

# Dual-Domain Image Synthesis Using Segmentation-Guided GAN

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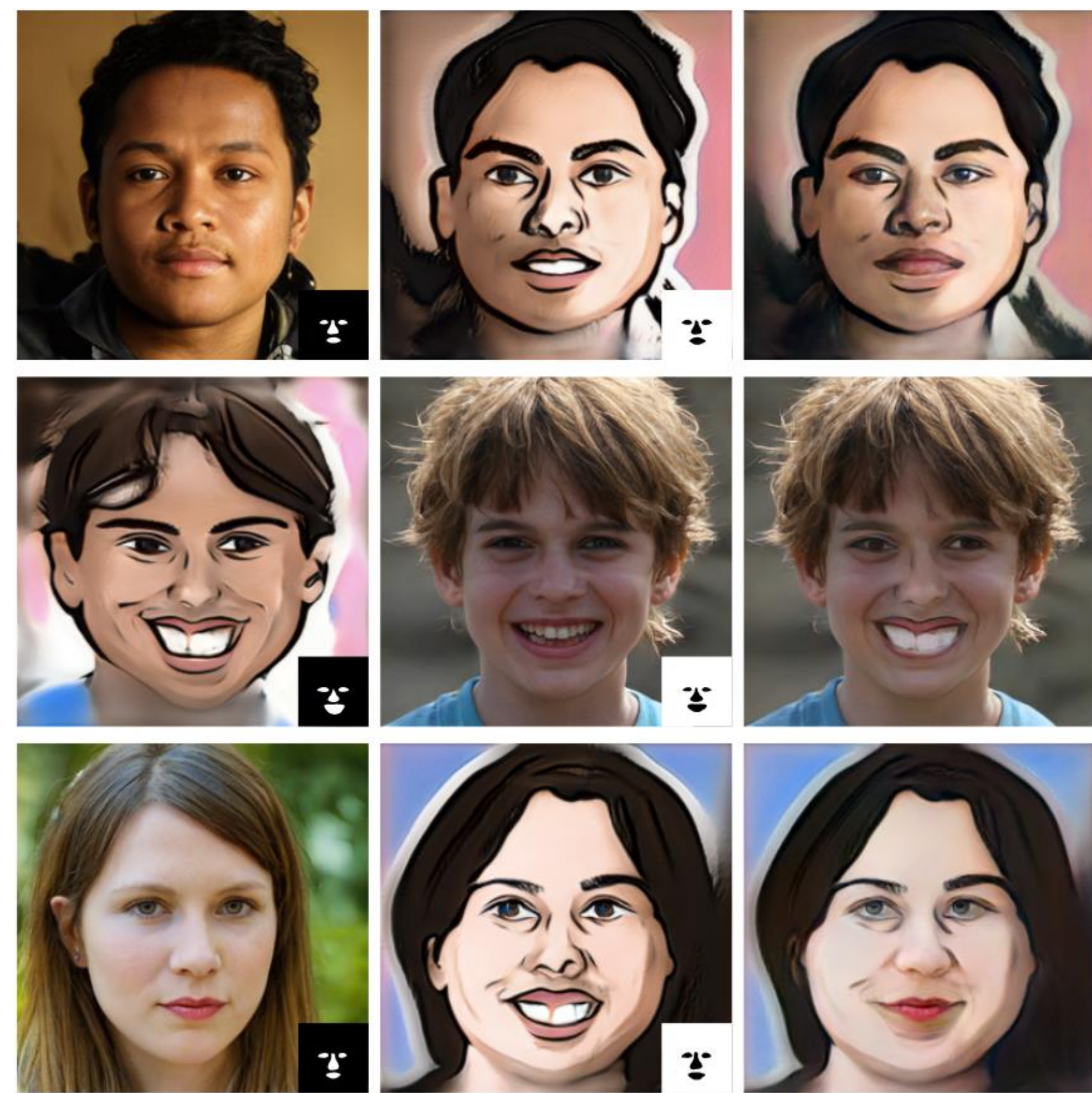
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## Overview

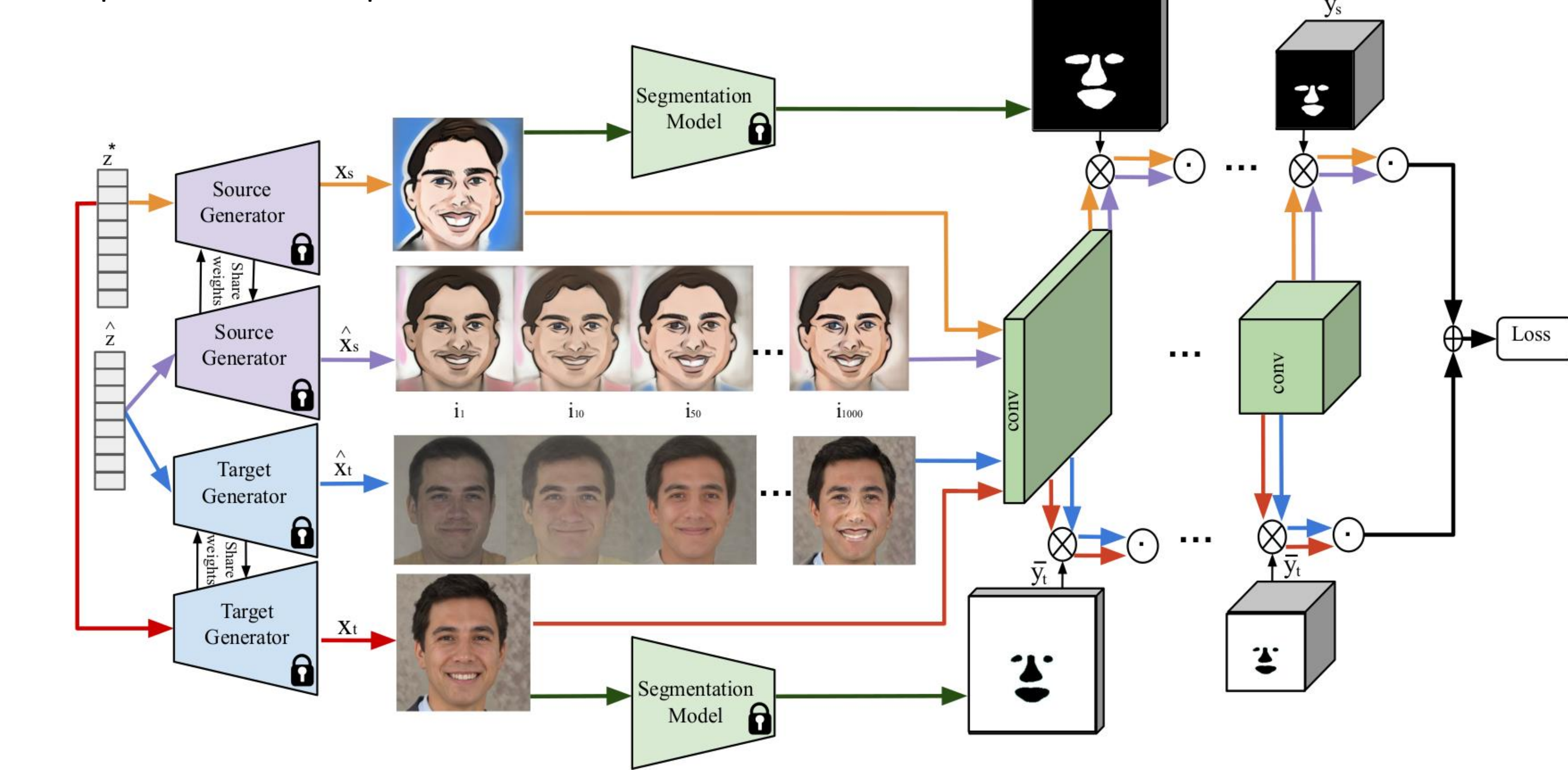
- A segmentation-guided approach to synthesise images that integrate features from two distinct domains.

- Images synthesised by our dual-domain model belong to one domain within the semantic-mask, and to another in the rest of the image - smoothly integrated.

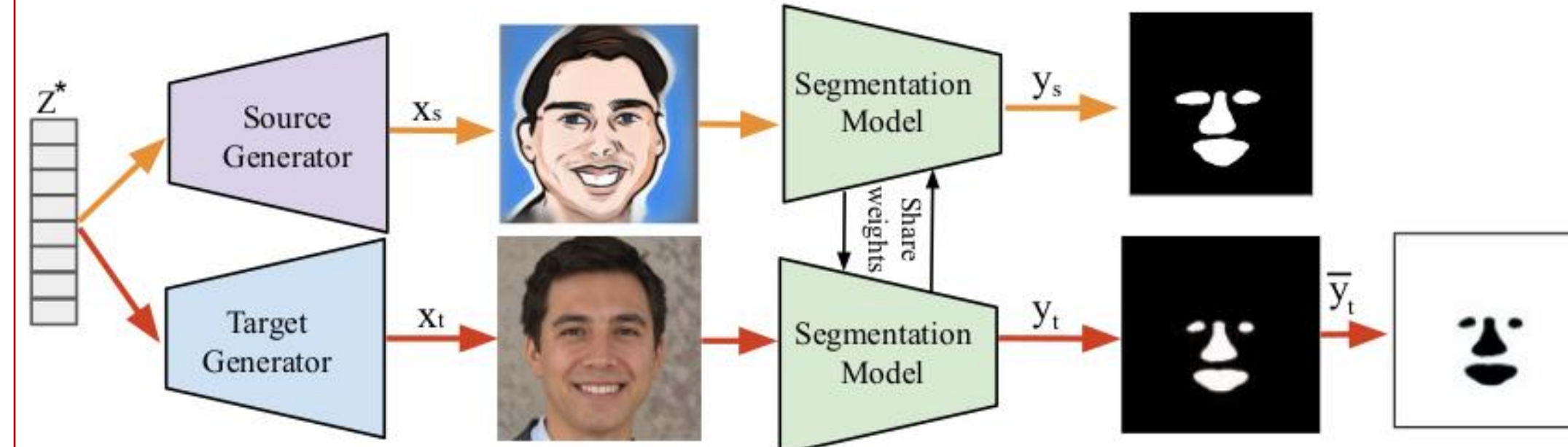


## Method

Perceptual latent loss optimisation.



Semantic masks.

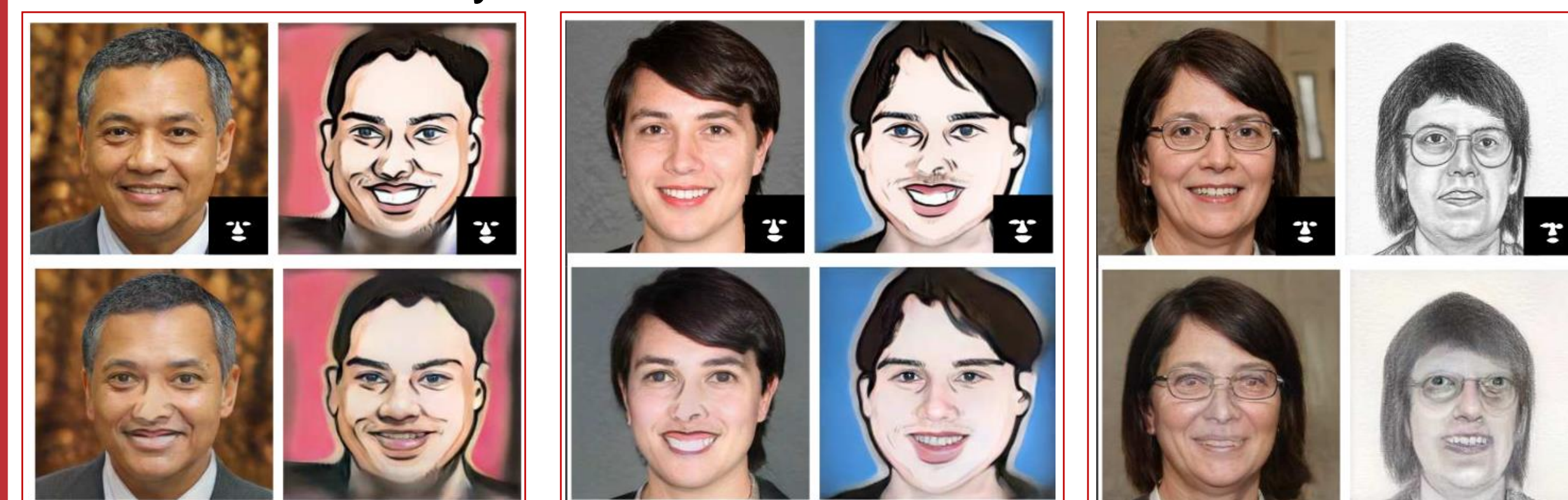


Naive crossover image.

$$x_s \otimes y_s + x_t \otimes y_t = x_e$$

## Qualitative Results

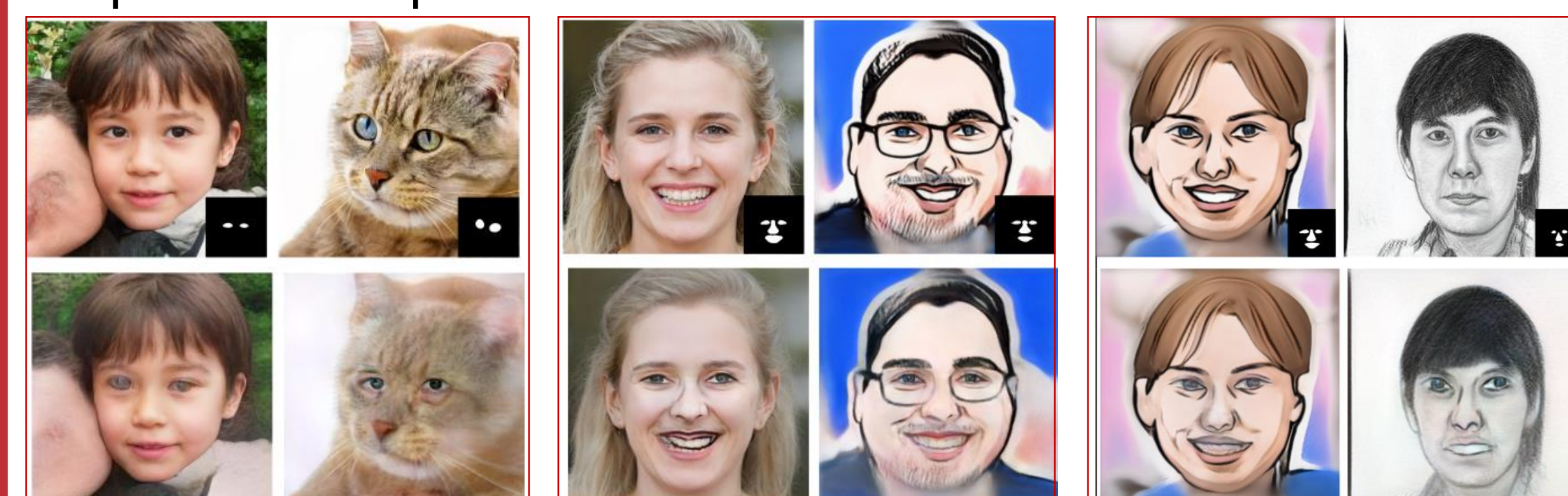
Semantic mask: eye/nose/mouth.



Semantic mask: hair.

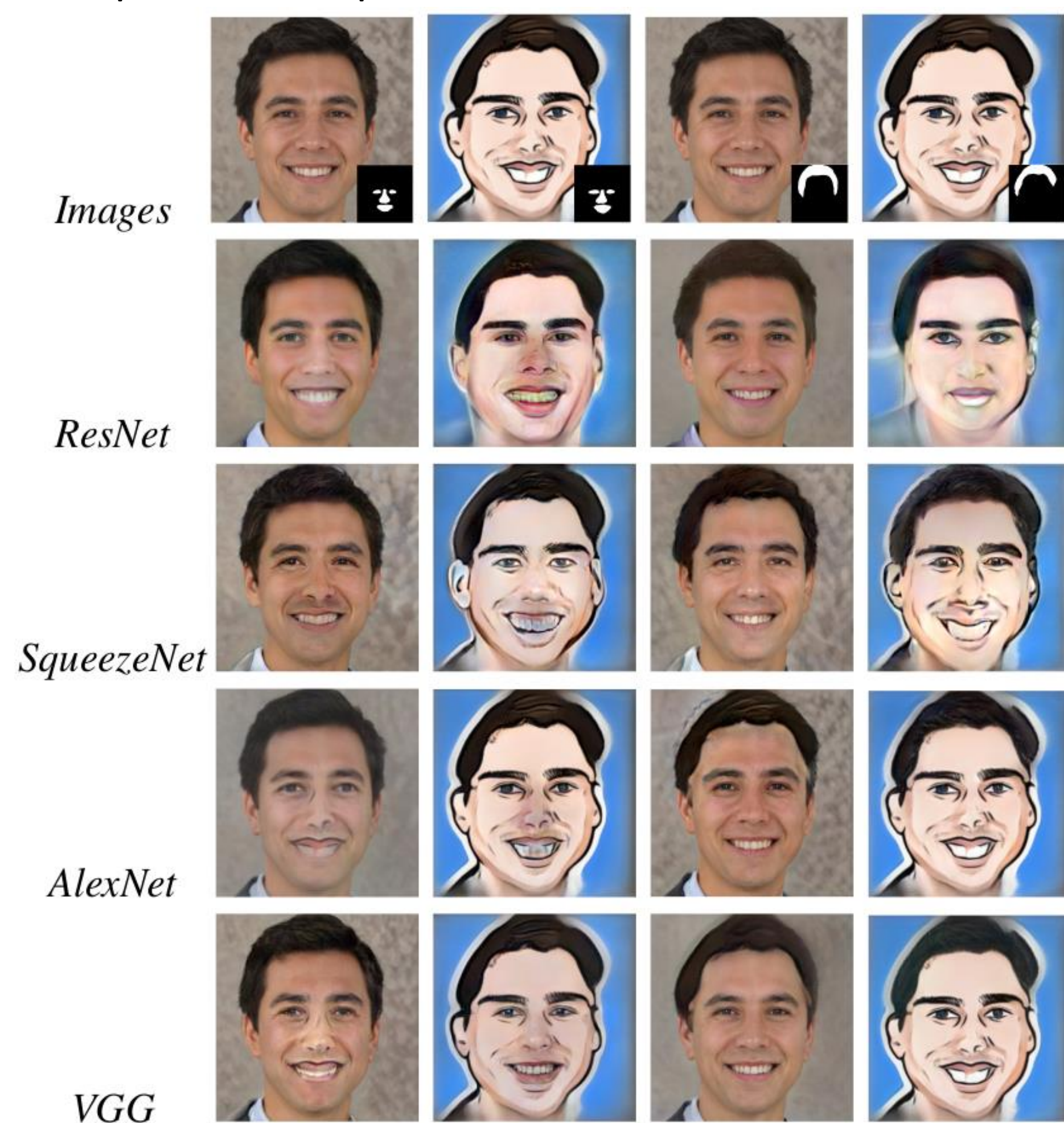


Unpaired examples.



## Ablation Study

The impact of four pre-trained backbones.



## Quantitative Results

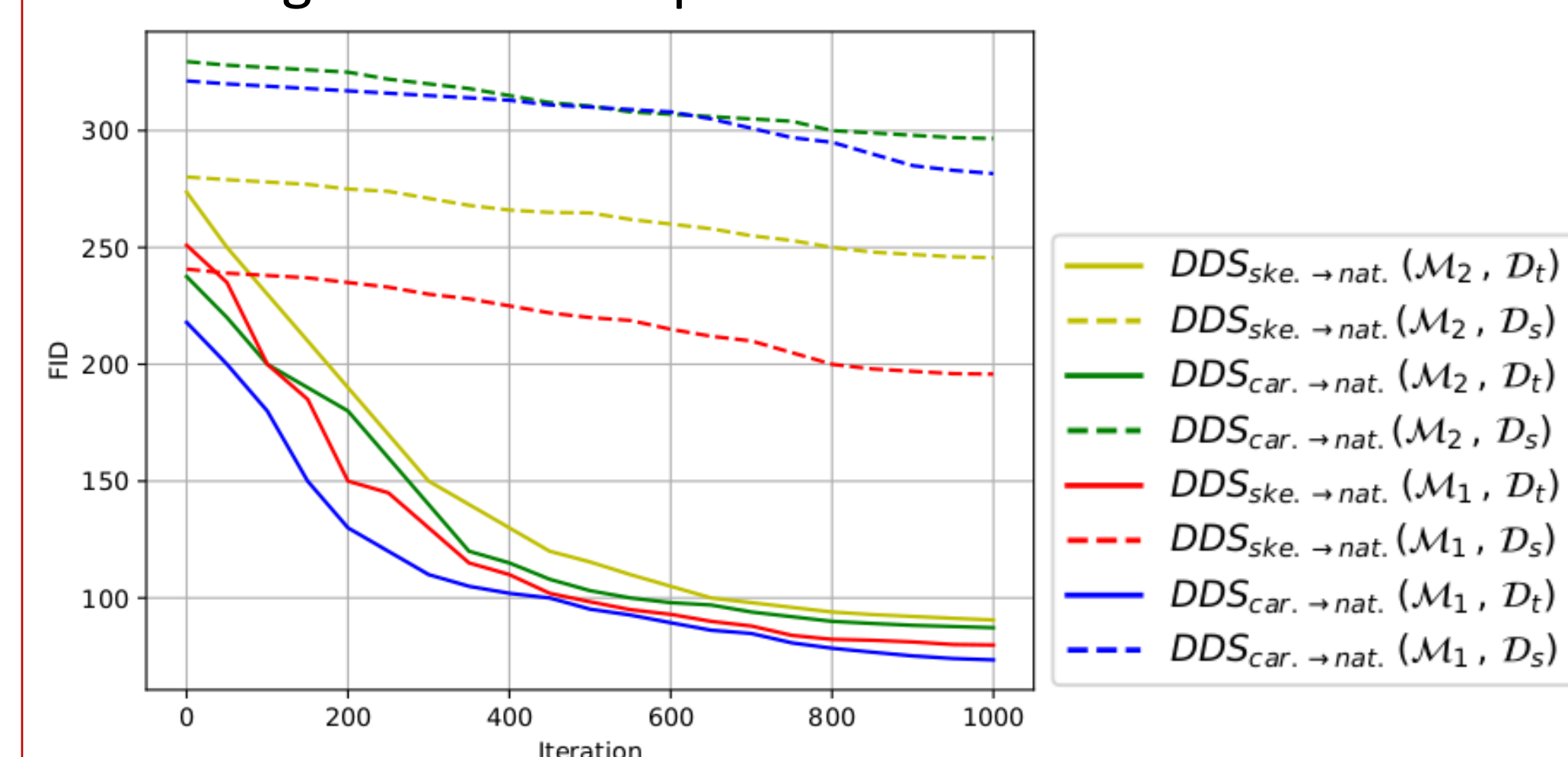
Metric comparisons on the face domains.

		$DDScaricature \rightarrow natural$			$DDSnatural \rightarrow caricature$			$DDSketch \rightarrow natural$			$DDSnatural \rightarrow sketch$		
		FID↓	SSIM↑	PSNR↑	FID↓	SSIM↑	PSNR↑	FID↓	SSIM↑	PSNR↑	FID↓	SSIM↑	PSNR↑
$\mathcal{M}_1$	$\mathcal{D}_s$	281.61	0.39	27.98	259.12	0.38	27.95	195.80	0.31	27.87	225.31	0.33	27.81
	$\{x_c\}$	114.03	0.69	29.45	121.21	0.75	28.75	200.35	0.71	29.81	207.41	0.65	29.28
	$\mathcal{D}_t$	<b>73.51</b>	<b>0.70</b>	<b>29.51</b>	<b>74.51</b>	<b>0.76</b>	<b>28.76</b>	<b>79.87</b>	<b>0.73</b>	<b>29.84</b>	<b>97.65</b>	<b>0.66</b>	<b>29.29</b>
$\mathcal{M}_2$	$\mathcal{D}_s$	296.61	0.47	27.99	290.63	0.42	27.92	245.61	0.38	27.87	262.90	0.36	27.83
	$\{x_c\}$	155.91	0.73	29.63	95.30	0.71	28.43	177.03	<b>0.66</b>	29.25	152.41	0.61	<b>28.54</b>
	$\mathcal{D}_t$	<b>87.28</b>	<b>0.74</b>	<b>29.65</b>	<b>76.96</b>	<b>0.72</b>	<b>28.45</b>	<b>90.58</b>	0.64	<b>29.31</b>	<b>94.83</b>	<b>0.62</b>	28.49

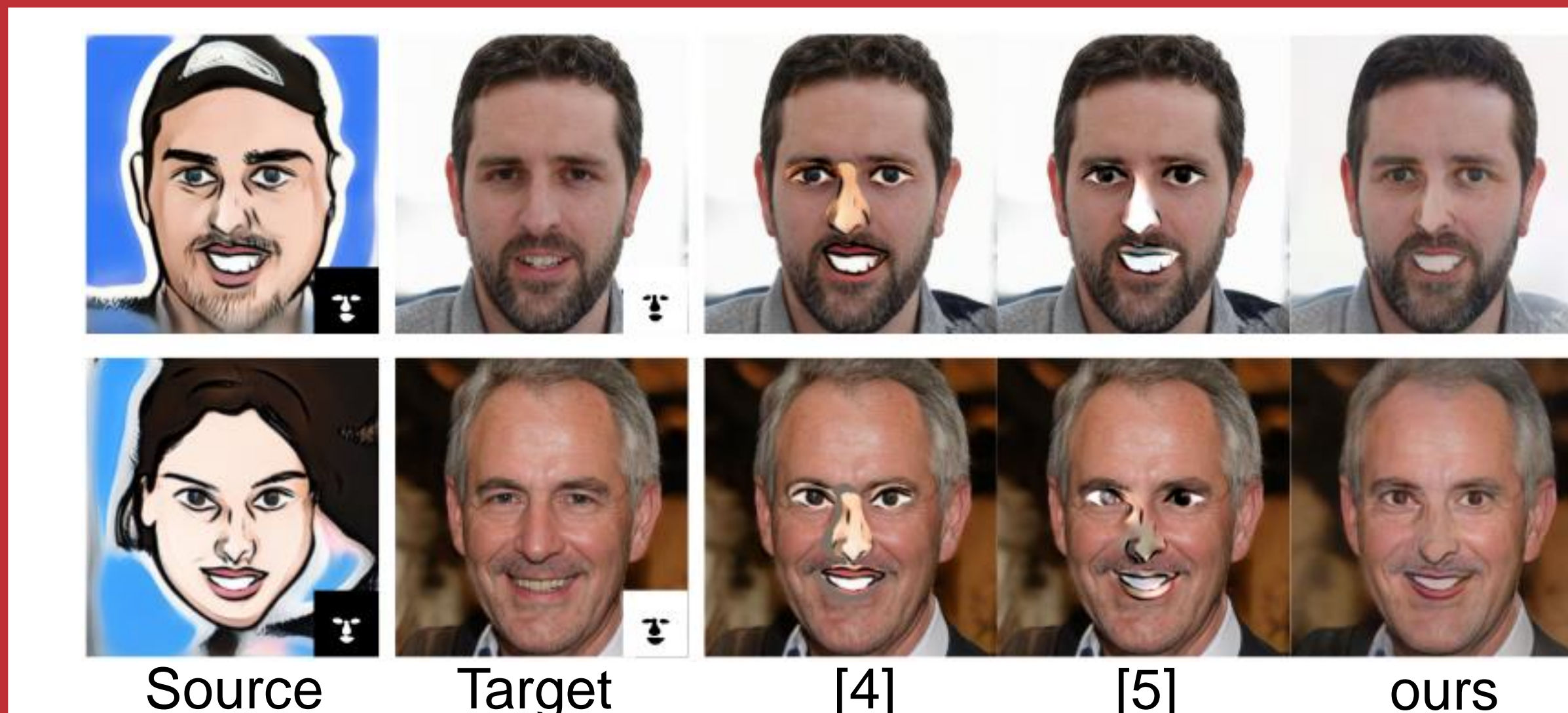
The impact of backbones.

		$DDScar. \rightarrow nat.$			$DDSnat. \rightarrow car.$		
		FID↓	SSIM↑	PSNR↑	FID↓	SSIM↑	PSNR↑
ResNet	$\mathcal{D}_t$	95.66	0.55	28.89	98.71	0.47	27.93
SqueezeNet	$\mathcal{D}_t$	89.48	0.62	29.15	94.29	0.52	28.05
AlexNet	$\mathcal{D}_t$	88.63	0.66	29.36	93.27	0.71	28.11
VGG	$\mathcal{D}_t$	<b>87.28</b>	<b>0.71</b>	<b>29.58</b>	<b>76.96</b>	<b>0.72</b>	<b>28.39</b>

FID during latent code optimisation iterations.



## Dual-Domain Synthesis vs. Image Blending



## References

- [1] U. Ojha, et al., Few-shot Image Generation via Cross-domain Correspondence. CVPR, 2021.
- [2] T. Karras, et al., Analyzing and Improving the Image Quality of StyleGAN. CVPR, 2020.
- [3] N. Tritong, et al., Repurposing GANs for One-shot Semantic Part Segmentation. CVPR, 2021.
- [4] K. Sofiiuk et al., Foreground-aware semantic representations for image harmonization. WACV, 2021.
- [5] L. Zhang et al., Deep image blending. WACV, 2020.

## Code

