Identity-Preserving Aging and De-Aging of Faces in the StyleGAN Latent Space

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Introduction

- **Context**: **Face-age synthesis** is relevant to **forensics** and **cross-age face recognition**, yet most GAN/Diffusion methods have heavy data and computing requirements.
- **Motivation**: Current methods **lack** age synthesis **control** and **not always ensure identity** (ID) is preserved after age editing, while also being **expensive** and **complex** to train.
- **Goal**: To **efficiently** and **effectively** synthesize **aged and de-aged** faces by finding an "age direction" in the StyleGAN space, **improving identity preservation** via feature selection, and providing **specific steps** to age in years.

Key contributions

- **Efficiency**: Light requirements on data and computing resources for face aging and de-aging.
- **Improve on ID Preservation**: feature selection by comparing PCA/LDA reconstructions.
- **Synthesizing to a specific age**: provide specific latent space offsets to age and de-age subjects.
- **Dataset and evaluation code**: Release of a fully synthetic dataset with 20k IDs × 11 age variations and age synthesis evaluation toolset.

Method Overview

1. **Moving along age direction.** Extending [1], use a Linear SVR to fit StyleGAN2 latent vectors $w \rightarrow y$ true age label, find age direction $\hat{\lambda}$ through SVR coefficients (λ), and move latent vector using scalar s:

Eq. 1 $\quad w' = w + s\,\hat{\lambda}$

2. **Constrain change in latent components.** Use element-wise mask Φ to constrain the movement of select components, computed by comparing reconstructions from PCA and LDA spaces using labeled datasets on ID and age:

Eq. 2 $\quad w' = w + (\Phi \odot s\,\hat{\lambda})$

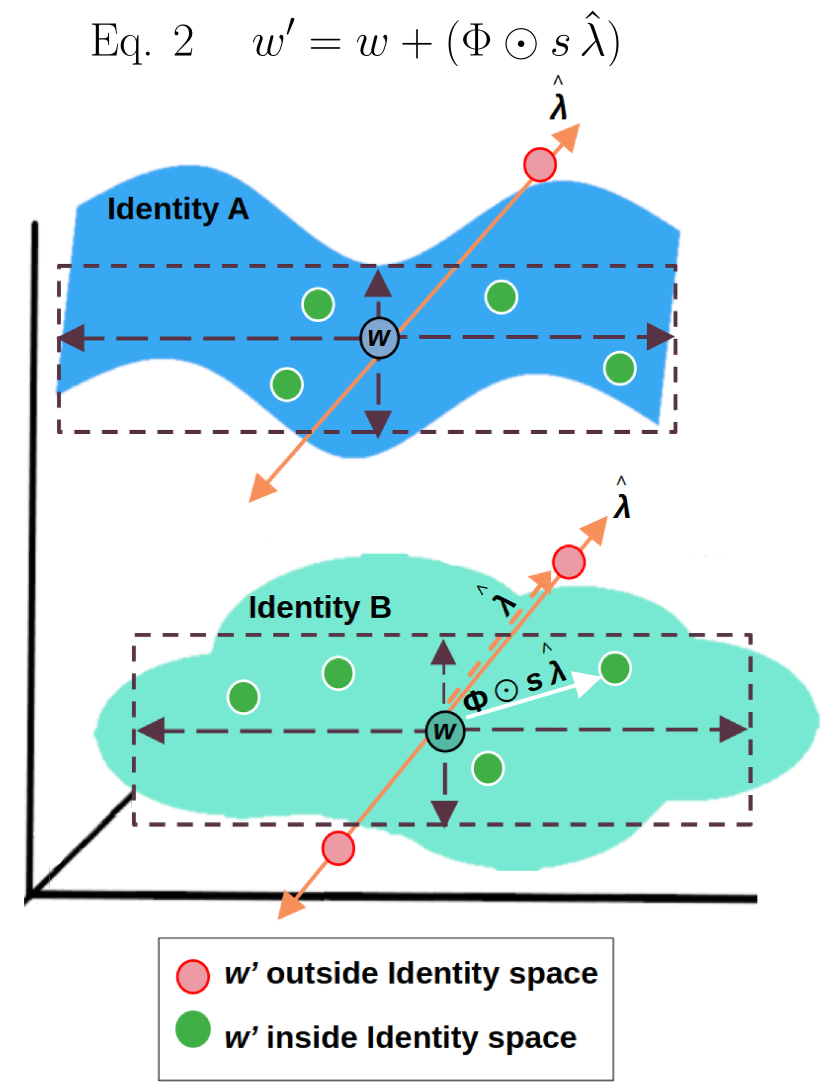

Figure: Aged latent w' inside ID region using Eq. 2.

3. **Map scalar $s \mapsto y$ age.** Compute scalar offset Δs for a specific age using polynomial fittings per age group.

Aging and de-aging to specific years

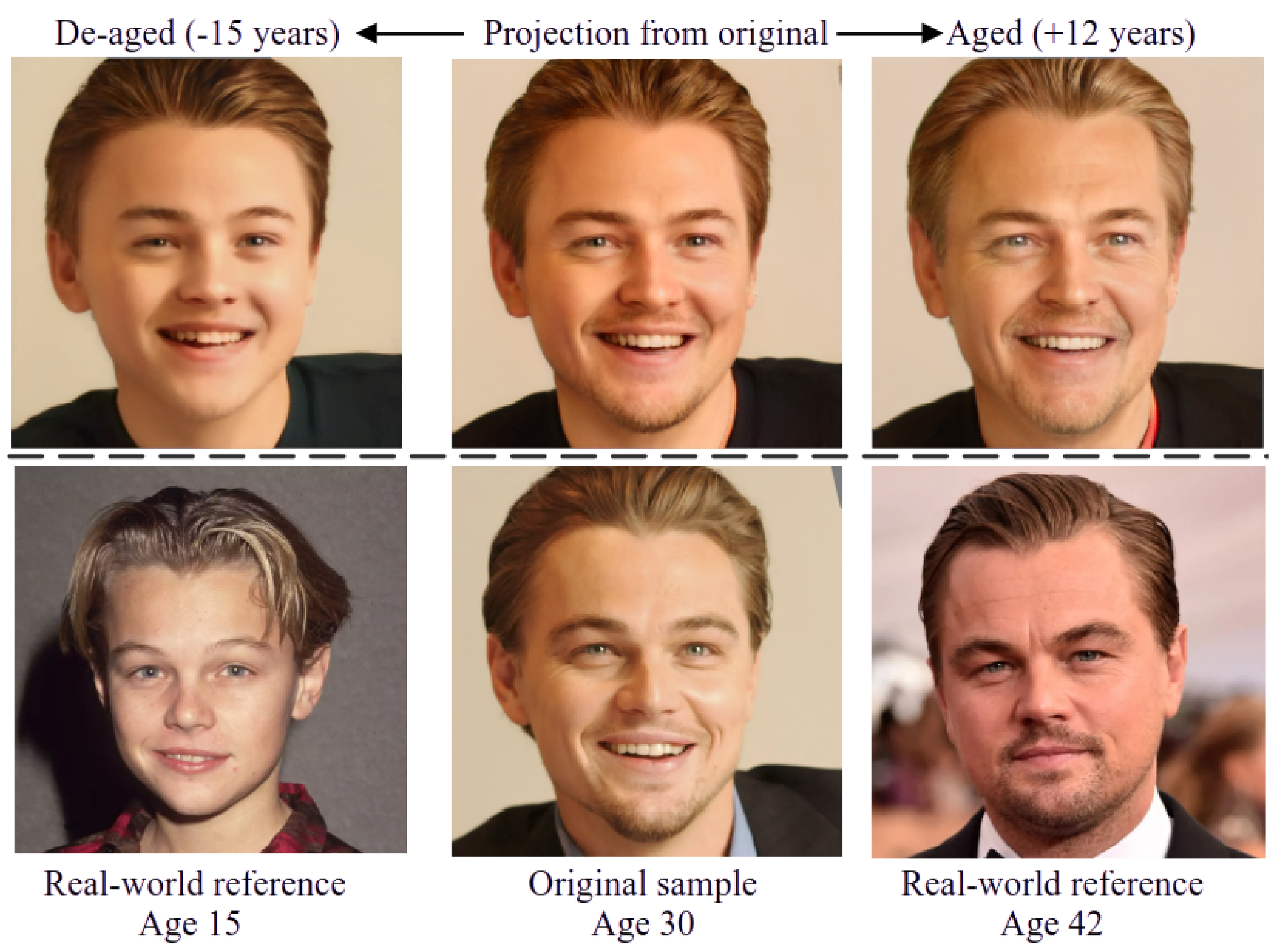

Figure: Young adult sample projected to the latent space (middle column) and controlled transformations for de-aging (left column) and aging (right column). The bottom row serves as real-world reference for the synthesized subjects.

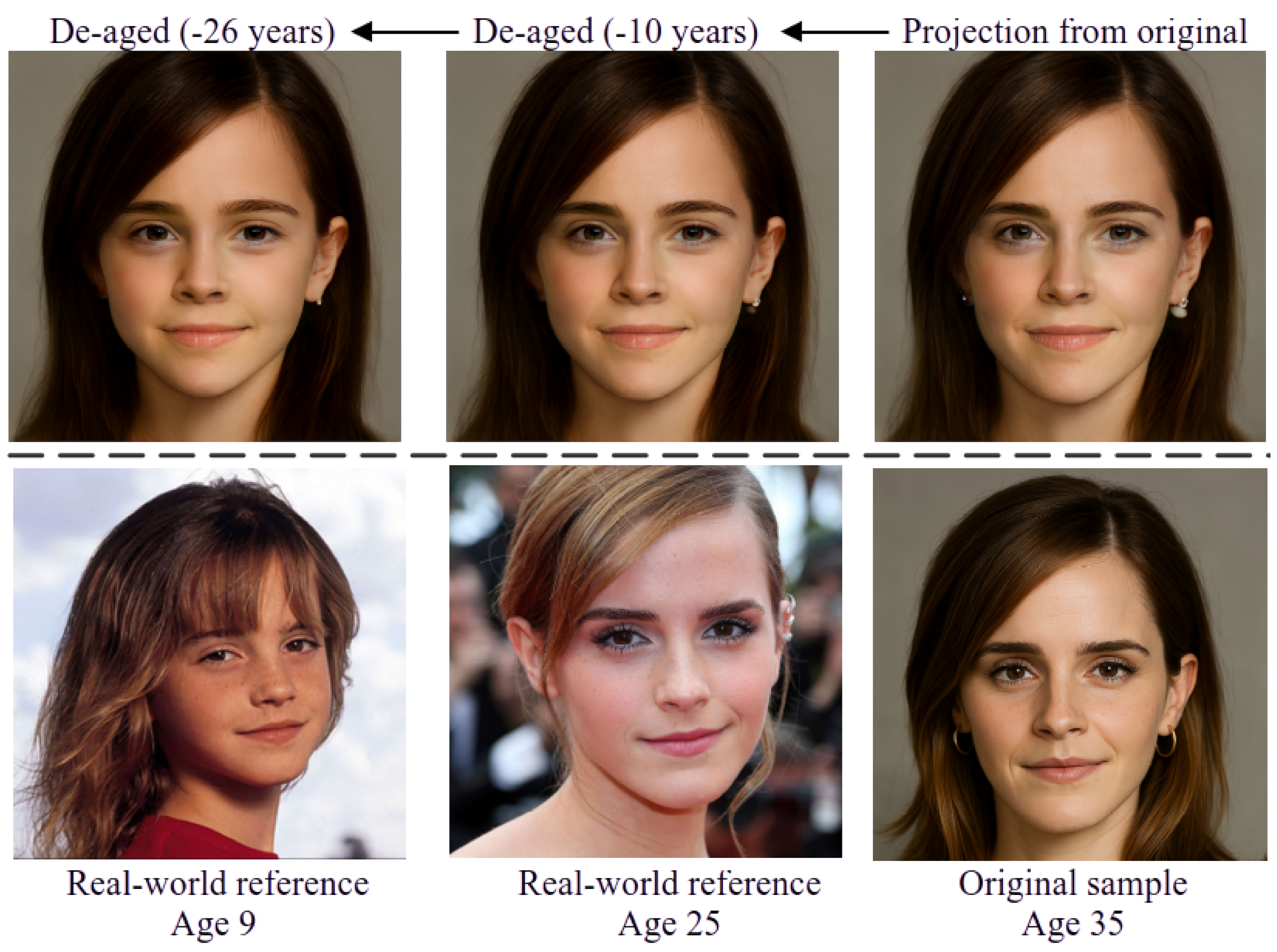

Figure: Left: Young adult sample projected to the latent space (middle column) and controlled transformations for de-aging and aging. De-aging a young adult sample from their latent space projection by 10 years and 26 years . The real-world references are present in the bottom row.

Fully synthetic aged dataset

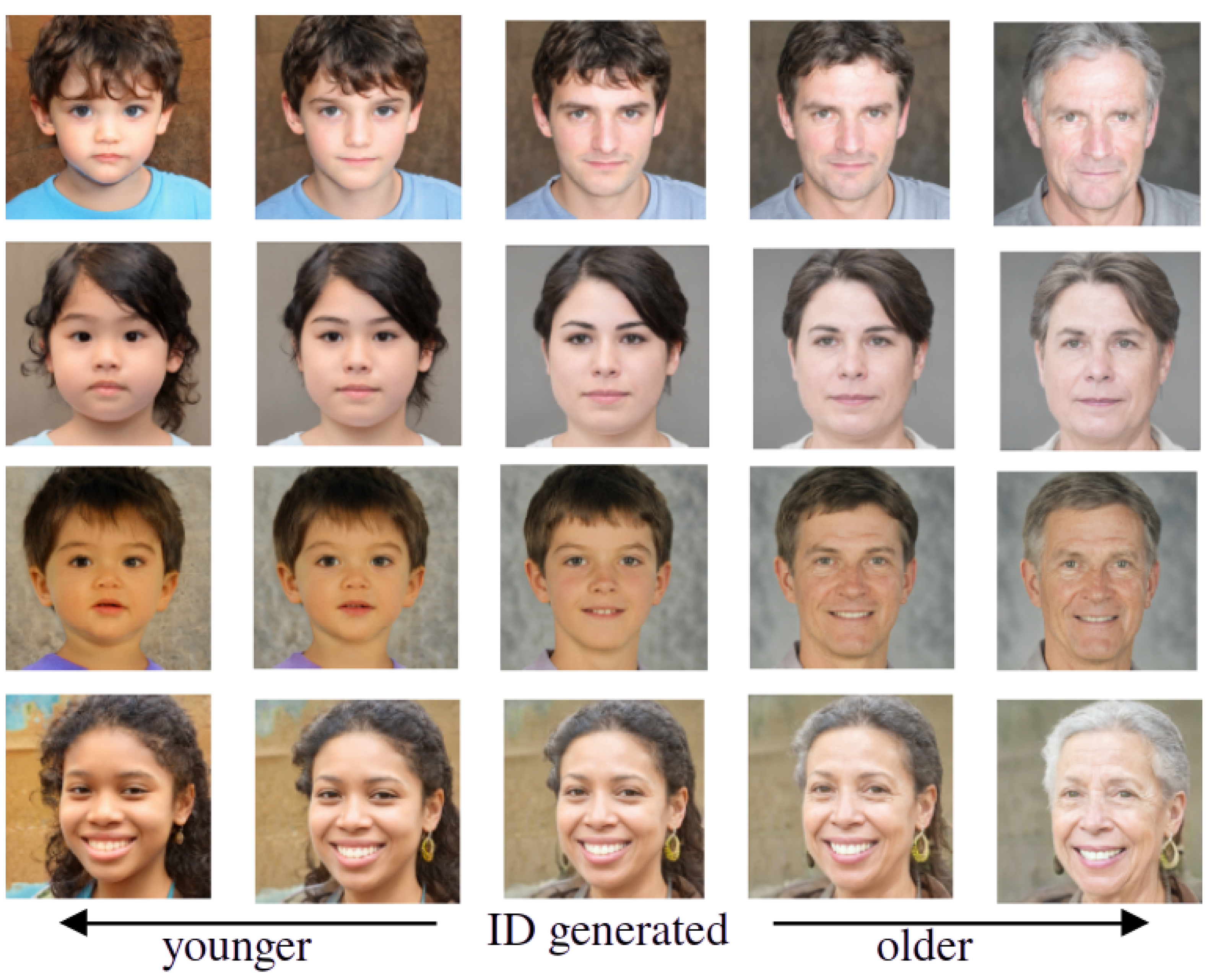

Figure: Samples from fully synthetic dataset generated. IDs generated using Langevin sampling [2] and linear approach for aging and de-aging the synthetic identities.

Experimental Setup

- **Datasets**: Train and test partiions of UTKFace (age), train partition of Color FERET (identity).
- **Age estimation and face recognition**: MobileNetV2 age estimator; EdgeFace-S face recognition backbone calibrated on IJBC.

ID preservation and age

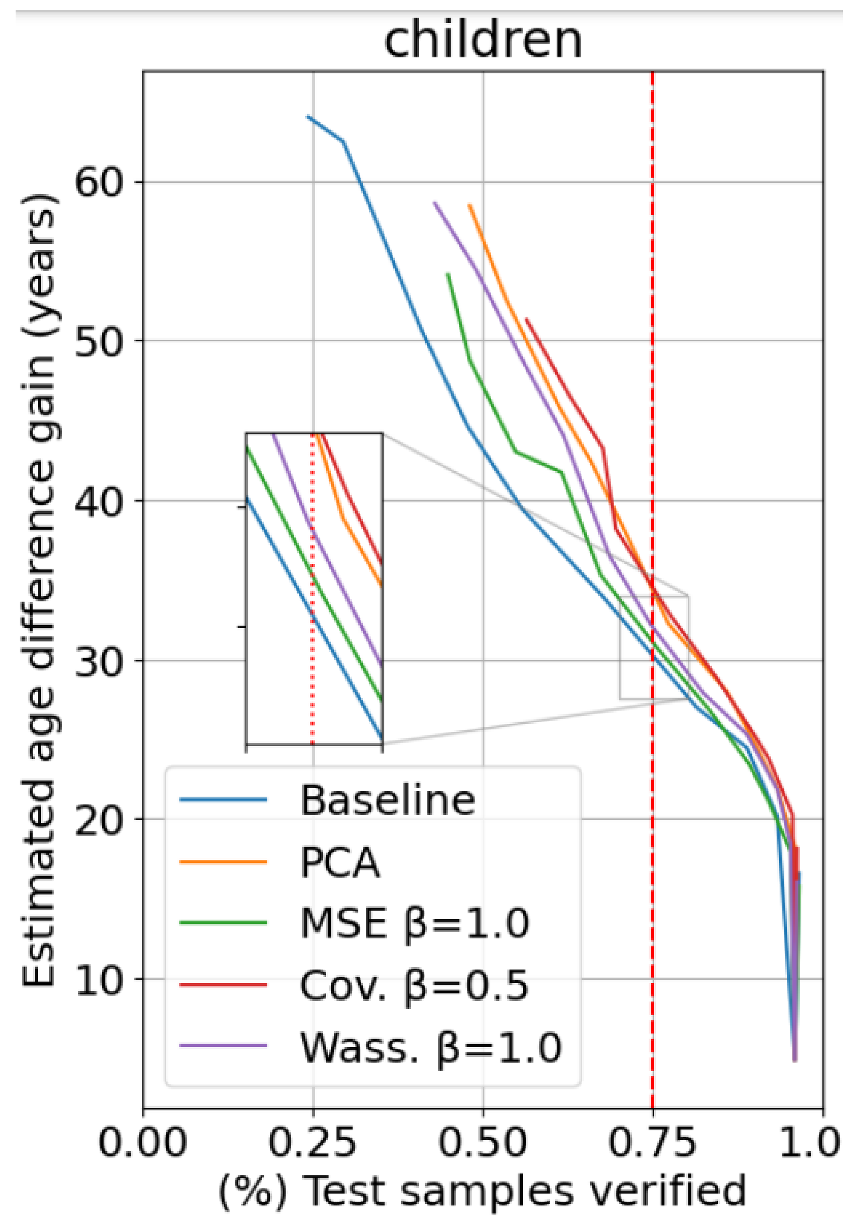

Figure: Age gain per number of samples verified for the children age group. LDA reconstruction metrics for MSE, Covariance, and Wasserstein distance.

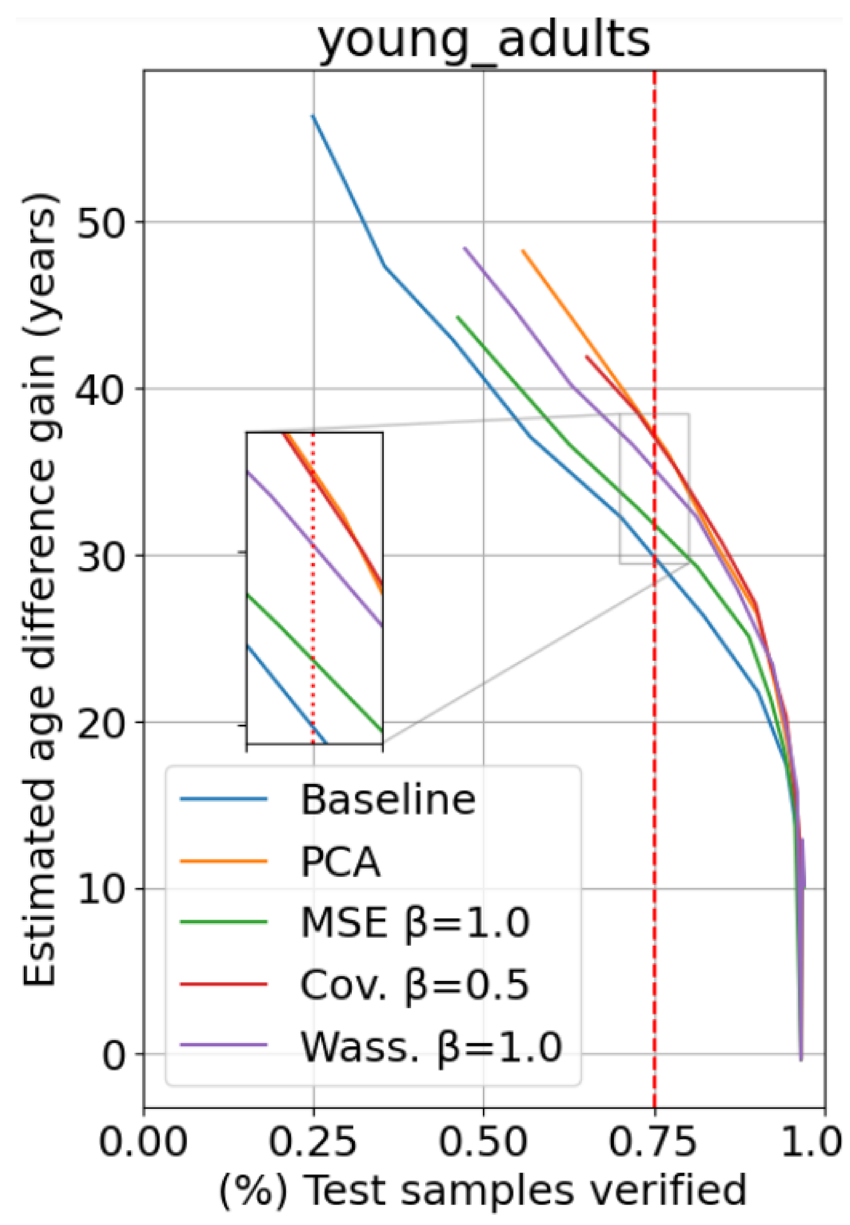

Figure: Age gain for young adults per number of samples verified. MSE, Covariance, and Wasserstein distance used for LDA reconstructions.

Selected references

[1] Colbois, L. et al. On the use of automatically generated synthetic image datasets for benchmarking face recognition. In 2021 IEEE International Joint Conference on Biometrics (IJCB), IEEE Press, 2021.

[2] Geissbühler, D. et al. Face datasets generation via latent space exploration from brownian identity diffusion. In Proceedings of the 42nd International Conference on Machine Learning (ICML) (to appear). PMLR, 2025