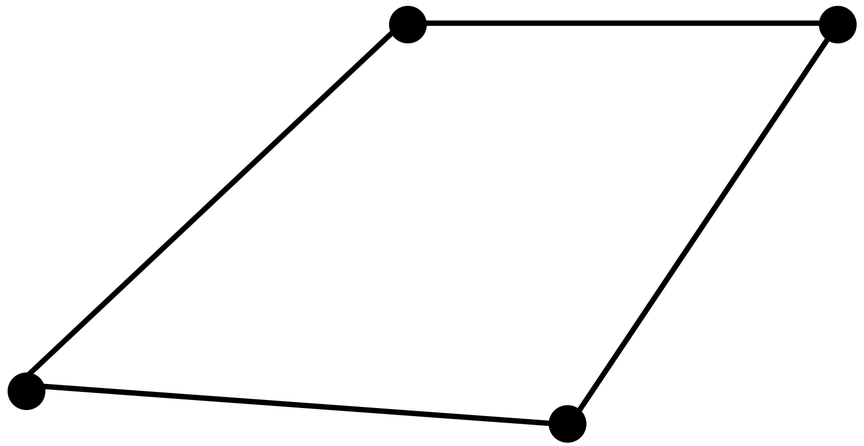
Meshes

Faces

Vertices

i,j,k

Ordering Matters in Face Indices



Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

Vertices + Faces

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

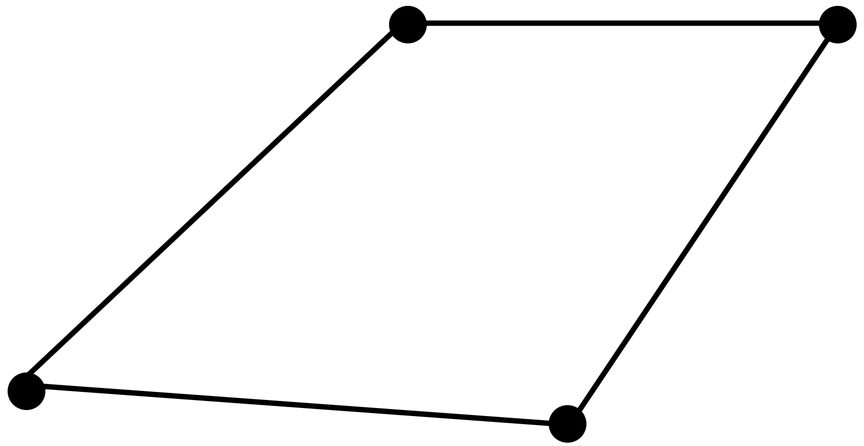
Meshes

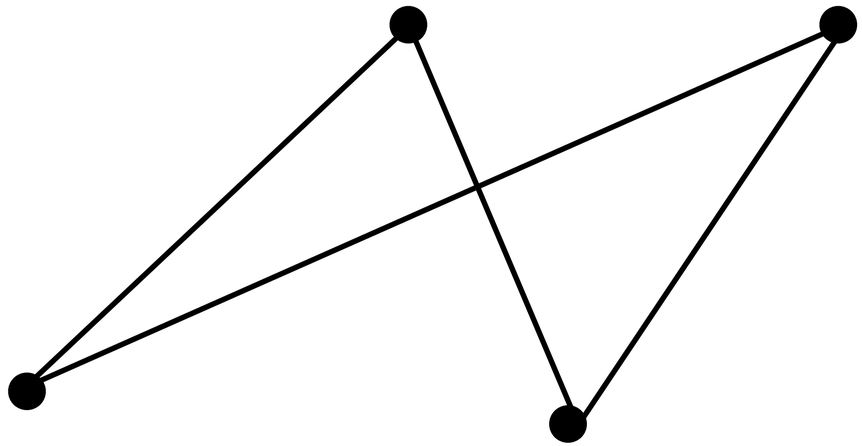
Faces

Vertices

i,j,k

Ordering Matters in Face Indices





Vertices + Faces

Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

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Meshes

Faces

Vertices

i,j,k

Arbitrary Polygons can be non-planar

Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

Vertices + Faces

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Meshes

Faces

Vertices

i,j,k
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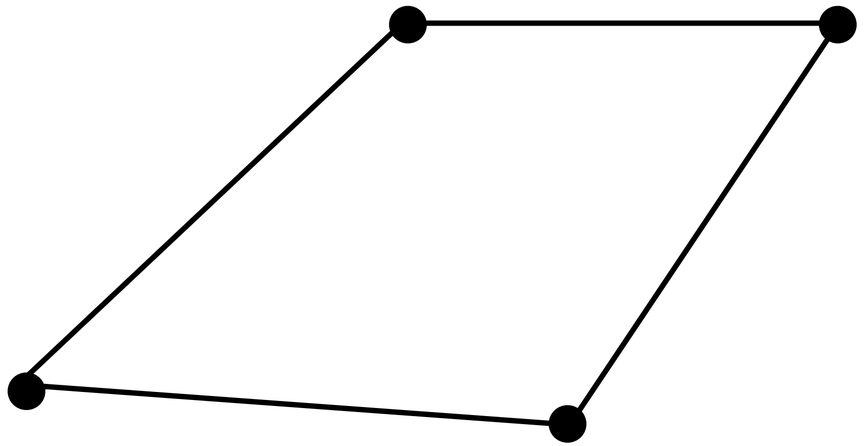
Arbitrary Polygons can be non-planar



Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

Vertices + Faces

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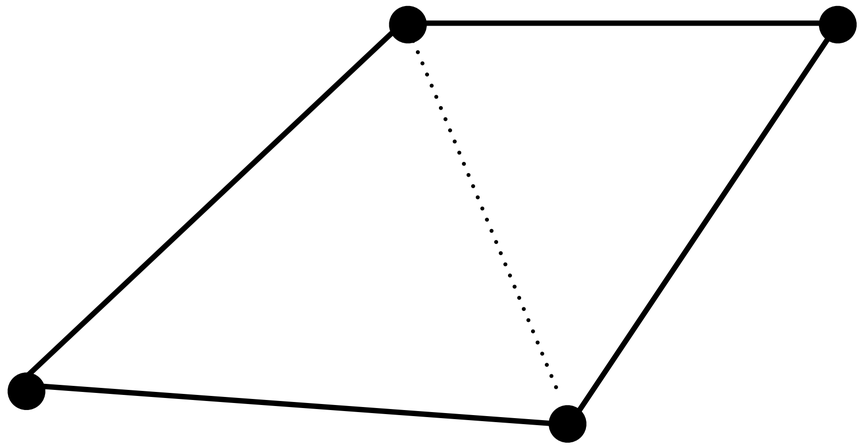
Meshes

Faces

Vertices

i,j,k

Arbitrary Polygons can be non-planar



Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

Vertices + Faces

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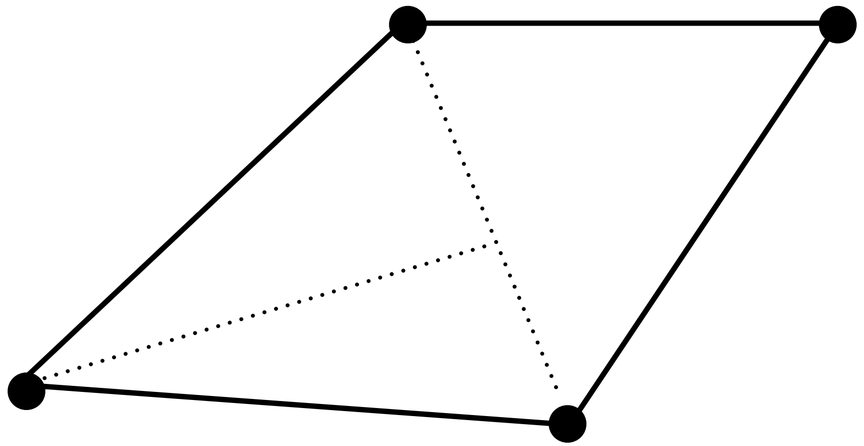
Meshes

Faces

Vertices

i,j,k

Arbitrary Polygons can be non-planar



Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

Vertices + Faces

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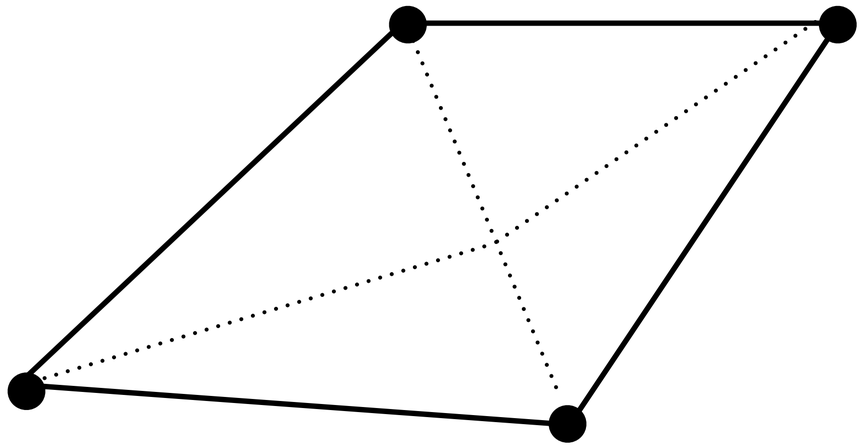
Meshes

Faces

Vertices

i,j,k

Arbitrary Polygons can be non-planar



Positions of Vertices

Connectivity
(indices of vertices
that make a ‘face’)

Vertices + Faces

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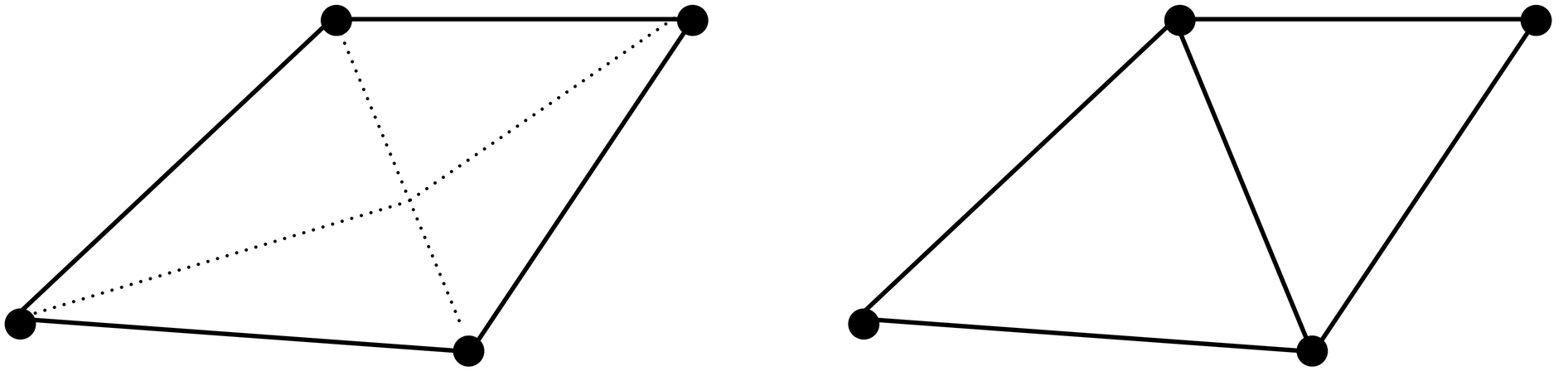
Meshes

Faces

Vertices

i,j,k

Arbitrary Polygons can be non-planar



restrict to *Triangular* Meshes

Positions of Vertices

Connectivity (indices of vertices that make a ‘face’)

Vertices + Faces

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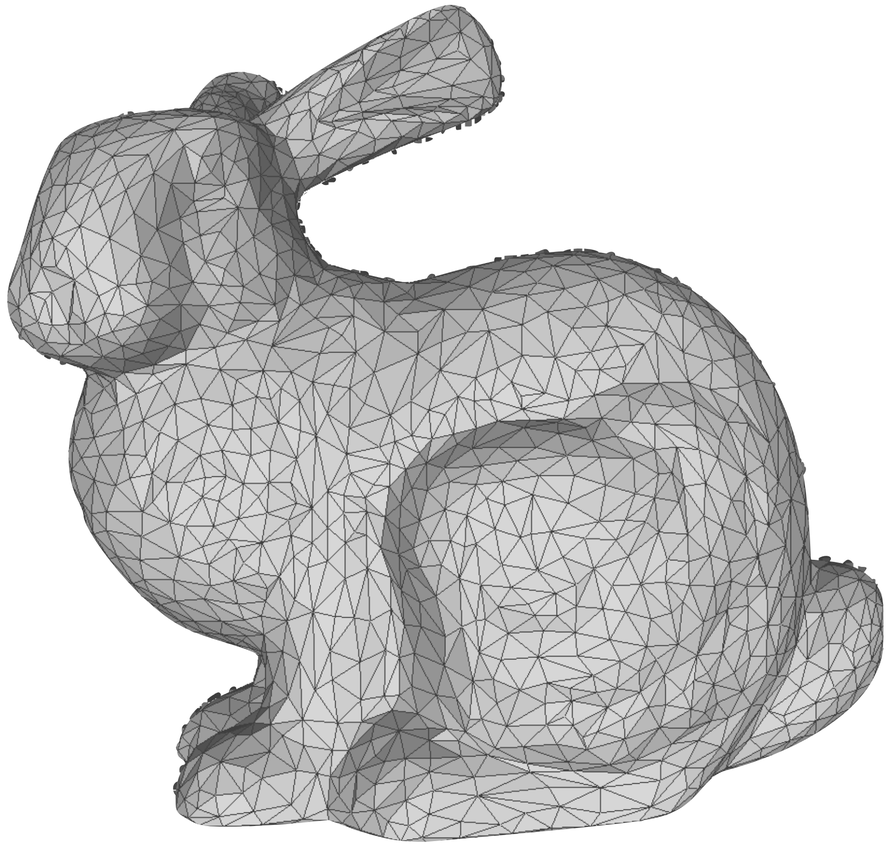
Triangular Meshes



Vertices + Faces

Vertices

x1,y1,z1
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Positions of Vertices

Faces

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Connectivity (indices of **three** vertices that make a ‘face’)

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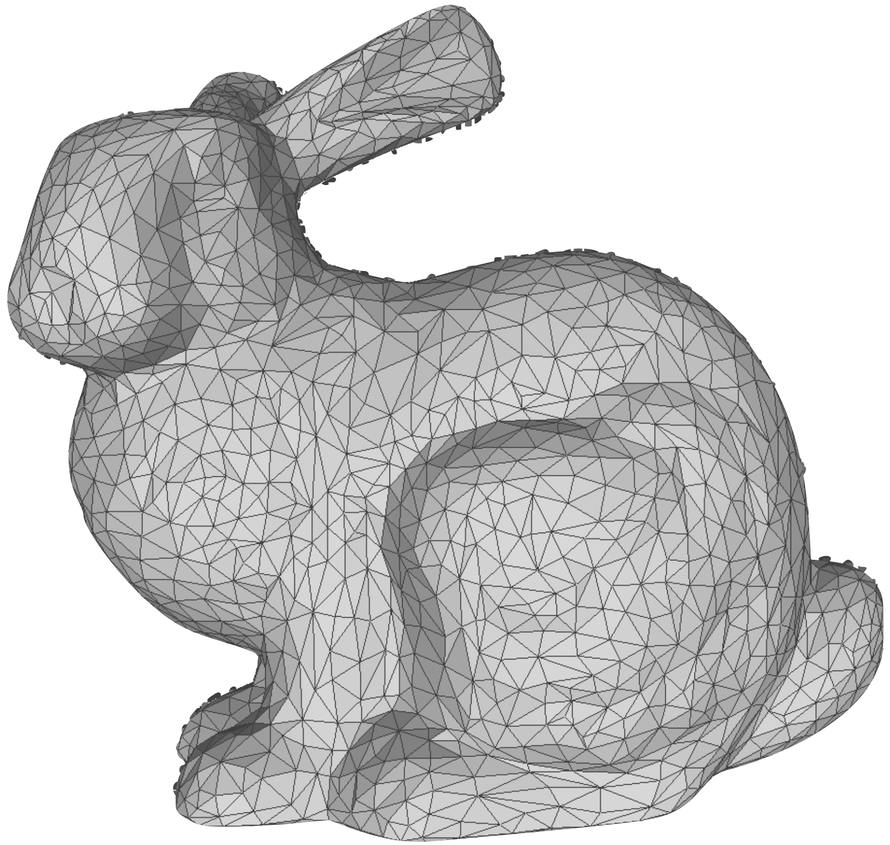
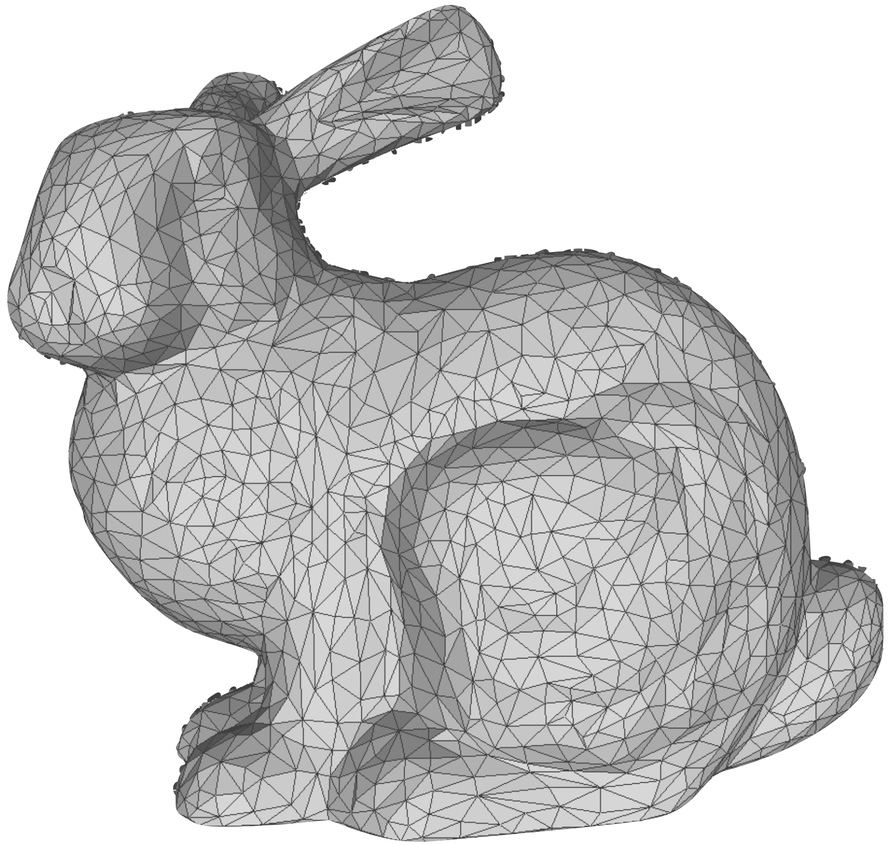
Is a point inside or outside the shape?



Vertices + Faces

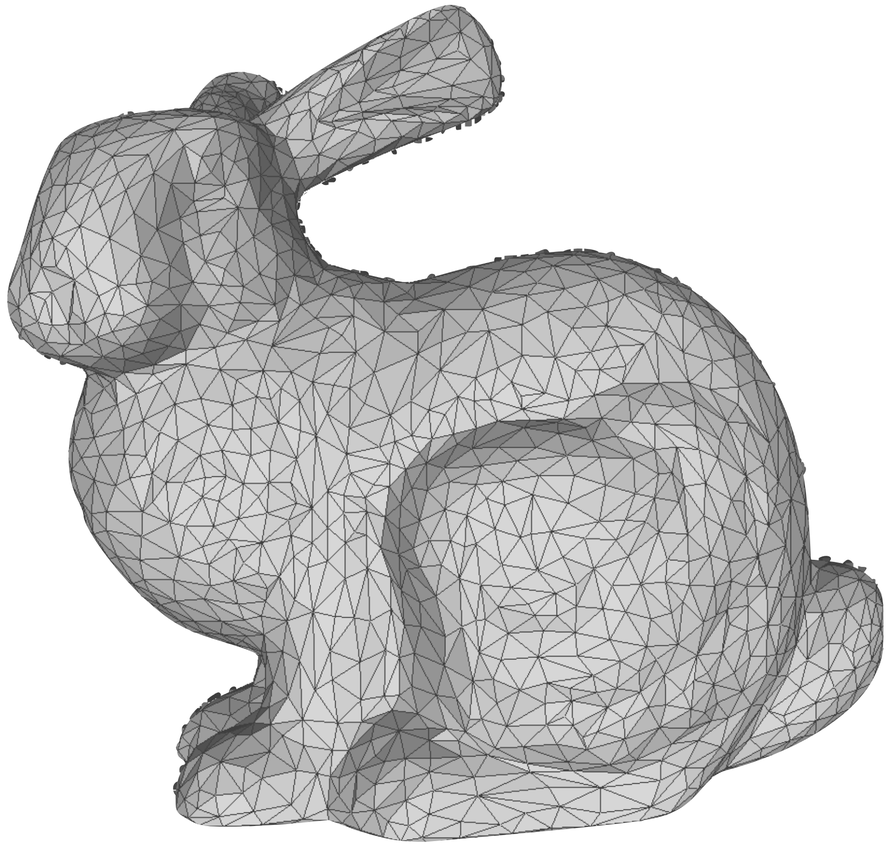
Is a point inside or outside the shape?



Vertices + Faces

Meshes can be “watertight”, i.e., if you filled the mesh with water, nothing would leak out

Is a point inside or outside the shape?

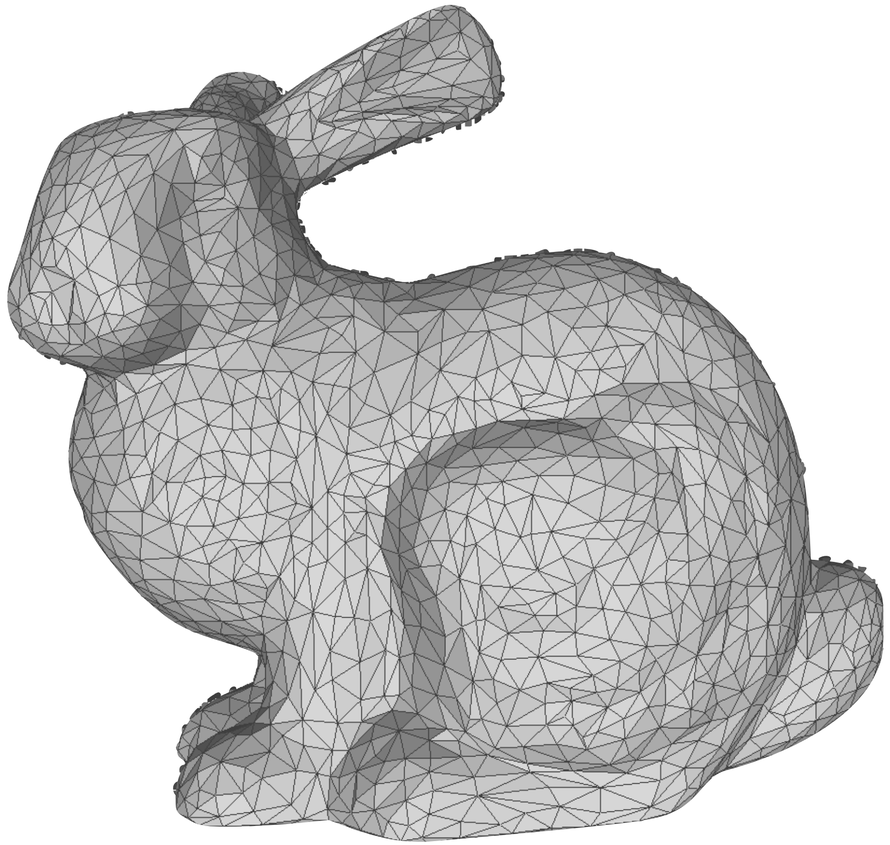


Vertices + Faces

Meshes can be “watertight”, i.e., if you filled the mesh with water, nothing would leak out

If mesh is watertight, can define “inside” and “outside”

Is a point inside or outside the shape?



Vertices + Faces

Meshes can be “watertight”, i.e., if you filled the mesh with water, nothing would leak out

If mesh is watertight, can define “inside” and “outside”

If not, needs further processing, see “Generalized Winding Numbers”

Triangular Meshes

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Triangular Meshes

Efficient to compute ray-triangle intersections

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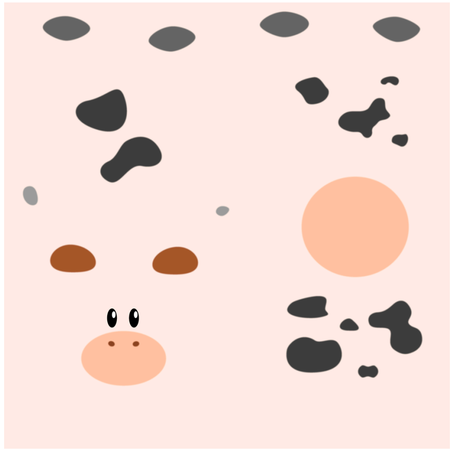
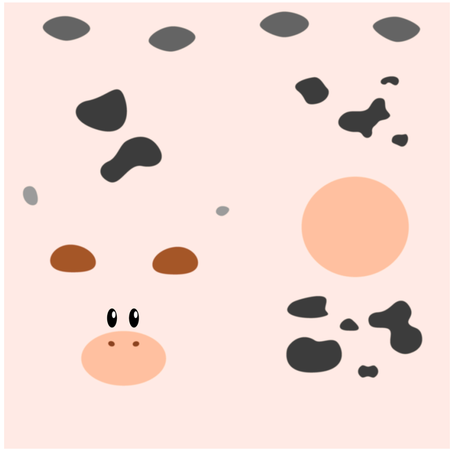
Triangular Meshes



Efficient to compute ray-triangle intersections

Triangular Meshes



Efficient to compute ray-triangle intersections

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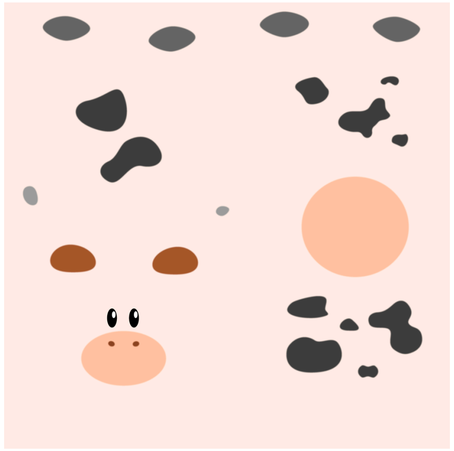
Triangular Meshes



Efficient to compute ray-triangle intersections

Easy to texture and render (common representation across graphics)

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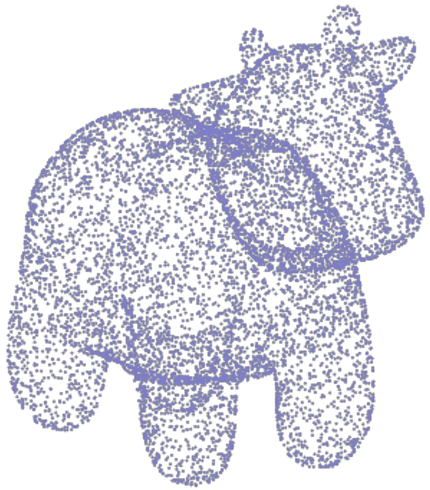
Surface Representations

Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani



Surface Representations

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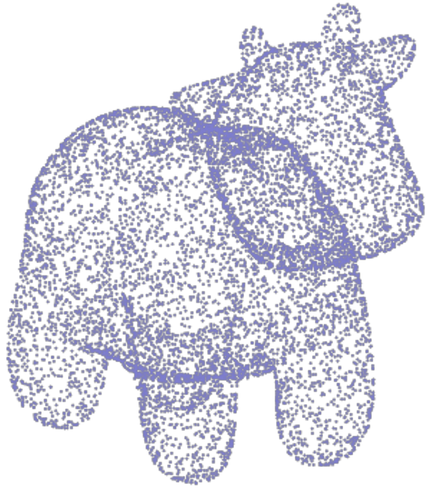

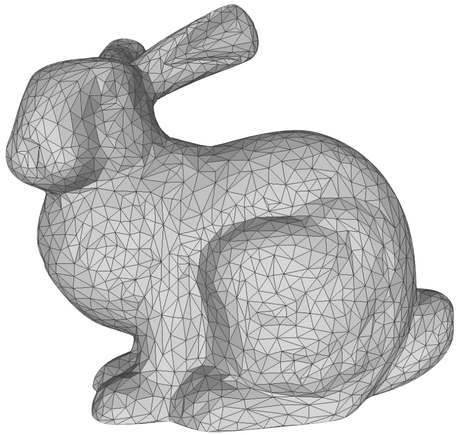

Surface Representations

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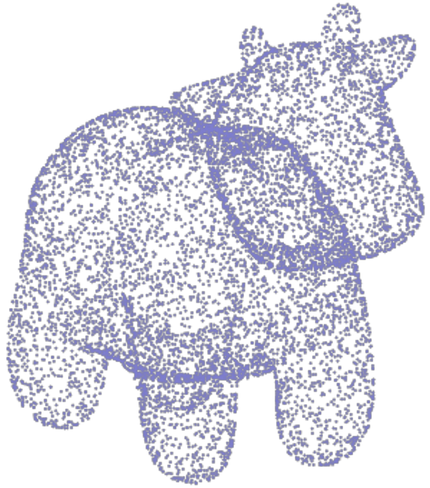

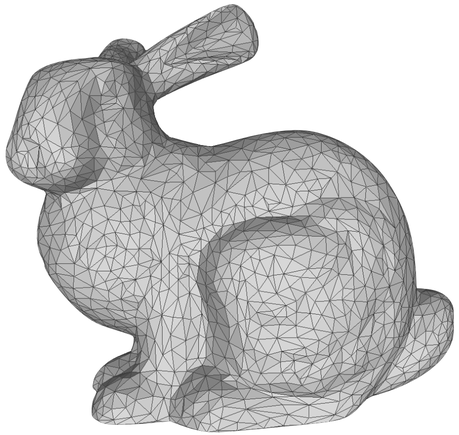

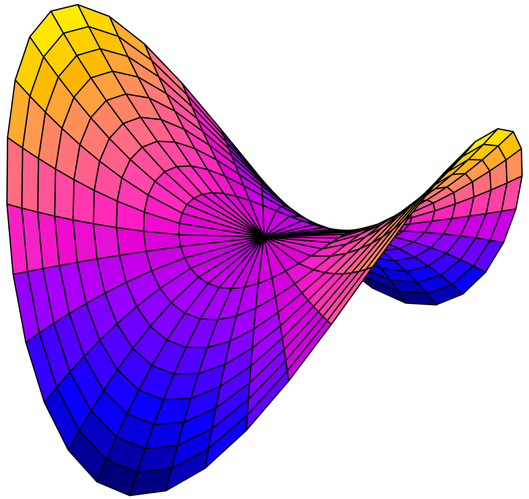

Surface Representations

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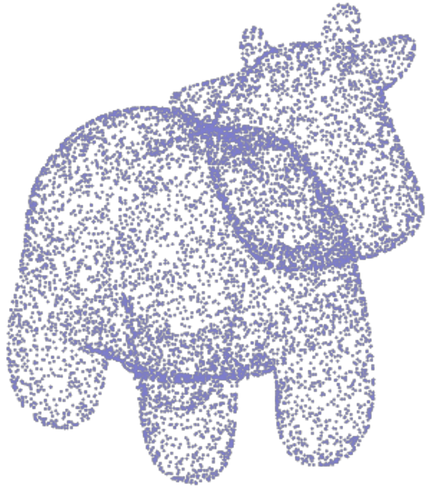

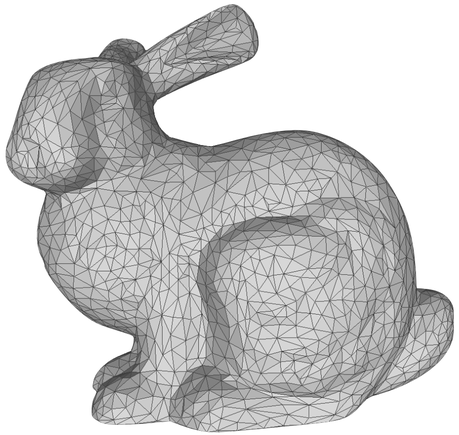

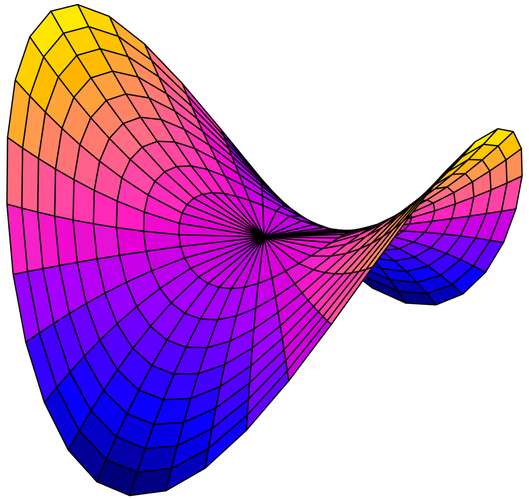

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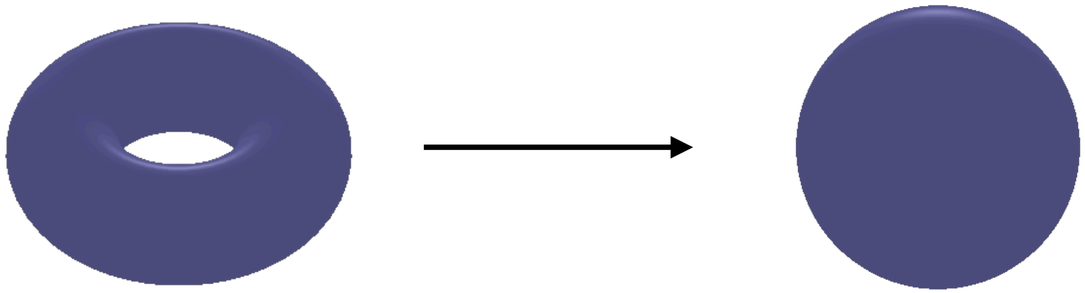
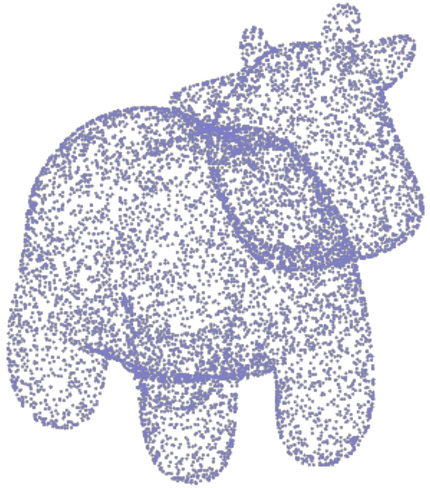
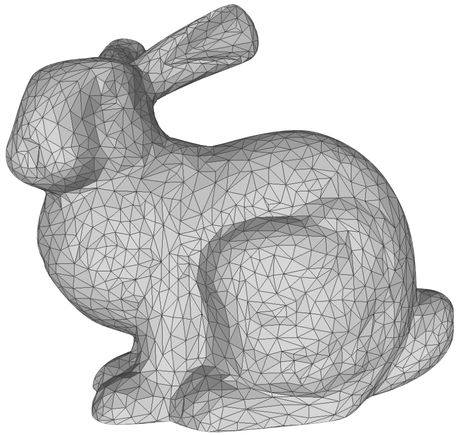
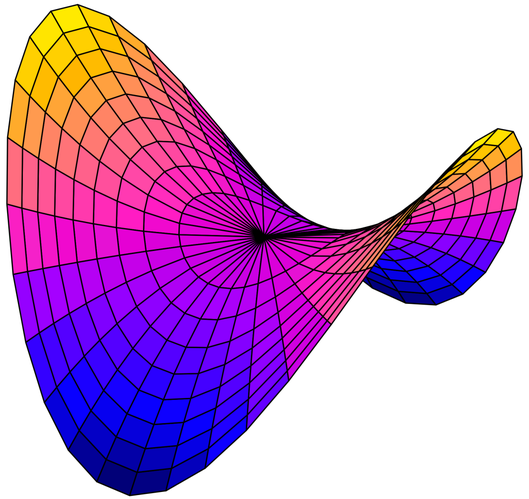


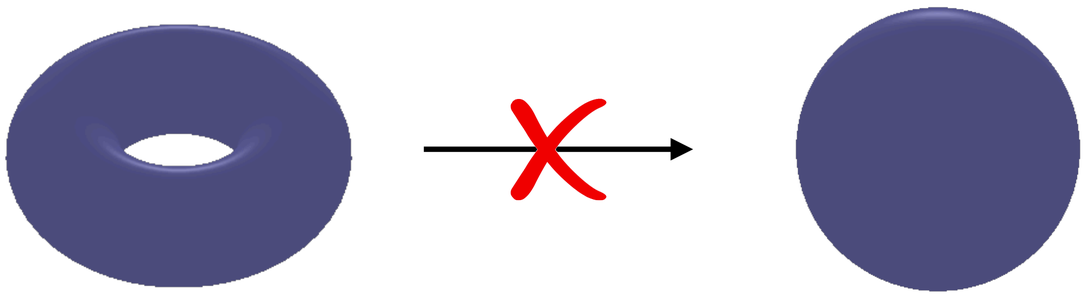
Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani





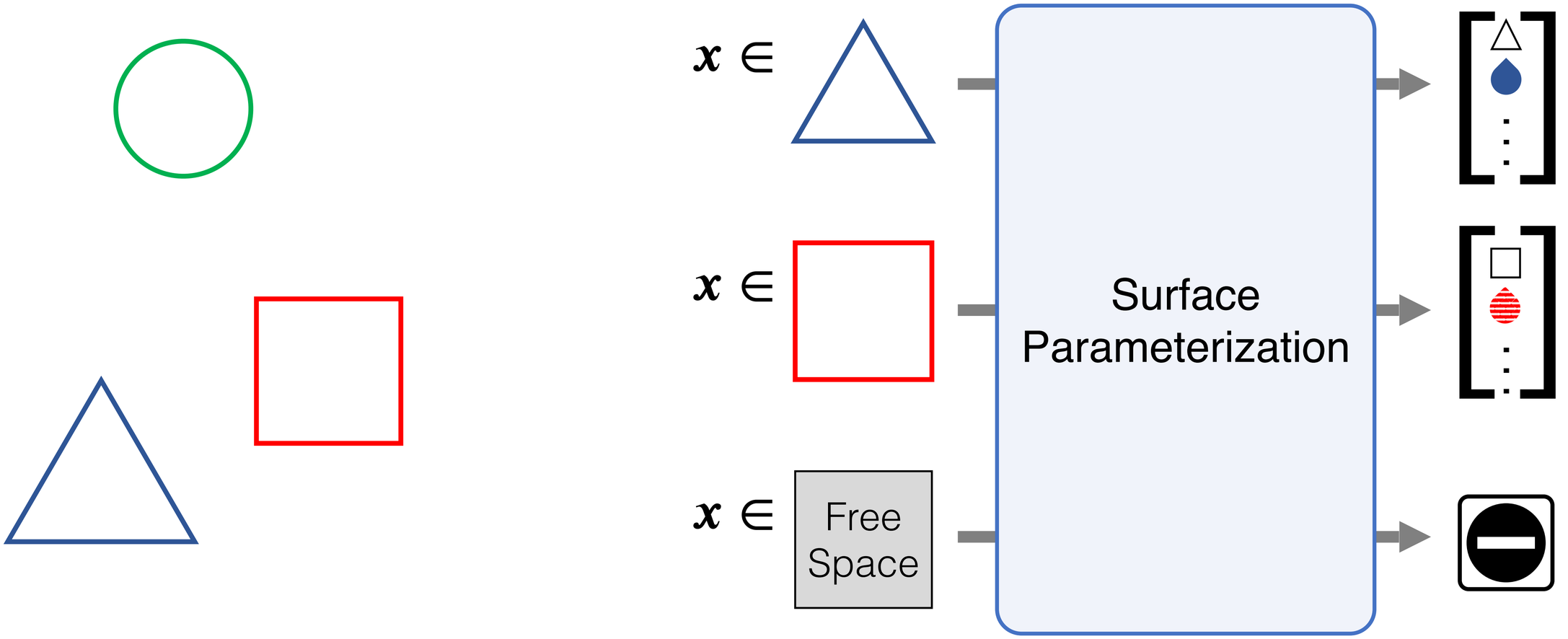


Surface Representations

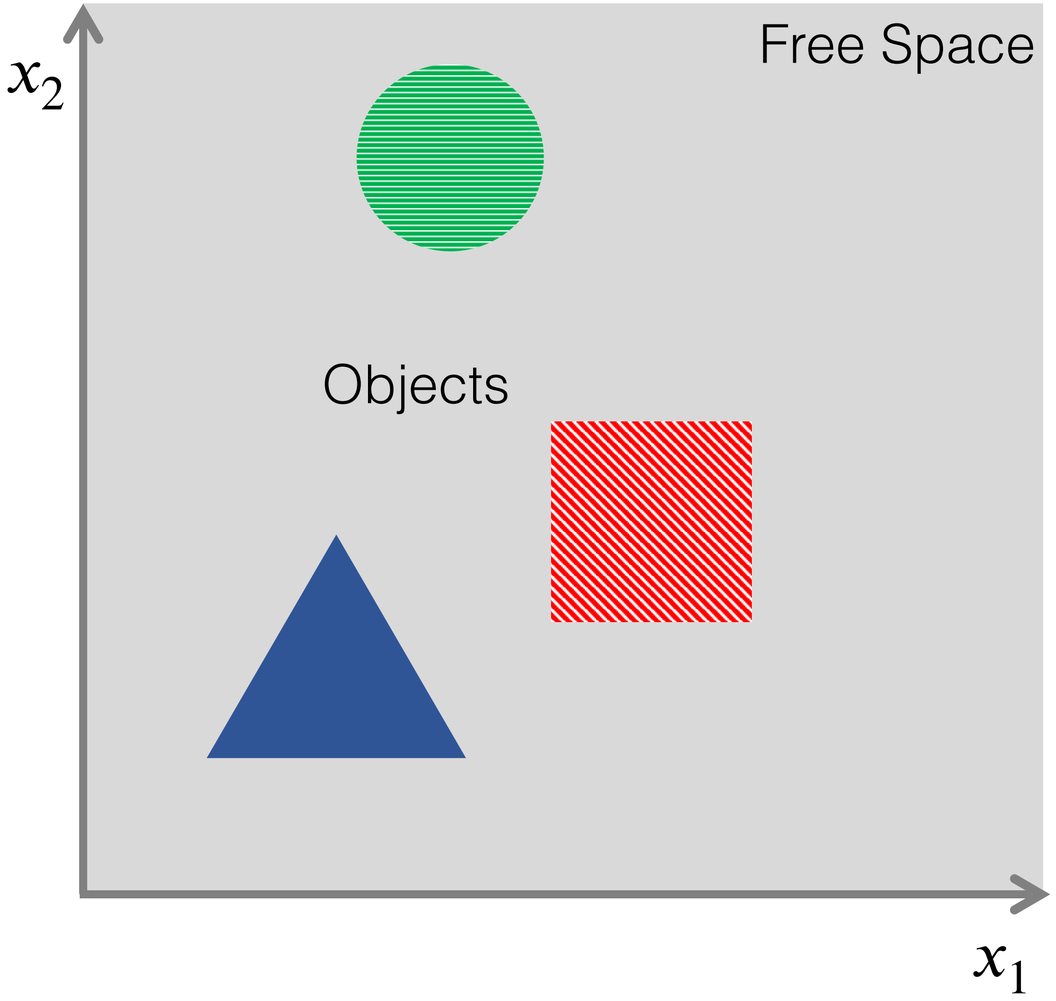


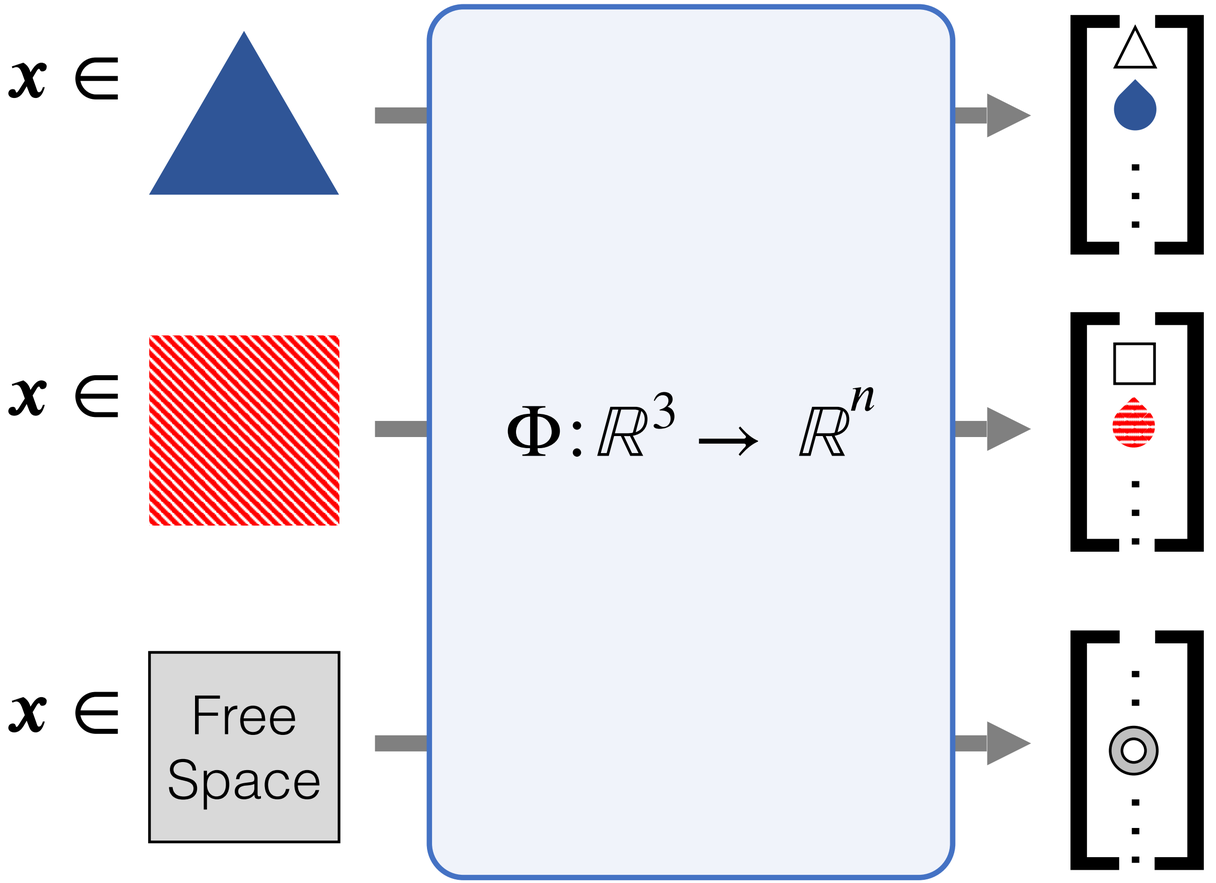
Slide credit: CMU 16-889: Learning for 3D Vision, Prof. Shubham Tulsiani

Surface representations only parameterize stuff on surfaces of things.

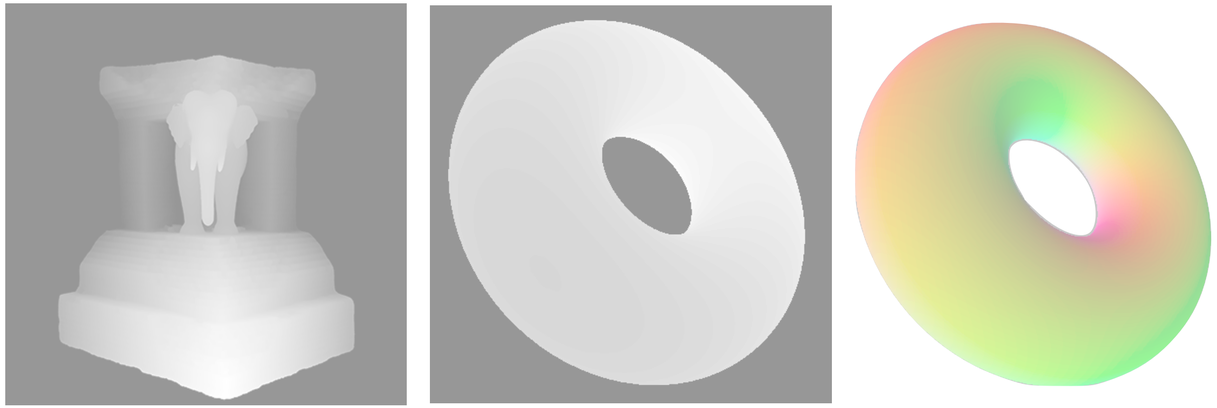


What if we wanted to parameterize stuff **everywhere?**

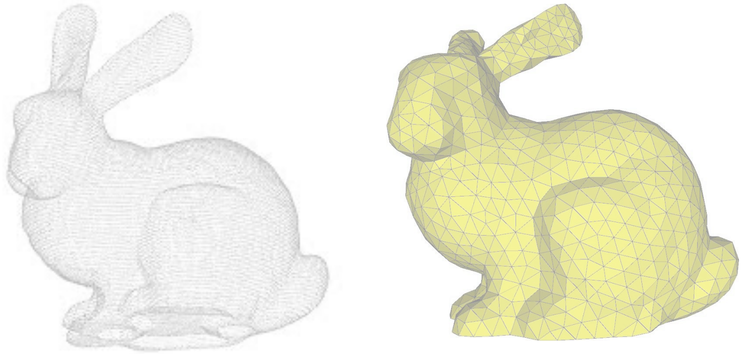




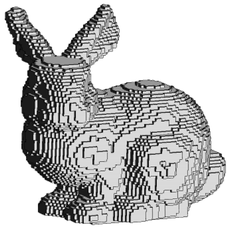
2.5D Representations

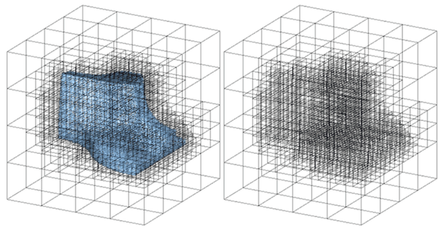


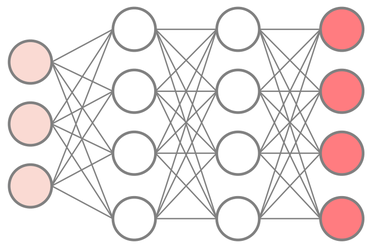
Surface Representations

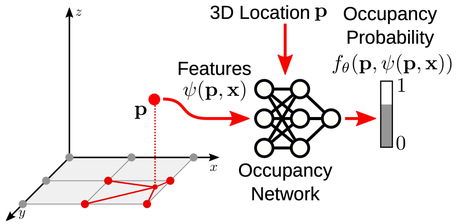


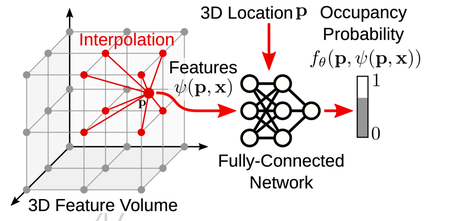
Field Parameterizations











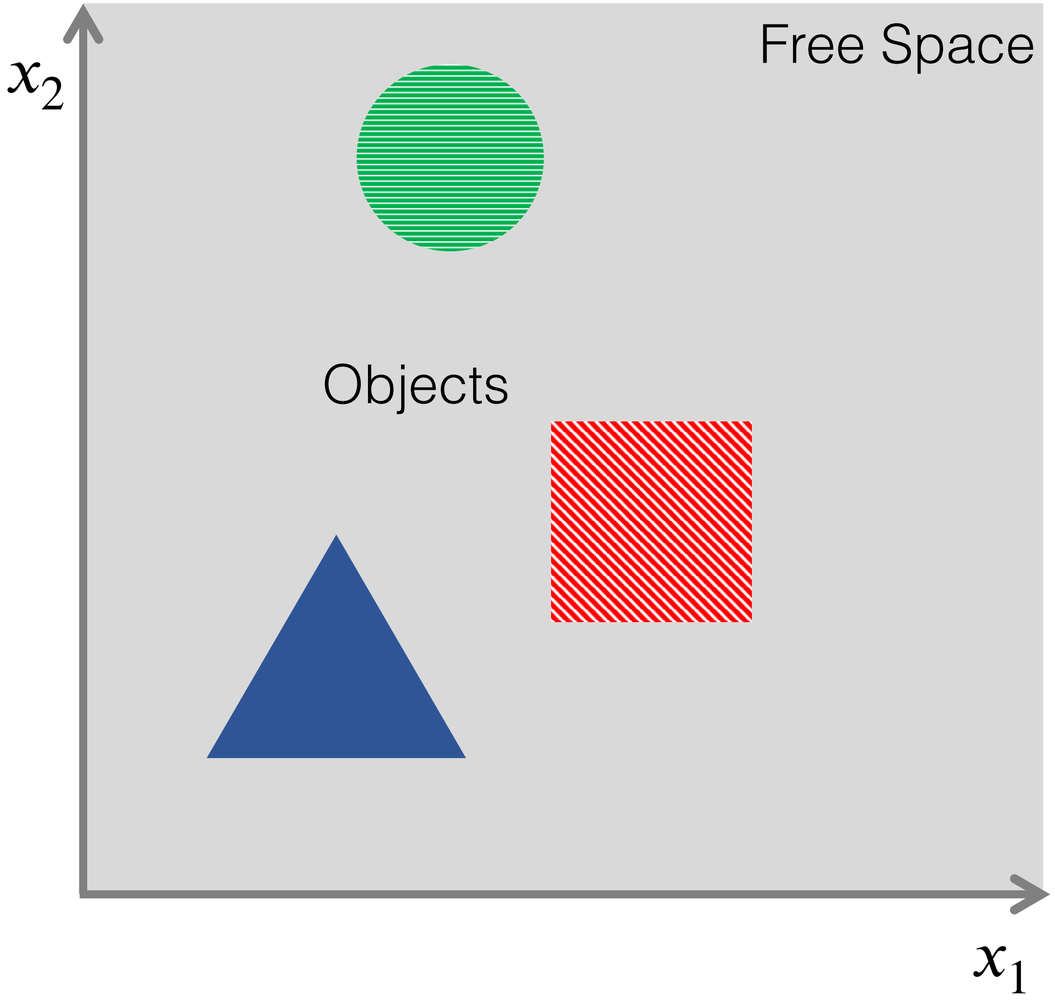
Definition: Field (physics)

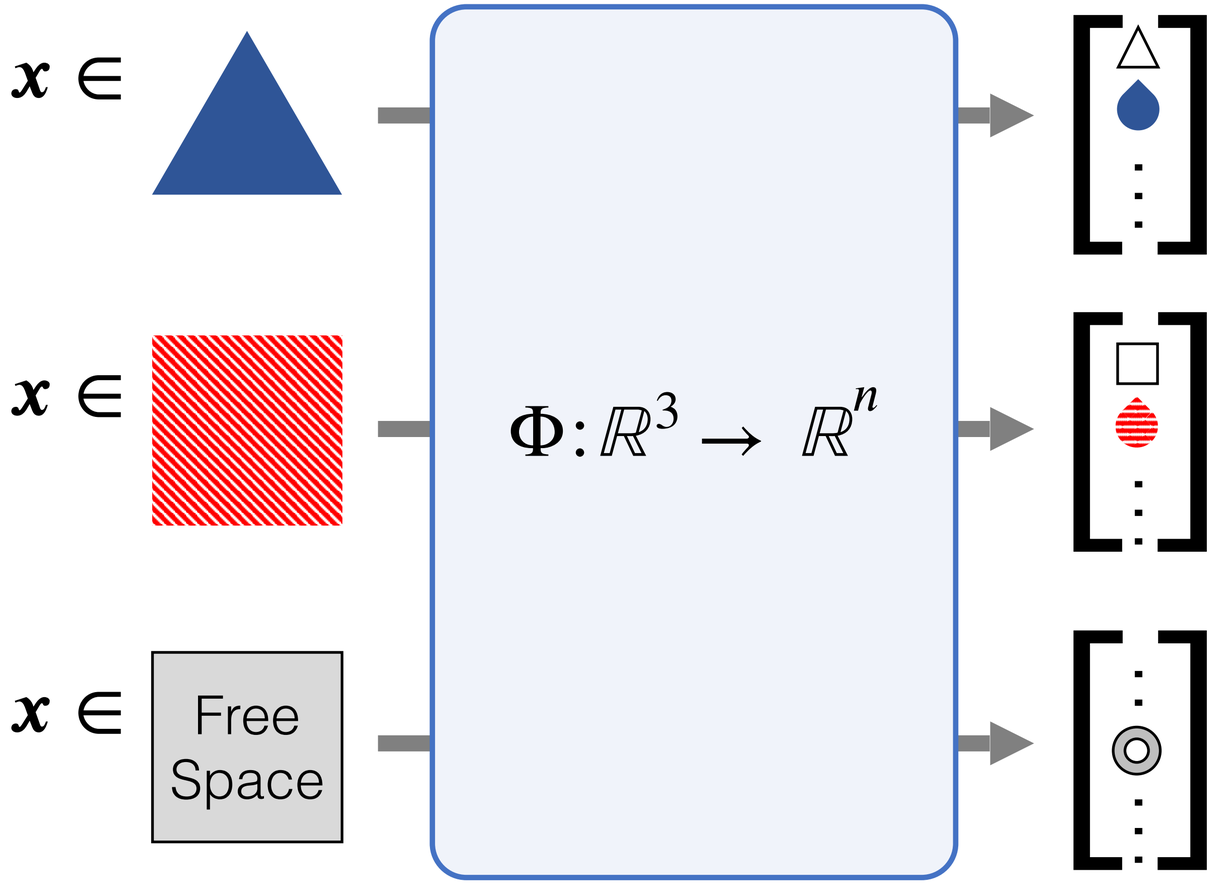
> A physical quantity represented by a scalar, vector, or tensor, that has a value for each point in space and time.

Will use term “field” for any function that takes a space, time, or space-time coordinate as input to map it to some quantity at that coordinate.

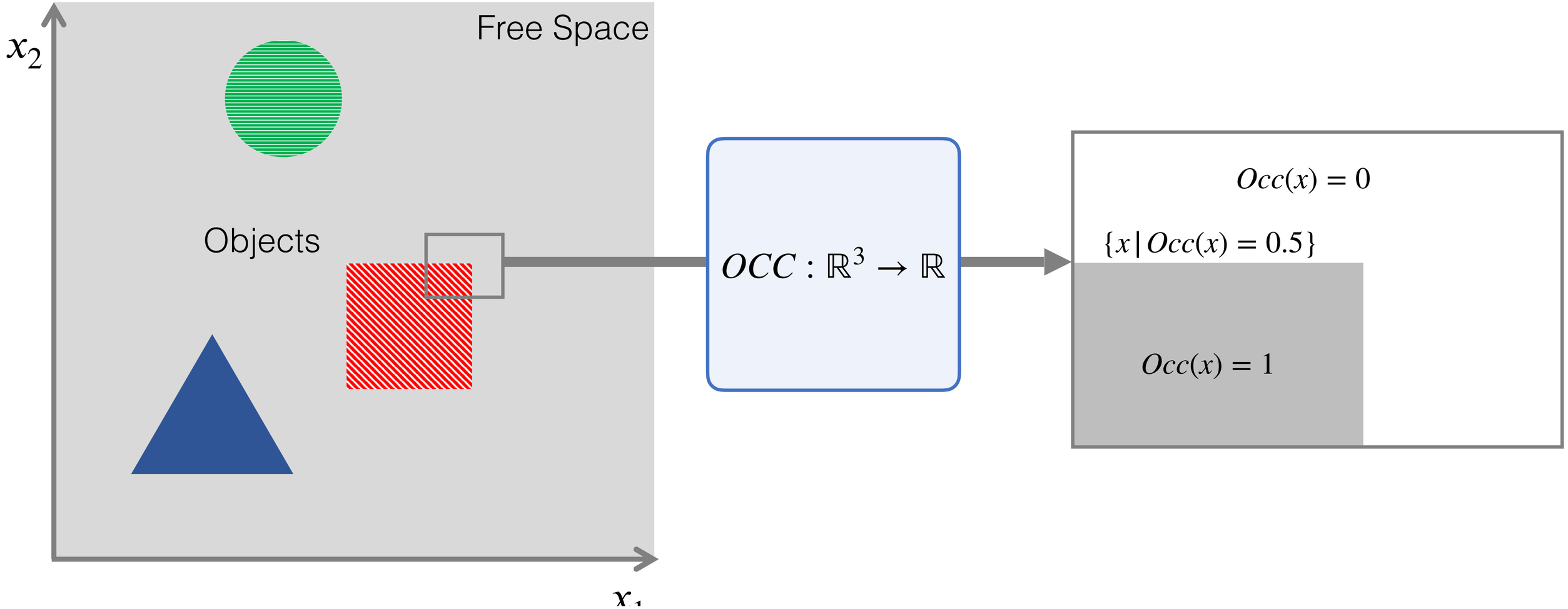
$$\Phi : \mathbb{R}^3 \rightarrow \mathbb{R}^n$$

How to parameterize surfaces?



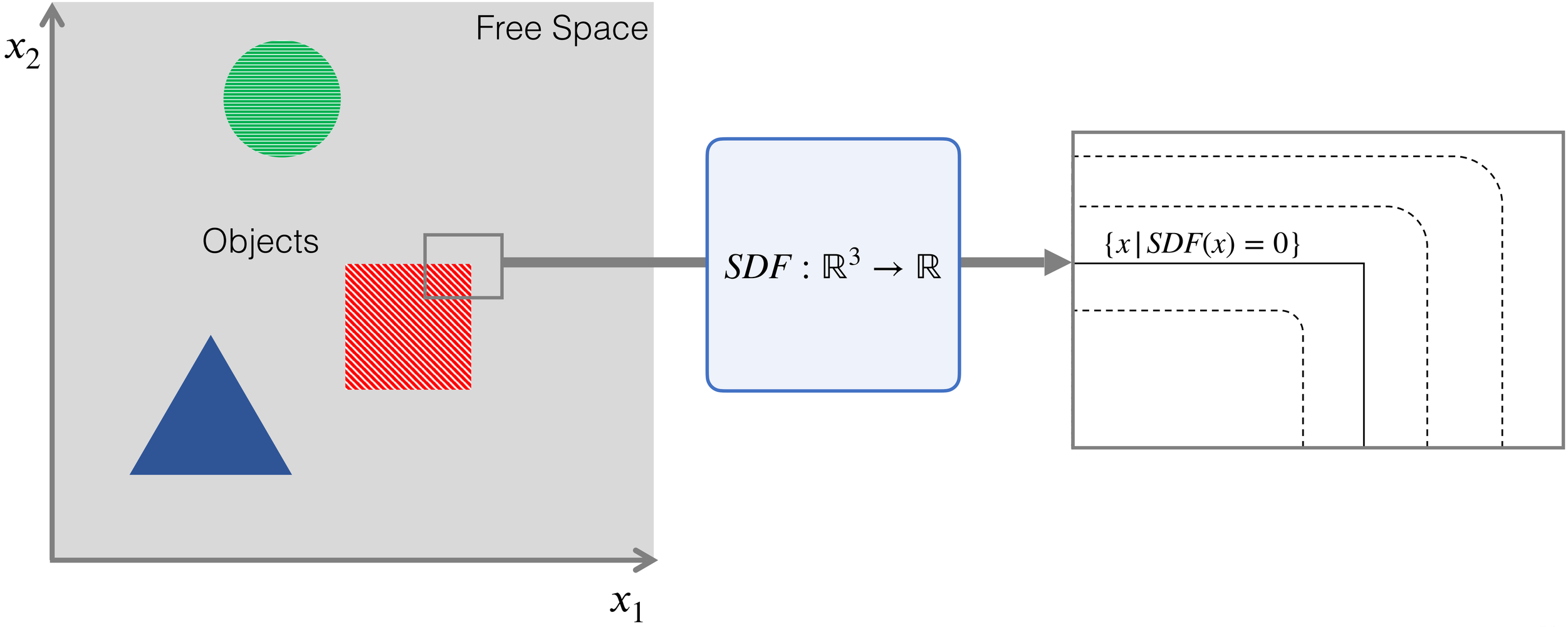


The Occupancy Field



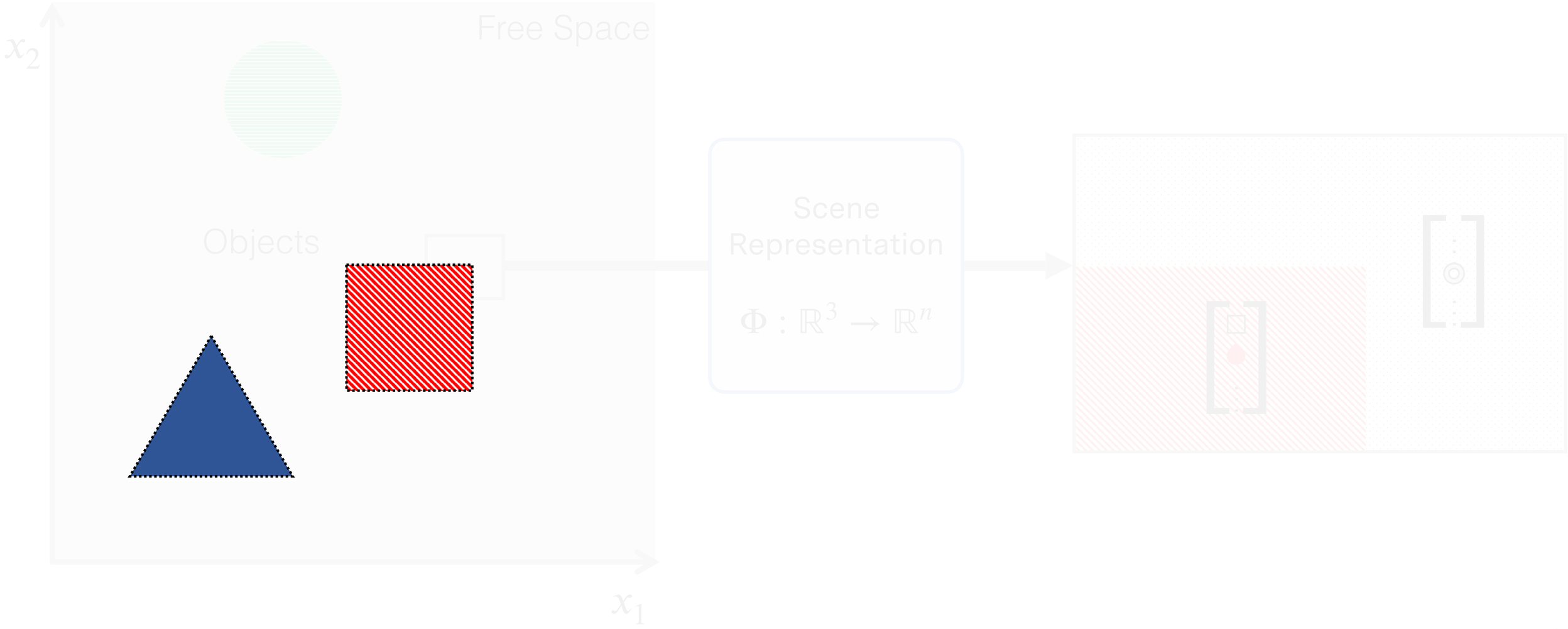
Occupancy Networks: Learning 3D Reconstruction in Function Space, Mescheder et al.
IM-Net: Learning Implicit Fields for Generative Shape Modeling, Chen et al.

The Signed Distance Field



DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, Park et al. 2019

The Signed Distance Field



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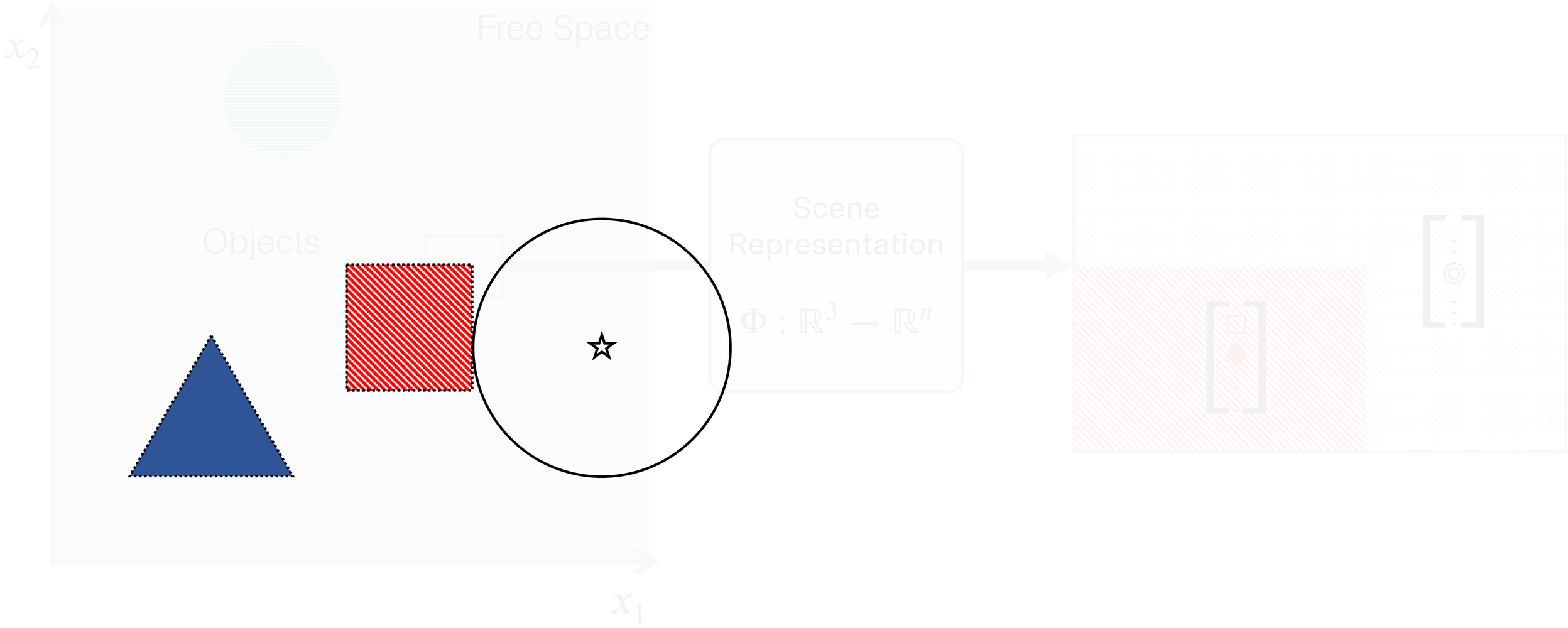

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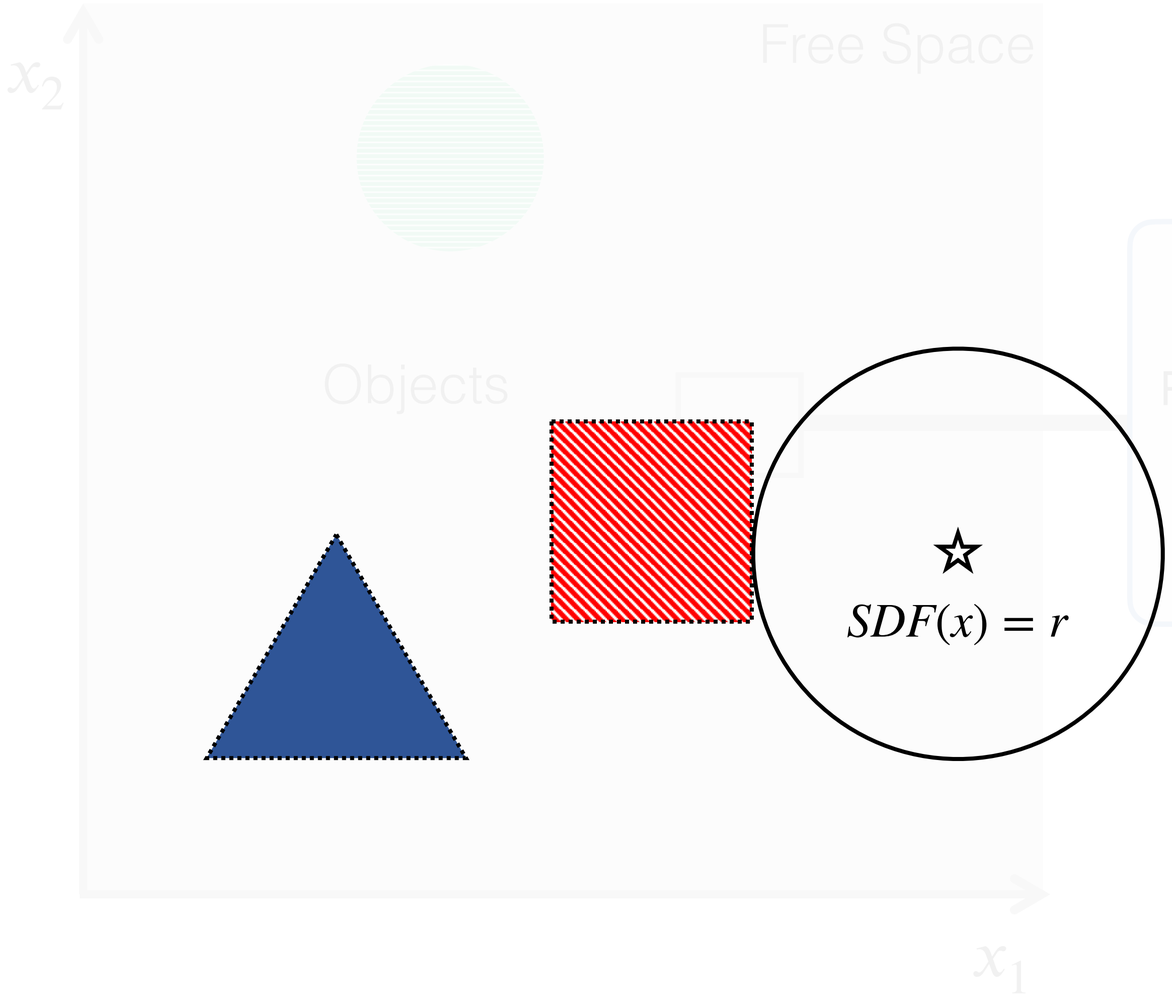

DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, Park et al. 2019

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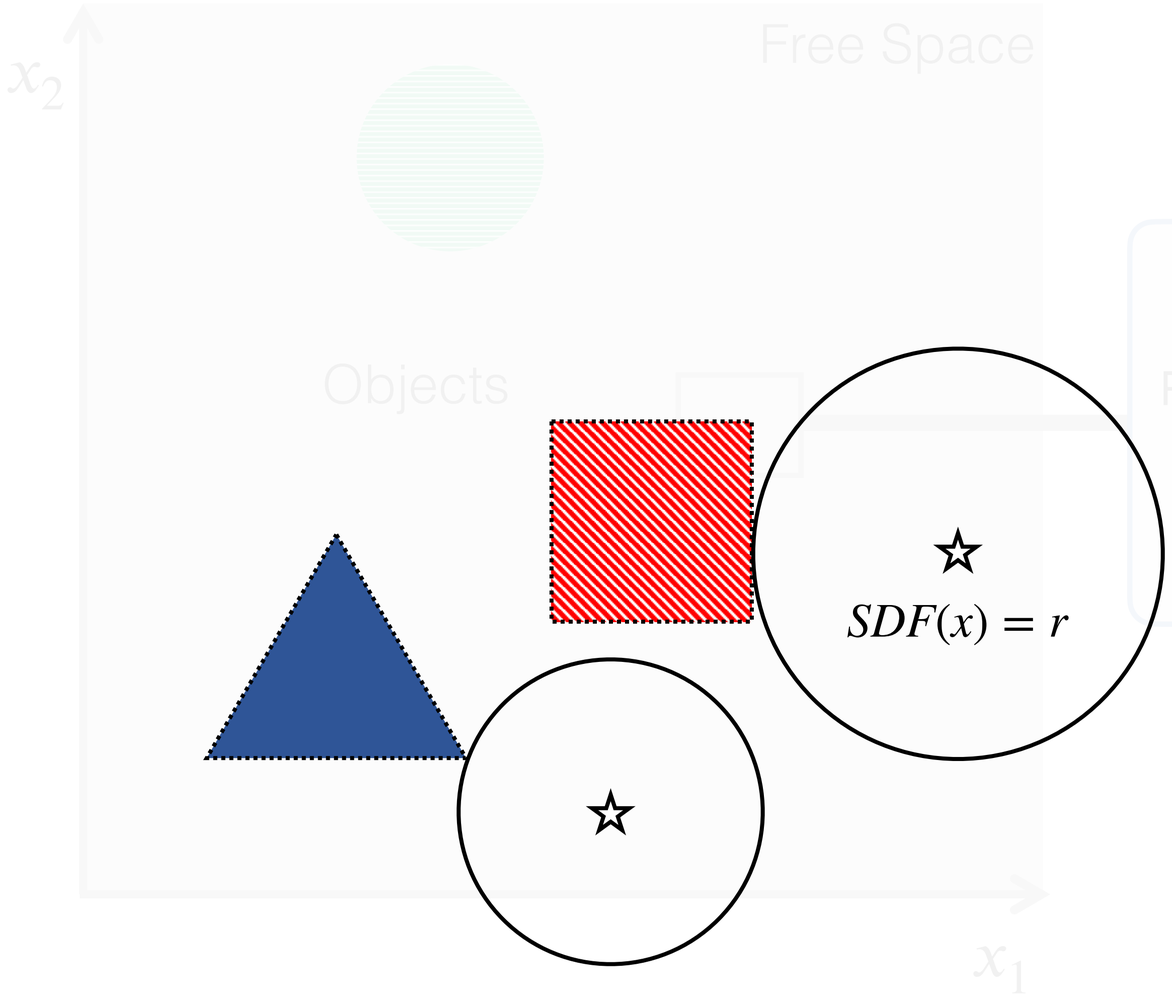

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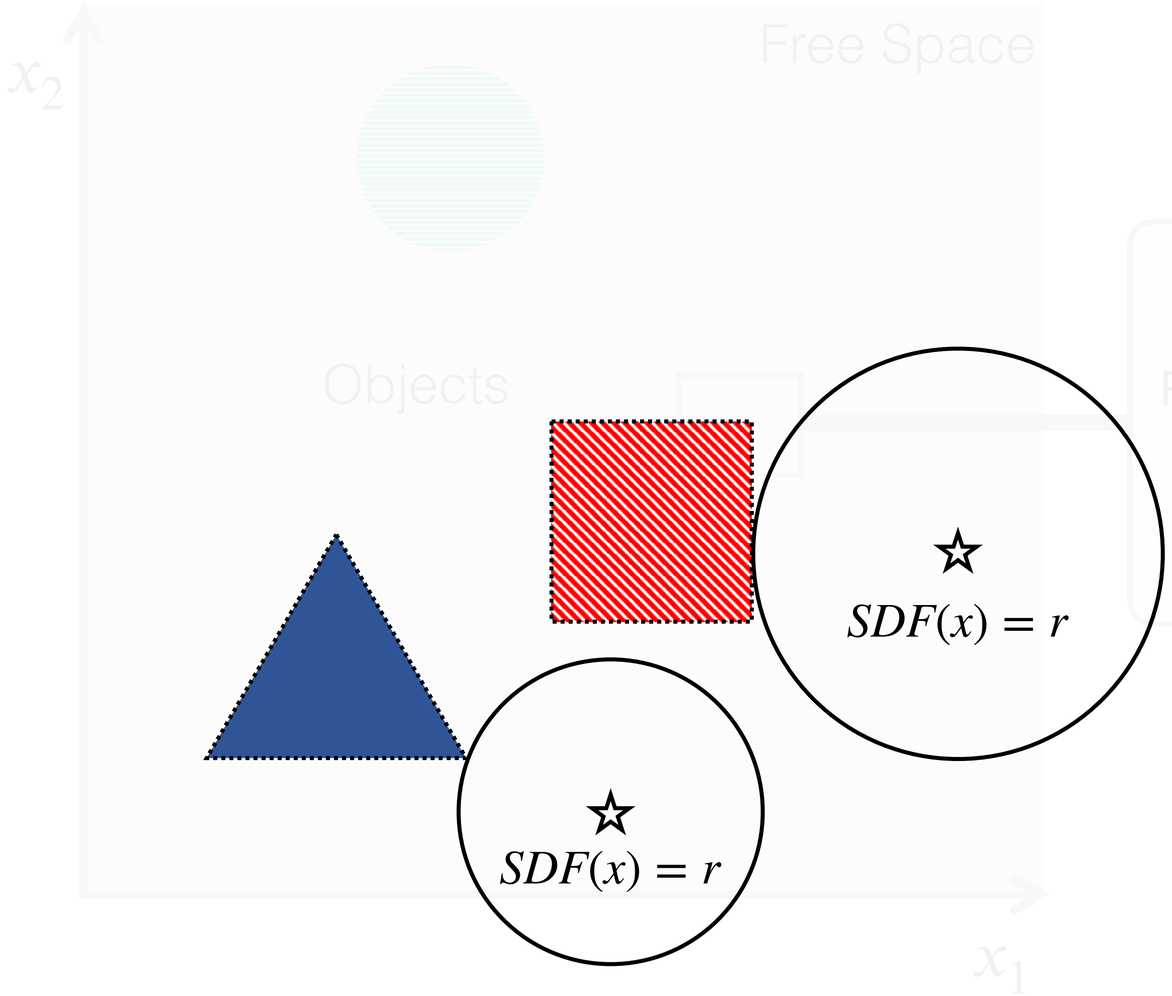

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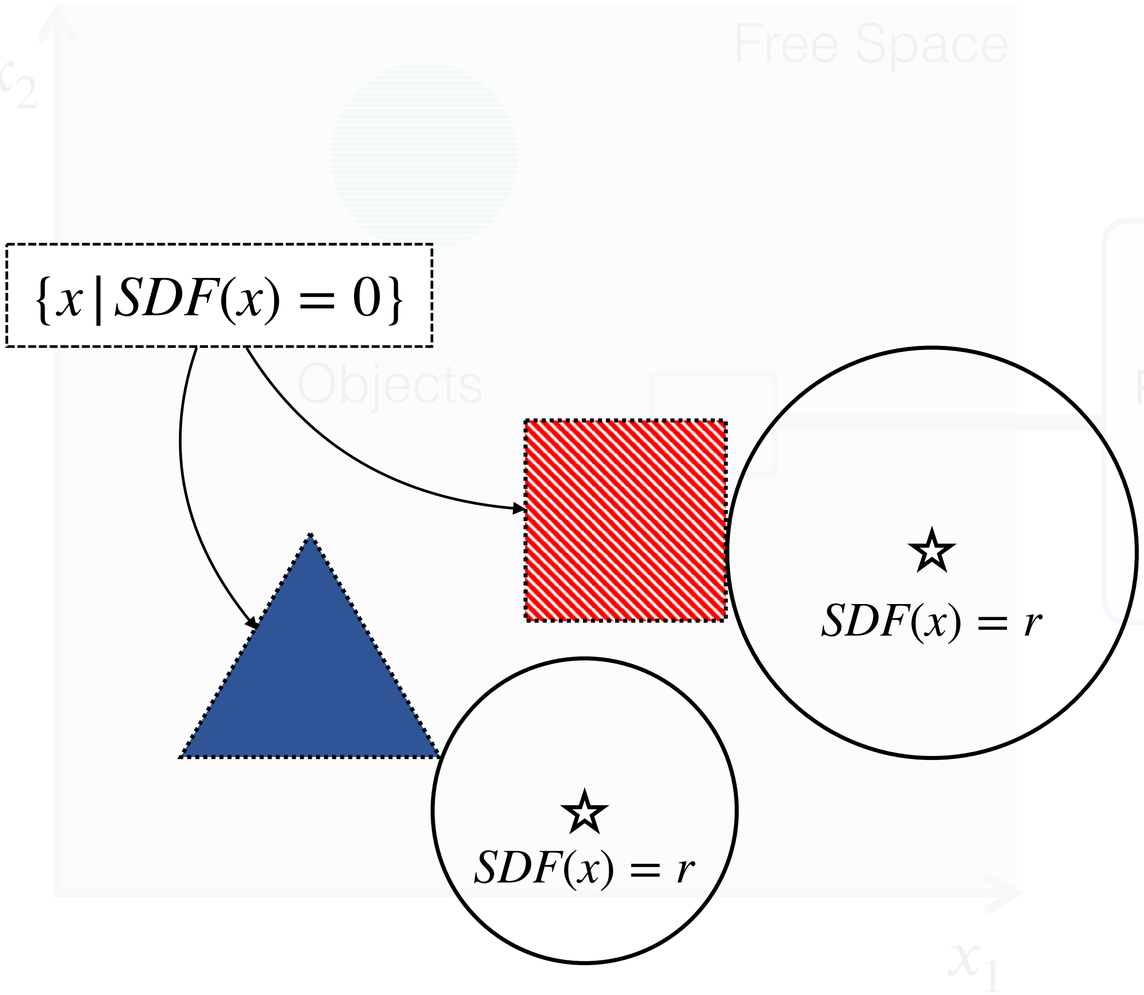

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Implicit Surfaces

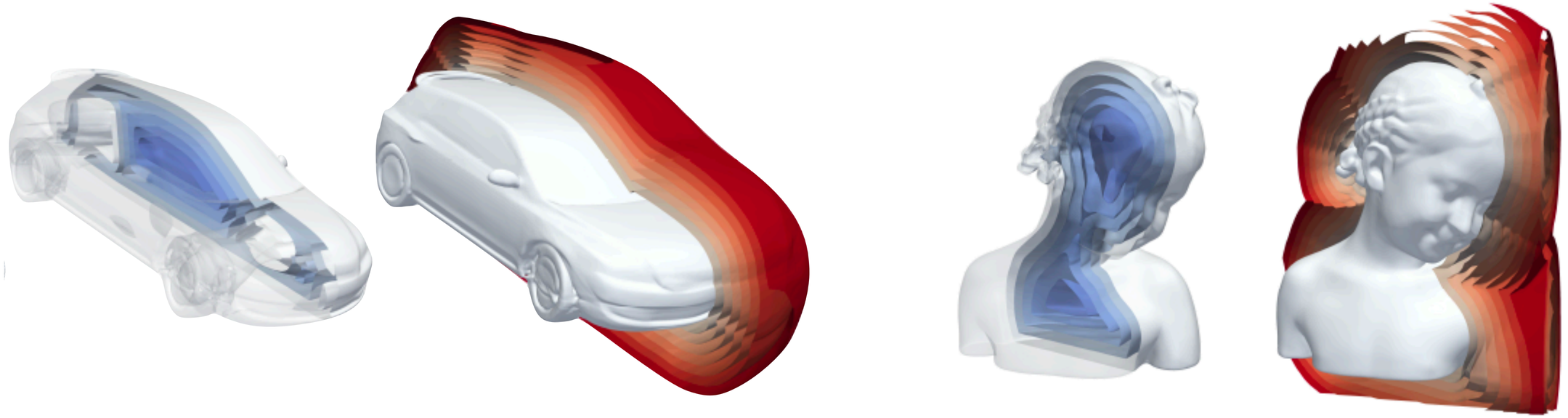
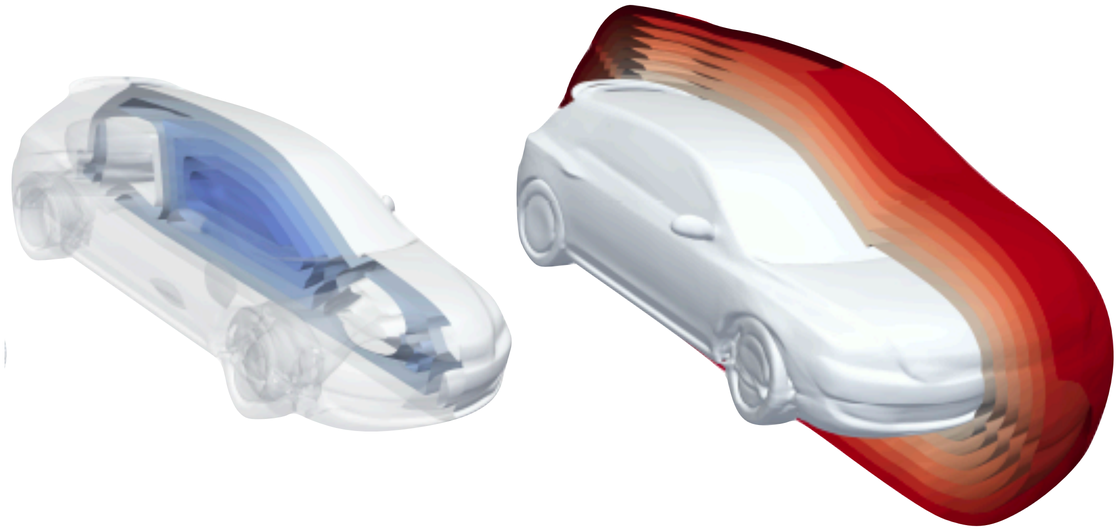


Image credits: IGR: Implicit Geometric Regularization for Learning Shapes. *Gropp et. al*

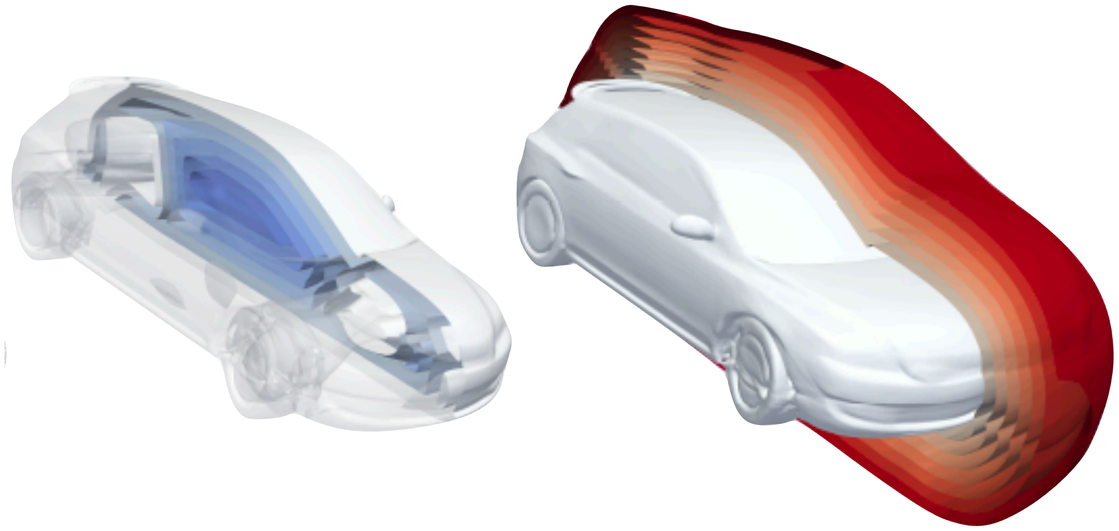
Implicit Surfaces



Level sets of Occupancy, SDF parameterize surface

Image credits: IGR: Implicit Geometric Regularization for Learning Shapes. *Gropp et. al*

Implicit Surfaces



Level sets of Occupancy, SDF parameterize surface

Easy to answer questions about occupancy

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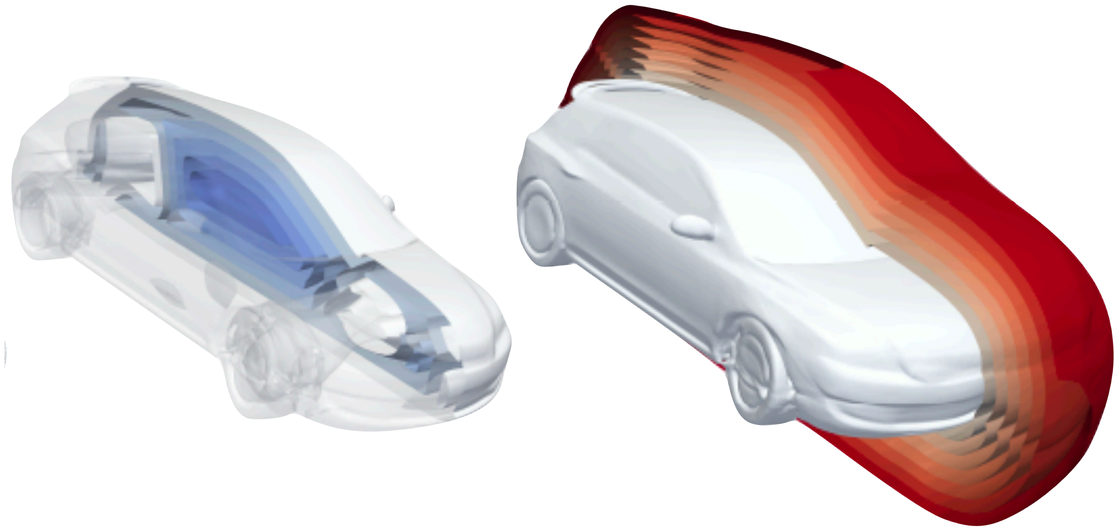
Implicit Surfaces



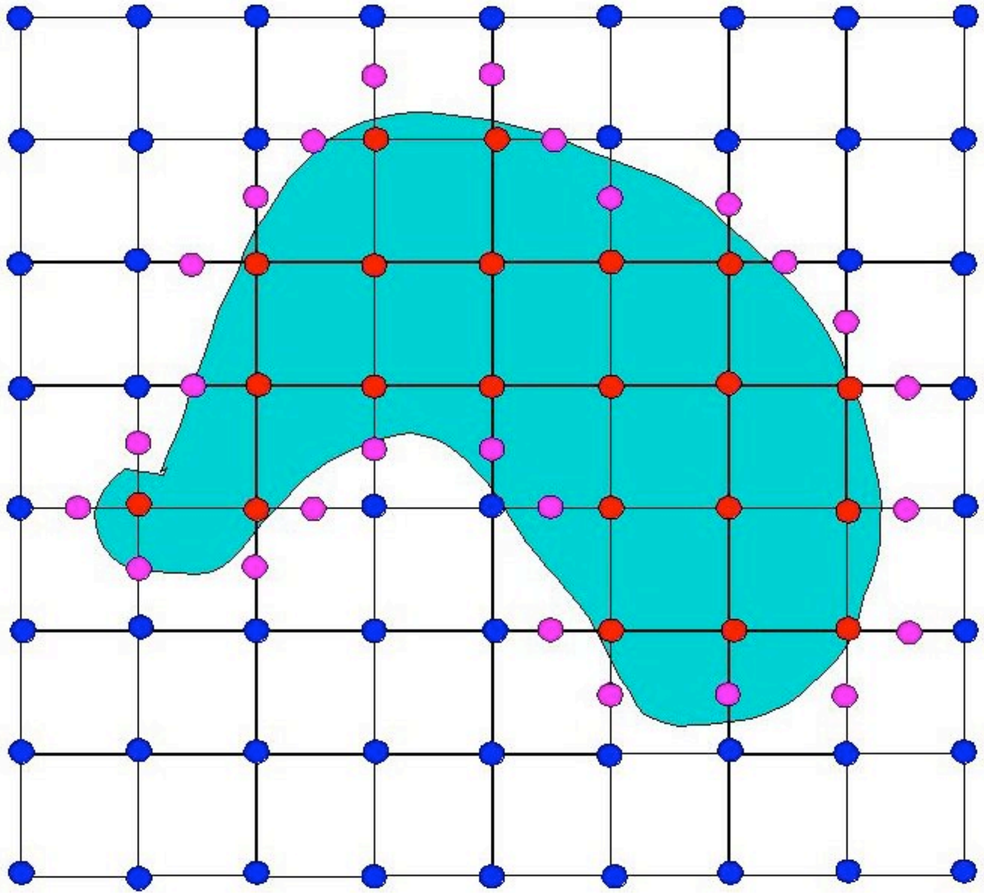
Level sets of Occupancy, SDF parameterize surface

Easy to answer questions about occupancy

Difficult to reason about the surface: have to first **find** zero-level-set!

Image credits: IGR: Implicit Geometric Regularization for Learning Shapes. *Gropp et. al*

Marching Cubes: Extracting 2D Mesh from 3D Implicit Representation



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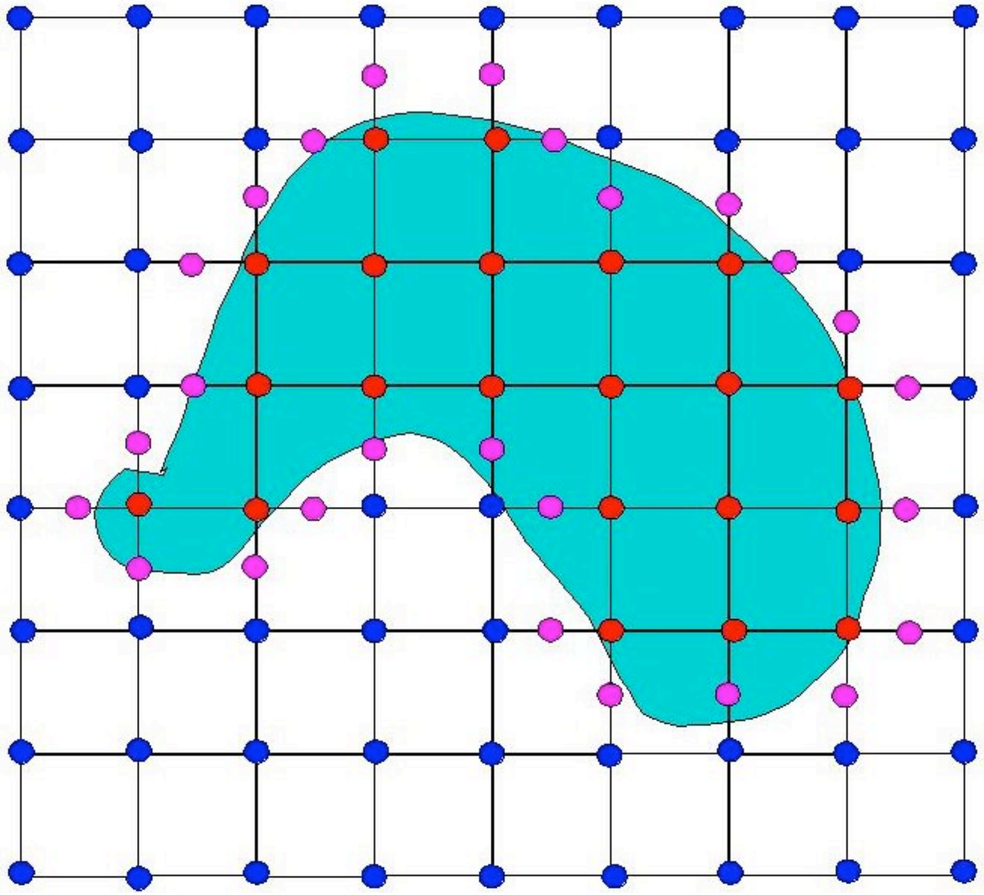
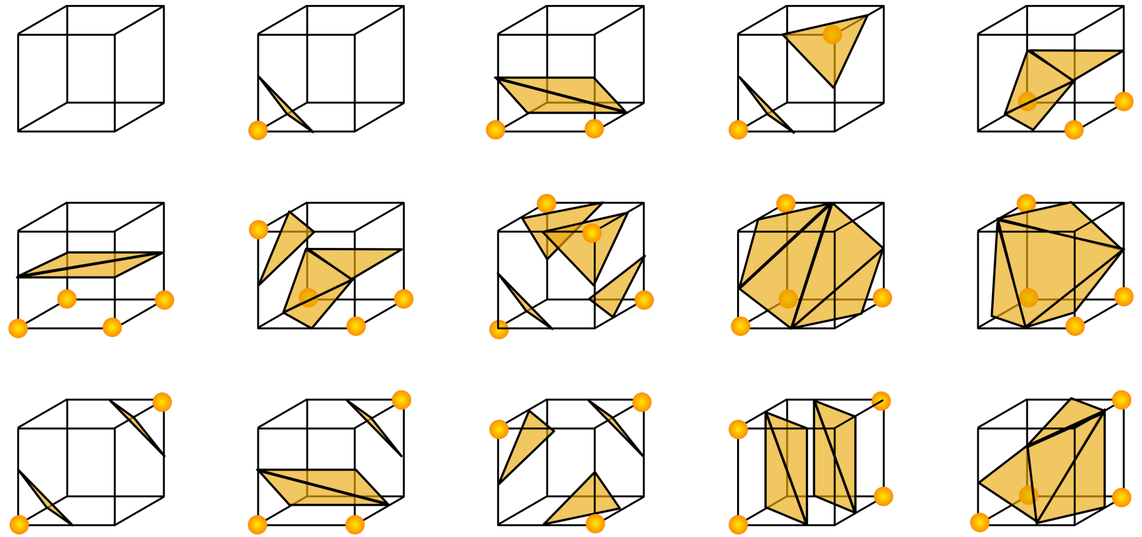
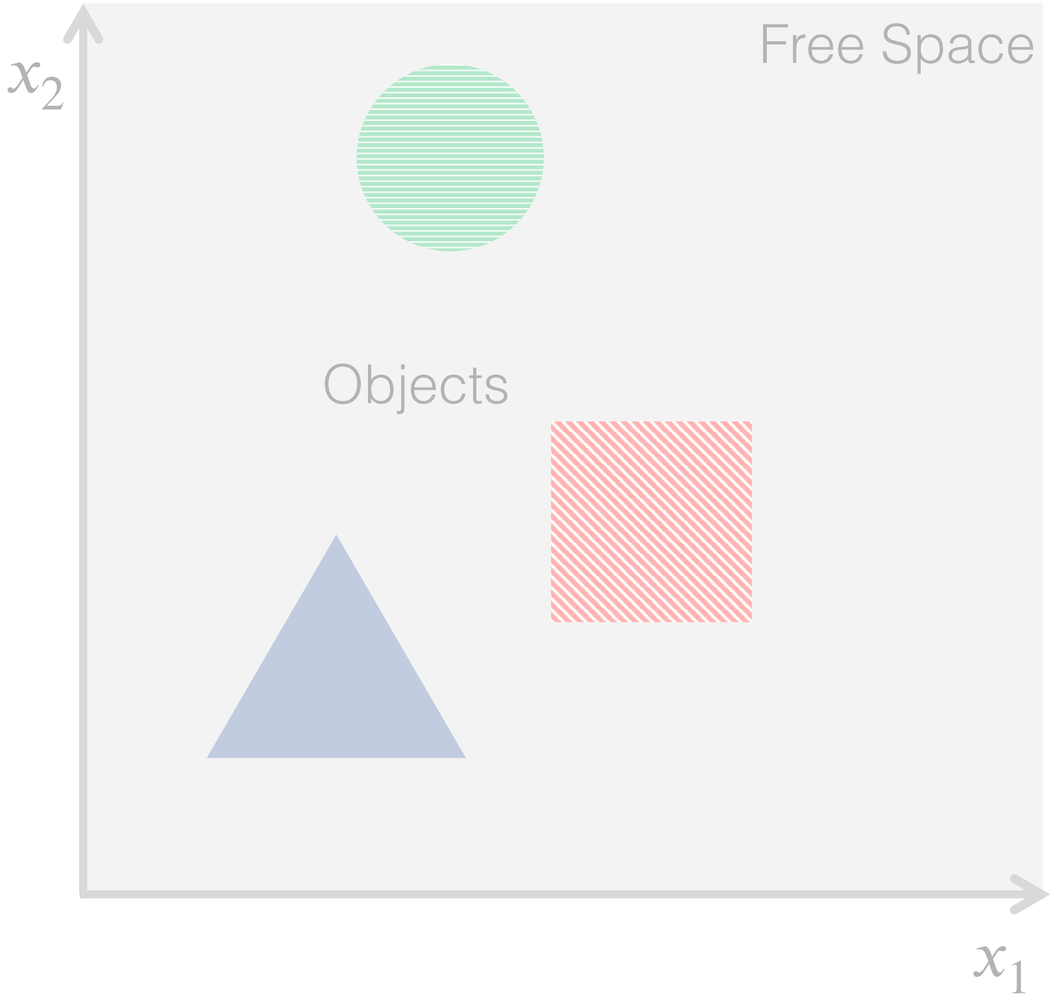
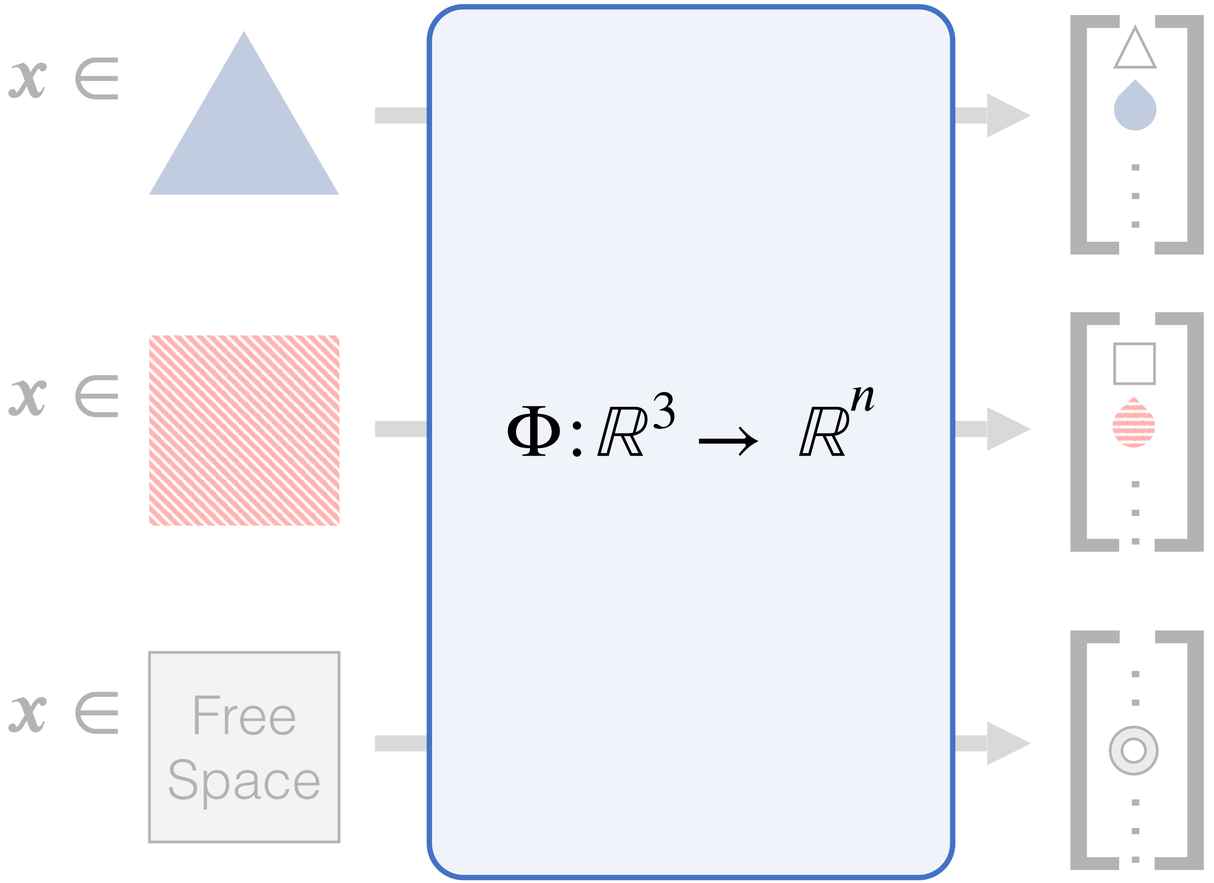




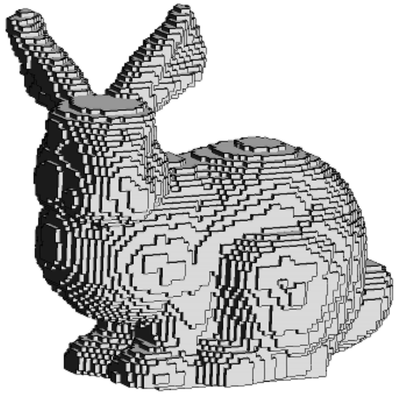
How to parameterize surfaces?

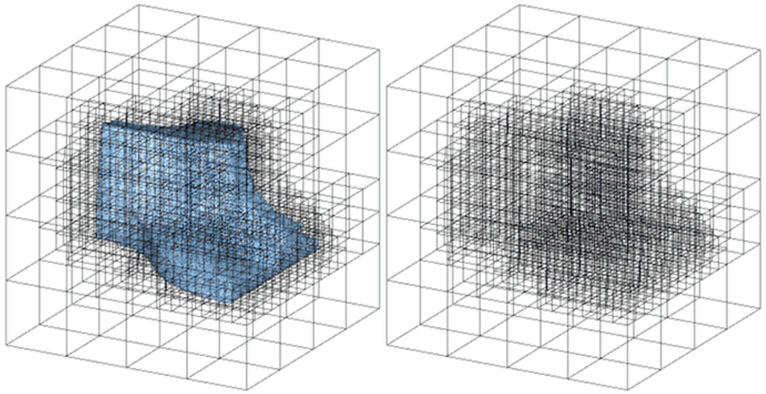


How to parameterize 3D function?

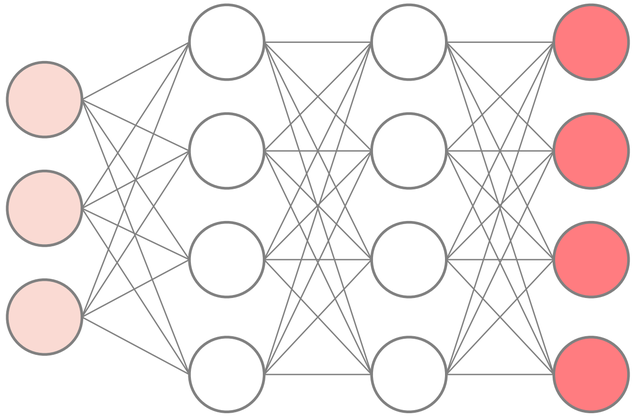


Parameterizing Fields

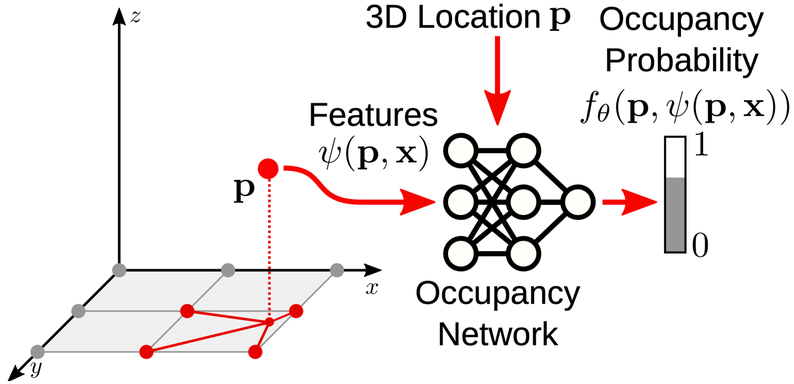


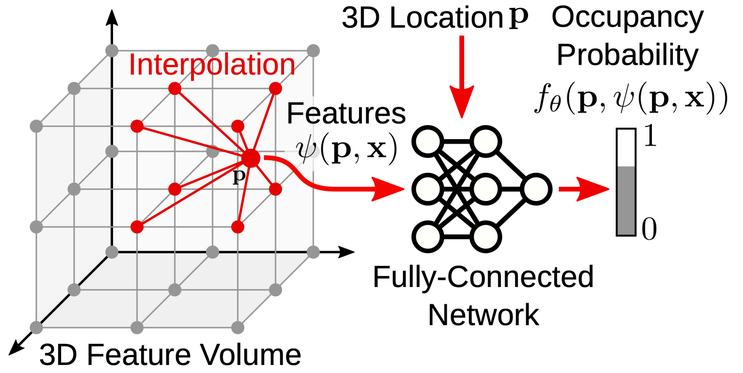


Discrete Parameterizations



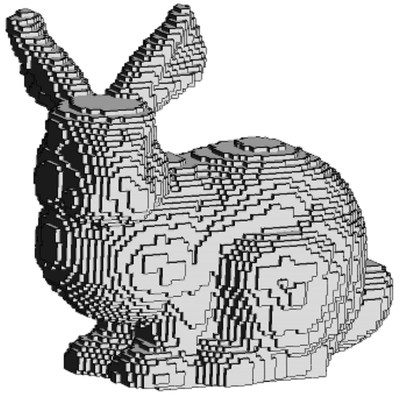
Continuous Parameterizations

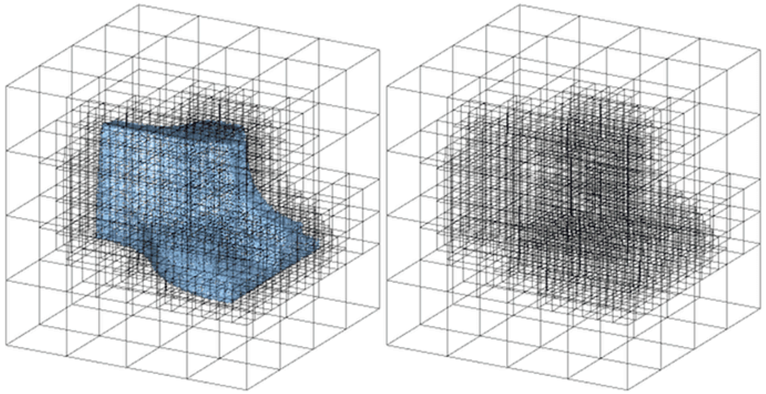




Hybrid Parameterizations

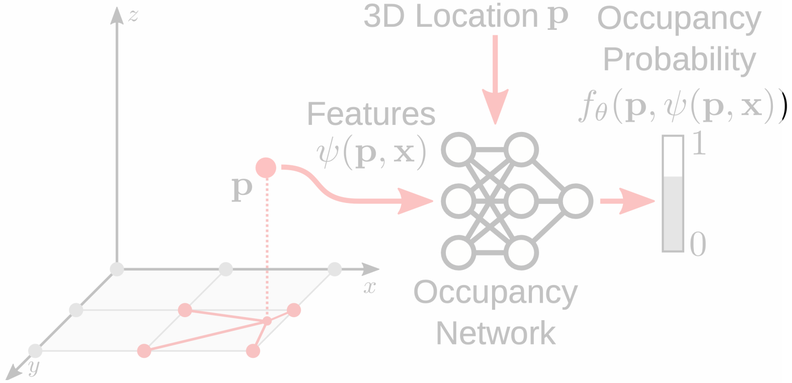
Voxel Grids

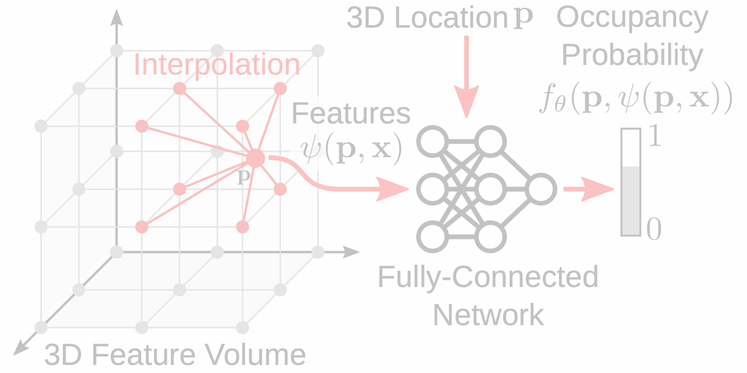




Discrete Parameterizations

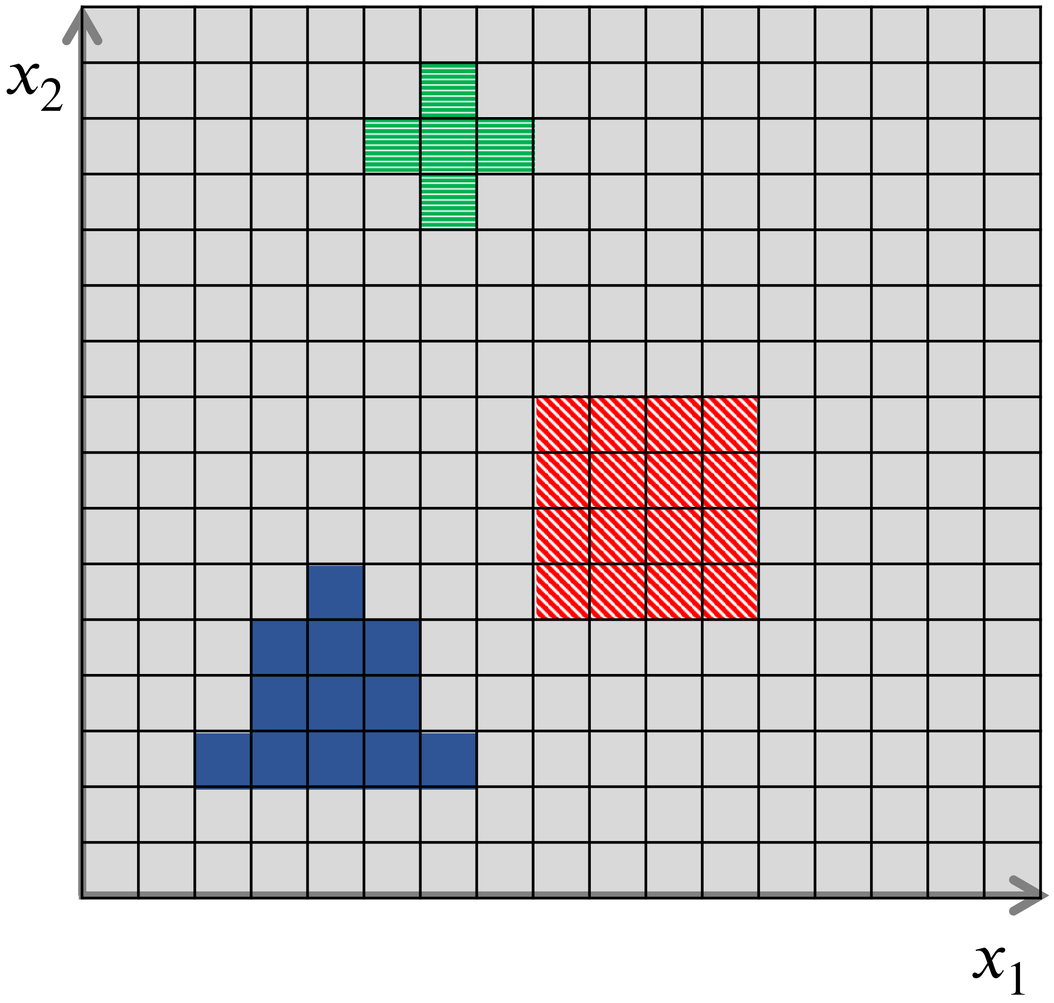
Continuous Parameterizations

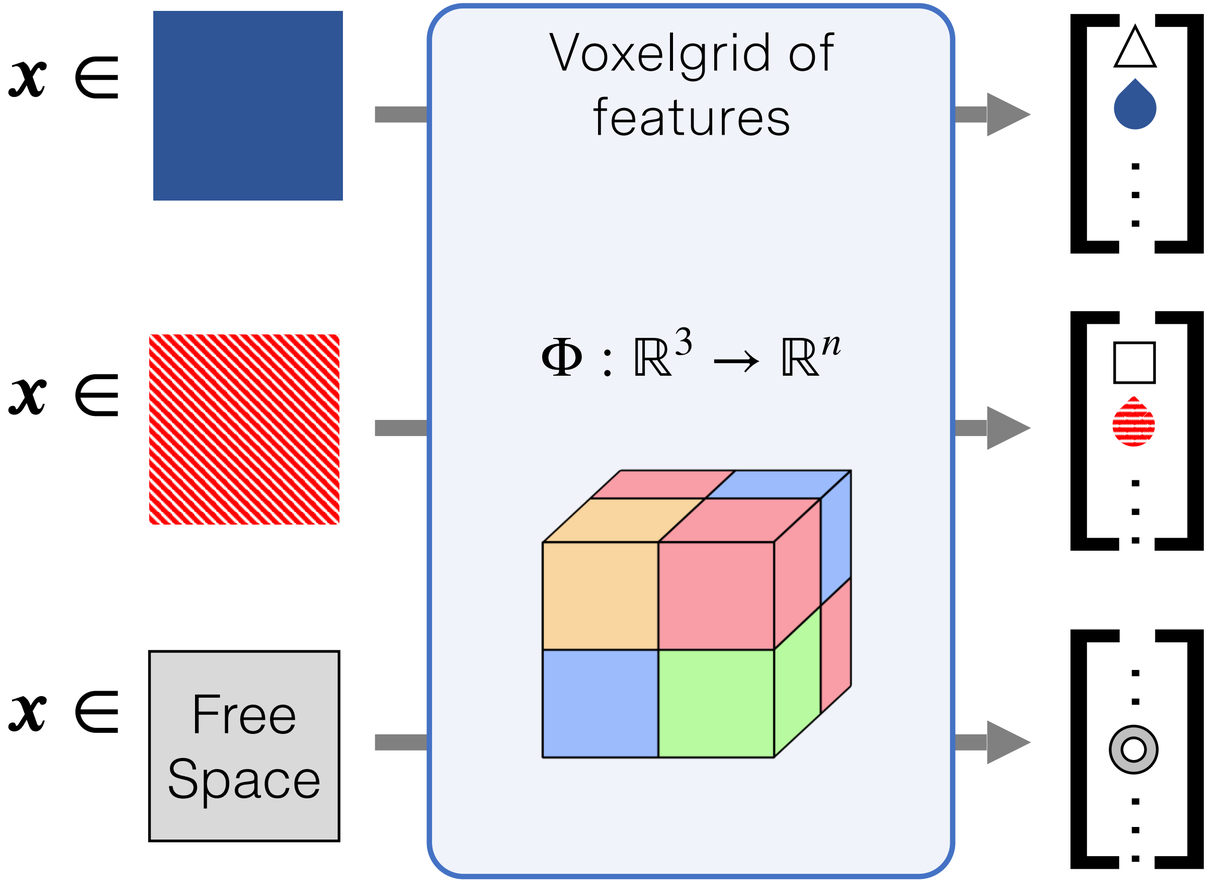




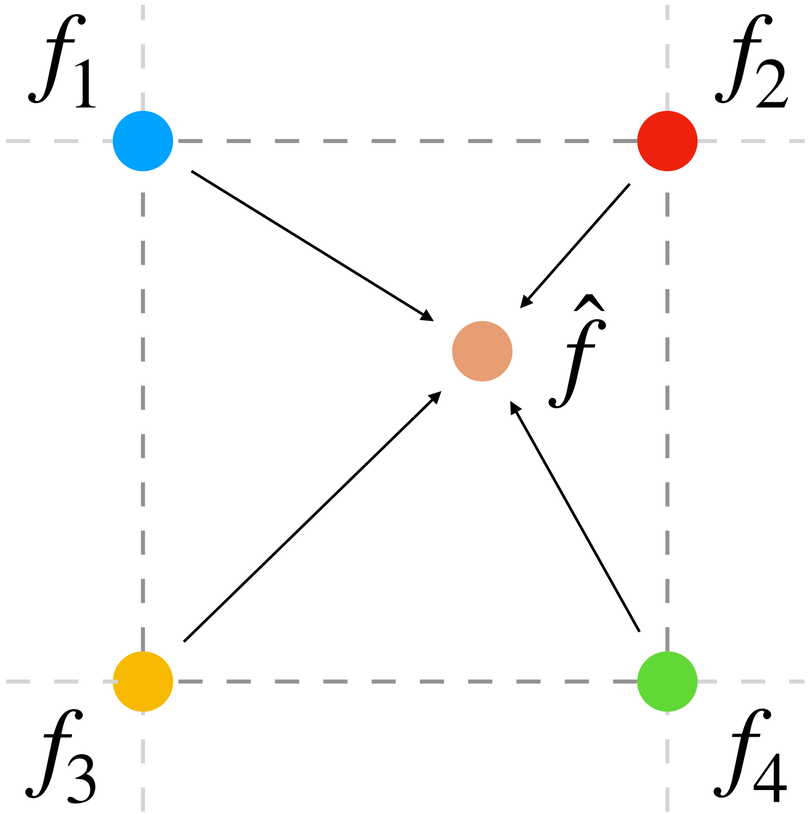
Hybrid Parameterizations

Voxel Grids


x_2
x_1


$x \in$
$x \in$
$x \in$
Free Space
Voxelgrid of features
$\Phi : \mathbb{R}^3 \rightarrow \mathbb{R}^n$

Interpolation: Querying *continuous* values



Interpolation in a 2D voxel grid.

- Only stores values at vertex locations, i.e. corners
- Values at intermediate coordinates are defined via interpolation w/ some kernel k

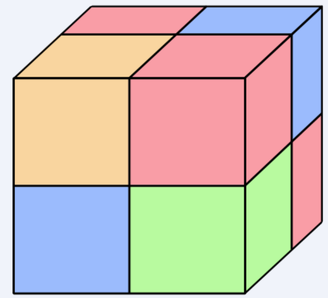
$$\hat{f}(\mathbf{x}) = \sum_{i=1}^{N} f_i k(\mathbf{x}, \mathbf{x}_i)$$

Voxel grids

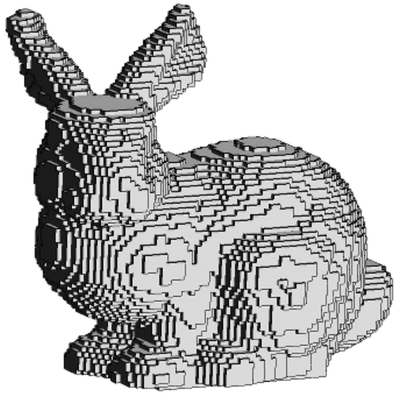
- For d spatial dimensions and resolution n, memory grows $O(n^d)$
- Fast sampling: d-linear interpolation
  = index into array 2^d times & weighted sum.
- Convenient processing as it exposes *locality.* Can easily run convolutions, nearest-neighbor lookups, etc.
- Intractable in higher dimensions :/

Voxelgrid of features

$\Phi : \mathbb{R}^3 \rightarrow \mathbb{R}^n$



Multi-Resolution Representations



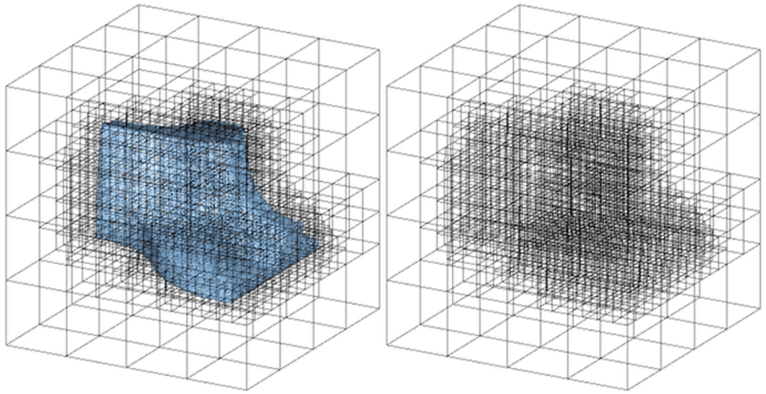
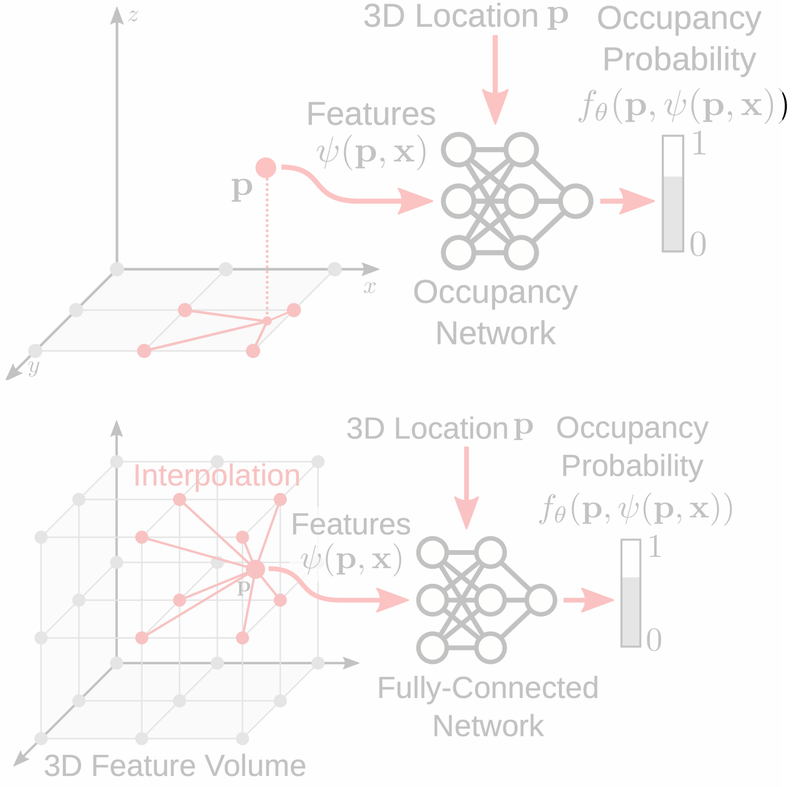


Image Source: https://doc.cgal.org/latest/Orthtree/index.html

Discrete Parameterizations

Continuous Parameterizations



Hybrid Parameterizations

Octrees

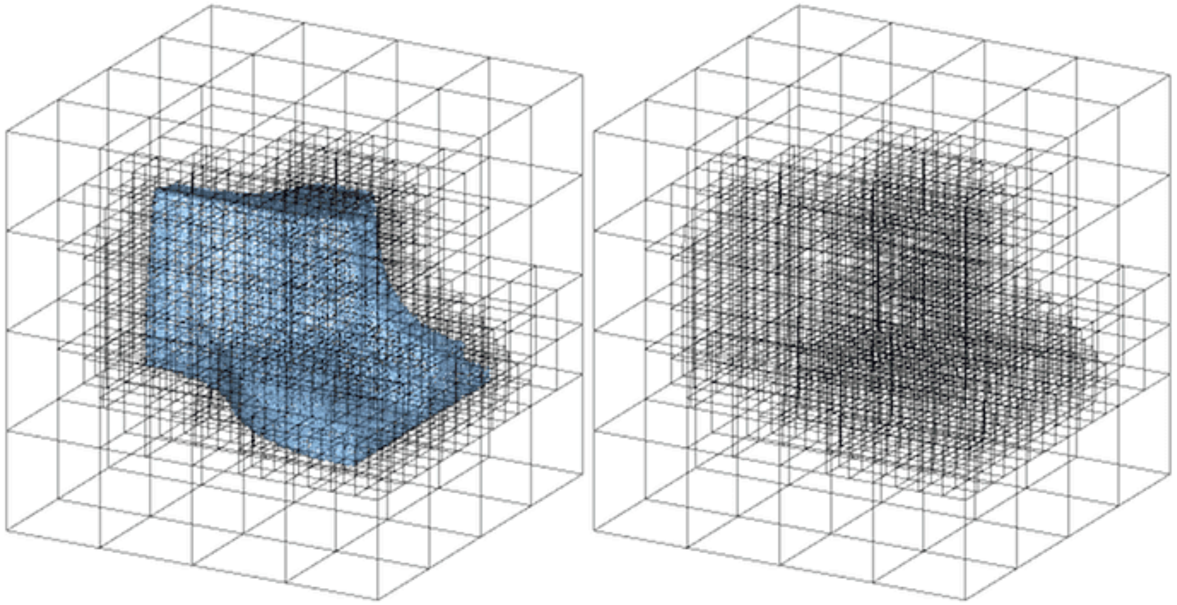


Image Source: https://doc.cgal.org/latest/Orthtree/index.html

Divide volume into 8 voxels

If any box has more than *N* points in it, divide it into 8 voxels

Do not divide voxels with zero points.

Octrees

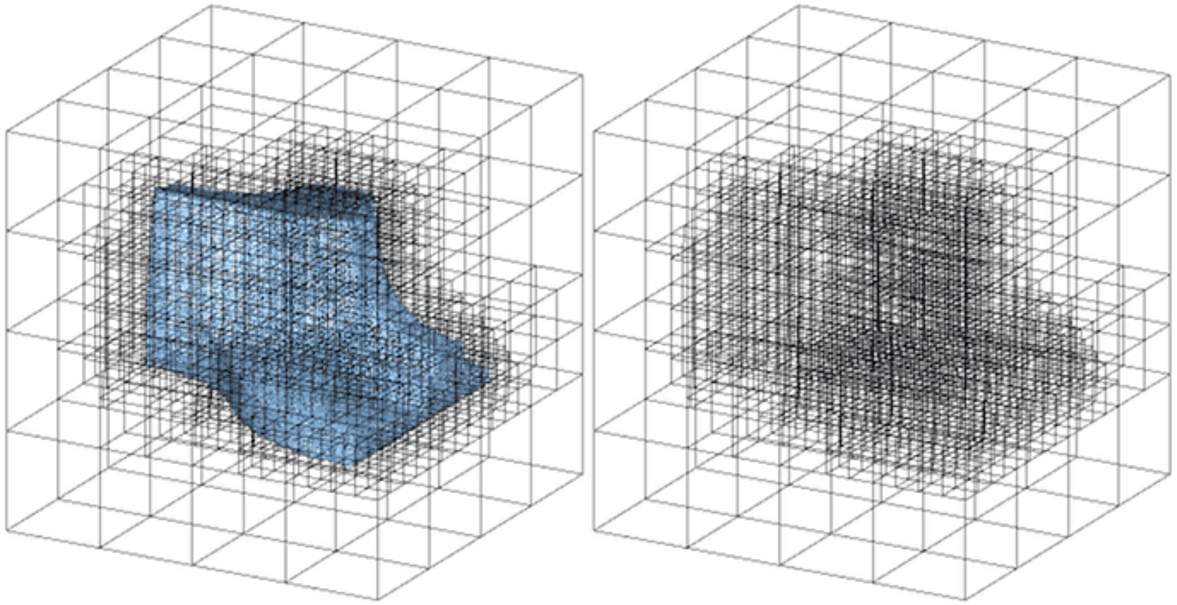


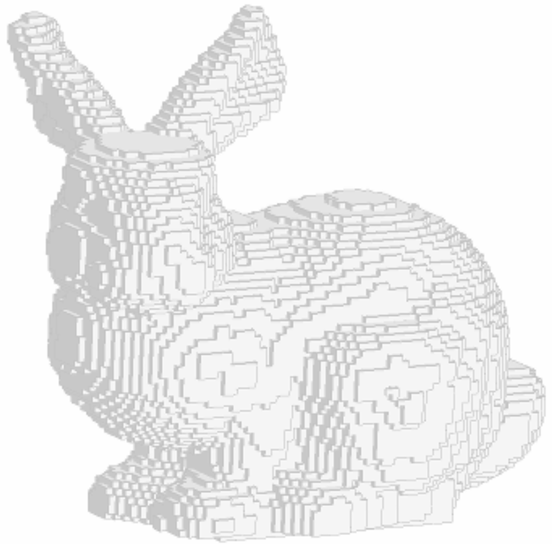
Image Source: https://doc.cgal.org/latest/Orthtree/index.html

Saves memory (less resolution in empty parts)

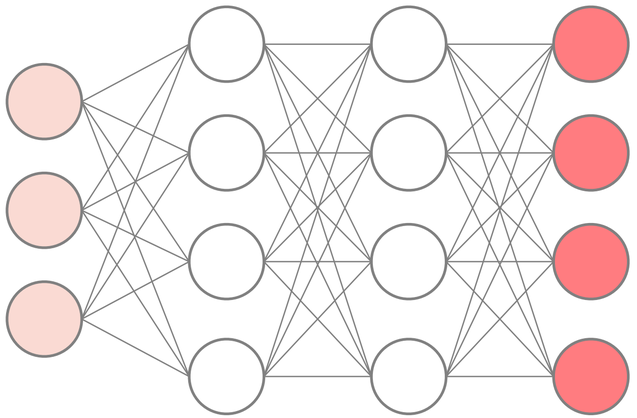
Sub-division is not differentiable: can’t easily build neural network that outputs Octree

To sample point, have to traverse multi-resolution hierarchy. Still fast, though.

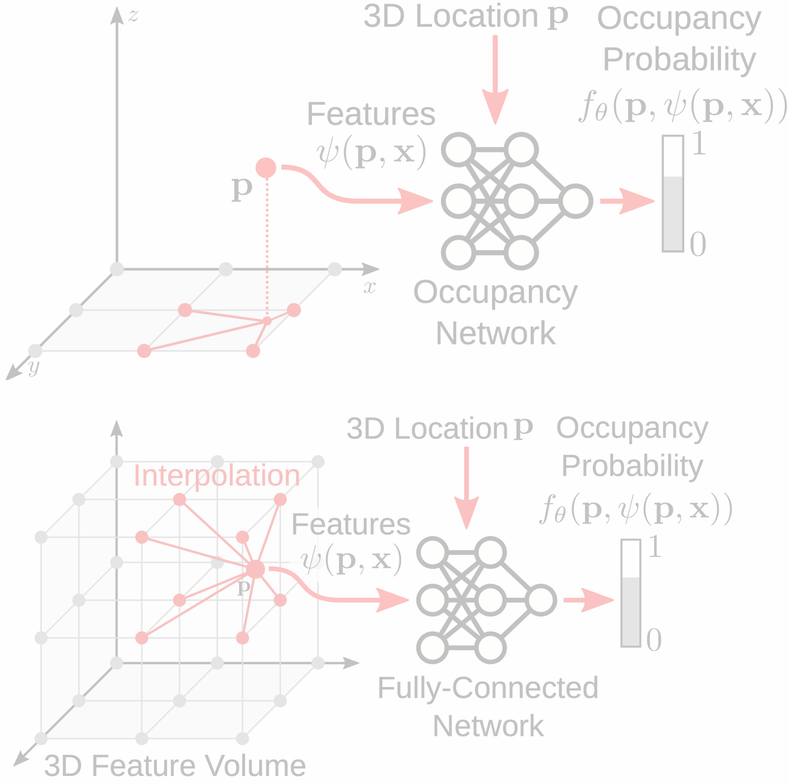
Neural Fields



Discrete Parameterizations

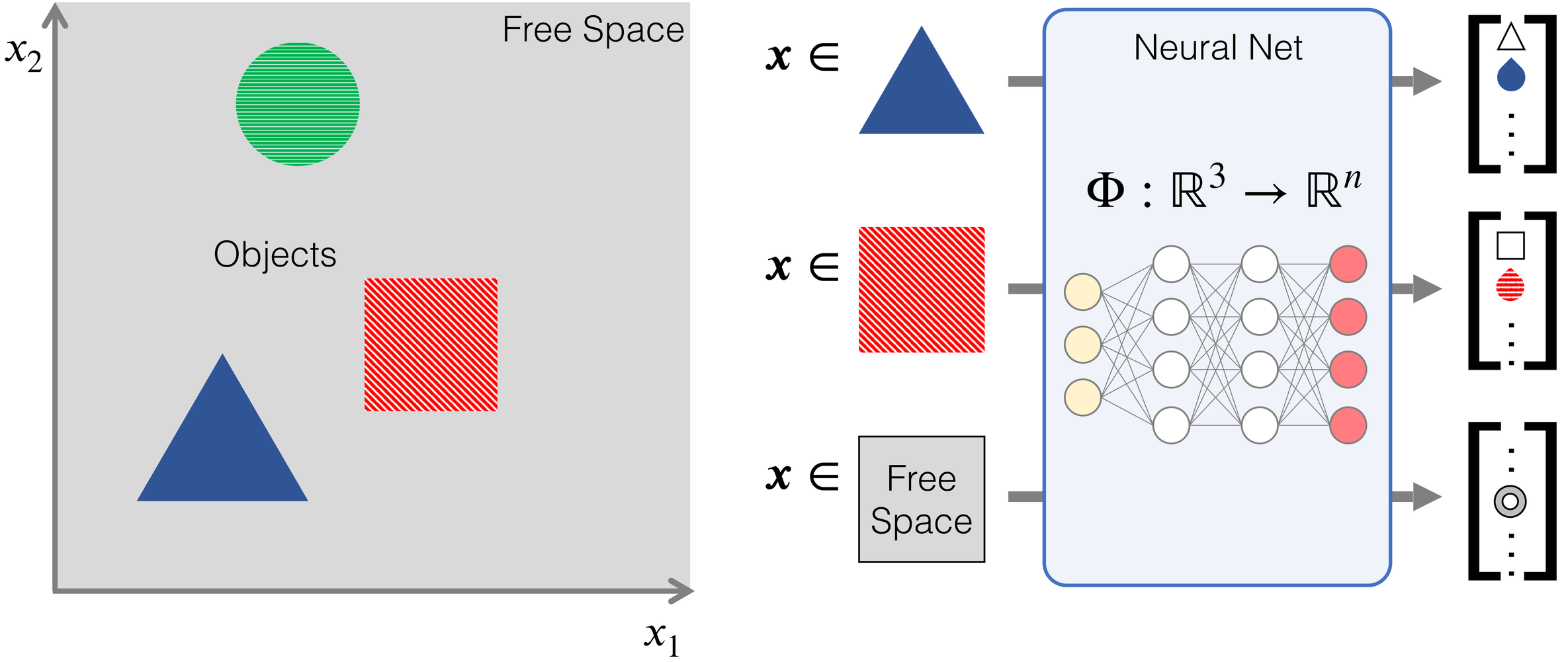


Neural Fields



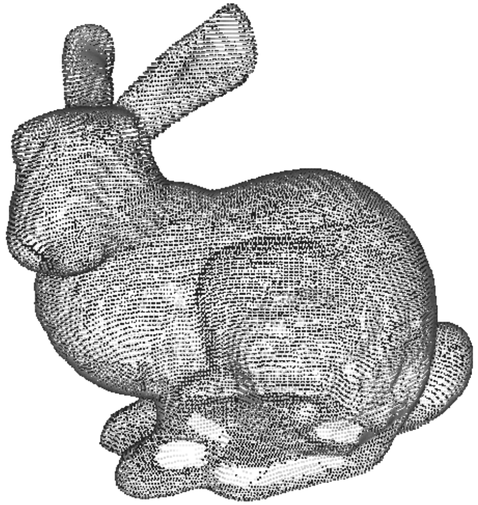
Hybrid Parameterizations

Neural fields: Parameterize Field as Neural Network!

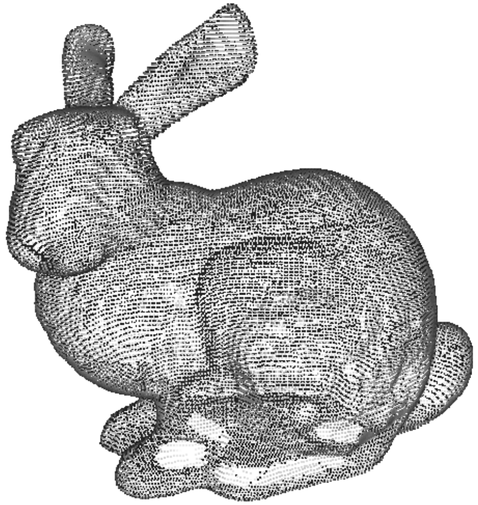


Occupancy Networks: Learning 3D Reconstruction in Function Space, Mescheder et al.
IM-Net: Learning Implicit Fields for Generative Shape Modeling, Chen et al.
DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, Park et al. 2019
Sitzmann et al: Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations, NeurIPS 2019.

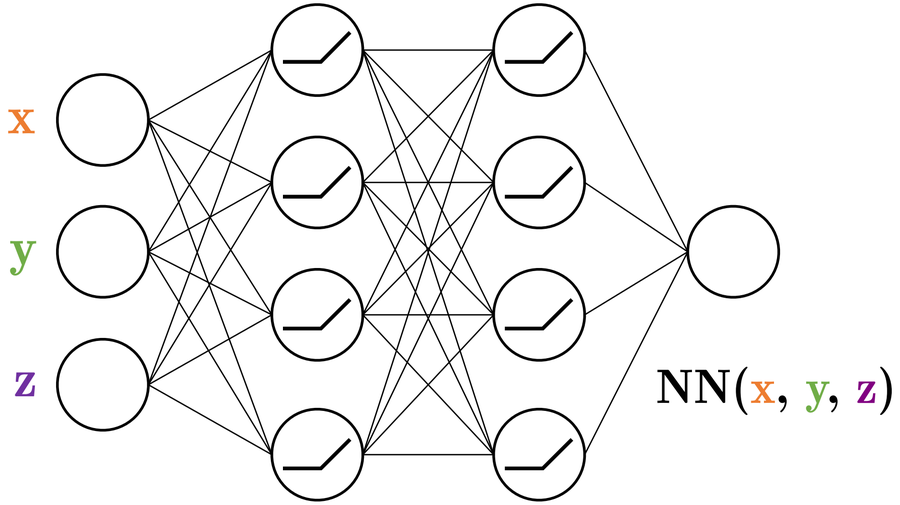
Shapes



Shapes



ReLU MLP



Mescheder et al. 2018
Park et al. 2018
Chen et al. 2018

Shapes

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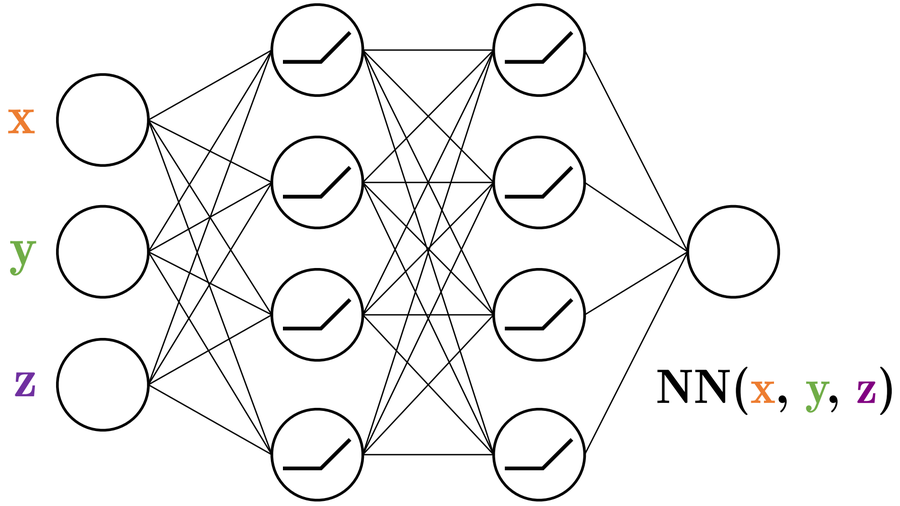

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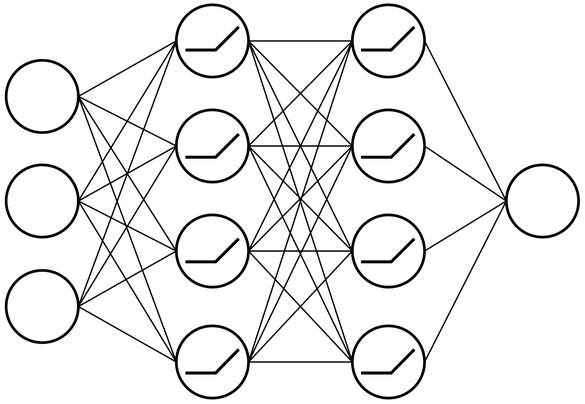
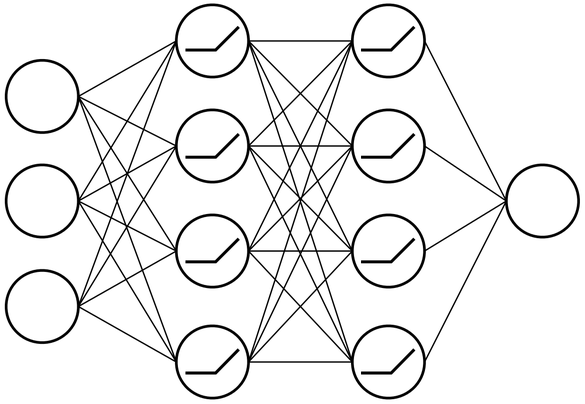


Images

Shapes

ReLU MLP



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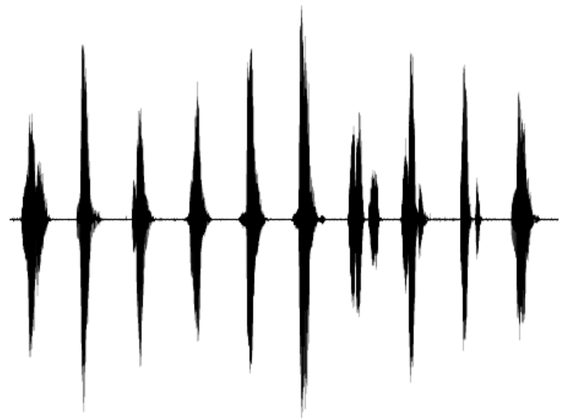
Audio



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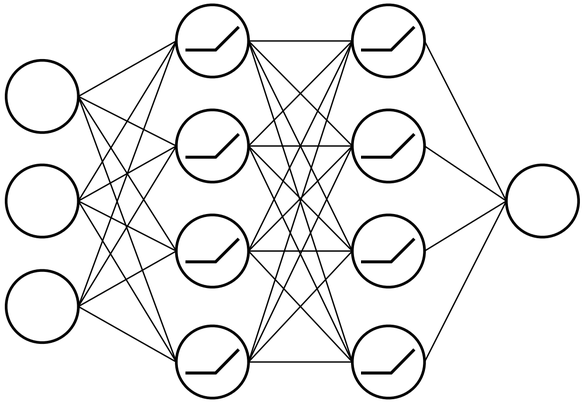
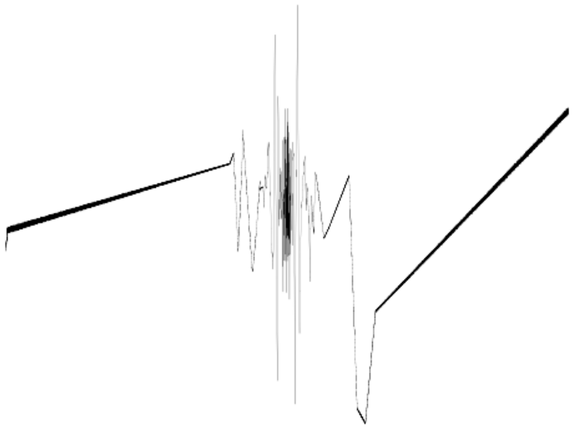


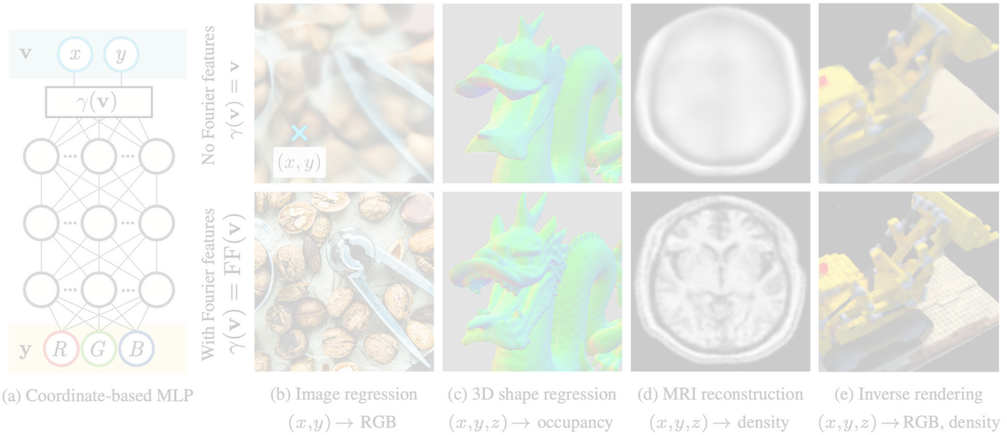


SIREN: Neural Implicit Representations With Periodic Activation Functions

Sitzmann & Martel et al. NeurIPS 2020

Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains

Tancik, Srinivasan, Mildenhall NeurIPS 2020



(a) Coordinate-based MLP

(b) Image regression $(x,y) \rightarrow$ RGB

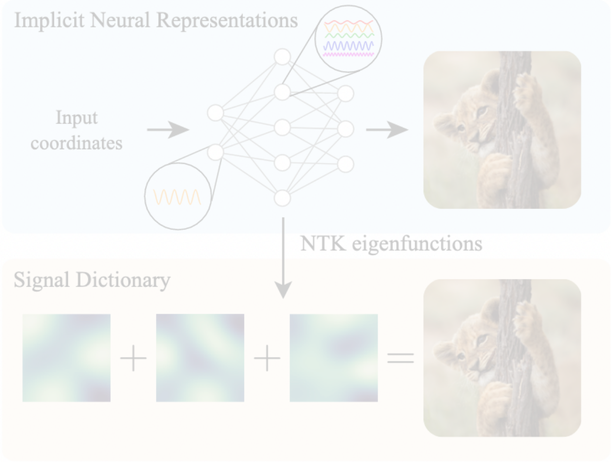
(c) 3D shape regression $(x,y,z) \rightarrow$ occupancy

(d) MRI reconstruction $(x,y,z) \rightarrow$ density

(e) Inverse rendering $(x,y,z) \rightarrow$ RGB, density

A Structured Dictionary Perspective on Implicit Neural Representations

Yüce & Ortiz-Jiménez et al. CVPR 2022



Gaussian Activated Neural Radiance Fields for High Fidelity Reconstruction & Pose Estimation

Chng et al. ECCV 2022

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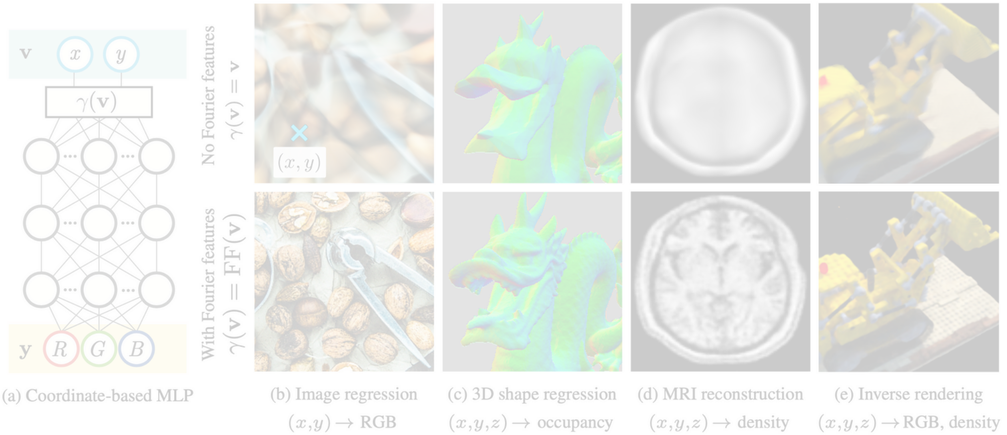

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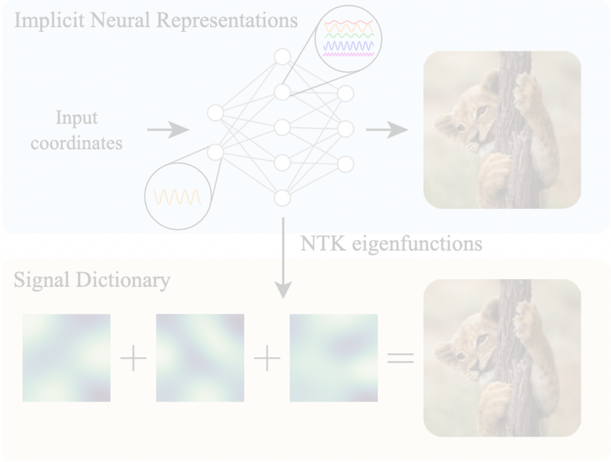

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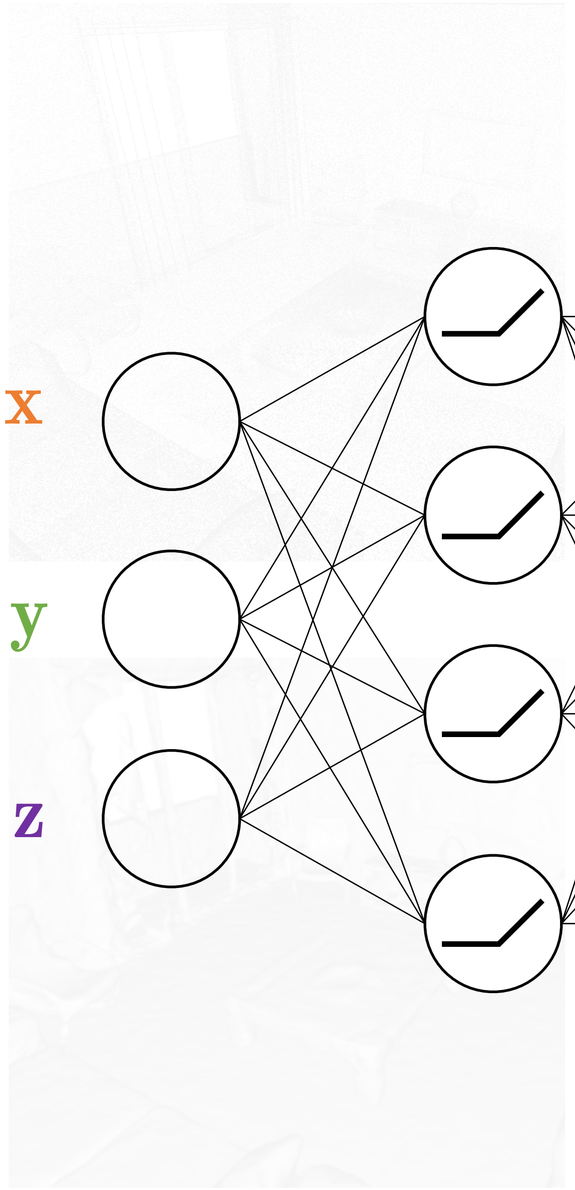
Images

Shapes

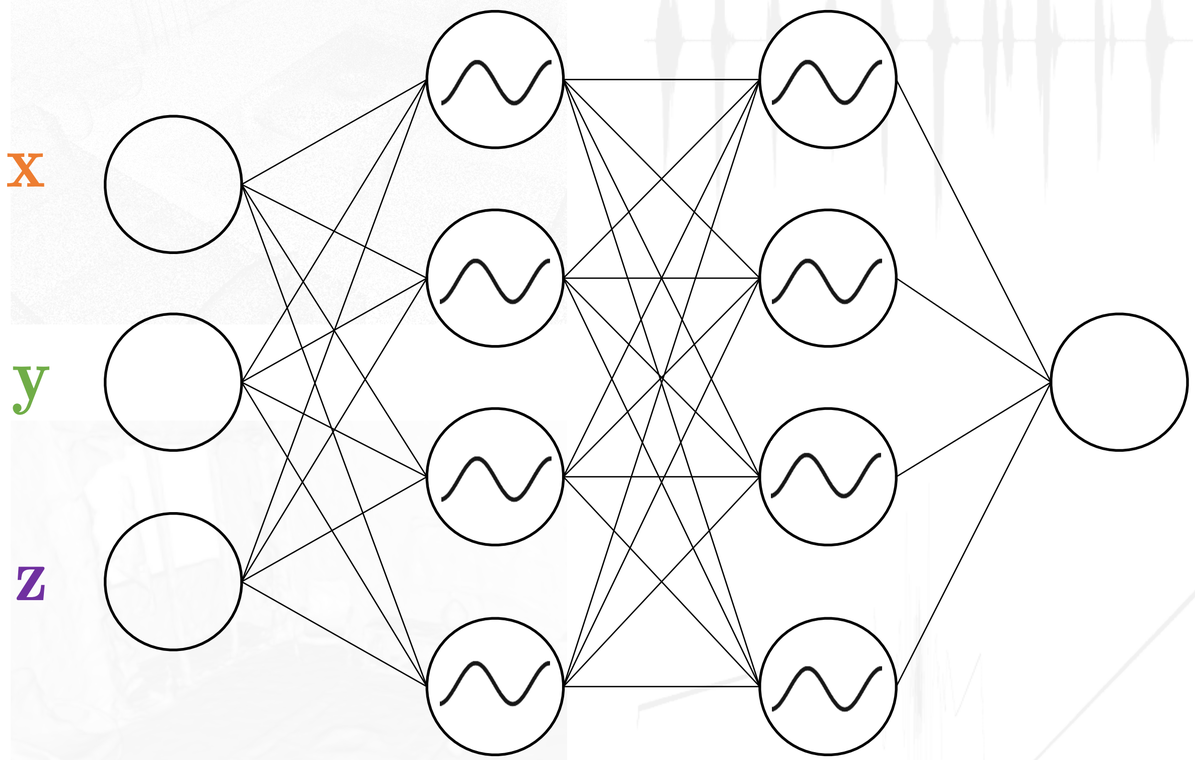
Audio

Quantities defined by a differential equation



Sitzmann et al.: Implicit neural representations with periodic activation functions, NeurIPS 2020

SIREN: Sinusoidal Representation Networks



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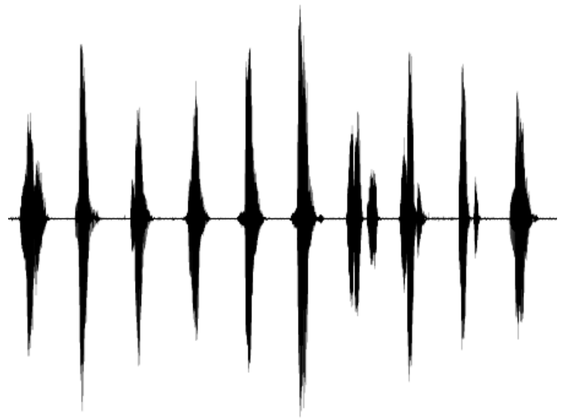

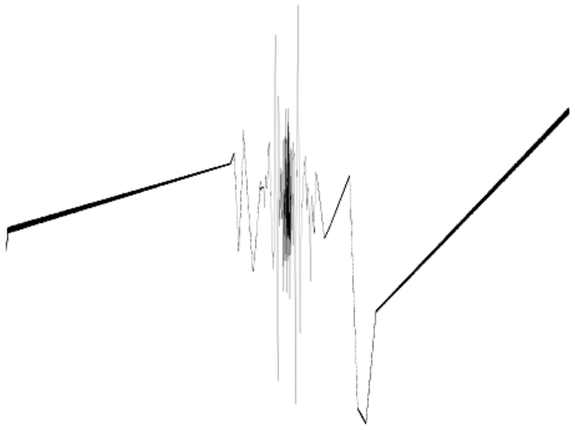

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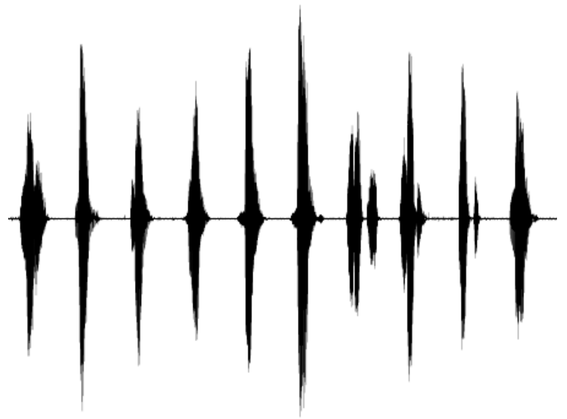
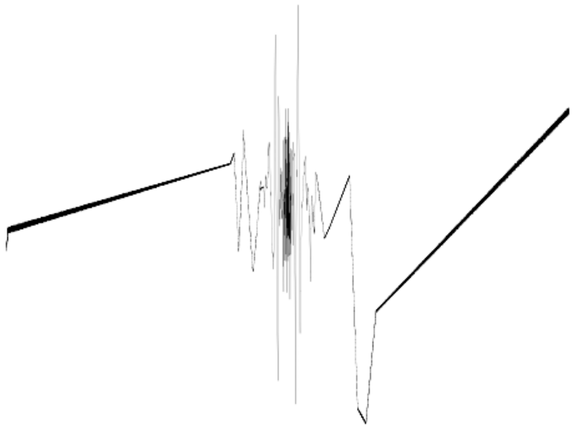
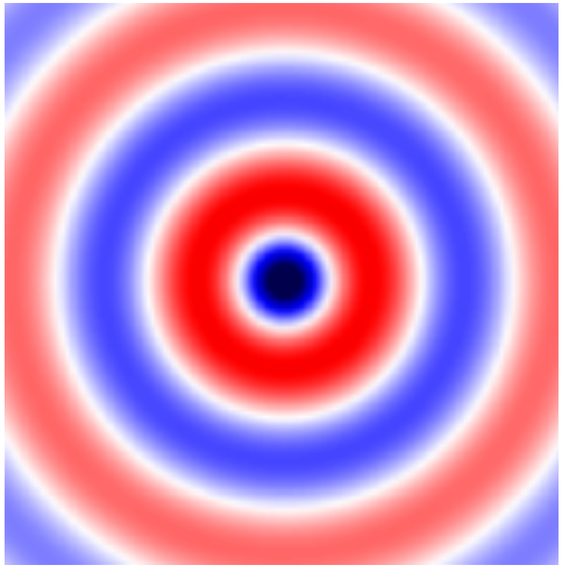




Quantities defined by a differential equation



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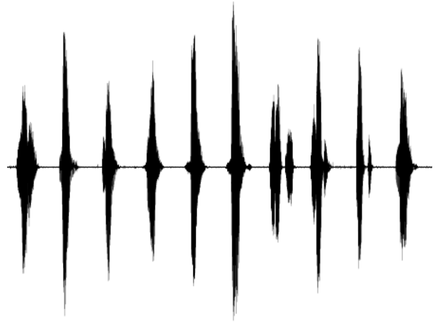
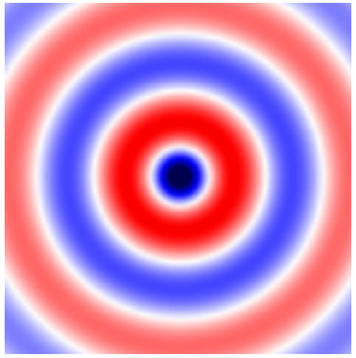
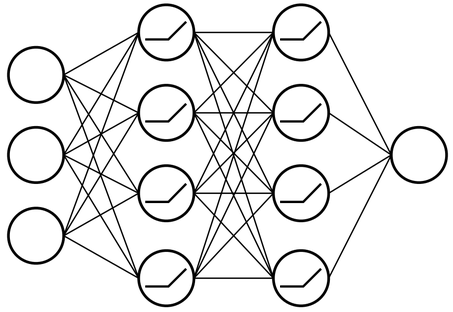
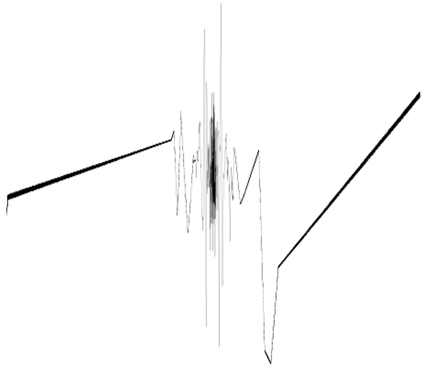
Quantities defined by a differential equation

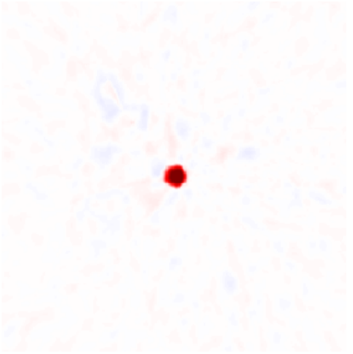




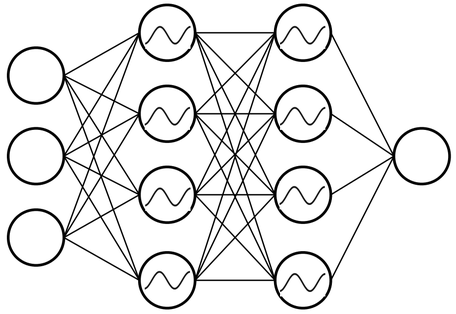
ReLU MLP







SIREN



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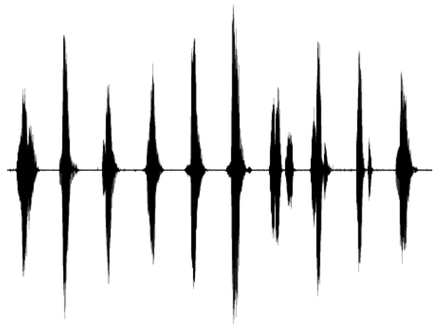
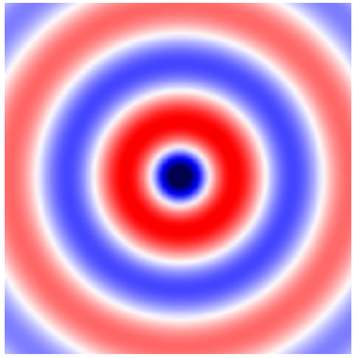
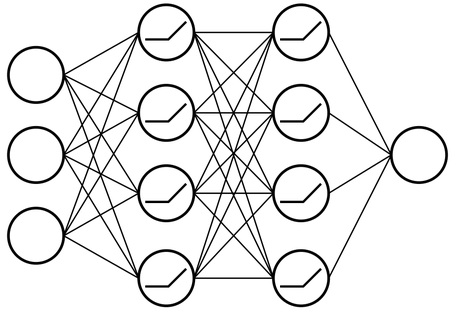
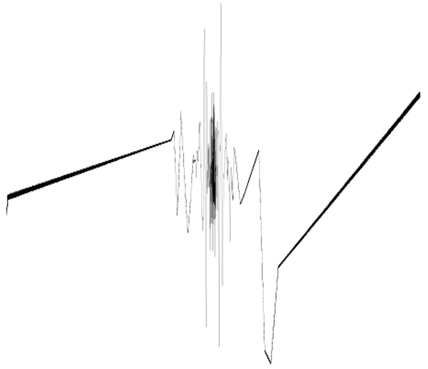
Quantities defined by a differential equation

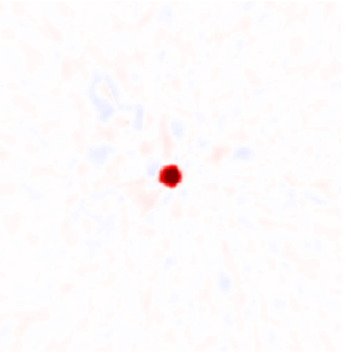




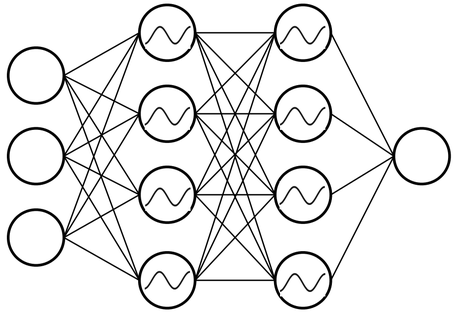
ReLU MLP

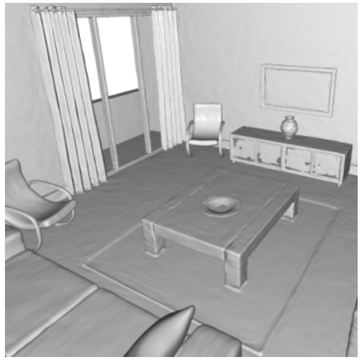


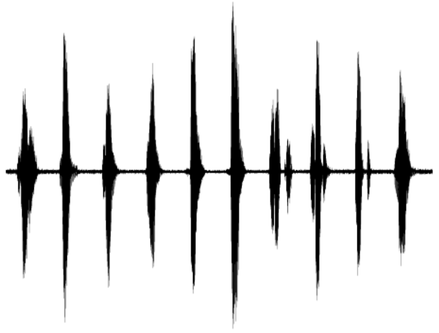


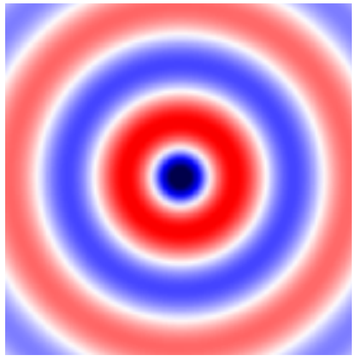


SIREN



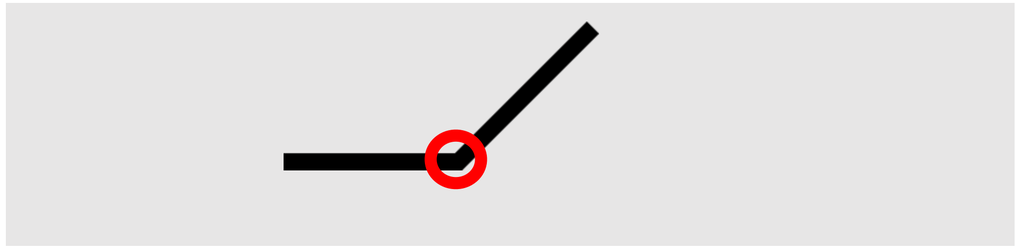


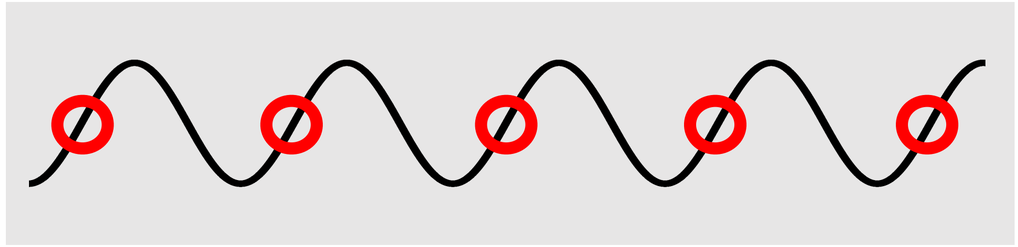




Locality

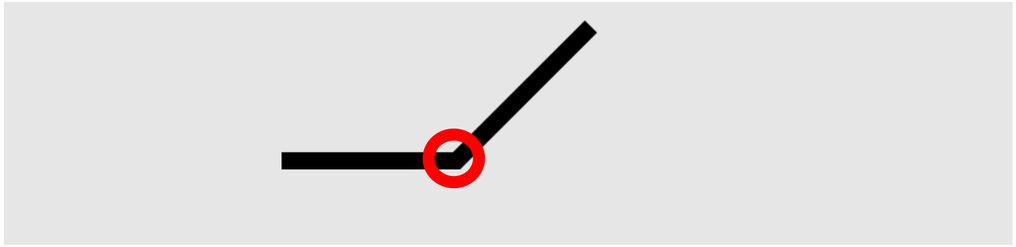
$\delta/\delta x$ $\delta^2/\delta x^2$

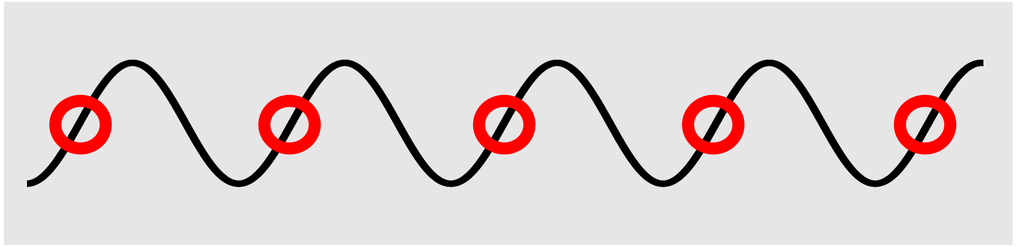




Periodicity allows SIREN to replicate activations across input domain

Locality

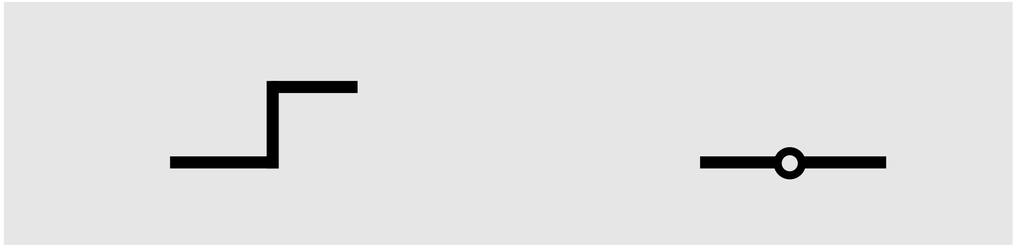


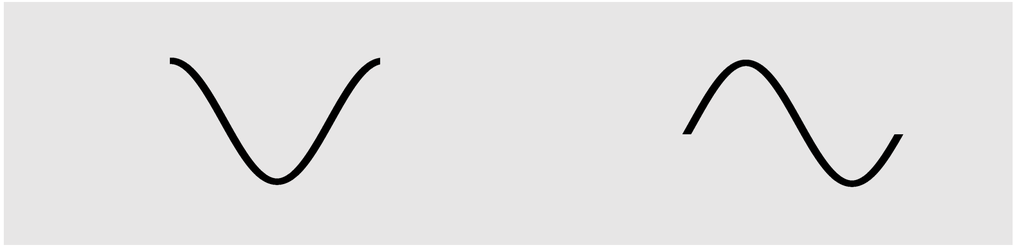


Periodicity allows SIREN to replicate activations across input domain

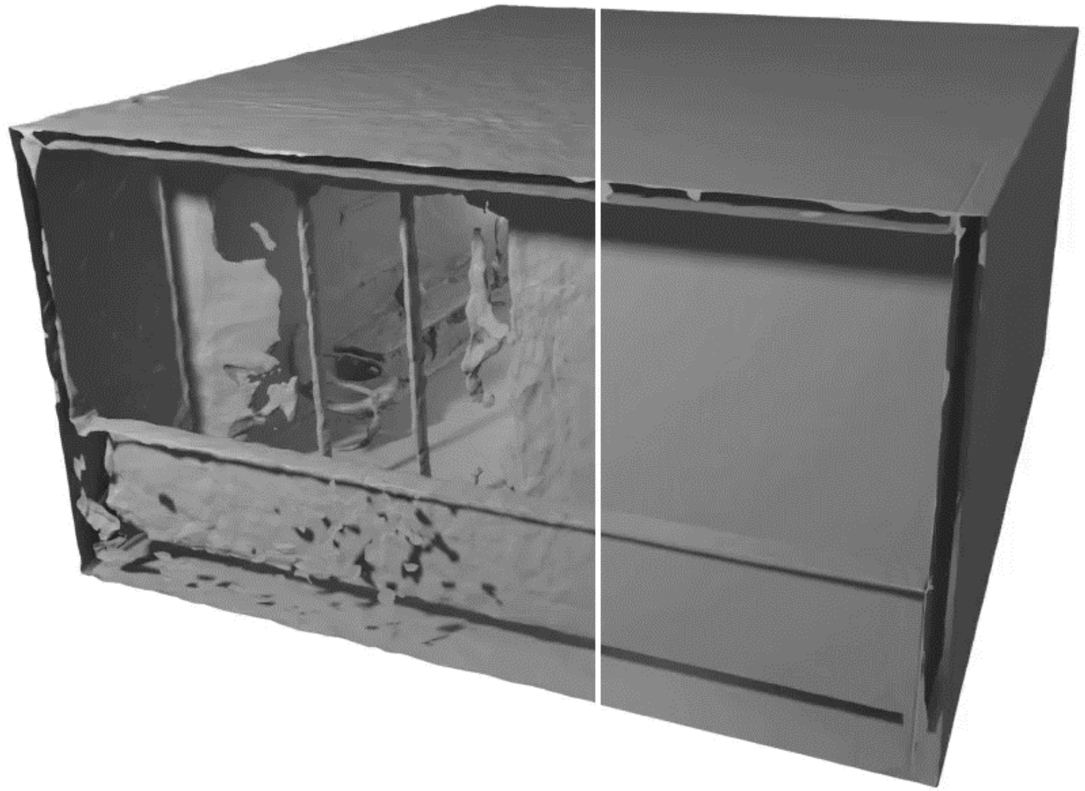
Derivatives

$\delta/\delta x$ $\delta^2/\delta x^2$



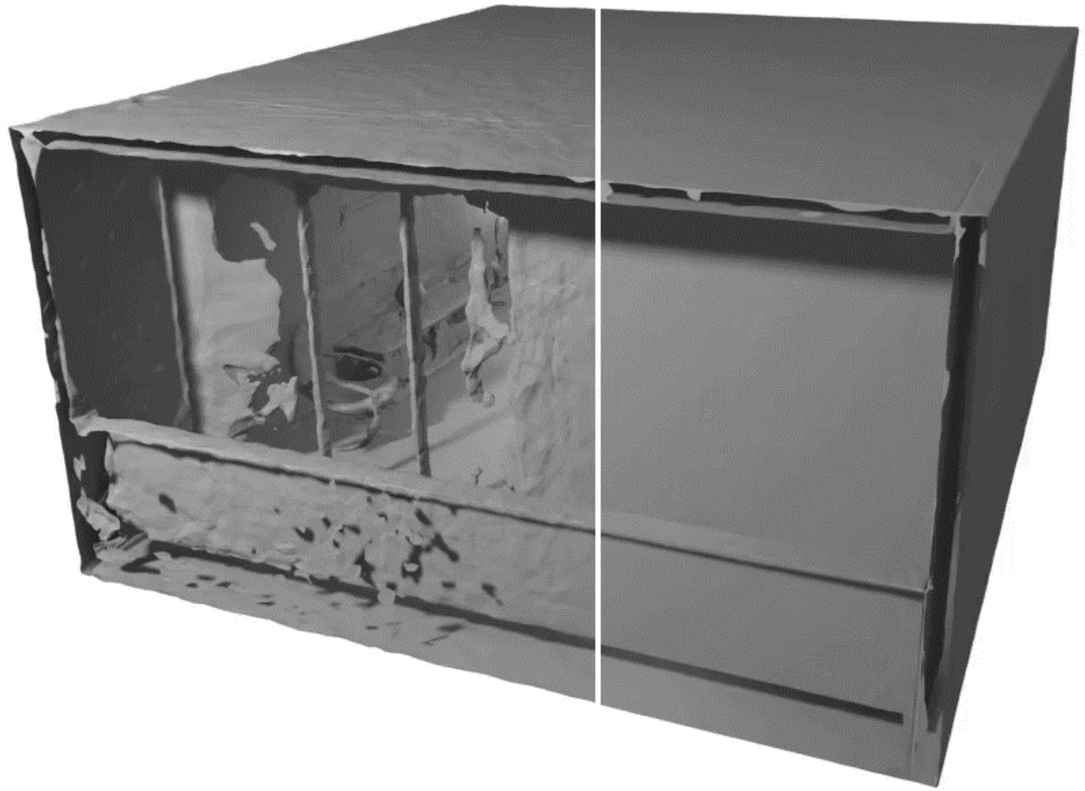


All derivatives exist, are nonzero and bounded by 1



ReLU

SIREN



ReLU

SIREN

~1MB compared to
110MB of full mesh!

ReLU

SIREN

Background: Kernel Regression

Given "training" set $\{(x_i, y_i)\}_i$, a kernel function makes predictions on a point $\mathbf{x}$ by interpolating labels $\mathbf{y}_i$ in the training set according to pairwise weights between $\mathbf{x}_i$ to $\mathbf{x}$ as measured by a kernel function:

$$f(\mathbf{x}) = \sum_{i=1}^{n} (\mathbf{K}^{-1}\mathbf{y})_i k(\mathbf{x}_i, \mathbf{x})$$

Where $\mathbf{K}_{ij} = k(\mathbf{x}_i, \mathbf{x}_j)$, k is kernel function with $k \geq 0$.

The Neural Tangent Kernel

$$f(\mathbf{x}) = \sum_{i=1}^{n} (\mathbf{K}^{-1}\mathbf{y})_i k(\mathbf{x}_i, \mathbf{x})$$

It turns out (Jacot et al. 2018) that in the limit of an infinitely wide MLP $f(x)$ with initialization θ_0, test-time predictions are made according to a kernel:

$$k_{NTK}(\mathbf{x}_1, \mathbf{x}_2) = \langle \nabla_\theta f_{\theta_0}(\mathbf{x}_1), \nabla_\theta f_{\theta_0}(\mathbf{x}_2) \rangle$$

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In other words: “Neural” implicit representations interpolate the training set according to a relatively simple rule. No “intelligence”, no AI, no magic.

The Neural Tangent Kernel

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What we can do is design the kernel and pick the space of $(\mathbf{x}, \mathbf{y})$,
the space in which our neural network will interpolate.

The Neural Tangent Kernel

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$$k_{NTK}(\mathbf{x}_1, \mathbf{x}_2) = \langle \nabla_\theta f_{\theta_0}(\mathbf{x}_1), \nabla_\theta f_{\theta_0}(\mathbf{x}_2) \rangle$$

We do **not** know of an equivalent rule for transformers to date - work in progress!

The Neural Tangent Kernel

$$f(\mathbf{x}) = \sum_{i=1}^{n} (\mathbf{K}^{-1}\mathbf{y})_i k(\mathbf{x}_i, \mathbf{x})$$

It turns out (Jacot et al. 2018) that in the limit of an infinitely wide MLP $f(x)$ with initialization θ_0, test-time predictions are made according to a kernel:

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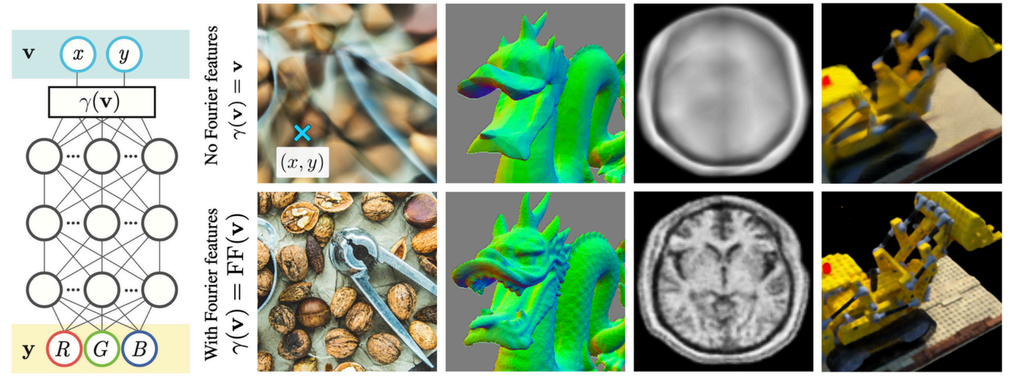
What does this mean for neural fields?

SIREN: Neural Implicit Representations With Periodic Activation Functions

Sitzmann & Martel et al. NeurIPS 2020

Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains

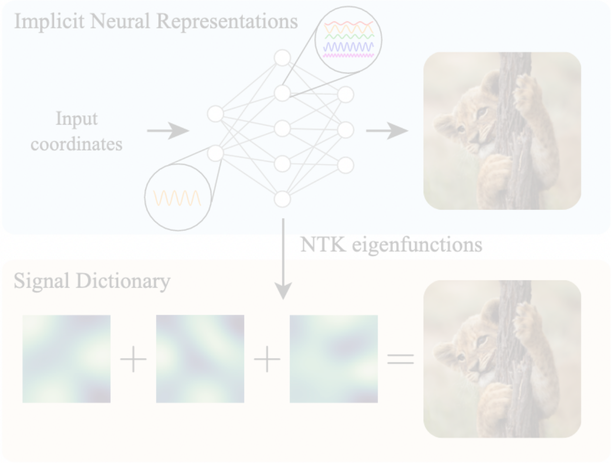
Tancik, Srinivasan, Mildenhall et al, NeurIPS 2020



(a) Coordinate-based MLP | (b) Image regression $(x,y) \rightarrow$ RGB | (c) 3D shape regression $(x,y,z) \rightarrow$ occupancy | (d) MRI reconstruction $(x,y,z) \rightarrow$ density | (e) Inverse rendering $(x,y,z) \rightarrow$ RGB, density

A Structured Dictionary Perspective on Implicit Neural Representations

Yüce & Ortiz-Jiménez et al. CVPR 2022



Gaussian Activated Neural Radiance Fields for High Fidelity Reconstruction & Pose Estimation

Chng et al. ECCV 2022

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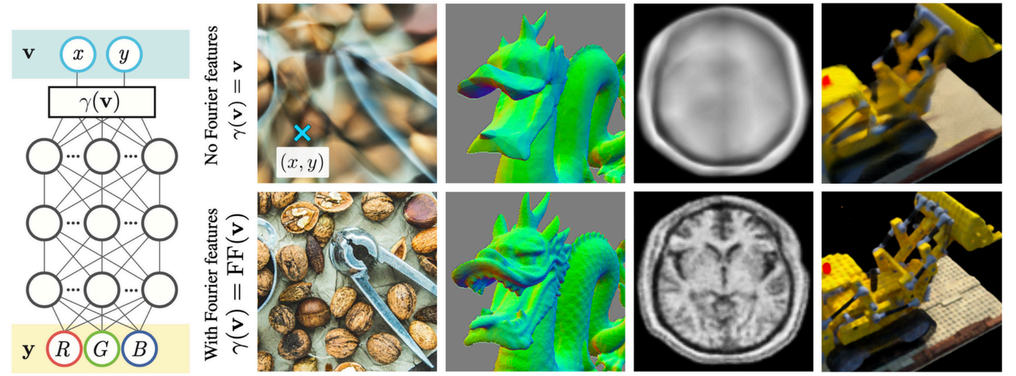

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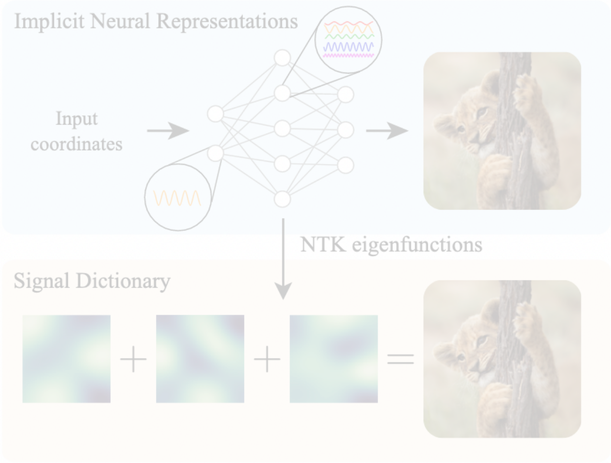

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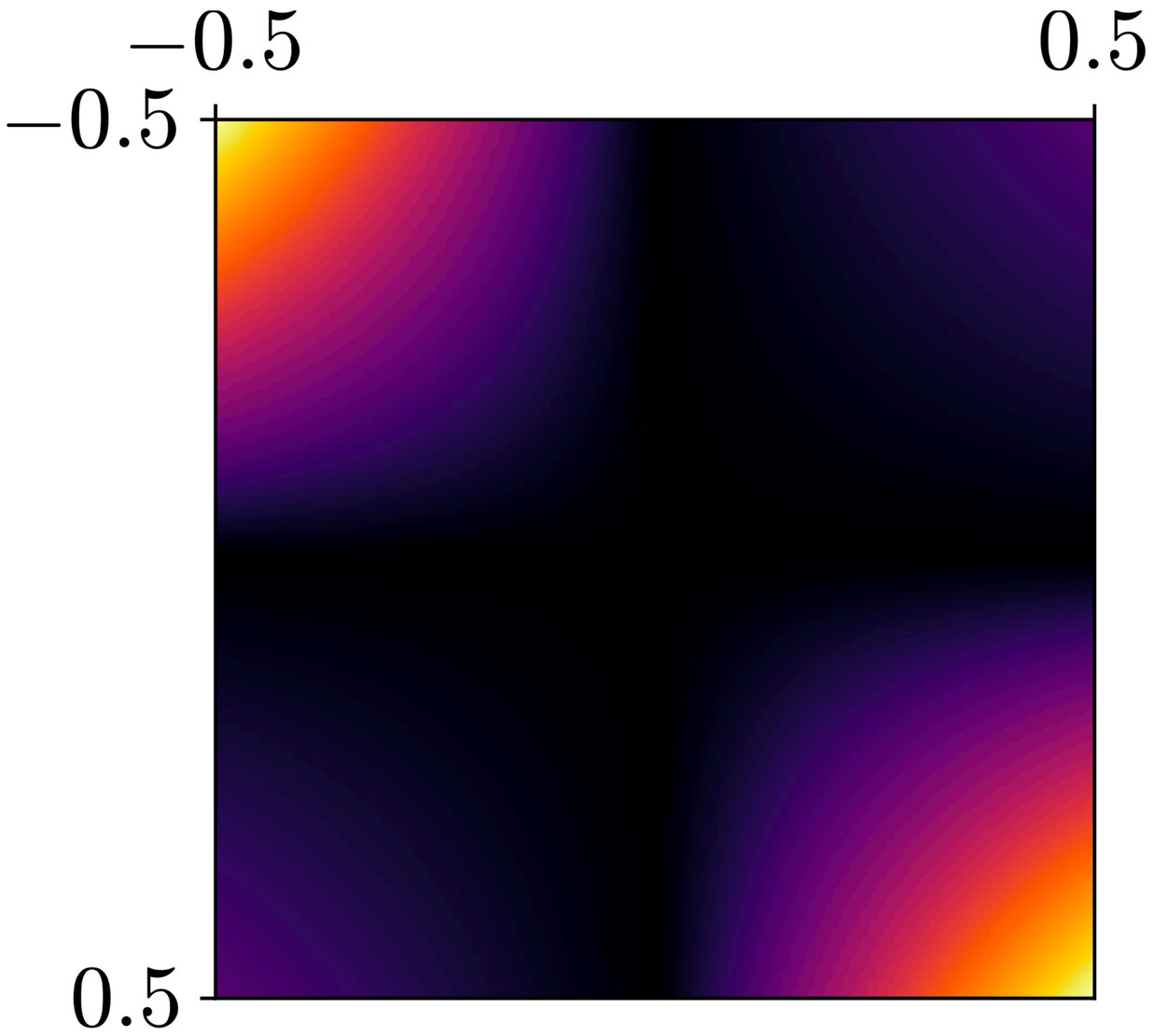
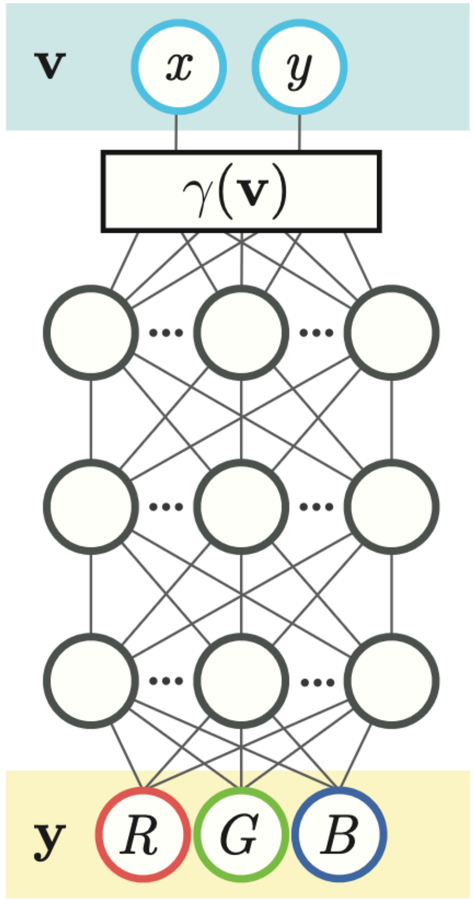


NTK kernel $k_{NTK}(x_i, x_j)$ for a 4-layer ReLU MLP with one scalar input.

From “Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains”, Tancik, Srinivasan, Mildenhall et al.

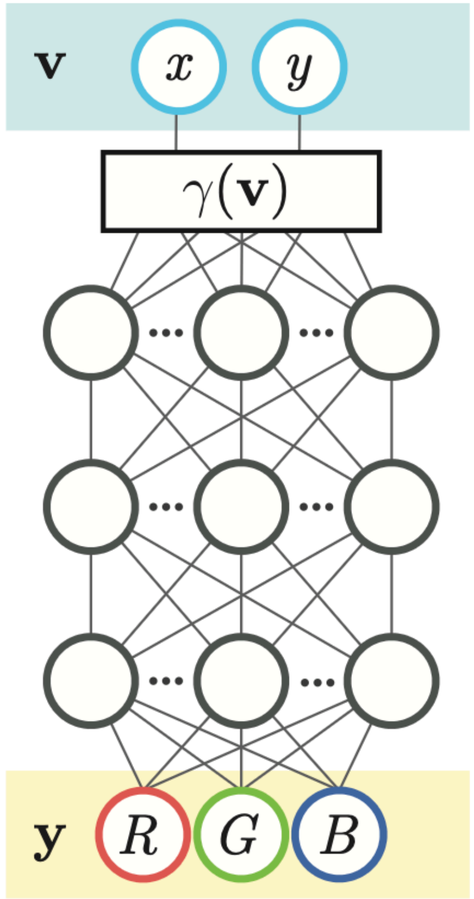
NTK of ReLU neural net is quite non-local.

Feature Embeddings



Reconstructing continuous distributions of 3D protein…, Zhong et al.; Neural Radiance Fields, Mildenhall et al.

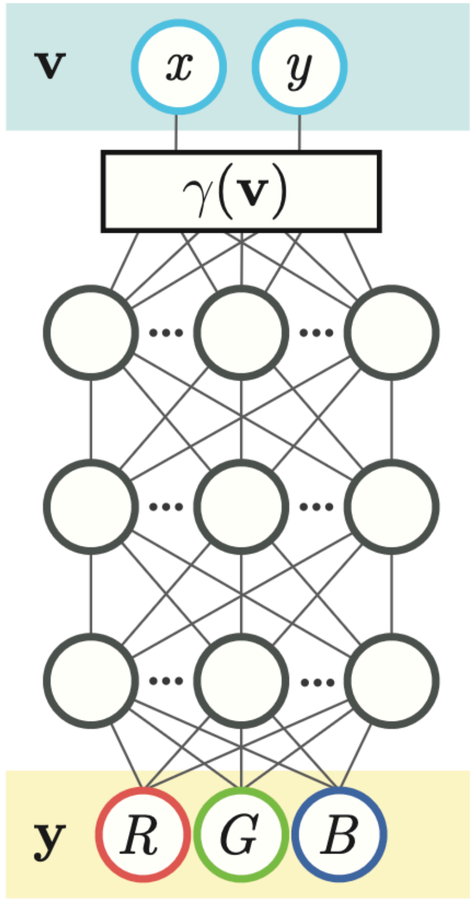
Feature Embeddings



$$\gamma(\mathbf{x}) = [\gamma_1(\mathbf{x}), \ldots, \gamma_n(\mathbf{x})]$$

Reconstructing continuous distributions of 3D protein…, Zhong et al.; Neural Radiance Fields, Mildenhall et al.

Feature Embeddings



$$\gamma(\mathbf{x}) = [\gamma_1(\mathbf{x}), \ldots, \gamma_n(\mathbf{x})]$$

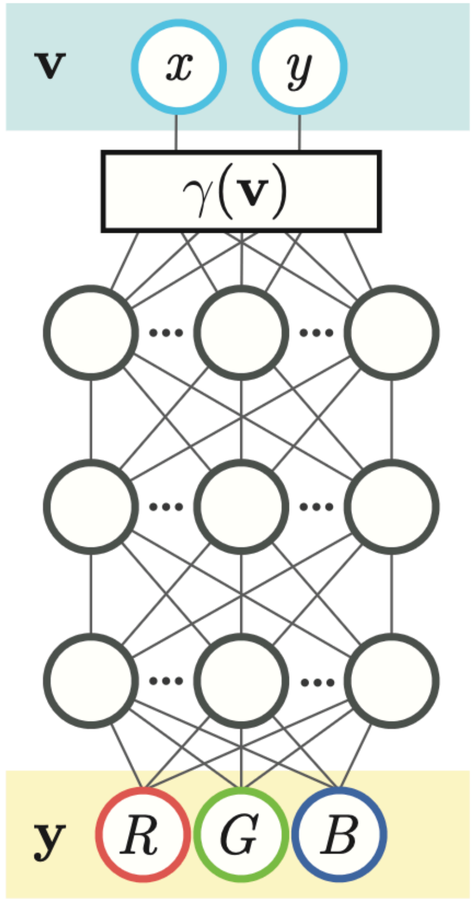
$$\gamma_{2i}(\mathbf{x}) = \sin(2^{i-1}\pi x_i)$$

$$\gamma_{(2i+1)}(\mathbf{x}) = \cos(2^{i-1}\pi x_i)$$

Sinusoidal Embeddings
Zhong et al. ICLR 2020
Mildenhall et al., ECCV 2020

Reconstructing continuous distributions of 3D protein…, Zhong et al.; Neural Radiance Fields, Mildenhall et al.

Feature Embeddings



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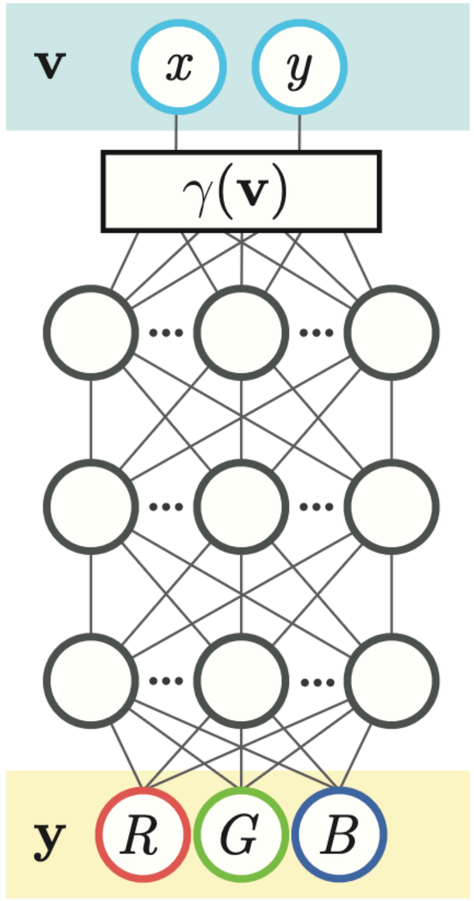
Sinusoidal Embeddings
Zhong et al. ICLR 2020
Mildenhall et al., ECCV 2020

$$\gamma(\mathbf{x}) = \exp(-\frac{\|t - x\|^2}{2\sigma^2})$$

Gaussian Embeddings
Zheng et al., arXiv 2021

Reconstructing continuous distributions of 3D protein…, Zhong et al.; Neural Radiance Fields, Mildenhall et al.

Feature Embeddings



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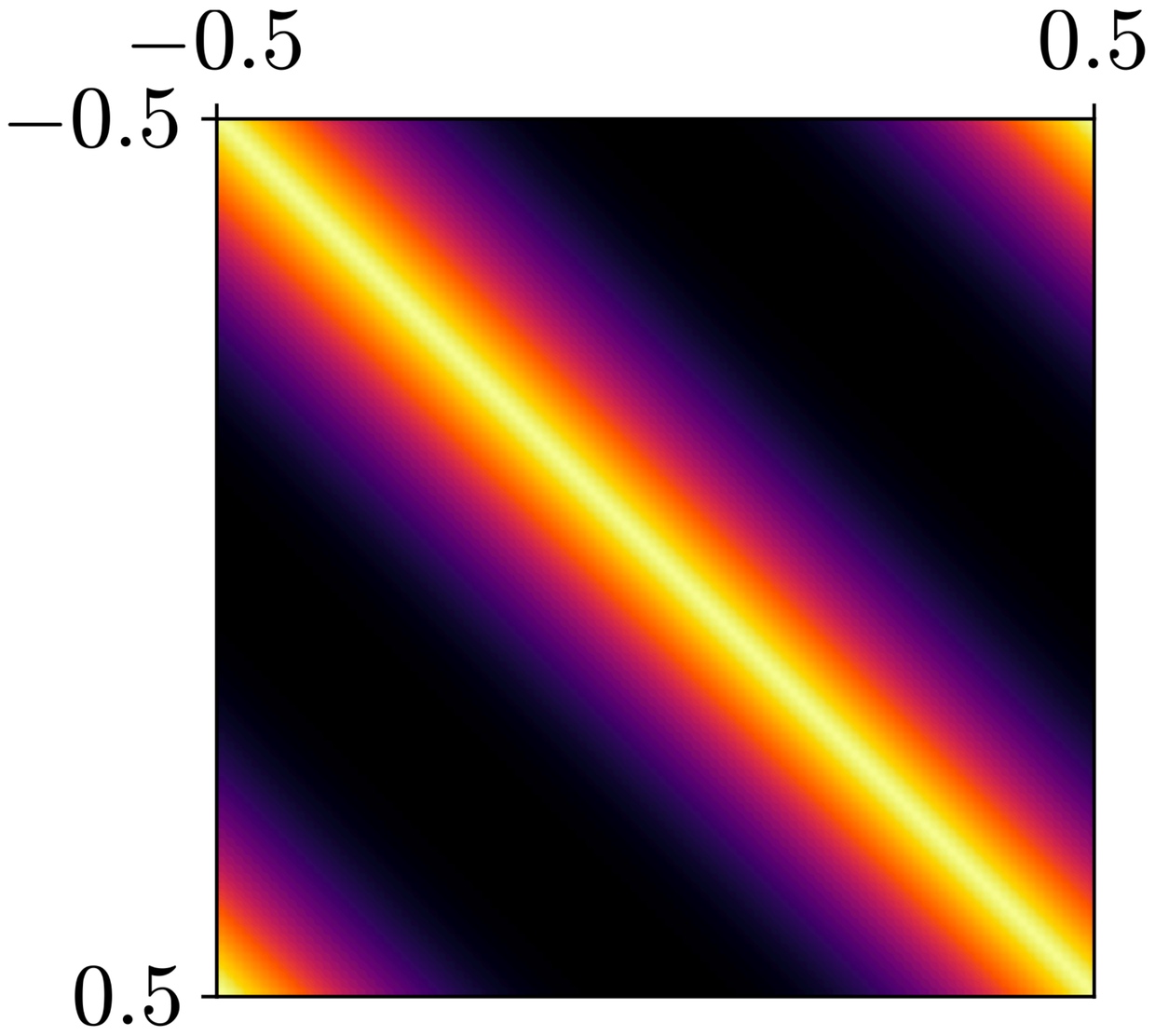


NTK kernel $k_{NTK}(\gamma(x_i), \gamma(x_j))$ for a 4-layer ReLU MLP with one scalar input and **Sinusoidal Feature Mapping**

$$\gamma(x) = [\cos(2\pi x), \sin(2\pi x)].$$

From “Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains”, Tancik, Srinivasan, Mildenhall et al.

NTK is local (note diagonal).

SIREN

ReLU

SIREN

SIREN

ReLU

SIREN

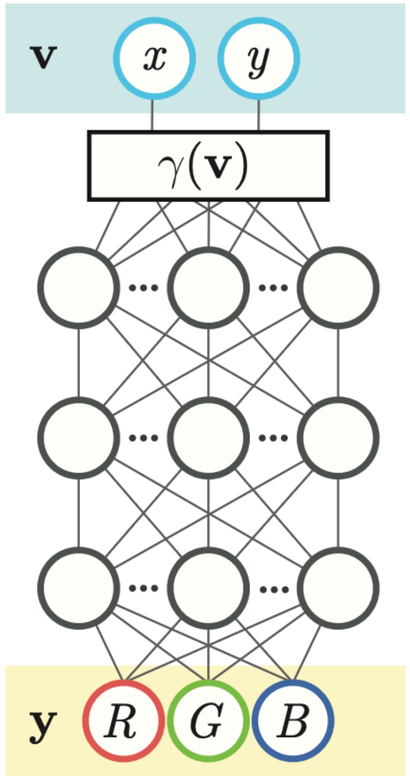
SIREN

~1MB compared to
110MB of full mesh!

ReLU

SIREN

Fourier Features

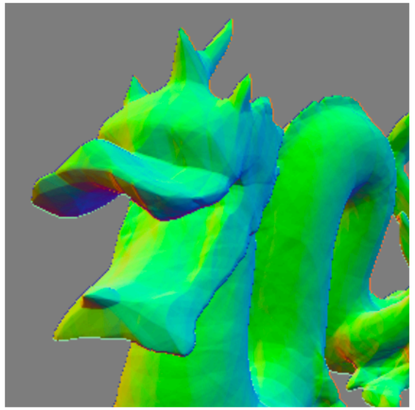


(a) Coordinate-based MLP

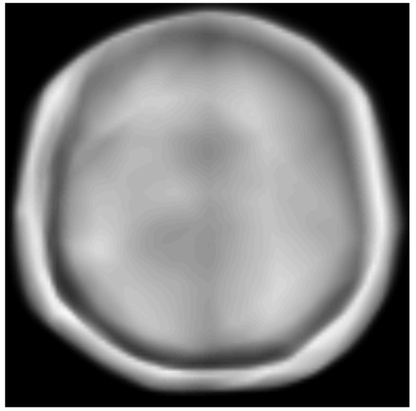
No Fourier features $\gamma(\mathbf{v}) = \mathbf{v}$

With Fourier features $\gamma(\mathbf{v}) = \mathrm{FF}(\mathbf{v})$

(b) Image regression
$(x,y) \rightarrow$ RGB

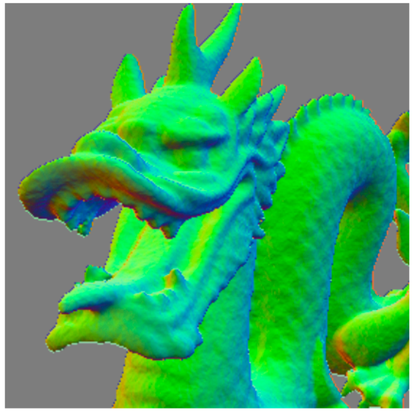


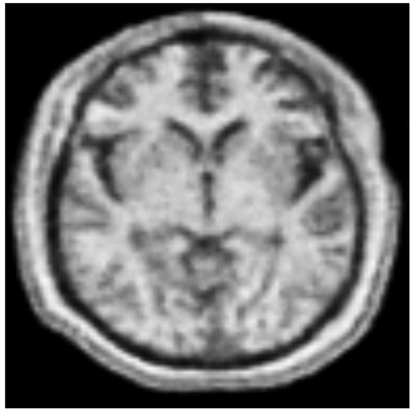
(c) 3D shape regression
$(x,y,z) \rightarrow$ occupancy

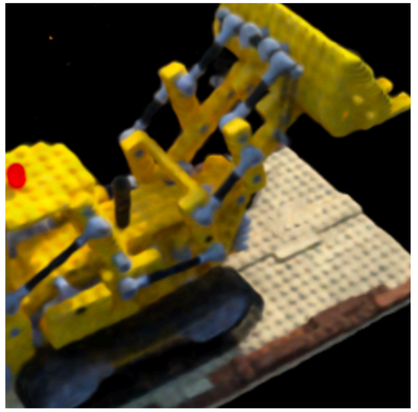


(d) MRI reconstruction
$(x,y,z) \rightarrow$ density

(e) Inverse rendering
$(x,y,z) \rightarrow$ RGB, density







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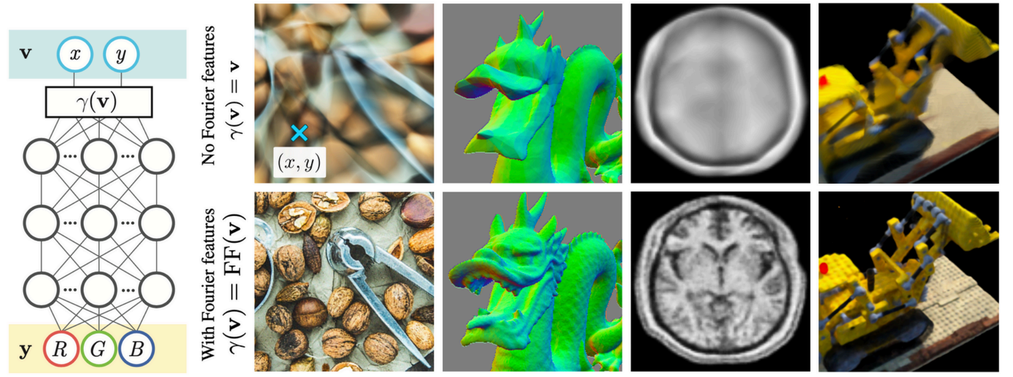

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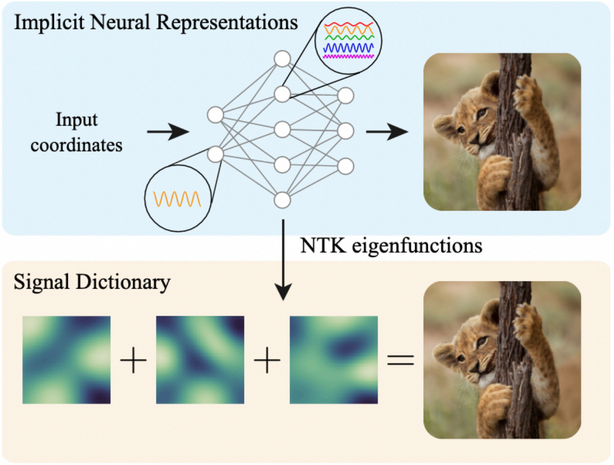

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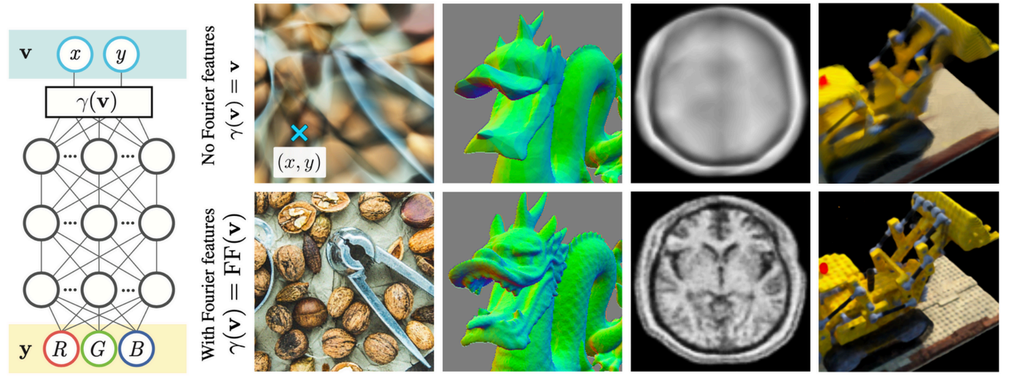
Tancik, Srinivasan, Mildenhall NeurIPS 2020



(a) Coordinate-based MLP

(b) Image regression $(x,y) \rightarrow$ RGB

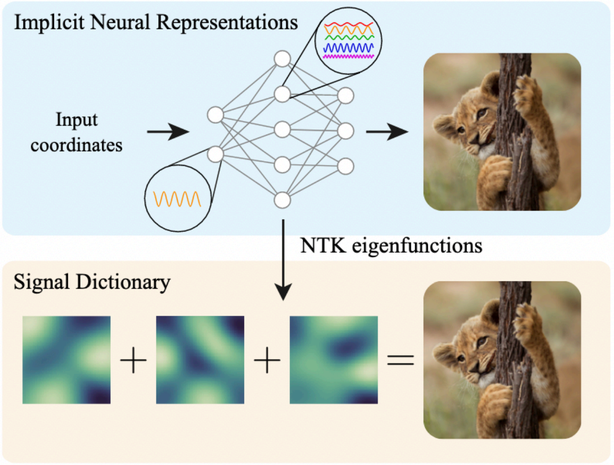
(c) 3D shape regression $(x,y,z) \rightarrow$ occupancy

(d) MRI reconstruction $(x,y,z) \rightarrow$ density

(e) Inverse rendering $(x,y,z) \rightarrow$ RGB, density

A Structured Dictionary Perspective on Implicit Neural Representations

Yüce & Ortiz-Jiménez et al. CVPR 2022

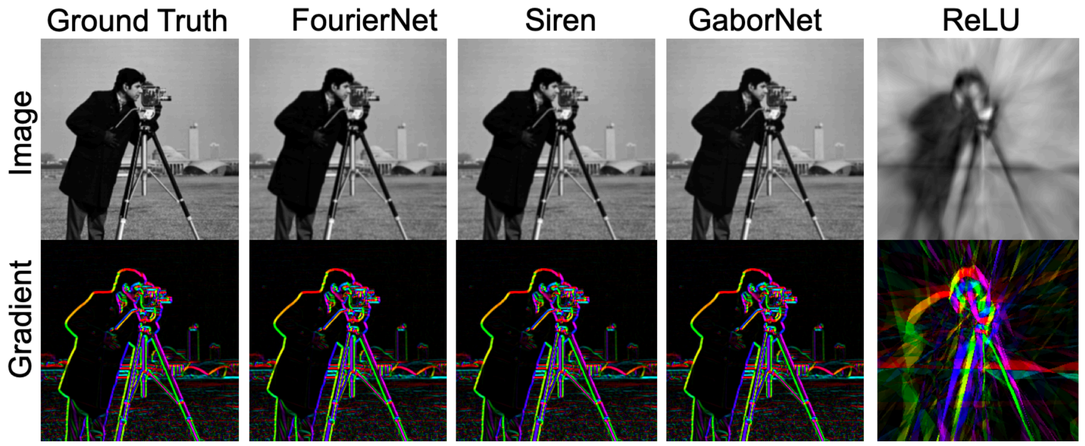


Gaussian Activated Neural Radiance Fields for High Fidelity Reconstruction & Pose Estimation

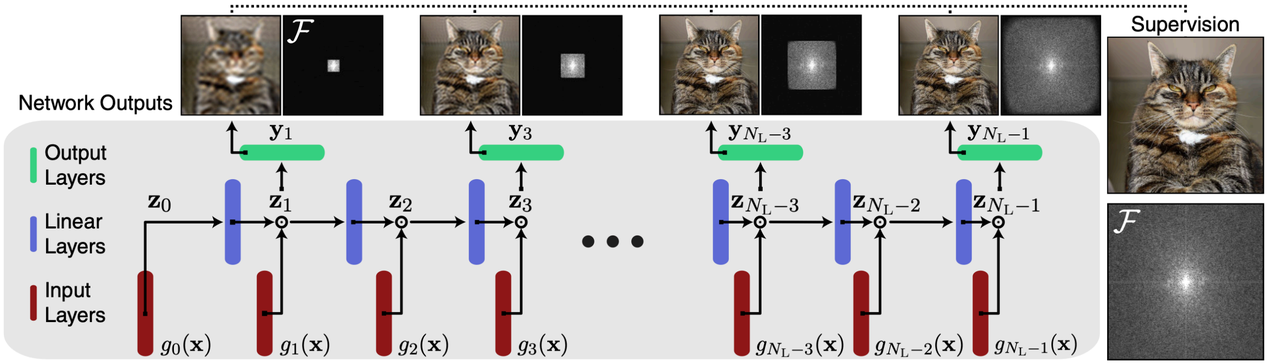
Chng et al. ECCV 2022

Neural (?) Fields with analytical (but not tractably computable) Fourier spectrum!

Multiplicative Filter Networks
Fathony et al. ICLR 2021



BACON: Band-limited coordinate networks for multiscale scene representation
Lindell et al. CVPR 2022



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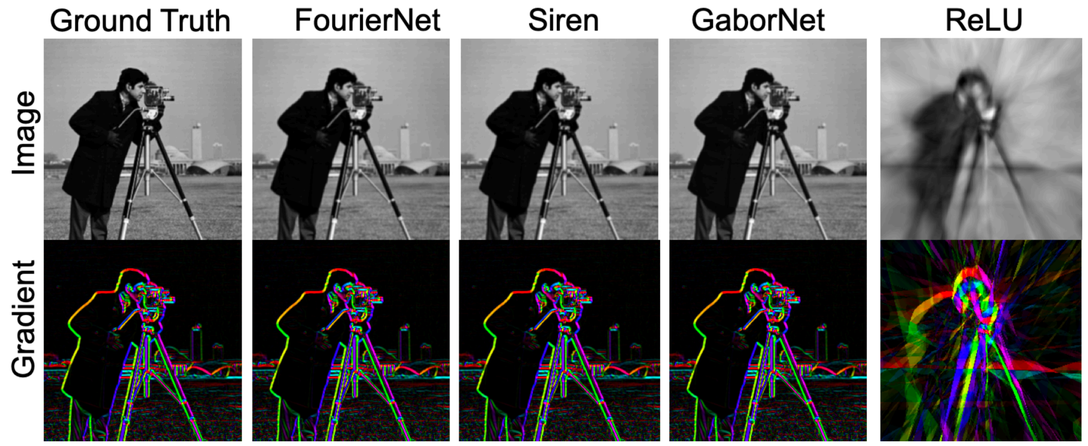

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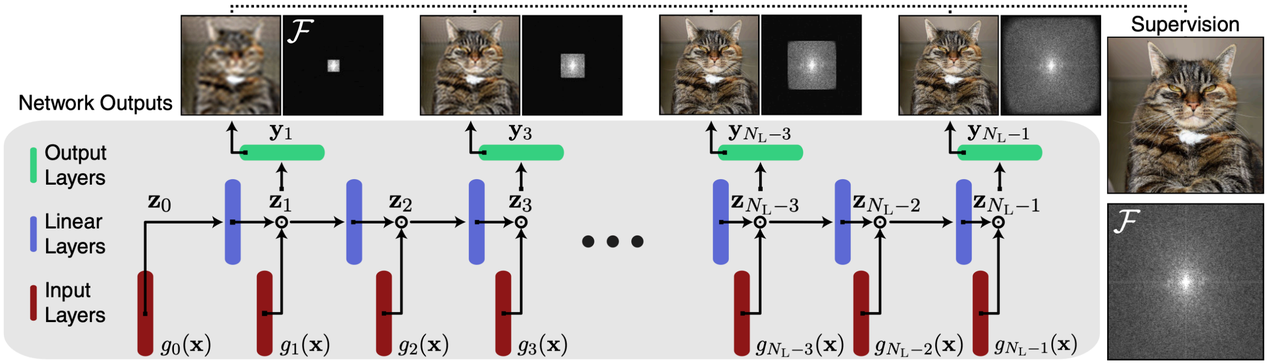

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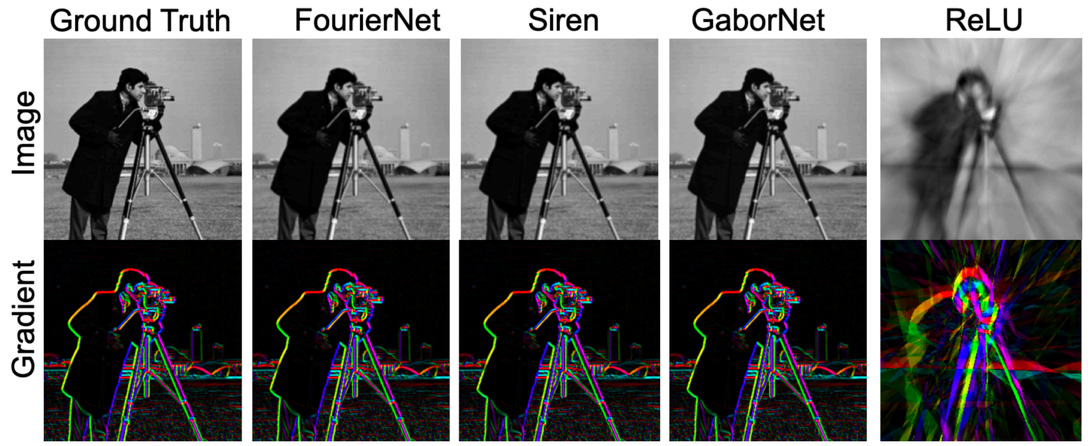

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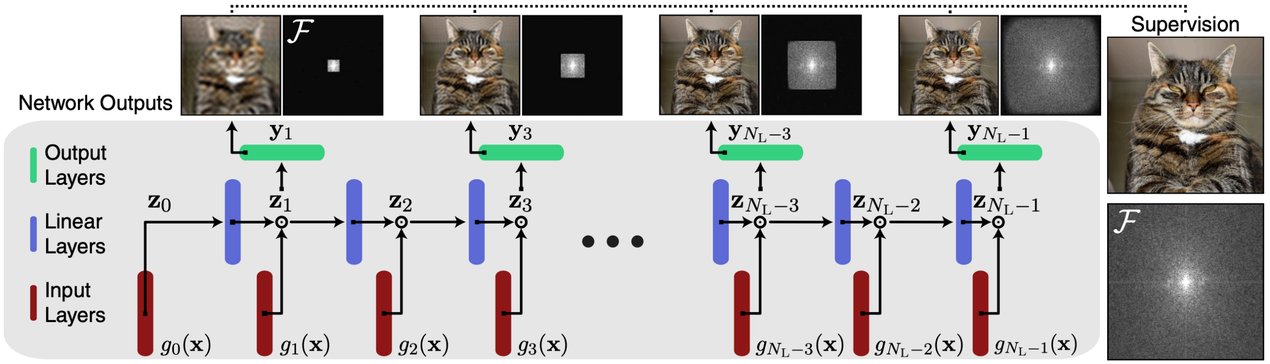


EUROGRAPHICS 2022
D. Meneveaux and G. Patanè
(Guest Editors)

Volume 41 (2022), Number 2
STAR – State of The Art Report

Neural Fields in Visual Computing and Beyond

Yiheng Xie[1,2] Towaki Takikawa[3,4] Shunsuke Saito[5] Or Litany[4] Shiqin Yan[1] Numair Khan[1] Federico Tombari[6,7]
James Tompkin[1] Vincent Sitzmann[8†] Srinath Sridhar[1†]

[1]Brown University [2]Unity Technologies [3]University of Toronto [4]NVIDIA [5]Meta Reality Labs Research [6]Google [7]Technical University of Munich
[8]Massachusetts Institute of Technology [†]*Equal advising*

https://neuralfields.cs.brown.edu/

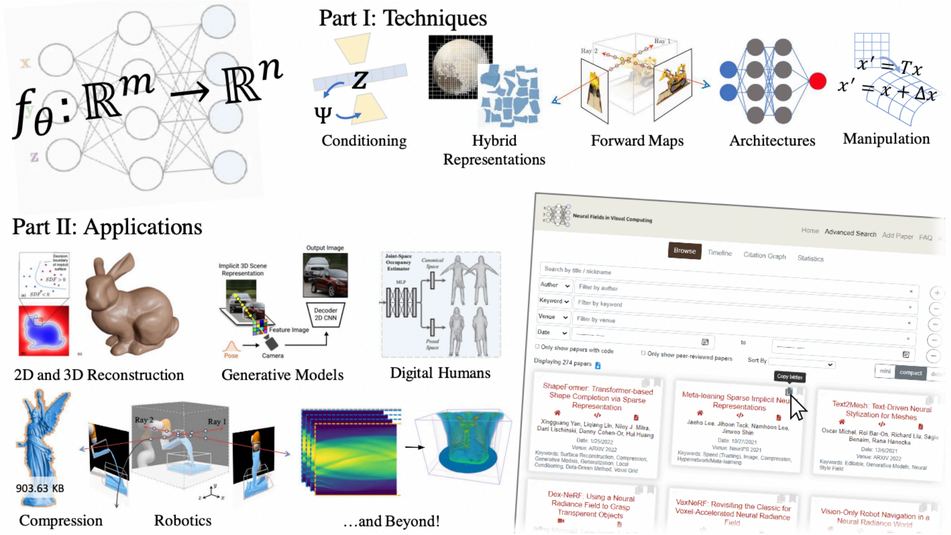
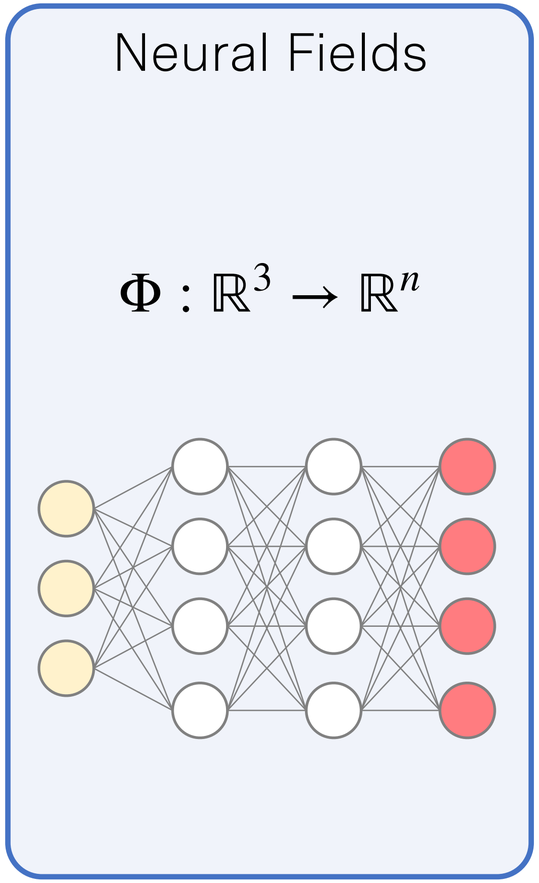


Figure 1: **Contribution of this report.** Following a survey of over 250 papers, we provide a review of (**Part I**) techniques in neural fields such as prior learning and conditioning, representations, forward maps, architectures, and manipulation, and of (**Part II**) applications in visual computing including 2D image processing, 3D scene reconstruction, generative modeling, digital humans, compression, robotics, and beyond. This report is complemented by a community-driven website with search, filtering, bibliographic, and visualization features.

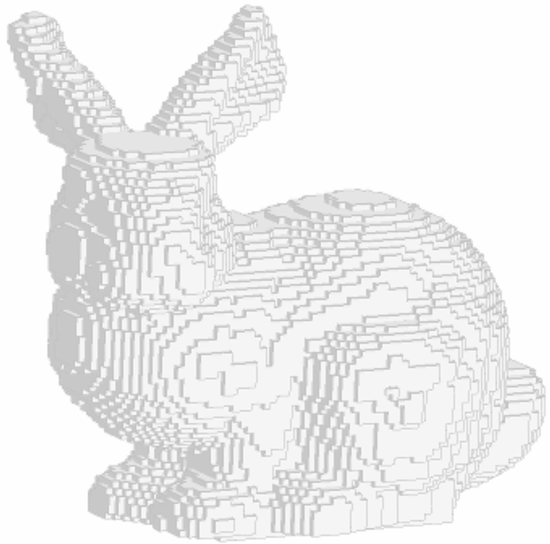
Neural Fields

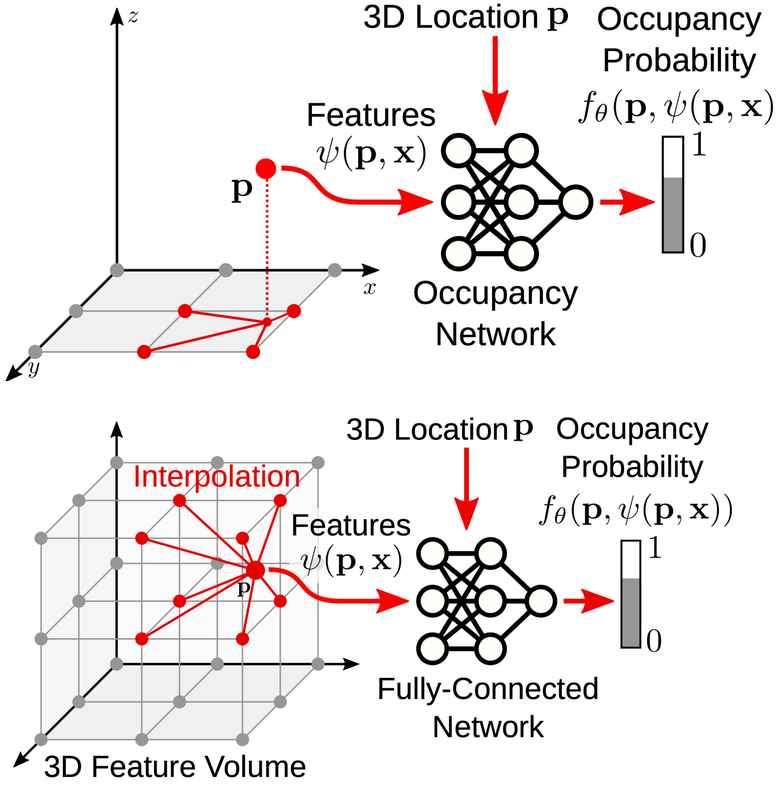
- Storage memory **does not grow with spatial resolution or number of spatial dimensions**.
- **Slow** sampling: Each query takes a forward pass through the neural net. Means GPU-memory intensive forward passes.
- Does **not** expose locality: Can't identify set of parameters / direction in parameter space that encodes particular spatial location.
- **Inconvenient processing**: cannot run convolutions.
- But: automatic adaptive resolution. Over optimization, will converge to assign more compute to higher-frequency areas.



Note: Despite their name, has nothing to do with Machine Learning itself.
It's as "smart" as a voxelgrid.

Hybrid discrete / continuous reps



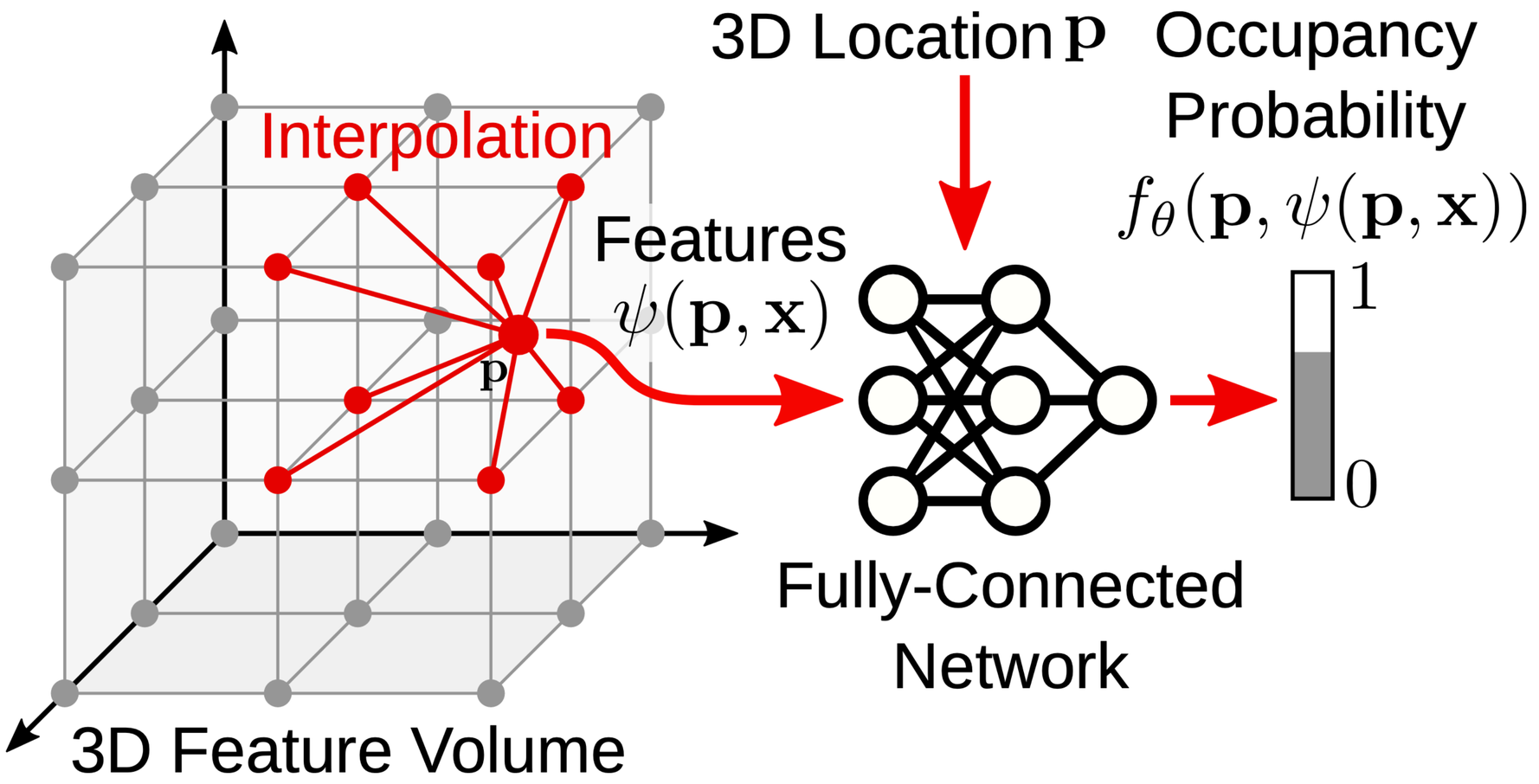


Discrete Parameterizations

Continuous Parameterizations

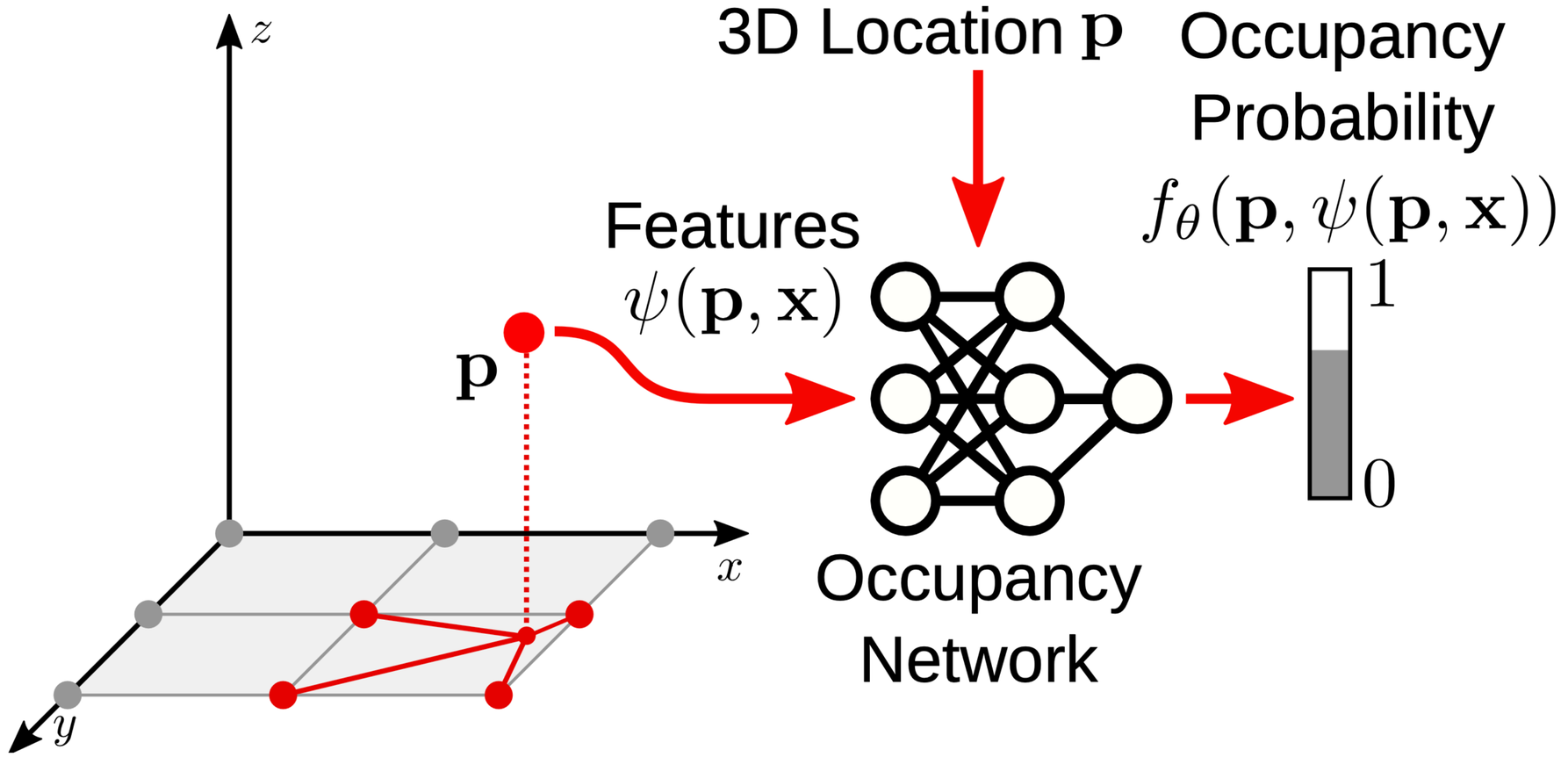
Hybrid Parameterizations

Basic idea: Use Neural Net as Interpolation Kernel



Convolutional Occupancy Networks [Peng et al. 2020]
Local Implicit Grid Representations for 3D Scenes [Jiang et al. 2020]
Implicit Functions in Feature Space for 3D Shape Reconstruction and Completion [Chibane et al. 2020]
Deep Local Shapes: Learning Local SDF Priors for Detailed 3D Reconstruction [Chabra et al. 2020]

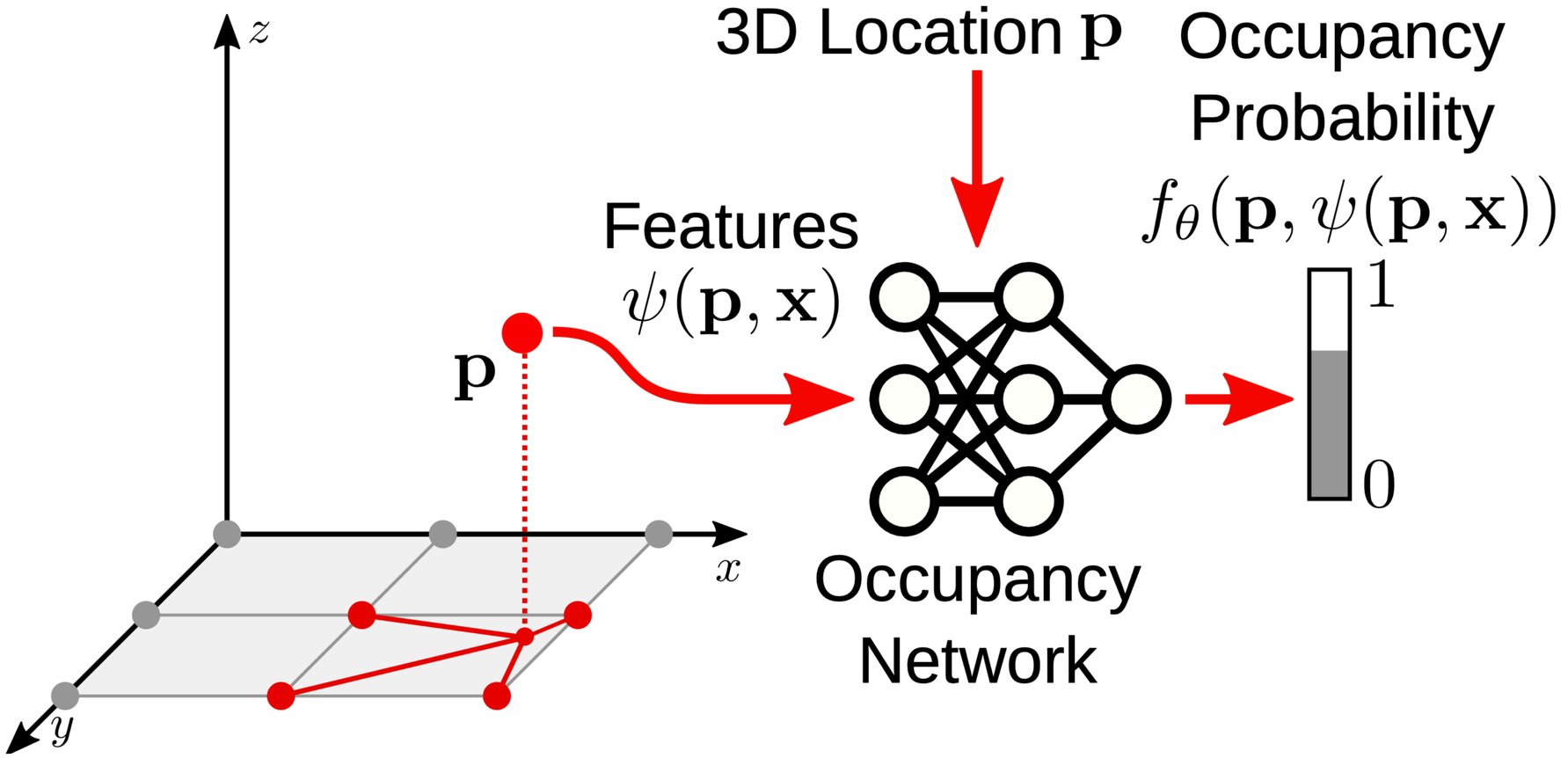
Ground plan & Orthographic Projection



Any assumptions made on scene? Any limitations?

Convolutional Occupancy Networks [Peng et al. 2020]

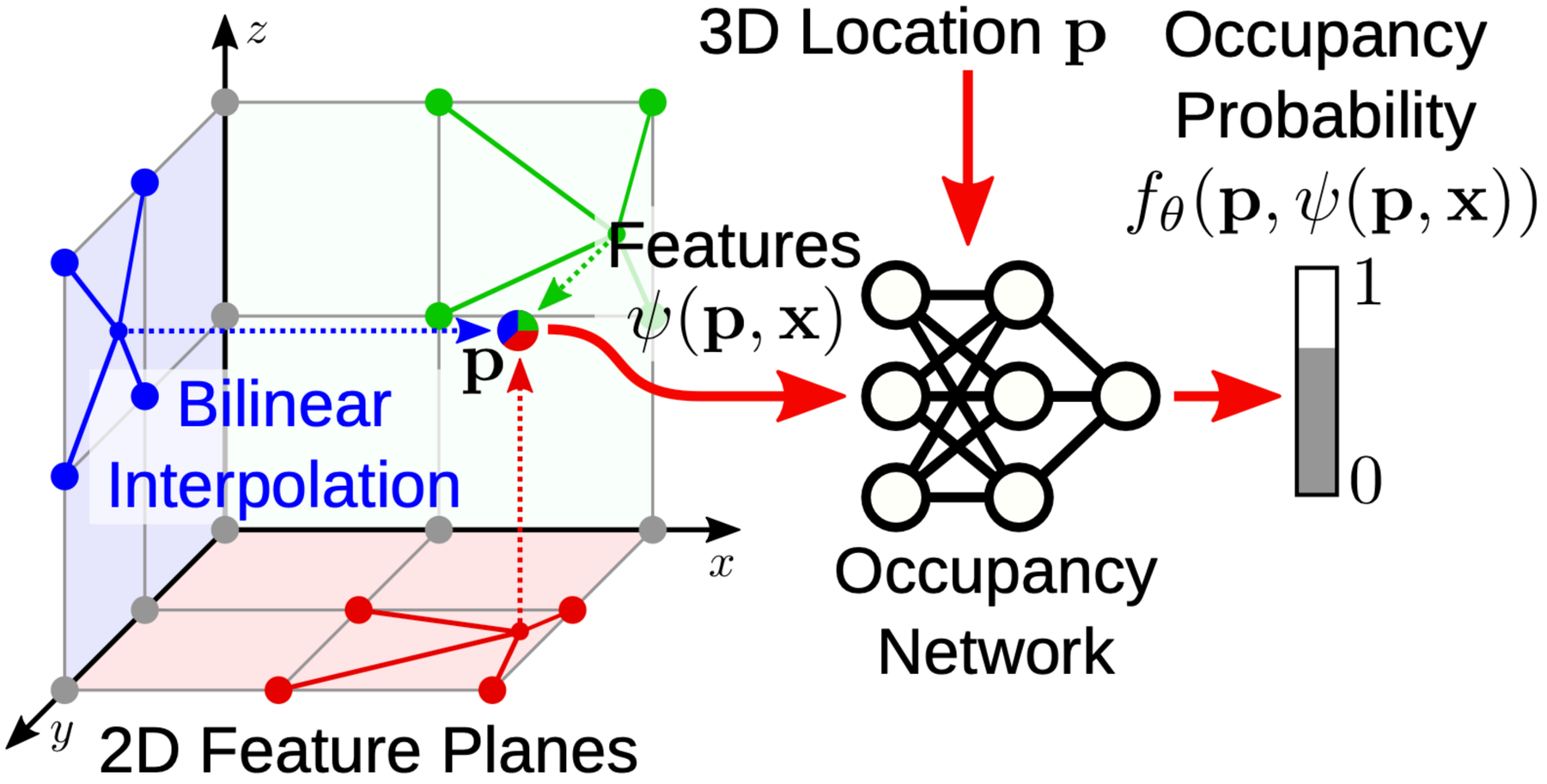
Ground plan & Orthographic Projection



No. You can still represent *any scene* - some info stored in NN, some in grid.

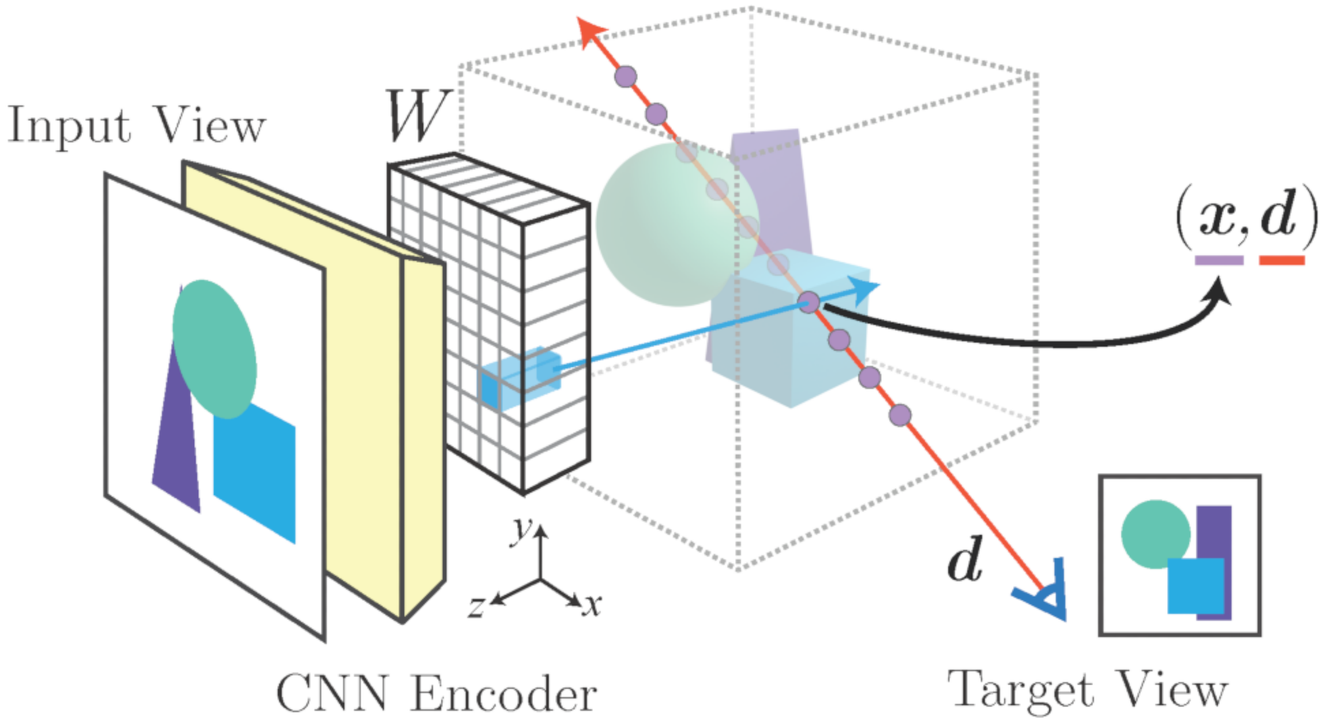
Convolutional Occupancy Networks [Peng et al. 2020]

Tri-Planes and Orthographic Projection



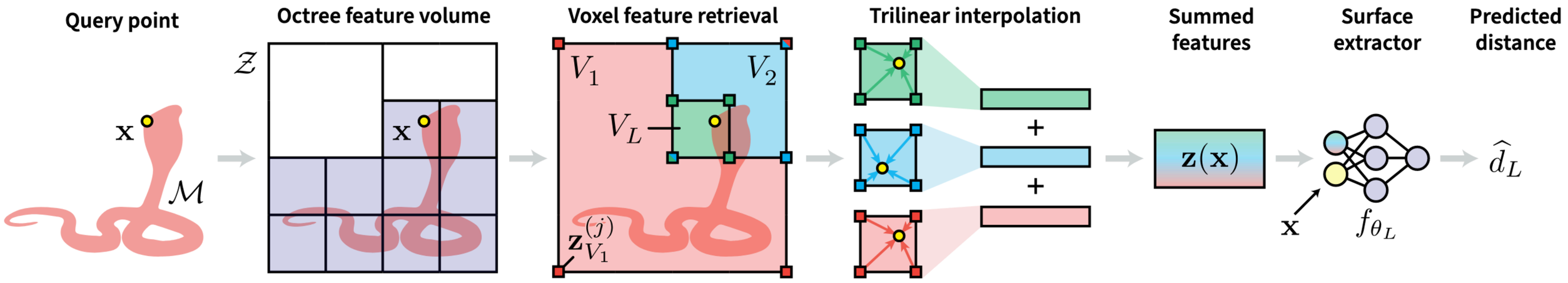
Convolutional Occupancy Networks [Peng et al. 2020]

Image Grids & Perspective Projection



PixelNeRF (Yu et al. 2020)

Multi-scale Voxel Grids



Neural Geometric Level of Detail: Real-time Rendering with Implicit 3D Shapes, Takikawa, Litalien et al. 2021

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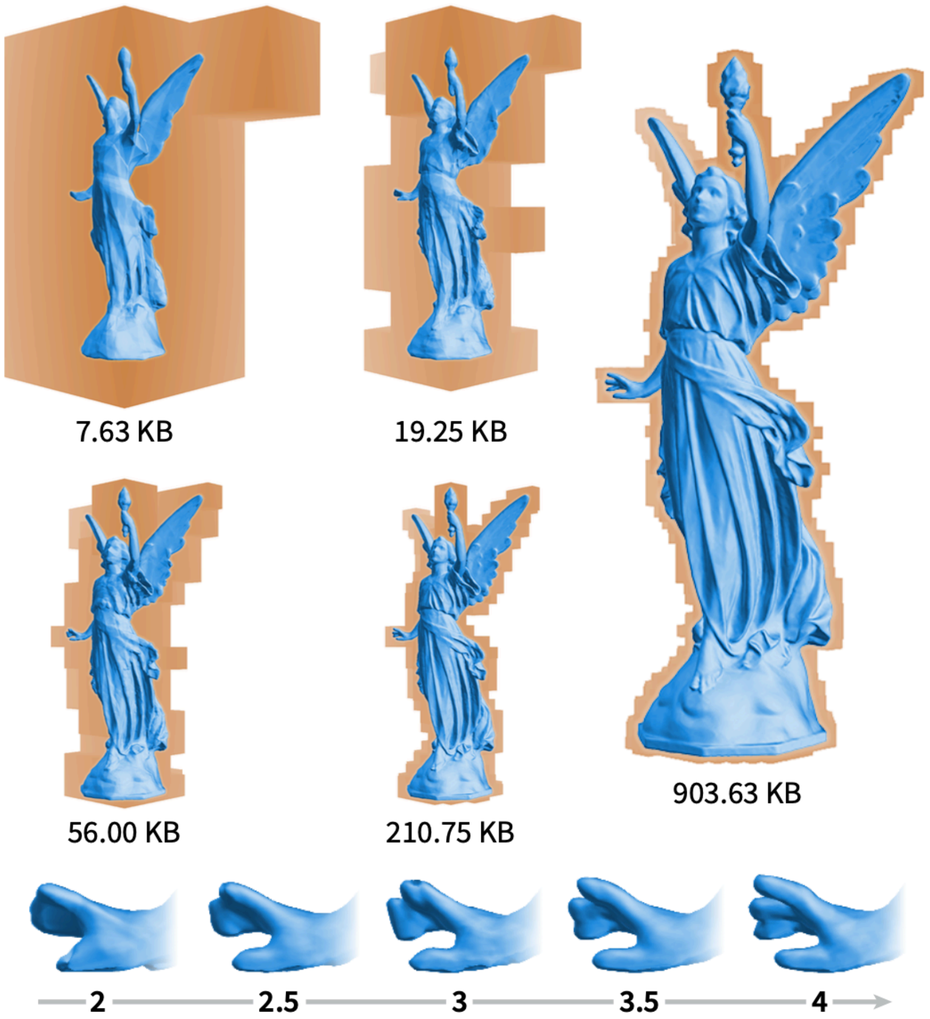

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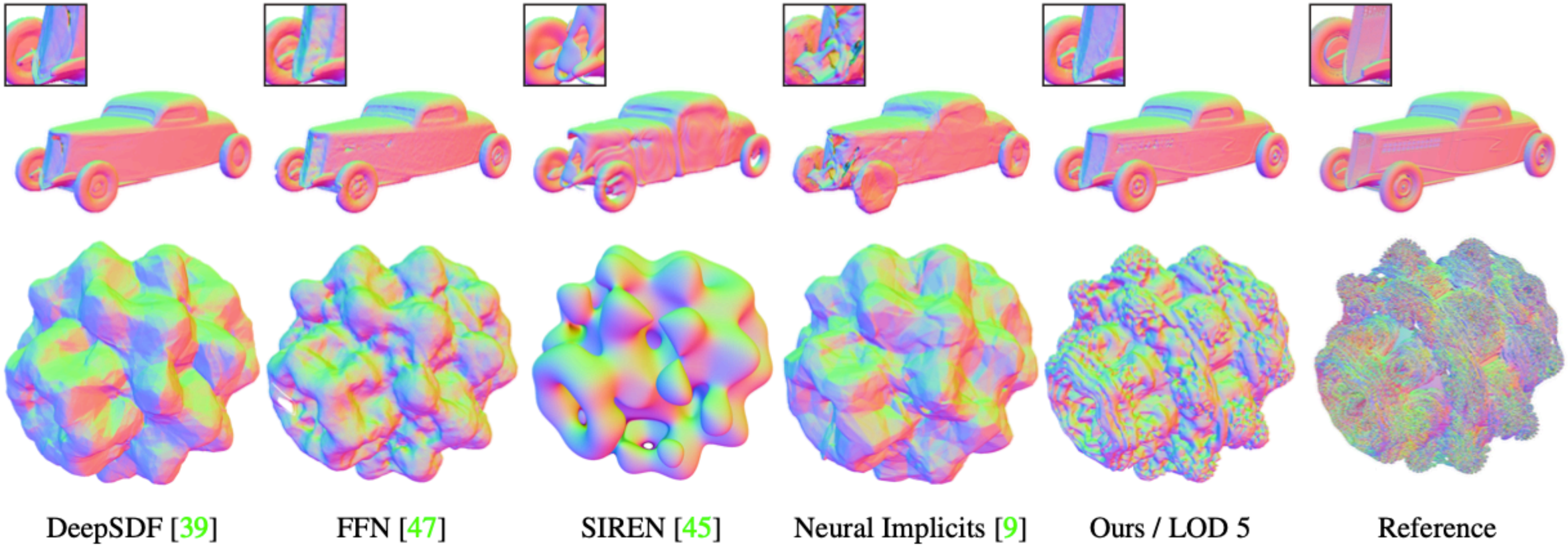
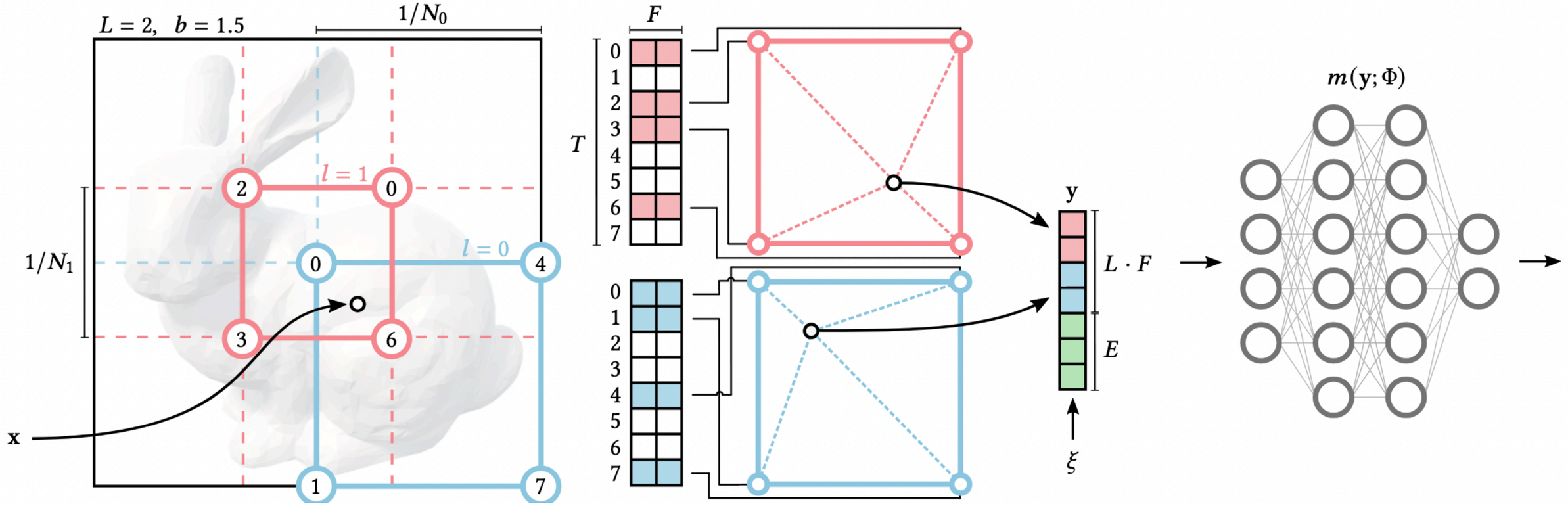


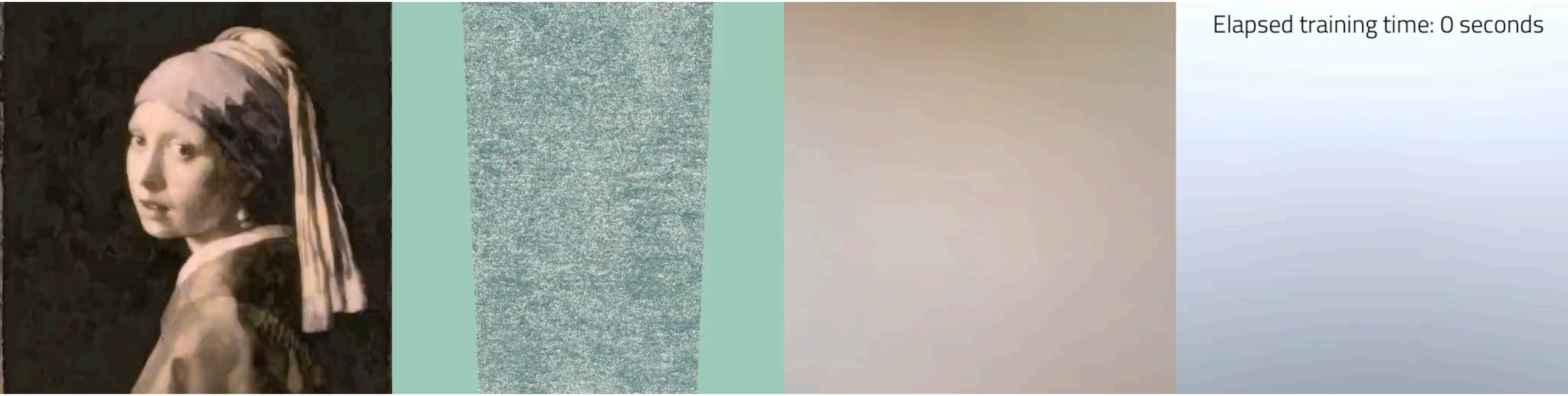
Neural Geometric Level of Detail: Real-time Rendering with Implicit 3D Shapes, Takikawa, Litalien et al. 2021

Multi-scale Voxel Grids + Hash Table



Instant Neural Graphics Primitives with a Multiresolution Hash Encoding, Müller et al. 2022

Multi-scale Voxel Grids + Hash Table



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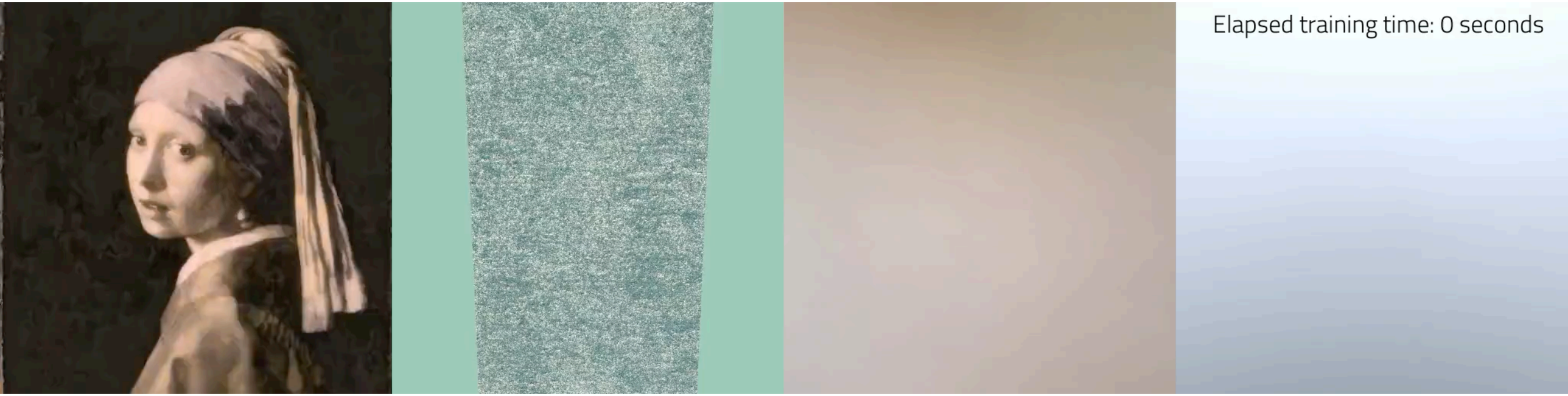
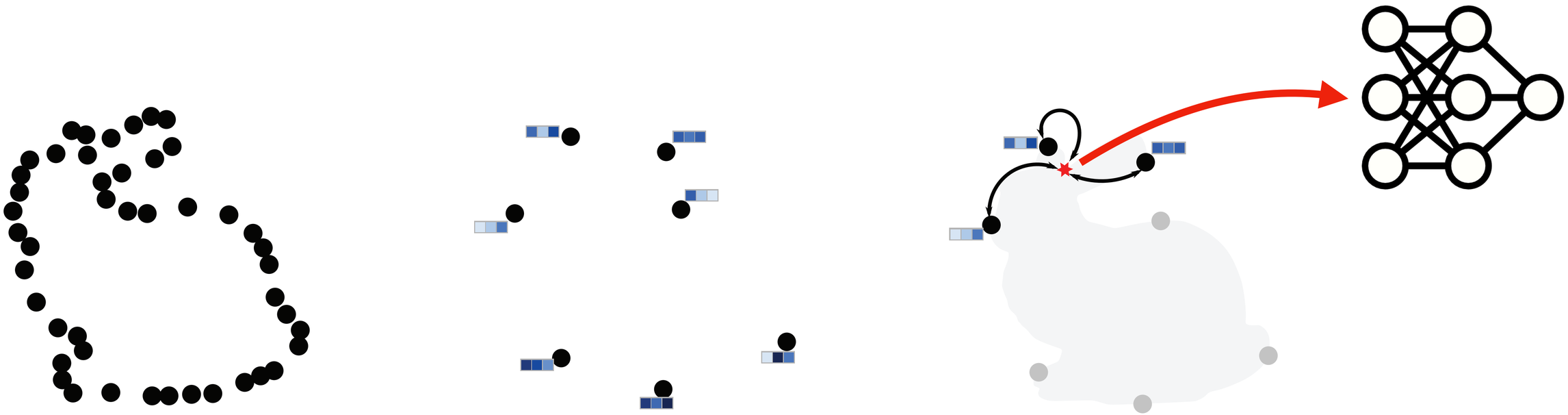


Instant Neural Graphics Primitives with a Multiresolution Hash Encoding, Müller et al. 2022

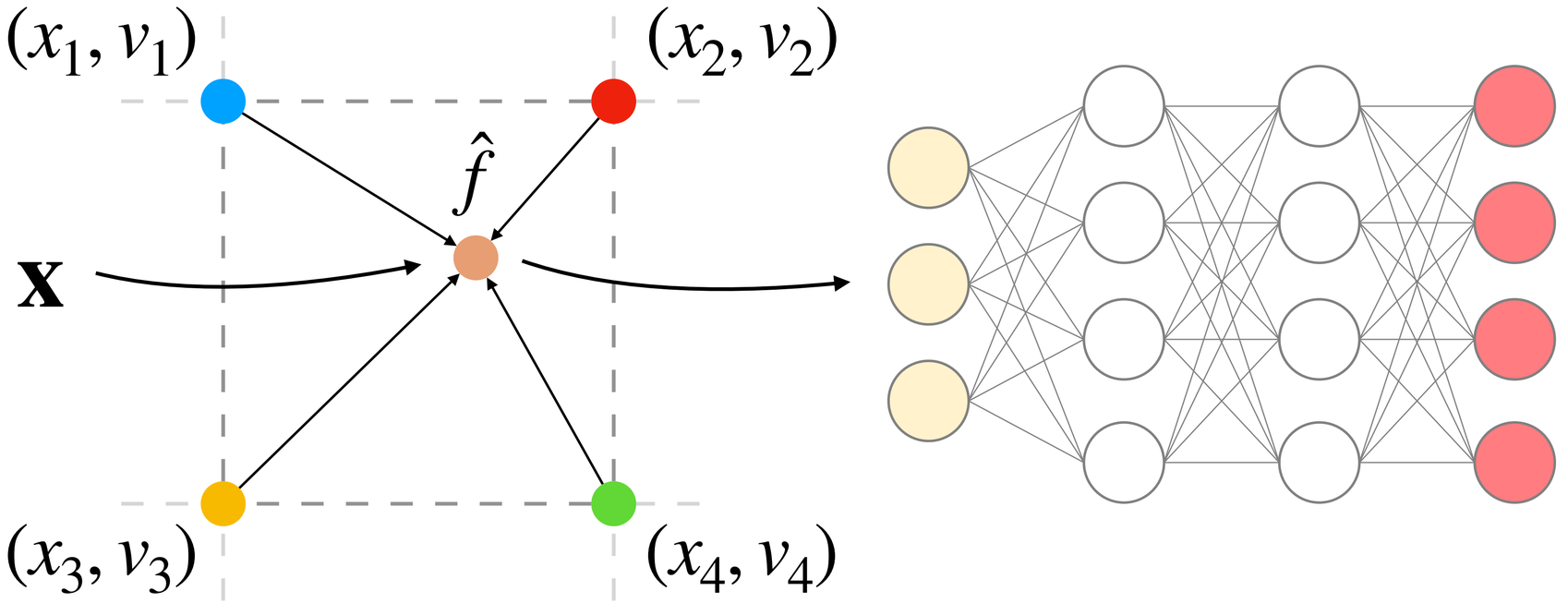
Point Cloud & Nearest Neighbor



Hybrid representations can be used to decode a surface representation into a volume representation!

AirNet (Giebenhain et al. 2021)

ReLU Fields: How much MLP do you need?



ReLU Fields: The Little Non-linearity That Could (Karnewar et al. 2022)

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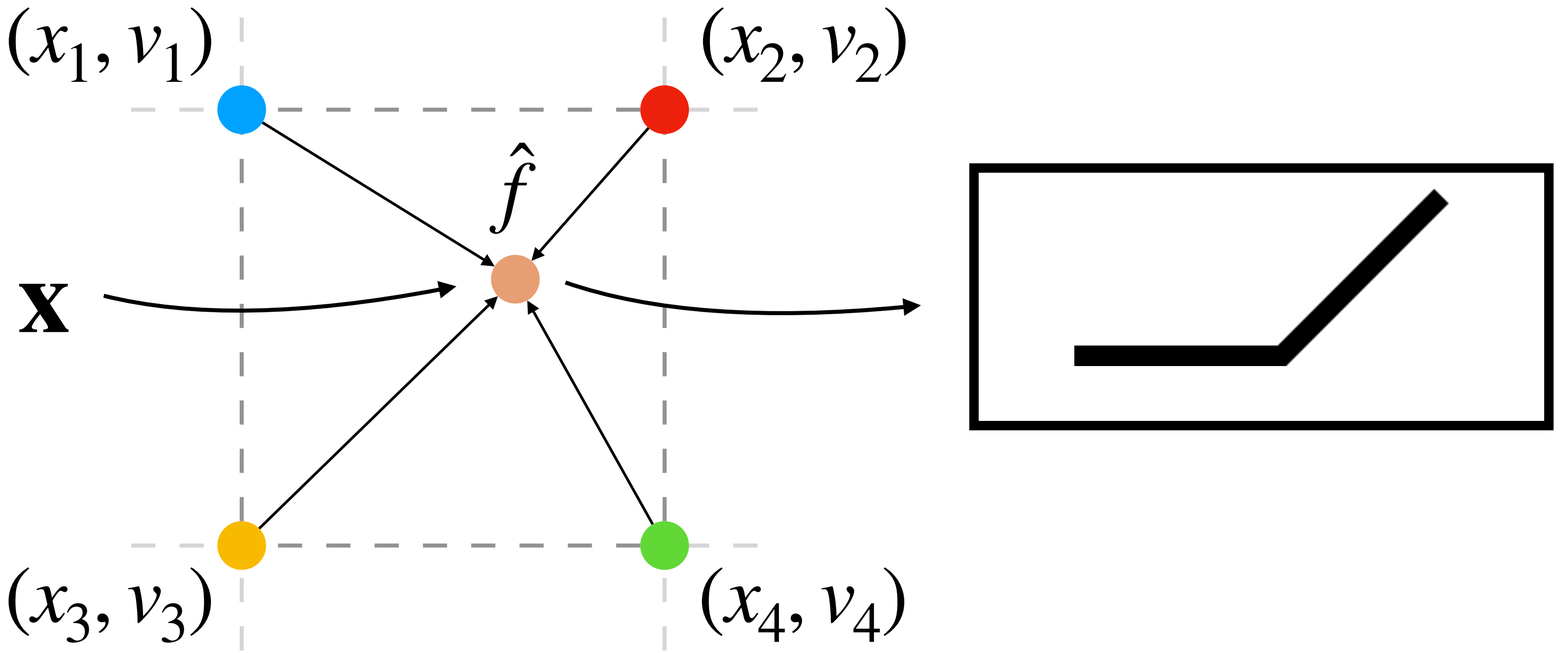

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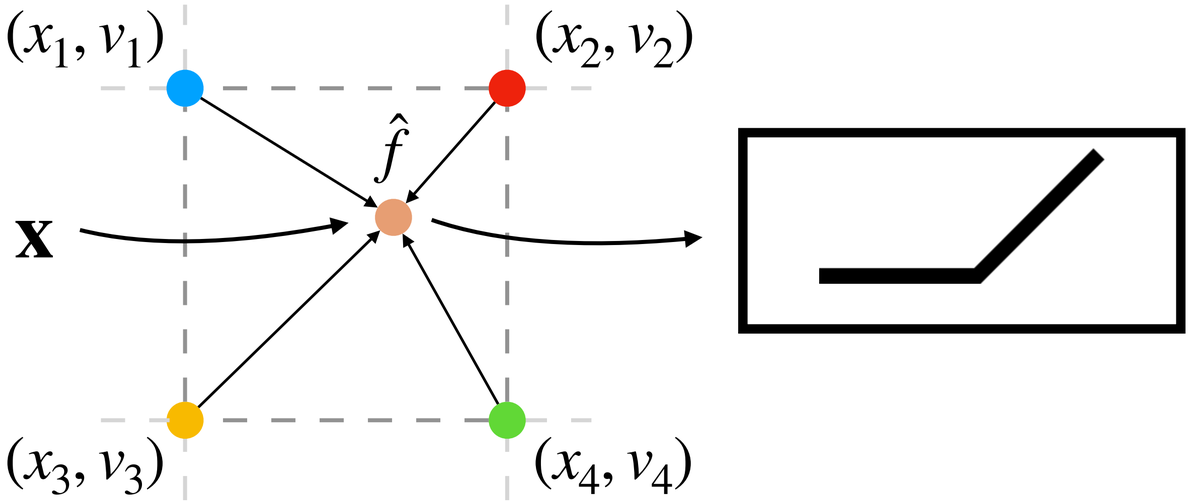

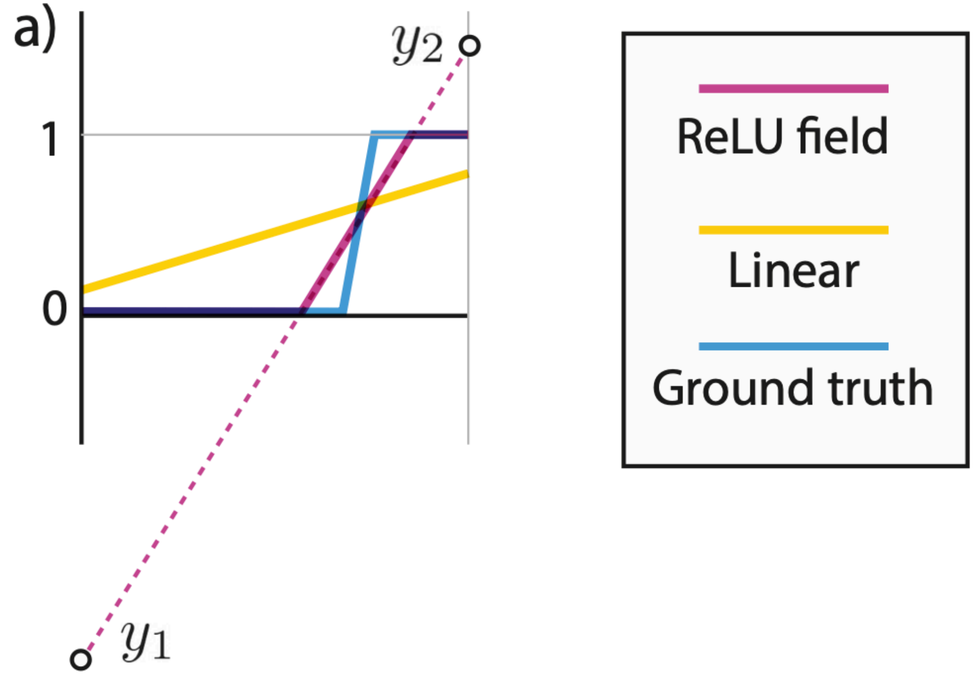

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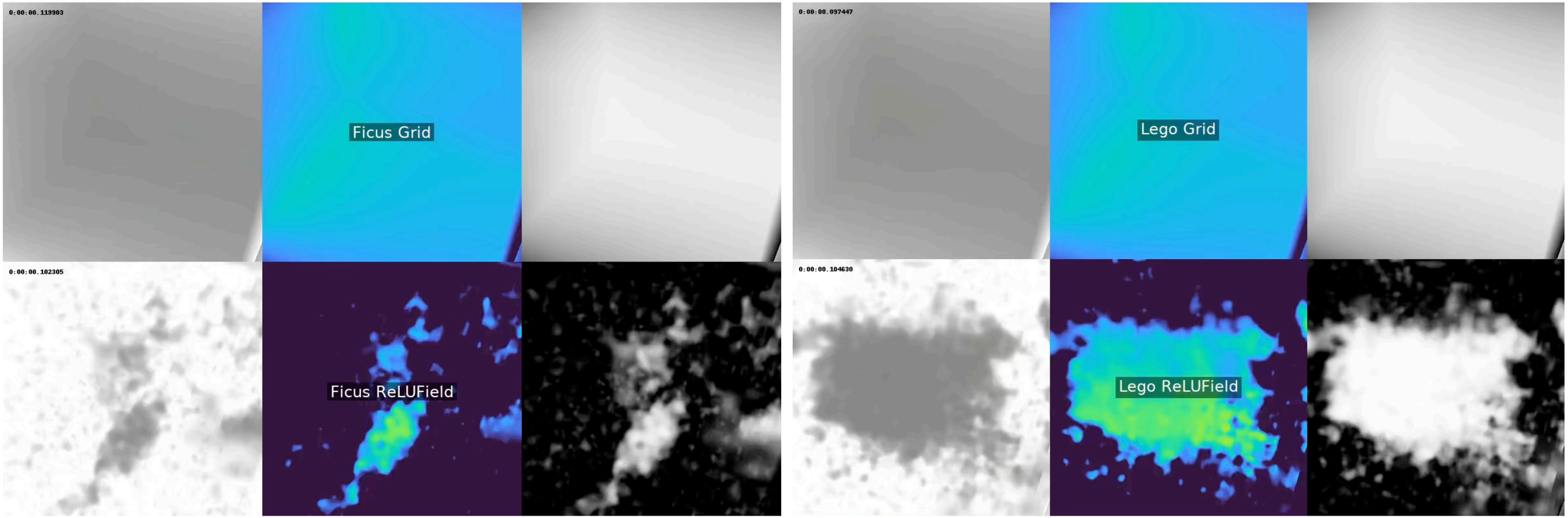

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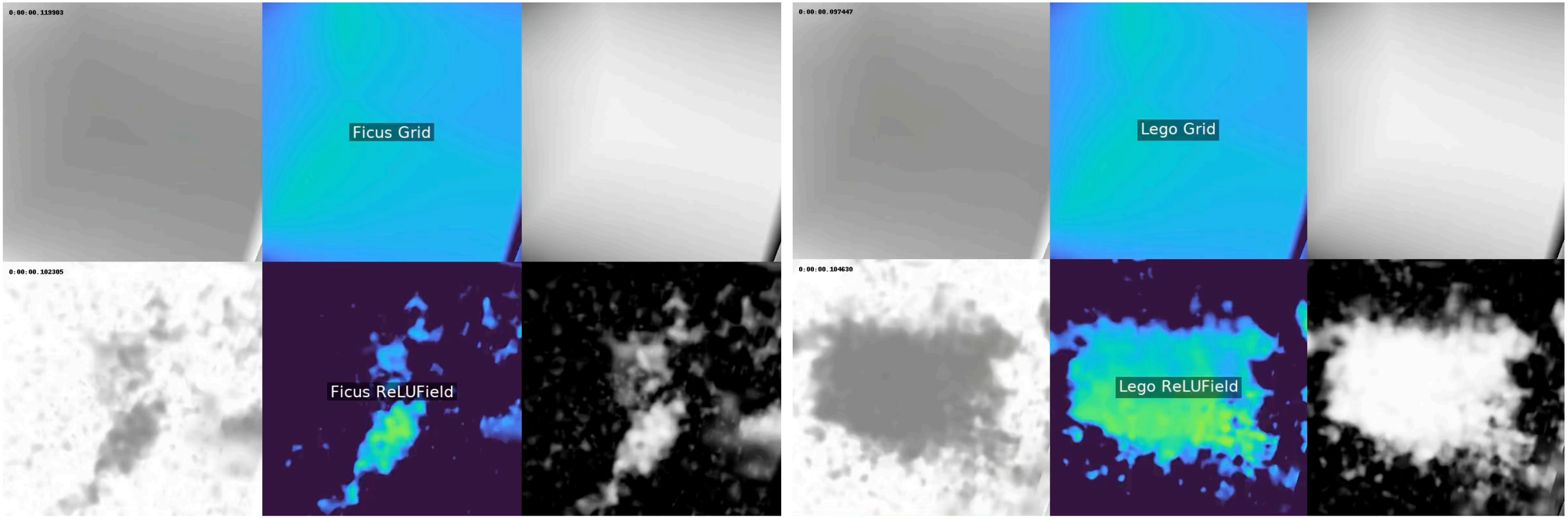

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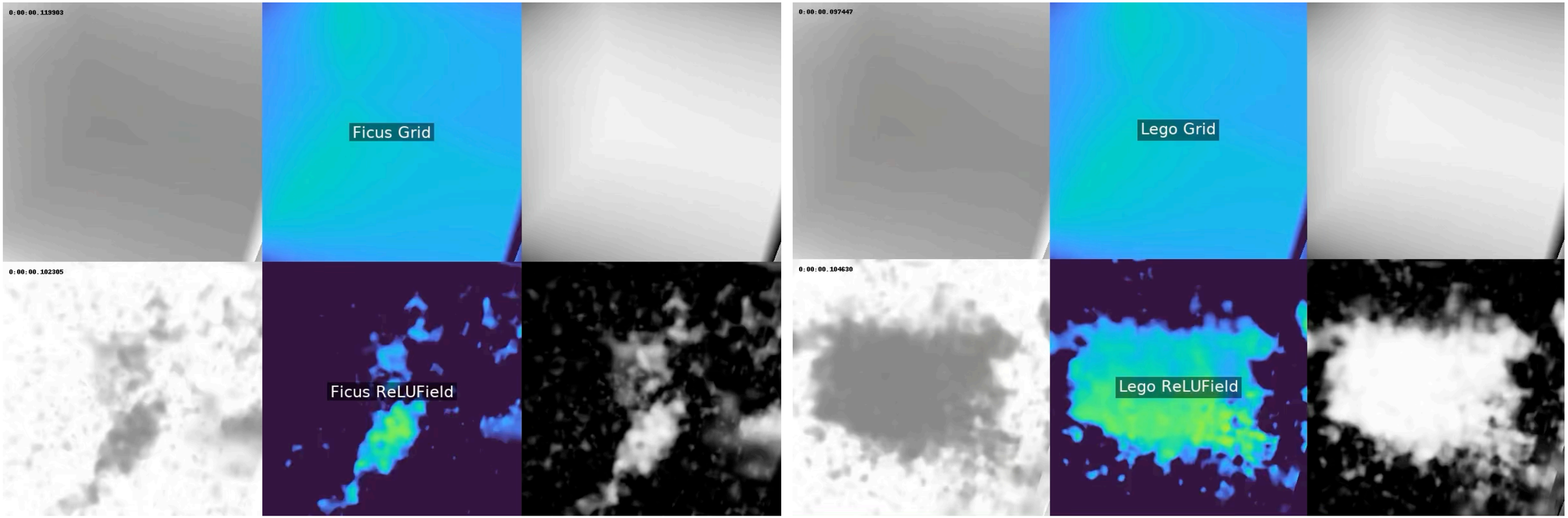
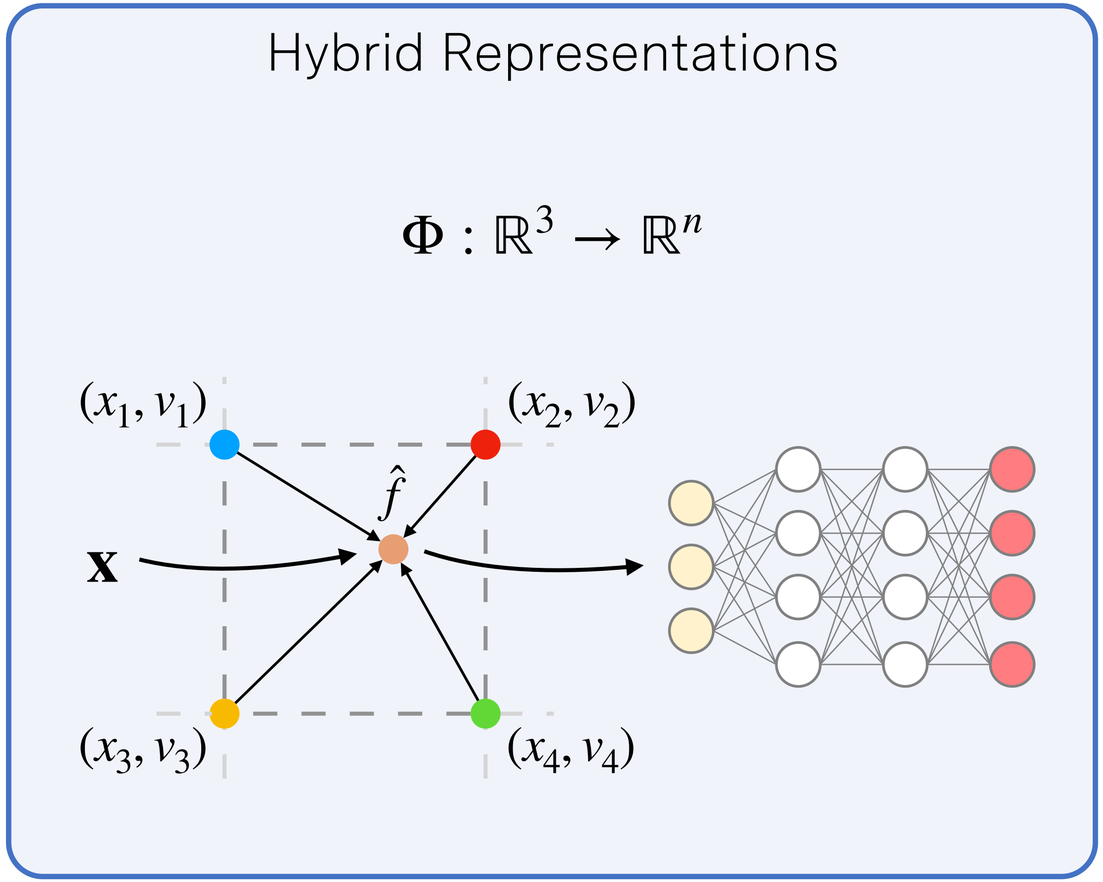


ReLU Fields: The Little Non-linearity That Could (Karnewar et al. 2022)

Hybrid Representations

- Very natural to trade off memory with compute.
- Neural network can locally “super resolve” discrete representation: Basically acts as interpolation kernel.
- Can be the best of both worlds: Fast and “continuous”.



How can we represent unbounded scenes?

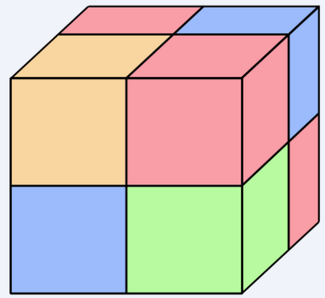
Image Source: Wikipedia

How can we represent unbounded scenes?

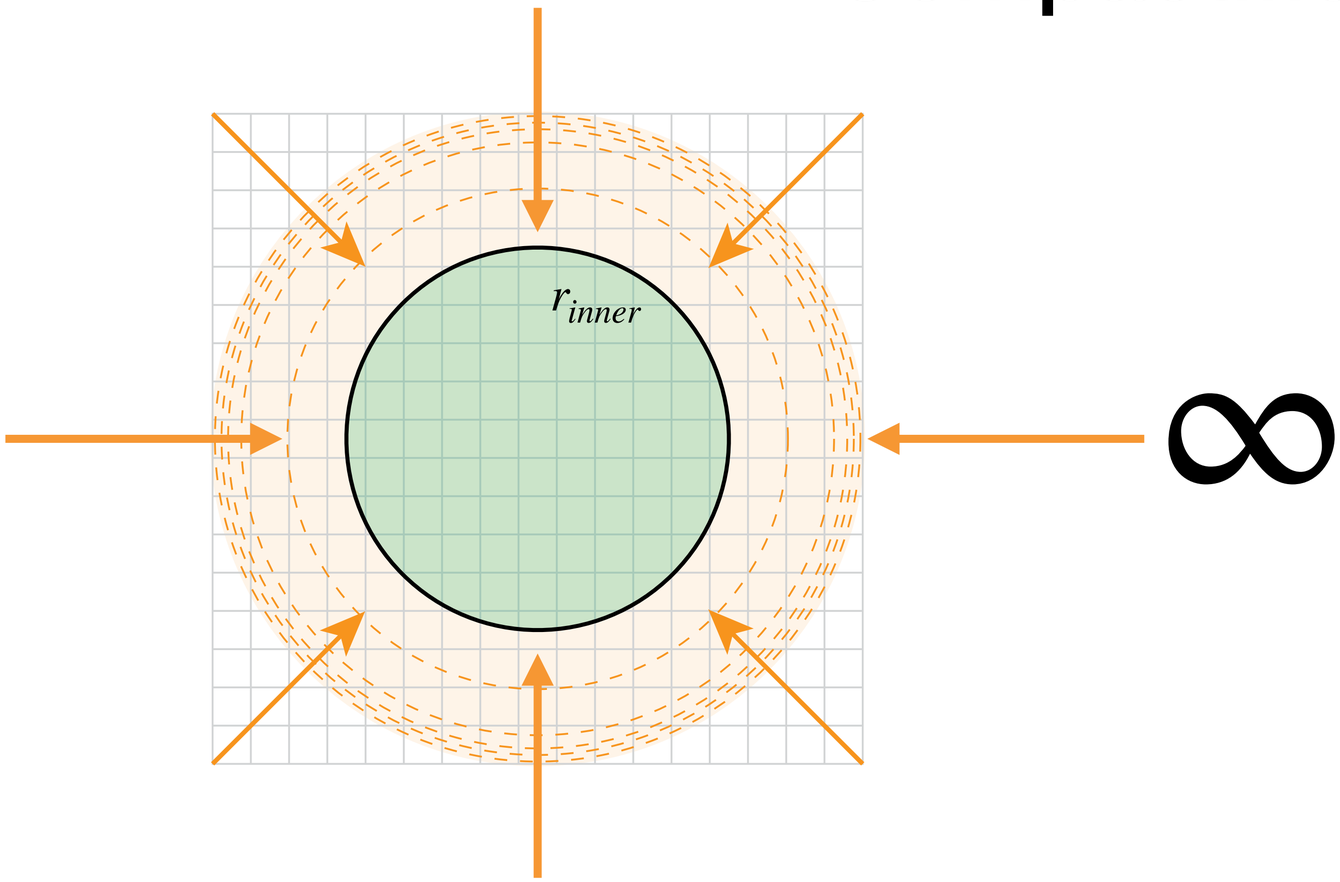
Image Source: Wikipedia

Scene Representation

$$\Phi : \mathbb{R}^3 \rightarrow \mathbb{R}^n$$

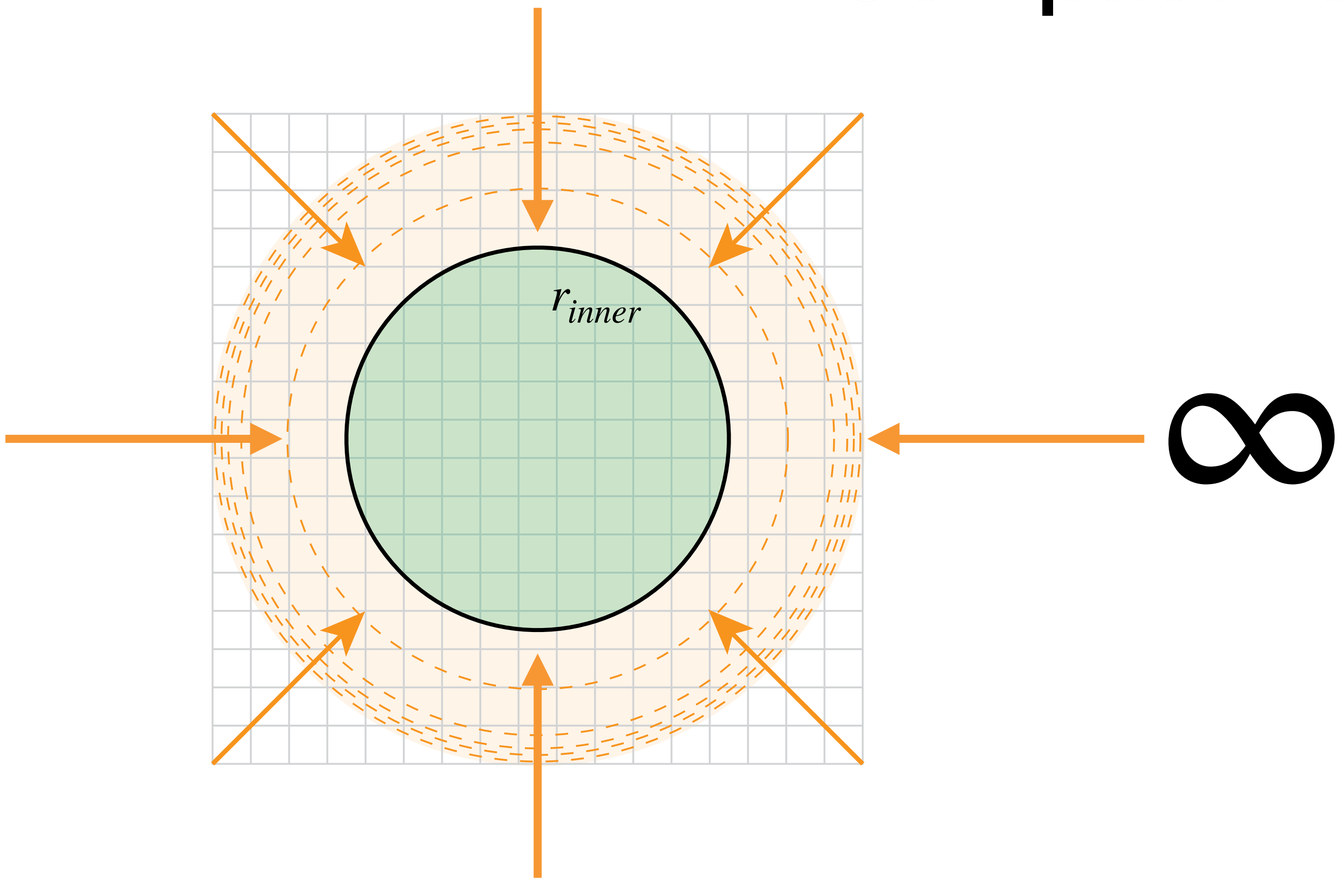


Parameterizing Unbounded Scenes: Compactification



Come up with nonlinear mapping that “squashes” space, such that infinity is mapped to some **finite** value. Aligns with intuition “further away, less resolution”.

Parameterizing Unbounded Scenes: Compactification



$$\mathbf{x}' = \frac{(1+k) - k/||\mathbf{u}||}{\mathbf{u}/||\mathbf{u}||} r_{inner}$$

$$\mathbf{u} = \frac{\mathbf{x}}{r_{inner}}$$

Example Compactification function from "Mip-NeRF 360: Unbounded Anti-Aliased Neural Radiance Fields", Barron et al., CVPR 2022

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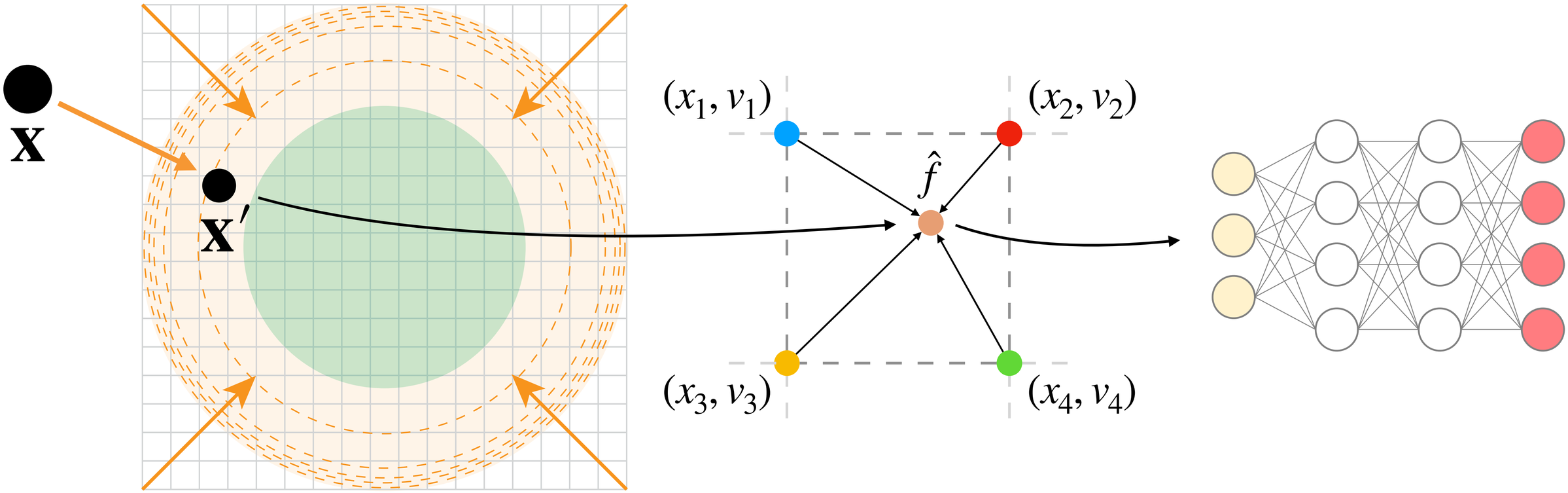
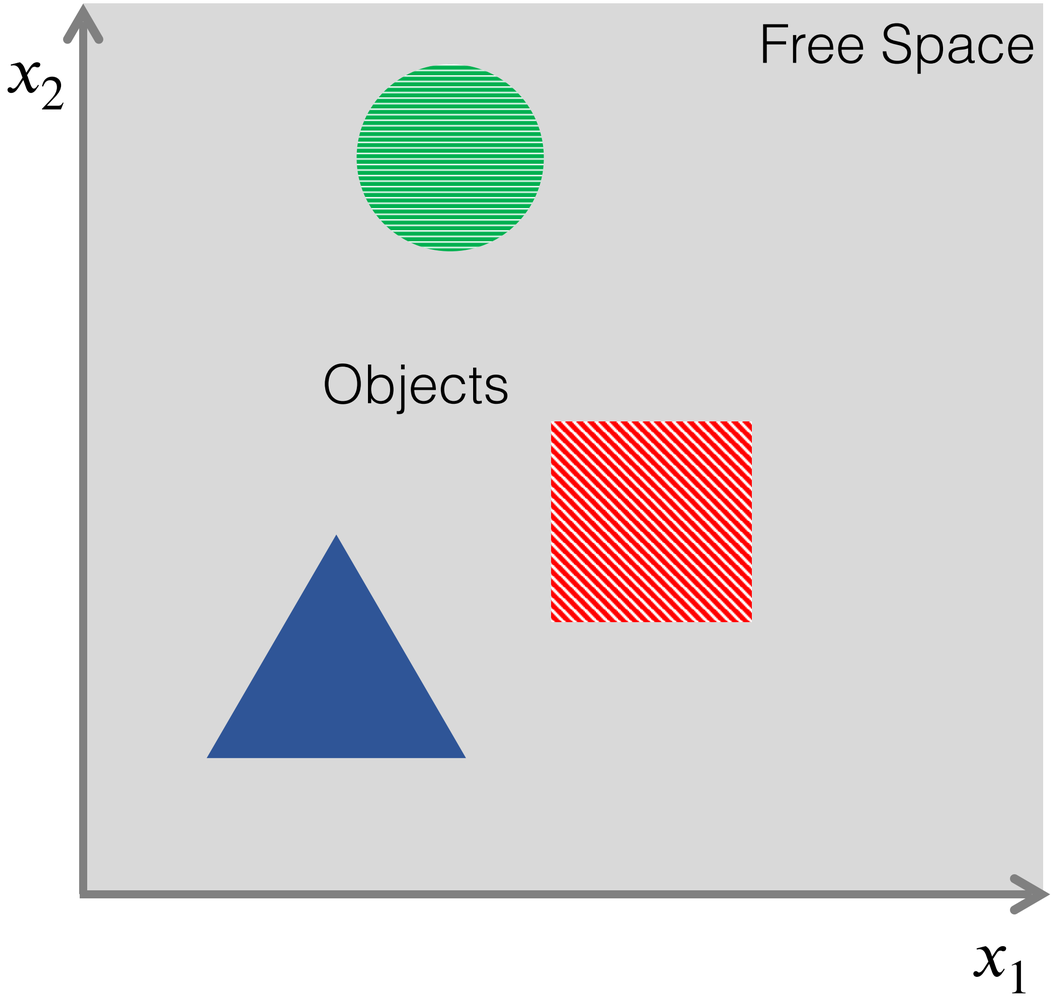
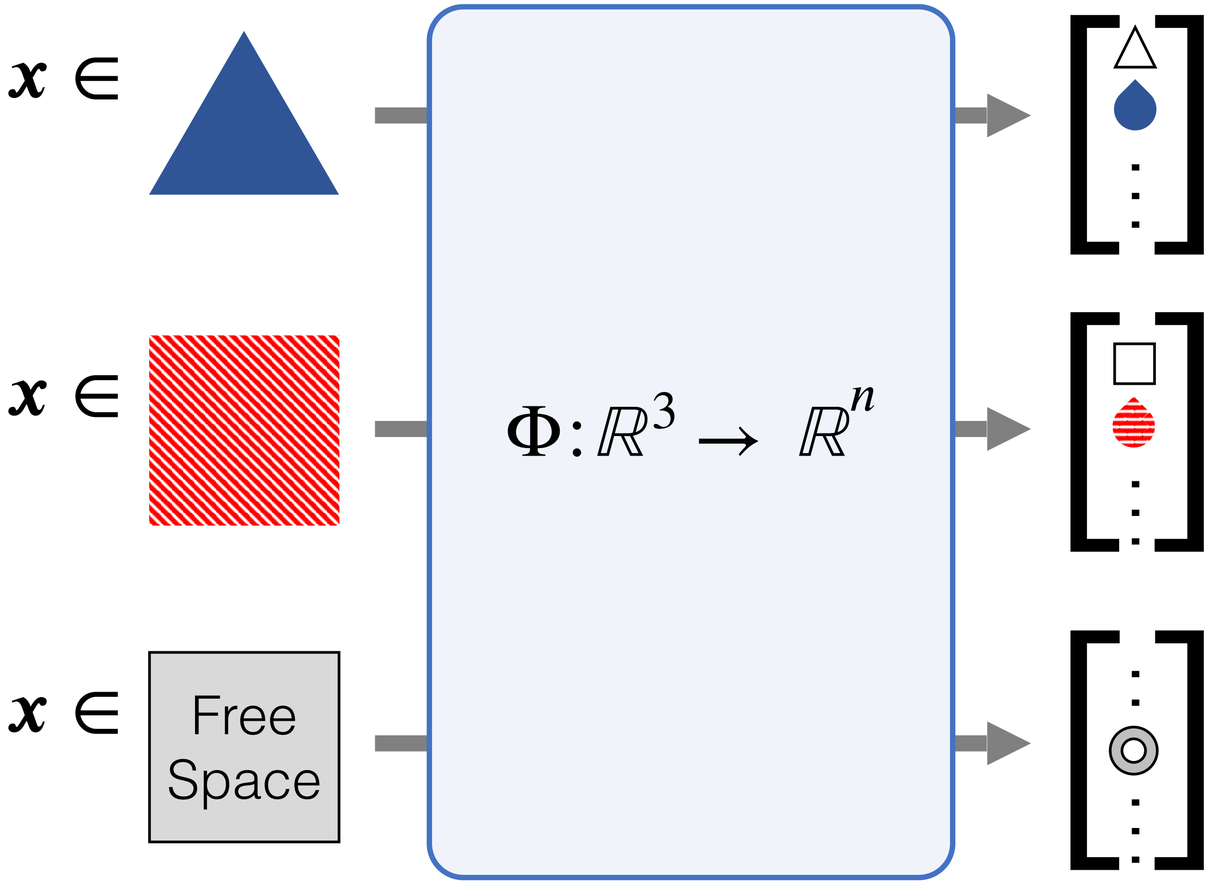
Parameterizing Unbounded Scenes: Compactification

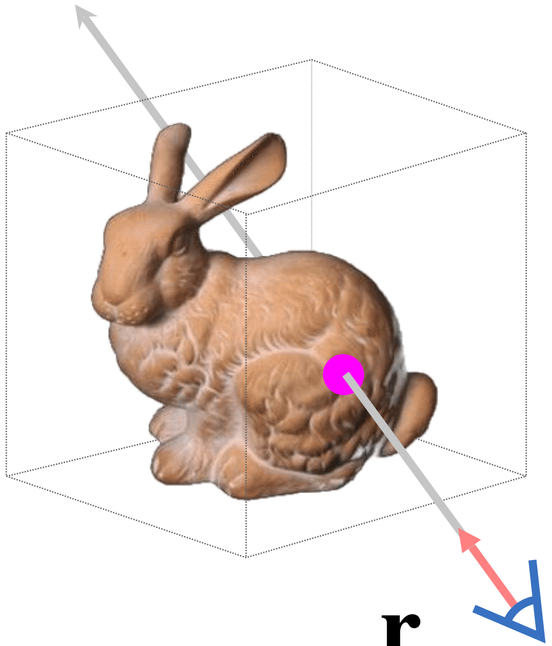


Do we have to parameterize 3D Scene as 3D Function?



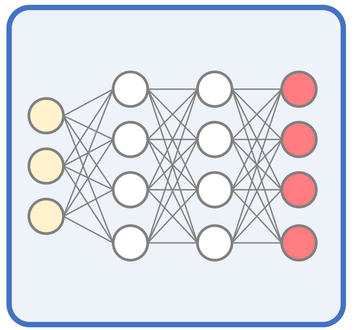


3D-structured Representation



$\mathbf{r}$

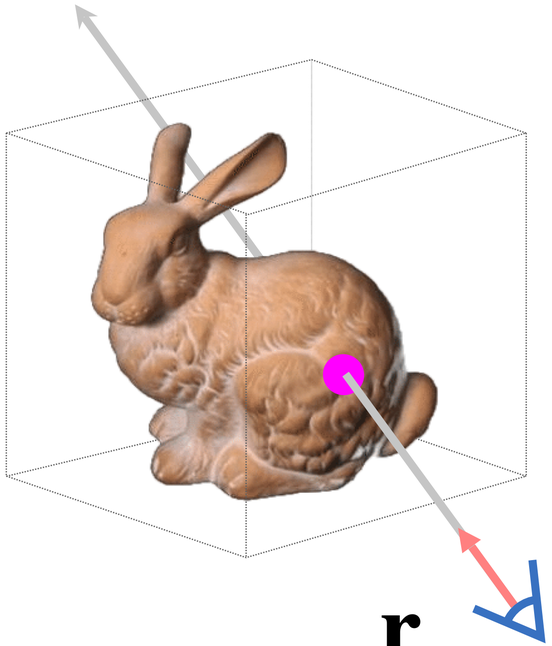
Camera Ray



$\Phi^{3D} : \mathbb{R}^3 \rightarrow \mathbb{R}^n$

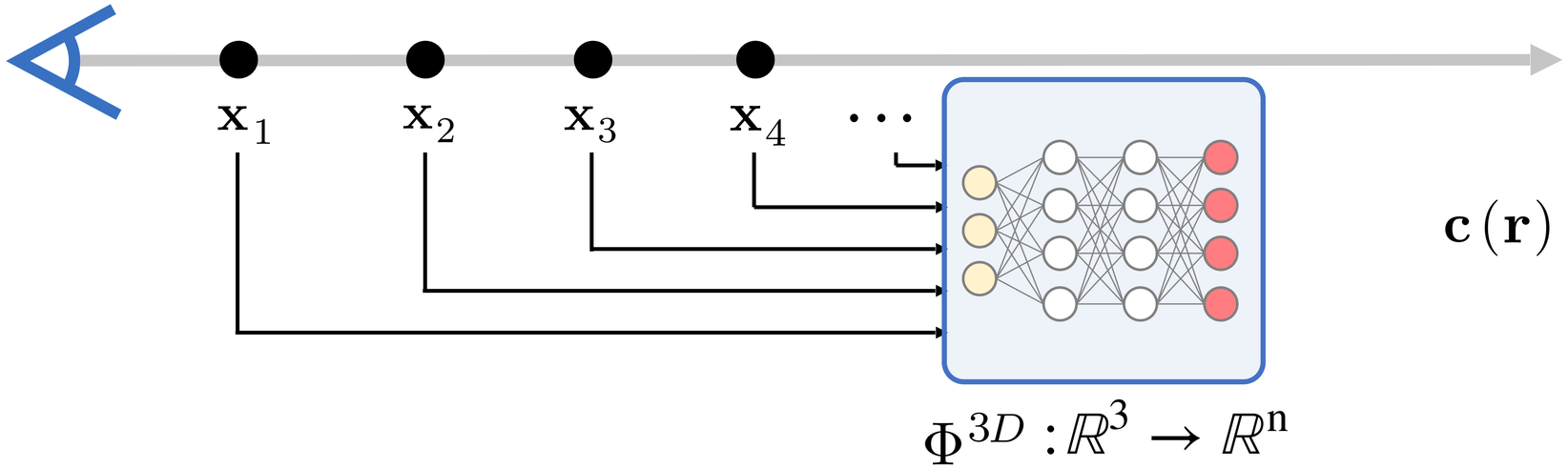
$\mathbf{c}(\mathbf{r}) =$ 

3D-structured Representation

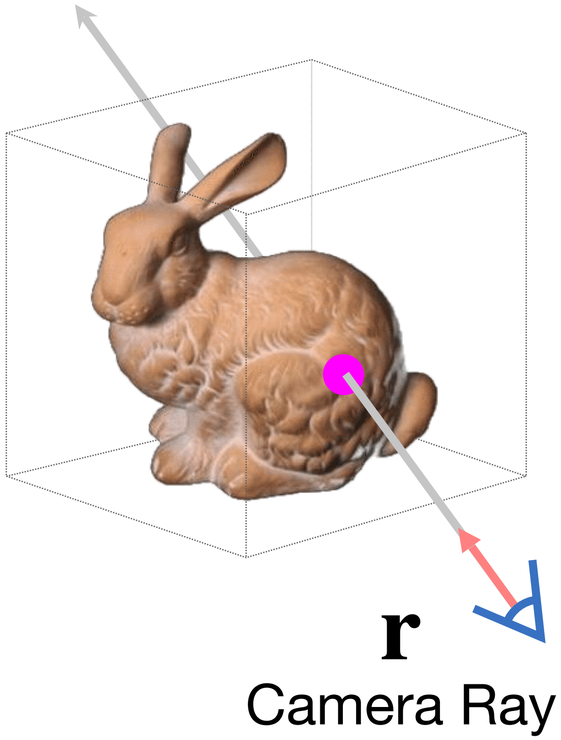


$\mathbf{r}$

Camera Ray

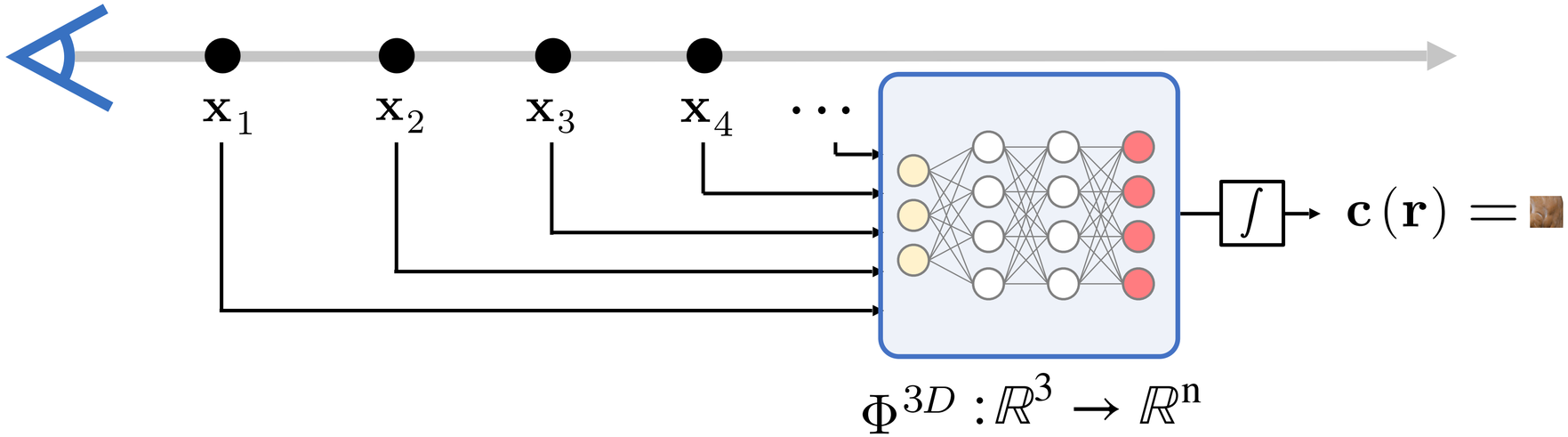


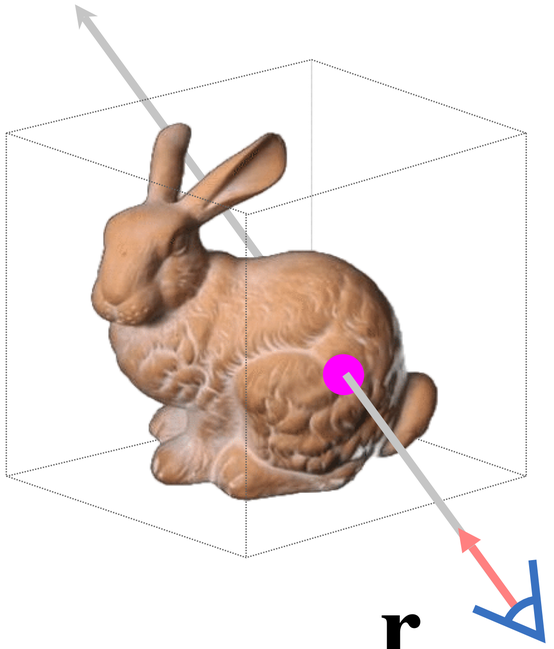
3D-structured Representation



$\mathbf{r}$

Camera Ray





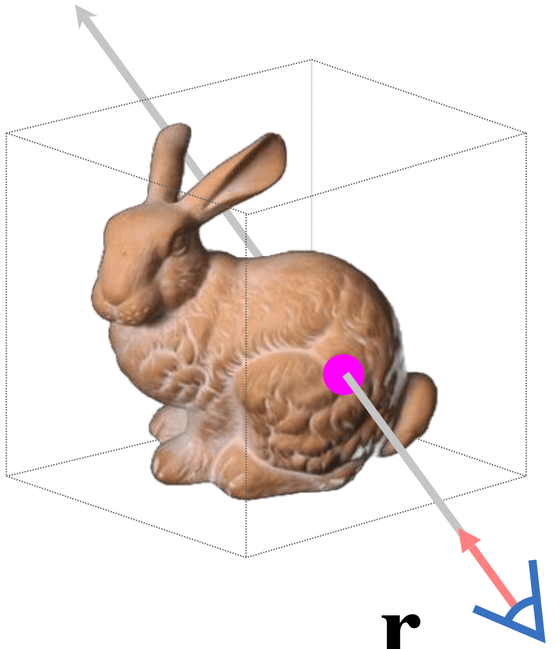
$\mathbf{r}$

Camera Ray

Light Field

$\mathbf{c}(\mathbf{r}) =$

[Adelson et al. 1991, Levoy et al. 1996, Gortler et al. 1996]



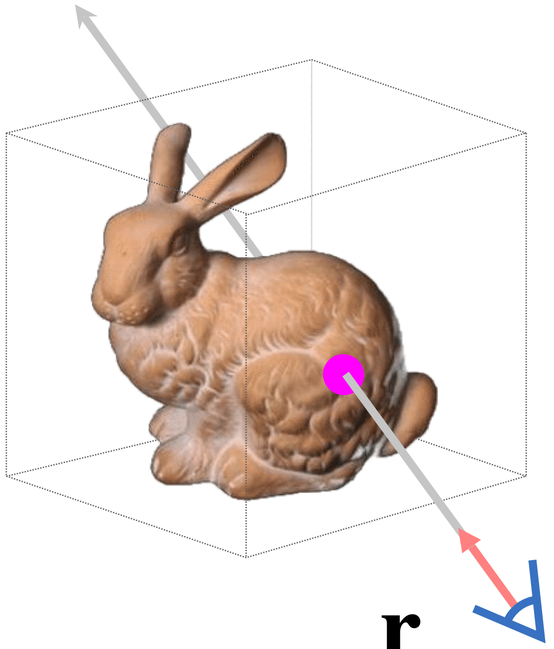
$\mathbf{r}$

Camera Ray

Light Field Networks

$\mathbf{c}(\mathbf{r}) =$

Light Field Networks



$\mathbf{r}$

Camera Ray

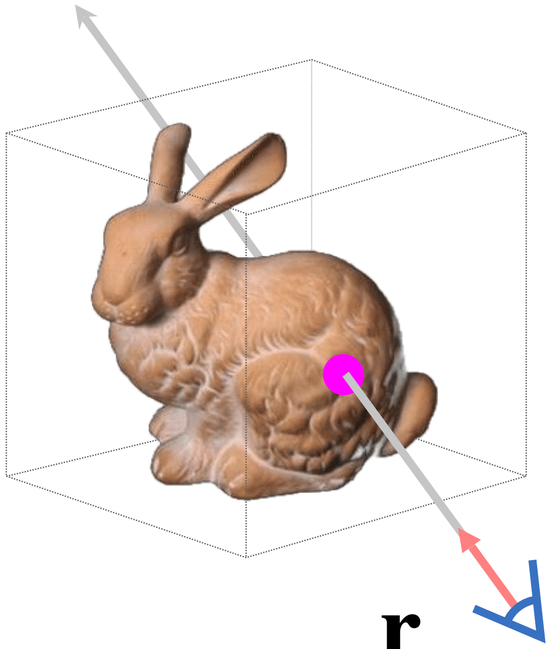
$\mathbf{x}_1$ $\mathbf{x}_2$ $\mathbf{x}_3$ $\mathbf{x}_4$ $\cdots$

$\Phi^{3D} : R^3 \rightarrow R^n$

$\int$

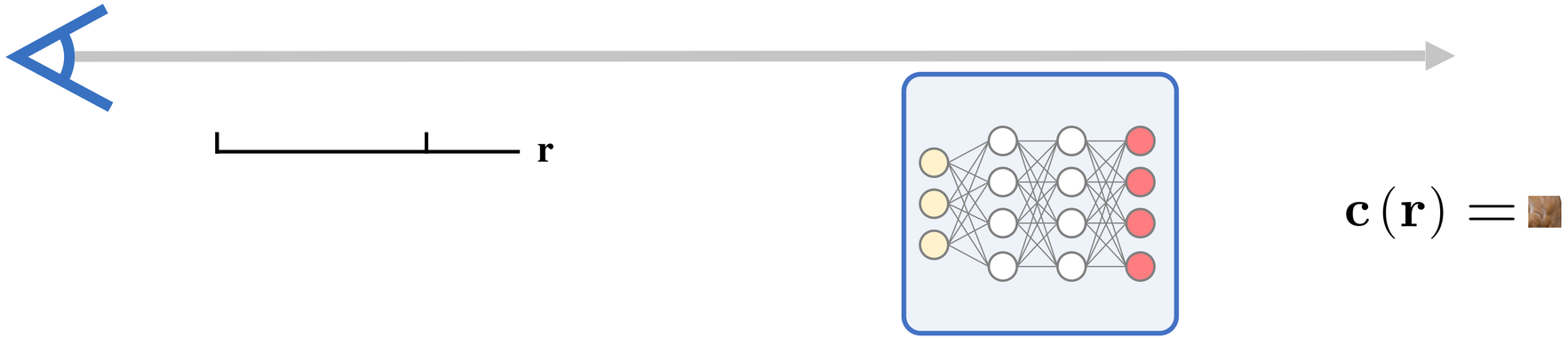
$\mathbf{c}(\mathbf{r}) =$

Light Field Networks



$\mathbf{r}$

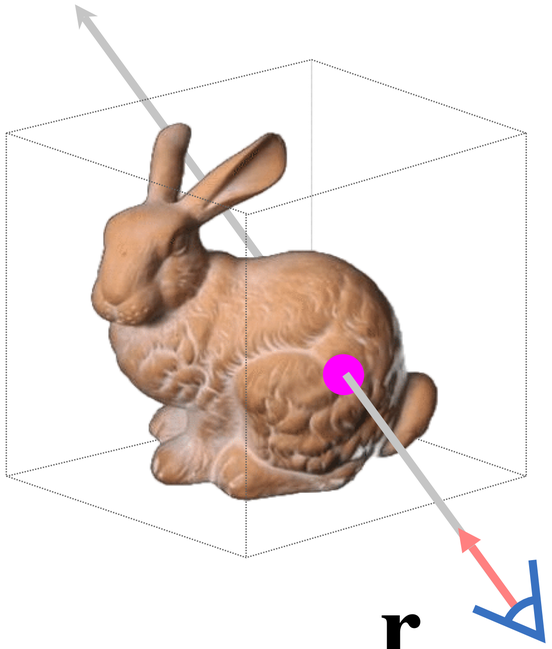
Camera Ray



$\mathbf{c}(\mathbf{r}) =$

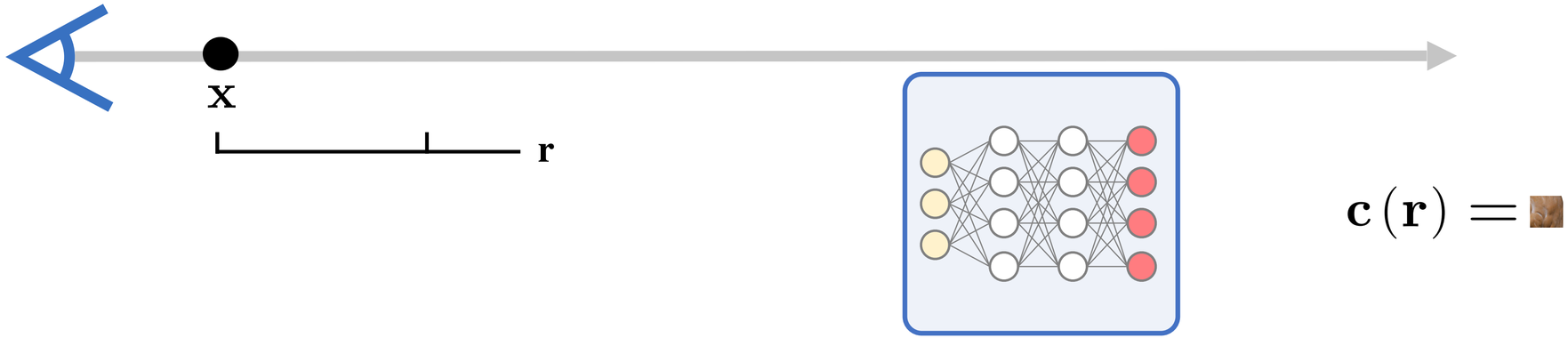
An Alternative Scene Representation

Light Field Networks



$\mathbf{r}$

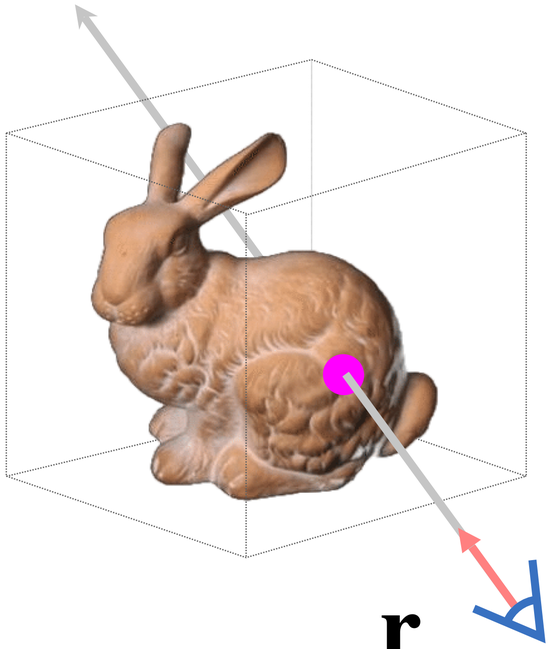
Camera Ray



$\mathbf{c}(\mathbf{r}) =$

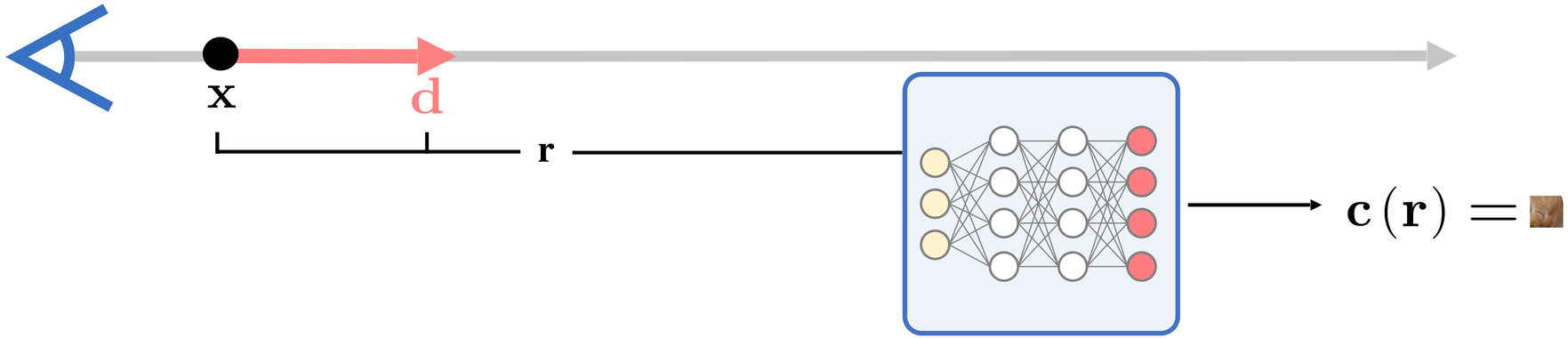
An Alternative Scene Representation

Light Field Networks



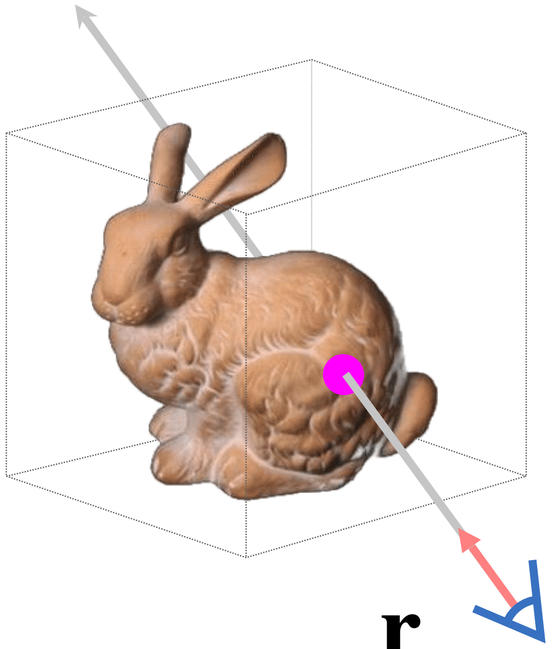
r

Camera Ray



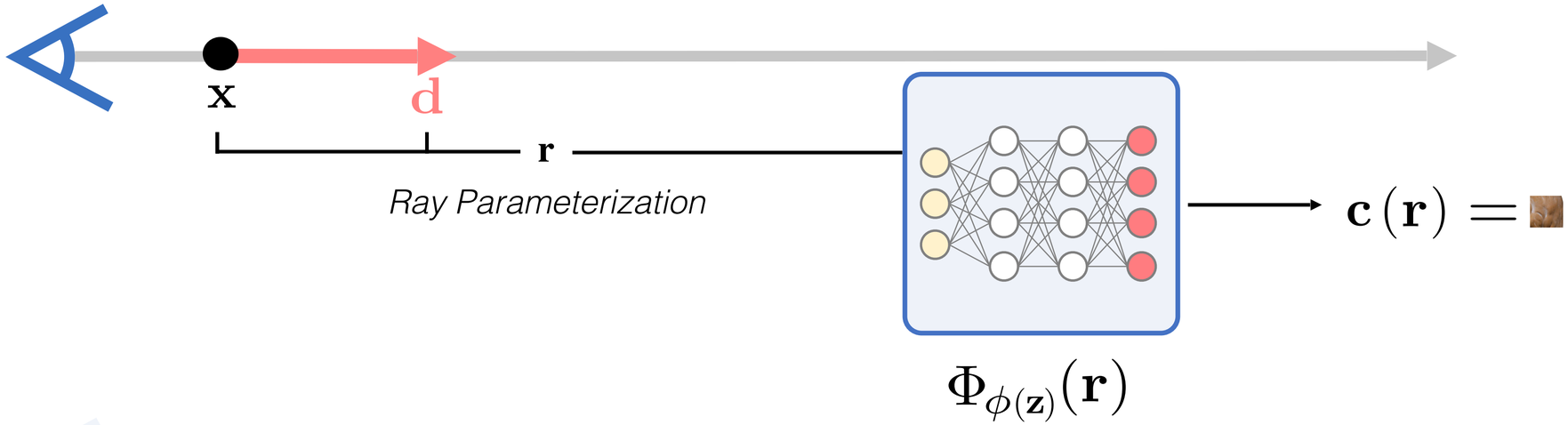
An Alternative Scene Representation

Light Field Networks



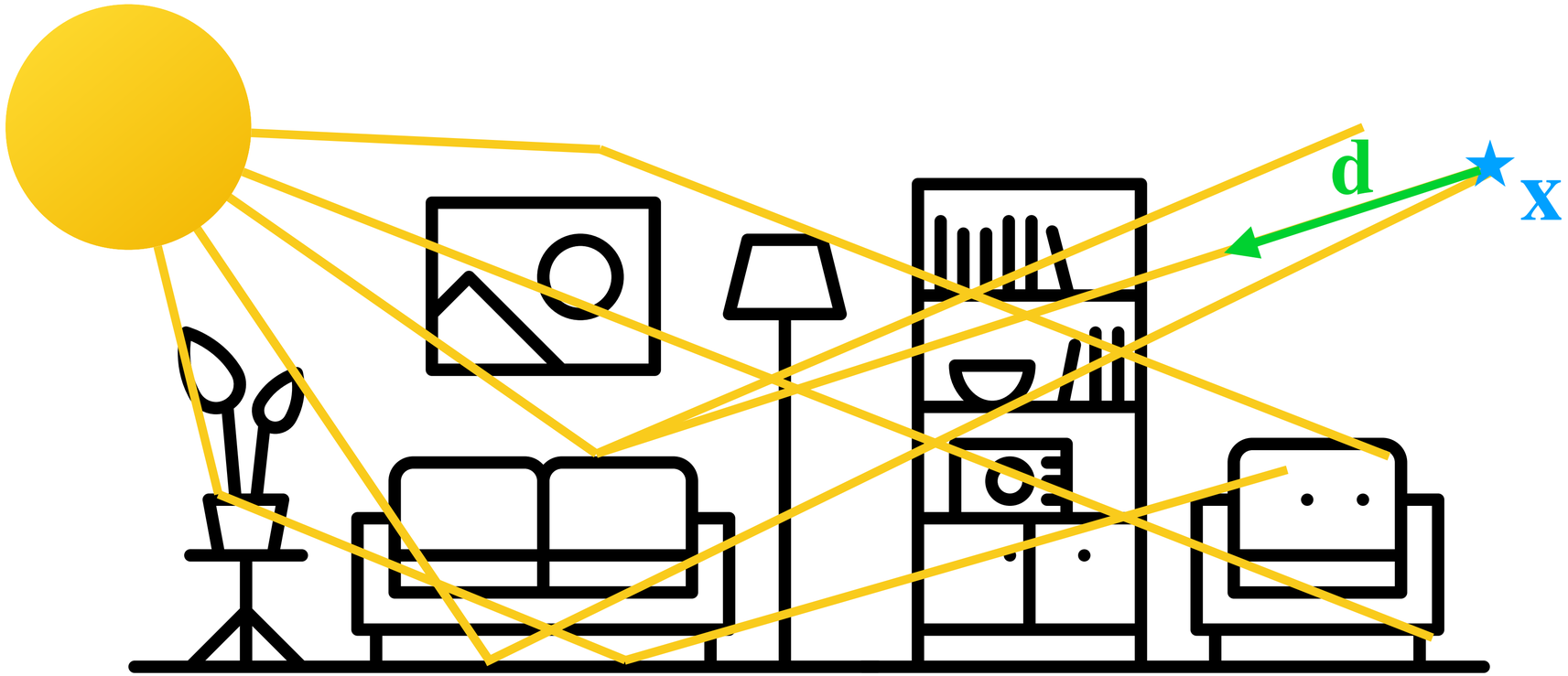
$\mathbf{r}$

Camera Ray



An Alternative Scene Representation

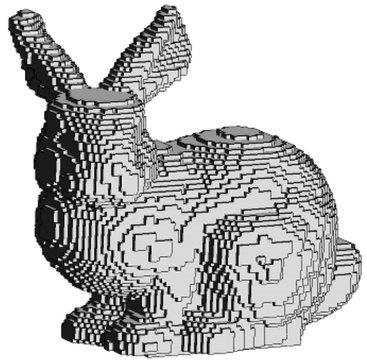
Just because Scene is 3D, don't have to store information in 3D data structure…

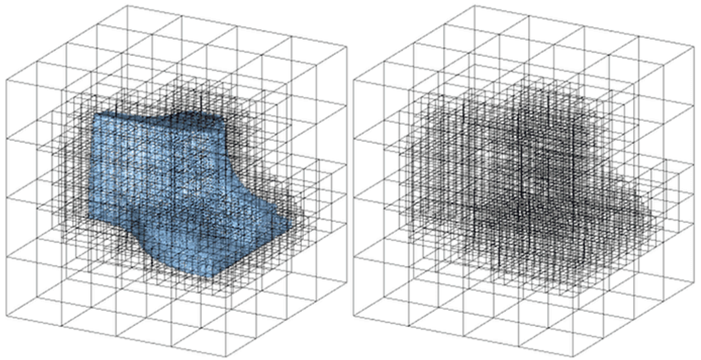


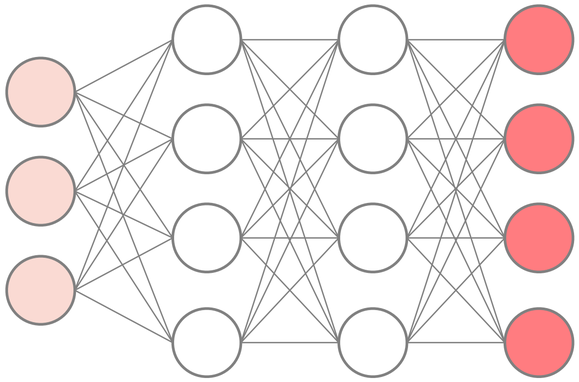
$$LF : \mathbb{R}^3 \times \mathbb{S}^2 \rightarrow \mathbb{R}^3, \quad LF(\mathbf{x}, \mathbf{d}) = \mathbf{c}$$

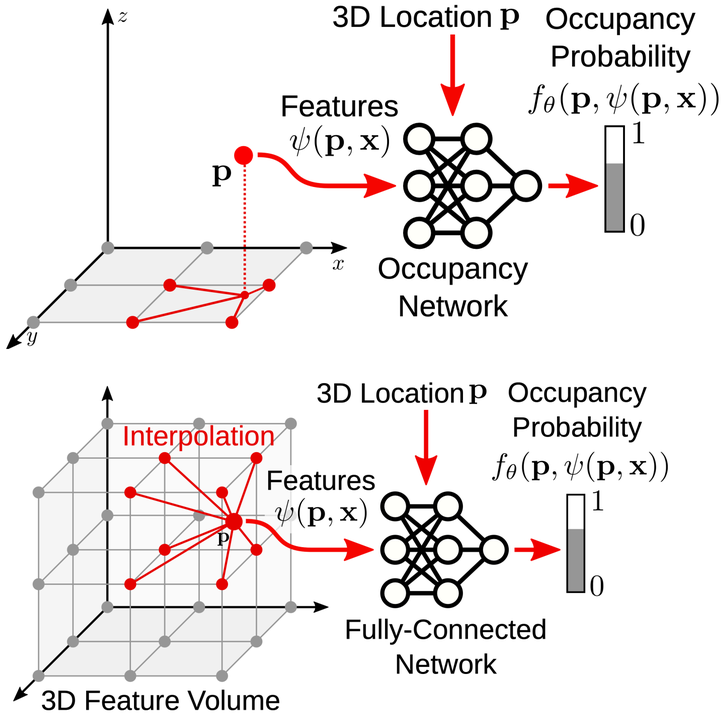
Light Field is 5-dimensional! What parameterizations are possible…?

Summary









- No “Artificial Intelligence”, “understanding” or “Machine Learning” when fitting a single representation to a single 3D thing, even if there are neural networks in them.
- It becomes *a lot* more interesting when considering *inference,* i.e., we want representation to be output of an encoder! More on that later in “Prior-based reconstruction”.