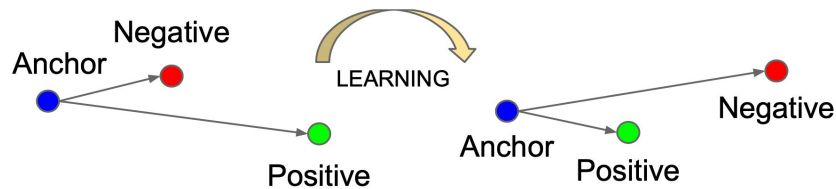
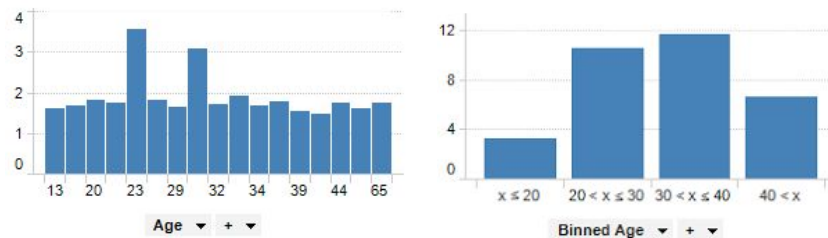


Deep Learning

Lecture 14

Recap

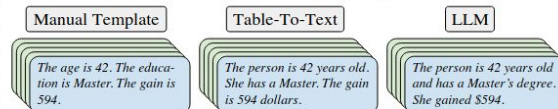
- Encoding
- Pretraining
- Tabular DL
- Tabular DL as text



1. Tabular data with k labeled rows

age	education	gain	income
39	Bachelor	2174	$\leq 50K$
36	HS-grad	0	$> 50K$
64	12th	0	$\leq 50K$
29	Doctorate	1086	$> 50K$
42	Master	594	

2. Serialize feature names and values into natural-language string with different methods



3. Add task-specific prompt

Does this person earn more than 50000 dollars? Yes or no? Answer:

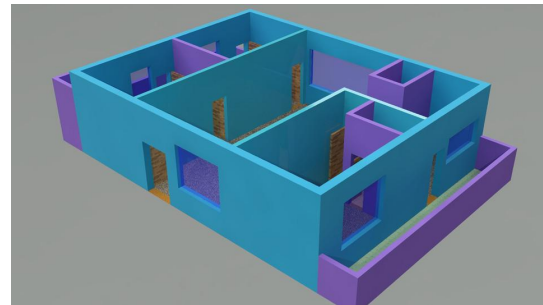
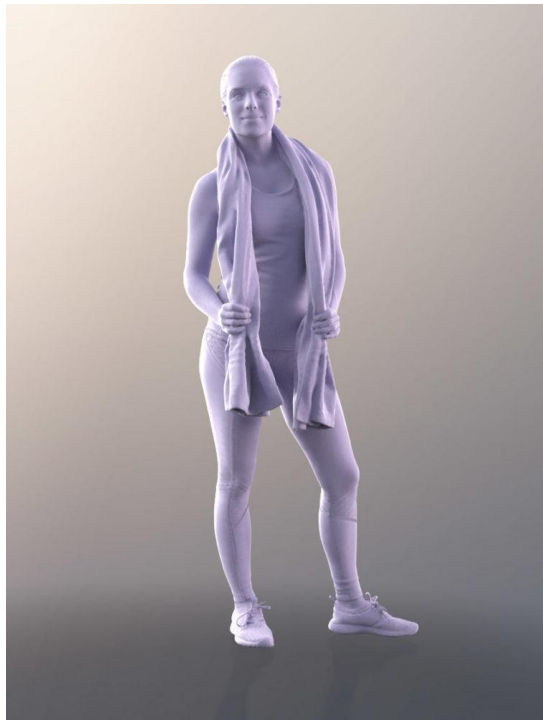
4a. Fine-tune LLM using labeled examples



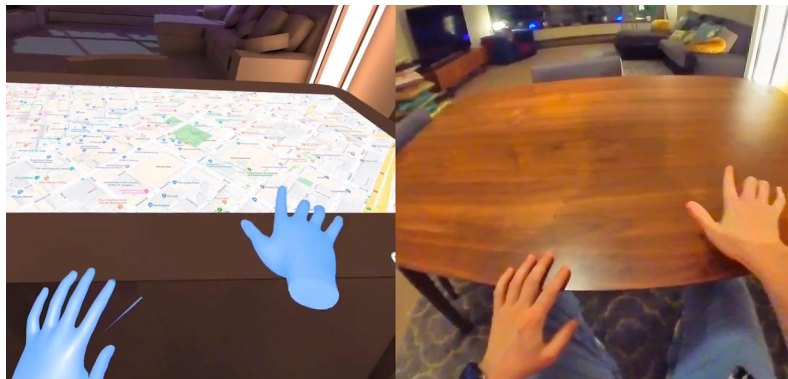
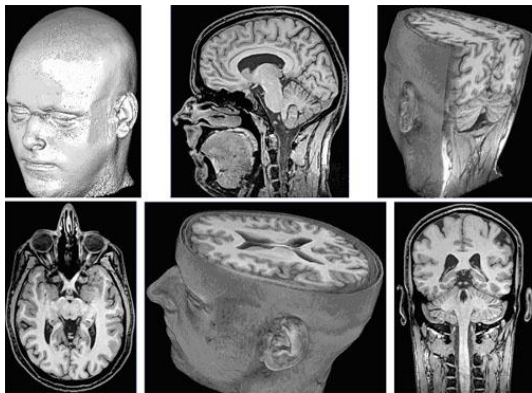
4b. Use LLM for prediction on unlabeled examples



Why we need 3D?



3D applications



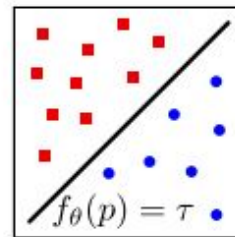
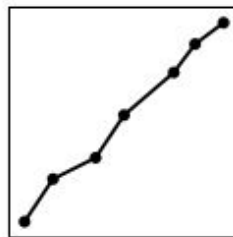
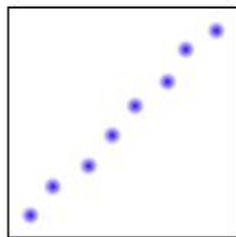
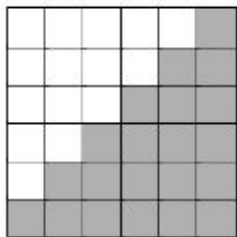
Possible 3D tasks

- classification, clusterization
- generation of 3D data
- 3D reconstruction of object from one or a few views
- animation of static meshes



3D Reconstruction

3D data representations



(a) Voxel

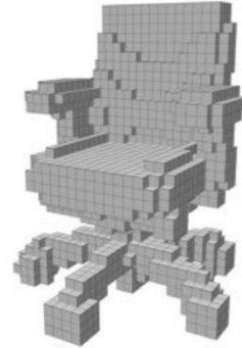
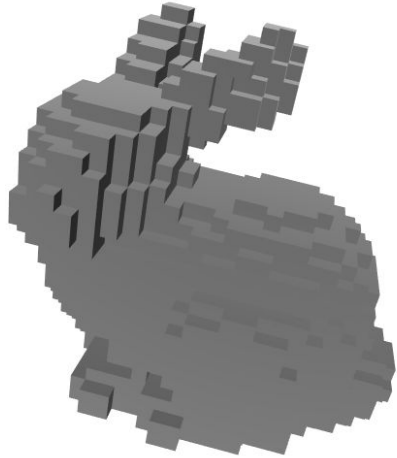
(b) Point

(c) Mesh

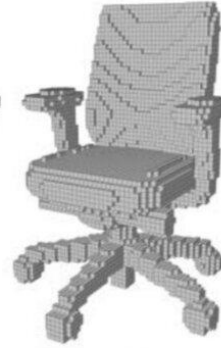
(d) Functions

Information

Voxels (eng. volumetric + pixel)



10.41%



5.09%

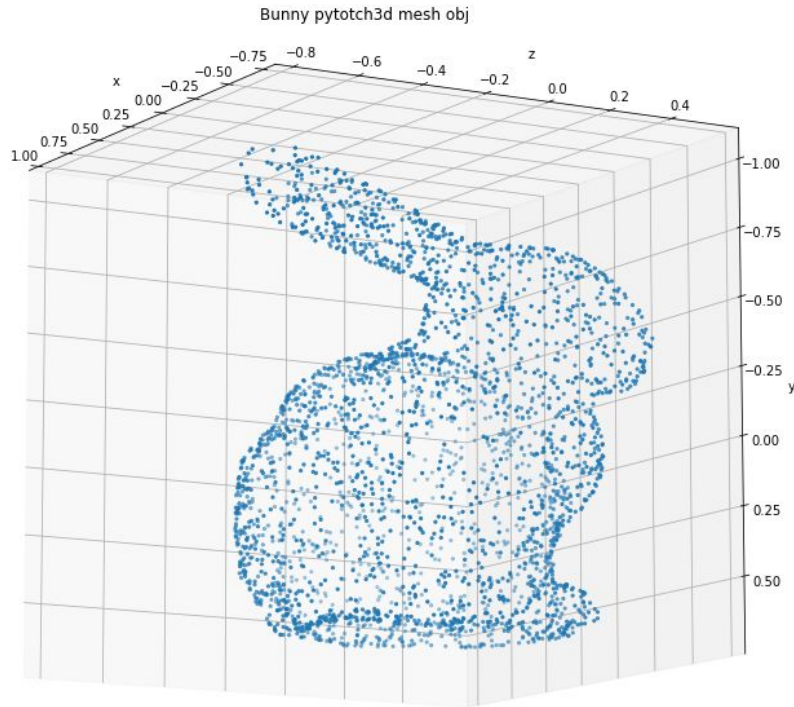


2.41%

- Natural generalization of approaches that have been used for image processing.
- Can obtain from any other type of representation.
- Connection with the physical properties of objects

The higher the resolution, the better the approximation of the original shape but the lower the fraction of occupied voxels.

Point Clouds



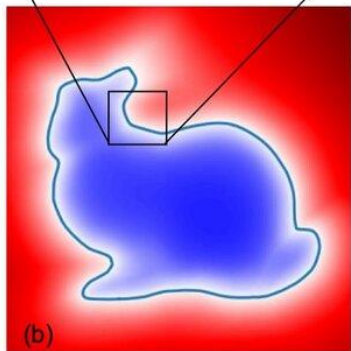
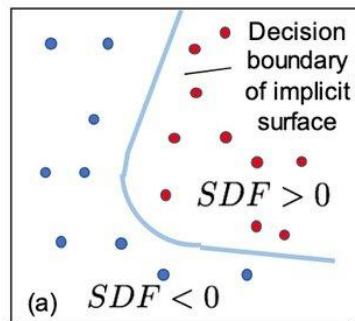
- Natural data format in spatial scanning problems.
 - You can multiply the points in the point list with linear transformation matrices.
 - Can be easily obtained from polygonal and functional models.
-
- ❑ Data disorder.
 - ❑ No information about the connections between points
-> no topology.
 - ❑ Hard postprocessing.

Meshes



- Natural format for use in computer graphics and games.
- Can better describe the spatial features of objects (topology, surface shape)
- ❑ Need a special mathematical apparatus for extracting features from polygonal models(convolution on graphs).
- ❑ Format is sensitive to data outliers.

Implicit 3D representations (Signed distance function)



(c)

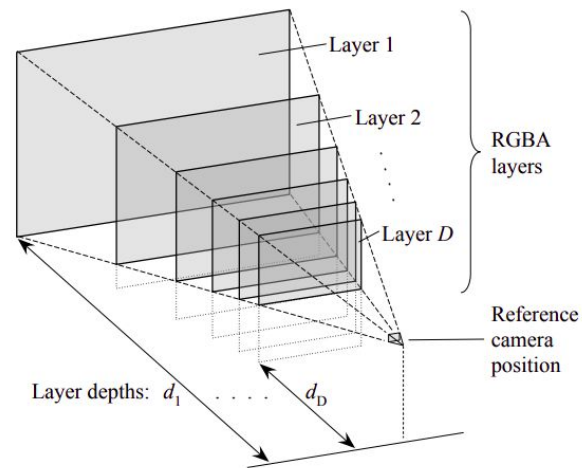
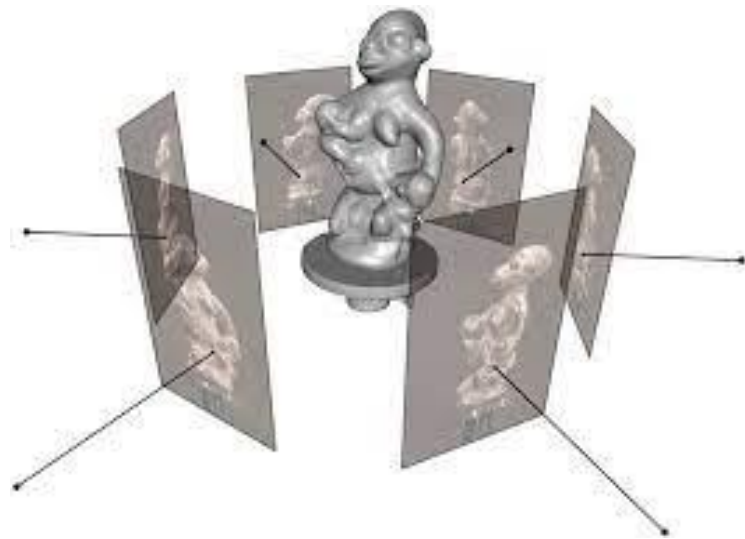


$$SDF(x) = \begin{cases} \rho(x, \partial\Omega), & x \notin \Omega \\ -\rho(x, \partial\Omega), & x \in \Omega \end{cases}$$

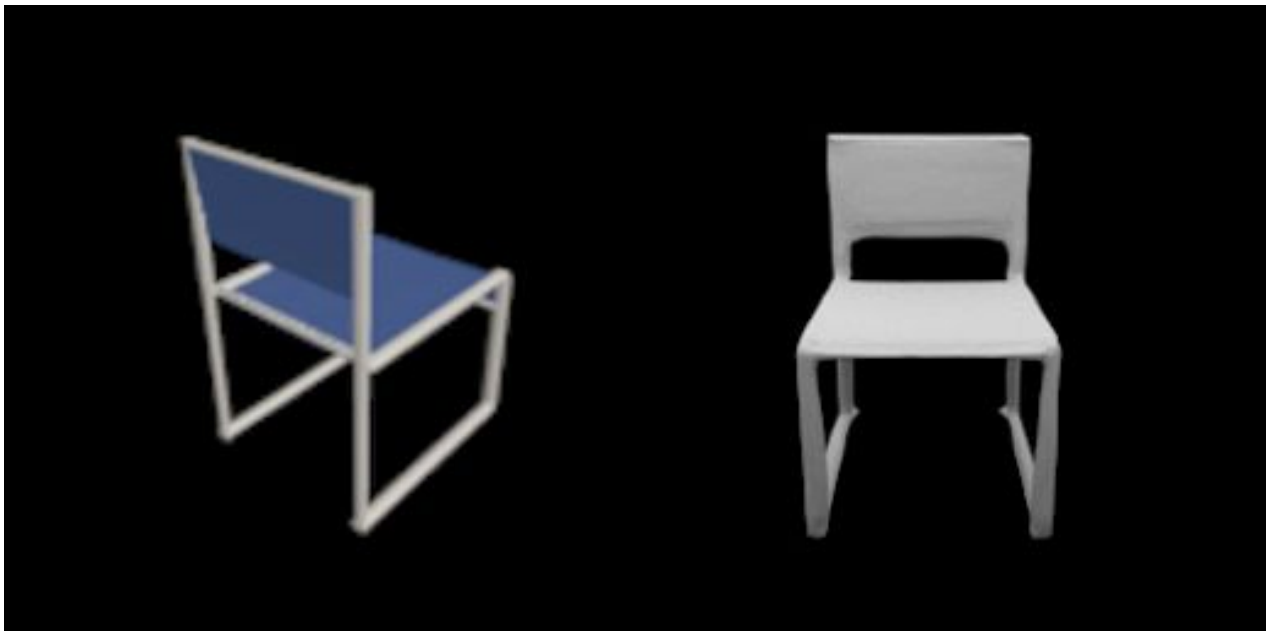
$$\rho(x, \partial\Omega) = \inf_{y \in \partial\Omega} \rho(x, y)$$

- Compact description
- Physically correct model.
- Model scalability.
- Can obtain all other formats.
- ❑ Small number of datasets.
- ❑ Can't be obtained from other formats.
- ❑ difficult to work with textures.

Multi-view and multi-plane representation

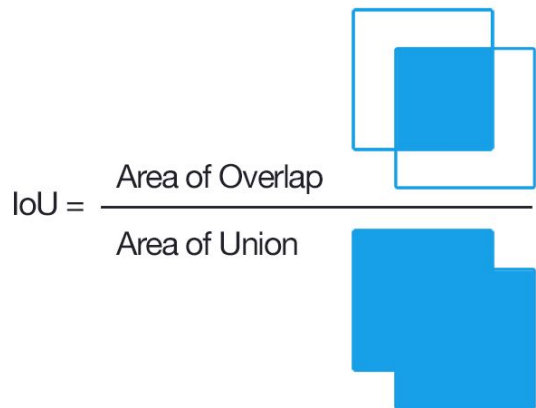


3D reconstruction from single RGB image

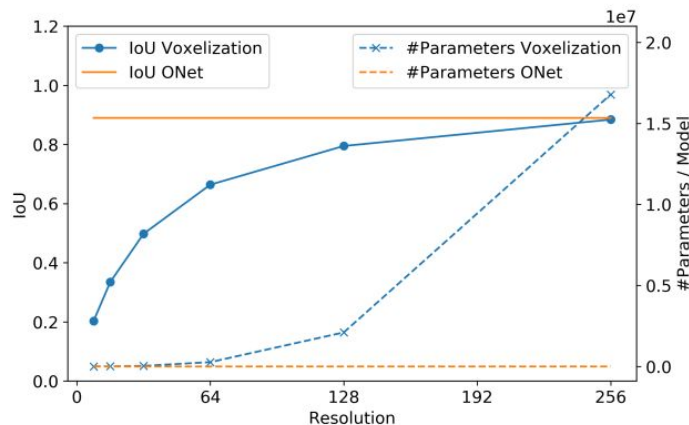


IoU metric

$$IoU(A, B) = \frac{|A \cap B|}{|A \cup B|}$$



- Can calculate volume of the objects.
- Volume VS surface.
- Can have different insides.
- Not so good for point clouds and voxels.



Chamfer and normal loss/distance

$$\Lambda_{P,Q} = \{(p, \arg \min_{q \in Q} \|p - q\|) : p \in P\},$$

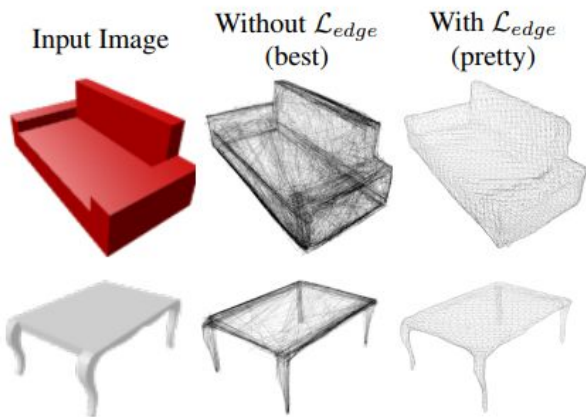
$$\mathcal{L}_{cham}(P, Q) = |P|^{-1} \sum_{(p,q) \in \Lambda_{P,Q}} \|p - q\|^2 + \sum_{(q,p) \in \Lambda_{Q,P}} \|q - p\|^2$$

$$\mathcal{L}_{norm}(P, Q) = -|P|^{-1} \sum_{(p,q) \in \Lambda_{P,Q}} |u_q \cdot u_p| - |Q|^{-1} \sum_{(q,p) \in \Lambda_{Q,P}} |u_p \cdot u_q|$$



Edge loss / regularizer

$$\mathcal{L}_{edge}(V, E) = \frac{1}{|E|} \sum_{(v, v') \in E} \|v - v'\|^2, \quad E \subseteq V \times V.$$



Smooth loss / regularizer

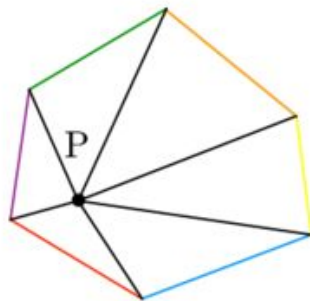
$$\mathcal{L}_{sm}(x) = \sum_{\theta_i \in \mathcal{E}} (\cos \theta_i + 1)^2.$$



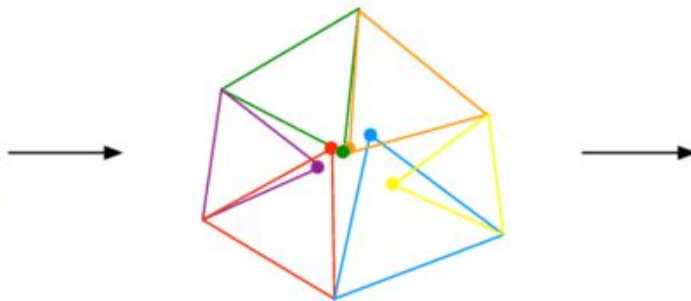
Laplacian loss / regularizer

$$\mathcal{U}(\mathbf{p}) = \frac{1}{n} \sum_{i=0}^{n-1} \mathbf{p}_i - \mathbf{p} \quad \delta_p = p - \sum_{k \in \mathcal{N}(p)} \frac{1}{\|\mathcal{N}(p)\|} k,$$

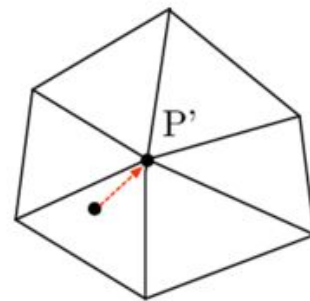
Initial configuration



Each edge of the ball propose an optimal new position for P



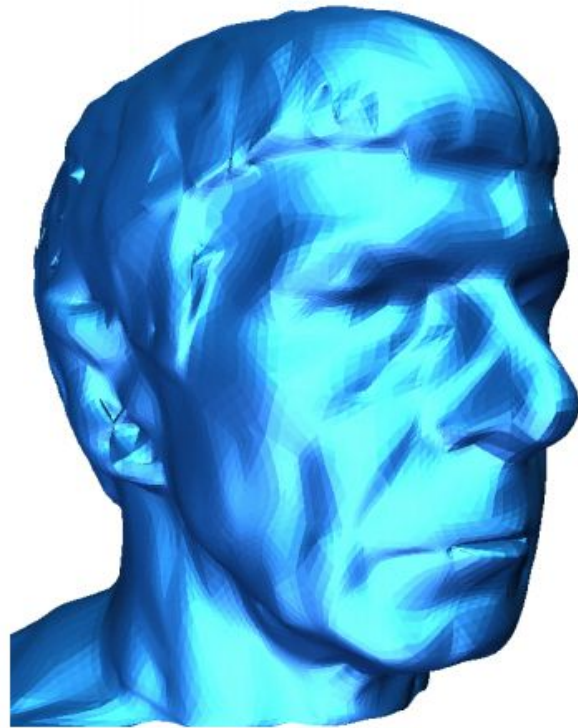
New configuration



Laplacian loss / regularizer

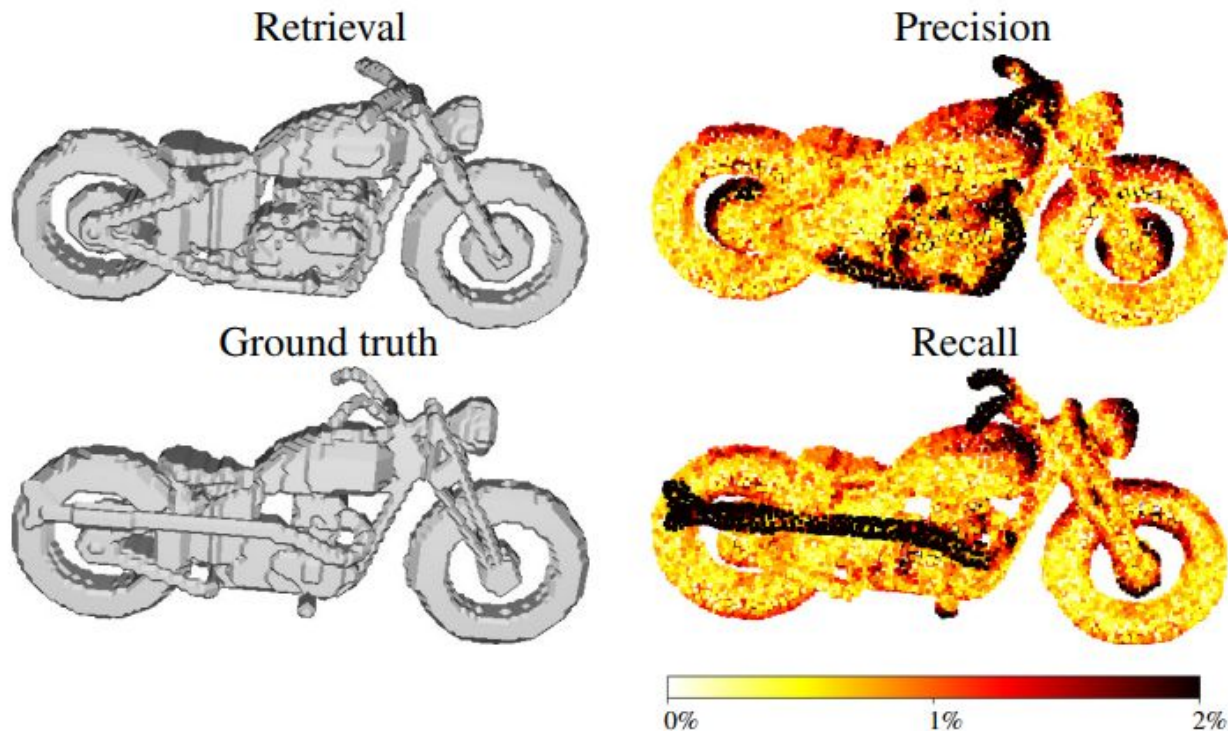


(a)

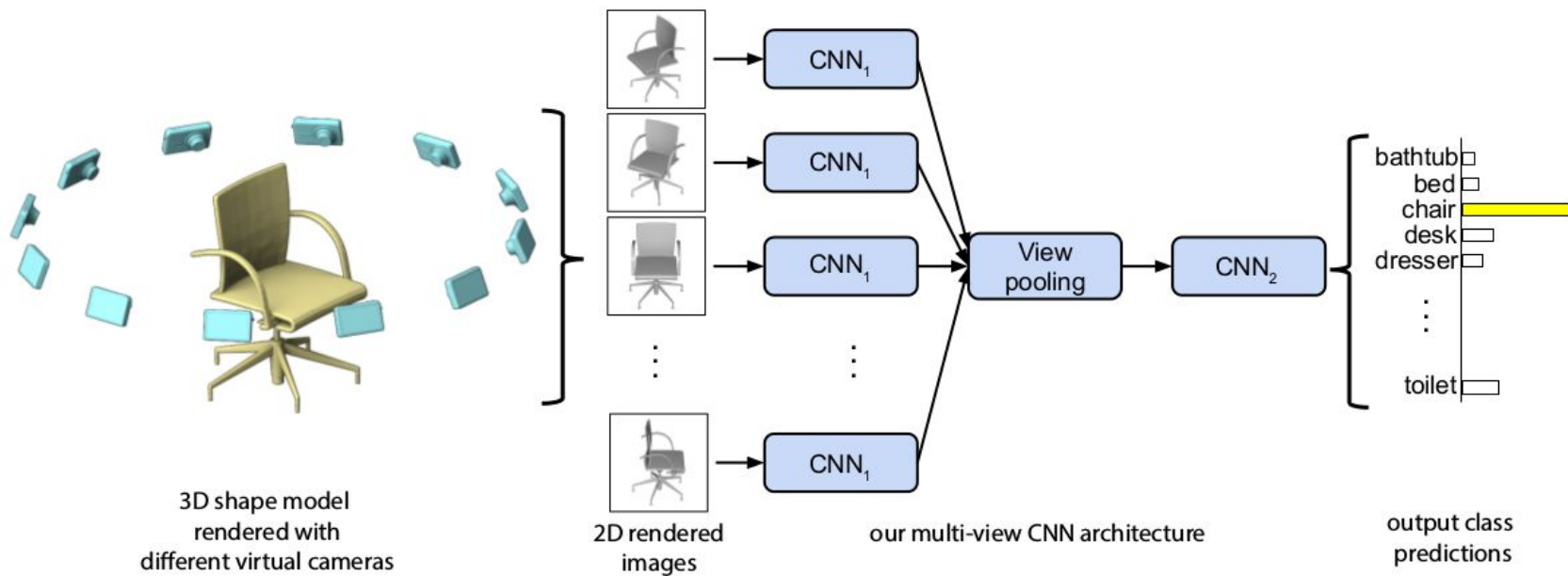


(b)

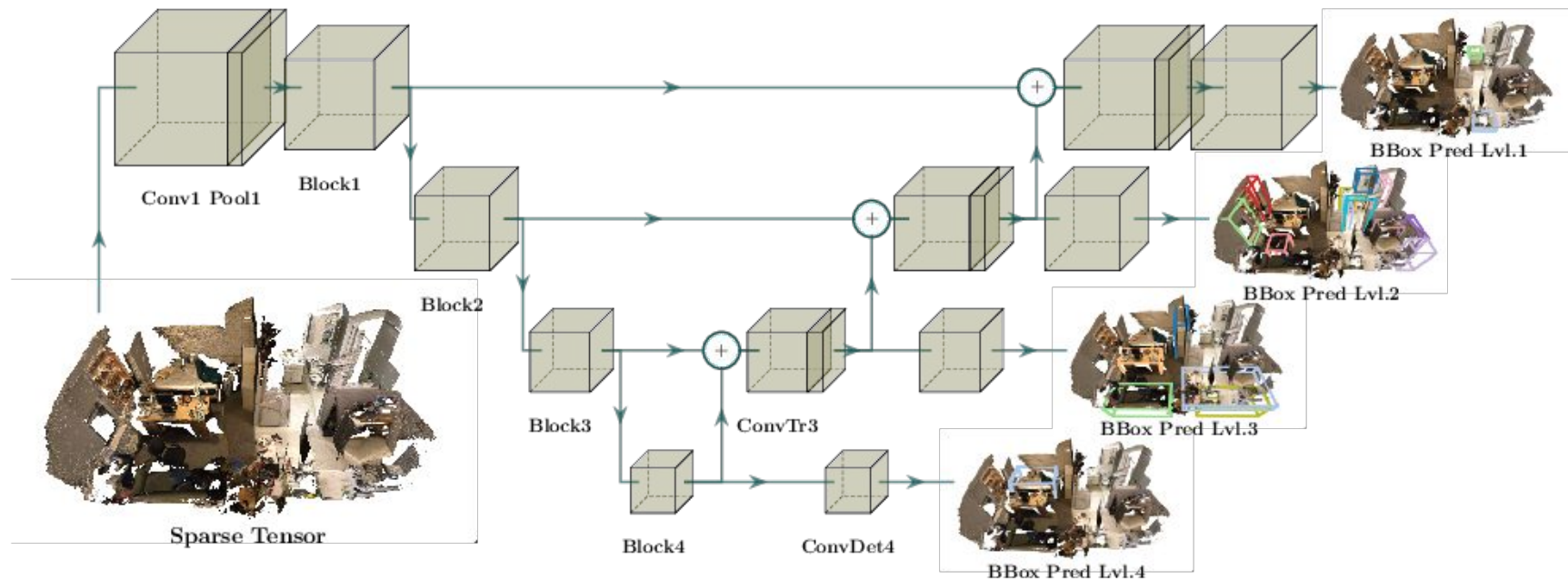
Other metrics (f1 score, Hausdorff losses, etc)



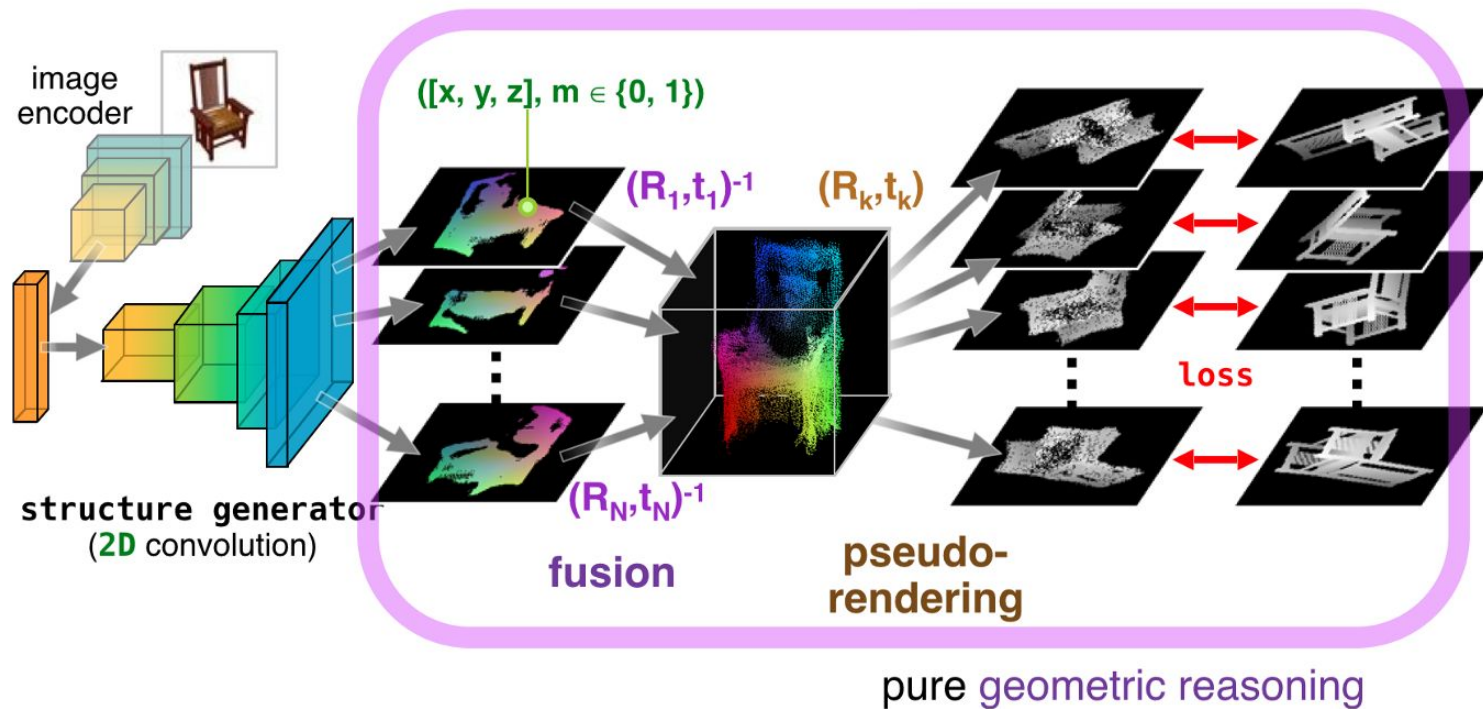
Possible networks



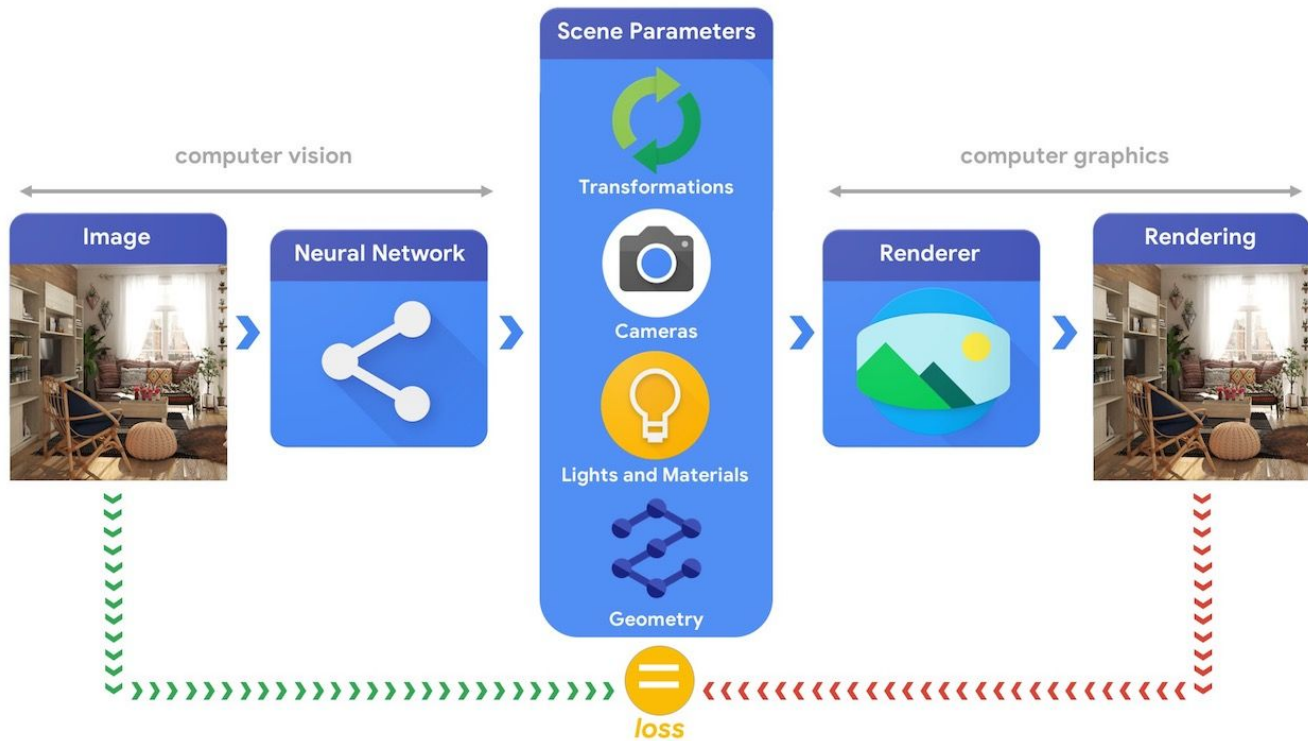
Possible networks



Possible Networks



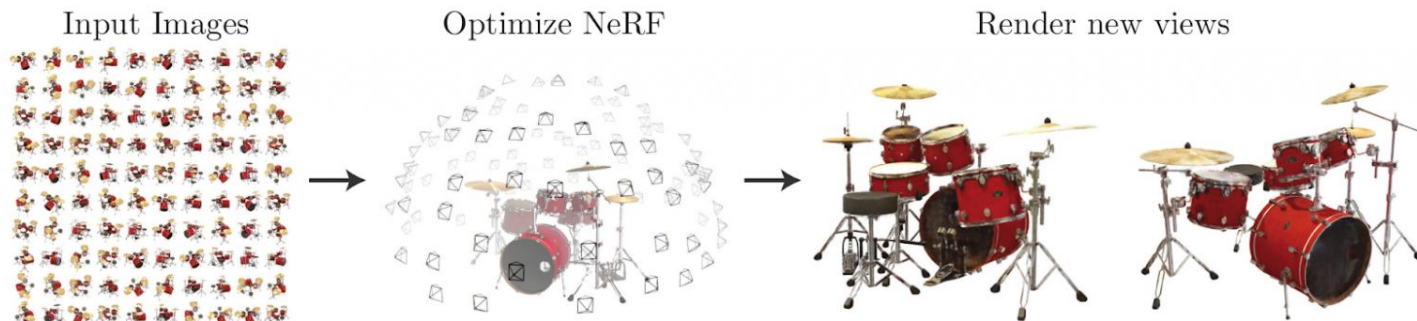
Rendering



NeRF



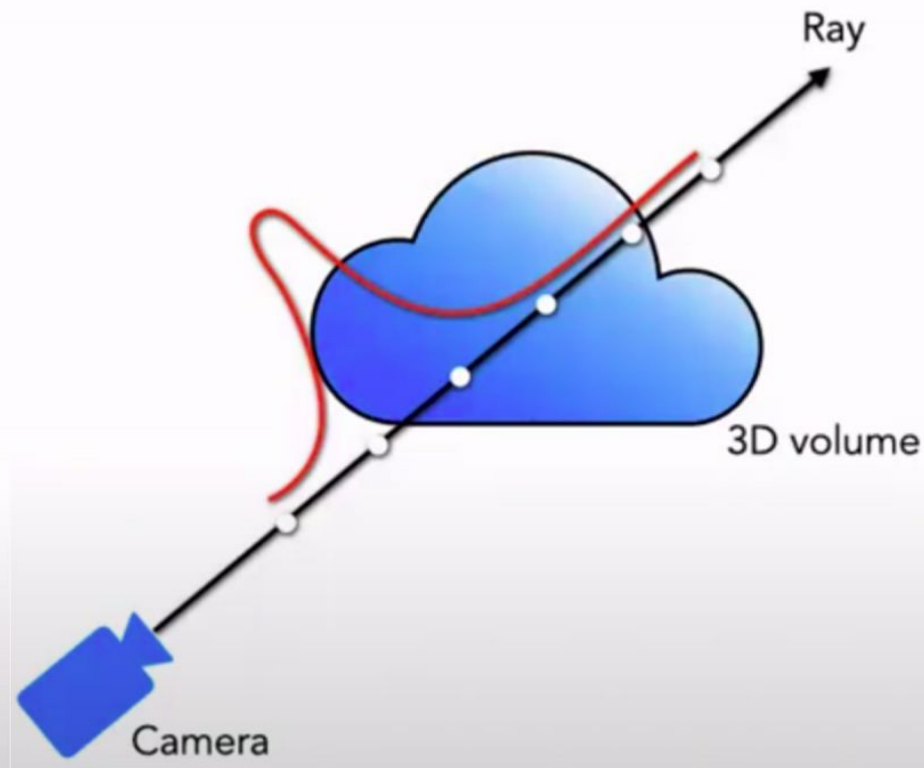
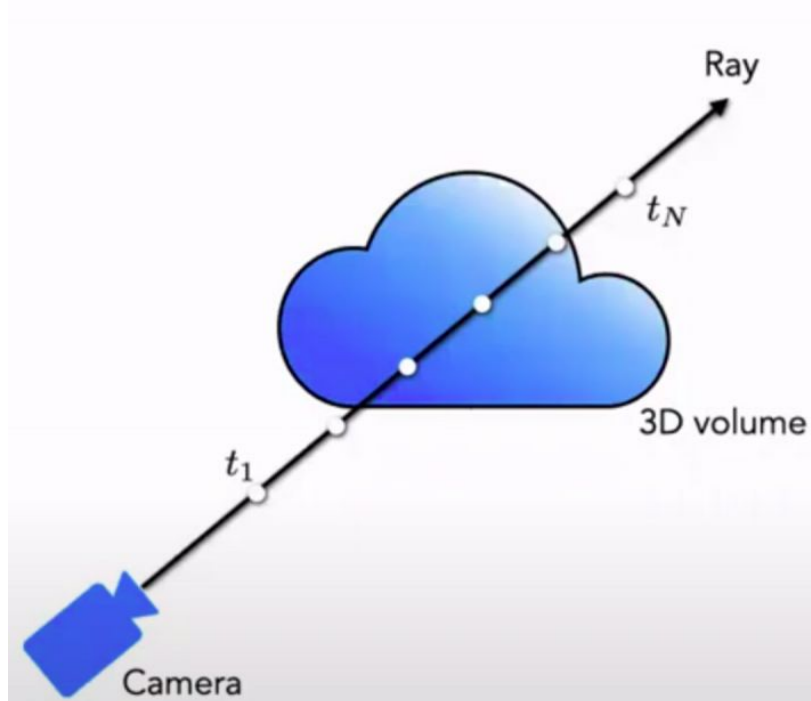
NeRF(Neural Radiance Fields)



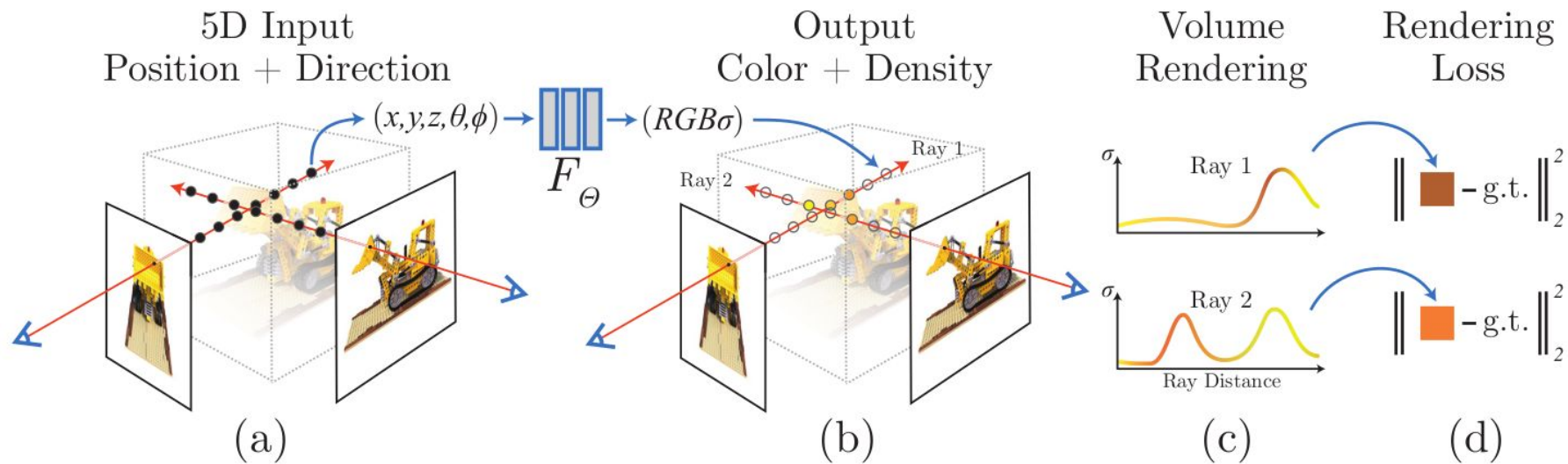
$$(x, y, z, \theta, \phi) \rightarrow \begin{matrix} \text{[Blue Box]} \\ \text{[Grey Box]} \\ \text{[Grey Box]} \end{matrix} \rightarrow (RGB\sigma)$$

F_{Θ}

NeRF(Neural Radiance Fields)



NeRF



NeRF



Recap

- 3D applications
- 3D data representations
- Some losses for 3D tasks
- One really popular model (NeRF)