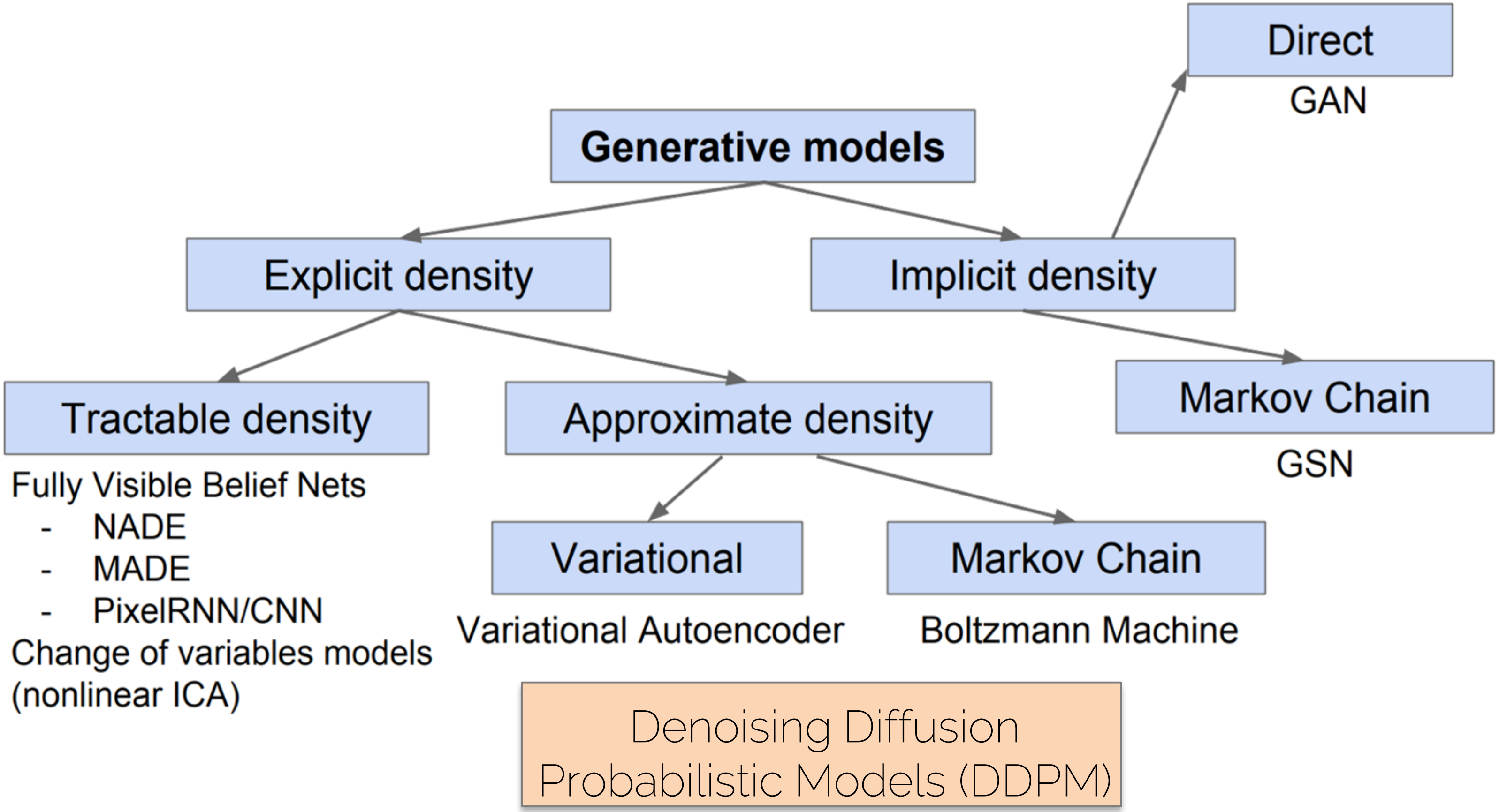
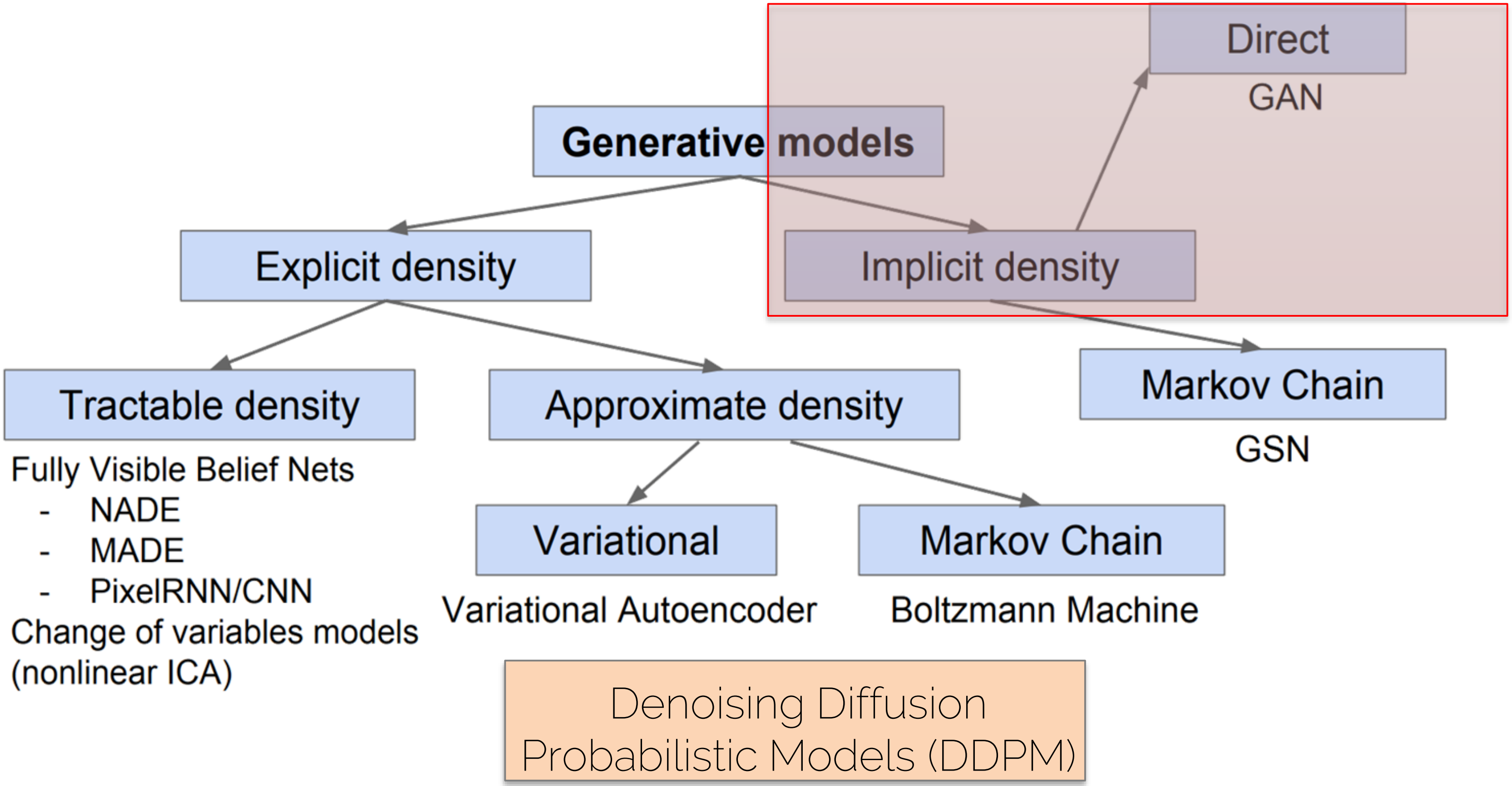
Generative Neural Networks

Taxonomy of Generative Models



Goodfellow, Tutorial on Generative Adversarial Networks, 2017

Taxonomy of Generative Models

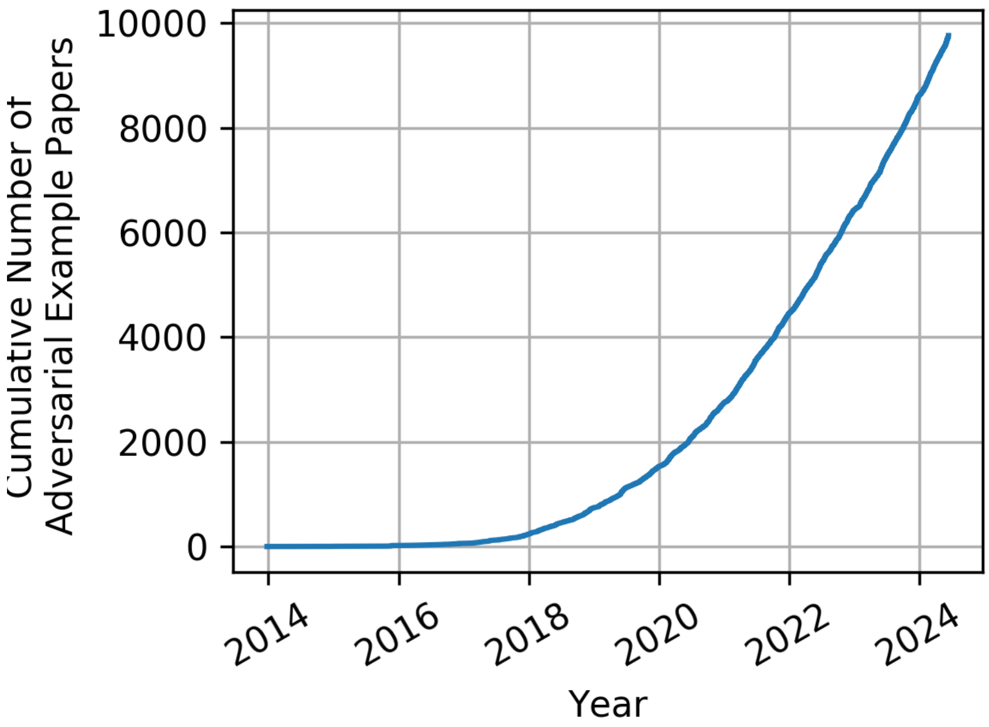


Goodfellow, Tutorial on Generative Adversarial Networks, 2017

Generative Adversarial Networks (GANs)

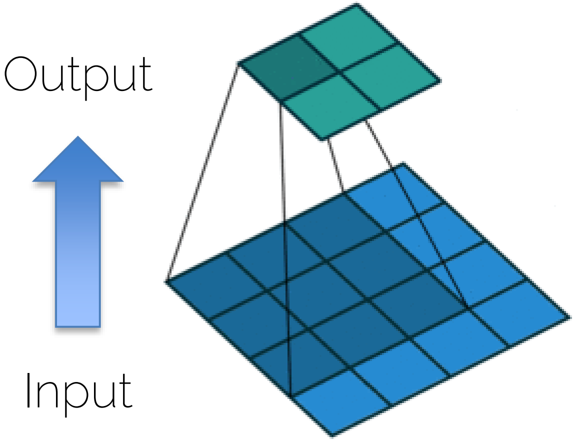
Generative Adversarial Networks (GANs)

List of All (arXiv) Adversarial Example Papers

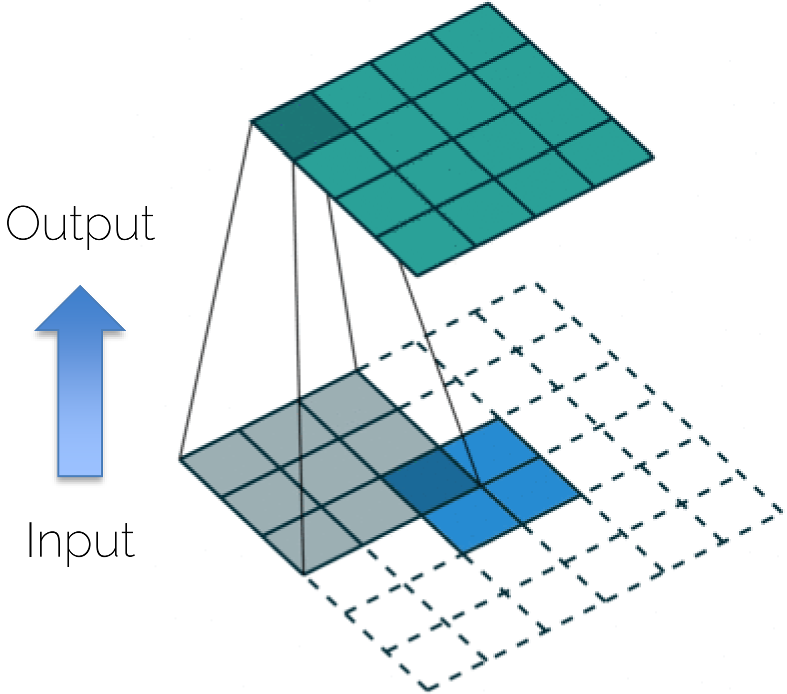


https://nicholas.carlini.com/writing/2019/all-adversarial-example-papers.html

Convolution & Up Convolution



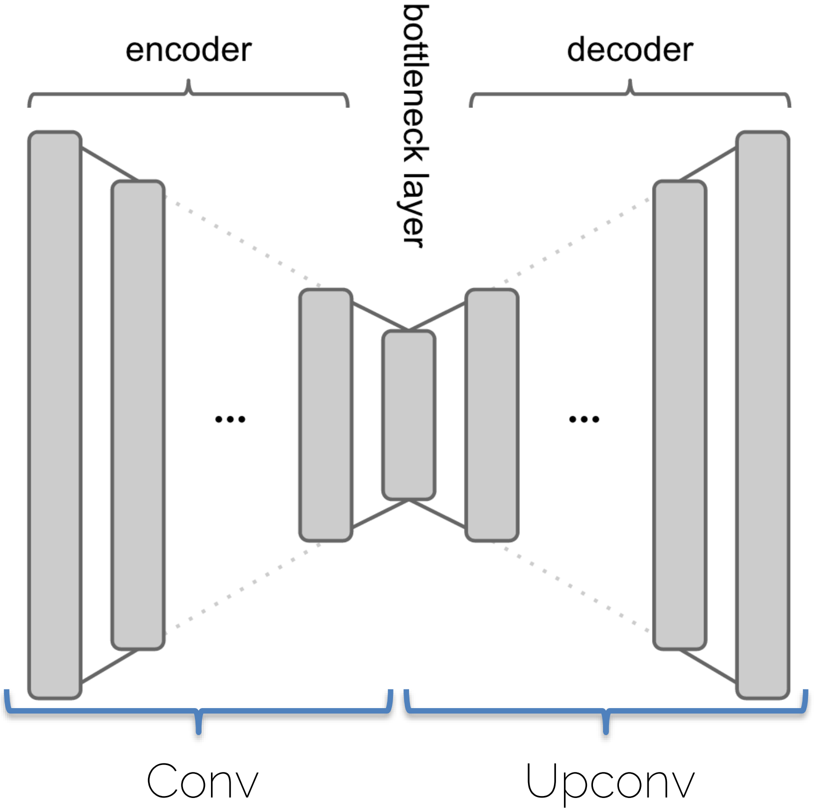
Convolution
no padding, no stride

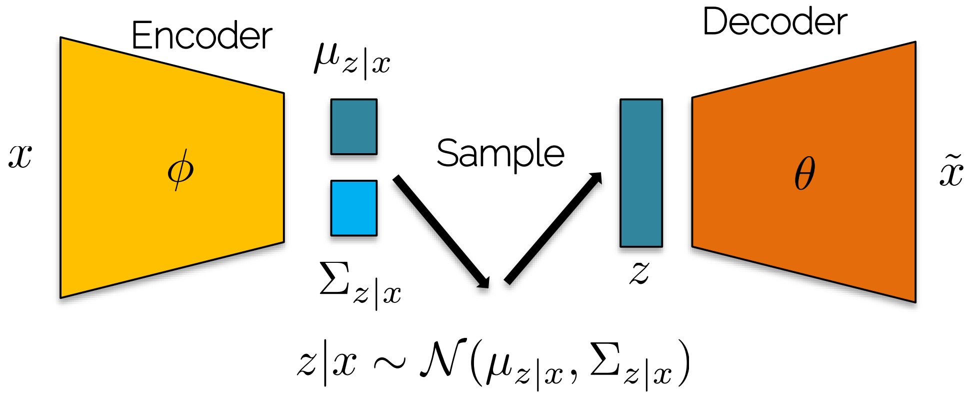


Up (transposed) convolution
no padding, no stride

https://github.com/vdumoulin/conv_arithmetic

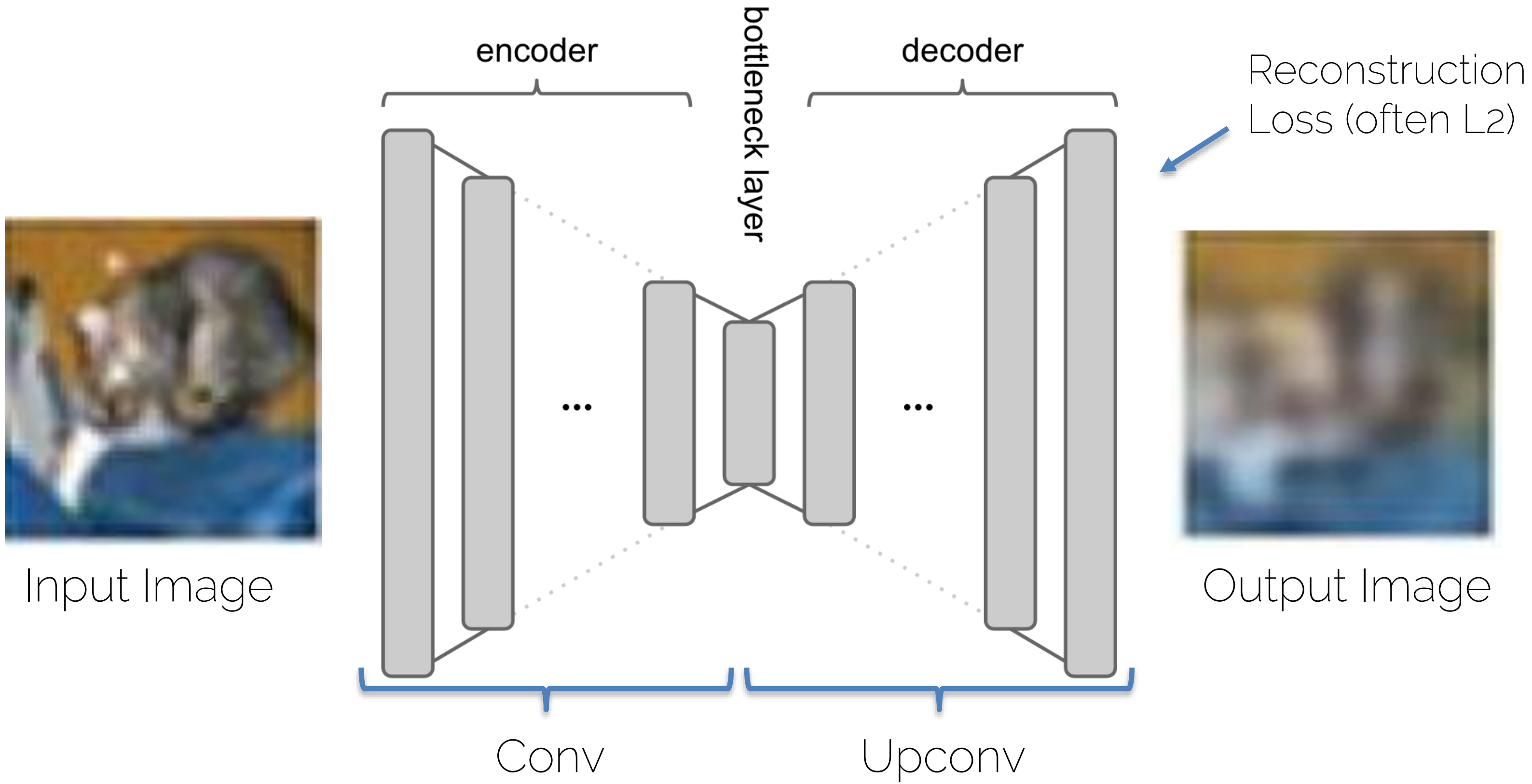
Autoencoders & Variational Autoencoders



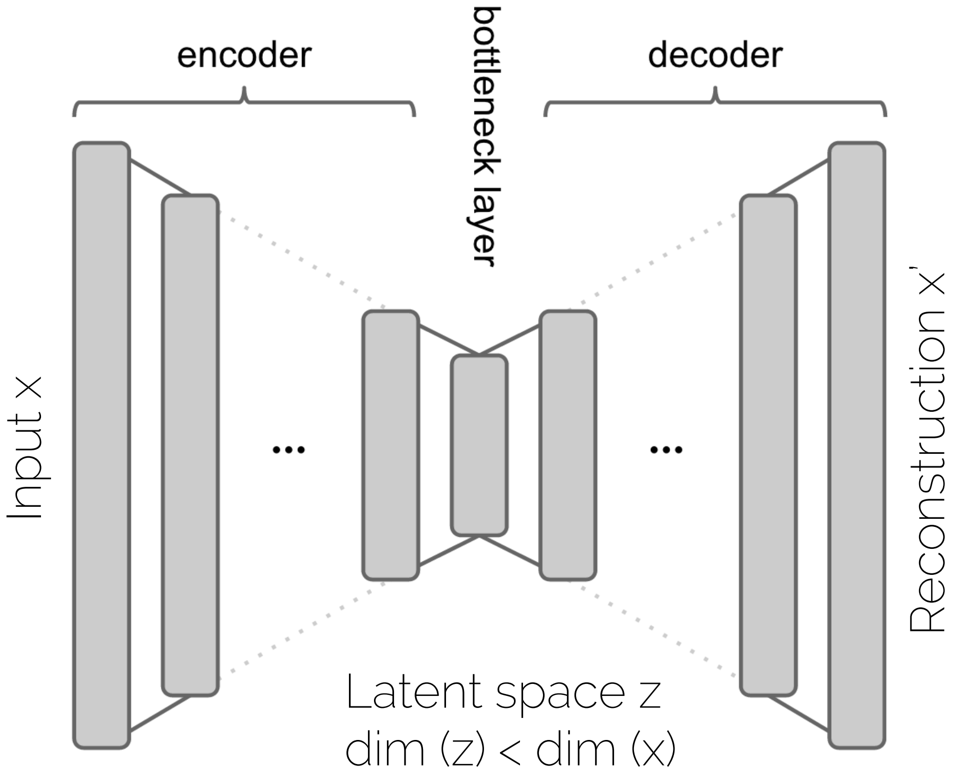


$$\mathcal{L}\left(x^{(i)}, \theta, \phi\right) = \underbrace{\mathbb{E}_z\left[\log p_\theta\left(x^{(i)} \mid z\right)\right]}_{\text{Reconstruct the Input Data}} - \underbrace{D_{KL}\left(q_\phi\left(z \mid x^{(i)}\right) \| \, p_\theta(z)\right)}_{\text{KL Divergence}}$$

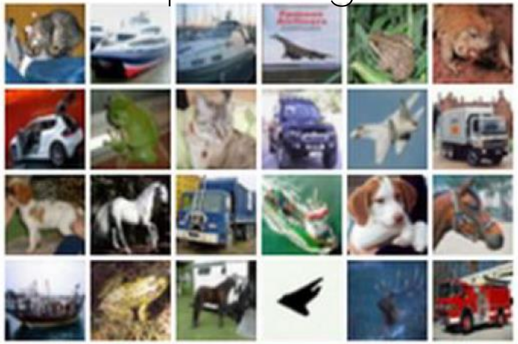
Autoencoder: Reconstruction



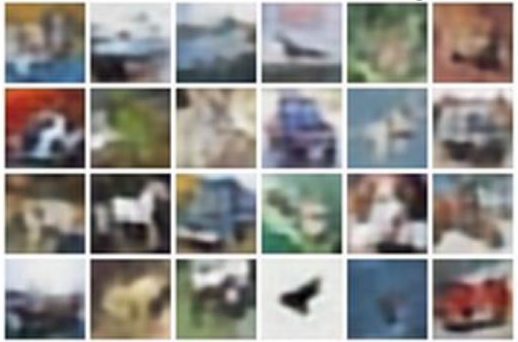
Training Autoencoders



Input images

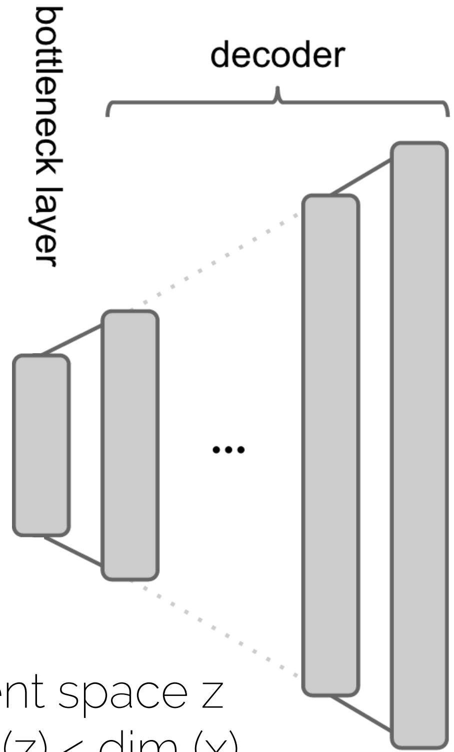


Reconstructed images



Decoder as Generative Model

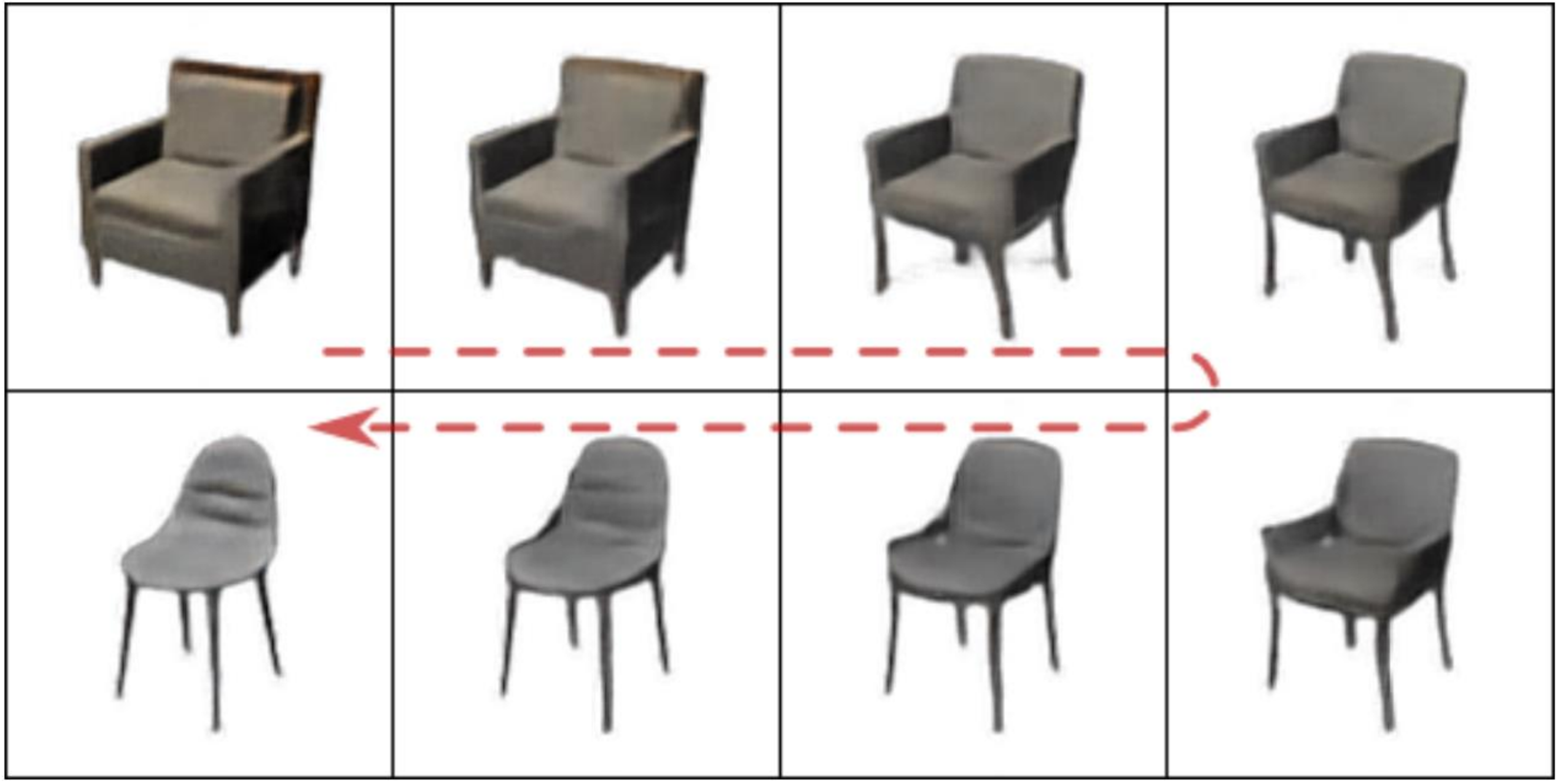
"Test time":
-> reconstruction from
'random' vector



Latent space z
dim (z) < dim (x)

Output Image

Decoder as Generative Model



Interpolation between two chair models

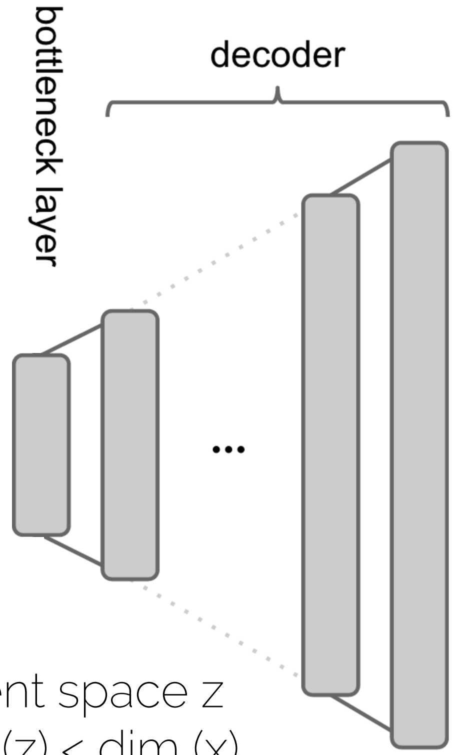
[Dosovitsky et al. 14] Learning to Generate Chairs

Decoder as Generative Model

Morphing between chair models

[Dosovitsky et al. 14] Learning to Generate Chairs

Decoder as Generative Model



"Test time":
-> reconstruction from 'random' vector

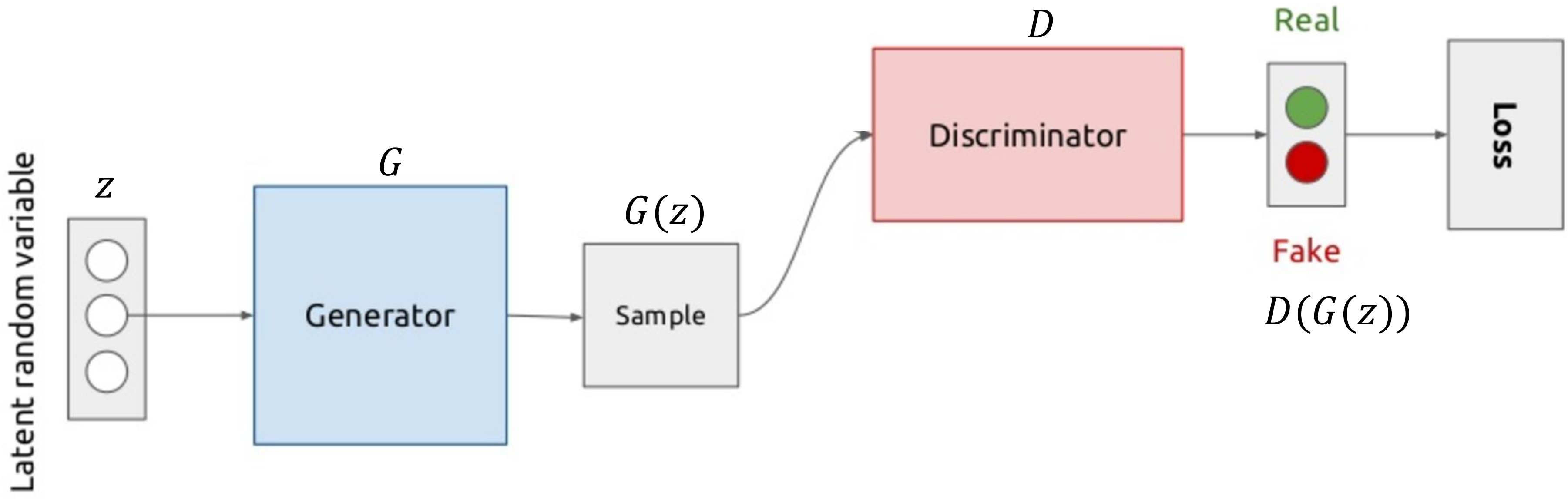
Latent space z
dim (z) < dim (x)

Reconstruction Loss
Often L2, i.e., sum of squared dist.
-> L2 distributes error equally
-> mean is opt.
-> result is blurry.

Output Image

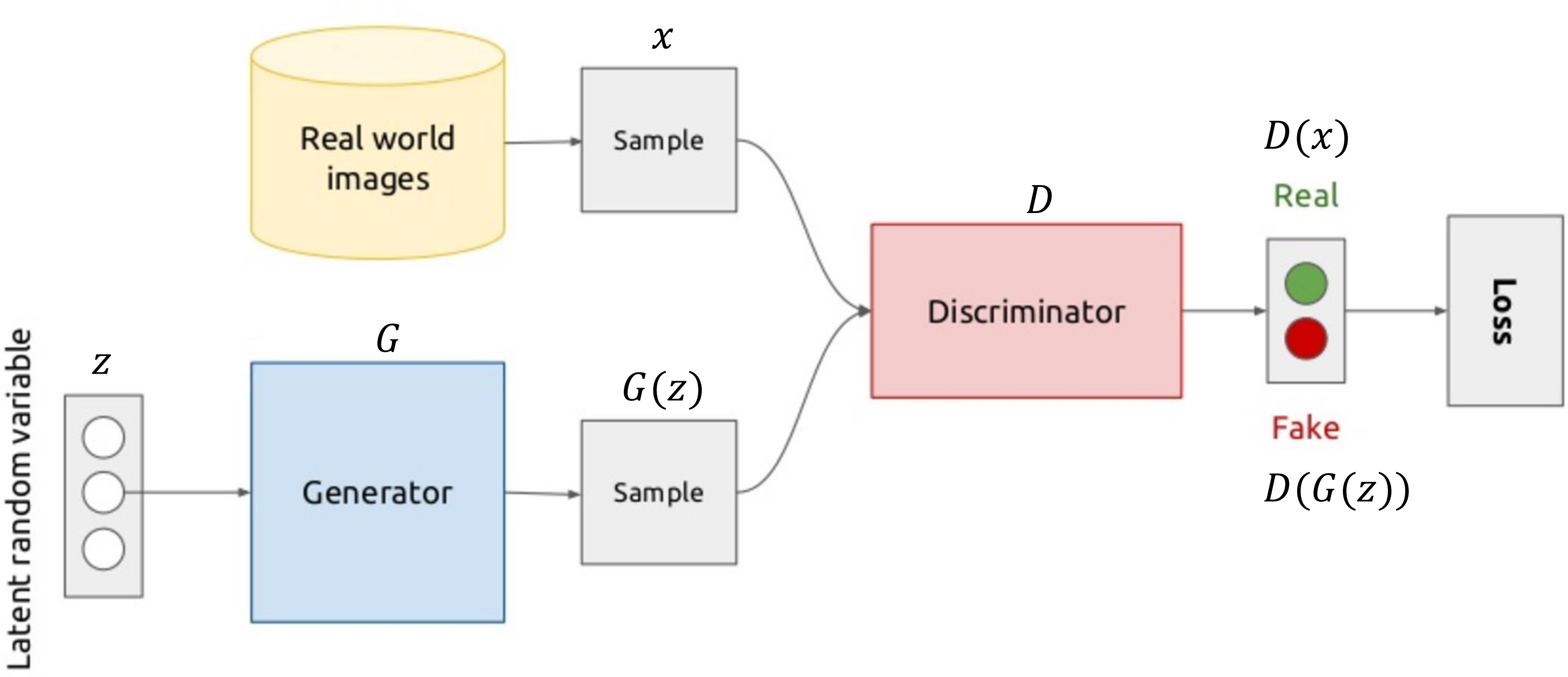
Instead of L2, can we "learn" a loss function?

Generative Adversarial Networks (GANs)



[Goodfellow et al. 14] GANs (slide McGuinness)

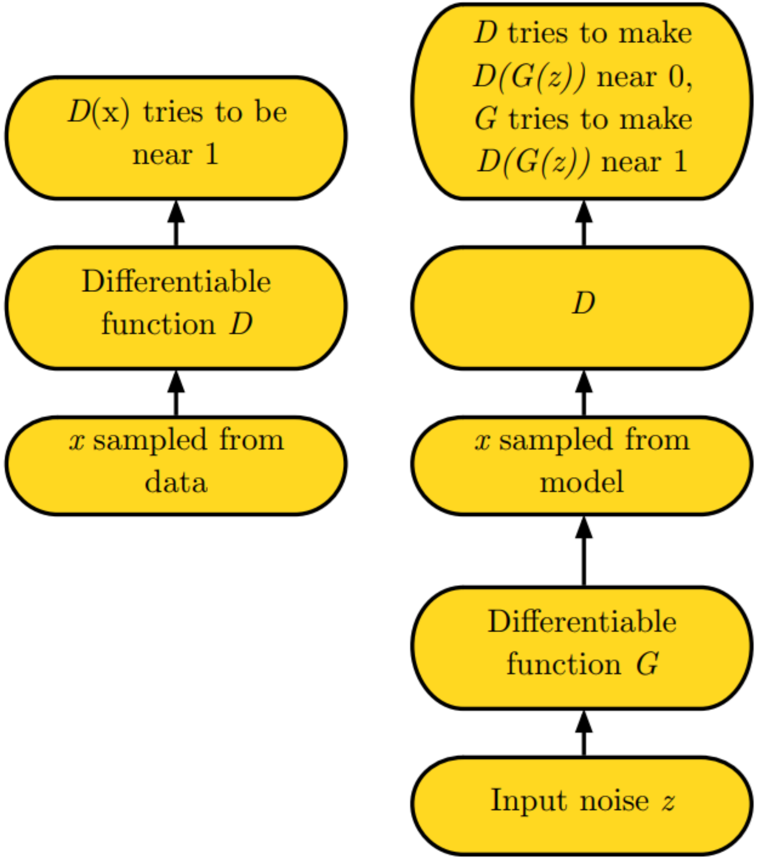
Generative Adversarial Networks (GANs)



[Goodfellow et al. 14] GANs (slide McGuinness)

Generative Adversarial Networks (GANs)

real data



fake data

[Goodfellow et al. 14/16] GANs

GANs: Loss Functions

Discriminator loss

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

Generator loss

$$J^{(G)} = -J^{(D)}$$

- Minimax Game:
  - G minimizes probability that D is correct
  - Equilibrium is saddle point of discriminator loss

-> D provides supervision (i.e., gradients) for G

GANs: Loss Functions

Discriminator loss

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

Generator loss

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D\left(G(\boldsymbol{z})\right)$$

- Heuristic Method (often used in practice)
  - G maximizes the log-probability of D being mistaken
  - G can still learn even when D rejects all generator samples

[Goodfellow et al. 14/16] GANs

Alternating Gradient Updates

- Step 1: Fix G, and perform gradient step to

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

- Step 2: Fix D, and perform gradient step to

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D\left(G(\boldsymbol{z})\right)$$

Vanilla GAN

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

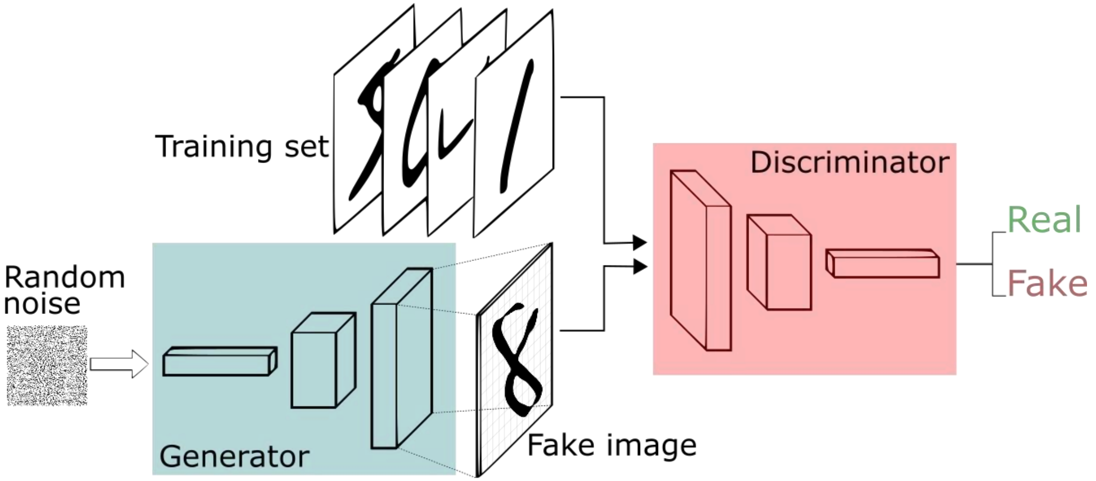
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

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

end for

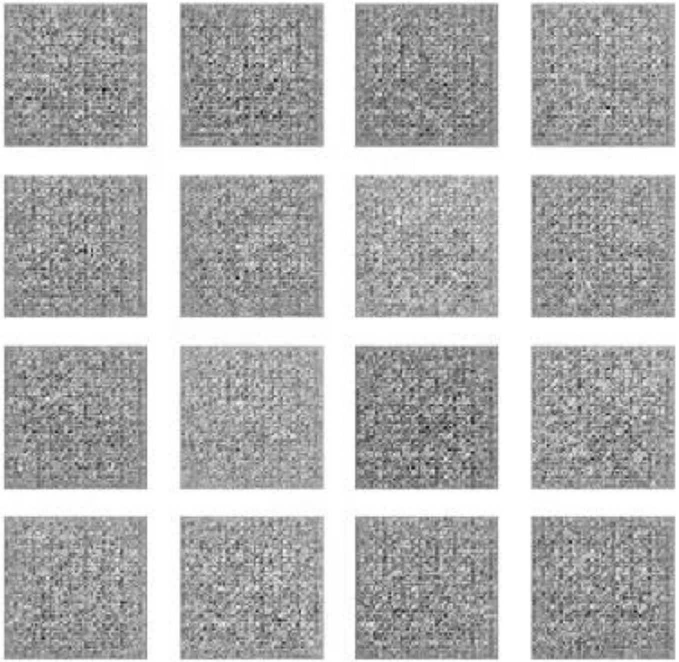
https://papers.nips.cc/paper/5423-generative-adversarial-nets

Putting it all Together



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

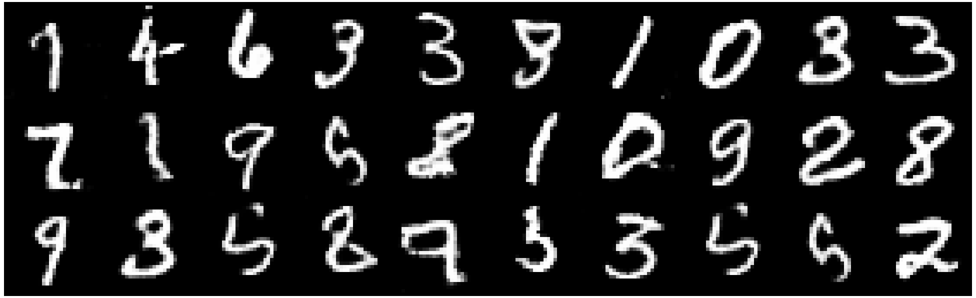
Training a GAN

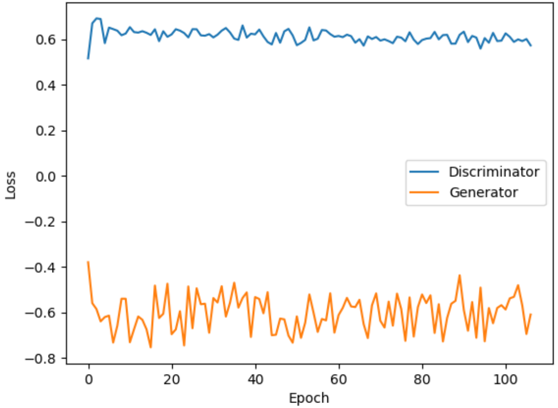


https://medium.com/ai-society/gans-from-scratch-1-a-deep-introduction-with-code-in-pytorch-and-tensorflow-cb03cdcdba0f

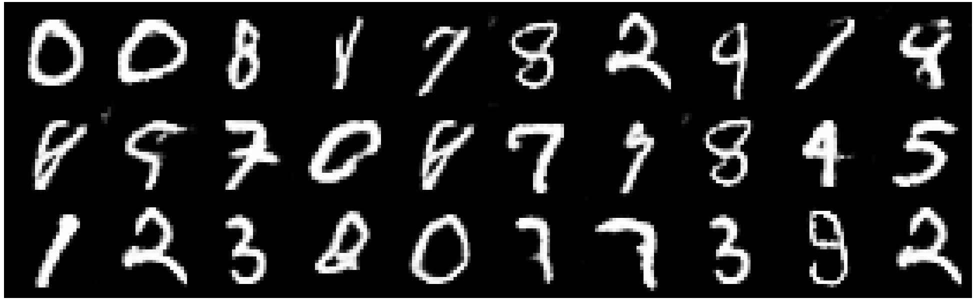
GANs: Loss Functions

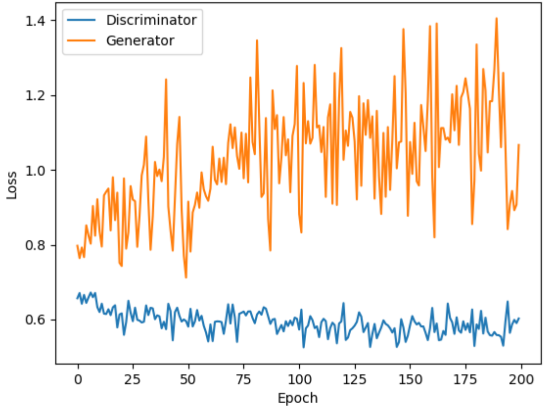
Minimax





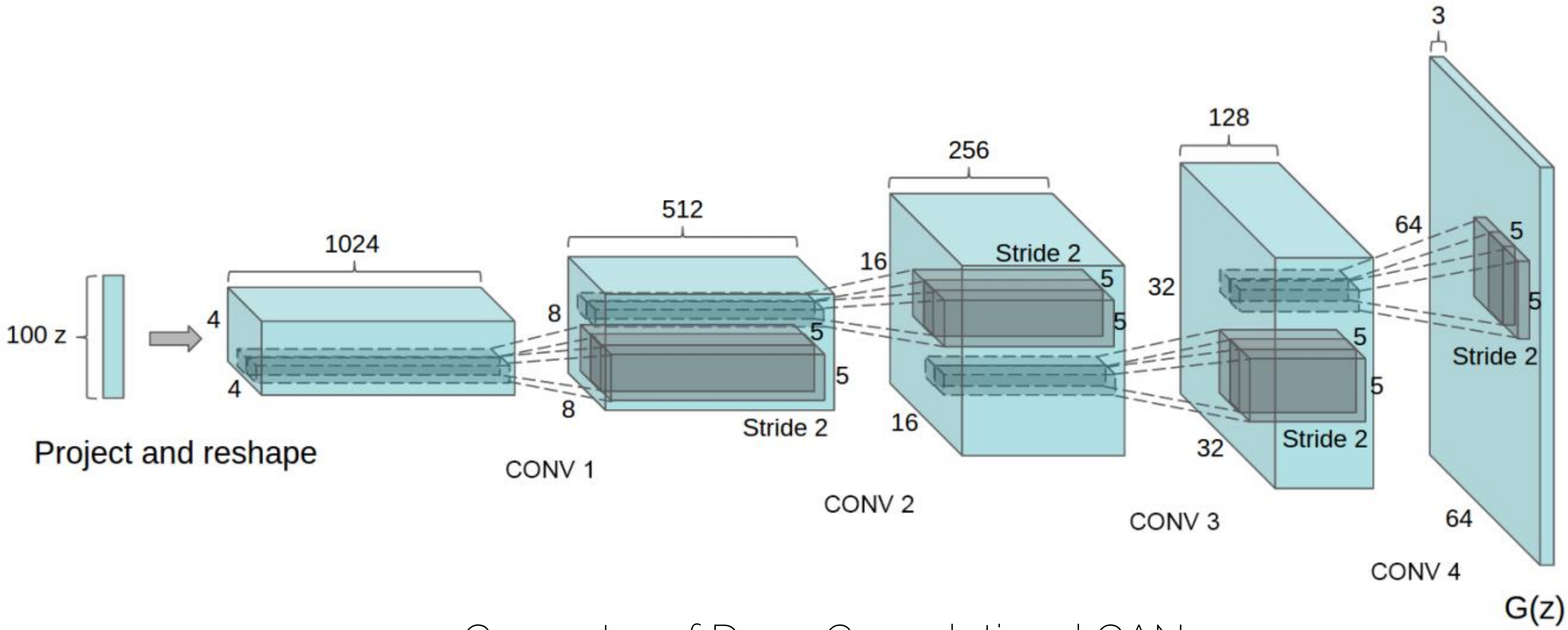
Heuristic





[Goodfellow et al. 14/16] GANs

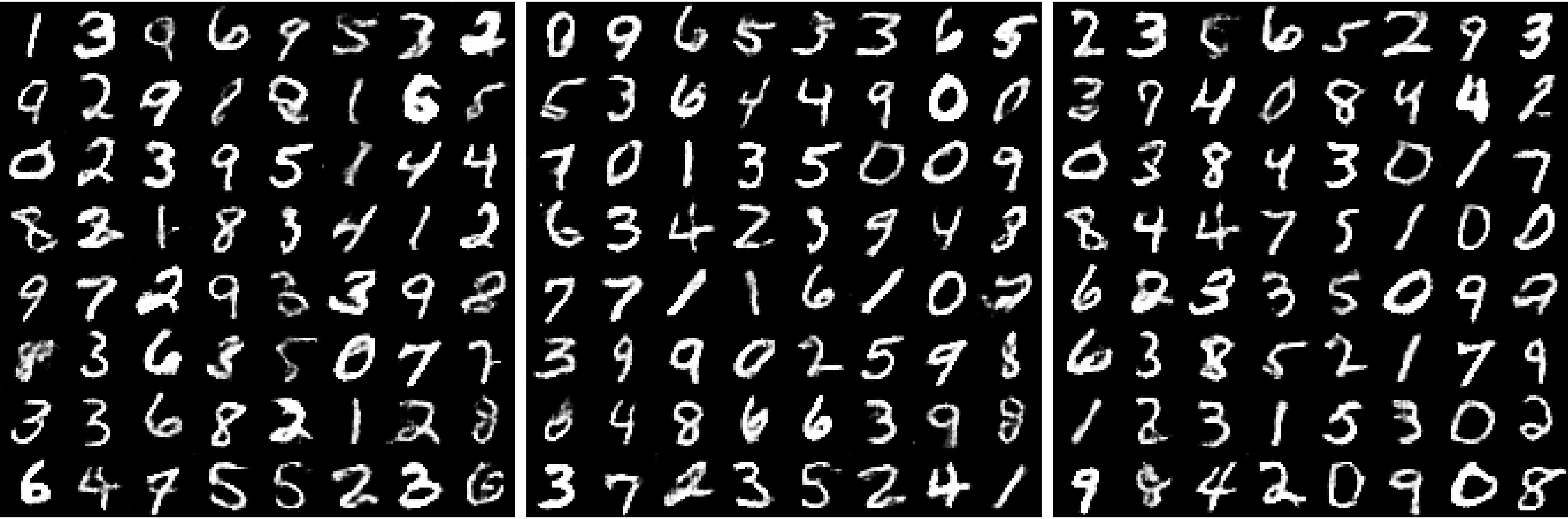
DCGAN: Generator



Generator of Deep Convolutional GANs

DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

DCGAN: Results



Results on MNIST

DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

DCGAN: Results

Results on CelebA (200k relatively well aligned portrait photos)

DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

DCGAN: Results

Asian face dataset

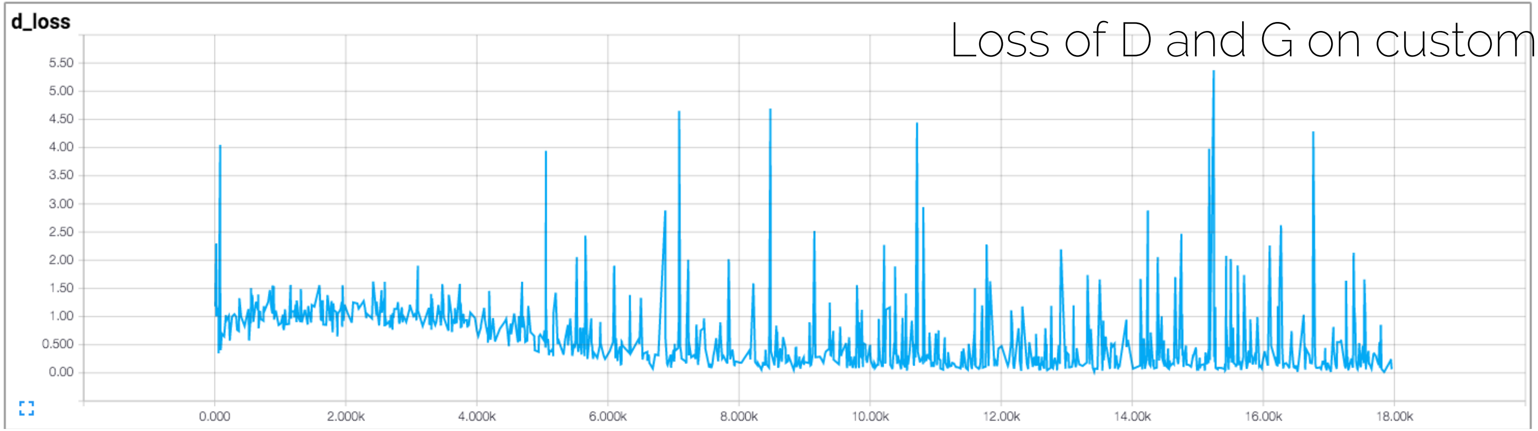
DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

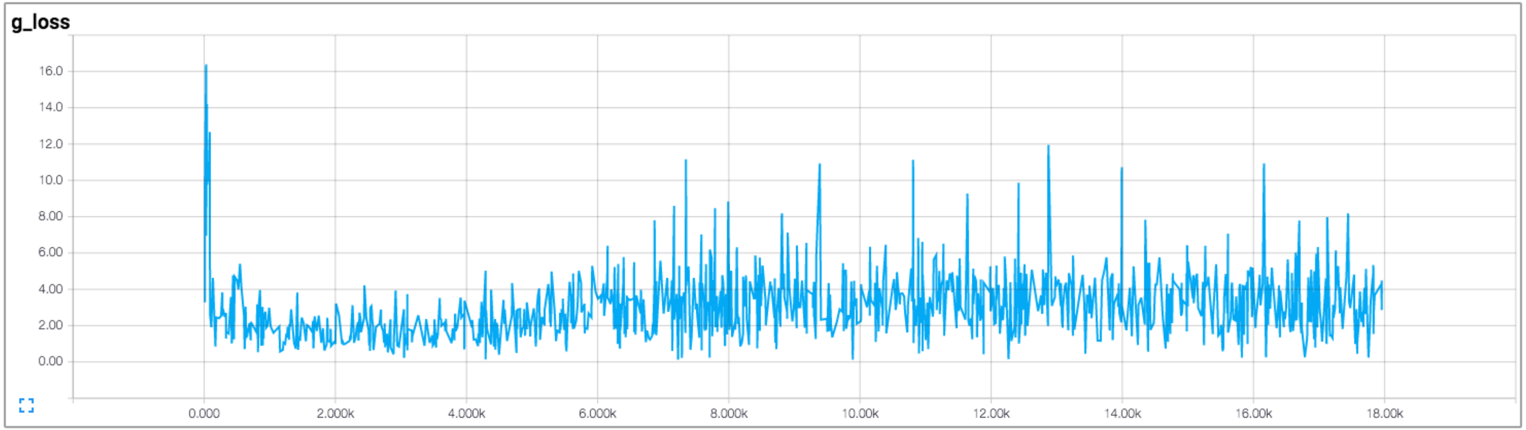
DCGAN: Results

DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

DCGAN: Results

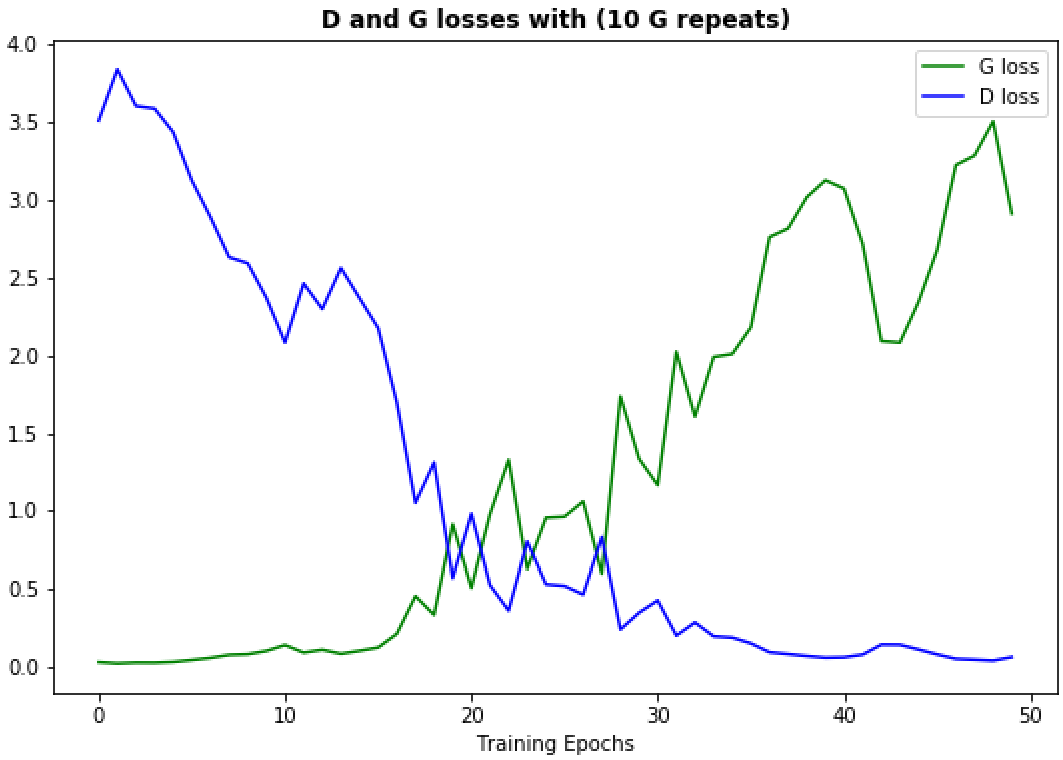
Loss of D and G on custom dataset





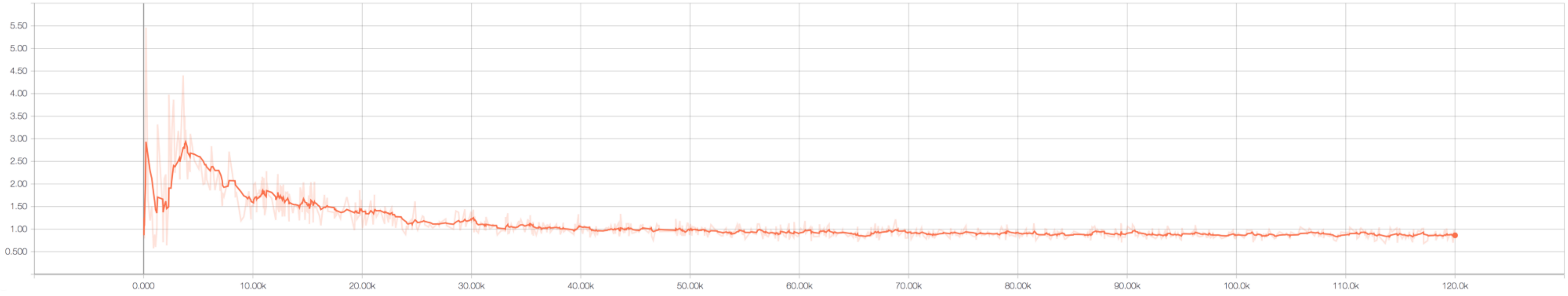
DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

"Bad" Training Curves

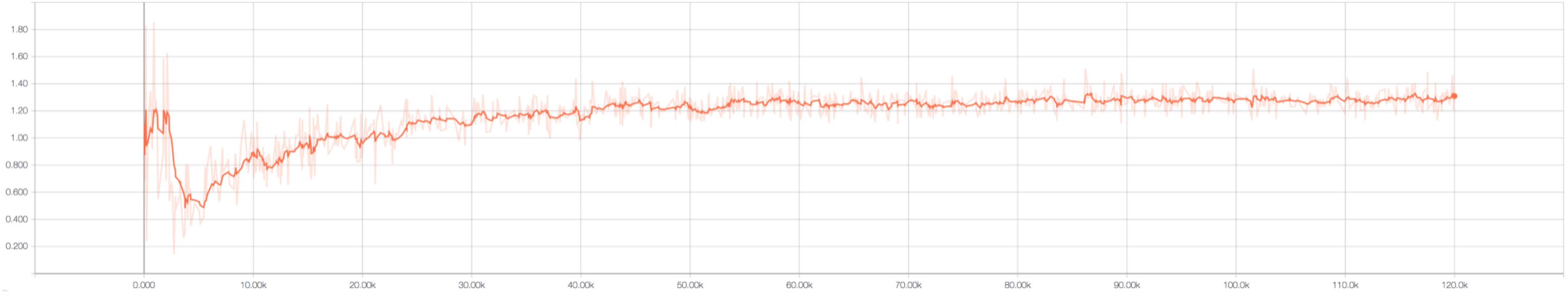


https://stackoverflow.com/questions/44313306/dcgans-discriminator-getting-too-strong-too-quickly-to-allow-generator-to-learn

"Good" Training Curves



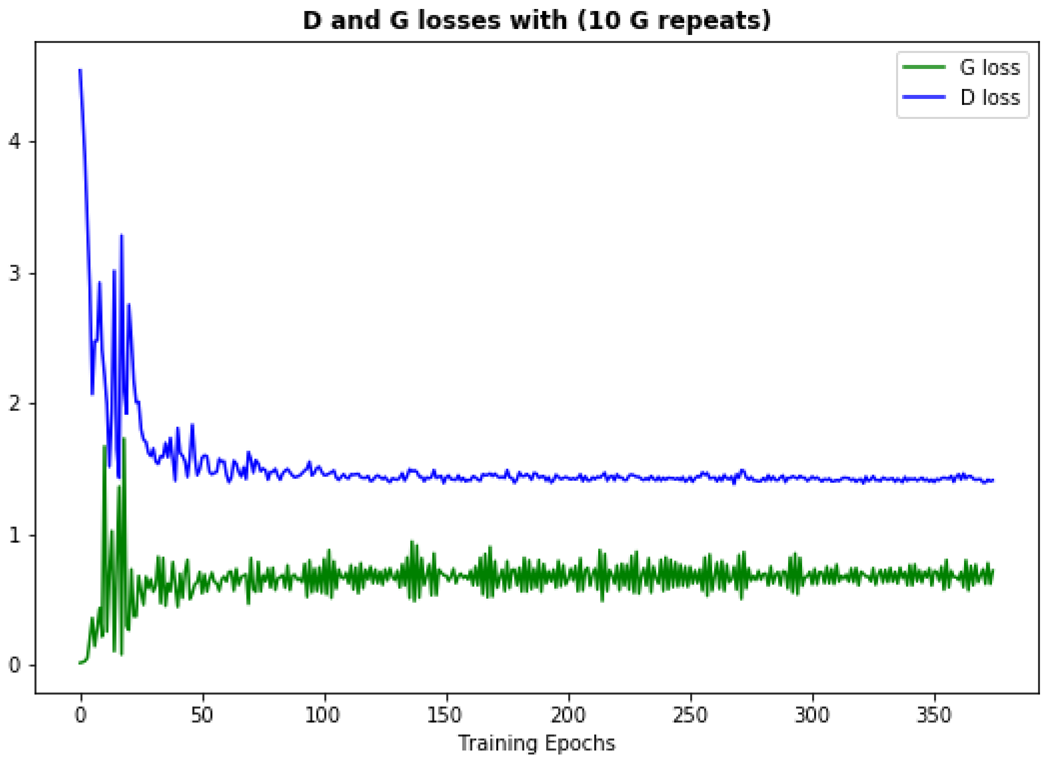
Generator's Error through Time



Discriminator's Error through Time

https://medium.com/ai-society/gans-from-scratch-1-a-deep-introduction-with-code-in-pytorch-and-tensorflow-cb03cdcdba0f

“Good” Training Curves



https://stackoverflow.com/questions/42690721/how-to-interpret-the-discriminators-loss-and-the-generators-loss-in-generative

Training Schedules

- Adaptive schedules

For instance

```
while loss_discriminator > t_d:
    train discriminator
while loss_generator > t_g:
    train generator
```

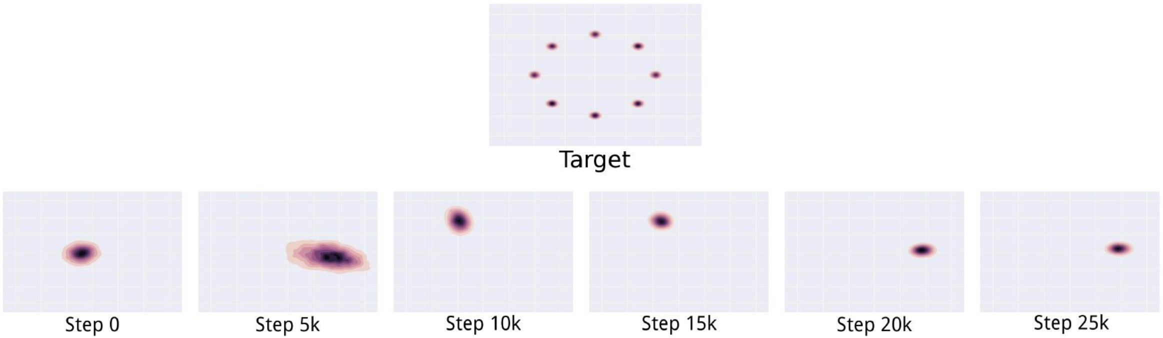
Weak vs Strong Discriminator

- Need balance ☺
- Discriminator too weak?
  - No good gradients (cannot get better than teacher…)
- Generator too weak?
  - Discriminator will always be right

Mode Collapse

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

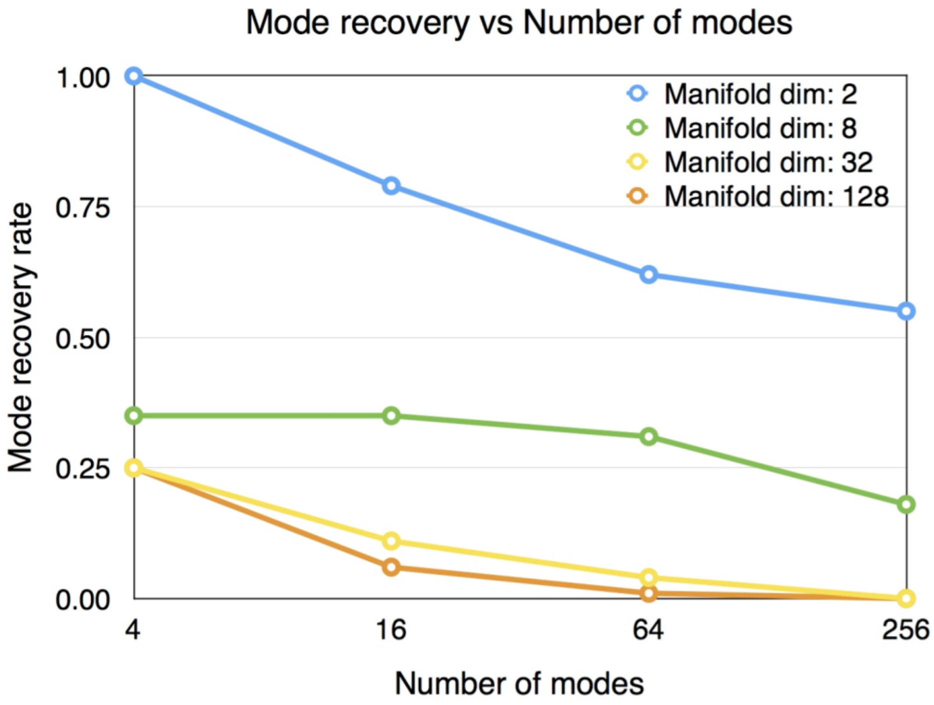
- D in inner loop -> convergence to correct dist.
- G in inner loop -> easy to convergence to one sample



[Metz et al. 16]

Mode Collapse

- Same data dimension
- Performance correlates with dim of manifold
- Performance correlates with # of modes



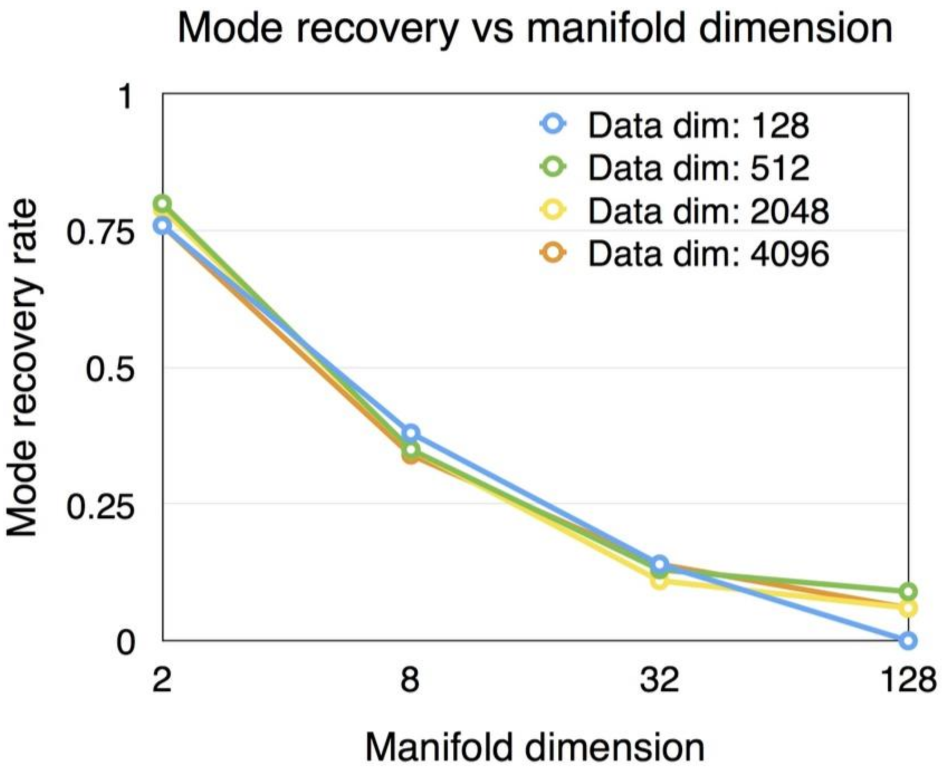
-> More modes, smaller recovery rate!
-> part of the reason, why we often see GAN-results on specific domains (e.g., faces)

Slide credit Ming-Yu Liu

Mode Collapse

- Same # of modes
- Performance correlates with dim of manifold
- Performance non-correlated with data dimensions

-> Larger latent space, more mode collapse

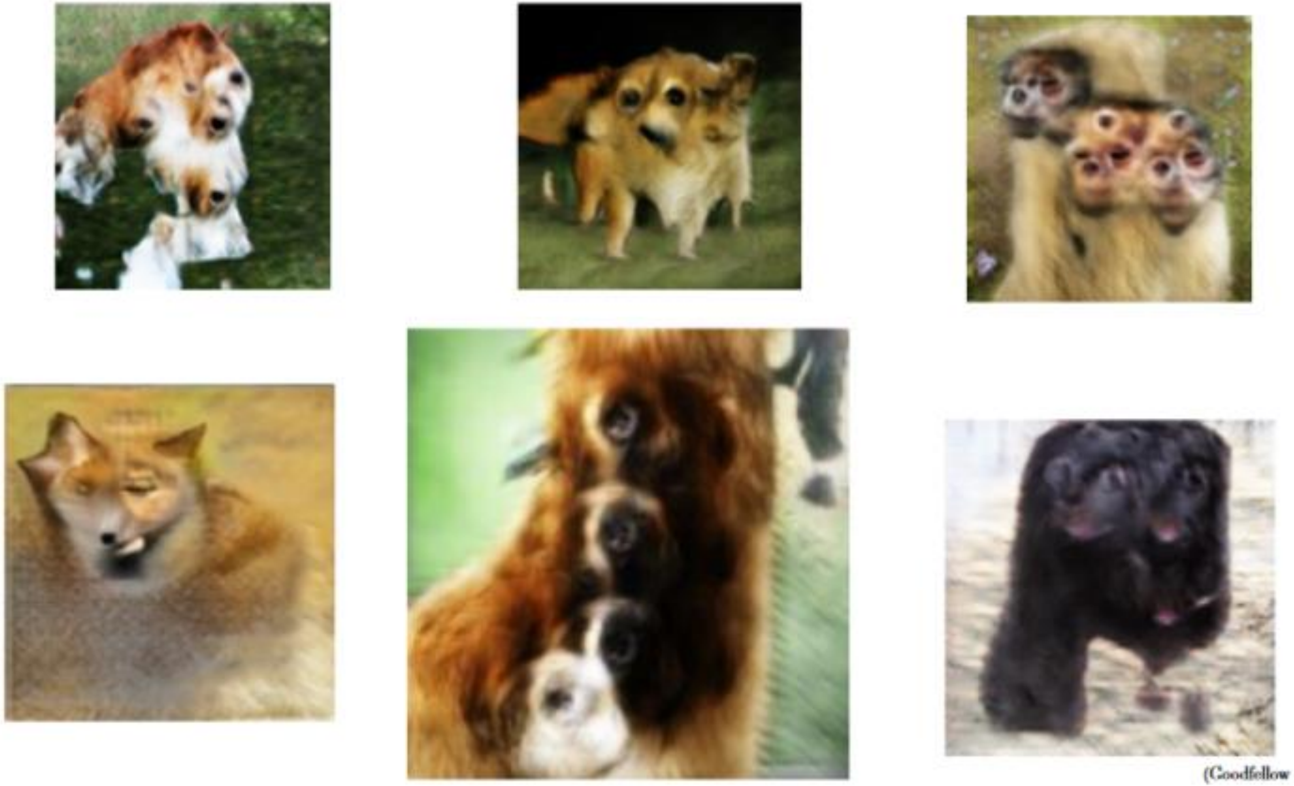


Slide credit Ming-Yu Liu

Problems with Global Structure

(Goodfellow 2016)

Problems with Counting



(Goodfellow 2016)

Evaluation of GAN Performance

Evaluation of GAN Performance

- Main difficulty of GANs: we don't know how good they are
- People cherry pick results in papers -> some of them will always look good, but how to quantify?
- Do we only memorize, or do we generalize?
- GANs are difficult to evaluate! [This et al., ICLR 2016]

Evaluation of GAN Performance

- Human evaluation:
  - Every n updates, show a series of predictions
  - Check train curves
  - What does 'look good' mean at the beginning?
    - Need variety!
    - But don't have 'realistic' predictions yet…
  - If it doesn't look good? Go back, try different hyperparameters…

Evaluation of GAN Performance

- Inception Score (IS)
  - Measures saliency and diversity
  - Train an accurate classifier
  - Train an image generation model (conditional)
  - Check how accurate the classifier can recognize the generated images
  - Makes some assumptions about data distributions…

Evaluation of GAN Performance

- Inception Score (IS)
  - Saliency: check whether the generated images can be classified with high confidence (i.e., high scores only on a single class)
  - Diversity: check whether we obtain samples from all classes

<u>What if we only have one good image per class?</u>

Evaluation of GAN Performance

- Frechet Inception Distance (FID)
  - Calculates the feature distance between the real and synthetic distribution (modelled by multivariate Gaussian)
  - Pros:
    - More robust to noise then IS
    - No class concept needs
  - Cons:
    - Still relies on pretrained Inception-V3 model features

Evaluation of GAN Performance

- Could also look at discriminator
  - If we end up with a strong discriminator, then generator must also be good
  - Use D features, for classification network
  - Only fine-tune last layer
  - If high class accuracy -> we have a good D and G

Caveat: doesn't seem widespread in the community

Next: Making GANs Work in Practice

- Training / Hyperparameters (most important)
- Choice of loss function
- Choice of architecture

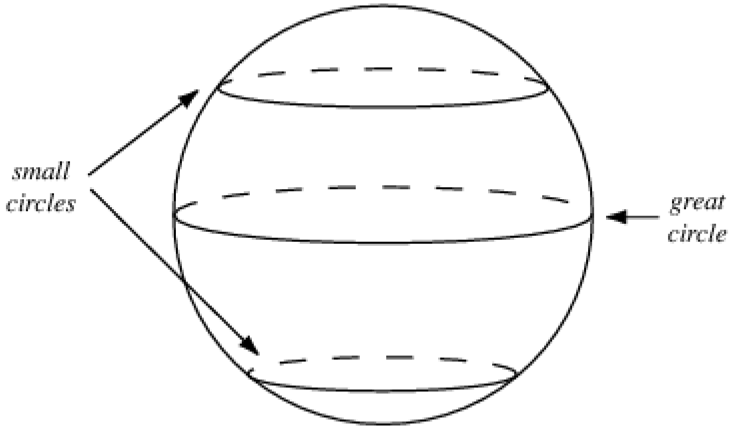
GAN Hacks: Normalize Inputs

- Normalize the inputs between -1 and 1
- Tanh as the last layer of the generator output
- No-brainer ☺

https://github.com/soumith/ganhacks

GAN Hacks: Sampling

- Use a spherical z
- Don't sample from a uniform distribution
- Sample from a Gaussian Distribution

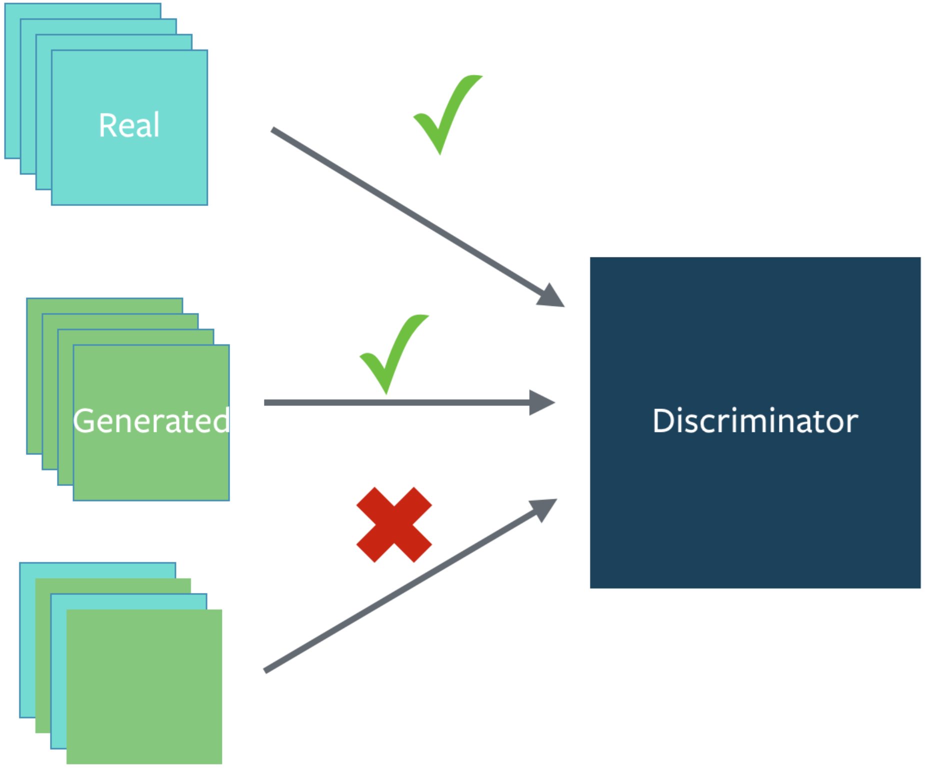


- When doing interpolations, do the interpolation via a great circle, rather than a straight line from point A to point B

- Tom White's Sampling Generative Networks ref code https://github.com/dribnet/plat has more details

GAN Hacks: BatchNorm

- Use Batch Norm
- Construct different mini-batches for real and fake, i.e. each mini-batch needs to contain only all real images or all generated images.



GAN Hacks: Use ADAM

- See Adam usage [Radford et al. 15]
- SGD for discriminator
- ADAM for generator

GAN Hacks: One-sided Label Smoothing

- Prevent discriminator from giving too large gradient signal to generator:

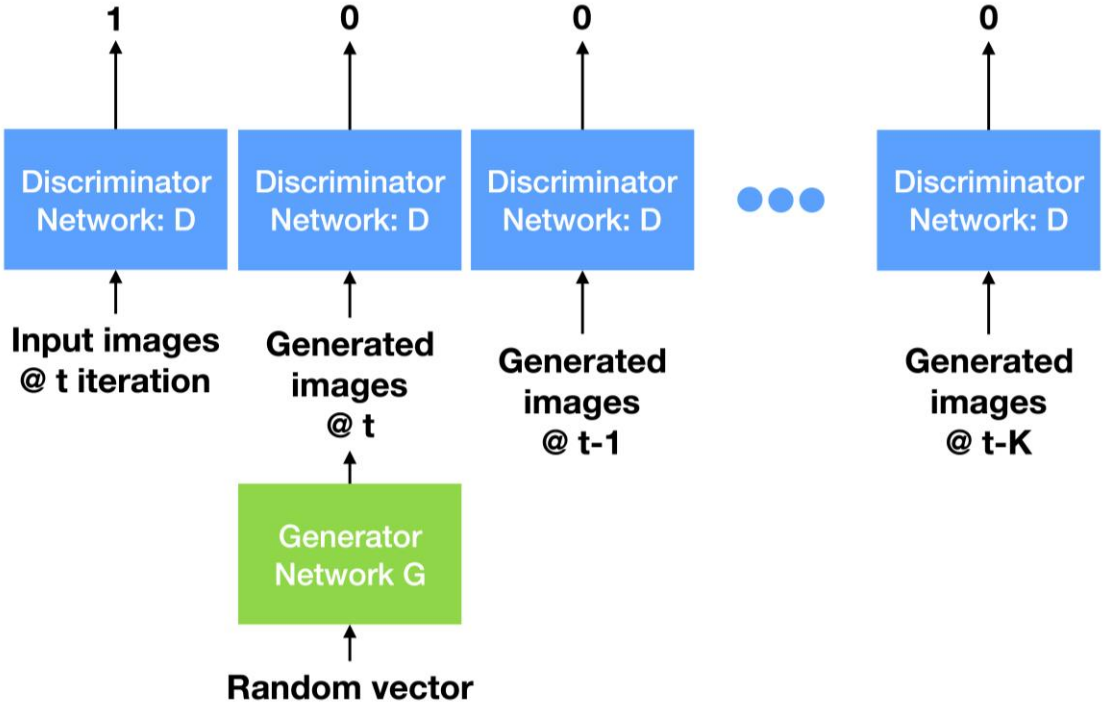
$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \lambda \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

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

-> reduces confidence; i.e., makes disc. 'weaker'
-> encourages 'extreme samples' (prevents extrapolating)

Salimans et al. 17 "Improved Techniques for Training GANs"

GAN Hacks: Historical Generator Batches

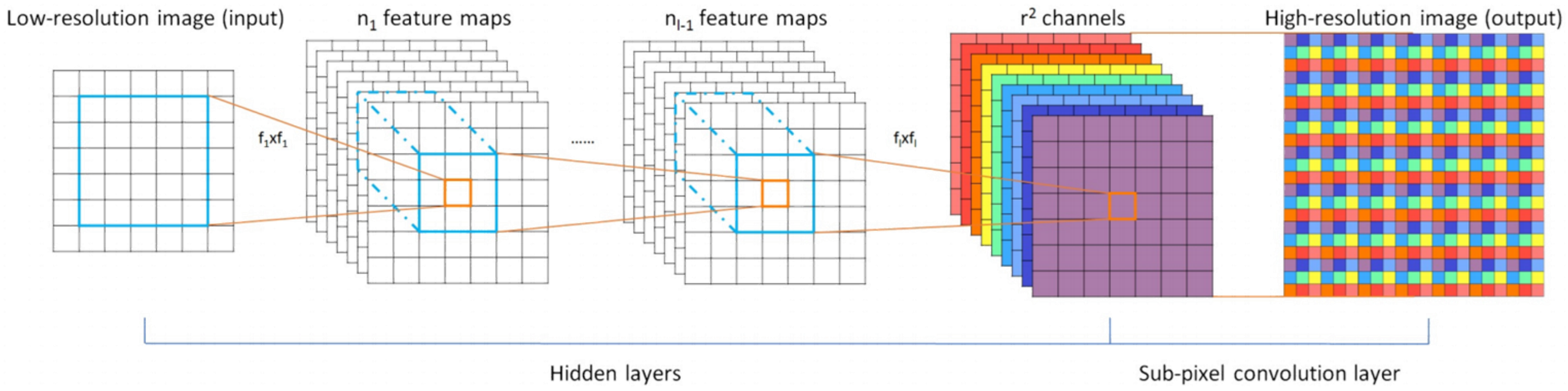


Help stabilize discriminator training in early stage

Srivastava et al. 17 “Learning from Simulated and Unsupervised Images through Adversarial Training”

GAN Hacks: Avoid Sparse Gradients

- Stability of GAN game suffers if gradients are sparse
- LeakyReLU -> good in both G and D
- Downsample -> use average pool, conv+stride
- Upsample -> upconv+stride, PixelShuffle



[Shi et al. 16] https://arxiv.org/pdf/1609.05158.pdf

Exponential Averaging of Weights

- Problem: discriminator is noisy due to SGD

- Rather than taking final result of a GAN, would be biased on last latest iterations (i.e., latest training samples),
- -> exponential average of weights
- -> keep second 'vector' of weights that are averaged
  -> almost no cost, average of weights from last n iters

Other Objective Functions

"heuristic is standard…"

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

Other Objective Functions

"heuristic is standard…"

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

The loss function alone will not make it suddenly work!

GAN Losses: EBGAN

- Discriminator is AE (Energy-based GAN)
- a good autoencoder: we want the reconstruction cost D(x) for real images to be low.
- a good critic: we want to penalize the discriminator if the reconstruction error for generated images drops below a value m.

$$\mathcal{L}_D(x, z) = D(x) + [m - D(G(z))]^+$$

$$\mathcal{L}_G(z) = D(G(z))$$

$$D(x) = ||Dec(Enc(x)) - x||$$

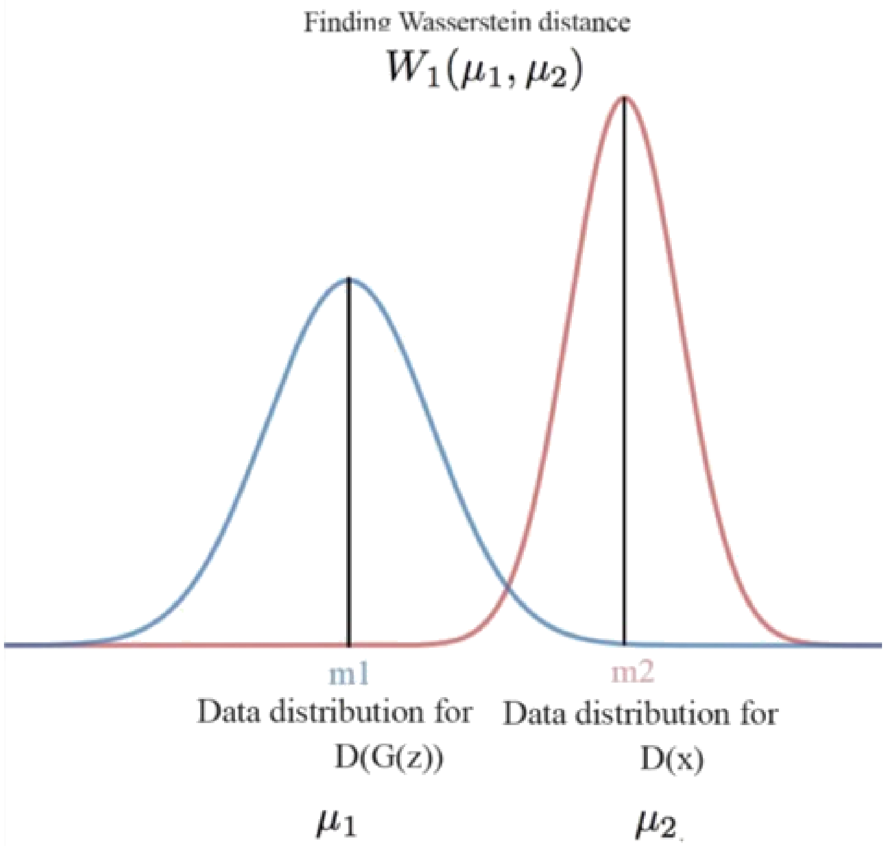
where $[\,\mathrm{u}\,]^+ = max(0, \mathrm{u}\,)$

https://medium.com/@jonathan_hui/gan-energy-based-gan-ebgan-boundary-equilibrium-gan-began-4662cceb7824

GAN Losses: BEGAN

- Similar to EBGAN

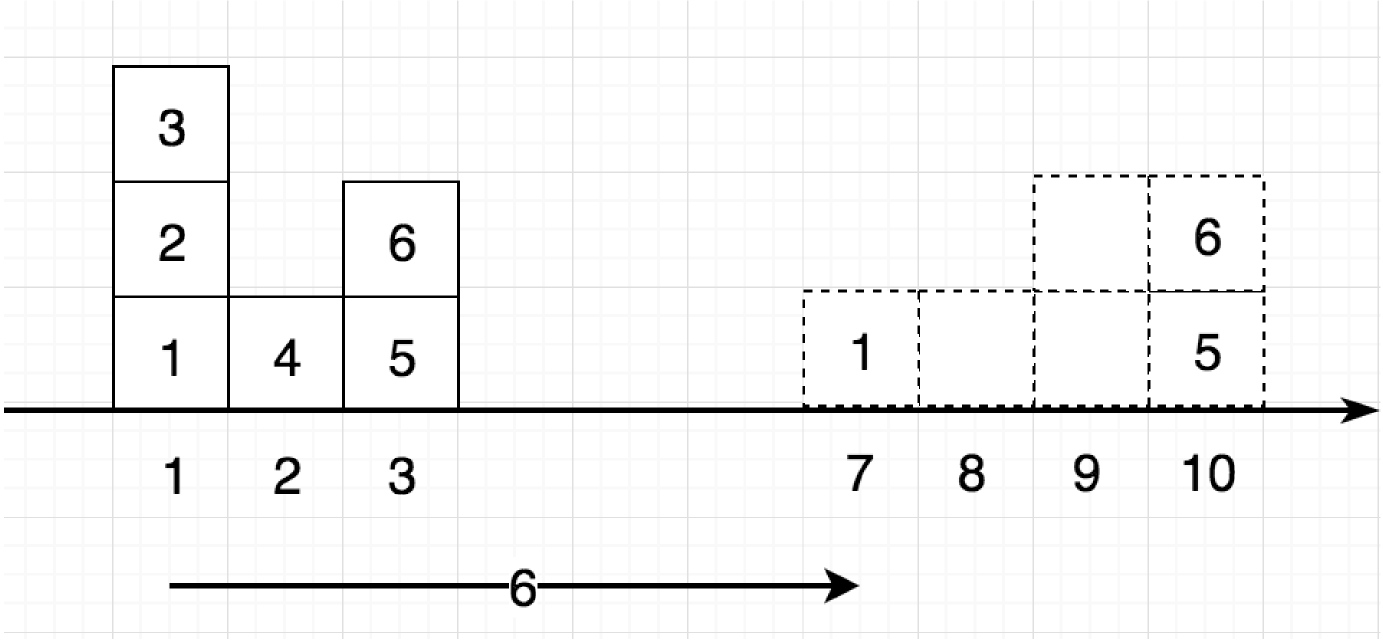
- Instead of reconstruction loss, measure difference in data distribution of real and generated images



https://medium.com/@jonathan_hui/gan-energy-based-gan-ebgan-boundary-equilibrium-gan-began-4662cceb7824

GAN Losses: WGAN

- Earth Mover Distance / Wasserstein Distance



Minimum amount of work to move earth from p(x) to q(x)

https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN Losses: WGAN

- Formulate EMD via it's dual:

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

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

1-Lipschitz function: upper bound between densities

https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN Losses: WGAN

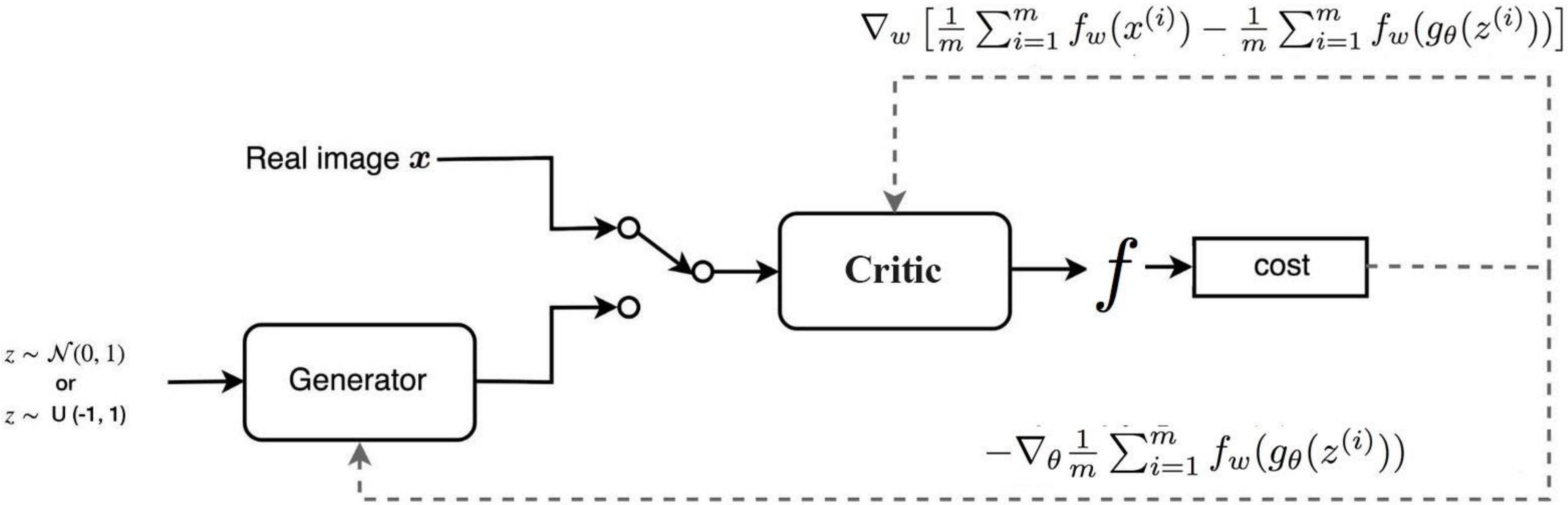
$$|f(x_1) - f(x_2)| \leq |x_1 - x_2|.$$

f is a critic function, defined by a neural network
-> f needs to be 1-Lipschitz; WGAN restricts max weight value in f; weights of the discriminator must be within a certain range controlled by hyperparameters c

$$w \leftarrow w + \alpha \cdot \mathrm{RMSProp}(w, g_w)$$
$$w \leftarrow \mathrm{clip}(w, -c, c)$$

https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN Losses: WGAN



https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN Losses: WGAN

	Discriminator/Critic	Generator
GAN	$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right]$	$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)$
WGAN	$\nabla_w \frac{1}{m} \sum_{i=1}^{m} \left[f\left(x^{(i)}\right) - f\left(G\left(z^{(i)}\right)\right) \right]$	$\nabla_\theta \frac{1}{m} \sum_{i=1}^{m} f\left(G\left(z^{(i)}\right)\right)$

https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

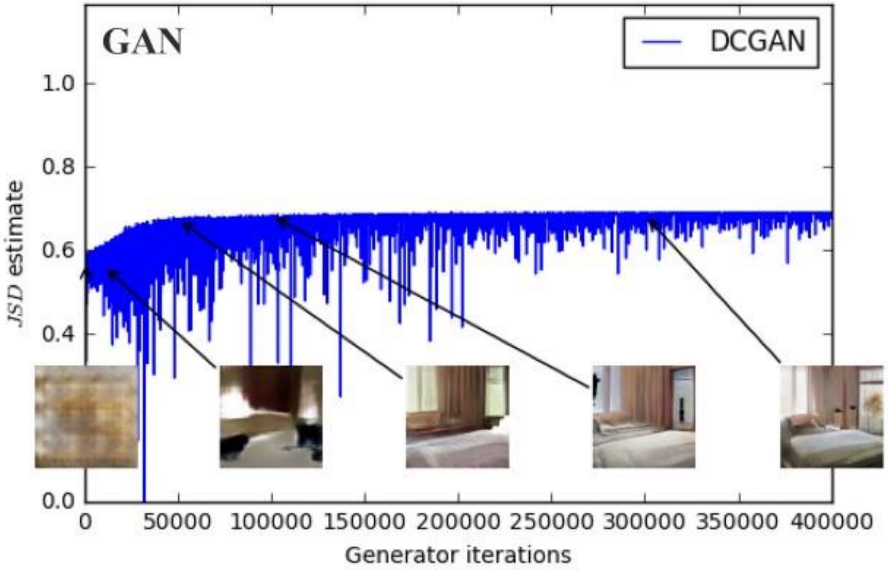
GAN Losses: WGAN

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

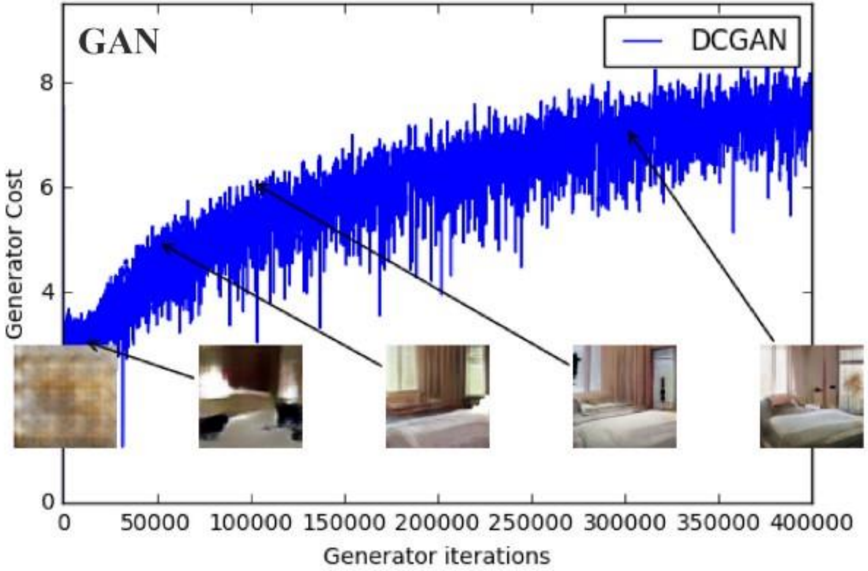
Require: : α, the learning rate. c, the clipping parameter. m, the batch size. n_{critic}, the number of iterations of the critic per generator iteration.
Require: : w_0, initial critic parameters. θ_0, initial generator's parameters.

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

GAN Losses: GAN



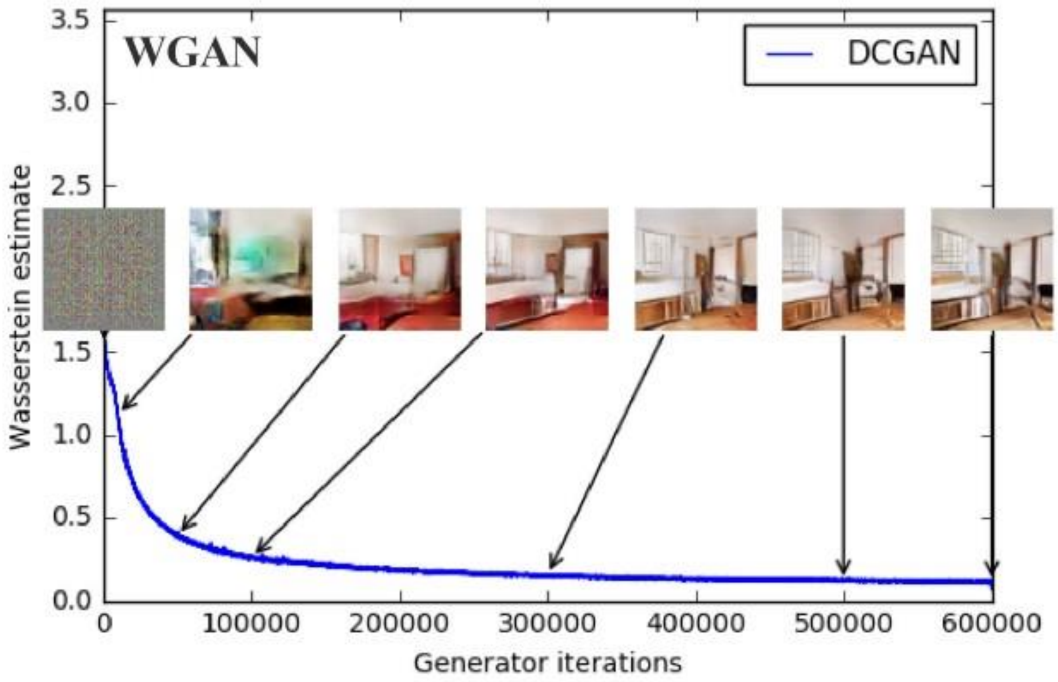
$$\frac{1}{m}\sum_{i=1}^{m}\log\left(1-D\left(G\left(z^{(i)}\right)\right)\right)$$



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

https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN Losses: WGAN



$$\frac{1}{m}\sum_{i=1}^{m} f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^{m} f_w(g_\theta(z^{(i)}))$$

GAN Losses: WGAN

- + mitigates mode collapse
- + generator still learns when critic performs well
- + actual convergence

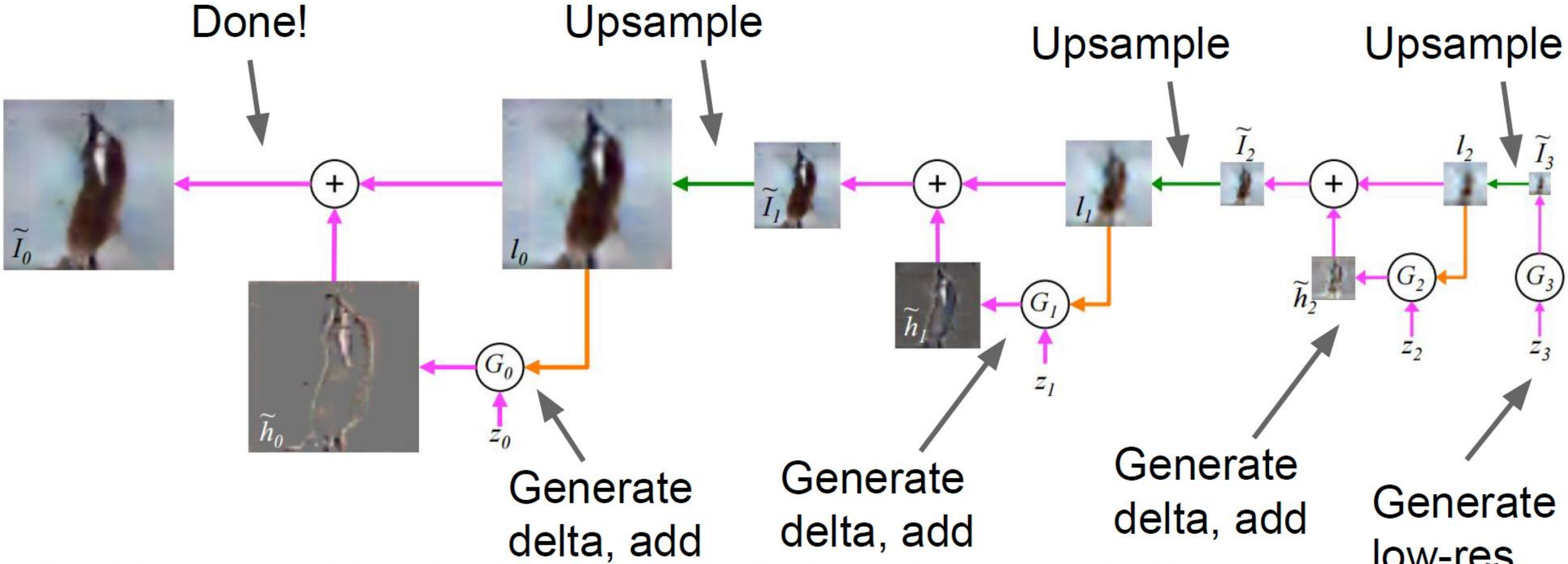
- Enforcing Lipschitz constraint is difficult
- Weight clipping is "terrible"
  - -> too high: takes long time to reach limit; slow training
    -> too small: vanishing gradients when layers are big

GAN Losses

- Many more variations!!!
- High-level understanding: “loss” is a meta loss to train the actual loss (i.e., D) to provide gradients for G
- Always start simple: if things don’t converge, don’t randomly shuffle loss around; always try easy things first (AE, VAE, ‘simple heuristic’ GAN)

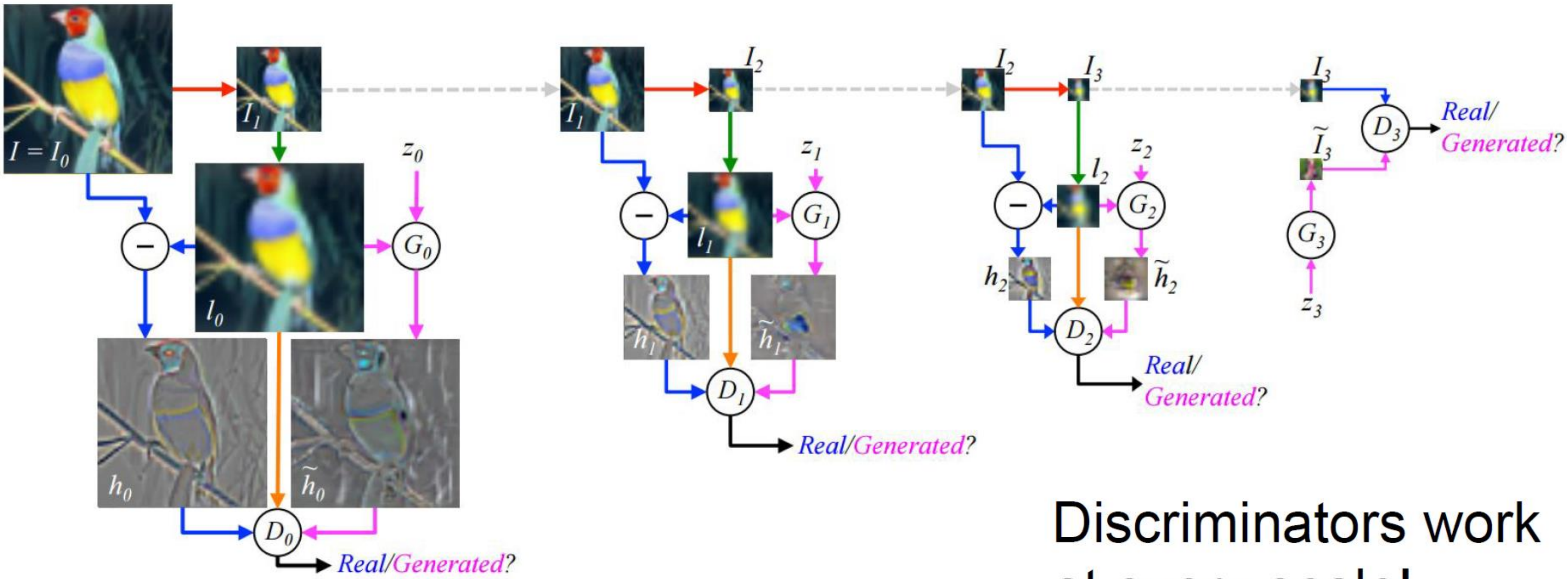
GAN Architectures

Multiscale GANs



Denton et al, "Deep generative image models using a Laplacian pyramid of adversarial networks", NIPS 2015

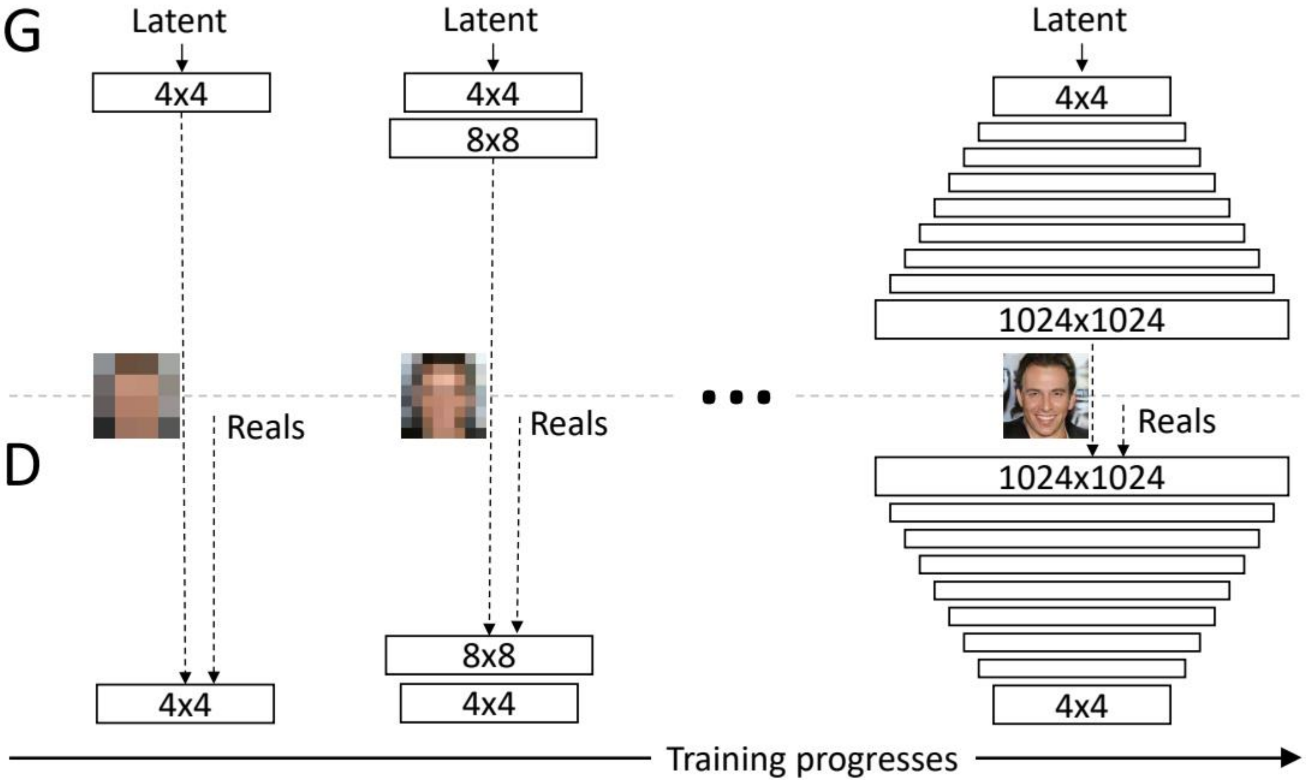
Multiscale GANs



Discriminators work at every scale!

Denton et al, NIPS 2015

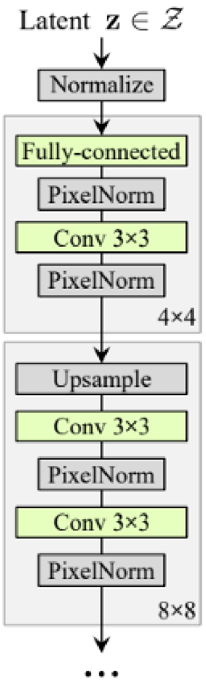
Progressive Growing GANs



https://github.com/tkarras/progressive_growing_of_gans [Karras et al. 17]

StyleGAN[x] Architectures

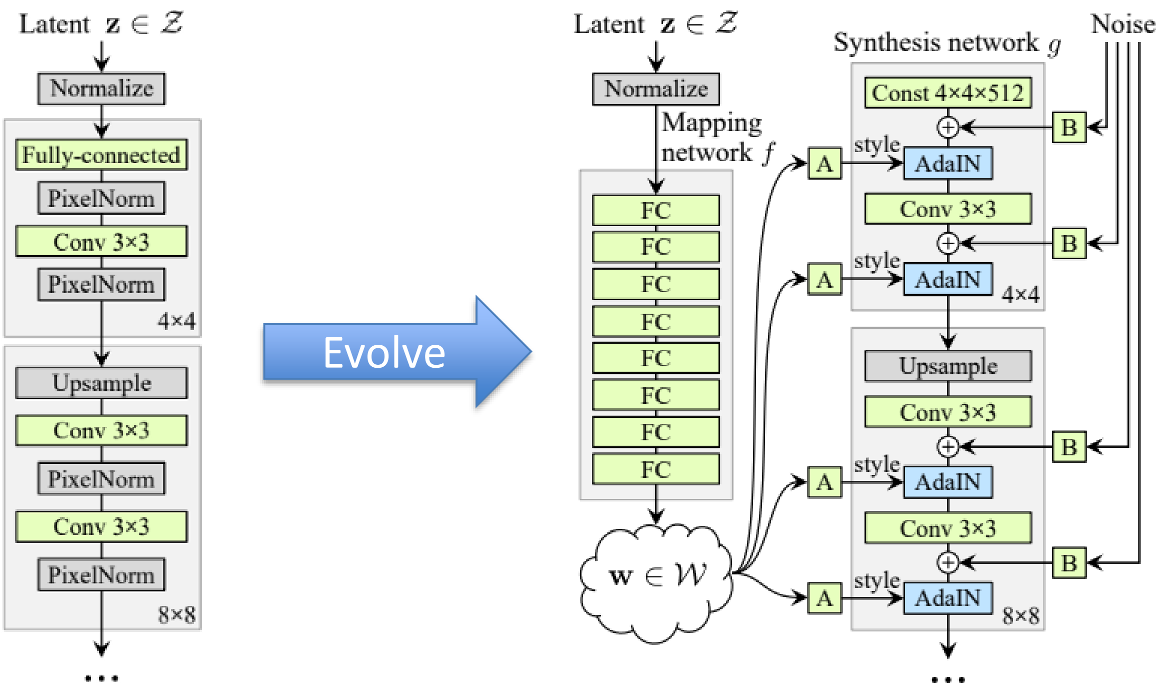
StyleGAN Architectures



Progressive GAN

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

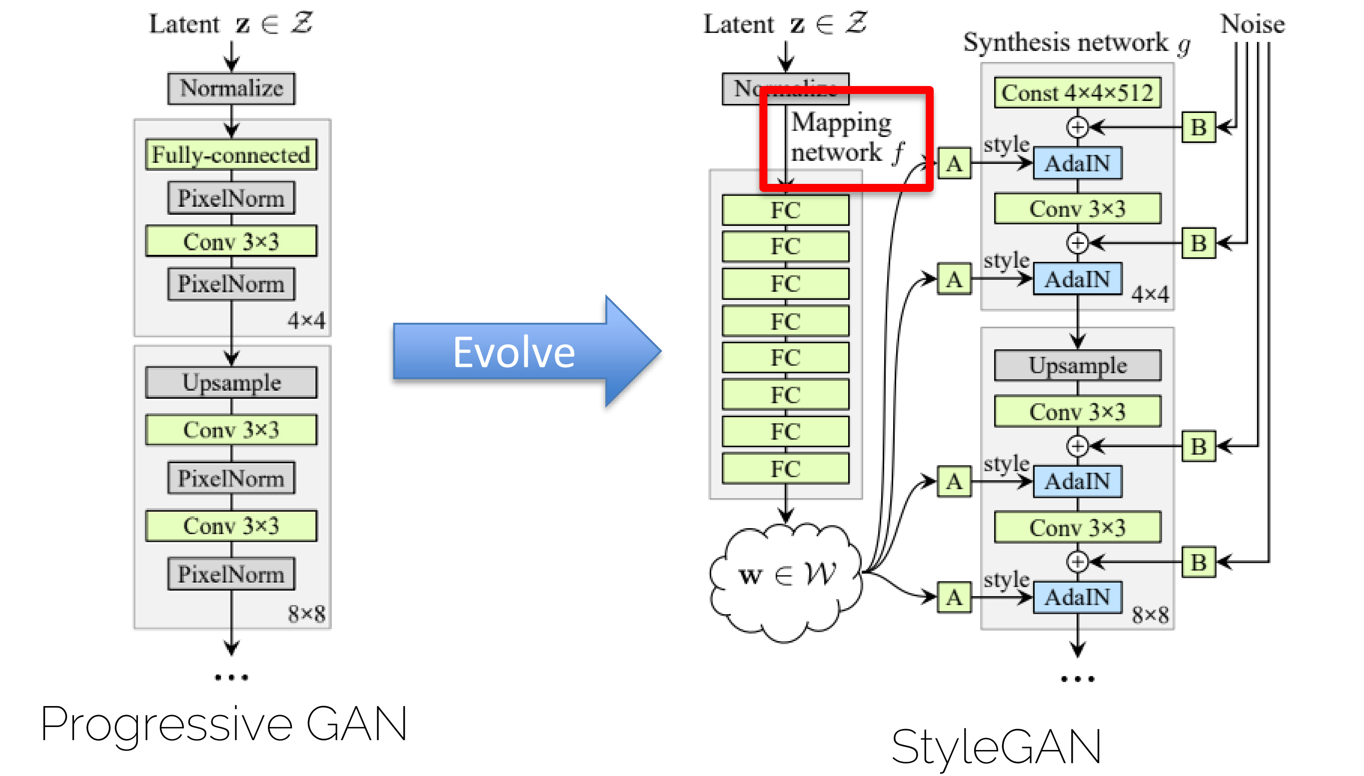
StyleGAN[x] Architectures



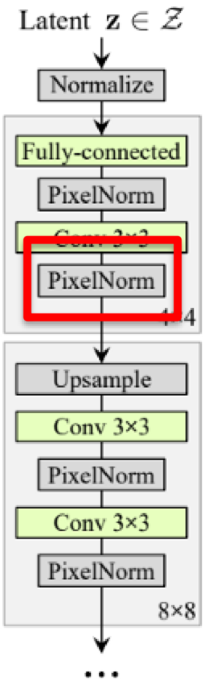
Progressive GAN

StyleGAN

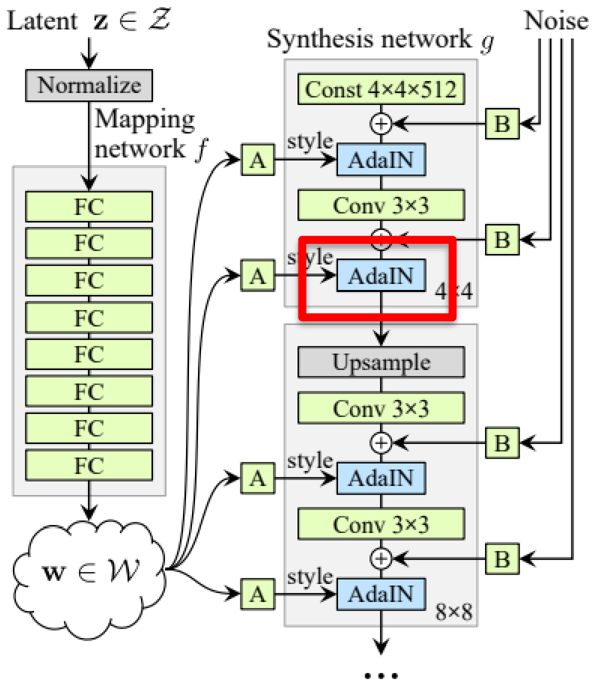
StyleGAN – Mapping Network



StyleGAN – Style Normalization

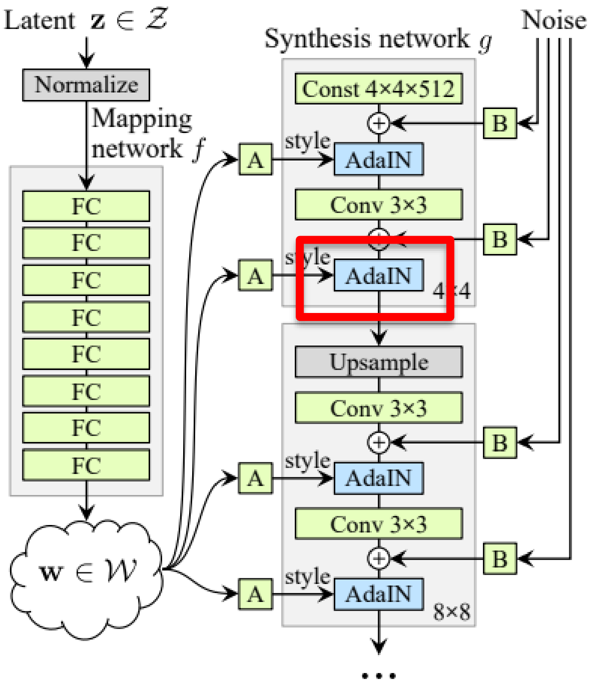


Progressive GAN



StyleGAN

StyleGAN – Style Normalization

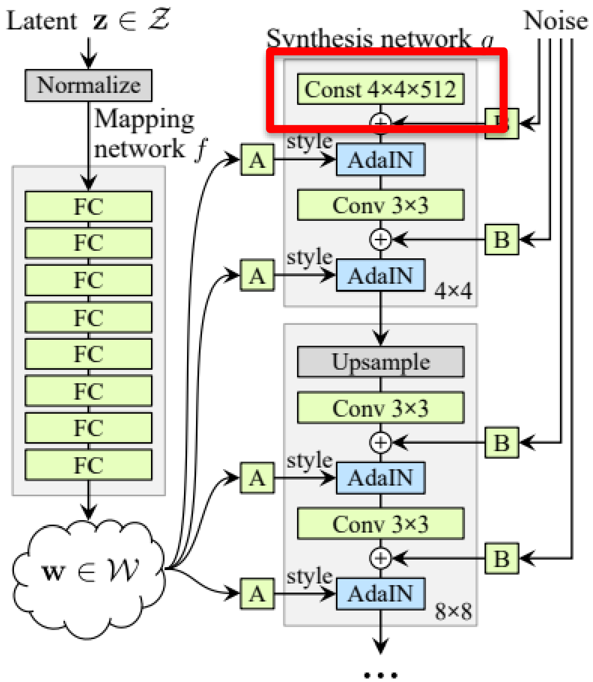


StyleGAN

$$AdaIN(x, y) = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y)$$

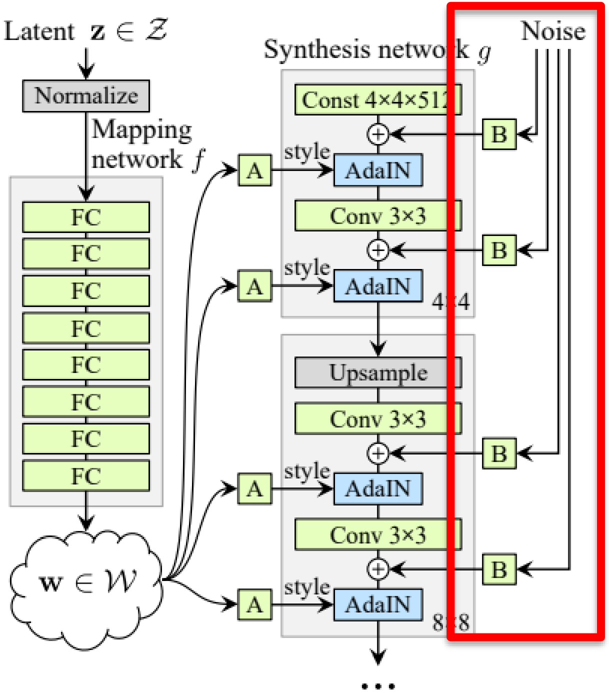
1. x: the activation from the previous layer
2. y: the style features (e.g. extracted from CNN) of your target style image
3. No trainable variables – mean and var directly calculated

StyleGAN – Constant Input



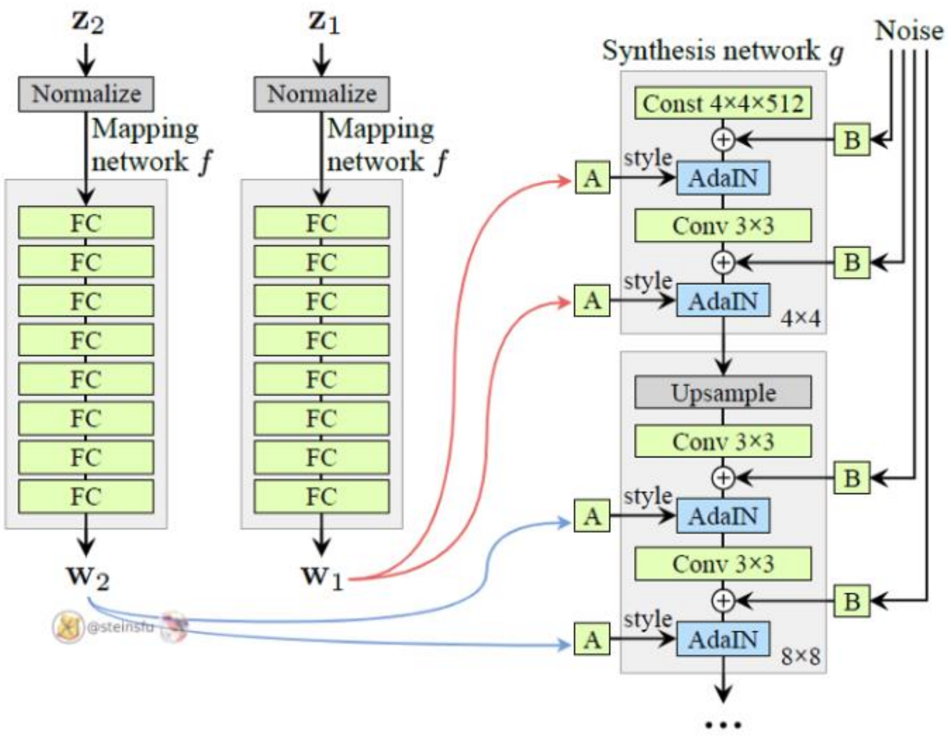
StyleGAN

StyleGAN – Style Normalization



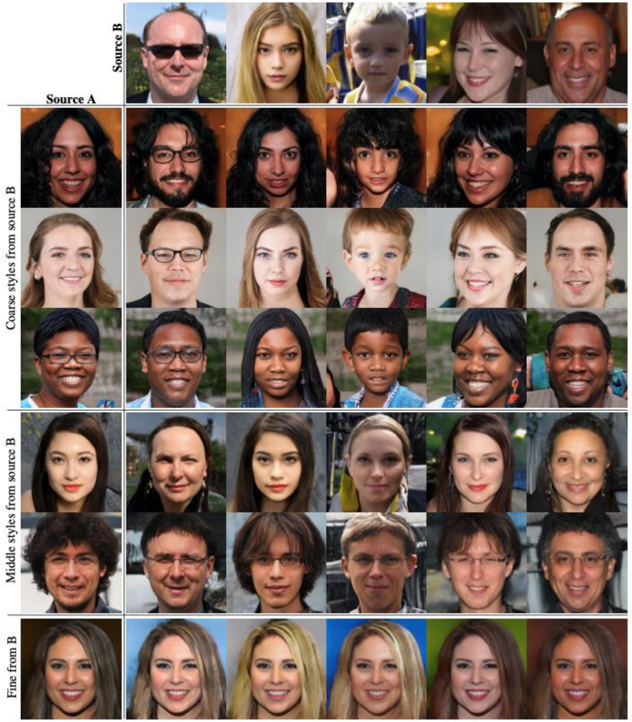
StyleGAN

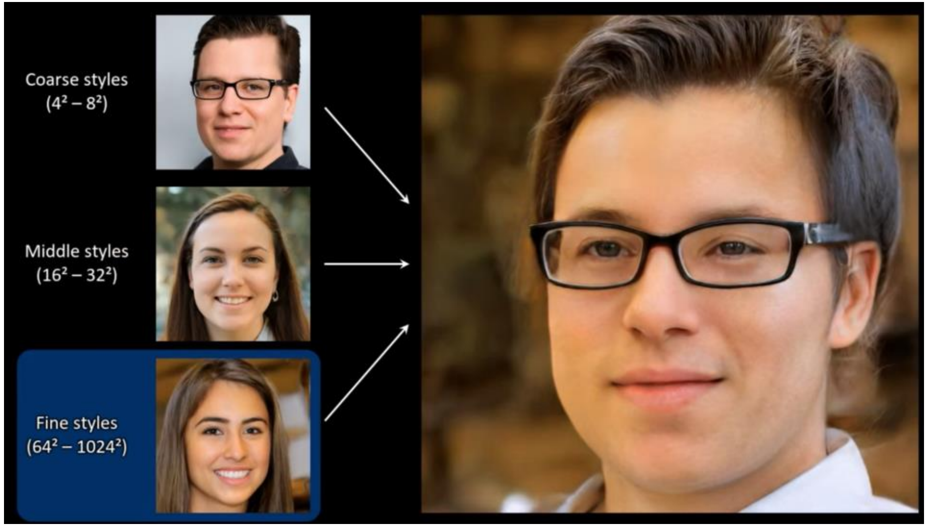
StyleGAN – Mixing Regularization



https://medium.com/@steinsfu/stylegan-vs-stylegan2-vs-stylegan2-ada-vs-stylegan3-c5e201329c8a

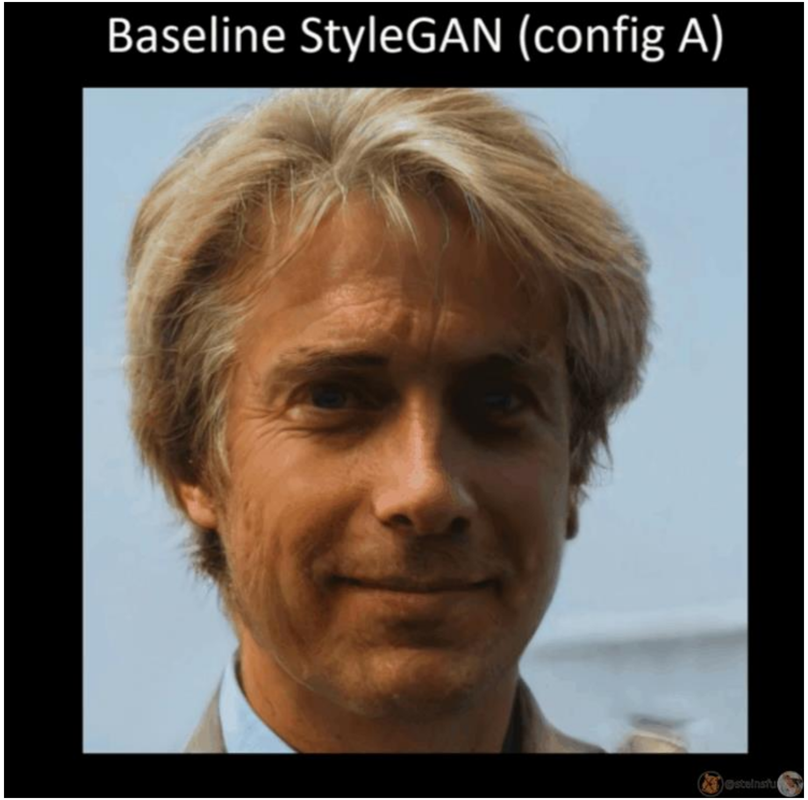
StyleGAN





https://www.youtube.com/watch?v=kSLJriaOumA

StyleGAN2 – No Droplets

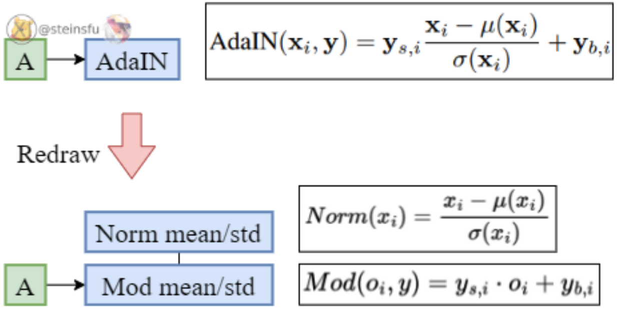


Normalization

$$AdaIN(x,y) = \boxed{\sigma(y)}\boxed{\left(\frac{x-\mu(x)}{\sigma(x)}\right)} + \boxed{\mu(y)}$$

Modulation

Without Normalization, the droplet artifact disappear

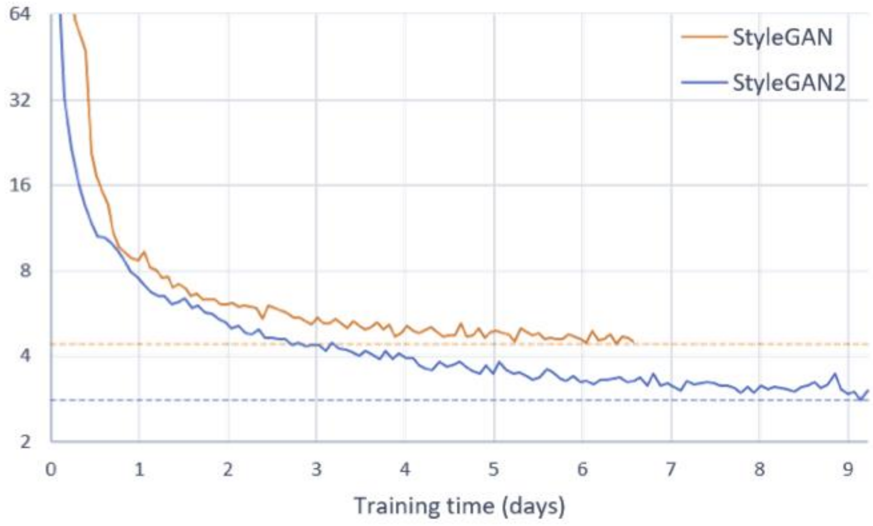


https://www.youtube.com/watch?v=c-NJtV9Jvp0, Stein Sfu StyleGAN1,2,3

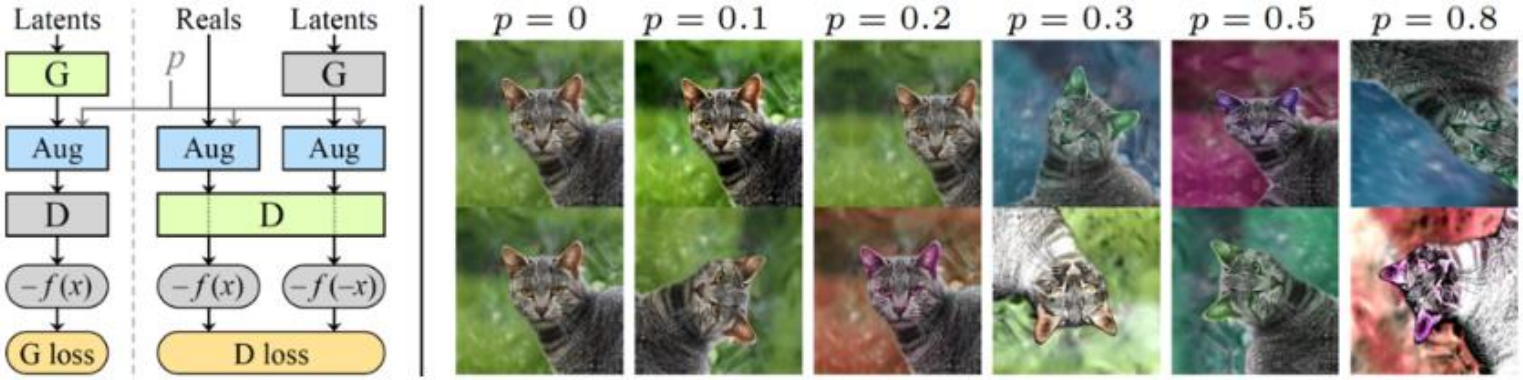
StyleGAN2 – Additional Changes

- Remove redundant operations
- Noise added outside of style area
- Normalization and modulation only applied on standard deviation
- Modulation and Convolution combined in single operation
- Training strategy changes, see: https://github.com/NVlabs/stylegan2

FID Score



StyleGAN2-ADA – Limited Data



The Discriminator latents are directly augmented with probability p.

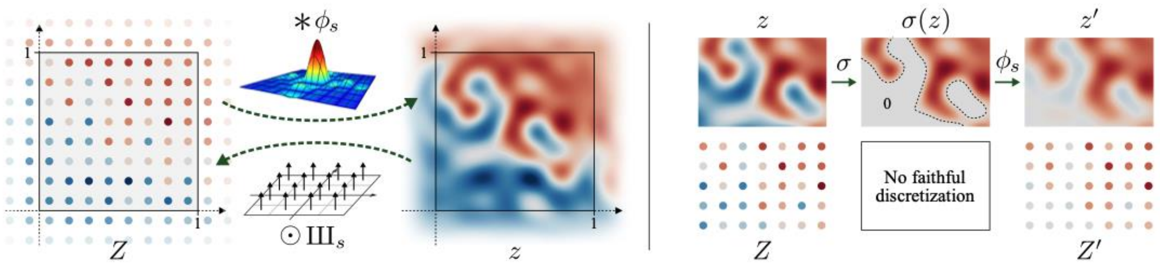
Better for limited Data

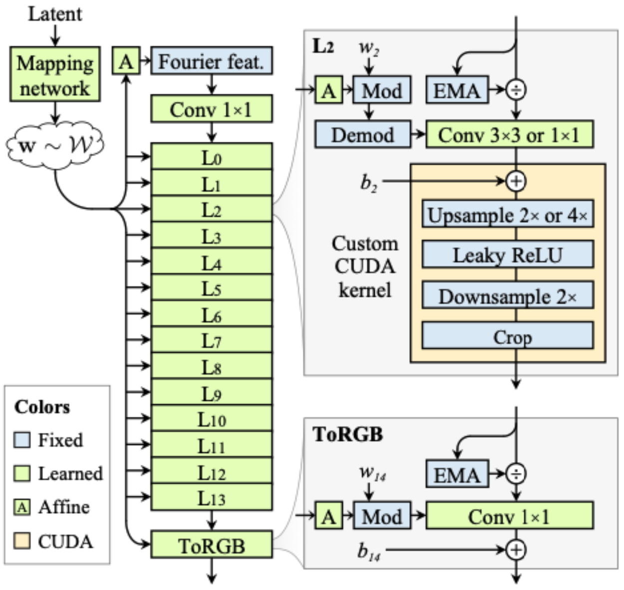
No manual augmentation

https://www.youtube.com/watch?v=kSLJriaOumA

StyleGAN3 – No Aliasing

StyleGAN3 – No Aliasing





Most Important differences:

- Input constant replaced with continuous Fourier feature
- Remove per pixel noise – no positional references
- Smaller mapping network depth
- Better upsampling with updated approximations of the Fourier low pass filter

Karras et al.: Alias-Free Generative Adversial Networks

Reading Homework

- GANs [Goodfellow et al. 2014] Generative adversarial networks
  - https://arxiv.org/abs/1406.2661
- [Radford et al. 2015] Unsupervised representation learning with deep convolutional generative adversarial networks
  - https://arxiv.org/abs/1511.06434
- [Karras et al. 19] A style-based generator architecture for generative adversarial networks.
  - https://arxiv.org/abs/1812.04948

Thanks for watching!