DEEP LEARNING FOR FACE IMAGE EDITING

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LTCI day

- Introduction
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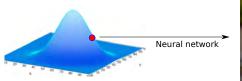
- Image editing is a common, critical and time-consuming task in such domains as film post-production
 - Movie industry often employs hundreds of digital artists for editing
- In particular, facial images, are of great importance
 - Controlling facial attributes : hair, smile, glasses etc





- For classical methods, this is a challenging task
 - Requires prior knowledge/model about facial images

- Since 2014, deep generative models have seen an explosion of research activity
- Deep generative models : deep neural networks
 - Input: random vector
 - Output : random image (or data)



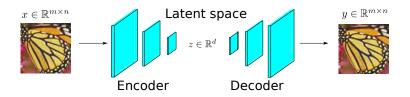
Probabilistic model in latent space



Synthesis of random image

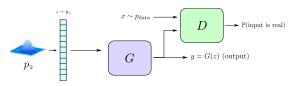
• These rely on the concept of a latent space

• The latent space is (almost always) a smaller dimensional space



 More compact, better properties. Can be used for image editing/restoration/analysis

Most common deep generative networks: Variational Autoencoders*,
Generative Adversarial Networks† (GANs)



We work with the recent StyleGAN[‡]; produces high-quality results

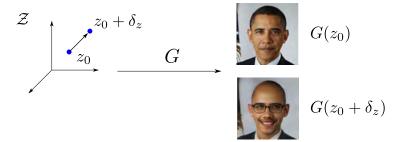


^{*} Auto-Encoding Variational Bayes, D. P. Kingma, M. Welling, arXiv preprint arXiv:1312.6114, 2013

Generative Adversarial Nets, Goodfellow et al, NIPS 2014

[‡] **Analyzing and improving the image quality of stylegan**, Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., and Aila, T. CVPR 2020

 Main idea of our work: navigate in the latent space to achieve an editing goal



Previous work on this subject^{†,‡}

^{*} A latent transformer for disentangled face editing in images and videos, Yao, X., Newson, A., Gousseau, Y., and Hellier, P., ICCV 2021

[†] Interfacegan: Interpreting the Disentangled Face Representation Learned by Gans, Shen, Y., Yang, C., Tang, X. and Zhou, B,

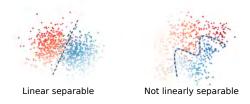
- PhD work of Xu Yao, CIFRE PhD with Interdigital
- Published in ICCV 2021*



Collaborators

^{*} A latent transformer for disentangled face editing in images and videos, Yao, X., Newson, A., Gousseau, Y., and Hellier, P., ICCV 2021

 Previous approaches* often suppose that facial attributes are linearly separable in the latent space



- This is a limiting hypothesis. Thus, we remove this it in this work
- ullet We train a neural network to navigate in StyleGAN's latent space ${\mathcal W}$

$$w_1 = w_0 + \alpha T(w_0), \tag{1}$$

^{*} Interfacegan: Interpreting the Disentangled Face Representation Learned by Gans, Shen, Y., Yang, C., Tang, X. and Zhou, B, PAMI, 2020

• We minimise the following loss functions:

$$\mathcal{L}_{cls}(w) = -y_k \log (p_k) - (1 - y_k) \log (1 - p_k), \tag{2}$$

- $p_k = C(T_k(w))_k$: probability of the target attribute k
- $y_k \in \{0,1\}$: desired label

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$$\mathcal{L}_{\mathsf{attr}}(w) = \sum_{i \neq k} (1 - \gamma_{i,k}) \| p_i - C(w)_i \|_2^2, \tag{3}$$

- ullet $\gamma_{i,k}$: absolute correlation between a_i and target attribute a_k
 - Mesured on the database

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$$\mathcal{L}_{\text{rec}}(w) = \|T(w) - w\|_2^2. \tag{4}$$

Do not move too far from original latent code: maintain identity

Final loss

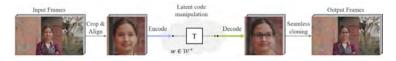
$$\mathcal{L} = \mathbb{E}_w \left[\mathcal{L}_{\mathsf{cls}}(w) + \lambda_{\mathsf{attr}} \mathcal{L}_{\mathsf{attr}}(w) + \lambda_{\mathsf{rec}} \mathcal{L}_{\mathsf{rec}}(w) \right], \tag{5}$$

• For more efficient training, we train a classifier in the latent space

Final loss

$$\mathcal{L} = \mathbb{E}_w \left[\mathcal{L}_{\mathsf{cls}}(w) + \lambda_{\mathsf{attr}} \mathcal{L}_{\mathsf{attr}}(w) + \lambda_{\mathsf{rec}} \mathcal{L}_{\mathsf{rec}}(w) \right], \tag{5}$$

- For more efficient training, we train a classifier in the latent space
- We also propose a pipeline to edit videos
 - Preprocessing: landmark detection
 - Image editing: Encode*, manipulate, generate
 - Seamless cloning[†]



[†] Poisson image editing, Pérez, P., Gangnet, M., and Blake, A., Siggraph 2003

^{*} Encoding in style: a Stylegan Encoder for Image-to-Image Translation, Richardson, E., Alaluf, Y., Patashnik, O., Nitzan, Y., Azar, Y., Shapiro, S., and Cohen-Or, D., CVPR, 2021

Image attribute editing results

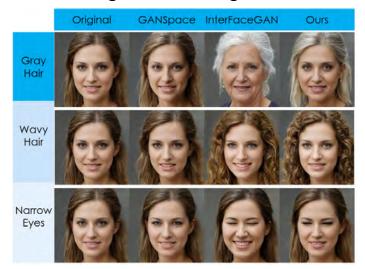
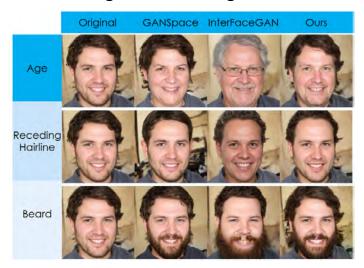
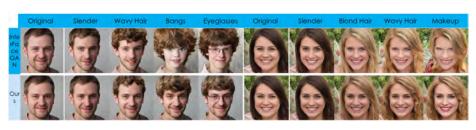


Image attribute editing results

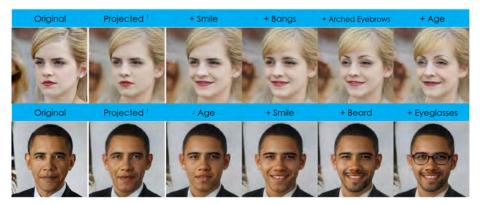


Sequential editing results: synthetic images



• Our approach preserves identity and other attributes better

Sequential editing results: real images



Conclusion

Summary

- We proposed a latent space-based face attribute editing algorithm*
 - Uses the latent space of StyleGAN
- State-of-the art, disentangled, results on real (non-synthetic) results, identity preservation
- Video pipeline to edit videos

Limitations and future work

- A different network needs to be trained for each attribute
 - Better to try and modify the latent space itself
- The non-linearity of the latent space is still an open question
- More work needed on stability and robustness in videos

^{*} A latent transformer for disentangled face editing in images and videos, Yao, X., Newson, A., Gousseau, Y., and Hellier, P., ICCV 2021

References

References

- A latent transformer for disentangled face editing in images and videos, Yao, X., Newson, A., Gousseau, Y., and Hellier, P., ICCV 2021
- Interfacegan: Interpreting the Disentangled Face Representation Learned by Gans, Shen, Y., Yang, C., Tang, X. and Zhou, B, PAMI, 2020
- Ganspace: Discovering interpretable gan controls, Härkönen, E., Hertzmann, A., Lehtinen, J., and Paris, S., NIPS 2020
- Analyzing and improving the image quality of stylegan, Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., and Aila, T. CVPR 2020