

# RelightAnyone: A Generalized Relightable 3D Gaussian Head Model

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Figure 1. We present RelightAnyone, a method for reconstructing and relighting head avatars from multi-view (top row) or single images in-the-wild (bottom row), trained on a limited dataset of multi-view OLAT faces and larger datasets of multi-view flat-lit faces.

## Abstract

3D Gaussian Splatting (3DGS) has become a standard approach to reconstruct and render photorealistic 3D head avatars. A major challenge is to relight the avatars to match any scene illumination. For high quality relighting, existing methods require subjects to be captured under complex time-multiplexed illumination, such as one-light-at-a-time (OLAT). We propose a new generalized relightable 3D Gaussian head model that can relight any subject observed in a single- or multi-view images without requiring OLAT data for that subject. Our core idea is to learn a mapping from flat-lit 3DGS avatars to corresponding relightable Gaussian parameters for that avatar. Our model consists of two stages: a first stage that models flat-lit 3DGS avatars without OLAT lighting, and a second stage that learns the mapping to physically-based reflectance parameters for high-quality relighting. This two-stage design allows us to train the first stage across diverse existing multi-view datasets without OLAT lighting ensuring cross-subject generalization, where we learn a dataset-specific lighting code for self-supervised lighting alignment. Subsequently, the second stage can be trained on a significantly smaller dataset of subjects captured under OLAT illumination. Together, this allows our method to generalize well and relight any subject from the first stage as if we had captured them under OLAT lighting. Furthermore, we can fit our model to unseen subjects from as little as a single image, allowing several applications in novel view synthesis and relighting for digital avatars.

## 1. Introduction

For decades, researchers have strived to create photorealistic digital head avatars from images of real people. With the recent introduction of 3D Gaussian Splatting (3DGS) [27], the problem has become easier. 3DGS allows efficient scene reconstruction from multiple views, and then real-time rendering from any novel angle. As such, by now there are several methods [1, 55, 72, 81] for reconstructing and animating 3D avatars using 3DGS.

A main challenge that prevents the widespread use of 3DGS for deploying digital avatars across diverse virtual environments is the lack of disentanglement of human facial reflectance from scene illumination. Such avatars require the ability to decompose the illumination into a subject-specific albedo, together with diffuse and specular reflection parameters, to enable efficient relighting, allowing us to place the avatar into any virtual environment. The seminal work of Debevec *et al.* [10] demonstrates that faces captured under an OLAT lighting condition within a light stage enable high quality physically accurate face reflectance modeling that is fit for relighting. Recent works like *Relightable Gaussian Codec Avatars (RGCA)* [64] leverage OLAT-based captures and extend 3DGS with parameters separating surface material from scene illumination to achieve efficient 3D avatar relighting. Specifically, a model is trained to predict the extended 3DGS parameters in the texture-space of a coarse template mesh. The prediction includes learned radiance transfer functions (*e.g.* diffuse color, specular roughness, normals, etc.) so that the avatar can be relit under desired en-

vironment lighting. While results are impressive, the learned avatars are person-specific; each new subject requires another lightstage capture and model retraining, which is both labor- and compute-intensive.

Similar to URAvatar [35], in this work we aim to generalize this approach to allow relighting of anyone, not captured under time-multiplexed illumination. However, URAvatar heavily relies on capturing a large number of diverse subjects under OLAT lighting for training their prior model. Unfortunately, building such a large OLAT datasets is very expensive and time-consuming. On the other hand, capturing subjects under fixed lighting is much easier and a significant number of diverse identities are already available in multi-view flat-lit human head datasets (*e.g.* Ava-256 [42], Nersemble [30]). Our core idea is to leverage existing flat-lit datasets for identity generalization, together with a comparably smaller amount of public OLAT data [60] for relighting.

Specifically, we accomplish this by learning a mapping from fixed, flat-lit 3DGS avatars to the corresponding relightable RGCA parameters. Our model consists of two stages. In the first stage, we train a network to predict a 3DGS avatar under fixed lighting, conditioned on the subject identity. This includes an MLP to predict the coarse mesh shape, and CNNs to predict Gaussian parameters in texture space. We train this network on several different fixed-lighting datasets to ensure generalization to new identities. However, each dataset comes with the challenge that it has different illumination conditions and camera parameters. Thus, learning a uniform neutral color space for relighting is hard. Therefore, we propose a learned dataset-specific lighting code, which we optimize via our self-supervised lighting alignment. In a second stage, we then introduce a UNet to map from flat-lit 3DGS parameters to RGCA parameters for relighting. Importantly, we show that this second network can be trained on a comparably smaller OLAT dataset while not compromising identity generalization.

Once trained, our method allows several applications for generalized avatar reconstruction and relighting. First, we can trivially relight any subject seen in the fixed-lighting datasets, leading to the interesting application of creating synthetic OLAT renders and expanding existing fixed-light datasets to OLAT datasets. Second, we can fit our model to unseen subjects under unseen lighting conditions. We demonstrate fitting and relighting subjects from as little as a single input image in the wild, yielding a powerful approach to build avatars that can be relit and rendered from any novel view. In summary, our main contributions are:

- A relightable and generalizable Gaussian head model with a novel two-stage pipeline enabling unified training across diverse multi-view datasets, both flat-lit and with OLAT lighting.
- A method for self-supervised lighting alignment across

flat-lit multi-view head avatar datasets, through the introduction of a learnable dataset-specific lighting code.

- A relighting network for mapping Gaussian colors under full-on lights to relightable Gaussian parameters.
- A fitting approach that allows our model to be fitted to multi-view images or a single portrait photo in the wild, yielding high quality relightable 3DGS head avatars.

## 2. Related Work

We first outline relevant work on 2D relighting, which is typically constrained to the original camera view. We then review methods more closely related to ours that address 3D human face relighting.

**2D Relighting.** Portrait relighting has been a long-standing research topic, with early methods primarily relying on deep convolutional architectures. While initial works implicitly learned the relighting process in a black-box manner [46, 69], later methods moved toward more explicit, physics-based designs, incorporating image intrinsics and reflectance models directly into their architectures [24, 29, 43, 50, 51, 76]. To address the challenge of acquiring large-scale light stage data, alternative solutions were proposed, such as reducing hardware requirements [67] or using synthetic data [86].

More recently, the paradigm of 2D relighting has shifted towards generative methods, leveraging the success of image [12, 63] and video [5, 6, 19, 68] diffusion models. These new approaches have been applied to portrait and scene relighting [23, 31, 45, 52, 53, 87], as well as related tasks such as illumination harmonization [61, 89] and general inverse rendering [22, 36]. While harmonization methods like IC-Light [89] excel at matching a foreground to a background, they generally lack mechanisms for fine-grained, explicit lighting control via HDRI maps. Furthermore, general-purpose inverse rendering methods, such as DiffusionRenderer [36], often fail to model the complex and unique reflectance of human skin, resulting in unrealistic material properties when applied to portraits.

**3D Face Relighting.** Beyond image-to-image translation, a significant body of work has focused on 3D relighting, which enables simultaneous relighting and novel-view synthesis. Traditional methods capture the precise skin geometry and reflectance of a subject under complex, calibrated hardware, which is then used to create a high-fidelity, relightable avatar for that specific person [10, 16–18, 41, 62, 77, 78]. This high-quality capture data has also been used to train person-specific neural representations. Early neural methods focused on learning relightable textures on 3D meshes [4, 47, 91], while more recent works have adopted volumetric representations based on Neural Radiance Fields [48, 49, 65, 79], Mixtures of Volumetric

Primitives [39, 80, 83], or 3DGS [27, 64, 66]. A state-of-the-art example in this domain is RGCA [64], which achieves exceptionally high-quality results by introducing a learnable radiance transfer for 3D Gaussians, enabling real-time relighting with all-frequency reflections.

To bypass the need for expensive light stages, many works have investigated more accessible, light-weight setups. These approaches vary in their hardware requirements, from desktop setups [34], to setups using co-located light and cameras [2, 20]. Others use the sun as a dominant point source [74], or create avatars from simple monocular inputs [3, 13, 56, 82, 88]. Although more accessible, these in-the-wild optimization techniques still struggle to match the relighting fidelity of avatars captured in a light stage.

This quality gap, combined with the inherently ill-posed nature of these in-the-wild captures, motivated the development of generalized methods that learn a strong generative prior from large-scale datasets. One common approach is to learn intrinsic skin properties (*e.g.*, surface normals, albedo, roughness) [14, 15, 21, 32, 33, 37]. However, this approach is often limited to the skin and is difficult to unify across the entire head. Another popular approach is to leverage 3D-aware GANs, such as EG3D [8] as a prior to synthesize relightable faces [11, 25, 40, 44, 57, 59, 60, 71]. However, since these methods are often trained on only 2D portrait collections, their learned 3D geometry is often incomplete and lacks texture on the back of the head, leading to unrealistic or artifact-filled novel-view synthesis for non-frontal poses. A different line of work achieves better 3D consistency by learning generalizable volumetric representations from multi-view datasets [35, 58, 70, 84]. Closest to ours, URAvatar [35] builds upon RGCA, but it requires a large-scale, difficult-to-acquire dataset with multi-view OLAT capture for every subject. In contrast, our specially designed two-stage pipeline bypasses this data-acquisition bottleneck. We leverage existing, more common multi-view flat-lit datasets [9, 30, 42] supplemented by only a small OLAT dataset [60]. Furthermore, URAvatar requires an unwrapped albedo texture for identity conditioning, which is non-trivial to obtain, especially in in-the-wild scenarios, and unwrapping can fail when only a single image is available.

### 3. Method

We first review RGCA [64] in Section 3.1. We then detail our proposed two-stage pipeline in Section 3.2 and, finally, describe fitting to unseen identities in Section 3.3.

#### 3.1. Preliminary: RGCA

A 3D Gaussian is parameterized by a translation vector  $\mathbf{t}_k \in \mathbb{R}^3$ , a unit quaternion  $\mathbf{q}_k \in \mathbb{R}^4$ , scale factors  $\mathbf{s}_k \in \mathbb{R}_+^3$ , an opacity value  $o_k \in [0, 1]$ , and a color  $\mathbf{c}_k \in \mathbb{R}_+^3$ . To make 3D Gaussians relightable, the color is parameterized to interact with incident lighting. More specifically, in RGCA [64], the

Gaussian color is computed as the sum of a diffuse color  $\mathbf{c}_k^{\text{diffuse}}$  and a specular color  $\mathbf{c}_k^{\text{specular}}$ . The diffuse color is computed as

$$\mathbf{c}_k^{\text{diffuse}} = \rho_k \odot \sum_{i=1}^{(n+1)^2} \mathbf{L}_i \odot \mathbf{d}_k^i \quad (1)$$

where  $\rho_k \in \mathbb{R}_+^3$  is the diffuse albedo.  $\mathbf{L} = \{\mathbf{L}_i\}$  and  $\mathbf{d}_k = \{\mathbf{d}_k^i\}$  are the  $n$ -th order spherical harmonics (SH) coefficients of the incident light and intrinsic radiance transfer function (where  $\mathbf{d}_k^i \in \mathbb{R}^3$ ), respectively. The specular reflection is represented as a spherical Gaussian  $G_s(\boldsymbol{\omega}; \mathbf{a}_k, \sigma_k)$ , defined by the lobe  $\mathbf{a}$  and roughness  $\sigma_k \in (0, 1)$ . The final specular color from the viewing direction  $\boldsymbol{\omega}_k^o$  is then calculated as:

$$\mathbf{c}_k^{\text{specular}}(\boldsymbol{\omega}_k^o) = v_k(\boldsymbol{\omega}_k^o) \int_{\mathbb{S}^2} \mathbf{L}(\boldsymbol{\omega}) G_s(\boldsymbol{\omega}; \mathbf{a}_k, \sigma_k) d\boldsymbol{\omega} \quad (2)$$

$$\mathbf{a}_k = 2(\boldsymbol{\omega}_k^o \cdot \mathbf{n}_k) \mathbf{n}_k - \boldsymbol{\omega}_k^o \quad (3)$$

where  $v_k \in (0, 1)$  is a view-dependent visibility term, and  $\mathbf{n}_k$  is a view-dependent specular normal. The integral in Eq. 2 can be efficiently evaluated for point sources represented with Dirac delta functions, or for prefiltered environment maps [26]. In summary, a non-relightable 3D Gaussian under full-on lighting  $\mathbf{g}_k^f$ , and its relightable counterpart  $\mathbf{g}_k^r$  can be denoted as:

$$\mathbf{g}_k^f = \{\mathbf{t}_k, \mathbf{q}_k, \mathbf{s}_k, o_k, \mathbf{c}_k^f\} \quad (4)$$

$$\mathbf{g}_k^r = \{\mathbf{t}_k, \mathbf{q}_k, \mathbf{s}_k, o_k, \rho_k, \mathbf{d}_k, \sigma_k, v_k, \mathbf{n}_k\} \quad (5)$$

#### 3.2. RelightAnyone

As shown in Fig. 2, our two-stage pipeline first learns a multi-identity Gaussian avatar model under full-on lighting from different datasets (Stage 1). A subsequent Stage 2 relighting network then maps full-on Gaussian colors to relightable RGCA parameters. The network and training details are described below; please refer to the supplementary material for further implementation details.

**Stage 1: Multi-Identity Full-On Model.** Our Stage 1 architecture differs from RGCA by utilizing a learnable identity code  $\mathbf{z}_{\text{id}} \in \mathbb{R}^{256}$  and a low-dimensional, dataset-specific lighting code  $\mathbf{z}_l \in \mathbb{R}^4$ . More specifically, it is composed of three decoders: a mesh decoder  $\mathcal{D}_{\text{mesh}}$ , a decoder  $\mathcal{D}_g$  that outputs geometry-related Gaussian parameters, and a Gaussian color decoder  $\mathcal{D}_c$ .  $\mathcal{D}_{\text{mesh}}$  is implemented as a multilayer perceptron. Both  $\mathcal{D}_g$  and  $\mathcal{D}_c$  are 2D convolutional neural networks that decode 3D Gaussians in a shared UV texture map of a coarse template mesh. Formally, we have:

$$\mathbf{V} = \mathcal{D}_{\text{mesh}}(\mathbf{z}_{\text{id}}) \quad (6)$$

$$\{\delta \mathbf{t}_k, \mathbf{q}_k, \mathbf{s}_k, o_k\}_{k=1}^M = \mathcal{D}_g(\mathbf{z}_{\text{id}}) \quad (7)$$

$$\{\mathbf{c}_k^f\}_{k=1}^M = \mathcal{D}_c(\mathbf{z}_{\text{id}}, \mathbf{z}_l) \quad (8)$$

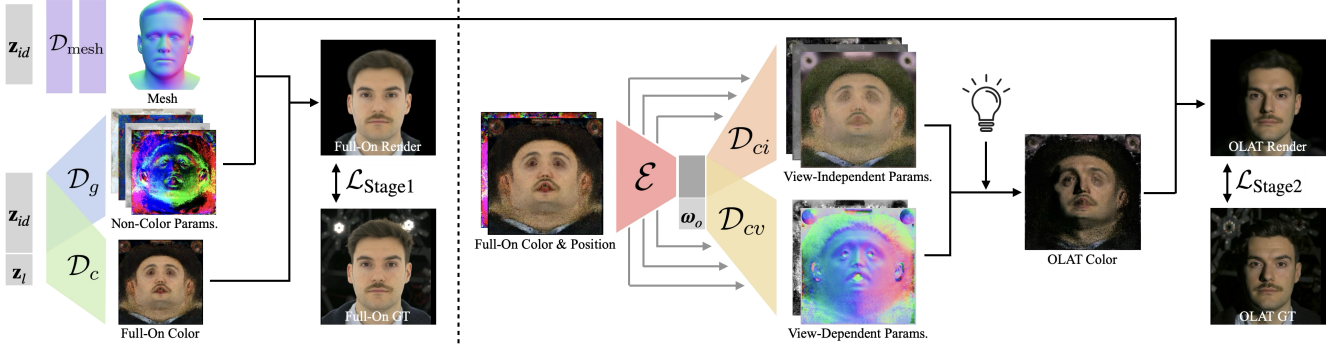


Figure 2. Pipeline of RelightAnyone: We first train a Stage 1 network that, given a learned subject identity code and a learned lighting code that distinguishes between different illuminations of different datasets, predicts a Gaussian avatar under full-on lighting, where the parameters of the Gaussian primitives are encoded in UV texture maps. Then, the Stage 2 relighting network maps the full-on Gaussian parameter textures from Stage 1 to RGCA parameters to allow for relighting of the avatar.

Here,  $\mathbf{V} \in \mathbb{R}^{5143 \times 3}$  represents the base mesh vertices.  $\delta \mathbf{t}_k$  denotes the position offset of the 3D Gaussian w.r.t. the base mesh. The final Gaussian position  $\mathbf{t}_k$  is computed as  $\mathbf{t}_k = \hat{\mathbf{t}}_k + \delta \mathbf{t}_k$ , where  $\hat{\mathbf{t}}_k$  is derived by applying barycentric interpolation to the vertices using the corresponding UV coordinates. We use  $M = 1024 \times 1024$  in all our experiments as the total number of Gaussians.

The lighting code  $\mathbf{z}_l$  is first concatenated with  $\mathbf{z}_{id}$  and fed into  $\mathcal{D}_c$  to disentangle dataset-specific illumination properties. Although our datasets are generally evenly-lit, the exact lighting distributions still differ.  $\mathbf{z}_l$  allows the network to separate this dataset-specific lighting impact from the canonical appearance of the subjects, leading to a “cleaner” and more structured identity latent space (Fig. 7). This disentanglement also enables us to transfer lighting between datasets by simply swapping their  $\mathbf{z}_l$  codes. This capability is essential because the Stage 2 relighting network is trained to map Gaussian colors to relightable parameters under one specific, full-on lighting condition corresponding to one dataset. Therefore, to use the relighting network, we must first generate the Gaussian colors  $\mathbf{c}_k^f$  under that exact full-on condition for which it was trained.

We train our Stage 1 model with an L1 and an SSIM loss on the rendered images, a geometry reconstruction loss, and a scale regularization term  $\mathcal{L}_s$ , in a manner similar to the original RGCA. We introduce another term  $\mathcal{L}_t$  that regularizes the Gaussian position offsets  $\delta \mathbf{t}_k$  to be small:

$$\mathcal{L}_{\text{Stage1}} = \lambda_{l1} \mathcal{L}_{l1} + \lambda_{\text{ssim}} \mathcal{L}_{\text{ssim}} + \lambda_{\text{geo}} \mathcal{L}_{\text{geo}} + \lambda_s \mathcal{L}_s + \lambda_t \mathcal{L}_t \quad (9)$$

**Stage 2: Relighting Network.** Our Stage 2 model is a UNet that translates Gaussian colors under full-on illumination to relightable Gaussian parameters. This UNet features a shared encoder  $\mathcal{E}$  and corresponding skip connections, which

feed into two distinct decoder branches: a view-independent decoder  $\mathcal{D}_{ci}$  and a view-dependent decoder  $\mathcal{D}_{cv}$ :

$$\{\rho_k, \mathbf{d}_k, \sigma_k\}_{k=1}^M = \mathcal{D}_{ci}(\mathcal{E}(\mathbf{c}_k^f, \mathbf{t}_k)) \quad (10)$$

$$\{v_k, \delta \mathbf{n}_k\}_{k=1}^M = \mathcal{D}_{cv}(\mathcal{E}(\mathbf{c}_k^f, \mathbf{t}_k), \omega_o) \quad (11)$$

Here,  $\omega_o$  is the viewing direction from the camera position to the center of the head mesh, and is concatenated to every pixel of the feature map at the network’s bottleneck. The normal residual  $\delta \mathbf{n}_k$  is added to the barycentric interpolated coarse mesh normal  $\hat{\mathbf{n}}_k$  to obtain the final normal  $\mathbf{n}_k$ :  $\mathbf{n}_k = (\hat{\mathbf{n}}_k + \delta \mathbf{n}_k) / \|\hat{\mathbf{n}}_k + \delta \mathbf{n}_k\|$ . Given any light conditions, these decoded RGCA parameters can then be used to compute the relit Gaussian colors by applying Eq. 1 and Eq. 2. To enable the network to learn shape-dependent shading variations, we concatenate the 3D Gaussian positions  $\mathbf{t}_k$  with full-on Gaussian colors, using this as three additional channels for the encoder’s input. This is needed because, for example, if two subjects have identical base colors under full-on lighting but possess different facial geometries, they should look different under the same point light due to effects like self-shadowing. To learn a meaningful mapping, the relighting network must be trained on subjects captured under diverse and known lighting conditions (*e.g.*, OLAT illuminations). However, calibrated multi-view *and* lighting setups are expensive, and, thus, only a few public datasets exist with limited number of identities. We therefore train our Stage 2 model after the Stage 1 model is trained, rather than using an end-to-end approach. This sequential method allows training on both flat-lit and OLAT datasets while also keeping the pre-trained identity prior of Stage 1 intact.

In RGCA, the albedo parameter  $\rho_k$  is not decoded by a network but is instead optimized jointly with the network parameters, starting from an initial mean texture. This approach is not feasible in our generalized case because we aim to predict the albedo for unseen subjects. However, allowing

the network to predict the albedo in an unconstrained manner leads to a non-meaningful decomposition of the albedo and shading parameters. We therefore introduce two regularization terms to mitigate this issue. The first term,  $\mathcal{L}_\rho$ , is an L2 loss that regularizes the predicted albedo, encouraging it to stay close to the mean texture computed under full-on lighting. The second term,  $\mathcal{L}_{\text{mono}}$ , encourages the diffuse SH coefficients  $\mathbf{d}_k$  to stay close to monochromatic:

$$\mathcal{L}_{\text{mono}} = \frac{1}{3} \sum_{i \in \{r, g, b\}} (\mathbf{d}_{ki} - \frac{\mathbf{d}_{kr} + \mathbf{d}_{kg} + \mathbf{d}_{kb}}{3})^2 \quad (12)$$

where  $\mathbf{d}_{kr}$ ,  $\mathbf{d}_{kg}$ , and  $\mathbf{d}_{kb}$  represent the RGB channels. The final loss function for Stage 2 training is then defined as:

$$\mathcal{L}_{\text{Stage2}} = \lambda_{l1} \mathcal{L}_{l1} + \lambda_{\text{ssim}} \mathcal{L}_{\text{ssim}} + \lambda_{c_-} \mathcal{L}_{c_-} + \lambda_n \mathcal{L}_n + \lambda_\rho \mathcal{L}_\rho + \lambda_{\text{mono}} \mathcal{L}_{\text{mono}} \quad (13)$$

where  $\mathcal{L}_{c_-}$  [64] penalizes negative colors in the diffuse term as SH can yield negative values and  $\mathcal{L}_n$  is an L2 loss regularizing the normal residual  $\delta \mathbf{n}_k$  to be small.

### 3.3. Model Fitting

Our model can be fitted to unseen identities from single image or multi-view images using a two-step optimization process, similar to previous avatar personalization works [7, 35, 73, 84]: first an inversion step to find an optimal identity code and scene lighting while keeping the networks frozen, followed by a finetuning step that updates the network parameters.

During the fitting process, the model is always executed as a full pipeline, combining Stage 1 and Stage 2, with the lighting code  $\mathbf{z}_l$  set to the value associated with the dataset containing the OLAT data used to train Stage 2. The final image is rendered from the relightable Gaussians predicted by Stage 2, rather than the intermediate full-on Gaussians from Stage 1. This is crucial because the scene lighting is unknown and must be optimized as part of the fitting.

**Inversion.** In the inversion step, we optimize the identity code and the scene lighting. We initialize  $\mathbf{z}_{\text{id}}$  as the mean of the learned training subject codes. The lighting is parameterized as the same set of fixed-position point lights used in training. We optimize an RGB-intensity for each point light. The loss for this step combines image and shape reconstruction losses, as well as a L2 regularizer on  $\mathbf{z}_{\text{id}}$ :

$$\mathcal{L}_{\text{fit}}^1 = \lambda_{l1} \mathcal{L}_{l1} + \lambda_{\text{ssim}} \mathcal{L}_{\text{ssim}} + \lambda_{\text{geo}} \mathcal{L}_{\text{geo}} + \lambda_{\text{id}} \|\mathbf{z}_{\text{id}}\|^2 \quad (14)$$

**Finetuning.** In the finetuning step, we further refine the Stage 1 network weights to capture person-specific details. We keep the Stage 2 network frozen to preserve the learned relighting prior. To prevent overfitting and maintain a plausible avatar structure, we incorporate an additional locality

regularization loss  $\mathcal{L}_{\text{lr}}$  [84], a technique proven effective for prior preservation:

$$\mathcal{L}_{\text{fit}}^2 = \mathcal{L}_{\text{fit}}^1 + \lambda_{\text{lr}} \mathcal{L}_{\text{lr}} \quad (15)$$

## 4. Experiments

We now present our experiments, starting with a discussion of the datasets we use for training, followed by an illustration of qualitative fitting and relighting results, an ablation study to validate our design choices, and finally comparisons to existing methods.

### 4.1. Datasets

A key component of our method is that we can train on various existing multi-view face datasets despite different camera and lighting configurations. For all our results, we use four datasets, as described below.

**D1 - 3DPR [60].** This is the one dataset with OLAT illumination, which we use to train Stage 2 of our pipeline. It consists of 40 cameras (we use 25 frontal cameras) and we processed the neutral expression for 127 subjects (116 for training and 11 for testing). The data contains 331 point lights, as well as fully-lit frames that we use to train Stage 1.

**D2 - Ava-256 [42].** Consisting of 80 cameras (we use 55 frontal cameras), lit from 360 degrees. We processed 240 subjects and use one neutral frame for each subject in Stage 1 training.

**D3 - SDFM [9].** Consisting of 8 cameras arranged as 4 stereo pairs (we omit the cross-polarized cameras), lit from 4 frontal flashes. We processed 151 subjects and use one neutral frame for each subject in Stage 1 training.

**D4 - Nersemble [30].** Consisting of 16 cameras, lit from 8 frontal flashes but has a light background that reflects light from behind. We processed 411 subjects and use one neutral frame from each subject in Stage 1 training.

Although some datasets come with tracked geometry, we run the VHAP face tracker [54, 55] for all the datasets to obtain meshes in the same topology, in the same canonical space. We then crop each frame based on the mesh projection in the image plane to  $1024 \times 1024$  resolution. We also compute a mask based on the mesh and matting [38, 85] to mask out the regions below the neck. Datasets D1, D3 and D4 provide color calibration but D2 does not. Therefore, we do a warmup run (2000 iterations) of the Stage 1 model without the lighting code  $\mathbf{z}_l$  but instead optimize a  $3 \times 3$  color matrix for D2, which we use afterwards to color calibrate the images in D2 and train again with the lighting code learning enabled.

### 4.2. Qualitative Results

Once trained, we can fit our model to unseen subjects to build 3D Gaussian head representations, and then relight those



Figure 3. Reconstruction and relighting examples from multi-view (rows 1-5) and single images in the wild (rows 6-7). From top to bottom, the first two subjects are from D2; subject 3 is from D3; subject 4 and 5 are from D4, and subject 6 and 7 are self-captured in-the-wild images. Our method can accurately reconstruct a detailed and multi-view stable Gaussian avatar in Stage 1 (column “Reconstruction”) that can be relit with arbitrary environment maps using Stage 2, even under harsh outdoor illumination. Images best viewed zoomed-in.

under any environment lighting. Several results are shown in Fig. 3. The first 5 rows show training subjects from the flat-lit datasets (D2, D3 and D4), where we perform fitting on all input views. The last 2 rows show fitting to single portrait images in the wild. In all cases, the reconstructed 3DGS head avatar has good 3D consistency under novel view rendering, and can be relit in any outdoor or indoor environment. Please see Fig. 1 for additional results. These fitting and relighting results show that our method generalizes to any identity, which is possible due to our two-stage pipeline designed to train across a variety of existing datasets, without the need for a large corpus of OLAT data.

We also show the ability of our network to separate albedo from reflectance parameters for an unseen subject in Fig. 4, illustrating the learned intrinsic decomposition of an in-the-wild image with unknown lighting.

### 4.3. Ablation

**Two-Stage vs. Single-Stage.** A straight-forward way to improve over RGCA for multi-identity relighting is to directly add an identity code and keep it single-stage. More specifically, this single-stage model shares a similar structure as our Stage 1 model but it replaces  $\mathcal{D}_c$  with two decoders  $\mathcal{D}'_{ci}$  and  $\mathcal{D}'_{cv}$  that directly predict relightable 3D Gaussian parameters:

$$\{\rho_k, \mathbf{d}_k, \sigma_k\}_{k=1}^M = \mathcal{D}'_{ci}(\mathbf{z}_{id}) \quad (16)$$

$$\{v_k, \delta \mathbf{n}_k\}_{k=1}^M = \mathcal{D}'_{cv}(\mathbf{z}_{id}, \boldsymbol{\omega}_o) \quad (17)$$

Note that this network design allows only training with OLAT datasets (*i.e.*, D1), and it is closer to what is done in other related work [35, 84] as they have larger OLAT datasets. We train this single-stage model with the same train-test split. For each test subject, we fit the trained model



Figure 4. For a single image of an unseen subject in-the-wild (a), our method predicts a Gaussian avatar (b) with an intrinsic decomposition into diffuse albedo (c), diffuse shading (d), specular component (e), and specular normals (f).

Table 1. Ablation of using two-stage vs. single-stage design with image metrics on the test subjects in D1.

	PSNR $\uparrow$	RMSE $\downarrow$	SSIM $\uparrow$	LPIPS $\downarrow$
Single-Stage	25.49	0.1092	0.76	0.2732
Two-Stage (Ours)	<b>30.06</b>	<b>0.0655</b>	<b>0.87</b>	<b>0.2358</b>

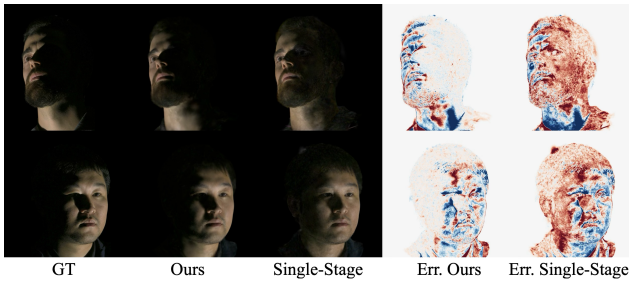


Figure 5. Ablation of the two-stage pipeline on the test subjects in D1 under OLAT lighting. The single-stage pipeline especially struggles in the shadowed areas. The render errors are in the range of  $-0.1$  to  $0.1$ . Images best viewed zoomed-in.

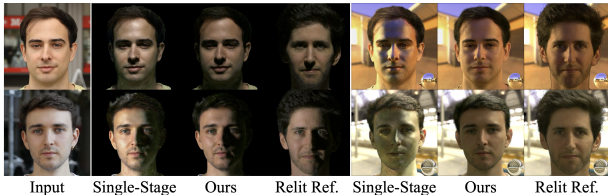


Figure 6. Ablation of the proposed two-stage pipeline vs. the single-stage pipeline on in-the-wild images. The single-stage pipeline struggles with preserving hard shadows which leads to severe artifacts in the environment relighting case.

on a fully-lit frame, and evaluate the relighting performance on the ground truth OLAT frames. Quantitative results are reported in Table 1, using image metrics including PSNR, RMSE, SSIM [75] and LPIPS [90]. We also show some examples with the corresponding error maps in Fig. 5. We notice that the single-stage model struggles in keeping hard shadows. We further demonstrate in Fig. 6 that when the lighting is unknown and must be optimized, the single-stage model fails entirely in keeping the learned relighting prior and produces obvious relit artifacts.



Figure 7. Ablation of the dataset-specific lighting code. Without  $z_l$ , the lighting differences in the datasets are entangled in the representation, leading to blotchy artifacts during re-lighting.

**Lighting Code  $z_l$ .** We now ablate the effect of incorporating the dataset-specific lighting code. The ablated model modifies  $\mathcal{D}_c$  to take only  $z_{id}$  as input. After training, we test the model by passing the full-on Gaussian textures of subjects from Stage 1 (who lack OLAT data, *i.e.*, from D2, D3, or D4) through Stage 2 to get their relit version. Note that relit ground truth is not available for these subjects. We therefore only show qualitative point light relit examples. Without  $z_l$ , the dataset-specific lighting impacts are entangled with the subjects' appearance. Because the relighting network is trained only on D1, passing subjects directly from D2, D3 or D4 results in blotchy artifacts in relit renders, as shown in Fig. 7. In contrast, with our model, we can align all datasets to D1 by swapping the lighting code before passing them through the relighting network, resulting in smooth and photo-realistic relit renders.

#### 4.4. Comparisons

We compare our method with generalized relighting methods that are based on 3D-aware GANs, as well as 2D diffusion-based methods. Unfortunately, the method closest to ours (*i.e.*, URAvatar [35]) has no code available.

**3D GAN-Based Methods.** We first compare with 3D GAN-based relighting methods: NeRFFaceLighting (NFL) [25], Lite2Relight [59], and a very recent state-of-the-art 3DPR [60]. We first report quantitative image metrics in Table 2, using the same test set as 3DPR and reuse their numbers from the original paper. Note that since some of the baselines cannot handle high-frequency relighting, we evaluate the relighting performance of the methods on the same set of low resolution ( $10 \times 20$ ) environment maps used in 3DPR. The ground truth relit results are generated with image-based

Table 2. Comparison against 3D GAN-based relighting methods on the test subjects in D1 with environment-map relighting.

	PSNR $\uparrow$	RMSE $\downarrow$	SSIM $\uparrow$	LPIPS $\downarrow$
NFL [25]	16.97	0.2926	0.77	0.2385
Lite2Relight [59]	16.72	0.2619	0.79	0.2506
3DPR [60]	21.02	0.1801	0.83	0.1996
Ours (single image)	26.57	0.0996	0.86	0.1671
Ours (multi-view)	<b>29.07</b>	<b>0.0746</b>	<b>0.91</b>	<b>0.1649</b>

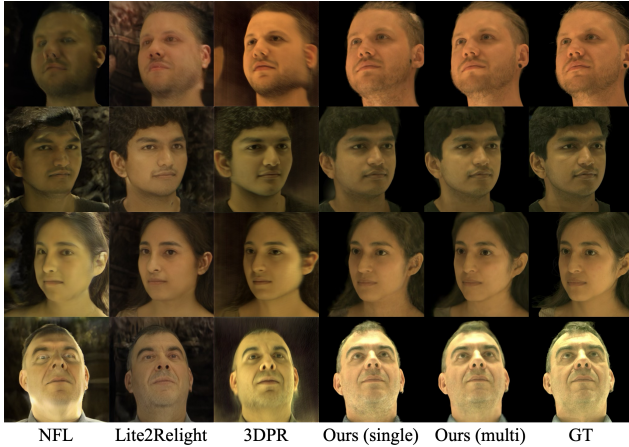


Figure 8. Examples from the comparison against 3D GAN-based relighting methods on test subjects in D1: Note how our proposed method matches the illumination of the ground truth most closely and preserves the most details.

relighting [10]. We show some image examples in Fig. 8. We also note two shared limitations of these 3D GAN-based methods: (1) The heads are distorted for non-frontal poses as these methods are trained on 2D portrait collections without enforcing explicit multi-view consistency. (2) They cannot fit to multi-view images. In contrast, we can fit to both multi-view and a single image of a person and are fully view consistent. Please refer to the supplementary material for novel view synthesis comparison.

**2D Diffusion-Based Methods.** We also compare against some recent diffusion-based techniques, IC-Light [89] and DiffusionRenderer [36]. Note that these are purely 2D relighting methods, which means they cannot generate novel views of a subject. This is already a limitation compared to ours. IC-Light (background-conditioned model) only learns to relight the foreground such that it matches with the provided background. It lacks a way for fine-grained lighting control such as using an HDRI map. In Fig. 9, we show frames from a sequence relit by a rotating environment map. IC-Light fails to capture the main light source and the relit results are incoherent across frames, also exhibiting an unnatural metallic sheen on the skin. DiffusionRenderer tackles relighting with an inverse rendering approach, first estimat-



Figure 9. Comparison with 2D diffusion-based methods on relighting an avatar with a rotating environment map. IC-Light relights the image based on the background and fails to match the main light. DiffusionRenderer estimates an overly-diffuse skin material.

ing the intrinsic material properties of the scene. However, the estimated skin reflectance tends to be overly diffuse, as shown in Fig. 9 and it also fails to render realistic shadows.

## 5. Conclusion

We present *RelightAnyone*, a new model for 3DGS head avatar reconstruction and relighting. Unlike previous methods, our approach is based on the unification of multiple existing multi-view face datasets. Our novel two-stage design allows us to train a flat-lit Gaussian reconstruction stage on datasets without OLAT illumination, followed by a mapping network that learns to infer physically-based relightable parameters for flat-lit avatars, trained on substantially less time-multiplexed OLAT data. This is possible due to our strategy for self-supervised lighting alignment across datasets. However, our model still has limitations. First, it struggles with hair reconstruction and relighting, primarily due to inaccuracies in tracked hair geometry and the difficulty of establishing reliable UV correspondences for hair strands. Future work could consider a separate model for hair and face, as in [28]. Second, our model is currently trained only on the neutral expression. Extending it to dynamic performances and capturing expression-dependent appearance would require a larger dataset with diverse expressions captured under both OLAT and fully-lit conditions. Nevertheless, we present a powerful model that can be fit to unseen subjects in unseen environments, from as little as a single image in-the-wild, with superior performance over previous state-of-the-art methods.

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