Groupe de lecture :

SPLAT THE NET :

RADIANCE FIELDS WITH SPLATTABLE NEURAL PRIMITIVES

Buonomo Camille,
17/12/2025,

Xilong Zhou*, Bao-Huy Nguyen*, Loıc Magne, Vladislav Golyanik, Thomas Leimkuhler (slides), Christian Theobal

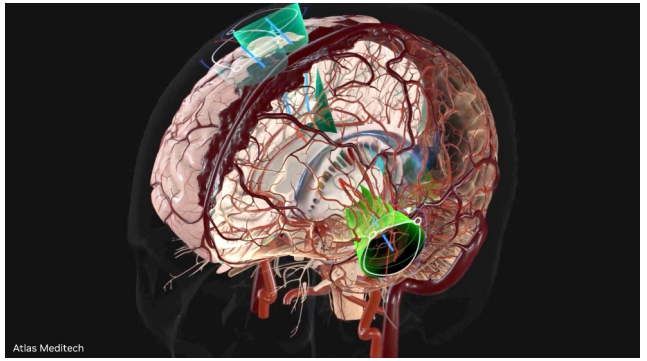
Virtual Scenes are Essential for…

[wilo.com]

Computer Graphics
e.g., Virtual Reality

[ce.cit.tum.de]

Computer Vision & AI
e.g., Robotics



[developer.nvidia.com]

Medicine
e.g., Surgical Planning

[Xie et al., 2025]

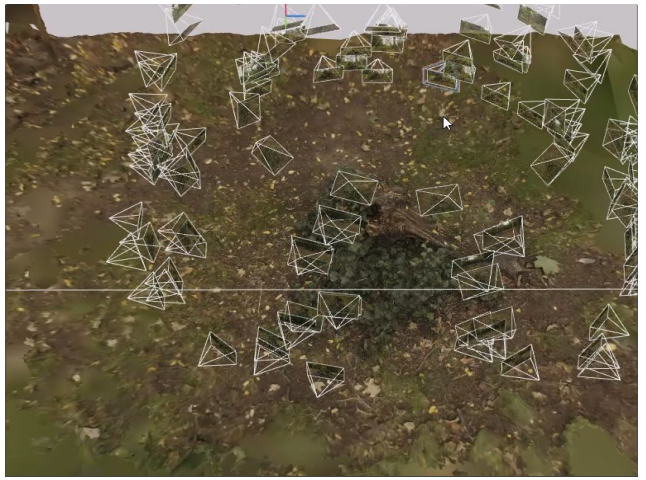
Earth Sciences
e.g., Climate Simulations

[pompeiisites.org]

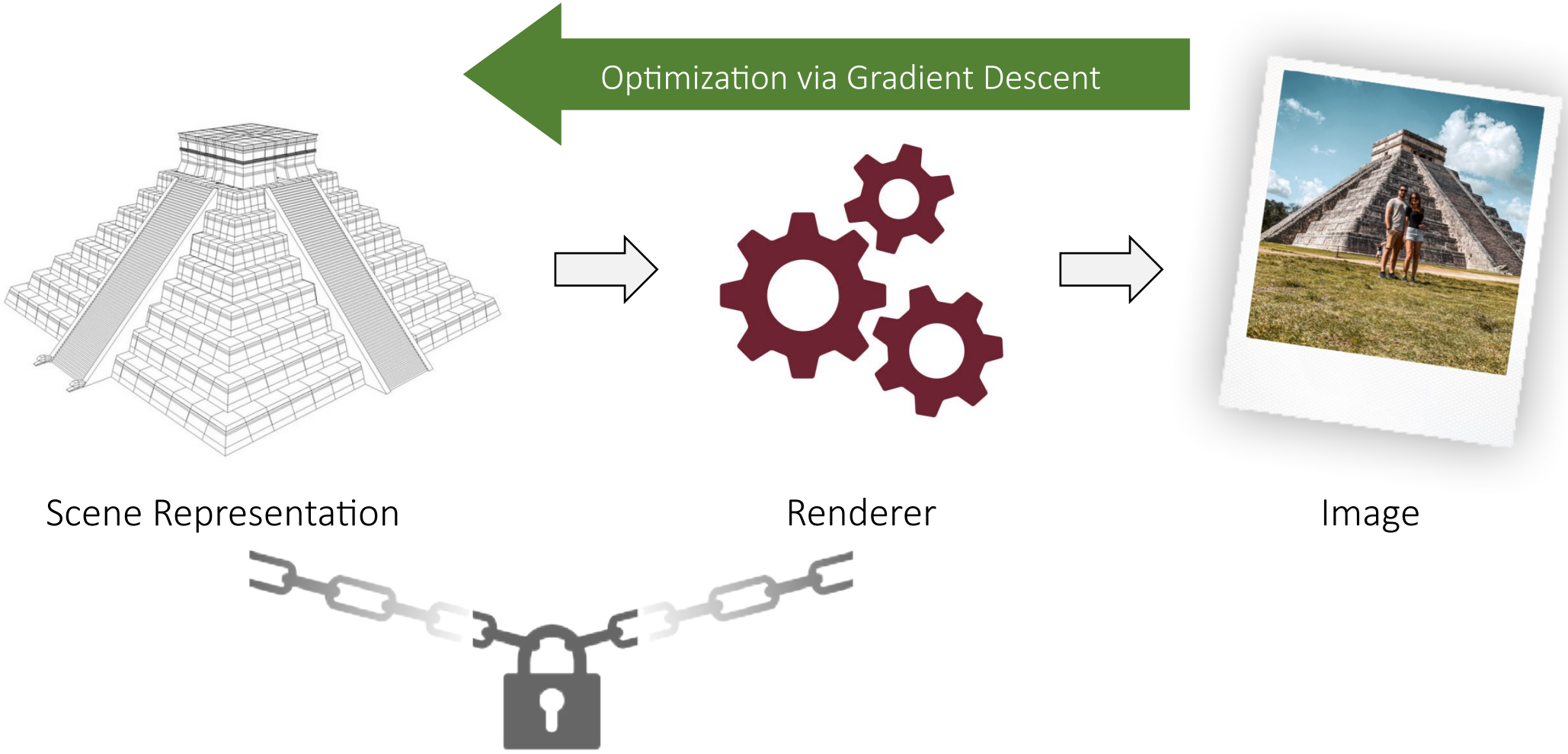
Archaeology
e.g., Masonry Analysis

…

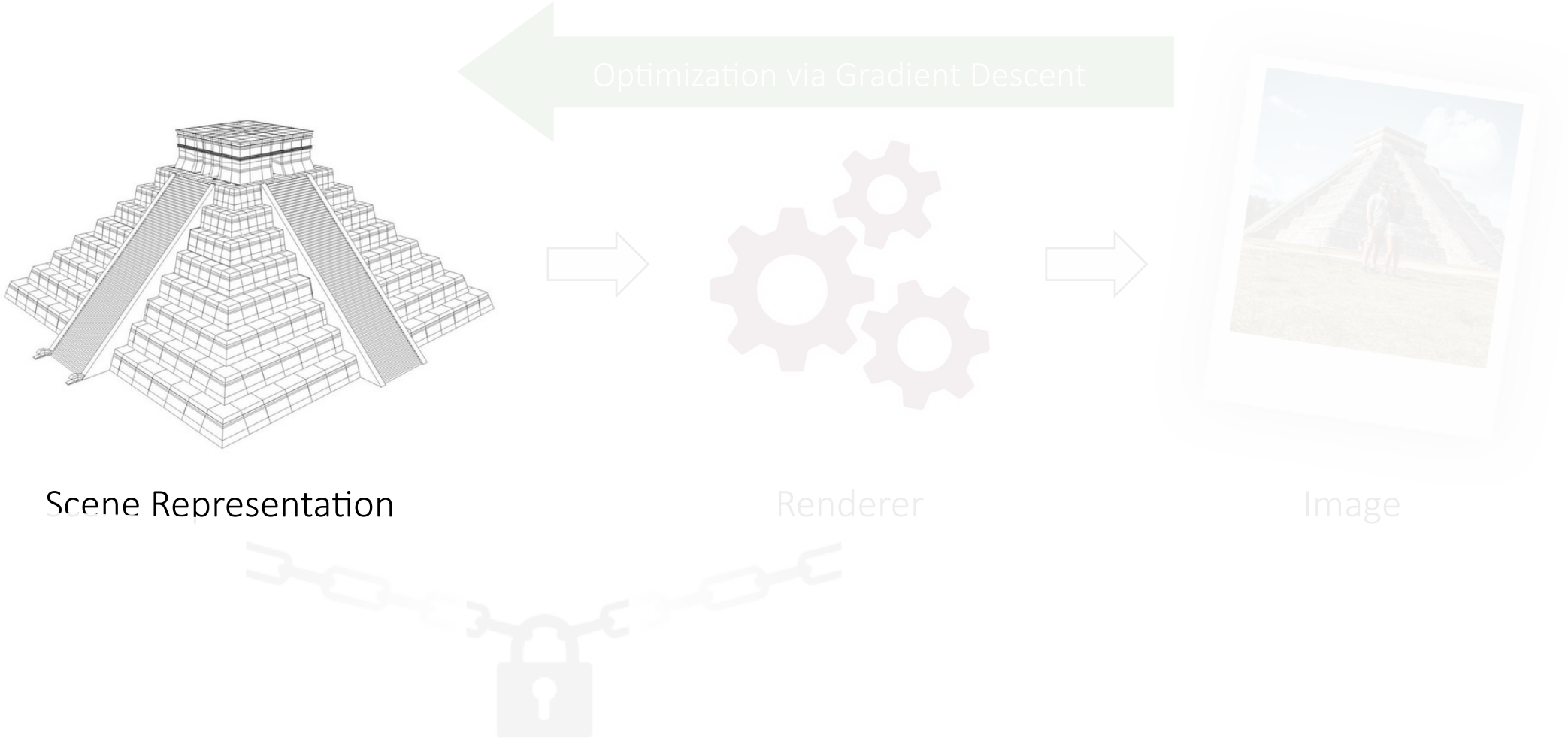
Reconstruction from Observations



Virtual Scenes and Images



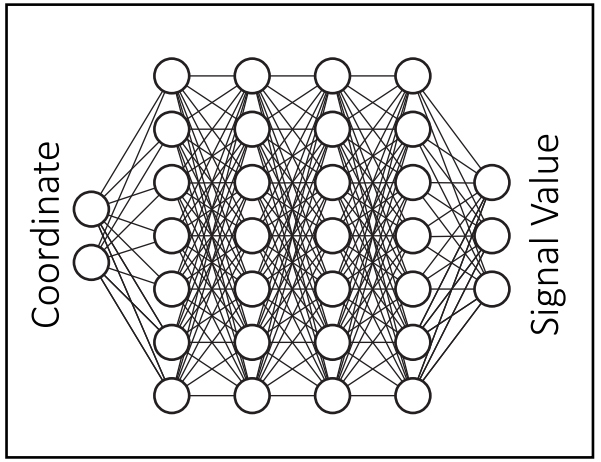
Virtual Scenes and Images



Scene Representation Zoo

Mesh

Voxel Grid



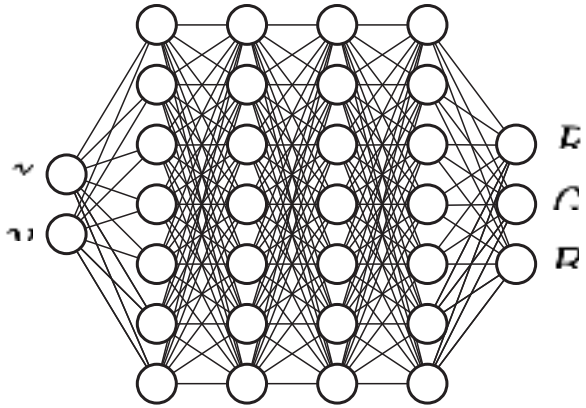
Neural Field

⚠ Topology difficult to optimize

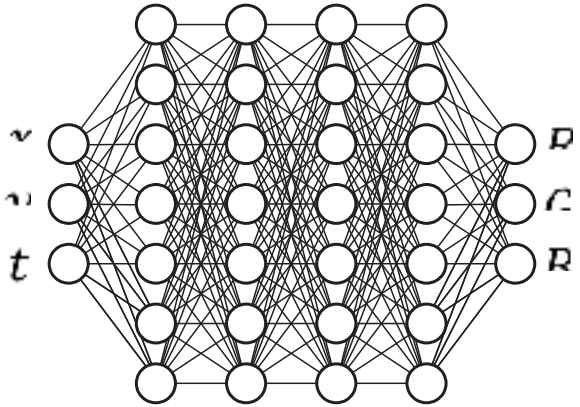
⚠ Making rendering differentiable is hard

⚠ Too much memory

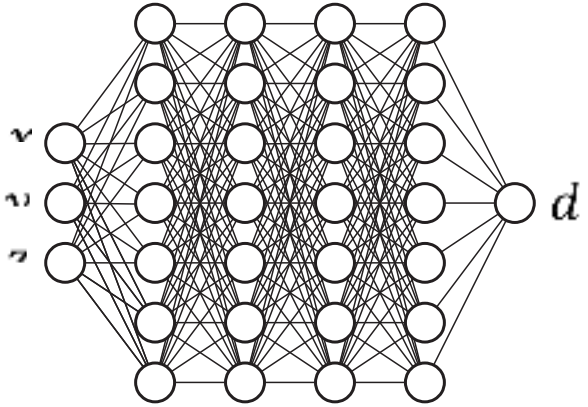
Neural Fields



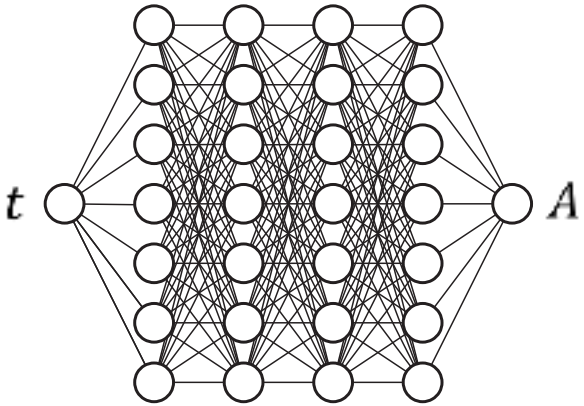
Image



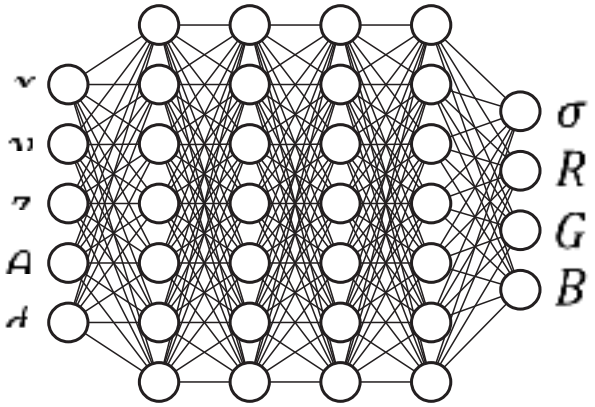
Video



Signed Distance Field



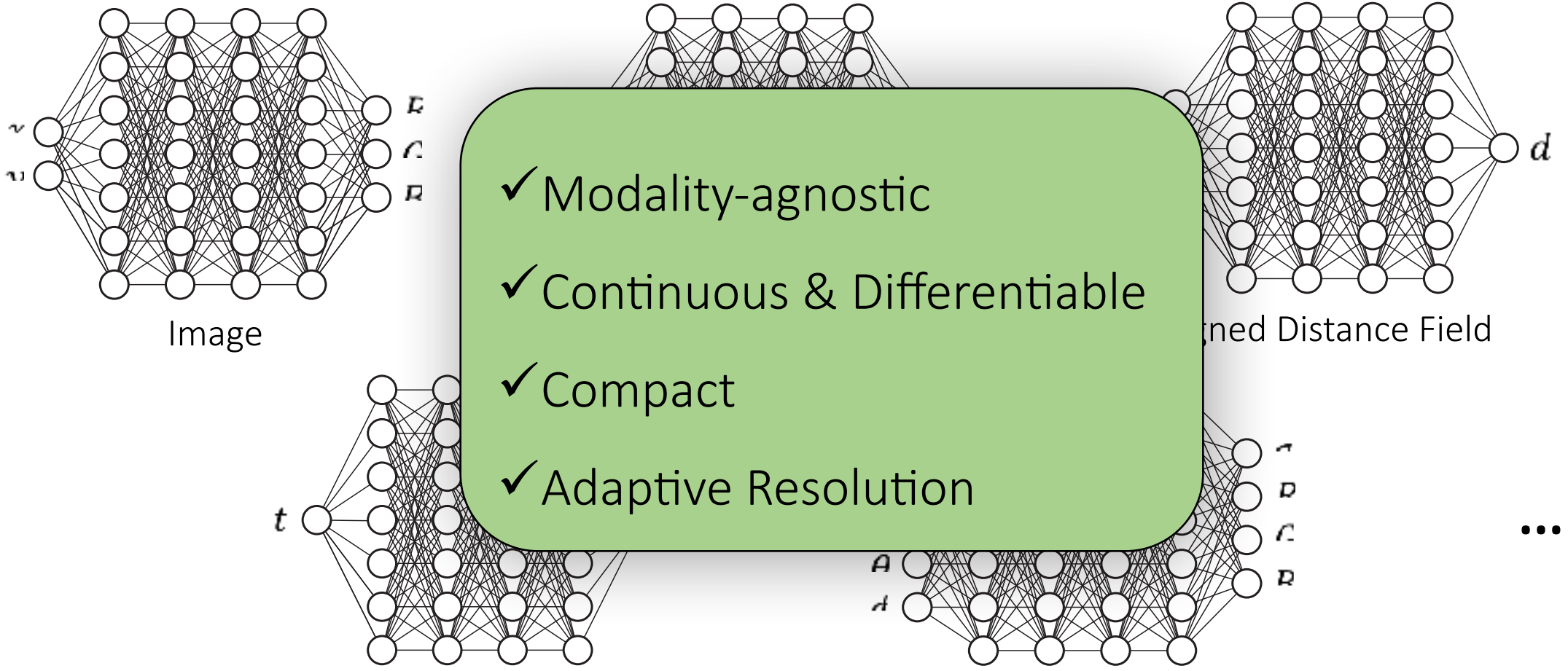
Sound



Radiance Field

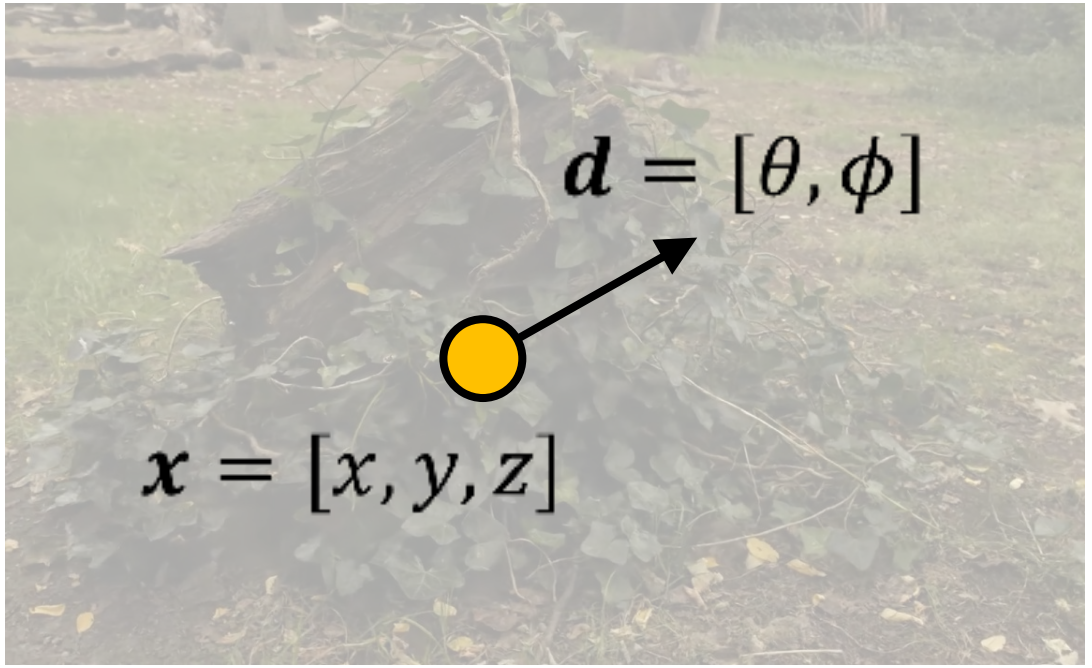
...

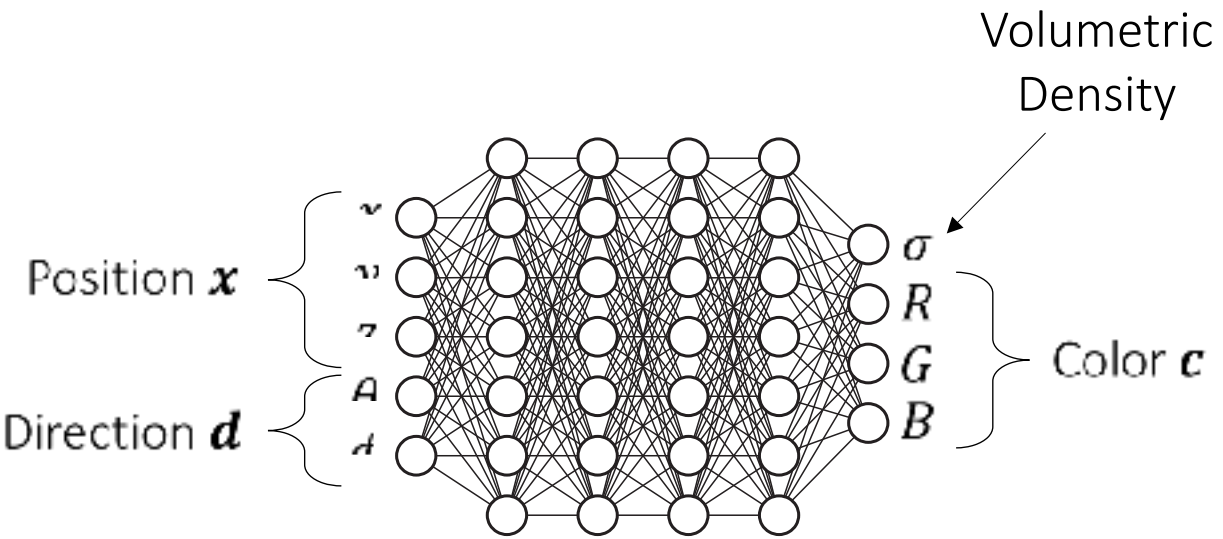
Neural Fields



- ✓ Modality-agnostic
- ✓ Continuous & Differentiable
- ✓ Compact
- ✓ Adaptive Resolution

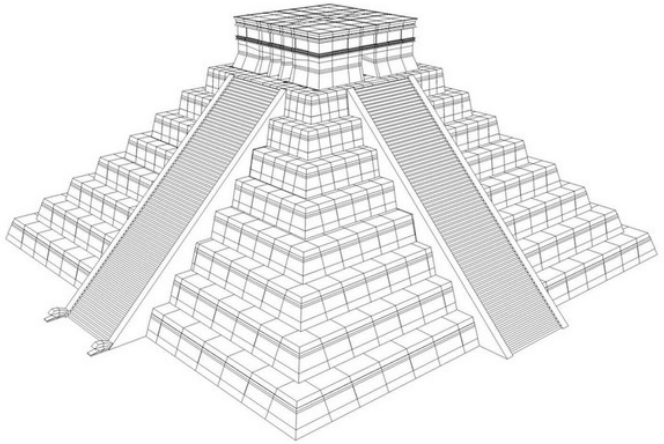
Neural Radiance Fields





Mildenhall, Srinivasan, Tancik, Barron, Ramamoorthi, Ng. **NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis.** ECCV 2020.

Virtual Scenes and Images

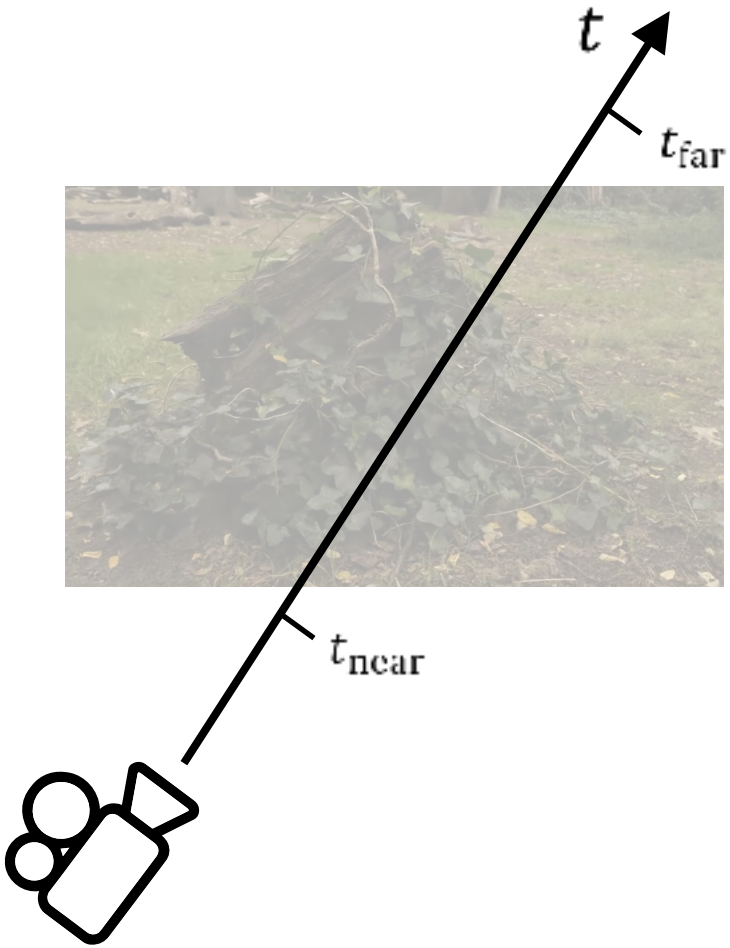


Scene Representation

Renderer

Image

Emission—Absorption Rendering

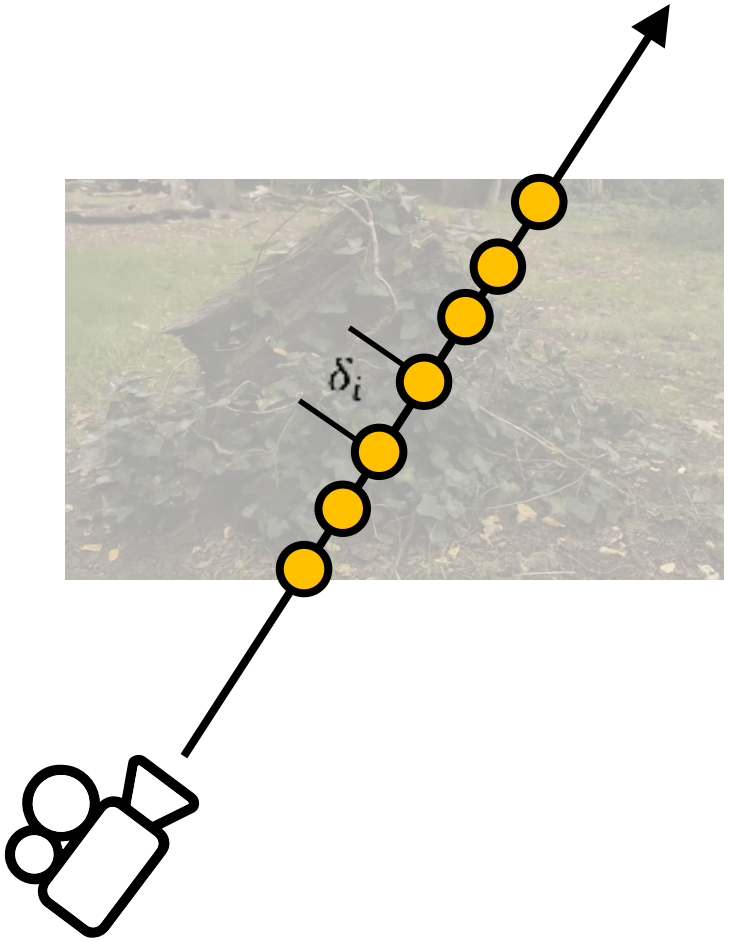


$$\underbrace{C}_{\text{Pixel Color}} = \int_{t_{\text{near}}}^{t_{\text{far}}} \underbrace{T(t)}_{\text{Transmittance}} \overbrace{\sigma(\boldsymbol{x}(t))}^{\text{Vol. Density}} \overbrace{\boldsymbol{c}(\boldsymbol{x}(t), \boldsymbol{d})}^{\text{Color}} \, dt$$

$$T(t) = \exp\left(- \int_{t_{\text{near}}}^{t} \overbrace{\sigma(\boldsymbol{x}(s))}^{\text{Vol. Density}} \, ds \right)$$

Kajiya, Von Herzen. **Ray Tracing Volume Densities.** SIGGRPAH 1984.

Emission—Absorption Rendering



Pixel Color

Vol. Density

Color

$$C = \sum_i T_i \left(1 - \exp(-\sigma_i \delta_i)\right) \boldsymbol{c}_i$$

Transmittance

$$T_i = \exp\left(-\sum_{j<i} \sigma_j \delta_j\right)$$

Max. **Optical Models for Direct Volume Rendering.** TVCG 1995.

Rendering Algorithm

```
For each pixel:

    Sample locations on view ray

    Evaluate network for each sample

    Perform volume rendering:
```

$$C = \sum_i \exp\left(-\sum_{j<i} \sigma_j \delta_j\right)\left(1 - \exp(-\sigma_i \delta_i)\right) \boldsymbol{c}_i$$

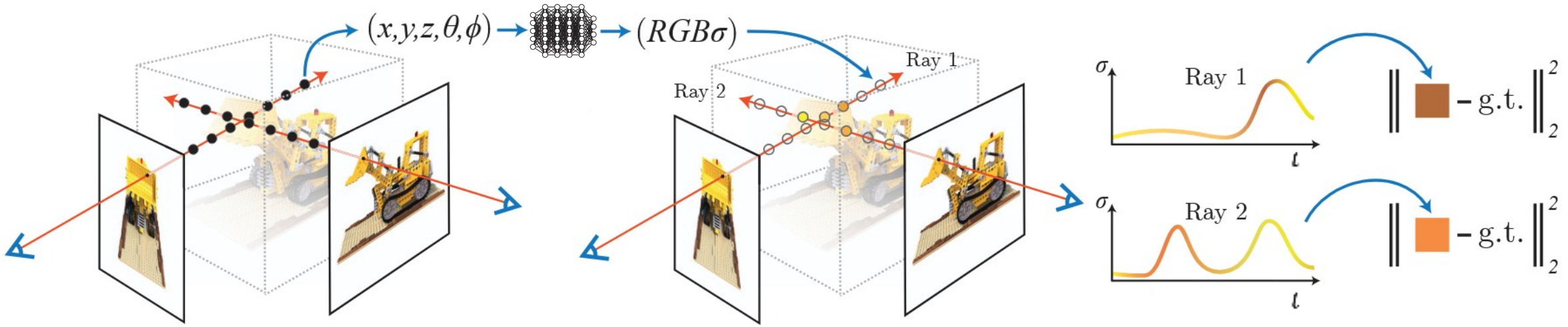
Training

5D Input
Position + Direction

4D Output
Density + Color

Volume
Rendering

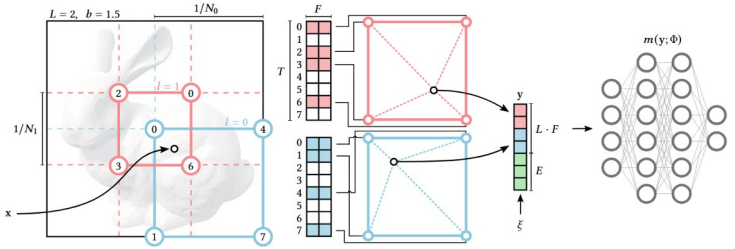
Rendering
Loss

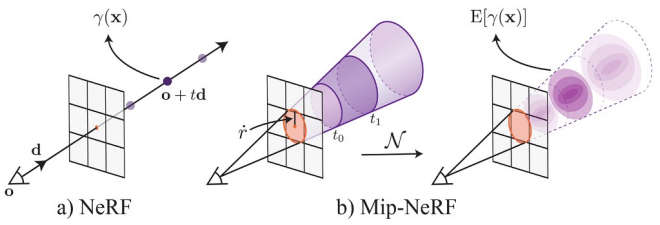


[Mildenhall et al., 2020]

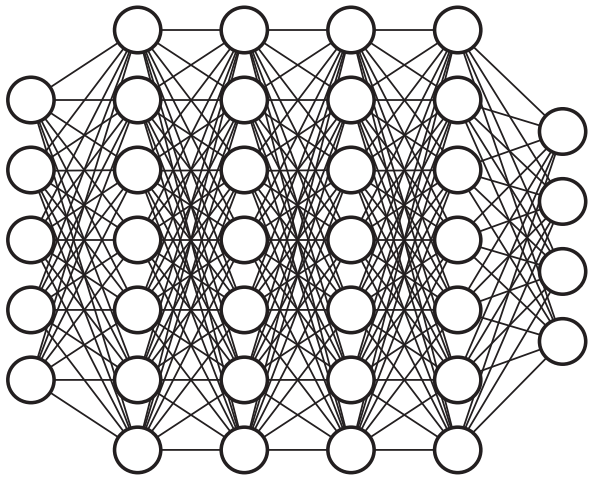
Improvements & Extensions

- Architectures
  - Positional encoding [Mildenhall et al. 2020, Tancik et al. 2020, …]
  - Explicit and hybrid models [Mueller et al. 2022, Fridovich-Keil et al. 2022, …]
  - …
- Training schemes
  - Coarse-to-fine and multiscale [Mildenhall et al. 2020, Barron et al. 2022, …]
  - Efficient ray sampling [Deng et al. 2022, Lombardi et al. 2021, …]
  - …
- Higher dimensions
  - Dynamic scenes [Park et al. 2021, Tretschk et al. 2021, …]
  - Relighting [Srinivasan et al. 2021, Martin-Brualla et al. 2021, …]
  - …
- …



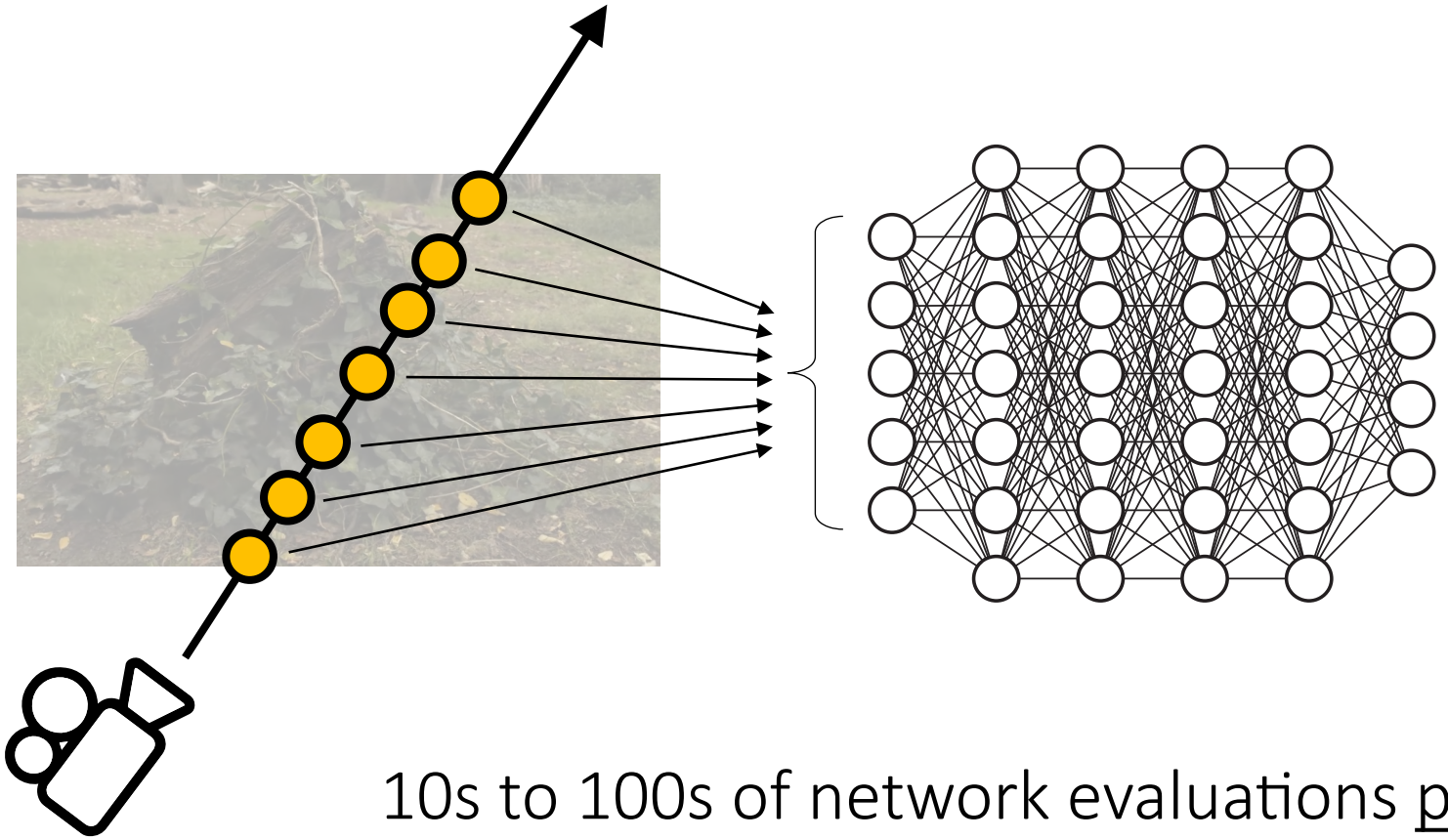


Neural Radiance Fields are Compact



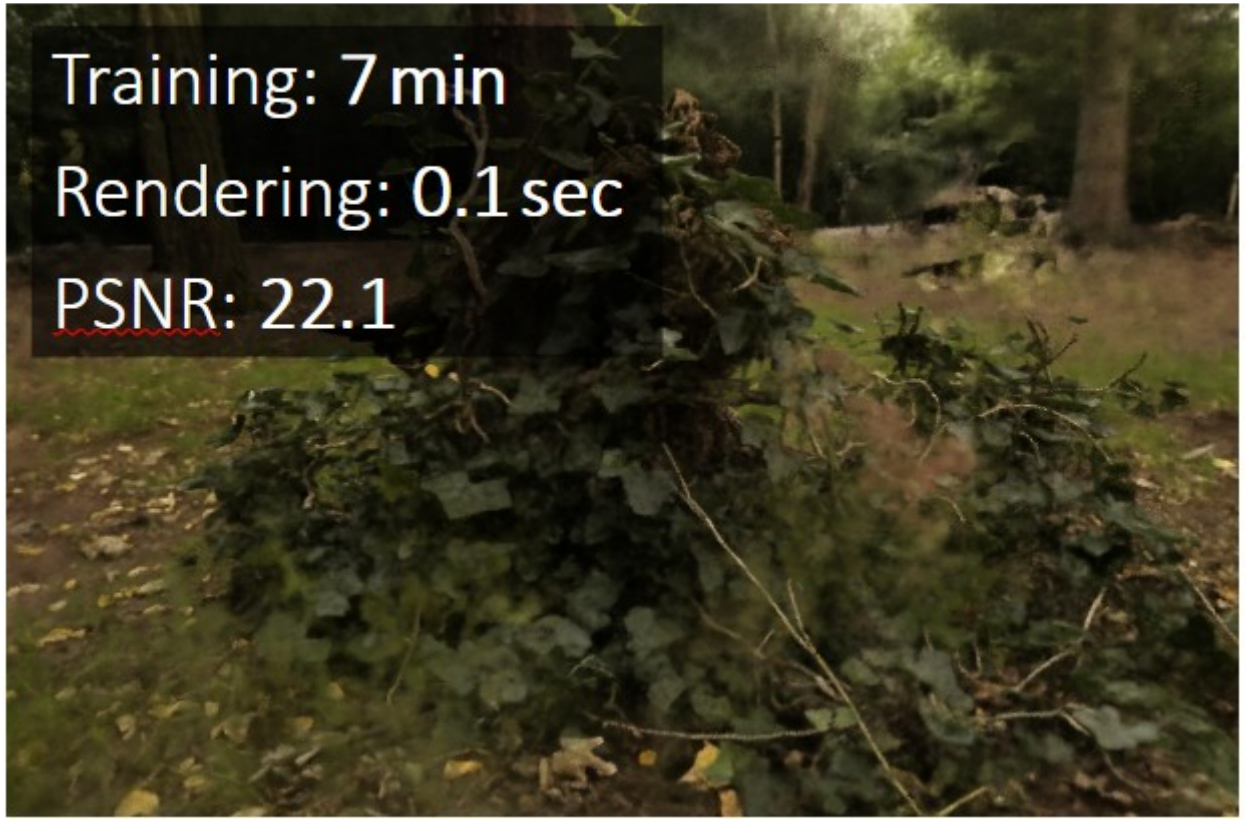
5 MB

Neural Radiance Fields are Inefficient



10s to 100s of network evaluations per pixel

Speed vs. Quality



Mueller, Evans, Schied, Keller. **Instant Neural Graphics Primitives with a Multiresolution Hash Encoding.** SIGGRAPH 2022.

Barron, Mildenhall, Verbin, Srinivasan, Hedman. **Mip-NeRF 360: Unbounded Anti-Aliased Neural Radiance Fields.** CVPR 2022.

Scene Representation Zoo

Mesh

⚠ Topology difficult to optimize

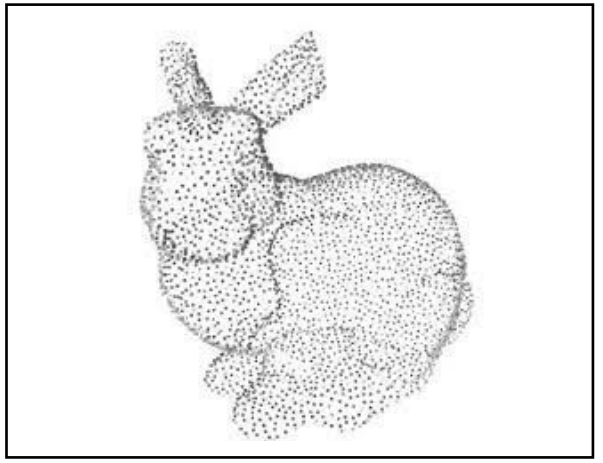
⚠ Making rendering differentiable is hard

Voxel Grid

⚠ Too much memory

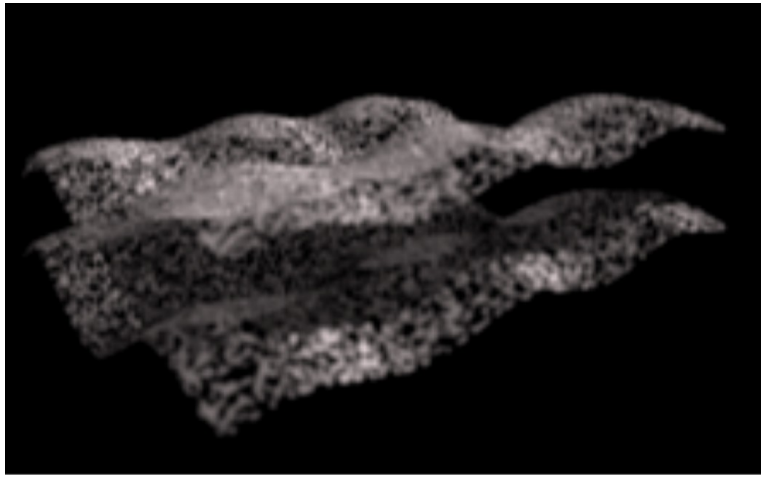
Neural Field

⚠ Too slow

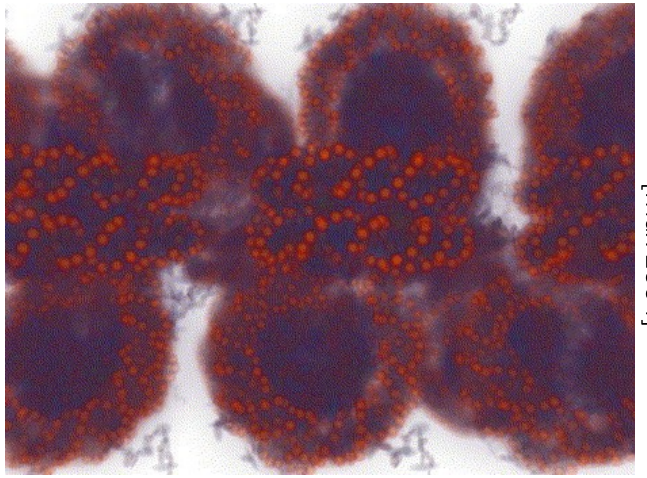


Unstructured Primitives

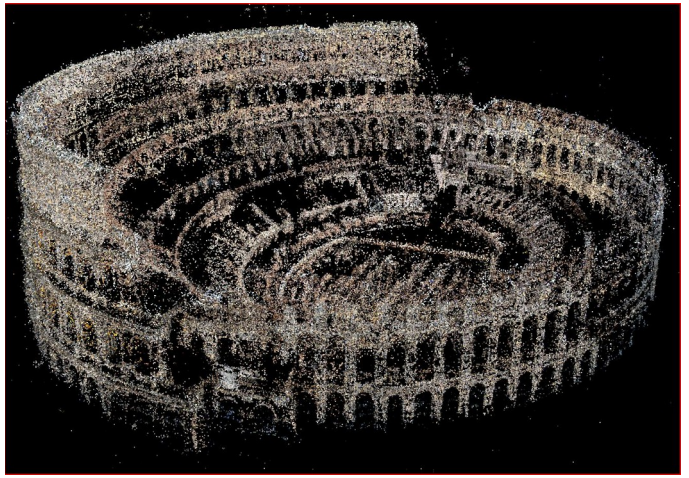
Point-based Graphics



[Levoy & Whitted 1985]

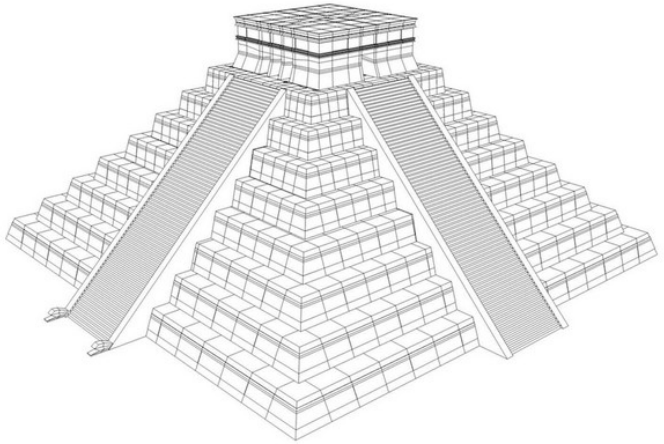


[Max 2004]



[Bergmeir et al. 2016]

Virtual Scenes and Images

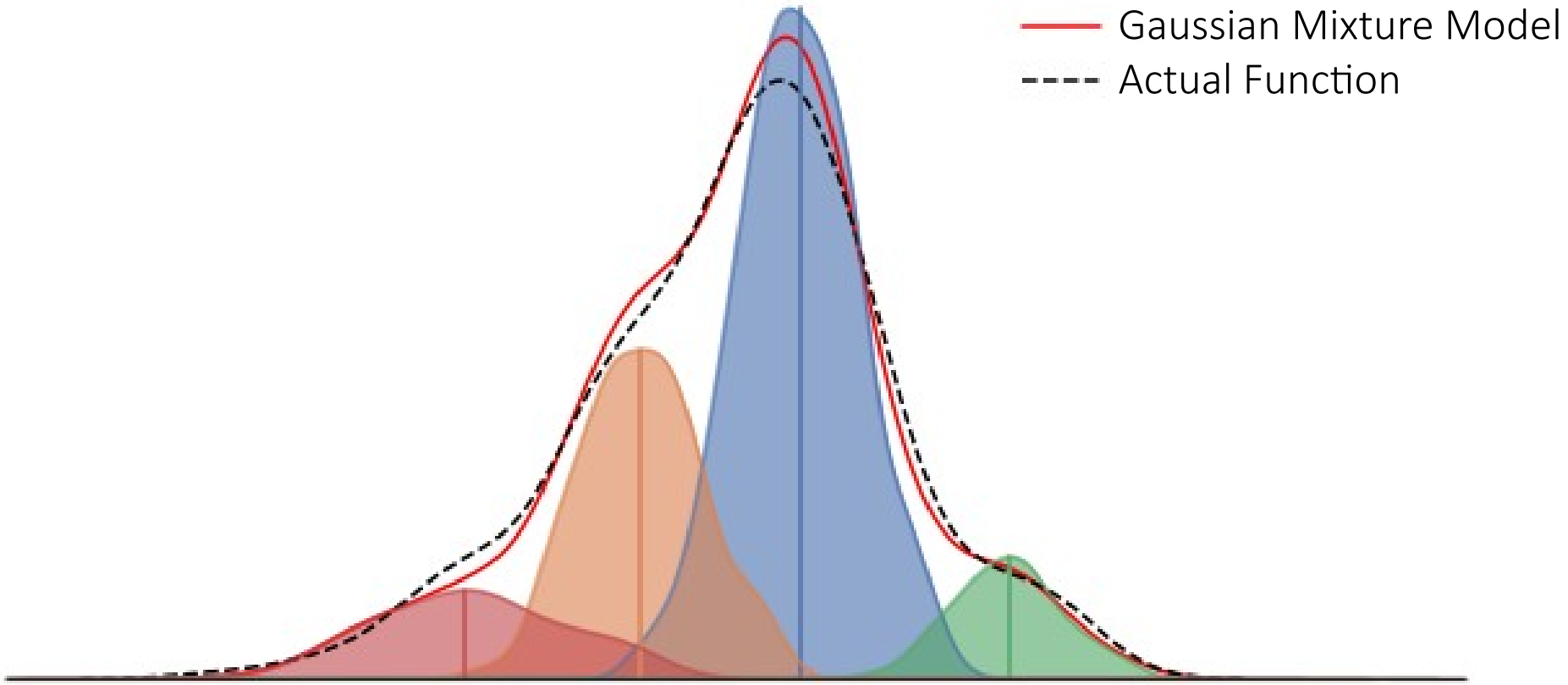


Scene Representation

Renderer

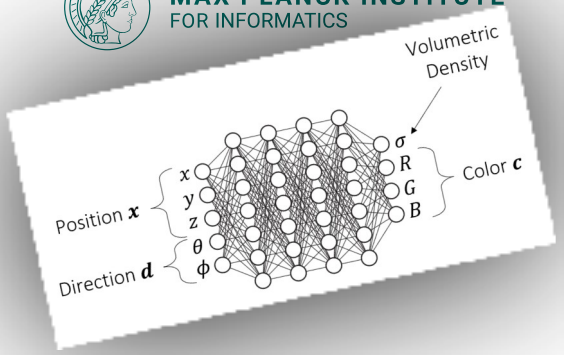
Image

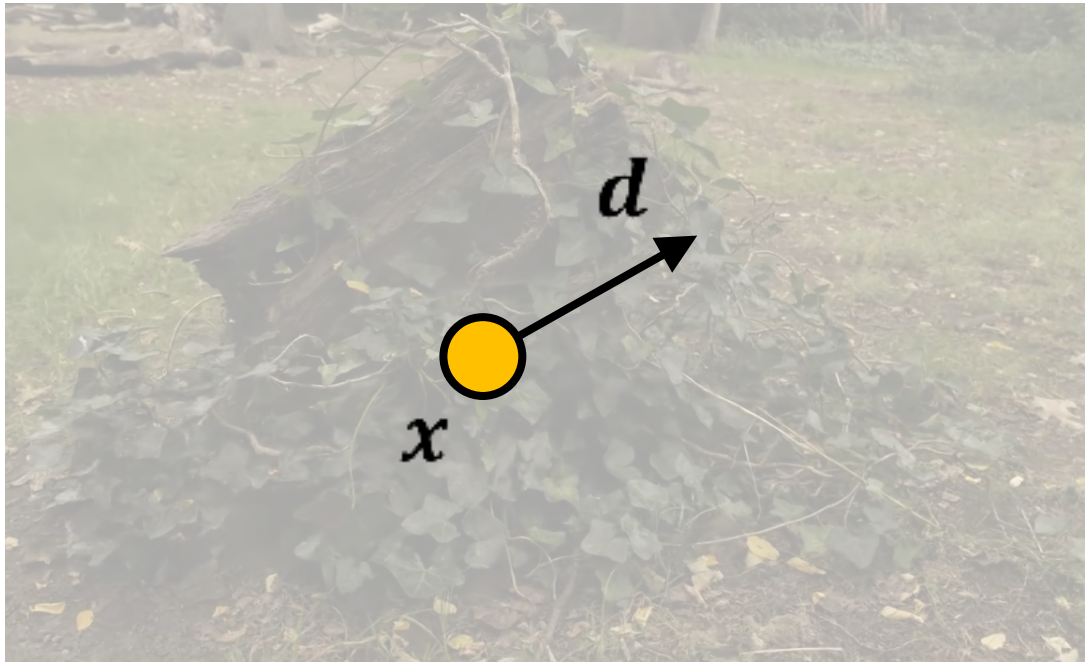
Gaussian Mixture Models



[github.com/DandiMahendris]

Scene as 3D Gaussian Mixture Model





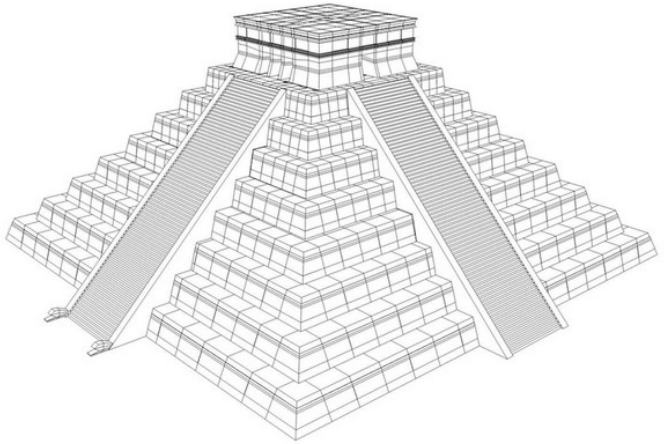
$$\overbrace{\sigma(\boldsymbol{x})}^{\text{Volumetric Density}} = \sum_i \overbrace{G^{(3D)}(\boldsymbol{x}; \boldsymbol{\mu}_i, \Sigma_i, o_i)}^{\text{3D Gaussian}}$$

Mean Covariance Opacity

Additionally:

Each Gaussian has a color $\boldsymbol{c}$,
which is a function of direction $\boldsymbol{d}$

Virtual Scenes and Images

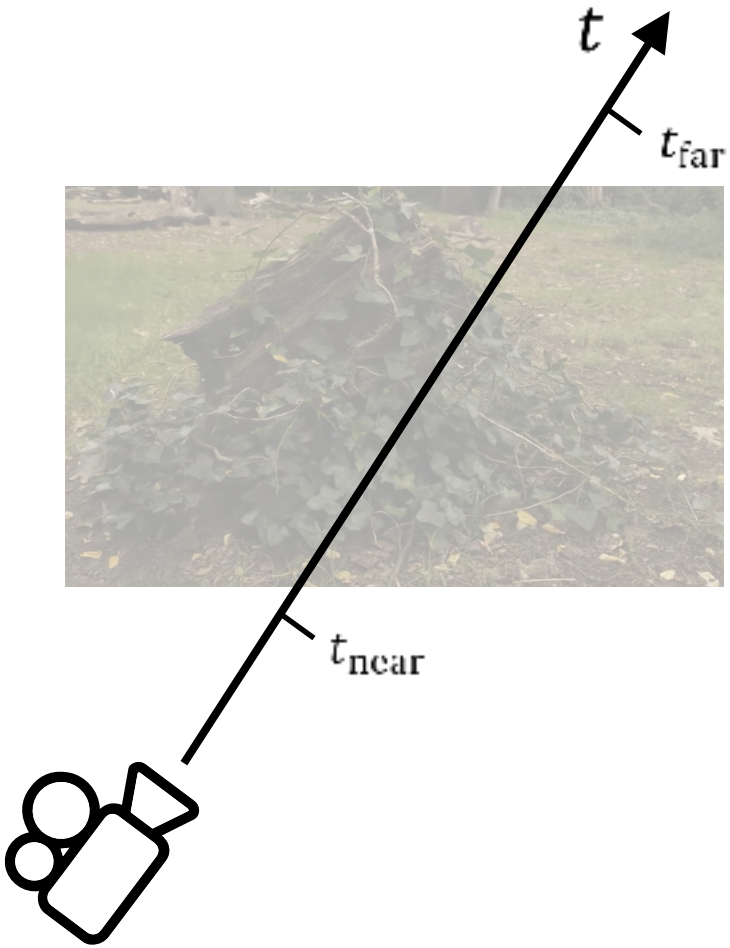


Scene Representation

Renderer

Image

Emission—Absorption Rendering



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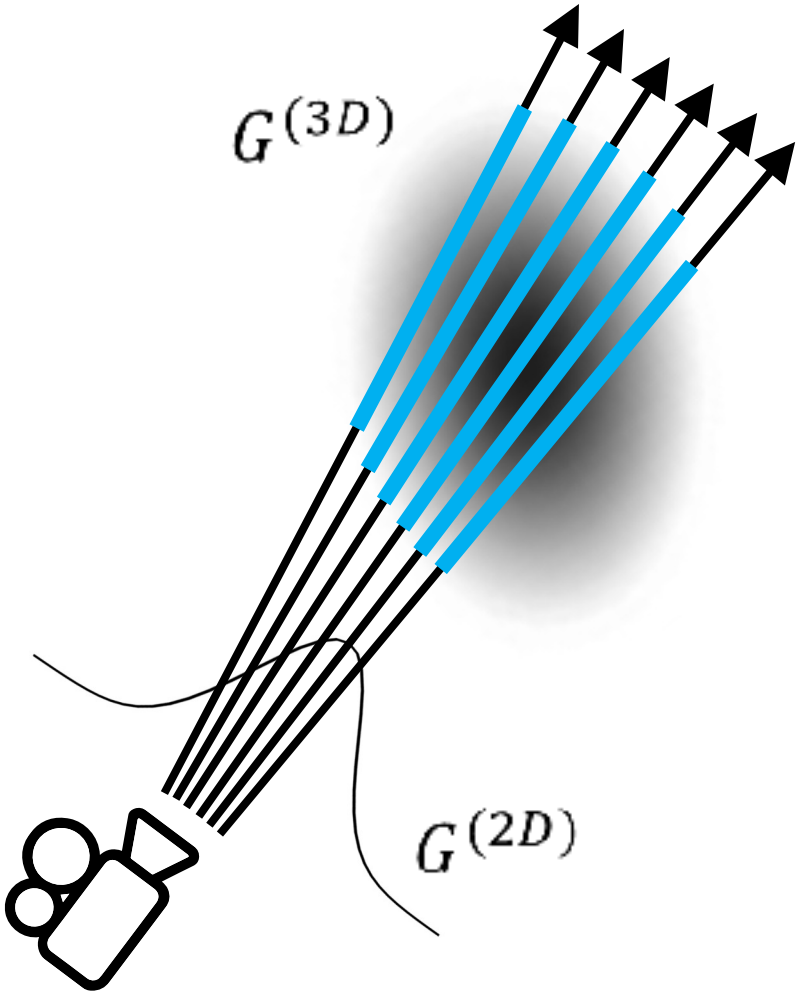
Kajiya, Von Herzen. **Ray Tracing Volume Densities.** SIGGRPAH 1984.

Splatting



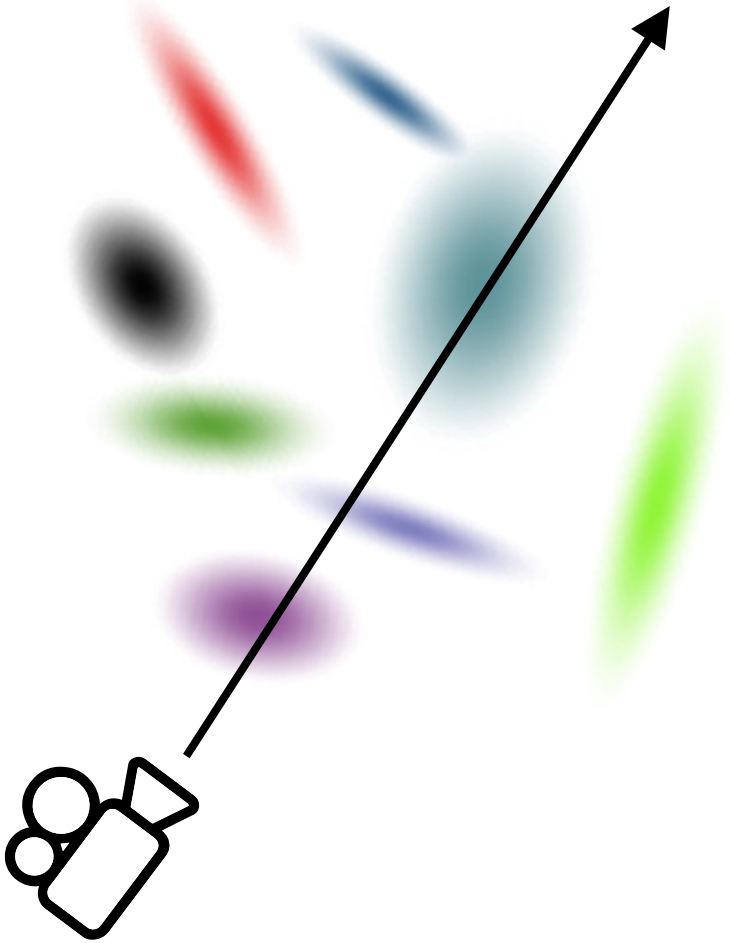
$$G^{(3D)} \xrightarrow[\text{projection}]{} G^{(2D)}$$

(under mild assumptions –

I am skipping a couple of details here)

Zwicker, Pfister, van Baar, Gross. **EWA Volume Splatting.** Visualization 2001.

Splatting



Projected Gaussian Shape

Gaussian Color

Pixel Color

$$C = \sum_i G_i^{(2D)} \, \boldsymbol{c}_i \underbrace{\prod_{j<i} \left(1 - G_j^{(2D)}\right)}_{\text{Transmittance}}$$

Transmittance
(ensure that Gaussians occlude the ones behind)

Zwicker, Pfister, van Baar, Gross. **EWA Volume Splatting.** Visualization 2001.

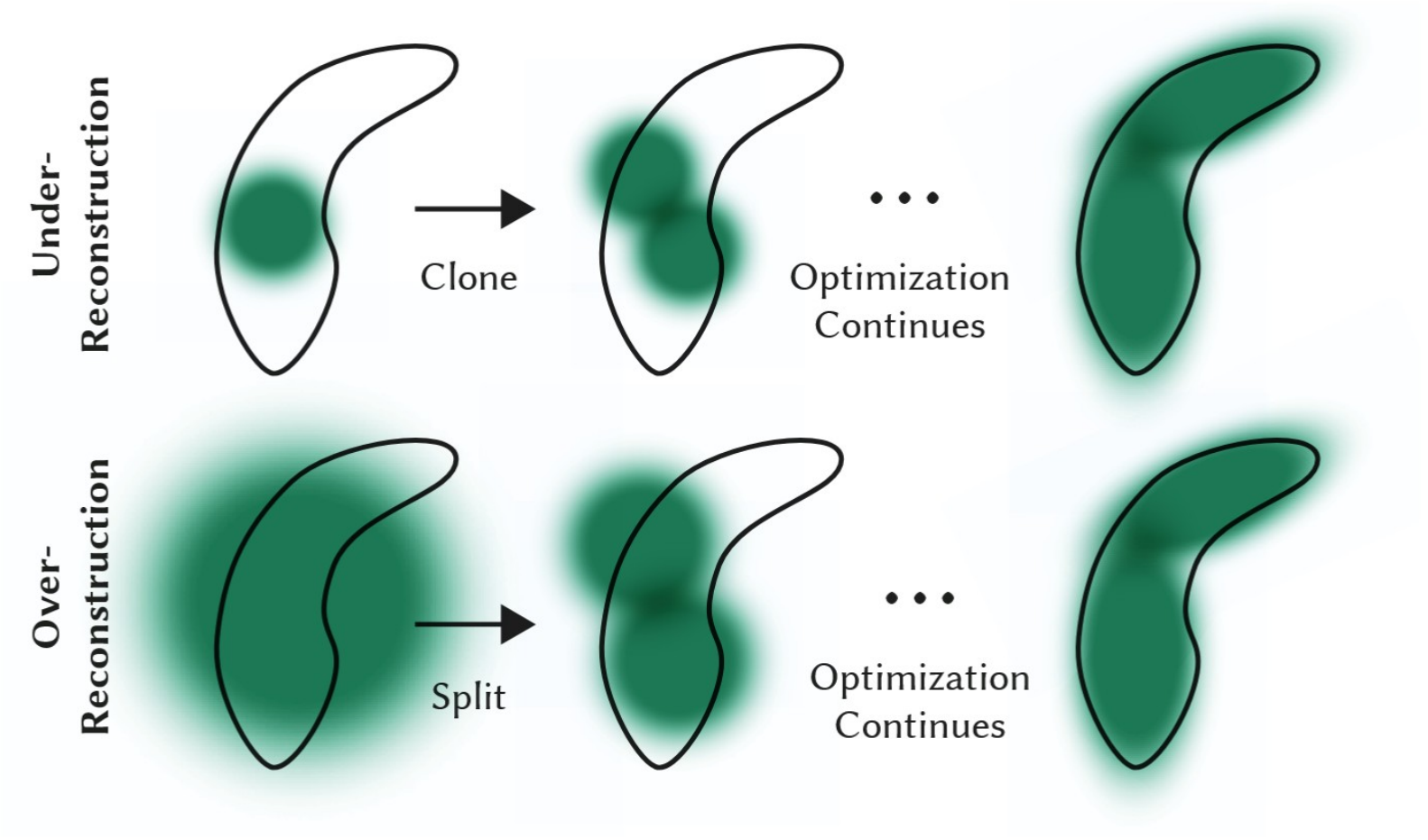
Rendering Algorithm

```
Project Gaussians to the screen

Sort Gaussians based on depth

For each pixel:

    Identify Gaussians overlapping the pixel
```

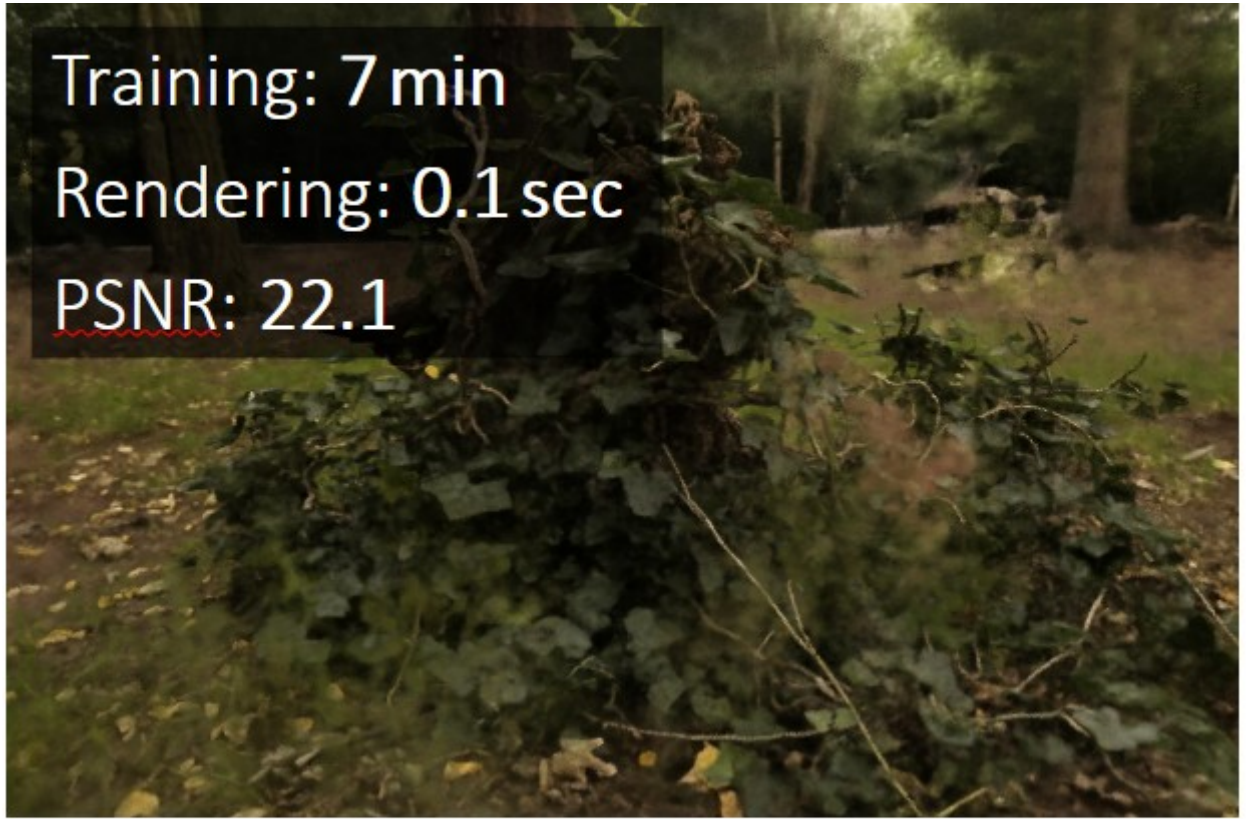
Splat Gaussians: $$C = \sum_i G_i^{(2D)} \, \boldsymbol{c}_i \prod_{j<i} \left(1 - G_j^{(2D)}\right)$$

First Result

Population Control



Speed & Quality

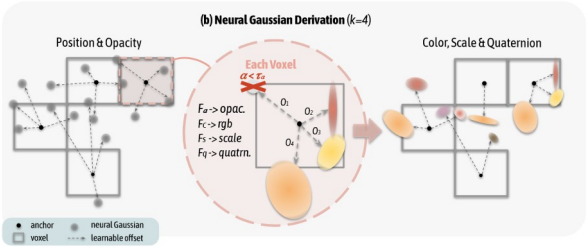


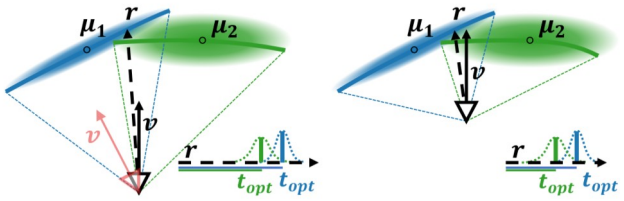
Mueller, Evans, Schied, Keller. **Instant Neural Graphics Primitives with a Multiresolution Hash Encoding.** SIGGRAPH 2022.

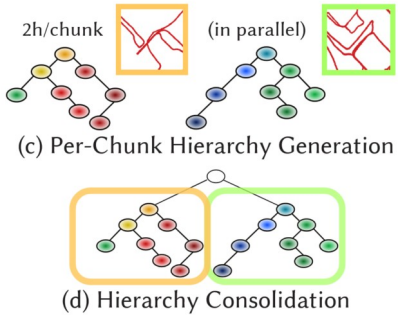
3D Gaussian Splatting

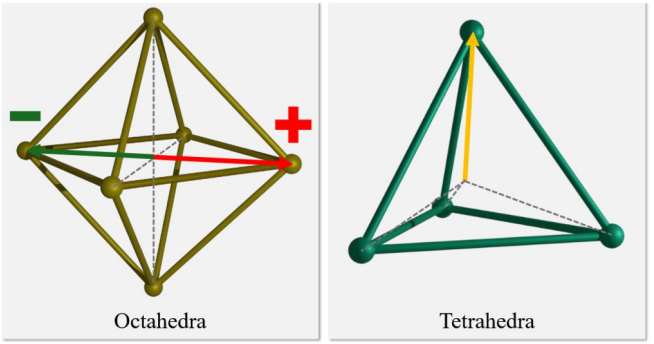
Improvements & Extensions

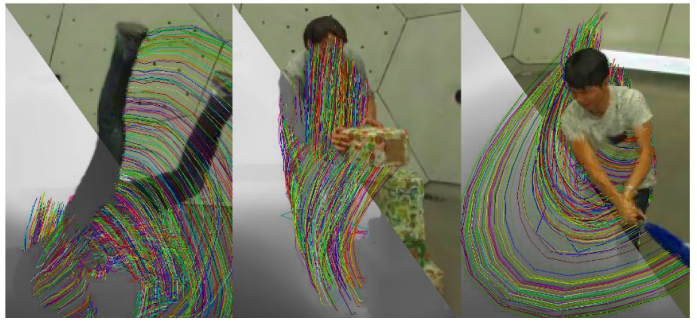
- Model
  - Anti-aliasing [Yu et al. 2023, …]
  - Structural constraints [Lu et al. 2024, …]
  - Temporal coherence [Radl et al. 2024, …]
  - Primitive types [Liu et al. 2025, …]
  - Compression [Niedermayr et al. 2024]
  - Hierarchical [Kerbl et al., 2024]
  - …
- Higher dimensions
  - Dynamic scenes [Luiten et al. 2024, …]
  - Relighting [Bi et al. 2024, …]
  - …
- …











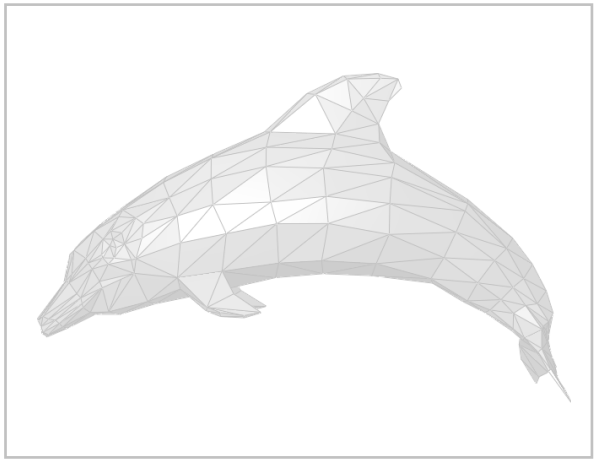
3D Gaussians are Not Compact

A Gaussian has
limited expressive power

Scenes routinely require
millions of Gaussians

Typically:
> 1 GB per scene

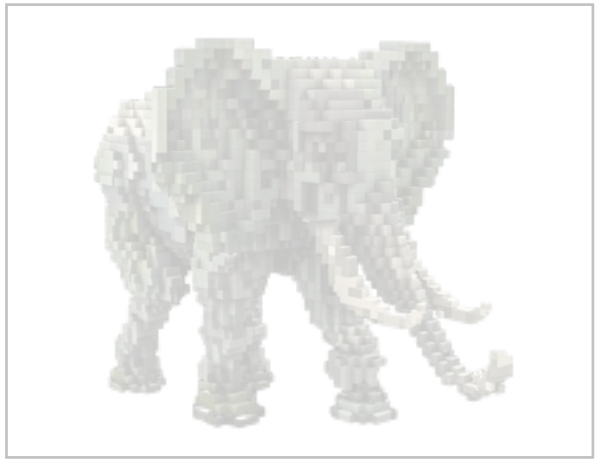
Scene Representation Zoo



Mesh

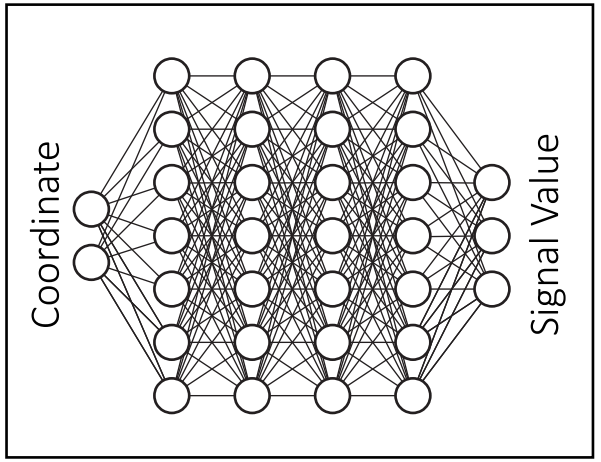
⚠ Topology difficult to optimize

⚠ Making rendering differentiable is hard



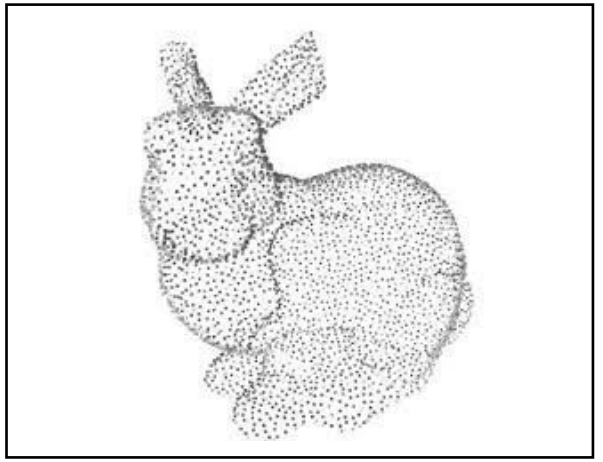
Voxel Grid

⚠ Too much memory



Neural Field

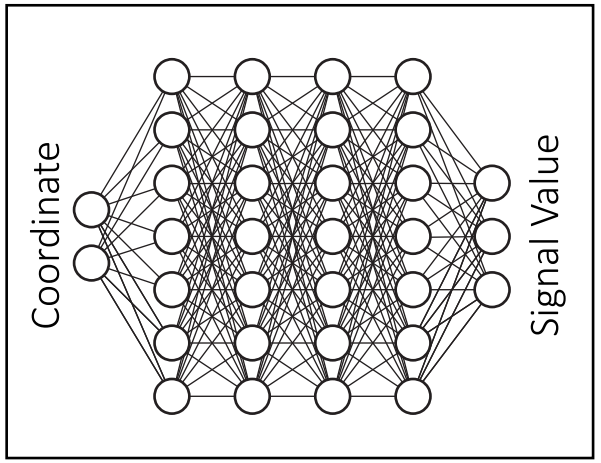
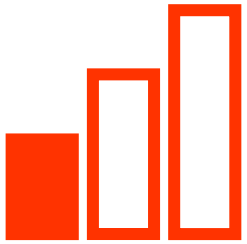
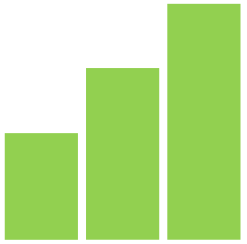
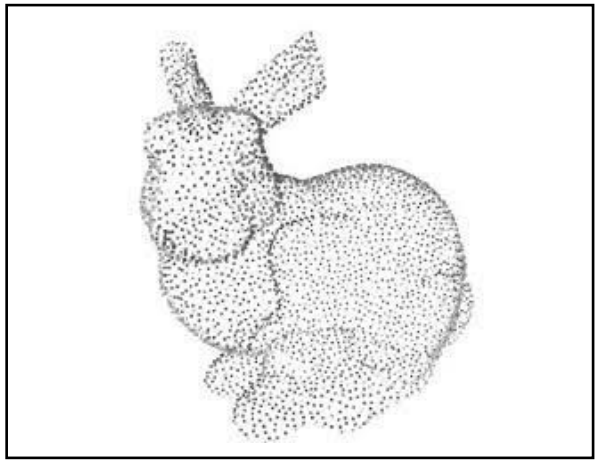
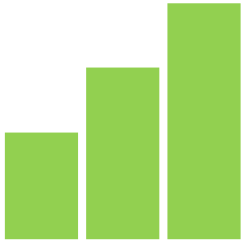
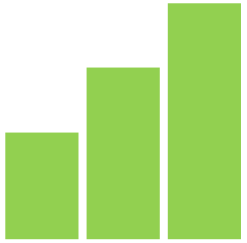
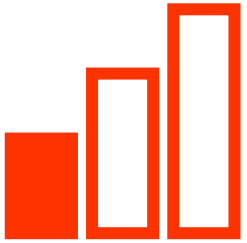
⚠ Too slow



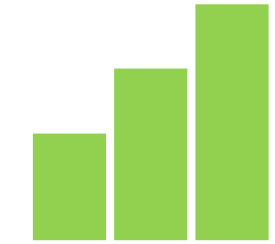
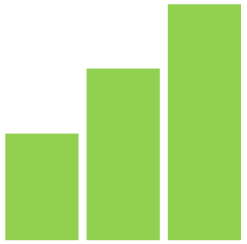
Unstruct. Primitives

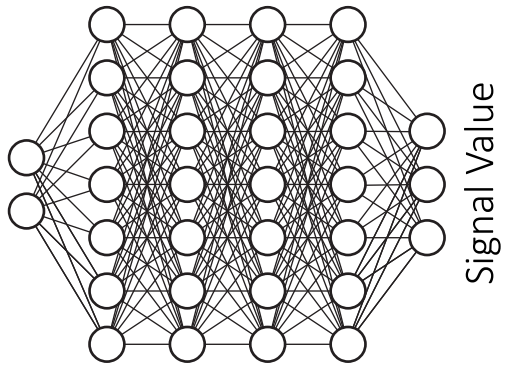
⚠ Limited expressivity

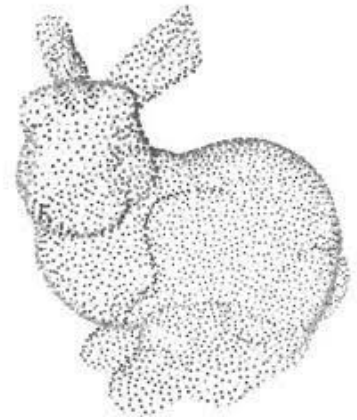
Scene Representation Zoo

	Quality	Speed	Expressivity
Neural Field 			
Unstruct. Primitives 			

Scene Representation Zoo

	Quality	Speed	Expressivity
Neural Field			
Unstruct. Primitives			

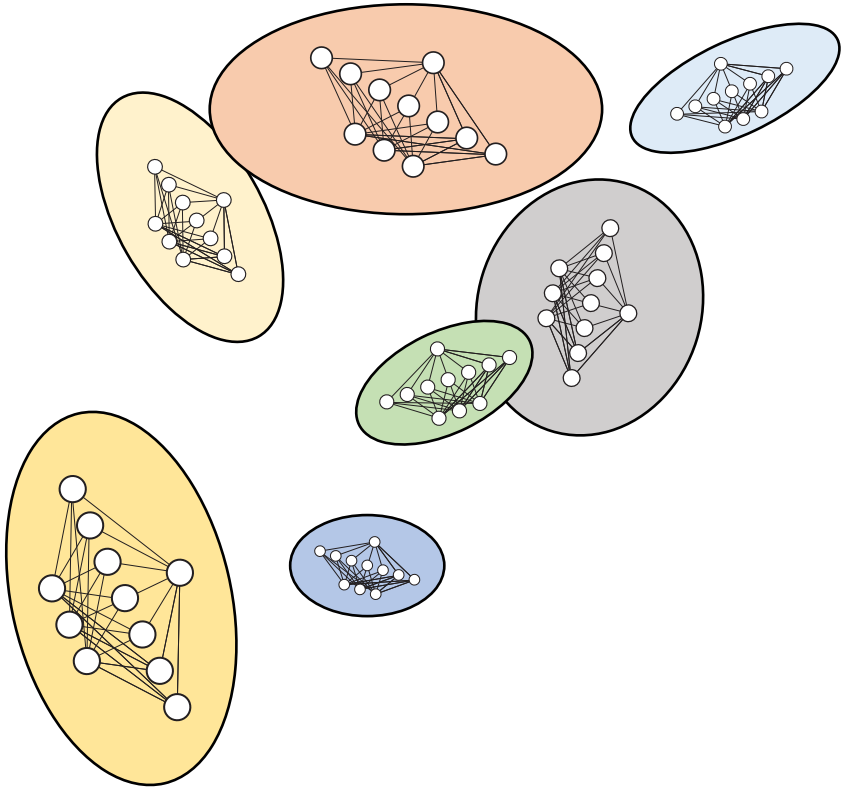




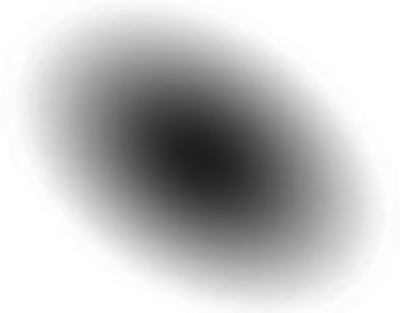
Splatting of
Unstructured Primitives

Neural
Representation

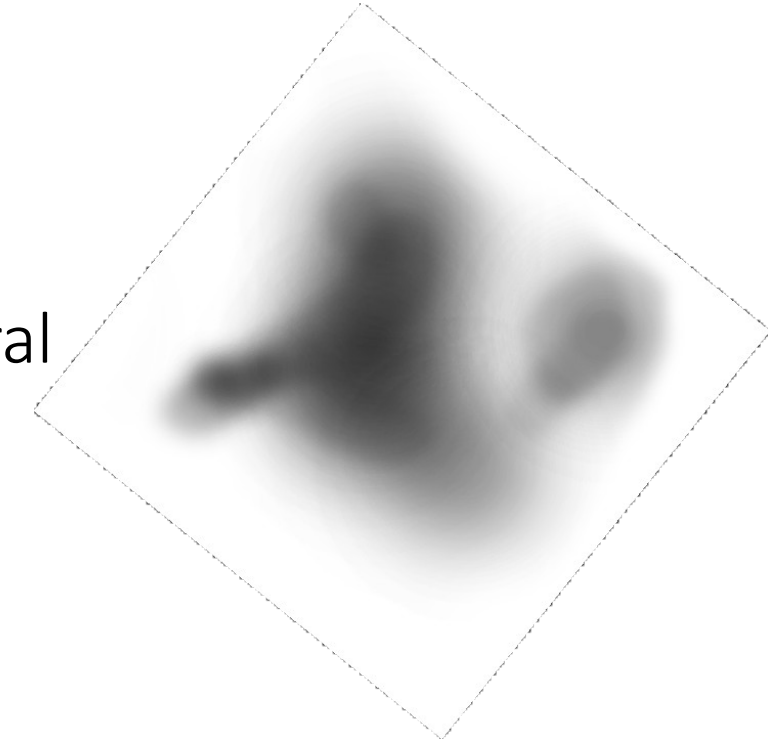
Neural Primitives



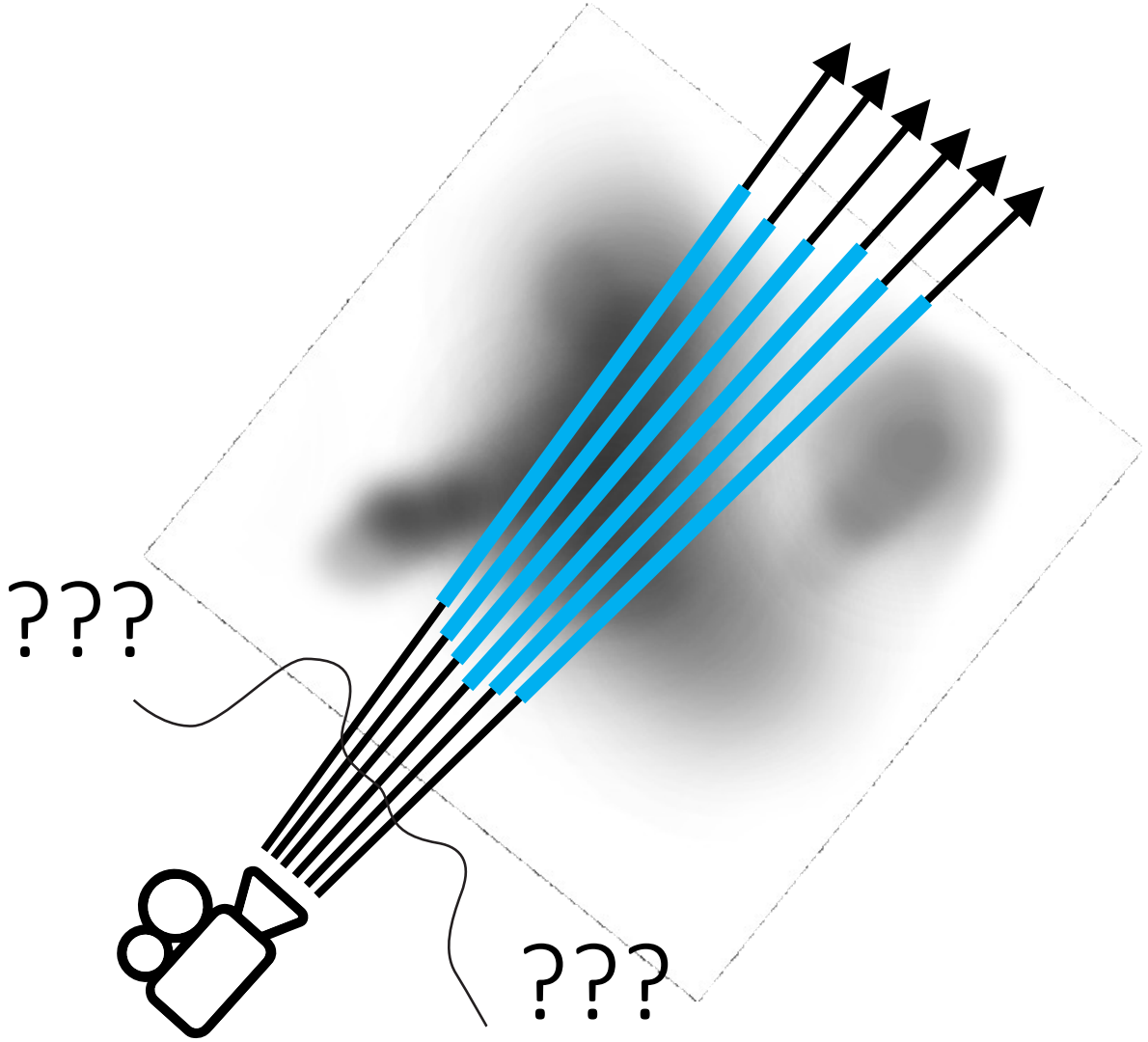
Gaussian



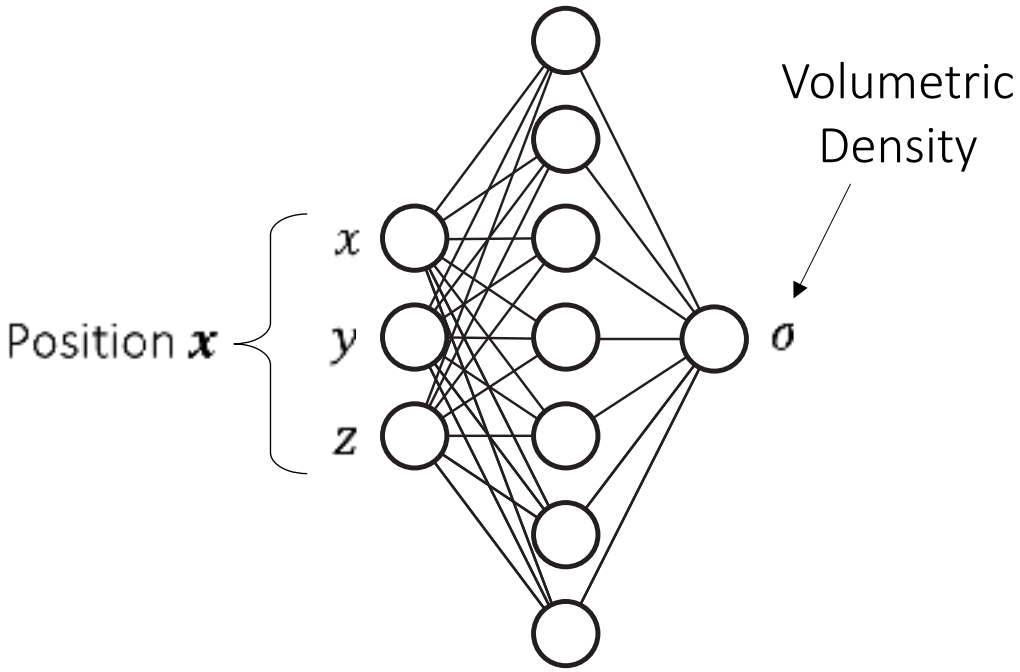
Neural

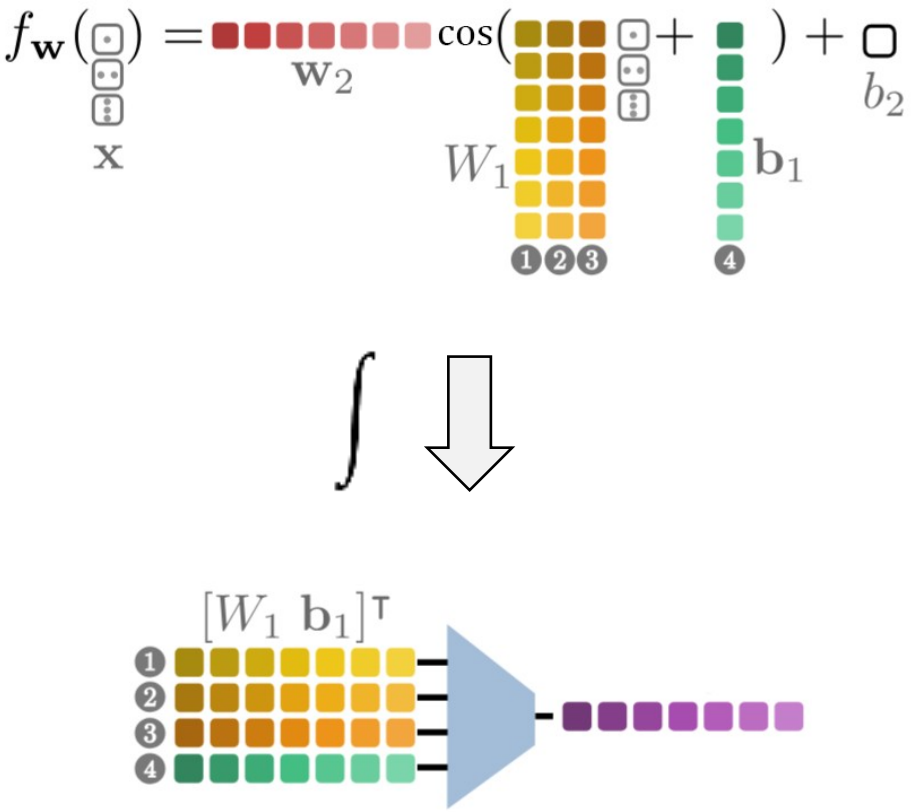


How to Splat a Neural Primitive?



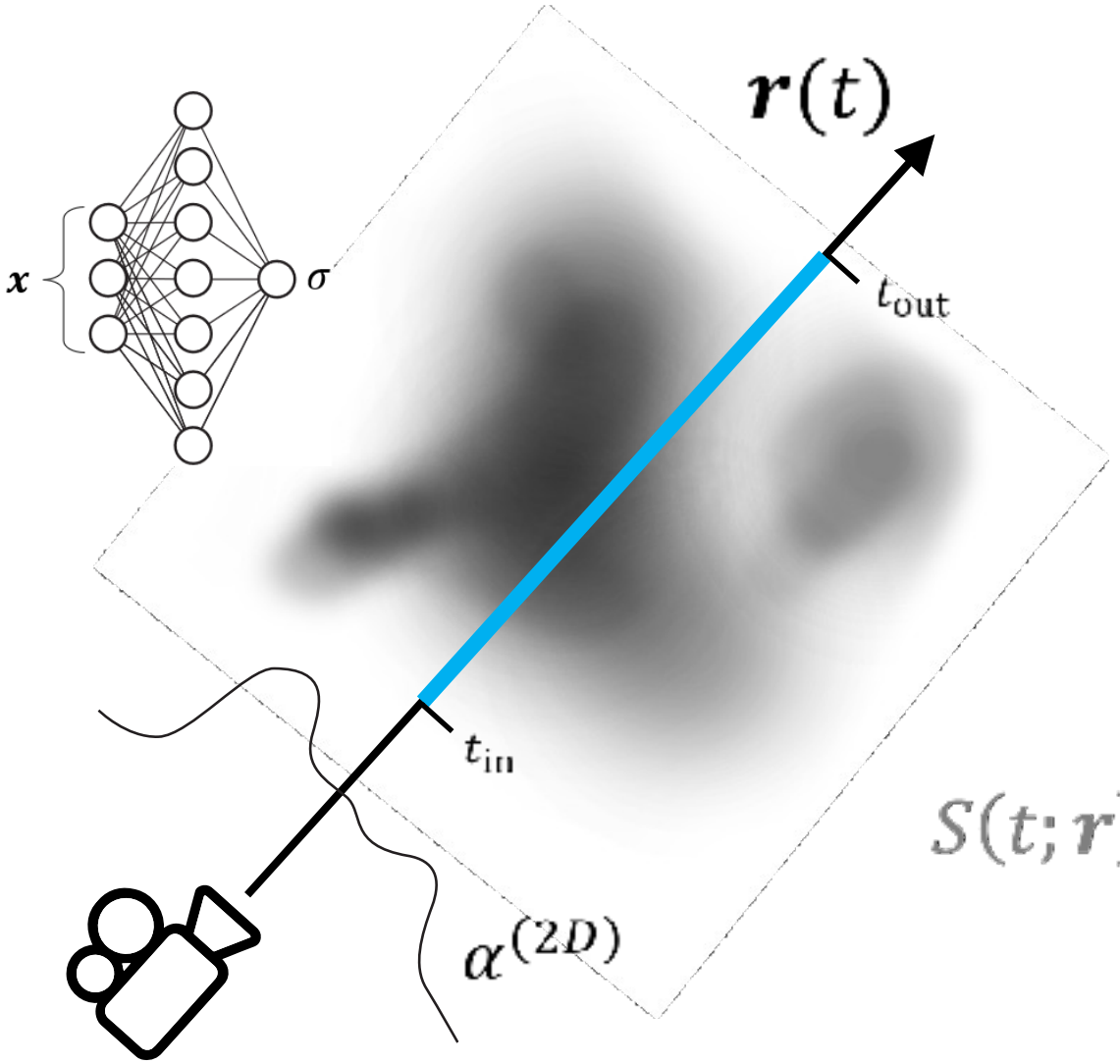
Integrating a Shallow Network





Lloyd, Irani, Ahmadi. **Using Neural Networks for Fast Numerical Integration and Optimization.** IEEE Access 2020.
Subr. **Q-NET: A Network for Low-dimensional Integrals of Neural Proxies.** Computer Graphics Forum 2021.

Integrating a Neural Primitive

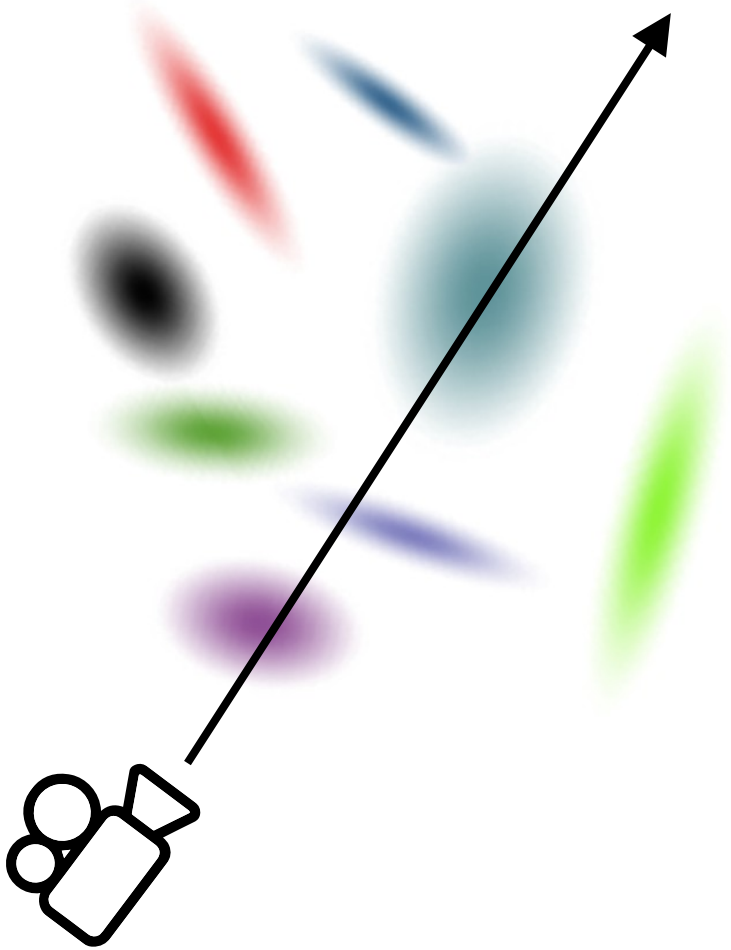


$$\alpha^{(2D)} = \int_{t_{\text{in}}}^{t_{\text{out}}} \sigma(\boldsymbol{x}(t))$$

$$= S(t_{\text{out}}; \boldsymbol{r}) - S(t_{\text{in}}; \boldsymbol{r})$$

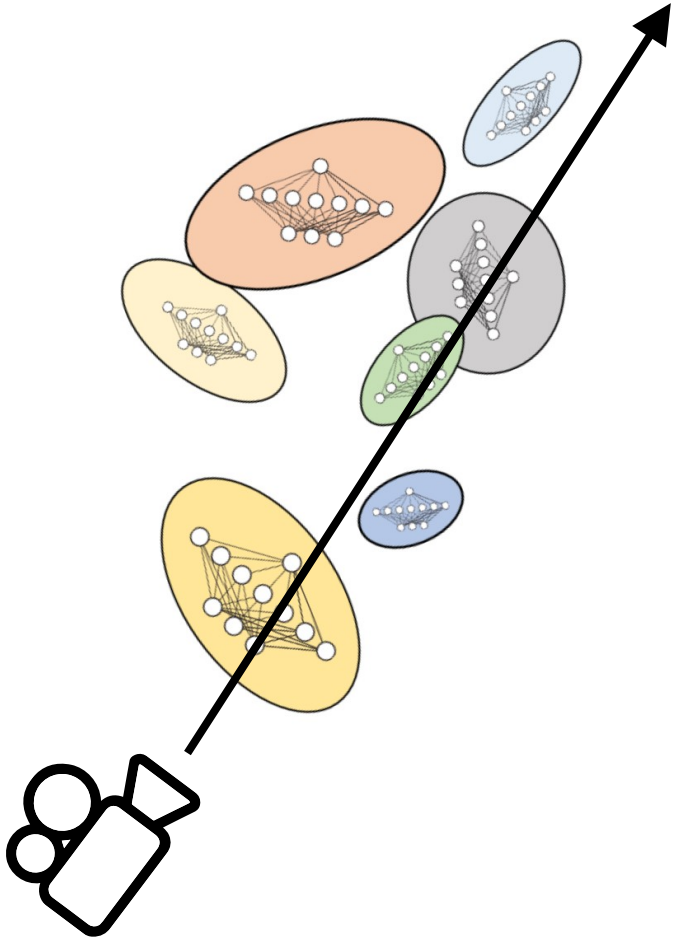
$$S(t; \boldsymbol{r}) = [W_2 \oslash W_1 \boldsymbol{d}] \sin(t W_1 \boldsymbol{d} + W_1 \boldsymbol{o} + \boldsymbol{b}_1) + t\, \boldsymbol{b}_2$$

Gaussian Splatting



$$C = \sum_i G_i^{(2D)} \, \boldsymbol{c}_i \prod_{j<i} \left(1 - G_j^{(2D)}\right)$$

Neural Primitive Splatting



$$C = \sum_i \overset{\alpha_i^{(2D)}}{\cancel{G_i^{(2D)}}}\, \boldsymbol{c}_i \prod_{j<i} \left(1 - \overset{\alpha_j^{(2D)}}{\cancel{G_j^{(2D)}}}\right)$$

Results

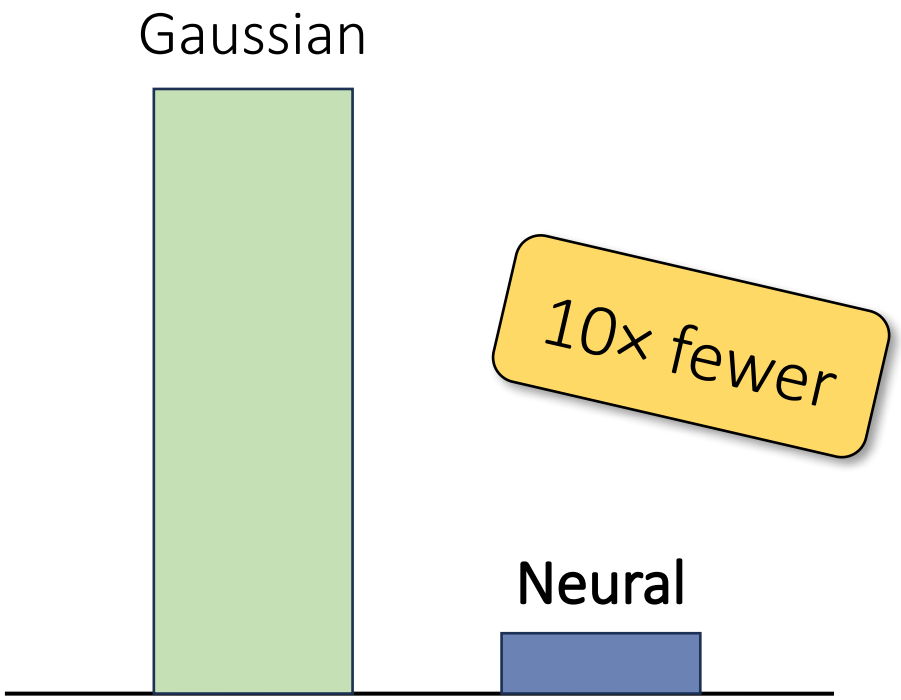
10k Primitives

Speed & Quality

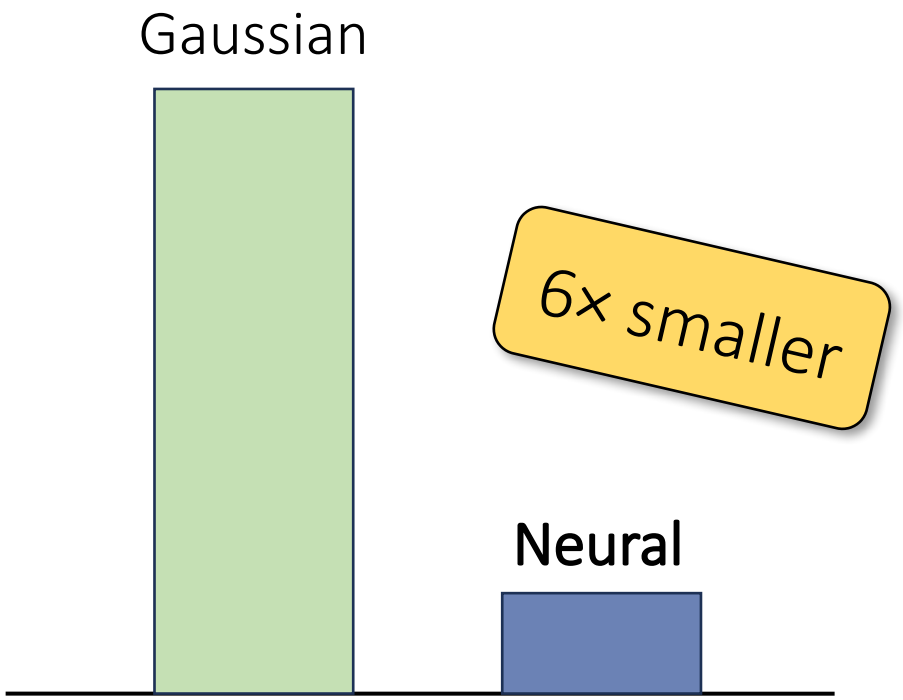
3D Gaussian Splatting

Neural Splatting

Neural Primitives are Compact

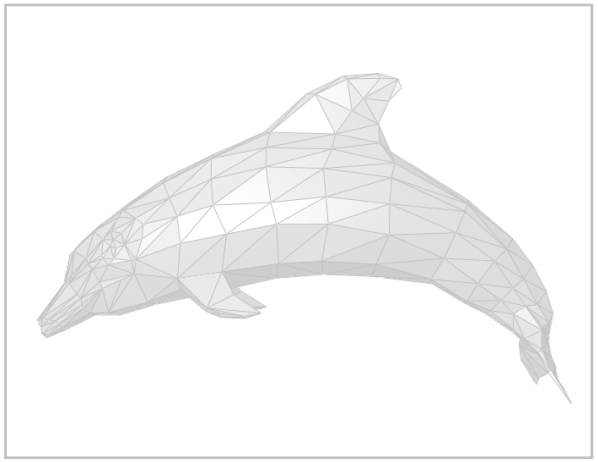


Primitives

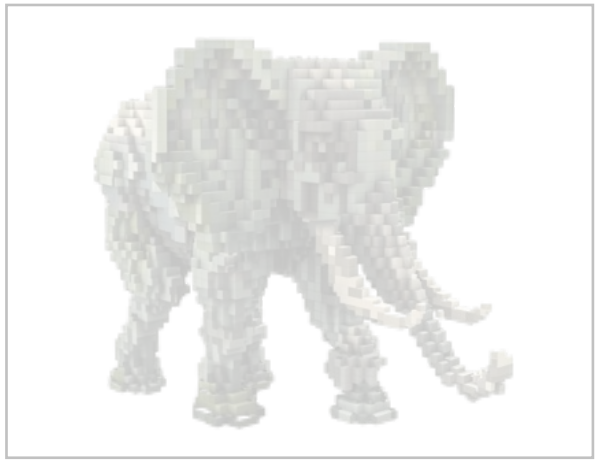


Memory

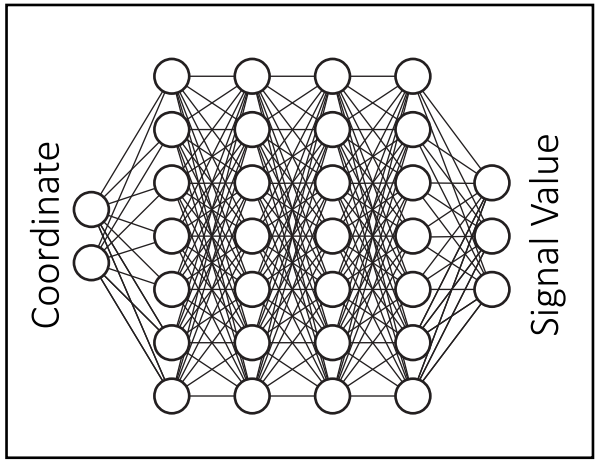
Representations for Virtual Scenes



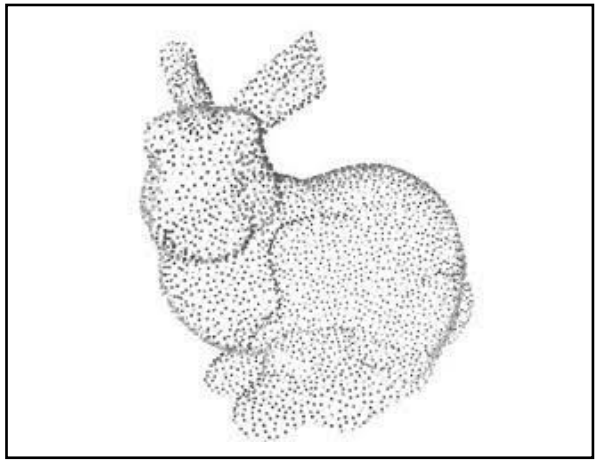
Mesh



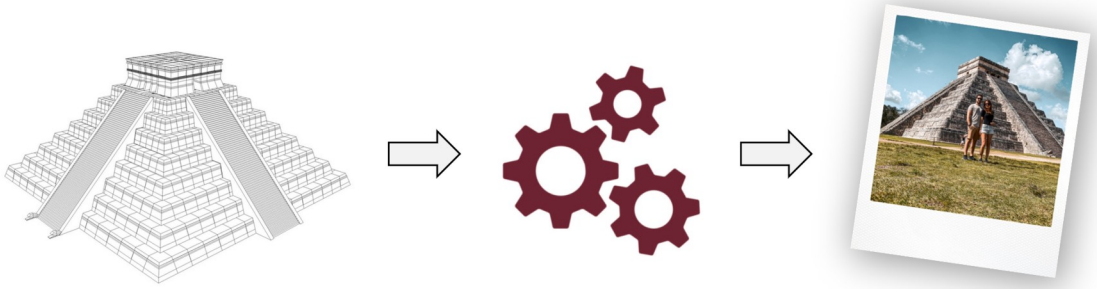
Voxel Grid



Neural Field



Unstructured Primitives



Neural Radiance Fields

3D Gaussian Splatting

Neural Primitive Splatting

The Team

Bao Hyu Nguyen

George Kopanas

Loïc Magne

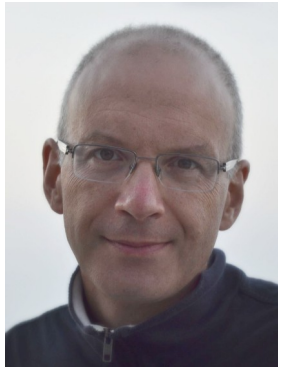
Xilong Zhou

Thomas Leimkuhler

Bernhard Kerbl

Vladislav Golyanik

Christian Theobalt



George Drettakis

Thank you!

3D Gaussian Splatting for
Real-time Radiance Field Rendering

Kerbl, Kopanas, Leimkuehler, Drettakis
2023

Splat the Net: Radiance Fields
with Splattable Neural Primitives

Zhou, Nguyen, Magne, Golyanik, Leimkuehler, Theobalt
2025