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

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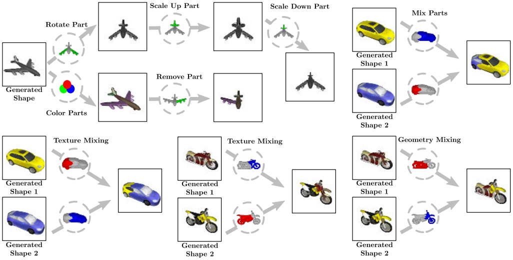
https://ktertikas.github.io/part_nerf



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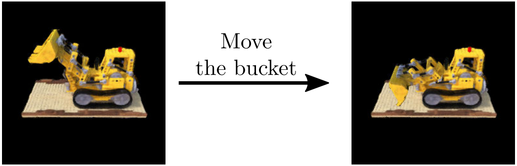

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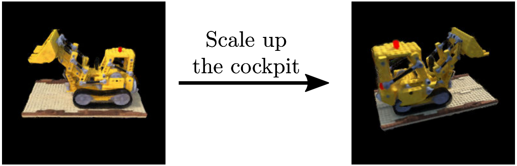

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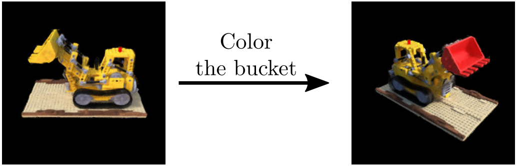

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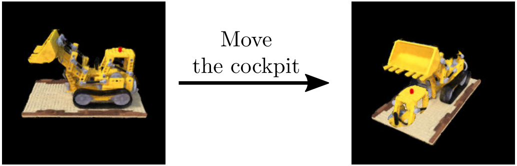

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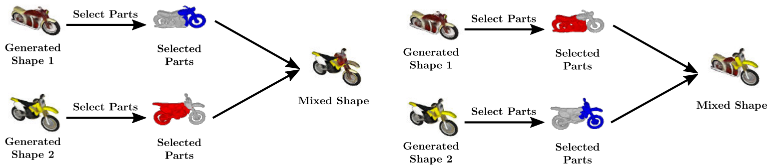

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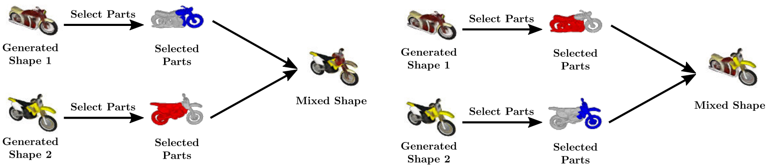
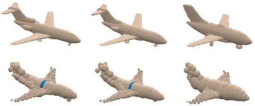


We can specify **what object regions to edit** through parts.

Generative Models for 3D Object Synthesis

Part-based Generative Models



Hao et al. 2020

Hertz et al. 2022

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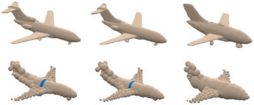

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✓ Explicit part-level control

✗ Require 3D supervision

✗ Cannot change the appearance of an object

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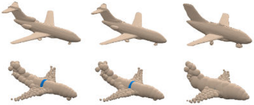

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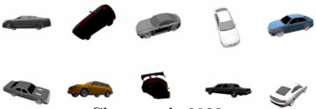

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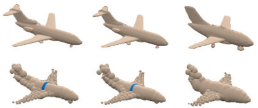

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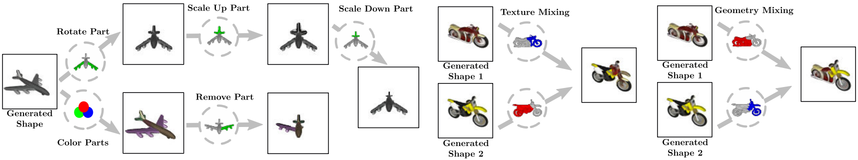
NeRF-based Generative Models:

✓ Can generate high quality 3D meshes
✓ Require 2D supervision during training
✗ No explicit part-level control

Can we learn a **part-aware generative model of 3D objects** capable of performing **local edits** on the **shape and appearance** of the generated 3D object?



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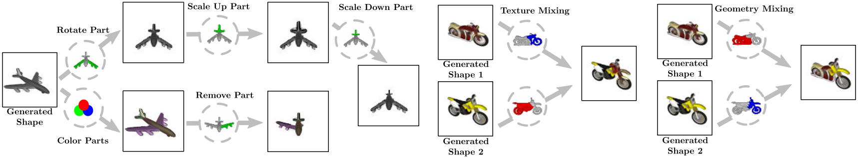

Bonus: We want our model to be **trained only from posed images**!!!

Key Idea: Enable local control through parts

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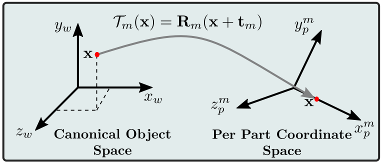
1. an *affine transformation* $T_m(\mathbf{x}) = \mathbf{R}_m(\mathbf{x} + \mathbf{t}_m)$ that maps a 3D point $\mathbf{x}$ to the **local coordinate system of the part**, where $\mathbf{t}_m \in \mathbb{R}^3$ is the translation vector and $\mathbf{R}_m \in SO(3)$ is the rotation matrix



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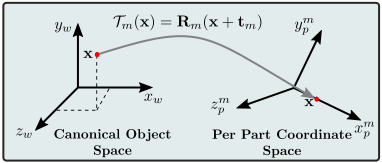
2. a *scale* vector $\mathbf{s}_m \in \mathbb{R}^3$, representing the **spatial extent of each part**



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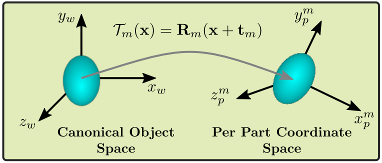

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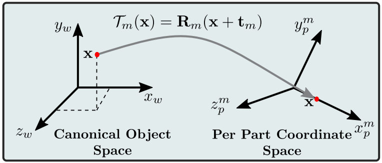
3. two latent codes: **shape** $\mathbf{z}_m^s \in \mathbb{R}^{L_s}$ and **texture** $\mathbf{z}_m^t \in \mathbb{R}^{L_t}$ that control and shape and the appearance of each part.



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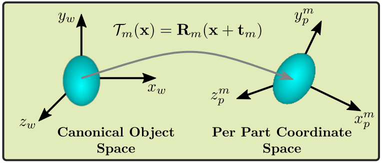
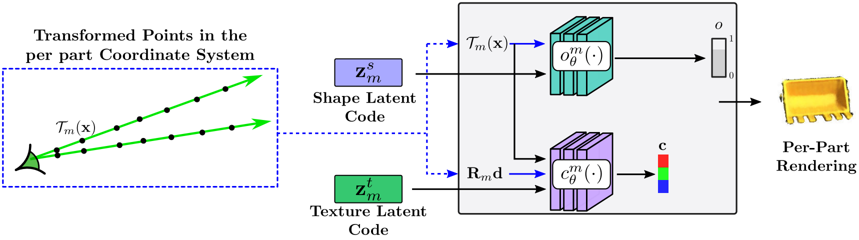


Spatial Extent

Part Representation

We employ two networks: a **color network** c_θ and an **occupancy network** o_θ to predict the color and the occupancy value respectively.



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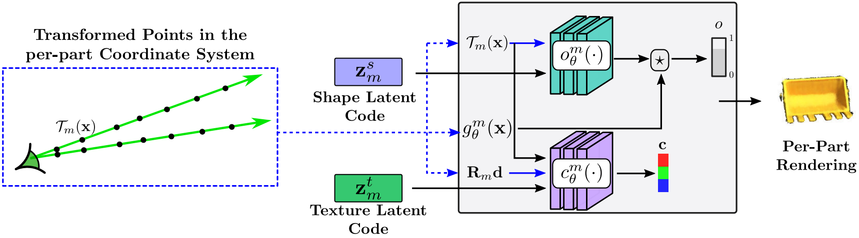

To enforce that **each part only captures continuous regions of the object**, we multiply its occupancy function with **the occupancy function of an axis-aligned 3D ellipsoid**

$$h_\theta^m(\mathbf{x}) = o_\theta^m(\mathbf{x}) g_\theta^m(\mathbf{x}),$$

where $g_\theta^m(\mathbf{x}) = g(T_m(\mathbf{x}), \mathbf{s}_m)$ is the **occupancy function of the m-th ellipsoid**.

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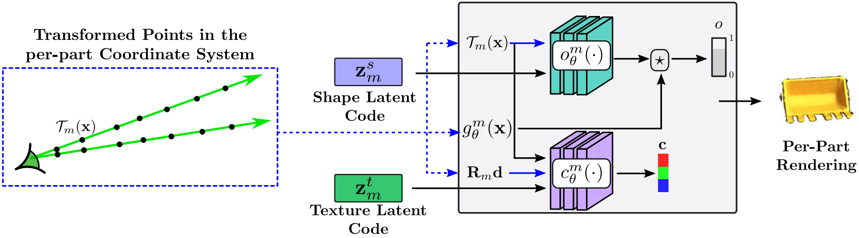

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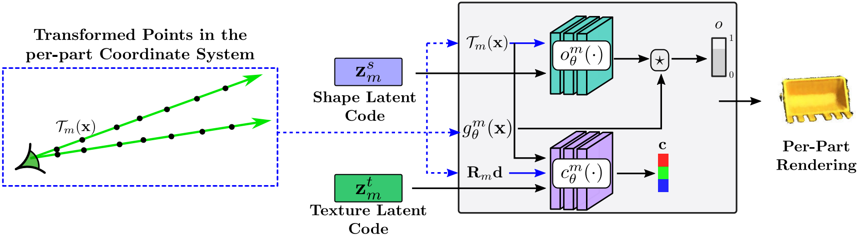

Instead of predicting volume densities, we predict occupancy values and the **rendering equation** of the m-th part becomes:

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

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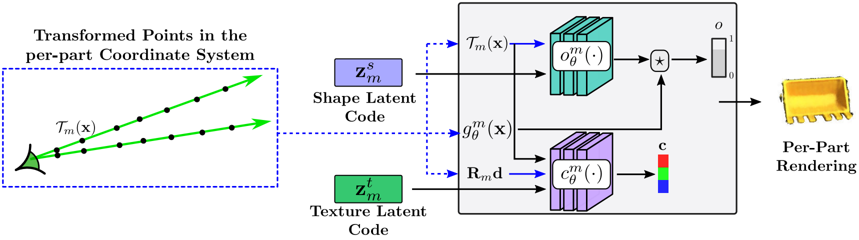

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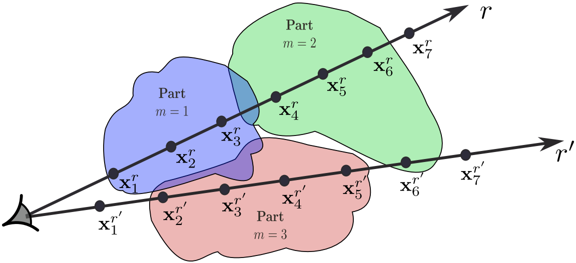
where $h_\theta^m(\mathbf{x}_i^r)$ is the occupancy value at point $\mathbf{x}_i^r$ and $c_\theta^m(\mathbf{x}_i^r, \mathbf{d}^r)$ its color.

Hard Assignment between Rays and Parts

Given the ordered set of points $\mathcal{X}_r$ sampled along ray r, we define a hard assignment between rays and parts, by **associating a ray with the first part it intersects**.



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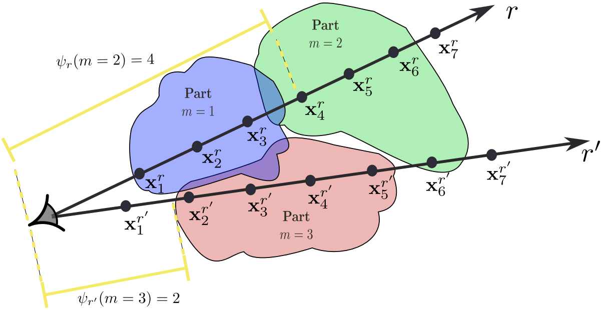

$$\underbrace{\psi_r(m)}_{\text{Index of the first point inside each part intersecting with each ray}} = \min\left\{i \in \{1,\ldots,N\} \,:\, h_\theta^m(\mathbf{x}_i^r) \geq \tau\right\}$$

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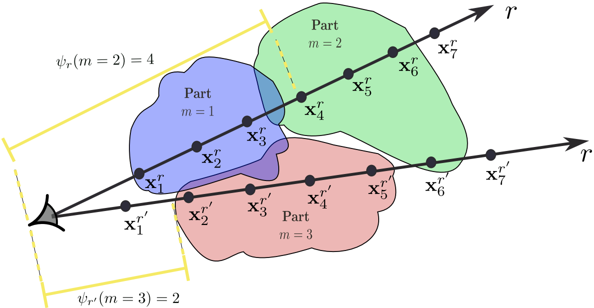

We define the set of rays $\mathcal{R}_m$ associated with the m-th part, as **the set of rays that first intersect with it**, namely:

$$\underbrace{\mathcal{R}_m}_{\substack{\text{Set of rays}\\ \text{assigned to part} m}} = \left\{ r \in \mathcal{R} \,:\, m = \underset{k \in \{0 \ldots M\}}{\operatorname{argmin}} \,\psi_r(k) \right\}.$$

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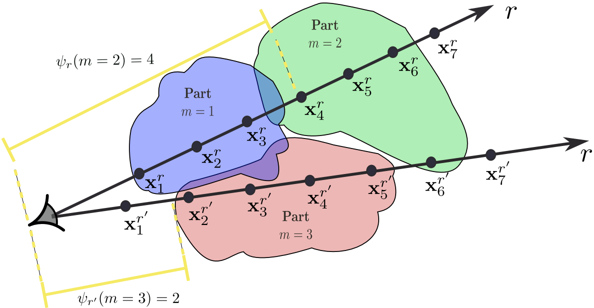

The **rendering equation for the entire object using M NeRFs** becomes

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

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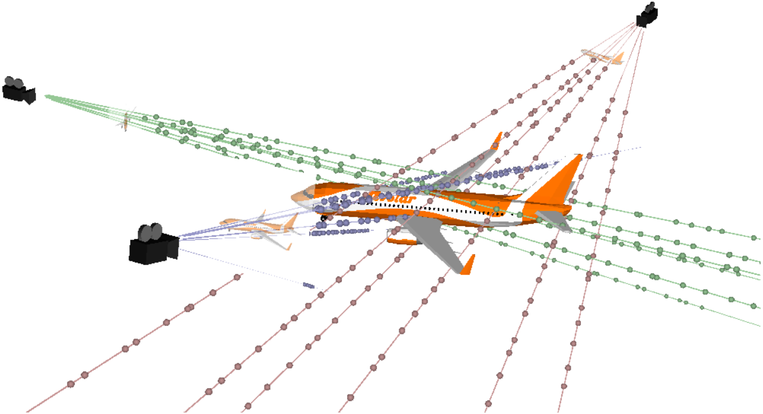

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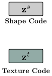

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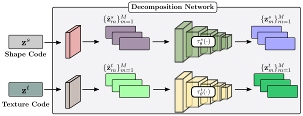

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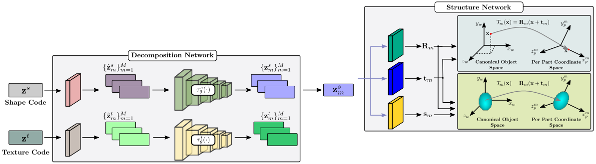

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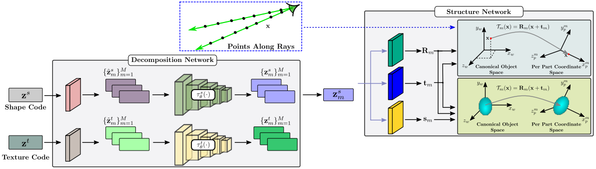

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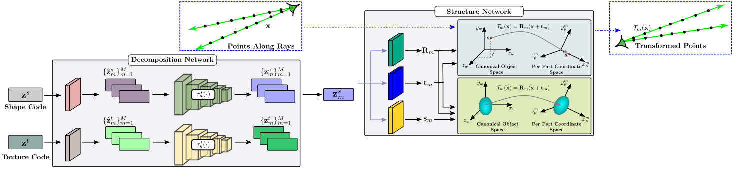

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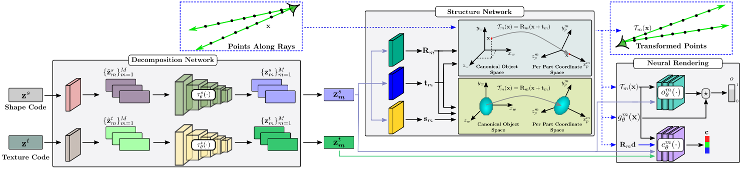

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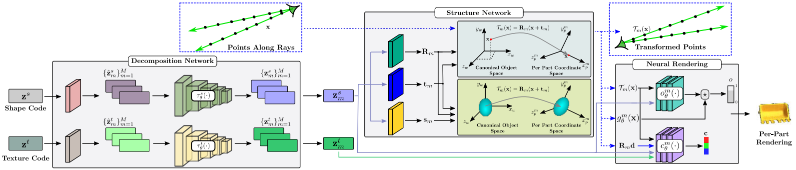

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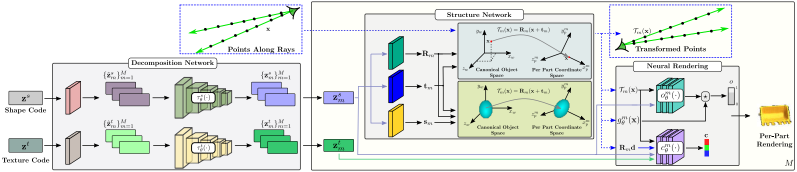

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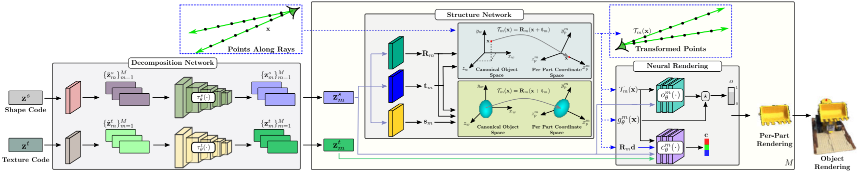

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Optimization Objective

Our optimization objective $\mathcal{L}$ is the sum over six terms combined with two regularizers on the shape and texture embeddings $\mathbf{z}^s, \mathbf{z}^t$, namely

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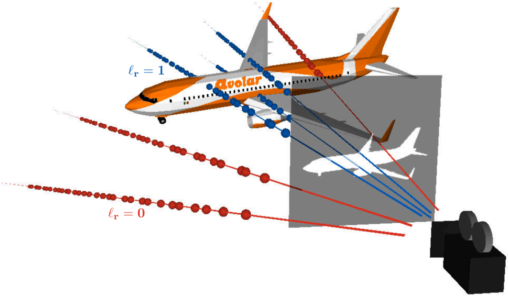

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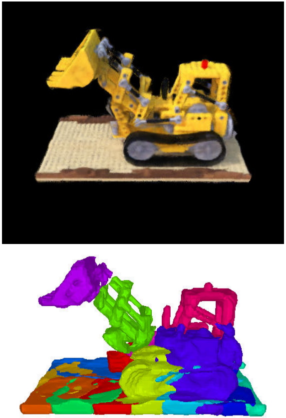
- **Overlapping Loss**: Prevent overlapping parts.
- **Control Loss**: Ensure uniform control across the shape.

How well does it work?

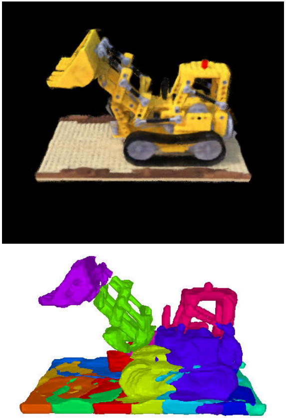
Scene-Specific Editing

No Editing

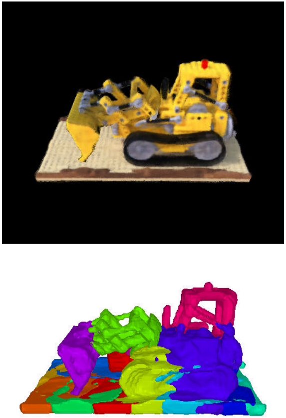


Scene-Specific Editing

No Editing

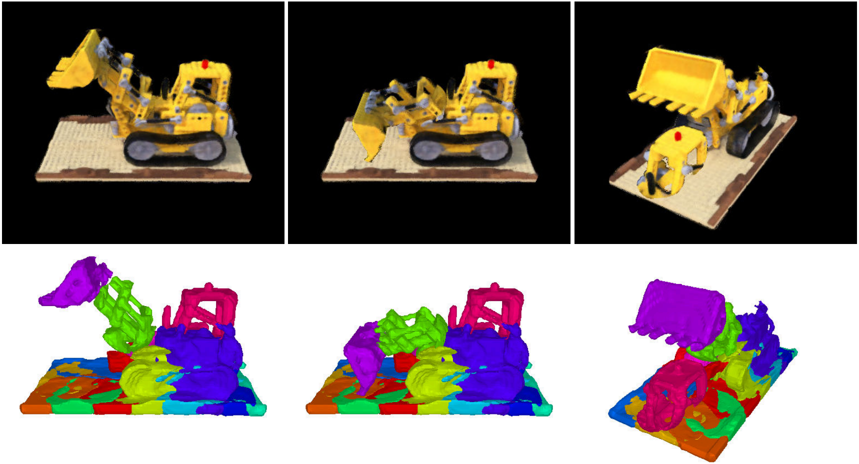


Rotation



Scene-Specific Editing

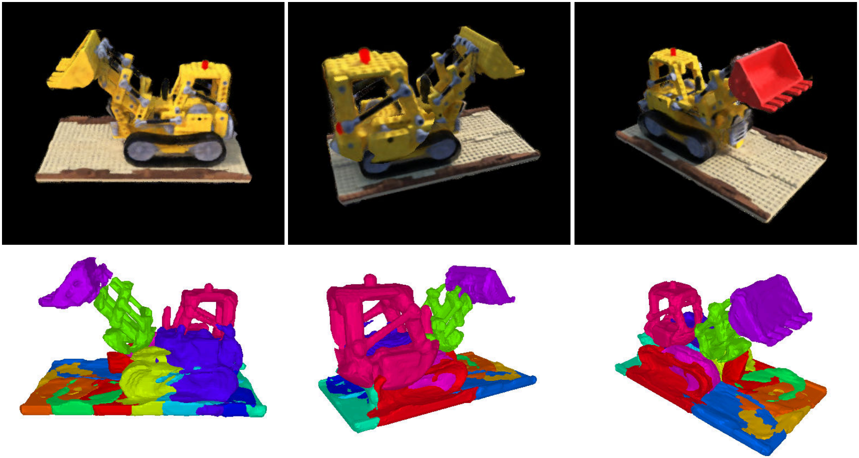
No Editing | Rotation | Translation



During all editing operations, **only a specific parts of the object changes**, while the rest do not change.

Scene-Specific Editing

No Editing | Scaling | Color



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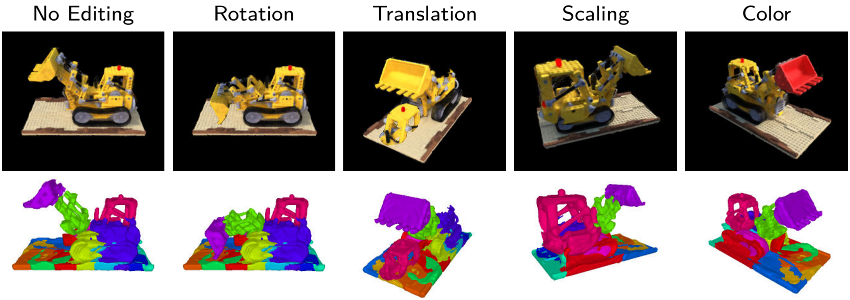
Impact of Hard Ray-Part Assignment



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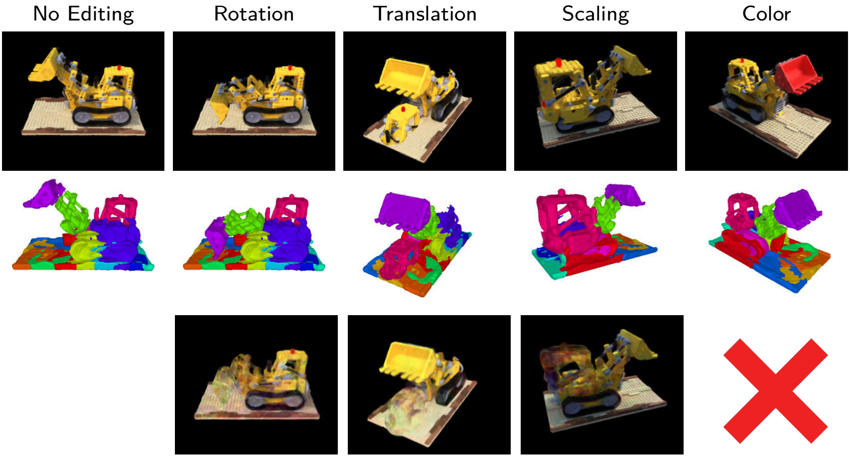
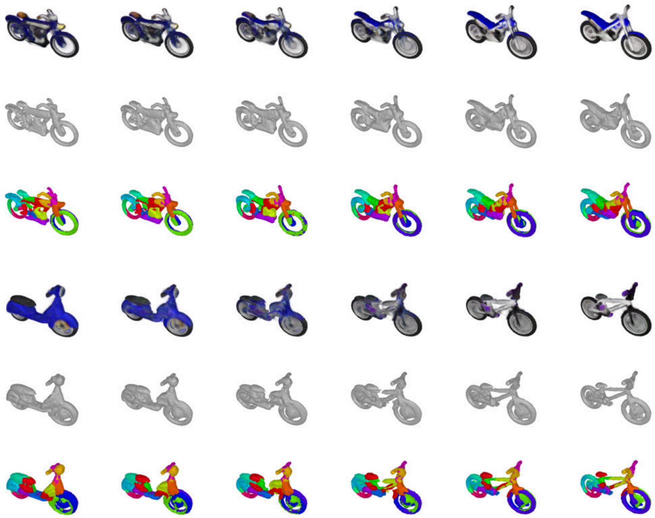


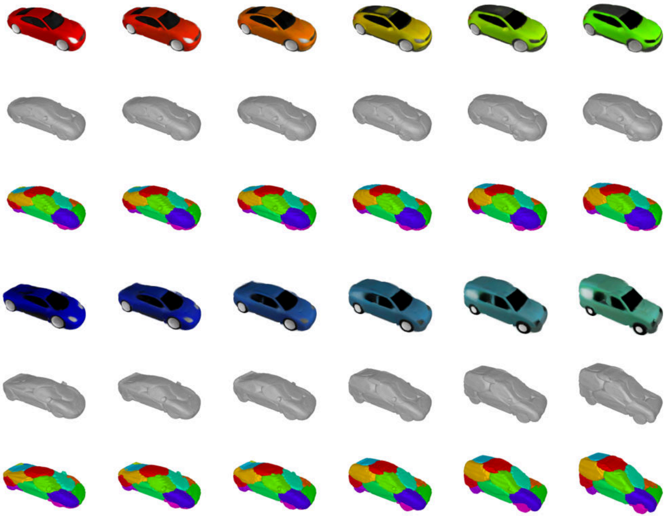
The **hard ray-part assignment** enforces that the color of a ray is determined by **a single NeRF/part**, hence transforming one part **does not alter the other parts**.

Shape Synthesis

Shape Interpolations



Shape Interpolations



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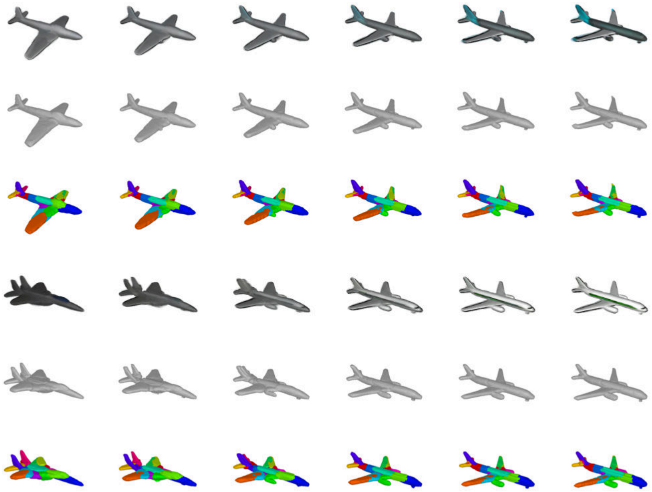
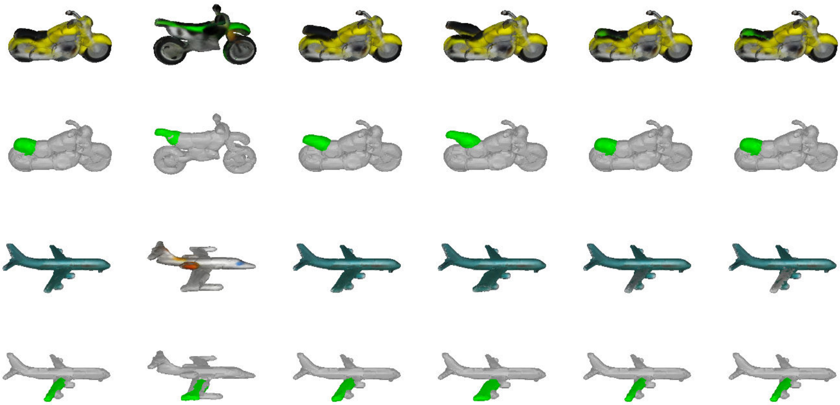
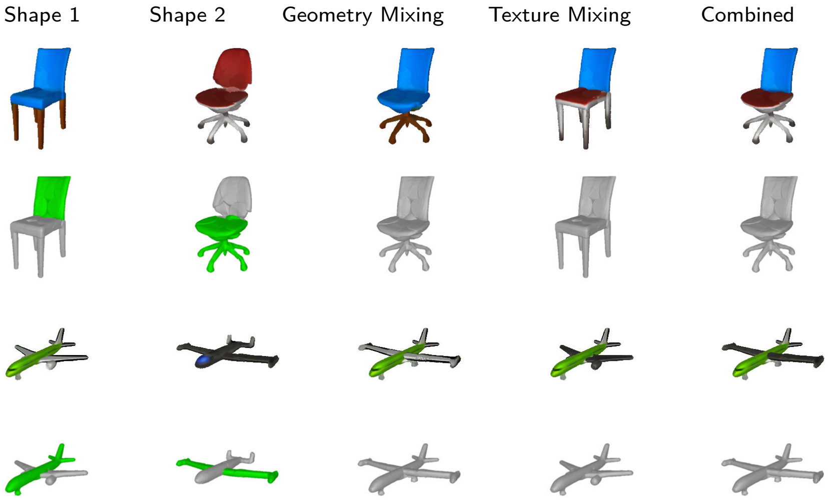


Part Interpolation

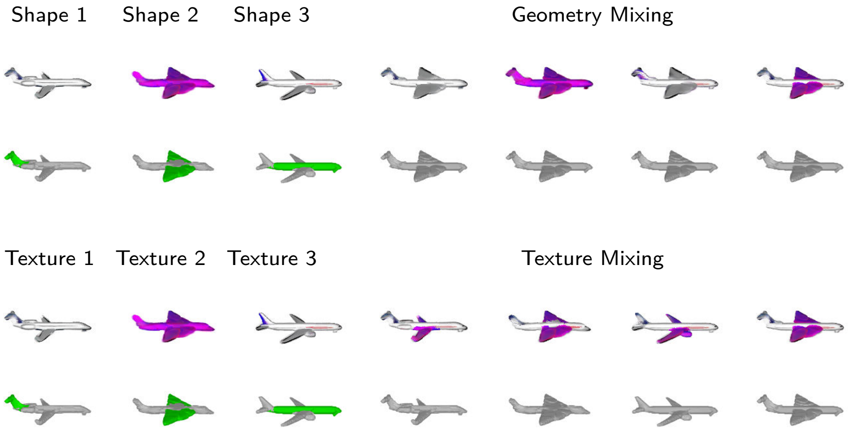
Shape 1 | Shape 2 | Shape Code Interpolation | Texture Code Interpolation



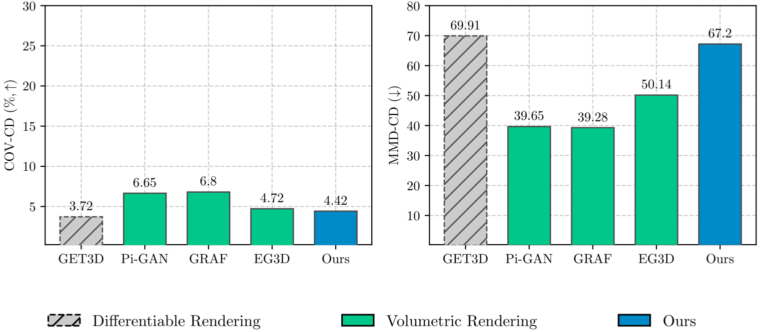
Shape Mixing



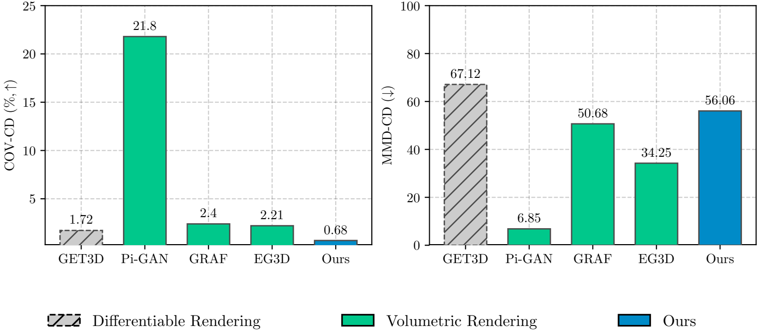
Shape Mixing



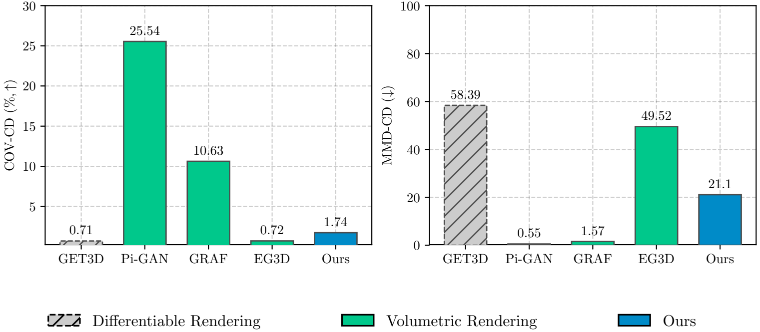
ShapeNet Comparison - Chairs



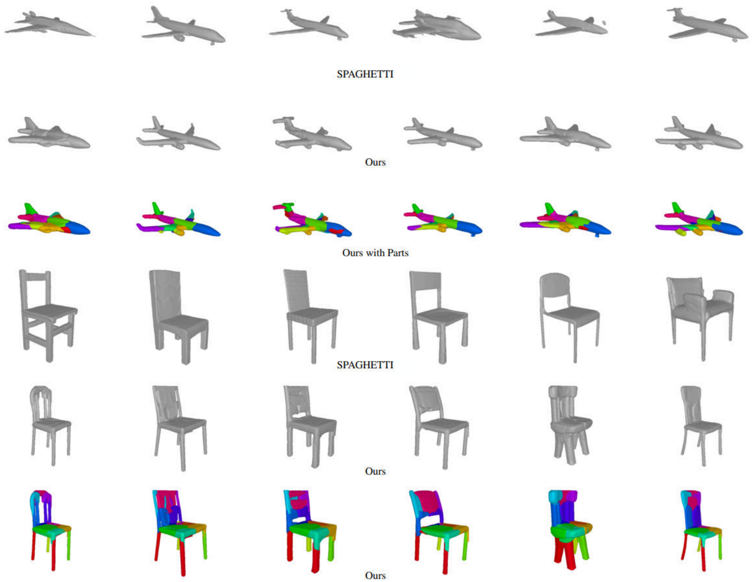
ShapeNet Comparison - Motorbikes



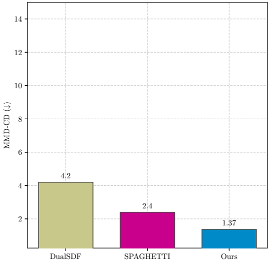
ShapeNet Comparison - Cars



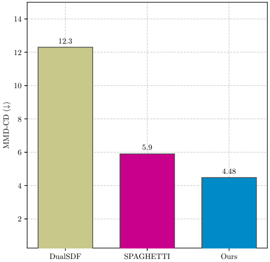
ShapeNet Comparison to Part-based Methods



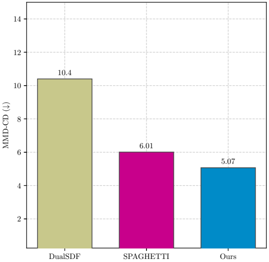
ShapeNet Comparison - Part-based Methods



Airplanes



Tables



Chairs

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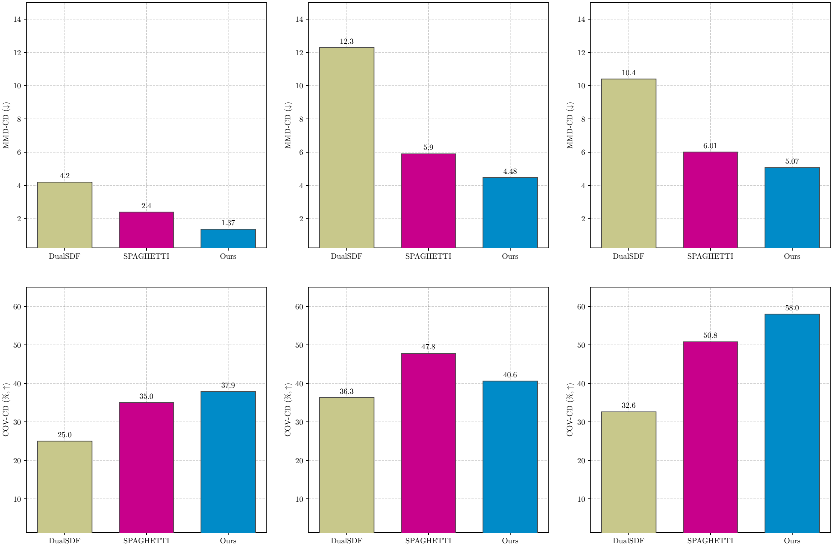
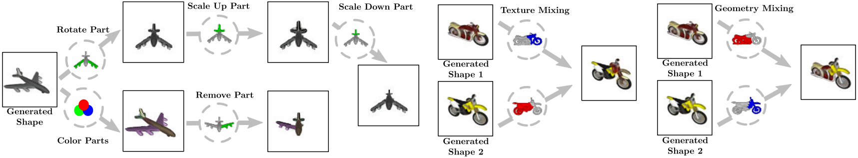


Airplanes Tables Chairs

Summary and Limitations



- We introduced the **first part-aware generative model that parametrizes parts as NeRFs**.

	Representation	Supervision	Parts	Shape Editing	Texture Editing	Mixing
GET3D	Mesh	2D	✗	✗	✗	✗
GRAF	Neural Field	2D	✗	✗	✗	✗
Pi-GAN			✗	✗	✗	✗
EG3D			✗	✗	✗	✗
DualSDF	Implicit	3D	✓	✓	✗	✗
SPAGHETTI			✓	✓	✗	✓
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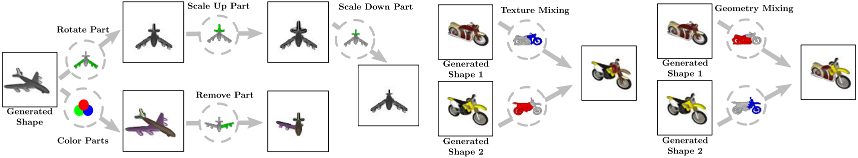

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EG3D			✗	✗	✗	✗
DualSDF	Implicit	3D	✓	✓	✗	✗
SPAGHETTI			✓	✓	✗	✓
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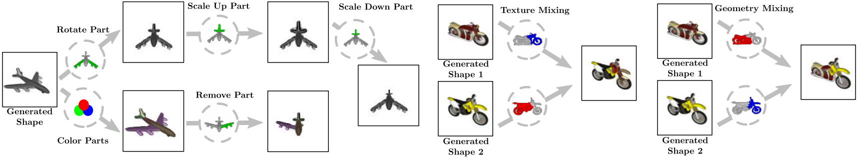

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DualSDF SPAGHETTI	Implicit	3D	✓ ✓	✓ ✓	✗ ✗	✗ ✓
PartNeRF	Neural Field	2D	✓	✓	✓	✓

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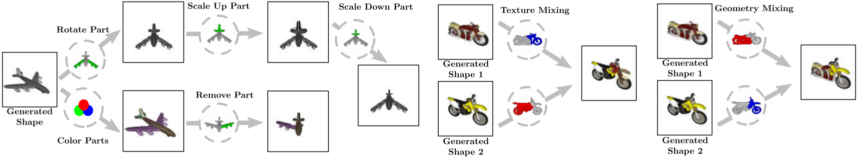

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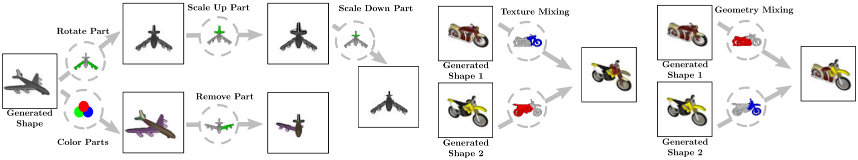

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- The generated parts are not necessarily interpretable.

Thank you for your attention!