UNIT: Unsupervised Image-to-Image Translation Networks

한양대학교 AILAB 석사과정 엄희송

NIPS 2017

Ming-Yu Liu, Thomas Breuel, Jan Kautz (NVIDIA)

Left: input. **Right: neural network generated.** Resolution: 640x480

Left: input. **Right: neural network generated.** Resolution: 640x480

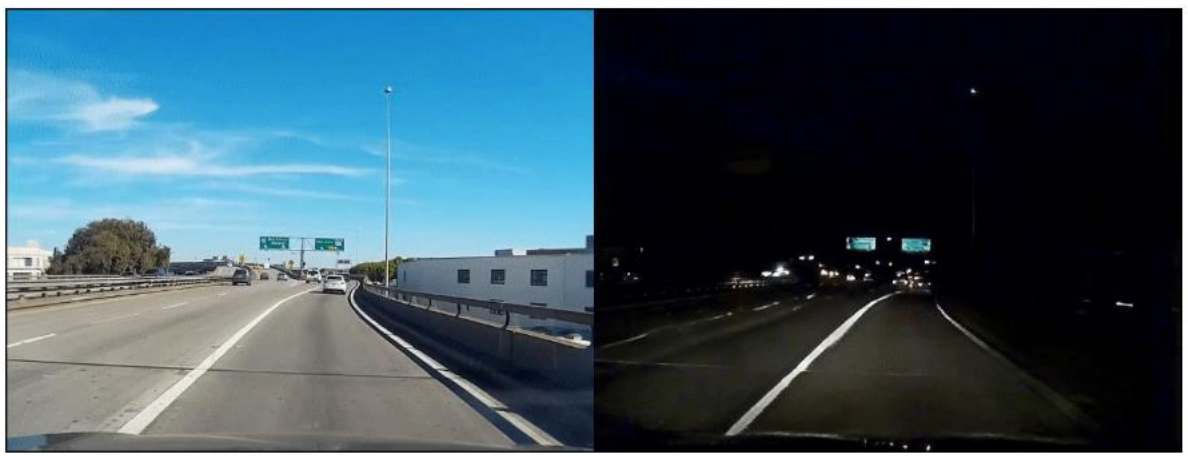


IMAGE-TO-IMAGE TRANSLATION

"Mapping an image in one domain to a corresponding image in another domain."

Semantic Image Synthesis with Spatially-Adaptive Normalization, figure 16. https://arxiv.org/abs/1903.07291

IMAGE-TO-IMAGE TRANSLATION

Conditional GAN – pix2pix

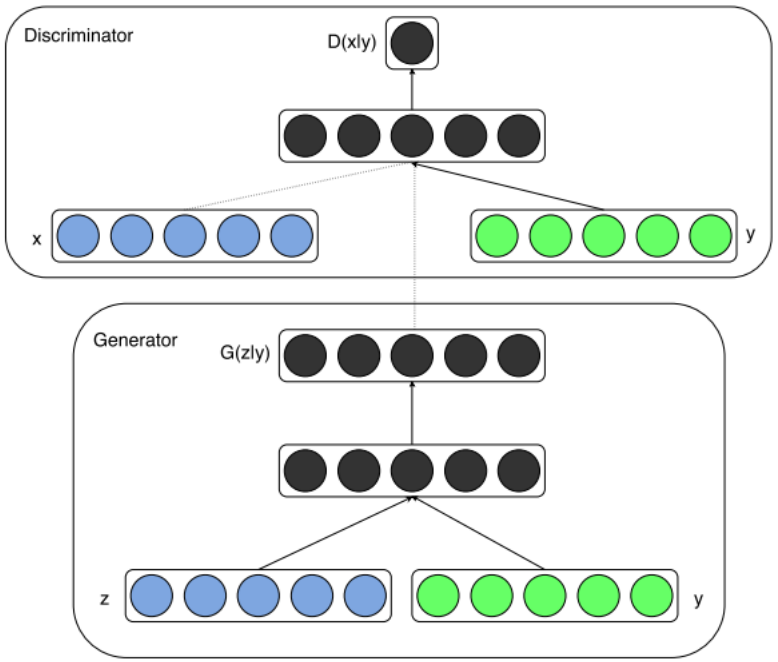
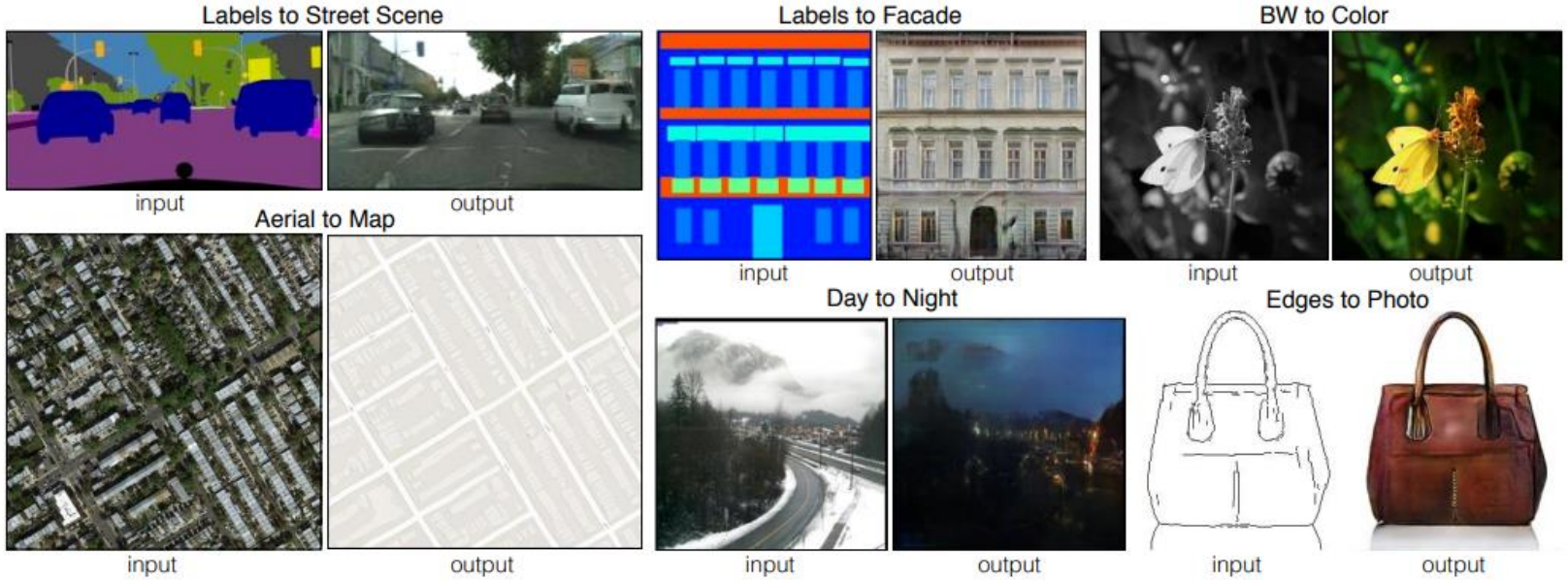
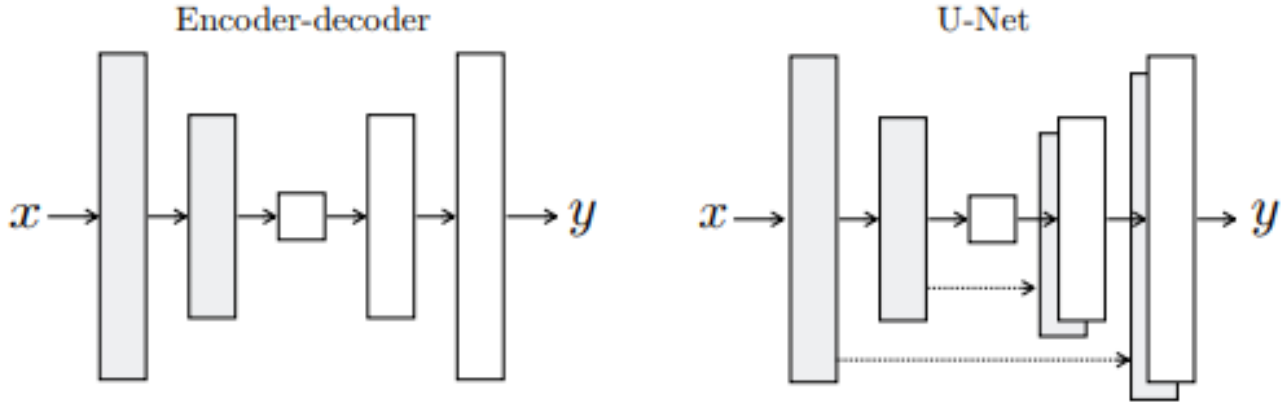


Figure 1: Conditional adversarial net

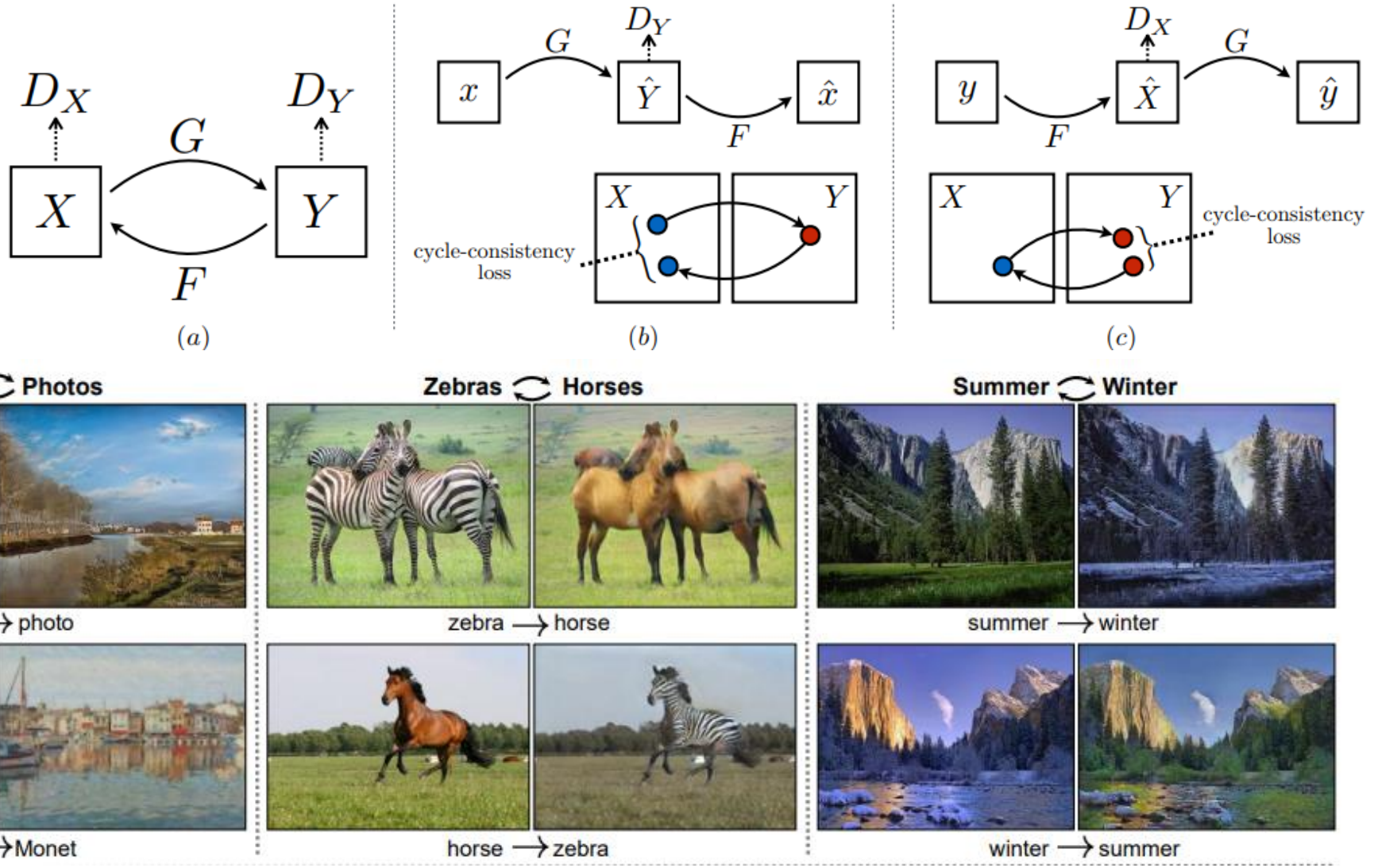




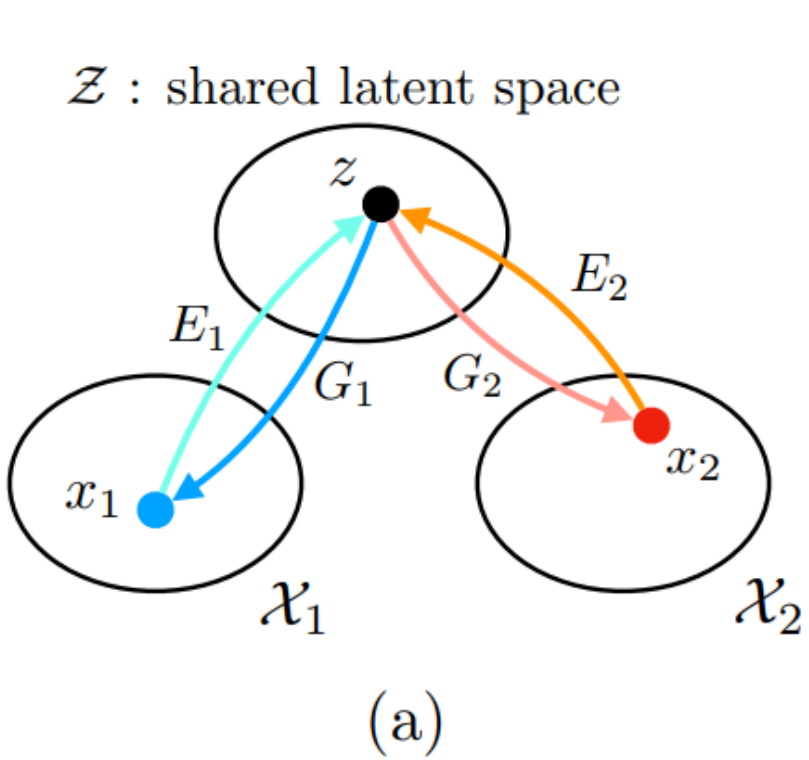
Conditional Generative Adversarial Nets, figure 1. https://arxiv.org/abs/1411.1784
Image-to-Image Translation with Conditional Adversarial Networks, figure 1 & 3. https://arxiv.org/pdf/1611.07004

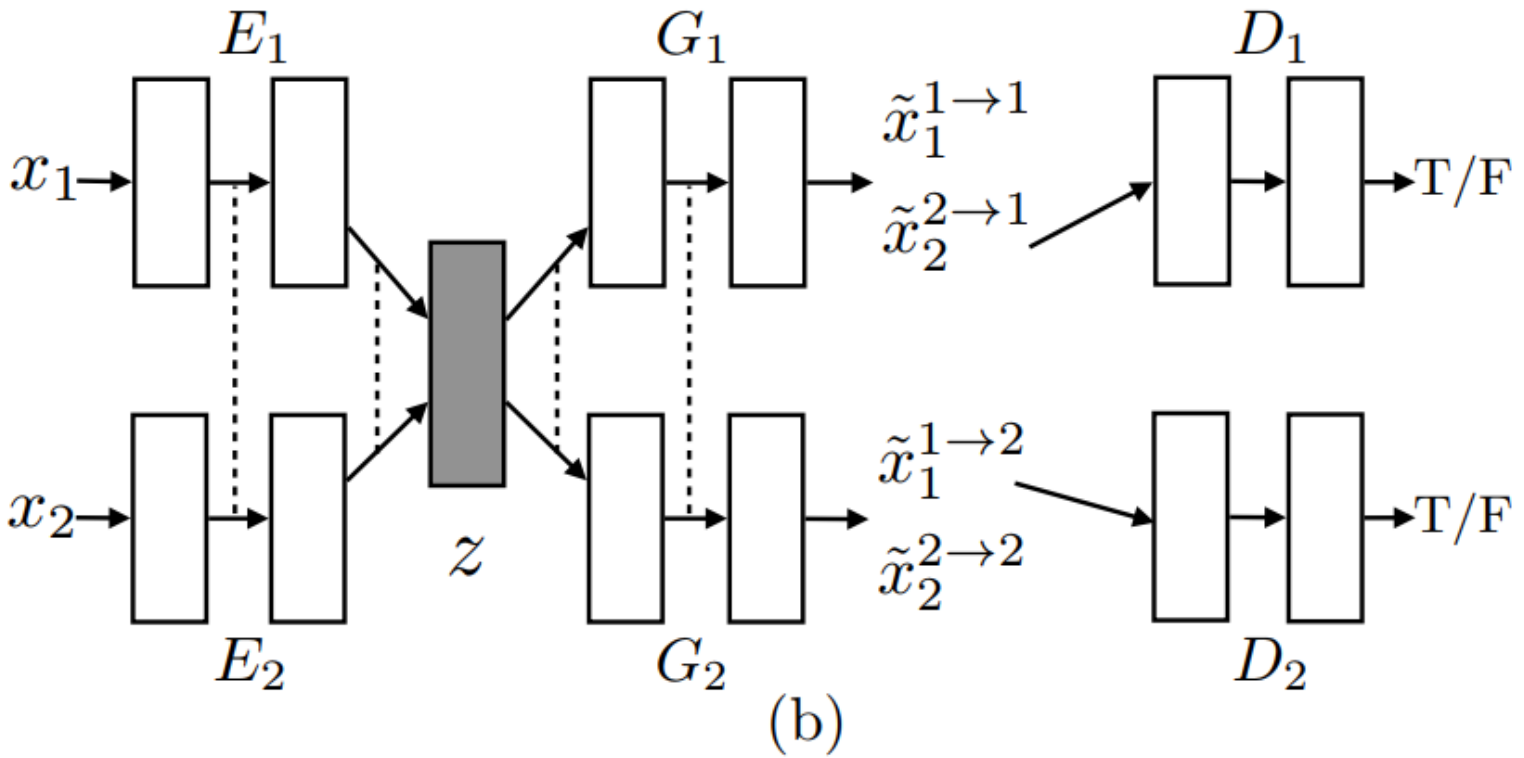
IMAGE-TO-IMAGE TRANSLATION

CycleGAN



Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Network, figure 1. https://arxiv.org/pdf/1703.10593

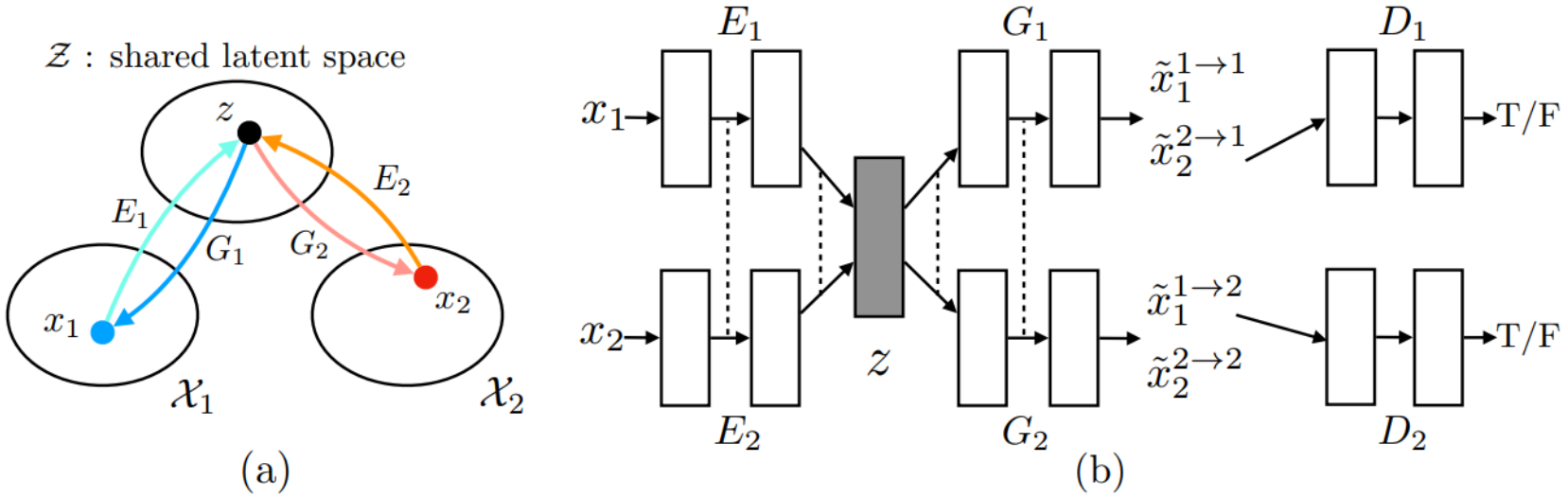

$\mathcal{Z}$: shared latent space
z
E_1
E_2
G_1
G_2
x_1
x_2
$\mathcal{X}_1$
$\mathcal{X}_2$
(a)


E_1
G_1
D_1
x_1
$\tilde{x}_1^{1\to1}$
$\tilde{x}_2^{2\to1}$
T/F
x_2
z
$\tilde{x}_1^{1\to2}$
$\tilde{x}_2^{2\to2}$
T/F
E_2
G_2
D_2
(b)

E: Encoder, G: Generator (encoder-decoder 에서 decoder 부분), D: Discriminator

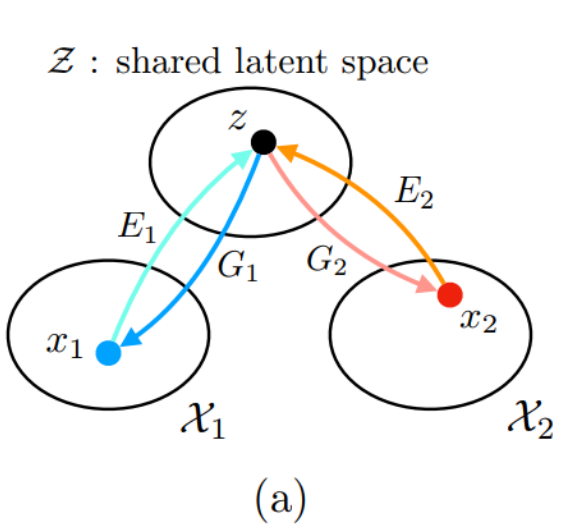
$\tilde{x}_1^{1\to1}$, $\tilde{x}_2^{2\to2}$: self-reconstructed images

$\tilde{x}_1^{2\to1}$, $\tilde{x}_2^{1\to2}$: domain-translated images

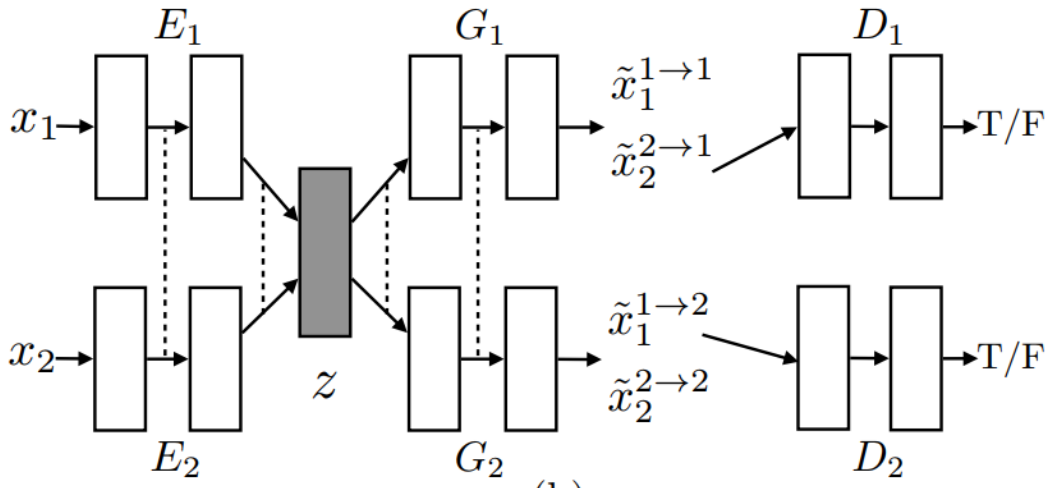


목적함수

$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$



(a)



(b)

목적함수

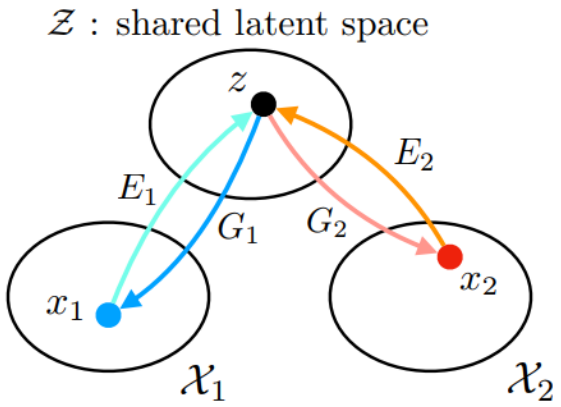
$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$

2 쌍의 VAE(Variational Auto-Encoder)를 사용

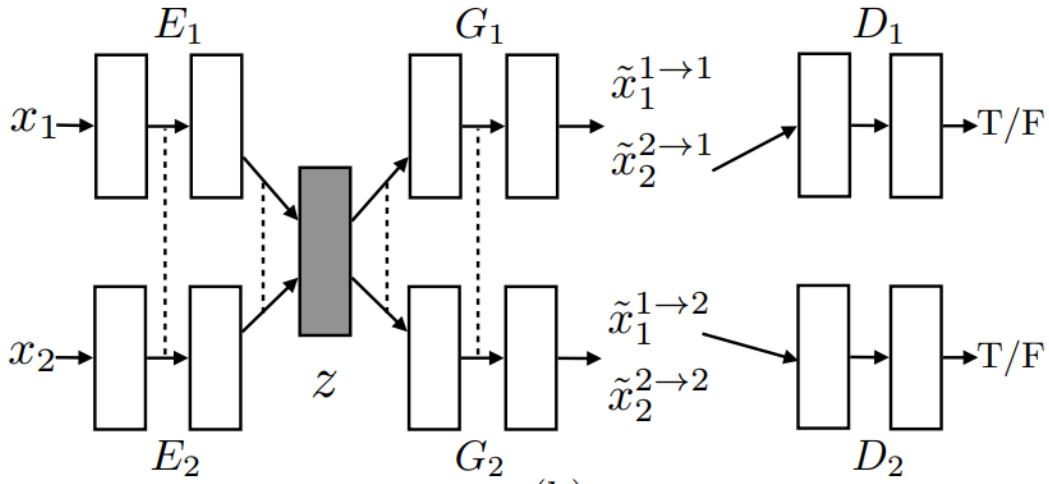
VAE 1: $x_1 \rightarrow z_1 \rightarrow x_1'$
VAE 2: $x_2 \rightarrow z_2 \rightarrow x_2'$

$$\mathcal{L}_{\text{VAE}_1}(E_1,G_1) = \lambda_1 \text{KL}(q_1(z_1|x_1)||p_\eta(z)) - \lambda_2 \mathbb{E}_{z_1\sim q_1(z_1|x_1)}[\log p_{G_1}(x_1|z_1)]$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) = \lambda_1 \text{KL}(q_2(z_2|x_2)||p_\eta(z)) - \lambda_2 \mathbb{E}_{z_2\sim q_2(z_2|x_2)}[\log p_{G_2}(x_2|z_2)]$$

두 VAE를 각각 self-reconstructed image를
생성할 수 있도록 학습시킴.



(a)



(b)

목적함수

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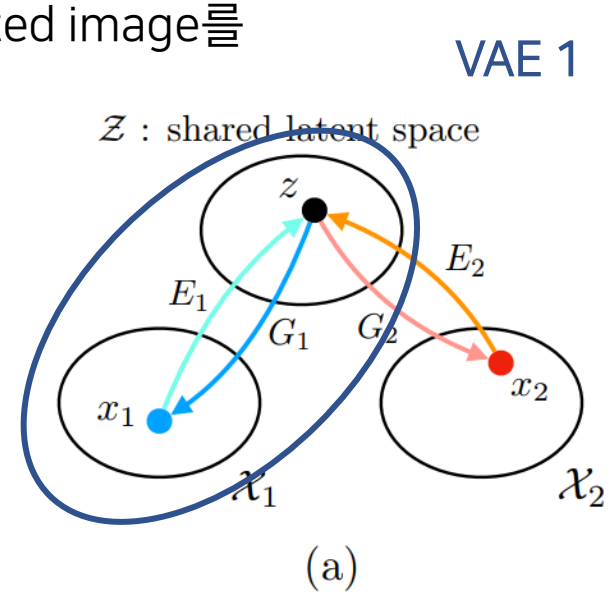
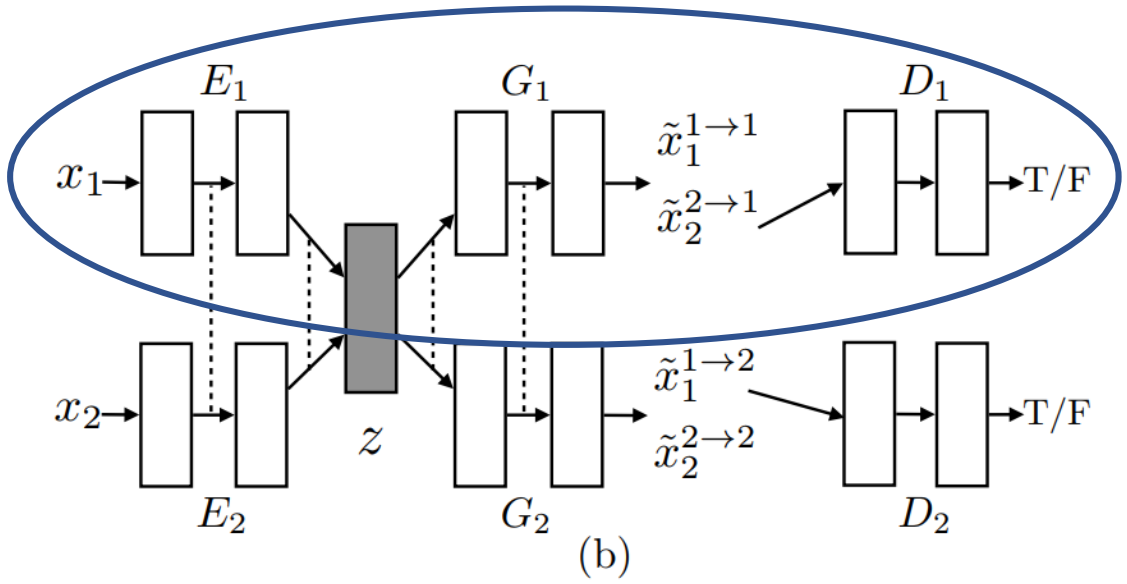
두 VAE를 각각 self-reconstructed image를 생성할 수 있도록 학습시킴.





목적함수

$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
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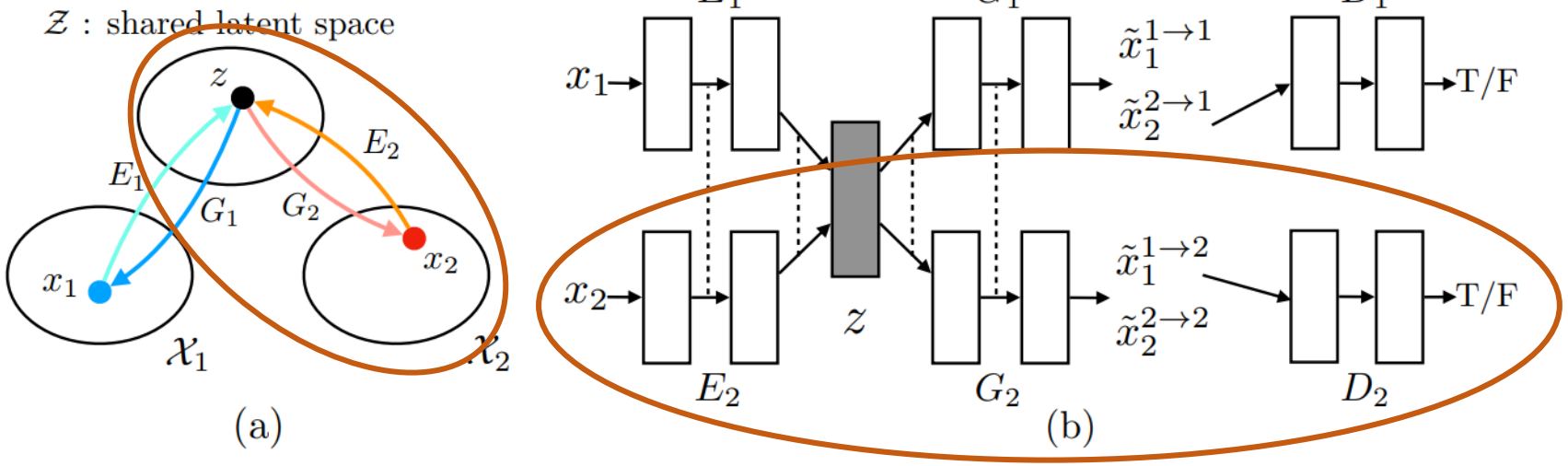
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) = \lambda_1 \text{KL}(q_2(z_2|x_2)||p_\eta(z)) - \lambda_2 \mathbb{E}_{z_2\sim q_2(z_2|x_2)}[\log p_{G_2}(x_2|z_2)]$$

두 VAE를 각각 self-reconstructed image를 생성할 수 있도록 학습시킴.

VAE 2

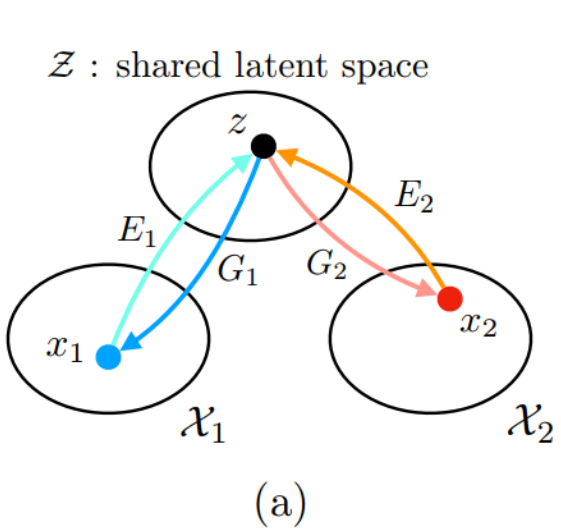


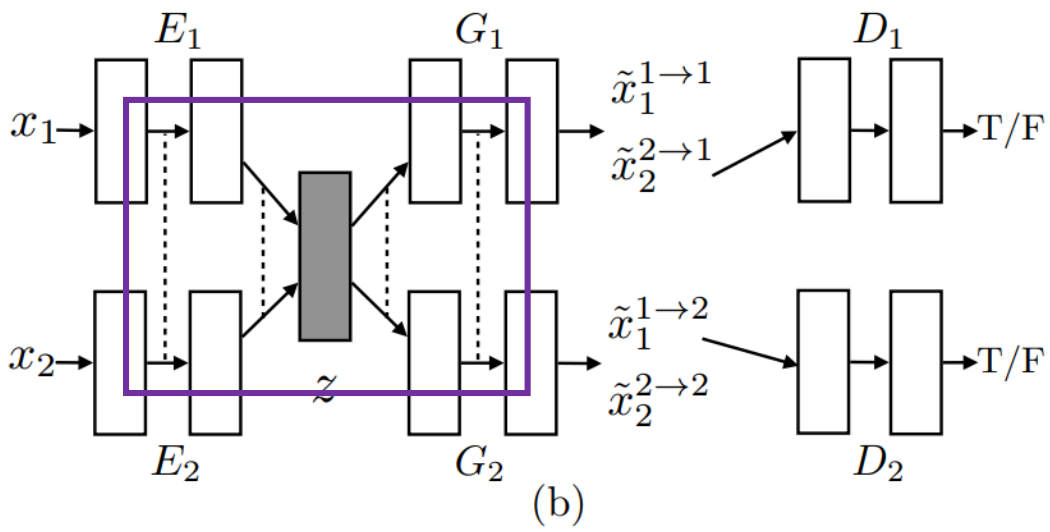
Weight Sharing

$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$

Tie last few layer of E & first few layer of G (Dashed lines)

GAN training 과 같이 적용시킬 때 common latent code z 로 encoding 하도록 학습이 가능하다.

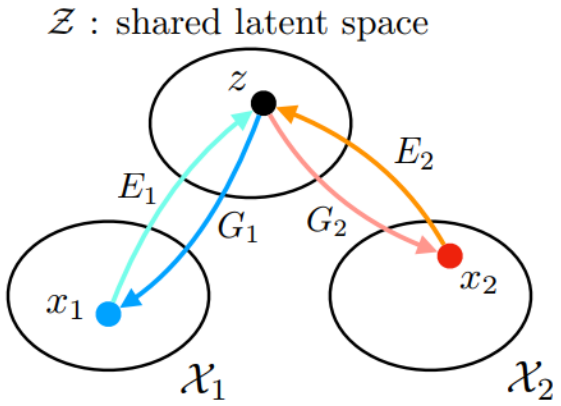




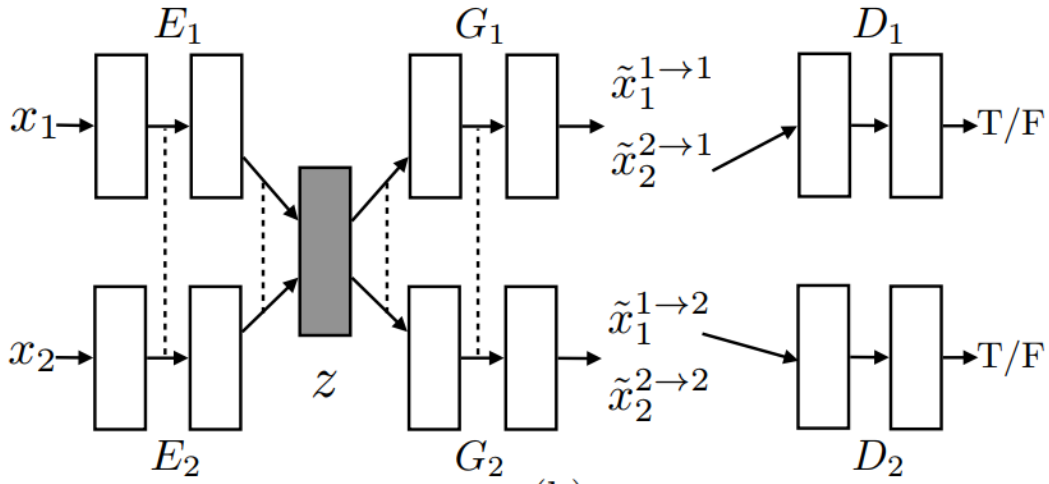
$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$

$$\mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) = \lambda_0 \mathbb{E}_{x_1 \sim P_{\mathcal{X}_1}}[\log D_1(x_1)] + \lambda_0 \mathbb{E}_{z_2 \sim q_2(z_2|x_2)}[\log(1 - D_1(G_1(z_2)))]$$
$$\mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) = \lambda_0 \mathbb{E}_{x_2 \sim P_{\mathcal{X}_2}}[\log D_2(x_2)] + \lambda_0 \mathbb{E}_{z_1 \sim q_1(z_1|x_1)}[\log(1 - D_2(G_2(z_1)))]$$

Adversarial loss 에서는 domain-translated images 를 이용해 discriminator에서 판별함.



(a)



(b)

$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$

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$$\mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) = \lambda_0 \mathbb{E}_{x_2 \sim P_{\mathcal{X}_2}}[\log D_2(x_2)] + \lambda_0 \mathbb{E}_{z_1 \sim q_1(z_1|x_1)}[\log(1 - D_2(G_2(z_1)))]$$

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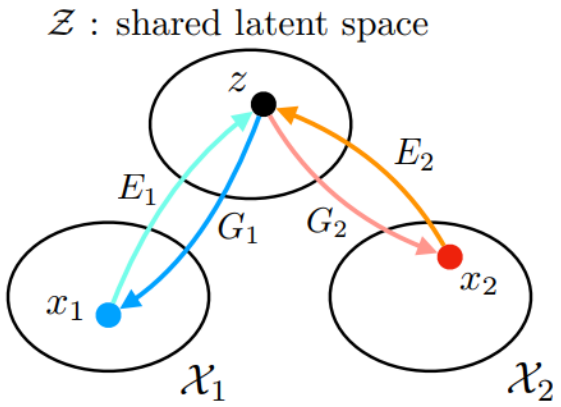
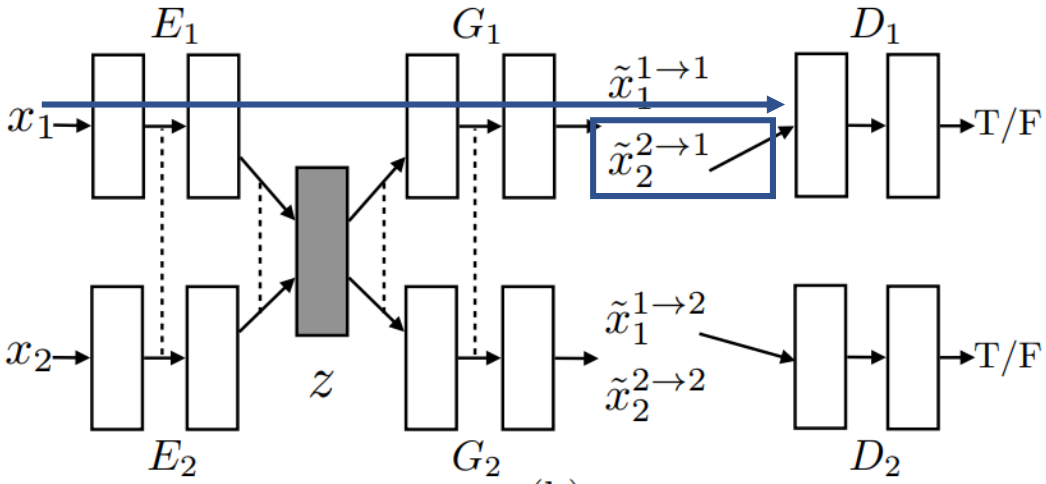


(a)



(b)

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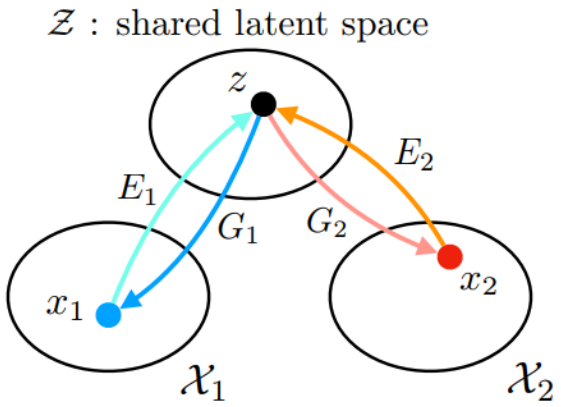
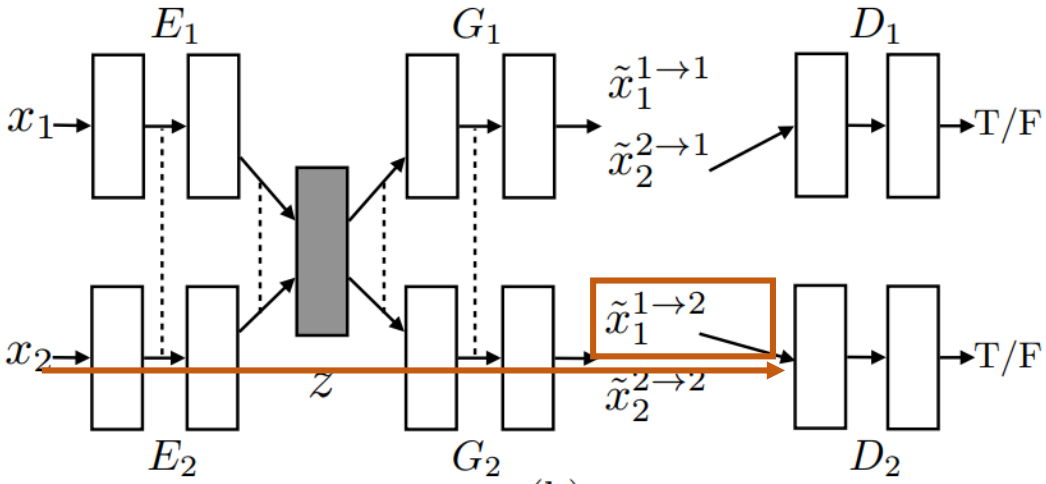


(a)



(b)

$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
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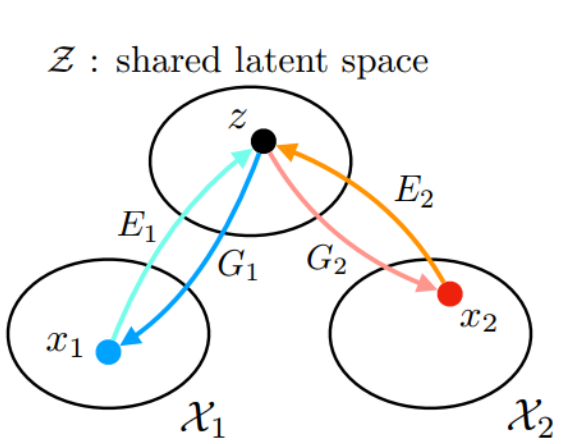
$$\mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2) = \lambda_3 \text{KL}(q_1(z_1|x_1)||p_\eta(z)) + \lambda_3 \text{KL}(q_2(z_2|x_1^{1\to2})||p_\eta(z)) - \lambda_4 \mathbb{E}_{z_2\sim q_2(z_2|x_1^{1\to2})}[\log p_{G_1}(x_1|z_2)]$$

$$\mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1) = \lambda_3 \text{KL}(q_2(z_2|x_2)||p_\eta(z)) + \lambda_3 \text{KL}(q_1(z_1|x_2^{2\to1})||p_\eta(z)) - \lambda_4 \mathbb{E}_{z_1\sim q_1(z_1|x_2^{2\to1})}[\log p_{G_2}(x_2|z_1)].$$

Cycle-consistency loss
는 cycleGAN 과 동일한 개념.

$$x_1 = F^*_{2\to1}(F^*_{1\to2}(x_1))$$

$$x_2 = F^*_{1\to2}(F^*_{2\to1}(x_2))$$



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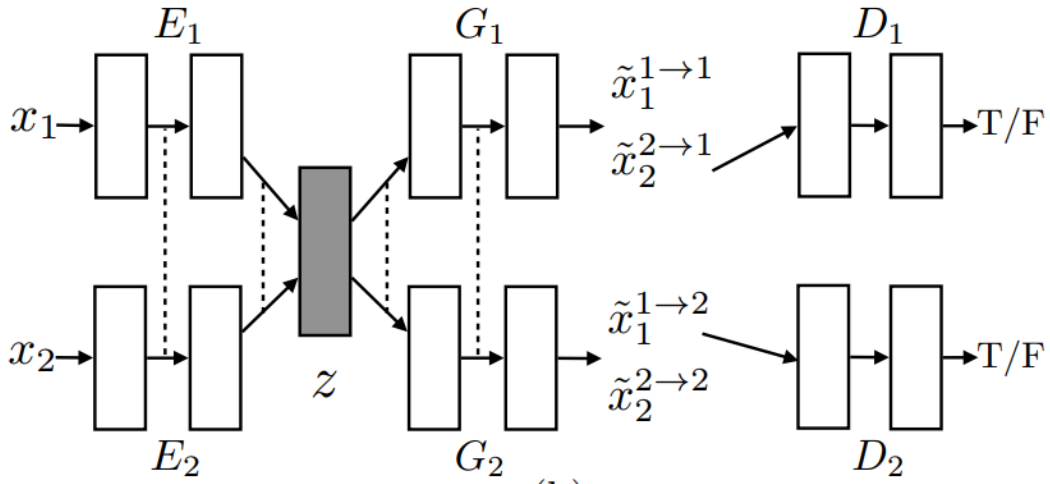

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$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$

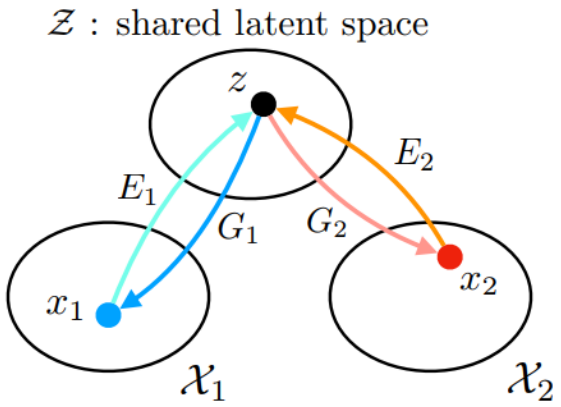
$$\mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2) = \lambda_3 \text{KL}(q_1(z_1|x_1)||p_\eta(z)) + \lambda_3 \text{KL}(q_2(z_2|x_1^{1\to2})||p_\eta(z)) - \lambda_4 \mathbb{E}_{z_2\sim q_2(z_2|x_1^{1\to2})}[\log p_{G_1}(x_1|z_2)]$$

$$\mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1) = \lambda_3 \text{KL}(q_2(z_2|x_2)||p_\eta(z)) + \lambda_3 \text{KL}(q_1(z_1|x_2^{2\to1})||p_\eta(z)) - \lambda_4 \mathbb{E}_{z_1\sim q_1(z_1|x_2^{2\to1})}[\log p_{G_2}(x_2|z_1)].$$

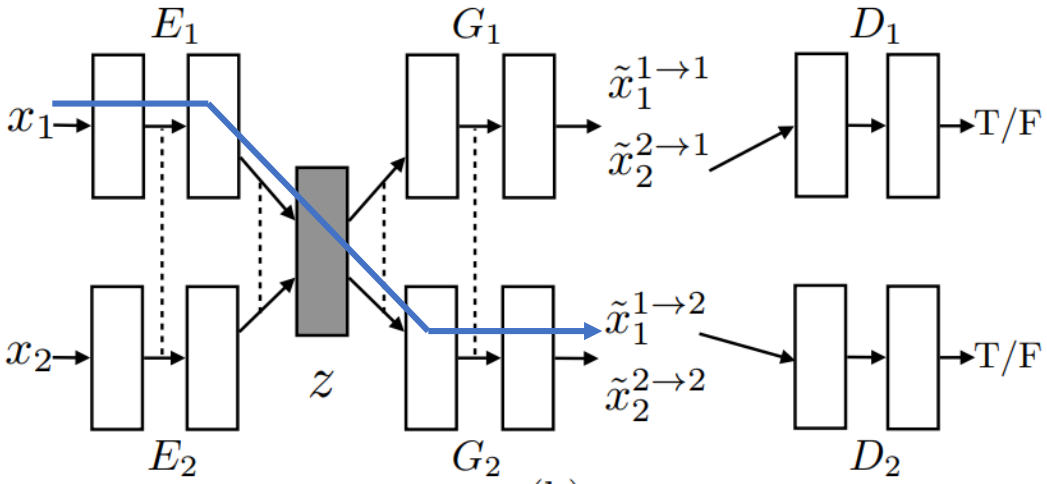
Cycle-consistency loss
는 cycleGAN 과 동일한 개념.

$$x_1 = F^*_{2\to1}(F^*_{1\to2}(x_1))$$

$$x_2 = F^*_{1\to2}(F^*_{2\to1}(x_2))$$



(a)



(b)

$$\min_{E_1,E_2,G_1,G_2} \max_{D_1,D_2} \mathcal{L}_{\text{VAE}_1}(E_1,G_1) + \mathcal{L}_{\text{GAN}_1}(E_2,G_1,D_1) + \mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2)$$
$$\mathcal{L}_{\text{VAE}_2}(E_2,G_2) + \mathcal{L}_{\text{GAN}_2}(E_1,G_2,D_2) + \mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1)$$

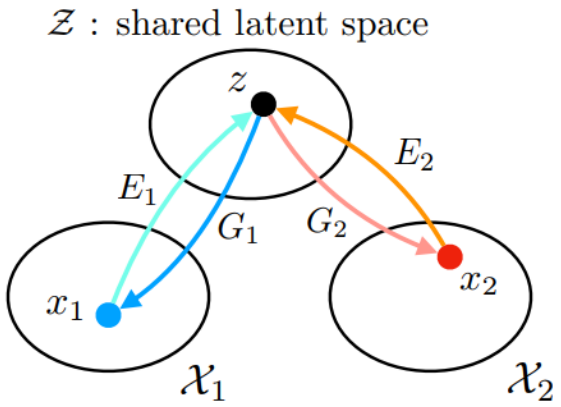
$$\mathcal{L}_{\text{CC}_1}(E_1,G_1,E_2,G_2) = \lambda_3 \text{KL}(q_1(z_1|x_1)||p_\eta(z)) + \lambda_3 \text{KL}(q_2(z_2|x_1^{1\to2})||p_\eta(z)) - \lambda_4 \mathbb{E}_{z_2\sim q_2(z_2|x_1^{1\to2})}[\log p_{G_1}(x_1|z_2)]$$

$$\mathcal{L}_{\text{CC}_2}(E_2,G_2,E_1,G_1) = \lambda_3 \text{KL}(q_2(z_2|x_2)||p_\eta(z)) + \lambda_3 \text{KL}(q_1(z_1|x_2^{2\to1})||p_\eta(z)) - \lambda_4 \mathbb{E}_{z_1\sim q_1(z_1|x_2^{2\to1})}[\log p_{G_2}(x_2|z_1)].$$

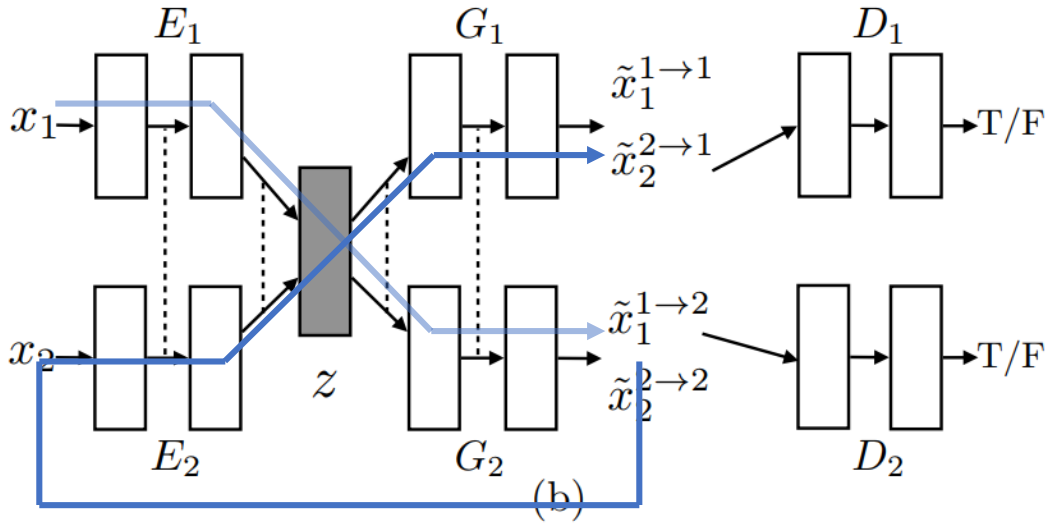
Cycle-consistency loss
는 cycleGAN 과 동일한 개념.

$$x_1 = F^*_{2\to1}(F^*_{1\to2}(x_1))$$

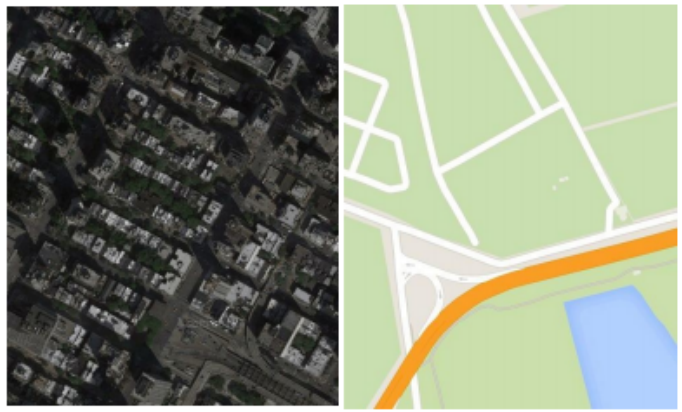
$$x_2 = F^*_{1\to2}(F^*_{2\to1}(x_2))$$

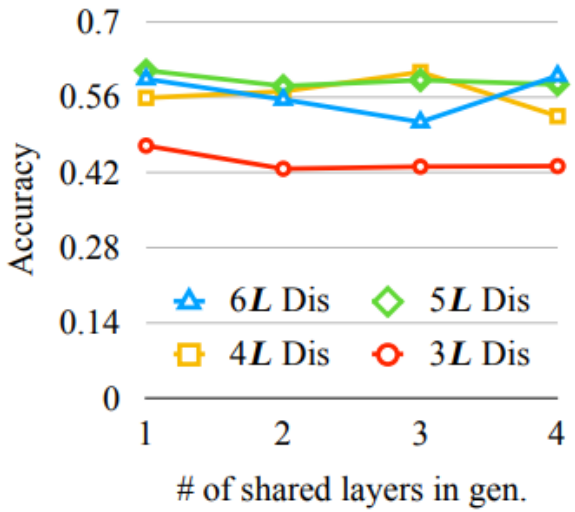


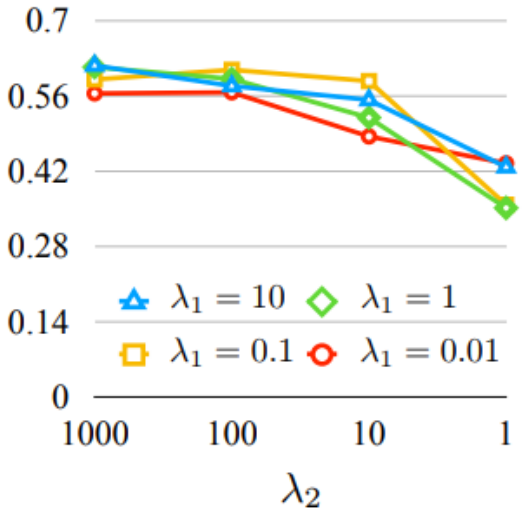
(a)



(b)







Method	Accuracy
~~Weight Sharing~~	0.569±0.029
~~Cycle Consistenc~~	0.568±0.010
Proposed	0.600±0.015

(a) (b) (c) (d)

Figure 2: (a) Illustration of the Map dataset. Left: satellite image. Right: map. We translate holdout satellite images to maps and measure the accuracy achieved by various configurations of the proposed framework. (b) Translation accuracy versus different network architectures. (c) Translation accuracy versus different hyper-parameter values. (d) Impact of weight-sharing and cycle-consistency constraints on translation accuracy.

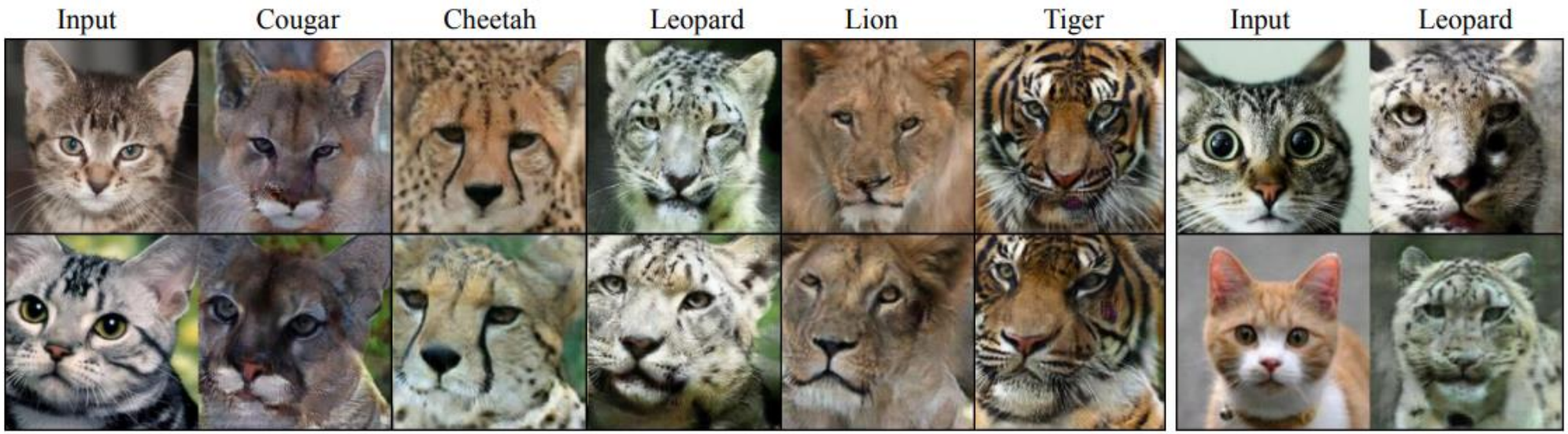


Figure 5: Cat species translation results.

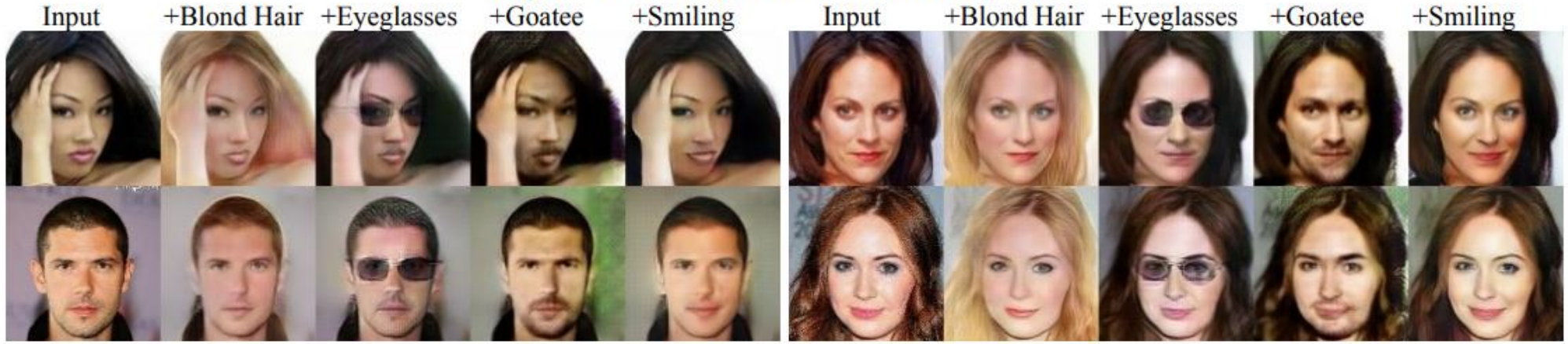


Figure 6: Attribute-based face translation results.

EXPERIMENTS

Figure 3: Street scene image translation results. For each pair, left is input and right is the translated image.

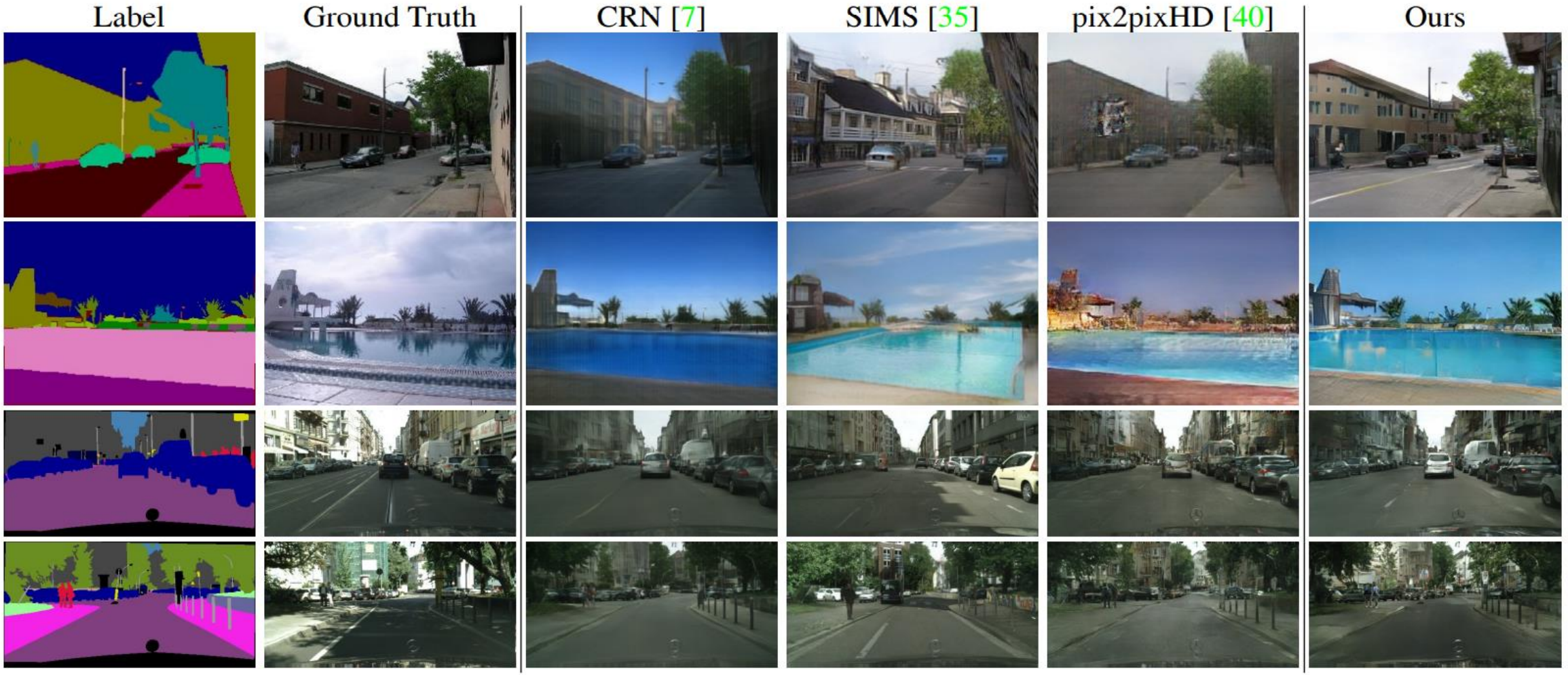


Figure 6: Visual comparison of semantic image synthesis results on the ADE20K outdoor and Cityscapes datasets. Our method produces realistic images while respecting the spatial semantic layout at the same time.

Conclusion & Future Works

우리가 제안한 모델은 두 도메인 간 translation 을 매우 잘 한다.

Future work로 해결해야 할 과제는 다음과 같다.

1. 현재 모델은 gaussian space assumption 때문에 unimodal. ➔ MUNIT 논문
2. Saddle point 때문에 unstable training.