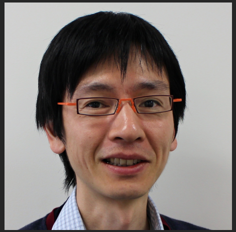
CVPR VIRTUAL JUNE 19-25

Blur, Noise, and Compression Robust Generative Adversarial Networks



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Project page

Background: Limitation of standard GAN

Recreates training images faithfully
despite image degradation (e.g., blur, noise, and compression)

Blur
+Noise
+Compression

Real

Training images

Training

Generated (FID: 34.9)

Standard GAN

Blur
+Noise
+Compression

GAN: Goodfellow et al., NIPS 2014

Proposal: BNCR-GAN (blur, noise, and compression robust GAN)

Learns to **generate clean images** from **degraded images**
w/o knowledge of **degradation params** (e.g., blur kernel types, noise amounts, Q factor values)

Blur
+Noise
+Compression

Real

Training images

No additional information

Training

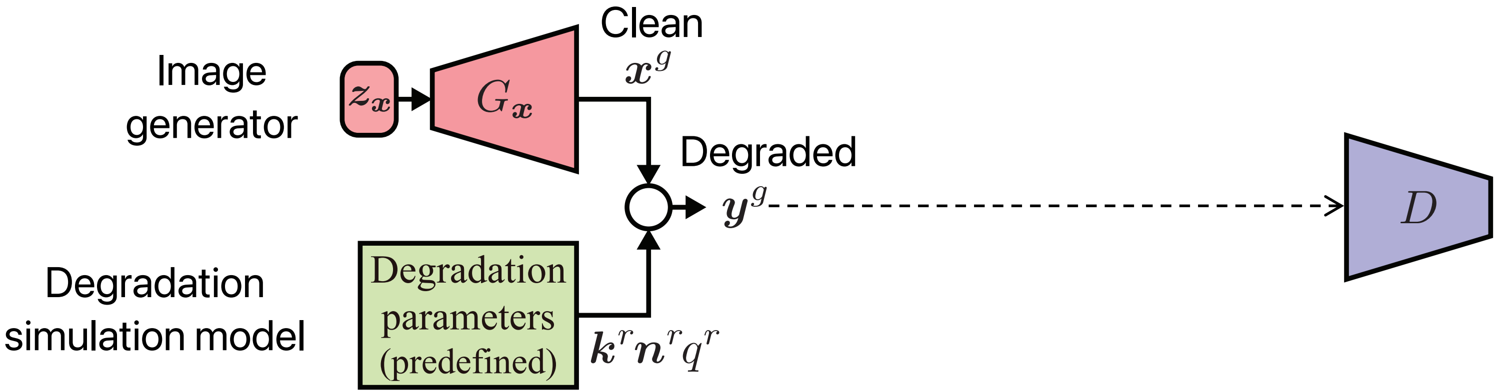
Generated (FID: **24.2**)

BNCR-GAN

Clean

Related work 1: AmbientGAN

Learns to **generate clean image** from **degraded images**,
but, requires **degradation parameters** are **predefined**



AmbientGAN generator

Discriminator

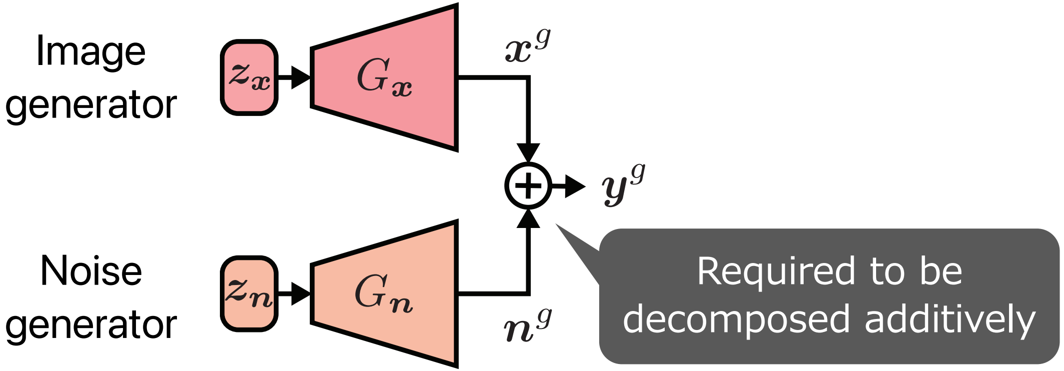
Simulates image degradation before
passing generated images to the discriminator

Distinguishes real degraded images
from degraded generated images

AmbientGAN: Bora et al., ICLR 2018

Related work 2: NR-GAN (noise robust GAN)

Eliminates the **AmbientGAN requirement** by introducing a **noise generator**, but, its application is **limited to additive and reversible degradation** (i.e., noise)



NR-GAN generator

Challenge to be addressed

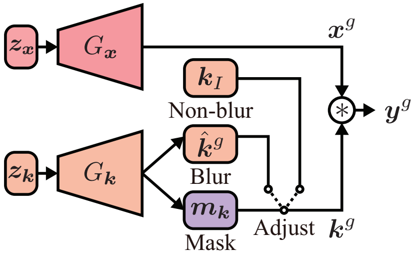
Application to irreversible degradation (e.g., blur, compression, and combination of all)

NR-GAN: Kaneko et al., CVPR 2020

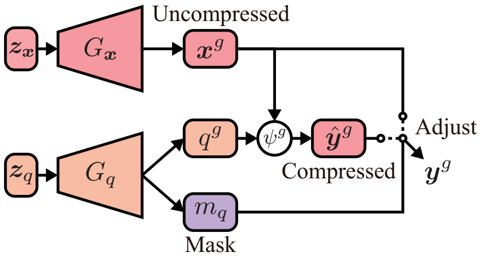
Key ideas

Masking architectures (Mask)

- **Adjust degradation strengths** using **bypasses** before and after degradation



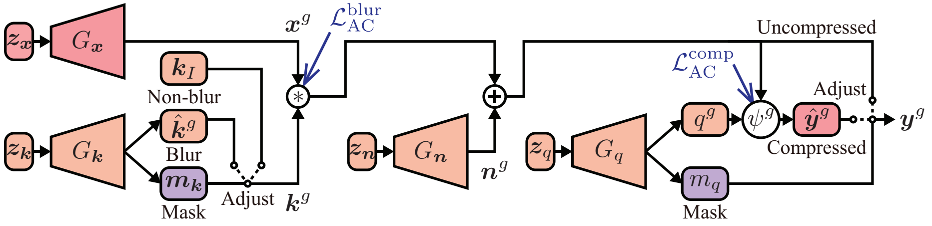
BR-GAN with mask



CR-GAN with mask

Adaptive consistency losses (L_{AC})

- **Impose consistency** between irreversible degradation processes **according to degradation strengths**



BNCR-GAN with L_{AC}

BR-GAN (blur robust GAN)

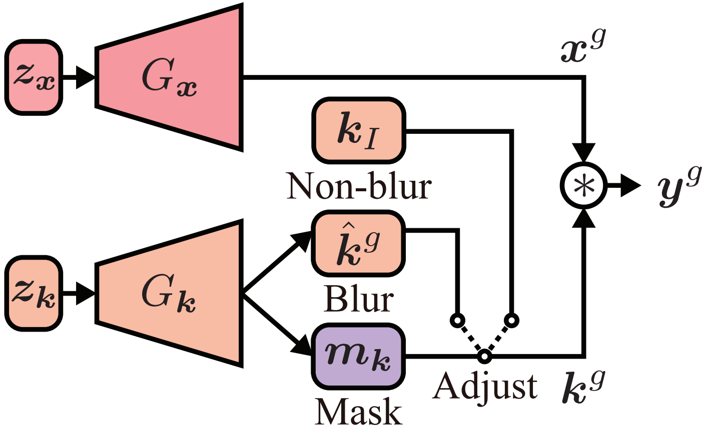
Objective function

$$\begin{aligned}\mathcal{L}_{\text{BR-GAN}} &= \mathbb{E}_{\boldsymbol{y}^r}[\log D_{\boldsymbol{y}}(\overline{\boldsymbol{y}^r})] \\ &+ \mathbb{E}_{\boldsymbol{z_x},\boldsymbol{z_k}}[\log(1 - D_{\boldsymbol{y}}(\overbrace{\underbrace{G_{\boldsymbol{x}}(\boldsymbol{z_x})}_{\text{Image}} \underbrace{*}_{\text{Convolution}} \underbrace{G_{\boldsymbol{k}}(\boldsymbol{z_k})}_{\text{Blur kernel}}}^{\text{Blurred image}}))]\end{aligned}$$

Masking architecture

$$\boldsymbol{k}^g = \underbrace{\boldsymbol{m_k}}_{\text{Mask}} \cdot \underbrace{\hat{\boldsymbol{k}}^g}_{\text{Blur}} + (\boldsymbol{1} - \boldsymbol{m_k}) \cdot \underbrace{\boldsymbol{k}_I}_{\text{Non-blur}}$$

Blur strength is adjusted by trainable mask



BR-GAN generator

CR-GAN (compression robust GAN)

Objective function

Compressed image

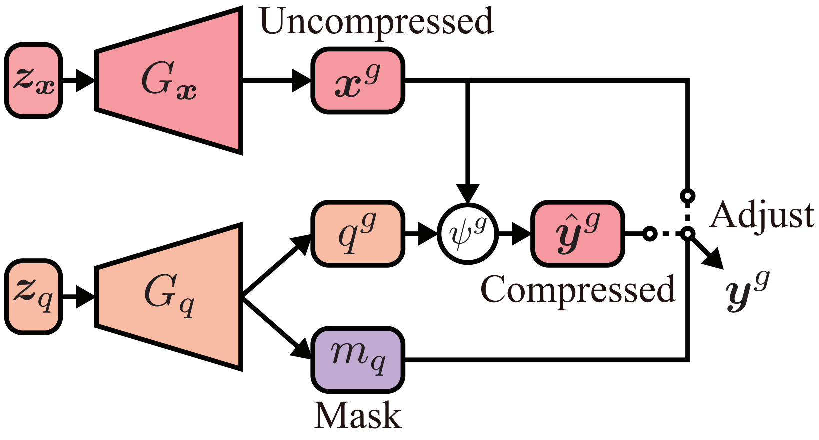
$$\mathcal{L}_{\text{CR-GAN}} = \mathbb{E}_{\boldsymbol{y}^r}[\log D_{\boldsymbol{y}}(\boldsymbol{y}^r)] + \mathbb{E}_{\boldsymbol{z_x}, \boldsymbol{z}_q}[\log(1 - D_{\boldsymbol{y}}(\psi^g(G_{\boldsymbol{x}}(\boldsymbol{z_x}), G_q(\boldsymbol{z}_q))))]$$

Differentiable JPEG Image Q factor

Masking architecture

$$\boldsymbol{y}^g = m_q \hat{\boldsymbol{y}}^g + (1 - m_q)\boldsymbol{x}^g$$

Mask Compressed Uncompressed

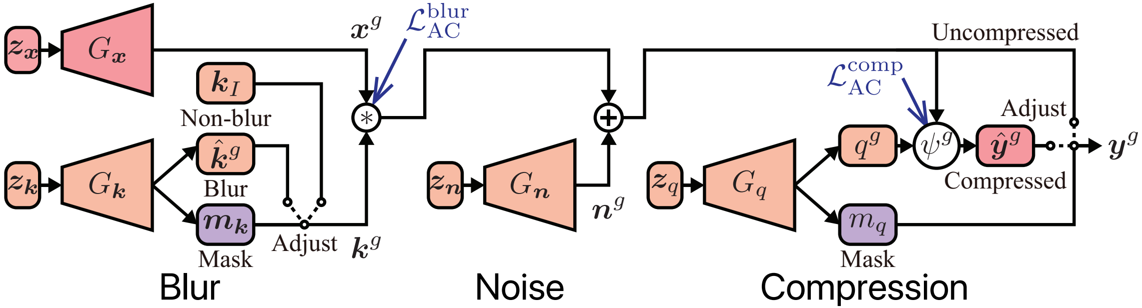


CR-GAN generator

Compression strength is adjusted by trainable mask

BNCR-GAN (blur, noise, and compression robust GAN)

BNCR-GAN generator



Objective function

$$\mathcal{L}_{\text{BNCR-GAN}} = \mathbb{E}_{y^r}[\log D_y(y^r)] + \mathbb{E}_{z_x, z_k, z_n, z_q}[\log(1 - D_y(\psi^g(G_x(z_x) * G_k(z_k) + G_n(z_n), G_q(z_q))))]$$

Blurred, noisy, and compressed image

Image Blur kernel Noise Q factor

Adaptive consistency losses

$$\mathcal{L}_{\mathrm{AC}}^{\mathrm{blur}} = \mathbb{E}_{z_x, z_k}[e^{-\mu_k H(G_k(z_k))} \| G_x(z_x) - G_x(z_x) * G_k(z_k) \|^2]$$

$$\mathcal{L}_{\mathrm{AC}}^{\mathrm{comp}} = \mathbb{E}_{z_x, z_q}[\underbrace{e^{-\mu_q \frac{100 - G_q(z_q)}{100}}}_{\text{Adaptive term}} \underbrace{\| G_x(z_x) - \psi^g(G_x(z_x), G_q(z_q)) \|^2}_{\text{Consistency term}}]$$

Consistency is imposed adaptively according to blur/compression strength

Comparative and ablation studies on CIFAR-10

Blur robust image generation

FID↓	Blur	$\frac{1}{2}$Blur
GAN	43.1	27.4
AmbientGAN	24.2	20.7
BR-GAN	23.4	20.2
BR-GAN w/o mask	26.6	22.9

Compression robust image generation

FID↓	Comp	$\frac{1}{2}$Comp
GAN	33.3	24.7
AmbientGAN	40.5	22.8
CR-GAN	26.3	22.7
CR-GAN w/o mask	38.6	31.1

Blur, noise, and compression robust image generation

FID↓	B+N+C	$\frac{1}{2}$B+N+C
GAN	58.0	34.3
AmbientGAN	46.8	25.6
BR-GAN	52.3	31.6
NR-GAN	58.1	34.6
CR-GAN	51.1	36.8
BNCR-GAN	34.1	25.7
BNCR-GAN w/o $\mathcal{L}_{AC}$	41.0	28.6

- **BR-GAN**, **CR-GAN**, and **BNCR-GAN outperform or are comparable** to **AmbientGAN** despite disadvantageous training conditions
- **Masking architectures (mask)** and **adaptive consistency losses (L_{AC})** contribute to **performance improvement**

CIFAR-10: Krizhevsky, 2009

Examples of generated images on FFHQ 1/3

Blur robust image generation

Real

Training images
(blur)

Generated (FID: 34.1)

Standard GAN
(baseline)

Generated (FID: **25.3**)

BR-GAN
(proposed)

FFHQ: Karras et al., CVPR 2019

Examples of generated images on FFHQ 2/3

Compression robust image generation

Real

Training images
(compression)

Generated (FID: 45.5)

Standard GAN
(baseline)

Generated (FID: **25.7**)

CR-GAN
(proposed)

FFHQ: Karras et al., CVPR 2019

Examples of generated images on FFHQ 3/3

Blur, noise, and compression robust image generation

Real

Training images
(blur + noise + compression)

Generated (FID: 34.9)

Standard GAN
(baseline)

Generated (FID: **24.2**)

BNCR-GAN
(proposed)

FFHQ: Karras et al., CVPR 2019

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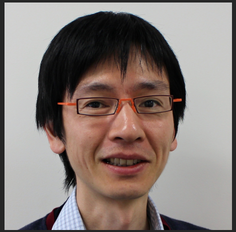

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