

Discovering Interpretable Directions in the Semantic Latent Space of Diffusion Models

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Background

Problem:

The latent space of diffusion models is not yet well understood.

Previous work:

 Kwon et al. [14]

- Introduces h -space as semantic latent space
- Semantic directions are found using CLIP

Contributions

We propose 2 unsupervised and 3 supervised approaches for intuitive **semantically disentangled image editing without**:

- CLIP guidance
- Changes in diffusion model architecture and fine-tuning

Semantic Image Editing

Unsupervised

Global edits by PCA

Incremental PCA on bottleneck activation from images generally yields global semantic directions.

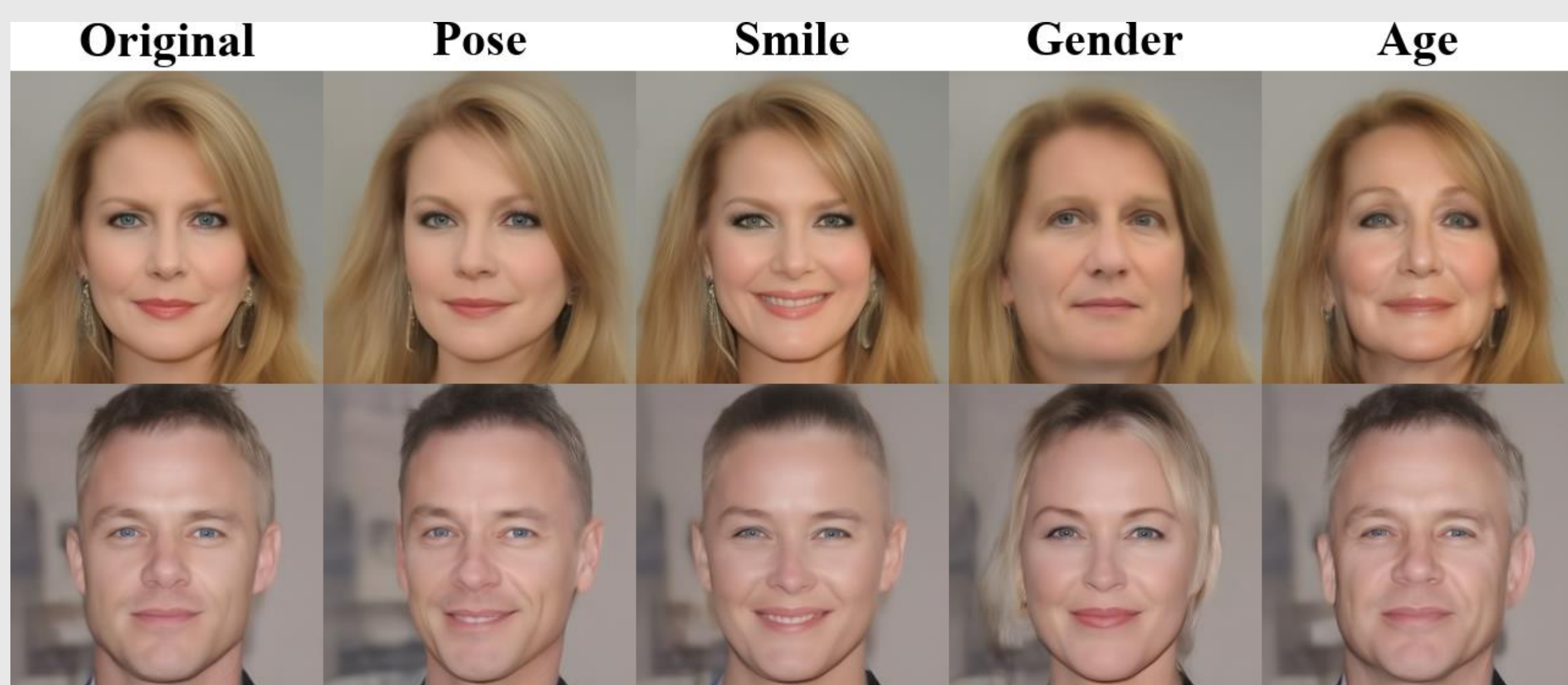


Image-specific edits

- Directions in h -space that change $\epsilon_t^\theta(\mathbf{x}_t)$ the most
- Eigenvectors of Jacobian of denoiser

$$\mathbf{J}_t \triangleq \frac{\partial \epsilon_t^\theta(\mathbf{x}_t, \mathbf{h}_t)}{\partial \mathbf{h}_t} = \mathbf{U}_t \Sigma_t \mathbf{V}_t^T$$

- Challenge: dimension of full bottleneck h -space.
- Solution: **power iteration** to circumvent the intractable computational cost

$$\mathbf{J}_t^T \mathbf{J}_t \mathbf{v} = \frac{\partial}{\partial \mathbf{h}_t} \langle \epsilon_t^\theta(\mathbf{x}_t, \mathbf{h}_t), \mathbf{J}_t \mathbf{v} \rangle$$

$$\mathbf{J}_t \mathbf{v} = \frac{\partial}{\partial a} \epsilon_t^\theta(\mathbf{x}_t, \mathbf{h}_t + a\mathbf{v}) \Big|_{a=0}$$



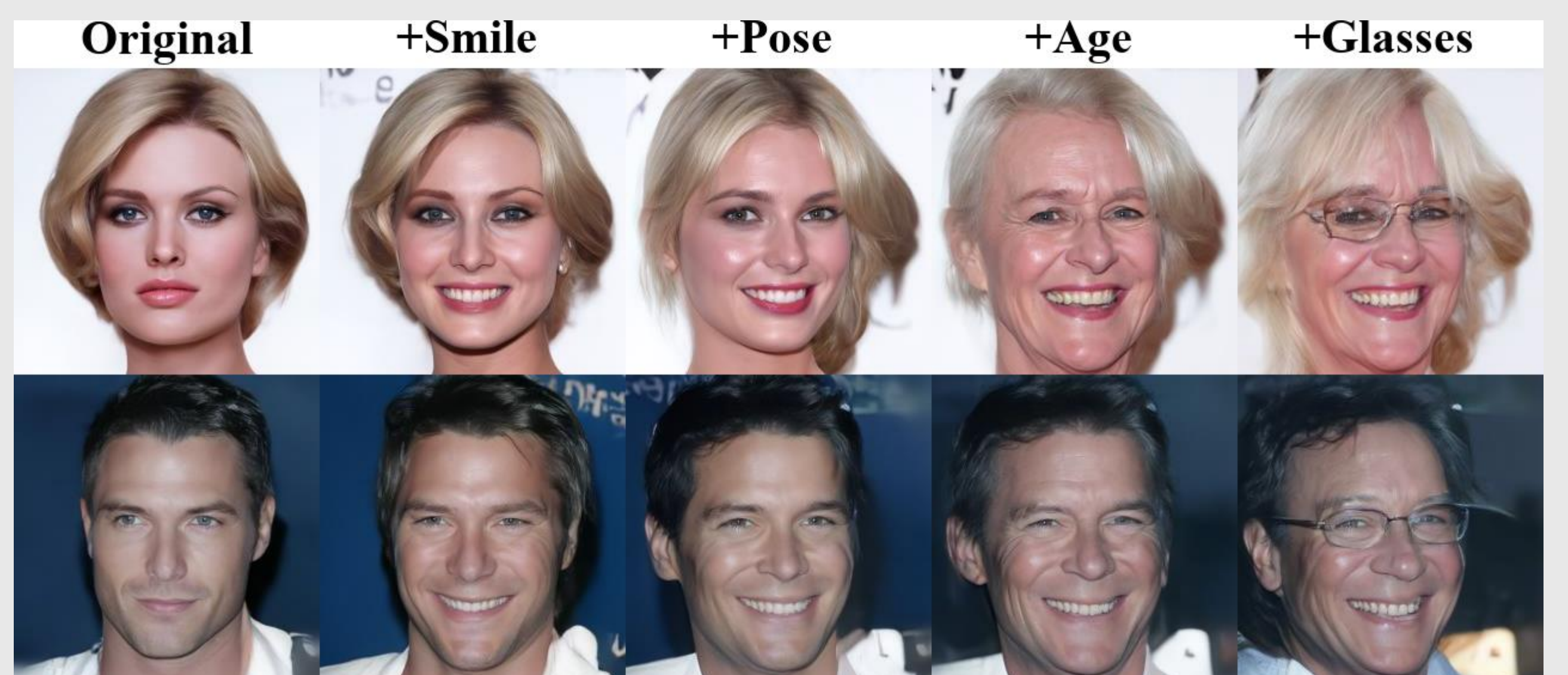
Supervised

Edits by examples

Semantic directions based on latent representation of image with (+) and without (-) binary attribute:

$$\mathbf{w} = \frac{1}{n} \sum_{i=1}^n (\mathbf{q}_i^+ - \mathbf{q}_i^-)$$

Sequential edits:

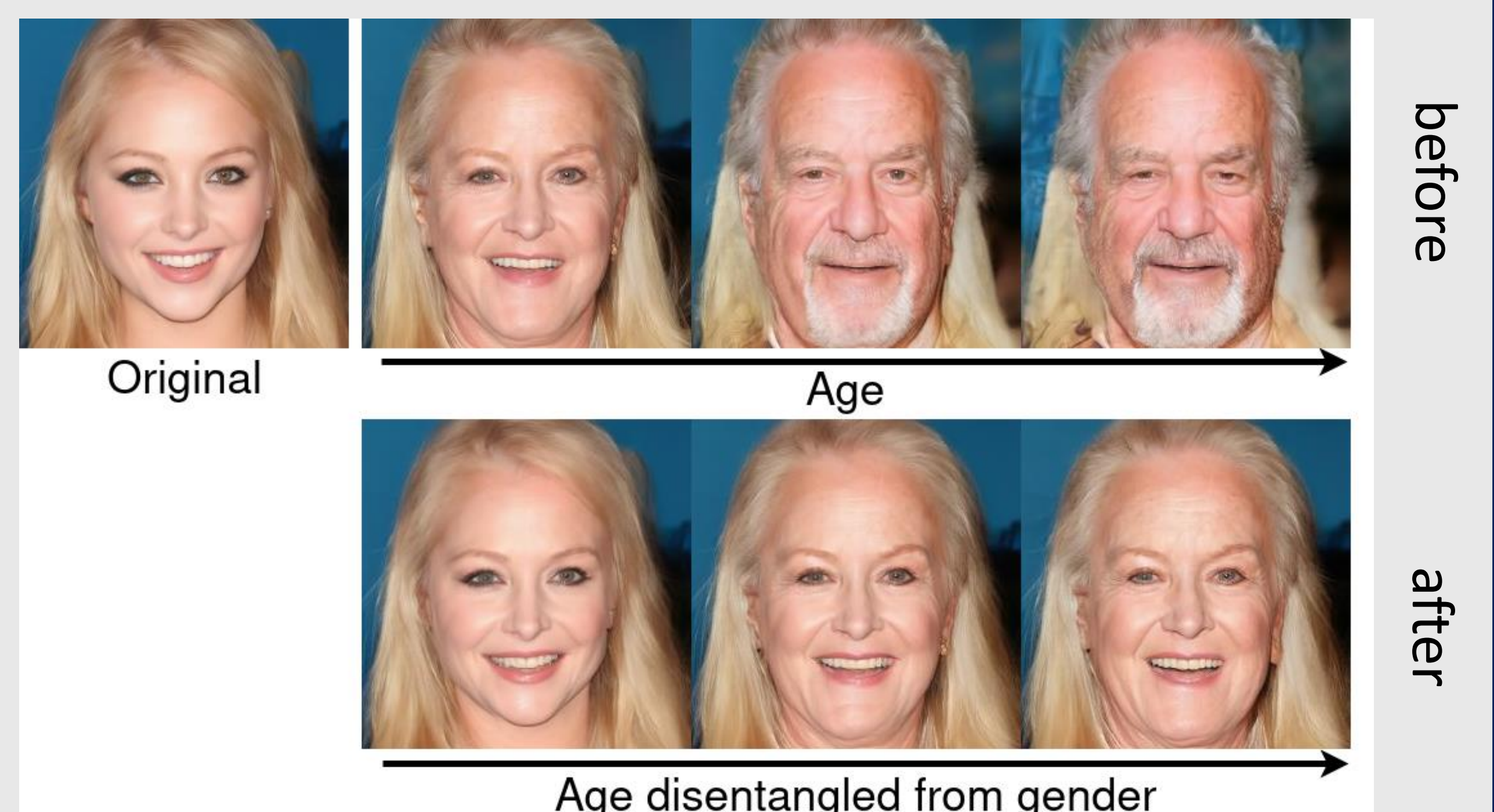


Classifier Annotation

Addition: use a pre-trained attribute classifier on the model generated images to gather positive and negative examples

Disentanglement

To remove effects of K directions \mathbf{w}_k from \mathbf{w}_0 , project \mathbf{w}_0 onto the orthogonal complement of $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_K]$. This yields an updated direction \mathbf{w}_0 disentangled from \mathbf{w}_k .



Project Website

<https://github.com/renhaa/semantic-diffusion>

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