



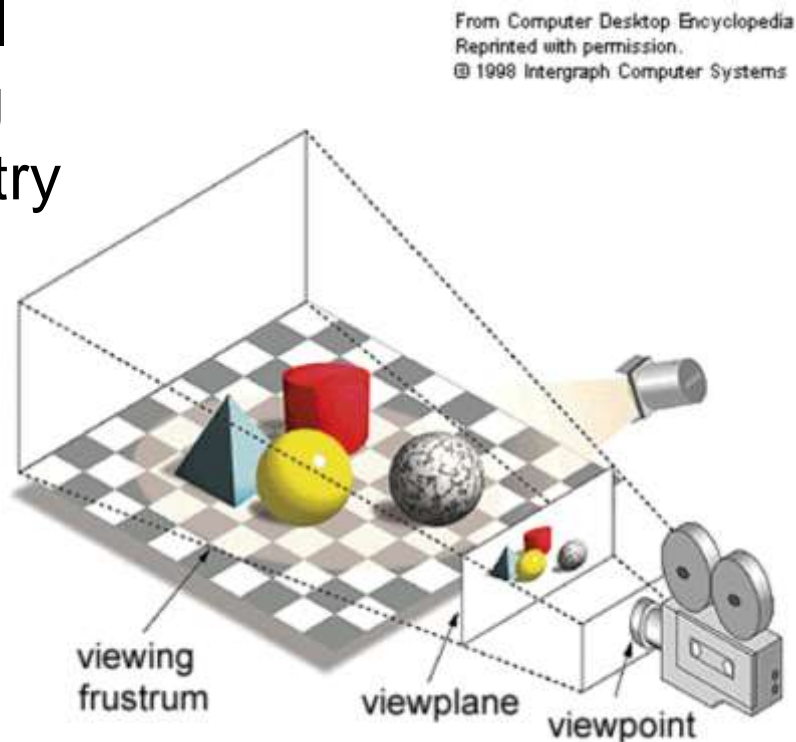
# Lecture 20: Advanced Topics: Neural Rendering II

Lan Xu  
SIST, ShanghaiTech  
Fall, 2023

# What's Rendering

## 3D scene

- Material
- Lighting
- Geometry
- ...



## Camera Def.

- Intrinsics
- Focal length
- Principal point
- ...

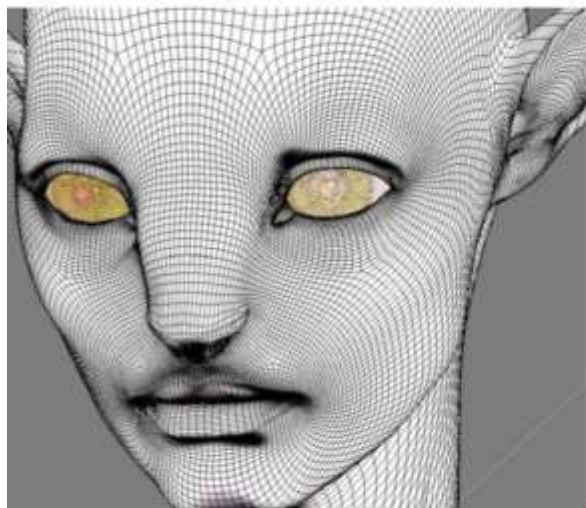
## View point

- Extrinsic
- 6DoF(rot + trans)
- ...

# Photo-realistic Image Synthesis

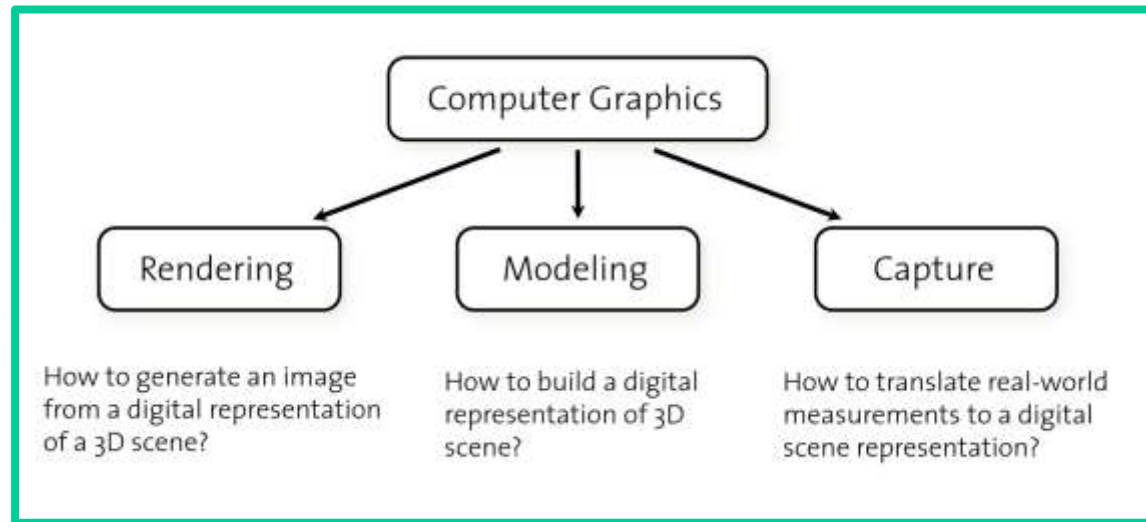
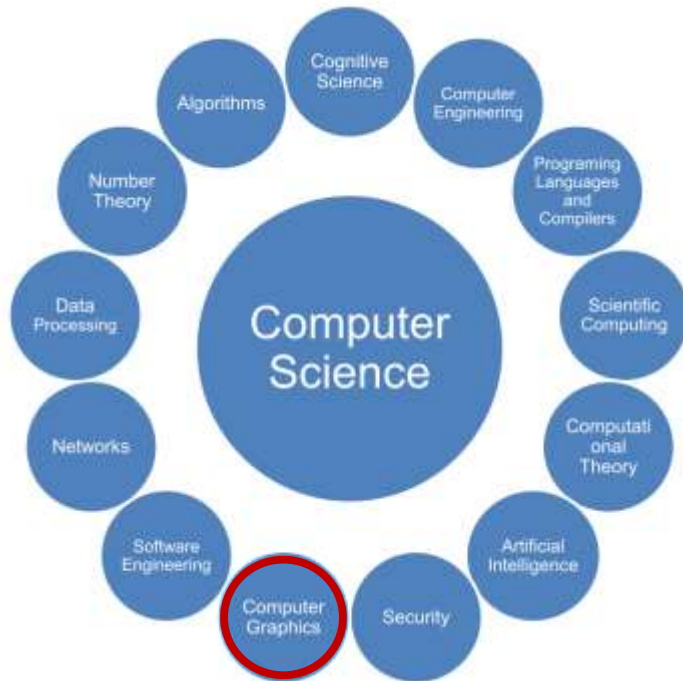
- The Rendering Equation [Kajiya 86]

$$L_o(\mathbf{x}, \omega_o, \lambda, t) = L_e(\mathbf{x}, \omega_o, \lambda, t) + \int_{\Omega} f_r(\mathbf{x}, \omega_i, \omega_o, \lambda, t) L_i(\mathbf{x}, \omega_i, \lambda, t) (\omega_i \cdot \mathbf{n}) d\omega_i$$



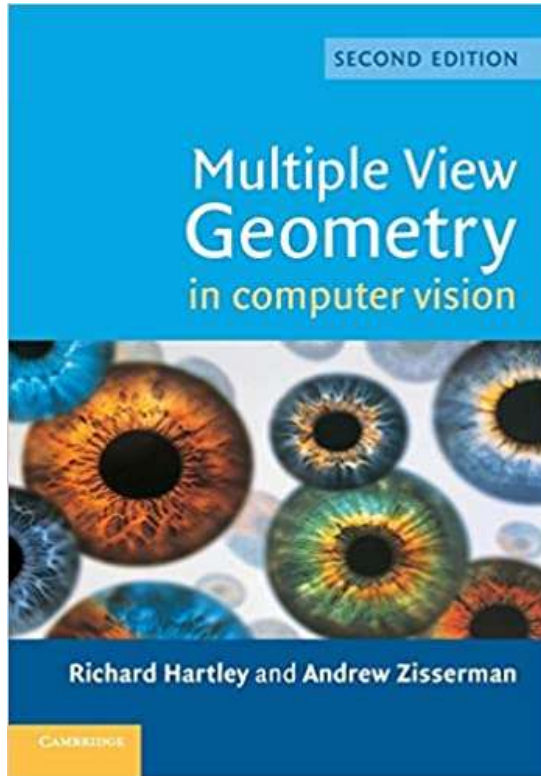
# Computer Graphics?

- Both inverse process and forward process
- From **real world** to **virtual representation**, then to **vivid rendering**



# Recall traditional pipeline

- Systematic knowledge with representative methods



Cambridge University Press,  
March 2004.

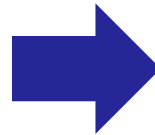


**Building Rome in a day**, Sameer Agarwala , Yasutaka Furukawaa ,  
Noah Snavely, Ian Simonb , Brian Curless, Steven M. Seitz and Richard  
Szeliski, *Communications of the ACM*, 2011



# Recall traditional pipeline

- Various Applications
- Yet time-consuming → artist in-the-loop



architecture



digital twin



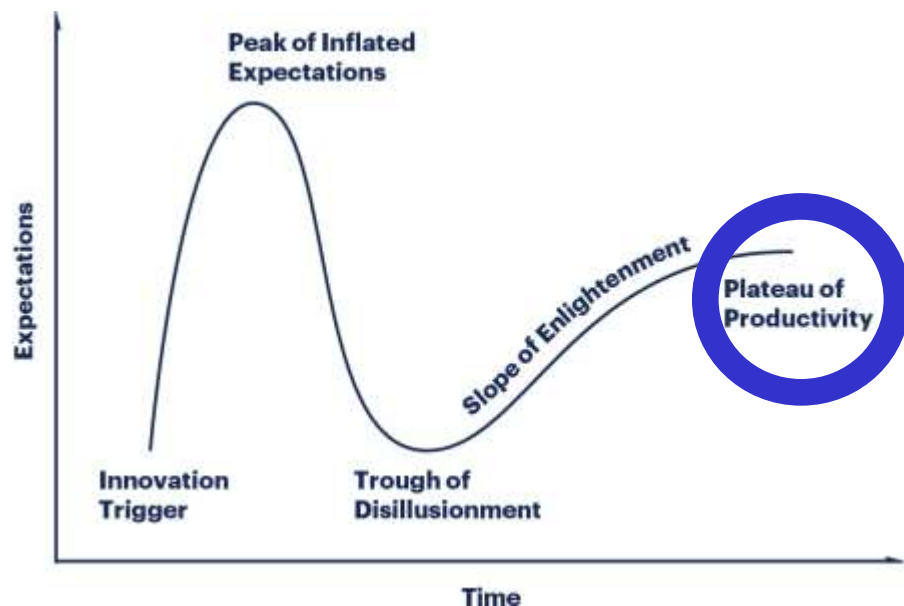
Movie



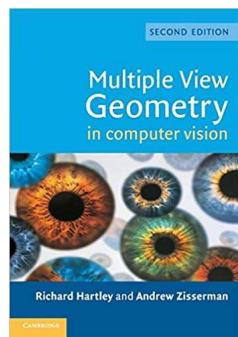
E-commerce

# Recall traditional pipeline

- Traditional Pipeline: mature in the past decades



2021: Epic Games buys Capturing Reality

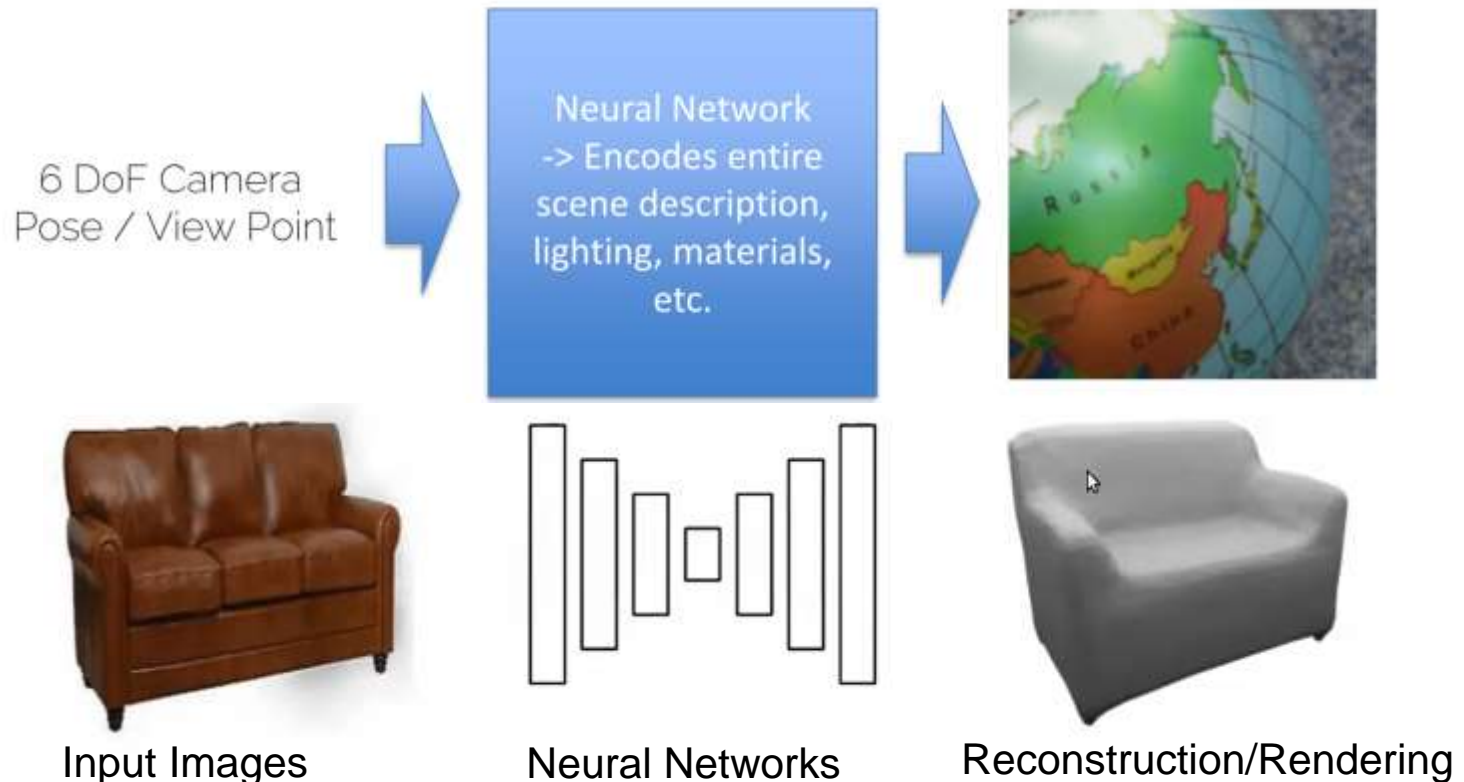


2004

Symbol

# Idea of Neural Rendering

- Neural reconstruction from 2D images directly
- Novel view point synthesis





# Idea of Neural Rendering

- Definition: Deep neural network for **image or video generation** that enable **explicit or implicit control** of **scene properties**

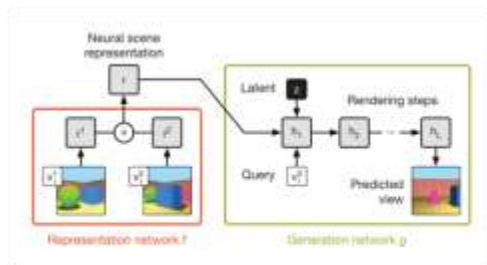
1)  
Generative  
networks that  
synthesize raw  
pixel output

2)  
Output  
controllable by  
interpretable  
paras or by  
video/audio input.

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

- Required Data (image, video, mesh, etc.)
- Controllable Parameters (camera, pose, lighting, etc. )
- Multi-modal Synthesis
- Temporal Coherence
- **Computer Graphics Module**
- Generality

# Neural Representation History

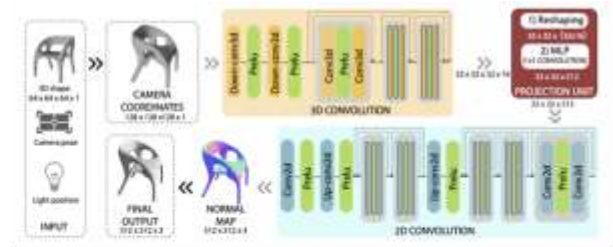


Generative Query Networks  
[Eslami et al. 2018]



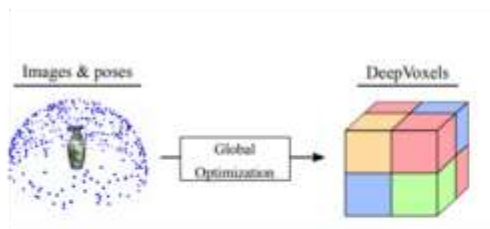
[Flynn et al., 2016; Zhou et al., 2018b;  
Mildenhall et al. 2019]

## Multiplane Images (MPIs)



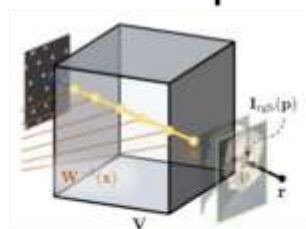
RenderNet [Nguyen-Phuoc et al. 2018]

## Voxel Grids + CNN decoder



DeepVoxels  
[Sitzmann et al. 2019]

## Voxel Grids + Ray Marching



Neural Volumes  
[Lombardi et al. 2019]



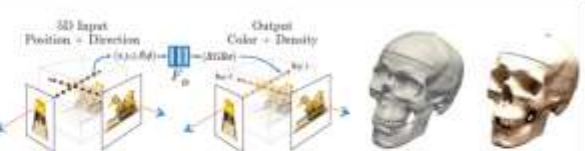
SRN

[Sitzmann et al. 2019b]



NeRF

[Mildenhall et al. 2020]



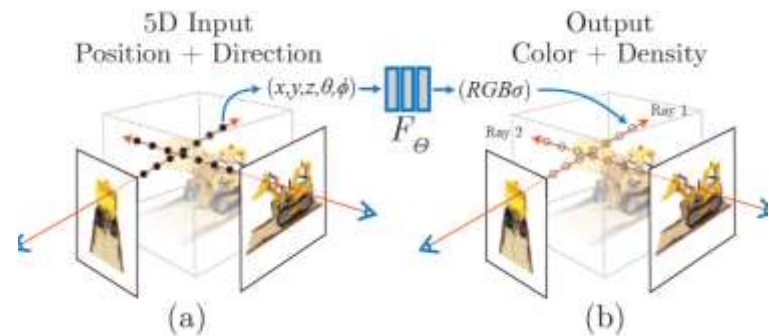
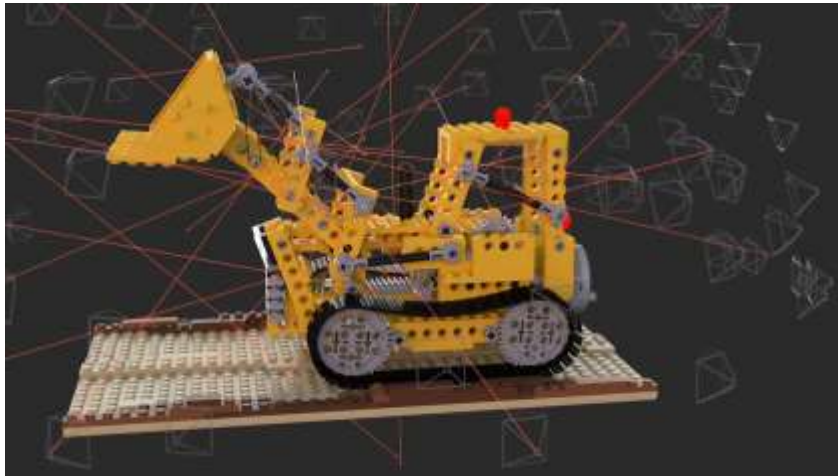
IDR

[Yariv et al. 2020]

## Implicit Fields

# Neural Implicit Representation

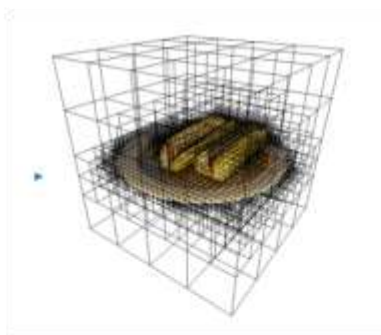
- NeRF: Neural Radiance Field
- 1) Color + Density; 2)- Positional Encoding + Volume Rendering



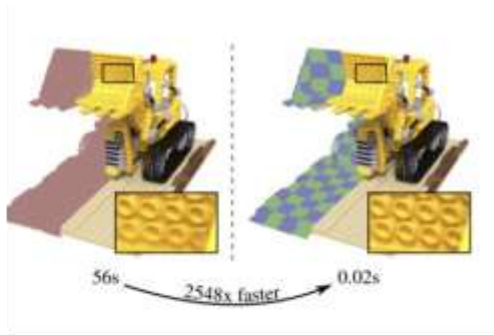
Representing Scenes as Neural Radiance Fields for View Synthesis, Mildenhall et al., *ECCV 2020 Oral - Best Paper Honorable Mention*

# Powerful NeRF everywhere

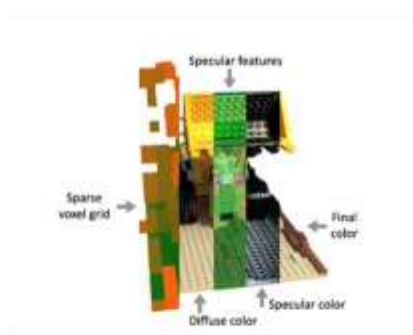
## ■ Fast Rendering and Fast Training



Yu et. al, 2021



Reiser et. al, 2021



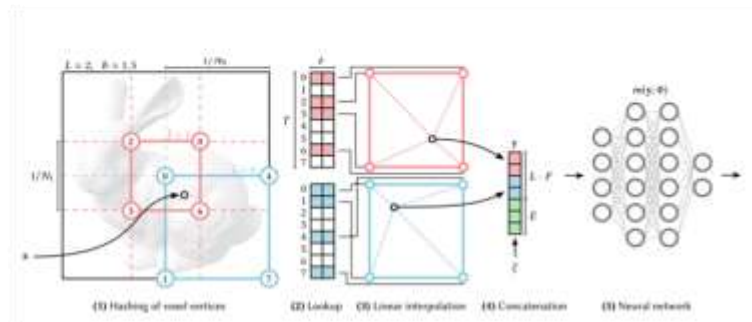
Hedman et. al, 2021



Garbin et. al, 2021



Wang et. al, 2022

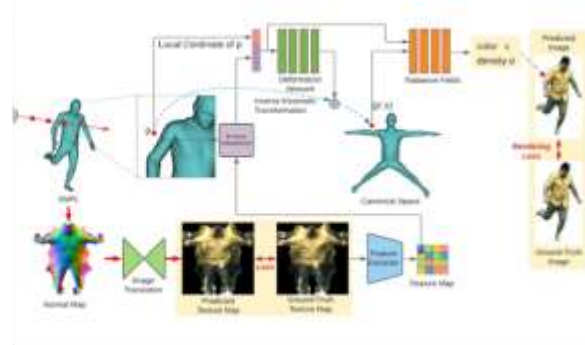


Müller, et. al, 2022

- Dynamic Modeling



Peng et al. 2020, 2021



A 3D model of a zoo enclosure. A person in a dark suit stands in the center, surrounded by several animals: a lion, a tiger, a cheetah, a leopard, a small cat, and a panda. The enclosure is enclosed by a yellow fence and has a white background.

13

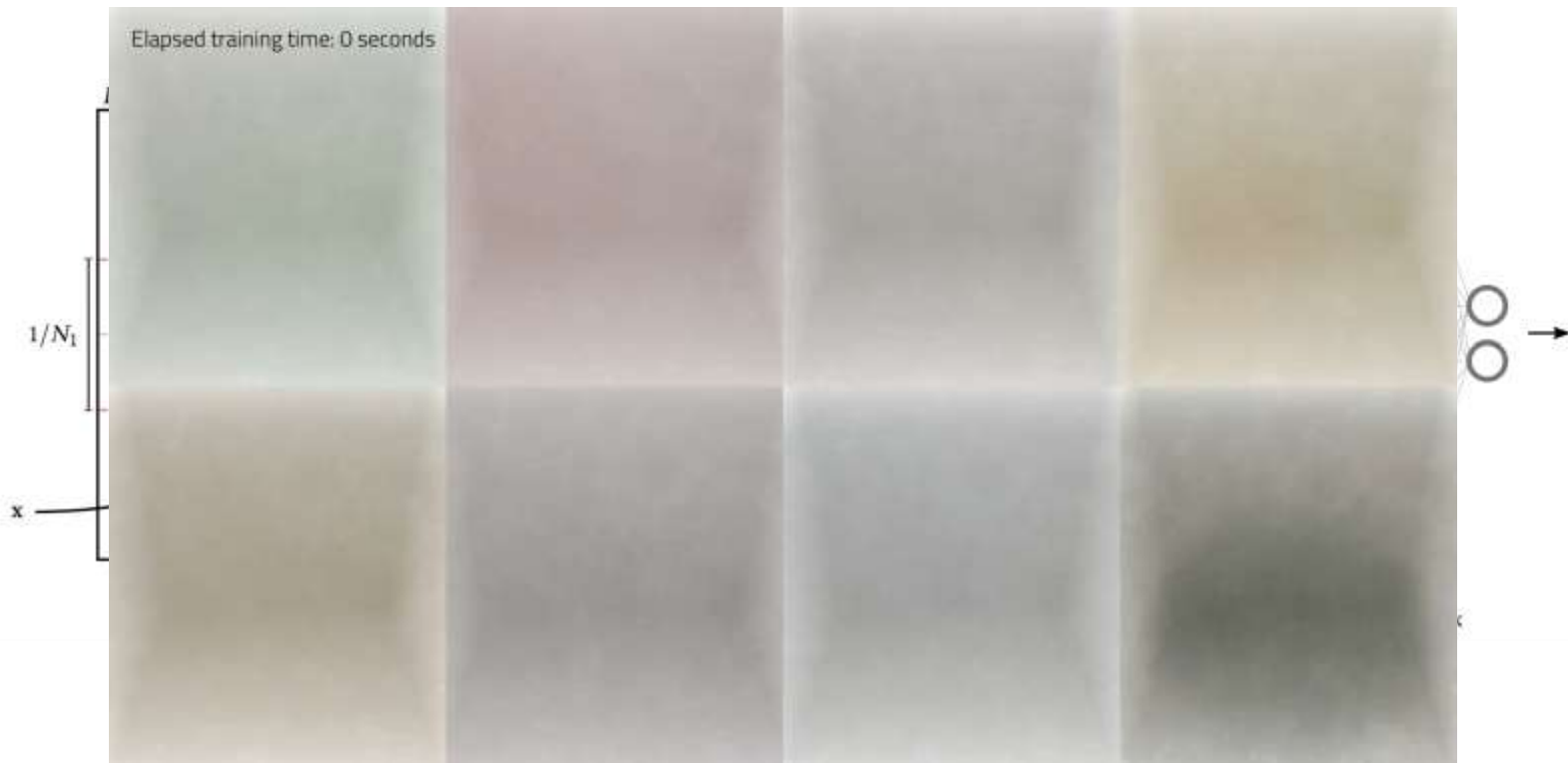






# Instant Neural Graphics Primitives

- Multi-resolution hash encoding
- Shallow MLP, CUDA implementation



Instant Neural Graphics Primitives with a Multiresolution Hash Encoding, Müller et al., *ACM Transactions on Graphics (SIGGRAPH 2022)*

# Instant Neural Graphics Primitives

- Multi-resolution hash encoding
- Shallow MLP

## INSTANT NEURAL GRAPHICS PRIMITIVES WITH A MULTIRESOLUTION HASH ENCODING

Thomas Müller Alex Evans Christoph Schied Alexander Keller

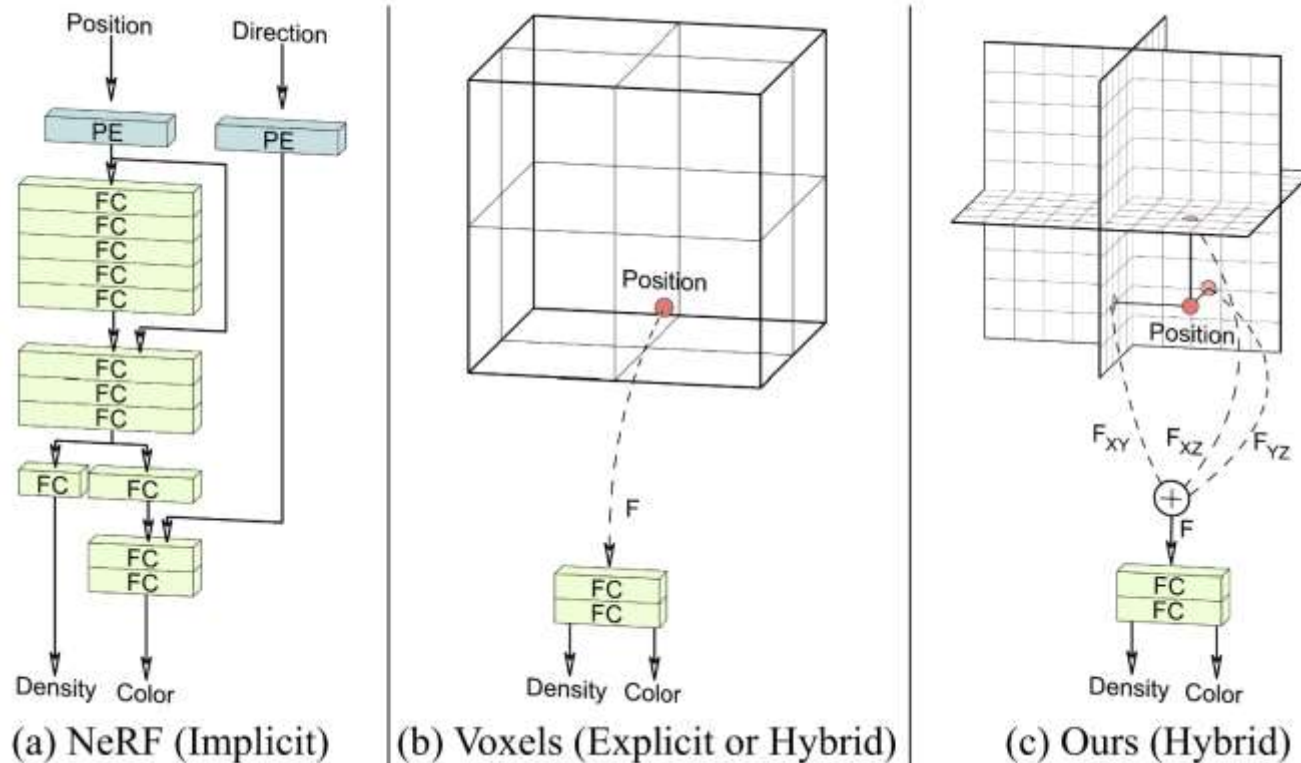
<https://nvlabs.github.io/instant-ngp>



Instant Neural Graphics Primitives with a Multiresolution Hash Encoding, Müller et al., *ACM Transactions on Graphics (SIGGRAPH 2022)*

# Tri-plane feature representation

- Pack the continue feature manifold into planes



EG3D: Efficient Geometry-aware 3D Generative Adversarial Networks, Chan et al., *CVPR 2022*

# Tri-plane feature representation

- Pack the continue feature manifold into planes

## Efficient Geometry-aware 3D Generative Adversarial Networks

Eric Chan<sup>\*12</sup> Connor Lin<sup>\*1</sup> Matthew Chan<sup>\*1</sup> Koki Nagano<sup>\*2</sup>  
Boxiao Pan<sup>1</sup> Shalini De Mello<sup>2</sup> Orazio Gallo<sup>2</sup> Leonidas Guibas<sup>1</sup>  
Jonathan Tremblay<sup>2</sup> Sameh Khamis<sup>2</sup> Tero Karras<sup>2</sup> Gordon Wetzstein<sup>1</sup>  
<sup>1</sup>Stanford University <sup>2</sup>NVIDIA



\*equal contribution

EG3D: Efficient Geometry-aware 3D Generative Adversarial Networks, Chan et al., *CVPR 2022*

# Tri-plane feature representation

- Pack the continue feature manifold into planes



EG3D: Efficient Geometry-aware 3D Generative Adversarial Networks, Chan et al., *CVPR 2022*

# Tensorial Radiance Fields

- Similar Plane-based feature representation
- Adopt tensor factorization

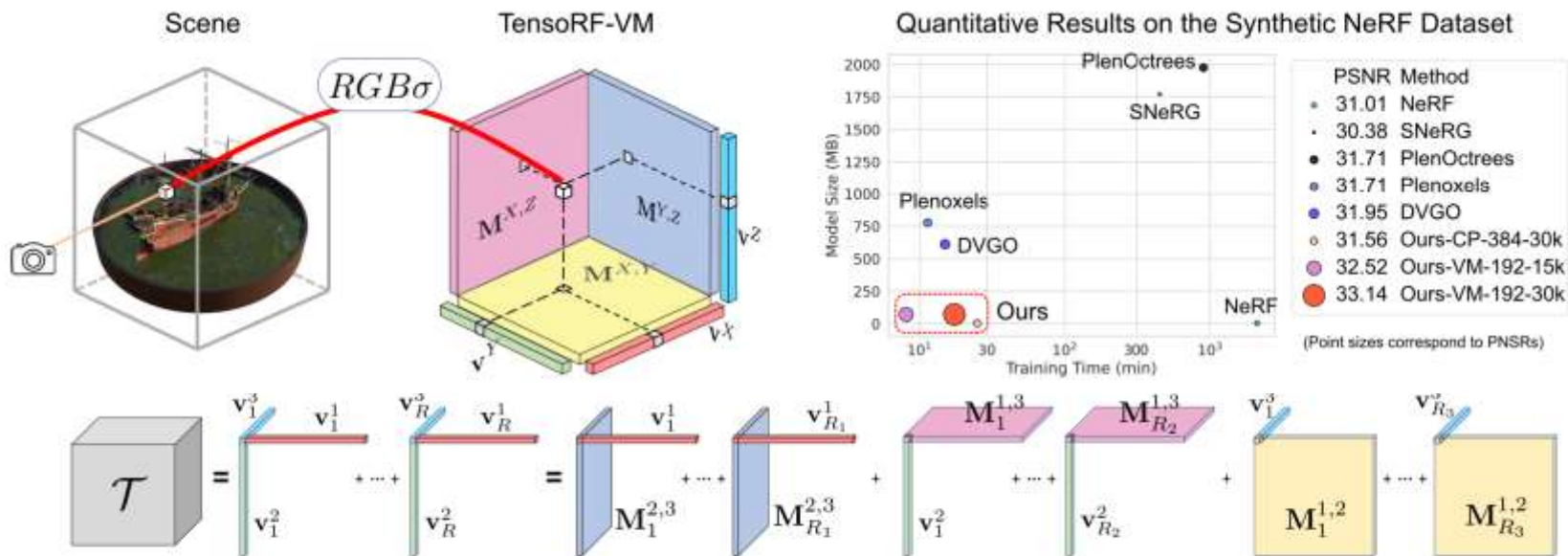


Fig. 2: Tensor factorization. Left: CP decomposition (Eqn. 1), which factorizes a tensor as a sum of vector outer products. Right: our vector-matrix decomposition (Eqn. 3), which factorizes a tensor as a sum of vector-matrix outer products.

TensorRF: Tensorial Radiance Fields, Chen et al., *ECCV 2022*



# Tensorial Radiance Fields

- Similar Plane-based feature representation
- Adopt tensor factorization

## TensoRF: Tensorial Radiance Fields

Anpei Chen\*  
ShanghaiTech University

Zexiang Xu\*  
Adobe Research

Andreas Geiger  
University of Tübingen  
MPI-IS, Tübingen

Jingyi Yu  
ShanghaiTech University

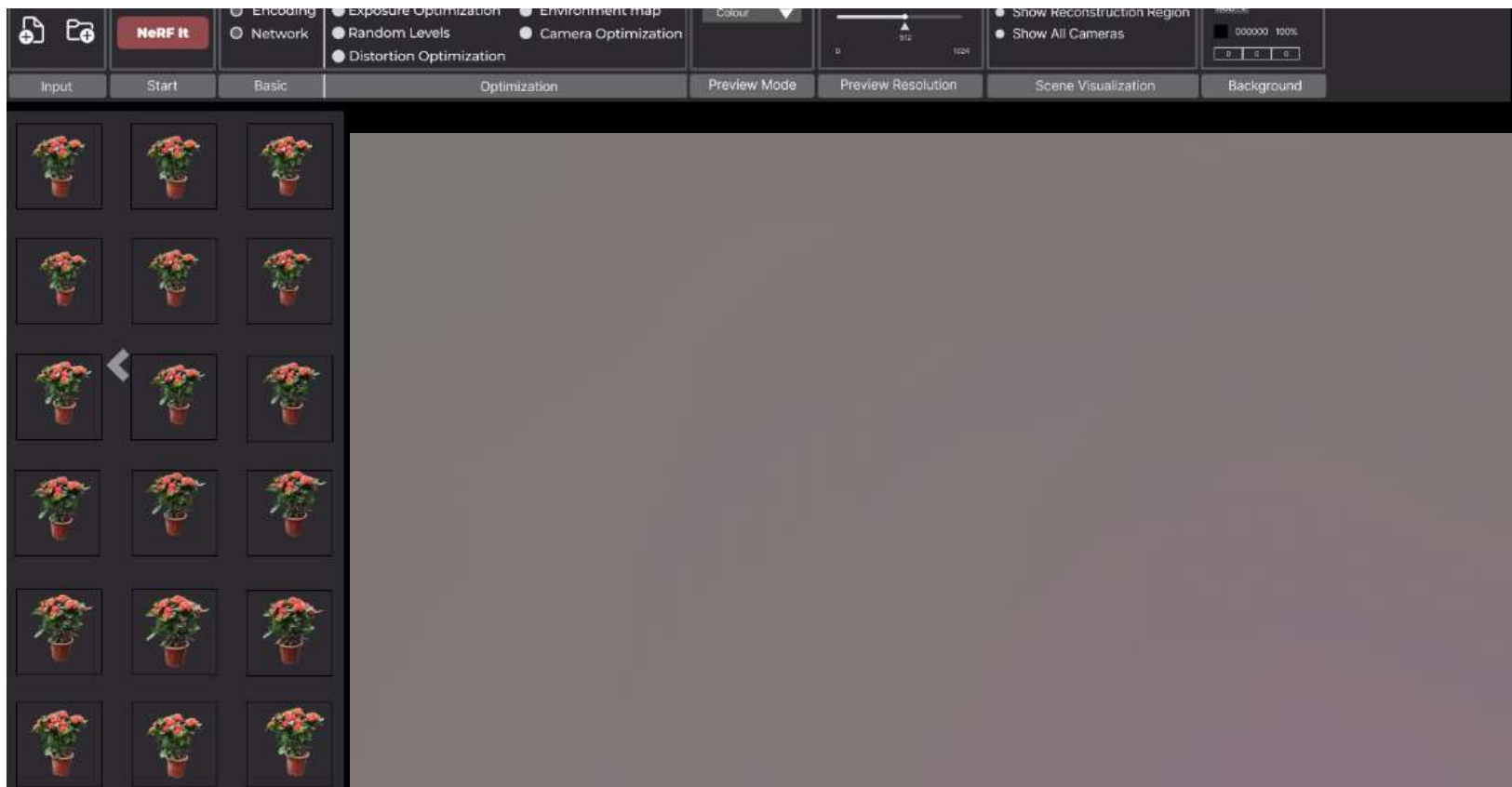
Hao Su  
UC San Diego

\*Denotes Equal contribution

TensorRF: Tensorial Radiance Fields, Chen et al., *ECCV 2022*

# Recall: Neural Engine for Static Scene

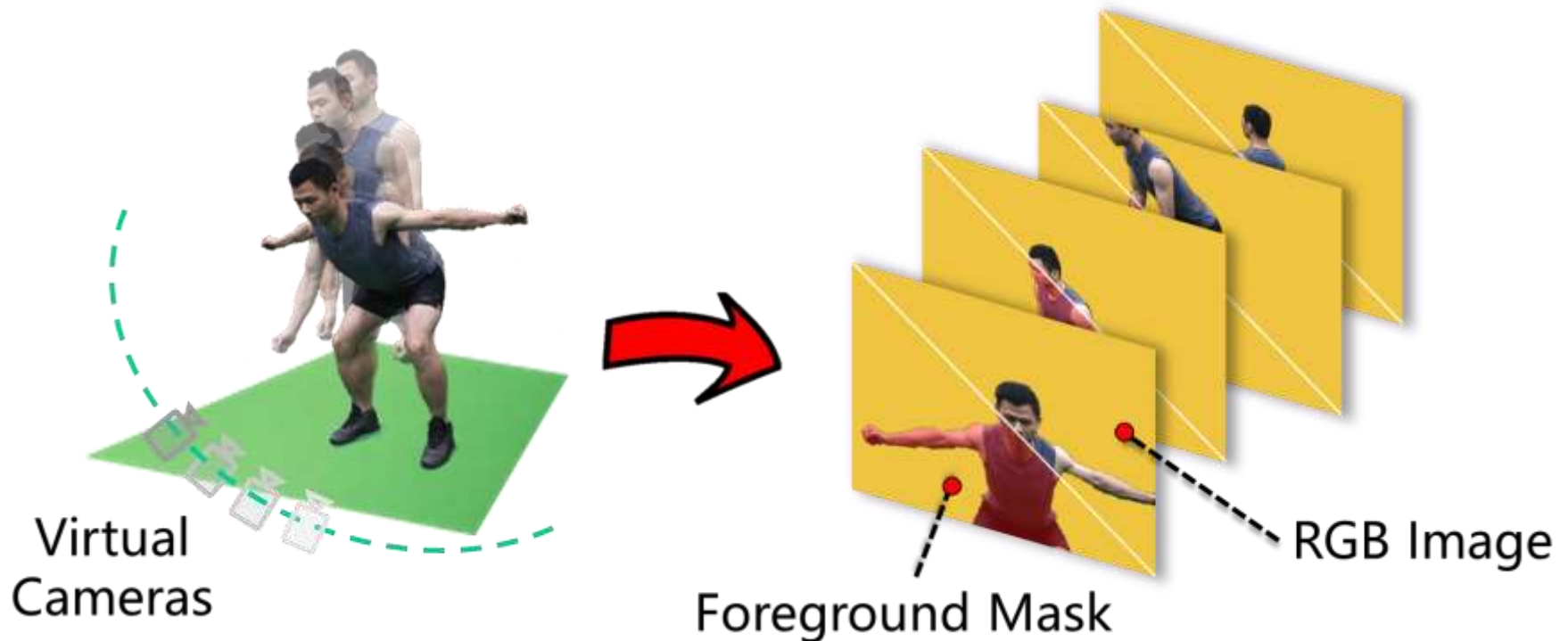
- Various attributes: appearance, geometry, etc.



Human Performance Modeling and Rendering via Neural Animated Mesh, Zhao et al., *ACM Transactions on Graphics (SIGGRAPH ASIA 2022)*

# Neural Engine for Dynamic Scene

- Photo-realistic Neural Human Rendering
- Inherent Attribute Modeling



# Neural Engine for Dynamic Scene

- Why neural: element editing; custom scene design



Editable Free-Viewpoint Video using a Layered Neural Representation, Zhang et al., *ACM Transactions on Graphics (SIGGRAPH 2021)*

# Neural Engine for Dynamic Scene

- Why neural: ultra-fast, per-frame static to dynamic

Human Performance Modeling and Rendering  
via Neural Animated Mesh

Paper ID:220

Human Performance Modeling and Rendering via Neural Animated Mesh, Zhao et al., *ACM Transactions on Graphics (SIGGRAPH ASIA 2022)*

# Neural Engine for Dynamic Scene

- Even Sparse-view and generalizable setting

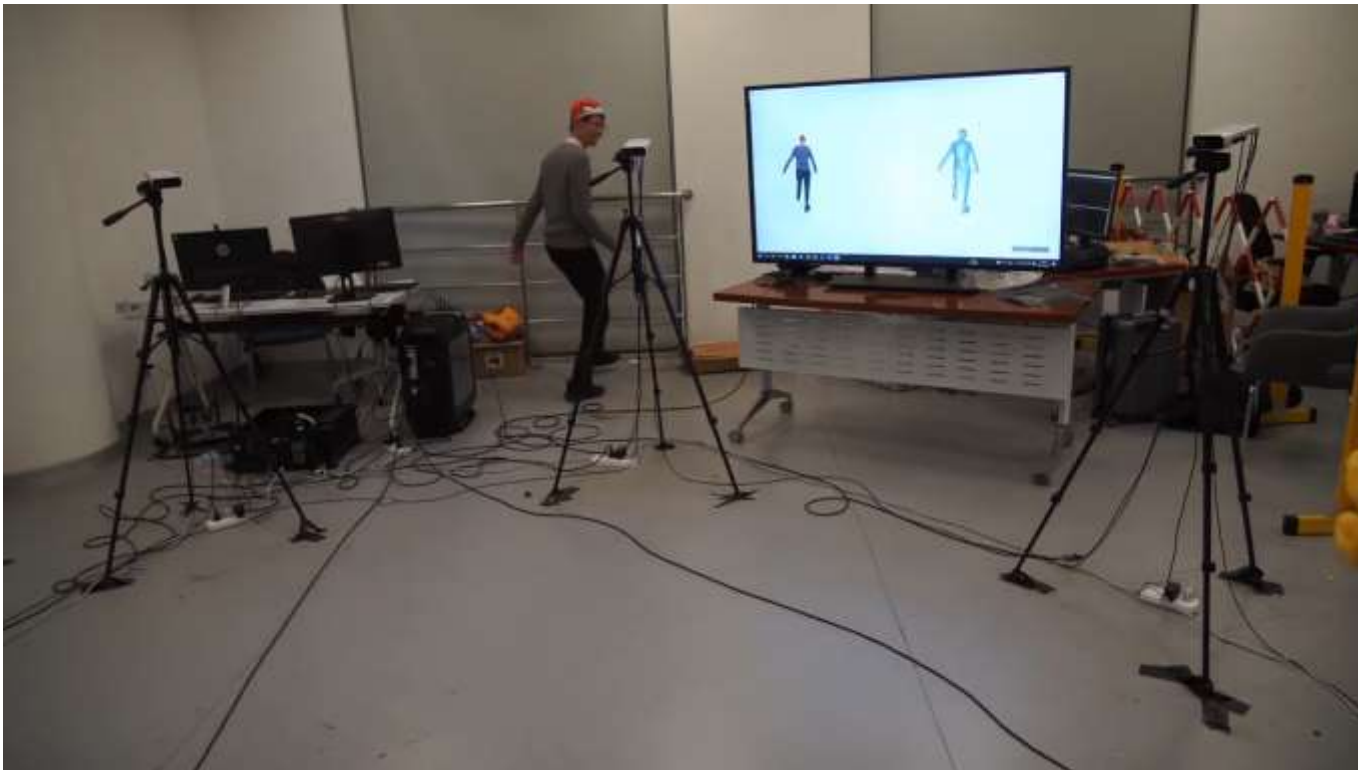


NeuralHumanFVV: Real-Time Neural Volumetric Human Performance Rendering using RGB Cameras, Suo et al., *IEEE CVPR 2021*



# Neural Engine for Dynamic Scene

- Even generalize to multi-person/ human-object interactions



NeuralHOFusion: Neural Volumetric Rendering under Human-object Interactions, Jiang et al.,  
*IEEE CVPR 2022*

# Neural Engine for Dynamic Scene

- Even generalize to multi-person/ human-object interactions

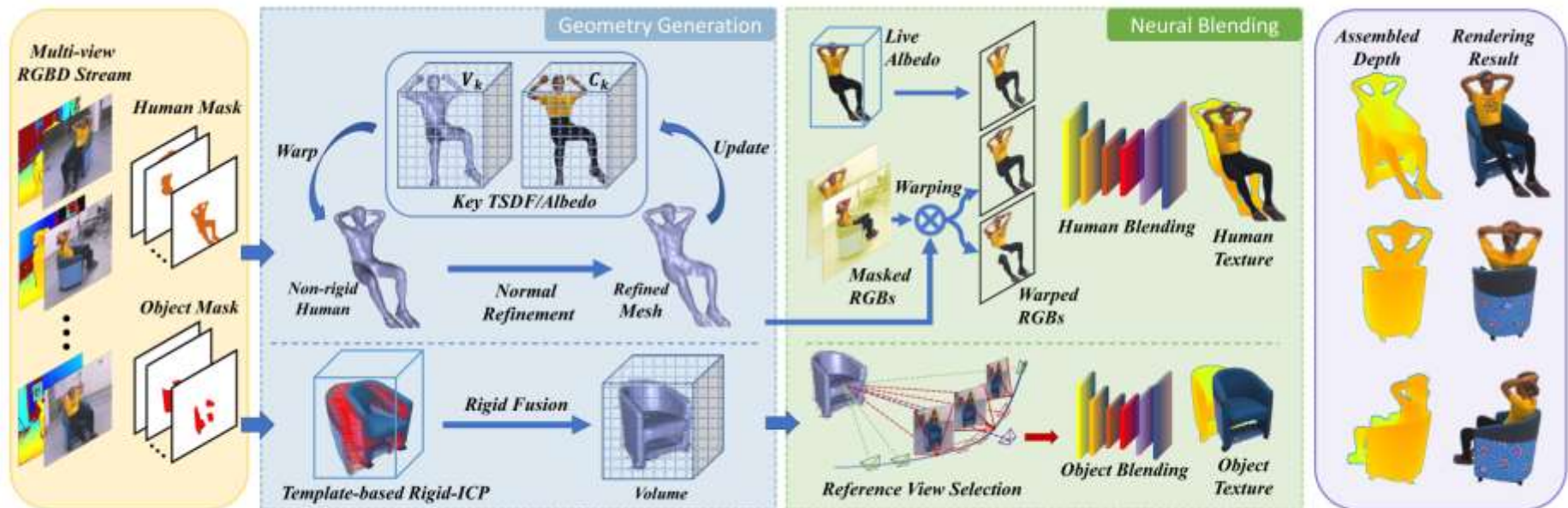


Figure 2. Our approach consists of two stages. The geometry module includes neural human reconstruction (Sec. 4.1) and template-aid object fusion (Sec. 4.2), and the blending module includes neural human blending (Sec. 4.3) and temporal neural object blending (Sec. 4.4).

NeuralHOFusion: Neural Volumetric Rendering under Human-object Interactions, Jiang et al.,  
*IEEE CVPR 2022*

# Neural Engine for Dynamic Scene

- Even for monocular RGB and Human-object setting



*Instant-NVR*: Instant Neural Volumetric Rendering for Human-object Interaction from Monocular RGBD Stream

Yuheng Jiang<sup>1,2\*</sup> Kaixin Yao<sup>1,2\*</sup> Zhuo Su<sup>3</sup> Zhehao Shen<sup>1</sup> Haimin Luo<sup>1</sup> Lan Xu<sup>1</sup>

<sup>1</sup>ShanghaiTech University <sup>2</sup>NeuDim <sup>3</sup>Pico IDL, ByteDance



Instant-NVR: Instant Neural Volumetric Rendering for Human-object Interactions from Monocular RGBD Stream, Jiang et al., *IEEE CVPR 2023*

# Neural Engine for Dynamic Scene

- Even for monocular RGB and Human-object setting
- Tracking-(mapping)-rendering

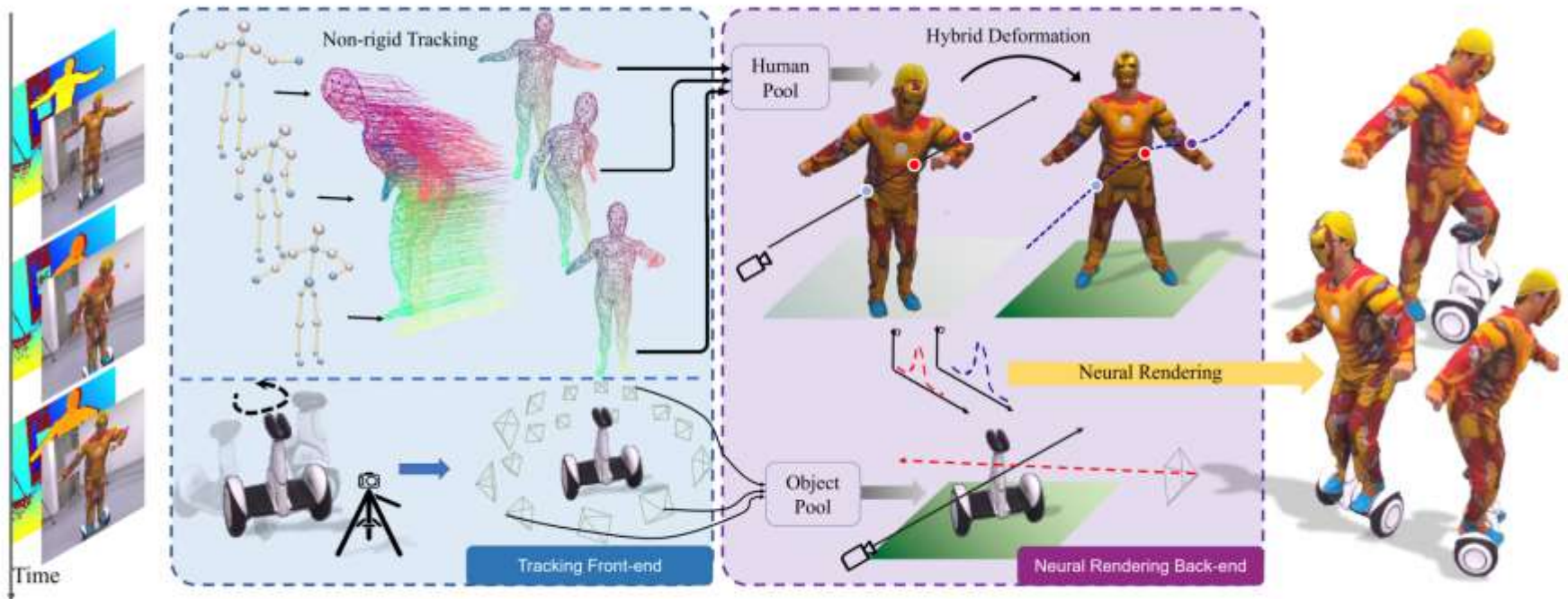


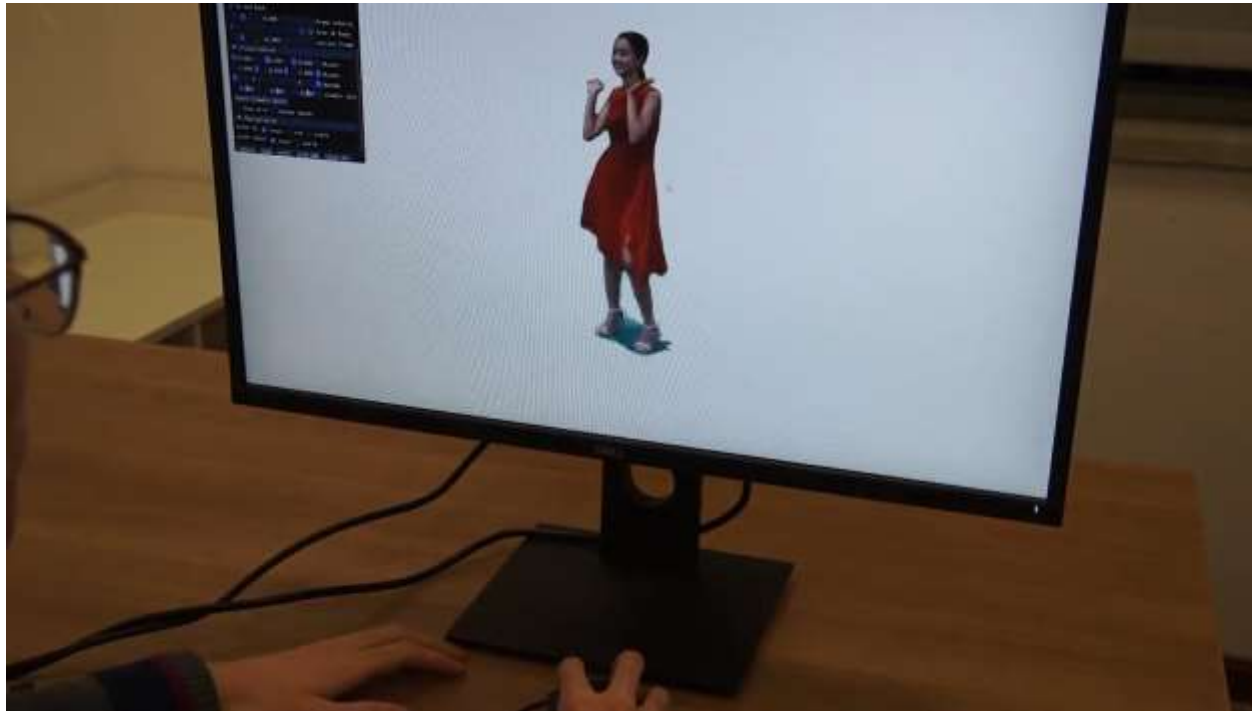
Figure 2. Our approach consists of two stages. The tracking front-end (Sec. 4.1) captures human and object motions, while the rendering back-end (Sec. 4.2) separately reconstructs the human-object radiance fields on-the-fly, for instant novel view synthesis with photo-realism.

Instant-NVR: Instant Neural Volumetric Rendering for Human-object Interactions from Monocular RGBD Stream, Jiang et al., *IEEE CVPR 2023*



# Neural Engine for Dynamic Scene

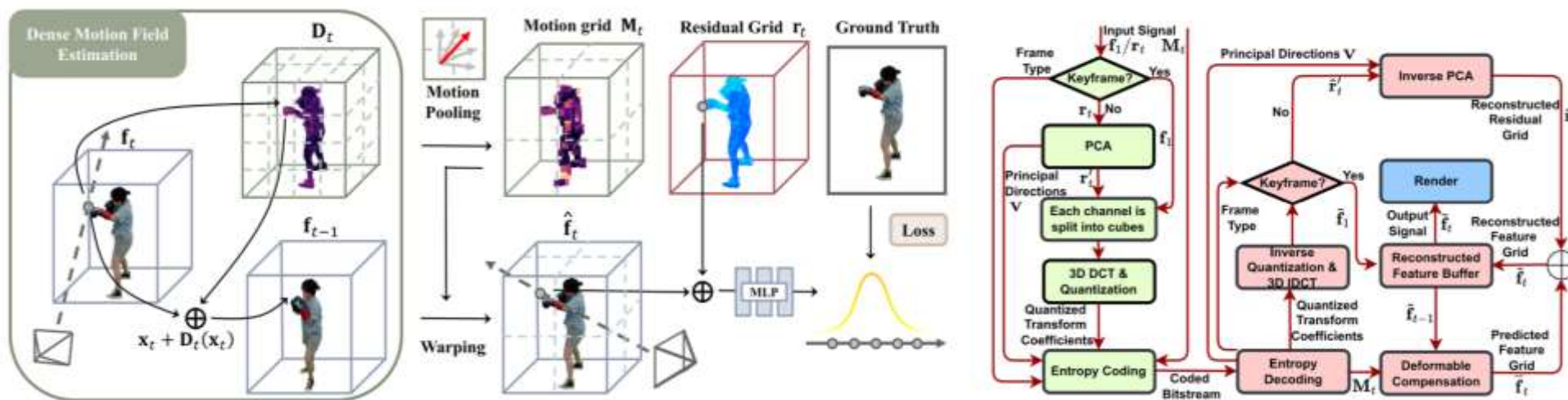
- Key idea: how to view the 4D spatial-temporally continue feature manifolds
- Fourier PlenOctree: 4D feature compression



Fourier PlenOctrees for Dynamic Radiance Field Rendering in Real-time, Wang et al., *IEEE CVPR 2022*

# Neural Engine for Dynamic Scene

- Key idea: how to view the 4D spatial-temporally continue feature manifolds
  - Streamable feature compression
  - Residual Radiance Field with codec for arbitrary long sequences



Neural Residual Radiance Fields for Streamable Free-Viewpoint Videos, Wang et al., *IEEE CVPR 2023*



# Neural Engine for Dynamic Scene

- Key idea: how to view the 4D spatial-temporally continue feature manifolds
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Neural Residual Radiance Fields for Streamable Free-Viewpoint Videos, Wang et al., *IEEE CVPR 2023*

# Neural Engine for Dynamic Scene

- Key idea: how to view the 4D spatial-temporally continue feature manifolds
  - Streamable feature compression
  - Residual Radiance Field with codec for arbitrary long sequences

## Neural Residual Radiance Fields for Streamably Free-Viewpoint Videos

Liao Wang<sup>1,3</sup>, Qiang Hu<sup>1</sup>, Qihan He<sup>1,4</sup>, Ziyu Wang<sup>1</sup>, Jingyi Yu<sup>1</sup>

Tinne Tuytelaars<sup>2</sup>, Lan Xu<sup>1</sup>, Minye Wu<sup>2</sup>

CVPR 2023

<sup>1</sup>ShanghaiTech University, <sup>2</sup>KU Leuven, <sup>3</sup>NeuDim, <sup>4</sup>DGene



上海科技大学  
ShanghaiTech University



NeuDim

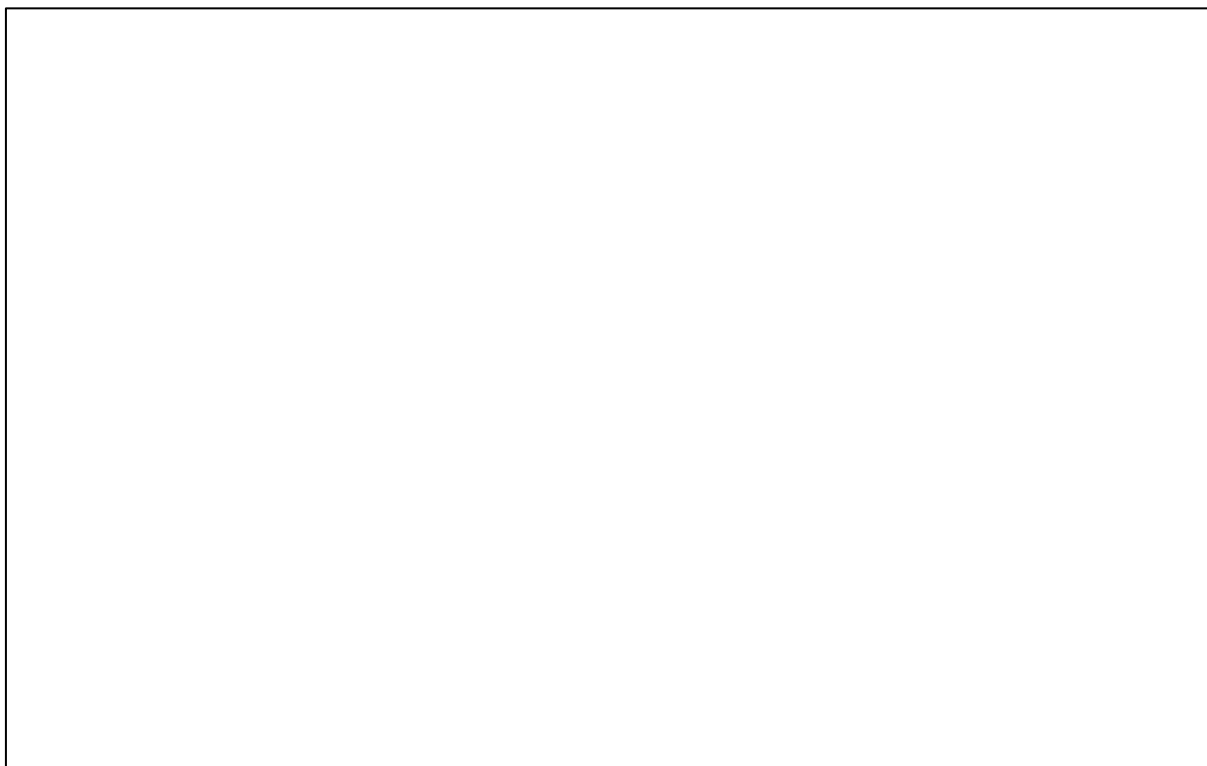


DGene

Neural Residual Radiance Fields for Streamable Free-Viewpoint Videos, Wang et al., *IEEE CVPR 2023*

# Neural Engine for Dynamic Scene

- Key idea: how to view the 4D spatial-temporally continue feature manifolds
  - Streamable feature even on mobile devices?



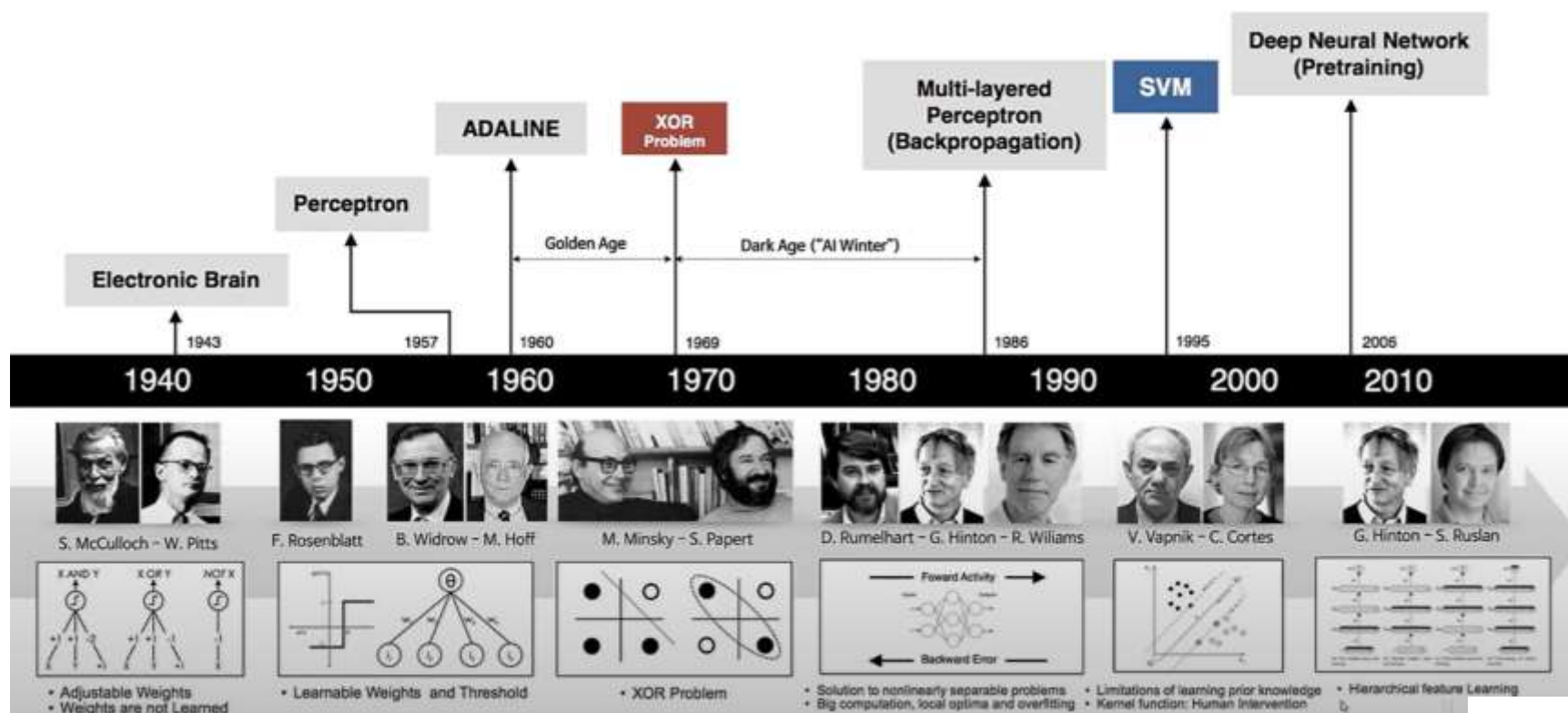
VideoRF: Rendering Dynamic Radiance Fields as 2D Feature Video Streams, Wang et al., *Arxiv 2023*



A quick summary.....

# Summary: Why deep learning?

- A long story with a huge recent success



# Summary: Why deep learning?

- A long story with a huge recent success



ACM Turing Award 2019 (Nobel Prize of Computing)  
Yann LeCun, Geoffrey Hinton, and Yoshua Bengio



# Summary: Why deep learning?

- Huge recent success
- with **chaos**, **peer-pressure**, or even **misunderstandings**



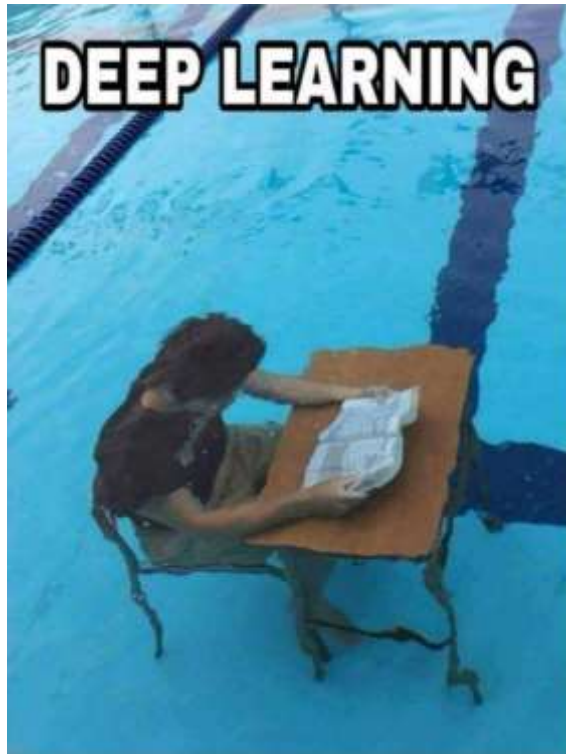
This guy didn't know  
about neural networks



This guy learned  
about neural networks

# Summary: Why deep learning?

- Huge recent success
- with **chaos**, **peer-pressure**, or even **misunderstandings**



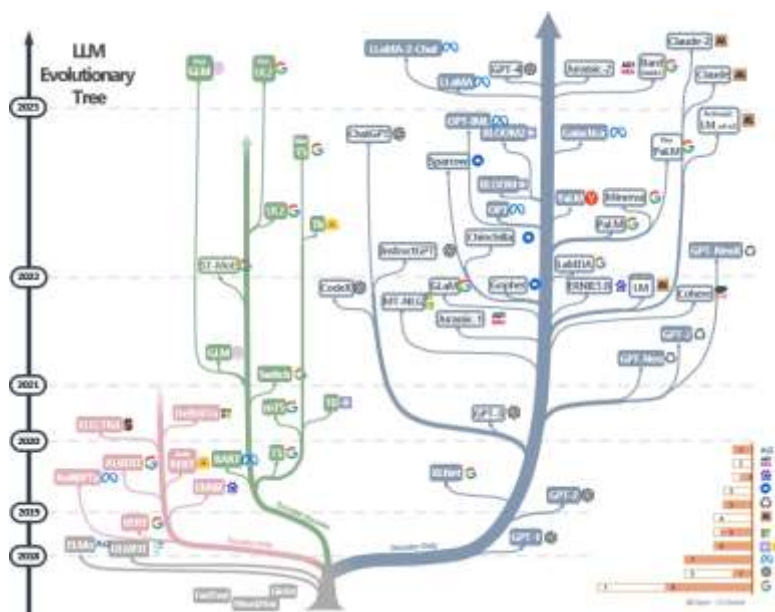
# Summary: Why deep learning?

- New paradigm IS happening!
- Large model, Large computing, Large data
- **Move fast** and be **open-minded** to the new party



# Summary: Why deep learning?

- New paradigm IS happening!
- Large model, Large computing, Large data
- **Move fast** and be **open-minded** to the new party





Keep moving, my friends .....