

Motivation

Context

- Cannot be trained without domain (or attribute) labels.
- Users can only control the classes used for training.
- Editing the results via latent space exploration is limited [1].

Our Method:

- Does not require labels for training. It can be trained on unlabeled datasets (e.g., FFHQ or LSUN).
- Discovers **style prototypes**, which users can use like domain labels.
- Allows users to **control** the synthesis results. Users can interpolate between two prototypes (or references) or edit specific region only.

Key Observations

(1) We can control the feature space using augmentation

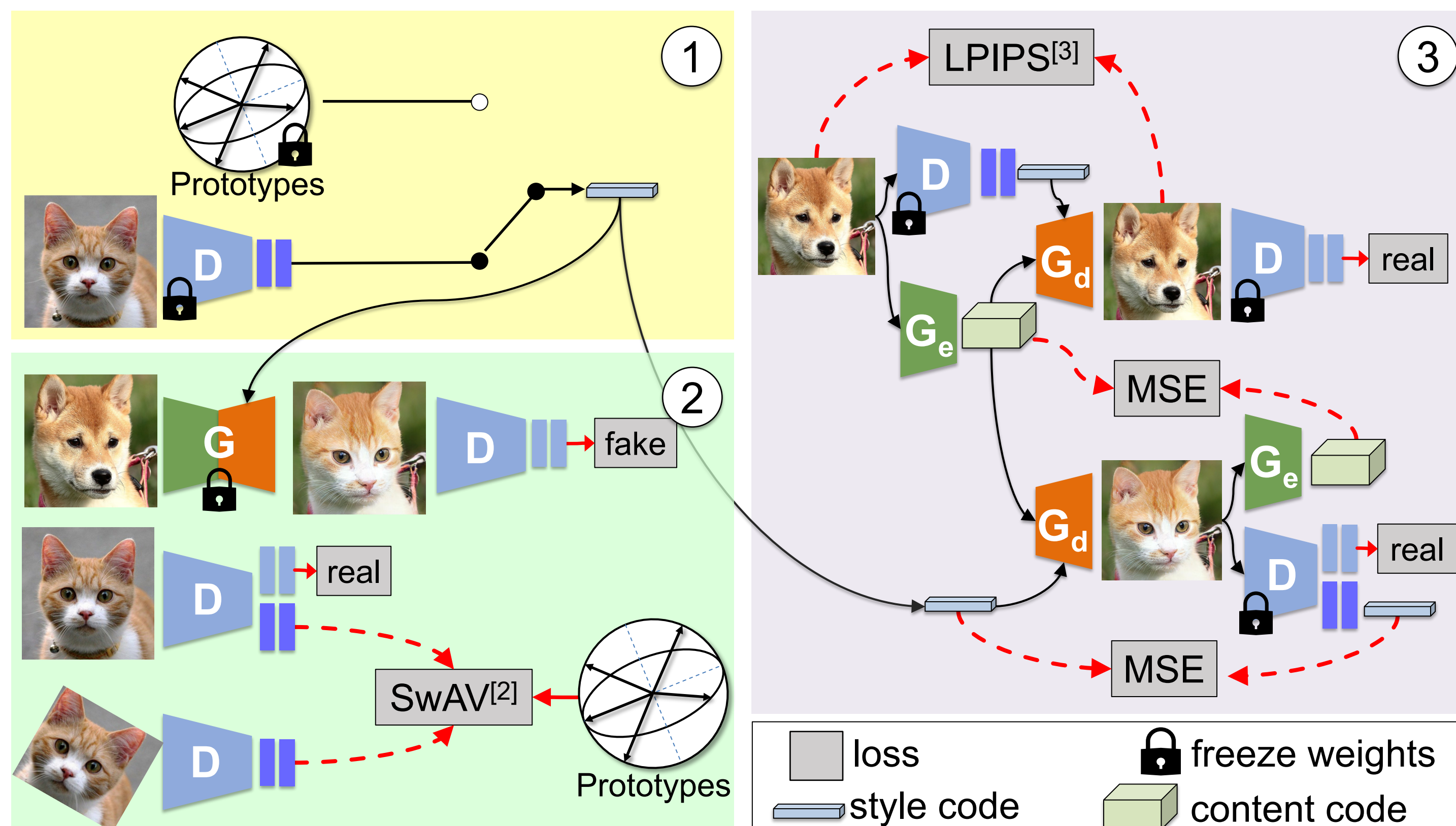


The 4 samples closest to the reference in the features space
(left) Flip, RandomResizedCrop, ColorDistortion
(right) (left) - ColorDistortion + RandomAffine

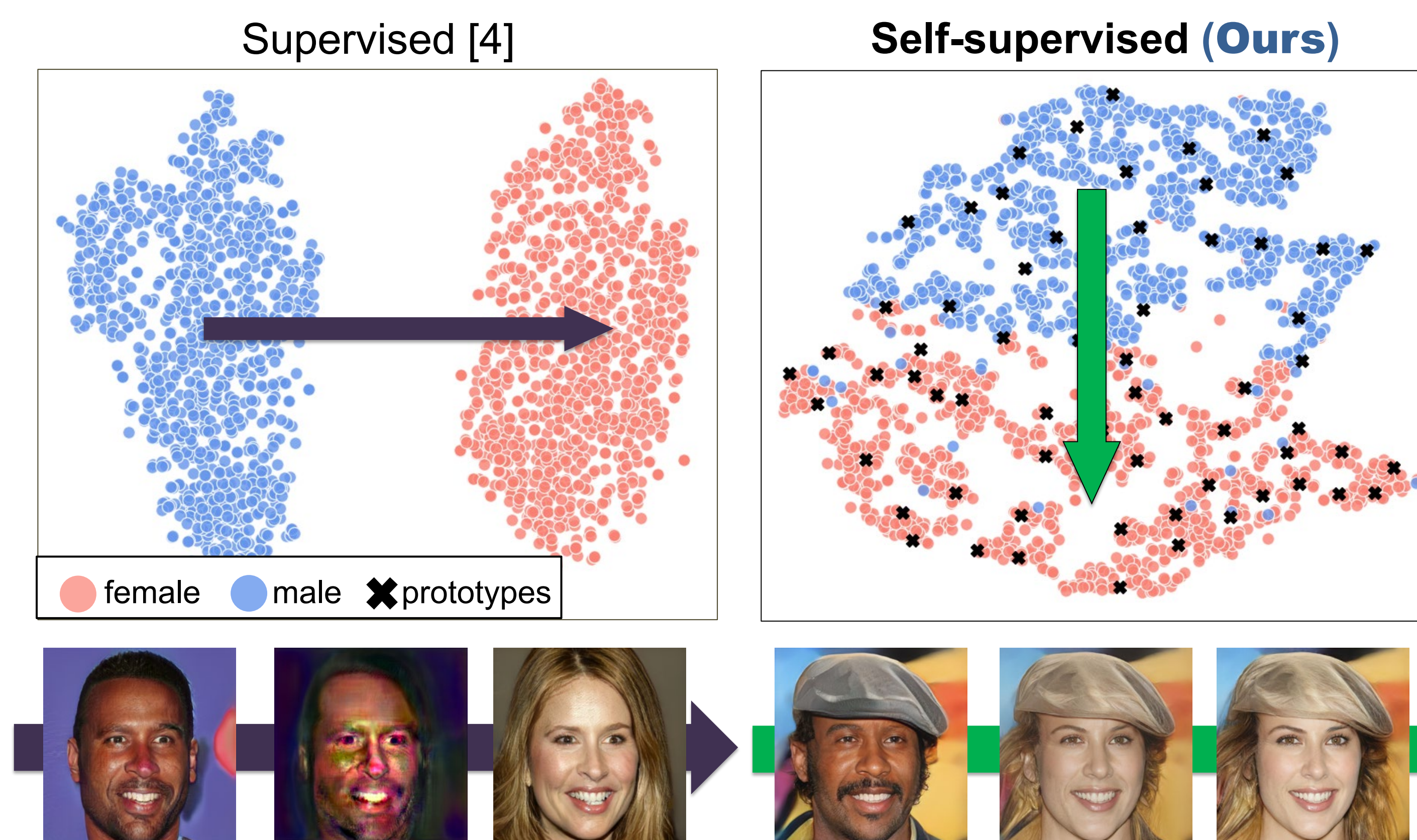
(2) Discriminators can be reused as style encoders

- Significantly reduce the number of parameters (25~35% ▼).
- Can leverage the advantages of the self-supervised discriminators.
- Don't have to throw away the discriminator after training!

Methods Overview



Latent Space Comparison

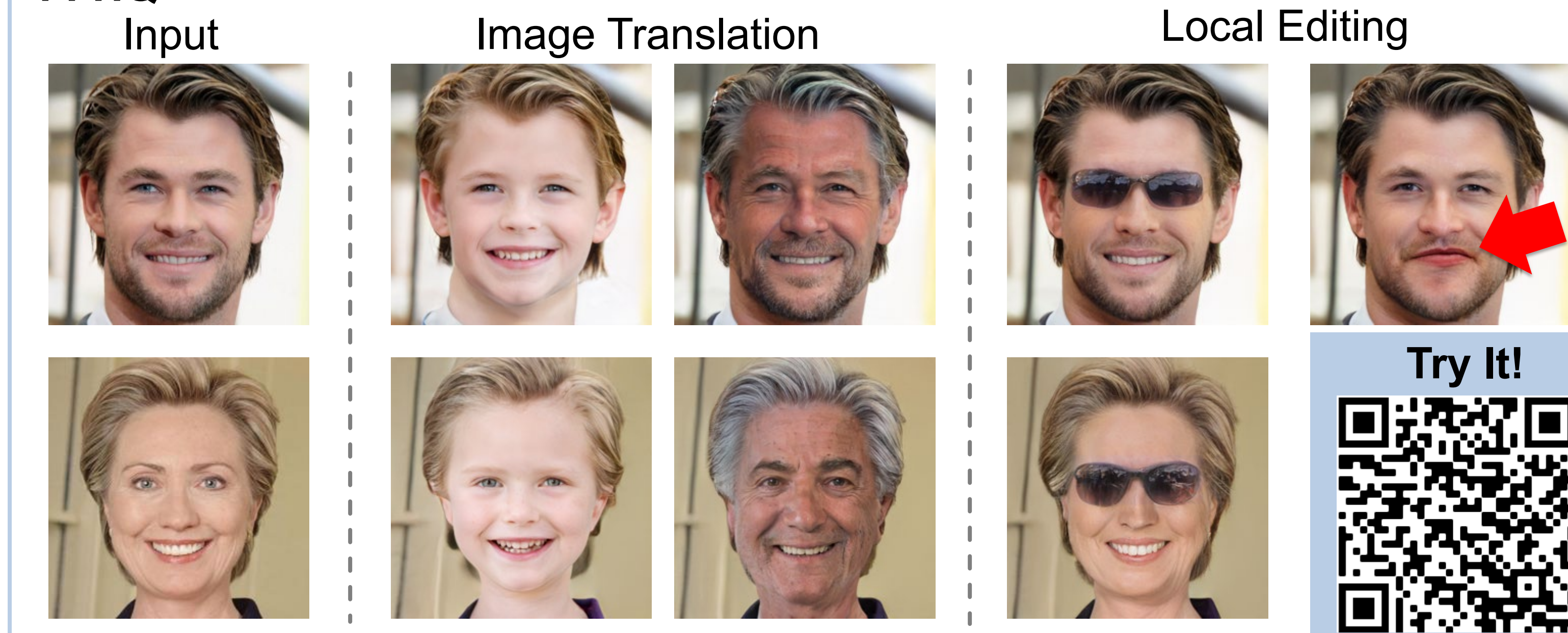


Qualitative Examples

LSUN Churches (□: reference)



FFHQ



References

- [1] Liu et al. "Smoothing the Disentangled Latent Style Space for Unsupervised Image-to-Image Translation." In CVPR, 2021.
- [2] Caron et al. "Unsupervised learning of visual features by contrasting cluster assignments." In NIPS, 2020.
- [3] Zhang et al. "The Unreasonable Effectiveness of Deep Features as a Perceptual Metric." In CVPR, 2018.
- [4] Choi et al. "StarGAN v2: Diverse Image Synthesis for Multiple Domains." In CVPR, 2020.