Transforming Facial Images Using Generative Adversarial Networks

Group 34

Teng Ma, Qingyuan Jin, Isha Srivastava, Jiaqi Yan

{tema, q1jin, isrivast, j3yan} @ucsd.edu

Introduction

Generative Adversarial Network (GAN) is a class of machine learning systems that, given a training set, learns to generate new data with the same statistics as the training set. The question driving developments in GANs is: Given an input set X, can we make a new x' that looks like it should be in X?

Predicting

Our goal is to generate new facial images with realistic characteristics from original faces that look at least superficially authentic to human observers. The model that we have used for this task is CycleGAN.

Given a domain X of male images, our task is to generate new images that would closely resemble images of females in domain Y and vice versa.

face transfer

Data

We chose 747 male facial images and 1153 female facial images, from CelebFaces Attributes Dataset (CelebA). They are 512 ✕ 512 colored images without normalization.

Features

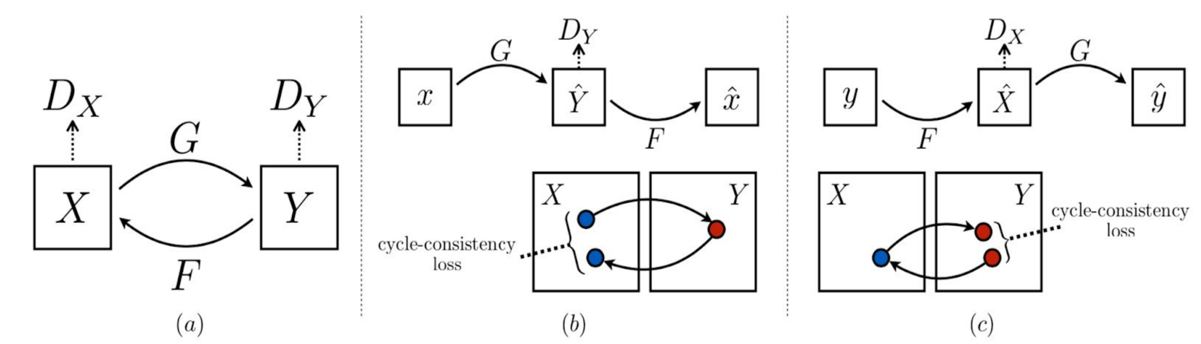
GANs learn the underlying structure of the given data without specify a target value. CycleGAN network can automatically learn features combining many aspects properly like colors, corners and edges. Generator can generate new features similar to the expected one.

Models

CycleGANs combine two GAN networks together and use 2 losses:

- Adversarial loss : ensure the ability to generate reasonable fake images
- Cycle-consistency loss: guarantee individual input matching desired output

We use cycleGANs networks to transfer face between male and female.



(a) Our model contains two mapping functions G : X → Y and F : Y → X, and associated adversarial discriminators D_Y and D_X. D_Y encourages G to translate X into outputs indistinguishable from domain Y, and vice versa for DX and F. To further regularize the mappings, we introduce two cycle consistency losses that capture the intuition that if we translate from one domain to the other and back again we should arrive at where we started: (b) forward cycle-consistency loss: x → G(x) → F (G(x)) ≈ x, and (c) backward cycle-consistency loss: y → F (y) → G(F (y)) ≈ y

Adversarial Loss:

$$loss_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y\sim p_{data}(y)}[log D_Y(y)] + \mathbb{E}_{x\sim p_{data}(x)}[log(1 - D_Y(G(x))]$$

Cycle-consistency Loss:

$$L_{cyc}(G, F) = \mathbb{E}_{x\sim p_{data}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y\sim p_{data}(y)}[\|G(F(x)) - y\|_1]$$

Total Loss:

$$L(G, F, D_X, D_Y) = L_{GAN}(G, D_Y, X, Y) + L_{GAN}(F, D_X, X, Y) + \lambda L_{cyc}(G, F)$$

Optimization Function:

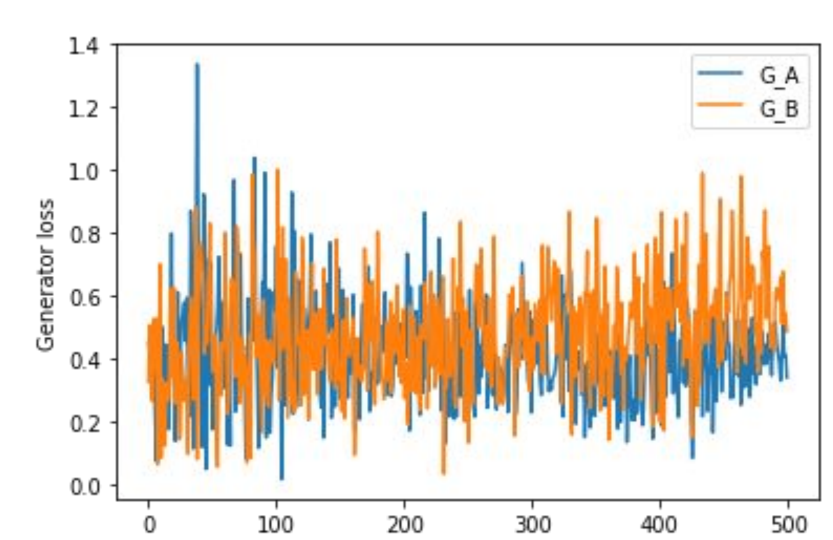
$$G^*, F^* = arg \min_{G,F} \max_{D_X, D_Y} L(G, F, D_X, D_Y)$$

Results

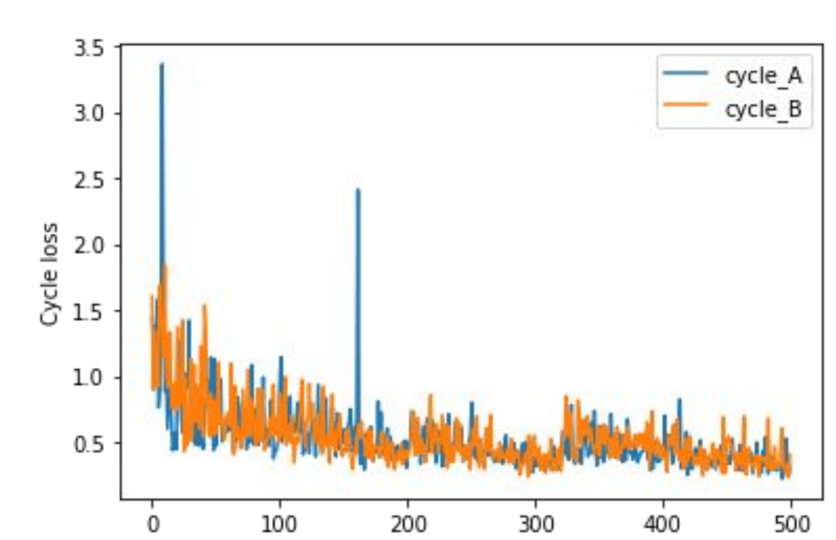
- Male facial image: 647 for training and 100 for testing
- Female facial image: 1053 for training and 100 for testing

$$loss\_G\_GAN = \mathbb{E}_{x\sim p_{data}(x)}[(D(G(x)) - 1)^2]$$

$$loss\_cycle = L_{cyc}(G, F)$$



Generator loss VS Epoch



Cycle loss VS Epoch

male face → female face

female face → male face

Discussion

- We use cycleGANs networks to transfer face between male and female and some results are pretty good as shown above.
- However, the fake male faces which transfer from female faces sometimes are not satisfied. This is because model is hard to transfer hair and results in a male face with female hair which make the picture look strange.
- And the result on test data is not satisfied as train data. We think this is due to our limited amount of train data which is not sufficient to represent the whole face collection. So the model cannot learn enough knowledge to fit different type of faces.

Future work

- Explore more edge-cutting algorithms, such as TL-GAN
- Speed up the training, apply mini-batch, and scale down the output image.
- Transfer more facial features, like with-glasses and no-glasses, long hair and short hair, blue eyes and black eyes and so on.

Acknowledgement

- Gatys, L., Ecker, A. and Bethge, M. (2016). A Neural Algorithm of Artistic Style. Journal of Vision, 16(12), p.326.
- J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks," 2017 IEEE International Conference on Computer Vision (ICCV), 2017.
- P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-Image Translation with Conditional Adversarial Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017.
- S. GUAN, "Generating custom photo-realistic faces using AI", Insight Fellows Program, 2019. [Online]. Available: https://blog.insightdatascience.com/generating-custom-photo-realistic-faces-using-ai-d170b1b59255. [Accessed: 04- Jun- 2019].