Exploring 3D-aware Latent Spaces for Efficiently Learning Numerous Scenes

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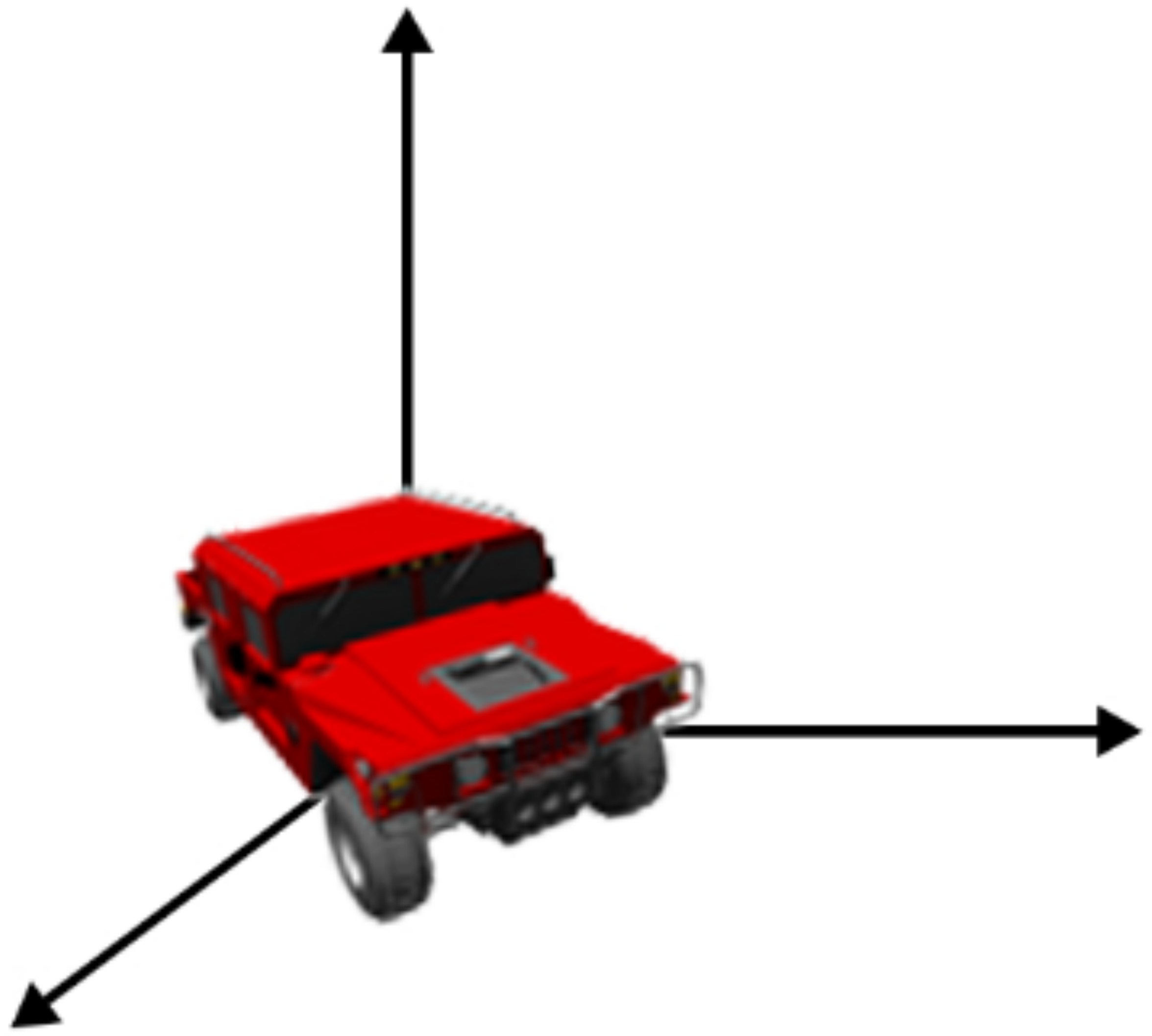
3da-ae.github.io

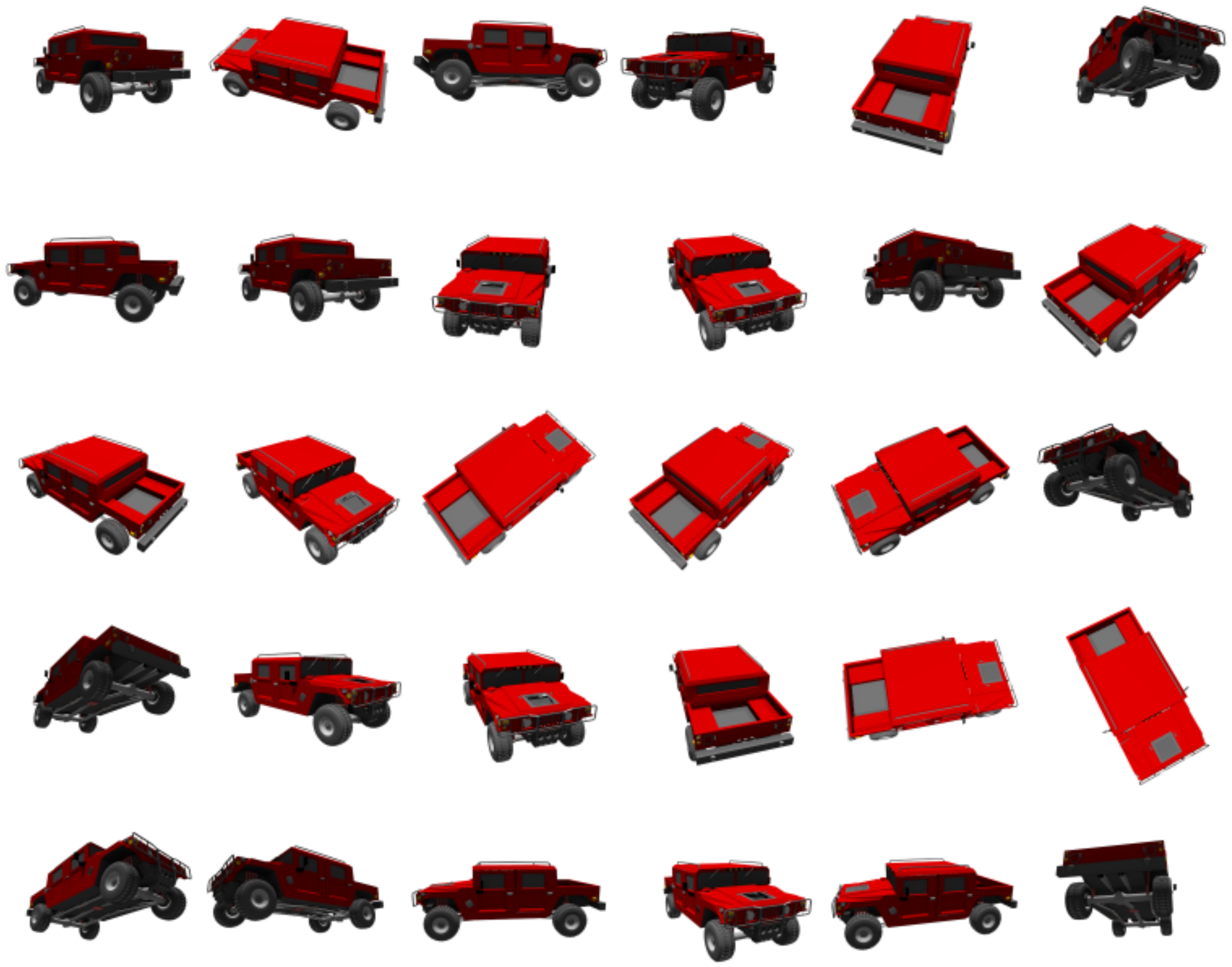
Pre-requisites

The inverse graphics problem



Mesh
Voxel grid
Point Cloud
SDF

Rendering



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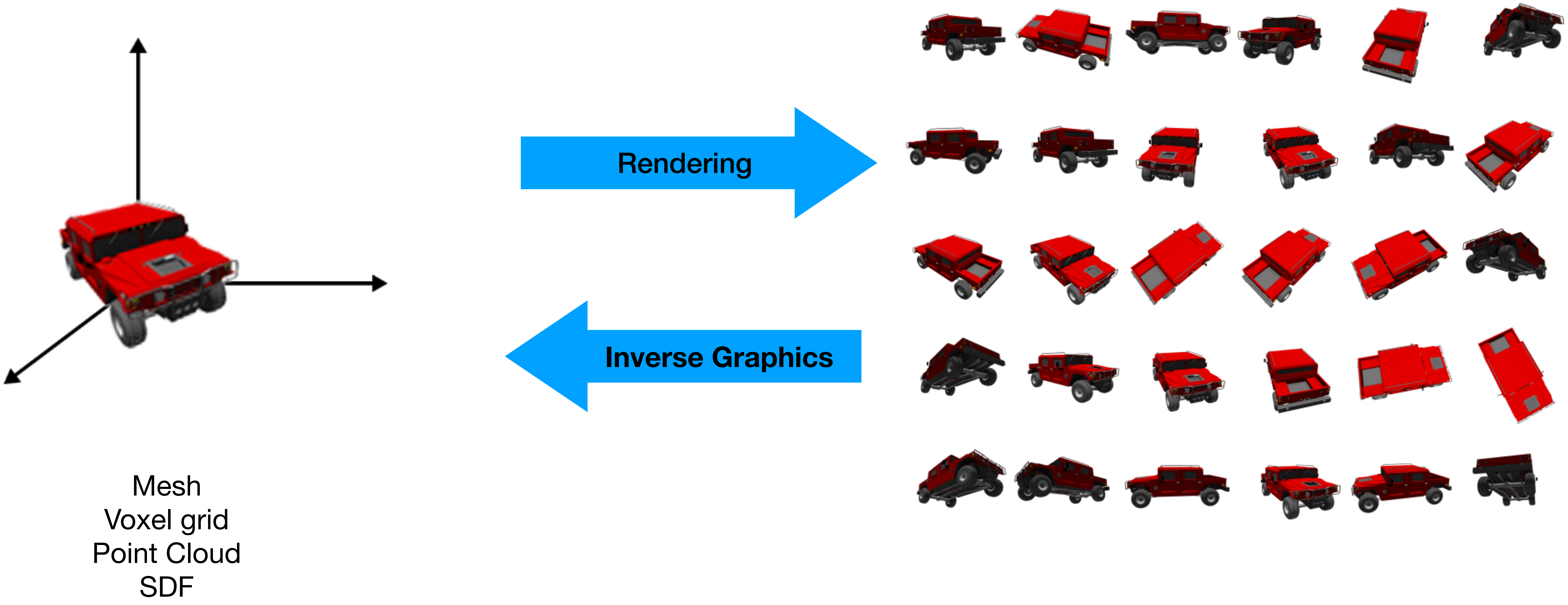
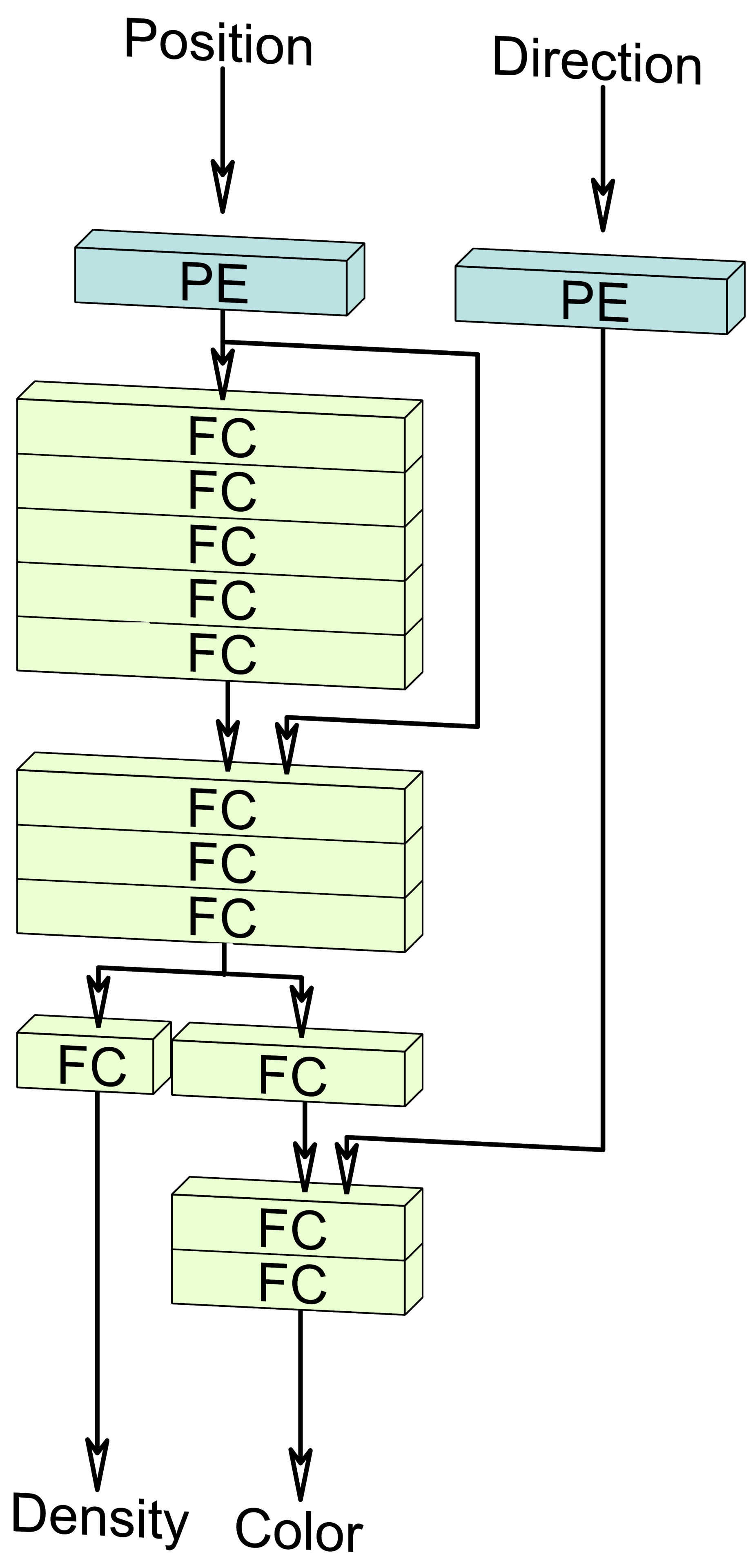
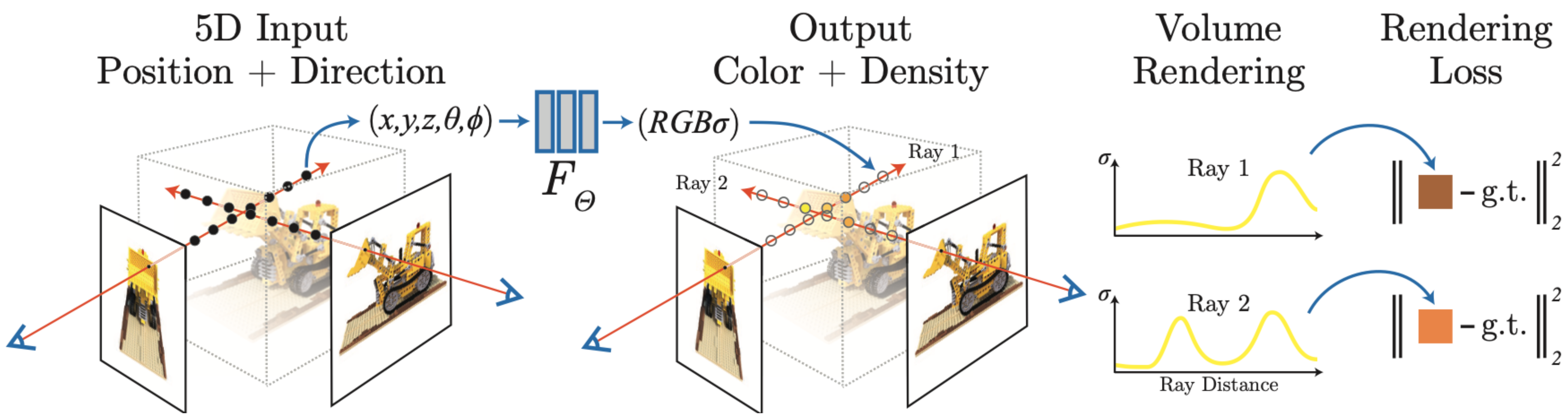


Neural Radiance Fields



[Efficient Geometry-aware 3D GANs]

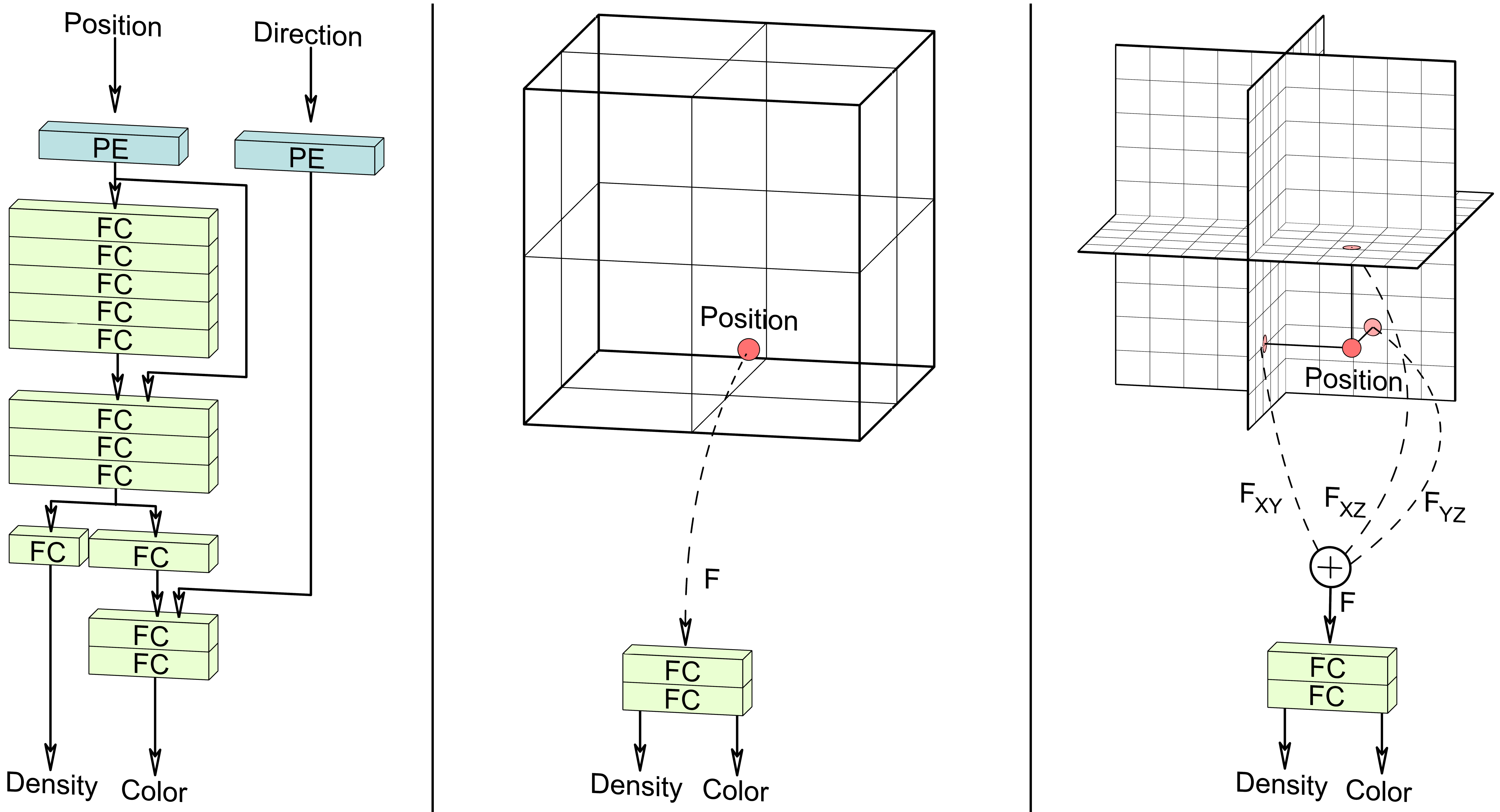


[NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis]

- **NeRFs are implicit representations trained to replicate views of a scene**
- **NeRF ≅ MLP + Volume Rendering Equations**

Tri-Planes scene representations

Each of shape (T, T, F) !



(a) NeRF (Implicit) (b) Voxels (Explicit or Hybrid) (c) Ours (Hybrid)

[Efficient Geometry-aware 3D GANs]

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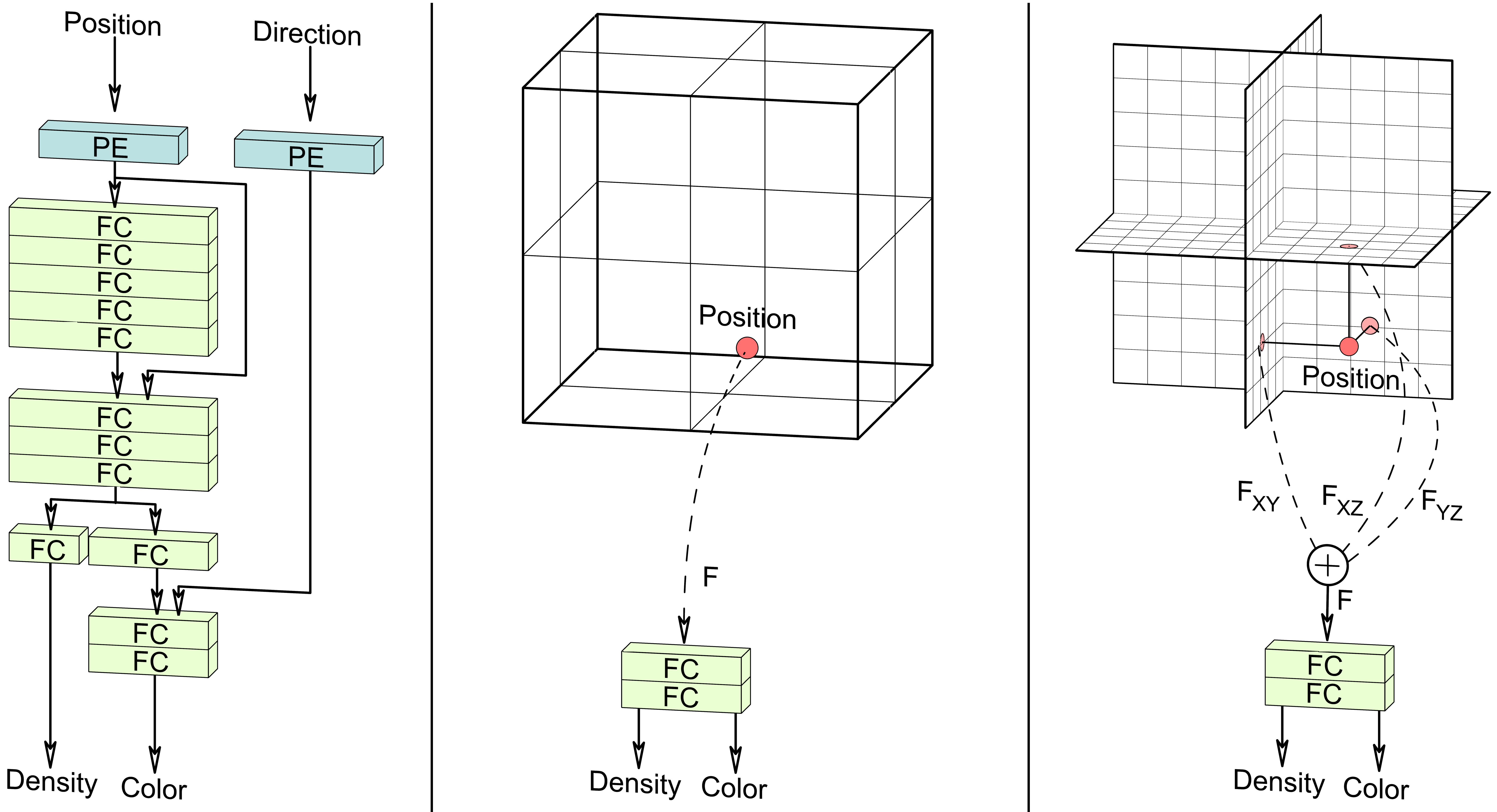


(a) NeRF (Implicit) (b) Voxels (Explicit or Hybrid) (c) Ours (Hybrid)

[Efficient Geometry-aware 3D GANs]

- **Tri-Planes are explicit-implicit representations**
- **Tri-Planes ≅ Three planes + tinyMLP + Volume Rendering Equations**
- **Both NeRFs and Tri-Planes are not scalable**

Inverse Graphics Problem

How to model a scene using its captured images?

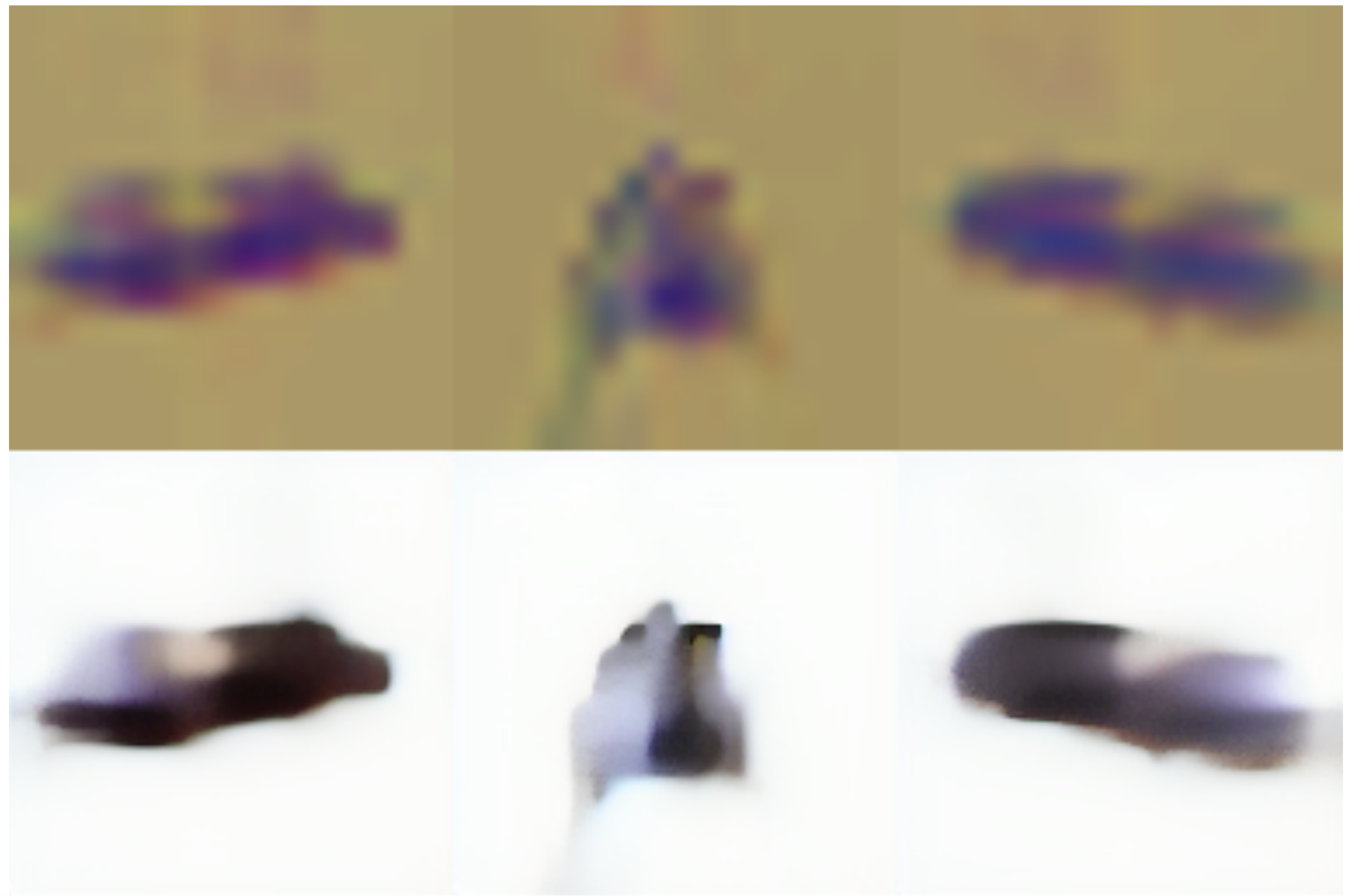
(Scaled) Inverse Graphics Problem

How to model abundantly many scenes at once?

3D-aware latent space

- **Goal:** Scale scene representation training in a specially-crafted latent space
  - Improves performances
  - Other applications

- **Neural scene representations main assumption:**
  - The underlying scene behind images is 3D
  - The renderings of the scene are 3D consistent



Tri-Planes trained in a standard AE.

3D-aware latent space

- To train scene representations in a latent space, we have to design a 3D-aware latent space

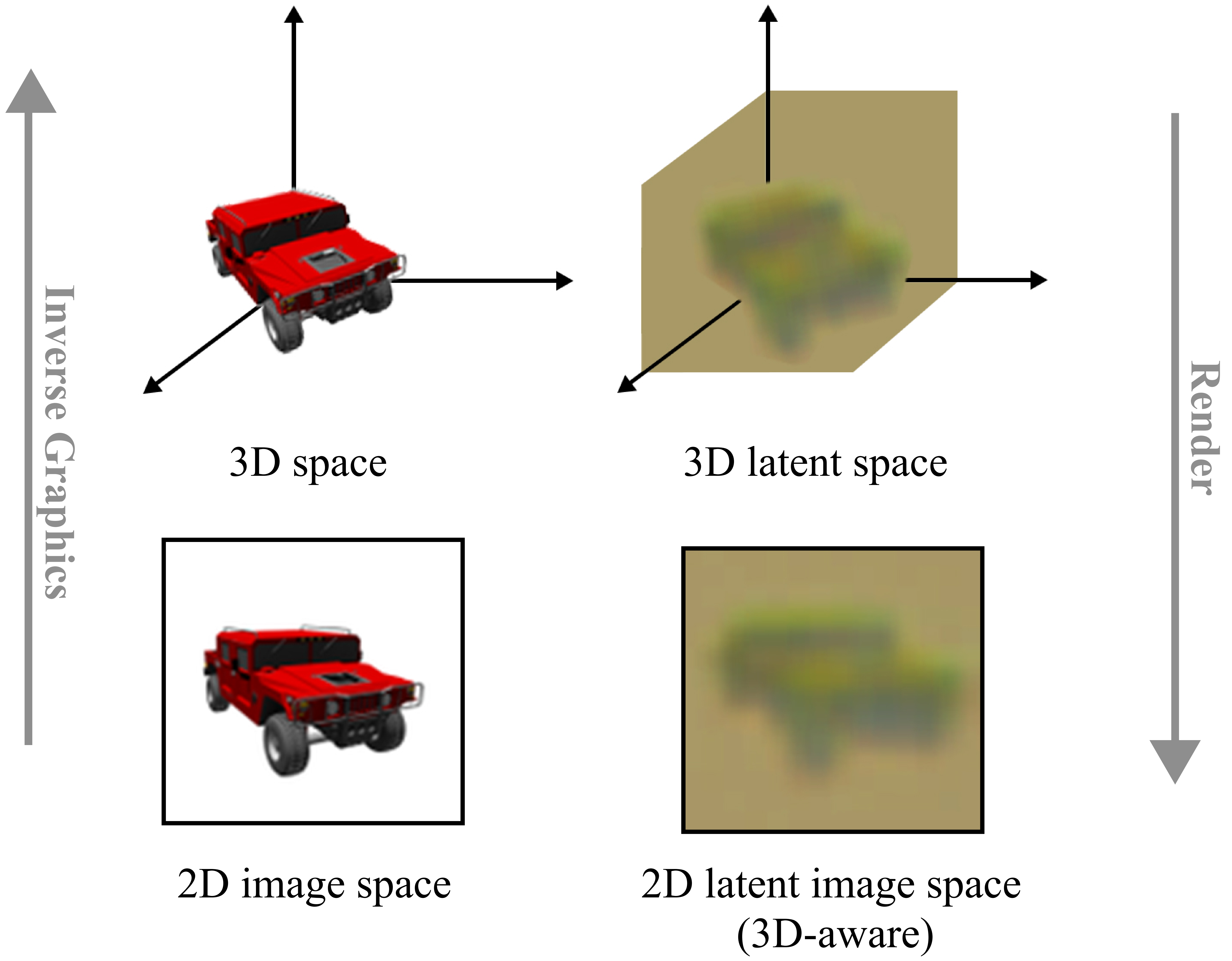


Figure 1. **3D-aware latent space.** We draw inspiration from the relationship between the 3D space and image space and introduce the idea of a 3D latent space. We propose a 3D-aware autoencoder that encodes images into a 3D-aware (2D) latent image space, in which we train our scene representations.

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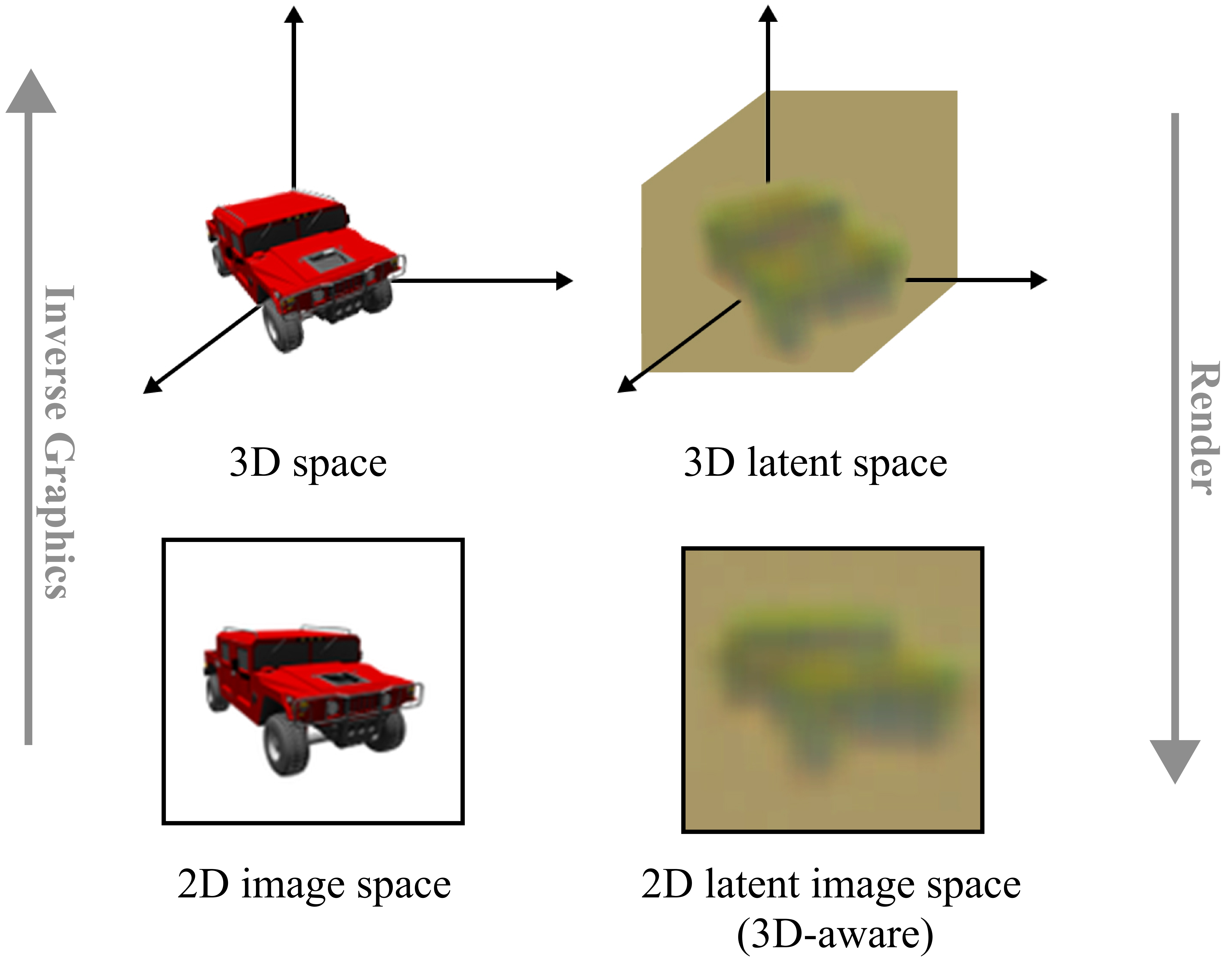

As such, we have two goals:
1. Learn a 3D-aware latent space
2. Leverage that latent space to scale the learning of 3D scenes

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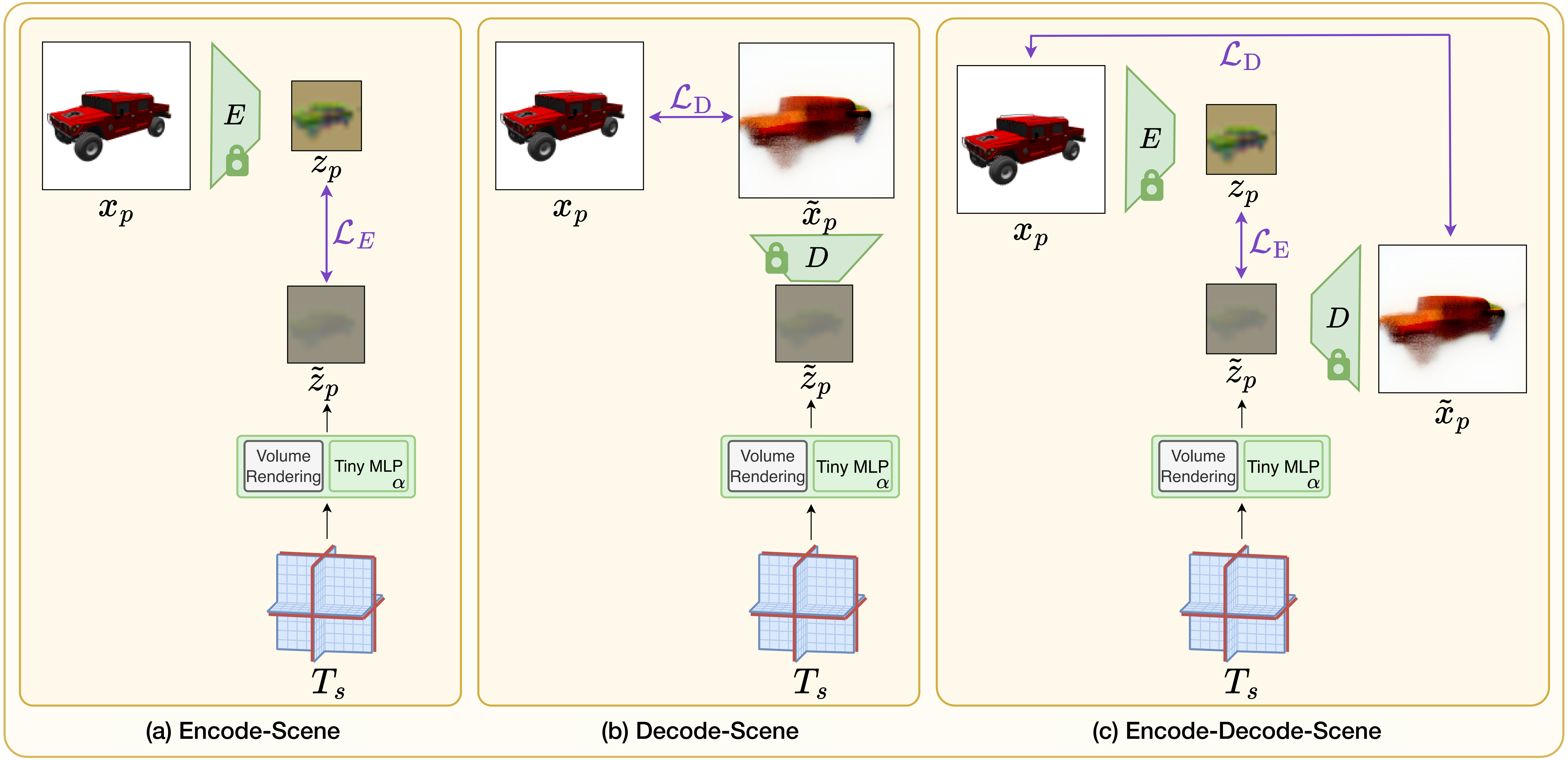

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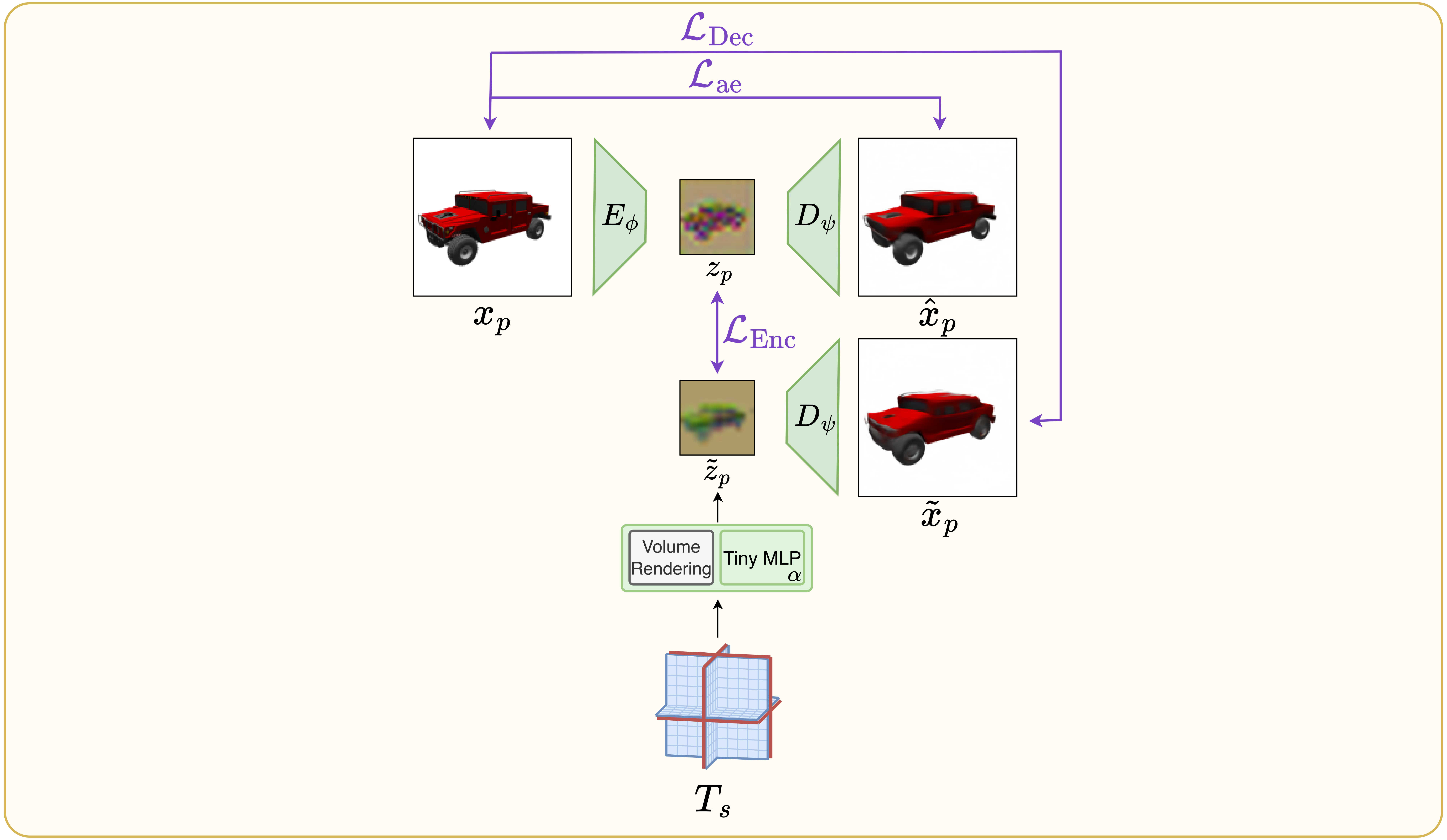

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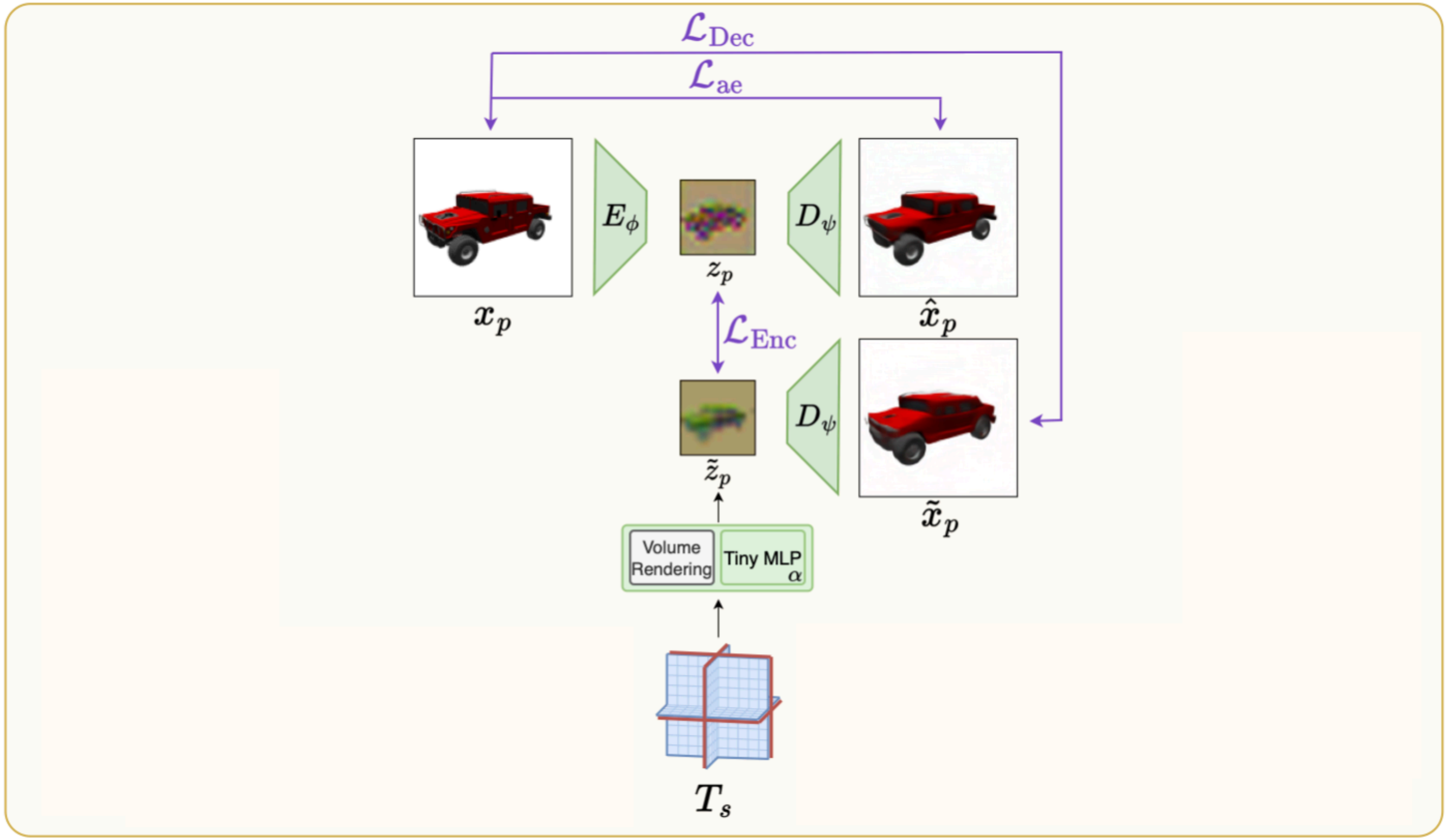
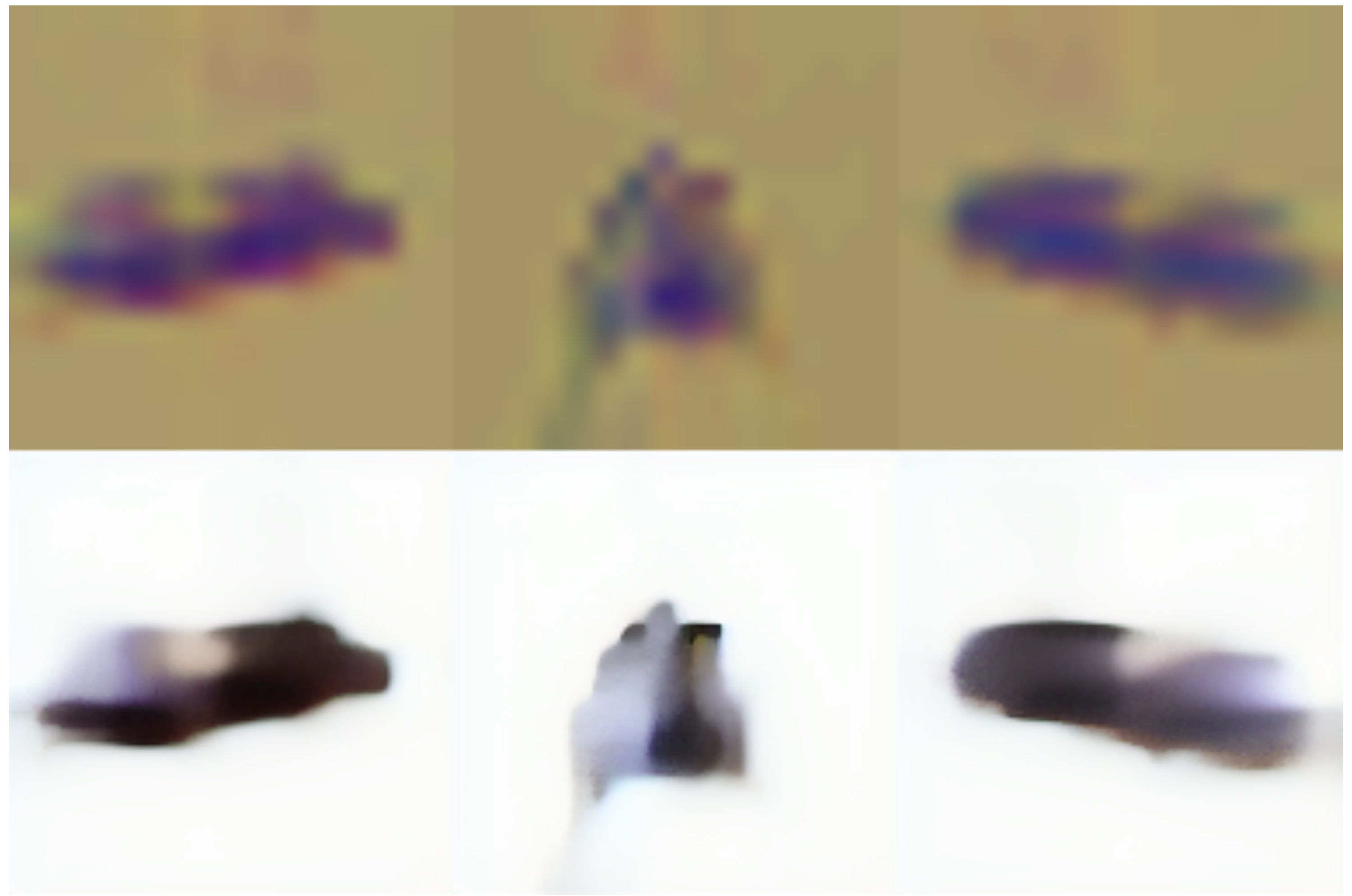


$$\min_{\phi,\psi,\alpha,T} \lambda_{\text{ae}}\mathcal{L}_{\text{ae}}(\phi,\psi) + \lambda_{\text{Enc}}\mathcal{L}_{\text{Enc}}(\phi,\alpha,T) + \lambda_{\text{Dec}}\mathcal{L}_{\text{Dec}}(\psi,\alpha,T) \ ,$$

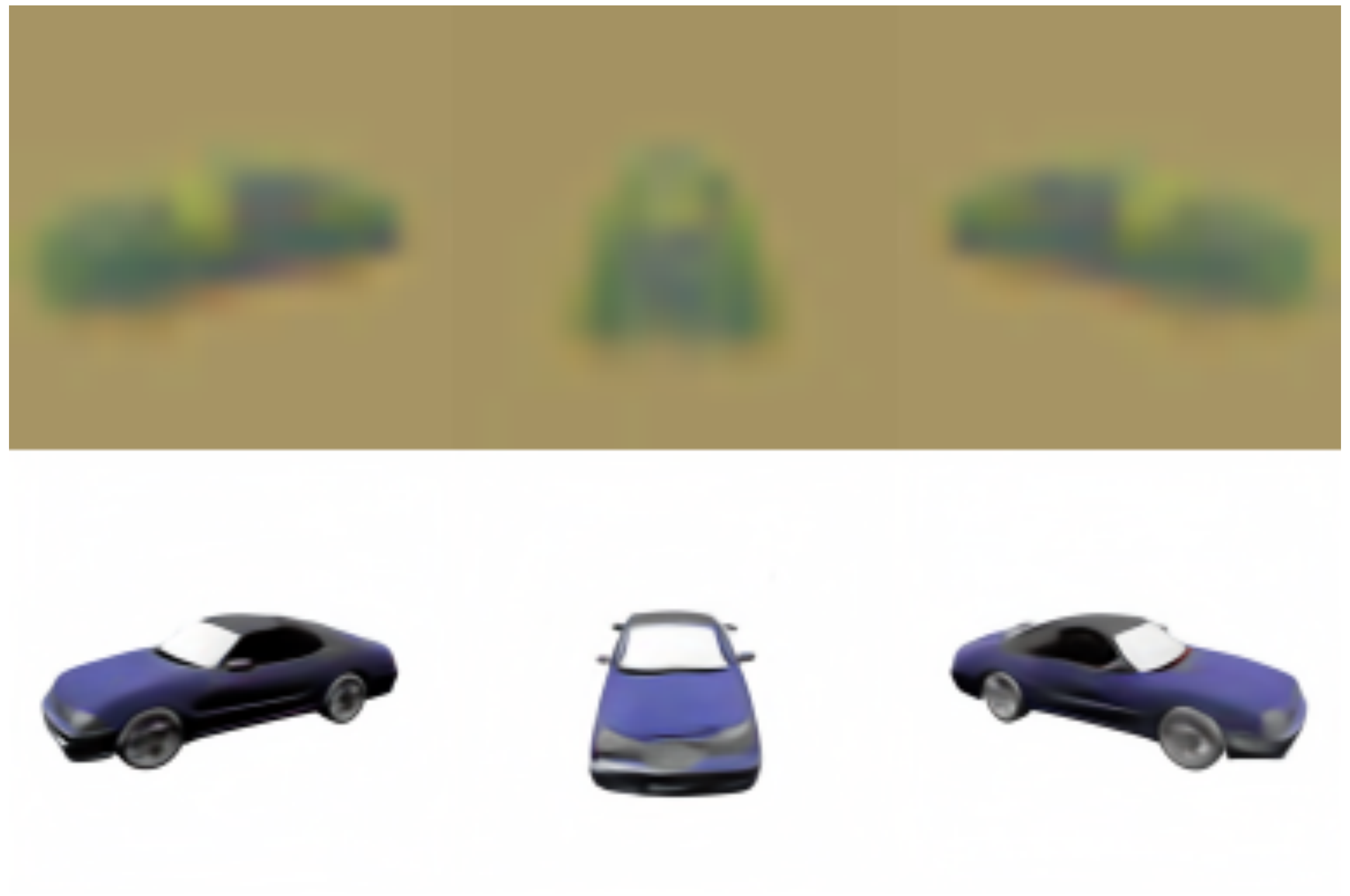
with

$$\begin{cases} \mathcal{L}_{\text{ae}}(\phi,\psi) = \mathbb{E}_{x_p}\|x_p - D_\psi(E_\phi(x_p))\| \ , \\ \mathcal{L}_{\text{Enc}}(\phi,\alpha,T) = \mathbb{E}_{x_p}\|E_\phi(x_p) - \mathcal{R}_\alpha(T,p)\| \ , \\ \mathcal{L}_{\text{Dec}}(\psi,\alpha,T) = \mathbb{E}_{x_p}\|x_p - D_\psi(\mathcal{R}_\alpha(T,p))\| \ , \end{cases}$$

3D-aware latent space

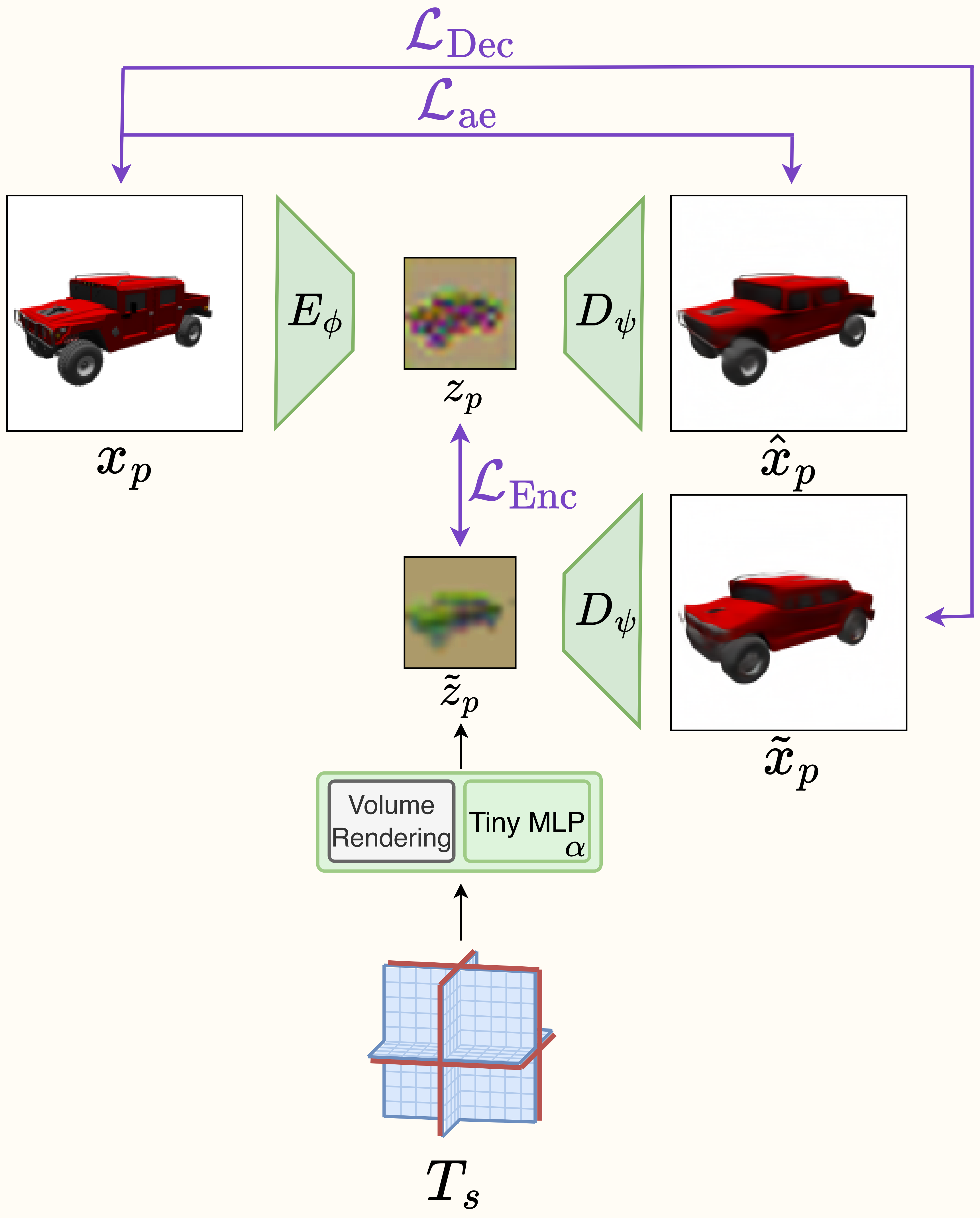


Tri-Planes trained in a standard AE.

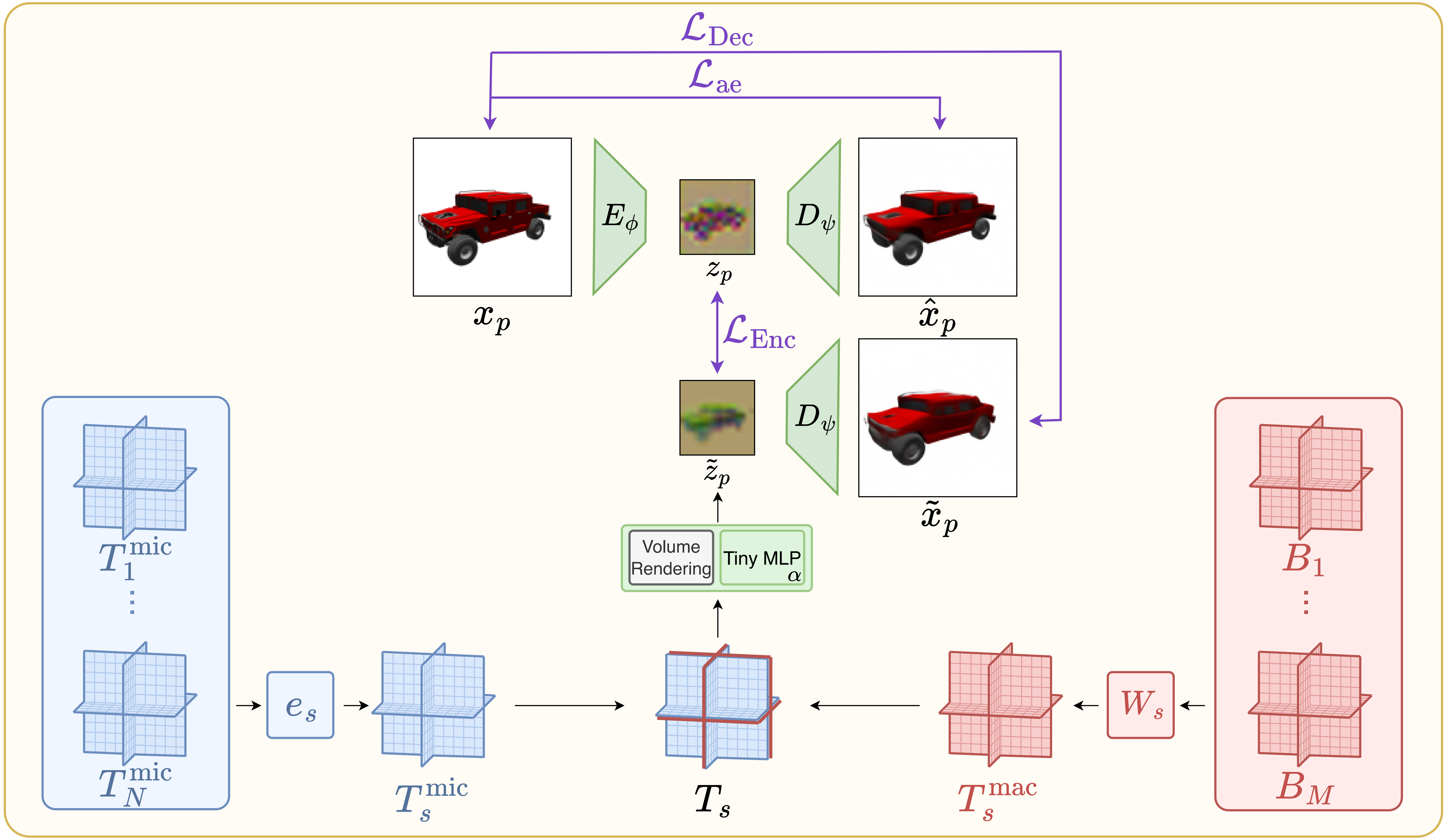


Tri-Planes trained in a 3Da-AE.

How to learn a 3D-aware latent space?



How to further scale training in a 3D-aware latent space?



How to further scale training in a 3D-aware latent space?

Results

3D-aware autoencoder

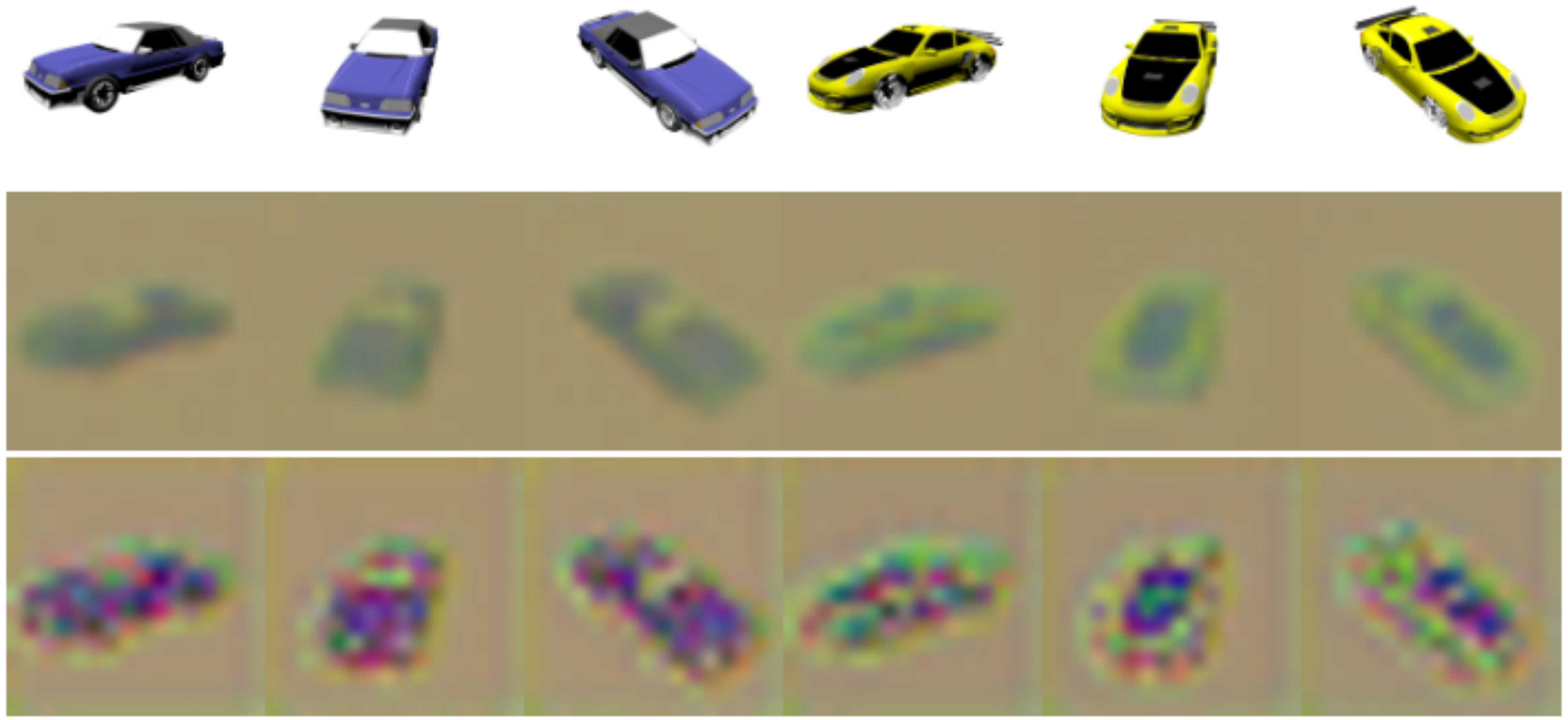


Figure 3. **Latent space comparison.** Top: ground truth image. Middle: latent image obtained with the 3D-aware encoder. Bottom: latent image obtained with the baseline encoder. Qualitative results show that our 3D-aware encoder better preserves 3D consistency and geometry in the latent space.

Renderings

Experiment	Latent Space	Micro-Planes	Macro-Planes	Train scenes	Exploit scenes
Ours-Micro	✓	✓	✗	26.52	26.95
Ours-Macro	✓	✗	✓	25.67	26.10
Tri-Planes-Macro (RGB)	✗	✗	✓	27.84	28.00
Tri-Planes (RGB)	✗	✓	✗	**28.24**	28.40
Ours-No-Prior	✓	✓	✓	27.72	28.13
Ours	✓	✓	✓	28.05	**28.48**

Table 2. **Quality comparison.** Average PSNR demonstrated by our method with a comparison to Tri-Planes and ablations of our pipeline. All metrics are computed on never-seen test views. Here, we consider $N_{\text{train}} = 500$, $N_{\text{exploit}} = 100$, and $M = 50$. For compute constraints, Tri-Planes metrics are averaged on 50 scenes.

(a) Tri-Planes (RGB) (b) Ours (c) Ground truth

Figure 8. **Visual comparison**. Visual comparison of novel view synthesis quality for our method and Tri-Planes (RGB).

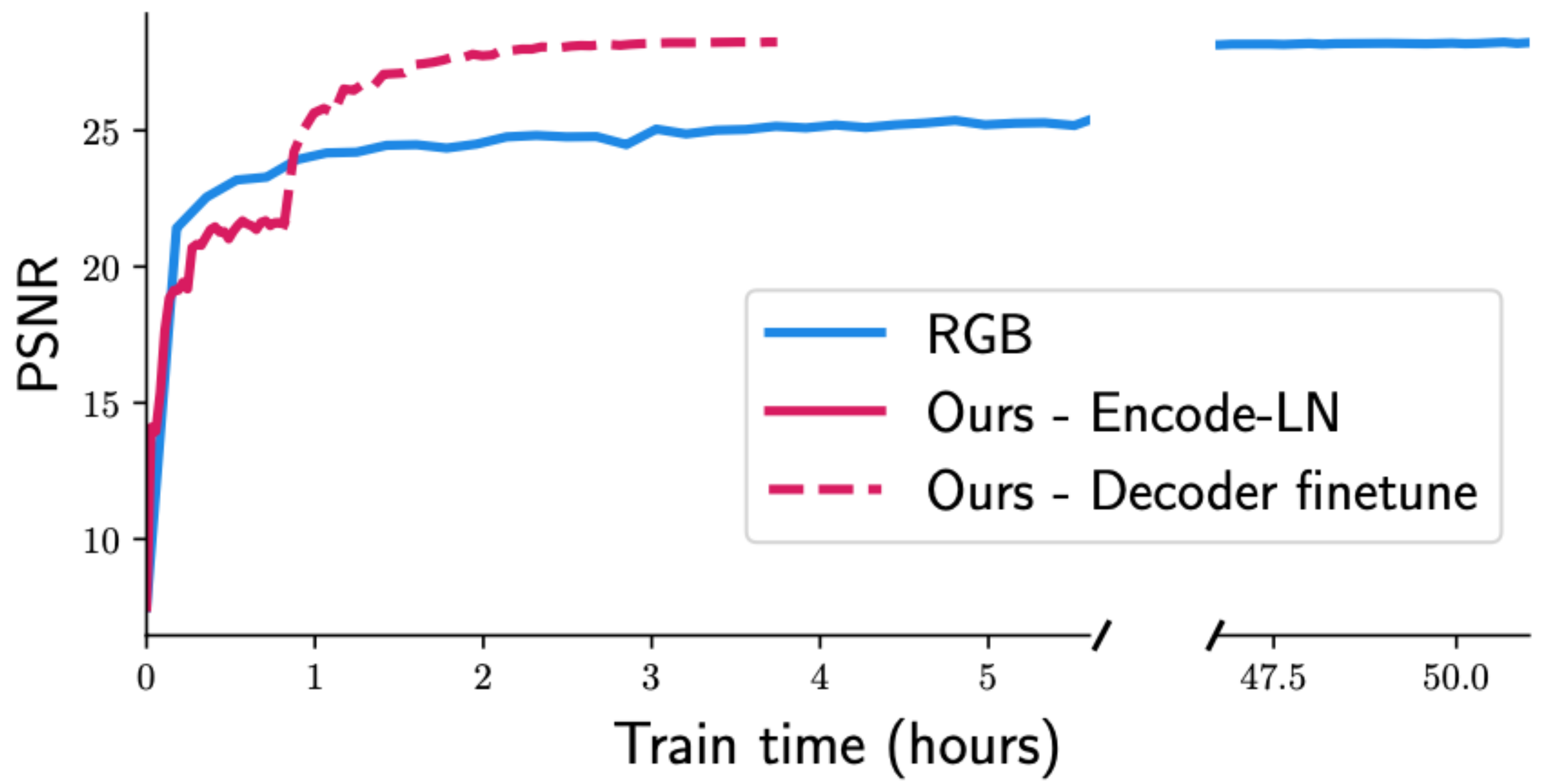


Figure 6. **Quality evolution.** Evolution of the average test-view PSNR demonstrated in the exploit phase of our method compared to RGB Tri-Planes ($N_{\text{exploit}} = 100$). Our method achieves comparable quality in less training time.

Resource costs

	t_{scene} (min)	$t^{\text{eff}}_{\text{scene}}$ (min)	m_{scene} (MB)	$m^{\text{eff}}_{\text{scene}}$ (MB)	Rendering Time (ms)	Rendering Resolution
Encoder	—	—	0	0.13	—	—
Decoder	—	—	0	0.19	9.7	128×128
Tri-Planes (RGB)	32	32	1.5	1.5	23.3	128×128
Our method	2	4.5	0.48	0.84	11.0	128×128

Table 1. **Cost comparison.** Per scene cost comparison with Tri-Planes trained in the image space. Here, we consider $N_{\text{train}} = 500$, $N_{\text{exploit}} = 1000$, $t_{\text{EC}} = 40$ hours, $M = 50$, $F^{\text{mac}} = 22$. Our method reduces the effective training time by 86% per scene, and the effective memory cost by 44% per scene.

$$t^{\text{eff}}_{\text{scene}} = \frac{t_{\text{EC}}}{N_{\text{exploit}}} + t_{\text{scene}} \qquad m^{\text{eff}}_{\text{scene}} = \frac{m_{\text{EC}}}{N_{\text{exploit}}} + m_{\text{scene}}$$

Resource costs

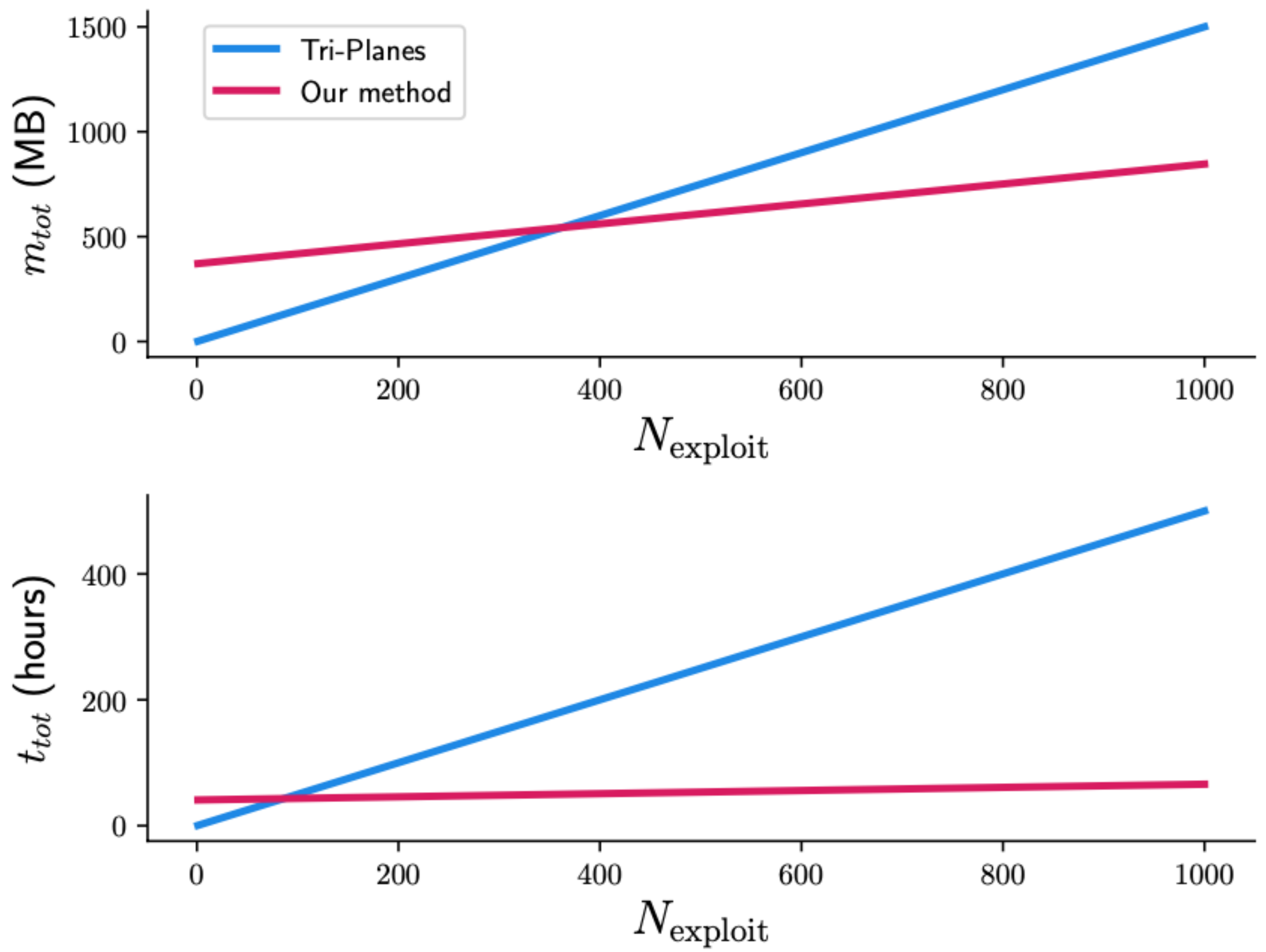


Figure 7. **Cost evolution.** Total memory and train time evolution when scaling the number of trained scenes N_{exploit}. The entry training cost t_{EC} and memory costs m_{EC} are taken into account. Our method demonstrates more favorable scalability properties as compared to Tri-Planes (RGB).

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Accepted at 3DMV-CVPR workshop

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