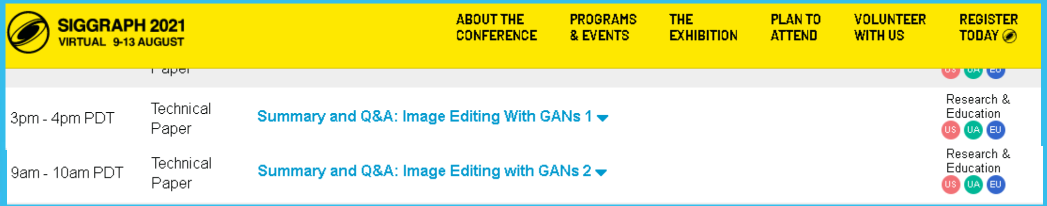
2021 SIGGRAPH
Image editing with GAN


SIGGRAPH 2021
VIRTUAL 9-13 AUGUST

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3pm - 4pm PDT	Technical Paper	Summary and Q&A: Image Editing With GANs 1	Research & Education US UA EU
9am - 10am PDT	Technical Paper	Summary and Q&A: Image Editing with GANs 2	Research & Education US UA EU

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https://s2021.siggraph.org/full-program/?filter1=sstype123

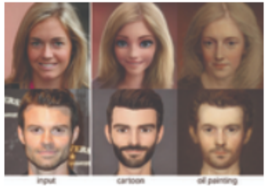
3pm - 4pm PDT | Technical Paper | **Summary and Q&A: Image Editing With GANs 1** | Research & Education

US UA EU

Presentations:

TryOnGAN: Body-aware Try-on via Layered Interpolation
Authors: Kathleen M. Lewis, Srivatsan Varadharajan, Ira Kemelmacher-Shlizerman

StyleCariGAN: Caricature Generation via StyleGAN Feature Map Modulation
Authors: Wonjong Jang, Gwangjin Ju, Yucheol Jung, Jiaolong Yang, Xin Tong, Seungyong Lee



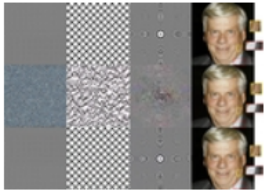
AgileGAN: Stylizing Portraits by Inversion-consistent Transfer Learning
Authors: Guoxian Song, Linjie Luo, Jing Liu, Wan Chun Ma, Chunpong Lai, Chuanxia Zheng, Tat Jen Cham

https://s2021.siggraph.org/full-program/?filter1=sstype123

9am - 10am PDT	Technical Paper	Summary and Q&A: Image Editing with GANs 2	Research & Education US UA EU

Presentations:

Designing an Encoder for StyleGAN Image Manipulation
Authors: Omer Tov, Yuval Alaluf, Yotam Nitzan, Or Patashnik, Daniel Cohen-Or



SWAGAN: A Style-based Wavelet-driven Generative Model
Authors: Rinon Gal, Dana Cohen Hochberg, Amit Bermano, Daniel Cohen-Or

StyleFlow: Attribute-conditioned Exploration of StyleGAN-generated Images Using Conditional Continuous Normalizing Flows
Authors: Rameen Abdal, Peihao Zhu, Niloy Mitra, Peter Wonka

TryOnGAN: Body-Aware Try-On via Layered Interpolation

https://www.youtube.com/watch?v=r4NgwLeJWvY

- Our virtual try-on method, TryOnGAN, transfers a garment from one person to a different person while preserving person identity (body shape, pose, skin color) and garment details (folds, sleeves, shape).

https://www.youtube.com/watch?v=r4NgwLeJWvY

2D VIRTUAL TRY-ON

Person

Garment of Interest

photorealism and **fine-grained control**

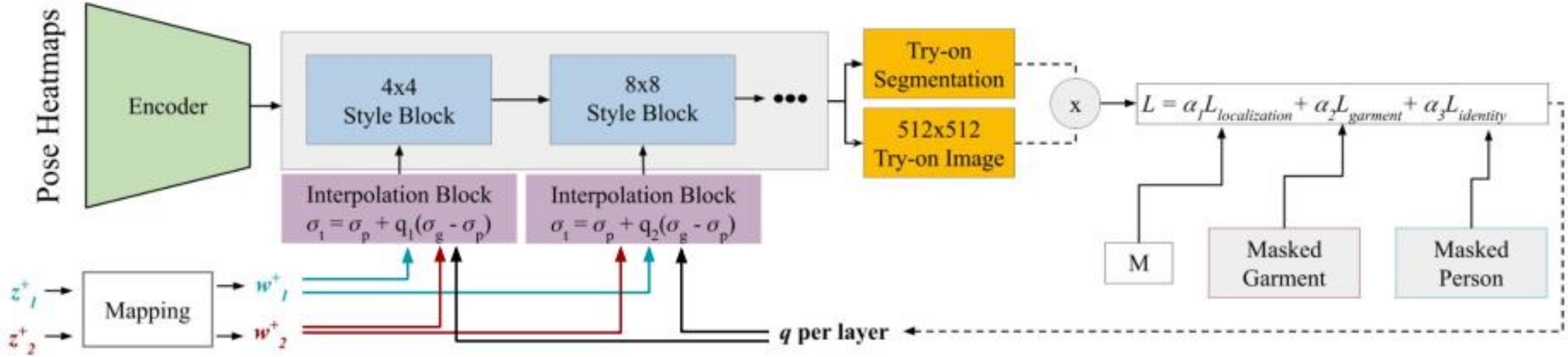


Figure 5: The try-on optimization setup illustrated here takes two latent codes z_1^+ and z_2^+ (representing two input images) and an encoded pose heatmap as input into a pose-conditioned StyleGAN2 generator (gray). The generator produces the try-on image and its corresponding segmentation by interpolating between the latent codes using the interpolation-coefficients q. By minimizing the loss function over the space of interpolation coefficients per layer, we are able to transfer garment(s) g from a garment image I_g, to the person image I_p.

Figure 6: Our method can synthesize the *same style shirt* for varied poses and body shapes by fixing the style vector. We present several different styles in multiple poses. In this figure, each row is a fixed style, and each column in a fixed pose and body shape.

Figure 7: Example images and segmentations generated by our TryOnGAN.

Figure 8: Typical projection examples. It is useful to see the effect of projection on the quality of the garment representation, since it directly impacts the final try on result. Improving the projection is independent of our optimization algorithm and is part of future work.

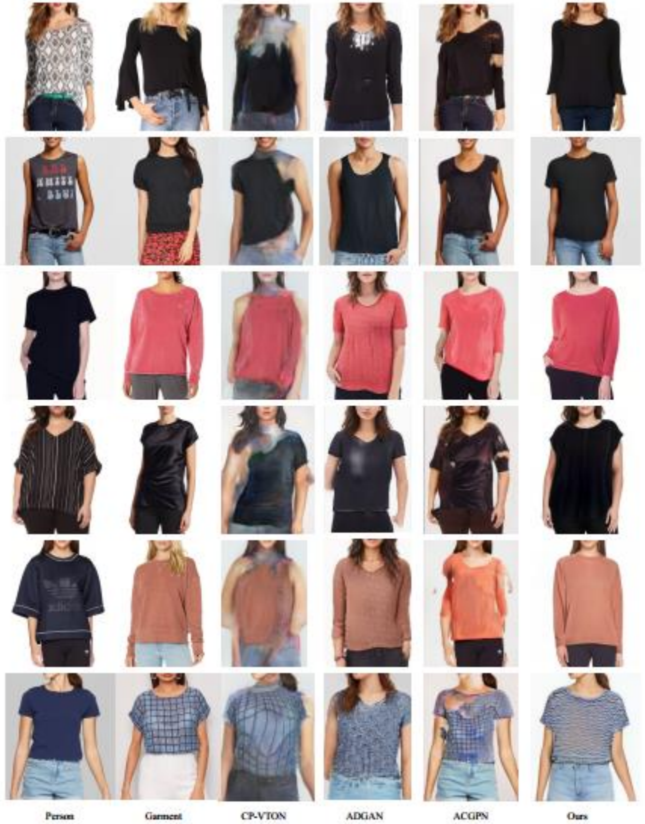


Figure 9: Qualitative comparison with Wang et al. [2018a], Men et al. [2020], and Yang et al. [2020] on real image try-on. Each row represents a different pair of inputs. Note the difference in garment quality, adjustment to difference in body shape, skin color, and pose. TryOnGAN outperforms the state of the art significantly.

Figure 10: Results from our method for shirt try-on on real images. Note how try-on works well with different body shapes, and adjusts to the new poses. Some details are missing from the garment due to artifacts in projection, however the overall shape is well preserved.

Figure 12: Results from our method for ten shirt try-on examples on generated images. Note how try-on works well with different body shapes, and adjusts to the new poses. Our method is able to transfer complex garment patterns and textures. Zoom in for details.

Figure 13: Results from our method for pants try-on on generated images. Note how try-on works well with different body shapes, and adjusts to the new poses. Our method can also synthesize garment details such as buttons and pockets that weren't in the original person image. Each row corresponds to a different try on result. Columns represent person, garment, and result.

Figure 15: Ablation study showing the importance of each loss term in the optimization. The study is done on real images.

Failure cases

Figure 14: Failure cases for our method on real images. Our method typically fails when garment detail or pose wasn't represented well in the training dataset.

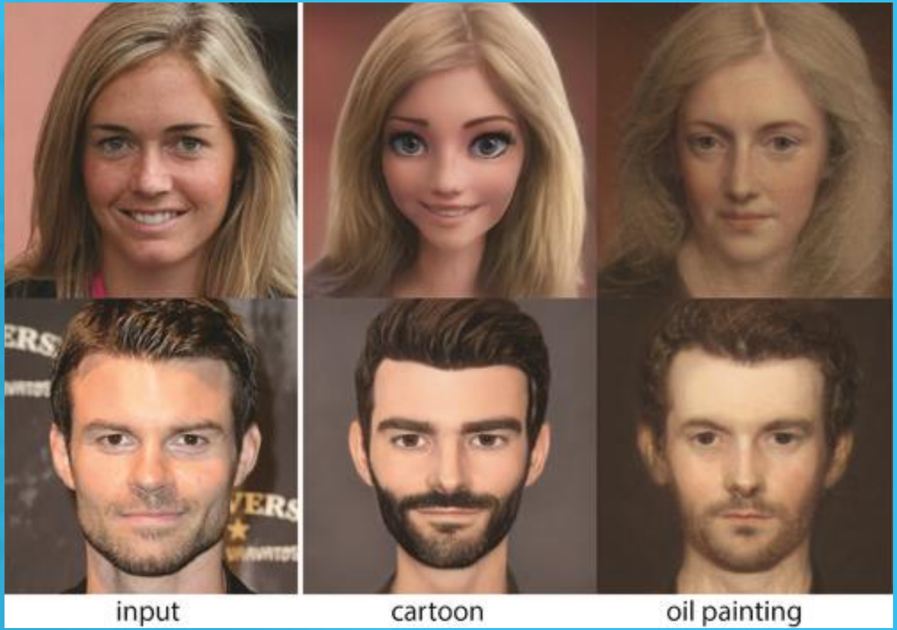
Figure 16: Ablation study: we compare greedy search for interpolation coefficients as in Collins et al. [2020] to our optimization approach on generated image try-on. We observe that details like sleeve length and pattern are preserved much better with the per layer optimization approach. Note that we do not compare directly to Collins et al. [2020] since we also modified the StyleGAN architecture to include segmentation and condition on pose. The red boxes highlight incorrect sleeve-length and artifacts generated by the greedy search method.

StyleCariGAN: Caricature Generation via StyleGAN Feature Map Modulation

- This paper presents a caricature generation framework based on StyleGAN, which automatically creates a realistic and detailed caricature from an input photo with optional controls on shape exaggeration and color stylization.

https://github.com/PeterZhouSZ/StyleCariGAN

AgileGAN: Stylizing Portraits by Inversion-consistent Transfer Learning



http://www.agilegan.com/

- This paper introduce AgileGAN, a portrait stylization method by inversion-consistent transfer learning, which can agilely create high-quality portrait stylization models wit h limited numbers of unpaired style exemplars and short training time.

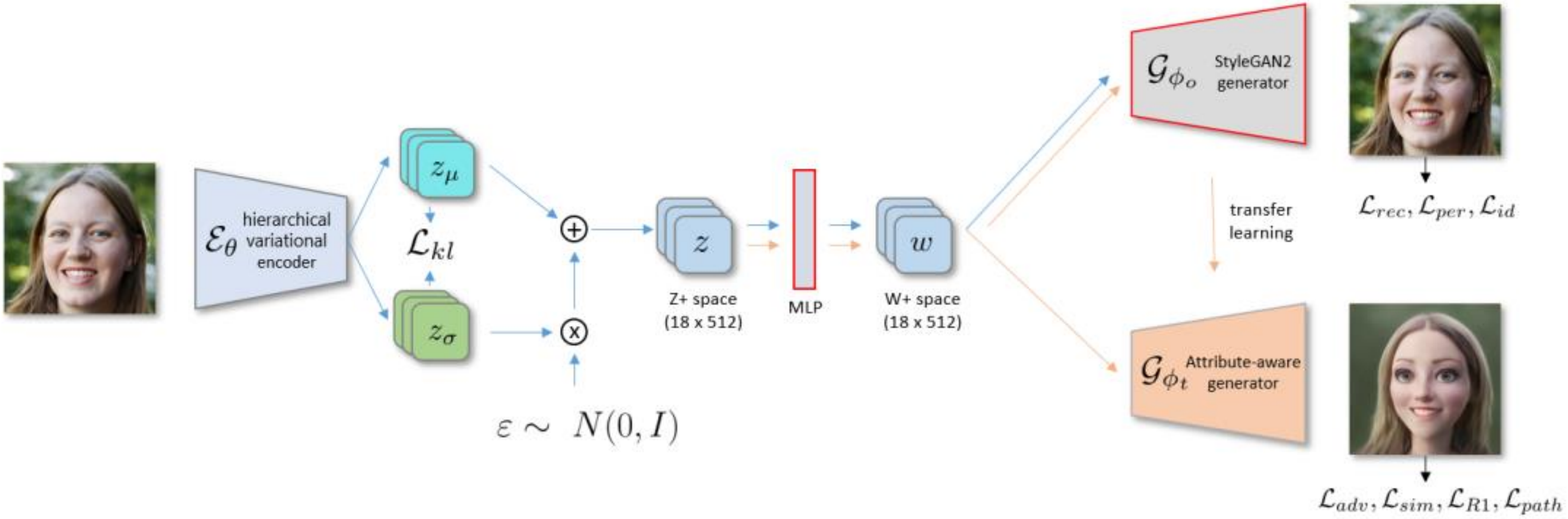
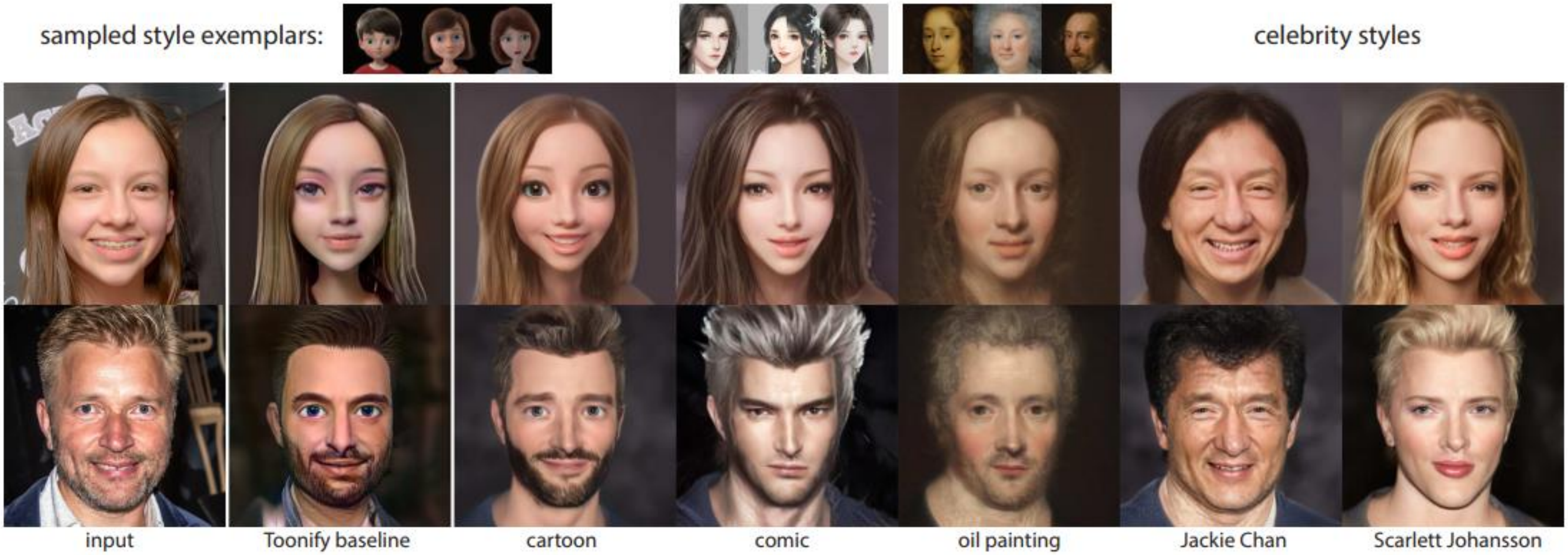
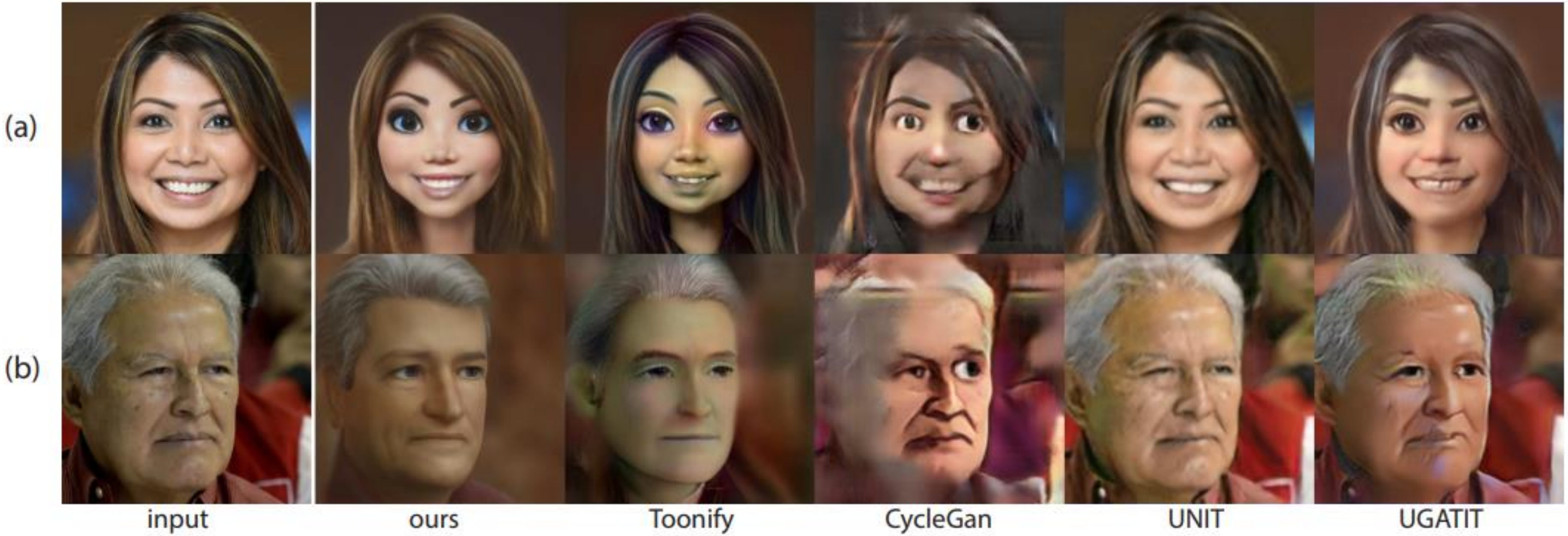


Fig. 3. Pipeline overview. Our hierarchical VAE consists of an encoder and generator with different color arrows representing the different training dataflows based on StyleGAN2. The blue arrows indicate image embedding, and the orange ones are for transfer learning. black borders indicate the block weights, which are derived from a StyleGAN2 pre-trained on the FFHQ dataset, that are frozen during training. The input is courtesy of Erin Wagner(Public Domain).


sampled style exemplars:
celebrity styles
input
Toonify baseline
cartoon
comic
oil painting
Jackie Chan
Scarlett Johansson

Qualitative comparison

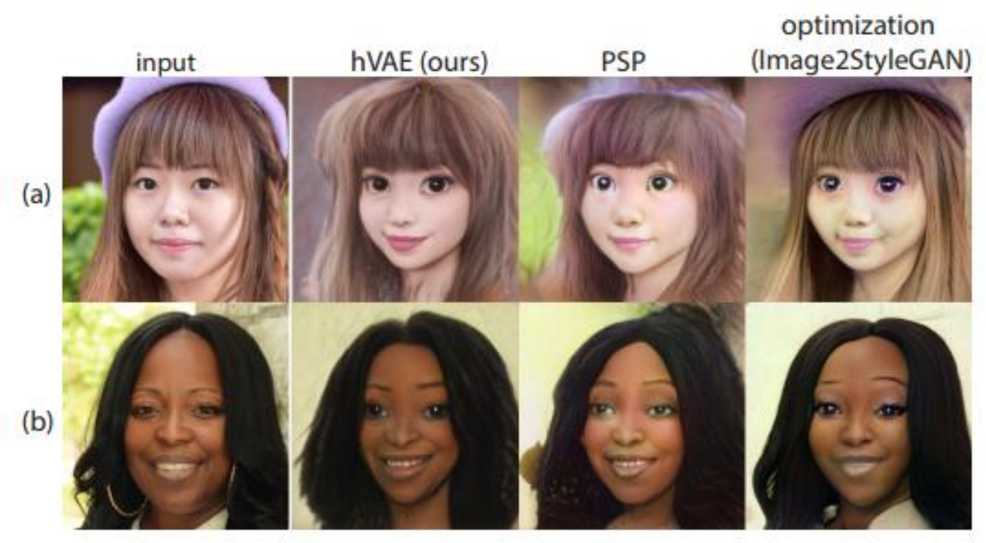


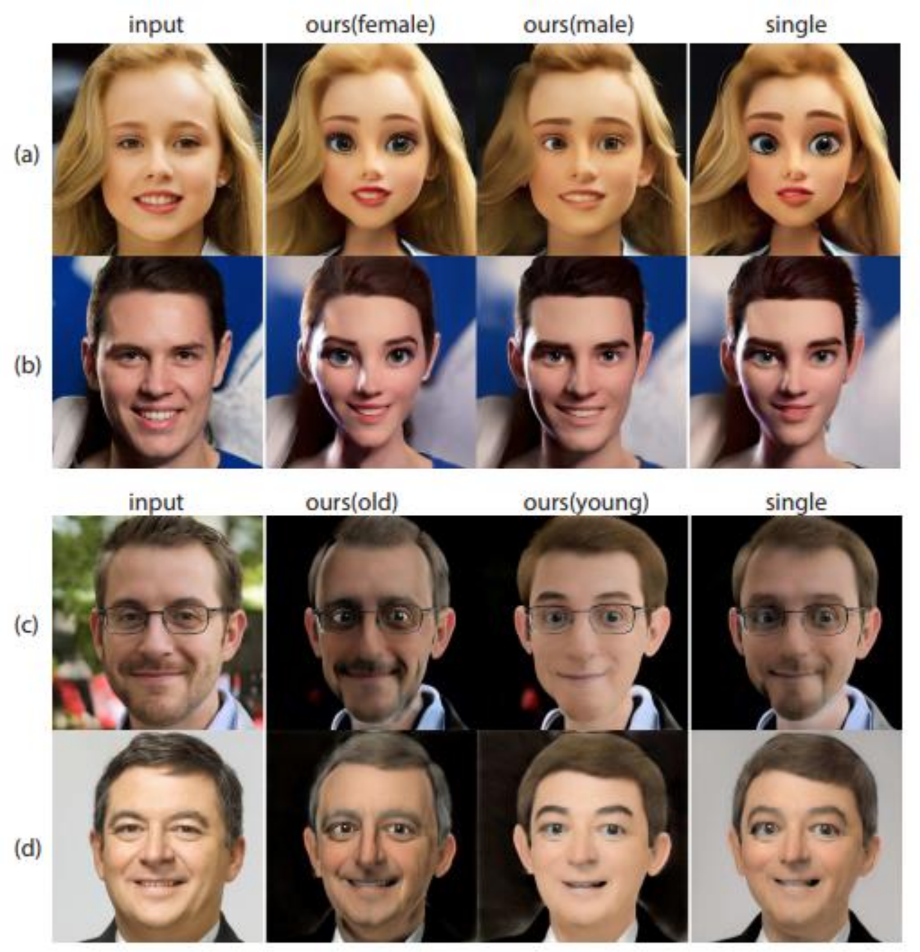
	input	hVAE (ours)	PSP	in-domain	optimization (Toonify)	optimization (Image2StyleGAN)

(a)

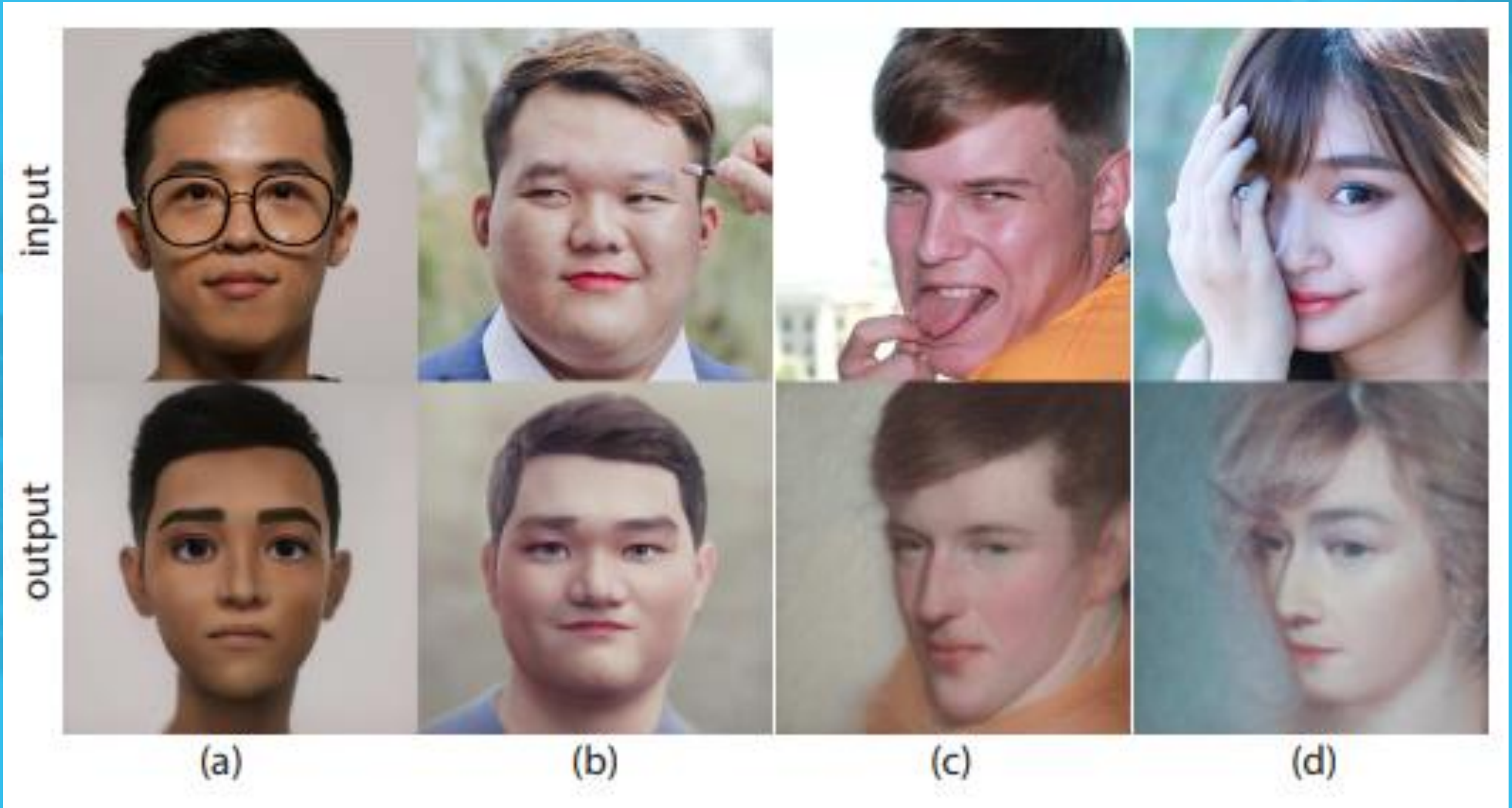
(b)

(c)

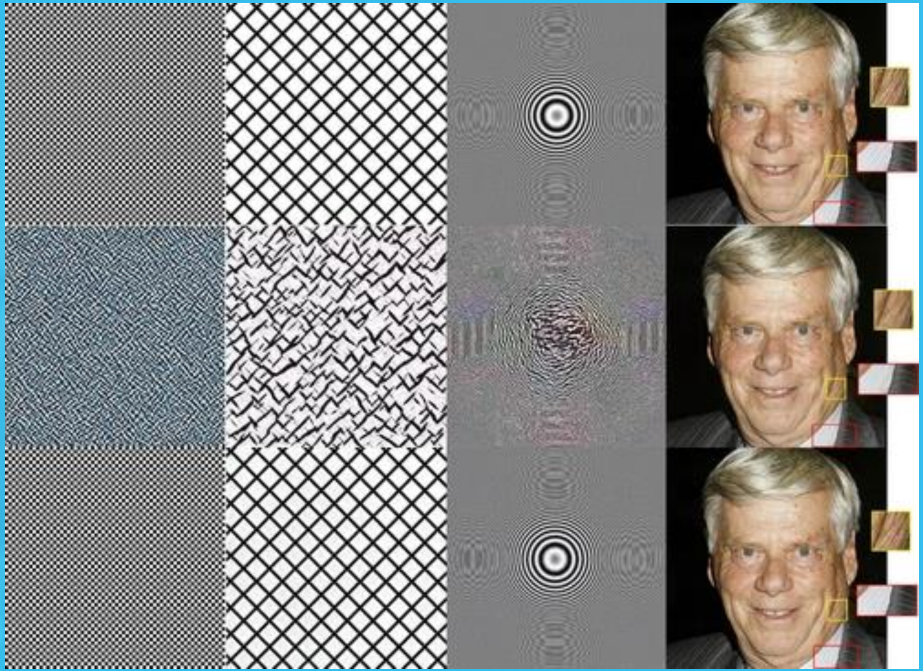

input
hVAE (ours)
PSP
optimization
(Image2StyleGAN)
(a)
(b)


input
ours(female)
ours(male)
single
(a)
(b)
input
ours(old)
ours(young)
single
(c)
(d)


(a)
(b)


input
output
(a)
(b)
(c)
(d)

SWAGAN: A Style-based Wavelet-driven Generative Model



- This paper present SWAGAN, a style and wavelet-based generative adversarial network designed to side-step the spectral bias of neural networks and alleviate the recently identified high-frequency deficiency in image synthesis models.

https://paperswithcode.com/paper/swagan-a-style-based-wavelet-driven

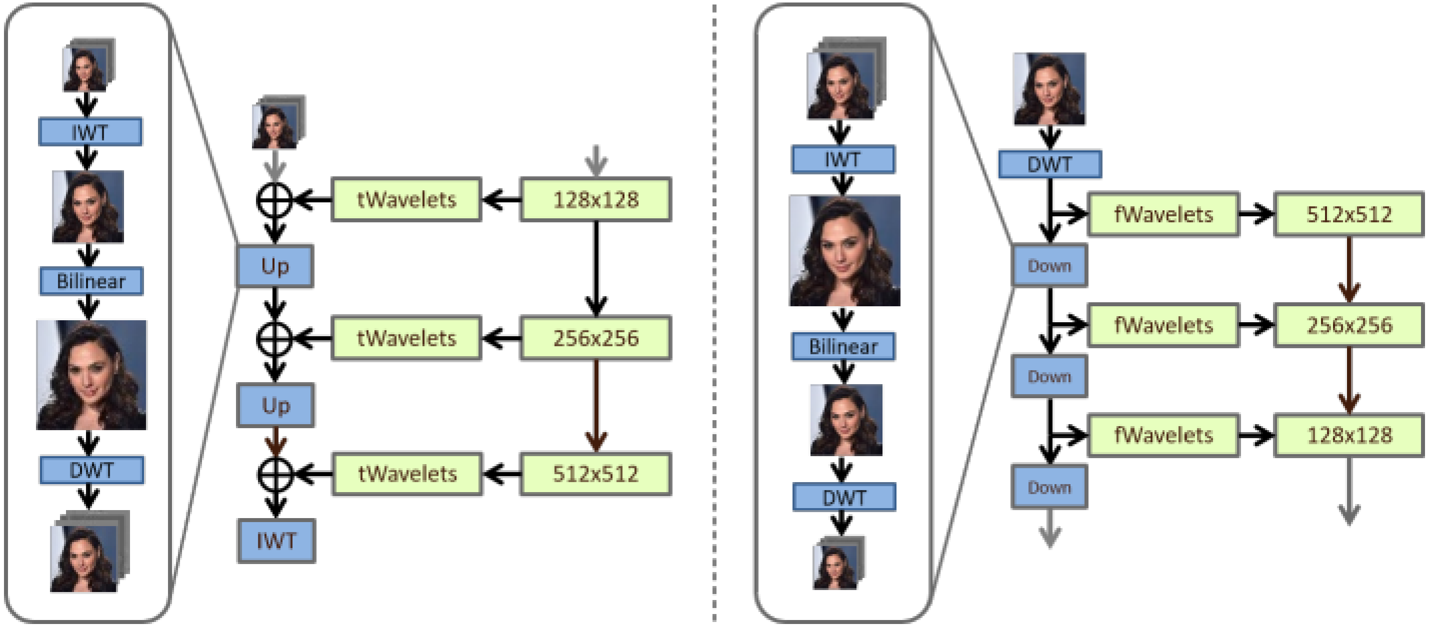
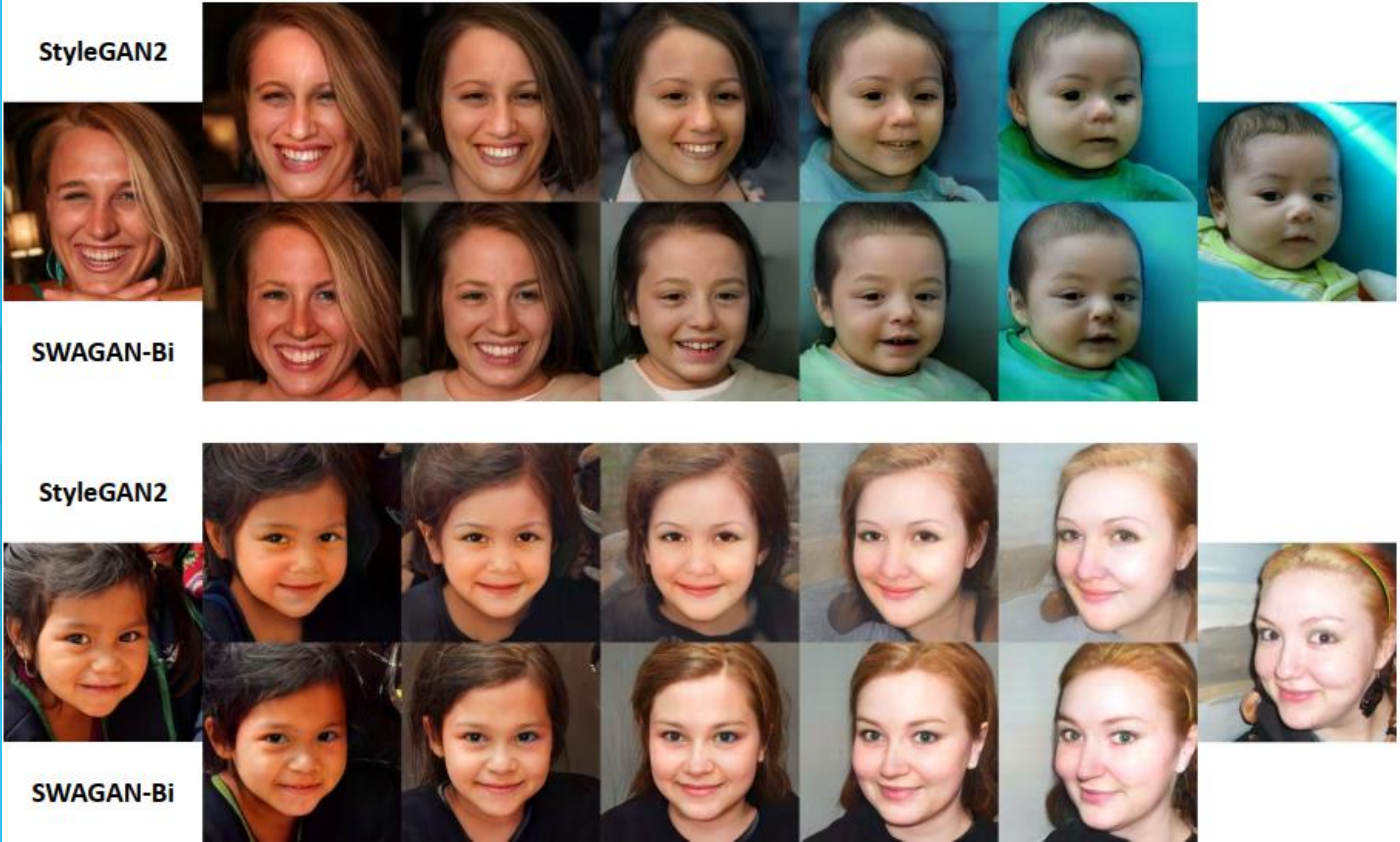
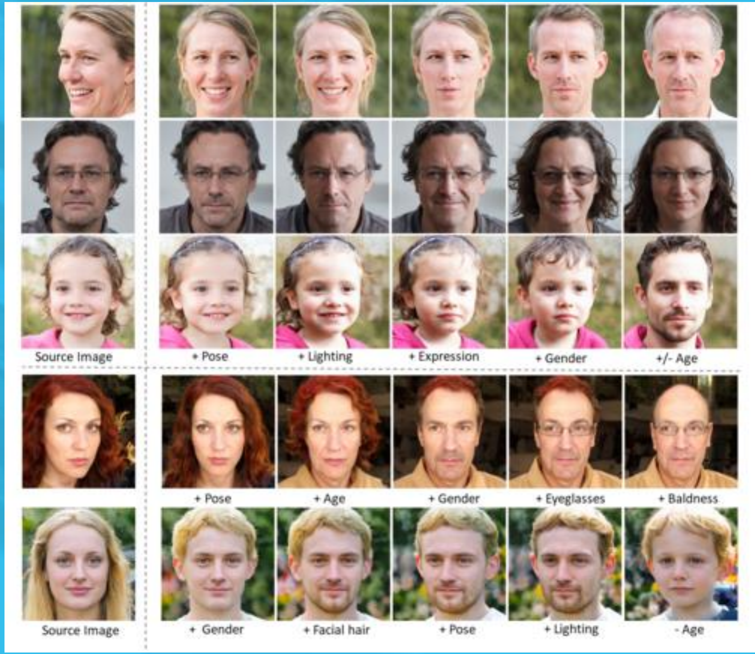


Figure 3. Our SWAGAN generator (left) and discriminator (right) architectures. Each ConvBlock is equivalent to a feature-resolution increasing block of the StyleGAN2 architecture, which is itself composed of two style blocks. *tWavelets* and *fWavelets* correspond to the tRGB and fRGB layers of StyleGAN2 and their purpose is to learn a mapping between wavelet decompositions and high dimensional features. Inverse wavelet transforms are denoted by *IWT*, while *Up* and *Down* are non-learning layers responsible for converting an image to an initial wavelet-decomposition of a higher or lower resolution, respectively.

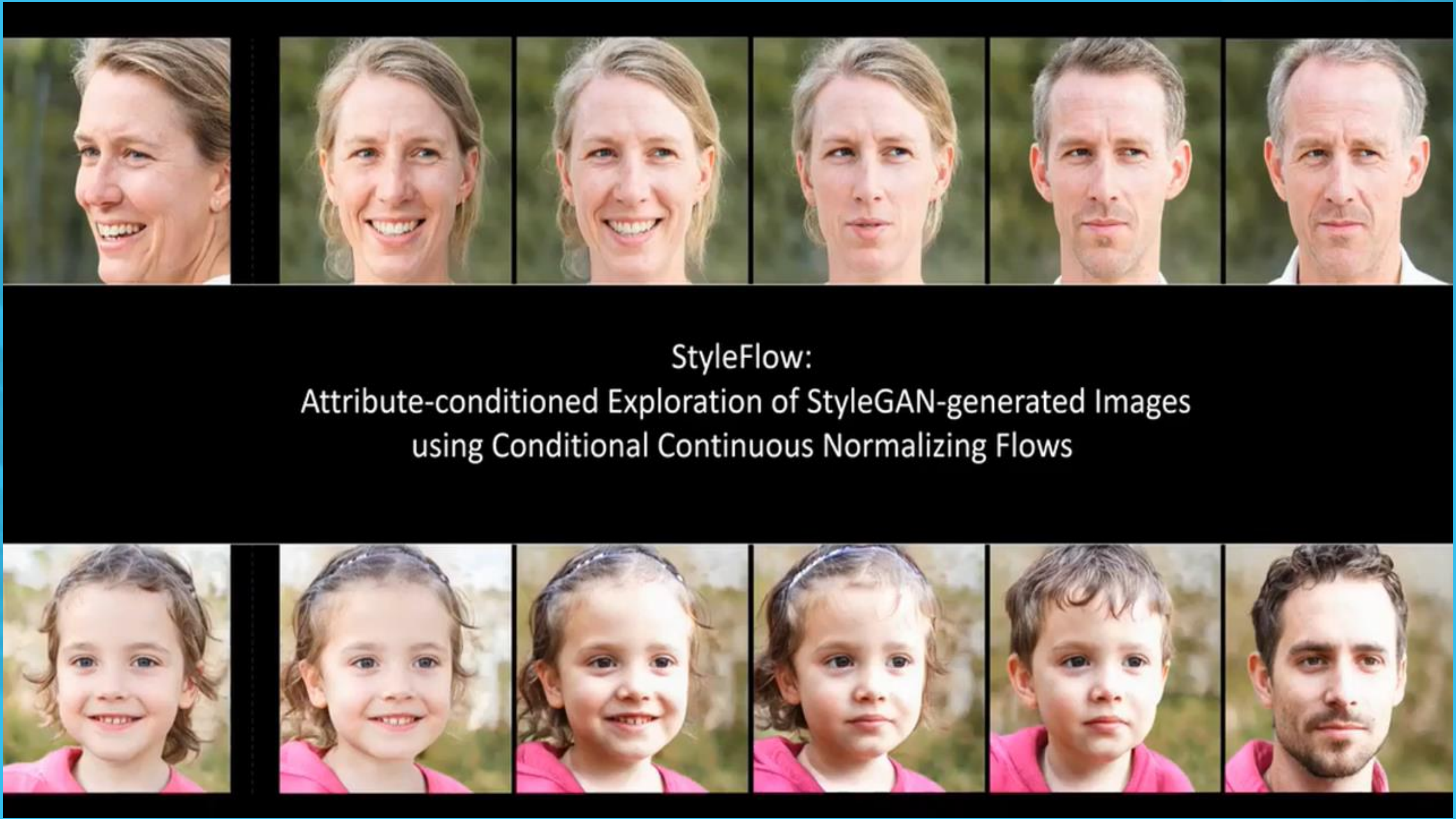

StyleGAN2
SWAGAN-Bi
StyleGAN2
SWAGAN-Bi

StyleFlow: Attribute-conditioned Exploration of StyleGAN-generated Images Using Conditional Continuous Normalizing Flows



- This paper presents StyleFlow, a simple, effective, and robust framework for attri bute-guided editing of StyleGAN-genera ted images. We show fine- grained res ults on real photographs.

https://youtu.be/LRAUJUn3EqQw



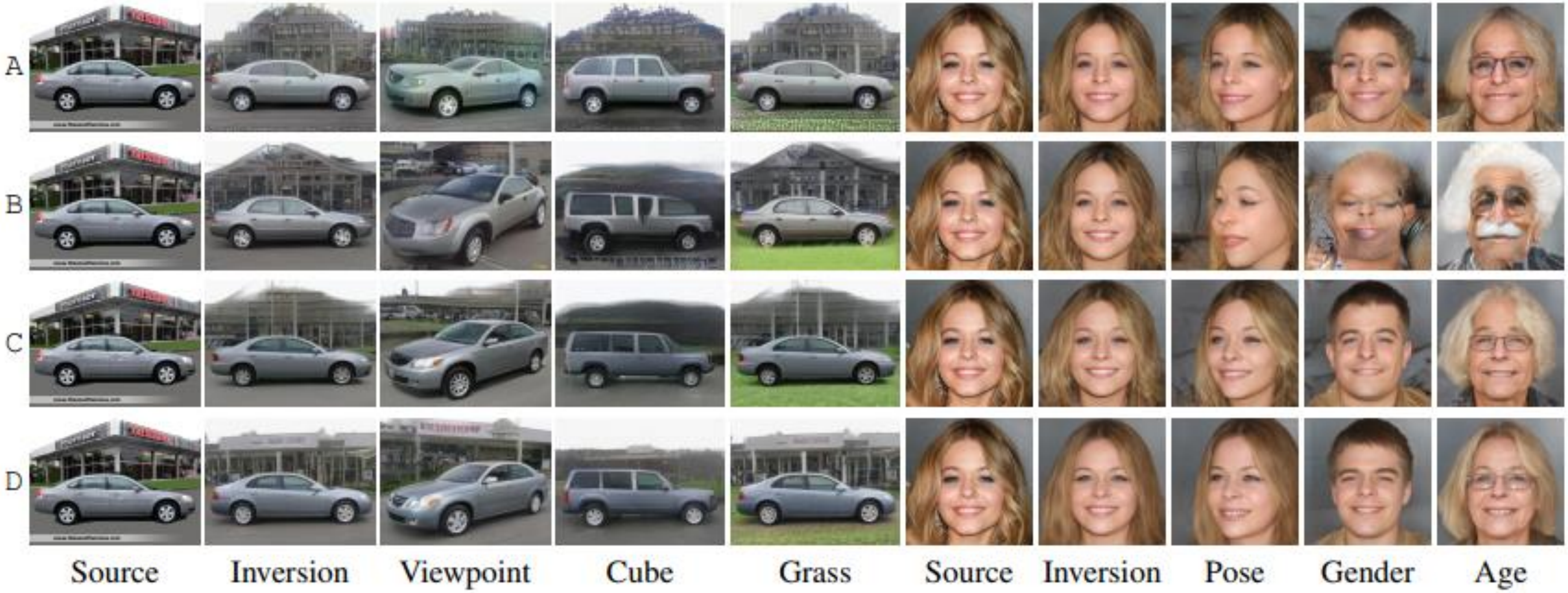
https://youtu.be/LRAUJUn3EqQw

Designing an Encoder for StyleGAN Image Manipulation

Path	Description
FFHQ Inversion	FFHQ e4e encoder.
Cars Inversion	Cars e4e encoder.
Horse Inversion	Horse e4e encoder.
Church Inversion	Church e4e encoder.

- Identifying the existence of the distortion-editability and distortion-perception tradeoffs within the StyleGAN latent space, we suggest principles for designing encoders for facilitating editing on real images by balancing these tradeoffs.

https://github.com/omertov/encoder4editing


A
B
C
D
Source
Inversion
Viewpoint
Cube
Grass
Source
Inversion
Pose
Gender
Age

Conclusion

- The field of GAN is in the ascendant, and there are still many places that can be studied in depth. I believe that next year’s SIGGRAPH will definitely have a lot of GAN papers.