Introduction to Neural Scene Representation and Neural Rendering

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We Live in a World that is 3D and Contains Dynamics

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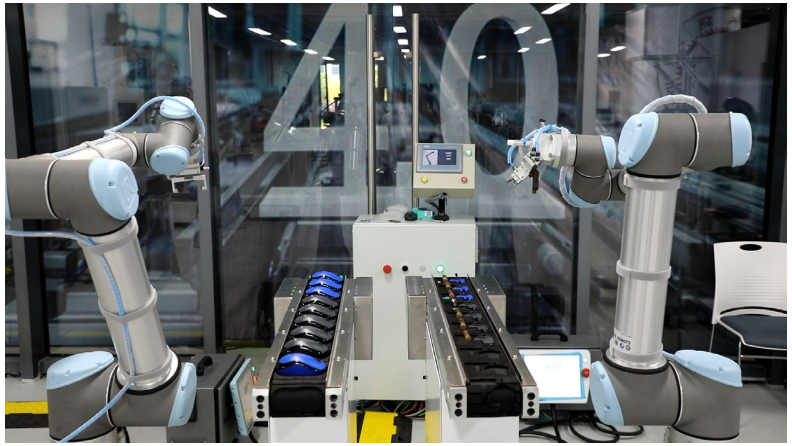
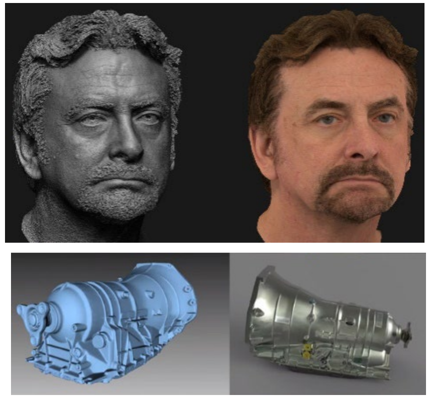
We Digitize Our World in 3D

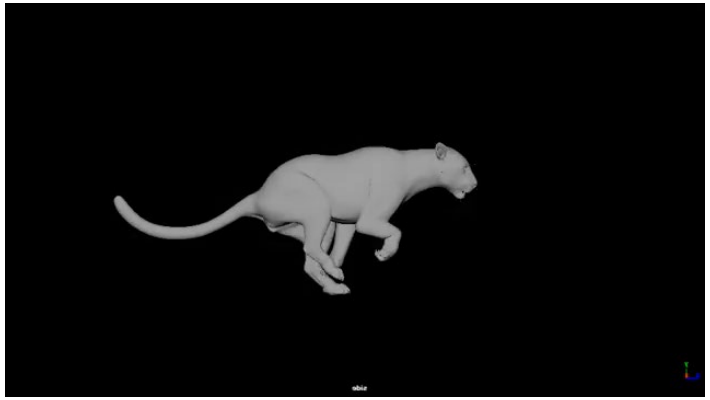
Future AI: Towards 3D Aware

3D Reconstruction of Real-world Scenes





Geometry
+ Appearance



Motion
+ Deformation

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Photo-realistic Rendering

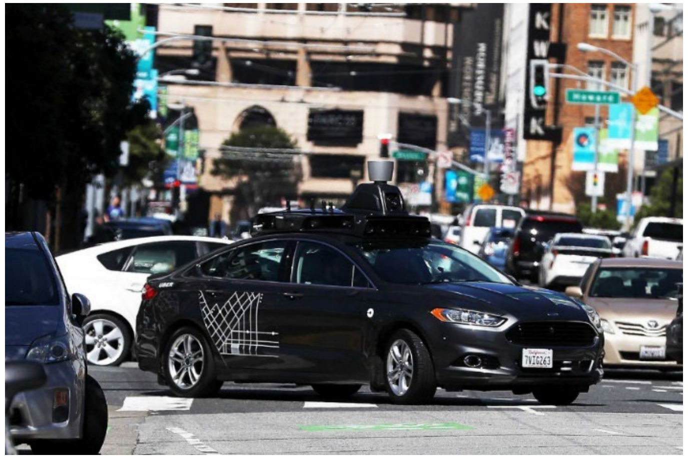
- **Image Synthesis** of Real-world Scenes with 3D Control.

Applications

AR / VR

Gaming / Movie

Healthcare



Autonomous Driving

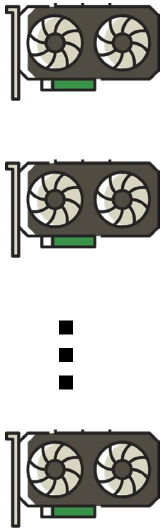
Robot Grasping

Human-robot Interaction

Why are they challenging?

Problem formulation

Captured images → Processing → Rendering of real-world place



[Mildenhall et al., Neural Radiance Fields (NeRF), ECCV 2020]
[Wu et al., Scalable Neural Indoor Scene Rendering, SIGGRAPH 2022]

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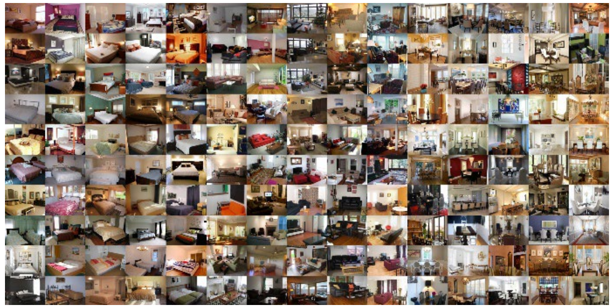
Classical Computer Graphics Pipeline



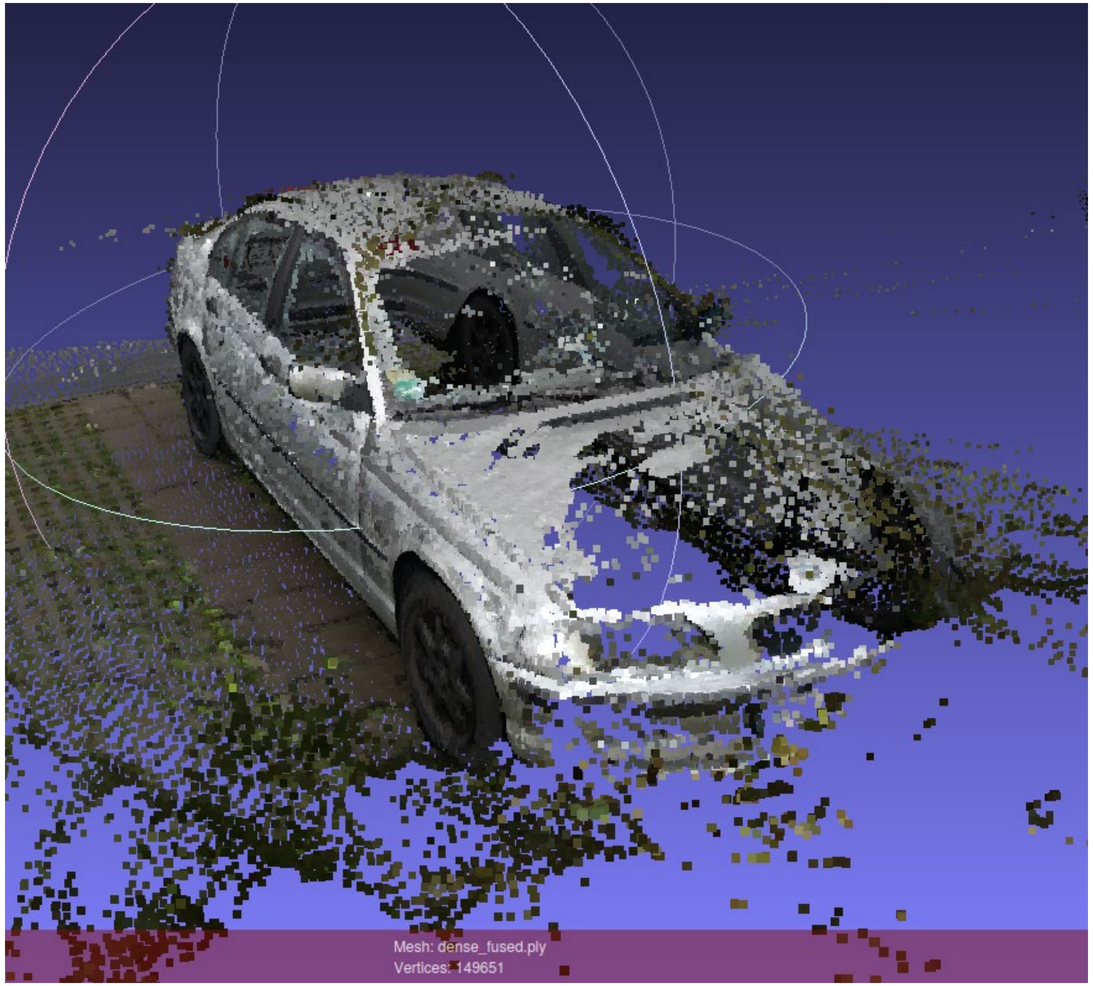
3D Reconstruction

Image Synthesis

Image-based 3D Reconstruction

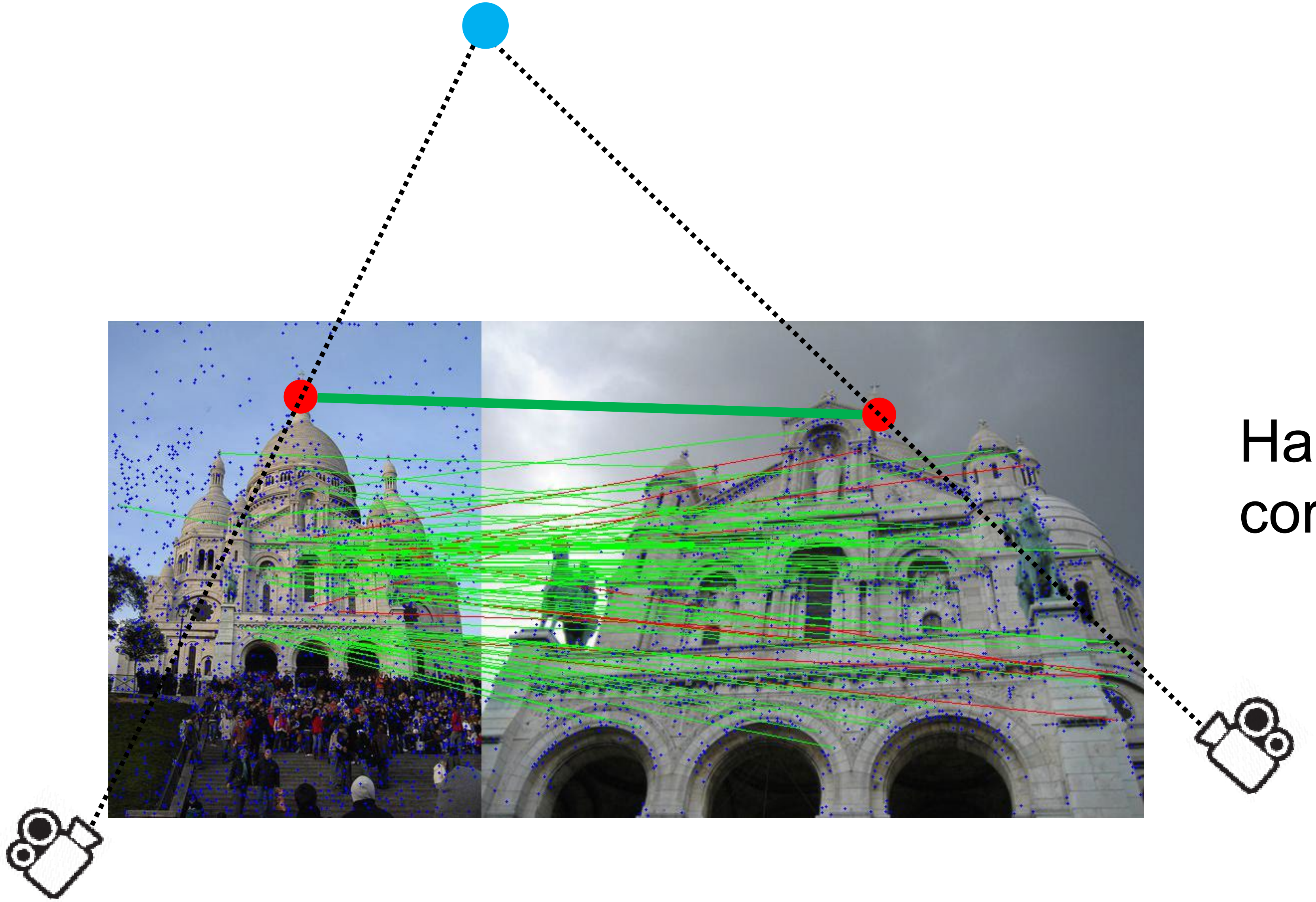
Computer Graphics Rendering

Image-based 3D Reconstruction



COLMAP [Johannes et al. 2016, Schoenberger et al. 2016]
(Input: 100 images)

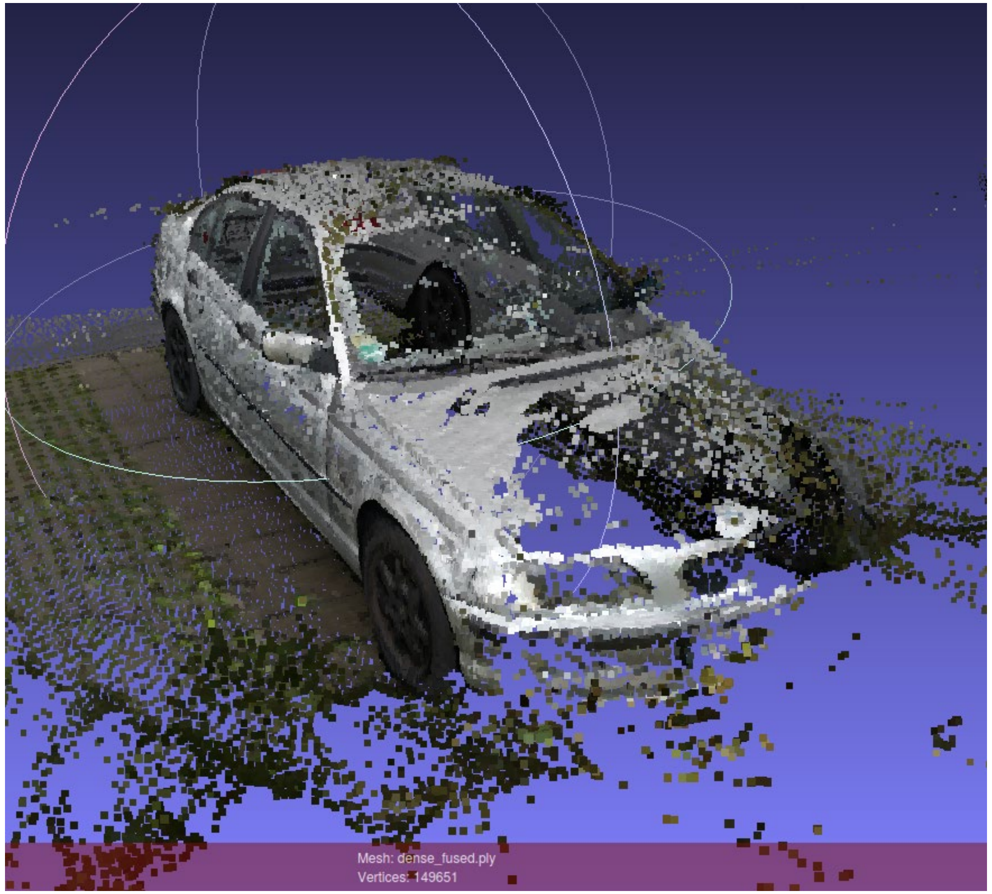
Challenges in Image-based Reconstruction



Hard to extract reliable correspondences!

Computer Graphics Rendering

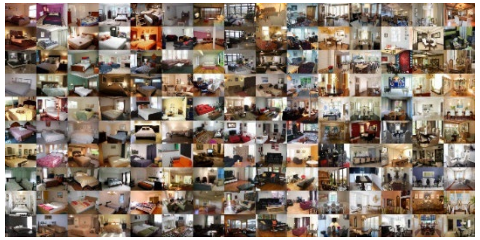
Rendering requires very high-quality 3D models



VS

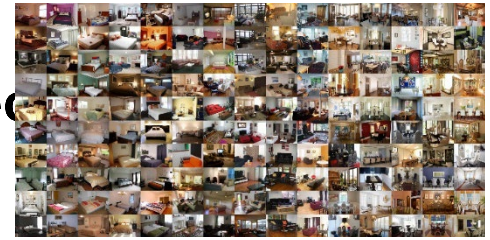
Neural Scene Representation and Neural Rendering
To the rescue

Neural Scene Representation and Neural Rendering



Scene Representation

Neural Rendering



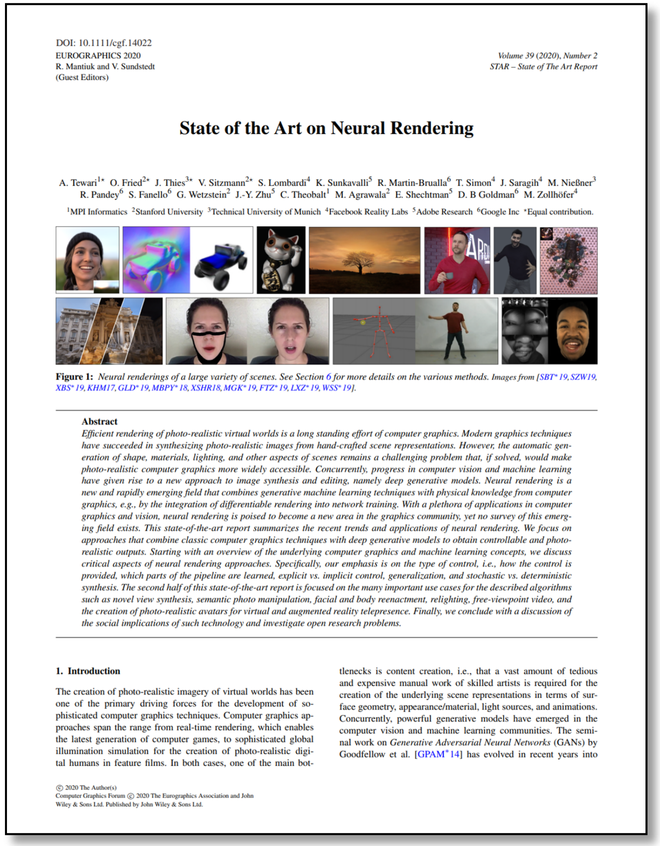
3D Reco

Image Loss

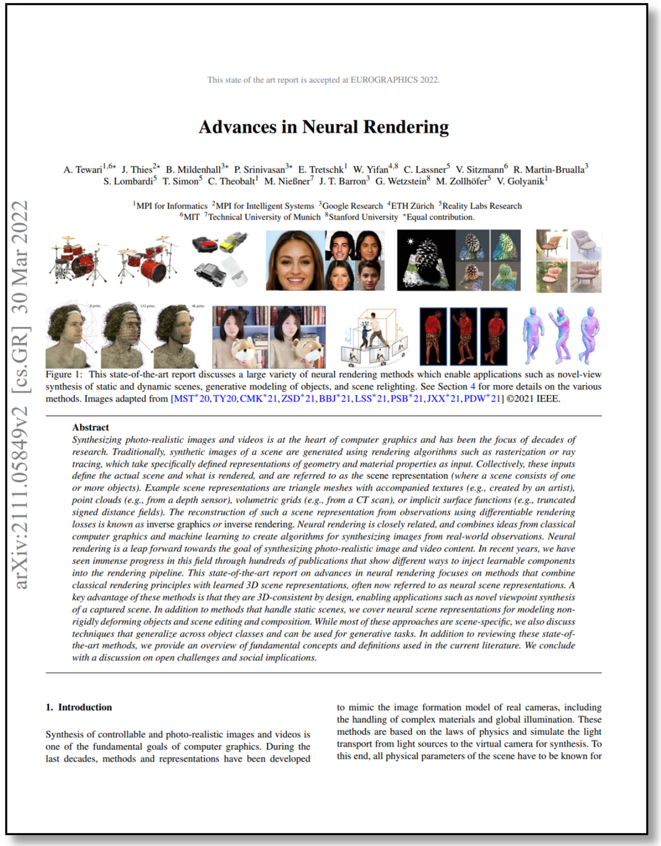
Co puter Graphics Rende g

Neural Scene Representation and Neural Rendering

Neural Rendering



[Tewari et al. 2020]



[Tewari et al. 2021]

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Neural Rendering - Definition

- Definition:

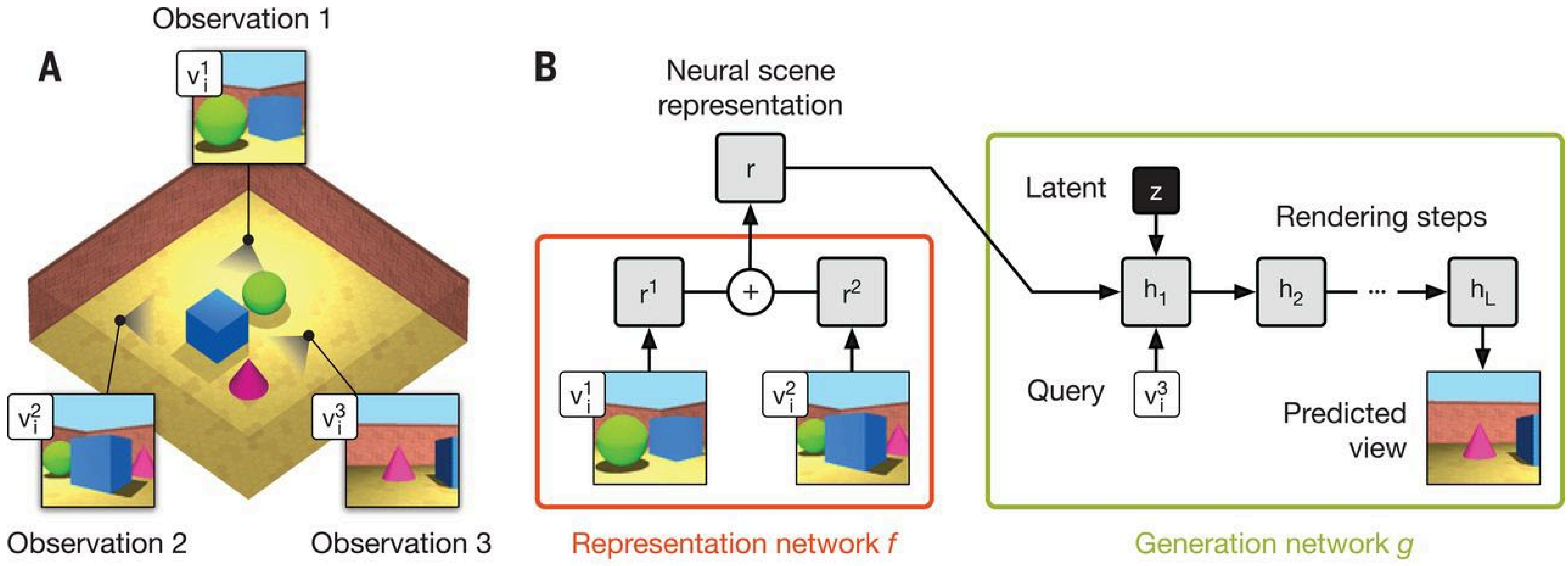
*"Deep neural networks for **image or video generation** that enable **explicit or implicit control** of **scene properties**"*

1)
Generative networks that synthesis raw pixel output

2)
Controllable by interpretable parameters or by video/audio input.

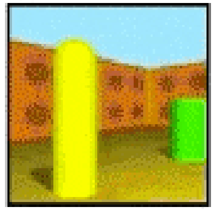
3)
Illumination, camera, pose, geometry, appearance, or semantic structure controllable

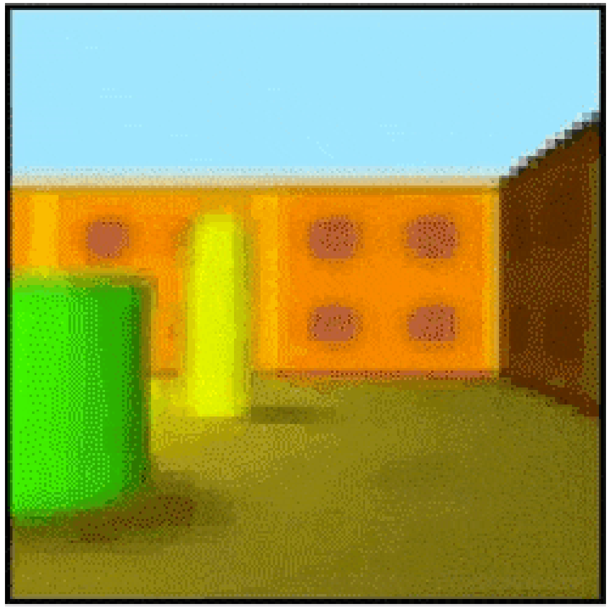
Generative Query Network (GQN)



Neural scene representation and rendering, Eslami et al. 2018

Generative Query Network (GQN)

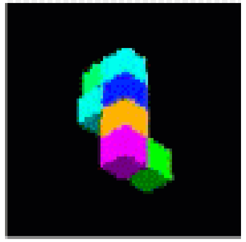




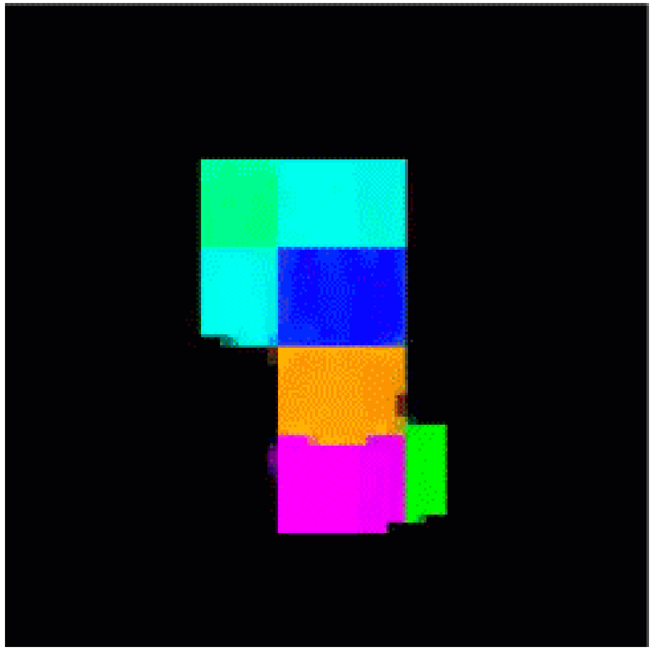
Neural scene representation and rendering, Eslami et al. 2018

Generative Query Network (GQN)

observation



neural rendering



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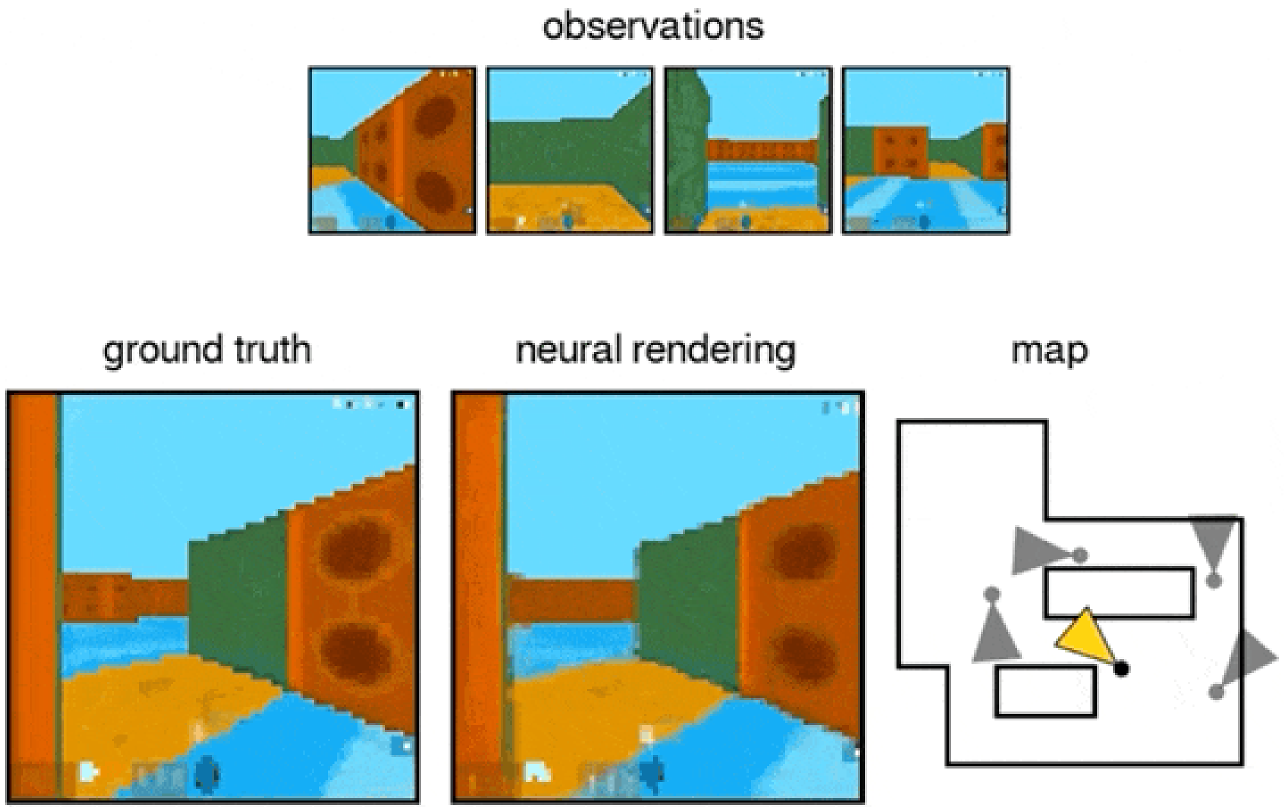


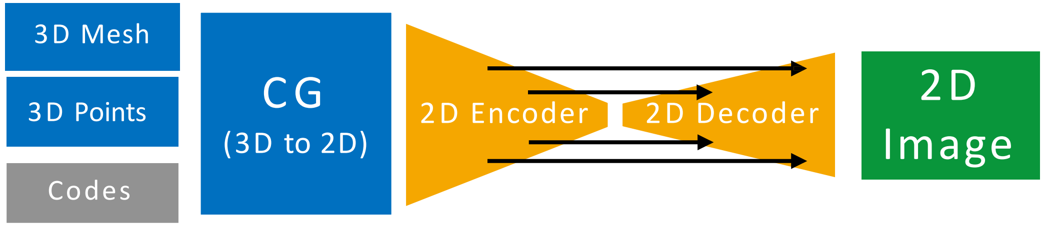
Neural scene representation and rendering, Eslami et al. 2018

Neural Rendering Zoo

“Regress it”

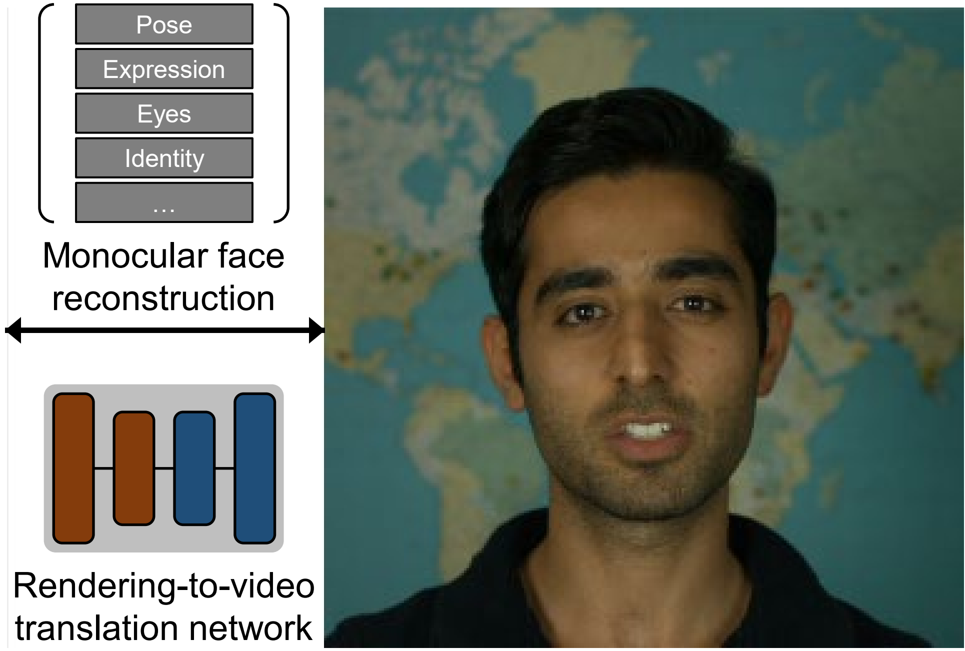
e.g., GQN

”Make it more real”



e.g., DVP or DNR

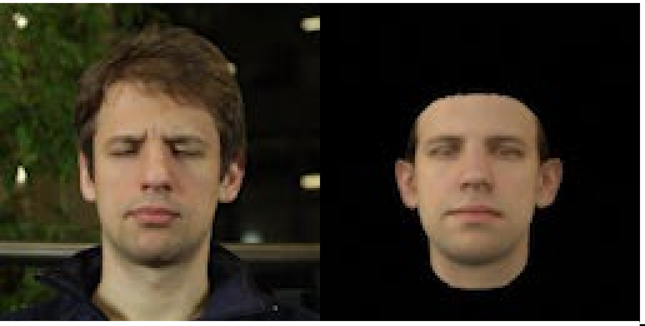
Deep Video Portraits (DVP)



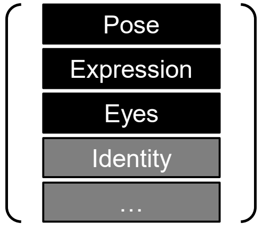
Training video

Deep Video Portraits, Kim et al. 2018

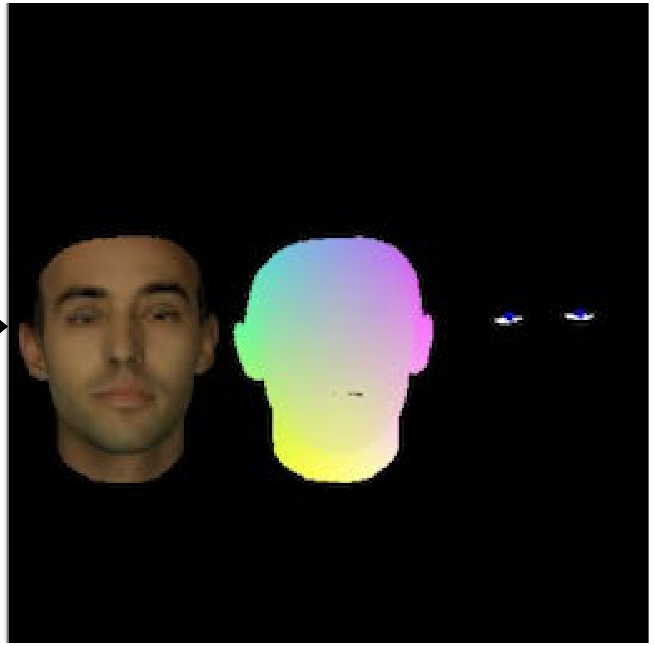
Deep Video Portraits (DVP)



Face reenactment



Modified face parameters

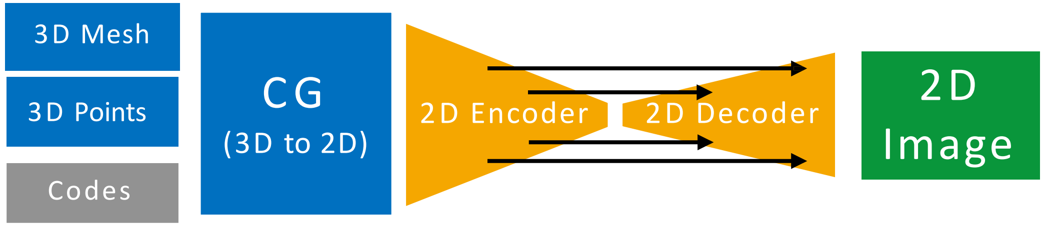
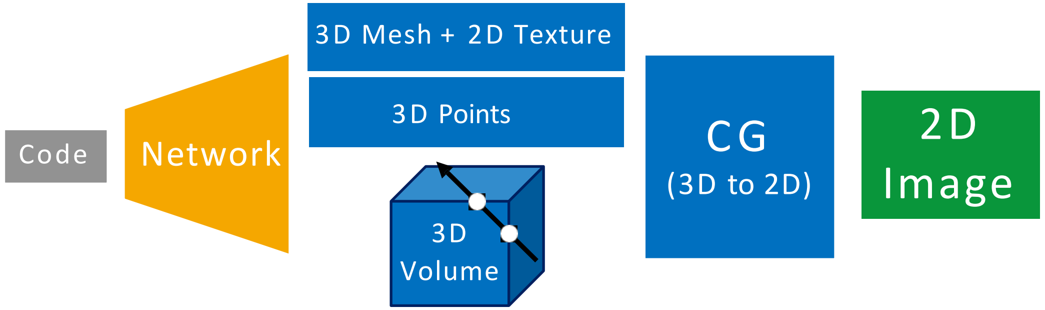


User interaction

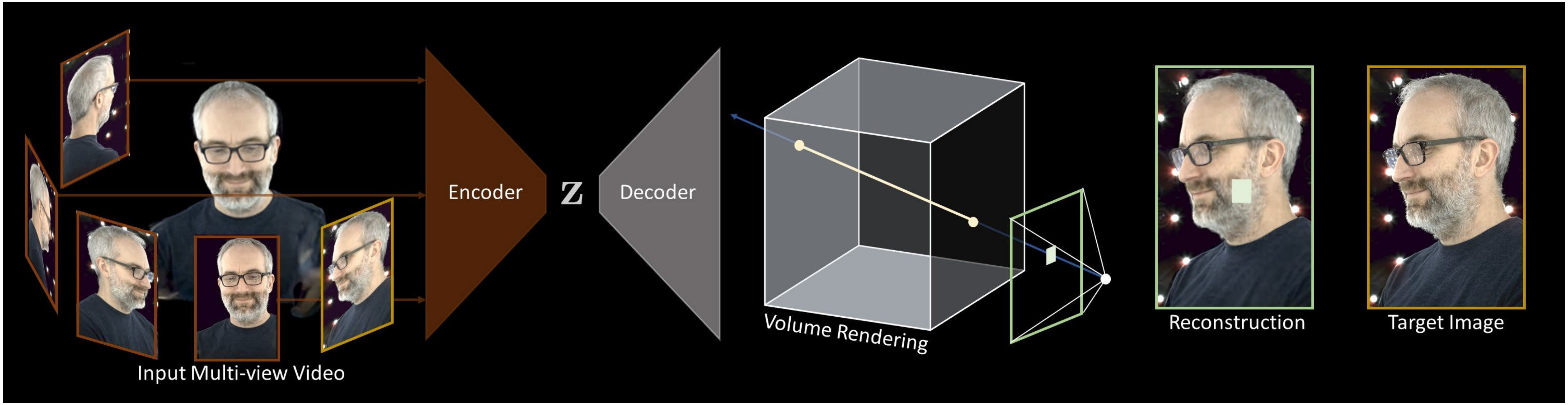
Modified rendering

Deep Video Portraits, Kim et al. 2018

Neural Rendering Zoo

"Regress it"		e.g., GQN
"Make it more real"		e.g., DVP or DNR
"Regress & render"		e.g., Neural Volumes

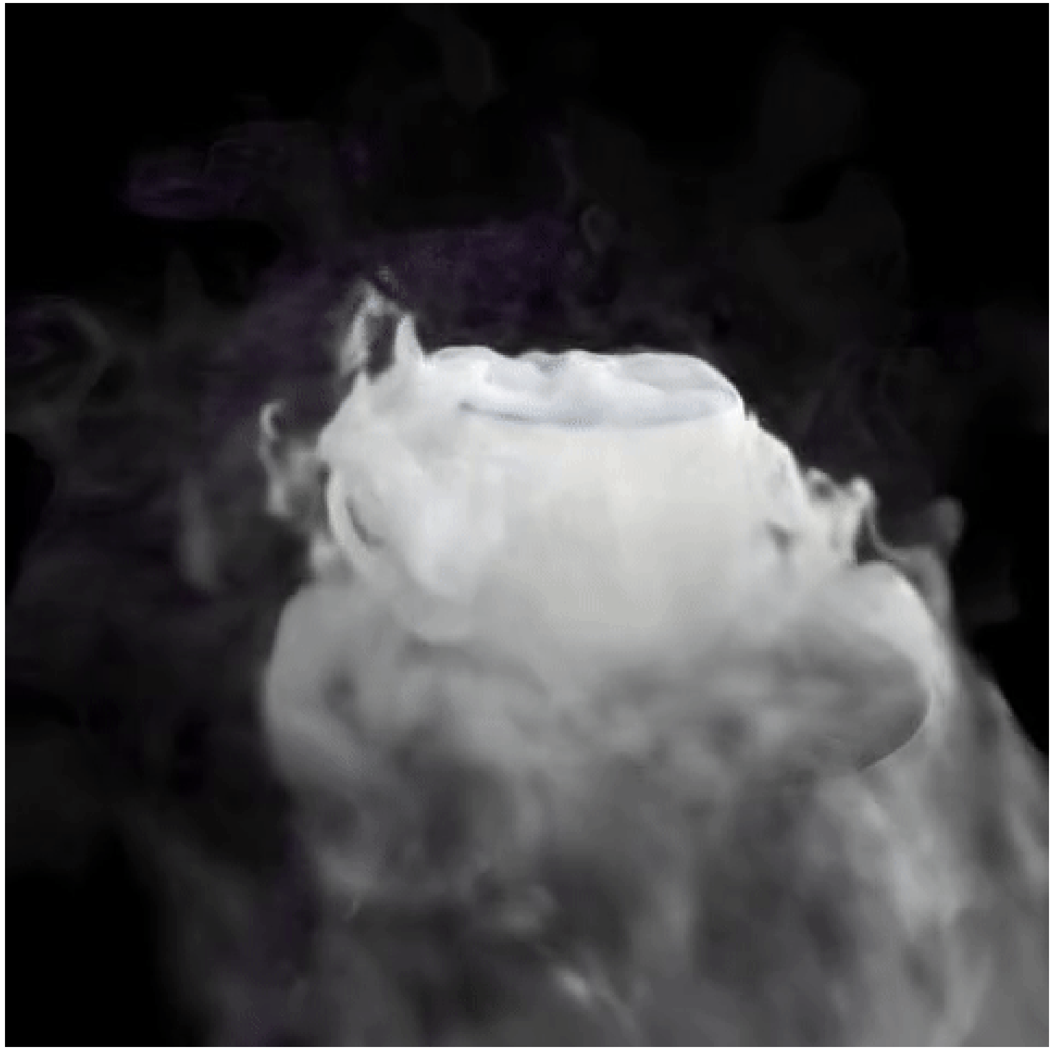
Neural Volumes



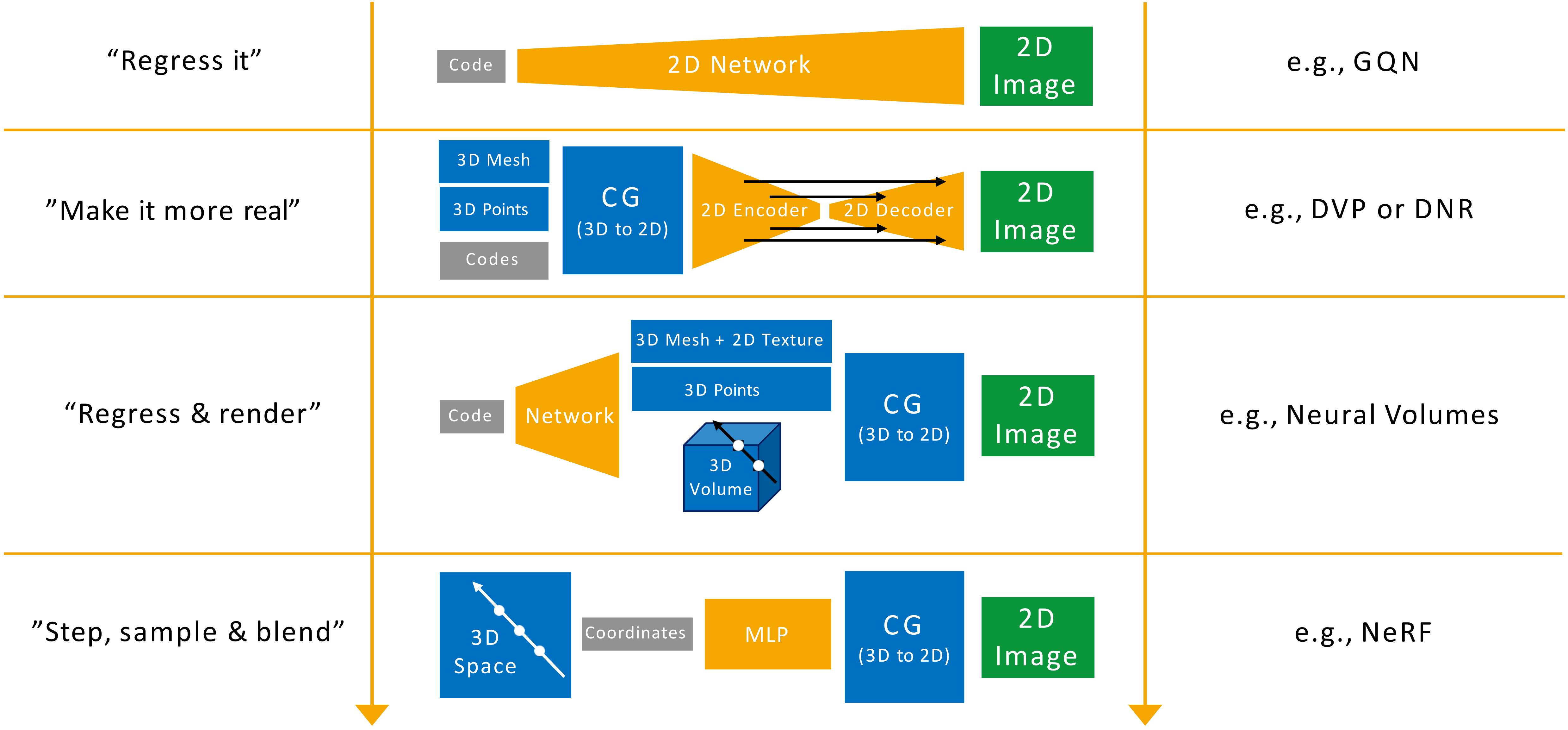
Neural Volumes: Learning Dynamic Renderable Volumes from Images, Lombardi et al. 2019

Neural Volumes

Neural Volumes



Neural Rendering Zoo



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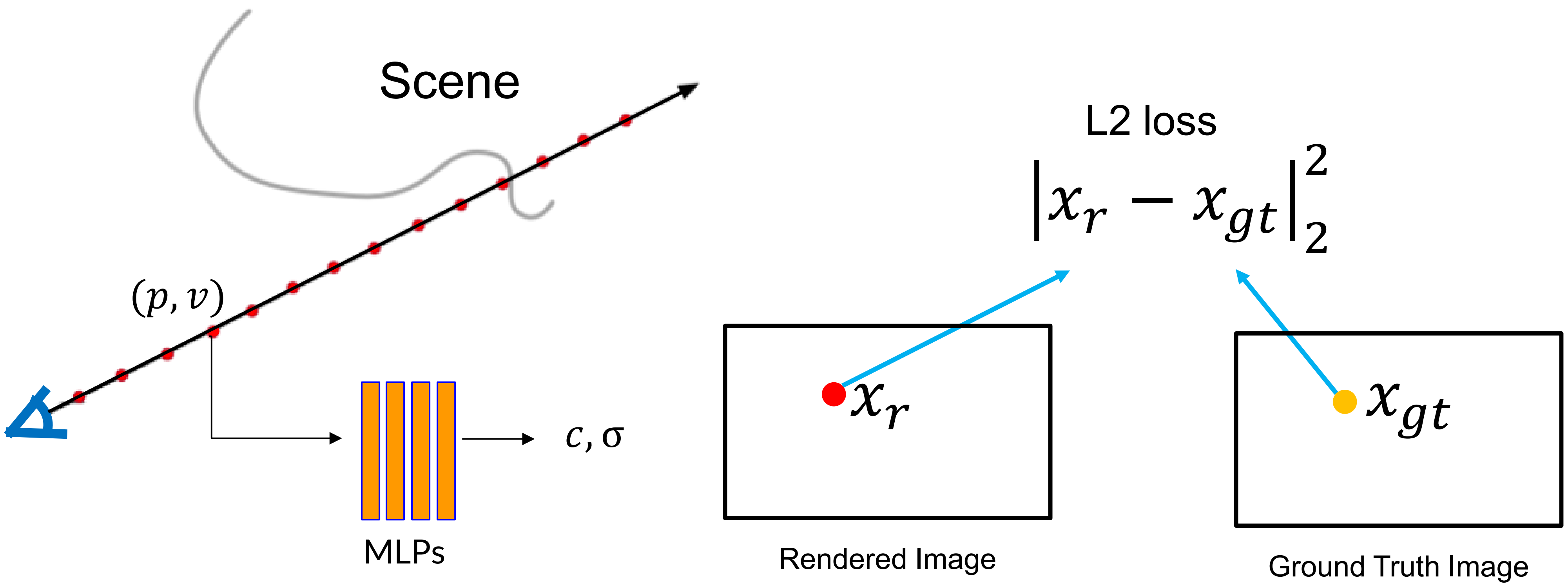
Neural Radiance Fields (NeRF)

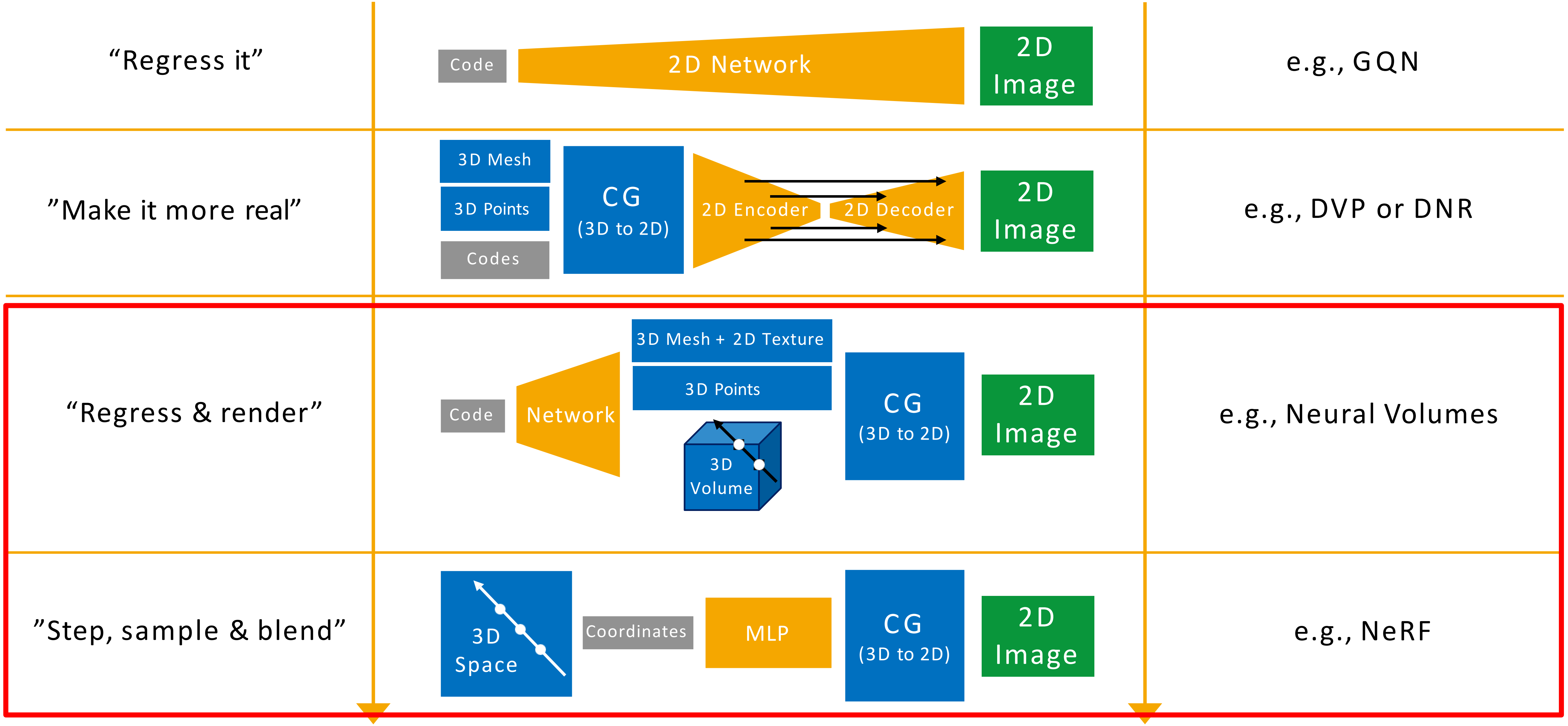


[Mildenhall et al. 2020]

Neural Radiance Fields (NeRF)

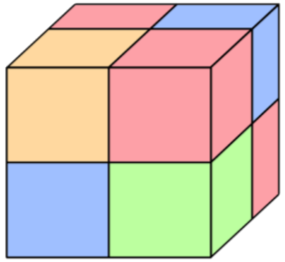
[Mildenhall et al. 2020]

Neural Rendering Zoo

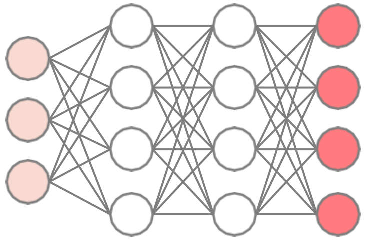


Overview

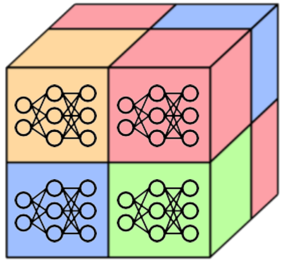
Scene Representation



Voxelgrids



Implicit Function



Hybrid
Implicit/Explicit

• • •

(We'll talk more about other representations in our next class)

Renderer

Volumetric

Sphere-Tracing
Volumetric

Volumetric

Both Scene Representation and Differentiable Renderer often adapted from traditional computer graphics.

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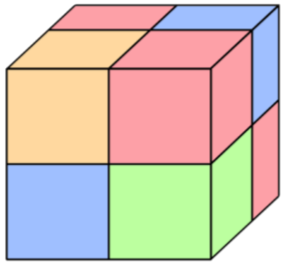
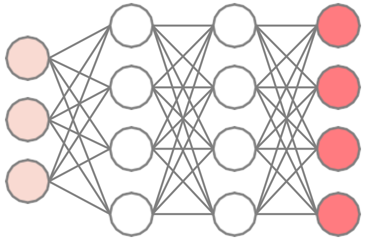
Requirements

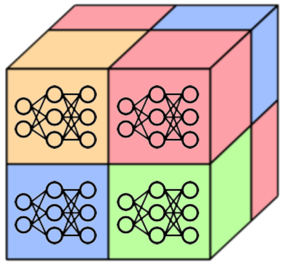
Scene Representation



Voxelgrids



Implicit Function



Hybrid Implicit/Explicit

• • •

Renderer

Volumetric

Sphere-Tracing
Volumetric

Volumetric

Pros

Cons

Voxel-based methods

DeepVoxels

Sitzmann et al., CVPR 2018

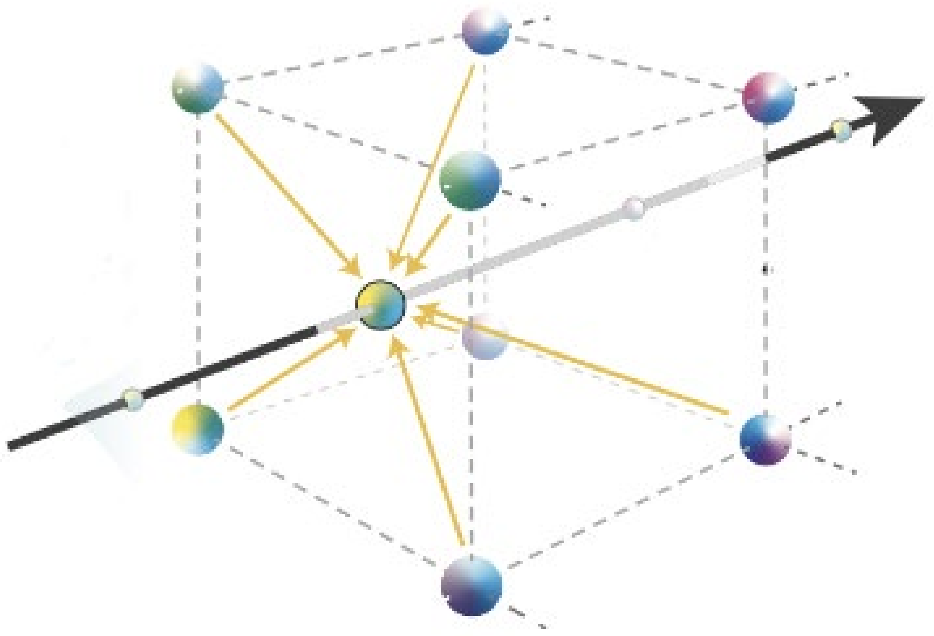
Neural Volumes

Lombardi et al., SIGGRAPH 2019

HoloGAN

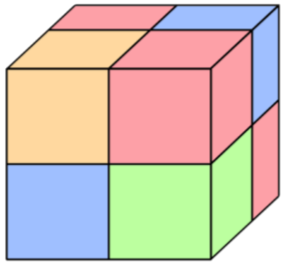
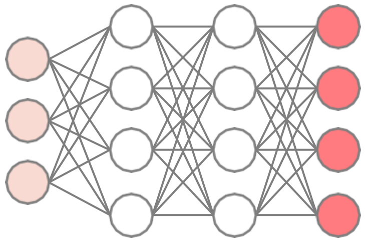
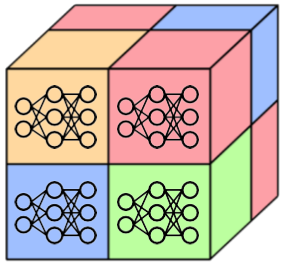
Phuoc et al., ICCV 2019

Voxel-based methods



Trilinear Interpolation

Requirements

				...
Scene Representation	Voxelgrids	Implicit Function	Hybrid Implicit/Explicit	
Renderer	Volumetric	Sphere-Tracing Volumetric	Volumetric	
Pros	Fast rendering			
Cons	Memory $O(n^3)$ Limited spatial resolution			

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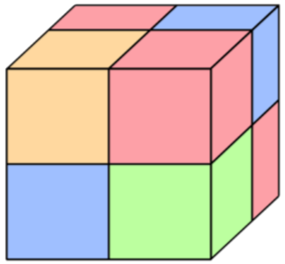
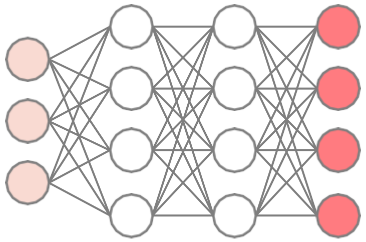
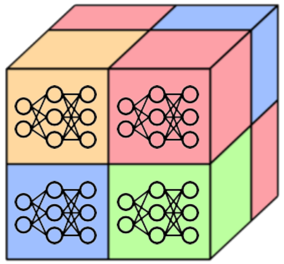
Requirements

Scene Representation	 Voxelgrids	 Implicit Function	 Hybrid Implicit/Explicit	• • •
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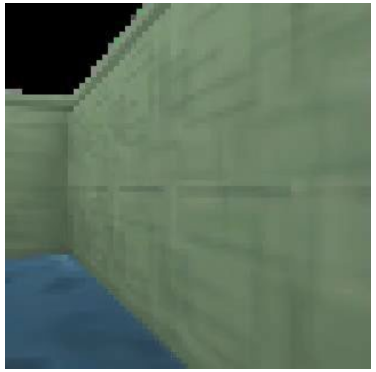
Neural Implicit Approaches

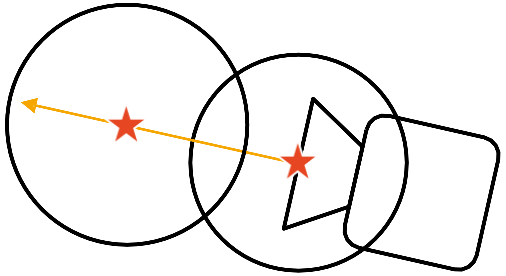


Scene Representation Networks
Generalizes across scenes
Sitzmann et al., NeurIPS 2019

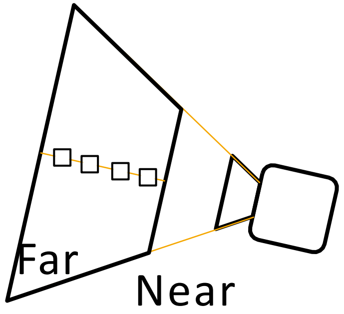
Differentiable Volumetric Rendering
Generalizes across scenes
Niemeyer et al., CVPR 2020

NeRF
Single-scene
Mildenhall et al., ECCV 2020

Implicit Differentiable Renderer
Single-scene
Yariv et al., NeurIPS 2020

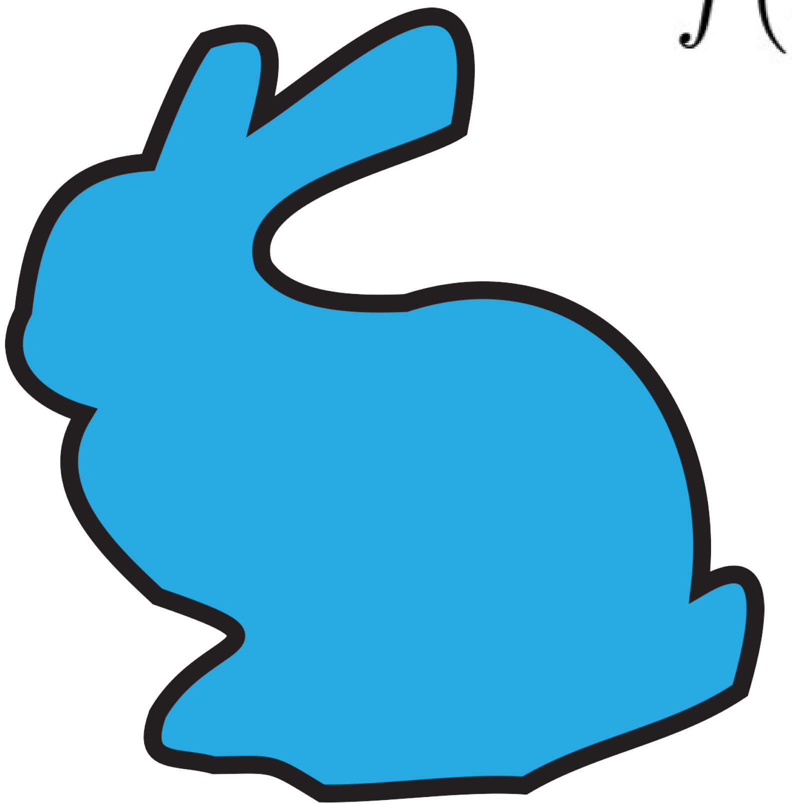


Sphere tracing



Volumetric

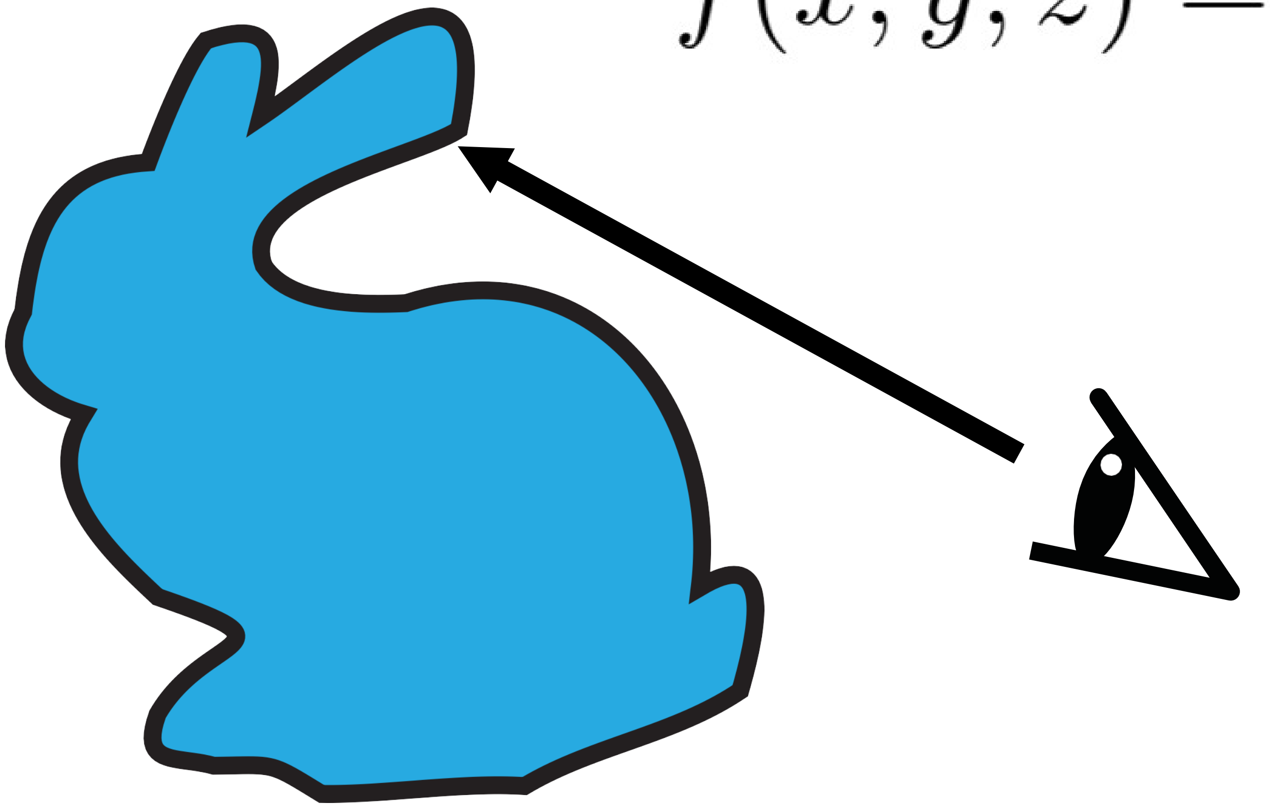
Sphere Tracing



$$f(x, y, z) = d$$

[Source: Takikawa et al]

Sphere Tracing



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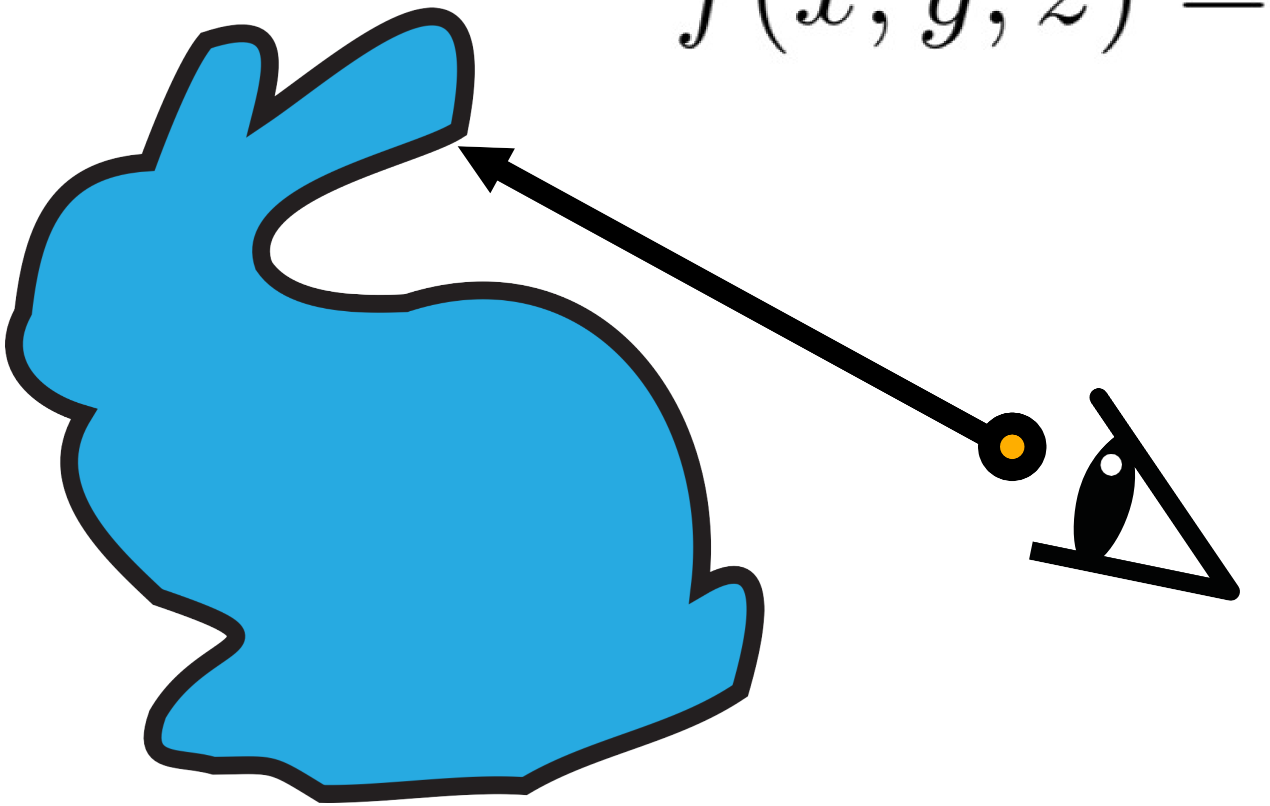

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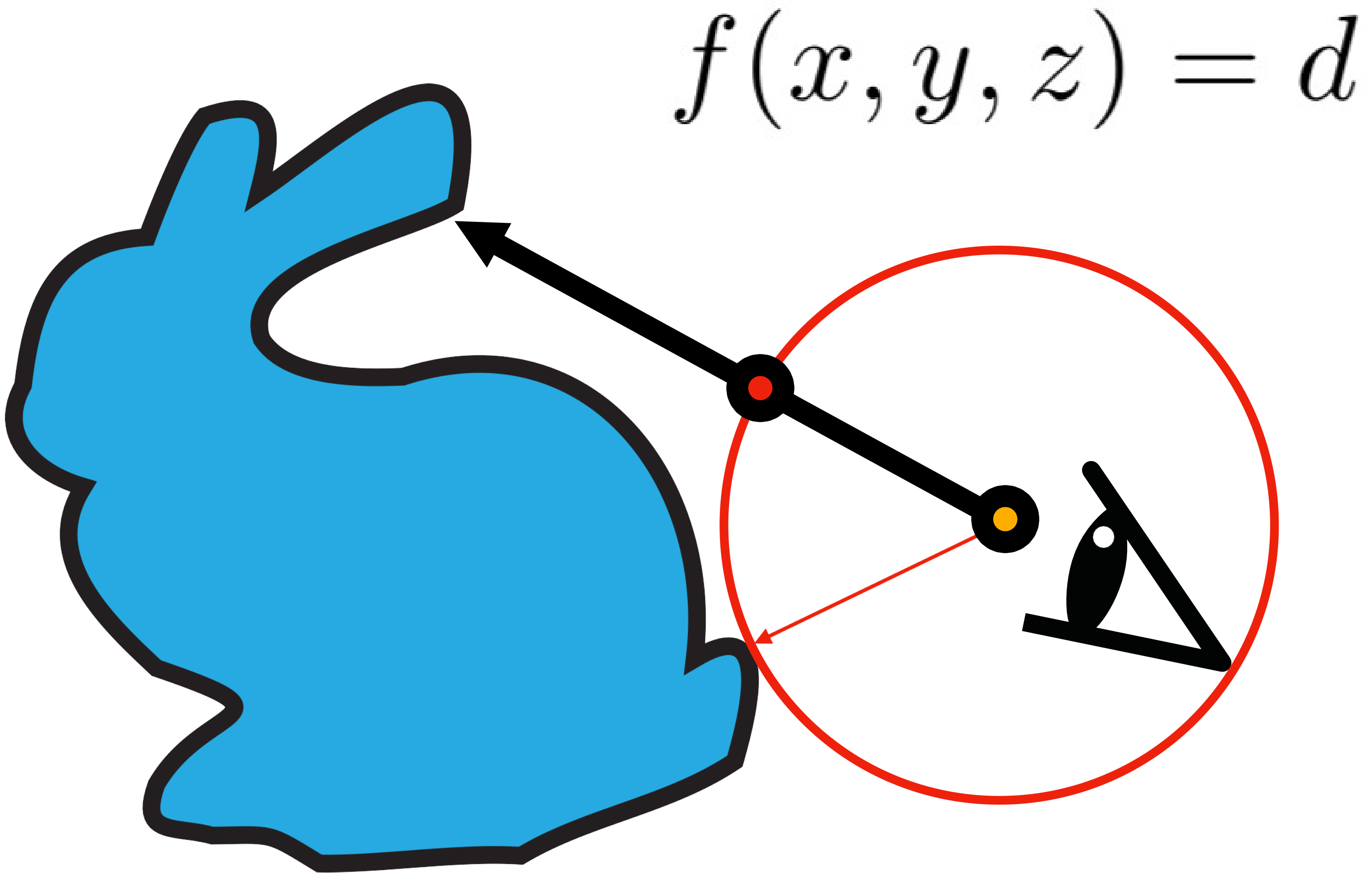

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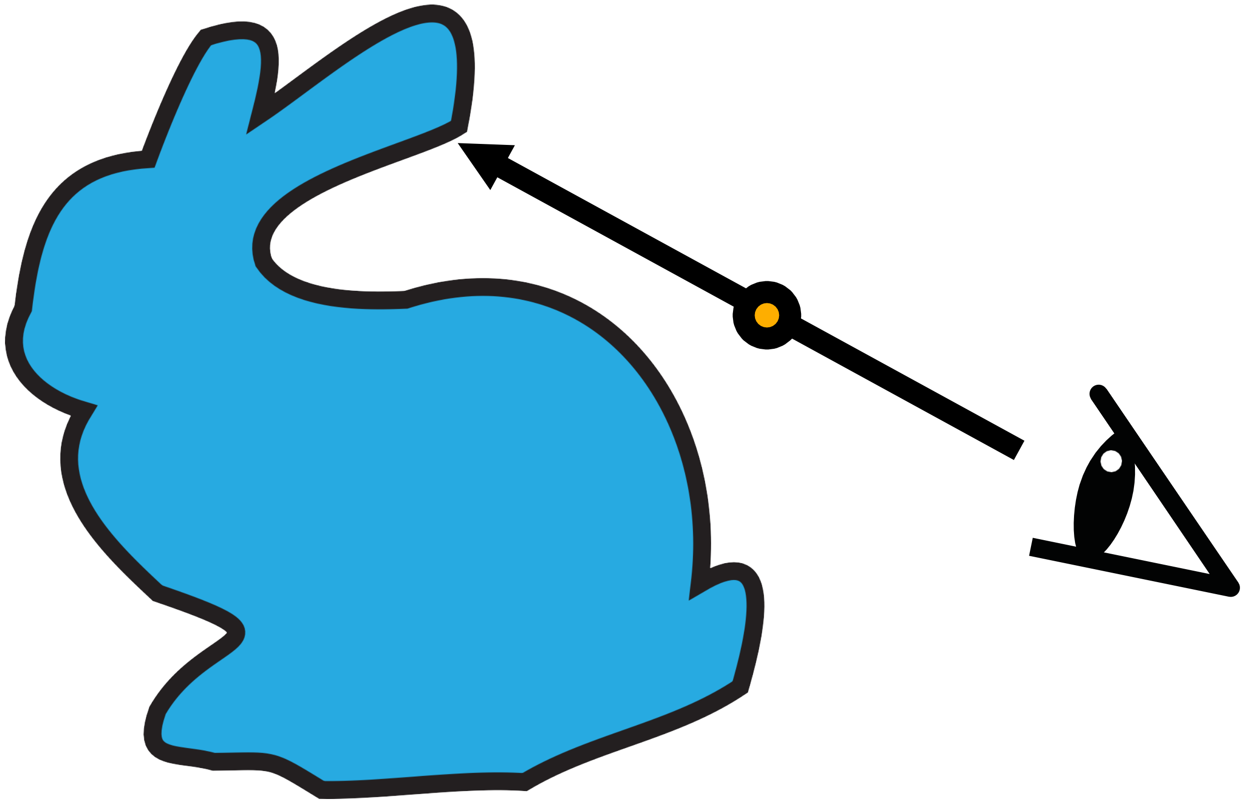

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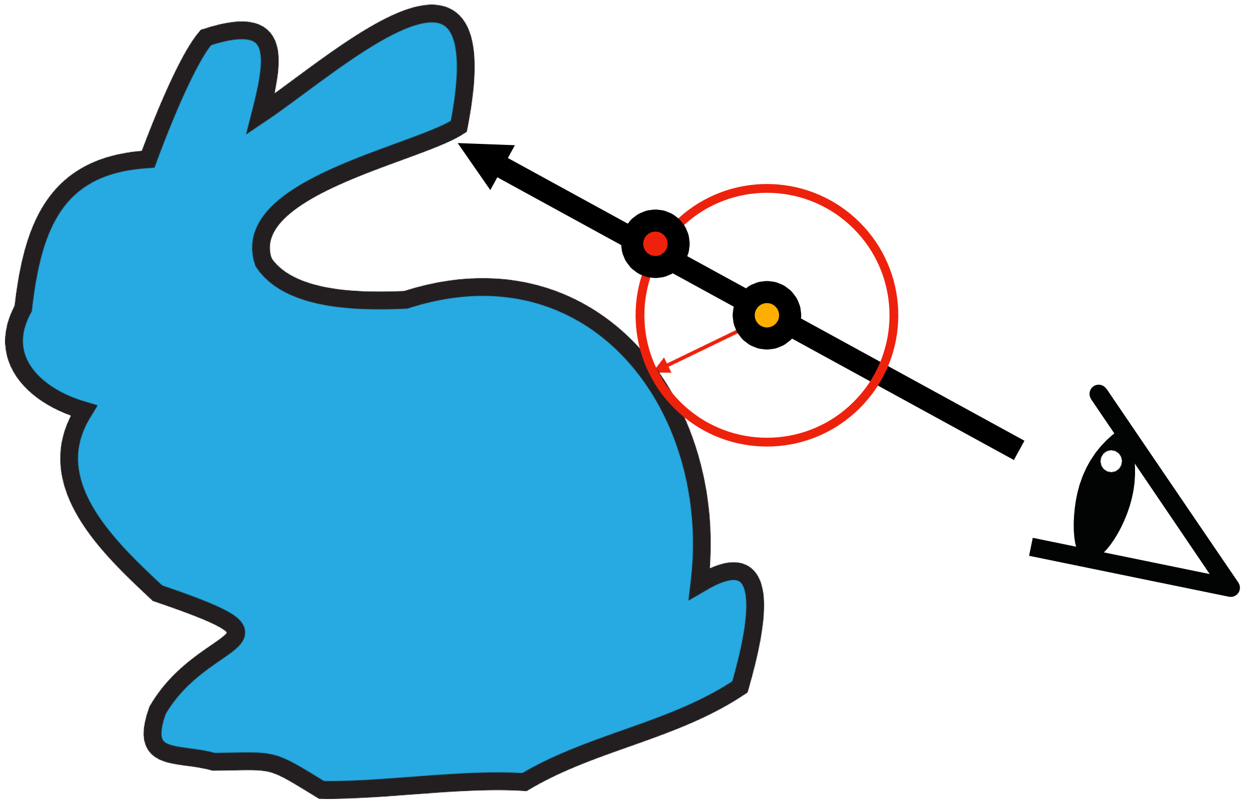

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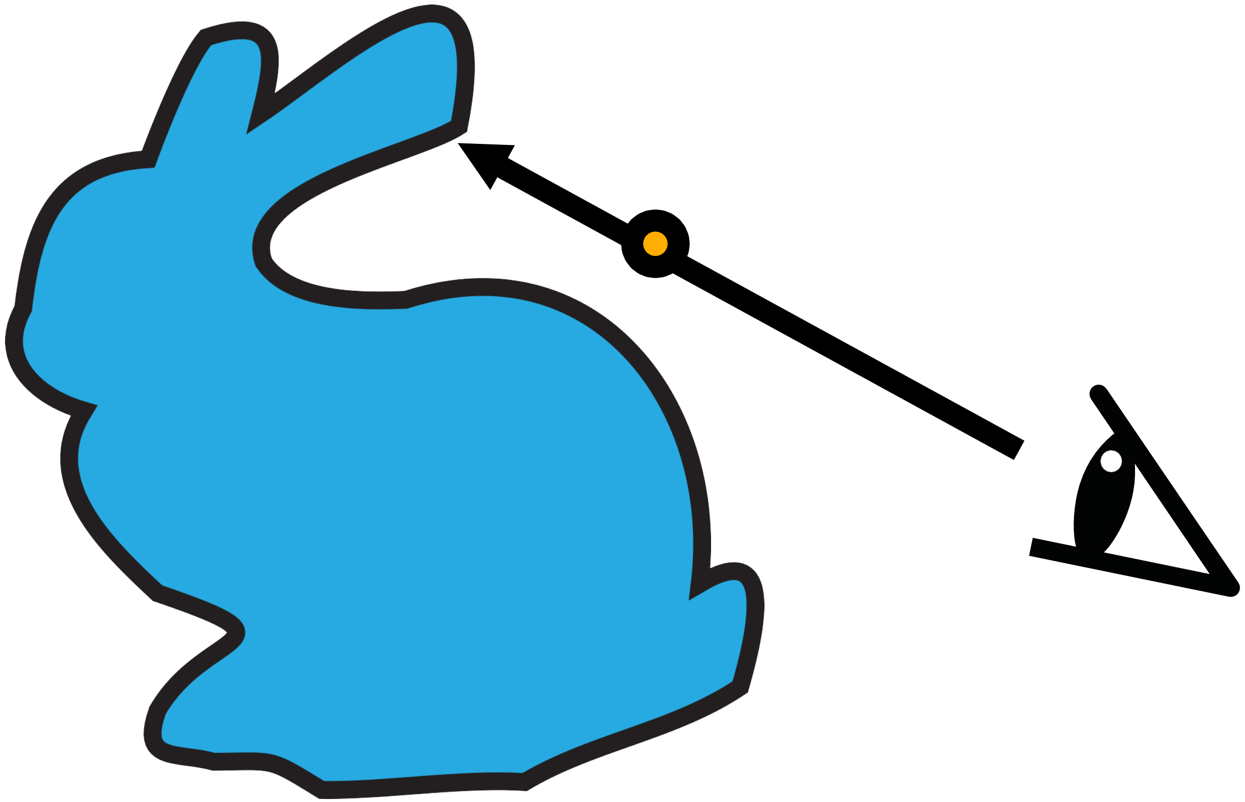

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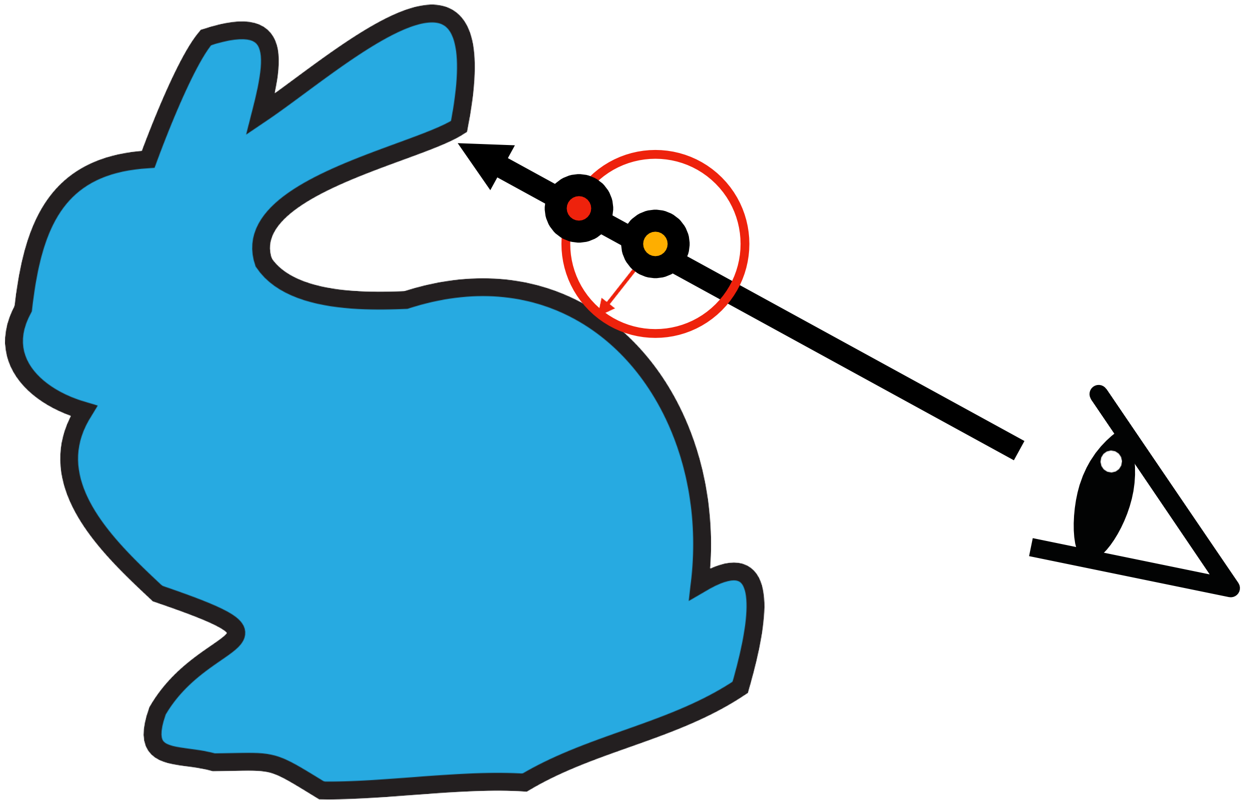

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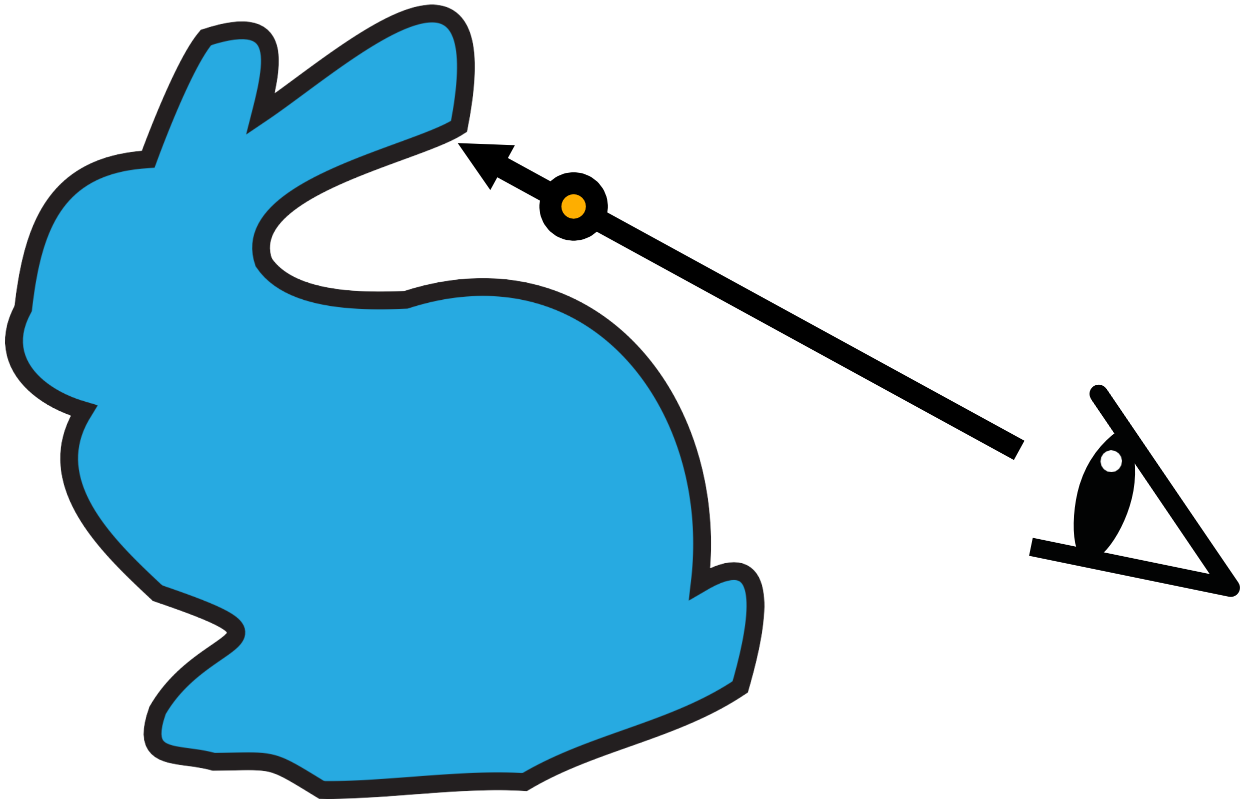

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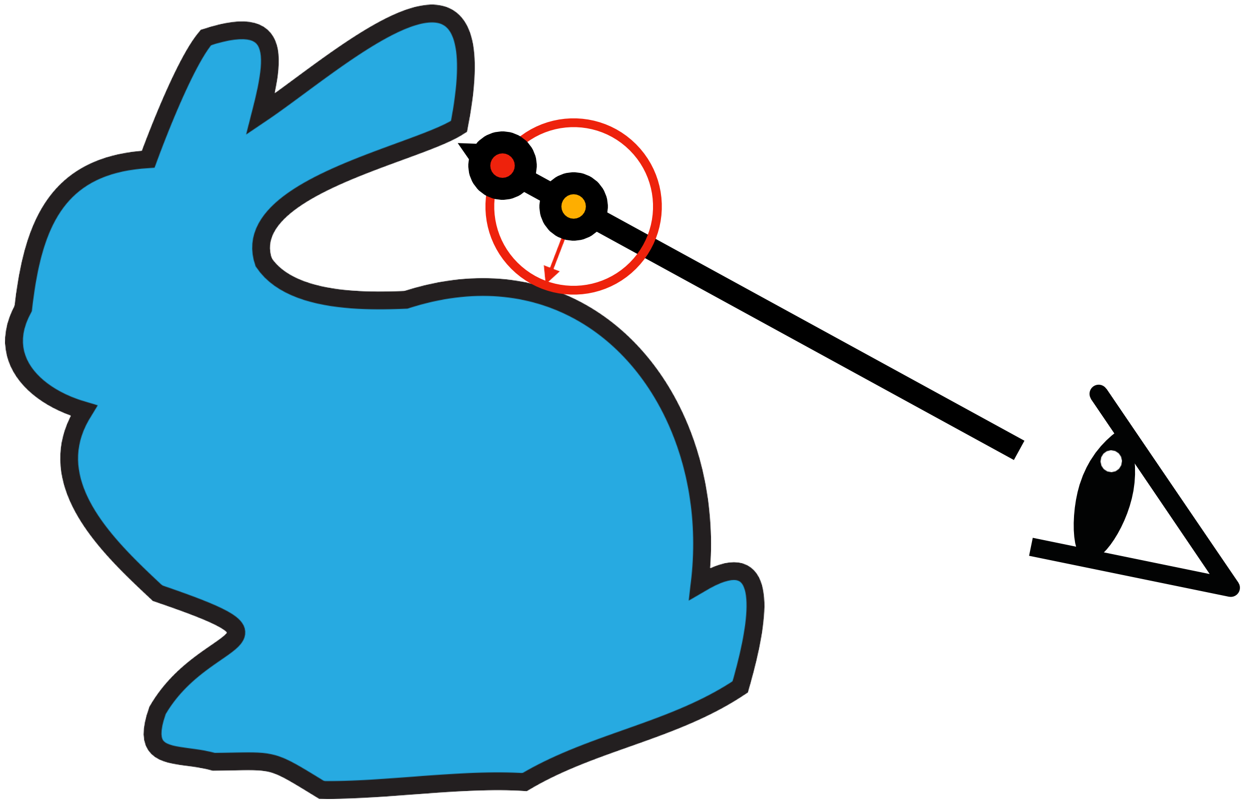

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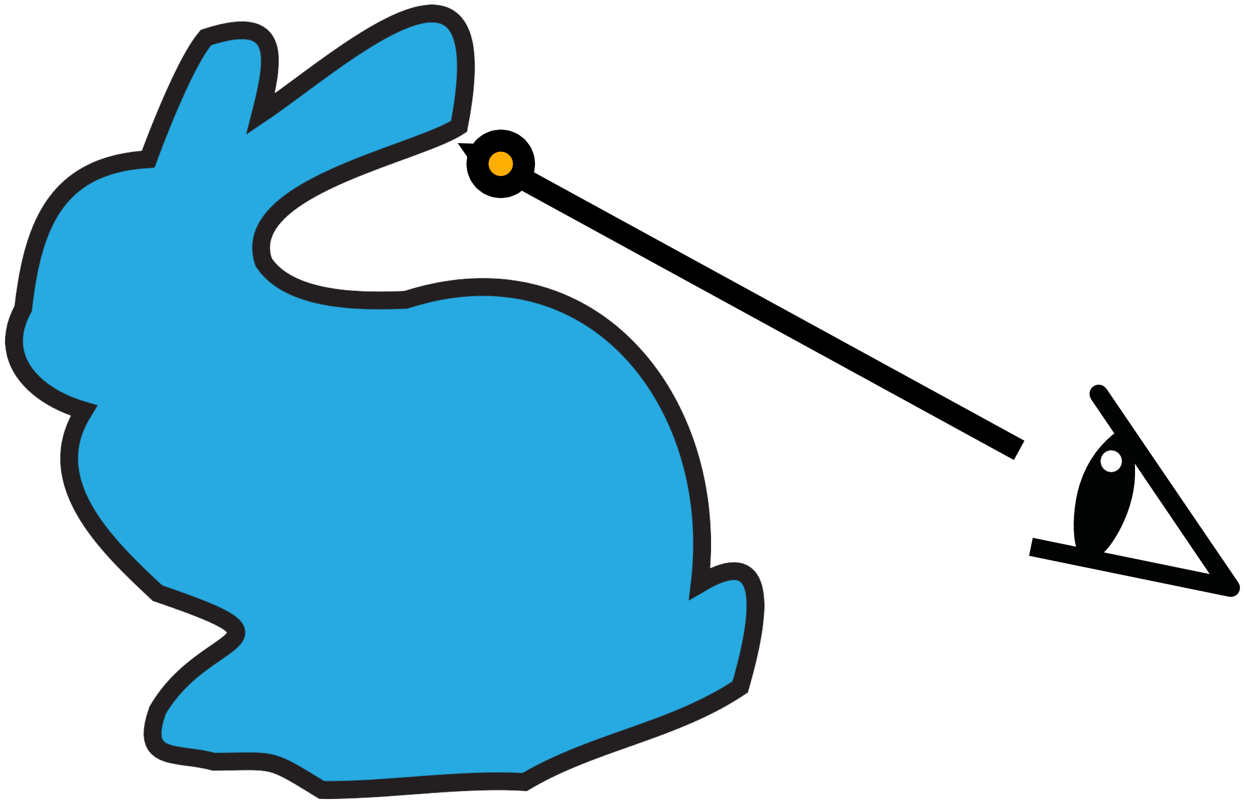

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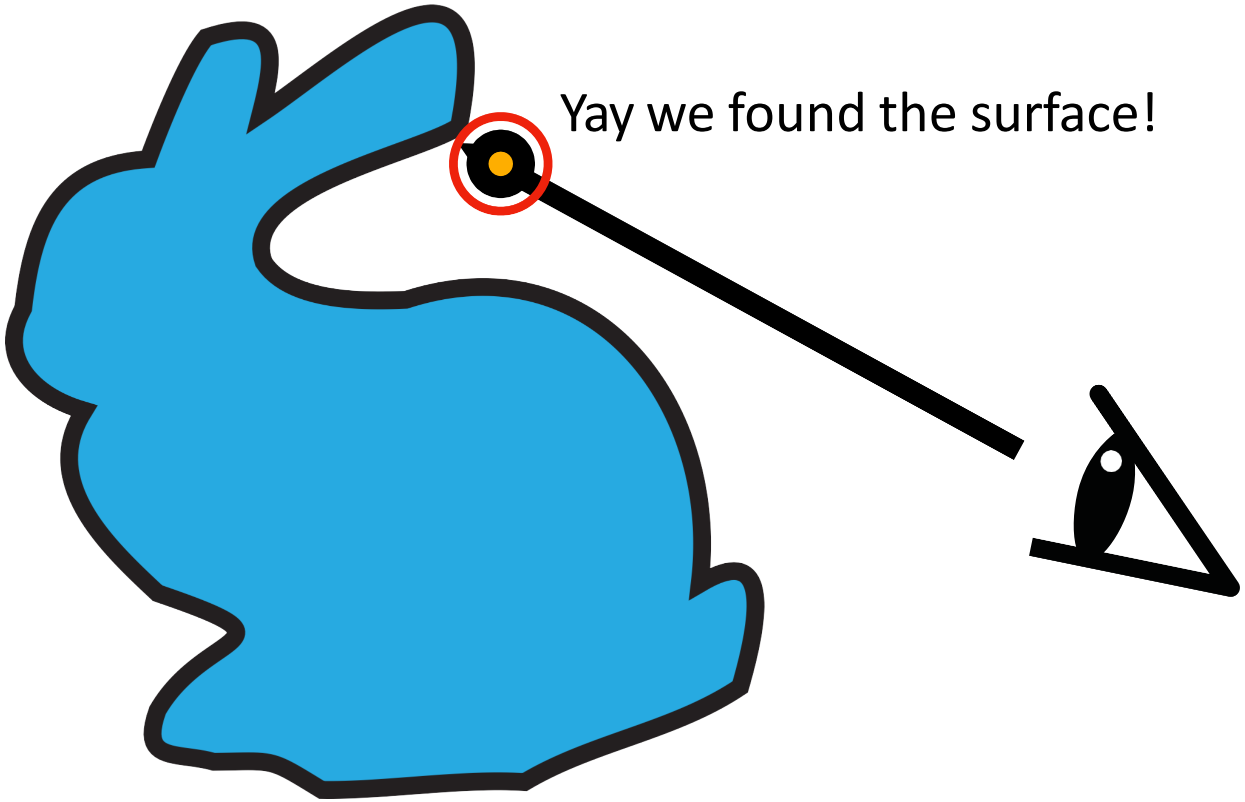

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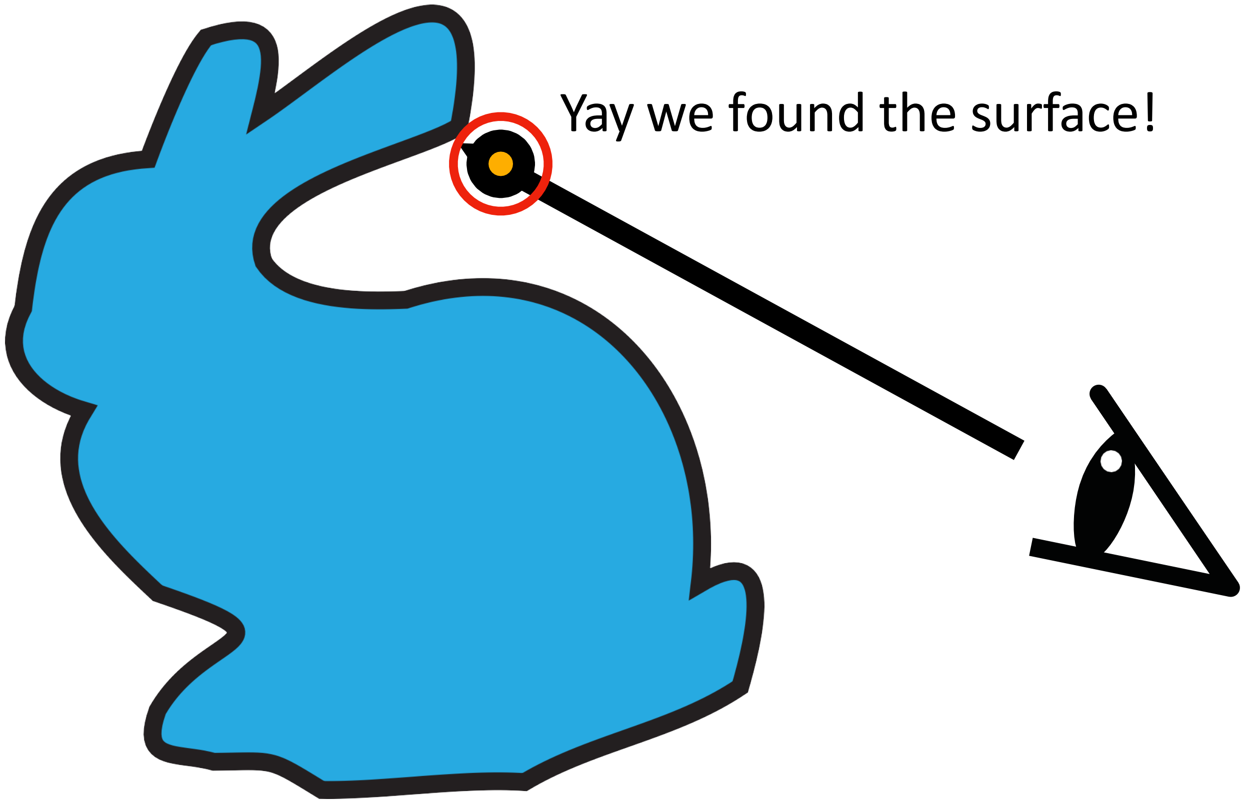
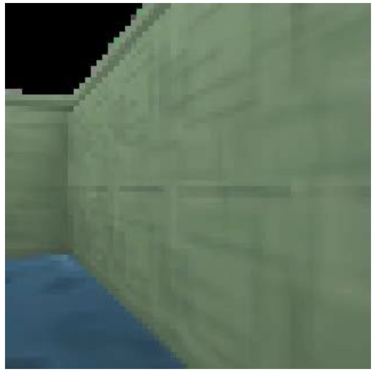
Sphere Tracing

$$f(x, y, z) = d$$



[Source: Takikawa et al]

Neural Implicit Approaches



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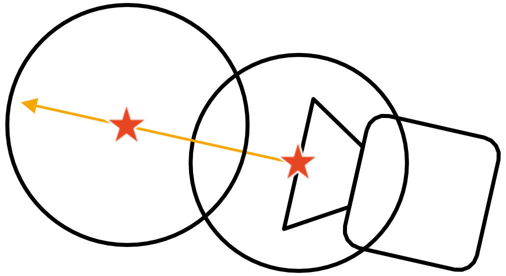
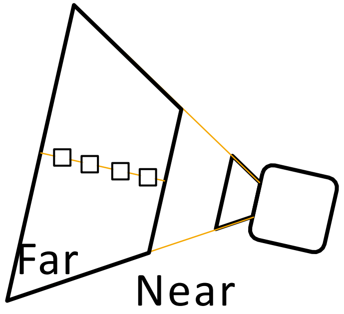
Single-scene
Yariv et al., NeurIPS 2020

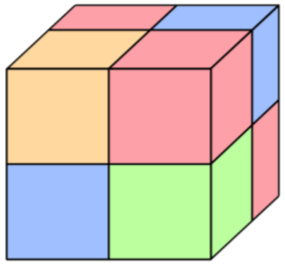
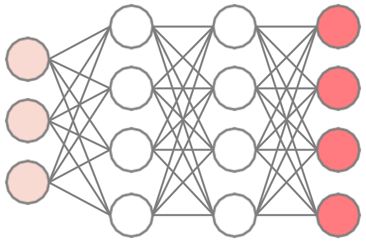
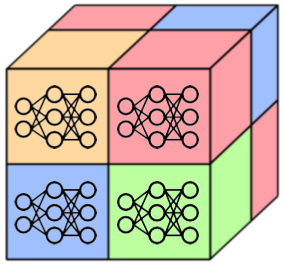


Sphere tracing
- Faster
- Fewer network evaluations
- Convergence more difficult

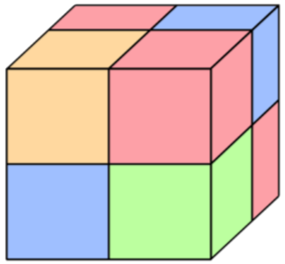


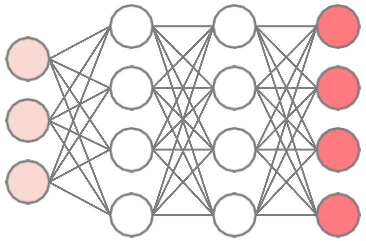
Volumetric
- Higher Quality
- Easy convergence
- Very expensive

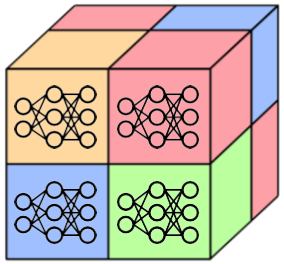
Requirements

				
Scene Representation	Voxelgrids	Implicit Function	Hybrid Implicit/Explicit	• • •
Renderer	Volumetric	Sphere-Tracing Volumetric	Volumetric	
Pros	Fast rendering	High quality Compact Admits *global* priors		
Cons	Memory $O(n^3)$ Limited spatial resolution	Extremely expensive, slow rendering		

Requirements







Scene Representation	Voxelgrids	Implicit Function	Hybrid Implicit/Explicit	• • •
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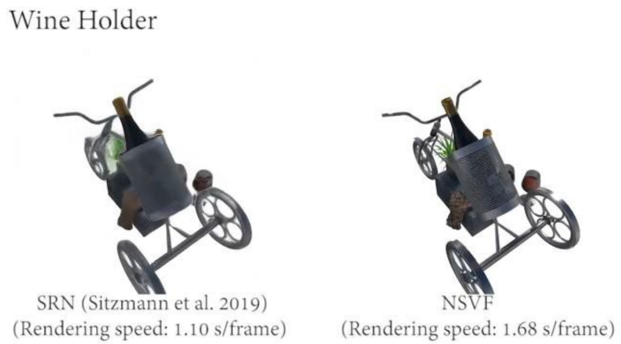
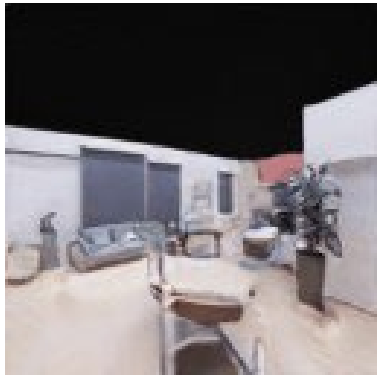
Hybrid Implicit / Explicit



Neural Sparse Voxel Fields,
Liu et. al., NeurIPS 2020

PiFU, Saito et al., ICCV 2019
GRF, Trevithick et al., arXiv 2020
pixelNeRF, Yu et. al., CVPR 2021
MVSNerf, Chen et al., arXiv 2021
Learn *local* (image patch-based) priors



Unconstrained Scene Generation with
Locally Conditioned Radiance Fields,
DeVries et al., arXiv 2021

Lingjie Liu

Neural Sparse Voxel Fields (NSVF)

- Avoid sampling points in empty space as much as possible.

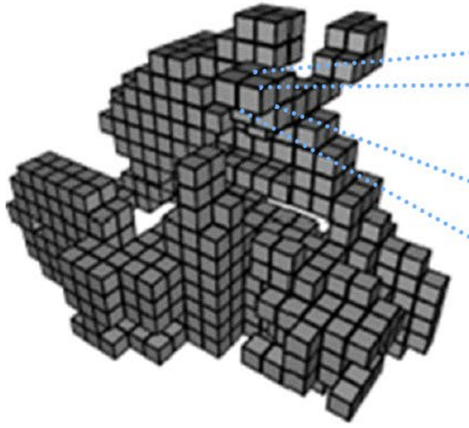


Illustration of Sparse Voxels

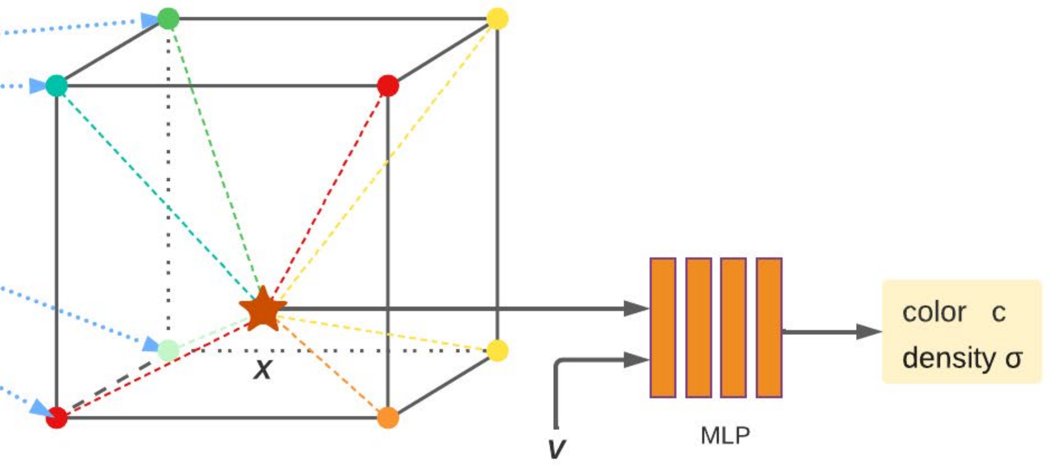
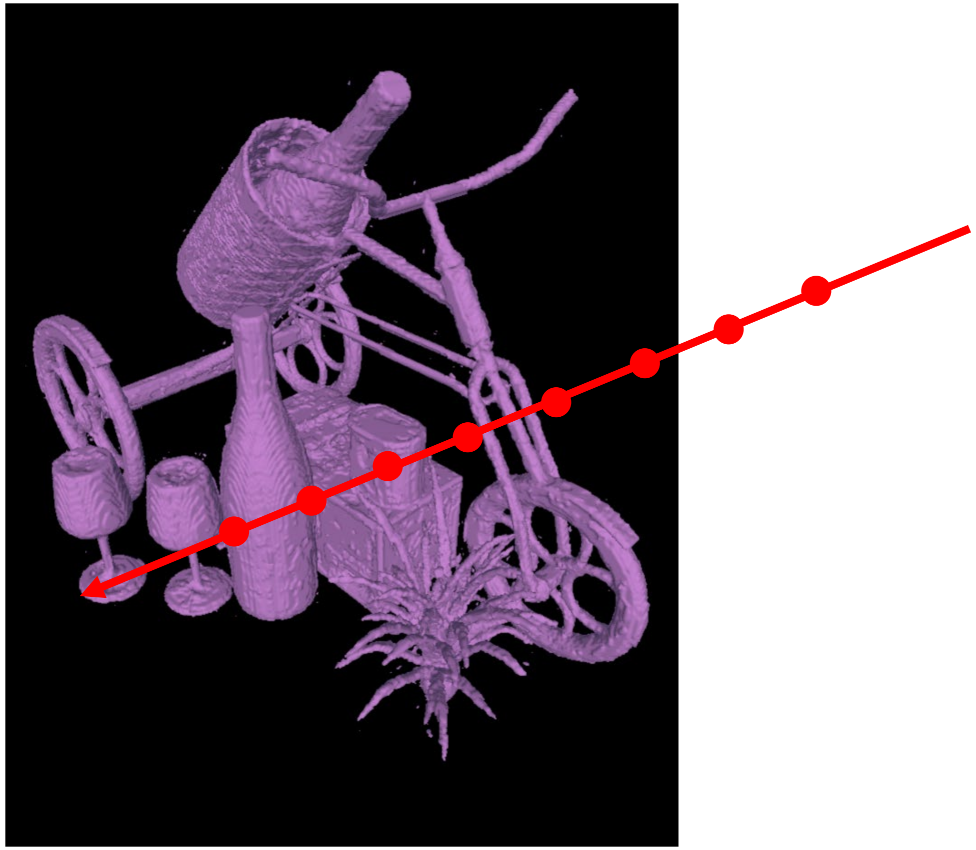


Illustration of a voxel-bounded neural field

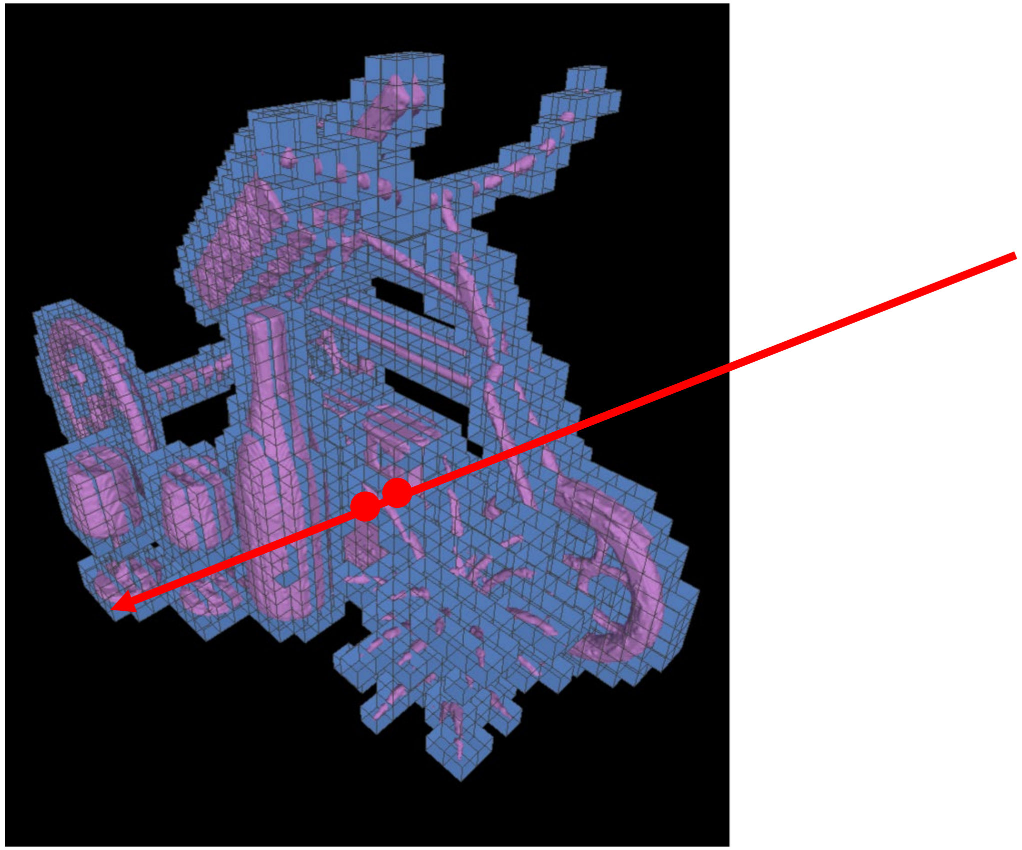
Neural Sparse Voxel Fields, Liu et al. 2020

Neural Sparse Voxel Fields (NSVF)

- Avoid sampling points in empty space as much as possible.



Sample in the whole space



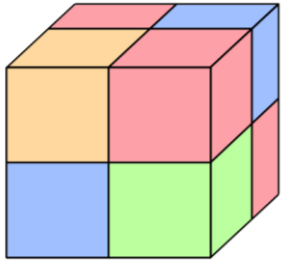
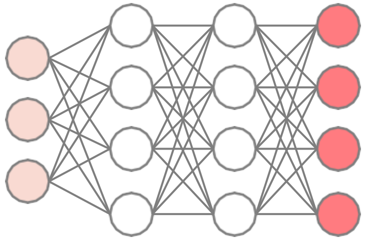
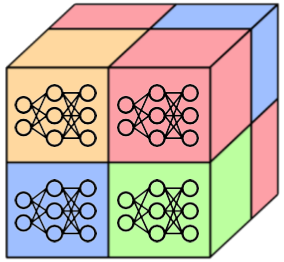
Only sample inside the sparse-voxels

Comparison

NeRF (Mildenhall et al. 2020)
(Rendering speed: 100 s/frame)

Ours (NSVF)
(Rendering speed: 2.62 s/frame)

Requirements

Scene Representation	 Voxelgrids	 Implicit Function	 Hybrid Implicit/Explicit	• • •
Renderer	Volumetric	Sphere-Tracing Volumetric	Volumetric	
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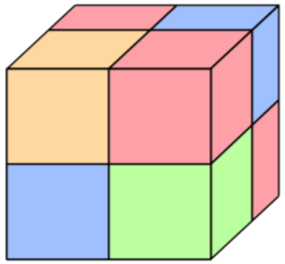
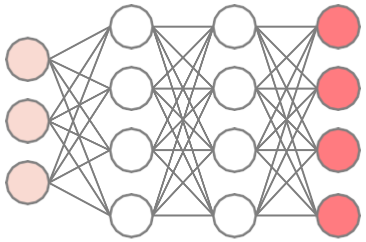
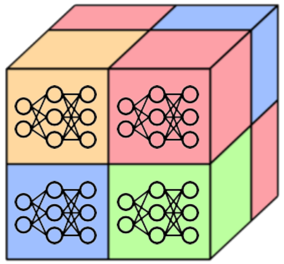
Cons	Memory $O(n^3)$ Limited spatial resolution	Extremely expensive, slow rendering	No compact representation No *global* priors	

Neural Scene Representation and Neural Rendering

Neural Fields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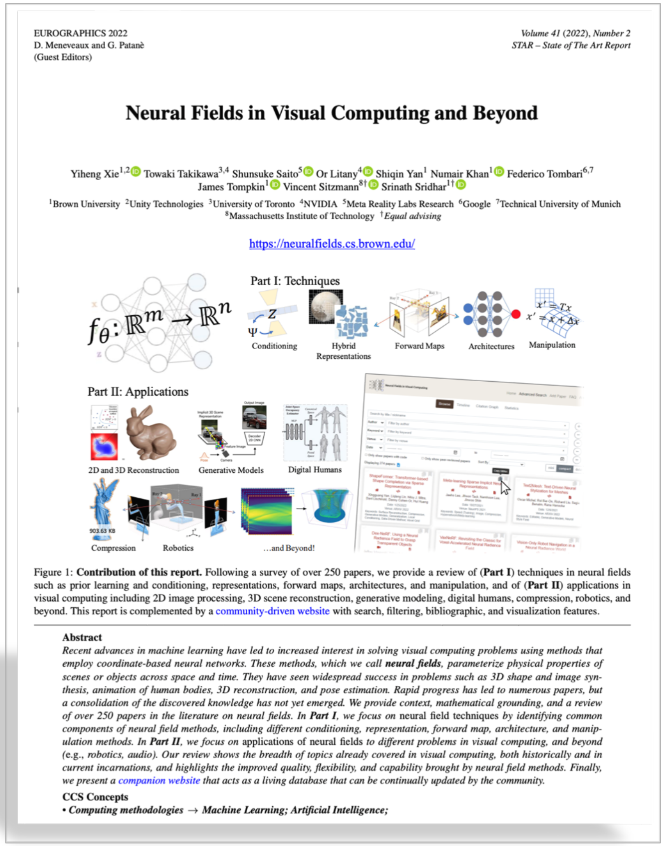

EUROGRAPHICS 2022
D. Meneveaux and G. Patanè
(Guest Editors)

Volume 41 (2022), Number 2
STAR – State of The Art Report

Neural Fields in Visual Computing and Beyond

Yiheng Xie[1,2] Towaki Takikawa[3,4] Shunsuke Saito[5] Or Litany[4] Shiqin Yan[1] Numair Khan[1] Federico Tombari[6,7]
James Tompkin[1] Vincent Sitzmann[8†] Srinath Sridhar[1†]

[1]Brown University [2]Unity Technologies [3]University of Toronto [4]NVIDIA [5]Meta Reality Labs Research [6]Google [7]Technical University of Munich
[8]Massachusetts Institute of Technology [†]*Equal advising*

https://neuralfields.cs.brown.edu/

Part I: Techniques
Conditioning
Hybrid Representations
Forward Maps
Architectures
Manipulation

Part II: Applications
2D and 3D Reconstruction
Generative Models
Digital Humans
Compression
Robotics
...and Beyond!

Figure 1: **Contribution of this report.** Following a survey of over 250 papers, we provide a review of (**Part I**) techniques in neural fields such as prior learning and conditioning, representations, forward maps, architectures, and manipulation, and of (**Part II**) applications in visual computing including 2D image processing, 3D scene reconstruction, generative modeling, digital humans, compression, robotics, and beyond. This report is complemented by a community-driven website with search, filtering, bibliographic, and visualization features.

Abstract
Recent advances in machine learning have led to increased interest in solving visual computing problems using methods that employ coordinate-based neural networks. These methods, which we call ***neural fields****, parameterize physical properties of scenes or objects across space and time. They have seen widespread success in problems such as 3D shape and image synthesis, animation of human bodies, 3D reconstruction, and pose estimation. Rapid progress has led to numerous papers, but a consolidation of the discovered knowledge has not yet emerged. We provide context, mathematical grounding, and a review of over 250 papers in the literature on neural fields. In* ***Part I****, we focus on neural field techniques by identifying common components of neural field methods, including different conditioning, representation, forward map, architecture, and manipulation methods. In* ***Part II****, we focus on applications of neural fields to different problems in visual computing, and beyond (e.g., robotics, audio). Our review shows the breadth of topics already covered in visual computing, both historically and in current incarnations, and highlights the improved quality, flexibility, and capability brought by neural field methods. Finally, we present a companion website that acts as a living database that can be continually updated by the community.*

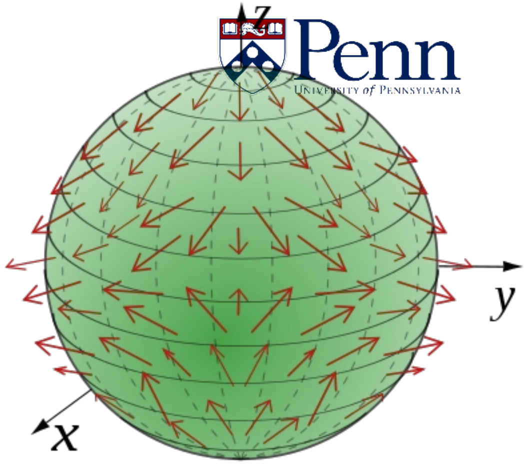
CCS Concepts
• ***Computing methodologies → Machine Learning; Artificial Intelligence;***

Lingjie Liu

Definition of Fields

A *field* is a quantity defined for all spatial and / or temporal coordinates.

Examples of Fields



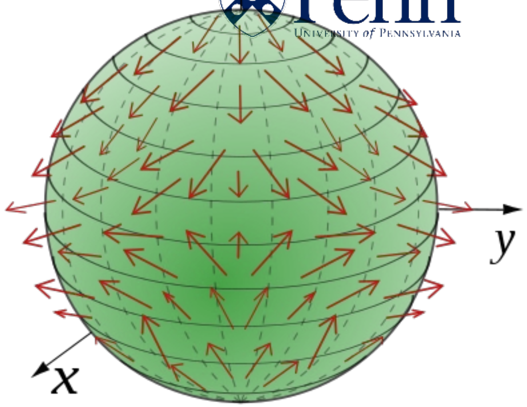
Vector Field

Fields

[Source: Wikipedia]

Examples of Fields

Image

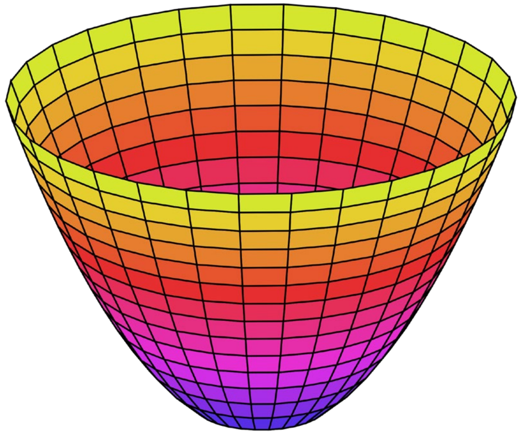


Vector Field

Fields

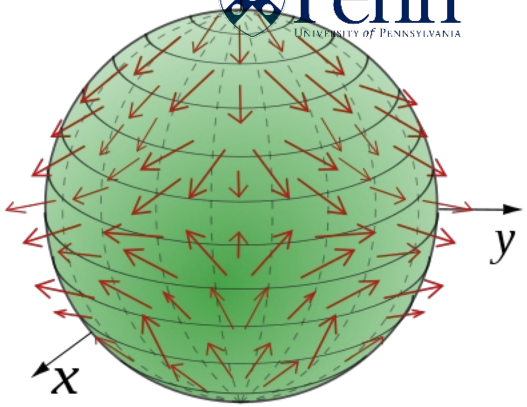
[Source: Wikipedia]

Examples of Fields



3D Parabola
(Explicit Surface)

Image

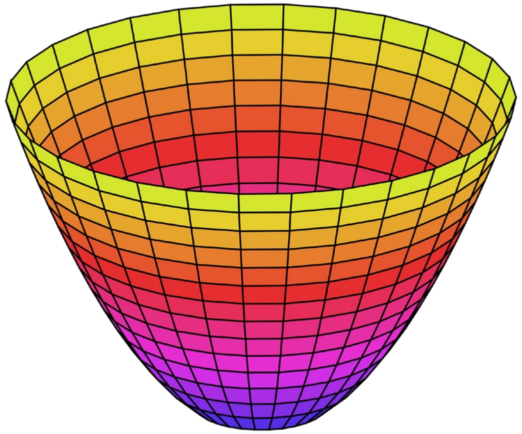


Vector Field

Fields

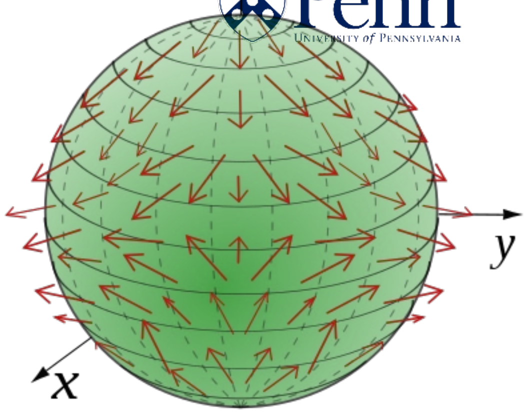
[Source: Wikipedia]

Examples of Fields

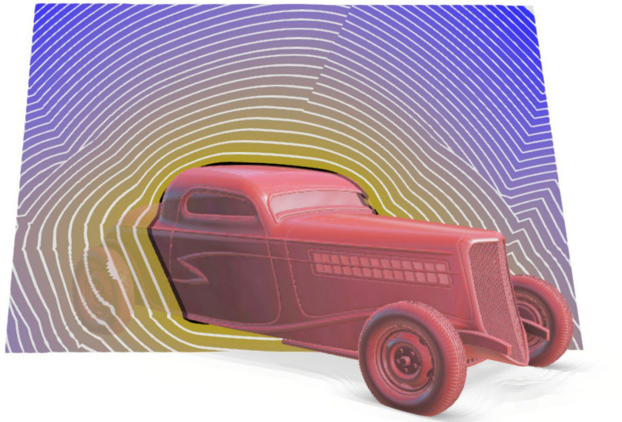


3D Parabola
(Explicit Surface)

Image



Vector Field

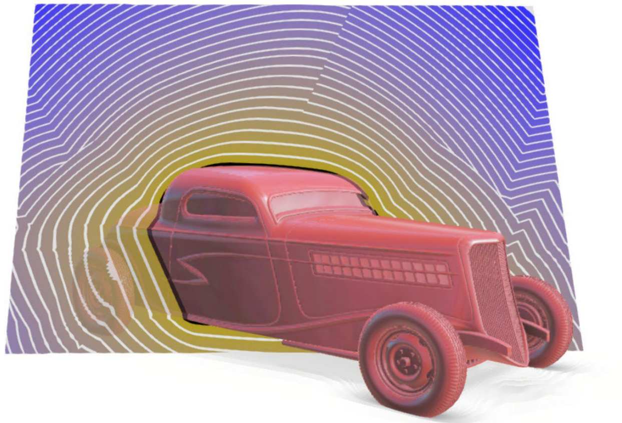


3D Signed Distance Fields
(Implicit Surface)

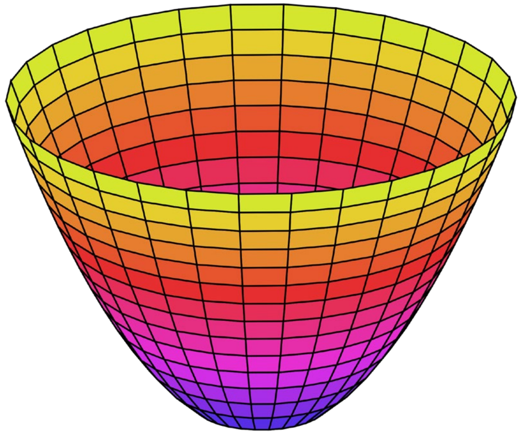
Fields

[Source: Wikipedia]

Examples of Fields

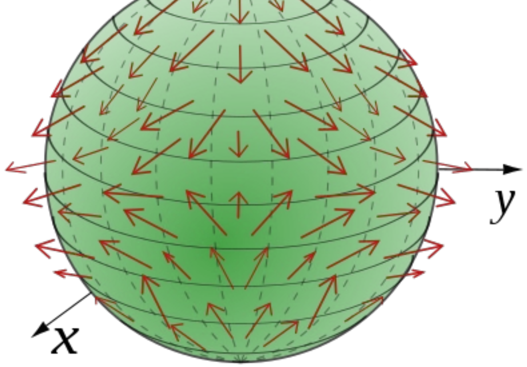


3D Signed Distance Fields
(Implicit Surface)

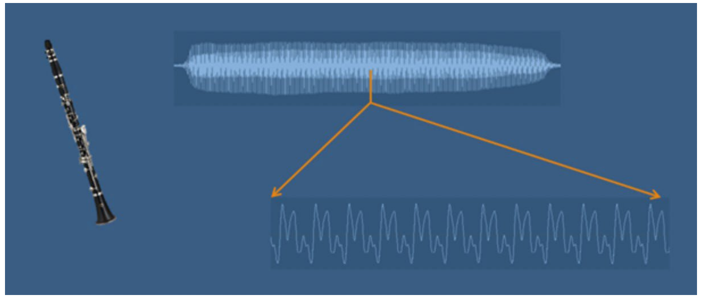


3D Parabola
(Explicit Surface)

Image



Vector Field



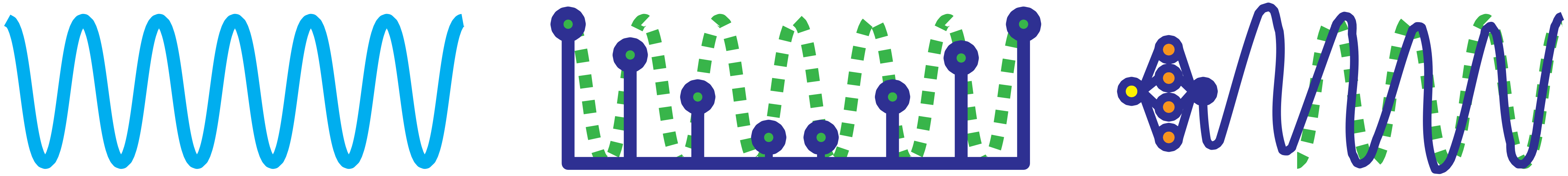
Audio

Fields

[Source: Wikipedia]

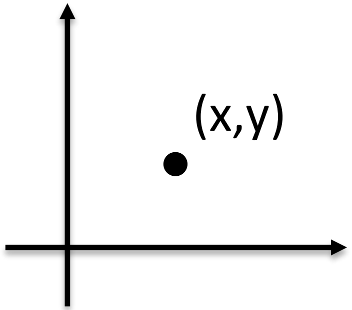
What are neural fields?

Fields / signals can be represented in many ways.

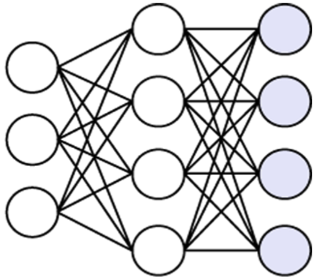


Continuous Discrete Neural

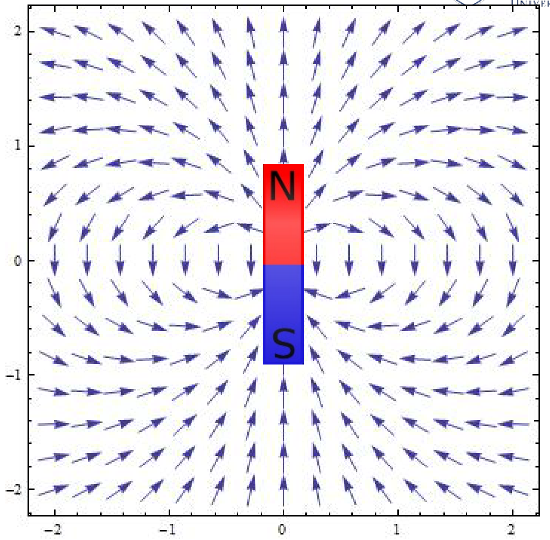
What are neural fields?



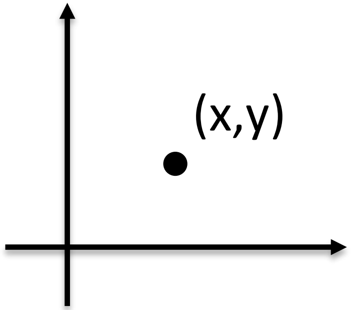
$\Phi: \mathbb{R}^2 \rightarrow \mathbb{R}^2$



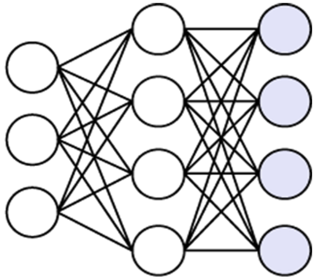
Neural Network (Φ)



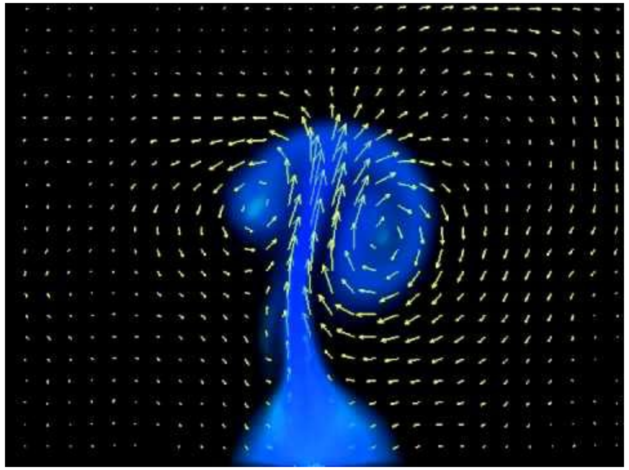
Magnetic Field



$\Phi: \mathbb{R}^2 \rightarrow \mathbb{R}^2$



Neural Network (Φ)

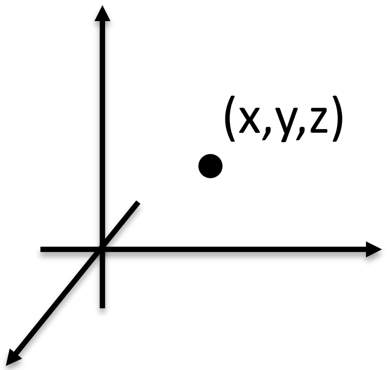


Eulerian Flow Field of a Fluid

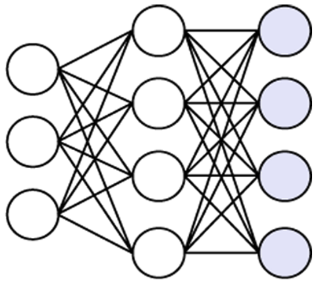
[Koldora CC]

Lingjie Liu

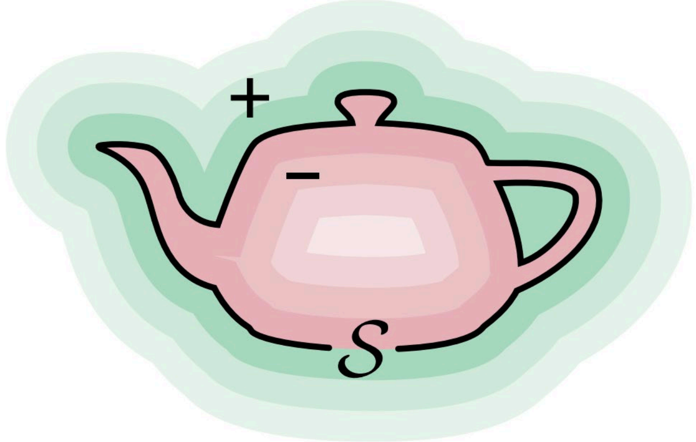
What are neural fields?



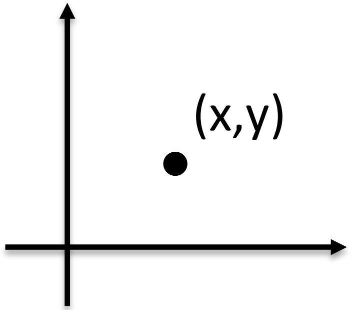
$\Phi: \mathbb{R}^n \rightarrow \mathbb{R}$



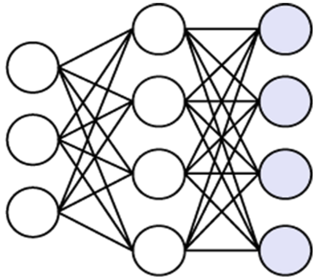
Neural Network (Φ)



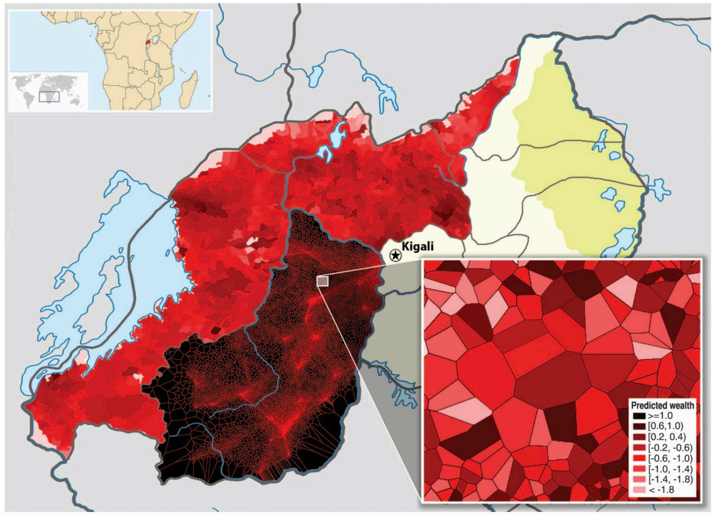
Signed Distance Function (SDF)



$\Phi: \mathbb{R}^2 \rightarrow \mathbb{R}^n$



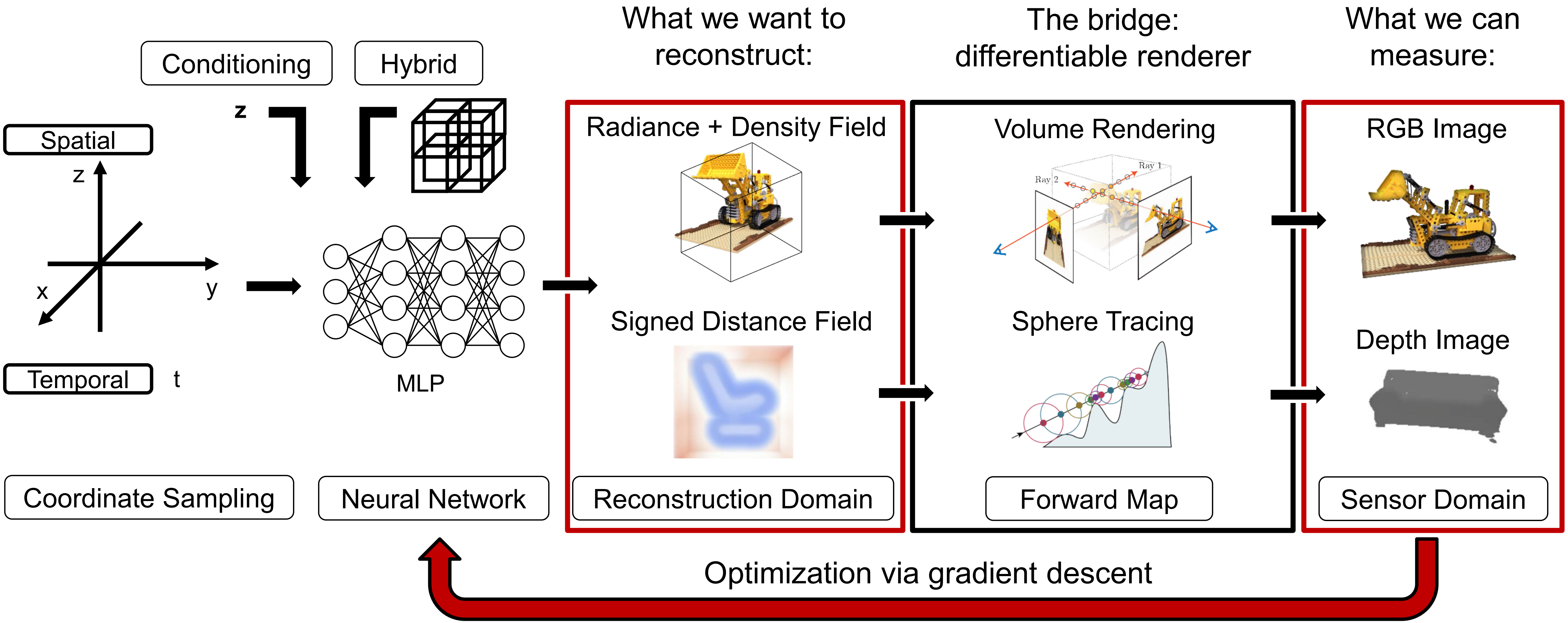
Neural Network (Φ)



Geospatial Data

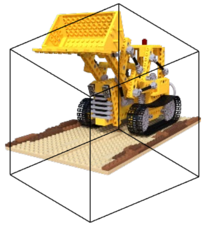
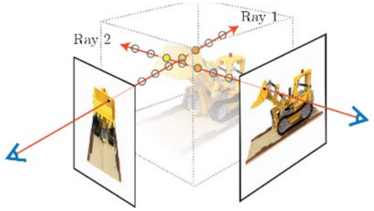
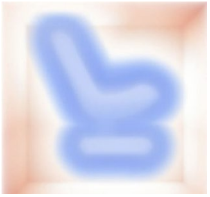
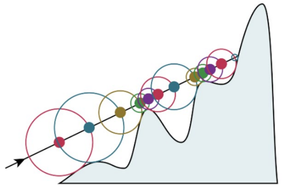
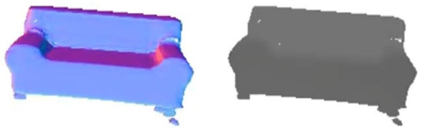
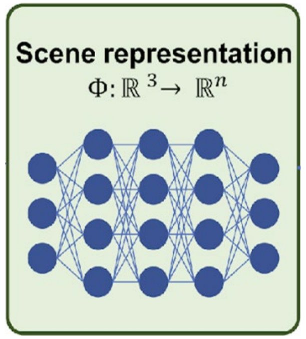
[Blumenstock et al. 2015]

Neural Fields General Framework



Lingjie Liu

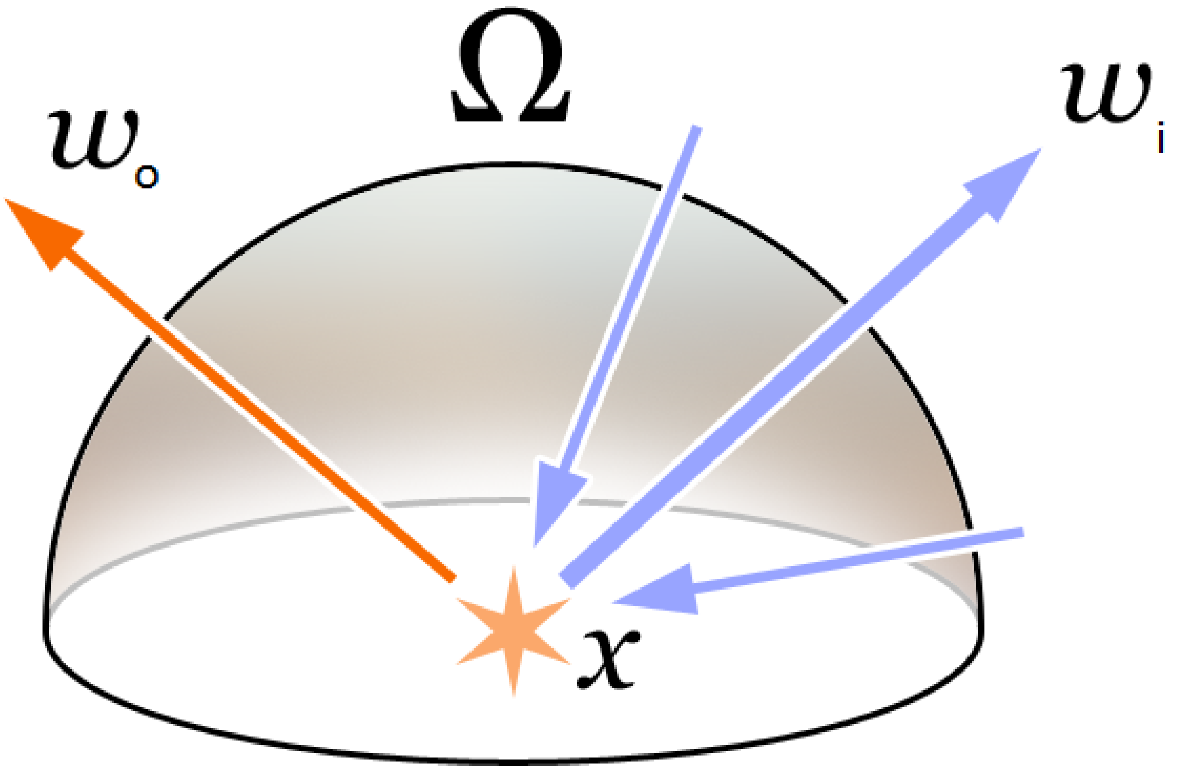
Differentiable Rendering

Reconstruction	Forward Map	Sensor Domain
Radiance Field 	Volume Rendering 	RGB Image Depth 
SDF 	Sphere Tracing 	Normal Depth 
	Neural Renderer	Output Rendering 

Figures adapted from:
Mildenhall et al. 2020 (NeRF)
Sitzmann et al. 2019 (SRN)

Lingjie Liu

BRDF Shading



$$L(\mathbf{x},\vec{\omega}_o) = L_e(\mathbf{x},\vec{\omega}_o) + \int_S f_r(\mathbf{x},\vec{\omega}_i \rightarrow \vec{\omega}_o) L(\mathbf{x}',\vec{\omega}_i) G(\mathbf{x},\mathbf{x}') V(\mathbf{x},\mathbf{x}') d\omega_i$$

Course Link:
https://neural-representation-2024.github.io/topics.html

TAs

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Email: mengxuyi@seas.upenn.edu

Chuhao Chen
Email: morphling233@gmail.com

Preliminary Syllabus

No.	Date	Content
1	Aug 28 (Wed)	Intro
2	Sept 4 (Wed)	Intro 2
3 - 12	Sept 9 (Mon) – Oct 9 (Wed)	Paper Presentations (round 1)
13 - 16	Oct 14 (Mon) – Oct 23 (Wed)	Guest Talks
17 – 26	Oct 28 (Mon) – Nov 27 (Wed)	Paper Presentations (round 2)
27	Dec 2 (Mon)	Practice lecture (e.g., NerfStudio)
28	Dec 4 (Wed)	Discussion on your favorite papers in Neural Representation and Neural Rendering (5 mins per person)
29	Dec 9 (Mon)	Summary + Brainstorming new ideas

Next Class

1. Present some pioneering works in this field, e.g., NeRF, SRN, Neural Volumes, …
2. Fundamentals of Classical 3D Representations and Rendering in Computer Graphics

Topic and Papers

Fast Inference

BakedSDF: Meshing Neural SDFs for Real-Time View Synthesis
Yariv et al.
SIGGRAPH 2023

3D Gaussian Splatting for Real-Time Radiance Field Rendering
Kerbl et al.
SIGGRAPH 2023 (Best Paper Award)

2D Gaussian Splatting for Geometrically Accurate Radiance Fields
Huang et al.
SIGGRAPH 2024

Fast Training

Instant Neural Graphics Primitives with a Multiresolution Hash Encoding
Müller et al.
ACM ToG 2022

TensoRF: Tensorial Radiance Fields
Chen and Xu et al.
ECCV 2022
\+ **Factor Fields: A Unified Framework for Neural Fields and Beyond**
Chen et al.
SIGGRAPH 2023

Antialiasing

Mip-NeRF: A Multiscale Representation for Anti-Aliasing Neural Radiance Fields
Barron et al.
ICCV 2021 (Oral, Best Paper Honorable Mention)
\+ **Mip-NeRF 360: Unbounded Anti-Aliased Neural Radiance Fields**
Barron et al.
CVPR 2022 (Oral Presentation)
\+ **Zip-NeRF: Anti-Aliased Grid-Based Neural Radiance Fields**
Barron et al.
ICCV 2023 (Oral Presentation, Best Paper Finalist)

Mip-NeRF v.s. Mip-NeRF 360 v.s. Zip-NeRF:
Common: *Address the aliasing artifacts of NeRF.*
Mip-NeRF: *Mitigates aliasing artifacts at different resolutions by replacing point sampling with Gaussian sampling.*
Mip-NeRF 360: *Extends Mip-NeRF to unbounded scenes using a non-linear scene parameterization to allocate appropriate capacity for foreground and background.*
Zip-NeRF: *Addresses z-aliasing artifacts from Mip-NeRF 360's resampling and adapts to an efficient grid representation using multisampling within a conical frustum.*

Mip-Splatting: Alias-free 3D Gaussian Splatting
Yu et al.
CVPR 2024 (Best Student Paper Finalist)

Note: For a paper bundle, you only need to present one of the papers in the bundle according to their preference, but you are encouraged to discuss the connections between the papers in the bundle.

Large (Unbounded) Scenes

MERF: Memory-Efficient Radiance Fields for Real-time View Synthesis in Unbounded Scenes
Reiser et al.
SIGGRAPH 2023
+ SMERF: Streamable Memory Efficient Radiance Fields for Real-Time Large-Scene Exploration
Duckworth and Hedman et al.
SIGGRAPH 2024 (Best Paper Honorable Mention)
MERF v.s. SMERF:
- ***Common:*** *Use compact representation to achieve high-quality real-time volumetric rendering.*
- ***MERF:*** *Proposed a combination of a low-resolution 3D grid and a set of higher-resolution 2D planes.*
- ***SMERF:*** *Supports real-time rendering on mobile devices; dedicates each viewpoint a MERF for large scenes.*

Grid-guided Neural Radiance Fields for Large Urban Scenes
Xu et al.
CVPR 2023

Generalization

pixelNeRF Neural Radiance Fields from One or Few Images
Yu et al.
CVPR 2021
PixelSplat: 3D Gaussian Splats from Image Pairs for Scalable Generalizable 3D Reconstruction
Charatan et al.
CVPR 2024 (Oral)
(infers a 3D Gaussian scene from two input views in a single forward pass.)
LRM: Large Reconstruction Model for Single Image to 3D
Hong et al.
ICLR 2024 (Oral)

3D Generative Model

[Per-scene optimization: diffusion distillation]

DreamFusion: Text-to-3d using 2D diffusion
Poole et al.
ICLR 2023
+ ProlificDreamer: High-Fidelity and Diverse Text-to-3D Generation with Variational Score Distillation
Wang et al.
NeurIPS 2023 (Spotlight)

[Single-view image → Multi-view image → 3D reconstruction]
Cat3D: Create Anything in 3D with Multi-View Diffusion Models
Gao et al.
arXiv 2024

InstantMesh: Efficient 3D Mesh Generation from a Single Image with Sparse-view Large Reconstruction Models
Xu et al.
arXiv 2024
+ LGM: Large Multi-View Gaussian Model for High-Resolution 3D Content Creation
Tang et al.
ECCV 2024 (Oral)
+ One-2-3-45++: Fast Single Image to 3D Objects with Consistent Multi-View Generation and 3D Diffusion
Liu et al.
CVPR 2024

[Pose-free 3D Generation]

PF-LRM: Pose-Free Large Reconstruction Model for Joint Pose and Shape Prediction
Wang et al.
arXiv 2024
+ SpaRP: Fast 3D Object Reconstruction and Pose Estimation from Sparse Views
Xu et al.
ECCV 2024
PF-LRM v.s. SpaRP:
Common: 3D reconstruction from sparse unknown-posed images.
PF-LRM: Explicit matching through pointcloud + differentiable PnP solver.
SpaRP: Distill stable diffusion model to predict NOCS images for camera pose estimation.

[Native 3D Generation]
Splatter Image: Ultra-Fast Single-View 3D Reconstruction
Szymanowicz et al.
CVPR 2024

[Multi-view ImageNet]
EG3D: Efficient Geometry-aware 3D Generative Adversarial Networks
Chan et al.
CVPR 2022
3D generation on ImageNet
Skorokhodov et al.
ICLR 2023 (Oral)

Penn University of Pennsylvania

Lingjie Liu

Dynamic Scenes & Human

Shape of Motion: 4D Reconstruction from a Single Video
Wang et al.
arXiv 2024
\+ **MoSca: Dynamic Gaussian Fusion from Casual Videos via 4D Motion Scaffolds**
Li et al.
arXiv 2024

K-Planes: Explicit Radiance Fields in Space, Time, and Appearance
Fridovich-Keil et al.
CVPR 2023
4K4D: Real-Time 4D View Synthesis at 4K Resolution
Xu et al.
CVPR 2024

Pose Estimation

COLMAP-Free 3D Gaussian Splatting
Fu et al.
CVPR 2024
Local-to-Global FlowCam: Training Generalizable 3D Radiance Fields without Camera Poses via Pixel-Aligned Scene Flow
Smith et al.
NeurIPS 2023

Lighting

TensoIR: Tensorial Inverse Rendering
Jin et al.
CVPR 2023
Relightable 3D Gaussian: Real-time Point Cloud Relighting with BRDF Decomposition and Ray Tracing
Zhang et al.
ECCV 2024

Physics Simulation

PhysGaussian: Physics-Integrated 3D Gaussians for Generative Dynamics
Xie et al.
CVPR 2024 (Highlight)
PhysAvatar: Learning the Physics of Dressed 3D Avatars from Visual Observations
Zheng et al.
ECCV 2024

Editing & Multi-modality

Instruct-NeRF2NeRF: Editing 3D Scenes with Instructions
Haque et al.
ICCV 2023 (Oral)
PlatoNeRF: 3D Reconstruction in Plato's Cave via Single-View Two-Bounce Lidar
Klinghoffer et al.
CVPR 2024 (Oral, Best Paper Award Finalist)

Robotics

LERF: Language Embedded Radiance Fields
Kerr et al.
ICCV 2023 (Oral)
+ **LERF-TOGO: Language Embedded Radiance Fields for Zero-Shot Task-Oriented Grasping**
Rashid et al.
CORL 2023 (Best Paper Finalist)
LERF v.s. LERF-TOGO:
Common: Embed language embeddings into 3D scene representation.
LERF: Enables pixel-aligned zero-shot queries on the distilled 3D CLIP embedding.
LERF-TOGO: Extends LERF to task-oriented grasping by adding DINO feature grouping.

Unifying 3D Representation and Control of Diverse Robots with a Single Camera
Li et al.
arXiv 2024

Surface Reconstruction

NeuS: Learning Neural Implicit Surfaces by Volume Rendering for Multi-view Reconstruction
Wang et al.
NeurIPS 2021
+ **NeuS2: Fast Learning of Neural Implicit Surfaces for Multi-view Reconstruction**
Wang et al.
ICCV 2023

Gaussian Opacity Fields: Efficient and Compact Surface Reconstruction in Unbounded Scenes
Yu et al.
arXiv 2024

Differentiable Mesh Extraction

NeurCross: A Self-Supervised Neural Approach for Representing Cross Fields in Quad Mesh Generation
Dong et al.
arXiv 2024

Flexible Isosurface Extraction for Gradient-Based Mesh Optimization
Shen et al.
SIGGRAPH 2023

Before the seminar

- Read the papers of the week.

- Submit at least two questions for discussion before the seminar to a Google form (https://docs.google.com/forms/d/e/1FAIpQLSfSxryv_JO9Ffbd7iKCIqnczqPWJUqv3OGFI6K-2sAKOJmBYQ/viewform). This is important – your contribution will be marked. The deadline for submitting questions is one hour before each class session (so Monday 2:30 PM and Wednesday 2:30 PM).

During the seminar (Starting from Sept 9, two rounds)

- Overview (10 minutes)
  - The instructor or TAs give a brief introduction on the topic.

- 2x Presentations (each 25 minutes, 25 % of grade):
  - Two pre-assigned participants present the paper of their choice.
  - 5 minutes on motivation, background and related work.
  - 20 minutes of presentation of the paper.

- Discussion and Feedback (30 minutes, 25% of grade across weeks):
  - One participant is assigned at random at the beginning of the seminar to lead the discussion. Everyone leads the discussion at least once in the seminar series.
  - The discussion leader receives a digest of the submitted questions just before the seminar.
  - The discussion leader raises questions appropriately throughout the discussion, covers future work aspects, and finally provides a summary of the strengths and weaknesses of the techniques and of the discipline.
  - The students provide feedback to the presenting student on their presentation with respect to what has worked well, and what could be improved and how.

Grading Criteria

2x Presentations (50% of grade)	Discussion (25% of grade)	Other Activity Participation (25% of grade)
Form (30%) *To time? Verbal speed & clarity? Body posture? Engagement with audience?*	**Moderation (30%)** *Integrates questions well? Pushes forward discussion? Good summary? Strengths and weaknesses of paper?*	**Practice Lecture (30%)** *Listen attentively to the lecture? Engage in small coding exercises?*
Content (50%) *Structure/storyline? Main points? Paper connections? Valid conclusions?*	**Questions (70%)** ***One question per paper (two questions per class) should be submitted at least one hour before the class during which the paper will be presented. (However, students are permitted to submit questions late (but before the discussion), up to two occurrences, without facing any penalties)***	**Discussion on your favorite papers (35%)** *Each person has 5 minutes to present their favorite paper. Is your presentation clear? Explain clearly why you chose it and what you like about it?*
Answers (20%) *Good answers to questions? Knowledgeable?*		**Brainstorming (35%)** *Actively participate in the discussion? Contribute your own ideas or opinions?*

TODOs After this Class

1. ***Paper Selection and Registration***: **[Important! Deadline: Sept 3]**
Please select and register for the two papers you would like to present using the following Excel link:
https://docs.google.com/spreadsheets/d/1_FJueXqWnKWoYOGZTNiwp2qRmSP0u1H6ayEYE5j3Ib0/edit?gid=0#gid=0

2. ***Presentation Preparation***:
- Ensure you are fully prepared **one class before your scheduled class for presentation**.
- Upload your slides to the Google folder (https://drive.google.com/drive/folders/1NO-JdWIRtKiLGZOMQxCOUso0AjdtrypY) **at least one hour before the class prior to your assigned class for presentation**. This is important in case of an emergency requiring us to reschedule your talk.
- For example, if you're presenting on Monday, upload your slides by the previous Wednesday at 2:30 PM. If presenting on Wednesday, upload by Monday at 2:30 PM.

3. ***Class Participation***:
•Before each class, please read the papers that will be discussed and submit two questions **at least one hour before the class** using the following link:
https://docs.google.com/forms/d/e/1FAIpQLSfSxryv_JO9Ffbd7iKCIqnczqPWJUqv3OGFI6K-2sAKOJmBYQ/viewform

Acknowledgments

- Advances in Neural Rendering
- Neural Fields in Visual Computing and Beyond
- awesome-NeRF: a curated list of awesome neural radiance fields papers
- MPII Summer Semester 2023: Computer Vision and Machine Learning for Computer Graphics

Any Questions?