# Neural Radiance Field

A novel, data-driven solution to the long-standing problem in computer graphics of the realistic rendering of virtual worlds.

Haizhao Dai 2022/08/26









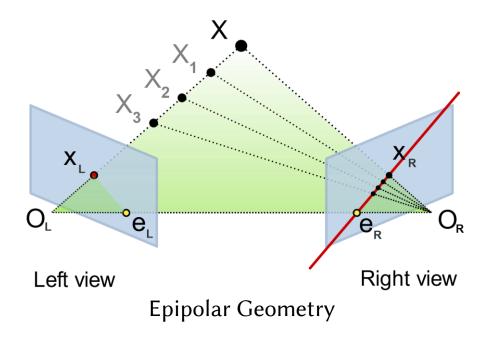


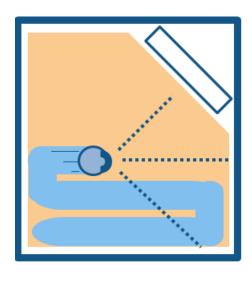
#### Overview

- Novel View Synthesis & Reconstructions
- Scene Representations
  - Neural Scene Representations
  - Light Field / Radiance Field
- Differentiable Rendering (TODO)
  - Volume Rendering
- Positional Encoding (Mip-NeRF)
- Sampling Strategies

## Novel View Synthesis & Reconstructions

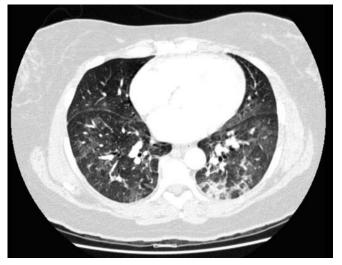
- Photo-realistic rendering.
  - Rasterization / Ray tracing,
- Synthesizing views under camera viewpoint transformations from one or multiple input images.



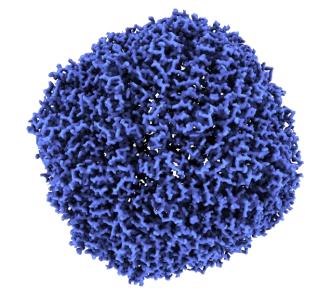




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Tomography

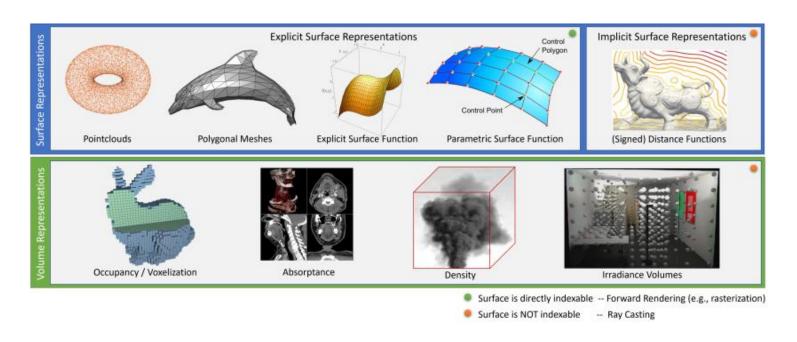


### Scene Representations

- Specifically defined representations of geometry and material properties.
  - A scene consists of one or more objects.
- Surface and volumetric representations.
- Discretized and continuous representations.
- Explicit and implicit representations.

## Surface and Volumetric Representations

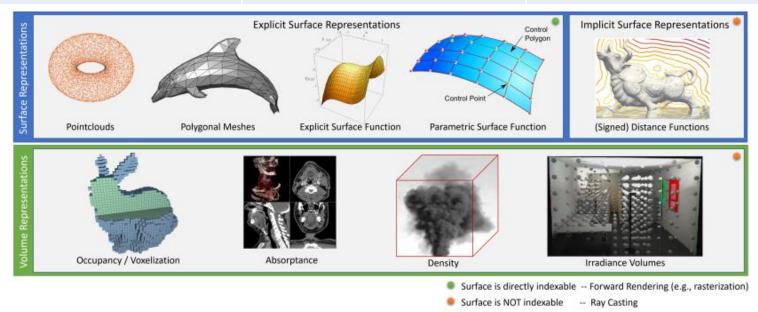
- Surface representations store property w.r.t. the surface such as colors, normal vectors or brdf.
- Volumetric representations volumetric properties such as densities, opacities or occupancies.



# Discretized and Continuous Representations

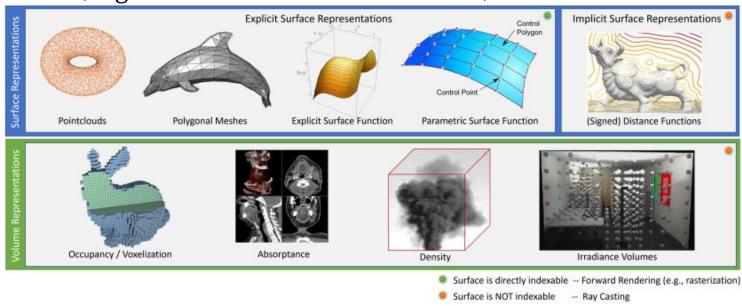
 For both surface and volumetric representations, there are continuous and discretized counterparts.

	Discretized	Continuous
Surface	Pointclouds, meshes	Parametric Surfaces, SDFs
Volumetric	Voxels, 3D textures	Neural Networks



### Explicit and Implicit Representations

- Explicit and implicit representation are meant to surface representations.
- Explicit: y = f(x), i.e.  $(u, v) \mapsto (\cos(u)\sin(v), \sin(u)\sin(v), \cos(v))$ 
  - Images/Textures, Pointclouds, Meshes, Parametric Surface, (Volumetric Representations).
- Implicit:  $F(x, y) = 0 \implies y = y(x)$ , i.e.  $x^2 + y^2 1 = 0$ 
  - Neural Network, Signed Distance Function/Level Set, Gaussian Mixtures.



#### Explicit Continuous Volumetric Representations

- NeRF can be categorized as explicit continuous volumetric representations.
  - Why not other representations?
- Explicit v.s. Implicit.
- Continuous v.s. Discretized.
- Surface v.s. Volume.
- Why some one says NeRF is implicit representation?
  - Embedding.

$$(x,y,z,\theta,\phi) \to \mathbb{R} \longrightarrow (RGB\sigma)$$

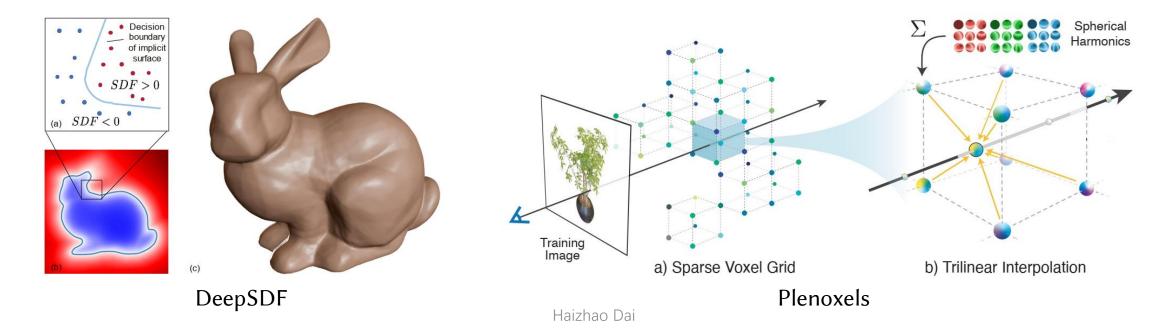
$$F_{\Theta}$$

### Neural Scene Representations

- NeRF can be categorized as neural scene representation.
- DeepSDF (Park et al. CVPR 2019)
- Plenoxels (Yu et al. CVPR 2022)

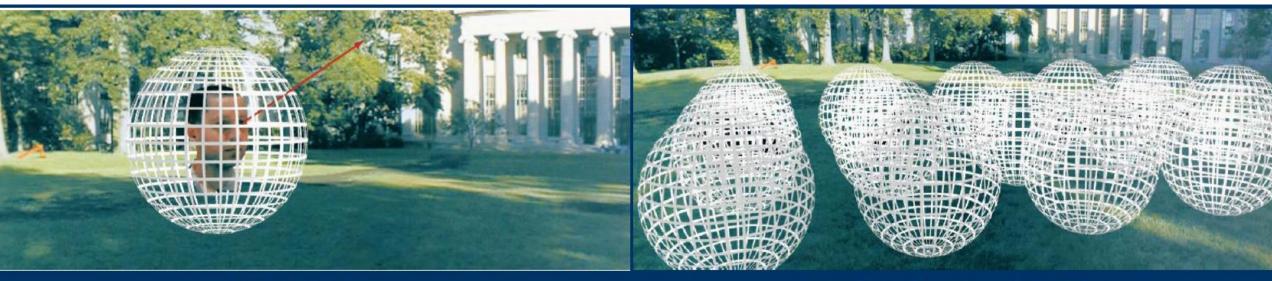
$$(x,y,z,\theta,\phi) \to \square \longrightarrow (RGB\sigma)$$

$$F_{\Theta}$$



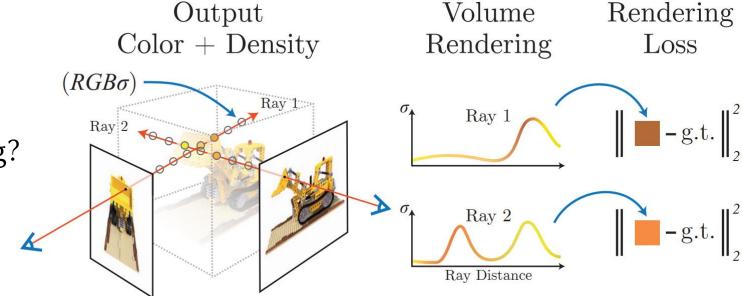
### Light Field / Radiance Field

- The light field describes the amount of light flowing in every direction through every point in space at every time point.
- Plenoptic function:  $L(x, y, z, \theta, \phi, \lambda, t)$ .
- Substitute  $\lambda$  with RGB, t with different frame.



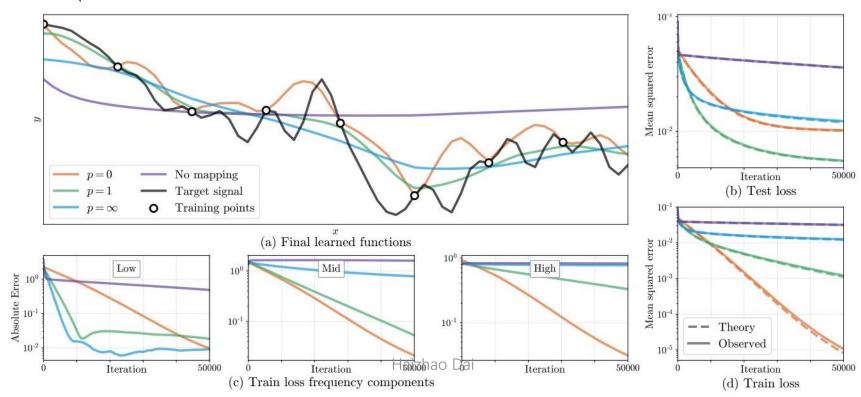
# Differentiable Rendering

- Last week, we have introduced the volume rendering.
- Continuous:
  - $C(\mathbf{r}) = \int_{t_n}^{t_f} T(t) \sigma(\mathbf{r}(t)) \mathbf{c}(\mathbf{r}(t), \mathbf{d}) dt$
  - $T(t) = \exp(-\int_{t_n}^t \sigma(\mathbf{r}(s)) ds)$
- Discretized:
  - $\hat{C}(\mathbf{r}) = \sum_{i=1}^{N} T_i \alpha_i c_i$
  - $T_i = \prod_{i=1}^N (1 \alpha_i)$
- What is differentiable rendering?
  - Inverse rendering



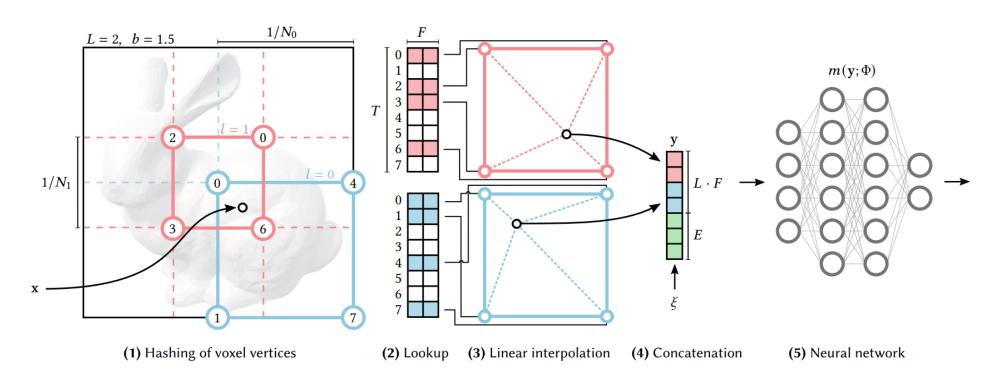
# Positional Encoding

- Attention Is All You Need. (Vaswani et al. NeurIPS 2017)
- A mapping that maps input coordinates from low dimensional space to high dimensional encoding space.
  - Fourier Features Let Networks Learn High Frequency Functions in Low Dimensional Domains. (Tancik et al. NeurIPS 2020



## Hash Encoding

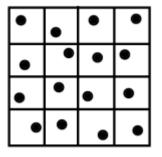
• Instant Neural Graphics Primitives with a Multiresolution Hash Encoding. Muller et al. Siggraph 2022 Best Paper Award



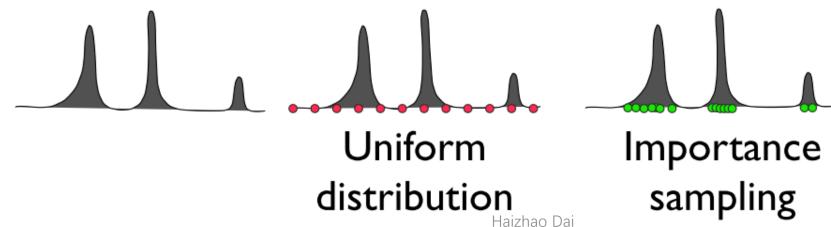
# Sampling Strategies

- Monte Carlo Integral.
- Stratified sampling.





• Importance sampling.



#### Discussions

- Why NeRF works?
  - Positional Encoding (Neural Tangent Kernel Analysis)
  - 5D Neural Radiance Fields based on MLP (Neural Representations)
  - Volume Rendering (Differentiable Rendering)
  - Sampling (Performance Improvement)
- What are the limitations of NeRF?
  - Extremely slow for rendering and training
  - Bad Surface reconstruction
  - · Cannot model reflection and refraction well
  - Hard to edit the local area
  - ...

#### References

- DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation. Park et al. CVPR 2019.
- Plenoxels Radiance Fields without Neural Networks. Yu et al. CVPR 2022.
- Advances in Neural Rendering. Tewari et al. EuroGraphics 2022.
- Instant Neural Graphics Primitives with a Multiresolution Hash Encoding. Muller et al. Siggraph 2022 Best Paper.