RayZer: A Self-supervised Large View Synthesis Model

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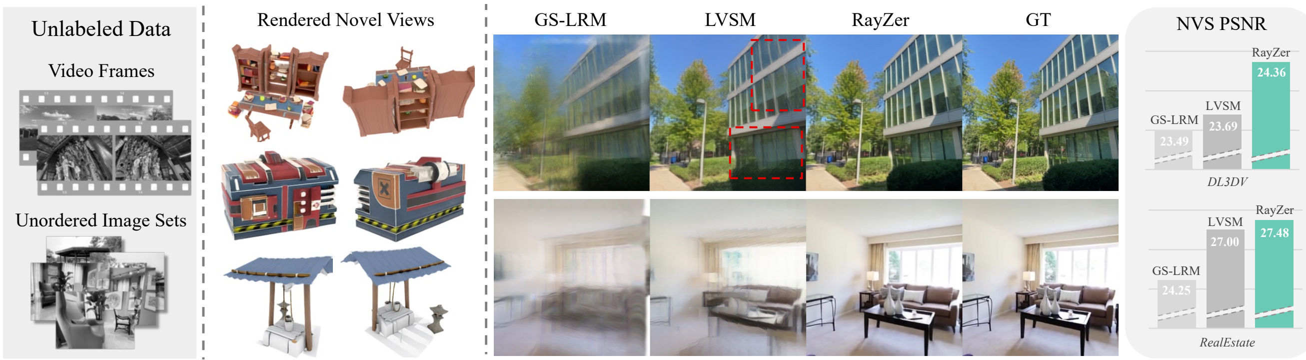

Figure 1. We propose **RayZer**, a **self-supervised** multi-view 3D Vision model trained on *unlabeled data* without any annotations, *e.g.*, camera pose labels. At inference, RayZer supports *feed-forward* novel view synthesis from *unposed & uncalibrated* images. RayZer achieves novel view synthesis performance comparable to that of supervised "oracle" methods (GS-LRM and LVSM), which require camera labels in both training and inference, and even **outperforms** them when they rely on (potentially noisy) COLMAP camera annotations. We show two examples on the right, where COLMAP camera annotations lead to consistent failures of GS-LRM and LVSM during inference.

Abstract

We present RayZer, a self-supervised multi-view 3D Vision model trained without any 3D supervision, i.e., camera poses and scene geometry, while exhibiting emerging 3D awareness. Concretely, RayZer takes unposed and uncalibrated images as input, recovers camera parameters, reconstructs a scene representation, and synthesizes novel views. During training, RayZer relies solely on its self-predicted camera poses to render target views, eliminating the need for any ground-truth camera annotations and allowing RayZer to be trained with 2D image supervision. The emerging 3D awareness of RayZer is attributed to two key factors. First, we design a self-supervised framework, which achieves 3D-aware auto-encoding of input images by disentangling camera and scene representations. Second, we design a transformer-based model in which the only 3D prior is the ray structure, connecting camera, pixel, and scene simultaneously. RayZer demonstrates comparable or even superior novel view synthesis performance than "oracle" methods that rely on pose annotations in both training and testing. Project: https://hwjiang1510.github.io/RayZer/

1. Introduction

Self-supervised learning has driven the rise of foundation models, enabling training on vast amounts of unlabeled data and fueled by the scaling law [35]. This paradigm has proven highly effective for LLMs [55], VLMs [2], and visual generation [51]. In contrast, 3D Vision models still rely heavily on ground-truth 3D geometry and camera pose labels [25, 72], which are usually estimated from time-consuming optimization methods, *e.g.*, COLMAP [60], and are not always perfect. This reliance limits both learning scalability and effectiveness. To break free from this constraint, we move beyond the supervised paradigm and ask: *how far can we push a 3D Vision model without any 3D supervision*?

In this paper, we present **RayZer**, a large multi-view 3D model **trained with self-supervision** and **exhibiting emerging 3D awareness**. The input of RayZer is *unposed and uncalibrated* multi-view images, sampled from continuous video frames or unordered multi-view captures. RayZer first recovers the camera parameters, then reconstructs the scene representation, and finally renders novel views. The key insight of our self-supervised training is to use the camera poses *predicted by RayZer itself* to render views that provide *photometric supervision*, rather than following the standard protocol of using ground truth poses for rendering [26, 69, 87]. Thus, RayZer can be trained with **zero 3D supervision**, *i.e.*, no 3D geometry or camera pose supervision. During inference, RayZer predicts camera and scene representations in a *feed-forward* manner, without requiring per-scene optimization. We show inference results in Fig. 1.

As RayZer uses the camera poses predicted by itself for training, this self-supervised task can be interpreted as **3D-aware image auto-encoding** [38, 56, 90]. Initially, RayZer *disentangles* input images into camera parameters and scene representations (reconstruction). It then *re-entangles* these predicted representations back into images (rendering). To facilitate this disentanglement, we **control the information flow**. As shown in Fig. 2, we divide all images into *two parts*: one set predicts the scene representation (input views), while the other offers photometric self-supervision (target views). This is achieved by using estimated poses of the second set to render the scene representation predicted from the first set, thereby preventing trivial solutions that are not 3D-aware.

To facilitate self-supervised learning, RayZer is built only with *transformers* – no 3D representation, hand-crafted rendering equation, or 3D-informed architectures. This design is motivated by self-supervised large models in other modalities [2, 6, 51], enabling RayZer to flexibly and effectively learn domain-specific knowledge. The only 3D prior incorporated in RayZer is the **ray structure**, which simultaneously models the relationship between camera, pixels (image), and scene. Concretely, RayZer first predicts camera poses, which are then converted into pixel-aligned Plücker ray maps [52] to guide the scene reconstruction that follows. This ray-based representation serves as a strong prior for addressing the chicken-and-egg problem of structure and motion [63], effectively allowing the camera and scene representations to regularize each other during training.

We evaluate RayZer on three datasets, including both scene-level and object-level data with different camera configurations. We observe that RayZer demonstrates **comparable or even better novel view synthesis performance** than "oracle" methods [30, 86] that use pose labels in both training and testing. Interestingly, we identify that potentially noisy pose annotations from COLMAP can limit the performance of "oracle" models. The results not only demonstrate the effectiveness of RayZer, but also shows the potential of 3D Vision models to break free from supervised learning.

2. Related Work

Large-scale 3D Vision Models. 3D Vision models learn 3D representations and priors from data [14, 21, 36, 53, 54, 66, 67, 88, 89]. Recently, researchers have developed large-scale models to acquire general 3D knowledge. One research direction focuses on designing improved model architectures that incorporate the inductive biases of multi-view stereo [10, 13, 70, 81] and epipolar geometry [9, 12, 17, 23]. Another line of work leverages full transformer models that intentionally omit architectural 3D inductive biases [26, 49, 57]. For example, large reconstruction models (LRMs) [25, 69, 73, 86, 93], LEAP [26], and DUSt3R [18, 39, 71, 72, 78] employ transformers to convert 2D image input into 3D representations. SRT [57] and LVSM [30]

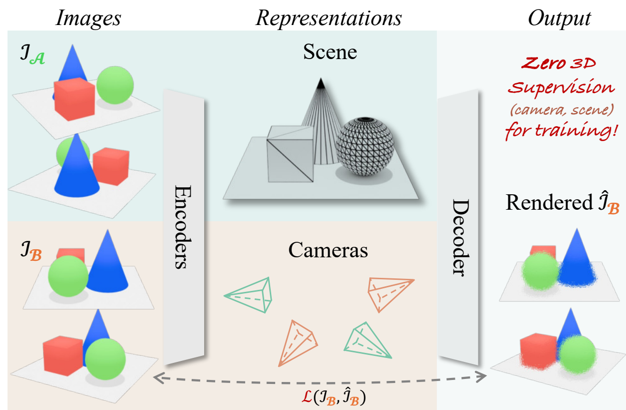

Figure 2. **Our proposed self-supervised training framework**. This is an abstract design that we later operationalize with our RayZer model (illustrated in Fig. 3 and Sec. 4). We divide the input images into two sets $\mathcal{I}_\mathcal{A}$ and $\mathcal{I}_\mathcal{B}$. We predict the scene representation from $\mathcal{I}_\mathcal{A}$, and use the predicted cameras of $\mathcal{I}_\mathcal{B}$ (shown in orange) to render the scene. We leverage photometric loss between raw input $\mathcal{I}_\mathcal{B}$ and its prediction $\hat{\mathcal{I}}_\mathcal{B}$ for training.

further replace 3D representations and physical rendering equations with latent representations and learned rendering functions, improving performance and scalability. However, they still require ground-truth camera poses for supervised training and/or accurate camera annotations during inference. To achieve scalable supervised learning, MegaSynth [29] and Stereo4D [31] leverage synthetic data and stereo videos to expand the data scale, however, curating data for different tasks can be laborious. In contrast, RayZer explores self-supervised training to break free from supervised learning.

Self-supervised 3D Representation Learning. Learning 3D-aware representations from unlabeled image data is a long-standing problem in 3D Vision. One line of work leverages single-view images. However, they either only work for a specific category [7, 34, 43, 47, 48, 77] or can only recover partial observations [8, 59, 76]. Some works explore semi-supervised learning and achieve better scalability [27, 79], but performance is still highly restricted to the model weights, which are initialized by fully supervised training [80]. The most relevant work is self-supervised learning from multi-view images [64, 74, 75]. For example, Zhou et al. [90], Lai et al. [38], and their following works [19, 82] use camera motion as 2D or 3D warping operations to regularize learning. However, this strong inductive bias limits the learning effectiveness. RUST [58] is a pioneering work in learning latent scene representations from unposed imagery. RayZer is different in three aspects. First, RayZer initially estimates camera poses and uses poses to condition the following latent reconstruction. In contrast, RUST operates in an inverse pipeline – it first reconstructs the scene and then estimates the camera poses. Second, RayZer employs different explicit pose representations to improve information disentanglement and 3D awareness, enabling novel view synthesis by geometrically interpolating predicted poses. Instead, RUST uses a latent pose representation, which makes scene-pose disentanglement challenging and they are not explicitly 3D-aware. Third, RayZer estimates camera poses for all views, while RUST estimate latent poses only for target views.

Optimization-based Unsupervised SfM, SLAM, and NVS. Although these methods are not directly comparable to RayZer, we discuss them due to the similar input-output formulations. In detail, these methods optimize target predictions on a per-scene basis [60, 62], while RayZer is a feed-forward parametrized model, learning priors by training on large data. The traditional SfM, SLAM, and NVS methods are unsupervised [24, 60]. Although generally performing well, they are restricted by the complicated hand-crafted workflow, leading to requirements of dense-view inputs [84], slow speed [60], and sensitivity to hyper-parameters [65]. Recent optimization-based NeRF and 3DGS works can also perform NVS from unposed images [4, 20, 44, 61]. However, they do not have learnable model parameters to encode priors, thus requiring off-the-shelf models trained with 3D supervision as regularization or providing initialization.

3. Preliminaries

We introduce two important building blocks of RayZer, *i.e.*, the latent set scene representation and how to render it.

Latent set scene representation. Compressing data into tokens in latent space is a common practice in text, image, video, etc. Recently, this representation has also been extended to 3D research [30, 57, 58, 83]. In contrast to classical explicit (*e.g.*, meshes and point clouds), implicit (*e.g.*, NeRF [46] and SDF [50]), and hybrid (*e.g.*, triplane [8] and 3DGS [37]) representations that are 3D-aware, the latent set representation is *not explicitly 3D-aware*. It serves as a *compression* of scene information, where the 3D-awareness properties are *fully learned*. The latent set scene representation can be denoted as $\mathbf{z} \in \mathbb{R}^{n\times d}$, where n is the number of tokens in the set and d is the latent feature dimension.

Rendering latent set scene representation requires a network, say R^θ, as introduced by SRT [57] and LVSM [30]. We formulate it as $v = R^\theta(\mathbf{z}, r)$, where r is a ray and v is the rendered property, *e.g.*, RGB values, of the corresponding pixel[1]. This formulation is the same as traditional Graphics rendering techniques [1, 33], as $v = R(\textsc{scene}, \textsc{ray})$, where R is a pre-defined and handcrafted rendering equation, *e.g.*, alpha-blending ray marching in NeRF. Differently, our "rendering equation" is a learned model parameterized with weights θ, and our scene representation is a latent token set as discussed previously. We omit the model parametrization, *e.g.*, weight θ, in the following description for clarity.

[1]For improved efficiency and performance, LVSM groups rays from the same image patch and decodes them jointly.

4. RayZer

In this section, we first introduce RayZer's self-supervised learning framework (Sec. 4.1). Then, we present the details of the RayZer model architecture (Sec. 4.2).

4.1. RayZer's Self-supervised Learning

We first formulate the input and output of RayZer. We then introduce the self-supervised learning framework.

We focus on the standard setting of modeling static scenes [60]. The **input** of RayZer is a set of *unposed and uncalibrated* multi-view images $\mathcal{I} = \{I_i \in \mathbb{R}^{H\times W\times 3} | i = 1, ..., K\}$, which can come from unlabeled video frames or image sets. The **output** is a parametrization of the inputs, *i.e.*, camera intrinsics, per-view camera poses, and scene representation, enabling novel view synthesis. To predict these representations, we build the RayZer model and train it with *self-supervised learning* – no 3D supervision, *i.e.*, 3D geometry, and camera pose annotations during training.

To train RayZer with self-supervision, we control the data information flow. We split the input images $\mathcal{I}$ into **two non-overlapping subsets** $\mathcal{I}_\mathcal{A}$ and $\mathcal{I}_\mathcal{B}$, where $\mathcal{I}_\mathcal{A} \cup \mathcal{I}_\mathcal{B} = \mathcal{I}$ and $\mathcal{I}_\mathcal{A} \cap \mathcal{I}_\mathcal{B} = \emptyset$. RayZer uses $\mathcal{I}_\mathcal{A}$ to predict the *scene representation*, and use $\mathcal{I}_\mathcal{B}$ *for providing supervision*. Thus, RayZer renders images that correspond to $\mathcal{I}_\mathcal{B}$, denoted as $\hat{\mathcal{I}}_\mathcal{B}$, and we apply photometric losses:

$$\mathcal{L} = \frac{1}{K_\mathcal{B}} \sum_{\hat{I} \in \hat{\mathcal{I}}_\mathcal{B}} (\texttt{MSE}(I, \hat{I}) + \lambda \cdot \texttt{Percep}(I, \hat{I})), \quad (1)$$

where $K_\mathcal{B} = |\mathcal{I}_\mathcal{B}|$ is the size (number of images) of $\mathcal{I}_\mathcal{B}$, $I \in \mathcal{I}_\mathcal{B}$ is the image that corresponds to a predicted image $\hat{I}$, and λ is the weight for perceptual loss [32, 42]. The two sets are randomly sampled during training.

4.2. RayZer Model

Overview. As introduced in Sec. 4.1, RayZer recovers both camera parameters and the scene representation from unposed, uncalibrated input images. A key design element of RayZer is its **cascaded** prediction of camera and scene representations. This is motivated by the fact that even noisy cameras can be a strong condition for better scene reconstruction [28, 60, 87], which is analogous to traditional structure-from-motion methods [60] and is in contrast with recent reconstruction-first methods [58, 69, 72]. This design can provide mutual regularization of predicting pose and scene during training, facilitating self-supervised learning.

RayZer builds a pure transformer-based model, benefiting from its scalability and flexibility. As shown in Fig. 3, RayZer first tokenizes input images and uses a transformer-based encoder to predict camera parameters of *all views*. In this step, the cameras are represented by their intrinsics and `SE(3)` camera poses. This **low-dimensional**, **geometri-**

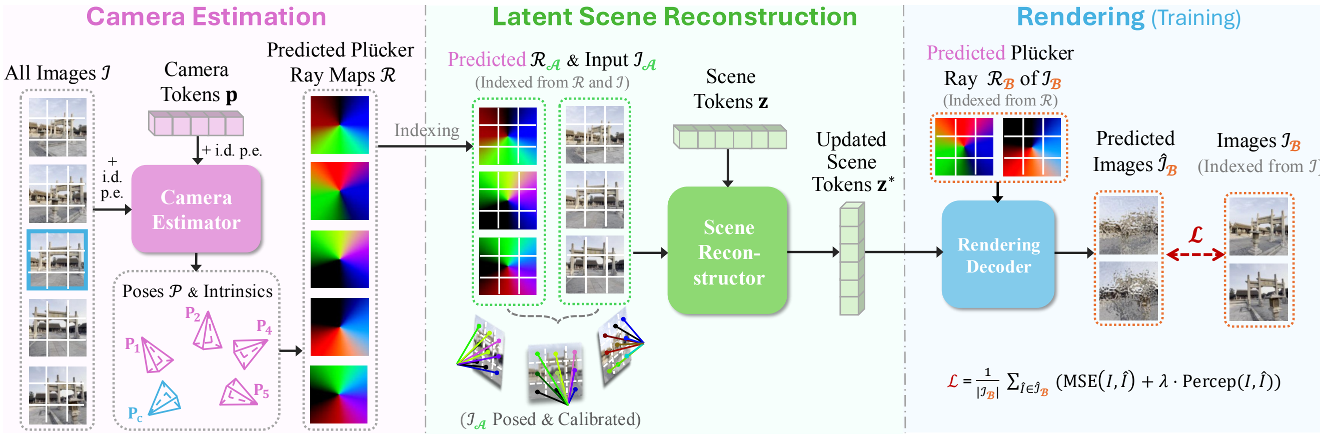

Figure 3. **RayZer self-supervised learning framework.** RayZer takes in unposed and uncalibrated multi-view images $\mathcal{I}$ and predicts per-view camera parameters and a scene representation, which supports novel view rendering. (**Left**) RayZer first estimates camera parameters, where one view is selected as the canonical reference view (in blue box). RayZer predicts the intrinsics and the relative camera poses $\mathcal{P}$ of all views. The predicted cameras are then converted into pixel-aligned Plücker ray maps $\mathcal{R}$. (**Middle**) RayZer uses a subset of input images, $\mathcal{I}_{\mathcal{A}}$, as well as their previously predicted camera Plücker ray maps, $\mathcal{R}_{\mathcal{A}}$, to predict a latent scene representation. Here, the Plücker ray maps, $\mathcal{R}_{\mathcal{A}}$, serve as an effective condition for scene reconstruction. (**Right**) RayZer can render a target image given the scene representation $\mathbf{z}^*$ and a target camera. During training, we use $\mathcal{R}_{\mathcal{B}}$, which is the previously predicted cameras Plücker ray maps of $\mathcal{I}_{\mathcal{B}}$, to render $\hat{\mathcal{I}}_{\mathcal{B}}$. This allows training RayZer end-to-end with self-supervised photometric losses between inputs $\mathcal{I}_{\mathcal{B}}$ and their renderings $\hat{\mathcal{I}}_{\mathcal{B}}$.

cally well-defined parametrization helps disentangle image information from the camera representation.

RayZer then transforms the `SE(3)` camera poses and intrinsics into Plücker ray maps [52], representing the predicted cameras as pixel-aligned rays. This ray-based representation captures both the 2D ray-pixel alignment and the 3D ray geometry, providing **fine-grained**, ray-level details that encapsulate the physical properties of the camera model. The ray maps serve as a condition for improving the reconstruction stage that follows.

From the image and predicted Plücker rays of $\mathcal{I}_{\mathcal{A}}$, RayZer uses another transformer-based encoder to predict the latent set scene representation (introduced in Sec. 3 and detailed later). Then, RayZer uses the previously estimated cameras of $\mathcal{I}_{\mathcal{B}}$ to predict $\hat{\mathcal{I}}_{\mathcal{B}}$, providing photometric self-supervision (Eq. 1). We now formally introduce the RayZer model.

Image Tokenization. For all K input images $\mathcal{I} = \{I_i \in \mathbb{R}^{H\times W\times 3} | i = 1, ..., K\}$, we patchify them into non-overlapping patches following ViT [16]. Each patch is in $\mathbb{R}^{s\times s\times 3}$, where s is the patch size. We use a linear layer to encode each patch into a token in $\mathbb{R}^d$, leading to a patch-aligned token map $f_i \in \mathbb{R}^{h\times w\times d}$ for each image, where $h = H/s$, $w = W/s$, and d is the latent dimension.

We then add positional embeddings (p.e.) to the tokens, enabling the following model to be aware of the spatial location and the corresponding image index of each token. Specifically, we combine the sinusoidal spatial p.e. [16] and the sinusoidal image index p.e. [3] using a linear layer; note that the image index p.e. is shared among all tokens from the same image. When training on continuous video frames, these image index embeddings also encode sequential priors, which benefits pose estimation. Finally, we reshape the token maps of all images into a set, denoted as $\mathbf{f} \in \mathbb{R}^{Khw\times d}$ (recall that the transformer is invariant to the permutation of tokens). For brevity, we will use this notation for latent token sets throughout the rest of the paper.

Camera Estimator. The camera estimator $\mathcal{E}_{cam}$ predicts camera parameters, *i.e.*, camera poses and intrinsics, for all input images. We use a learnable camera token in $\mathbb{R}^{1\times d}$ as the initial feature for this prediction for all views. We repeat the token K times and add them with image index p.e. such that they correspond to the K images. We denote this camera feature initialization as $\mathbf{p} \in \mathbb{R}^{K\times d}$. We then use the camera estimator composed of full self-attention transformer layers to update the camera tokens, as:

$$\{\mathbf{f}^*, \mathbf{p}^*\} = \mathcal{E}_{cam}(\{\mathbf{f}, \mathbf{p}\}), \tag{2}$$

where $\{\cdot, \cdot\}$ denotes concatenation along the token dimension (the union set of two token sets), and $\mathbf{f}^*$ and $\mathbf{p}^*$ are the updated tokens. We note that $\mathbf{f}^*$ is not used for the following computation – it is only used as context to update $\mathbf{p}$ in the transformer layers. For clarity, we formulate the transformer layers as follows:

$$\mathbf{y}^0 = \{\mathbf{f}, \mathbf{p}\}, \tag{3}$$

$$\mathbf{y}^l = \mathrm{TransformerLayer}^l(\mathbf{y}^{l-1}),\ l = 1, ..., l_T \tag{4}$$

$$\{\mathbf{f}^*, \mathbf{p}^*\} = \mathrm{split}(\mathbf{y}^{l_T}), \tag{5}$$

where l_T is the number of layers, and the split operation recovers the two token sets, inverting Eq. 3. This notation remains consistent throughout the rest of the paper.

We then predict the camera parameters for each image independently. For camera pose prediction, we follow prior works of using relative camera poses to resolve ambiguity [28, 84]. We select one view as the canonical reference (*e.g.*, with identity rotation and zero translation), while for every non-canonical view, we predict its relative pose with respect to the canonical view. We parametrize the `SO(3)` rotation using a continuous 6D representation [92], and we predict the relative pose with a two-layer MLP as follows:

$$p_i = \text{MLP}_{pose}([\mathbf{p}_i^*, \mathbf{p}_c^*]), \tag{6}$$

where $[\cdot, \cdot]$ denotes concatenation along the feature dimension, $\mathbf{p}_i^*$ and $\mathbf{p}_c^*$ (all in $\mathbb{R}^d$) are the camera tokens for image I_i and the canonical view, respectively. The output $p_i \in \mathbb{R}^9$ represents the predicted pose parameters, which are then transformed into an `SE(3)` pose $\mathbf{P}_i$ for image I_i.

For intrinsics prediction, following prior works [22, 38], we parameterize intrinsics using a single focal length value, under the assumptions that i) the focal lengths along the x and y axes are identical, ii) all views share the same intrinsics, and iii) the principal point is at the image center. We predict the focal length using a two-layer MLP:

$$\text{focal} = \text{MLP}_{focal}(\mathbf{p}_c^*). \tag{7}$$

The predicted focal length is then converted into the intrinsics matrix $\mathbf{K} \in \mathbb{R}^{3\times3}$.

Scene Reconstructor. As discussed in Sec. 4.1, we predict the scene representation from image set $\mathcal{I_A}$ and additionally condition it on the previously predicted camera parameters $\mathcal{P_A} = \{(\mathbf{P}_i, \mathbf{K}) | I_i \in \mathcal{I_A}\}$. We first convert $\mathcal{P_A}$ to pixel-aligned Plücker rays [52] for each image, denoted as $\mathcal{R} \in \mathbb{R}^{K\times H\times W\times 6}$. Similar to image inputs, we also tokenize the Plücker rays into patch-level tokens using a linear layer, yielding $\mathbf{r} \in \mathbb{R}^{Khw\times d}$. We index the image and Plücker rays tokens corresponding to the image set $\mathcal{I_A}$, denoted as $\mathbf{f_A}$ and $\mathbf{r_A}$ (each in $\mathbb{R}^{K_\mathcal{A}hw\times d}$, respectively). We fuse these tokens along the feature dimension with a two-layer MLP:

$$\mathbf{x_A} = \text{MLP}_{fuse}([\mathbf{f_A}, \mathbf{r_A}]), \tag{8}$$

where $\mathbf{x_A} \in \mathbb{R}^{K_\mathcal{A}hw\times d}$ represents the fused tokens. Importantly, we use the raw image tokens $\mathbf{f}$ rather than the pose transformer output $\mathbf{f}^*$ for this fusion. This design choice prevents leakage of information from the image set $\mathcal{I_B}$, since the camera estimator transformer producing $\mathbf{f}^*$ has access to a global context that includes tokens from $\mathcal{I_B}$.

We then employ a scene reconstructor $\mathcal{E}_{scene}$ consisting of full self-attention transformer layers to predict the latent scene representation. To initialize this representation, we use a set of learnable tokens $\mathbf{z} \in \mathbb{R}^{L\times d}$, where L denotes the number of tokens. We formulate the process as follows:

$$\{\mathbf{z}^*, \mathbf{x}_\mathcal{A}^*\} = \mathcal{E}_{scene}(\{\mathbf{z}, \mathbf{x_A}\}). \tag{9}$$

The update rule is identical to the transformer layers in the camera estimator $\mathcal{E}_{cam}$. Here, $\mathbf{z}^*$ represents the final latent scene representation predicted from $\mathcal{I_A}$. Meanwhile, $\mathbf{x}_\mathcal{A}^*$ is discarded.

Rendering Decoder. We first define the rendering decoder and then describe its training usage.

We use a transformer-based decoder with full self-attention for rendering, following LVSM [30]. For a target image, we begin by representing it as pixel-aligned Plücker rays and tokenize these rays using a linear layer to obtain target tokens $\mathbf{r} \in \mathbb{R}^{hw\times d}$. Next, we fuse the scene information by updating the tokens with a decoder $\mathcal{D}_{render}$ comprising transformer layers:

$$\{\mathbf{r}^*, \mathbf{z}'\} = \mathcal{D}_{render}(\{\mathbf{r}, \mathbf{z}^*\}), \tag{10}$$

where $\mathbf{z}'$ is subsequently discarded, while the update rule of $\mathcal{D}_{render}$ is the same as previously introduced modules. Finally, we decode the RGB values at the patch level with an MLP:

$$\hat{I} = \text{MLP}_{rgb}(\mathbf{r}^*), \tag{11}$$

where $\hat{I} \in \mathbb{R}^{hw\times(3s^2)}$. We reshape $\hat{I}$ to recover the 2D spatial structure, yielding a final rendered image in $\mathbb{R}^{H\times W\times 3}$.

During training, we use the predicted Plücker ray maps $\mathcal{R_B}$, which correspond to $\hat{\mathcal{I}}_B$, to render images of $\hat{\mathcal{I}}_B$ and then compute the self-supervised loss as defined in Eq. 1.

5. Experiments

In this section, we introduce the experimental setting and present the evaluation results. For the implementation, RayZer employs 24 transformer layers, with 8 layers for each of the camera estimator, scene encoder, and rendering decoder. We train RayZer with a learning rate of 4×10^{-4} with a cosine scheduler for 50,000 iterations and a batch size of 256. The weight of perceptual loss is $\lambda = 0.2$. For all experiments, we used a resolution of 256 with a patch size of 16. More details are in the Appendix.

5.1. Experimental Setup

We introduce our experimental setup, including datasets, evaluation protocol and metrics, as well as baseline methods.

Datasets. We use three datasets to evaluate RayZer, including two scene-level datasets, DL3DV [45] and RealEstate [91], and an object-level dataset Objaverse [15] (rendered as videos). We train and test on each dataset separately. The numbers of input views ($\mathcal{I_A}$) and target views ($\mathcal{I_B}$) are set to 16 and 8 for DL3DV, 5 and 5 for RealEstate, and 12 and 8 for Objaverse, respectively. We sample input images with the index ranges of 64-96, 128-192, and 50-65 on DL3DV, RealEstate, and Objaverse, respectively. These values are chosen based on data difficulty, especially camera baseline, following prior works [9, 86, 93]. We use the offical DL3DV train-test split, and split RealEstate following [9]. More details can be found in the Appendix.

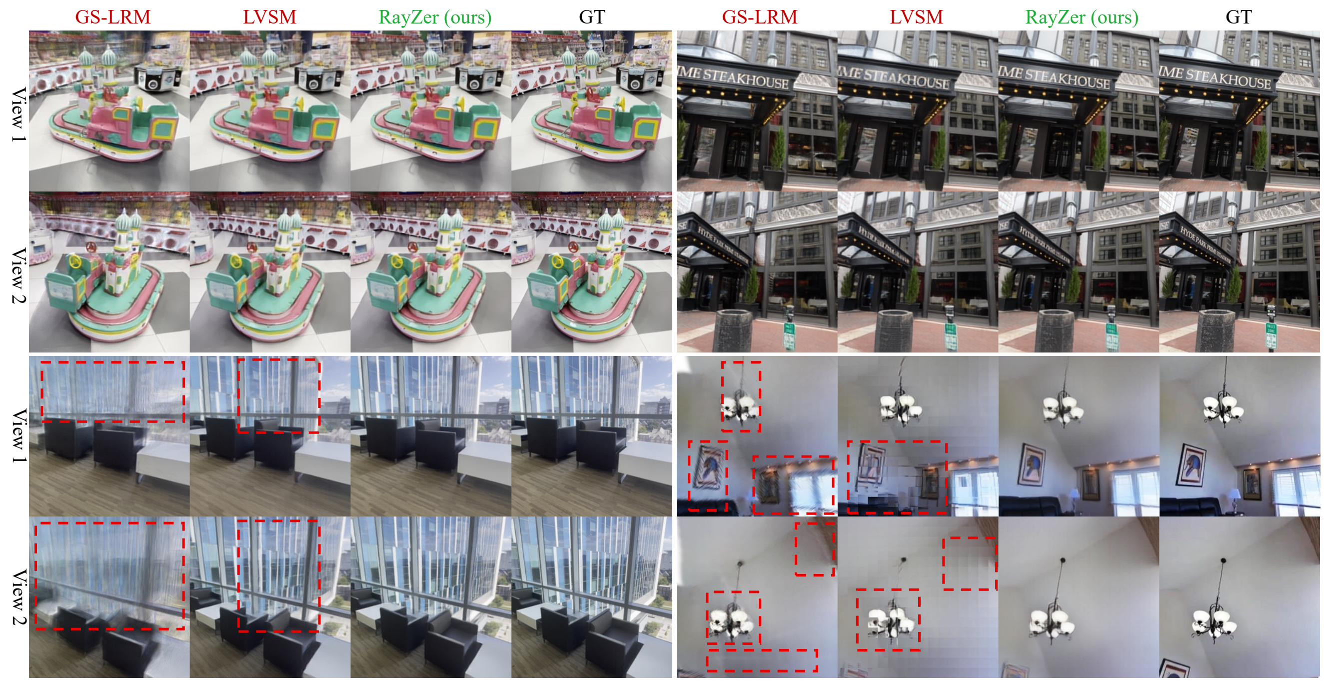

Figure 4. **Visualization results on RealEstate and DL3DV**. We compare RayZer with "oracle" methods GS-LRM and LVSM, which use COLMAP pose annotations in both training and testing. Our self-supervised RayZer model does not use any pose annotations. Generally, RayZer performs on par with "oracle" methods (first row), and can outperform them on cases that COLMAP usually struggles to handle, *e.g.*, glasses and white walls (highlighted with red boxes). The results verify our analysis on the problems of using COLMAP in Sec. 5.2.

Evaluation Protocol and Metrics. We evaluate novel view synthesis quality. Specifically, the evaluation protocol of RayZer is different from the "oracle" and supervised methods, which use ground-truth poses to render images. Instead, we use **predicted poses** to render novel views, thereby assessing the compatibility between the predicted poses and the scene representation. Since the model is trained without explicit pose annotations, the learned poses exist in a different space, and their direct correspondence to standard pose annotations is unknown. This evaluation protocol follows RUST [58]. We note that the target views are used only for pose estimation and not for scene representation prediction, ensuring that no information leakage occurs.

Baselines. We compare RayZer with two types of methods, including 1) **"oracle" methods**, *i.e.*, GS-LRM [86] and LVSM [30] (encoder-decoder version), that use ground-truth camera poses during **both** training (as supervision) and inference (as pre-requisite). LVSM also uses latent set scene representation. Thus, it serves as the main comparison for the "oracle" methods; 2) **supervised method**, *i.e.*, PF-LRM [69], which requires camera supervision to learn pose estimation and reconstruction; thus, it is pose-free during inference. For fair comparisons, we use 16 transformer layers in total for GS-LRM and LVSM. Thus, their number of parameters is the same as RayZer, except that RayZer has another camera estimator to handle unposed images. We use 24 transformer layers for PF-LRM. We also consider the self-supervised method RUST [58], but since it does not have an official public implementation, we ablate the key design differences between RUST and RayZer in Table 7 instead.

	Training Supervision	Inference w. COLMAP Cam.	Even Sample PSNR↑	Even Sample SSIM↑	Even Sample LPIPS↓	Random Sample PSNR↑	Random Sample SSIM↑	Random Sample LPIPS↓
"Oracle" methods (assume inputs are posed & use pose annotations during training)								
GS-LRM	2D + Camera	Yes	23.49	0.712	0.252	23.02	0.705	0.266
LVSM	2D + Camera	Yes	23.69	0.723	0.242	23.10	0.703	0.257
Unsupervised methods (inputs are un-posed & no pose annotations used during training)								
RayZer	2D	No	**24.36**	**0.757**	**0.209**	**23.72**	**0.733**	**0.222**

Table 1. **Evaluation results on DL3DV**. The camera annotations used by the "oracle" models come from **COLMAP**. The results are reported with continuous video frames (ordered) as the input. The results for the unordered image set input are in Table. 4. The input and target views can be evenly or randomly sampled from video frames. We bold our result if it is better than the "oracle" models.

5.2. Results

Main results. Table 1-3 summarizes the results on the three datasets. Remarkably, without any 3D labels (e.g., camera pose annotations) during training, RayZer achieves performance comparable to the best "oracle" model, LVSM. In fact, RayZer even outperforms LVSM on DL3DV and RealEstate10k while performing slightly worse on Objaverse. We conjecture that this is because the camera poses in DL3DV and RealEstate are annotated by COLMAP, which can be imperfect and set an upper bound for "oracle" methods that are supervised by COLMAP annotations. In contrast, our self-supervised approach enables the model to learn a

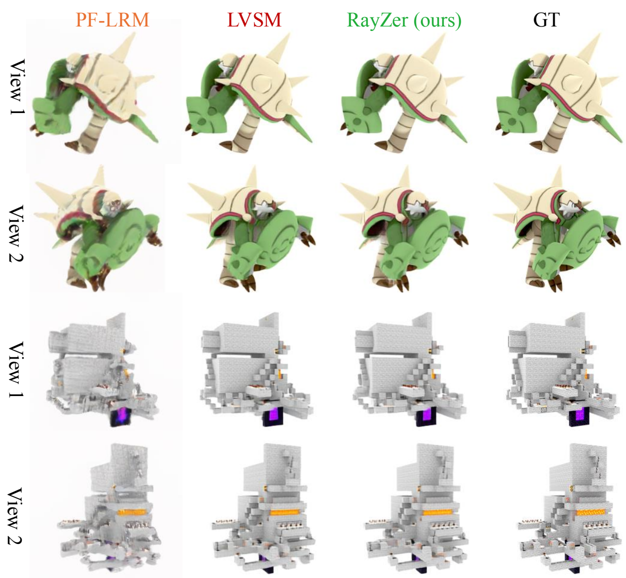

Figure 5. **Visualization results on Objaverse**. RayZer performs on par with LVSM and outperforms the supervised method PF-LRM.

	Training Supervision	Inference w. COLMAP Cam.	Even Sample PSNR↑	SSIM↑	LPIPS↓	Random Sample PSNR↑	SSIM↑	LPIPS↓
"Oracle" methods (assume inputs are posed & use pose annotations during training)								
GS-LRM	2D + Camera	Yes	24.25	0.770	0.227	23.21	0.748	0.251
LVSM	2D + Camera	Yes	27.00	0.851	0.157	25.88	0.828	0.175
Unsupervised methods (inputs are un-posed & no pose annotations used during training)								
RayZer	2D	No	**27.48**	**0.861**	**0.146**	**26.32**	**0.835**	**0.164**

Table 2. **Evaluation results on RealEstate** with continuous video frames inputs. The camera annotations come from **COLMAP**.

pose space that optimally benefits latent reconstruction and novel view synthesis. This hypothesis is further supported by the results on Objaverse – a synthetic dataset with perfect pose annotations from the rendering tool – where LVSM, acting as a true oracle, outperforms RayZer. Nonetheless, the small performance gap showcases the effectiveness of our self-supervised training. Visualizations in Fig. 4 further support our conjecture regarding COLMAP's noisy poses, as both LVSM and GS-LRM consistently underperform on challenging cases that COLMAP usually fails. These results not only validate our self-supervised learning approach but also demonstrate its potential to break free from the limitations of supervised learning.

Using unordered image sets for training. RayZer can be trained on continuous video frames (Table 1-3) or unordered image sets (Table 4). Note that these two training settings are applied separately. As shown in Table 4, we observe that the model trained with unordered image sets performs worse than the one trained with continuous video frames. We notice that the difference is at the pose estimation stage – specifically, the image index positional embedding encourages local pose smoothness that benefits the learning of pose estimation on continuous frames. This finding suggests that scaling training data using video resources, which are plentiful online, could be more advantageous than relying

	Training Supervision	Inference w. GT Cam.	Even Sample PSNR↑	SSIM↑	LPIPS↓	Random Sample PSNR↑	SSIM↑	LPIPS↓
"Oracle" methods (assume inputs are posed & use pose annotations during training)								
LVSM	2D + GT Cam.	Yes	32.34	0.950	0.050	32.34	0.949	0.051
Supervised methods (inputs are un-posed & use pose annotations during training)								
PF-LRM	2D + GT Cam.	Yes (render)	25.48	0.882	0.110	25.43	0.881	0.111
Unsupervised methods (inputs are un-posed & no pose annotations used during training)								
RayZer	2D	No	31.52	0.945	0.052	31.42	0.943	0.053

Table 3. **Evaluation results on Objaverse** with continuous video frames inputs. The camera annotations are Blender ground-truth. PF-LRM uses ground-truth poses to render novel views, same with oracle methods, and we evaluate its predicted pose in Table 5.

	Training Supervision	Inf. w. GT Pose	Continuous Inputs	Even Sample PSNR↑	SSIM↑	LPIPS↓	Random Sample PSNR↑	SSIM↑	LPIPS↓
(1)	2D	No	✓	24.36	0.757	0.209	23.72	0.733	0.222
(2)	2D	No	✗	20.56	0.576	0.334	20.02	0.566	0.356

Table 4. **Evaluating RayZer performance when using continuous or unordered images for training** on DL3DV. In evaluations, the input frames are sampled from continuous video frames. (1) keeps their temporal continuity (encoded by the image index p.e.) during training. (2) randomly shuffles the images during training.

on unordered image sets that are often limited in scale and contain noisy content [41, 68].

5.3. Analysis of Camera Poses

RayZer's learned camera pose space. We visualize some camera poses predicted by RayZer in Fig. 6. Although RayZer predicts `SE(3)` camera poses, we observe that these poses do not exactly match the real-world pose space. This result indicates that the `SE(3)` poses, which are later converted into Plücker ray maps, offer a degree of flexibility. Since both the rendering decoder and the scene representation operate in latent space, RayZer remains robust to any warping between the learned pose space and the actual real-world poses, as long as the poses are compatible with the scene representation and the decoder.

3D Awareness of predicted camera poses. We further investigate whether the pose space learned by RayZer is 3D aware. To this end, we interpolate the predicted poses of input views to synthesize more novel views, where the camera pose of a novel view is interpolated from two neighboring input views. We use ground-truth camera poses to calculate the interpolation coefficients, checking whether predicted poses follow the same geometric interpolation rules. We include the details of the interpolation method in Appendix. As shown in Table 5, RayZer demonstrates significantly better performance than PF-LRM and the naive baseline of copying the nearest rendered input view. These results verify that poses predicted by RayZer are interpolatable and 3D-aware.

Probing the learned camera pose space. To probe how much actual pose information is learned by RayZer, we follow RUST [58] to fit a lightweight 2-layer MLP head on the pose features. We freeze the camera estimator's transformers and train the MLP under camera supervision. As shown in Table 6, our probing outperforms the supervised baseline (which has the same model architecture and uses

	Training Supervision	Inference w. GT Pose	Even Sample PSNR↑	SSIM↑	LPIPS↓	Random Sample PSNR↑	SSIM↑	LPIPS↓
Supervised methods (inputs are un-posed & use pose annotations during training)								
PF-LRM	2D + GT Pose	No	20.63	0.819	0.160	21.27	0.827	0.154
Unsupervised methods (inputs are un-posed & no pose annotations used during training)								
RayZer-copy	2D	No	19.56	0.812	0.159	20.17	0.820	0.150
RayZer	2D	No	**27.01**	**0.900**	**0.075**	**26.87**	**0.896**	**0.078**

Table 5. **Evaluating 3D awareness of predicted camera poses** on Objaverse. Unlike Table 3, here we render novel views by interpolating predicted poses of input views, where the interpolation coefficients are calculated from GT poses. This experiment tests whether the learned `SE(3)` poses are geometrically well-defined and 3D-aware. We also compare against a naive baseline "RayZer-copy" that simply copies the nearest rendered input view.

transformers trained from scratch), indicating that RayZer's novel view synthesis self-supervision facilitates a better latent pose space. In contrast, supervised learning struggles due to the challenges of low-dimensional pose representation [5, 11, 40, 85, 92].

5.4. Ablation Study

We ablate the main design choices of RayZer from three aspects, including scene representation, 3D prior, and the overall model paradigm. As shown in Table 7 (1), when using the 3DGS representation rather than the latent set representation, the training does not converge. This verifies the optimization difficulty of explicit 3D representation [37, 86] and demonstrates the flexibility of the latent representation with its learned rendering decoder.

Table 7 (2) and (3) ablate the prior of camera representation. Without Plücker ray maps, we observe a degraded performance in (2), showing the effectiveness of using Plücker ray maps to regularize the solution of structure-and-motion problem. Besides, we observe a slightly better performance of (3), which directly uses camera tokens $\mathbf{p}^*$, compared to (2). The reason is that the camera tokens $\mathbf{p}^* \in \mathbb{R}^d$ can leak target image information, while `SE(3)` poses used in (2) serve as an information bottleneck to enforce this disentanglement. Moreover, `SE(3)` poses are geometrically well-defined, allowing us to interpolate them and generate novel views along the interpolated camera trajectory, while the latent camera representation is not directly interpolable.

Table 7 (4) ablates the overall paradigm. When the model first predicts the latent scene and then estimates poses, we observe a degraded performance. In detail, the pose estimator takes the scene representation and target image feature tokens as inputs. The result verifies our insight that pose estimation can be a strong condition for scene reconstruction, championing traditional pose-first methods in the context of self-supervised learning. Note that combining (3) and (4) will be a model that is similar to RUST conceptually.

6. Conclusion

We introduce RayZer, a self-supervised large multi-view 3D Vision model trained with zero 3D supervision, *i.e*., no 3D geometry and camera annotations. RayZer achieves comparable or even better novel view synthesis performance than prior works that use pose labels in both training and inference, verifying the feasibility of breaking free from supervised learning.

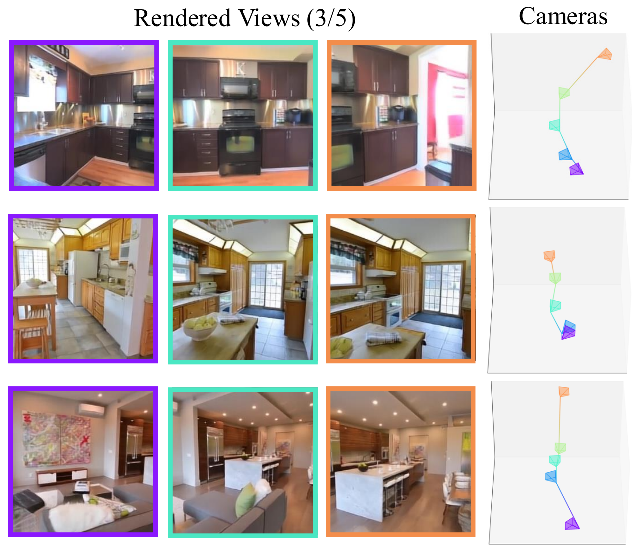

Figure 6. **Visualization of RayZer predicted cameras learned with self-supervision**. We visualize 3 out of 5 rendered views due to space limit, where the image index is highlighted by its color.

	Pose Encoder ($\mathcal{E}_{pose}$)	*Rotation Acc.*↑ *(%)* R@10°	R@20°	R@30°	*Translation Acc.*↑ *(%)* t@0.1	t@0.2	t@0.3
DL3DV	supervised	39.3	63.0	77.8	15.7	33.1	44.4
	self-supervised	**47.6**	**72.5**	**84.0**	**20.8**	**44.0**	**60.5**
RealEstate	supervised	87.0	96.4	99.6	44.6	59.3	82.5
	self-supervised	**99.6**	**99.9**	**100**	**61.2**	**84.2**	**92.8**
Objaverse	supervised	19.8	46.7	66.0	15.1	37.2	53.8
	self-supervised	**33.6**	**69.2**	**86.8**	**20.1**	**52.7**	**75.5**

Table 6. **Effectiveness of self-supervised pre-training for pose estimation**. We train a two-layer MLP (with supervised learning) to read out latent camera tokens $\mathbf{p}^*$ predicted by the pose encoder $\mathcal{E}_{pose}$, where the backbone is frozen. At the same time, we also compare with the baseline where both encoder $\mathcal{E}_{pose}$ and the pose prediction MLP are trained with supervised learning from scratch.

		Even Sample PSNR	SSIM	LPIPS	Random Sample PSNR	SSIM	LPIPS
(0)	RayZer	**24.36**	**0.757**	**0.209**	**23.72**	**0.733**	**0.222**
(1)	**Representation** - 3DGS + rasterization	–	–	failed		–	–
(2)	**Prior** - no Plücker ray, use `SE(3)` pose	22.73	0.687	0.249	21.88	0.647	0.274
(3)	**Prior** - no explicit pose, use latent camera	23.13	0.700	0.251	22.36	0.668	0.272
(4)	**Paradigm** - scene first, not pose first	13.31	0.338	0.732	13.12	0.337	0.729

Table 7. **Ablation study of RayZer designs** on DL3DV with continuous inputs. (1) is a variant uses the 3D Gaussian representation rather than latent scene representation with its learned rendering decoder used by RayZer; (2) does not use Plücker ray maps $\mathcal{R}_{\mathcal{A}}$ for conditioning latent reconstruction. Instead, it encodes the `SE(3)` poses $\mathbf{P}_{\mathcal{A}}$ and intrinsics $\mathbf{K}$ into tokens as condition; (3) directly uses the latent camera tokens $\mathbf{p}^*$, rather than converting it to any explicit forms of cameras, to condition the latent scene reconstruction; (4) first reconstructs latent scene and then estimates pose as Plücker ray maps, contrasting our pose-first paradigm.

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