Scene Representation Networks:

Continuous 3D-Structure-Aware Neural Scene Representations

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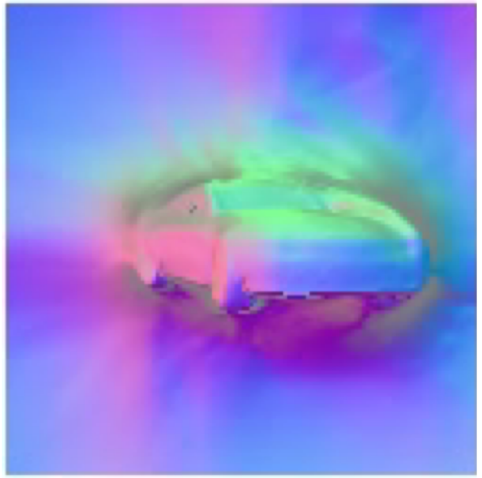
Stanford University

single image
camera pose
intrinsics

Novel Views

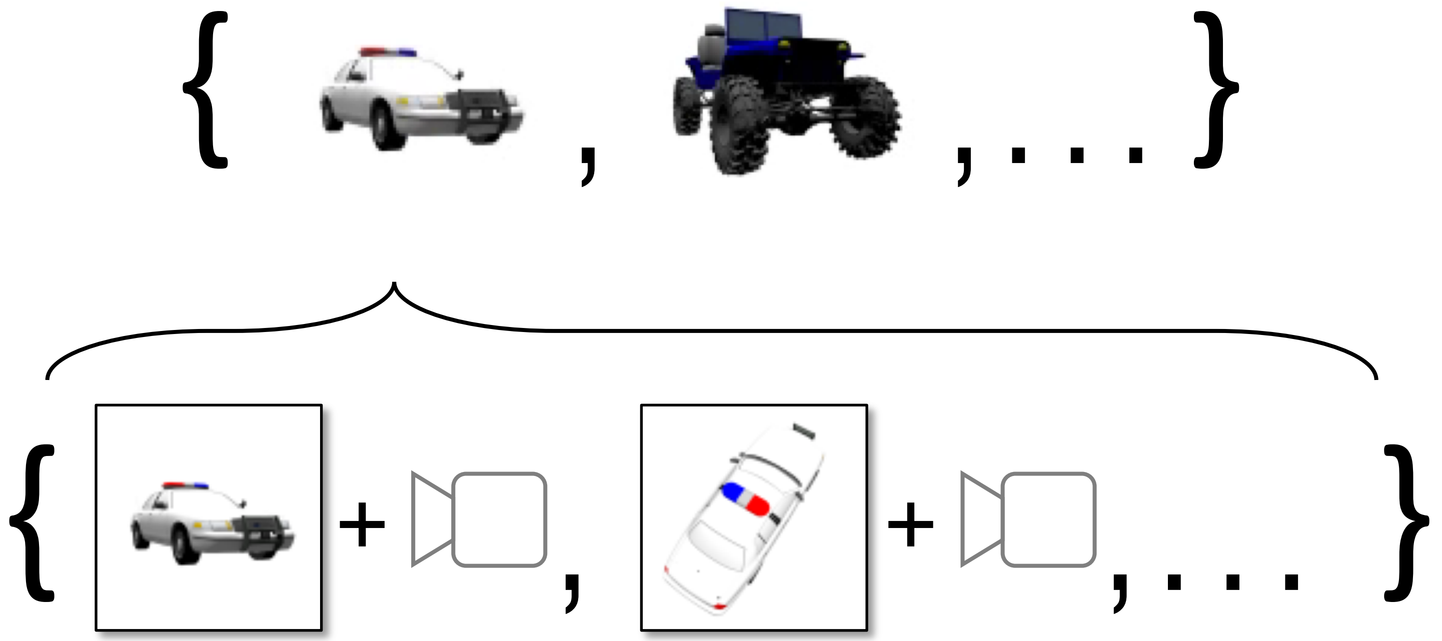
Surface Normals



Self-supervised Scene Representation Learning

Latent 3D Scenes

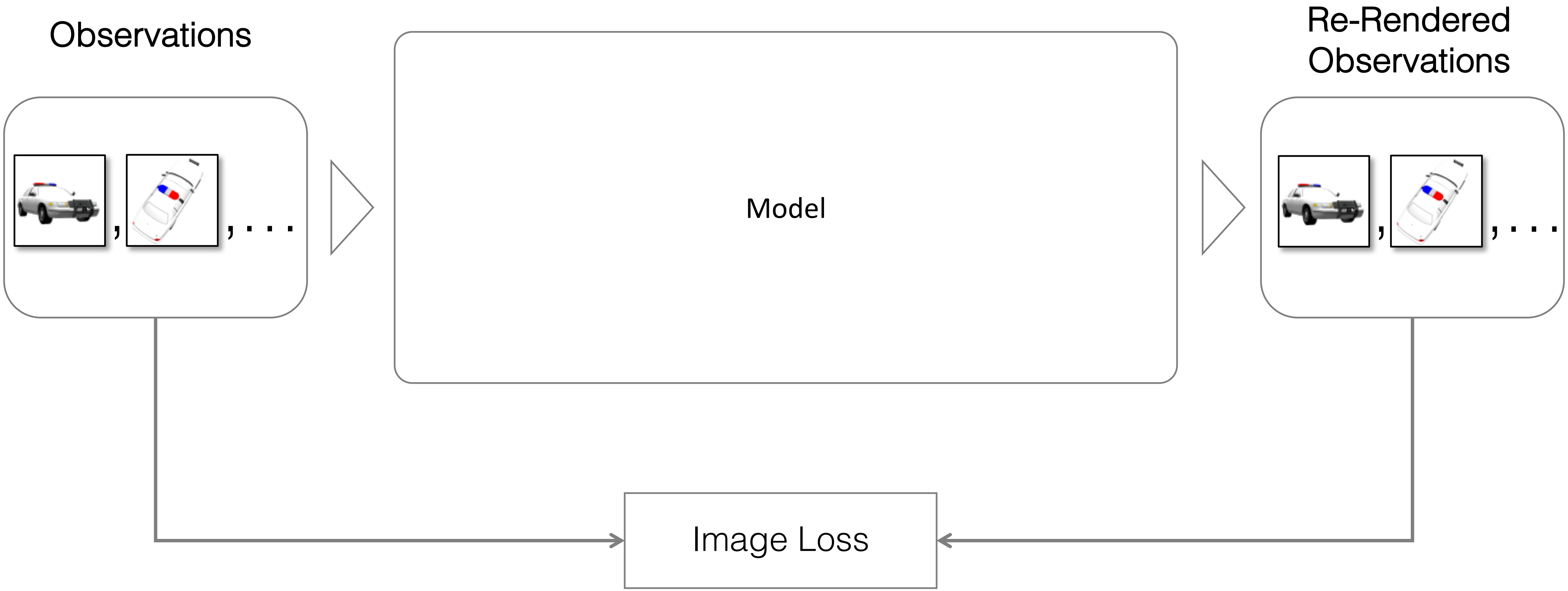
Observations
Image + Pose & Intrinsics



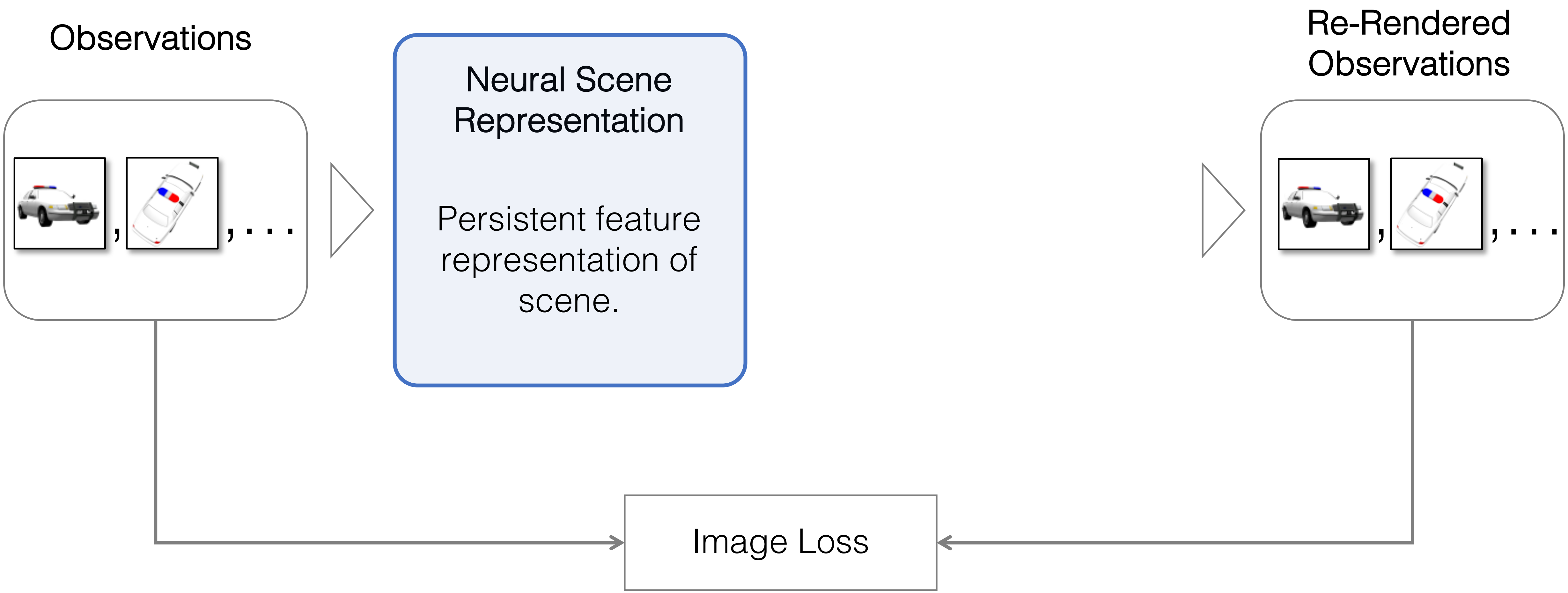
What can we learn about latent 3D scenes from observations?

Vision: Learn rich representations just by watching video!

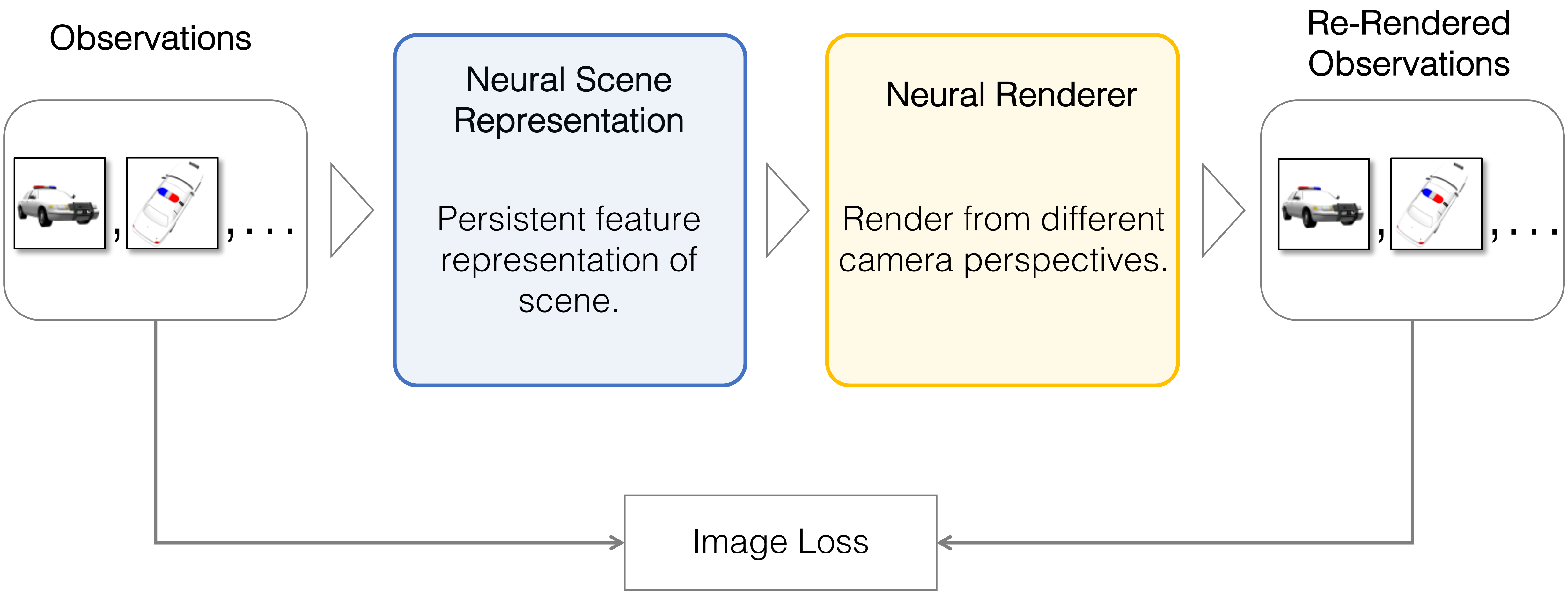
Self-supervised Scene Representation Learning



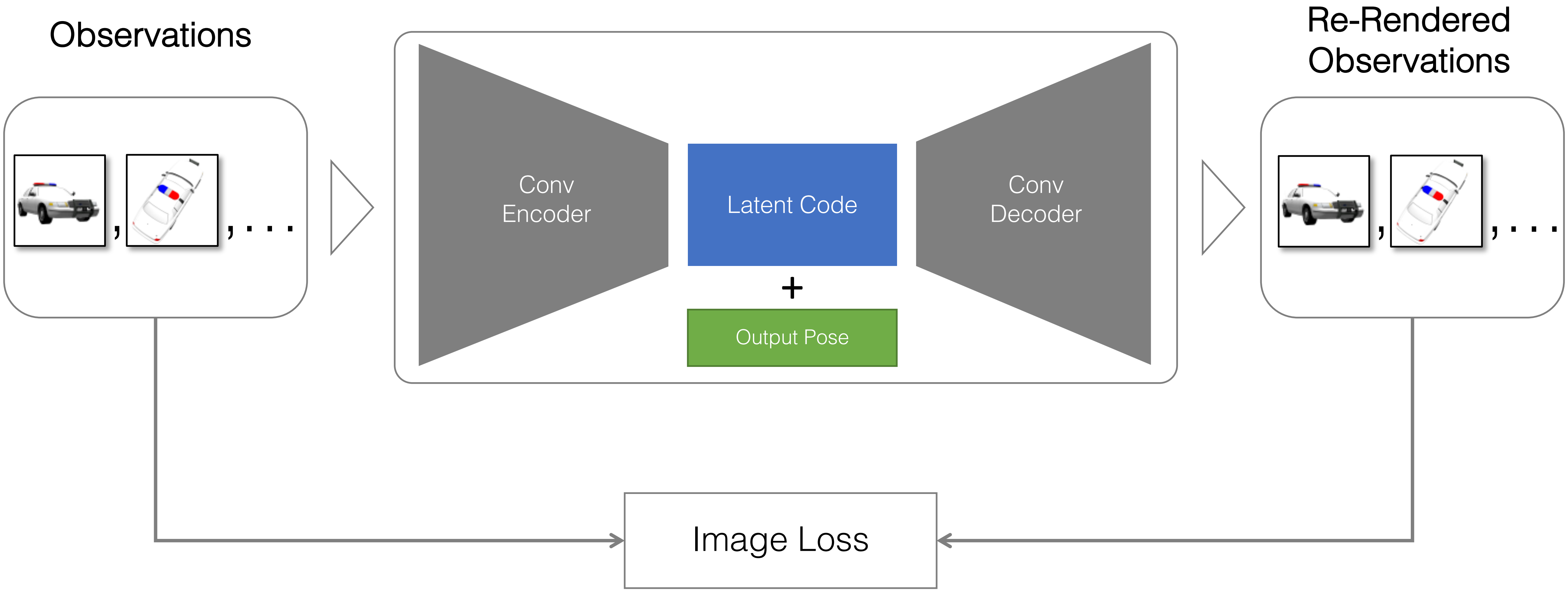
Self-supervised Scene Representation Learning



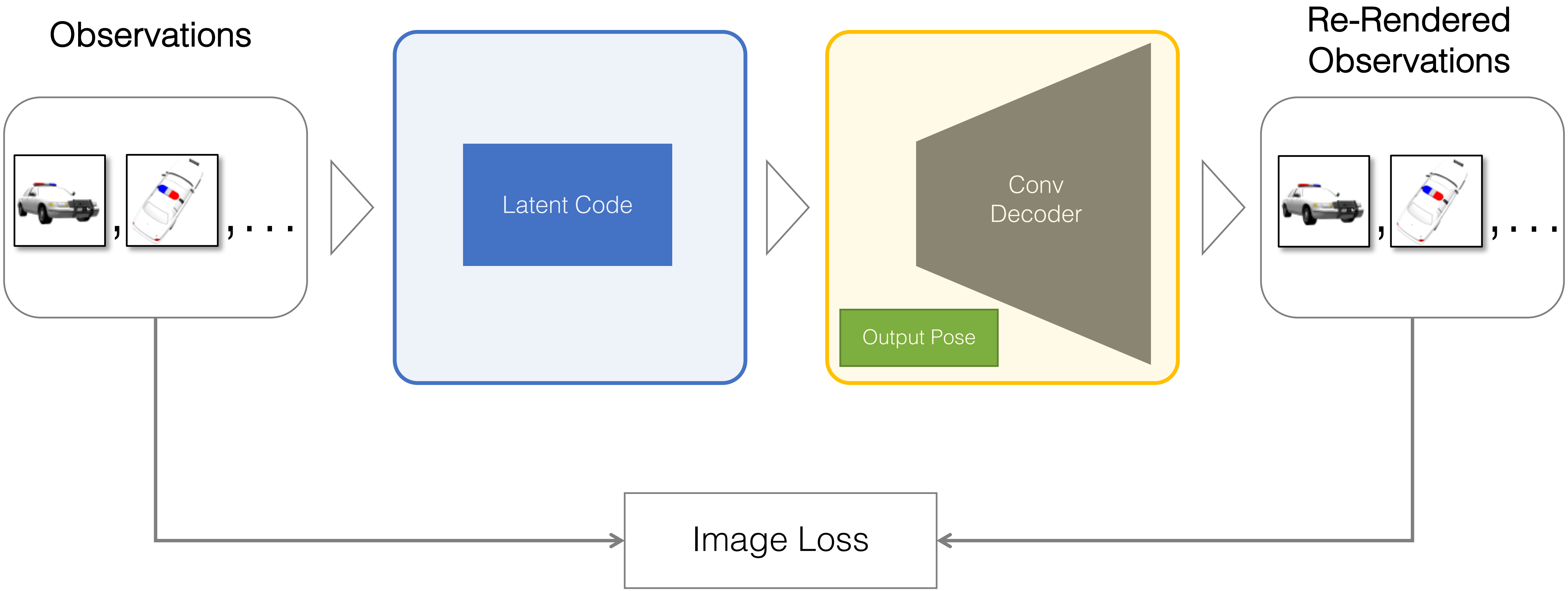
Self-supervised Scene Representation Learning



2D baseline: Autoencoder



2D baseline: Autoencoder



Doesn't capture 3D properties of scenes.

Trained on ~2500 shapenet cars with 50 observations each.

Need 3D inductive bias!

Related Work

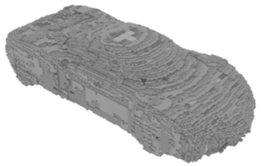
	3D inductive bias / 3D structure	Self-supervised with posed images
Scene Representation Learning	✗	✓
2D Generative Models	✗	✓
3D Computer Vision	✓	✗

Scene Representation Learning

Tatarchenko et al., 2015
Worrall et al., 2017
Eslami et al., 2018
…

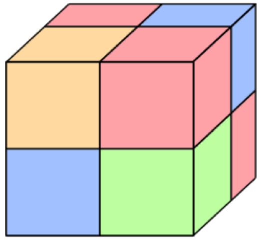
2D Generative Models

Goodfellow et al., 2014
Kingma et al., 2013
Kingma et al., 2018
…



3D Computer Vision

Choy et al., 2016
Huang et al., 2018
Park et al., 2018
…

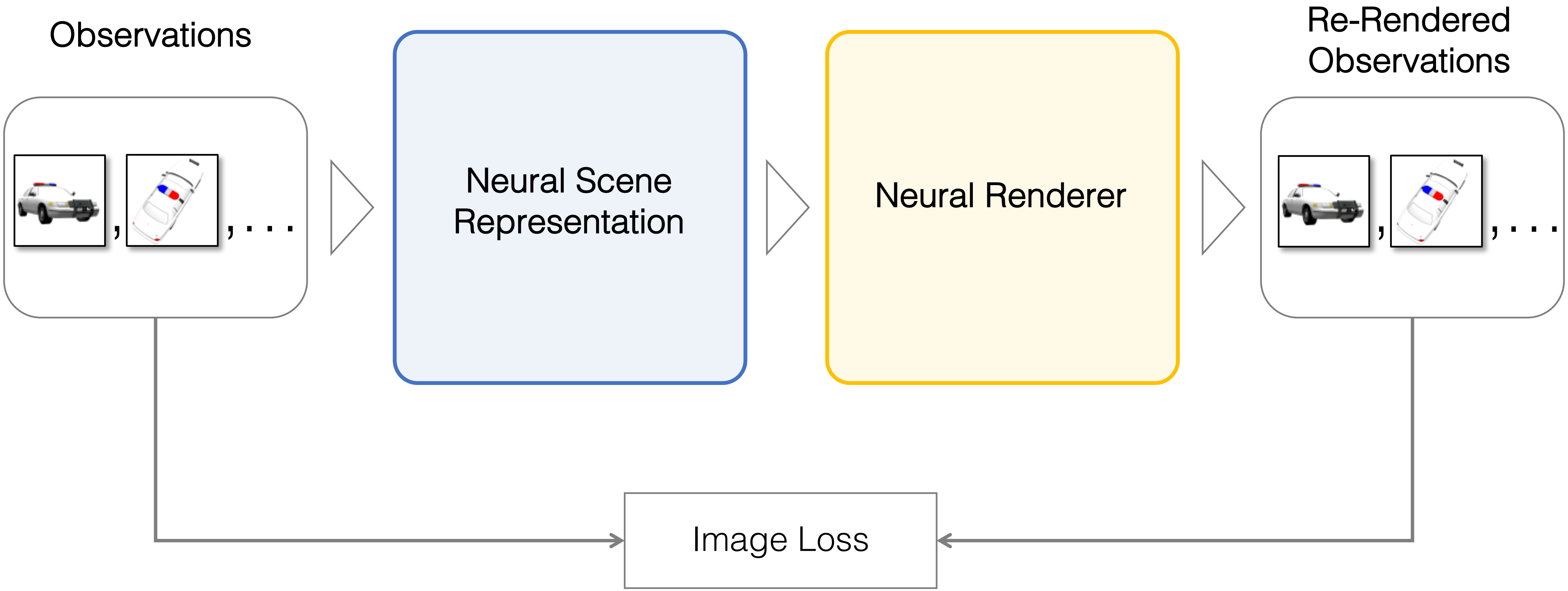


Voxel-based Representations

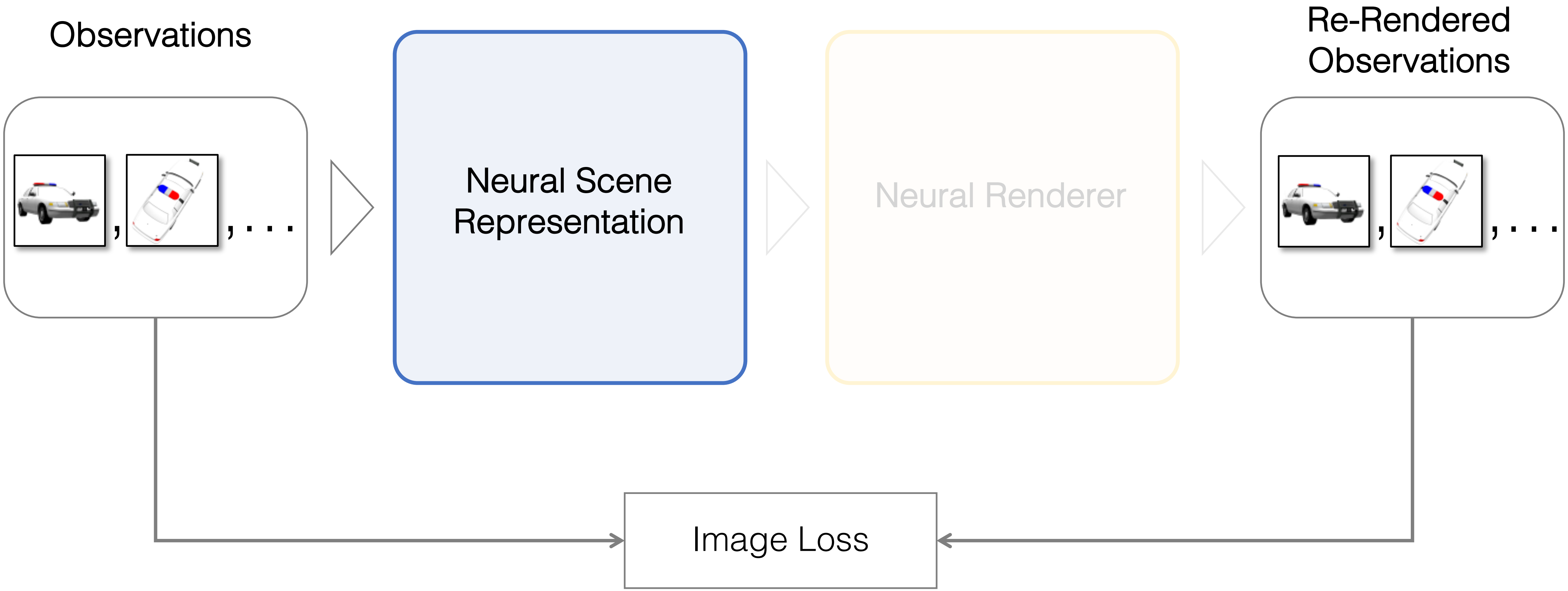
Sitzmann et al., 2019
Lombardi et al., 2019
Phuoc et al., 2019
…

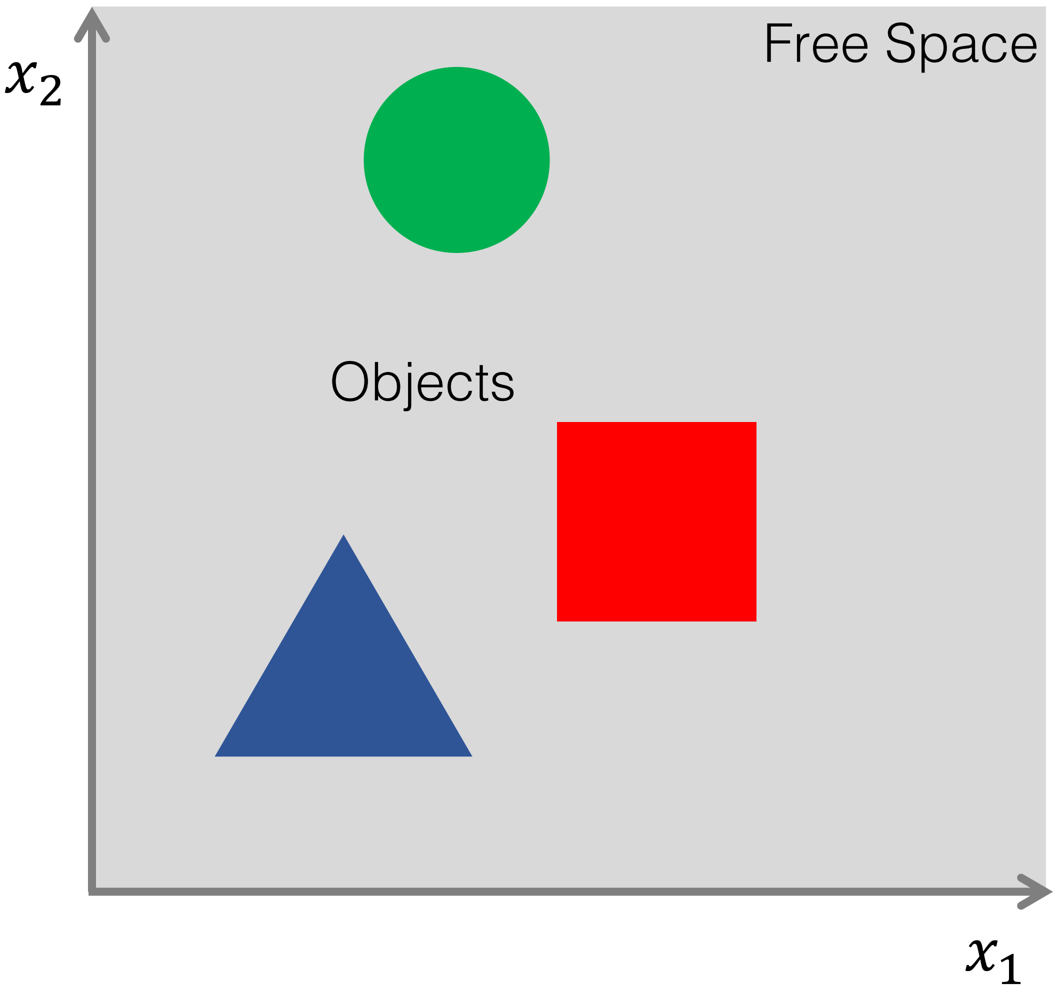
- Memory inefficient: $O(n^3)$.
- Doesn't parameterize scene surfaces smoothly.
- Generalization is hard.

Scene Representation Networks



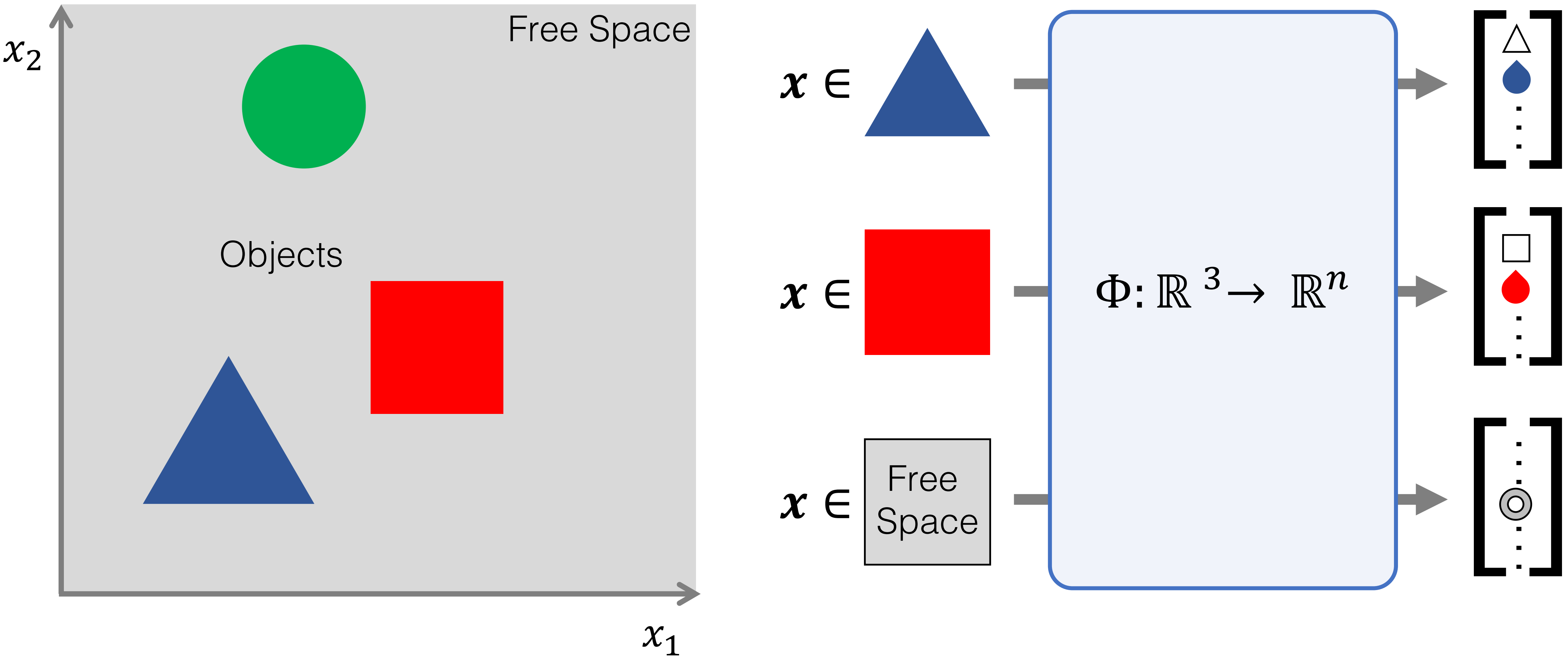
Scene Representation Networks



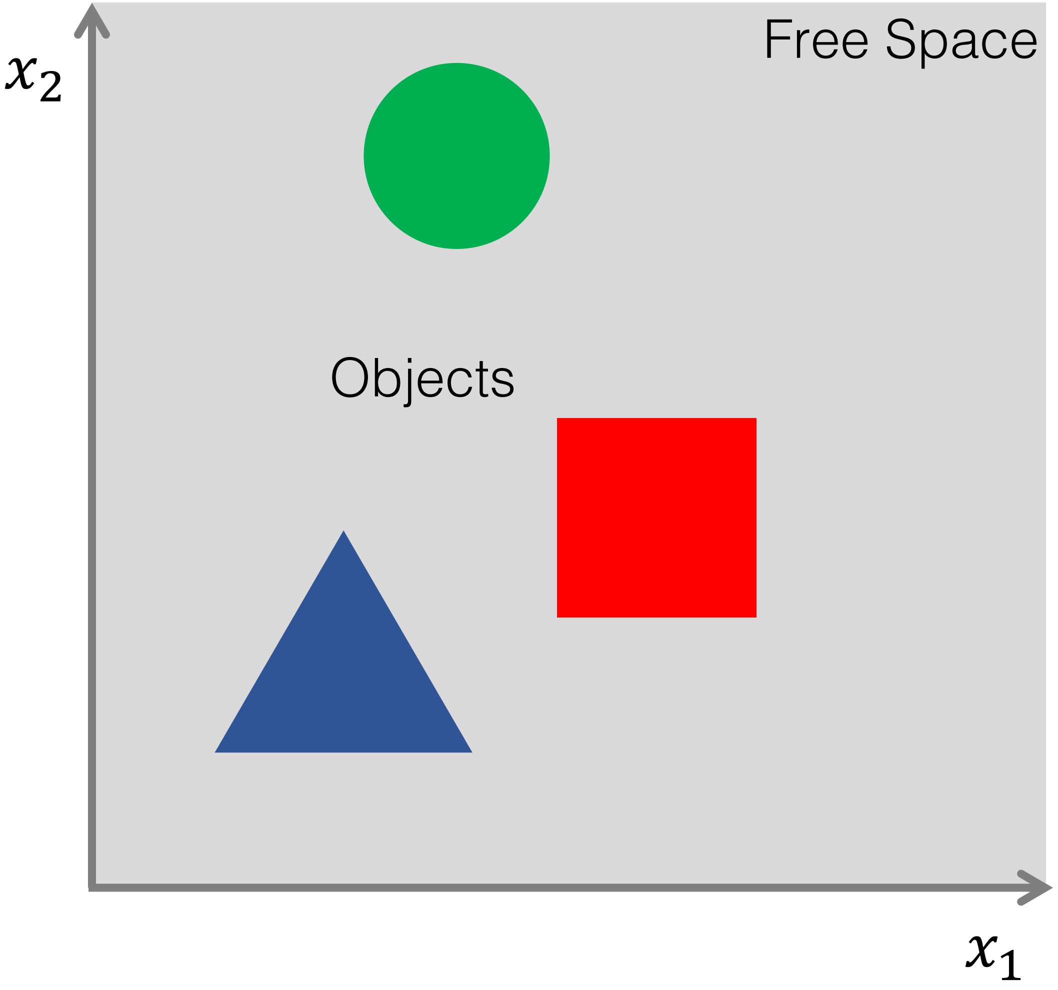


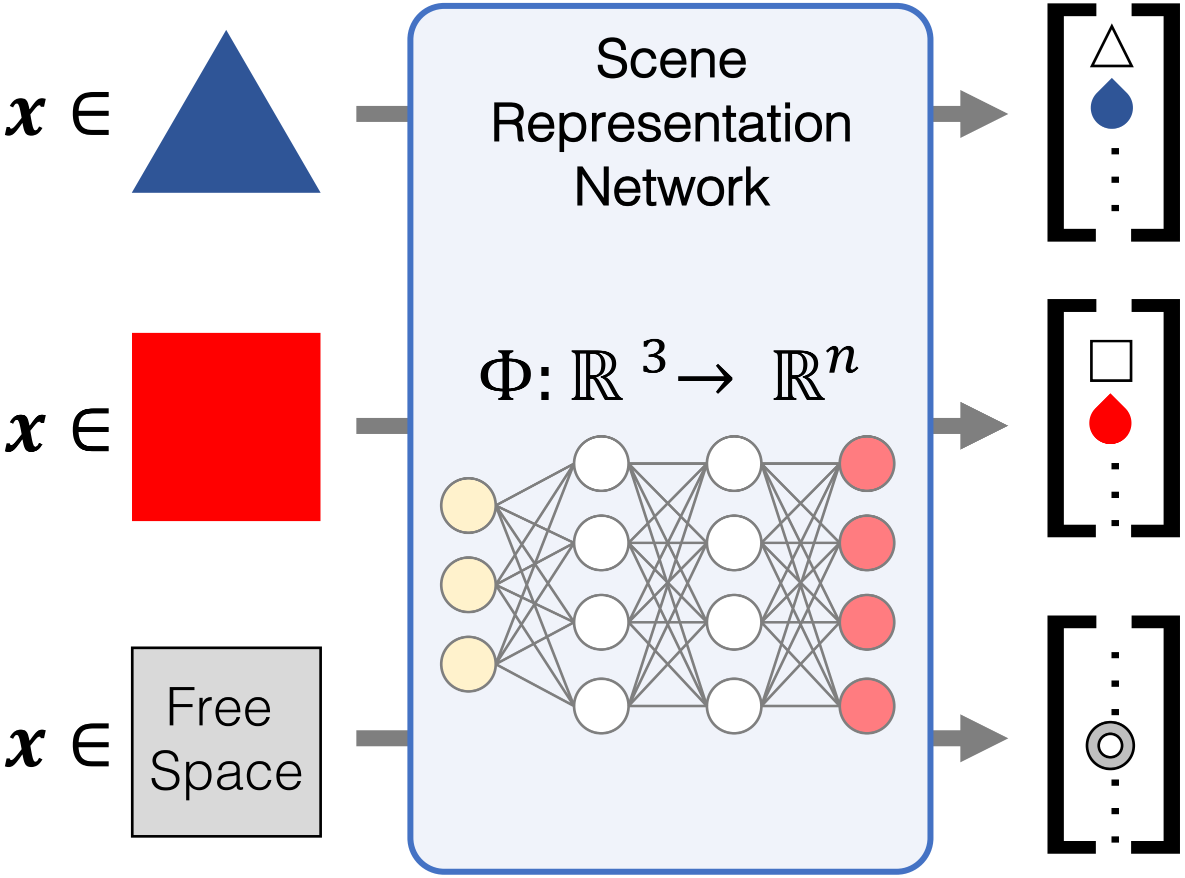
Free Space
x_2
Objects
x_1

Model scene as function Φ that maps coordinates to features.



Scene Representation Network parameterizes Φ as MLP.



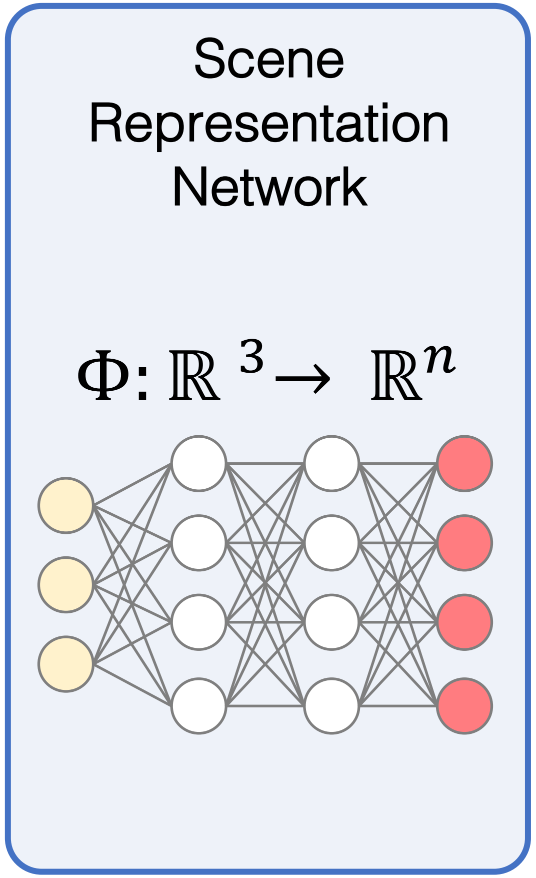


Scene Representation Network parameterizes Φ as MLP.

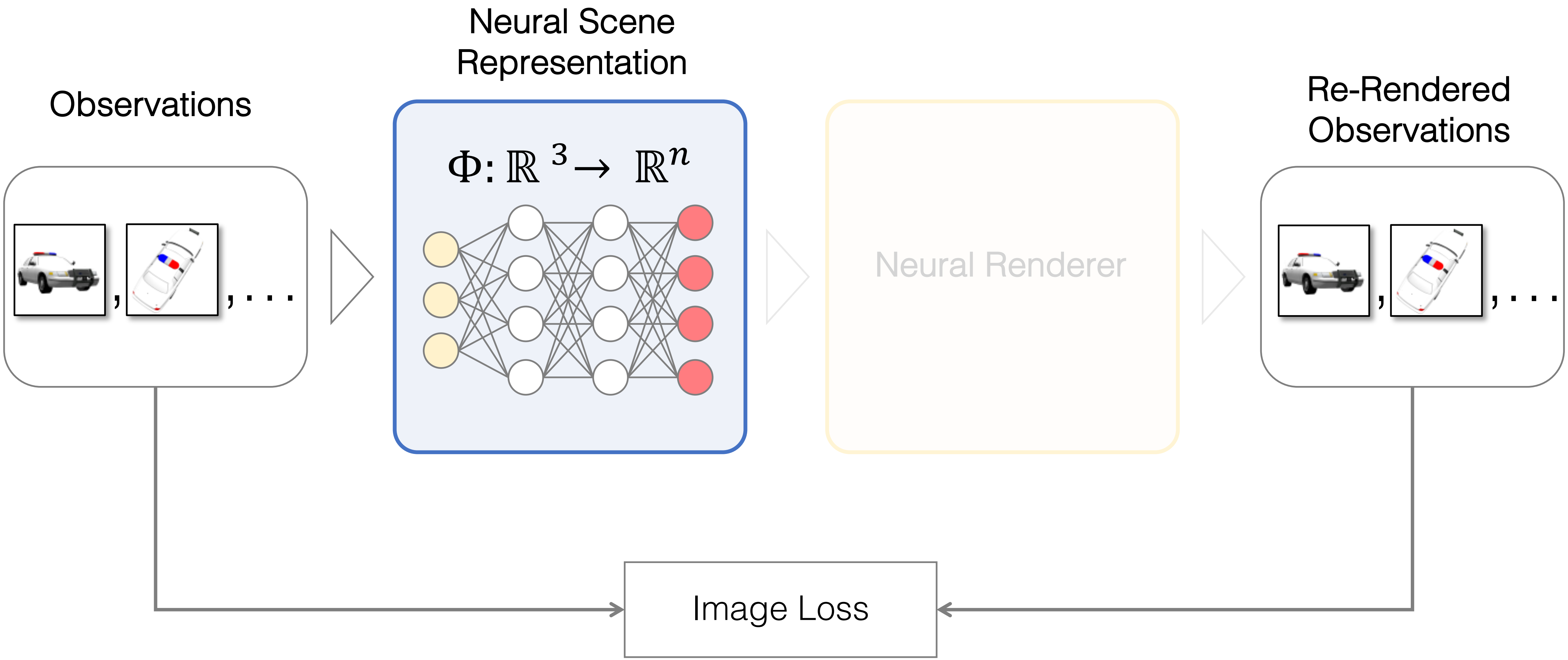
Can sample anywhere,
at arbitrary resolutions.

Parameterizes scene
surfaces smoothly.

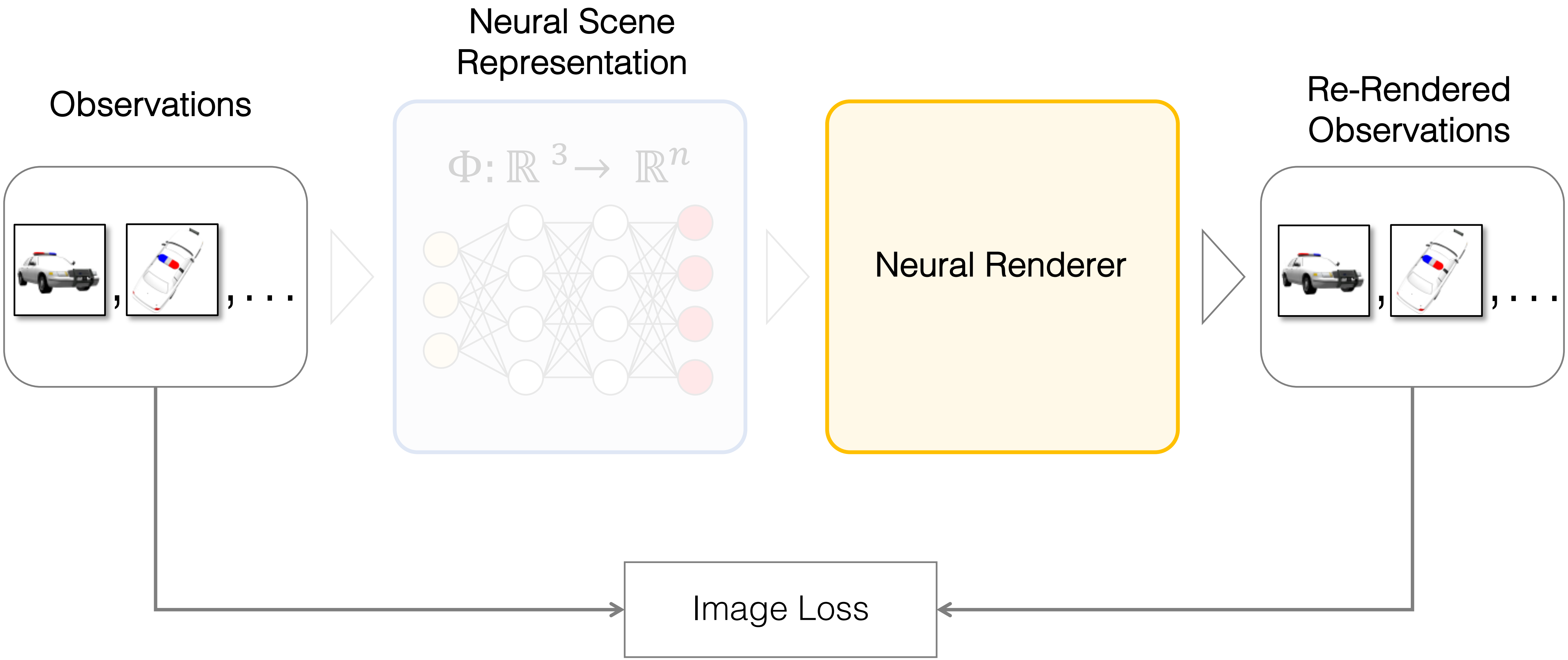
Memory scales with scene
complexity.



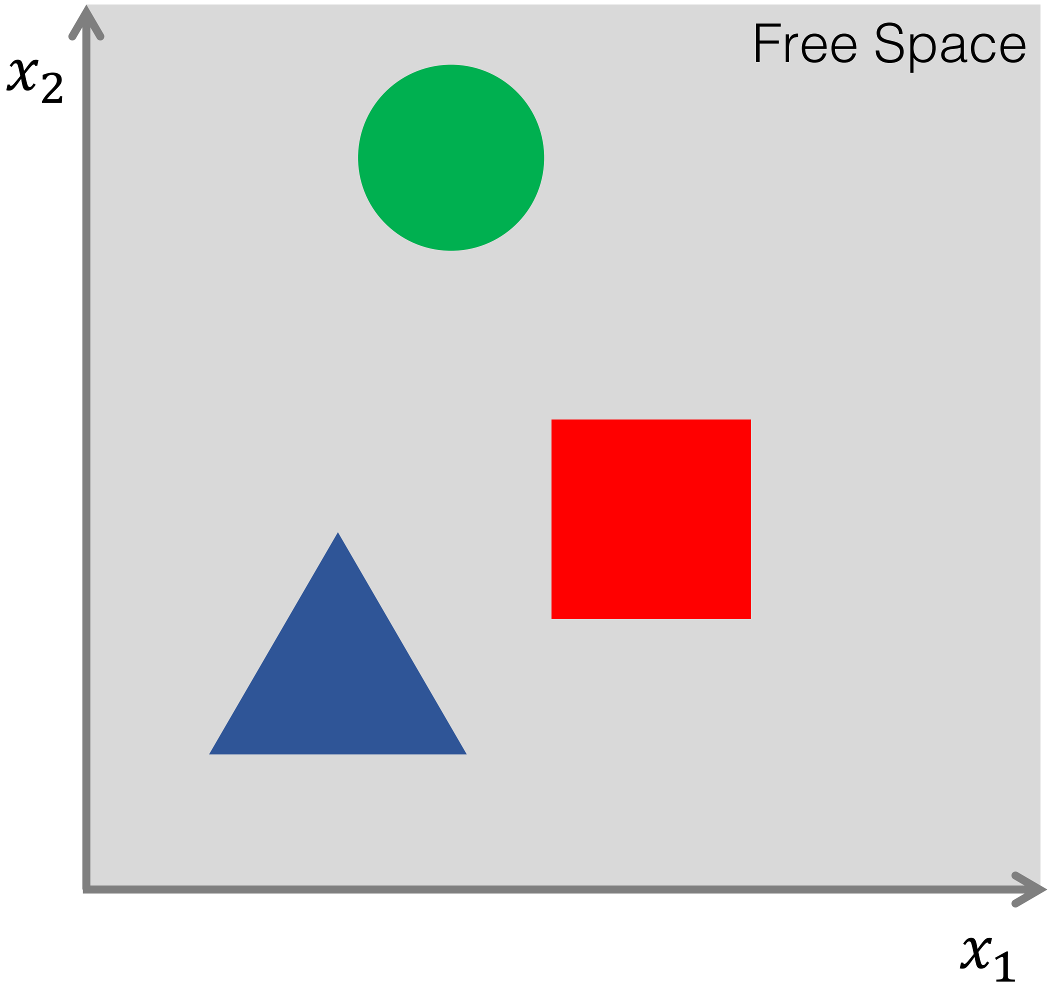
Scene Representation Networks



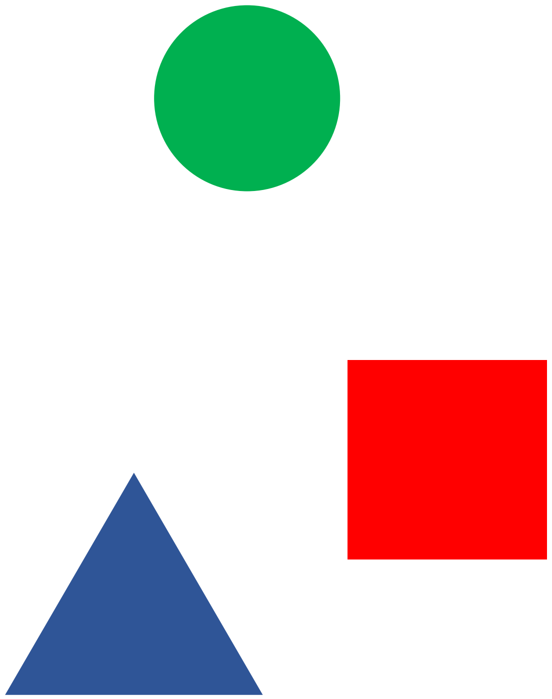
Scene Representation Networks



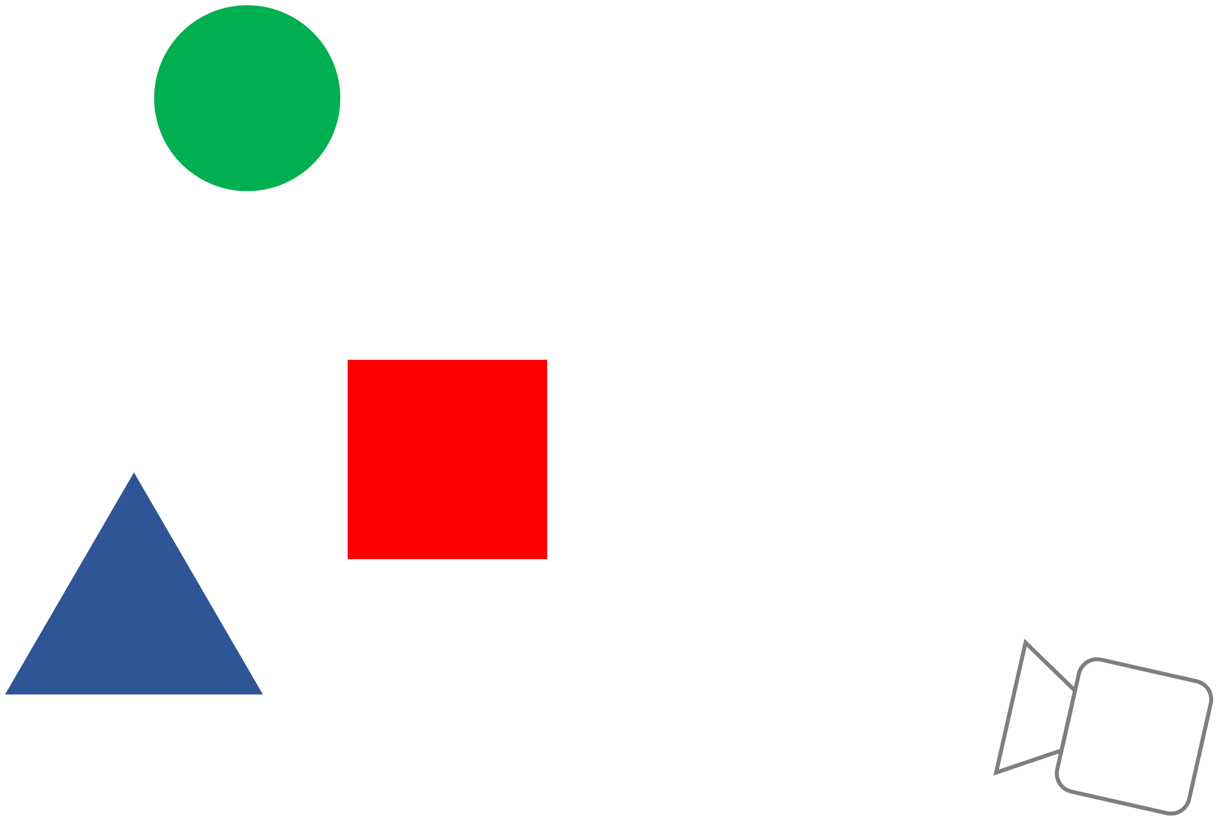
Neural Renderer.



Neural Renderer.

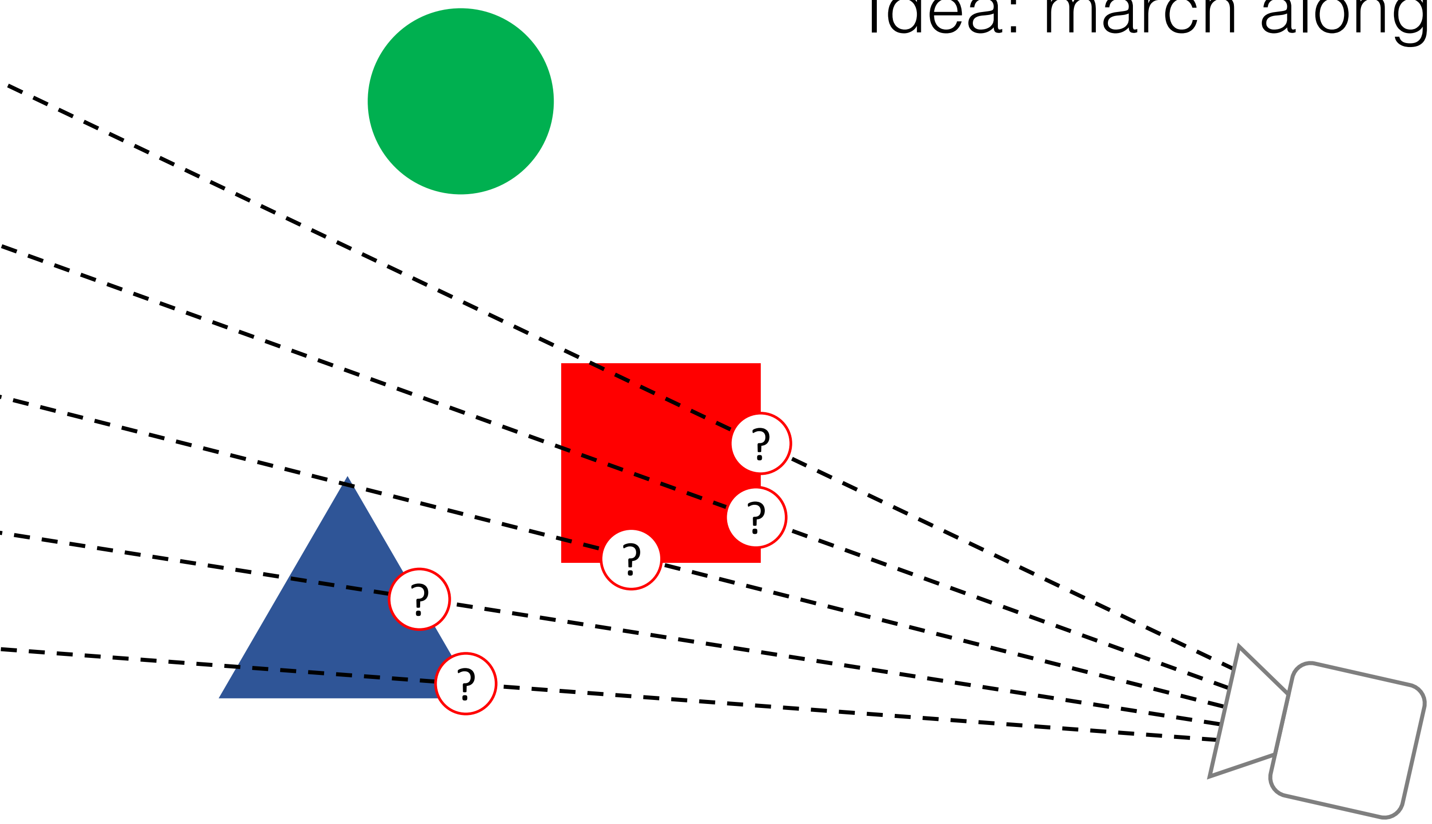


Neural Renderer.

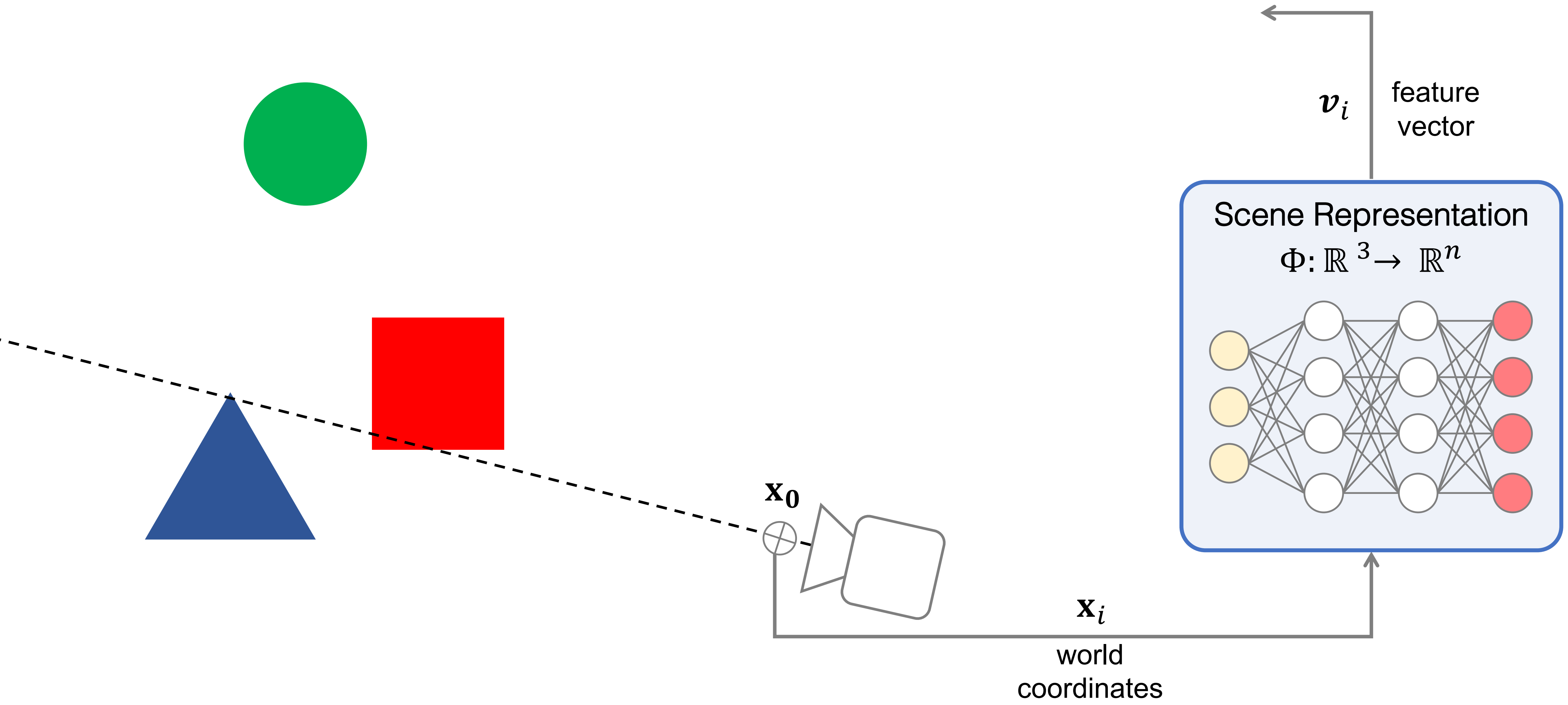


Neural Renderer Step 1: Intersection Testing.

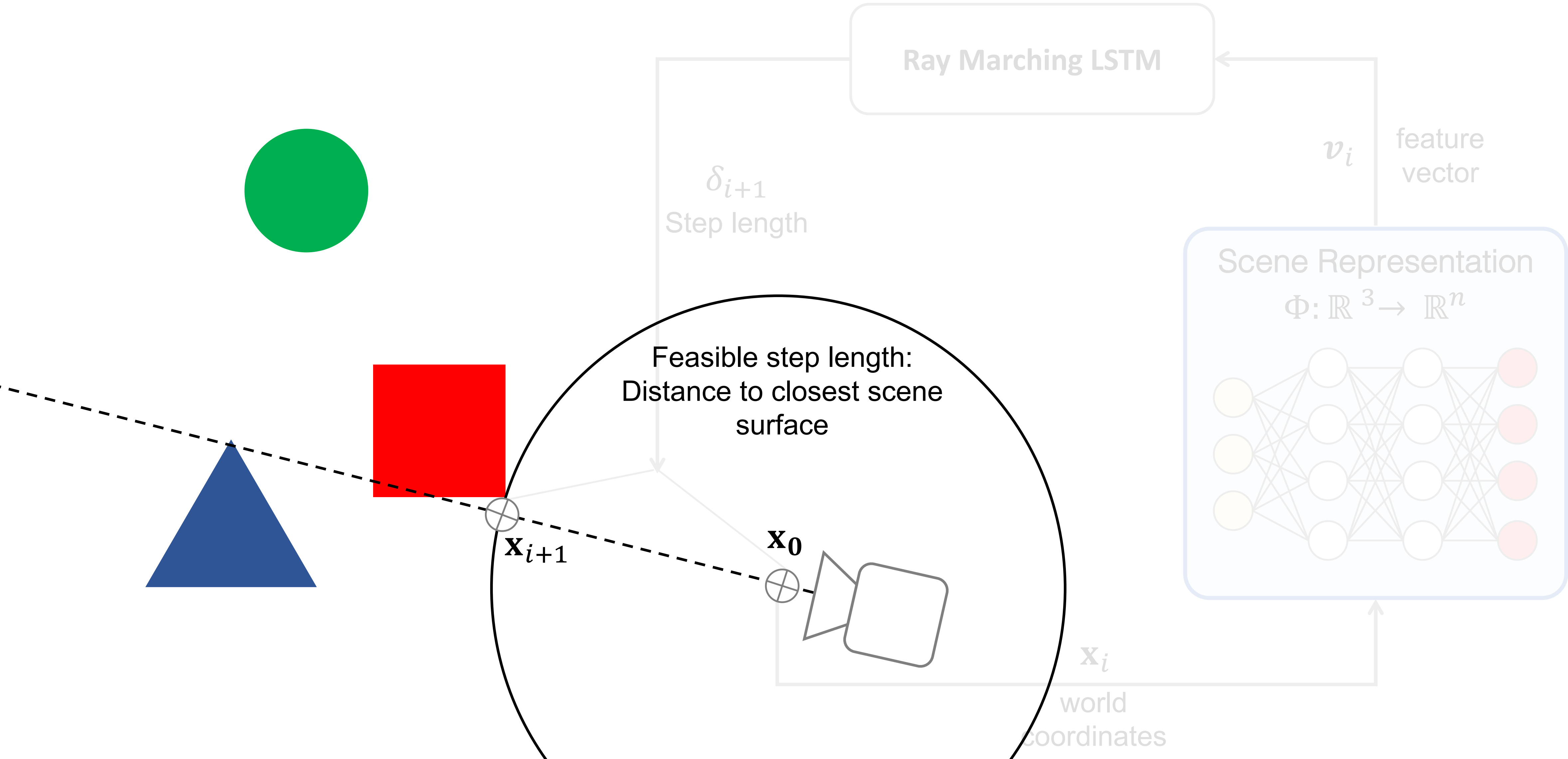
Idea: march along ray until arrived at surface.



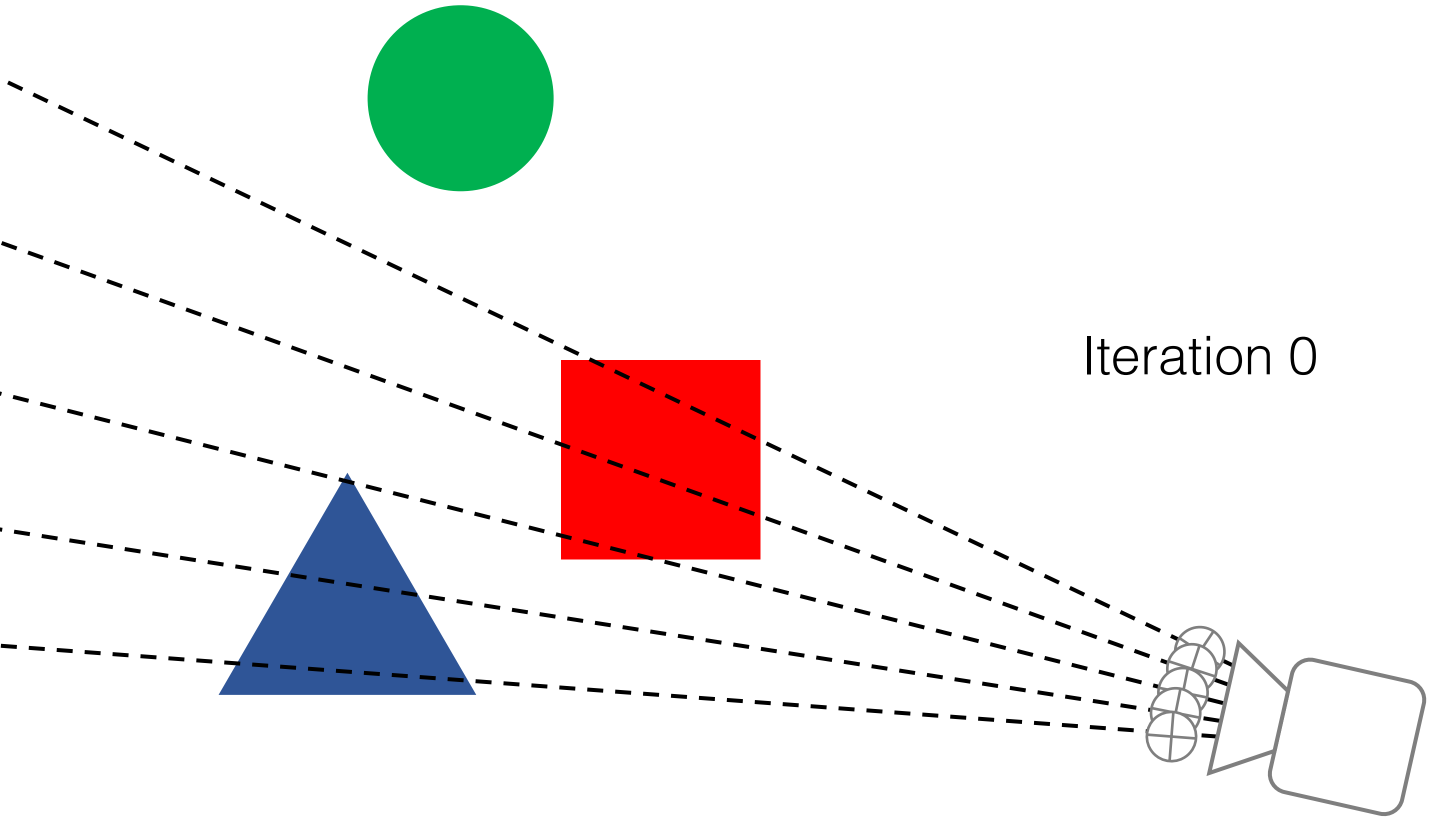
Neural Renderer Step 1: Intersection Testing.



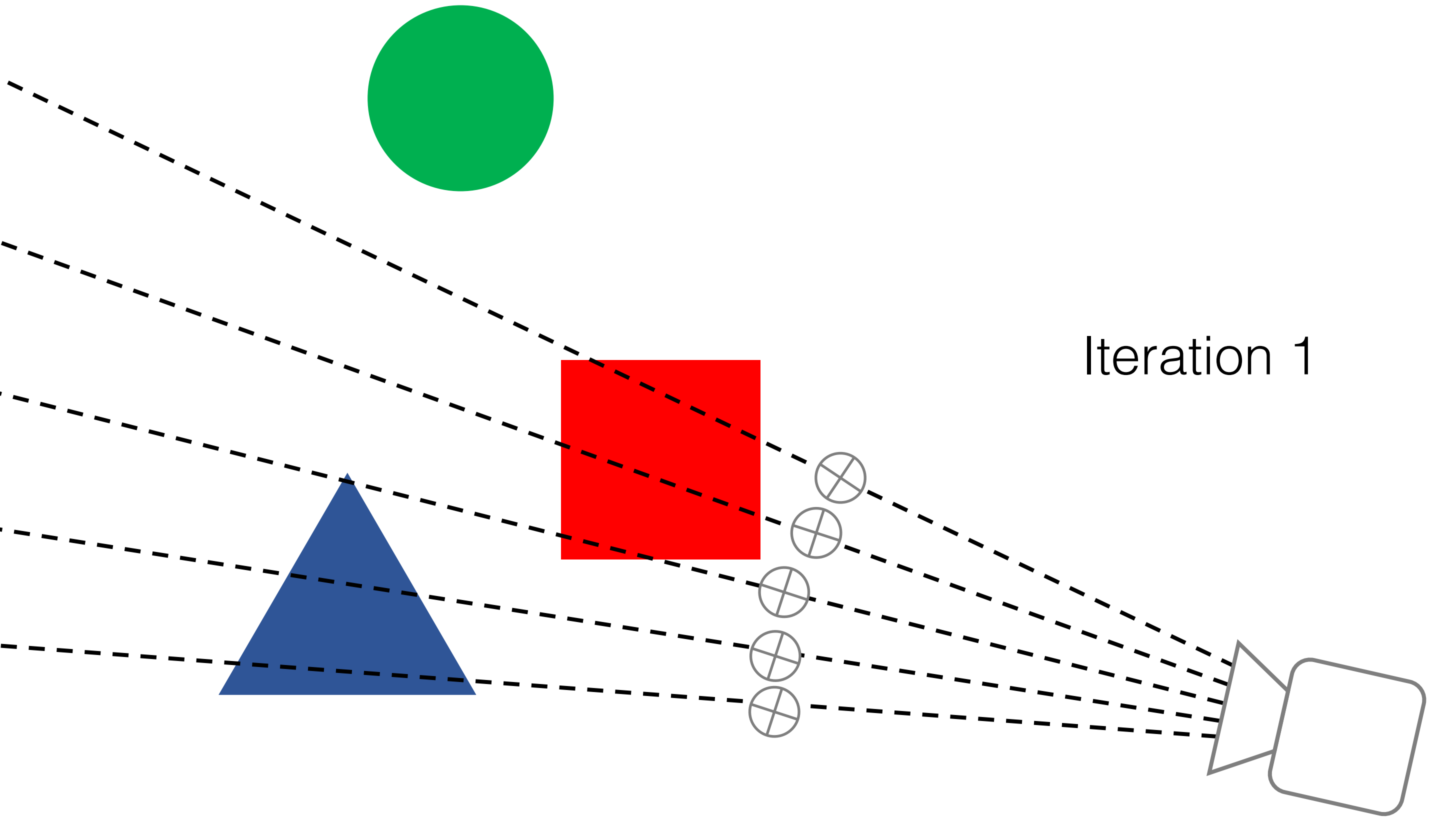
Neural Renderer Step 1: Intersection Testing.



Neural Renderer Step 1: Intersection Testing.



Neural Renderer Step 1: Intersection Testing.



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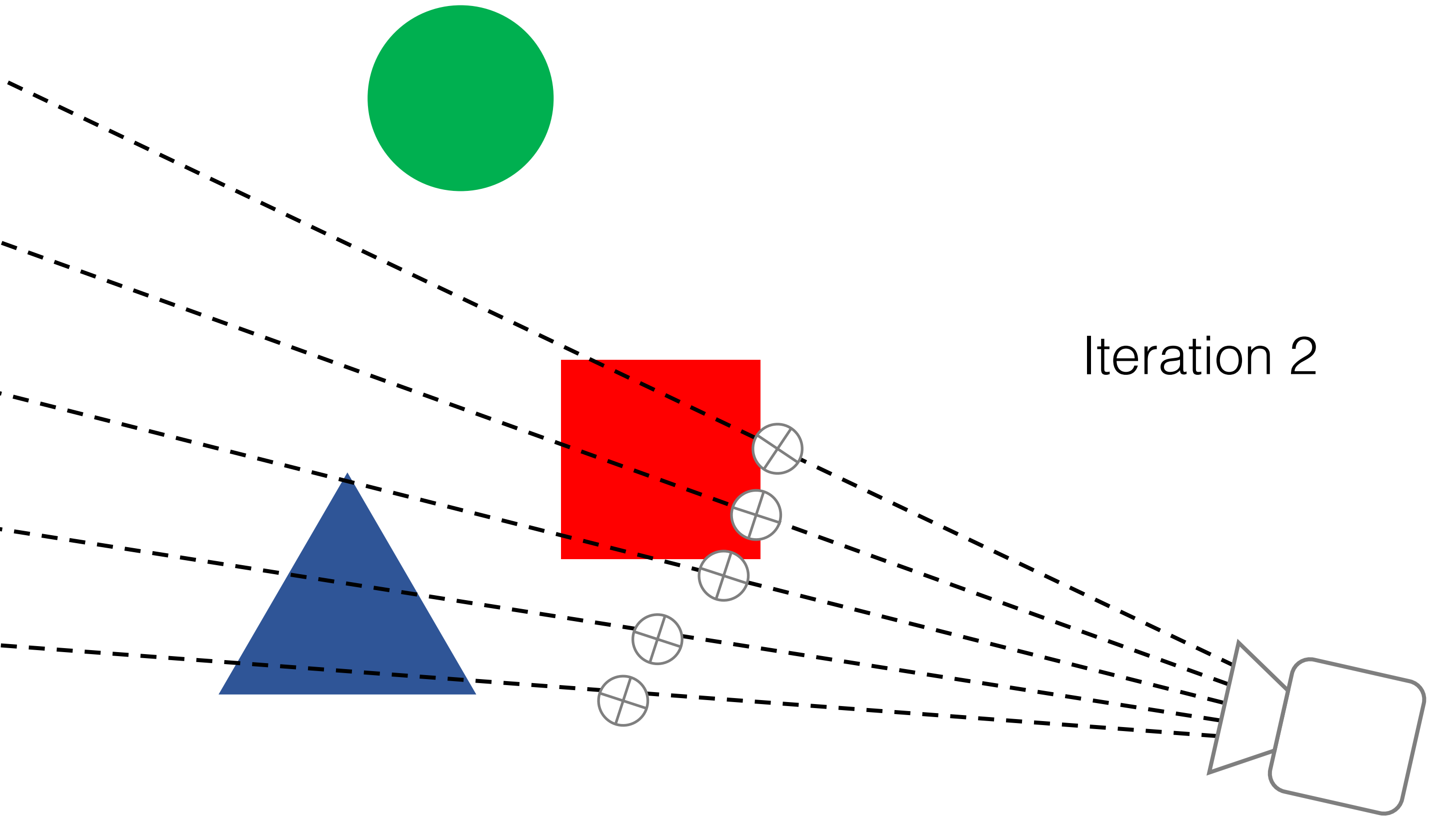

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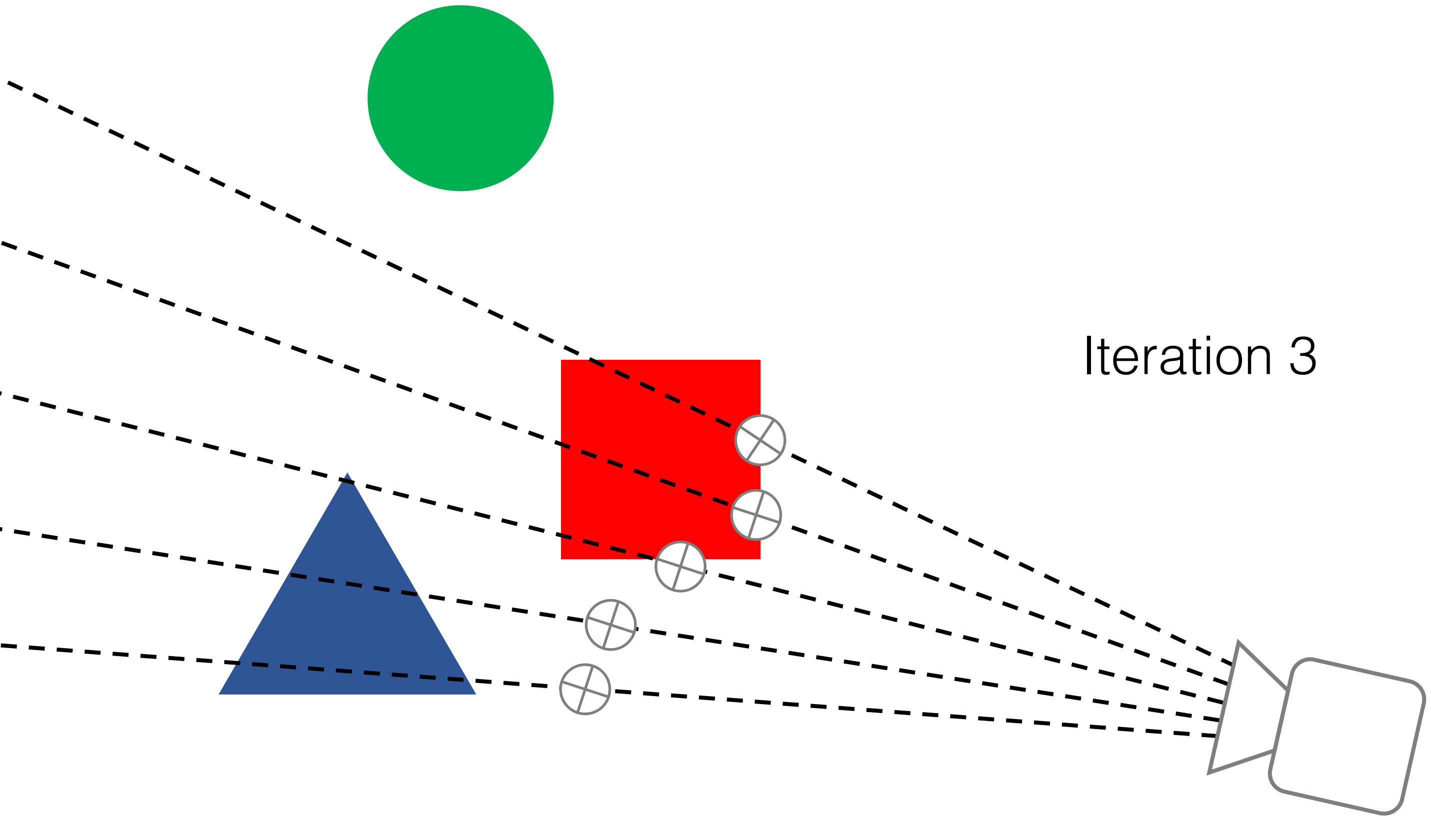
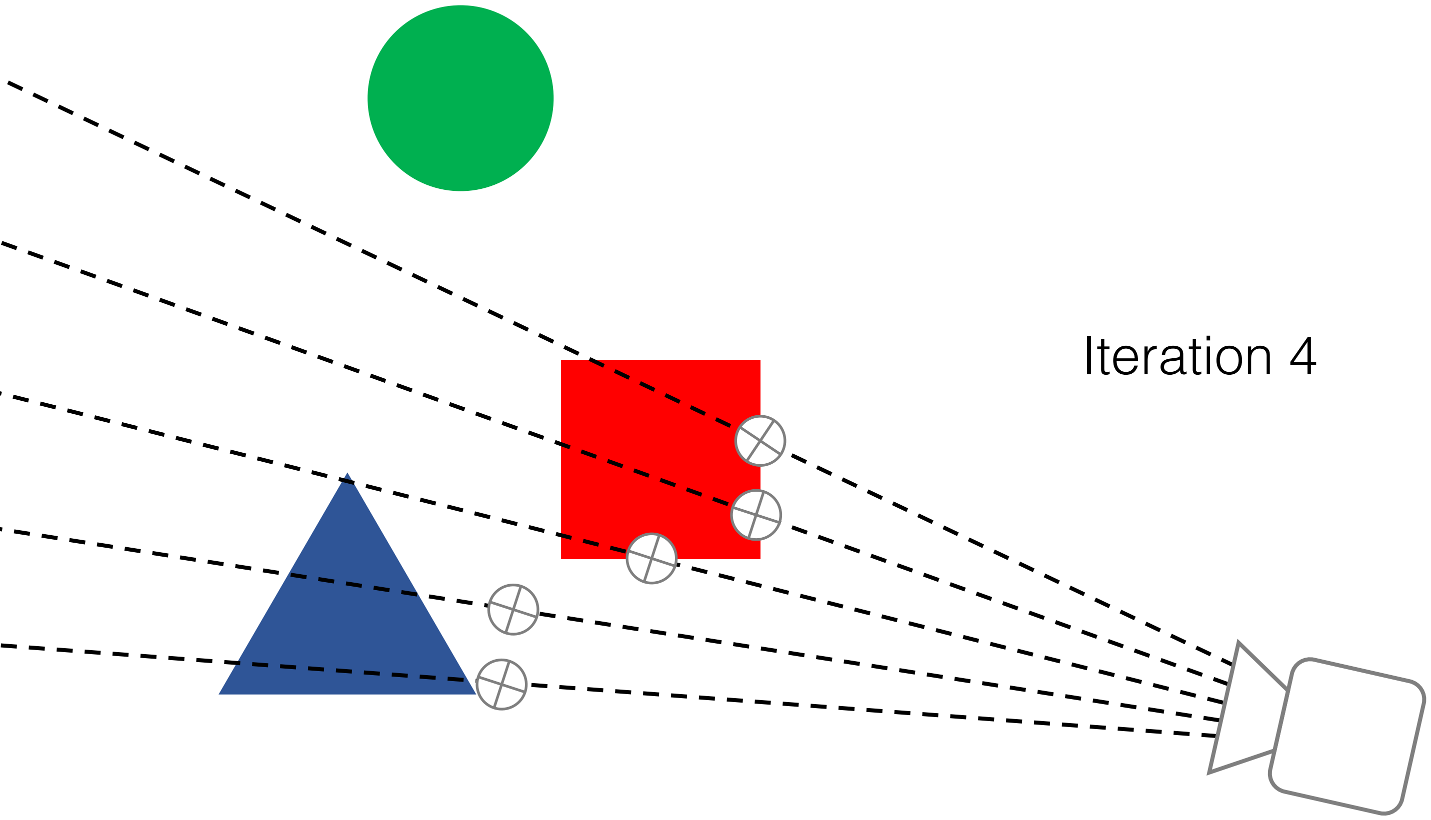
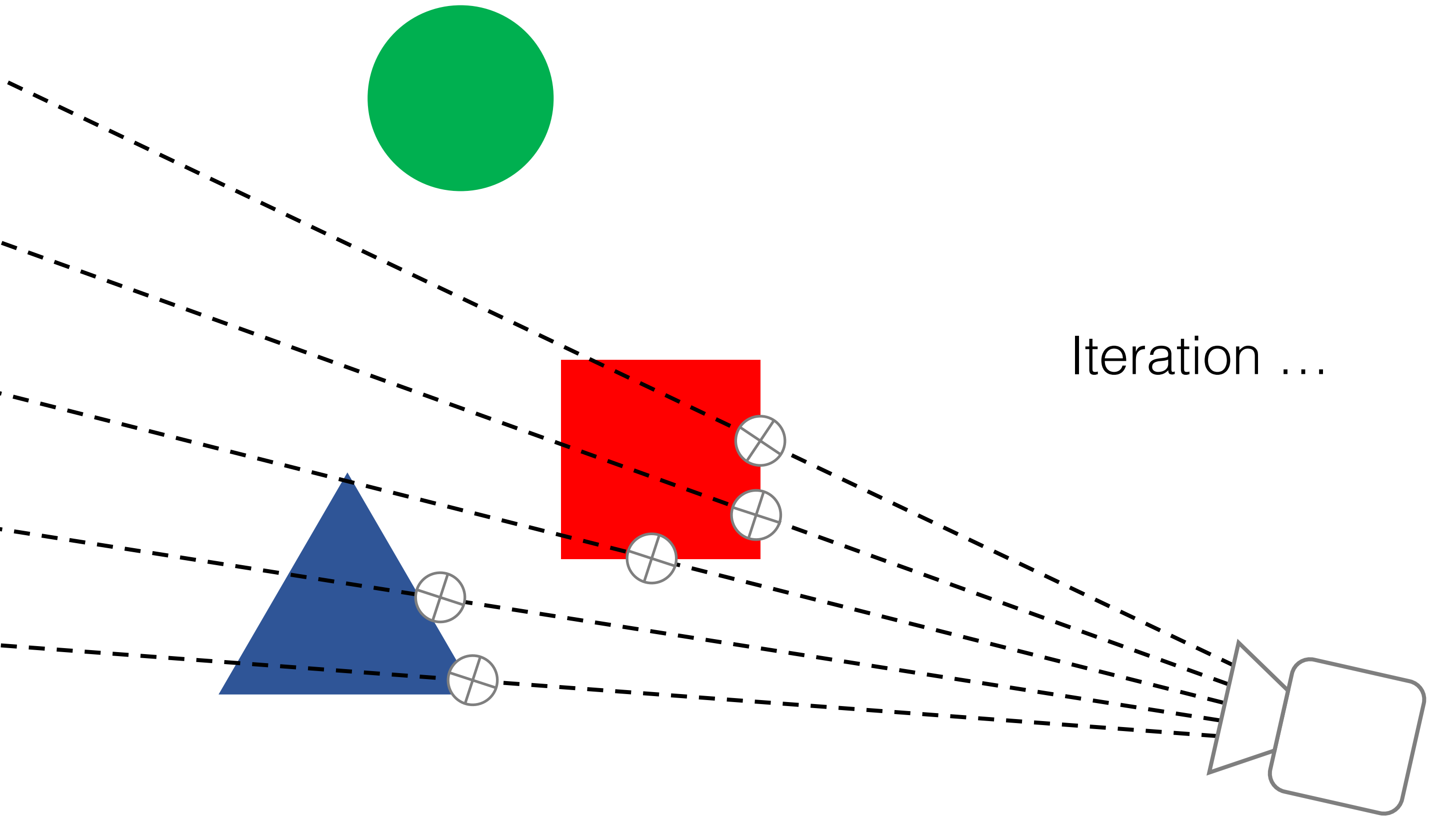


Neural Renderer Step 2: Color Generation

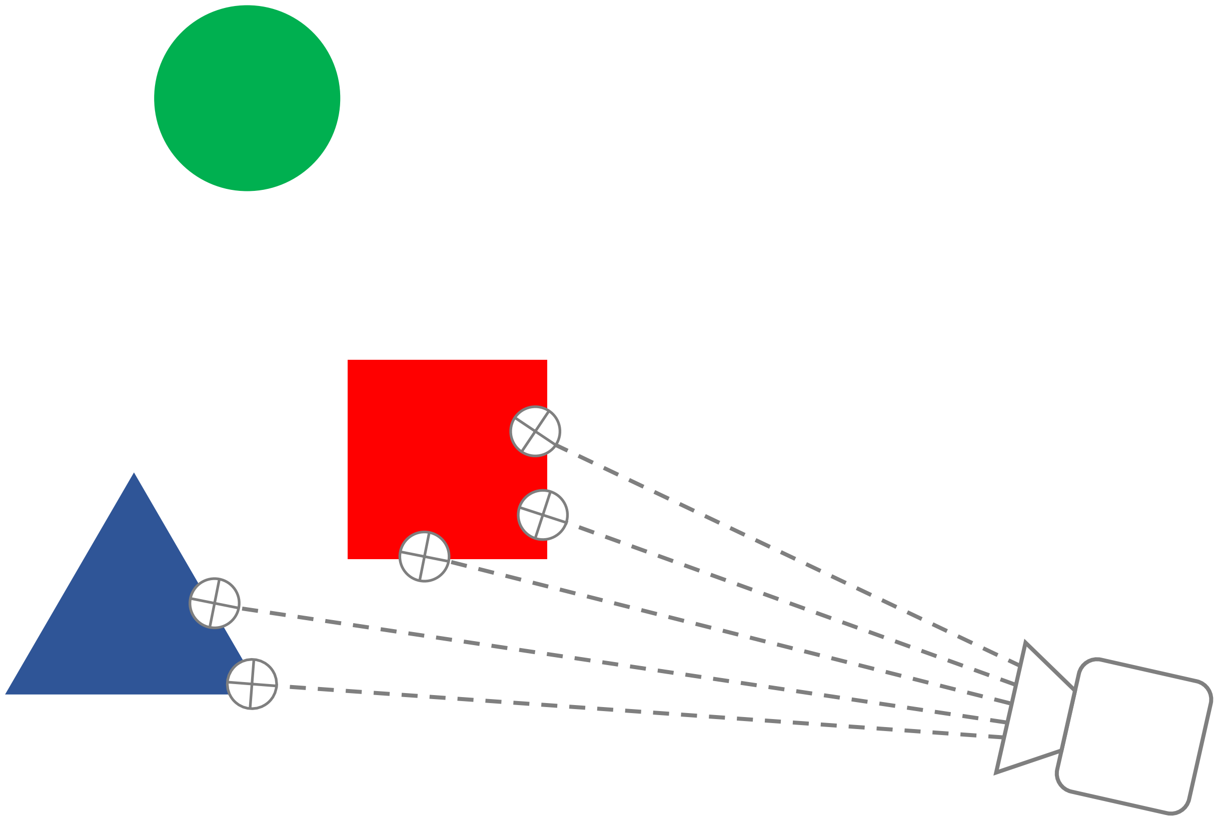


Neural Renderer Step 1: Intersection Testing.



Iteration …

Neural Renderer Step 1: Intersection Testing.



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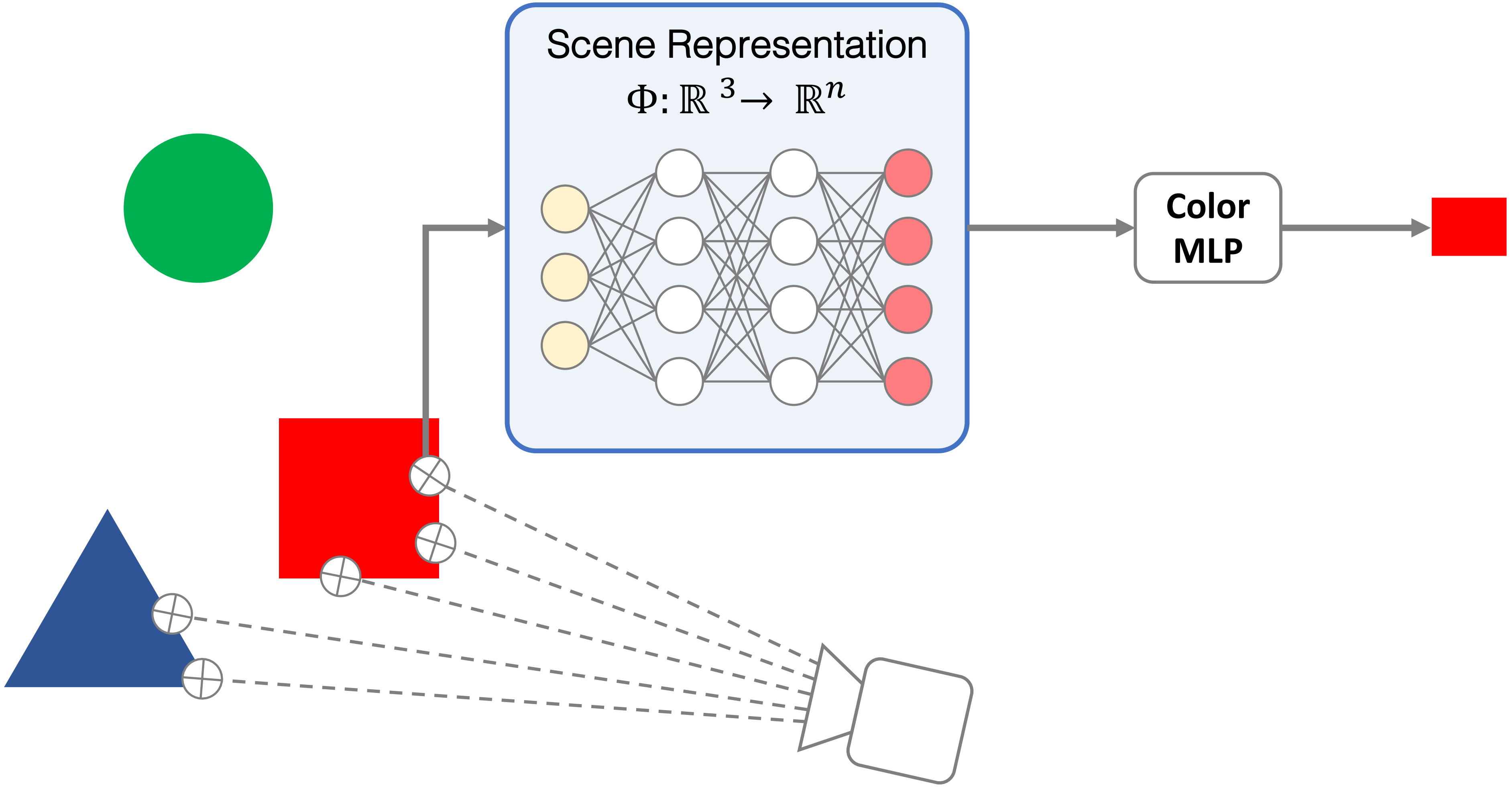
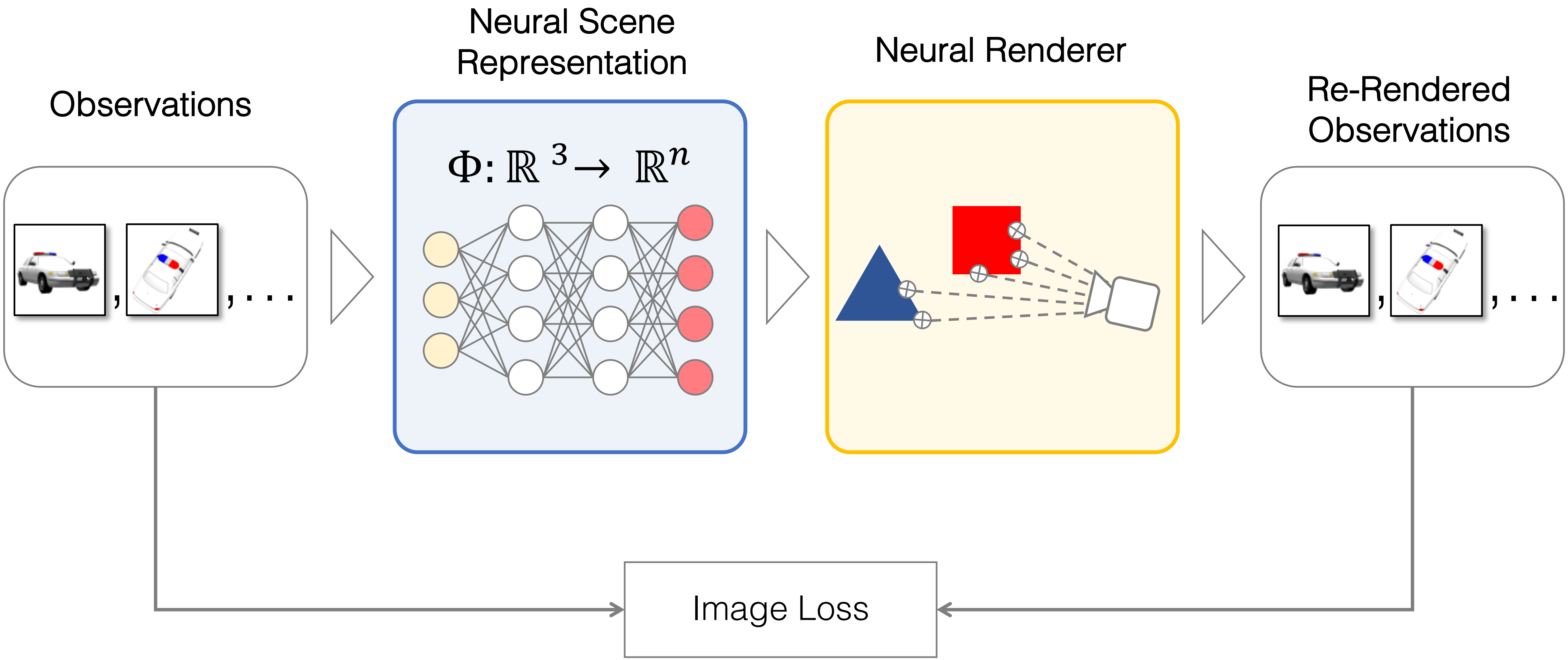


Can now train end-to-end with posed images only!



Generalizing across a class of scenes

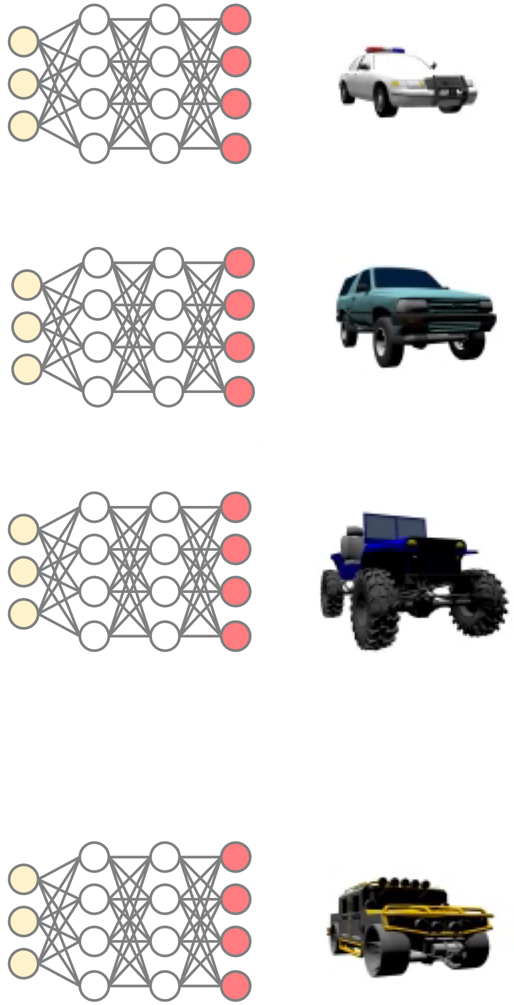
Each scene represented by its own SRN.

parameters $\phi_0 \in \mathbb{R}^l$

parameters $\phi_1 \in \mathbb{R}^l$

parameters $\phi_2 \in \mathbb{R}^l$

parameters $\phi_n \in \mathbb{R}^l$



Each scene represented by its own SRN.

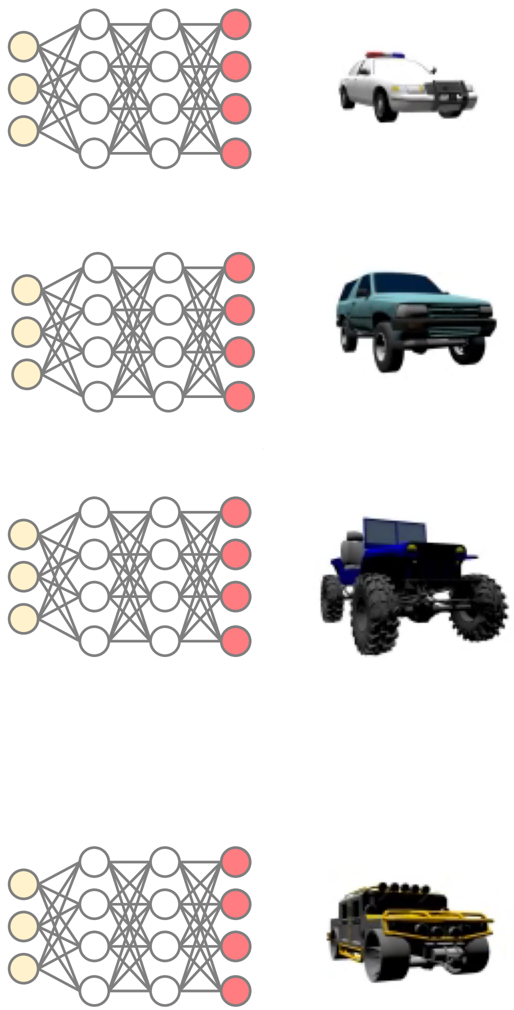
ϕ_i live on k-dimensional subspace of $\mathbb{R}^l$, $k < l$.

parameters $\phi_0 \in \mathbb{R}^l$

parameters $\phi_1 \in \mathbb{R}^l$

parameters $\phi_2 \in \mathbb{R}^l$

parameters $\phi_n \in \mathbb{R}^l$



Each scene represented by its own SRN.

embedding $z_0 \in \mathbb{R}^k$

embedding $z_1 \in \mathbb{R}^k$

embedding $z_2 \in \mathbb{R}^k$

embedding $z_n \in \mathbb{R}^k$

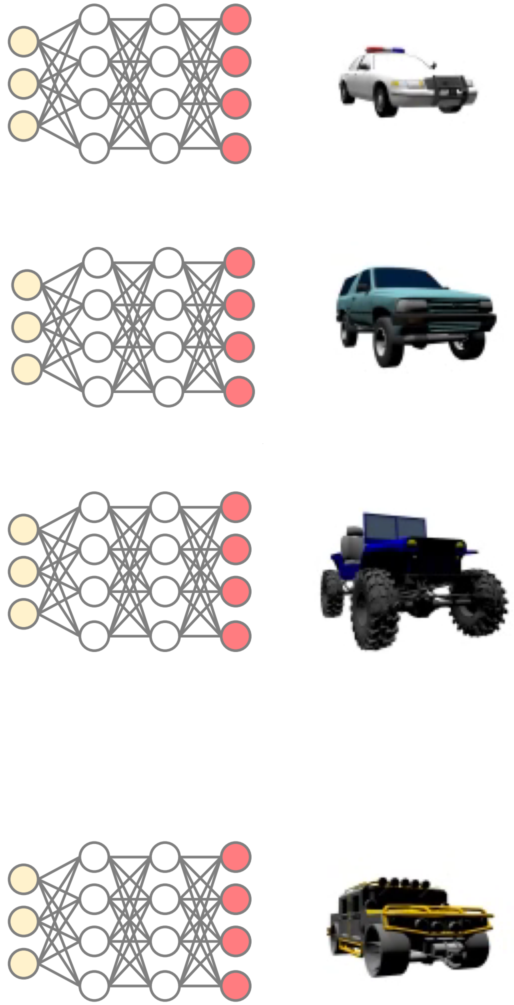
Represent each scene with
low-dimensional embedding

parameters $\phi_0 \in \mathbb{R}^l$

parameters $\phi_1 \in \mathbb{R}^l$

parameters $\phi_2 \in \mathbb{R}^l$

parameters $\phi_n \in \mathbb{R}^l$



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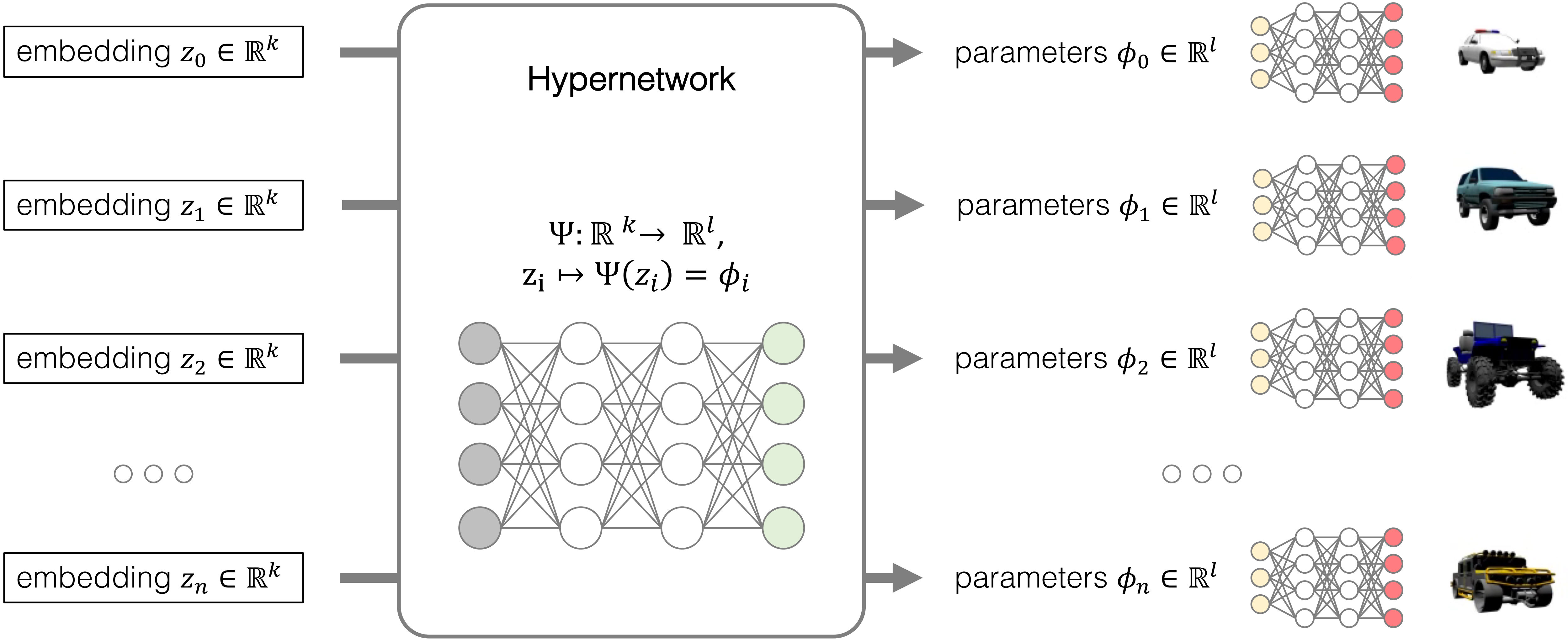


Results

Novel View Synthesis – Baseline Comparison

Shapenet v2 – ***single-shot reconstruction*** of objects in held-out test set

Training

- Shapenet cars / chairs.
- 50 observations per object.

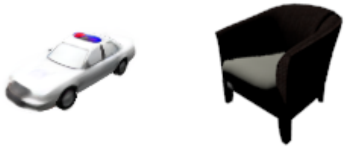
Testing

- Cars / chairs from unseen test set
- Single observation!

Input pose

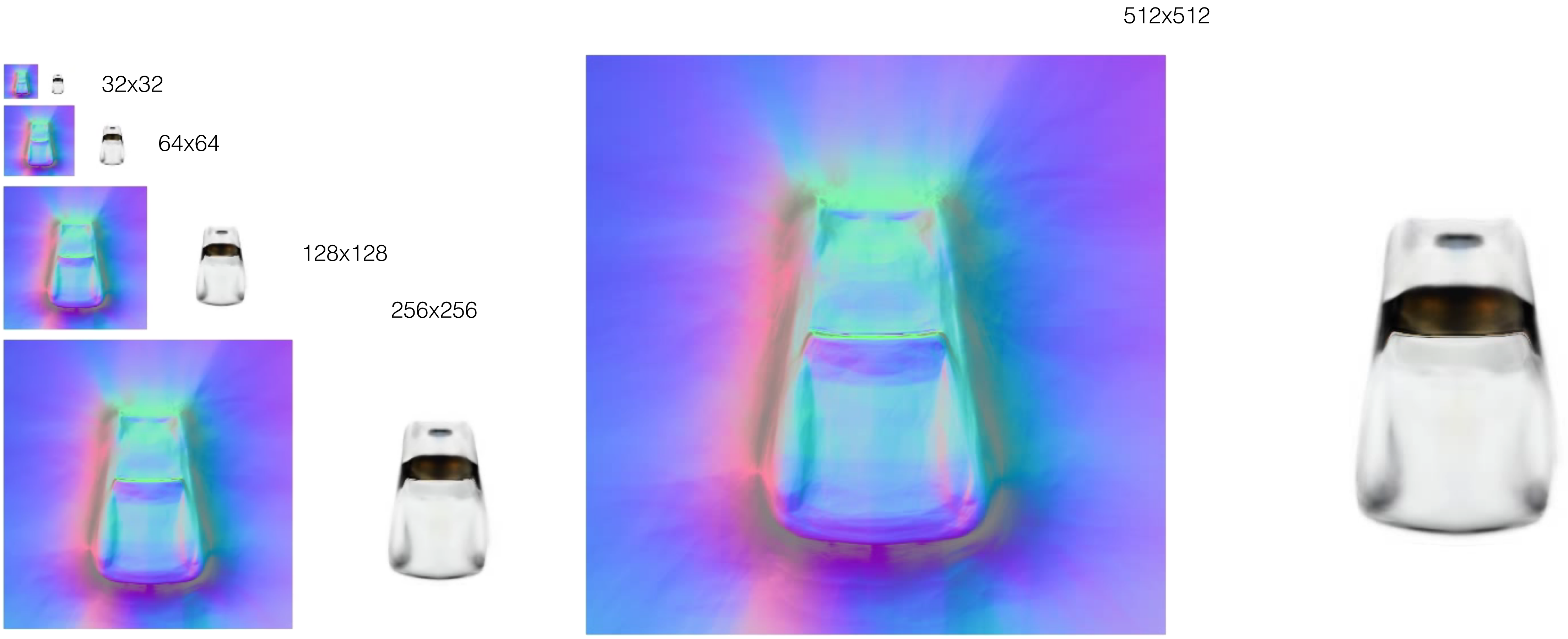

Novel View Synthesis – SRN Output

Shapenet v2 – *single-shot reconstruction* of objects in held-out test set



Input
pose

Sampling at arbitrary resolutions



Surface Normals

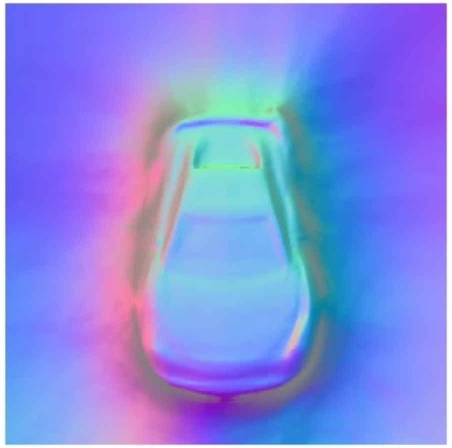
RGB

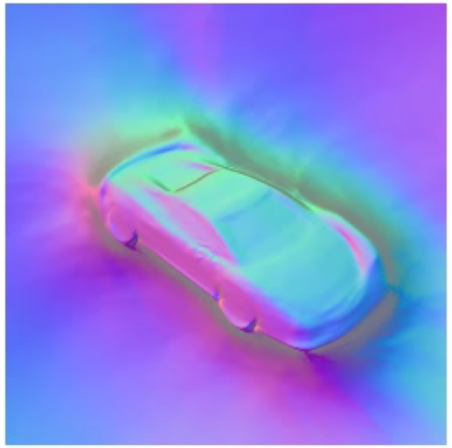
Generalization to unseen camera poses

Camera close-up

Camera Roll

SRNs





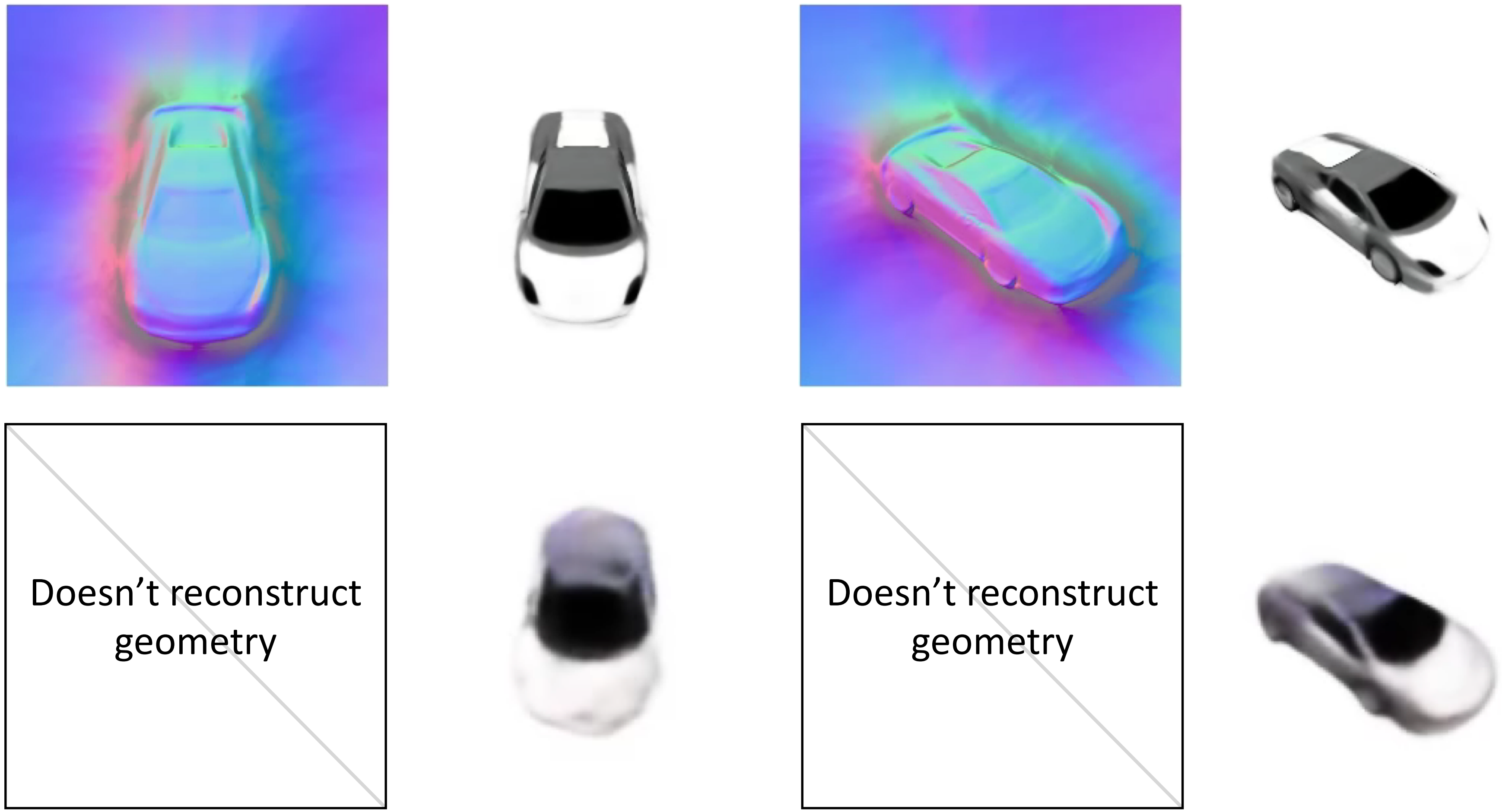
Generalization to unseen camera poses

Camera close-up

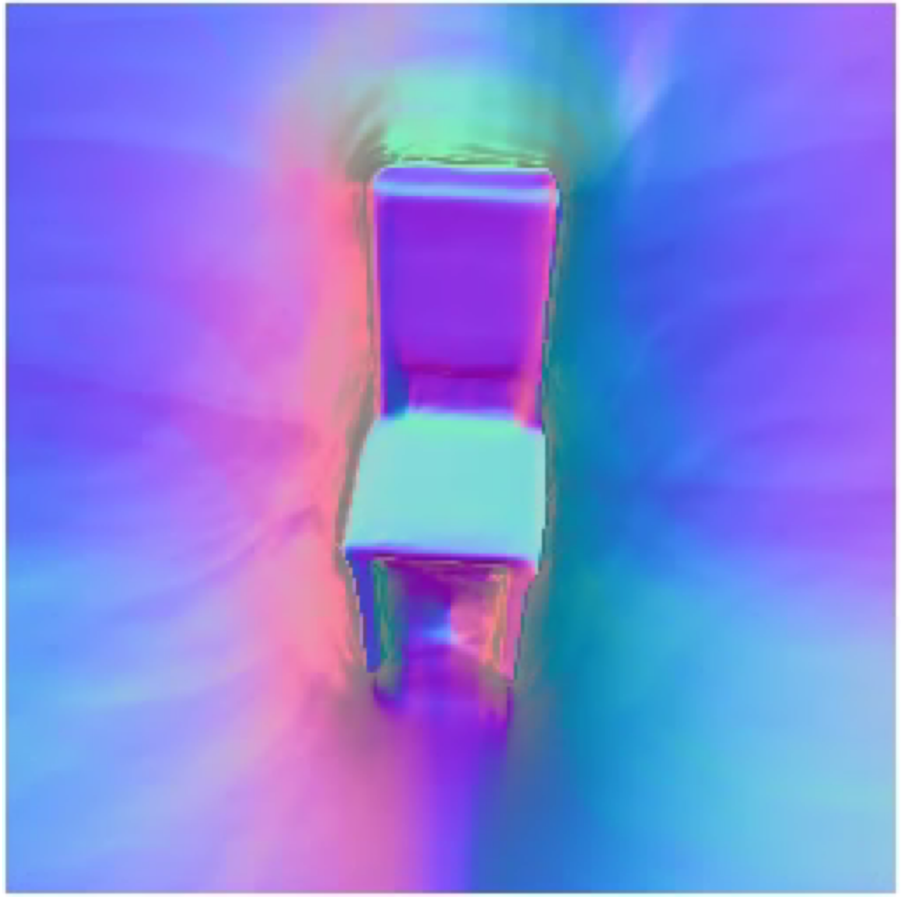
Camera Roll

SRNs

Tatarchenko et al.



Latent code interpolation



Surface Normals

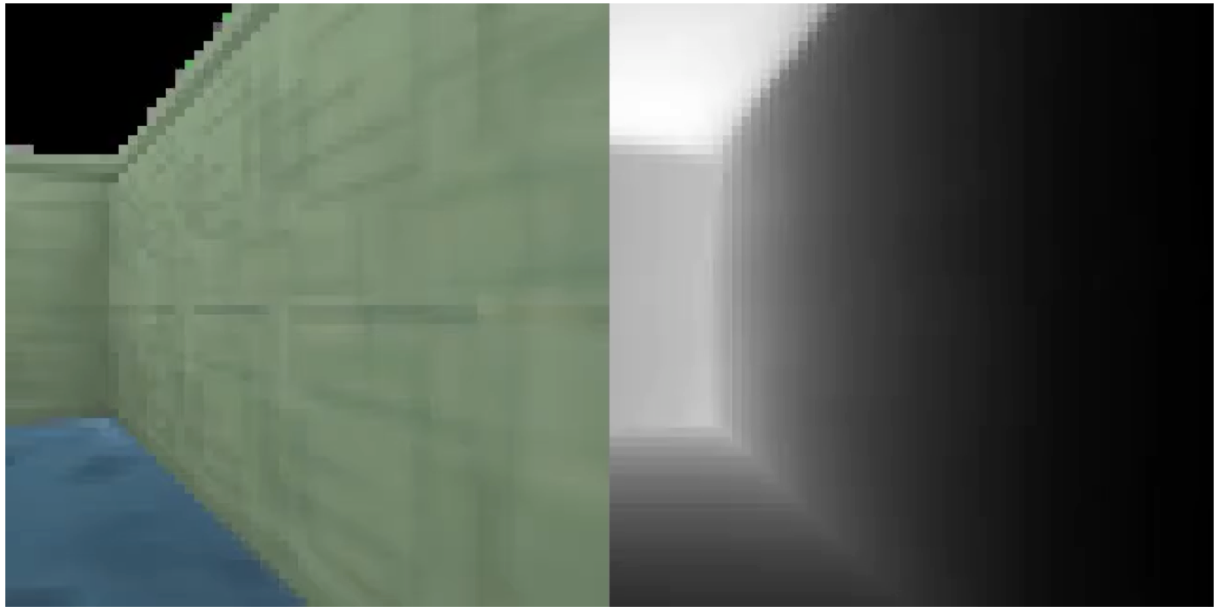
RGB

Latent code interpolation

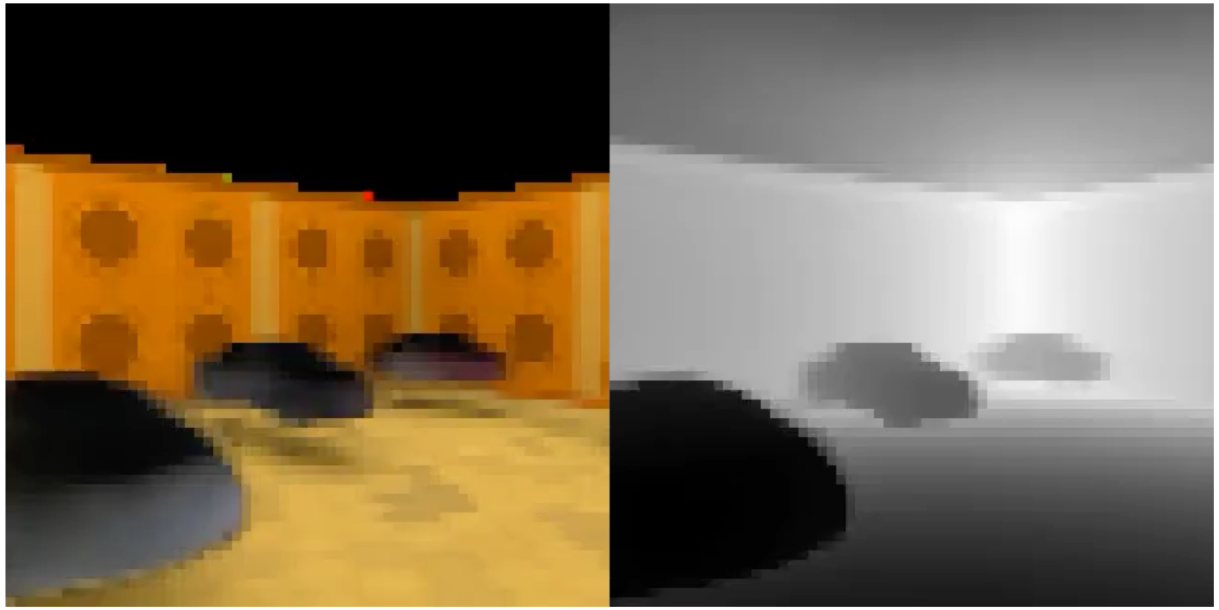
Surface Normals

RGB

Can represent room-scale scenes, but aren't compositional.



Training set novel-view synthesis on GQN rooms (Eslami et al. 2018) with Shapenet cars, 50 observations.



Work-in-progress: Compositional SRNs generalize to unseen numbers of objects!

Scene Representation Networks: Continuous 3D-structure-aware Neural Scene Representations

Vincent Sitzmann Michael Zollhöfer Gordon Wetzstein

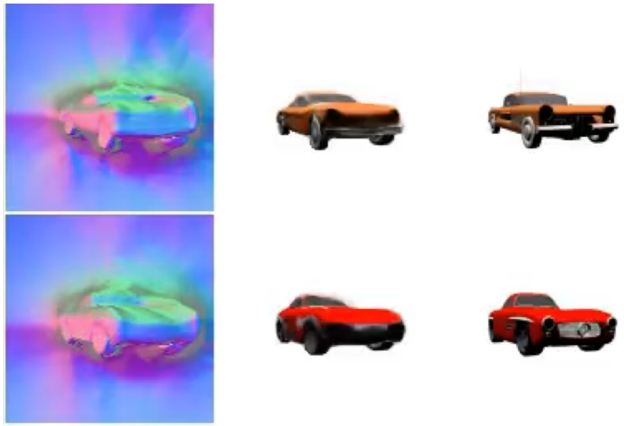
Find me at Poster # 71!

Looking for research positions in scene representation learning.

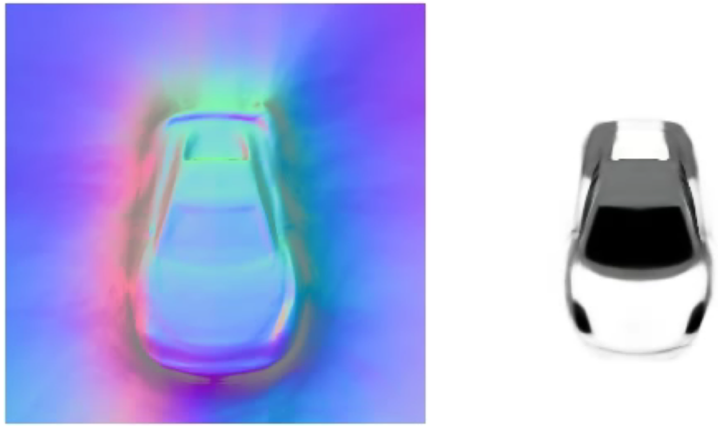
vsitzmann.github.io

@vincesitzmann

Interpolation



Single-shot reconstruction



Camera pose extrapolation