Advanced Deep Generative Models I: Generative Adversarial Networks

AI602: Recent Advances in Deep Learning

Lecture 4

Slide made by

Jongheon Jeong and Jongjin Park

KAIST EE & AI

Table of Contents

1. **Generative Models**
   - Why generative model?
   - Two types of generative models

2. **Generative Adversarial Networks (GAN)**
   - Advantages and disadvantages of GAN
   - Conditional GANs

3. **Improved Techniques for GANs**
   - Loss, regularization and normalization
   - GAN architectures
   - Data augmentations for GANs

4. **Summary**

Table of Contents

1. **Generative Models**
   - Why generative model?
   - Two types of generative models

2. **Generative Adversarial Networks (GAN)**
   - Advantages and disadvantages of GAN
   - Conditional GANs

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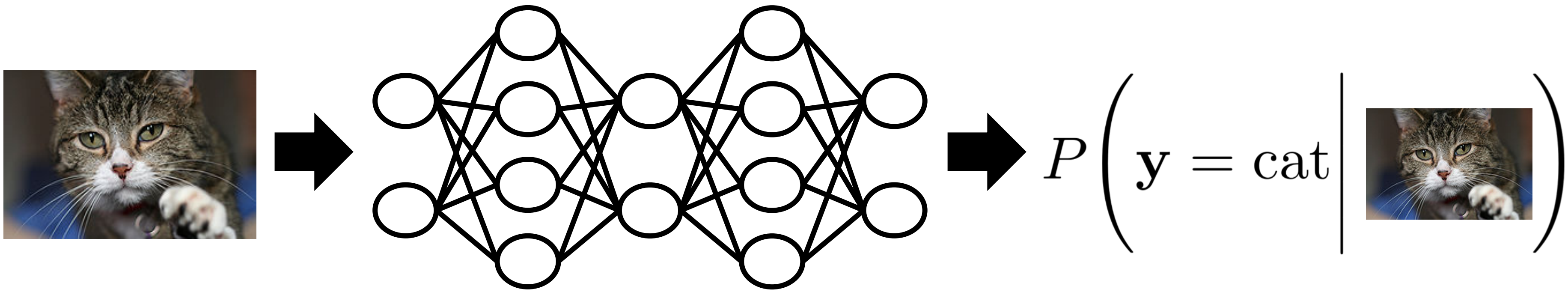
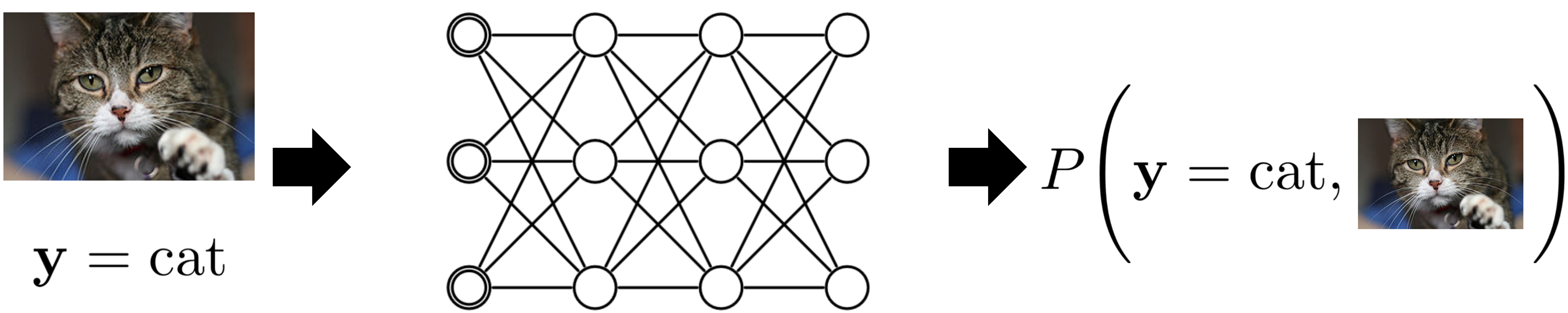
4. **Summary**

Generative Model and Discriminative Model

- Given an observed variable $\mathbf{x}$ and a target variable $\mathbf{y}$
- **Discriminative modeling** estimates the conditional distribution $P(\mathbf{y}|\mathbf{x})$
  - **Example**: ImageNet classifiers



- **Generative modeling** estimates the joint distribution $P(\mathbf{x}, \mathbf{y})$
  - **Example**: Boltzmann machines, sum-product networks

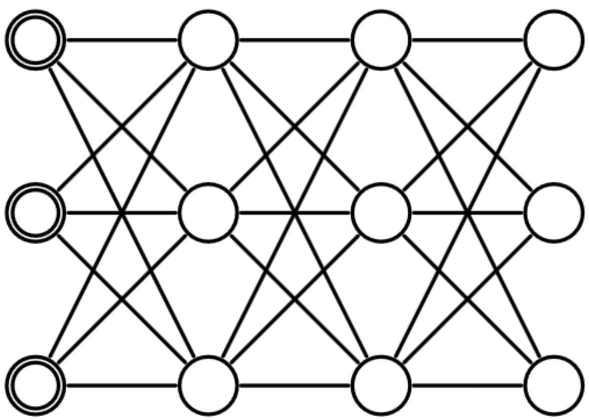


* source : https://en.wikipedia.org/wiki/Cat#/media/File:Kittyply_edit1.jpg

Why Generative Model?

- Without assuming $\mathbf{y}$, generative models learn $P(\mathbf{x})$ from given data
- $P(\mathbf{x})$ enables us to generate new data similar to the training dataset
- We can use various **sampling methods** for generation based on $P(\mathbf{x})$
  - Is it possible to do the same thing with discriminative models?

$P(\mathbf{x})$



$\sim P(\mathbf{x})$

$\sim P(\mathbf{x})$

$\sim P(\mathbf{x})$

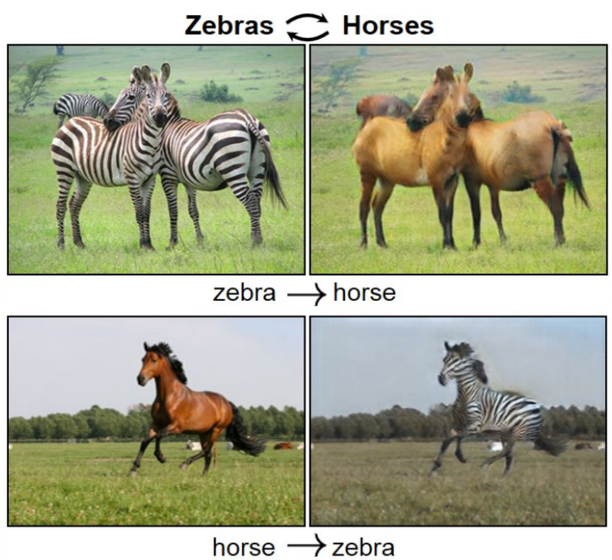
$\sim P(\mathbf{x})$

* source : https://en.wikipedia.org/wiki/File:Cat_poster_1.jpg

Why Generative Model?

- $P(\mathbf{x})$ enables us to generate new data similar to the training dataset
- Many real-world problems can be formulated assuming generative models
- Common applications?
  - Vision: super-resolution, style transfer, image inpainting, …
  - Audio: audio synthesis, speech generation, voice conversion, …
  - And many more..

Super-resolution [Ledig et. al., 2017]



Style transfer [Zhu et. al., 2017]

High-res image generation [Karras et. al., 2018]

Two Types of Generative Models

- Explicit models directly estimate the (usually "unnormalized") data distribution
  - **Example 1:** Multivariate Gaussian distributions
    - $P(\mathbf{x}) \propto \exp\left(-\frac{1}{2}(\mathbf{x}-\mu)\Sigma^{-1}(\mathbf{x}-\mu)\right)$
    - Tractable inference, low expressive power
  - **Example 2:** Graphical models (RBM, DBM, …)
    - $P(\mathbf{x}) \propto \exp\left(\sum_i b_i x_i + \sum_{i,j} w_{ij} x_i x_j\right)$
    - Intractable inference, high expressive power with compact representations
  - **Many more examples**: Variational Auto-encoder, Flow-based models, …
    - … which we will be discussed more in the next lecture

- **Generative adversarial network (GAN)** is an instance of implicit models
  - One does not have to access $P(\mathbf{x})$ for sampling → More efficient in some cases
  - $P(\mathbf{x})$ is rather implicitly defined by its model
  - GANs assume that $P(x) \sim G(z)$
    - z = "random noise", and G = "a neural network"
  - **Sampling?** A simple forward computation of $G(z)$

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Table of Contents

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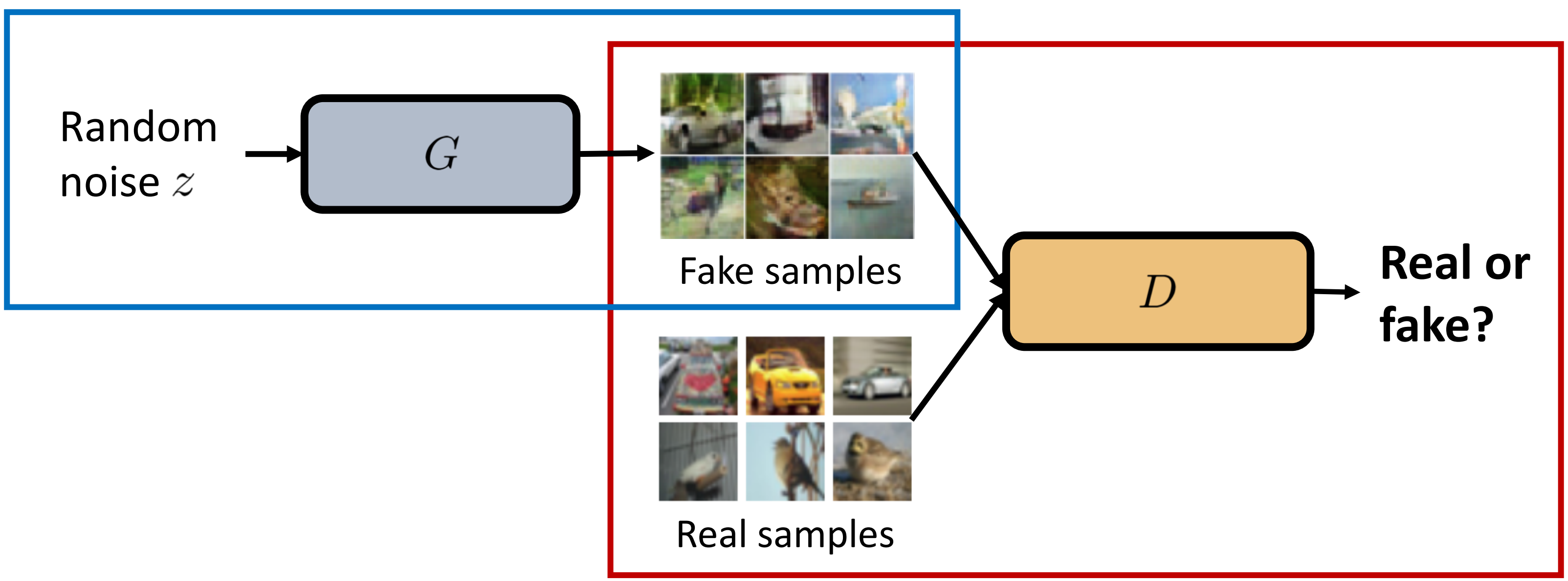
4. **Summary**

- Classical (usually explicit) generative methods struggle on complex data
  - Sampling from **high-dimensional, complex** distributions can be intractable

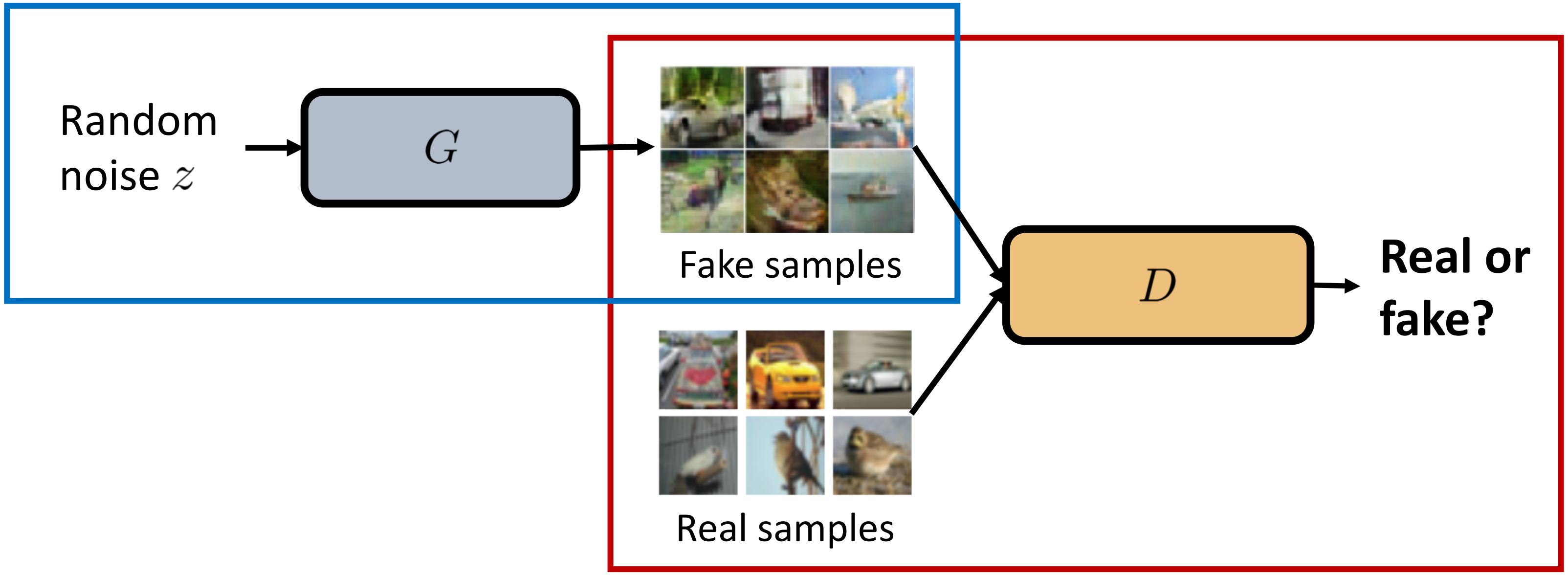
- GANs [Goodfellow, et. al., 2014] do not explicitly model $p_{\text{model}}(\mathbf{x})$
  - **Two player game** between discriminator network D and generator network G
  - D **tries to discriminate** real data and samples generated by G ("fake" samples)
  - G **tries to fool** D by generating more "realistic" images
  - GAN utilizes **neural networks** to model the sampling function itself



- **Two player game** between discriminator network D and generator network G
- **Training objective**:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x\sim p_{\text{data}}} \log \underbrace{D_{\theta_d}(x)}_{\substack{\text{Discriminator output} \\ \text{for real data}}} + \mathbb{E}_{z\sim p_z} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\substack{\text{Discriminator output} \\ \text{for generated fake data}}})\right]$$

  - D maximizes the objective: $D(x) \rightarrow 1$ and $D(G(z)) \rightarrow 0$
  - G minimizes the objective: $D(G(z)) \rightarrow 1$



- **Training objective** [Goodfellow, et. al., 2014]:

$$\min_{\theta_g} \max_{\theta_d} V(\theta_d, \theta_g) = \left[\mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

- Alternative training between D and G
  - Objective for D :

$$\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

  - Objective for G :

$$\min_{\theta_g} \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

- In practice, directly optimizing the G-objective can be problematic
  - (cont'd) … will be discussed in the later slides

- Discriminator
  - For fixed G, the D optimizes:

$$\begin{aligned} V(\theta_d, \theta_g) &= \mathbb{E}_{x \sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \\ &= \int_x p_{\text{data}}(x) \log(D_{\theta_d}(x)) dx + \int_z p_z(z) \log(1 - D_{\theta_d}(G_{\theta_g}(z)) dz \\ &= \int_x p_{\text{data}}(x) \log(D_{\theta_d}(x)) + p_g(x) \log(1 - D_{\theta_d}(x)) dx \end{aligned}$$

  - Optimal discriminator is

$$D_{\theta_d^*}(\mathbf{x}) = \frac{p_{\text{data}}(\mathbf{x})}{p_{\text{data}}(\mathbf{x}) + p_g(\mathbf{x})}$$

  - If $p_{\text{data}} = p_g$, optimal discriminator $D_{\theta_d^*}(\mathbf{x}) = \frac{1}{2}$

- Generator
  - For fixed $D_{\theta_d^*}$, the G optimizes:

$$\begin{aligned}
V(\theta_d^*, \theta_g) &= \mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d^*}(x) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d^*}(G(z))) \\
&= \mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d^*}(x) + \mathbb{E}_{x\sim p_g} \log(1 - D_{\theta_d^*}(x)) \\
&= \mathbb{E}_{x\sim p_{\text{data}}} \left[\log \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_g(\mathbf{x})}\right] + \mathbb{E}_{x\sim p_g} \left[\log \frac{p_g(x)}{p_{\text{data}}(x) + p_g(x)}\right] \\
&= -\log 4 + KL\left(p_{\text{data}} \,\middle\|\, \frac{p_{\text{data}} + p_g}{2}\right) + KL\left(p_g \,\middle\|\, \frac{p_{\text{data}} + p_g}{2}\right) \\
&= -\log 4 + 2 \cdot \boxed{JS(p_{\text{data}} \,\|\, p_g)}
\end{aligned}$$

- Provided that the discriminator (D) is optimal
  - G-objective = minimizing the **Jensen-Shannon (JS) divergence**
  - Many previous generative models used the KL divergence (a.k.a. Max. likelihood)
  - **KL divergence vs JS divergence?**
    - JS helps to capture sharper and clearer modes in the distribution
    - But JS can cause a missing mode problem (“**mode collapse**”)

GAN Training Algorithm: In Practice

- Training GANs via alternating updates between D and G
- **Recall**: G optimizes JS divergence when D is optimal
  - **Q**: But how can we ensure that D is indeed "optimal"?
  - Simplest practice: Just update D more (e.g., for k-steps) per each G update

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

* source : Goodfellow, et. al., Generative adversarial nets, NIPS 2014

GAN Training Algorithm: In Practice

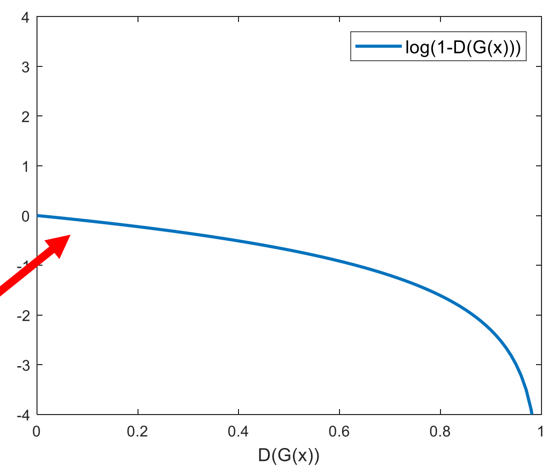
- Alternative training between D and G
  - Objective for D :

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

  - Objective for G :

$$\min_{\theta_g} \mathbb{E}_{z \sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

- In practice, directly optimizing the G-objective can be problematic
  - **Gradient vanishing**: Especially when $G(z)$ looks "bad" to D (e.g., early of training)
  - Learning via back-propagation becomes significantly difficult



Gradients → 0 when
G is too worse than D

GAN Training Algorithm: In Practice

- Alternative training between D and G
  - Objective for D :

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

  - Objective for G :

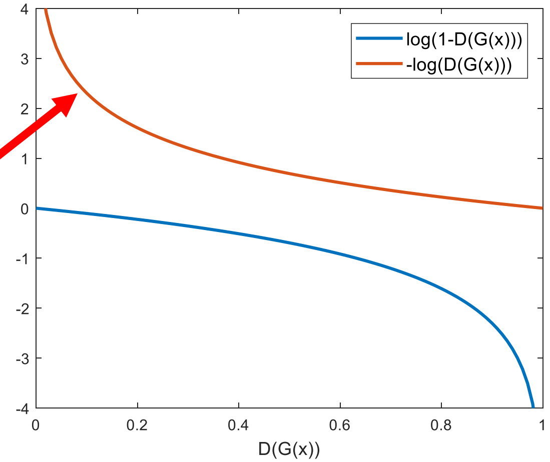
$$\min_{\theta_g} \mathbb{E}_{z \sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

- **Non-saturating loss** is practically more favorable in this respect

$$-\log(D_{\theta_d}(G_{\theta_g}(z)))$$

  - This G-objective gives much stronger gradients in this scenario

Stronger gradients when
G is too worse than D



* source : http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture12.pdf

Table of Contents

1. Generative Models
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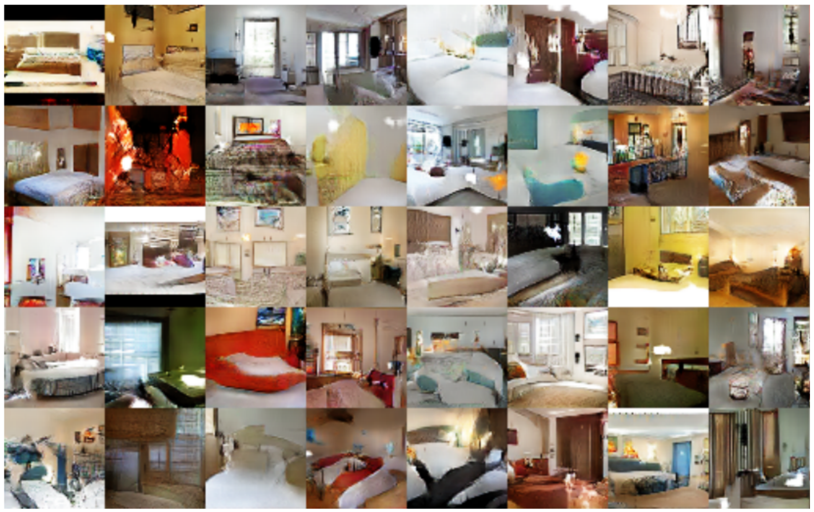
4. Summary

Generated Samples with GAN

- GAN could generate “sharper” and “clearer” images than previous approaches
  - Most of the previous works suffered from “blurred”, unrealistic generations



Bedroom images

Faces images

ImageNet

- Then, **what makes GAN be able to generate realistic samples**?
  - GAN utilizes the function approximation power of neural networks
    - But it is also the cases for other models (e.g., Variational Auto-encoder; VAE)
  - What else can be a possible explanation?

* source : Radford, et. al., Unsupervised representation learning with deep convolutional generative adversarial networks.

Difference with Previous Generative Models

- Maximum likelihood methods (= KL divergence minimization)

$$KL(p_{\text{data}} \parallel p_g) = \int_x p_{\text{data}}(x) \log \frac{p_{\text{data}}(x)}{p_g(x)} dx$$

  - $p_{\text{data}}(x) > p_g(x)$
    - When $p_{\text{data}}(x) > 0, p_g(x) \to 0$, the integrand grows quickly to infinity
    - **High penalty** when generator's distribution **does not cover parts of the train data**
  - $p_{\text{data}}(x) < p_g(x)$
    - When $p_{\text{data}}(x) \to 0, p_g(x) > 0$, the integrand goes to 0
    - **Low penalty** for generating **fake looking samples**
  - KL divergence solution tends to **cover all the modes**

- Inverse KL divergence $KL(p_g \parallel p_{\text{data}})$ tends to **fit single mode**

Difference with Previous Generative Models

- Maximum likelihood methods (= KL divergence minimization)

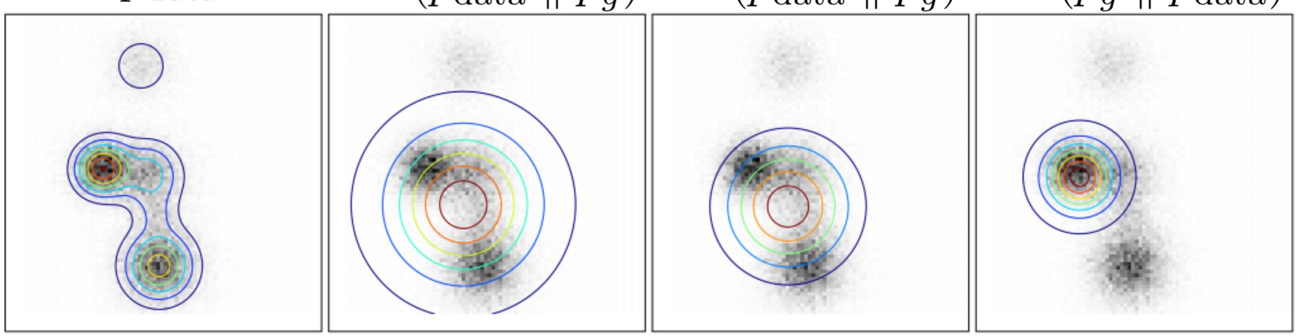
$$KL(p_{\text{data}} \parallel p_g) = \int_x p_{\text{data}}(x) \log \frac{p_{\text{data}}(x)}{p_g(x)} dx$$

  - KL divergence solution tends to **cover all the modes**
- Inverse KL divergence $KL(p_g \parallel p_{\text{data}})$ tends to **fit single mode**
- Jensen-Shannon divergence

$$JS(p_{\text{data}} \parallel p_g) = KL\left(p_{\text{data}} \middle\| \frac{p_{\text{data}} + p_g}{2}\right) + KL\left(p_g \middle\| \frac{p_{\text{data}} + p_g}{2}\right)$$

  - (A bit like a) combination of the two divergences
  - Using JS-divergence instead of KL helps to generate realistic images [Huszar 2015]

p_{data} $\quad KL(p_{\text{data}} \parallel p_g)$ $\quad JS(p_{\text{data}} \parallel p_g)$ $\quad KL(p_g \parallel p_{\text{data}})$



* source : https://www.inference.vc/how-to-train-your-generative-models-why-generative-adversarial-networks-work-so-well-2/

1. **Training instability**
   - GANs are notoriously unstable to train, with much sensitivity to hyperparameters
   - GAN as a two-player non-cooperative game [Salimans, et. al., 2016]
     - The Nash equilibrium of such games can be extremely hard to achieve
     - Reducing the D-objective can significantly increase the G's, and vice versa

2. **Mode collapse problem**
   - G can "collapse" to produce the same outputs to beat D
   - G may easily fool D if it is good at making a single perfect image
   - JS itself does not explicitly penalize such cases as much as KL

Examples of the mode collapse problem in GAN

* source : Arjovsky, et. al., Wasserstein GAN, ICML 2017

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Conditional GANs

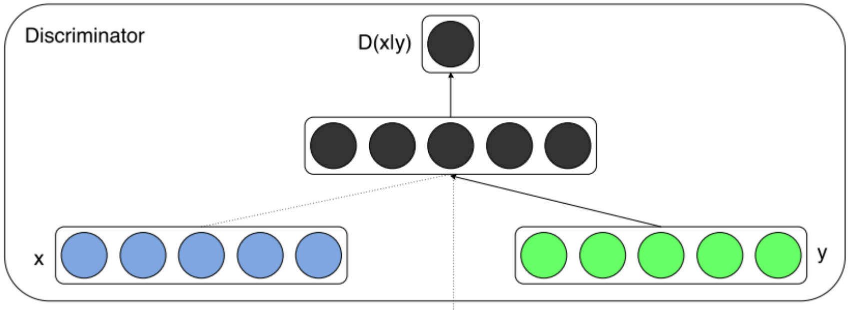
- By default, the standard GANs are unconditional
  - One cannot control the mode of the distribution to be generated
- **Conditional GANs** (cGANs) aim to incorporate an additional attribute y
  - (+) Controllable generation (e.g., class-wise generation)
  - (+) Improved quality for complex generation tasks

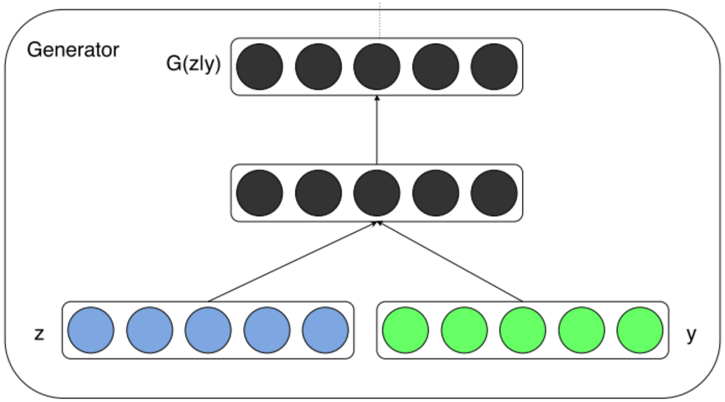
- **Recall**: Training objective for unconditional GAN [Goodfellow et al., 2014]:

$$\min_G \max_D \left[\mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

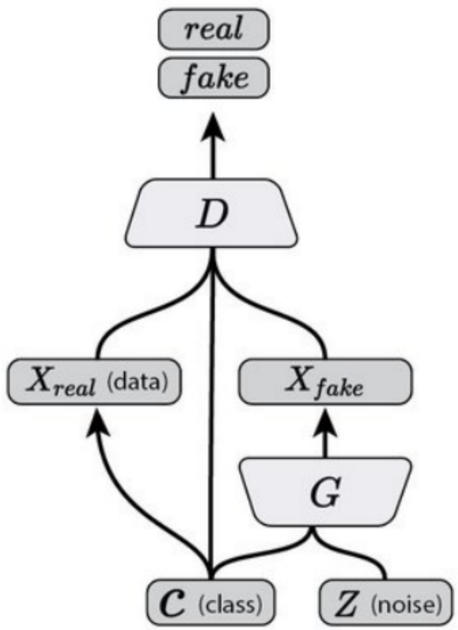
- Mirza et al. (2014) formulated a cGAN objective by:

$$\min_G \max_D \left[\mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d}(x|y) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z|y)))\right]$$

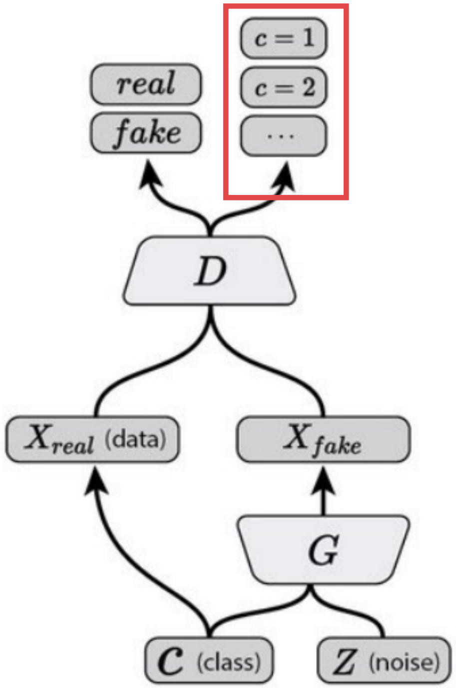




- Many works have been proposed then to better encode y
  - e.g., Reed et al. (2016): Concatenate y to inputs for hidden features of D
- Odena et al. (2017): **Auxiliary Classifier GAN** (ACGAN)
  - Modified D to have an auxiliary classifier for the class of both real and fake inputs
  - D should preserve the information to reconstruct the class as well as "real vs. fake"



Conditional GAN
[Mirza et al., 2014]



ACGAN
[Odena et al., 2017]

* source : Basart , Analysis of Generative Adversarial Models, 2017

Conditional GANs: Auxiliary Classifier GAN (ACGAN)

- The training objective function consists of two parts:
  - **GAN loss**: the log-likelihood of the correct source, L_S

$$
\begin{aligned}
L_S &= \mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \\
&= \mathbb{E}_{x\sim p_{\text{data}}} \log P(S = \text{real}|x) + \mathbb{E}_{z\sim p_z} \log P(S = \text{fake}|G_{\theta_g}(z))
\end{aligned}
$$

  - **Classification loss**: the log-likelihood of the correct class, L_C

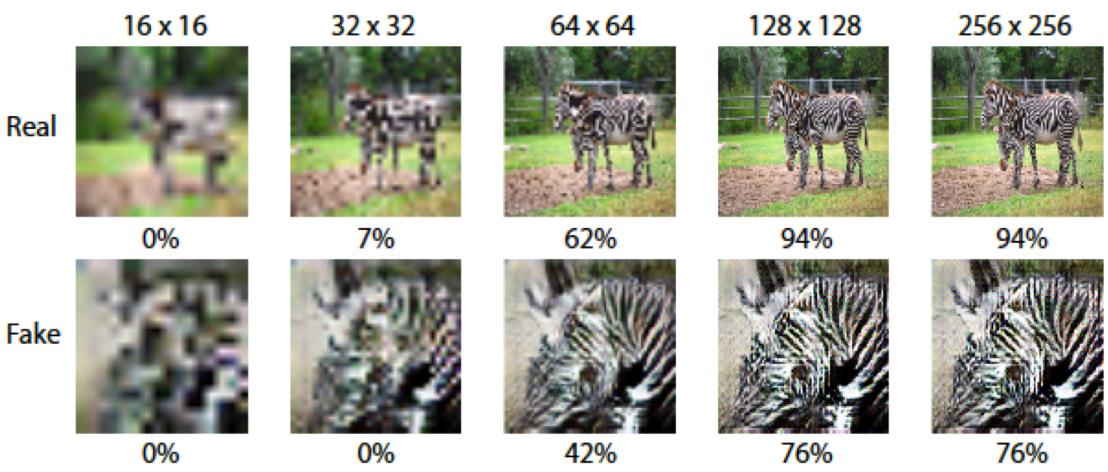
$$
L_C = \mathbb{E}_{x\sim p_{\text{data}}} \log P(C = c|x) + \mathbb{E}_{z\sim p_z, c\sim p_c} \log P(C = c|G_{\theta_g}(z, c)))
$$

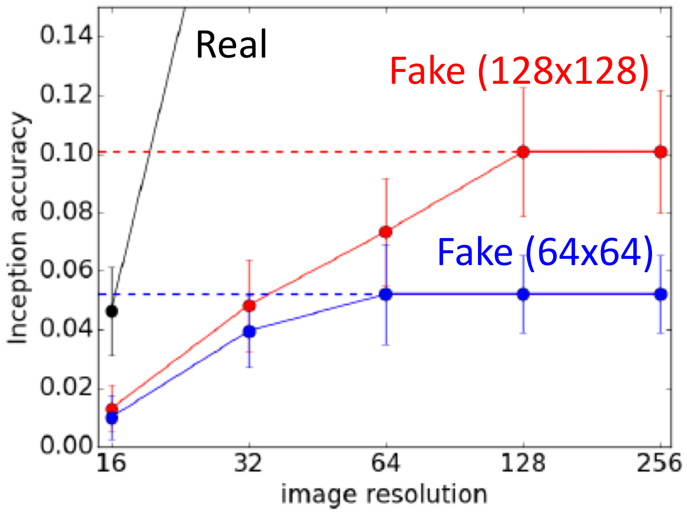
- D maximizes $L_S + L_C$, while G maximizes $-L_S + L_C$
  - **Remark:** L_C is used not only for D, but also G
  - **Remark:** There can be some balancing weight for both losses for better training
    - i.e., D and G maximize $L_S + \lambda_1 L_C$ and $-L_S + \lambda_2 L_C$, respectively

- ACGAN could allow diverse & higher resolution images than previous cGANs
  - The first cGAN approach that could scale up to the ImageNet dataset

1. Evaluation of cGAN conditioning via Inception accuracy

- Increased discriminability on Inception → Better conditioning
- Higher-res conditional generations via ACGAN improves Inception accuracy





* source : Odena et al., Conditional Image Synthesis with Auxiliary Classifier GANs, ICML 2017

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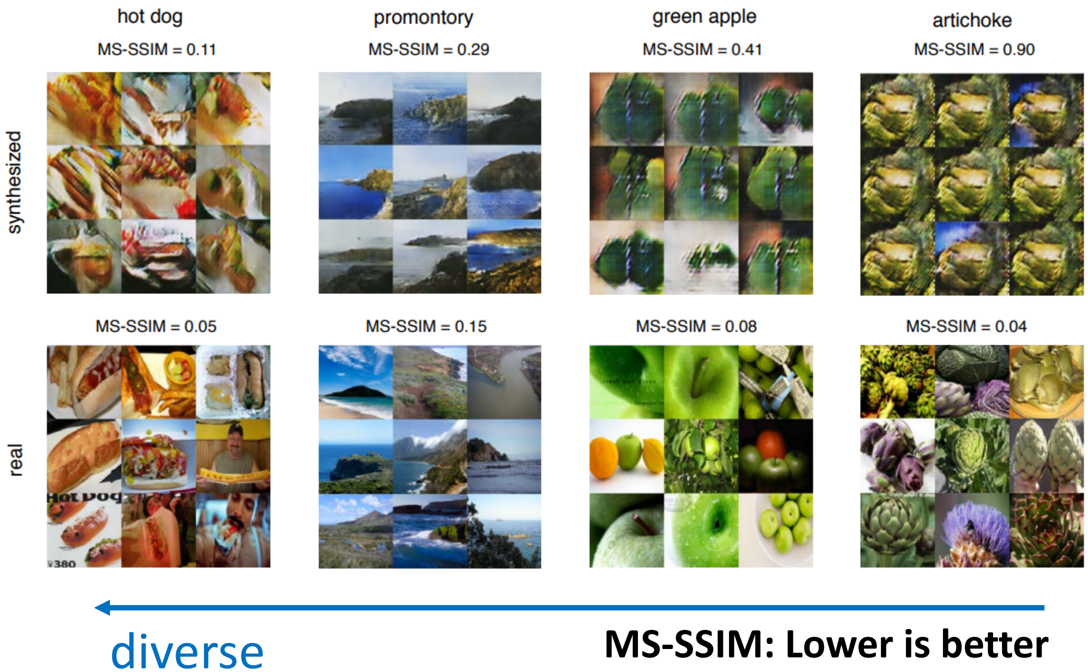
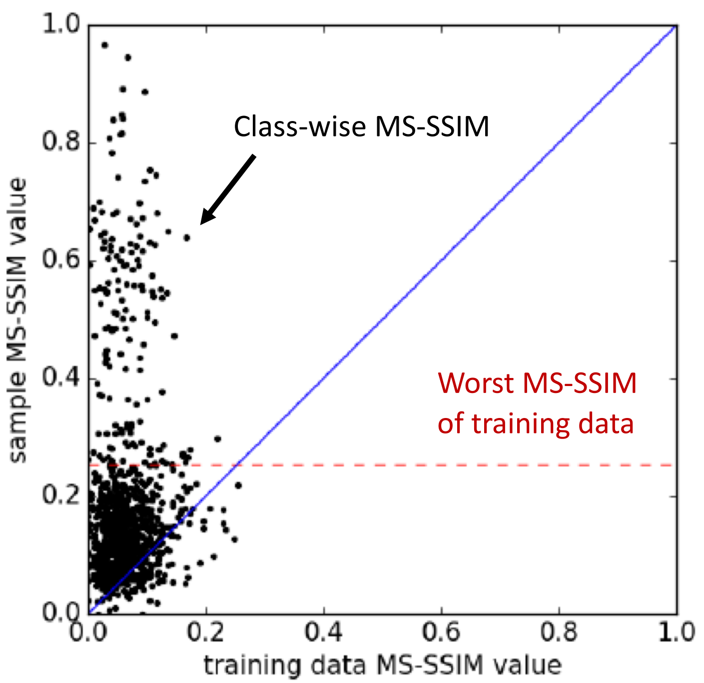
  - The first cGAN approach that could scale up to the ImageNet dataset

2. Comparison of multiscale structural similarity (MS-SSIM)

- MS-SSIM ranges 0.0 ~ 1.0; Higher MS-SSIM → perceptually more similar
- ACGAN achieves similar MS-SSIM to the training set on many of ImageNet classes





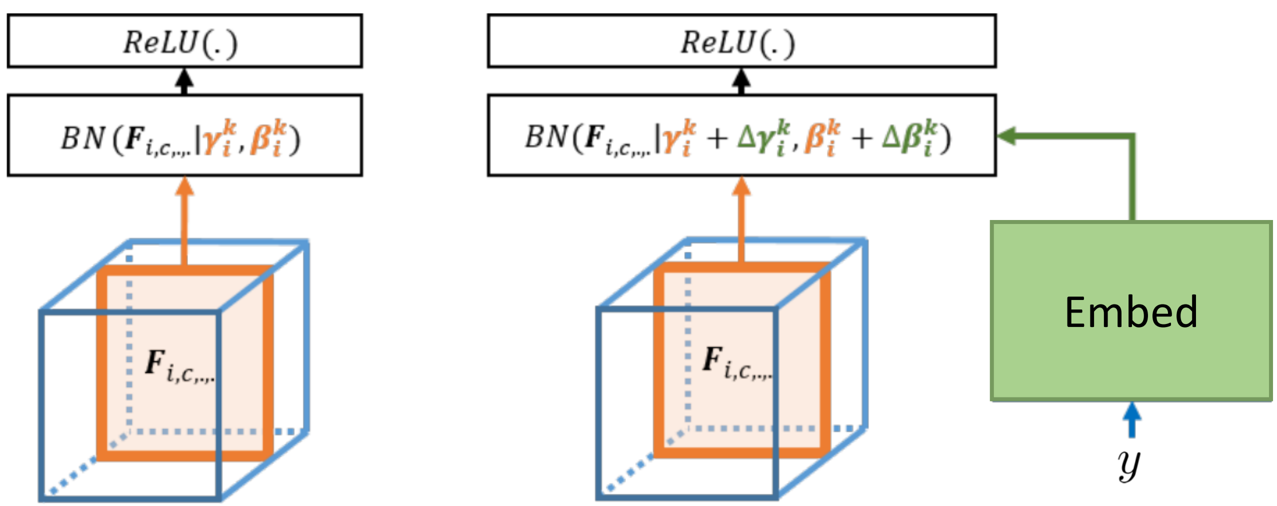
* source : Odena et al., Conditional Image Synthesis with Auxiliary Classifier GANs, ICML 2017

Conditional GANs: Conditional Batch Normalization (CBN)

- **Conditional BN** [Dumoulin et al., 2017, DeVries et al., 2017]
  - Recent practice of designing cGAN generator instead of concatenating y
  - Modulate Batch Normalization (BN) layers depending on the condition

- **Idea**: Predict the affine scaling parameters, γ and β in BN, from y

$$z = \gamma(y) \cdot \left(\frac{x - \mu(x)}{\sigma(x)}\right) + \beta(y)$$



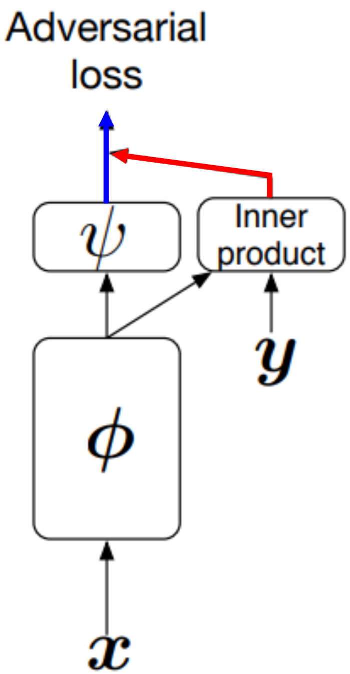
Batch Normalization | Conditional Batch Normalization

* source : de Vries et. al., Modulating early visual processing by language, NIPS 2017

Conditional GANs: Projection Discriminator

- **Projection discriminator** [Miyato et al., 2018]
  - Recent practice of designing cGAN discriminator instead of feeding y

- Miyato et al. (2018): projecting y into D-representation is very effective



$$D(x, y; \theta) := \mathcal{A}(f(x, y; \theta))$$

$\mathcal{A}$: an activation function of design choice

- e.g., sigmoid for vanilla GAN

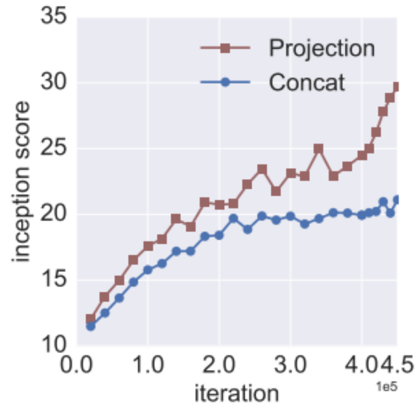
$$f(x, y) := y^{\mathrm{T}} V \phi(x) + \psi(\phi(x))$$

The discriminator is modeled by a inner-product (projection) of the class embedded vector y

* source : Miyato et. al., cGANS with Projection Discriminator, ICLR 2018

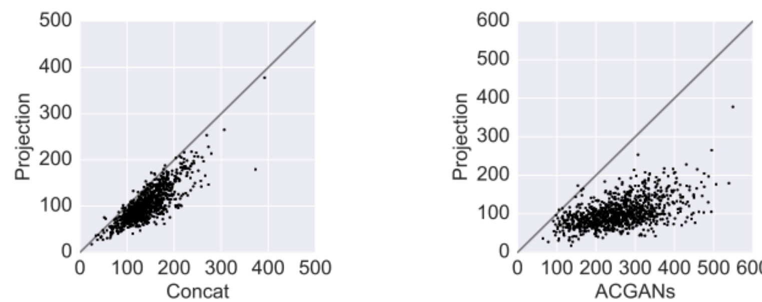
Conditional GANs: Projection Discriminator

- Projection discriminator significantly outperforms "concat" and "ACGAN"



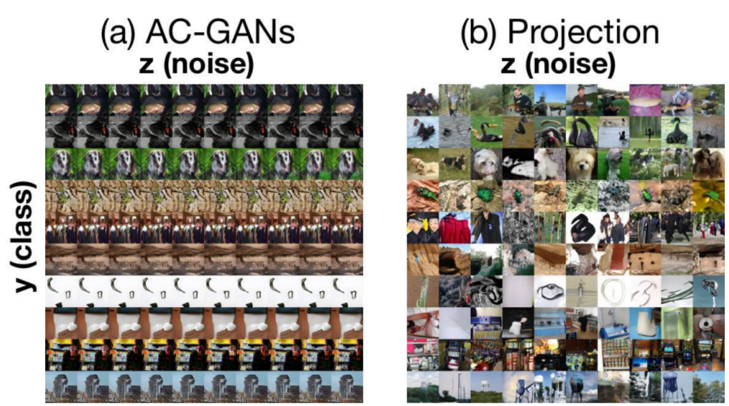
Inception score: higher is better
Intra (class-wise) FID: lower is better

Method	Inception Score	Intra FID
AC-GANs	28.5±.20	260.0
concat	21.1±.35	141.2
projection	**29.7**±.61	**103.1**
*projection (850K iteration)	**36.8**±.44	**92.4**



FID for each class

- "Projection" is also more robust against mode-collapse than others



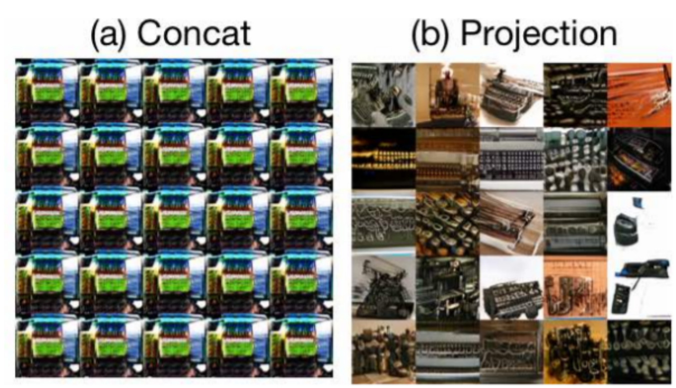


Table of Contents

1. **Generative Models**
   - Why generative model?
   - Two types of generative models

2. **Generative Adversarial Networks (GAN)**
   - Advantages and disadvantages of GAN
   - Conditional GANs

3. **Improved Techniques for GANs**
   - Loss, regularization and normalization
   - GAN architectures
   - Data augmentations for GANs

4. **Summary**

Table of Contents

1. **Generative Models**
   - Why generative model?
   - Two types of generative models

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   - Advantages and disadvantages of GAN
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4. **Summary**

- Many heuristics have been proposed to alleviate training issues in GANs
  - However, it was hard to explain why they actually work in general

- **1-Wasserstein distance** (a.k.a. Earth Mover's distance):
  - **A distance measure between two probability distributions**

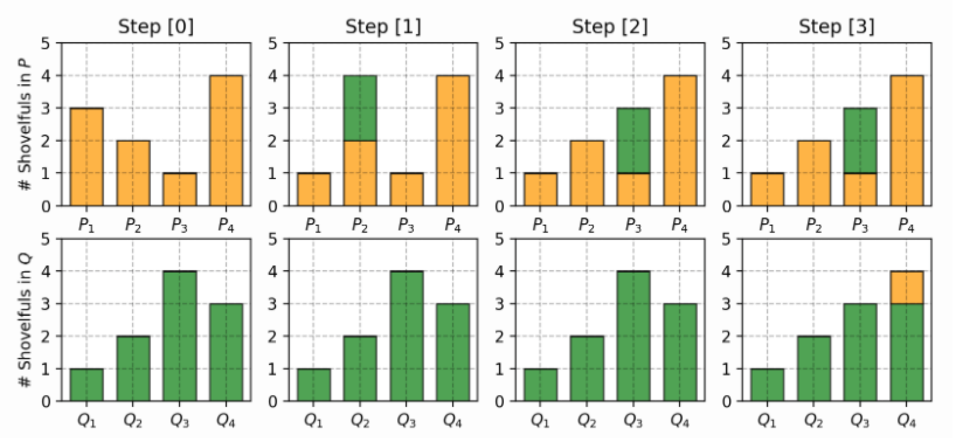
$$W(p_{\text{data}}, p_g) = \inf_{\gamma \in \Pi(p_{\text{data}}, p_g)} \mathbb{E}_{(x,y)\sim\gamma} \|x - y\|$$

  - Minimal amount of "work" to transform a distribution P to Q
  - **Work?** the amount of *dirt* in a chunk times the distance it was moved

- **Example:**

$$P_1 = 3, P_2 = 2, P_3 = 1, P_4 = 4$$
$$Q_1 = 1, Q_2 = 2, Q_3 = 4, Q_4 = 3$$

$$W(P, Q) = 5$$



* source : https://lilianweng.github.io/lil-log/2017/08/20/from-GAN-to-WGAN.html#wasserstein-gan-wgan

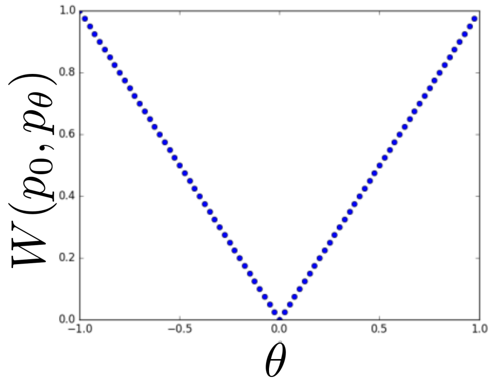
- **Why Wasserstein?** - When two distributions have no overlap
  - It still gives non-zero and smooth notion of the distance (and gradients)

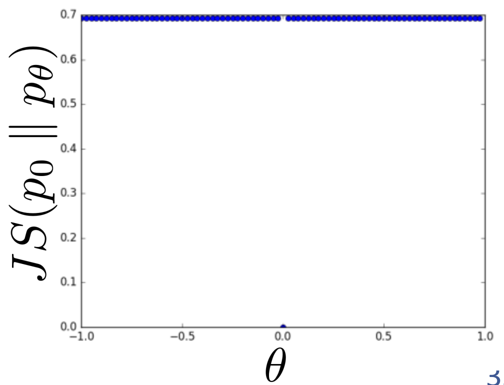
- **Example** [Arjovsky, et. al., 2017]: **Wasserstein vs JS (or KL)**
  - Let $Z \sim U[0,1]$, p_0 be the distribution of $(0, Z) \in \mathbb{R}^2$
  - $g_\theta(Z) = (\theta, Z)$ with θ, a single real parameter, and p_θ is the distribution of $g_\theta(Z)$
  - Distance between two distributions are:

$$W(p_0, p_\theta) = |\theta|$$

$$JS(p_0 \parallel p_\theta) = \begin{cases} \log 2 & \text{if } \theta \neq 0, \\ 0 & \text{if } \theta = 0 \end{cases}$$

$$KL(p_0 \parallel p_\theta) = KL(p_\theta \parallel p_0) = \begin{cases} \infty & \text{if } \theta \neq 0, \\ 0 & \text{if } \theta = 0 \end{cases}$$



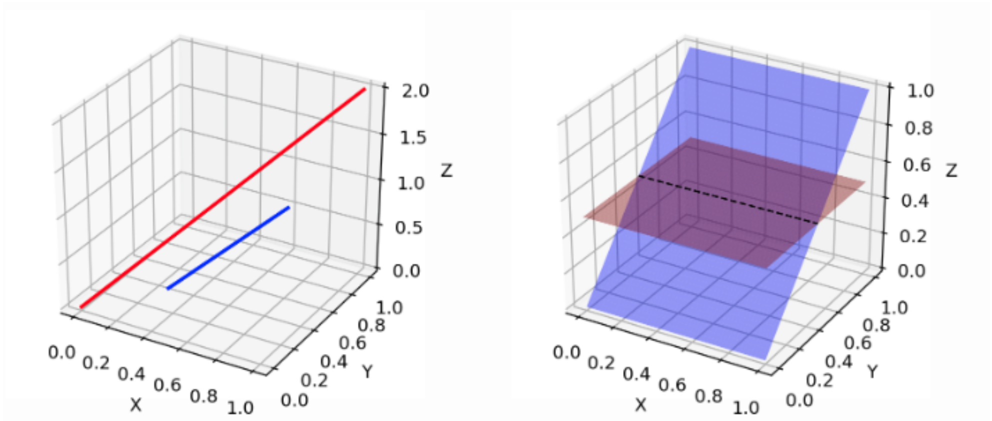


  - Parameter θ can be learned on the Wasserstein distance
  - Parameter θ cannot be learned on JS or KL divergence

Comparison between Wasserstein Distance and Other Distance Metrics

- This example shows that there exist distributions that
  - **Don't converge under the JS, KL, or inverse KL**
    - For the **JS, KL, and inverse KL, there are cases where the gradient is always 0**
    - This is especially not good from an optimization perspective
  - **Do converge under the Wasserstein distance**

- Easy to get similar results, if p_{data} and p_g are on low-dimensional manifolds in high dimensional space



Low dimensional manifolds in high dimension space can hardly have overlaps.
(Left) two lines in a 3-d space. (Right) two surfaces in 3-d space

* source: https://lilianweng.github.io/lil-log/2017/08/20/from-GAN-to-WGAN.html#wasserstein-gan-wgan

Wasserstein Distance in GAN Objective

- Infimum over joint distribution $\gamma \in \Pi(p_{\text{data}}, p_g)$ is computationally **intractable**

- Using Kantorovich-Rubinstein duality [Villani, 2009]:

$$W(p_{\text{data}}, p_g) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{x \sim p_{\text{data}}}[f(x)] - \mathbb{E}_{x \sim p_g}[f(x)]$$

  - The supremum is over all the 1-Lipschitz functions $f : \mathcal{X} \to \mathbb{R}$
  - Let f is parameterized by w, then one could consider solving the problem

$$\max_{w \in \mathcal{W}} \mathbb{E}_{x \sim p_{\text{data}}}[f_w(x)] - \mathbb{E}_{z \sim p_z}\left[f_w(g_{\theta_g}(z))\right]$$

  - To enforce the Lipschitz constraint, **clamp the weights** to a fixed box (e.g., $\mathcal{W} = [-0.01, 0.01]^\ell$, where ℓ is dimension of parameter $w \in \mathcal{W}$)

* source: WGAN and Kantorovich-Rubinstein duality https://vincentherrmann.github.io/blog/wasserstein/

- Comparison of GAN and WGAN
  - Discriminator (outputs probability of real or fake) becomes a continuous function to help compute Wasserstein distance (with weight clamping)

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\boxed{\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].}$$

$$\boxed{\begin{aligned} &g_w \leftarrow \nabla_w \left[\tfrac{1}{m}\textstyle\sum_{i=1}^m f_w(x^{(i)}) - \tfrac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))\right] \\ &w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w) \\ &w \leftarrow \text{clip}(w, -c, c) \end{aligned}}$$

  end for

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Update the generator by descending its stochastic gradient:

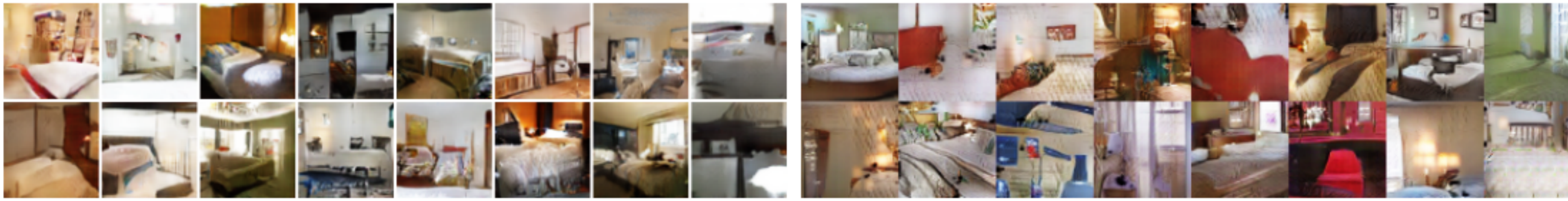
$$\boxed{\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).}$$

$$\boxed{\begin{aligned} &g_\theta \leftarrow -\nabla_\theta \tfrac{1}{m}\textstyle\sum_{i=1}^m f_w(g_\theta(z^{(i)})) \\ &\theta \leftarrow \theta - \alpha \cdot \text{RMSProp}(\theta, g_\theta) \end{aligned}}$$

end for

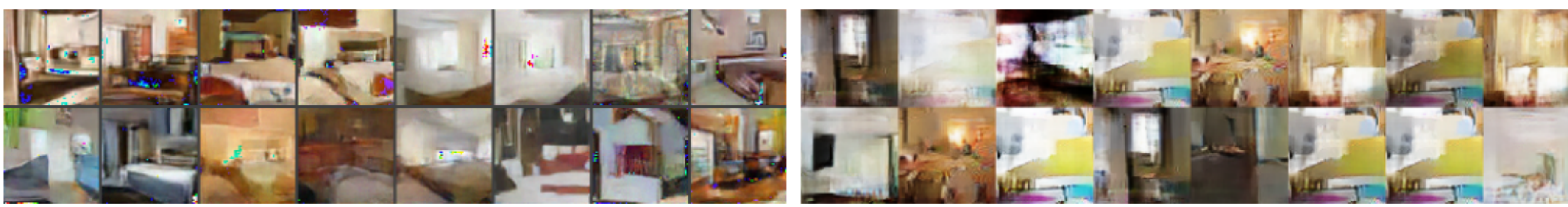
The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

WGAN vs GAN



(Left) WGAN vs. (Right) GAN with DCGAN architecture . Both produce high quality samples

(Left) WGAN vs. (Right) GAN with less parameter models and without batch normalization



(Left) WGAN vs. (Right) GAN with MLP generator.
Vanilla GAN does mode collapse, while WGAN still produces good samples

* source : Arjovsky, et. al., Wasserstein GAN, ICML 2017

- WGAN uses the **weight clamping** to maintain Lipschitz constraint
  - (-) Still naïve, ad-hoc and heuristic
  - (-) It often leads to significant optimization difficulties

- **Two representative methods for the direct Lipschitz constraint on D**
  1. **Gradient penalty** on Wasserstein GANs (WGAN-GP) [Gulrajani, et. al., 2017]
     - Use gradient penalty to maintain Lipschitz constraint

$$\mathbb{E}_{\hat{x}\sim p_{\hat{x}}}\left[\left(\|\nabla_{\hat{x}}D(\hat{x})\|_2 - 1\right)^2\right]$$

where $\hat{x} = \varepsilon x + (1-\varepsilon)G(z)$

  2. **Spectral normalization** for generative adversarial networks [Miyato, et. al., 2018]
     - Control the Lipschitz constant of D by constraining the spectral norm per layer

$$\bar{W}_{SN}(W) = W/\sigma(W)$$

where $\sigma(W)$ is the spectral norm of W

- Stabilizing GAN dynamics is still an open research topic

- Significant research efforts has been made to stabilize GANs
  - Different GAN losses [Arjovsky et al., 2017; Mao et al., 2017; Berthelot et al., 2017]
  - Regularization on D [Gulrajani et al., 2017; Roth et al., 2017; Kodali et al., 2017]
  - Normalization [Miyato et al., 2018]

GAN	Discriminator Loss	Generator Loss
MM GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{GAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$
NS GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{NSGAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] - \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{NSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[\log(D(\hat{x}))]$
WGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} = -\mathbb{E}_{x\sim p_d}[D(x)] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{WGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
WGAN GP	$\mathcal{L}_{\mathrm{D}}^{\mathrm{WGANGP}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_g}[(\|\|\nabla D(\alpha x + (1-\alpha\hat{x})\|\|_2 - 1)^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{WGANGP}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
LS GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{LSGAN}} = -\mathbb{E}_{x\sim p_d}[(D(x)-1)^2] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{LSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[(D(\hat{x}-1))^2]$
DRAGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{DRAGAN}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_d+\mathcal{N}(0,c)}[(\|\|\nabla D(\hat{x})\|\|_2 - 1)^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{DRAGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(1-D(\hat{x}))]$
BEGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{BEGAN}} = \mathbb{E}_{x\sim p_d}[\|\|x - \mathrm{AE}(x)\|\|_1] - k_t\mathbb{E}_{\hat{x}\sim p_g}[\|\|\hat{x} - \mathrm{AE}(\hat{x})\|\|_1]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{BEGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\|\|\hat{x} - \mathrm{AE}(\hat{x})\|\|_1]$

- **Then, which method should we actually use to train our GANs?**
  - How to choose a proper combination of hyperparameters?
  - Should one use a completely different method for different datasets?

- Significant research efforts has been made to stabilize GANs
- **Then, which method should we actually use to train our GANs?**
  - How to choose a proper combination of hyperparameters?
  - Should one use a completely different method for different datasets?

- Two large-scale studies empirically evaluate various existing GAN techniques
  - [Lucic et al., 2018] "Are GANs Created Equal? A Large-Scale Study"
  - [Kurach et al., 2019] "A Large-Scale Study on Regularization and Normalization in GANs"

- **TL;DR**: No evidence that "non-saturating loss" < most of existing methods

$$\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p_z} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))\right]$$

$$\min_{\theta_g} \mathbb{E}_{z\sim p_z} - \log(D_{\theta_d}(G_{\theta_g}(z)))$$

1. … Given that there could be sufficient hyperparameter search
2. "Spectral normalization (SN)" is the only that showed consistent gain

- Kurach et al. (2019): An extensive comparison over various GAN practices
  - **Regularization/normalization**
    - Gradient penalty [Gulrajani et al., 2017] (**GP**)
    - DRAGAN [Kodali et al., 2017] (**DR**)
    - Spectral normalization [Miyato et al., 2018] (**SN**)
    - LayerNorm [Ba et al., 2016] (**LN**)
    - BatchNorm [Ioffe & Szegedy, 2015] (**BN**)
    - L2 regularization (**L2**)
  - **Loss functions**
    - Non-saturating loss [Goodfellow et al., 2014] (**NS**)
    - Least-squares loss [Mao et al., 2017] (**LS**)
    - Wasserstein loss [Arjovsky et al., 2017] (**WGAN**)
  - **Hyperparameter choices**: (a) **Fixed** or (b) **Bayesian optimization**

Parameter	Discrete Value
Learning rate α	$\{0.0002, 0.0001, 0.001\}$
Reg. strength λ	$\{1, 10\}$
$(\beta_1, \beta_2, n_{dis})$	$\{(0.5, 0.900, 5), (0.5, 0.999, 1), (0.5, 0.999, 5), (0.9, 0.999, 5)\}$

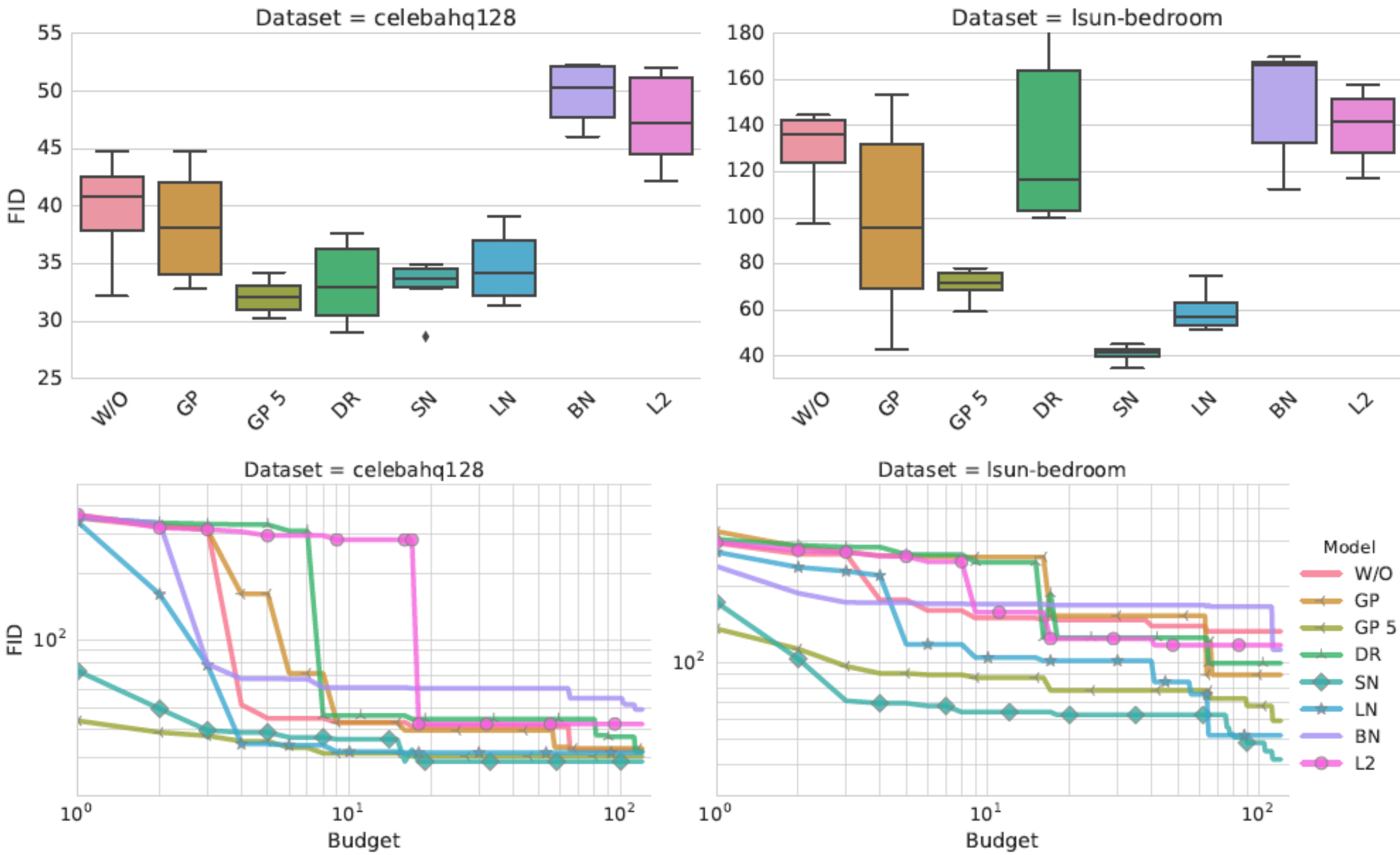
Table 1. Hyperparameter ranges used in this study. The Cartesian product of the fixed values suffices to uncover most of the recent results from the literature.

Parameter	Range	Log
Learning rate α	$[10^{-5}, 10^{-2}]$	Yes
λ for L_2	$[10^{-4}, 10^{1}]$	Yes
λ for non-L_2	$[10^{-1}, 10^{2}]$	Yes
$\beta_1 \times \beta_2$	$[0, 1] \times [0, 1]$	No

Table 2. We use sequential Bayesian optimization (Srinivas et al., 2010) to explore the hyperparameter settings from the specified ranges. We explore 120 hyperparameter settings in 12 rounds of optimization.

- Kurach et al. (2019): An extensive comparison over various GAN practices

1. **Effect of different regularization and normalization**
   - All the models are trained with non-saturating loss (NS)
   - Compared the FID distribution for top 5% models over HPs (lower is better)

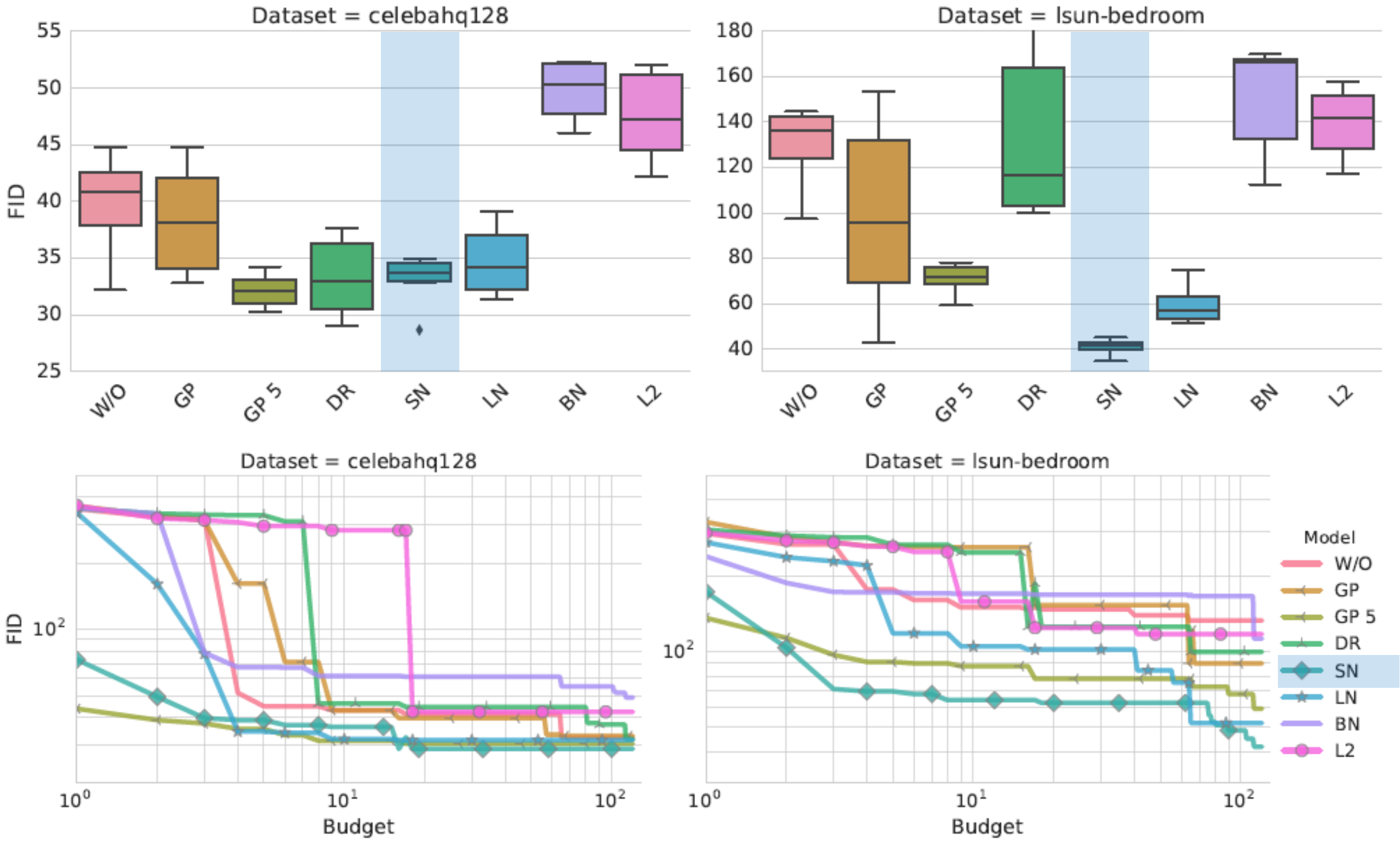


- Kurach et al. (2019): An extensive comparison over various GAN practices

1. **Effect of different regularization and normalization**

   Remark 1. None of them fully address the stability issues

   Remark 2. Spectral normalization (SN) is generally a better practical choice



- Kurach et al. (2019): An extensive comparison over various GAN practices

2. Effect of different training loss

Remark 1. Non-saturating loss (NS) was enough to achieve good FIDs

Remark 2. SN still consistently improves FID, while GP makes some mixed conclusion

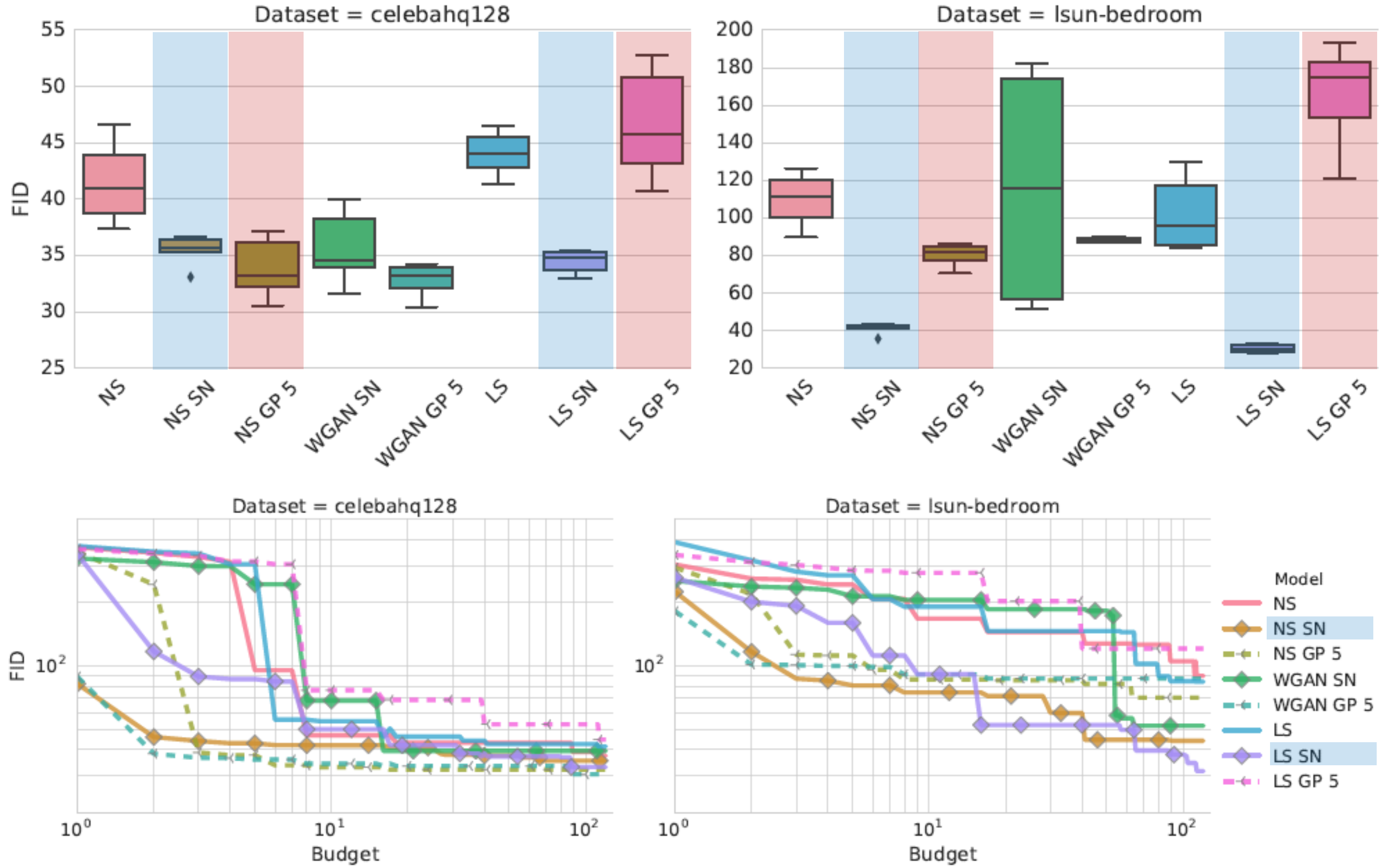


Table of Contents

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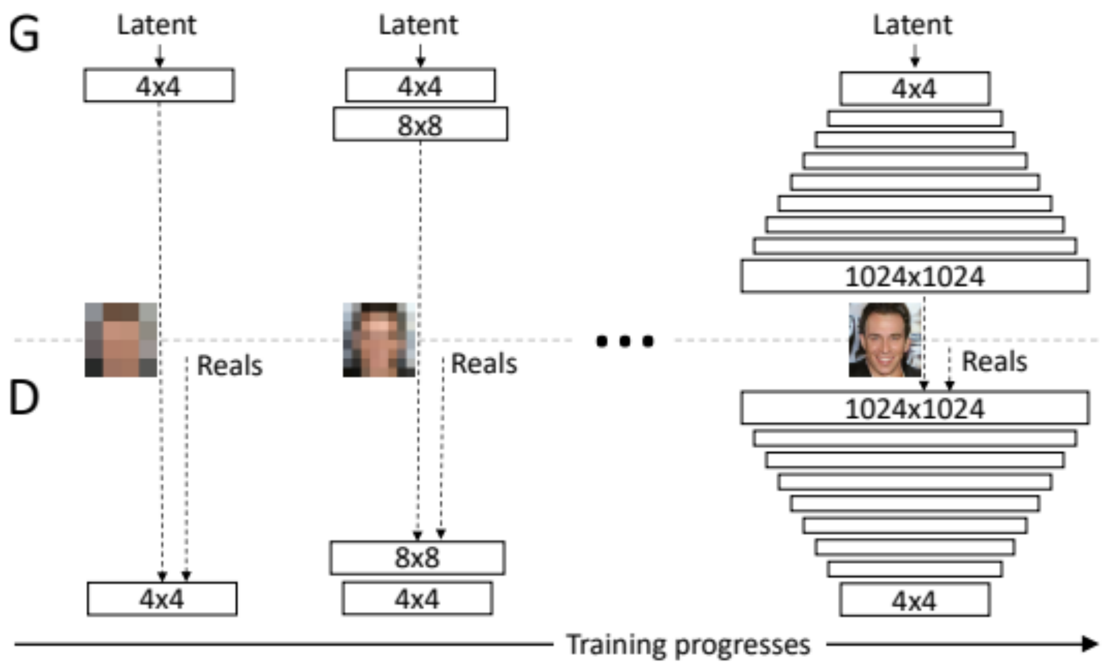
4. **Summary**

Progressive GAN: High-Resolution Image Generation [Karras et al., 2018]

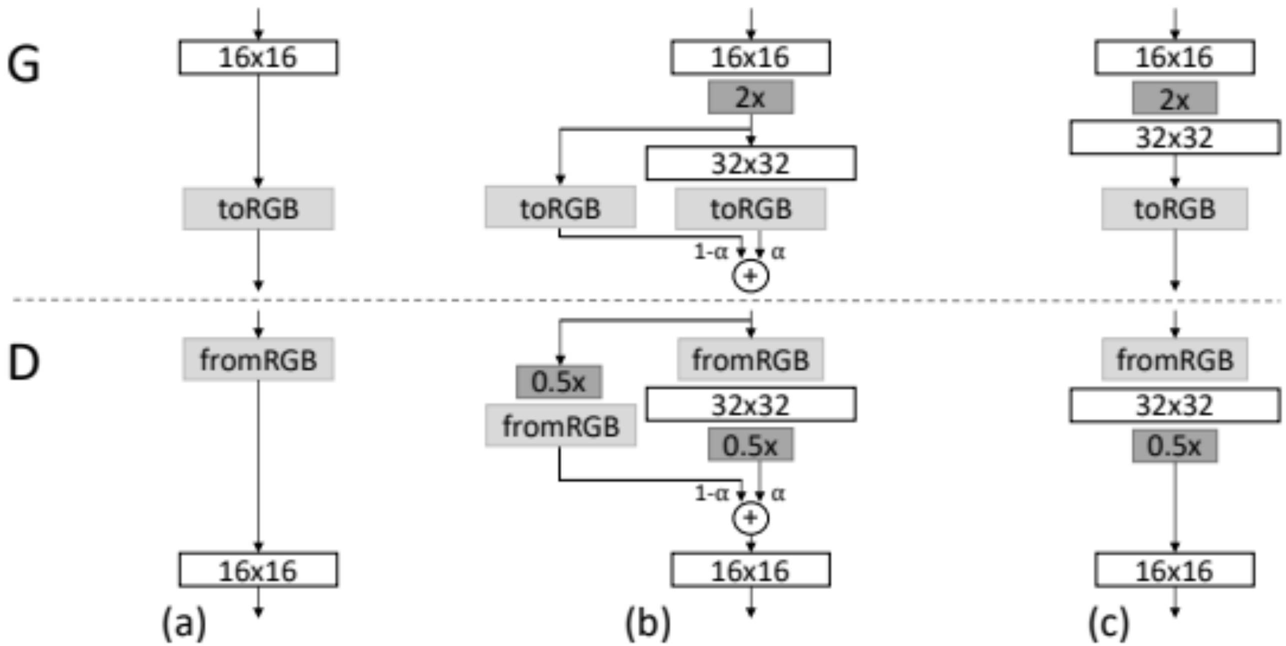
- Previous GANs could produce sharp images, but only at small resolutions
  - It was still unstable on higher-resolution training despite some progress
- Karras et al. (2018): **Progressive growing of G and D** (Progressive-GAN)
  - Training GANs to directly generate high-res image might be too difficult!
  - Progressive-GAN starts from learning low-resolution images
  - It adds new layers to G and D during training for up-scaling into higher-resolution



* source : Karras, et. al., Progressive growing of GANs for improved quality, stability, and variation, ICLR 2018

- **Smooth fade-in** to the new layers during up-scale training
  - To prevent "sudden shocks" to the pre-trained smaller-resolution layers

  - **Example**: Upscaling transition **(b)** from 16 × 16 to 32 × 32 (**(a)** → **(c)**)



  - Simply treat the higher resolution like a residual block
  - The fade-in weight α increases linearly from 0 to 1 during training

* source : Karras, et. al., Progressive growing of GANs for improved quality, stability, and variation, ICLR 2018

Progressive GAN: High-Resolution Image Generation [Karras et al., 2018]

1024x1024 images generated using the CELEBA-HQ dataset
https://www.youtube.com/watch?v=G06dEcZ-QTg&feature=youtu.be

Visual quality comparison: LSUN bedroom

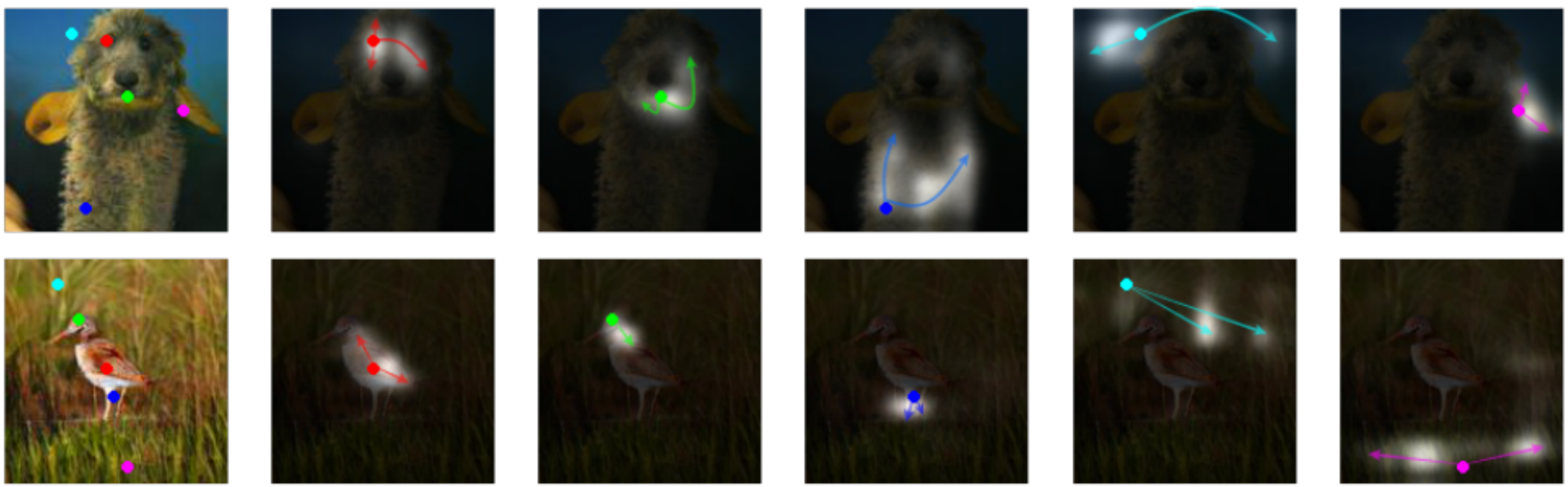
LSUN other categories generated image (256x256)

* source : Karras, et. al., Progressive growing of GANs for improved quality, stability, and variation, ICLR 2018

Self-Attention GAN: Attention-Driven Image Generation Tasks [Wang et al., 2018]

- Previous GANs often failed to capture geometric or structural patterns
- Using only convolutional layers may be computationally inefficient
  - Especially for modeling long-range dependencies in images

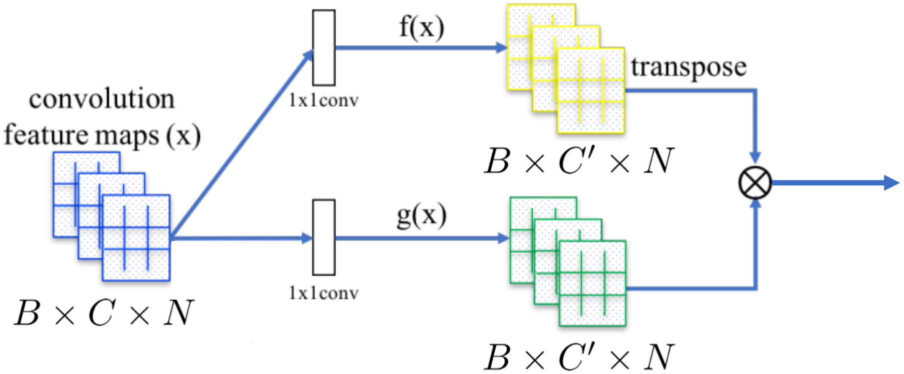
- **Self-Attention GAN** (SAGAN) [Wang et al., 2018]
  - The non-local model (i.e. self-attention module) of for both G and D
  - To efficiently model the relationships between spatial regions

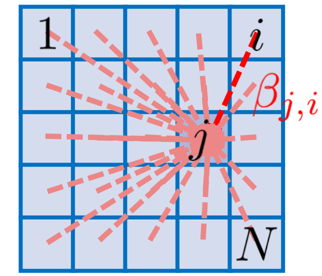


⟶ : attention between regions

* source : Zhang, et. al., Self-Attention Generative Adversarial Networks, ICML 2019

- **The self-attention module of SAGAN**





$$\beta_{j,i} \text{ for } \begin{array}{l} i = 1, \cdots, N \\ j = 1, \cdots, N \end{array}$$

  - The Image features are first transformed into two feature spaces.

$$f(x) = W_f x,\ g(x) = W_g x$$

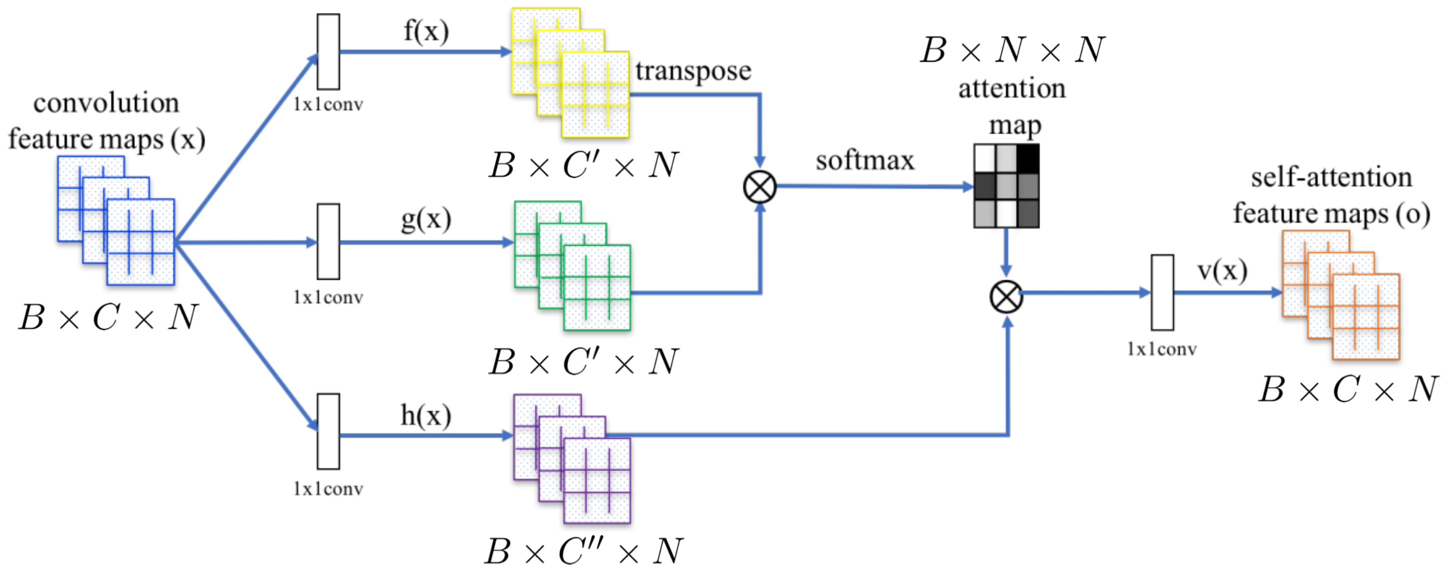
  - Then calculate the attention.

$$\beta_{j,i} = \frac{\exp(s_{ij})}{\sum_{i=1}^{N} \exp(s_{ij})},\ \text{where } s_{ij} = f(x_i)^T g(x_j)$$

  - $\beta_{j,i}$ indicates the extent to which the model attends to the i th location when synthesizing the j th region

* source : Zhang, et. al., Self-Attention Generative Adversarial Networks, ICML 2019

- **The self-attention module of SAGAN**



  - Here the output of the attention layer is:

$$o_j = v\left(\sum_{i=1}^{N} \beta_{j,i} h(x_i)\right),\ h(x_i) = W_h x_i,\ v(x_i) = W_v x_i.$$

  - In addition, multiply the output of the attention layer by a scale parameter and add back the input feature map (as similar as Residual block).

$$y_i = \gamma o_i + x_i$$

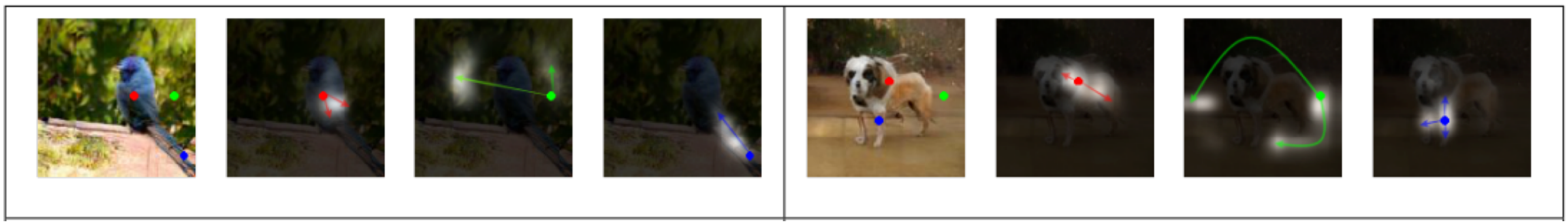
* source : Zhang, et. al., Self-Attention Generative Adversarial Networks, ICML 2019

Self-Attention GAN: Attention-Driven Image Generation Tasks [Wang et al., 2018]

- SAGAN improves upon state-of-the-art class-conditional ImageNet generation

Model	Inception Score	Intra FID	FID
AC-GAN (Odena et al., 2017)	28.5	260.0	/
SNGAN-projection (Miyato & Koyama, 2018)	36.8	92.4	27.62*
SAGAN	**52.52**	**83.7**	**18.65**

Table 2. Comparison of the proposed SAGAN with state-of-the-art GAN models (Odena et al., 2017; Miyato & Koyama, 2018) for class conditional image generation on ImageNet. FID of SNGAN-projection is calculated from officially released weights.



Visualization of generated samples & their attention maps

- Comparison between Self-Attention and Residual block in GANs
  - Ablation on the features index where the blocks added

Model	no attention	SAGAN				Residual			
		$feat_8$	$feat_{16}$	$feat_{32}$	$feat_{64}$	$feat_8$	$feat_{16}$	$feat_{32}$	$feat_{64}$
FID	22.96	22.98	22.14	**18.28**	18.65	42.13	22.40	27.33	28.82
IS	42.87	43.15	45.94	51.43	**52.52**	23.17	44.49	38.50	38.96

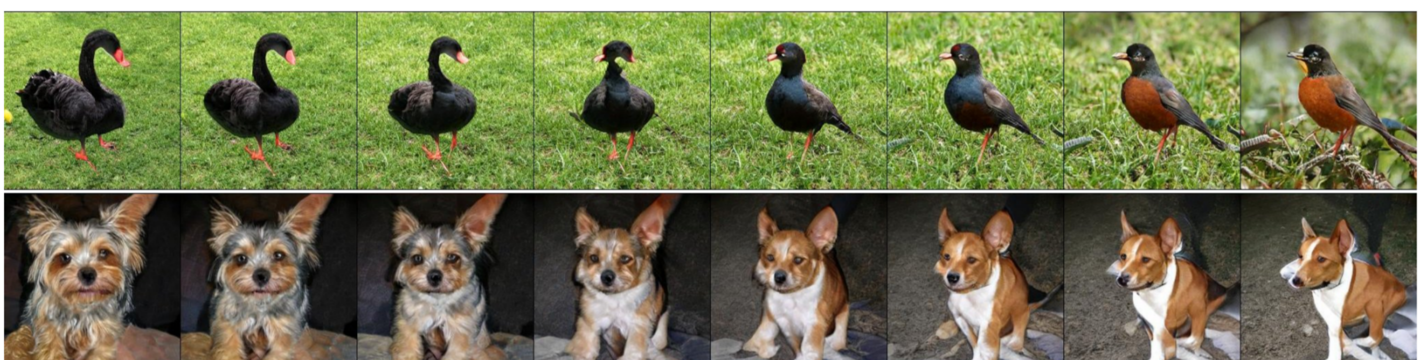
The improvements depend not only on residual connections, but also on attentions

* source : Zhang, et. al., Self-Attention Generative Adversarial Networks, ICML 2019

BigGAN: High-resolution, Diverse Image Generation [Brock et al., 2019]

- BigGAN is a holistic approach of recent techniques for training GANs
- Current cGAN techniques can be successfully scaled up to generate high-resolution, diverse samples from complex datasets such as ImageNet

- Achieved state-of-the-art results in terms of IS and FID on 128×128 ImageNet



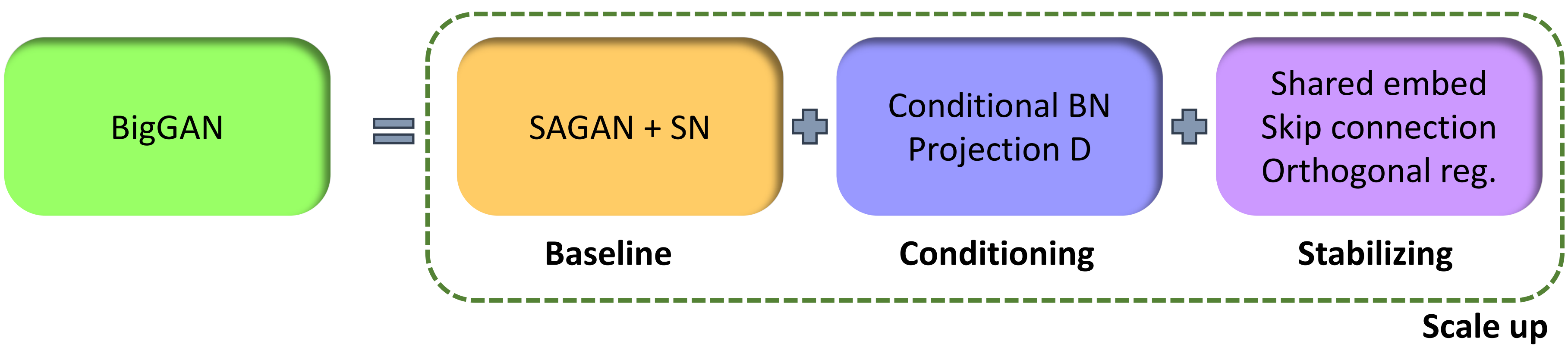
* source : Brock, et. al., Large Scale GAN Training for High Fidelity Natural Image Synthesis, ICLR 2019

BigGAN: High-resolution, Diverse Image Generation [Brock et al., 2019]

- **A holistic approach of previous GAN techniques**
  1. Based on SAGAN [Zhang et al., 2019] + Spectral normalization [Miyato et al., 2018]
  2. Class-conditional modeling
     - G: **Class-conditional BatchNorm** [Dumoulin et al., 2017]
     - D: **Projection discriminator** [Miyato et al., 2018]
- **Several further techniques needed to stabilize the large-scale training**
  1. Shared embedding of $\mathbf{y}$ across multiple layers
  2. Skip connection (residual) of the latent variable
  3. Orthogonal regularization

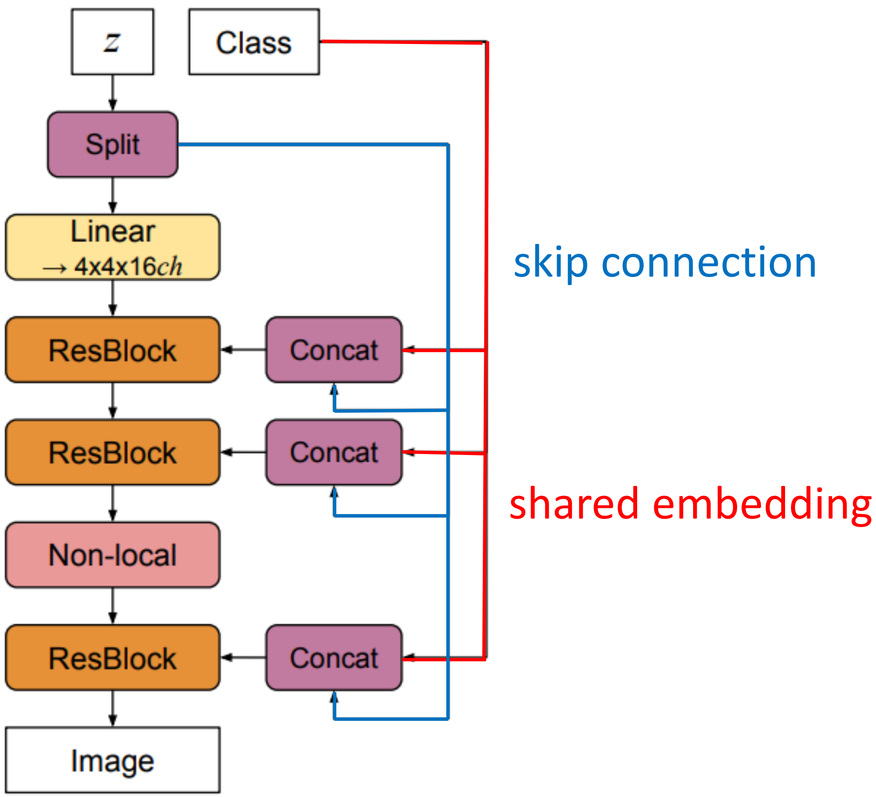
weight matrix

$$R_\beta(W) = \beta \| W^\top W \odot (\mathbf{1} - I) \|_\mathrm{F}^2$$



* source : Brock, et. al., Large Scale GAN Training for High Fidelity Natural Image Synthesis, ICLR 2019

- Shared embedding of class information
  - Instead of having a separate layer at the end for embedding [Miyato et al., 2018]
  - Linearly projected to each layer's gains and biases [Perez et al., 2018]
- Skip connections (skip-z) from z across multiple layers of G
  - Allows z to directly influence the features at different resolutions



The BigGAN architecture

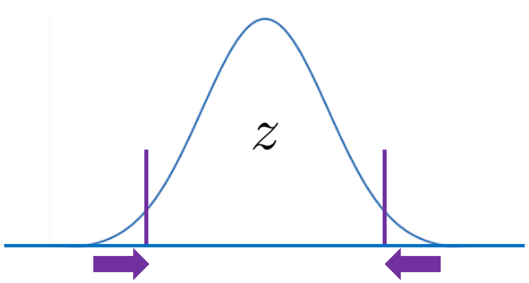
BigGAN: High-resolution, Diverse Image Generation [Brock et al., 2019]

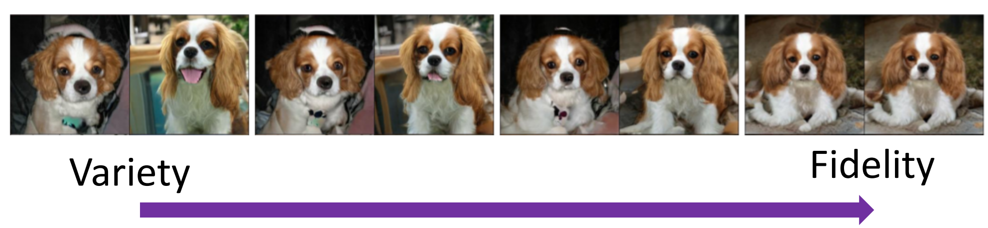
Batch	Ch.	Param (M)	Shared	Skip-z	Ortho.	Itr $\times 10^3$	FID	IS
256	64	81.5	SA-GAN Baseline			1000	18.65	52.52
512	64	81.5	✗	✗	✗	1000	15.30	58.77($\pm$1.18)
1024	64	81.5	✗	✗	✗	1000	14.88	63.03($\pm$1.42)
2048	64	81.5	✗	✗	✗	732	12.39	76.85($\pm$3.83)
2048	96	173.5	✗	✗	✗	295($\pm$18)	9.54($\pm$0.62)	92.98($\pm$4.27)
2048	96	160.6	✓	✗	✗	185($\pm$11)	9.18($\pm$0.13)	94.94($\pm$1.32)
2048	96	158.3	✓	✓	✗	152($\pm$7)	8.73($\pm$0.45)	98.76($\pm$2.84)
2048	96	158.3	✓	✓	✓	165($\pm$13)	8.51($\pm$0.32)	99.31($\pm$2.10)
2048	64	71.3	✓	✓	✓	371($\pm$7)	10.48($\pm$0.10)	86.90($\pm$0.61)

Scale up

Stabilize

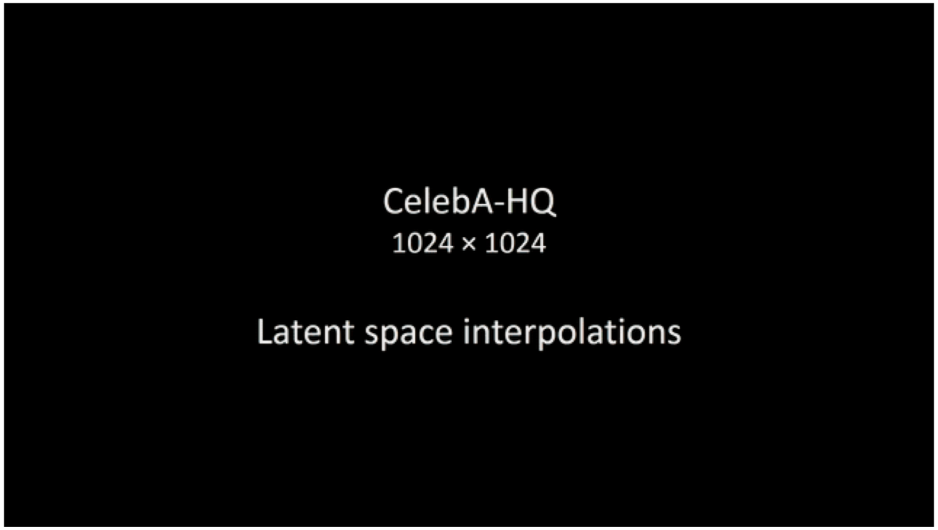
- Increasing the **batch size by 8x** improves the state-of-the-art IS by 46%
- Increasing the **width (# channels) by 1.5x** leads to a further improvement
- **Truncation trick** could further fine-control FID
    - Trade-off between variety vs. fidelity
    - Simply truncate the variance of the latent variable





* source : Brock, et. al., Large Scale GAN Training for High Fidelity Natural Image Synthesis, ICLR 2019

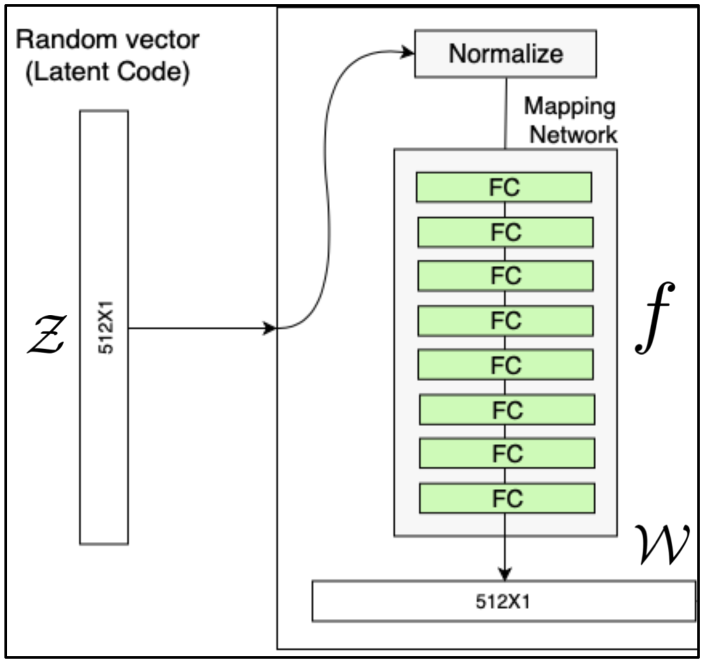
- Interpolation on the latent space of GAN yields smooth, but non-linear changes
  - Features not in both end-points appear along the interpolation path

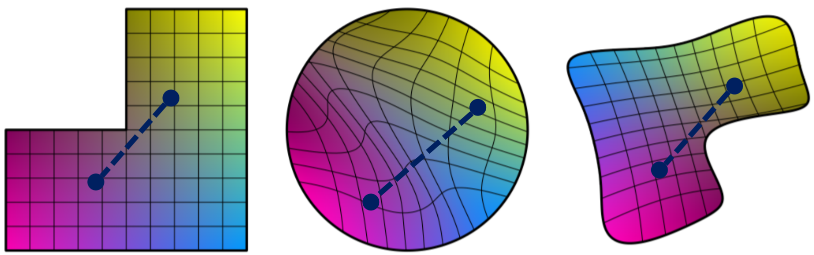


Latent space interpolations with Progressive GAN

- The input latent space must follow the probability density of the training data, and this leads to some degree of unavoidable entanglement
- Karras et al. (2019): Intermediate latent space representing a “style”
  - Significantly relaxes the restriction, and allowed to be disentangled

- StyleGAN proposes to use a **non-linear mapping network** $f : \mathcal{Z} \rightarrow \mathcal{W}$
  - Implemented using an 8-layer fully-connected neural network





(a) Distribution of features in training set (b) Mapping from $\mathcal{Z}$ to features (c) Mapping from $\mathcal{W}$ to features

Illustration of disentanglement

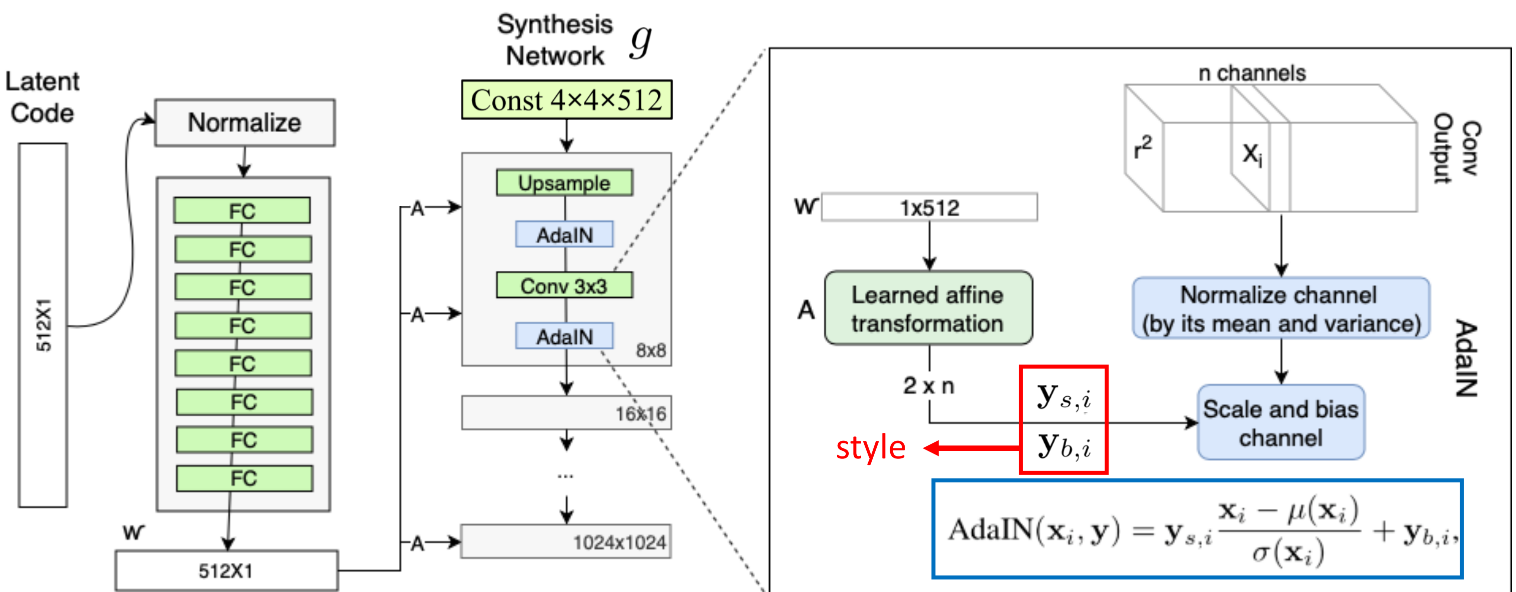
- Direct mapping from $\mathcal{Z}$ to meaningful features might be too complex
- Mapping from $\mathcal{W}$ to the features, on the other hand, can be more simpler

* source : Rani Horev's blog

- **Adaptive instance normalization** (AdaIN)
  - Motivated by the instance normalization [Huang et al., 2017]

$$\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i}\frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$$

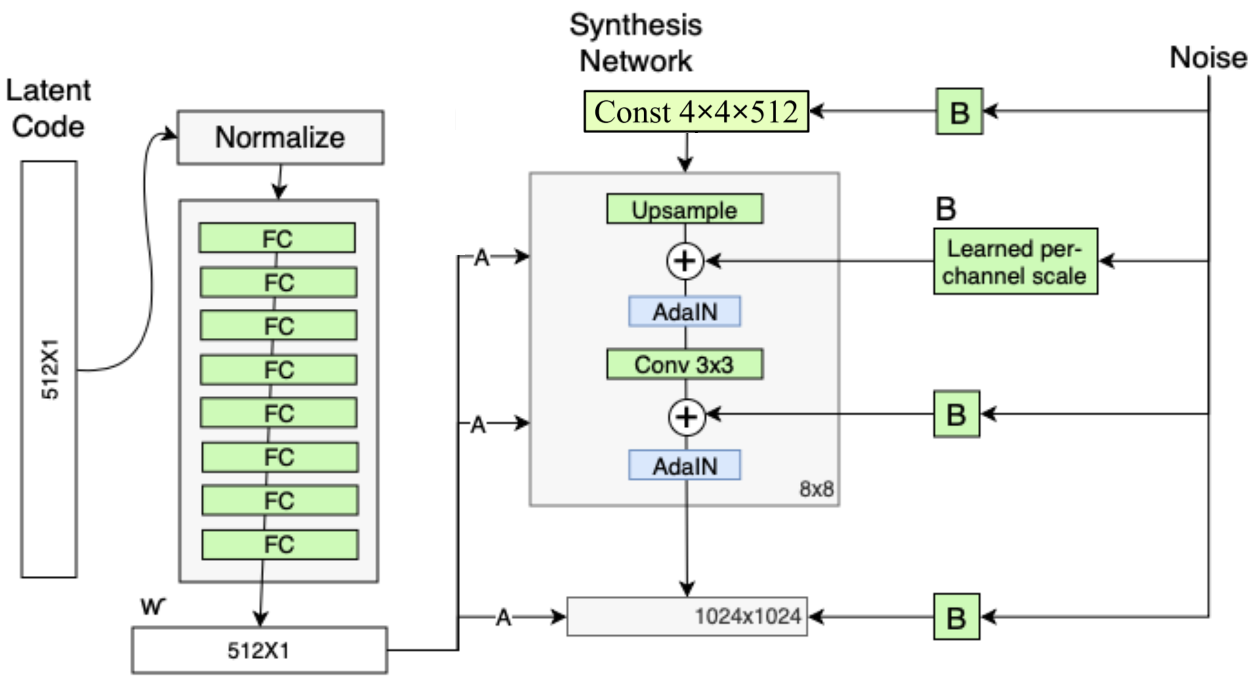
- $\mathbf{y} = (\mathbf{y_s}, \mathbf{y_b})$ **is called by a "style"**
  - A learned affine-transformation of $w \in \mathcal{W}$
  - Controls high-level attributes (e.g., pose, identity of face images)
- Applied after all the convolutional layer in the **synthesis network** g



* source : Rani Horev's blog

- **Explicit noise inputs for stochastic variation**
  - Single-channel images of Gaussian noise
  - Aims to control the stochastic details, e.g., freckles, hair of face images
- A noise channel n is fed to every layer of the synthesis network g
  - Broadcasted across features with learned per-feature scaling factors B

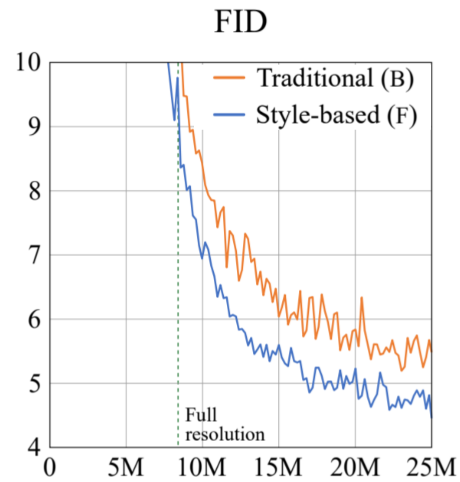
$$s(x_i, n) = x_i + B_i \cdot n$$



* source : Rani Horev's blog

- StyleGAN improves state-of-the-art in terms of FID

	Method	CelebA-HQ	FFHQ
A	Baseline Progressive GAN [30]	7.79	8.04
B	+ Tuning (incl. bilinear up/down)	6.11	5.25
C	+ Add mapping and styles	5.34	4.85
D	+ Remove traditional input	5.07	4.88
E	+ Add noise inputs	**5.06**	4.42
F	+ Mixing regularization	5.17	**4.40**



- Better interpolation properties, and disentangles the latent factors of variation

- Karras et al. (2020a): Some buggy-artifacts in StyleGAN samples
  - **Blob-shaped artifacts** found in most of StyleGAN images (and hidden features)

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.

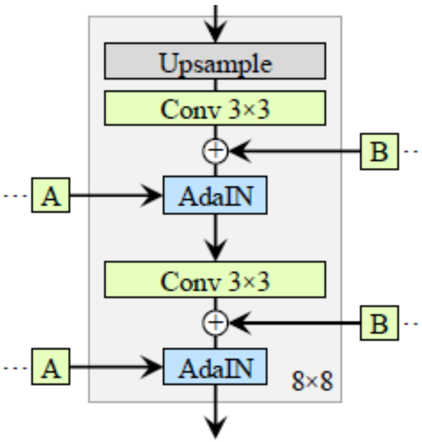
- **StyleGAN2** includes several design modifications to address this issue

Configuration	FFHQ, 1024×1024				LSUN Car, 512×384			
	FID ↓	Path length ↓	Precision ↑	Recall ↑	FID ↓	Path length ↓	Precision ↑	Recall ↑
A Baseline StyleGAN [24]	4.40	212.1	**0.721**	0.399	3.27	1484.5	**0.701**	0.435
B + Weight demodulation	4.39	175.4	0.702	0.425	3.04	862.4	0.685	0.488
C + Lazy regularization	4.38	158.0	0.719	0.427	2.83	981.6	0.688	0.493
D + Path length regularization	4.34	**122.5**	0.715	0.418	3.43	651.2	0.697	0.452
E + No growing, new G & D arch.	3.31	124.5	0.705	0.449	3.19	471.2	0.690	0.454
F + Large networks (StyleGAN2)	**2.84**	145.0	0.689	**0.492**	**2.32**	**415.5**	0.678	**0.514**
Config A with large networks	3.98	199.2	0.716	0.422	–	–	–	–

- **Blob-shaped artifacts** found in most of StyleGAN images (and hidden features)
    1. The anomaly starts to appear around 64×64 resolution
    2. It becomes progressively stronger at higher resolutions

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.

- If so, why the discriminator could not detect those artifacts?
- Karras et al. (2020a): **AdaIN operation** can be problematic
    - AdaIN normalizes each feature map separately
    - This can destroy any magnitude information in the features relative to each other
- **Hypothesis**: they “sneak” some information past AdaIN

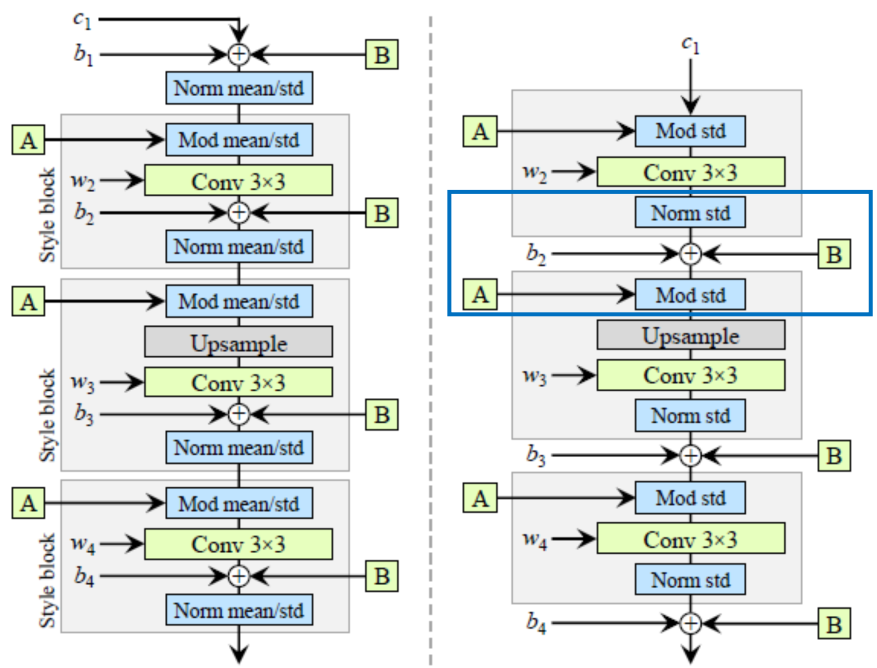


(a) StyleGAN

- Karras et al. (2020a): **AdaIN operation** can be problematic
  - AdaIN normalizes each feature map separately
  - This can destroy any magnitude information in the features relative to each other
- **Hypothesis**: they "sneak" some information past AdaIN
  - **Observation**: the artifacts disappear when the normalization step is removed

- **Generator architecture revisited ⇒ No artifacts anymore!**

1. **Bias outside the style block**
   - StyleGAN applies bias & noise "within" the style block
     - Inversely proportional impact to the current magnitude
   - This design is more predictable
2. **No norm/mod for means**
   - It was possible after (1) is made
   - Much simplifies the design



(b) StyleGAN (detailed)

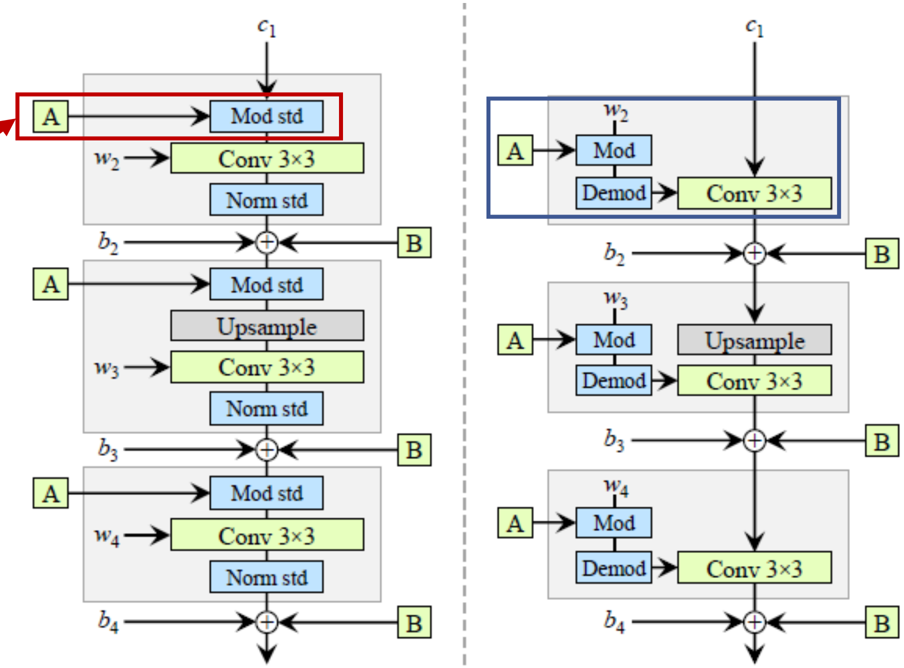
(c) Revised architecture

- Karras et al. (2020a): **AdaIN operation** can be problematic
  - AdaIN normalizes each feature map separately
  - This can destroy any magnitude information in the features relative to each other
- **Hypothesis**: they "sneak" some information past AdaIN
  - **Observation**: the artifacts disappear when the normalization step is removed
- **Generator architecture revisited ⇒ No artifacts anymore!**

3. **Weight de-modulation**
   - A "weaker notion" of AdaIN
   - AdaIN is originally for removing the effect of input modulation
   - StyleGAN2 instead implement these "Mod + AdaIN" by weight re-scaling

$$w'_{ijk} = s_i \cdot w_{ijk},$$

$$w''_{ijk} = w'_{ijk} \Big/ \sqrt{\sum_{i,k} {w'_{ijk}}^2 + \epsilon},$$

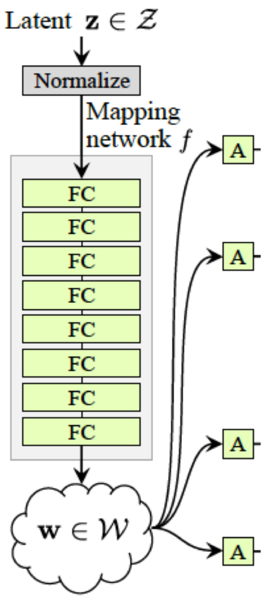


(c) Revised architecture (d) Weight demodulation

- **Path length regularization**
  - Recall the mapping network $f : \mathcal{Z} \to \mathcal{W}$
  - **Prior**: a fixed step in $\mathcal{W}$ results in a fixed-sized change in $g(w)$

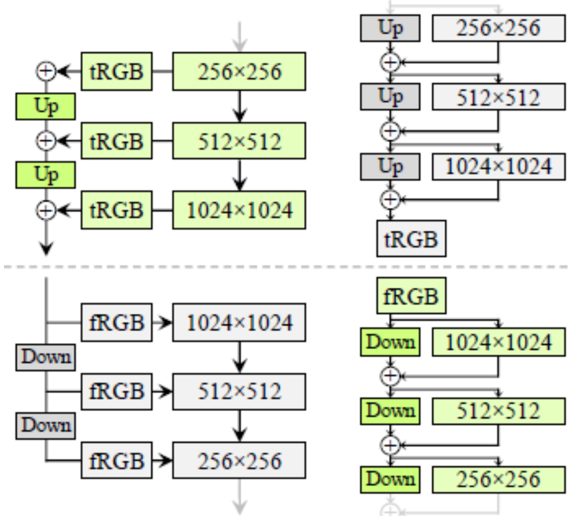
$$\mathbb{E}_{\mathbf{w},\mathbf{y}\sim\mathcal{N}(0,\mathbf{I})}\left(\left\|\mathbf{J}_{\mathbf{w}}^{T}\mathbf{y}\right\|_{2} - a\right)^{2}$$

    - $\mathbf{w} \sim f(\mathbf{z})$; $\mathbf{y}$: random image
    - $\mathbf{J}_{\mathbf{w}} = \partial g(\mathbf{w})/\partial \mathbf{w}$: The Jacobian matrix



- **Improved architectural design**
  - StyleGAN follows simple feedforward designs
  - StyleGAN2 considers better architectural choices
    - **Skip connections for G**
    - **Residual network design for D**

FFHQ	D original		D input skips		D residual	
	FID	PPL	FID	PPL	FID	PPL
G original	4.32	265	4.18	235	3.58	269
G output skips	4.33	169	3.77	127	**3.31**	**125**
G residual	4.35	203	3.96	229	3.79	243



(b) Input/output skips (c) Residual nets

StyleGAN2: Analyzing and Improving the Image Quality of StyleGAN [Karras et al., 2020a]

- StyleGAN2 successfully removes the buggy-artifacts of StyleGAN
  - **Weight de-modulation** significantly improves the recall of generations
  - Simply using **larger StyleGAN** could not be comparable with StyleGAN2

Configuration	FFHQ, 1024×1024				LSUN Car, 512×384			
	FID ↓	Path length ↓	Precision ↑	Recall ↑	FID ↓	Path length ↓	Precision ↑	Recall ↑
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Table of Contents

1. **Generative Models**
    - Why generative model?
    - Two types of generative models

2. **Generative Adversarial Networks (GAN)**
    - Advantages and disadvantages of GAN
    - Conditional GANs

3. **Improved Techniques for GANs**
    - Loss, regularization and normalization
    - GAN architectures
    - Data augmentations for GANs

4. **Summary**

- **Collecting more data** is perhaps the best way to generalize better
- **Data augmentation** (DA) makes artificial data instead of collecting more
  - Requires some knowledge on making “good” artificial data
- Have been especially effective for **discriminative modeling**

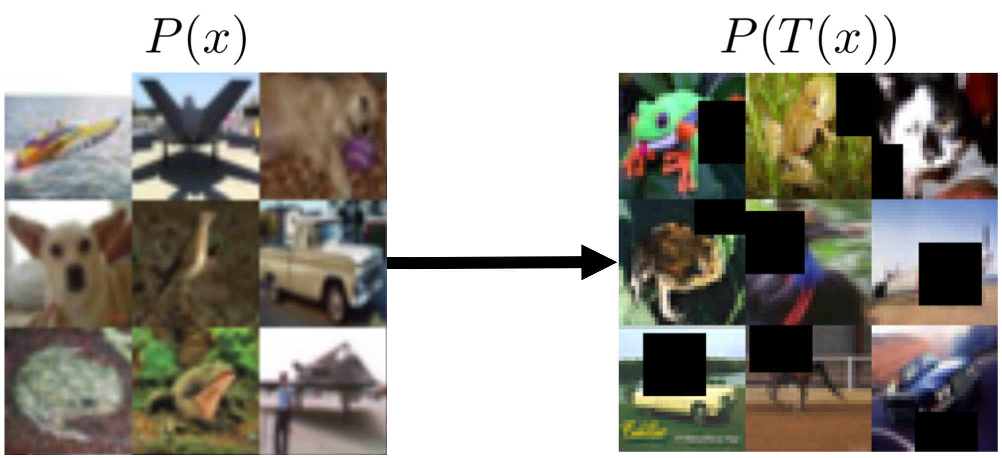
- **Example**: Rigid transformation symmetries
  - Translation, dilation, rotation, mirror symmetry, …
  - Forms an affine group on pixels: $\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \mapsto \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$

Translation **Dilation** **Rotation** **Mirror symmetry**

*source : https://github.com/joanbruna/MathsDL-spring18/blob/master/lectures/lecture2.pdf

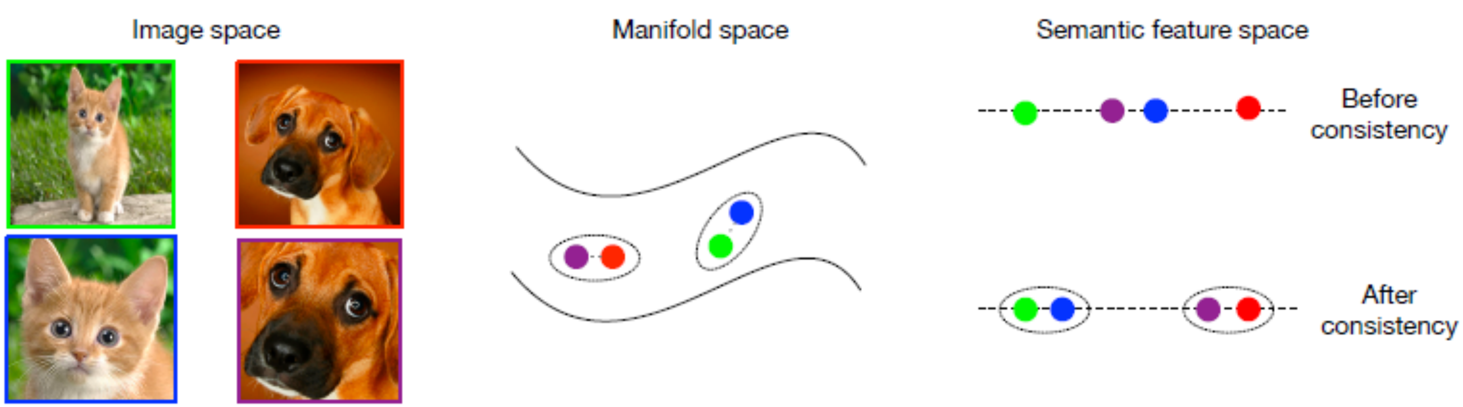
- **Collecting more data** is perhaps the best way to generalize better
- **Data augmentation** (DA) makes artificial data instead of collecting more
  - Requires some knowledge on making “good” artificial data
- Have been especially effective for **discriminative modeling**

- **DA for GANs?** (or for generative modeling in general?)
  - Not much explored until very recently [Zhang et al., 2019]
  - **Why?** Current DA practices for discriminative modeling might by too strong
  - How can we incorporate the distribution shifts $P(x) \to P(T(x))$?



- How can we incorporate the distribution shifts $P(x) \to P(T(x))$?
  - Naïve augmentation of real images would shift the data distribution

- Zhang et al. (2019): Consistency regularization for GANs (CRGAN)
  - **Enforcing only "consistency"** can effectively incorporate $T(x)$



Consistency Regularization for GANs [Zhang et al., 2019]

- **Enforcing consistency** can effectively incorporate $P(x) \rightarrow P(T(x))$
  - Training data is not directly augmented by T, but **only consider** $\boldsymbol{D(x) \approx D\big(T(x)\big)}$
  - D should learn representation that is invariant to T

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

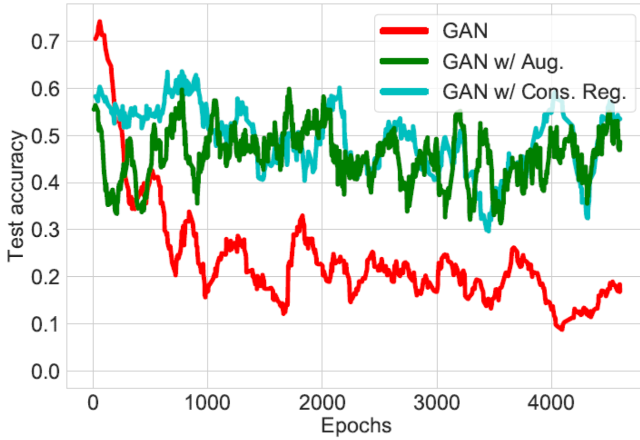
$$L_D^{cr} = L_D + \lambda L_{cr}, \qquad L_G^{cr} = L_G.$$

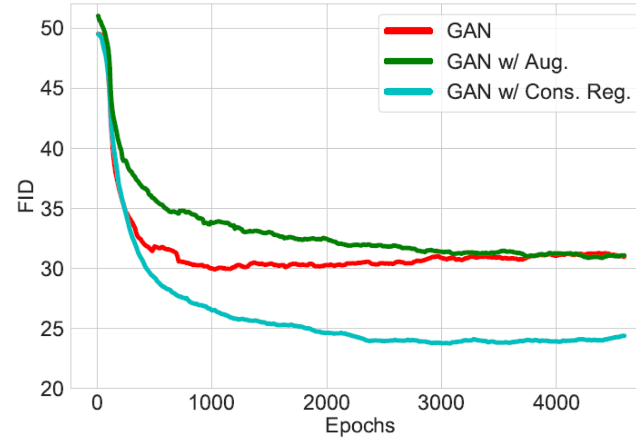
Algorithm 1 Consistency Regularized GAN (CR-GAN). We use $\lambda = 10$ by default.

Input: generator and discriminator parameters θ_G, θ_D, consistency regularization coefficient λ, Adam hyperparameters α, β_1, β_2, batch size M, number of discriminator iterations per generator iteration N_D

```
for number of training iterations do
    for t = 1, ..., N_D do
        for i = 1, ..., M do
            Sample z ~ p(z), x ~ p_data(x)
            Augment x to get T(x)
            L_cr^(i) ← ||D(x) − D(T(x))||^2        Only real images are augmented
            L_D^(i) ← D(G(z)) − D(x)
        end for
        θ_D ← Adam((1/M) Σ_{i=1}^{M} (L_D^(i) + λ L_cr^(i)), α, β1, β2)
    end for
    Sample a batch of latent variables {z^(i)}_{i=1}^{M} ~ p(z)        G is trained in the standard way
    θ_G ← Adam((1/M) Σ_{i=1}^{M} (−D(G(z))), α, β1, β2)
end for
```

- **Does CR really learn differently than simple augmentation?**





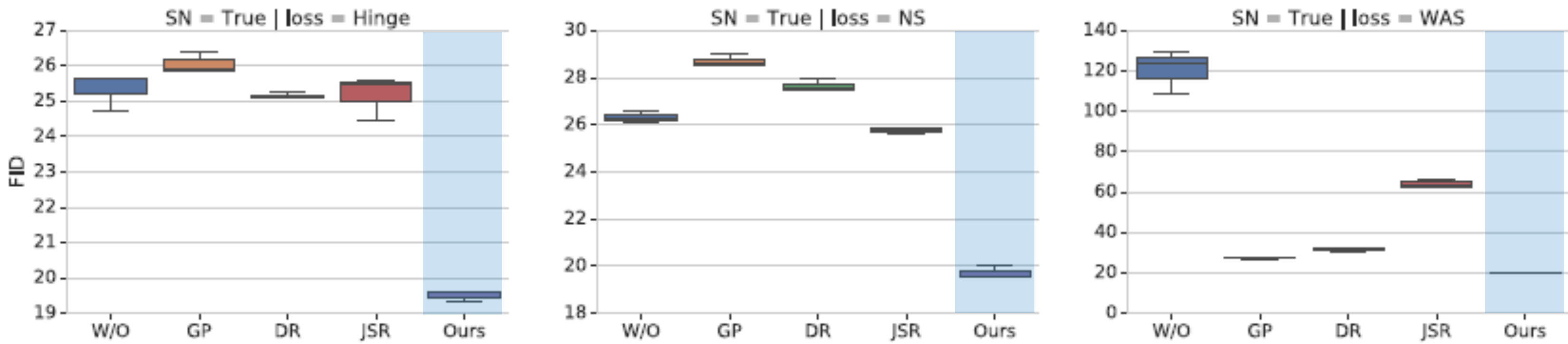
  - Both CR and Aug. prevent overfitting of the discriminator
  - However, CR is the one that could only meaningfully improve FIDs

- **Which augmentations should we use?**
  - The choice of augmentation does matter in GAN training
  - For CR, a simple choice of "Random shift & flip" worked best

Metric	Gaussian Noise	Random shift & flip	Cutout	Cutout w/ random shift & flip
FID	21.91±0.32	16.04±0.17	17.10±0.29	19.46±0.26

Table 3: FID scores on CIFAR-10 for different types of image augmentation. Gaussian noise is the worst, and random shift and flip is the best, consistent with general consensus on the best way to perform image optimization on CIFAR-10 (Zagoruyko & Komodakis, 2016).

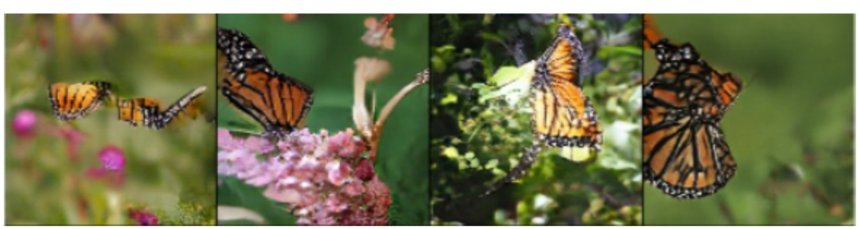
- **CR surprisingly stabilizes GAN training on various existing practices**



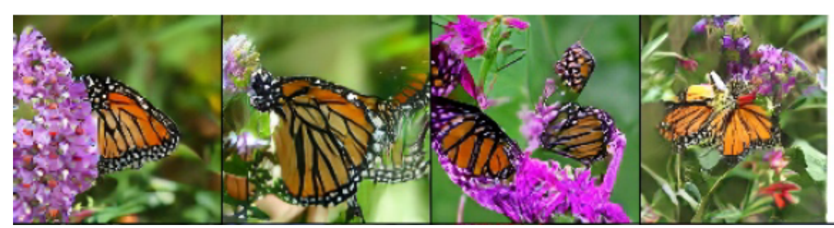
- **CR further improves state-of-the-art BigGAN training**

Dataset	SNGAN	SAGAN	BigGAN	BigGAN*	CR-BigGAN*
CIFAR-10	17.5	/	14.73	20.42	**11.48**
ImageNet	27.62	18.65	8.73	7.75	**6.66**

Comparison of FIDs (lower is better)

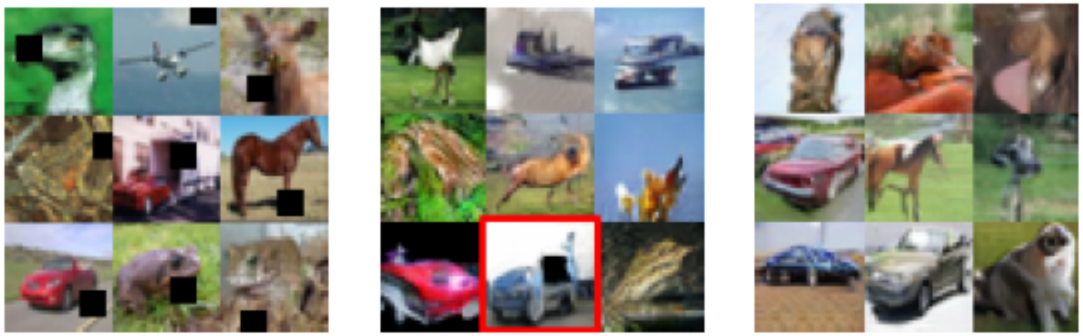


BigGAN



CR-BigGAN

- **Recall**: How can we incorporate the distribution shifts $P(x) \to P(T(x))$?
- **Then would it be just enough with CR for GANs?**
  - Still, CR does not perfectly prevent the shifting issue in GAN
  - For certain augmentations, e.g., CutOut, CR often make "leakages"



(a) 8×8 cutout. (b) CR samples. (c) bCR samples.

- Zhao et al. (2020): Balanced Consistency regularization (bCR)
  - bCR alleviates such leakages by also giving consistency to "fake" images

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

“Improved” Consistency Regularization for GANs [Zhao et al., 2020a]

- Zhao et al. (2020): Balanced Consistency regularization (bCR)
  - bCR alleviates such leakages by also giving consistency to “fake” images

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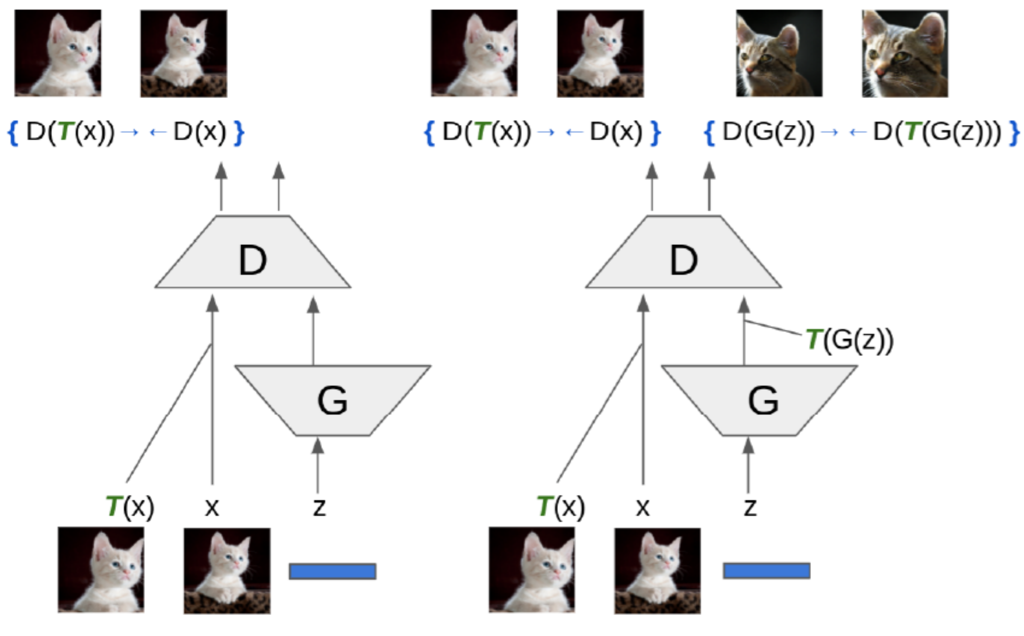


(1) CR-GAN (2) bCR-GAN

Algorithm 1 Balanced Consistency Regularization (bCR)

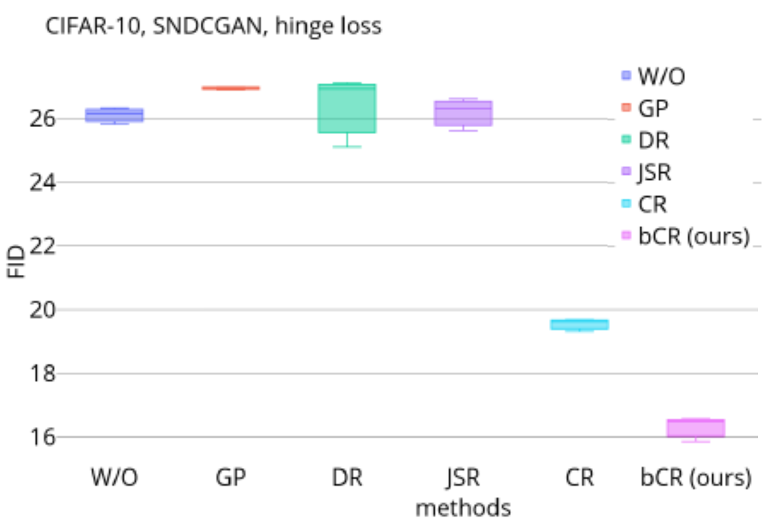
Input: parameters of generator θ_G and discriminator θ_D, consistency regularization coefficient for real images λ_{real} and fake images λ_{fake}, number of discriminator iterations per generator iteration N_D, augmentation transform T (for images, e.g. shift, flip, cutout, etc).

for number of training iterations **do**
  for $t = 1$ **to** N_D **do**
    Sample batch $z \sim p(z)$, $x \sim p_{\text{real}}(x)$
    Augment both real $T(x)$ and fake $T(G(z))$ images
    $L_D \leftarrow D(G(z)) - D(x)$
    $L_{\text{real}} \leftarrow \|D(x) - D(T(x))\|^2$
    $L_{\text{fake}} \leftarrow \|D(G(z)) - D(T(G(z)))\|^2$
    $\theta_D \leftarrow \text{AdamOptimizer}(L_D + \lambda_{\text{real}} L_{\text{real}} + \lambda_{\text{fake}} L_{\text{fake}})$
  end for
  Sample batch $z \sim p(z)$
  $L_G \leftarrow -D(G(z))$
  $\theta_G \leftarrow \text{AdamOptimizer}(L_G)$
end for

G is still trained in the standard way

- Zhao et al. (2020): Balanced Consistency regularization (bCR)
- Despite its simplicity, bCR could achieve state-of-the-art BigGAN training

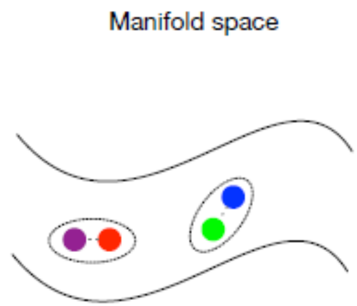
(a) Monarch Butterfly (our ICR vs baseline CR)



Models	CIFAR-10	ImageNet
SNGAN	17.50	27.62
BigGAN	14.73	8.73
CR-BigGAN	11.48	6.66
ICR-BigGAN (ours)	**9.21**	**5.38**

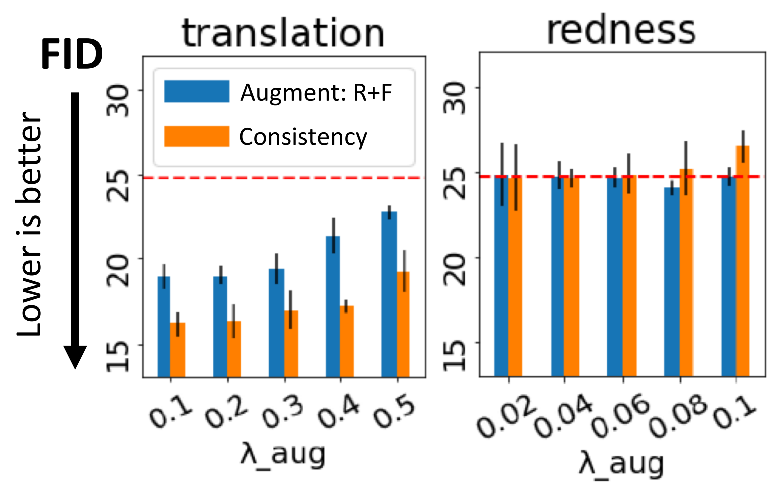
- **Is CR really necessary for GANs to incorporate data augmentations?**

- **Limitation of CR:** Fundamentally hard to incorporate stronger augmentations
- **Example**: Color jittering
  - The “redness” is not helpful to improve FID with CR
  - Forcing CR for such a stronger augmentation might be too restrictive for D representation



- How can we incorporate stronger augmentations for GANs?

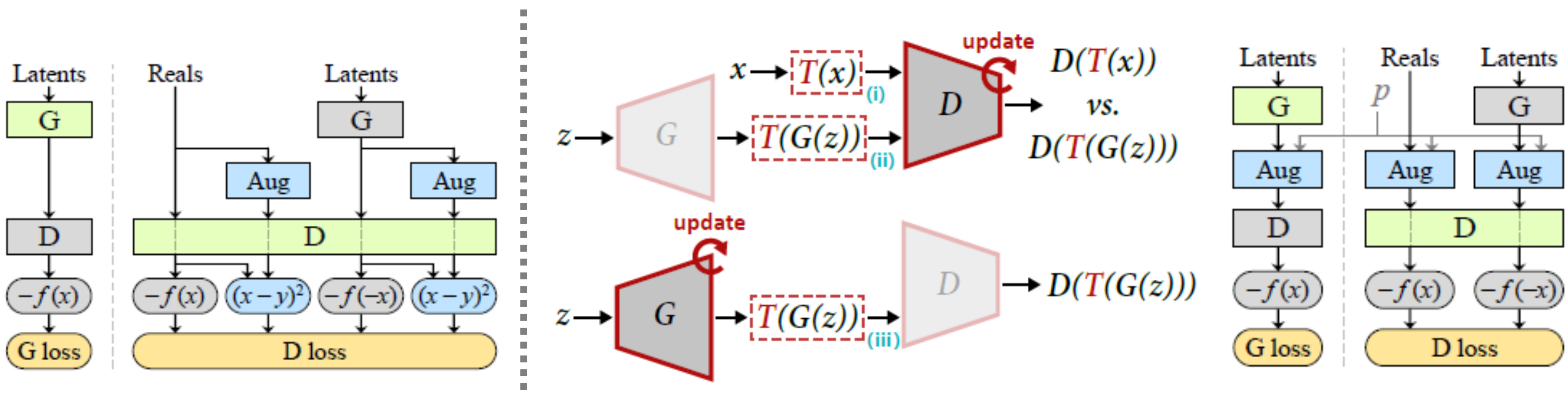
Original Image Translation Redness



* source: [ZhaoZ et al., 2020b] Image Augmentations for GAN Training, 2020.

- Is CR really necessary for GANs to incorporate data augmentations?
- **How can we incorporate stronger augmentations for GANs?**

- Two concurrent works propose a "even simpler" scheme for GANs
  - [Zhao et al., 2020b] "Differentiable Augmentation for Data-Efficient GAN Training"
  - [Karras et al., 2020b] "Training Generative Adversarial Networks with Limited Data"



Balanced CR (bCR) **DiffAug** **ADA**

- Is CR really necessary for GANs to incorporate data augmentations?
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- Two concurrent works propose a “even simpler” scheme for GANs
    - [Zhao et al., 2020b] “Differentiable Augmentation for Data-Efficient GAN Training”
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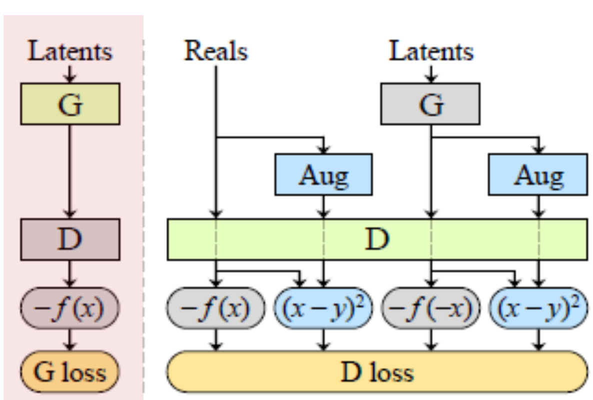
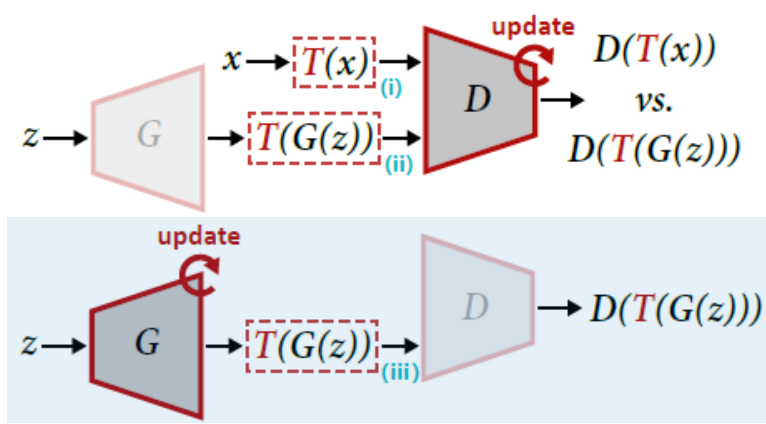
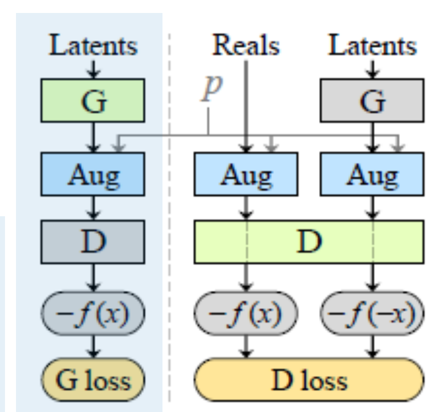
- **Idea**: Simply augment every input before D, even when G is trained
    - No CR needed anymore, and accept stronger augmentations without leakages



Balanced CR (bCR)



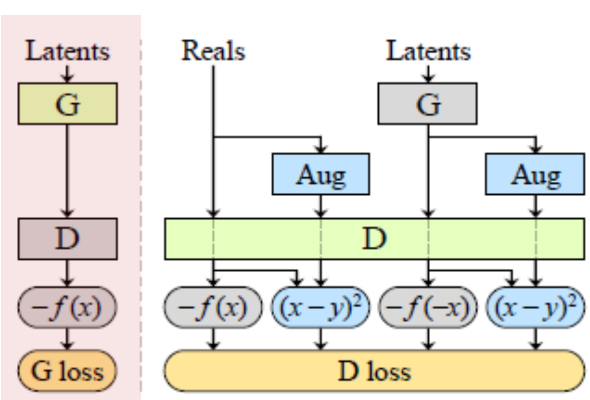
DiffAug



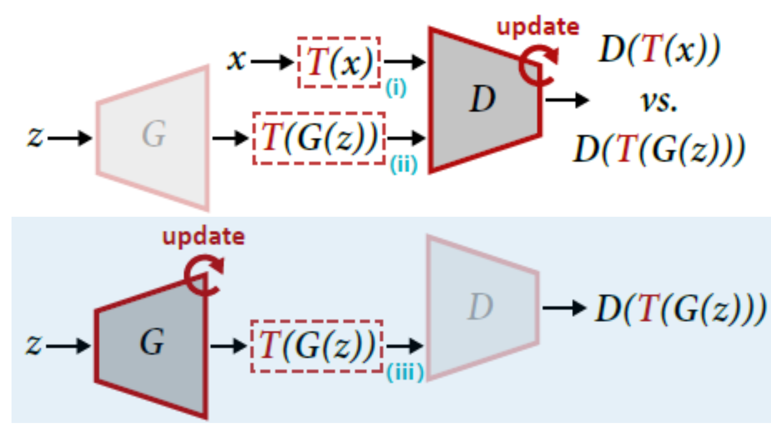
ADA

- Two concurrent works propose a “even simpler” scheme for GANs
- **Idea**: Simply augment every input before D, even when G is trained

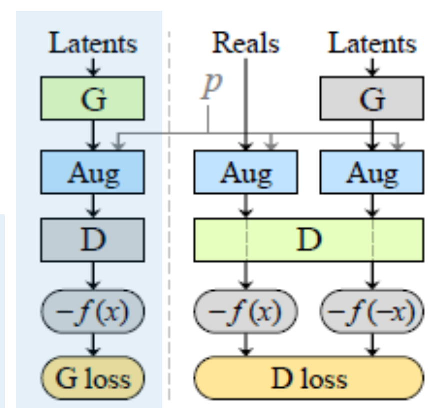
- Then, how could this approach have not been explored so far?
  - This requires a differentiable implementation of $T(\cdot)$ for training G
    - **Example**: Non-saturating loss should minimize $\mathbb{E}_z[-\log(D(T(\boldsymbol{G}(z)))]$
  - Nevertheless, most of the previous implementations of T were non-differentiable
    - … as they were rather considered as pre-processing steps
  - In this respect, the “differentiability” of T is becoming increasingly important



Balanced CR (bCR)



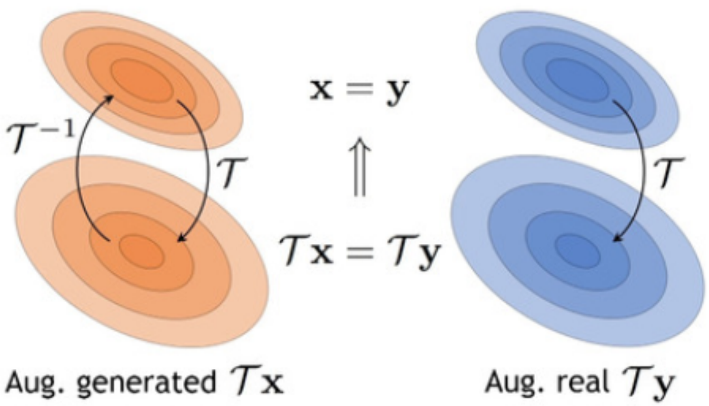
DiffAug



ADA

- **Adaptive Discriminator Augmentation (ADA)** [Karras et al., 2020b]

- Which augmentation should we use?
  - **Key point**: There should be no leakage of augmentations
- **Example**: Random 90° rotations as $\mathcal{T}$
  - Assume $\mathbf{x}$: generated distribution and $\mathbf{y}$: target distribution
  - **Q**: ADA matches $\mathcal{T}\mathbf{x} = \mathcal{T}\mathbf{y}$: then, does it always imply $\mathbf{x} = \mathbf{y}$?
  - **A**: No, imagine when $\mathbf{x}$ goes like "E" below → augmentation leakage



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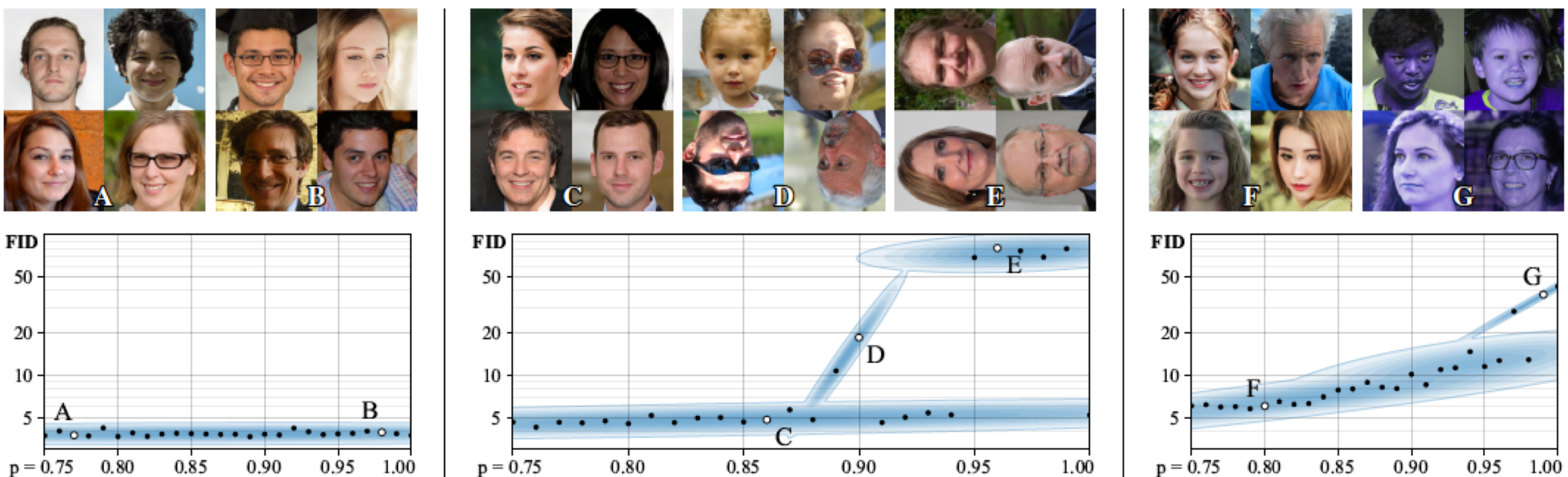
- **Idea**: The leakage of any $\mathcal{T}$ can be controlled by setting $p \in [0, 1]$

The prob. of executing $\mathcal{T}$



(a) Isotropic image scaling (b) Random 90° rotations (c) Color transformations

- **Adaptive Discriminator Augmentation (ADA)** [Karras et al., 2020b]

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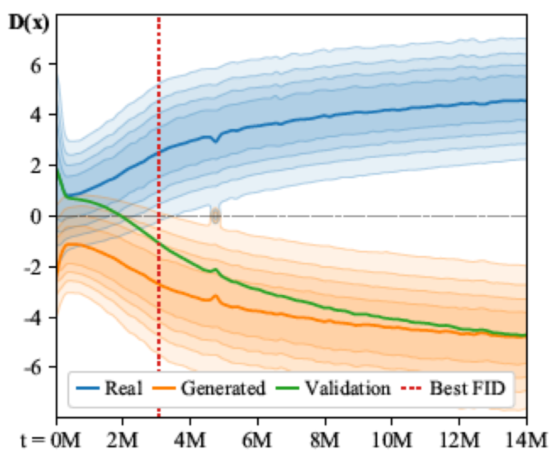
The prob. of executing $\mathcal{T}$

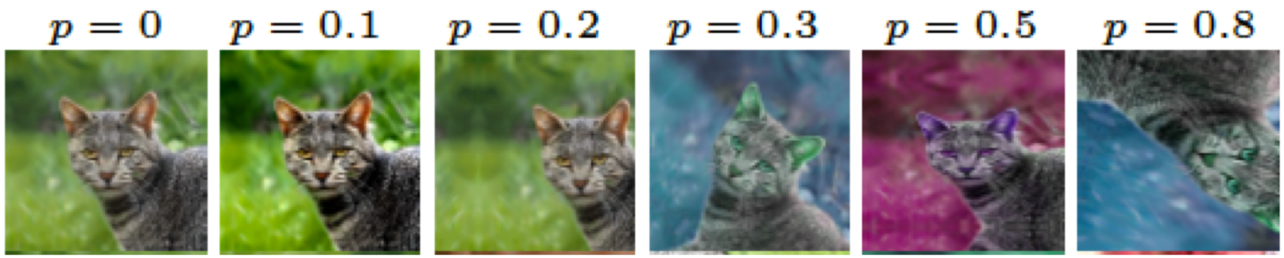
- ADA also proposes a heuristic to adaptively set p in training by observing r_v

$$r_v = \frac{\mathbb{E}[D_{\text{train}}] - \mathbb{E}[D_{\text{validation}}]}{\mathbb{E}[D_{\text{train}}] - \mathbb{E}[D_{\text{generated}}]}$$

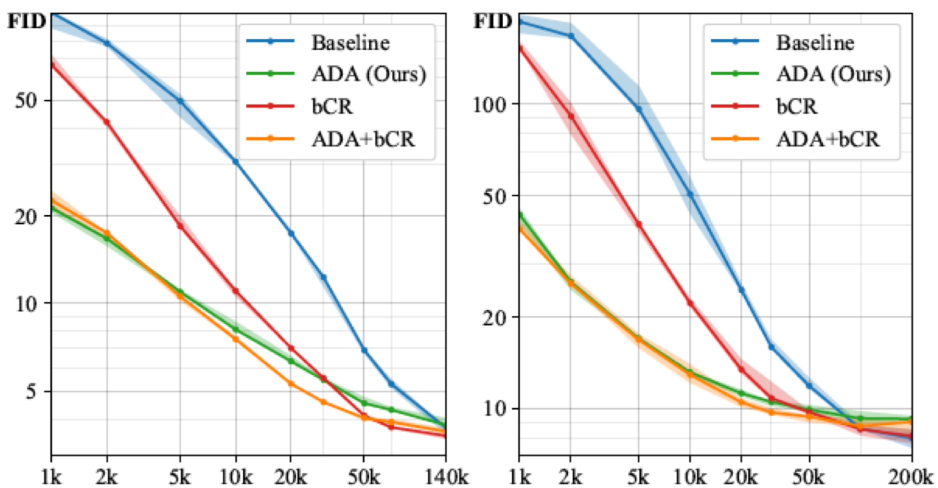
  - $r_v = 0$: No overfitting / $r_v = 1$: Complete overfitting
  - p of the augmentation is initially set to 0
  - Increase/decrease p when r_v is low/high, resp.



- **Adaptive Discriminator Augmentation (ADA)** [Karras et al., 2020b]
- ADA successfully incorporate wider augmentations than bCR



- ADA works significantly better than bCR when # sample is small



(a) FFHQ (256 × 256) (b) LSUN CAT (256 × 256)

Dataset		Baseline	ADA	+ bCR
FFHQ	1k	100.16	**21.29**	22.61
	5k	49.68	10.96	**10.58**
	10k	30.74	8.13	**7.53**
	30k	12.31	5.46	**4.57**
	70k	5.28	4.30	**3.91**
	140k	3.71	3.81	**3.62**
LSUN CAT	1k	186.91	43.25	**38.82**
	5k	96.44	16.95	**16.80**
	10k	50.66	13.13	**12.90**
	30k	15.90	10.50	**9.68**
	100k	**8.56**	9.26	8.73
	200k	**7.98**	9.22	9.03

(c) Median FID

- **Adaptive Discriminator Augmentation (ADA)** [Karras et al., 2020b]
- ADA significantly improves GAN training especially on limited-sized datasets

Dataset	Method	Scratch FID	Scratch KID $\times 10^3$	Transfer KID $\times 10^3$	+ Freeze-D KID $\times 10^3$
MetFaces	Baseline	57.26	35.66	3.16	2.05
	ADA	**18.22**	**2.41**	**0.81**	**1.33**
BreCaHAD	Baseline	97.72	89.76	18.07	6.94
	ADA	**15.71**	**2.88**	**3.36**	**1.91**
AFHQ Cat	Baseline	5.13	1.54	1.09	1.00
	ADA	**3.55**	**0.66**	**0.44**	**0.35**
AFHQ Dog	Baseline	19.37	9.62	4.63	2.80
	ADA	**7.40**	**1.16**	**1.40**	**1.12**
AFHQ Wild	Baseline	3.48	0.77	0.31	**0.12**
	ADA	**3.05**	**0.45**	**0.15**	0.14

(a) Small datasets

Method	Unconditional FID ↓	Unconditional IS ↑	Conditional FID ↓	Conditional IS ↑
ProGAN [19]	15.52	8.56 ±0.06	–	–
AutoGAN [13]	12.42	8.55 ±0.10	–	–
BigGAN [5]	–	–	14.73	9.22
+ Tuning [22]	–	–	8.47	9.07 ±0.13
MultiHinge [22]	–	–	6.40	9.58 ±0.09
FQ-GAN [52]	–	–	5.59 ±0.12	8.48
Baseline	8.32 ±0.09	9.21 ±0.09	6.96 ±0.41	9.53 ±0.06
+ ADA (Ours)	5.33 ±0.35	**10.02** ±0.07	3.49 ±0.17	**10.24** ±0.07
+ Tuning (Ours)	**2.92** ±0.05	9.83 ±0.04	**2.42** ±0.04	10.14 ±0.09

(b) CIFAR-10

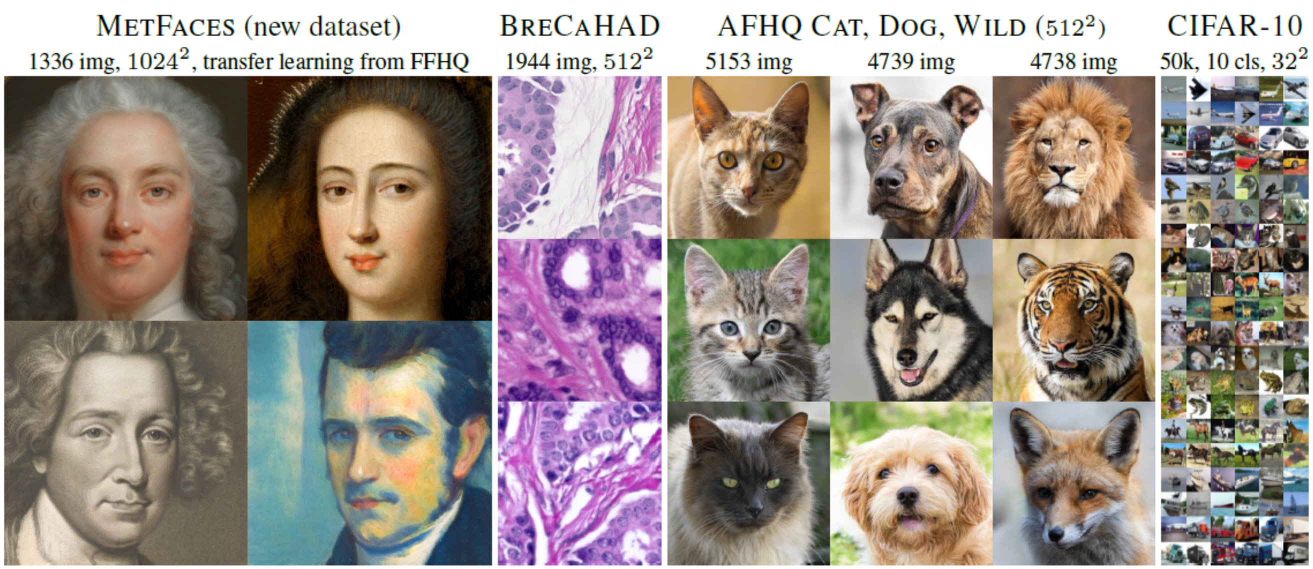


Table of Contents

1. **Generative Models**
    - Why generative model?
    - Two types of generative models

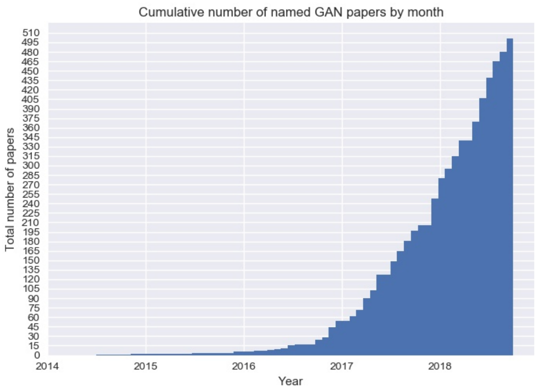
2. **Generative Adversarial Networks (GAN)**
    - Advantages and disadvantages of GAN
    - Conditional GANs

3. **Improved Techniques for GANs**
    - Loss, regularization and normalization
    - GAN architectures
    - Data augmentations for GANs

4. **Summary**

Summary

- **GAN has been one of the prominent topic in deep learning since 2014**
- Thousands of papers about GAN:
  - Theoretical aspects of GANs
  - Stabilizing GAN training dynamics
  - Applications of GAN to various AI tasks
  - … and many more



- **GANs are especially good at generating "high-precision" samples**
  - Achieving "high-recall", however, is still challenging
  - Lots of improvement in loss, regularization, and architecture have been made
  - Some large-scale studies have revealed sober views on them, nevertheless

- **Recent approaches in GANs are actively revisiting various DA techniques**
  - Consistency regularization [Zhang et al., 2019; Zhao et al., 2020a]
  - Differentiable augmentations [Zhao et al., 2020b; Karras et al., 2020b]

* source : https://github.com/hindupuravinash/the-gan-zoo

References

[Goodfellow, et. al., 2014] Generative adversarial nets, NIPS 2014
link: http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf

[Theis, et. al., 2016] A note on the evaluation of generative models, ICLR 2016
link: http://bethgelab.org/media/publications/1511.01844v1.pdf

[Radford, et. al., 2015] Unsupervised representation learning with deep convolutional generative adversarial networks.
link: https://arxiv.org/pdf/1511.06434.pdf

[Ledig, et. al., 2017] Photo-realistic single image super-resolution using a generative adversarial networks, CVPR 2017
link: http://openaccess.thecvf.com/content_cvpr_2017/papers/Ledig_Photo-Realistic_Single_Image_CVPR_2017_paper.pdf

[Zhu, et. al., 2017] Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks, ICCV 2017
link: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8237506

[Karras, et. al., 2018] Progressive growing of GANs for improved quality, stability, and variation, ICLR 2018
link: https://arxiv.org/abs/1710.10196

[Salimans, et. al., 2016] Improved techniques for training GANS, NIPS 2016
link: https://arxiv.org/abs/1606.03498

[Huszar 2015] How (not) to train your generative model: scheduled sampling, likelihood, adversary?
link: https://arxiv.org/pdf/1511.05101.pdf

[Mirza et al., 2014] Conditional Generative Adversarial Nets
link: https://arxiv.org/pdf/1411.1784.pdf

References

[Odena, et. al., 2017] Conditional Image Synthesis with Auxiliary Classifier GANs, ICML 2017
link: https://arxiv.org/pdf/1610.09585.pdf

[Basart et. al., 2017] Analysis of Generative Adversarial Models
link: https://newtraell.cs.uchicago.edu/files/ms_paper/xksteven.pdf

[Dumoulin, et. al., 2017] A Learned Representation for Artistic Style, ICLR 2017
link: https://arxiv.org/pdf/1610.07629.pdf

[DeVries, et. al., 2017] Modulating early visual processing by language, NIPS 2017
link: https://arxiv.org/pdf/1707.00683.pdf

[Miyato, et. al., 2018] cGANs with Projection Discriminator, ICLR 2018
link: https://arxiv.org/pdf/1802.05637.pdf

[Arjovsky, et. al., 2017] Wasserstein GAN, ICML 2017
link: https://arxiv.org/pdf/1701.07875.pdf

[Arjovsdky and Bottou, 2017] Towards principled methods for training generative adversarial networks, ICLR 2017
link: https://arxiv.org/pdf/1701.04862.pdf

[Villani, 2009] Optimal transport: old and new, Grundlehren der mathematischen wissenschaften 2009
link: http://cedricvillani.org/wp-content/uploads/2012/08/preprint-1.pdf

[Reed, et. al., 2016] Generative adversarial text to image synthesis, ICML 2016
link: https://arxiv.org/pdf/1605.05396.pdf

[Wang, et. al., 2004] Image quality assessment: from error visibility to structural similarity, IEEE transactions on image processing 2004
link: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1284395

References

[Radford, et. al., 2015] Unsupervised representation learning with deep convolutional generative adversarial networks, 2015
link: https://arxiv.org/pdf/1511.06434.pdf

[Gulrajani, et. al., 2017] Improved training of Wasserstein GANs, NIPS 2017
link: https://arxiv.org/pdf/1704.00028.pdf

[Miyato, et. al., 2018] Spectral normalization for generative adversarial networks, ICLR 2018

link: https://arxiv.org/pdf/1802.05957.pdf

[Zhang, et. al., 2019] Self-Attention Generative Adversarial Networks, ICML 2019
link: https://arxiv.org/pdf/1805.08318.pdf

[Wang, et. al., 2018] Non-local neural networks, CVPR 2018
link: https://arxiv.org/pdf/1711.07971.pdf

[Brock, et. al., 2019] Large Scale GAN Training for High Fidelity Natural Image Synthesis, ICLR 2019
link: https://arxiv.org/pdf/1809.11096.pdf

[Perez, et. al., 2019] FiLM: Visual Reasoning with a General Conditioning Layer, AAAI 2018
link: https://arxiv.org/pdf/1709.07871.pdf

[Karras, et. al., 2019] Large Scale GAN Training for High Fidelity Natural Image Synthesis, CVPR 2019
link: https://arxiv.org/pdf/1809.11096.pdf

[Huang, et. al., 2017] Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization, ICCV 2017
link: https://arxiv.org/pdf/1703.06868.pdf

References

[Lucic et al., 2018] Are GANs Created Equal? A Large-Scale Study, NIPS 2018
link: https://arxiv.org/abs/1711.10337

[Kurach et al., 2019] A Large-Scale Study on Regularization and Normalization in GANs, ICML 2019
link: http://proceedings.mlr.press/v97/kurach19a.html

[Kodali et al., 2017] On Convergence and Stability of GANs, 2018
link: https://arxiv.org/abs/1705.07215v5

[Ba et al., 2016] Layer Normalizatiton, 2016
link: https://arxiv.org/abs/1607.06450

[Ioffe & Szegedy, 2015] Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, ICML 2015
link: https://arxiv.org/abs/1502.03167

[Mao et al., 2017] Least Squares Generative Adversarial Networks, 2016
link: https://arxiv.org/abs/1611.04076

[Zhang et al., 2019] Consistency Regularization for Generative Adversarial Networks, ICLR 2020
link: https://arxiv.org/abs/1910.12027

[Karras et al., 2020a] Analyzing and Improving the Image Quality of StyleGAN, CVPR 2020
link: https://arxiv.org/abs/1912.04958

[Karras et al., 2020b] Training Generative Adversarial Networks with Limited Data, NeurIPS 2020
link: https://arxiv.org/abs/2006.06676

[Zhao et al., 2020a] Improved Consistency Regularization for GANs, 2020
link: https://arxiv.org/abs/2002.04724

[Zhao et al., 2020b] Differentiable Augmentation for Data-Efficient GAN Training, NeurIPS 2020
link: https://arxiv.org/abs/2006.10738