

Introduction

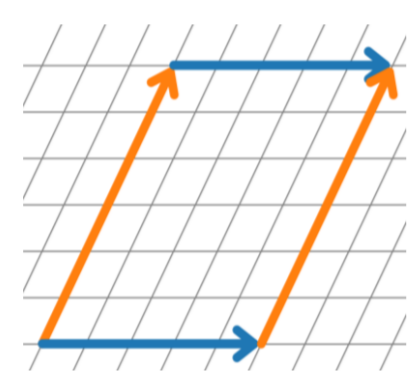
Background

- Deep generative models are known for their ability to produce high-quality images.
- They do not provide an inherent way to edit images semantically.
- Several studies have proposed to find linear or nonlinear semantic paths in the latent space of pretrained models.

Related work

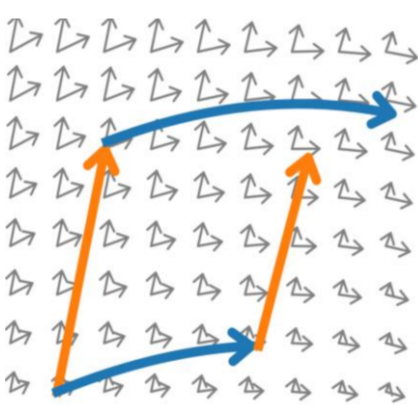
Linear methods (e.g., [1])

- ✓ provide commutative edits.
- ✗ fail to discover nonlinear semantic paths.



Nonlinear methods (e.g., [2])

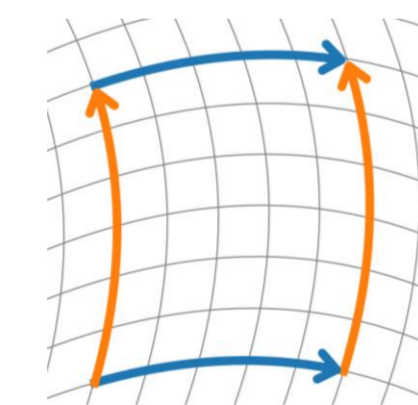
- ✓ discover nonlinear semantic paths.
- ✗ do not provide commutative edits.



Our solution

The proposed method

- ✓ discovers nonlinear semantic paths.
- ✓ provides commutative edits.



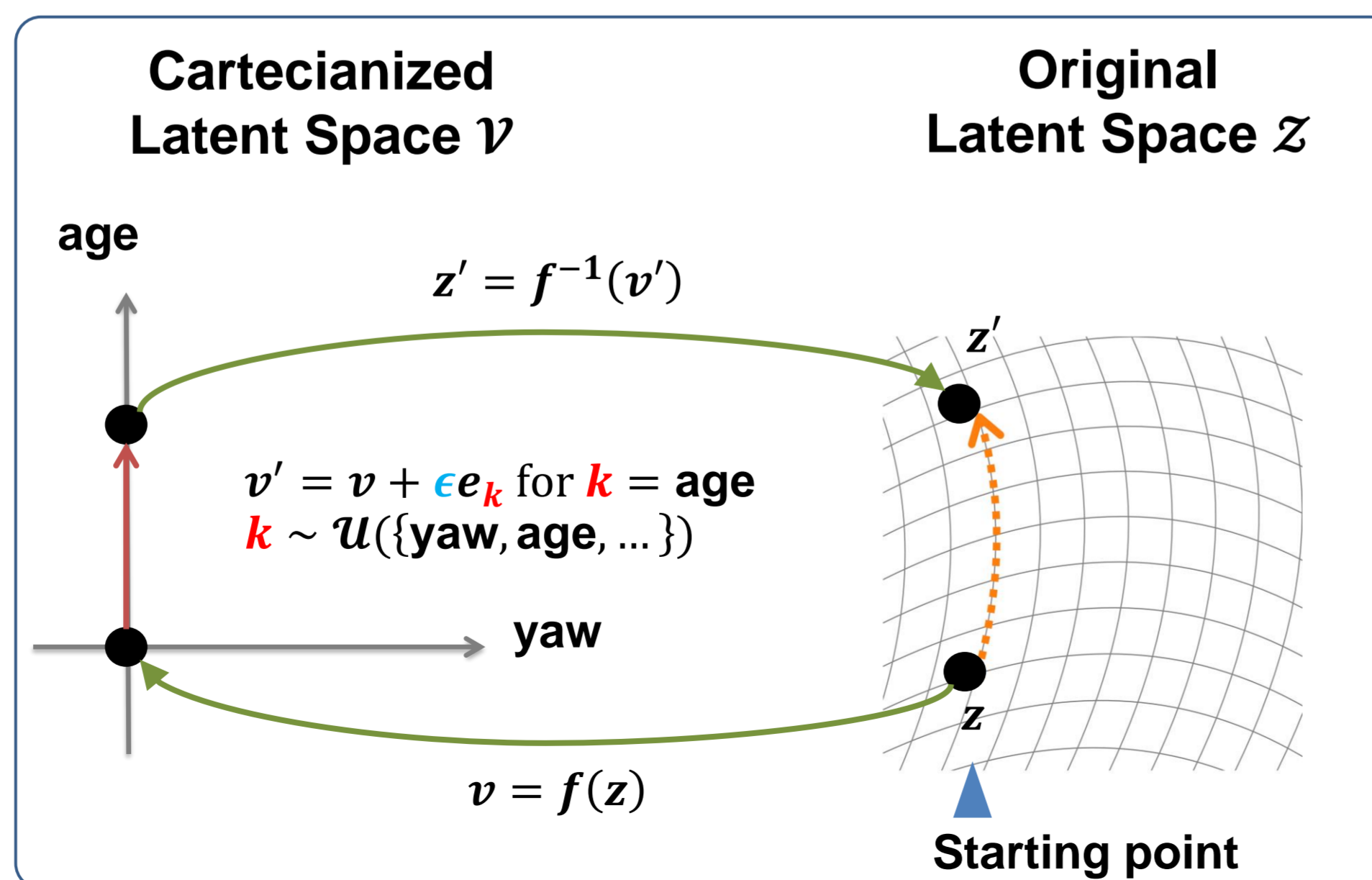
References

- [1] Voynov and Babenko. "Unsupervised Discovery of Interpretable Directions in the GAN Latent Space." In: ICML 2020.
- [2] Tzelepis *et al.* "WarpedGANSpace: Finding Non-Linear RBF Paths in GAN Latent Space." In: ICCV 2021.

Method

Deep Curvilinear Editing (DeCurvEd)

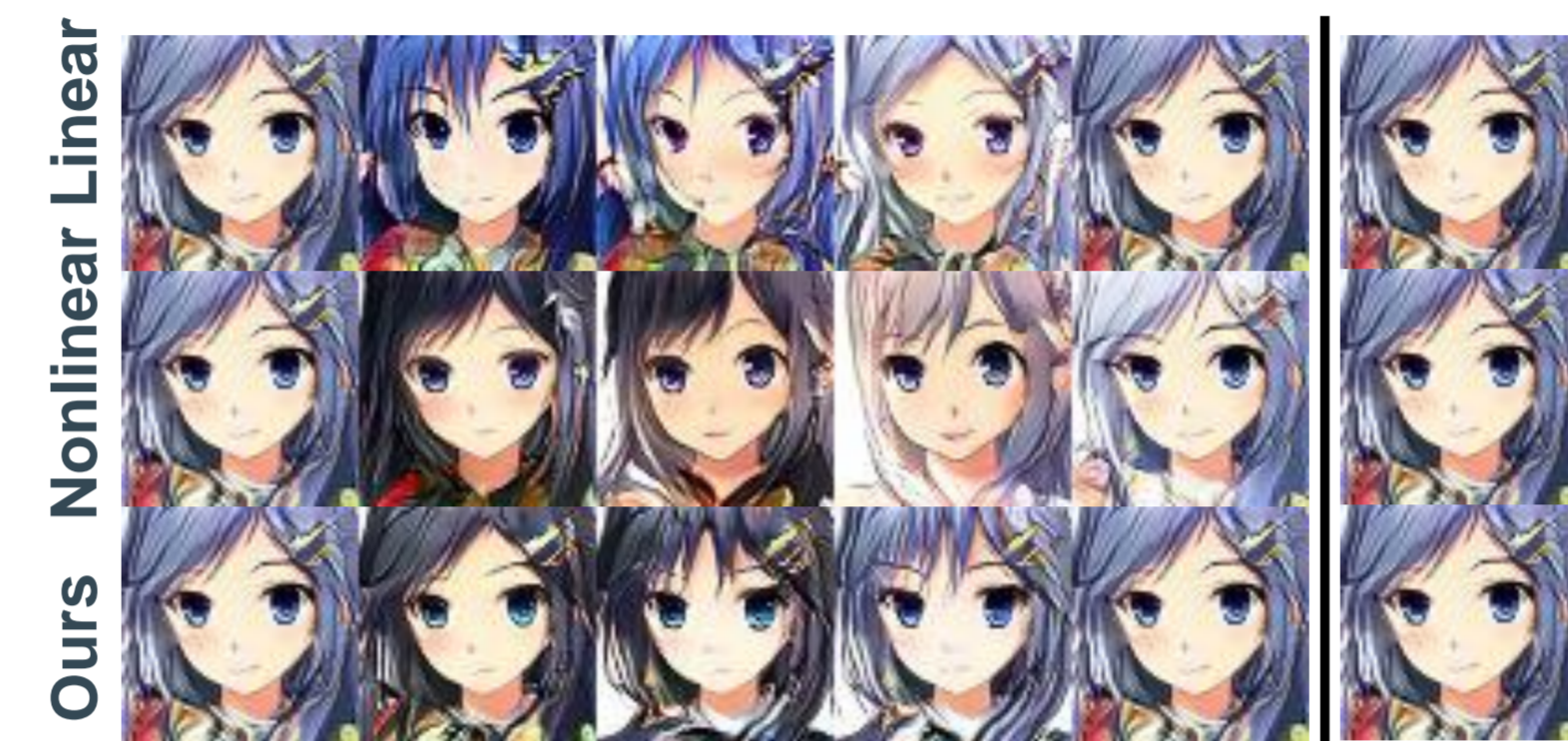
- An N -dimensional latent space \mathcal{Z} .
- An N -dimensional Euclidean space \mathcal{V} (Cartesianized latent space).
- A bijective function $f: \mathcal{Z} \rightarrow \mathcal{V}$ to define a curvilinear coordinate on \mathcal{Z} by transforming a Cartesian coordinate on \mathcal{V} .
- Edit a latent code z as
 1. Get a mapped latent code $v = f(z)$.
 2. Edit the mapped latent code $v' = v + \epsilon e_k$.
 3. Get an edited latent code $z' = f^{-1}(v')$.
- This edit is nonlinear and commutative because curvilinear coordinates are equivalent to commuting vector fields.
- We name the proposed method Deep Curvilinear Editing (DeCurvEd).
- DeCurvEd is available for any generative models.



Experimental Results

Commutativity

- Linear method is commutative, but the quality is inferior.
- Nonlinear method offers a better quality, but it is non-commutative.
- Ours method is commutative and offers the best quality.



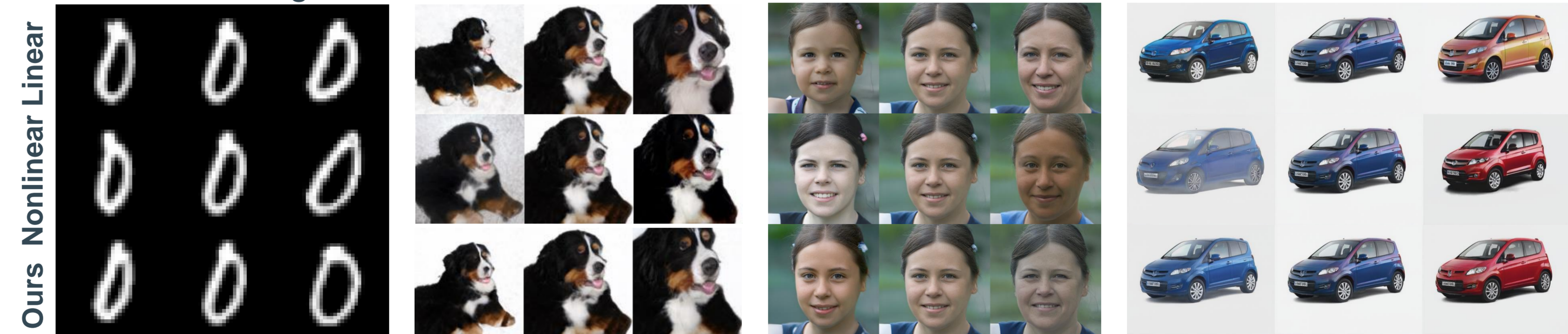
O: original, D: dark colored-hair, L: hair length.
 SNGAN + AnimeFaces.



O: original, V: vertical position, S: object size, B: background.
 BigGAN + ILSVRC.

Visualization results

- Linear and nonlinear methods exhibit undesirable side effects (e.g., age affects face color).
- Ours edits images without severe side effects.



← - Width + →
 MNIST + SNGAN

← - Object size + →
 ILSVRC + BigGAN

← - Age + →
 CelebA-HQ + StyleGAN2

← - Color + →
 LSUN Car + StyleGAN2

Identity error

- We calculate identity error to evaluate the disentanglement.
- Ours has the lowest error for two out of six attributes, the second lowest errors for the remaining.

	A	G	R	B	P	Y	Avg.
Linear	26.1	5.5	19.1	47.4	26.4	24.7	29.9
Nonlinear	27.6	56.2	33.6	6.3	14.6	8.4	29.3
Ours	21.1	15.4	25.3	6.0	18.9	9.6	19.2

A: age, G: gender, R: race, B: bangs, P: pitch, Y: yaw,
 Avg.: average. CelebA-HQ + StyleGAN2