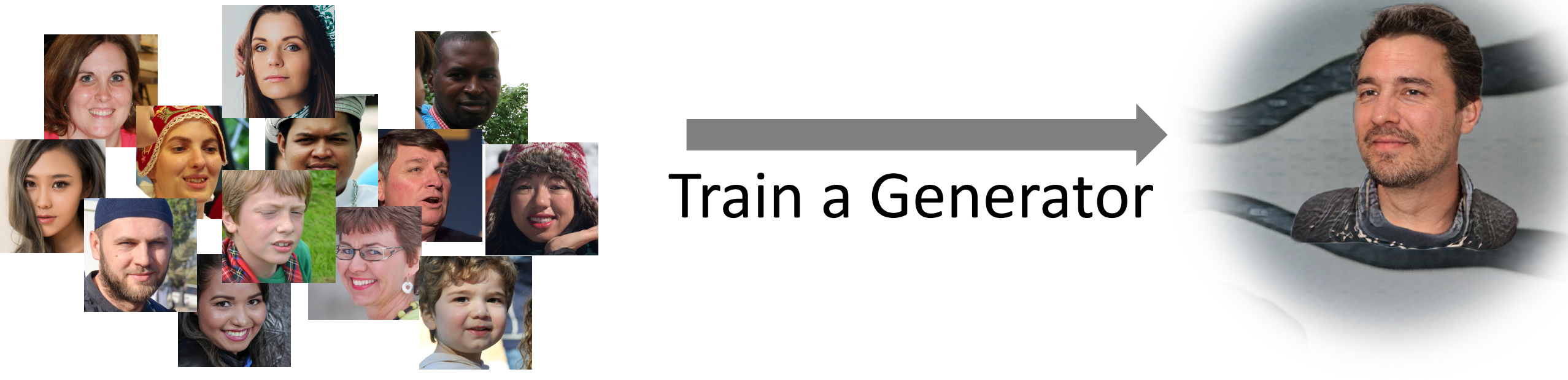


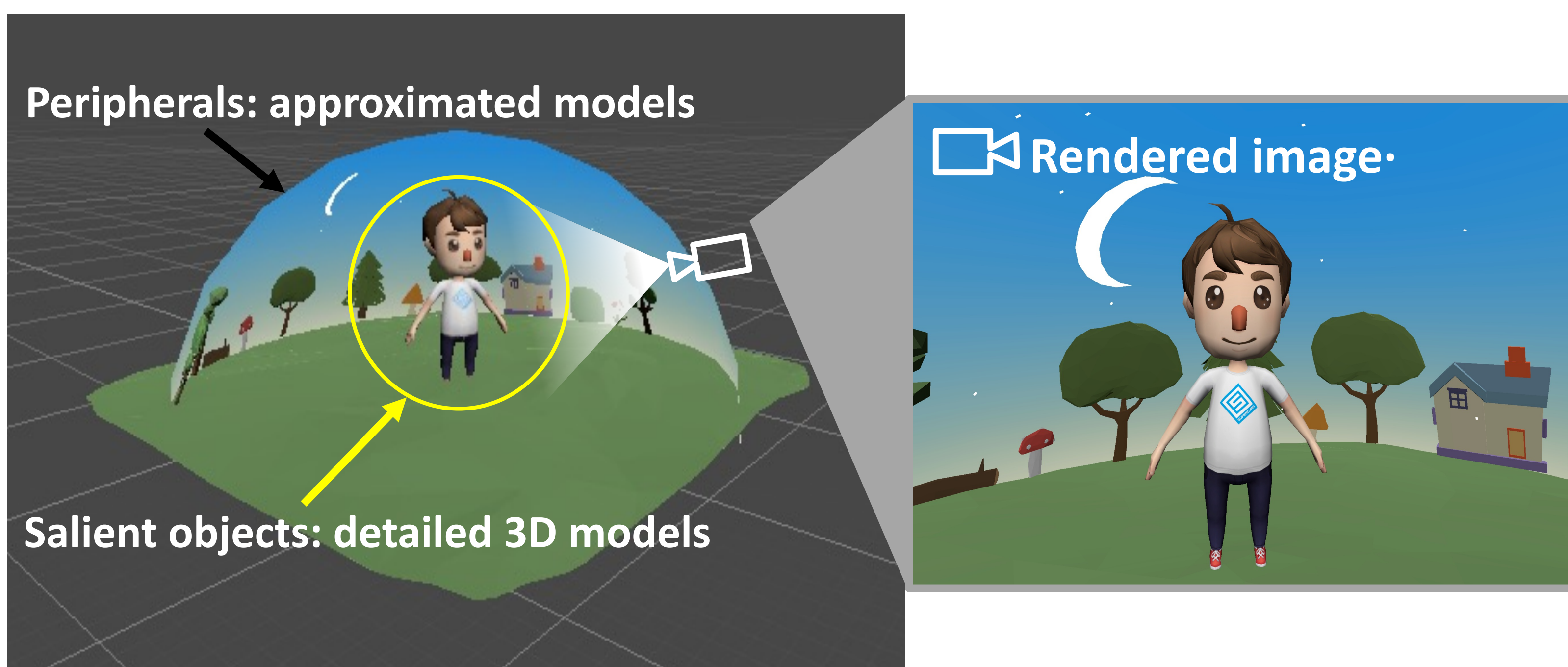
3D-aware GANs

- Goal : to generate 3D scenes
- Dataset: 2D images

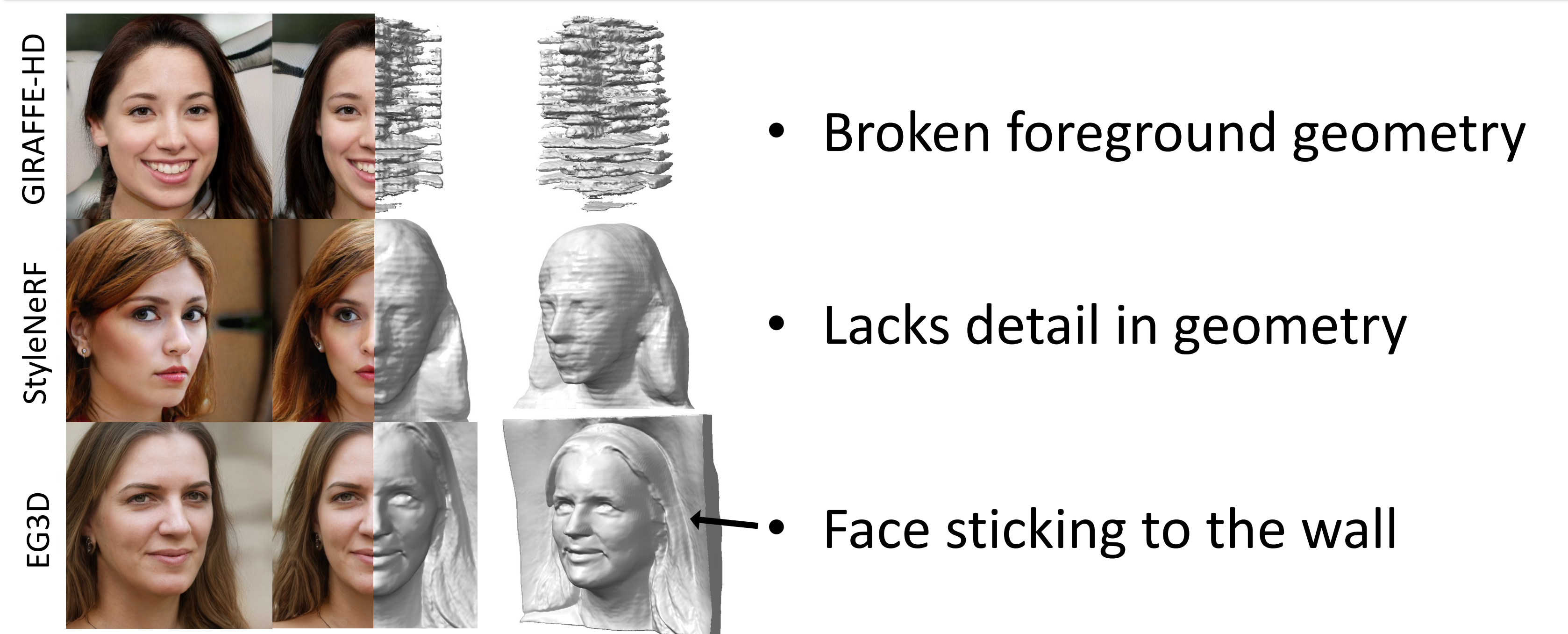


Motivation

- Who cares the backgrounds?
- Smart trick from the graphics community:

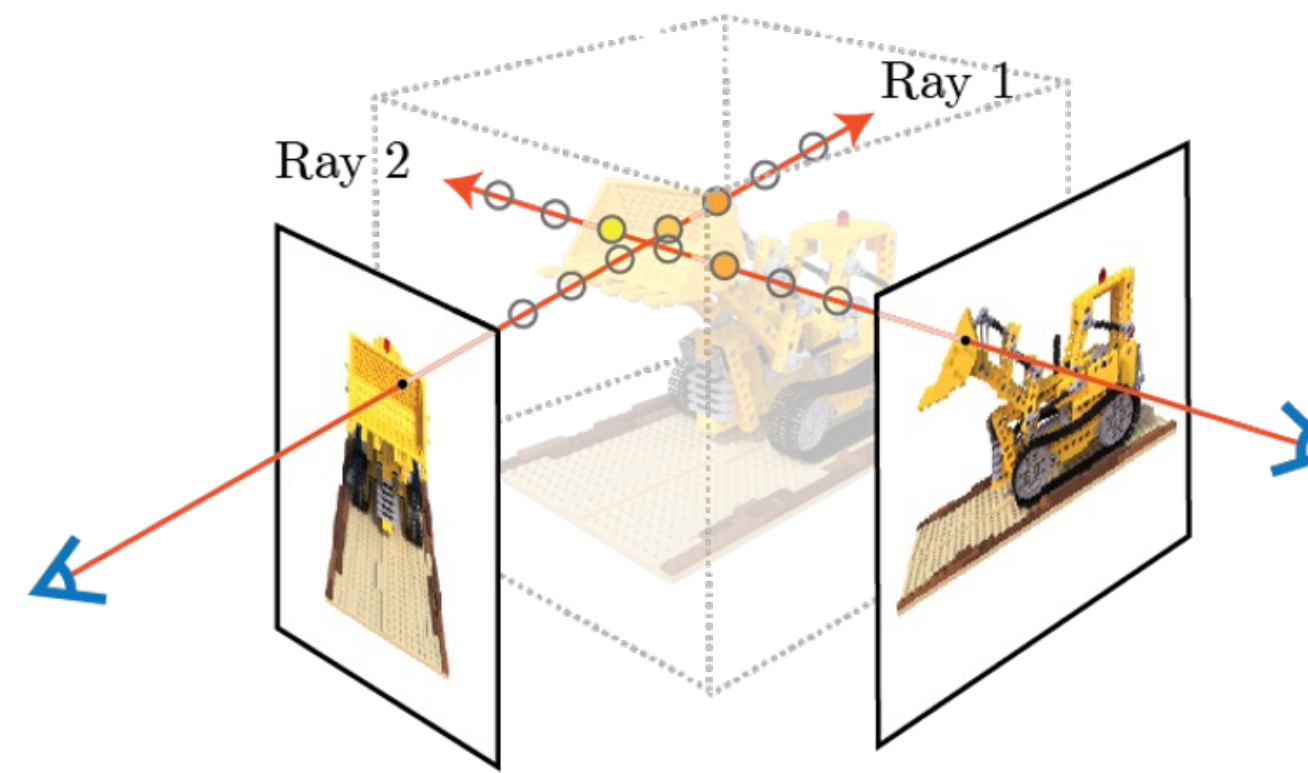


Problem of previous methods

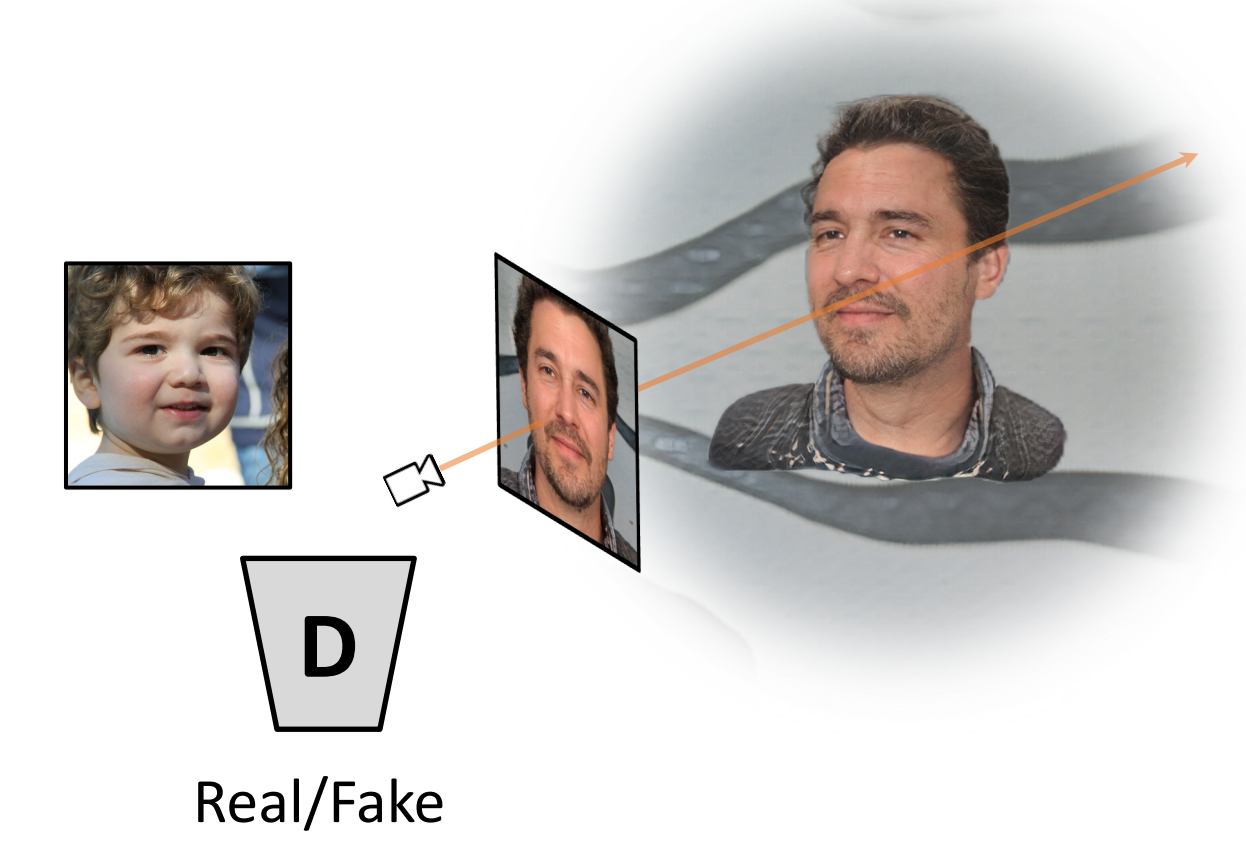


- Broken foreground geometry
- Lacks detail in geometry
- Face sticking to the wall

NeRFs :
 multi-view images
 = 3D supervision

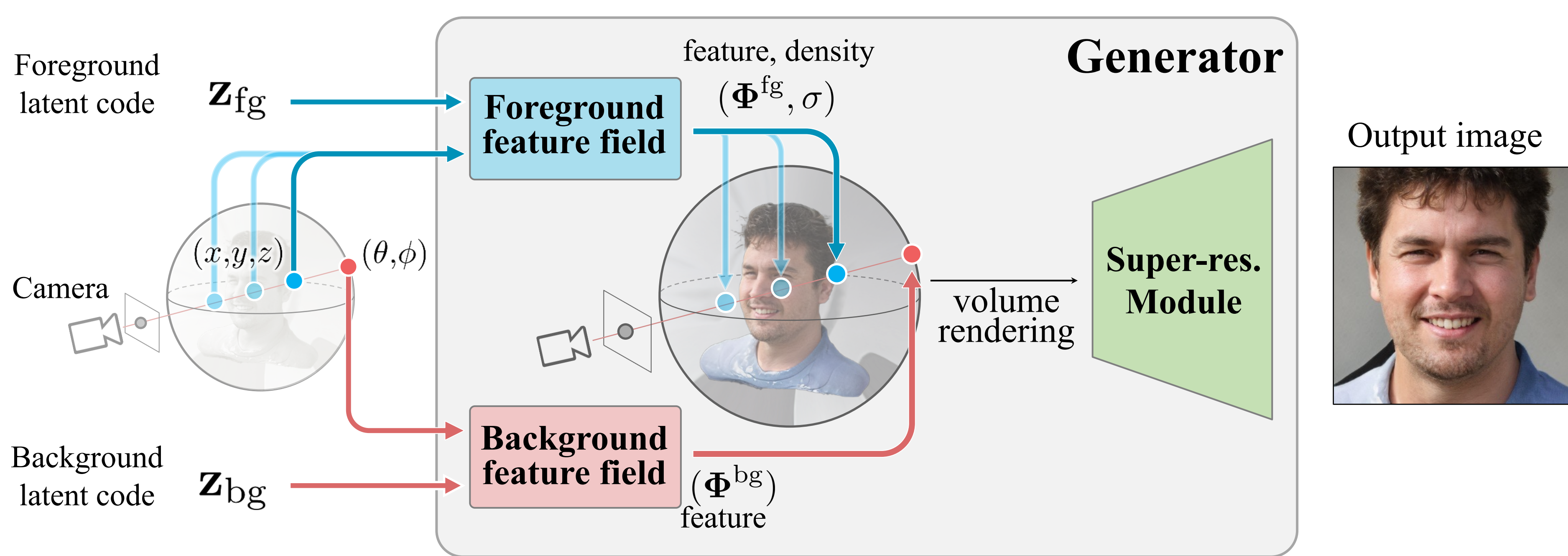


3D-aware GANs :
 Rendered 2D images should be realistic
 = no 3D supervision



Method

- Let's split a scene into a foreground and a simple background!
 > Foreground model : A typical 3D scene representation (tri-plane^[1], NeRF^[2])
 > **Background model** : A spherical surface with a fixed radius.



Note: The background model does not produce density.

- Modified volume rendering:
 The occupancy of the background is 1.

$$\phi(\mathbf{r}) = \sum_{i=1}^{N_{fg}} T_i (1 - \exp(-\sigma_i \delta_i)) \Phi_i^{fg} + T^{bg} \Phi^{bg}$$

- Loss for FG-BG separation:

$$\mathcal{L}_{bg} = \sum \min(T^{bg}, 1 - T^{bg})$$

- Foreground density reg \mathcal{L}_{fg} [3]:

$$\mathcal{L}_{fg} = \sum_r \left(\sum_{i,j} w_i^r w_j^r |t_i^r - t_j^r| + \frac{1}{3} \sum_i w_i^r \delta_i^r \right)$$

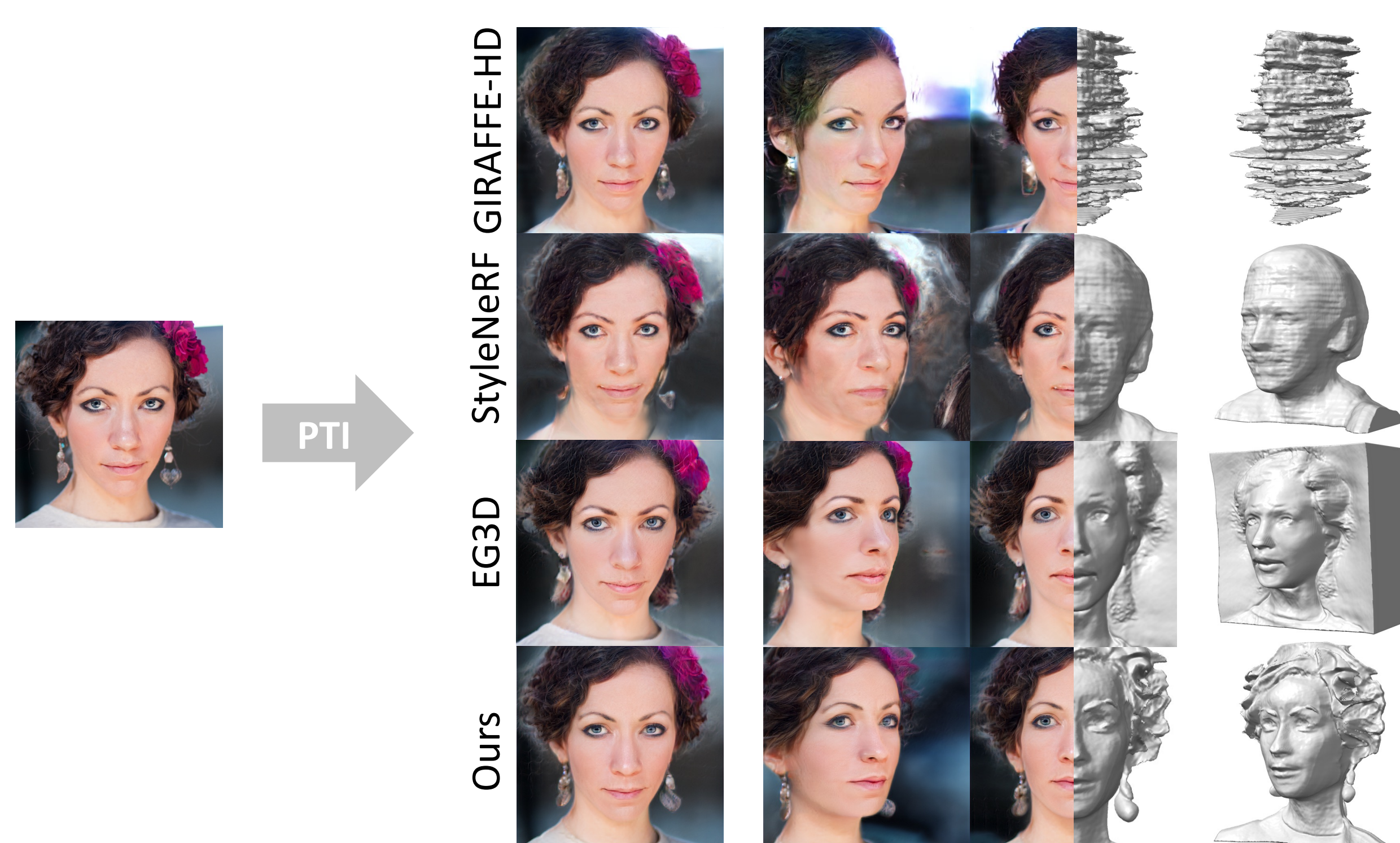
[1] Chan et al, Efficient Geometry-aware 3D Generative Adversarial Networks
 [2] Gu et al, StyleNeRF: A Style-based 3D-Aware Generator for High-resolution Image Synthesis
 [3] Barron et al, Mip-NeRF 360: Unbounded Anti-Aliased Neural Radiance Fields

Results

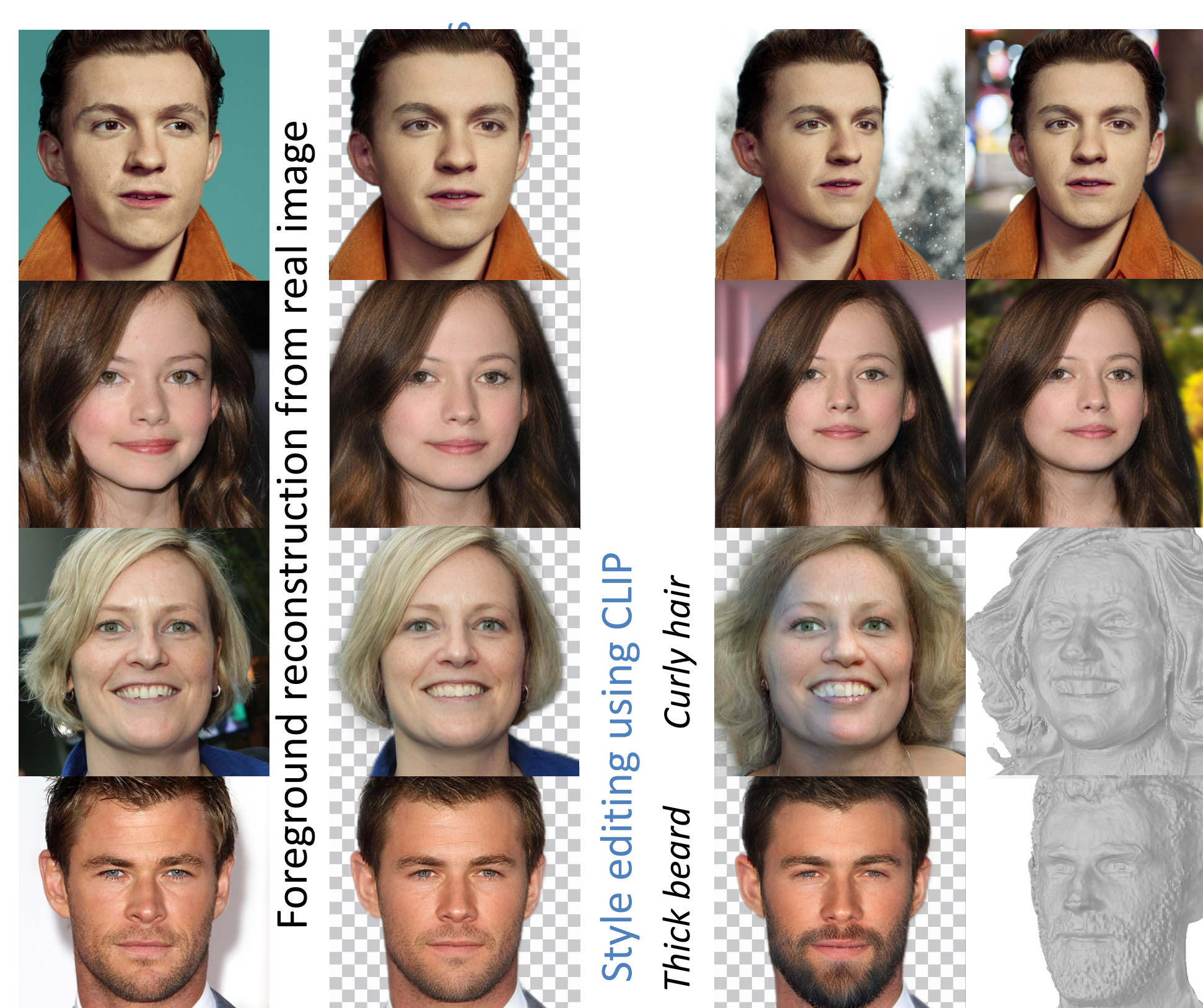
- Results on FFHQ/ AFHQv2-Cats



- Qualitative comparison: inversion of real images



- Applications



- Training stability

