CS294-158 Deep Unsupervised Learning

Lecture 5 & 6 Implicit Models -- Generative Adversarial Networks (GANs)

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UC Berkeley

Outline

- Motivation & Definition of Implicit Models
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Some Theory: Bayes-optimal Discriminator; Jensen-Shannon Divergence; Mode Collapse; Avoiding Saturation
- GAN Progression:
  - DC GAN (Radford et al, 2016)
  - Improved Training of GANs (Salimans et al, 2016)
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN, SAGAN
  - BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, VIB-GAN
- Creative Conditional GANs
- GANs and Representations
- GANs as Energy Models
- GANs and Optimal Transport, Implicit Likelihood Models, Moment Matching
- Other uses of Adversarial Loss: Transfer Learning, Fairness
- GANs and Imitation Learning

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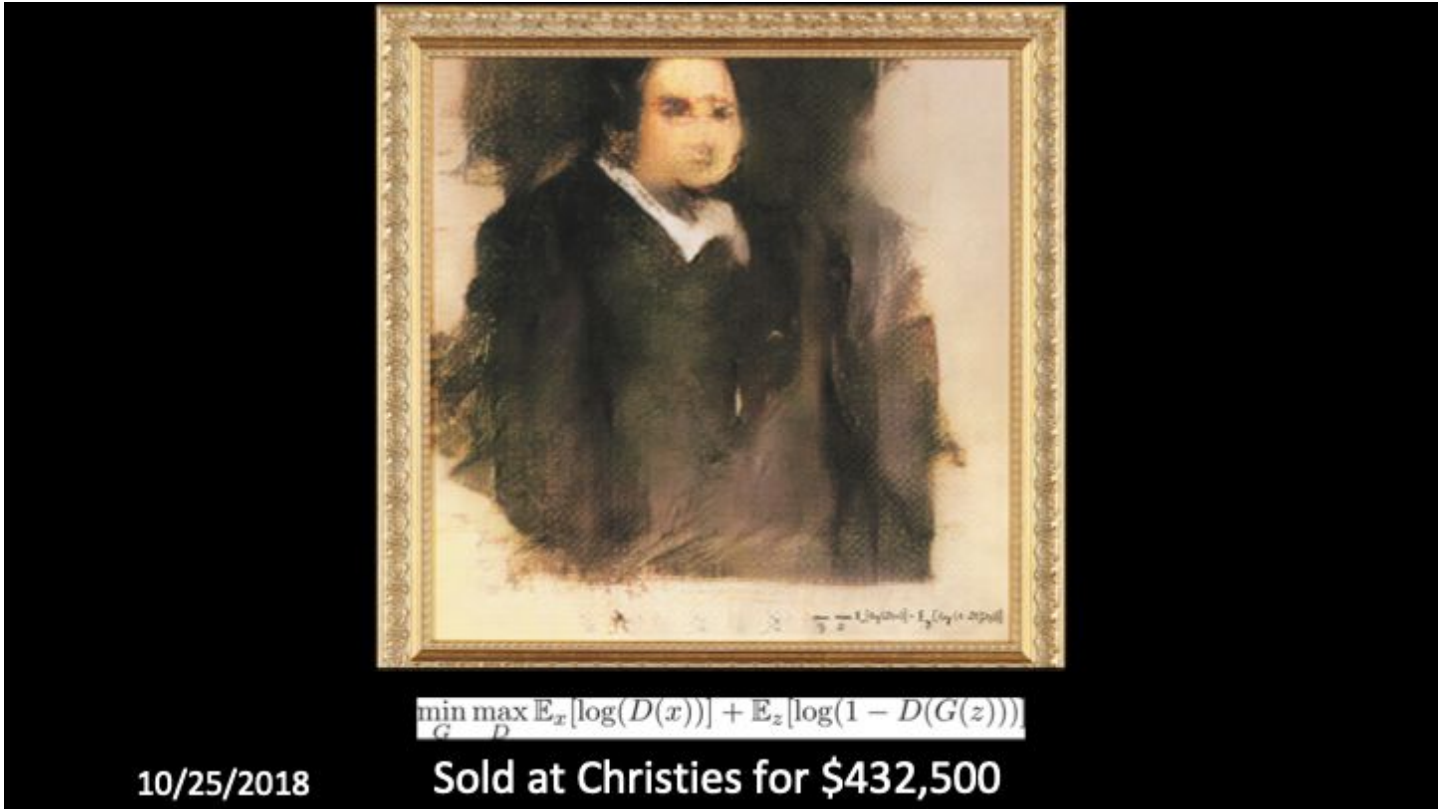
Motivation: GAN Progress

- Ian Goodfellow is first-author on the first GAN paper
- GAN is most prominent of Implicit Models

Motivation: BigGAN

[BigGAN, Brock, Donahue, Simonyan, 2018]

Motivation: GAN Art



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?

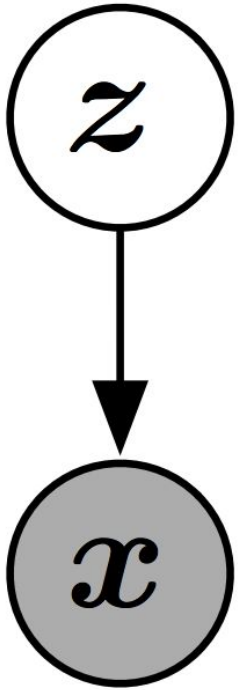
```
import glob, cv2, numpy as np
files = glob.glob('*.jpg')
def _sample():
    idx = np.random.randint(len(files))
    return cv2.imread(files[idx])
def sample(*, n_samples):
    samples = np.array([_sample() for _ in range(n_samples)])
    return samples
```

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 $p_{\text{data}} : x_1, x_2, \cdots, x_n$
- Given a sampler $q_\phi(z) = \text{DNN}(z; \phi)$ 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 induced p_{model} are
- With density models, we used $KL(p_{\text{data}}||p_{\text{model}})$ which gave us the objective $\mathbb{E}_{x\sim p_{\text{data}}}[\log p_\theta(x)]$ (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.

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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**[§]
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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.

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)

Generative Adversarial Networks

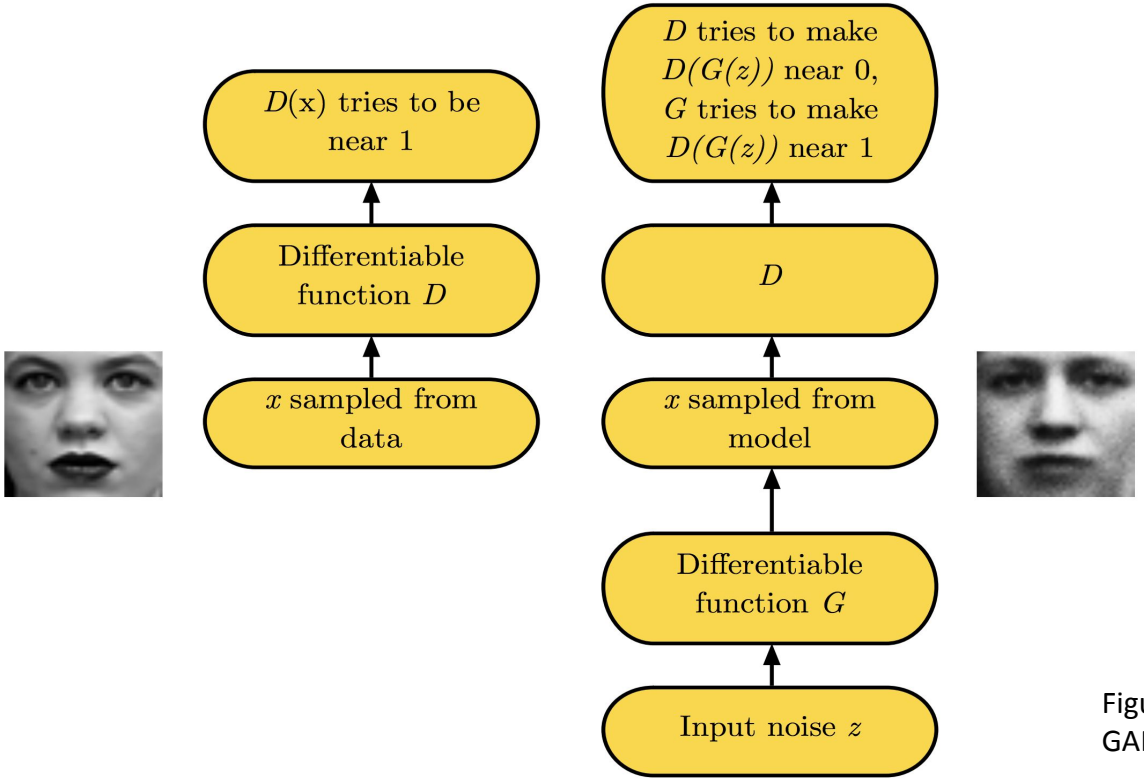


Figure from NeurIPS 2016 GAN Tutorial (Goodfellow)

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]

GAN

See it in action: https://poloclub.github.io/ganlab/

GAN samples from 2014

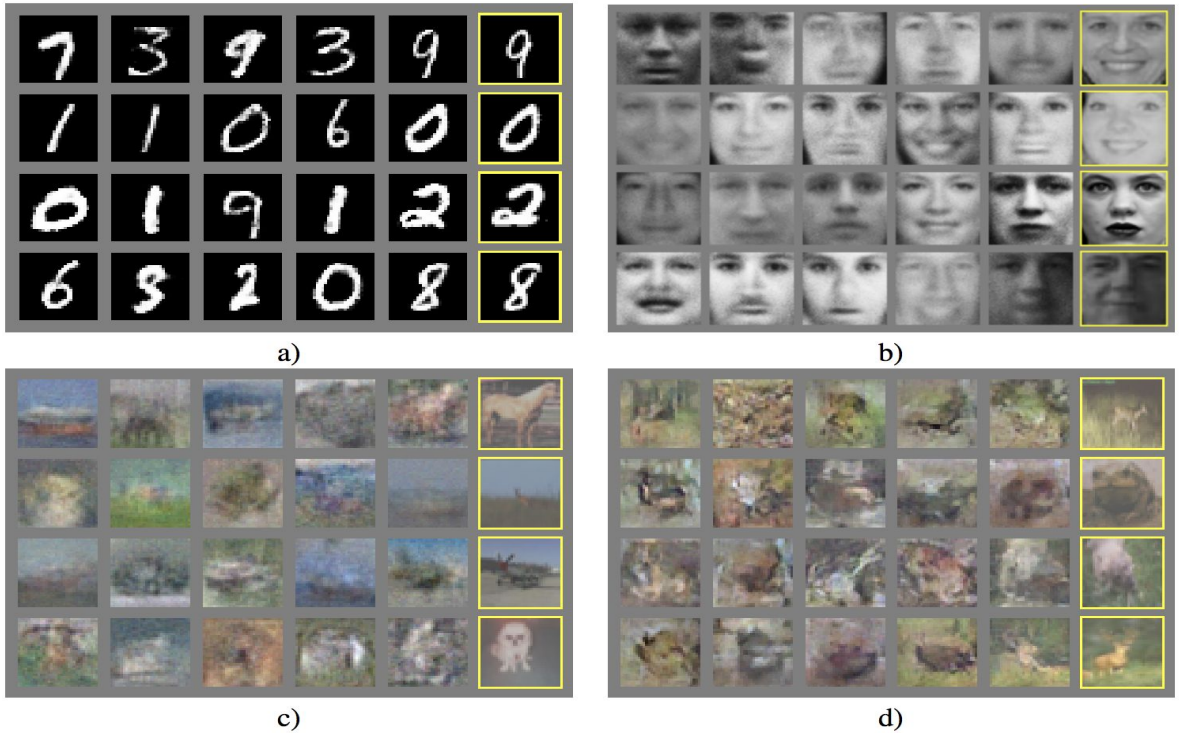


Figure from Goodfellow et al 2014

How to evaluate?

- Evaluation for GANs is still an open problem
- Unlike density models, you cannot report explicit likelihood estimates on test sets.

Parzen-Window density estimator

- Also known as Kernel Density Estimator (KDE)
- An estimator with kernel K and bandwidth h:

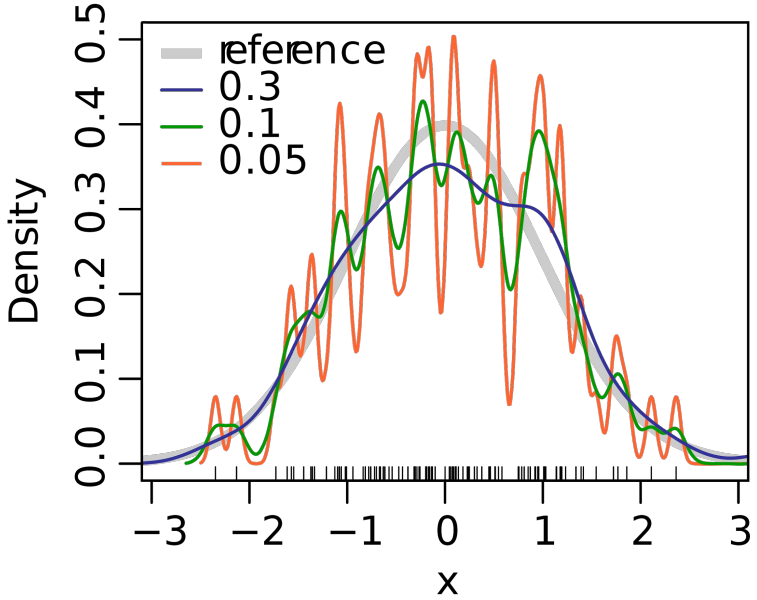
$$\hat{p_h}(x) = \frac{1}{nh} \sum_i K\left(\frac{x - x_i}{h}\right)$$

- In generative model evaluation, K is usually density function of standard Normal distribution

Bishop 2006

Parzen-Window density estimator

- Bandwidth h matters
- Bandwidth h chosen according to validation set



Bishop 2006

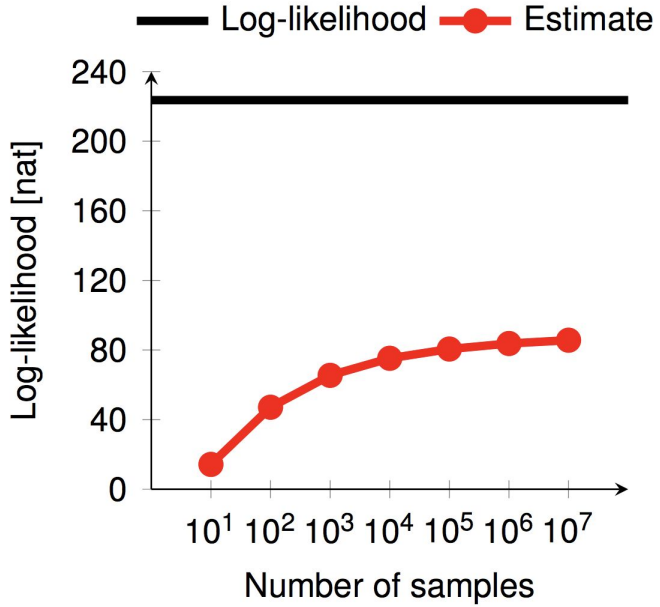
Evaluation

Model	MNIST	TFD
DBN [3]	138 ± 2	1909 ± 66
Stacked CAE [3]	121 ± 1.6	$\mathbf{2110 \pm 50}$
Deep GSN [5]	214 ± 1.1	1890 ± 29
Adversarial nets	$\mathbf{225 \pm 2}$	$\mathbf{2057 \pm 26}$

Parzen Window density estimates (Goodfellow et al, 2014)

Parzen-Window density estimator

- Parzen Window estimator can be unreliable



Model	Parzen est. [nat]
Stacked CAE	121
DBN	138
GMMN	147
Deep GSN	214
Diffusion	220
GAN	225
True distribution	**243**
GMMN + AE	282
k-means	313

[A note on the evaluation of generative models (Theis, Van den Oord, Bethge 2015)]

Inception Score

- Can we side-step high-dim density estimation?
- 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

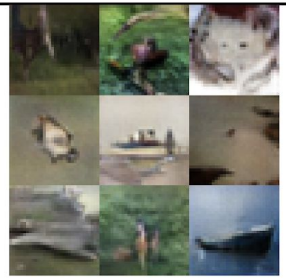
Inception Score

- 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.	$11.24 \pm .12$	$8.09 \pm .07$	$7.54 \pm .07$	$6.86 \pm .06$

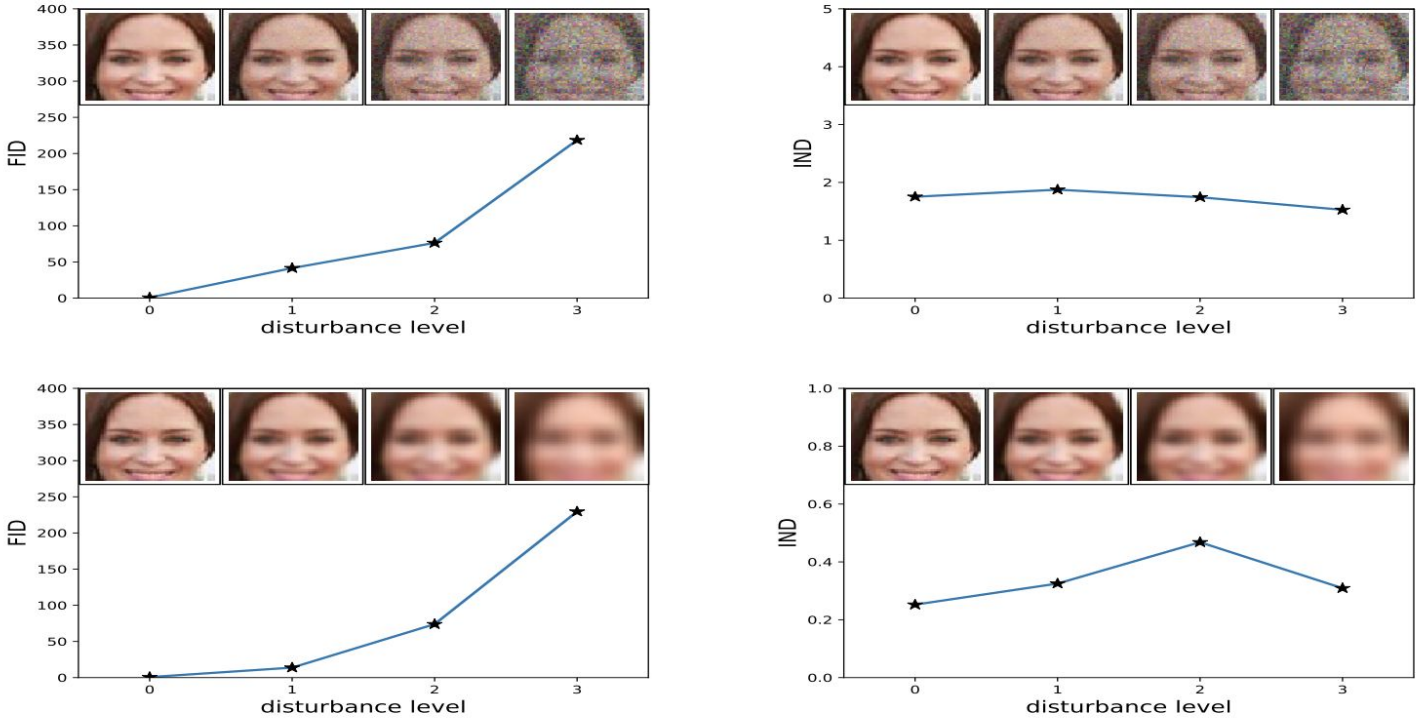
Fréchet Inception Distance

- 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

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

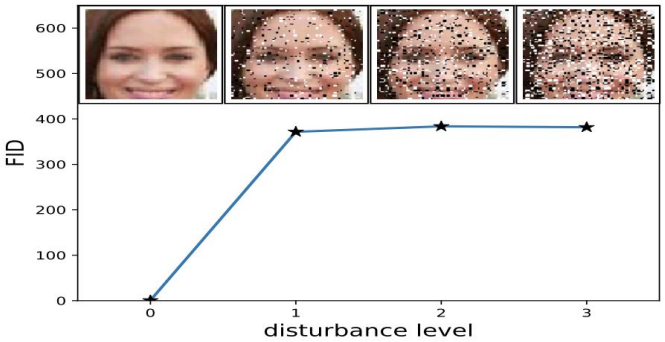
[Heusel et al, 2017]

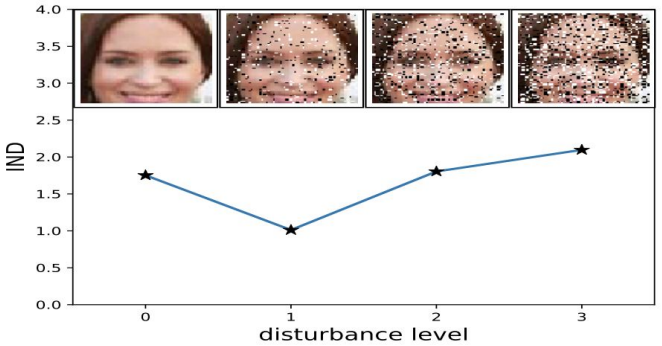
Fréchet Inception Distance

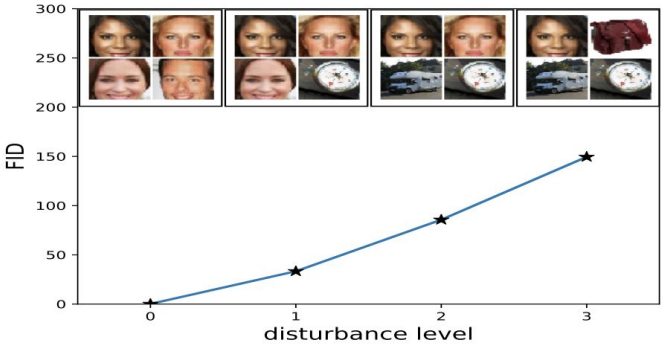


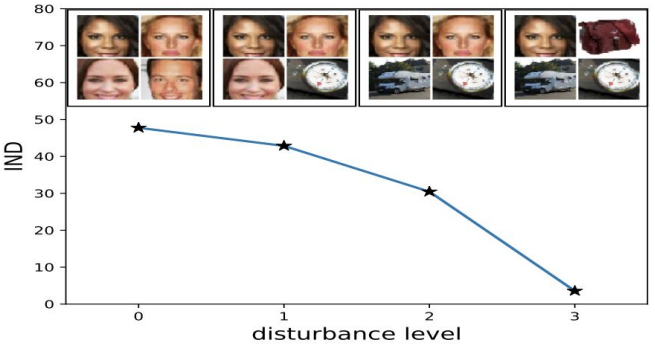
[Heusel et al, 2017]

Fréchet Inception Distance









[Heusel et al, 2017]

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

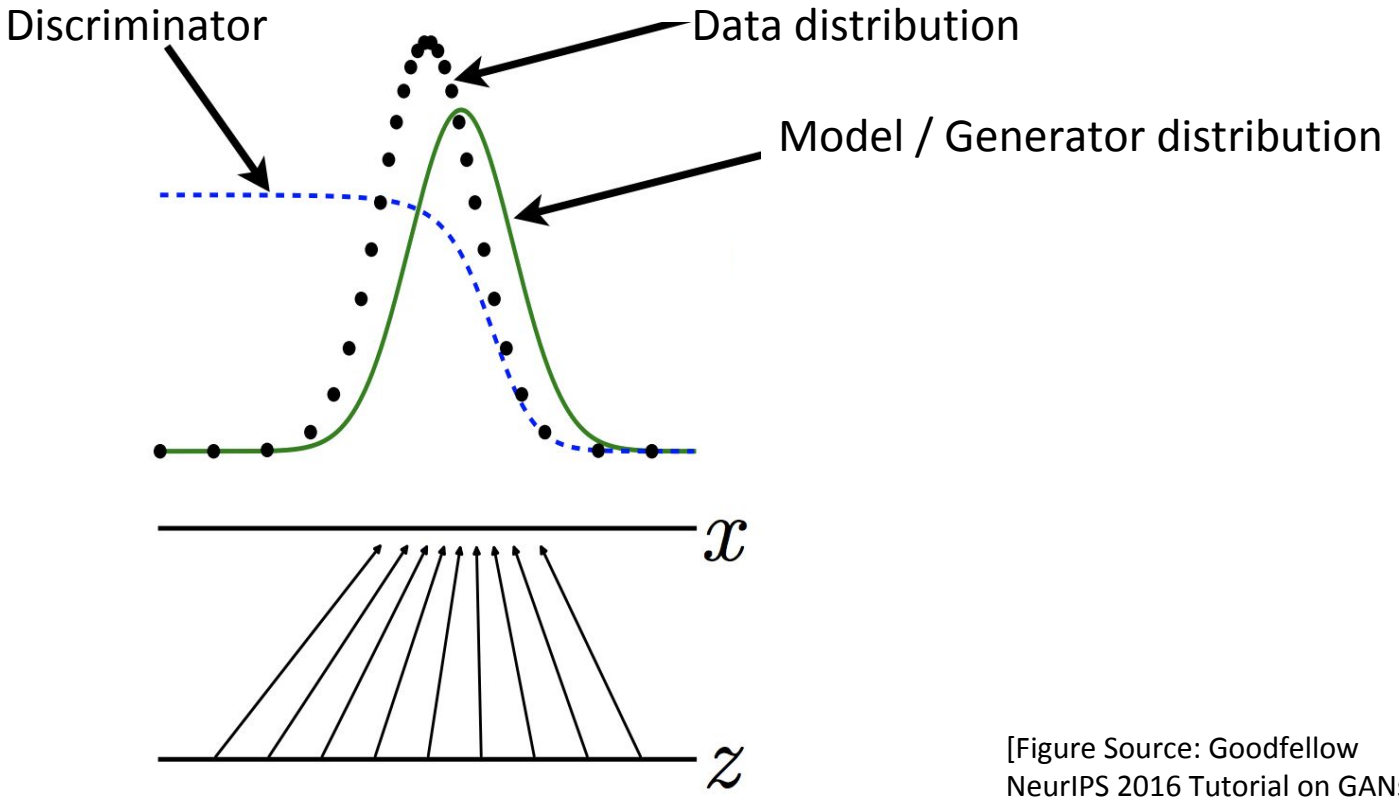
- What's the optimal discriminator given generated and true distributions?

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

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

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

GAN: Bayes-Optimal Discriminator



[Figure Source: Goodfellow NeurIPS 2016 Tutorial on GANs]

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

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

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

Behaviors across divergence measures

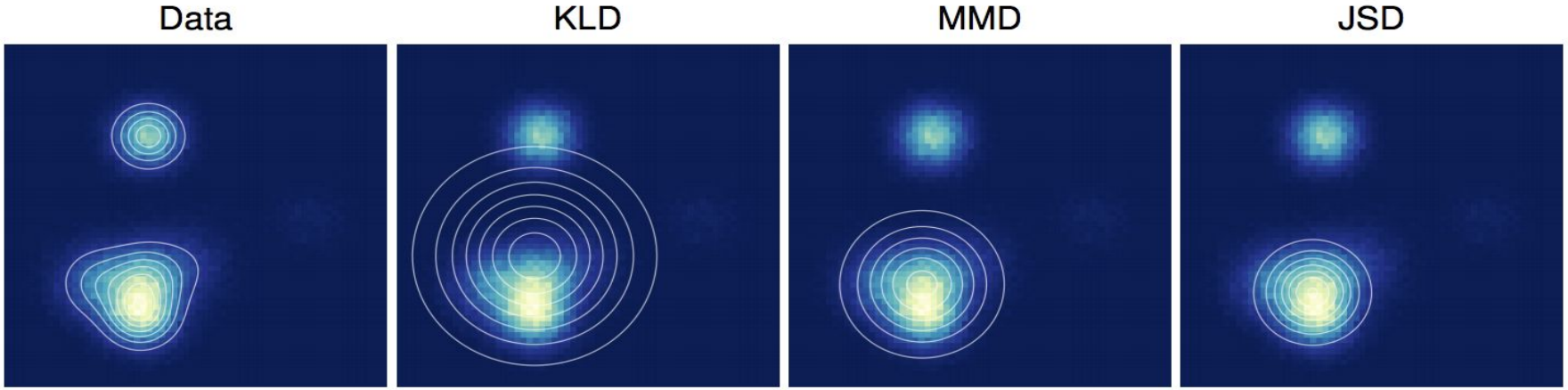
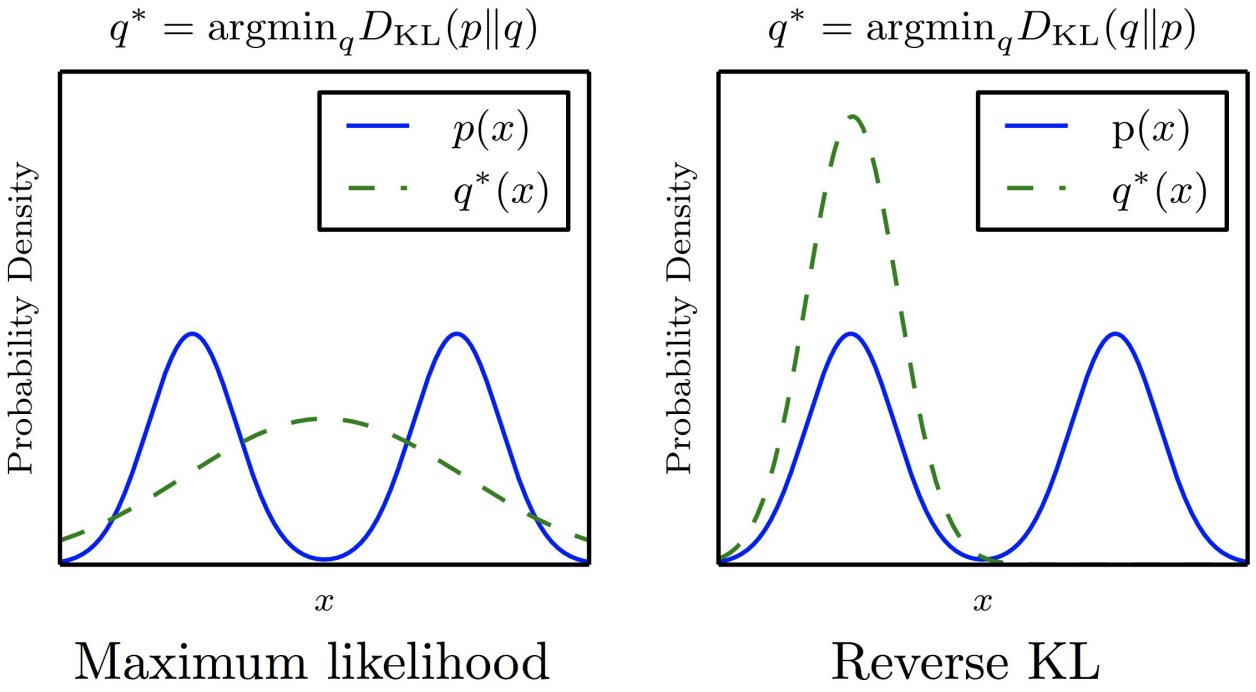


Figure 1: An isotropic Gaussian distribution was fit to data drawn from a mixture of Gaussians by either minimizing Kullback-Leibler divergence (KLD), maximum mean discrepancy (MMD), or Jensen-Shannon divergence (JSD). The different fits demonstrate different tradeoffs made by the three measures of distance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

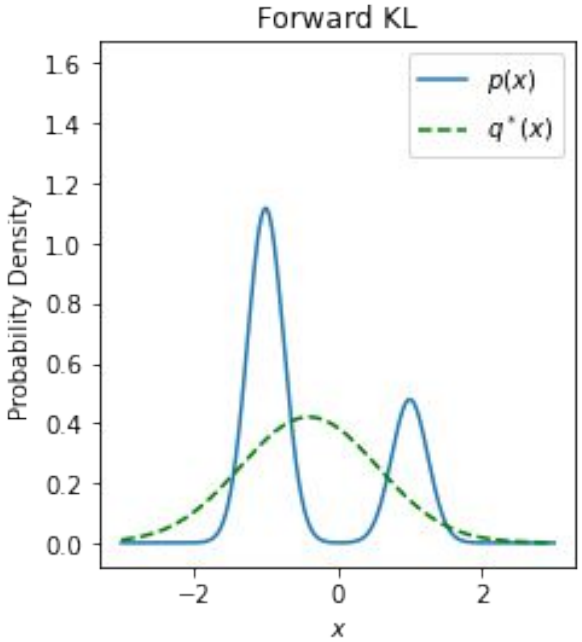
["A note on the evaluation of generative models" -- Theis, Van den Oord, Bethge 2015]

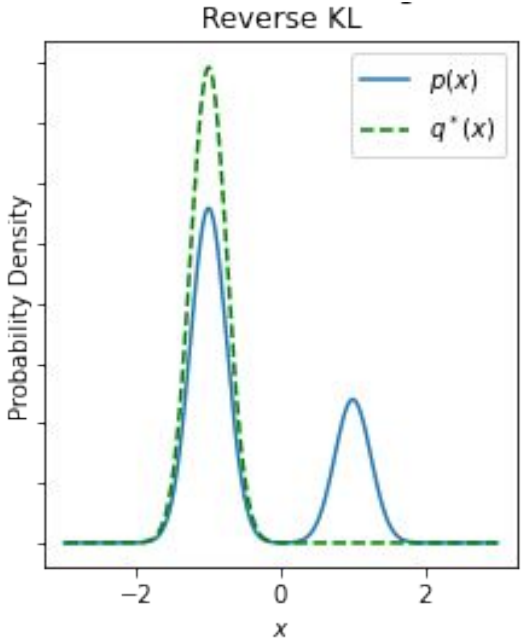
Direction of KL divergence

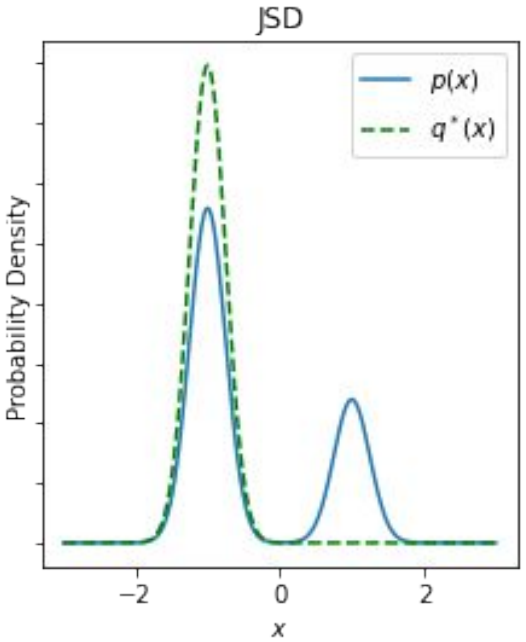


Deep Learning Textbook (Goodfellow 2016)- Chapter 3

KL and JSD


Forward KL
Probability Density
x
p(x)
q*(x)

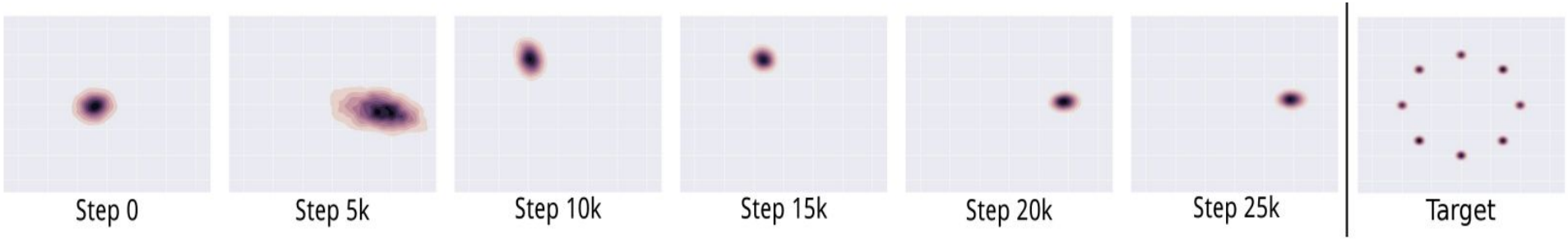

Reverse KL
Probability Density
x
p(x)
q*(x)


JSD
Probability Density
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.
  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

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

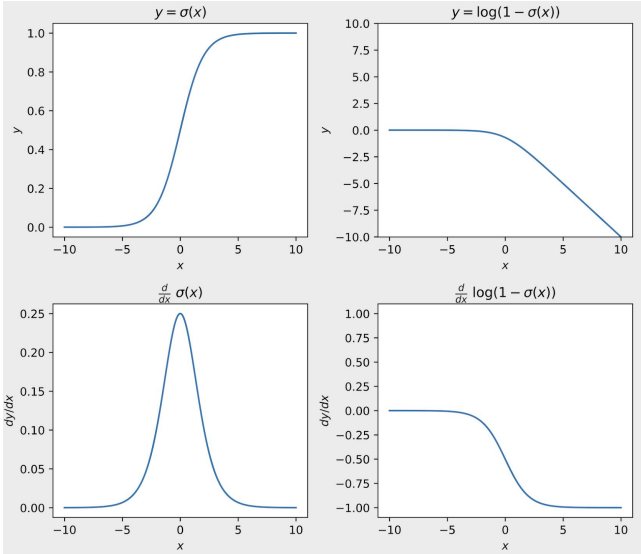
Mini-Exercise

- 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.

$$\nabla_{G(z)} \log(1 - D(G(z))) \text{ where } D(x) = \text{sigmoid}(x; \theta) = \sigma(x; \theta) \qquad \nabla_x \sigma(x) = \sigma(x)(1 - \sigma(x))$$



Avoiding Discriminator Saturation: (1) Alternating Optimization

- Alternate gradient steps on discriminator and generator objectives

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

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

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

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

Avoiding Discriminator Saturation: (2) Non Saturating Formulation

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

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

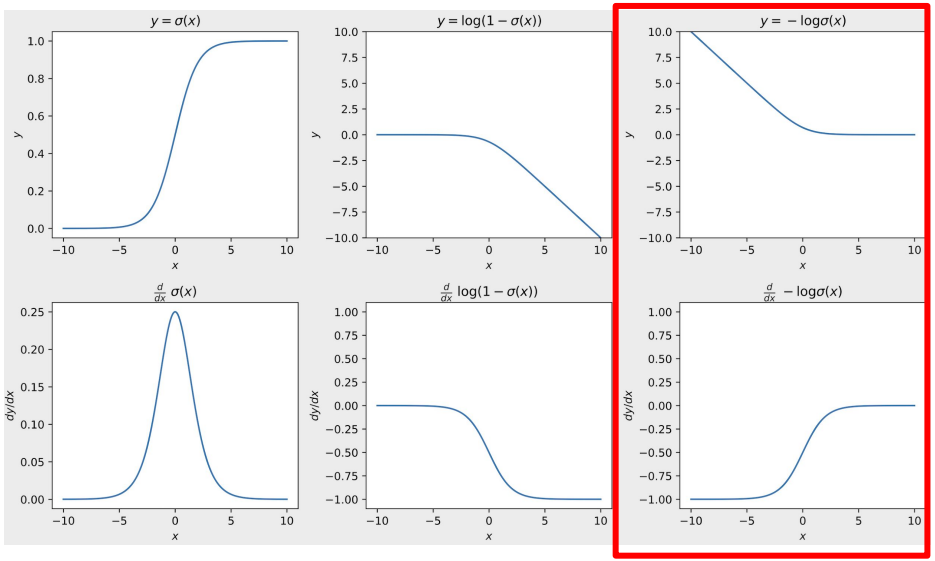
Not zero-sum

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

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

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



Outline

- Motivation & Definition of Implicit Models
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- Some Theory: Bayes-optimal Discriminator; Jensen-Shannon Divergence; Mode Collapse; Avoiding Saturation
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Deep Convolutional GAN (DCGAN)

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS

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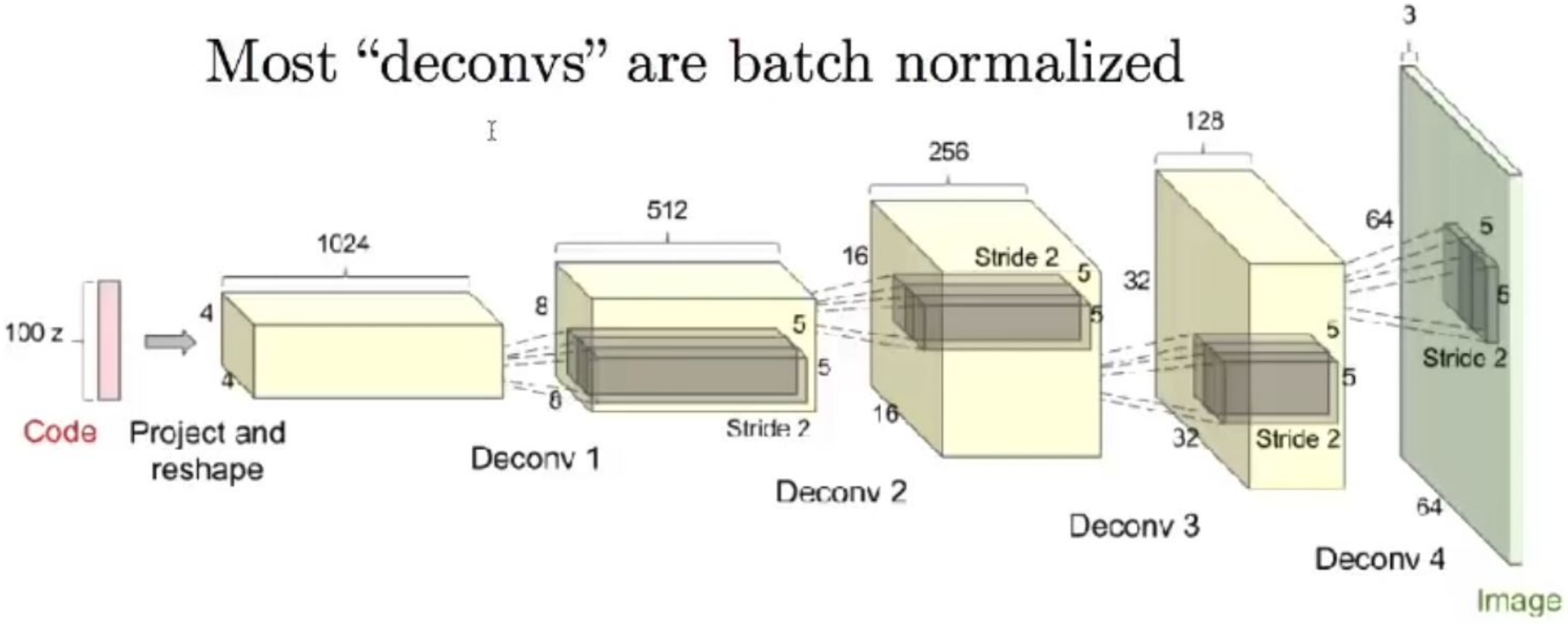
ABSTRACT

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)



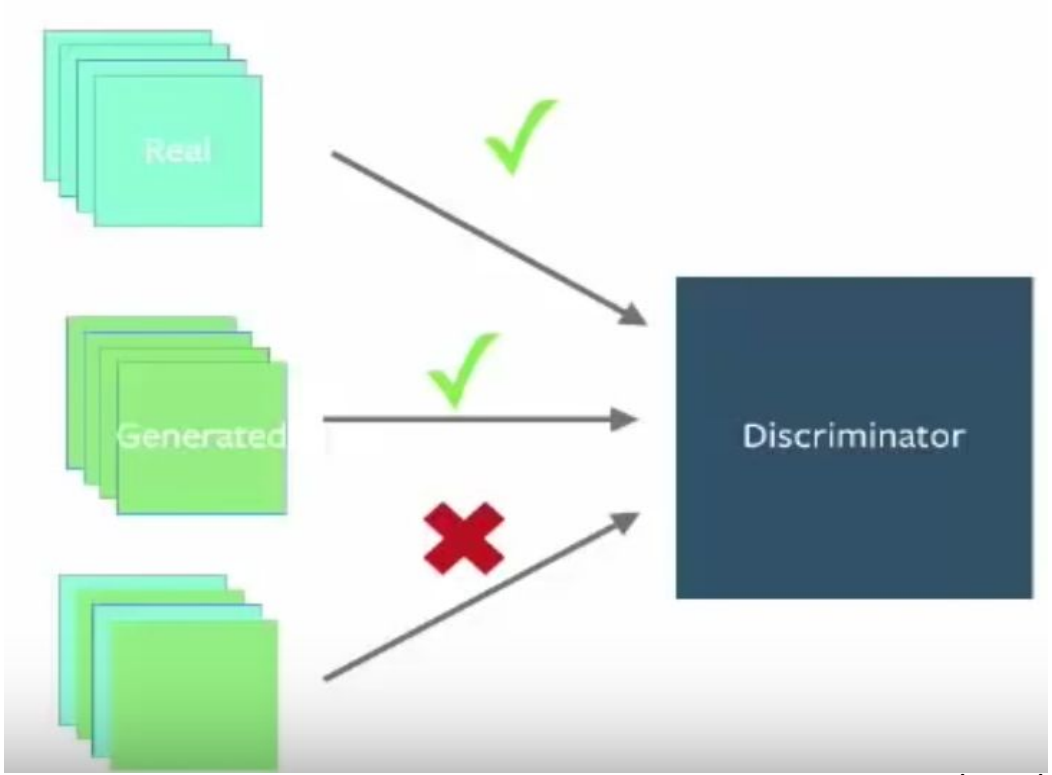
[Radford et al 2016]

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

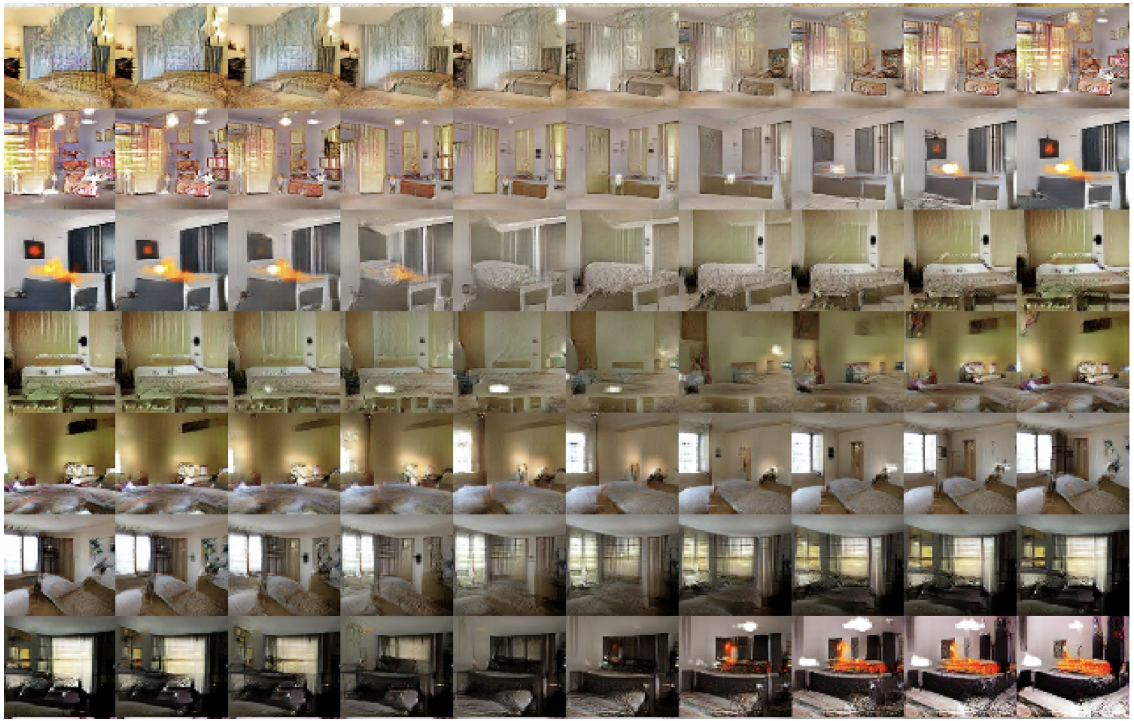
[Radford et al 2016]

DCGAN - Key Results

[Radford et al 2016]

DCGAN - Key Results

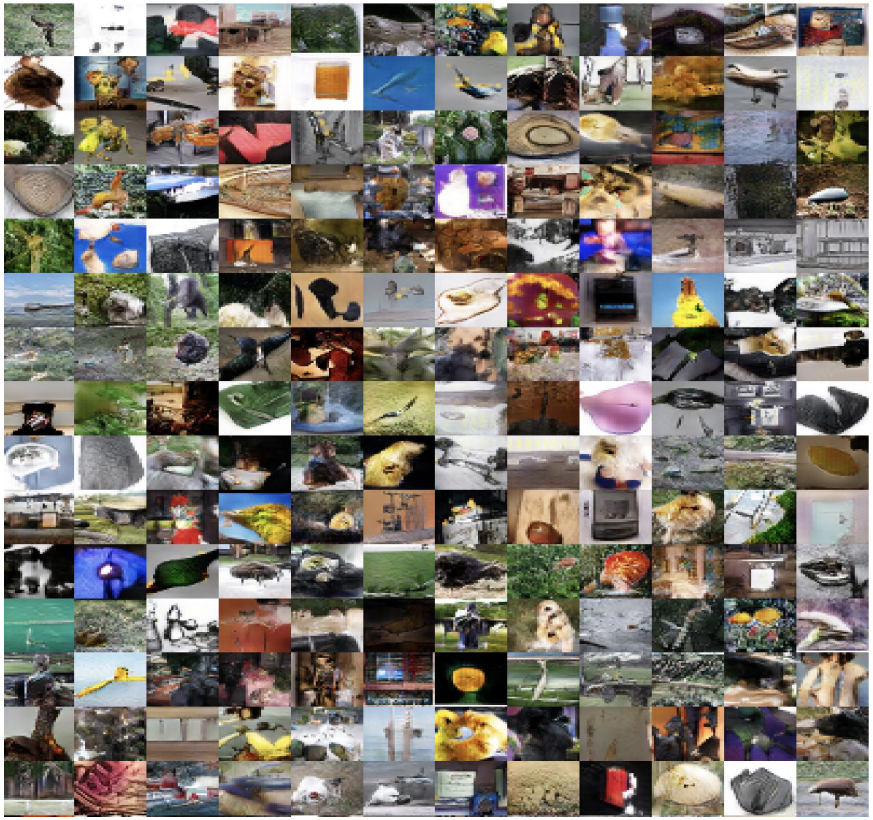
- Smooth interpolations in high dimensions



[Radford et al 2016]

DCGAN - Key Results

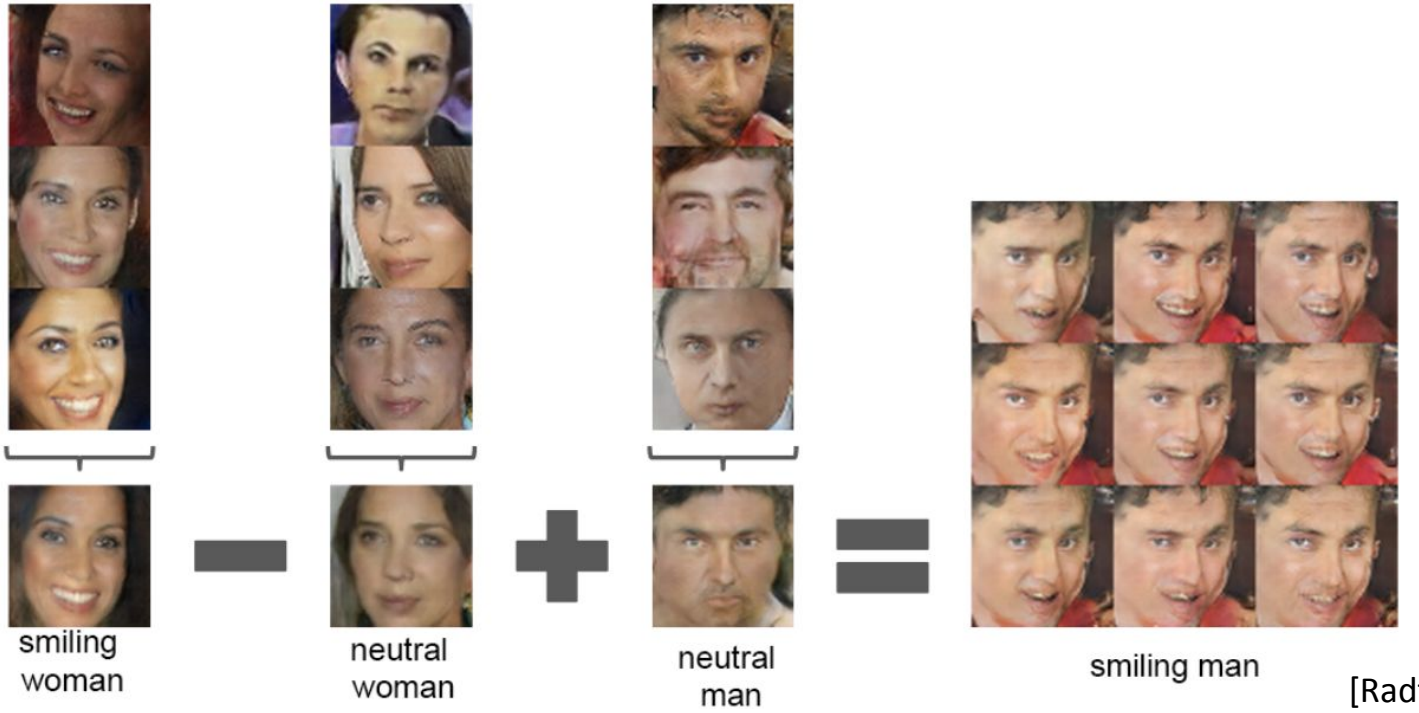
- Imagenet samples



[Radford et al 2016]

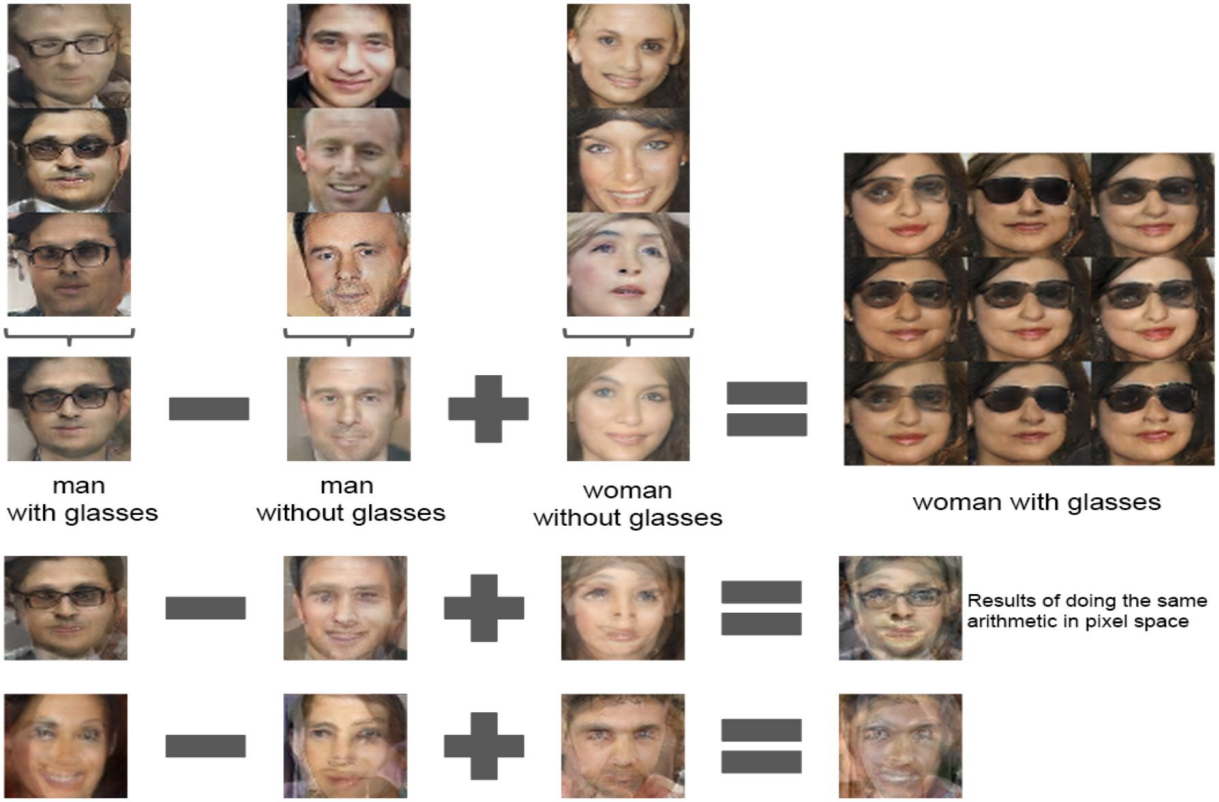
DCGAN - Key Results

- Vector Arithmetic



[Radford et al 2016]

DCGAN - Key Results



[Radford et al 2016]

DCGAN - Key Results

[Radford et al 2016]

DCGAN - Key Results

Representation Learning

Model	Accuracy	Accuracy (400 per class)	max # of features units
1 Layer K-means	80.6%	63.7% (±0.7%)	4800
3 Layer K-means Learned RF	82.0%	70.7% (±0.7%)	3200
View Invariant K-means	81.9%	72.6% (±0.7%)	6400
Exemplar CNN	84.3%	77.4% (±0.2%)	1024
DCGAN (ours) + L2-SVM	82.8%	73.8% (±0.4%)	512

[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
- Representation Learning
- **Problems to address:**
  - Unstable training
  - Brittle architecture / hyperparameters

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Improved training of GANs

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

Improved Techniques for Training GANs

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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

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

Salimans 2016

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?

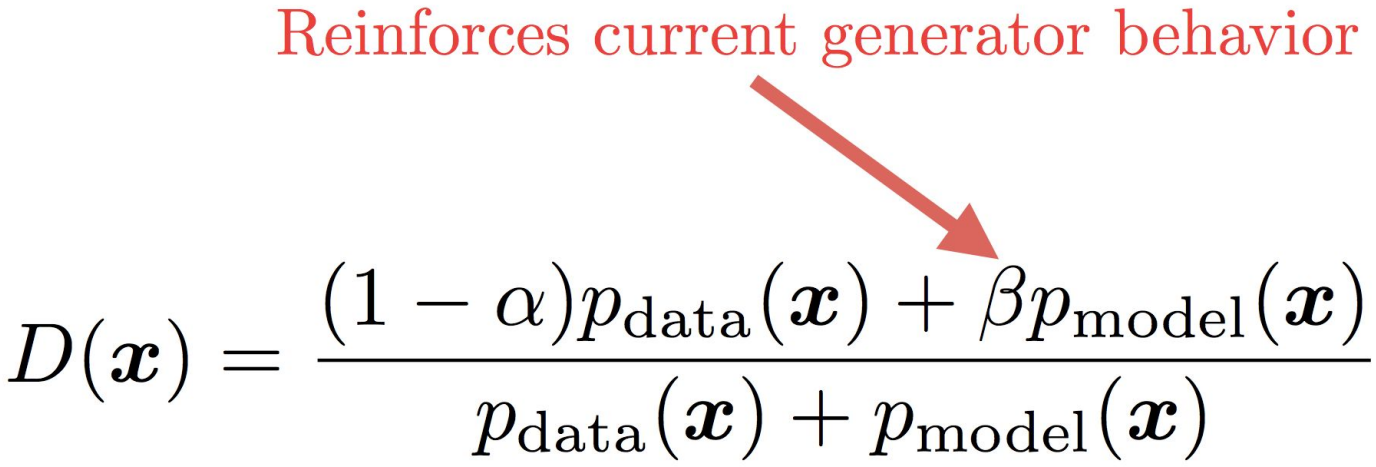


Figure source:
NeurIPS tutorial
Goodfellow 2016

Improved training of GANs

- Virtual Batch Normalization

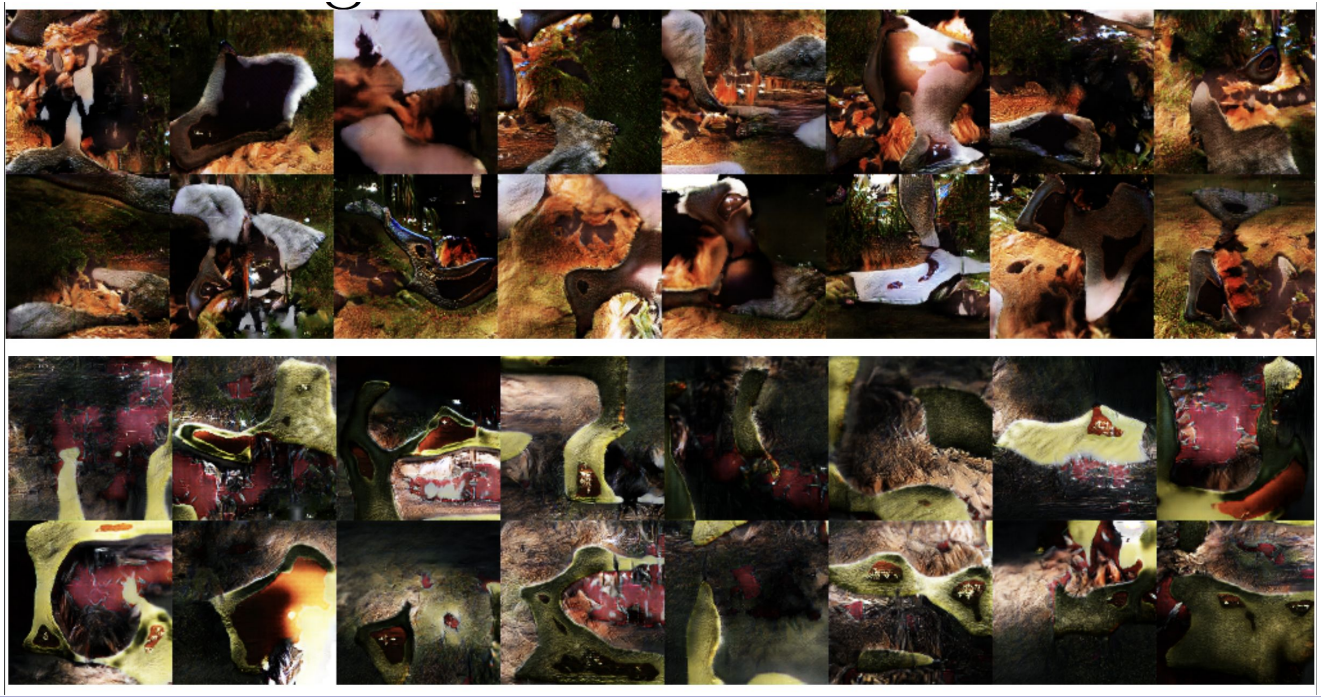


Figure source:
NeurIPS tutorial
Goodfellow 2016

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

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

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

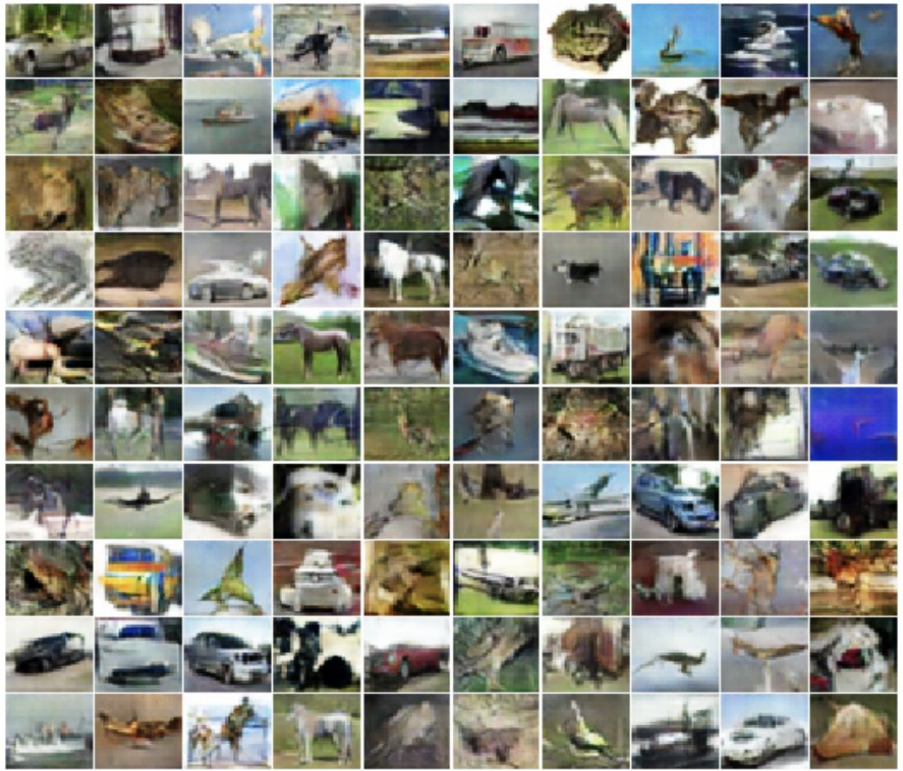
Improved training of GANs

- Inception Score

$$\exp(\mathbb{E}_{\boldsymbol{x}}\mathbf{KL}(p(y|\boldsymbol{x})||p(y)))$$

  - Correlates with human judgement
  - Captures some necessity for diversity

Improved training of GANs



Salimans 2016

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Wasserstein Distance

- We have seen $KL(P_r \| P_g)$ and $JSD(P_r, P_g) = KL(P_r \| (\frac{P_r + P_g}{2}) + KL(P_g \| (\frac{P_r + P_g}{2}))$

- Another distance measure inspired from Optimal Transport is the Earth Mover (EM) distance

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

- Goal: Design a GAN objective function such that the generator minimizes the Earth Mover / Wasserstein distance between data and generated distributions.

Kantorovich Rubinstein Duality

- $W(P_r, P_g) = \inf_{\gamma \in \Pi(P_r, P_g)} \mathbb{E}_{(x,y)\sim\gamma} \left[||x - y|| \right]$
- Intractable to estimate
- Kantorovich Rubinstein Duality: $W(P_r, P_g) = \sup_{\|f_L\| \leq 1} \mathbb{E}_{x\sim P_r} \left[f(x) \right] - \mathbb{E}_{x\sim P_g} \left[f(x) \right]$
- Search over joint distributions is now a search over 1-Lipschitz functions

Wasserstein GAN

Wasserstein GAN

Martin Arjovsky[1], Soumith Chintala[2], and Léon Bottou[1,2]

[1]Courant Institute of Mathematical Sciences
[2]Facebook AI Research

- Kantorovich Rubinstein Duality: $W(P_r, P_g) = \sup_{\|f_L\| \leq 1} \mathbb{E}_{x \sim P_r}[f(x)] - \mathbb{E}_{x \sim P_g}[f(x)]$

- Supremum over linear (function space) expectations => search over K-Lipschitz gives you K times the Wasserstein distance.

Wasserstein GAN

- $f : X \to Y$ is K-Lipschitz if for distance functions d_X and d_Y on X and Y $d_Y(f(x_1), f(x_2)) \leq K d_x(x_1, x_2)$
- Assume that we search over a parameterized family of functions f_w with $w \in \mathscr{W}$
- $\max_{w \in \mathscr{W}} \mathbb{E}_{x \sim P_r}[f_w(x)] - \mathbb{E}_{x \sim P_g}[f_w(x)] \leq \sup_{\|f_L\| \leq K} \mathbb{E}_{x \sim P_r}[f(x)] - \mathbb{E}_{x \sim P_g}[f(x)] = K \cdot W(P_r, P_g)$
- For P_g induced by $g_\theta(z)$ we can backprop through $\mathbb{E}_{x \sim P_r}[f_w(x)] - \mathbb{E}_{x \sim P_g}[f_w(x)] : -\mathbb{E}_{z \sim p(z)}[\nabla_\theta f_w(g_\theta(z))]$

Wasserstein GAN - Pseudocode

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

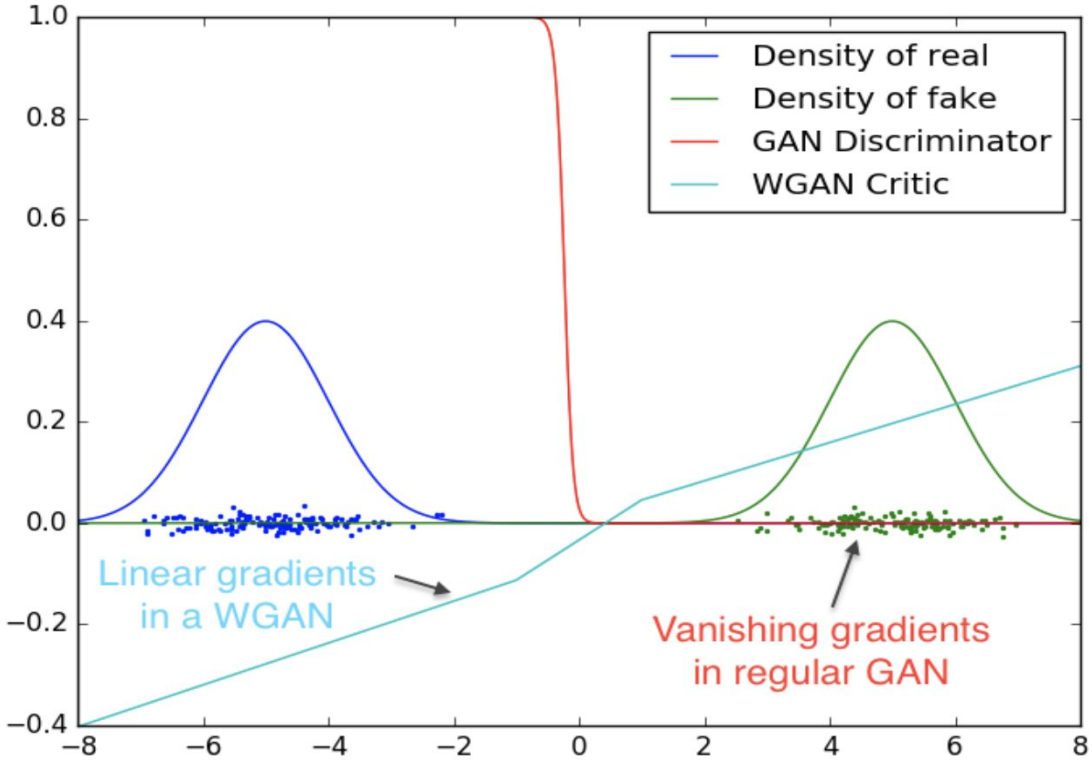
Require: : α, the learning rate. c, the clipping parameter. m, the batch size. n_{critic}, the number of iterations of the critic per generator iteration.

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)

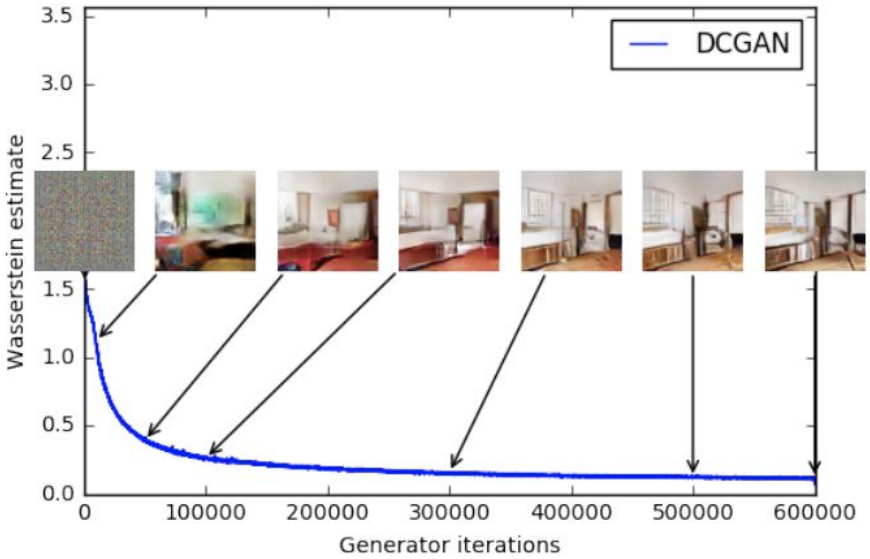
Wasserstein GAN - Training critic to converge



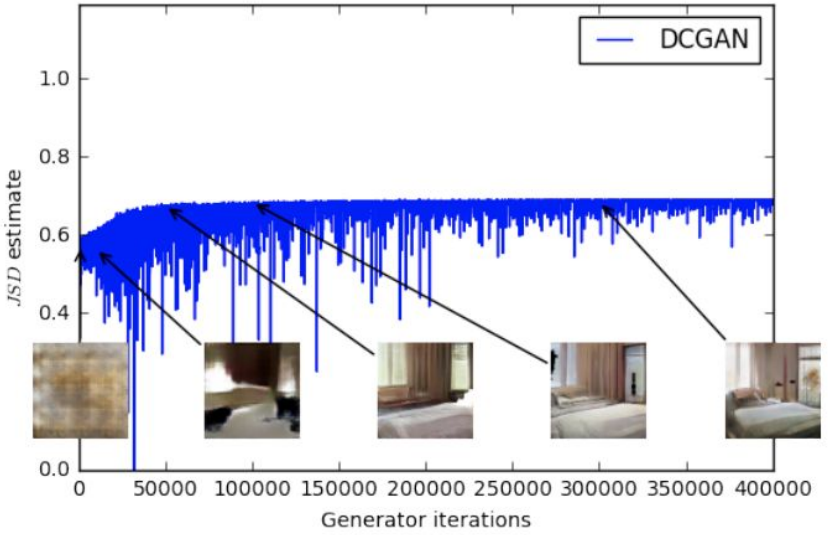
(Arjovsky et al 2017)

Wasserstein distance correlates with sample quality

Wasserstein Estimate

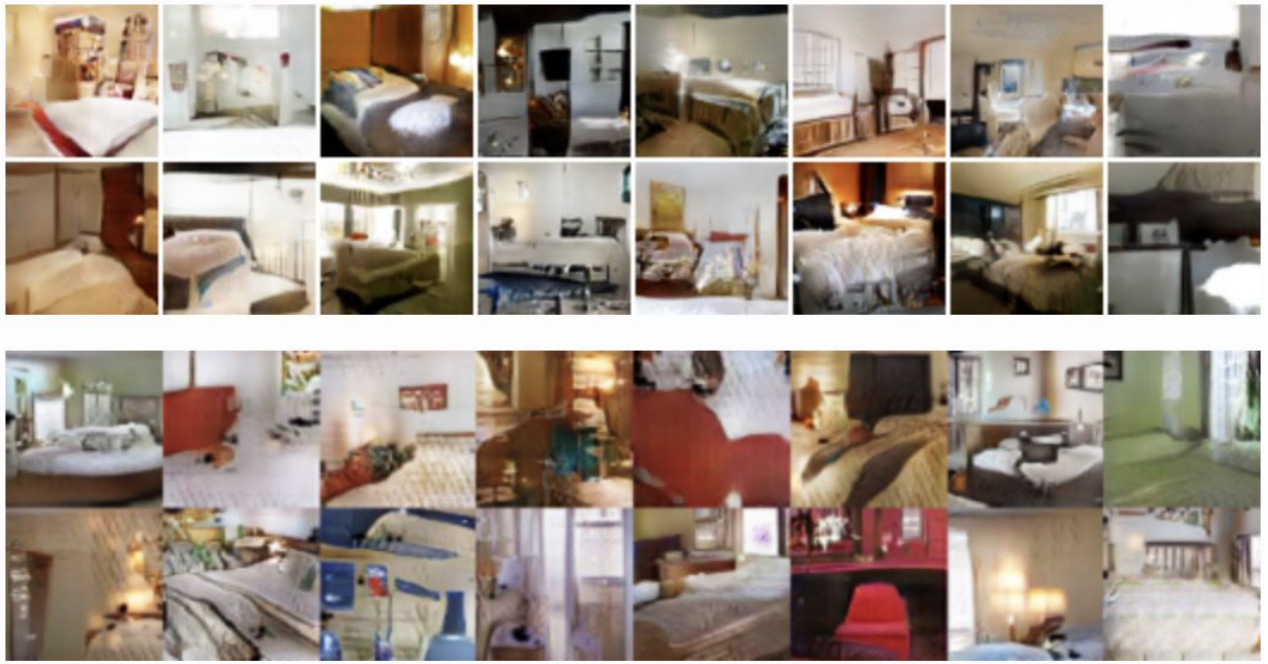


JSD Estimate



(Arjovsky et al 2017)

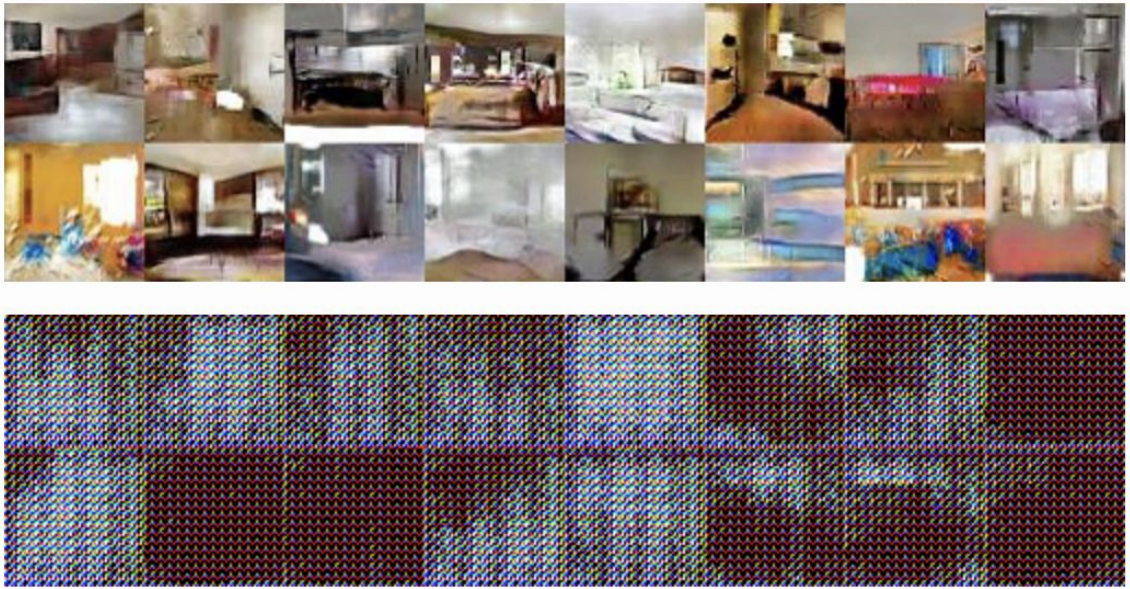
WGAN Samples on par with DCGAN



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

(Arjovsky et al 2017)

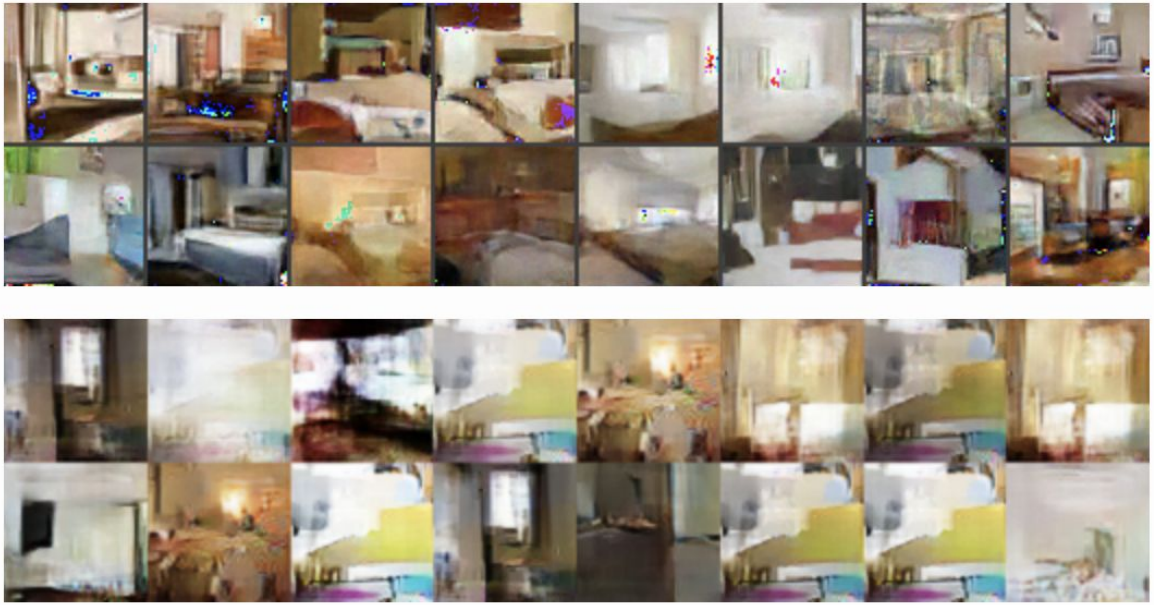
WGAN robust to architecture choices



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)

WGAN Summary

- New divergence measure for optimizing the generator
- Addresses instabilities with JSD version (sigmoid cross entropy)
- Robust to architectural choices
- Progress on mode collapse and stability of derivative wrt input
- Introduces the idea of using lipschitzness to stabilize GAN training
- Negative:

> Weight clipping is a clearly terrible way to enforce a Lipschitz constraint. If the clipping parameter is large, then it can take a long time for any weights to reach their limit, thereby making it harder to train the critic till optimality. If the clipping is small, this can easily lead to vanishing gradients when the number of layers is big, or batch normalization is not used (such as in RNNs). We experimented with simple variants (such as projecting the weights to a sphere) with little difference, and we stuck with weight clipping due to its simplicity and already good performance. However, we do leave the topic of enforcing Lipschitz constraints in a neural network setting for further investigation, and we actively encourage interested researchers to improve on this method.

(Arjovsky et al 2017)

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WGAN-GP: Gradient Penalty for Lipschitzness

Improved Training of Wasserstein GANs

Ishaan Gulrajani[1]*, **Faruk Ahmed**[1], **Martin Arjovsky**[2], **Vincent Dumoulin**[1], **Aaron Courville**[1,3]
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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 for Lipschitzness

Proposition 1. *Let $\mathbb{P}_r$ and $\mathbb{P}_g$ be two distributions in $\mathcal{X}$, a compact metric space. Then, there is a 1-Lipschitz function f^* which is the optimal solution of $\max_{\|f\|_L \leq 1} \mathbb{E}_{y \sim \mathbb{P}_r}[f(y)] - \mathbb{E}_{x \sim \mathbb{P}_g}[f(x)]$. Let π be the optimal coupling between $\mathbb{P}_r$ and $\mathbb{P}_g$, defined as the minimizer of: $W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\pi \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\pi}[\|x - y\|]$ where $\Pi(\mathbb{P}_r, \mathbb{P}_g)$ is the set of joint distributions $\pi(x, y)$ whose marginals are $\mathbb{P}_r$ and $\mathbb{P}_g$, respectively. Then, if f^* is differentiable[‡], $\pi(x = y) = 0$[§], and $x_t = tx + (1-t)y$ with $0 \leq t \leq 1$, it holds that $\mathbb{P}_{(x,y)\sim\pi}\left[\nabla f^*(x_t) = \frac{y - x_t}{\|y - x_t\|}\right] = 1$.*

Corollary 1. *f^* has gradient norm 1 almost everywhere under $\mathbb{P}_r$ and $\mathbb{P}_g$.*

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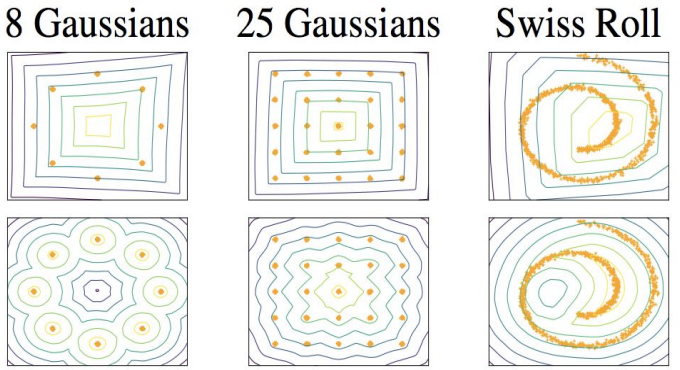
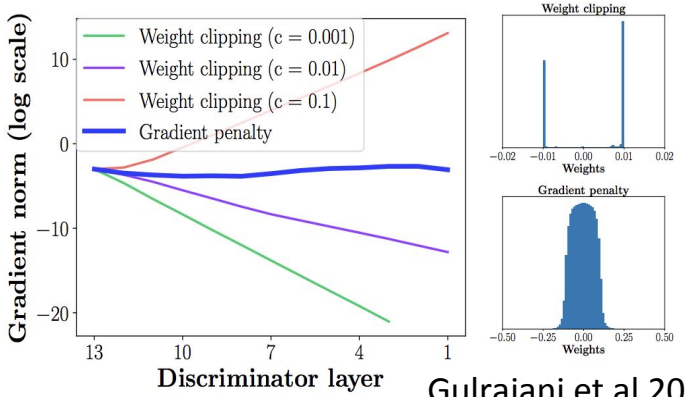
WGAN-GP: Gradient Penalty for Lipschitzness

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

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





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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

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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.

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WGAN-GP: Robustness to architectures

Nonlinearity (G)	[ReLU, LeakyReLU, $\frac{\text{softplus}(2x+2)}{2} - 1$, tanh]
Nonlinearity (D)	[ReLU, LeakyReLU, $\frac{\text{softplus}(2x+2)}{2} - 1$, tanh]
Depth (G)	[4, 8, 12, 20]
Depth (D)	[4, 8, 12, 20]
Batch norm (G)	[True, False]
Batch norm (D; layer norm for WGAN-GP)	[True, False]
Base filter count (G)	[32, 64, 128]
Base filter count (D)	[32, 64, 128]

Min. score	Only GAN	Only WGAN-GP	Both succeeded	Both failed
1.0	0	8	192	0
3.0	1	88	110	1
5.0	0	147	42	11
7.0	1	104	5	90
9.0	0	0	0	200

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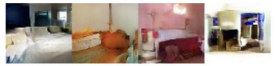
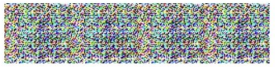
WGAN-GP: Robustness to architectures

DCGAN	LSGAN	WGAN (clipping)	WGAN-GP (ours)
Baseline (G: DCGAN, D: DCGAN)				
G: No BN and a constant number of filters, D: DCGAN				
G: 4-layer 512-dim ReLU MLP, D: DCGAN				
No normalization in either G or D				
Gated multiplicative nonlinearities everywhere in G and D				
tanh nonlinearities everywhere in G and D				
101-layer ResNet G and D				

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WGAN-GP: High quality samples

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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		Supervised	
Method	Score	Method	Score
ALI [8] (in [27])	$5.34 \pm .05$	SteinGAN [26]	6.35
BEGAN [4]	5.62	DCGAN (with labels, in [26])	6.58
DCGAN [22] (in [11])	$6.16 \pm .07$	Improved GAN [23]	$8.09 \pm .07$
Improved GAN (-L+HA) [23]	$6.86 \pm .06$	AC-GAN [20]	$8.25 \pm .07$
EGAN-Ent-VI [7]	$7.07 \pm .10$	SGAN-no-joint [11]	$8.37 \pm .08$
DFM [27]	$7.72 \pm .13$	WGAN-GP ResNet (ours)	$8.42 \pm .10$
WGAN-GP ResNet (ours)	$7.86 \pm .07$	**SGAN** [11]	$8.59 \pm .12$

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WGAN-GP: Summary

- Robustness to architectural choices
- Became a very popular GAN model - 2000+ citations, has been used in NVIDIA's Progressive GANs, StyleGAN, etc - biggest GAN successes
- Residual architecture widely adopted.
- Possible negative- slow wall clock time due to gradient penalty.
- Gradient penalty applied on a heuristic distribution of samples from current generator. Could be unstable when learning rates are high.

Outline

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- Other uses of Adversarial Loss: Transfer Learning, Fairness
- GANs and Imitation Learning

Progressive growing of GANs

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

Tero Karras NVIDIA
Timo Aila NVIDIA
Samuli Laine NVIDIA
Jaakko Lehtinen NVIDIA and Aalto University
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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.

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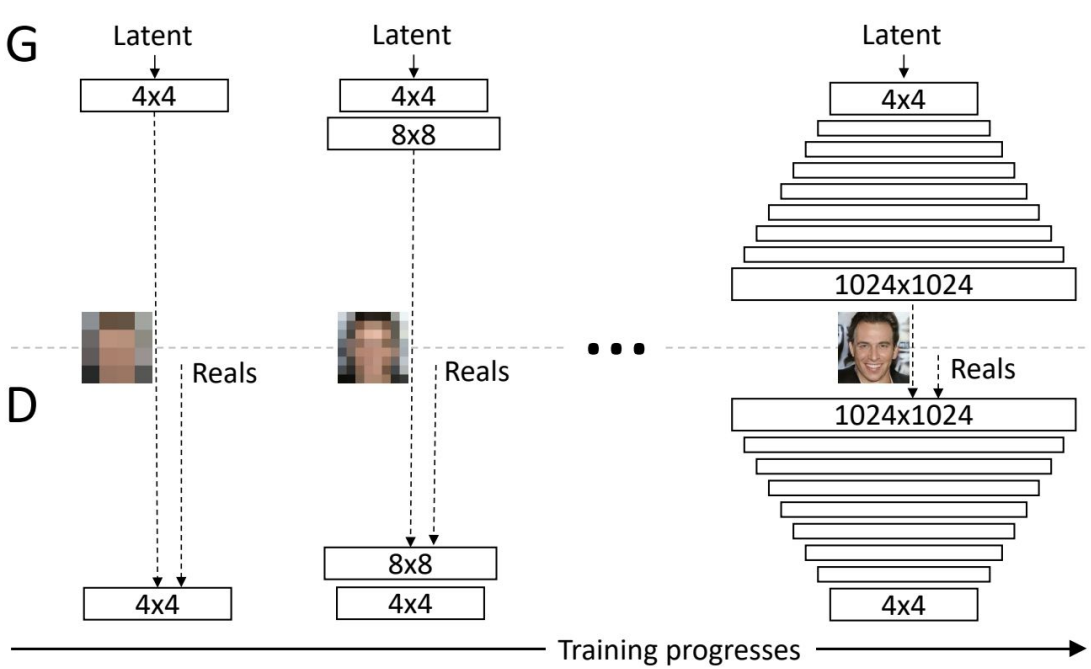
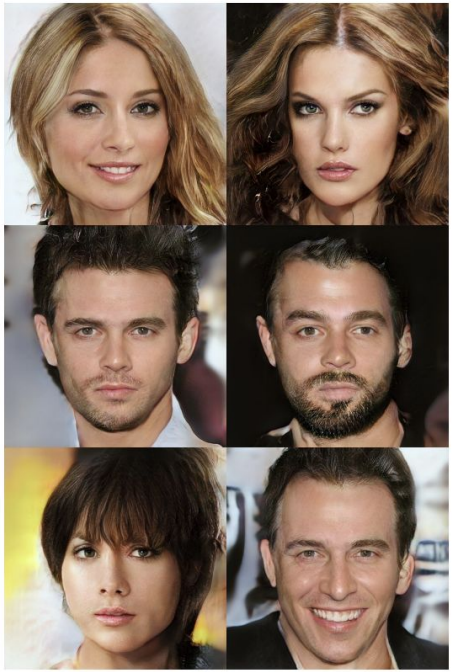
Progressive growing of GANs





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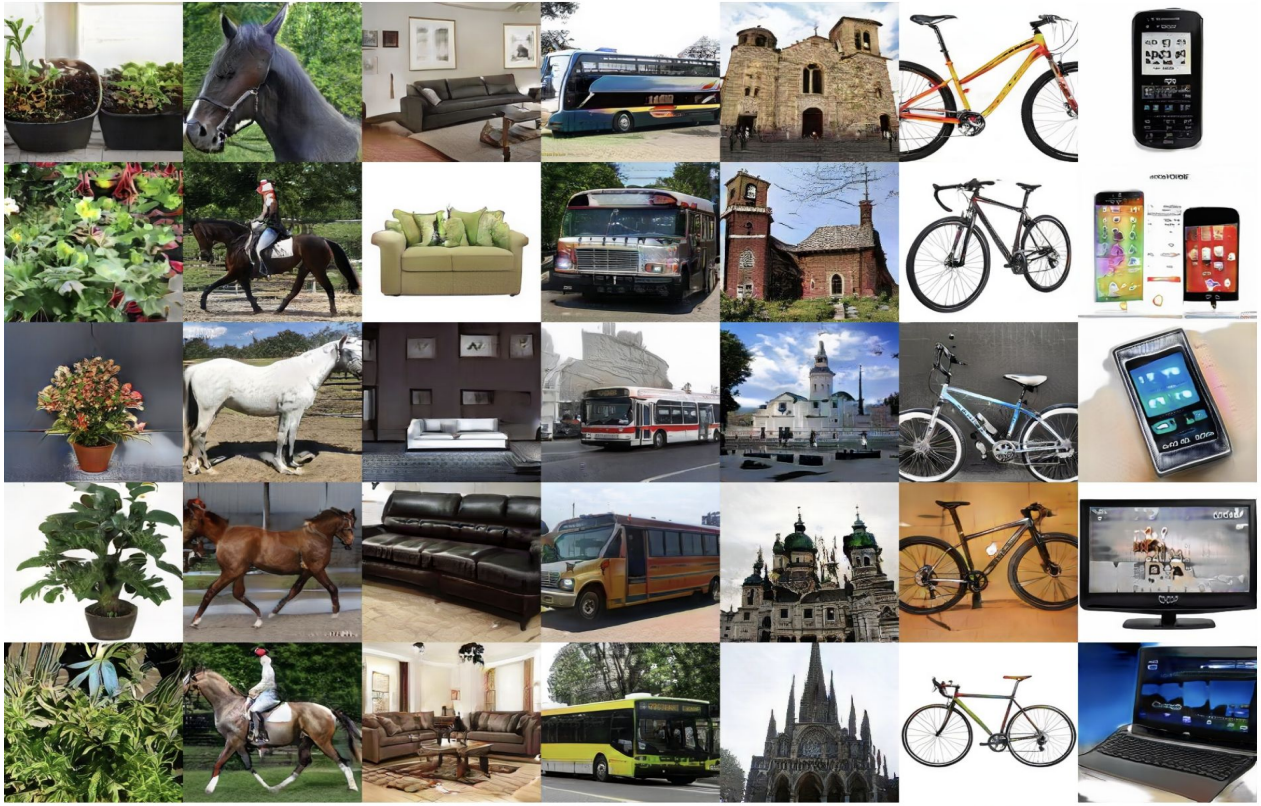
Progressive growing of GANs



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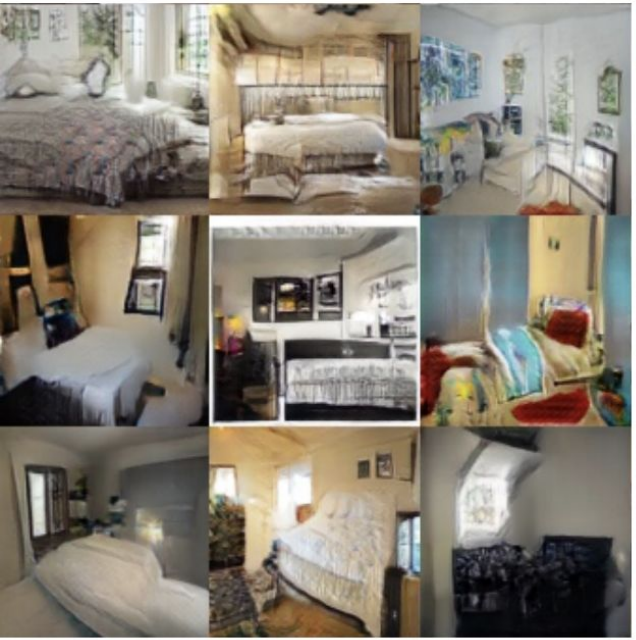
Progressive growing of GANs



Mao et al. (2016b) (128 × 128)

Gulrajani et al. (2017) (128 × 128)

Our (256 × 256)

Karras et al 2017

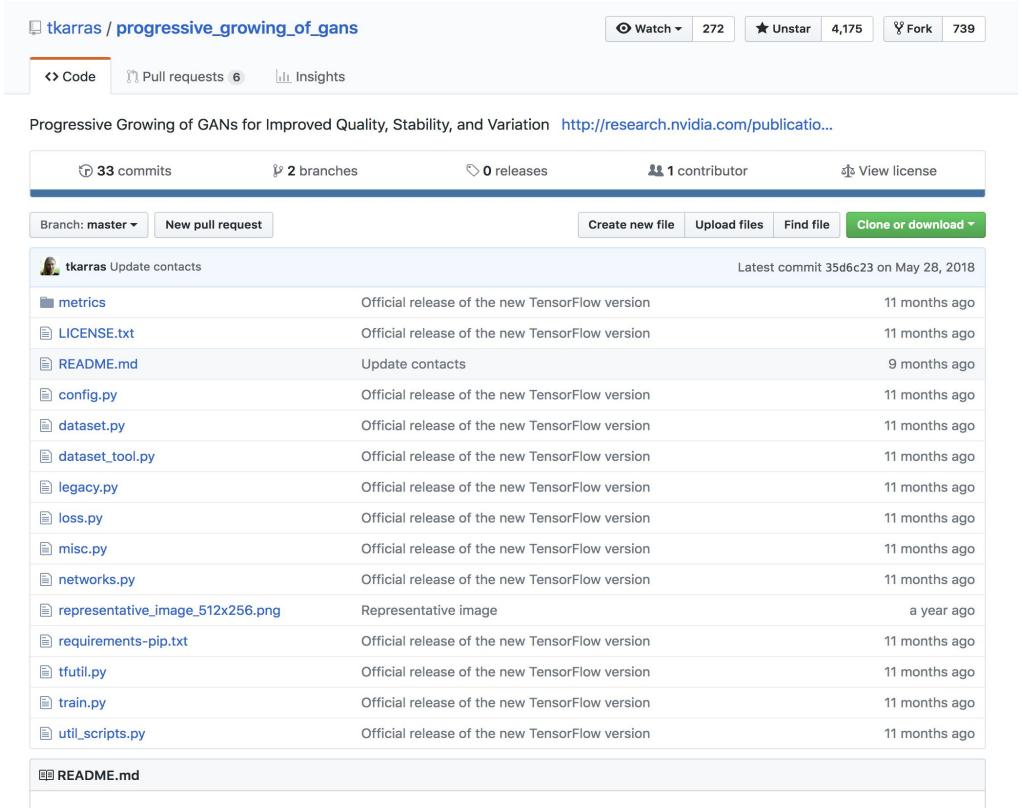
Progressive growing of GANs

Karras et al 2017

Progressive growing of GANs

Karras et al 2017

Progressive growing of GANs



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- GANs and Imitation Learning

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)

$$f(\boldsymbol{x}, \theta) = W^{L+1} a_L(W^L(a_{L-1}(W^{L-1}(\dots a_1(W^1 \boldsymbol{x}) \dots))))$$

$$D(\boldsymbol{x}, \theta) = \mathcal{A}(f(\boldsymbol{x}, \theta))$$

$$\min_G \max_D V(G, D)$$

$$\arg\max_{\|f\|_{\text{Lip}} \leq K} V(G, D)$$

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Spectral Normalization GAN (SNGAN)

- Key idea: Connecting Lipschitzness of discriminator to spectral norm of each layer.

$$g : \boldsymbol{h}_{in} \mapsto \boldsymbol{h}_{out}$$

$$\|g\|_{\text{Lip}} = \sup_{\boldsymbol{h}} \sigma(\nabla g(\boldsymbol{h}))$$

$$\sigma(A) := \max_{\boldsymbol{h}:\boldsymbol{h}\neq \mathbf{0}} \frac{\|A\boldsymbol{h}\|_2}{\|\boldsymbol{h}\|_2} = \max_{\|\boldsymbol{h}\|_2 \leq 1} \|A\boldsymbol{h}\|_2$$

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Spectral Normalization GAN (SNGAN)

$$\|g\|_{\text{Lip}} = \sup_{\boldsymbol{h}} \sigma(\nabla g(\boldsymbol{h})) = \sup_{\boldsymbol{h}} \sigma(W) = \sigma(W)$$

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

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

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

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

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Spectral Normalization GAN (SNGAN)

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

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

Geometric GAN

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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 $x \in \mathbb{R}^{128 \times 128 \times 3}$
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 $x \in \mathbb{R}^{128 \times 128 \times 3}$
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.

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Spectral Normalization GAN (SNGAN)

Miyato et al 2017

Spectral Normalization GAN (SNGAN)

```
# Batch Norm for convolution layers
def batch_normalization(x, *, eps=1e-8): # x in NHWC
  with tf.variable_scope('conv_bn'):
    mean, var = tf.nn.moments(x, [0, 1, 2], keep_dims=True)
    u = (x - mean)*tf.rsqrt(var + epsilon)
    scale, offset = tf.split(tf.get_variable('scale_offset',
                                [1, 1, 1, x.shape[-1].value] * 2))
    return u * scale + offset
```

Conditional Batch Normalization

```
# Conditional Batch Norm for convolution layers
def conditional_batch_normalization(x, y, *, eps=1e-8): # x in NHWC
  # x: 4D [b, h, w, c]; y: 2D [b, num_classes] (one-hot encoded)
  with tf.variable_scope('cond_conv_bn'):
    mean, var = tf.nn.moments(x, [0, 1, 2], keep_dims=True)
    u = (x - mean)*tf.rsqrt(var + epsilon)
    scale, offset = tf.split(
                    tf.layers.dense(y, 2 * x.shape[-1].value), 2, -1)
    return u * scale + offset
```

Conditional Batch Normalization with spec-norm

```
# Conditional Batch Norm (with SN) for convolution layers
def conditional_batch_normalization(x, y, *, eps=1e-8): # x in NHWC
  # x: 4D [b, h, w, c]; y: 2D [b, num_classes] (one-hot encoded)
  with tf.variable_scope('cond_conv_bn'):
    mean, var = tf.nn.moments(x, [0, 1, 2], keep_dims=True)
    u = (x - mean)*tf.rsqrt(var + epsilon)
    scale, offset = tf.split(
                    dense(y, 2 * x.shape[-1].value, use_sn=True), 2, -1)
    return u * scale + offset
```

Power Iteration to implement spec-norm

```
# Power Iteration
def spec_norm(w_, *, n_iterations=1):
  w = tf.reshape(w_, [-1, w.shape[-1]])
  u = tf.get_variable('u', shape=(w.shape[0], 1), trainable=False)
  for _ in range(n_iterations):
    v = tf.nn.l2_normalize(tf.matmul(w, u, transpose_a=True), epsilon)
    u = tf.nn.l2_normalize(tf.matmul(w, v), epsilon)
  u, v = tf.stop_gradient(u), tf.stop_gradient(v)
  norm_value = tf.matmul(tf.matmul(tf.transpose(u), w), v)
  w_normalized = tf.reshape(w / norm_value, w_.shape)
  return w_normalized
```

Power Iteration to implement spec-norm

```
# Power Iteration
def dense(x, *, n_out, name='dense', sn_iters=1, use_sn=True):
  with tf.get_variable(name):
    w = tf.get_variable('w', [x.shape[-1].value, n_out])
    if use_sn:
      w = spec_norm(w, n_iterations=sn_iters)
    b = tf.get_variable('b', [n_out], initializer=tf.zeros_initializer())
    return tf.nn.bias_add(tf.matmul(x, w), b)
```

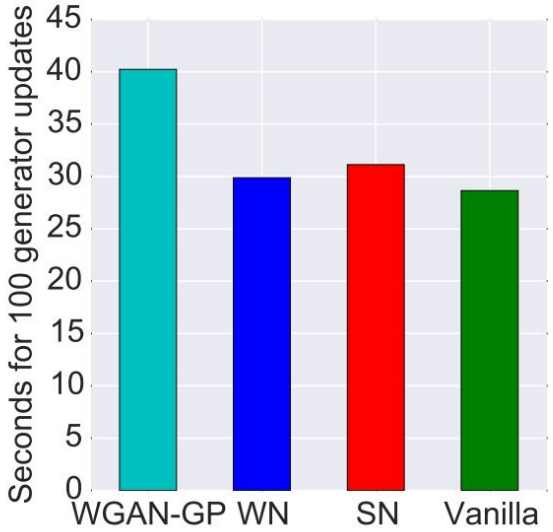
Power Iteration to implement spec-norm

```
# Power Iteration
def conv2d(x, *, n_out, kernels, strides, name, sn_iters=1, use_sn=True):
  with tf.get_variable(name):
    w = tf.get_variable('w', [*kernels, x.shape[-1].value, n_out])
    if use_sn:
      w = spec_norm(w, n_iterations=sn_iters)
    b = tf.get_variable('b', [n_out], initializer=tf.zeros_initializer())
    return tf.nn.bias_add(tf.nn.conv2d(x, w, [1, *strides, 1])
```

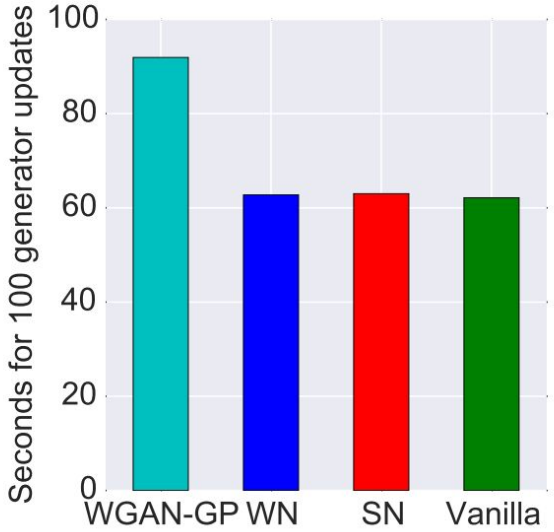
SNGAN: Summary

- 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)

SNGAN: Computational Benefits

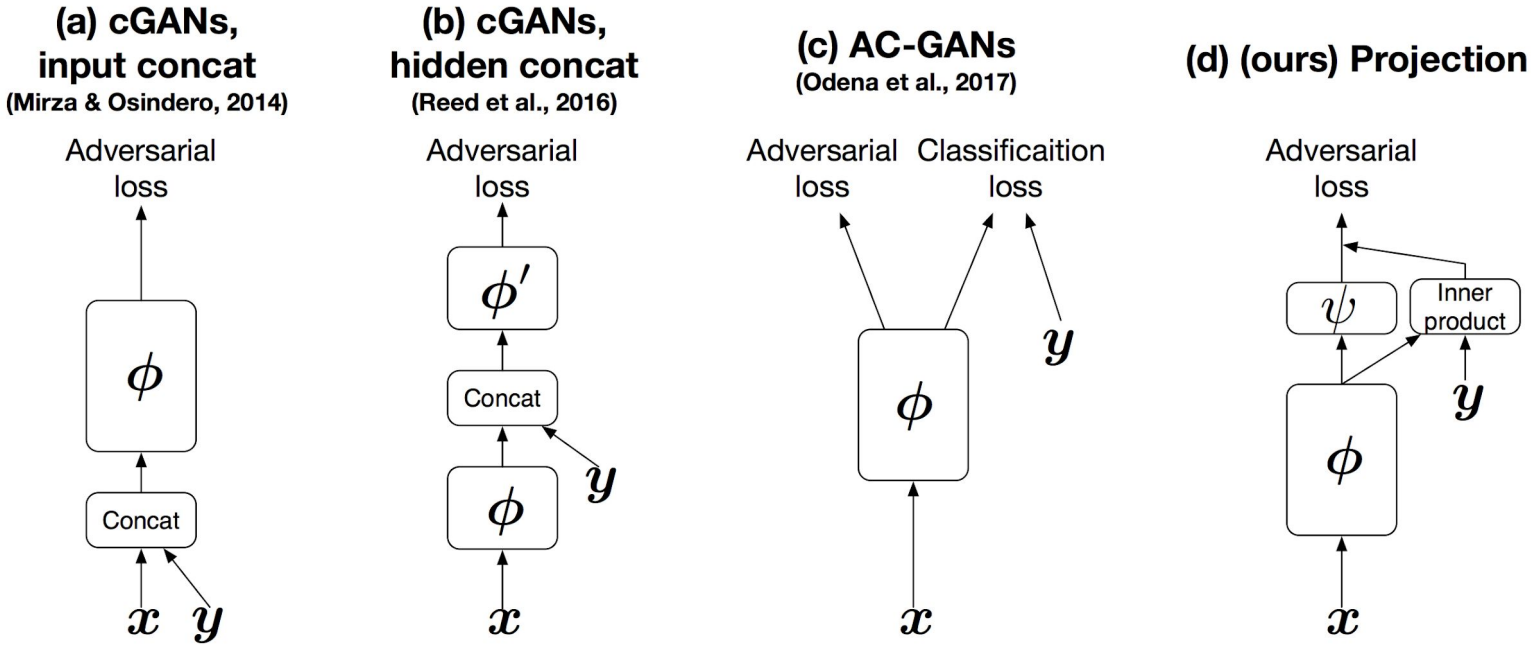


(a) CIFAR-10 (image size:32 × 32 × 3)



(b) STL-10 (images size:48 × 48 × 3)

Projection Discriminator



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Self Attention GAN (SAGAN)

Self-Attention Generative Adversarial Networks

Han Zhang* Rutgers University

Ian Goodfellow Google Brain

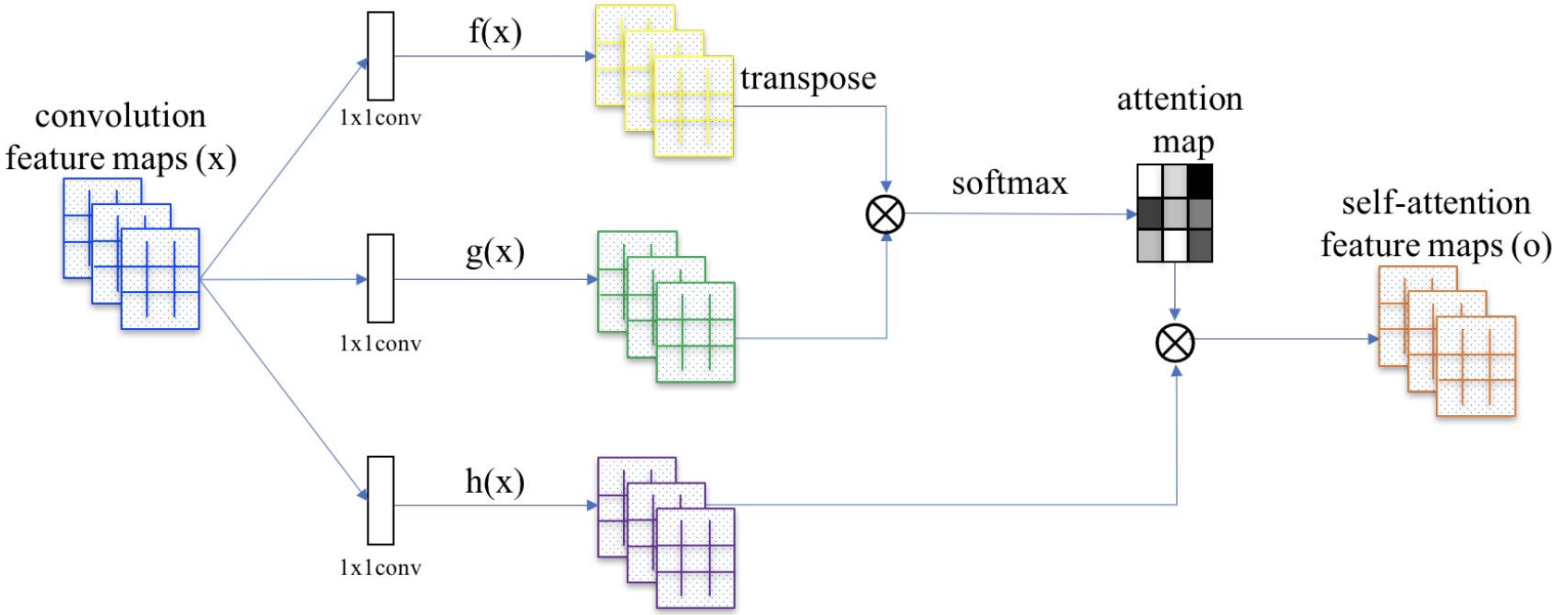
Dimitris Metaxas Rutgers University

Augustus Odena Google Brain

Abstract

In this paper, we propose the Self-Attention Generative Adversarial Network (SAGAN) which allows attention-driven, long-range dependency modeling for image generation tasks. Traditional convolutional GANs generate high-resolution details as a function of only spatially local points in lower-resolution feature maps. In SAGAN, details can be generated using cues from all feature locations. Moreover, the discriminator can check that highly detailed features in distant portions of the image are consistent with each other. Furthermore, recent work has shown that generator conditioning affects GAN performance. Leveraging this insight, we apply spectral normalization to the GAN generator and find that this improves training dynamics. The proposed SAGAN achieves the state-of-the-art results, boosting the best published Inception score from 36.8 to 52.52 and reducing Fréchet Inception distance from 27.62 to 18.65 on the challenging ImageNet dataset. Visualization of the attention layers shows that the generator leverages neighborhoods that correspond to object shapes rather than local regions of fixed shape.

Self Attention GAN (SAGAN)



Zhang et al 2018

Self Attention GAN (SAGAN)

$$\boldsymbol{f(x) = W_f x},\ \boldsymbol{g(x) = W_g x}$$

$$\beta_{j,i} = \frac{\exp(s_{ij})}{\sum_{i=1}^{N} \exp(s_{ij})}$$

$$\boldsymbol{s_{ij} = f(x_i)^T g(x_j)}$$

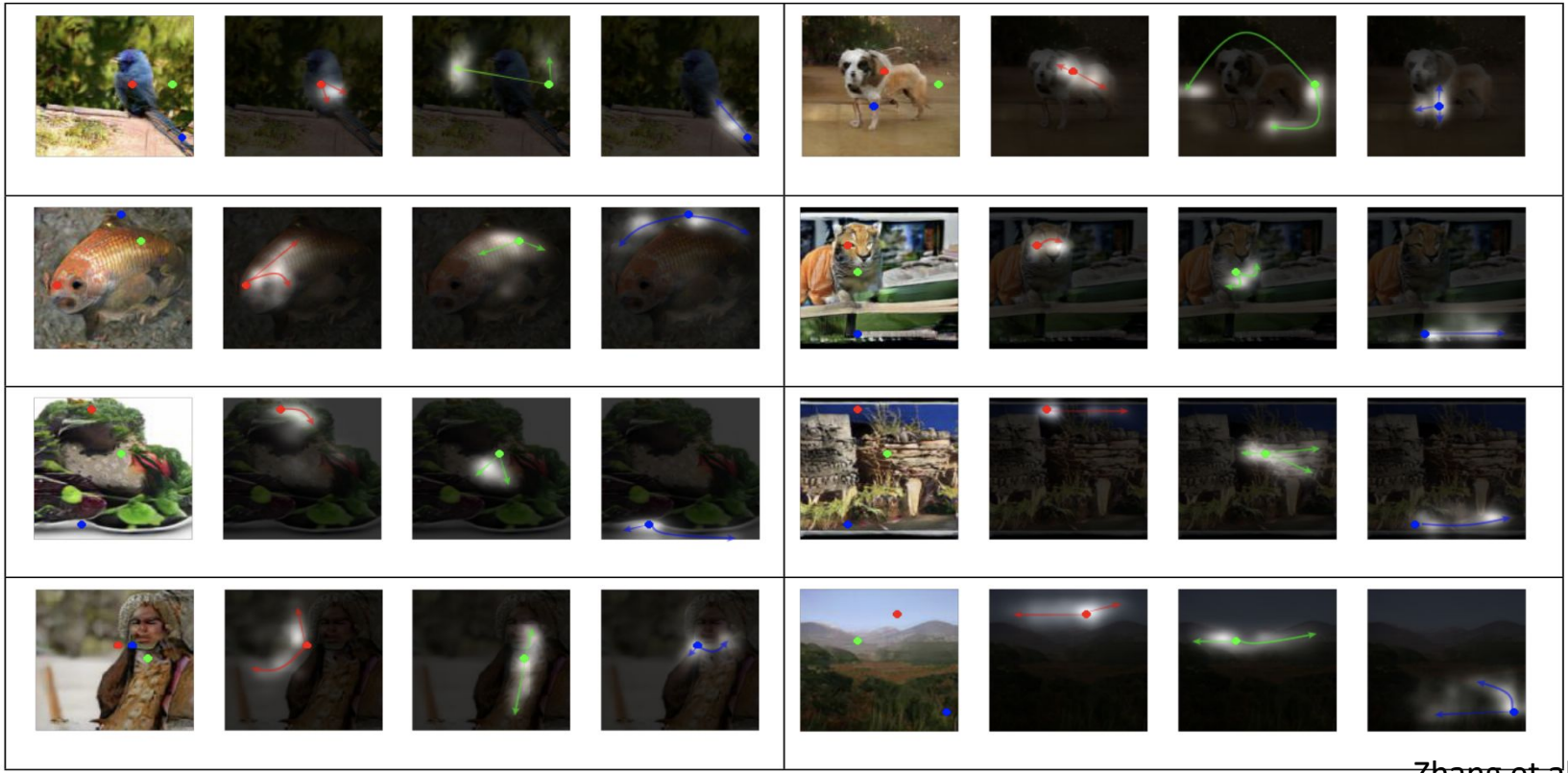
$$\boldsymbol{y_i = \gamma o_i + x_i}$$

Zhang et al 2018

Self Attention GAN (SAGAN)

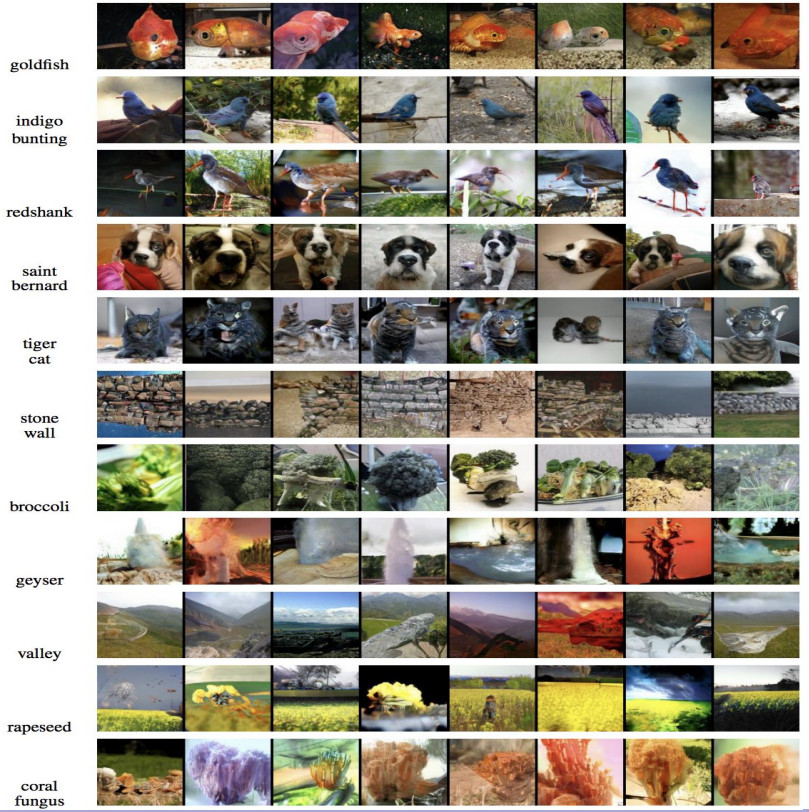
- Salient bits:
  - Applies spectral normalization to both the generator and discriminator weight matrices
    - This is counter-intuitive to popular belief that you only have to mathematically condition the discriminator
  - Uses self-attention in both the generator and discriminator
  - Hinge Loss
  - First GAN to produce “good” unconditional full Imagenet samples
  - Conditional models
    - Conditional BN for G, Projection Discriminator for D

Self Attention GAN (SAGAN)



Zhang et al 2018

Self Attention GAN (SAGAN)



Zhang et al 2018

Self Attention GAN (SAGAN)

Model	Inception Score	FID
AC-GAN [31]	28.5	/
SNGAN-projection [17]	36.8	27.62*
SAGAN	**52.52**	**18.65**

Table 2: Comparison of the proposed SAGAN with state-of-the-art GAN models [19, 17] for class conditional image generation on ImageNet. FID of SNGAN-projection is calculated from officially released weights.

Zhang et al 2018

Outline

- Motivation & Definition of Implicit Models
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Some Theory: Bayes-optimal Discriminator; Jensen-Shannon Divergence; Mode Collapse; Avoiding Saturation
- **GAN Progression:**
  - DC GAN (Radford et al, 2016)
  - Improved Training of GANs (Salimans et al, 2016)
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN, SAGAN
  - ***BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, VIB-GAN***
- Creative Conditional GANs
- GANs and Representations
- GANs as Energy Models
- GANs and Optimal Transport, Implicit Likelihood Models, Moment Matching
- Other uses of Adversarial Loss: Transfer Learning, Fairness
- GANs and Imitation Learning

BigGAN

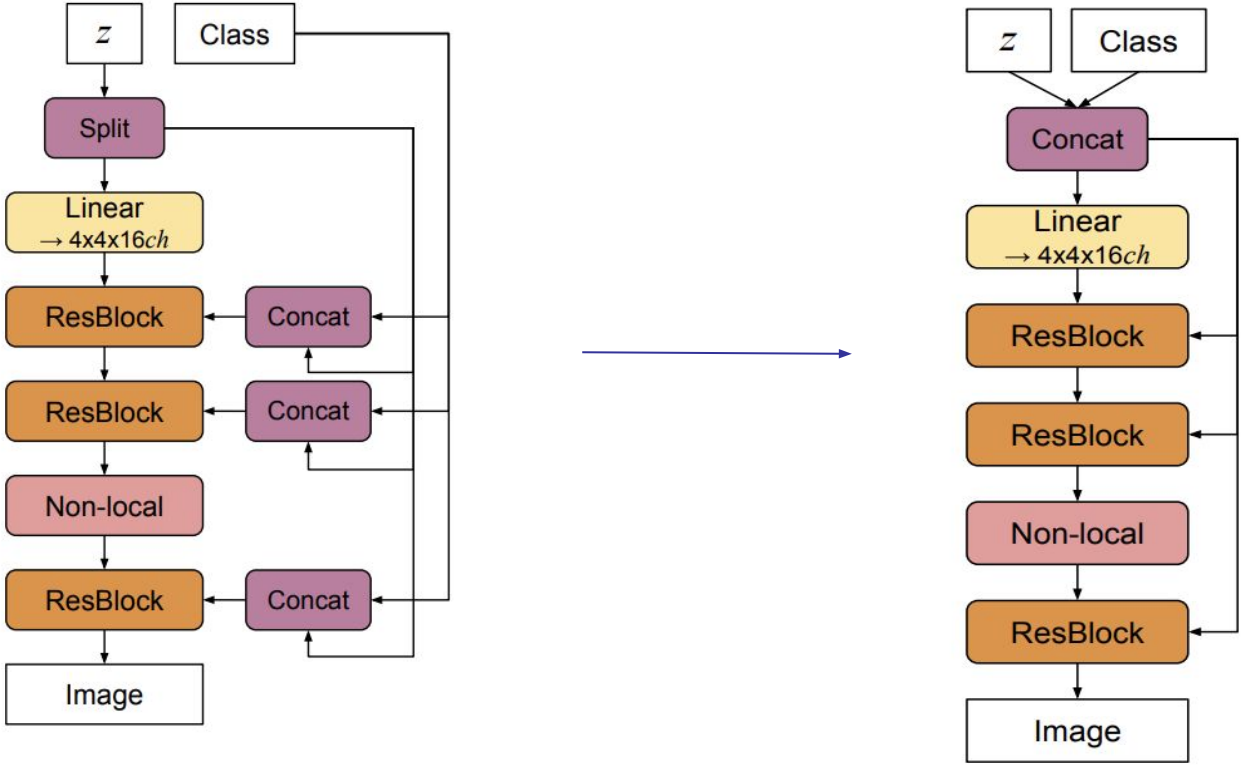
BigGAN

BigGAN

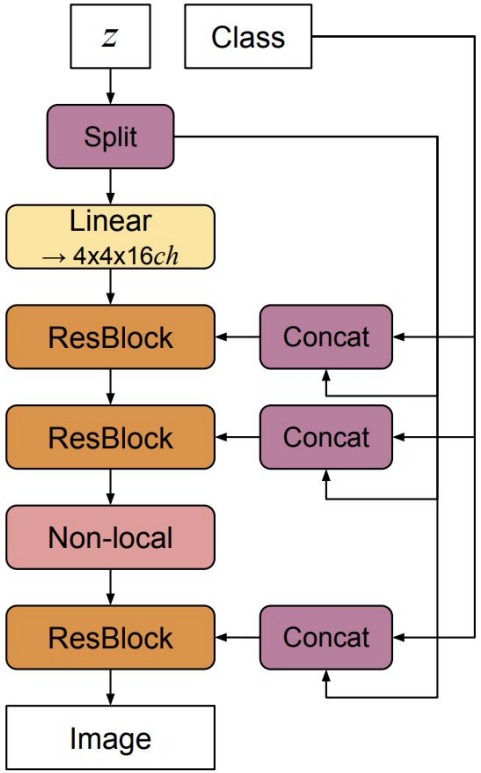
$$R_\beta(W) = \beta \|W^\top W - I\|_{\mathrm{F}}^2$$

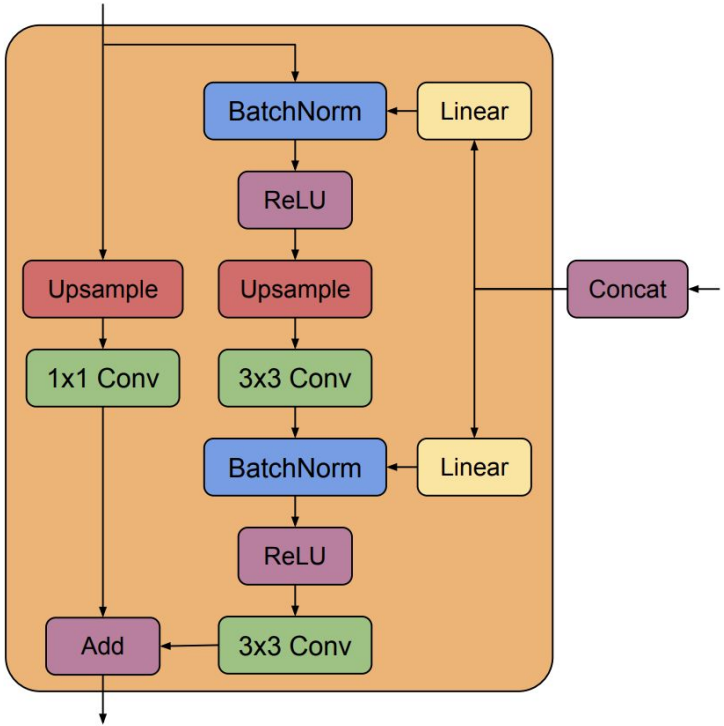
$$R_\beta(W) = \beta \|W^\top W \odot (\mathbf{1} - I)\|_{\mathrm{F}}^2,$$

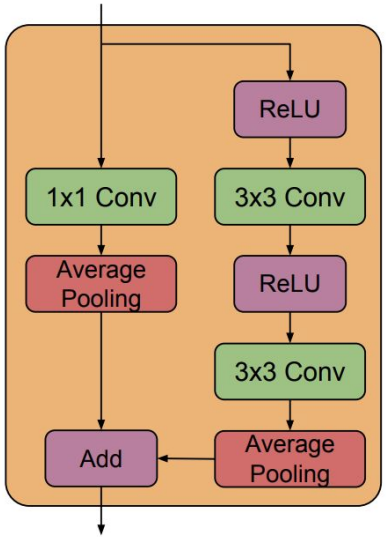
BigGAN and BigGAN-deep



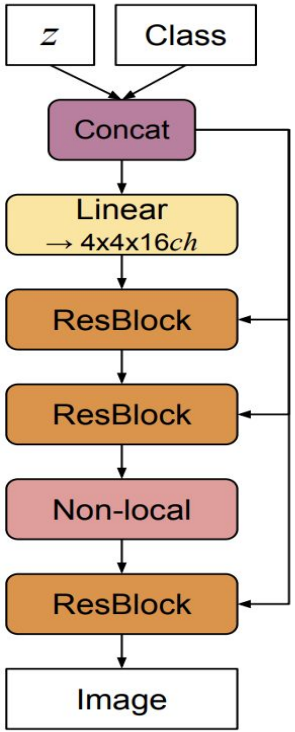
BigGAN

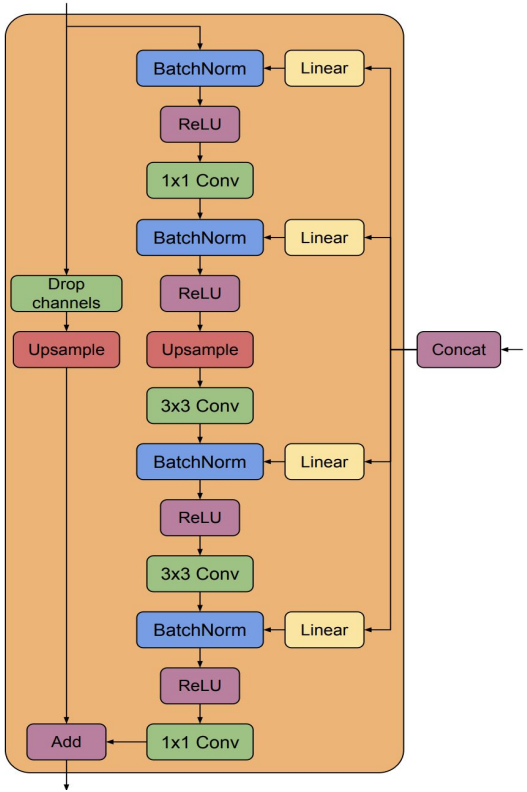

z
Class
Split
Linear
→ 4x4x16ch
ResBlock
Concat
ResBlock
Concat
Non-local
ResBlock
Concat
Image

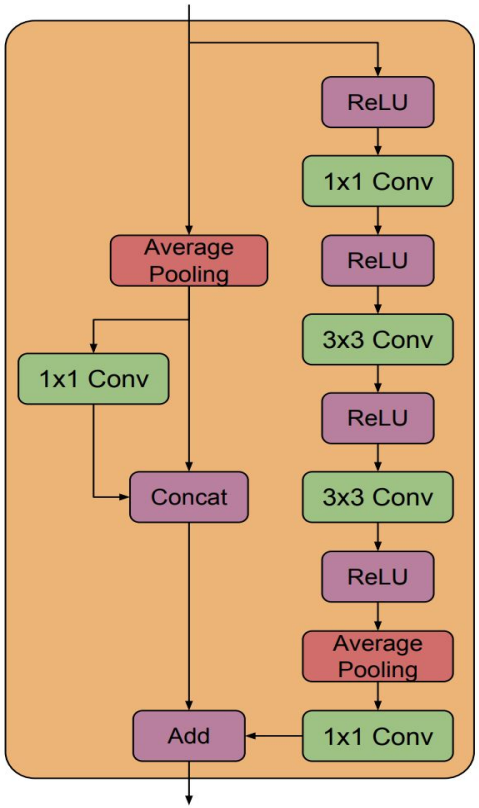

BatchNorm
Linear
ReLU
Upsample
Upsample
Concat
1x1 Conv
3x3 Conv
BatchNorm
Linear
ReLU
Add
3x3 Conv


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 $(20 + 128) \rightarrow 4 \times 4 \times 16ch$
ResBlock up $16ch \rightarrow 16ch$
ResBlock up $16ch \rightarrow 8ch$
ResBlock up $8ch \rightarrow 8ch$
ResBlock up $8ch \rightarrow 4ch$
Non-Local Block (64×64)
ResBlock up $4ch \rightarrow 2ch$
ResBlock up $2ch \rightarrow ch$
ResBlock up $ch \rightarrow ch$
BN, ReLU, 3×3 Conv $ch \rightarrow 3$
Tanh

(a) Generator

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

(b) Discriminator

BigGAN

- Salient bits
  - 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)

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

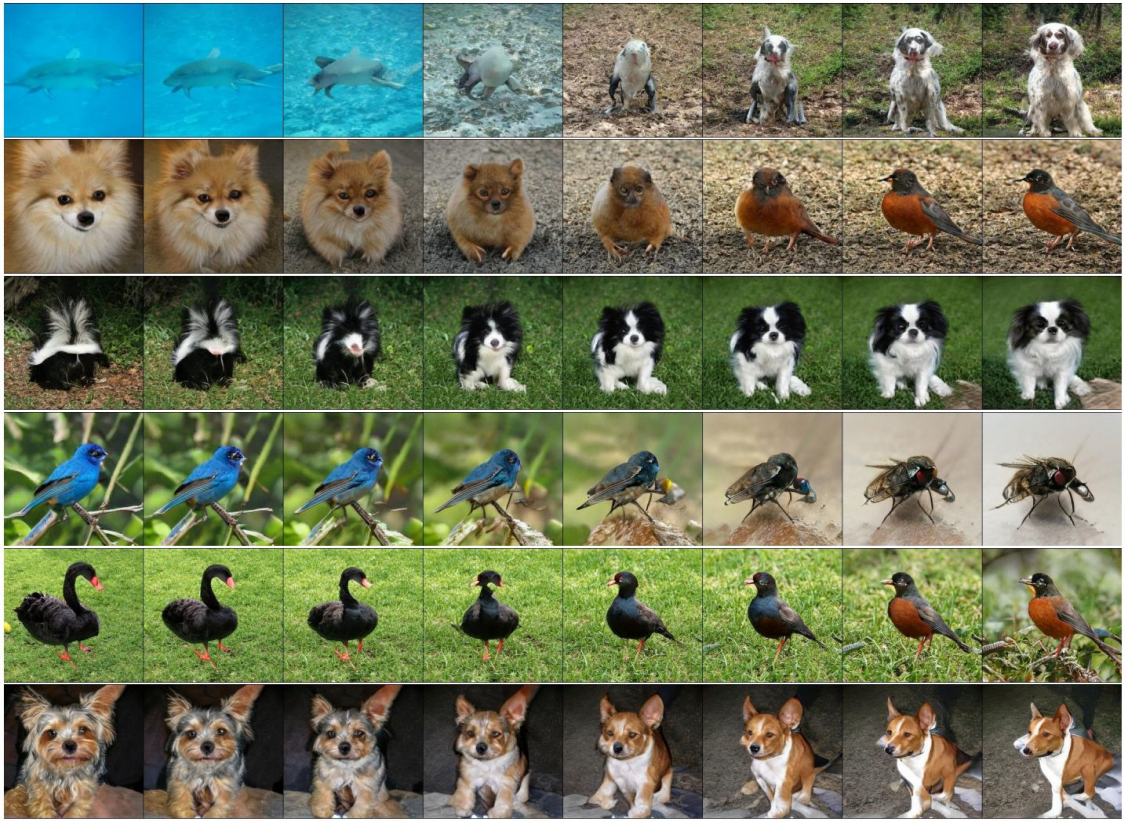
(a) 128×128

(b) 256×256

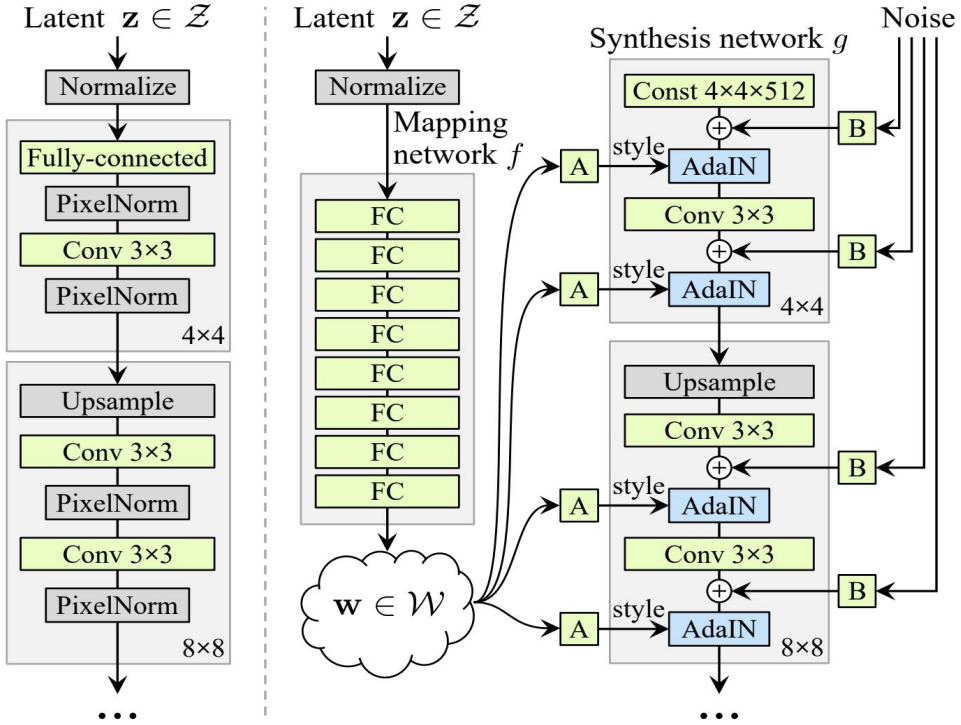
(c) 512×512

(d)

BigGAN



StyleGAN



(a) Traditional (b) Style-based generator

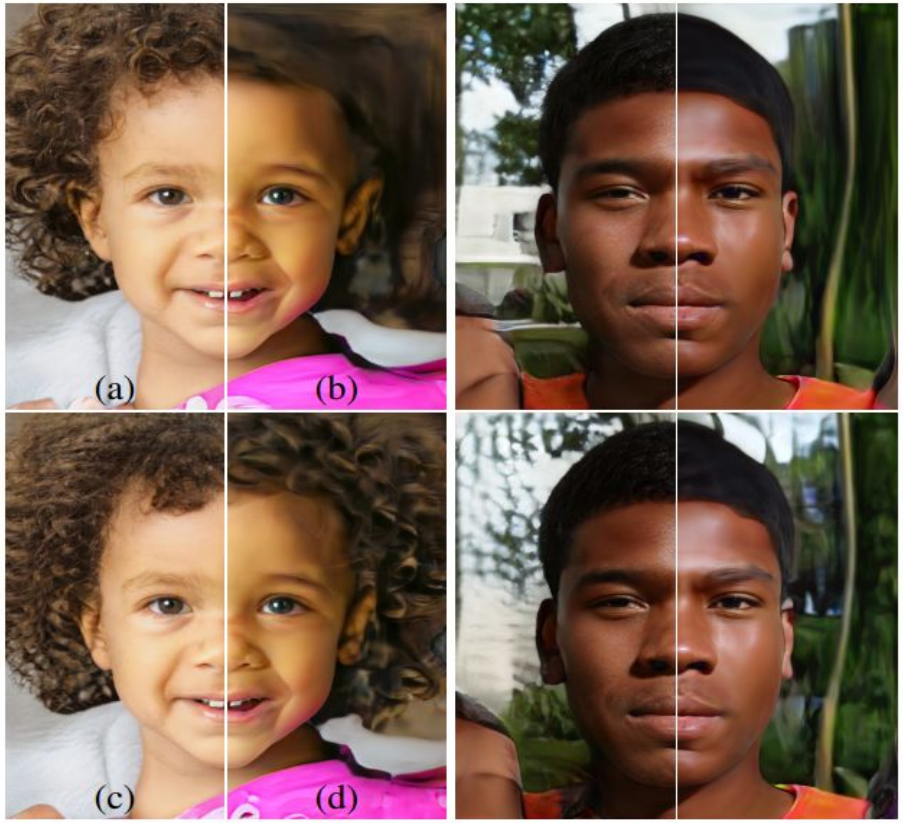
StyleGAN - Adaptive Instance Norm

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

StyleGAN - Style Transfer

StyleGAN

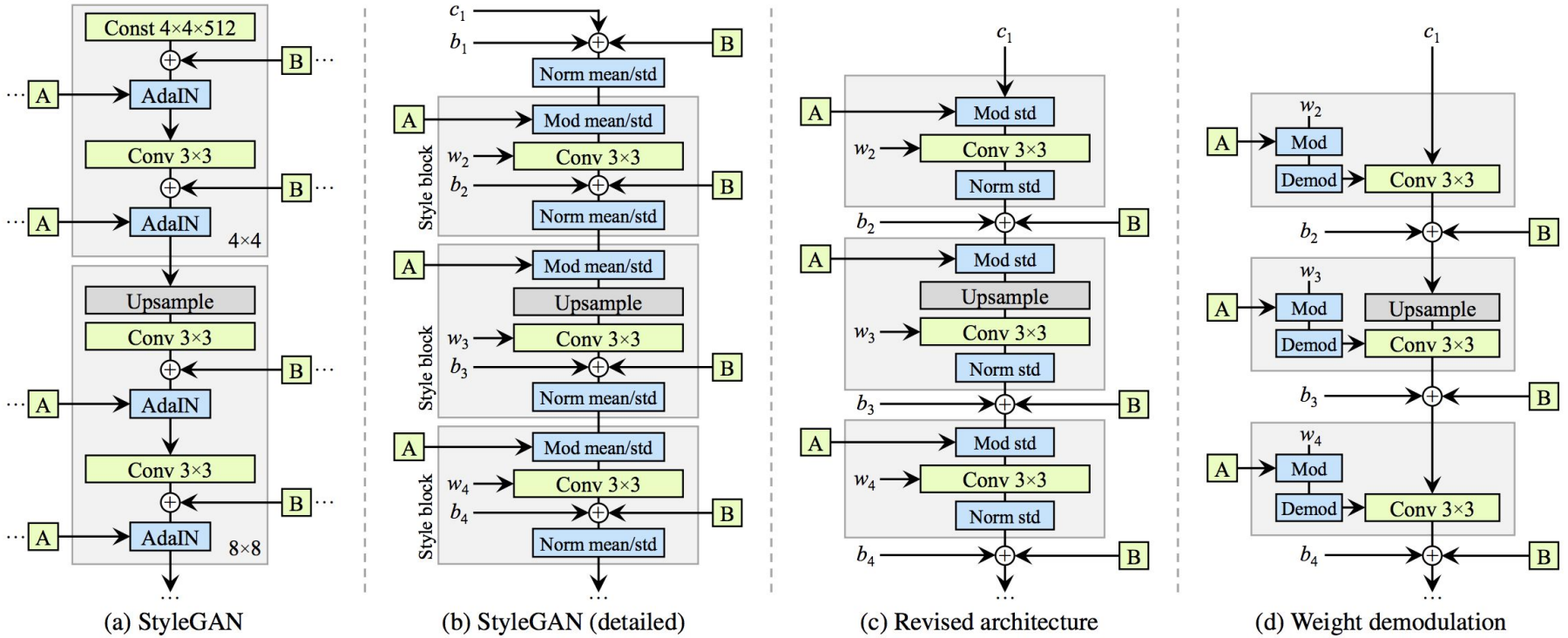
StyleGAN - Effect of adding noise



StyleGAN-v2

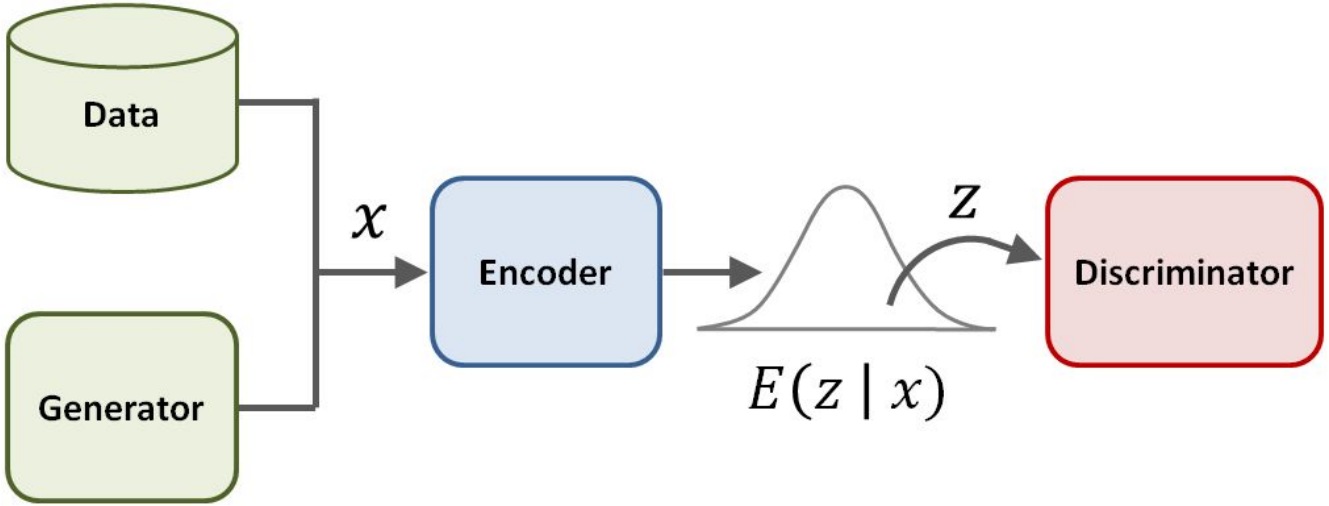
Figure 1. Instance normalization causes water droplet -like artifacts in StyleGAN images. These are not always obvious in the generated images, but if we look at the activations inside the generator network, the problem is always there, in all feature maps starting from the 64x64 resolution. It is a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

StyleGAN-v2


Const 4×4×512
B
A
AdaIN
Conv 3×3
4×4
Upsample
8×8
(a) StyleGAN
c_1
b_1
Norm mean/std
Mod mean/std
Style block
w_2
b_2
w_3
b_3
w_4
b_4
(b) StyleGAN (detailed)
Mod std
Norm std
(c) Revised architecture
Mod
Demod
(d) Weight demodulation

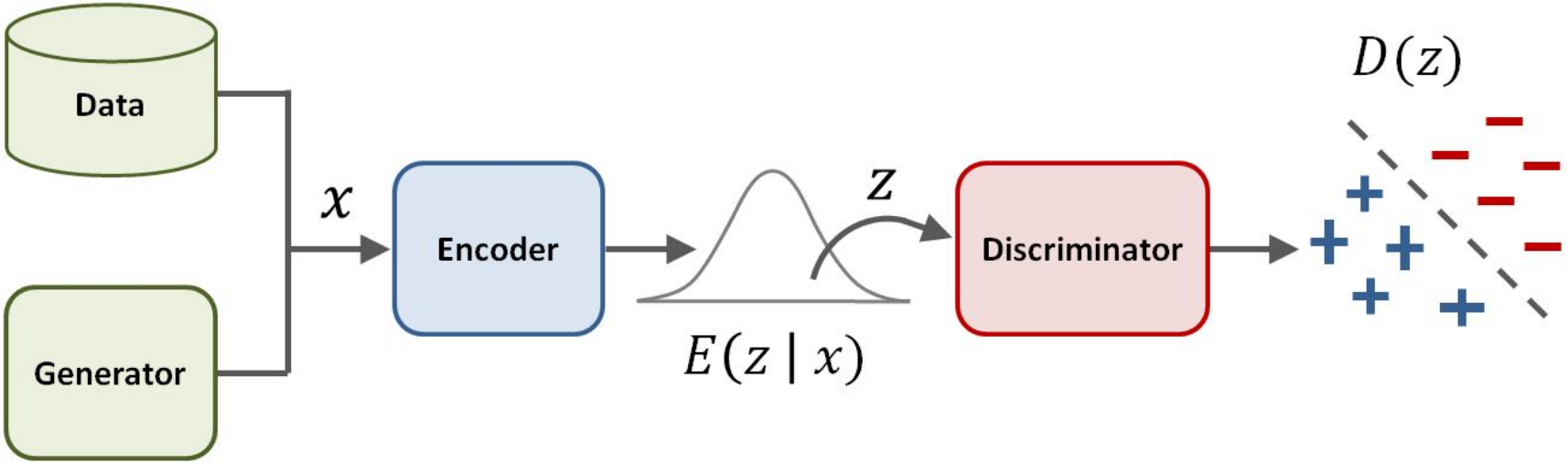
StyleGAN-v2

Information Bottleneck



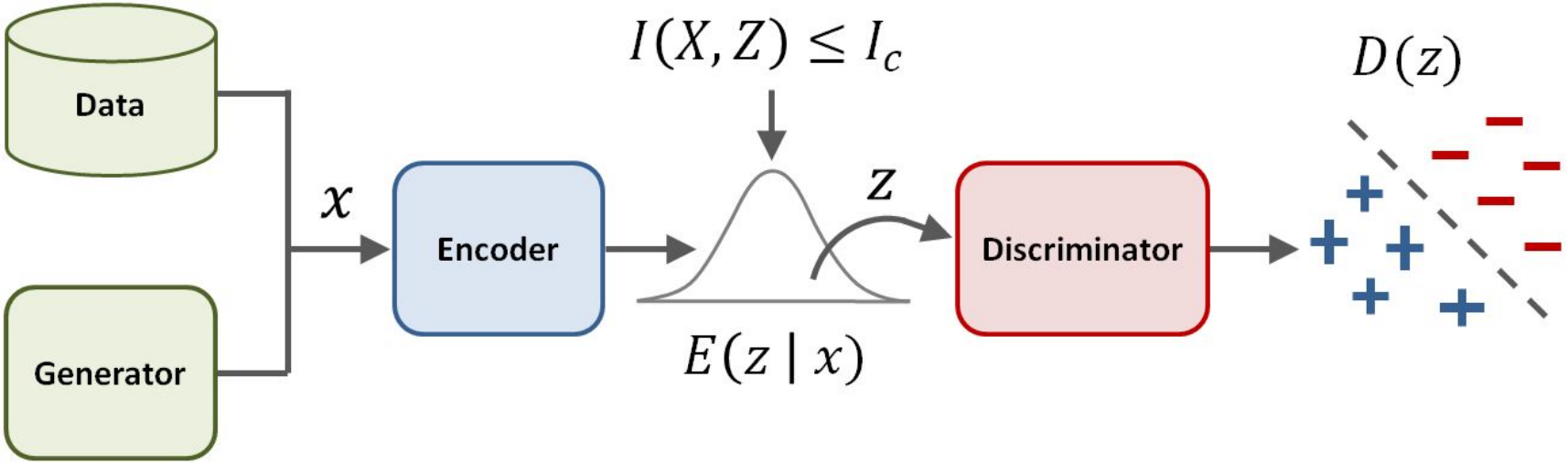
Variational Information Bottleneck [Alemi et al., 2016]
Variational Information Bottleneck GAN [Peng et al, 2019]

Information Bottleneck



Variational Information Bottleneck [Alemi et al., 2016]
Variational Information Bottleneck GAN [Peng et al, 2019]

Information Bottleneck



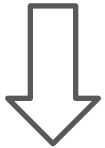
Variational Information Bottleneck [Alemi et al., 2016]
Variational Information Bottleneck GAN [Peng et al, 2019]

Information Bottleneck

$$I(X, Z) \leq I_c$$

Information Bottleneck

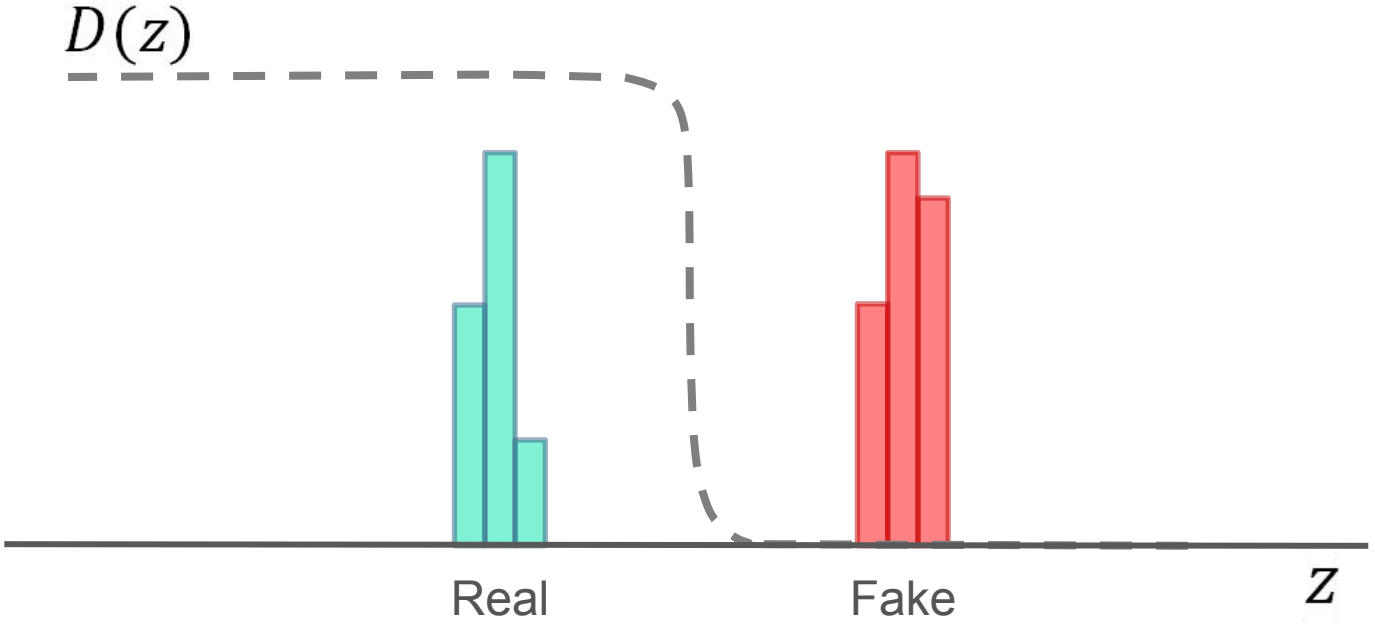
$$I(X, Z) \leq I_c$$



$$\mathbb{E}_{\mathbf{x} \sim \tilde{p}(\mathbf{x})} \left[\mathrm{KL} \left[E(\mathbf{z}|\mathbf{x}) || r(\mathbf{z}) \right] \right] \leq I_c$$

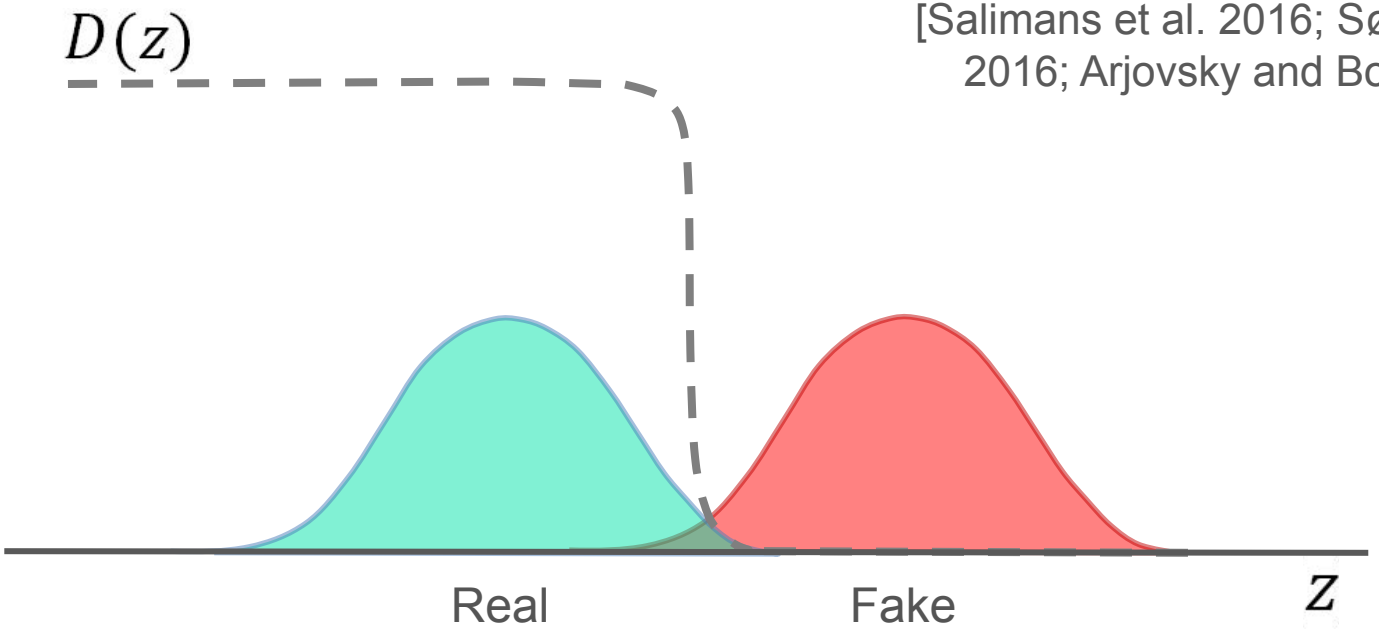
Variational Information Bottleneck (VIB)
[Alemi et al., 2016]

Variational Information Bottleneck



Variational Information Bottleneck

Instance Noise
[Salimans et al. 2016; Sønderby et al. 2016; Arjovsky and Bottou 2017]



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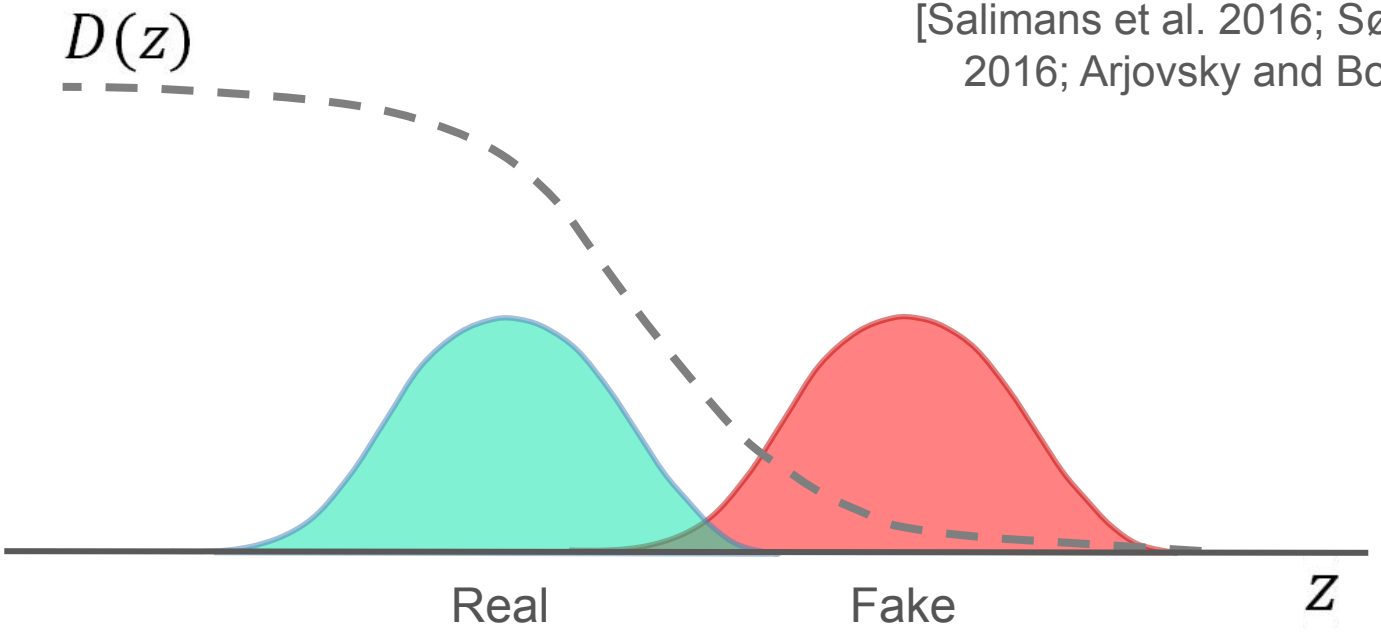

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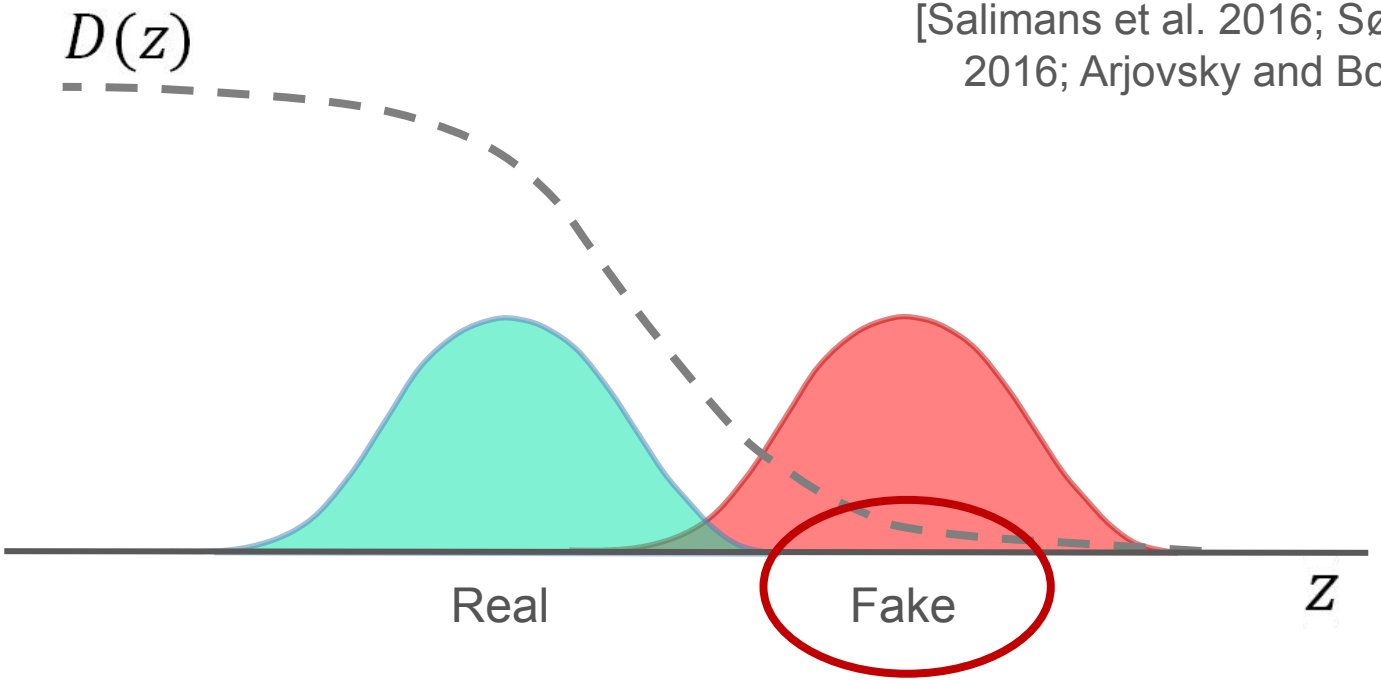

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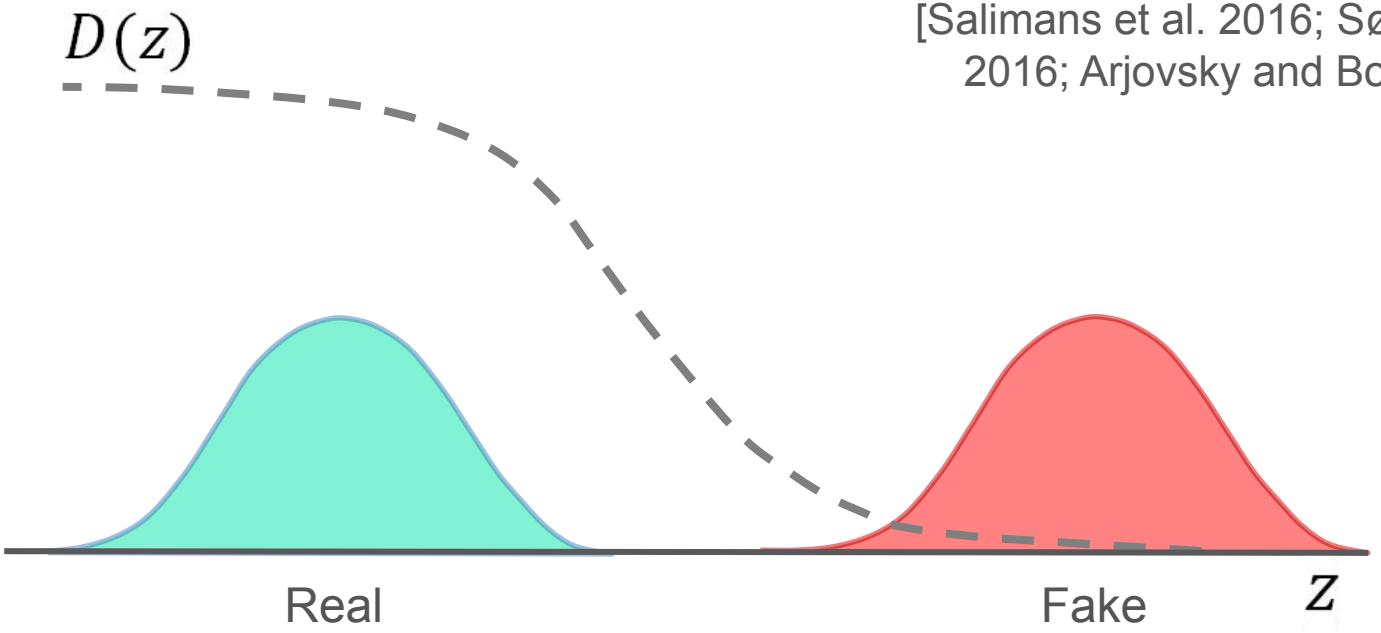

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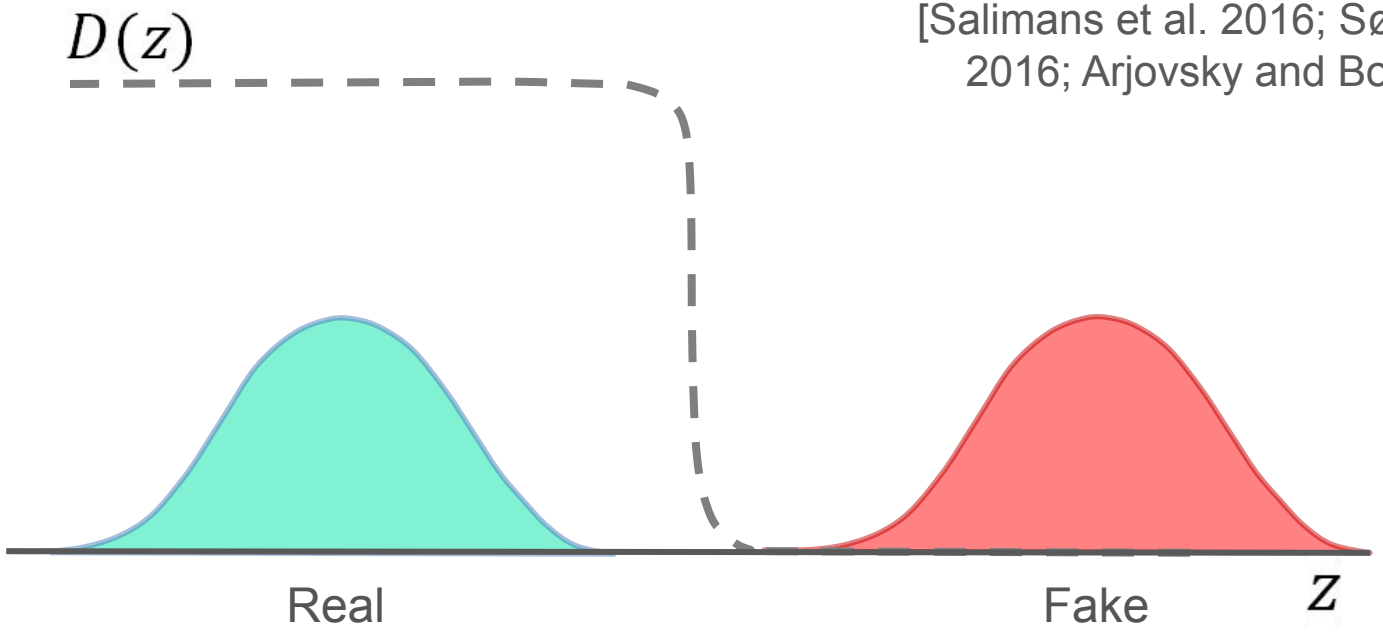
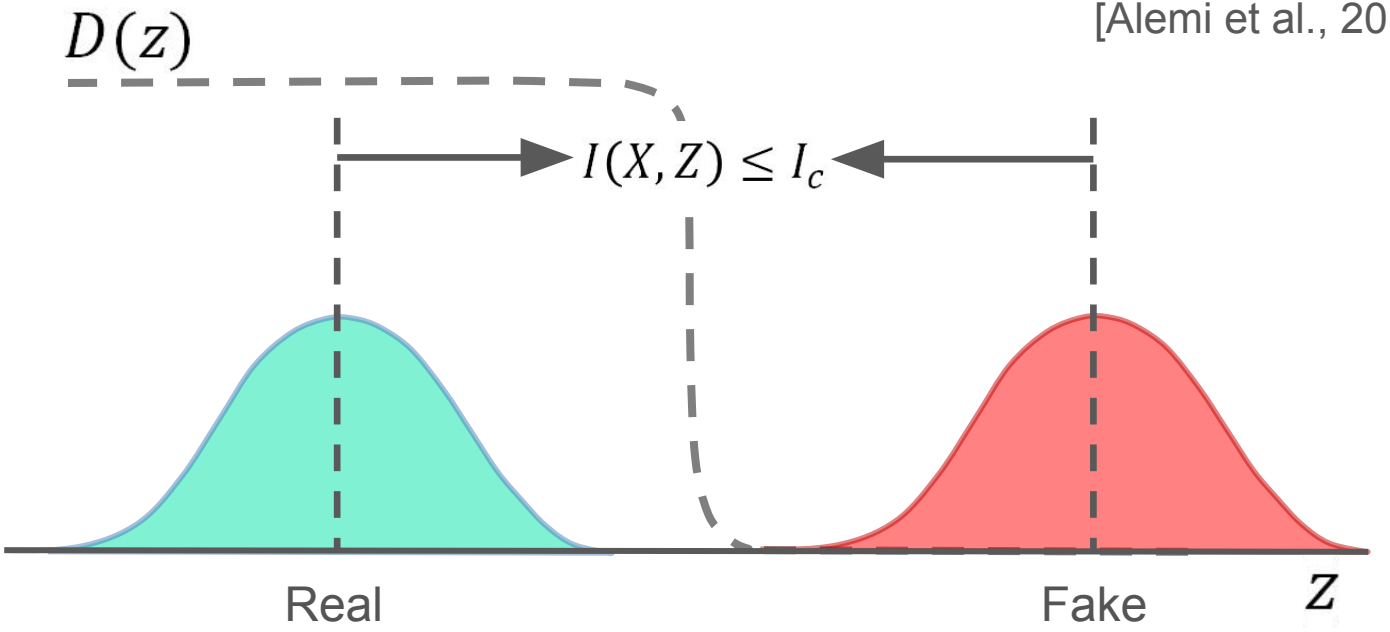


Variational Information Bottleneck

Variational Information Bottleneck
[Alemi et al., 2016]



Variational Information Bottleneck

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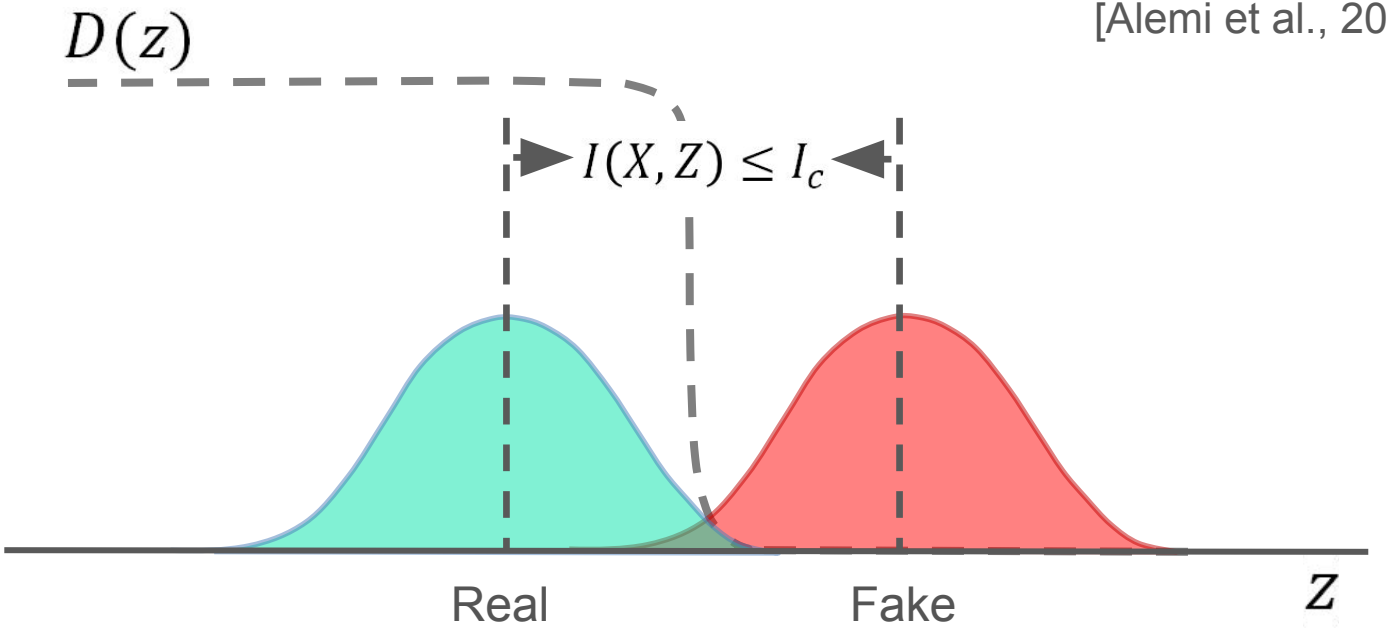

Variational Information Bottleneck

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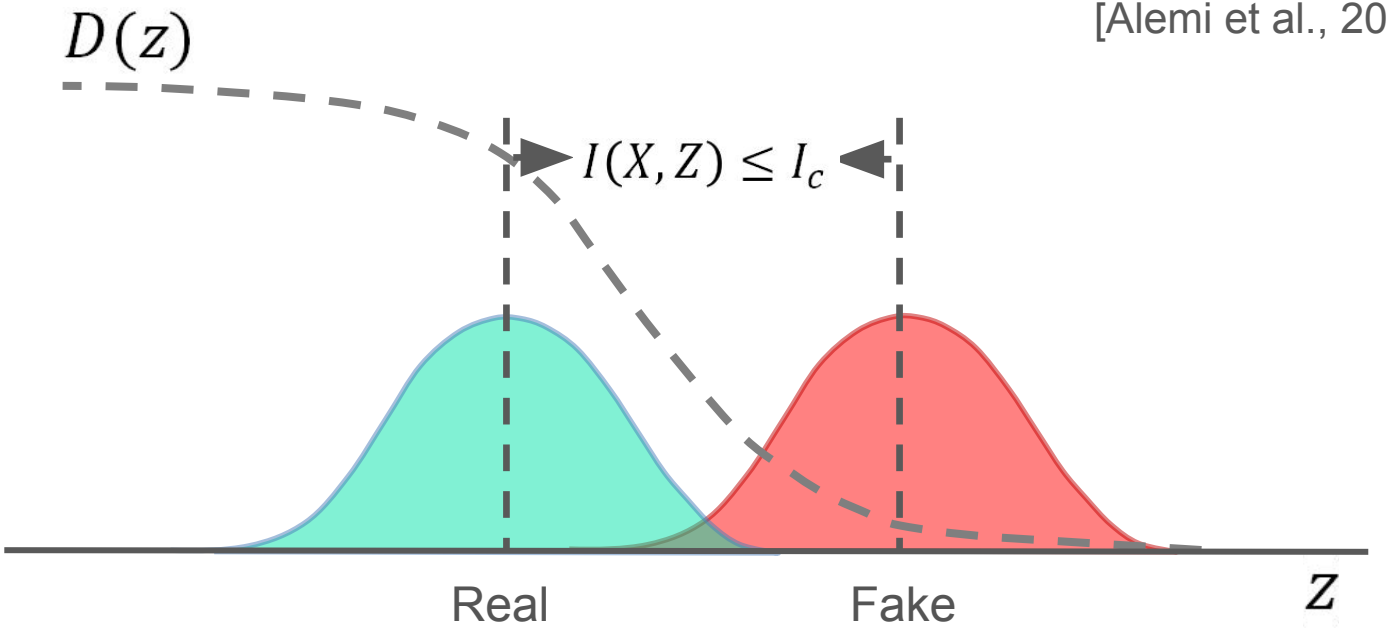
[Alemi et al., 2016]



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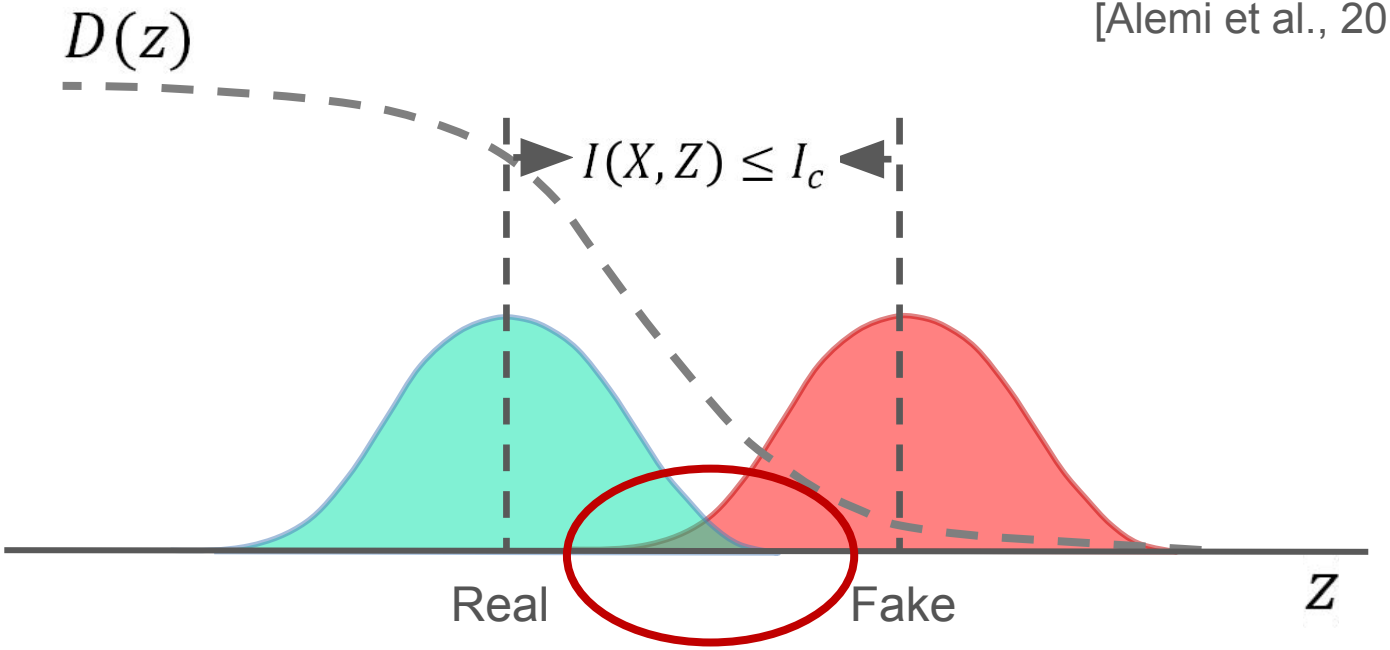


Outline

- Motivation & Definition of Implicit Models
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Some Theory: Bayes-optimal Discriminator; Jensen-Shannon Divergence; Mode Collapse; Avoiding Saturation
- GAN Progression:
  - DC GAN (Radford et al, 2016)
  - Improved Training of GANs (Salimans et al, 2016)
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN, SAGAN
  - BigGAN, BigGAN-Deep, StyleGAN, StyleGAN-v2, VIB-GAN
- ***Creative Conditional GANs***
- GANs and Representations
- GANs as Energy Models
- GANs and Optimal Transport, Implicit Likelihood Models, Moment Matching
- Other uses of Adversarial Loss: Transfer Learning, Fairness
- GANs and Imitation Learning

Conditional GANs / pix2pix

$\mathbf{x}$

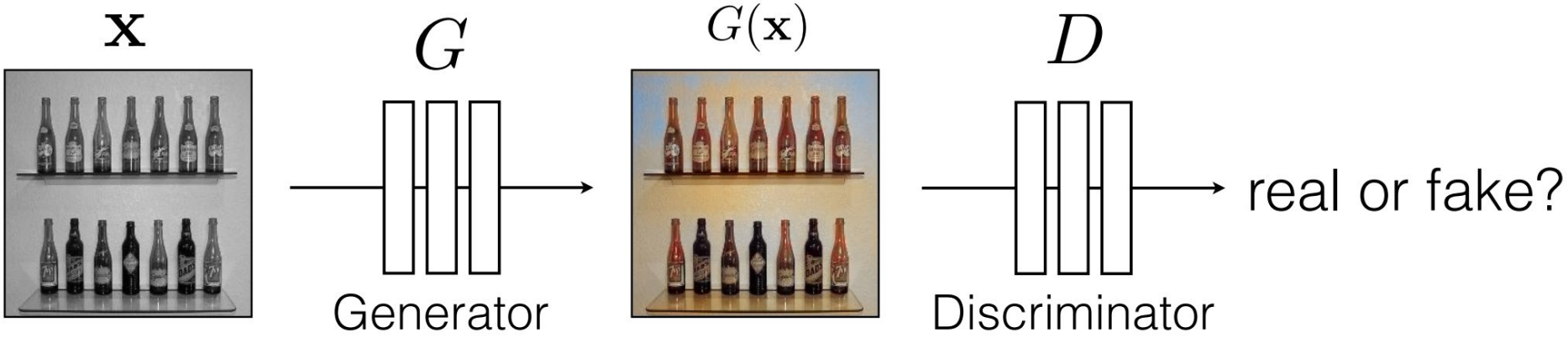
G

Generator

$G(\mathbf{x})$

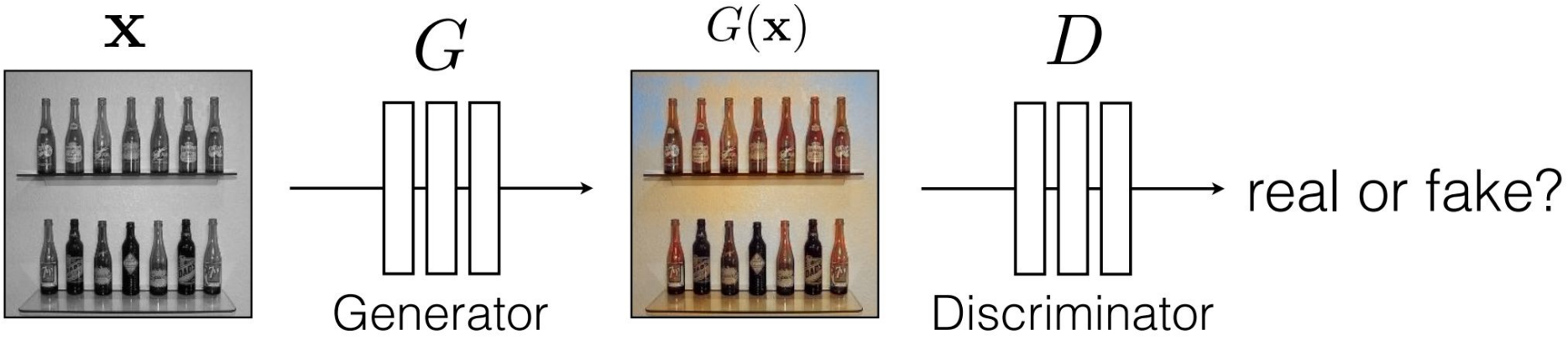
Slide: Phillip Isola

Conditional GANs / pix2pix



Slide: Phillip Isola

Conditional GANs / pix2pix

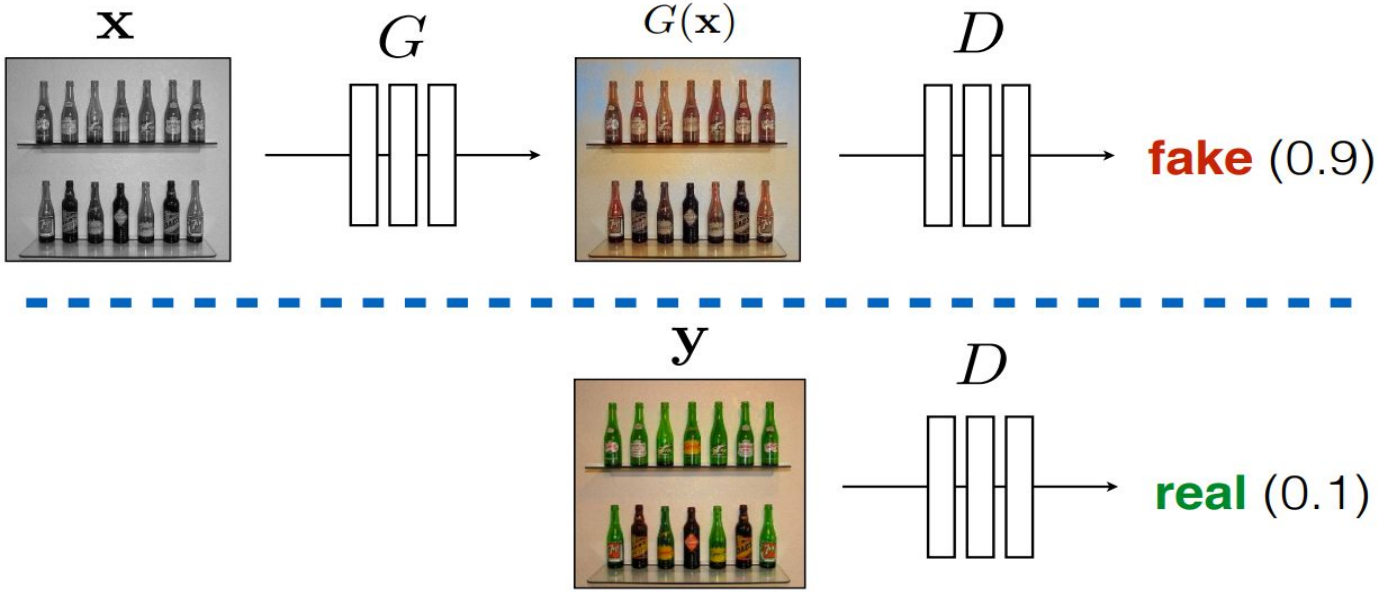


G tries to synthesize fake images that fool **D**

D tries to identify the fakes

Slide: Phillip Isola

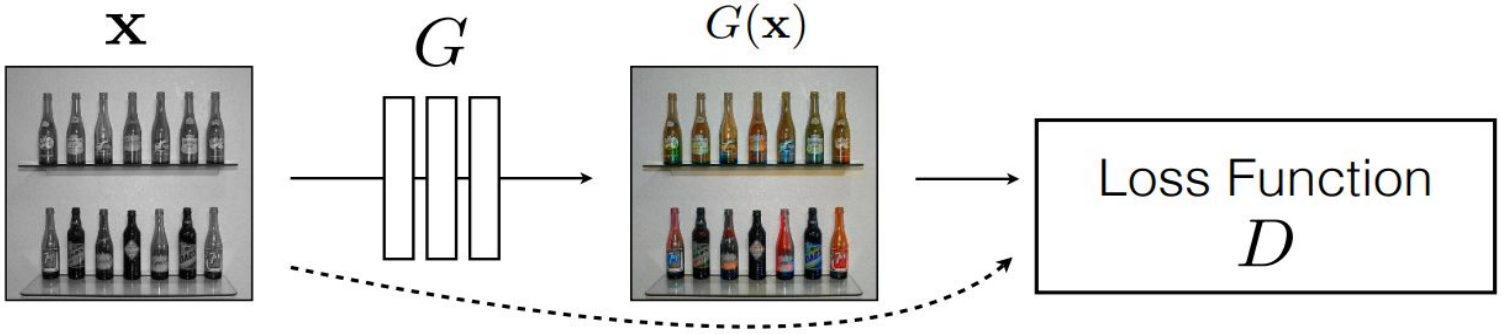
Conditional GANs / pix2pix



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

Slide: Phillip Isola

Conditional GANs / pix2pix

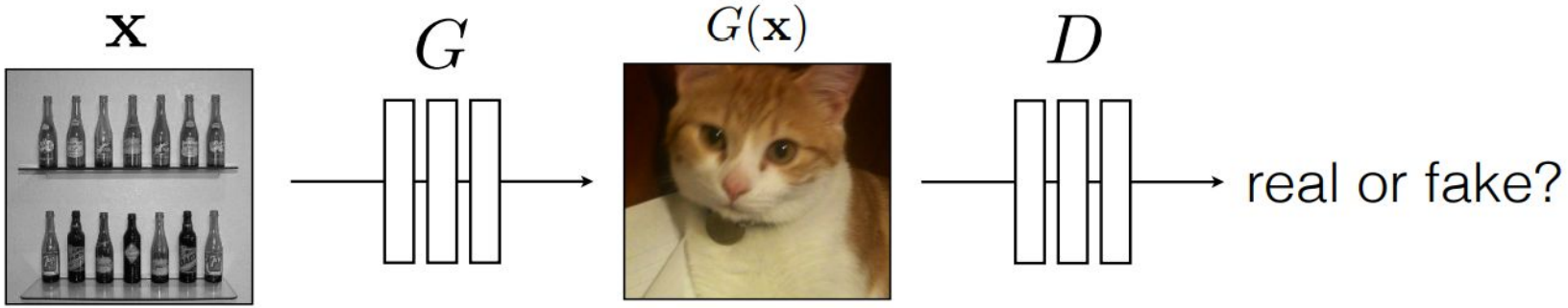


G's perspective: **D** is a loss function.

Rather than being hand-designed, it is *learned*.

Slide: Phillip Isola

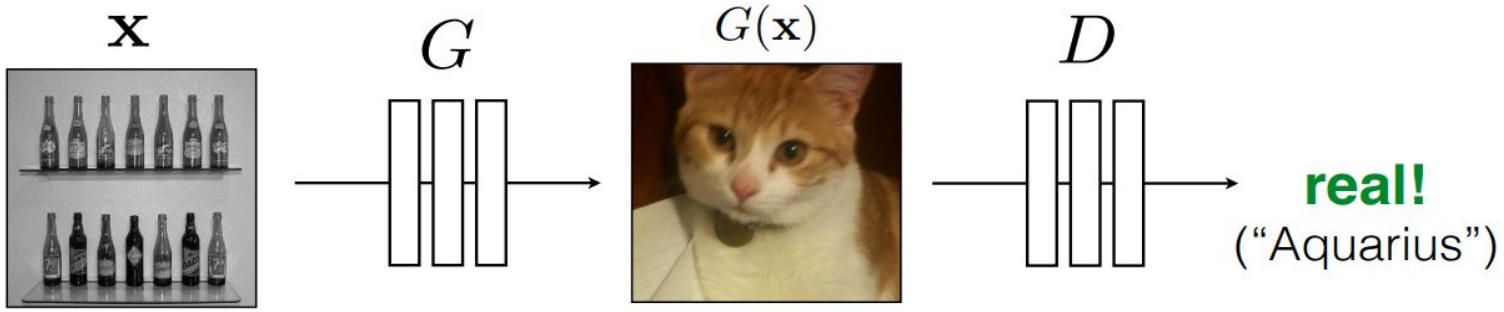
Conditional GANs / pix2pix



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

Slide: Phillip Isola

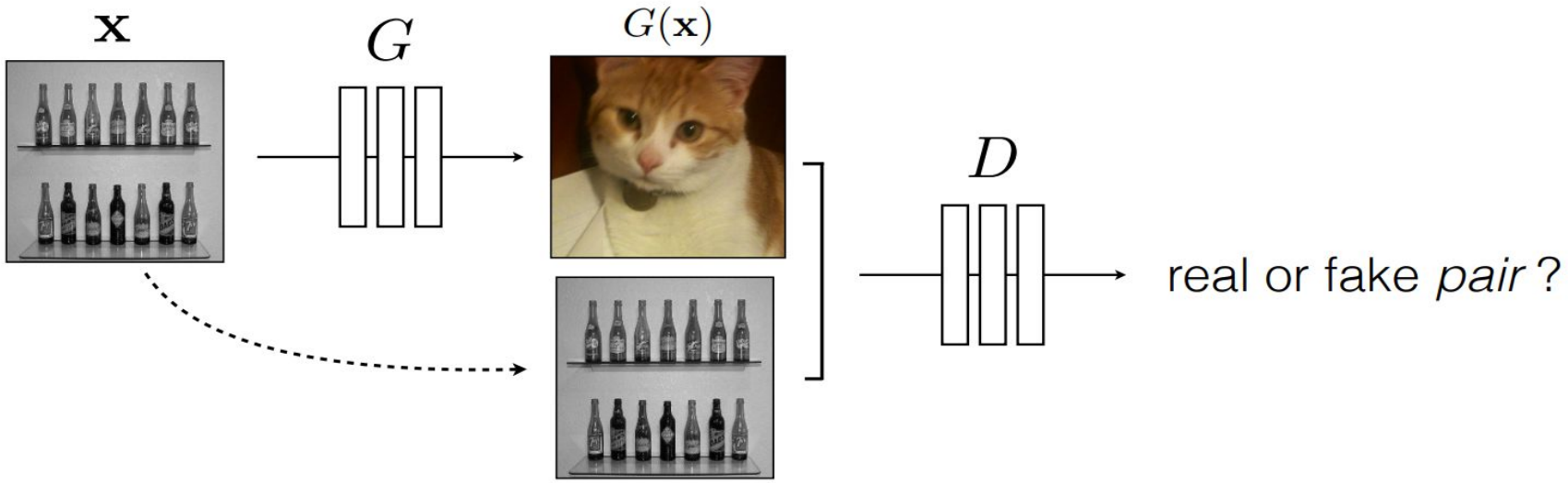
Conditional GANs / pix2pix



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

Slide: Phillip Isola

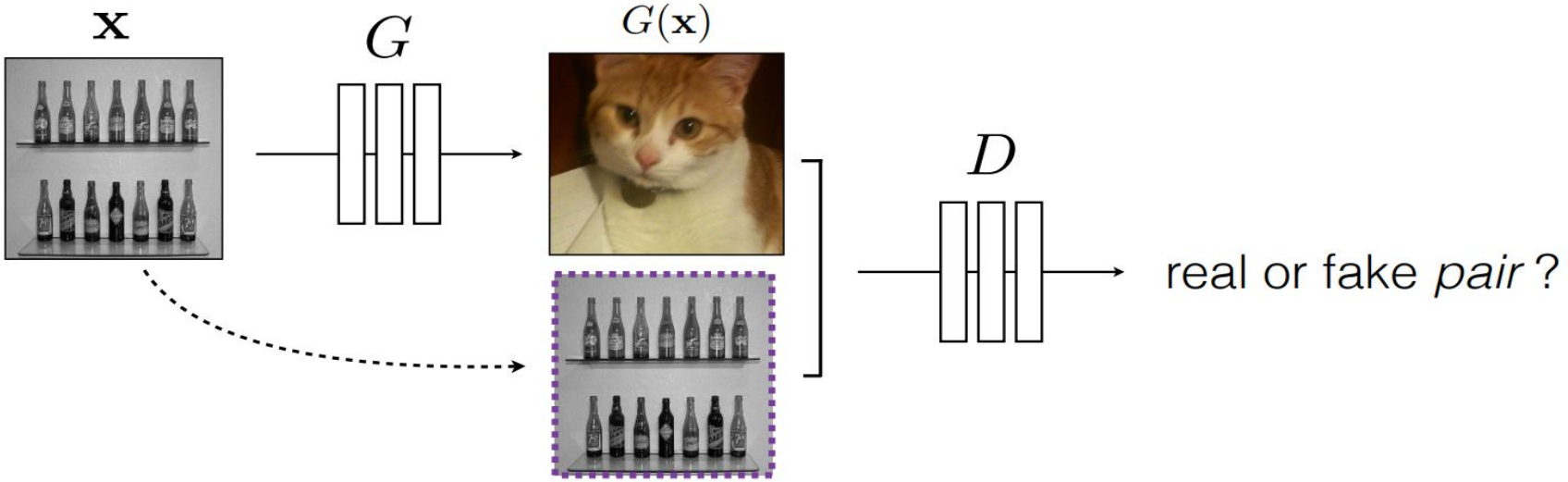
Conditional GANs / pix2pix



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

Slide: Phillip Isola

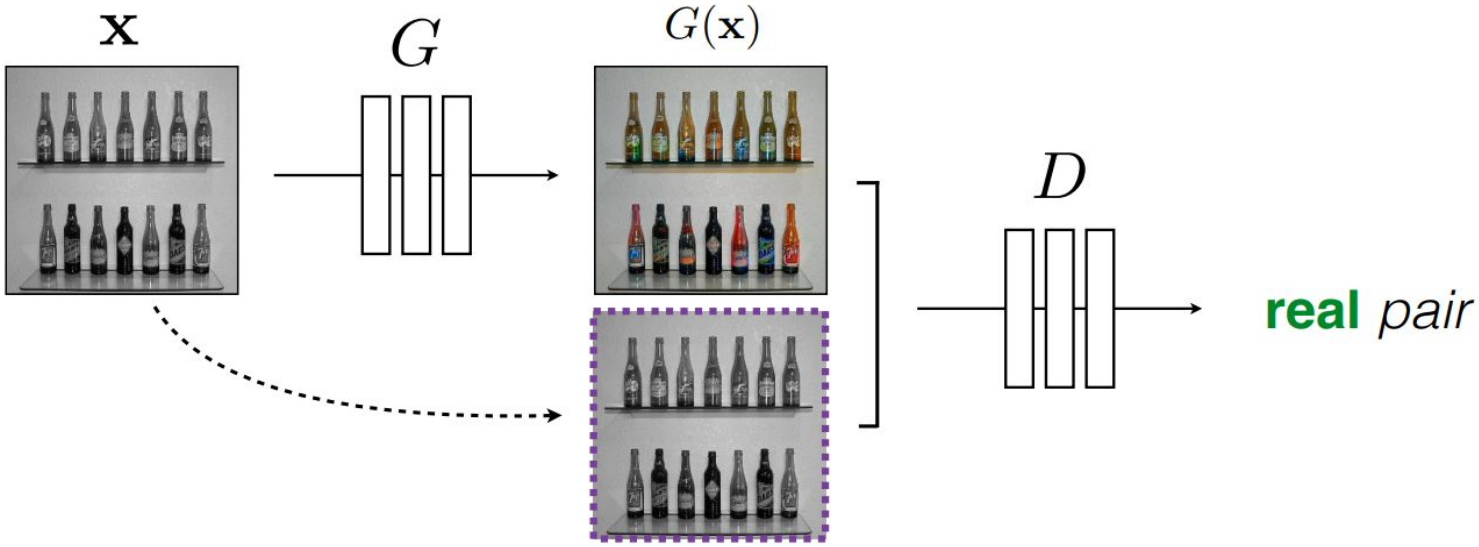
Conditional GANs / pix2pix



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

Slide: Phillip Isola

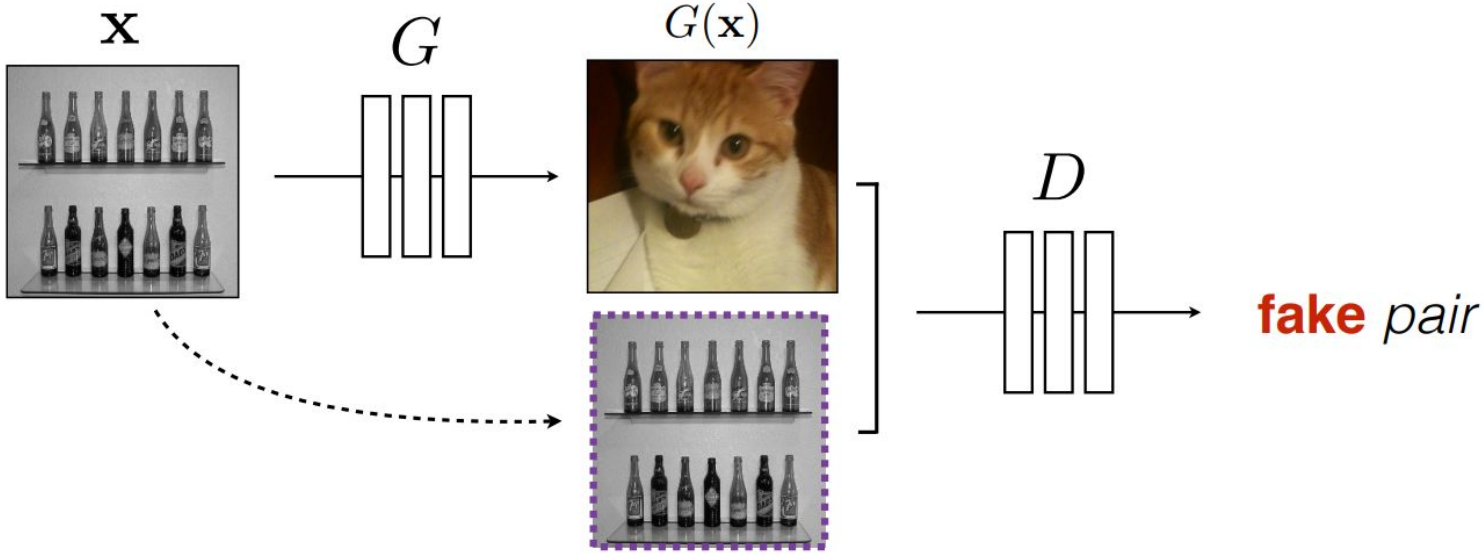
Conditional GANs / pix2pix



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

Slide: Phillip Isola

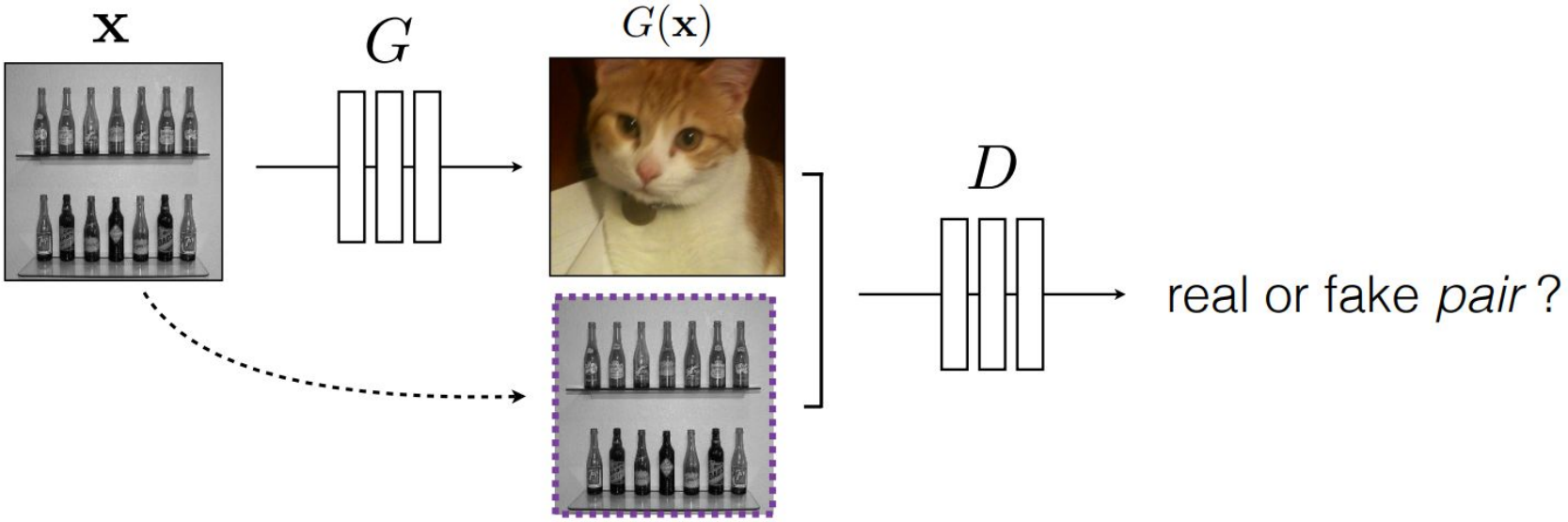
Conditional GANs / pix2pix



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

Slide: Phillip Isola

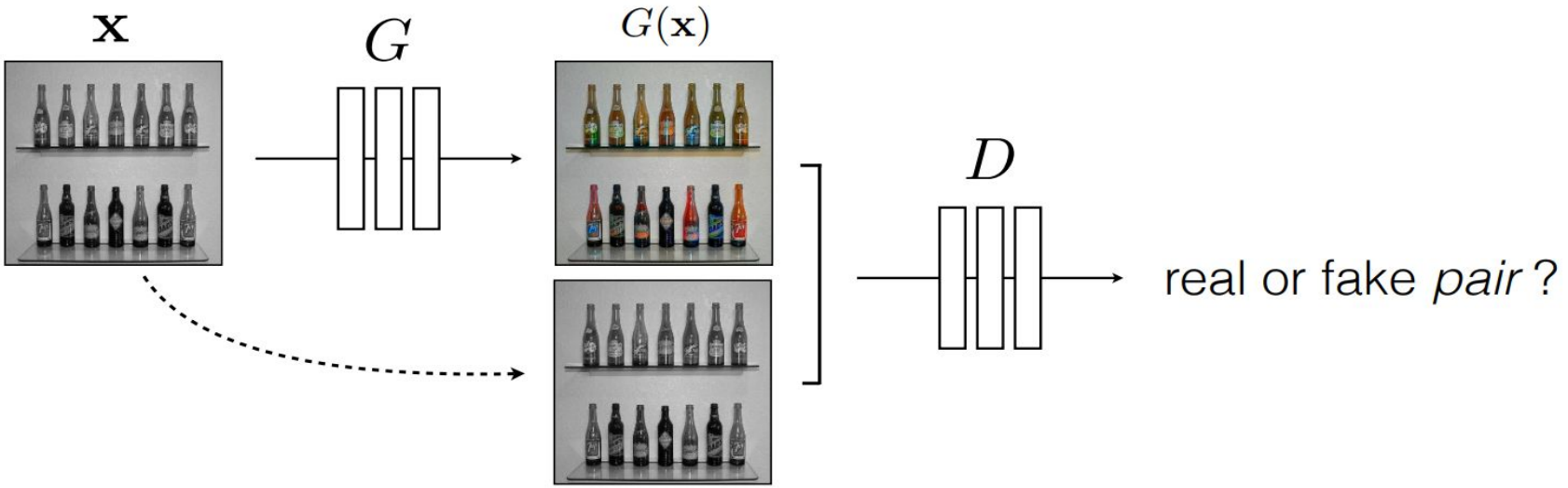
Conditional GANs / pix2pix



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

Slide: Phillip Isola

Conditional GANs / pix2pix



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

Slide: Phillip Isola

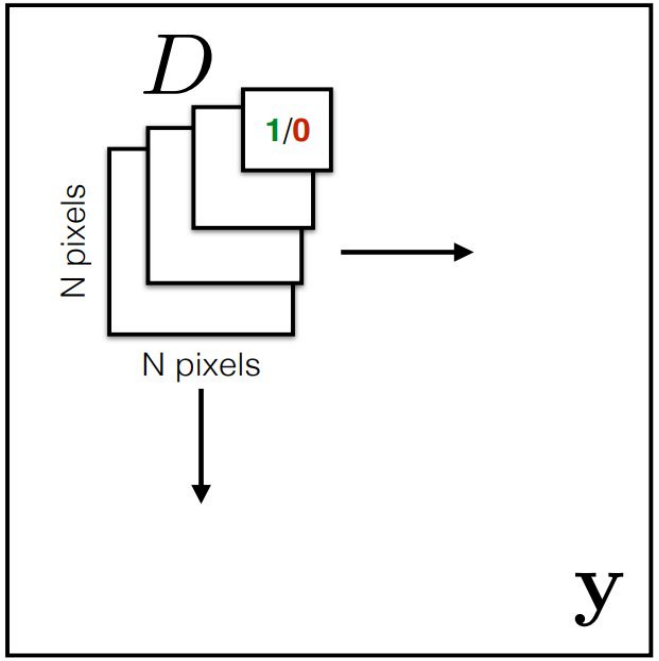
Conditional GANs / pix2pix

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

Slide: Phillip Isola

Conditional GANs / pix2pix

Shrinking the capacity: Patch Discriminator



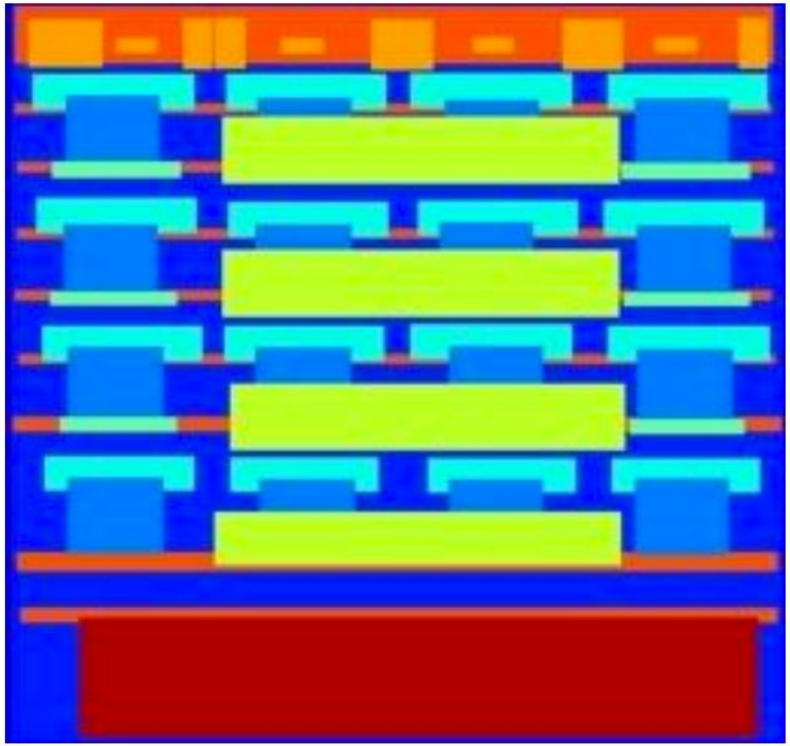
Rather than penalizing if output *image* looks fake, penalize if each overlapping *patch* in output looks fake

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

Slide: Phillip Isola

Conditional GANs / pix2pix

Input



1x1 Discriminator

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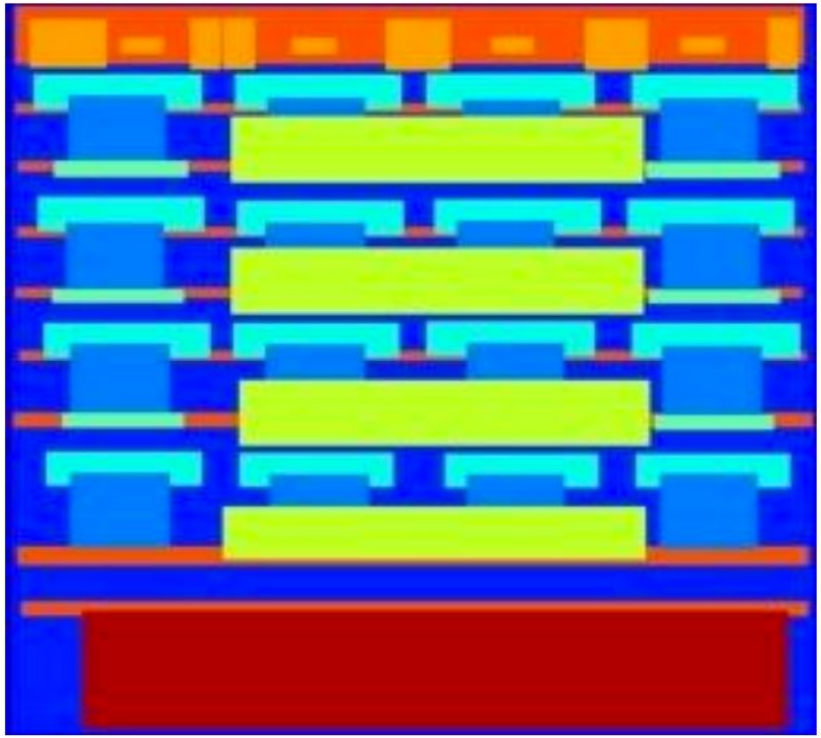
Conditional GANs / pix2pix

Input



16x16 Discriminator

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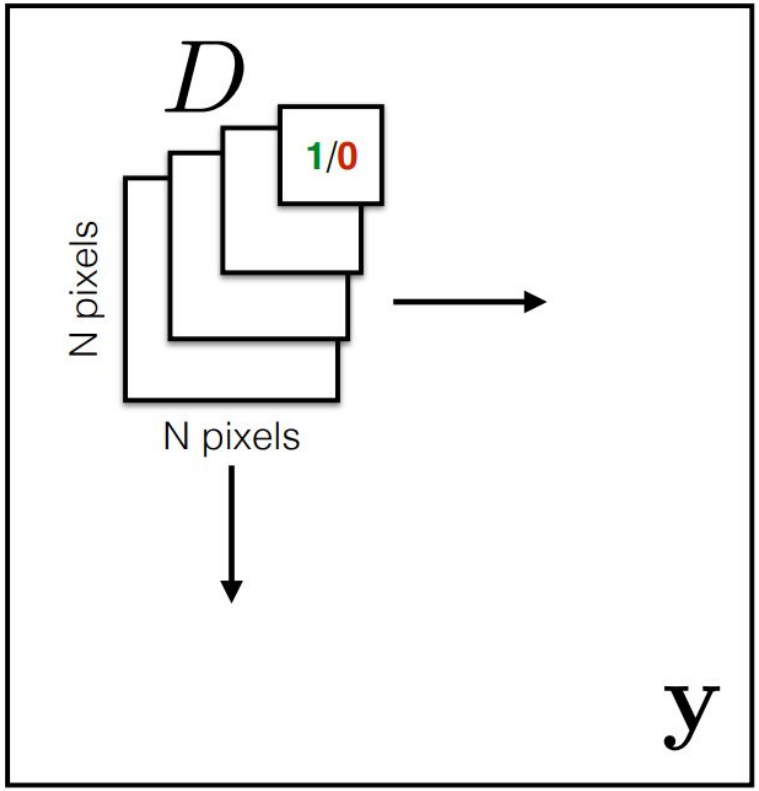
Conditional GANs / pix2pix

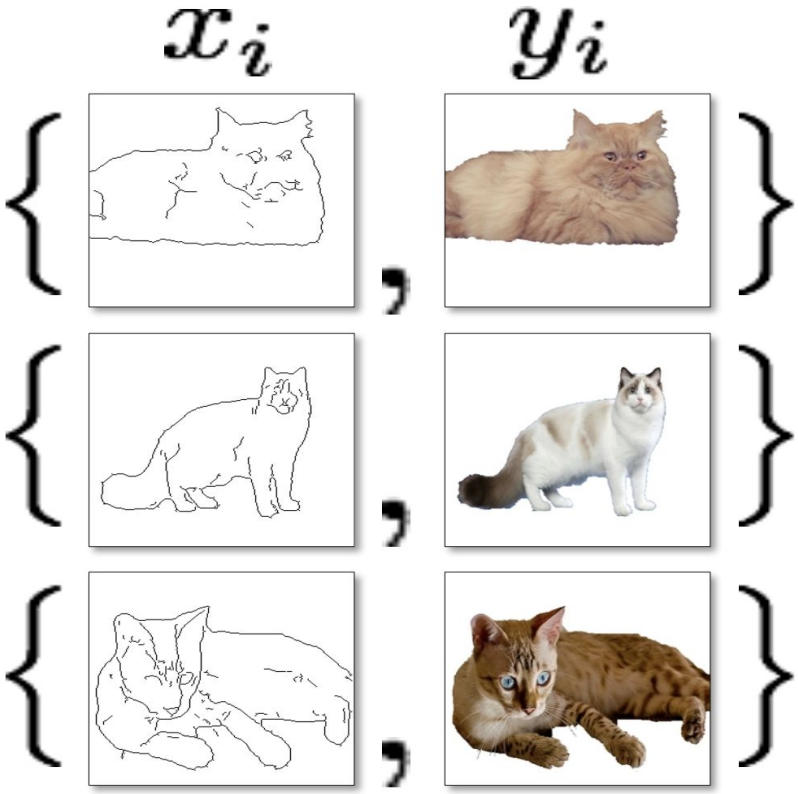


Rather than penalizing if output *image* looks fake, penalize if each overlapping *patch* in output looks fake

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

Slide: Phillip Isola

Conditional GANs / pix2pix



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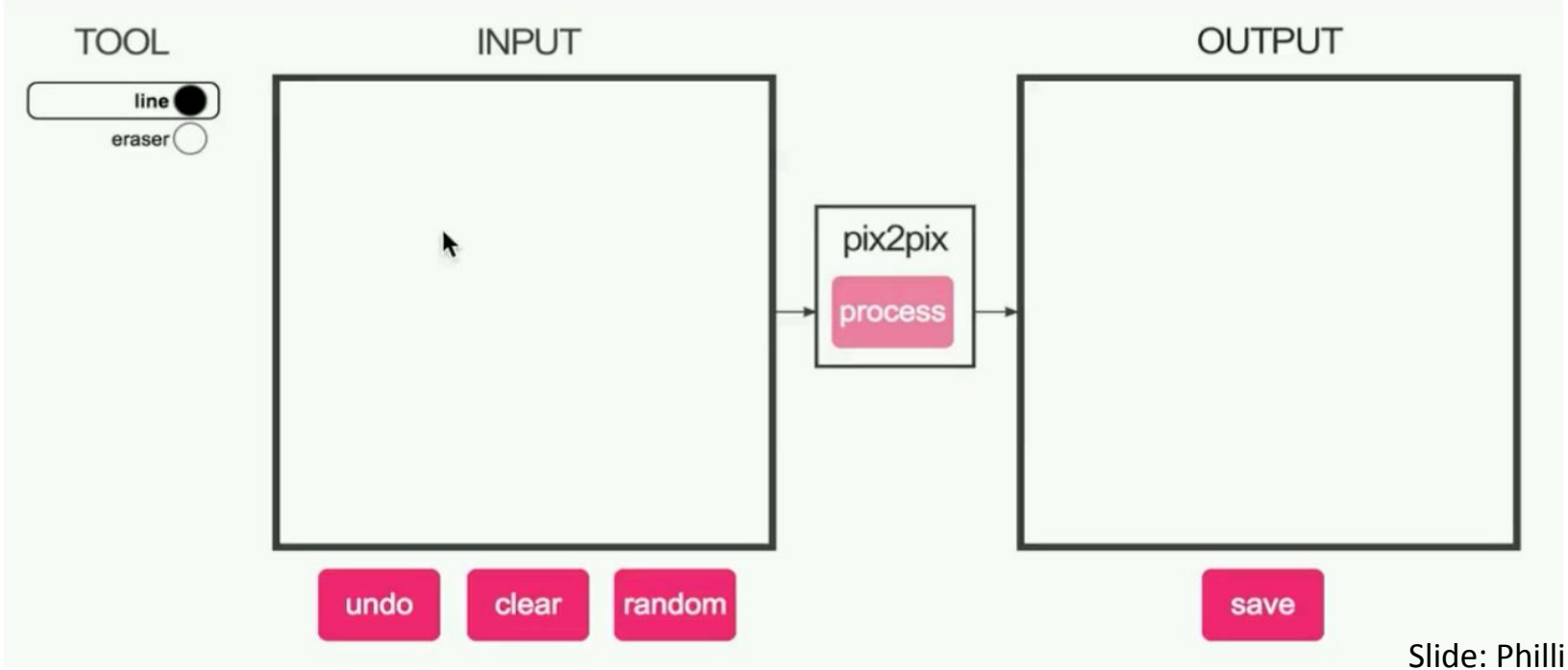
Conditional GANs / pix2pix

#edges2cats [Chris Hesse]



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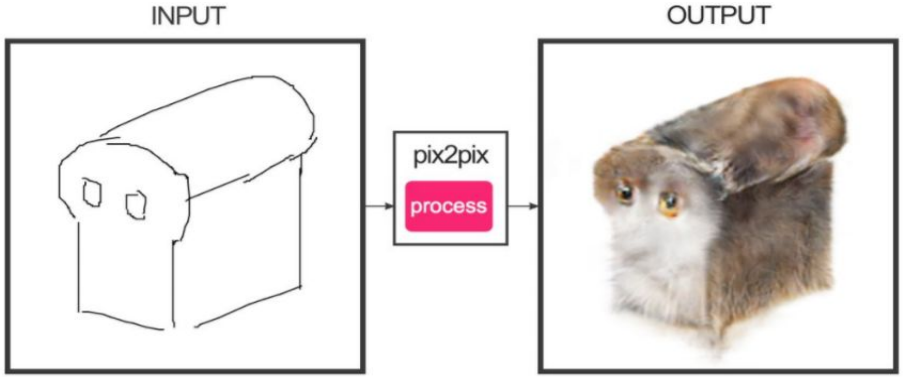
Conditional GANs / pix2pix

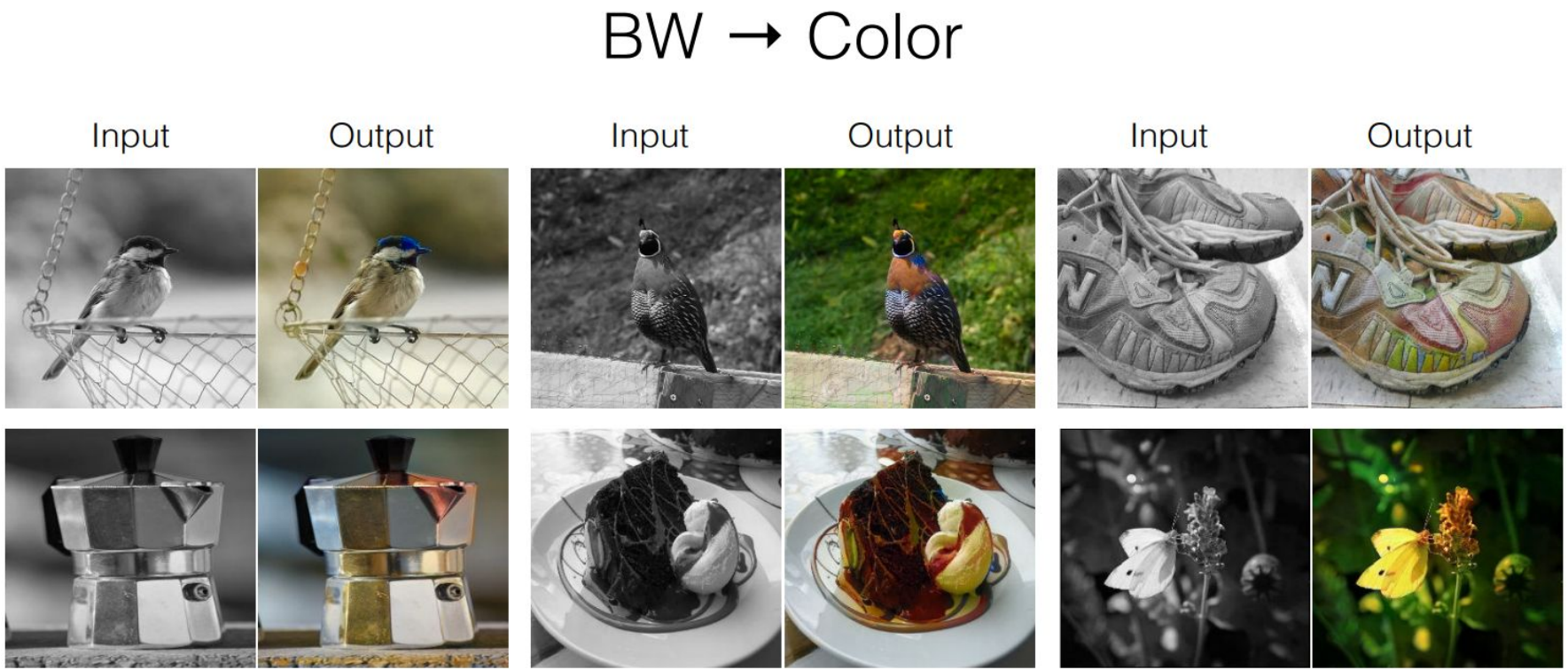


Ivy Tasi @ivymyt

Vitaly Vidmirov @vvid

Slide: Phillip Isola

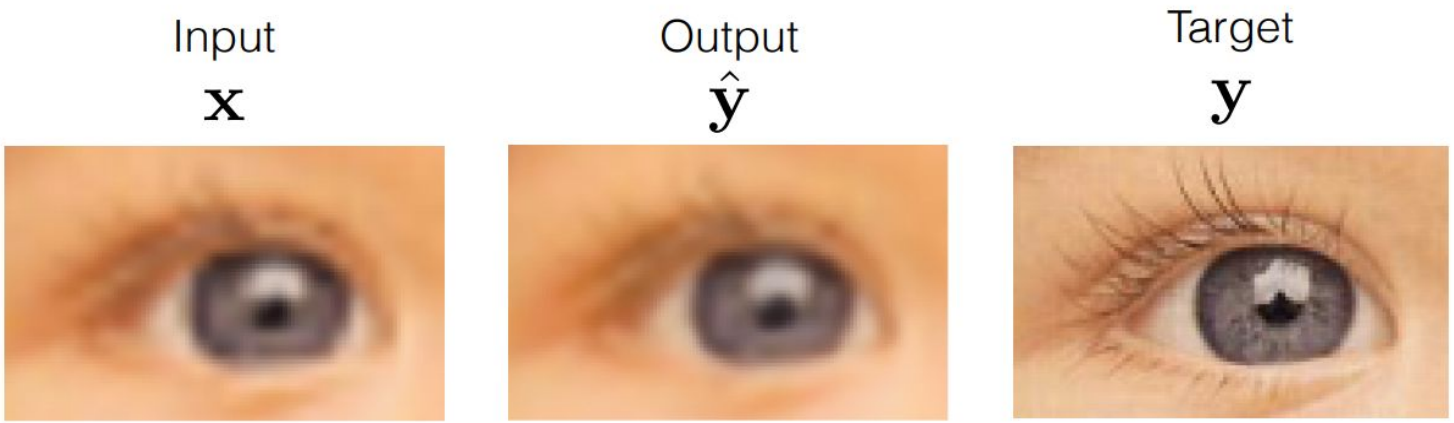
Conditional GANs / pix2pix



Slide: Phillip Isola

Conditional GANs / pix2pix

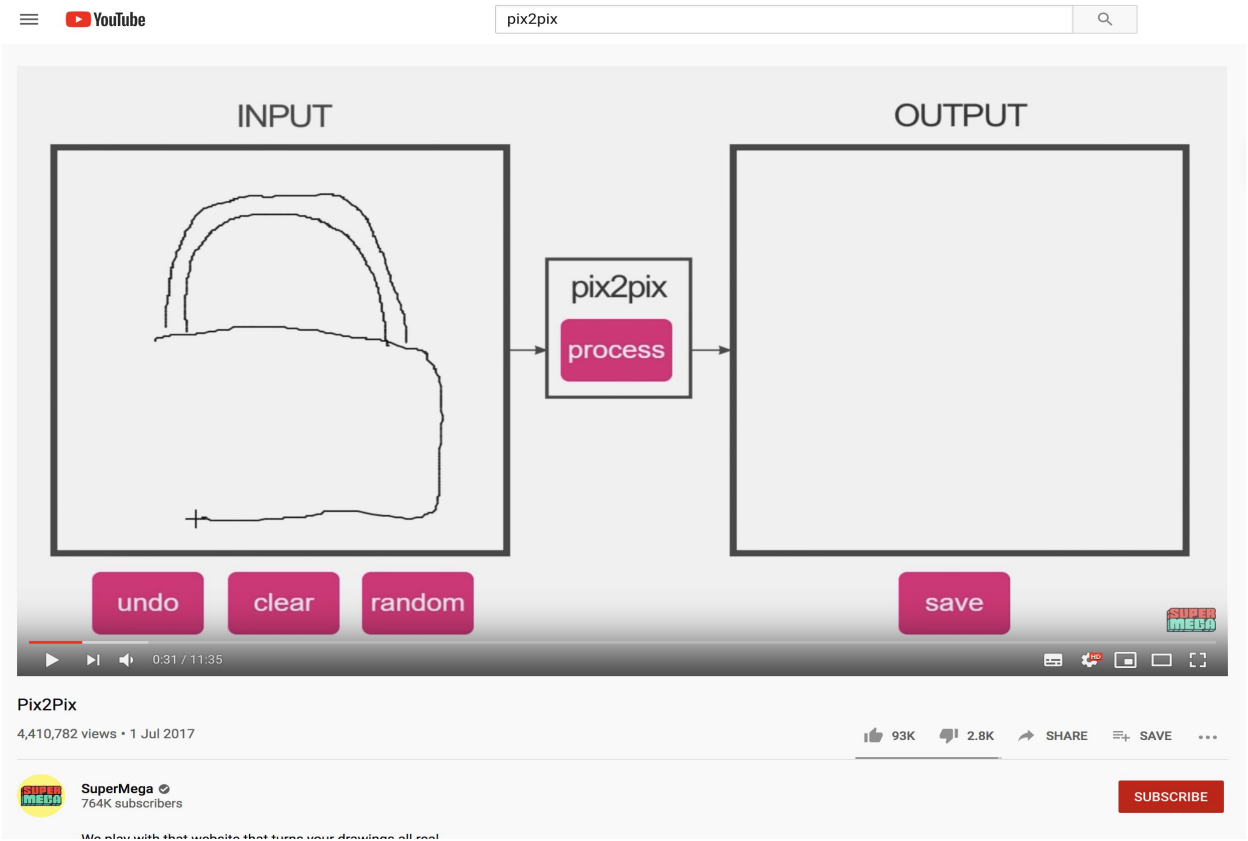
Structured Prediction



$$L(\hat{\mathbf{y}}, \mathbf{y}) = \|\hat{\mathbf{y}} - \mathbf{y}\|_2$$

Slide: Phillip Isola

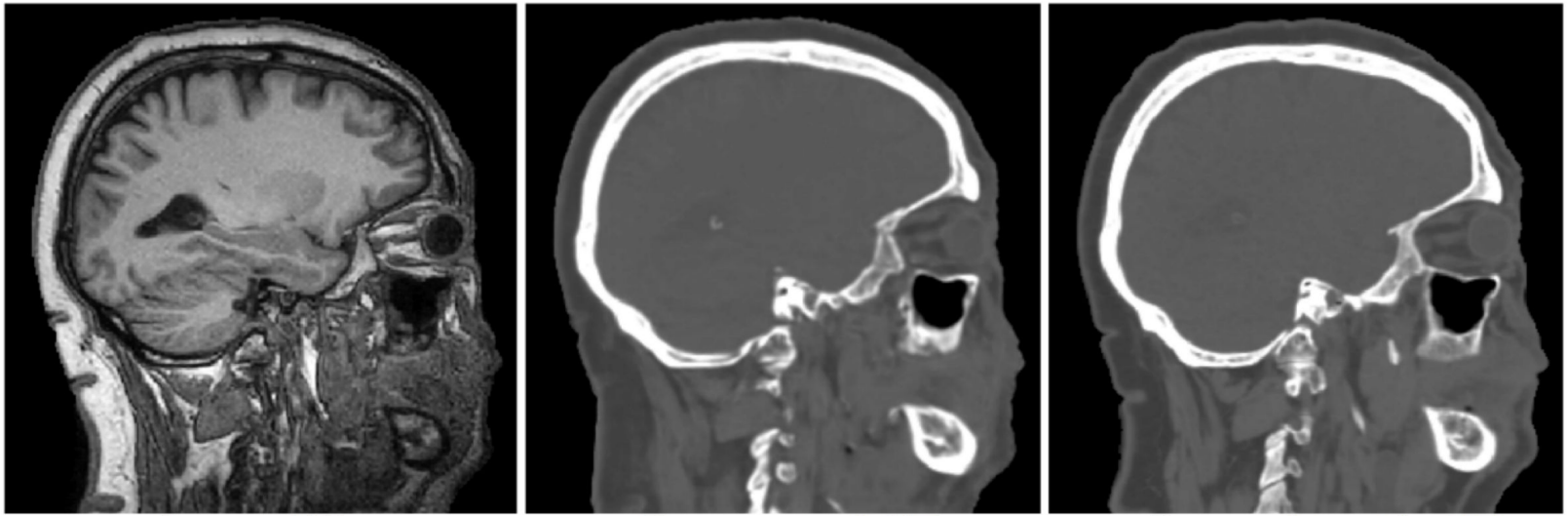
pix2pix impact among artists



Slide: Phillip Isola

pix2pix for medical imaging

MR → CT [Wolterink et al] arxiv: 1708.01155



Input MR | Generated CT | Ground truth CT

- MRI reconstruction [Quan et al.] arxiv:1709.00753
- Cardiac MR images from CT [Chartsias et al. 2017]

Slide: Phillip Isola

Video2Video (NVIDIA)

Everybody Dance Now

NVIDIA GauGAN: sketch->photorealistic image

Learning to paint (GANs + RL)

https://learning-to-paint.github.io/

Outline

- Motivation & Definition of Implicit Models
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Some Theory: Bayes-optimal Discriminator; Jensen-Shannon Divergence; Mode Collapse; Avoiding Saturation
- GAN Progression:
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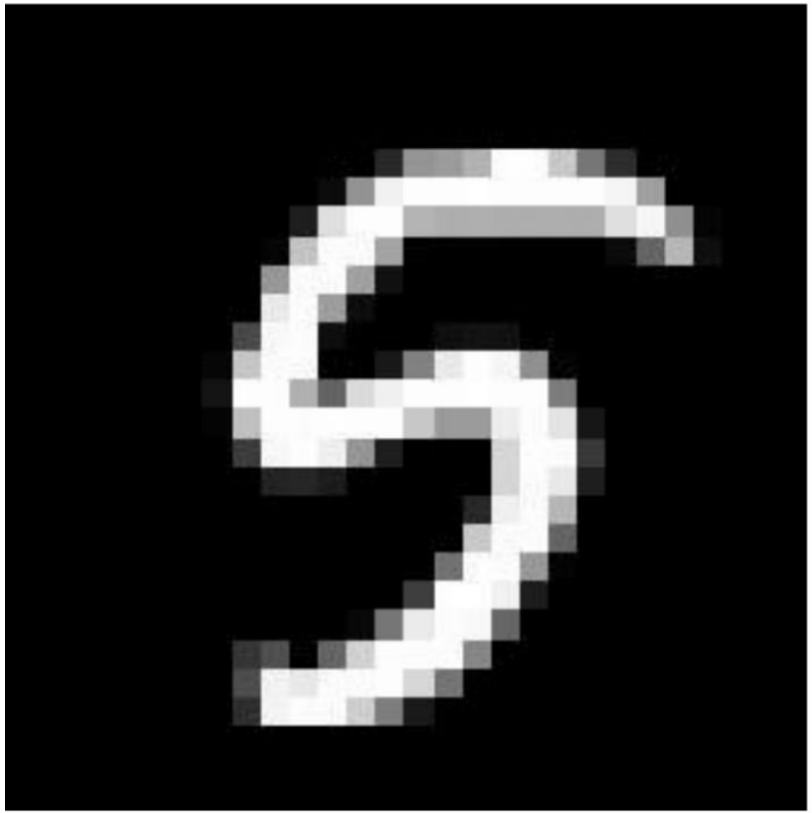
GANs for unsupervised feature learning

- InfoGAN (Information Maximizing GAN)
- BiGAN (Bidirectional Generative Adversarial Networks)
  - BigBiGAN (Big Bidirectional Generative Adversarial Networks)

InfoGAN



```
array([[151, 157, 250, ...,  20,   0,   0],
       [148, 161, 242, ...,  15,   0,   0],
       [235, 228, 255, ...,   3,   0,   0],
       ...,
       [252, 254, 176, ..., 240, 253, 253],
       [253, 253, 253, ..., 253, 200, 200],
       [253, 253, 253, ..., 253, 200, 200]]
, dtype=uint8)
```

InfoGAN

```
array([[151, 157, 250, ...,  20,   0,   0],
       [148, 161, 242, ...,  15,   0,   0],
       [235, 228, 255, ...,   3,   0,   0],
       ...,
       [252, 254, 176, ..., 240, 253, 253],
       [253, 253, 253, ..., 253, 200, 200],
       [253, 253, 253, ..., 253, 200, 200]]
, dtype=uint8)
```

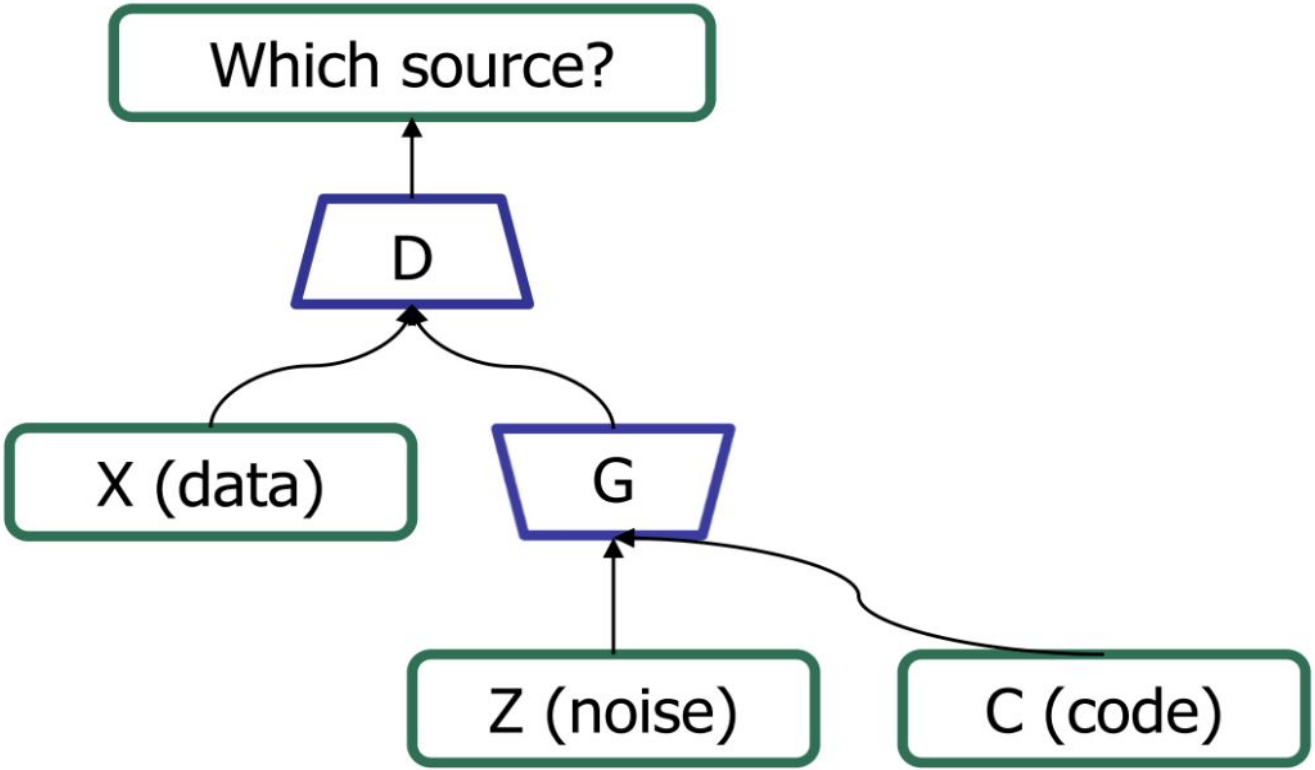
Data: x

Simple factors interact to create complex observations.

Digit type: “5”
Rotation: Tilting to the right
Width: Medium
……

Latent Code: c

InfoGAN



InfoGAN

Simple idea: Independent factors in latent code should maximally explain variations in generated images.

Formally: We want to maximize the mutual information between latent code and generated images:

$$\max_G I(c; x) = H(x) - H(x|c)$$
$$= H(c) - H(c|x)$$

where $x = G(z, c)$

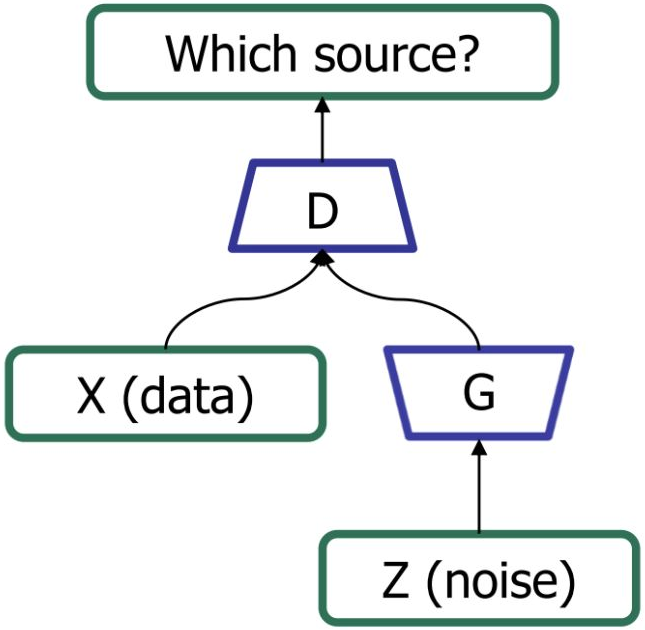
InfoGAN

Mutual information can be maximized easily with a variational lower bound:

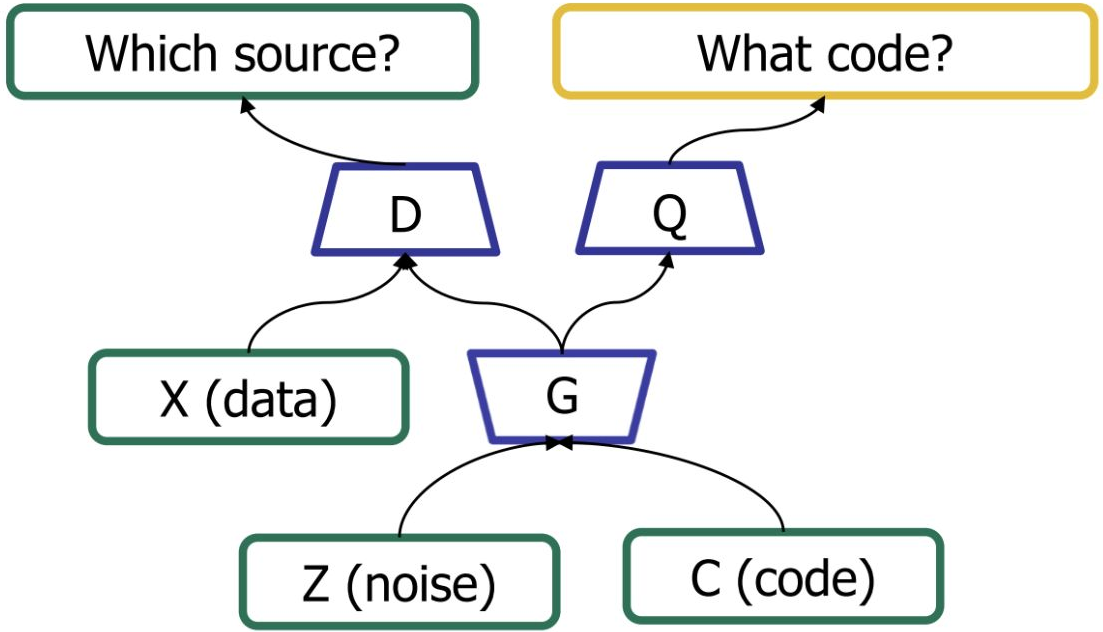
$$
\begin{aligned}
I(c; G(z,c)) &= H(c) - H(c|G(z,c)) \\
&= H(c) + \mathbb{E}_{x\sim G(z,c)}[\mathbb{E}_{c'\sim P(c|x)}[\log P(c'|x)]] \\
&= H(c) + \mathbb{E}_{x\sim G(z,c)}[\mathbb{E}_{c'\sim P(c|x)}[\log Q(c'|x)] + \underbrace{D_{\mathrm{KL}}(P(\cdot|x) \parallel Q(\cdot|x))}_{\geq 0}] \\
&\geq H(c) + \mathbb{E}_{x\sim G(z,c)}[\mathbb{E}_{c'\sim P(c|x)}[\log Q(c'|x)]]
\end{aligned}
$$

Simply MLE for a classifier/regressor

InfoGAN

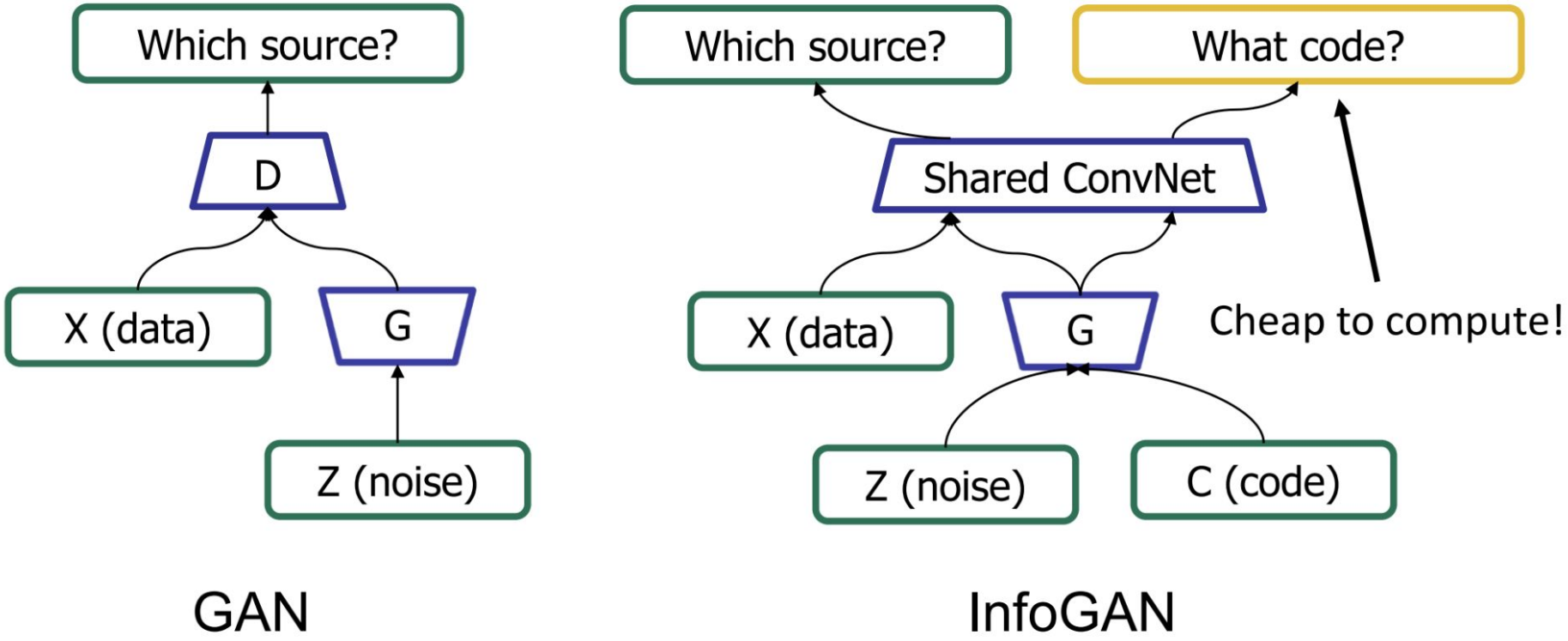


GAN

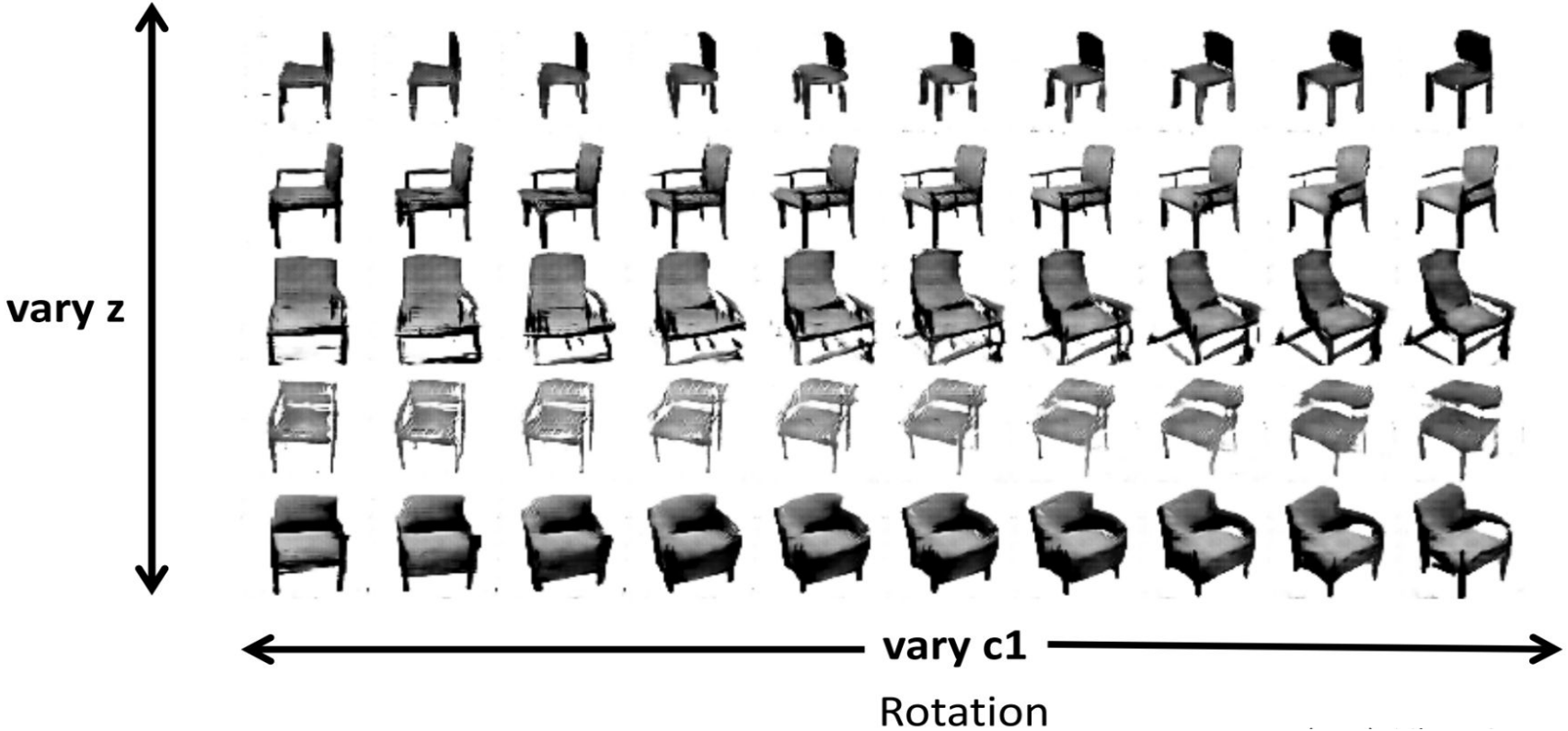


InfoGAN

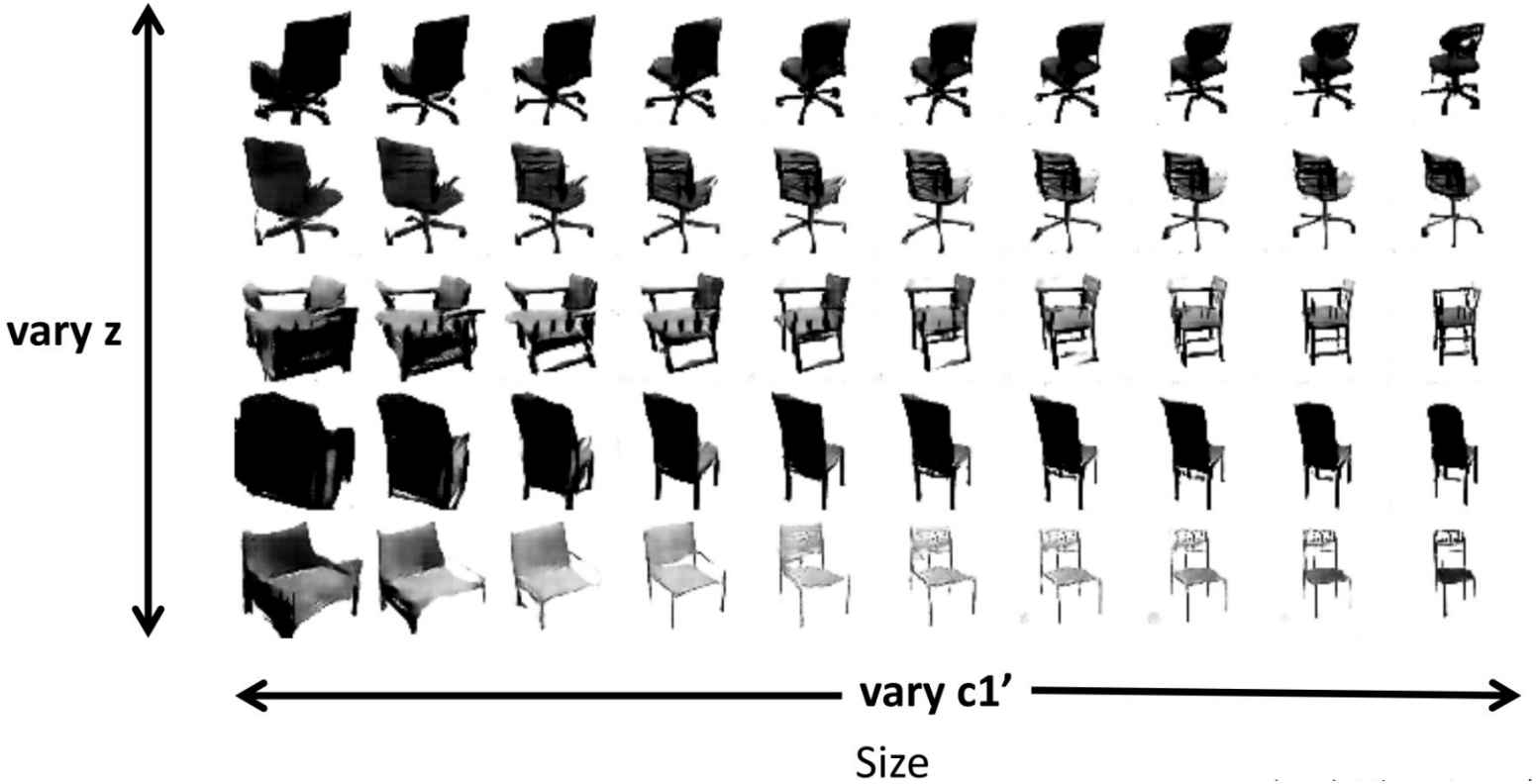
InfoGAN


Which source?
D
X (data)
G
Z (noise)
GAN
Which source?
What code?
Shared ConvNet
X (data)
G
Cheap to compute!
Z (noise)
C (code)
InfoGAN

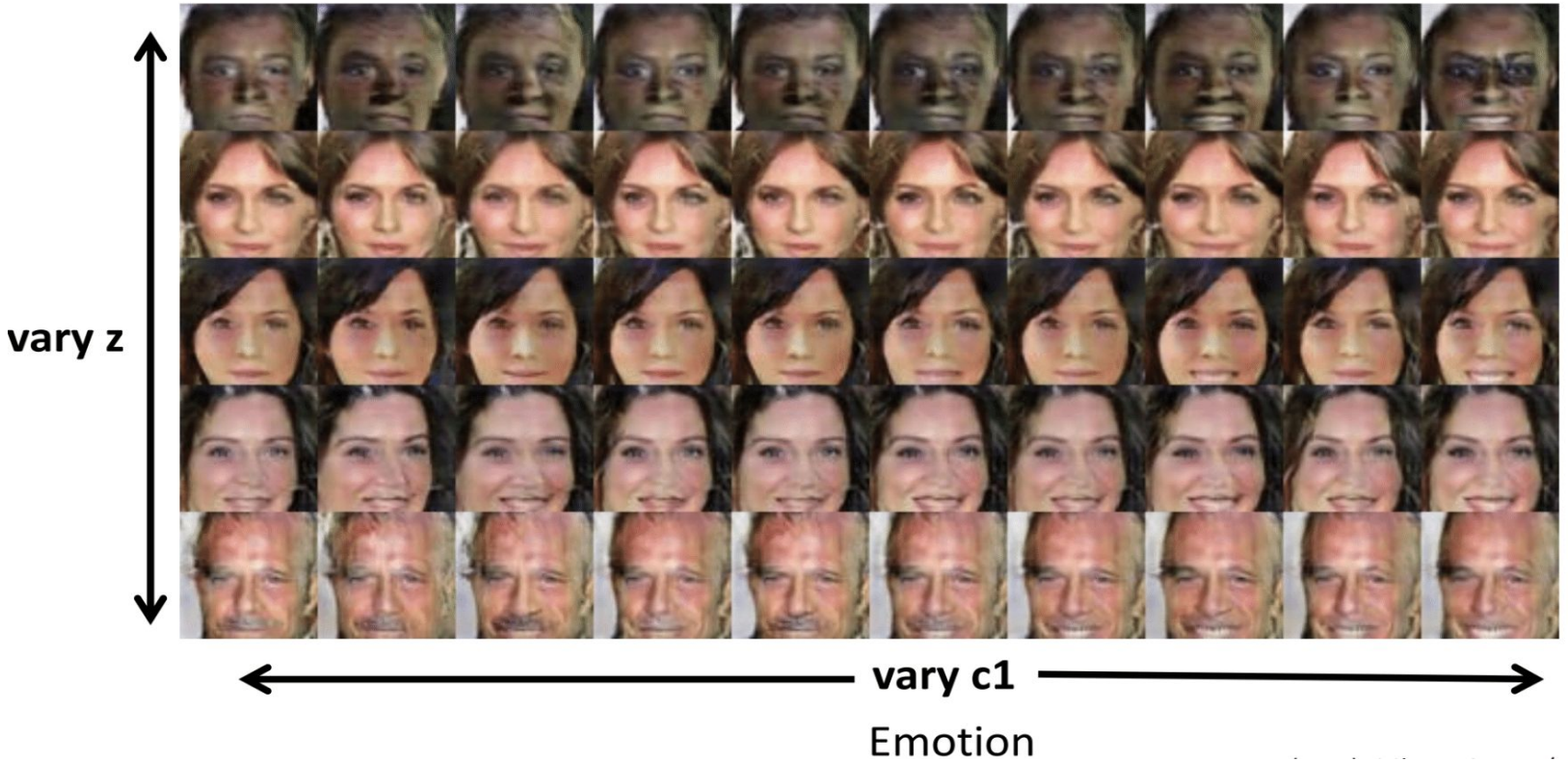
InfoGAN



InfoGAN



InfoGAN



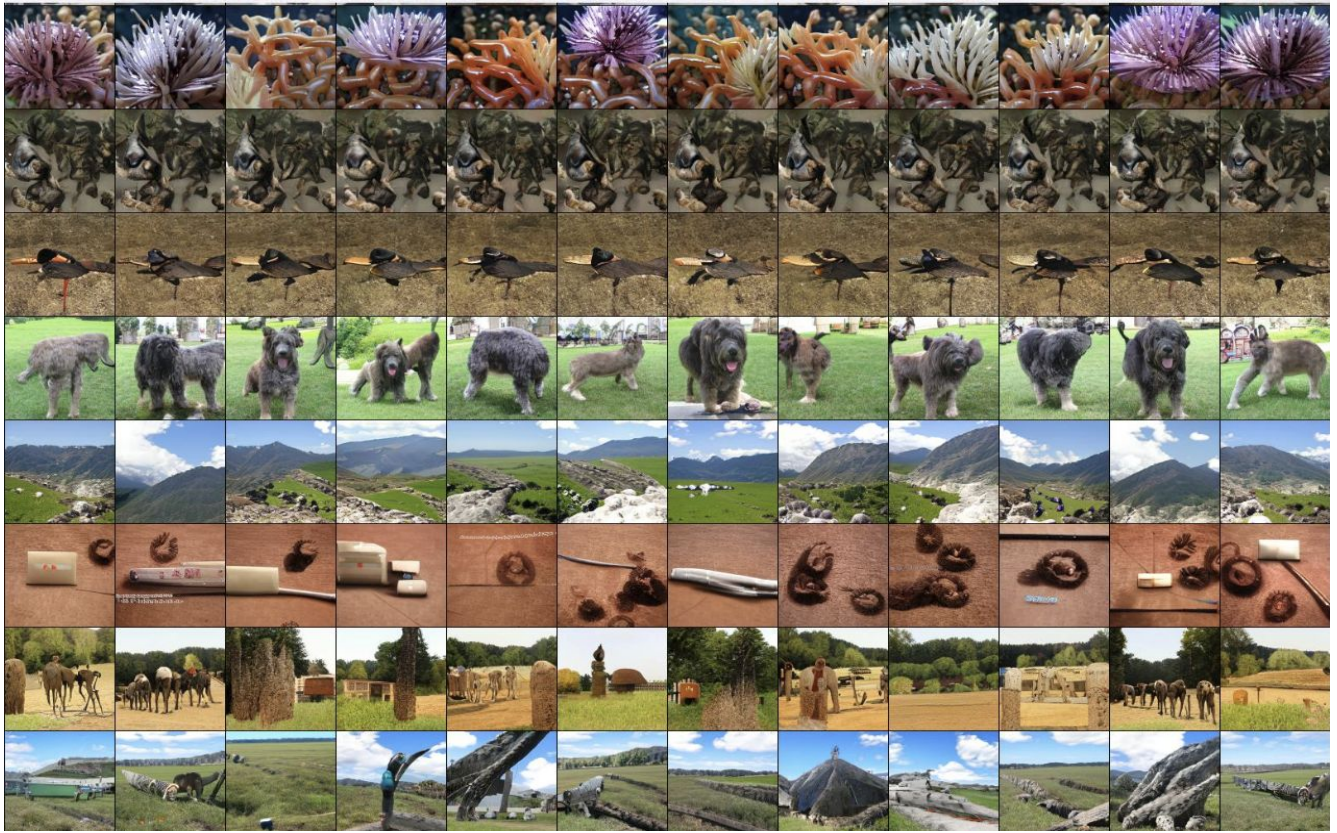
InfoGAN

Unsupervised Category Discovery - BigGAN

Trained with no labels!

z = concat([
(a) $[N(0,I)]^{120}$,
(b) UniformCateg(1024)
])

Each row is one value of the categorical (b); columns are Gaussian samples (a)



Slide: Jeff Donahue

Unsupervised Category Discovery - BigGAN

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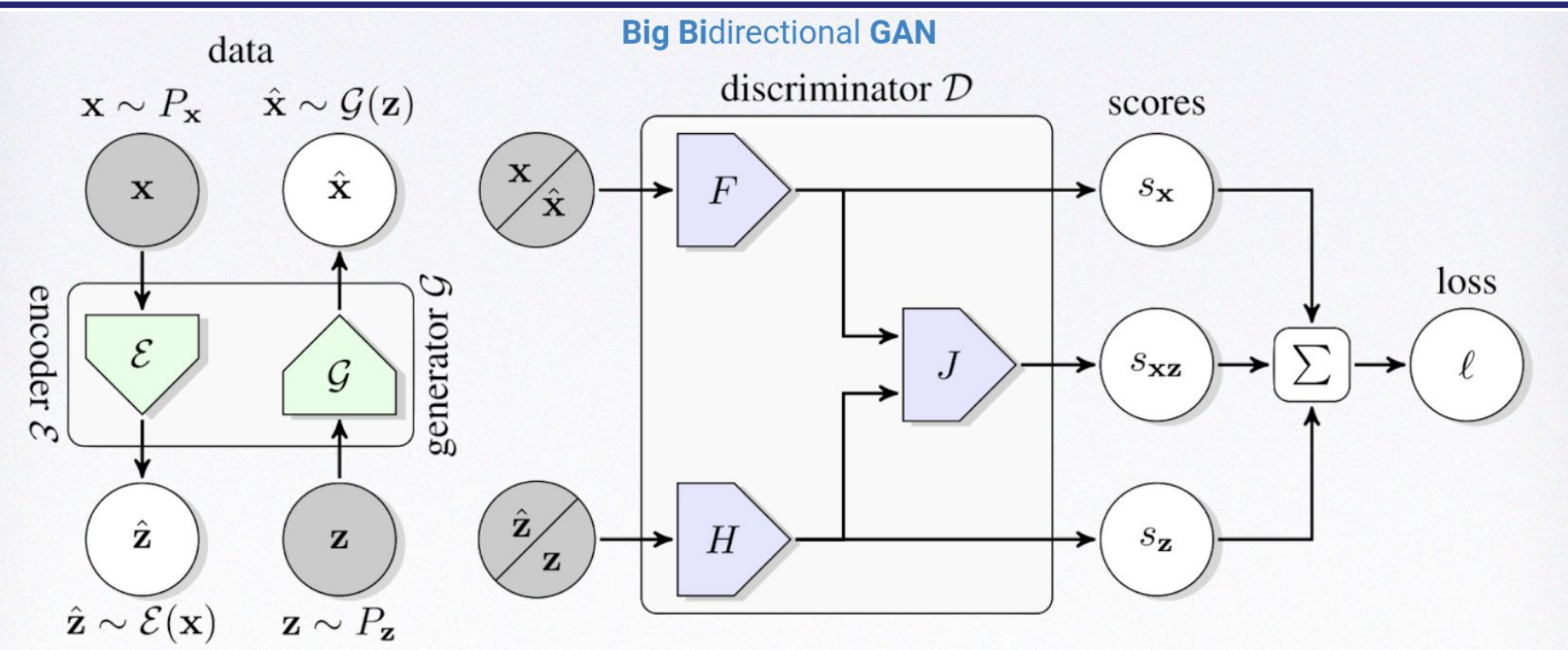
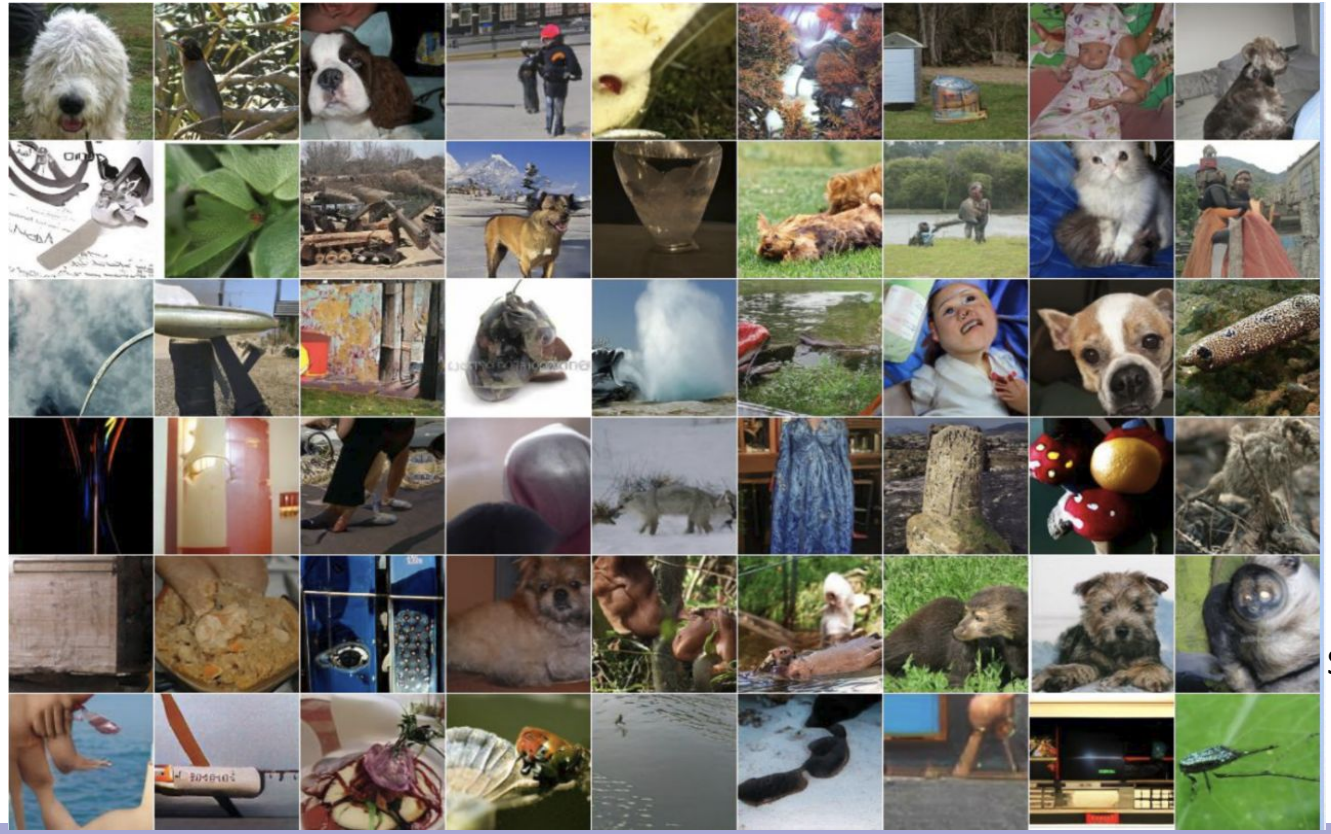
Big Bidirectional GAN



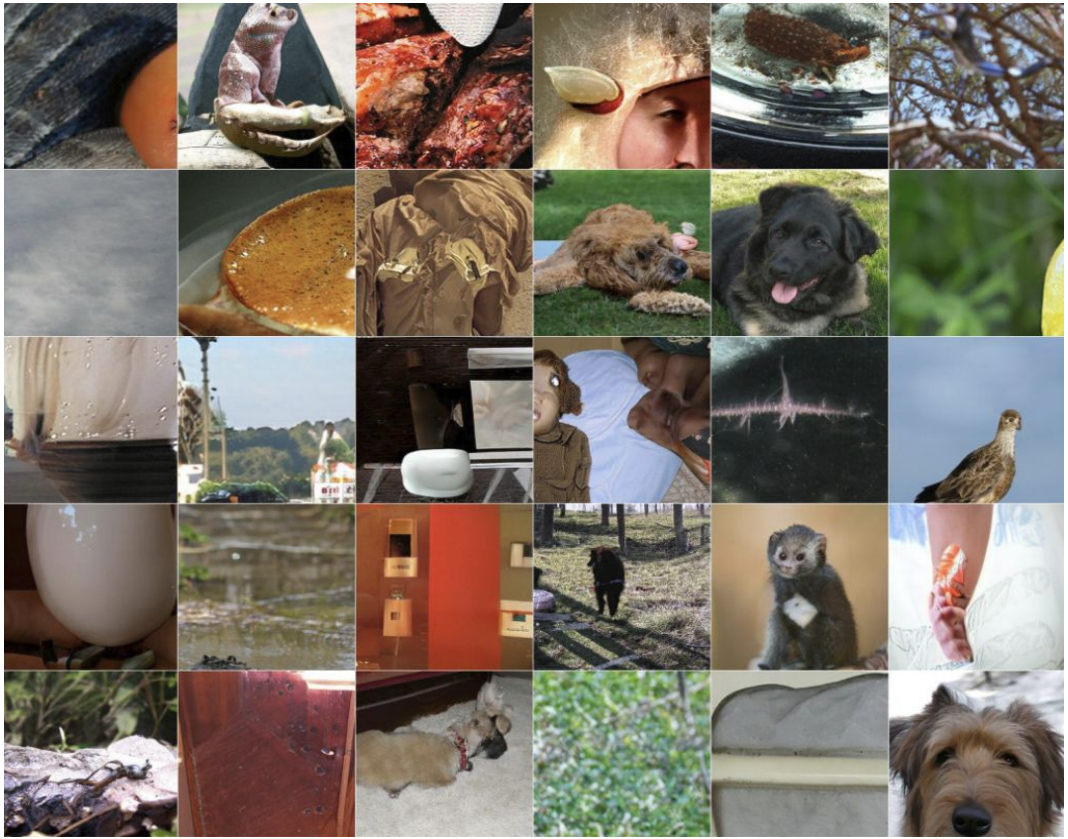
Slide: Jeff Donahue

BigBiGAN:Unconditional Image Generation



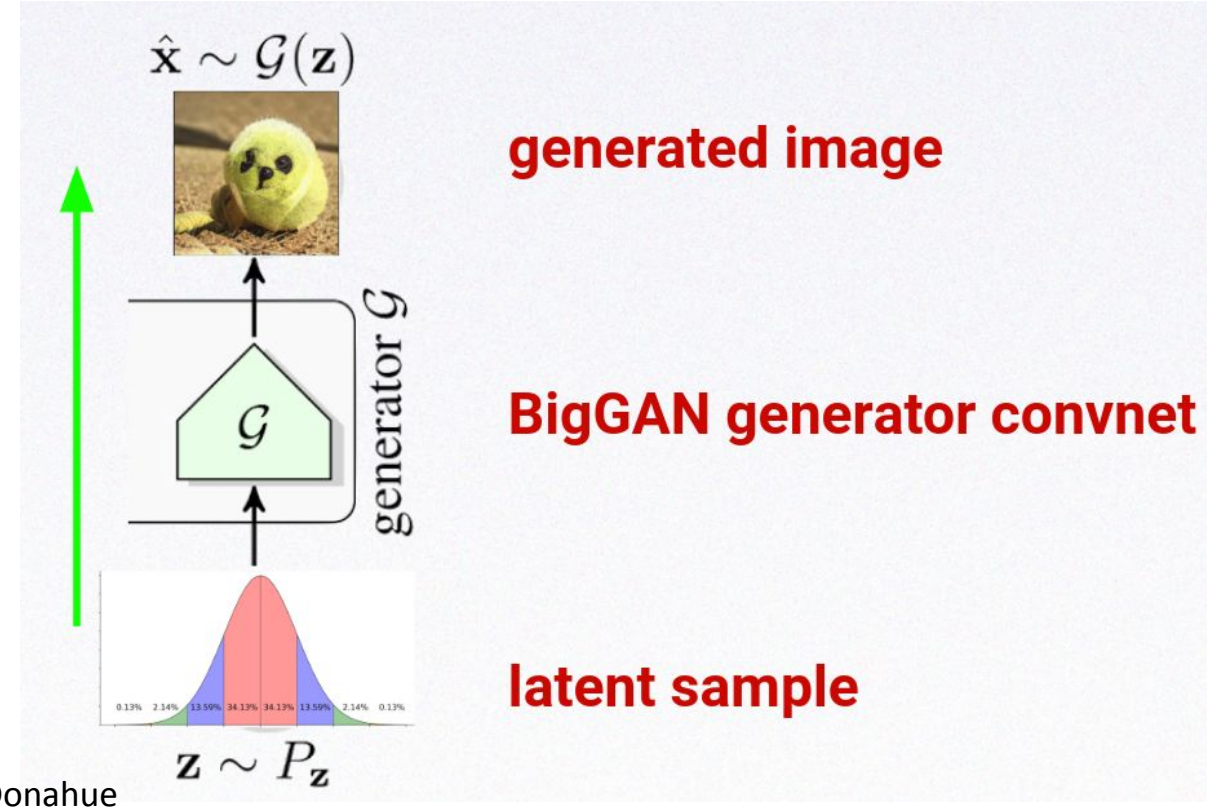
Slide: Jeff Donahue

BigBiGAN - Unconditional Image Generation



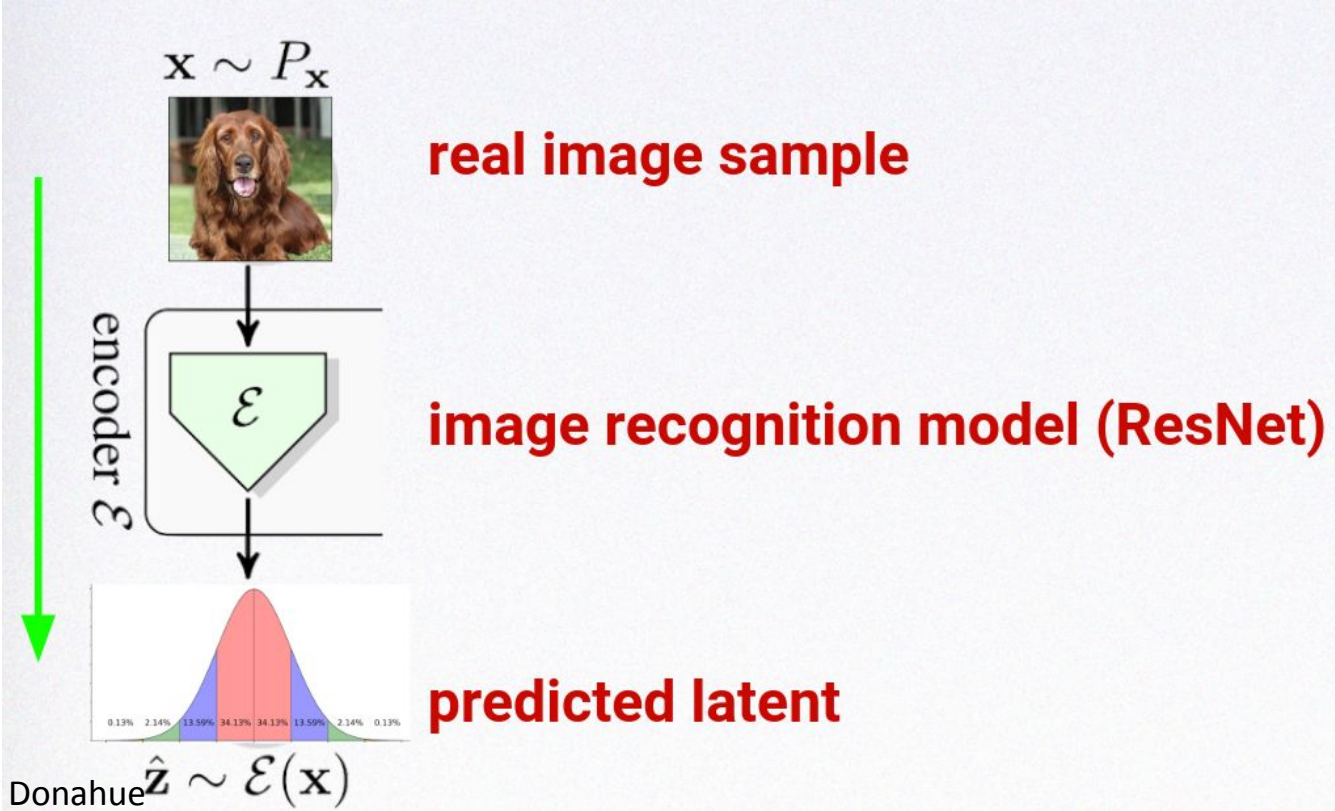
Slide: Jeff Donahue

BigBiGAN



Slide: Jeff Donahue

BigBiGAN



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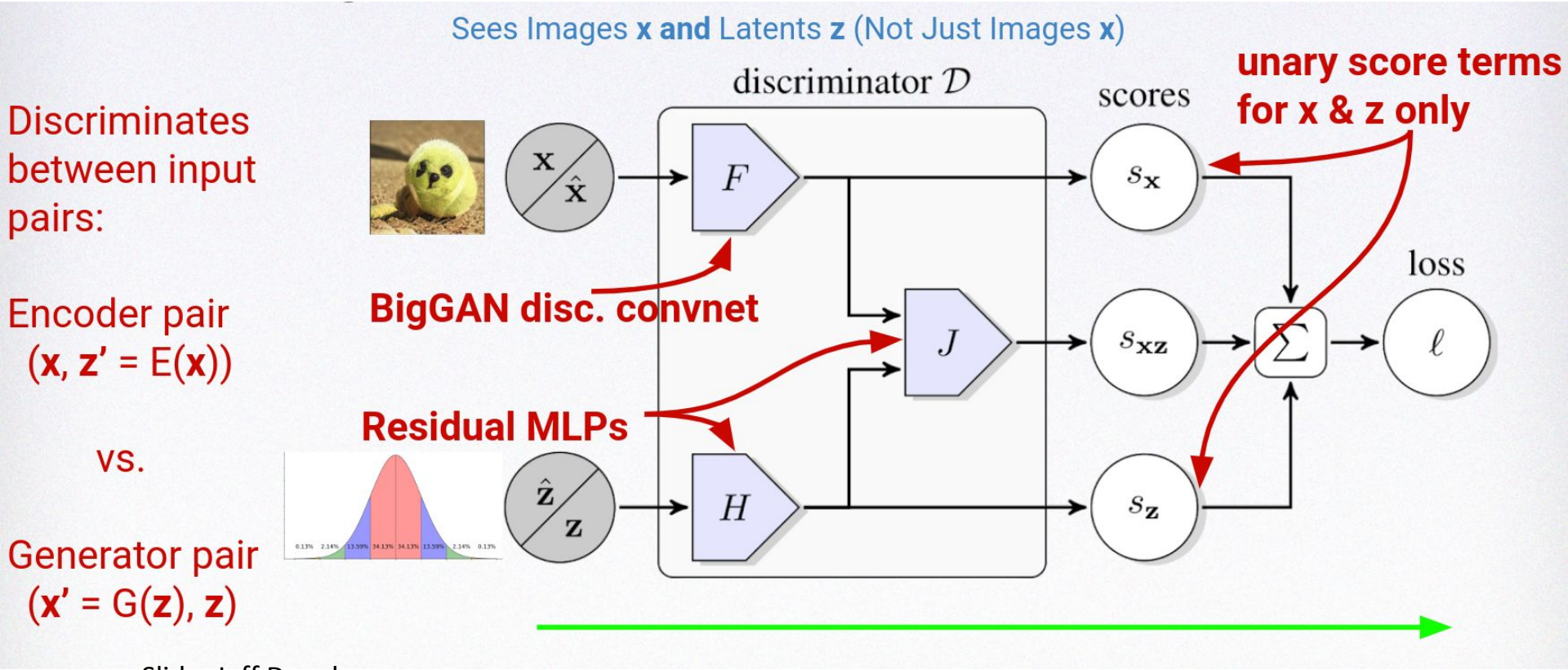
BigBiGAN



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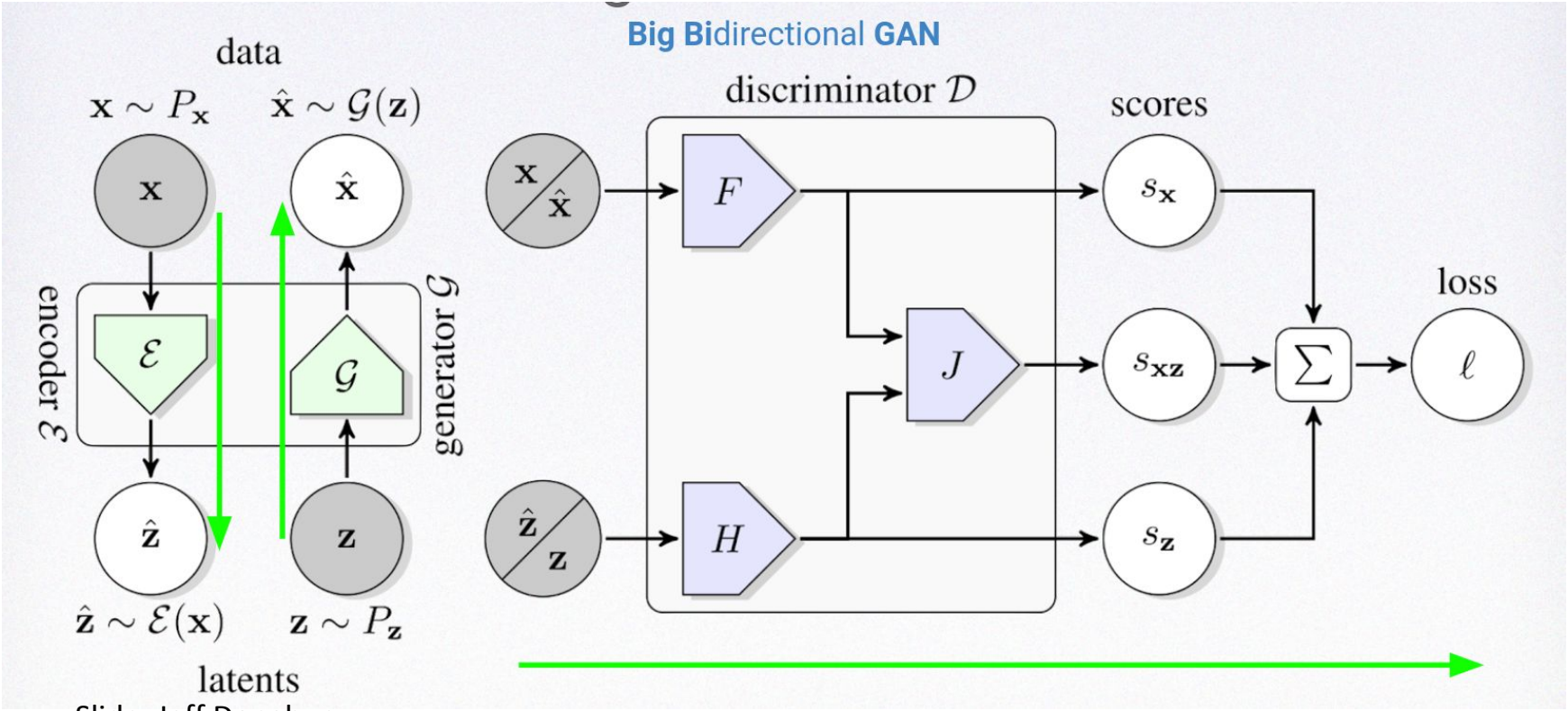
BigBiGAN



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BigBiGAN: Representation Learning

Method	Architecture	Feature	Top-1	Top-5
BiGAN [7, 42]	AlexNet	Conv3	31.0	-
SS-GAN [4]	ResNet-19	Block6	38.3	-
Motion Segmentation (MS) [30, 6]	ResNet-101	AvePool	27.6	48.3
Exemplar (Ex) [8, 6]	ResNet-101	AvePool	31.5	53.1
Relative Position (RP) [5, 6]	ResNet-101	AvePool	36.2	59.2
Colorization (Col) [41, 6]	ResNet-101	AvePool	39.6	62.5
Combination of MS+Ex+RP+Col [6]	ResNet-101	AvePool	-	69.3
CPC [39]	ResNet-101	AvePool	48.7	73.6
Rotation [11, 24]	RevNet-50 $\times 4$	AvePool	55.4	-
Efficient CPC [17]	ResNet-170	AvePool	61.0	83.0
BigBiGAN (ours)	ResNet-50	AvePool	55.4	77.4
	ResNet-50	BN+CReLU	56.6	78.6
	RevNet-50 $\times 4$	AvePool	60.8	81.4
	RevNet-50 $\times 4$	BN+CReLU	61.3	81.9

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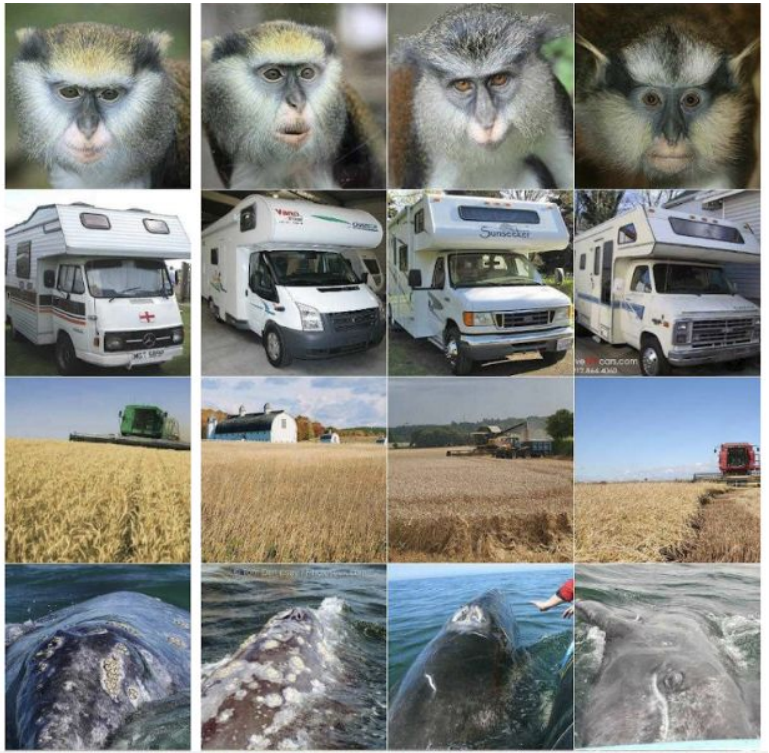
BigBiGAN: Latent Space NNs



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BigBiGAN Reconstructions

Computing a reconstruction $\mathbf{x}' = G(E(\mathbf{x}))$:

(1) Sample a real image $\mathbf{x} \sim P_x$

(2) Encoder predicts latents $\mathbf{z}' = E(\mathbf{x})$

(3) Generator predicts reconstruction $\mathbf{x}' = G(\mathbf{z}')$

(Big)BiGAN is not directly trained for reconstruction!
Arises out of the objective: approx. reconstruction $\mathbf{x}' \cong G(E(\mathbf{x}))$ optimally confuses the joint data-latent discriminator.

Reconstructions give insight into the semantics modeled.

real images **x**

reconstructions $\mathbf{x}' = G(E(\mathbf{x}))$

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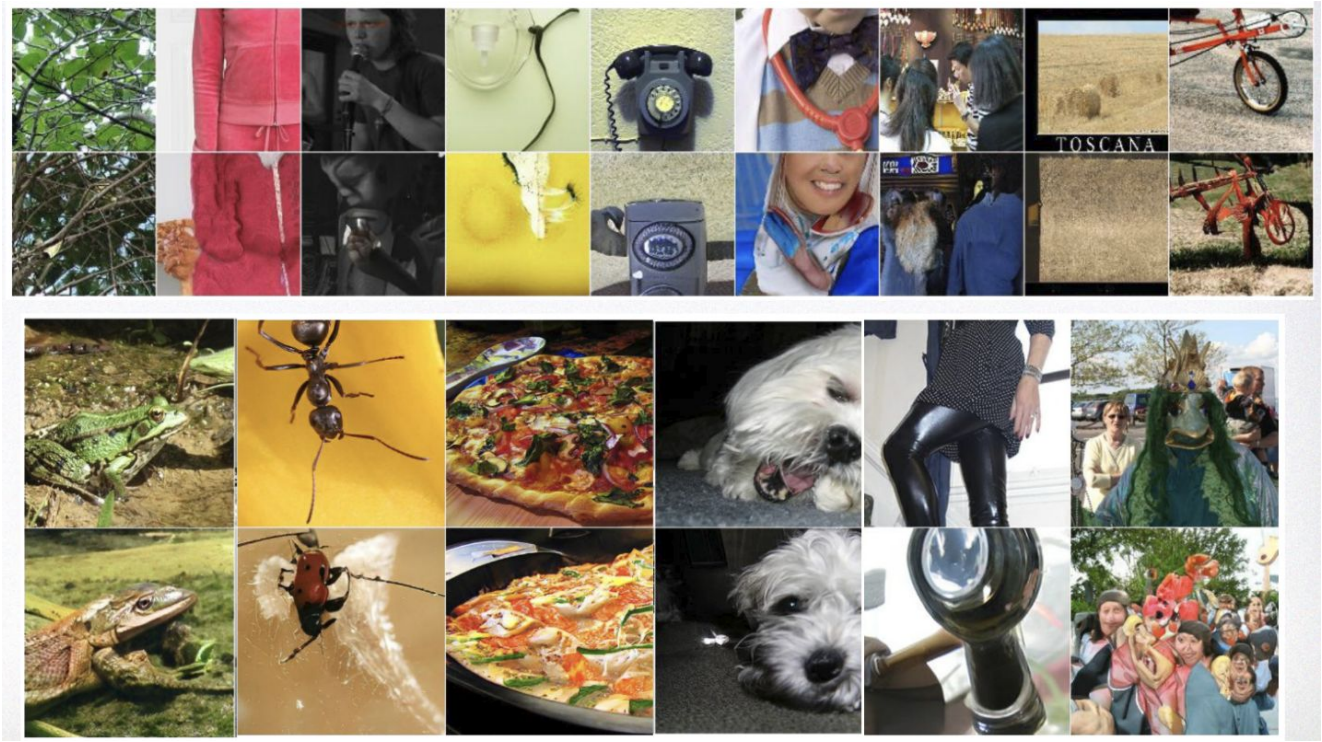
BigBiGAN Reconstructions



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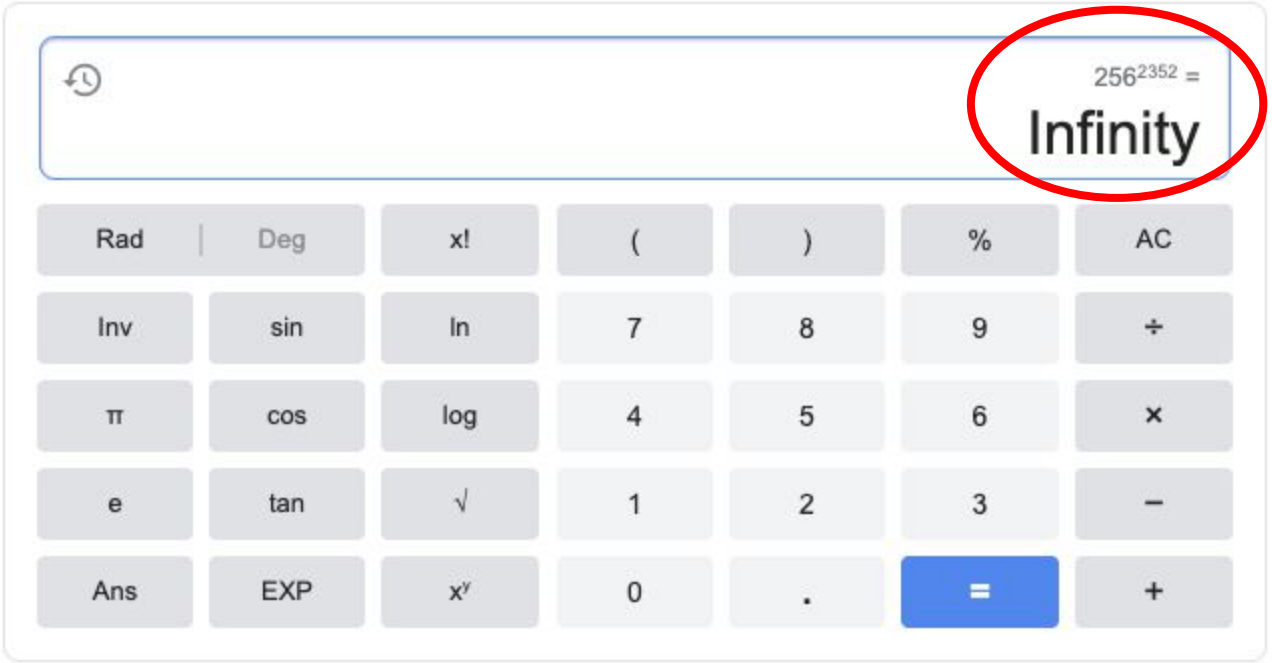
Energy Models

- Assign energy $E(x)$ to every possible x

$$p(x) = \frac{1}{Z} e^{-E(x)} \qquad Z = \sum_{x \in \mathcal{X}} e^{-E(x)}$$

  - Low energy makes for high probability x
  - High energy makes for low probability x
- Practical challenge: domain of x usually very large
  - E.g. all possible 28x28x3 images = 256^(28*28*3) ~ 10^16464

Energy Models



Energy Models -- Definition

- Assign energy $E(x)$ to every possible x

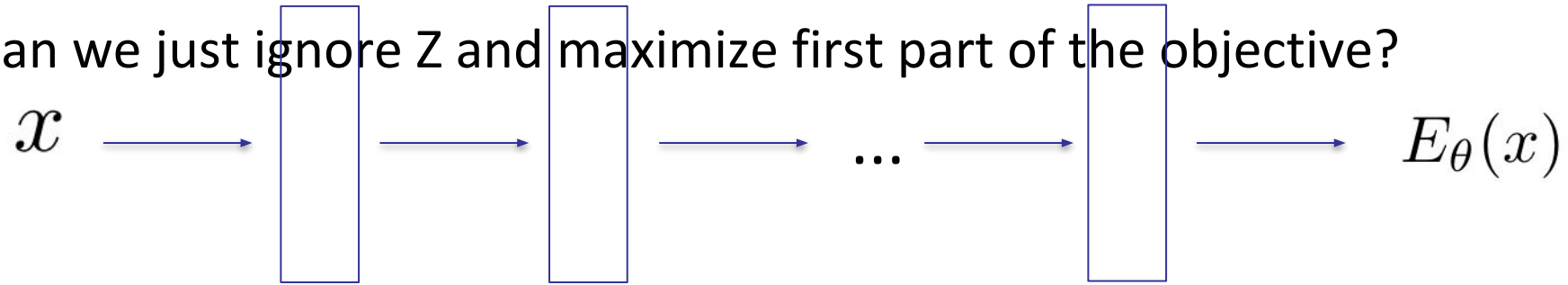
$$p(x) = \frac{1}{Z} e^{-E(x)} \qquad Z = \sum_{x \in \mathcal{X}} e^{-E(x)}$$

  - Low energy makes for high probability x
  - High energy makes for low probability x
- Practical challenge: domain of x usually very large
  - E.g. all possible 28x28x3 images = 256^(28*28*3) ~ 10^16464

  $\rightarrow$ **Z impractical to compute**

Energy Models -- Maximum Likelihood

Can we just ignore Z and maximize first part of the objective?



$$\max_\theta \mathbb{E}_{x\sim p_{\text{data}}} [\log p_\theta(x)] = \max_\theta \mathbb{E}_{x\sim p_{\text{data}}} \log \left(\frac{e^{-E_\theta(x)}}{Z(\theta)} \right) = \max_\theta \mathbb{E}_{x\sim p_{\text{data}}} [-E_\theta(x)] - \log Z(\theta)$$

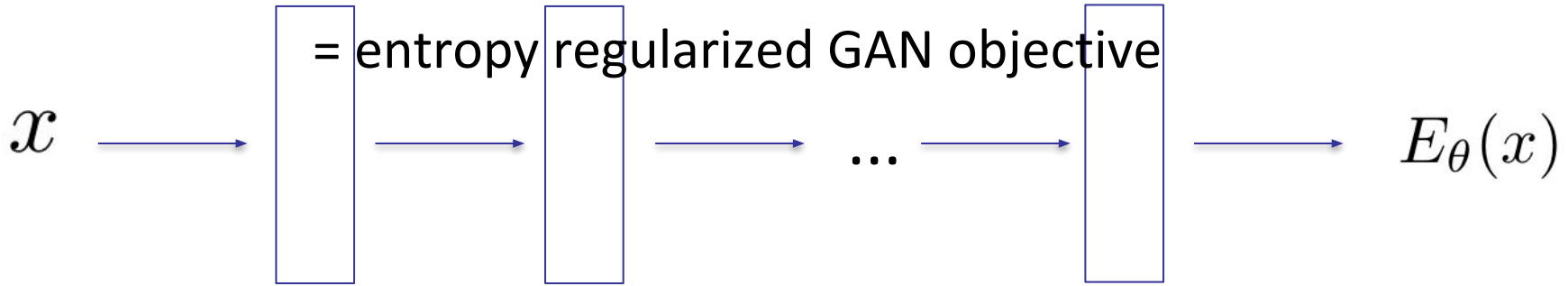
Variational Lower Bound for log Z

$$
\begin{aligned}
\log Z = & \quad \log \textstyle\sum_{x \in \mathcal{X}} e^{-E_\theta(x)} \\
= & \quad \log \textstyle\sum \frac{q_\phi(x)}{q_\phi(x)} e^{-E_\theta(x)} \\
= & \quad \log \mathbb{E}_{x \sim q_\phi} \frac{e^{-E_\theta(x)}}{q_\phi(x)} \\
\geq & \quad \max_{q_\phi} \textstyle\sum_x \log \frac{e^{-E_\theta(x)}}{q_\phi(x)} \\
= & \quad \max_{q_\phi} \textstyle\sum_x -E_\theta(x) + \mathcal{H}(q_\phi)
\end{aligned}
$$

$$
-\log Z \leq \min_{q_\phi} \mathbb{E}_{x \sim q_\phi} \left[E_\theta(x) \right] - \mathcal{H}(q_\phi)
$$

Energy Models -- Maximum Likelihood

= entropy regularized GAN objective



$$\max_\theta \mathbb{E}_{x\sim p_{\text{data}}}\left[\log p_\theta(x)\right] = \max_\theta \mathbb{E}_{x\sim p_{\text{data}}} \log\left(\frac{e^{-E_\theta(x)}}{Z(\theta)}\right) = \max_\theta \mathbb{E}_{x\sim p_{\text{data}}}\left[-E_\theta(x)\right] - \log Z(\theta)$$

$$= \max_\theta \mathbb{E}_{x\sim p_{\text{data}}}\left[-E_\theta(x)\right] + \min_{q_\phi} \mathbb{E}_{x\sim q_\phi}\left[E_\theta(x)\right] - \mathcal{H}(q_\phi)$$

GANs and Energy Models

$$\max_{\theta} \min_{q_\phi} \mathbb{E}_{x \sim p_{\text{data}}} \left[-E_\theta(x) \right] + \mathbb{E}_{x \sim q_\phi} \left[E_\theta(x) \right] - \mathcal{H}(q_\phi)$$

- Specific parameterizations of E can lead to different GAN models

? Is Entropy easy to compute

- Generally, no… but can be done for some models, worth investigating!

GANs and Energy Models

Inspiring, clean comprehensive mathematical write-up

- John Schulman
  Notes On GANs, Energy-Based Models, and Saddle Points
  http://joschu.net/docs/gan-notes.pdf (2016)

Early papers:

- Taesup Kim and Yoshua Bengio
  Deep Directed Generative Models with Energy-Based Probability Estimation
  https://arxiv.org/abs/1606.03439
- Junbo Zhao, Michael Mathieu, Yann LeCun
  Energy-based Generative Adversarial Network
  https://arxiv.org/abs/1609.03126

Recent related papers:

- Adji B. Dieng, Francisco J. R. Ruiz, David M. Blei, Michalis K. Titsias
  Prescribed Generative Adversarial Networks
  https://arxiv.org/abs/1910.04302
- Aditya Grover, Manik Dhar, Stefano Ermon
  Flow-GAN: Combining Maximum Likelihood and Adversarial Learning in Generative Models
  https://arxiv.org/abs/1705.08868

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Recall: Wasserstein Distance

- Earth Mover (EM) distance

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

- W-GAN optimizes the dual

- How about optimizing the primal directly?

  $\longrightarrow$ Optimal Transport GANs

GANs and Optimal Transport

- Improving GANs using Optimal Transport
  Tim Salimans, Han Zhang, Alec Radford, Dimitris Metaxas
  ICLR 2018
  https://arxiv.org/abs/1803.05573

- Sinkhorn AutoDiff GAN: Learning Generative Models with Sinkhorn Divergences
  Aude Genevay, Gabriel Peyre, Marco Cuturi
  AISTATS 2018
  https://arxiv.org/abs/1706.00292

- Cramer GAN: The Cramer Distance as a Solution to Biased Wasserstein Gradients
  Marc Bellemare, Ivo Danihelka, W Dabney, S Mohamed, B Laskhiminarayanan, S Hoyer, R Munos
  https://arxiv.org/abs/1705.10743

Implicit Likelihood Models

- Implicit Maximum Likelihood Estimation
  Ke Li, Jitendra Malik
  https://arxiv.org/abs/1809.09087
- Diverse Image Synthesis from Semantic Layouts via Conditional IMLE
  Ke Li, Tianhao Zhang, Jitendra Malik
  https://arxiv.org/abs/1811.12373

Algorithm 1 Implicit maximum likelihood estimation (IMLE) procedure

Require: The dataset $D = \{\mathbf{x}_i\}_{i=1}^n$ and a sampling mechanism for the implicit model P_θ

Initialize θ to a random vector

for $k = 1$ **to** K **do**

  Draw i.i.d. samples $\tilde{\mathbf{x}}_1^\theta, \ldots, \tilde{\mathbf{x}}_m^\theta$ from P_θ

  Pick a random batch $S \subseteq \{1, \ldots, n\}$

  $\sigma(i) \leftarrow \arg\min_j \left\| \mathbf{x}_i - \tilde{\mathbf{x}}_j^\theta \right\|_2^2 \ \forall i \in S$

  for $l = 1$ **to** L **do**

    Pick a random mini-batch $\tilde{S} \subseteq S$

    $\theta \leftarrow \theta - \eta \nabla_\theta \left(\frac{n}{|\tilde{S}|} \sum_{i \in \tilde{S}} \left\| \mathbf{x}_i - \tilde{\mathbf{x}}_{\sigma(i)}^\theta \right\|_2^2 \right)$

  end for

end for

return θ

→ every training data point needs to have a closeby generated neighbor

Moment Matching

- Key idea: Match the moments of the data and model distributions to bring them closer
- Called the two-sample test in hypothesis testing

Given samples $X = \{x_i\}_{i=1}^N$ from P_X , $Y = \{y_j\}_{j=1}^M$ from P_Y , how do we compare P_X and P_Y?

- Not feasible to compute higher order moments in high dimensions

Moment Matching

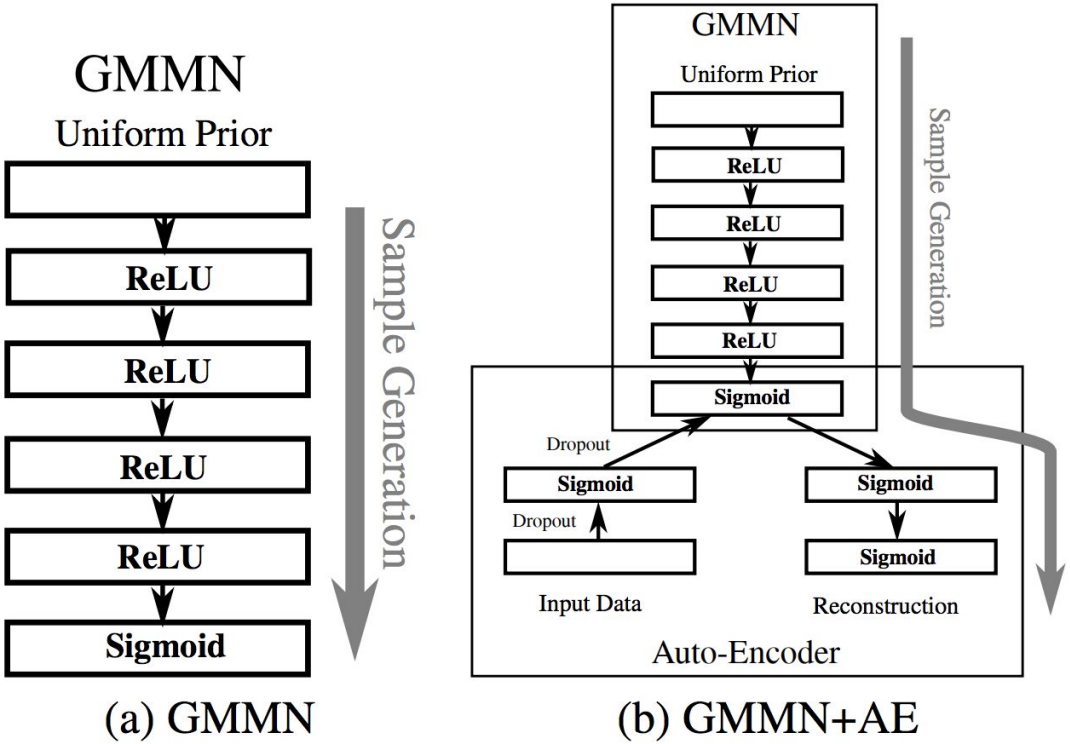
- Kernel trick

$$
\begin{aligned}
L_{MMD} &= \| \frac{1}{N} \sum_{i=1}^{N} \phi(x_i) - \frac{1}{M} \sum_{j=1}^{M} \phi(y_j) \|^2 \\
&= \frac{1}{N^2} \sum_{i=1}^{N} \sum_{i'=1}^{N} \phi(x_i)^T \phi(x_i') + \frac{1}{M^2} \sum_{j=1}^{M} \sum_{j'=1}^{M} \phi(y_j)^T \phi(y_j') - \frac{2}{MN} \sum_{i=1}^{N} \sum_{j=1}^{M} \phi(x_i)^T \phi(y_j) \\
&= \frac{1}{N^2} \sum_{i=1}^{N} \sum_{i'=1}^{N} k(x_i, x_{i'}) - \frac{2}{MN} \sum_{i=1}^{N} \sum_{j=1}^{M} k(x_i, y_j) + \frac{1}{M^2} \sum_{j=1}^{M} \sum_{j'=1}^{M} k(y_j, y_{j'})
\end{aligned}
$$

Moment Matching

- Identity function ϕ is equivalent to matching sample means
- Kernel trick allows you to optimize mean discrepancy in higher dimensional spaces.
- Example $k(x, x') = \exp\left(\frac{-||x - x'||^2}{2\sigma}\right)$
- Refer to Gretton et al 2007, 2012 - Mathematical Treatment

Generative Moment Matching Networks



Li, Swersky, Zemel (2015)

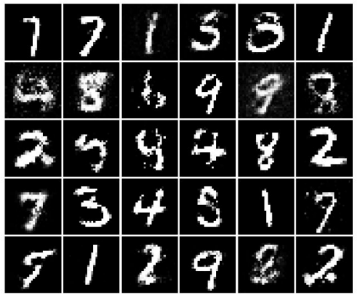
Generative Moment Matching Networks

Input : Dataset $\{\mathbf{x}_1^d, ..., \mathbf{x}_N^d\}$, prior $p(\mathbf{h})$, network $f(\mathbf{h}; \mathbf{w})$ with initial parameter $\mathbf{w}^{(0)}$

Output: Learned parameter $\mathbf{w}^*$

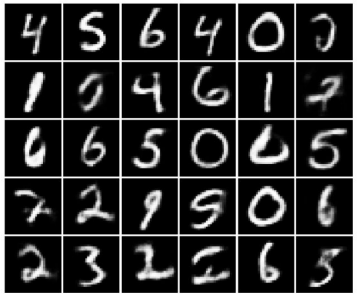
while *Stopping criterion not met* **do**
  Get a minibatch of data $\mathbf{X}^d \leftarrow \{\mathbf{x}_{i_1}^d, ..., \mathbf{x}_{i_b}^d\}$
  Get a new set of samples $\mathbf{X}^s \leftarrow \{\mathbf{x}_1^s, ..., \mathbf{x}_b^s\}$
  Compute gradient $\frac{\partial \mathcal{L}_{\text{MMD}}}{\partial \mathbf{w}}$ on $\mathbf{X}^d$ and $\mathbf{X}^s$
  Take a gradient step to update $\mathbf{w}$
end

Li, Swersky, Zemel (2015)



(a) GMMN MNIST samples

(b) GMMN TFD samples



(c) GMMN+AE MNIST samples

(d) GMMN+AE TFD samples

Generative Moment Matching Networks

- Need a good kernel for the mean discrepancy measure

> For universal kernels like the Gaussian kernel, defined as $k(x, x') = \exp(-\frac{1}{2\sigma}|x - x'|^2)$, where σ is the bandwidth parameter, we can use a Taylor expansion to get an explicit feature map ϕ that contains an infinite number of terms and covers all orders of statistics. Minimizing MMD under this feature expansion is then equivalent to minimizing a distance between *all* moments of the two distributions.

- Not shown to scale well beyond MNIST and TFD (and some variants on CIFAR 10 later) - needs autoencoding, large minibatch and mixture of kernels with different bandwidths

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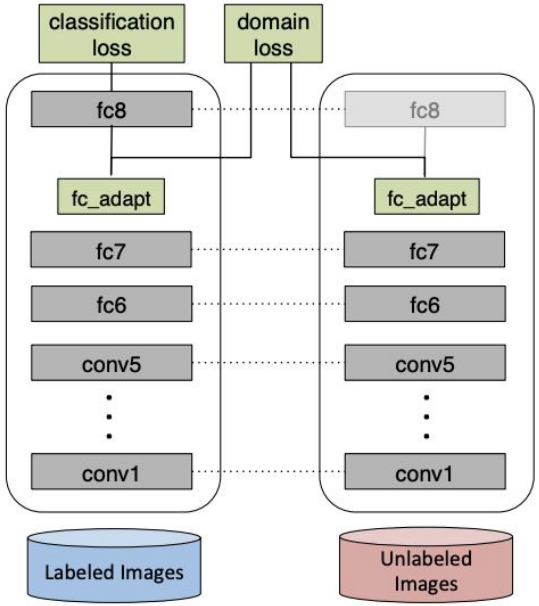
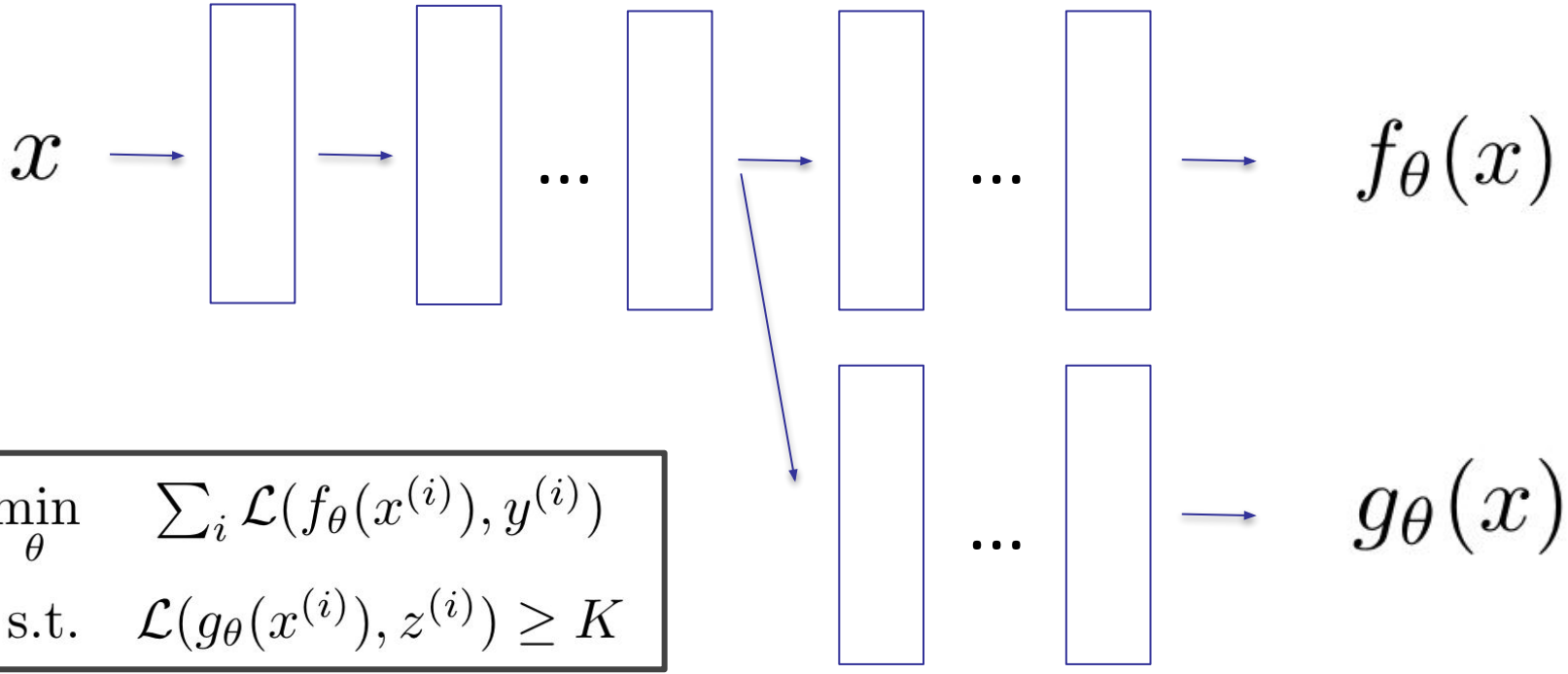
Other Uses of Adversarial Loss -- Transfer

- Deep Domain Confusion: Maximizing fc
  Eric Tzeng, Judy Hoffman, Ning Zhang, I
  https://arxiv.org/abs/1412.3474



Other Uses of Adversarial Loss -- Fairness



$$\begin{aligned} \min_{\theta} \quad & \textstyle\sum_i \mathcal{L}(f_\theta(x^{(i)}), y^{(i)}) \\ \text{s.t.} \quad & \mathcal{L}(g_\theta(x^{(i)}), z^{(i)}) \geq K \end{aligned}$$

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GANs and Imitation Learning: GAIL

GAIL: Generative Adversarial Imitation Learning
Jonathan Ho, Stefano Ermon
NeurIPS 2016
https://arxiv.org/pdf/1606.03476.pdf

Imitation learning as a GAN problem:

$$\mathbb{E}_{\pi}[\log(D(s,a))] + \mathbb{E}_{\pi_E}[\log(1 - D(s,a))] - \lambda H(\pi)$$

- Discriminator tries to distinguish trajectories (s,a) from demonstrator vs. from learned imitation policy pi
- Learned policy pi tries to make itself indistinguishable from demonstrator
- Note: matches Energy-Based Model GAN formulation

GANs and Imitation Learning: GAIL

GAIL: Generative A
Jonathan Ho, Stefa
NeurIPS 2016
https://arxiv.org/p

Algorithm 1 Generative adversarial imitation learning

1: **Input:** Expert trajectories $\tau_E \sim \pi_E$, initial policy and discriminator parameters θ_0, w_0
2: **for** $i = 0, 1, 2, \ldots$ **do**
3: Sample trajectories $\tau_i \sim \pi_{\theta_i}$
4: Update the discriminator parameters from w_i to w_{i+1} with the gradient

$$\hat{\mathbb{E}}_{\tau_i}[\nabla_w \log(D_w(s,a))] + \hat{\mathbb{E}}_{\tau_E}[\nabla_w \log(1 - D_w(s,a))] \tag{17}$$

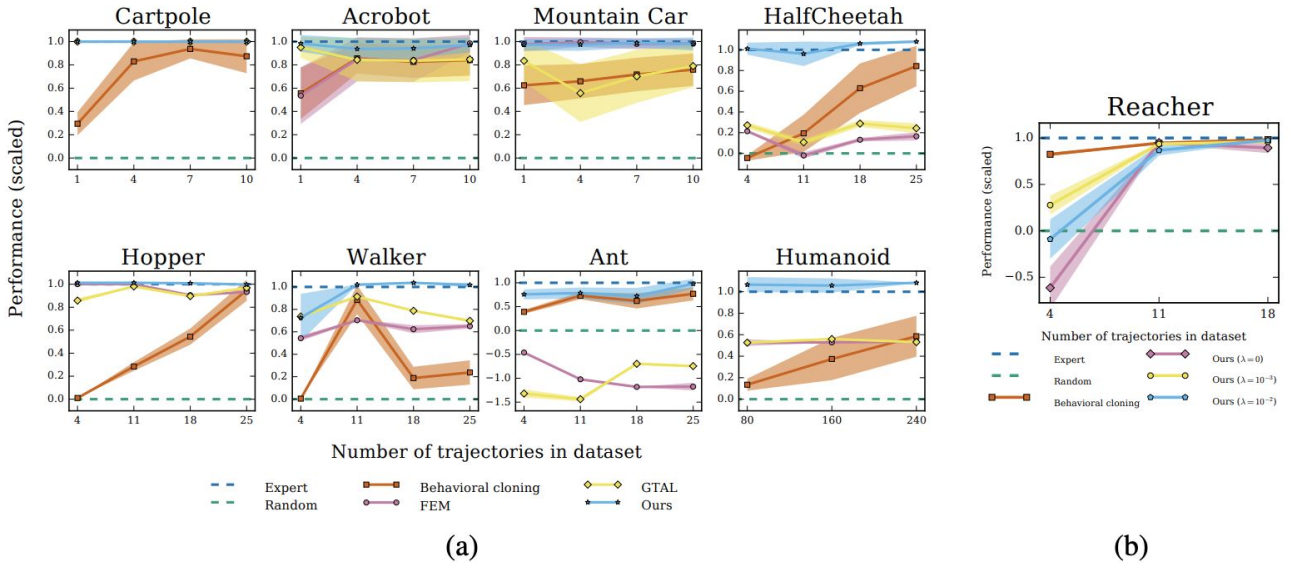
5: Take a policy step from θ_i to θ_{i+1}, using the TRPO rule with cost function $\log(D_{w_{i+1}}(s,a))$. Specifically, take a KL-constrained natural gradient step with

$$\begin{aligned} &\hat{\mathbb{E}}_{\tau_i}[\nabla_\theta \log \pi_\theta(a|s) Q(s,a)] - \lambda \nabla_\theta H(\pi_\theta), \\ &\text{where } Q(\bar{s},\bar{a}) = \hat{\mathbb{E}}_{\tau_i}[\log(D_{w_{i+1}}(s,a)) \,|\, s_0 = \bar{s}, a_0 = \bar{a}] \end{aligned} \tag{18}$$

6: **end for**

GANs and Imitation Learning: GAIL

GAIL: Generative Advers
Jonathan Ho, Stefano Err
NeurIPS 2016
https://arxiv.org/pdf/16(



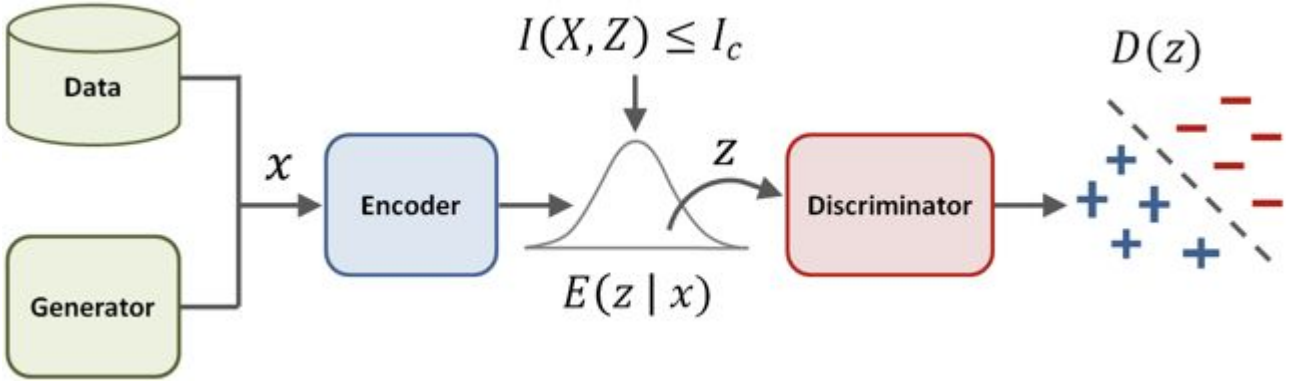
(a) (b)

Figure 1: (a) Performance of learned policies. The y-axis is negative cost, scaled so that the expert achieves 1 and a random policy achieves 0. (b) Causal entropy regularization λ on Reacher.

GANs and Imitation Learning: VAIL

Recall: Variational Discriminator Bottleneck GAN

Variational Discriminator Bottleneck: Improving Imitation Learning, Inverse RL, and GANs by Constraining Information Flow
Xue Bin Peng, Angjoo Kanazawa, Sam Toyer, Pieter Abbeel, Sergey Levine
ICLR 2019
https://arxiv.org/pdf/1810.00821.pdf



VAIL

VAIL

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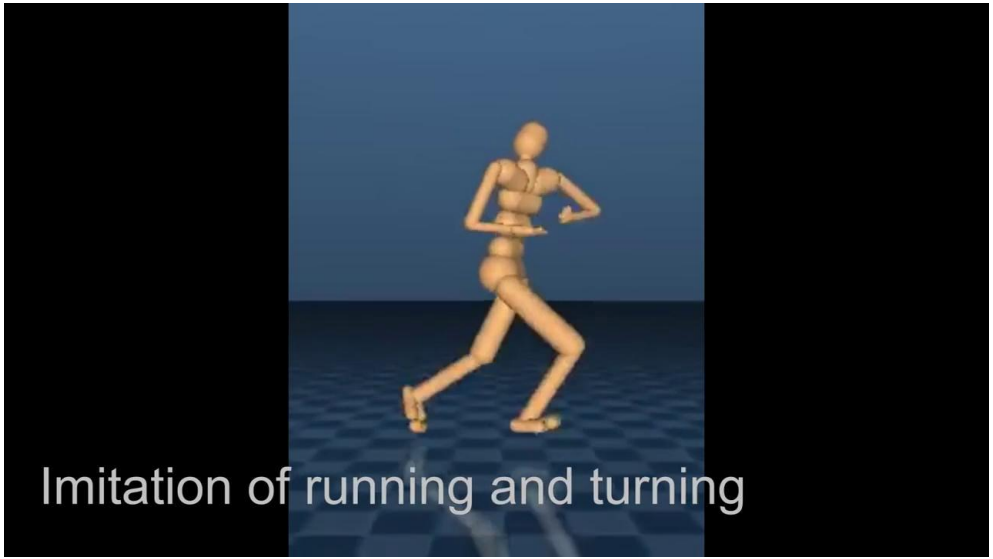
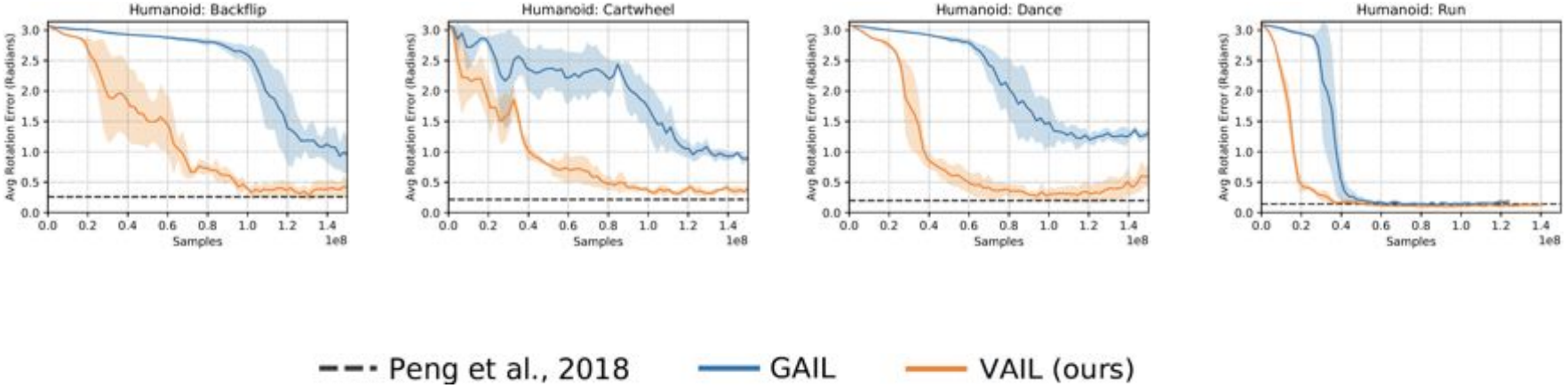


[Merel et al 2017]

VAIL

Variational Discriminator Bottleneck: Improving Imitation Learning, Inverse RL, and GANs by Constraining Information Flow
Xue Bin Peng, Angjoo Kanazawa, Sam Toyer, Pieter Abbeel, Sergey Levine
ICLR 2019
https://arxiv.org/pdf/1810.00821.pdf



Summary

- Motivation & Definition of Implicit Models
- Original GAN (Goodfellow et al, 2014)
- Evaluation: Parzen, Inception, Frechet
- Some Theory: Bayes-optimal Discriminator; Jensen-Shannon Divergence; Mode Collapse; Avoiding Saturation
- GAN Progression:
  - DC GAN (Radford et al, 2016)
  - Improved Training of GANs (Salimans et al, 2016)
  - WGAN, WGAN-GP, Progressive GAN, SN-GAN, SAGAN
  - BigGAN, StyleGAN
  - More GANs: BigGAN-Deep, StyleGAN-v2, VIB-GAN, LOGAN
- Creative Conditional GANs
- GANs and Representations
- GANs as Energy Models
- GANs and Optimal Transport
- Implicit Likelihood Models
- Moment Matching
- Other uses of Adversarial Loss: Transfer Learning, Fairness
- GANs and Imitation Learning