

# NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis

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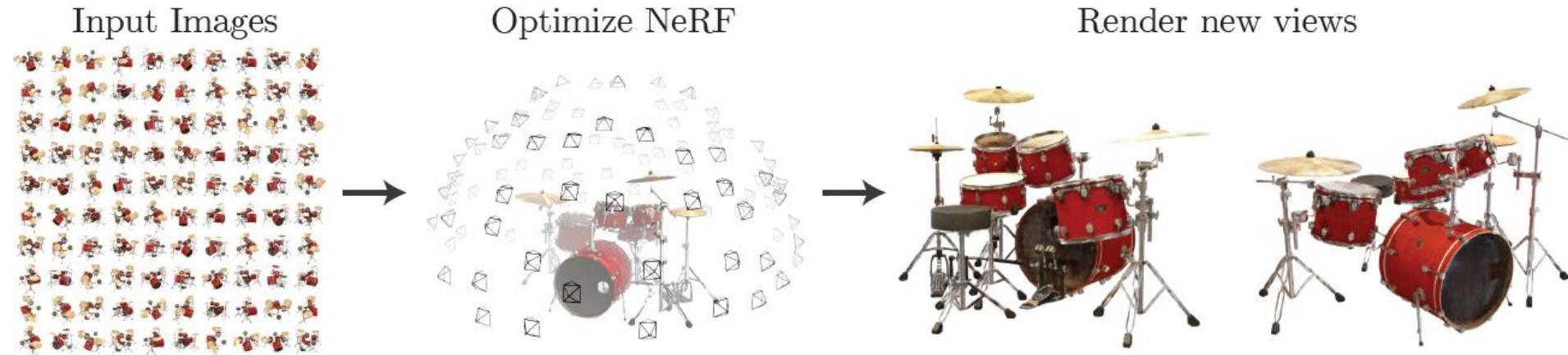
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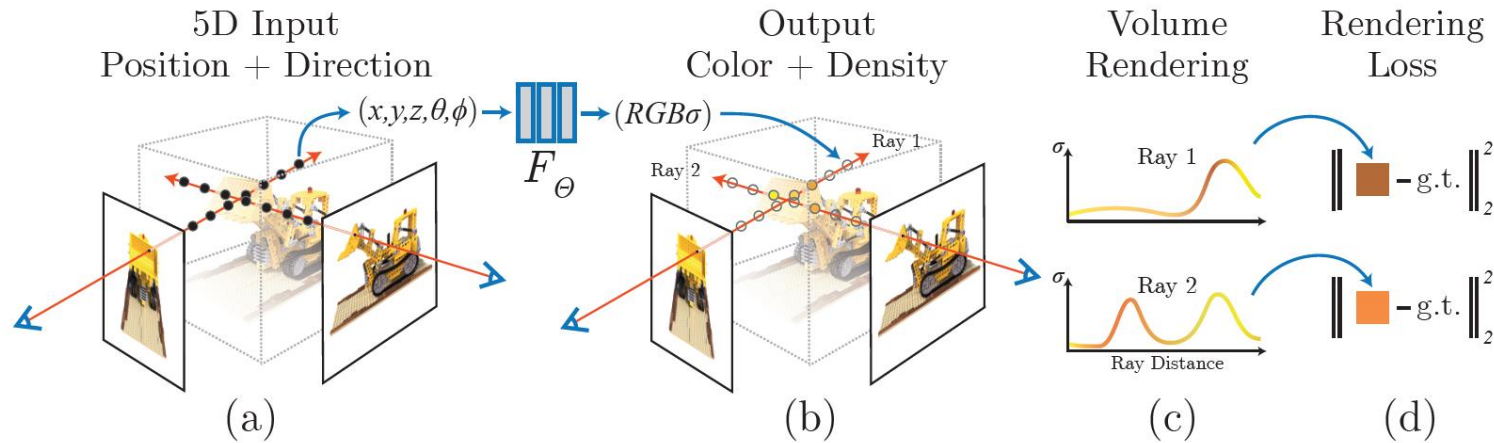
# NeRF

B. Mildenhall, P. Srinivasan, and M. Tancik, "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis," in Proceedings of European Conference on Computer Vision, (Springer, 2020).

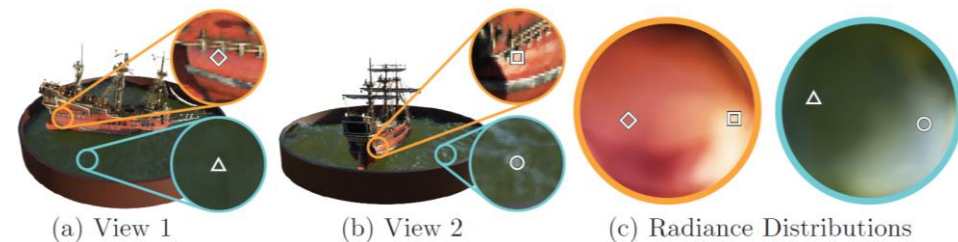
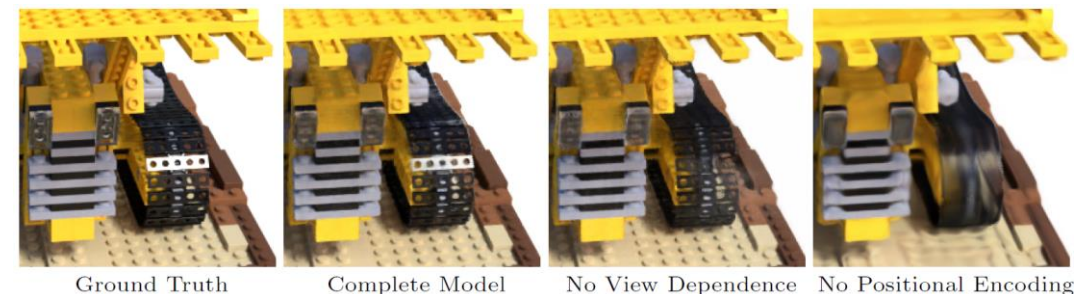


- Neural radiance fields (NeRF): scene representation using neural network
- Input images rendered from discretized viewpoint → Rendering new views which is not included in training dataset





- N of 2D image  $\rightarrow$  Synthesizing random view image
- $F_\theta : (\mathbf{x}, \mathbf{d}) \rightarrow (\mathbf{c}, \sigma)$   
Replacing with deep neural network
- $\mathbf{c}$  : with respect to location  $\mathbf{x}$  and viewing direction  $\mathbf{d}$   
 $\sigma$  : with respect to location  $\mathbf{x}$
- Continuous radiance field is synthesized for the changing in viewing direction.





## Volume rendering

$$C(\mathbf{r}) = \int_{t_n}^{t_f} T(t) \underbrace{\sigma(\mathbf{r}(t))}_{\text{density}} \underbrace{\mathbf{c}(\mathbf{r}(t), \mathbf{d})}_{\text{RGB}} dt, \text{ where } T(t) = \exp\left(-\int_{t_n}^t \sigma(\mathbf{r}(s)) ds\right).$$

$$t_i \sim \mathcal{U}\left[t_n + \frac{i-1}{N}(t_f - t_n), t_n + \frac{i}{N}(t_f - t_n)\right].$$

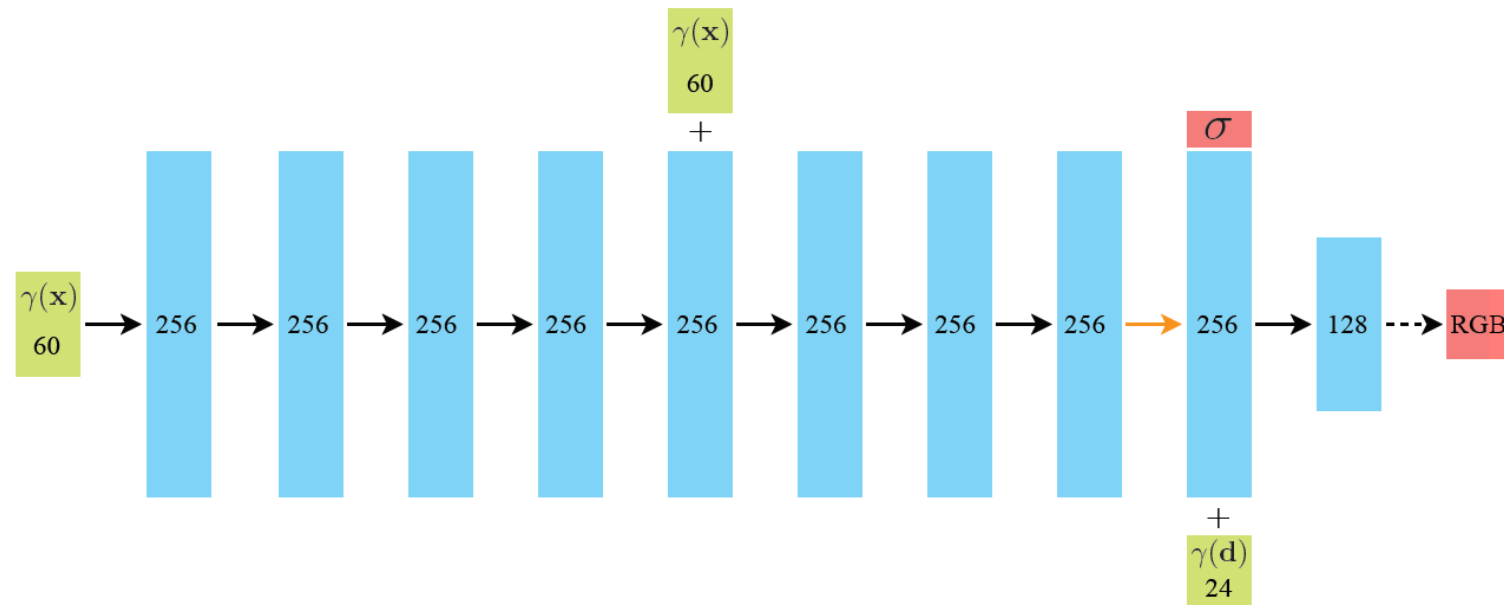
$$\hat{C}(\mathbf{r}) = \sum_{i=1}^N T_i (1 - \exp(-\sigma_i \delta_i)) \mathbf{c}_i, \text{ where } T_i = \exp\left(-\sum_{j=1}^{i-1} \sigma_j \delta_j\right), \delta_i = t_{i+1} - t_i$$

- $\mathbf{r}(t) = \mathbf{o} + t\mathbf{d} \rightarrow$  ray
- $\sigma(\mathbf{r}(t)) \rightarrow$  the differential probability of a ray terminating at an infinitesimal particle at location  $\mathbf{x}$
- $T(t) \rightarrow$  accumulated transmittance, the probability that the ray travels from  $t_n$  to  $t$  without hitting any other particle.
- Deterministic quadrature limit resolution of NeRF  $\rightarrow$  stratified sampling



## Implementation – positional encoding and network architecture

$$\gamma(p) = (\sin(2^0 \pi p), \cos(2^0 \pi p), \dots, \sin(2^{L-1} \pi p), \cos(2^{L-1} \pi p)) .$$



- Mapping the inputs to a higher dimensional space using high frequency functions before passing them to the network  
→ better fitting of data that contains high frequency variation
- This paper set  $L = 10$  for  $\gamma(\mathbf{x})$  and  $L = 4$  for  $\gamma(\mathbf{d})$ .





## Hierarchical volume sampling

- Sample  $N_c$  locations using stratified sampling  $\rightarrow$  evaluate “coarse” network
- Given “coarse” network, producing a more informed sampling of points  $N_f \rightarrow$  evaluate “fine” network
- Final rendered color of the ray  $\hat{C}_f(\mathbf{r})$  is computed using  $N_c + N_f$  samples.

$$\hat{C}_c(\mathbf{r}) = \sum_{i=1}^{N_c} w_i c_i, \quad w_i = T_i(1 - \exp(-\sigma_i \delta_i)), \quad \hat{w}_i = w_i / \sum_{j=1}^{N_c} w_j$$

## Implementation details

- At each optimization iteration,  
randomly sampling camera rays  $\rightarrow$  hierarchical sampling  $N_c + N_f \rightarrow$  volume rendering  $\rightarrow$  computing loss
- $\mathcal{L} = \sum_{r \in \mathcal{R}} [\|\hat{C}_c(\mathbf{r}) - \mathcal{C}(\mathbf{r})\|_2^2 + \|\hat{C}_f(\mathbf{r}) - \mathcal{C}(\mathbf{r})\|_2^2]$
- 4096 rays,  $N_c = 64, N_f = 128$ .
- The optimization for a single scene typically takes around 100-300k iterations to converge on a single Nvidia V100 GPU (about 1-2 days)



## Results

