INVERSE GRAPHICS

MODULE 2:
3D Scene Representations & Neural Rendering

RENDERING
Inverse Graphics & Differentiable Rendering

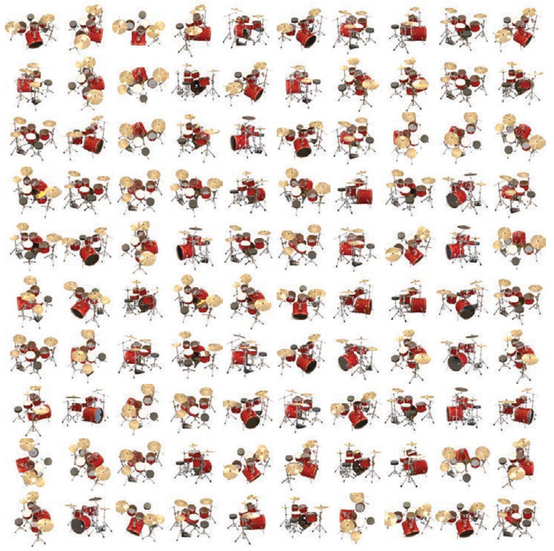
6.S980 | 2023-10-05

Rendering (Graphics): Given 3D Scene + Camera parameters, yield images

3D Scene

Camera Poses

Render



Images

Inverse Graphics: Given Images, Infer Camera Poses & 3D Scene!

Images

Reconstruct

3D Scene

Camera Poses

How to get camera poses?

Images

Reconstruct

3D Scene

Camera Poses

Can assume we know the camera poses.

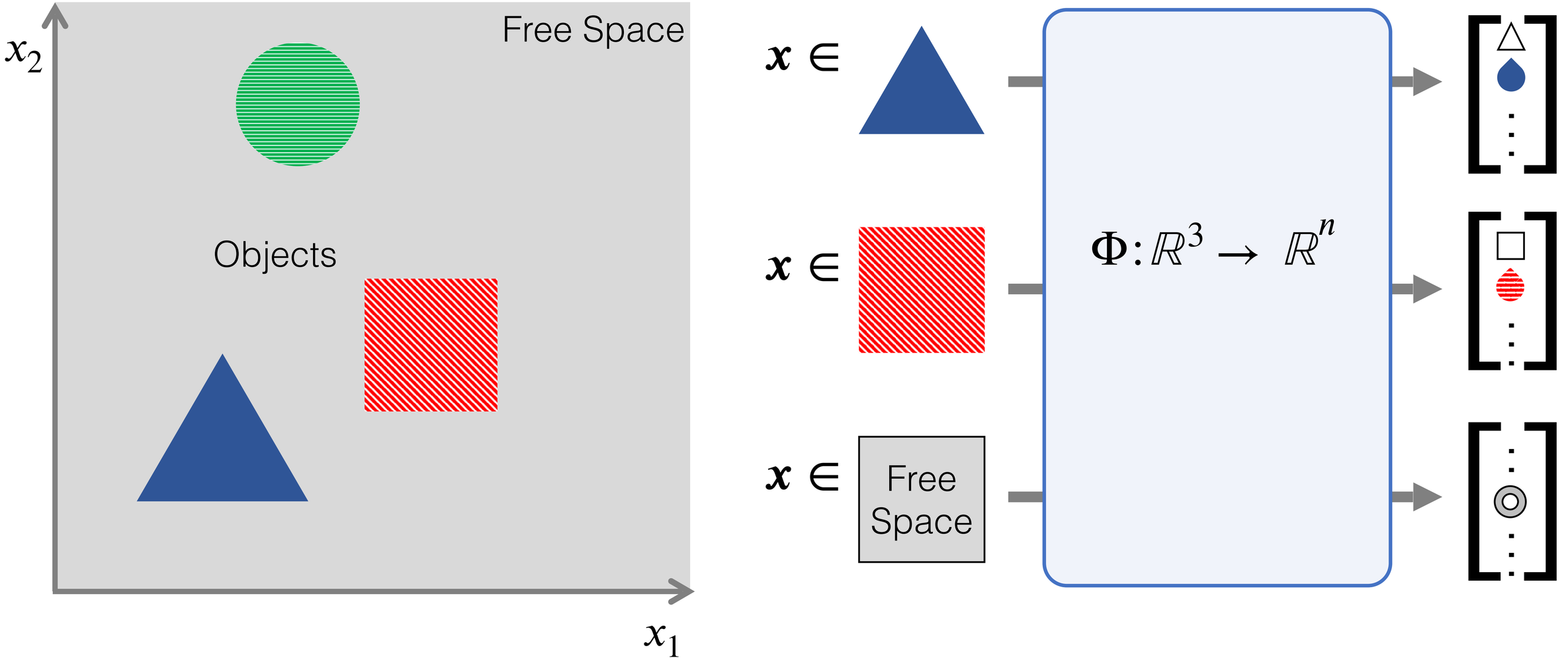
Images

Camera Poses

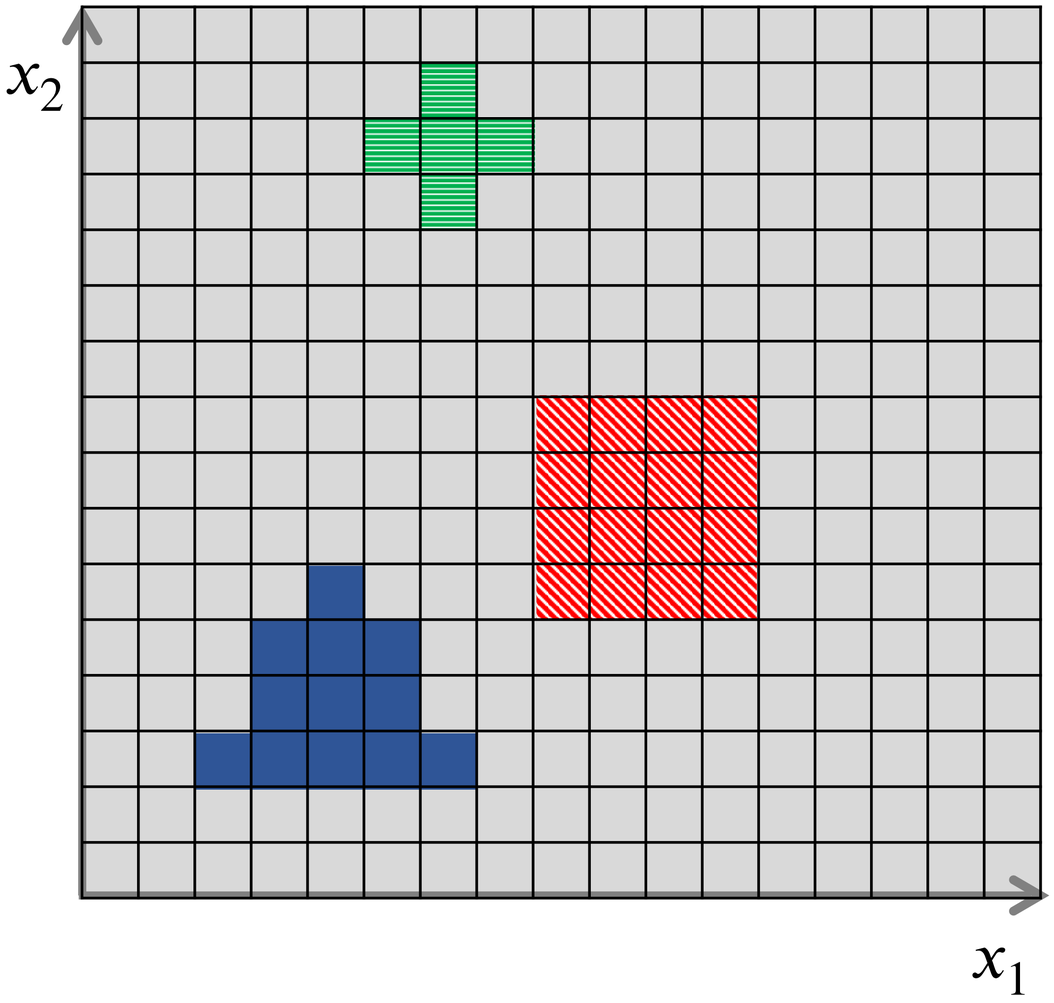
Reconstruct

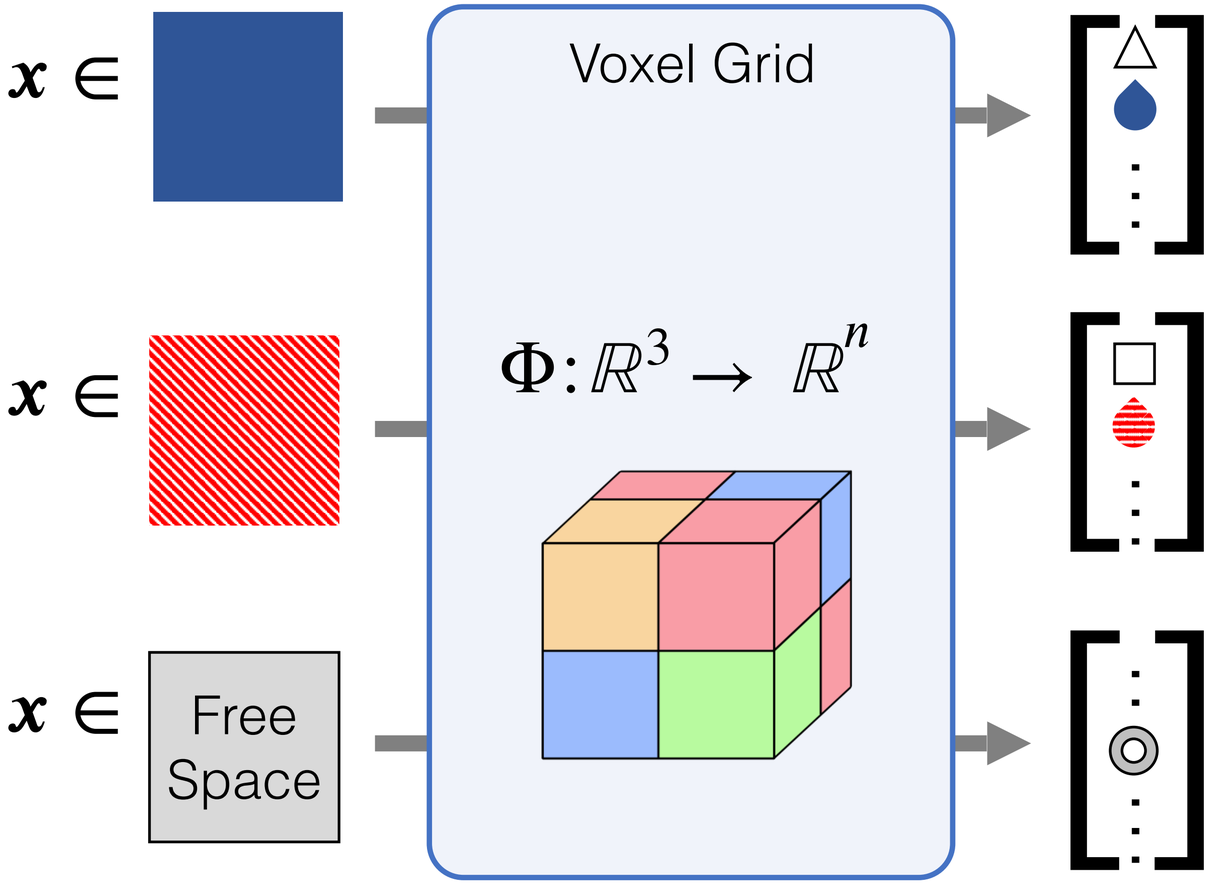
3D Scene

Starting Point: 3D Scene Representation



Starting Point: 3D Scene Representation





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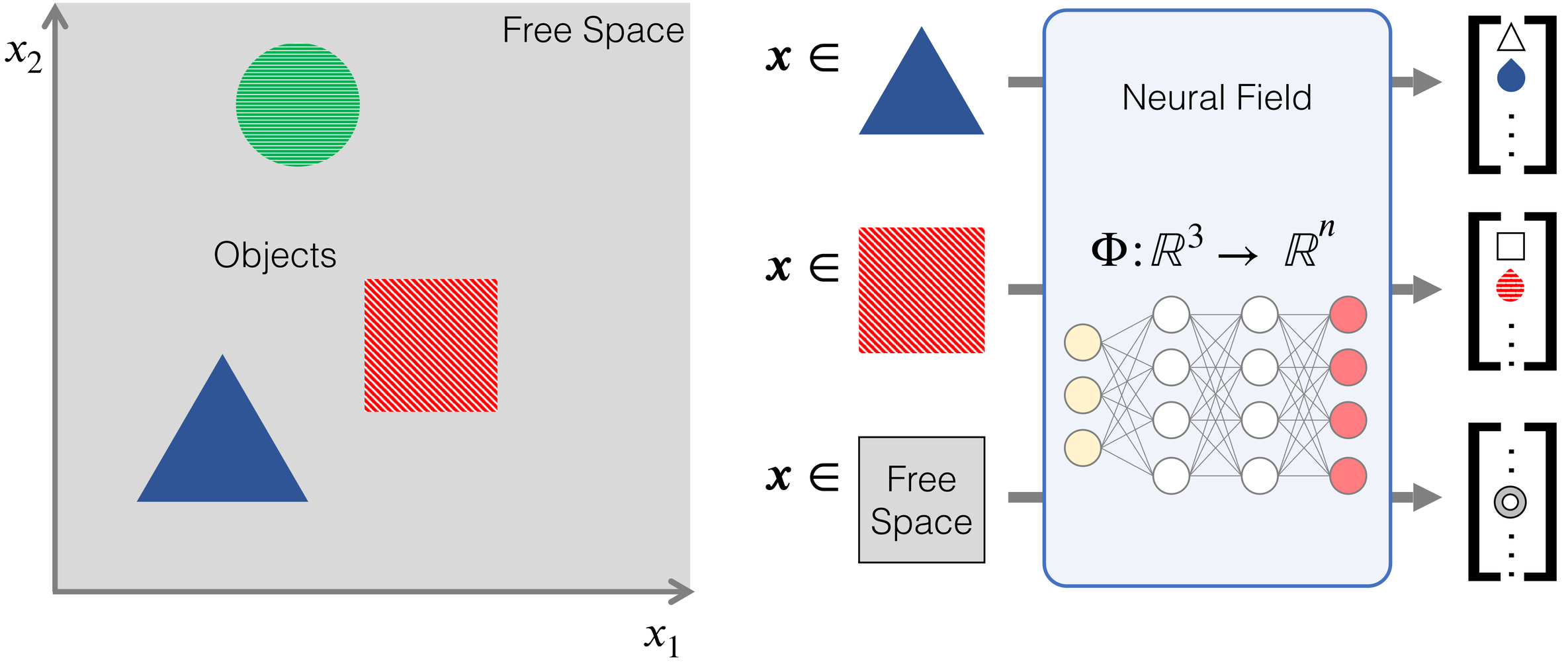


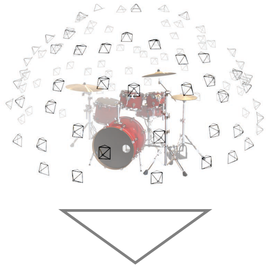
Differentiable Rendering

Scene Representation

Renderer

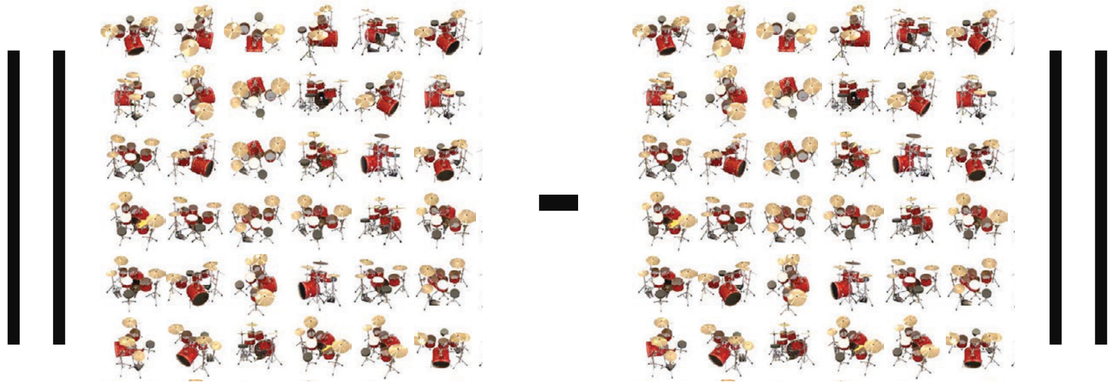
Rendered Images

Differentiable Rendering



Scene Representation

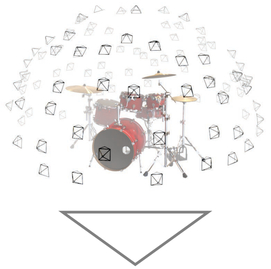
Renderer



Rendered Images

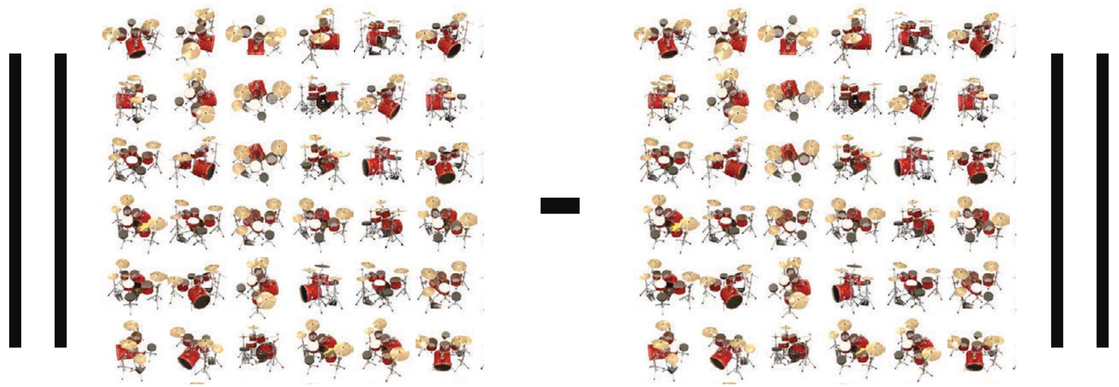
GT Images

Differentiable Rendering



Scene Representation

Differentiable Renderer

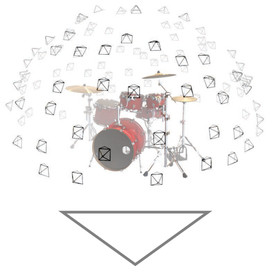


Rendered Images

GT Images

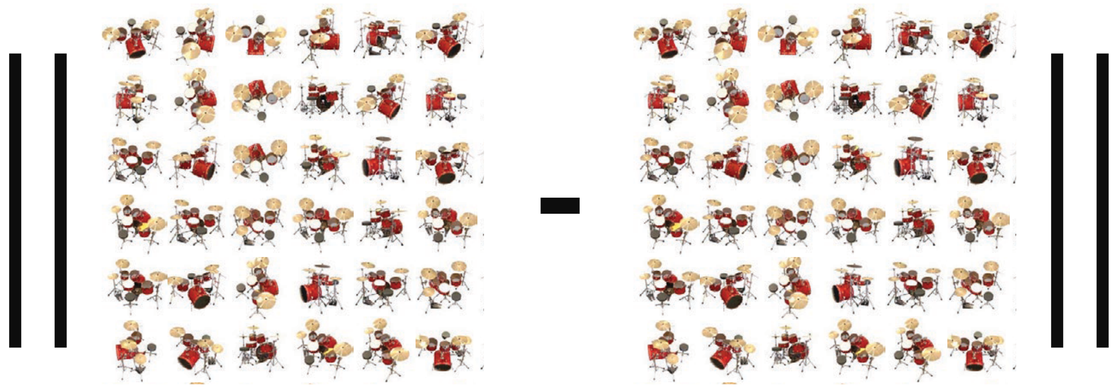
Optimization via SGD

Differentiable Rendering



Scene Representation

Differentiable Renderer



Rendered Images

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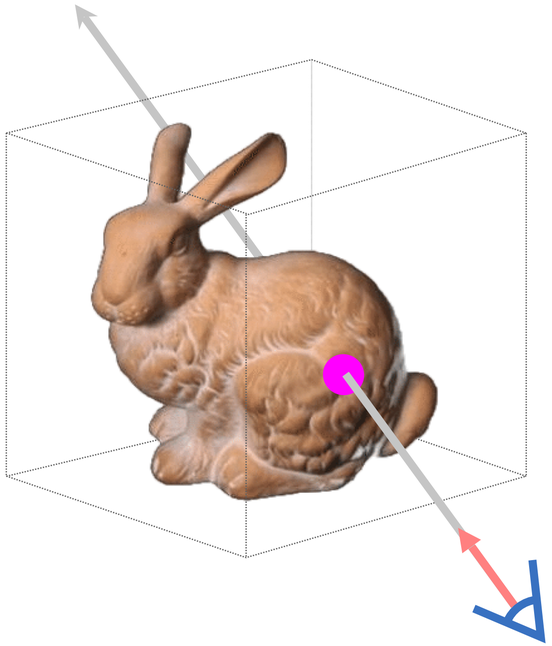
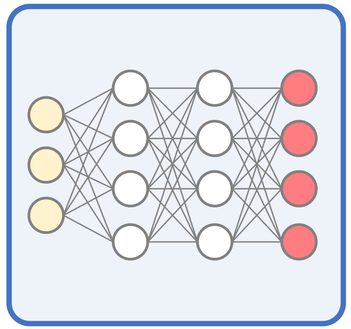
Given an *observable* variable (pixel colors), we will build a differentiable forward model that we then use to estimate *unobserved (latent) variables* (geometry, appearance)!

General structure of Neural Renderers for 3D Fields





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

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

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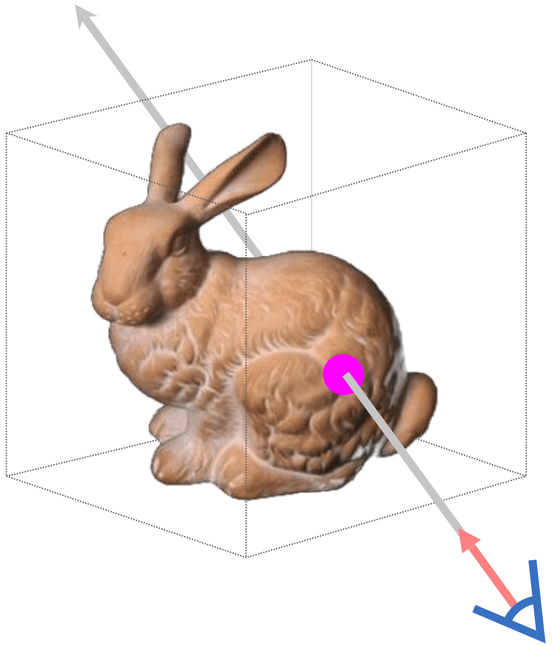

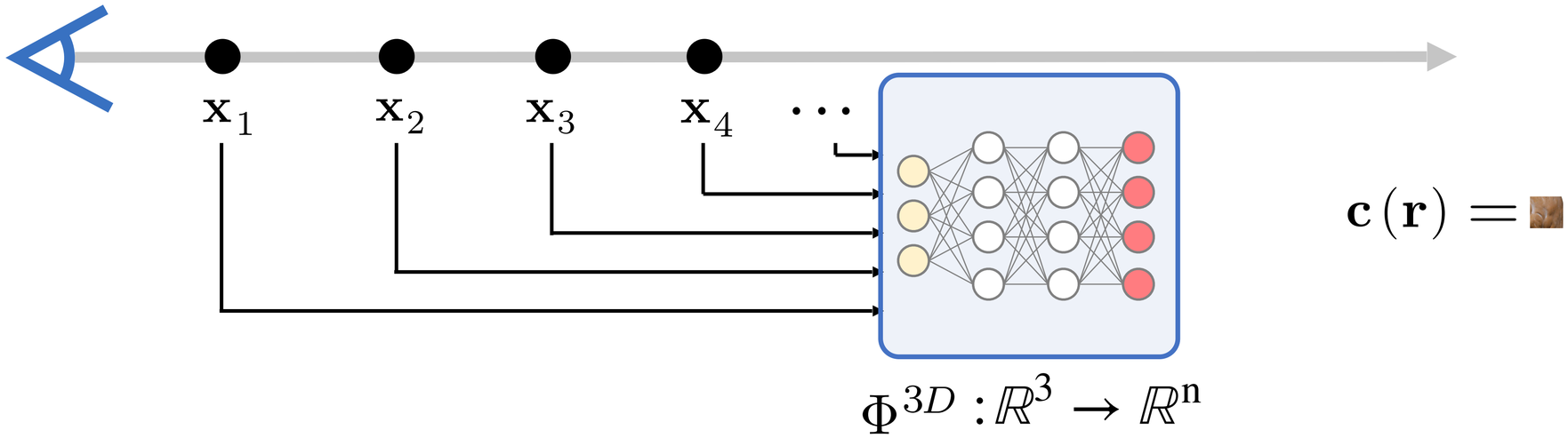

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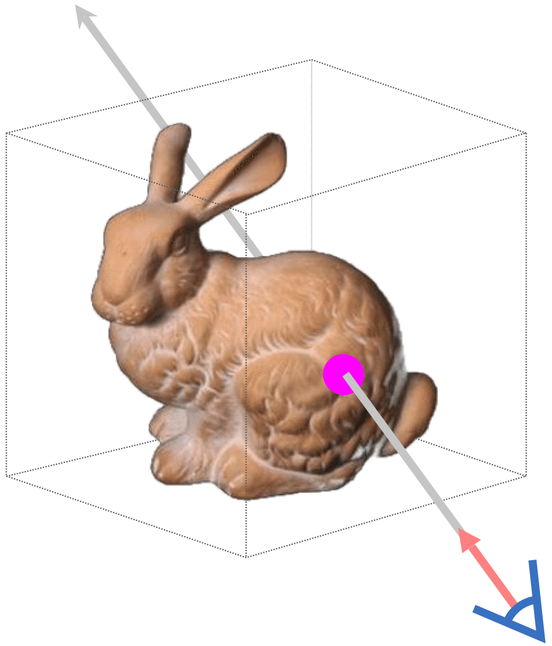

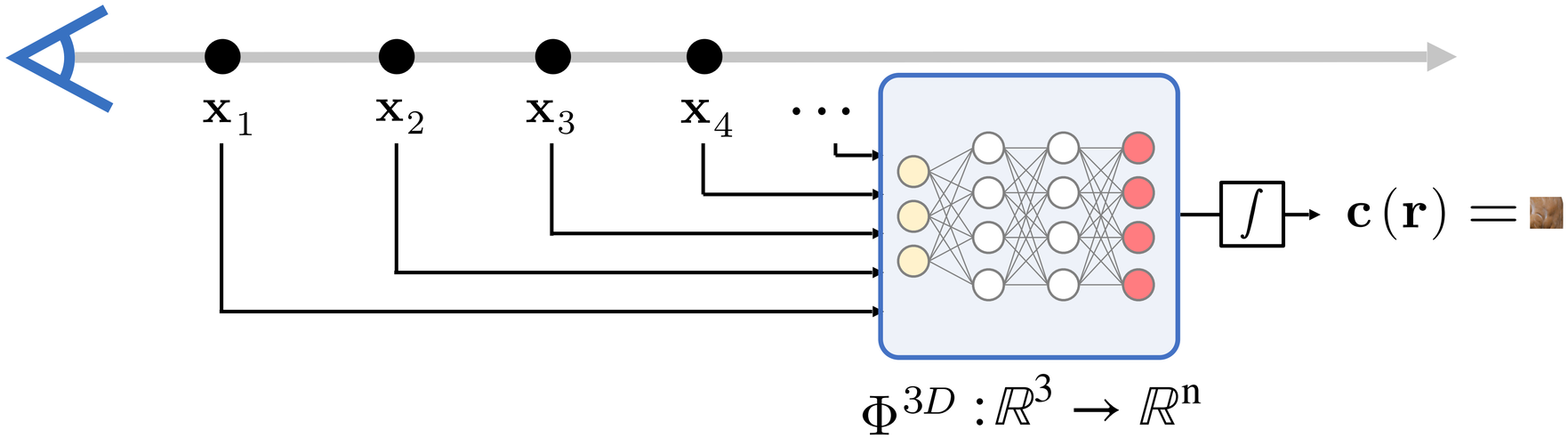

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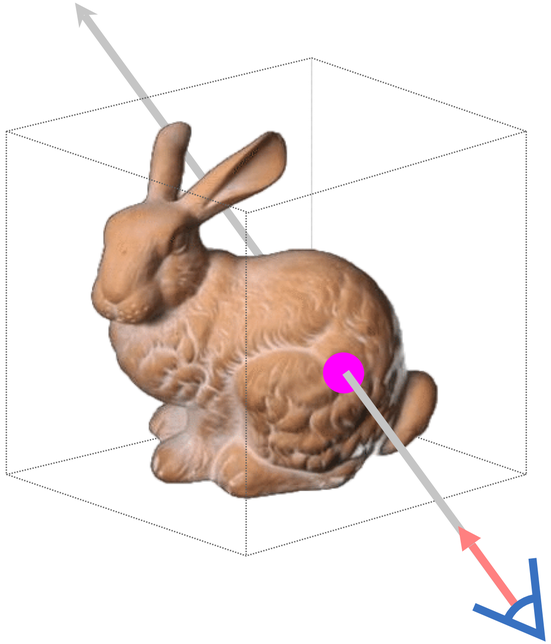

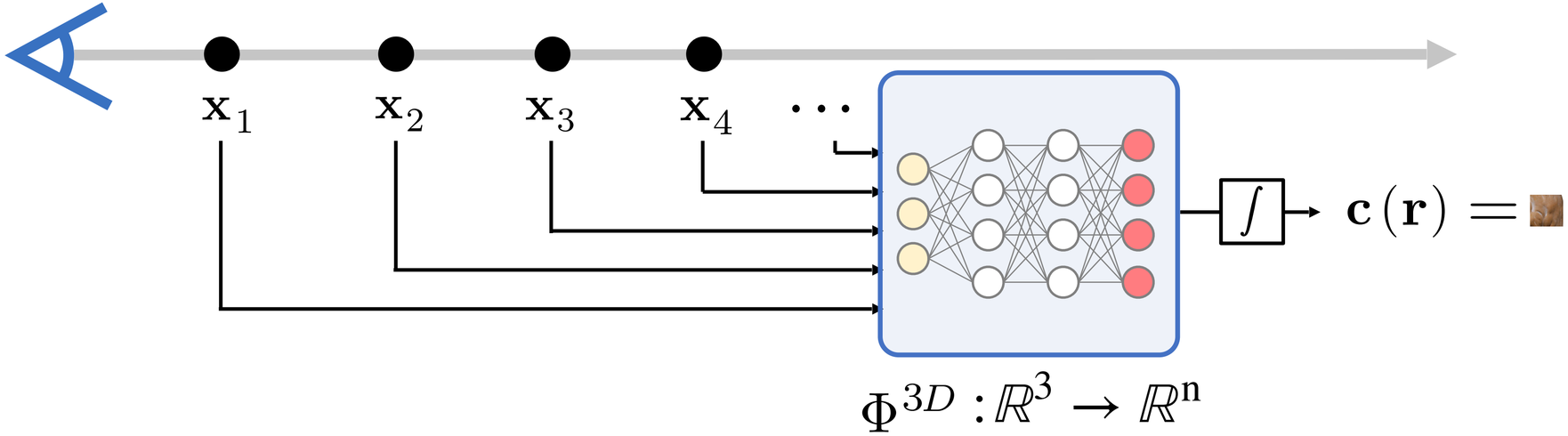

Sphere-Tracing [JC Hart, 1996]

Volumetric

Hybrid implicit-volumetric

Learned aggregation

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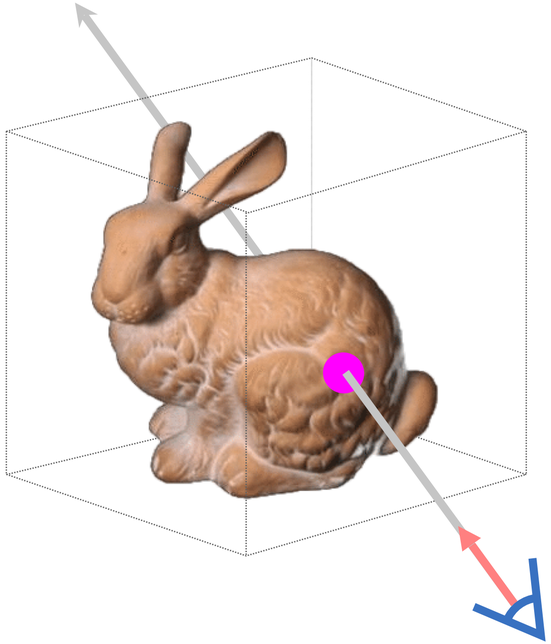

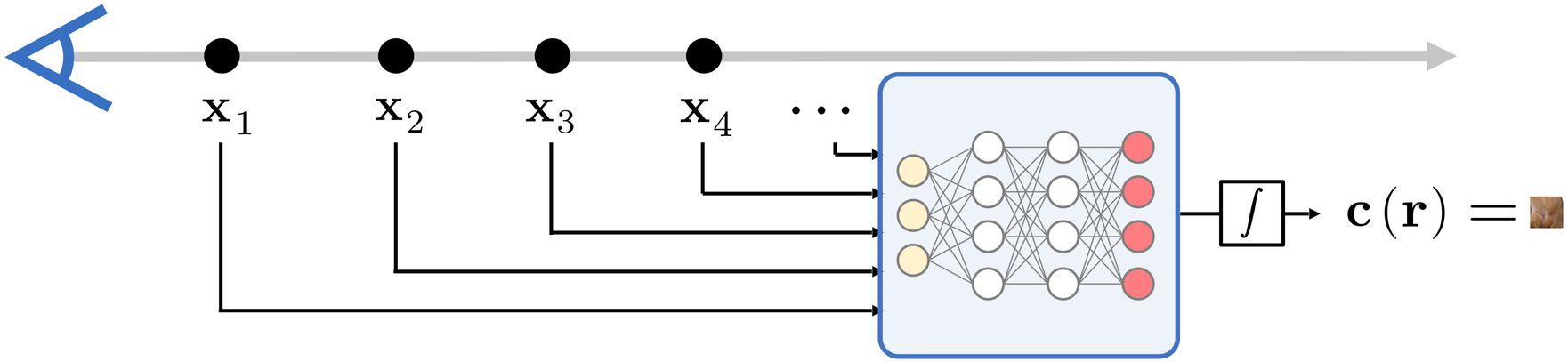

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Summary: volume rendering integral estimate

Rendering model for ray $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d}$:

$$\mathbf{c} \approx \sum_{i=1}^{n} T_i \alpha_i \mathbf{c}_i$$

colors

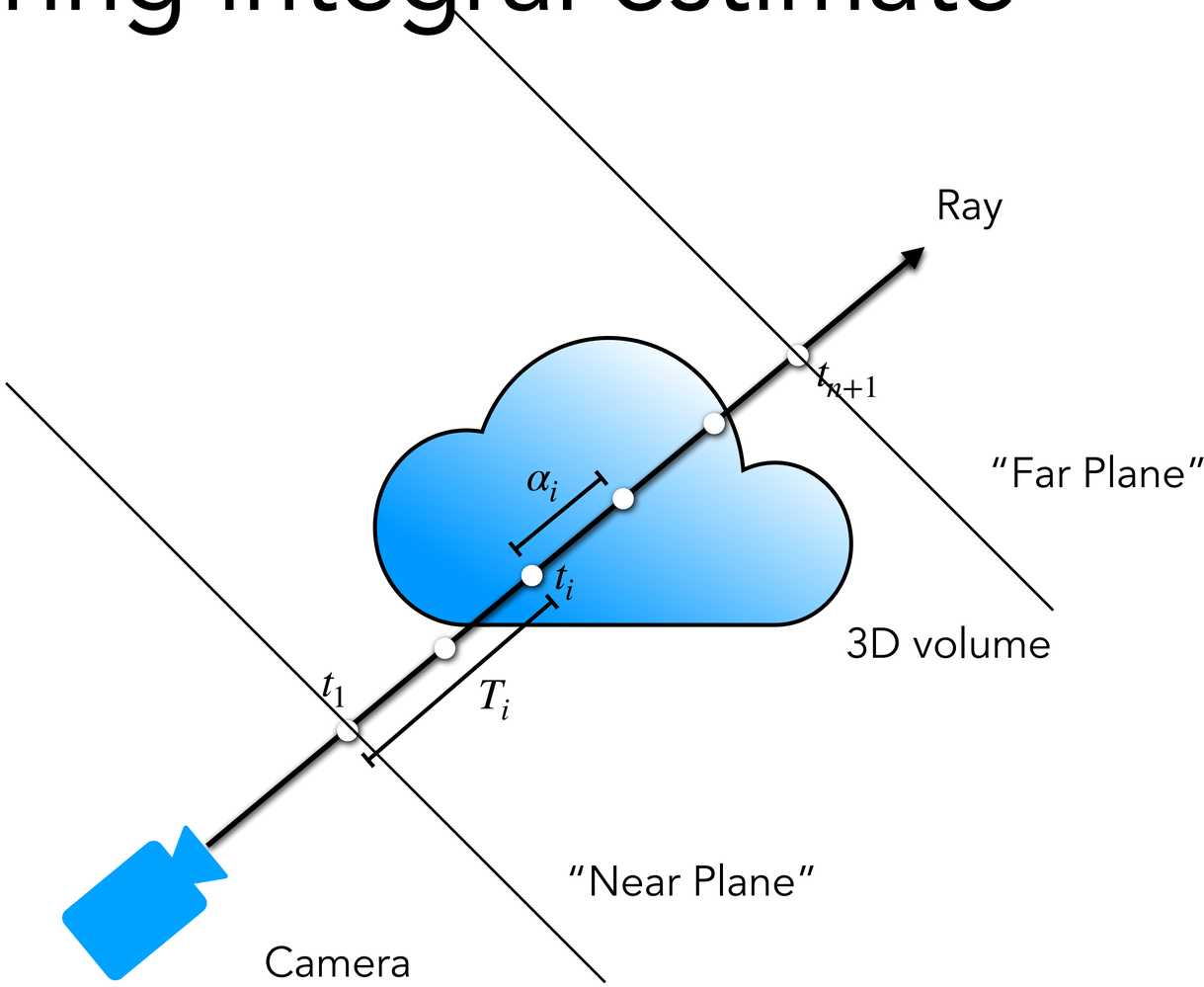
weights

How much light is blocked earlier along ray:

$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

How much light is contributed by ray segment *i*:

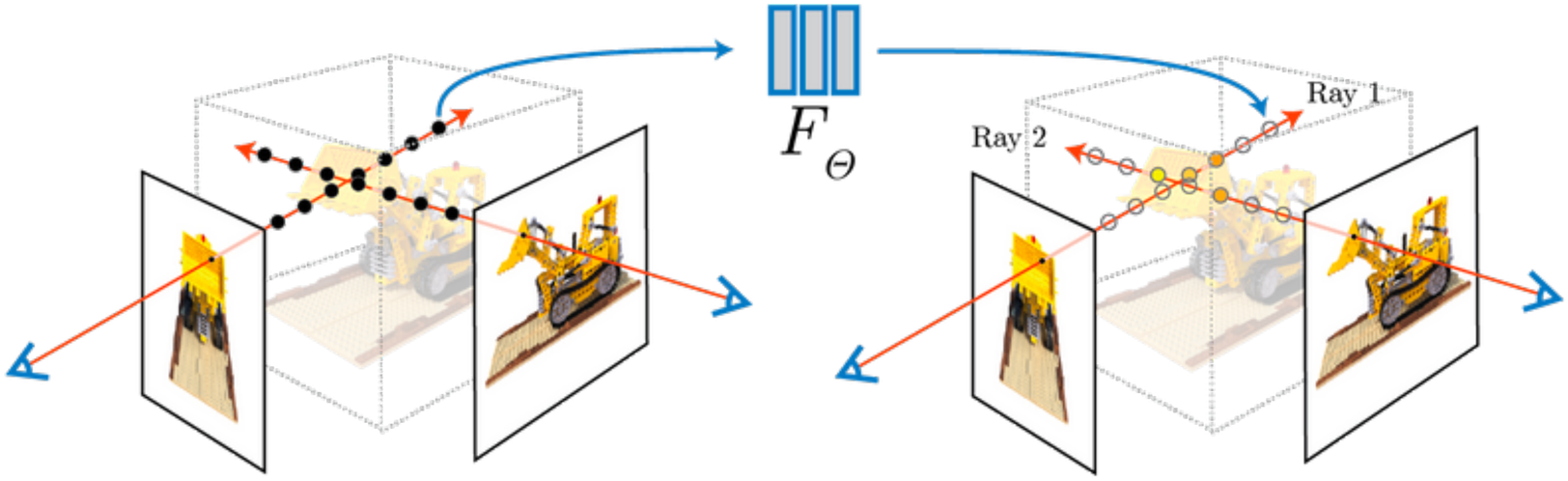
$$\alpha_i = 1 - \exp(-\sigma_i \delta_i)$$

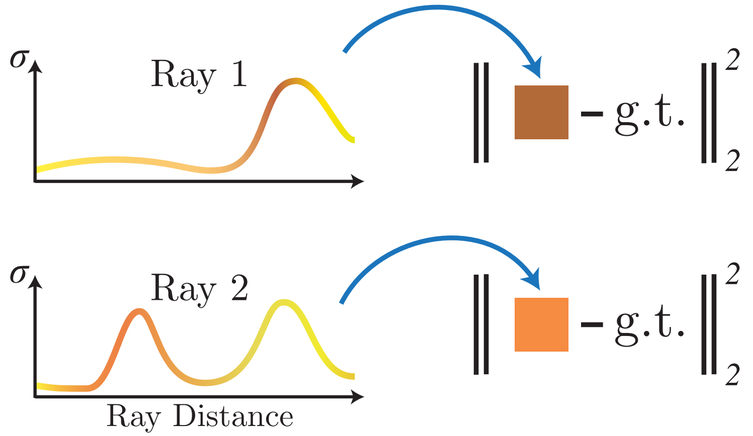


Neural Radiance Field: Parameterize Radiance Field via neural network

$$(x,y,z,\theta,\phi) \rightarrow \boxed{\quad} \rightarrow (RGB\sigma)$$

$$F_\Theta$$





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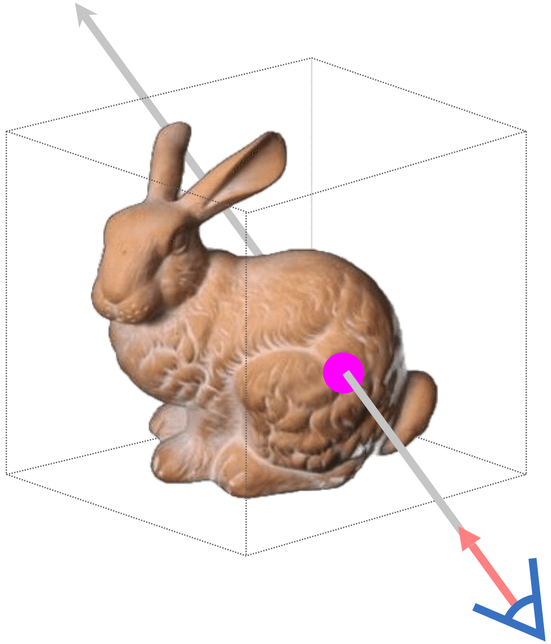

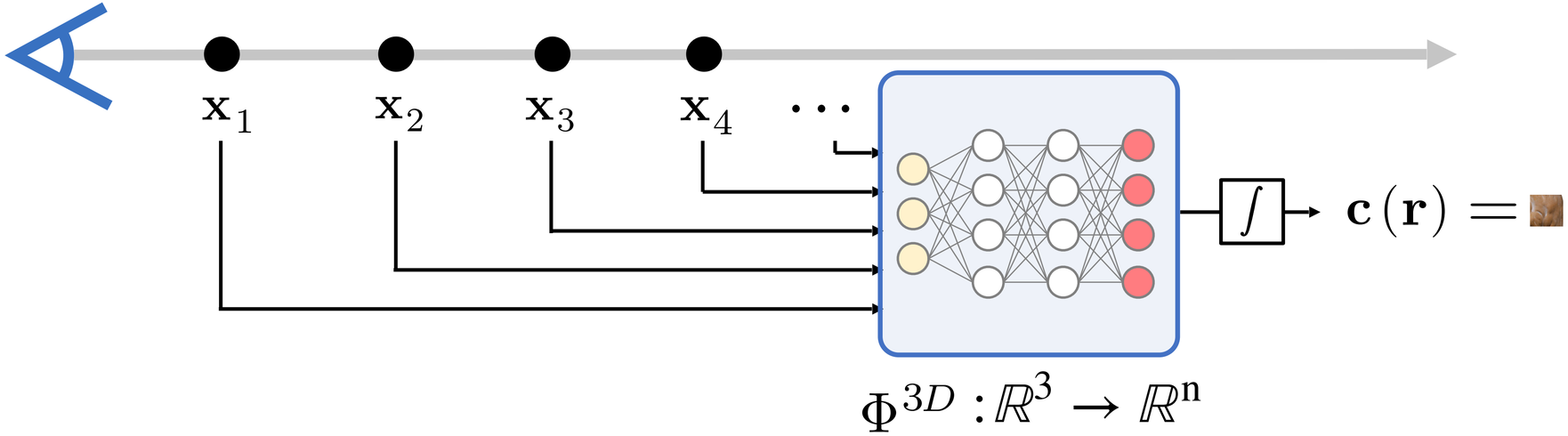

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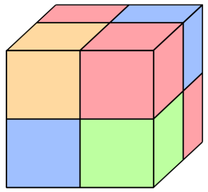
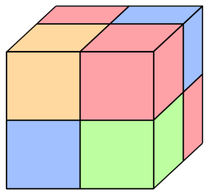
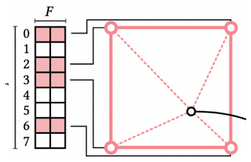
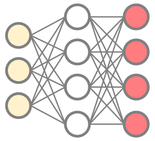


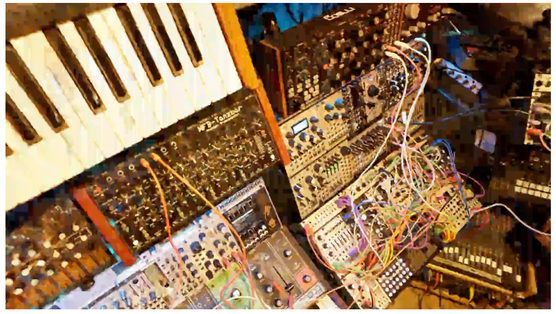
Voxel Grid

Plenoxels: Radiance Fields …
[Yu et al. 2022]
Direct Voxel Grid Optimization
[Sun et al. 2021]

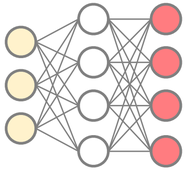





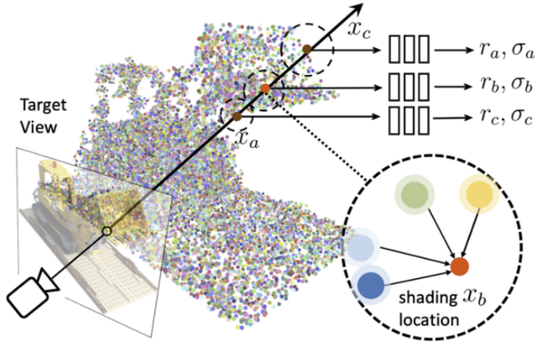
Voxel Grid + Hashmap + MLP



InstantNGP: Instant Neural …
[Müller et al. 2022]

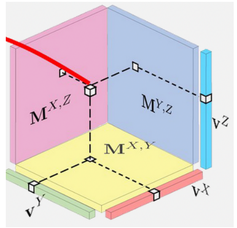



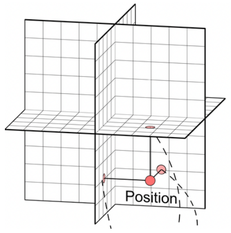
Point Cloud + MLP

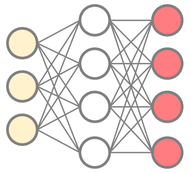


(b) Point-NeRF Representation with Volum

PointNeRF: Point-based Neural …
[Xu et al. 2022]

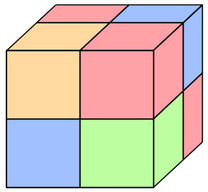






Tensor Factorization / Triplane + MLP

Efficient Geometry-aware 3D…
[Chan et al. 2022]
TensorRF: Tensor Radiance Fields
[Chen & Xu et al. 2022]



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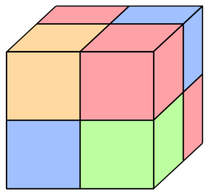
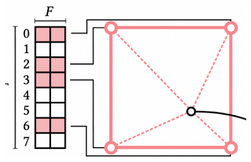

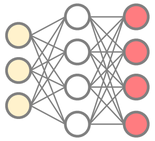

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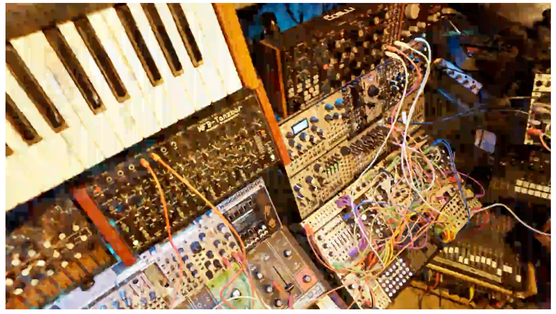

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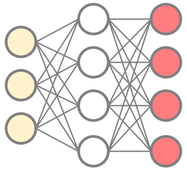
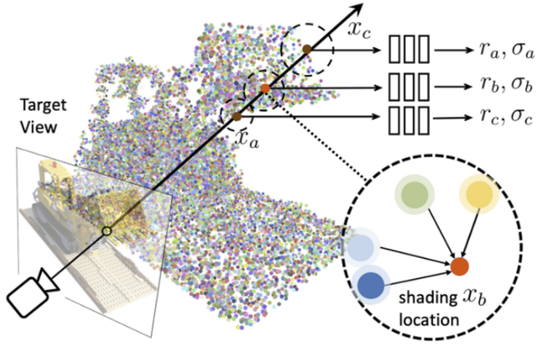


Point Cloud + MLP



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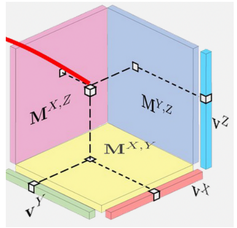

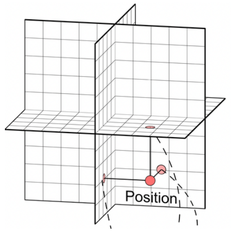

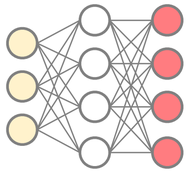

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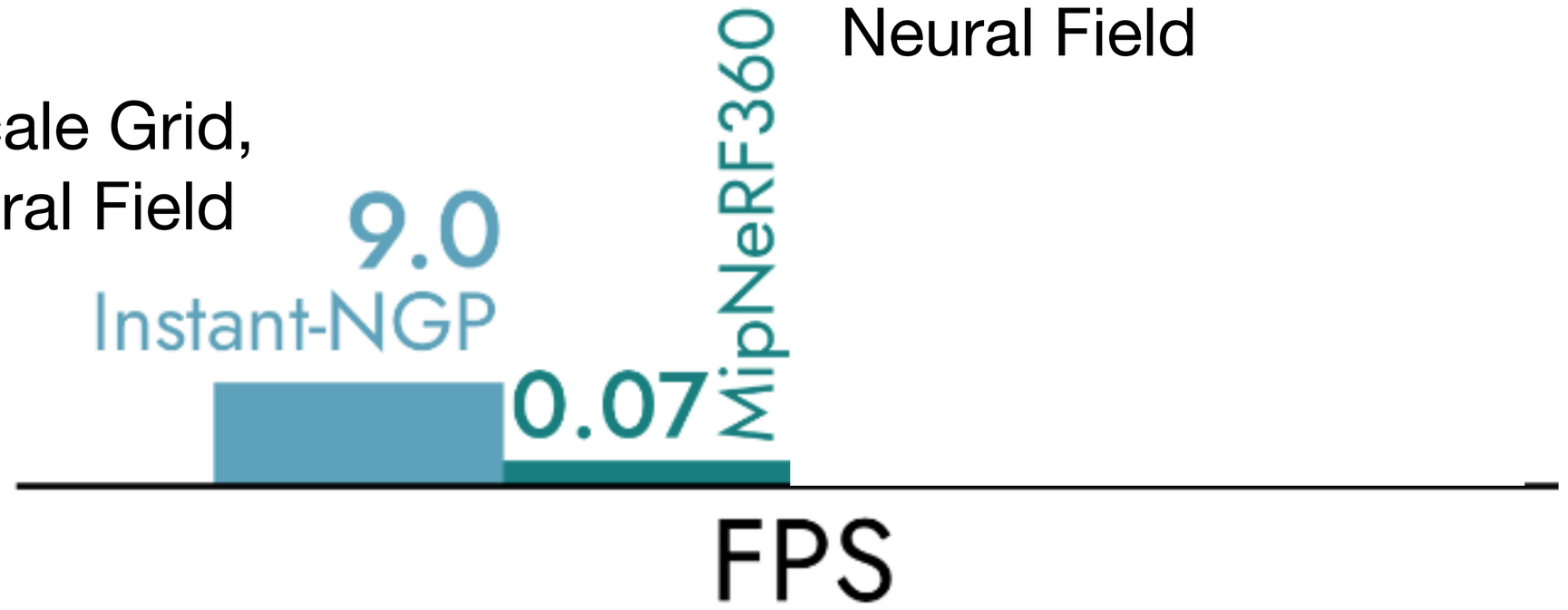
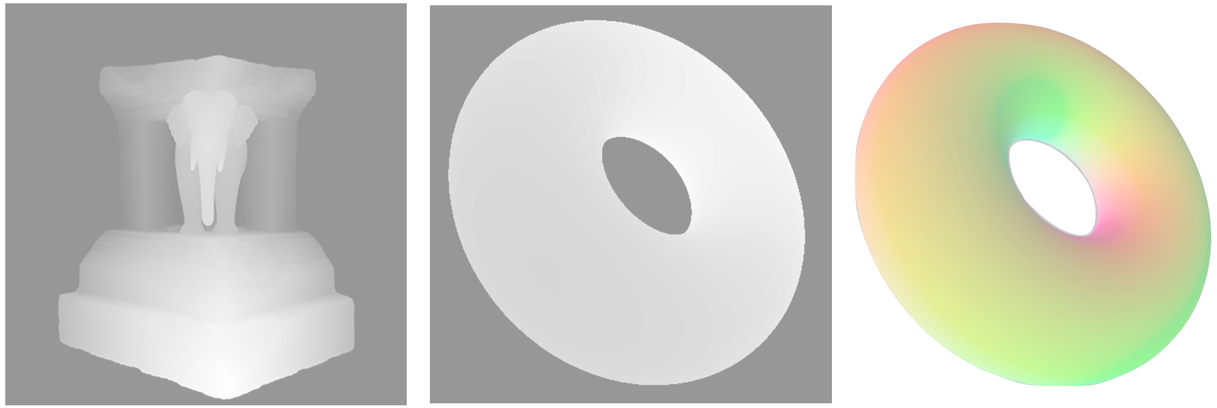
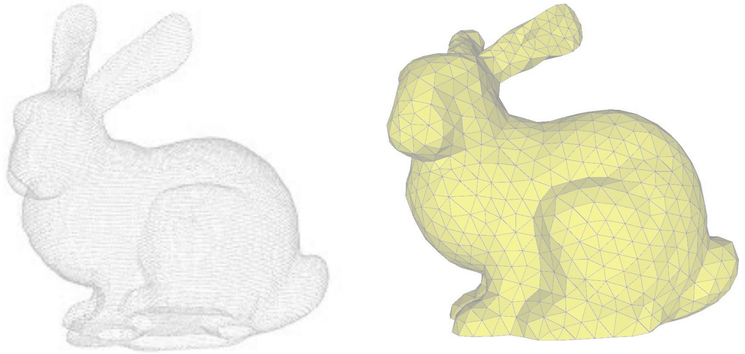
Hybrid Multi-Scale Grid,
HashMap, Neural Field



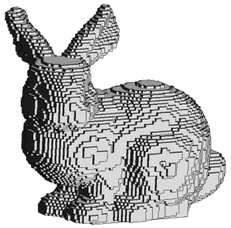
2.5D Representations

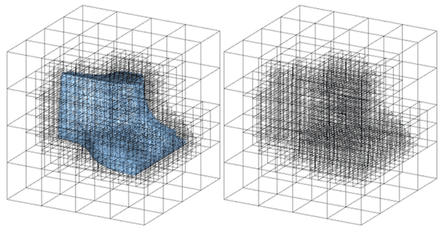


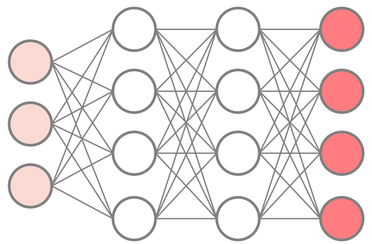
Surface Representations

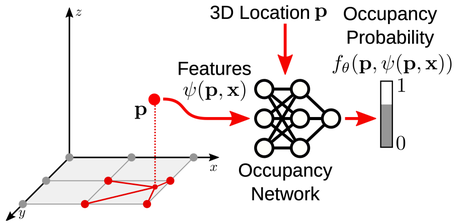


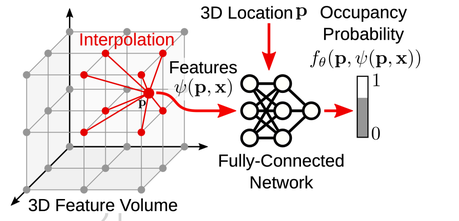
Field Parameterizations



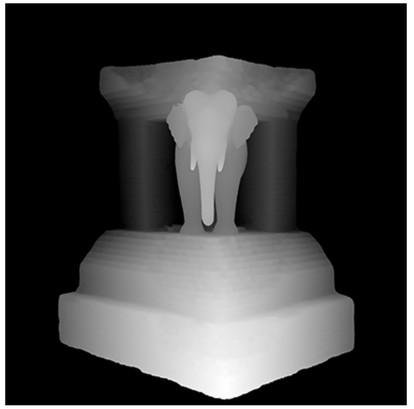


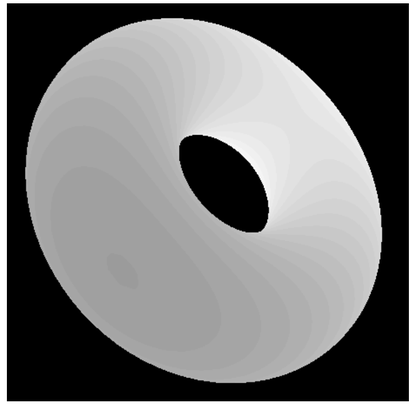


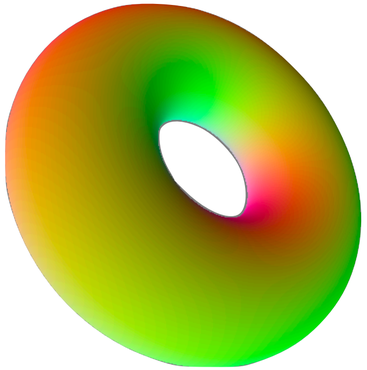




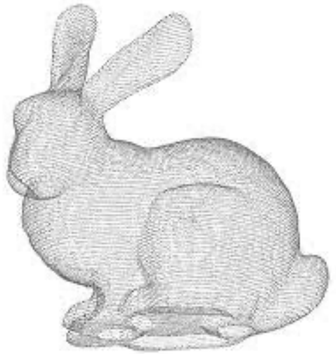
2.5D Representations

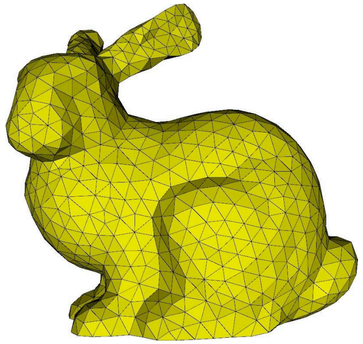




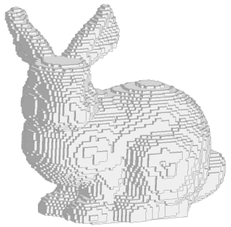


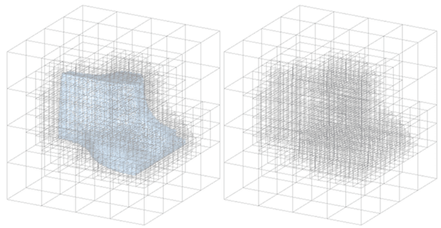
Surface Representations

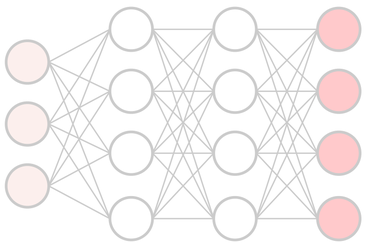


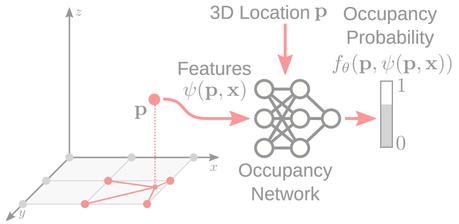


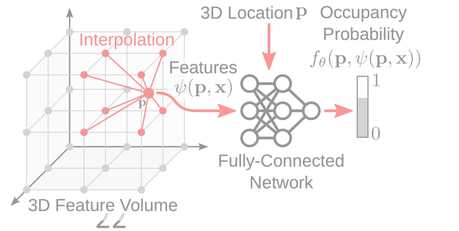
Field Parameterizations







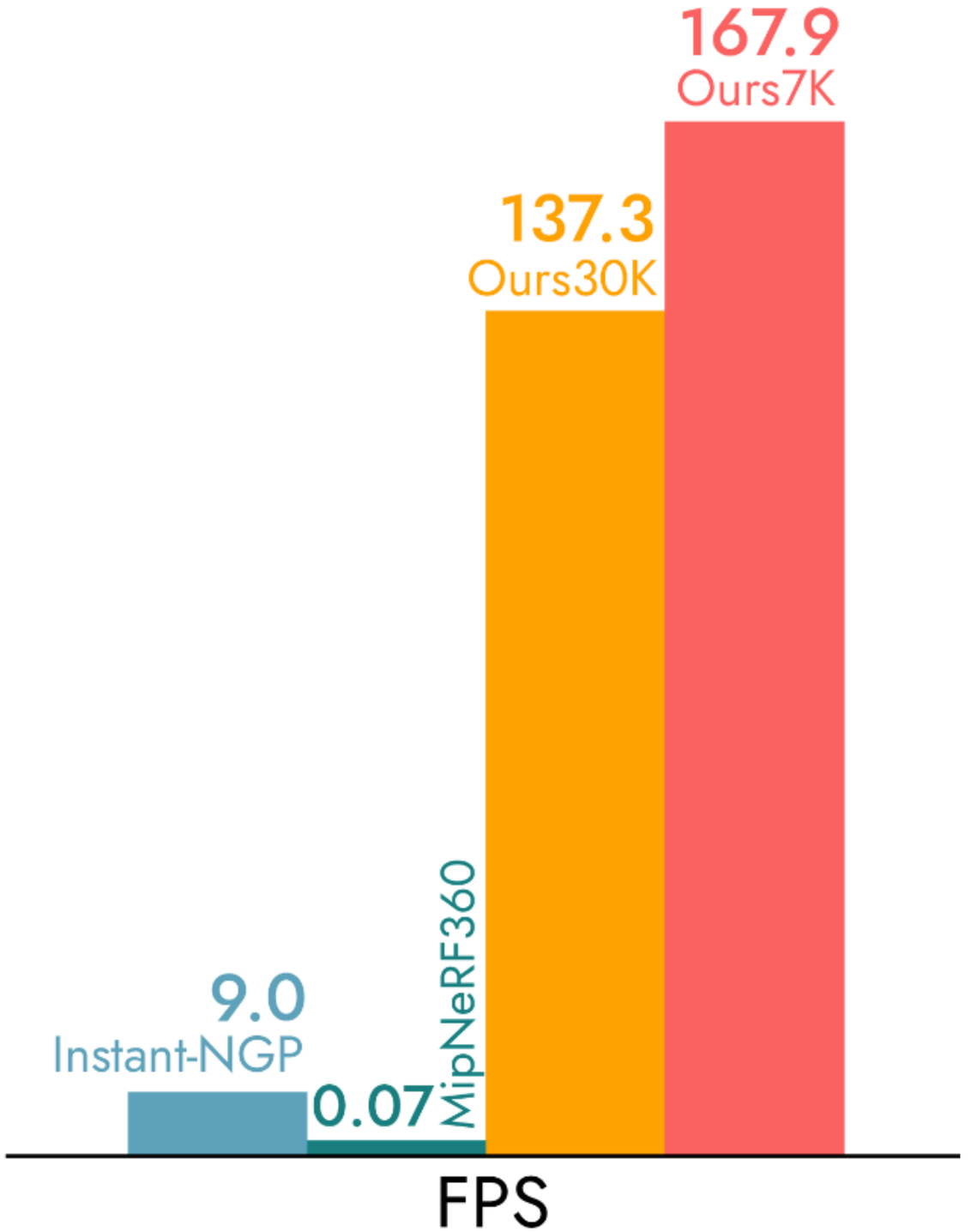




3D Gaussian Splatting for Real-Time Radiance Field Rendering

BERNHARD KERBL*, Inria, Université Côte d'Azur, France
GEORGIOS KOPANAS*, Inria, Université Côte d'Azur, France
THOMAS LEIMKÜHLER, Max-Planck-Institut für Informatik, Germany
GEORGE DRETTAKIS, Inria, Université Côte d'Azur, France

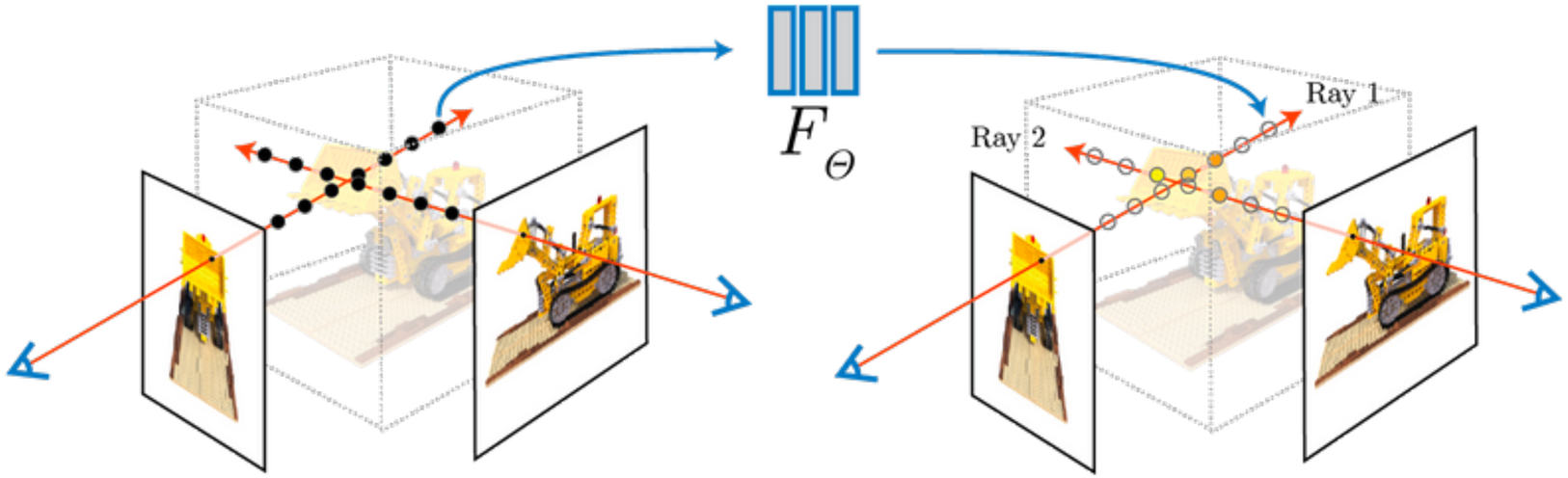
Fig. 1. Our method achieves real-time rendering of radiance fields with quality that equals the previous method with the best quality [Barron et al. 2022], while only requiring optimization times competitive with the fastest previous methods [Fridovich-Keil and Yu et al. 2022; Müller et al. 2022]. Key to this performance is a novel 3D Gaussian scene representation coupled with a real-time differentiable renderer, which offers significant speedup to both scene optimization and novel view synthesis. Note that for comparable training times to InstantNGP [Müller et al. 2022], we achieve similar quality to theirs; while this is the maximum quality they reach, by training for 51min we achieve state-of-the-art quality, even slightly better than Mip-NeRF360 [Barron et al. 2022].

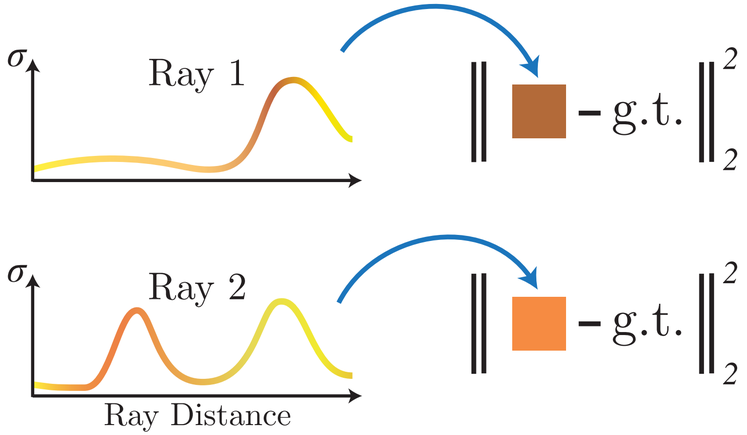

167.9
Ours7K
137.3
Ours30K
9.0
Instant-NGP
0.07
MipNeRF360
FPS

Neural Radiance Field: Parameterize Radiance Field densely, at *every* point in space

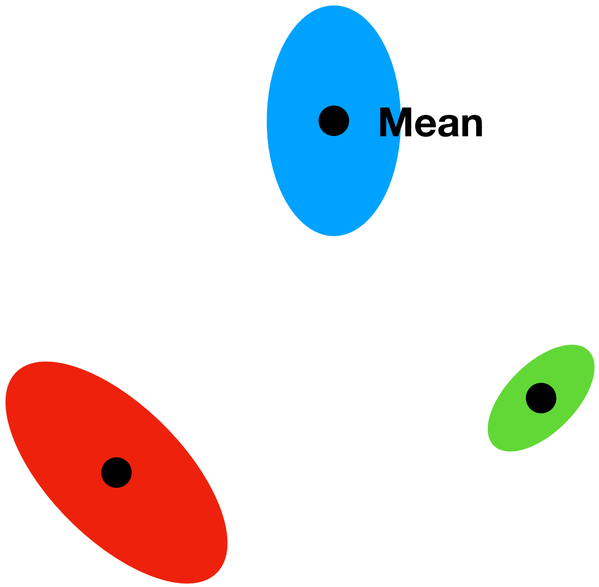
$$(x,y,z,\theta,\phi) \rightarrow \boxed{\quad} \rightarrow (RGB\sigma)$$

$$F_\Theta$$



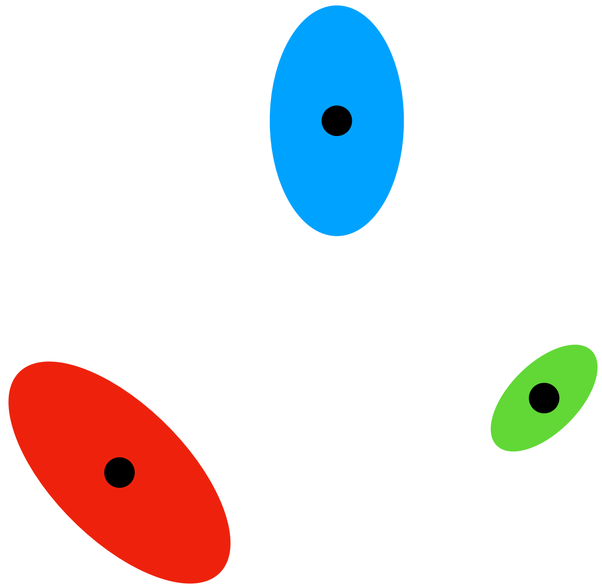


Key Idea: Parameterize Radiance Field *sparsely, only where density is nonzero*



3D Gaussian Blobs floating in Space

Key Idea: Parameterize Radiance Field *sparsely, only where density is nonzero*



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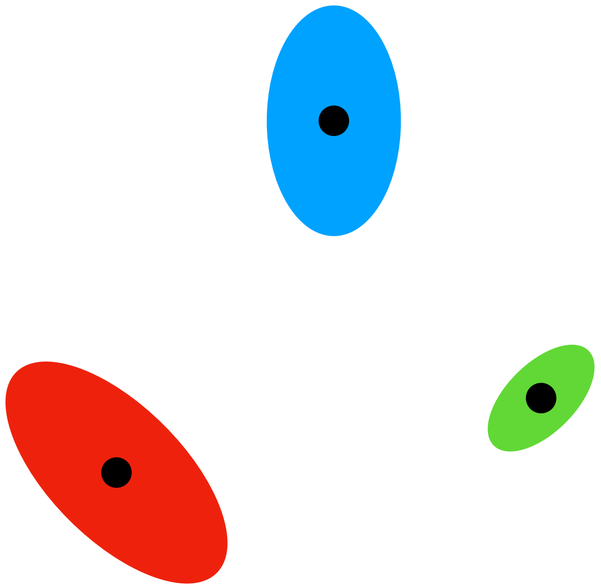
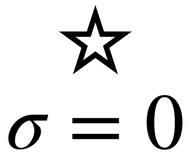
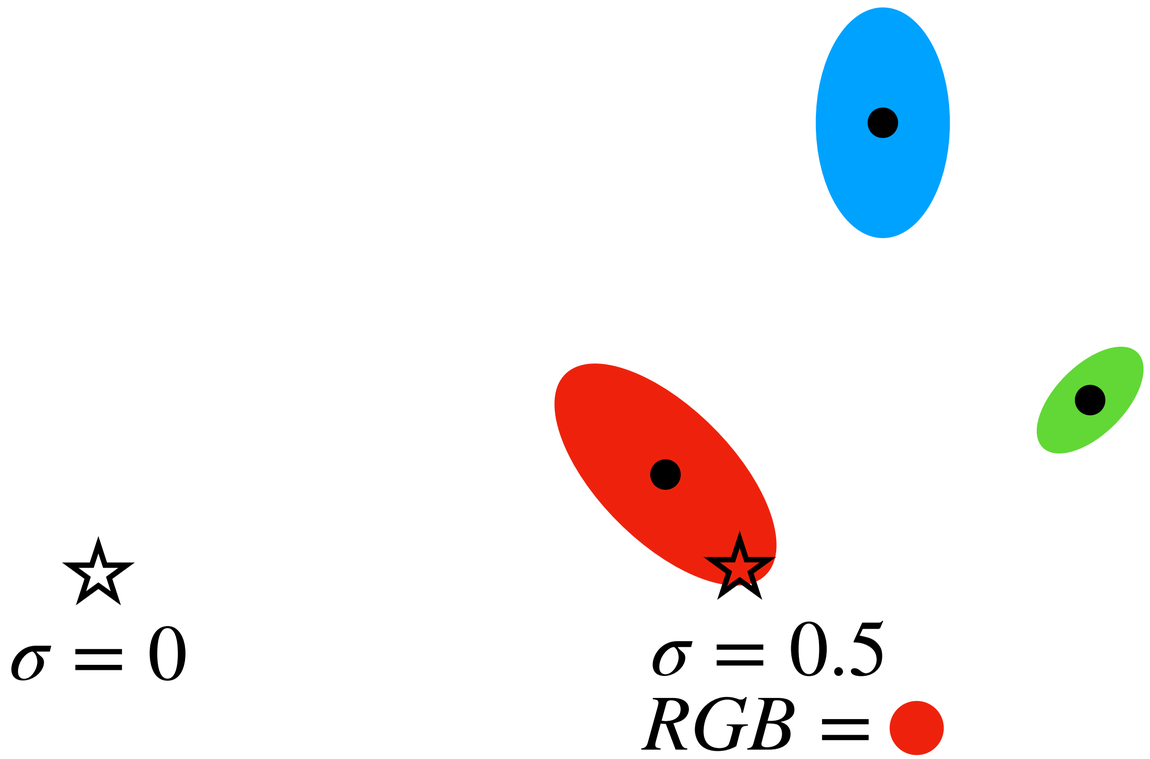


3D Gaussian Blobs floating in Space



$\sigma = 0$

Key Idea: Parameterize Radiance Field *sparsely, only where density is nonzero*



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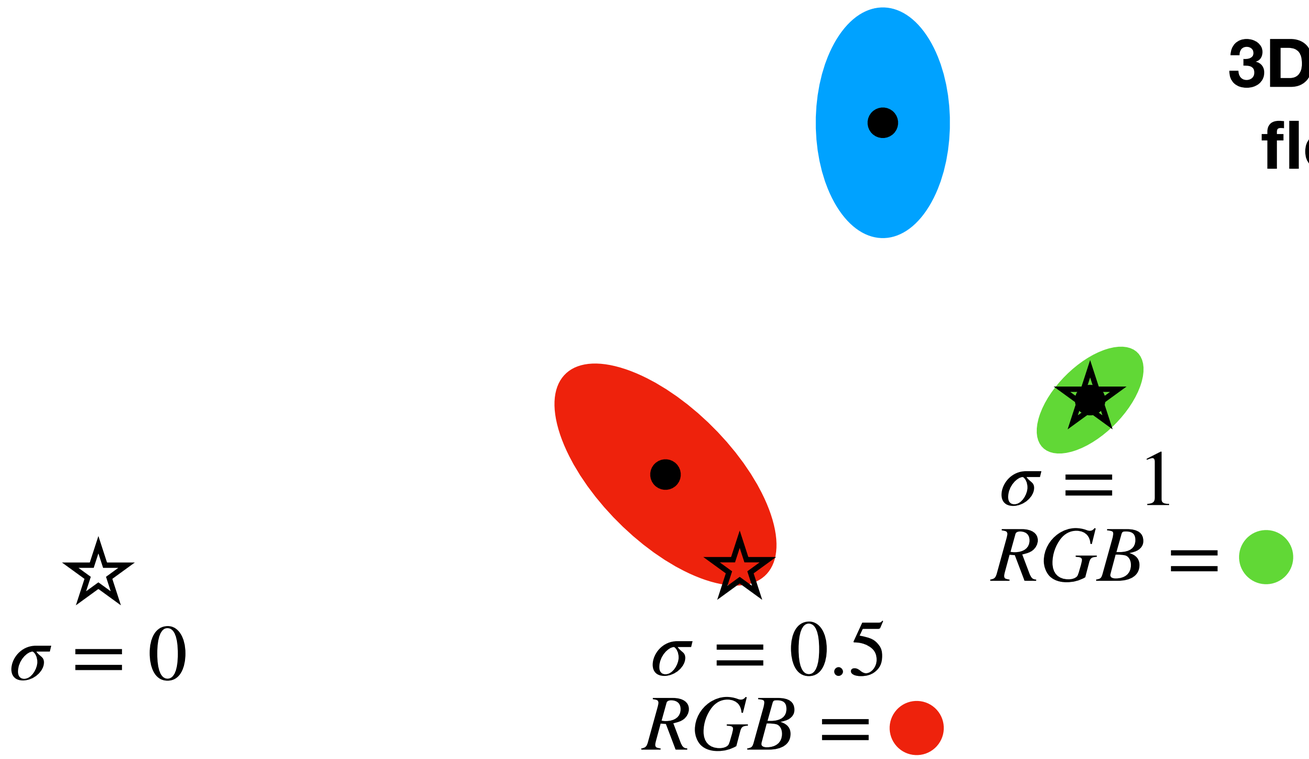


Anisotropic Volumetric 3D Gaussians

Final Rendering

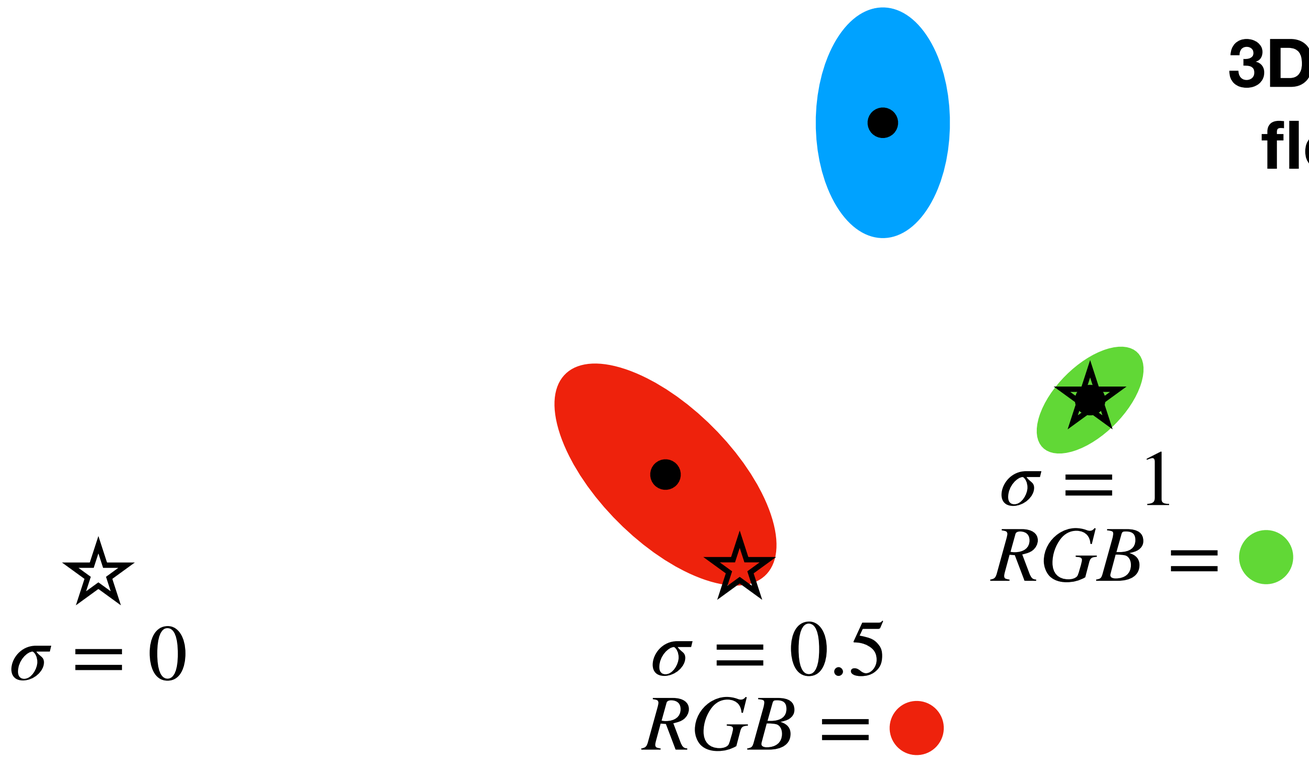
3D Gaussian Visualization

Anisotropic Volumetric 3D Gaussians

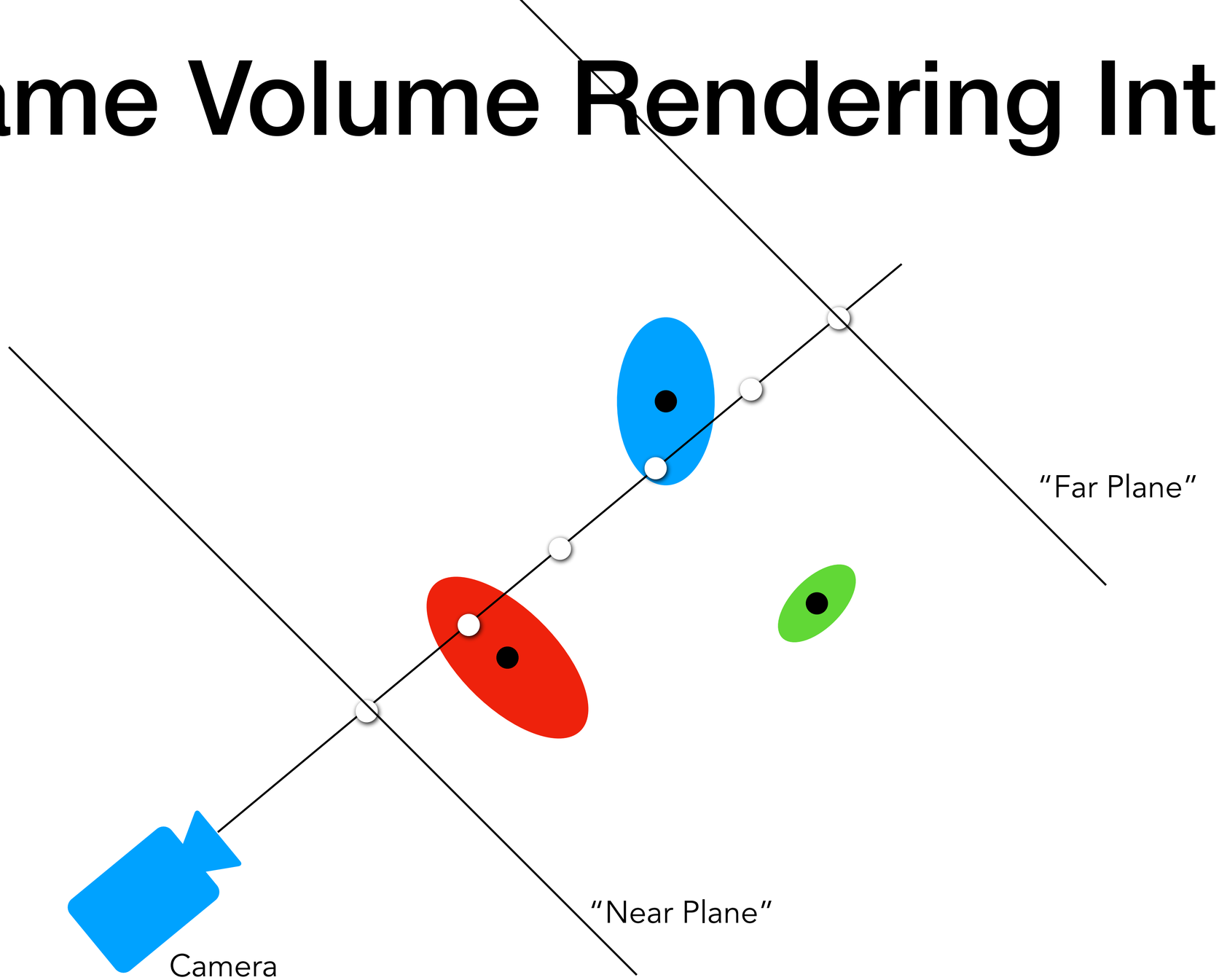
Final Rendering

3D Gaussian Visualization

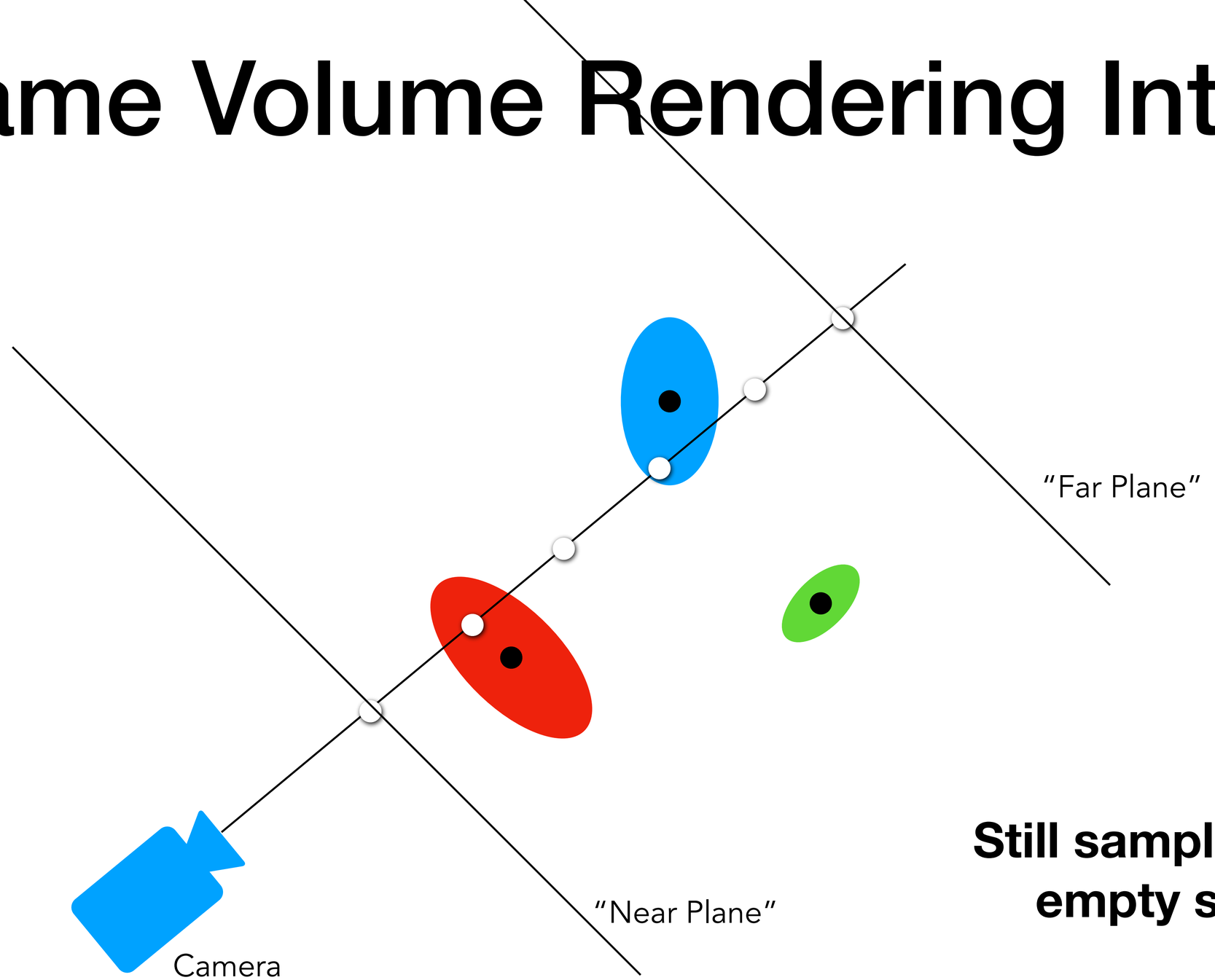
How to Render?



Same Volume Rendering Integral!

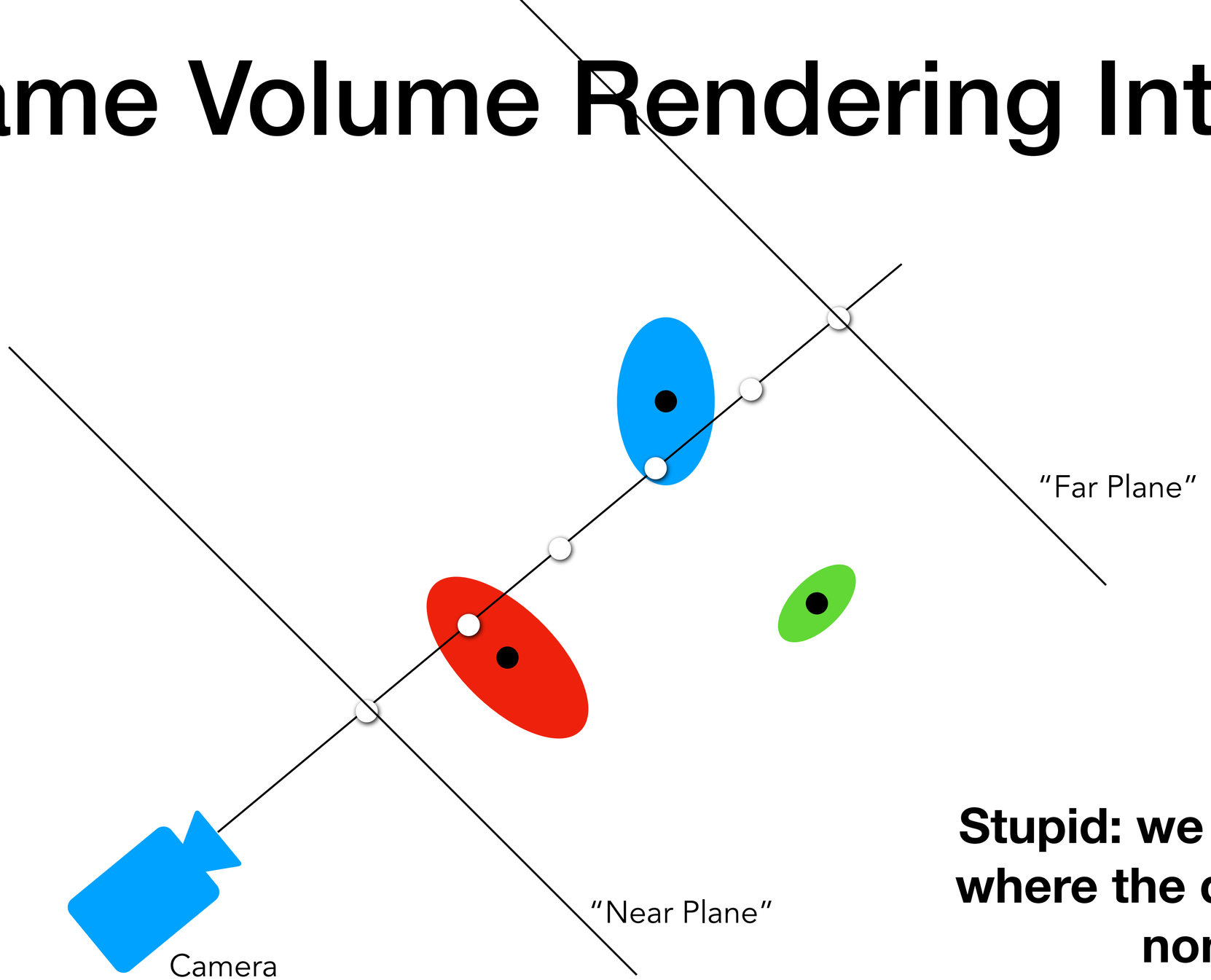


Same Volume Rendering Integral!



Still sampling lots of empty space…

Same Volume Rendering Integral!

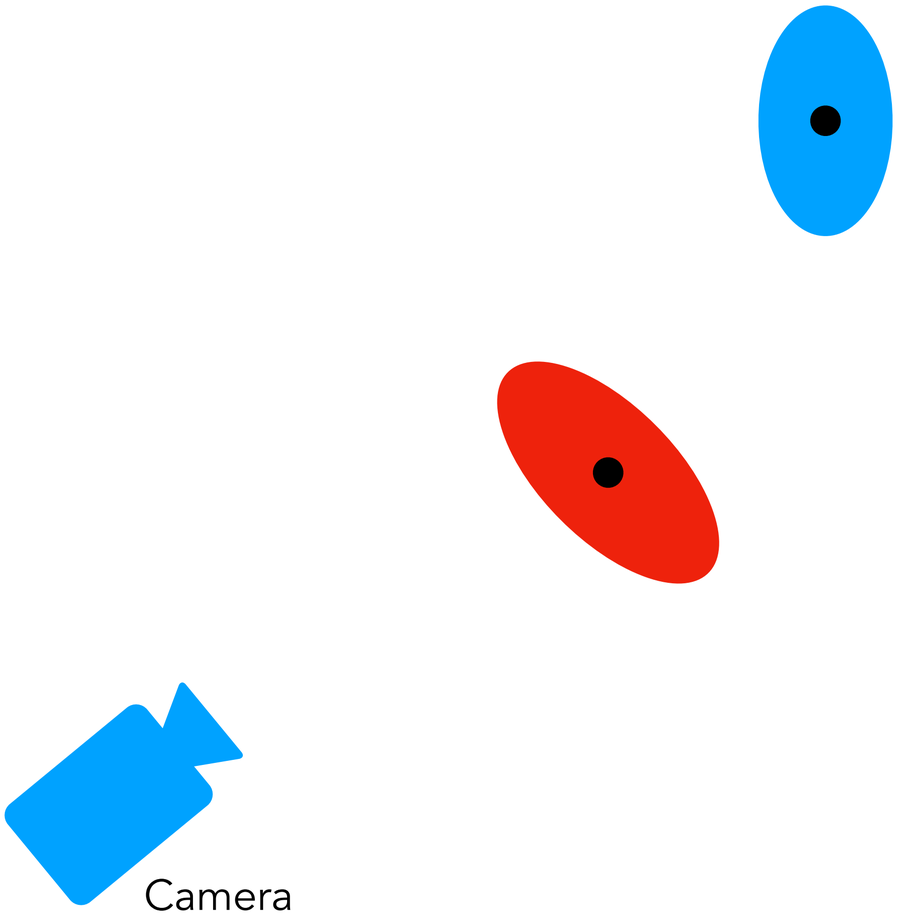


Stupid: we *already know* where the density will be nonzero!

Gaussians are closed under affine transforms, integration

$$\mathcal{G}_{\mathbf{V}}(\mathbf{x}-\mathbf{p}) = \frac{1}{2\pi|\mathbf{V}|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\mathbf{p})^T \mathbf{V}^{-1}(\mathbf{x}-\mathbf{p})}$$

3D Covariance!



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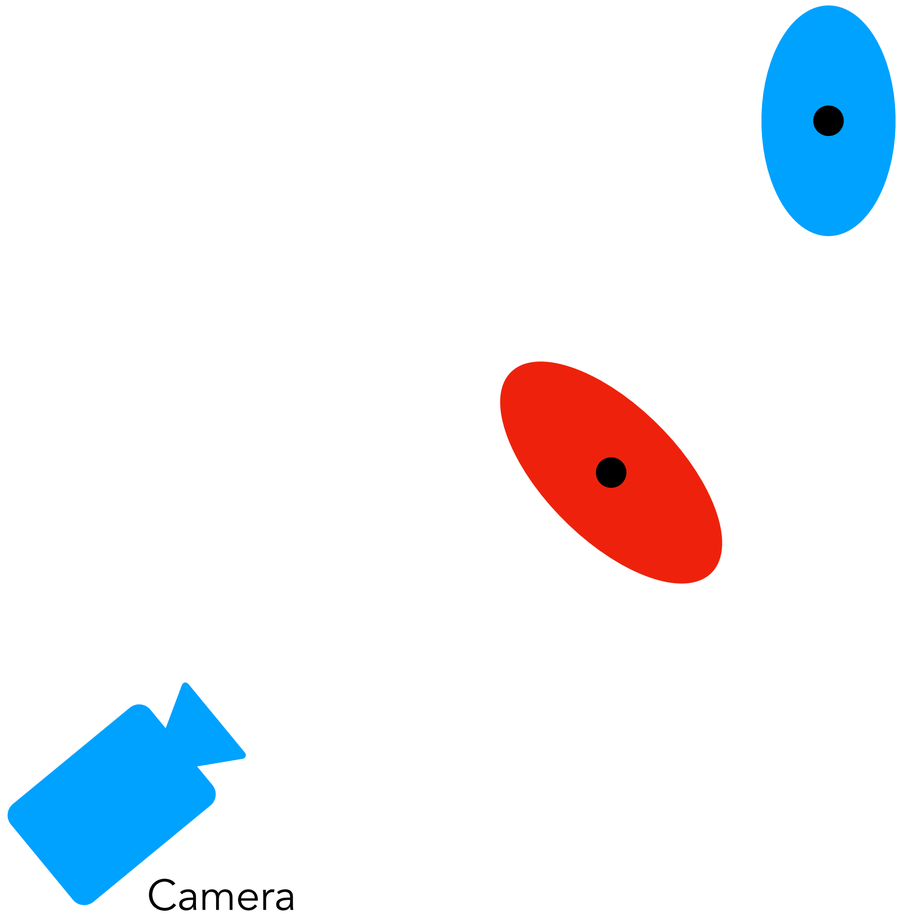


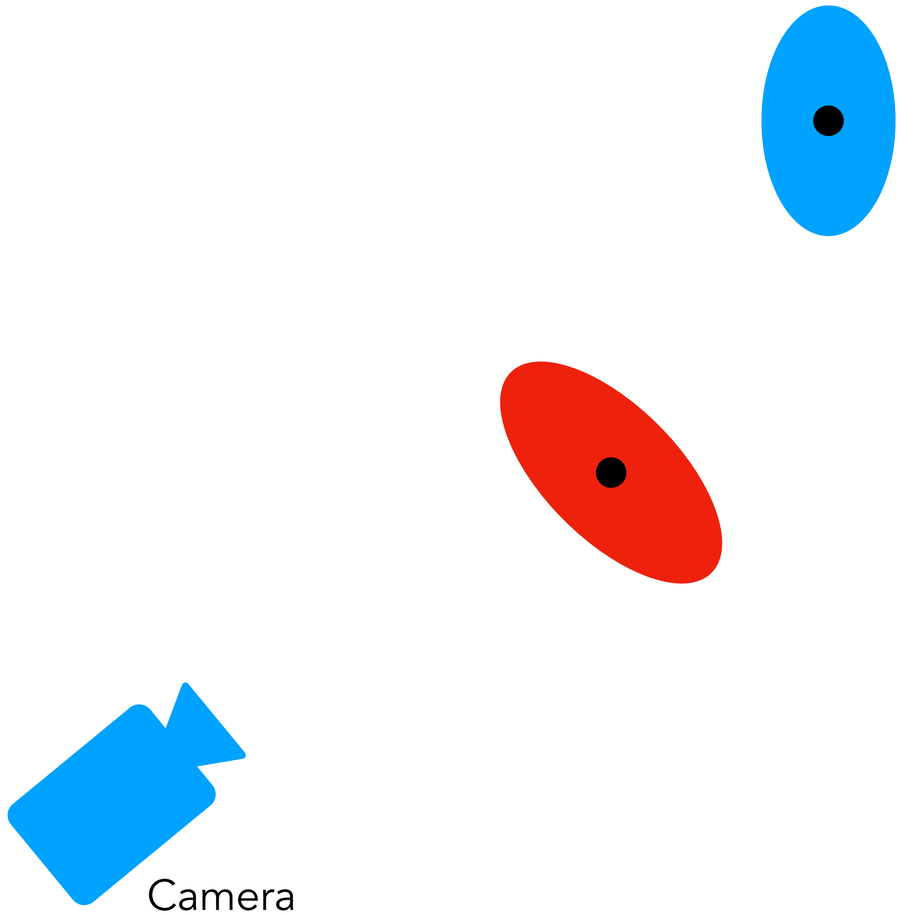
$$\mathcal{G}_{\mathbf{V}}(\mathbf{x}-\mathbf{p}) = \frac{1}{2\pi|\mathbf{V}|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\mathbf{p})^T \mathbf{V}^{-1}(\mathbf{x}-\mathbf{p})}$$

3D Covariance!

Affine mapping $\Phi = \mathbf{M}\mathbf{x} + \mathbf{p}$ of coordinates (such as cam2world matrix!):

$$\mathcal{G}_{\mathbf{V}}(\Phi^{-1}(\mathbf{u}) - \mathbf{p}) = \frac{1}{|\mathbf{M}^{-1}|}\mathcal{G}_{\mathbf{M}\mathbf{V}\mathbf{M}^T}(\mathbf{u} - \Phi(\mathbf{p}))$$

Gaussians are closed under affine transforms, integration



$$\mathcal{G}_{\mathbf{V}}(\mathbf{x}-\mathbf{p}) = \frac{1}{2\pi|\mathbf{V}|^{\frac{1}{2}}} e^{-\frac{1}{2}(\mathbf{x}-\mathbf{p})^T \mathbf{V}^{-1}(\mathbf{x}-\mathbf{p})}$$

3D Covariance!

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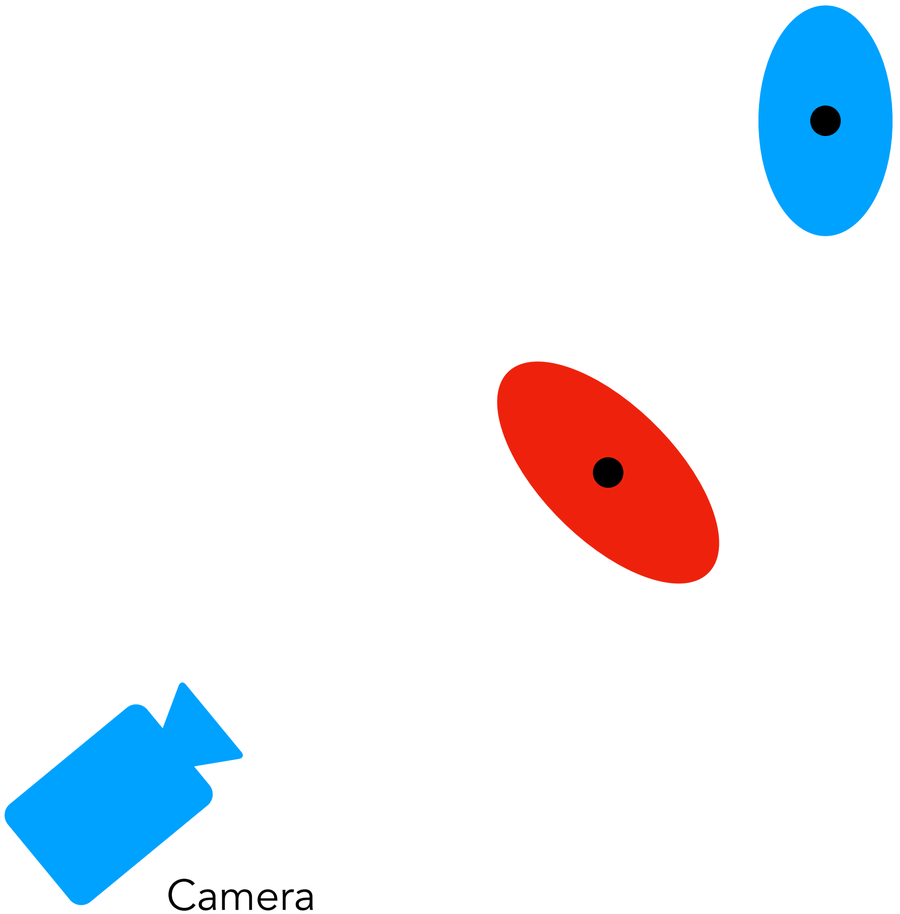
Integrate along axis:

$$\int_{\mathbb{R}} \mathcal{G}^3_{\mathbf{V}}(\mathbf{x}-\mathbf{p})\, dx_2 = \mathcal{G}^2_{\hat{\mathbf{V}}}(\hat{\mathbf{x}}-\hat{\mathbf{p}})$$

$$\mathbf{V} = \begin{pmatrix} a & b & c \\ b & d & e \\ c & e & f \end{pmatrix} \Leftrightarrow \begin{pmatrix} a & b \\ b & d \end{pmatrix} = \hat{\mathbf{V}}$$

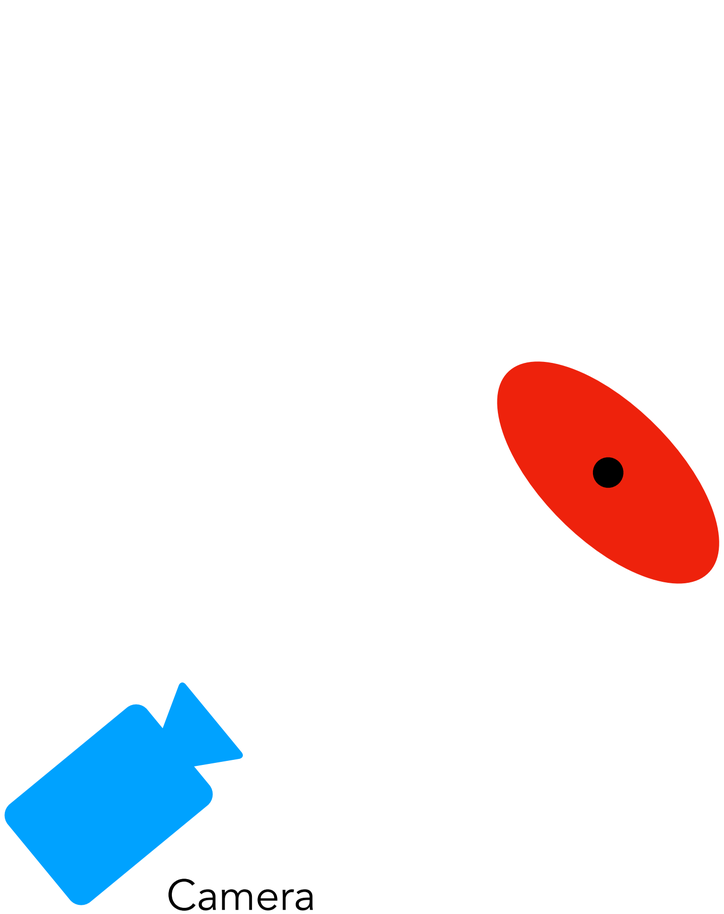
Step 1: Transform Gaussians into Camera Coordinates



Cam2world is affine mapping $\phi(x) = \mathbf{W}\mathbf{x} + \mathbf{p}$:

$$\mathcal{G}_{\mathbf{V}_k''}(\varphi^{-1}(\mathbf{u}) - \mathbf{t}_k) = \frac{1}{|\mathbf{W}^{-1}|}\mathcal{G}_{\mathbf{V}_k'}(\mathbf{u} - \mathbf{u}_k) = r_k'(\mathbf{u})$$

Step 1: Transform Gaussians into Camera Coordinates



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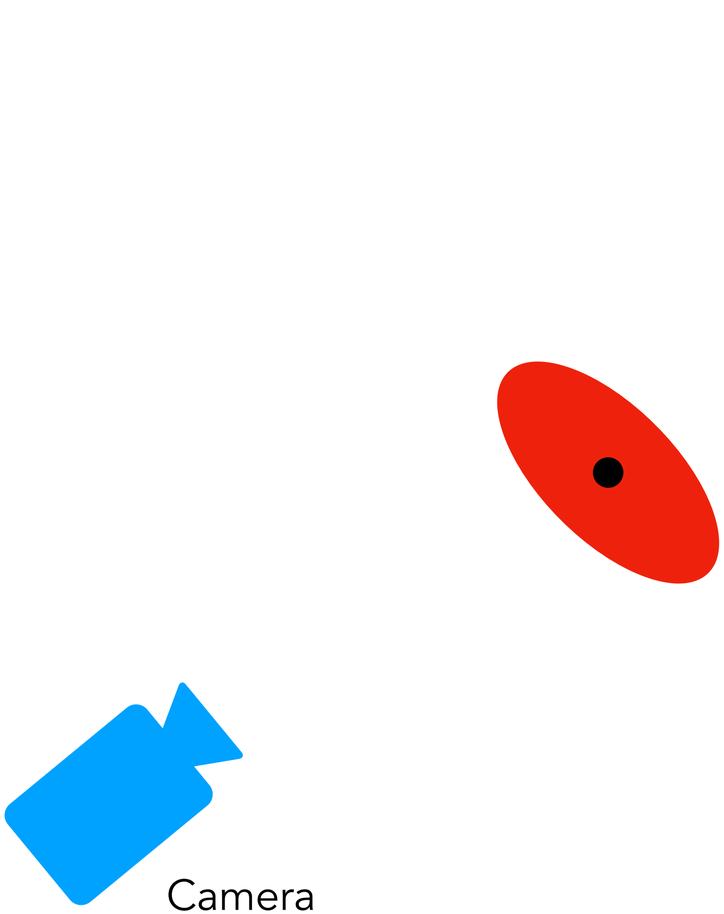
Projection $\mathbf{m}(u)$ is *not* an affine mapping :/

$$\begin{pmatrix} x_0 \\ x_1 \\ x_2 \end{pmatrix} = \mathbf{m}(\mathbf{u}) = \begin{pmatrix} u_0/u_2 \\ u_1/u_2 \\ \|(u_0, u_1, u_2)^T\| \end{pmatrix}$$

$$\begin{pmatrix} u_0 \\ u_1 \\ u_2 \end{pmatrix} = \mathbf{m}^{-1}(\mathbf{x}) = \begin{pmatrix} x_0/l \cdot x_2 \\ x_1/l \cdot x_2 \\ 1/l \cdot x_2 \end{pmatrix},$$

Step 1: Transform Gaussians into Camera Coordinates



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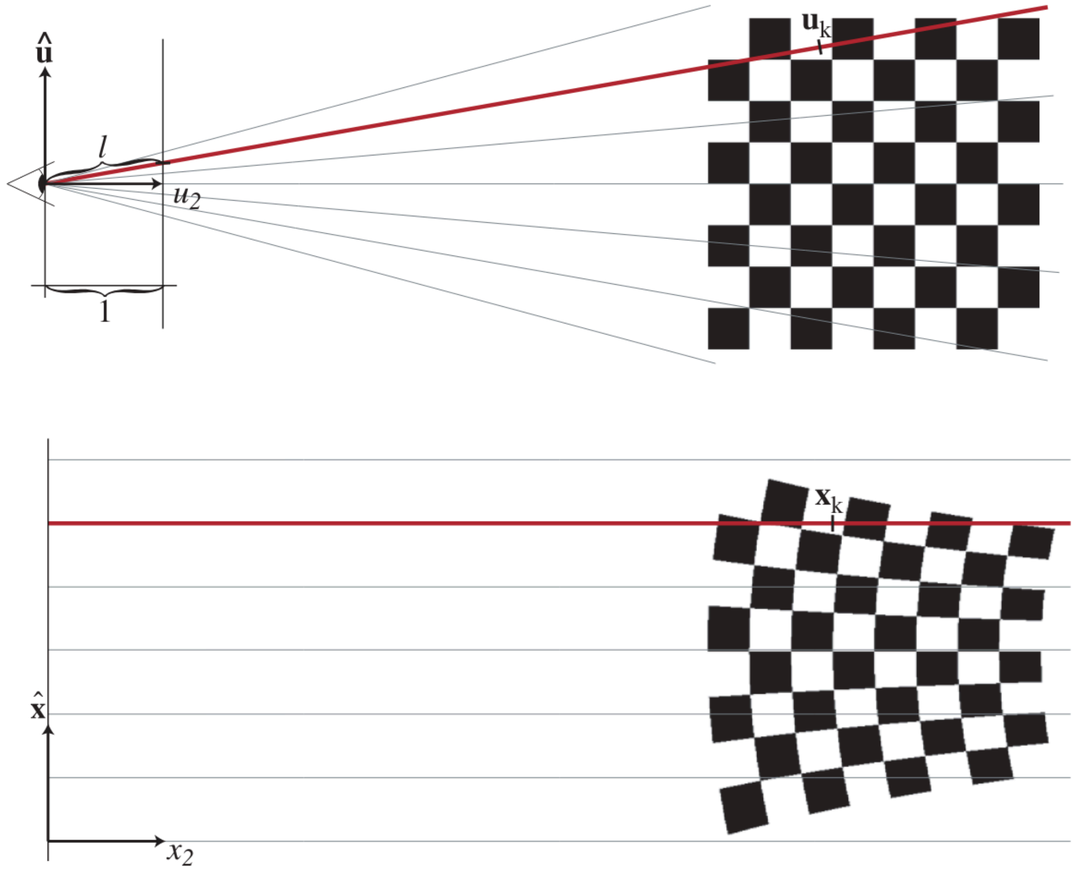
$$\begin{pmatrix} u_0 \\ u_1 \\ u_2 \end{pmatrix} = \mathbf{m}^{-1}(\mathbf{x}) = \begin{pmatrix} x_0/l \cdot x_2 \\ x_1/l \cdot x_2 \\ 1/l \cdot x_2 \end{pmatrix},$$

But can approximate with first-order Taylor Expansion as:

$$\mathbf{m}_{\mathbf{u}_k}(\mathbf{u}) = \mathbf{x}_k + \mathbf{J}_{\mathbf{u}_k} \cdot (\mathbf{u} - \mathbf{u}_k) \qquad \mathbf{J}_{\mathbf{u}_k} = \frac{\partial \mathbf{m}}{\partial \mathbf{u}}(\mathbf{u}_k)$$

Step 1: Transform Gaussians into Camera Coordinates



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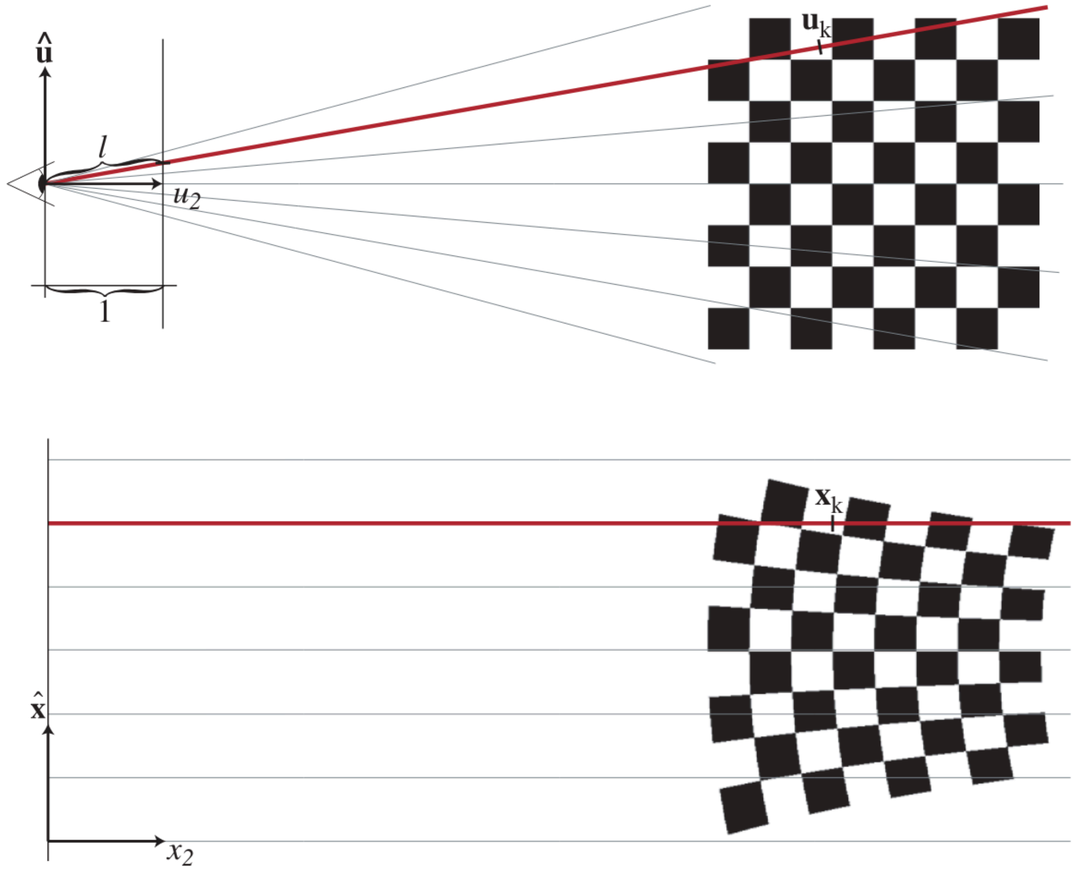

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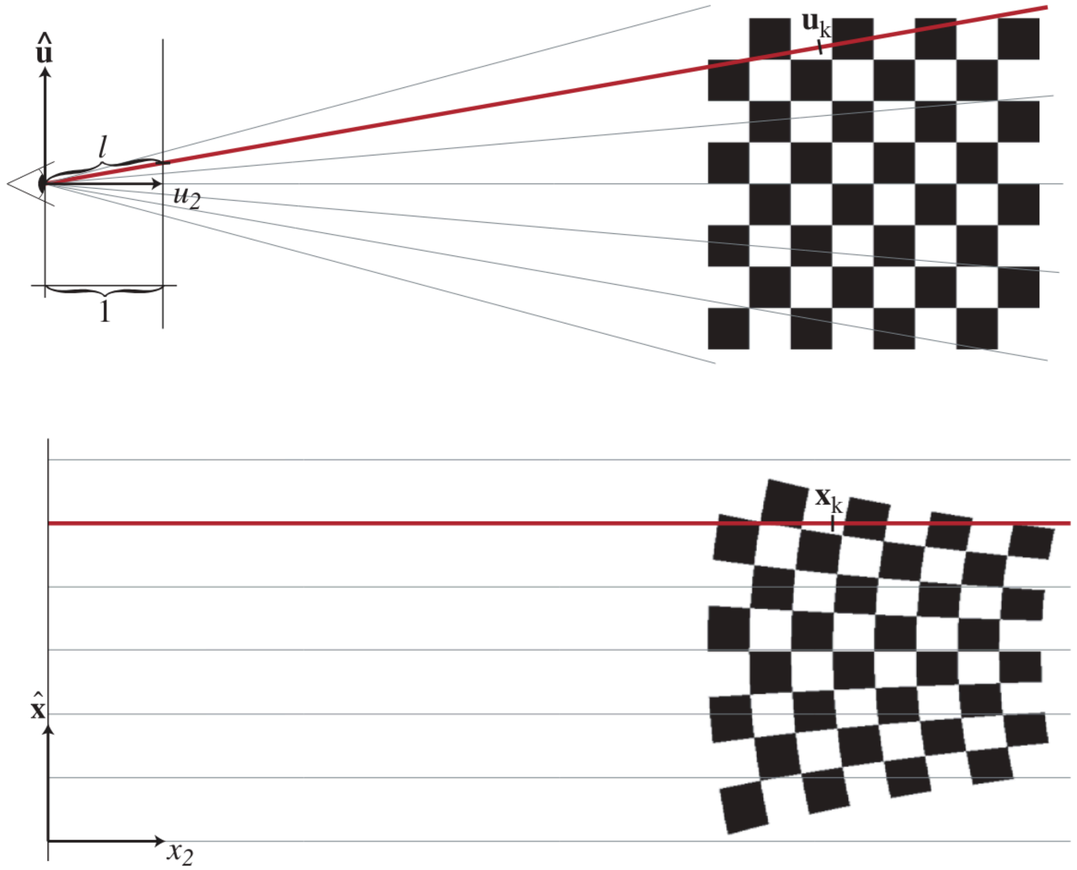
$$\mathbf{m}_{\mathbf{u}_k}(\mathbf{u}) = \mathbf{x}_k + \mathbf{J}_{\mathbf{u}_k} \cdot (\mathbf{u} - \mathbf{u}_k) \qquad \mathbf{J}_{\mathbf{u}_k} = \frac{\partial \mathbf{m}}{\partial \mathbf{u}}(\mathbf{u}_k)$$

Projected, 2D Gaussians are then:

$$\frac{1}{|\mathbf{W}^{-1}||\mathbf{J}^{-1}|}\mathcal{G}_{\mathbf{V}_k}(\mathbf{x} - \mathbf{x}_k)$$

$$\begin{aligned} \mathbf{V}_k &= \mathbf{J}\mathbf{V}'_k\,\mathbf{J}^T \\ &= \mathbf{J}\mathbf{W}\mathbf{V}''_k\mathbf{W}^T\mathbf{J}^T. \end{aligned}$$

Step 1: Transform Gaussians into Camera Coordinates



But can approximate with first-order Taylor Expansion as:

$$\mathbf{m}_{\mathbf{u}_k}(\mathbf{u}) = \mathbf{x}_k + \mathbf{J}_{\mathbf{u}_k} \cdot (\mathbf{u} - \mathbf{u}_k) \qquad \mathbf{J}_{\mathbf{u}_k} = \frac{\partial \mathbf{m}}{\partial \mathbf{u}}(\mathbf{u}_k)$$

Projected, 2D Gaussians are then:

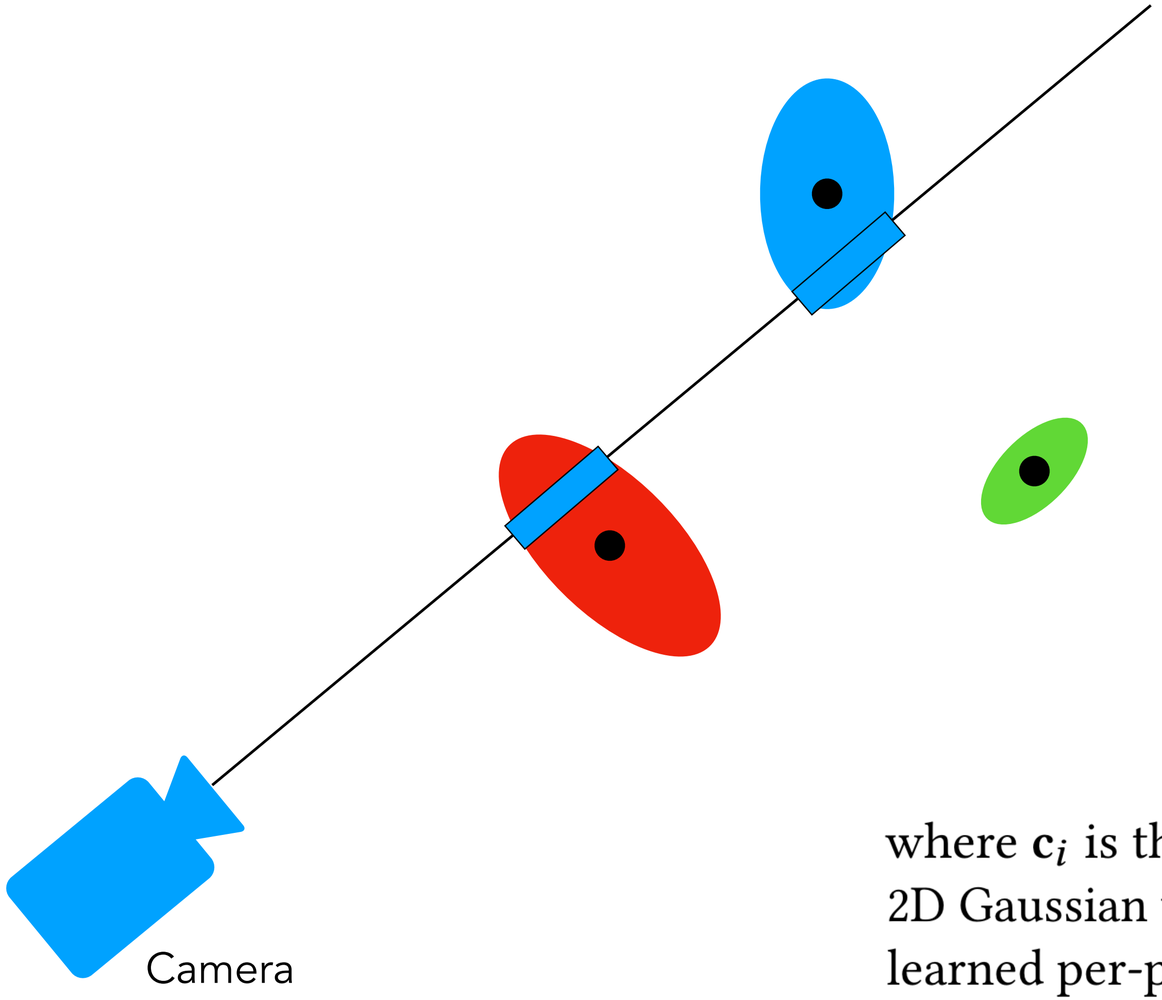
$$\frac{1}{|\mathbf{W}^{-1}||\mathbf{J}^{-1}|}\mathcal{G}_{\mathbf{V}_k}(\mathbf{x} - \mathbf{x}_k)$$

$$\begin{aligned} \mathbf{V}_k &= \mathbf{J}\mathbf{V}'_k\,\mathbf{J}^T \\ &= \mathbf{J}\mathbf{W}\mathbf{V}''_k\mathbf{W}^T\mathbf{J}^T. \end{aligned}$$

Finally, can integrate along rays:

$$\begin{aligned} q_k(\hat{\mathbf{x}}) &= \int_{\mathbb{R}} \frac{1}{|\mathbf{J}^{-1}||\mathbf{W}^{-1}|}\mathcal{G}_{\mathbf{V}_k}(\hat{\mathbf{x}} - \hat{\mathbf{x}}_k, x_2 - x_{k2})\,dx_2 \\ &= \frac{1}{|\mathbf{J}^{-1}||\mathbf{W}^{-1}|}\mathcal{G}_{\hat{\mathbf{V}}_k}(\hat{\mathbf{x}} - \hat{\mathbf{x}}_k) \end{aligned}$$

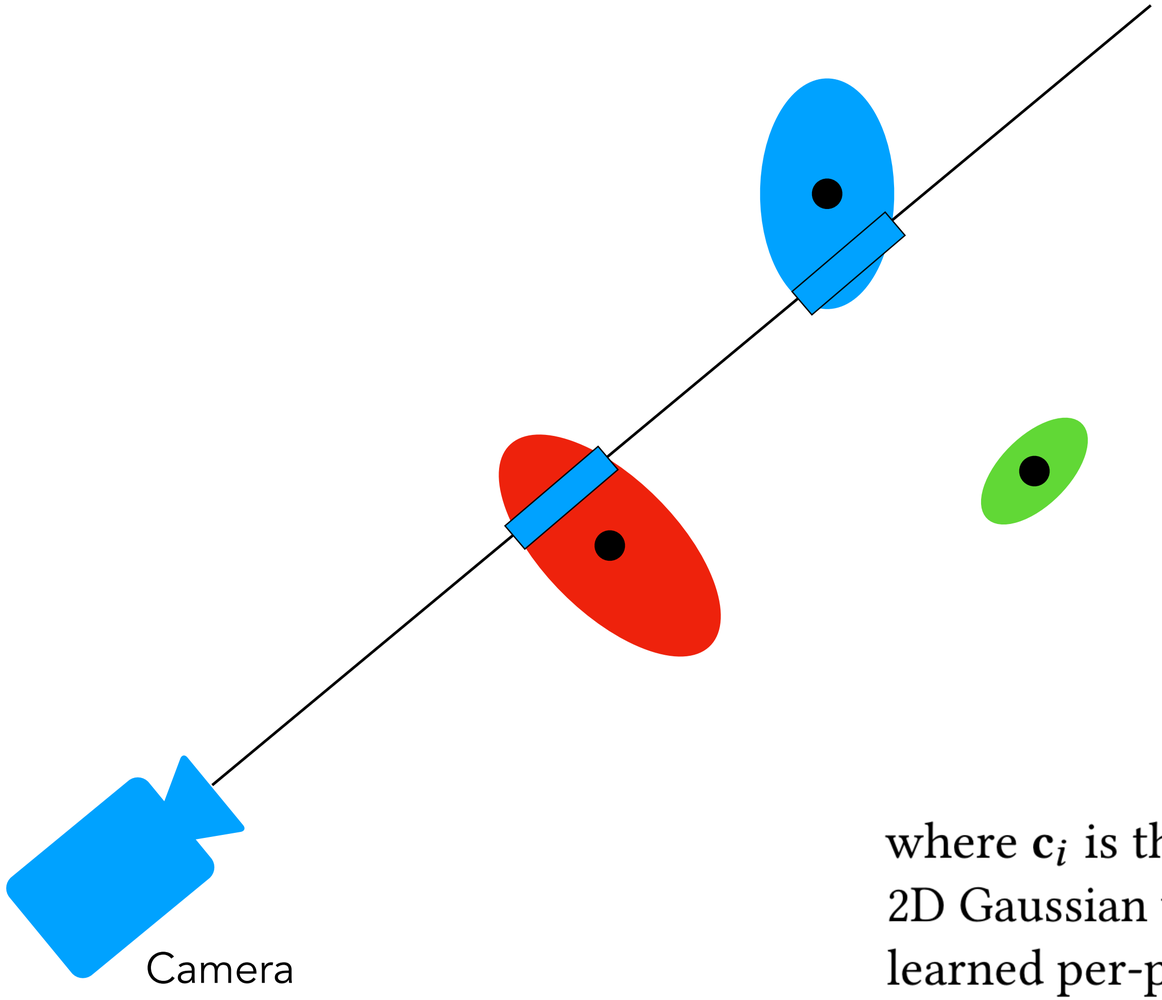
Can compute volume rendering integral without ever sampling a single 3D point in space!



$$C = \sum_{i \in \mathcal{N}} c_i \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j), \tag{3}$$

where $\mathbf{c}_i$ is the color of each point and α_i is given by evaluating a 2D Gaussian with covariance Σ [Yifan et al. 2019] multiplied with a learned per-point opacity.

Any problems for inverse graphics, though…?



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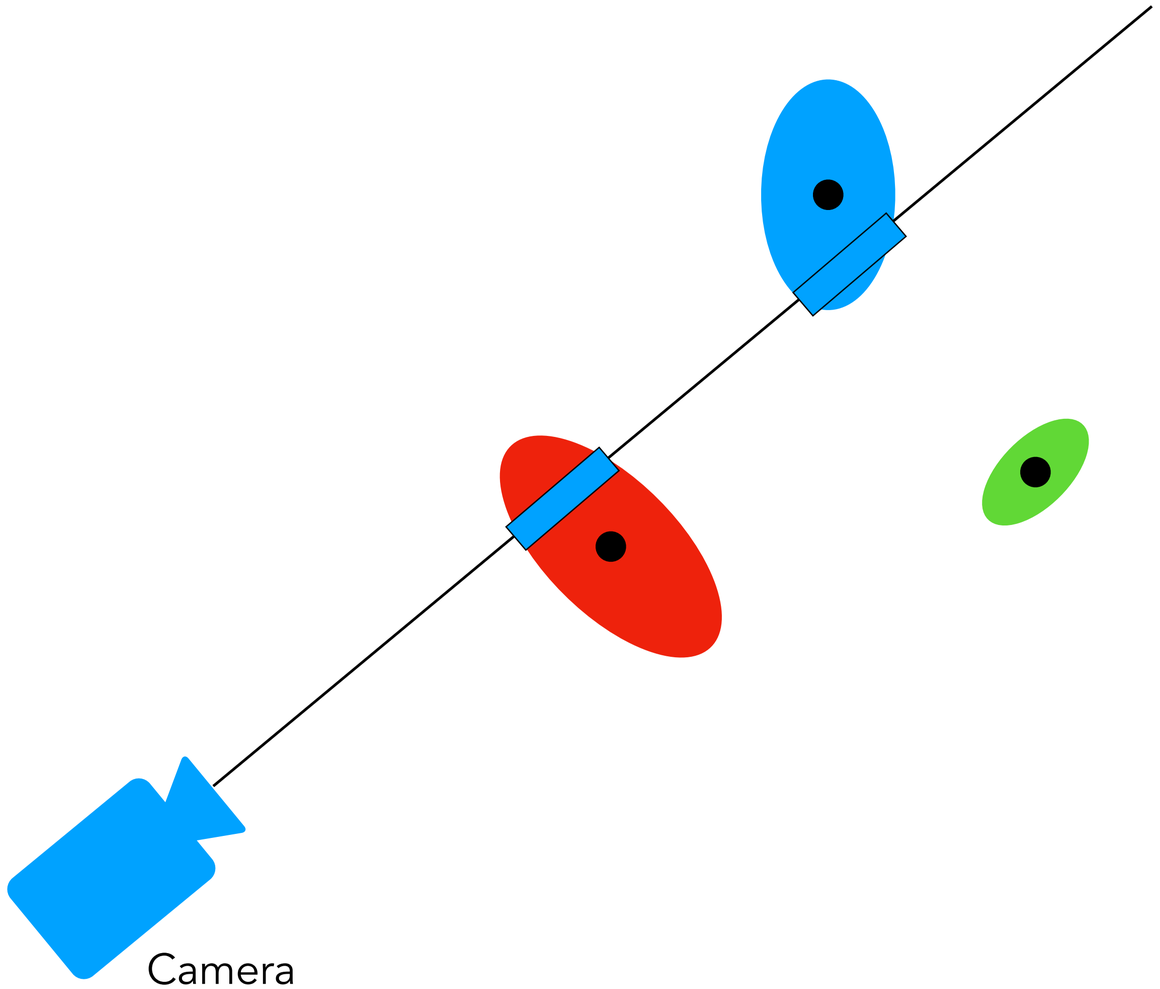
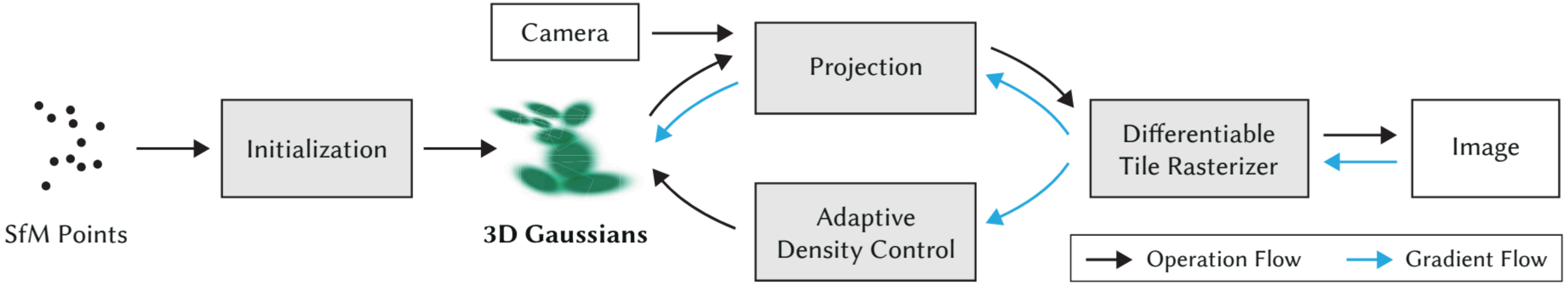
where $\mathbf{c}_i$ is the color of each point and α_i is given by evaluating a 2D Gaussian with covariance Σ [Yifan et al. 2019] multiplied with a learned per-point opacity.

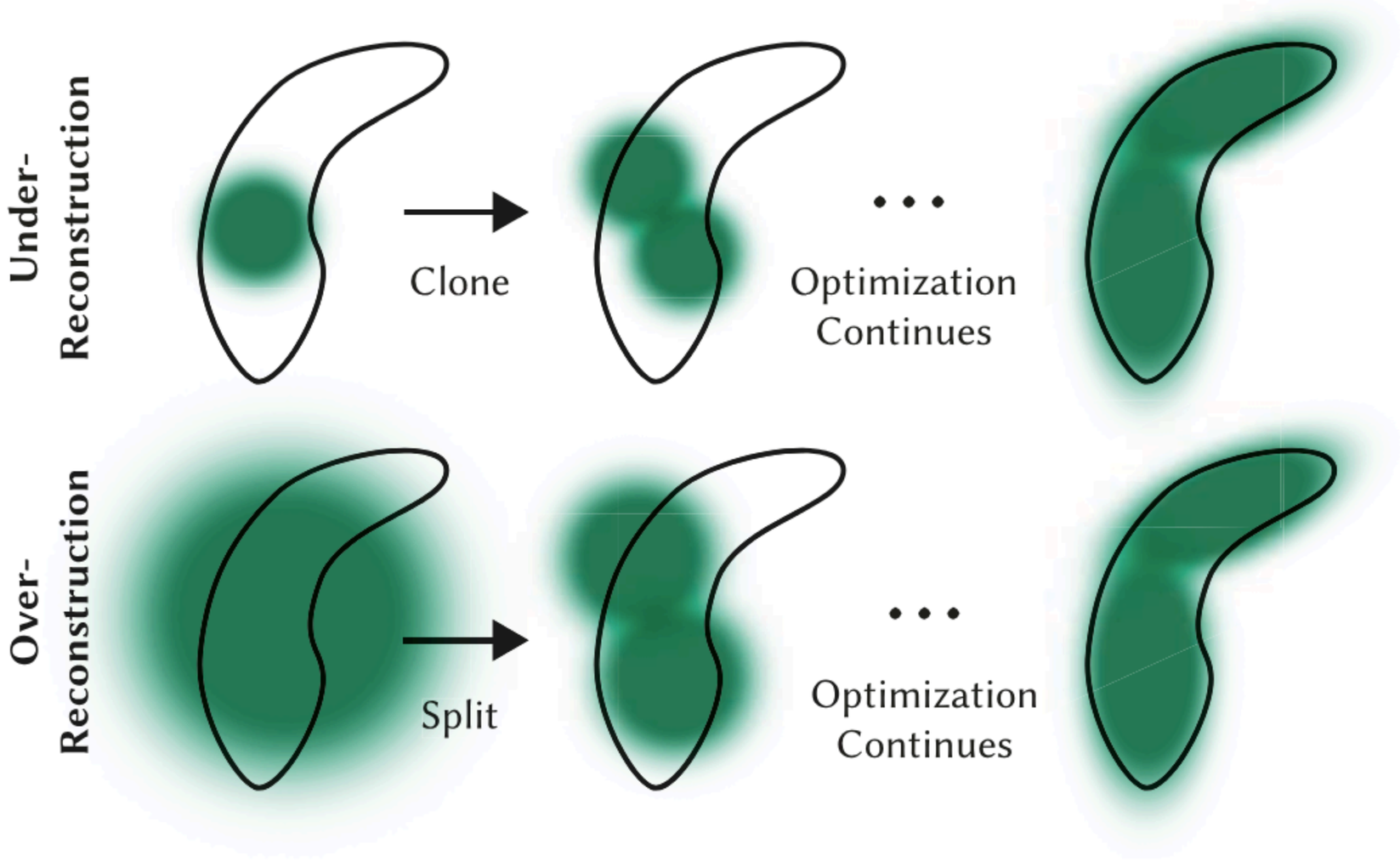
Problem: Local minima…



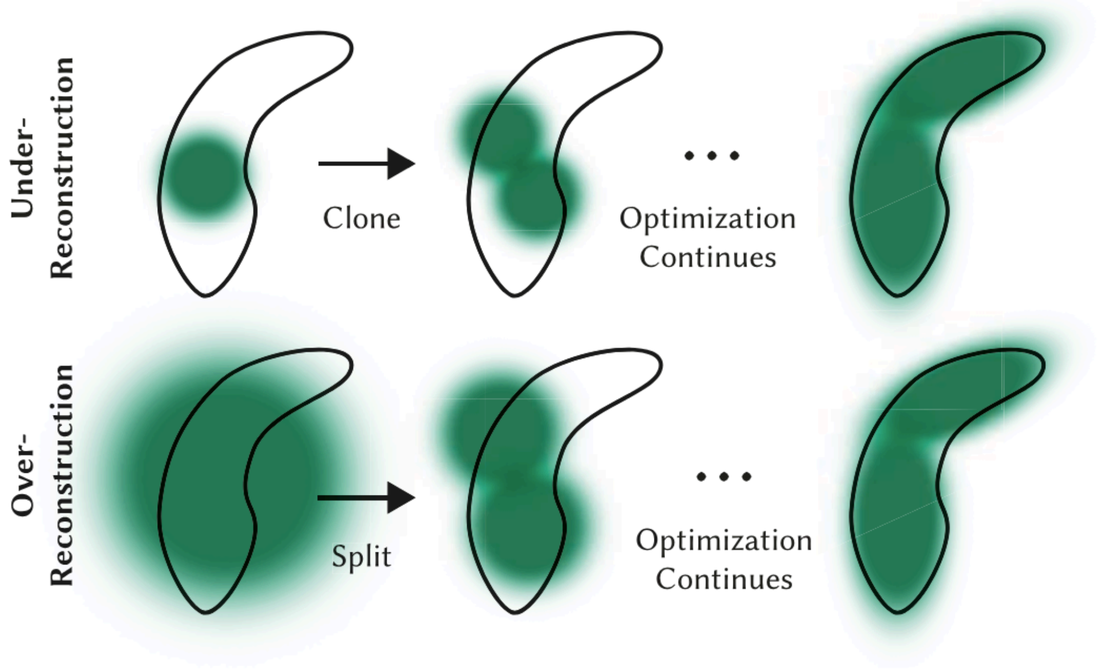
Fix 1: Start from SFM point cloud.



Fix 2: Heuristic *pruning* and *spawning* operations

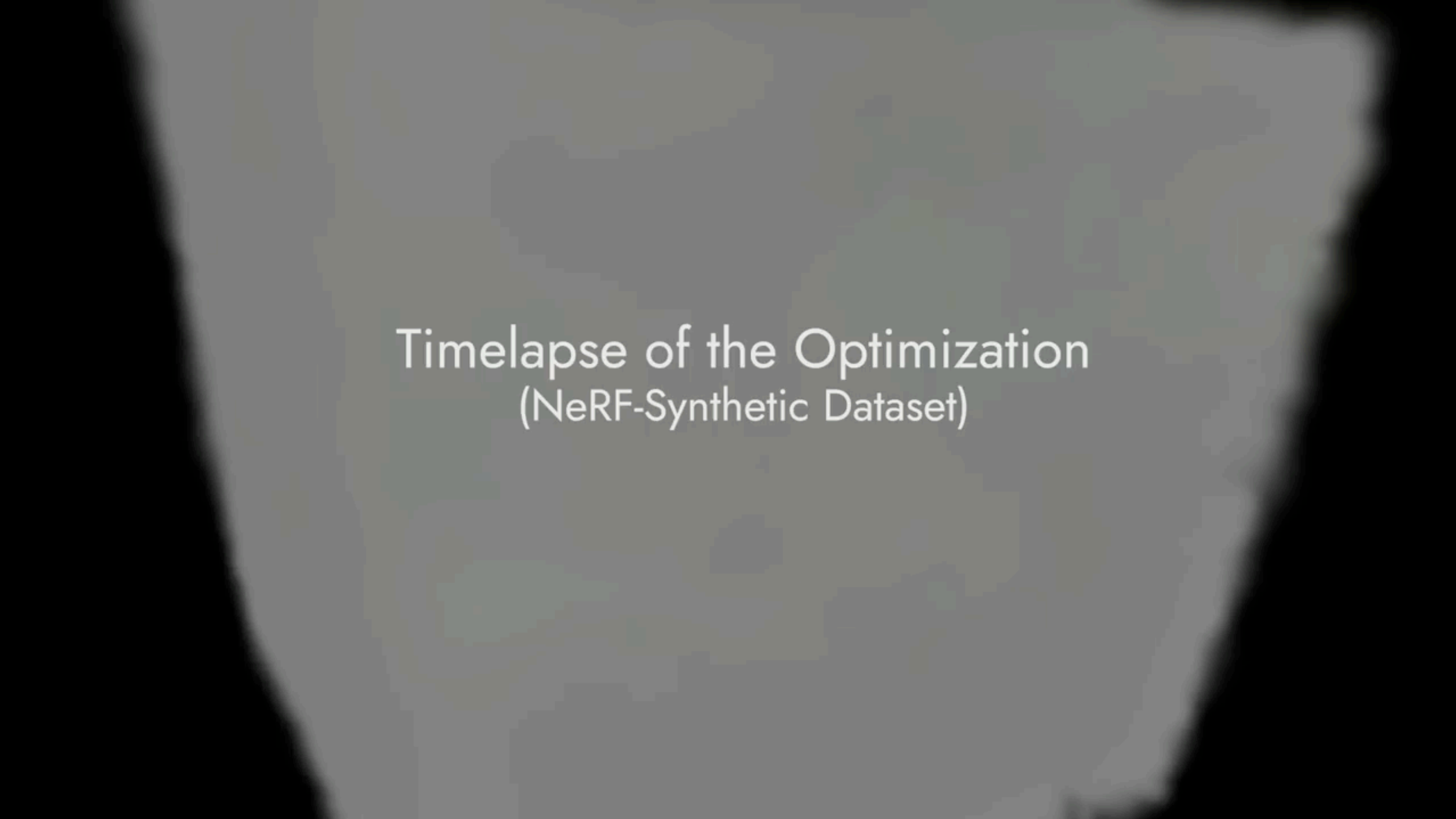


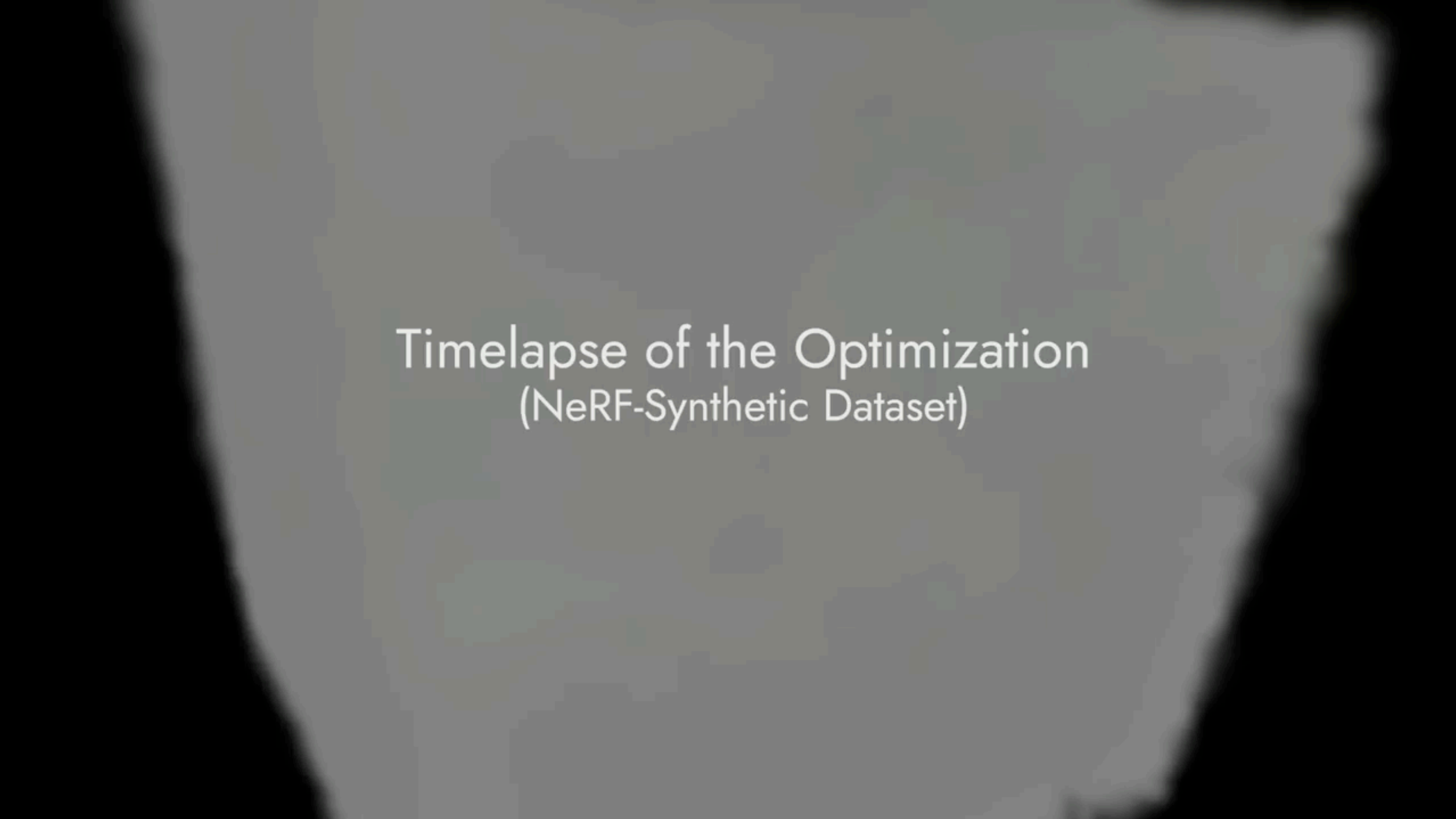
Fix 2: Heuristic *pruning* and *spawning* operations



Our adaptive control of the Gaussians needs to populate empty areas. It focuses on regions with missing geometric features ("under-reconstruction"), but also in regions where Gaussians cover large areas in the scene (which often correspond to "over-reconstruction"). We observe that both have *large* view-space positional gradients. Intuitively, this is likely because they correspond to regions that are not yet well reconstructed, and the optimization tries to move the Gaussians to correct this.

Since both cases are good candidates for densification, we densify Gaussians with an average magnitude of view-space position gradients above a threshold τ_{pos}, which we set to 0.0002 in our tests.

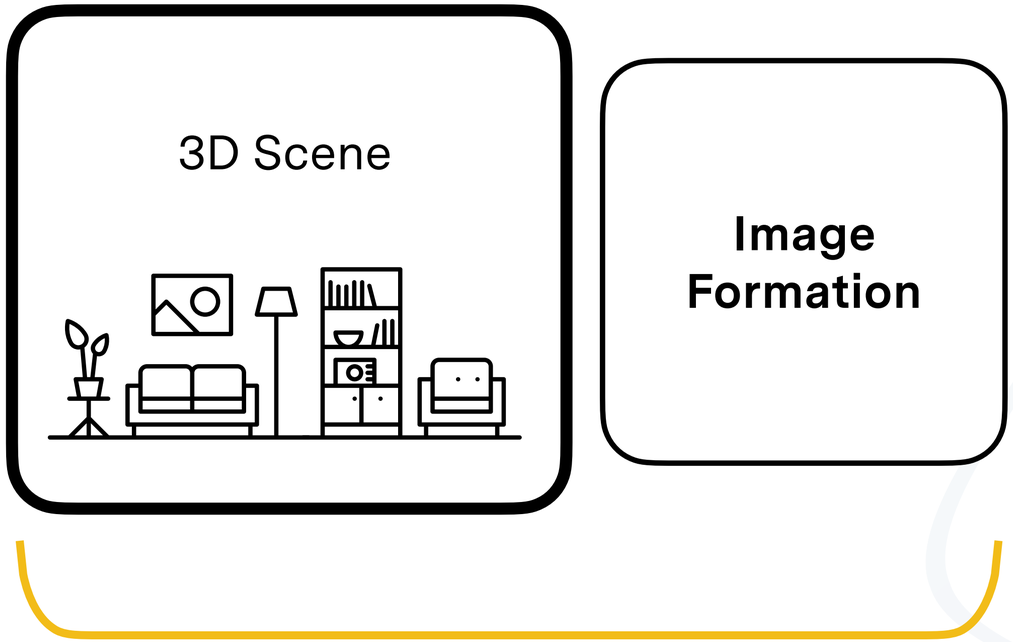

Timelapse of the Optimization
(NeRF-Synthetic Dataset)


Timelapse of the Optimization
(NeRF-Synthetic Dataset)


Menu Views Capture
3D Gaussians
Camera Point view
All interactive sessions are recorded at 1080p with an A6000
Metrics
92.95 (10.76 ms)
Playroom


Menu Views Capture
3D Gaussians
Camera Point view
All interactive sessions are recorded at 1080p with an A6000
Metrics
92.95 (10.76 ms)
Playroom

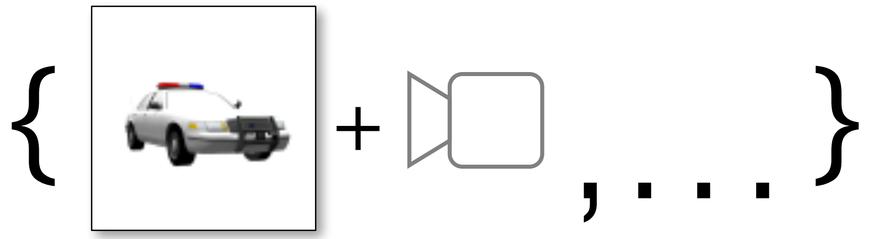
Today: Differentiable Rendering, AKA “Inverse Graphics”



Overfitting case: Inference = Fitting via Gradient Descent

Sitzmann et al: Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations, NeurIPS 2020.

Overfitting case: Inference = Fitting via Gradient Descent



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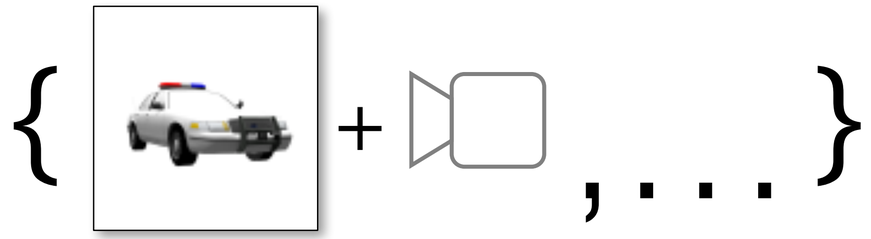
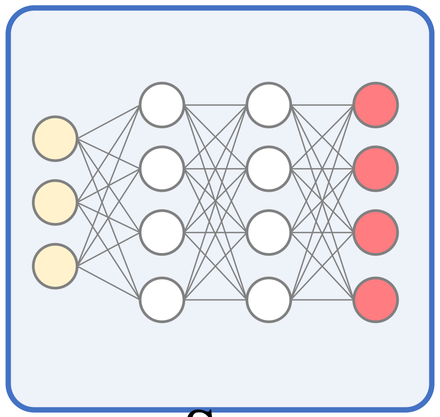
Overfitting case: Inference = Fitting via Gradient Descent





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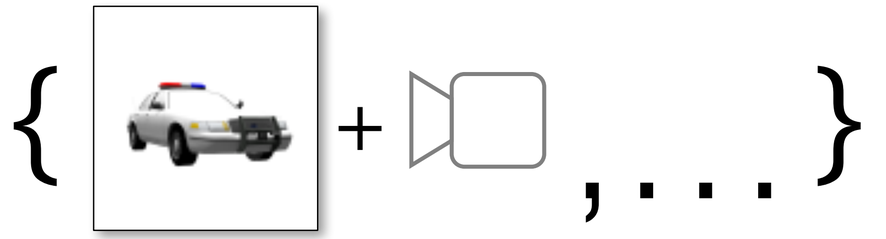
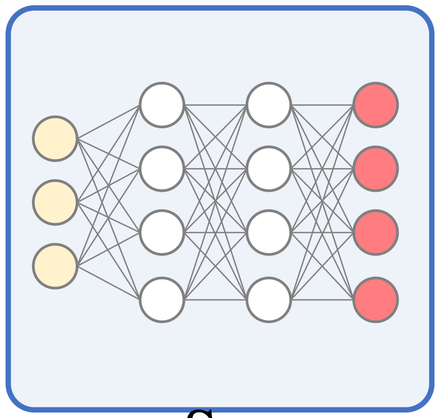
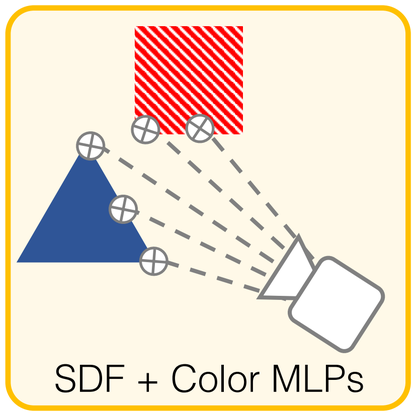
Overfitting case: Inference = Fitting via Gradient Descent





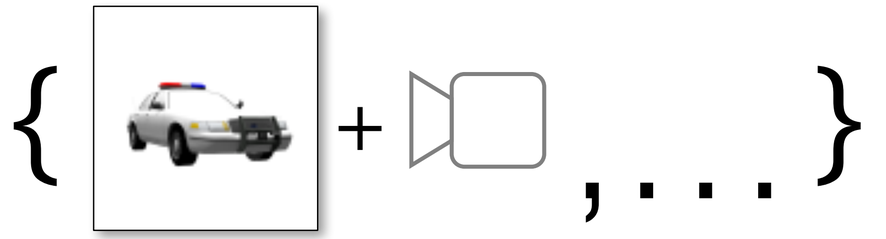
Srn_{ϕ}

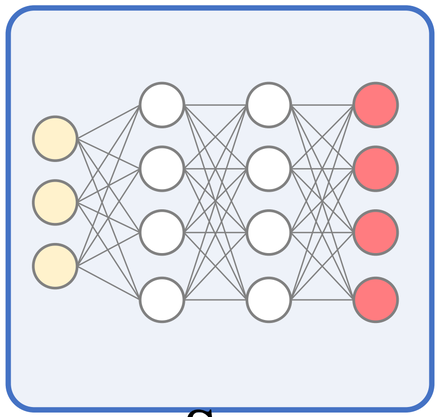


Render_{θ}

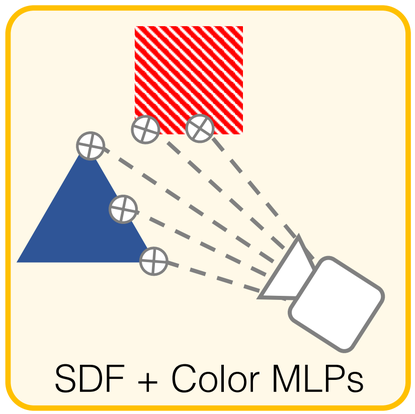
Sitzmann et al: Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations, NeurIPS 2020.

Overfitting case: Inference = Fitting via Gradient Descent





Srn_{ϕ}

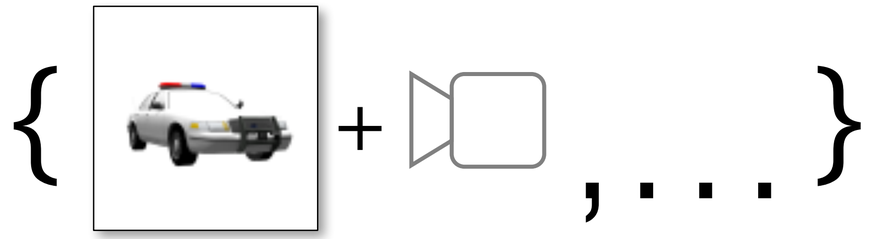


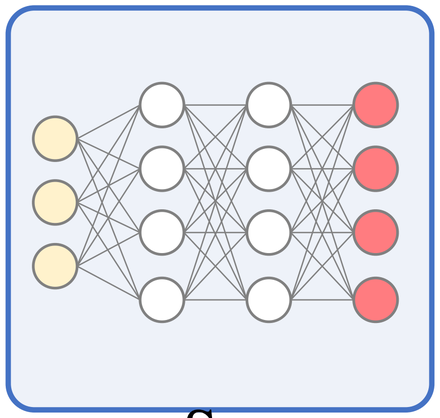
Render_{θ}

$$\min \left\| \text{Render}_{\theta}(\text{Srn}_{\phi}, \xi_i) - \mathcal{I}_i \right\|$$

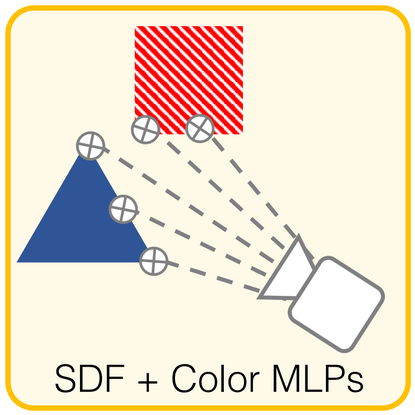
Sitzmann et al: Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations, NeurIPS 2020.

Overfitting case: Inference = Fitting via Gradient Descent





Srn_{ϕ}



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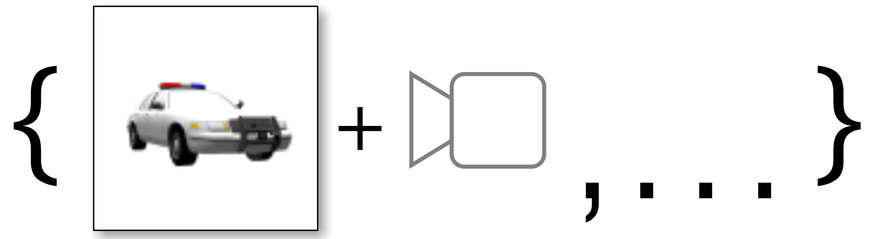
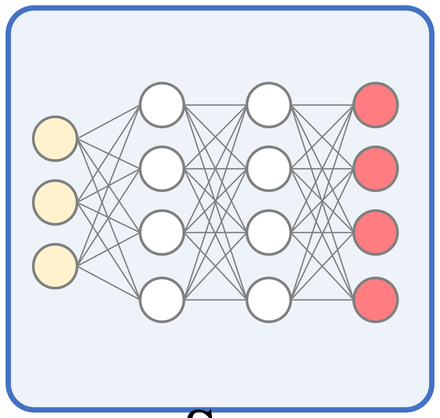
Optimization

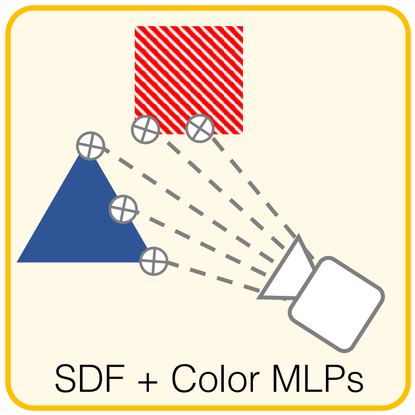
Sitzmann et al: Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations, NeurIPS 2020.

Overfitting case: Inference = Fitting via Gradient Descent





Srn_{ϕ}



Render_{θ}

$$\min \left\| \text{Render}_{\theta}(\text{Srn}_{\phi}, \xi_i) - \mathcal{I}_i \right\|$$

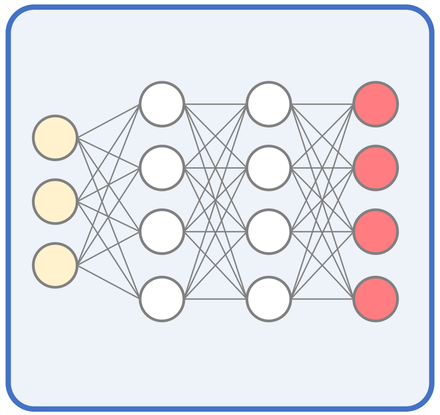
Optimization

Novel View Synthesis

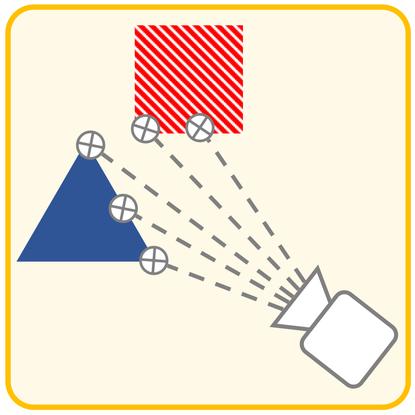
Normal map RGB

Sitzmann et al: Scene Representation Networks: Continuous 3D-Structure-Aware Neural Scene Representations, NeurIPS 2020.

What if observations don't constrain scene representation?

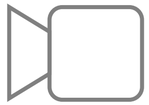


Srn_{ϕ}



Render_{θ}

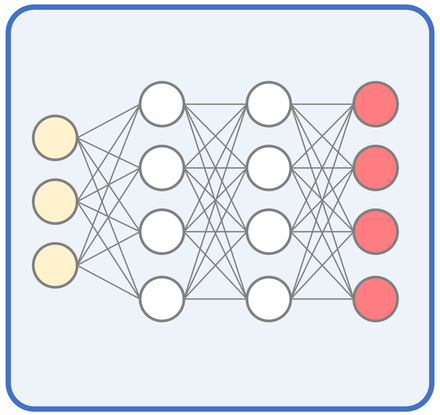
$+$



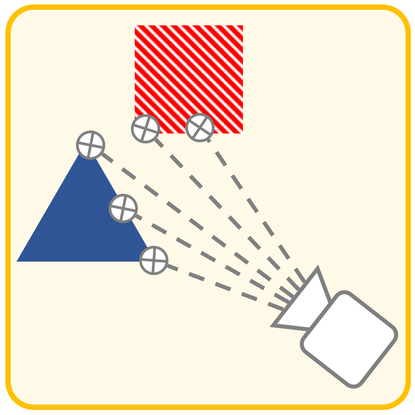
$(\mathcal{I}, \xi)$

$$\underset{\phi,\theta}{\text{argmin}} \left\| \text{Render}_{\theta}(\text{Srn}_{\phi}, \xi) - \mathcal{I} \right\|$$

What if observations don't constrain scene representation?



Srn_{ϕ}



Render_{θ}

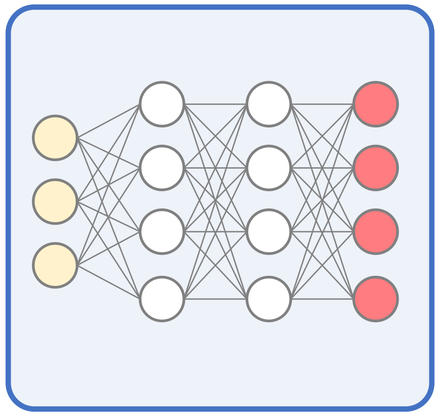
$+$

$(\mathcal{I}, \xi)$

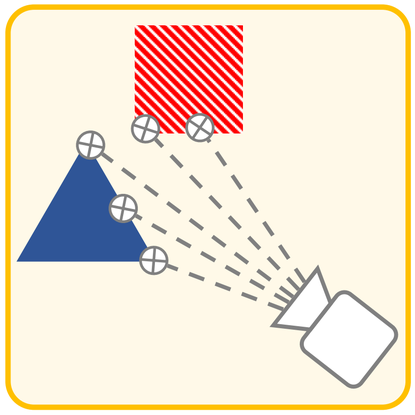
No 3D inform.

$$\underset{\phi,\theta}{\text{argmin}} \left\| \text{Render}_{\theta}(\text{Srn}_{\phi}, \xi) - \mathcal{I} \right\|$$

What if observations don't constrain scene representation?



Srn_{ϕ}



Render_{θ}

$+$

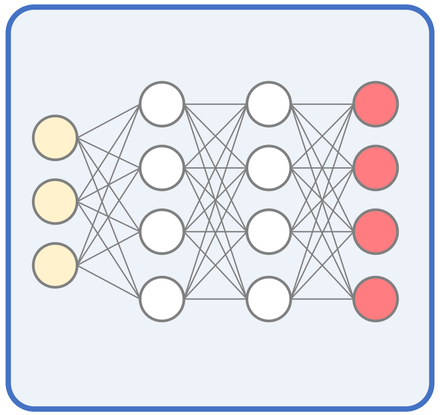
$(\mathcal{I}, \xi)$

No 3D inform.

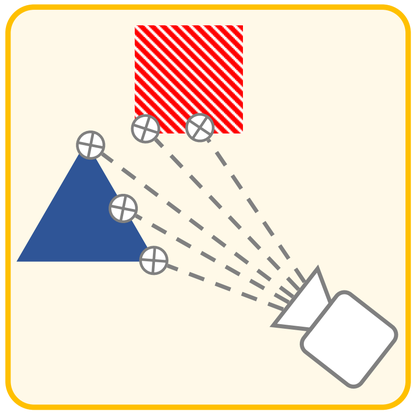
$$\underset{\phi,\theta}{\text{argmin}} \left\| \text{Render}_{\theta}(\text{Srn}_{\phi}, \xi) - \mathcal{I} \right\|$$

Input

What if observations don't constrain scene representation?



Srn_{ϕ}



Render_{θ}

$+$

$(\mathcal{I}, \xi)$

No 3D inform.

$$\underset{\phi,\theta}{\text{argmin}} \left\| \text{Render}_{\theta}(\text{Srn}_{\phi}, \xi) - \mathcal{I} \right\|$$

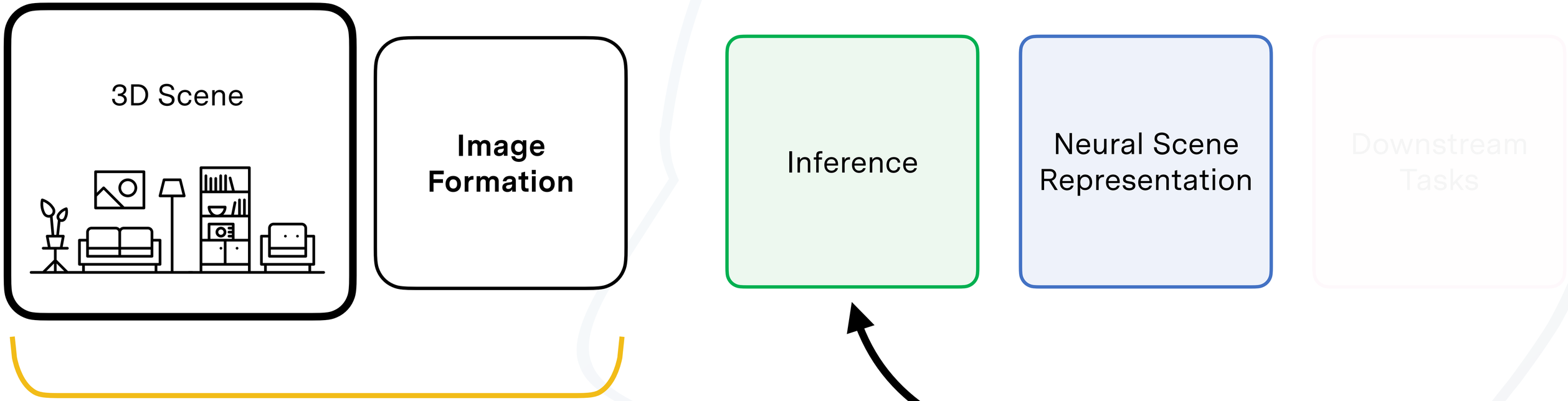
Input

Normal map

RGB

GT

Today: Differentiable Rendering, AKA “Inverse Graphics”



Graphics

Let’s learn this!