COMP547

DEEP UNSUPERVISED LEARNING

Lecture #8 – Generative Adversarial Networks

KOÇ UNIVERSITY

Aykut Erdem // Koç University // Spring 2025

Previously on COMP547

- Motivation
- Training Latent Variable Models (including VAE and IWAE)
- Variations
- Related ideas

Image: Synthetic faces sampled from NVAE model by Vahdat and Kautz

Lecture overview

- Motivation
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- GAN Progression
- Conditional GANs, Cycle-Consistent Adversarial Networks
- Applications

Disclaimer: Much of the material and slides for this lecture were borrowed from
—Pieter Abbeel, Peter Chen, Jonathan Ho, Aravind Srinivas' Berkeley CS294-158 class
—Aaron Courville's IFT6135 class
—Bill Freeman, Antonio Torralba and Phillip Isola's MIT 6.869 class

Lecture overview

- **Motivation**
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Motivation: Evolution of GANs

- 5 years of GAN progress

2014

2015

2016

2018

2019

2020

2021

- GAN is most prominent of Implicit Models

I.J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio. **Generative Adversarial Networks**. NIPS 2014.

A. Radford, L. Metz, S. Chintala. **Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks**. ICLR 2016.

M.-Y. Liu, O. Tuzel. Coupled Generative Adversarial Networks. NIPS 2016.

T. Karras, T. Aila, S. Laine, J. Lehtinen. **Progressive Growing of GANs for Improved Quality, Stability, and Variation**. ICLR 2018.

T. Karras, S. Laine, T. Aila. **A style-based generator architecture for generative adversarial networks**. In CVPR 2018.

T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, T. Aila. **Analyzing and Improving the Image Quality of StyleGAN**. CVPR 2020.

T. Karras, M. Aittala, S. Laine, E. Härkönen, J. Hellsten, J. Lehtinen, T. Aila. **Alias-Free Generative Adversarial Networks**. NeurIPS 2021.

Slide adapted from Ian Goodfellow

Motivation: BigGAN

Andrew Brock, Jeff Donahue, Karen Simonyan, **Large Scale GAN Training for High Fidelity Natural Image Synthesis**, ICLR 2019

So far...

- Autoregressive models
  - MADE, PixelRNN/CNN, Gated PixelCNN, PixelSNAIL
- Flow models
  - Autoregressive Flows, NICE, RealNVP, Glow, Flow++
- Latent Variable Models
  - VAE, IWAE, VQ-VAE, VLAE, PixelVAE

- **Common aspect**: Likelihood-based models
  - exact (autoregressive and flows)
  - approximate (VAE)

Generative Models

- Sample
- Evaluate likelihood
- Train
- Representation

→ What if all we care about is sampling?

Building a sampler

- How about this sampler?

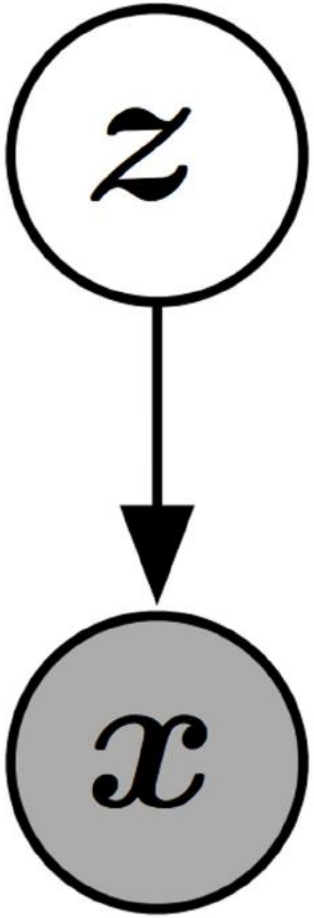
```
import glob, cv2, numpy as np
files = glob.glob(‘*.jpg’)
def _sample():
    idx = np.random.randint(len(files))
    return cv2.imread(files[idx])
def sample(*, n_samples):
    samples = np.array([_sample() for _ in range(n_samples)])
    return samples
```

Building a sampler

- You don't just want to sample the exact data points you have.
- You want to build a generative model that can understand the underlying distribution of data points and
  - smoothly interpolate across the training samples
  - output samples similar but not the same as training data samples
  - output samples representative of the underlying factors of variation in the training distribution.
  - Example: digits with unseen strokes, faces with unseen poses, etc.

Implicit Models

- Sample z from a fixed noise source distribution (uniform or gaussian).
- Pass the noise through a deep neural network to obtain a sample x.
- Sounds familiar? Right:
  - Flow Models
  - VAE
- What's going to be different here?
  - Learning the deep neural network **without** explicit density estimation



Implicit Models

Given samples from data distribution $p_{data} : x_1, x_2, \ldots, x_n$

Given a sampler $q_\phi(z) = \mathrm{DNN}(z; \phi)$ where $z \sim p(z)$

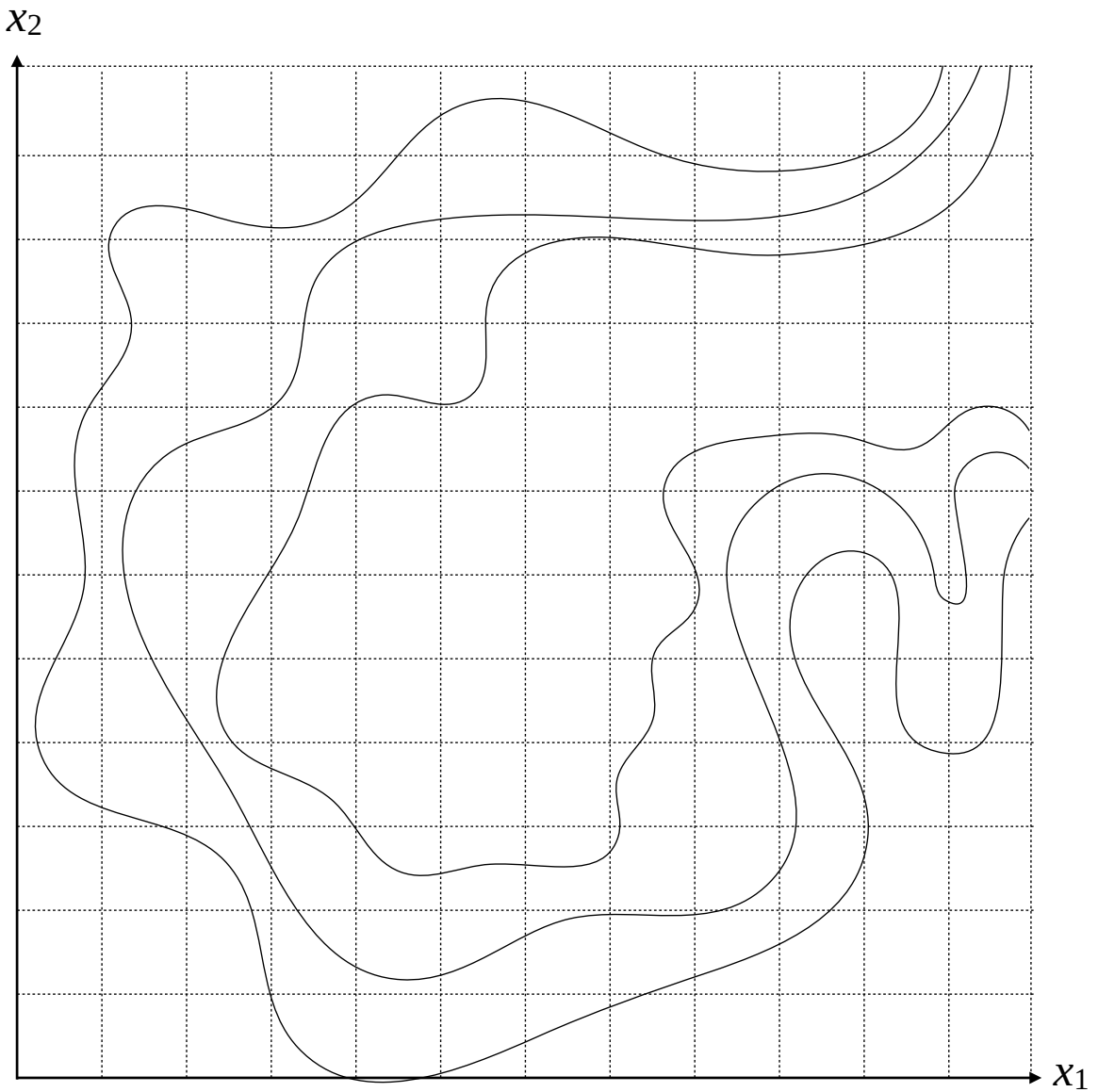
$x = q_\phi(z)$ induces a density function p_{model}

- Do not have an explicit form for p_{data} or p_{model}; can only draw samples
- Make p_{model} as close to p_{data} as possible by learning an appropriate ϕ

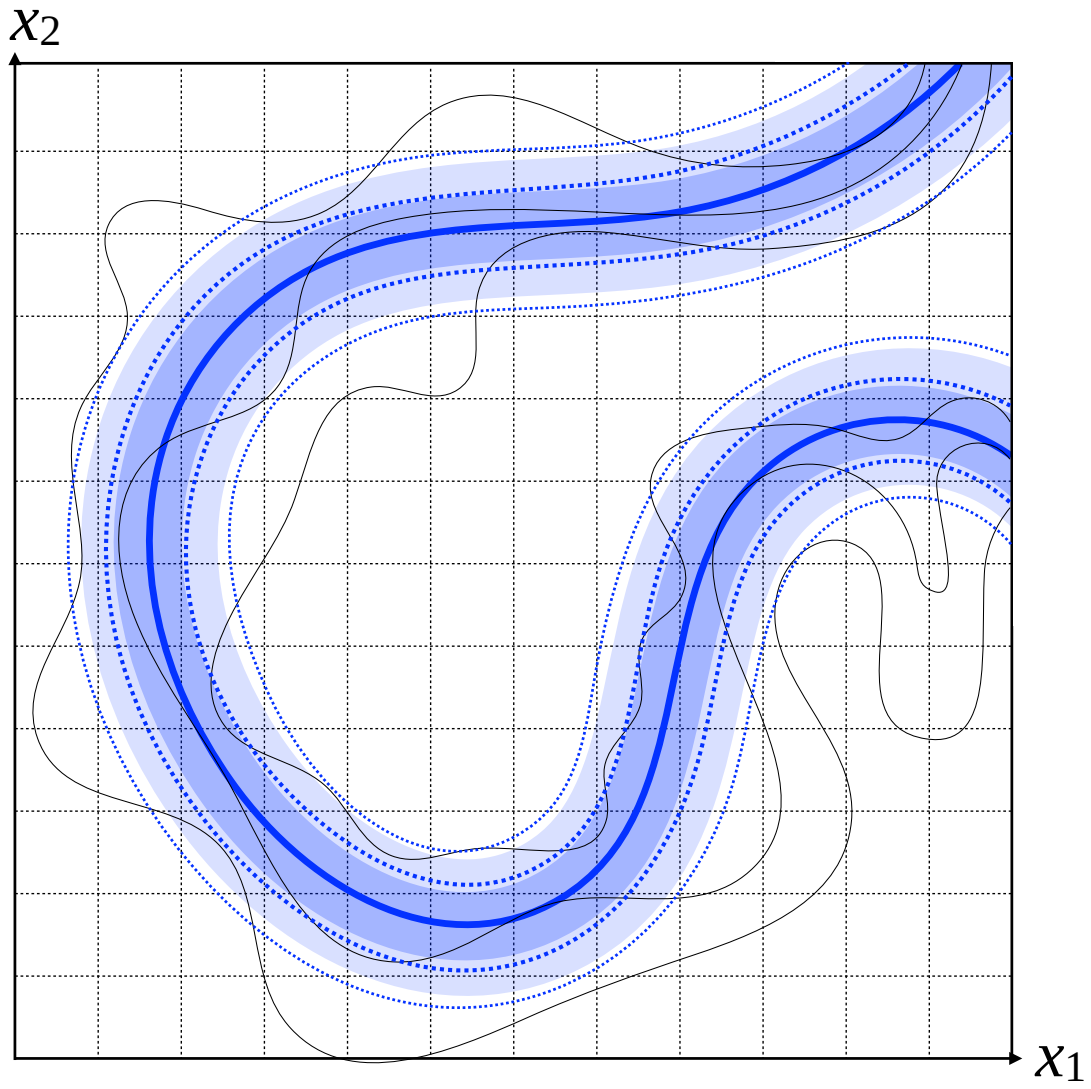
Departure from maximum likelihood

- We need some measure of how far apart p_{data} and induces p_{model} are
- With density models, we used $KL(p_{data} \| p_{model})$ which gave us the objective $\mathbb{E}_{x \sim p_{data}} [\log p_\theta(x)]$ (discarding the term independent of θ) where we explicitly modeled p_{model} as $p_\theta(x)$
- Not having an explicit $p_\theta(x)$ requires us to come up distance measures that potentially behave differently from maximum likelihood.
- Example: Maximum Mean Discrepancy (MMD), Jensen Shannon Divergence (JSD), Earth Mover's Distance, etc.

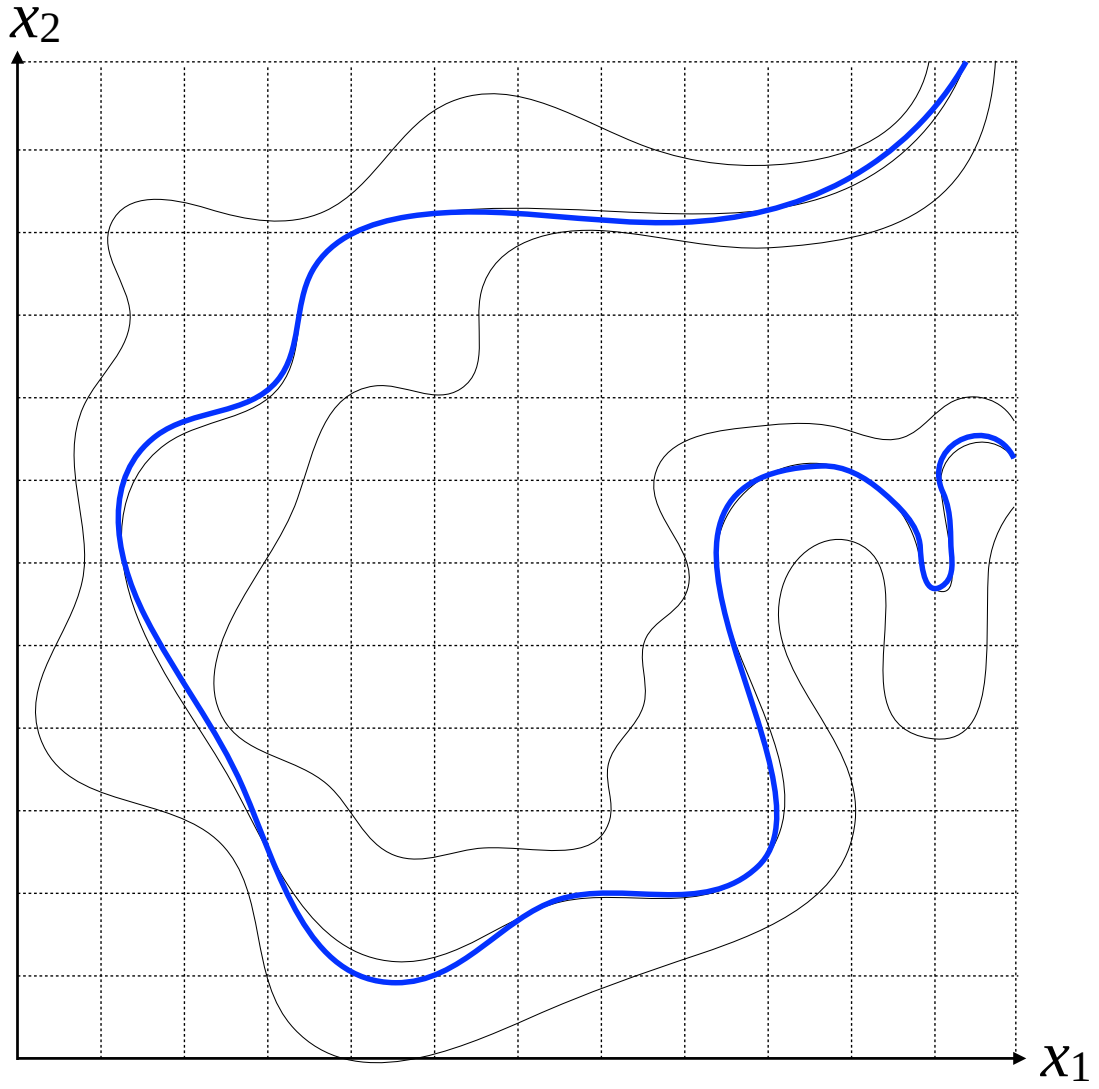
Cartoon of the Image manifold



What makes GANs special?



more traditional max-likelihood approach



GAN

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[Lisa_labo] Adversarial sampling

kyunghyun.cho@aalto.fi ×

Ian Goodfellow <goodfellow.ian@gmail.... Tue, May 27, 2014, 9:07 PM

to lisa_labo

I had an idea for a new (or at least, I think it's new) way to train a generative model last night at Les Trois Brasseurs.

The basic idea is that you have two adversarial nets. One is the generator net, which I call g. One is the discriminator net, which I call d. We have some source of noise, like an isotropic normal distribution, giving us samples z. Given a noise sample z, we can get a sample s = g(z).

The discriminator net gives us d(x), which gives the probability that x came from the data distribution, rather than the model distribution.

During training, we train the parameters of d to minimize d(g(z)) and maximize d(x) from the training set. We also train the parameters of g to maximize d(g(z)).

In theory, the advantages are:
-We can train without any partition function difficulties or inference
-We can sample from it without any markov chain

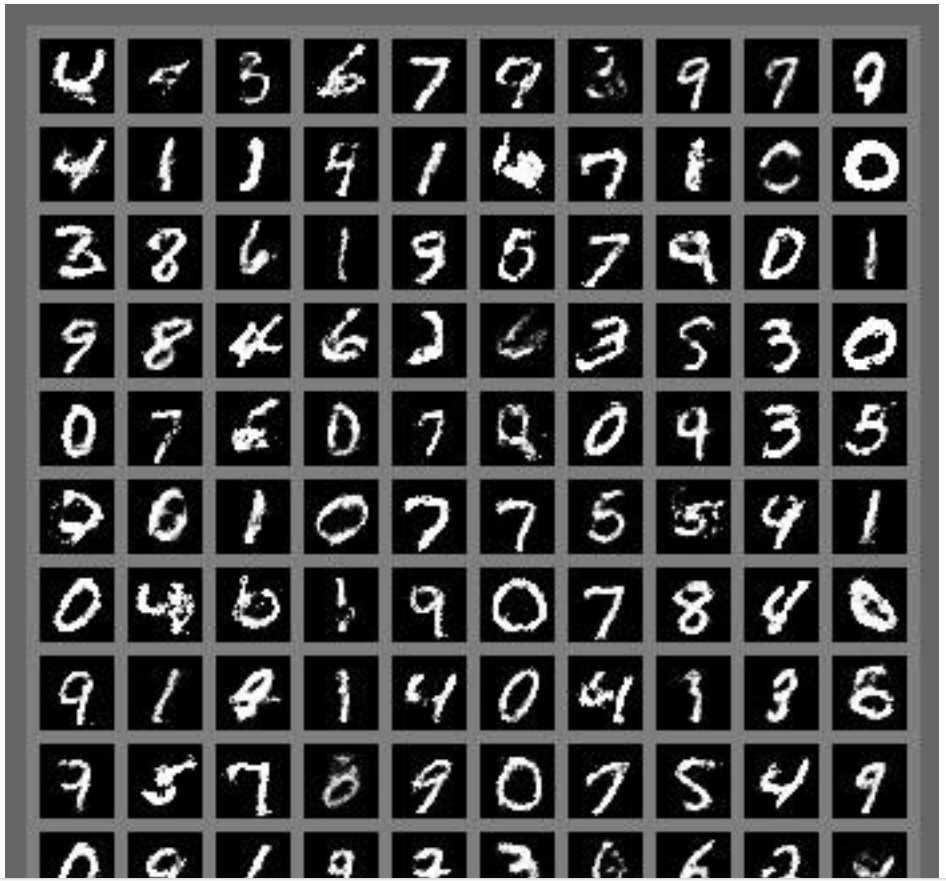
In theory, the disadvantages are:
-It's just a sampler box, not an explicit representation of a pdf (though, as with any sampler box, you could add approximate inference of z by training a predictor net for z)

I coded it up, and it is basically working. In practice, there is one more disadvantage: the gradient through d on g(z) tends to be fairly small, so d learns much faster than g. This can prevent g from learning at all, if d manages to completely "win" and saturate the log likelihood. I am able to fix this problem with a hack, which is that I rescale the gradient on g(z) to have unit norm. So the problem is not that the gradient is uninformative, just that the gradient magnitude for g is too small relative to d.

Any comments / suggestions? I'd like to come up with a way of getting rid of the bias, and also a cleaner solution to the vanishing gradient issue than my hack. Also, what is the best way of quantitatively evaluating a sampler box? So far I am just looking at samples, which doesn't tell me whether I'm overfitting.

Samples attached. These samples are generated using z ~ N(0, I_100), d = [Relu(1200), Relu(1200), Sigmoid(784)] and d = [Maxout(240, 5), Maxout(240, 5), Sigmoid], with dropout in d but not in g.

Lisa_labo mailing list



kyunghyuncho.bsky.social
@kyunghyuncho.bsky.social

congratulations, @ian-goodfellow.bsky.social, for the test-of-time award at @neuripsconf.bsky.social!

this award reminds me of how GAN started with this one email ian sent to the Mila (then Lisa) lab mailing list in May 2014. super insightful and amazing execution!

Generative Adversarial Networks

Generative Adversarial Nets

Ian J. Goodfellow[*], **Jean Pouget-Abadie**[†], **Mehdi Mirza**, **Bing Xu**, **David Warde-Farley**, **Sherjil Ozair**[‡], **Aaron Courville**, **Yoshua Bengio**[§]
Département d'informatique et de recherche opérationnelle
Université de Montréal
Montréal, QC H3C 3J7

Abstract

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

[Goodfellow et al 2014]

Generative Adversarial Networks

$$\min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}} [\log D(x)] + \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z)))]$$

- Two player minimax game between generator (G) and discriminator (D)
- (D) tries to maximize the log-likelihood for the binary classification problem
  - data: real (1)
  - generated: fake (0)
- (G) tries to minimize the log-probability of its samples being classified as “fake” by the discriminator (D)

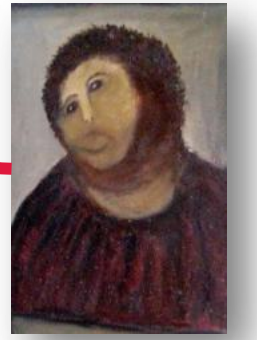
Intuition behind GANs

$$\min_G \max_D \mathbb{E}_{x \sim p_{\text{data}}} [\log D(x)] + \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z)))]$$

D_ω : *Discriminator (Art Forgery Detective)*

$\boldsymbol{x}_{real}$

$\boldsymbol{x}_{fake}$



G_θ

Generative Adversarial Networks

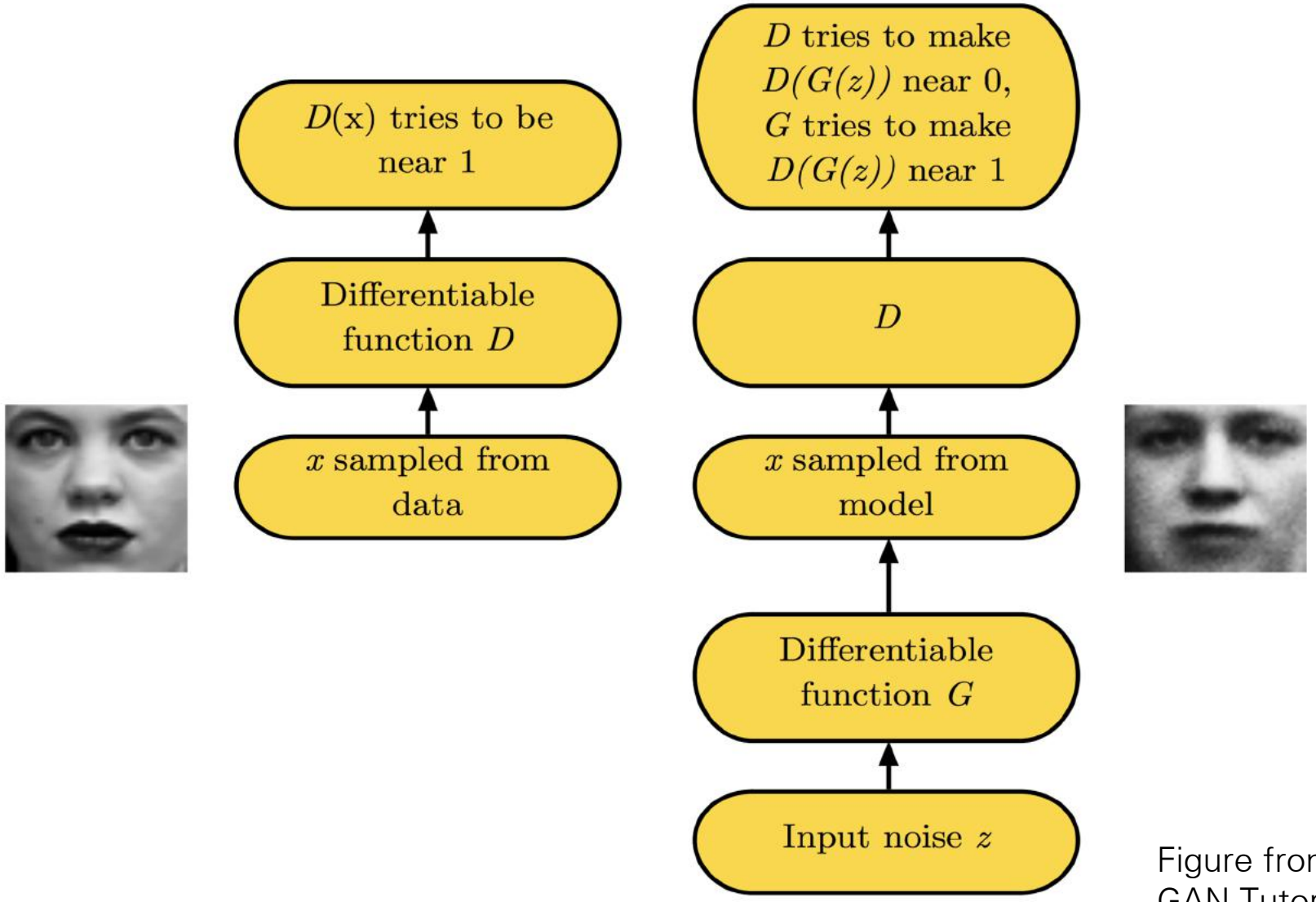


Figure from NeurIPS 2016 GAN Tutorial (Goodfellow)

GANs - Pseudocode

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:

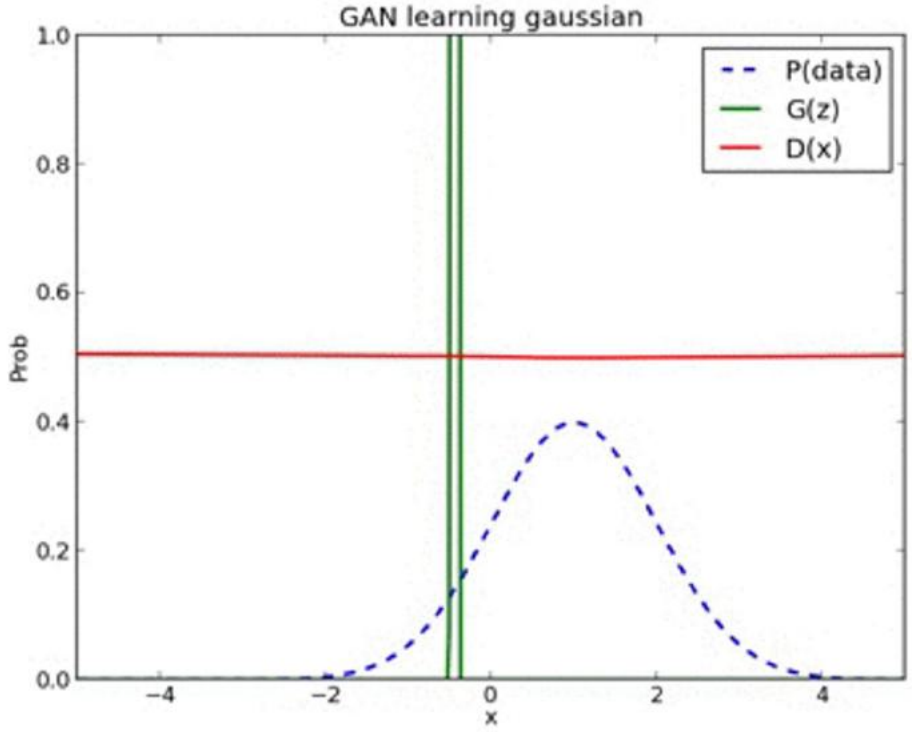
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

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

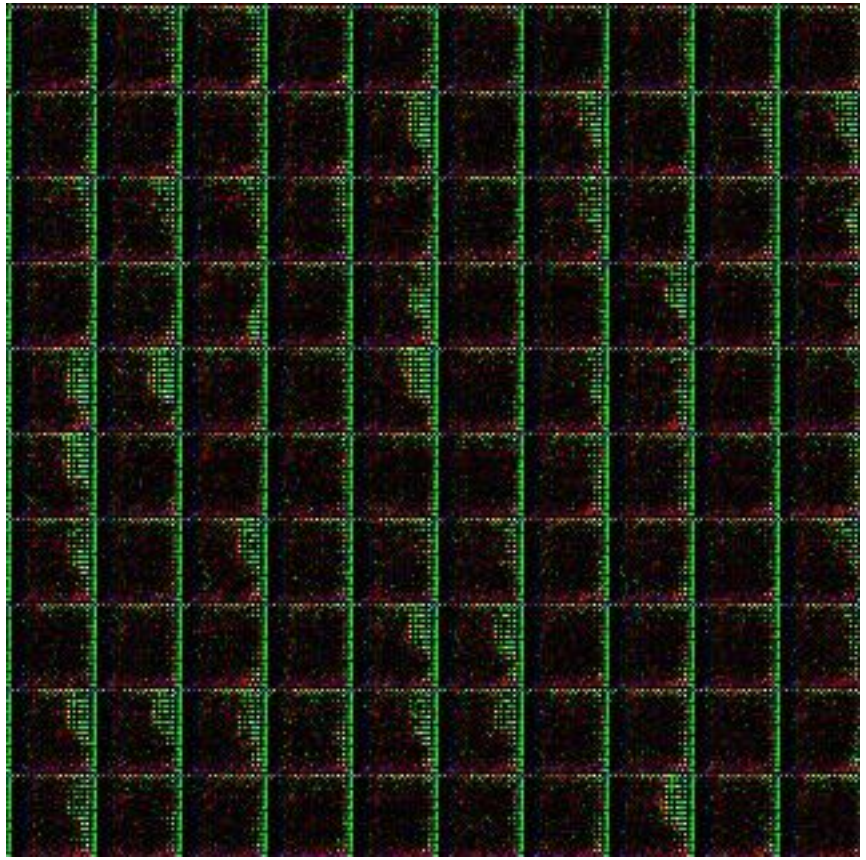
[Goodfellow et al 2014]

Training Procedure



Source: Alec Radford

Generating 1D points



Source: OpenAI blog

Generating images

GAN in Action

https://poloclub.github.io/ganlab/

GAN samples from 2014

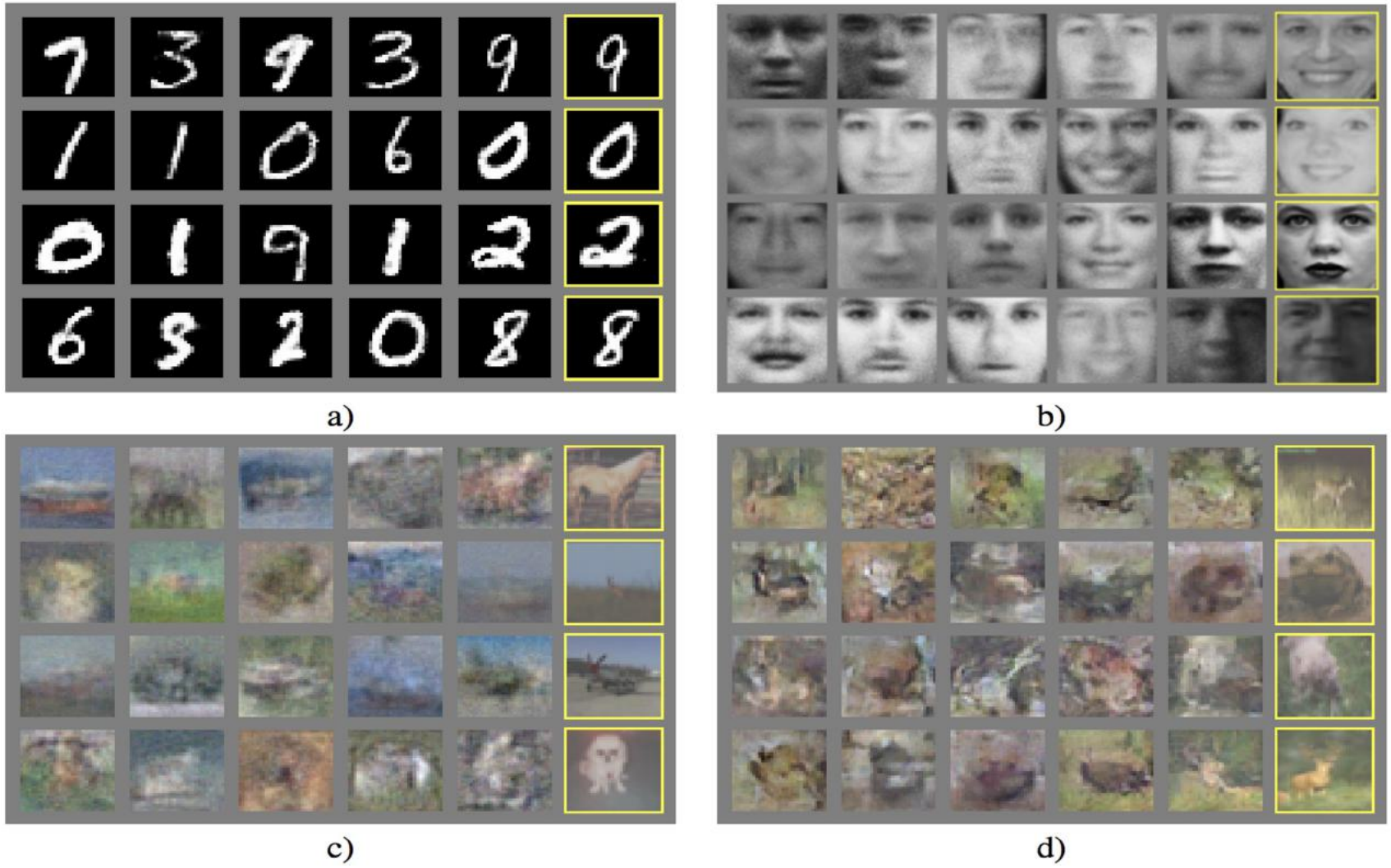


Figure from [Goodfellow et al. 2014]

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How to evaluate?

- Evaluation for GANs is still an open problem

- Unlike density models, you cannot report explicit likelihood estimates on test sets.

Inception Score

- **One idea:** good generators generate samples that are semantically diverse
- Semantics predictor: trained Inception Network v3
  - p(y|x), y is one of the 1000 ImageNet classes
- Considerations:
  - each image x should have distinctly recognizable object -> p(y|x) should have low entropy
  - there should be as many classes generated as possible -> p(y) should have high entropy

Inception Score

- Inception model: $p(y|x)$
- Marginal label distribution: $p(y) = \int_x p(y|x)p_g(x)$
- Inception Score:

$$\begin{aligned}\mathrm{IS}(x) =& \exp(\mathbb{E}_{x\sim p_g}\left[D_{\mathrm{KL}}\left[p(y|x) \parallel p(y)\right]\right]) \\ =& \exp(\mathbb{E}_{x\sim p_g, y\sim p(y|x)}\left[\log p(y|x) - \log p(y)\right]) \\ =& \exp(H(y) - H(y|x))\end{aligned}$$

[Improved GAN: Salimans et al 2016]

Inception Score

Samples				
Model	Real data	Our methods	-VBN+BN	-L+HA
Score $\pm$ std.	$11.24 \pm .12$	$8.09 \pm .07$	$7.54 \pm .07$	$6.86 \pm .06$

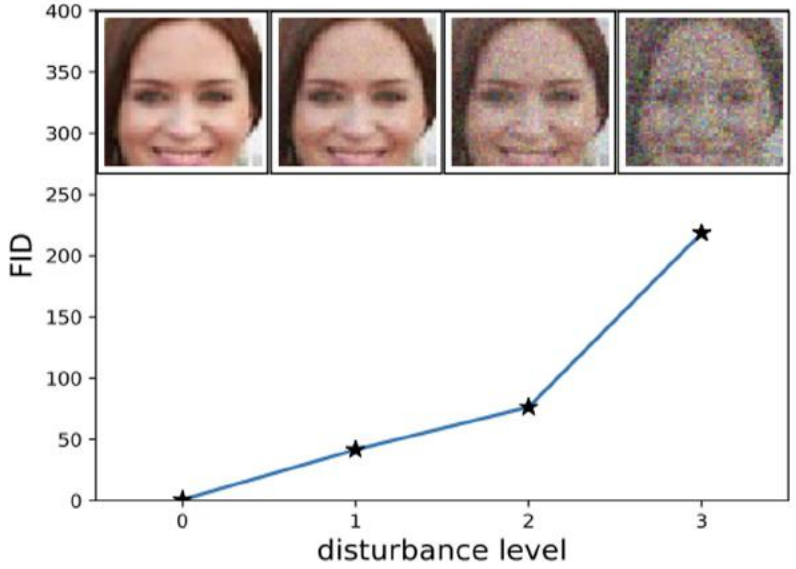
Fréchet Inception Distance

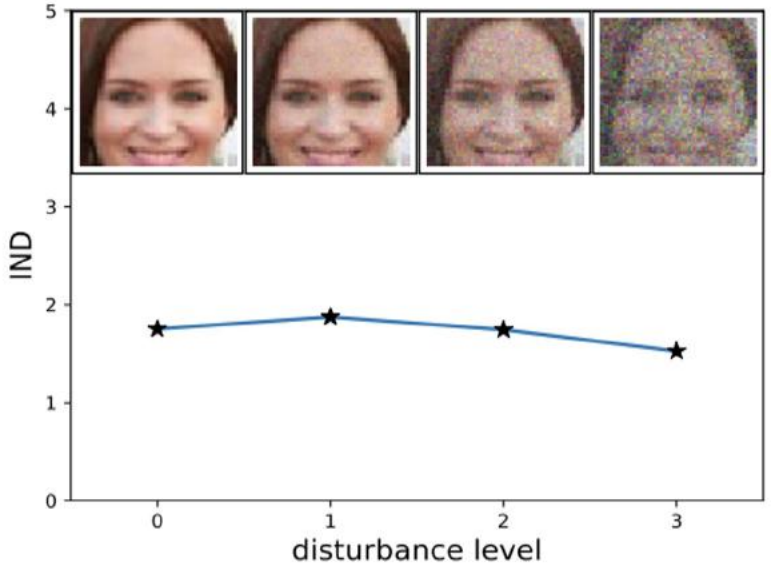
- Inception Score doesn't sufficiently measure diversity: a list of 1000 images (one of each class) can obtain perfect Inception Score
- FID was proposed to capture more nuances
- Embed image x into some feature space (2048-dimensional activations of the Inception-v3 pool3 layer), then compare mean (m) & covariance (C) of those random features

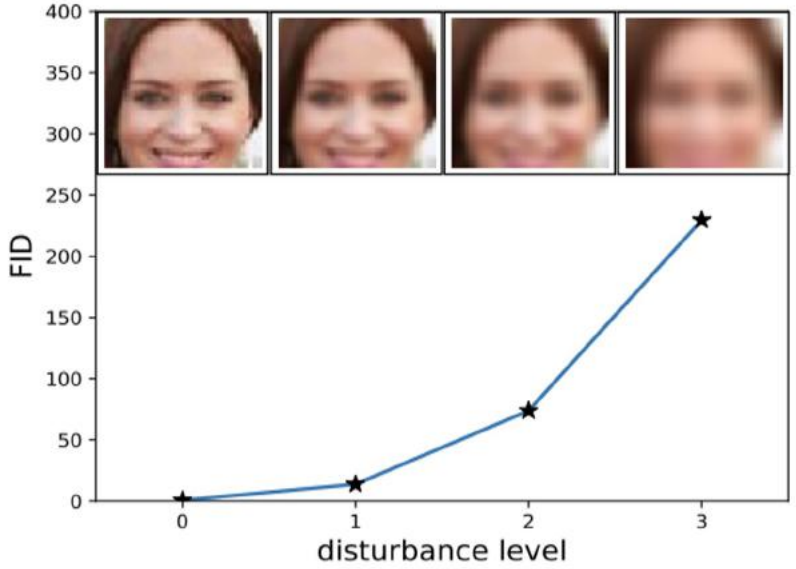
$$d^2((\boldsymbol{m}, \boldsymbol{C}), (\boldsymbol{m}_w, \boldsymbol{C}_w)) = \|\boldsymbol{m} - \boldsymbol{m}_w\|_2^2 + \mathrm{Tr}\big(\boldsymbol{C} + \boldsymbol{C}_w - 2\big(\boldsymbol{C}\boldsymbol{C}_w\big)^{1/2}\big)$$

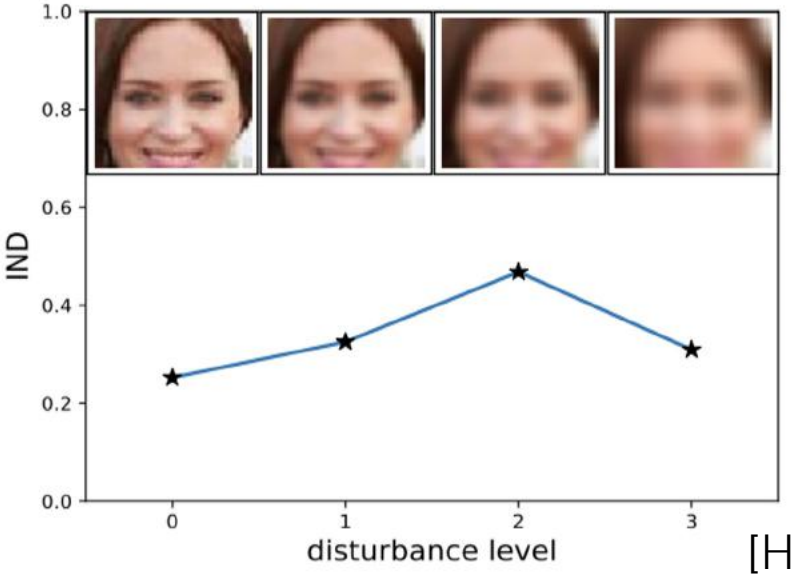
[Heusel et al, 2017]

Fréchet Inception Distance



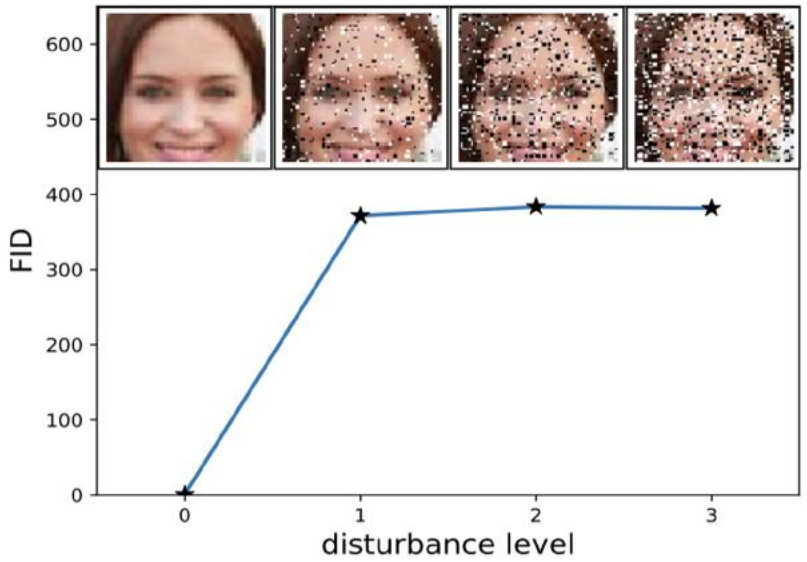


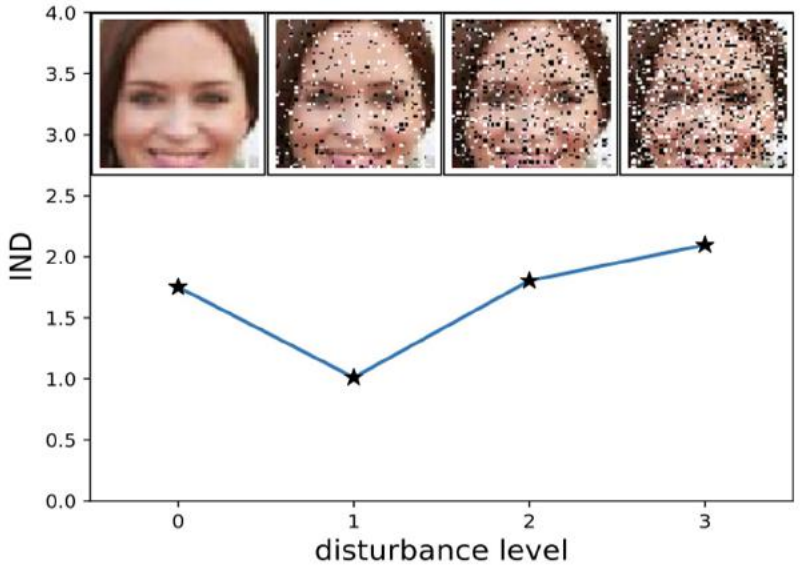


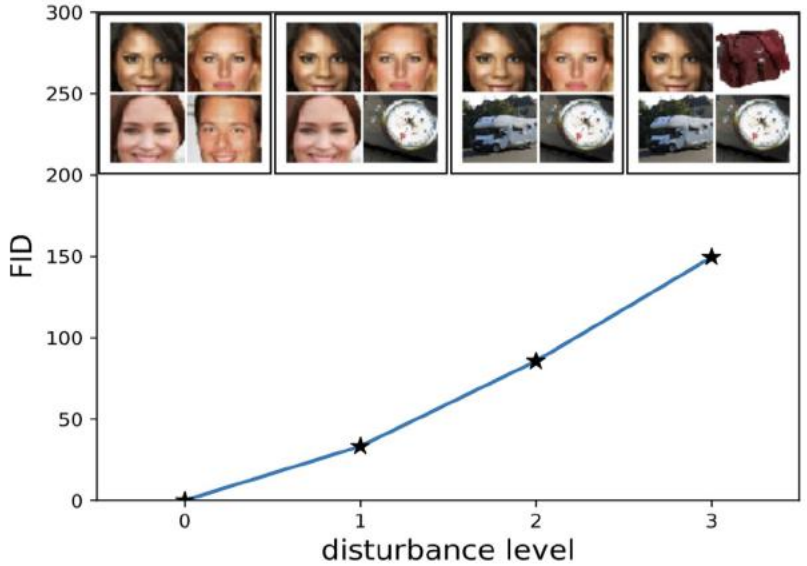


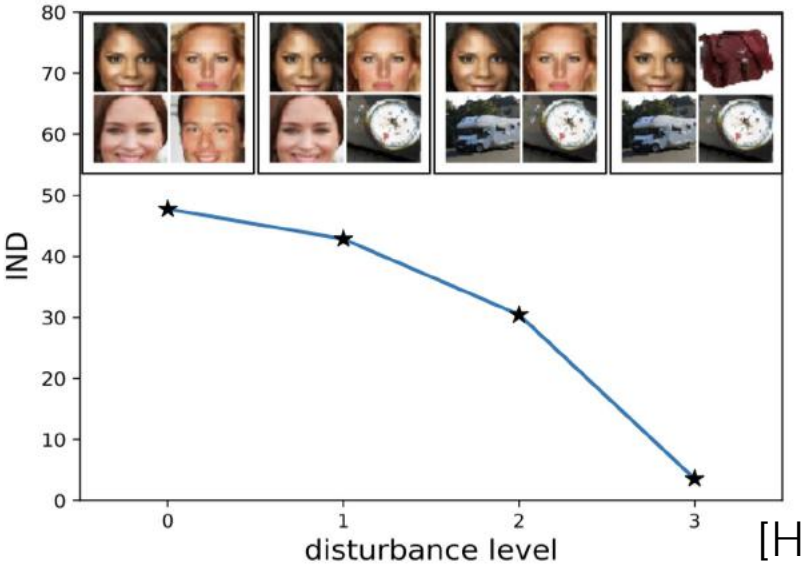
[Heusel et al, 2017]

Fréchet Inception Distance









[Heusel et al, 2017]

Fréchet Inception Distance

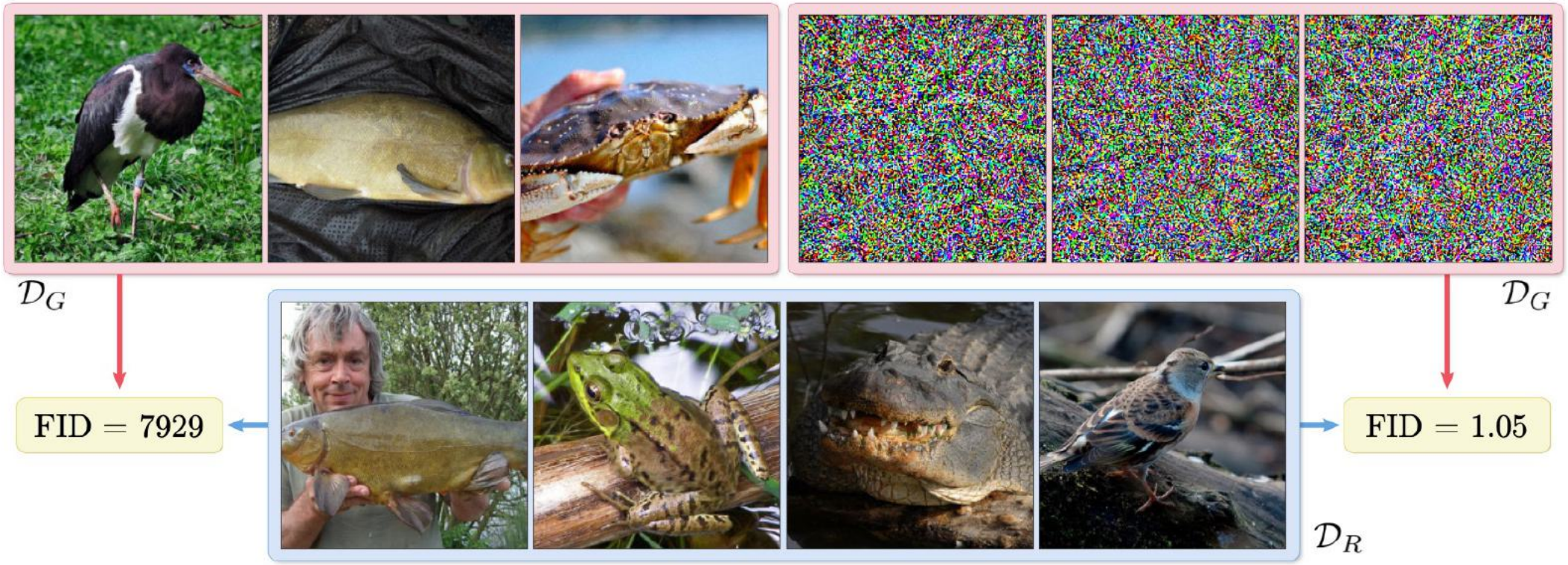


Figure 1. **Does the Fréchet Inception Distance (FID) accurately measure the distances between image distributions?** We generate datasets that demonstrate the unreliability of FID in judging perceptual (dis)similarities between image distributions. The top left box shows a sample of a dataset constructed by introducing imperceptible noise to each ImageNet image. Despite the remarkable visual similarity between this dataset and ImageNet (bottom box), an extremely large FID (almost 8000) between these two datasets showcases FID's failure to capture perceptual similarities. On the other hand, a remarkably low FID (almost 1.0) between a dataset of random noise images (samples shown in the top right box) and ImageNet illustrates FID's failure to capture perceptual dissimilarities.

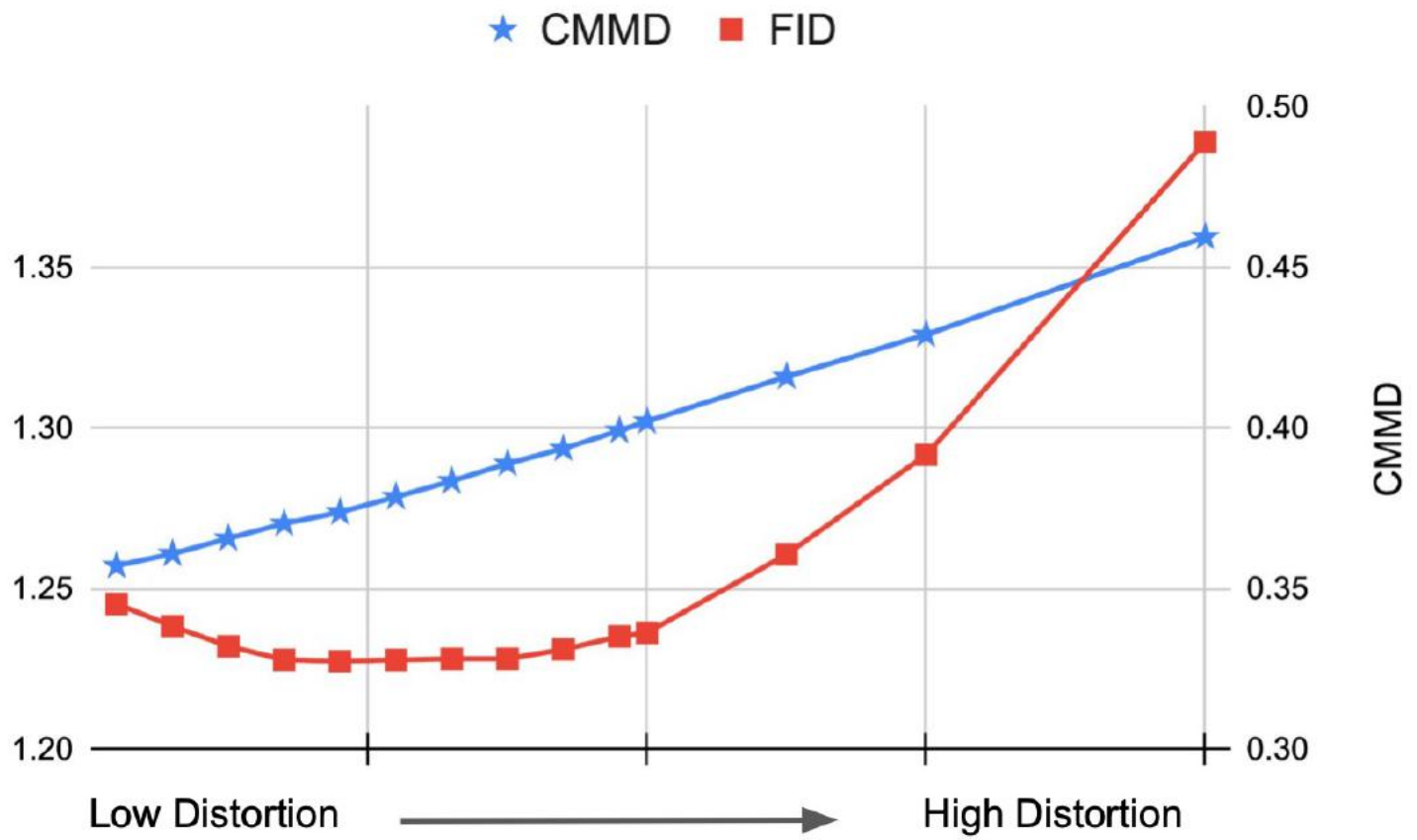
One solution: Replace the Inception component of FID with a robustly trained counterpart!

CLIP-MMD

- CMMD: A distance that uses CLIP features with the MMD distance

$$\hat{\mathrm{dist}}^2_{\mathrm{MMD}}(X,Y) = \frac{1}{m(m-1)}\sum_{i=1}^{m}\sum_{j\neq i}^{m} k(\mathbf{x}_i,\mathbf{x}_j) + \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j\neq i}^{n} k(\mathbf{y}_i,\mathbf{y}_j) - \frac{2}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} k(\mathbf{x}_i,\mathbf{y}_j).$$

$$k(\mathbf{x},\mathbf{y}) = \exp(-\|\mathbf{x}-\mathbf{y}\|^2/2\sigma^2)$$



CLIP-MMD

Figure 5. *Behavior of FID and CMMD under distortions. Images in the first row (FID: 21.40, CMMD: 0.721) are undistorted. Images in the second (FID: 18.02, CMMD: 1.190) are distorted by randomly replacing each VQGAN token with probability $p = 0.2$. The image quality clearly degrades as a result of the distortion, but FID suggests otherwise, while CMMD correctly identifies the degradation.*

Generative Adversarial Networks

- Key pieces of GAN
  - Fast sampling
  - No inference
  - Notion of optimizing directly for what you care about – perceptual samples

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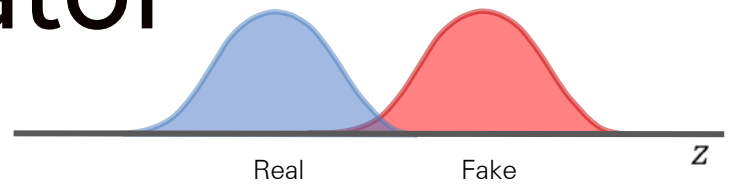
GAN: Bayes-Optimal Discriminator



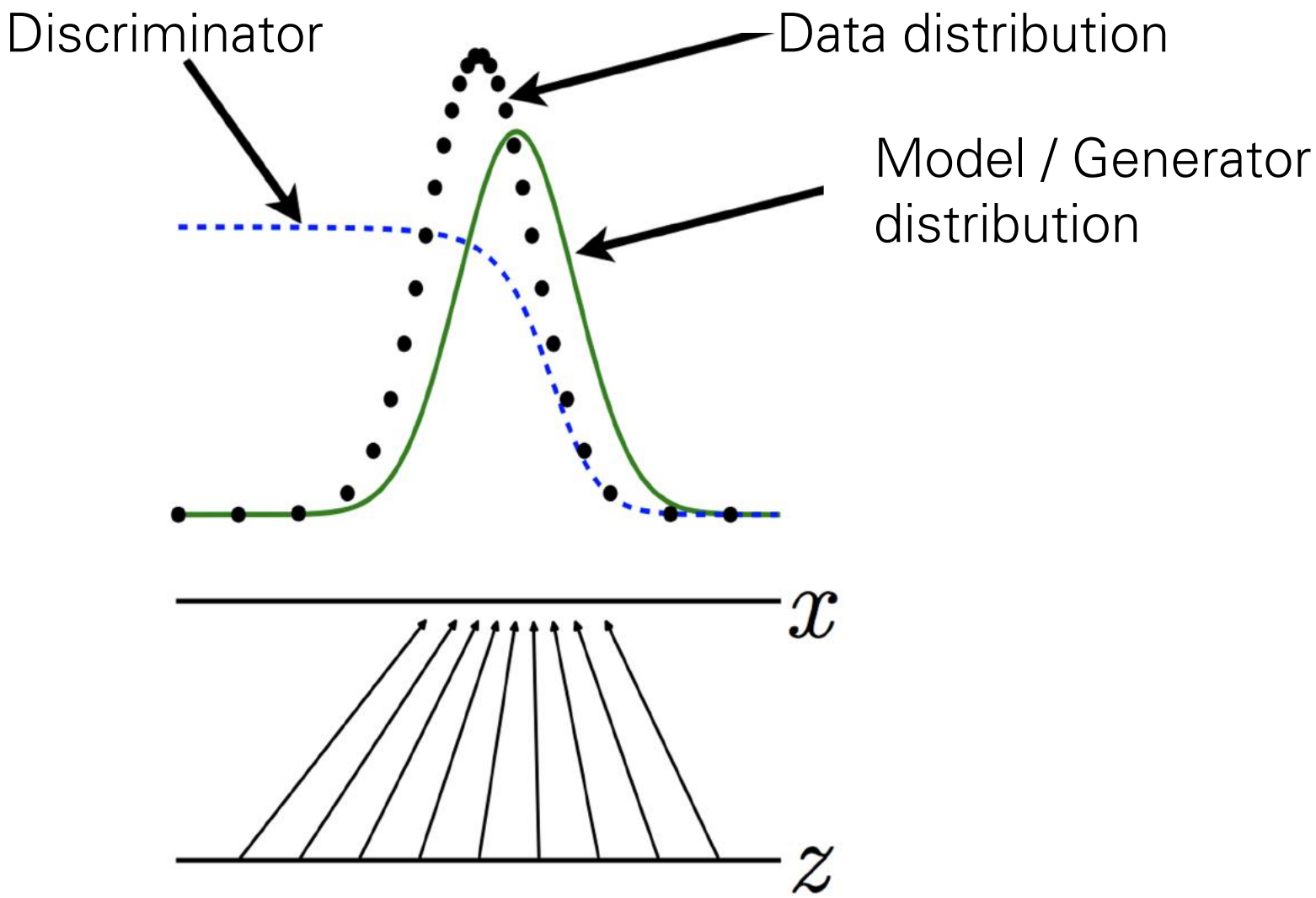
- What's the optimal discriminator given generated and true distributions?

$$
\begin{aligned}
V(G,D) &= \mathbb{E}_{x\sim p_{\text{data}}}\left[\log D(x)\right] + \mathbb{E}_{z\sim p(z)}\left[\log(1-D(G(z)))\right] \\
&= \int_x p_{\text{data}}(x)\log D(x)dx + \int_z p(z)\log(1-D(G(z)))dz \\
&= \int_x p_{\text{data}}(x)\log D(x)dx + \int_x p_g(x)\log(1-D(x))dx \\
&= \int_x \left[p_{\text{data}}(x)\log D(x) + p_g(x)\log(1-D(x))\right]dx
\end{aligned}
$$

$$
\nabla_y \left[a\log y + b\log(1-y)\right] = 0 \implies y^* = \frac{a}{a+b} \quad \forall \quad [a,b]\in\mathbb{R}^2\backslash[0,0]
$$

$$
\implies D^*(x) = \frac{p_{\text{data}}(x)}{(p_{\text{data}}(x)+p_g(x))}
$$

GAN: Bayes-Optimal Discriminator



[Figure Source: Goodfellow NeurIPS 2016 Tutorial on GANs]

GAN: Generator Objective under Bayes-Optimal Discriminator D*?

$$
\begin{aligned}
V(G, D^*) &= \mathbb{E}_{x \sim p_{\text{data}}} \left[\log D^*(x) \right] + \mathbb{E}_{x \sim p_g} \left[\log (1 - D^*(x)) \right] \\
&= \mathbb{E}_{x \sim p_{\text{data}}} \left[\log \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_g(x)} \right] + \mathbb{E}_{x \sim p_g} \left[\log \frac{p_g(x)}{p_{\text{data}}(x) + p_g(x)} \right] \\
&= -\log(4) + \underbrace{KL\left(p_{\text{data}} \| \left(\frac{p_{\text{data}} + p_g}{2} \right) \right) + KL\left(p_{\text{g}} \| \left(\frac{p_{\text{data}} + p_g}{2} \right) \right)}_{\text{(Jensen-Shannon Divergence (JSD) of } p_{\text{data}} \text{ and } p_g) \geq 0}
\end{aligned}
$$

$$V(G^*, D^*) = -\log(4) \text{ when } p_g = p_{\text{data}}$$

Compare this with ML objective: $KL(p_{data} \| p_g)$

Behaviors across divergence measures

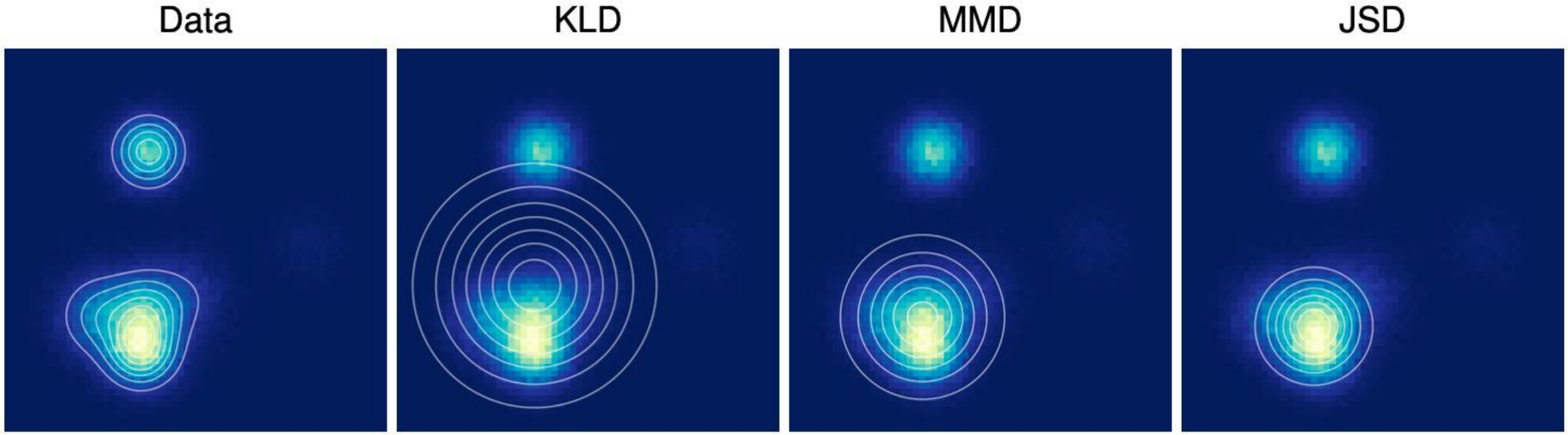
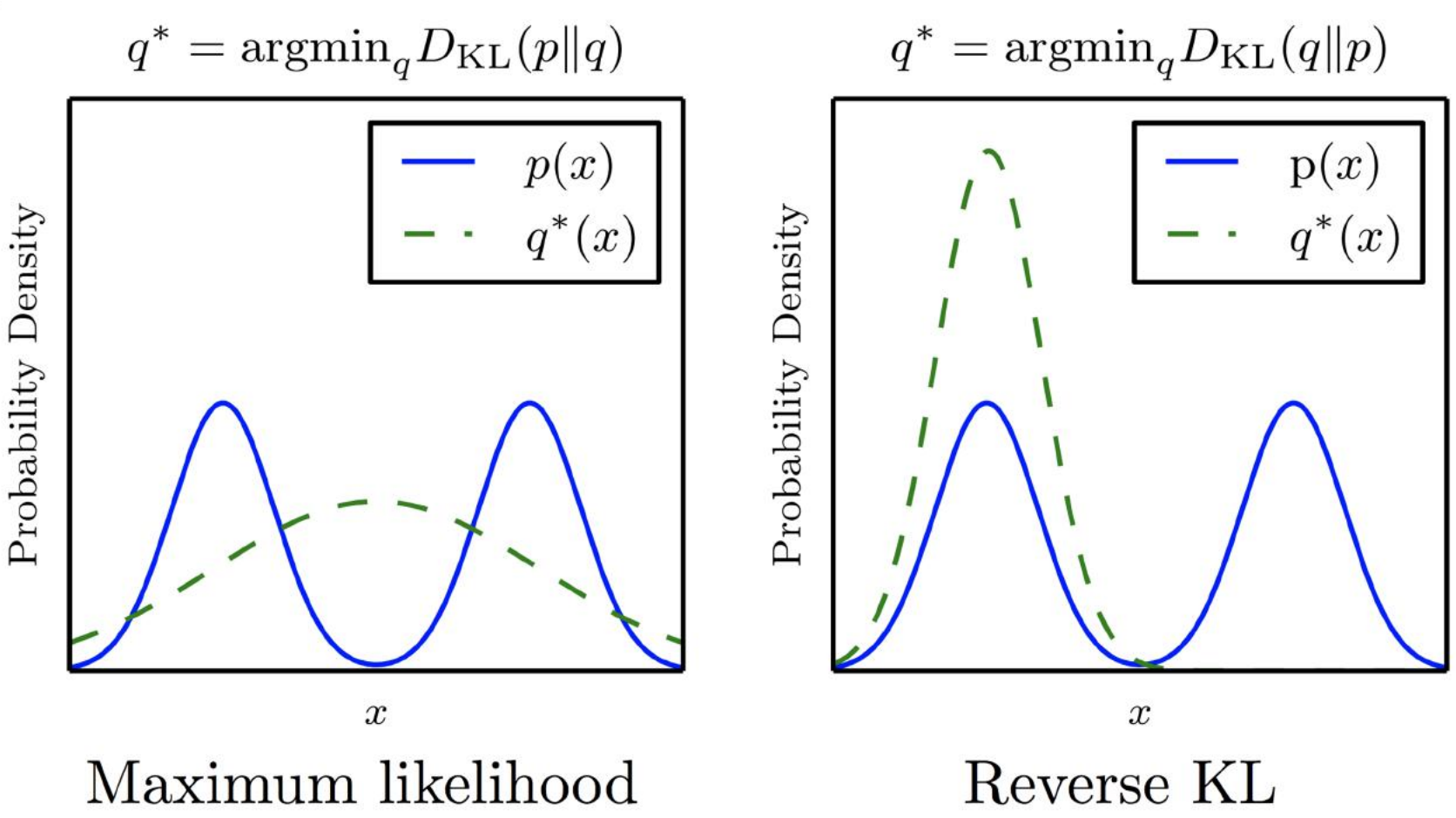


Figure 1: An isotropic Gaussian distribution was fit to data drawn from a mixture of Gaussians by either minimizing Kullback-Leibler divergence (KLD), maximum mean discrepancy (MMD), or Jensen-Shannon divergence (JSD). The different fits demonstrate different tradeoffs made by the three measures of distance between distributions.

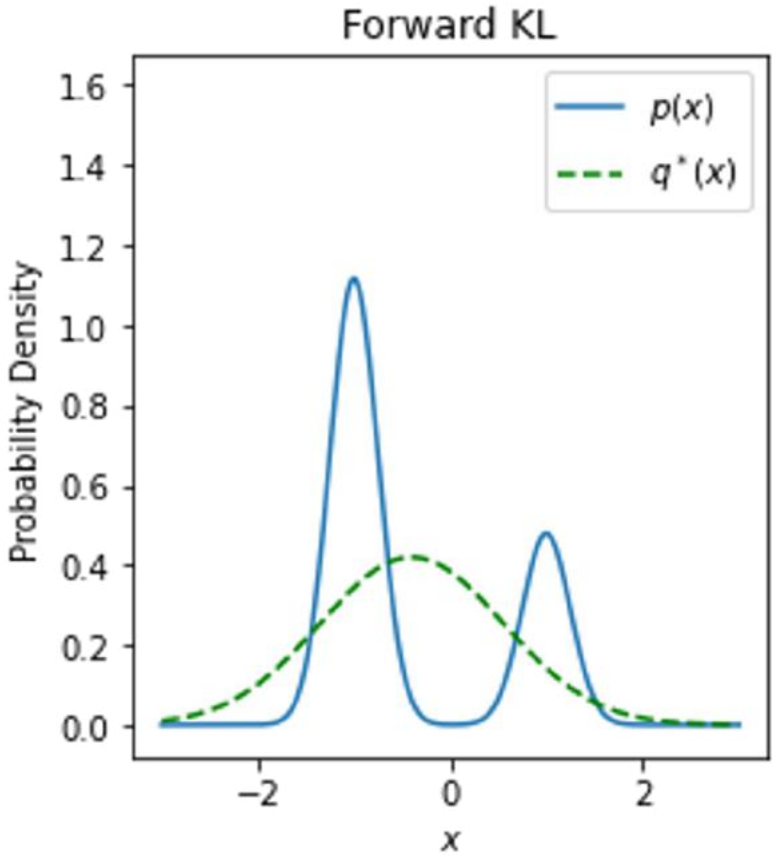
["A note on the evaluation of generative models" -- Theis, Van den Oord, Bethge 2016]

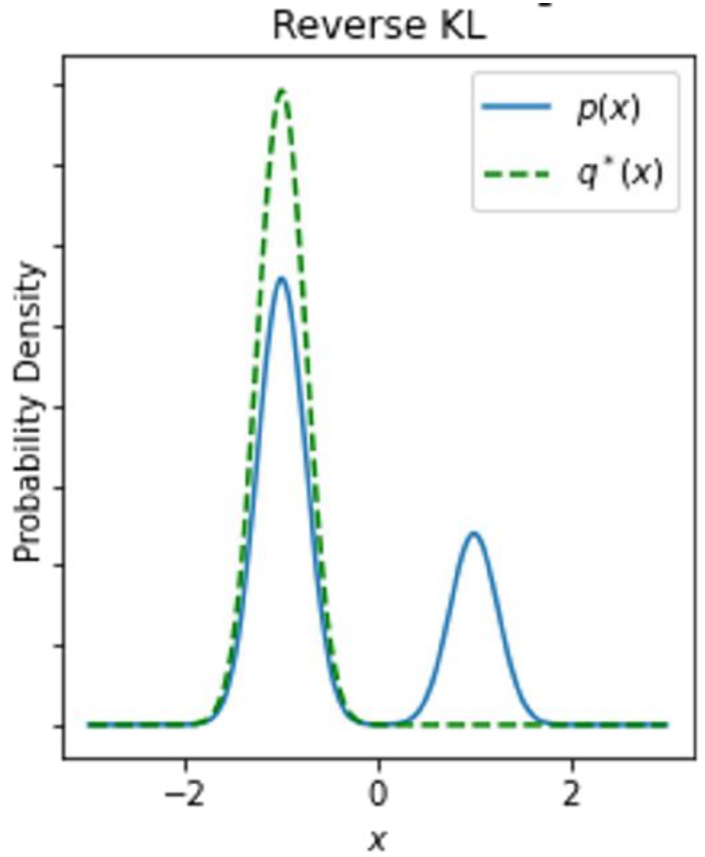
Direction of KL divergence

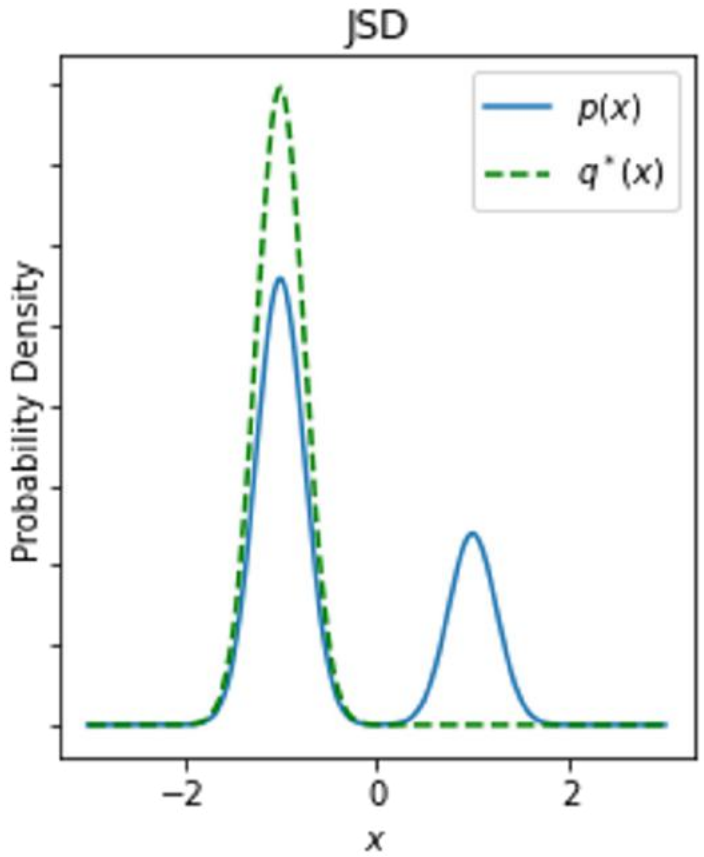


Deep Learning Textbook (Goodfellow 2016) - Chapter 3

KL and JSD


Forward KL
Probability Density
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−2
0
2
x
p(x)
q*(x)

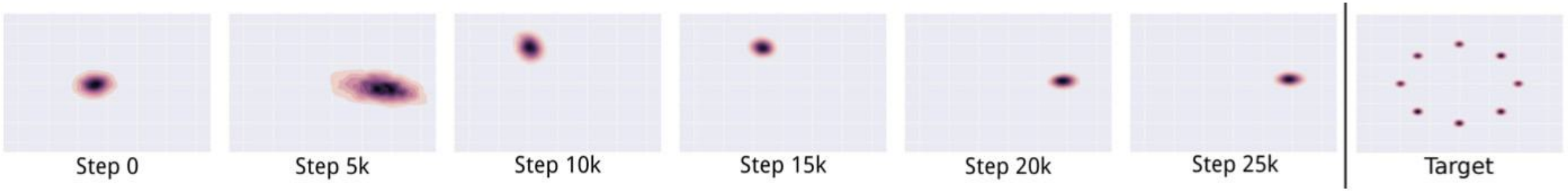

Reverse KL
Probability Density
−2
0
2
x
p(x)
q*(x)


JSD
Probability Density
−2
0
2
x
p(x)
q*(x)

Mode covering vs Mode seeking: Tradeoffs

- For compression, one would prefer to ensure all points in the data distribution are assigned probability mass.
- For generating good samples, blurring across modes spoils perceptual quality because regions outside the data manifold are assigned non-zero probability mass.
- Picking one mode without assigning probability mass on points outside can produce "better-looking" samples.
- **Caveat:** More expressive density models can place probability mass more accurately. For example, using mixture of Gaussians as opposed to a single isotropic gaussian.

Mode Collapse



- Standard GAN training collapses when the true distribution is a mixture of gaussians!

(Figure from Metz et al. 2016)

Back to GANs

Recall

$$\min_G \max_D \underbrace{\mathbb{E}_{x \sim p_{\text{data}}} [\log D(x)] + \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z)))]}_{\text{Discriminator}}$$

Mini-Exercise

- Is it feasible to run the inner optimization to completion?
- For this specific objective, would it create problems if we were able to do so?

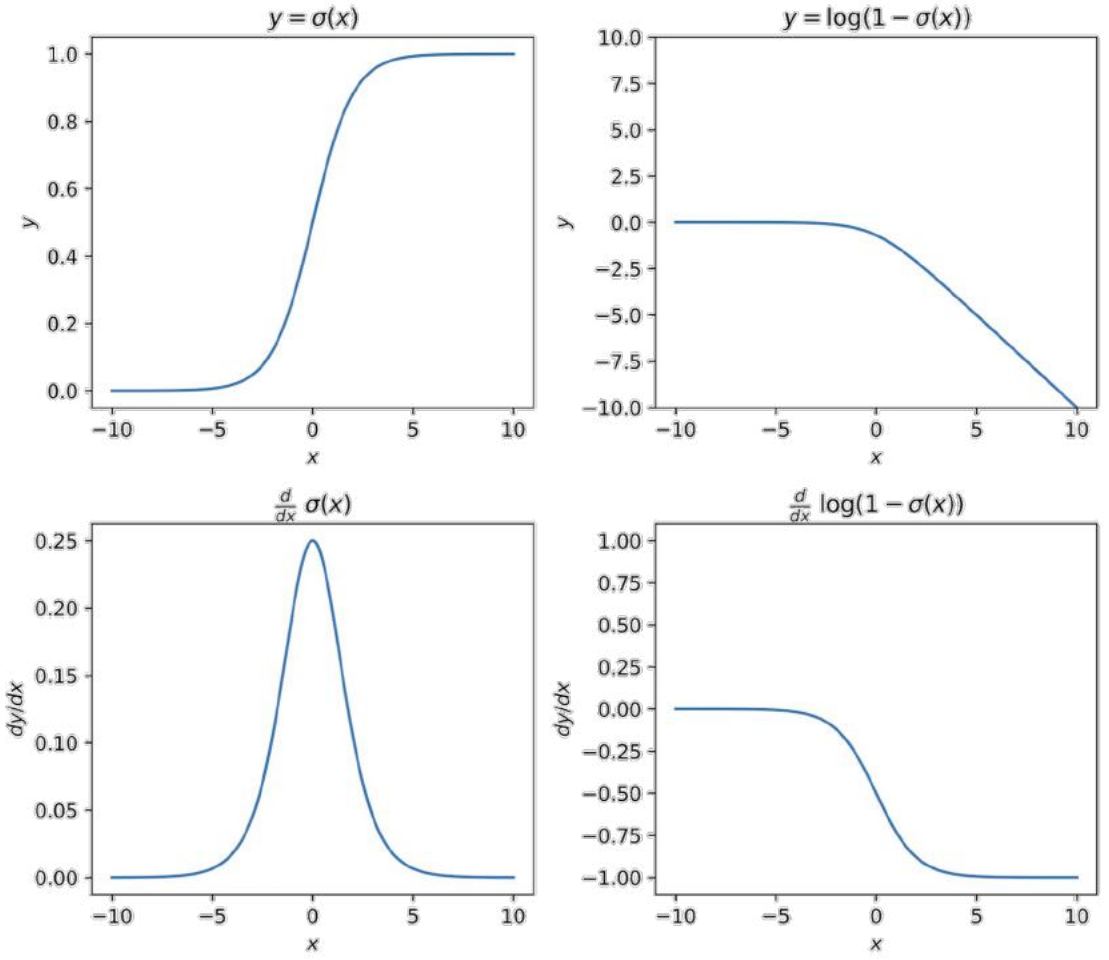
Discriminator Saturation

- Generator samples confidently classified as fake by the discriminator receive no gradient for the generator update.

$$\nabla_{G(z)} \log(1 - D(G(z)))$$ where

$$D(x) = \text{sigmoid}(x; \theta) = \sigma(x; \theta)$$

$$\nabla_x \sigma(x) = \sigma(x)(1 - \sigma(x))$$



Avoiding Discriminator Saturation: (1) Alternating Optimization

- Alternate gradient steps on discriminator and generator objectives

$$L^{(D)}(\theta_D, \theta_G) = -\mathbb{E}_{x \sim p_{\text{data}}} [\log D(x; \theta_D)] - \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z; \theta_G), \theta_D))]$$

$$L^{(G)}(\theta_D, \theta_G) = \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z; \theta_G), \theta_D))]$$

$$\theta_D \coloneqq \theta_D - \alpha^{(D)} \nabla_{\theta_D} L^{(D)}(\theta_D, \theta_G)$$
$$\theta_G \coloneqq \theta_G - \beta^{(G)} \nabla_{\theta_G} L^{(G)}(\theta_D, \theta_G)$$

- Balancing these two updates is hard for the zero-sum game

Avoiding Discriminator Saturation: (2) Non-Saturating Formulation

$$L^{(D)} = -\mathbb{E}_{x \sim p_{\text{data}}} [\log D(x)] - \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z)))]$$

$$L^{(G)} = -L^{D} \equiv \min_{G} \mathbb{E}_{z \sim p(z)} \log(1 - D(G(z)))$$

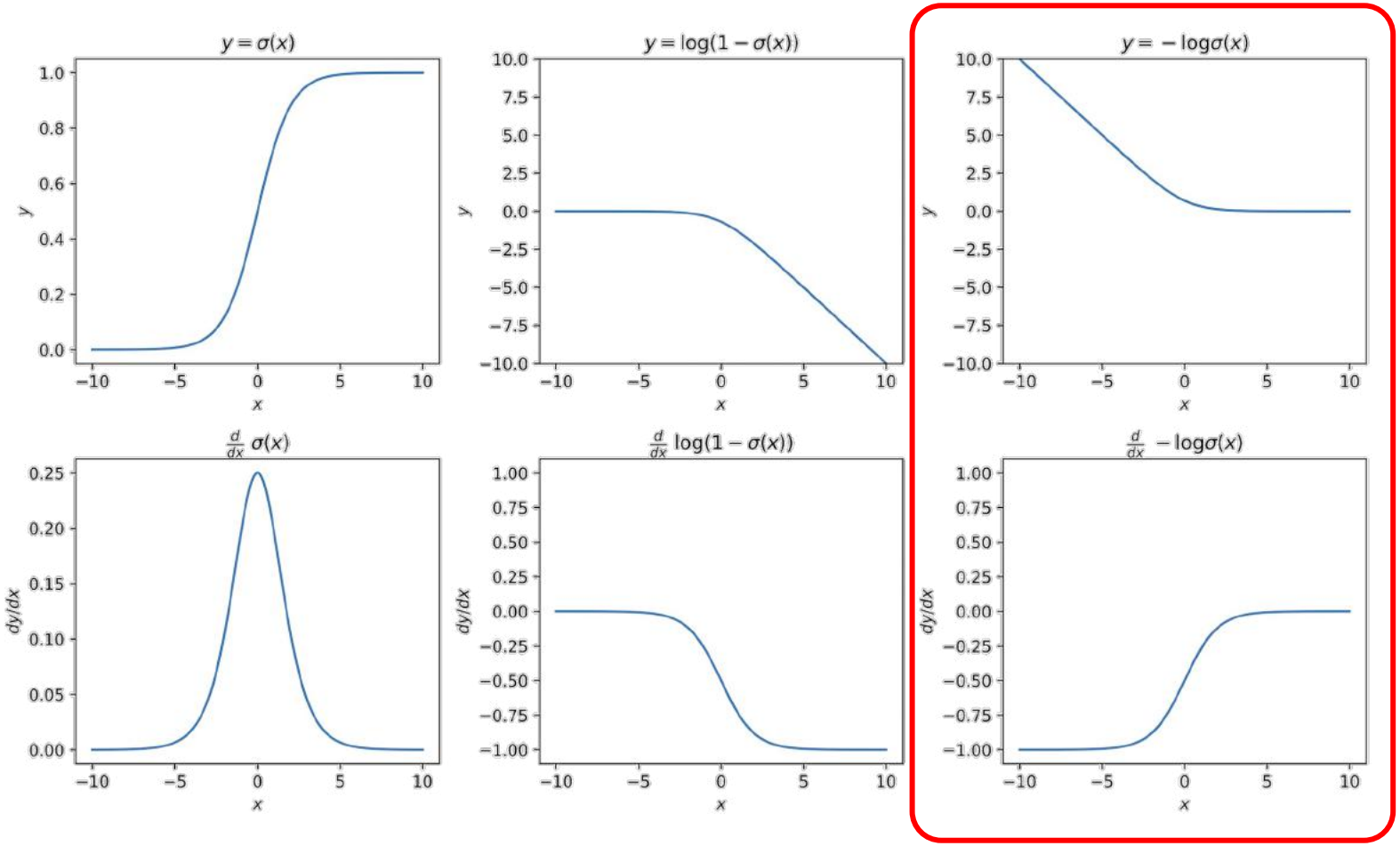
Not zero-sum

$$L^{(D)} = -\mathbb{E}_{x \sim p_{\text{data}}} [\log D(x)] - \mathbb{E}_{z \sim p(z)} [\log(1 - D(G(z)))]$$

$$L^{(G)} = -\mathbb{E}_{z \sim p(z)} \log(D(G(z)) \equiv \max_{G} \mathbb{E}_{z \sim p(z)} \log(D(G(z))$$

Avoiding Discriminator Saturation: (2) Non Saturating Formulation

- ORIGINAL ISSUE: Generator samples confidently classified as fake by the discriminator receive no gradient for the generator update.
- FIX: non-saturating loss for when discriminator confident about fake



Lecture overview

- Motivation
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- **GAN Progression**
  - DC GAN (Radford et al, 2016)
  - Improved Training of GANs (Salimans et al'16)
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN
  - BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, StyleGAN-v3, VQ-GAN
- Conditional GANs, Cycle-Consistent Adversarial Networks
- Applications

GAN Zoo

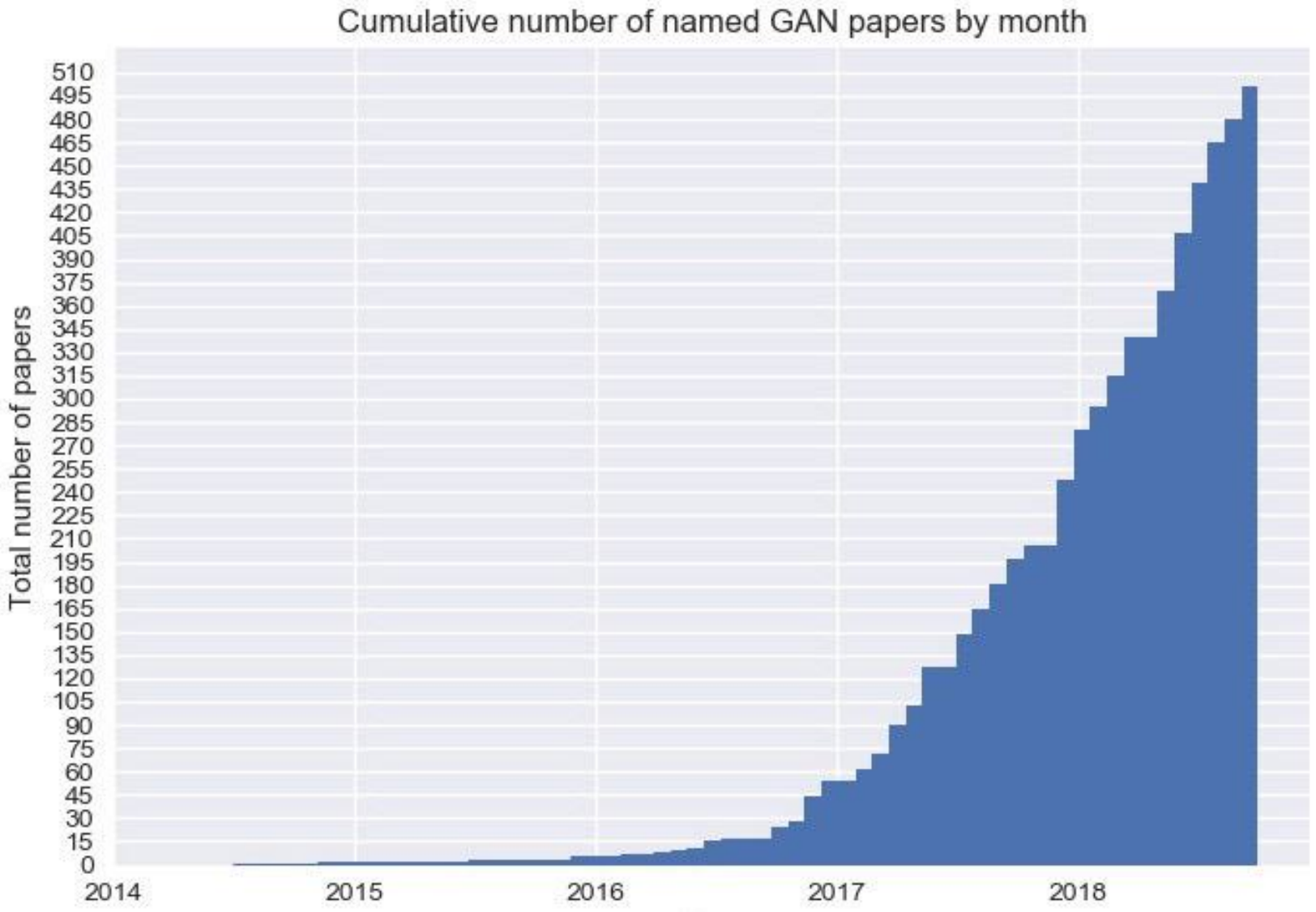
AN — Generative Adversarial Networks
3D-GAN — Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling acGAN — Face Aging With Conditional Generative Adversarial Networks
AC-GAN — Conditional Image Synthesis With Auxiliary Classifier GANs
AdaGAN — AdaGAN: Boosting Generative Models
AEGAN — Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
AffGAN — Amortised MAP Inference for Image Super-resolution
AL-CGAN — Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
ALI — Adversarially Learned Inference
AMGAN — Generative Adversarial Nets with Labeled Data by Activation Maximization
AnoGAN — Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
ArtGAN — ArtGAN: Artwork Synthesis with Conditional Categorial GANs
b-GAN — b-GAN: Unified Framework of Generative Adversarial Networks
Bayesian GAN — Deep and Hierarchical Implicit Models
BEGAN — BEGAN: Boundary Equilibrium Generative Adversarial Networks
BiGAN — Adversarial Feature Learning
BS-GAN — Boundary-Seeking Generative Adversarial Networks
CGAN — Conditional Generative Adversarial Nets
CCGAN — Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks CatGAN — Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks CoGAN — Coupled Generative Adversarial Networks
Context-RNN-GAN — Contextual RNN-GANs for Abstract Reasoning Diagram Generation
C-RNN-GAN — C-RNN-GAN: Continuous recurrent neural networks with adversarial training
CS-GAN — Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets CVAE-GAN — CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
CycleGAN — Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
DTN — Unsupervised Cross-Domain Image Generation
DCGAN — Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
DiscoGAN — Learning to Discover Cross-Domain Relations with Generative Adversarial Networks DR-GAN — Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
DualGAN — DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
EBGAN — Energy-based Generative Adversarial Network
f-GAN — f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
GAWWN — Learning What and Where to Draw
GoGAN — Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
GP-GAN — GP-GAN: Towards Realistic High-Resolution Image Blending
IAN — Neural Photo Editing with Introspective Adversarial Networks
iGAN — Generative Visual Manipulation on the Natural Image Manifold
IcGAN — Invertible Conditional GANs for image editing
ID-CGAN- Image De-raining Using a Conditional Generative Adversarial Network
Improved GAN — Improved Techniques for Training GANs
InfoGAN — InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets LAGAN — Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis LAPGAN — Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks
LR-GAN — LR-GAN: Layered Recursive Generative Adversarial Networks for Image Generation
LSGAN — Least Squares Generative Adversarial Networks
LS-GAN — Loss-Sensitive Generative Adversarial Networks on Lipschitz Densities
MGAN — Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks
MAGAN — MAGAN: Margin Adaptation for Generative Adversarial Networks
MAD-GAN — Multi-Agent Diverse Generative Adversarial Networks
MalGAN — Generating Adversarial Malware Examples for Black-Box Attacks Based on GAN
MaliGAN — Maximum-Likelihood Augmented Discrete Generative Adversarial Networks
MARTA-GAN — Deep Unsupervised Representation Learning for Remote Sensing Images
McGAN — McGan: Mean and Covariance Feature Matching GAN
MDGAN — Mode Regularized Generative Adversarial Networks
MedGAN — Generating Multi-label Discrete Electronic Health Records using Generative Adversarial Networks
MIX+GAN — Generalization and Equilibrium in Generative Adversarial Nets (GANs)
MPM-GAN — Message Passing Multi-Agent GANs
MV-BiGAN — Multi-view Generative Adversarial Networks
pix2pix — Image-to-Image Translation with Conditional Adversarial Networks
PPGN — Plug & Play Generative Networks: Conditional Iterative Generation of Images in Latent Space
PrGAN — 3D Shape Induction from 2D Views of Multiple Objects
RenderGAN — RenderGAN: Generating Realistic Labeled Data
RTT-GAN — Recurrent Topic-Transition GAN for Visual Paragraph Generation
SGAN — Stacked Generative Adversarial Networks
SGAN — Texture Synthesis with Spatial Generative Adversarial Networks
SAD-GAN — SAD-GAN: Synthetic Autonomous Driving using Generative Adversarial Networks
SalGAN — SalGAN: Visual Saliency Prediction with Generative Adversarial Networks
SEGAN — SEGAN: Speech Enhancement Generative Adversarial Network
SeGAN — SeGAN: Segmenting and Generating the Invisible
SeqGAN — SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient
SimGAN — Learning from Simulated and Unsupervised Images through Adversarial Training
SketchGAN — Adversarial Training For Sketch Retrieval
SL-GAN — Semi-Latent GAN: Learning to generate and modify facial images from attributes
Softmax-GAN — Softmax GAN
SRGAN — Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network
S2GAN — Generative Image Modeling using Style and Structure Adversarial Networks
SSL-GAN — Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
StackGAN — StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
TGAN — Temporal Generative Adversarial Nets
TAC-GAN — TAC-GAN — Text Conditioned Auxiliary Classifier Generative Adversarial Network
TP-GAN — Beyond Face Rotation: Global and Local Perception GAN for Photorealistic and Identity Preserving Frontal View Synthesis Triple-GAN — Triple Generative Adversarial Nets
Unrolled GAN — Unrolled Generative Adversarial Networks
VGAN — Generating Videos with Scene Dynamics
VGAN — Generative Adversarial Networks as Variational Training of Energy Based Models
VAE-GAN — Autoencoding beyond pixels using a learned similarity metric
VariGAN — Multi-View Image Generation from a Single-View
ViGAN — Image Generation and Editing with Variational Info Generative AdversarialNetworks
WGAN — Wasserstein GAN
WGAN-GP — Improved Training of Wasserstein GANs
WaterGAN — WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images

Deep Hunt, blog by Avinash Hindupur
https://deephunt.in/the-gan-zoo-79597dc8c347

GAN Zoo

3D-ED-GAN - Shape Inpainting using 3D Generative Adversarial Network and Recurrent Convolutional Networks
3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
3D-PhysNet - 3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations
3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
ABC-GAN - GANs for LIFE: Generative Adversarial Networks for Likelihood Free Inference
AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
acGAN - Face Aging With Conditional Generative Adversarial Networks
ACGAN - Coverless Information Hiding Based on Generative adversarial networks
acGAN - On-line Adaptative Curriculum Learning for GANs
ACtuAL - ACtuAL: Actor-Critic Under Adversarial Learning
AdaGAN - AdaGAN: Boosting Generative Models
Adaptive GAN - Customizing an Adversarial Example Generator with Class-Conditional GANs
AdvEntuRe - AdvEntuRe: Adversarial Training for Textual Entailment with Knowledge-Guided Examples
AdvGAN - Generating adversarial examples with adversarial networks
AE-GAN - AE-GAN: adversarial eliminating with GAN
AE-OT - Latent Space Optimal Transport for Generative Models
AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
AF-DCGAN - AF-DCGAN: Amplitude Feature Deep Convolutional GAN for Fingerprint Construction in Indoor Localization System
AffGAN - Amortised MAP Inference for Image Super-resolution
AIM - Generating Informative and Diverse Conversational Responses via Adversarial Information Maximization
AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
ALI - Adversarially Learned Inference (github)
AlignGAN - AlignGAN: Learning to Align Cross-Domain Images with Conditional Generative Adversarial Networks
AlphaGAN - AlphaGAN: Generative adversarial networks for natural image matting
AM-GAN - Activation Maximization Generative Adversarial Nets
AmbientGAN - AmbientGAN: Generative models from lossy measurements (github)
AMC-GAN - Video Prediction with Appearance and Motion Conditions
AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
APD - Adversarial Distillation of Bayesian Neural Network Posteriors
APE-GAN - APE-GAN: Adversarial Perturbation Elimination with GAN
ARAE - Adversarially Regularized Autoencoders for Generating Discrete Structures (github)
ARDA - Adversarial Representation Learning for Domain Adaptation
ARIGAN - ARIGAN: Synthetic Arabidopsis Plants using Generative Adversarial Network
ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
ASDL-GAN - Automatic Steganographic Distortion Learning Using a Generative Adversarial Network
ATA-GAN - Attention-Aware Generative Adversarial Networks (ATA-GANs)
Attention-GAN - Attention-GAN for Object Transfiguration in Wild Images
AttGAN - Arbitrary Facial Attribute Editing: Only Change What You Want (github)
AttnGAN - AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks (github)
AVID - AVID: Adversarial Visual Irregularity Detection
B-DCGAN - B-DCGAN:Evaluation of Binarized DCGAN for FPGA
b-GAN - Generative Adversarial Nets from a Density Ratio Estimation Perspective
BAGAN - BAGAN: Data Augmentation with Balancing GAN
Bayesian GAN - Deep and Hierarchical Implicit Models
Bayesian GAN - Bayesian GAN (github)
BCGAN - Bayesian Conditional Generative Adverserial Networks
BCGAN - Bidirectional Conditional Generative Adversarial networks
BEAM - Boltzmann Encoded Adversarial Machines
BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
BEGAN-CS - Escaping from Collapsing Modes in a Constrained Space
Bellman GAN - Distributional Multivariate Policy Evaluation and Exploration with the Bellman GAN
BGAN - Binary Generative Adversarial Networks for Image Retrieval (github)
Bi-GAN - Autonomously and Simultaneously Refining Deep Neural Network Parameters by a Bi-Generative Adversarial Network Aided Genetic Algorithm
BicycleGAN - Toward Multimodal Image-to-Image Translation (github)
BiGAN - Adversarial Feature Learning
BinGAN - BinGAN: Learning Compact Binary Descriptors with a Regularized GAN
BourGAN - BourGAN: Generative Networks with Metric Embeddings
BranchGAN - Branched Generative Adversarial Networks for Multi-Scale Image Manifold Learning
BRE - Improving GAN Training via Binarized Representation Entropy (BRE) Regularization (github)
BridgeGAN - Generative Adversarial Frontal View to Bird View Synthesis
BS-GAN - Boundary-Seeking Generative Adversarial Networks
BubGAN - BubGAN: Bubble Generative Adversarial Networks for Synthesizing Realistic Bubbly Flow Images
BWGAN - Banach Wasserstein GAN
C-GAN - Face Aging with Contextual Generative Adversarial Nets
C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training (github)
CA-GAN - Composition-aided Sketch-realistic Portrait Generation
CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks (github)
CAN - CAN: Creative Adversarial Networks, Generating Art by Learning About Styles and Deviating from Style Norms
CapsGAN - CapsGAN: Using Dynamic Routing for Generative Adversarial Networks
CapsuleGAN - CapsuleGAN: Generative Adversarial Capsule Network
CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
CatGAN - CatGAN: Coupled Adversarial Transfer for Domain Generation
CausalGAN - CausalGAN: Learning Causal Implicit Generative Models with Adversarial Training
CC-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks (github)
cd-GAN - Conditional Image-to-Image Translation
CDcGAN - Simultaneously Color-Depth Super-Resolution with Conditional Generative Adversarial Network
CE-GAN - Deep Learning for Imbalance Data Classification using Class Expert Generative Adversarial Network
CFG-GAN - Composite Functional Gradient Learning of Generative Adversarial Models
CGAN - Conditional Generative Adversarial Nets
CGAN - Controllable Generative Adversarial Network
Chekhov GAN - An Online Learning Approach to Generative Adversarial Networks
ciGAN - Conditional Infilling GANs for Data Augmentation in Mammogram Classification
CinCGAN - Unsupervised Image Super-Resolution using Cycle-in-Cycle Generative Adversarial Networks
CipherGAN - Unsupervised Cipher Cracking Using Discrete GANs
ClusterGAN - ClusterGAN : Latent Space Clustering in Generative Adversarial Networks
CM-GAN - CM-GANs: Cross-modal Generative Adversarial Networks for Common Representation Learning
CoAtt-GAN - Are You Talking to Me? Reasoned Visual Dialog Generation through Adversarial Learning
CoGAN - Coupled Generative Adversarial Networks
ComboGAN - ComboGAN: Unrestrained Scalability for Image Domain Translation (github)
ConceptGAN - Learning Compositional Visual Concepts with Mutual Consistency
Conditional cycleGAN - Conditional CycleGAN for Attribute Guided Face Image Generation
constrast-GAN - Generative Semantic Manipulation with Contrasting GAN
Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
CorrGAN - Correlated discrete data generation using adversarial training
Coulomb GAN - Coulomb GANs: Provably Optimal Nash Equilibria via Potential Fields
Cover-GAN - Generative Steganography with Kerckhoffs' Principle based on Generative Adversarial Networks
cowboy - Defending Against Adversarial Attacks by Leveraging an Entire GAN
CR-GAN - CR-GAN: Learning Complete Representations for Multi-view Generation
Cramèr GAN - The Cramer Distance as a Solution to Biased Wasserstein Gradients
Cross-GAN - Crossing Generative Adversarial Networks for Cross-View Person Re-identification
crVAE-GAN - Channel-Recurrent Variational Autoencoders
CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
CSG - Speech-Driven Expressive Talking Lips with Conditional Sequential Generative Adversarial Networks
CT-GAN - CT-GAN: Conditional Transformation Generative Adversarial Network for Image Attribute Modification
CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (github)
D-GAN - Differential Generative Adversarial Networks: Synthesizing Non-linear Facial Variations with Limited Number of Training Data
D-WCGAN - I-vector Transformation Using Conditional Generative Adversarial Networks for Short Utterance Speaker Verification
D2GAN - Dual Discriminator Generative Adversarial Nets
D2IA-GAN - Tagging like Humans: Diverse and Distinct Image Annotation
DA-GAN - DA-GAN: Instance-level Image Translation by Deep Attention Generative Adversarial Networks (with Supplementary Materials)
DADA - DADA: Deep Adversarial Data Augmentation for Extremely Low Data Regime Classification
DAGAN - Data Augmentation Generative Adversarial Networks
DAN - Distributional Adversarial Networks
DBLRGAN - Adversarial Spatio-Temporal Learning for Video Deblurring
DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (github)
DE-GAN - Generative Adversarial Networks with Decoder-Encoder Output Noise
DeblurGAN - DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks (github)
DeepFD - Learning to Detect Fake Face Images in the Wild
Defense-GAN - Defense-GAN: Protecting Classifiers Against Adversarial Attacks Using Generative Models (github)
Defo-Net - Defo-Net: Learning Body Deformation using Generative Adversarial Networks
DeliGAN - DeLiGAN : Generative Adversarial Networks for Diverse and Limited Data (github)
DF-GAN - Learning Disentangling and Fusing Networks for Face Completion Under Structured Occlusions
DialogWAE - DialogWAE: Multimodal Response Generation with Conditional Wasserstein Auto-Encoder
DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
DistanceGAN - One-Sided Unsupervised Domain Mapping
DM-GAN - Dual Motion GAN for Future-Flow Embedded Video Prediction
DMGAN - Disconnected Manifold Learning for Generative Adversarial Networks
DNA-GAN - DNA-GAN: Learning Disentangled Representations from Multi-Attribute Images
DOPING - DOPING: Generative Data Augmentation for Unsupervised Anomaly Detection with GAN
dp-GAN - Differentially Private Releasing via Deep Generative Model
DP-GAN - DP-GAN: Diversity-Promoting Generative Adversarial Network for Generating Informative and Diversified Text
DPGAN - Differentially Private Generative Adversarial Network
DR-GAN - Representation Learning by Rotating Your Faces
DRAGAN - How to Train Your DRAGAN (github)
Dropout-GAN - Dropout-GAN: Learning from a Dynamic Ensemble of Discriminators
DRPAN - Discriminative Region Proposal Adversarial Networks for High-Quality Image-to-Image Translation
DSH-GAN - Deep Semantic Hashing with Generative Adversarial Networks
DSP-GAN - Depth Structure Preserving Scene Image Generation
DTLC-GAN - Generative Adversarial Image Synthesis with Decision Tree Latent Controller
DTN - Unsupervised Cross-Domain Image Generation
DTR-GAN - DTR-GAN: Dilated Temporal Relational Adversarial Network for Video Summarization
DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
Dualing GAN - Dualing GANs
DVGAN - Human Motion Modeling using DVGANs
Dynamics Transfer GAN - Dynamics Transfer GAN: Generating Video by Transferring Arbitrary Temporal Dynamics from a Source Video to a Single Target Image
E-GAN - Evolutionary Generative Adversarial Networks
EAR - Generative Model for Heterogeneous Inference
EBGAN - Energy-based Generative Adversarial Network
ecGAN - eCommerceGAN : A Generative Adversarial Network for E-commerce
ED//GAN - Stabilizing Training of Generative Adversarial Networks through Regularization
Editable GAN - Editable Generative Adversarial Networks: Generating and Editing Faces Simultaneously
EGAN - Enhanced Experience Replay Generation for Efficient Reinforcement Learning
EL-GAN - EL-GAN: Embedding Loss Driven Generative Adversarial Networks for Lane Detection
ELEGANT - ELEGANT: Exchanging Latent Encodings with GAN for Transferring Multiple Face Attributes
EnergyWGAN - Energy-relaxed Wassertein GANs (EnergyWGAN): Towards More Stable and High Resolution Image Generation
ESRGAN - ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks
ExGAN - Eye In-Painting with Exemplar Generative Adversarial Networks
ExposureGAN - Exposure: A White-Box Photo Post-Processing Framework (github)
ExprGAN - ExprGAN: Facial Expression Editing with Controllable Expression Intensity
f-CLSWGAN - Feature Generating Networks for Zero-Shot Learning
f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
FairGAN - FairGAN: Fairness-aware Generative Adversarial Networks
Fairness GAN - Fairness GAN
FakeGAN - Detecting Deceptive Reviews using Generative Adversarial Networks
FBGAN - Feedback GAN (FBGAN) for DNA: a Novel Feedback-Loop Architecture for Optimizing Protein Functions
FBGAN - Featurized Bidirectional GAN: Adversarial Defense via Adversarially Learned Semantic Inference
FC-GAN - Fast-converging Conditional Generative Adversarial Networks for Image Synthesis
FF-GAN - Towards Large-Pose Face Frontalization in the Wild
FGGAN - Adversarial Learning for Fine-grained Image Search
Fictitious GAN - Fictitious GAN: Training GANs with Historical Models
FIGAN - Frame Interpolation with Multi-Scale Deep Loss Functions and Generative Adversarial Networks
Fila-GAN - Synthesizing Filamentary Structured Images with GANs
First Order GAN - First Order Generative Adversarial Networks (github)
Fisher GAN - Fisher GAN
Flow-GAN - Flow-GAN: Bridging implicit and prescribed learning in generative models
FrankenGAN - rankenGAN: Guided Detail Synthesis for Building Mass-Models Using Style-Synchonized GANs
FSEGAN - Exploring Speech Enhancement with Generative Adversarial Networks for Robust Speech Recognition
FTGAN - Hierarchical Video Generation from Orthogonal Information: Optical Flow and Texture
FusedGAN - Semi-supervised FusedGAN for Conditional Image Generation
FusionGAN - Learning to Fuse Music Genres with Generative Adversarial Dual Learning
FusionGAN - Generating a Fusion Image: One's Identity and Another's Shape
G2-GAN - Geometry Guided Adversarial Facial Expression Synthesis
GAAN - Generative Adversarial Autoencoder Networks
GAF - Generative Adversarial Forests for Better Conditioned Adversarial Learning
GAGAN - GAGAN: Geometry-Aware Generative Adverserial Networks
GAIA - Generative adversarial interpolative autoencoding: adversarial training on latent space interpolations encourage convex latent distributions
GAIN - GAIN: Missing Data Imputation using Generative Adversarial Nets
GAMN - Generative Adversarial Mapping Networks
GAN - Generative Adversarial Networks (github)
GAN Lab - GAN Lab: Understanding Complex Deep Generative Models using Interactive Visual Experimentation
GAN Q-learning - GAN Q-learning
GAN-AD - Anomaly Detection with Generative Adversarial Networks for Multivariate Time Series
GAN-ATV - A Novel Approach to Artistic Textual Visualization via GAN
GAN-CLS - Generative Adversarial Text to Image Synthesis (github)
GAN-RS - Towards Qualitative Advancement of Underwater Machine Vision with Generative Adversarial Networks
GAN-SD - Virtual-Taobao: Virtualizing Real-world Online Retail Environment for Reinforcement Learning
GAN-sep - GANs for Biological Image Synthesis (github)
GAN-VFS - Generative Adversarial Network-based Synthesis of Visible Faces from Polarimetric Thermal Faces
GAN-Word2Vec - Adversarial Training of Word2Vec for Basket Completion
GANAX - GANAX: A Unified MIMD-SIMD Acceleration for Generative Adversarial Networks
GANCS - Deep Generative Adversarial Networks for Compressed Sensing Automates MRI
GANDI - Guiding the search in continuous state-action spaces by learning an action sampling distribution from off-target samples
GANG - GANGs: Generative Adversarial Network Games
GANG - Beyond Local Nash Equilibria for Adversarial Networks
GANosaic - GANosaic: Mosaic Creation with Generative Texture Manifolds
GANVO - GANVO: Unsupervised Deep Monocular Visual Odometry and Depth Estimation with Generative Adversarial Networks
GAP - Context-Aware Generative Adversarial Privacy
GAP - Generative Adversarial Privacy
GATS - Sample-Efficient Deep RL with Generative Adversarial Tree Search
GAWWN - Learning What and Where to Draw (github)
GC-GAN - Geometry-Contrastive Generative Adversarial Network for Facial Expression Synthesis
GcGAN - Geometry-Consistent Adversarial Networks for One-Sided Unsupervised Domain Mapping
GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data (github)
GeoGAN - Generating Instance Segmentation Annotation by Geometry-guided GAN
Geometric GAN - Geometric GAN
GIN - Generative Invertible Networks (GIN): Pathophysiology-Interpretable Feature Mapping and Virtual Patient Generation
GLCA-GAN - Global and Local Consistent Age Generative Adversarial Networks
GM-GAN - Gaussian Mixture Generative Adversarial Networks for Diverse Datasets, and the Unsupervised Clustering of Images
GMAN - Generative Multi-Adversarial Networks
GMM-GAN - Towards Understanding the Dynamics of Generative Adversarial Networks
GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
GONet - GONet: A Semi-Supervised Deep Learning Approach For Traversability Estimation
GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending (github)
GP-GAN - GP-GAN: Gender Preserving GAN for Synthesizing Faces from Landmarks
GPU - A generative adversarial framework for positive-unlabeled classification
GRAN - Generating images with recurrent adversarial networks (github)
Graphical-GAN - Graphical Generative Adversarial Networks
GraphSGAN - Semi-supervised Learning on Graphs with Generative Adversarial Nets
GraspGAN - Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping
GT-GAN - Deep Graph Translation
HAN - Chinese Typeface Transformation with Hierarchical Adversarial Network
HAN - Bidirectional Learning for Robust Neural Networks
HiGAN - Exploiting Images for Video Recognition with Hierarchical Generative Adversarial Networks
HP-GAN - HP-GAN: Probabilistic 3D human motion prediction via GAN
HR-DCGAN - High-Resolution Deep Convolutional Generative Adversarial Networks
hredGAN - Multi-turn Dialogue Response Generation in an Adversarial Learning framework
IAN - Neural Photo Editing with Introspective Adversarial Networks (github)
IcGAN - Invertible Conditional GANs for image editing (github)
ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
IdCycleGAN - Face Translation between Images and Videos using Identity-aware CycleGAN
IFcVAEGAN - Conditional Autoencoders with Adversarial Information Factorization
iGAN - Generative Visual Manipulation on the Natural Image Manifold (github)
IGMM-GAN - Coupled IGMM-GANs for deep multimodal anomaly detection in human mobility data
Improved GAN - Improved Techniques for Training GANs (github)
In2I - In2I : Unsupervised Multi-Image-to-Image Translation Using Generative Adversarial Networks
InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets (github)
IntroVAE - IntroVAE: Introspective Variational Autoencoders for Photographic Image Synthesis
IR2VI - IR2VI: Enhanced Night Environmental Perception by Unsupervised Thermal Image Translation
IRGAN - IRGAN: A Minimax Game for Unifying Generative and Discriminative Information Retrieval models
IRGAN - Generative Adversarial Nets for Information Retrieval: Fundamentals and Advances
ISGAN - Invisible Steganography via Generative Adversarial Network
ISP-GPM - Inner Space Preserving Generative Pose Machine
Iterative-GAN - Two Birds with One Stone: Iteratively Learn Facial Attributes with GANs (github)
IterGAN - IterGANs: Iterative GANs to Learn and Control 3D Object Transformation
IVE-GAN - IVE-GAN: Invariant Encoding Generative Adversarial Networks
iVGAN - Towards an Understanding of Our World by GANing Videos in the Wild (github)
IWGAN - On Unifying Deep Generative Models
JointGAN - JointGAN: Multi-Domain Joint Distribution Learning with Generative Adversarial Nets
JR-GAN - JR-GAN: Jacobian Regularization for Generative Adversarial Networks
KBGAN - KBGAN: Adversarial Learning for Knowledge Graph Embeddings
KGAN - KGAN: How to Break The Minimax Game in GAN
l-GAN - Representation Learning and Adversarial Generation of 3D Point Clouds
LAC-GAN - Grounded Language Understanding for Manipulation Instructions Using GAN-Based Classification
LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis
LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks (github)
LB-GAN - Load Balanced GANs for Multi-view Face Image Synthesis
LBT - Learning Implicit Generative Models by Teaching Explicit Ones
LCC-GAN - Adversarial Learning with Local Coordinate Coding
LD-GAN - Linear Discriminant Generative Adversarial Networks
LDAN - Label Denoising Adversarial Network (LDAN) for Inverse Lighting of Face Images
LeakGAN - Long Text Generation via Adversarial Training with Leaked Information
LeGAN - Likelihood Estimation for Generative Adversarial Networks
LGAN - Global versus Localized Generative Adversarial Nets
Lipizzaner - Towards Distributed Coevolutionary GANs
LR-GAN - LR-GAN: Layered Recursive Generative Adversarial Networks for Image Generation
LS-GAN - Loss-Sensitive Generative Adversarial Networks on Lipschitz Densities
LSGAN - Least Squares Generative Adversarial Networks
M-AAE - Mask-aware Photorealistic Face Attribute Manipulation
MAD-GAN - Multi-Agent Diverse Generative Adversarial Networks
MAGAN - MAGAN: Margin Adaptation for Generative Adversarial Networks
MAGAN - MAGAN: Aligning Biological Manifolds
MalGAN - Generating Adversarial Malware Examples for Black-Box Attacks Based on GAN
MaliGAN - Maximum-Likelihood Augmented Discrete Generative Adversarial Networks
manifold-WGAN - Manifold-valued Image Generation with Wasserstein Adversarial Networks
MARTA-GAN - Deep Unsupervised Representation Learning for Remote Sensing Images
MaskGAN - MaskGAN: Better Text Generation via Filling in the ______
MC-GAN - Multi-Content GAN for Few-Shot Font Style Transfer (github)
MC-GAN - MC-GAN: Multi-conditional Generative Adversarial Network for Image Synthesis
McGAN - McGan: Mean and Covariance Feature Matching GAN
MD-GAN - Learning to Generate Time-Lapse Videos Using Multi-Stage Dynamic Generative Adversarial Networks
MDGAN - Mode Regularized Generative Adversarial Networks
MedGAN - Generating Multi-label Discrete Electronic Health Records using Generative Adversarial Networks
MedGAN - MedGAN: Medical Image Translation using GANs
MEGAN - MEGAN: Mixture of Experts of Generative Adversarial Networks for Multimodal Image Generation
MelanoGAN - MelanoGANs: High Resolution Skin Lesion Synthesis with GANs
memoryGAN - Memorization Precedes Generation: Learning Unsupervised GANs with Memory Networks
MeRGAN - Memory Replay GANs: learning to generate images from new categories without forgetting
MGAN - Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks (github)
MGGAN - Multi-Generator Generative Adversarial Nets
MGGAN - MGGAN: Solving Mode Collapse using Manifold Guided Training
MIL-GAN - Multimodal Storytelling via Generative Adversarial Imitation Learning
MinLGAN - Anomaly Detection via Minimum Likelihood Generative Adversarial Networks
MIX+GAN - Generalization and Equilibrium in Generative Adversarial Nets (GANs)
MIXGAN - MIXGAN: Learning Concepts from Different Domains for Mixture Generation
MLGAN - Metric Learning-based Generative Adversarial Network
MMC-GAN - A Multimodal Classifier Generative Adversarial Network for Carry and Place Tasks from Ambiguous Language Instructions
MMD-GAN - MMD GAN: Towards Deeper Understanding of Moment Matching Network (github)
MMGAN - MMGAN: Manifold Matching Generative Adversarial Network for Generating Images
MoCoGAN - MoCoGAN: Decomposing Motion and Content for Video Generation (github)
Modified GAN-CLS - Generate the corresponding Image from Text Description using Modified GAN-CLS Algorithm
ModularGAN - Modular Generative Adversarial Networks
MolGAN - MolGAN: An implicit generative model for small molecular graphs
MPM-GAN - Message Passing Multi-Agent GANs
MS-GAN - Temporal Coherency based Criteria for Predicting Video Frames using Deep Multi-stage Generative Adversarial Networks
MTGAN - MTGAN: Speaker Verification through Multitasking Triplet Generative Adversarial Networks
MuseGAN - MuseGAN: Symbolic-domain Music Generation and Accompaniment with Multi-track Sequential Generative Adversarial Networks
MV-BiGAN - Multi-view Generative Adversarial Networks
N2RPP - N2RPP: An Adversarial Network to Rebuild Plantar Pressure for ACLD Patients
NAN - Understanding Humans in Crowded Scenes: Deep Nested Adversarial Learning and A New Benchmark for Multi-Human Parsing
NCE-GAN - Dihedral angle prediction using generative adversarial networks
ND-GAN - Novelty Detection with GAN
NetGAN - NetGAN: Generating Graphs via Random Walks
OCAN - One-Class Adversarial Nets for Fraud Detection
OptionGAN - OptionGAN: Learning Joint Reward-Policy Options using Generative Adversarial Inverse Reinforcement Learning
ORGAN - Objective-Reinforced Generative Adversarial Networks (ORGAN) for Sequence Generation Models
ORGAN - 3D Reconstruction of Incomplete Archaeological Objects Using a Generative Adversary Network
OT-GAN - Improving GANs Using Optimal Transport
PacGAN - PacGAN: The power of two samples in generative adversarial networks
PAN - Perceptual Adversarial Networks for Image-to-Image Transformation
PassGAN - PassGAN: A Deep Learning Approach for Password Guessing
PD-WGAN - Primal-Dual Wasserstein GAN
Perceptual GAN - Perceptual Generative Adversarial Networks for Small Object Detection
PGAN - Probabilistic Generative Adversarial Networks
PGD-GAN - Solving Linear Inverse Problems Using GAN Priors: An Algorithm with Provable Guarantees
PGGAN - Patch-Based Image Inpainting with Generative Adversarial Networks
PIONEER - Pioneer Networks: Progressively Growing Generative Autoencoder
Pip-GAN - Pipeline Generative Adversarial Networks for Facial Images Generation with Multiple Attributes
pix2pix - Image-to-Image Translation with Conditional Adversarial Networks (github)
pix2pixHD - High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs (github)
PixelGAN - PixelGAN Autoencoders
PM-GAN - PM-GANs: Discriminative Representation Learning for Action Recognition Using Partial-modalities
PN-GAN - Pose-Normalized Image Generation for Person Re-identification
POGAN - Perceptually Optimized Generative Adversarial Network for Single Image Dehazing
Pose-GAN - The Pose Knows: Video Forecasting by Generating Pose Futures
PP-GAN - Privacy-Protective-GAN for Face De-identification
PPAN - Privacy-Preserving Adversarial Networks
PPGN - Plug & Play Generative Networks: Conditional Iterative Generation of Images in Latent Space
PrGAN - 3D Shape Induction from 2D Views of Multiple Objects
ProGanSR - A Fully Progressive Approach to Single-Image Super-Resolution
Progressive GAN - Progressive Growing of GANs for Improved Quality, Stability, and Variation (github)
PS-GAN - Pedestrian-Synthesis-GAN: Generating Pedestrian Data in Real Scene and Beyond
PSGAN - Learning Texture Manifolds with the Periodic Spatial GAN
PSGAN - PSGAN: A Generative Adversarial Network for Remote Sensing Image Pan-Sharpening
PS²-GAN - High-Quality Facial Photo-Sketch Synthesis Using Multi-Adversarial Networks
RadialGAN - RadialGAN: Leveraging multiple datasets to improve target-specific predictive models using Generative Adversarial Networks
RaGAN - The relativistic discriminator: a key element missing from standard GAN
RAN - RAN4IQA: Restorative Adversarial Nets for No-Reference Image Quality Assessment (github)
RankGAN - Adversarial Ranking for Language Generation
RCGAN - Real-valued (Medical) Time Series Generation with Recurrent Conditional GANs
ReConNN - Reconstruction of Simulation-Based Physical Field with Limited Samples by Reconstruction Neural Network
Recycle-GAN - Recycle-GAN: Unsupervised Video Retargeting
RefineGAN - Compressed Sensing MRI Reconstruction with Cyclic Loss in Generative Adversarial Networks
ReGAN - ReGAN: RE[LAX|BAR|INFORCE] based Sequence Generation using GANs (github)
RegCGAN - Unpaired Multi-Domain Image Generation via Regularized Conditional GANs
RenderGAN - RenderGAN: Generating Realistic Labeled Data
Resembled GAN - Resembled Generative Adversarial Networks: Two Domains with Similar Attributes
ResGAN - Generative Adversarial Network based on Resnet for Conditional Image Restoration
RNN-WGAN - Language Generation with Recurrent Generative Adversarial Networks without Pre-training (github)
RoCGAN - Robust Conditional Generative Adversarial Networks
RPGAN - Stabilizing GAN Training with Multiple Random Projections (github)
RTT-GAN - Recurrent Topic-Transition GAN for Visual Paragraph Generation
RWGAN - Relaxed Wasserstein with Applications to GANs
SAD-GAN - SAD-GAN: Synthetic Autonomous Driving using Generative Adversarial Networks
SAGA - Generative Adversarial Learning for Spectrum Sensing
SAGAN - Self-Attention Generative Adversarial Networks
SalGAN - SalGAN: Visual Saliency Prediction with Generative Adversarial Networks (github)
SAM - Sample-Efficient Imitation Learning via Generative Adversarial Nets
sAOG - Deep Structured Generative Models
SAR-GAN - Generating High Quality Visible Images from SAR Images Using CNNs
SBADA-GAN - From source to target and back: symmetric bi-directional adaptive GAN
ScarGAN - ScarGAN: Chained Generative Adversarial Networks to Simulate Pathological Tissue on Cardiovascular MR Scans
SCH-GAN - SCH-GAN: Semi-supervised Cross-modal Hashing by Generative Adversarial Network
SD-GAN - Semantically Decomposing the Latent Spaces of Generative Adversarial Networks
Sdf-GAN - Sdf-GAN: Semi-supervised Depth Fusion with Multi-scale Adversarial Networks
SEGAN - SEGAN: Speech Enhancement Generative Adversarial Network
SeGAN - SeGAN: Segmenting and Generating the Invisible
SegAN - SegAN: Adversarial Network with Multi-scale L1 Loss for Medical Image Segmentation
Sem-GAN - Sem-GAN: Semantically-Consistent Image-to-Image Translation
SeqGAN - SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient (github)
SeUDA - Semantic-Aware Generative Adversarial Nets for Unsupervised Domain Adaptation in Chest X-ray Segmentation
SG-GAN - Semantic-aware Grad-GAN for Virtual-to-Real Urban Scene Adaption (github)
SG-GAN - Sparsely Grouped Multi-task Generative Adversarial Networks for Facial Attribute Manipulation
SGAN - Texture Synthesis with Spatial Generative Adversarial Networks
SGAN - Stacked Generative Adversarial Networks (github)
SGAN - Steganographic Generative Adversarial Networks
SGAN - SGAN: An Alternative Training of Generative Adversarial Networks
SGAN - CT Image Enhancement Using Stacked Generative Adversarial Networks and Transfer Learning for Lesion Segmentation Improvement
sGAN - Generative Adversarial Training for MRA Image Synthesis Using Multi-Contrast MRI
SiftingGAN - SiftingGAN: Generating and Sifting Labeled Samples to Improve the Remote Sensing Image Scene Classification Baseline in vitro
SiGAN - SiGAN: Siamese Generative Adversarial Network for Identity-Preserving Face Hallucination
SimGAN - Learning from Simulated and Unsupervised Images through Adversarial Training
SisGAN - Semantic Image Synthesis via Adversarial Learning
Sketcher-Refiner GAN - Learning Myelin Content in Multiple Sclerosis from Multimodal MRI through Adversarial Training
SketchGAN - Adversarial Training For Sketch Retrieval
SketchyGAN - SketchyGAN: Towards Diverse and Realistic Sketch to Image Synthesis
Skip-Thought GAN - Generating Text through Adversarial Training using Skip-Thought Vectors
SL-GAN - Semi-Latent GAN: Learning to generate and modify facial images from attributes
SLSR - Sparse Label Smoothing for Semi-supervised Person Re-Identification
SN-DCGAN - Generative Adversarial Networks for Unsupervised Object Co-localization
SN-GAN - Spectral Normalization for Generative Adversarial Networks (github)
SN-PatchGAN - Free-Form Image Inpainting with Gated Convolution
Sobolev GAN - Sobolev GAN
Social GAN - Social GAN: Socially Acceptable Trajectories with Generative Adversarial Networks
Softmax GAN - Softmax GAN
SoPhie - SoPhie: An Attentive GAN for Predicting Paths Compliant to Social and Physical Constraints
speech-driven animation GAN - End-to-End Speech-Driven Facial Animation with Temporal GANs
Spike-GAN - Synthesizing realistic neural population activity patterns using Generative Adversarial Networks
Splitting GAN - Class-Splitting Generative Adversarial Networks
SR-CNN-VAE-GAN - Semi-Recurrent CNN-based VAE-GAN for Sequential Data Generation (github)
SRGAN - Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network
SRPGAN - SRPGAN: Perceptual Generative Adversarial Network for Single Image Super Resolution
SS-GAN - Semi-supervised Conditional GANs
ss-InfoGAN - Guiding InfoGAN with Semi-Supervision
SSGAN - SSGAN: Secure Steganography Based on Generative Adversarial Networks
SSL-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
ST-CGAN - Stacked Conditional Generative Adversarial Networks for Jointly Learning Shadow Detection and Shadow Removal
ST-GAN - Style Transfer Generative Adversarial Networks: Learning to Play Chess Differently
ST-GAN - ST-GAN: Spatial Transformer Generative Adversarial Networks for Image Compositing
StackGAN - StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks (github)
StainGAN - StainGAN: Stain Style Transfer for Digital Histological Images
StarGAN - StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation (github)
StarGAN-VC - StarGAN-VC: Non-parallel many-to-many voice conversion with star generative adversarial networks
SteinGAN - Learning Deep Energy Models: Contrastive Divergence vs. Amortized MLE
StepGAN - Improving Conditional Sequence Generative Adversarial Networks by Stepwise Evaluation
Super-FAN - Super-FAN: Integrated facial landmark localization and super-resolution of real-world low resolution faces in arbitrary poses with GANs
SVSGAN - SVSGAN: Singing Voice Separation via Generative Adversarial Network
SWGAN - Solving Approximate Wasserstein GANs to Stationarity
SyncGAN - SyncGAN: Synchronize the Latent Space of Cross-modal Generative Adversarial Networks
S^2GAN - Generative Image Modeling using Style and Structure Adversarial Networks
T2Net - T2Net: Synthetic-to-Realistic Translation for Solving Single-Image Depth Estimation Tasks
table-GAN - Data Synthesis based on Generative Adversarial Networks
TAC-GAN - TAC-GAN - Text Conditioned Auxiliary Classifier Generative Adversarial Network (github)
TAN - Outline Colorization through Tandem Adversarial Networks
tcGAN - Cross-modal Hallucination for Few-shot Fine-grained Recognition
TD-GAN - Task Driven Generative Modeling for Unsupervised Domain Adaptation: Application to X-ray Image Segmentation
tempCycleGAN - Improving Surgical Training Phantoms by Hyperrealism: Deep Unpaired Image-to-Image Translation from Real Surgeries
tempoGAN - tempoGAN: A Temporally Coherent, Volumetric GAN for Super-resolution Fluid Flow
TequilaGAN - TequilaGAN: How to easily identify GAN samples
Text2Shape - Text2Shape: Generating Shapes from Natural Language by Learning Joint Embeddings
textGAN - Generating Text via Adversarial Training
TextureGAN - TextureGAN: Controlling Deep Image Synthesis with Texture Patches
TGAN - Temporal Generative Adversarial Nets
TGAN - Tensorizing Generative Adversarial Nets
TGAN - Tensor-Generative Adversarial Network with Two-dimensional Sparse Coding: Application to Real-time Indoor Localization
TGANs-C - To Create What You Tell: Generating Videos from Captions
tiny-GAN - Analysis of Nonautonomous Adversarial Systems
TP-GAN - Beyond Face Rotation: Global and Local Perception GAN for Photorealistic and Identity Preserving Frontal View Synthesis
TreeGAN - TreeGAN: Syntax-Aware Sequence Generation with Generative Adversarial Networks
Triple-GAN - Triple Generative Adversarial Nets
tripletGAN - TripletGAN: Training Generative Model with Triplet Loss
TV-GAN - TV-GAN: Generative Adversarial Network Based Thermal to Visible Face Recognition
Twin-GAN - Twin-GAN -- Unpaired Cross-Domain Image Translation with Weight-Sharing GANs
UGACH - Unsupervised Generative Adversarial Cross-modal Hashing
UGAN - Enhancing Underwater Imagery using Generative Adversarial Networks
Unim2im - Unsupervised Image-to-Image Translation with Generative Adversarial Networks (github)
UNIT - Unsupervised Image-to-image Translation Networks (github)
Unrolled GAN - Unrolled Generative Adversarial Networks (github)
UT-SCA-GAN - Spatial Image Steganography Based on Generative Adversarial Network
UV-GAN - UV-GAN: Adversarial Facial UV Map Completion for Pose-invariant Face Recognition
VA-GAN - Visual Feature Attribution using Wasserstein GANs
VAC+GAN - Versatile Auxiliary Classifier with Generative Adversarial Network (VAC+GAN), Multi Class Scenarios
VAE-GAN - Autoencoding beyond pixels using a learned similarity metric
VariGAN - Multi-View Image Generation from a Single-View
VAW-GAN - Voice Conversion from Unaligned Corpora using Variational Autoencoding Wasserstein Generative Adversarial Networks
VEEGAN - VEEGAN: Reducing Mode Collapse in GANs using Implicit Variational Learning (github)
VGAN - Generating Videos with Scene Dynamics (github)
VGAN - Generative Adversarial Networks as Variational Training of Energy Based Models (github)
VGAN - Text Generation Based on Generative Adversarial Nets with Latent Variable
ViGAN - Image Generation and Editing with Variational Info Generative Adversarial Networks
VIGAN - VIGAN: Missing View Imputation with Generative Adversarial Networks
VoiceGAN - Voice Impersonation using Generative Adversarial Networks
VOS-GAN - VOS-GAN: Adversarial Learning of Visual-Temporal Dynamics for Unsupervised Dense Prediction in Videos
VRAL - Variance Regularizing Adversarial Learning
WaterGAN - WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images
WaveGAN - Synthesizing Audio with Generative Adversarial Networks
WaveletGLCA-GAN - Global and Local Consistent Wavelet-domain Age Synthesis
weGAN - Generative Adversarial Nets for Multiple Text Corpora
WGAN - Wasserstein GAN (github)
WGAN-CLS - Text to Image Synthesis Using Generative Adversarial Networks
WGAN-GP - Improved Training of Wasserstein GANs (github)
WGAN-L1 - Subsampled Turbulence Removal Network
WS-GAN - Weakly Supervised Generative Adversarial Networks for 3D Reconstruction
X-GANs - X-GANs: Image Reconstruction Made Easy for Extreme Cases
XGAN - XGAN: Unsupervised Image-to-Image Translation for many-to-many Mappings
ZipNet-GAN - ZipNet-GAN: Inferring Fine-grained Mobile Traffic Patterns via a Generative Adversarial Neural Network
α-GAN - Variational Approaches for Auto-Encoding Generative Adversarial Networks (github)
β-GAN - Annealed Generative Adversarial Networks
Δ-GAN - Triangle Generative Adversarial Networks

An explo-GAN of papers



Explosive growth — All the named GAN variants cumulatively since 2014.

Credit: Bruno Gavranović

Deep Hunt, blog by Avinash Hindupur

Lecture overview

- Motivation
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- **GAN Progression**
  - **DC GAN (Radford et al, 2016)**
  - Improved Training of GANs (Salimans et al'16)
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN
  - BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, StyleGAN-v3, VQ-GAN
- Conditional GANs, Cycle-Consistent Adversarial Networks
- Applications

Deep Convolutional GAN (DCGAN)

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS

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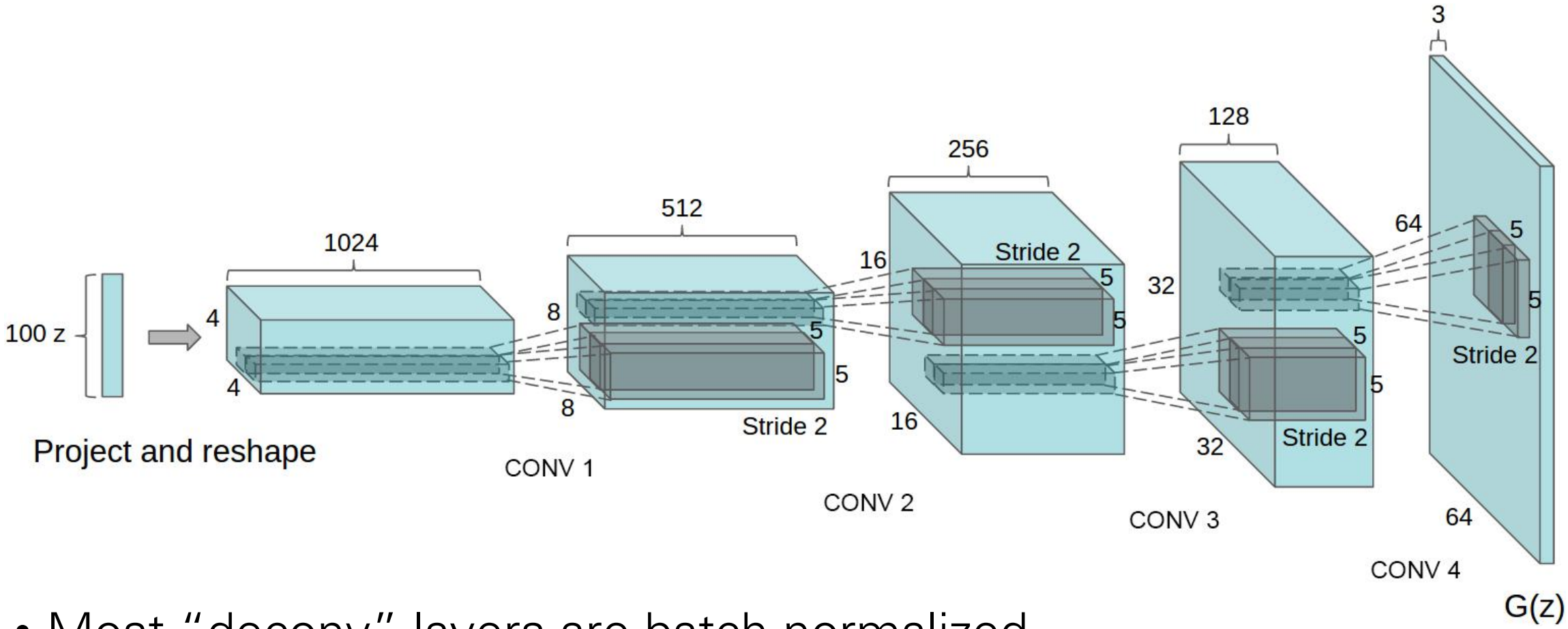
ABSTRACT

In recent years, supervised learning with convolutional networks (CNNs) has seen huge adoption in computer vision applications. Comparatively, unsupervised learning with CNNs has received less attention. In this work we hope to help bridge the gap between the success of CNNs for supervised learning and unsupervised learning. We introduce a class of CNNs called deep convolutional generative adversarial networks (DCGANs), that have certain architectural constraints, and demonstrate that they are a strong candidate for unsupervised learning. Training on various image datasets, we show convincing evidence that our deep convolutional adversarial pair learns a hierarchy of representations from object parts to scenes in both the generator and discriminator. Additionally, we use the learned features for novel tasks - demonstrating their applicability as general image representations.

Deep Convolutional GAN (DCGAN)



- Most "deconv" layers are batch normalized

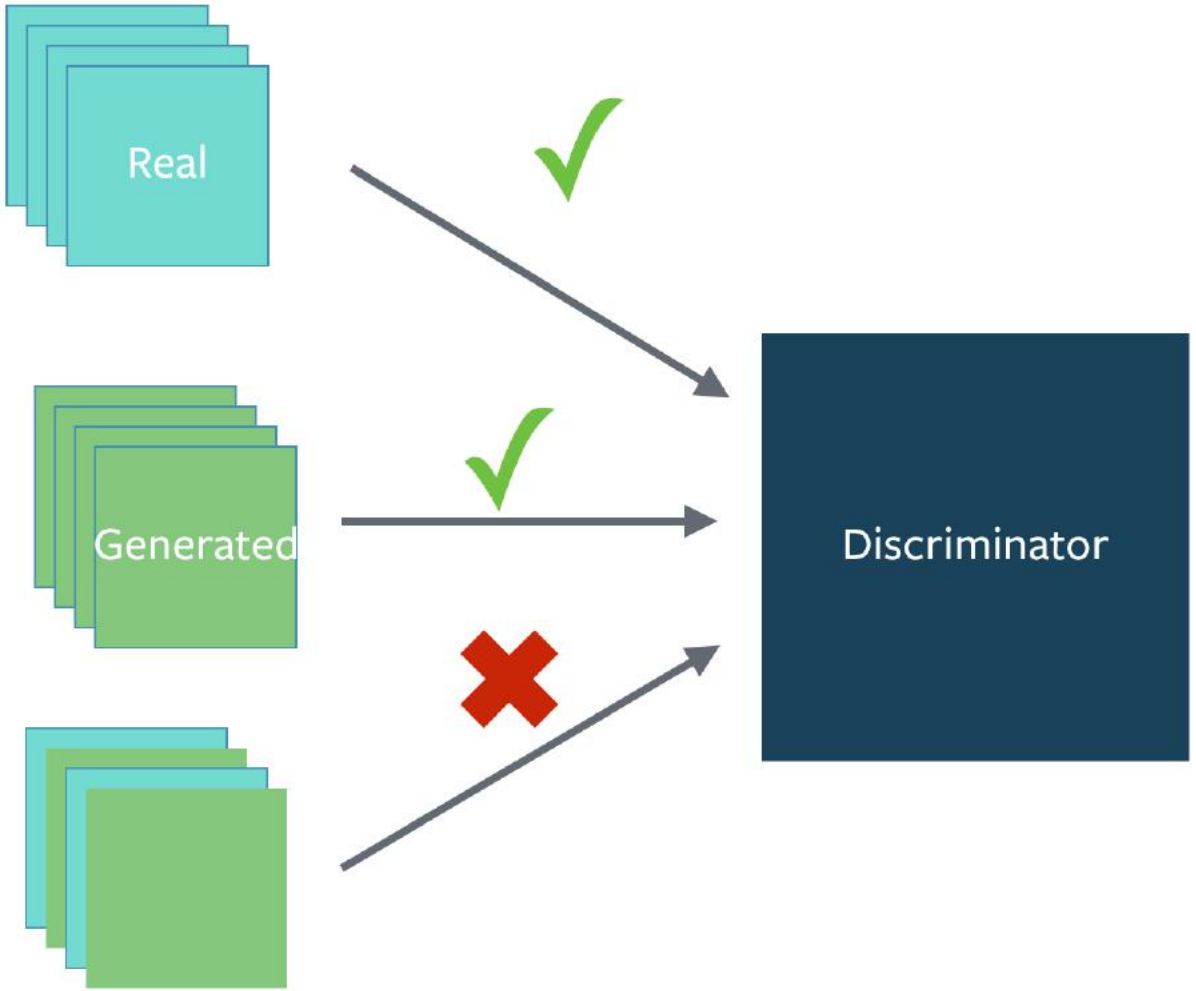
[Radford et al 2016]

DCGAN - Architecture Design

- Supervised Learning CNNs not directly usable
  - Remove max-pooling and mean-pooling
  - Upsample using transposed convolutions in the generator
  - Downsample with strided convolutions and average pooling
  - Non-Linearity: ReLU for generator, Leaky-ReLU (0.2) for discriminator
  - Output Non-Linearity: tanh for Generator, sigmoid for discriminator
  - Batch Normalization used to prevent mode collapse
  - Batch Normalization is not applied at the output of G and input of D
- Optimization details
  - Adam: small LR - 2e-4; small momentum: 0.5, batch-size: 128

[Radford et al 2016]

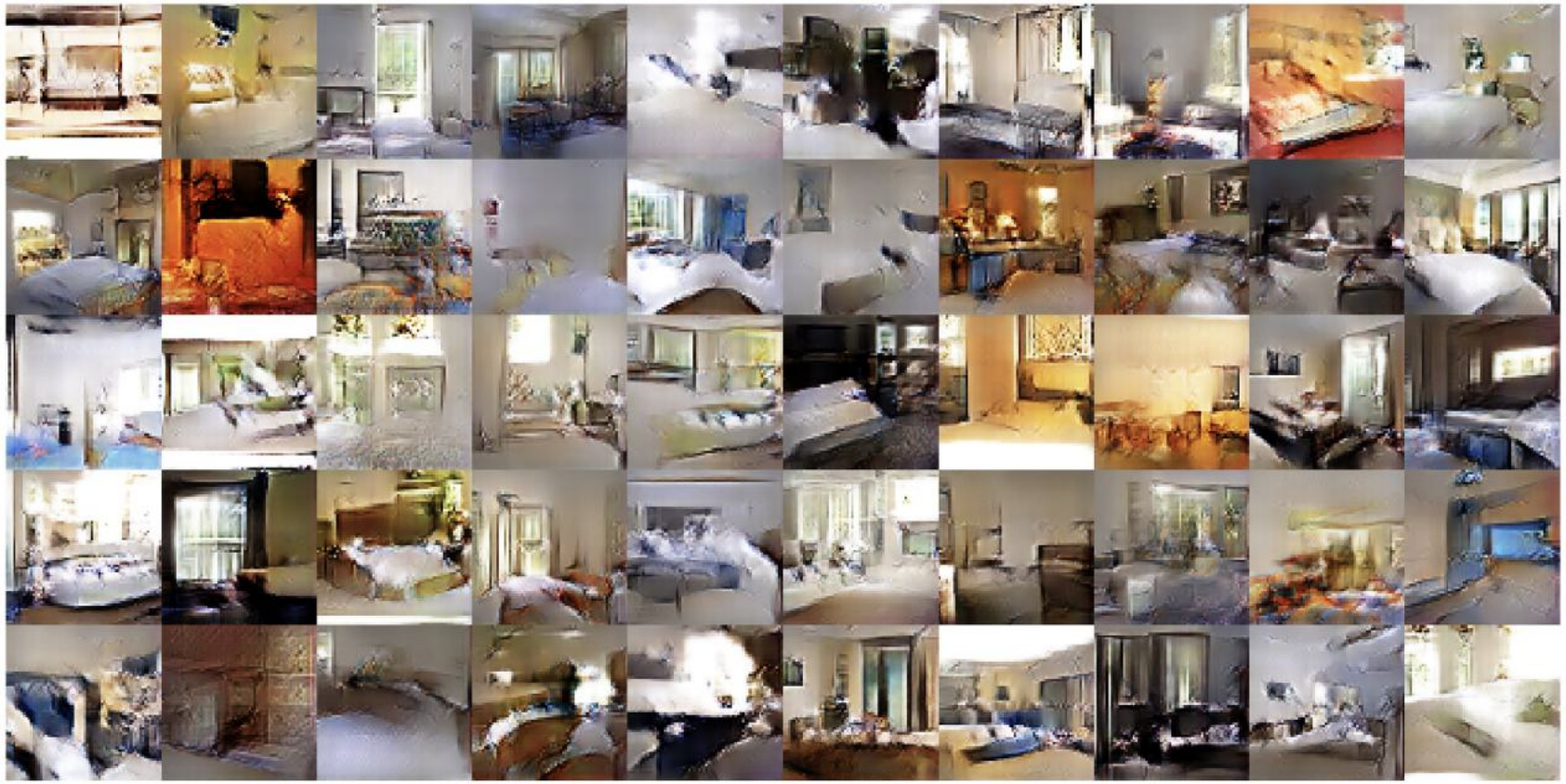
DCGAN Batch Norm



[Chintala 2016]

DCGAN - Key Results

- Good samples on datasets with 3M images (Faces, Bedrooms) for the first time



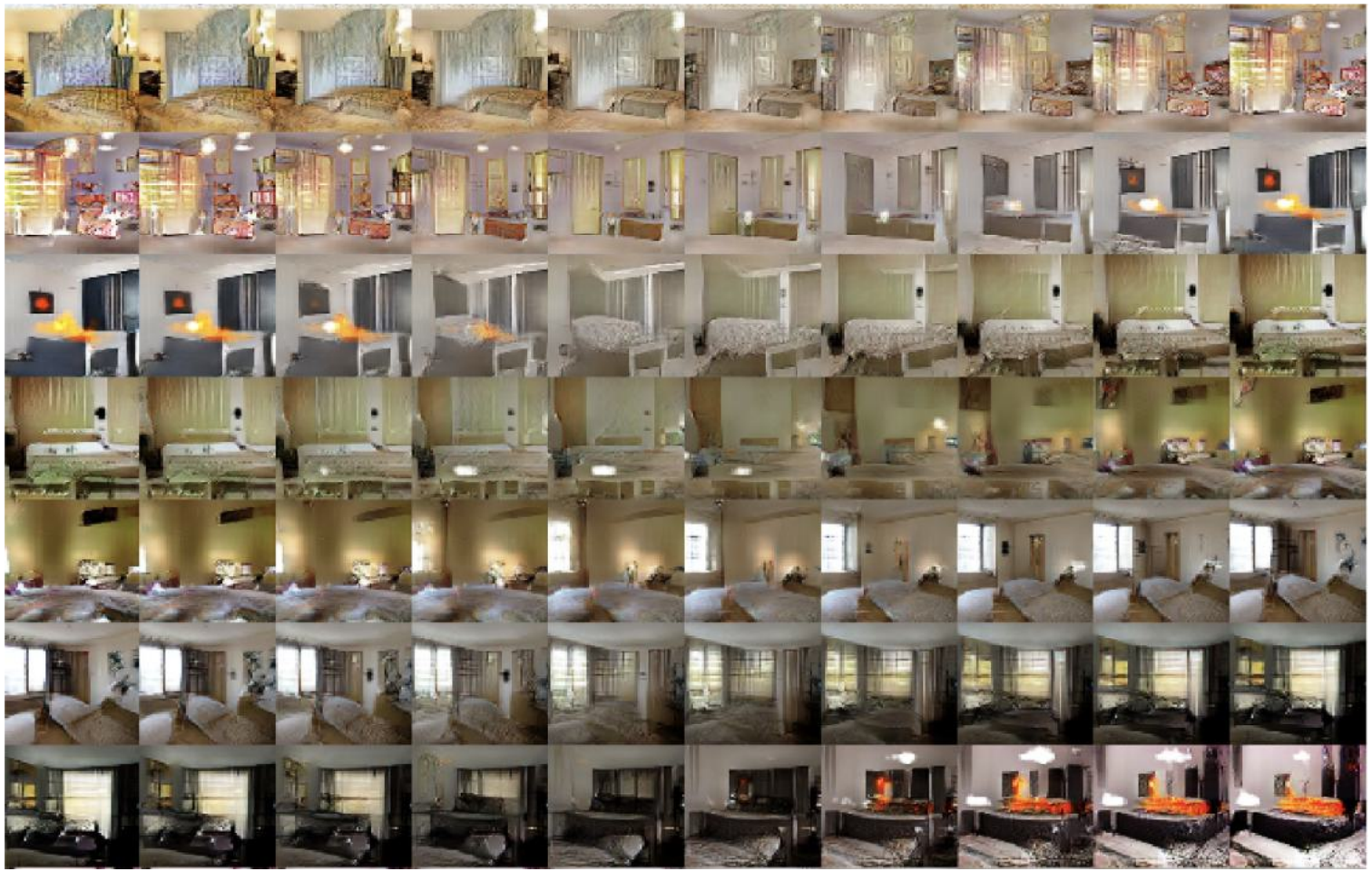
[Radford et al 2016]

DCGAN - Key Results

[Radford et al 2016]

DCGAN - Key Results

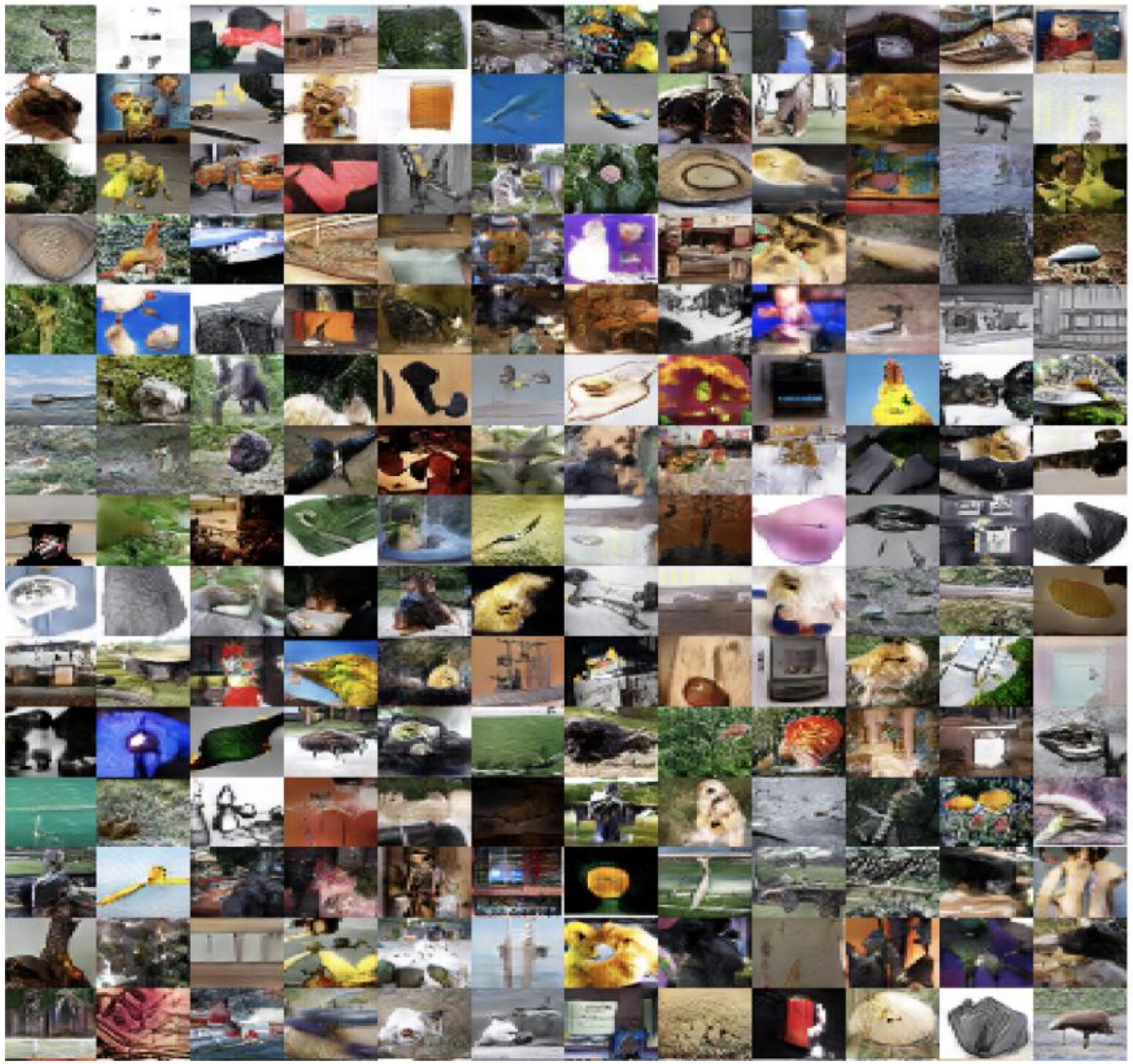
- Smooth interpolations in high dimensions



[Radford et al 2016]

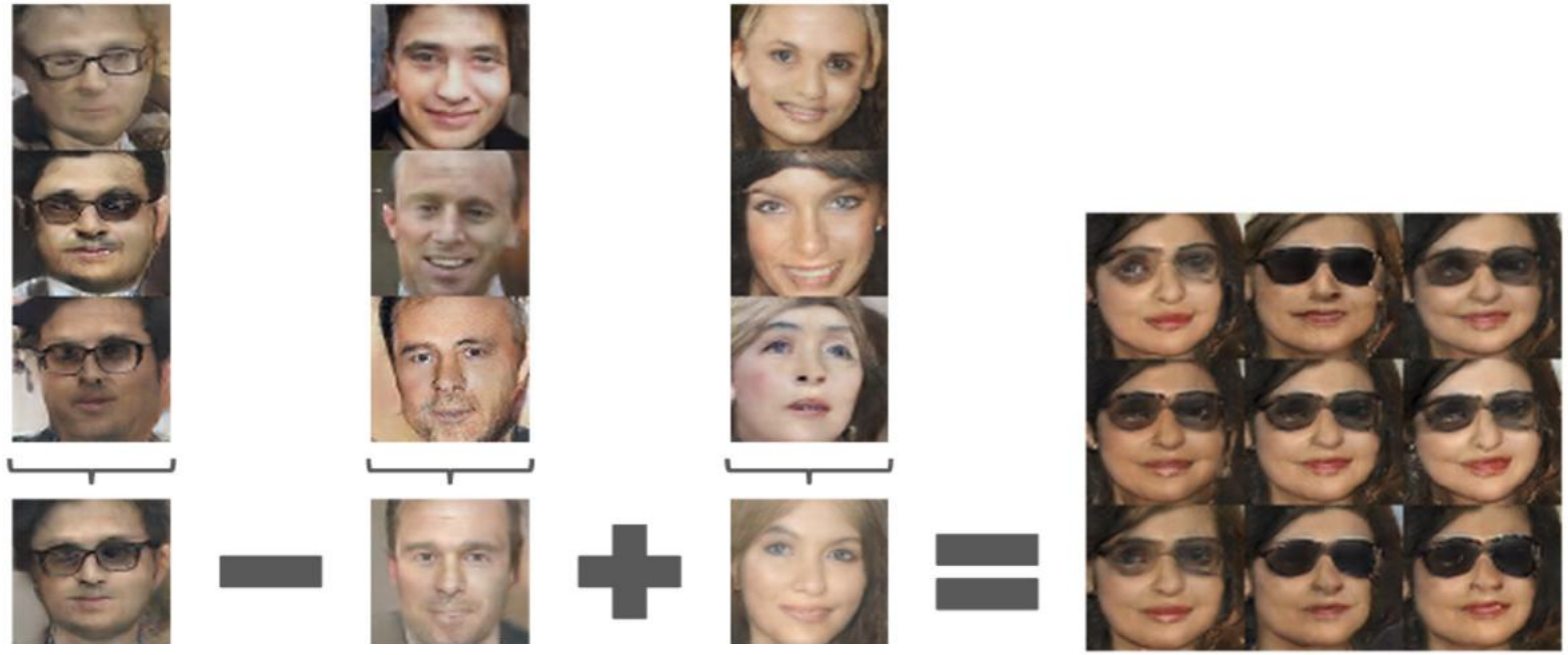
DCGAN - Key Results

- Imagenet samples



[Radford et al 2016]

DCGAN - Key Results



man with glasses − man without glasses + woman without glasses = woman with glasses

Results of doing the same arithmetic in pixel space

[Radford et al 2016]

DCGAN - Conclusions

- Incredible samples for any generative model
- GANs could be made to work well with architecture details
- Perceptually good samples and interpolations
- **Problems to address:**
  - Unstable training
  - Brittle architecture / hyperparameters

Lecture overview

- Motivation
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- **GAN Progression**
  - DC GAN (Radford et al, 2016)
  - **Improved Training of GANs (Salimans et al'16)**
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN
  - BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, StyleGAN-v3, VQ-GAN
- Conditional GANs, Cycle-Consistent Adversarial Networks
- Applications

Improved training of GANs

- Feature Matching
- Minibatch discrimination
- Historical Averaging
- Virtual batch normalization
- One-sided label smoothing

Improved Techniques for Training GANs

Tim Salimans tim@openai.com
Ian Goodfellow ian@openai.com
Wojciech Zaremba woj@openai.com
Vicki Cheung vicki@openai.com
Alec Radford alec.radford@gmail.com
Xi Chen peter@openai.com

[Salimans 2016]

Improved training of GANs

- Feature Matching

$$||\mathbb{E}_{x \sim p_{\text{data}}} f(x) - \mathbb{E}_{z \sim p(z)} f(G(z))||^2$$

Generator objective

[Salimans 2016]

Improved training of GANs

- Minibatch discrimination

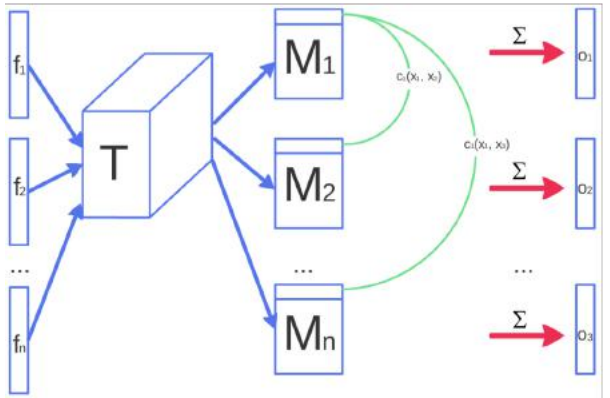
$$\mathbf{f}(\boldsymbol{x}_i) \in \mathbb{R}^A \qquad T \in \mathbb{R}^{A \times B \times C} \qquad M_i \in \mathbb{R}^{B \times C}$$

$$c_b(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(-||M_{i,b} - M_{j,b}||_{L_1}) \in \mathbb{R}$$

$$o(\boldsymbol{x}_i)_b = \sum_{j=1}^{n} c_b(\boldsymbol{x}_i, \boldsymbol{x}_j) \in \mathbb{R}$$

$$o(\boldsymbol{x}_i) = \left[o(\boldsymbol{x}_i)_1, o(\boldsymbol{x}_i)_2, \ldots, o(\boldsymbol{x}_i)_B\right] \in \mathbb{R}^B$$

$$o(\mathbf{X}) \in \mathbb{R}^{n \times B}$$



[Salimans 2016]

Allows to incorporate side information from other samples and is superior to feature matching in the unconditional setting.
Helps addressing mode collapse by allowing discriminator to detect if the generated samples are too close to each other.

Improved training of GANs

- Historical Averaging

$$||\boldsymbol{\theta} - \frac{1}{t}\sum_{i=1}^{t}\boldsymbol{\theta}[i]||^2$$

Improved training of GANs

- One-sided label smoothing

Default discriminator cost:

```
cross_entropy(1., discriminator(data))
+ cross_entropy(0., discriminator(samples))
```

One-sided label smoothed cost (Salimans et al 2016):

```
cross_entropy(.9, discriminator(data))
+ cross_entropy(0., discriminator(samples))
```

Figure source: NeurIPS tutorial Goodfellow 2016

Improved training of GANs

- Why one-sided?

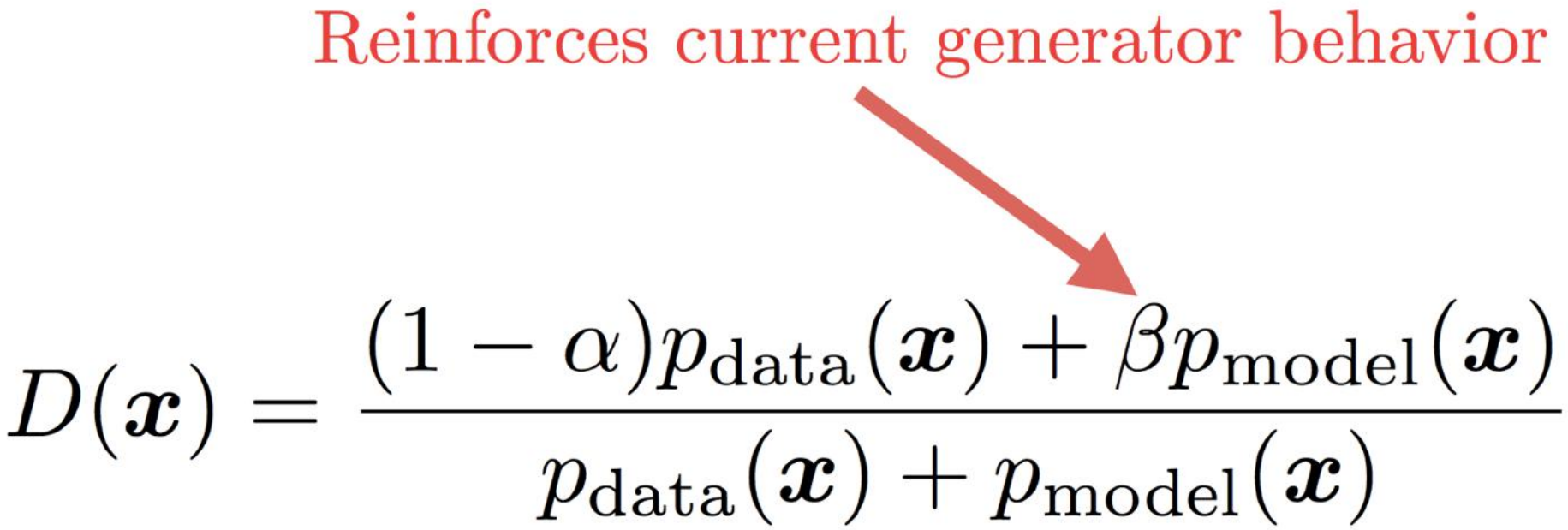


Figure source:
NeurIPS tutorial
Goodfellow 2016

Improved training of GANs

- Virtual Batch Normalization
  - Use a reference batch (fixed) to compute normalization statistics
  - Construct a batch containing the sample and reference batch

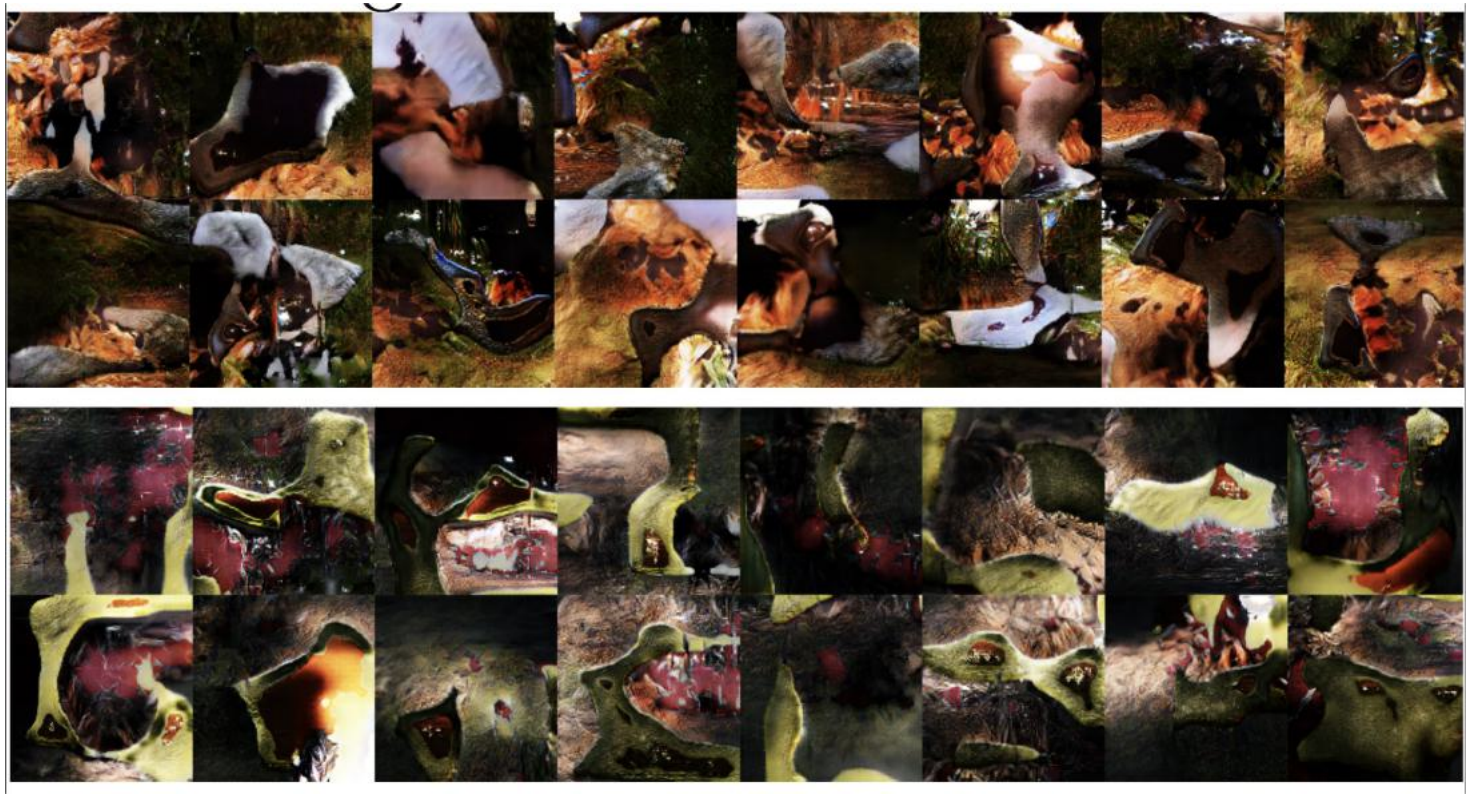


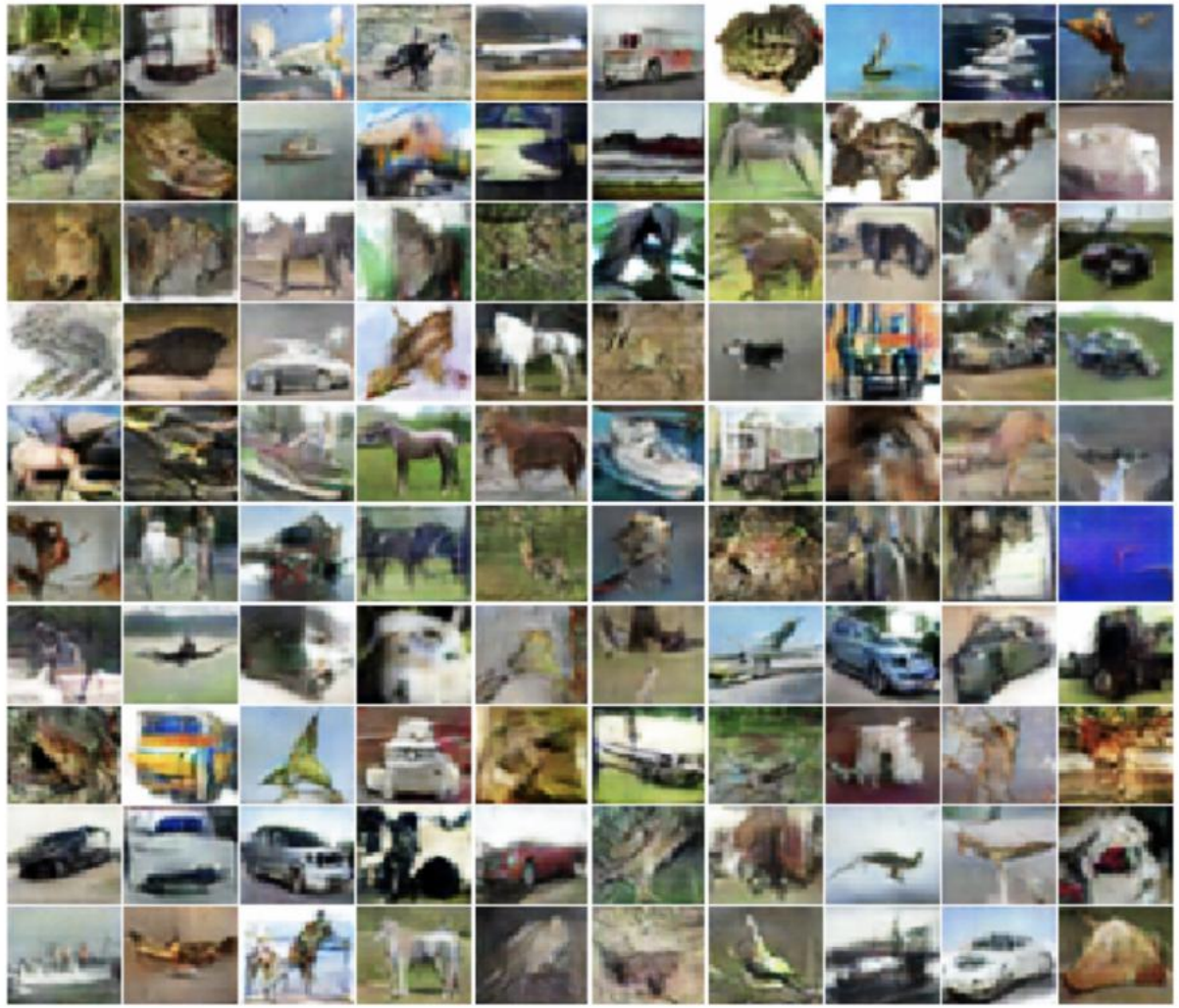
Figure source:
NeurIPS tutorial
Goodfellow 2016

Improved training of GANs

- Semi-Supervised Learning
  - Predict labels in addition to fake/real in the discriminator
  - Approximate way of modeling p(x,y)
  - Generator doesn't have to be made conditional p(x|y)
  - Use a deeper architecture for the discriminator compared to generator

$$
\begin{aligned}
L &= -\mathbb{E}_{\boldsymbol{x},y\sim p_{\text{data}}(\boldsymbol{x},y)}[\log p_{\text{model}}(y|\boldsymbol{x})] - \mathbb{E}_{\boldsymbol{x}\sim G}[\log p_{\text{model}}(y=K+1|\boldsymbol{x})] \\
&= L_{\text{supervised}} + L_{\text{unsupervised}}, \text{ where} \\
L_{\text{supervised}} &= -\mathbb{E}_{\boldsymbol{x},y\sim p_{\text{data}}(\boldsymbol{x},y)} \log p_{\text{model}}(y|\boldsymbol{x}, y<K+1) \\
L_{\text{unsupervised}} &= -\{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})} \log[1-p_{\text{model}}(y=K+1|\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{x}\sim G} \log[p_{\text{model}}(y=K+1|\boldsymbol{x})]\}
\end{aligned}
$$

Improved training of GANs



Salimans 2016

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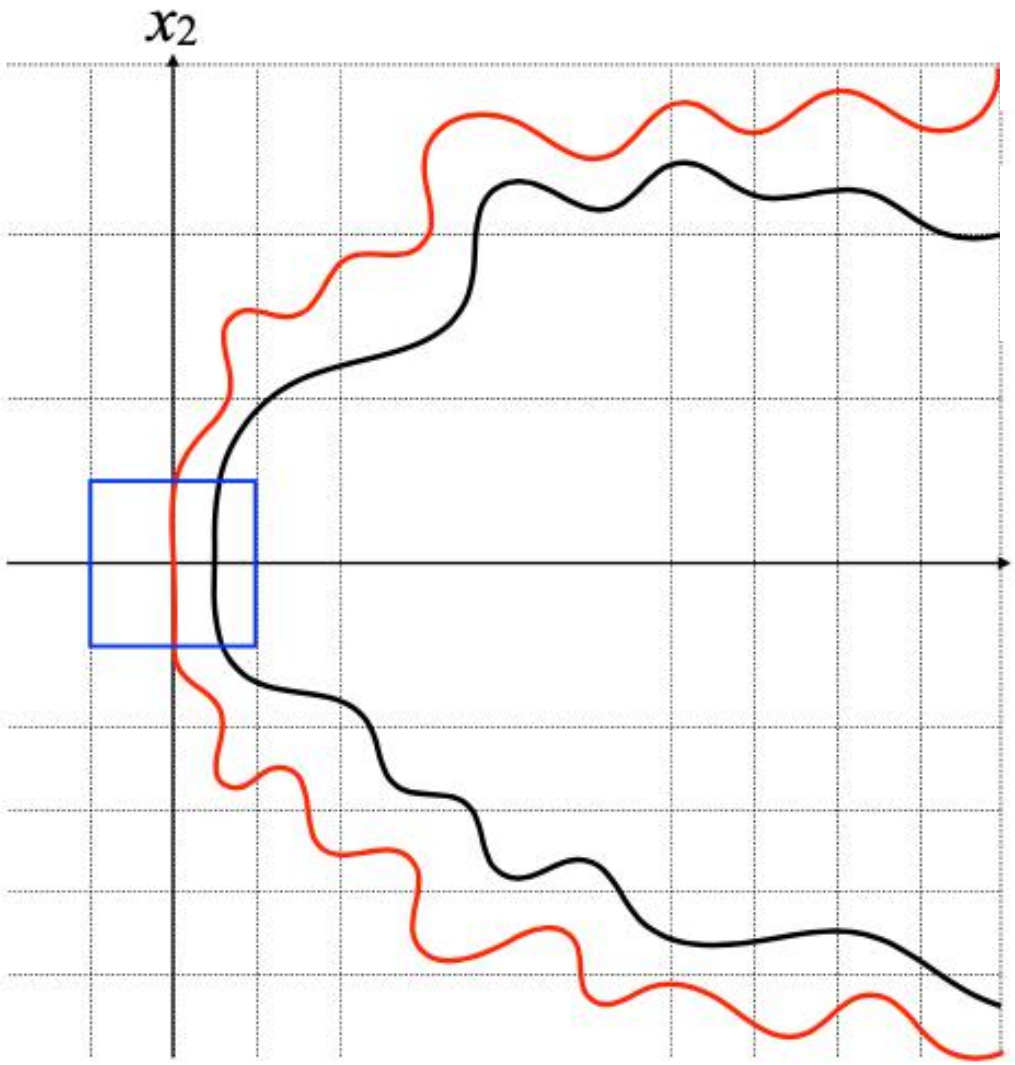
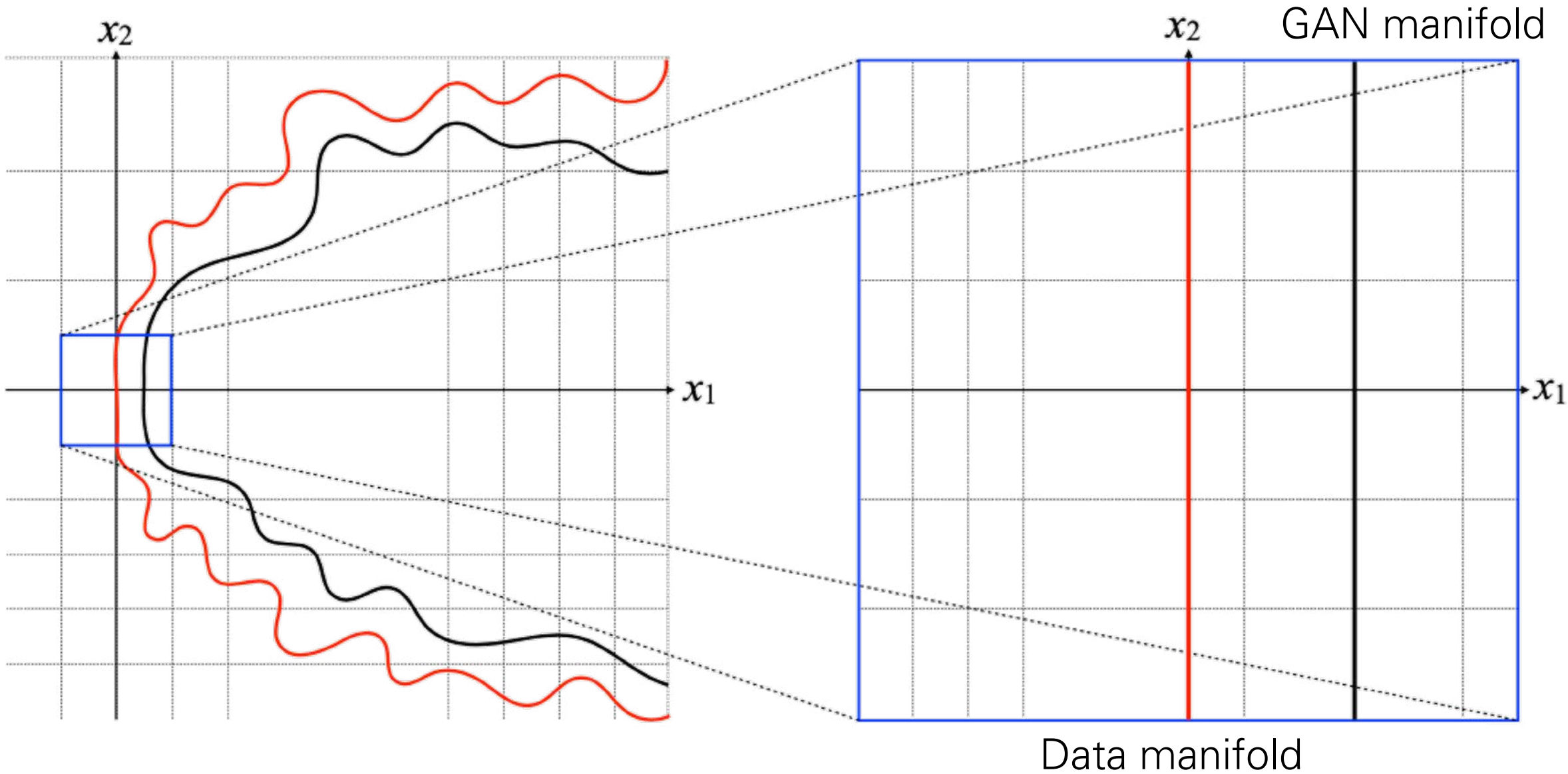
Training a GAN: Distances between Manifolds



Data manifold

GAN manifold
(Generative model)

Training a GAN: Distances between Manifolds

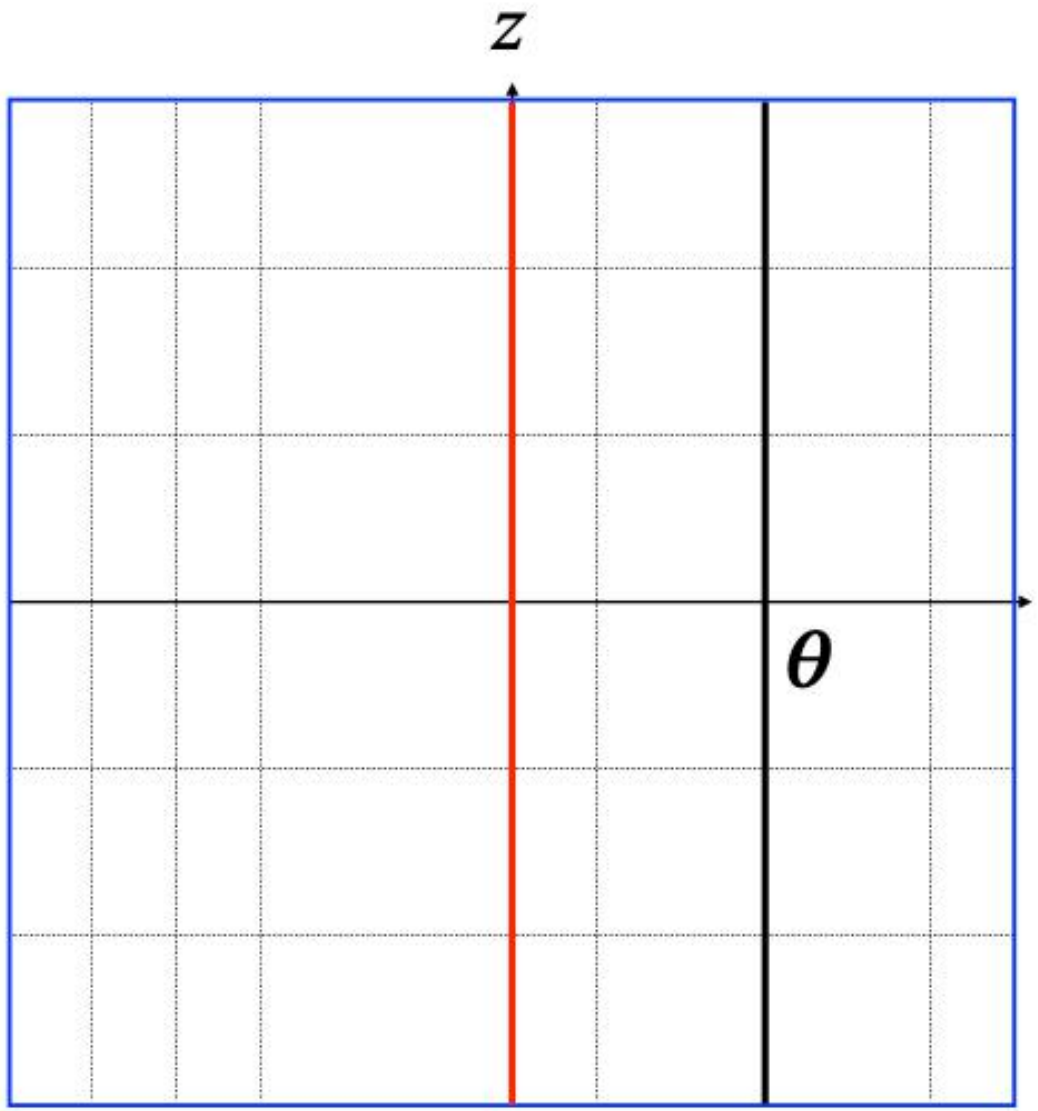


Jensen-Shannon Divergence

$$\mathrm{JS}\left(\mathbb{P}_r \| \mathbb{P}_g\right) = \mathrm{KL}\left(\mathbb{P}_r \| \frac{\mathbb{P}_r + \mathbb{P}_g}{2}\right) + \mathrm{KL}\left(\mathbb{P}_g \| \frac{\mathbb{P}_r + \mathbb{P}_g}{2}\right)$$

- What is the JS divergence in this simple case?

$$\mathrm{JS}\left(\mathbb{P}_r \| \mathbb{P}_g\right) = \begin{cases} \log 2 & \text{if } \theta \neq 0 \\ 0 & \text{if } \theta = 0 \end{cases}$$



Example from (Arjovsky et al. 2017)

Jensen-Shannon Divergence

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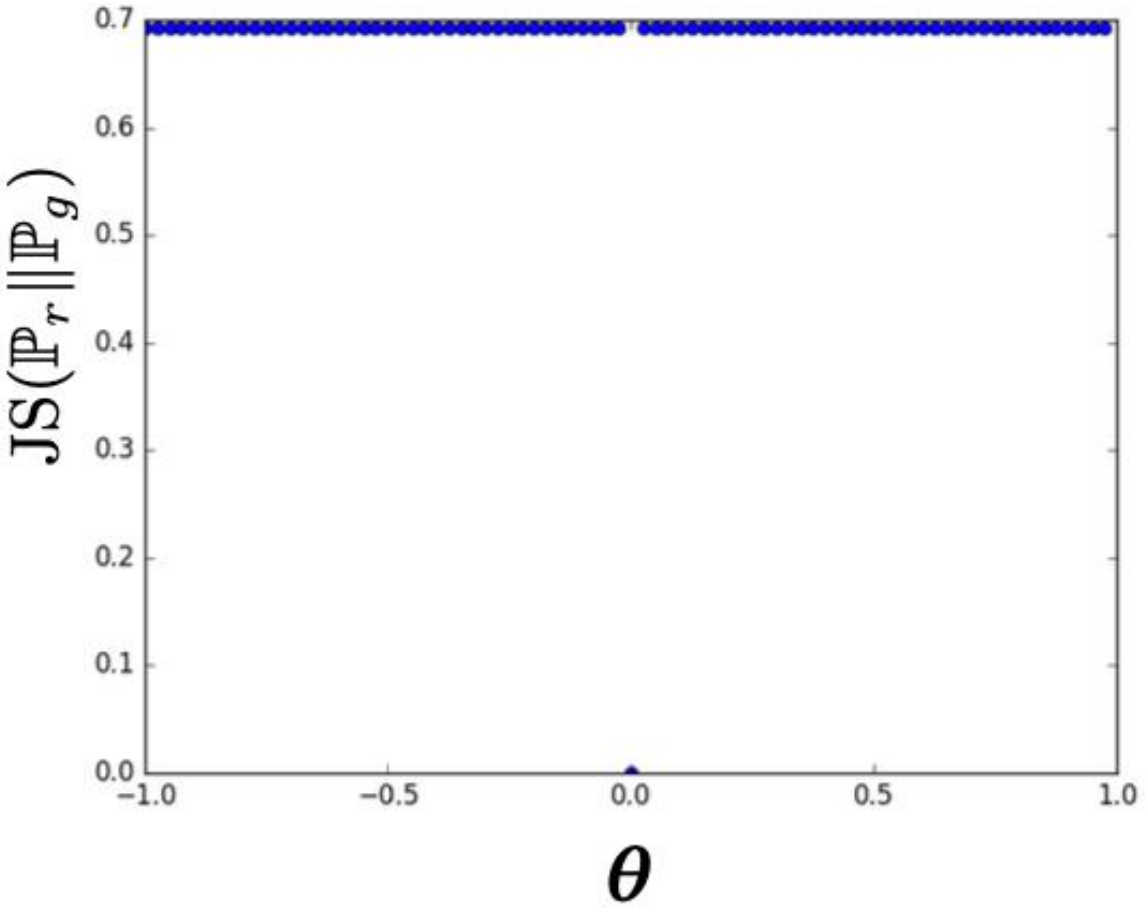
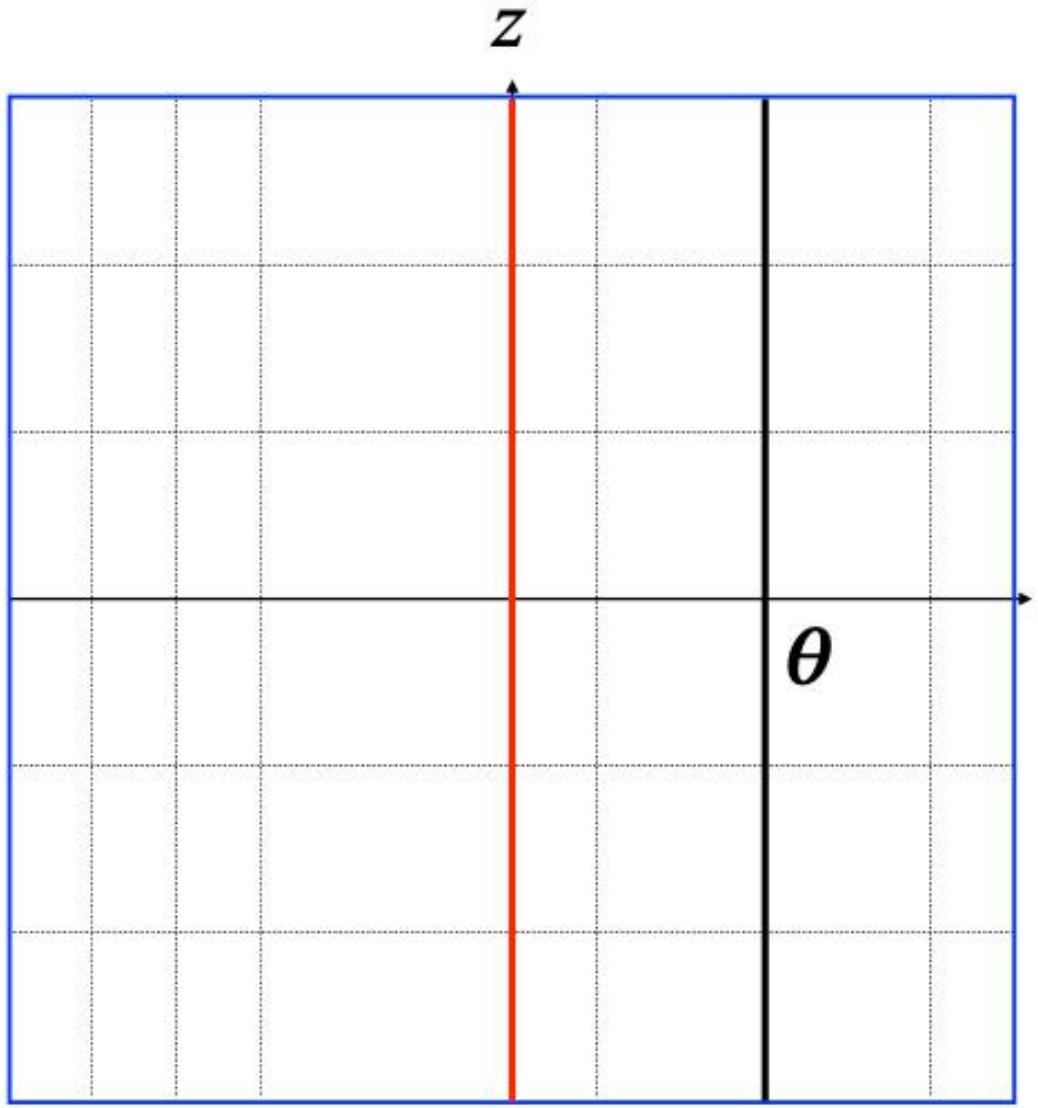




Example from (Arjovsky et al. 2017)

Wasserstein Distance

- JS divergence is not a useful learning signal to train GANs.
- Another distance measure inspired from Optimal Transport is the Earth Mover (EM) (also called Wassertein-1 Distance) distance

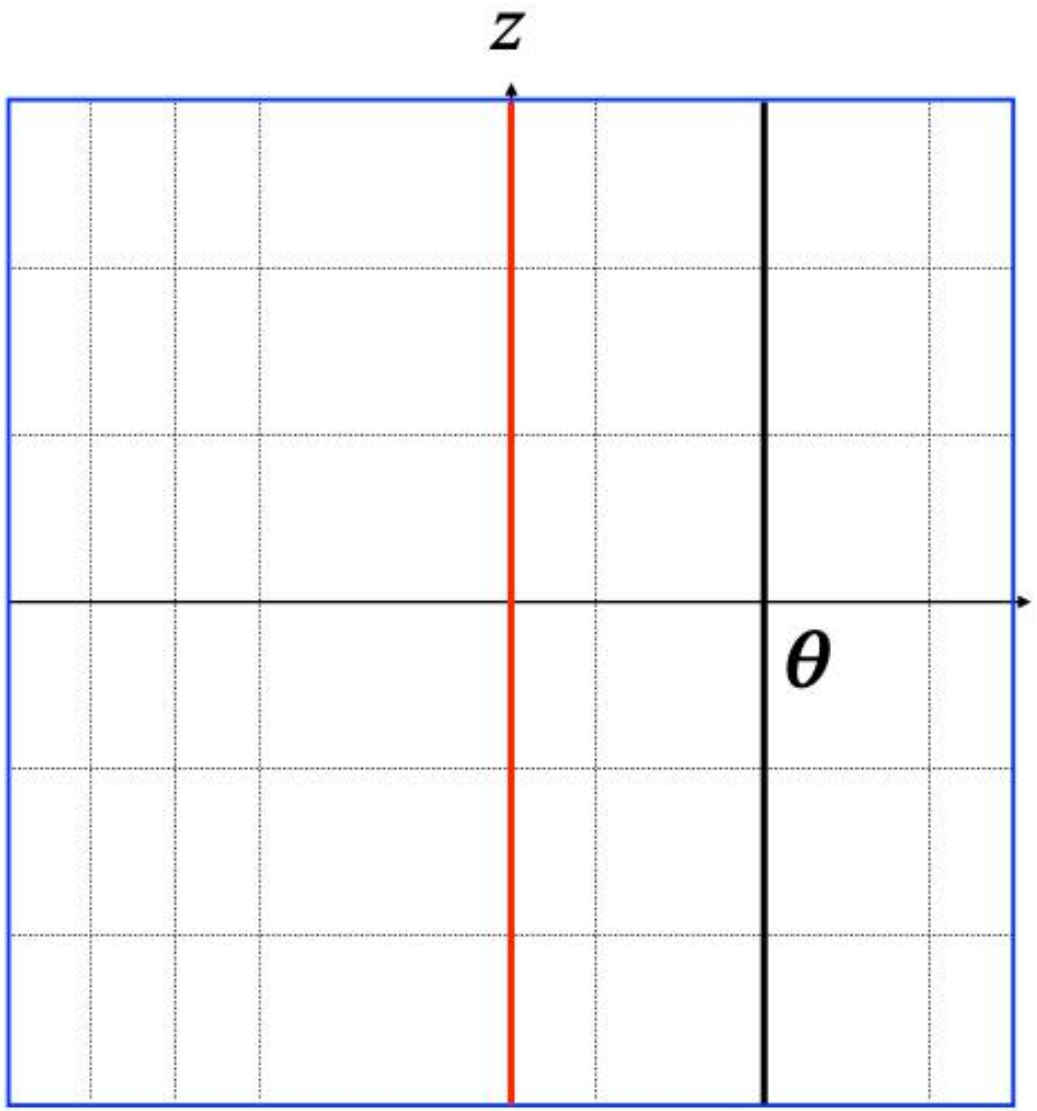
$$W\left(\mathbb{P}_r, \mathbb{P}_g\right) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma}[\|x - y\|]$$

- The EM distance is continuous everywhere and differentiable almost everywhere (under mild assumptions).

Wasserstein Distance

$$W\left(\mathbb{P}_r, \mathbb{P}_g\right) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma}[\|x - y\|]$$

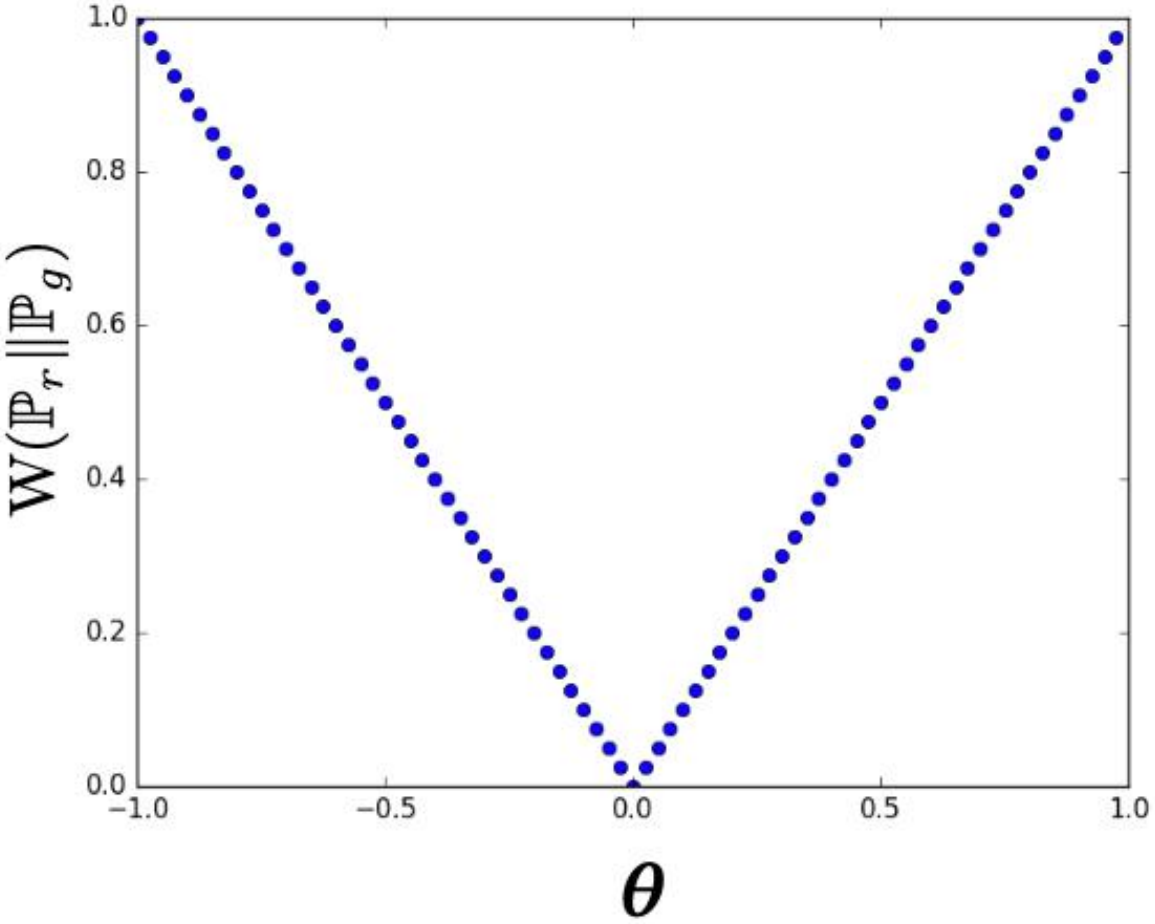
- What is the EM (or Wassertein) distance in this simple case?

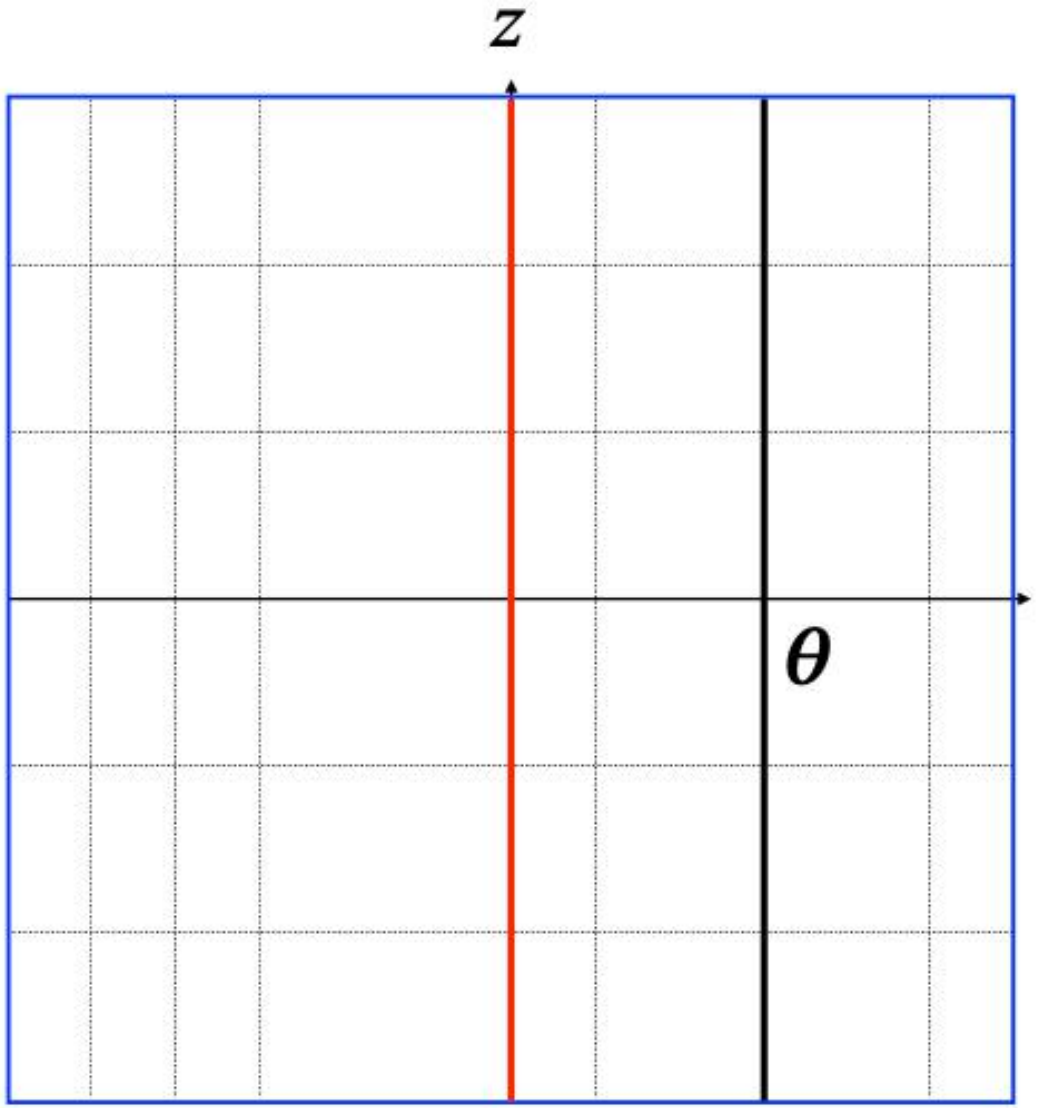


Example from (Arjovsky et al. 2017)

Wasserstein Distance

$$\mathrm{W}\left(\mathbb{P}_r \| \mathbb{P}_g\right) = |\theta|$$





Example from (Arjovsky et al. 2017)

Wasserstein Distance

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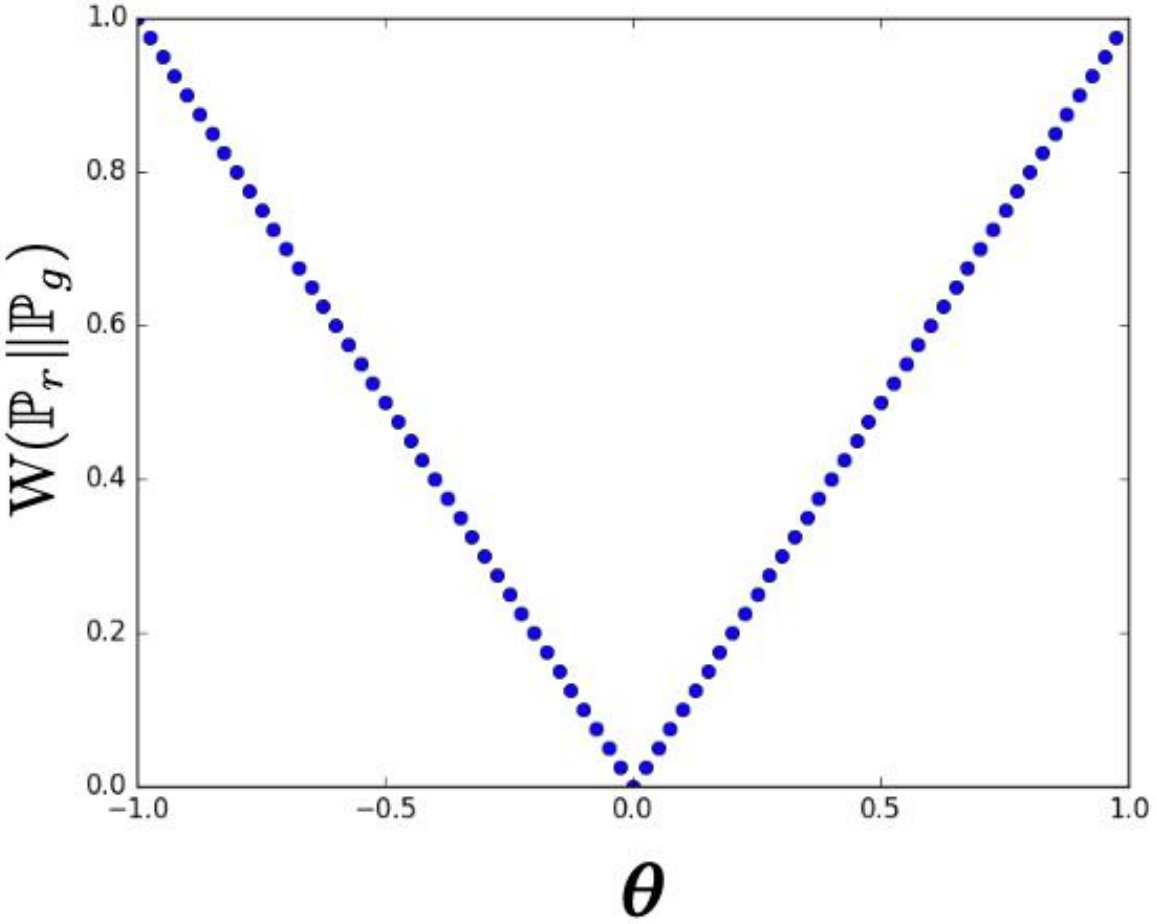
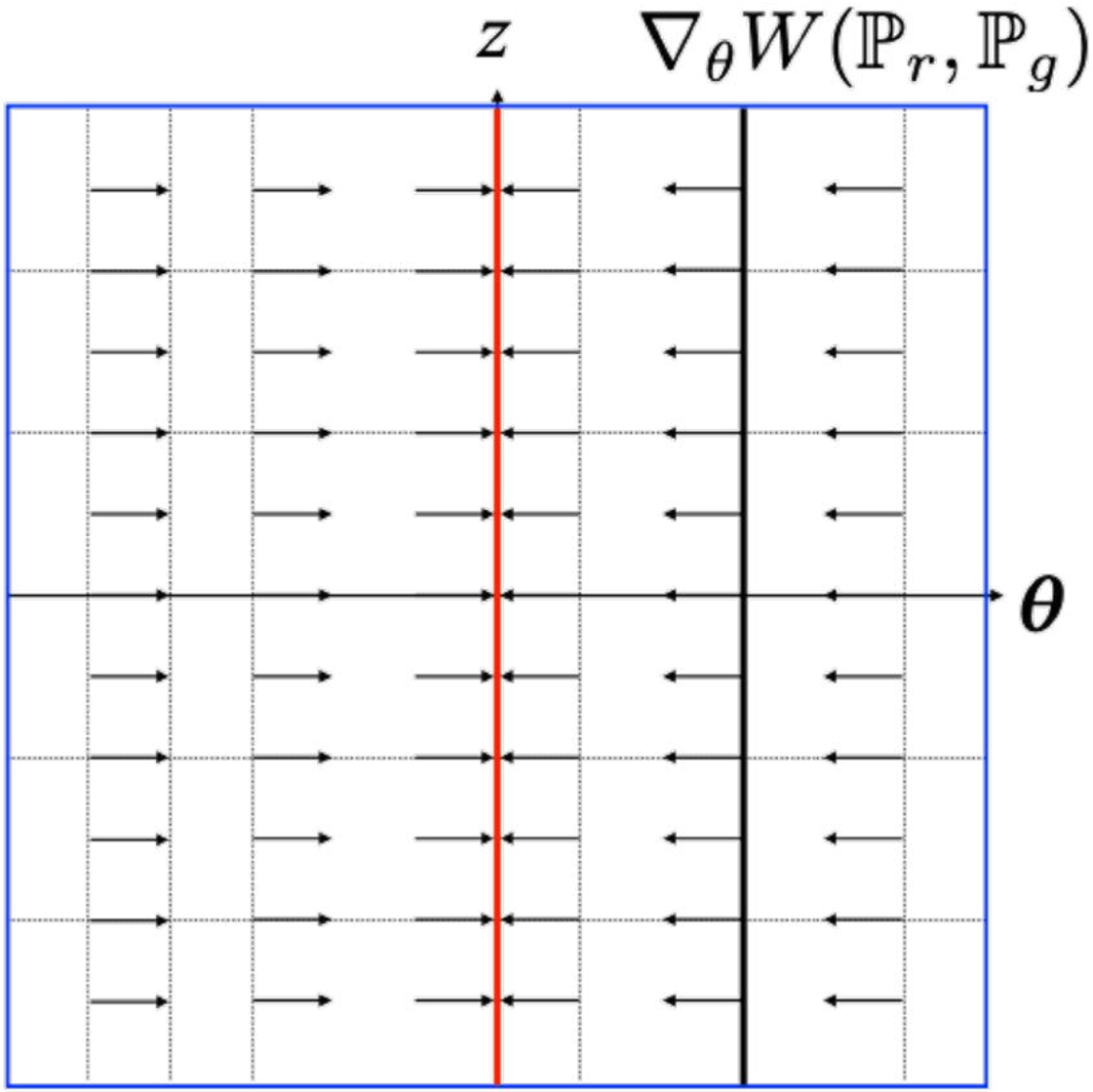




Example from (Arjovsky et al. 2017)

Wasserstein GAN

A real-valued function f: X→Y is called K-Lipschitz continuous if there exists a real constant $K \geq 0$ such that, for all x_1, x_2.

$$|f(x_1) - f(x_2)| \leq K |x_1 - x_2|$$

Here K is known as a Lipschitz constant for function $f(\cdot)$

- $\mathrm{W}(\mathbb{P}_r \| \mathbb{P}_g)$ might have nice properties compared to $\mathrm{JS}(\mathbb{P}_r \| \mathbb{P}_g)$
- However, the infimum is intractable in:

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma}[\|x - y\|]$$

- Can exploit Kantorovich-Rubinstein duality:

$$W(\mathbb{P}_r, \mathbb{P}_g) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{x\sim\mathbb{P}_r}[f(x)] - \mathbb{E}_{x\sim\mathbb{P}_g}[f(x)]$$

where the supremum is over all the 1-Lipschitz functions $f : \mathcal{X} \to \mathbb{R}$

Wasserstein GAN

- The WGAN Objective function:

$$\min_{G} \max_{D \in \mathcal{D}} \mathbb{E}_{\boldsymbol{x} \sim \mathbb{P}_r} [D(\boldsymbol{x})] - \mathbb{E}_{\tilde{\boldsymbol{x}} \sim \mathbb{P}_g} [D(\tilde{\boldsymbol{x}}))]$$

  where $\mathcal{D}$ is the set of 1-Lipschitz functions.

- Open question: how to effectively enforce the Lipschitz constraint on the critic D?
  - Arjovsky et al. (2017) propose to clip the weights of the critic to lie within a compact space [-c, c].
  - Results in a subset of the k-Lipschitz functions (k is a function of c).

Wasserstein GAN - Pseudocode

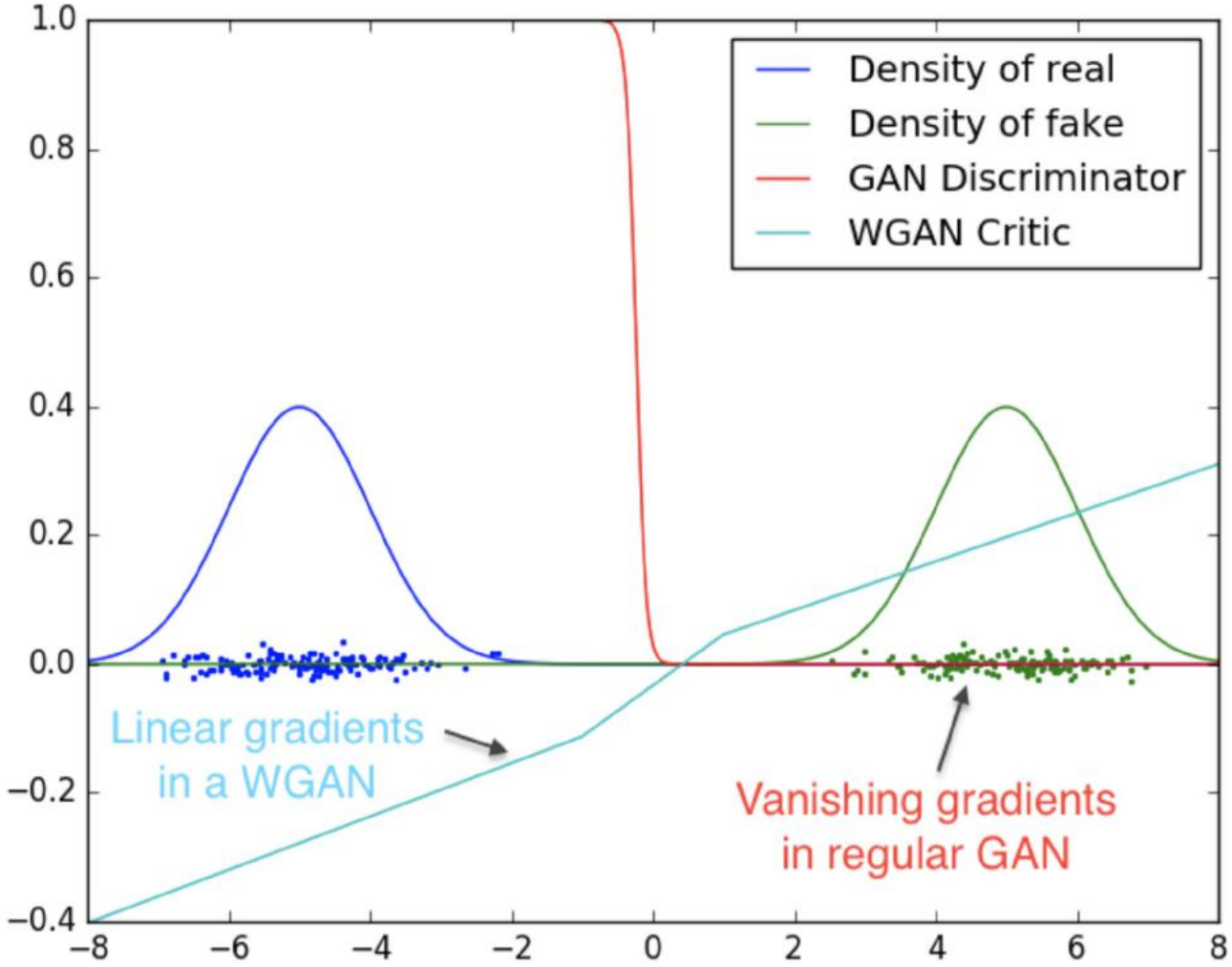
Algorithm 1 WGAN, our proposed algorithm. All experiments in the paper used the default values $\alpha = 0.00005$, $c = 0.01$, $m = 64$, $n_{\text{critic}} = 5$.

Require: : α, the learning rate. c, the clipping parameter. m, the batch size.
n_{critic}, the number of iterations of the critic per generator iteration.
Require: : w_0, initial critic parameters. θ_0, initial generator's parameters.

while θ has not converged **do**
  for $t = 0, ..., n_{\text{critic}}$ **do**
    Sample $\{x^{(i)}\}_{i=1}^{m} \sim \mathbb{P}_r$ a batch from the real data.
    Sample $\{z^{(i)}\}_{i=1}^{m} \sim p(z)$ a batch of prior samples.
    $g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^{m} f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^{m} f_w(g_\theta(z^{(i)}))\right]$
    $w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$
    $w \leftarrow \text{clip}(w, -c, c)$
  end for
  Sample $\{z^{(i)}\}_{i=1}^{m} \sim p(z)$ a batch of prior samples.
  $g_\theta \leftarrow -\nabla_\theta \frac{1}{m}\sum_{i=1}^{m} f_w(g_\theta(z^{(i)}))$
  $\theta \leftarrow \theta - \alpha \cdot \text{RMSProp}(\theta, g_\theta)$
end while

[Arjovsky et al 2017]

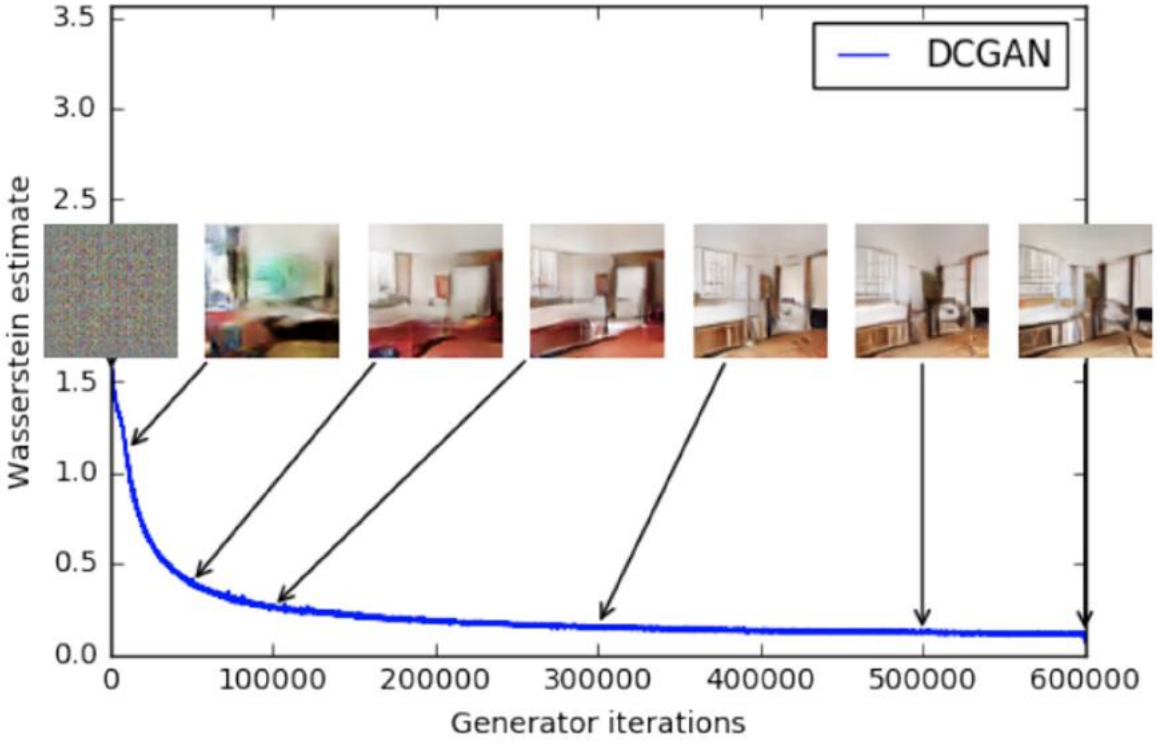
Wasserstein GAN - Training critic to converge



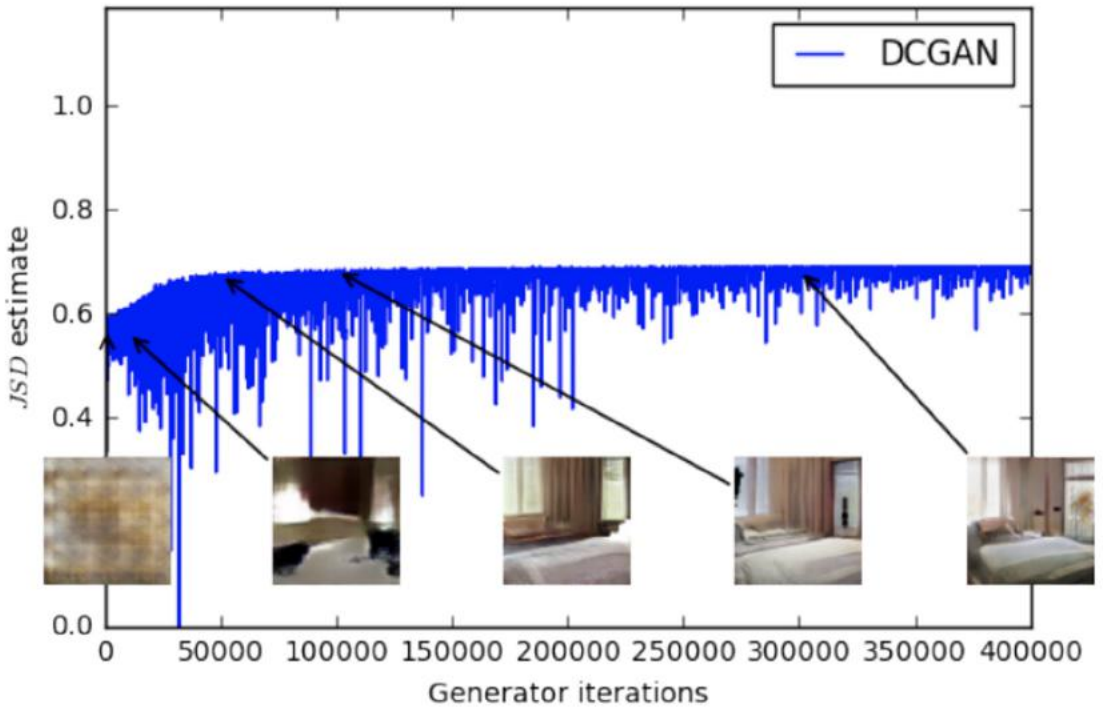
[Arjovsky et al 2017]

Wasserstein distance correlates with sample quality

Wasserstein Estimate

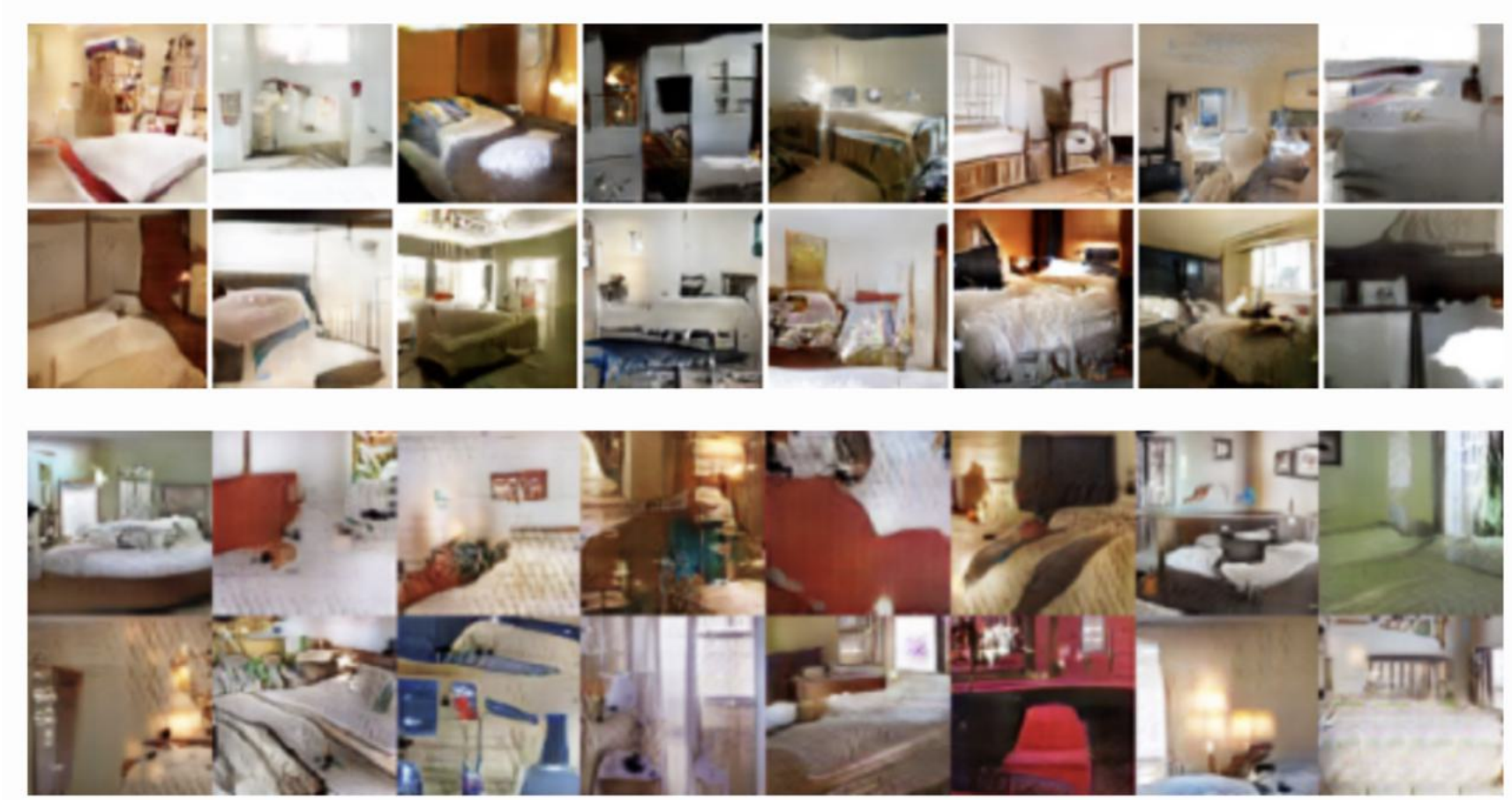


JSD Estimate



[Arjovsky et al 2017]

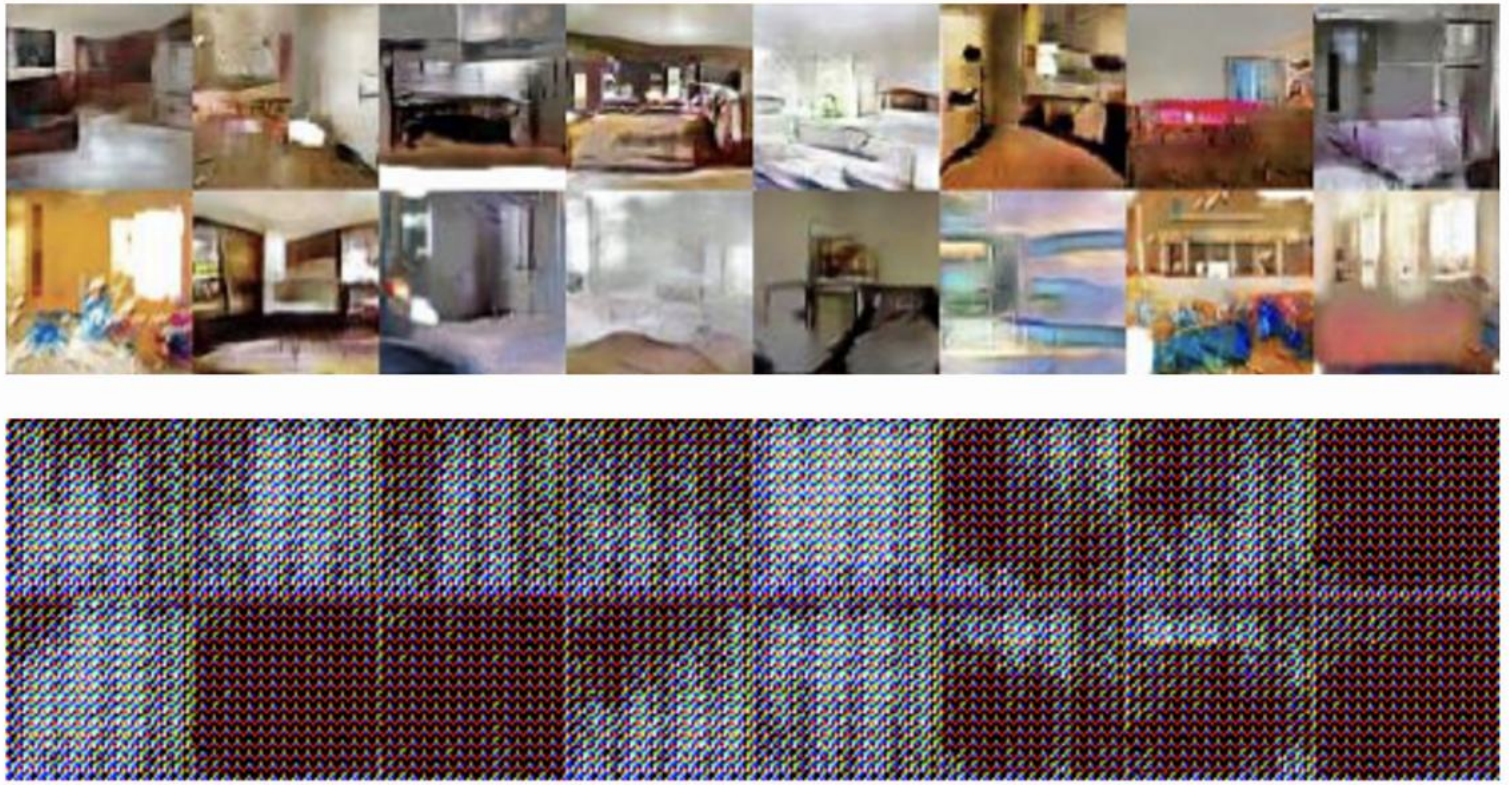
WGAN Samples on par with DCGAN



Top: WGAN with the same DCGAN architecture. Bottom: DCGAN

[Arjovsky et al 2017]

WGAN robust to architecture choices



Top: WGAN with DCGAN architecture, no batch norm. Bottom: DCGAN, no batch norm

[Arjovsky et al 2017]

WGAN robust to architecture choices

Top: WGAN with MLP architecture. Bottom: Standard GAN, same architecture

[Arjovsky et al 2017]

WGAN Summary

Standard GAN

$$\min_G \max_D \mathbb{E}_{x \sim P_r} [\log D(x)] + \mathbb{E}_{\tilde{x} \sim P_g} [\log(1 - D(\tilde{x}))]$$

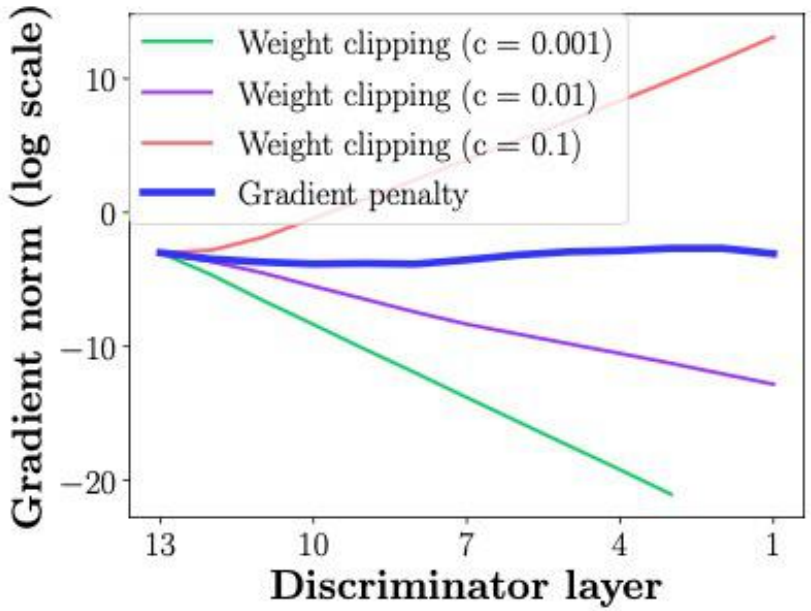
Wasserstein GAN

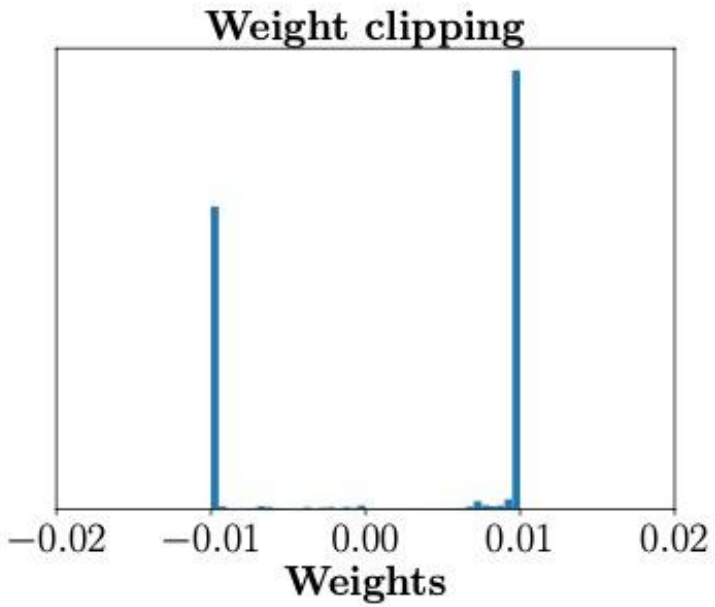
$$\min_G \max_{D \in \mathcal{D}} \mathbb{E}_{x \sim P_r} [D(x)] - \mathbb{E}_{\tilde{x} \sim P_g} [D(\tilde{x})]$$

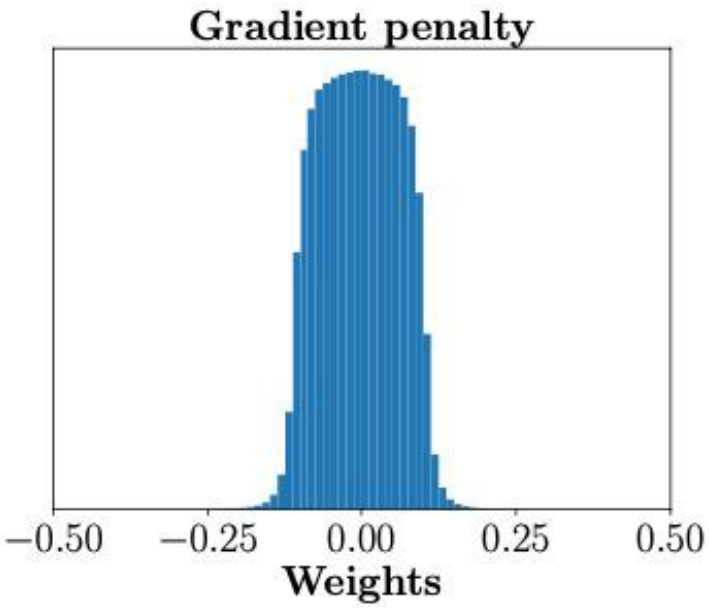
[Arjovsky et al 2017]

Issues with Weight Clipping

1. Underuse capacity
2. Exploding and vanishing gradients







WGAN-GP: Gradient Penalty Approach

Improved Training of Wasserstein GANs

Ishaan Gulrajani[1]*, **Faruk Ahmed**[1], **Martin Arjovsky**[2], **Vincent Dumoulin**[1], **Aaron Courville**[1,3]
[1] Montreal Institute for Learning Algorithms
[2] Courant Institute of Mathematical Sciences
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Abstract

Generative Adversarial Networks (GANs) are powerful generative models, but suffer from training instability. The recently proposed Wasserstein GAN (WGAN) makes progress toward stable training of GANs, but sometimes can still generate only poor samples or fail to converge. We find that these problems are often due to the use of weight clipping in WGAN to enforce a Lipschitz constraint on the critic, which can lead to undesired behavior. We propose an alternative to clipping weights: penalize the norm of gradient of the critic with respect to its input. Our proposed method performs better than standard WGAN and enables stable training of a wide variety of GAN architectures with almost no hyperparameter tuning, including 101-layer ResNets and language models with continuous generators. We also achieve high quality generations on CIFAR-10 and LSUN bedrooms. †

[Gulrajani et al 2017]

WGAN-GP: Gradient Penalty Approach

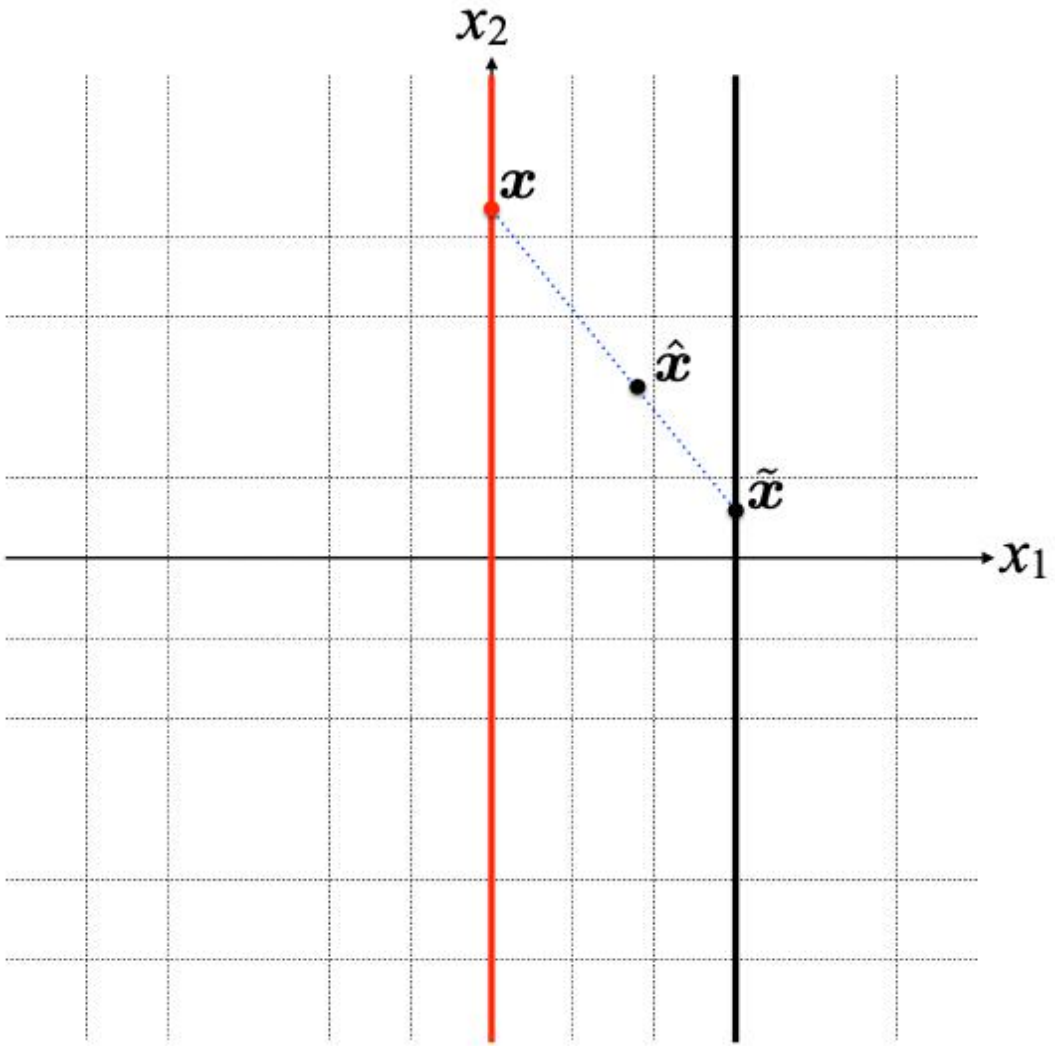
- **A property of the optimal WGAN critic:** If $\tilde{\boldsymbol{x}} \sim \mathbb{P}_g$ then there is a point $\boldsymbol{x} \sim \mathbb{P}_r$, such that for all points $\boldsymbol{x}_t = t\boldsymbol{x} + (1-t)\tilde{\boldsymbol{x}}$ (on a straight line between $\boldsymbol{x}$ and $\tilde{\boldsymbol{x}}$) then:

$$\nabla D^*(\boldsymbol{x}_t) = \frac{\boldsymbol{x} - \boldsymbol{x}_t}{\|\boldsymbol{x} - \boldsymbol{x}_t\|}$$

- This implies the optimal WGAN critic has gradient norm 1 at $\boldsymbol{x}_t$
- Gradient Penalty version of WGAN (i.e. WGAN-GP) objective

$$L = \underbrace{\mathop{\mathbb{E}}_{\tilde{\boldsymbol{x}} \sim \mathbb{P}_g}[D(\tilde{\boldsymbol{x}})] - \mathop{\mathbb{E}}_{x \sim \mathbb{P}_r}[D(\boldsymbol{x})]}_{\text{Original critic loss}} + \underbrace{\lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}}\left[\left(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1\right)^2\right]}_{\text{Our gradient penalty}}$$

WGAN-GP: Gradient Penalty Approach



- Gradient penalty:

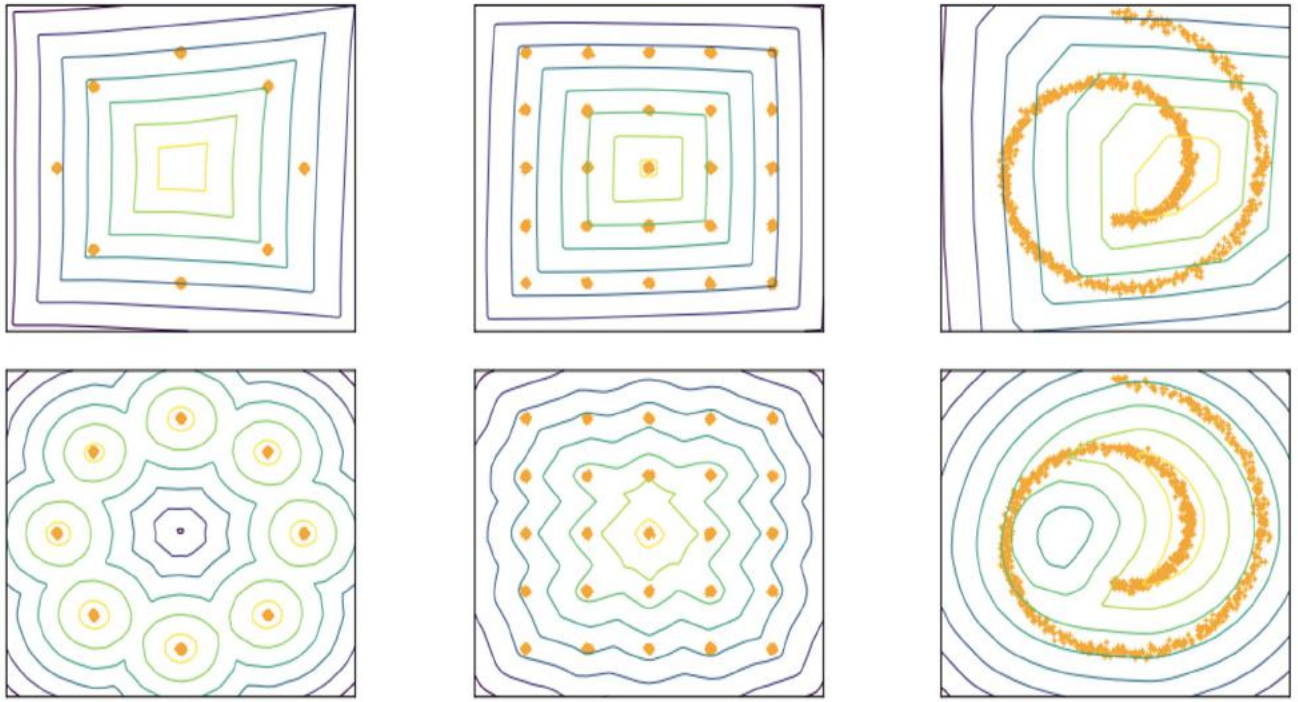
$$\mathop{\mathbb{E}}_{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}} \left[\left(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1 \right)^2 \right]$$

Sample along straight lines:

$$\epsilon \sim U[0,1], \boldsymbol{x} \sim \mathbb{P}_r, \tilde{\boldsymbol{x}} \sim \mathbb{P}_g$$
$$\hat{\boldsymbol{x}} = \epsilon \boldsymbol{x} + (1-\epsilon)\tilde{\boldsymbol{x}}$$

WGAN-GP: Gradient Penalty for Lipschitzness

8 Gaussian | 25 Gaussian | Swiss Roll



$$\max_D \underbrace{\mathbb{E}_{x\sim P_r}\left[D(x)\right] - \mathbb{E}_{\tilde{x}\sim P_g}\left[D(\tilde{x})\right]}_{\text{Wasserstein critic objective}} + \lambda \underbrace{\mathbb{E}_{\hat{x}\sim P_{\hat{x}}}\left[\left(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1\right)^2\right]}_{\text{Gradient Penalty for Lipschitzness}}$$

$$\hat{x} \leftarrow \epsilon x + (1-\epsilon)\tilde{x}$$

[Gulrajani et al 2017]

WGAN-GP: Pseudocode

Algorithm 1 WGAN with gradient penalty. We use default values of $\lambda = 10$, $n_{\text{critic}} = 5$, $\alpha = 0.0001$, $\beta_1 = 0$, $\beta_2 = 0.9$.

Require: The gradient penalty coefficient λ, the number of critic iterations per generator iteration n_{critic}, the batch size m, Adam hyperparameters α, β_1, β_2.
Require: initial critic parameters w_0, initial generator parameters θ_0.

while θ has not converged **do**
  for $t = 1, ..., n_{\text{critic}}$ **do**
    for $i = 1, ..., m$ **do**
      Sample real data $\boldsymbol{x} \sim \mathbb{P}_r$, latent variable $\boldsymbol{z} \sim p(\boldsymbol{z})$, a random number $\epsilon \sim U[0, 1]$.
      $\tilde{\boldsymbol{x}} \leftarrow G_\theta(\boldsymbol{z})$
      $\hat{\boldsymbol{x}} \leftarrow \epsilon \boldsymbol{x} + (1 - \epsilon)\tilde{\boldsymbol{x}}$
      $L^{(i)} \leftarrow D_w(\tilde{\boldsymbol{x}}) - D_w(\boldsymbol{x}) + \lambda(\|\nabla_{\hat{\boldsymbol{x}}} D_w(\hat{\boldsymbol{x}})\|_2 - 1)^2$
    end for
    $w \leftarrow \text{Adam}(\nabla_w \frac{1}{m} \sum_{i=1}^{m} L^{(i)}, w, \alpha, \beta_1, \beta_2)$
  end for
  Sample a batch of latent variables $\{\boldsymbol{z}^{(i)}\}_{i=1}^{m} \sim p(\boldsymbol{z})$.
  $\theta \leftarrow \text{Adam}(\nabla_\theta \frac{1}{m} \sum_{i=1}^{m} -D_w(G_\theta(\boldsymbol{z})), \theta, \alpha, \beta_1, \beta_2)$
end while

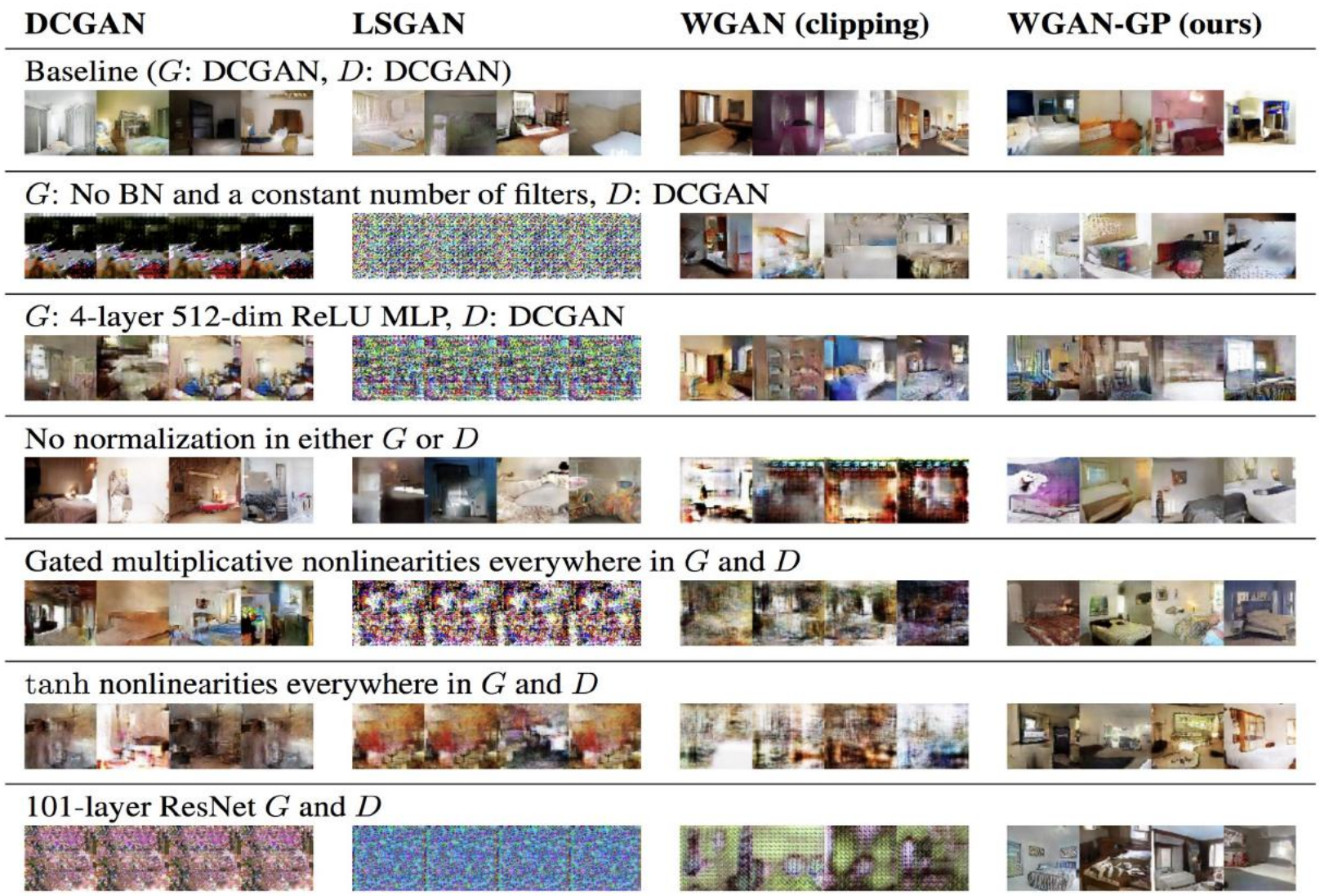
[Gulrajani et al 2017]

WGAN-GP: BatchNorm

No critic batch normalization Most prior GAN implementations [22, 23, 2] use batch normalization in both the generator and the discriminator to help stabilize training, but batch normalization changes the form of the discriminator's problem from mapping a single input to a single output to mapping from an entire batch of inputs to a batch of outputs [23]. Our penalized training objective is no longer valid in this setting, since we penalize the norm of the critic's gradient with respect to each input independently, and not the entire batch. To resolve this, we simply omit batch normalization in the critic in our models, finding that they perform well without it. Our method works with normalization schemes which don't introduce correlations between examples. In particular, we recommend layer normalization [3] as a drop-in replacement for batch normalization.

[Gulrajani et al 2017]

WGAN-GP: Robustness to architectures



[Gulrajani et al 2017]

WGAN-GP: High quality samples

[Gulrajani et al 2017]

WGAN-GP: High quality samples

Table 3: Inception scores on CIFAR-10. Our unsupervised model achieves state-of-the-art performance, and our conditional model outperforms all others except SGAN.

Unsupervised	
Method	Score
ALI [8] (in [27])	$5.34 \pm .05$
BEGAN [4]	5.62
DCGAN [22] (in [11])	$6.16 \pm .07$
Improved GAN (-L+HA) [23]	$6.86 \pm .06$
EGAN-Ent-VI [7]	$7.07 \pm .10$
DFM [27]	$7.72 \pm .13$
WGAN-GP ResNet (ours)	$7.86 \pm .07$

Supervised	
Method	Score
SteinGAN [26]	6.35
DCGAN (with labels, in [26])	6.58
Improved GAN [23]	$8.09 \pm .07$
AC-GAN [20]	$8.25 \pm .07$
SGAN-no-joint [11]	$8.37 \pm .08$
WGAN-GP ResNet (ours)	$8.42 \pm .10$
SGAN [11]	$8.59 \pm .12$

[Gulrajani et al 2017]

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- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- **GAN Progression**
  - DC GAN (Radford et al, 2016)
  - Improved Training of GANs (Salimans et al'16)
  - WGAN, WGAN-GP, **Progressive GAN**, SN-GAN
  - BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, StyleGAN-v3, VQ-GAN
- Conditional GANs, Cycle-Consistent Adversarial Networks
- Applications

Progressive growing of GANs

PROGRESSIVE GROWING OF GANS FOR IMPROVED QUALITY, STABILITY, AND VARIATION

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Timo Aila NVIDIA
Samuli Laine NVIDIA
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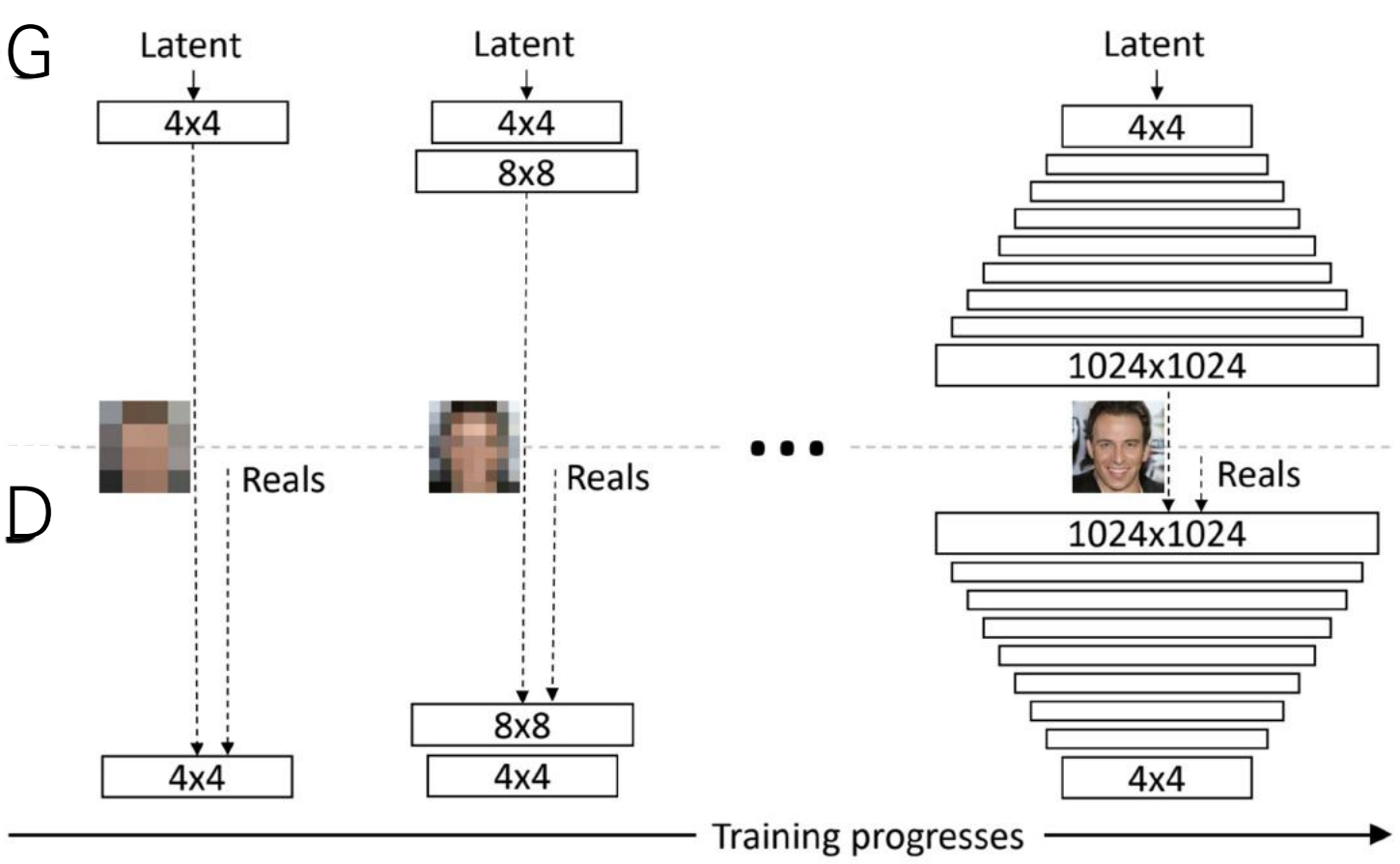
ABSTRACT

We describe a new training methodology for generative adversarial networks. The key idea is to grow both the generator and discriminator progressively: starting from a low resolution, we add new layers that model increasingly fine details as training progresses. This both speeds the training up and greatly stabilizes it, allowing us to produce images of unprecedented quality, e.g., CELEBA images at 1024^2. We also propose a simple way to increase the variation in generated images, and achieve a record inception score of 8.80 in unsupervised CIFAR10. Additionally, we describe several implementation details that are important for discouraging unhealthy competition between the generator and discriminator. Finally, we suggest a new metric for evaluating GAN results, both in terms of image quality and variation. As an additional contribution, we construct a higher-quality version of the CELEBA dataset.

[Karras et al. 2017]

Progressive growing of GANs

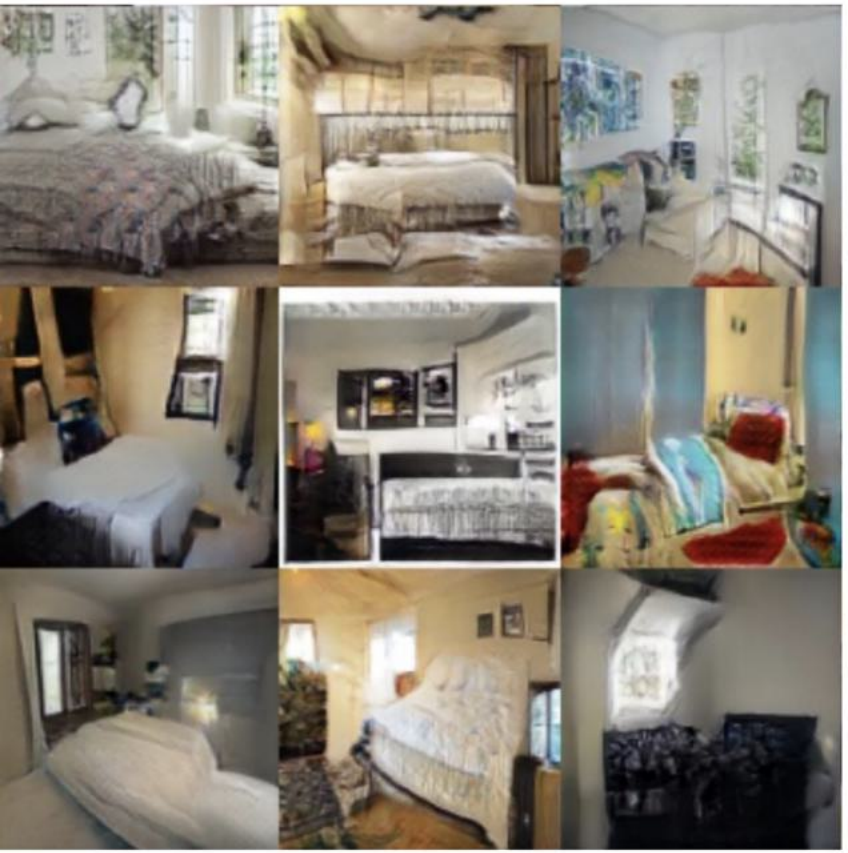


[Karras et al. 2017]

Progressive growing of GANs

[Karras et al. 2017]

Progressive growing of GANs



Mao et al. (2016b) (128 × 128)

Gulrajani et al. (2017) (128 × 128)

Our (256 × 256)

[Karras et al. 2017]

Progressive growing of GANs

[Karras et al. 2017]

Progressive growing of GANs

[Karras et al. 2017]

Progressive growing of GANs

CelebA-HQ
random interpolations

[Karras et al. 2017]

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- Conditional GANs, Cycle-Consistent Adversarial Networks
- Applications

Spectral Normalization GAN (SNGAN)

SPECTRAL NORMALIZATION FOR GENERATIVE ADVERSARIAL NETWORKS

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ABSTRACT

One of the challenges in the study of generative adversarial networks is the instability of its training. In this paper, we propose a novel weight normalization technique called spectral normalization to stabilize the training of the discriminator. Our new normalization technique is computationally light and easy to incorporate into existing implementations. We tested the efficacy of spectral normalization on CIFAR10, STL-10, and ILSVRC2012 dataset, and we experimentally confirmed that spectrally normalized GANs (SN-GANs) is capable of generating images of better or equal quality relative to the previous training stabilization techniques. The code with Chainer (Tokui et al., 2015), generated images and pretrained models are available at https://github.com/pfnet-research/sngan_projection.

[Miyato et al. 2017]

Spectral Normalization GAN (SNGAN)

(original) GAN formulation: $\min_G \max_D V(G, D)$

where $V(G, D) = \mathrm{E}_{\boldsymbol{x} \sim q_{\text{data}}}[\log D(\boldsymbol{x})] + \mathrm{E}_{\boldsymbol{x}' \sim p_G}[\log(1 - D(\boldsymbol{x}'))]$

WGAN formulation: $\min_G \left[\arg\max_{\|f\|_{\text{Lip}} \leq K} V(G, D) \right]$

where $\|f\|_{\text{Lip}} \leq K \Rightarrow \|f(\boldsymbol{x}) - f(\boldsymbol{x}')\| / \|\boldsymbol{x} - \boldsymbol{x}'\| \leq K$

- Idea: Use spectral normalization to enforce the Lipschitz constraint

Spectral Normalization GAN (SNGAN)

- **Spectral Normalization strategy:** enforce the Lipschitz contraint by constraining the spectral norm of each layer of the neural network.

$$\text{spectral norm of the matrix } A\text{:} \quad \sigma(A) := \max_{\boldsymbol{h}:\boldsymbol{h}\neq\mathbf{0}} \frac{\|A\boldsymbol{h}\|_2}{\|\boldsymbol{h}\|_2} = \max_{\|\boldsymbol{h}\|_2\leq 1} \|A\boldsymbol{h}\|_2$$

largest singular value of A

- Let g be a layer of a network: $g : \boldsymbol{h}_{in} \mapsto \boldsymbol{h}_{out}$

$$\text{for a linear layer } g(\boldsymbol{h}) = W\boldsymbol{h}\text{:} \quad \|g\|_{\text{Lip}} = \sup_{\boldsymbol{h}} \sigma(\nabla g(\boldsymbol{h})) = \sup_{\boldsymbol{h}} \sigma(W) = \sigma(W)$$

- For the network f, we assume the Lipschitz norm of the activation function (a) equals 1 (typically ok) and use the inequality:

$$\|g_1 \circ g_2\|_{\text{Lip}} \leq \|g_1\|_{\text{Lip}} \cdot \|g_2\|_{\text{Lip}}$$

Spectral Normalization GAN (SNGAN)

- The Lipschitz norm for the network is:

activation function for layer L

$$\|f\|_{\text{Lip}} \leq \|(\boldsymbol{h}_L \mapsto W^{L+1}\boldsymbol{h}_L)\|_{\text{Lip}} \cdot \|a_L\|_{\text{Lip}} \cdot \|(\boldsymbol{h}_{L-1} \mapsto W^{L}\boldsymbol{h}_{L-1})\|_{\text{Lip}}$$

$$\cdots \|a_1\|_{\text{Lip}} \cdot \|(\boldsymbol{h}_0 \mapsto W^{1}\boldsymbol{h}_0)\|_{\text{Lip}} = \prod_{l=1}^{L+1} \|(\boldsymbol{h}_{l-1} \mapsto W^{l}\boldsymbol{h}_{l-1})\|_{\text{Lip}} = \prod_{l=1}^{L+1} \sigma(W^l)$$

- Spectral Normalize the weights at each layer: $\bar{W}_{\text{SN}}(W) := W/\sigma(W)$

  where $\sigma(W)$ is efficiently approximated using the **power method.**

(as described on the next slide)

Spectral Normalization GAN (SNGAN)

Algorithm 1 SGD with spectral normalization

- Initialize $\tilde{\boldsymbol{u}}_l \in \mathcal{R}^{d_l}$ for $l = 1, \ldots, L$ with a random vector (sampled from isotropic distribution).
- For each update and each layer l: ⇢ (warm start $\tilde{\boldsymbol{u}}_l$ and $\tilde{\boldsymbol{v}}_l$ from previous iteration)
  1. Apply power iteration method to a unnormalized weight W^l: (single iteration seems to work)

$$\tilde{\boldsymbol{v}}_l \leftarrow (W^l)^{\mathrm{T}} \tilde{\boldsymbol{u}}_l / \|(W^l)^{\mathrm{T}} \tilde{\boldsymbol{u}}_l\|_2 \tag{20}$$

$$\tilde{\boldsymbol{u}}_l \leftarrow W^l \tilde{\boldsymbol{v}}_l / \|W^l \tilde{\boldsymbol{v}}_l\|_2 \tag{21}$$

  2. Calculate $\bar{W}_{\mathrm{SN}}$ with the spectral norm:

$$\bar{W}^l_{\mathrm{SN}}(W^l) = W^l / \sigma(W^l), \text{ where } \sigma(W^l) = \tilde{\boldsymbol{u}}_l^{\mathrm{T}} W^l \tilde{\boldsymbol{v}}_l \tag{22}$$

  3. Update W^l with SGD on mini-batch dataset $\mathcal{D}_M$ with a learning rate α:

$$W^l \leftarrow W^l - \alpha \nabla_{W^l} \ell(\bar{W}^l_{\mathrm{SN}}(W^l), \mathcal{D}_M) \tag{23}$$

Spectral Normalization GAN (SNGAN)

$$V_D(\hat{G}, D) = \mathop{\mathrm{E}}_{\boldsymbol{x}\sim q_{\mathrm{data}}(\boldsymbol{x})}\left[\min\left(0, -1 + D(\boldsymbol{x})\right)\right] + \mathop{\mathrm{E}}_{\boldsymbol{z}\sim p(\boldsymbol{z})}\left[\min\left(0, -1 - D\left(\hat{G}(\boldsymbol{z})\right)\right)\right]$$

$$V_G(G, \hat{D}) = -\mathop{\mathrm{E}}_{\boldsymbol{z}\sim p(\boldsymbol{z})}\left[\hat{D}\left(G(\boldsymbol{z})\right)\right],$$

Hinge loss

Geometric GAN

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[Miyato et al. 2017]

Spectral Normalization GAN (SNGAN)

$z \in \mathbb{R}^{128} \sim \mathcal{N}(0, I)$
dense, $4 \times 4 \times 1024$
ResBlock up 1024
ResBlock up 512
ResBlock up 256
ResBlock up 128
ResBlock up 64
BN, ReLU, 3×3 conv 3
Tanh

(a) Generator

RGB image $x \in \mathbb{R}^{128\times128\times3}$
ResBlock down 64
ResBlock down 128
ResBlock down 256
ResBlock down 512
ResBlock down 1024
ResBlock 1024
ReLU
Global sum pooling
dense $\rightarrow$ 1

(b) Discriminator for unconditional GANs.

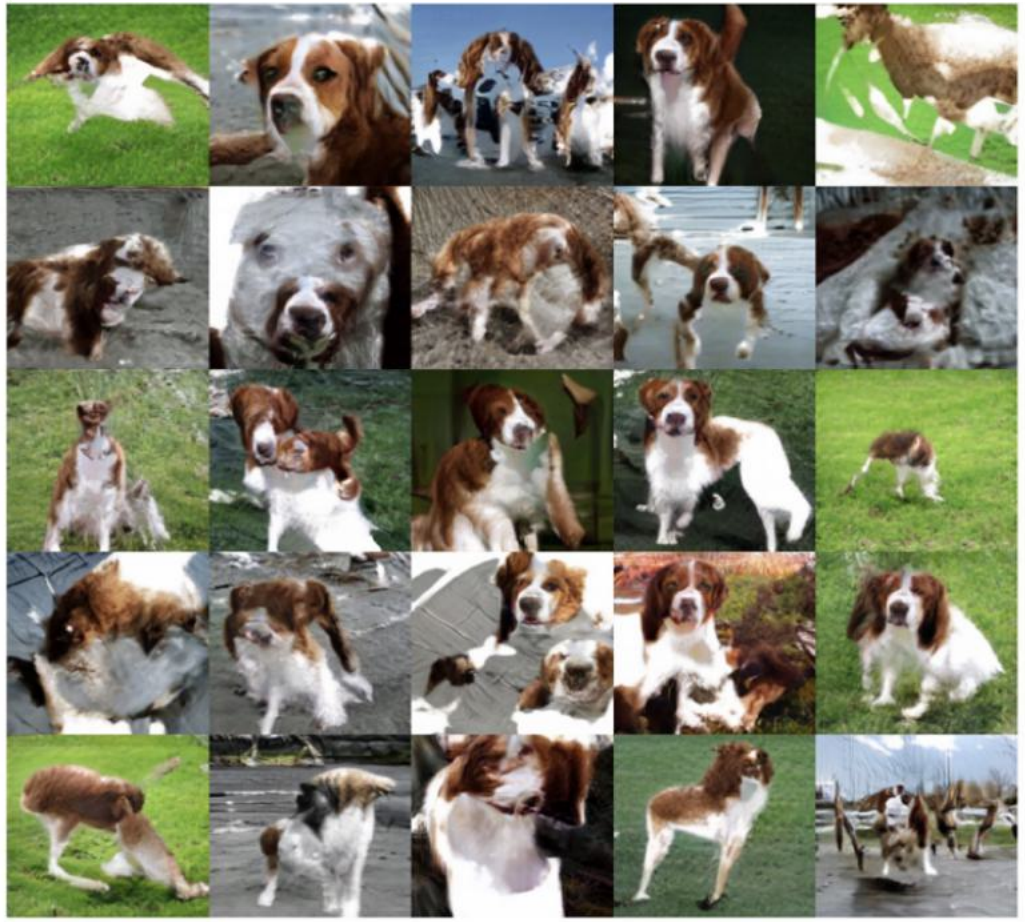
RGB image $x \in \mathbb{R}^{128\times128\times3}$
ResBlock down 64
ResBlock down 128
ResBlock down 256
Concat(Embed(y), $\boldsymbol{h}$)
ResBlock down 512
ResBlock down 1024
ResBlock 1024
ReLU
Global sum pooling
dense $\rightarrow$ 1

(c) Discriminator for conditional GANs. For computational ease, we embedded the integer label $y \in \{0, \ldots, 1000\}$ into 128 dimension before concatenating the vector to the output of the intermediate layer.

[Miyato et al. 2017]

Spectral Normalization GAN (SNGAN)

Welsh springer spaniel



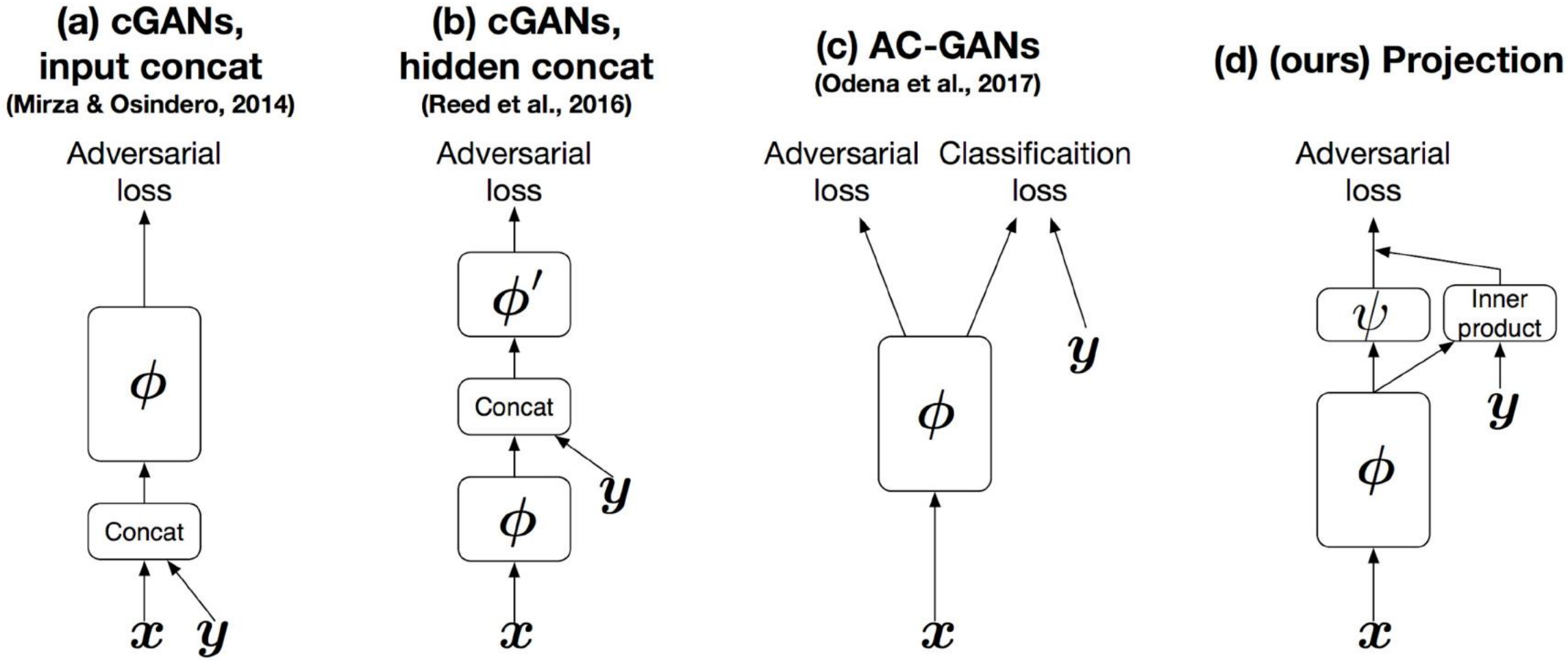
Pizza

[Miyato et al. 2017]

SNGAN: Summary

- High quality class conditional samples at Imagenet scale
- First GAN to work on full Imagenet (million image dataset)
- Computational benefits over WGAN-GP (single power iteration and no need of a backward pass)

Projection Discriminator



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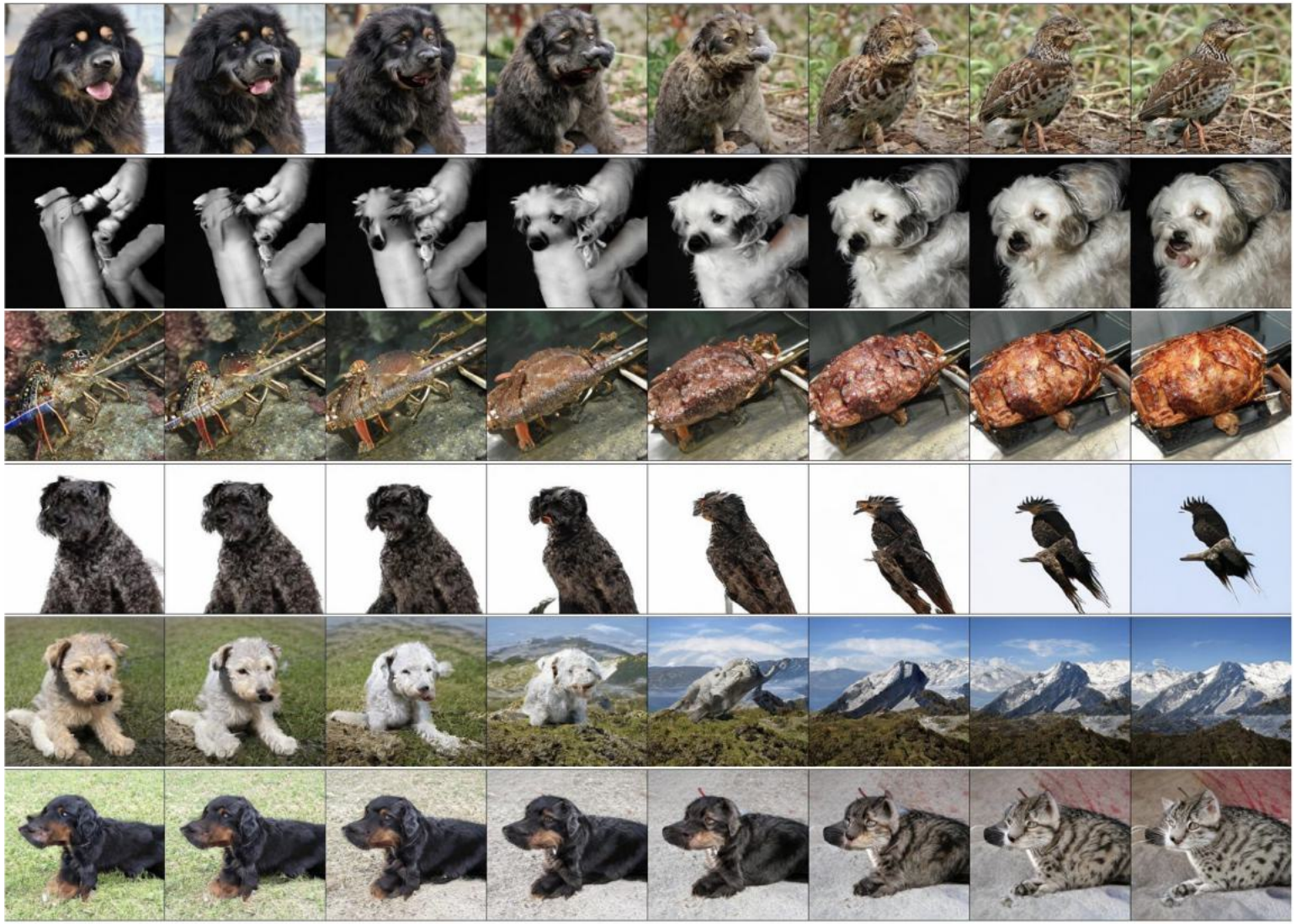
BigGAN

BigGAN



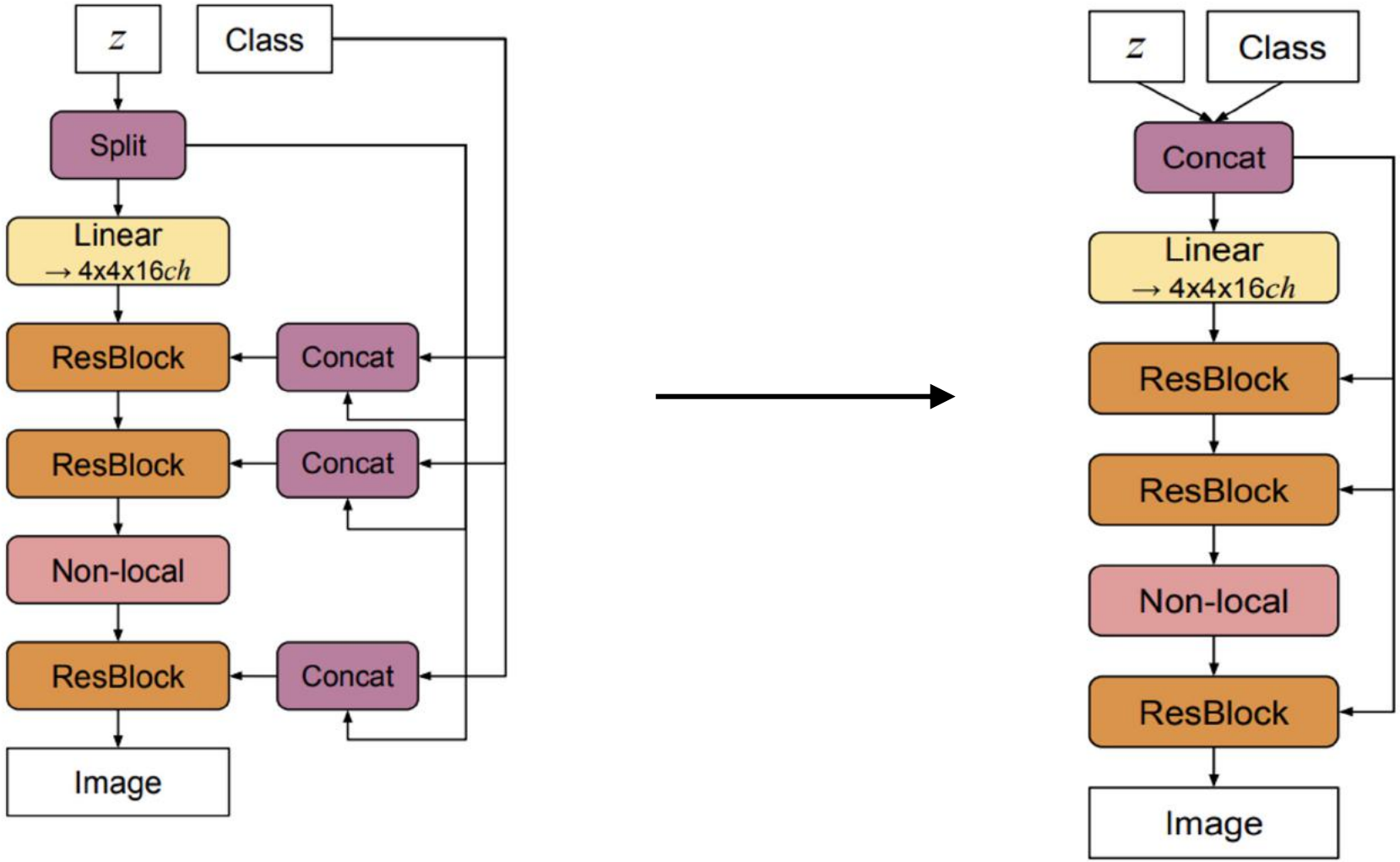
BigGAN

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

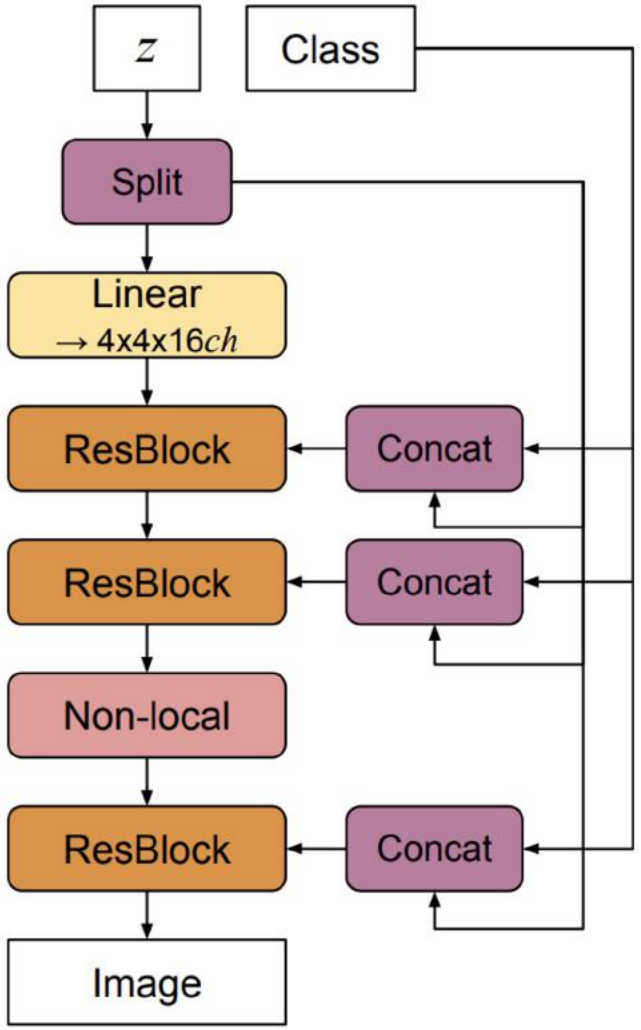
$$R_\beta(W) = \beta \|W^\top W \odot (\mathbf{1} - I)\|_{\mathrm{F}}^2,$$

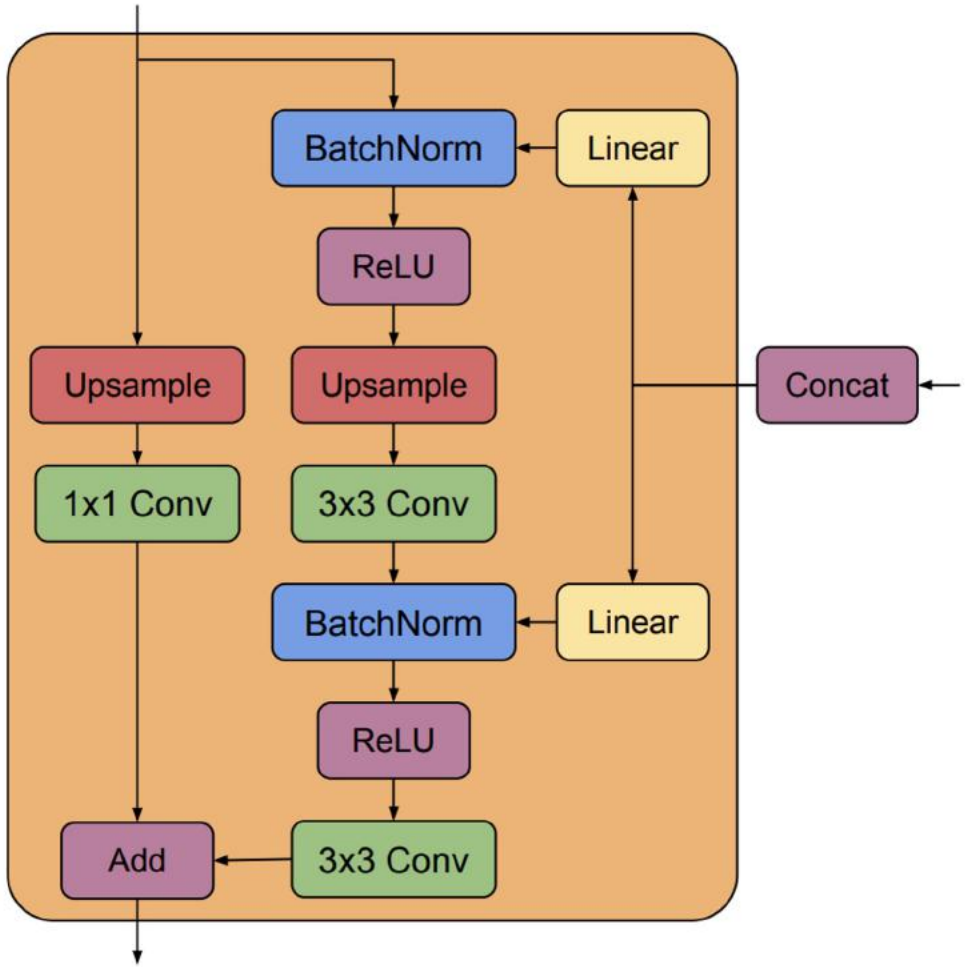
Orthogonal Regularization

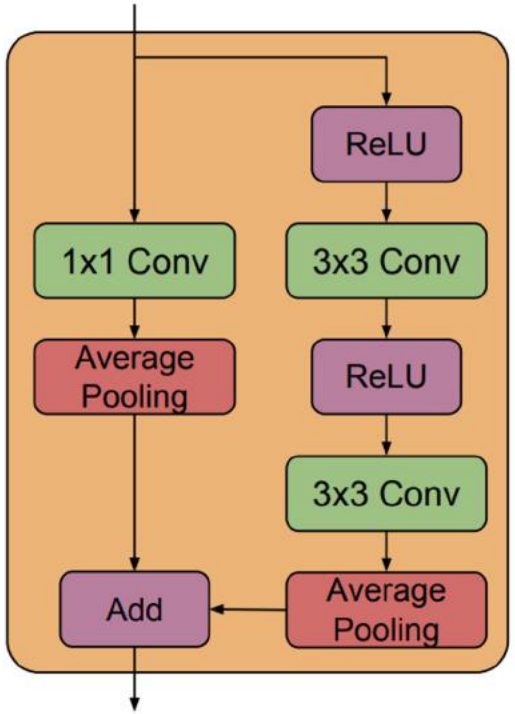
BigGAN and BigGAN-deep



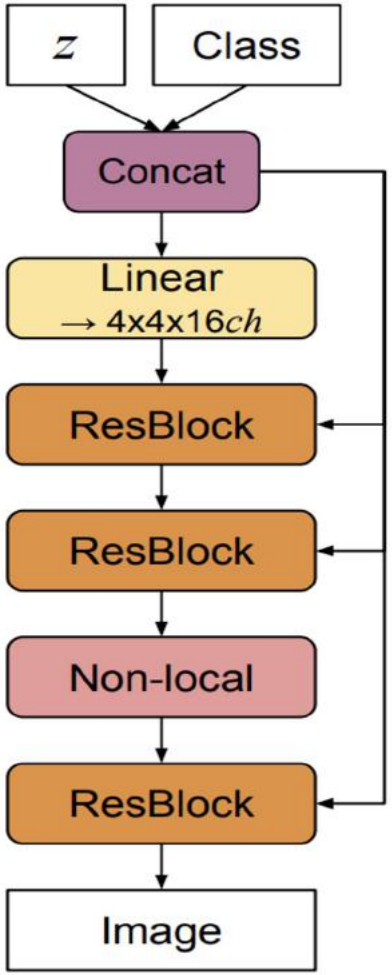
BigGAN

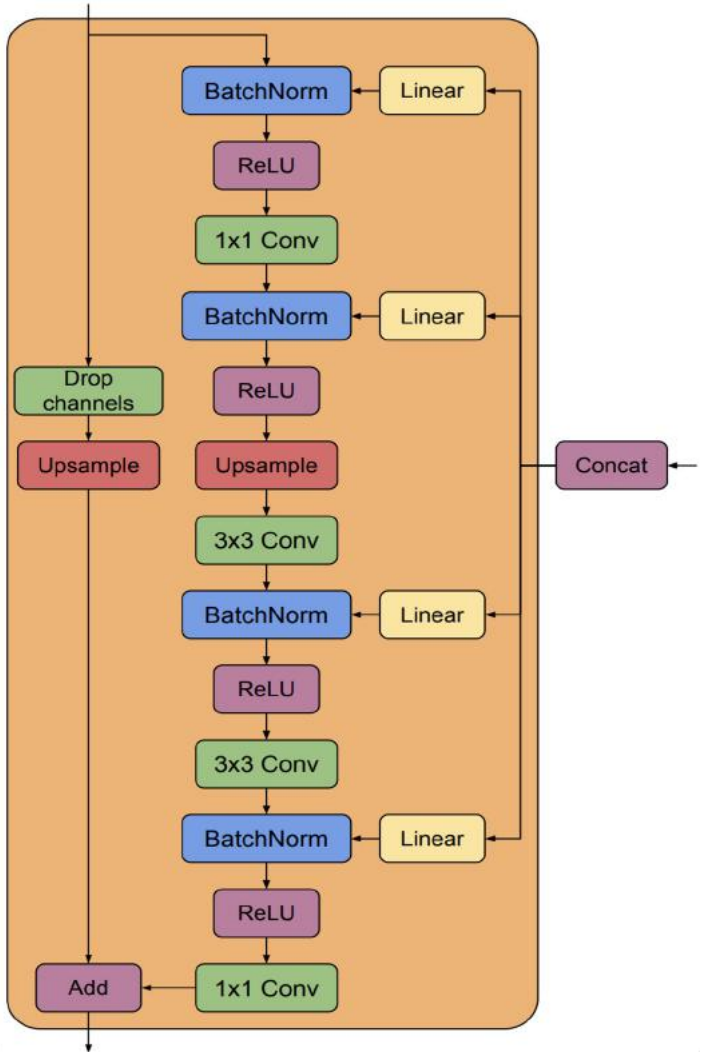

z
Class
Split
Linear
→ 4x4x16ch
ResBlock
Concat
ResBlock
Concat
Non-local
ResBlock
Concat
Image

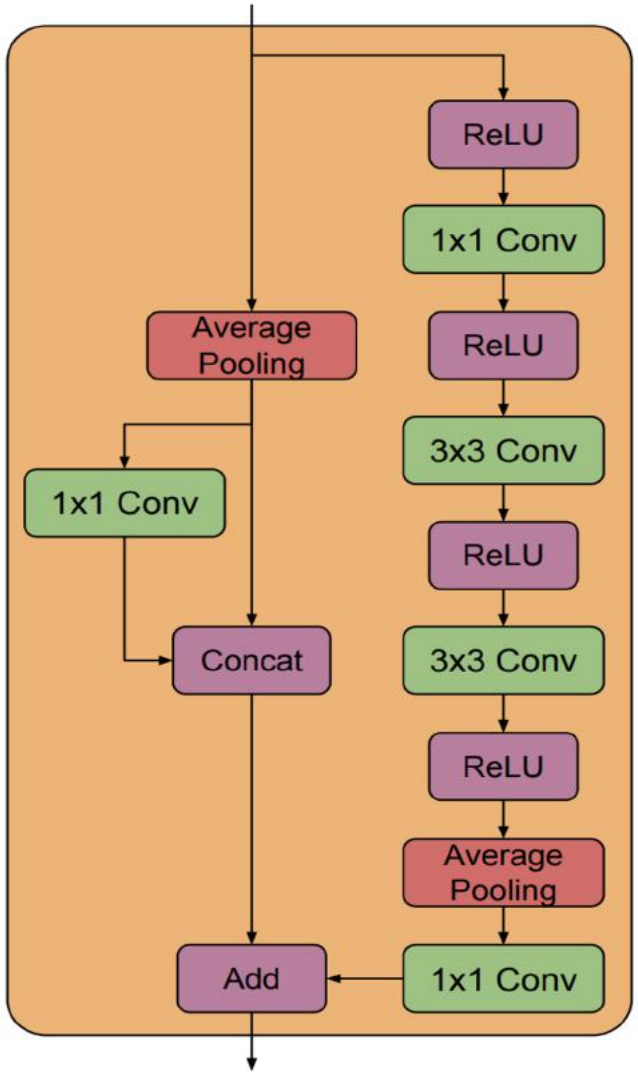

BatchNorm
Linear
ReLU
Upsample
Upsample
Concat
1x1 Conv
3x3 Conv
BatchNorm
Linear
ReLU
Add
3x3 Conv


ReLU
1x1 Conv
3x3 Conv
Average Pooling
ReLU
3x3 Conv
Add
Average Pooling

BigGAN-deep


z
Class
Concat
Linear
→ 4x4x16ch
ResBlock
ResBlock
Non-local
ResBlock
Image


BatchNorm
Linear
ReLU
1x1 Conv
BatchNorm
Linear
Drop channels
ReLU
Upsample
Upsample
Concat
3x3 Conv
BatchNorm
Linear
ReLU
3x3 Conv
BatchNorm
Linear
ReLU
Add
1x1 Conv


ReLU
1x1 Conv
Average Pooling
ReLU
3x3 Conv
1x1 Conv
ReLU
Concat
3x3 Conv
ReLU
Average Pooling
Add
1x1 Conv

BigGAN

Table 6: BigGAN architecture for 512×512 images. Relative to the 256×256 architecture, we add an additional ResBlock at the 512×512 resolution. Memory constraints force us to move the non-local block in both networks back to 64×64 resolution as in the 128×128 pixel setting.

$z \in \mathbb{R}^{160} \sim \mathcal{N}(0, I)$ Embed$(y) \in \mathbb{R}^{128}$
Linear $(20 + 128) \to 4 \times 4 \times 16ch$
ResBlock up $16ch \to 16ch$
ResBlock up $16ch \to 8ch$
ResBlock up $8ch \to 8ch$
ResBlock up $8ch \to 4ch$
Non-Local Block (64×64)
ResBlock up $4ch \to 2ch$
ResBlock up $2ch \to ch$
ResBlock up $ch \to ch$
BN, ReLU, 3×3 Conv $ch \to 3$
Tanh

(a) Generator

RGB image $x \in \mathbb{R}^{512 \times 512 \times 3}$
ResBlock down $ch \to ch$
ResBlock down $ch \to 2ch$
ResBlock down $2ch \to 4ch$
Non-Local Block (64×64)
ResBlock down $4ch \to 8ch$
ResBlock down $8ch \to 8ch$
ResBlock down $8ch \to 16ch$
ResBlock down $16ch \to 16ch$
ResBlock $16ch \to 16ch$
ReLU, Global sum pooling
Embed$(y) \cdot \boldsymbol{h}$ + (linear $\to 1$)

(b) Discriminator

BigGAN

- Increase your batch size (as much as you can)
- Use Cross-Replica (Sync) Batch Norm
- Increase your model size
- Wider helps as much as deeper
- Fuse class information at all levels
- Hinge Loss
- Orthonormal regularization & Truncation Trick

BigGAN

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)

BigGAN

Model	Res.	FID/IS	(min FID) / IS	FID / (valid IS)	FID / (max IS)
SN-GAN	128	$27.62/36.80$	N/A	N/A	N/A
SA-GAN	128	$18.65/52.52$	N/A	N/A	N/A
BigGAN	128	$8.7 \pm .6/98.8 \pm 3$	$7.7 \pm .2/126.5 \pm 0$	$9.6 \pm .4/166.3 \pm 1$	$25 \pm 2/206 \pm 2$
BigGAN	256	$8.7 \pm .1/142.3 \pm 2$	$7.7 \pm .1/178.0 \pm 5$	$9.3 \pm .3/233.1 \pm 1$	$25 \pm 5/291 \pm 4$
BigGAN	512	$8.1/144.2$	$7.6/170.3$	$11.8/241.4$	$27.0/275$
BigGAN-deep	128	$5.7 \pm .3/124.5 \pm 2$	$6.3 \pm .3/148.1 \pm 4$	$7.4 \pm .6/166.5 \pm 1$	$25 \pm 2/253 \pm 11$
BigGAN-deep	256	$6.9 \pm .2/171.4 \pm 2$	$7.0 \pm .1/202.6 \pm 2$	$8.1 \pm .1/232.5 \pm 2$	$27 \pm 8/317 \pm 6$
BigGAN-deep	512	$7.5/152.8$	$7.7/181.4$	$11.5/241.5$	$39.7/298$

BigGAN - Truncation Trick

(a)

(b)

Remarkably, our best results come from using a different latent distribution for sampling than was used in training. Taking a model trained with $z \sim \mathcal{N}(0, I)$ and sampling z from a *truncated normal* (where values which fall outside a range are resampled to fall inside that range) immediately provides a boost to IS and FID. We call this the *Truncation Trick*: truncating a z vector by resampling the values with magnitude above a chosen threshold leads to improvement in individual sample quality at the cost of reduction in overall sample variety. Figure 2(a) demonstrates this: as the threshold is reduced, and elements of z are truncated towards zero (the mode of the latent distribution), individual samples approach the mode of G's output distribution. Related observations about this trade-off were made in (Marchesi, 2016; Pieters & Wiering, 2014).

BigGAN - Sampling

The default behavior with batch normalized classifier networks is to use a running average of the activation moments at test time. Previous works (Radford et al., 2016) have instead used batch statistics when sampling images. While this is not technically an invalid way to sample, it means that results are dependent on the test batch size (and how many devices it is split across), and further complicates reproducibility.

We find that this detail is extremely important, with changes in test batch size producing drastic changes in performance. This is further exacerbated when one uses exponential moving averages of **G**'s weights for sampling, as the BatchNorm running averages are computed with non-averaged weights and are poor estimates of the activation statistics for the averaged weights.

To counteract both these issues, we employ "standing statistics," where we compute activation statistics at sampling time by running the **G** through multiple forward passes (typically 100) each with different batches of random noise, and storing means and variances aggregated across all forward passes. Analogous to using running statistics, this results in **G**'s outputs becoming invariant to batch size and the number of devices, even when producing a single sample.

BigGAN

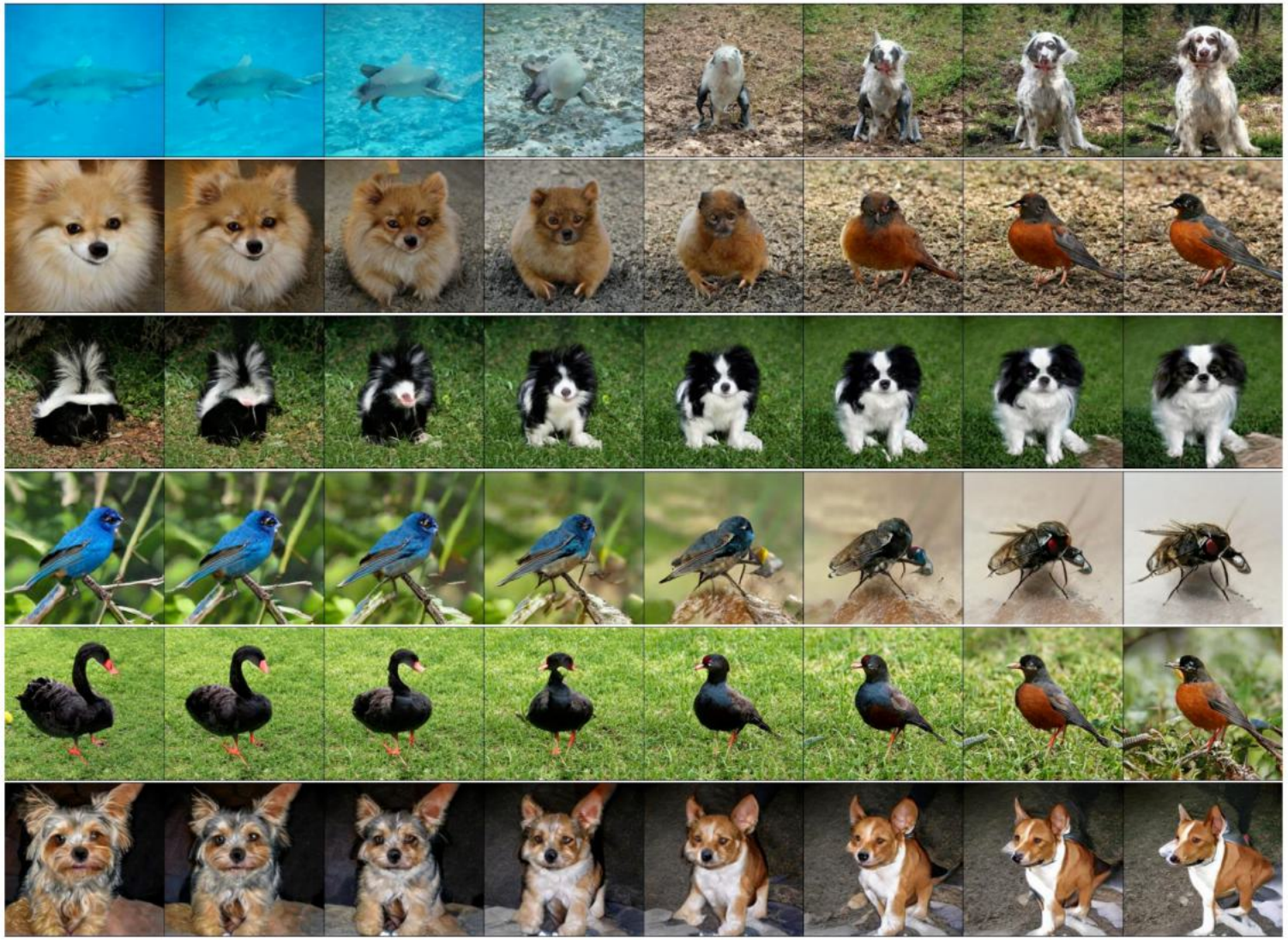
(a) 128×128

(b) 256×256

(c) 512×512

(d)

BigGAN



Lecture overview

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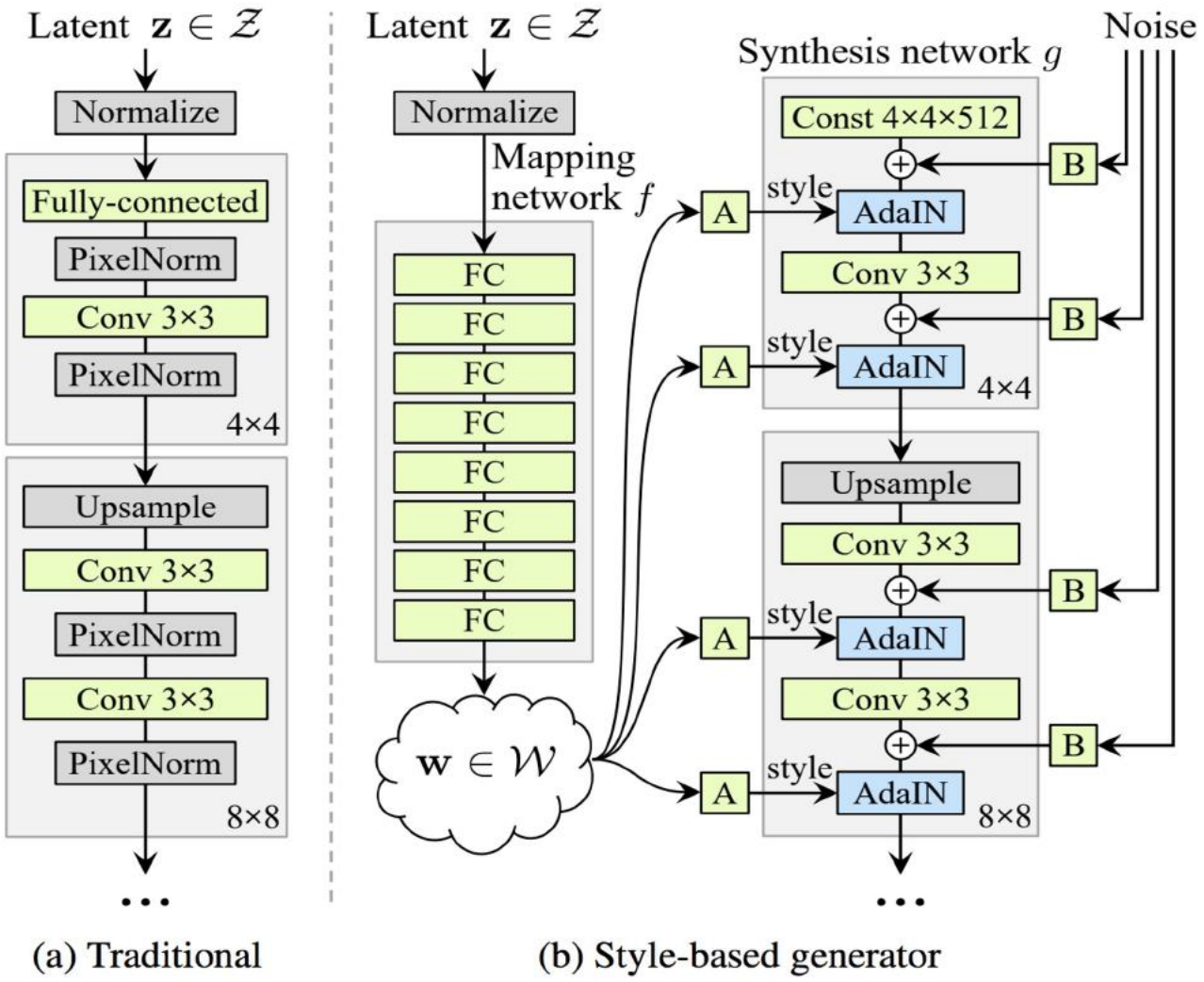
StyleGAN



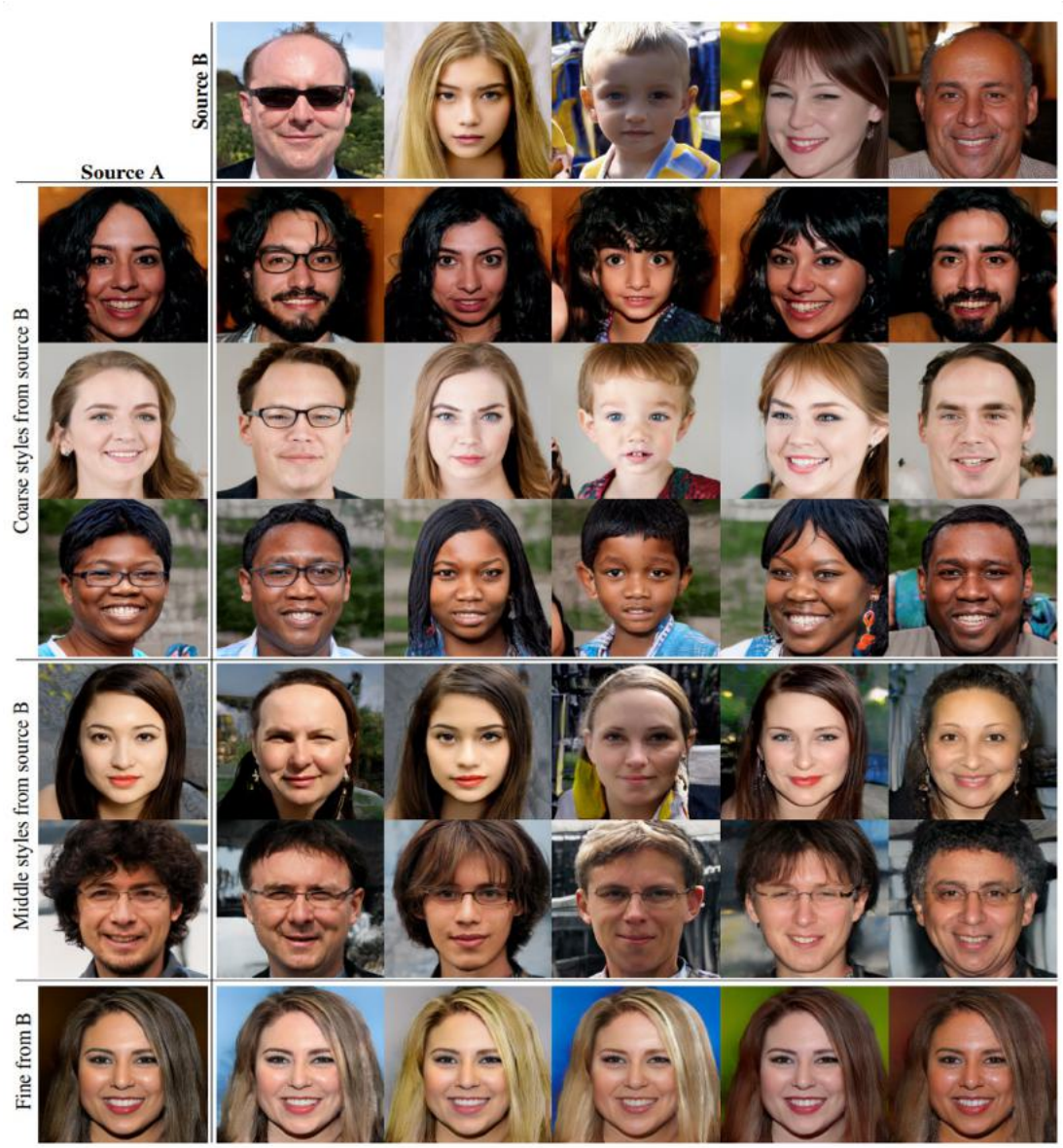
(a) Traditional (b) Style-based generator

Figure 1. While a traditional generator [30] feeds the latent code though the input layer only, we first map the input to an intermediate latent space $\mathcal{W}$, which then controls the generator through adaptive instance normalization (AdaIN) at each convolution layer. Gaussian noise is added after each convolution, before evaluating the nonlinearity. Here "A" stands for a learned affine transform, and "B" applies learned per-channel scaling factors to the noise input. The mapping network f consists of 8 layers and the synthesis network g consists of 18 layers — two for each resolution ($4^2 - 1024^2$). The output of the last layer is converted to RGB using a separate 1×1 convolution, similar to Karras et al. [30]. Our generator has a total of 26.2M trainable parameters, compared to 23.1M in the traditional generator.

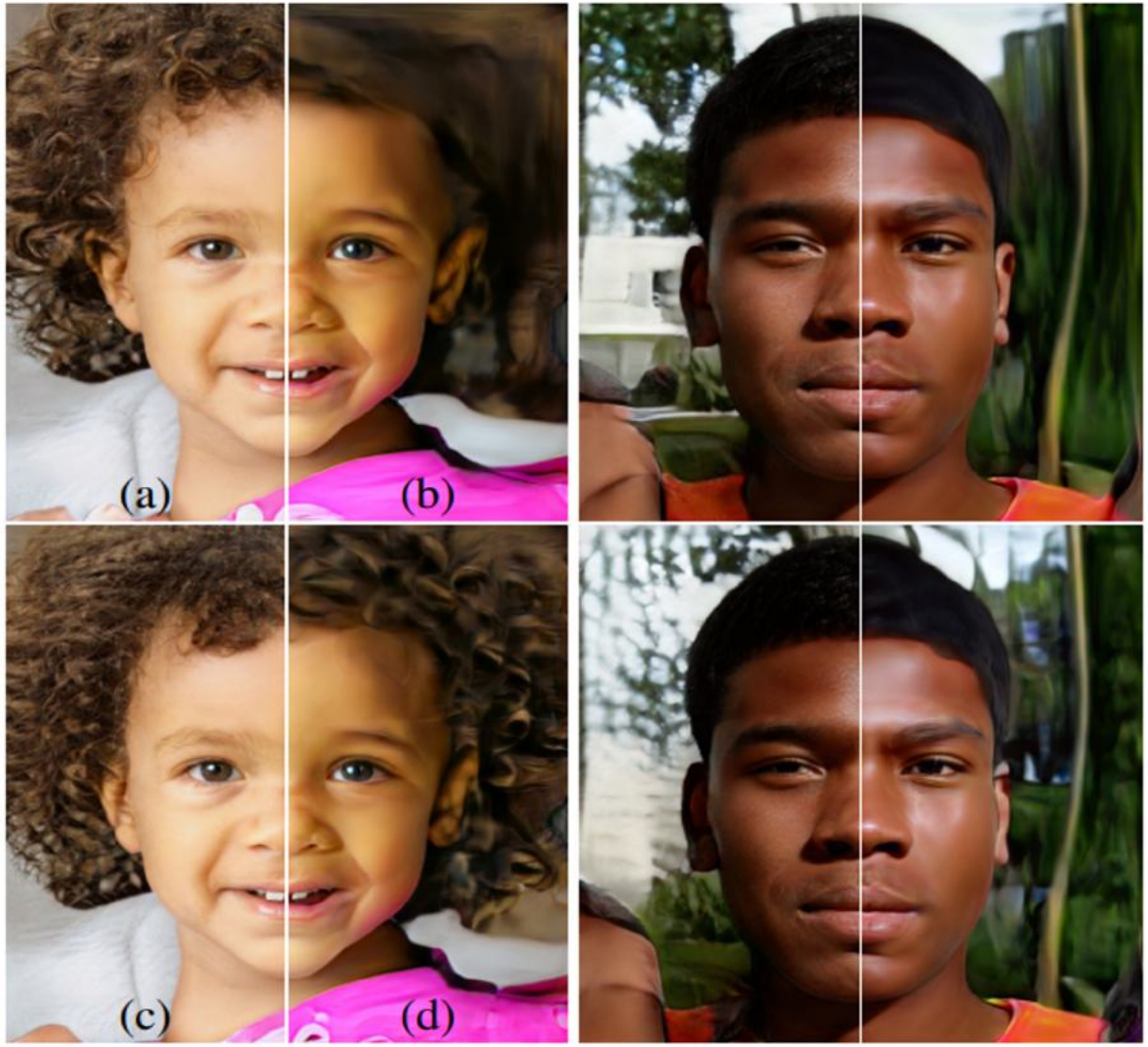
StyleGAN - Adaptive Instance Norm

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

StyleGAN - Style Transfer

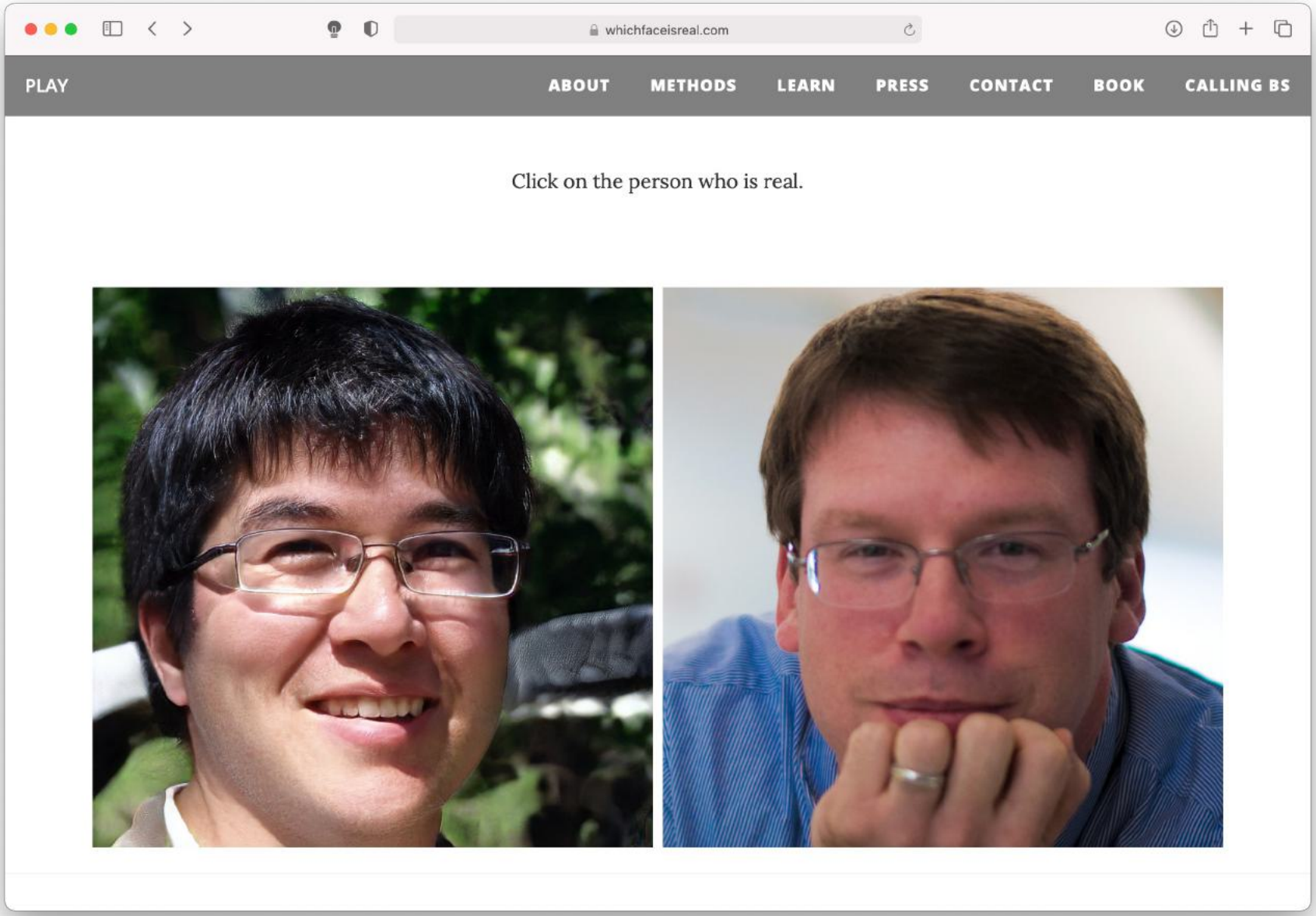


StyleGAN - Effect of adding noise



StyleGAN - Effect of noise

(a) Generated image (b) Stochastic variation (c) Standard deviation



https://www.whichfaceisreal.com/learn.html

StyleGAN Water Droplet-like Artifacts

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

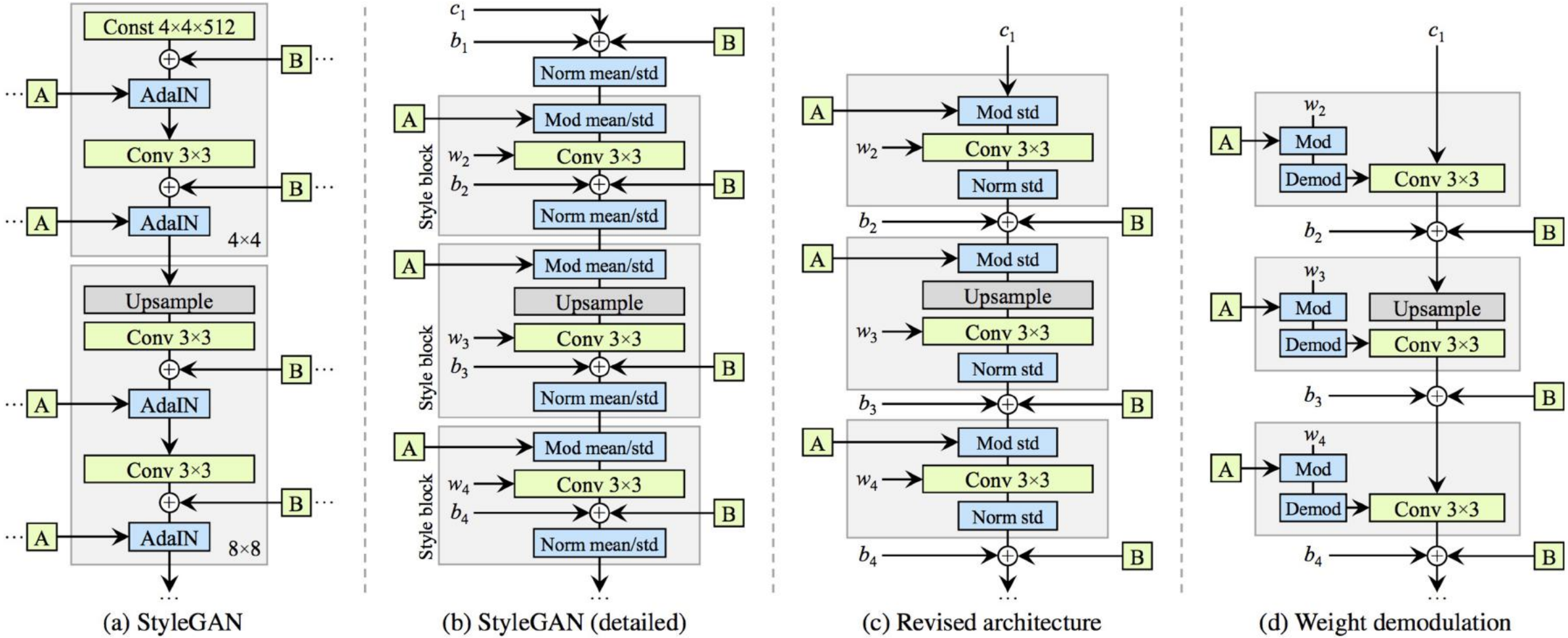


Fig. 2. We redesign the architecture of the StyleGAN synthesis network. (a) The original StyleGAN, where A denotes a learned affine transform from W that produces a style and B is a noise broadcast operation. (b) The same diagram with full detail. Here we have broken the AdaIN to explicit normalization followed by modulation, both operating on the mean and standard deviation per feature map. We have also annotated the learned weights (w), biases (b), and constant input (c), and redrawn the gray boxes so that one style is active per box. The activation function (leaky ReLU) is always applied right after adding the bias. (c) We make several changes to the original architecture that are justified in the main text. We remove some redundant operations at the beginning, move the addition of b and B to be outside active area of a style, and adjust only the standard deviation per feature map. (d) The revised architecture enables us to replace instance normalization with a "demodulation" operation, which we apply to the weights associated with each conv layer.

StyleGAN2 Phase Artifacts

Figure 6. Progressive growing leads to "phase" artifacts. In this example the teeth do not follow the pose but stay aligned to the camera, as indicated by the blue line.

StyleGAN2 Phase Artifacts

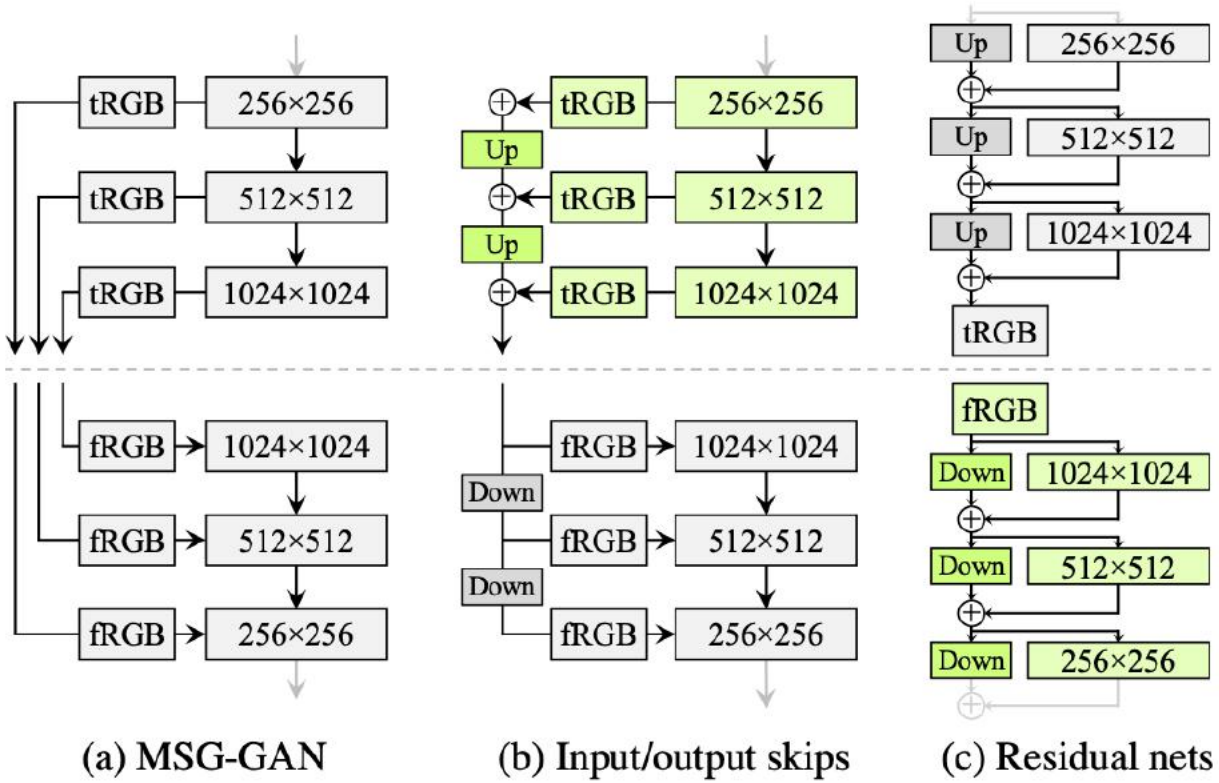
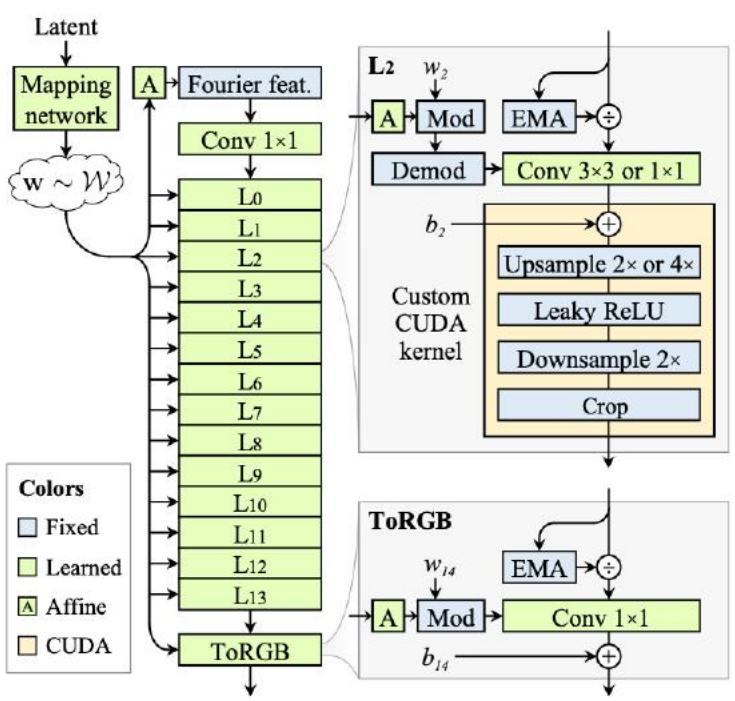


Figure 7. Three generator (above the dashed line) and discriminator architectures. Up and Down denote bilinear up and downsampling, respectively. In residual networks these also include 1×1 convolutions to adjust the number of feature maps. tRGB and fRGB convert between RGB and high-dimensional per-pixel data. Architectures used in configs E and F are shown in green.

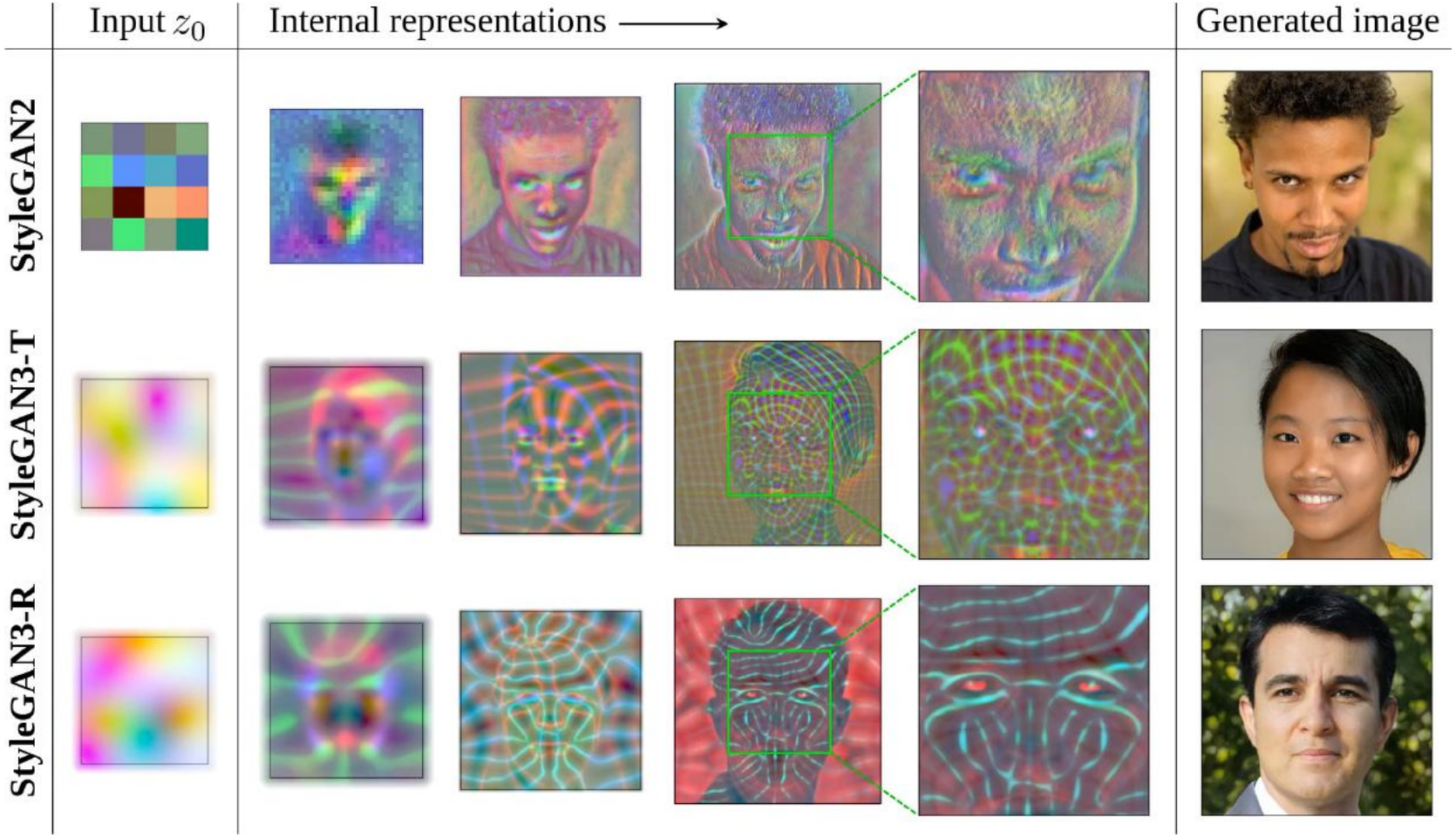

FFHQ, ψ = 0.50

StyleGAN3 to resolve “texture sticking”

StyleGAN3



Implementation requires custom CUDA kernel



- Internal activations encode phase information
- Fully equivariant to translation and rotation even at subpixel scale

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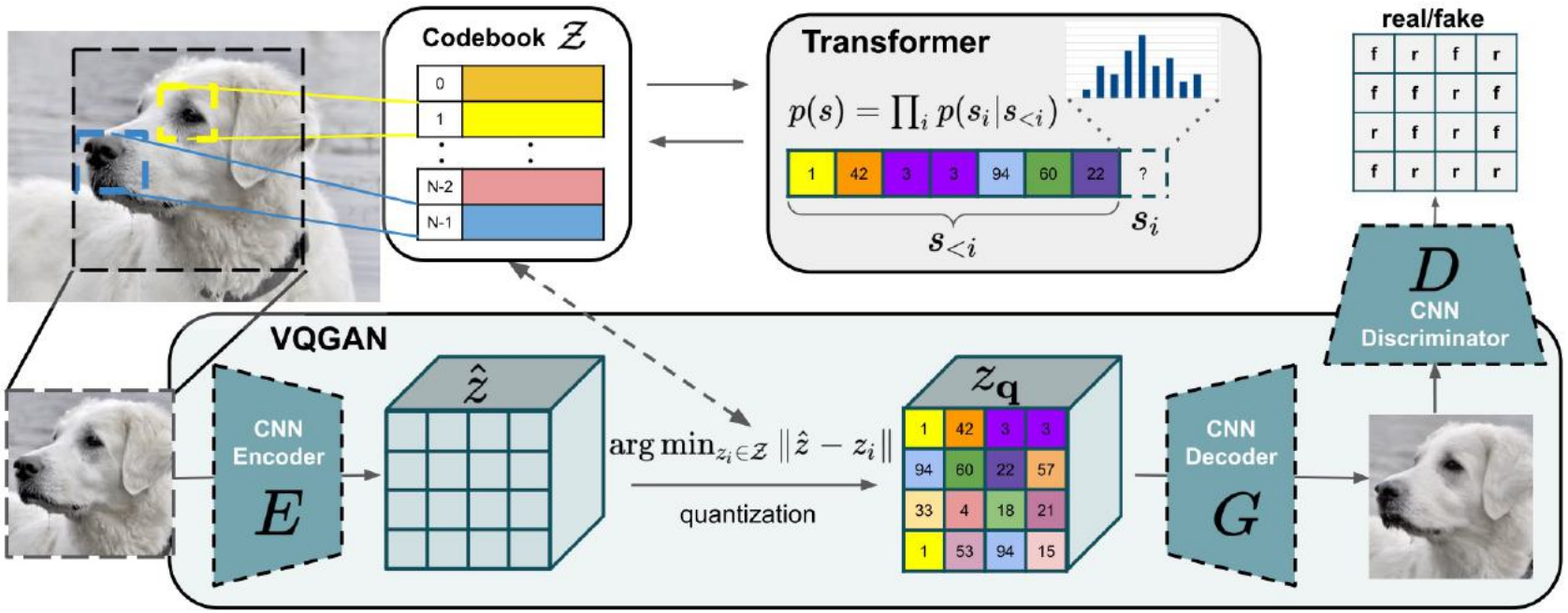
VQGAN



The complete objective for finding the optimal compression model $\mathcal{Q}^* = \{E^*, G^*, \mathcal{Z}^*\}$ then reads

$$\mathcal{Q}^* = \arg\min_{E,G,\mathcal{Z}} \max_D \mathbb{E}_{x\sim p(x)} \Big[\mathcal{L}_{\text{VQ}}(E, G, \mathcal{Z}) + \lambda \mathcal{L}_{\text{GAN}}(\{E, G, \mathcal{Z}\}, D)\Big], \quad (6)$$

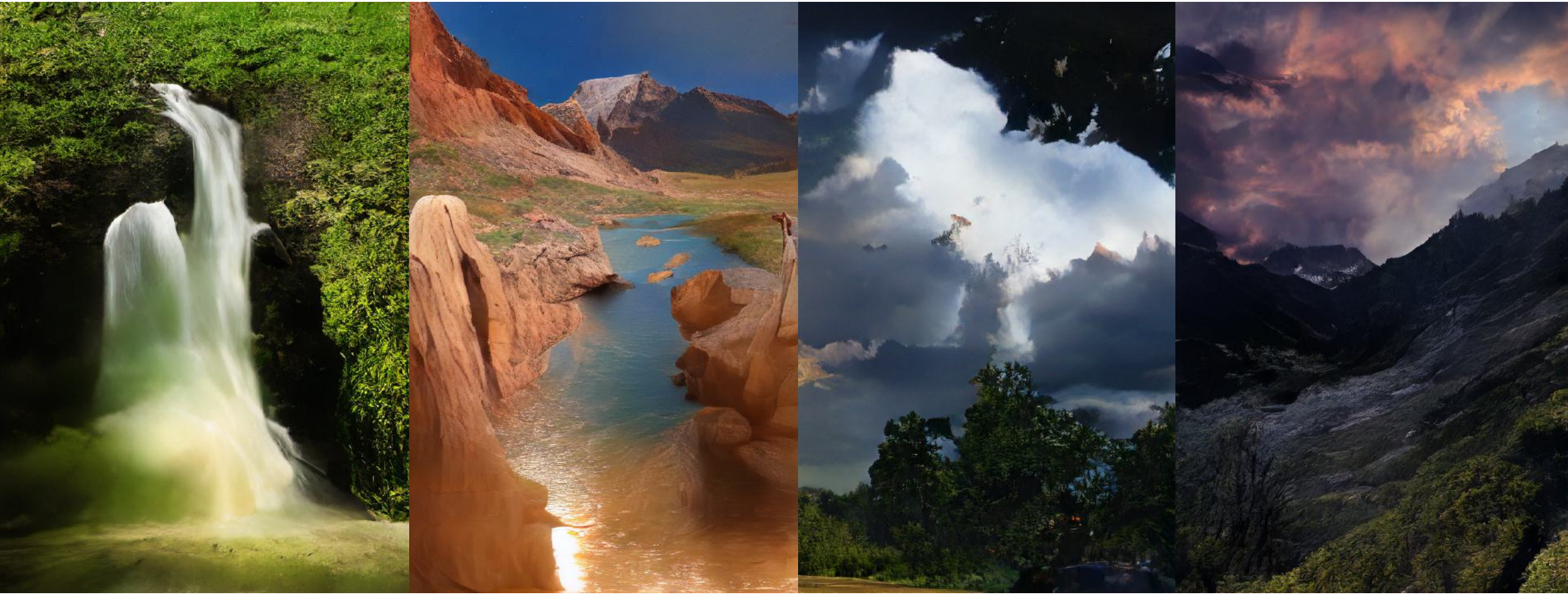
where we compute the adaptive weight λ according to

$$\lambda = \frac{\nabla_{G_L}[\mathcal{L}_{\text{rec}}]}{\nabla_{G_L}[\mathcal{L}_{\text{GAN}}] + \delta} \quad (7)$$

where $\mathcal{L}_{\text{rec}}$ is the perceptual reconstruction loss [81], $\nabla_{G_L}[\cdot]$ denotes the gradient of its input w.r.t. the last layer L of

- A convolutional VQGAN to learn a codebook of context-rich visual parts
- An autoregressive Transformer to generate novel samples

S-FLCKR Samples from Semantic Layouts



ImageNet Samples

Quantitative Evaluation

CelebA-HQ 256 × 256		FFHQ 256 × 256	
Method	FID ↓	Method	FID ↓
GLOW [33]	69.0	VDVAE ($t = 0.7$) [11]	38.8
NVAE [59]	40.3	VDVAE ($t = 1.0$)	33.5
PIONEER (B.) [21]	39.2 (25.3)	VDVAE ($t = 0.8$)	29.8
NCPVAE [1]	24.8	VDVAE ($t = 0.9$)	28.5
VAEBM [66]	20.4	*VQGAN*+P.SNAIL	21.9
Style ALAE [49]	19.2	BigGAN	12.4
DC-VAE [47]	15.8	**ours**	11.4
ours	10.7	U-Net GAN (+aug) [57]	10.9 (7.6)
PGGAN [27]	8.0	StyleGAN2 (+aug) [30]	3.8 (3.6)

Table 3. FID score comparison for face image synthesis. CelebA-HQ results reproduced from [1, 47, 66, 22], FFHQ from [57, 28].

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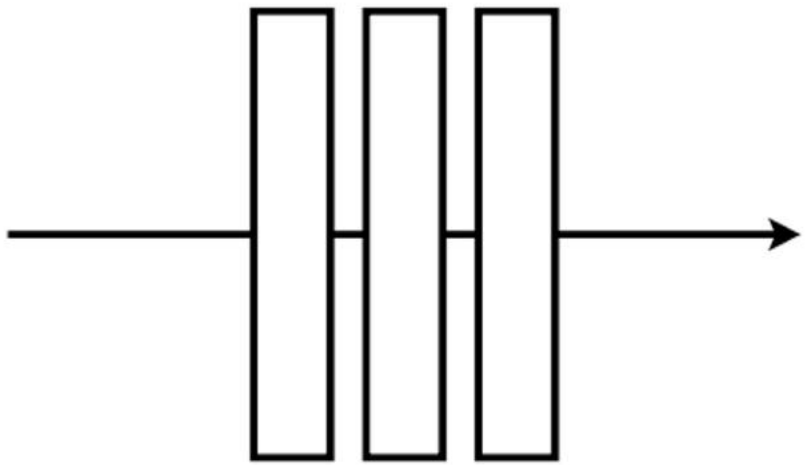
Conditional GANs / pix2pix

$\mathbf{x}$

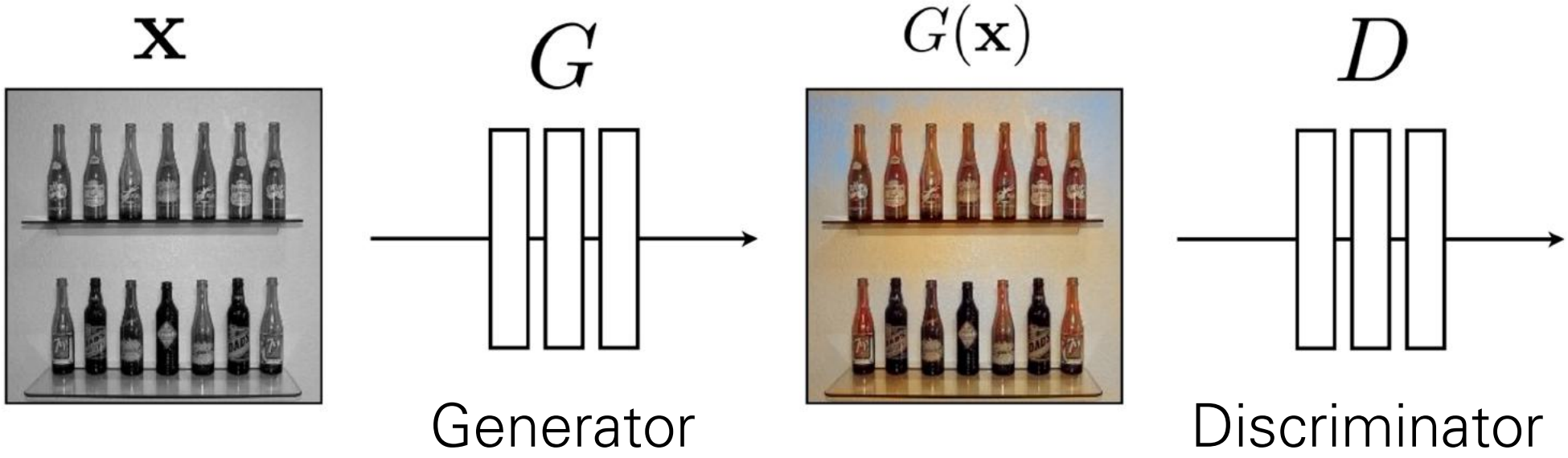
G



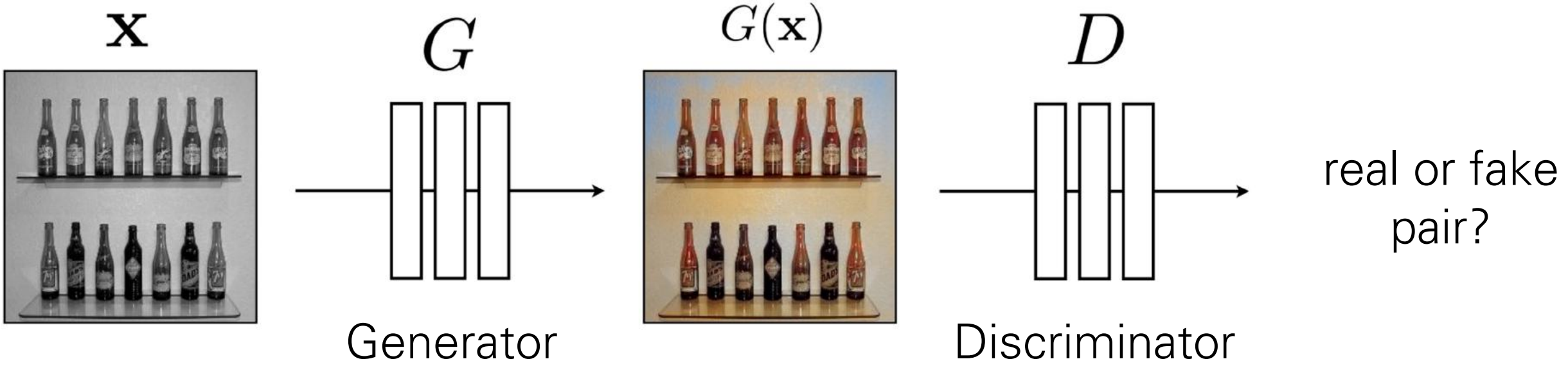
Generator

$G(\mathbf{x})$

Conditional GANs / pix2pix



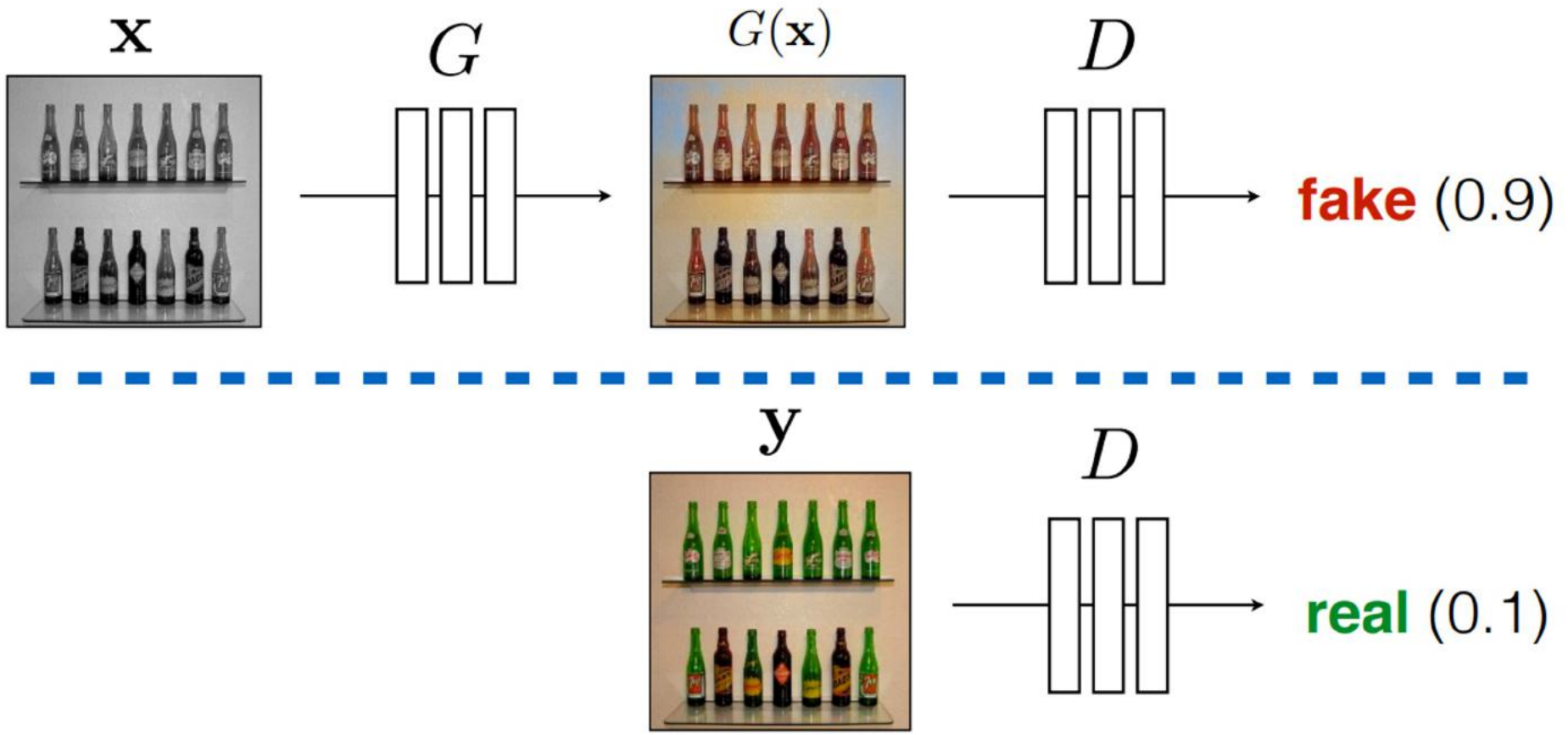
Conditional GANs / pix2pix



G tries to synthesize fake images that fool D

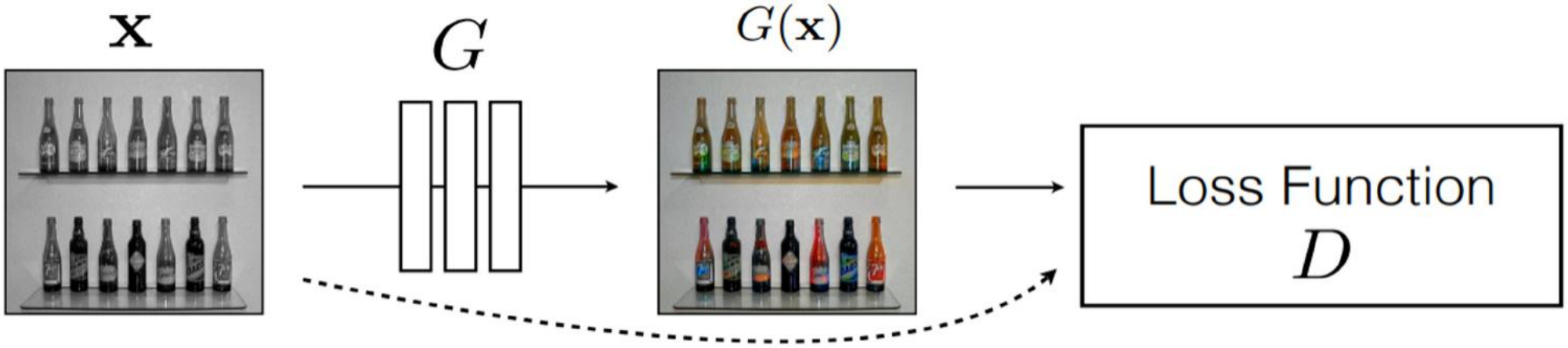
D tries to identify the fakes

Conditional GANs / pix2pix



$$\arg\max_D \mathbb{E}_{\mathbf{x},\mathbf{y}}[\log D(G(\mathbf{x})) + \log(1 - D(\mathbf{y}))]$$

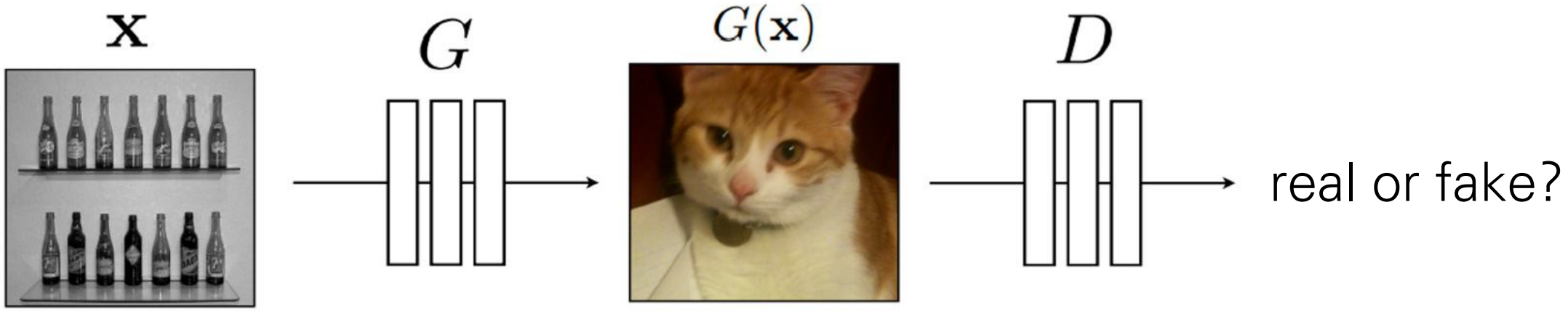
Conditional GANs / pix2pix



G's perspective: **D** is a loss function.

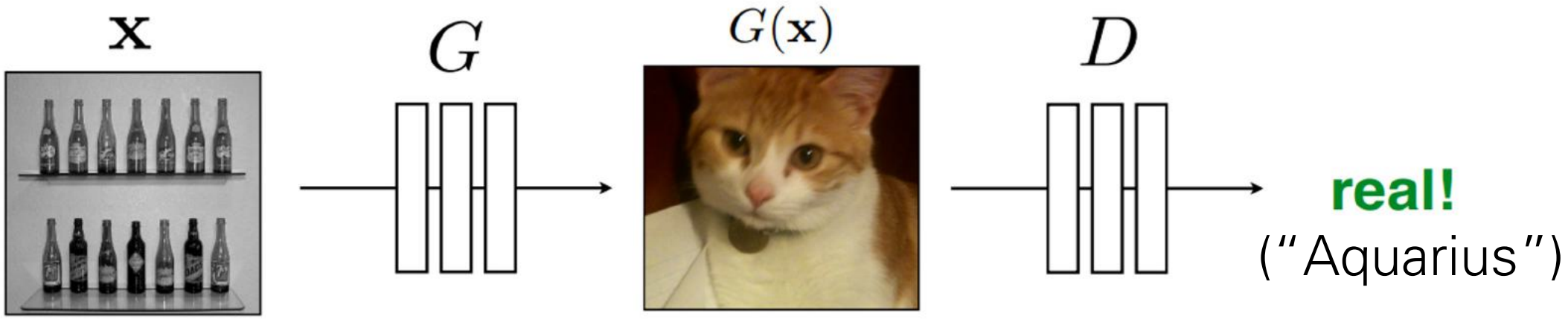
Rather than being hand-designed, it is learned.

Conditional GANs / pix2pix



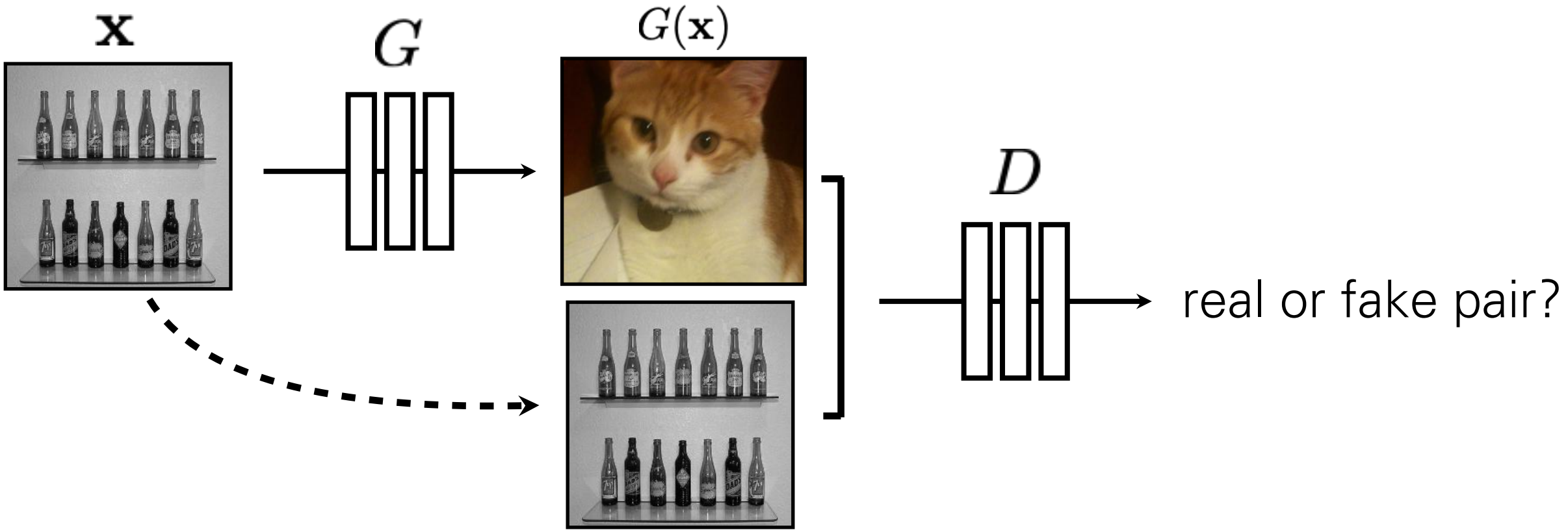
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y})) \;\;]$$

Conditional GANs / pix2pix



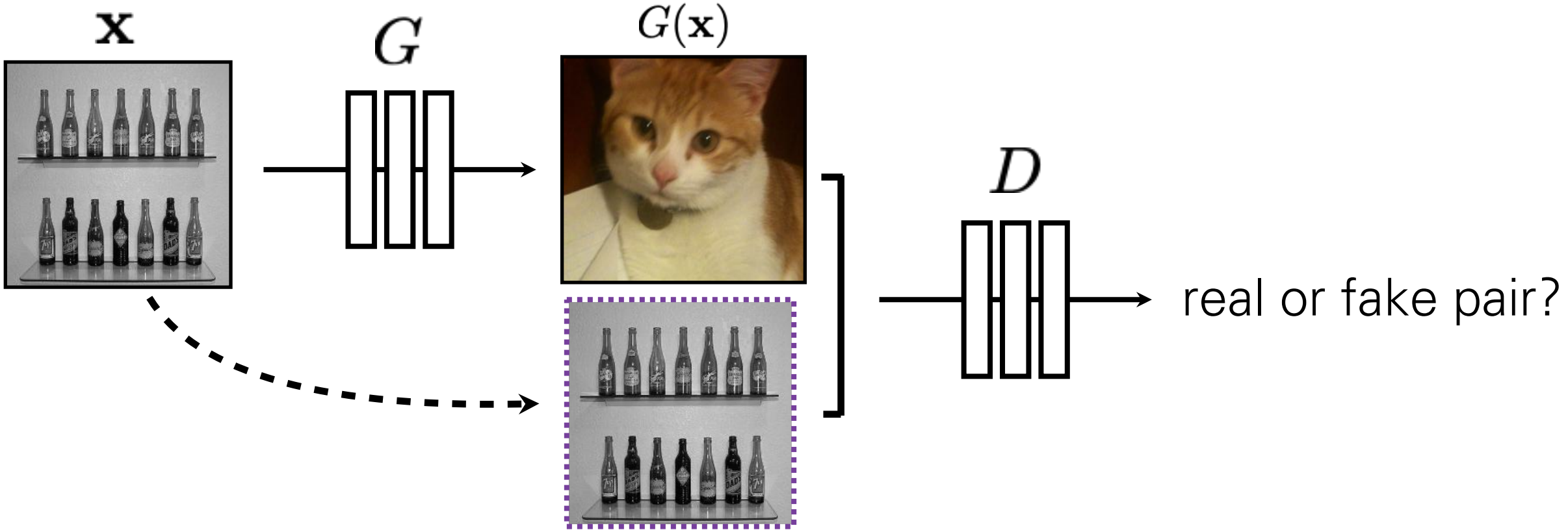
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y}))\;]$$

Conditional GANs / pix2pix



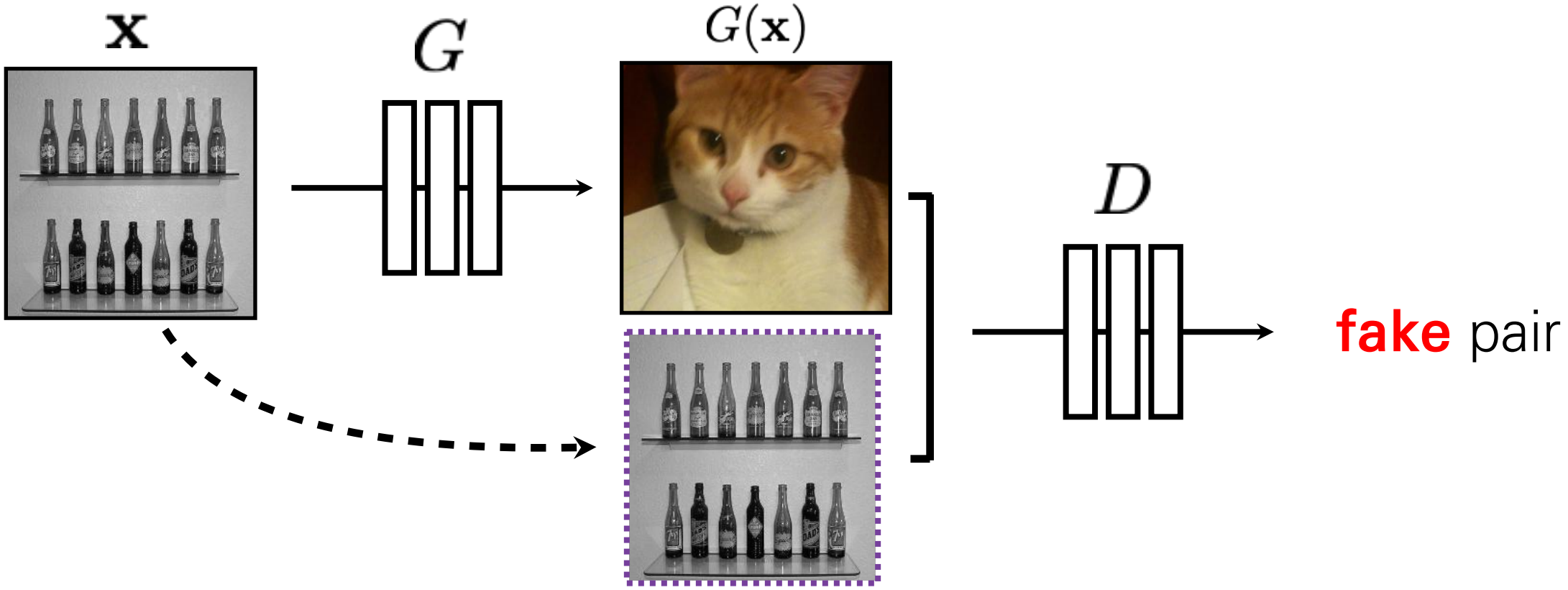
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y}))\;]$$

Conditional GANs / pix2pix



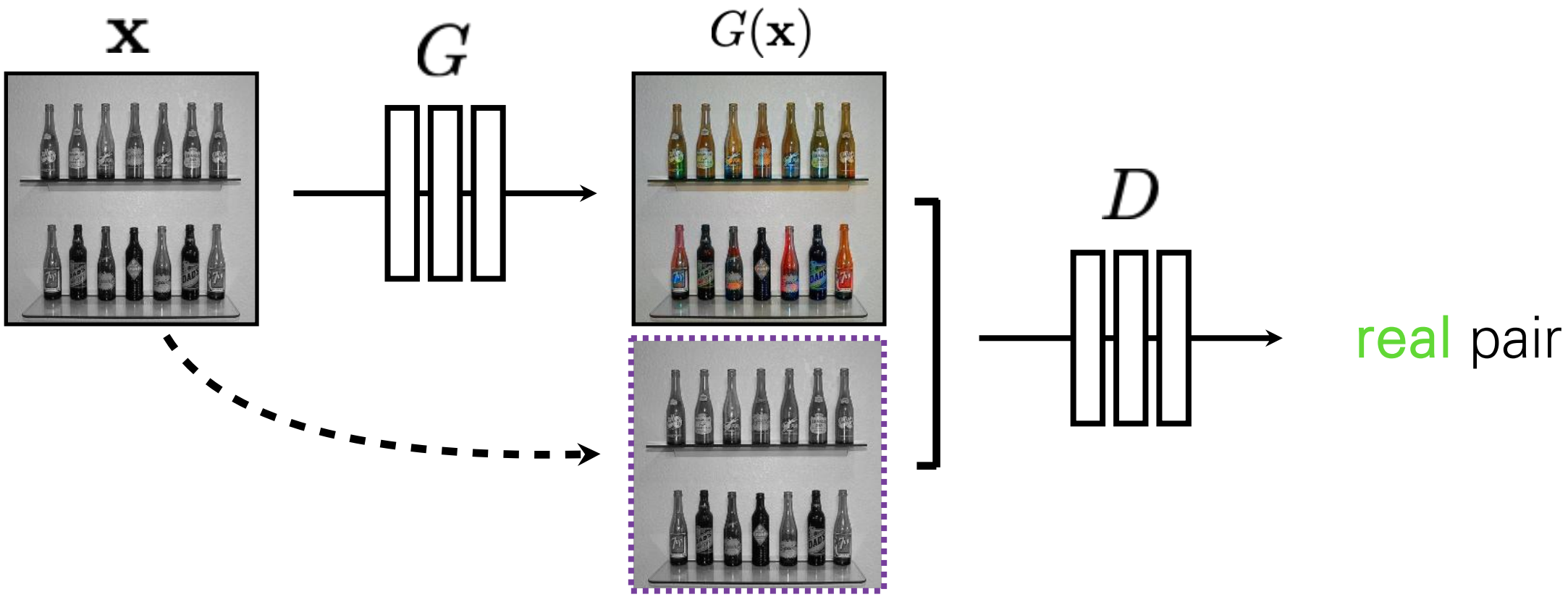
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;]$$

Conditional GANs / pix2pix



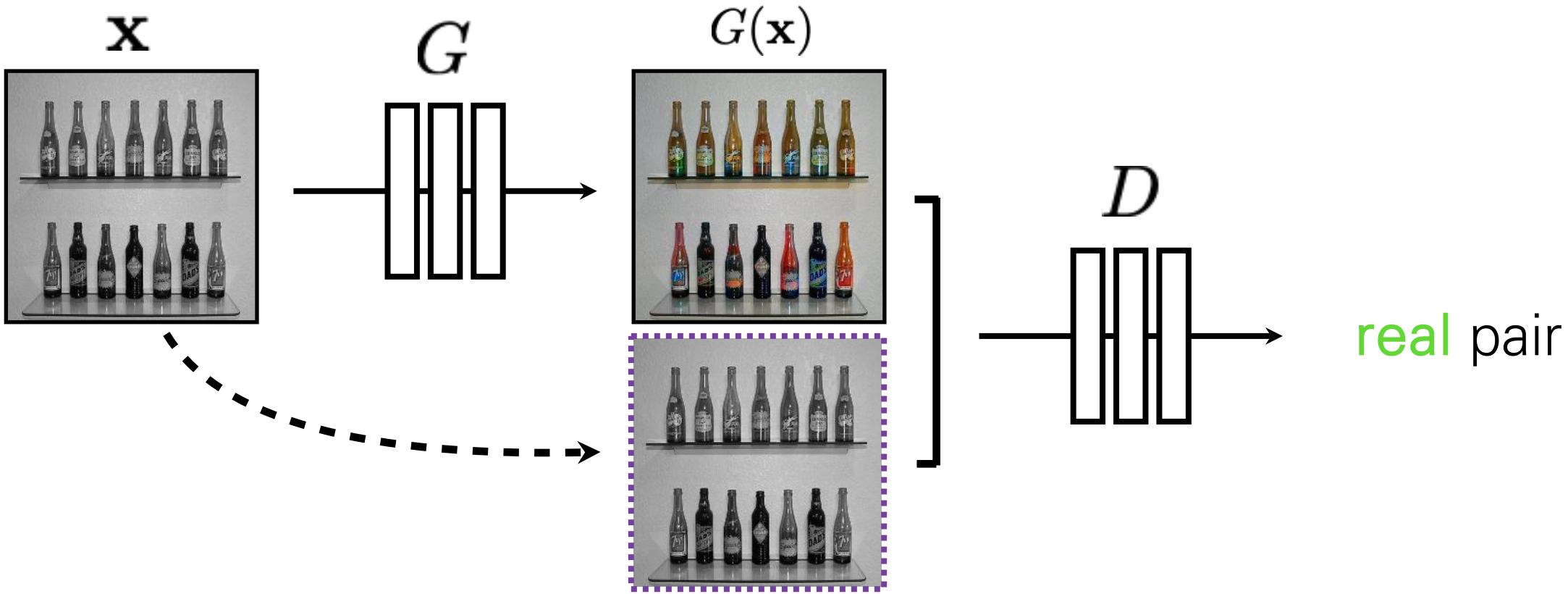
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;]$$

Conditional GANs / pix2pix



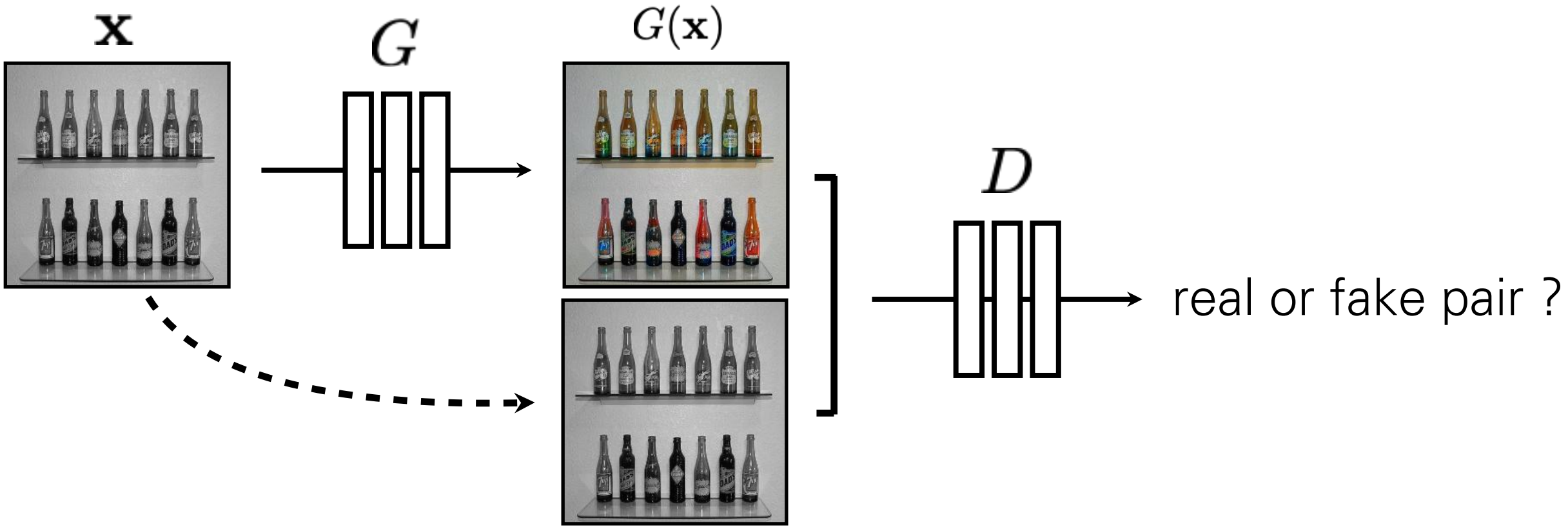
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;]$$

Conditional GANs / pix2pix



$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;]$$

Conditional GANs / pix2pix



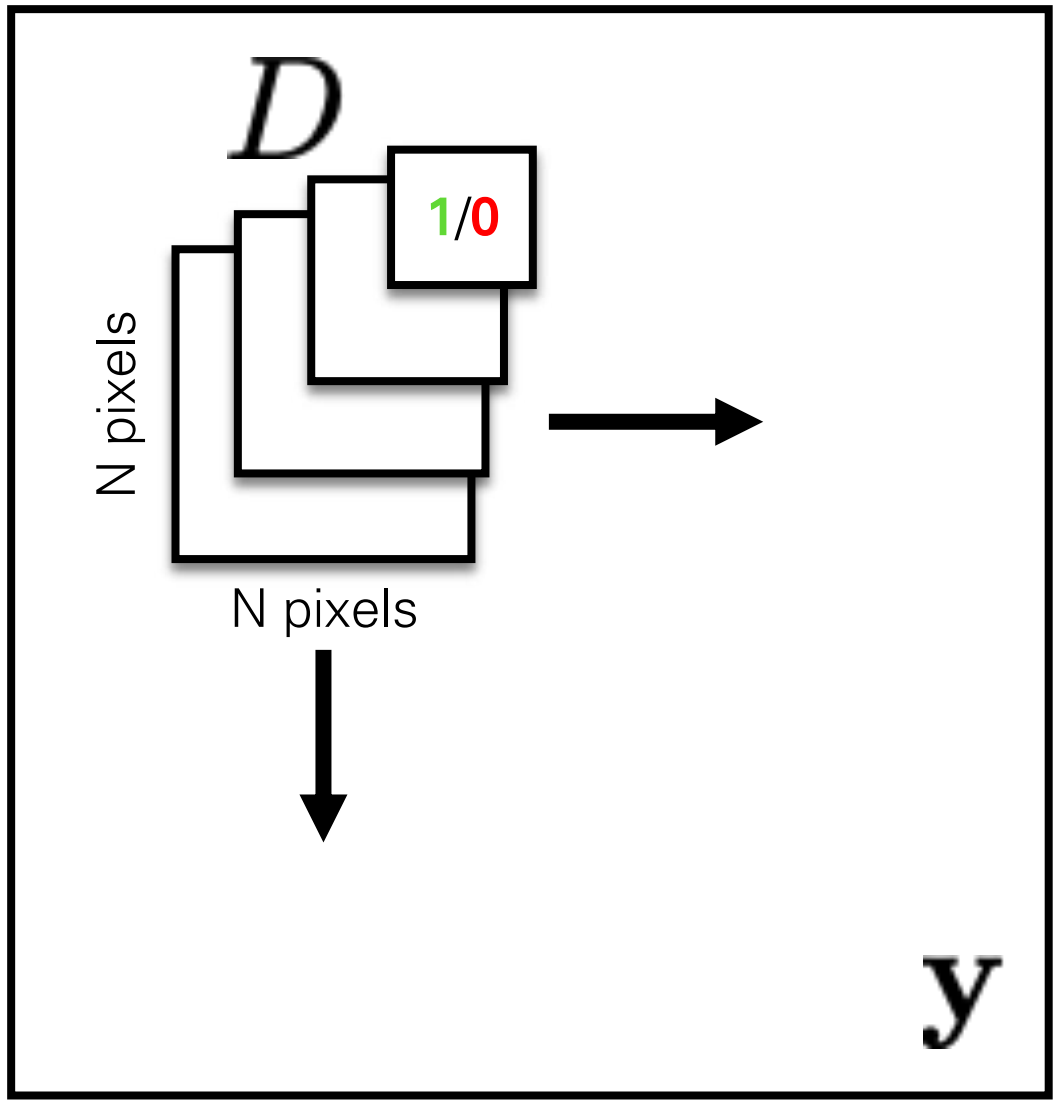
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\;\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;\;]$$

Conditional GANs / pix2pix

$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G)$$

Conditional GANs / pix2pix

Shrinking the capacity: Patch Discriminator

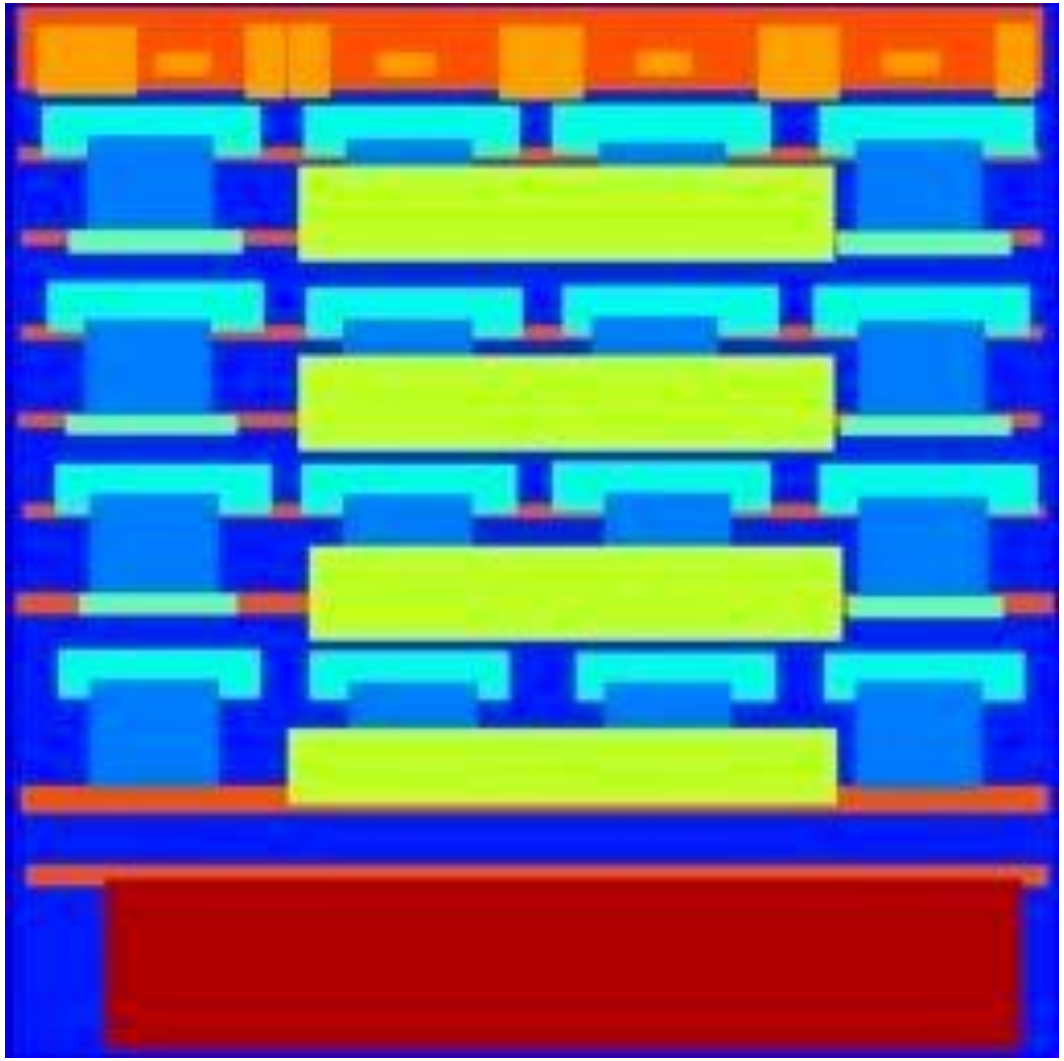


Rather than penalizing if output image looks fake, penalize if each overlapping patch in output looks fake

[Li & Wand 2016]
[Shrivastava et al. 2017]
[Isola et al. 2017]

Conditional GANs / pix2pix

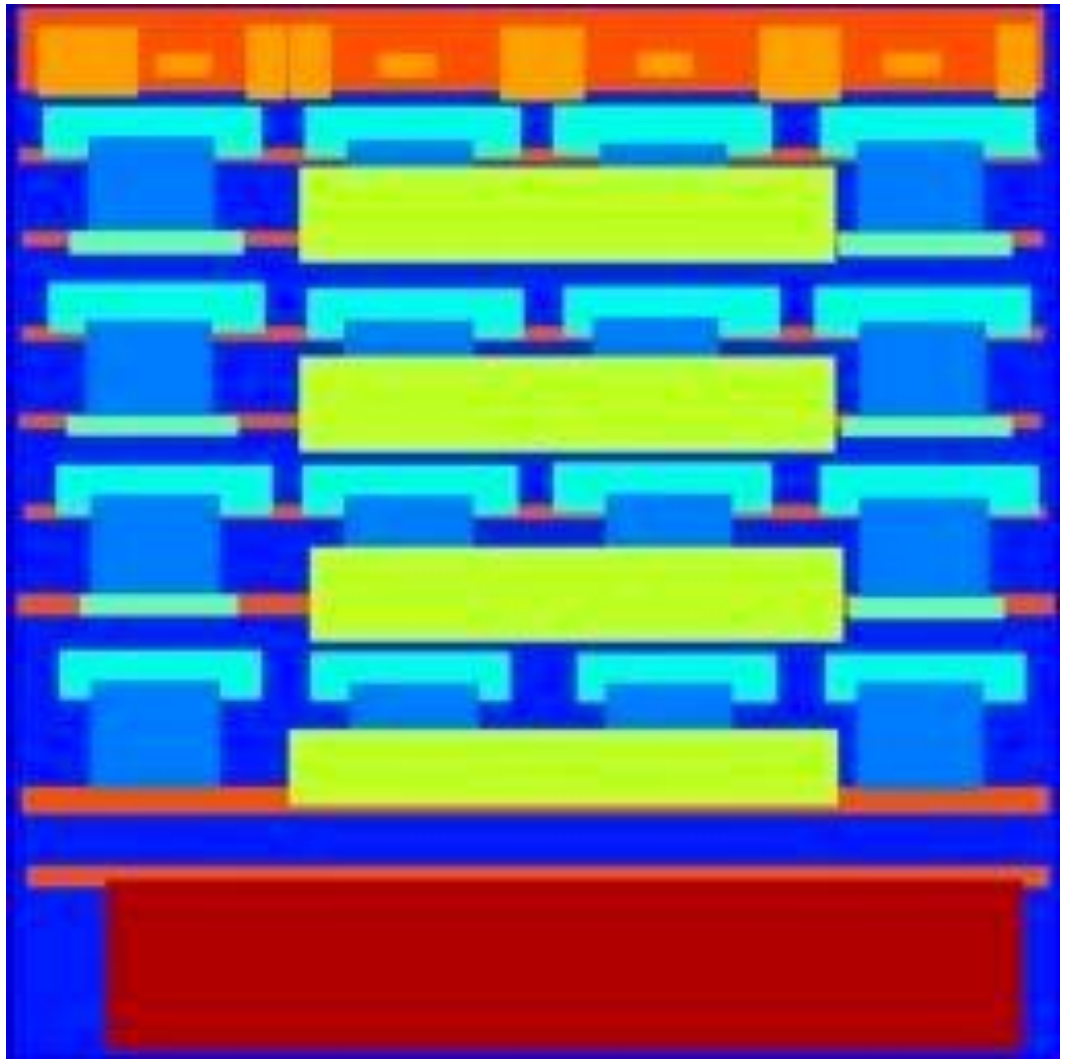
Input



1x1 Discriminator

Conditional GANs / pix2pix

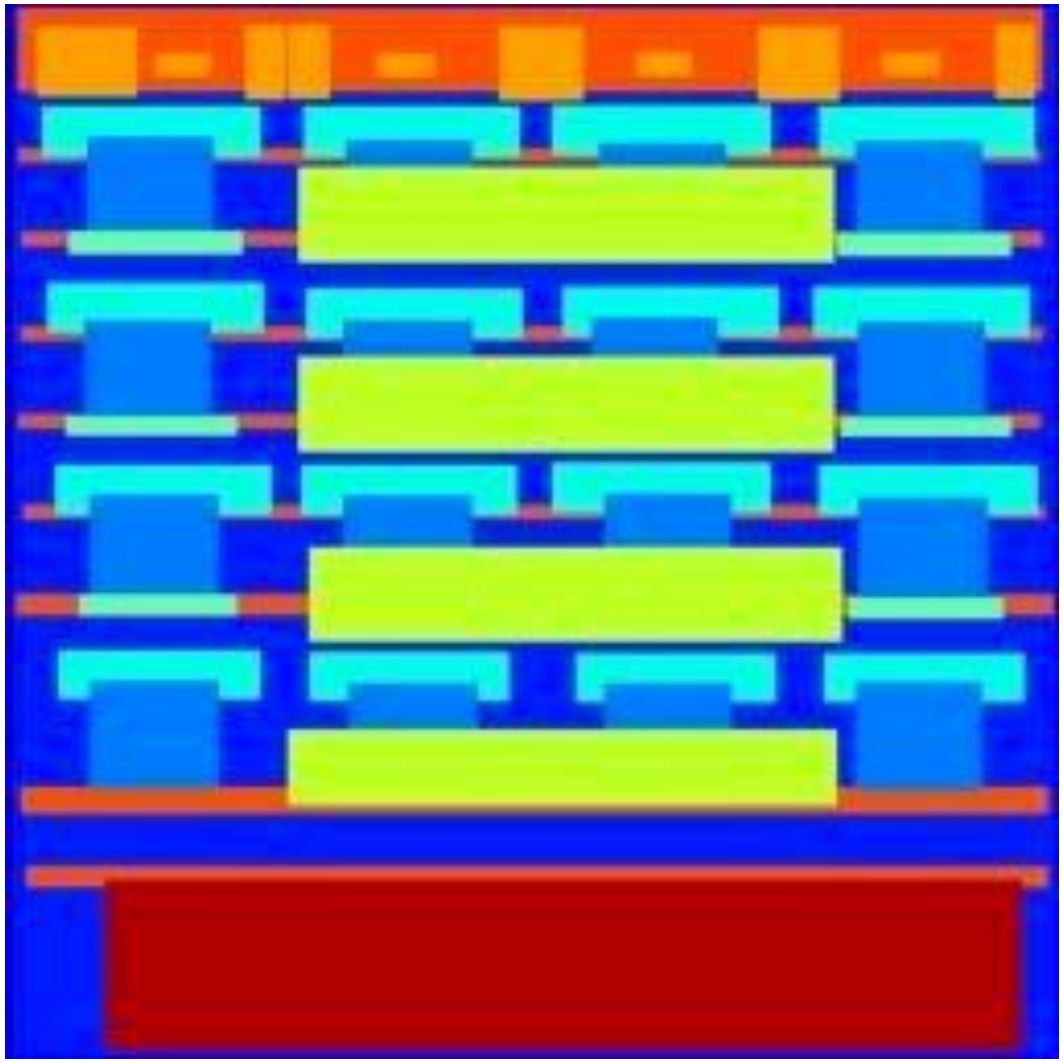
Input



16x16 Discriminator

Conditional GANs / pix2pix

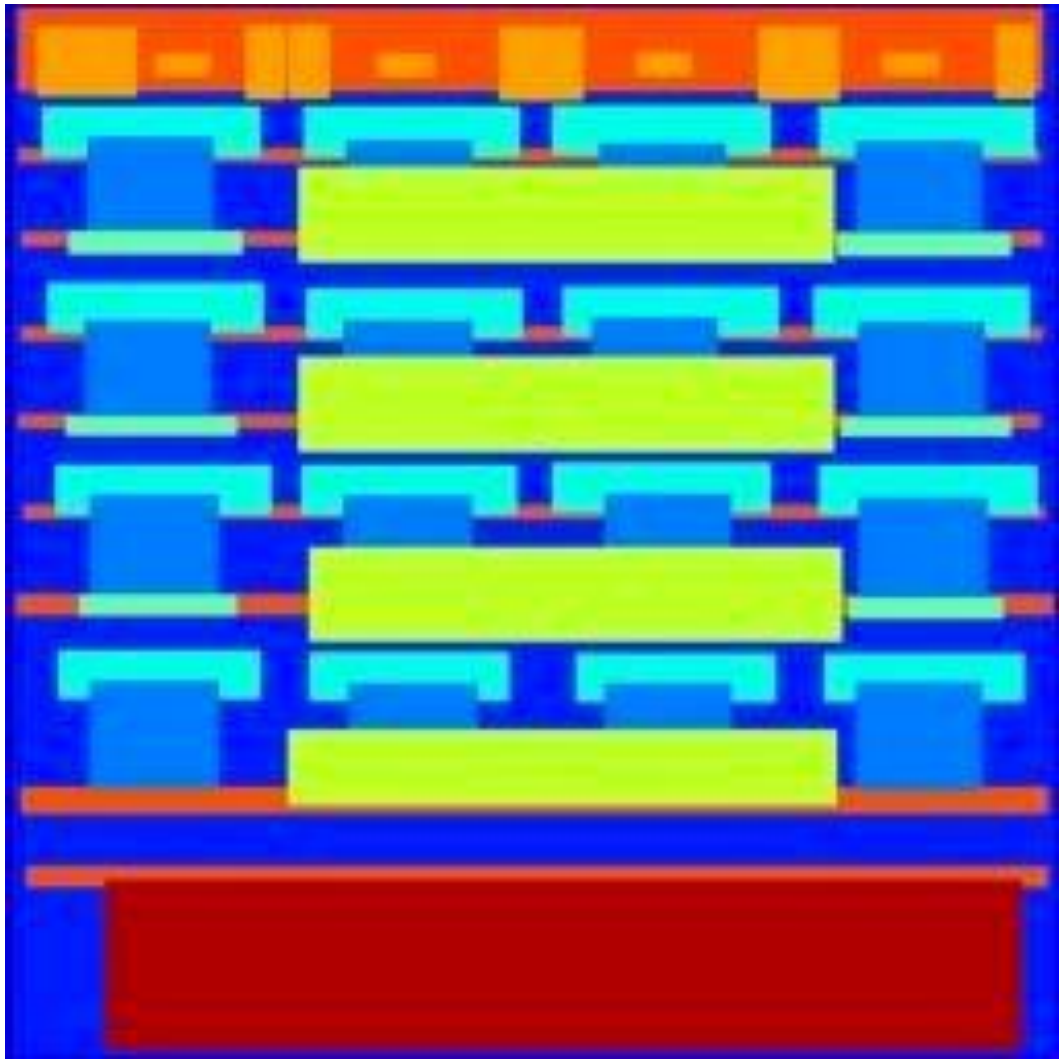
Input



70x70 Discriminator

Conditional GANs / pix2pix

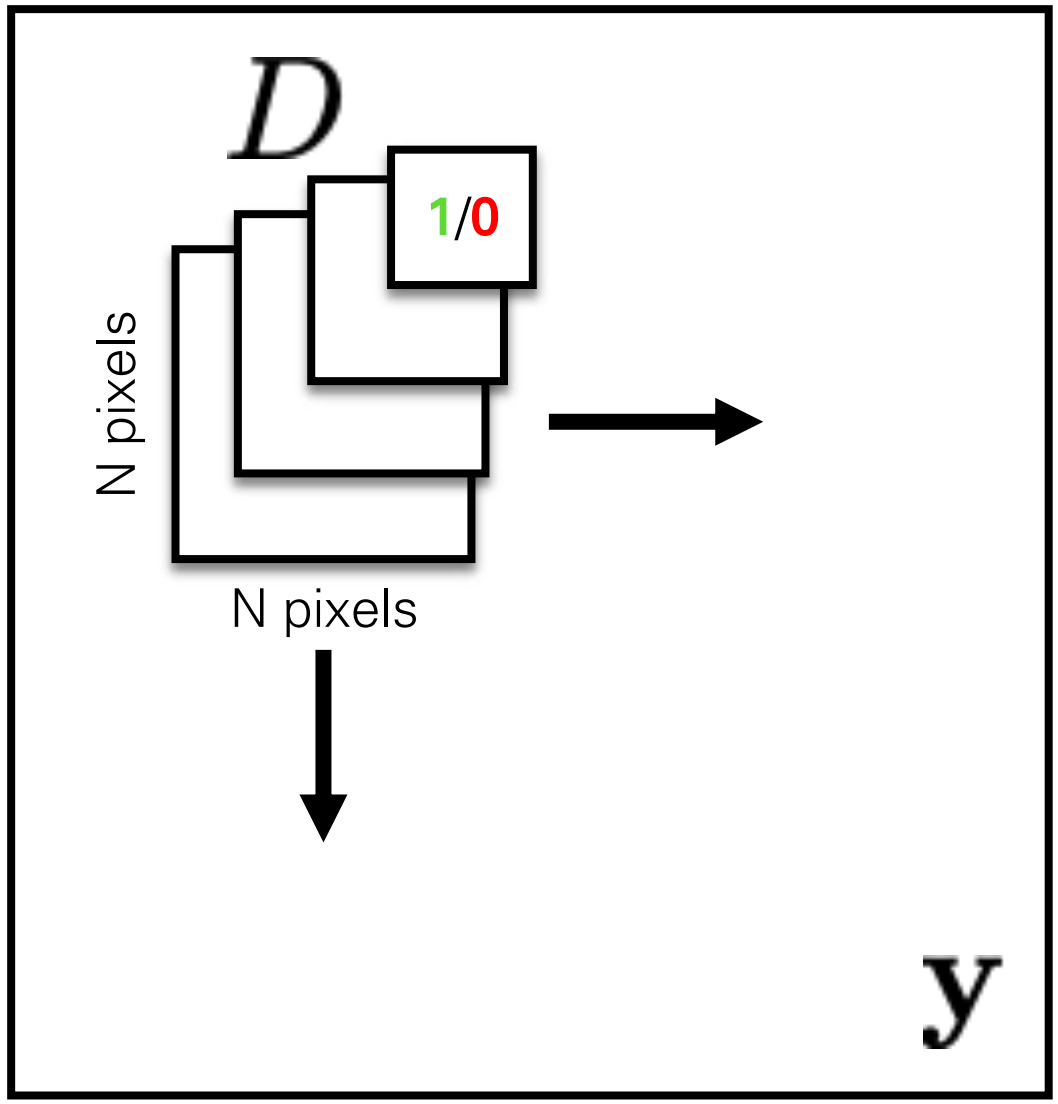
Input



16x16 Discriminator

Conditional GANs / pix2pix

Shrinking the capacity: Patch Discriminator

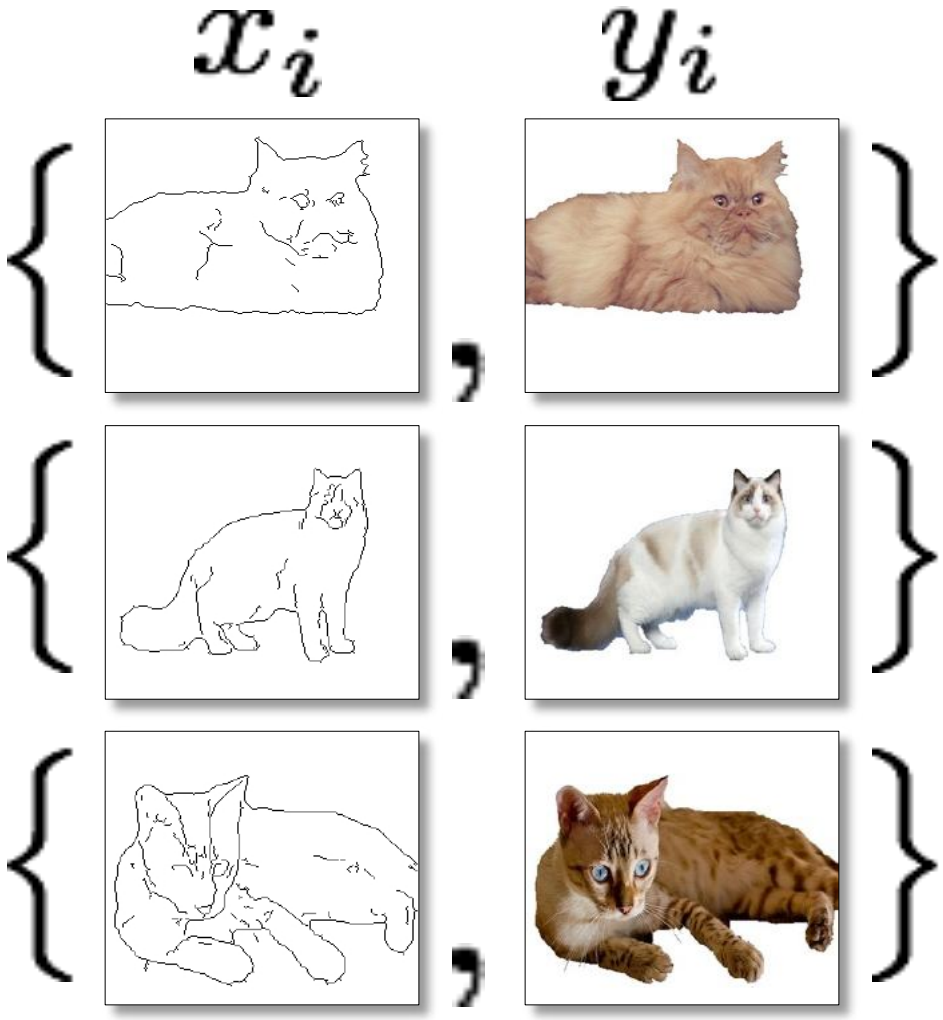


Rather than penalizing if output image looks fake, penalize if each overlapping patch in output looks fake

- Faster, fewer parameters
- More supervised observations
- Applies to arbitrarily large images

[Li & Wand 2016]
[Shrivastava et al. 2017]
[Isola et al. 2017]

Conditional GANs / pix2pix



Conditional GANs / pix2pix BW → Color

Input Output Input Output Input Output

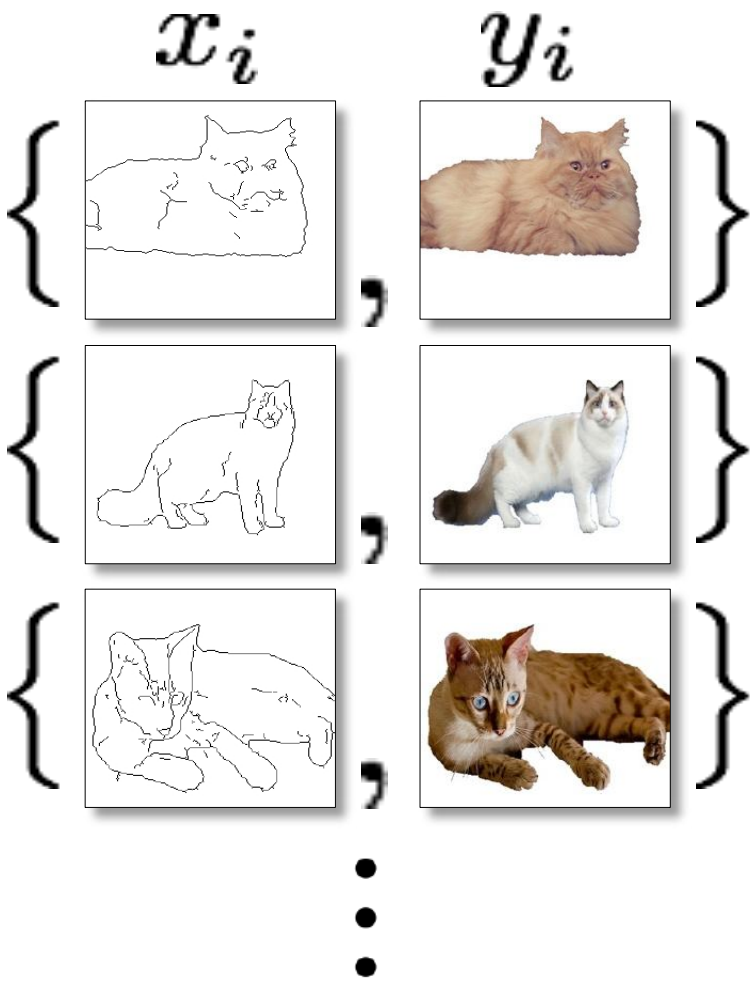
Data from [Russakovsky et al. 2015]

Lecture overview

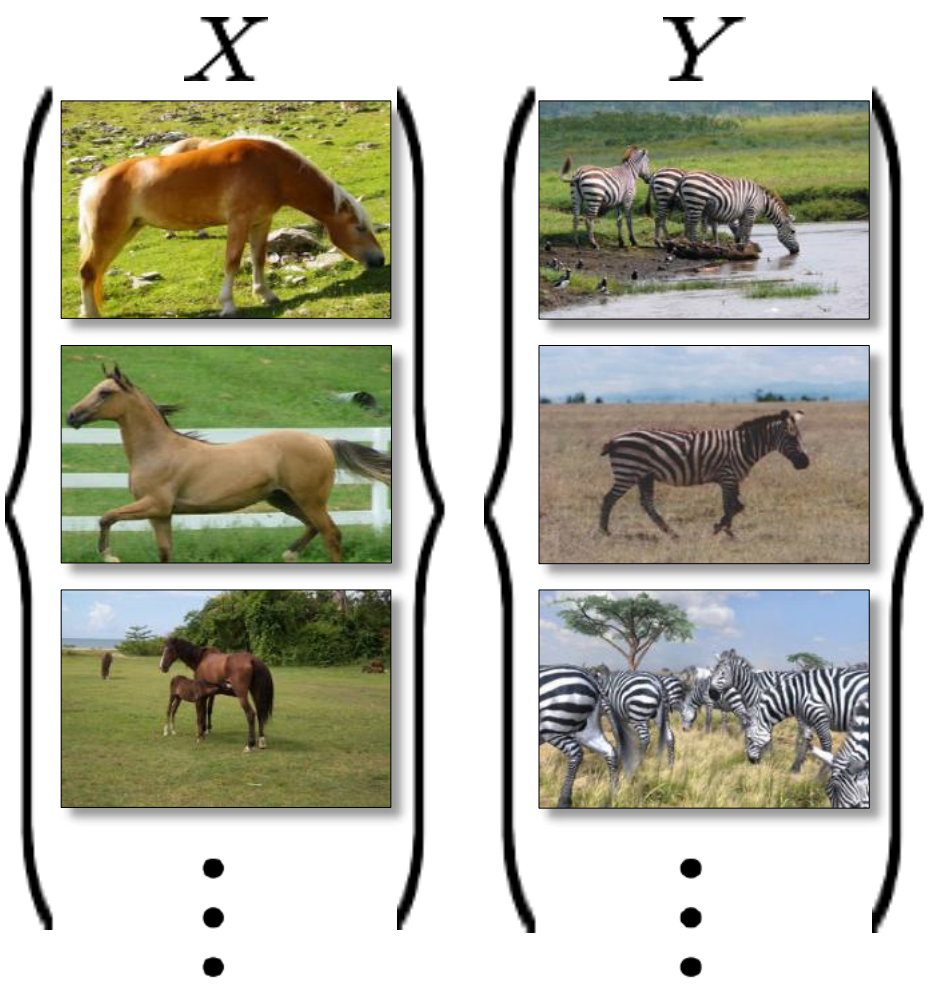
- Motivation
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- GAN Progression
- Conditional GANs, **Cycle-Consistent Adversarial Networks**
- Applications

Cycle-Consistent Adversarial Networks

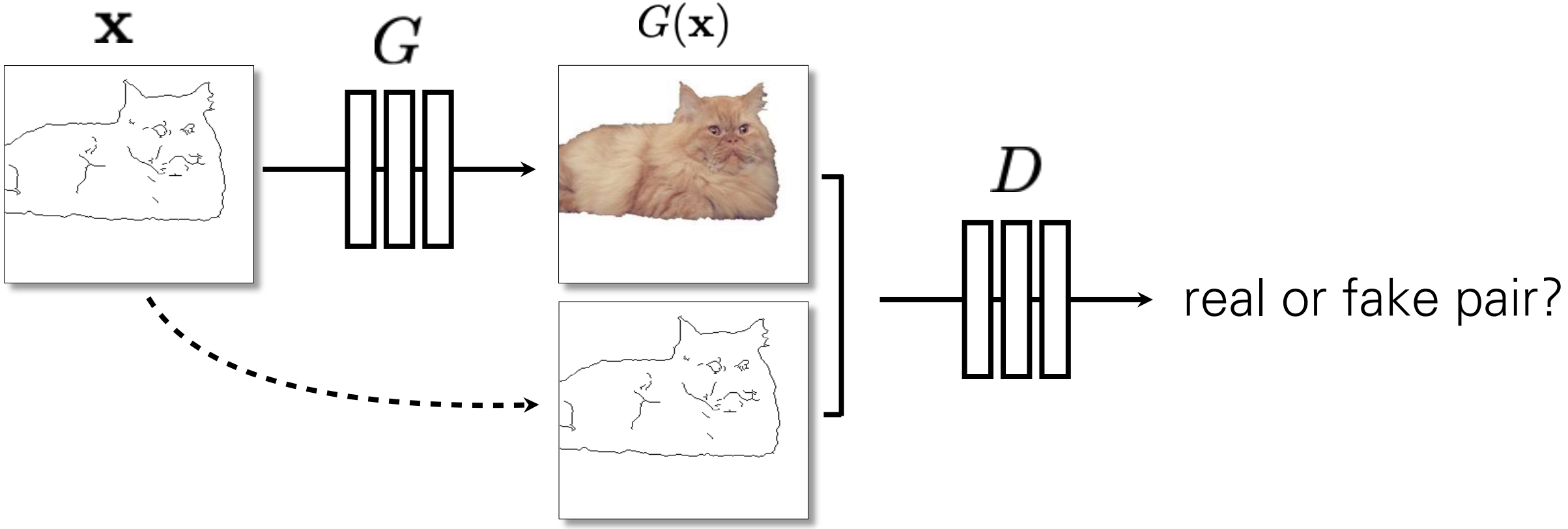
Paired data



Unpaired data

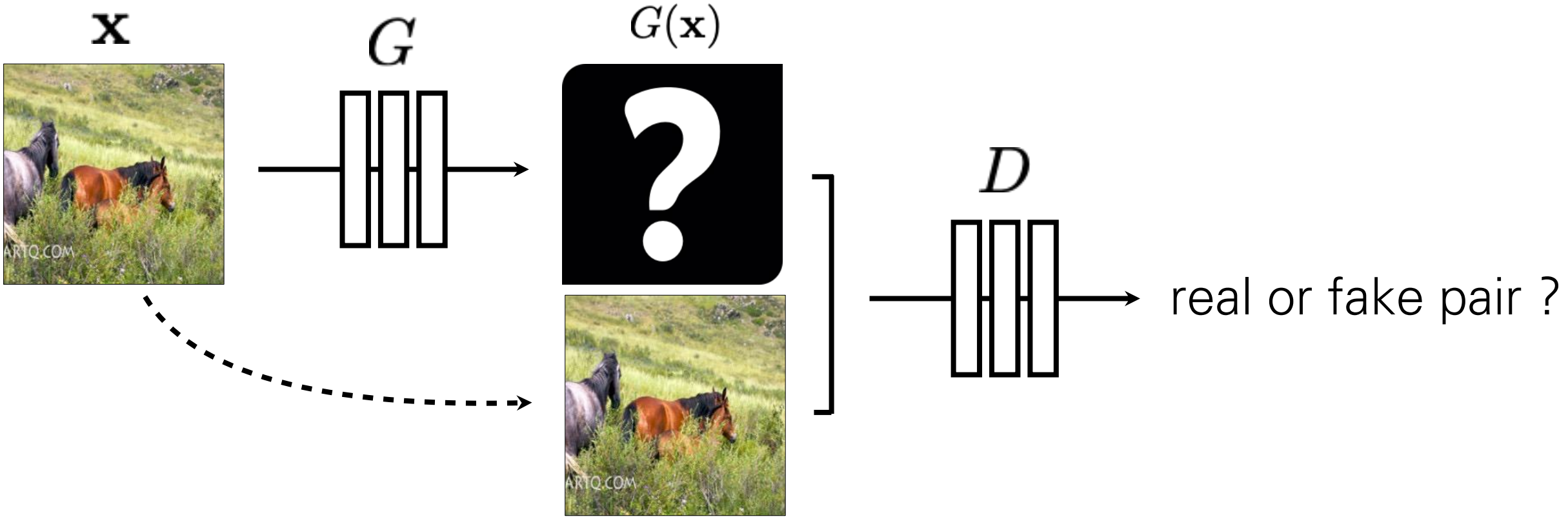


Cycle-Consistent Adversarial Networks



$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;]$$

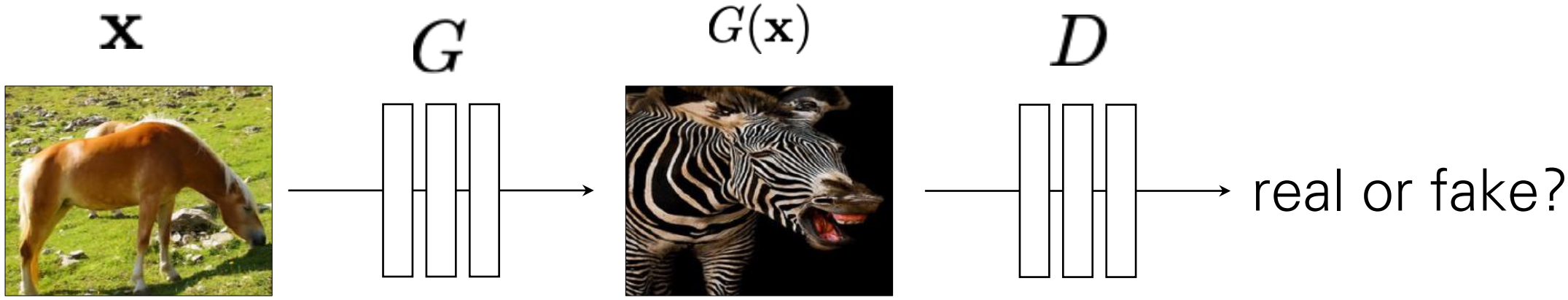
Cycle-Consistent Adversarial Networks



$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\;]$$

No input-output pairs!

Cycle-Consistent Adversarial Networks



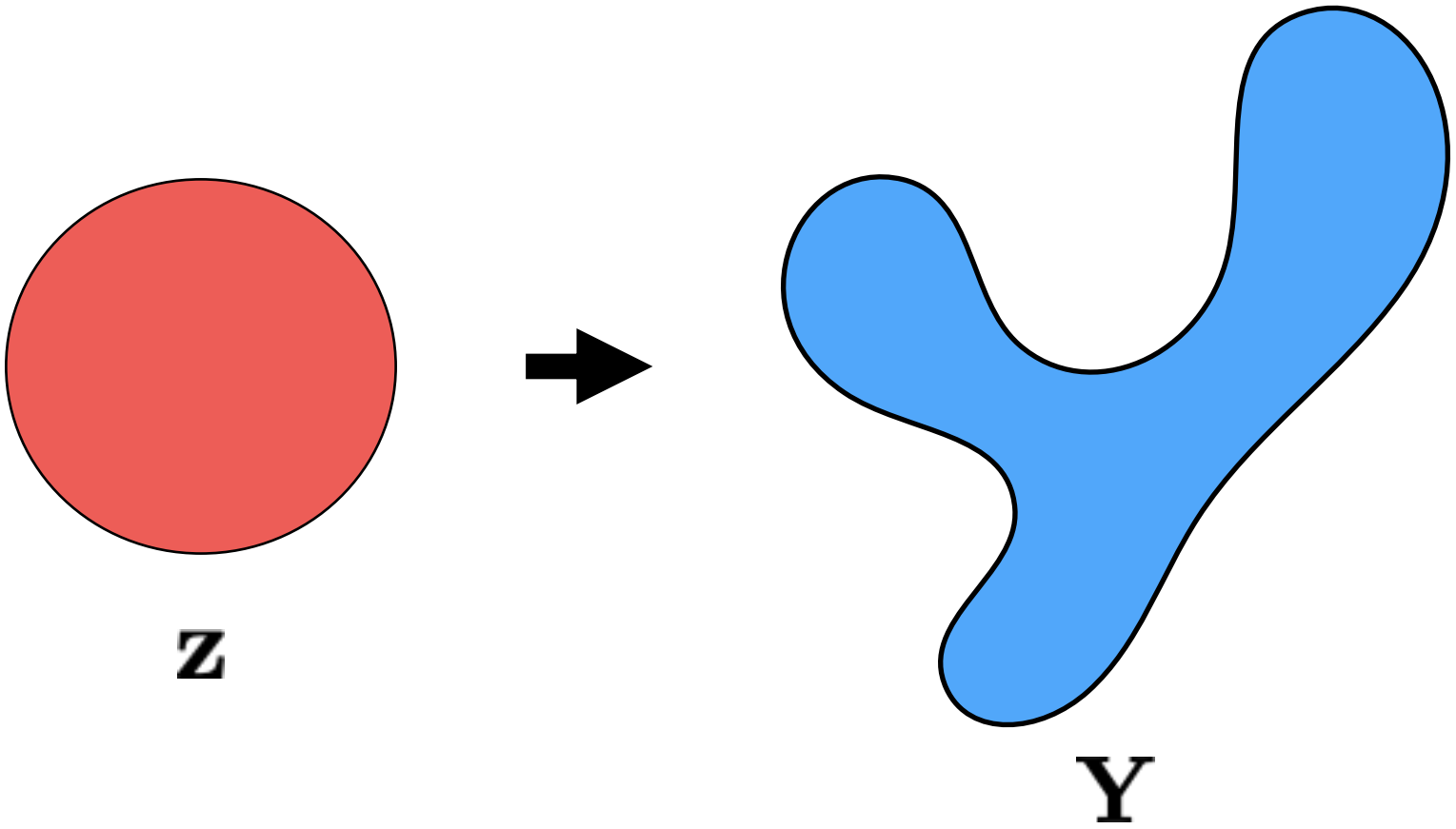
$$\arg\min_G \max_D \; \mathbb{E}_{\mathbf{x},\mathbf{y}}[\; \log D(G(\mathbf{x})) \quad + \quad \log(1 - D(\mathbf{y}))\;]$$

- Usually loss functions check if output matches a target instance
- GAN loss checks if output is part of an admissible set

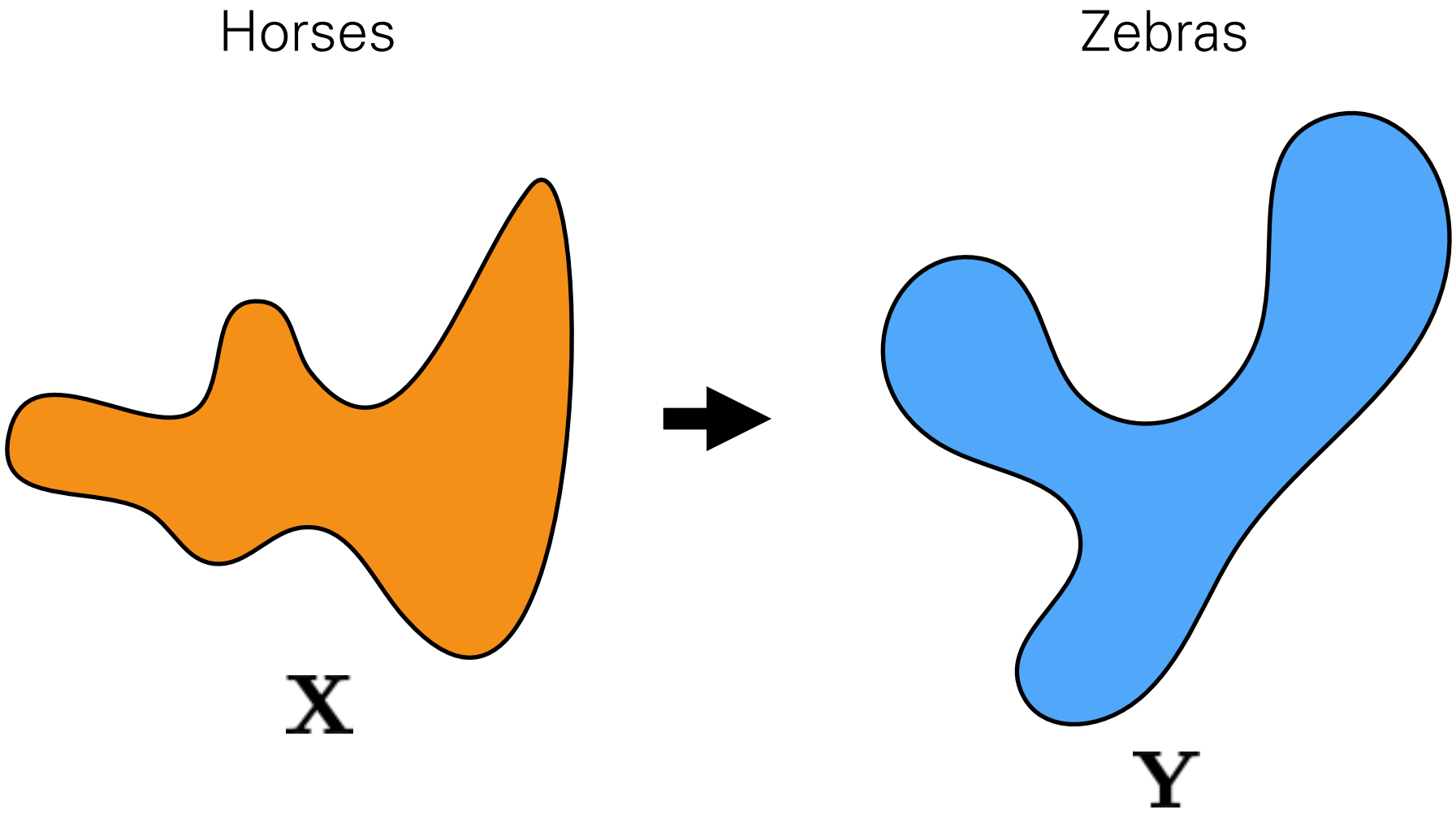
Cycle-Consistent Adversarial Networks

Gaussian

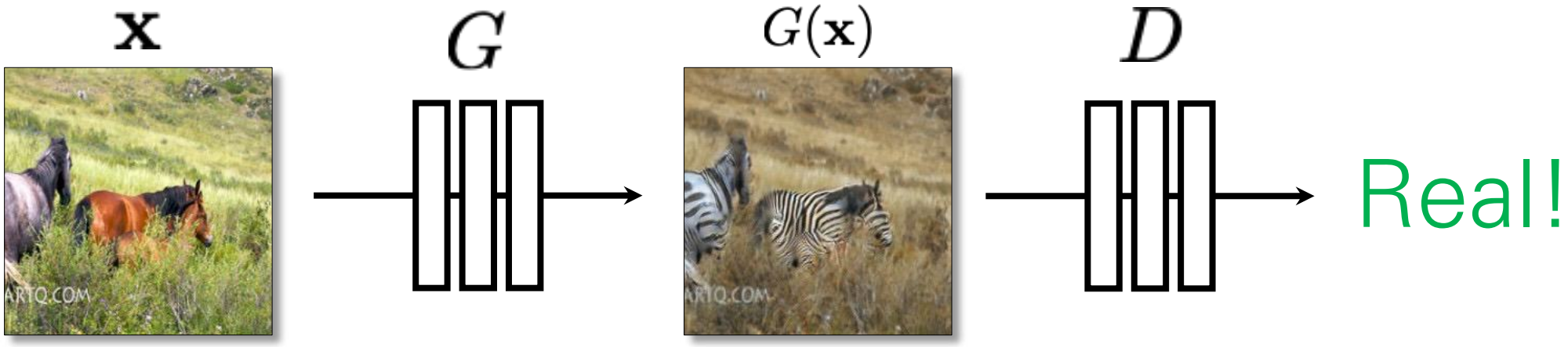
Target distribution



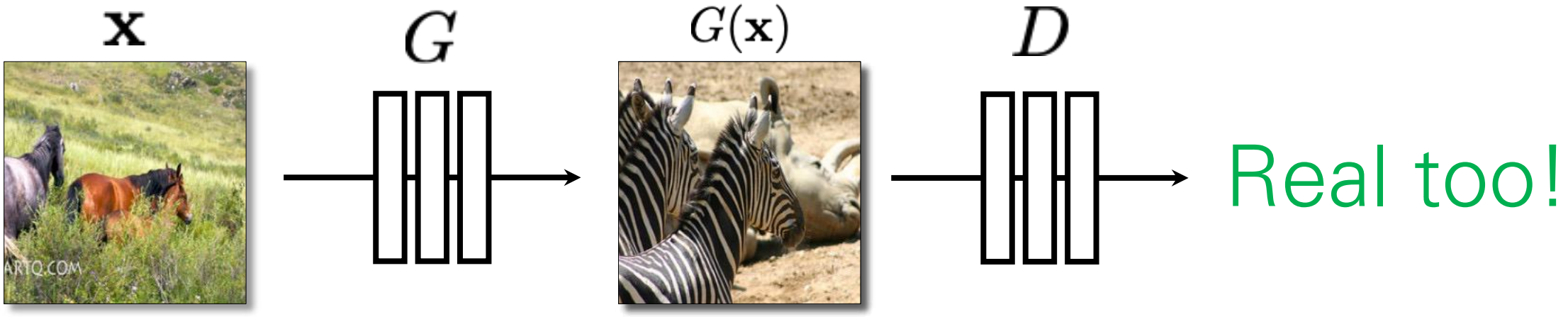
Cycle-Consistent Adversarial Networks



Cycle-Consistent Adversarial Networks

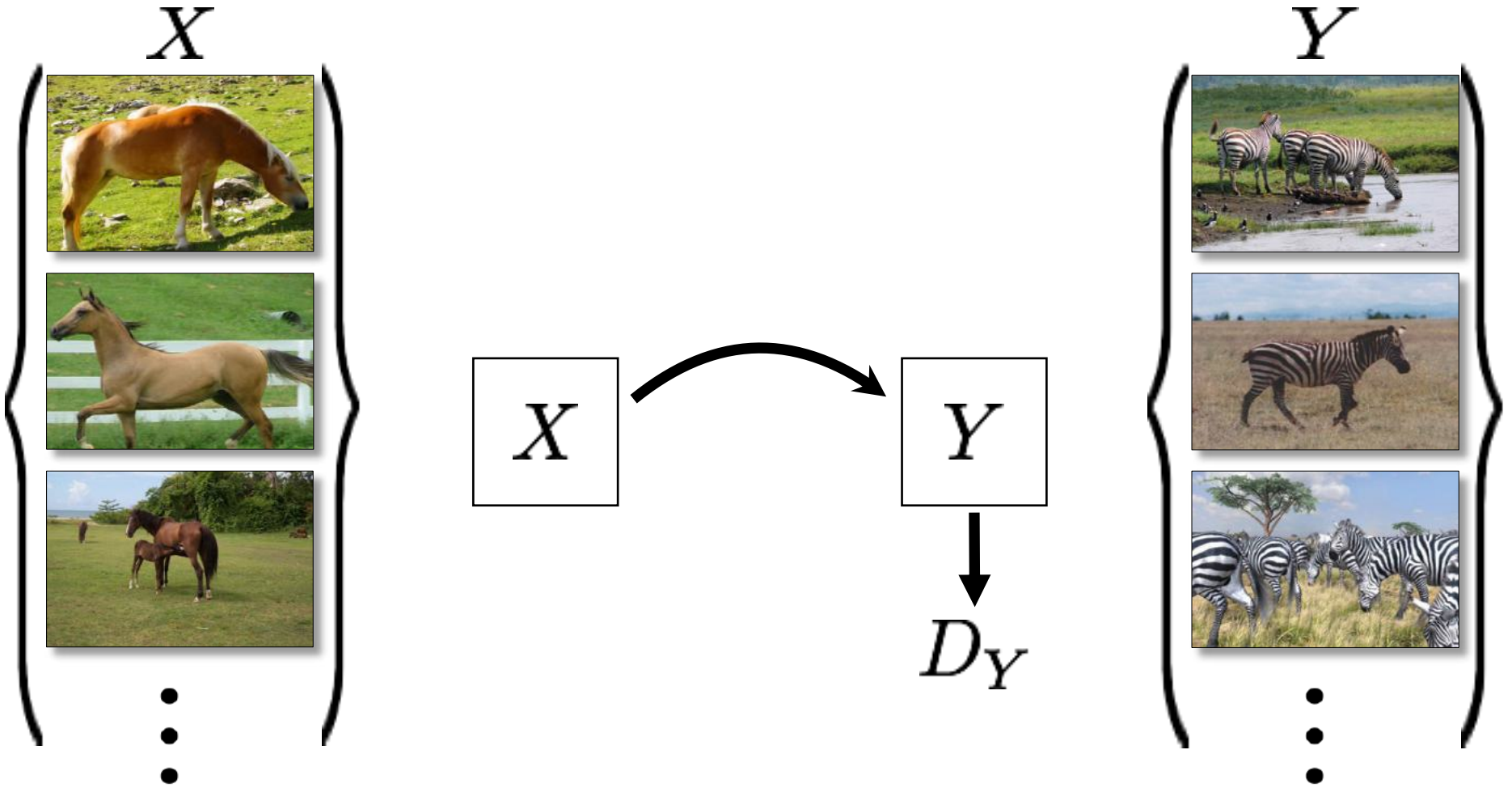


Cycle-Consistent Adversarial Networks



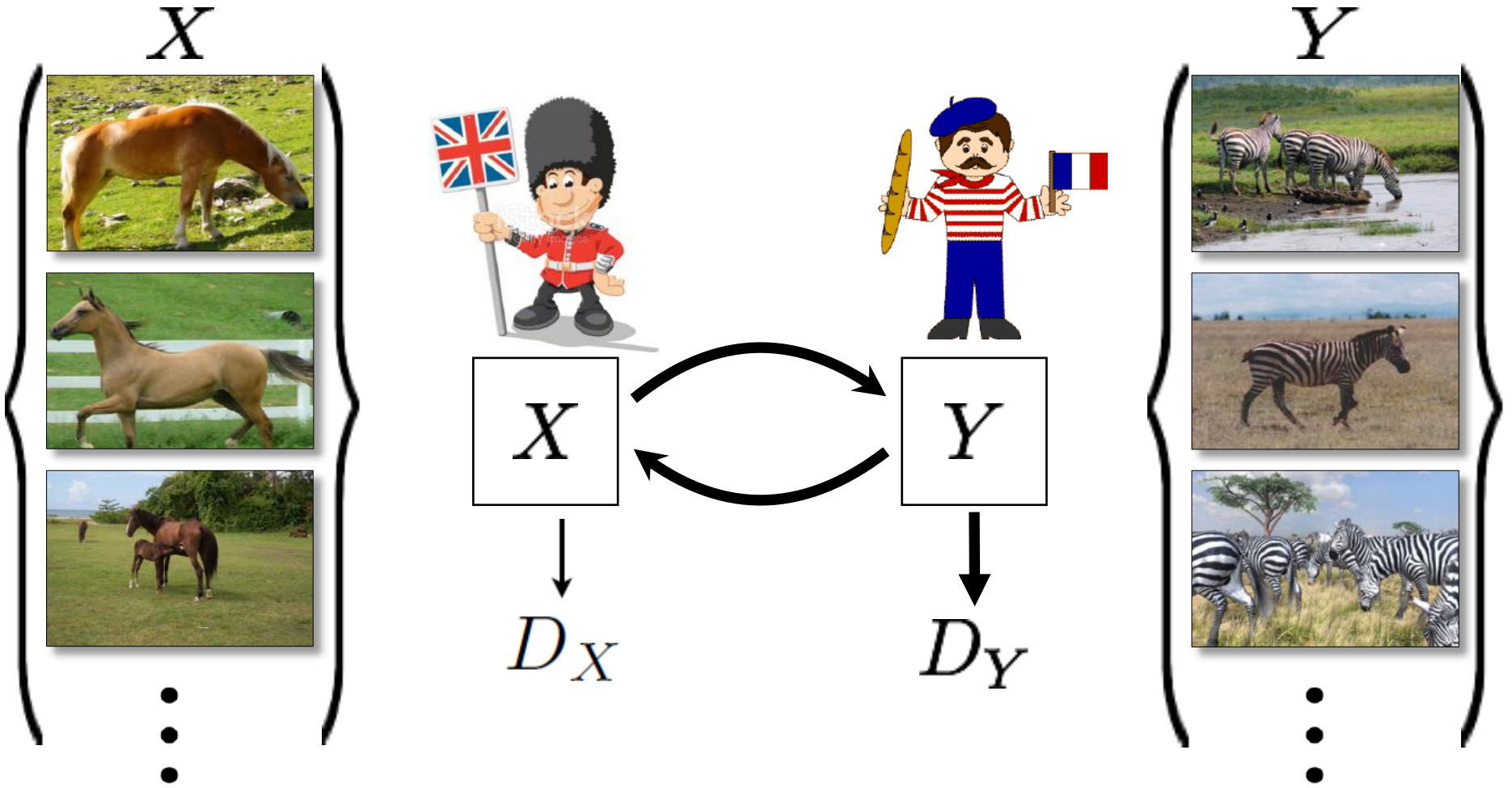
Nothing to force output to correspond to input

Cycle-Consistent Adversarial Networks

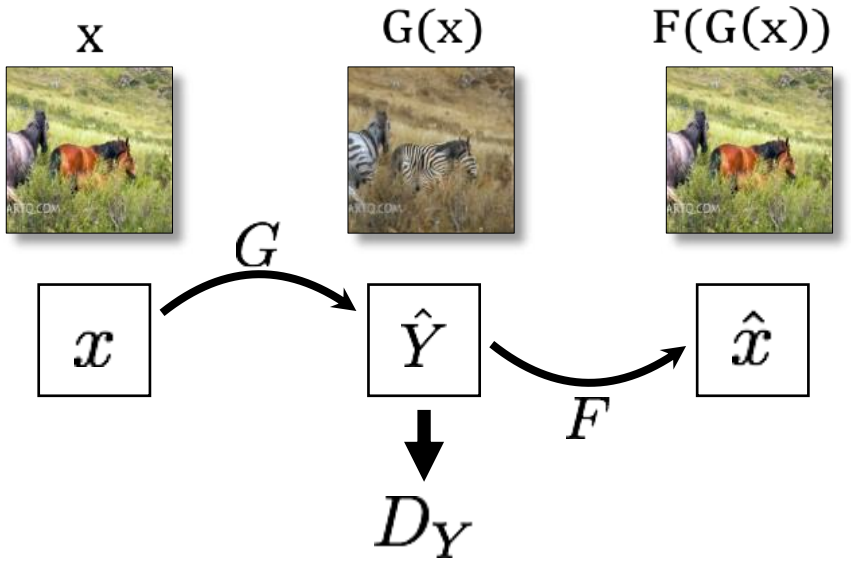


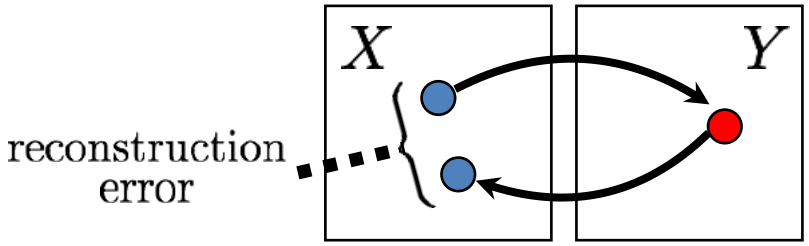
[Zhu et al. 2017], [Yi et al. 2017], [Kim et al. 2017]

Cycle-Consistent Adversarial Networks



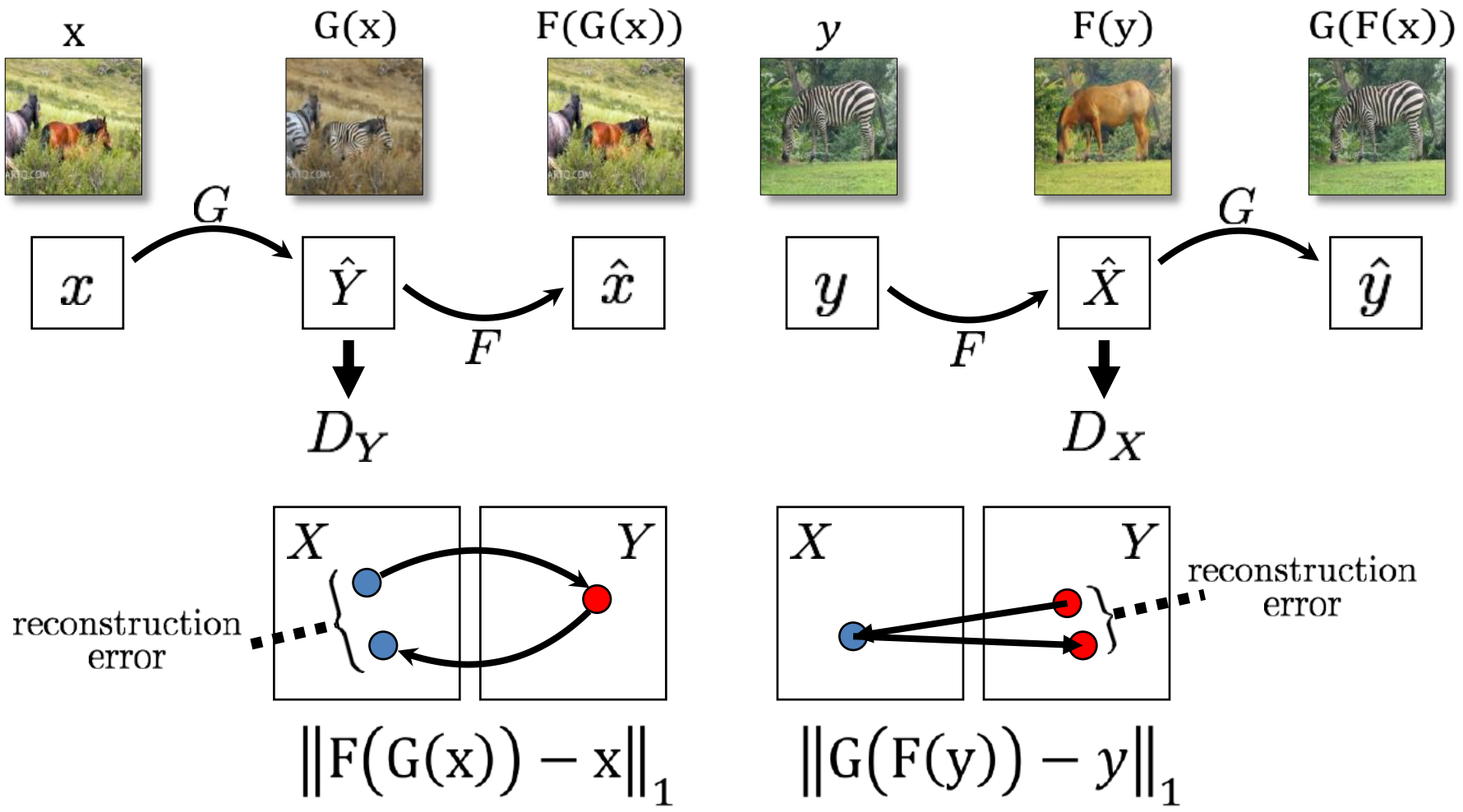
Cycle Consistency Loss





$$\|F(G(x)) - x\|_1$$

Cycle Consistency Loss



Cycle-Consistent Adversarial Networks

Cycle-Consistent Adversarial Networks

Cycle-Consistent Adversarial Networks

Photograph
@ Alexei Efros

Monet

Van Gogh

Cezanne

Ukiyo-e


Input
Monet
Van Gogh
Cezanne
Ukiyo-e

Lecture overview

- Motivation
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Theory of GANs
- GAN Progression
- Conditional GANs, Cycle-Consistent Adversarial Networks
- **Applications**

Semi-supervised Classification (Salimans et al., 2016; Dumoulin et al., 2016)

SVNH

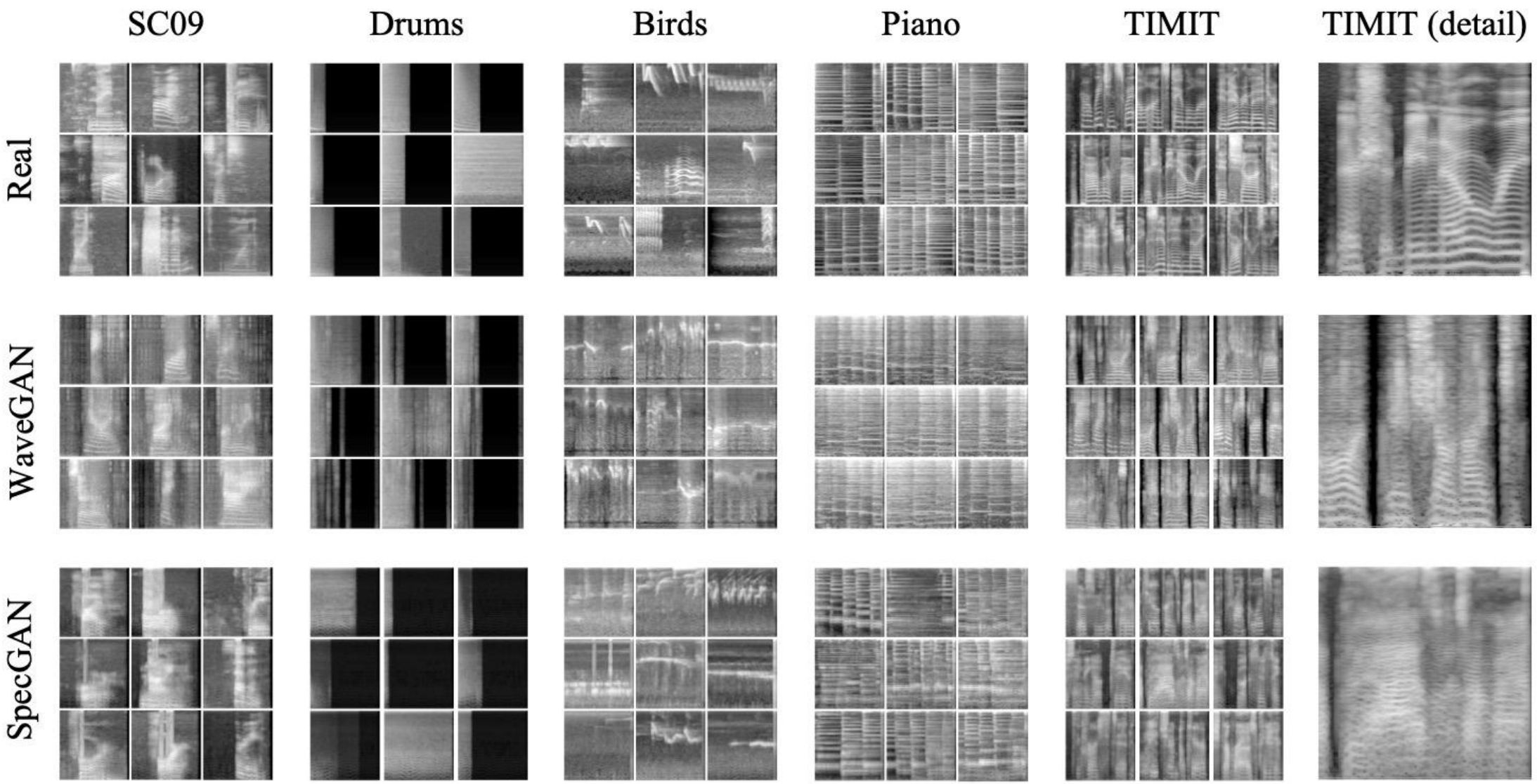
Model	Misclassification rate
VAE (M1 + M2) (Kingma et al., 2014)	36.02
SWWAE with dropout (Zhao et al., 2015)	23.56
DCGAN + L2-SVM (Radford et al., 2015)	22.18
SDGM (Maaløe et al., 2016)	16.61
GAN (feature matching) (Salimans et al., 2016)	$\mathbf{8.11 \pm 1.3}$
ALI (ours, L2-SVM)	19.14 ± 0.50
ALI (ours, no feature matching)	$\mathbf{7.42 \pm 0.65}$

Text Generation: MaskGAN (Fedus et al. 2018)

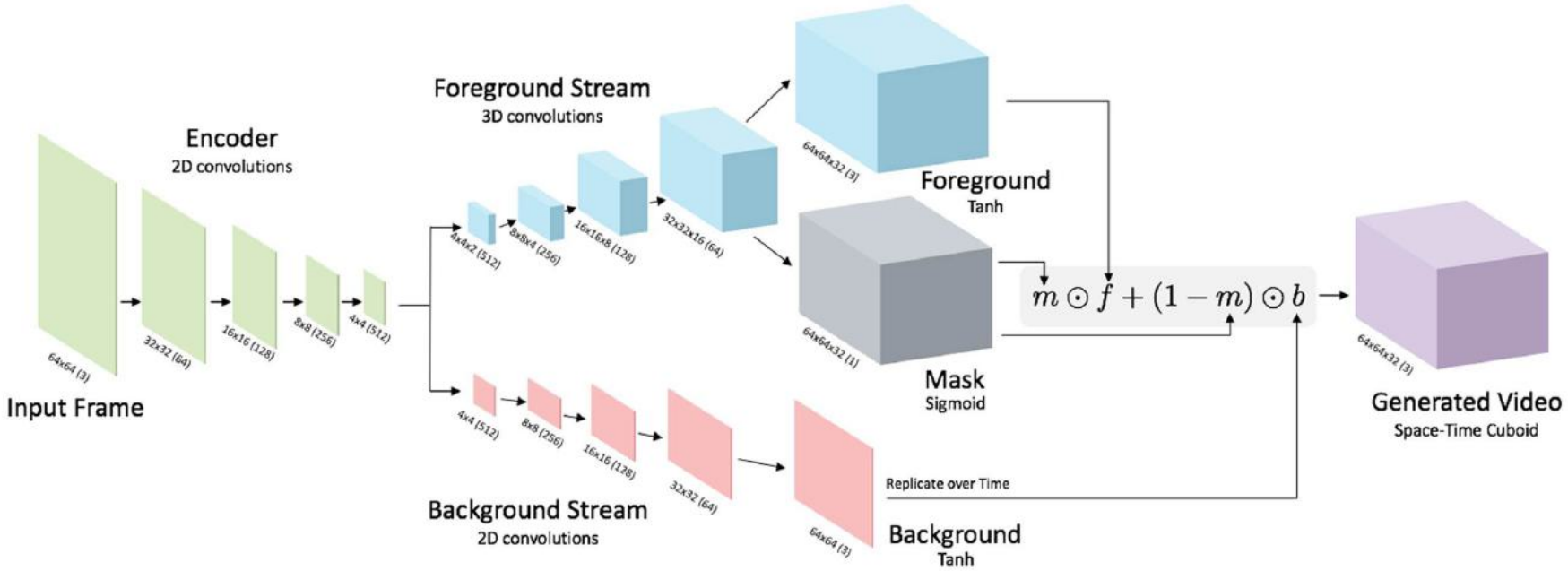
Ground Truth	**Pitch Black was a complete shock to me when I first saw it back in 2000 In the previous years I**
MaskGAN	Pitch Black was a complete shock to me when I first saw it back in 1979 I was really looking forward
MaskMLE	Black was a complete shock to me when I first saw it back in 1969 I live in New Zealand

Table 3: Conditional samples from IMDB for both MaskGAN and MaskMLE models.

Audio Synthesis: WaveGAN (Donahue et al. 2020)



Video Generation (Vondrick et al., 2016)



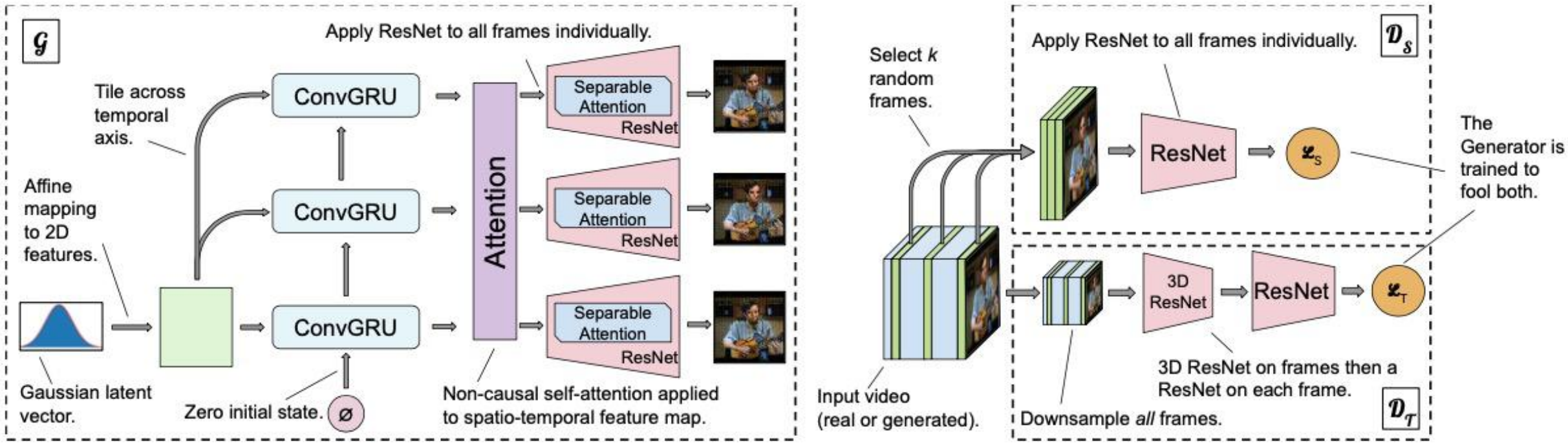
Beach

Golf

Train Station

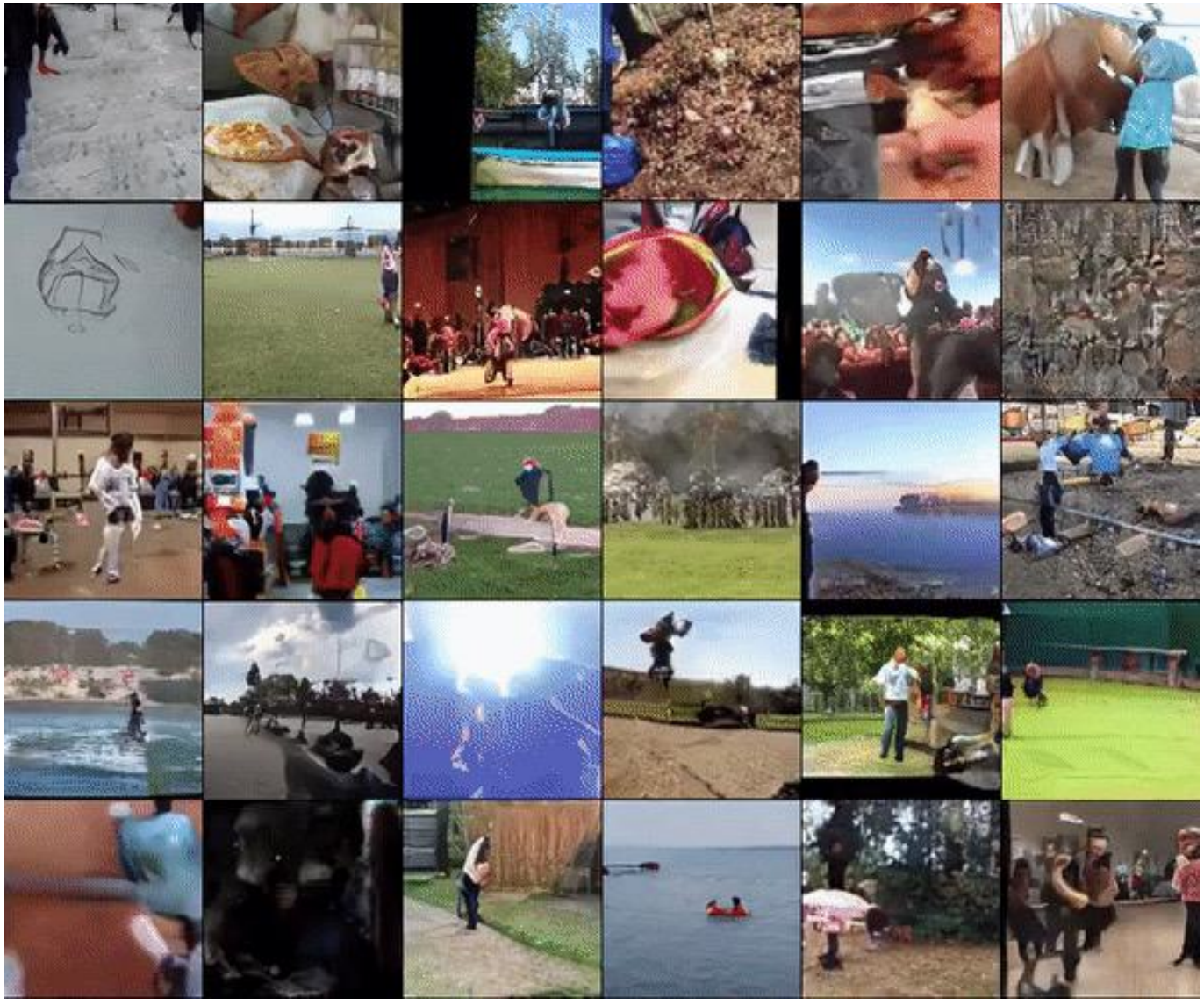
DVD-GAN: Efficient Video Generation

(Clark et al., 2019)



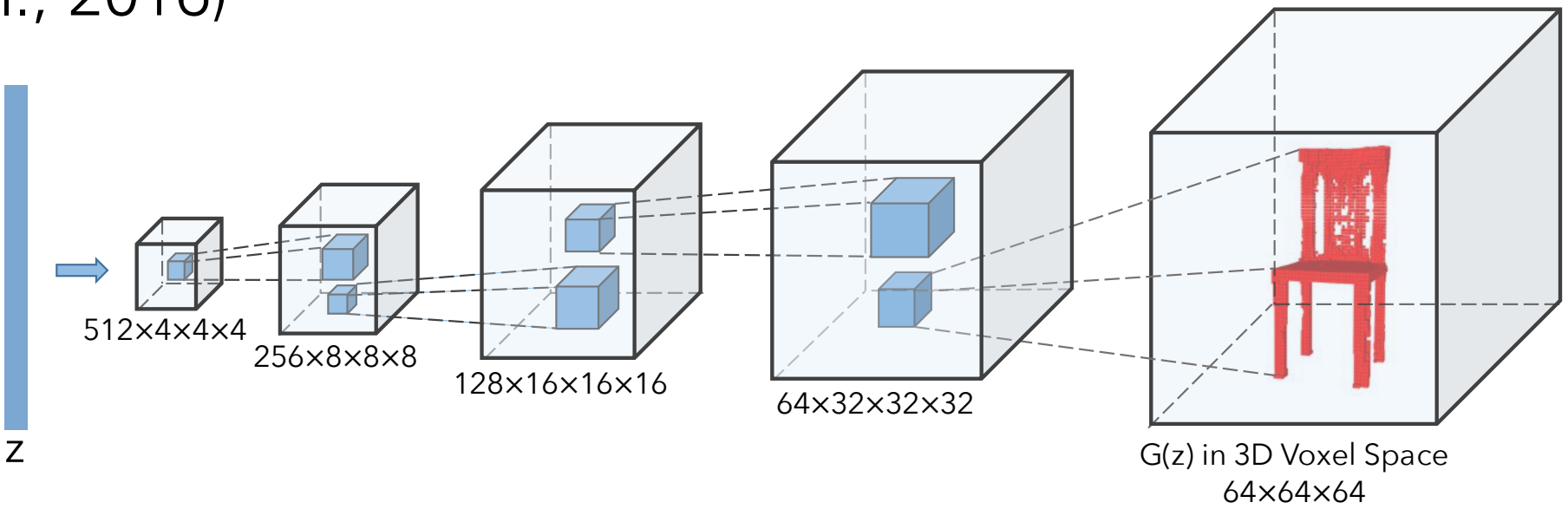
DVD-GAN: Efficient Video Generation

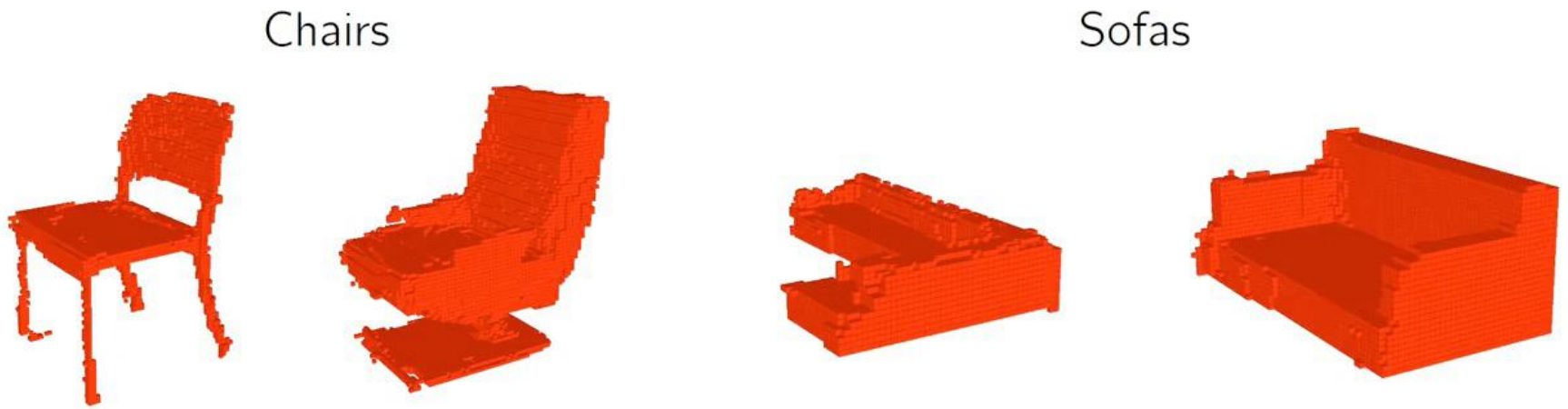
(Clark et al., 2019)



3DGAN: Generative Shape Modeling

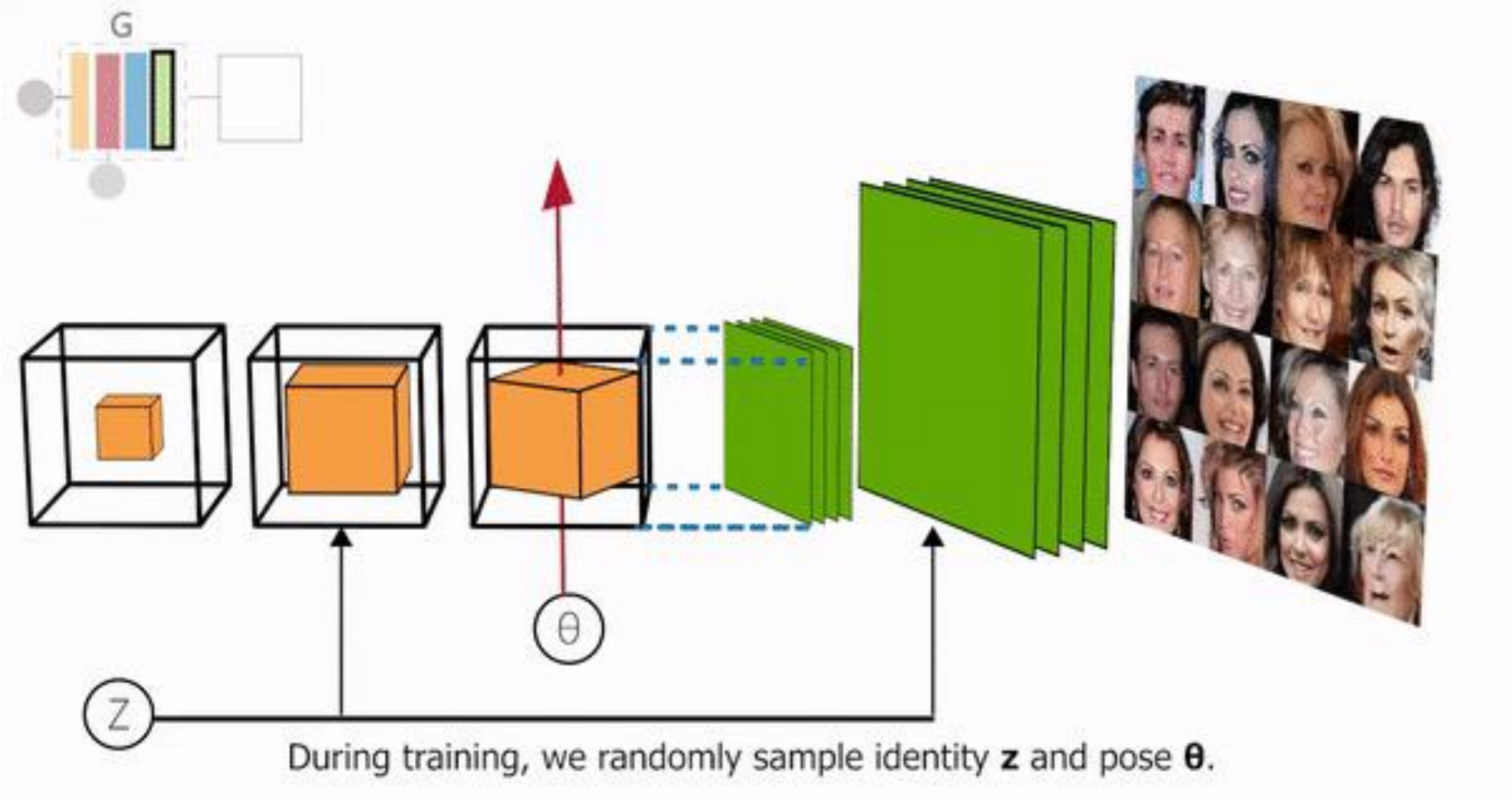
(Wu et al., 2016)





HoloGAN: Learning 3D Representations from Images

(Nguyen-Phuoc et al., 2020)



HoloGAN: Learning 3D Representations from Images

(Nguyen-Phuoc et al., 2020)

Motion Transfer: Everybody Dance Now

Vid2Vid: Video to Video Synthesis

StackGAN: Text-to-Image Synthesis (Zhang et al.'16)

The small bird has a red head with feathers that fade from red to gray from head to tail

The petals of this flower are white with a large stigma	A unique yellow flower with no visible pistils protruding from the center	This flower is pink and yellow in color, with petals that are oddly shaped	This is a light colored flower with many different petals on a green stem	This flower is yellow and green in color, with petals that are ruffled	The flower have large petals that are pink with yellow on some of the petals	A flower that has white petals with some tones of yellow and green filaments

SRGAN: Single Image Super-Resolution

(Ledig et al., 2017)

- Combine content loss with adversarial loss

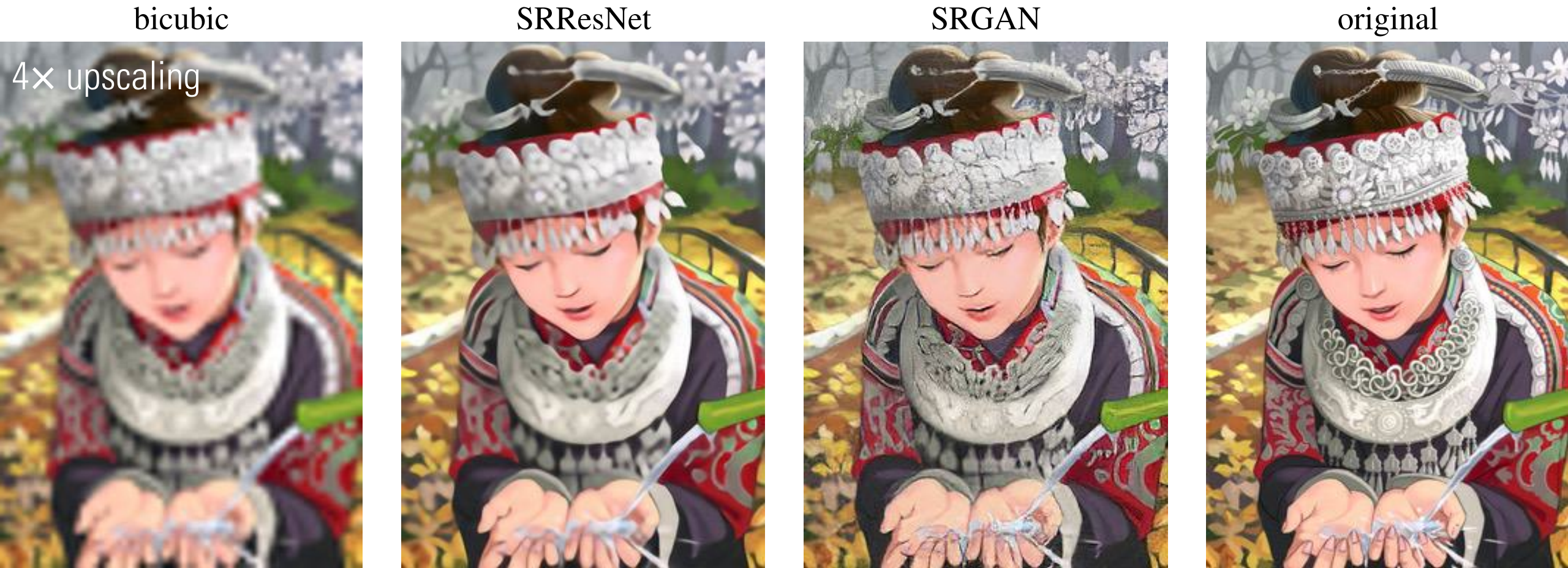
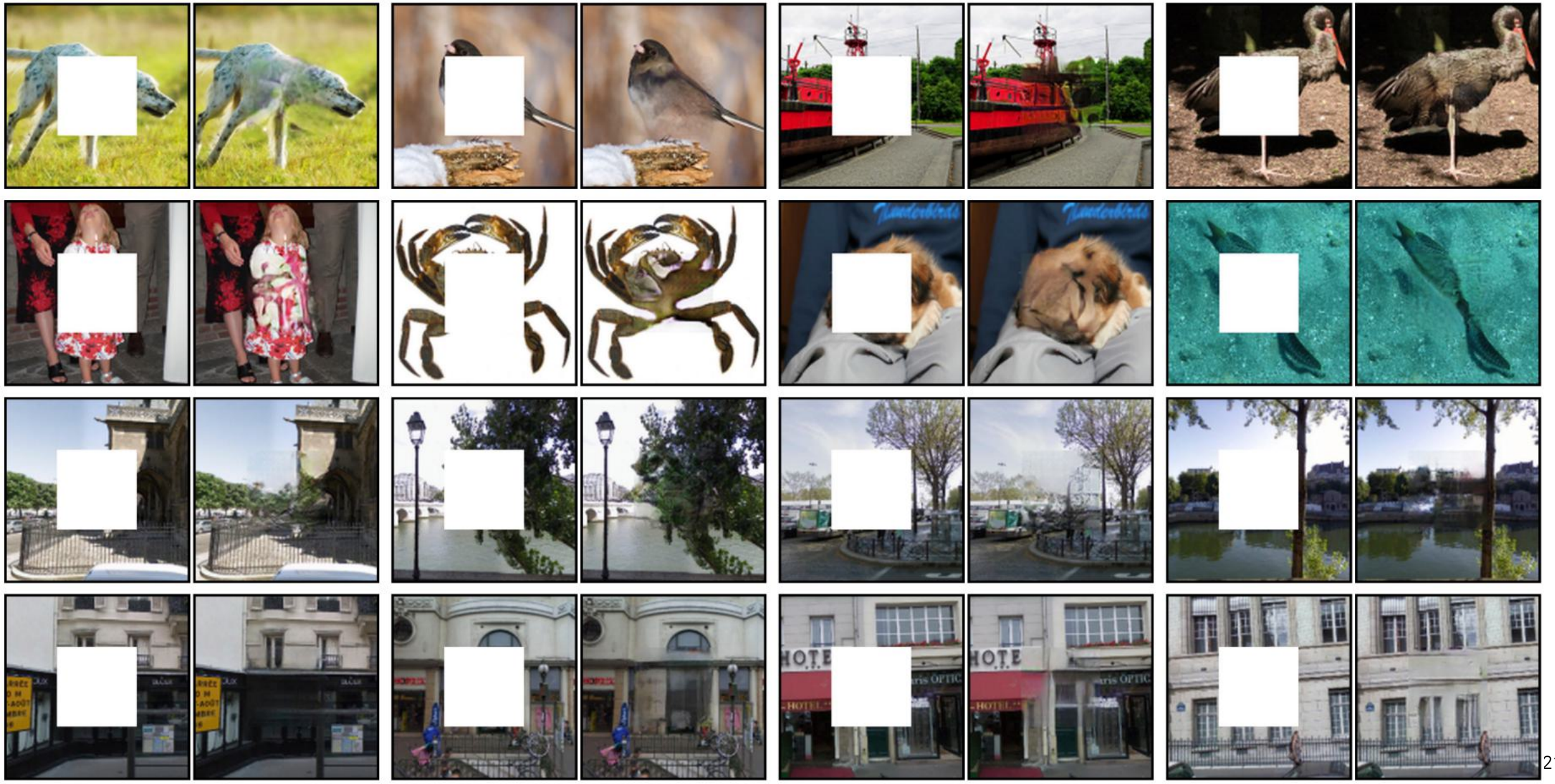


Image Inpainting (Pathak et al., 2016)



Unsupervised Domain Adaptation (Bousmalis et al., 2016)

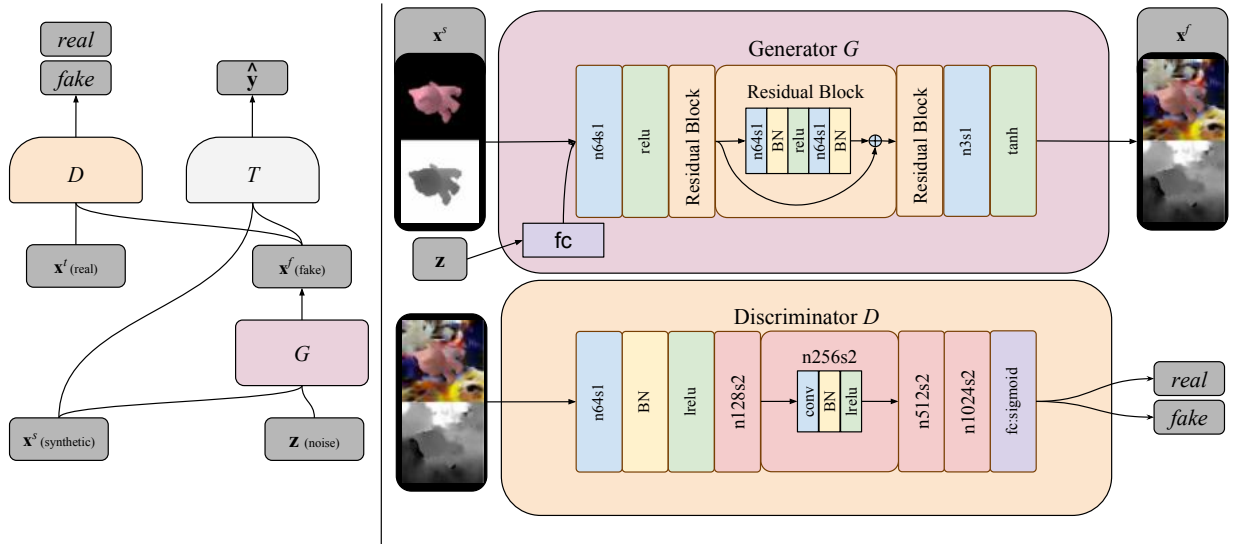
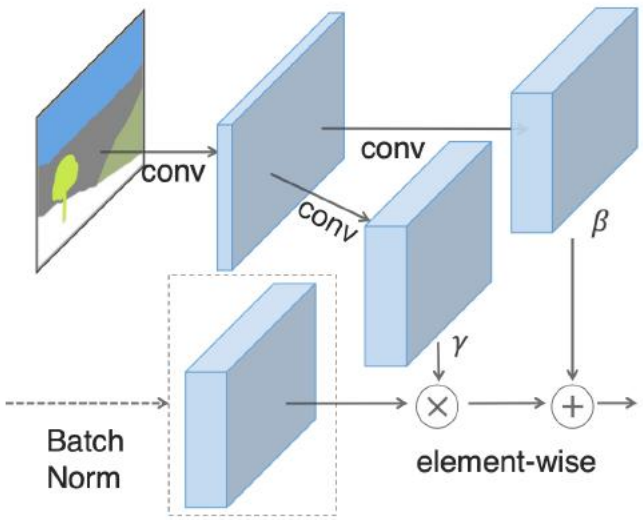


Image examples from the Linemod dataset

RGDB image samples
(conditioned on a synthetic image)

Semantic Image Editing: GauGAN



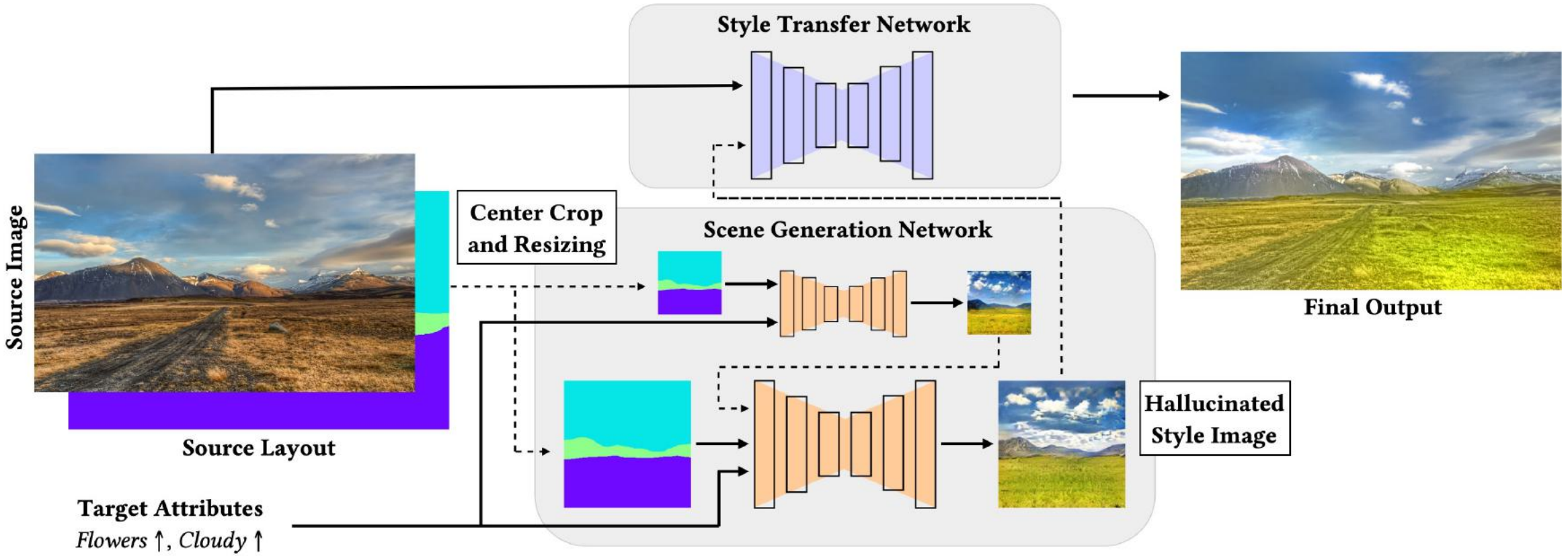
(Park et al. 2019)

Manipulating Attributes of Natural Scenes via Hallucination.

Levent Karacan, Zeynep Akata, Aykut Erdem & Erkut Erdem.

ACM Trans. on Graphics, Vol. 39, Issue 1, Article 7, February 2020.

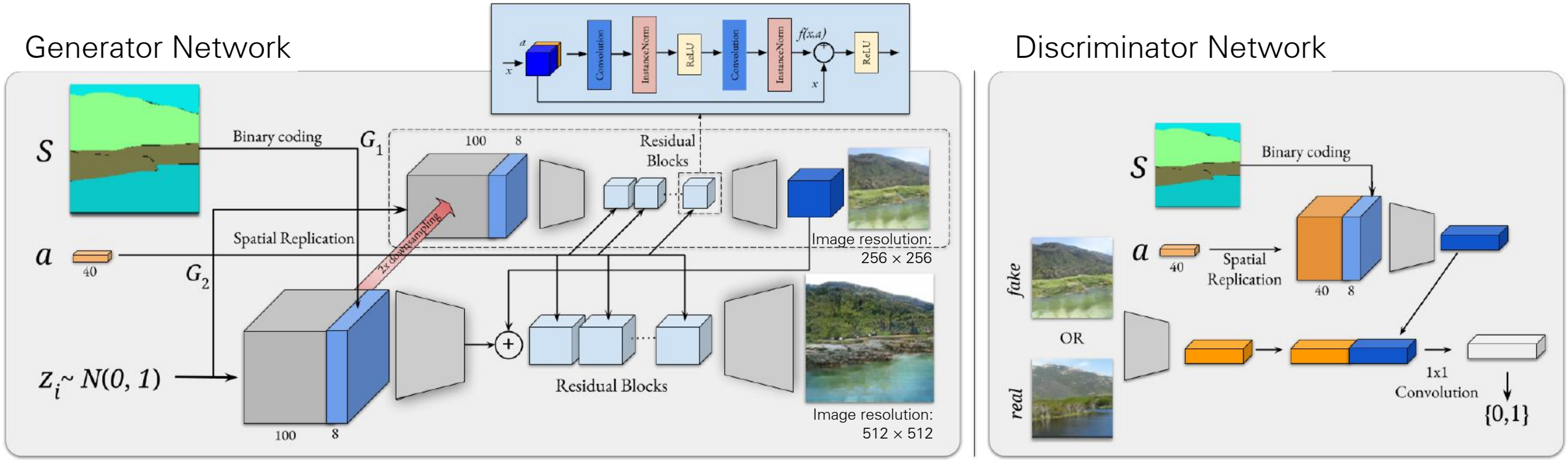
Semantic Image Editing (Karacan et al. 2020)



https://hucvl.github.io/attribute_hallucination/

Scene Generation Network (SGN)

- The semantic layout categories are encoded into 8-bit binary codes
- The transient attributes are represented by a 40-d vector.



- An architecture similar to Pix2pixHD model (Wang et al. 2018)
- **Generator network**: A coarse-to-fine model with 2 generator networks
- **Discriminator network**: A combination of three different discriminator networks operating at an image pyramid of 3 scales

T.-C. Wang et al. **High-resolution image synthesis and semantic manipulation with conditional GANs.** CVPR 2018.

Training Objective of SGNs

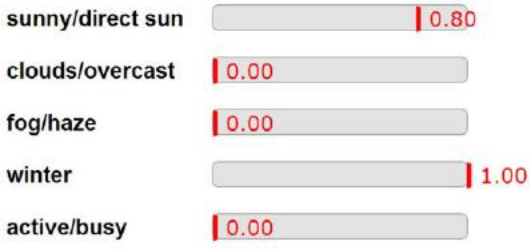
$$\mathcal{L}_{SGN} = \min_{G} \left(\left(\max_{D=\{D_1,D_2,D_3\}} \sum_{k=1,2,3} \mathcal{L}_{GAN}\left(G, D_k\right) \right) + \lambda \mathcal{L}_{percep}(G) \right)$$

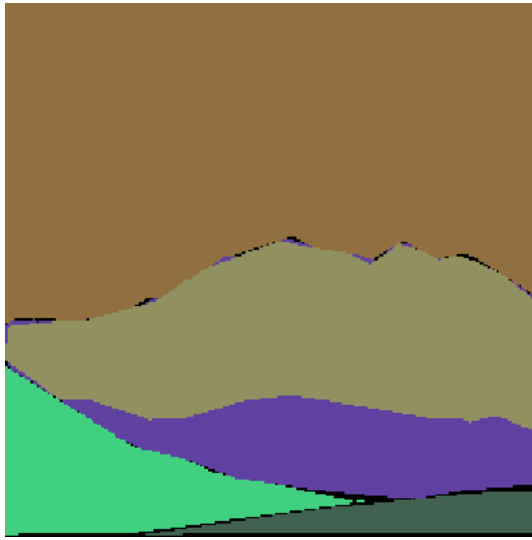
- Relative Negative Mining (RNM)
  - real image, relevant attributes and layout
    vs.
    fake image, relevant attributes and layout
    real image, mismatching layout (chosen from hard negatives)
    or mismatching attributes
- Layout-Invariant Perceptual Loss
  - $\mathcal{L}_{percep}(G) = E_{z\sim p_z(z);x,S,a\sim p_{data}(S,a)} \left[\|f_P(x) - f_P(G(z,a,S))\|_2^2 \right]$
  - f_P: CNN encoder for the scene parser network (Zhou et al., 2018)

B. Zhou, H. Zhao, X. Puig, S. Fidler, A. Barriuso, A. Torralba. **Scene Parsing through ADE20K Dataset.** CVPR 2017.

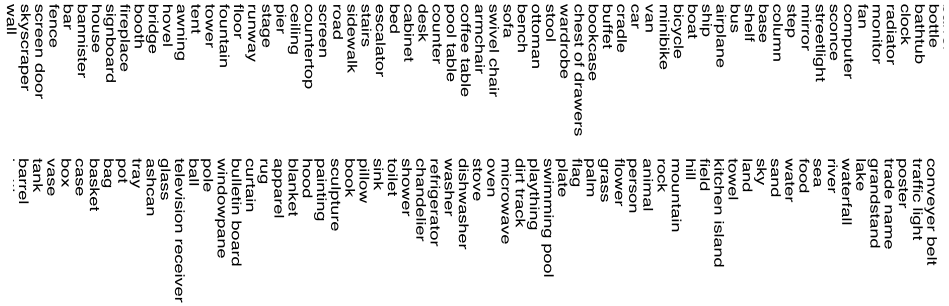
ALS18K Dataset

- A dataset of **17772 outdoor images** with layout and transient attribute labels, formed by combining and annotated images from
  - Transient Attributes dataset (Laffont et al., 2013)
  - ADE20K dataset (Zhou et al., 2017)





- 16434 images for training, 1338 images for testing
- **150 semantic categories**
- **40 transient attributes** in five categories



lighting: sunrise/sunset, bright, daylight, etc.
weather: sunny, warm, moist, foggy, cloudy, etc.
seasons: spring, summer, autumn, winter
subjective impressions: gloomy, soothing, beautiful, etc.
additional attributes: active/busy, cluttered, dirty/polluted, lush vegetation, etc.

P.-Y. Laffont, Z. Ren, X. Tao, C. Qian, J. Hays. **Data-driven Hallucination of Different Times of Day from a Single Outdoor Photo**. SIGGRAPH Asia 2013.

B. Zhou, H. Zhao, X. Puig, S. Fidler, A. Barriuso, A. Torralba. **Scene Parsing through ADE20K Dataset.** CVPR 2017.

Manipulating Attributes of Natural Scenes via Hallucination [Karacan et al., 2020]

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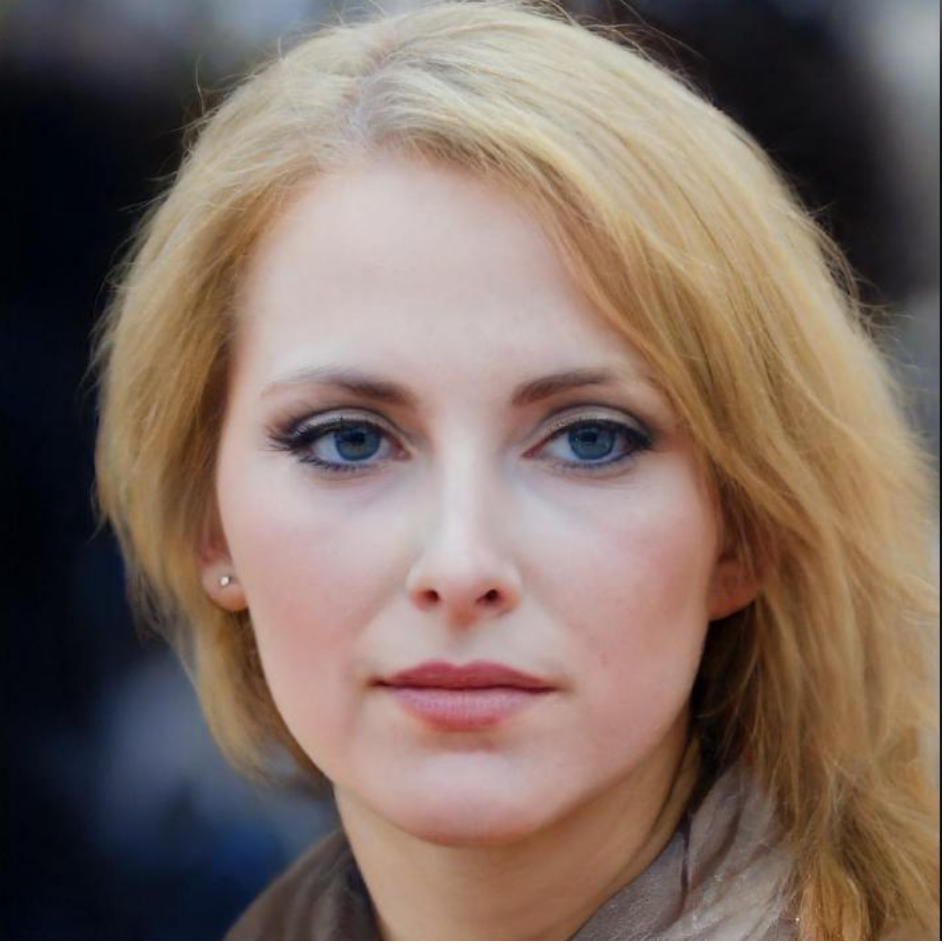
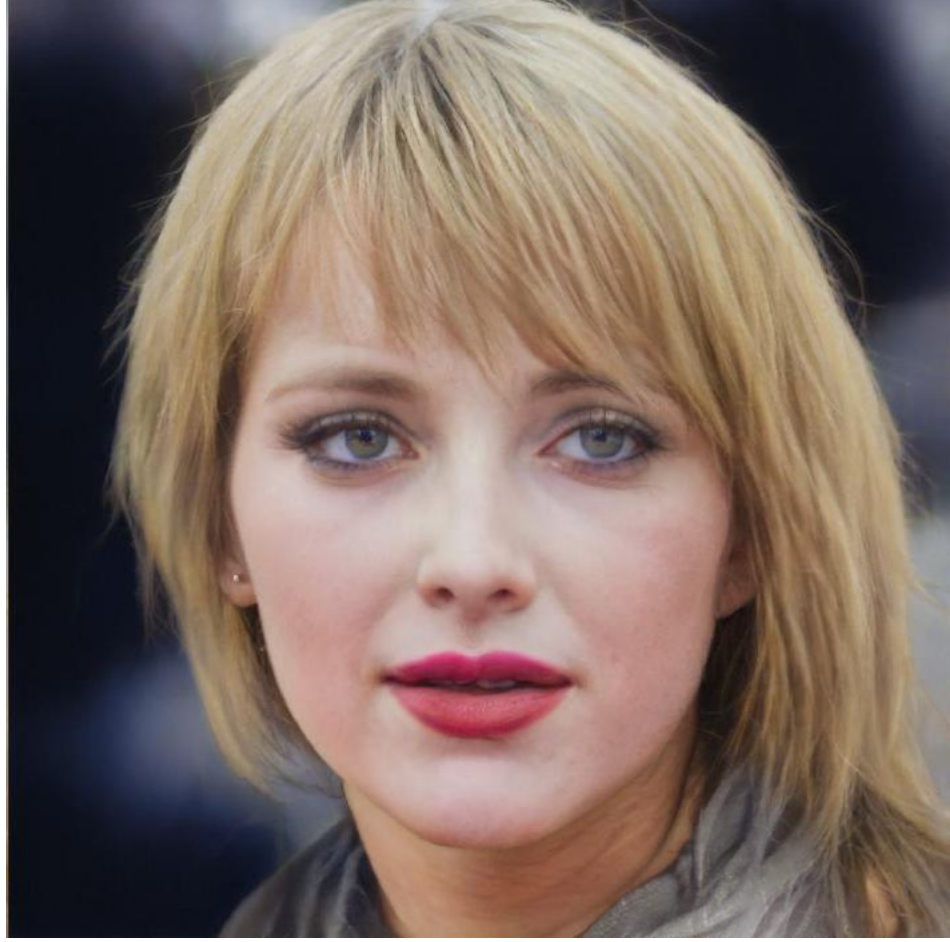




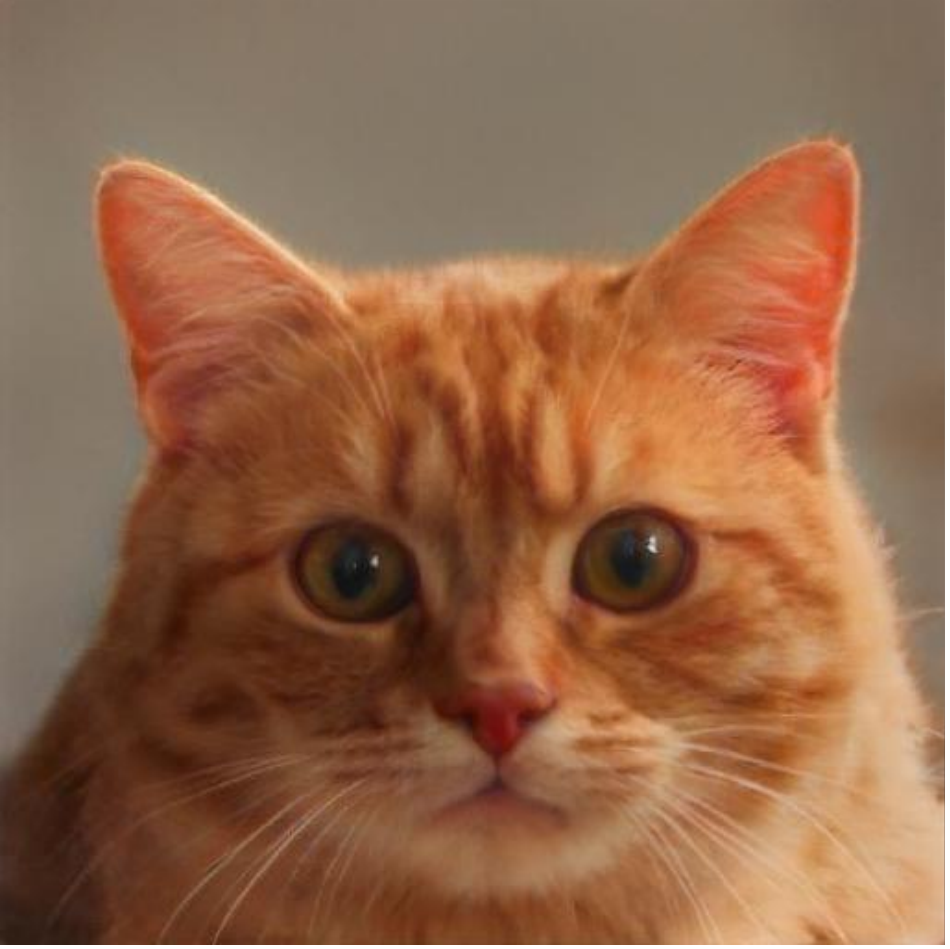
CLIP-Guided StyleGAN Inversion for Text-Driven Real Image Editing.

Canberk Baykal, Abdul Basit Anees, Duygu Ceylan, Aykut Erdem, Erkut Erdem, Deniz Yuret

ACM Transactions on Graphics, 2023





An old and grumpy British shorthair

CLIP-Guided StyleGAN Inversion for Text-Driven Real Image Editing.

Canberk Baykal, Abdul Basit Anees, Duygu Ceylan, Aykut Erdem, Erkut Erdem, Deniz Yuret

ACM Transactions on Graphics, 2023





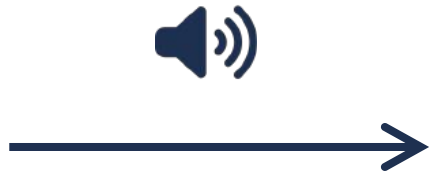

green jacket

Sleeveless blue blouse

black short

VidStyleODE: Disentangled Video Editing via StyleGAN and NeuralODE.

Moayed Haji Ali, Andrew Bond, Tolga Birdal, Duygu Ceylan, Levent Karacan, Erkut Erdem, Aykut Erdem. ICCV 2023

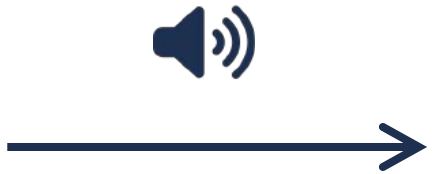


Audio-based Image Editing and Generation using Latent Diffusion Models

Burak Can Biner, Farrin Marouf Sofian, Umur Berkay Karakaş, Duygu Ceylan, Erkut Erdem, Aykut Erdem. In progress





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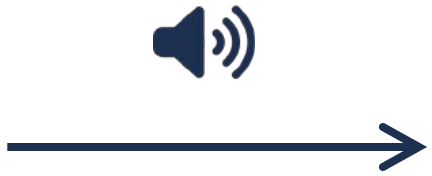

Audio-based Image Editing and Generation using Latent Diffusion Models

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Next lecture:
Denoising Diffusion Models