LatentSwap3D: Semantic Edits on 3D Image GANs

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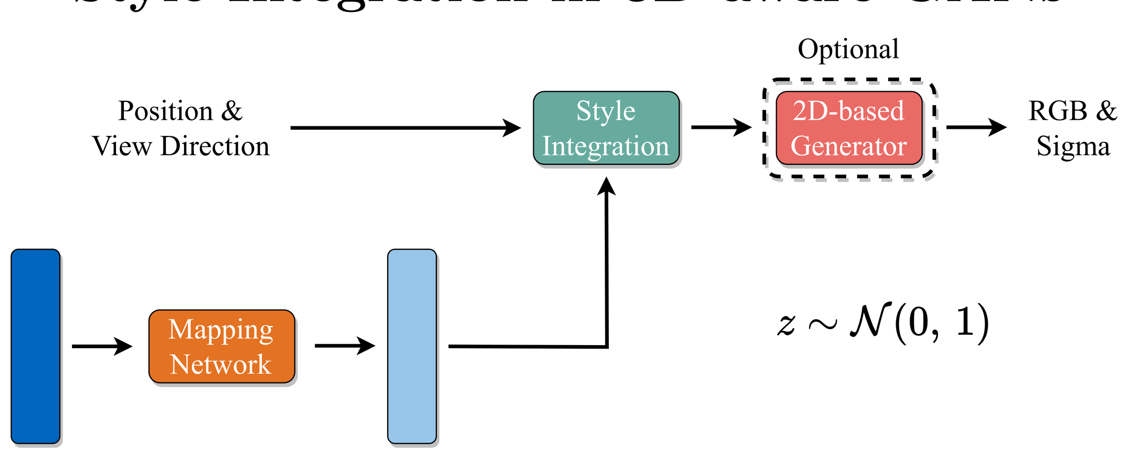
TL;DR

Proposing an attribute editing method for GANs
- is agnostic on the underlying architecture
- can be applied as is to both 2D and 3D

Difference between 2D & 3D

Style Integration in 3D-aware GANs



- Adaptive Instance Normalization

$$AdaIN(x, y) = \sigma(y)\frac{x - \mu(x)}{\sigma(x)} + \mu(y)$$

- Feature-wise Linear Modulation + SIREN

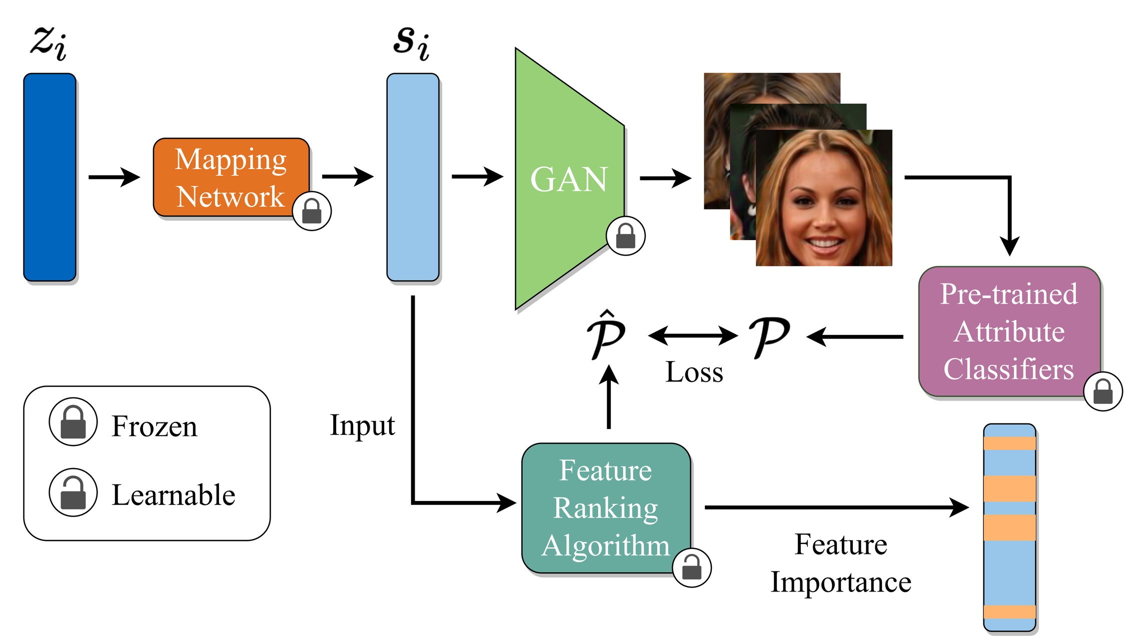
$$FiLM\_SIREN(x) = \sin(\gamma(y) \odot x + \beta(y))$$

More Information

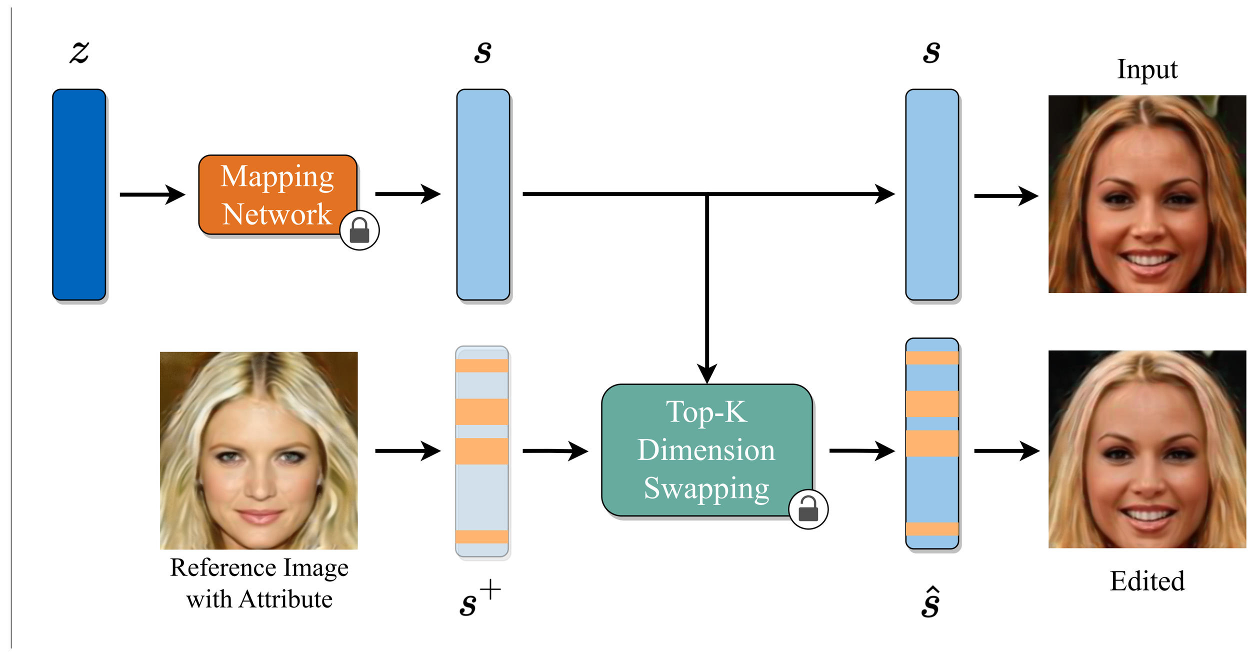
Project | GitHub | Contact

Approach - LatentSwap3D

a) Identifying Relevant Latent Dimensions

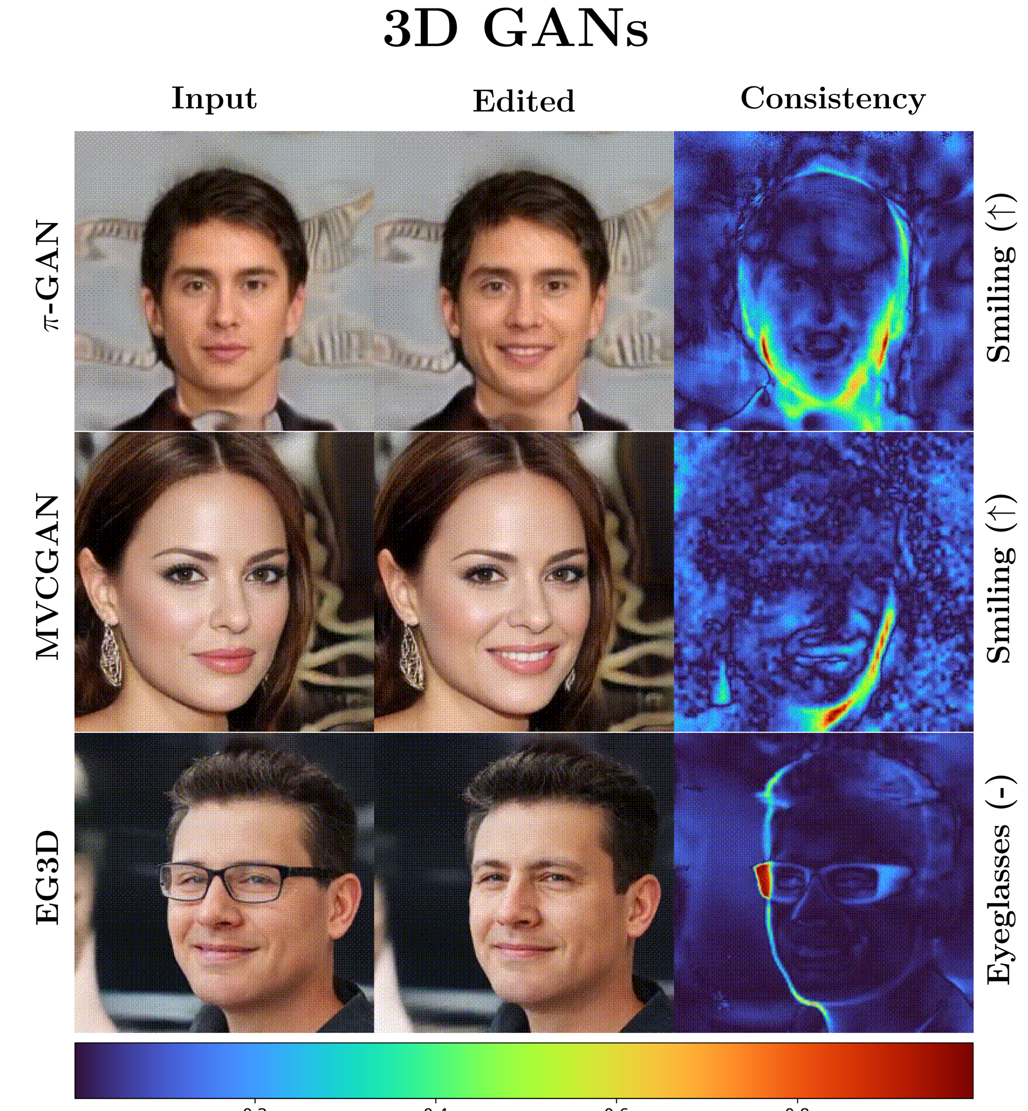


b) Attribute Editing on Latent Dimensions

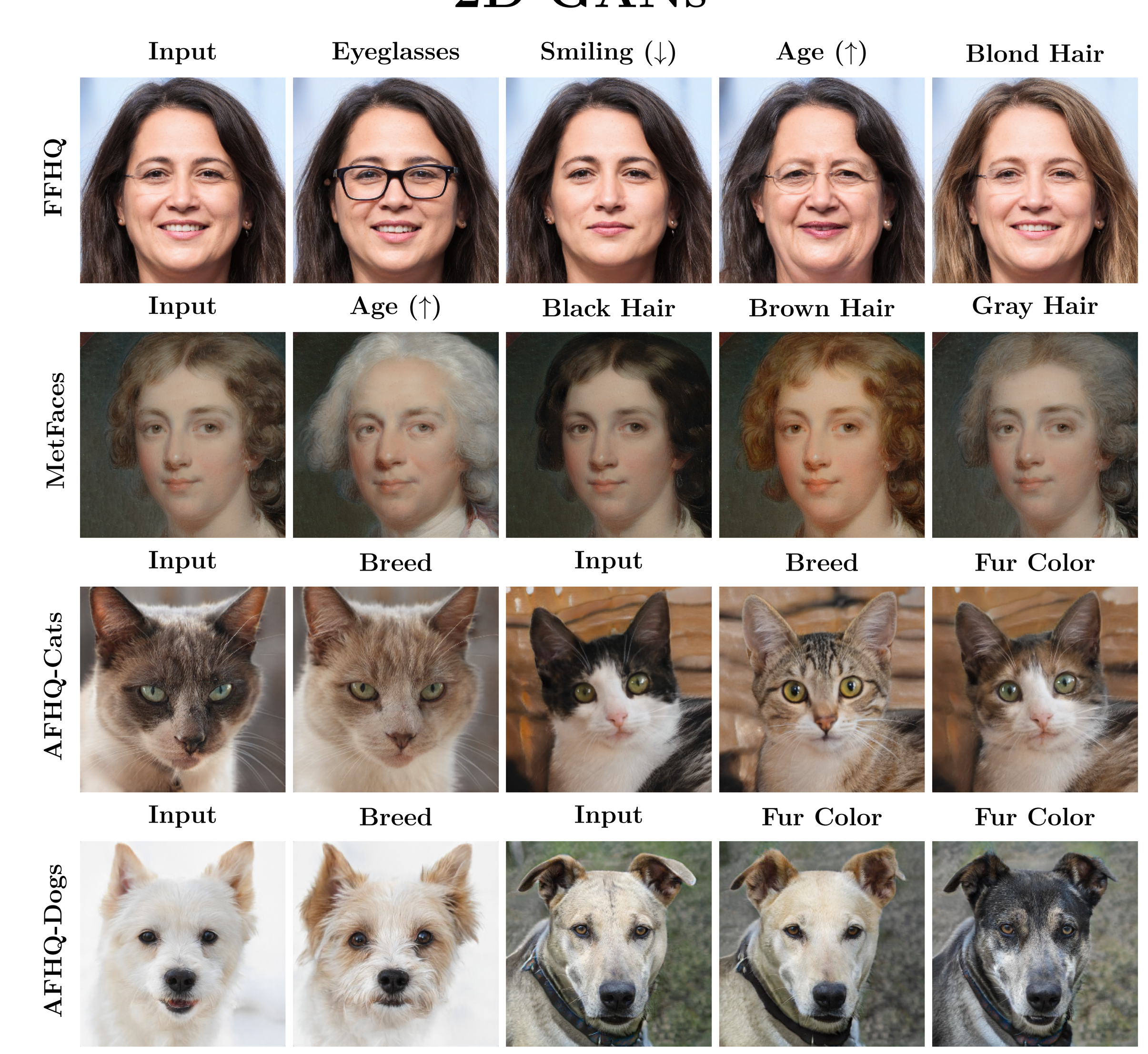


Qualitative Examples

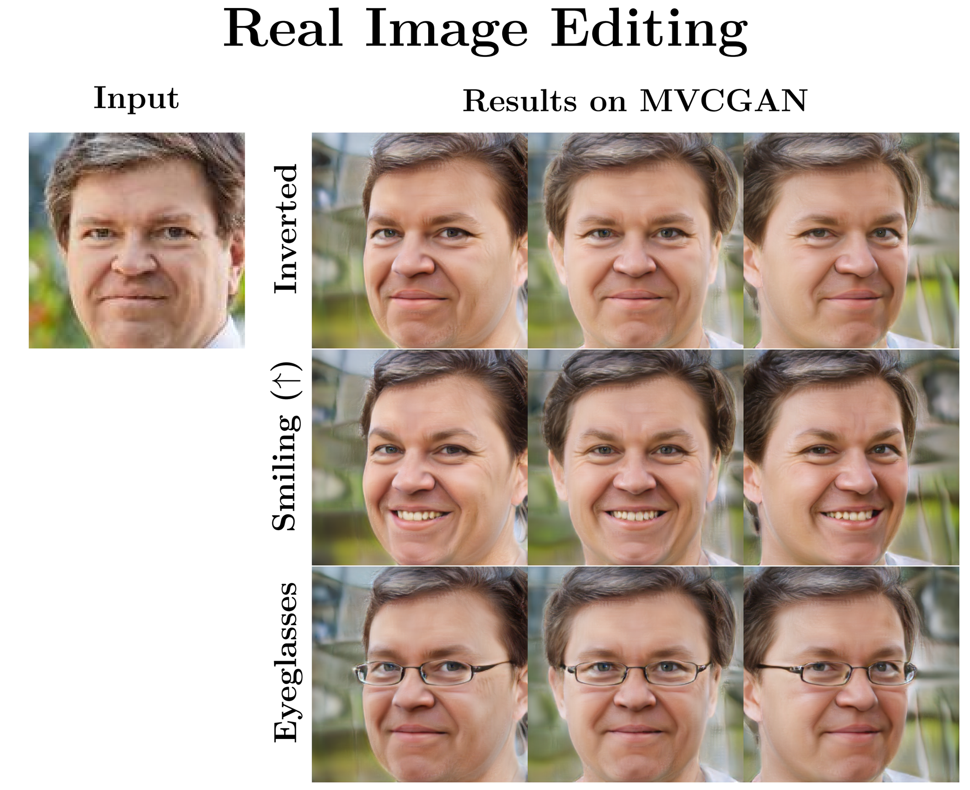
3D GANs



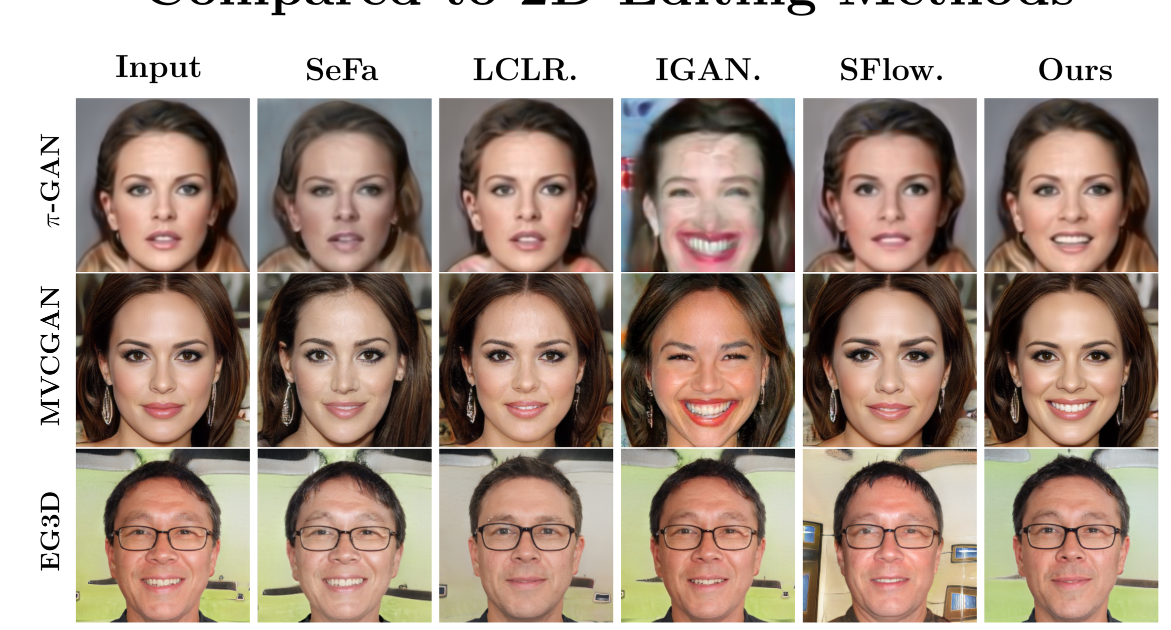
2D GANs



Real Image Editing



Compared to 2D Editing Methods



Quantitative Analysis

Semantic Correctness

	π-GAN	MVCGAN	EG3D
Unedited	4%	3%	9%
IGAN.	81%	84%	85%
SFlow.	83%	78%	88%
Ours	**88%**	**95%**	**93%**

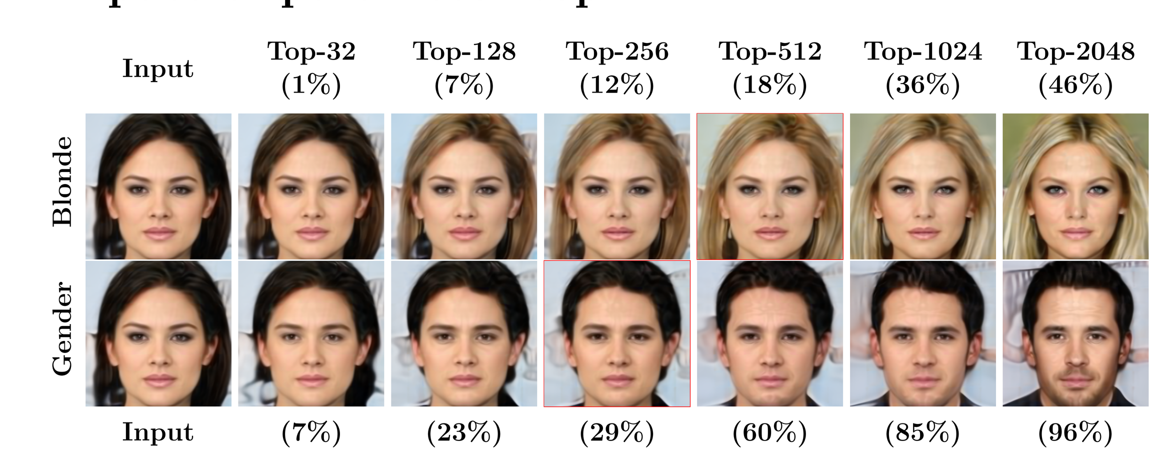
Identity Preservation

	π-GAN	MVCGAN	EG3D
LCLR.	54%	61%	69%
SeFa	62%	64%	58%
IGAN.	30%	51%	71%
SFlow.	68%	65%	72%
Ours	**74%**	**71%**	**73%**

Ablation Study

- **Consecutive Edits**

- **Impact of parameter top-K**



Conclusion & Limitations

- Exploring latent spaces of 3D GANs.
- Proposing a new method that enables attribute editing for any *pre-trained* 2D or 3D generative model **without re-training or fine-tuning**.
- Extending the method on real image editing by using GAN inversion methods.

- Under-represented Attributes in GANs.
- Real image inversion capabilities of 3D GANs.
- Supervised method for finding semantic edits.