Cycle GAN

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

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

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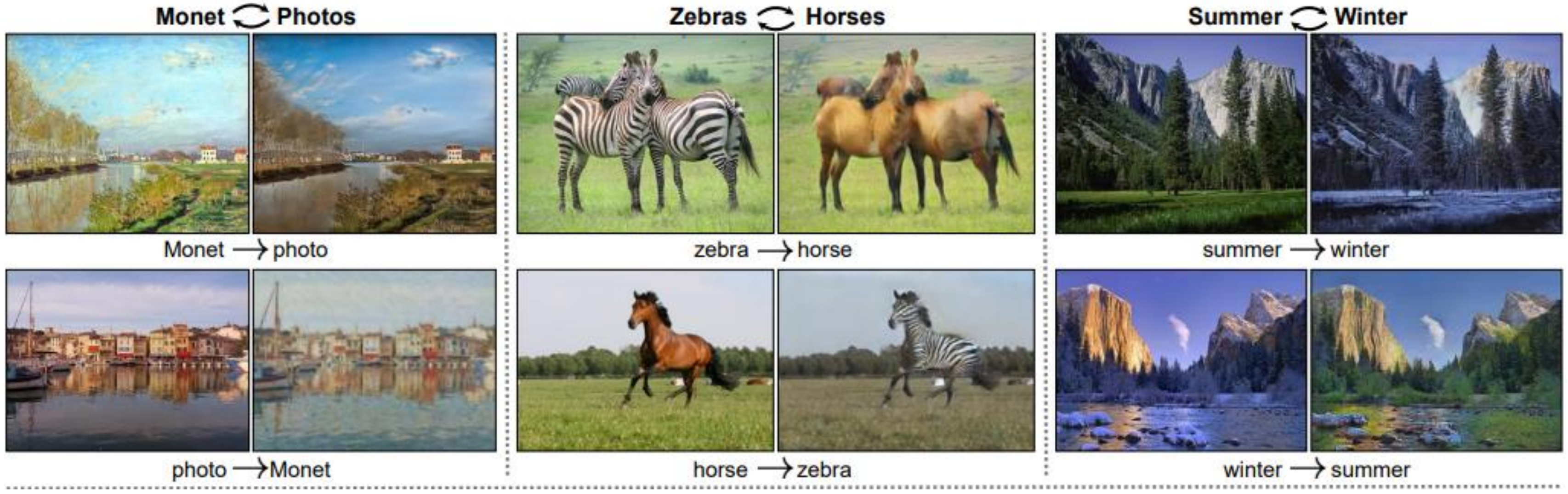


목차

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->Y를 학습.
  - Inverse mapping F: Y->X 를 이용한 cycle consistency loss를 추가하여 Unpaired image 를 학습.

Abstract

Paired & Unpaired training datasets

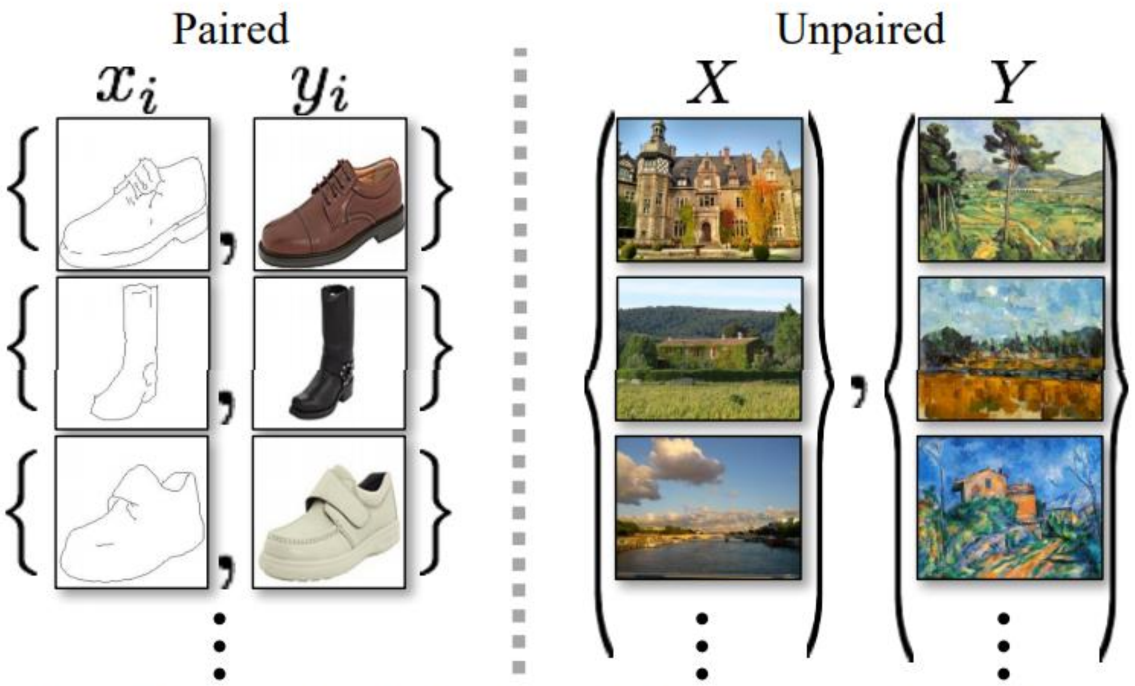
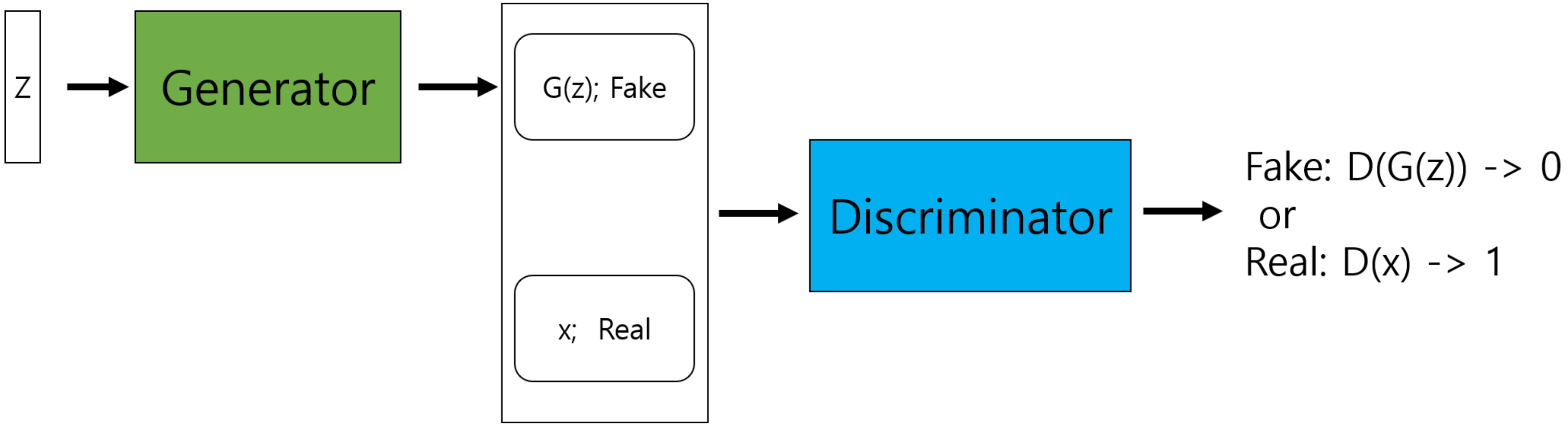


Figure 2: *Paired* training data (left) consists of training examples $\{x_i, y_i\}_{i=1}^N$, where the correspondence between x_i and y_i exists [22]. We instead consider *unpaired* training data (right), consisting of a source set $\{x_i\}_{i=1}^N$ ($x_i \in X$) and a target set $\{y_j\}_{j=1}$ ($y_j \in Y$), 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, G로부터 만들어졌는지 구분하는 network D와, D를 속이도록 학습하는 network G의 적대적(adversarial)관계를 이용한 생성모델 G를 만드는 프레임워크.
  - G(z)의 distribution은 x의 distribution과 같아지고, D는 둘을 구분하지 못하는 상태 D(x) = 0.5가 될 것이다.

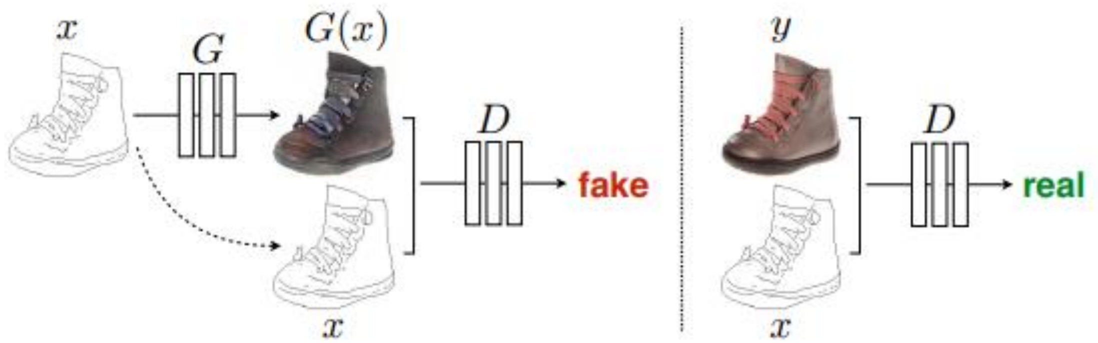


- Adversarial loss : $\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$

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.

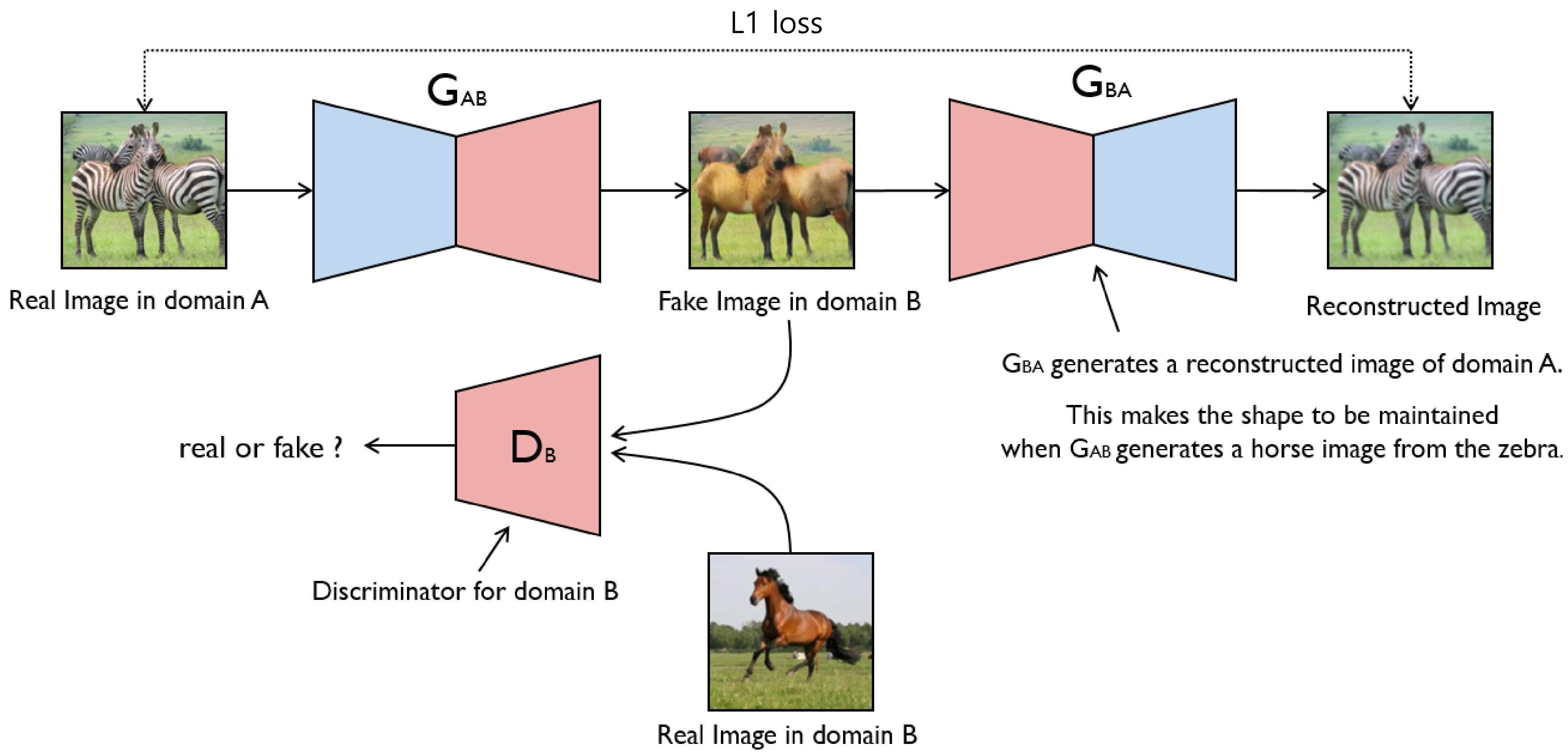
Cycle Consistency

- Unpaired image를 GAN에 학습시키면?
  - 각각의 input x에 대해, y가 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, $\mathrm{F}(G(x)) \approx \mathrm{x}$, $G(F(y)) \approx y$에서 비롯된 cycle consistency loss를 adversarial loss와 결합하여 학습을 진행.

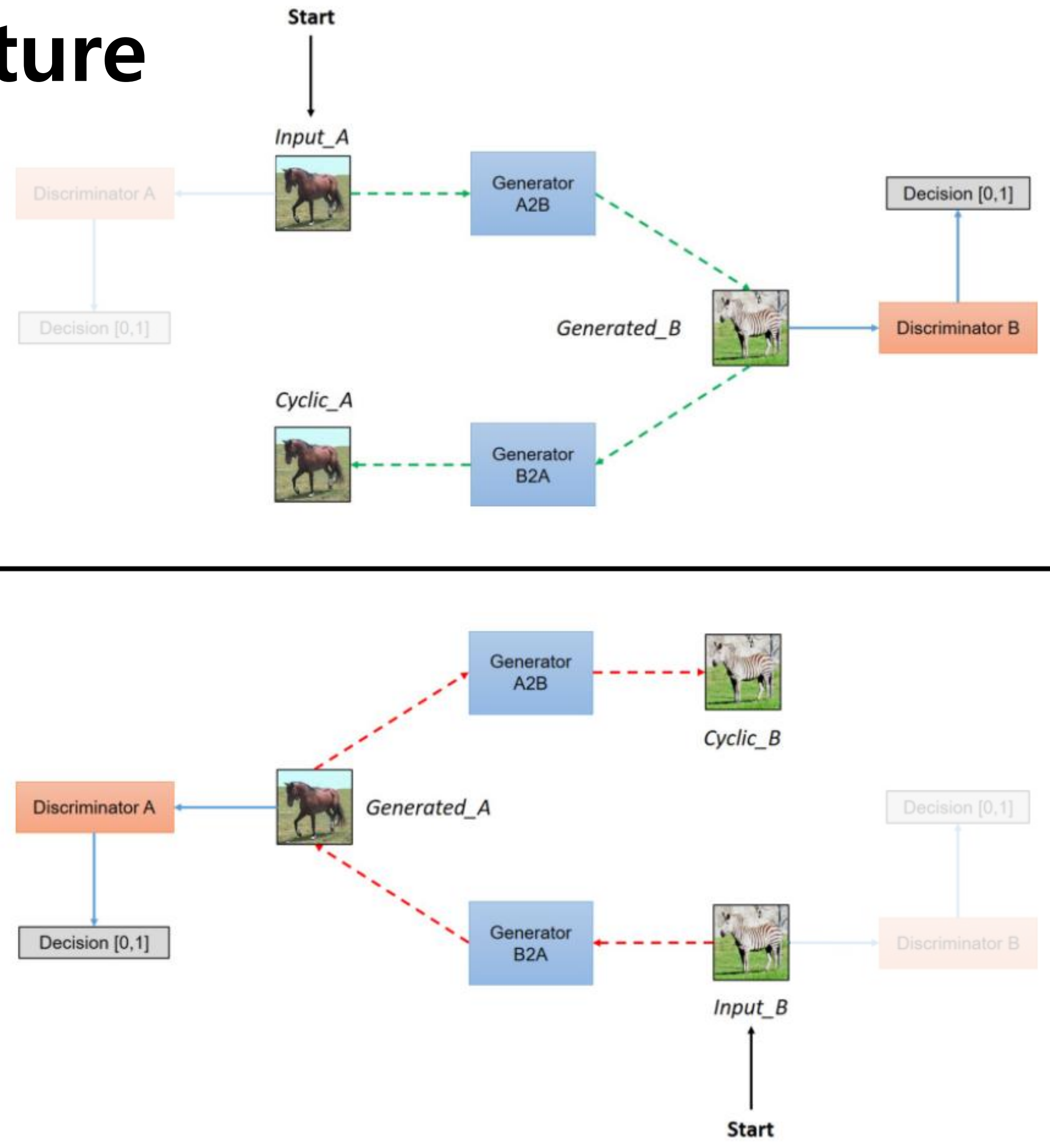
CycleGAN architecture

- A -> B로의 Translate 입장에서 본 architecture



CycleGAN architecture image from https://modelzoo.co/model/mnist-svhn-transfer

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

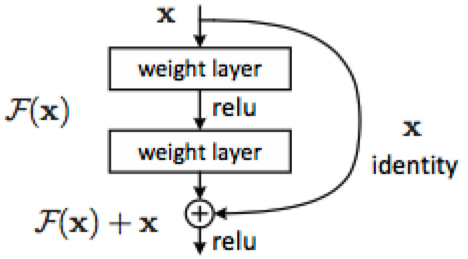
$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y\sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].$$

- Full Objective

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

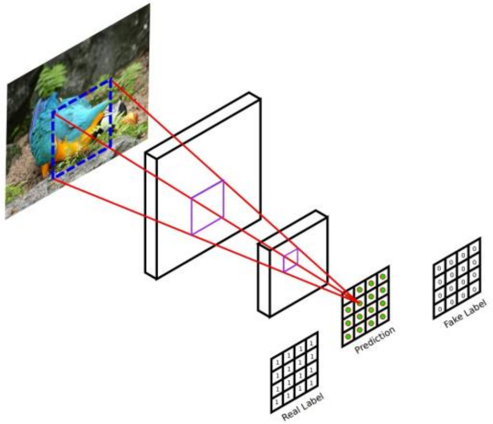
$$G^*, F^* = \arg\min_{G,F}\max_{D_x, D_Y} \mathcal{L}(G, F, D_X, D_Y).$$

CycleGAN Implementataion detail



Residual block

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


Markovian Discriminator

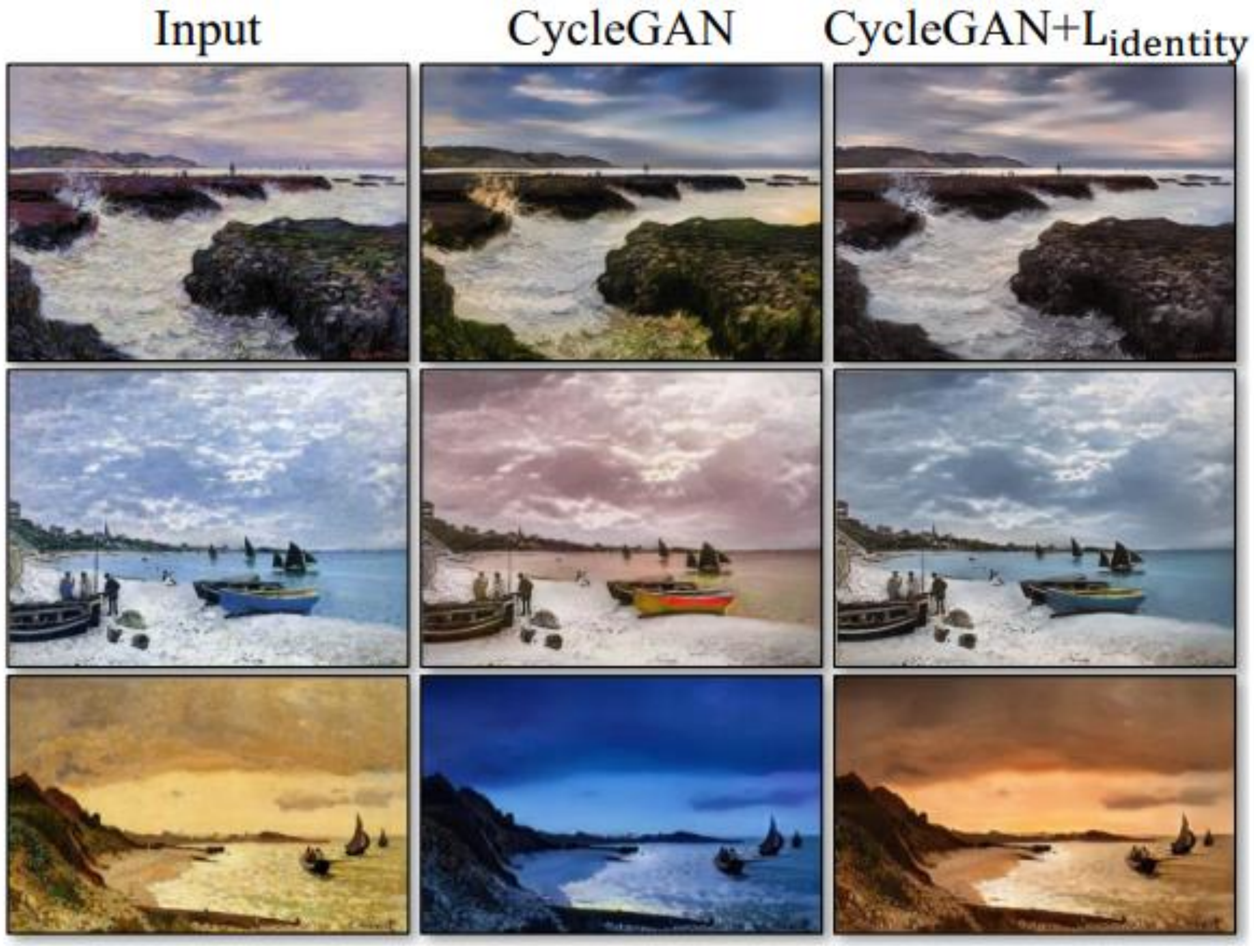
- Adversarial loss
  - LSGAN : Least-squares loss 사용.

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

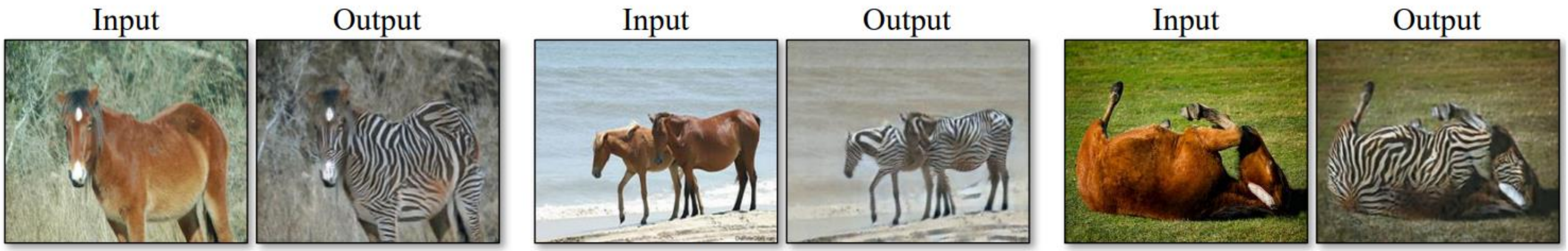
- Identity loss
  - Color composition을 보존하는데 도움을 주는 loss

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

CycleGAN Result



CycleGAN Result



horse → zebra

zebra → horse

CycleGAN Result

winter Yosemite → summer Yosemite

summer Yosemite → winter Yosemite

CycleGAN Result

apple → orange

orange → apple