JAGIELLONIAN UNIVERSITY IN KRAKÓW

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Neural rendering

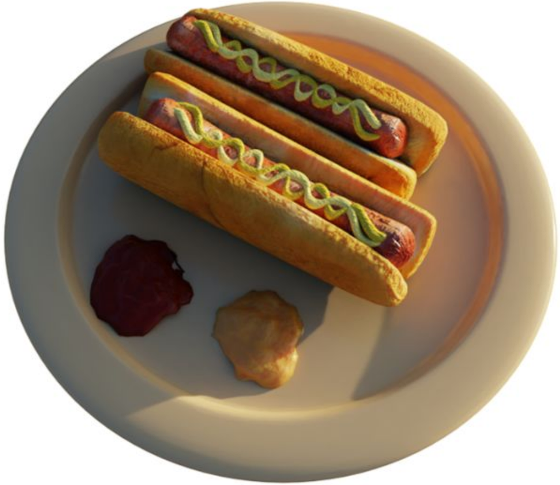
przemyslaw.spurek@uj.edu.pl

Neural Rendering

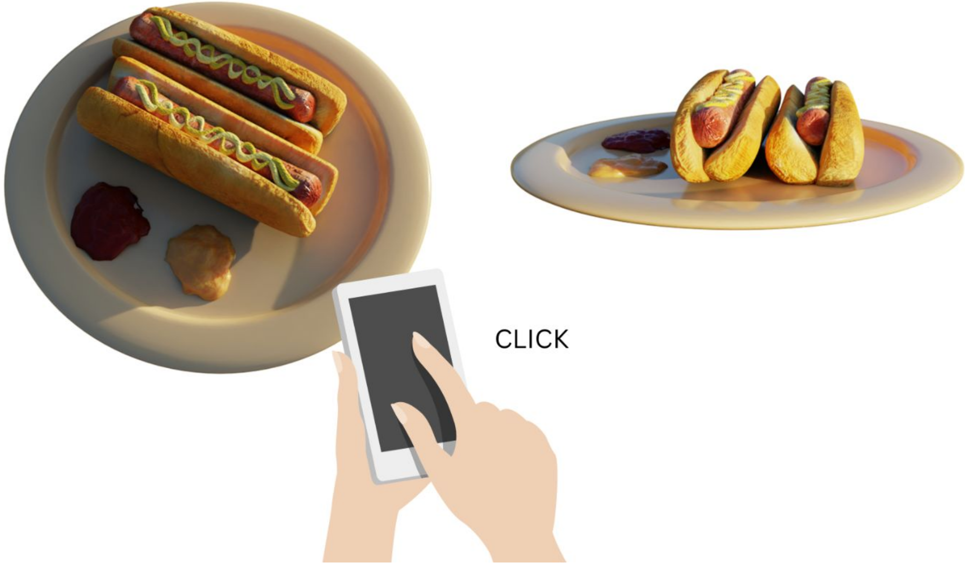
Our goal is to create 3D object

by using only 2D images.

Neural Rendering

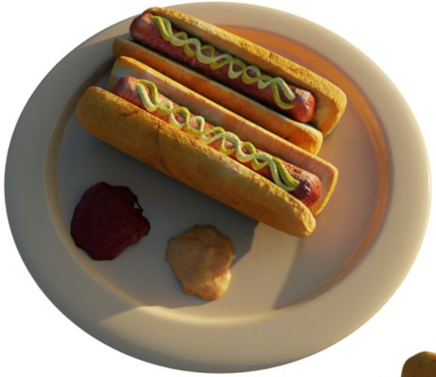


Neural Rendering



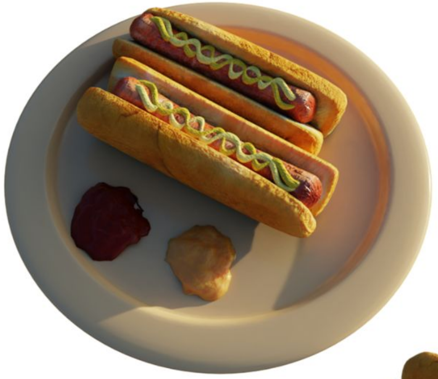
Neural Rendering

CLICK



Neural Rendering

3. photo

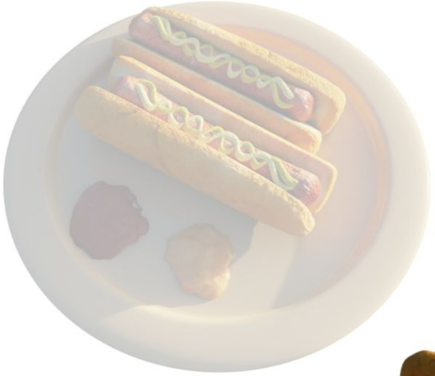


1. photo

2. photo

Neural Rendering

3. photo



1. photo

2. photo

Neural Rendering

Multi-view Images

1. photo

2. photo

3. photo

Neural Rendering

Multi-view Images

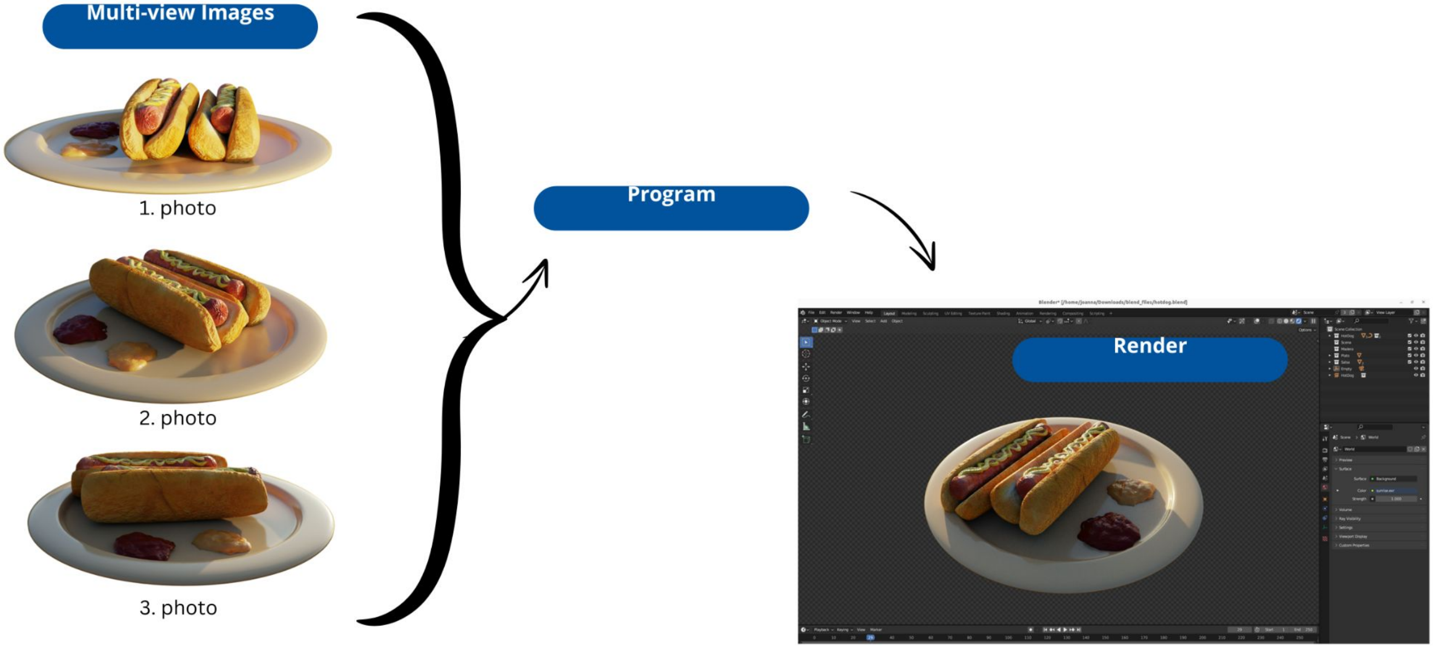
1. photo

2. photo

3. photo

Program

Neural Rendering

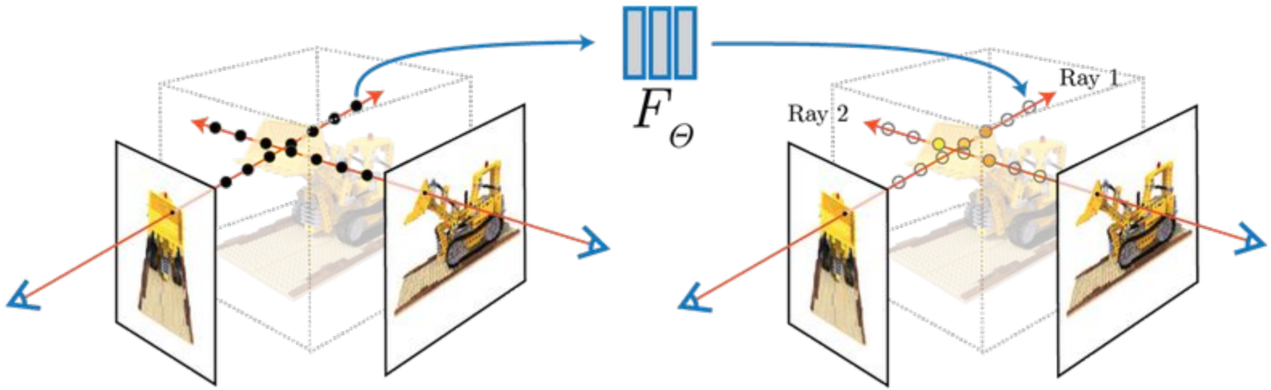


NeRF: Neural Radiance Fields

A neural radiance field (NeRF) is a fully-connected neural network that can generate novel views of complex 3D scenes, based on a partial set of 2D images.

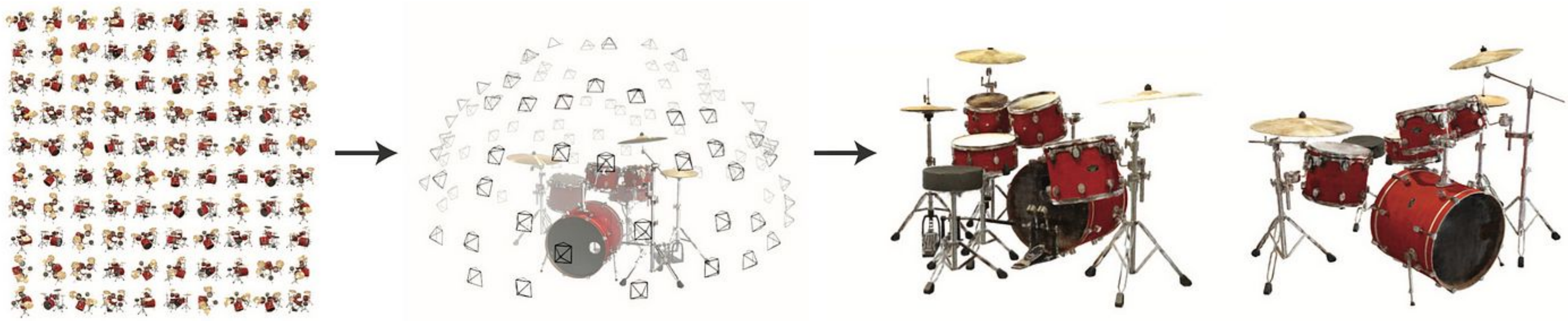
It is trained to use a rendering loss to reproduce input views of a scene. It works by taking input images representing a scene and interpolating between them to render one complete scene.

NeRF is a highly effective way to generate images for synthetic data.



Mildenhall, Ben, et al. "Nerf: Representing scenes as neural radiance fields for view synthesis." *Communications of the ACM* 65.1 (2021): 99-106.

NeRF: Neural Radiance Fields



Mildenhall, Ben, et al. "Nerf: Representing scenes as neural radiance fields for view synthesis." *Communications of the ACM* 65.1 (2021): 99-106.

3D Gaussian Splatting for Real-Time Radiance Field Rendering

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In comparison, Gaussian Splatting (GS) provides a similar quality of renders with more rapid training and inference. This is a consequence of GS not requiring neural networks. Instead, we encode information about the 3D objects in a set of Gaussian distributions.

These Gaussians can then be used in a similar manner to classical meshes. Consequently, GS can be swiftly developed when needed to, for example, model dynamic scenes. Unfortunately, GS is hard to condition as it necessitates a hundred thousand Gaussian components.

3D Gaussian Splatting

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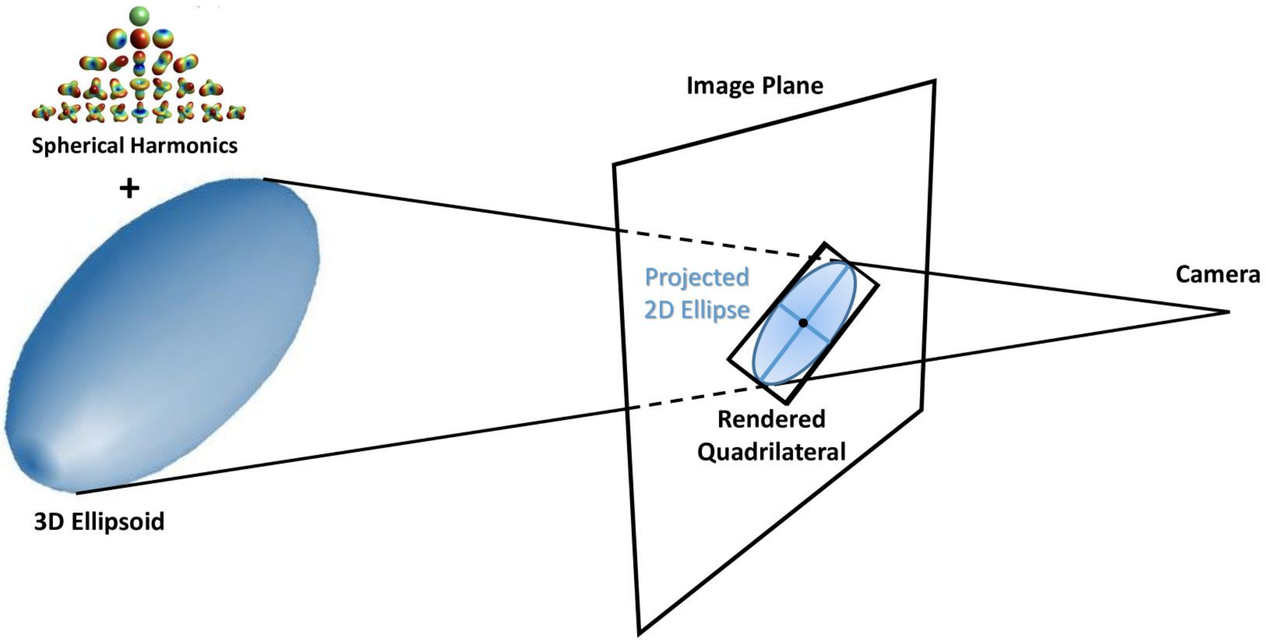
3D Gaussian Splatting



3D Gaussian Splatting

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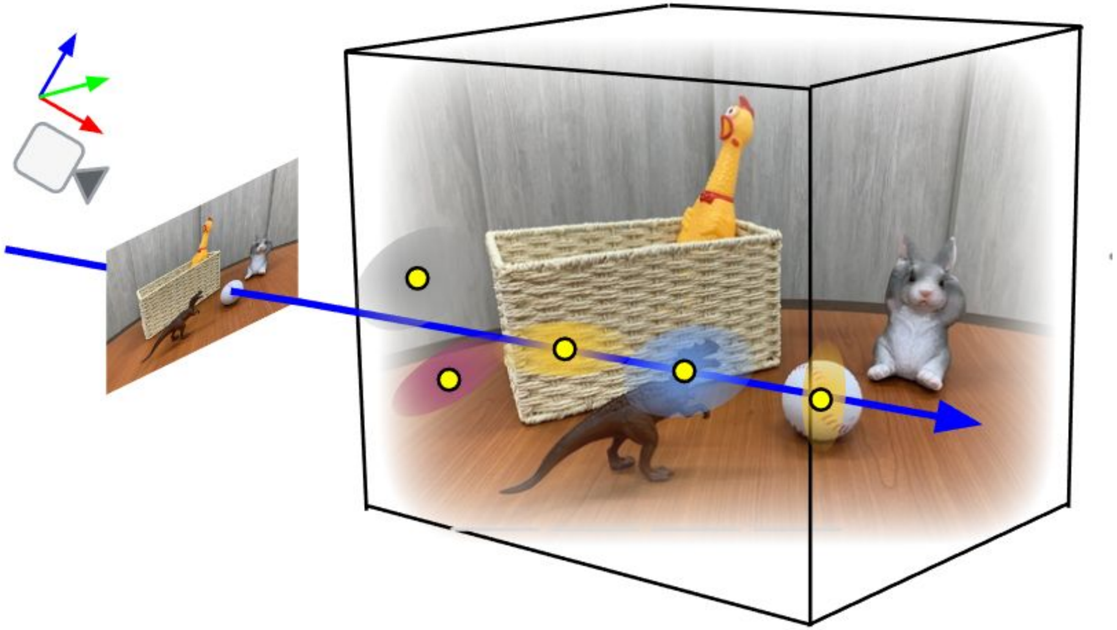
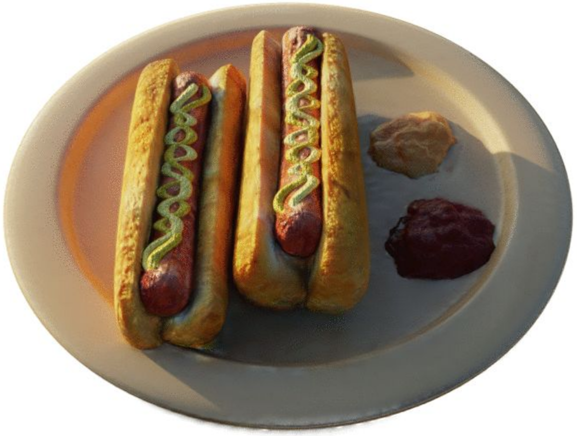
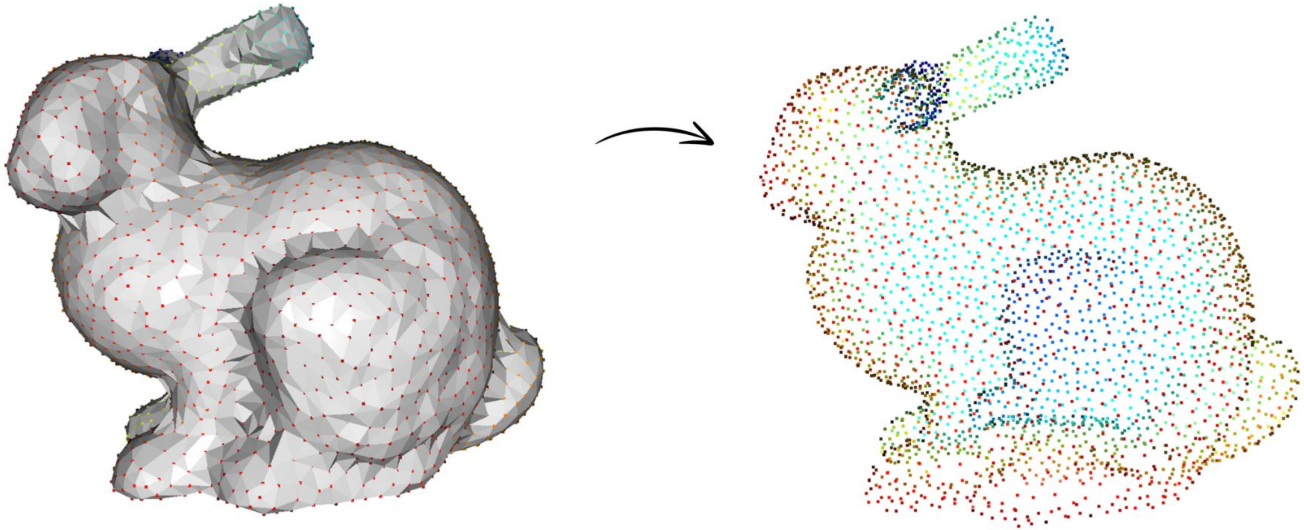


GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting

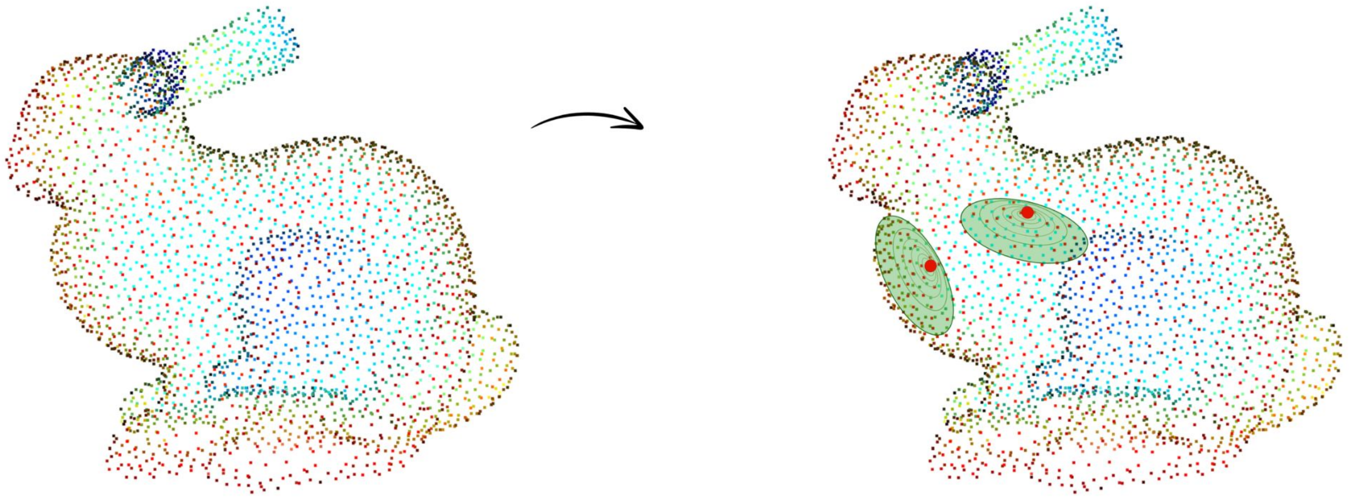
We introduce the Gaussian Mesh Splatting (GaMeS) model, which allows modification of Gaussian components in a similar way as meshes.



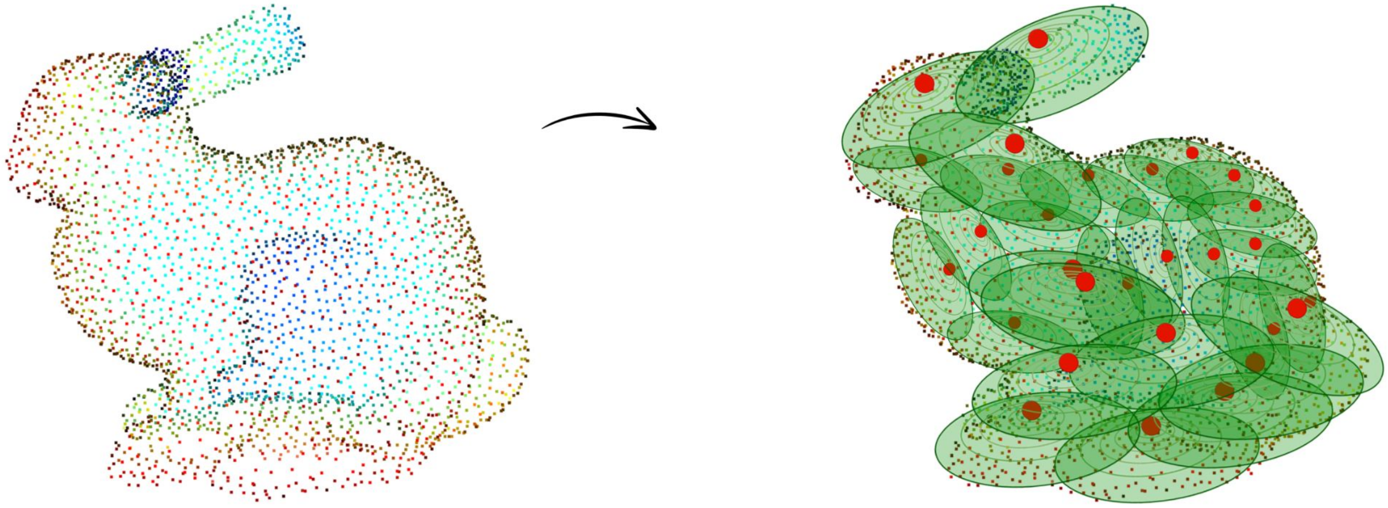
GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting



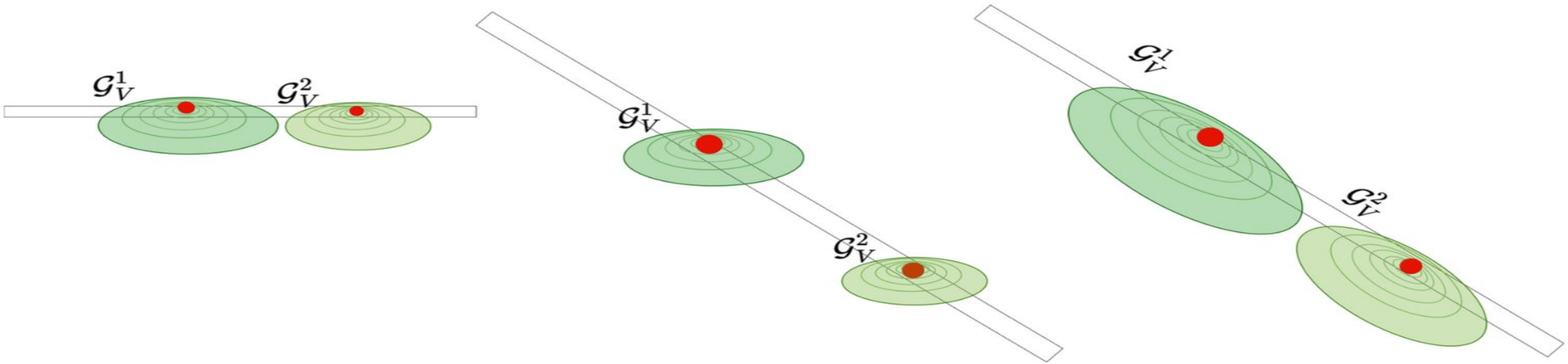
GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting



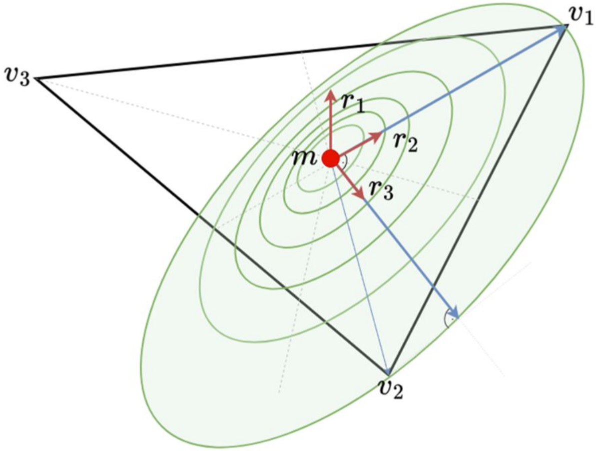
GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting

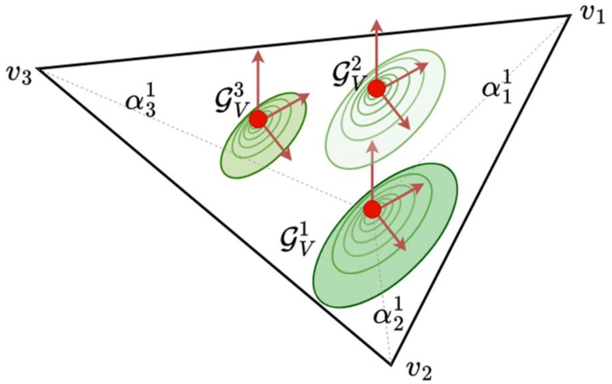


GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting



GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting





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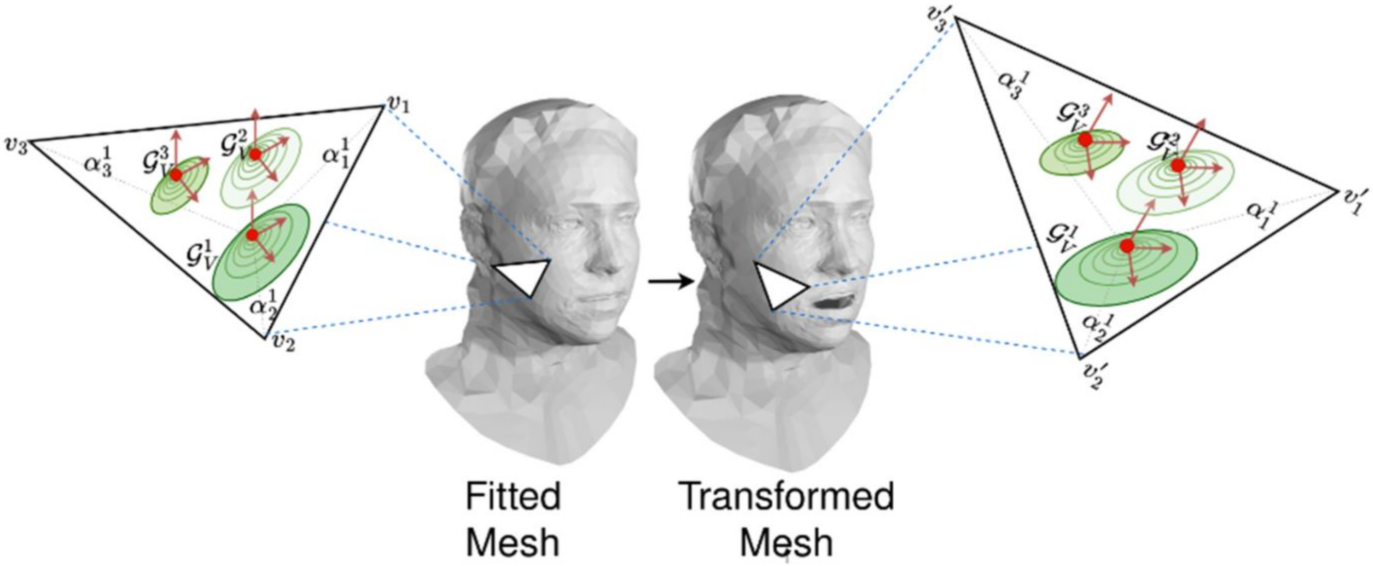
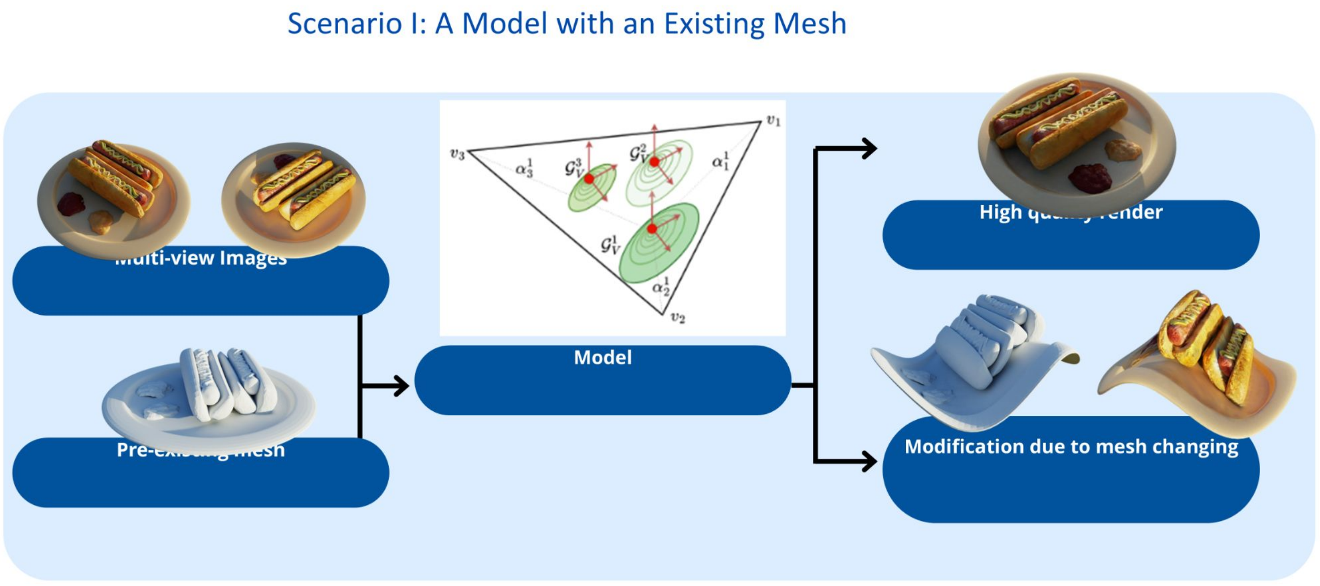
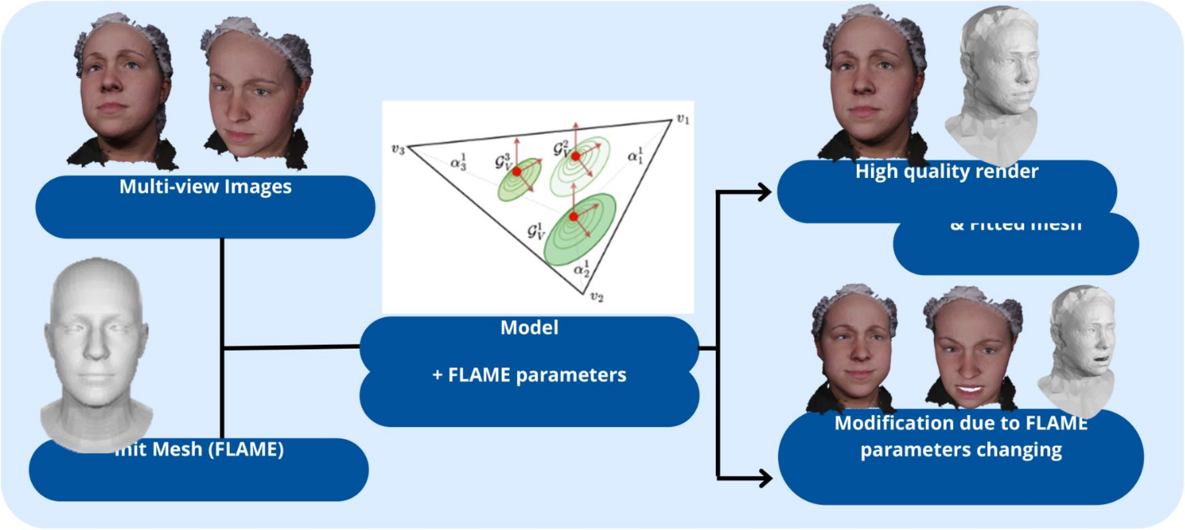


GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting



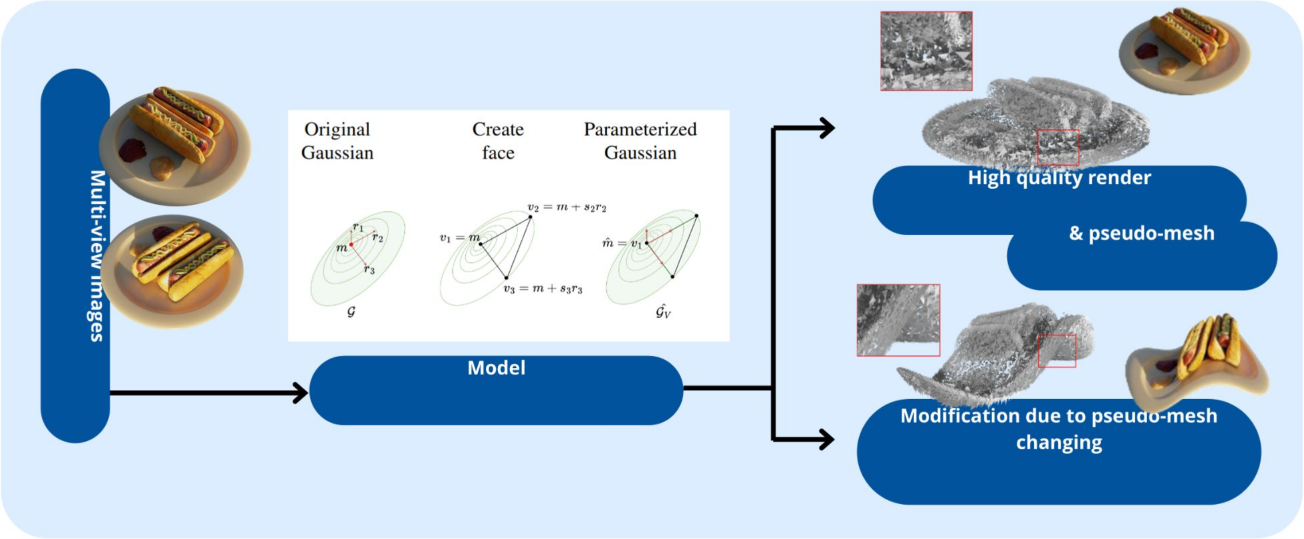
GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting

Scenario II: GaMeS with FLAME as an Init Mesh

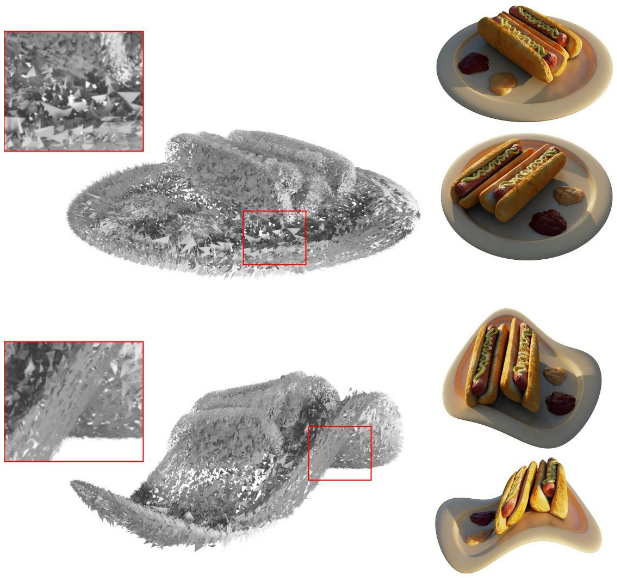


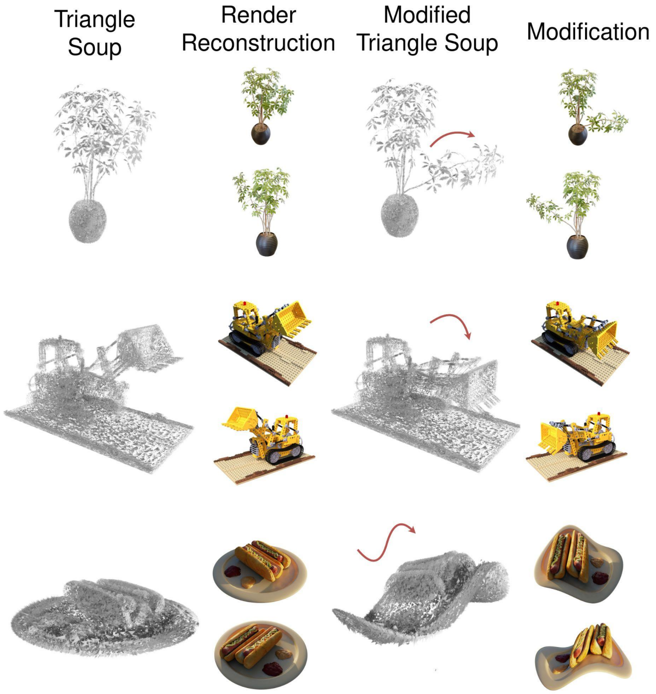
GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting

Scenario III: A Model without a Mesh

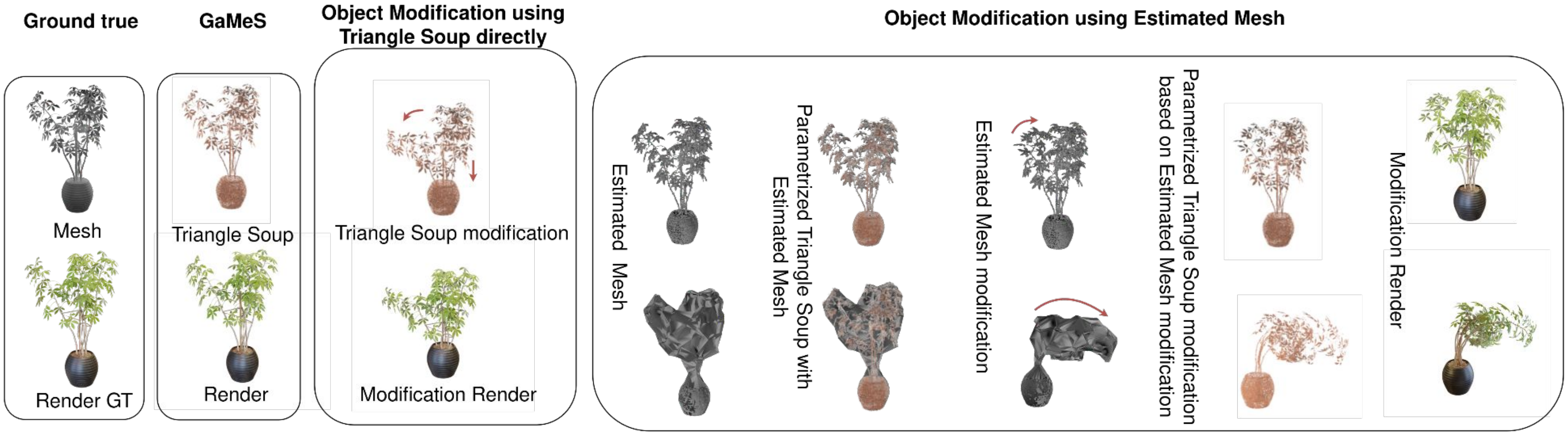


GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting





GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting



GaMeS: Mesh-Based Adapting and Modification of Gaussian Splatting

D-MiSo: Editing Dynamic 3D Scenes using Multi-Gaussians Soup

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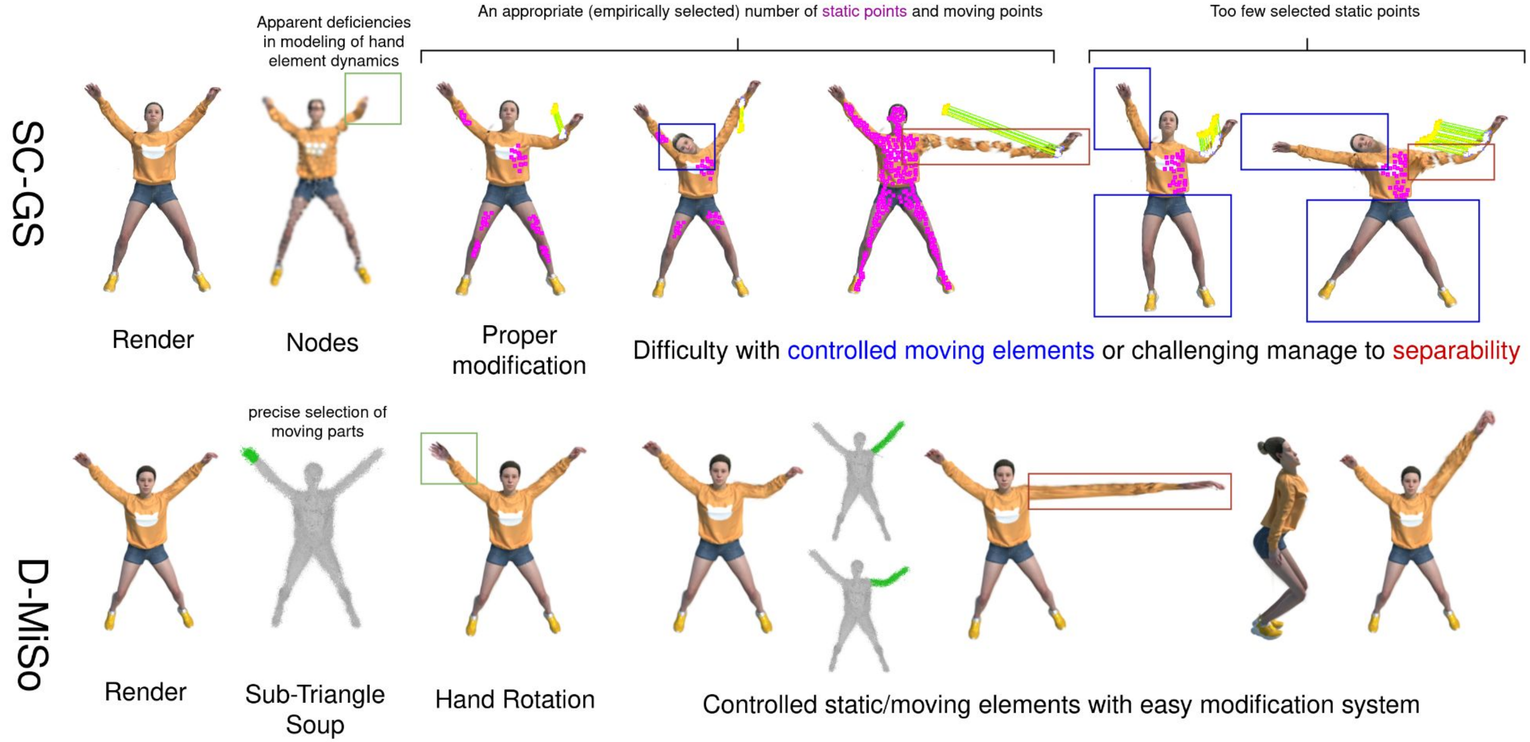
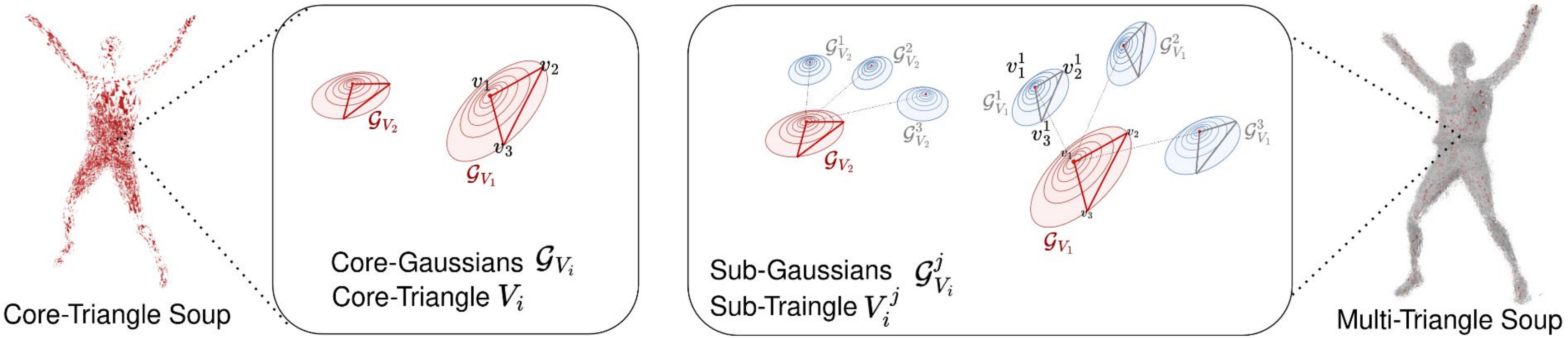
We we propose Dynamic Multi-Gaussian Soup (D-MiSo), which allows us to model the mesh-inspired representation of dynamic GS.

NEURAL INFORMATION PROCESSING SYSTEMS

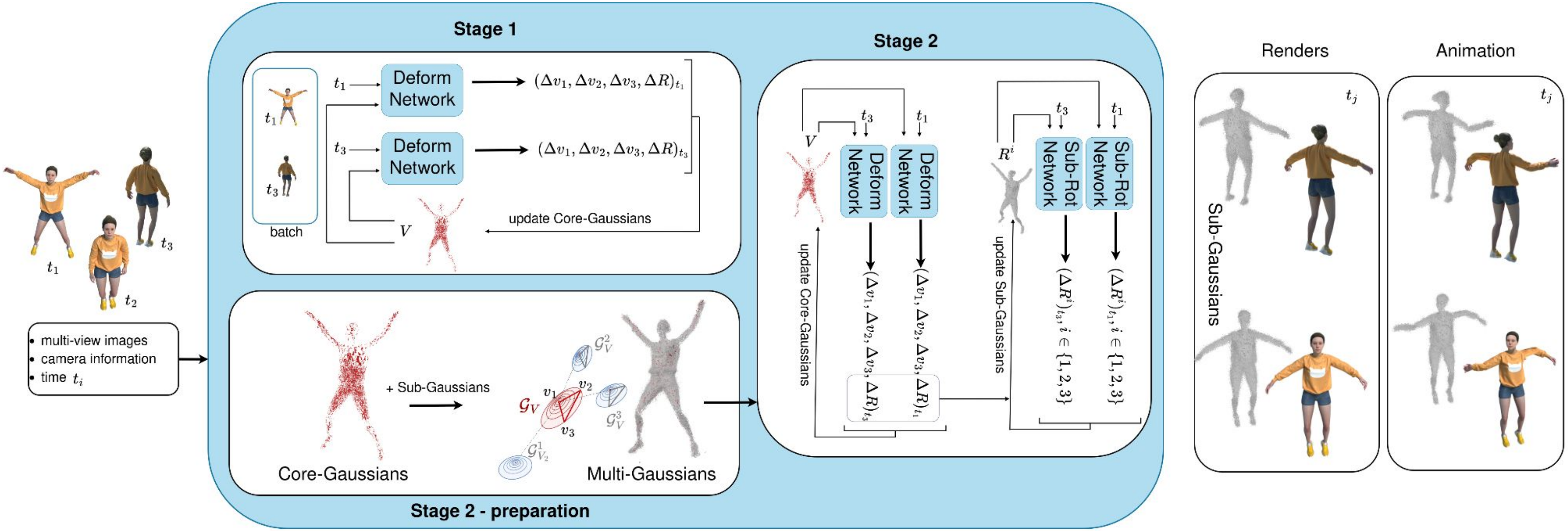
D-MiSo: Editing Dynamic 3D Scenes using Multi-Gaussians Soup



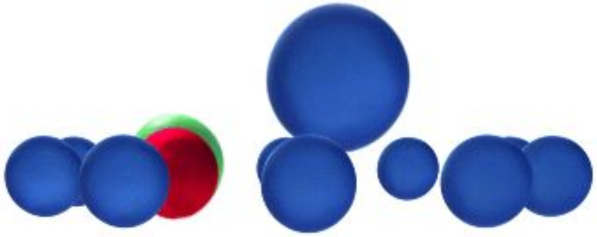
D-MiSo: Editing Dynamic 3D Scenes using Multi-Gaussians Soup



D-MiSo: Editing Dynamic 3D Scenes using Multi-Gaussians Soup



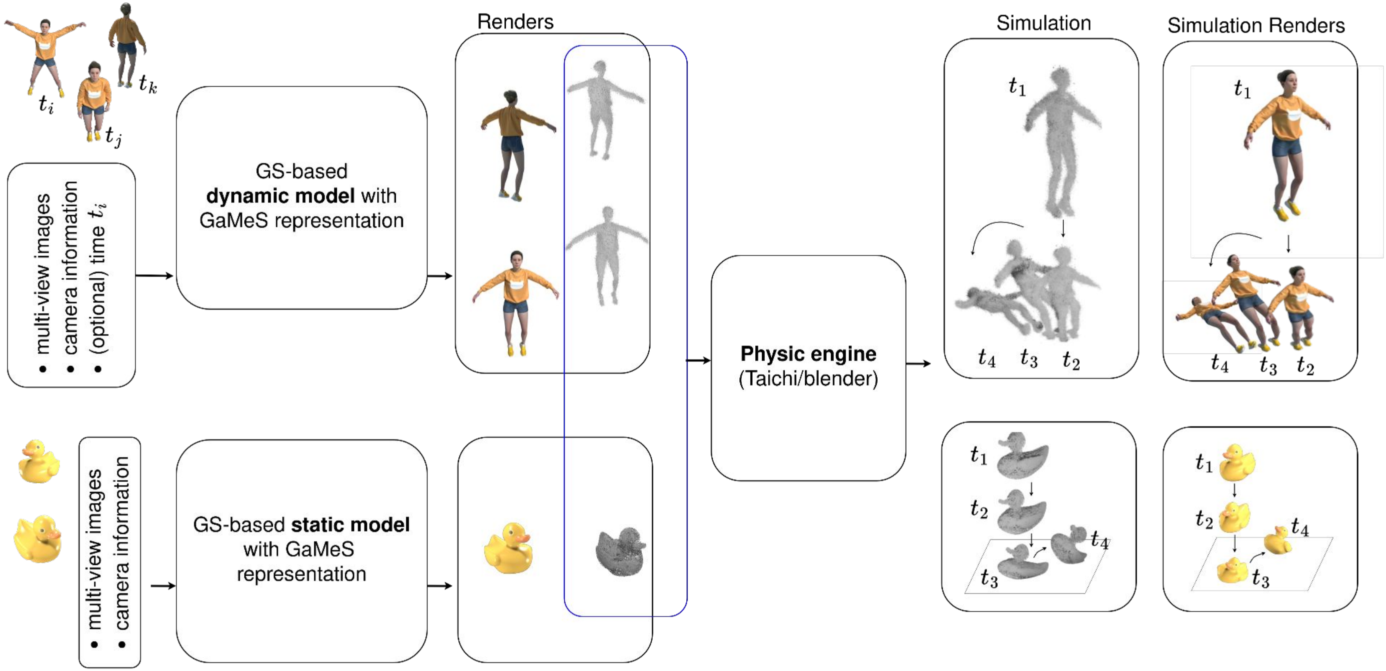
D-MiSo: Editing Dynamic 3D Scenes using Multi-Gaussians Soup



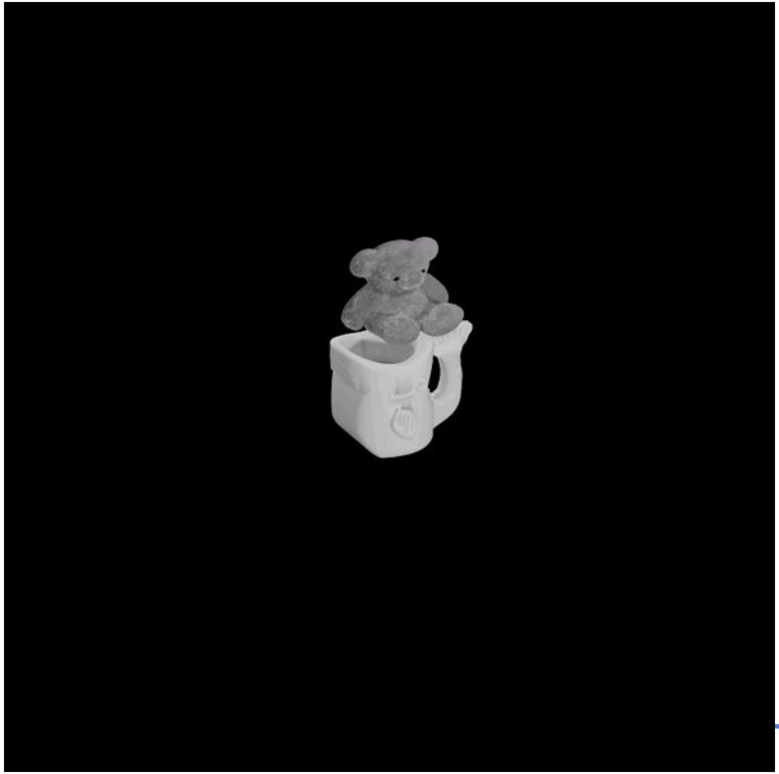
GASP: Gaussian Splatting for Physic-Based Simulations

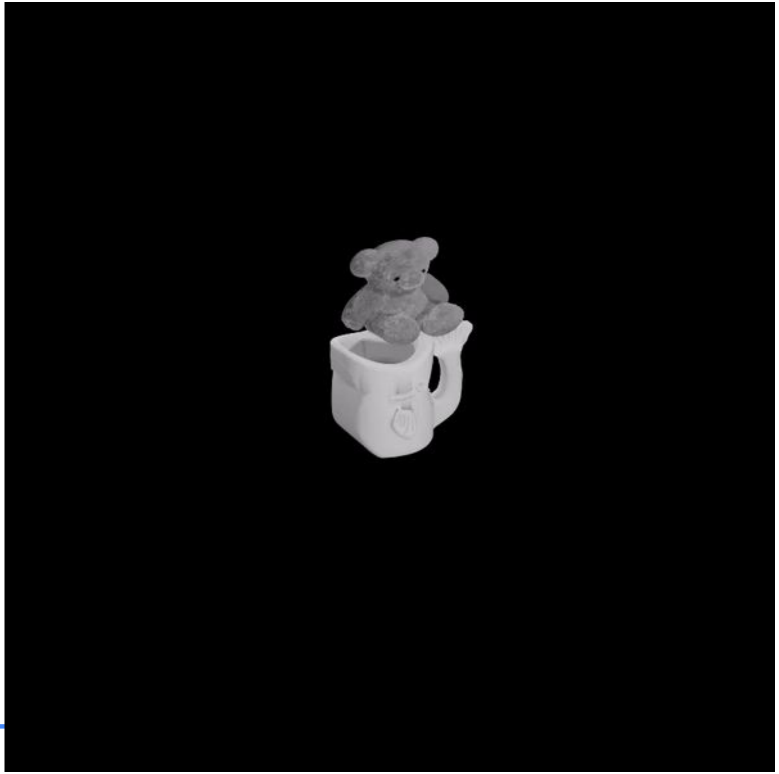
Our Gaussian Splatting for Physics-Based Simulations (GASP) model uses a physical engine (without any modifications) and flat Gaussian distributions, which are parameterized by three points (mesh faces).

GASP: Gaussian Splatting for Physic-Based Simulations

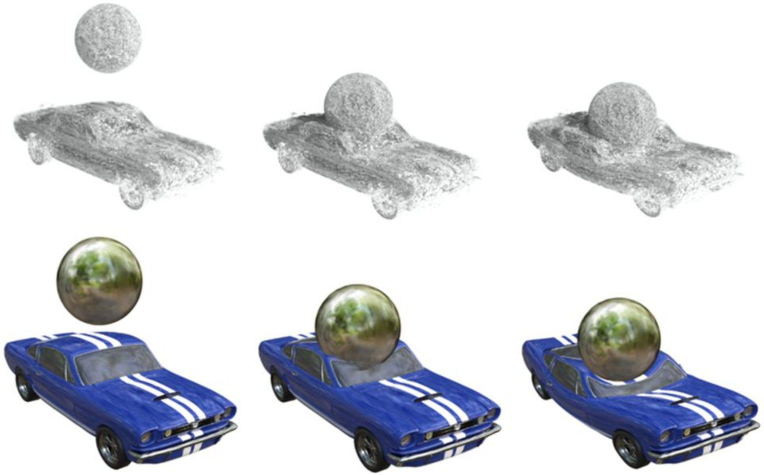


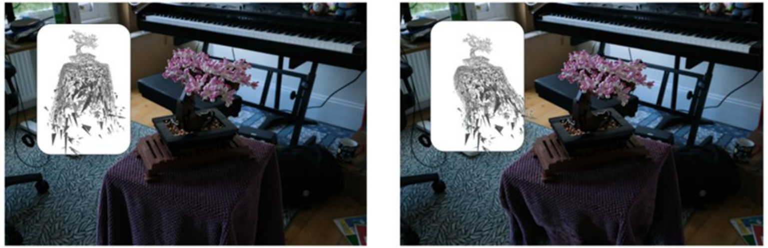
GASP: Gaussian Splatting for Physic-Based Simulations





GASP: Gaussian Splatting for Physic-Based Simulations





GASP: Gaussian Splatting for Physic-Based Simulations

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MiraGe: Editable 2D Images using Gaussian Splatting

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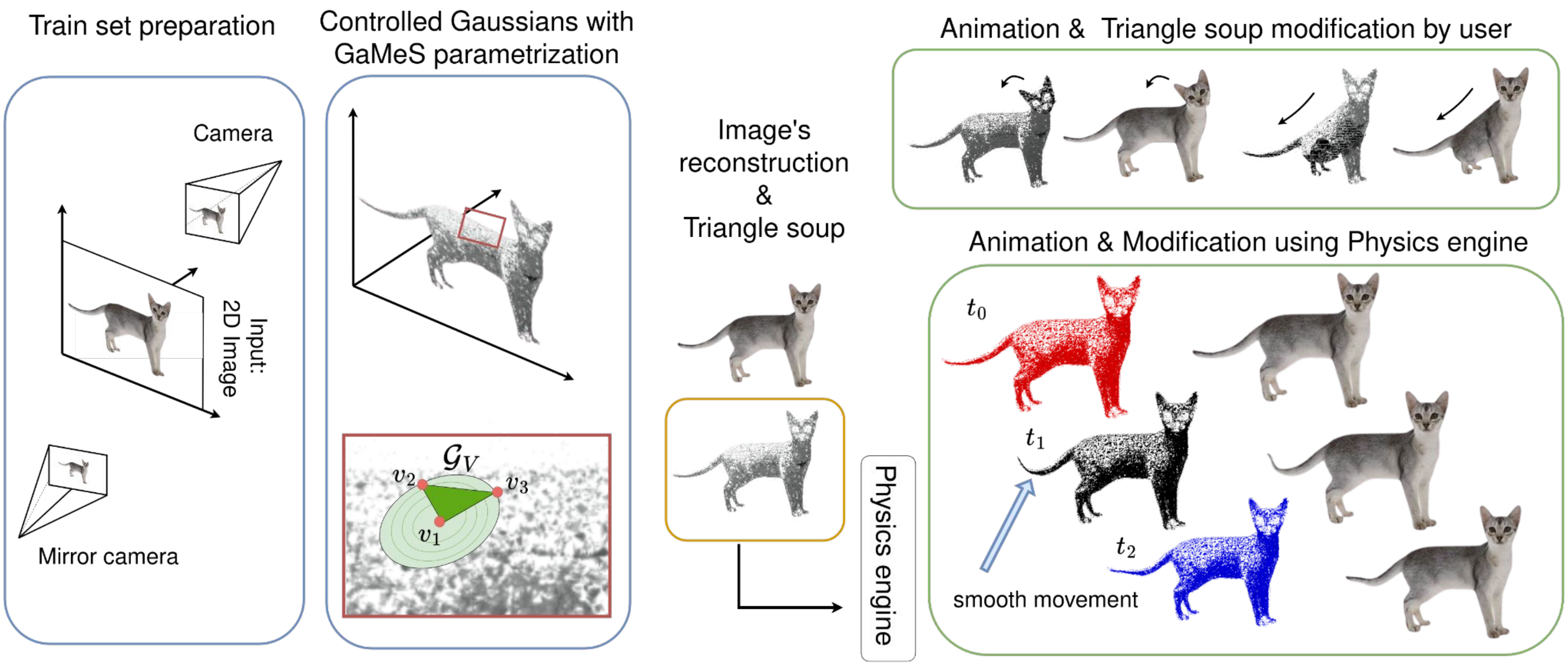
MiraGe improves the rendering quality and allows realistic image modifications, including the human-inspired perception of photos in the 3D world.

MiraGe: Editable 2D Images using Gaussian Splatting



MiraGe: Editable 2D Images using Gaussian Splatting

MiraGe: Editable 2D Images using Gaussian Splatting

Gaussian Splatting projects

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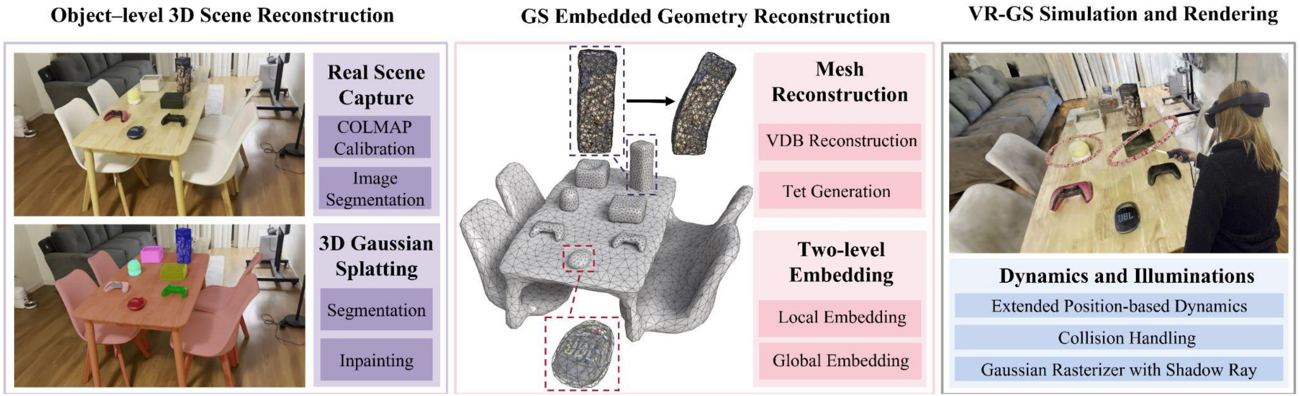
GaMeS in VR

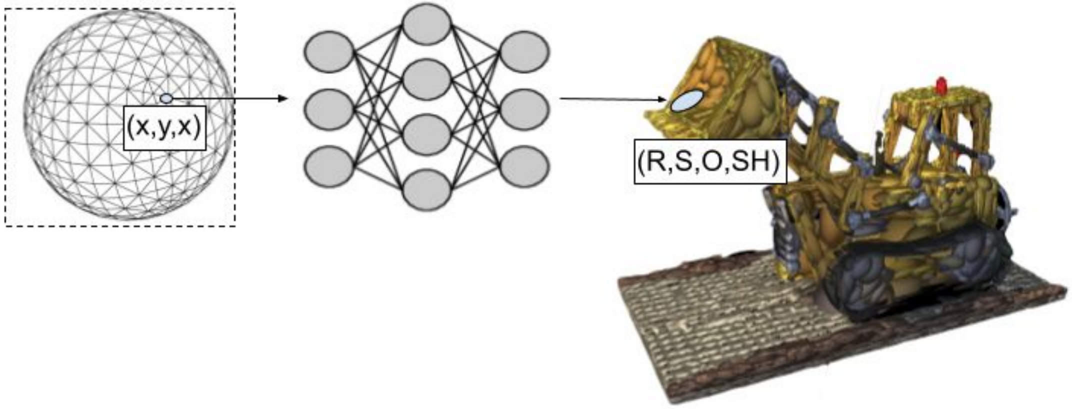
Our goal is to add GaMeS to VR/AR.
https://yingjiang96.github.io/VR-GS/



INR based GS

Our goal is to encode Gaussian Splatting in Neural Network weights.

https://theialab.github.io/laghashes/



Merging Gaussian Splatting objects

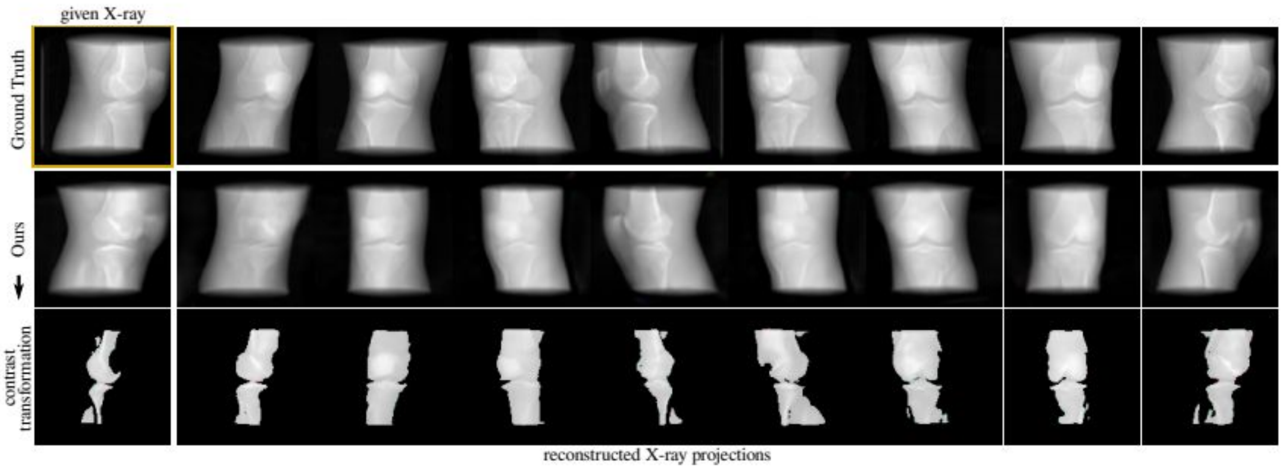
Our goal is to correctly merge Gaussian Splatting based objects.

https://waczjoan.github.io/GASP/

GS for medical Images

Our goal is to represent spectral images by Gaussian Splatting.

https://arxiv.org/pdf/2202.01020.pdf



Check out our other talks during ML in PL!

Friday:

Session 2 / Lecture Hall B / 10:35

Deep learning for effective analysis of high content screening
Adriana Borowa

Session 4 / Lecture Hall A / 14:30

Efficient fine-tuning of LLMs: exploring PEFT methods and LORA-XS insights
Klaudia Bałazy

Session 5 / Lecture Hall B / 14:30

Current trends in intrinsically interpretable Deep Learning
Dawid Rymarczyk

Neural rendering: the future of 3D modeling
Przemysław Spurek

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Saturday:

Session 7 / Lecture Hall A / 12:00

AdaGlimpse: Active Visual Exploration with Arbitrary Glimpse Position and Scale
Adam Pardyl

Session 8 / Lecture Hall B / 12:00

Augmentation-aware Self-supervised Learning with Conditioned Projector
Marcin Przewięźlikowski

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