

Cycle GAN

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

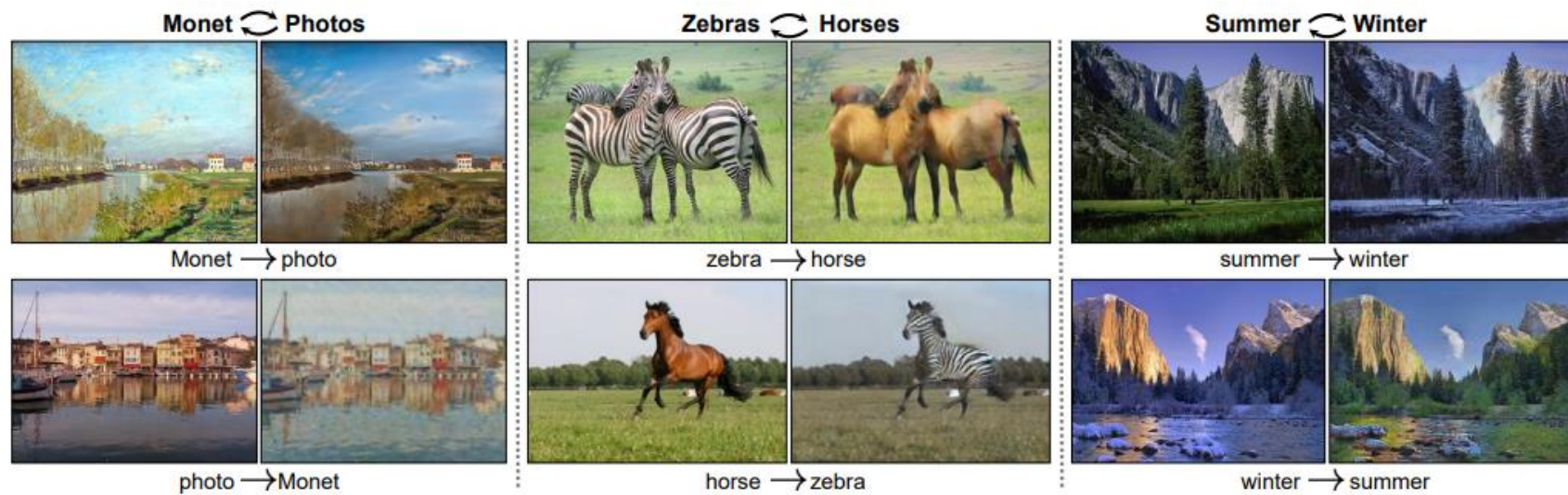
(<https://arxiv.org/abs/1703.10593>)

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목차

- ▣ Abstract
- ▣ GAN and pix2pix
- ▣ Cycle Consistency
- ▣ CycleGAN Architecture and Loss
- ▣ CycleGAN Implementation detail

Abstract

- 연구 배경
 - Image-to-Image translation 에서 aligned image pairs data를 이용하여 학습한다.
 - 대부분의 연구에서, Paired training data를 사용할 수 없다.
 - Paired image 없이, source domain X에서 target domain Y로 translate하게 학습
- 목표
 - Adversarial loss를 이용하여 mapping $G: X \rightarrow Y$ 를 학습.
 - Inverse mapping $F: Y \rightarrow X$ 를 이용한 cycle consistency loss를 추가하여 Unpaired image를 학습.

Abstract

Paired & Unpaired training datasets

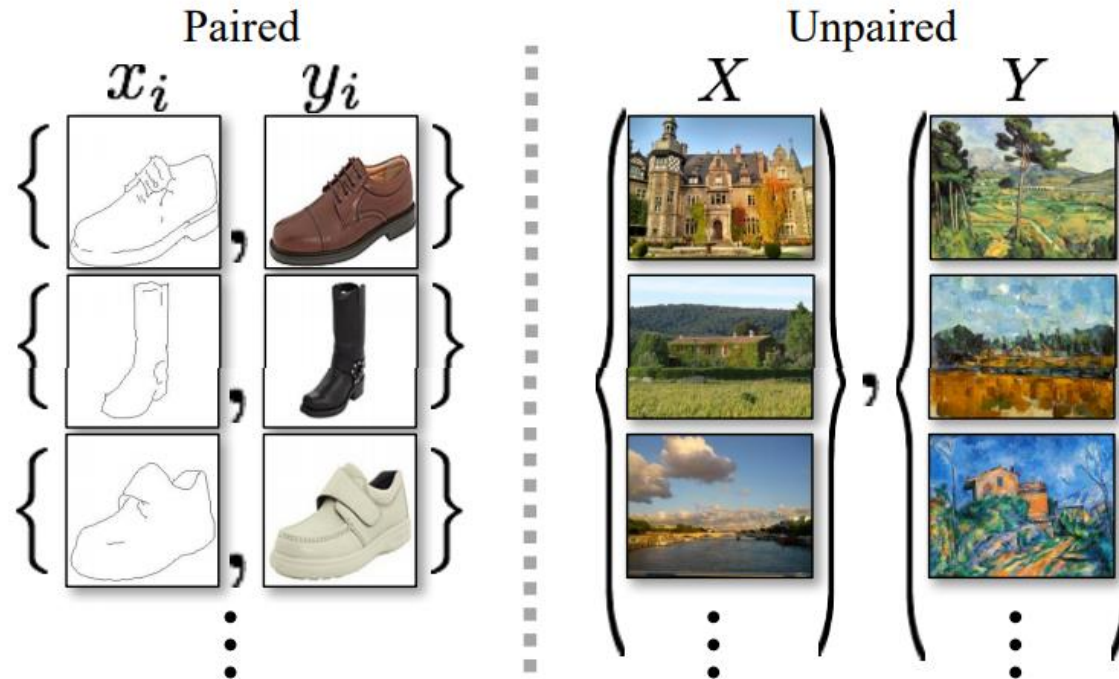


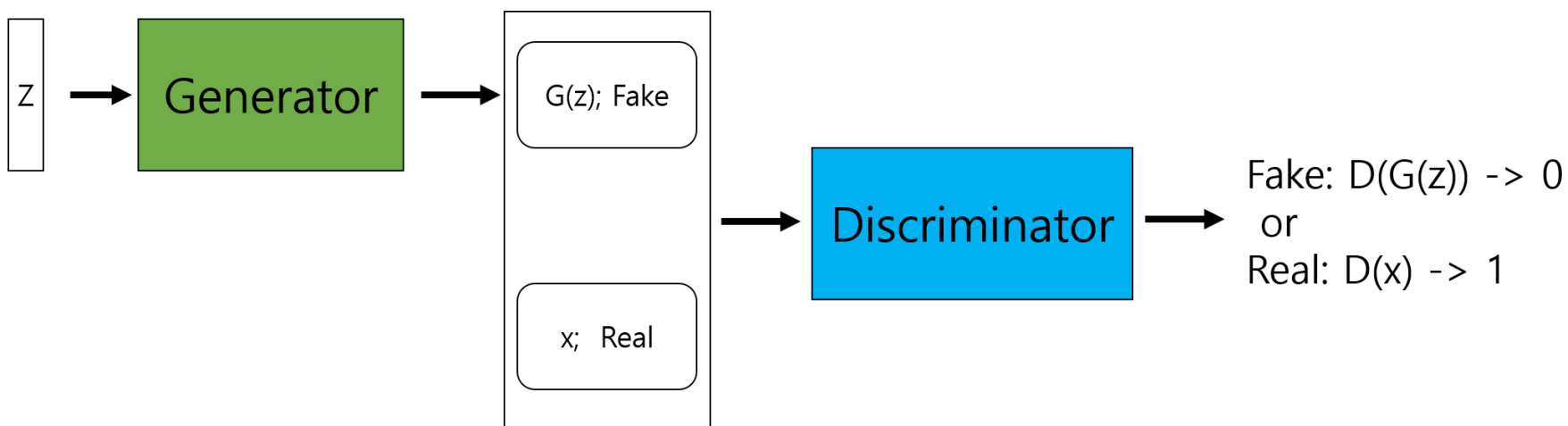
Figure 2: *Paired* training data (left) consists of training examples $\{x_i, y_i\}_{i=1}^N$, where the correspondence between x_i and y_i exists [22]. We instead consider *unpaired* training data (right), consisting of a source set $\{x_i\}_{i=1}^N$ ($x_i \in X$) and a target set $\{y_j\}_{j=1}^N$ ($y_j \in Y$), with no information provided as to which x_i matches which y_j .

GAN

GAN architecture and loss function

- Generative Adversarial Net(GAN)

- 실제 데이터(x)인지, G 로부터 만들어졌는지 구분하는 network D 와, D 를 속이도록 학습하는 network G 의 적대적 (adversarial)관계를 이용한 생성모델 G 를 만드는 프레임워크.
- $G(z)$ 의 distribution은 x 의 distribution과 같아지고, D 는 둘을 구분하지 못하는 상태 $D(x) = 0.5$ 가 될 것이다.

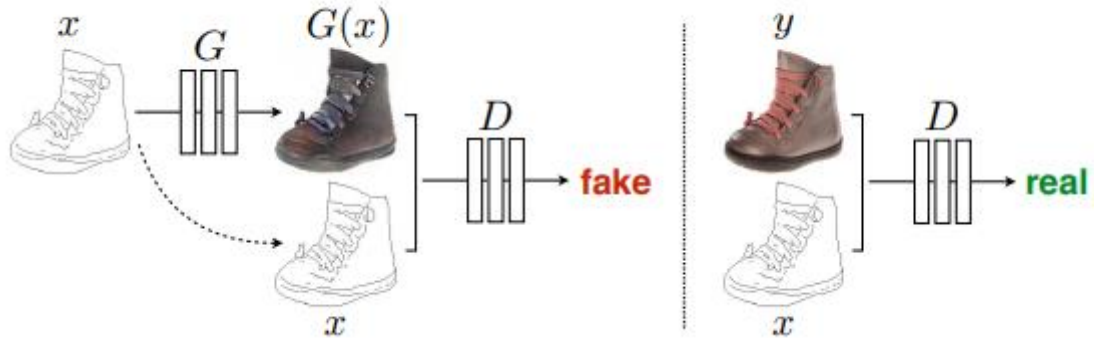


- Adversarial loss :
$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_z(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$

Pix2Pix

Image-to-Image Translation with Conditional Adversarial Networks (<https://arxiv.org/abs/1611.07004>)

- pix2pix
 - Image-to-Image translation 모델.
 - Input image를 D의 condition으로 사용하여 학습.
 - G는 U-Net model, D는 Markovian discriminator (PatchGAN)을 사용.
 - Paired image dataset을 사용.



$$G^* = \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G).$$



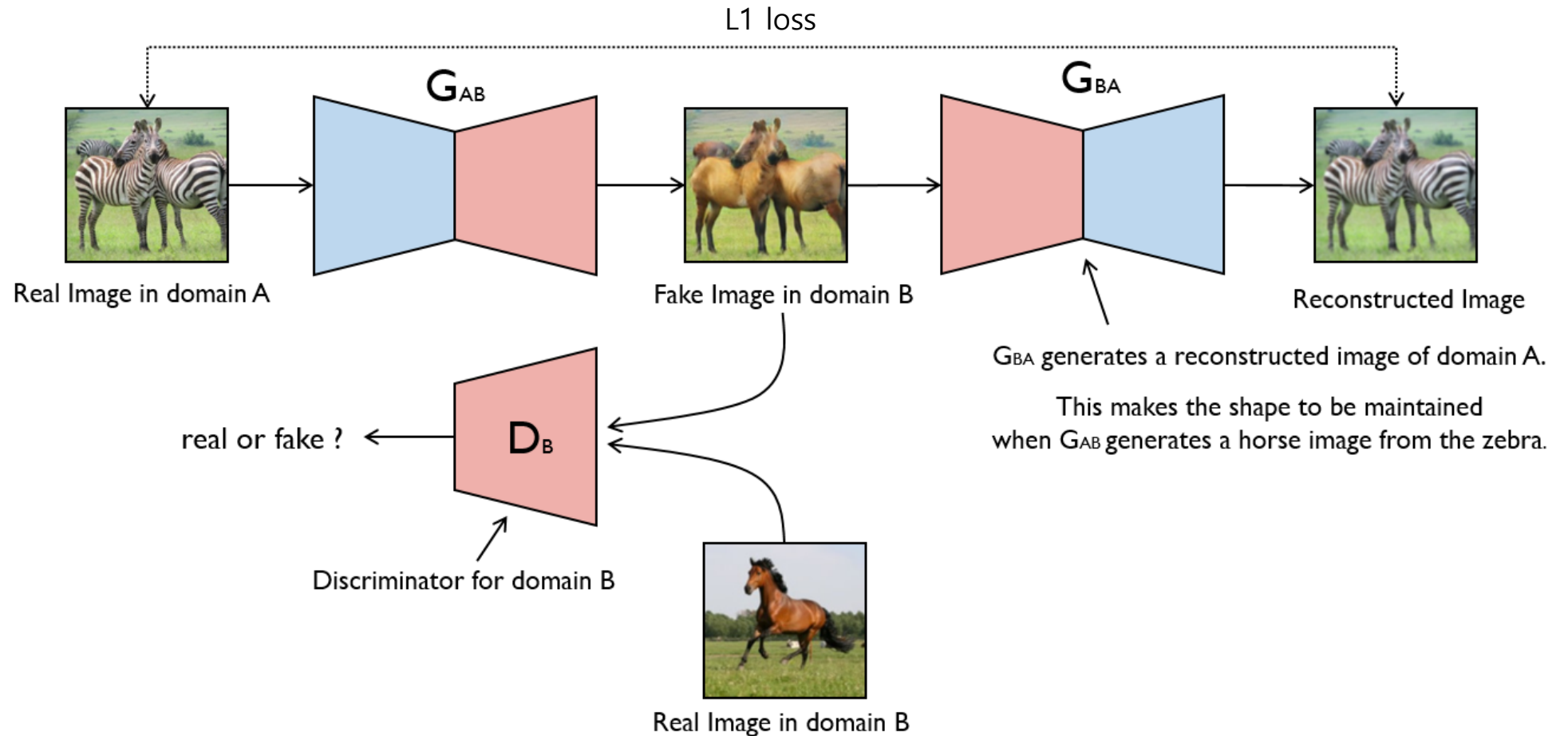
Figure 17: Example results of our method on automatically detected edges→shoes, compared to ground truth.

Cycle Consistency

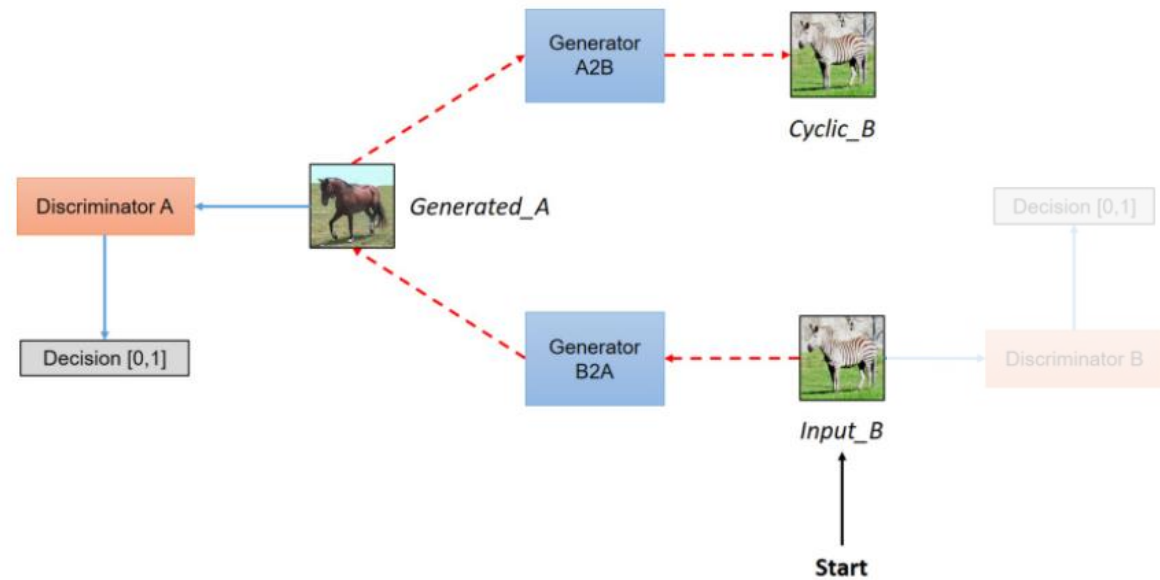
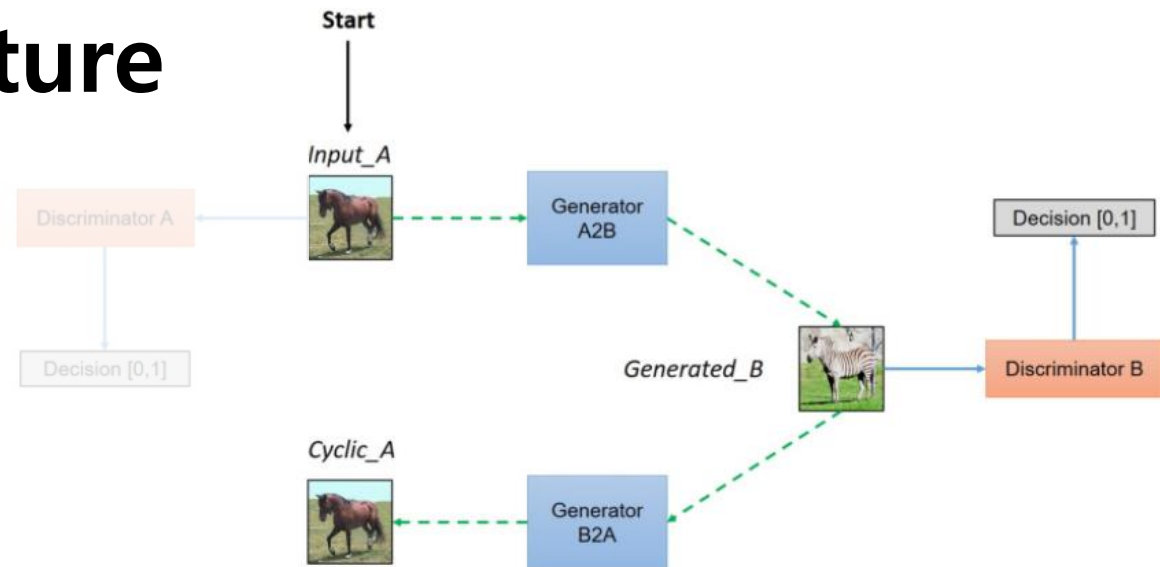
- Unpaired image를 GAN에 학습시키면?
 - 각각의 input x 에 대해, y 가 의미 있는 pair가 될 보장이 없음.
 - Mode collapse(all input images map to the same output image.) 가 종종 발생.
- 위의 이유로, Objective에 cycle consistent 특성을 추가.
 - If we translate, eg., a sentence from English to French, and then translate it back from French to English, we should arrive back at the original sentence
 - 두 translator $G: X \rightarrow Y$, $F: Y \rightarrow X$ 에 대해, $F(G(x)) \approx x$, $G(F(y)) \approx y$ 에서 비롯된 cycle consistency loss를 adversarial loss와 결합하여 학습을 진행.

CycleGAN architecture

- A -> B로의 Translate 입장에서 본 architecture



CycleGAN architecture



CycleGAN Loss

- Adversarial Loss

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

- Cycle Loss

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

- Full Objective

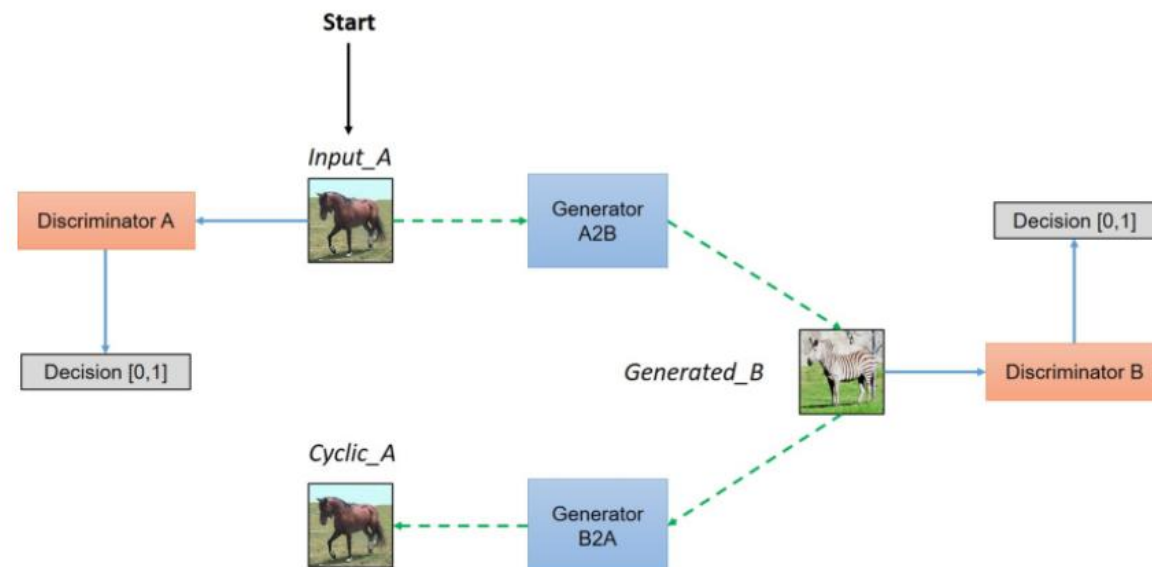
$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) + \lambda \mathcal{L}_{\text{cyc}}(G, F)$$

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

CycleGAN Implementataion detail

- Network Architecture

- G : ResNet구조 (3conv – 9resnetblock – 3conv)
- D : Markovian Discriminator(PatchGAN) (70x70 patch)



- Adversarial loss

- LSGAN : Least-squares loss 사용.

G to minimize $\mathbb{E}_{x \sim p_{\text{data}}(x)} [(D(G(x)) - 1)^2]$

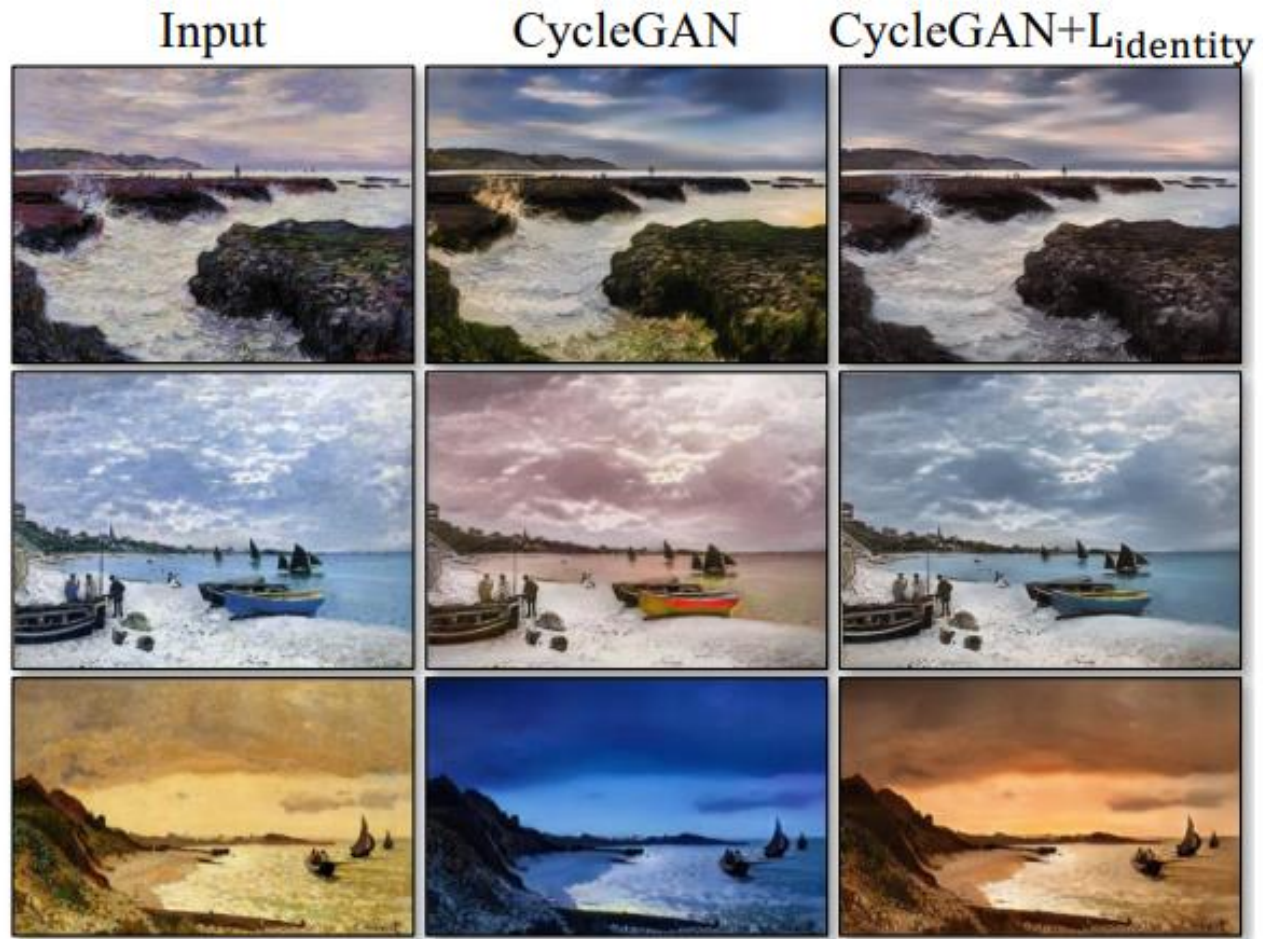
D to minimize $\mathbb{E}_{y \sim p_{\text{data}}(y)} [(D(y) - 1)^2] + \mathbb{E}_{x \sim p_{\text{data}}(x)} [D(G(x))^2]$.

- Identity loss

- Color composition을 보존하는데 도움을 주는 loss

$$\mathcal{L}_{\text{identity}}(G, F) = \mathbb{E}_{y \sim p_{\text{data}}(y)} [\|G(y) - y\|_1] + \mathbb{E}_{x \sim p_{\text{data}}(x)} [\|F(x) - x\|_1].$$

CycleGAN Result



CycleGAN Result

Input

Output



Input

Output



horse \rightarrow zebra

Input

Output



zebra \rightarrow horse



CycleGAN Result



winter Yosemite → summer Yosemite



summer Yosemite → winter Yosemite

CycleGAN Result



apple → orange



orange → apple

