[Paper Review] ICR-GAN: Improved Consistency Regularization for GANs 간단한 논문 리뷰

업데이트: May 18, 2021

- Paper : Improved Consistency Regularization for GANs (https://arxiv.org/abs/2002.04724) (AAAI 2021) / Zhengli Zhao, Sameer Singh, Honglak Lee, Zizhao Zhang, Augustus Odena, Han Zhang)
- GAN-Zoos! (GAN 포스팅 모음집) (https://happy-jihye.github.io/gan/)

> ⭐ 본 논문은 CR-GAN의 후속 논문이다. CR-GAN이 real image에 대해서만 augmentation을 했다면, ***Improved Consistency Regularization*** *은 real image뿐만 아니라 generated images와 latent space vector, Generator에 대해서도 Augmentation을 한다.*
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> - [Paper Review] CR-GAN: Consistency Regularization for Generative Adversarial Networks 간단한 논문 리뷰 (https://happy-jihye.github.io/gan/gan-17/)

Improved Consistency Regularization

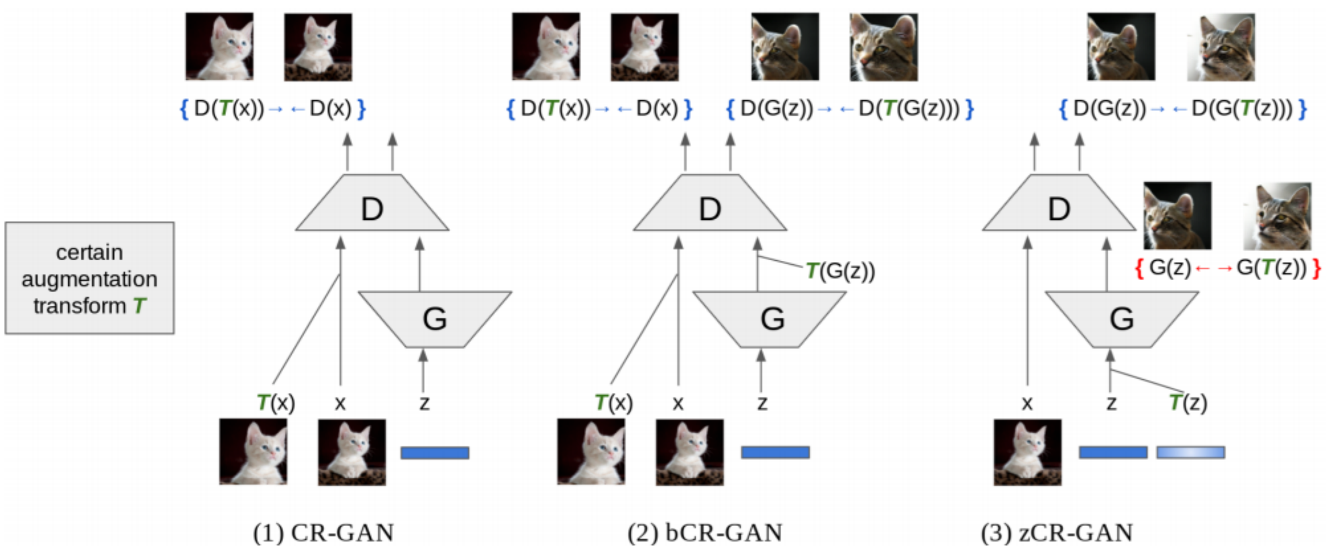

Figure 1: **Illustrations comparing our methods to the baseline.** (1) CR-GAN (Zhang et al. 2020) is the baseline, with consistency regularization applied only between real images and their augmentations. (2) In Balanced Consistency Regularization (bCR-GAN), we also introduce consistency regularization 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.

> - **bCR-GAN(Balanced Consistency Regularization)** : `Discriminator` - real image와 generated image 둘다 consistency regularization
> - **zCR-GAN(Latent Consistency Regularization)** : latent vector를 augment하여 이미지를 생성한 후, `G(z)` 와 `G(T(z))` pair에 대해 consistency regularization
> - **ICR-GAN(Improved Consistency Regularization)** : bCR + zCR 둘다 !

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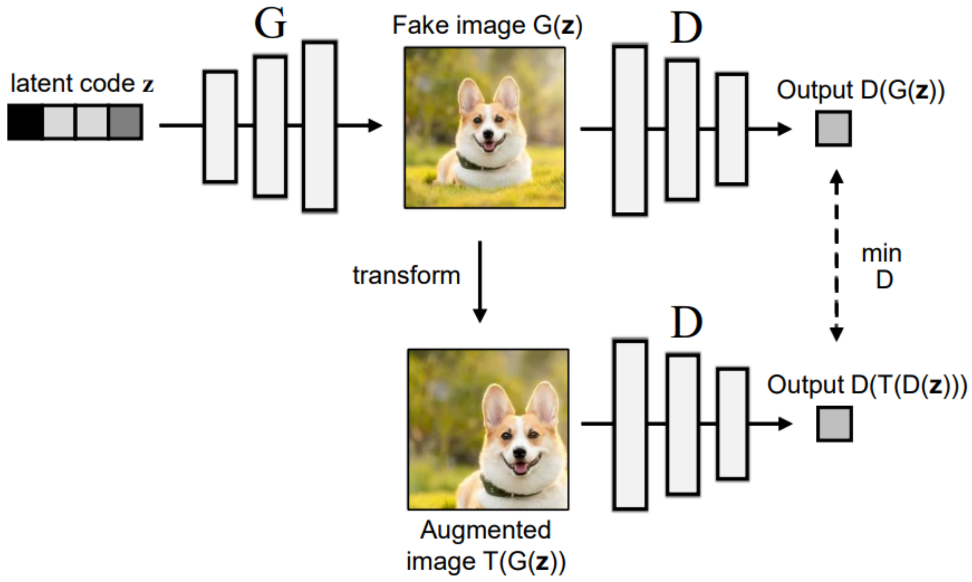
1. bCR-GAN



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> To address the lack of regularization on the generated samples, bCR-GAN introduces **balanced consistency regularization (bCR)**, where a **consistency term on the discriminator is applied to both real and generated samples**.

Algorithm 1 Balanced Consistency Regularization (bCR)

Input: parameters of generator θ_G and discriminator θ_D, consistency regularization coefficient for real images λ_{real} and fake images λ_{fake}, augmentation transform T (for images, e.g. shift, flip, cutout, etc).
for number of training iterations **do**
  Sample batch $z \sim p(z)$, $x \sim p_{\text{real}}(x)$
  Augment both real $T(x)$ and fake $T(G(z))$ images
  $L_D \leftarrow D(G(z)) - D(x)$
  $L_{\text{real}} \leftarrow \|D(x) - D(T(x))\|^2$
  $L_{\text{fake}} \leftarrow \|D(G(z)) - D(T(G(z)))\|^2$
  $\theta_D \leftarrow \text{AdamOptimizer}(L_D + \lambda_{\text{real}} L_{\text{real}} + \lambda_{\text{fake}} L_{\text{fake}})$
  $L_G \leftarrow -D(G(z))$
  $\theta_G \leftarrow \text{AdamOptimizer}(L_G)$
end for

- L_{fake} term이 추가되었다.
- 순서대로 adversarial Loss, CR-Loss, bCR-Loss !

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

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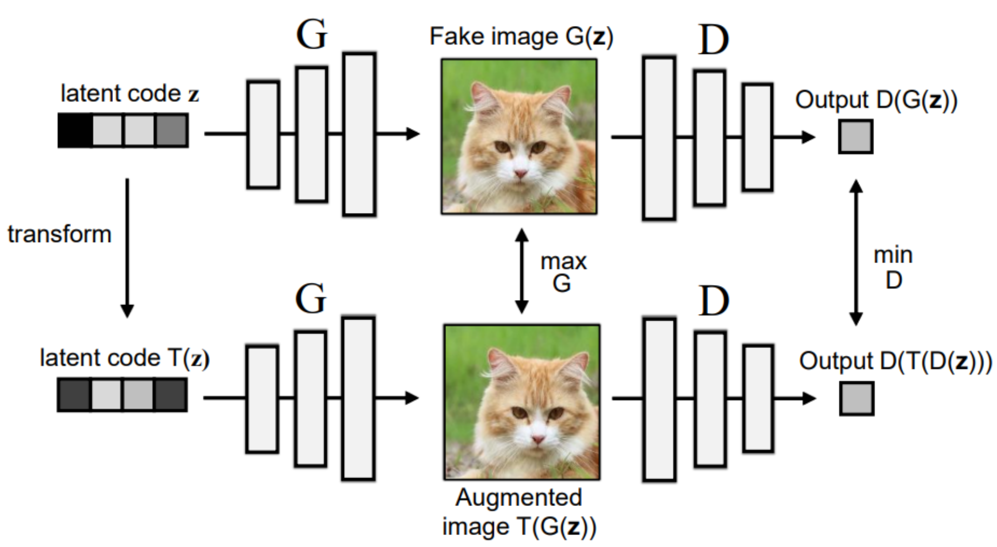
2. zCR-GAN



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> zCR-GAN introduces **latent consistency regularization (zCR), which regularizes the sensitivity of both the generator and discriminator changes in the prior**. Given augmented latent codes, the generator is encouraged to be sensitive to the augmentations while the discriminator is encouraged to be insensitive to them.

Algorithm 2 Latent Consistency Regularization (zCR)

Input: parameters of generator θ_G and discriminator θ_D, consistency regularization coefficient for generator λ_{gen} and discriminator λ_{dis}, augmentation transform T (for latent vectors, e.g. adding small perturbation noise$\sim \mathcal{N}(0, \sigma_{\text{noise}})$).
for number of training iterations **do**
  Sample batch $z \sim p(z)$, $x \sim p_{\text{real}}(x)$
  Sample perturbation noise $\Delta z \sim \mathcal{N}(0, \sigma_{\text{noise}})$
  Augment latent vectors $T(z) \leftarrow z + \Delta z$
  $L_D \leftarrow D(G(z)) - D(x)$
  $L_{\text{dis}} \leftarrow \|D(G(z)) - D(G(T(z)))\|^2$
  $\theta_D \leftarrow \text{AdamOptimizer}(L_D + \lambda_{\text{dis}} L_{\text{dis}})$
  $L_G \leftarrow -D(G(z))$
  $L_{\text{gen}} \leftarrow -\|G(z) - G(T(z))\|^2$
  $\theta_G \leftarrow \text{AdamOptimizer}(L_G + \lambda_{\text{gen}} L_{\text{gen}})$
end for

다음 알고리즘에서 pertubation noise Δz 에 따라 다양한 이미지를 만들도록 L_{gen}는 maximize하는 방향으로 학습하고,

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

`Discriminator` 가 Consistency Regularization을 잘 학습하도록 L_{dis}는 minimize하는 방향으로 학습한다.

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

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3. ICR-GAN

> bCR-GAN와 zCR-GAN을 합친게 ICR-GAN !

Unconditional image synthesis. Baseline (W/O), WGAN-GP (GP), DRAGAN (DR), Jenson-Shannon regularization (JSR), consistency regularization (CR)

Class-conditional image synthesis. Spectral normalization (SNGAN), BigGAN, consistency regularization (CR-BigGAN).

Methods	CIFAR-10 (DCGAN)	CIFAR-10 (ResNet)	CelebA (DCGAN)
W/O	24.73	19.00	25.95
GP	25.83	19.74	22.57
DR	25.08	18.94	21.91
JSR	25.17	19.59	22.17
CR	18.72	14.56	16.97
ICR (ours)	**15.87**	**13.36**	**15.43**

FIDs for unconditional image synthesis

Models	CIFAR-10	ImageNet
SNGAN	17.50	27.62
BigGAN	14.73	8.73
CR-BigGAN	11.48	6.66
bCR-BigGAN	10.54	6.24
zCR-BigGAN	10.19	5.87
ICR-BigGAN	**9.21**	**5.38**

FIDs for class-conditional image synthesis

ICR-GAN이 baseline보다 성능이 좋다

(b) Cock (our ICR vs baseline CR)

(c) Blenheim Spaniel (our ICR vs baseline CR)

Figure 9: Random ImageNet samples from our ICR-BigGAN (FID 5.38) vs CR-BigGAN (Zhang et al. (2020), FID 6.66).

태그: ai deeplearning GAN vision

카테고리: GAN

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댓글남기기