Paper Summary NeRF

Abstract

Represent a scene using a fully-connected deep network, whose input is a single continuous **5D** coordinate **(spatial location** (x, y, z) **and viewing direction** (θ, ϕ)**)**. **Output** is the volume density and view-dependent emitted radiance at that spatial location.

1. Introduction

Represent function by regressing from a single 5D coordinate (x, y, z, θ, ϕ) to a single volume density and view-dependent RGB color. To render this **NeRF** from a particular point:

1. March camera rays through the scene to generate a sampled set of 3D points.
2. Use those **points** and their **corresponding 2D viewing directions** as input to the NN to produce **an output set of colors** and **densities**.
3. Use classical volume rendering techniques to accumulate those colors and densities into 2D images.

Solve issue: 1. Transferring **input 5D coordinates** with a positional encoding that enables the MLP to represent higher frequency functions.

2. Propose a hierarchical sampling procedure to reduce the number of queries required to adequately simple this high-freq scene representation.

2. Related Work

Recent direction: Maps from a 3D spatial location to an implicit representation of the shape.

$*$ Paper circumvent problem by encoding a *continuous* volume within the parameters of a deep fully-connected NN, which not only produces significantly higher quality renderings than prior volumetric approaches, but also requires just a fraction of the storage cost of those *sampled* volumetric representations.

3. Neural Radiance Filed Scene Representation

Input: a 3D location $x = (x, y, z)$ and 2D viewing direction (θ, ϕ).

Output: an emitted color $c = (r, g, b)$ and volume density σ.

In practice, expressing direction as 3D Cartesian unit vector d. Approximate this continuous 5D scene representation with an MLP network $F_\Theta : (x, d) \to (c, \sigma)$ and optimize its weights Θ.

4. Volume Rendering with Radiance Field

$\sigma(x)$ can be interpreted as the differential probability of a ray terminating at an infinitesimal particle at location x.

The expected color $C(r)$ of camera ray $r(t) = o + td$ with near and far bounds t_n and t_f is:

$$C(r) = \int_{t_n}^{t_f} T(t)\sigma(r(t))c(r(t),d)dt$$

where $T(t) = exp(-\int_{t_n}^{t} \sigma(r(s))ds)$.

5. Optimizing a Neural Radiance Filed

Introducing two improvements to enable representing high-resolution complex scenes. The first is a **positional encoding** of the input coordinates that assist the MLP in representing high-frequency, and the second is a hierarchical sampling procedure that allows us to efficiently sample this high-frequency representation.

5.1 Positional encoding

1. Deep network are biased toward learning lower frequency functions

2. Mapping the inputs to a higher dimensional space using high frequency functions before passing them to the network enables better fitting of data that contains high frequency variation.

$*$ Reformulating F_θ as a composition of two function $F_\theta = F'_\Theta \circ \gamma$, one learned and one not. γ is a mapping from R into a higher dimensional space R^{2L} and F'_Θ is still a regular MLP. Formally, the encoding function used is:

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

$\gamma(\cdot)$ is applied separately to each of the three coordinate values in $\mathbf{x}$ and to the three components of the Cartesian viewing direction unit vector $\mathbf{d}$

5.2 Hierarchical Volume Sampling

Part 2

The task of NeRF is "Novel View Synthesis".

Def of this task is "creating new views of a specific subject starting from a number of pictures taken from given point of views".

What is "Radiance Field"?

Radiance field is a functional representation that jointly model **geometry** and **appearance**, and is able to model view-dependent effects.

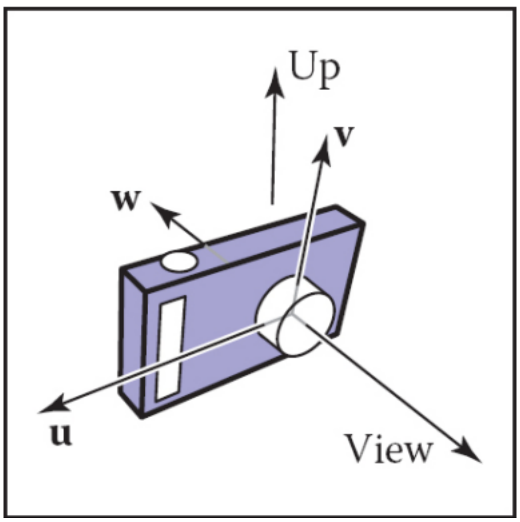
Geometry: $3d$ points location $\mathbf{x} = (x, y, z)$ and view direction $\mathbf{d}$ as a part of input.

Appearance: density σ and color (r, g, b).

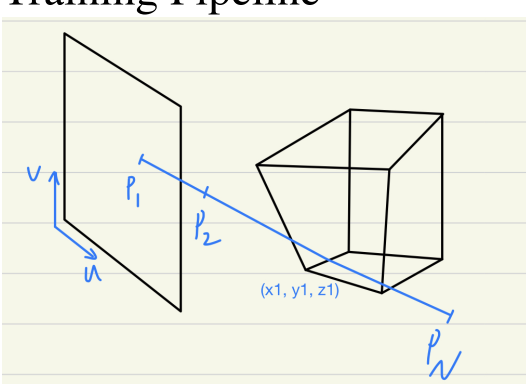
$$F_\Theta : (\mathbf{x} = (x, y, z), \mathbf{d} = (u, v)) \rightarrow (\mathbf{c} = (r, g, b), \sigma([(x, y, z)]))$$

$*$ $\sigma : \sigma(\mathbf{x})$ a function of only the location -> **multi-view consistent** because density σ is irrelevant with view direction, but just location (x, y, z).

$*$ $\mathbf{c}$ is relevant with both **view direction** and **position** because of relation between **specular characteristic** and view direction.

How to represent $\mathbf{d}$?  $\mathbf{d} = (\theta, \phi)$

Training Pipeline



1. Plug view direction $\mathbf{d} = (\theta, \phi)$ and position of points $p_1 = (x_1, y_1, z_1), ..., p_N = (x_N, y_N, z_N)$ into neural radiance field $F_\Theta(\mathbf{d}, p_i)$. Note: each point each time, and for these points in the fig above, they share the same view direction. After this, we will get N numbers of $(\mathbf{c}, \sigma)$.

Procedure **1** and **2** in the paper.

2. Using classical volume rendering techniques ([**16**] Ray Tracing Volume Densities) to accumulate those colors and densities into 2D image. Using formulae:

$$C(r) = \int_{t_n}^{t_f} T(t)\sigma(r(t))\mathbf{c}(r(t), d)dt$$

We can directly substitute σ and $\mathbf{c}$ into formulae, and also all elements in $T(t) = exp(-\int_{t_n}^{t} \sigma(r(s))ds)$ are known. We can easily get the value of expected color $C(r)$.

$t_n, ..., t_f$ are the same with points $p_1, ...p_N$. In practice, they use weighted sum to numerically approximate, where we can treat $T(t)$ as weight. **Uniform discretization for coarse network**

3. real color (or ground truth) $-$ expected color $\rightarrow L^2$ norm. That's how to train.

Optimization Techniques

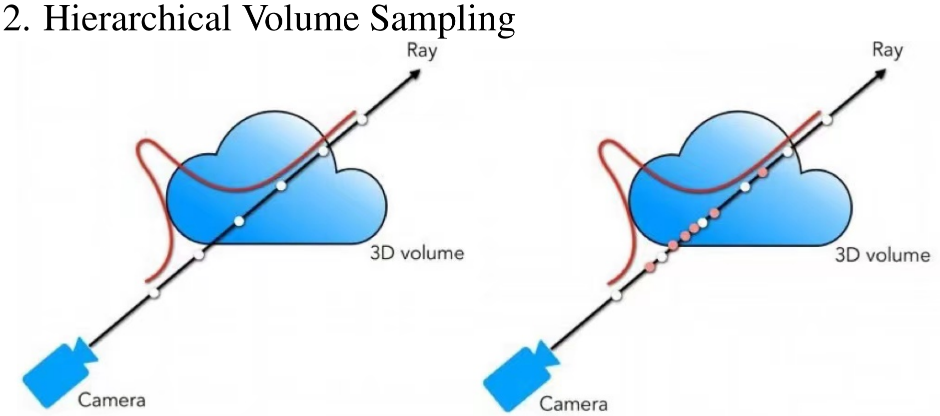
1. Positional encoding

Deep networks are biased towards learning low-frequency functions. Reformulating $F_\Theta = F'_\Theta \circ \gamma$. We can treat γ as a kind of **transformation** so that we can **increase the frequency** of our original input data to **decrease the blurring of performance**, and F'_Θ will train these transformed data. How does these work? Recall the formulation of $\gamma(p)$:

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

as the value of order increasing, the frequency of each transformed data will increase. γ is actually a mapping to map original data (**low-frequency**) to be high-frequency and increase performance.

2. Hierarchical Volume Sampling



Left: coarse, uniform sampling. Predict the density distribution according to σ, and then add more sample points at where density is high.

Right: fine sampling, Compute the final rendered color of the ray $\hat{C}_f(r)$ using all $N_c + N_f$ samples.

Loss function:

$$L = \sum_{r \in R} \left[||\hat{C}_c(r) - C(r)||_2^2 + ||\hat{C}_f(r) - C(r)||_2^2 \right]$$