ml_study_6

- Regularization in GAN
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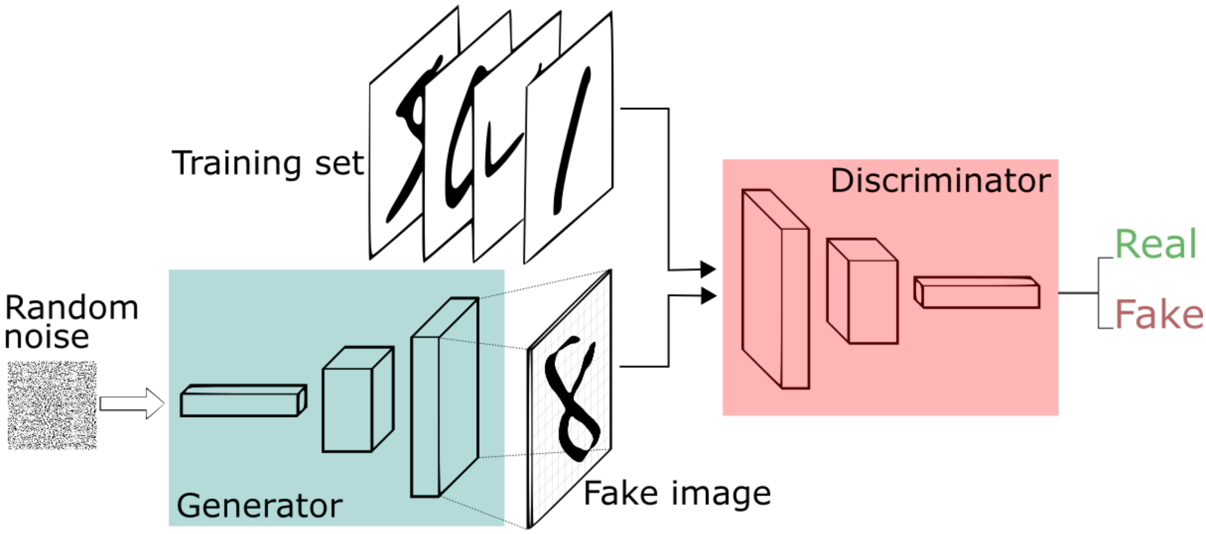
Regularization in GAN



$$L_D \leftarrow D(G(z)) - D(x)$$

- GAN은 **높은 차원의 공간**에서 (Latent Space) *Generator와 Discriminator의 Nash 평형을 찾는 문제*

⇒ 단순히 Gradient-based regularizatoin 적용시 이미지에 불필요한 특징이 과도하게 나타나는걸 억제할 수 없음

Figure 1. Instance normalization causes water droplet -like artifacts in StyleGAN images. These are not always obvious in the generated images, but if we look at the activations inside the generator network, the problem is always there, in all feature maps starting from the 64x64 resolution. It is a systemic problem that plagues all StyleGAN images.

- **제대로 Regularization이 적용된 모델이라면, Real Input을 다양하게 변화시켜도 동일한 결과를 나타내야 함**

Consistency Regularization

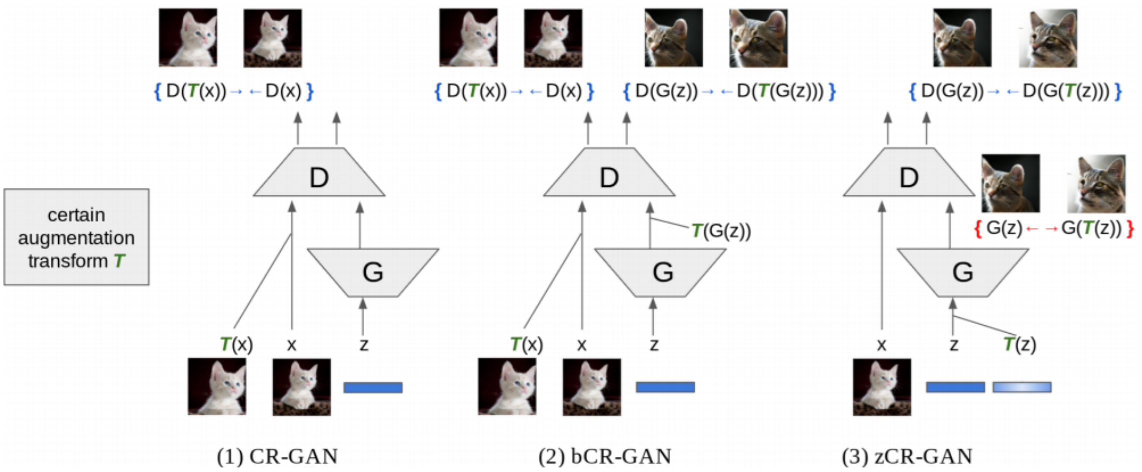
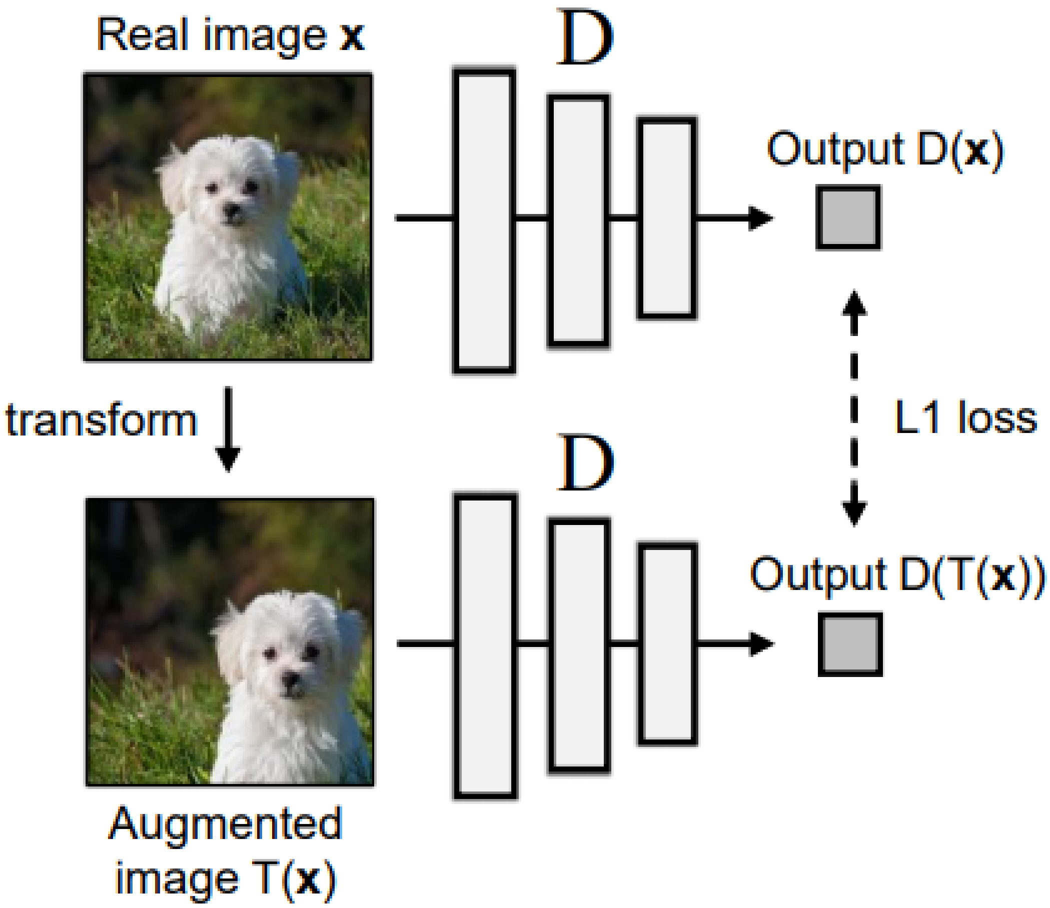


Figure 1: **Illustrations comparing our methods to the baseline.** (1) CR-GAN (Zhang et al. 2020) is the baseline, with consistency regularization applied only between real images and their augmentations. (2) In Balanced Consistency Regularization (bCR-GAN), we also introduce consistency regularization between generated fake images and their augmentations. With consistency regularization on both real and fake images, the discriminator is trained in a balanced way and less augmentation artifacts are generated. (3) Furthermore, we propose Latent Consistency Regularization (zCR-GAN), where latent z is augmented with noise of small magnitude. Then for the discriminator, we regularize the consistency between corresponding pairs; while for the generator we encourage the corresponding generated images to be more diverse. Note that $\{\rightarrow\leftarrow\}$ indicates a loss term encouraging pairs to be closer together, while $\{\leftarrow\rightarrow\}$ indicates a loss term pushing pairs apart.

- CR-GAN(Consistency Regularization)



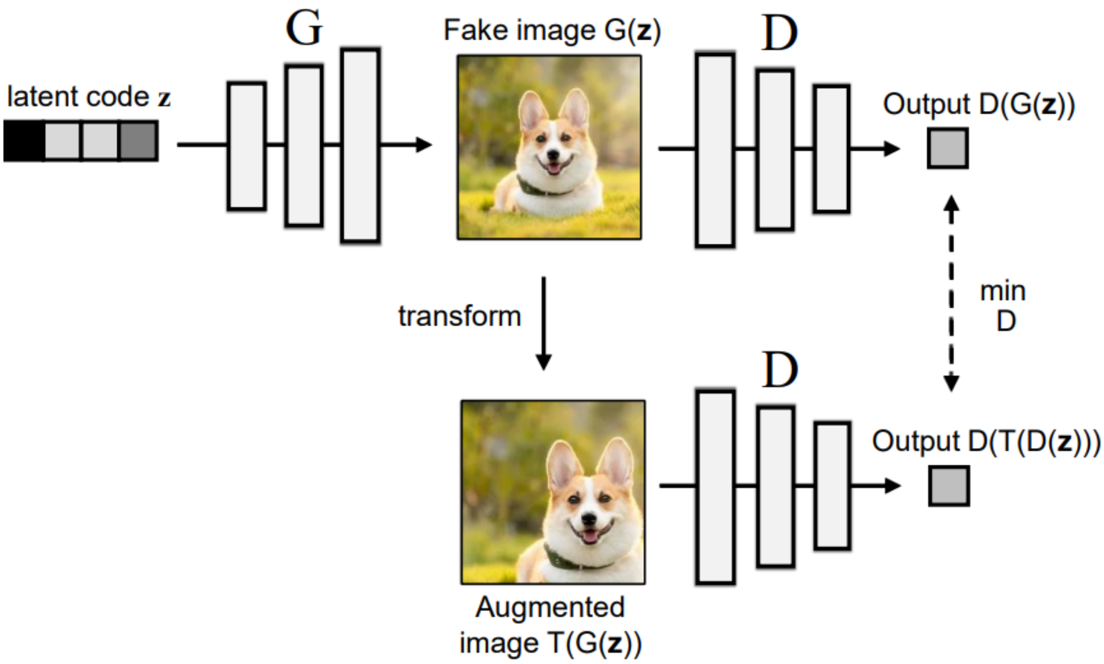
$$L_{cr} = \|D(x) - D(T(x))\|^2$$

* T(x) : stochastic data augmentation funtion

- Real Image Input에 Augmentation (=Discriminator에 일부 input 대해 적용)

▼ 적용 결과 example (왼쪽이 적용 후)

- bCR-GAN(Balanced Consistency Regularization)



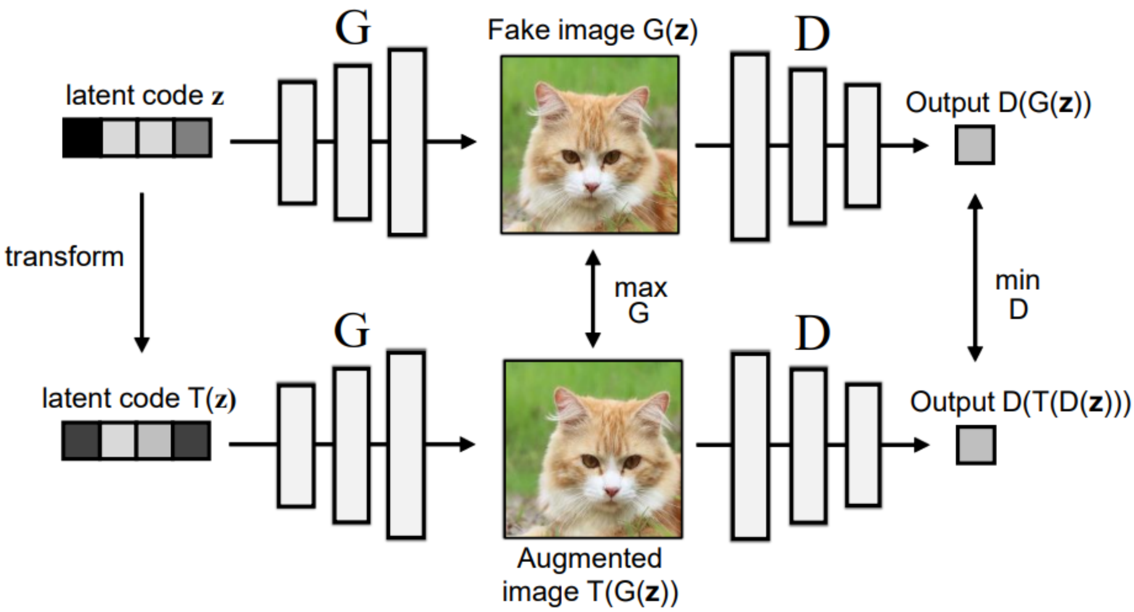
$$L_D \leftarrow D(G(z)) - D(x)$$

$$L_{\text{real}} \leftarrow \|D(x) - D(T(x))\|^2$$

$$L_{\text{fake}} \leftarrow \|D(G(z)) - D(T(G(z)))\|^2$$

- Real Image, Generated Image에도 regularization 적용 (=Discriminator 모든 input 대해 적용)

- zCR-GAN(Latent Consistency Regularization)



$$L_{\text{gen}} \leftarrow -\|G(z) - G(T(z))\|^2$$

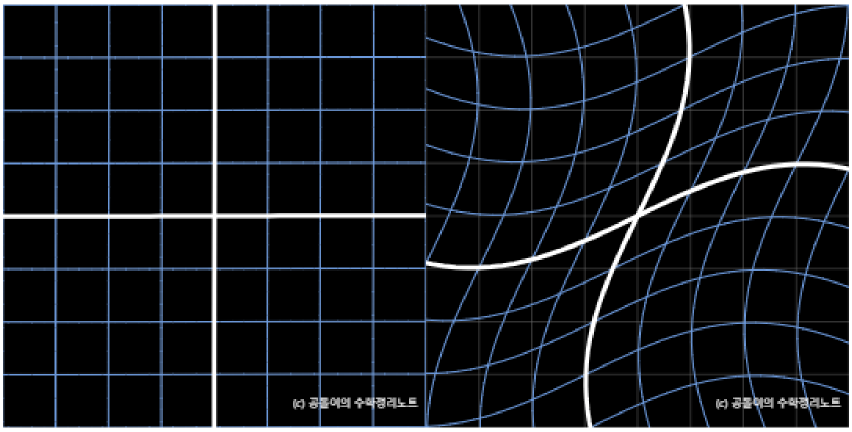
$$L_{\text{dis}} \leftarrow \|D(G(z)) - D(G(T(z)))\|^2$$

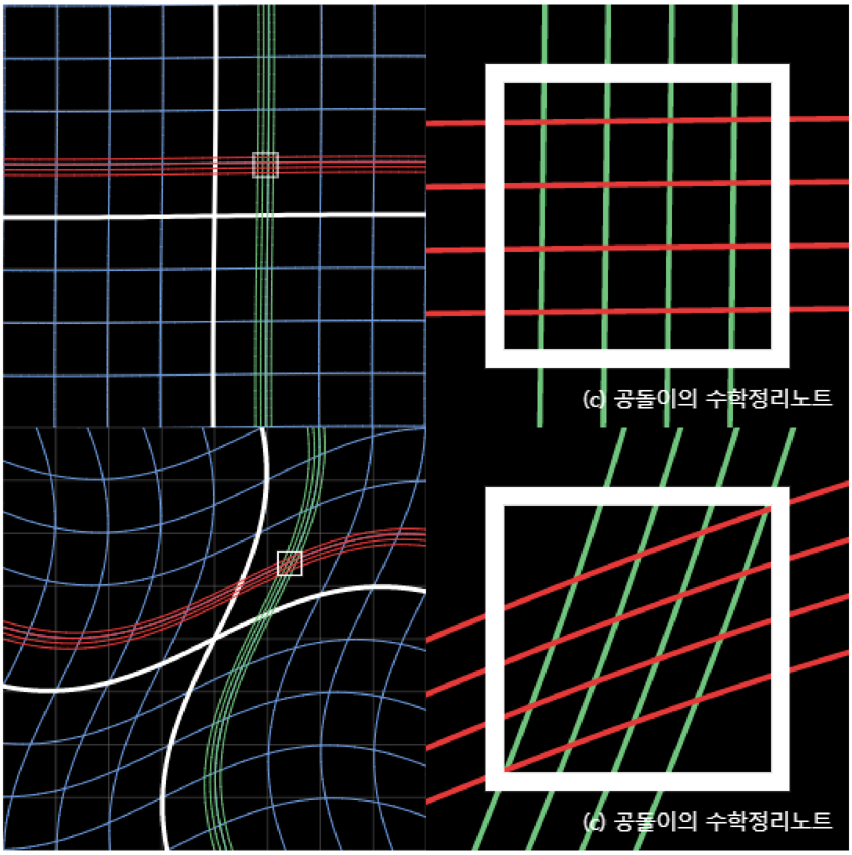
  - latent code의 변화를 주었을 때, Generator 결과물의 차이는 크게 나타나도록 반영 (L_gen)
  - discrimiator는 generator가 z와 T(z) 를 통해 내놓은 output에 대해 동일한 결과를 내도록 반영(L_dis)

Path Length Regularization

- (Remind) Jacobian 행렬
  - 행렬의 비선형 변환을 선형으로 근사

$$f(x,y) = \begin{bmatrix} x + \sin(y/2) \\ y + \sin(x/2) \end{bmatrix}$$





- 선형변환이 아닌 위 행렬을 국소적인 부분에서 선형으로 근사
- GAN에서의 gradient들도 이미지상에서의 변화량 만큼만 변해야 한다

(Improved) Consistency Regularization

[2002.04724] Improved Consistency Regularization for GANs (arxiv.org)

[Paper Review] CR-GAN: Consistency Regularization for Generative Adversarial Networks 간단한 논문 리뷰 - Happy Jihye (happy-jihye.github.io)

Path Length Regularization

Why Does Path Length Regularisation Work - 知乎 (zhihu.com)

자코비안(Jacobian) 행렬의 기하학적 의미 - 공돌이의 수학정리노트 (angeloyeo.github.io)