Generating Part-Aware Editable 3D Shapes without 3D Supervision

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CVPR, 2023

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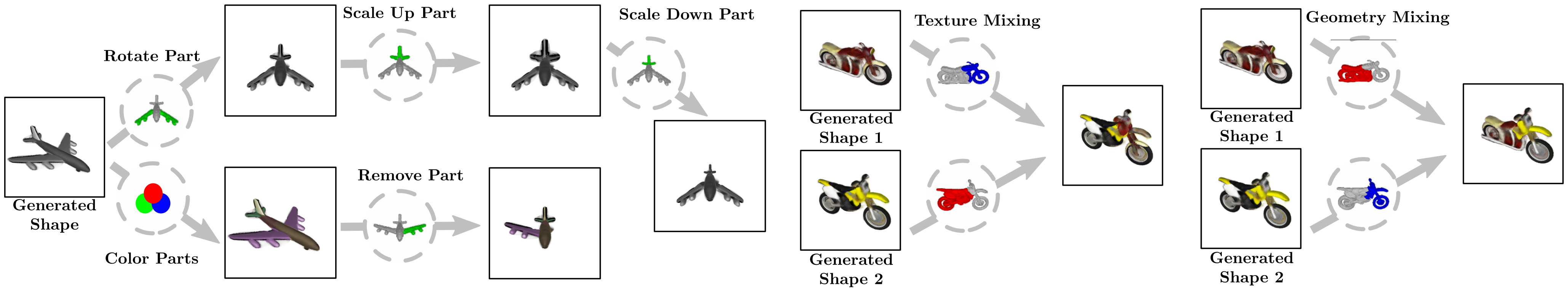

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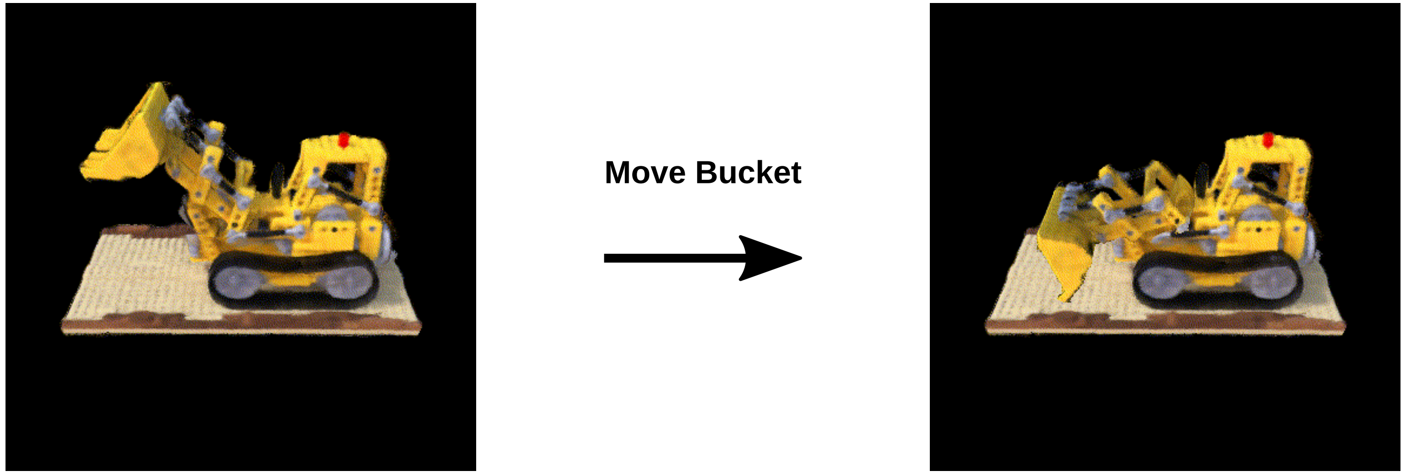

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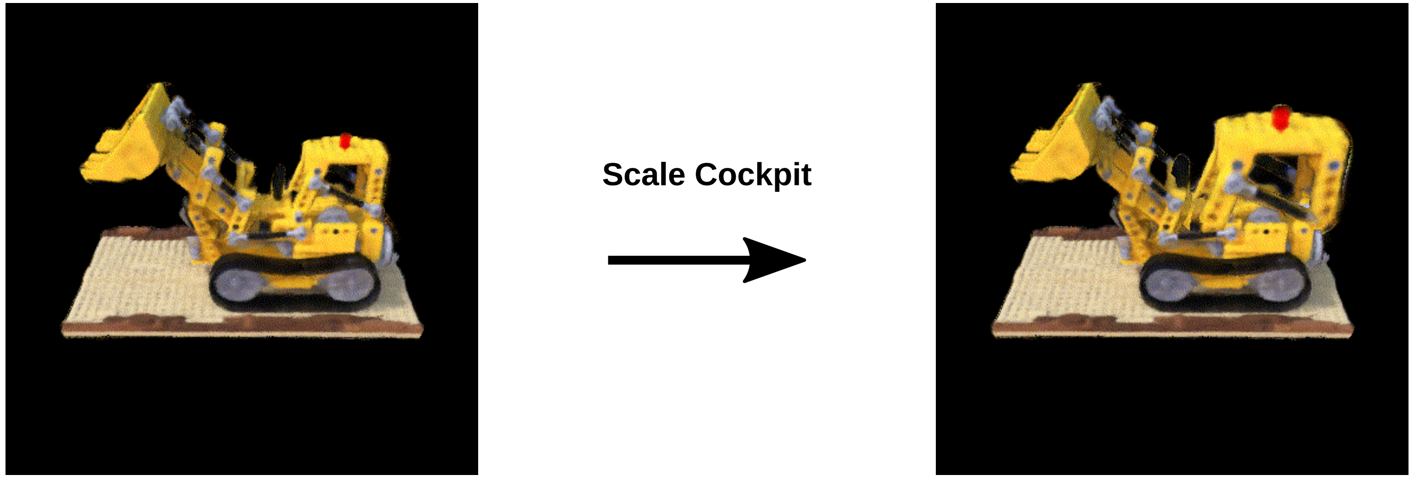

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Parts enable **local control**!

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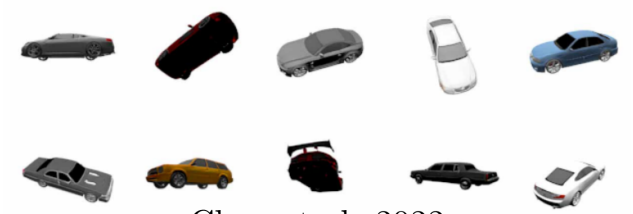

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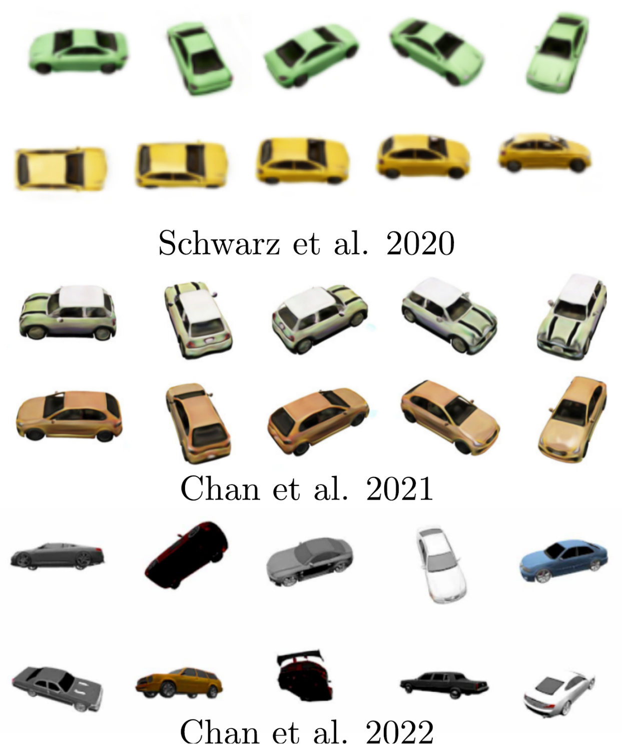

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  - ✓ 2D Supervision

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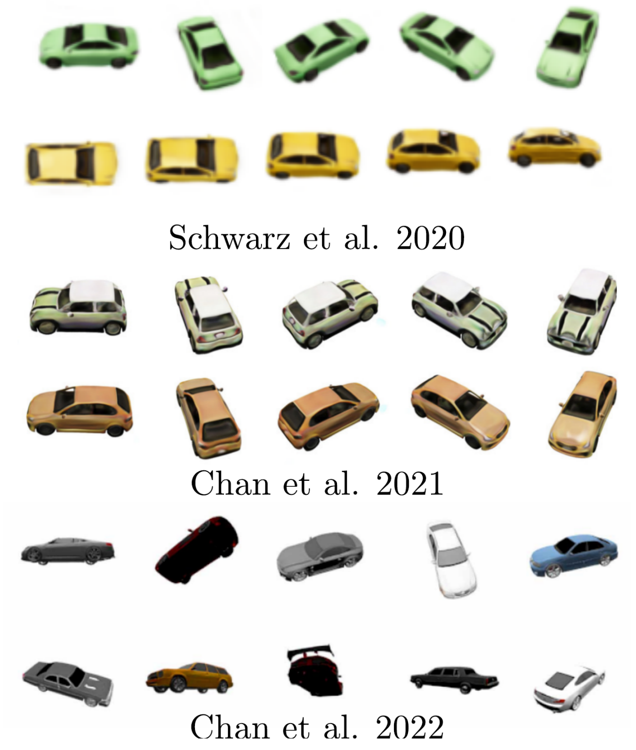

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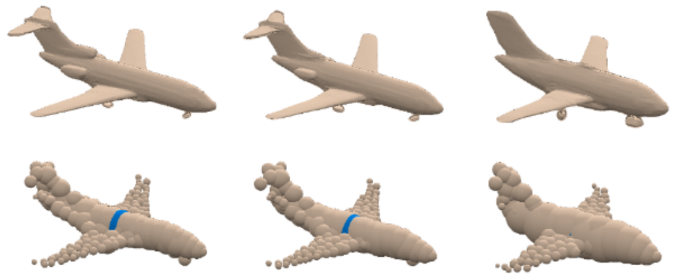

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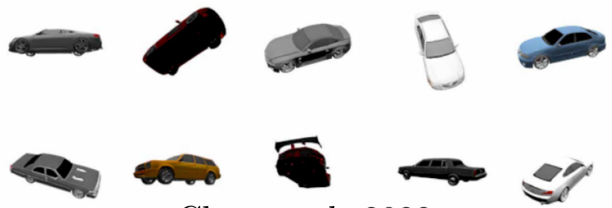

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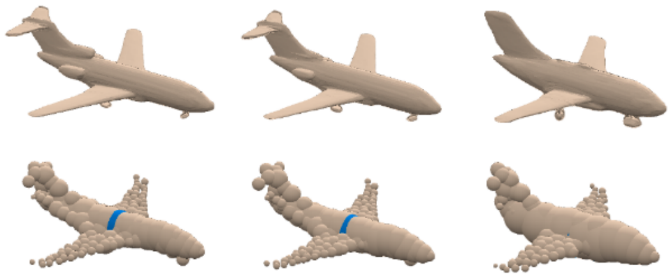

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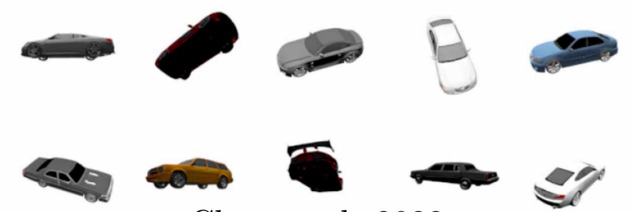

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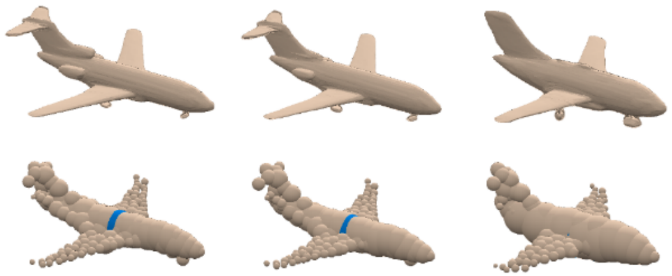

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✓ Explicit part-level control

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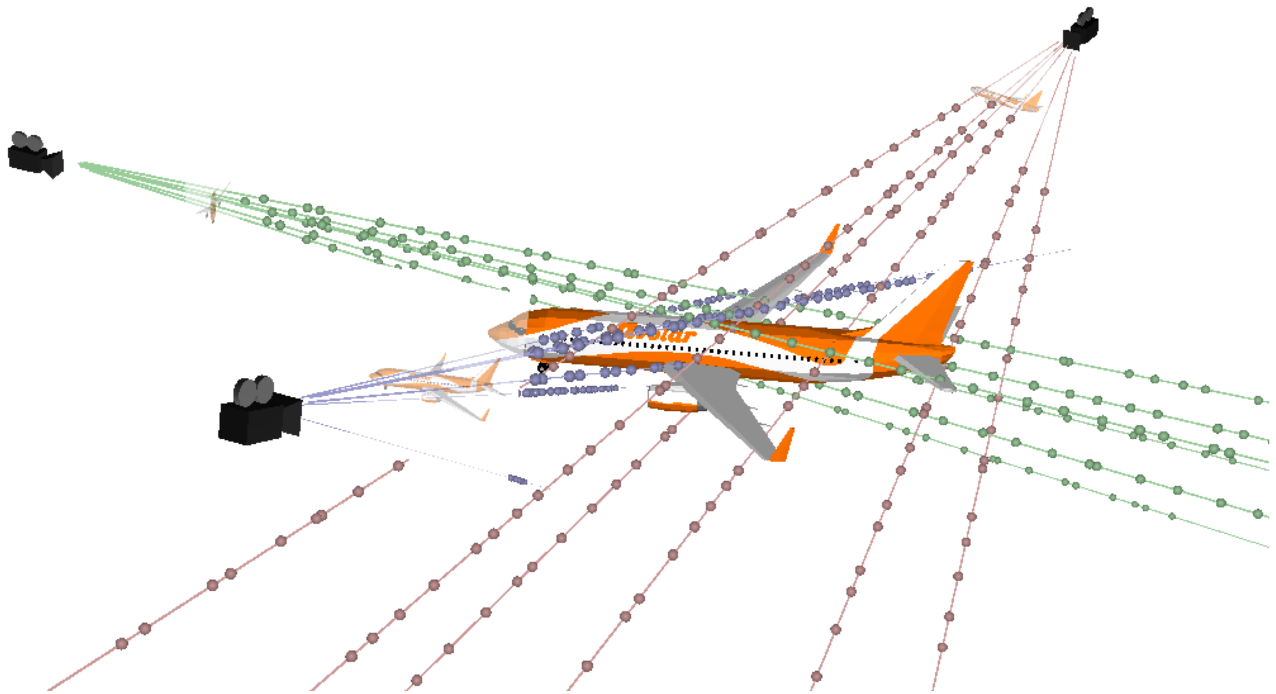
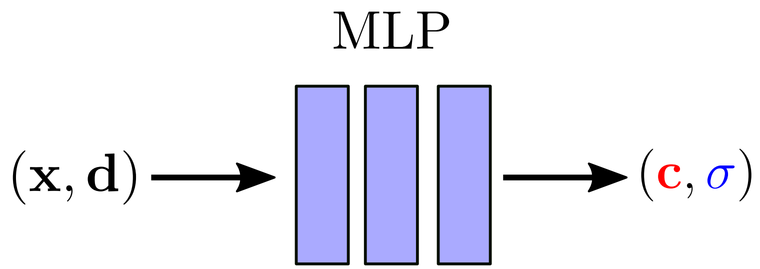
NeRFs map a *3D point* $\mathbf{x} \in \mathbb{R}^3$ and a *viewing direction* $\mathbf{d} \in \mathbb{S}^2$ to a *color* $\mathbf{c} \in \mathbb{R}^3$ and a *volume density* $\sigma \in \mathbb{R}^+$.





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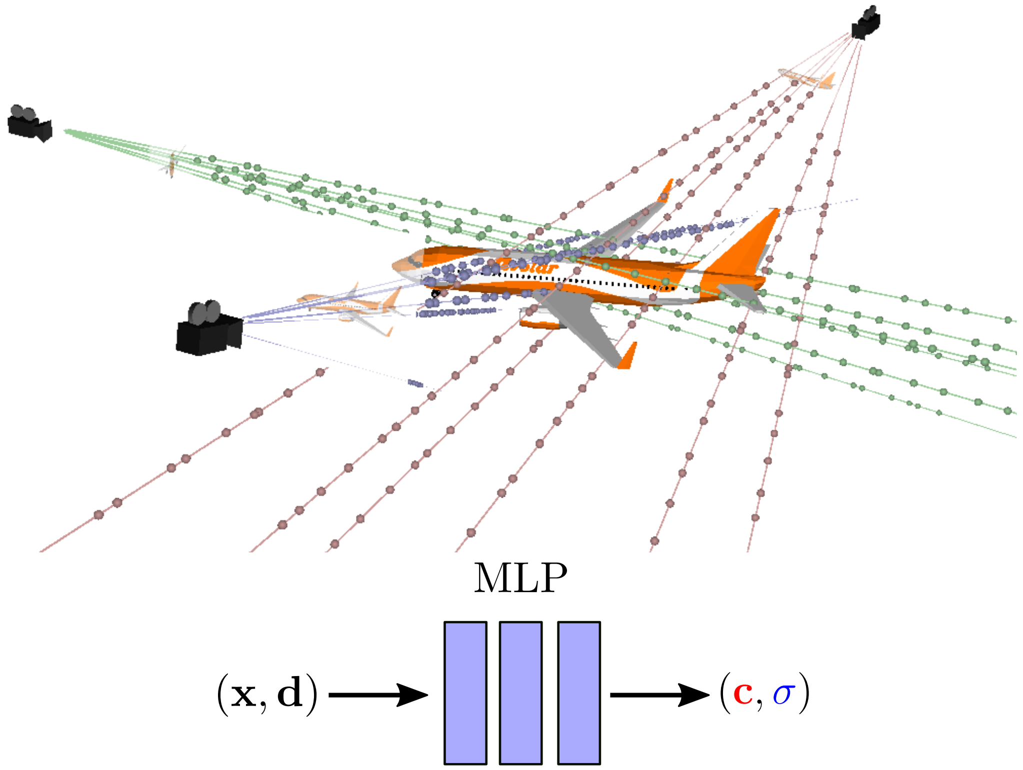

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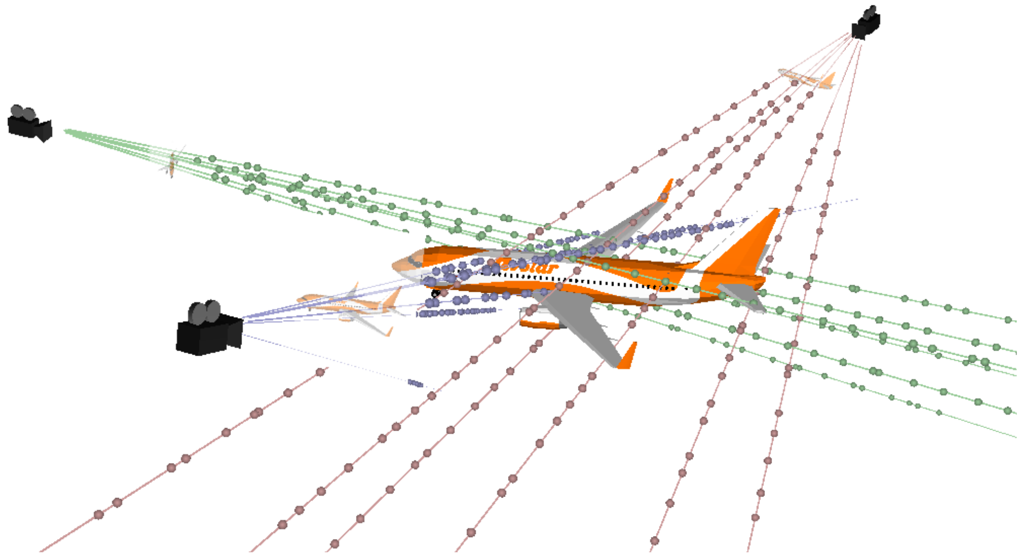
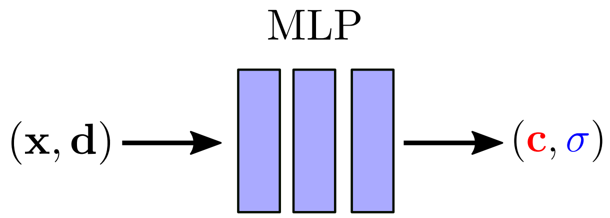
The **rendered color** for a ray r is calculated by accumulating the predicted $\{\mathbf{c}_i^r, \boldsymbol{\sigma}_i^r\}^N$ for N sampled points $\mathcal{X}_r = \{\mathbf{x}_i^r\}_{i=1}^N$ along r:

$$\hat{C}(r) = \sum_{i=1}^{N} \exp\Big(-\sum_{i<j} \boldsymbol{\sigma}_j^r \delta_j^r\Big)(1 - \exp(-\boldsymbol{\sigma}_i^r \delta_i^r))\mathbf{c}_i^r$$





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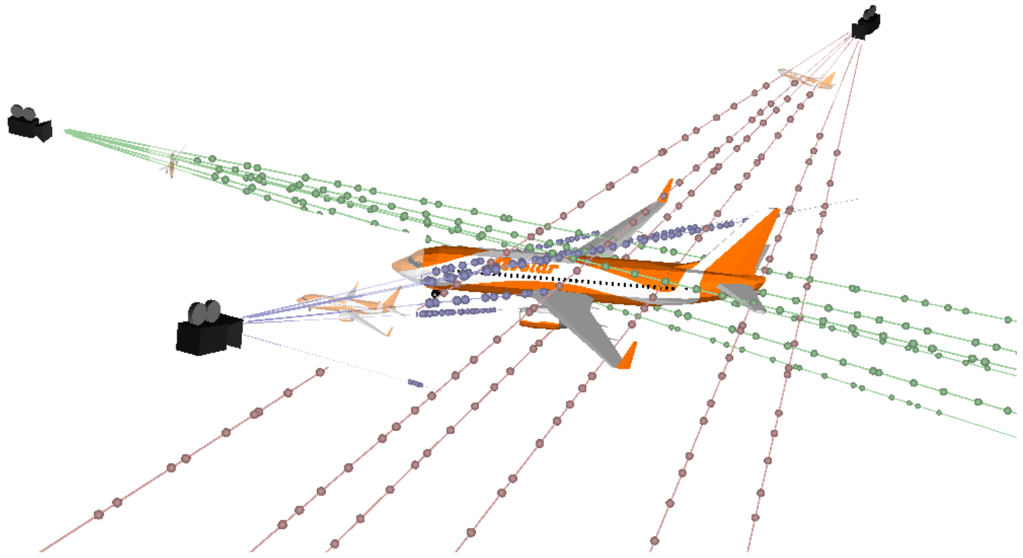
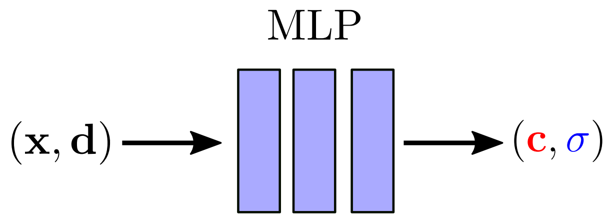
or equally

$$\hat{C}(r) = \sum_{i=1}^{N} o_i^r \prod_{j<i} \left(1 - o_j^r\right) \mathbf{c}_i^r$$

with $o_i^r = 1 - \exp(-\sigma_i^r \delta_i^r)$ the **occupancy value** at point $\mathbf{x}_i^r$ and δ_i^r the distance between two adjacent ray points.





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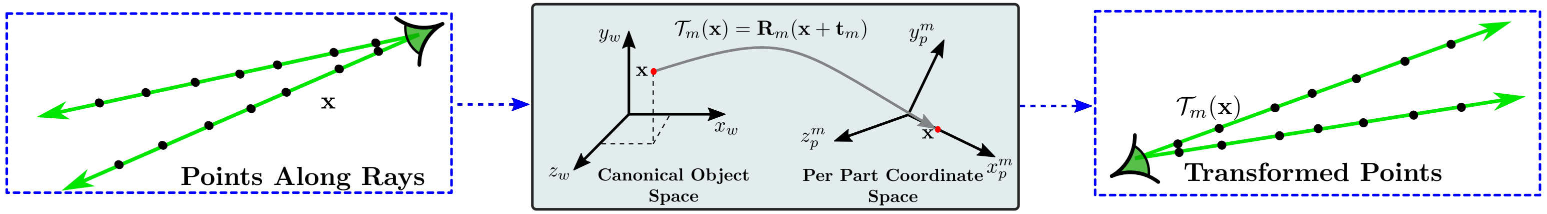

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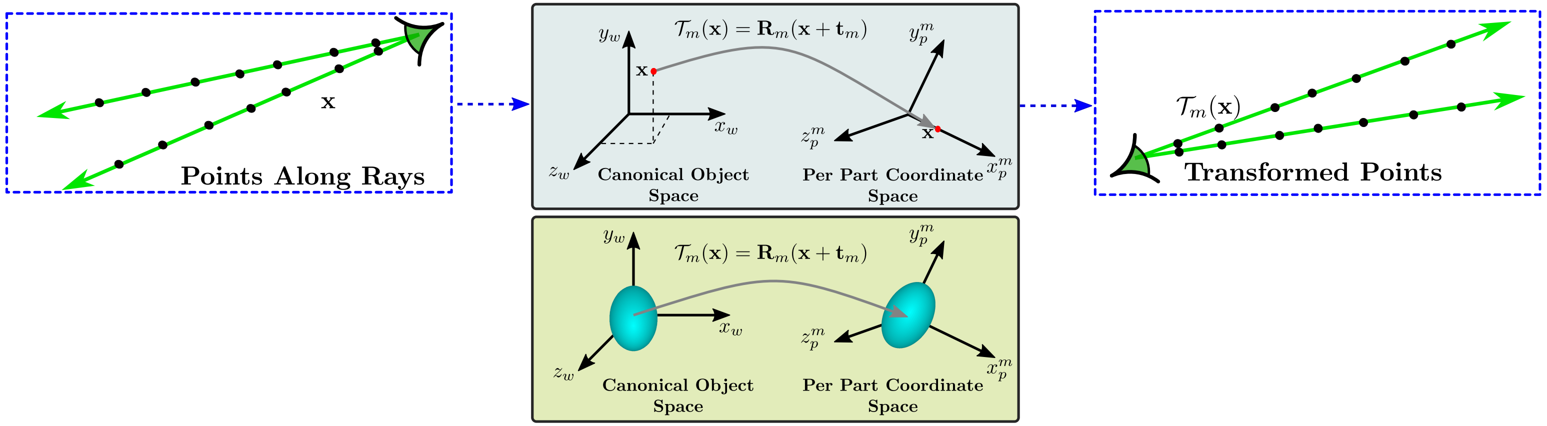

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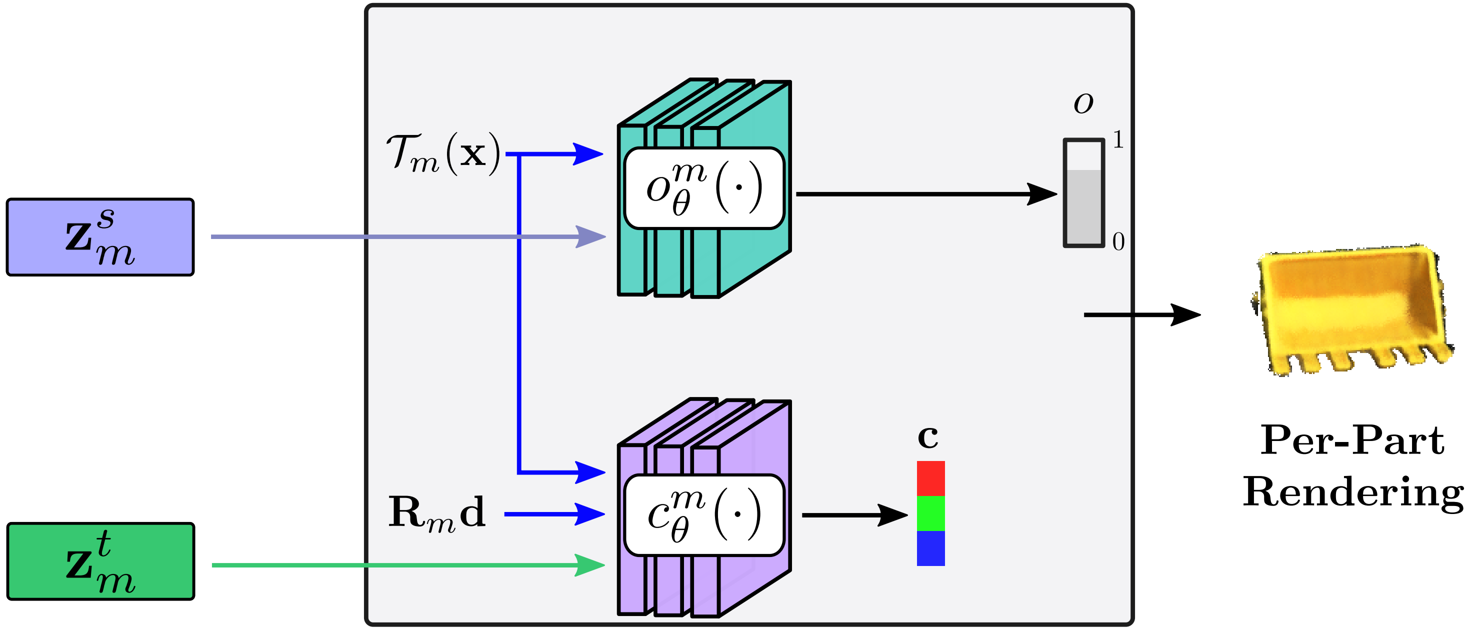

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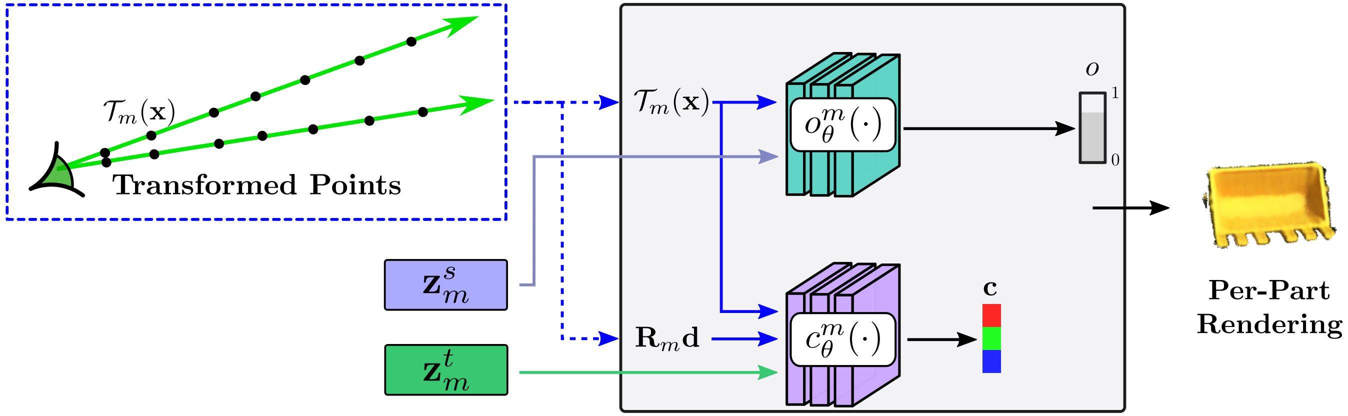

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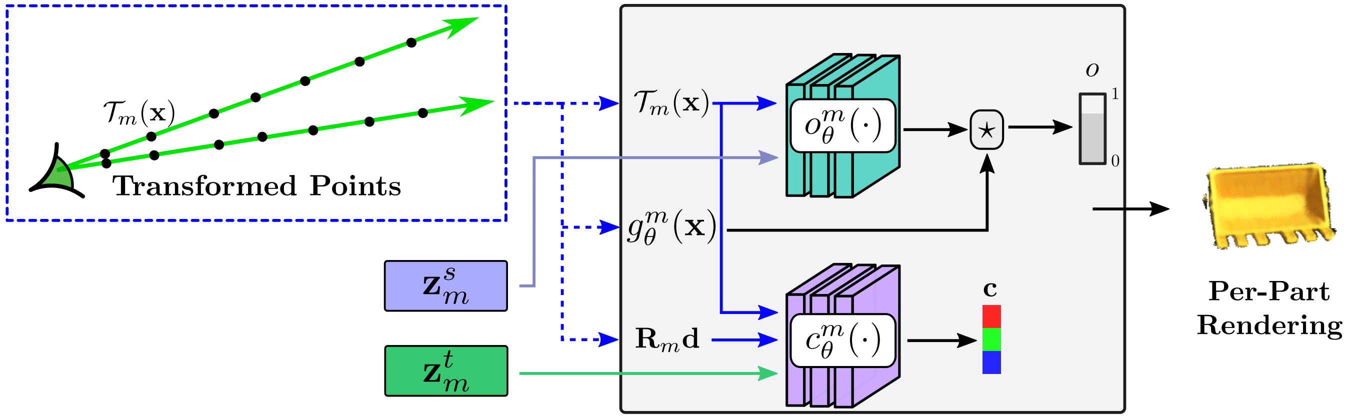

- To enforce that **each part captures local and continuous regions of the object**, we multiply the occupancy function with an **axis-aligned 3D ellipsoid occupancy function**:

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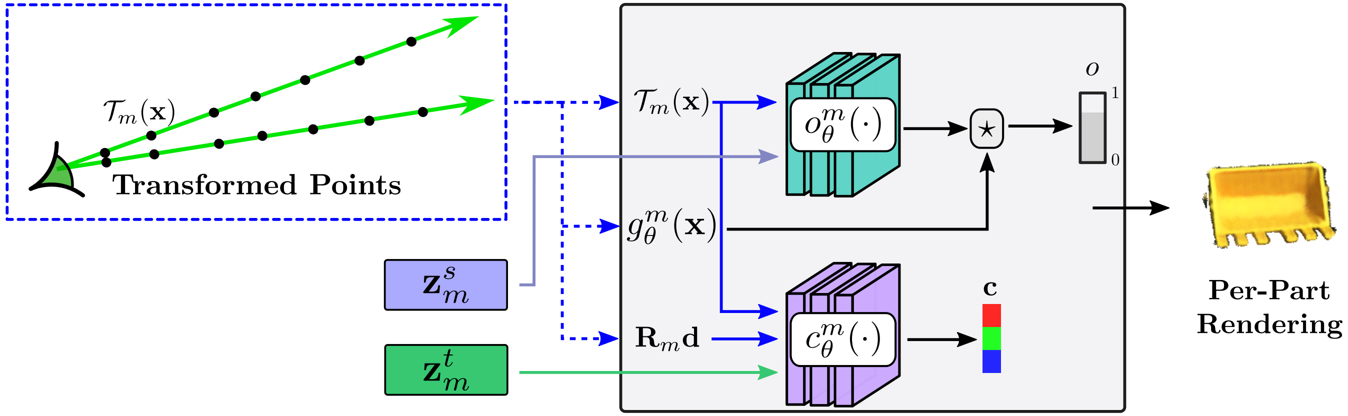

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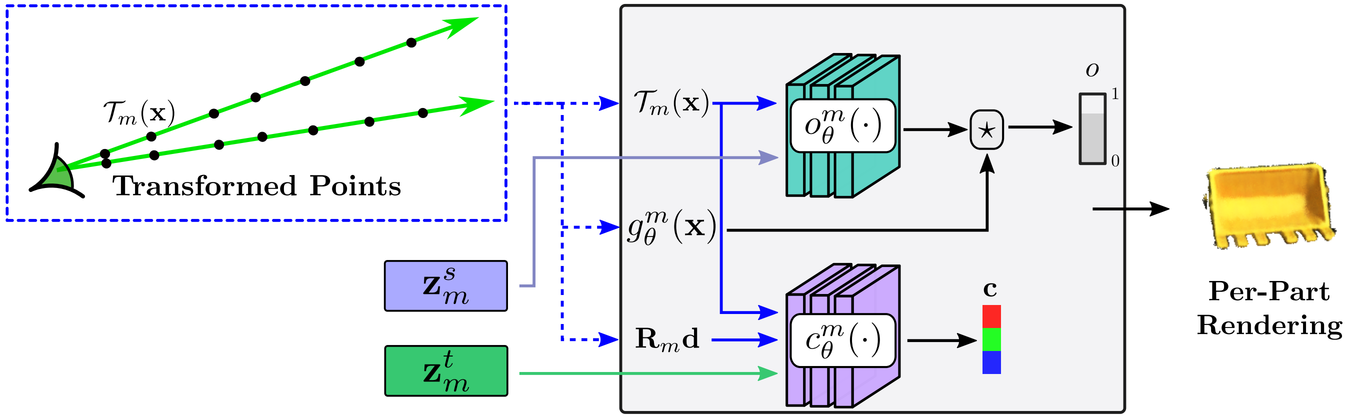

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- The **per-part rendering equation** now becomes:

$$\hat{C}_m(r) = \sum_{i=1}^{N} h_\theta^m(\mathbf{x}_i^r) \prod_{j<i} \left(1 - h_\theta^m(\mathbf{x}_j^r)\right) \mathbf{c}_\theta^m(\mathbf{x}_i^r)$$

Hard Assignment between Rays and Parts

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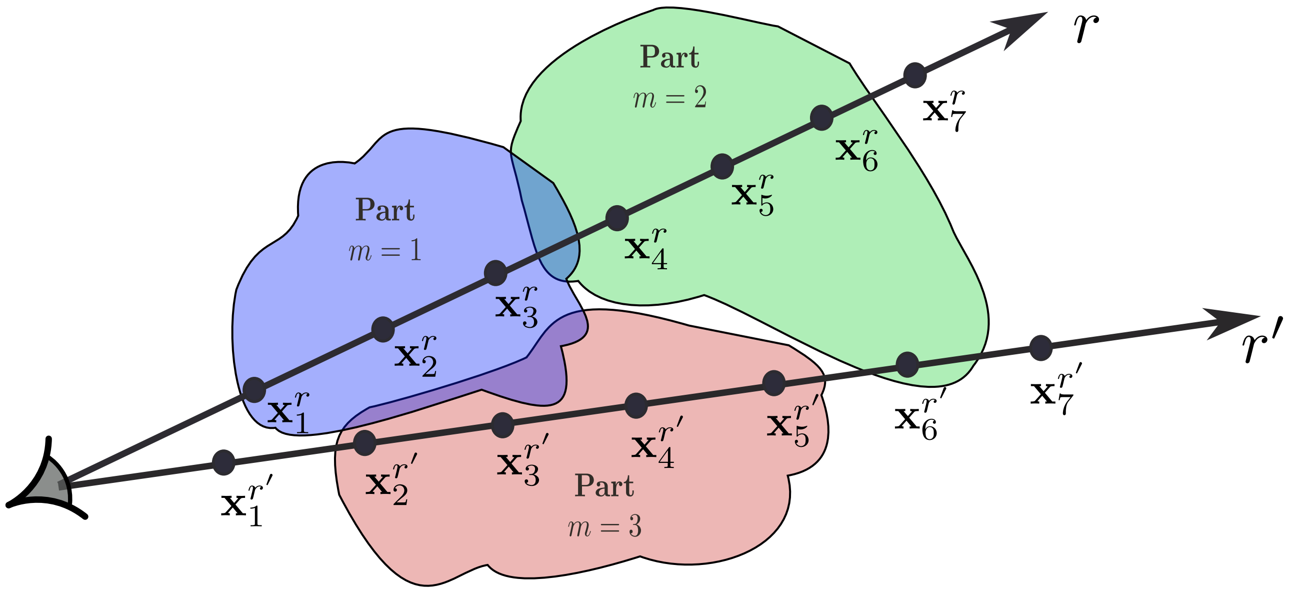
We impose a hard assignment between rays and parts, **associating a ray with the first part it itersects**.



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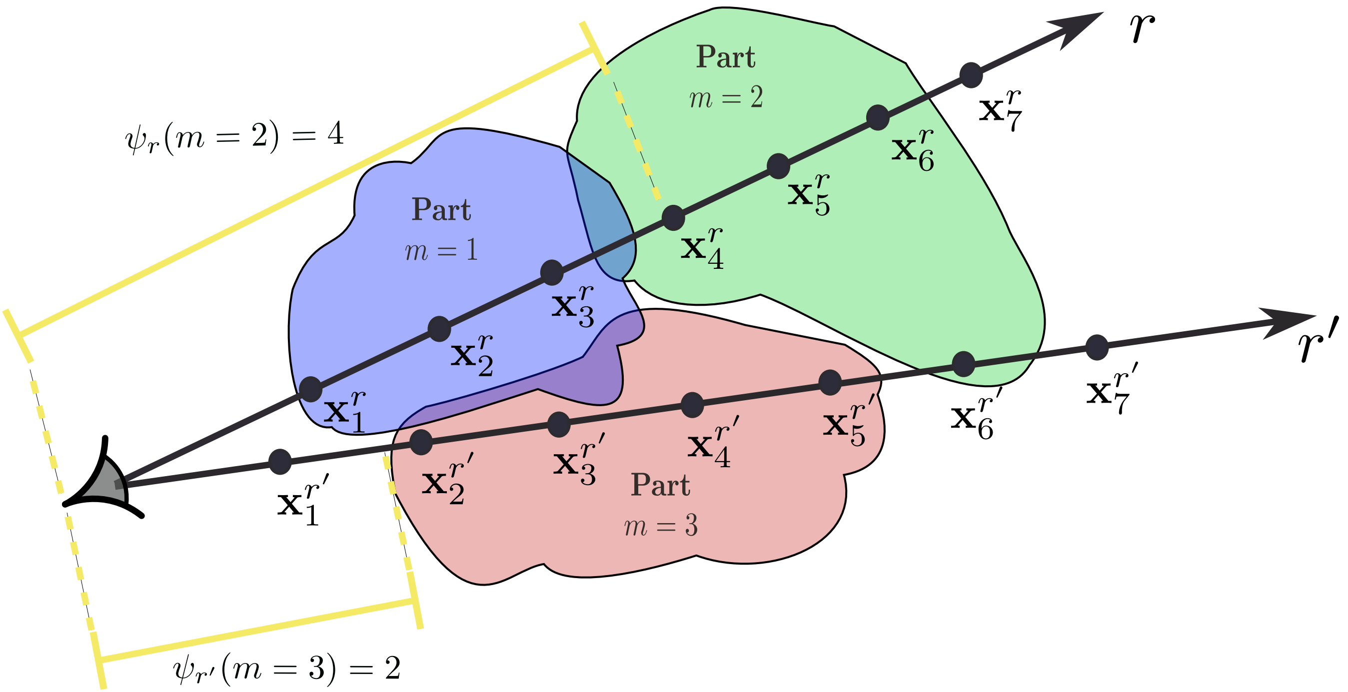

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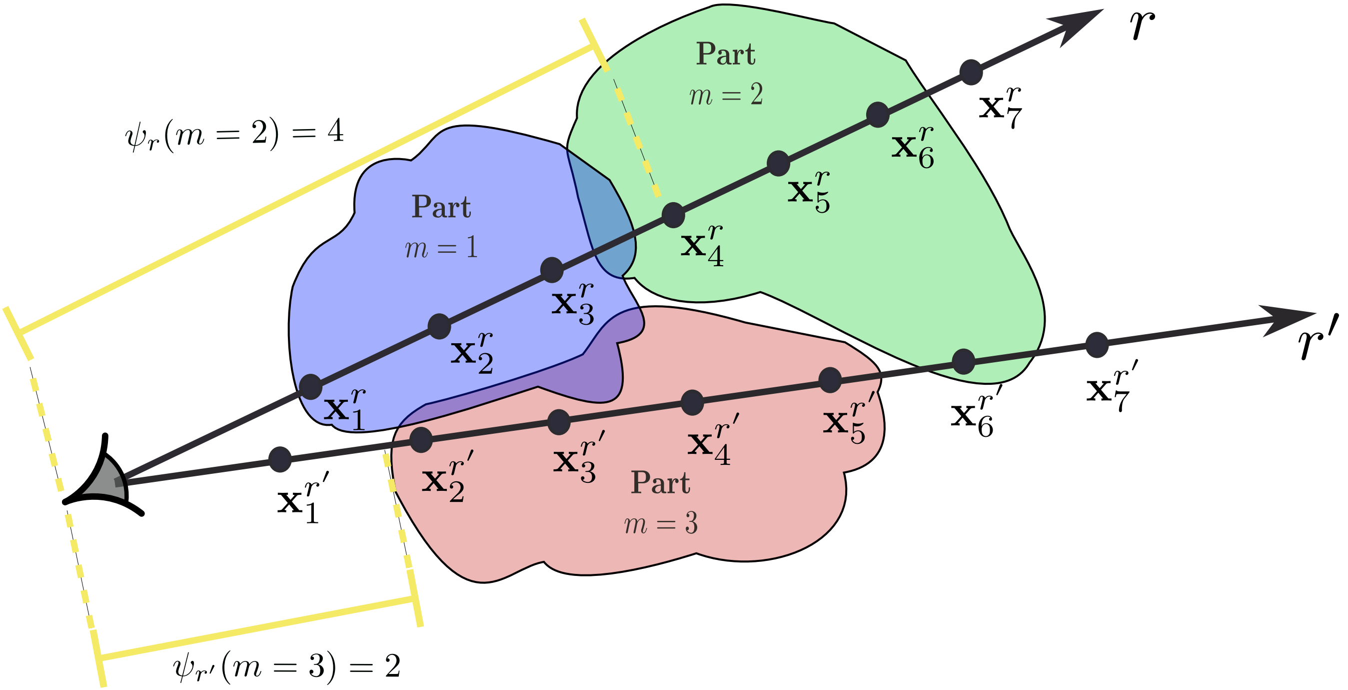

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We define the set of rays $\mathcal{R}_m$ as the **set of rays that first intersect with the** m-th **part**:

$$\mathcal{R}_m = \left\{ r \in \mathcal{R} \,:\, m = \operatorname*{arg\,min}_{k \in \{0 \ldots M\}} \psi_r(k) \right\}$$

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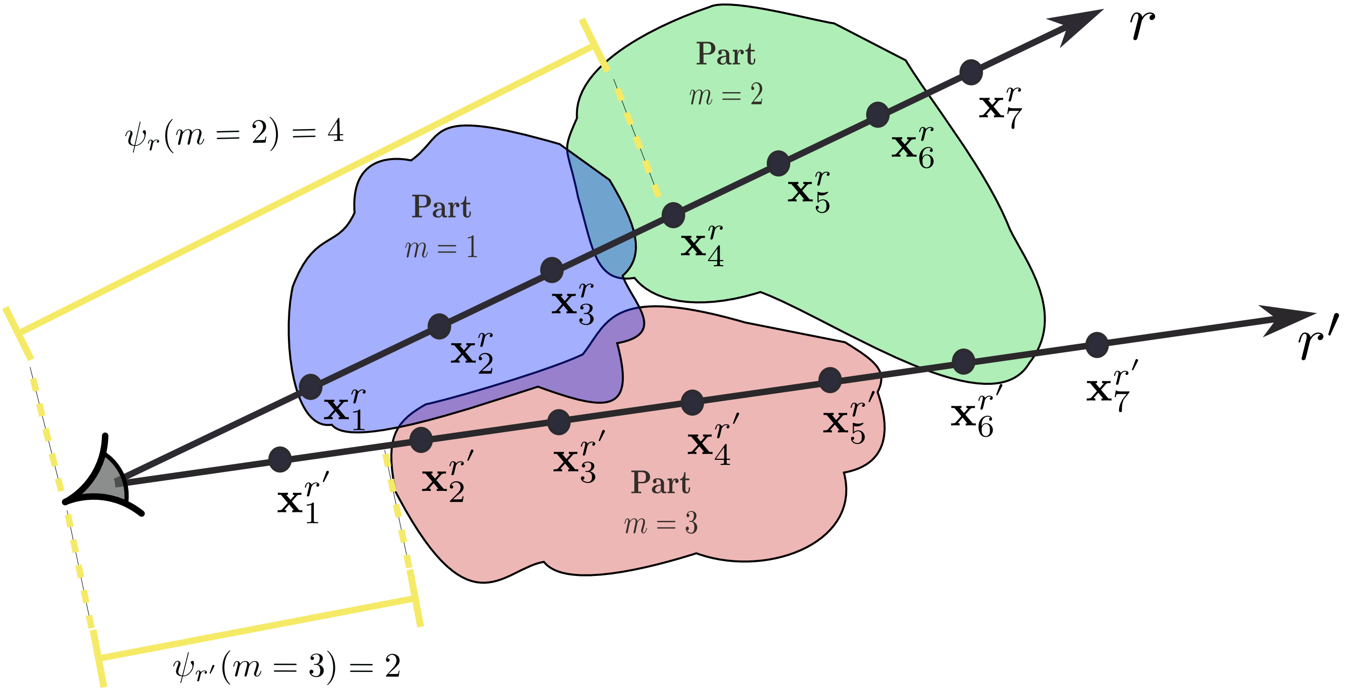

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The **rendering equation for the entire object** using M **NeRFs** becomes

$$\hat{C}(r) = \sum_{m=1}^{M} \mathbb{1}_{r \in \mathcal{R}_m} \hat{C}_m(r).$$

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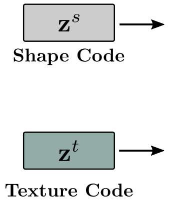

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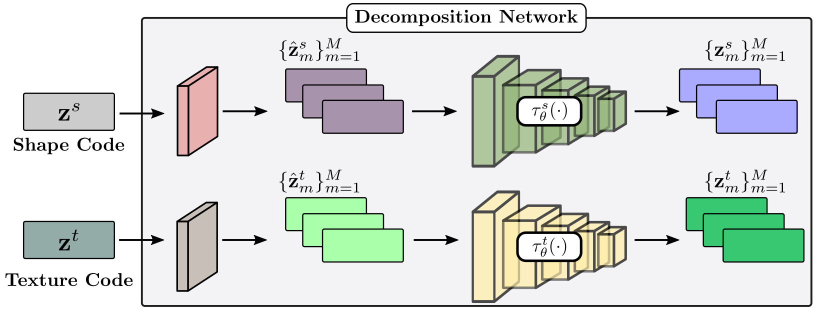

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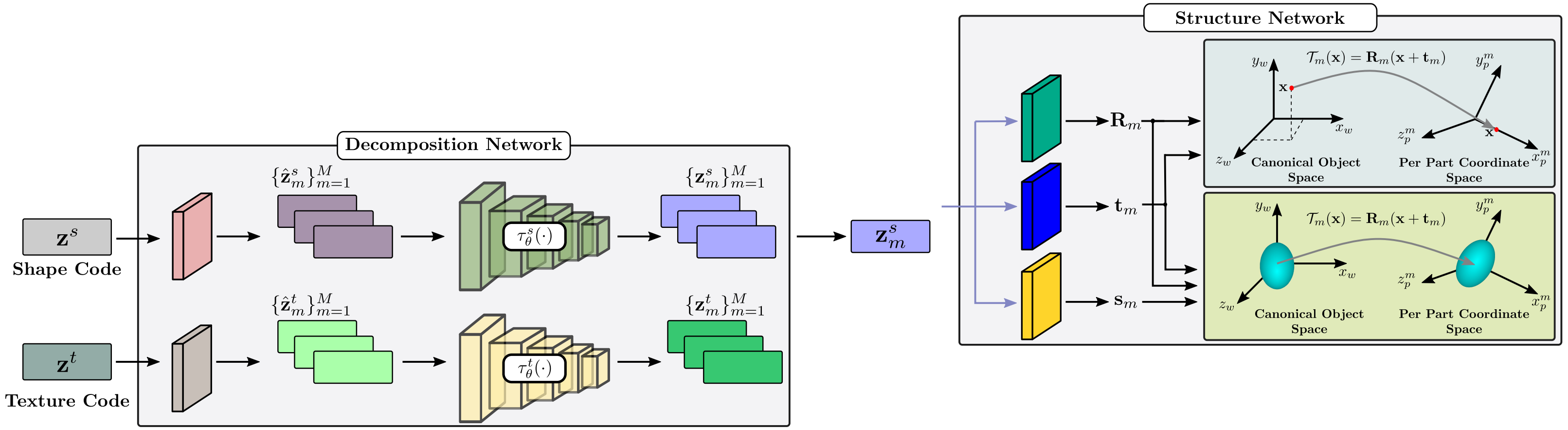

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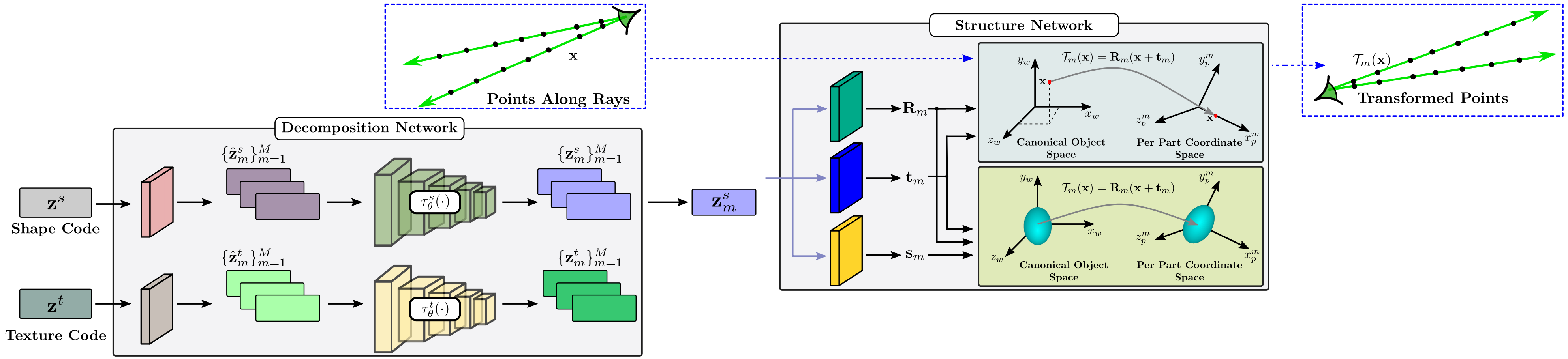

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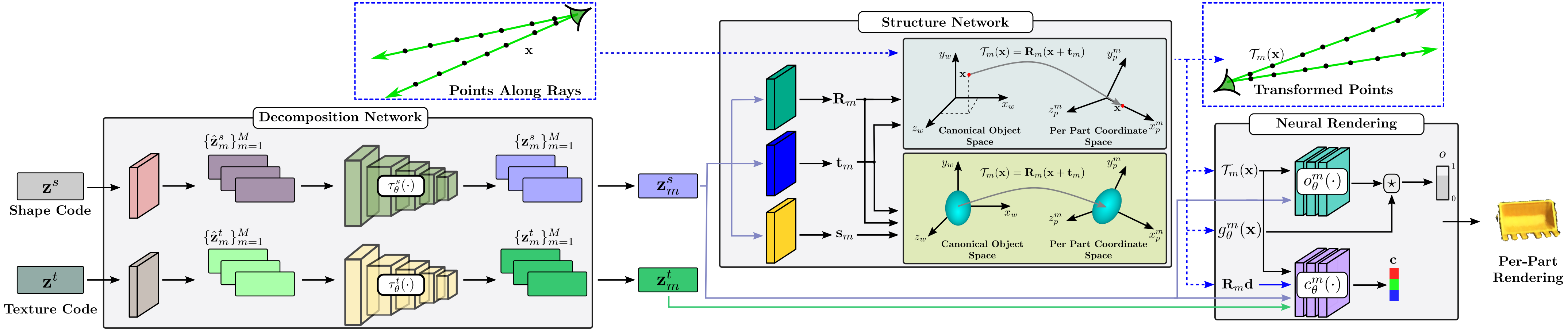

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- **Neural Rendering Network:** Renders a 2D image using M locally defined NeRFs.

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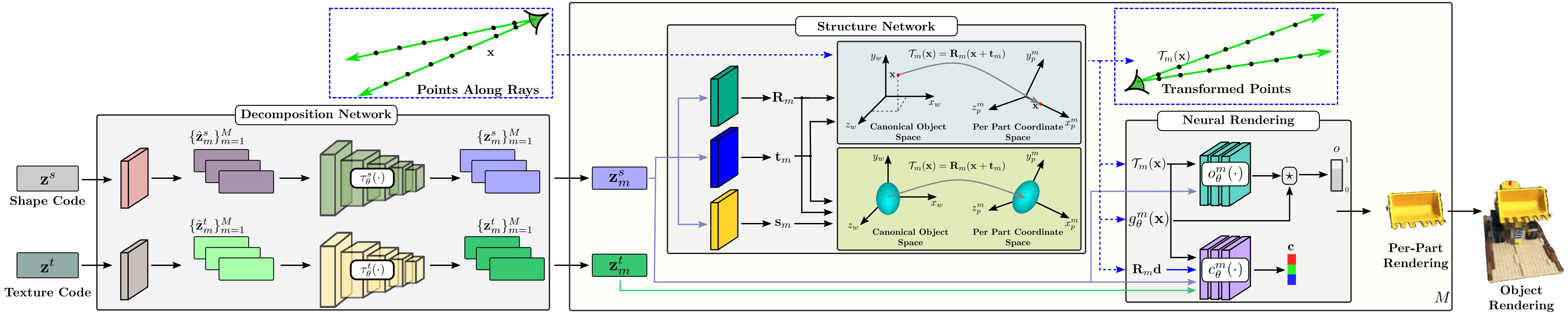

- **Decomposition Network:** Maps $\mathbf{z}^s$ and $\mathbf{z}^t$ to M latent codes that control the per-part shape and texture.
- **Structure Network:** Predicts the pose and scale for each part m.
- **Neural Rendering Network:** Renders a 2D image using M locally defined NeRFs.

Training

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- **Overlapping Loss:** The parts should not be overlapping.

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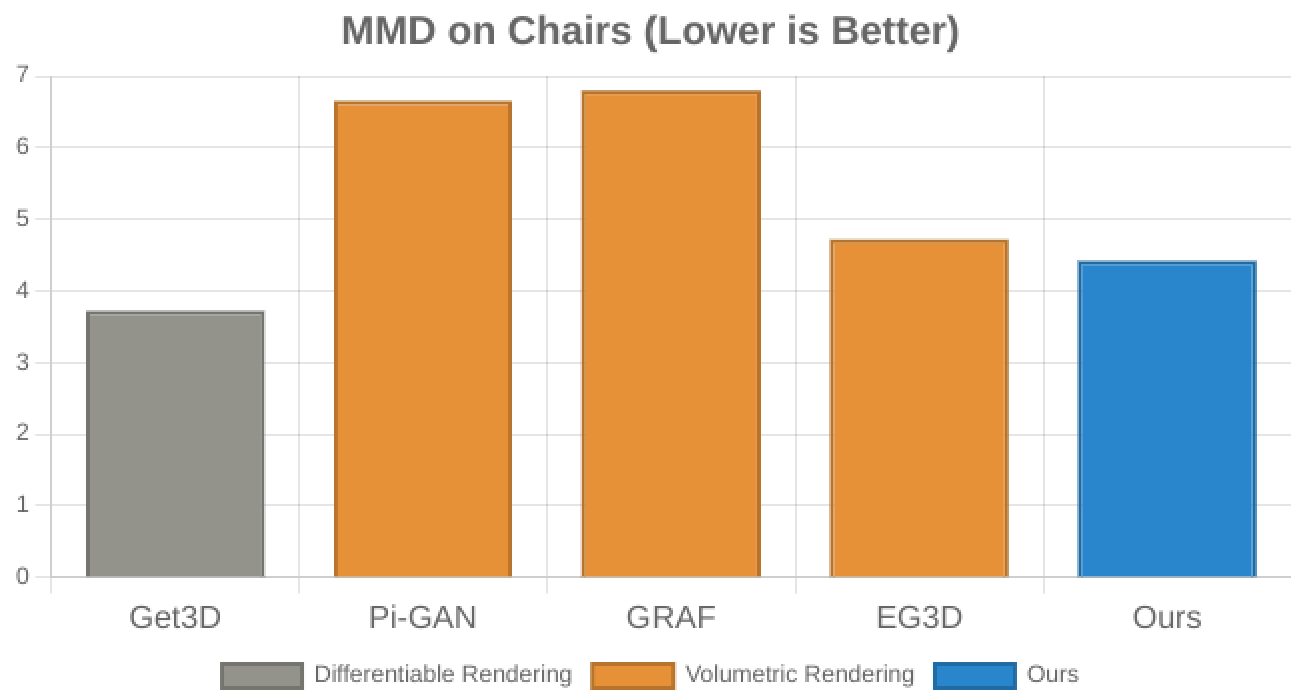
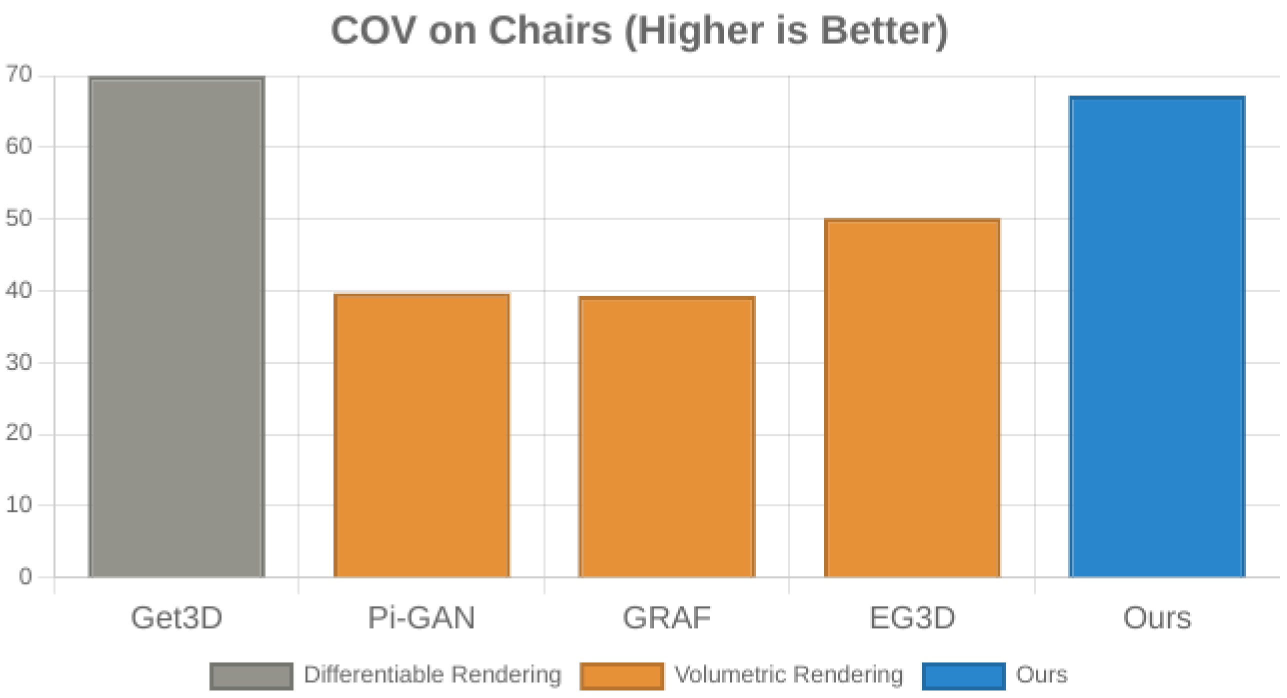
Quantitative Results

Comparisons with NeRF-based 3D Generative Methods





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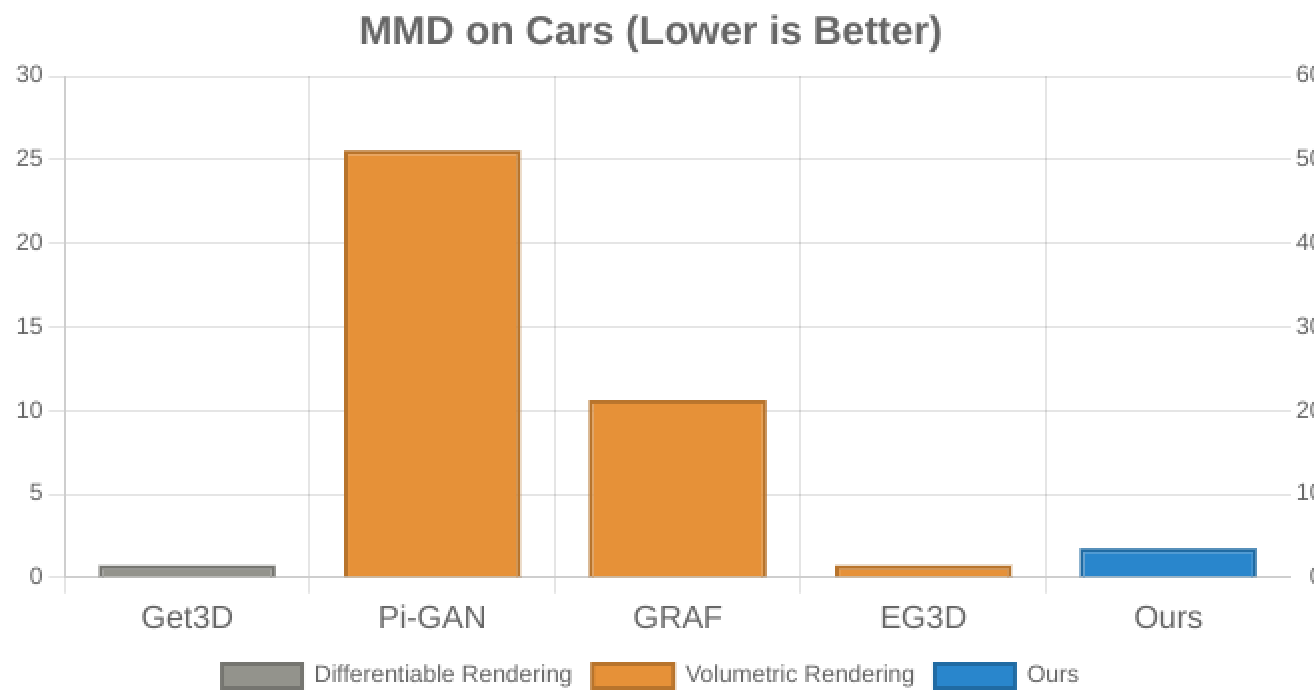
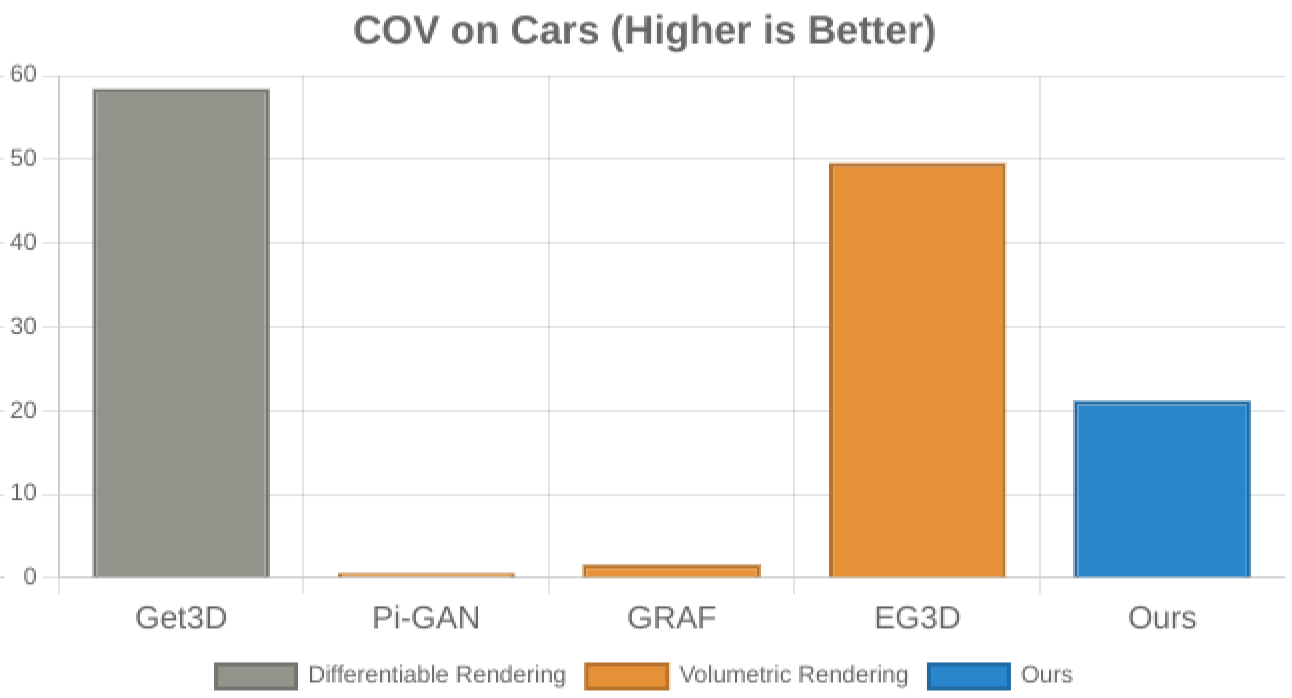
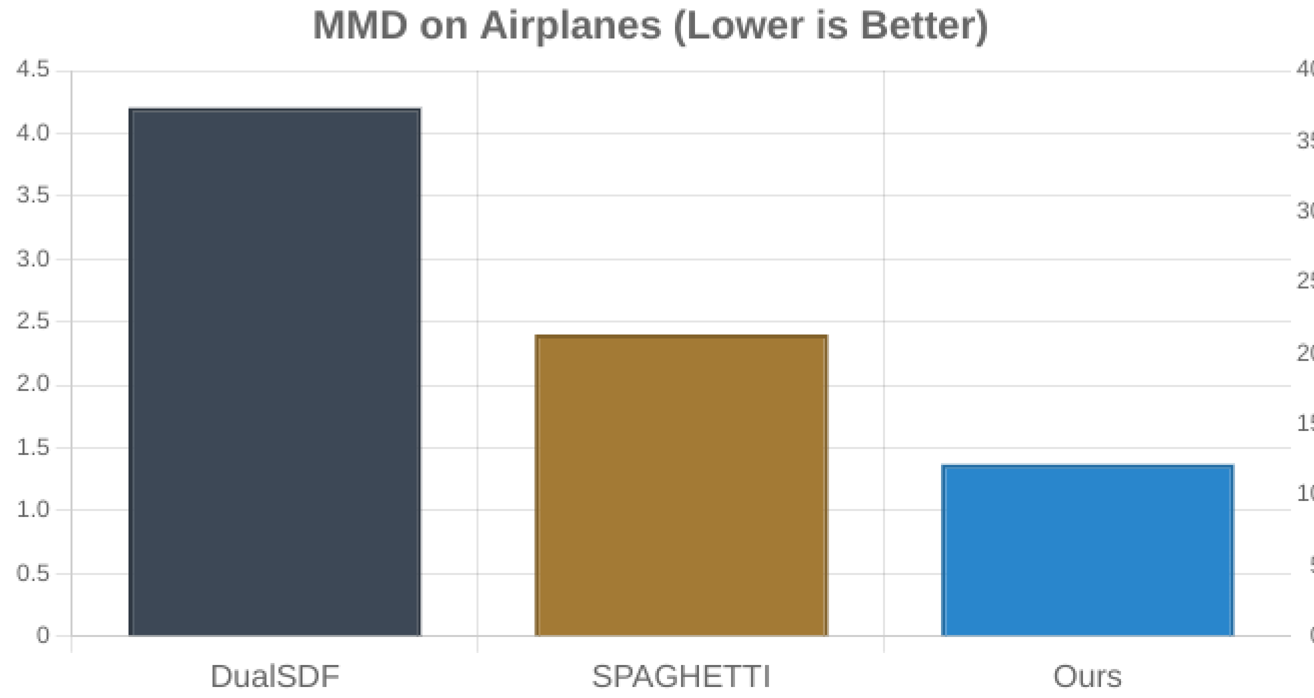
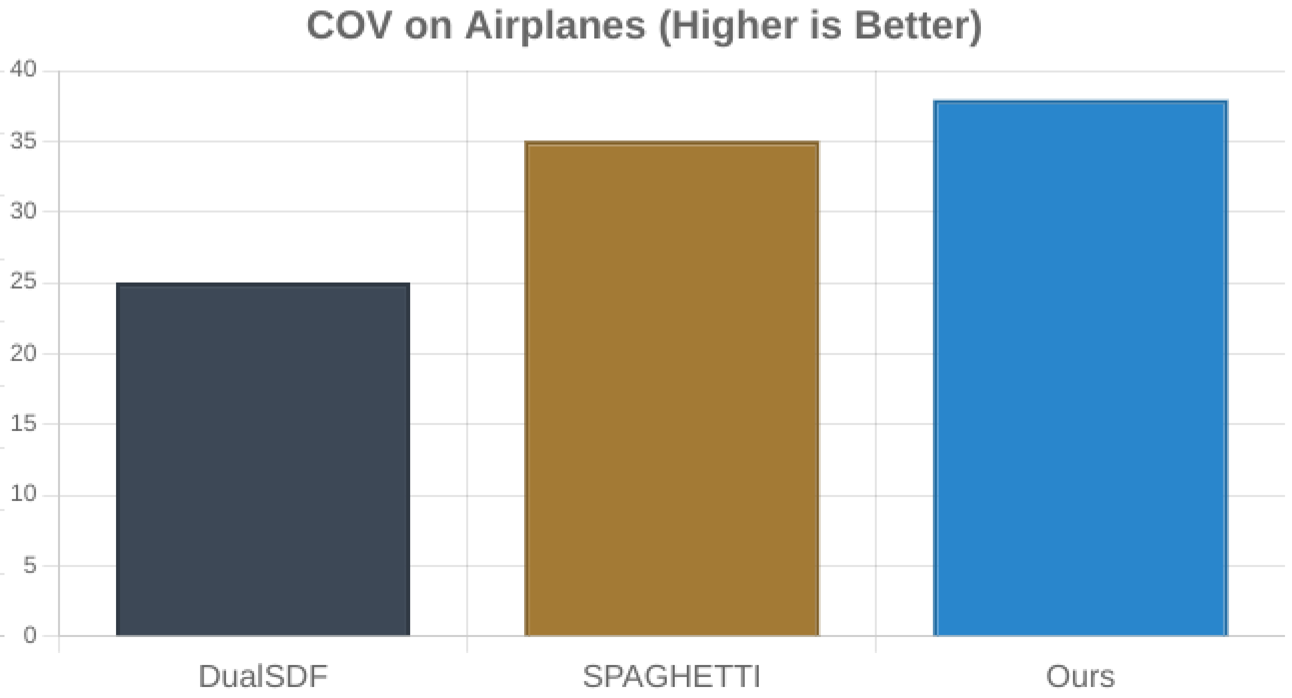




Quantitative Results

Comparisons with Part-Based 3D Generative Methods





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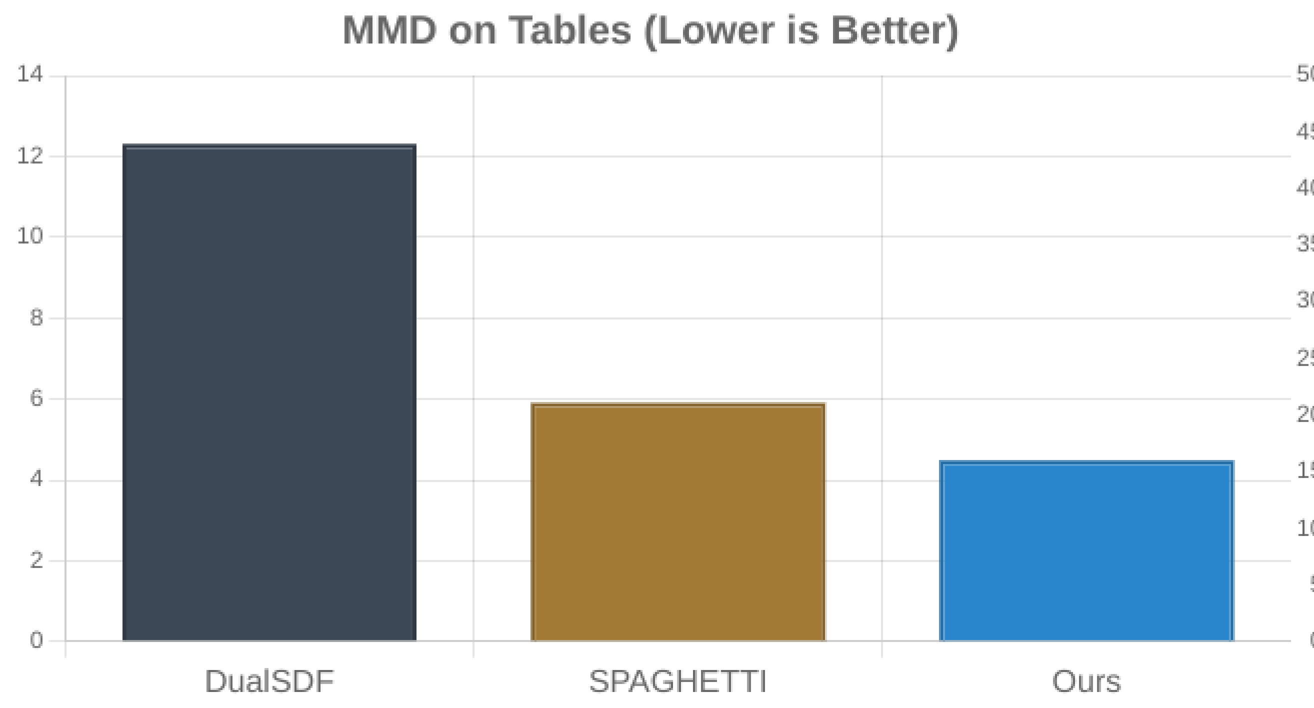
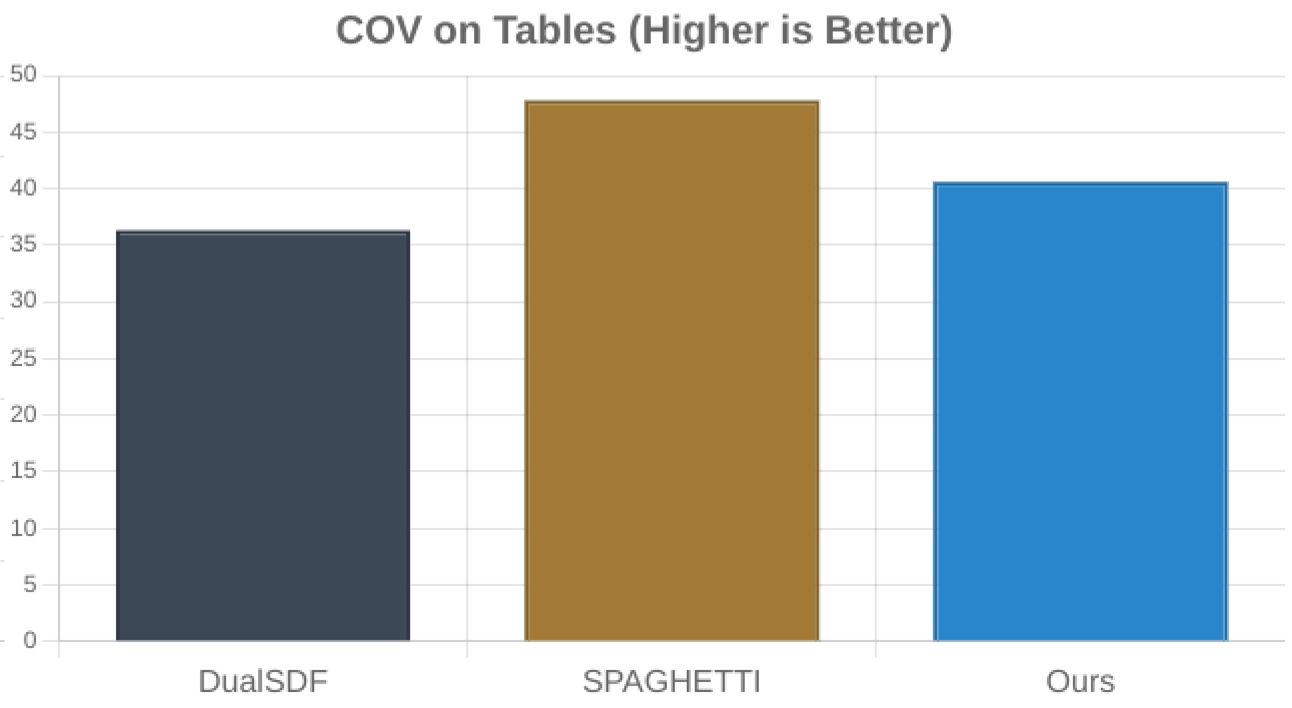




Scene-Specific Editing

No editing

Rotation

Translation

Scaling

Scaling

Colorization

Shape Mixing

Shape Mixing

Shape #1

Shape Mixing

Shape #1

Shape #2

Shape Mixing

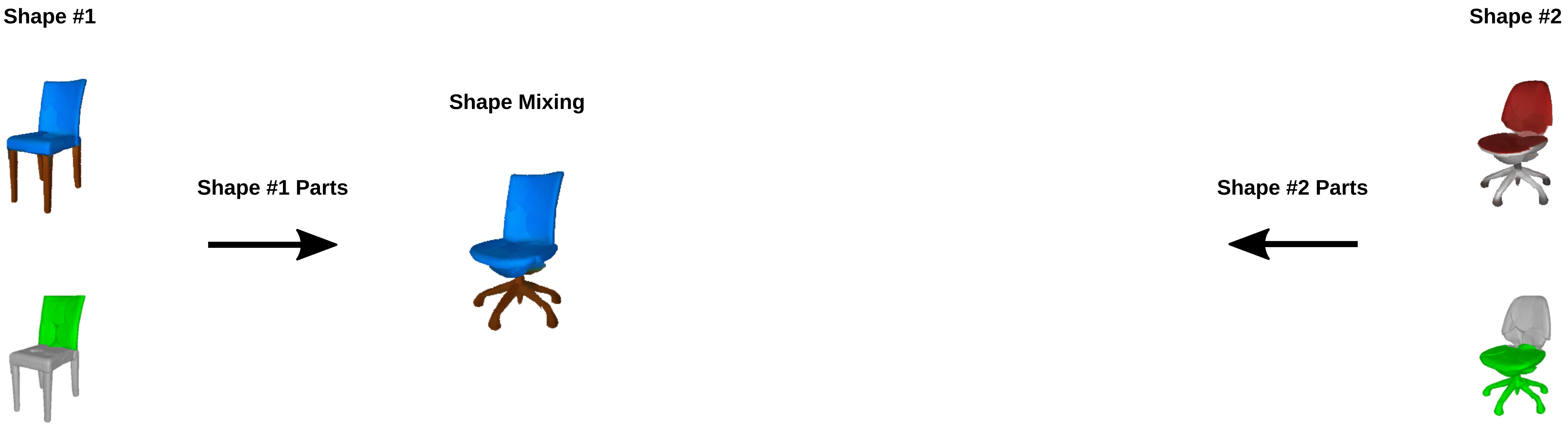
Shape #1

Shape #1 Parts

Shape #2

Shape #2 Parts

Shape Mixing



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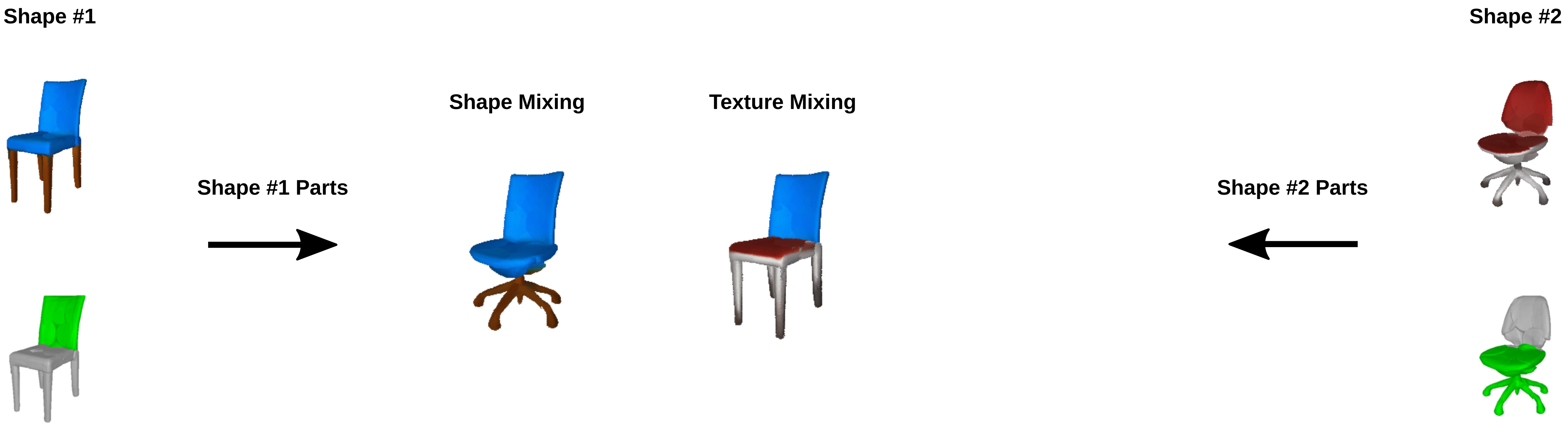

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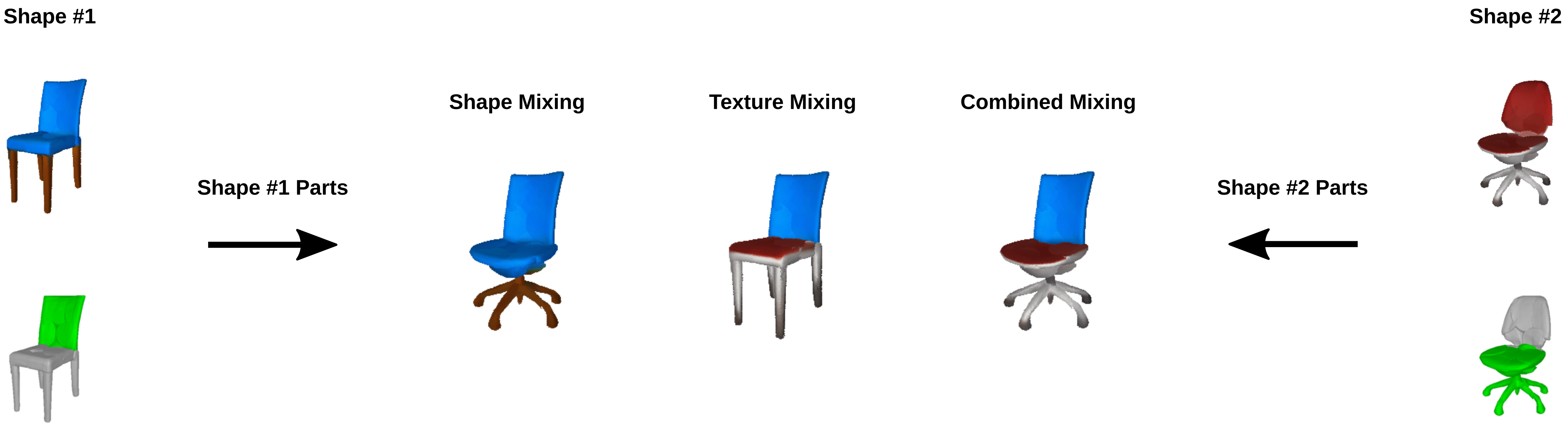
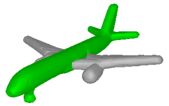


Shape Mixing

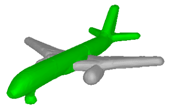
Shape Mixing

Shape #3

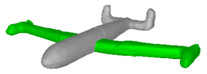


Shape Mixing

Shape #3

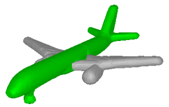


Shape #4



Shape Mixing

Shape #3



Shape #3 Parts

Shape #4 Parts

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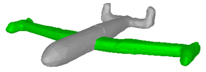

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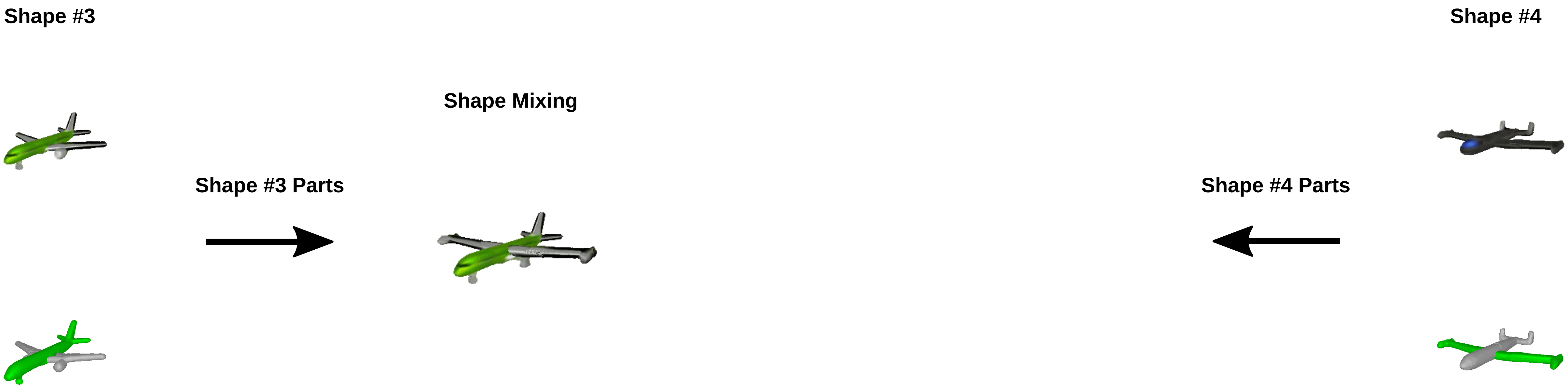

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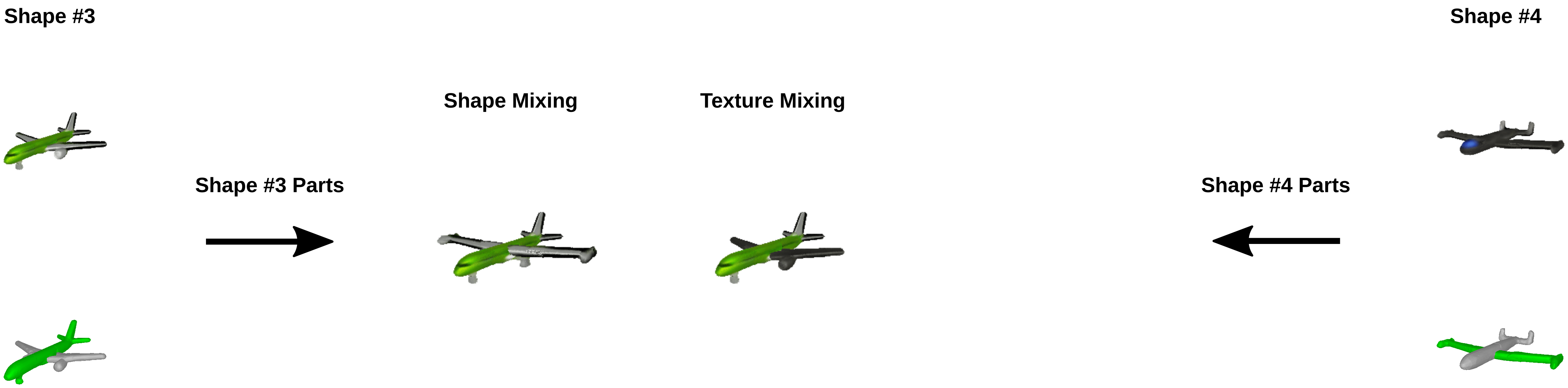

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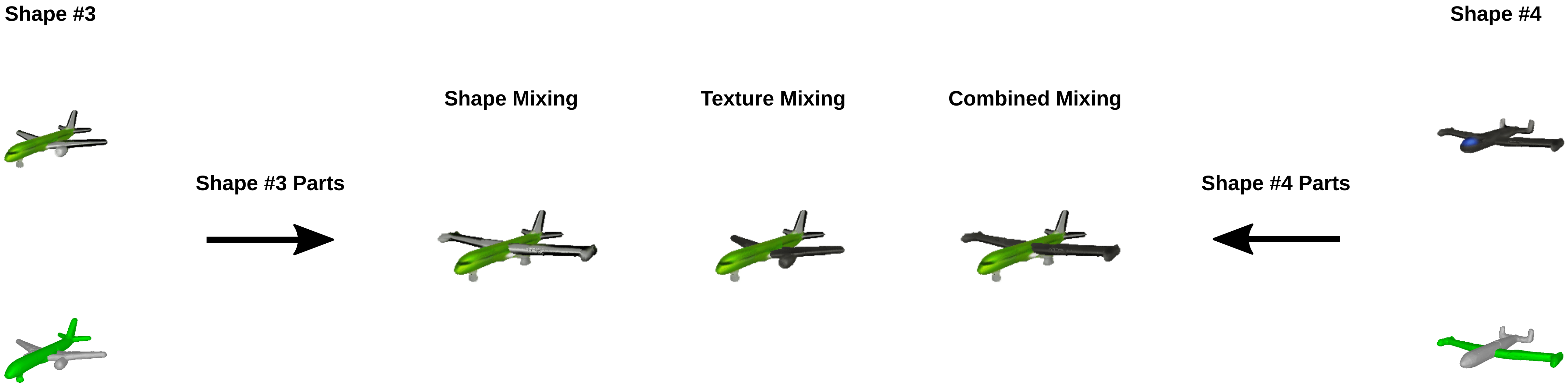
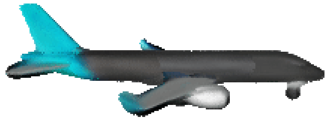


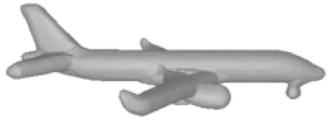
Shape Editing

Shape Editing

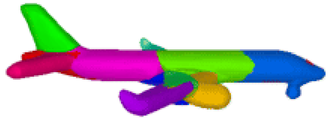
Renders



Geometry



Parts



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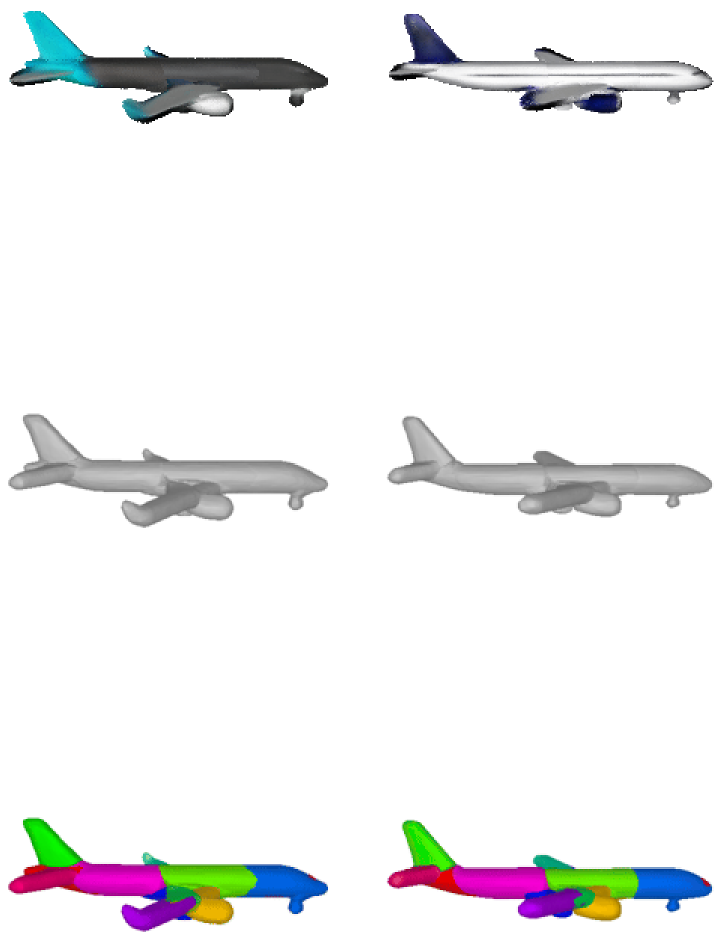

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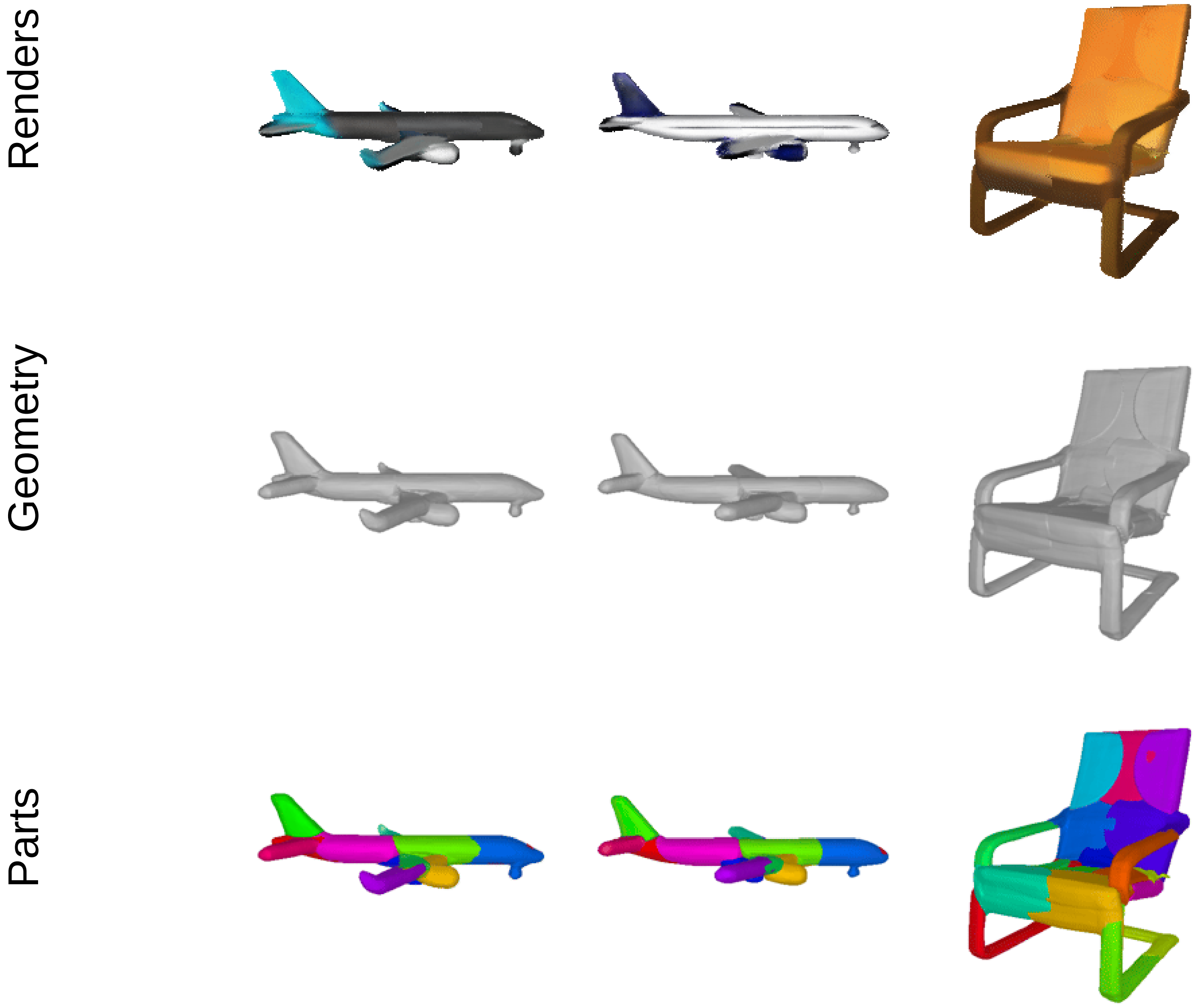

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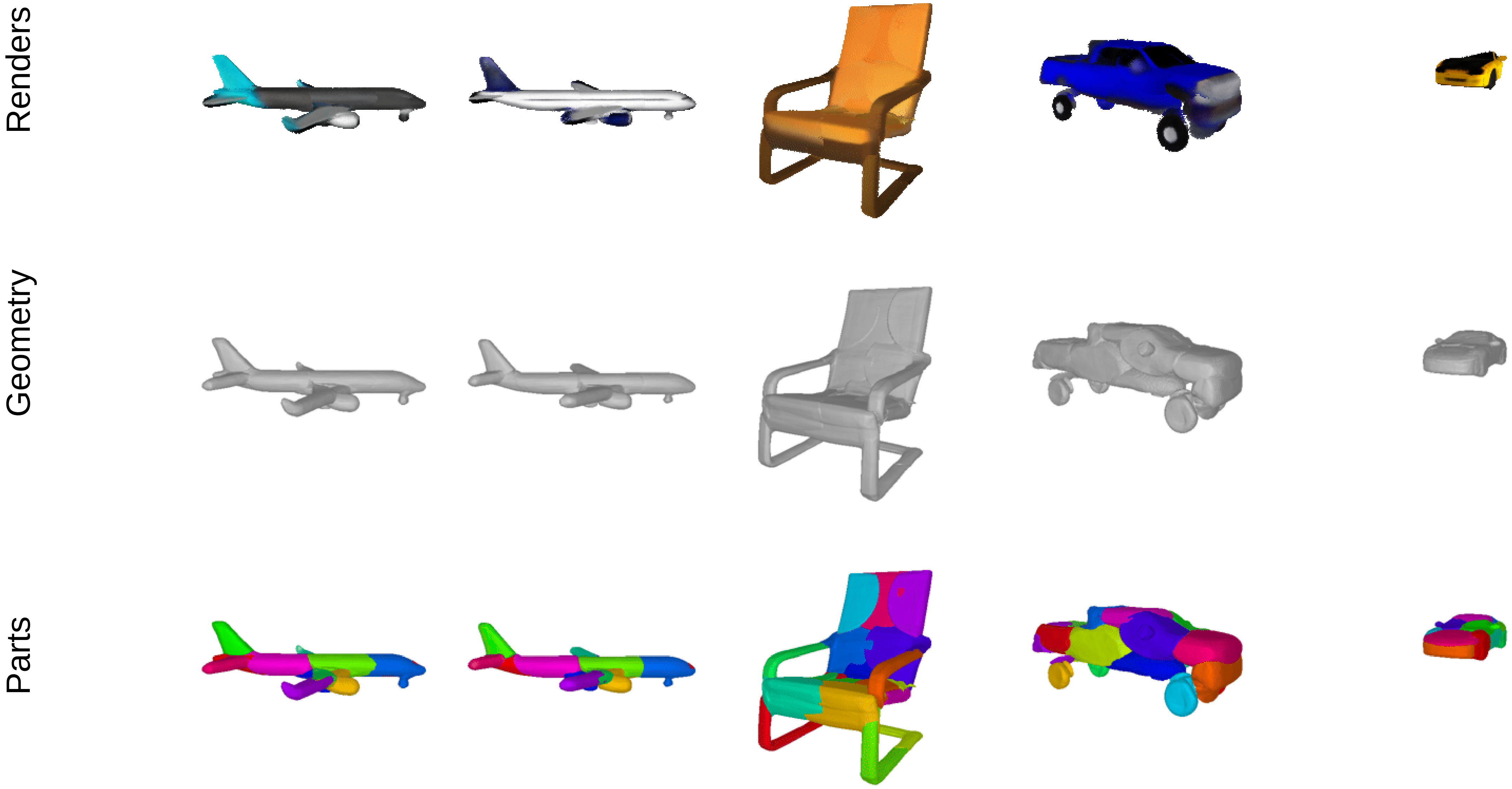

Shape Generation

Summary & Limitations

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Project Page: https://ktertikas.github.io/part_nerf

CVPR Poster: *TUE-PM-032*