Lecture 19: Deep Generative Models IV: Generative Adversarial Network (GAN)

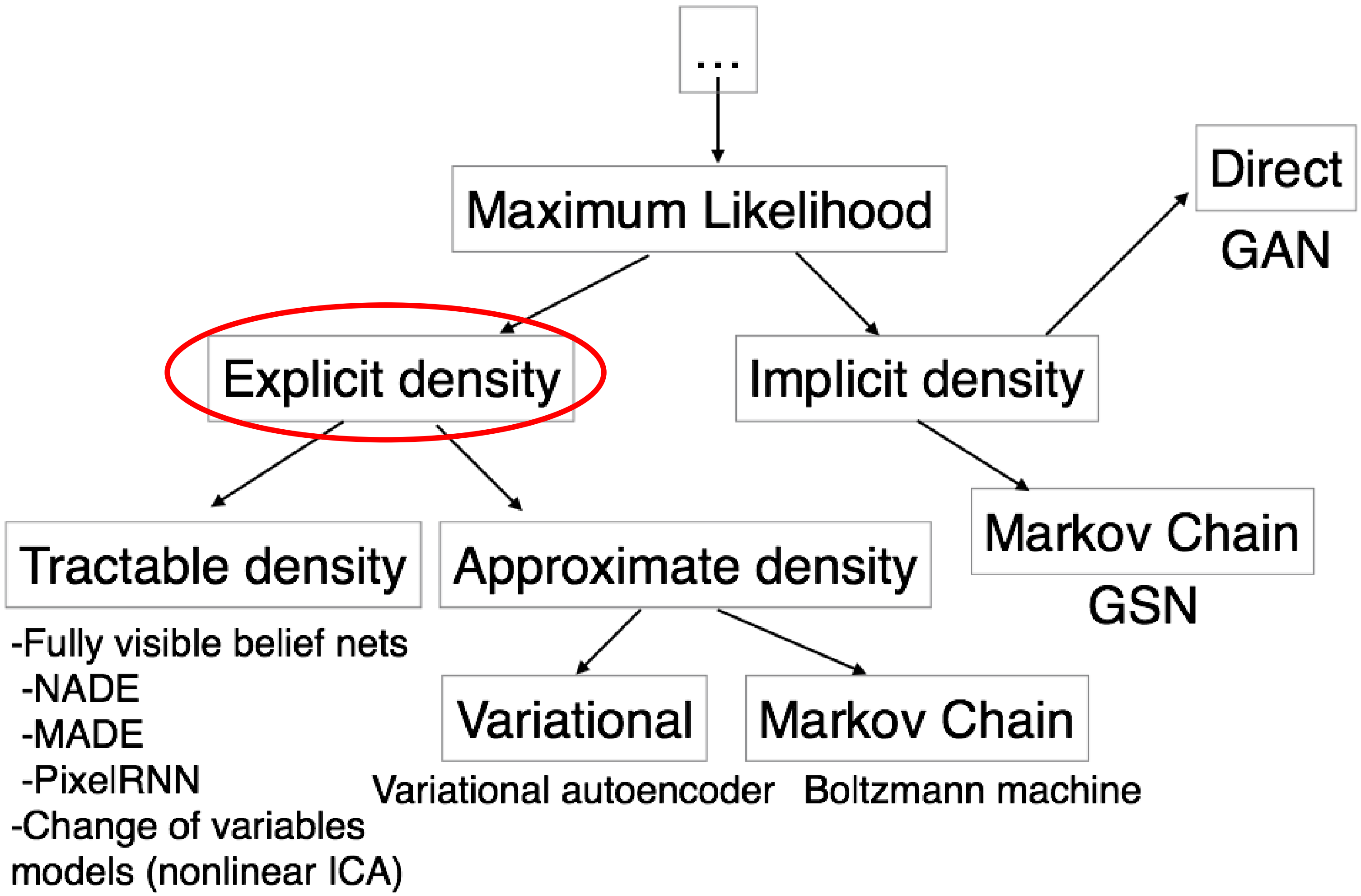
Xuming He, Lan Xu
SIST, ShanghaiTech
Fall, 2020

Outline

- Generative Adversarial Networks
  - Implicit generative models
  - Adversarial learning
  - Evaluation metrics

Acknowledgement: Feifei Li et al's cs231n notes

Taxonomy of Generative Models



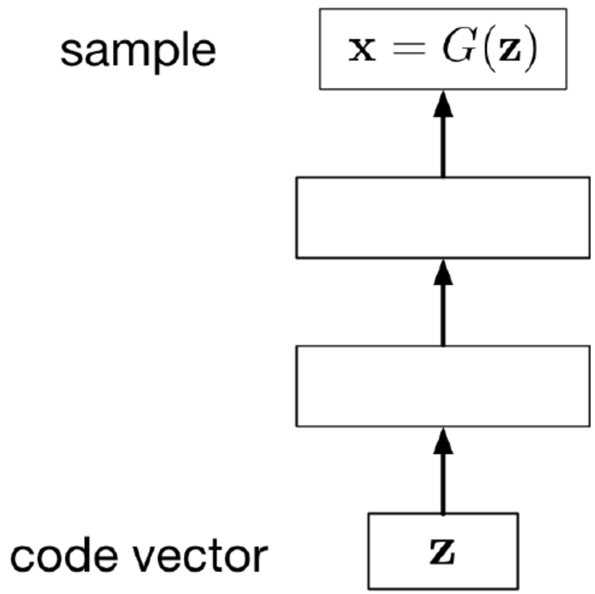
Implicit Generative Models

- Working with explicit model p(x) could be expensive
  - Variational Autoencoder (variational inference)
  - Boltzmann Machines (MCMC, not discussed)

- Representation learning may not require p(x)
  - Sometimes we are more interested in taking samples from p(x) instead of p itself

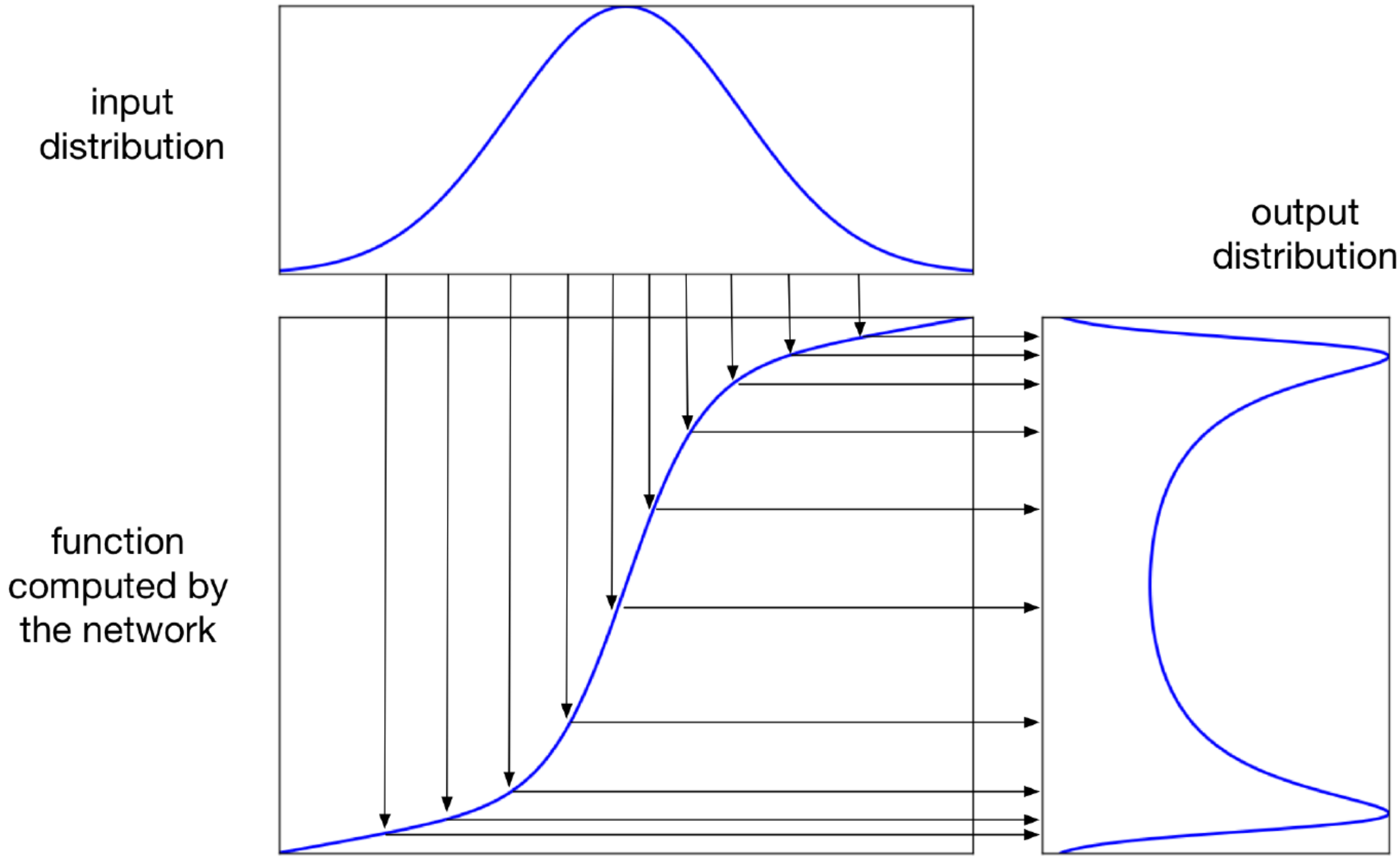
Implicit Generative Models

- Implicitly define a probability distribution
- Start by sampling the code vector z from a fixed, simple distribution
- A generator network computes a differentiable function G mapping z to an x in data space



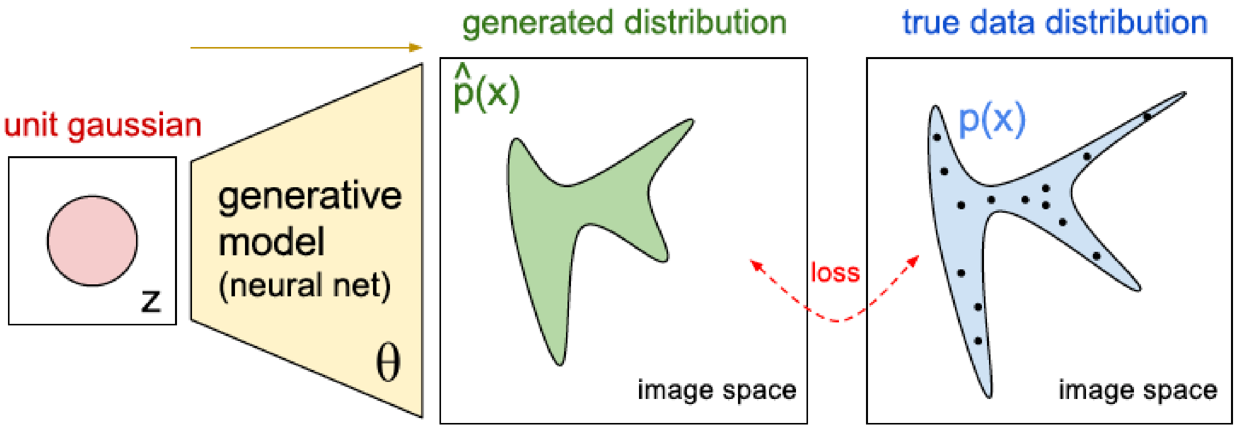
Implicit Generative Models

- Intuition: 1D example



Implicit Generative Models

- Intuition

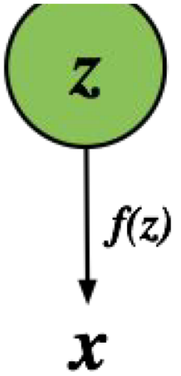


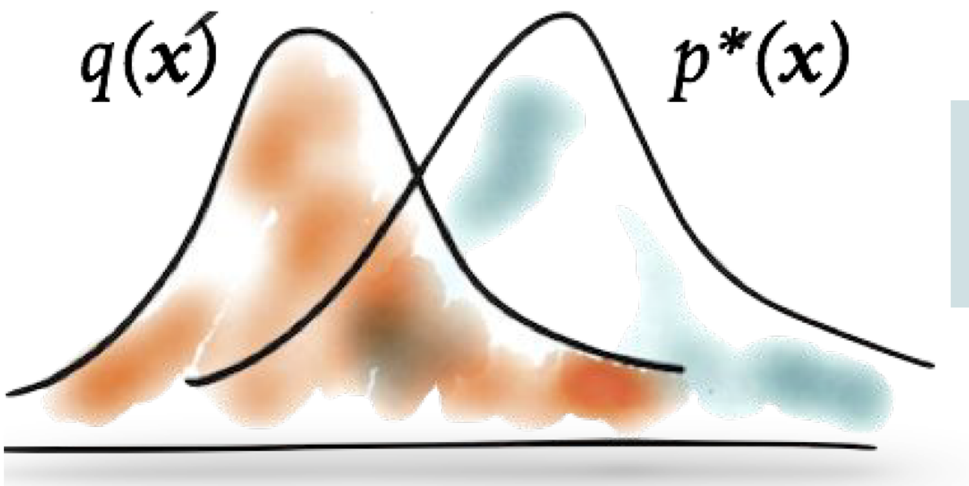
advocate/penalize samples within the blue/white region.

Learning by comparison

- Basic idea

For some models, we only have access to an unnormalised probability, partial knowledge of the distribution, or a simulator of data.





We compare the estimated distribution q(x) to the true distribution p*(x) using samples.

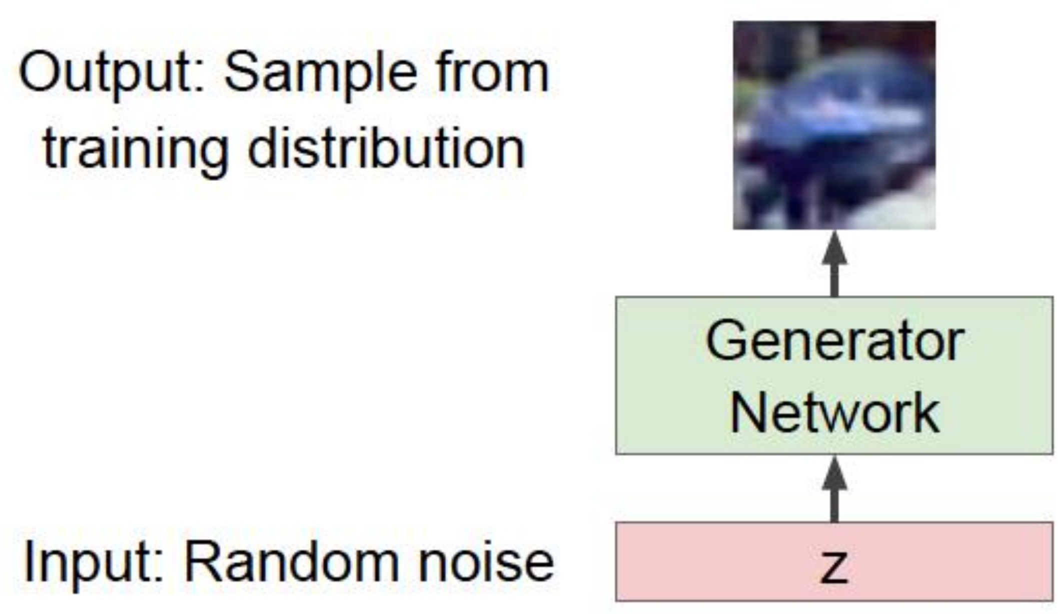
Outline

- Generative Adversarial Networks
  - Implicit generative models
  - Adversarial learning
  - Evaluation metrics

Acknowledgement: Feifei Li et al's cs231n notes

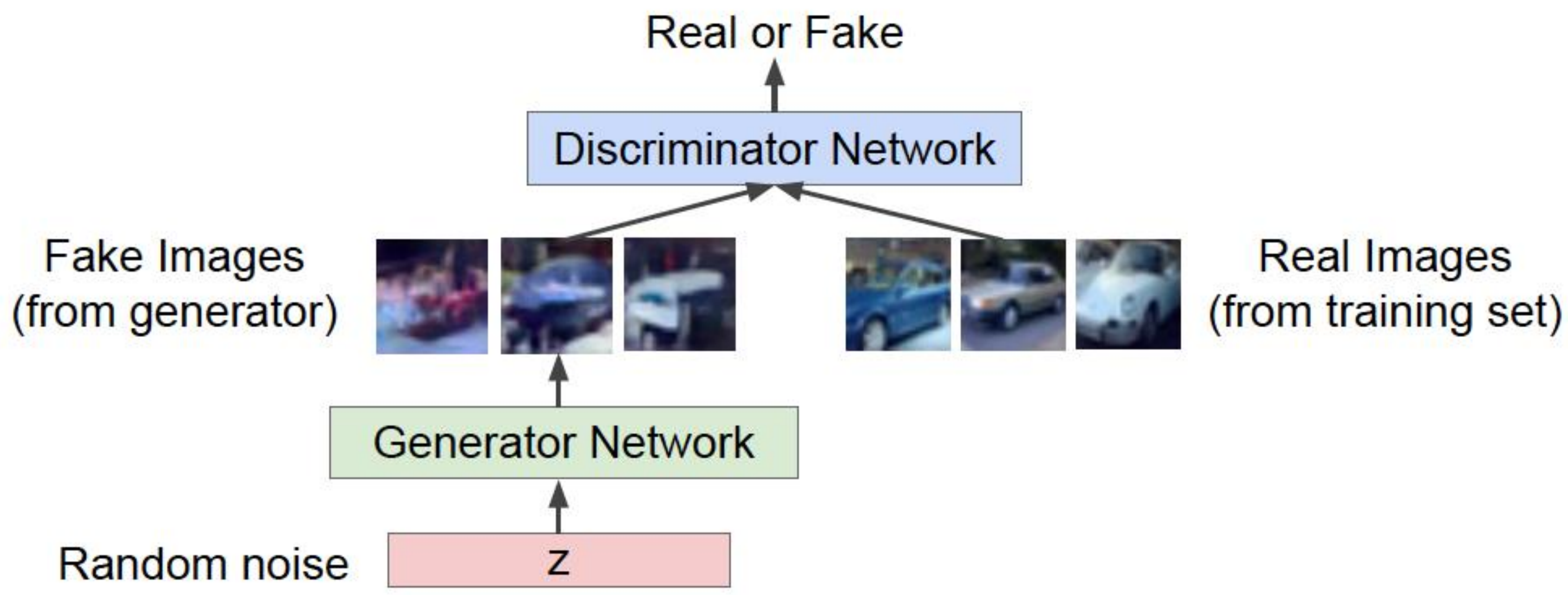
Generative Adversarial Networks

- Using a neural network to generate data



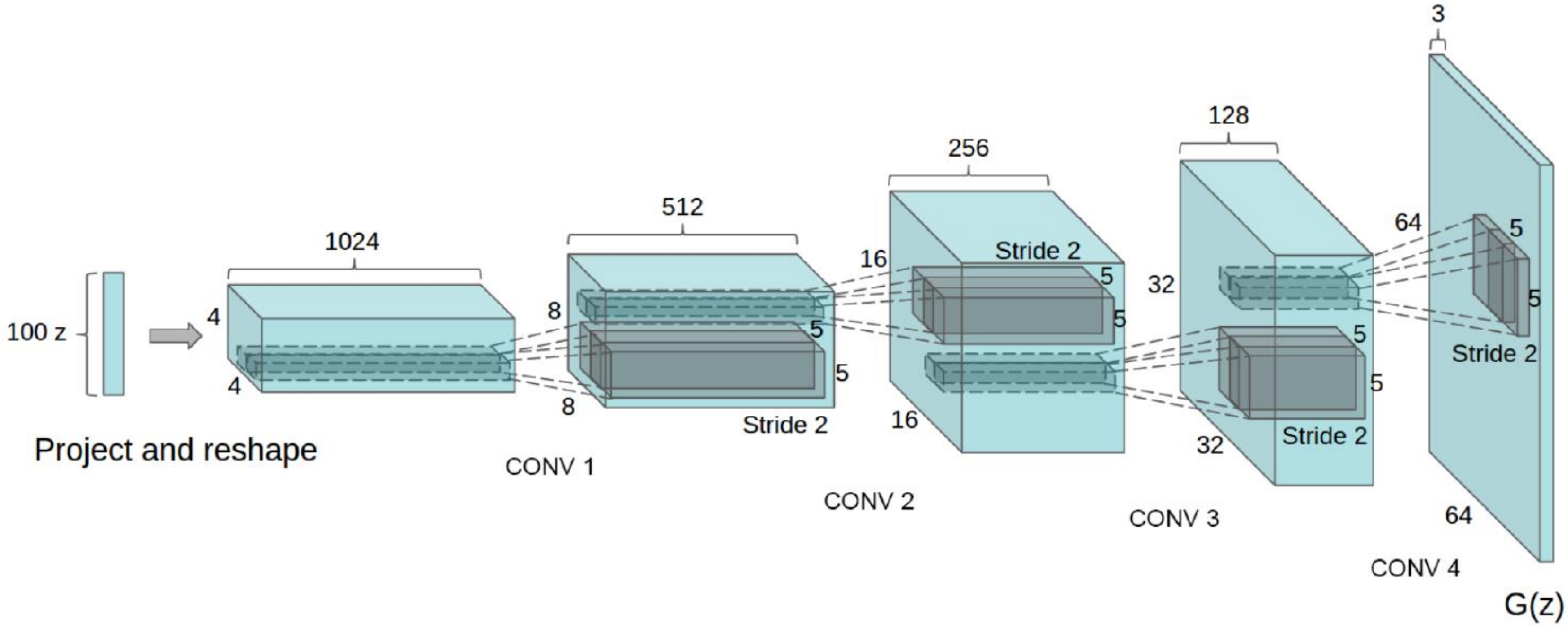
Generative Adversarial Networks

- Using another neural network to determine if the data is real or not



Typical generator architecture

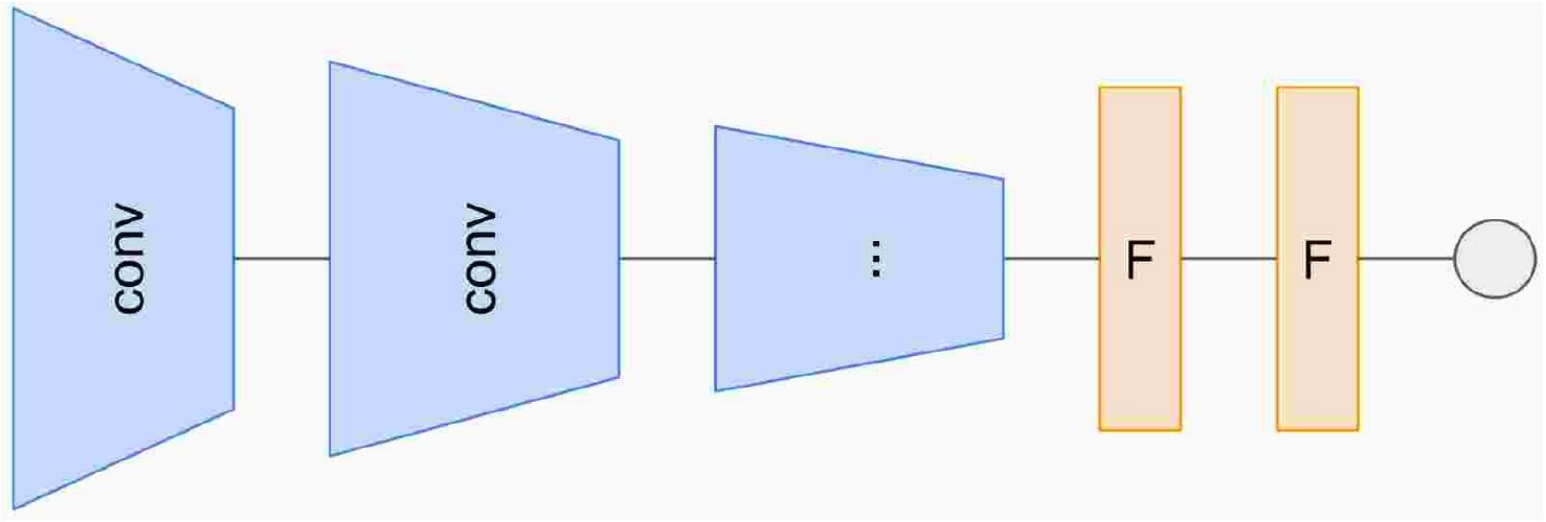
- For images



- Unit Gaussian distribution on z, typically 10-100 dim.
- Up-convolutional deep network (reverse recognition CNN)

Typical discriminator architecture

- For images



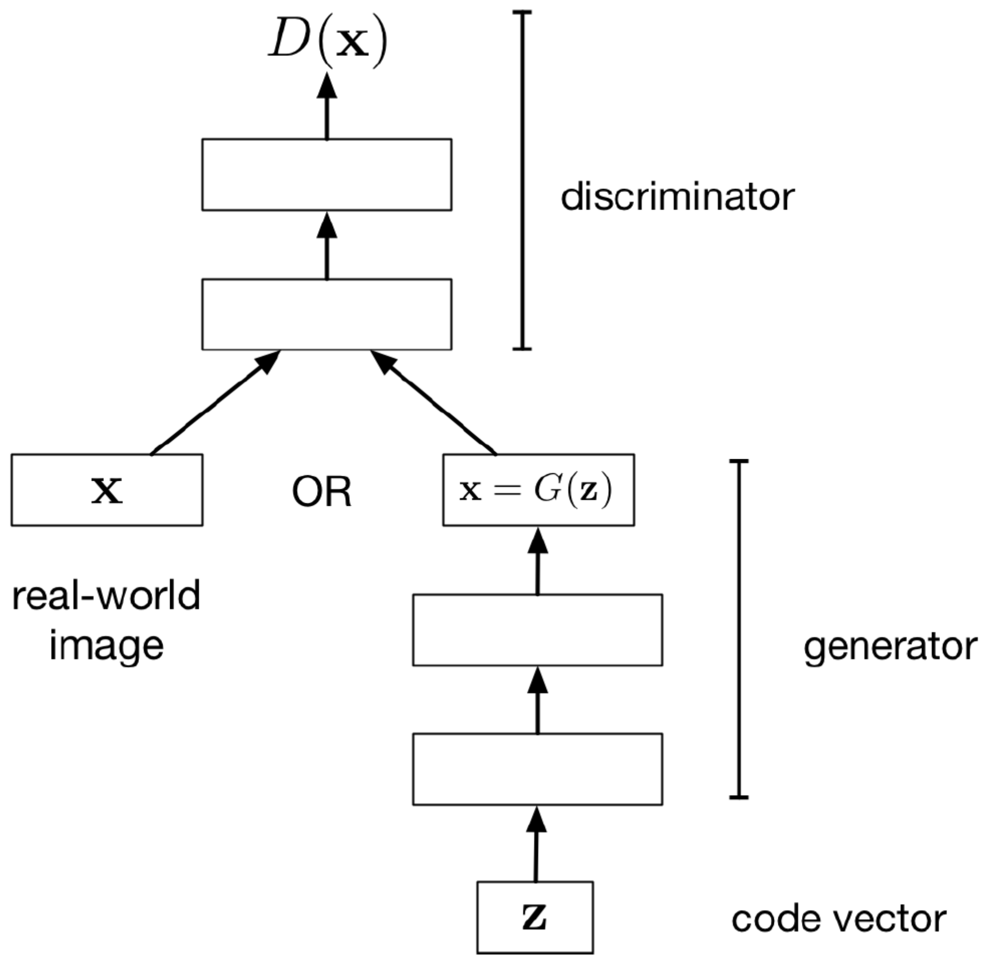
- Recognition CNN model
- Binary classification output: real / synthetic

Adversarial learning

- GAN objective for the generator is some complicated objective function defined by a neural network.
  - This means a new way of thinking about "distance".
  - We are training networks to minimize the "distance" or "divergence" between generated images and real images.
  - Instead of some hand-crafted distance metric like L1 or L2, we can make something completely new.
  - *A neural network, with the right architecture, is arguably the definition of perceptual similarity (assuming our visual system is some sort of neural network).*

Adversarial Learning

- Adversarial loss



Adversarial Learning

- Let D denote the discriminator's predicted probability of being real data
- Discriminator's cost function: cross-entropy loss for task of classifying real vs. fake images

$$\mathcal{J}_D = \mathbb{E}_{\mathbf{x}\sim\mathcal{D}}[-\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}}[-\log(1 - D(G(\mathbf{z})))]$$

- One possible cost function for the generator: the opposite of the discriminator's

$$\begin{aligned}\mathcal{J}_G &= -\mathcal{J}_D \\ &= \text{const} + \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]\end{aligned}$$

Two-player game

- Minimax formulation
  - The generator and discriminator are playing a zero-sum game against each other

$$\min_G \max_D \mathcal{J}_D$$

  - Using parametric models

Discriminator outputs likelihood in (0,1) of real image

Minimax objective function:

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

Learning procedure

- Minimax objective function

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

Alternate between:

1. **Gradient ascent** on discriminator

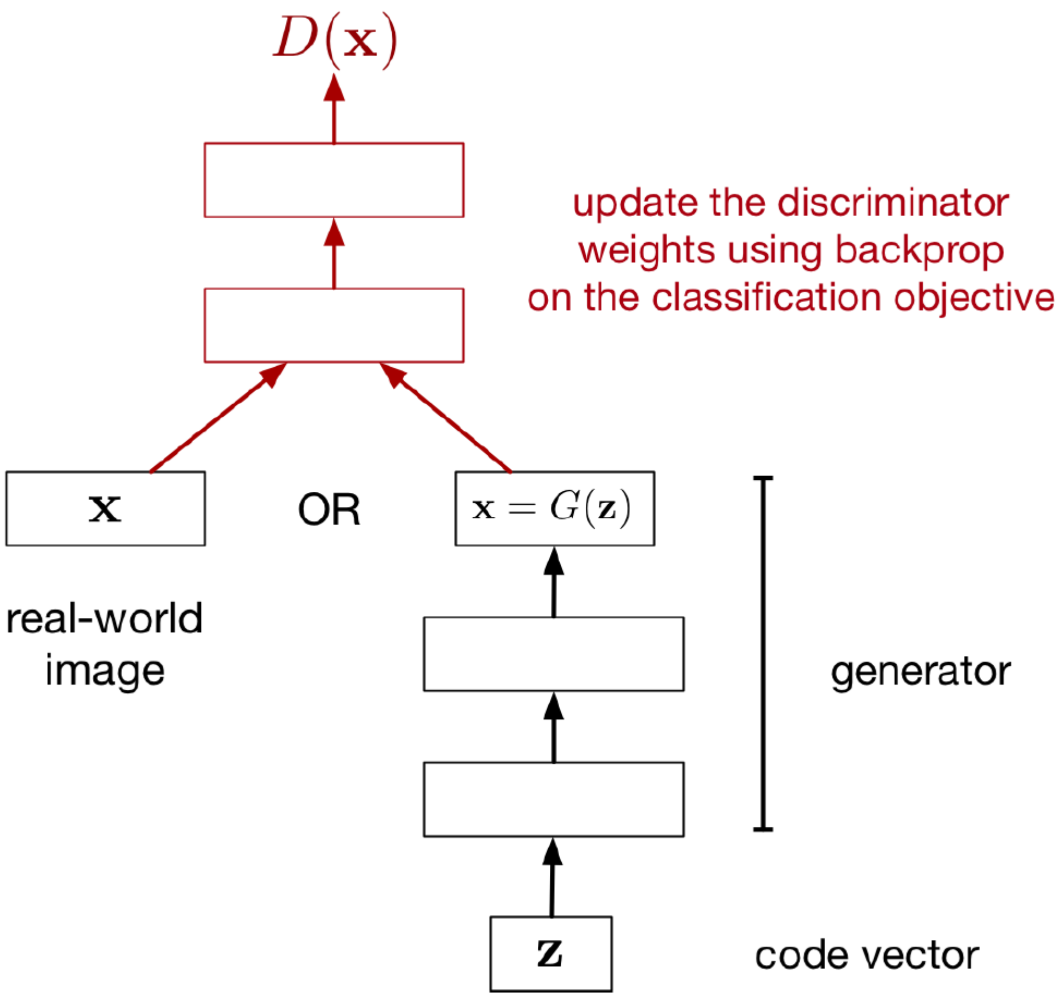
$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Gradient descent** on generator

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

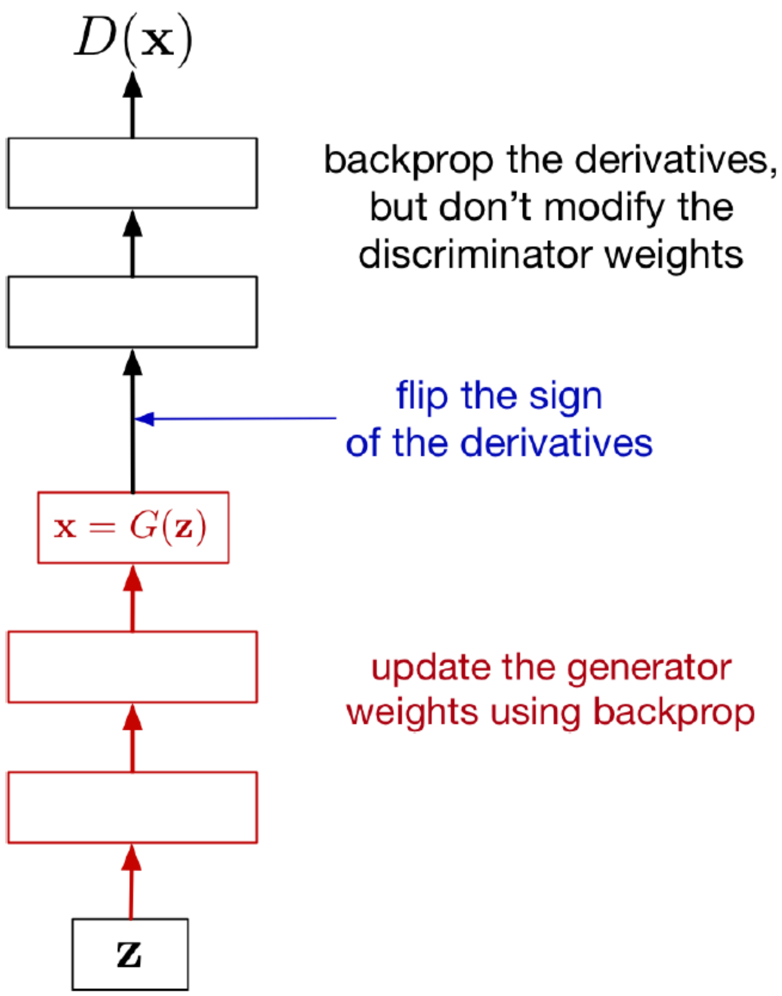
Learning procedure

- Updating the discriminator



Learning procedure

- Updating the generator

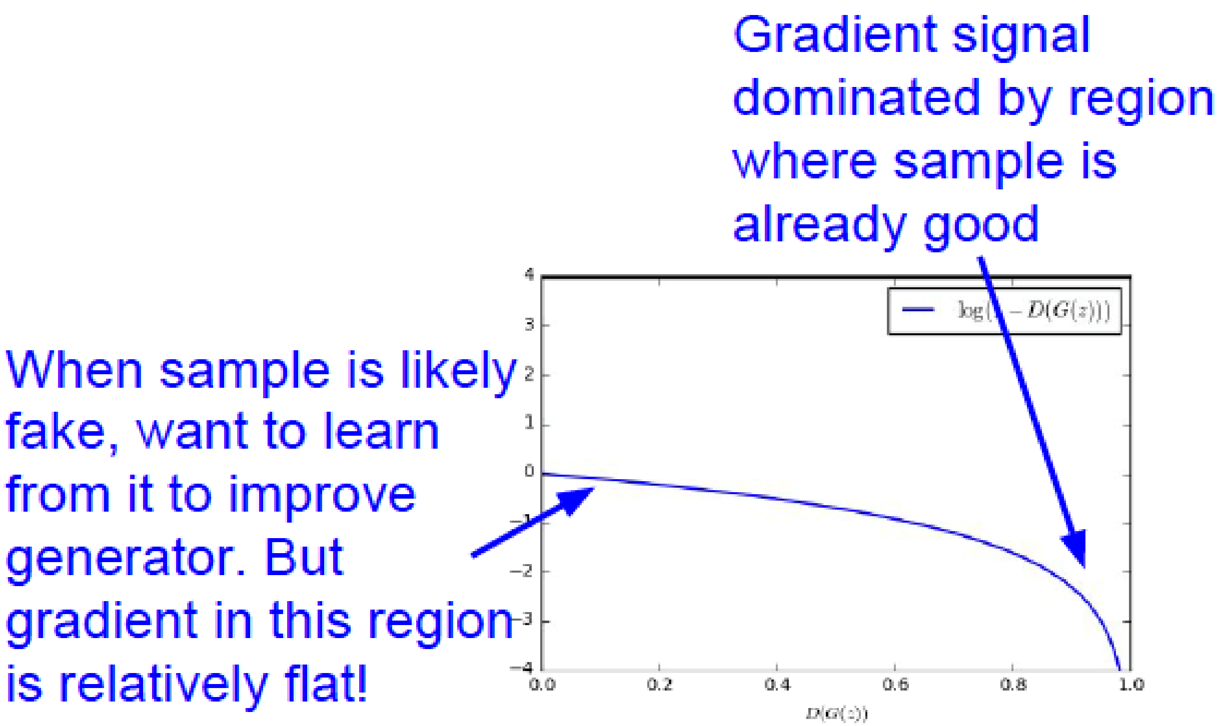


A better cost function

- The minimax cost function for the generator

$$\mathcal{J}_G = \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]$$

- One problem is saturation



A better cost function

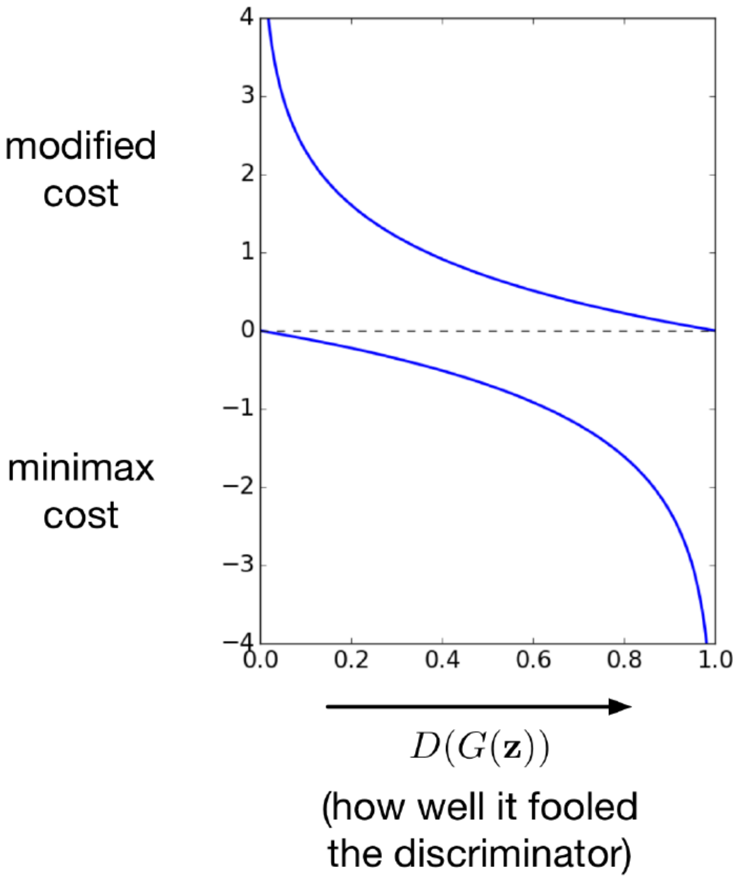
- Changing the generator cost
  - Original minimax cost:

$$\mathcal{J}_G = \mathbb{E}_{\mathbf{z}}[\log(1 - D(G(\mathbf{z})))]$$

  - Modified generator cost:

$$\mathcal{J}_G = \mathbb{E}_{\mathbf{z}}[-\log D(G(\mathbf{z}))]$$

  - This fixes the saturation problem.



Theoretical property

- Adversarial loss

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{x\sim data}\log D(x) - \frac{1}{2}\mathbb{E}_z \log(1 - D(G(z))) \quad (1)$$

$$J^{(G)} = -J^{(D)} \quad (2)$$

- The optimal discriminator $D^*(x) = \frac{p_{data}(x)}{p_{data}(x)+p_{model}(x)}$.
- In this case, $J^{(G)} = 2D_{JS}(p_{data}\|p_{model}) + const.$
- Jenson-Shannon divergence:
  $D_{JS}(p\|q) = \frac{1}{2}D_{KL}(p\|\frac{p+q}{2}) + \frac{1}{2}D_{KL}(q\|\frac{p+q}{2})$.

Theoretical property

- Stationary point

There is a theoretical point in this game at which the game will be stable and both players will stop changing.

- If the generated data exactly matches the distribution of the real data, the generator should output 0.5 for all points (argmax of loss function)
- If the discriminator is outputting a constant value for all inputs, then there is no gradient that should cause the generator to update

We rarely reach a completely stable point in practice due to practical issues

Theoretical property

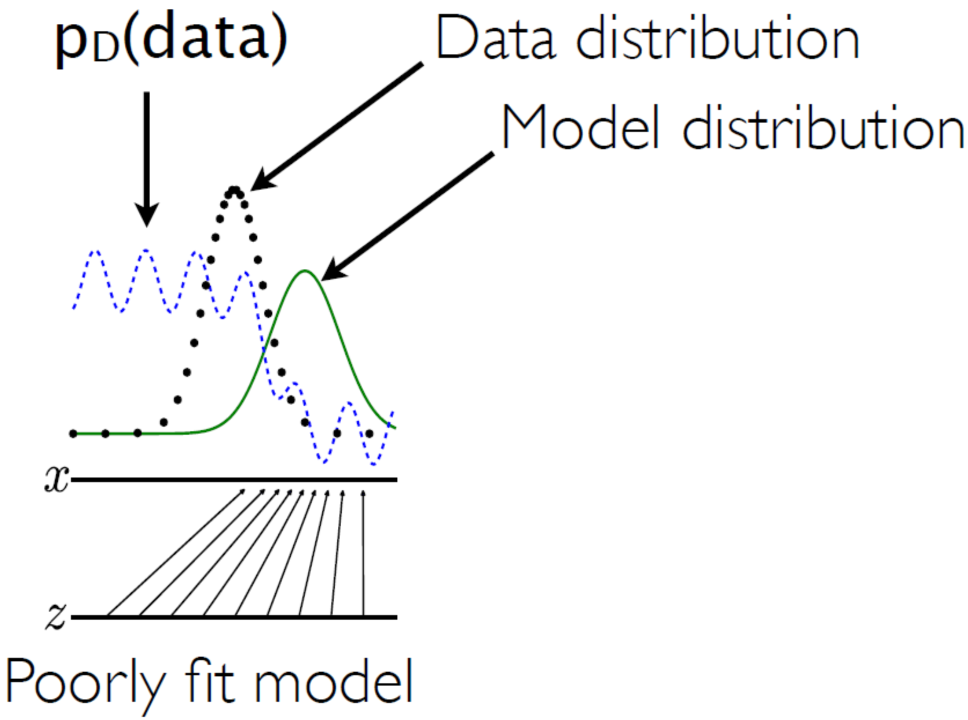
- Convergence

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

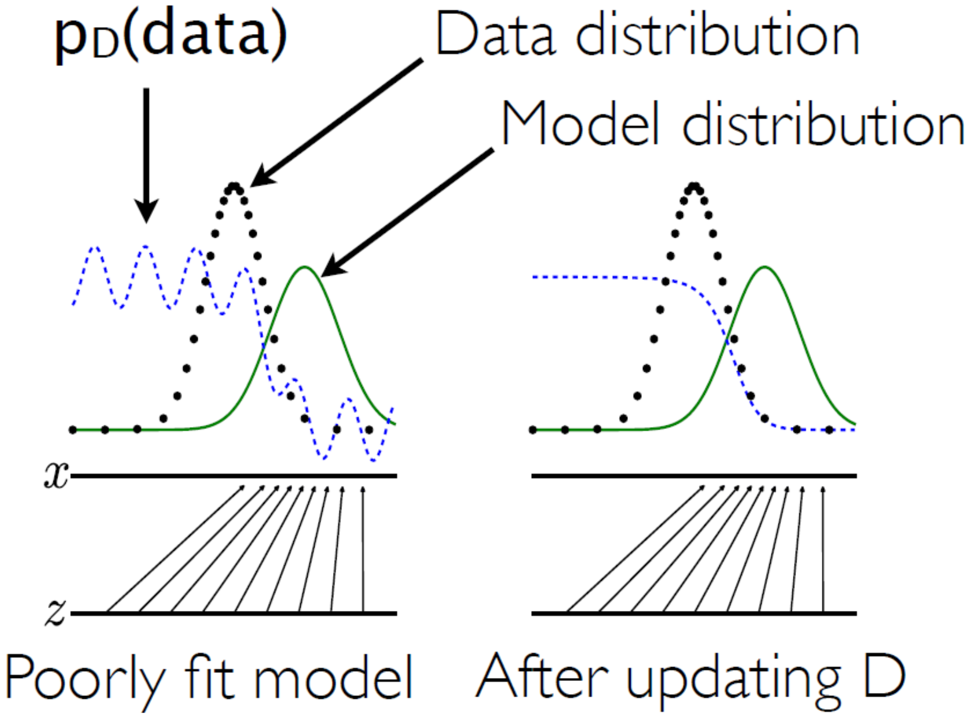
- Theoretical properties (assuming infinite data, infinite model capacity, direct updating of generator's distribution):
  - Unique global optimum.
  - Optimum corresponds to data distribution.
  - Convergence to optimum guaranteed.

If discriminator is finite and modest-sized, this message is incorrect. (regardless of training time, # samples, training objective etc..) See Sanjeev Arora, CVPR 2018 Tutorial

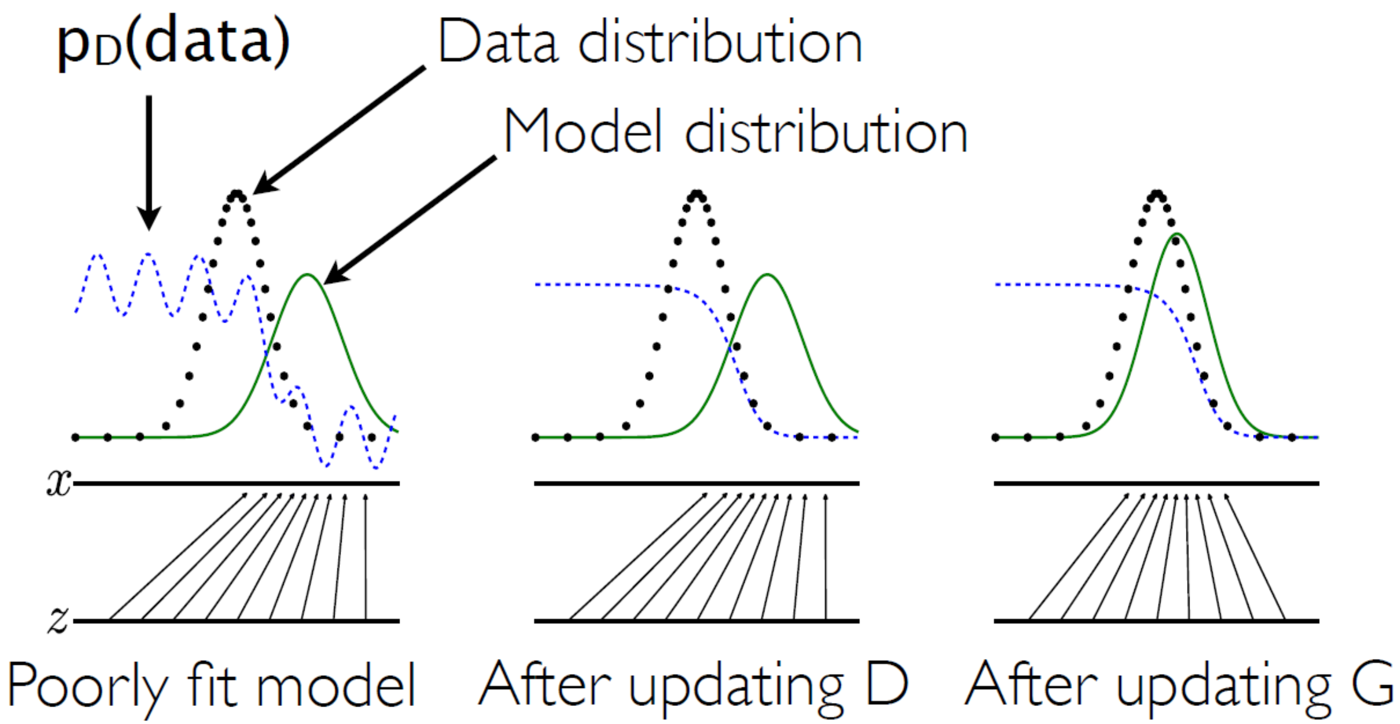
Training GANs



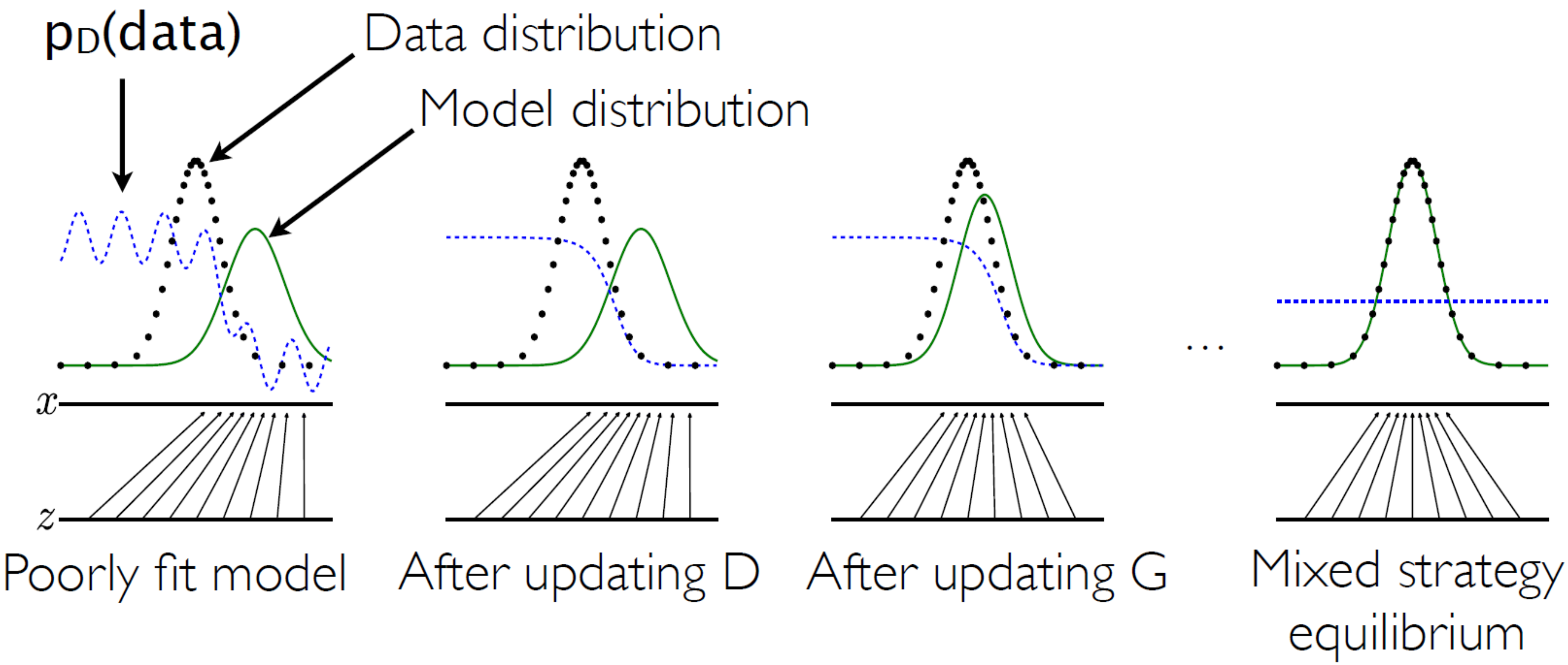
Training GANs



Training GANs



Training GANs



Training GANs

- Since GANs were introduced in 2014, there have been hundreds of papers introducing various architectures and training methods
- GAN Zoo: https://github.com/hindupuravinash/the-gan-zoo
- In general, training a GAN is tricky and unstable
- Many tricks:
  - S. Chintala, How to train a GAN, ICCV 2017 tutorial
  - https://github.com/soumith/talks/blob/master/2017-ICCV_Venice/How_To_Train_a_GAN.pdf

Generated Samples

Celebrities:

Karras et al., 2017. Progressive growing of GANs for improved quality, stability, and variation

Generated Samples

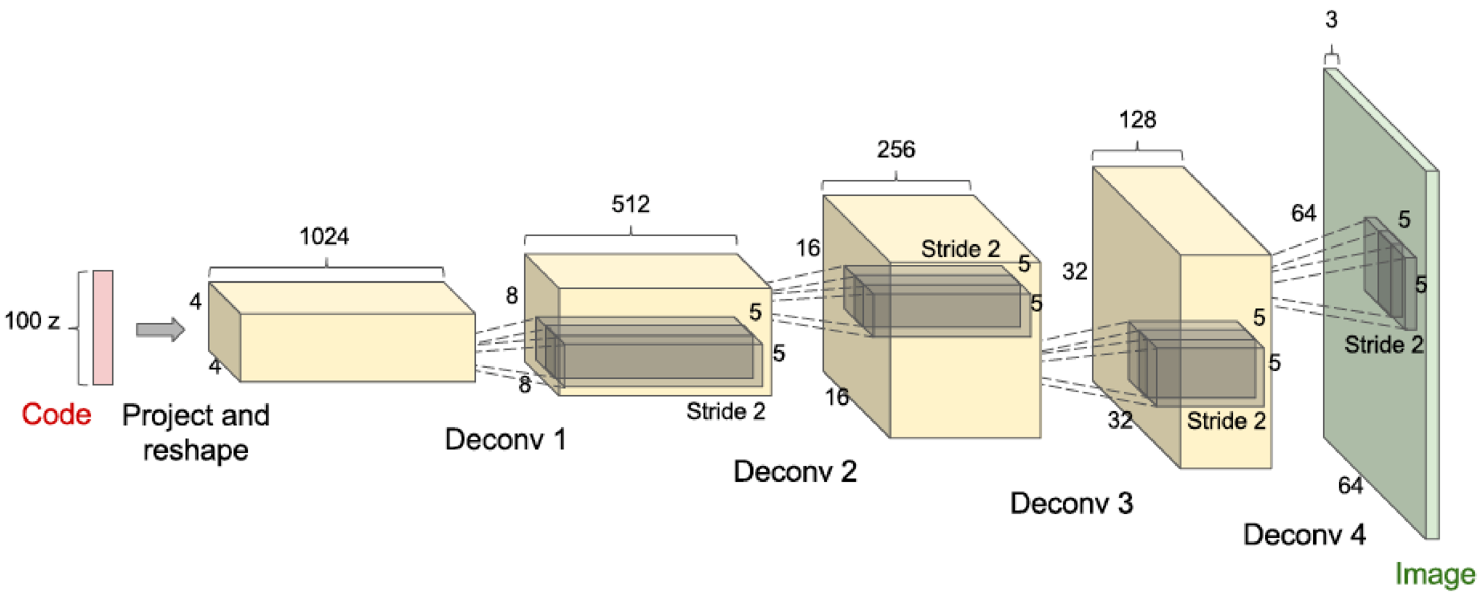
Objects:

POTTEDPLANT HORSE SOFA BUS CHURCHOUTDOOR BICYCLE TVMONITOR

DCGAN

- GAN with convolutional architetures
  - Generator is an upsampling convolutional network
  - Discriminator is a convolutional network

Deep Convolutional GAN [Radford et al., 2015]



Generated Samples

Generated Bad Samples

- Problems with Global Structure and Counting

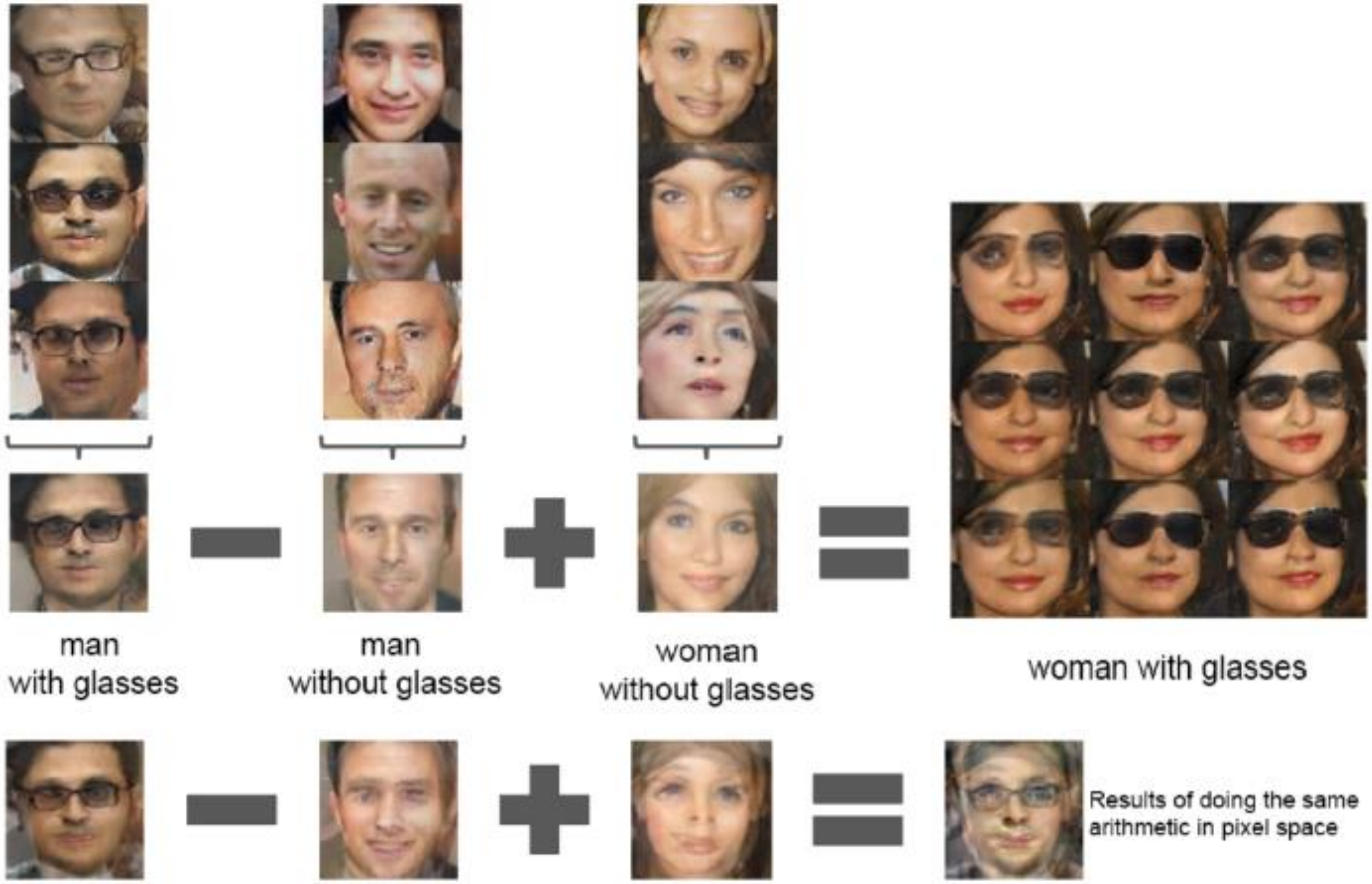
Walk Around Data Manifold

Interpolating between random points in laten space

Radford et al, ICLR 2016

Walk Around Data Manifold

- Vector Arithmetic



Outline

- Generative Adversarial Networks
  - Implicit generative models
  - Adversarial learning
  - Evaluation metrics

Acknowledgement: Feifei Li et al's cs231n notes

Evaluation metrics

- What makes a good generative model?
  - Each generated sample is indistinguishable from a real sample

  - Generated samples should have variety

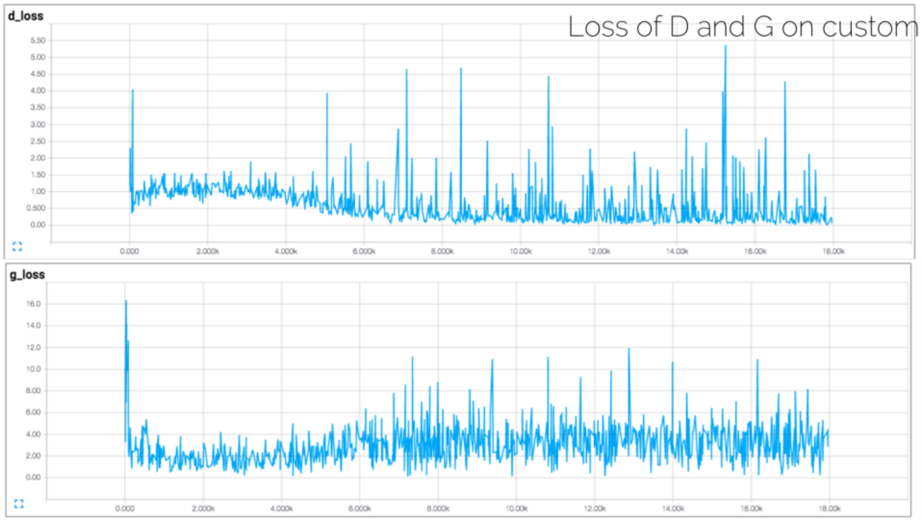
Images from Karras et al., 2017

Evaluation metrics

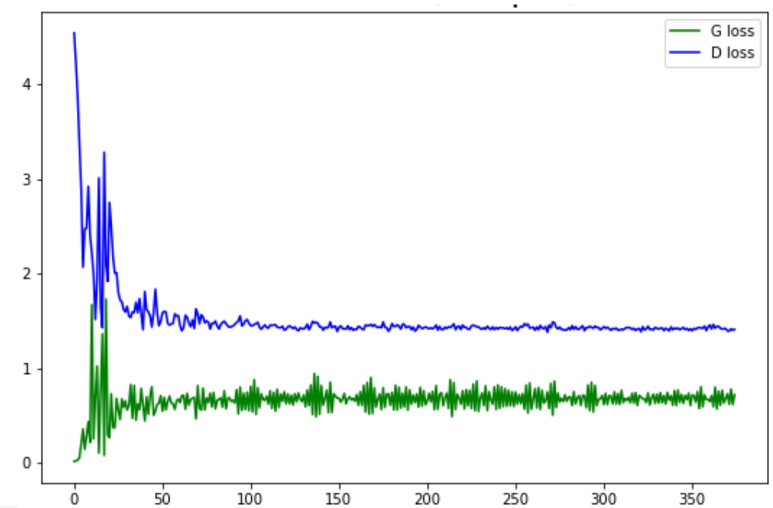
- How to evaluate the generated samples?
  - Cannot rely on the models' loss :-(
  - Human evaluation :-/
  - Use a pre-trained model :-)

Evaluation metrics

- “Good” Training Curves



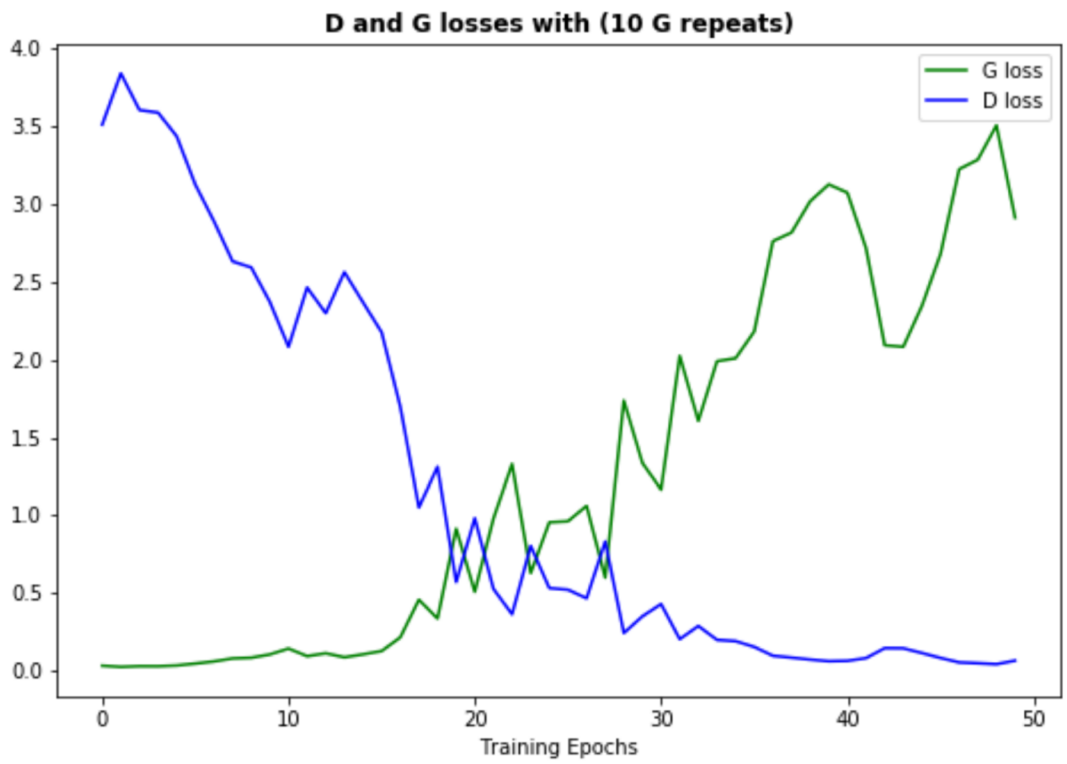
Loss of D and G on custom dataset



Generator’s Error through Time

Discriminator’s Error through Time

- “Bad” Training Curves



Evaluation metrics

- Inception Score (IS) [Salimans et al., 2016]
  - Inception model p trained on ImageNet
  - Given generated image x, assigned the label y by model p

$$p(y|\boldsymbol{x}) \;\Rightarrow\; \text{low entropy (one class)}$$

  - The distribution over all generated images should be spread

$$\int p(y|\boldsymbol{x} = G(z))dz \;\Rightarrow\; \text{high entropy (many classes)}$$

  - Combining the above, we get the final metric:

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

Evaluation metrics

- Frechet Inception Distance (FID) [Heusel et al. 2017]
  - Calculates the distance between real and fake data (lower the better)
  - Uses the embeddings of the real and fake data from the last pooling layer of Inception v3.
  - Converts the embeddings into continuous distributions and uses the *mean* and *covariance* of each to calculate their distance.

$$\mathrm{FID}(r,g) = ||\mu_r - \mu_g||_2^2 + \mathrm{Tr}(cov(r) + cov(g) - 2(cov(r)cov(g))^{\frac{1}{2}})$$

Evaluation metrics

- Comparisons

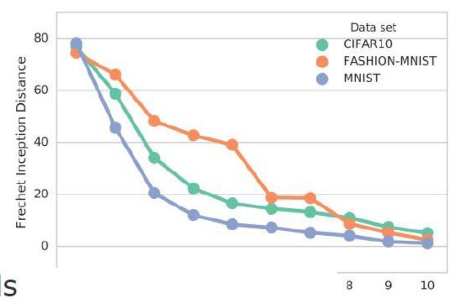
▪ IS vs FID

✓ FID considers the real dataset

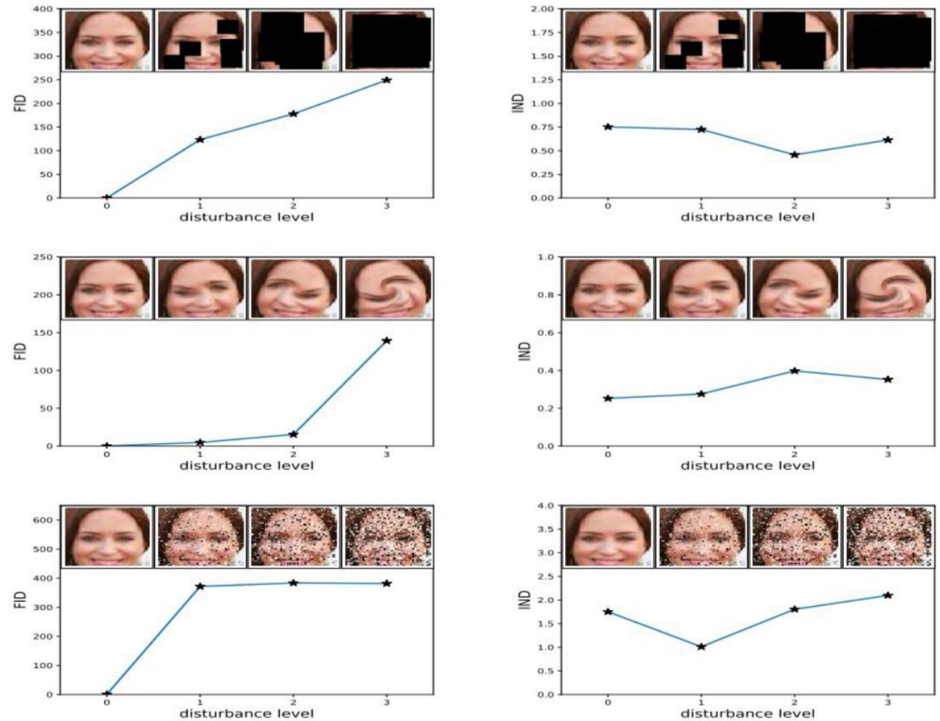
✓ FID requires less sampling (faster) (~10k instead of 50k in IS)

✓ FID more robust to noise and human judgement

✓ FID also sensitive to mode collapse



Generative Models



FID (lower is better) IS (higher is better)

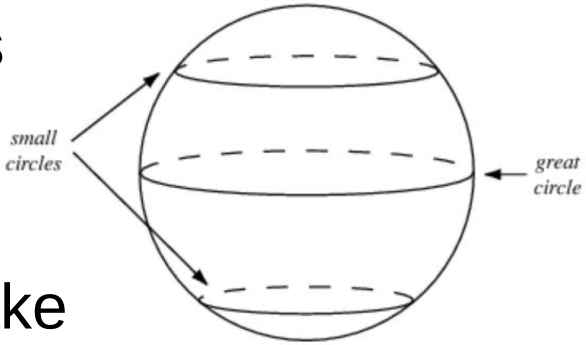
Images from Lucic et al., 2017 and Heusel et al., 2017

The GAN Zoo

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

- 3D-ED-GAN - Shape Inpainting using 3D Generative Adversarial Network and Recurrent Convolutional Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
- 3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
- 3D-PhysNet - 3D-PhysNet: Learning the Intuitive Physics of Non-Rigid Object Deformations
- 3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
- ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
- ABC-GAN - GANs for LIFE: Generative Adversarial Networks for Likelihood Free Inference
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- ACGAN - Coverless Information Hiding Based on Generative adversarial networks
- acGAN - On-line Adaptative Curriculum Learning for GANs
- ACtuAL - ACtuAL: Actor-Critic Under Adversarial Learning
- AdaGAN - AdaGAN: Boosting Generative Models
- Adaptive GAN - Customizing an Adversarial Example Generator with Class-Conditional GANs
- AdvEntuRe - AdvEntuRe: Adversarial Training for Textual Entailment with Knowledge-Guided Examples
- AdvGAN - Generating adversarial examples with adversarial networks
- AE-GAN - AE-GAN: adversarial eliminating with GAN
- AE-OT - Latent Space Optimal Transport for Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AF-DCGAN - AF-DCGAN: Amplitude Feature Deep Convolutional GAN for Fingerprint Construction in Indoor Localization System
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AIM - Generating Informative and Diverse Conversational Responses via Adversarial Information Maximization

GAN Hacks



- https://github.com/soumith/ganhacks
- Normalize the inputs: [-1, 1], Tanh
- Use a spherical z; Use Batch Norm
- Different mini-batches for real and fake
- SGD for discriminator; ADAM for generator
- One-sided Label Smoothing

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \lambda \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

Some value smaller than 1; e.g.,0.9

- Avoid Sparse Gradients: no ReLU and MaxPooling

  LeakyReLU → good in both G and D

  Downsample → use average pool, conv+stride

  Upsample → deconv+stride, PixelShuffle

Summary of GANs

Don't work with an explicit density function
Take game-theoretic approach: learn to generate from training distribution through 2-player game

Pros:
- Beautiful, state-of-the-art samples!

Cons:
- Trickier / more unstable to train
- Can't solve inference queries such as p(x), p(z|x)

Active areas of research:
- Better loss functions, more stable training (Wasserstein GAN, LSGAN, many others)
- Conditional GANs, GANs for all kinds of applications

- The GAN Zoo
  - https://github.com/hindupuravinash/the-gan-zoo