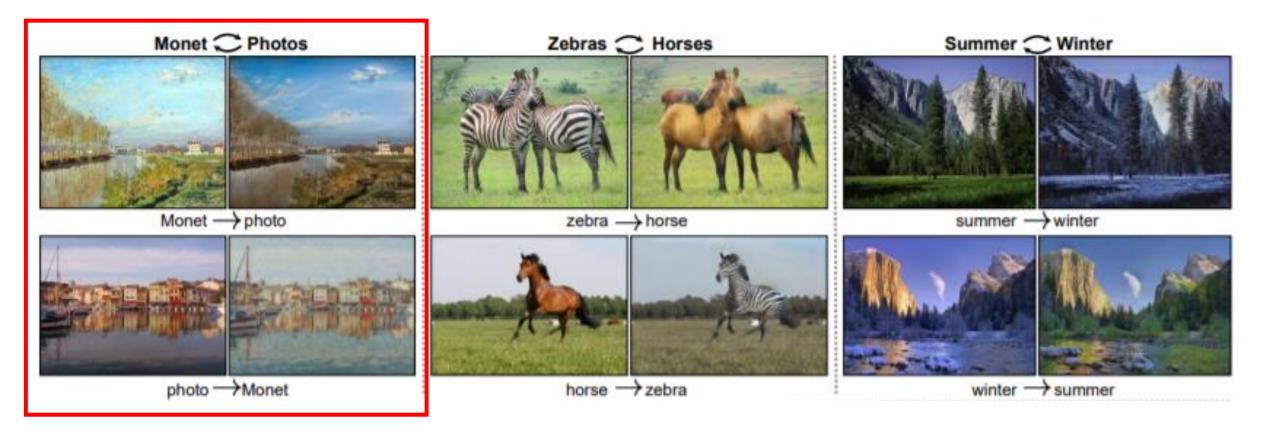
Cycle Generative Adversarial Networks

CycleGAN SMARCLE 신도현

Contents

- 1. What is CycleGAN?
- 2. Pix2pix GAN CycleGAN
- 3. Example of Application 'CycleGAN'
- 4. Limitation of CycleGAN

1. CycleGAN?







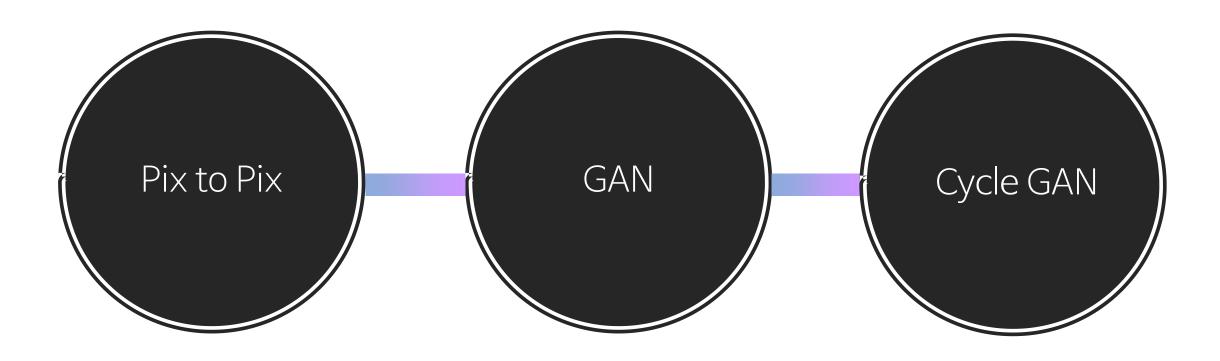
Face to Ramen?



Figure 1: Given any two unordered image collections X and Y, our algorithm learns to automatically "translate" an image from one into the other and vice versa: (*left*) Monet paintings and landscape photos from Flickr; (*center*) zebras and horses from ImageNet; (*right*) summer and winter Yosemite photos from Flickr. Example application (*bottom*): using a collection of paintings of famous artists, our method learns to render natural photographs into the respective styles.

1. CycleGAN?

2. Process





- Image-to-Image Translation
 with Conditional Adversarial Networks
- Supervised learning

- Train data

INPUT OUTPUT

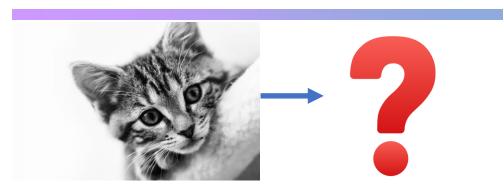
pix2pix
process

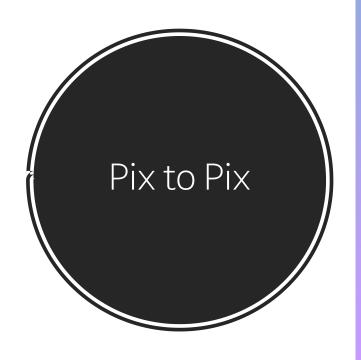
undo clear random

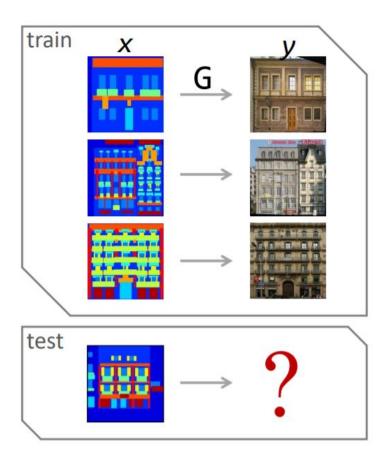
save

https://phillipi.github.io/pix2pix/

- Test data





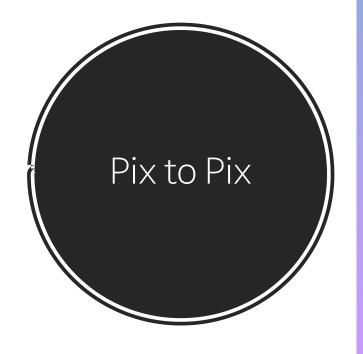


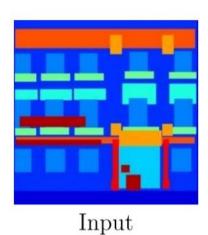
- Supervised
- loss: Minimize the difference between output G(x) and ground truth y

Data from [Tylecek, 2013]

Loss: Minimize the difference between output G(x) and the ground truth y

$$\sum_{(x,y)} \|y - G(x)\|_1$$











Ground Truth



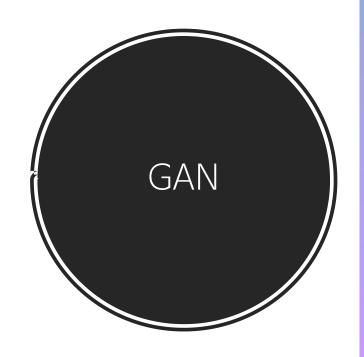


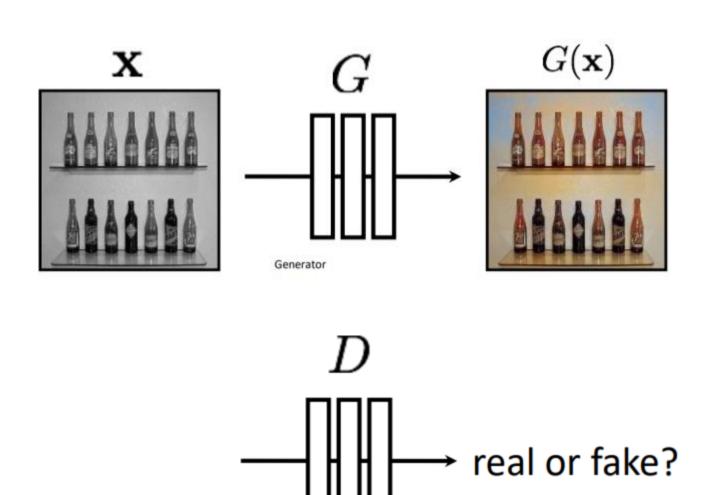


Output

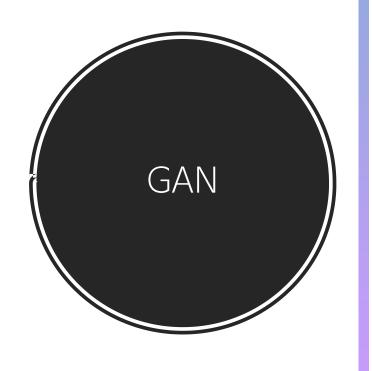


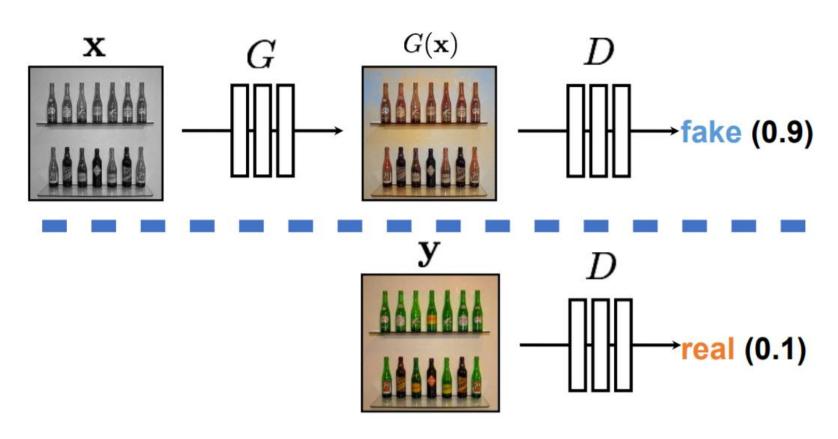
Ground Truth





Discriminator





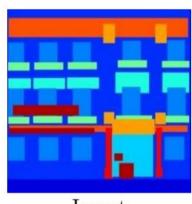
G tries to synthesize fake images that *fool* the *best* D:

$$\arg\min_{G} \max_{D} \mathbb{E}_{\mathbf{x},\mathbf{y}} [\log D(G(\mathbf{x})) + \log(1 - D(\mathbf{y}))]$$



Loss: Minimize the difference between and output G(x) and ground truth y

$$\sum_{(x,y)} \|y - G(x)\|_1 + L_{GAN}(G(x), y)$$







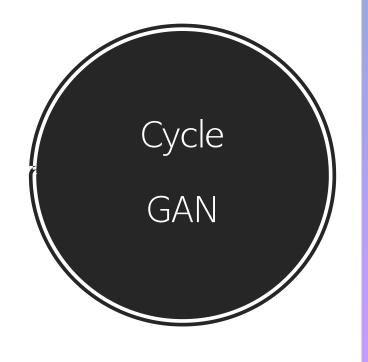
Ground Truth

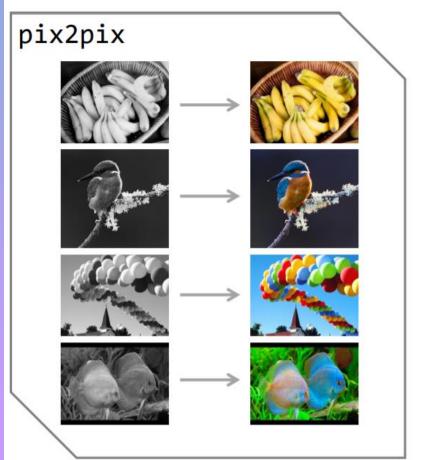


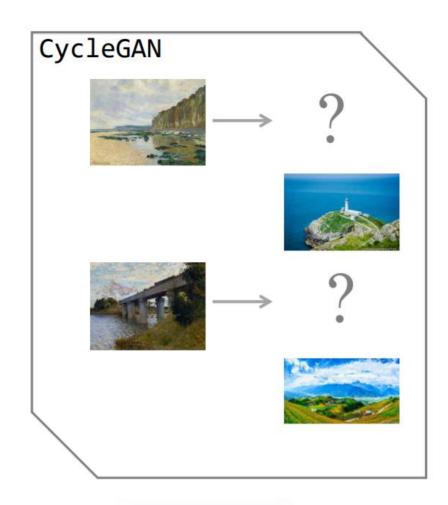
L1 loss only



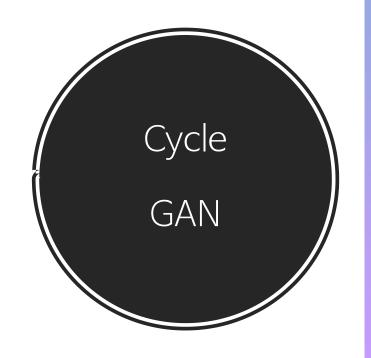
L1+GAN loss

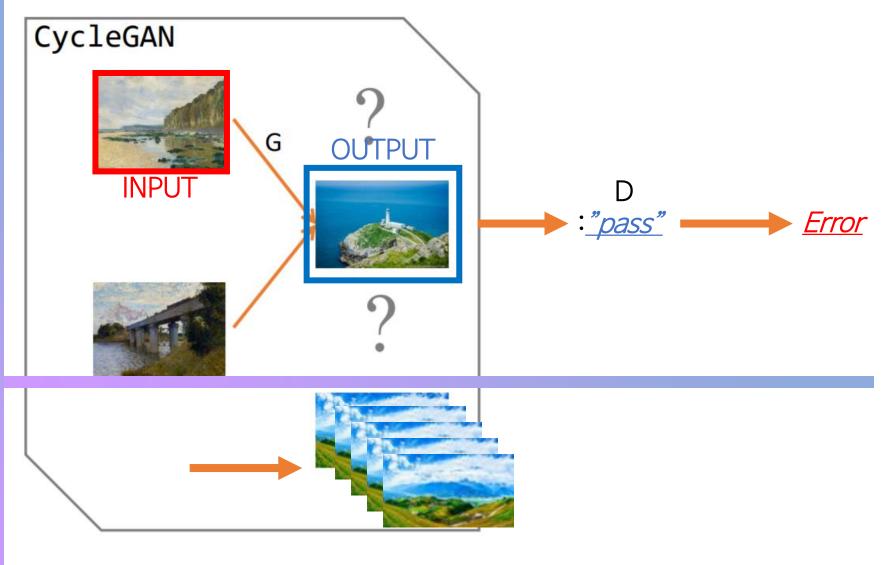






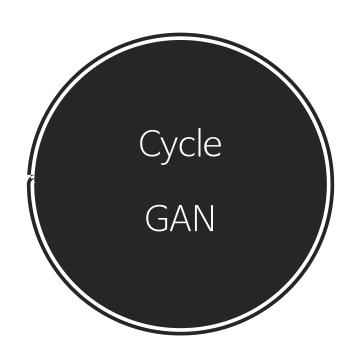
automatically "translate" an image



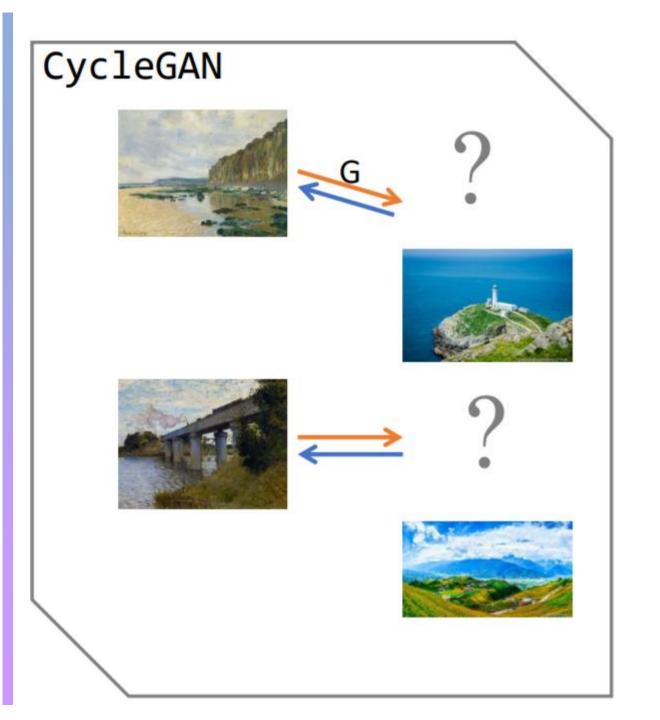


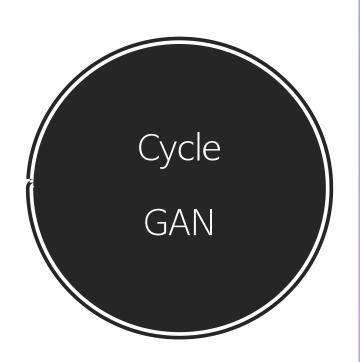
[기존 GAN loss 적용시]

- 1. G가 <u>input (1)</u>을 무시하고 <u>output(2)</u>을 만들 수 있다.
- 2. input에 관계없는 똑같은 output만 생성될 수 있다.



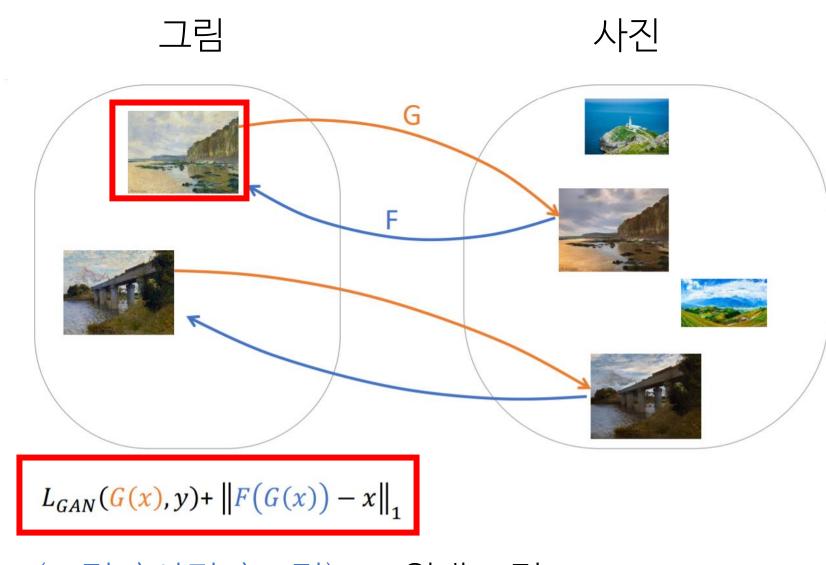
Key Object:



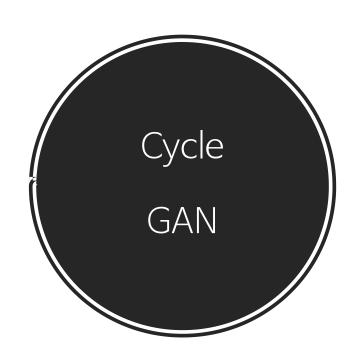


G: 그림 → 사진

F: 사진 → 그림

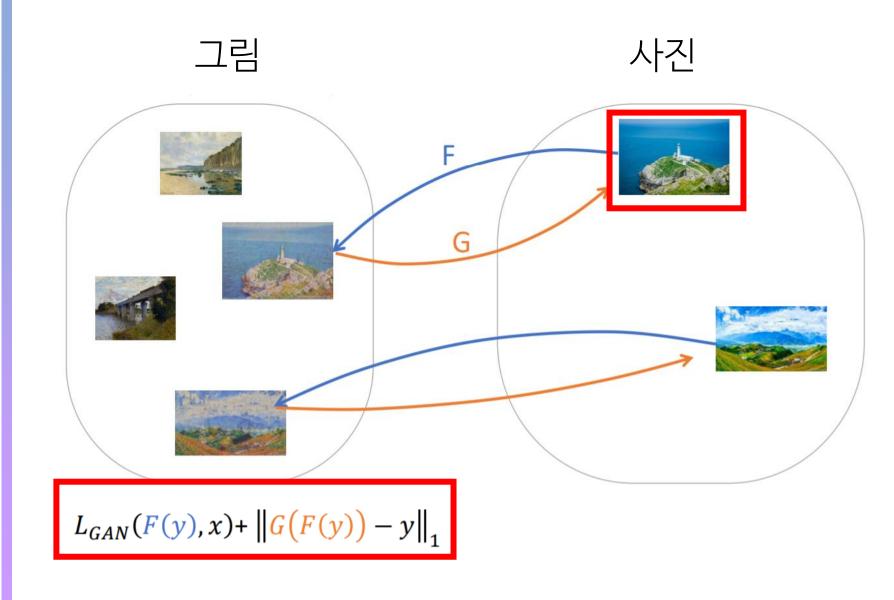


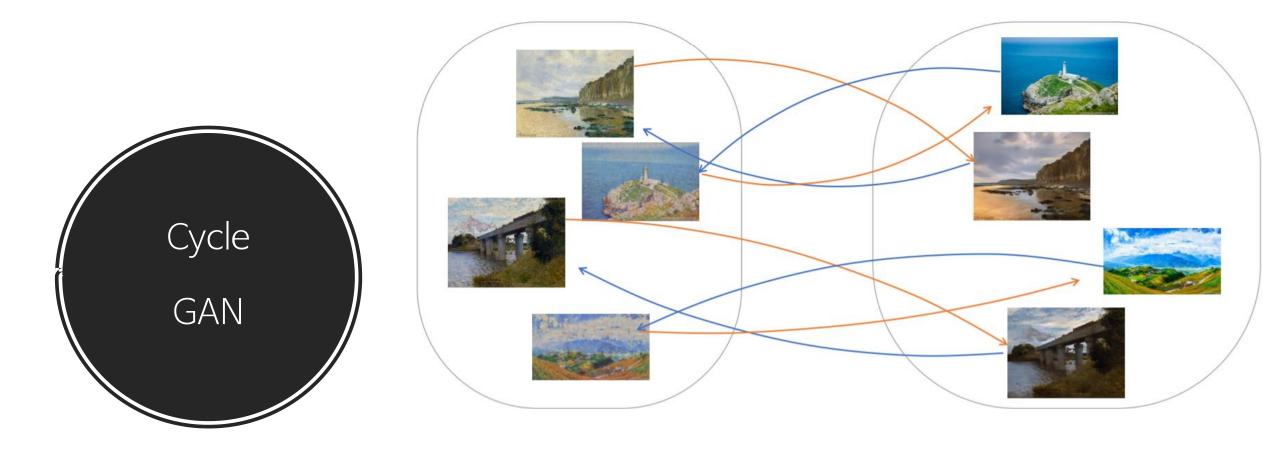
(그림-〉사진-〉그림) == 원래 그림



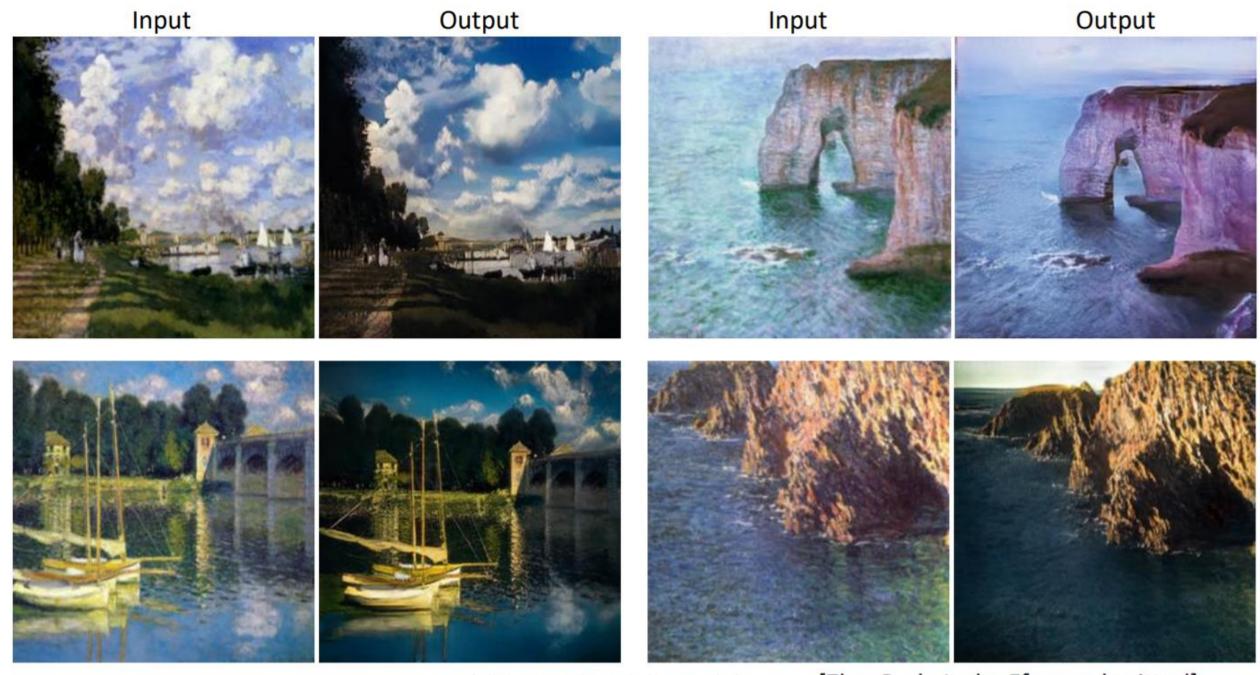
F: 사진 → 그림

G: 그림 → 사진



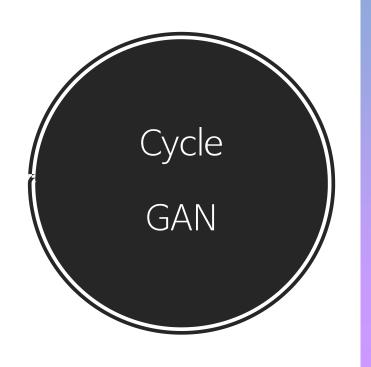


$$L_{GAN}(G(x), y) + ||F(G(x)) - x||_1 + L_{GAN}(F(y), x) + ||G(F(y)) - y||_1$$



(slides credit: Phillip Isola)

[Zhu, Park, Isola, Efros, submitted]











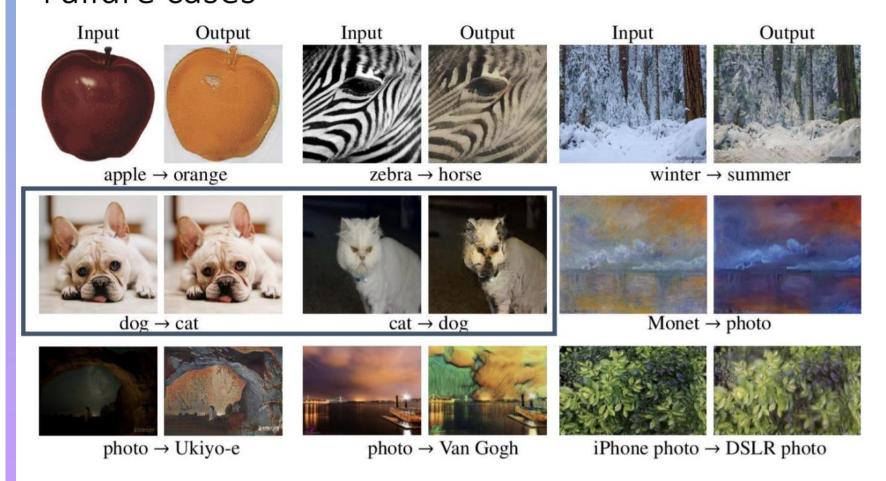
Ablation Study on Cityscapes dataset

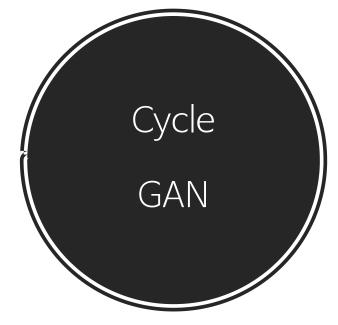
$$L_{GAN}(G(x), y) + ||F(G(x)) - x||_1 + L_{GAN}(F(y), x) + ||G(F(y)) - y||_1$$

Cycle GAN

Limitation

Failure cases





Limitation 1 / 100 data



Thank you

- [참고]
- - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks [Jun-Yan Zhu* Taesung Park* Phillip Isola Alexei A. Efros Berkeley Al Research (BAIR) laboratory, UC Berkeley]

https://arxiv.org/pdf/1703.10593v6.pdf

• - Finding connections among images using CycleGAN[Taesung Park, Naver D2, 2017]

https://www.slideshare.net/NaverEngineering/finding-connections-among-images-using-cyclegan