



中国科学技术大学

University of Science and Technology of China

# 数字人课程：三维数字人表示

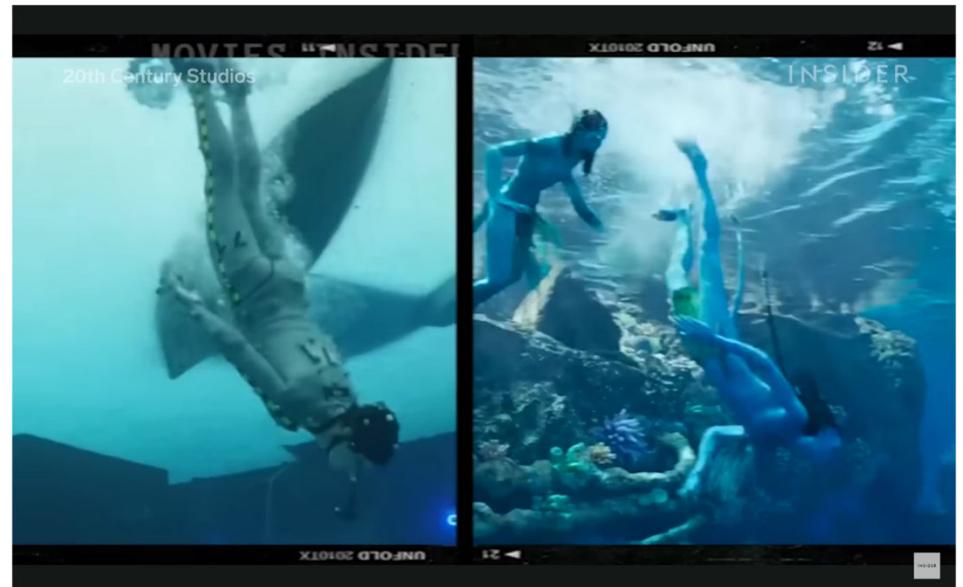


郭玉东  
中国科学技术大学

# 应用驱动的数字人表示



视频人脸特效



CG电影

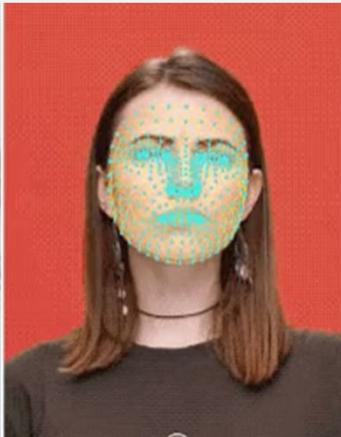
<https://developers.google.com/ar/develop/augmented-faces>  
<https://www.youtube.com/watch?v=IPQ5vTqqdgE>

# 应用驱动的数字人表示

面部动态几何、精细几何模型



视频人脸特



显式网格表示



电影

# 应用驱动的数字人表示



超写实数字主持人



沉浸式视频广告

<https://tv.cctv.com/2024/03/07/VIDEUrHr2Zkw6l0ZrmhN7KXP240307.shtml>  
<https://www.youtube.com/watch?v=34KeBnSwvmc>

# 应用驱动的数字人表示

外观看形象精确、立体式还原



超写实数字主

神经辐射场表示

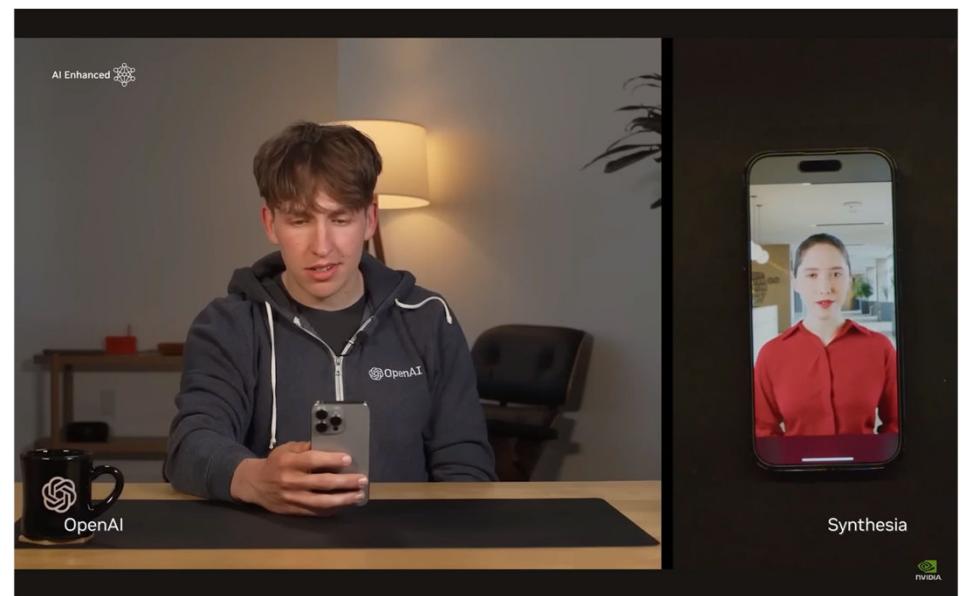


视频广告

# 应用驱动的数字人表示



全息沉浸式会议

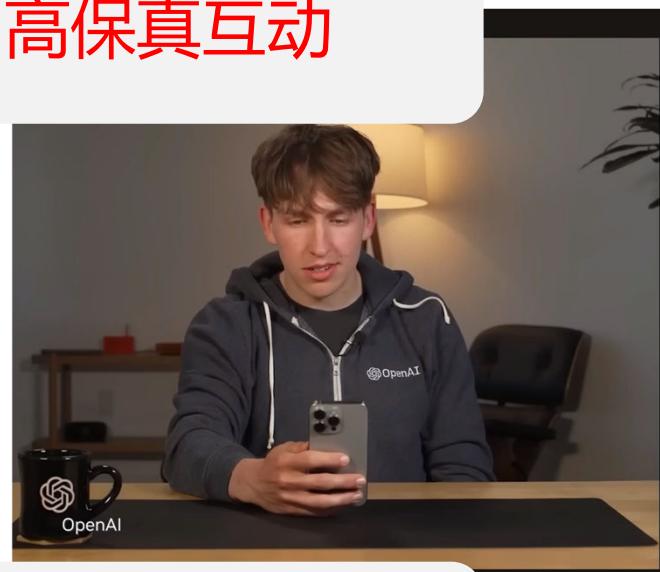


超写实AI Agent

<https://www.youtube.com/watch?v=xWwMrw7GeX8>  
<https://www.youtube.com/watch?v=8xMeliwBnlPU>

# 应用驱动的数字人表示

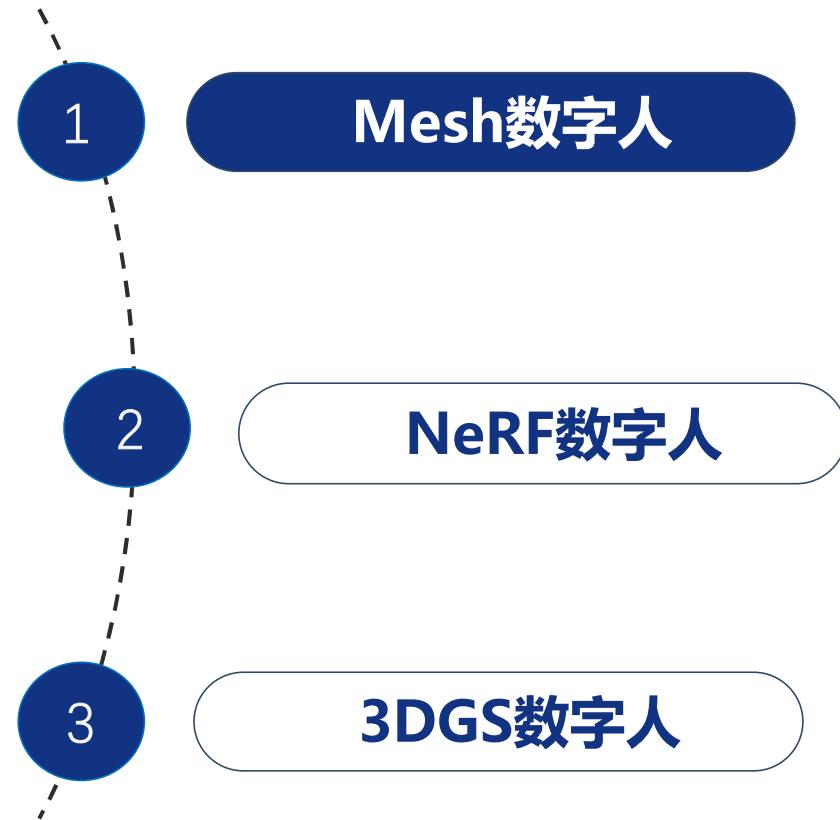
实时全息、高保真互动



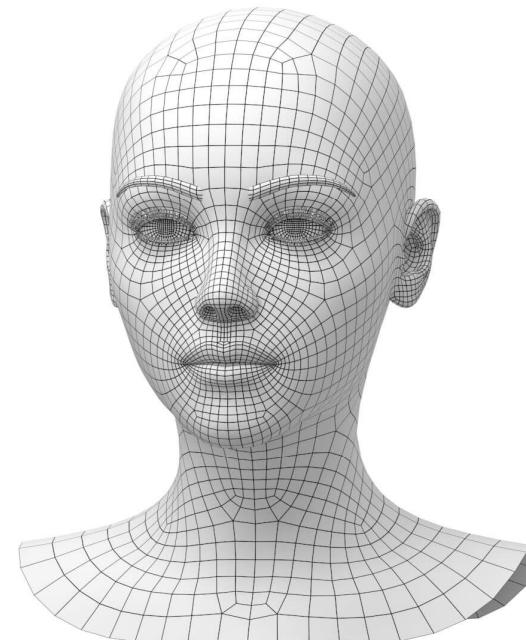
全息沉浸式会

三维高斯泼溅表示

AI Agent

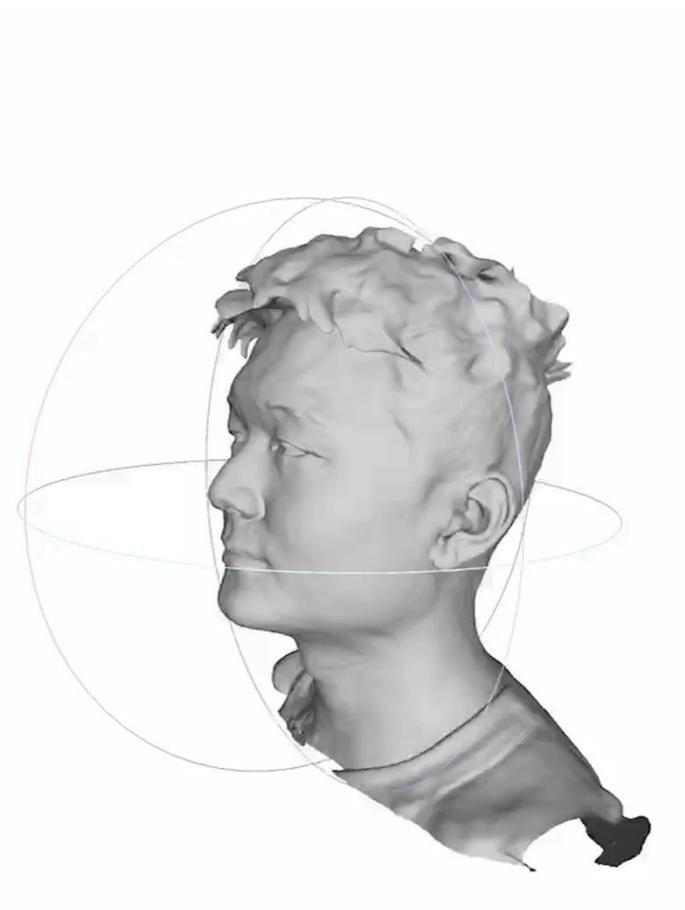


# ■ Mesh简介



$(V, E, F)$

# Mesh简介



精细几何

渲染高效

驱动方便

# 特定身份建模Challenge



多样性高

几何复杂

维度高

<https://github.com/NVlabs/ffhq-dataset>

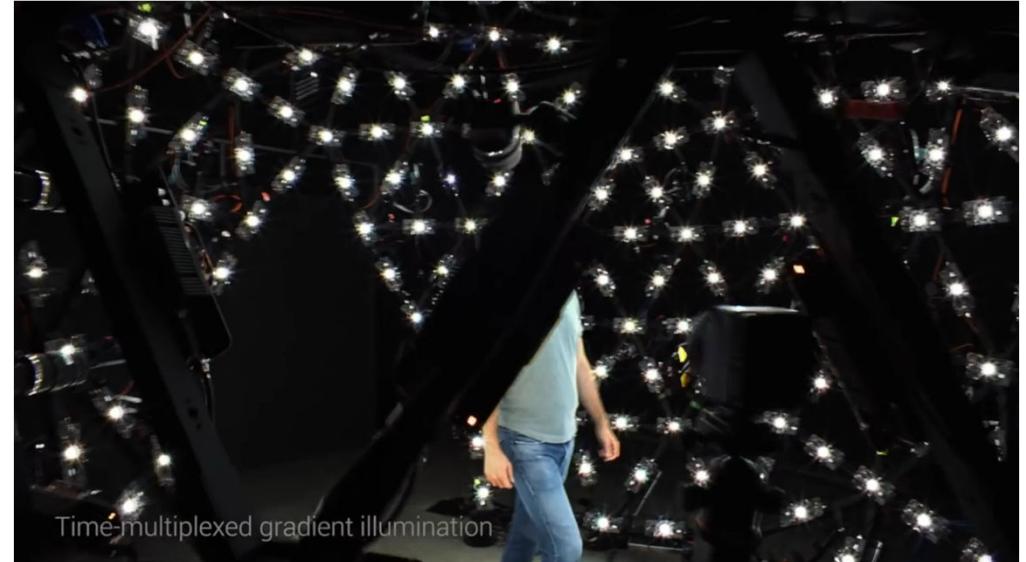
变量维度高，需要更多等式约束（观测）

# 精细Mesh数字人制作流程



GTC 2021, NVIDIA  
Multi-view Stereo

[https://www.youtube.com/watch?v=f\\_V30ueEXE4](https://www.youtube.com/watch?v=f_V30ueEXE4)  
<https://www.youtube.com/watch?v=anBRroZWfzI>



精细建模  
设备昂贵，成本高  
只适用于采集者，无法scale到他人

The Relightables, Google  
Photometric Stereo

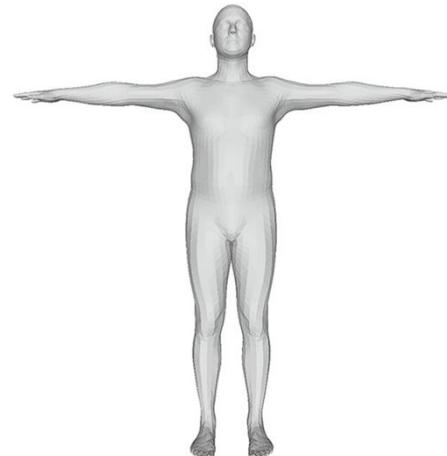
# 解决泛化问题Key Idea — 生成模型

- 利用低维Code生成高维真实数据的生成模型，将解高维方程转化为求解低维方程，从而可减少观测/输入



Latent Space  
128 Dim Vector Z

# 参数化表示—降维

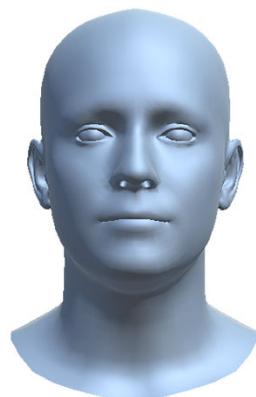


Domain先验

- Human Body
- Faces
- Hands

实用性

- 可泛化
- 参数量低
- 求解简便



$$\mathbf{x} \in \mathbb{R}^D \xrightarrow{f(\mathbf{x}, \theta)} \mathbf{z} \in \mathbb{R}^d$$

- 拓扑共享
- 顶点变形
- 高维向量

降维

- PCA
- Auto Encoder
- VAE

# How to Build

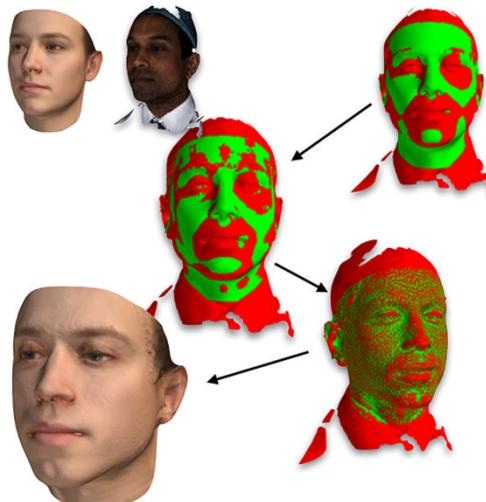
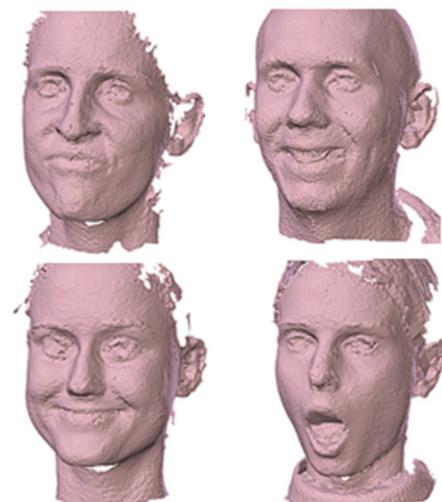


Data Capturing

Multi-view Images

Multi-view Stereo

Raw Scan Data



Non-Rigid ICP

拓扑一致的样本网格  
 $X \in R^{N \times D}$

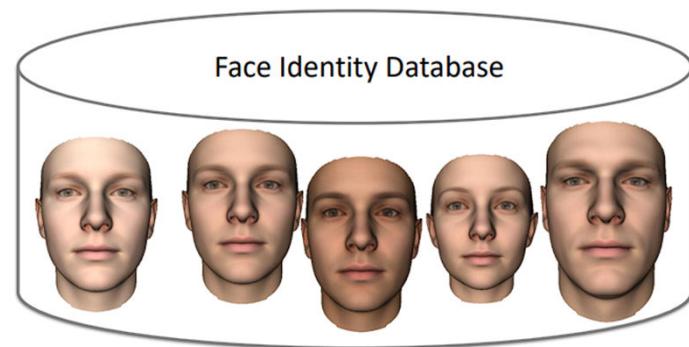
```
X_std = (X - mean(X)) / std(X)
C = cov(X_std)
vals, vecs = eig(C)
P_k = vecs[:, argsort(vals)[::-1]]
Components = P_k[:, :k]
Z = X_std @ Components
```

```
Z = Encoder(X)
X_rec = Decoder(Z)
loss = recon_loss(X, X_rec)
for _ in range(epochs):
    Z = Encoder(X)
    X_rec = Decoder(Z)
    loss = recon_loss(X, X_rec)
    optimizer.step(loss.backward())
```

Dim Reduction

$x \in \mathbb{R}^D \xrightarrow{f(x, \theta)} z \in \mathbb{R}^d$

# 人脸参数化表示—3DMM



A vector space of 3D shapes and colors of a class of objects  
• linear combinations of shapes  $\mathbf{S}$  and textures  $\mathbf{T}$

$$\mathbf{S} = \sum_i \alpha_i \mathbf{S}_i = \alpha_1 \cdot \text{shape}_1 + \alpha_2 \cdot \text{shape}_2 + \alpha_3 \cdot \text{shape}_3 + \alpha_4 \cdot \text{shape}_4 + \dots$$

$$\mathbf{T} = \sum_i \beta_i \mathbf{T}_i = \beta_1 \cdot \text{texture}_1 + \beta_2 \cdot \text{texture}_2 + \beta_3 \cdot \text{texture}_3 + \beta_4 \cdot \text{texture}_4 + \dots$$

- Often: Principal Component Analysis (PCA)



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A morphable model for the synthesis of 3D faces. SIGGRAPH 1999.

# 人脸参数化表示—3DMM

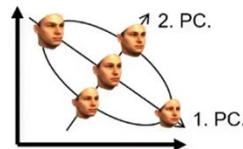
A vector space of 3D shapes and colors of a class of objects

- linear combinations of shapes  $\mathbf{S}$  and textures  $\mathbf{T}$

$$\mathbf{s} = \sum_i \alpha_i \mathbf{s}_i = \alpha_1 \cdot \text{shape}_1 + \alpha_2 \cdot \text{shape}_2 + \alpha_3 \cdot \text{shape}_3 + \alpha_4 \cdot \text{shape}_4 + \dots$$

$$\mathbf{T} = \sum_i \beta_i \mathbf{T}_i = \beta_1 \cdot \text{texture}_1 + \beta_2 \cdot \text{texture}_2 + \beta_3 \cdot \text{texture}_3 + \beta_4 \cdot \text{texture}_4 + \dots$$

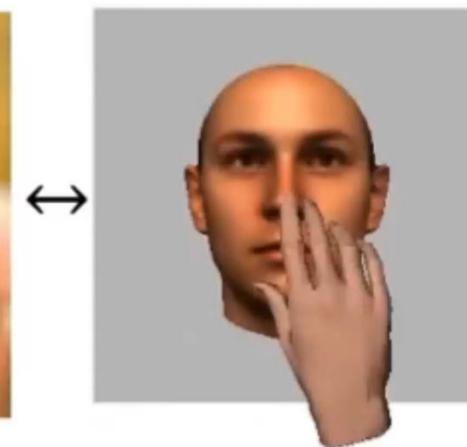
- Often: Principal Component Analysis (PCA)



Input Image



Synthetic Image

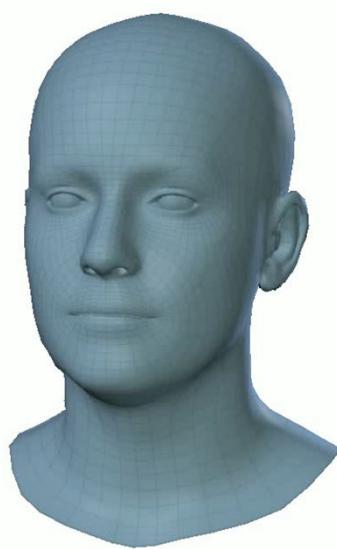


Fitting on in-the-wild images

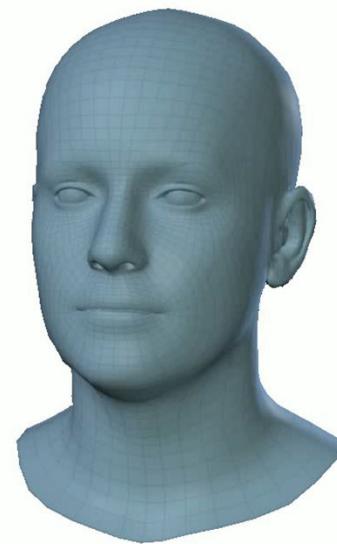
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A morphable model for the synthesis of 3D faces. SIGGRAPH 1999.

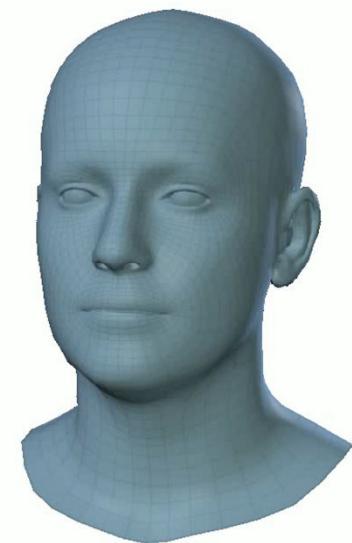
# 带表情参数化表示—FLAME



Identity



Expression



Pose

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Learning a model of facial shape and expression from 4D scans. SIGGRAPH Asia 2017.

# 带表情参数化表示

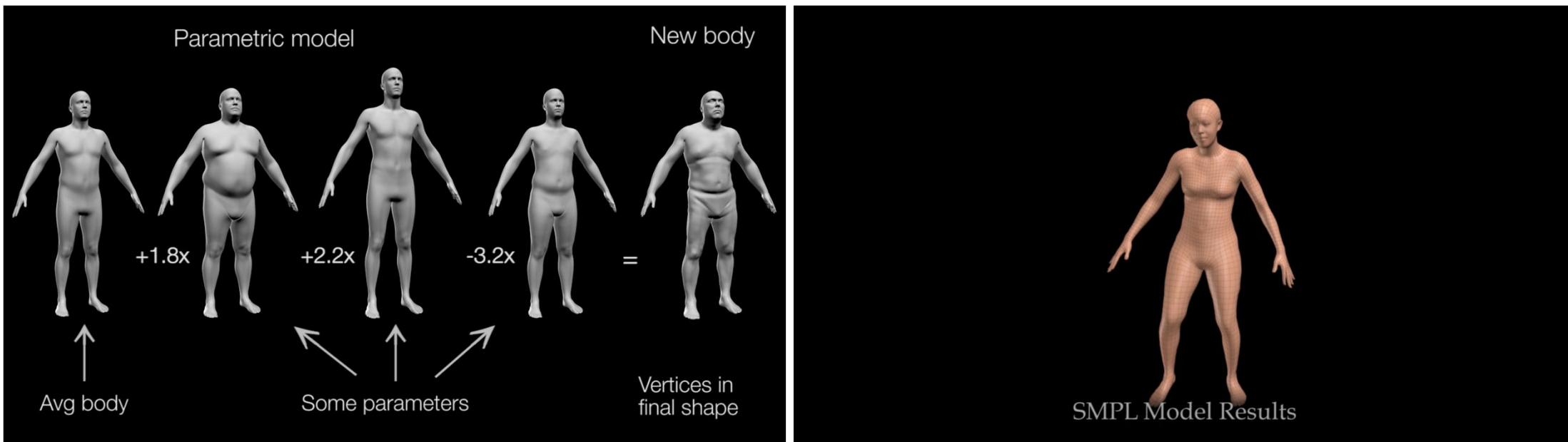
- 得益于低维表示及表情编码，可高效建模与驱动



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CNN-based Real-time Dense Face Reconstruction with Inverse-rendered Photo-realistic Face Images. TPAMI 2018.

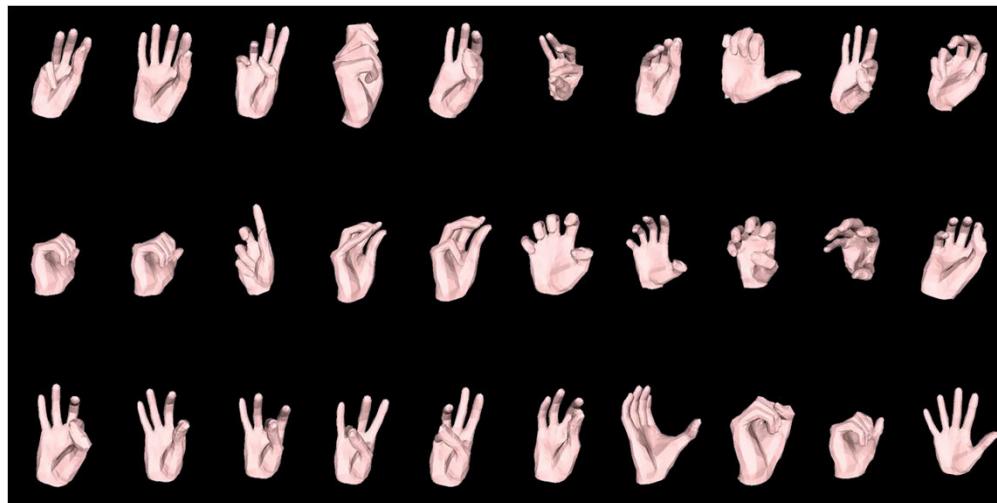
# Body参数化表示



1860个人体各种姿势下的扫描数据

SMPL: A Skinned Multi-Person Linear Model. SIGGRAPH Asia 2015.

# Hand参数化表示



31个人的2018个手部扫描数据

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Embodied Hands: Modeling and Capturing Hands and Bodies Together. SIGGRAPH Asia 2017.

# 产业界MetaHuman



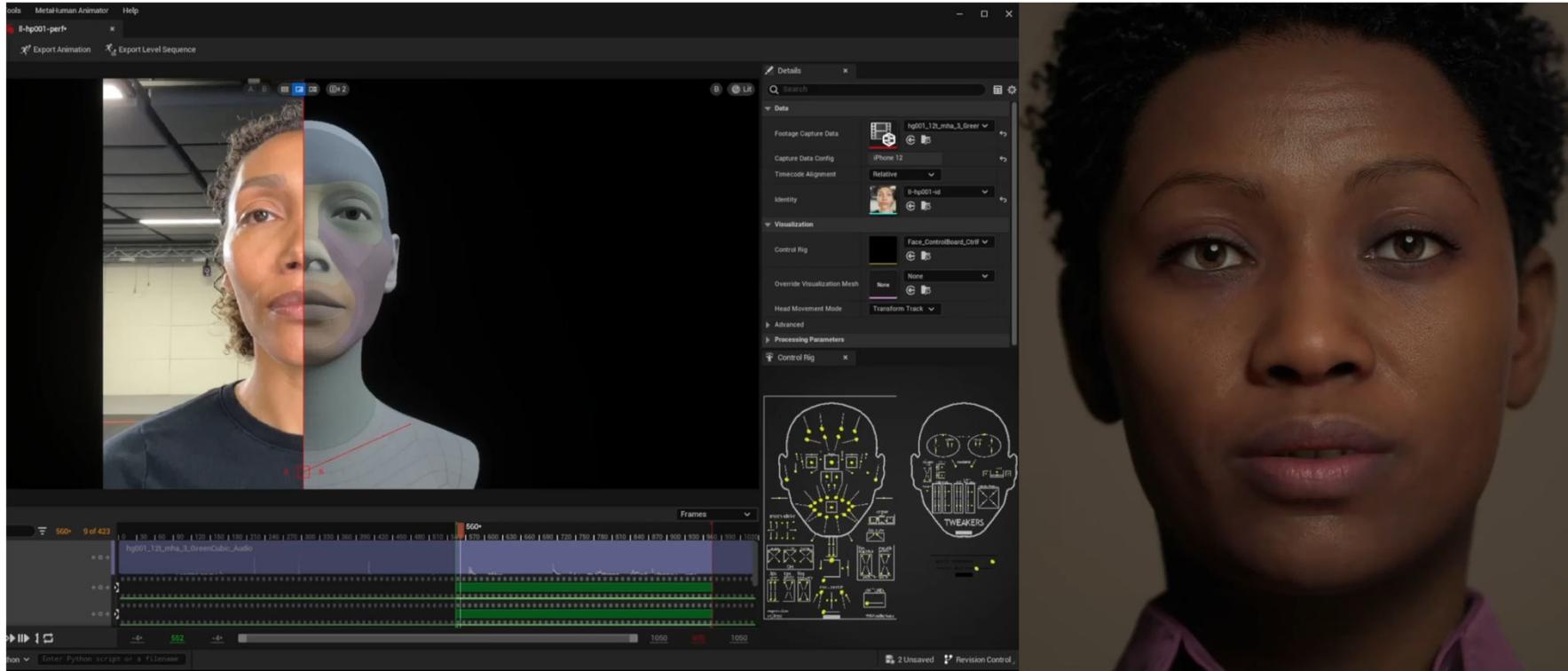
基于上万个人体的扫描数据构建

<https://www.unrealengine.com/en-US/metahuman>



- 更完整：头发、牙齿等手工建模的资产
- 更真实：相对学术界参数化模型
- 不够Photo-Realistic
- 难以方便地对特定用户进行复刻

# Mesh驱动—MetaHuman Animator



<https://www.unrealengine.com/en-US/metahuman>

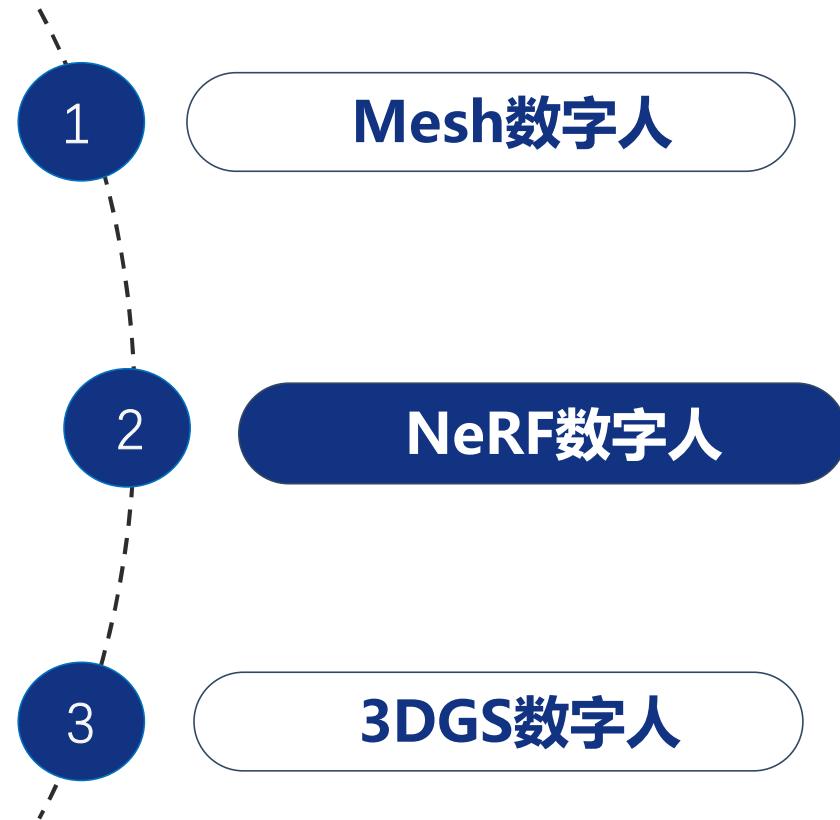
# 驱动Mesh人体—Siren数字人



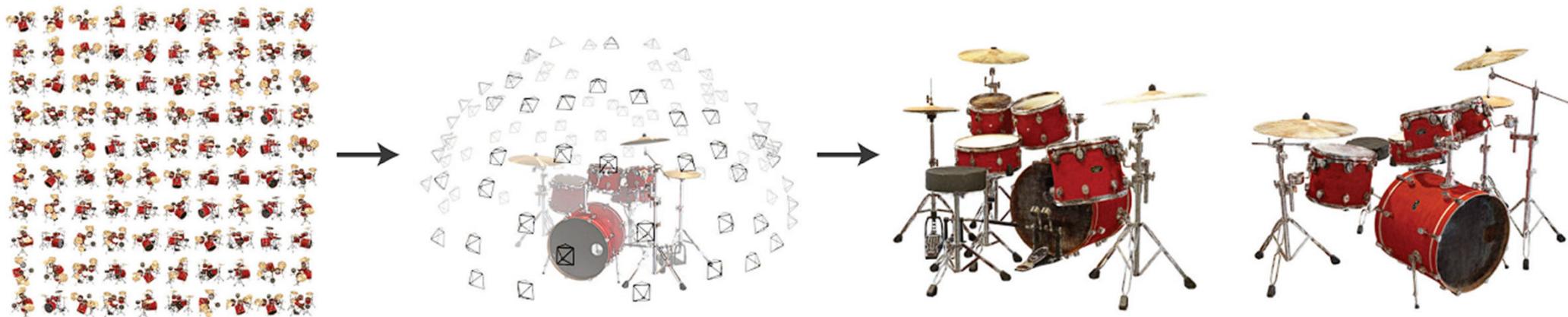
<https://www.youtube.com/watch?v=9owTAISsvwk>

# Mesh驱动人体—Siren数字人





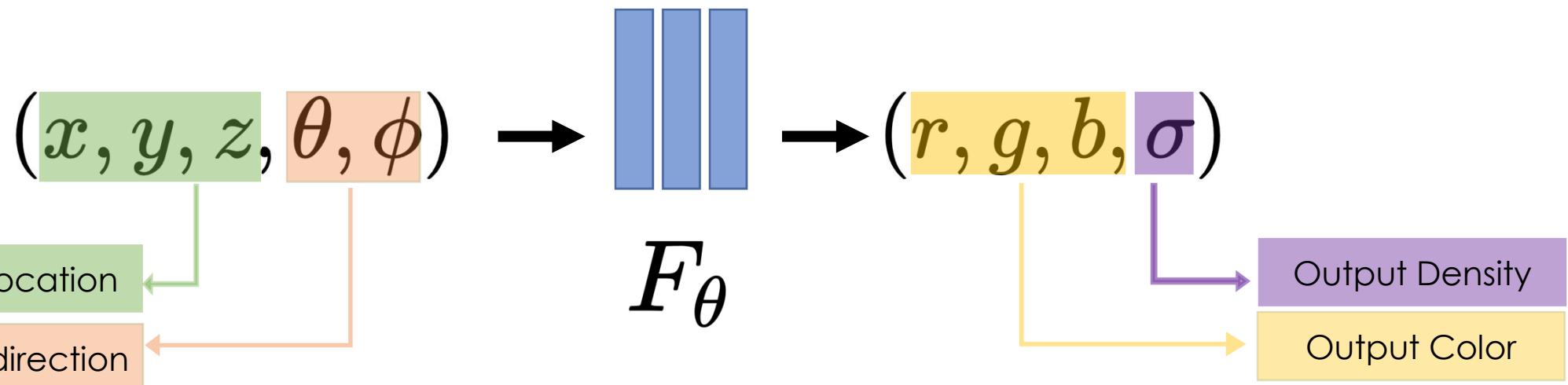
# NeRF简介—任务



NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.

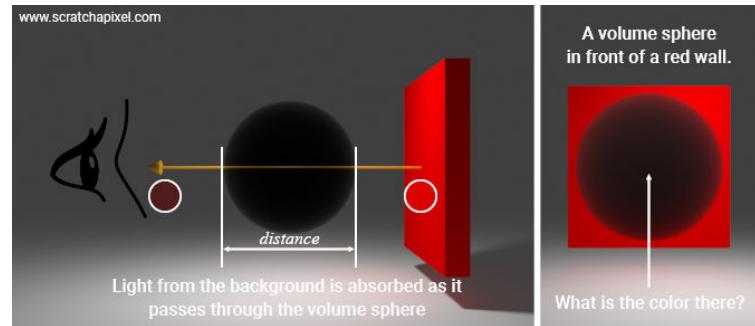
# NeRF简介—KeyIdea

学习场景的辐射场表示

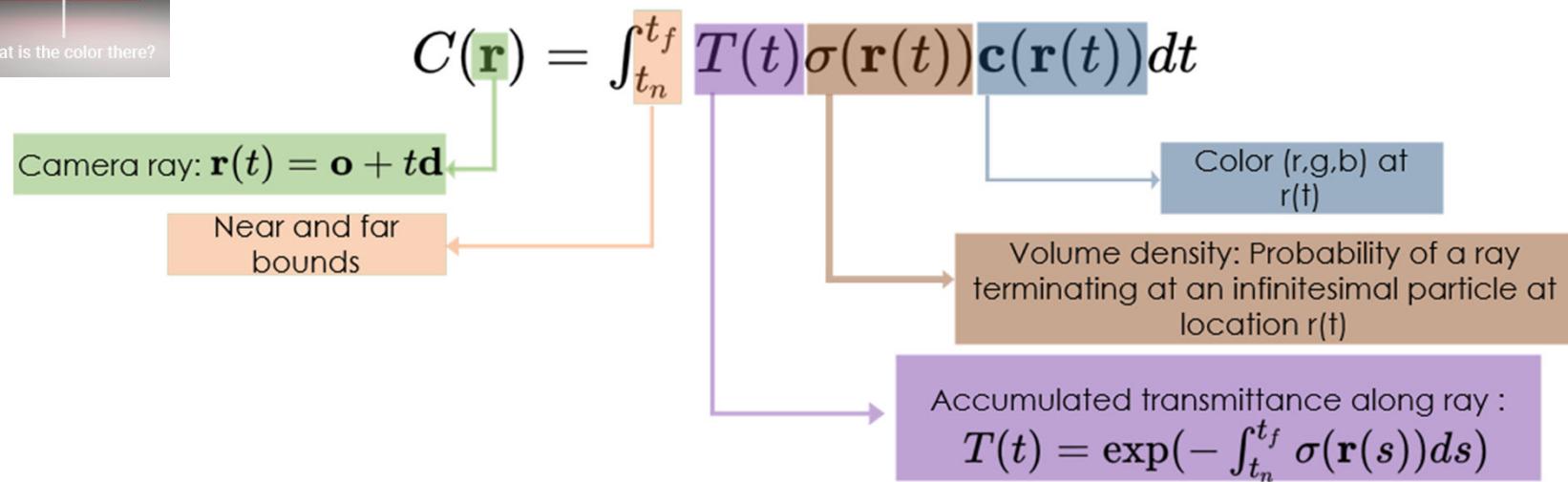


NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. ECCV 2020.

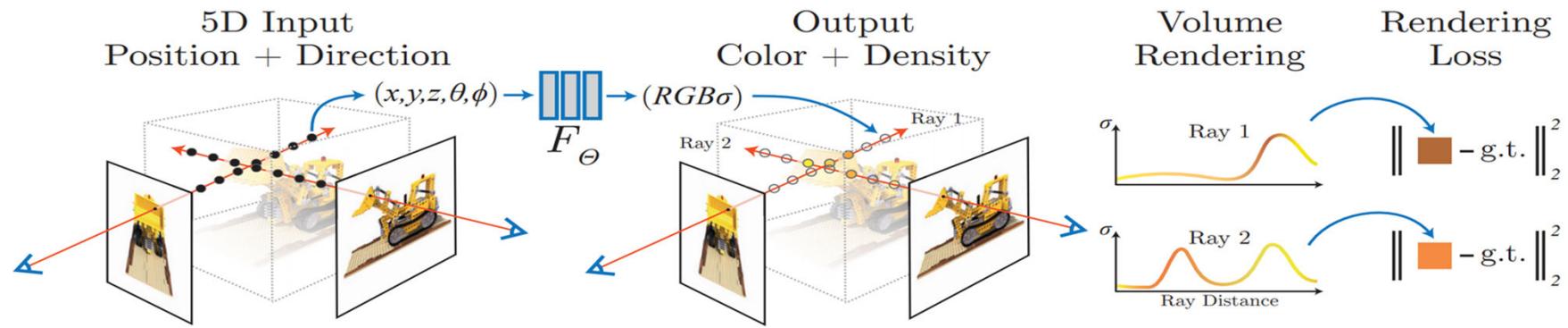
# NeRF简介—一体渲染



Given color and density  $(r, g, b, \sigma)$ , we calculate the color of every camera ray using:



# NeRF简介



## Training NeRF:

- 1) 逐像素沿着相机的射线在场景中生成一组采样的3D点
- 2) 采样点位置及视线方向输入MLP中，输出采样点的颜色和密度
- 3) 使用体渲染技术将这些颜色和密度累积成一个2D图像
- 4) 最小化渲染的颜色与GT颜色，Loss梯度回传

# NeRF优势 — PhotoRealistic建模

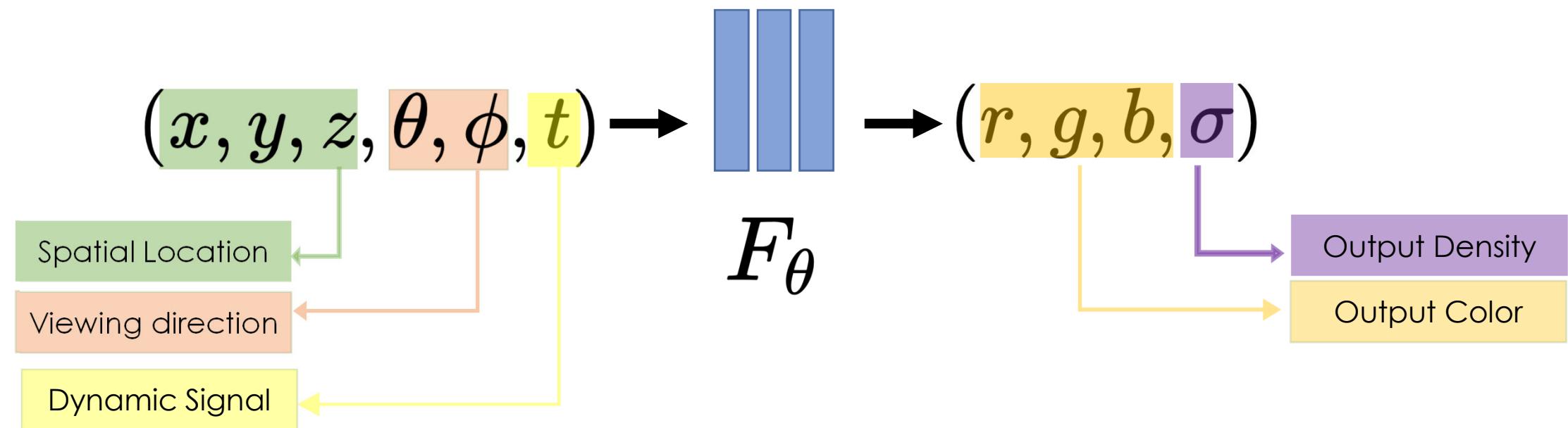
- 得益于NeRF强大的表达能力和端到端的可微过程



Instant Neural Graphics Primitives with a Multiresolution Hash Encoding. SIGGRAPH 2022.

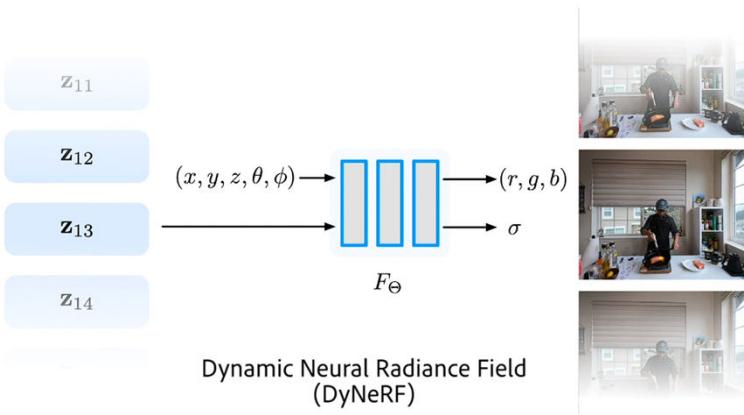
# NeRF数字人表示—KeyIdea

- 额外加一个动态输入（时间/驱动信号等）预测动态的辐射场



# NeRF数字人表示—DyNeRF

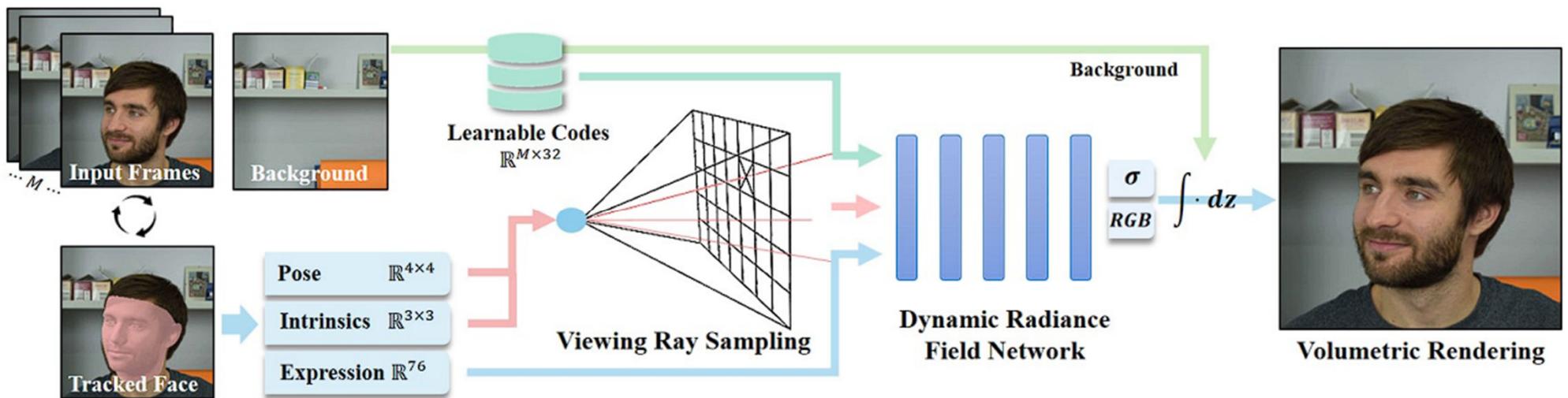
- 动态辐射场可渲染动态场景



Neural 3D Video Synthesis from Multi-view Video. CVPR 2022.

# NeRF数字人表示—NeRFace

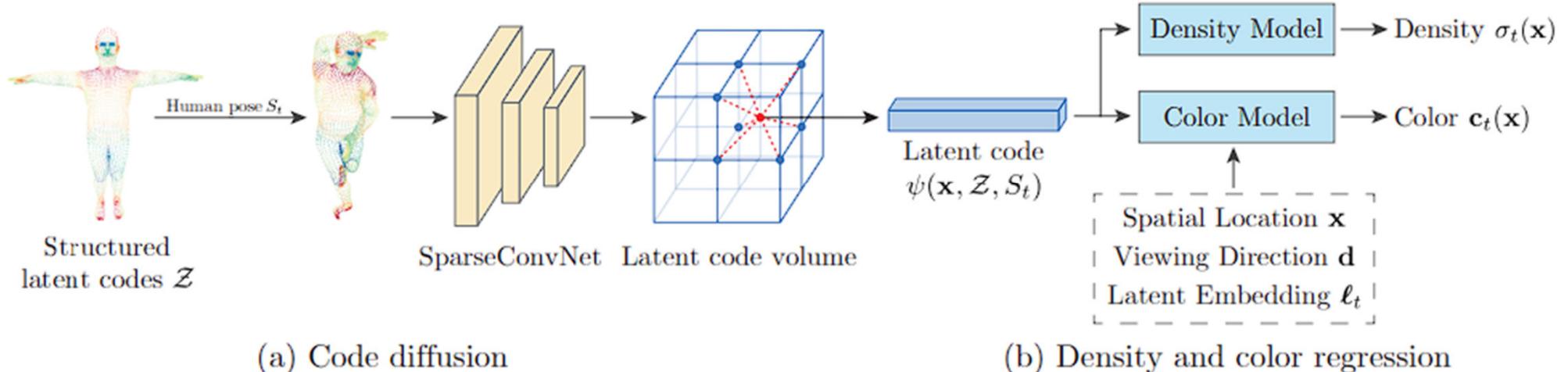
- 将表情信号作为动态辐射场的输入



Dynamic Neural Radiance Fields for Monocular 4D Facial Avatar Reconstruction. CVPR 2021.

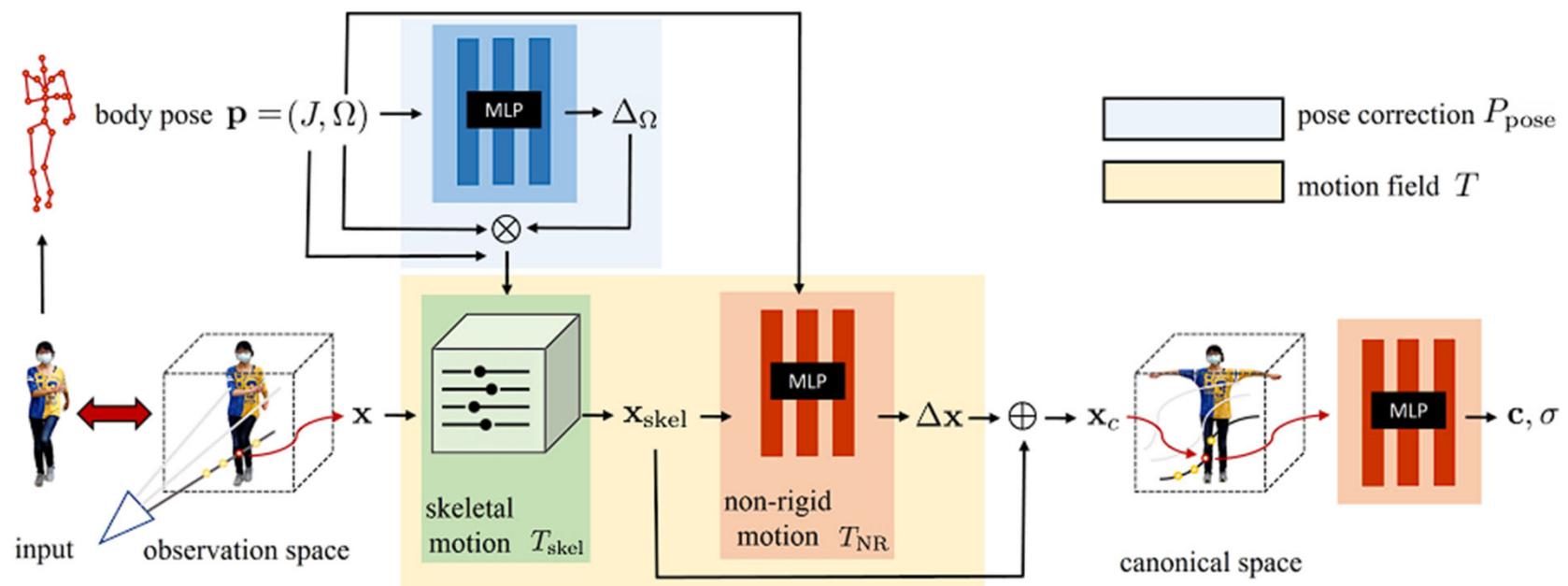
# NeRF数字人表示—NeuralBody

- 将辐射场绑定在动态Mesh人体上



# NeRF数字人表示—HumanNeRF

- 将辐射场绑定在骨架驱动的人体上



HumanNeRF: Free-viewpoint Rendering of Moving People from Monocular Video. CVPR 2022.

# NeRF数字人表示—HumanNeRF



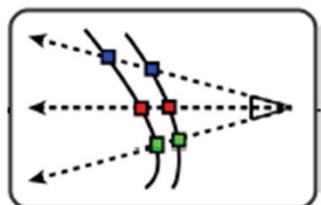
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HumanNeRF: Free-viewpoint Rendering of Moving People from Monocular Video. CVPR 2022.

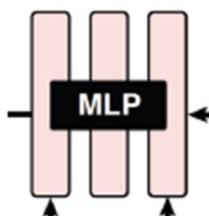
# NeRF的一些问题

## Rendering NeRF:

- 1) 逐像素沿着相机的射线在场景中生成一组**采样的**3D点
- 2) 采样点位置及视线方向输入**MLP**中，输出采样点的**颜色和密度**
- 3) 使用**体渲染**技术将这些颜色和密度累积成一个2D图像



\*



采样点数量

\*

逐点计算成本

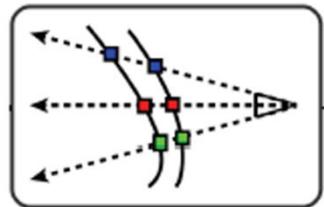
=

渲染成本

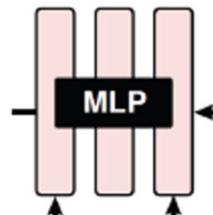
Training: 1~2 days

Rendering: ~10s / frame, 0.1 fps

# NeRF加速表示—Key Idea



\*



采样点数量

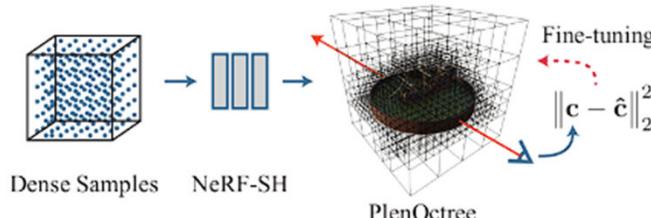
\*

逐点计算成本

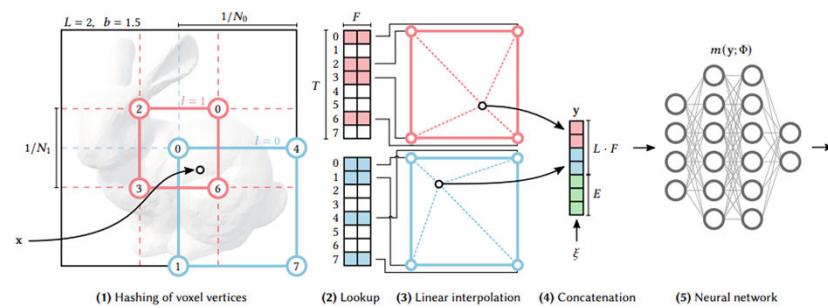
=

渲染成本

- 结构化 / 显式存储，消除/降低MLP计算成本，减少采样



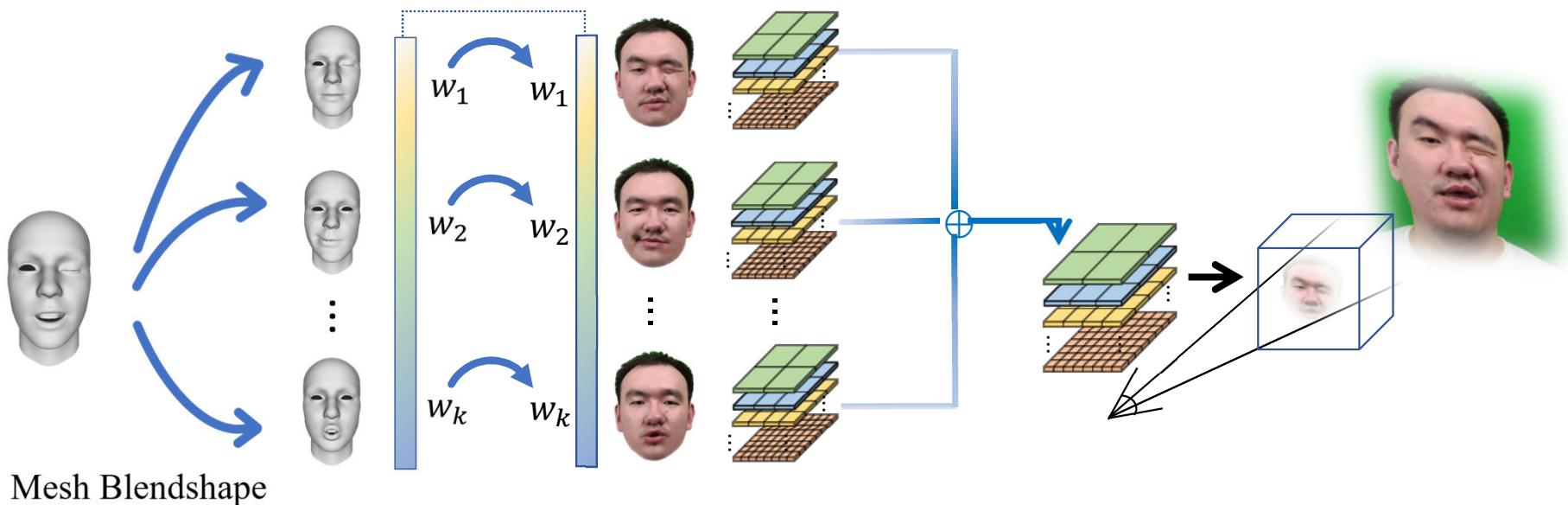
PlenOctrees, ICCV 2021



InstantNGP, SIGGRAPH 2022

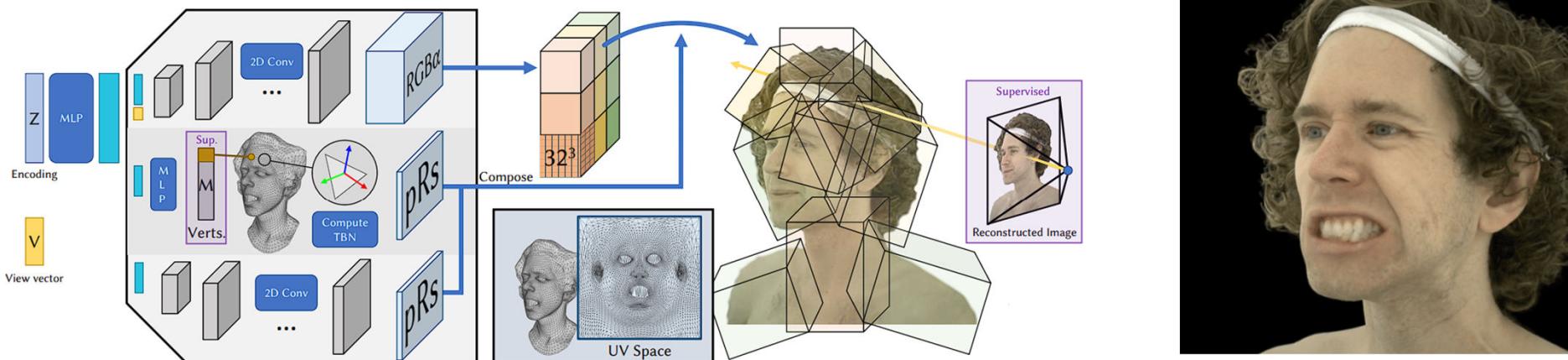
# NeRF加速数字人表示—NeRBlendshape

- 将每个表情Blendshape建模一个高效NeRF表示



# NeRF加速数字人表示—MVP

- 将三维辐射场规则化到体元 (Primitives) 表示:



Mixture of Volumetric Primitives. SIGGRAPH 2021.

# Still not that Efficient

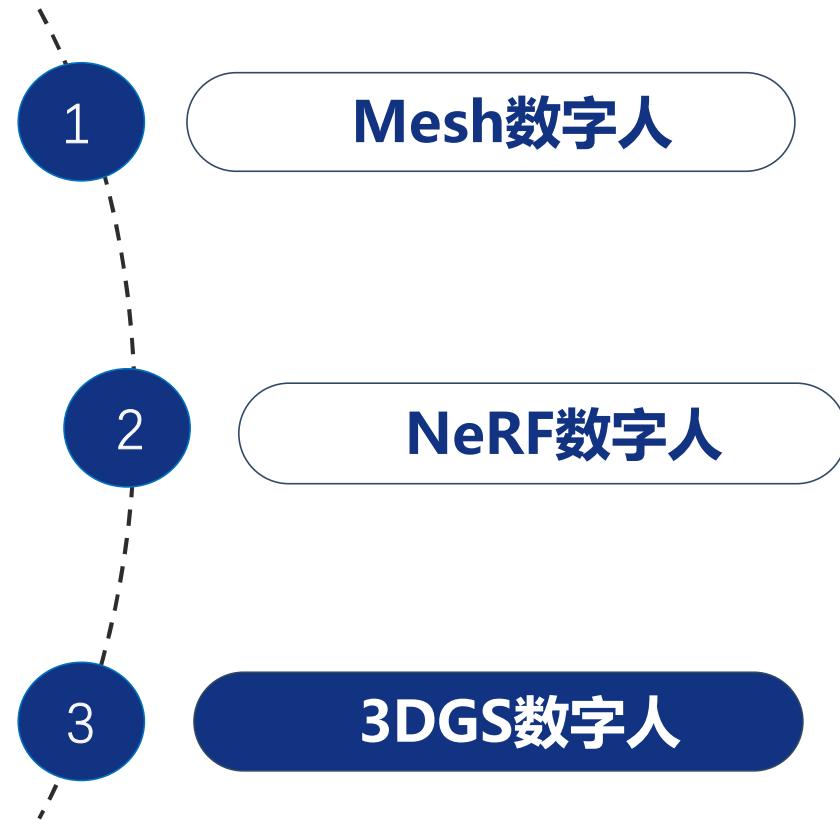
20 FPS: 512x512 on RTX 3090

Super fast than original NeRF

Not enough for **real-time interaction**

Poor performance on **mobile devices**



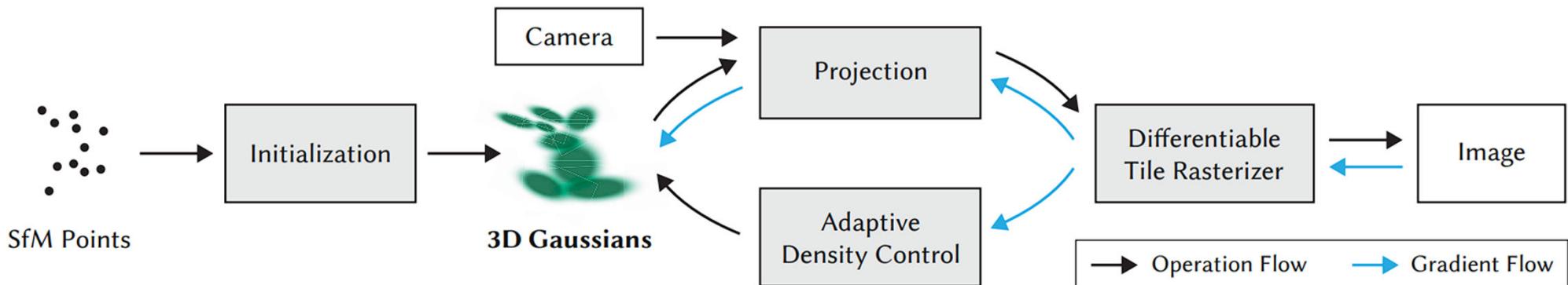


# 3DGS简介

- 将辐射场表示为分布在物体表面的具有一定辐射范围（高斯分布）的球体，并赋予每个球体颜色和密度属性表示附近的辐射场

- 显式表达，无需MLP
- Splatting, 无需采样

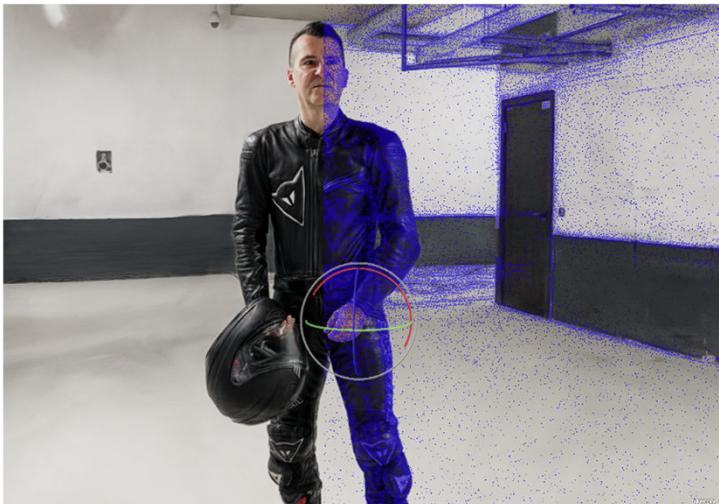
- 实时渲染，大于100FPS
- 快速训练，几十分钟



3D Gaussian Splatting for Real-Time Radiance Field Rendering. SIGGRAPH 2023.

# 3DGS简介

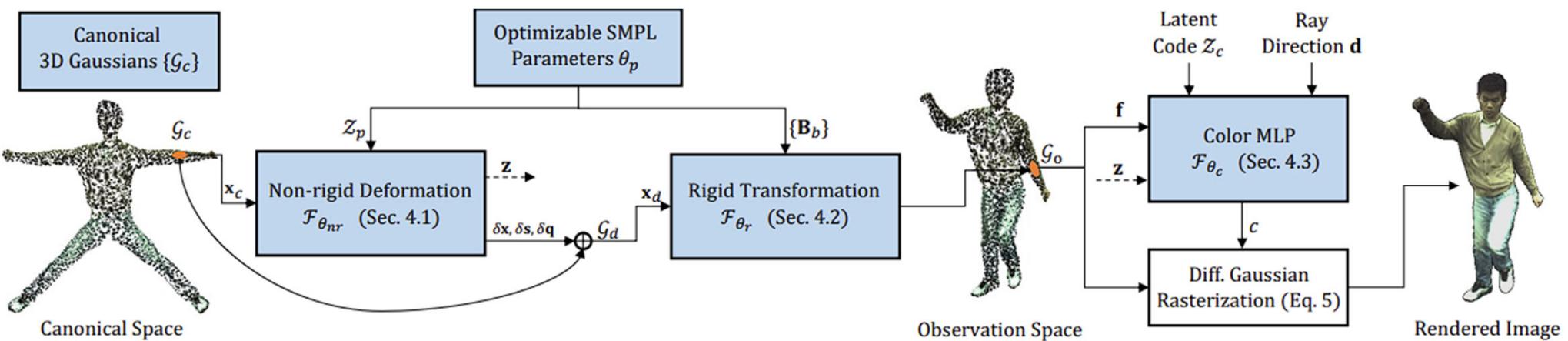
- 3DGS可实现高保真建模与Web端实时渲染



3D Gaussian Splatting for Real-Time Radiance Field Rendering. SIGGRAPH 2023.

# 3DGS数字人表示—Key Idea

- 将3DGS绑定在参数化Mesh上



3DGS-Avatar: Animatable Avatars via Deformable 3D Gaussian Splatting. CVPR 2024.

# 3DGS数字人表示

## 3. [CVPR '24] Animatable Gaussians: Learning Pose-dependent Gaussian Maps for High-fidelity Human Avatar Modeling

Authors: Zhe Li, Zerong Zheng, Lizhen Wang, Yebin Liu

► Abstract

[Paper](#) | [Project Page](#) | [Code](#)

## 4. [CVPR '24] GART: Gaussian Articulated Template Models

Authors: Jiahui Lei, Yufu Wang, Georgios Pavlakos, Lingjie Liu, Kostas Daniilidis

► Abstract

[Paper](#) | [Project Page](#) | [Code](#) | [Short Presentation](#)

## 5. [CVPR '24] Human Gaussian Splatting: Real-time Rendering of Animatable Avatars

Authors: Arthur Moreau, Jifei Song, Helisa Dhamo, Richard Shaw, Yiren Zhou, Eduardo Pérez-Pellitero

► Abstract

[Paper](#) | [Project Page](#) | [Short Presentation](#)

## 6. [CVPR '24] HUGS: Human Gaussian Splat

Authors: Muhammed Kocabas, Jen-Hao Rick Chang, James Gabriel, Oncel Tuzel, Anurag Ranjan

► Abstract

[Paper](#) | [Project Page](#) | [Code \(not yet\)](#)

## 7. [CVPR '24] Gaussian Shell Maps for Efficient 3D Human Generation

Authors: Rameen Abdal, Wang Yifan, Zifan Shi, Yinghao Xu, Ryan Po, Zhengfei Kuang, Qifeng Chen, Dit-Yan Yeung, Gordon Wetzstein

► Abstract

## 8. GaussianHead: High-fidelity Head Avatars with Learnable Gaussian Derivation

Authors: Jie Wang, Jiu-Cheng Xie, Xianyan Li, Chi-Man Pun, Feng Xu, Hao Gao

► Abstract

[Paper](#) | [Project Page](#) | [Code](#)

## 9. [CVPR '24] GaussianAvatars: Photorealistic Head Avatars with Rigged 3D Gaussians

Authors: Shenhua Qian, Tobias Kirschstein, Liam Schoneveld, Davide Davoli, Simon Giebenhain, Matthias Nießner

► Abstract

[Paper](#) | [Project Page](#) | [Code](#) | [Short Presentation](#)

## 10. [CVPR '24] GPS-Gaussian: Generalizable Pixel-wise 3D Gaussian Splatting for Real-time Human Novel View Synthesis

Authors: Shunyuan Zheng, Boyao Zhou, Ruizhi Shao, Boning Liu, Shengping Zhang, Liqiang Nie, Yebin Liu

► Abstract

[Paper](#) | [Project Page](#) | [Code](#) | [Short Presentation](#)

## 11. GauHuman: Articulated Gaussian Splatting from Monocular Human Videos

Authors: Shoukang Hu Ziwei Liu

► Abstract

[Paper](#) | [Project Page](#) | [Code](#) | [Short Presentation](#)

## 12. HeadGaS: Real-Time Animatable Head Avatars via 3D Gaussian Splatting

Authors: Helisa Dhamo, Yinyu Nie, Arthur Moreau, Jifei Song, Richard Shaw, Yiren Zhou, Eduardo Pérez-Pellitero

► Abstract

## 13. [CVPR '24] HiFi4G: High-Fidelity Human Performance Rendering via Compact Gaussian Splatting

Authors: Yuheng Jiang, Zhehao Shen, Penghao Wang, Zhuo Su, Yu Hong, Yingliang Zhang, Jingyi Yu, Lan Xu

► Abstract

[Paper](#) | [Project Page](#) | [Short Presentation](#) | [Dataset](#)

## 14. [CVPR '24] GaussianAvatar: Towards Realistic Human Avatar Modeling from a Single Video via Animatable 3D Gaussians

Authors: Liangxiao Hu, Hongwen Zhang, Yuxiang Zhang, Boyao Zhou, Boning Liu, Shengping Zhang, Liqiang Nie

► Abstract

[Paper](#) | [Project Page](#) | [Code](#) | [Short Presentation](#)

## 15. [CVPR '24] FlashAvatar: High-fidelity Head Avatar with Efficient Gaussian Embedding

Authors: Jun Xiang, Xuan Gao, Yudong Guo, Juyong Zhang

► Abstract

[Paper](#) | [Project Page](#) | [Code](#)

## 16. [CVPR '24] Relightable Gaussian Codec Avatars

Authors: Shunsuke Saito, Gabriel Schwartz, Tomas Simon, Junxuan Li, Giljoo Nam

► Abstract

[Paper](#) | [Project Page](#)

## 17. MonoGaussianAvatar: Monocular Gaussian Point-based Head Avatar

Authors: Yufan Chen, Lizhen Wang, Qijing Li, Hongjiang Xiao, Shengping Zhang, Hongxun Yao, Yebin Liu

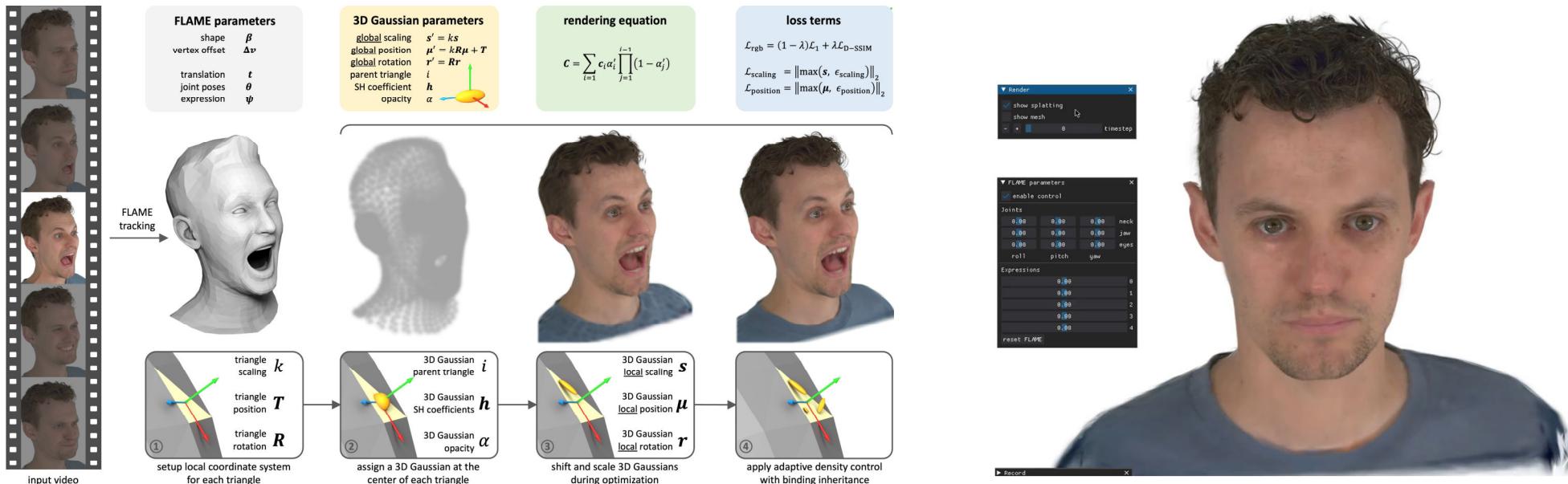
► Abstract

[Paper](#) | [Project Page](#) | [Code \(not yet\)](#) | [Short Presentation](#)

<https://github.com/MrNeRF/awesome-3D-gaussian-splatting>

# 3DGS数字人表示—GaussianAvatars

- 将3DGS绑定在FLAME Mesh

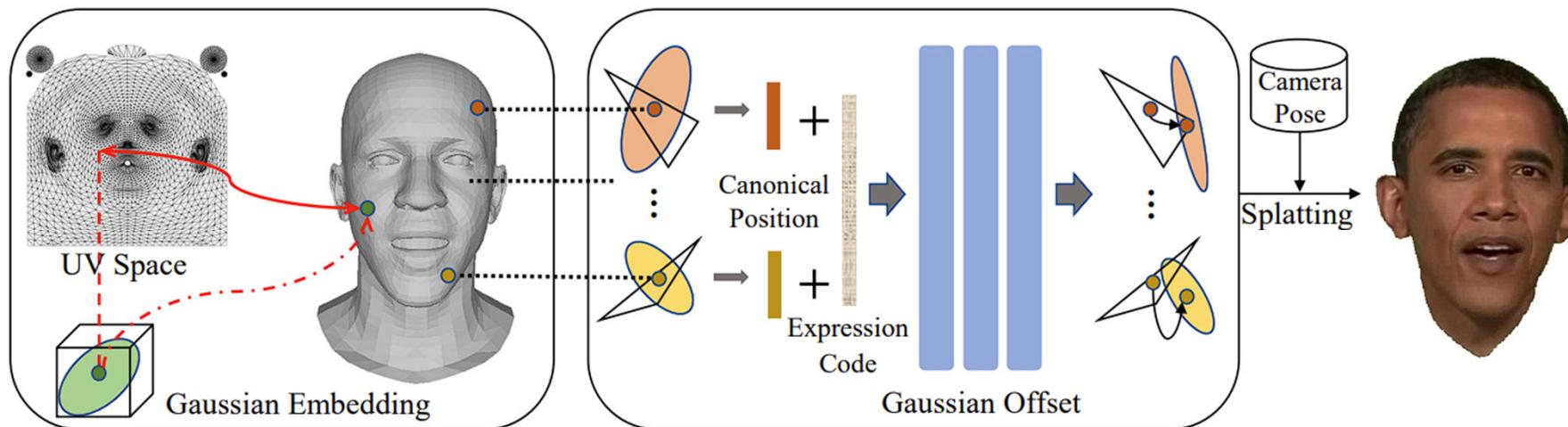


Deform Gaussians based on the underlying parametric head model

GaussianAvatars: Photorealistic Head Avatars with Rigged 3D Gaussians. CVPR 2024.

# 3DGS数字人表示—FlashAvatar

- 将3DGS绑定在FLAME Mesh UV Space



Deform Gaussians based on the underlying parametric head model

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FlashAvatar: High-fidelity Head Avatar with Efficient Gaussian Embedding. CVPR 2024.

# 3DGS数字人表示—FlashAvatar

- 将3DGS绑定在FLAME Mesh UV Space



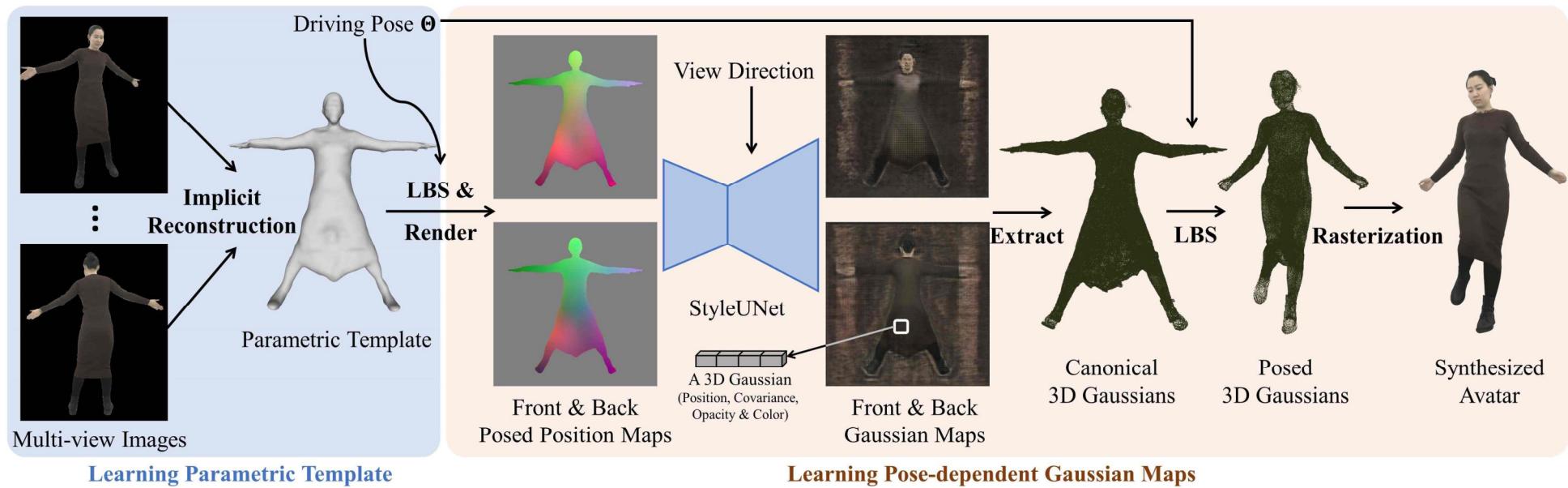
Uniformly resampling in the UV space  
for compression

Achieve 300+ FPS rendering

FlashAvatar: High-fidelity Head Avatar with Efficient Gaussian Embedding. CVPR 2024.

# 3DGS数字人表示—Animatable Gaussians

- 将3DGS绑定在SMPL Mesh上



Animatable Gaussians: Learning Pose-dependent Gaussian Maps for High-fidelity Human Avatar Modeling. CVPR 2024.

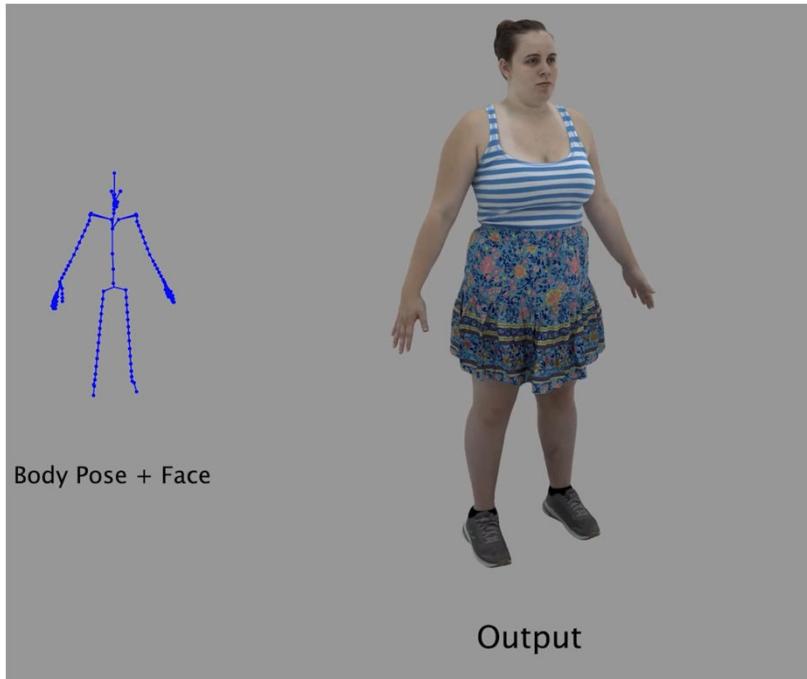
# 3DGS数字人表示—Animatable Gaussians



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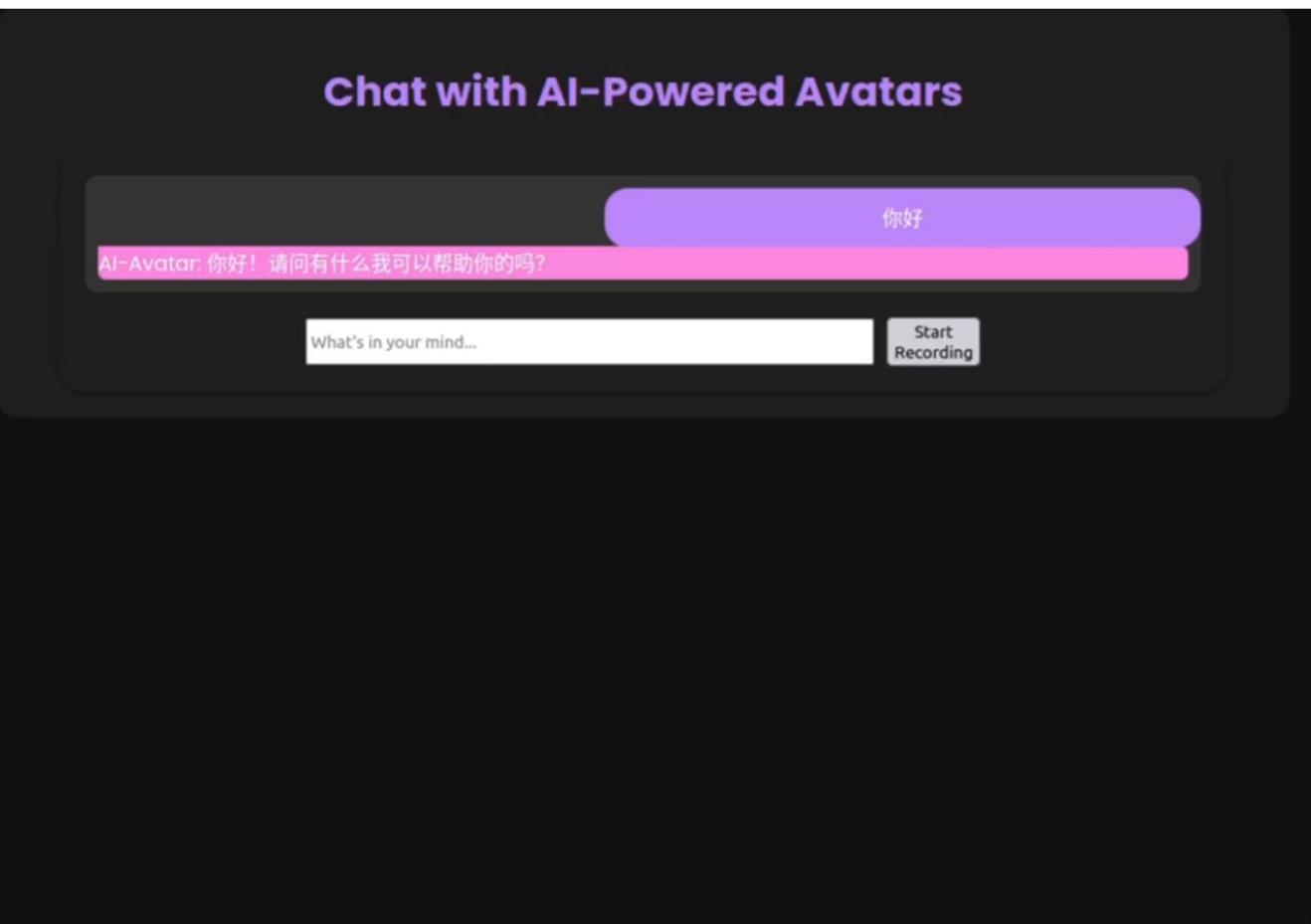
Animatable Gaussians: Learning Pose-dependent Gaussian Maps for High-fidelity Human Avatar Modeling. CVPR 2024.

# 驱动人体NeRF/3DGS



Faithful Full-Body Telepresence with Dynamic Clothing Driven by Sparse RGB-D Input. SIGGRAPH Asia 2023.  
Animatable Gaussians: Learning Pose-dependent Gaussian Maps for High-fidelity Human Avatar Modeling. CVPR 2024.

# 实时互动



# Summary

- Mesh数字人：

- 高效渲染
- 便于驱动

- 不够Photo-Realistic
- 1:1复刻真人难度高

- NeRF数字人：

- 建模方便
- 可实现高保真建模

- 效率低
- 无原生好的几何
- 无法原生驱动

- 3DGS数字人：

- 建模方便
- 可实现高保真建模
- 建模、渲染效率高

- 无原生好的几何
- 无法原生驱动