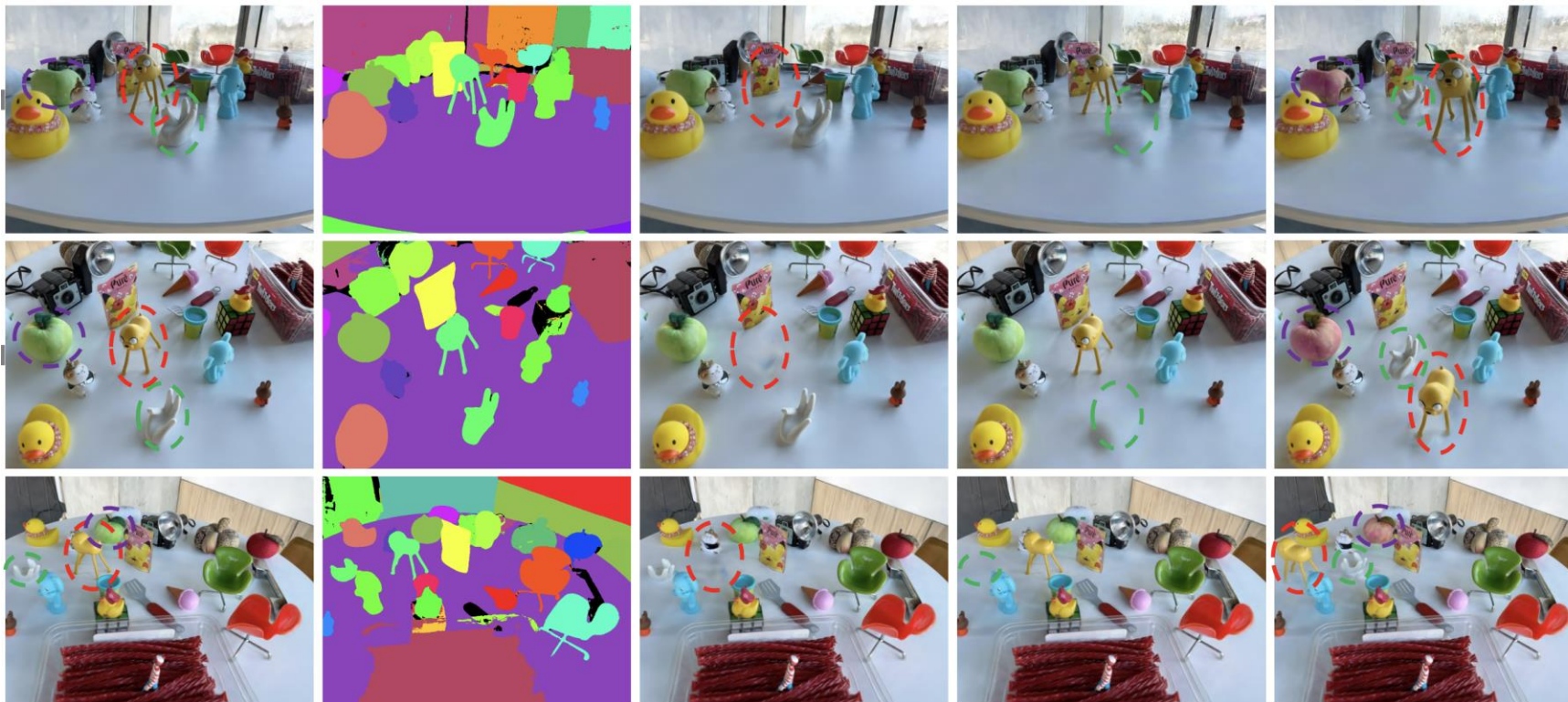


3D EDITING

Yunchao Zhang
HKU IDS

WHAT'S 3D EDITING?

- Consistent in different views.



(a) Rendered Views
(original scene)

(b) Rendered Anything Masks

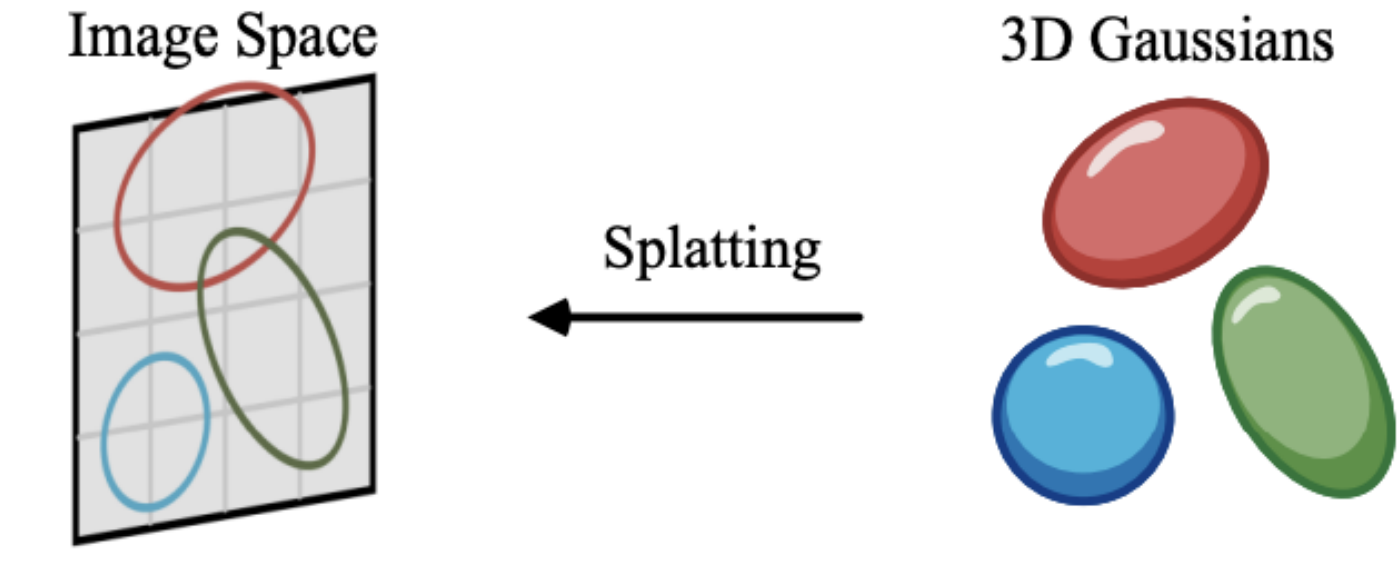
(c) 3D Object Removal
(red circle)

(d) 3D Object Inpainting
(green circle)

(e) 3D Object Scene Recomposition
(exchange red and green circle,
colorize purple circle)

BACKGROUND: 3D GAUSSIAN SPLATTING

- 3D Gaussians: Similar to the point cloud



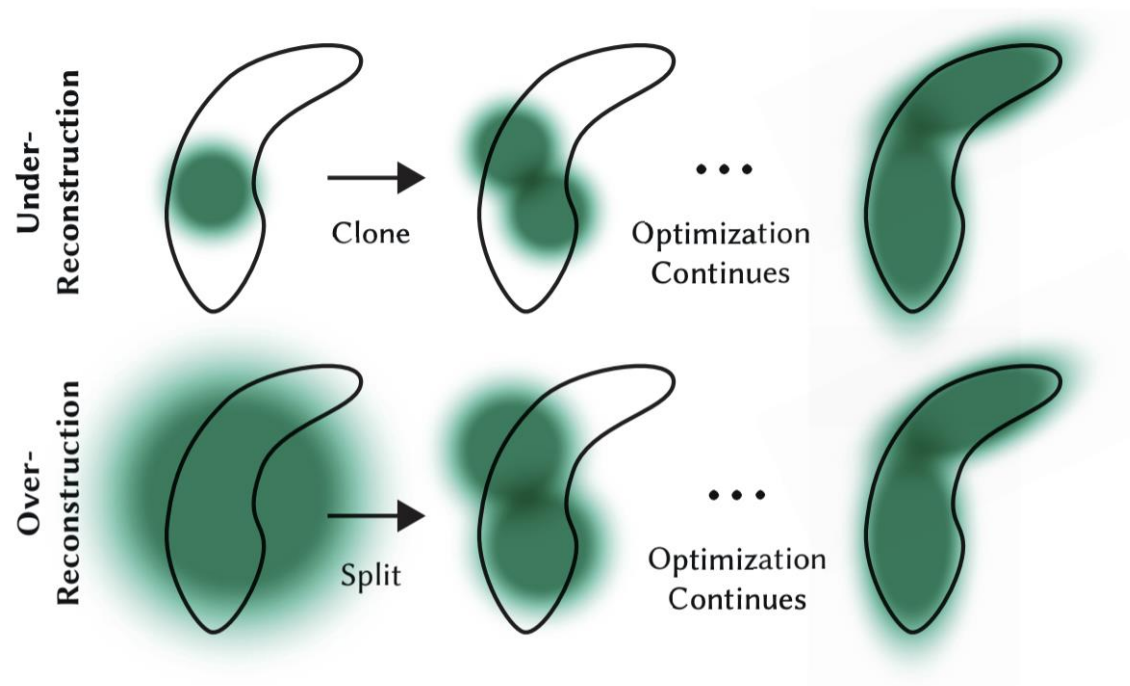
ORIGINAL 3DGS

- 1: Use COLMAP to estimate a initial point cloud



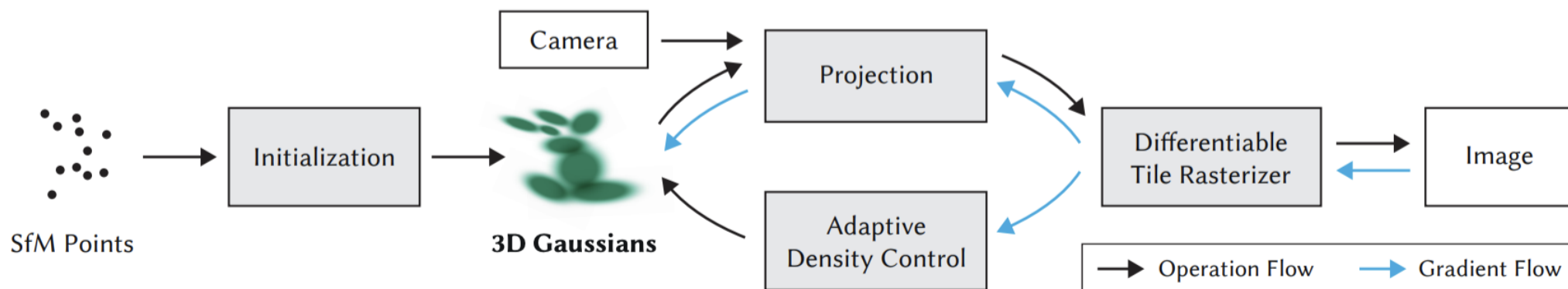
ORIGINAL 3DGS (CONT.)

- 2: Adaptive finetuning on the original 3DGS.



ORIGINAL 3DGS (CONT.)

- 3: Entire pipeline.



3DGS FOR EDITING

- Add extra attribute for each Gaussian.

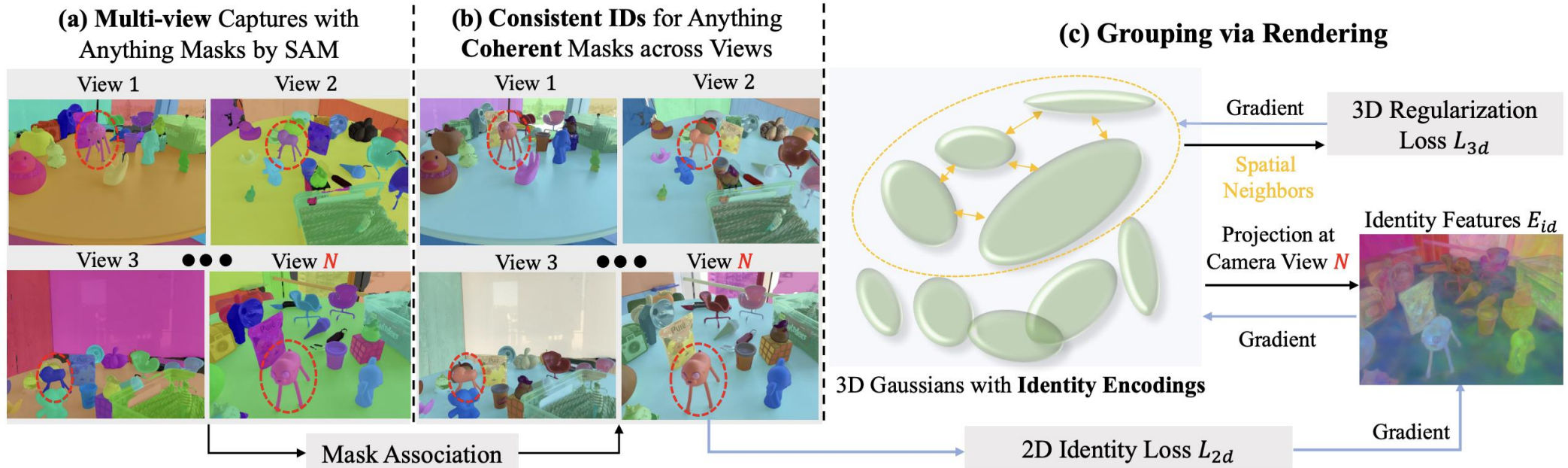
Gaussian Grouping: Segment and Edit Anything in 3D Scenes

Mingqiao Ye, Martin Danelljan, Fisher Yu, and Lei Ke ♠

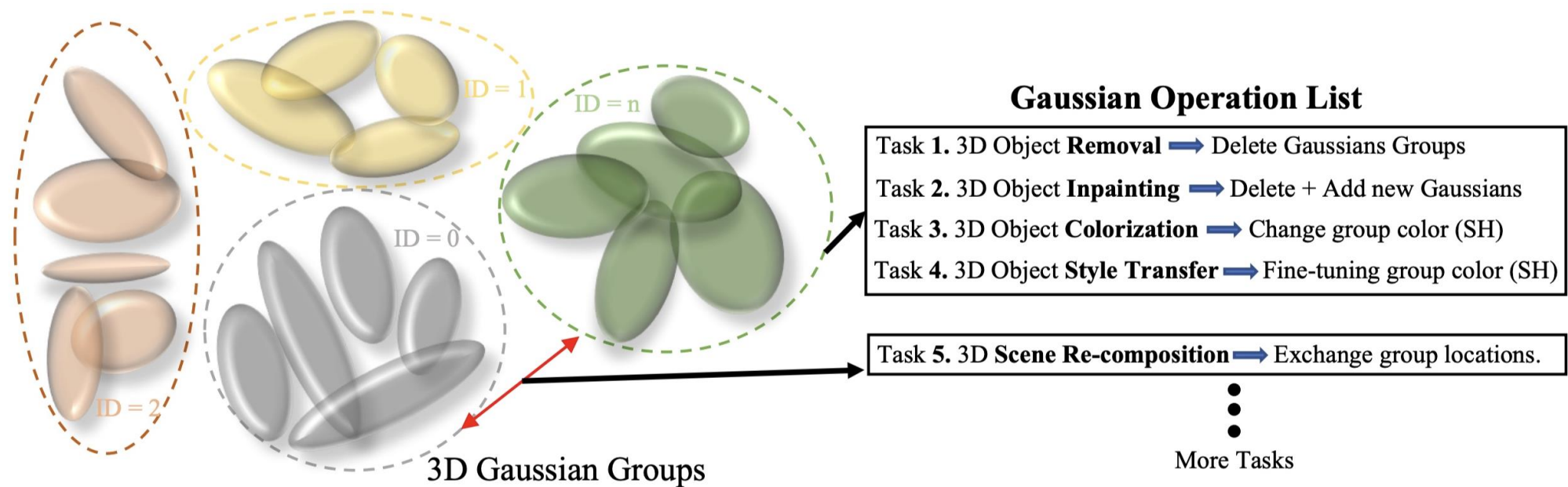
Computer Vision Lab, ETH Zurich

GAUSSIAN GROUPING: SEGMENT AND EDIT ANYTHING IN 3D SCENES

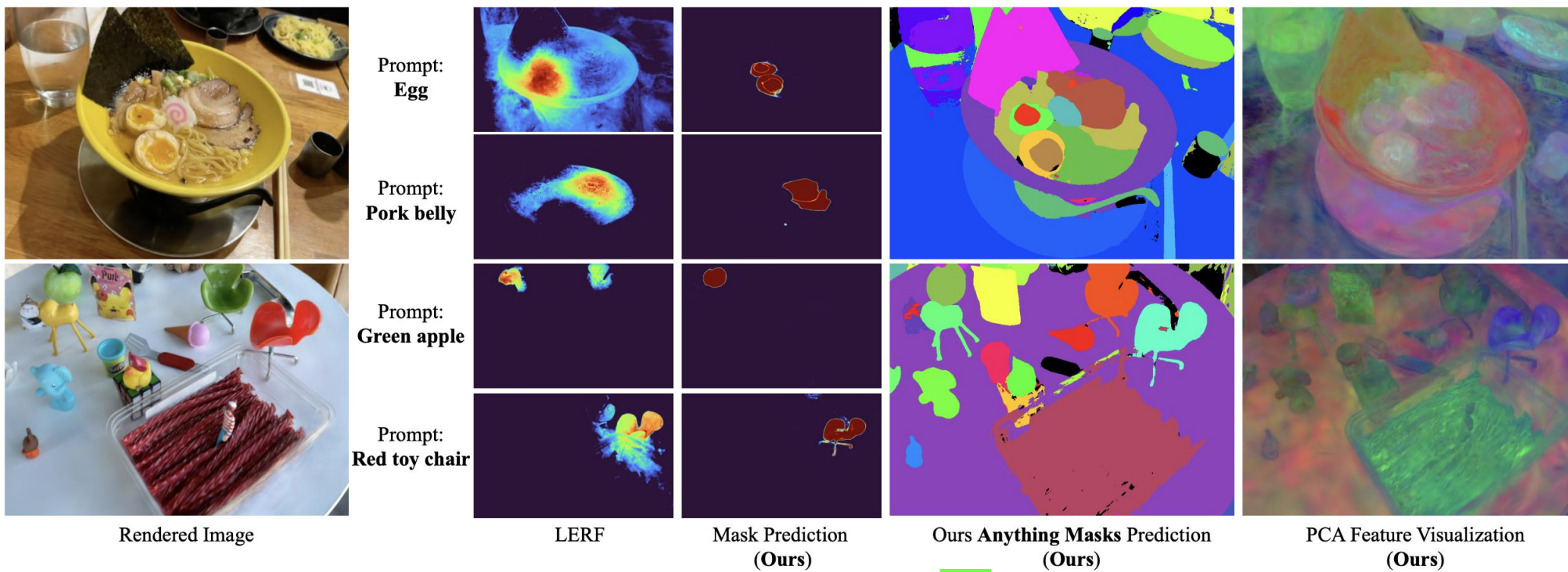
Seek semantic information from 2D foundation models.



DOWNSTREAM APPLICATION



3D SEGMENTATION



INPAINTING

Rendered
Image



SPIn-NeRF
(5h train)



Ours
(1h train
+ 20min
finetune)



DISCUSSION

- Inefficient training and inference: Each Gaussian is supervised individually, while editing tasks are operating on a group of correlated Gaussians.
 - Imagine operating an object in your mind?

NEW PARADIGM FOR 3D EDITING

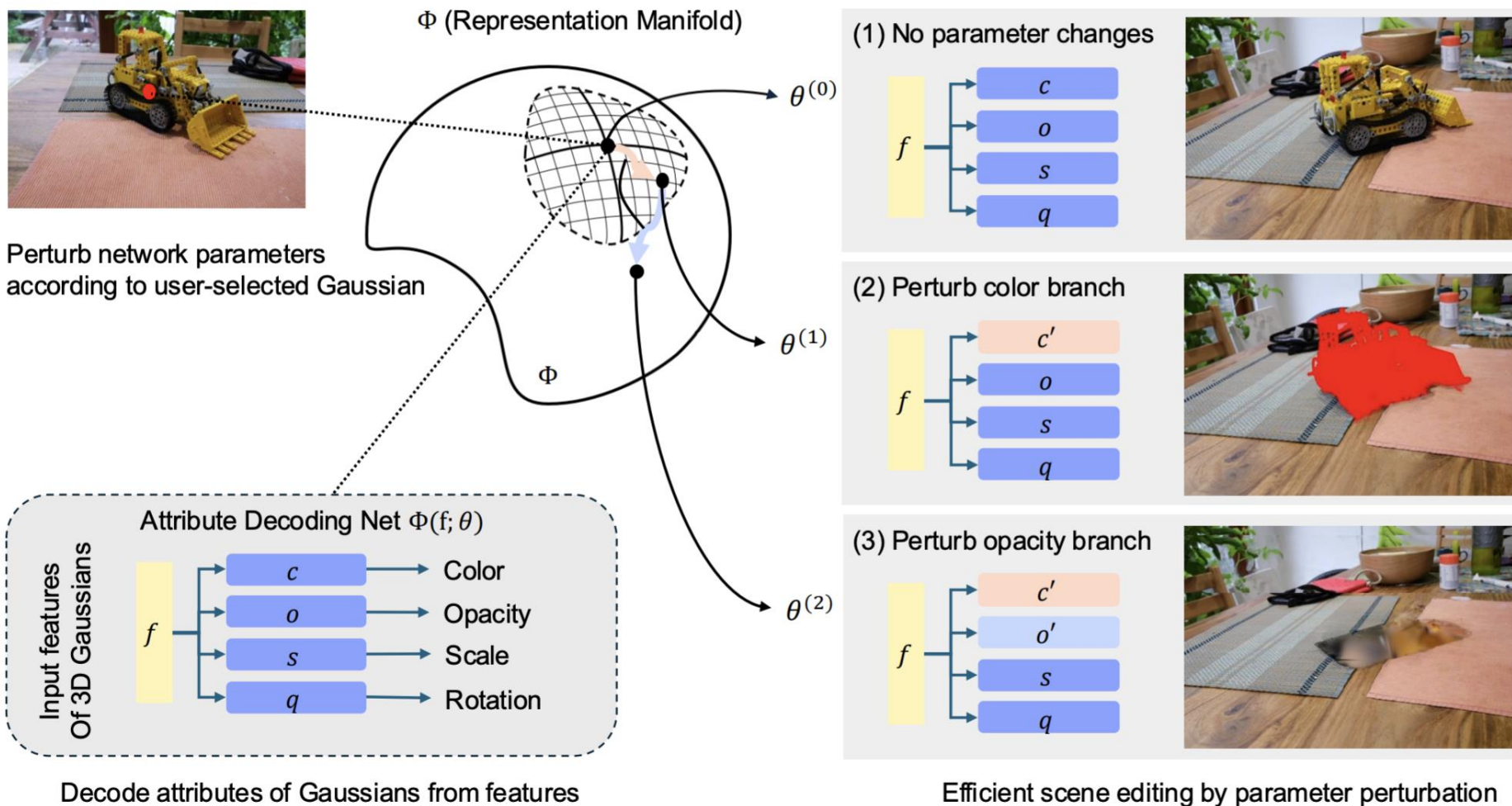
Build correlations among Gaussians for better editing.

InfoGaussian: Structure-Aware Dynamic Gaussians through Lightweight Information Shaping

Yunchao Zhang¹, Guandao Yang², Leonidas Guibas², Yanchao Yang¹

¹ The University of Hong Kong ² Stanford University

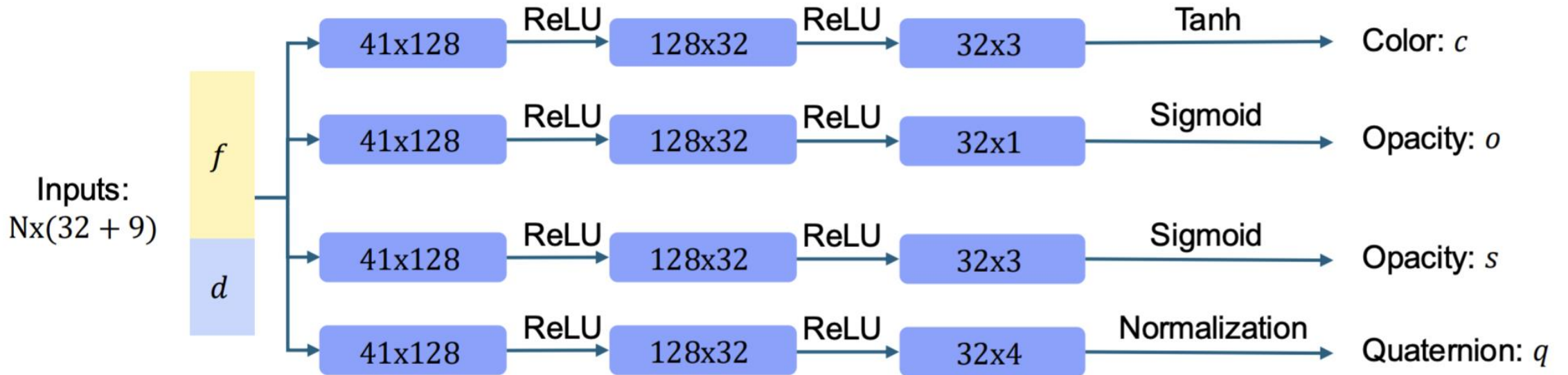
EFFICIENT STRUCTURE-AWARE 3D GAUSSIANS VIA LIGHTWEIGHT INFORMATION SHAPING



CORRELATION SHAPING ON ATTRIBUTE DECODING NET

Attribute decoding network:

- Input: Features of 3D Gaussians and view direction
- Output: Attributes (except centroid position) of 3D Gaussians

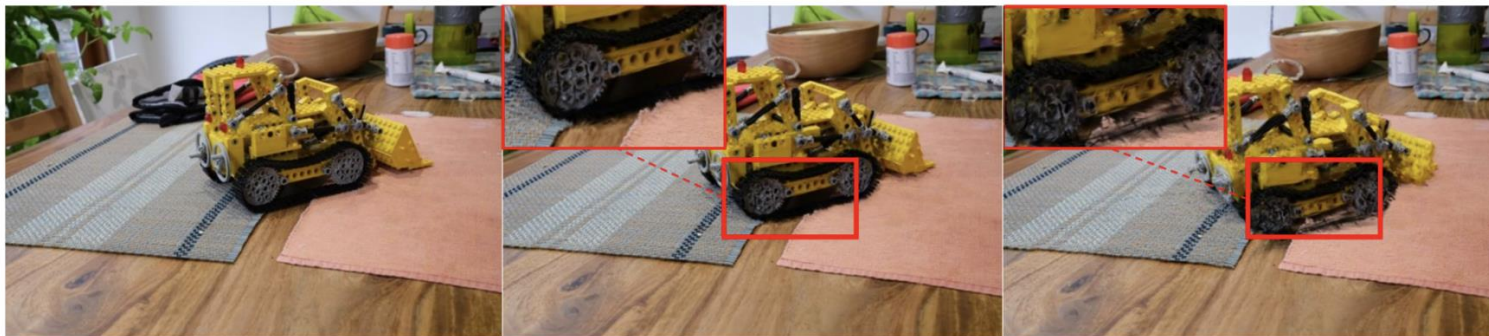


OPERATING ON NETWORK W/ OR W/O MI SHAPING

(a) w/o MI Shaping



(b) w/ MI Shaping



No Perturbation

1st Perturbation

3rd Perturbation

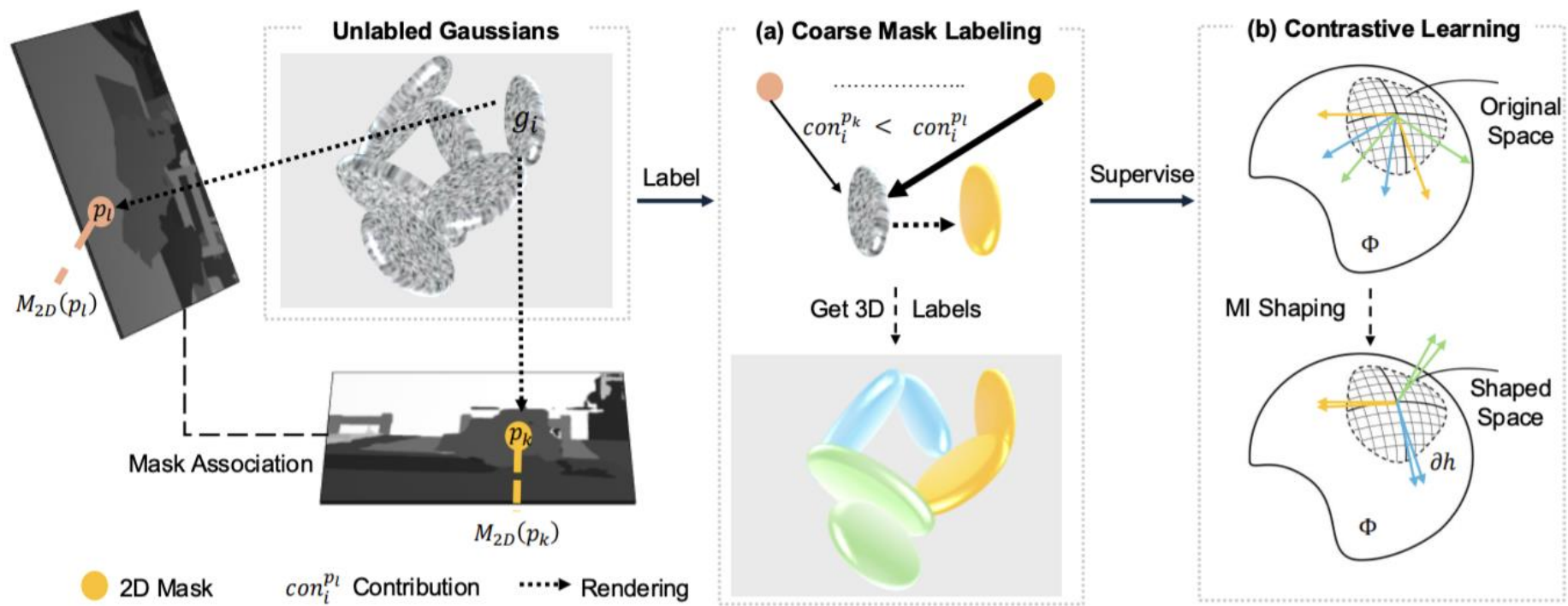
NEW MI LOSS

1. Consistent correlation shaping (e.g., two correlated Gaussians are still correlated after network parameter changes)
2. Faster gradient calculation without calculating Hessian Matrix.

$$\cos(\partial\Phi_i^{(d)}, \partial\Phi_j^{(d)}) \approx \cos(\partial h_i^{(0)}, \partial h_j^{(0)}), \quad d \in \mathbb{N},$$

$$\mathcal{L}_{\text{MI}} = -\log \frac{\exp(|\cos(\partial h_i, \partial h_{i+})|/\tau)}{\sum_{i+ \cup \{i-\}} \exp(|\cos(\partial h_i, \partial h_{i-})|/\tau)},$$

CONTRASTIVE LEARNING



CORRELATION SHAPING FOR 3D EDITING

Perturb the corresponding branch for the specific task.

- E.g., perturb opacity branch to remove the selected object

Available 3D editing tasks:

- 3D Object movement
- 3D object recolor
- 3D object inpainting (newly added)
- 3D object segmentation
- 3D object removal
- 3D object style transfer (newly added)

OPEN-VOCABULARY SEGMENTATION

Perturb any branch to detect the output change for segmentation.

Model	figurines		ramen		teatime		Average Training Cost		
	mIoU	mBIoU	mIoU	mBIoU	mIoU	mBIoU	Time/Minutes	Memory/M	#GS Used
JacobiNeRF (Xu et al., 2023)	22.4	27.6	7.2	6.9	42.6	36.9	*	*	*
LERF (Kerr et al., 2023)	33.5	30.6	28.3	14.7	49.7	42.6	*	*	*
DEVA (Cheng et al., 2023)	46.2	45.1	56.8	51.1	54.3	52.2	*	*	*
SA3D (Cen et al., 2023)	24.9	23.8	7.4	7.0	42.5	39.2	*	*	*
JacobiGS Xu et al. (2023)	62.2	60.1	64.3	57.7	69.7	70.1	30.2	160.2	17%
Gaussian Grouping Ye et al. (2023)	69.7	67.9	77.0	68.7	71.7	66.1	55.2	757.2	100%
Ours w/o DEVA & Regularization	72.2	69.8	79.5	69.9	77.2	70.1	19.7	160.2	15%
Ours w/o DEVA	72.5	70.3	79.1	69.9	77.8	70.2	19.7	160.2	15%
Ours	80.6	77.2	80.6	70.1	84.5	78.7	16.3	160.2	7%

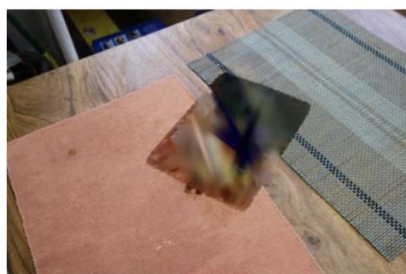
3D OBJECT REMOVAL

Perturb the opacity branch to decrease the opacity of the object.

Rendered Image



Gaussian Grouping



Ours



3D OBJECT MOVEMENT

Perturb any branch to apply the change on positions.



Jacobi Shaping



Ours

3D OBJECT INPAINTING

1. Do the removal
2. Use 2D object mask generated from segmentation and LAMA to inpaint the images after removal
3. Finetune Gaussians on the new dataset

3D OBJECT INPAINTING(CONT.)

Rendered Image



After removal



Inpainted Image



3D OBJECT STYLE TRANSFER

1. Select the object through segmentation
2. Freeze the parameters of other Gaussians, only finetune the parameters of the selected object (except position)
3. Dynamically edit original images using InstructPix2Pix (to solve the multi-view inconsistent issues). Finetune Gaussians on the new dataset.
4. During finetuning, only apply L1 loss inside the object mask and LPIPS loss within the bounding box of the object.

3D OBJECT STYLE TRANSFER(CONT.)

Rendered Image

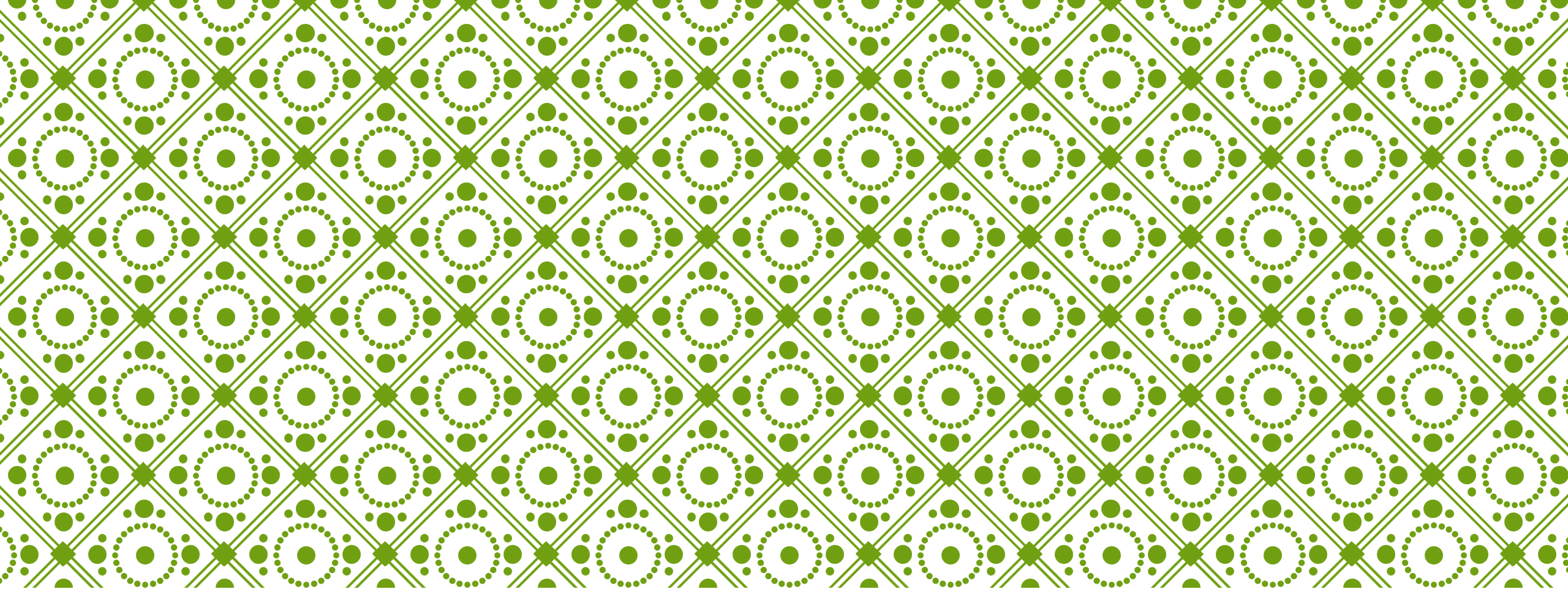


Instruct-GS2GS



Ours





THANK YOU

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