Domain Intersection and Domain Difference

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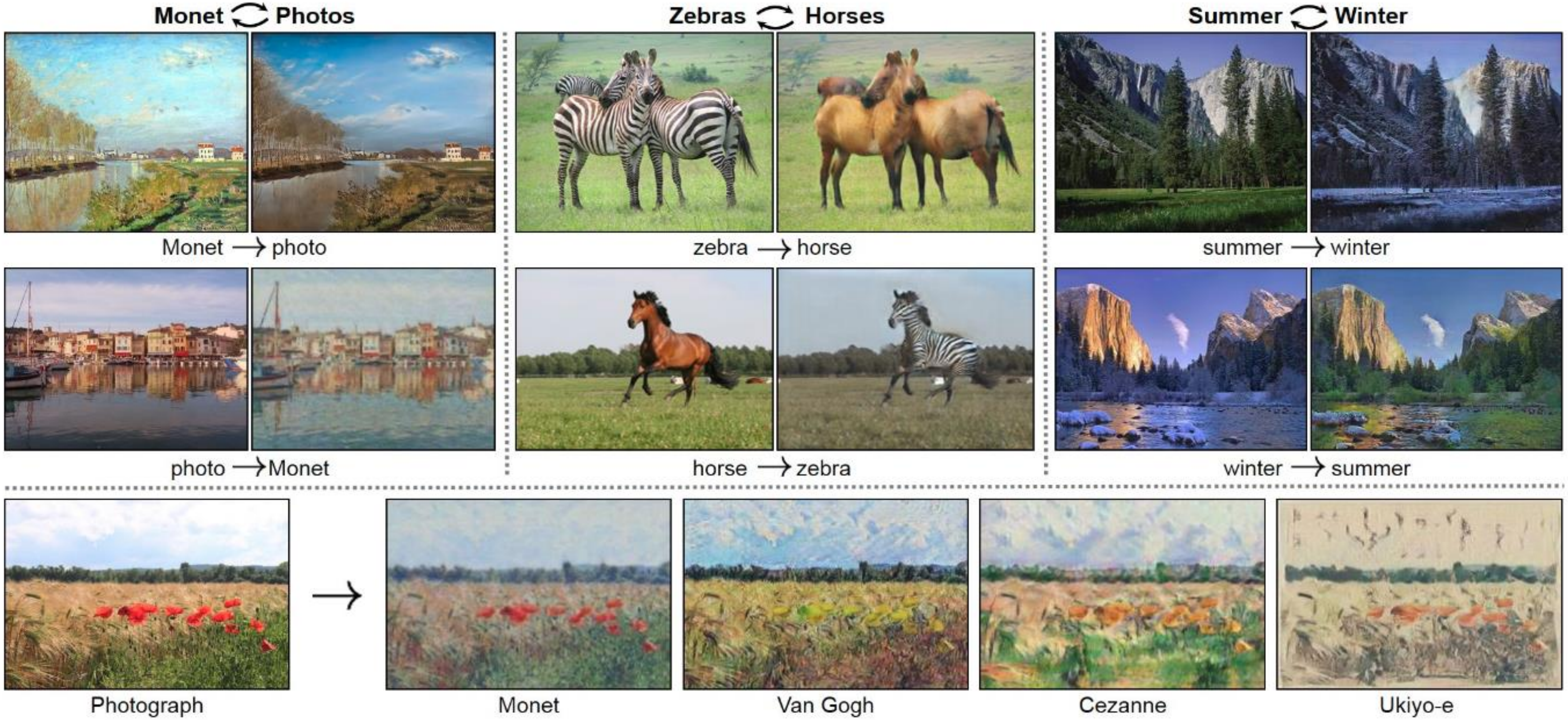
Image to Image Translation



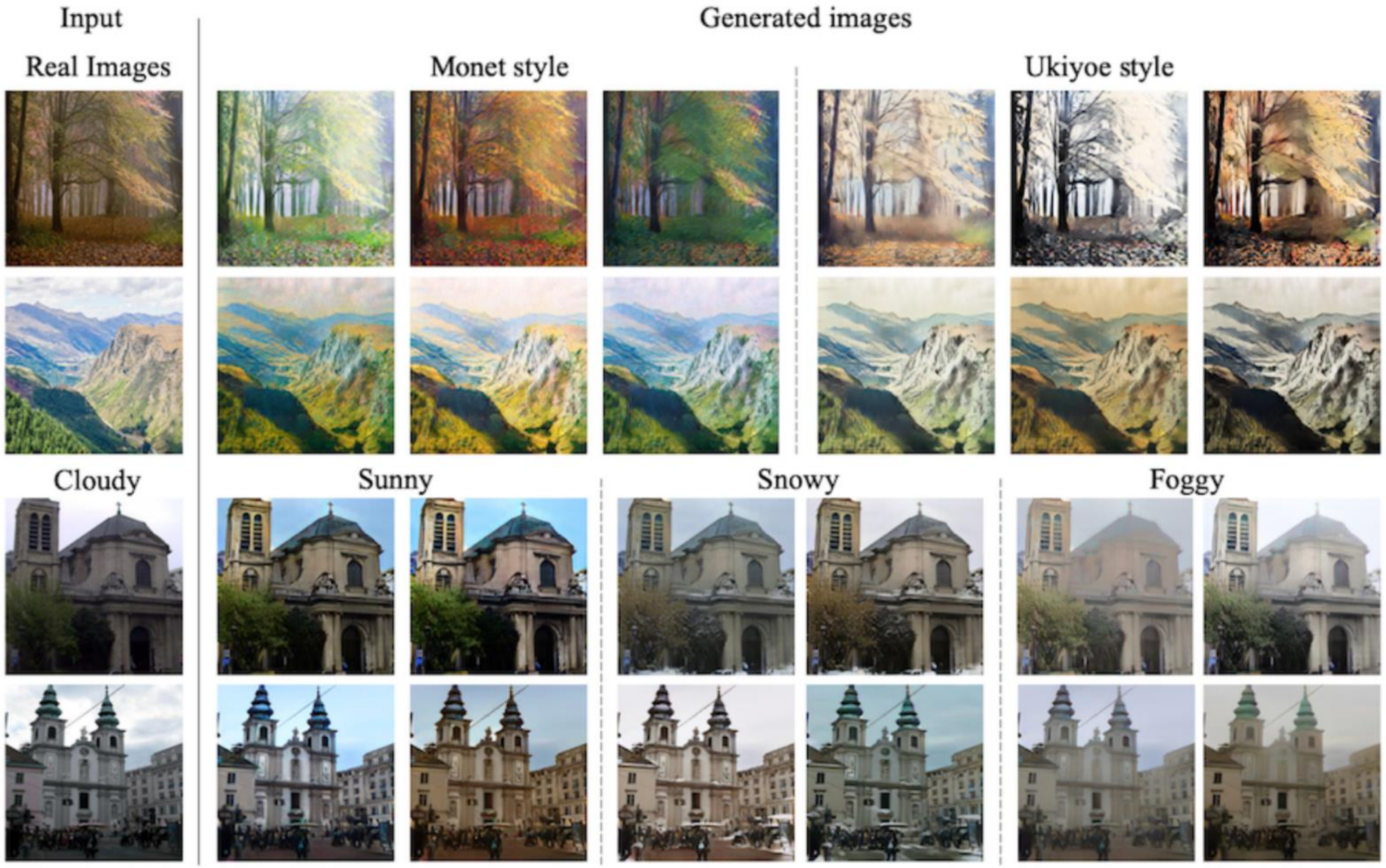
MUNIT: Style and Texture Changes

Sketch to Image Translation

(a) edges ↔ shoes (b) edges ↔ handbags

Huang et al., ECCV 2018

DRIT, DRIT++: Similar Textural and Style Changes



Lee et al., ECCV 2018

Cannot Transfer Content!

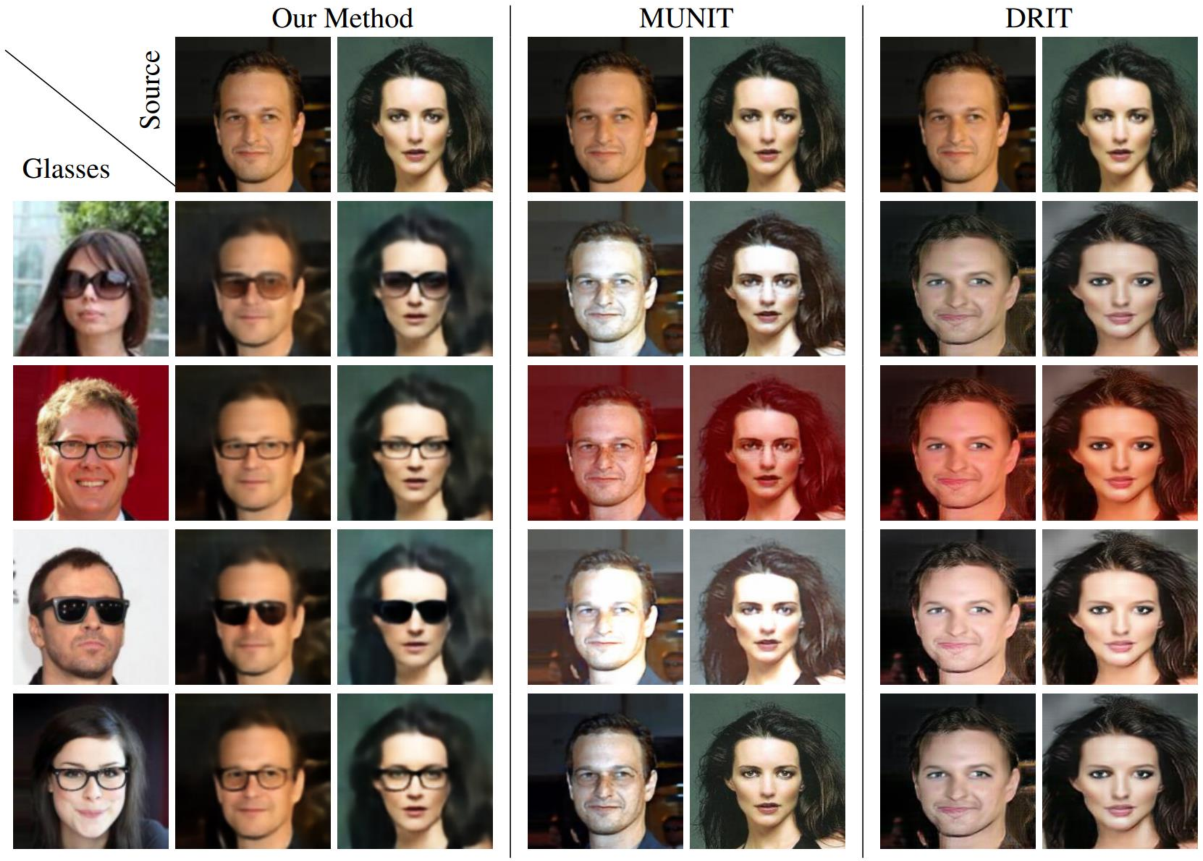


Figure 2: Glasses transfer. Our method vs literature baselines. Each image combines the domain A image in the top row, with the content of the guide image on the left column.

Press et al, ICLR 2019

Attribute Transfer

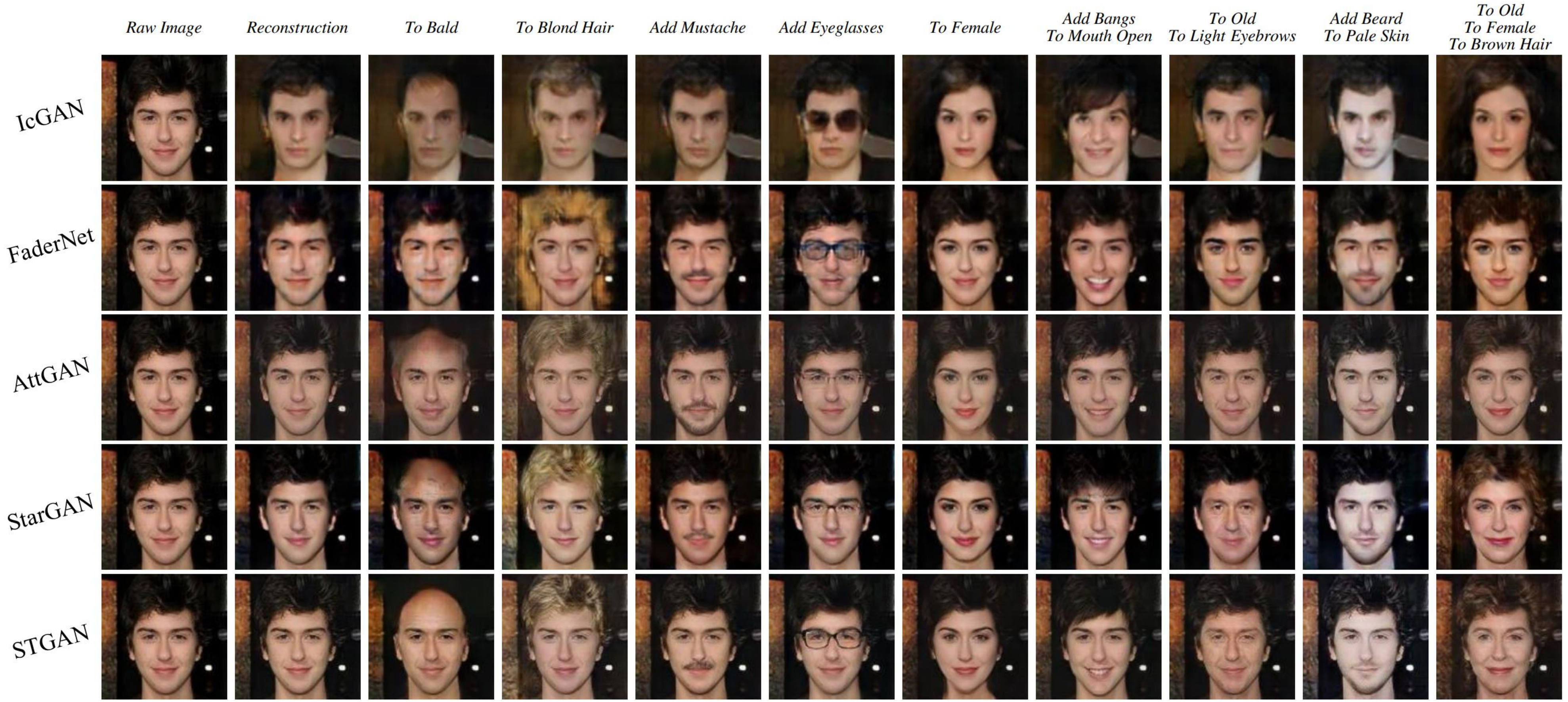


Figure 6: Facial attribute editing results on the CelebA dataset. The rows from top to down are results of IcGAN [26], FaderNet [17], AttGAN [11], StarGAN [7] and STGAN.

Liu et al, CVPR 2019

Only a single Attribute!
For example, Fader Networks:

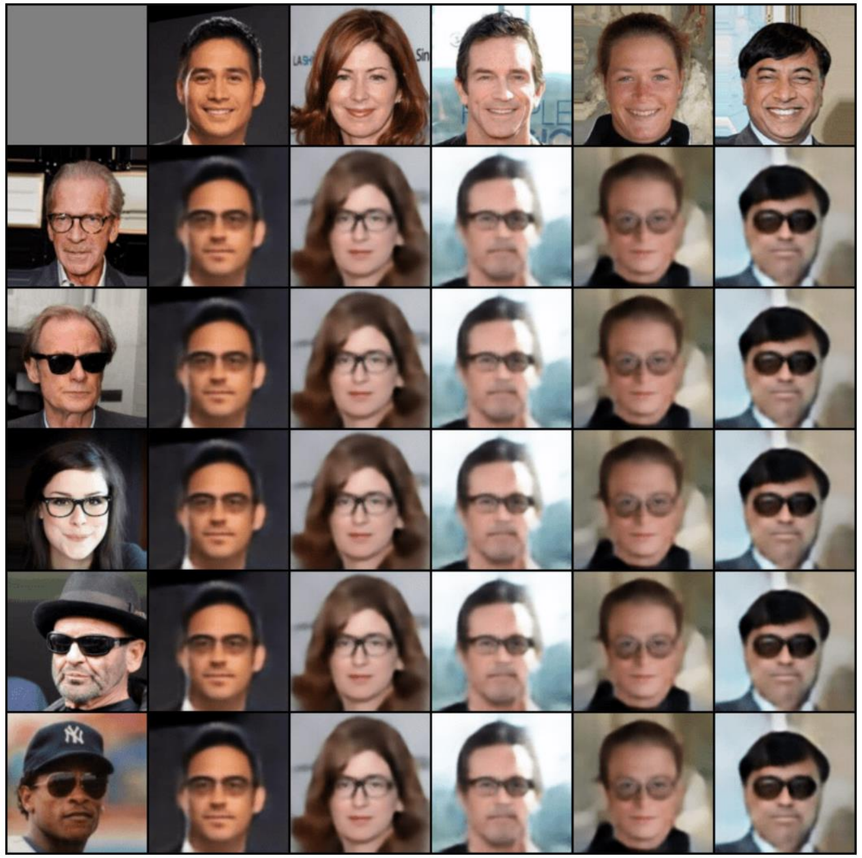
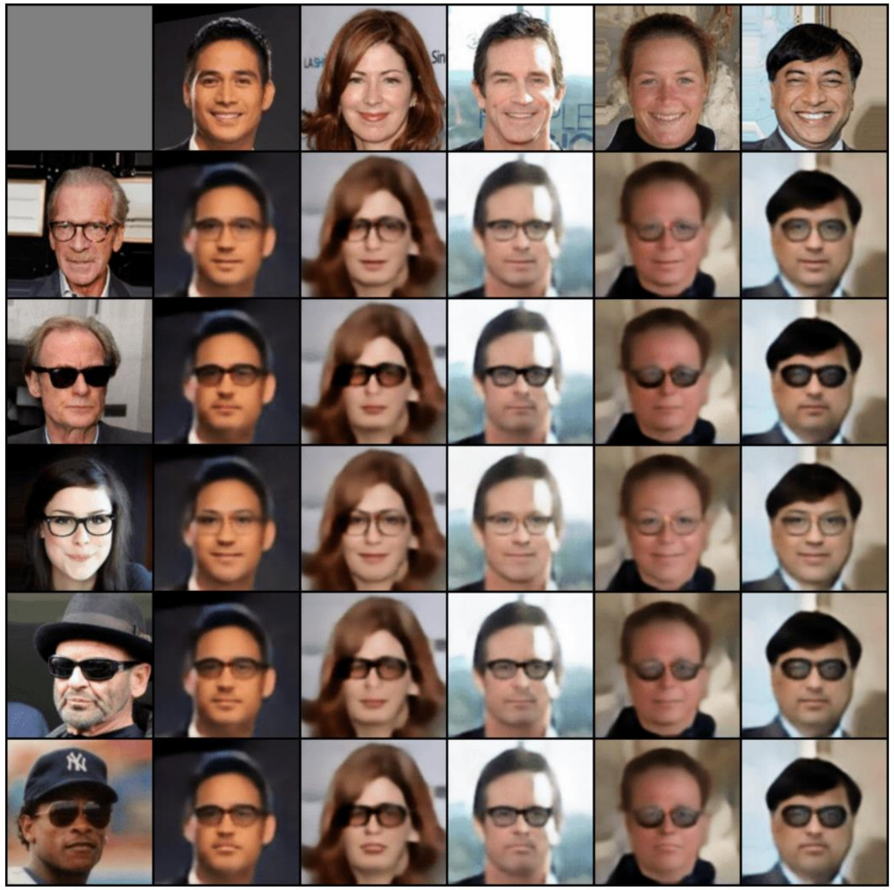


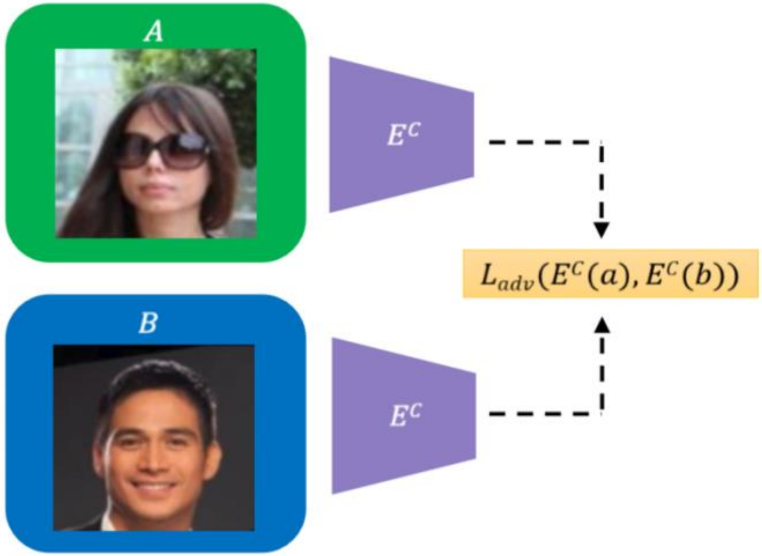
Figure 19. Translation from the domain of smiling persons to the domain of persons with glasses, using the Fader Networks method.

Domain Intersection and Domain Difference

- Our approach: Disentangle the **Common (Intersection)** and **Specific (Difference)** parts of each domain.
- Thus produced **three latent spaces:**
  - $E^c(A) = E^c(B)$: Common to A and B
  - $E^s_A(A)$ (or $E^s_B(B)$): Separate to A (respectively to B)



The "common" (or shared) Loss

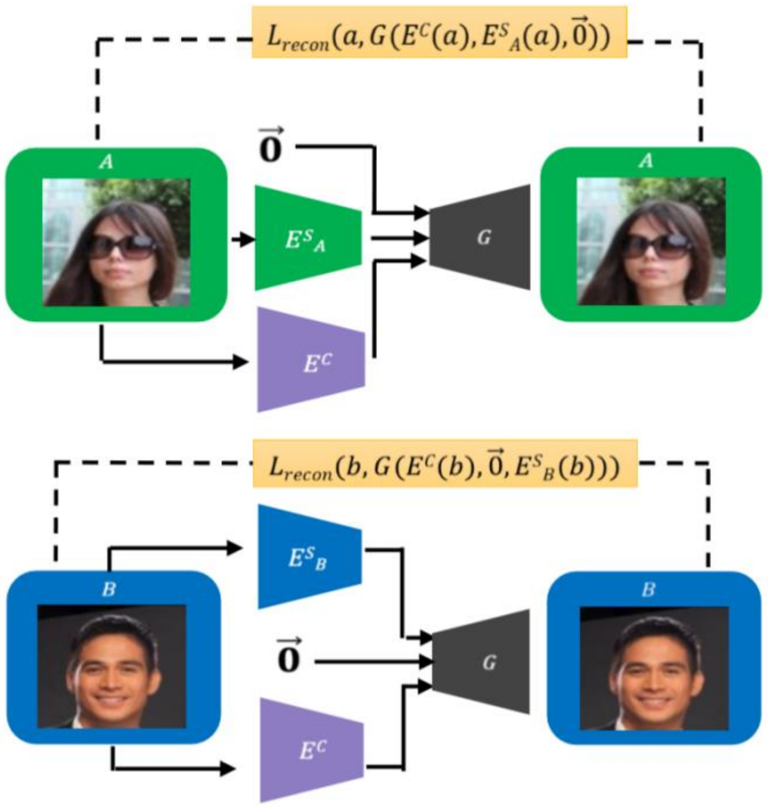


(c)

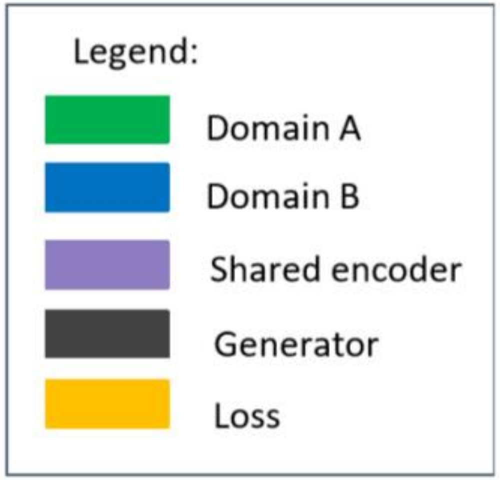
Legend:

- Domain A
- Domain B
- Shared encoder
- Generator
- Loss

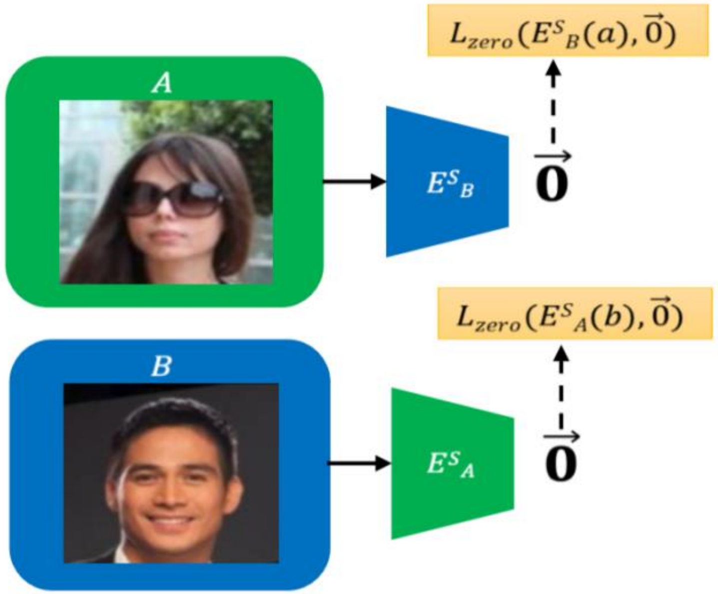
Reconstruction Losses



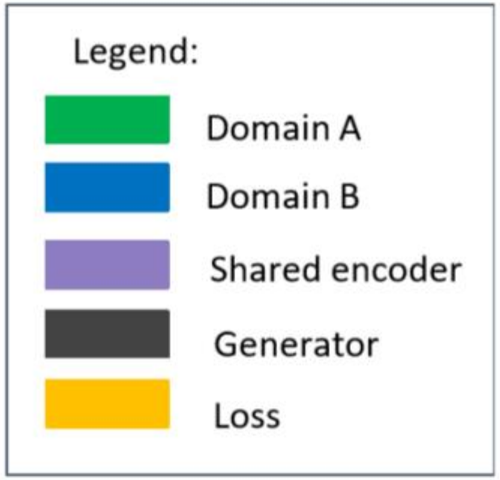
(b)



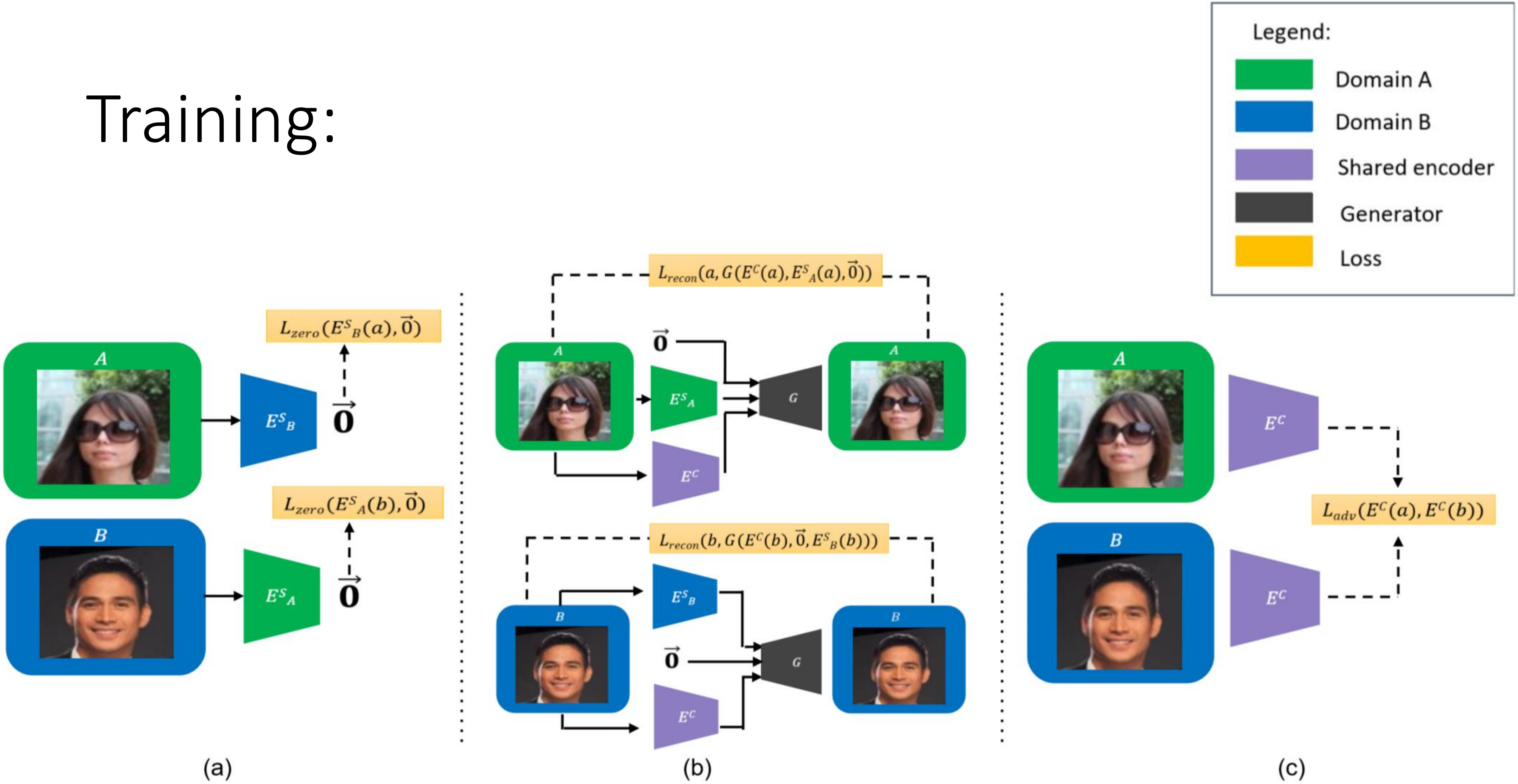
"Zero" Loss


$L_{zero}(E^S{}_B(a), \vec{0})$
A
$E^S{}_B$
$\vec{0}$
$L_{zero}(E^S{}_A(b), \vec{0})$
B
$E^S{}_A$
$\vec{0}$

(a)


Legend:
Domain A
Domain B
Shared encoder
Generator
Loss

Training:


Legend:
Domain A
Domain B
Shared encoder
Generator
Loss
A
B
$E^S{}_B$
$E^S{}_A$
$\vec{0}$
$L_{zero}(E^S{}_B(a), \vec{0})$
$L_{zero}(E^S{}_A(b), \vec{0})$
$L_{recon}(a, G(E^C(a), E^S{}_A(a), \vec{0}))$
$L_{recon}(b, G(E^C(b), \vec{0}, E^S{}_B(b)))$
E^C
G
$L_{adv}(E^C(a), E^C(b))$
(a)
(b)
(c)

Inference:

Legend:

- Domain A
- Domain B
- Shared encoder
- Generator
- Loss

(d) (e)

Results

Beard to Smile

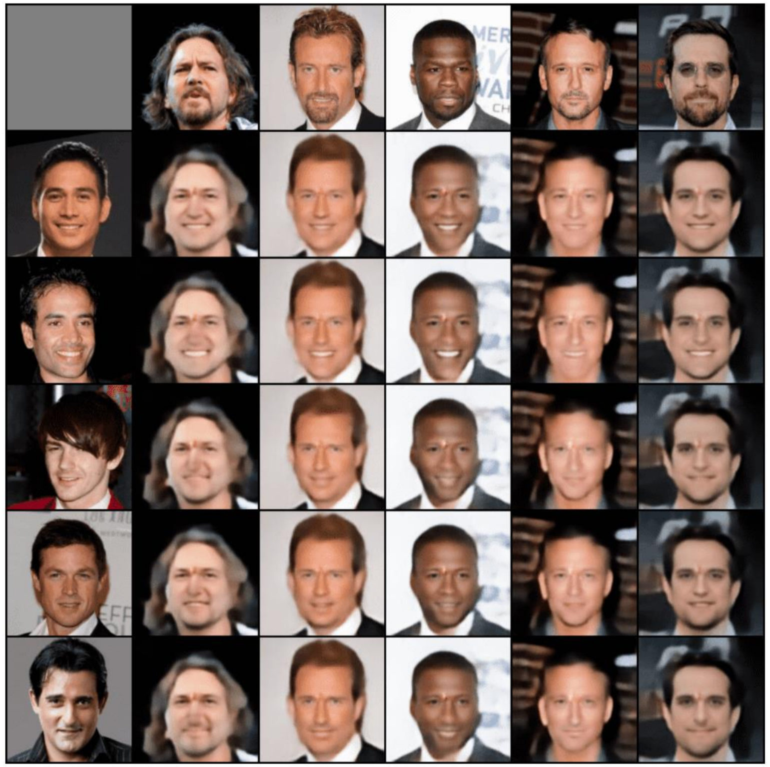


Figure 8. Translating from the domain of persons with facial hai
to the domain of smiling persons.

Glasses to Smile

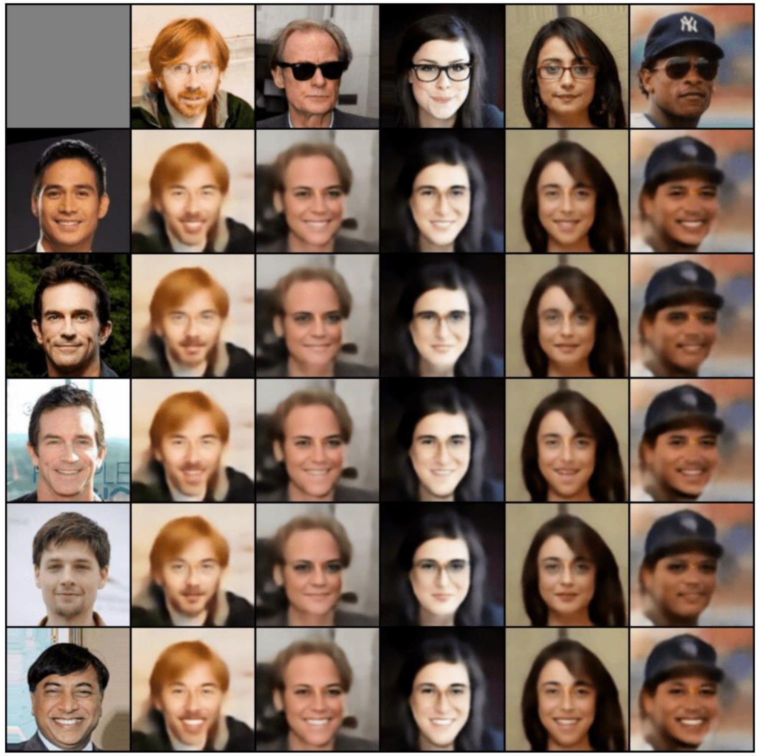
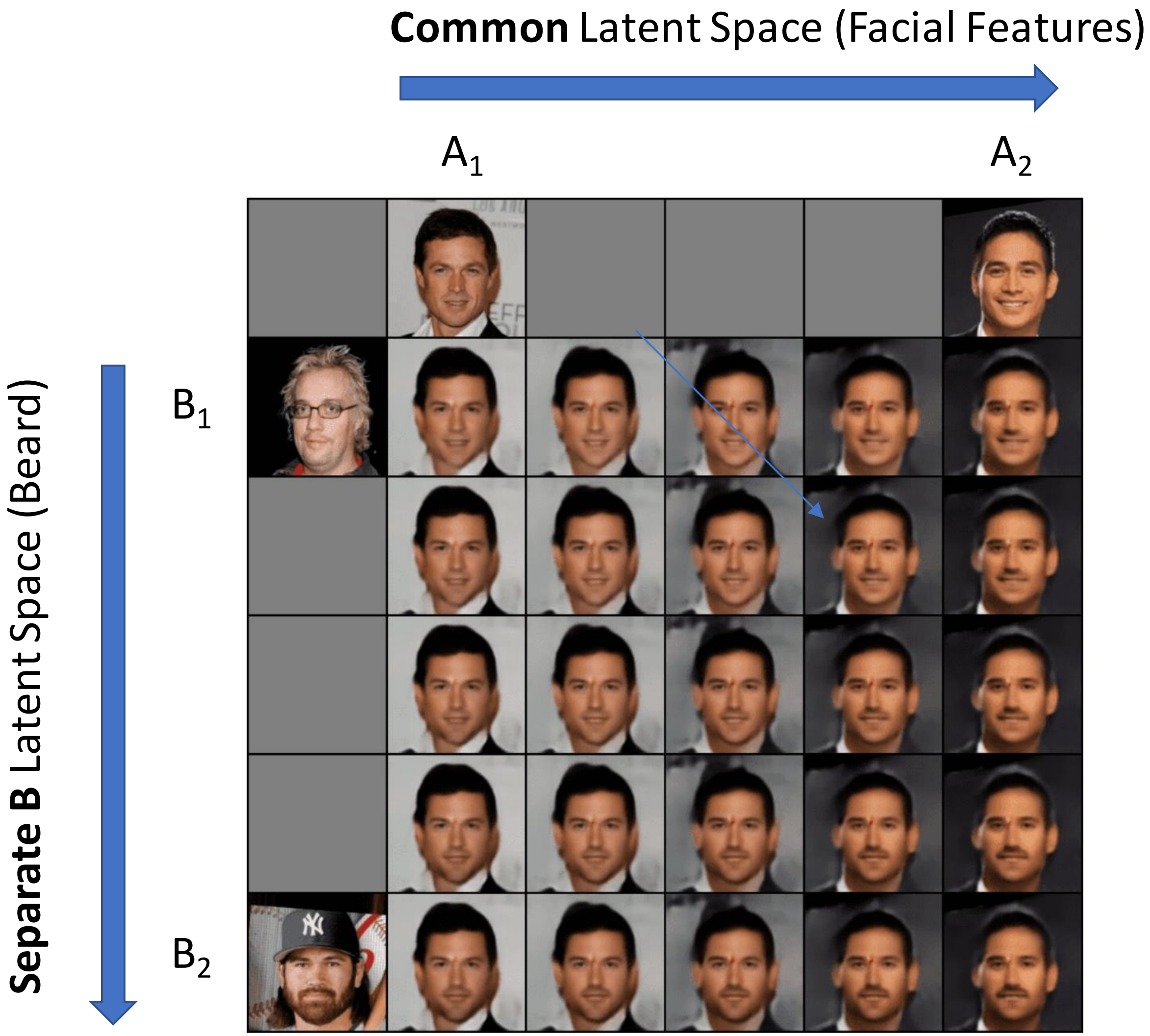


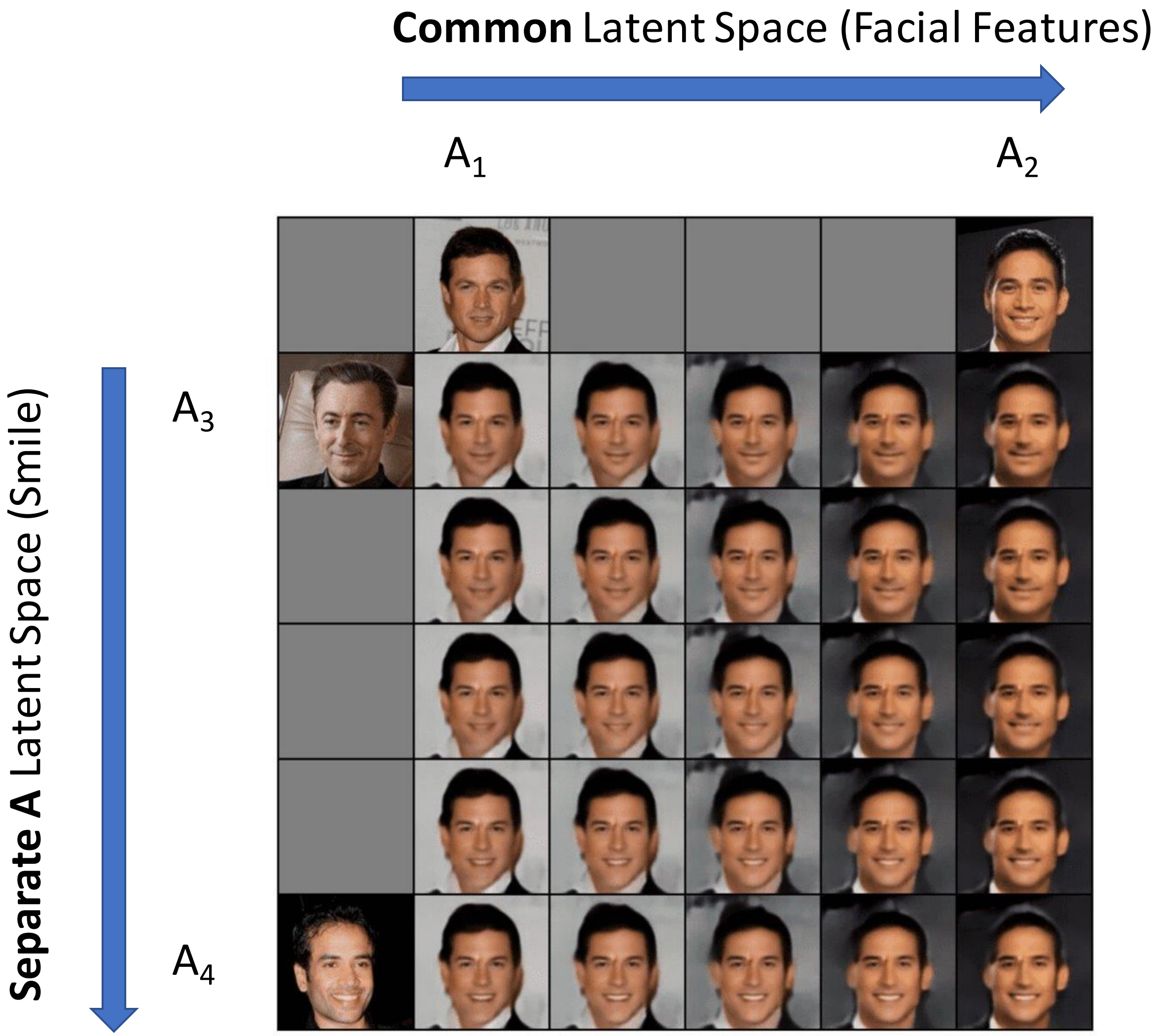
Figure 7. Translating from the domain of persons with glasses to the domain of smiling persons (reverse translation to Fig. 2 in main report)

Glasses ∩ Smile

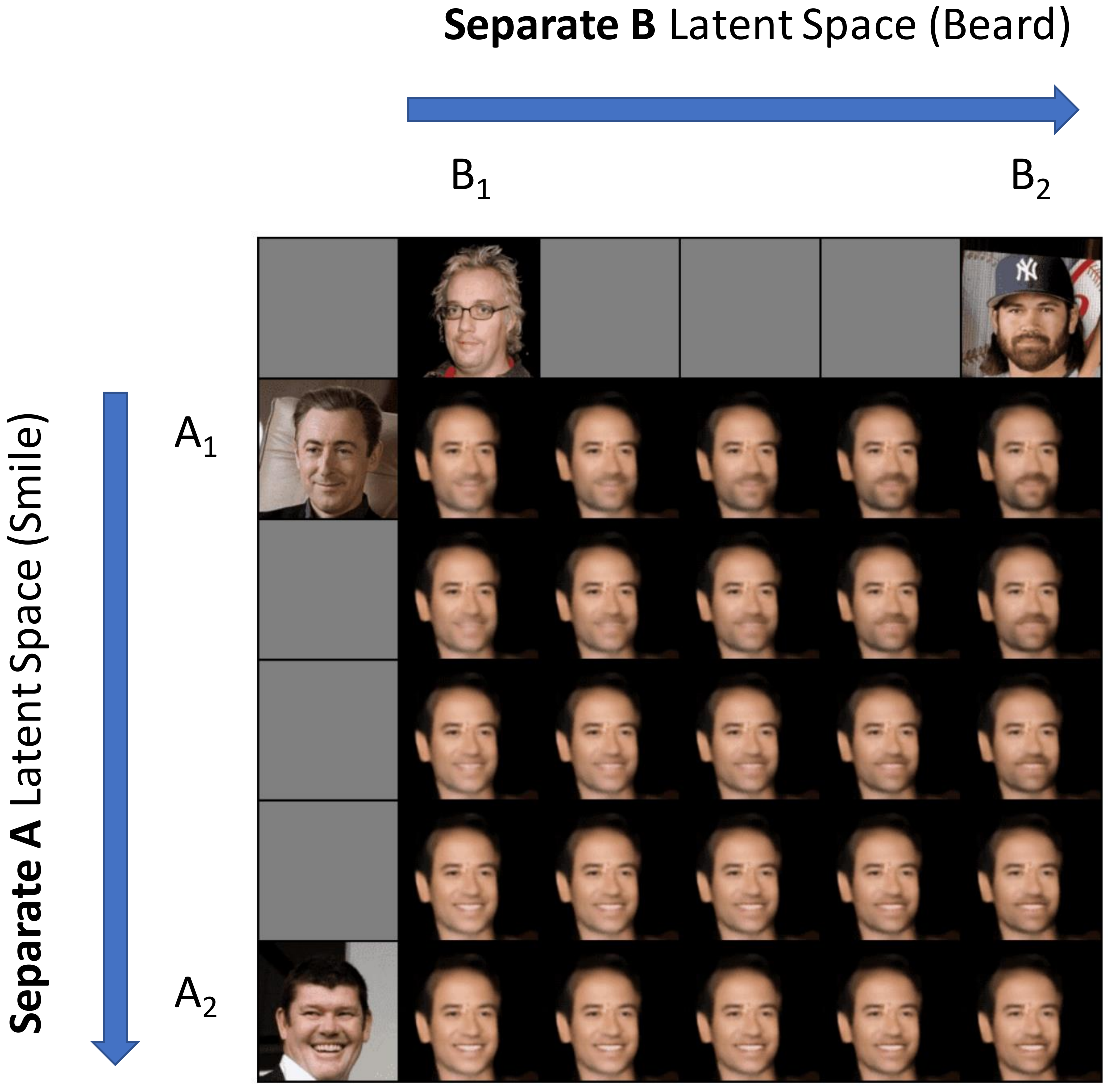
Interpolations



Interpolations



Interpolations

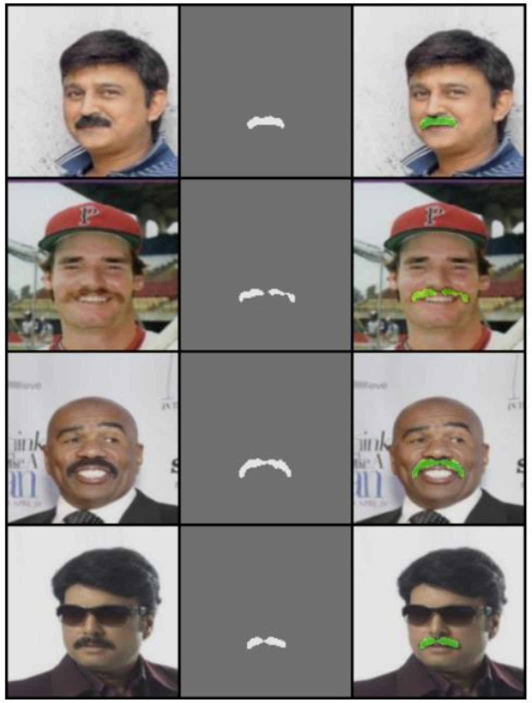


Theory and Domain Adaptation

- Under mild assumptions (such as our losses being minimized):
  - $E^c(A)$ and $E^s_A(A)$ are independent (Similarly for B).
  - $E^c(A)$ caputres the information underlying $e^c(A)$ (Similarly for B).
  - $E^s_A(A)$ holds the infromation underlying $e^s_A(A)$ (Similarly for B).
  - I.e. our losses are both **necessary and sufficient** for the desired **disentanglement**.

- Our disentanglement provides a useful representation for **(unsupervised) domain adaptation** beating SOTA.

Next: Masked Based Approach



Code and paper available online:
https://github.com/sagiebenaim/DomainIntersectionDifference

Questions?