Hands-On AI Based 3D Vision
Summer 25

Lecture 08 – 3D Gaussian Splatting (3DGS)

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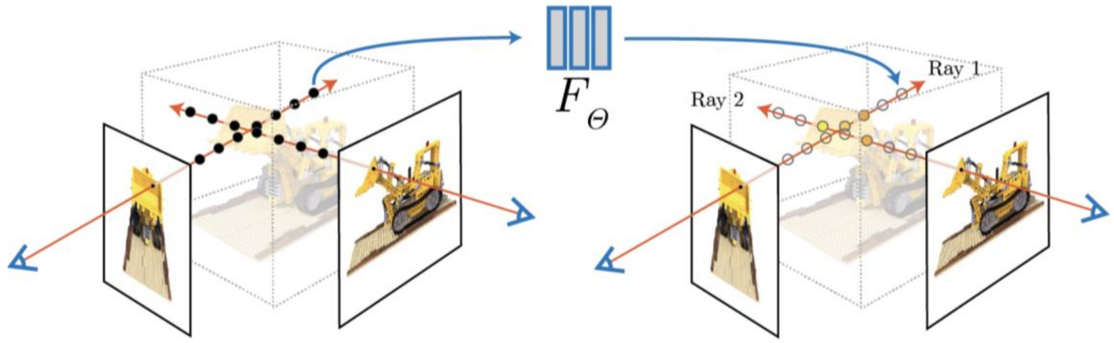
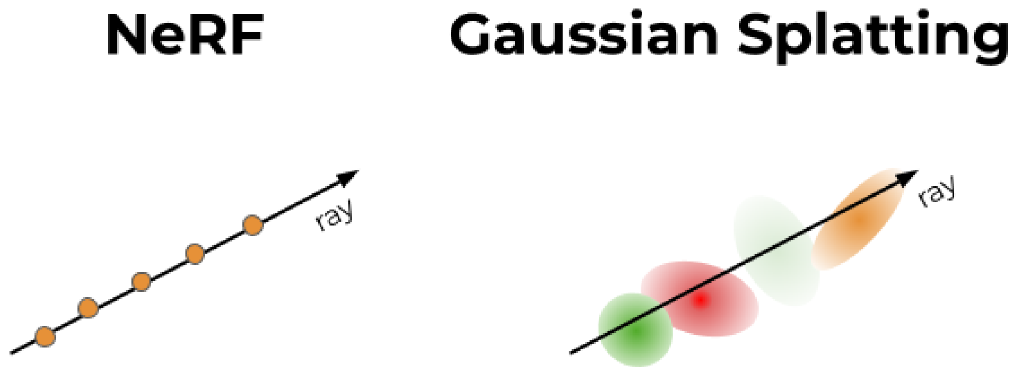
In this lecture, we will learn …

- **Problems of NERF**
- **Point-Based Rendering**
- **3D Gaussian Splatting (3DGS)** [Kerbl & Kopanas ‘23]
- Applications of 3DGS and addressing its limitations (i.e., dynamic scene, compression, surface reconstruction…)

Problems of Nerf

- NeRF suffers from slow training and rendering.
- We have to query a neural network to obtain color and density values for each point.



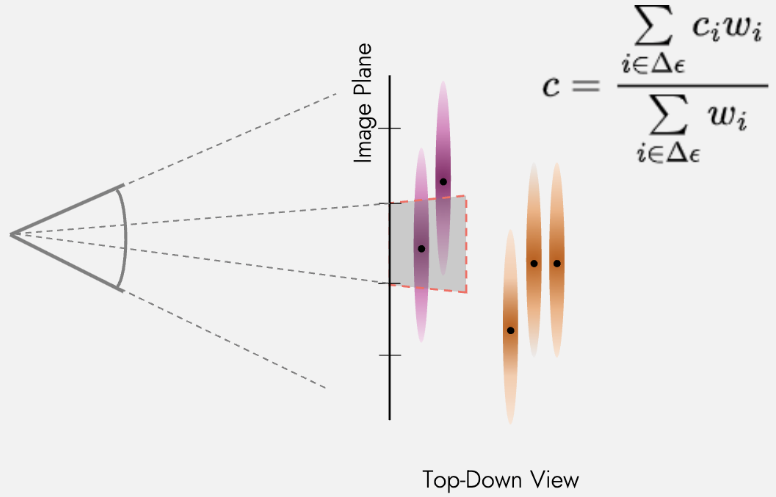


Point-Based Rendering

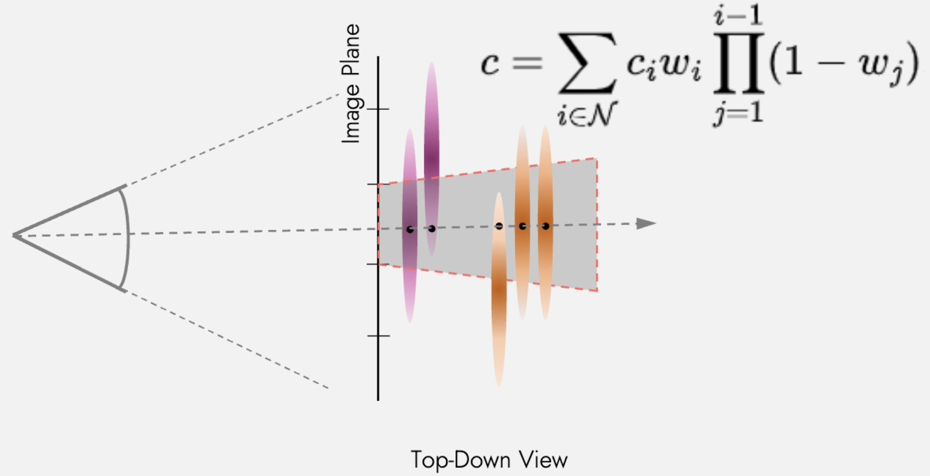
Surface Splatting vs Volume Splatting

1. How do we blend points in screen space?

[Zwicker1 '01] / [Yifan '19]



[Zwicker2 '01] / [Kerbl & Kopanas '23]



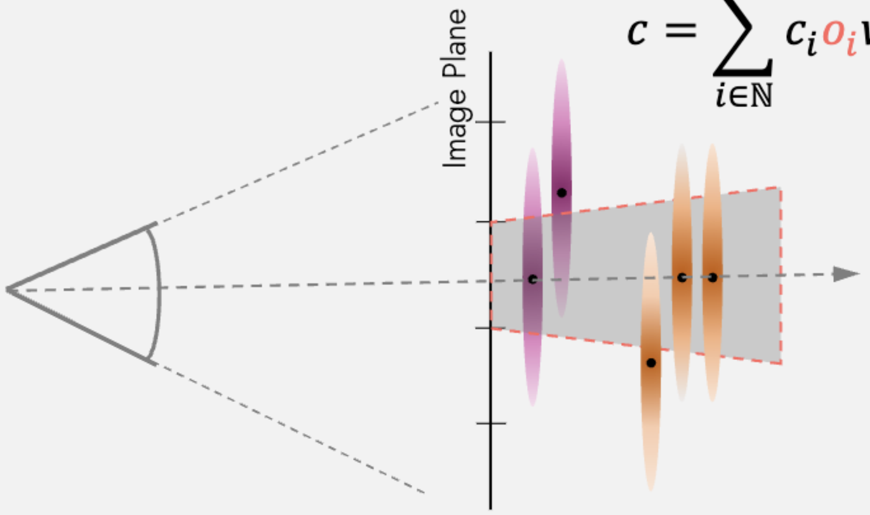
[Zwicker1 '01] Surface Splatting
[Yifan '19] Differentiable Surface Splatting for Point-Based Geometry Proccessing
[Zwicker2 '01] EWA Volume Splatting
[Kerbl & Kopanas '23] 3D Gaussian Splatting for Real-Time Radiance Field Rendering

Surface Splatting vs Volume Splatting

1. How do we blend points in screen space?
2. Opacity for each point, allows us to make points disappear.

[Zwicker2 '01] / [Kerbl & Kopanas '23]

$$c = \sum_{i \in \mathbb{N}} c_i o_i w_i \prod_{j=1}^{i-1} (1 - o_i w_j)$$



Top-Down View

[Zwicker2 '01] EWA Volume Splatting
[Kerbl & Kopanas '23] 3D Gaussian Splatting for Real-Time Radiance Field Rendering

Surface Splatting vs Volume Splatting

1. How do we blend points in screen space?
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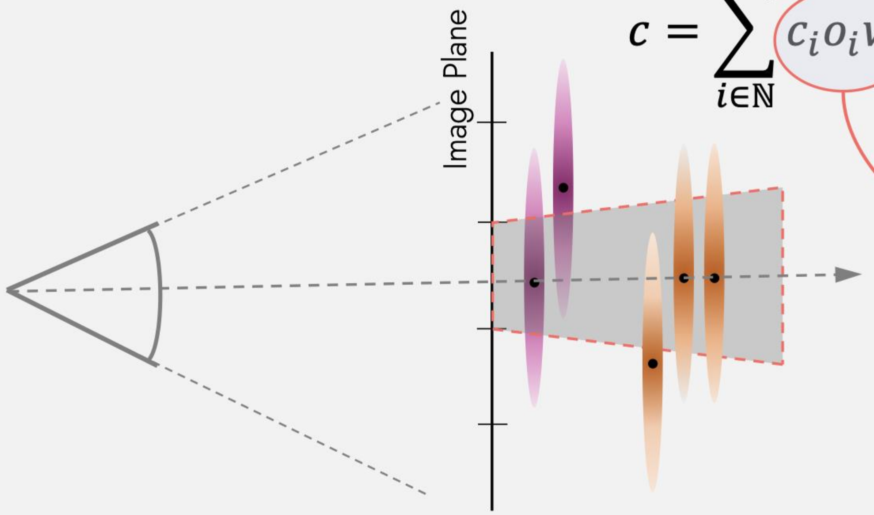
Ours

$$c = \sum_{i \in \mathbb{N}} c_i o_i w_i \prod_{j=1}^{i-1} (1 - o_i w_j)$$



Top-Down View

results in the MLP being evaluated at continuous positions over the course of optimization. We use these samples to estimate $C(\mathbf{r})$ with the quadrature rule discussed in the volume rendering review by Max [26]:

$$\hat{C}(\mathbf{r}) = \sum_{i=1}^{N} T_i (1 - \exp(-\sigma_i \delta_i))\mathbf{c}_i, \text{ where } T_i = \exp\left(-\sum_{j=1}^{i-1} \sigma_j \delta_j\right), \quad (3)$$

where $\delta_i = t_{i+1} - t_i$ is the distance between adjacent samples. This function for calculating $\hat{C}(\mathbf{r})$ from the set of $(\mathbf{c}_i, \sigma_i)$ values is trivially differentiable and reduces to traditional alpha compositing with alpha values $\alpha_i = 1 - \exp(-\sigma_i \delta_i)$.

Screenshot from NeRF [Mildenhall '20]

Goal: Reconstructing 3D world from images and videos

Input images

https://3dgstutorial.github.io/


Menu
Views
Capture
▶ 3D Gaussians
▶ Camera Point view
Die Aufnahme wurde begonnen
▼ Metrics
78.72 (12.70 ms)

3D Gaussian Splatting (3DGS) [Kerbl & Kopanas ‘23]

- Splat-based representation
- Use 3D Gaussians instead of points or a mesh.
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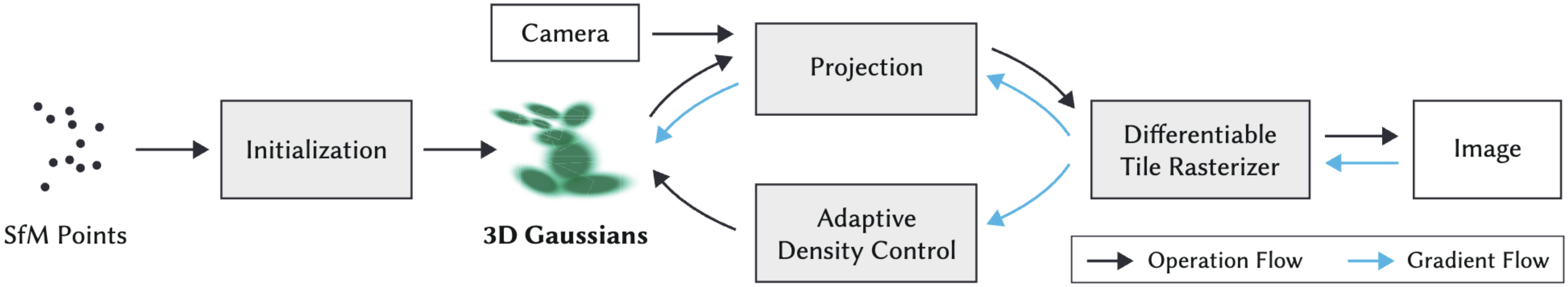

Method Overview

Parametrization of 3D Gaussian

How to parametrize 3D Gaussian?

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3D Gaussian parametrized by:

- Covariance **Σ**
- Mean) **μ**
- Opacity **o**
- Color ***c*** – RGB values or spherical harmonics (SH) coefficients.

How to optimize a covariance matrix $\mathbf{\Sigma}$?

- Not all symmetric matrices are covariance matrices and gradient updates can easily make them invalid.
- The covariance matrix $\mathbf{\Sigma}$ of a 3D Gaussian is analogous to describing the configuration of an ellipsoid.
- $\mathbf{\Sigma}$ has a physical meaning if its a positive-semi definite matrix. So factorize as follows:

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- **Σ** has a physical meaning if its a <u>positive-semi definite matrix</u>. So factorize as follows:

3x3 Covariance Matrix

$$\Sigma = RSS^T R^T$$

3x3 Rotation matrix

Diagonal scaling matrix (3 parameters for scale)

Projection of a covariance matrix **Σ** into 2D

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Projection of a covariance matrix $\boldsymbol{\Sigma}$ into 2D

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Diagonal scaling matrix (3 parameters for scale)

2x2 variance matrix

$$\Sigma' = JW\Sigma W^T J^T$$

$$G_{2D} = \mathcal{N}(\mathbf{x}_{2D}; \mu_{2D}, \Sigma')$$

Projected 2D Gaussian

Jacobian of the affine approximation of the projective transformation

Viewing Transformation

Image Formation Model of NeRF

$$C = \sum_{i=1}^{N} T_i \alpha_i \mathbf{c}_i$$

$$\alpha_i = (1 - \exp(-\sigma_i \delta_i)) \text{ and } T_i = \prod_{j=1}^{i-1} (1 - \alpha_i)$$

Color of a pixel

Transmittance

Color of each point

Image Formation Model of 3D Gaussian Splatting

$$\boxed{C} = \sum_{i \in \mathcal{N}} \boxed{c_i}\boxed{\alpha_i} \boxed{\prod_{j=1}^{i-1} (1 - \alpha_j)},$$

Color of a pixel

Color of each point

$\alpha = \mathbf{o}G_{2D}(\mathbf{x})$

Transmittance

NeRF vs Gaussian Splatting

$$C = \sum_{i=1}^{N} T_i \alpha_i \mathbf{c}_i$$

Nerf

$$\alpha_i = (1 - \exp(-\sigma_i \delta_i))$$

Gaussian Splatting

$$\alpha = \mathbf{o} G_{2D}(\mathbf{x})$$

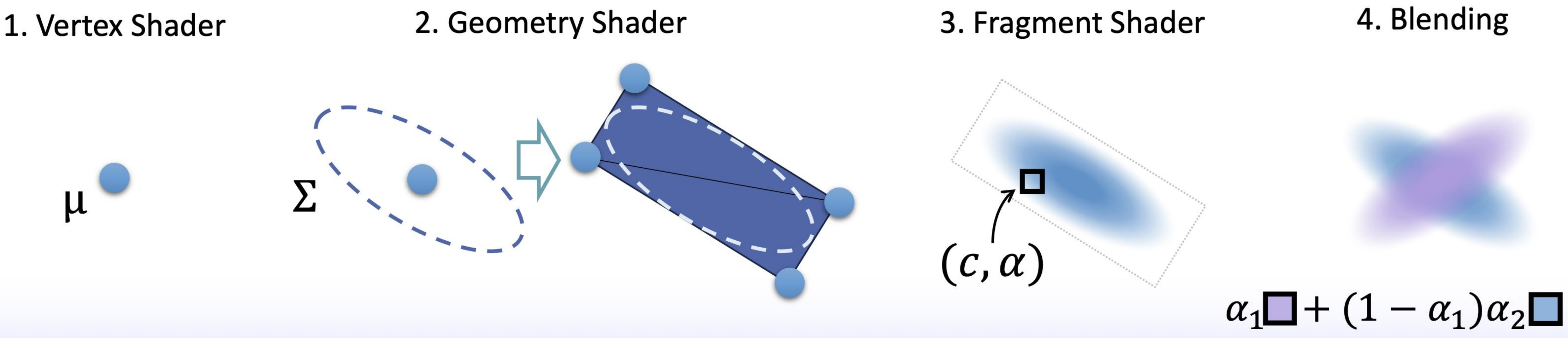
Color of a pixel

Transmittance

Color of each point

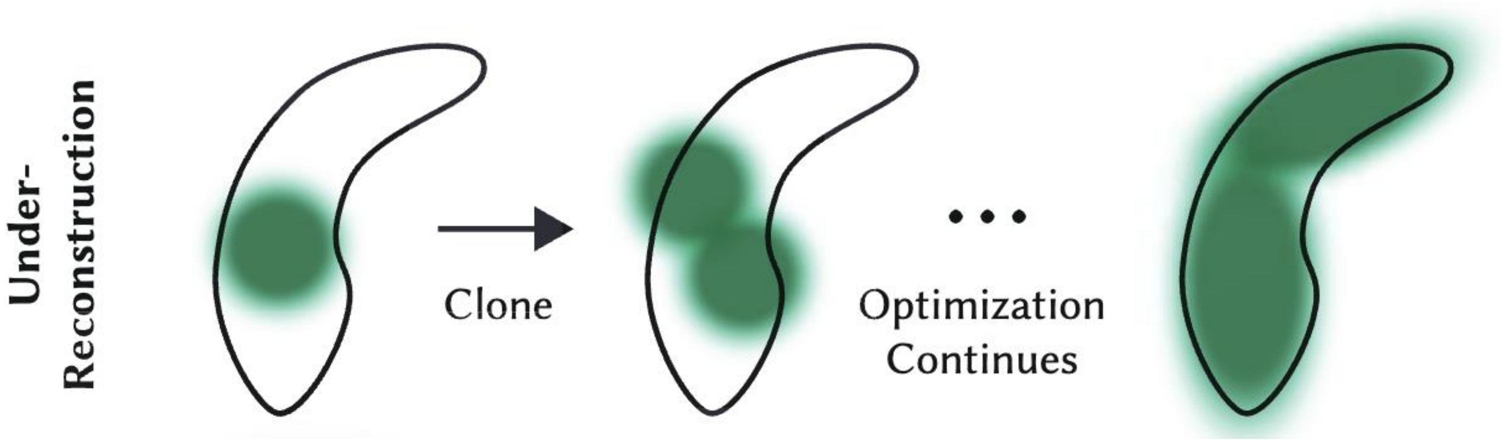
Gaussian Splatting: Why is it fast? A special case of alpha blending

$$I(x) = \sum_i \alpha_i(x) c_i \prod_j^i 1 - a_j(x), \qquad \alpha = oG(x), \qquad G(x) = e^{-0.5(x-\mu)^T \Sigma'^{-1}(x-\mu)}$$

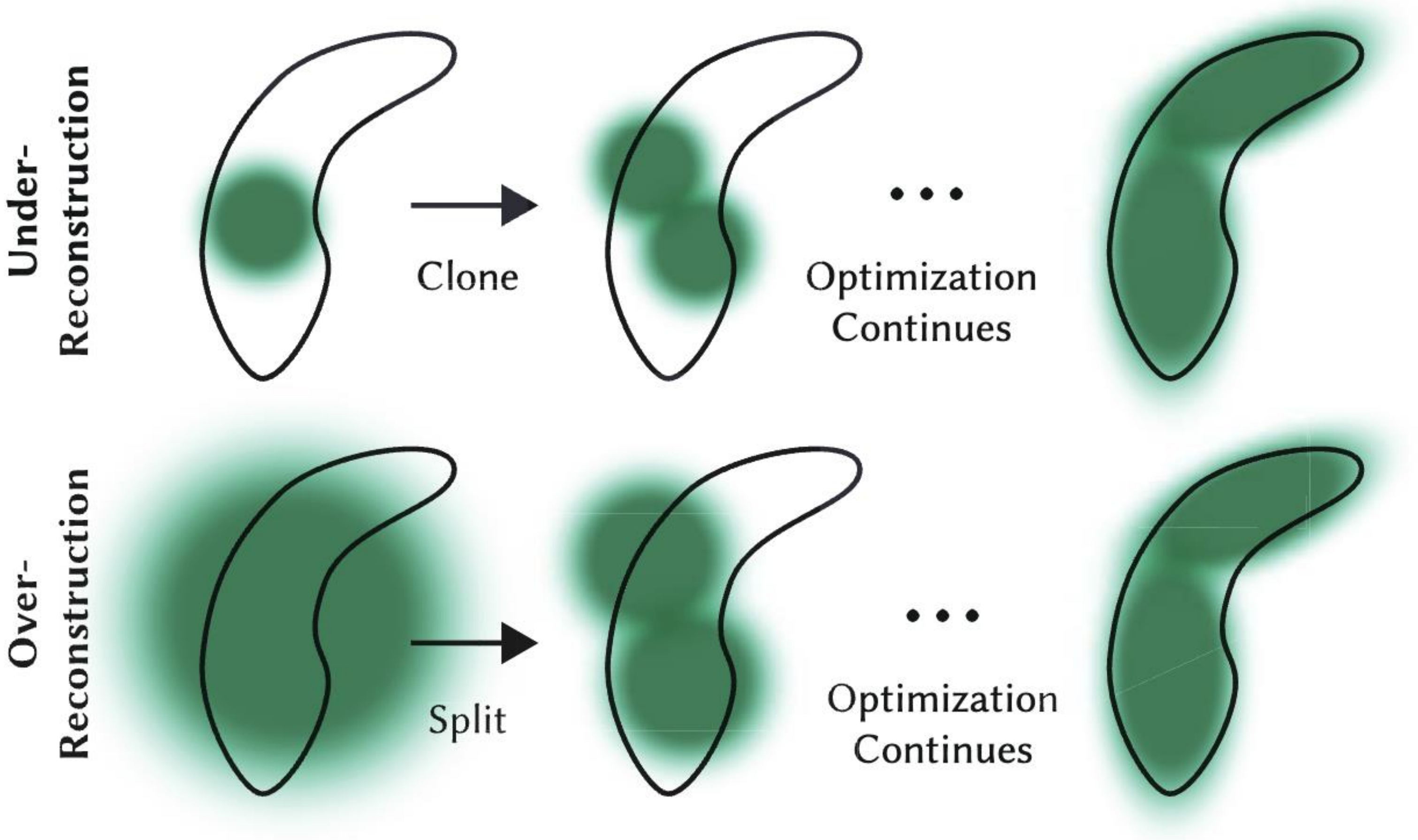


https://blog.42yeah.is/rendering/opengl/2023/12/20/rasterizing-splats.html

Adaptive Control of the Gaussians



Adaptive Control of the Gaussians



Optimization

$$\mathcal{L} = (1 - \lambda)\mathcal{L}_1 + \lambda\mathcal{L}_{\text{D-SSIM}}$$

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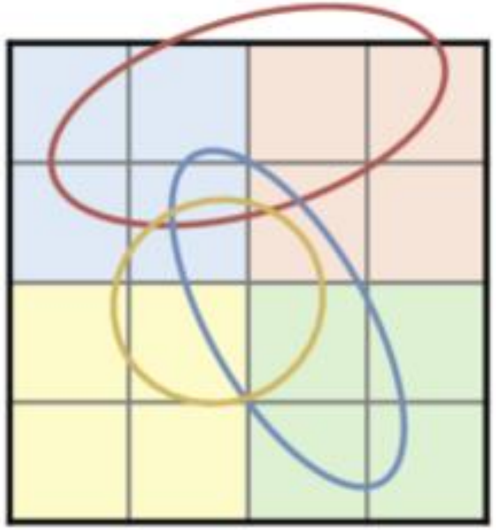
How to go from 5 FPS to 100+ FPS?

(Using the GPU efficiently)

Optimization

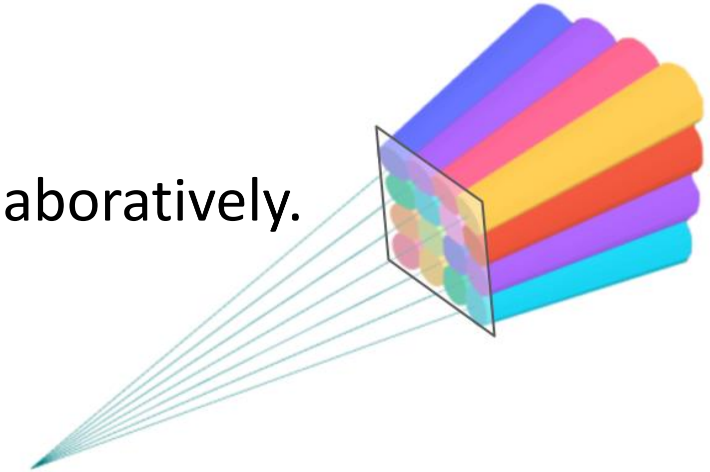


$$\mathcal{L} = (1 - \lambda)\mathcal{L}_1 + \lambda\mathcal{L}_{\text{D-SSIM}}$$

How to go from 5 FPS to 100+ FPS?

(Using the GPU efficiently)

- 1. Tiling
  - Split the image in 16x16 Tiles – helps threads to work collaboratively.
- 2. Single global sort
  - GPU sorts millions of primitives fast.

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Capture
3D Gaussians
Camera Point view
Metrics
89.37 (11.19 ms)


Menu
Views
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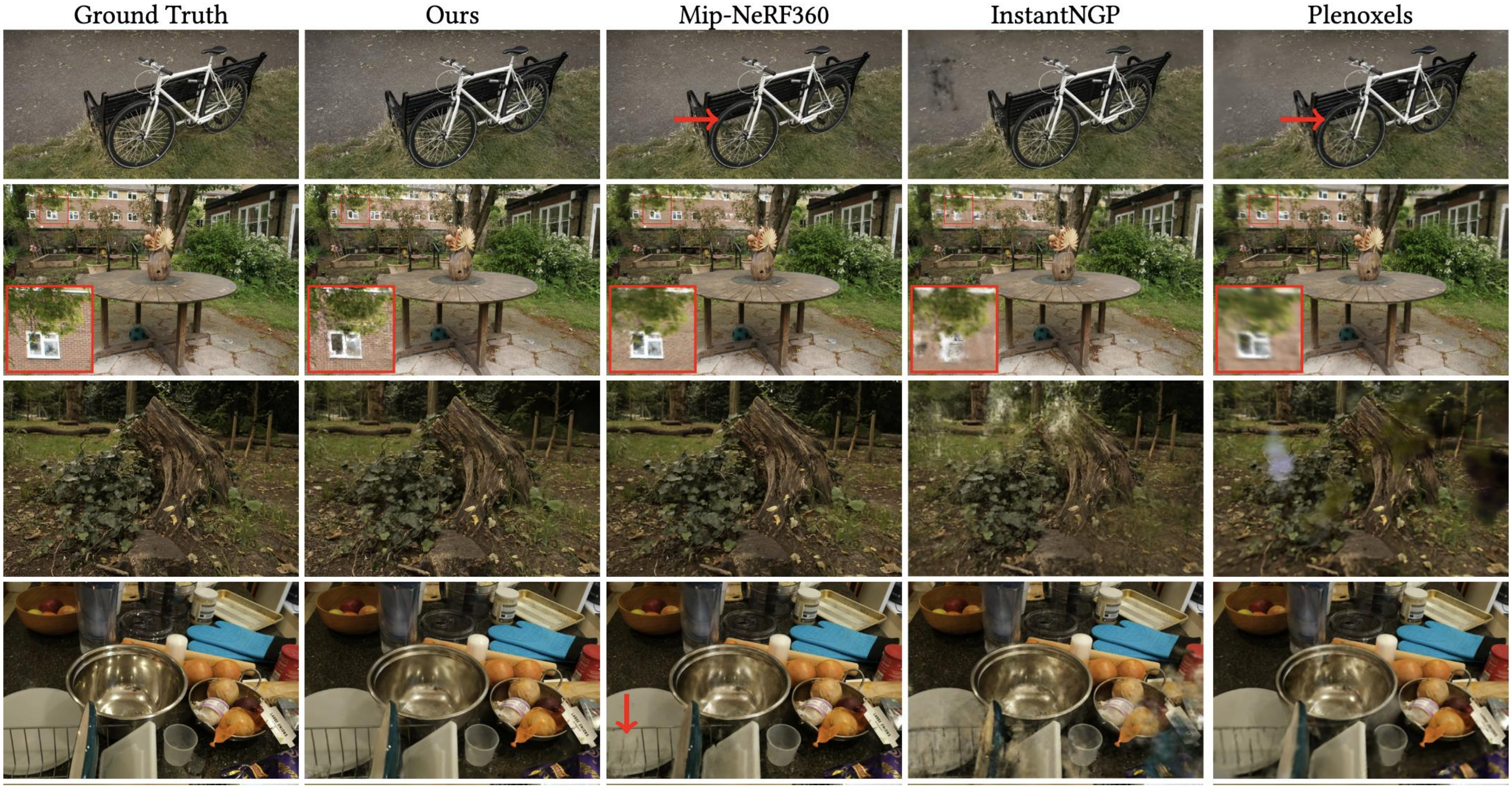
Camera Point view
Metrics
57.56 (17.37 ms)
VSync On


Ground Truth
Ours
Mip-NeRF360
InstantNGP
Plenoxels

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Limitations and its follow-up works

- **3DGS has a high storage cost.**
  - Compression
- **3DGS is a novel view synthesis method (mostly static scenes).**
  - Extending into dynamic scenes - Dynamic 3DGS
- **Unlike meshes, 3DGS does not provide a clean/compact surface.**
  - Surface Reconstruction (How to obtain surface from gaussian primitives?)

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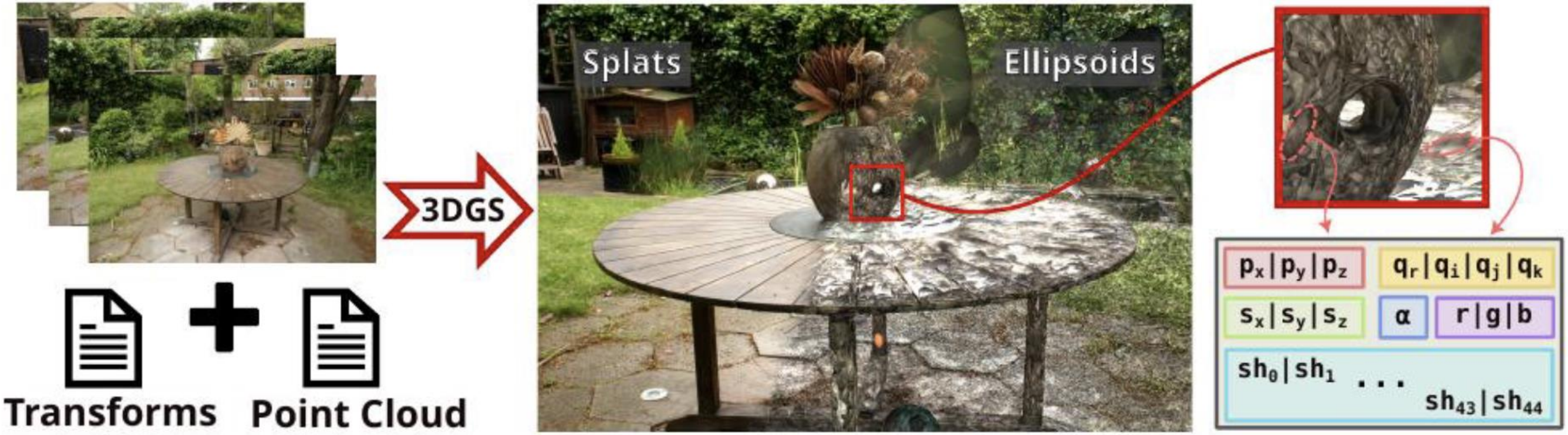
Storage cost of a 3DGS Scene

- 59 x 4 bytes to represent a single Gaussian
- Millions of them!



3DGS Compression – Follow-up works

- Compact3D: Smaller and Faster Gaussian Splatting with Vector Quantization
- EAGLES: Efficient Accelerated 3D Gaussians with Lightweight Encodings (ECCV 2024)
- LightGaussian: Unbounded 3D Gaussian Compression with 15x Reduction and 200+ FPS (NeurIPS 2024)
- Compact 3D Gaussian Representation for Radiance Field (CVPR 2024)
- Compressed 3D Gaussian Splatting for Accelerated Novel View Synthesis (CVPR 2024)
- Reducing the Memory Footprint of 3D Gaussian Splatting (I3D ’24)

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https://efficientgaussian.github.io/

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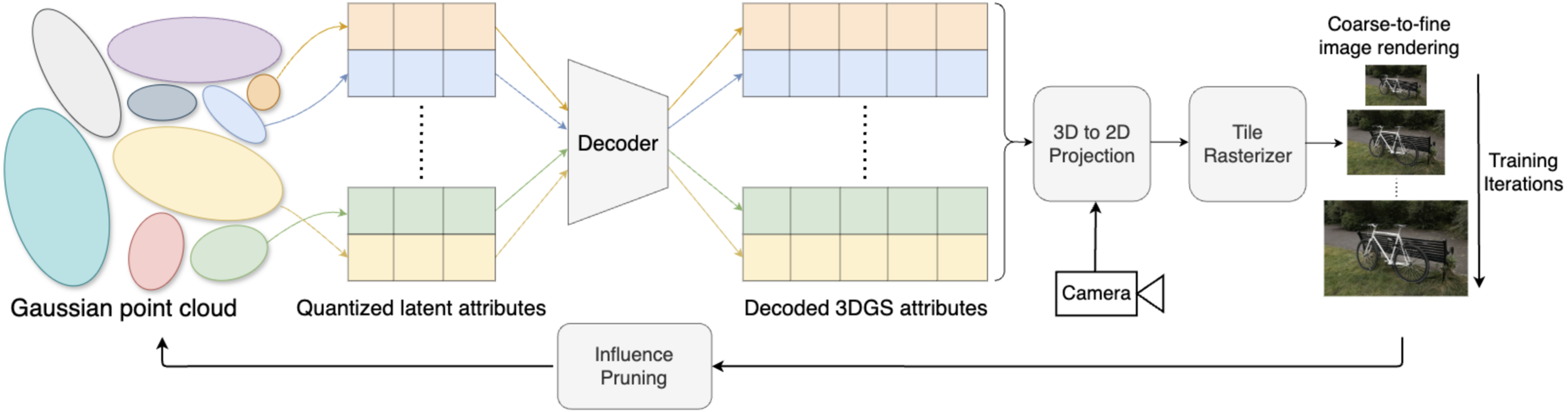

- Key components:
  - Quantized embeddings
  - Coarse-to-fine training
  - Influence pruning

Compression results

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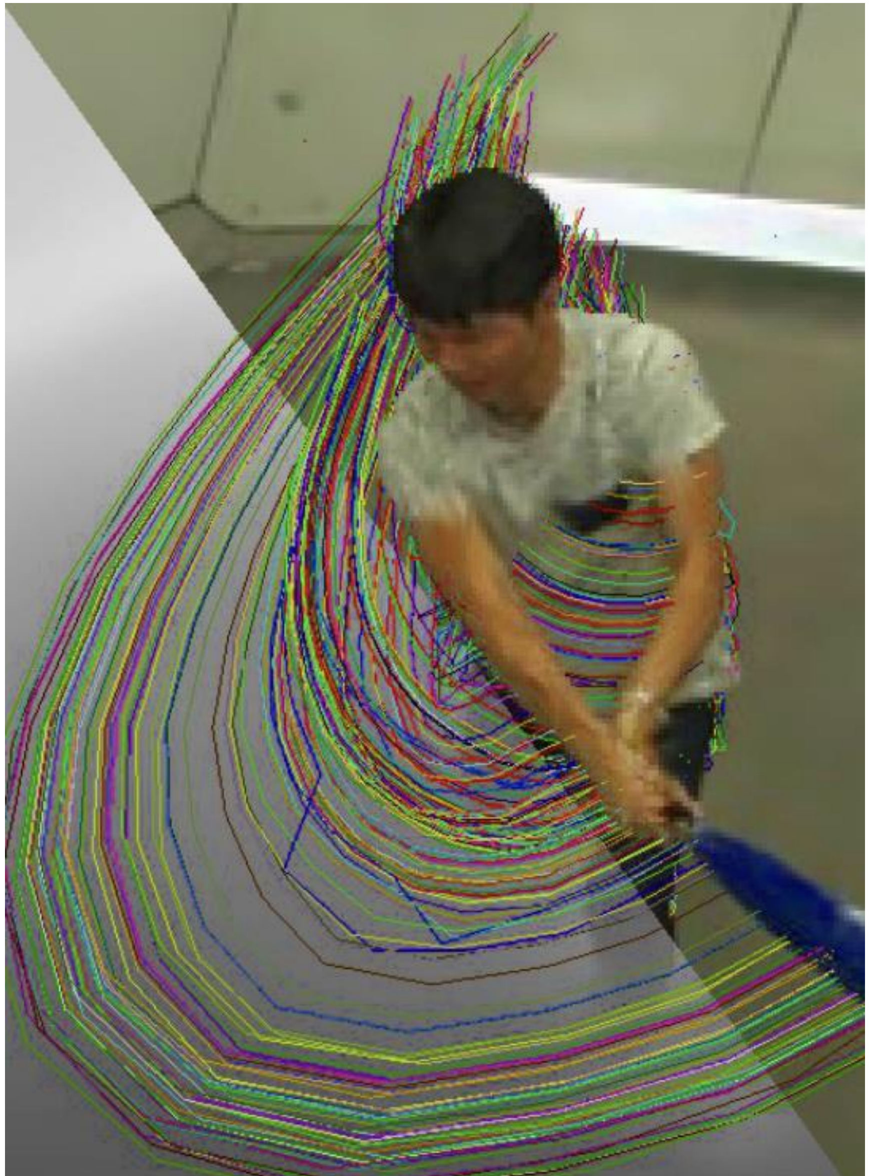
https://dynamic3dgaussians.github.io/

Dynamic 3D Gaussians: Tracking by Persistent Dynamic View Synthesis (3DV 2024)

- Fixed / Consistent over time:
  - 3D Size
  - Color
  - Opacity
- Changing over time (per timestep):
  - 3D Center
  - 3D Rotation



Tracking 3D Gaussians over time

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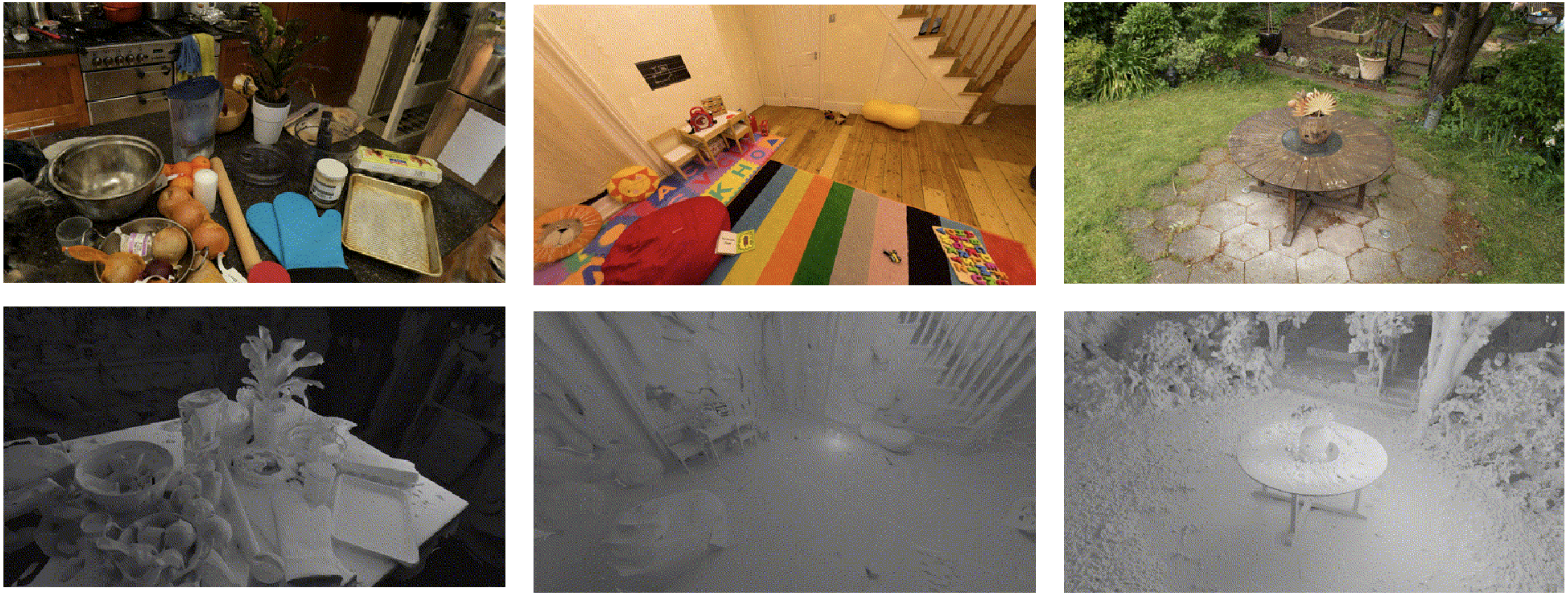
Mesh Extraction

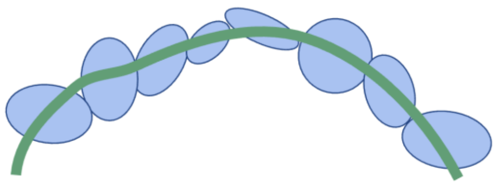
- The naive way of extracting meshes from gaussian splatting is usually done by running TSDF or Marchign Cubes
- Problem!
  - Reconstructed surfaces are not smooth. Hence extracted meshes are very noisy.

SuGaR: Surface-Aligned Gaussian Splatting for Efficient 3D Mesh Reconstruction and High-Quality Mesh Rendering (CVPR 2024)

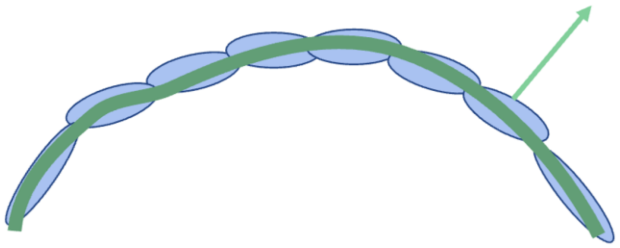


Density constraint: aligning gaussians with the true surface

- Gaussians should have limited overlap and be well-spread on the surface.



- Gaussians should be fully opaque or transparent (otherwise iso surfaces are meaningless)
- Gaussians should be as flat as possible. (One of the three scaling factors should be close to zero.)



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