Neural Radiance Fields

Jon Barron

Google Research

About me



UC Berkeley
PhD Student
2008-2013
Advisor: Jitendra Malik



Google Research: Perception
Research Scientist
2013-Now

Team:



Peter Hedman

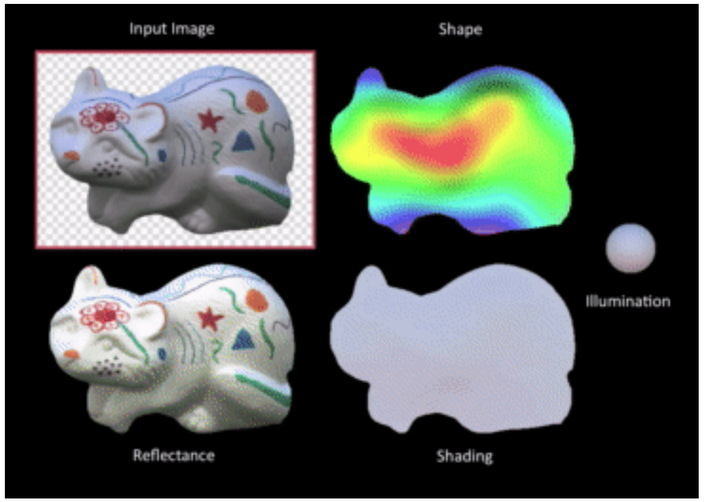


Pratul Srinivasan

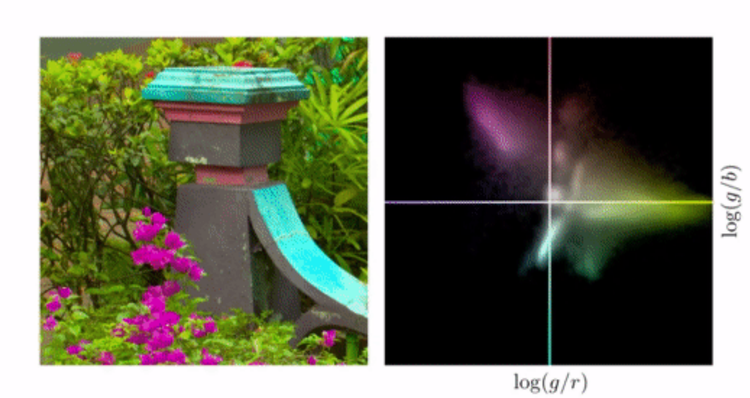


Ben Mildenhall

Research Interests



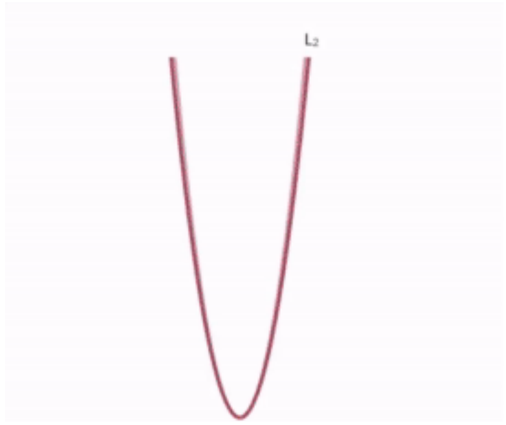
Inverse Rendering



Color Constancy



Smooth Motion / Depth Estimation



Loss Functions

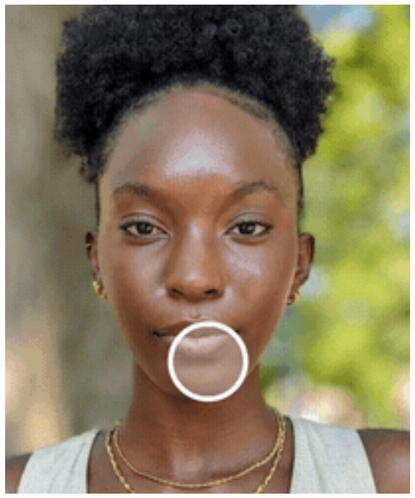
Research Impact



HDR+ / Night Sight



Lens Blur / Portrait Mode



Portrait Light



Google Glass



Jump

What is graphics?

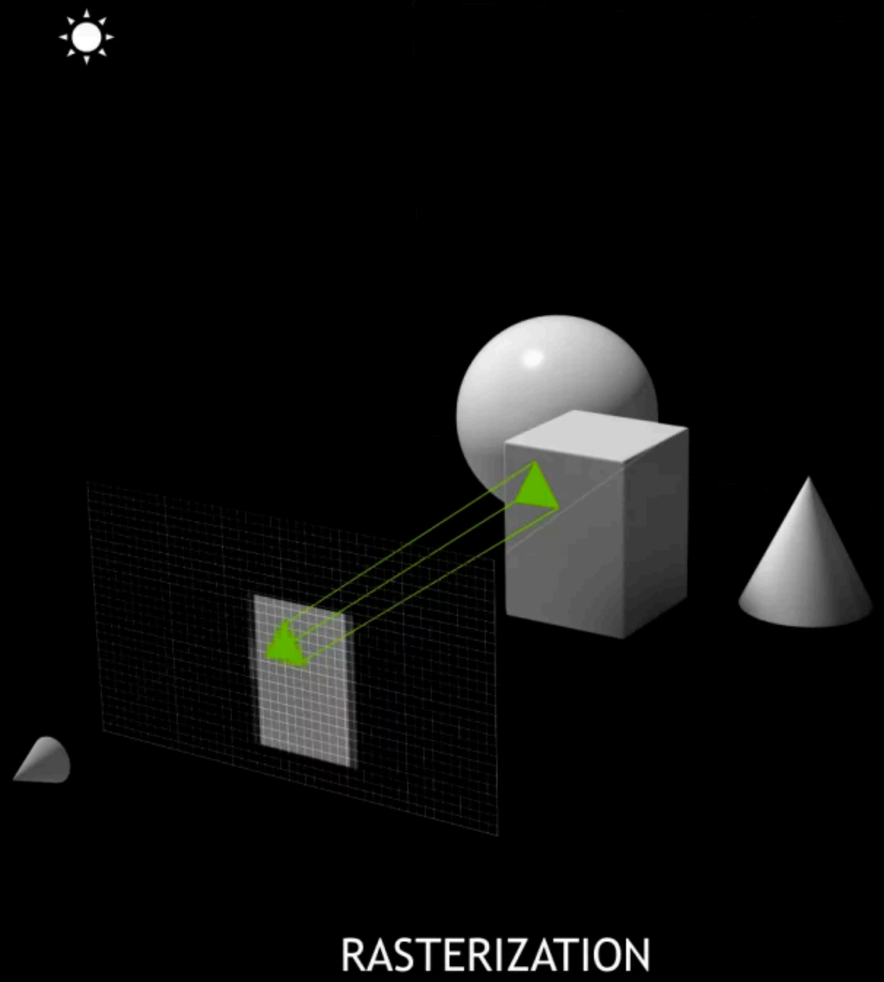
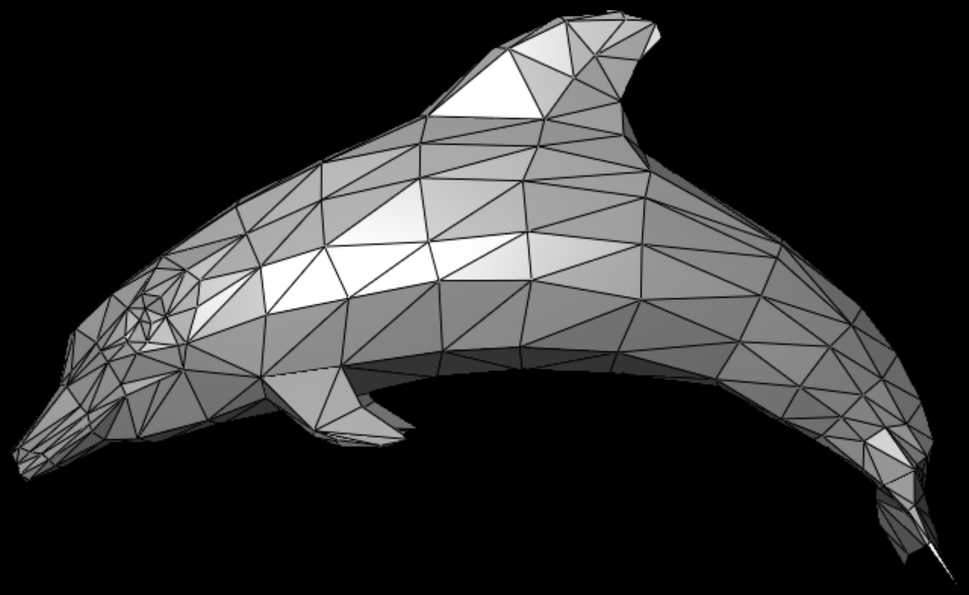


Image: Nvidia

What is graphics?



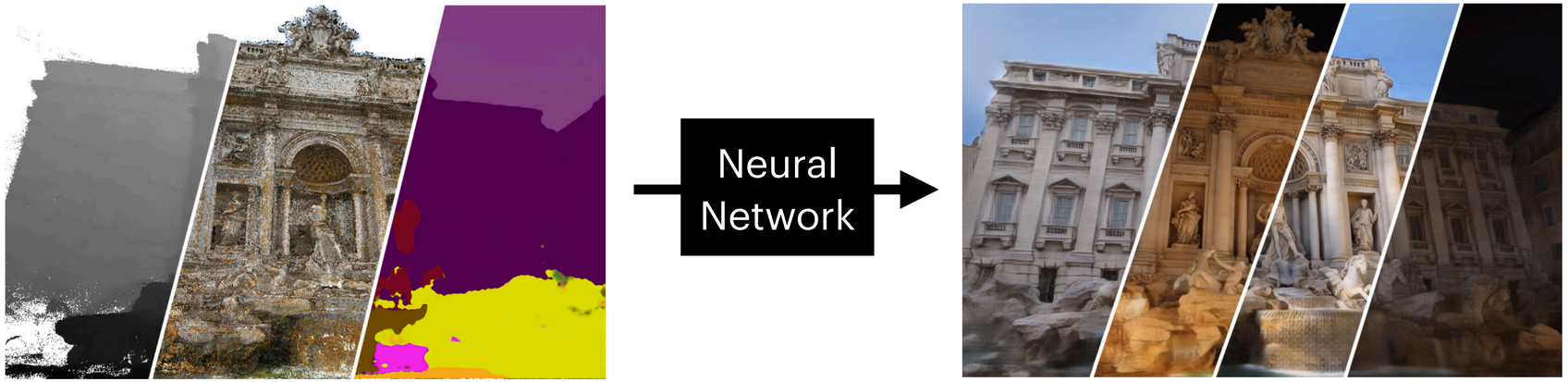
Mesh Rendering

Chrschn, Public domain, via Wikimedia Commons

Is this “neural rendering”?

Paradigm 1:

“The neural network is a black box that directly renders pixels”

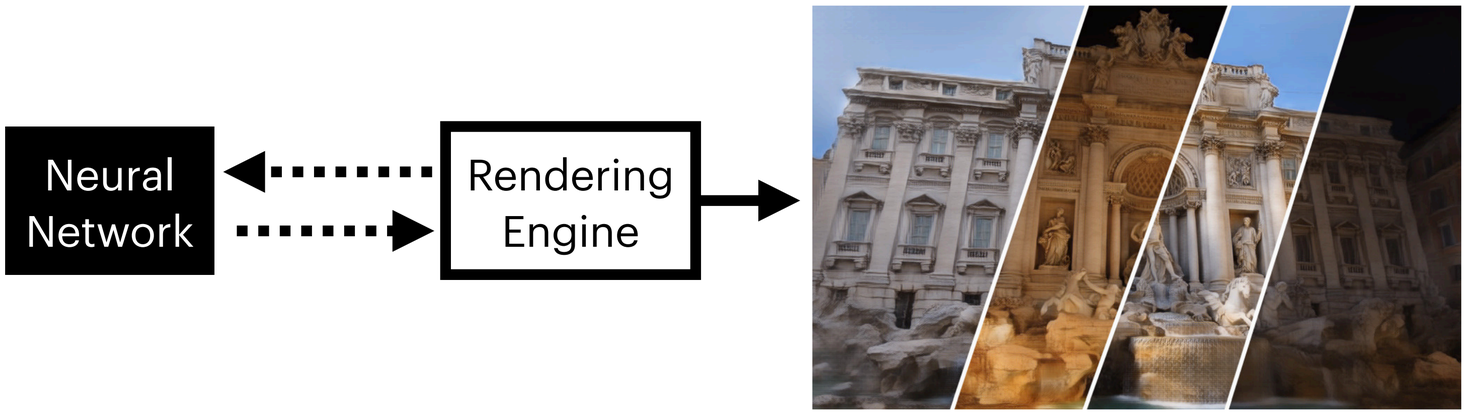


Neural Rerendering in the Wild, Meshry et al. CVPR 2019

Paradigm A:

“The neural network is a black box that models the geometry of the world, and a (non-learned) graphics engine renders it”

“Scene Representation”
“Implicit Representations”



NeRF in the Wild, Martin-Brualla et al. CVPR 2021

NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis



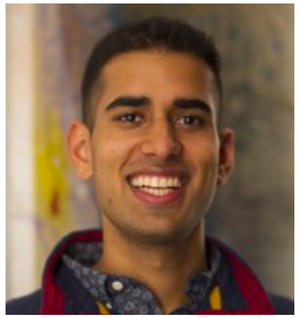
Ben Mildenhall*



UC Berkeley

Google

Pratul Srinivasan*



UC Berkeley

Google

Matt Tancik*



UC Berkeley

Jon Barron



Google Research

Google

Ravi Ramamoorthi



UC San Diego

UC San Diego

Ren Ng



UC Berkeley

Problem: View Interpolation







Inputs: sparsely sampled images of scene

Outputs: *new* views of same scene

tancik.com/nerf

RGB-alpha volume rendering for view synthesis

Soft 3D

(Penner & Zhang 2017)

Culmination of non-deep stereo matching techniques



Multiplane image methods

Stereo Magnification (Zhou et al. 2018)

Pushing the Boundaries… (Srinivasan et al. 2019)

Local Light Field Fusion (Mildenhall et al. 2019)

DeepView (Flynn et al. 2019)

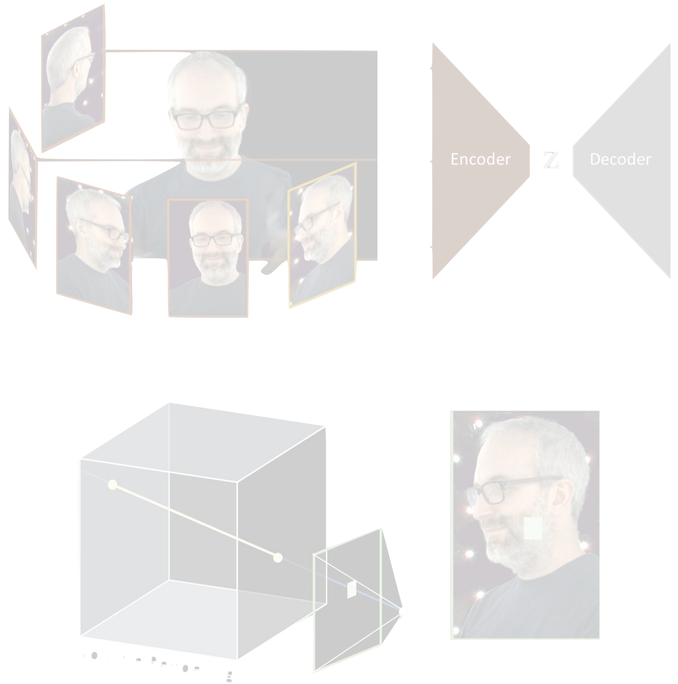
Single-View… (Tucker & Snavely 2020)

Typical deep learning pipelines - images go into a 3D CNN, big RGBA 3D volume comes out

Neural Volumes

(Lombardi et al. 2019)

Direct gradient descent to optimize an RGBA volume, regularized by a 3D CNN



RGB-alpha volume rendering for view synthesis

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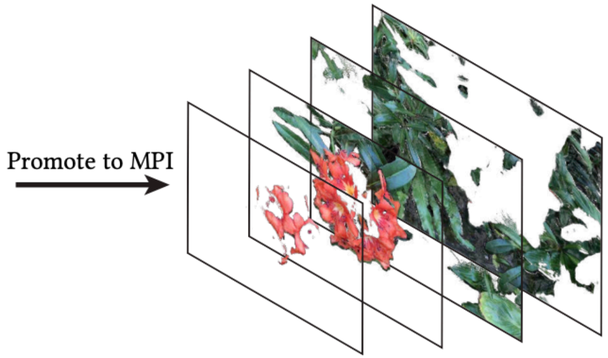
DeepView (Flynn et al. 2019)

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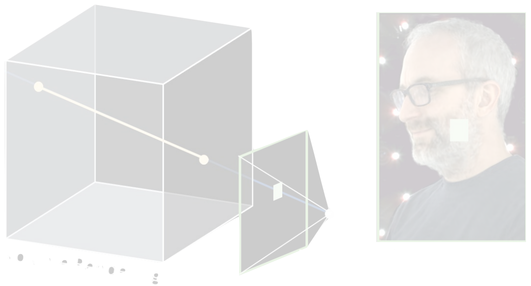
Input Sampled View



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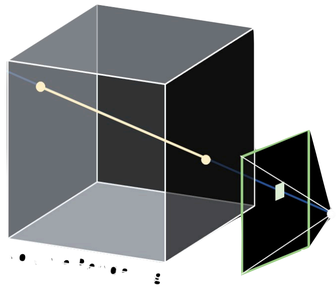
Promote to MPI

Neural Volumes

(Lombardi et al. 2019)

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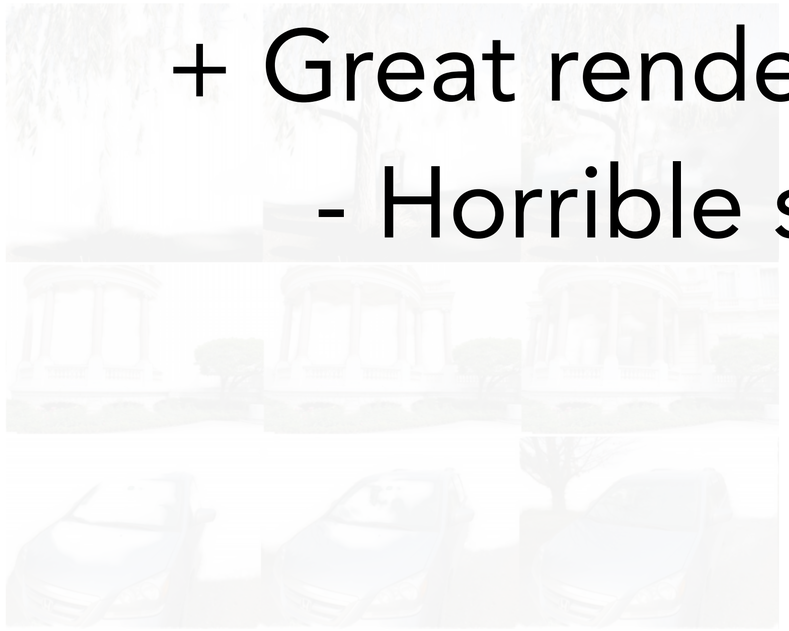
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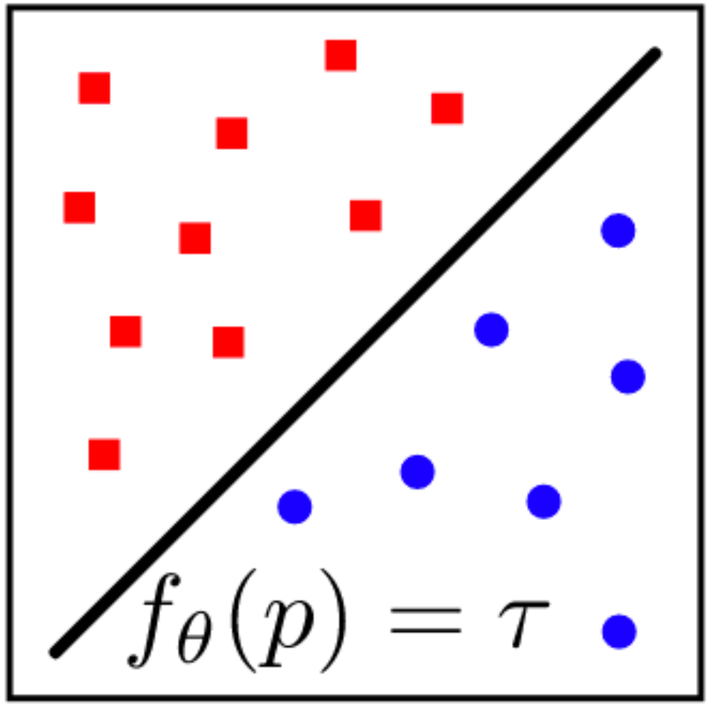
Neural Volumes
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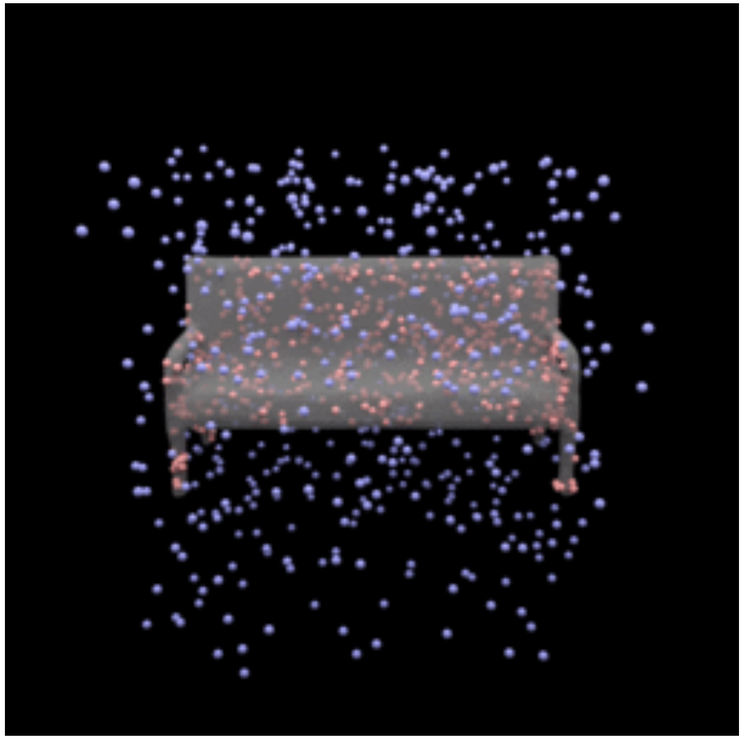
+ Great rendering model: good for optimization
- Horrible storage requirements (1-10 GB)





Neural networks as a continuous shape representation

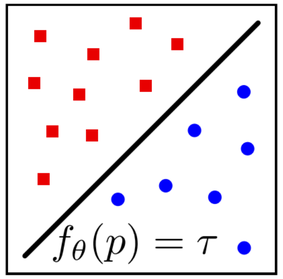




Occupancy Networks, Mescheder et al. CVPR 2019

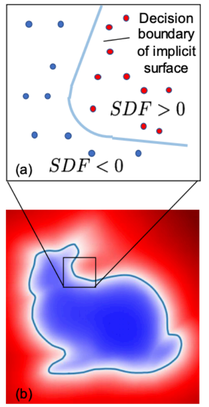
Neural networks as a continuous shape representation

Occupancy Networks
(Mescheder et al. 2019)
$(x, y, z) \rightarrow$ occupancy





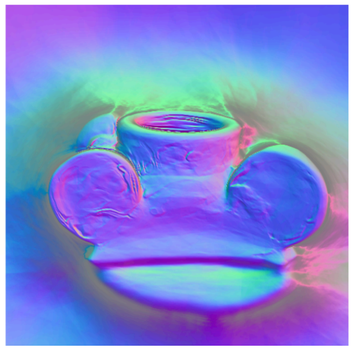
DeepSDF
(Park et al. 2019)
$(x, y, z) \rightarrow$ distance



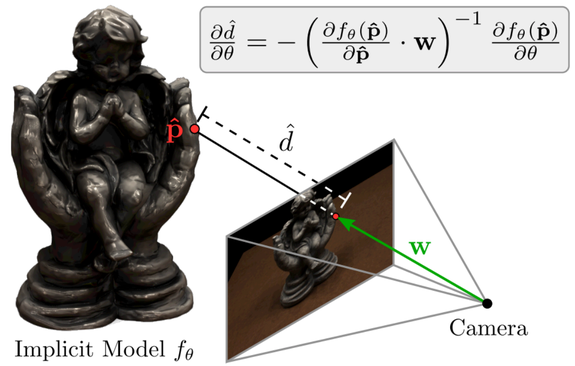


Scene Representation Networks
(Sitzmann et al. 2019)
$(x, y, z) \rightarrow$ latent vec. (color, dist.)





Differentiable Volumetric Rendering
(Niemeyer et al. 2020)
$(x, y, z) \rightarrow$ color, occ.



Neural networks as a continuous shape representation

Occupancy Networks
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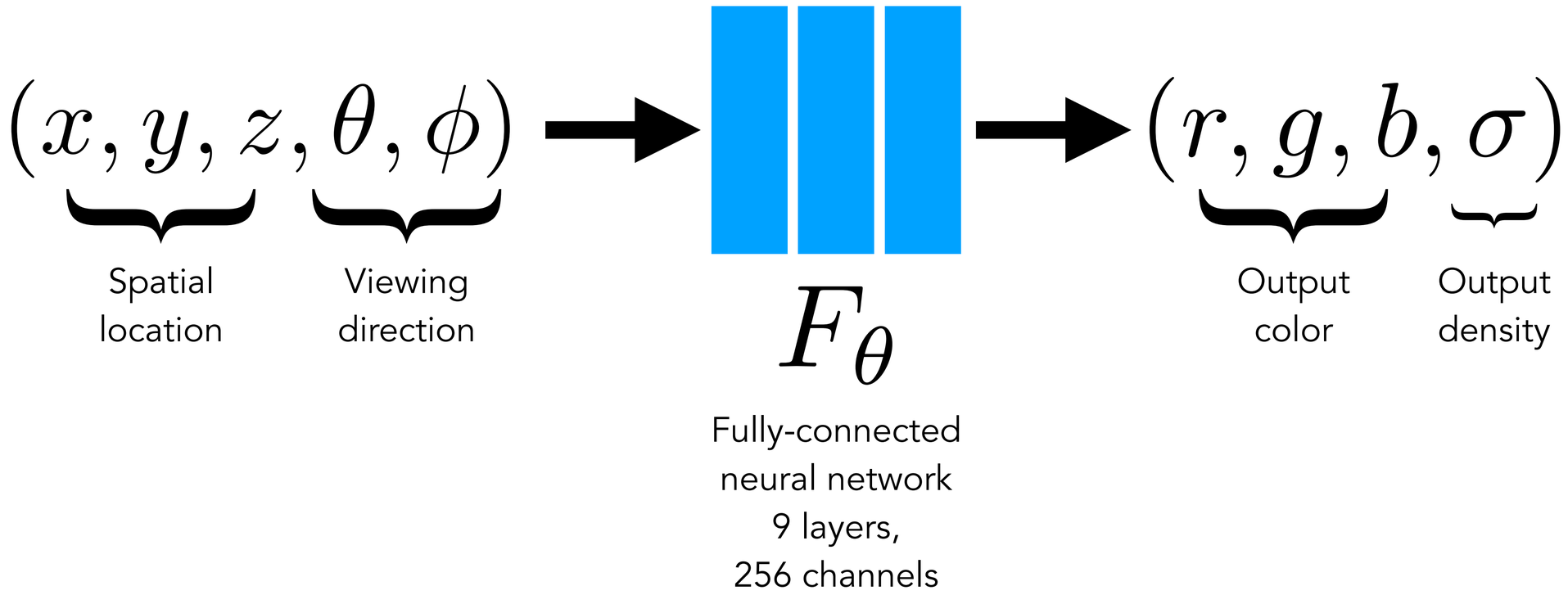


- Limited rendering model: difficult to optimize
+ Highly compressible (1-10 MB)

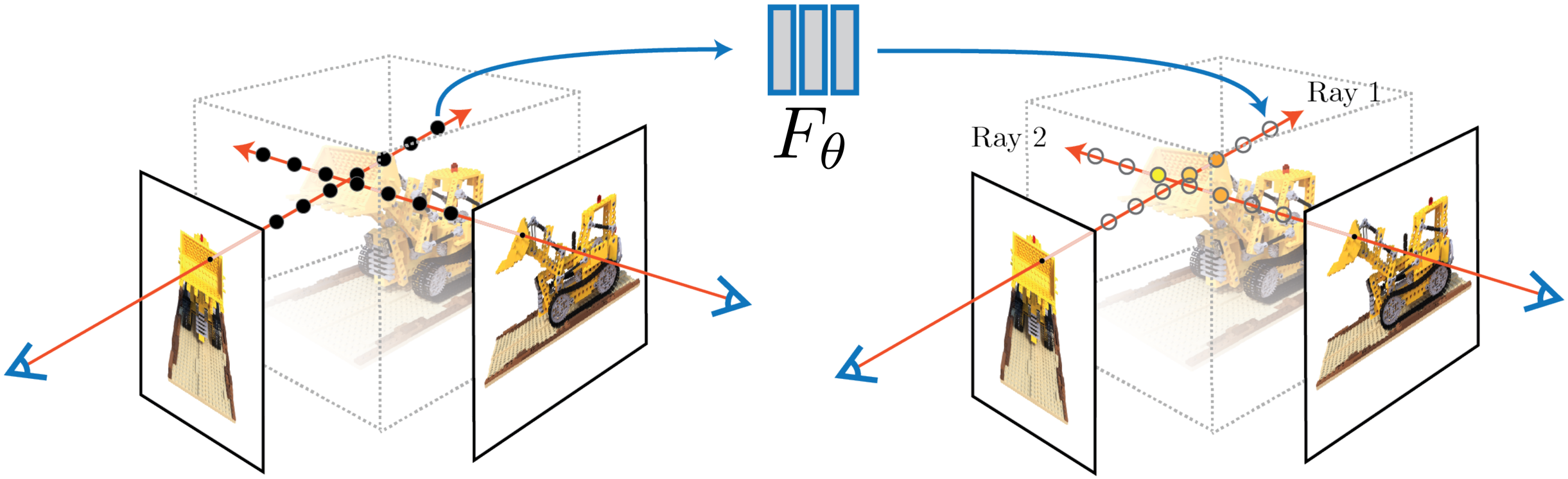
Scene Representation Networks
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NeRF (neural radiance fields)



Generate views with traditional volume rendering



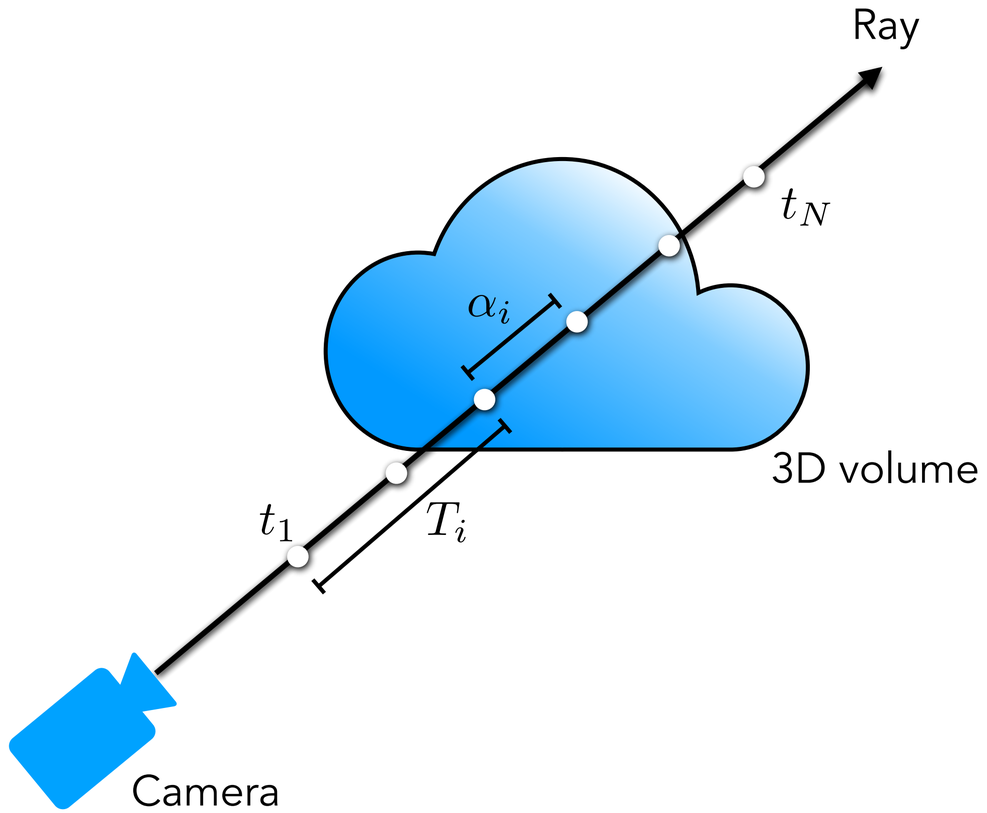
Volume rendering is trivially differentiable

Rendering model for ray r(t) = o + td:

$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

weights

colors



Volume rendering is trivially differentiable

Rendering model for ray r(t) = o + td:

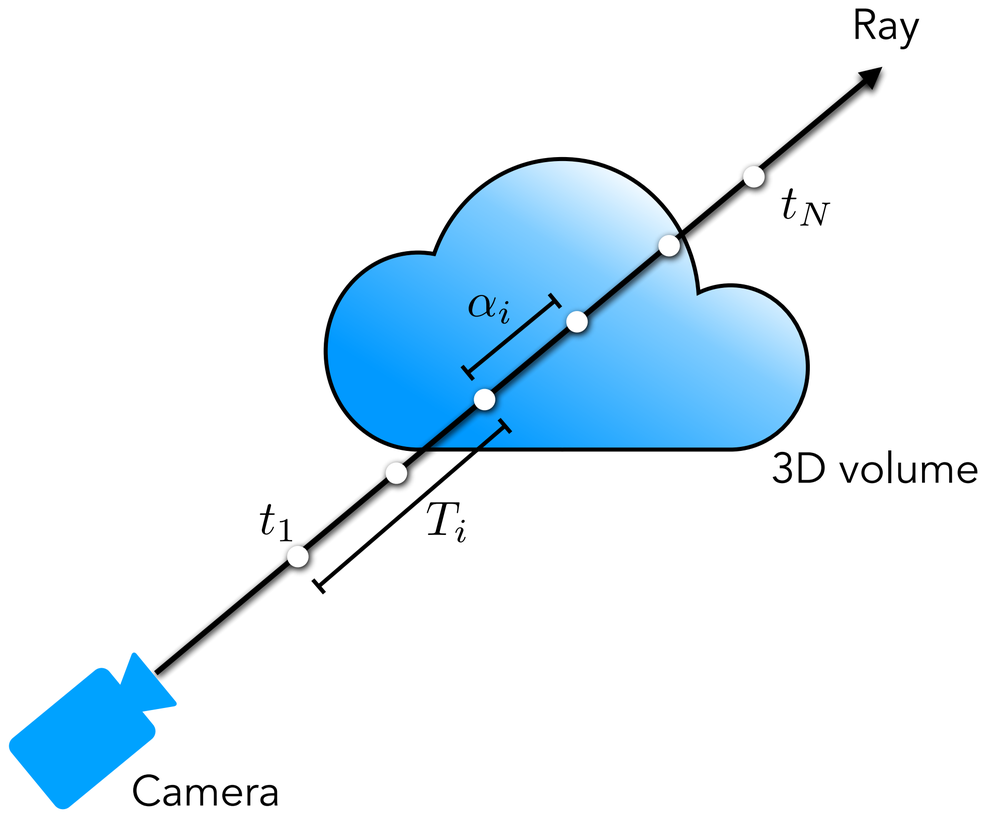
$$C \approx \sum_{i=1}^{N} T_i \alpha_i c_i$$

weights

colors

How much light is blocked earlier along ray:

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



Volume rendering is trivially differentiable

Rendering model for ray r(t) = o + td:

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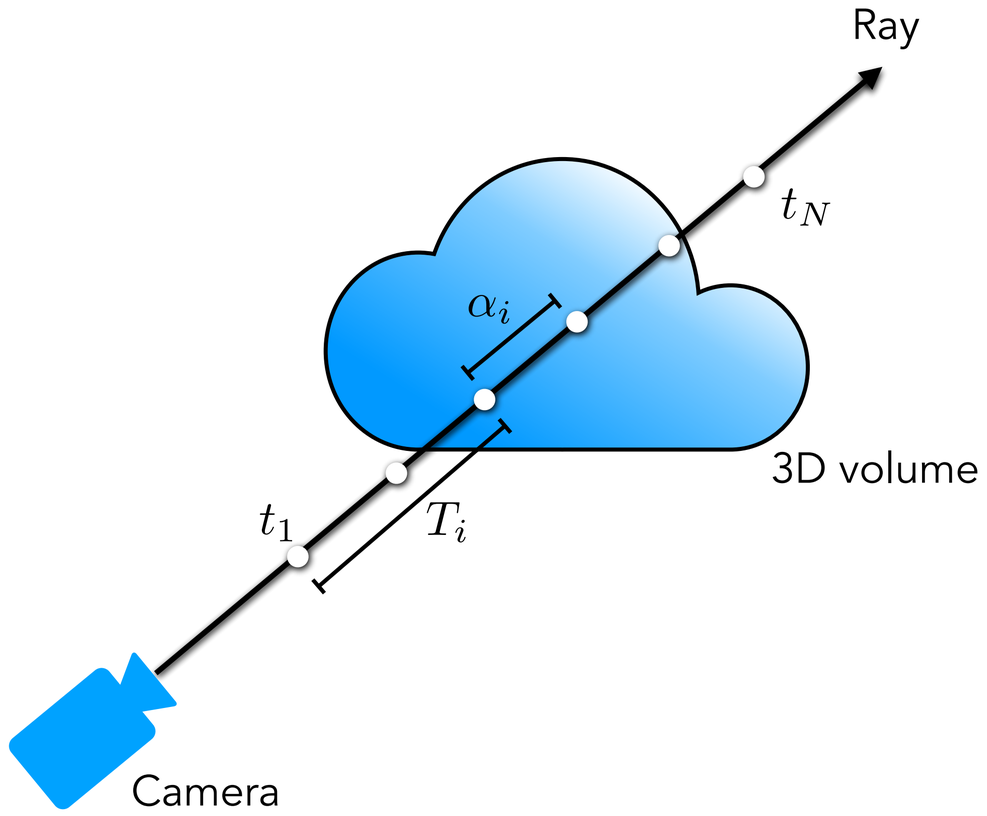
colors

How much light is blocked earlier along ray:

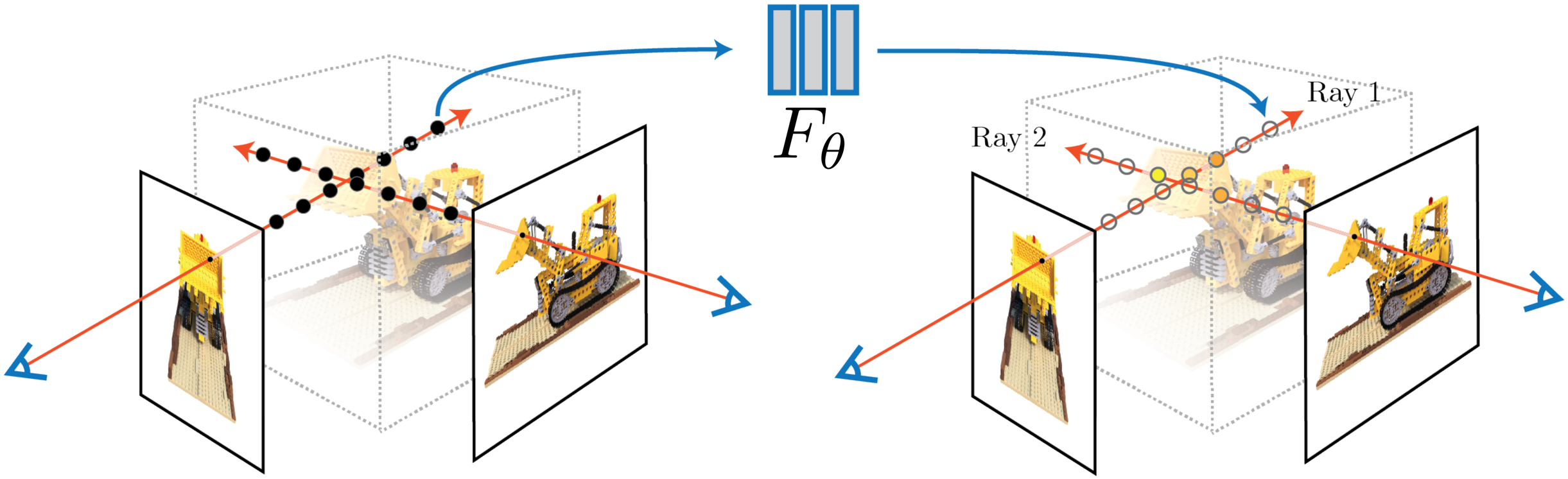
$$T_i = \prod_{j=1}^{i-1} (1 - \alpha_j)$$

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

$$\alpha_i = 1 - e^{-\sigma_i \delta t_i}$$



Optimize with gradient descent on rendering loss

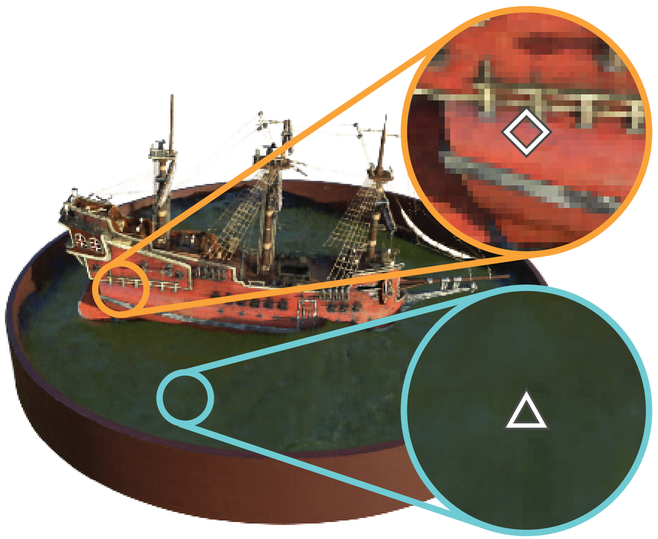


$$\min_\theta \sum_i || \text{render}_i(F_\theta) - I_i ||^2$$

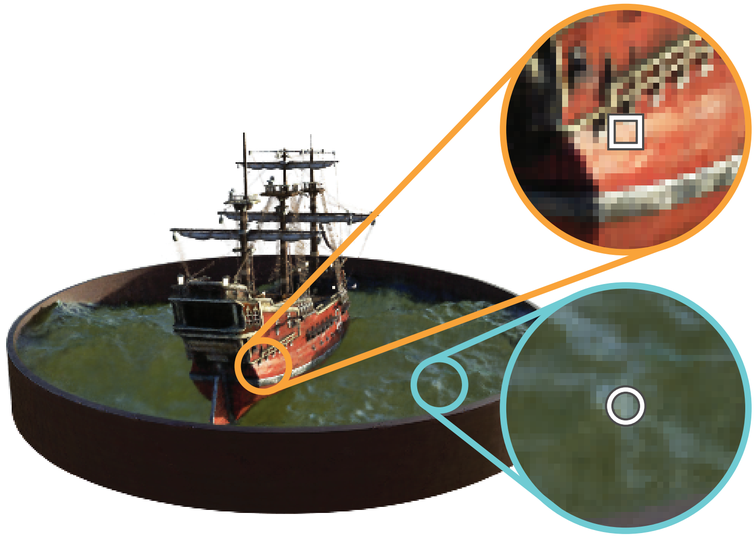
Training network to reproduce all input views of the scene



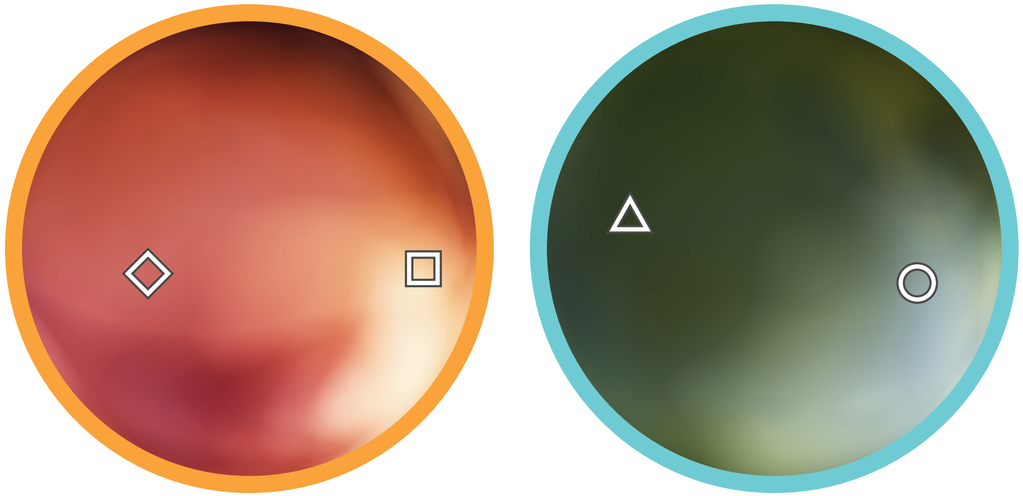
Viewing directions as input



(a) View 1



(b) View 2



(c) Radiance Distributions

Results





vs. Prior Work (Implicit / MLP)

SRN [Sitzmann et al. 2019]

NeRF







Nearest Input

vs. Prior Work (Implicit / MLP)

SRN [Sitzmann et al. 2019]



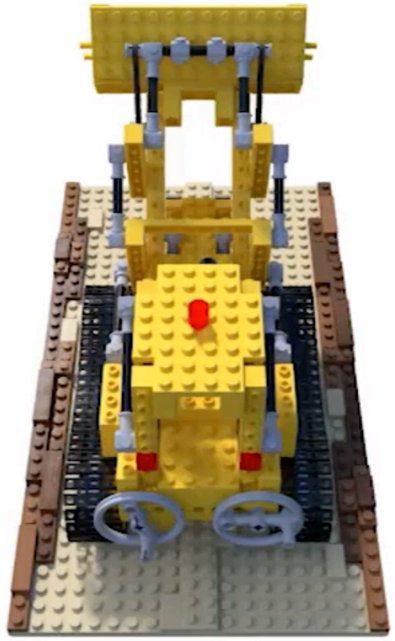
NeRF





Nearest Input















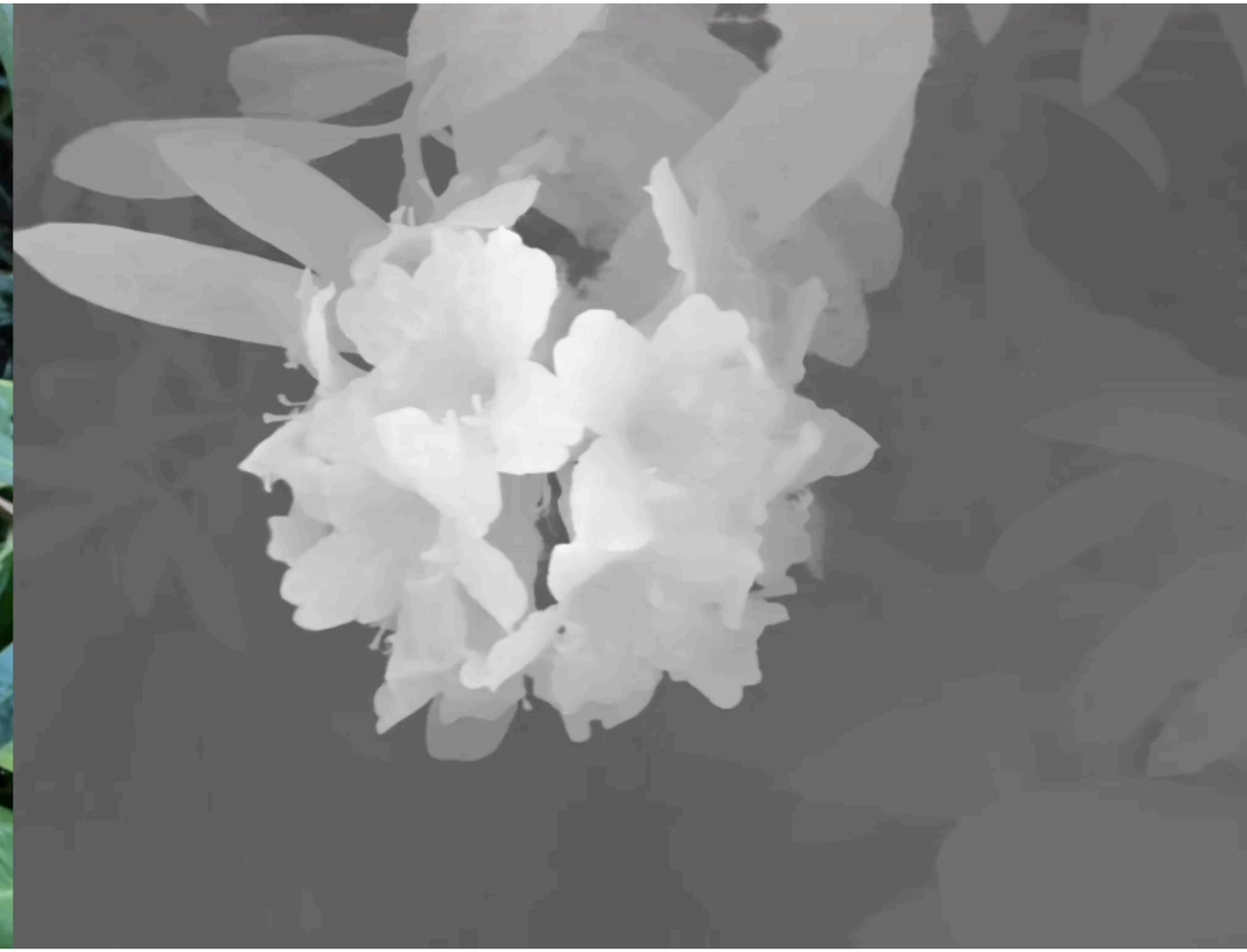


View-Dependent Effects



Detailed Geometry & Occlusion

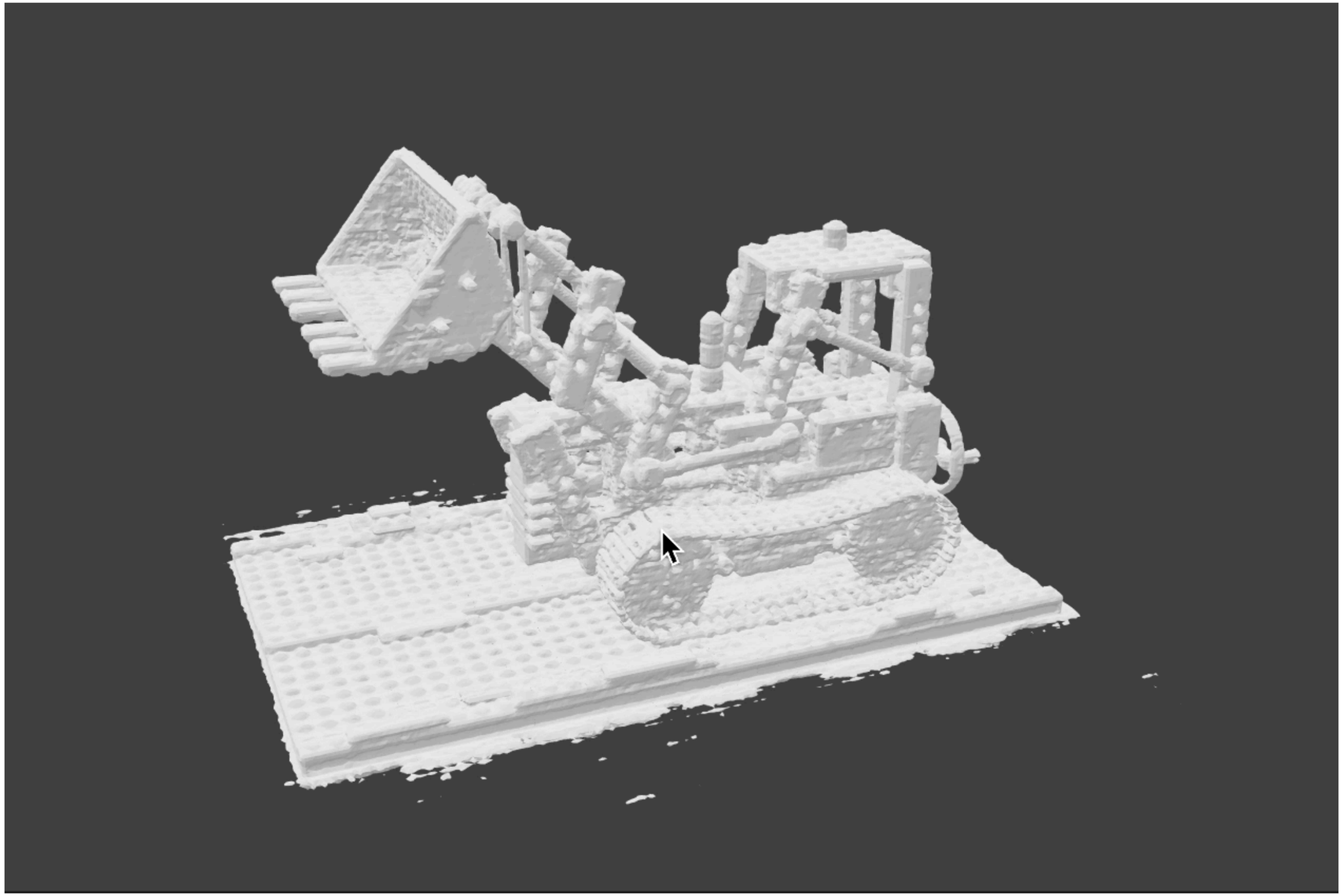




Detailed Geometry & Occlusion



Meshable



Baking Neural Radiance Fields for Real-Time View Synthesis

arXiv 2021

Peter Hedman Pratul P. Srinivasan Ben Mildenhall Jonathan T. Barron Paul Debevec

Google Research



Paper

Video



Demos

http://nerf.live/

Naive implementation produces blurry results



NeRF (Naive)

Naive implementation produces blurry results

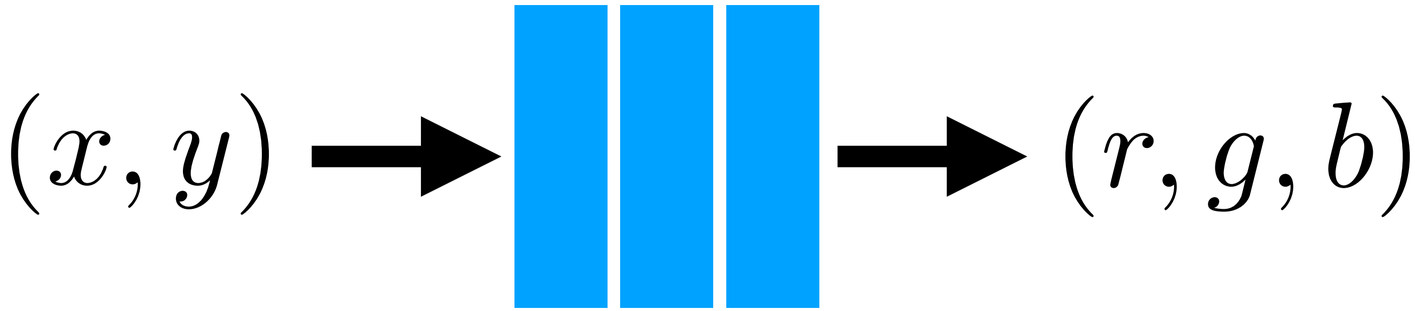


NeRF (Naive)



NeRF (with positional encoding)

Toy problem: memorizing a 2D image



Toy problem: memorizing a 2D image

Ground truth image

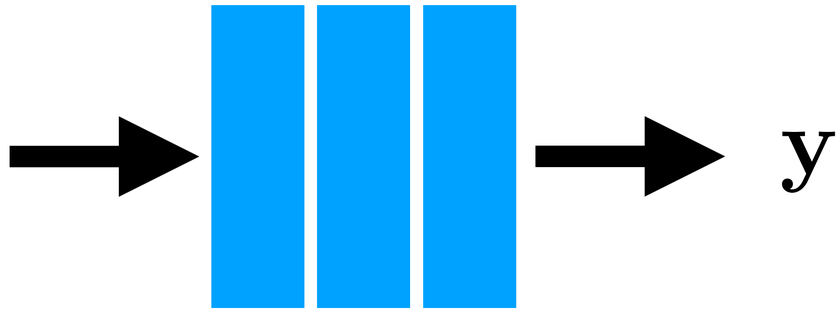


Standard fully-connected net





$$\begin{pmatrix} \sin(\mathbf{v}), \cos(\mathbf{v}) \\ \sin(2\mathbf{v}), \cos(2\mathbf{v}) \\ \sin(4\mathbf{v}), \cos(4\mathbf{v}) \\ \dots \\ \sin(2^{L-1}\mathbf{v}), \cos(2^{L-1}\mathbf{v}) \end{pmatrix}$$



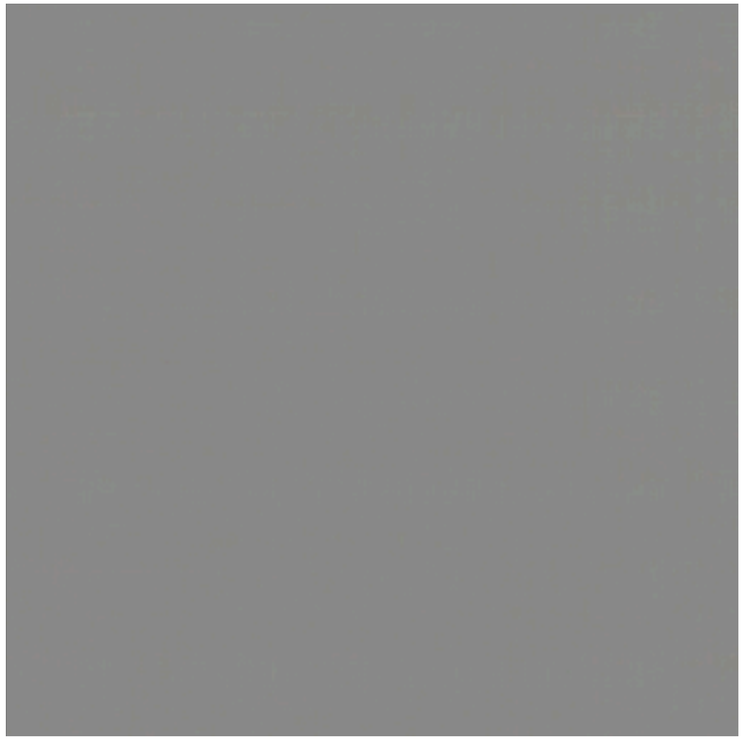
Ground truth image



Standard fully-connected net



With Positional Encoding



Positional encoding also directly improves our scene representation!



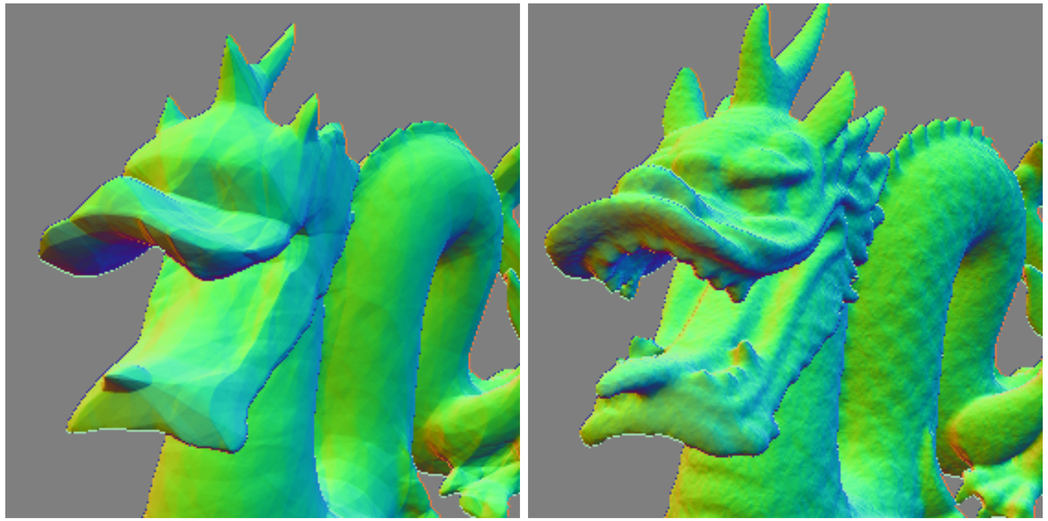
NeRF (Naive)



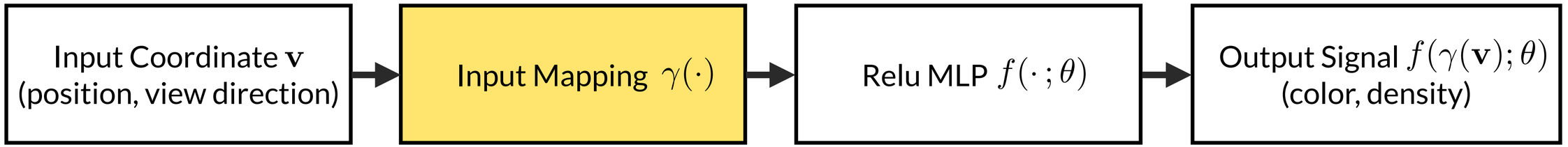
NeRF (with positional encoding)

Why?

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



Matthew Tancik*, Pratul Srinivasan*, Ben Mildenhall*,
Sara Fridovich-Keil, Nithin Ragahavan, Utkarsh Singhal,
Ravi Ramamoorthi, Jonathan T. Barron, Ren Ng



Positional Encoding [1]: $\gamma(\mathbf{v}) = [\cos(2^0\mathbf{v}), \sin(2^0\mathbf{v}), \ldots, \cos(2^{L-1}\mathbf{v}), \sin(2^{L-1}\mathbf{v})]$

Random Fourier Features [2]: $\gamma(\mathbf{v}) = [\cos(\mathbf{B}\mathbf{v}), \sin(\mathbf{B}\mathbf{v})]$ $\quad\quad$ $\mathbf{B} \sim \mathcal{N}(0, \sigma^2)$

[1] Vaswani et al.. NeurIPS, 2017

[2] Rahimi & Recht. NeurIPS, 2007

Neural Tangent Kernel

$$f(\mathbf{x};\theta) \approx \sum_i (\mathbf{K}^{-1}\mathbf{y})_i k(\mathbf{x}_i, \mathbf{x})$$

Under certain conditions,
neural networks are kernel regression(!)

$$k(\mathbf{x}_i, \mathbf{x}_j) = h_{\mathrm{NTK}}(\langle \mathbf{x}_i, \mathbf{x}_j \rangle)$$

$$h_{\mathrm{NTK}} : \mathbb{R} \to \mathbb{R}$$

ReLU MLPs correspond to a “dot product” kernel

Jacot et al., NeurIPS, 2018, Arora, et al., ICML, 2019, Basri et al., 2020., Du et al., ICLR, 2019., Lee et al., NeurIPS, 2019

Dot Product of Fourier Features

$$
\begin{aligned}
\langle \gamma(\mathbf{v}_1), \gamma(\mathbf{v}_2) \rangle &= \sum_j \left(\cos(\mathbf{b}_j^{\mathrm{T}} \mathbf{v}_1) \cos(\mathbf{b}_j^{\mathrm{T}} \mathbf{v}_2) + \sin(\mathbf{b}_j^{\mathrm{T}} \mathbf{v}_1) \sin(\mathbf{b}_j^{\mathrm{T}} \mathbf{v}_2) \right) \\
&= \sum_j \cos\left(\mathbf{b}_j^{\mathrm{T}} (\mathbf{v}_1 - \mathbf{v}_2) \right) \qquad \text{(cosine difference trig identity)} \\
&\triangleq h_\gamma(\mathbf{v}_1 - \mathbf{v}_2)
\end{aligned}
$$

Fourier Features → ***stationary*** kernel

Resulting *composed* NTK is stationary

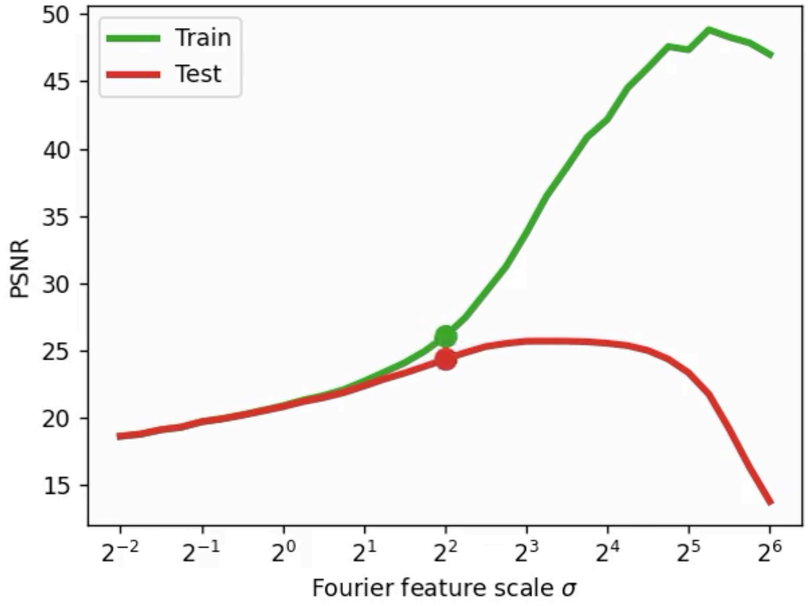
$$h_{\mathrm{NTK}}\Big(\langle \gamma(\mathbf{v})_i, \gamma(\mathbf{v})_j \rangle\Big) = h_{\mathrm{NTK}}(h_\gamma(\mathbf{v}_i - \mathbf{v}_j))$$

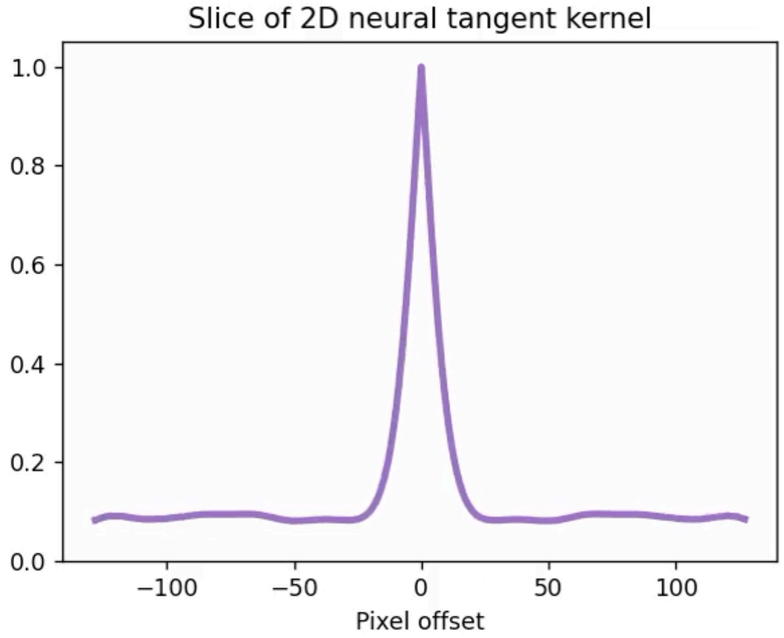
Resulting network regression function is a *convolution*

$$\hat{f} = (h_{\mathrm{NTK}} \circ h_\gamma) * \sum_{i=1}^{n} w_i \delta_{\mathbf{v}_i}$$

Mapping bandwidth controls underfitting / overfitting

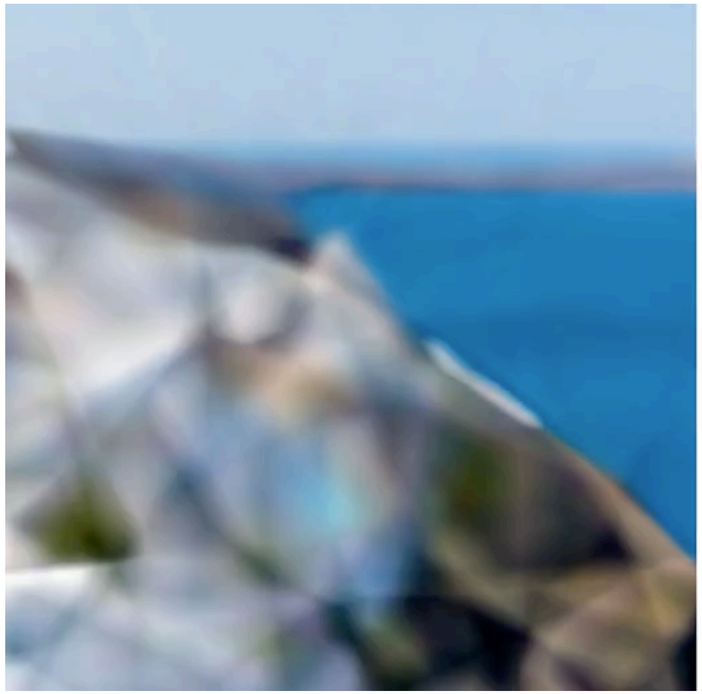


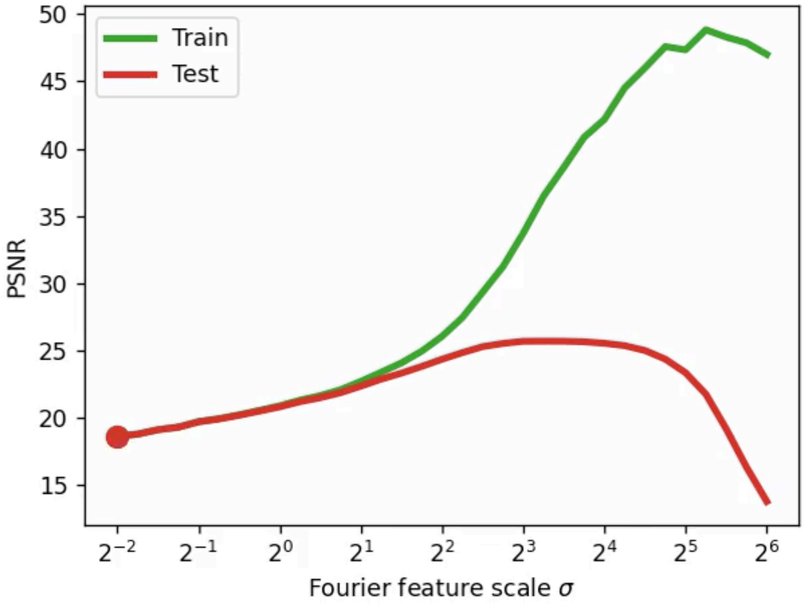


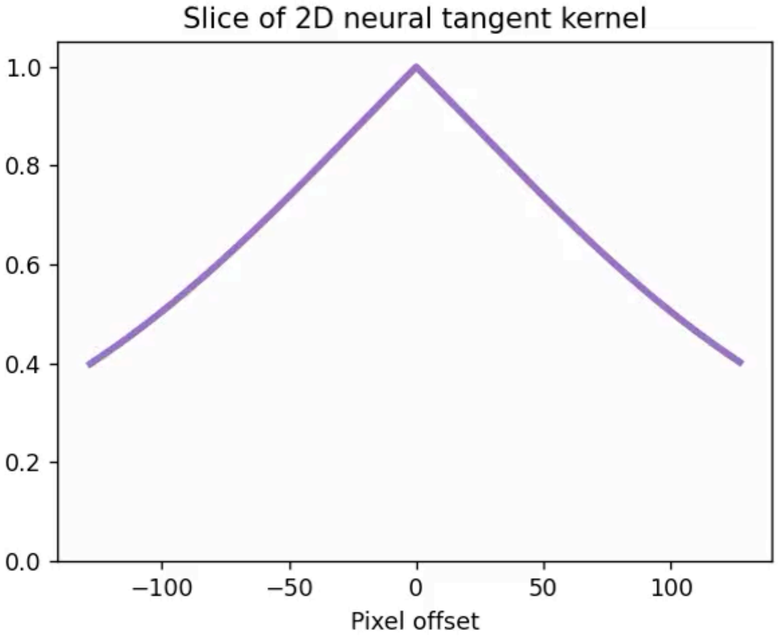


$$\gamma(\mathbf{v}) = [\cos(\mathbf{B}\mathbf{v}), \sin(\mathbf{B}\mathbf{v})] \qquad \mathbf{B} \sim \mathcal{N}(0, \sigma^2)$$

Mapping bandwidth controls underfitting / overfitting

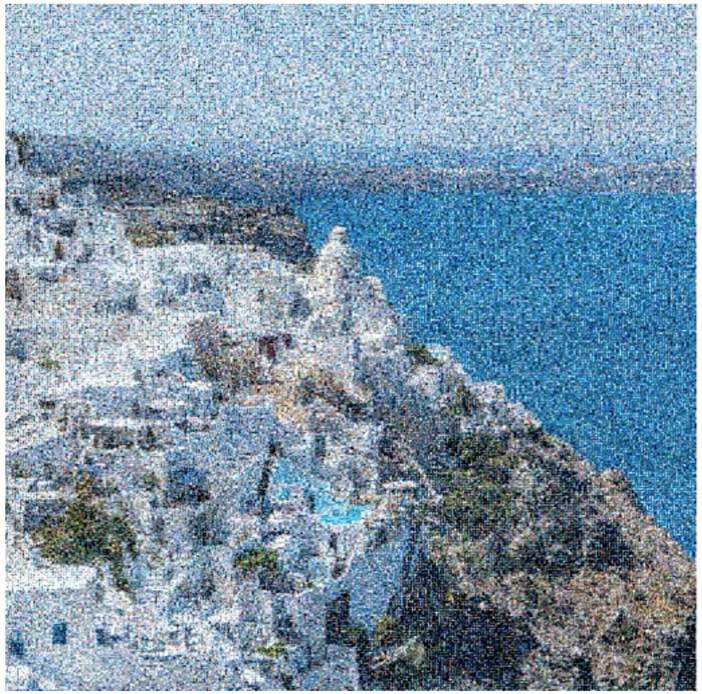


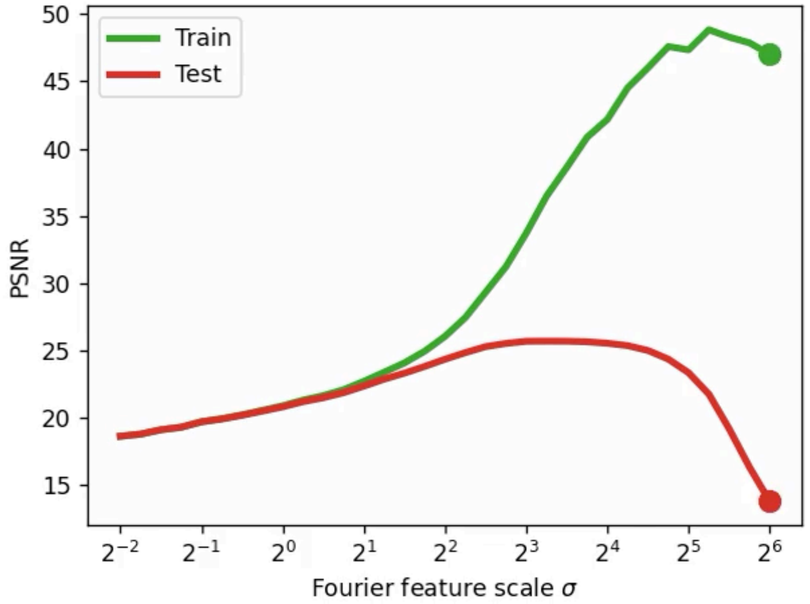


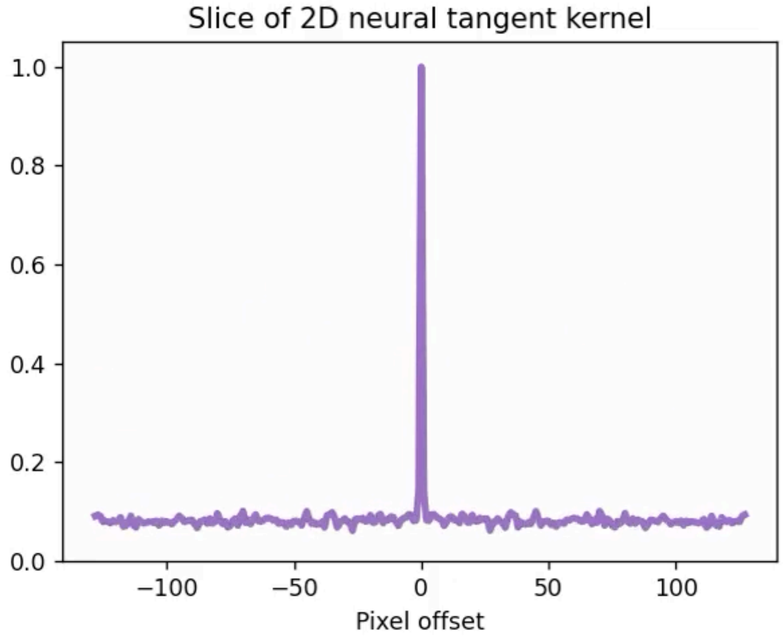


$$\gamma(\mathbf{v}) = [\cos(\mathbf{B}\mathbf{v}), \sin(\mathbf{B}\mathbf{v})] \qquad \mathbf{B} \sim \mathcal{N}(0, \sigma^2)$$

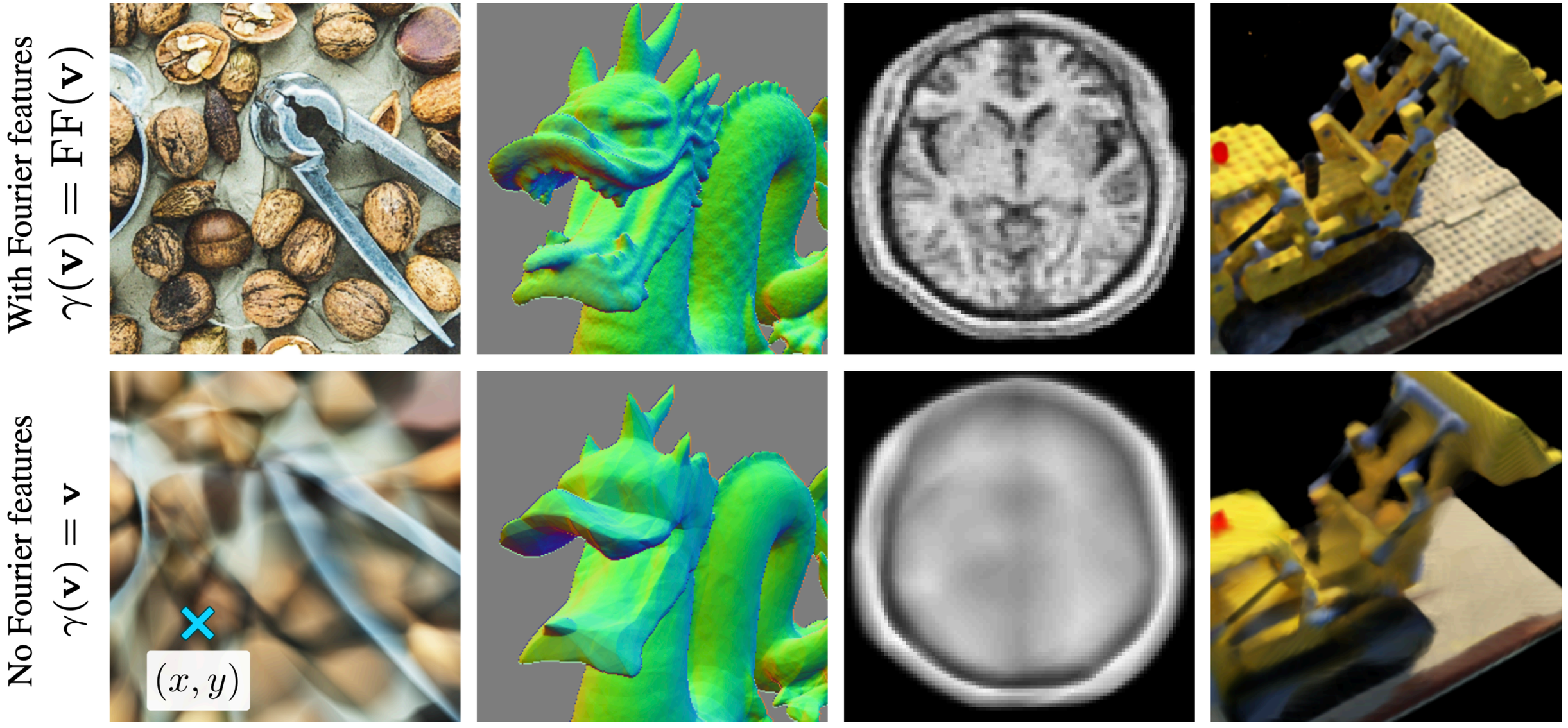
Mapping bandwidth controls underfitting / overfitting







$$\gamma(\mathbf{v}) = [\cos(\mathbf{B}\mathbf{v}), \sin(\mathbf{B}\mathbf{v})] \qquad \mathbf{B} \sim \mathcal{N}(0, \sigma^2)$$


With Fourier features
$\gamma(\mathbf{v}) = \mathrm{FF}(\mathbf{v})$
No Fourier features
$\gamma(\mathbf{v}) = \mathbf{v}$
(x, y)
(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

Try It!

```
B = SCALE * np.random.normal(shape=(input_dims, NUM_FEATURES))
x = np.concatenate([np.sin(x @ B), np.cos(x @ B)], axis=-1)
x = nn.Dense(x, features=256)
```

Coordinate based neural representation

$\neq$

a magic black box that learns things and generalizes

Coordinate based neural representation

$\neq$

a magic black box that learns things and generalizes

Coordinate based neural representation

$=$

a tiny n-dimensional lookup table with extremely high resolution

Learned Initializations for Optimizing Coordinate-Based Neural Representations

Matthew Tancik*[1] Ben Mildenhall*[1] Terrance Wang[1] Divi Schmidt[1]
Pratul P. Srinivasan[2] Jonathan T. Barron[2] Ren Ng[1]



Target

Init. Step 1 Step 2



Standard Initialization



Meta-learned Initialization (MAML)

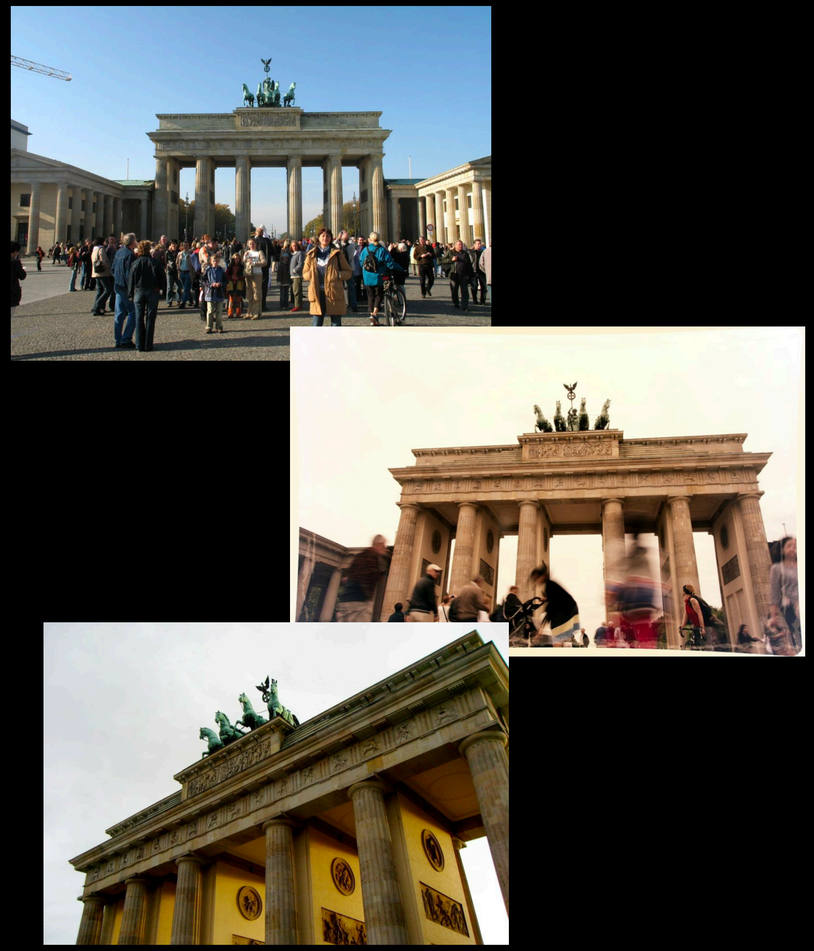
NeRF in the Wild: Neural Radiance Fields for Uncontrolled Photo Collections

CVPR 2021

Ricardo Martin-Brualla*, Noha Radwan*, Mehdi Sajjadi*,
Jonathan T. Barron, Alexey Dosovitskiy, Daniel Duckworth

Google Brain Berlin & Google Research

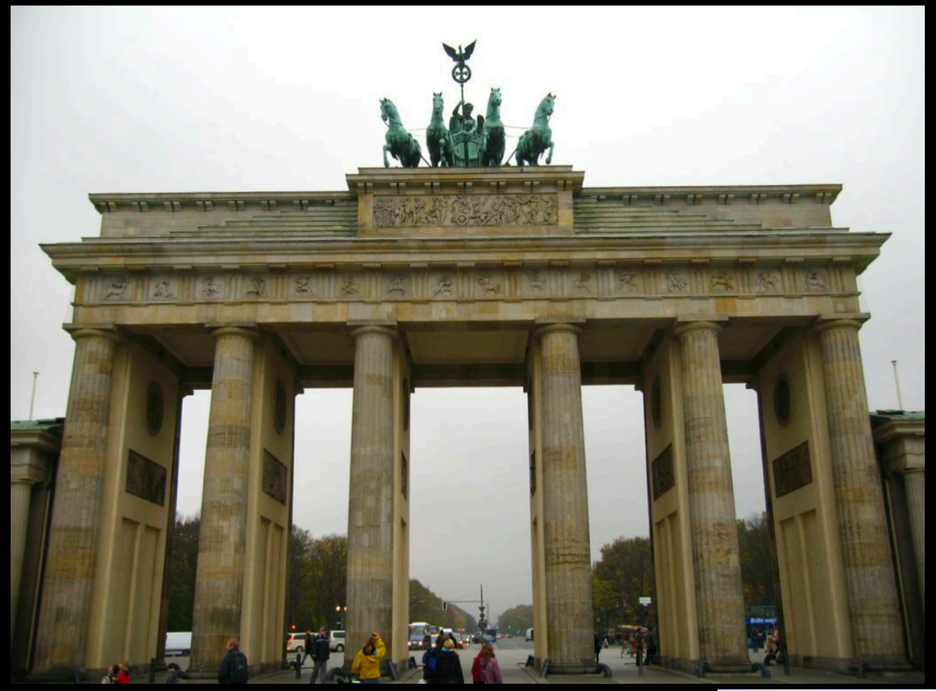
https://nerf-w.github.io/



Unconstrained photo collection



Novel views + Novel appearance







Photos by Flickr users: parados, itia4u, jobless / CC BY



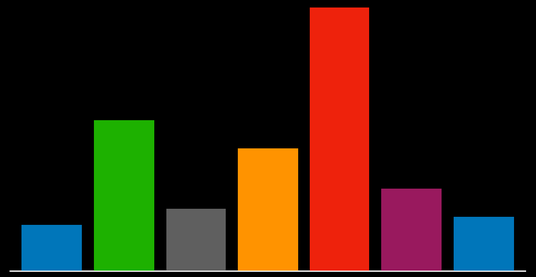




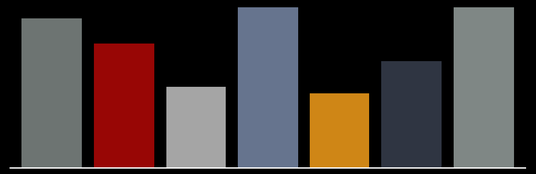
Photos by Flickr users: joshheumann, ojotes, chyauchentravelworld / CC BY

Inputs

Viewpoint



Appearance Embedding



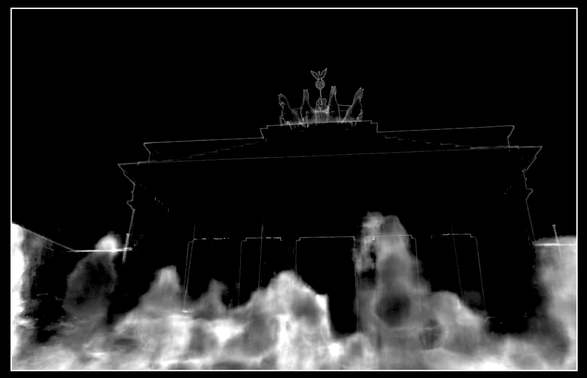
Transient Embedding



Static



Transient



Uncertainty



Reconstruction

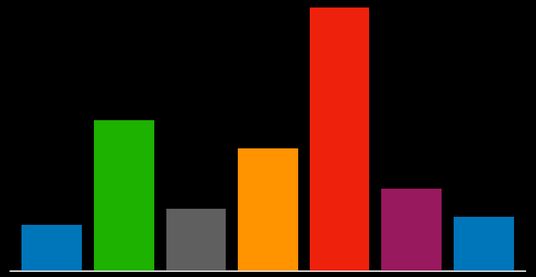


Target

Photos by Flickr users: vasnic64 / CC BY



Viewpoint



Appearance
Embedding





NeRF



Ours

“NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis”,
Mildenhall, Srinivasan, Tancik et. al., ECCV 2020

















Ours



Neural Rendering in the Wild

“Neural Rerendering In the Wild”, Meshry et. al., CVPR 2019

Thanks!

http://jonbarron.info

https://twitter.com/jon_barron