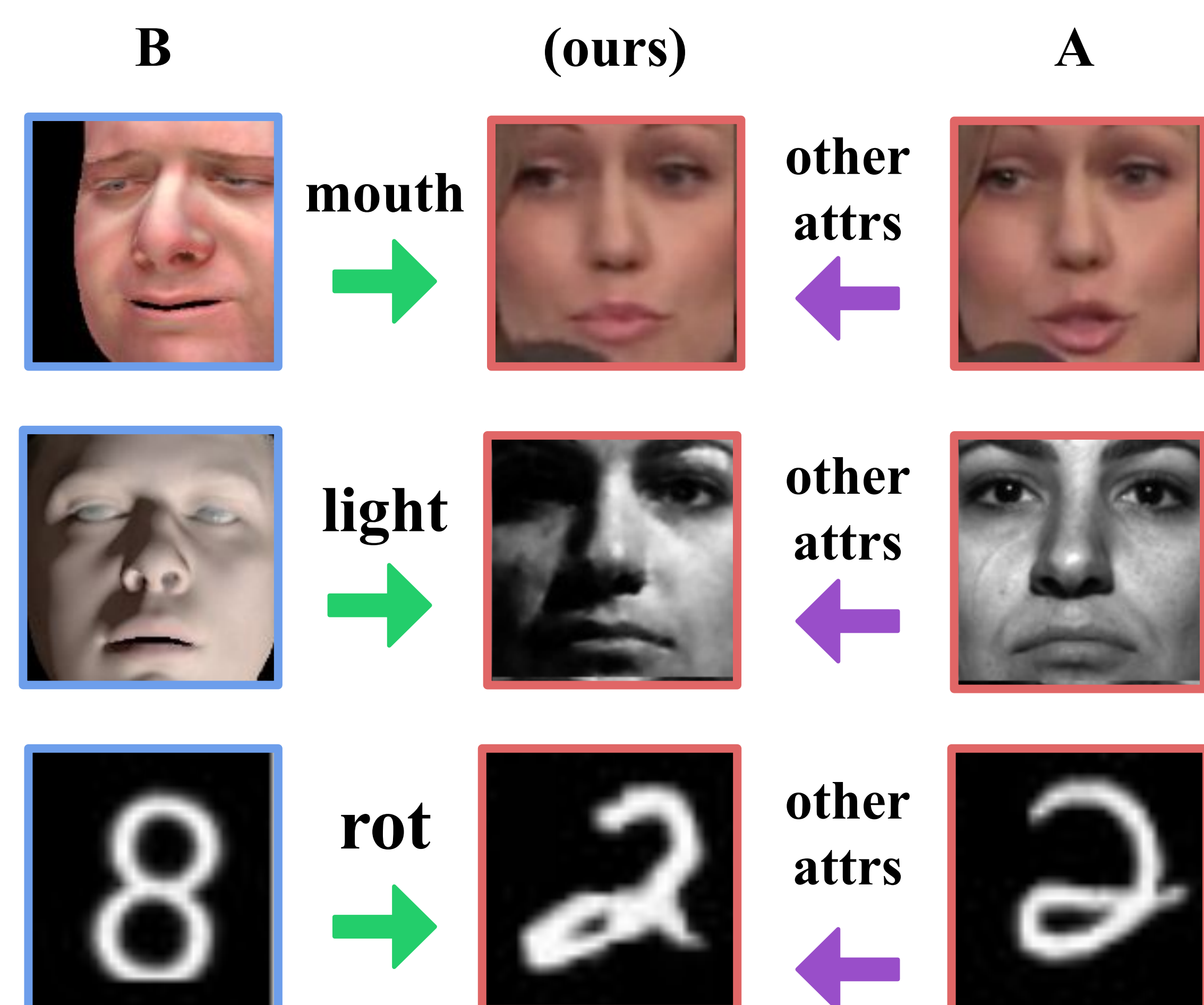
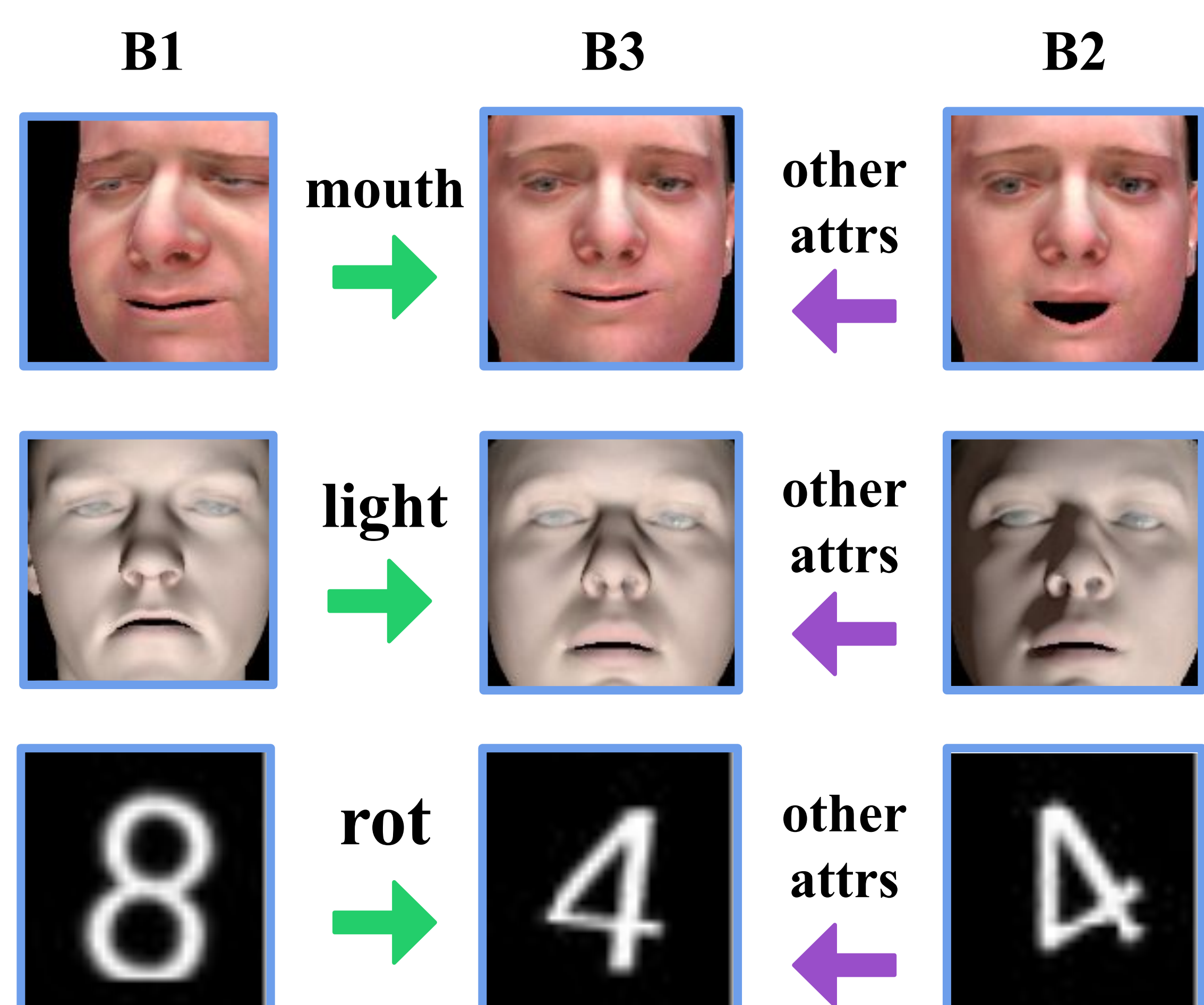


Task

Our model can manipulate a **single** specific **attribute** of a **real** image A using a **synthetic** reference B.



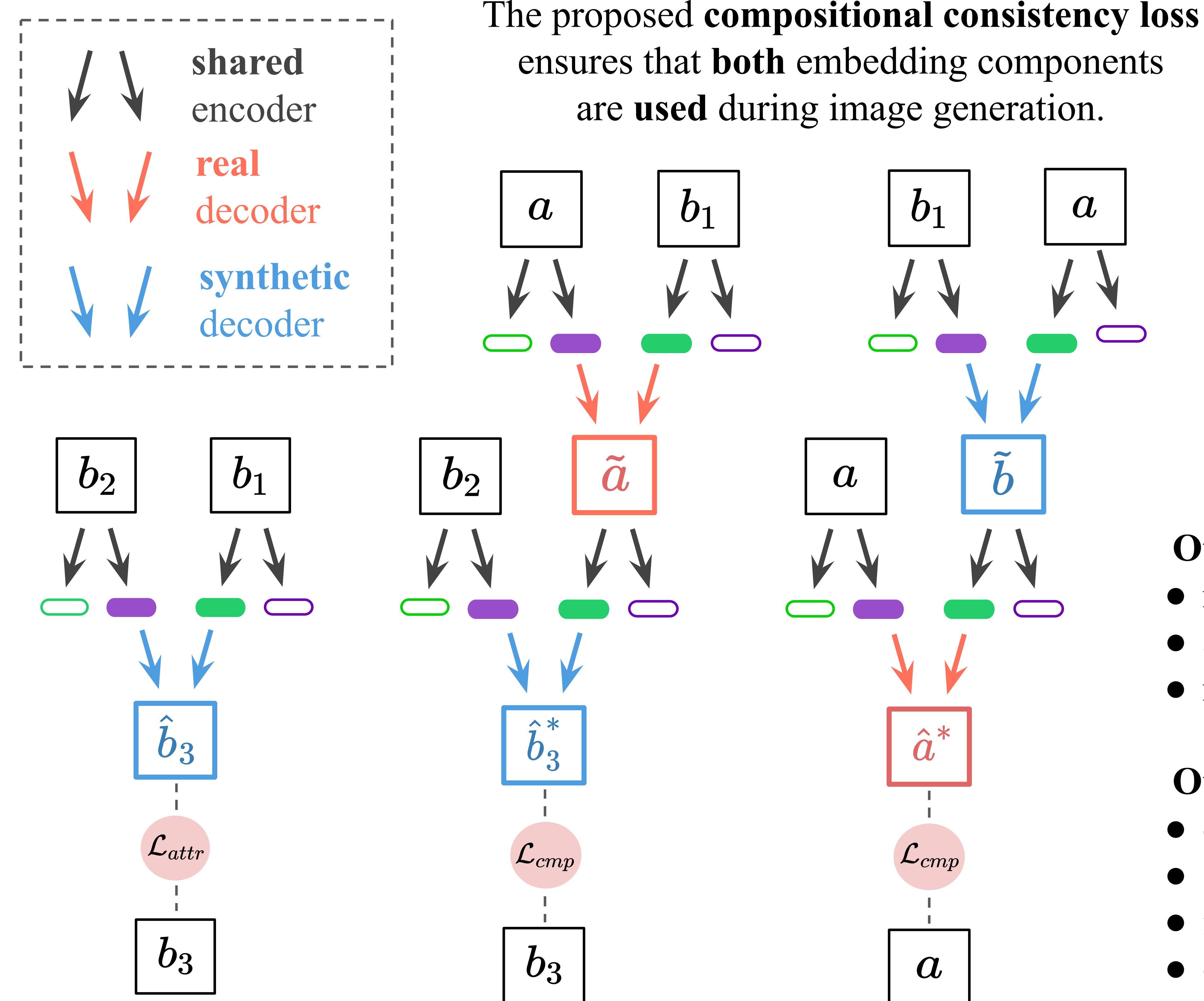
It is trained exclusively on **synthetic demonstrations** and unlabeled real images.



Related Work

Unsupervised Cross-Domain Adaptation produces entangled representations (e.g. CycleGAN).
Unsupervised Cross-Domain Disentanglement might disentangle wrong attributes (e.g. MUNIT).
Supervised Single-Domain Disentanglement fails to generalize to a different domain (e.g. InfoGAN, Cycle-Consistent VAE).
Existing Supervised Cross-Domain Disentanglement Methods yield degenerate solution that ignore parts of the learned embeddings (e.g. DiDA). The PuppetGAN model is more resilient against such degenerate solution.

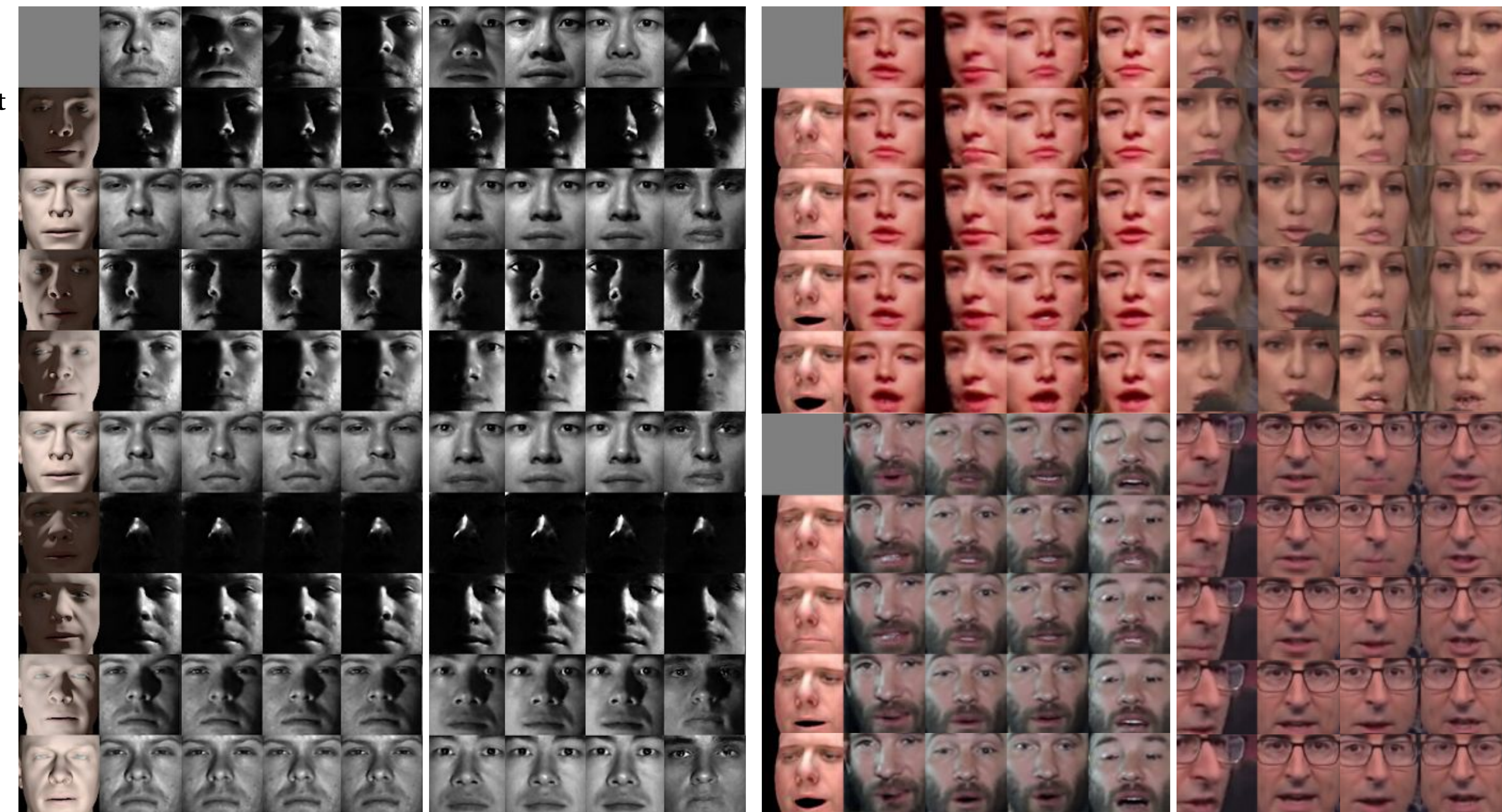
Method



(a) supervised disentanglement

(b) compositional consistency

Results



Other techniques we used:

- reconstruction and cycle losses
- adversarial domain alignment
- regularization with instance noise

Other findings reported in the paper:

- disentanglement quality metrics
- failure case analysis
- input outlier robustness
- comparison to other models

Disentanglement quality (MNIST \rightleftharpoons Rendered Digits)

Model	Size				Rotation			
	Acc \uparrow	$r_{\text{attr}}^{\text{syn}} \uparrow$	$r_{\text{rest}}^{\text{syn}} \downarrow$	$V_{\text{rest}} \downarrow$	Acc \uparrow	$r_{\text{attr}}^{\text{syn}} \uparrow$	$r_{\text{rest}}^{\text{syn}} \downarrow$	$V_{\text{rest}} \downarrow$
PuppetGAN	0.73	0.85	0.02	0.02	0.97	0.40	0.11	0.01
CycleGAN [28]	0.10	0.28	0.06	0.28	0.11	0.54	0.37	0.33
DiDA [2]	0.71	0.18	0.09	0.02	0.86	0.04	0.35	0.02
MUNIT [10]	0.96	0.06	0.09	0.01	1.00	0.00	0.15	0.01
Cycle-VAE [8]	0.17	0.92	0.16	0.01	0.29	0.45	0.10	0.01
PuppetGAN [†]	0.64	0.28	0.07	0.01	0.10	0.06	0.04	0.01

[†] larger discrepancy in attribute distributions between A and B \Rightarrow lower disentanglement quality