WELCOME TO THE

UCL x DeepMind lecture series

In this lecture series, leading research scientists from leading AI research lab, DeepMind, will give 12 lectures on an exciting selection of topics in Deep Learning, ranging from the fundamentals of training neural networks via advanced ideas around memory, attention, and generative modelling to the important topic of responsible innovation.

Please join us for a deep dive lecture series into Deep Learning!

TODAY'S SPEAKERS

Mihaela Rosca + Jeff Donahue

Mihaela Rosca is a Research Engineer at DeepMind and a PhD student at UCL, focusing on generative models research and probabilistic modelling, from variational inference to generative adversarial networks and reinforcement learning.

Jeff Donahue is a Research Scientist at DeepMind, currently focusing on adversarial generative models and unsupervised representation learning. He completed his Ph.D. at UC Berkeley, focusing on visual representation learning.

DeepMind

Generative adversarial networks

Jeff Donahue & Mihaela Rosca

UCL x DeepMind Lectures

DeepMind

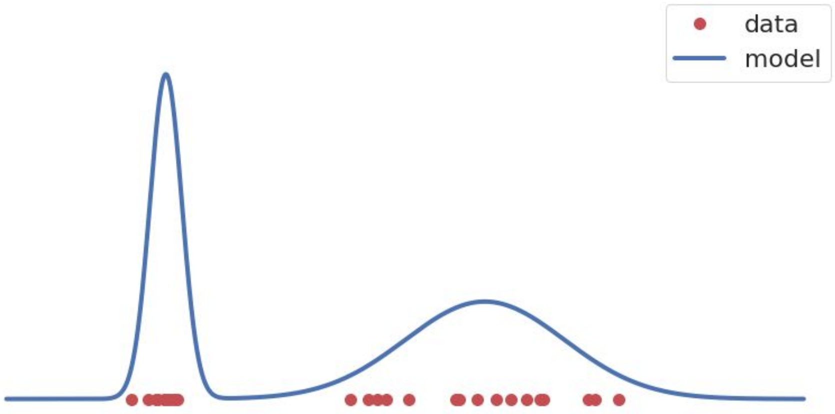
1 Overview

Generative models

Learn a model of the true (unknown) underlying data distribution from samples

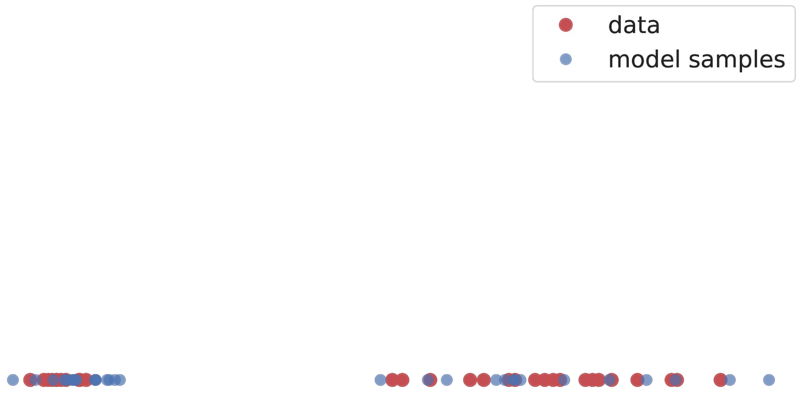
Generative models

Generative models



Learning an explicit distribution from data.

Generative models



Learning an implicit distribution from data.

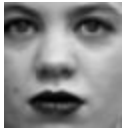
Generative model zoo

Explicit likelihood models:

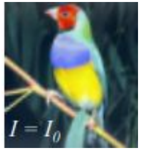
- Maximum likelihood
  - PPCA, Factor Analysis, Mixture models
  - PixelCNN/PixelRNN
  - Wavenet
  - Autoregressive language models
- Approximate maximum likelihood
  - Boltzmann machines
  - Variational autoencoders

Implicit models (no likelihoods):

- Generative adversarial networks
- Moment matching networks



Goodfellow, et al. **Generative adversarial networks.** NIPS (**2014**)



Denton, et al. **Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks.** NIPS (**2015**)

Radford et al. **Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks** ICLR (**2015**)

Miyato et al. **Spectral normalization for Generative Adversarial Networks** ICLR (**2018**)

Karras et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis** ICLR (**2018**)

Brock et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis** ICLR (**2019**)

Karras et al. **A Style-Based Generator Architecture for Generative Adversarial Networks** CVPR (**2019**)

Generative adversarial networks

Want to learn more?

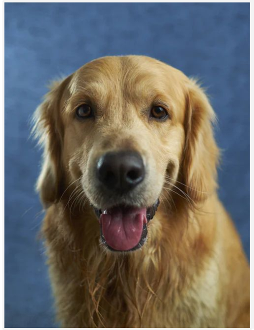
Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems (2014)

Learning an implicit model through a two player game.

Generative adversarial networks

Discriminator

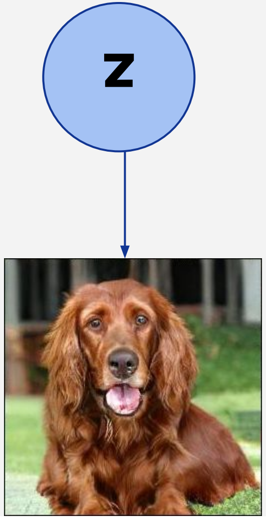
Learns to distinguish between real and generated data.



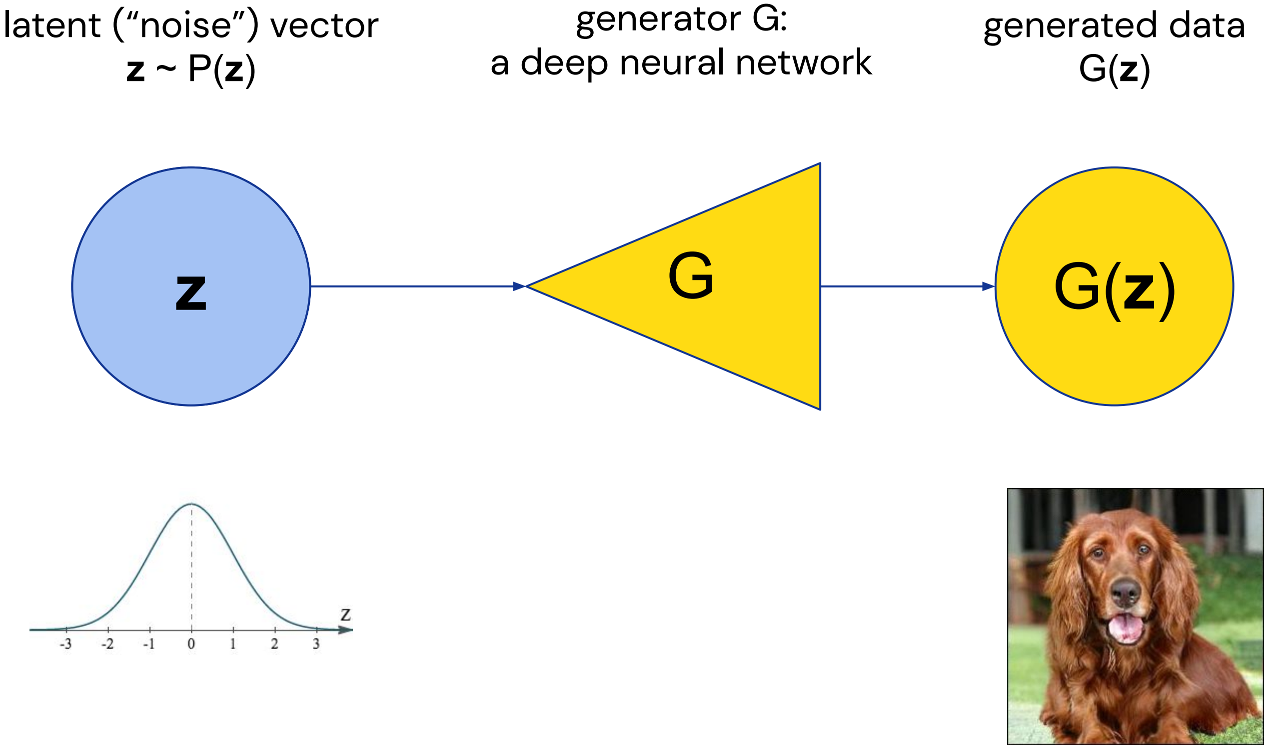
vs

Generator

Learns to generate data to “fool” the discriminator.



Generator



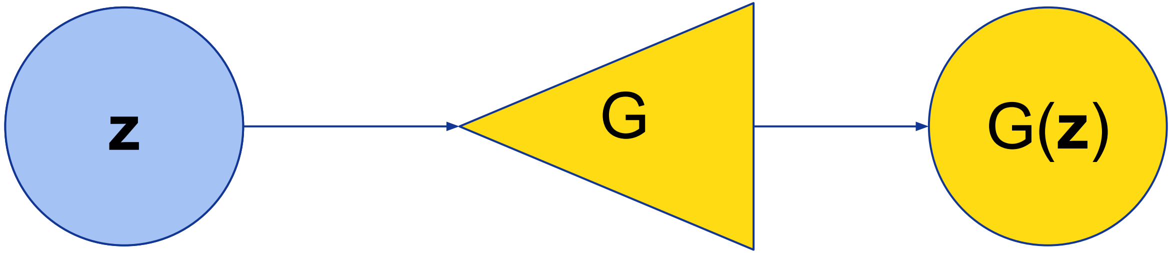
latent ("noise") vector
z ~ P(z)
generator G:
a deep neural network
generated data
G(z)
z
G
G(z)
-3 -2 -1 0 1 2 3
z

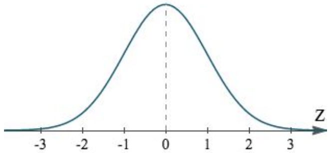
Generator

latent (“noise”) vector
z ~ P(**z**)

generator G:
a deep neural network

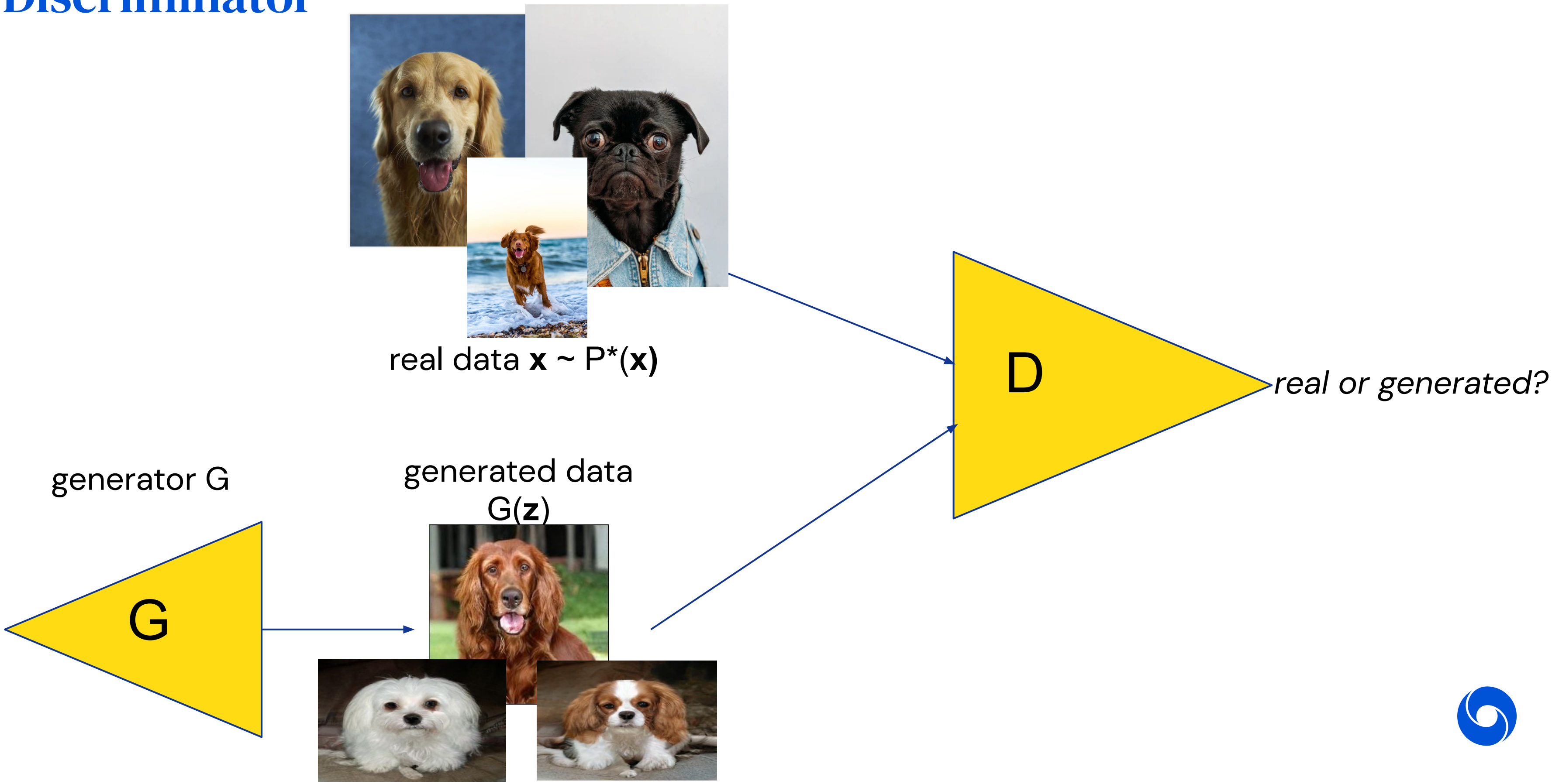
generated data
G(**z**)



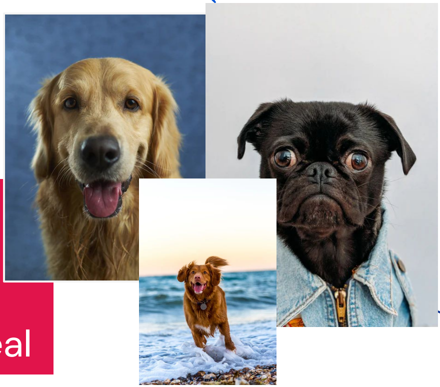


It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness...

Discriminator



~~Discriminator~~ Teacher (less adversarial view)



Generator
~~fool the discriminator~~
make the teacher happy by
making generated data look real

real data $\mathbf{x} \sim P^*(\mathbf{x})$

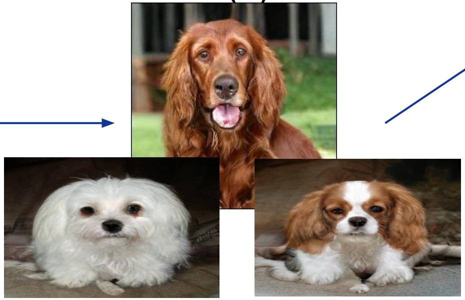
D

real or generated?

generator G

G

generated data
$G(\mathbf{z})$



Teacher
distinguish between real and
generated data, so that I can tell the
generator how to improve

Generative adversarial networks

Want to learn more?

Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems **(2014)**

$$\min_G \max_D V(D, G) = \underbrace{\mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})]}_{\text{log-probability that D correctly predicts real data } \mathbf{x} \text{ are real}} + \underbrace{\mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]}_{\text{log-probability that D correctly predicts generated data } G(\mathbf{z}) \text{ are generated}}$$

Generative adversarial networks

Want to learn more?

Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems (**2014**)

$$\min_G \max_D V(D,G) = \underbrace{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})]}_{\text{log-probability that D correctly predicts real data x are real}} + \underbrace{\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]}_{\text{log-probability that D correctly predicts generated data G(z) are generated}}$$

discriminator's (D) goal: **maximize** prediction accuracy

generator's (G) goal: **minimize** D's prediction accuracy, by **fooling** D into believing its outputs G(**z**) are real as often as possible

Generative adversarial networks

Want to learn more?

Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems (**2014**)

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ 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

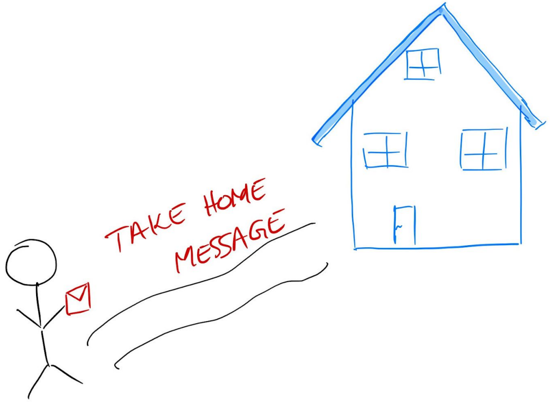
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

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

end for

Algorithm from Goodfellow et al. (2014)

GANs are an implicit generative model trained as a two player game.



Generative adversarial networks as zero sum game

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

- Bi level optimization of the same loss function.
- Connection to game theory literature.
  - Nash equilibria
  - Strategies
  - Fictitious play

Generative models as distance minimization

- The objective of generative models is often to minimize a divergence or distance.
- Most common: Maximum likelihood (KL divergence).

Why divergence/distance minimization?

$$D(p^*||p) = 0 \implies p = p^*$$

Generative models as distance minimization

- The objective of generative models is often to minimize a divergence or distance.
- Most common: Maximum likelihood (KL divergence).

Maximum likelihood

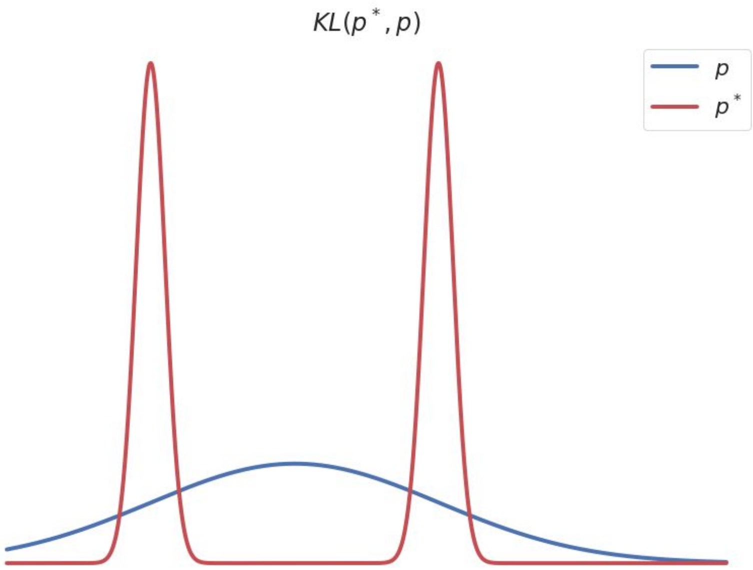
$$\mathrm{KL}(p^*(\mathbf{x})||p(\mathbf{x})) = \int p^*(\mathbf{x}) \log \frac{p^*(\mathbf{x})}{p(\mathbf{x})} d\mathbf{x}$$

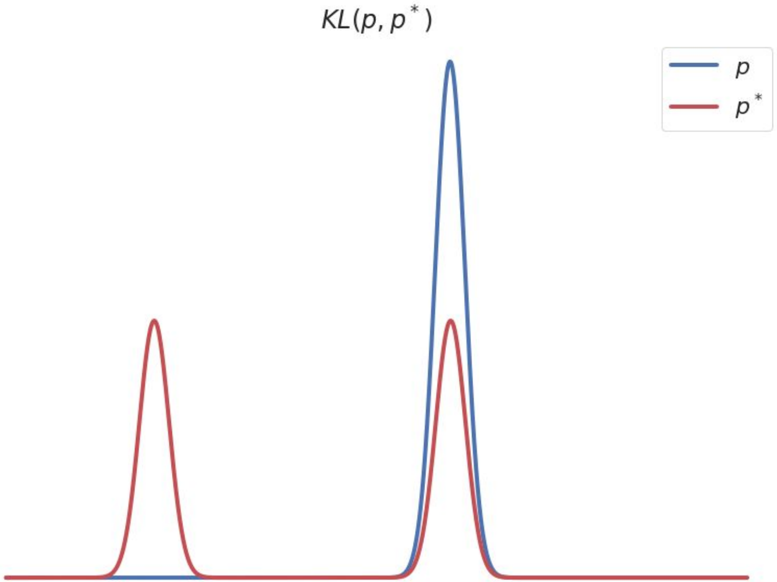
$$\mathrm{KL}(p^*(\mathbf{x})||p(\mathbf{x})) = 0 \implies p(\mathbf{x}) = p^*(\mathbf{x})$$

Effects of the choice of divergence - learned models

Want to learn more?

Goodfellow, et al. **NIPS 2016 Tutorial: Generative Adversarial Networks** Arxiv (**2016**)





Are GANs doing divergence minimization?

Want to learn more?

Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems (2014)

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

**If the discriminator (D) is optimal:
the generator is minimizing the Jensen Shannon divergence
between the true and generated distributions.**

Are GANs doing divergence minimization?

Want to learn more?

Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems **(2014)**

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

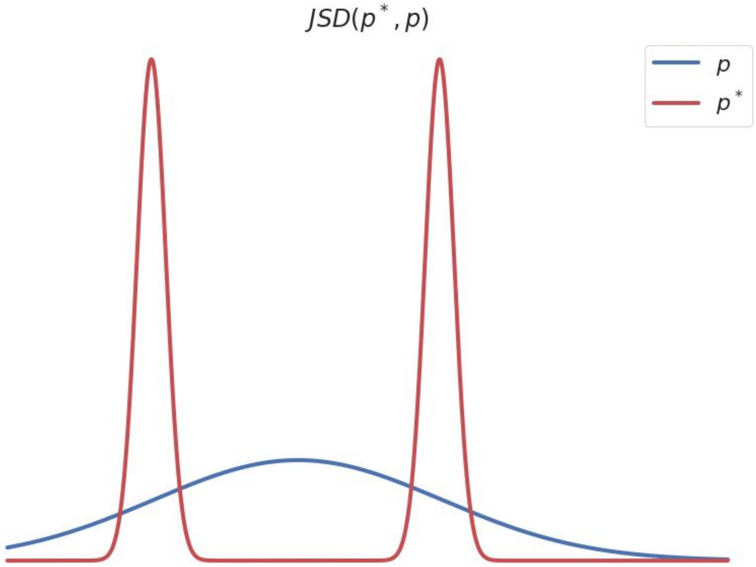
If the discriminator (D) is optimal:
the generator is minimizing the Jensen Shannon divergence between the true and generated distributions.

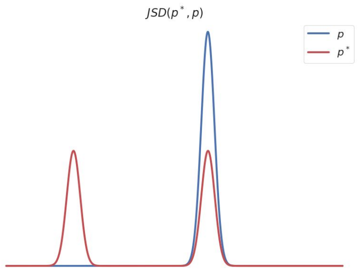
Connection to optimality:

$$JSD(p^*||p) = 0 \implies p = p^*$$

Jensen Shannon divergence

$$\mathrm{JSD}(p, p^*) = \frac{1}{2}\mathrm{KL}(p, \frac{p+p^*}{2}) + \frac{1}{2}\mathrm{KL}(p^*, \frac{p+p^*}{2})$$





GANs: More than Jensen Shannon divergence

In practice: D is not optimal:

→ limited computational resources

→ we do not have access to the true data distribution (just samples)

Properties of KL & Jensen Shannon divergences

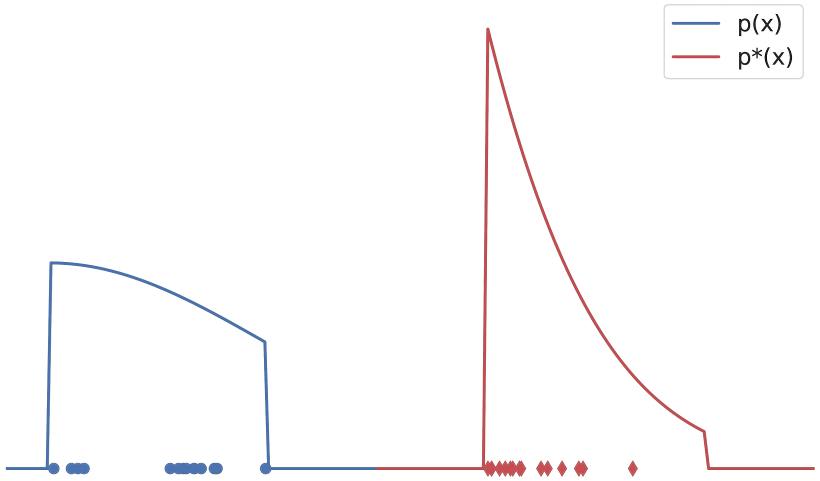
Want to learn more?

Gretton, et al **Interpretable comparison of distributions and models** Neural Information Processing Systems Tutorial **(2019)**

No learning signal from KL/JSD divergence if non overlapping support between the data and the model.

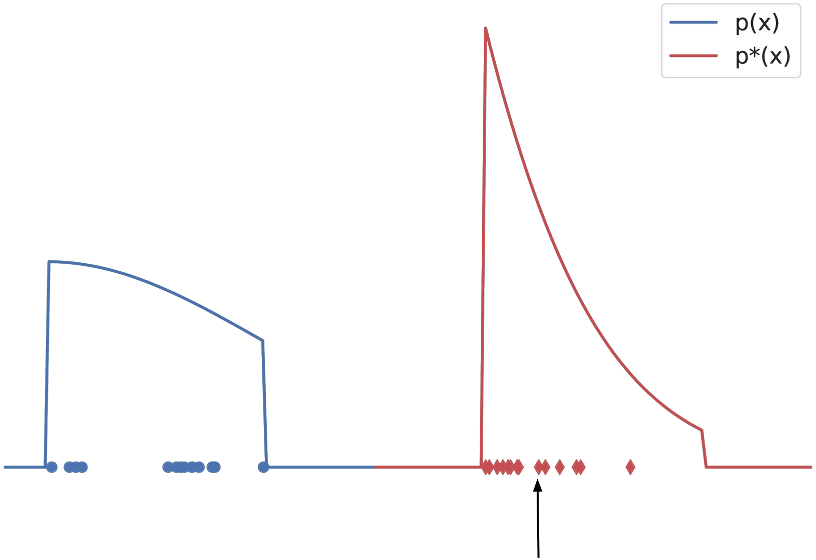
$$\mathrm{KL}(p^*(\mathbf{x})||p(\mathbf{x})) = \infty$$

$$\mathrm{JSD}(p^*(\mathbf{x})||p(\mathbf{x})) = \log 2$$



Non overlapping support

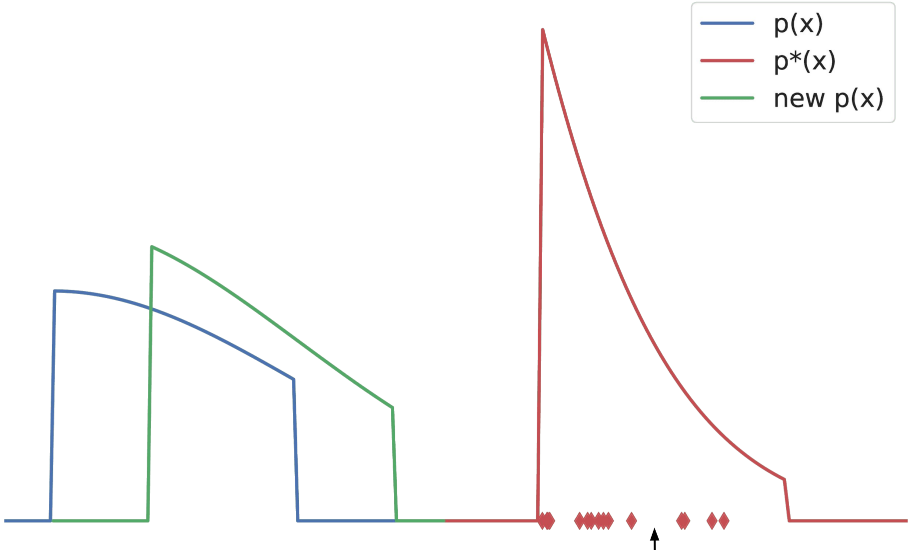
$$\mathrm{KL}(p^*(\mathbf{x})||p(\mathbf{x})) = \int p^*(\mathbf{x}) \log \frac{p^*(\mathbf{x})}{p(\mathbf{x})} d\mathbf{x}$$



$$\frac{p^*(\mathbf{x})}{p(\mathbf{x})} = \infty$$

Non overlapping support

Moving the model closer to the true distribution (new p) results in no change in KL/JSD.



$$\frac{p^*(\mathbf{x})}{p(\mathbf{x})} = \infty$$

Generative adversarial networks as zero sum game

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

Can we choose another V?

Generative adversarial networks as zero sum game

$$\min_{G} \max_{D} V(D, G)$$

Will it correspond to a distributional divergence?

Other divergences and distances

Want to learn more?

Gretton, et al **Interpretable comparison of distributions and models** Neural Information Processing Systems Tutorial (**2019**)

Wasserstein Distance

$$W(p^*, p) = \sup_{||f||_L \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(x)} f(x)$$

$$|f(x) - f(y)| \leq |x - y|$$

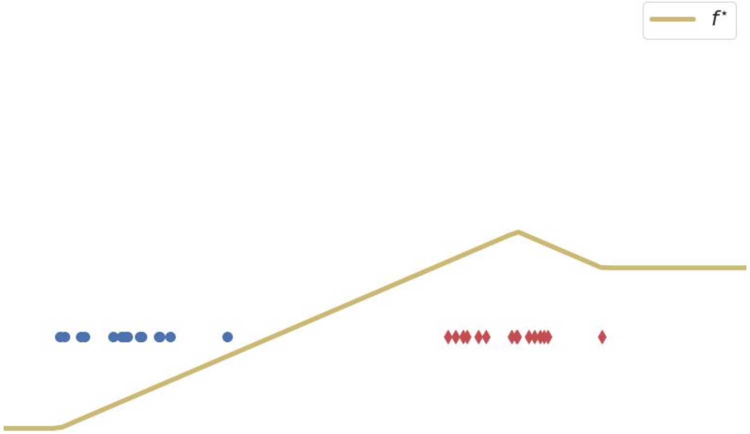
Other divergences and distances

Want to learn more?
Gretton, et al **Interpretable comparison of distributions and models**
Neural Information Processing Systems Tutorial **(2019)**

Wasserstein Distance

$$W(p^*, p) = \sup_{||f||_L \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(x)} f(x)$$

$$W(p^*, p) = 1.78$$



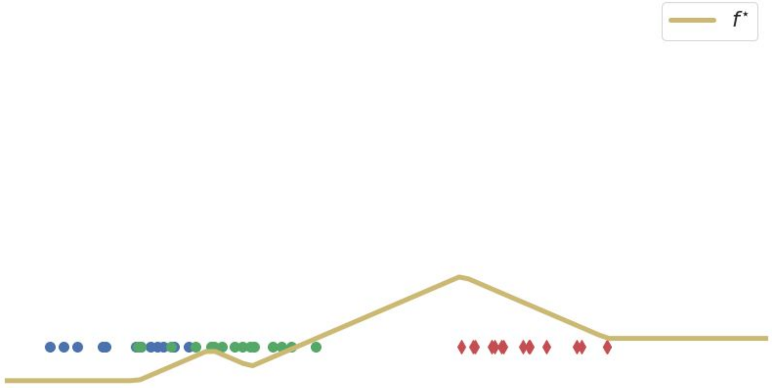
Other divergences and distances

Want to learn more?
Gretton, et al **Interpretable comparison of distributions and models** Neural Information Processing Systems Tutorial **(2019)**

Wasserstein Distance

$$W(p^*, p) = \sup_{||f||_L \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(x)} f(x)$$

$$W(p^*, p) = 1.6$$



Other divergences and distances

Want to learn more?
Gretton, et al **Interpretable comparison of distributions and models** Neural Information Processing Systems Tutorial (2019)

Wasserstein Distance | Estimation

$$W(p^*, p) = \sup_{||f||_L \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(x)} f(x)$$

Learning

$$\min_G W(p, p^*) = \min_G \sup_{||f||_L \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(z)} f(G(z))$$

Other divergences and distances

Want to learn more?

Arjovsky, et al **Wasserstein GAN.** International Conference on Machine Learning (2017)

Wasserstein Distance

$$W(p, p^*) = \sup_{||f||_L \leq 1} \mathbb{E}_{p(x)} f(x) - \mathbb{E}_{p^*(x)} f(x)$$

Wasserstein GAN

$$\min_G \max_{||D||_L \leq 1} \mathbb{E}_{p^*(x)} D(x) - \mathbb{E}_{p(z)} D(G(z))$$

Try to make D is 1-Lipschitz via gradient penalties, spectral normalization, weight clipping.

Other divergences and distances

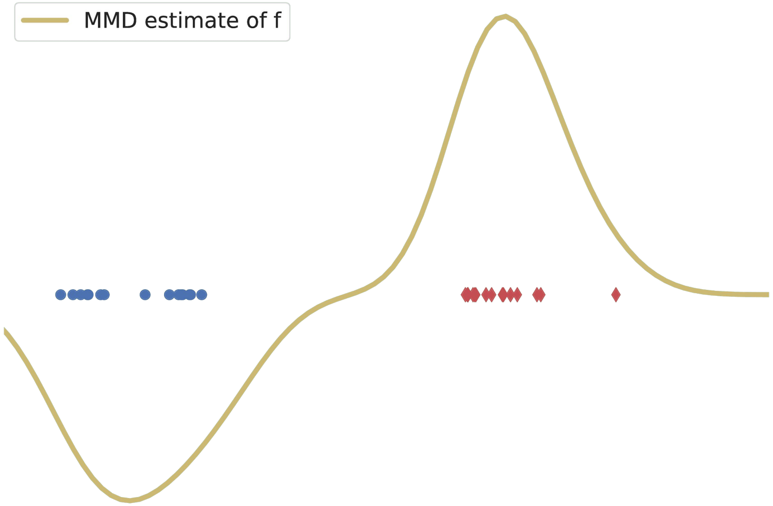
Want to learn more?

Gretton, et al **Interpretable comparison of distributions and models** Neural Information Processing Systems Tutorial (2019)

MMD

$$\mathrm{MMD}(p^*, p) = \sup_{||f||_{\mathcal{H}} \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(x)} f(x)$$

$\mathcal{H}$ *is a RKHS.*



Other divergences and distances

Want to learn more?

Li, et al **MMD GAN: Towards Deeper Understanding of Moment Matching Network.** Neural Information Processing Systems **(2017)**

MMD

$$\mathrm{MMD}(p^*, p) = \sup_{||f||_{\mathcal{H}} \leq 1} \mathbb{E}_{p^*(x)} f(x) - \mathbb{E}_{p(x)} f(x)$$

$\mathcal{H}$ *is a RKHS.*

MMD-GAN

$$\min_G \max_{||D||_{\mathcal{H}} \leq 1} \mathbb{E}_{p^*(x)} D(x) - \mathbb{E}_{p(z)} D(G(z))$$

Choose kernel with learned features (via D) $K_\phi(x, x') = K(\phi(X), \phi(X'))$

Other divergences and distances

Want to learn more?

Nowozin, et al **f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization.** Neural Information Processing Systems **(2016)**

f-divergences

$$D_f(p^*||p) = \int p(x) f\left(\frac{p^*(x)}{p(x)}\right) dx$$

variational lower bound

$$\int p(x) f\left(\frac{p^*(x)}{p(x)}\right) dx \geq \sup_{T \in \mathcal{T}} \left(\mathbb{E}_{p(x)} T(x) - \mathbb{E}_{p^*(x)} f^*(T(x))\right)$$

optimal T for KL: $f^*\left(\frac{p^*(x)}{p(x)}\right)$

f^* is the convex conjugate of f

Other divergences and distances

Want to learn more?

Nowozin, et al **f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization.** Neural Information Processing Systems (**2016**)

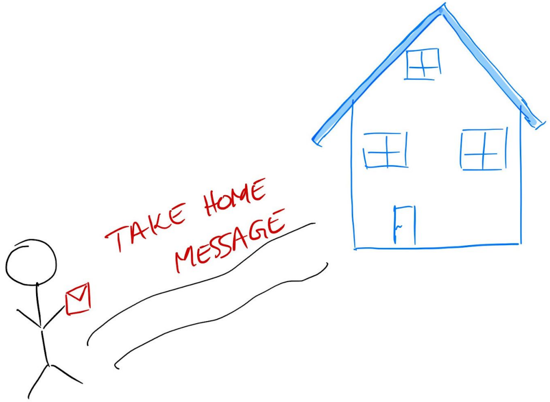
f-divergences

$$D_f(p^*||p) = \int p(x) f\left(\frac{p^*(x)}{p(x)}\right) dx$$

f-GAN

$$\min_G \max_D \mathbb{E}_{p(z)} D(G(z)) - \mathbb{E}_{p^*(x)} f^*(D(x))$$

Can create GAN training criteria inspired by multiple divergences & distances.



Why train a GAN instead of doing divergence minimization?

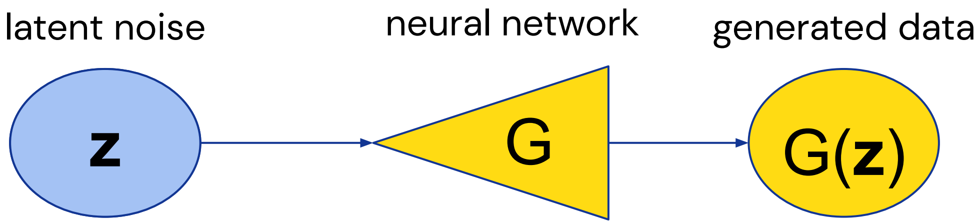
- Model type
- Computational Intractability
- Smooth learning signal
- Learned “divergence“

Implicit models and KL divergence

Model type

$$\mathrm{KL}(p^*(\mathbf{x})||p(\mathbf{x})) = \int p^*(\mathbf{x}) \log \frac{p^*(\mathbf{x})}{p(\mathbf{x})} dx$$

For implicit models, we do not have access to the explicit distribution p(x).



Implicit models and KL divergence

Model type

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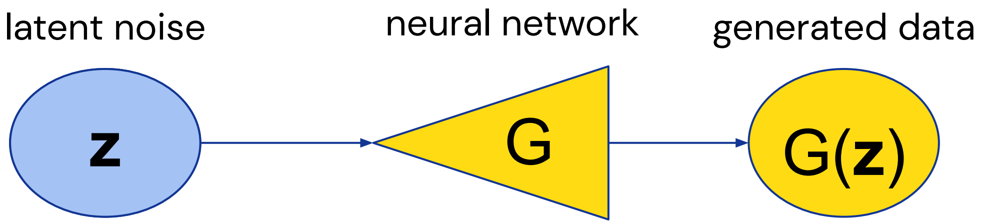

f-GAN

$$\min_G \max_D \mathbb{E}_{p(z)} D(G(z)) - \mathbb{E}_{p^*(x)} f^*(D(x))$$

Wasserstein distance & computational intractability

Computational intractability

$$W(p, p^*) = \sup_{||f||_L \leq 1} \mathbb{E}_{p(x)} f(x) - \mathbb{E}_{p^*(x)} f(x)$$

Computationally intractable for complex cases.

Wasserstein GAN

$$\min_G \max_{||D||_L \leq 1} \mathbb{E}_{p^*(x)} D(x) - \mathbb{E}_{p(z)} D(G(z))$$

Smooth learning signal

Want to learn more
Gretton, et al **Interpretable comparison of distributions and models** Neural Information Processing Systems Tutorial (2019)

No learning signal from KL/JSD divergence if non-overlapping support between the data and the model.

$$\mathrm{KL}(p^*(\mathbf{x})||p(\mathbf{x})) = \infty$$

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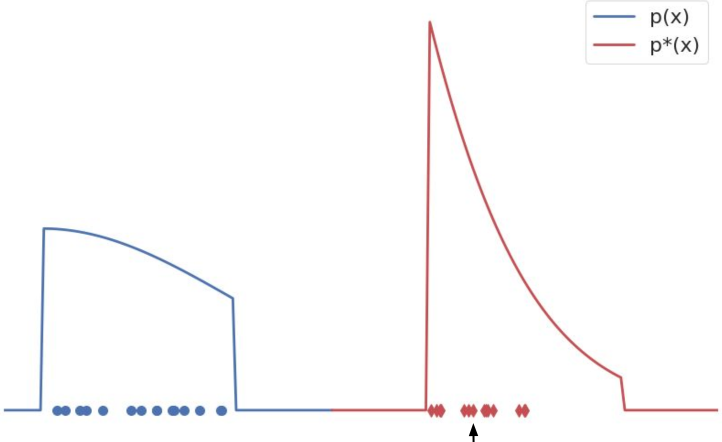
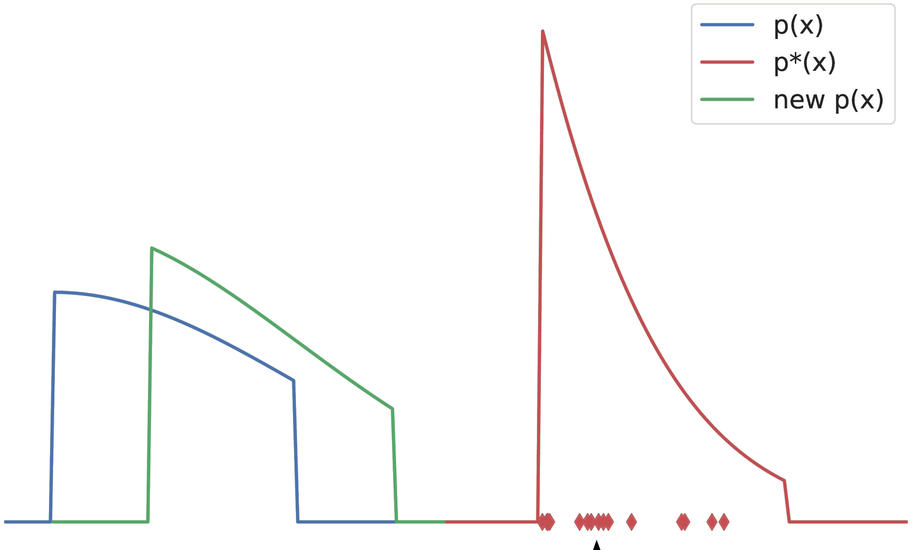


$$\frac{p^*(\mathbf{x})}{p(\mathbf{x})} = \infty$$

Smooth learning signal



$$\frac{p^*(\mathbf{x})}{p(\mathbf{x})} = \infty$$

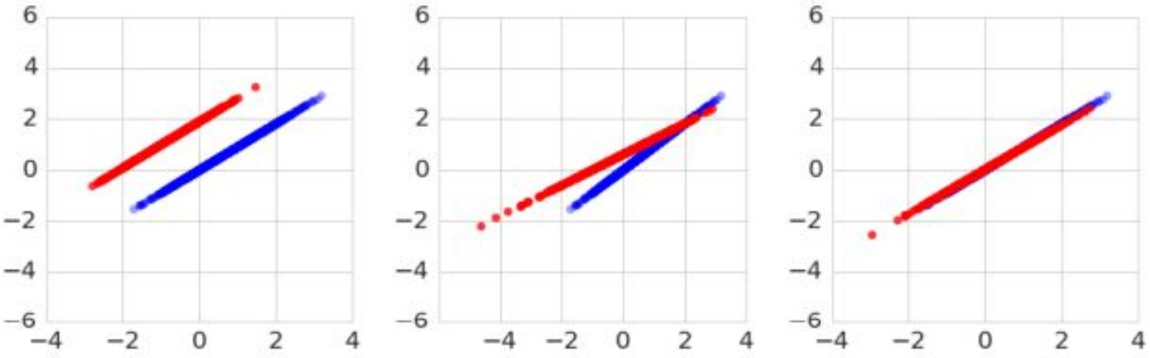
The density ratio jumps to infinity at the data distribution.

Smooth learning signal

Want to learn more?

Fedus, et al **Many paths to equilibrium.** International Conference for learning representations (2018)

But GANs still learn!



(a) Step 0 (b) Step 5000 (c) Step 12500

Red = data
Blue = model (changes in training)

true ratio

$$KL[p^*(x)||p(x)] = \int p^*(x) \log \left(\frac{p^*(x)}{p(x)} \right) dx \geq \sup_{D \in \mathcal{F}} \left(\mathbb{E}_{p^*(x)} D(x) - \mathbb{E}_{p(x)} e^{D(x)} \right)$$

ratio approximation used in GAN training

Want to learn more?

Gretton, et al **Interpretable comparison of distributions and models**
Neural Information Processing Systems Tutorial (**2019**)

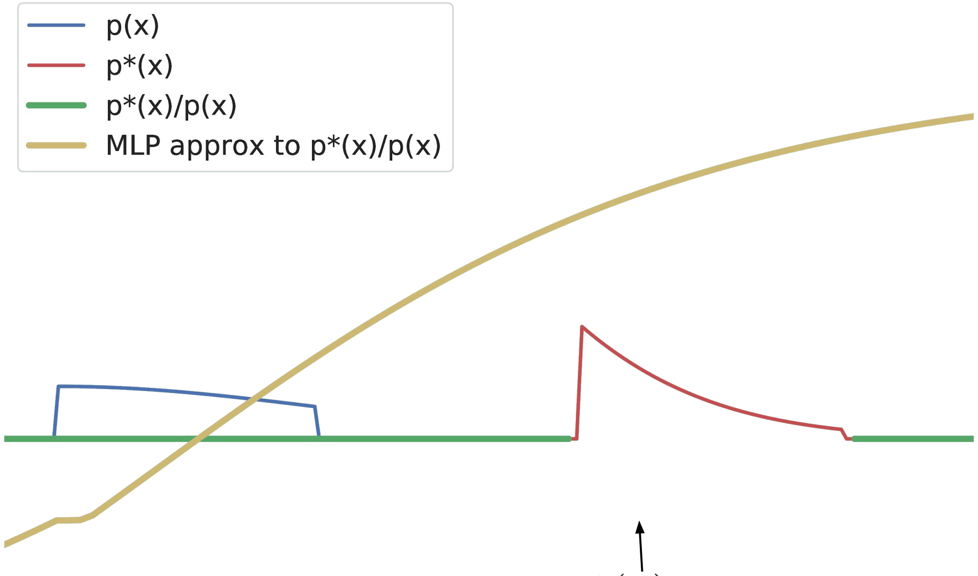
true ratio

$$KL[p^*(x)||p(x)] = \int p^*(x) \log\left(\frac{p^*(x)}{p(x)}\right) dx \geq \sup_{D\in\mathcal{F}} \left(\mathbb{E}_{p^*(x)} D(x) - \mathbb{E}_{p(x)} e^{D(x)}\right)$$

ratio approximation used in GAN training

$\mathcal{F}$ is the family of functions used to approximate the ratio (deep neural networks, RKHS).

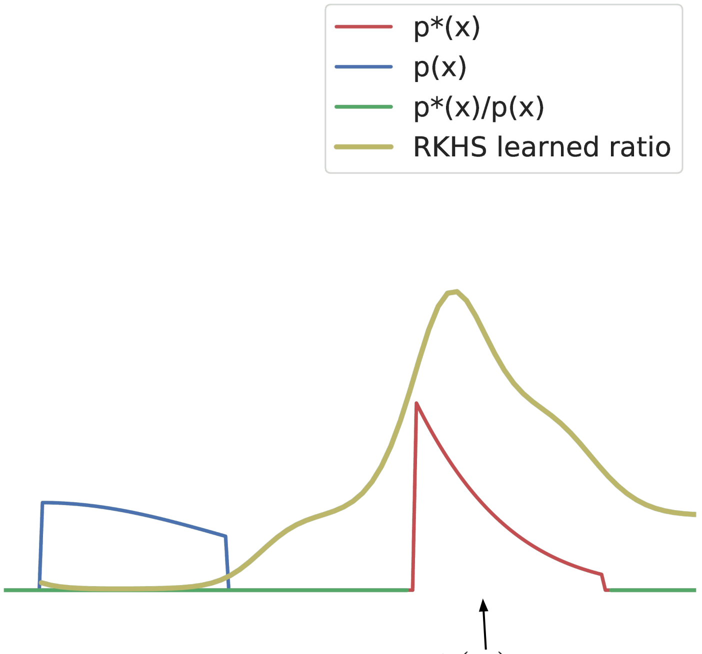
Smooth learning signal



$$\frac{p^*(\mathbf{x})}{p(\mathbf{x})} = \infty$$

Smooth approximation of the density ratio does not go to infinity.

Smooth learning signal



$$\frac{p^*(\mathbf{x})}{p(\mathbf{x})} = \infty$$

Smooth approximation of the density ratio does not go to infinity.

D is smooth approximation to the decision boundary of the underlying divergence:

- GANs do not do divergence minimization in practice
- GANs do not fail in cases where the underlying divergence would

Discriminators as learned "distances"

Want to learn more?

Arora, et al **Generalization and Equilibrium in Generative Adversarial Nets.** International Conference for machine learning (2017)

We can think of D (the teacher) as learning a "distance" between the data and model distribution that can provide useful gradients to the model.

Discriminators as "learned" distances

Original GAN

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

Wasserstein GAN

$$\min_G \max_{||D||_L \leq 1} \mathbb{E}_{p^*(x)} D(x) - \mathbb{E}_{p(z)} D(G(z))$$

$$\min_G \boxed{\max_D V(D,G)}$$

Discriminators as “learned” distances

$$\min_{G} \boxed{\max_{D} V(D,G)}$$

D provides a learned distance between the data and sample distributions, using **learned neural network features.**

GANs (learned distance) or divergence minimization?

GANs

- good samples
- learned loss function

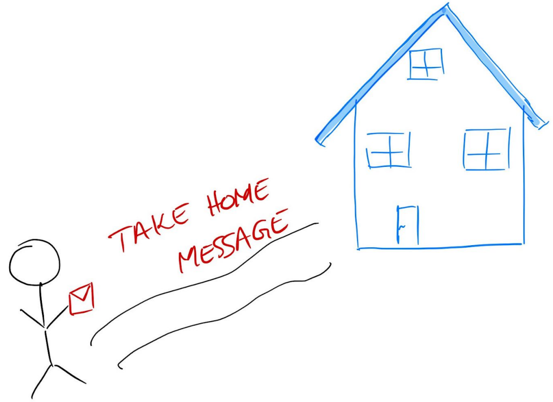
- hard to analyze dynamics (game theory)
- (in practice) no optimal convergence guarantees

Divergence minimization

- optimal convergence guarantees
- easy to analyze loss properties

- hard to get good samples
- loss functions don't correlate with human evaluation

In practice, GANs do not do divergence minimization.
The discriminator can be seen as a learned "distance".



Which GAN should I use?

Empirically, it has been observed that the underlying loss matters less than neural architectures, training regime, data.

Stay tuned!

Unconditional and conditional generative models

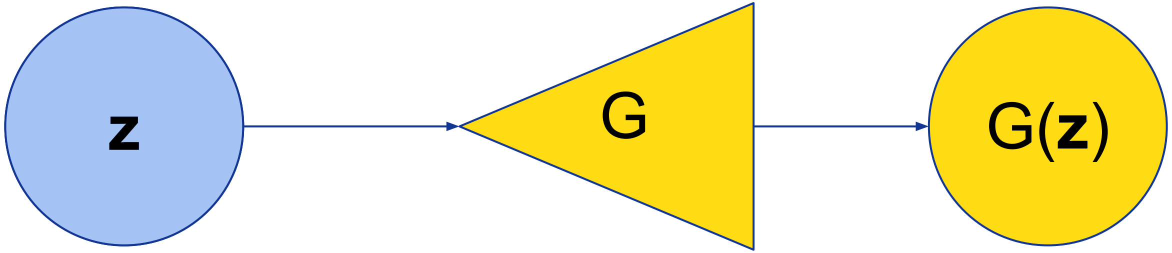
Unconditional	Conditional
provides a sample from the data distribution, but the user has no control over what kind of sample.	*we can specify what sample we want (dog vs cat).*

So far… unsupervised GANs

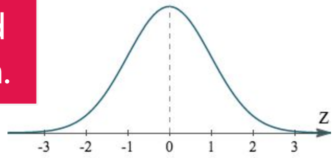
latent (“noise”) vector
z ~ P(**z**)

generator G:
a deep neural network

generated data
G(**z**)



Generator input is random noise to account for spread of data distribution.

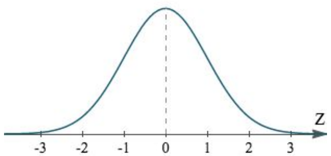


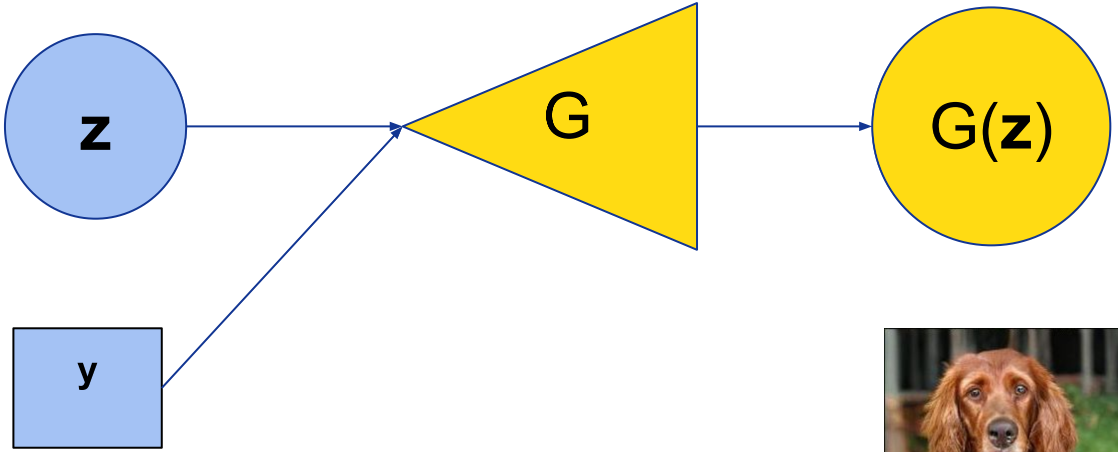
Conditioning information for training GANs

latent ("noise") vector
z ~ P(**z**)

generator G:
a deep neural network

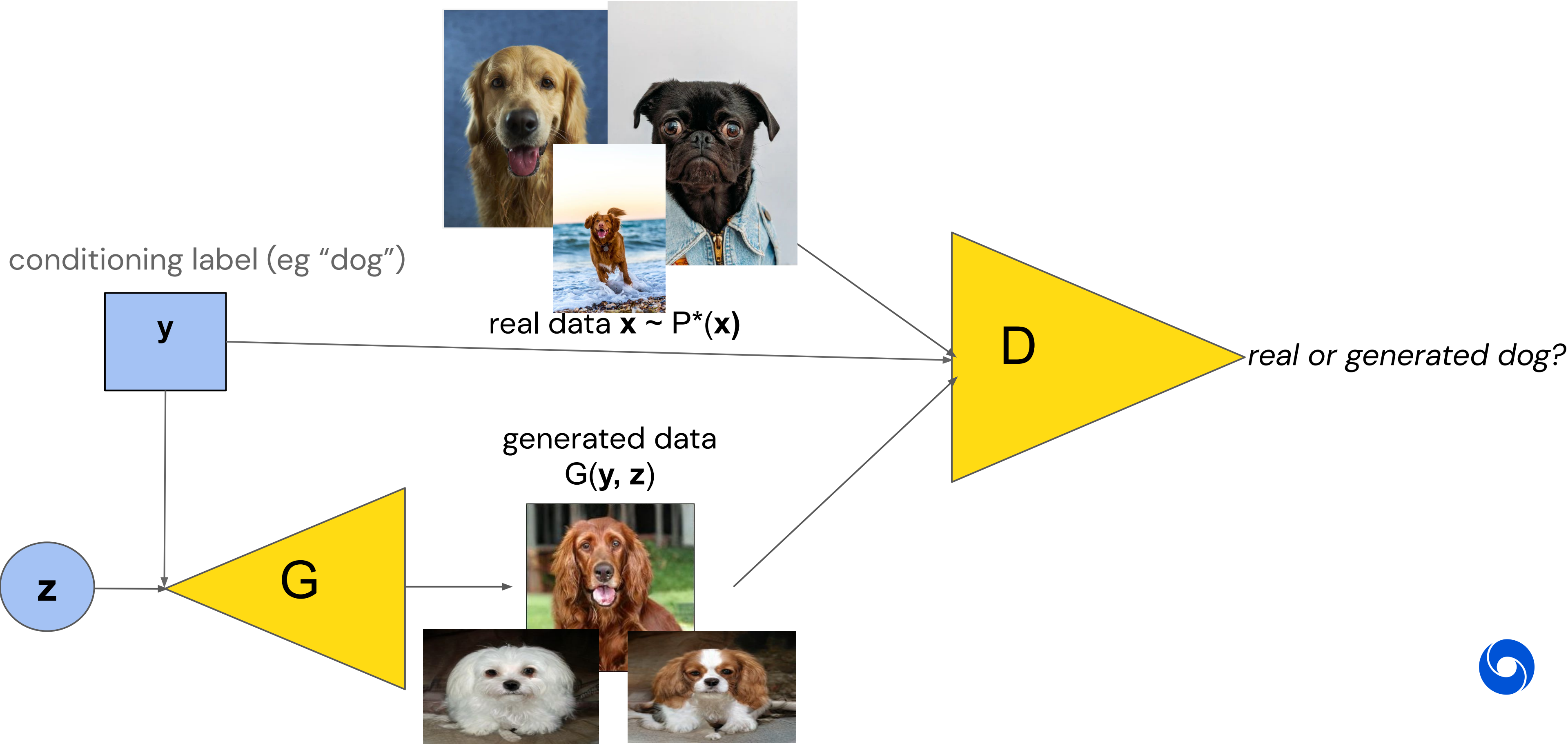
generated data
G(**z**)

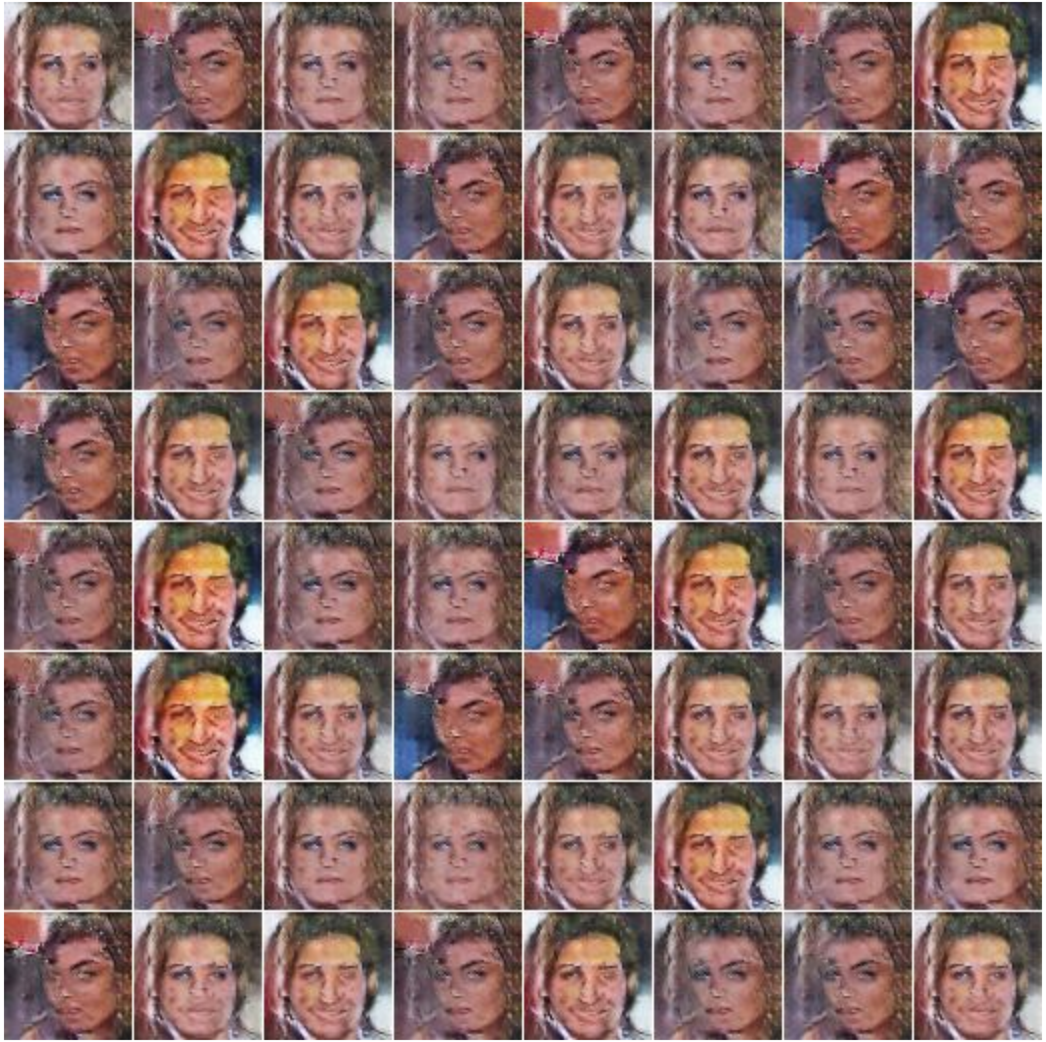


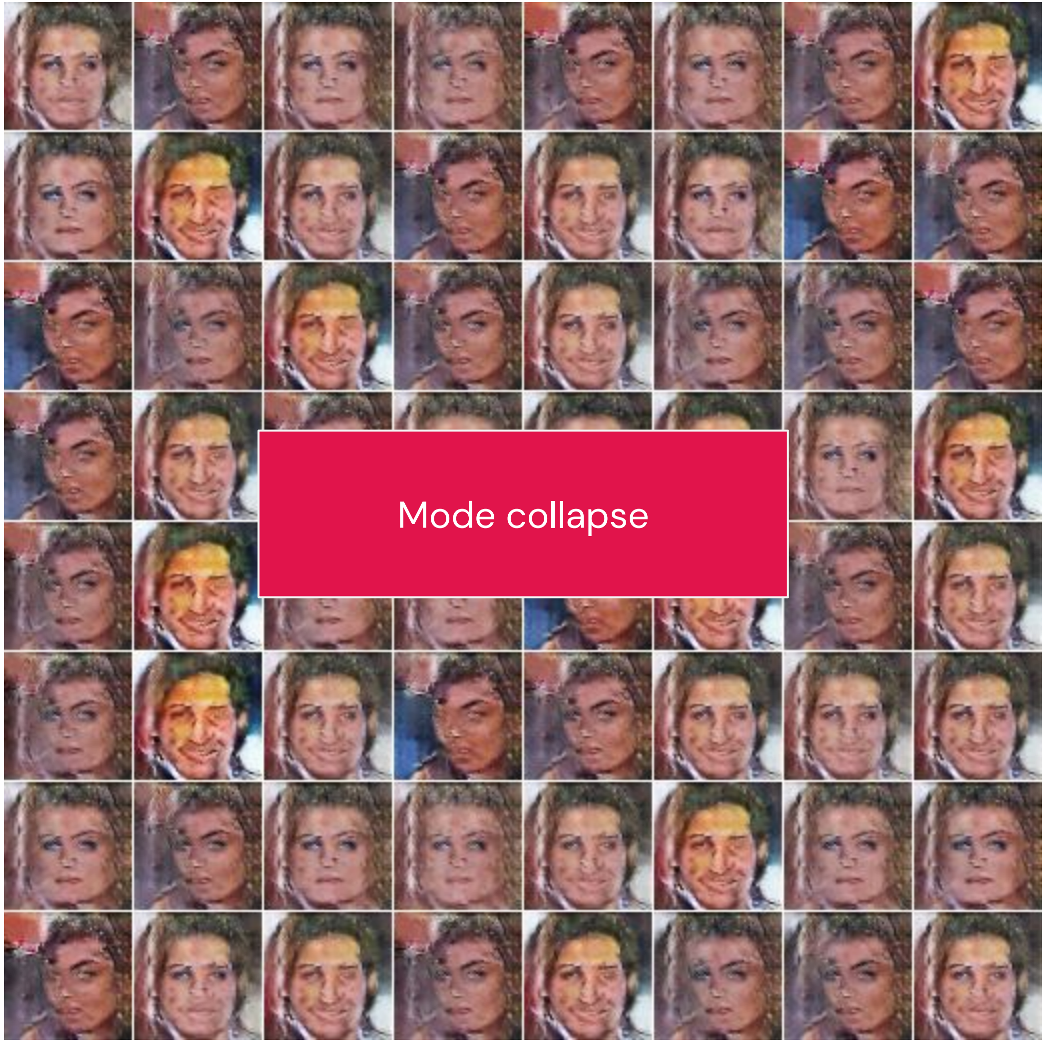


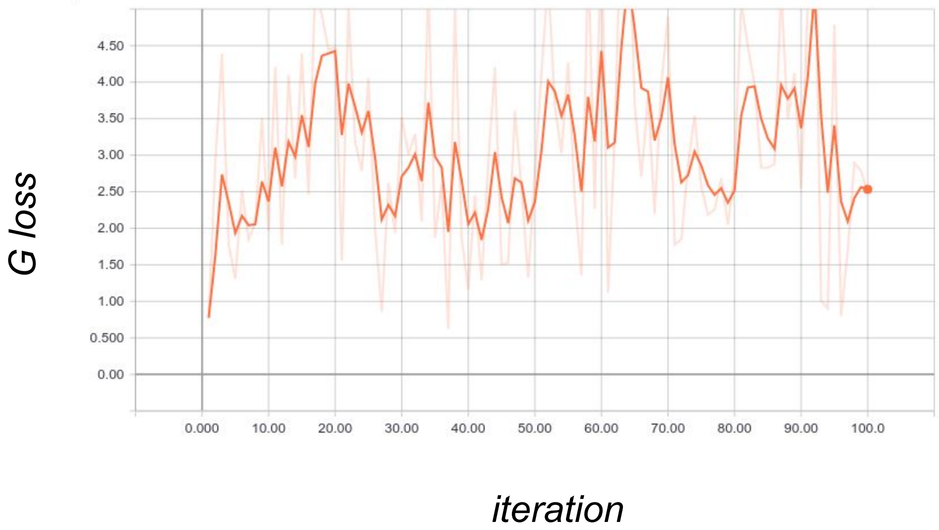
Add conditioning generation to specify information about generated sample.

Class conditional GANs






Mode collapse



G loss
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.500
0.00
0.000
10.00
20.00
30.00
40.00
50.00
60.00
70.00
80.00
90.00
100.0
iteration

DeepMind

2 Evaluating GANs

Evaluating generative models

Want to learn more?

Theis, et al **A note on the evaluation of generative models**
International Conference for Learning Representations (2016)

No evaluation metric is able to capture all desired properties.

- sample quality
- generalization
- representation learning

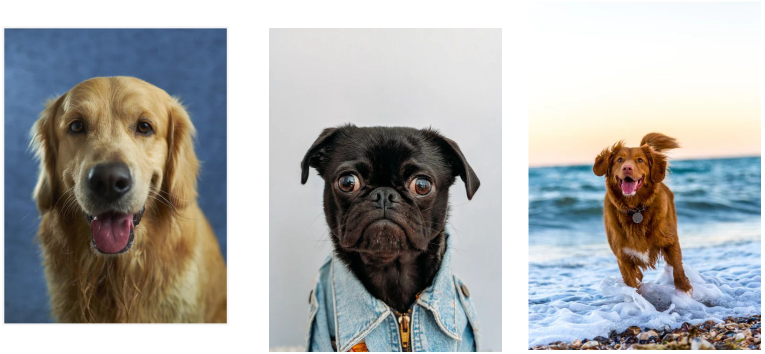
Evaluate based on end goal

- semi supervised learning: classification accuracy
- reinforcement learning: agent reward
- data generation: human (user) evaluation

GANs are implicit models

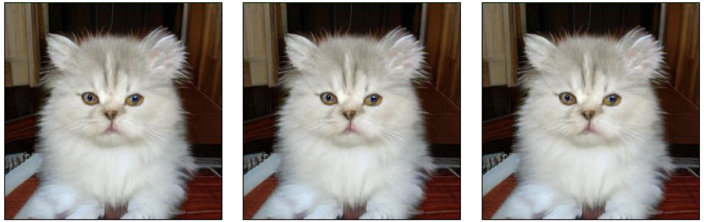
Log likelihoods are not available (and are very expensive to approximate).

Inception score



Data

Model



Inception Score

Want to learn more?

Salimans, et al **Improved techniques for training GANs**
Neural Information Processing Systems (2016)

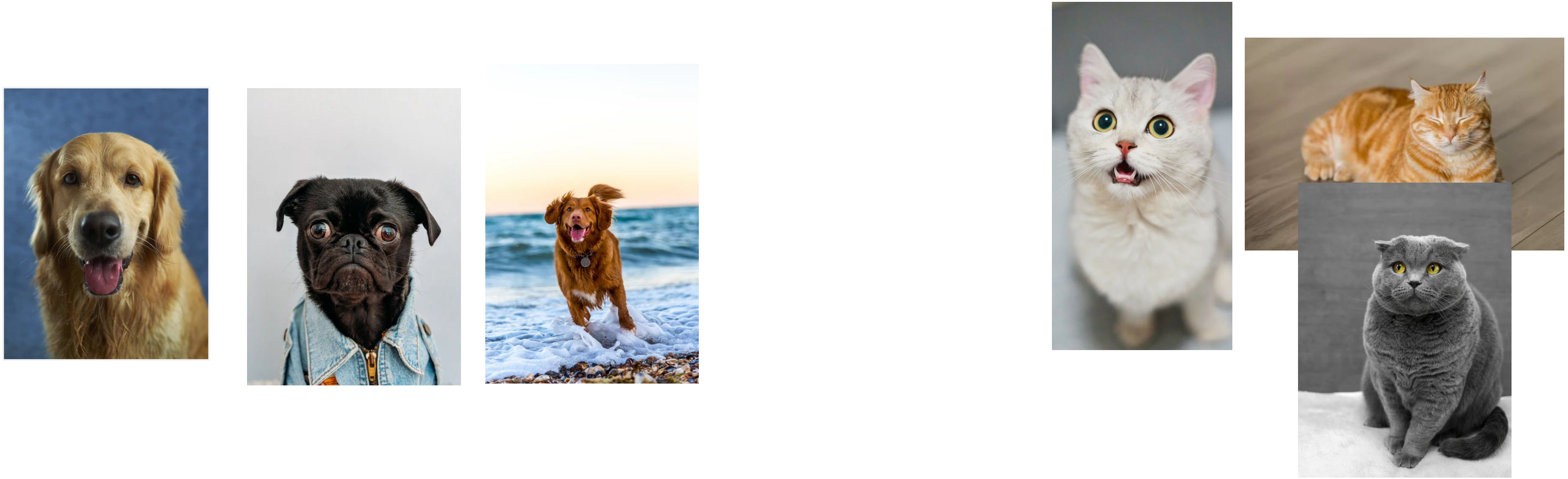
Use a pretrained Imagenet classifier to compare (via KL divergence)
the distribution of labels obtained from the data
the distribution of labels coming from samples

Measures:

- sample quality
- dropping classes (no cats)
- correlates with human evaluation
- does not measure differences beyond class labels
- requires pretrained classifier

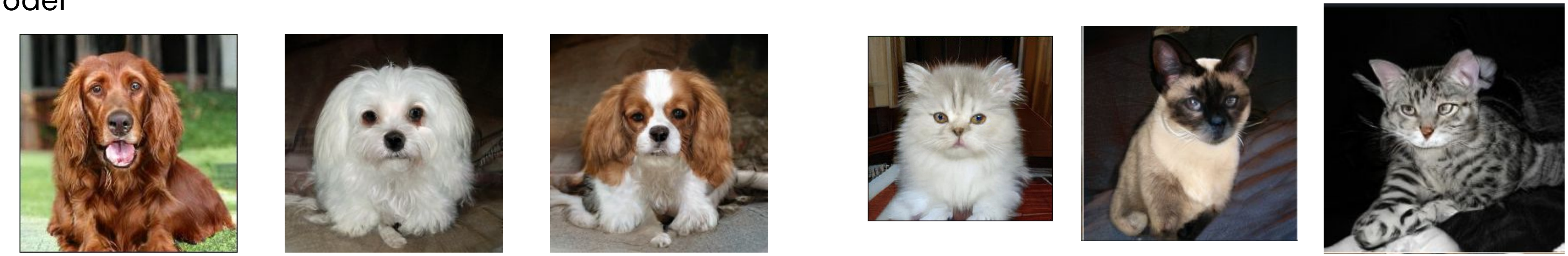
Higher is better.

Frechet Inception Distance



Data

Model



Frechet Inception Distance

Want to learn more?

Heusel, et al **GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium**

Neural Information Processing Systems (2017)

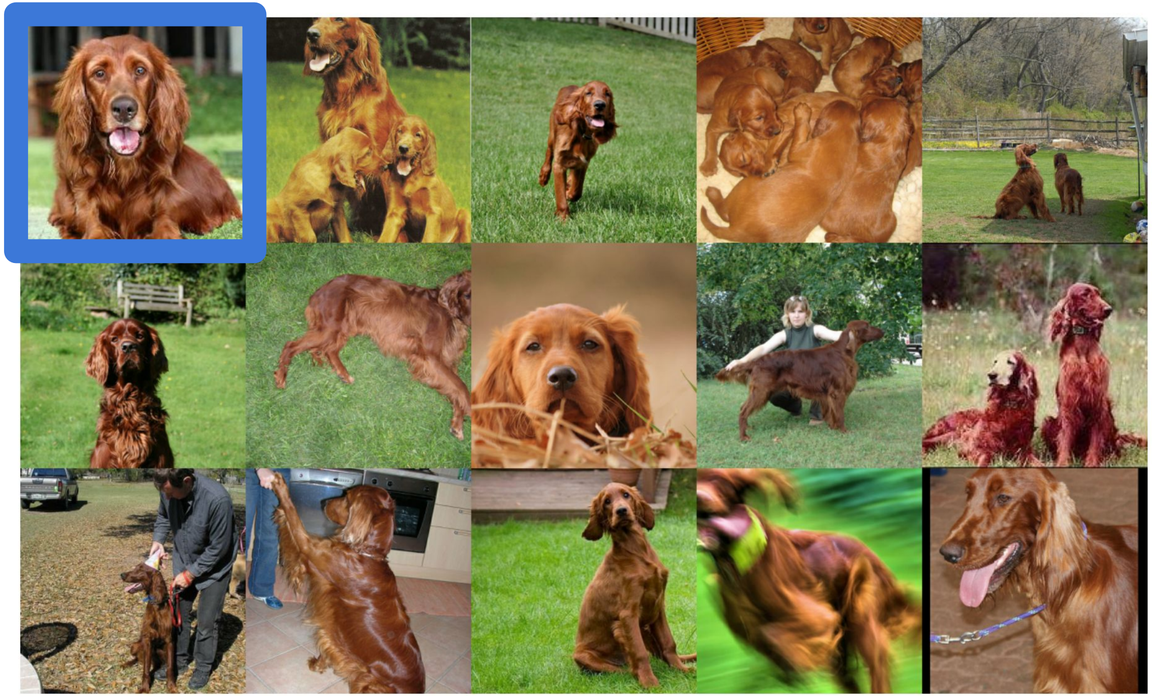
Use a pretrained Imagenet classifier to compare (via Frechet distance)
the distribution of layer features obtained from the data
the distribution of layer features coming from samples

Measures:
- sample quality
- dropping classes (no cats)
- captures feature level statistics (not just classes)
- correlates with human evaluation
- requires pretrained classifier
- biased for a small number of samples and KID for a fix (see Binkowski, et al., ICLR 2018)

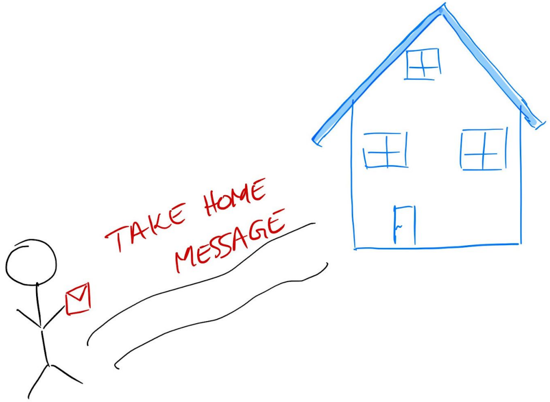
Lower is better.

Checking overfitting: Nearest neighbours

Nearest neighbors: most similar (in feature space of a pretrained ImageNet classifier) images in the dataset.



Multiple metrics are needed to evaluate GAN samples.



3 The GAN Zoo

DeepMind

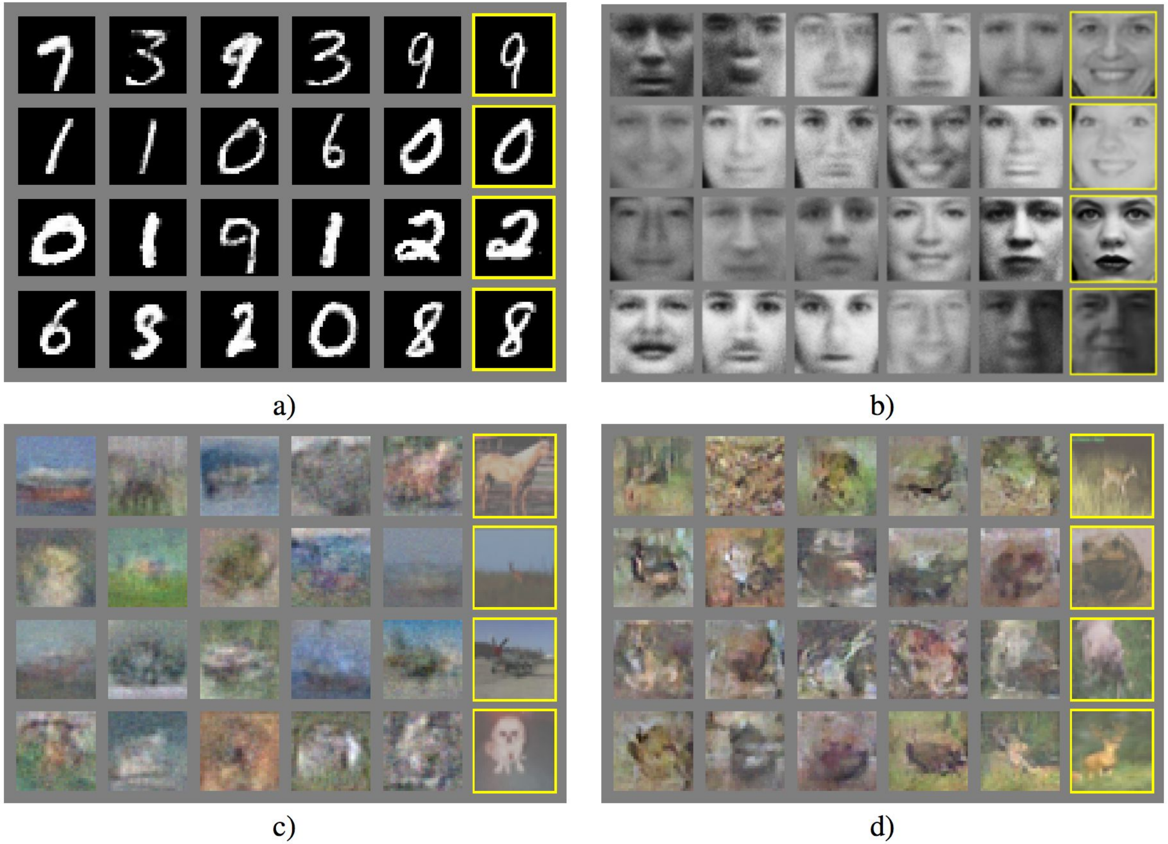
3.1 Image Synthesis with GANs: MNIST to ImageNet

The Original GANs (Goodfellow et al.)

Want to learn more?

Goodfellow, et al. **Generative adversarial networks..** Neural Information Processing Systems (**2014**)

- The original GAN paper (Goodfellow et al.)
- Simple data (~32x32 images)
- Simple models
- G and D in (a) and (b) were MLPs (not convolutional)
    - Images flattened to vectors for training, ignoring spatial structure

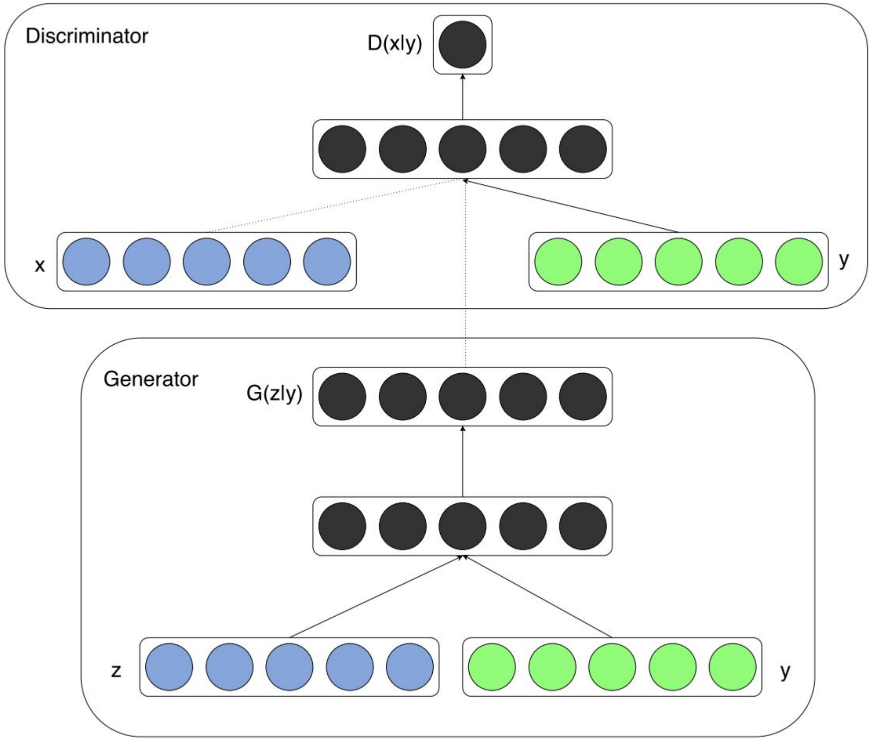


Conditional GANs (Mirza and Osindero)

Want to learn more?

Mirza and Osindero. **Conditional Generative Adversarial Nets**. arXiv:1411.1784 (**2014**)

- Generalised GANs to the **conditional** setting where we have some extra information associated with each datum, e.g.,
    - a category ID ("cat", "dog", ...)
    - an input image from another domain



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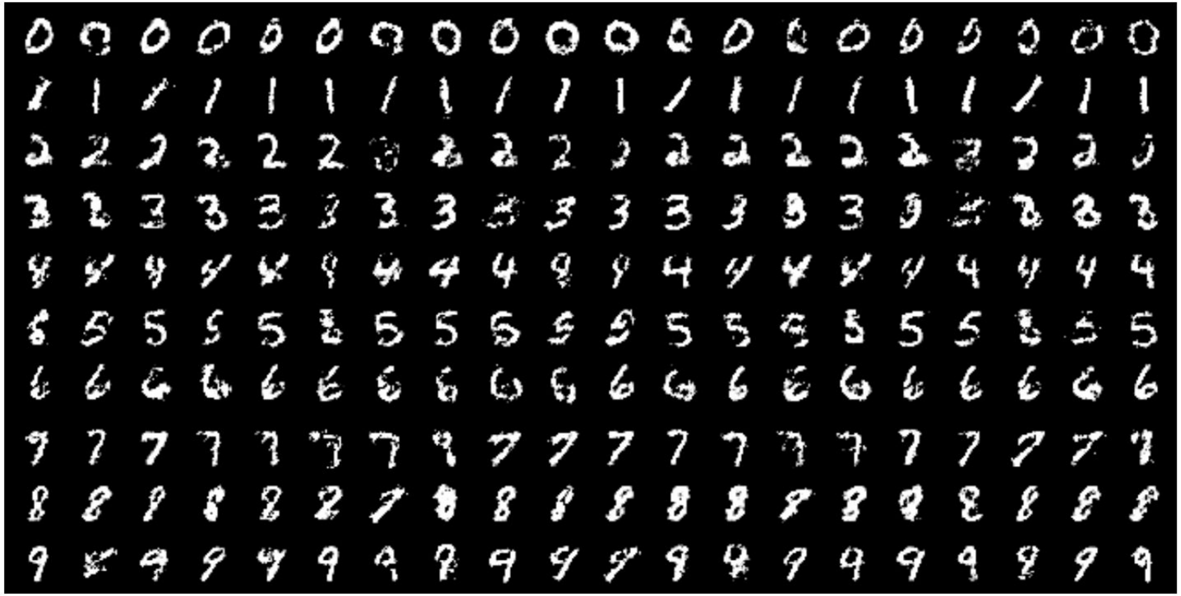


Want to learn more?

Mirza and Osindero. **Conditional Generative Adversarial Nets.** arXiv:1411.1784 (**2014**)

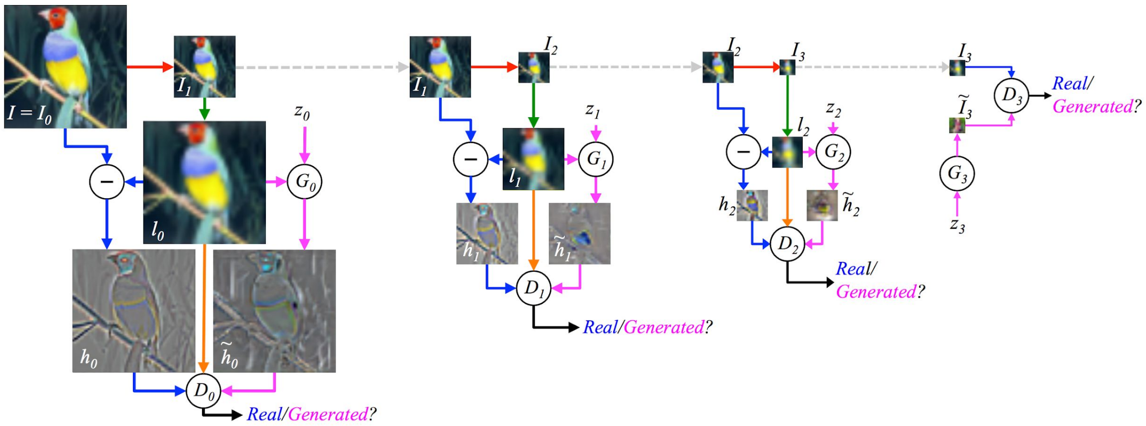
Laplacian GANs (LAPGAN, Denton et al.)

Want to learn more?

Denton, et al. **Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks.** Neural Information Processing Systems **(2015)**

- Start from a tiny image
- Upsample to a 2x larger image (blurry)
- Generate a Laplacian: the difference between the (blurry) upsampled image and the final image
- A *conditional* GAN after the initial resolution
  - G and D each take a lower resolution image as input, predicting e.g.:

P(is real 64x64 image | 32x32 image)

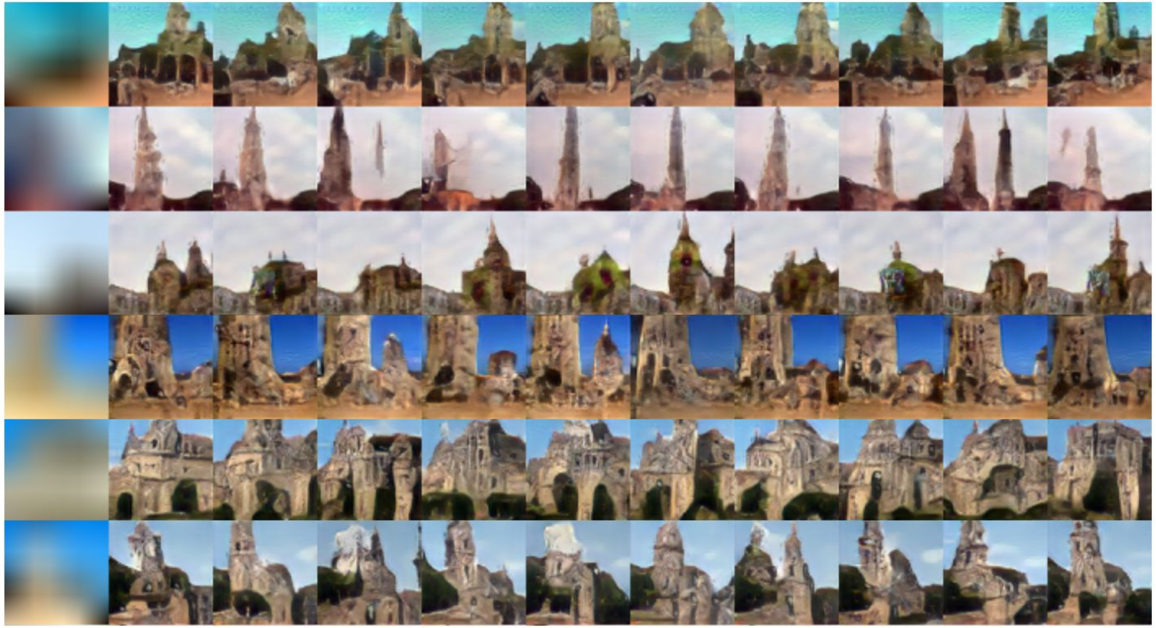


Laplacian GANs (LAPGAN, Denton et al.)

Want to learn more?

Denton, et al. **Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks.** Neural Information Processing Systems (**2015**)

Nice results at higher resolutions



Laplacian GANs (LAPGAN, Denton et al.)

Want to learn more?

Denton, et al. **Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks.** Neural Information Processing Systems (**2015**)

Fully convolutional generator architecture

The model can be applied to produce arbitrarily high-resolution results

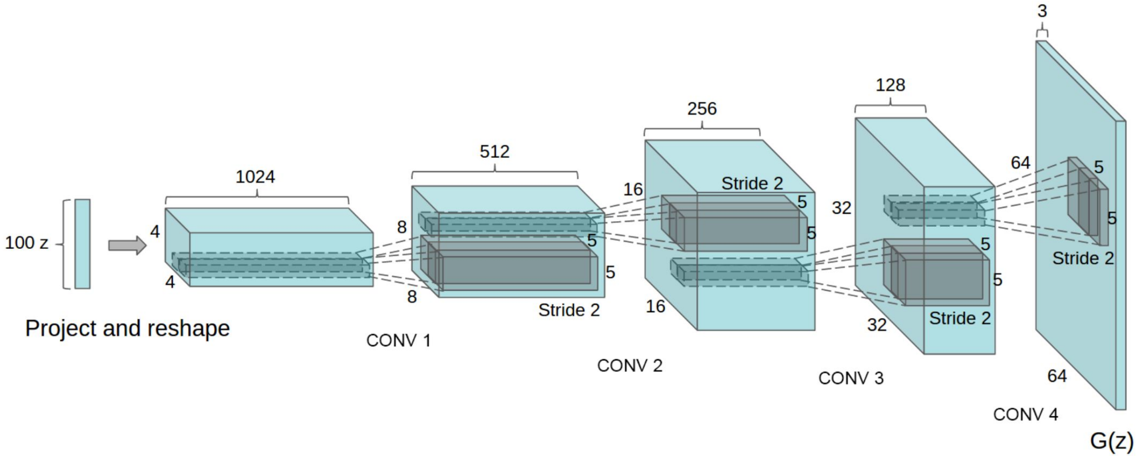
This model was trained on 32x32 images, but is applied recursively to upsample to 256x256.

Deep Convolutional GANs (DCGAN, Radford et al.)

Want to learn more?

Radford, et al. **Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks.** International Conference on Learning Representations (2016)

- Simply use deep convnets for G and D
- Importantly, **batch normalization** (Ioffe and Szegedy, 2015) helped to stabilize the difficult learning process



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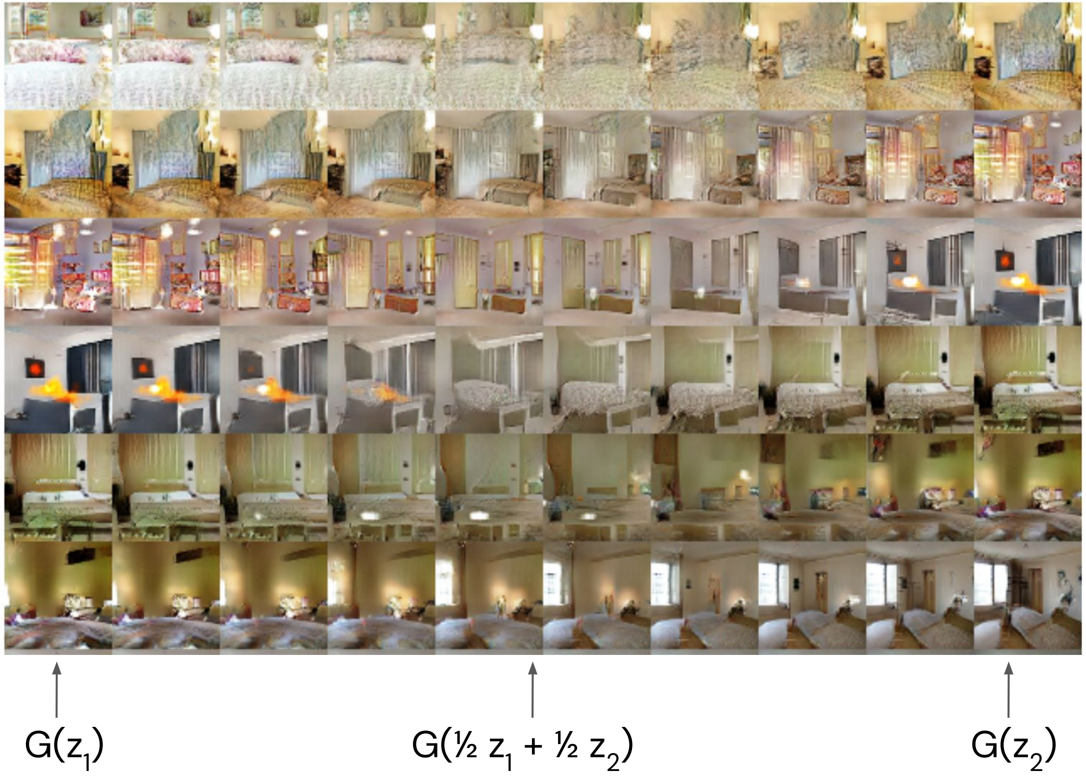

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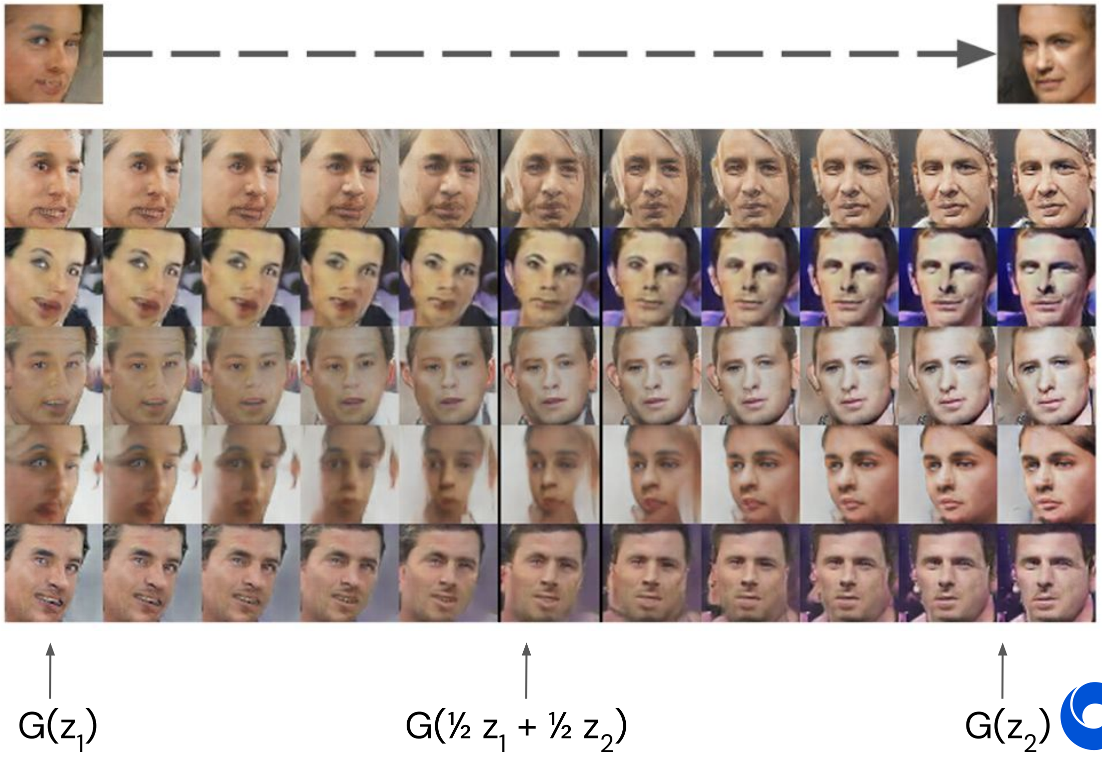
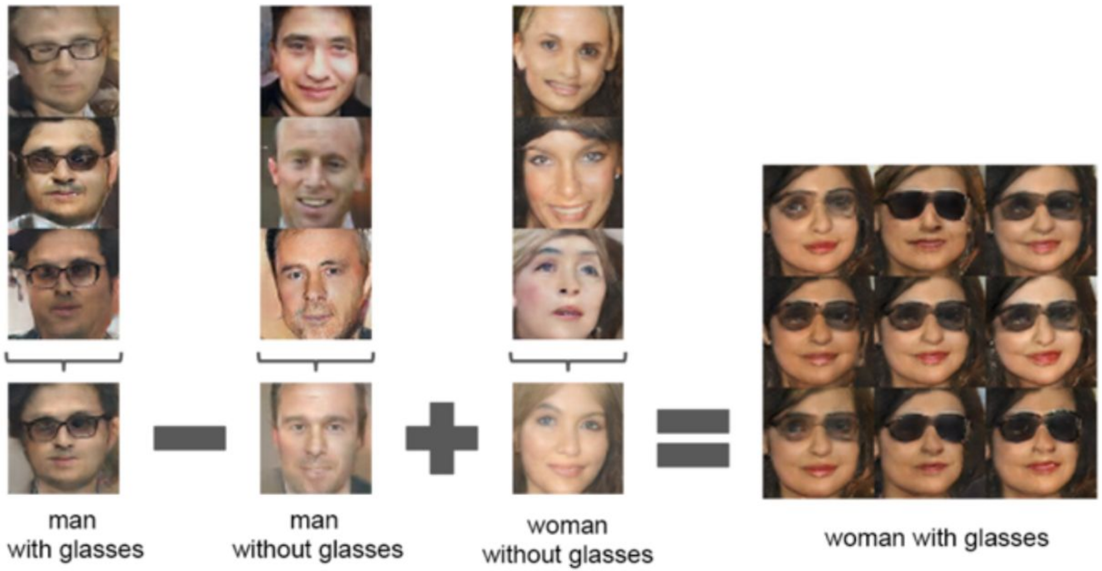


Deep Convolutional GANs (DCGAN, Radford et al.)

Want to learn more?

Radford, et al. **Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks.** International Conference on Learning Representations (2016)

- The DCGAN generator's noise/latent space appears to have **meaningful semantics**



Spectrally Normalised GANs (SNGAN, Miyato et al.)

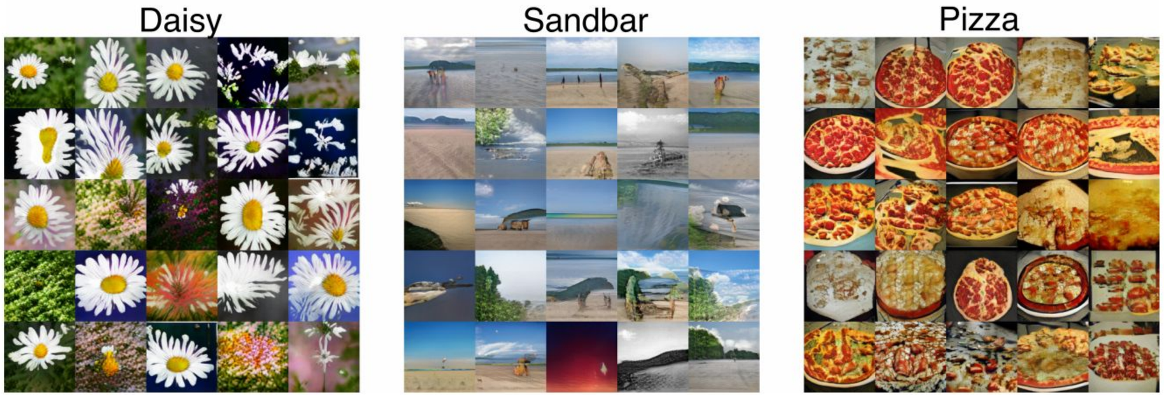
Want to learn more?

Miyato, et al. **Spectral Normalization for Generative Adversarial Networks.** International Conference on Learning Representations (**2018**)

- Stabilise GAN training by clamping the singular values of D's weights to 1

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

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



Projection Discriminator (Miyato et al.)

Want to learn more?

Miyato and Koyama. **cGANs with Projection Discriminator.** International Conference on Learning Representations (2018)

- Novel formulation of the class-conditional discriminator
- Learnt class embedding is projected onto the final hidden representation
- Theoretically justified under the underlying probabilistic model
- Empirically, performs better than prior formulations

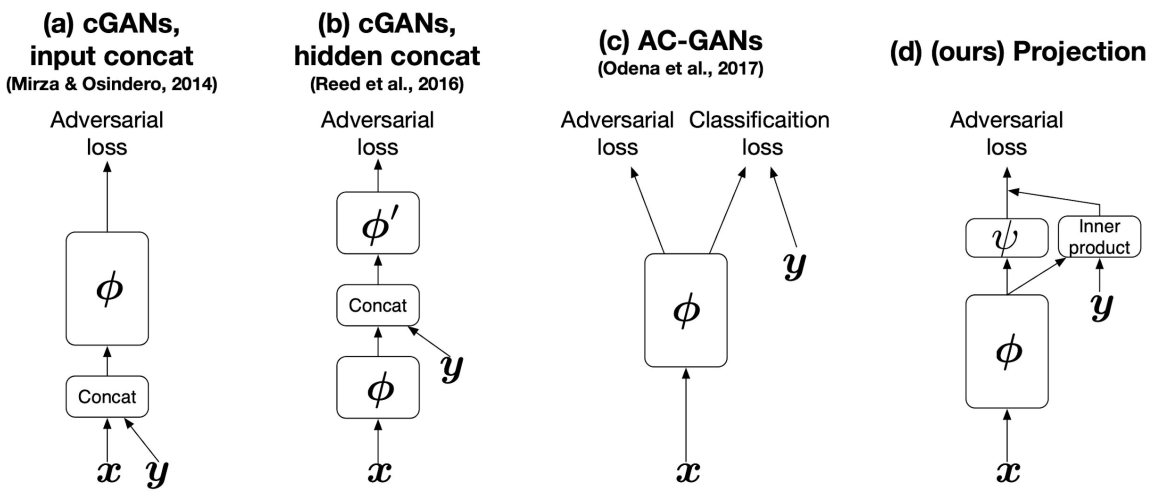


Figure 1: Discriminator models for conditional GANs

Projection Discriminator (Miyato et al.)

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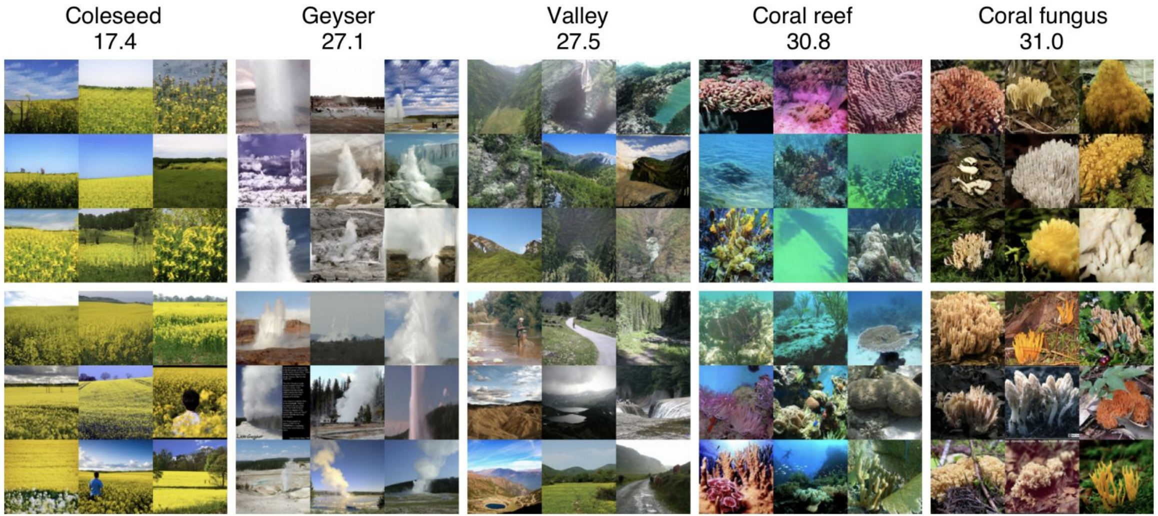


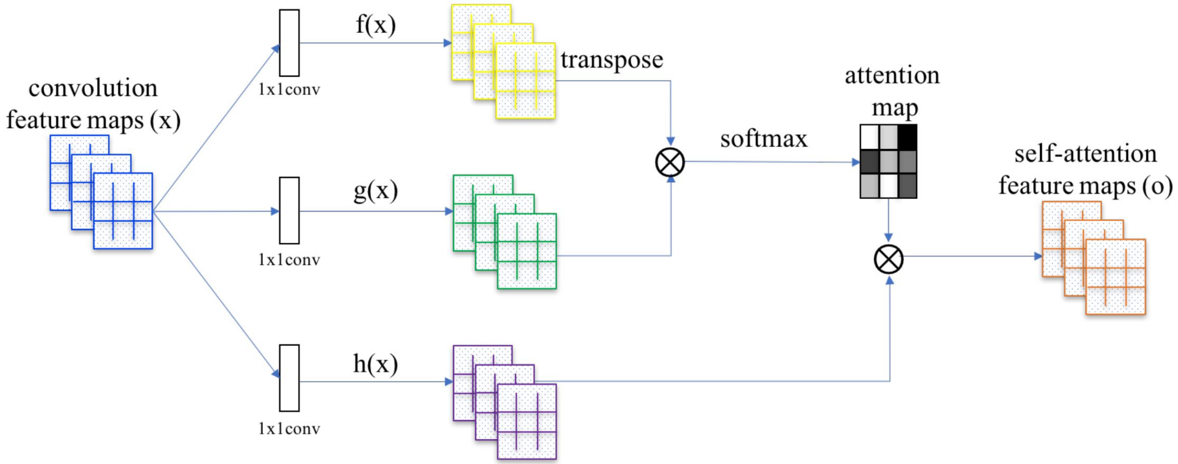
Self-Attention GANs (SAGAN, Zhang et al.)

Want to learn more?

Zhang, et al. **Self-Attention Generative Adversarial Networks.** International Conference on Machine Learning (**2019**)

- Added **self-attention** to give images better **global structure** and coherence

- Self-attention has had a big impact in a number of domains (especially language modeling, translation)



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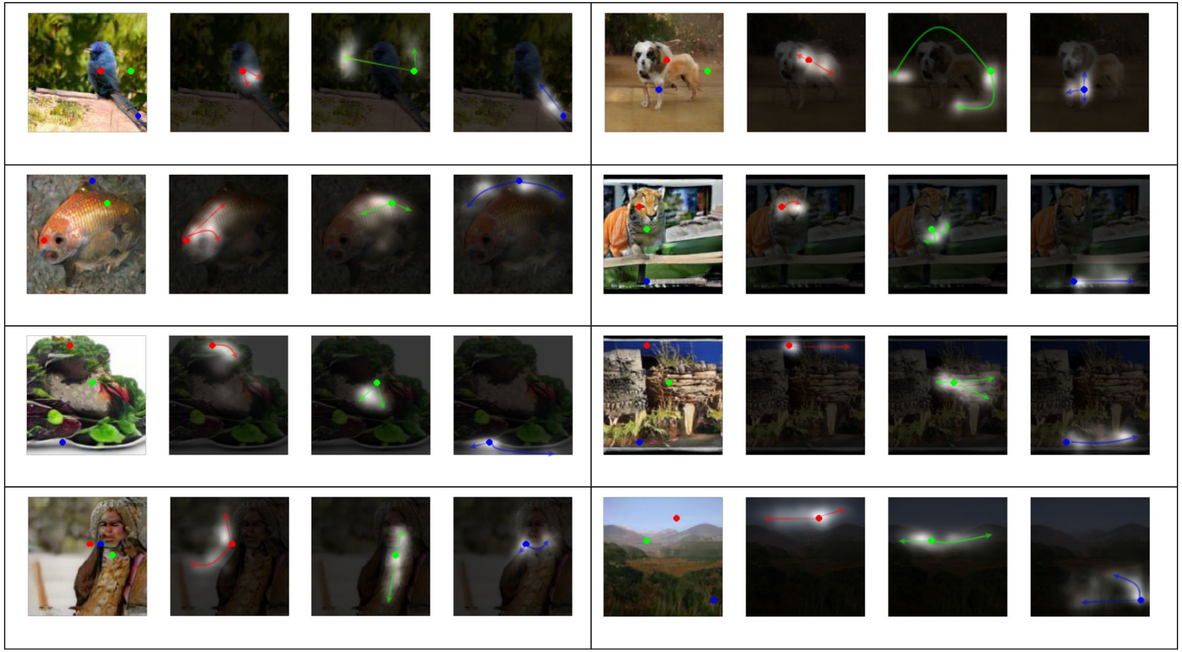

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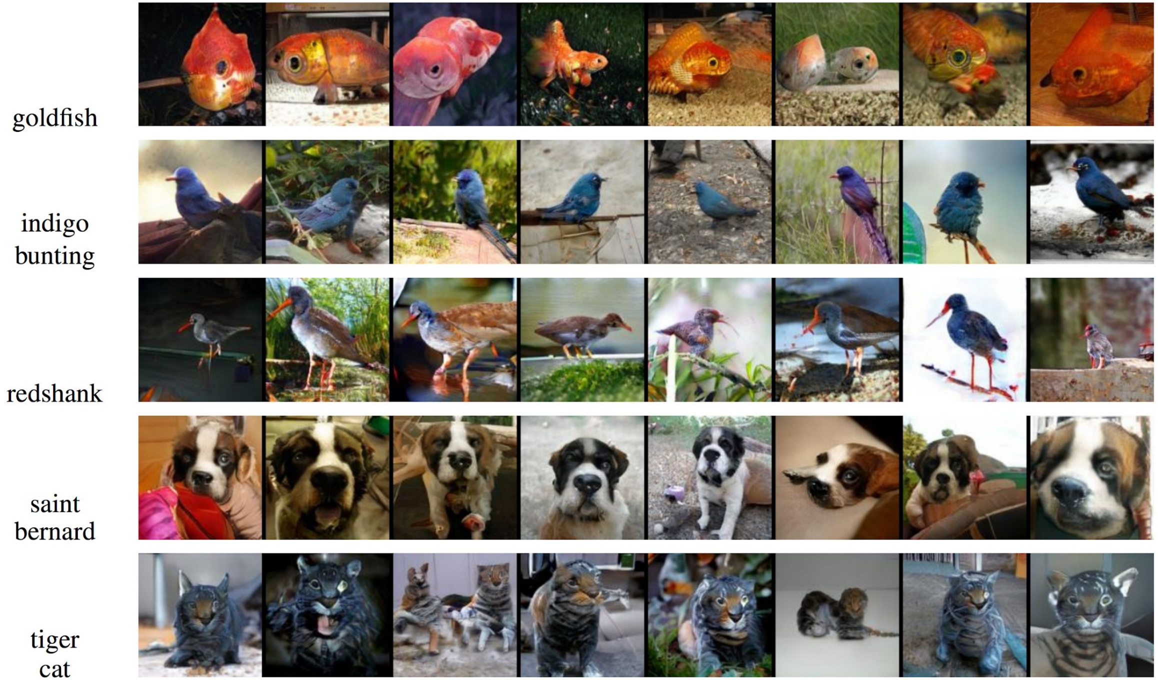


Want to learn more?

Zhang, et al. **Self-Attention Generative Adversarial Networks.** International Conference on Machine Learning **(2019)**

BigGANs (Brock et al.)

Want to learn more?

Brock, et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis.** International Conference on Learning Representations **(2019)**

- Make GANs really big
  - Big batches
  - Big models
  - Big datasets
  - Big (high res) images
- Trained on ImageNet (1.2M images) and JFT (300M images)

BigGANs (Brock et al.)

Want to learn more?

Brock, et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis.** International Conference on Learning Representations **(2019)**

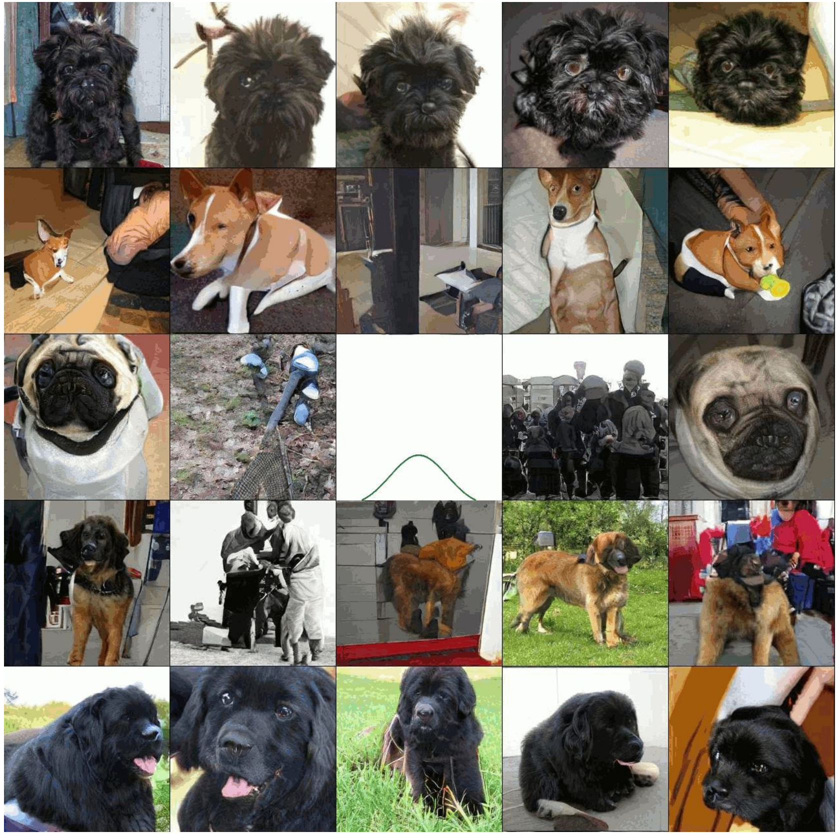
- Large empirical study to build a reliable recipe for large scale GAN training, including:
  - Hinge loss in D
  - Spectral norm
  - Self-attention
  - Projection disc
  - Orthogonal regularisation
  - "Skip connections" from noise
  - Class label embedding shared across layers

BigGANs (Brock et al.)

Want to learn more?

Brock, et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis.** International Conference on Learning Representations (**2019**)

- Introduced the **truncation trick**
- Change the scale of the noise **z** input to the generator
- Make the noise smaller (truncate) to increase image fidelity
    - Generates prototypical examples of each class
- Make the noise larger to increase variety
    - Generates the full class distribution



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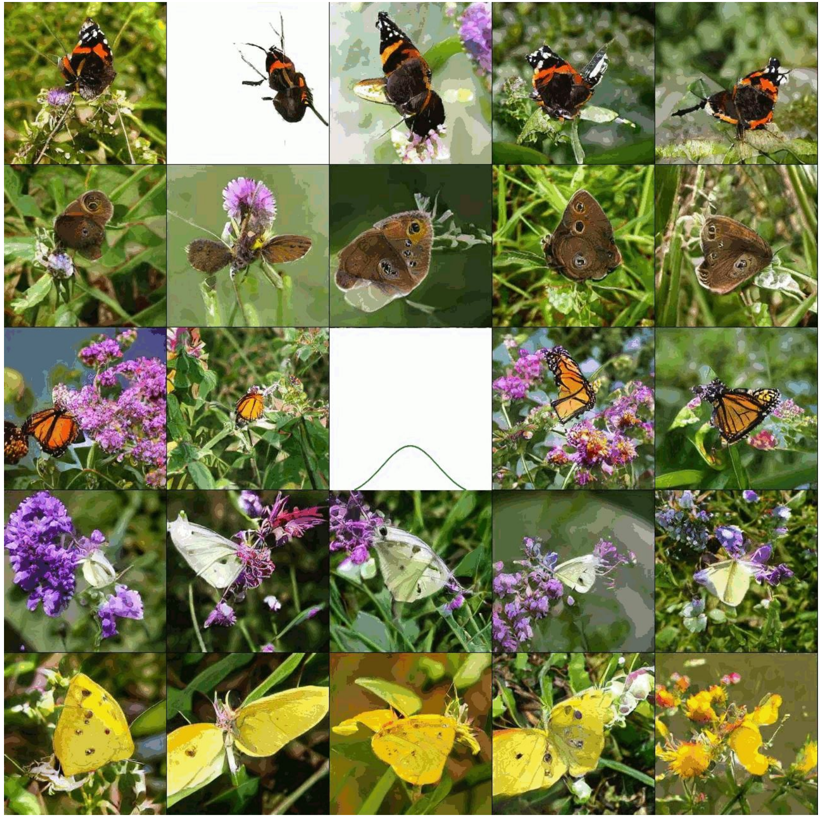

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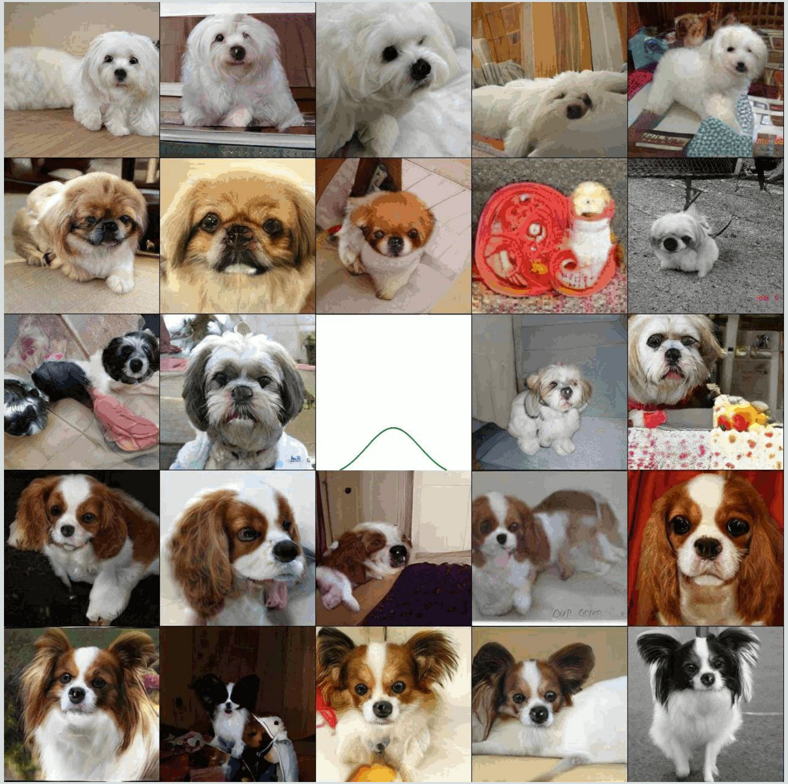
BigGANs (Brock et al.)



Want to learn more?

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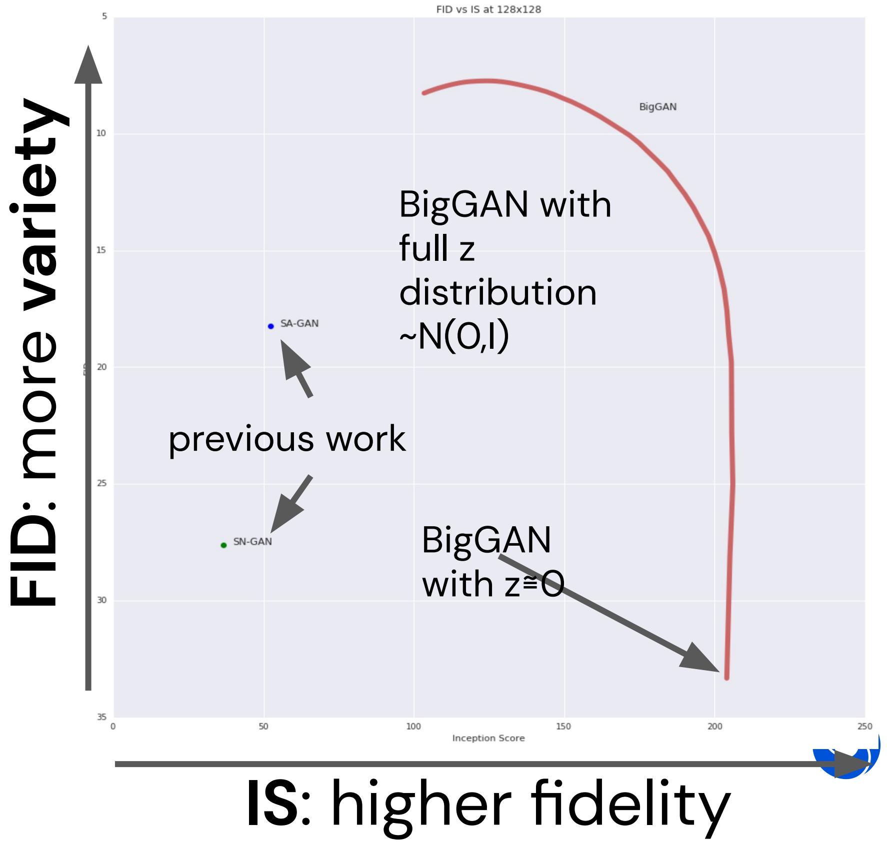
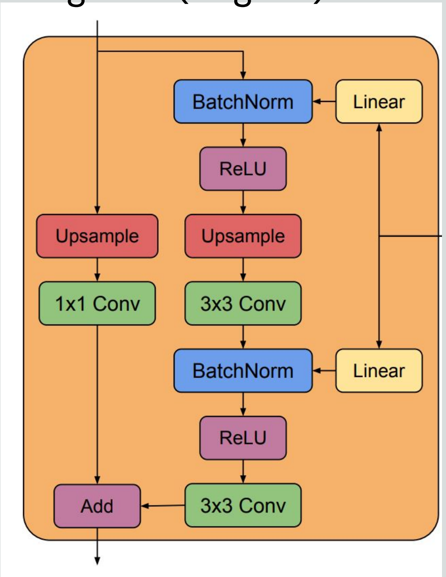


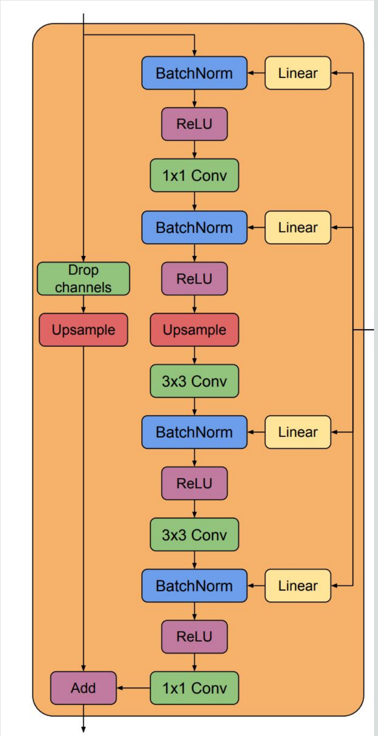
BigGANs (Brock et al.)

4x deeper, but more efficient!

BigGAN (original) Block

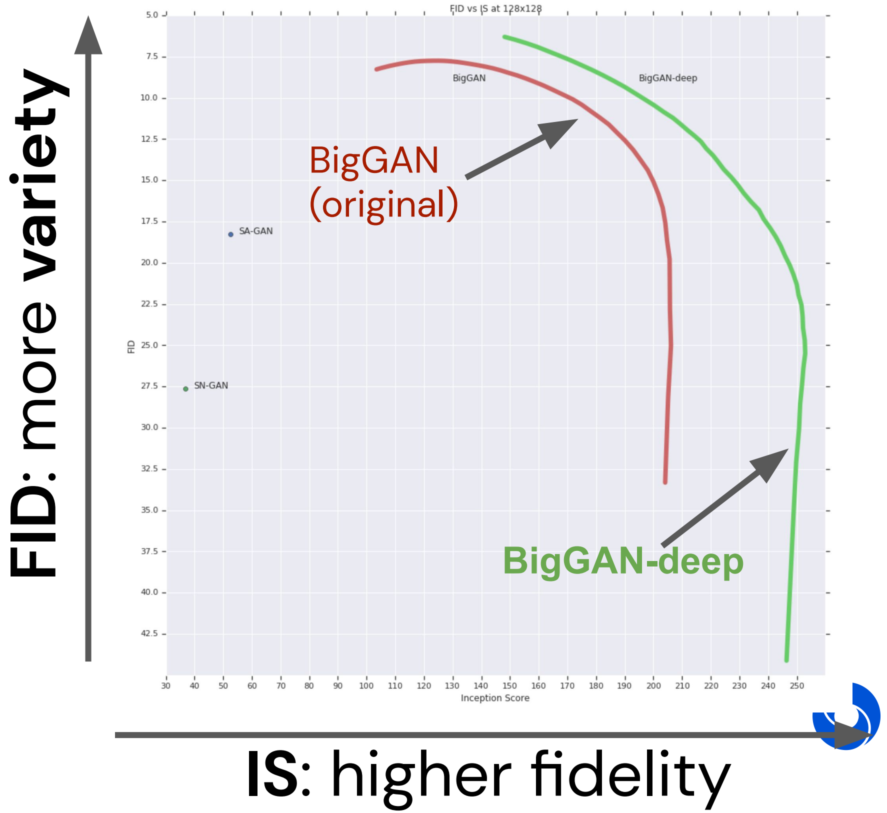


BigGAN-deep Block



Want to learn more?

Brock, et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis.** International Conference on Learning Representations (**2019**)



BigGANs (Brock et al.): failure modes

Want to learn more?

Brock, et al. **Large Scale GAN Training for High Fidelity Natural Image Synthesis.** International Conference on Learning Representations **(2019)**

LOGAN (Wu et al.)

Want to learn more?

Wu, et al. **LOGAN: Latent Optimisation for Generative Adversarial Networks.** arXiv:1912.00953 **(2019)**

- Uses **latent optimisation** to improve the adversarial dynamics between G & D
  - Natural gradient descent to optimise G's latent inputs

- Results in significant further improvements in BigGAN terms of fidelity and variety

BigGAN-deep
IS = 259.4
FID = 27.97

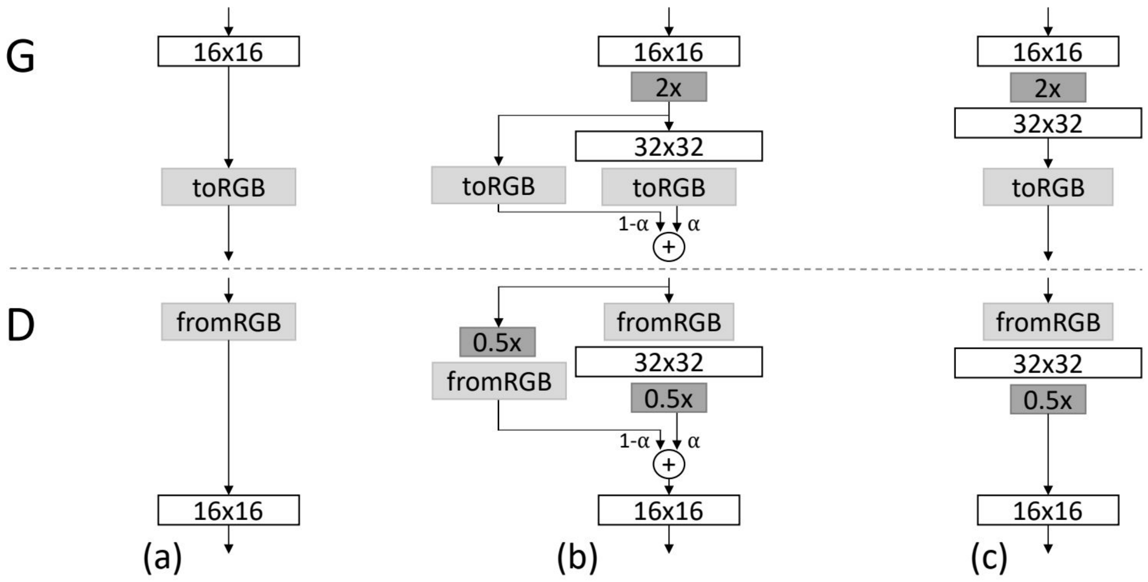
LOGAN
IS = 259.9
FID = 8.19

Progressive GANs (Karras et al.)

Want to learn more?

Karras, et al. **Progressive Growing of GANs for Improved Quality, Stability, and Variation.** International Conference on Learning Representations **(2018)**

- First, train a GAN to generate tiny (4x4) images
- After convergence, add a new layer (in G & D) to generate 8x8 resolution images
- Repeat for 16x16, 32x32, …
- Very compelling results in a restricted domain (faces)



Progressive GANs (Karras et al.)

- First, train a GAN to generate tiny (4x4) images
- After convergence, add a new layer (in G & D) to generate 8x8 resolution images
- Repeat for 16x16, 32x32, ...
- Very compelling results in a restricted domain (faces)

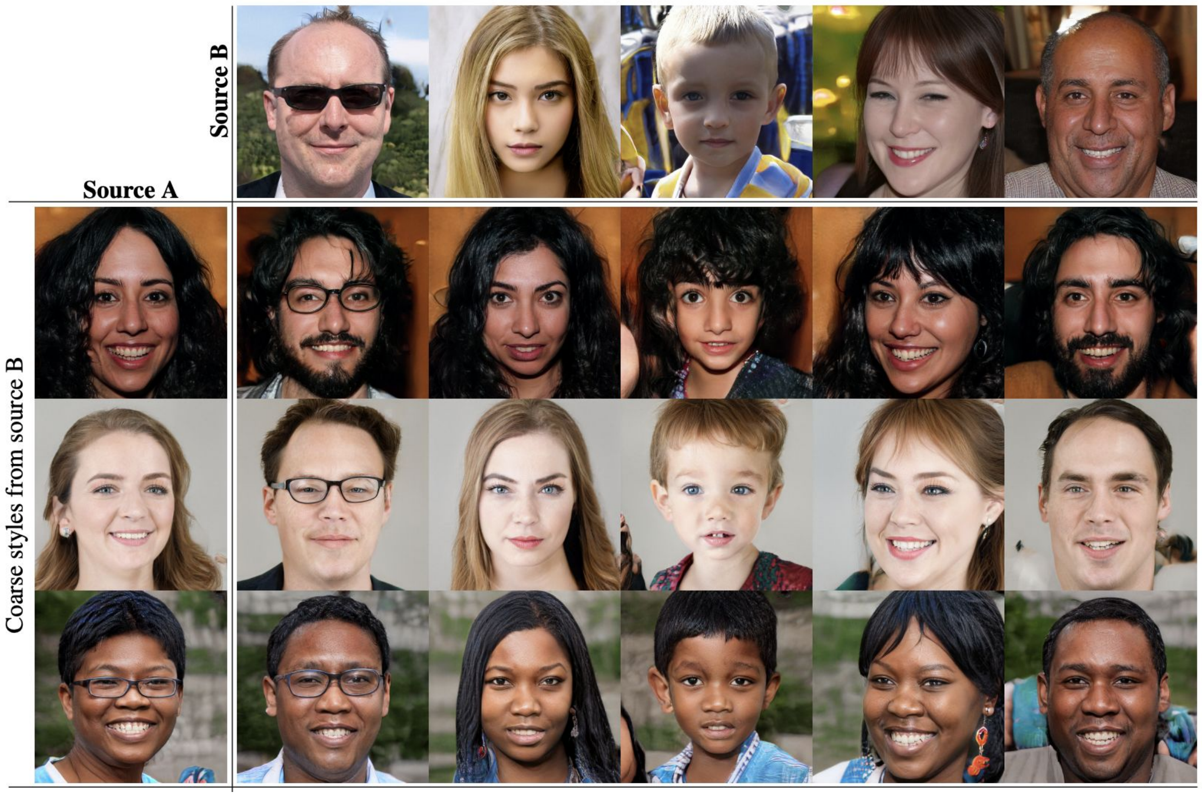
Want to learn more?

Karras, et al. **Progressive Growing of GANs for Improved Quality, Stability, and Variation.** International Conference on Learning Representations **(2018)**

Style GANs (Karras et al.)

StyleGANs were shown to be capable of generating remarkably photorealistic face images

Structured latent inputs (**z**) to the generator can be used to control its outputs in various interesting ways.



Want to learn more?

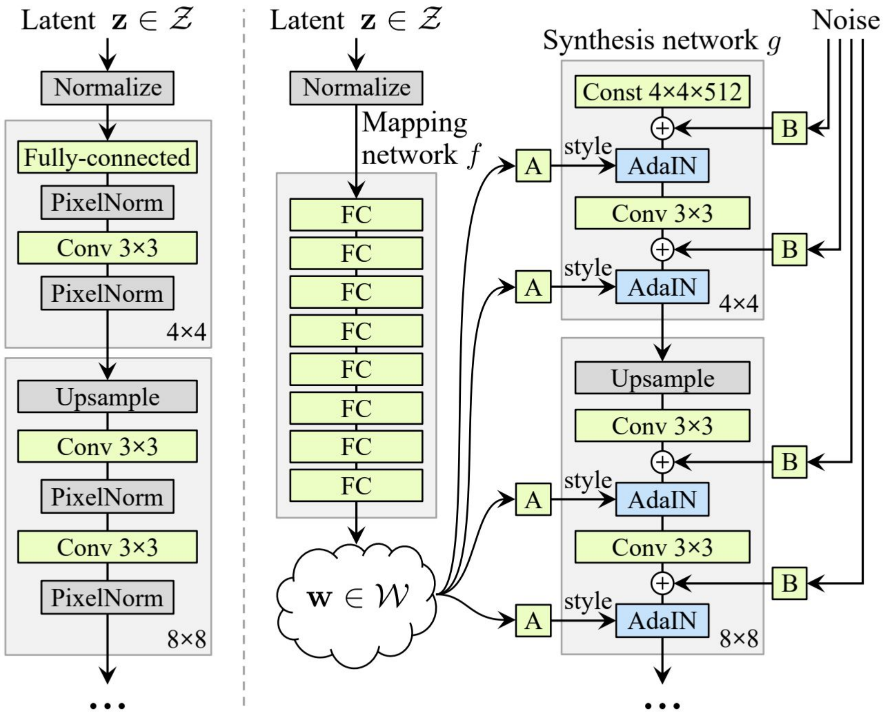
Karras, et al. **A Style-Based Generator Architecture for Generative Adversarial Networks.** IEEE Conference on Computer Vision and Pattern Recognition (**2019**)

Style GANs (Karras et al.)

Want to learn more?

Karras, et al. **A Style-Based Generator Architecture for Generative Adversarial Networks.** IEEE Conference on Computer Vision and Pattern Recognition (**2019**)

- Global latents transformed via an 8 layer MLP
- Incorporates spatial **pixel noise** at each layer
  - Single-channel "image" of noise
  - Broadcast via learnt per-channel scaling factors
- Model learns to associate global latents with the overall **style** of the image
  - Pixel noise modulates the local appearance



(a) Traditional (b) Style-based generator

Style GANs (Karras et al.)

Want to learn more?

Karras, et al. **A Style-Based Generator Architecture for Generative Adversarial Networks.** IEEE Conference on Computer Vision and Pattern Recognition (**2019**)

- Global latents transformed via an 8 layer MLP
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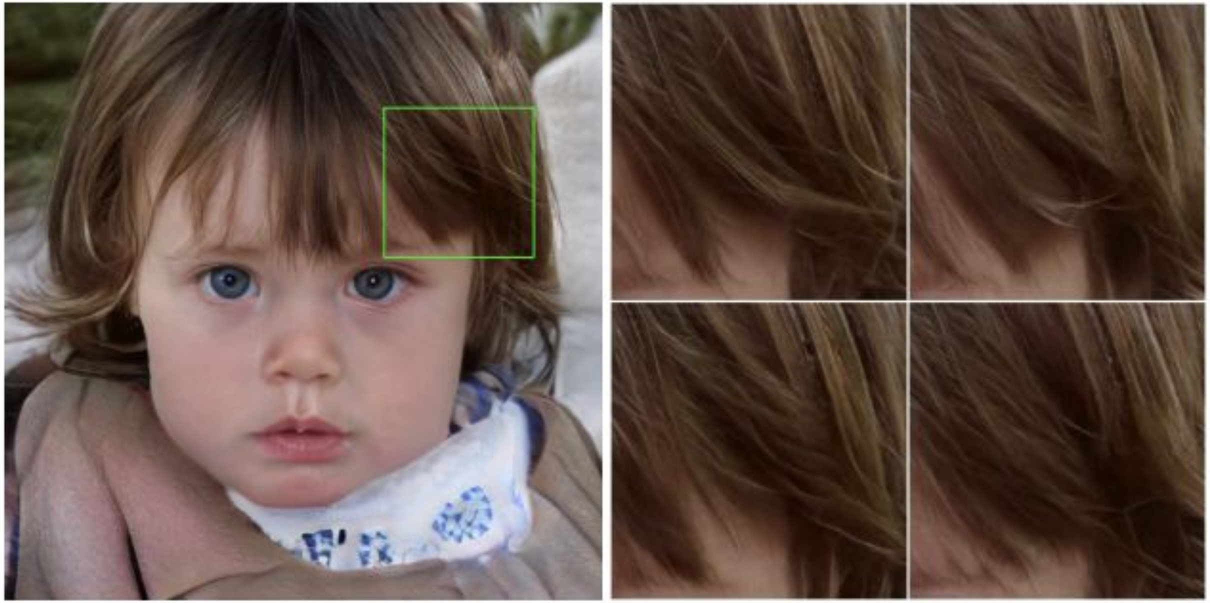
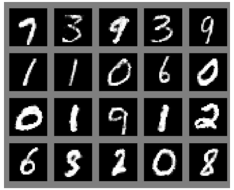


(a) Generated image (b) Stochastic variation

Takeaways: Image Synthesis

- Rapid progress scaling up GANs from simple images (MNIST) to large-scale databases of high resolution images (ImageNet, Flickr Faces HQ)

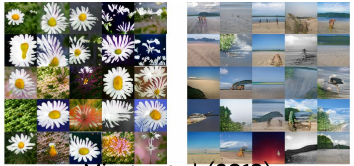
- Improvements from a variety of sources
  - G & D architectures
  - Conditioning
  - Normalisation
  - D parametrization
  - Latent space structure
  - Loss functions
  - Algorithmic



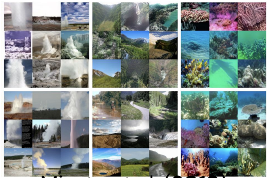
Goodfellow et al. (2014)

Denton et al. (2015)

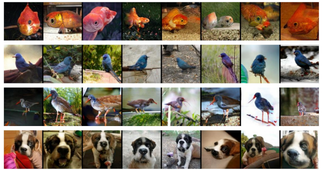
Radford et al. (2016)



Miyato et al. (2018)



Miyato et al. (2018)



Zhang et al. (2019)

Brock et al. (2019)

Karras et al. (2019)

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3.2

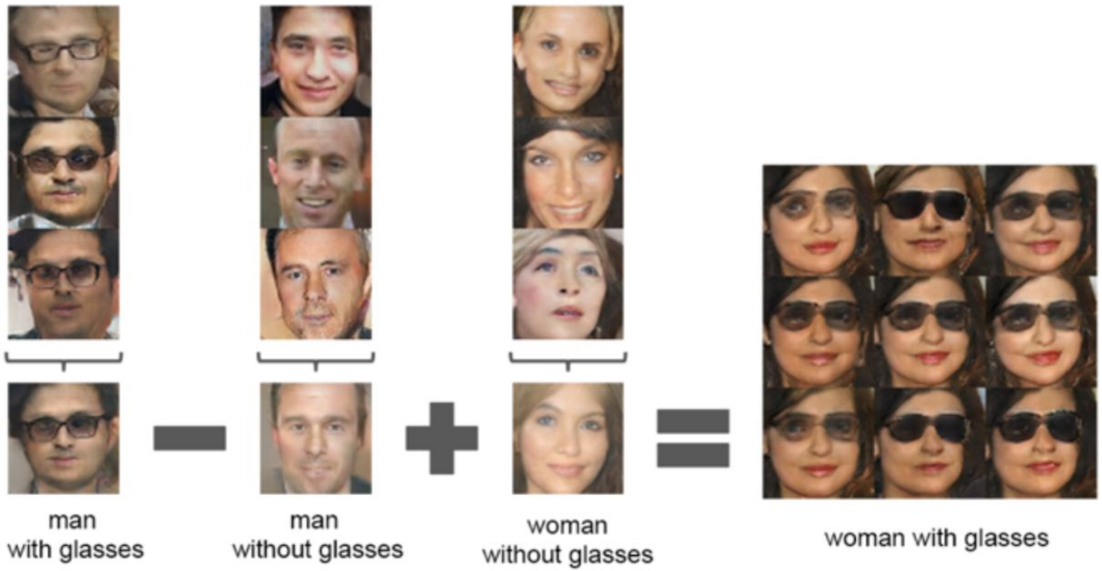
GANs for Representation Learning

Motivating Example #1:
Semantics in DCGAN Latent Space (Radford et al.)

Want to learn more?

Radford, et al. **Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks.** International Conference on Learning Representations (2016)

- The DCGAN generator's noise/latent space appears to have **meaningful semantics**



Motivating Example #2: Unsupervised Category Discovery with BigGANs

- **Unsupervised** BigGAN trained on unlabeled ImageNet learns to associate a discrete latent variable with interesting semantics
  - Qualitatively, the learnt clusters often resemble image categories
- This model was trained with a combination of discrete and continuous latents:
  - 120D Gaussian (N(0, 1))
  - 1024-way uniform categorical
- Rows correspond to categorical values, columns to Gaussian values

[Unpublished Results]

InfoGANs (Chen et al.)

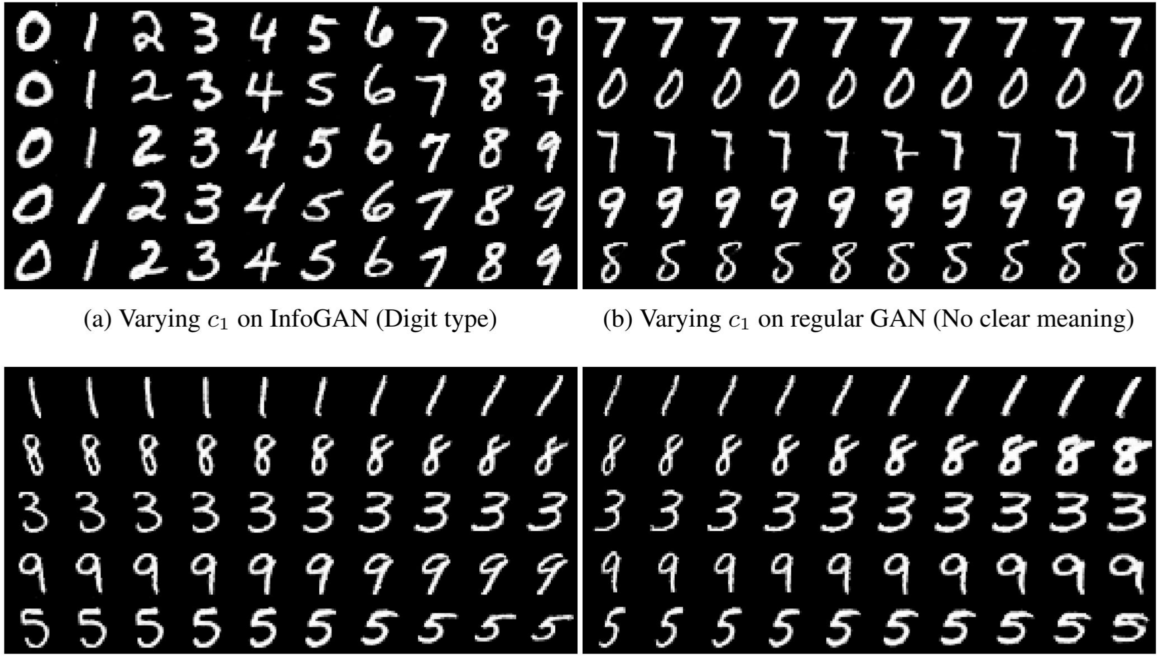
Want to learn more?

Chen, et al. **InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets.** arXiv:1606.03657 (**2016**)

- Information maximising GANs
- Adds an inference network to recover the latent codes **z** given the generator output G(**z**)

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I(c; G(z,c))$$

- With information maximising objective, generator learns (unsupervised) to associate a discrete (10-way categorical) latent variable with digit category



(a) Varying c_1 on InfoGAN (Digit type)

(b) Varying c_1 on regular GAN (No clear meaning)

(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

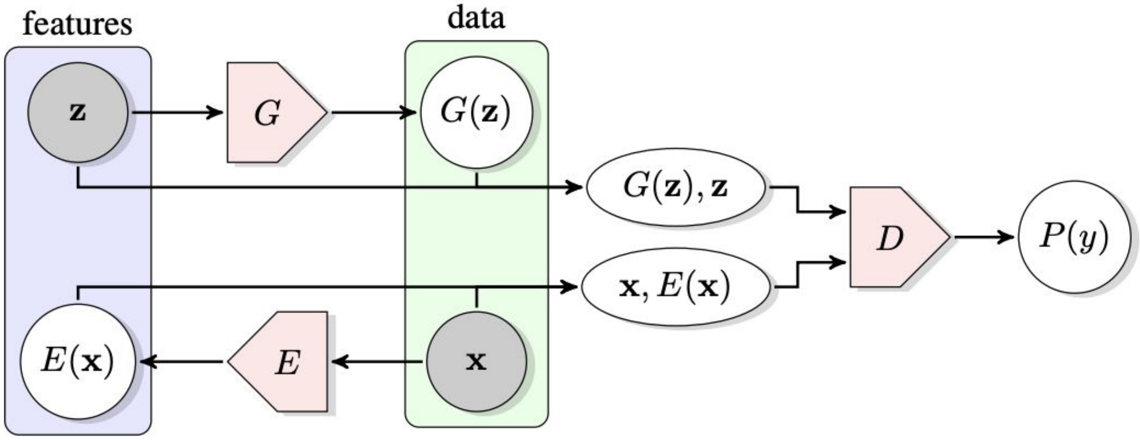
ALI / Bidirectional GANs (Dumoulin et al., Donahue et al.)

Want to learn more?

Dumoulin, et al. **Adversarially Learned Inference.** International Conference on Learning Representations (2017)

Donahue, et al. **Adversarial Feature Learning.** International Conference on Learning Representations (2017)

- Adversarial approach to feature representation learning and inference
- Adds an **encoder** network (E) which learns the inverse mapping from G, mapping from data **x** to latents **z**
- The **joint discriminator** sees tuples (**x**, **z**)



ALI / Bidirectional GANs (Dumoulin et al., Donahue et al.)

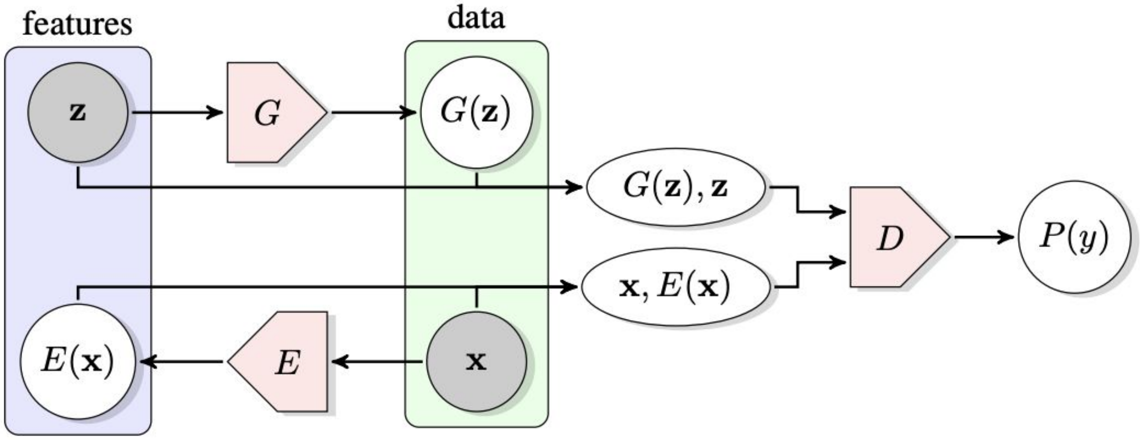
Want to learn more?

Dumoulin, et al. **Adversarially Learned Inference.** International Conference on Learning Representations (2017)

Donahue, et al. **Adversarial Feature Learning.** International Conference on Learning Representations (2017)

- The **joint discriminator** sees tuples (**x**, **z**)
  - **z** ~ P_z, **x** = G(**z**)
  - **x** ~ P_x, **z** = E(**x**)

- In the global optimum, E and G are inverses; for all **x** and **z** we have
  - **x** = G(E(**x**))
  - **z** = E(G(**z**))



ALI / Bidirectional GANs (Dumoulin et al., Donahue et al.)

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Donahue, et al. **Adversarial Feature Learning.** International Conference on Learning Representations (2017)

- In the global optimum, E and G are inverses; for all **x** and **z** we have
  - **x** = G(E(**x**))
  - **z** = E(G(**z**))

- In practice, this inversion property does not hold perfectly
  - But reconstructions still often capture interesting semantics

(a) CelebA samples.

(b) CelebA reconstructions.

BigBiGANs (Donahue et al.)

- BiGANs at scale: **BigBiGANs** are BiGANs trained using the BigGAN G and D architectures

- ResNet-style encoders E

- Reconstructions exhibit clear high-level semantics of the input images (despite being unsupervised), while clearly not being memorised copies

real data **x** (128x128)

BigBiGAN reconstructions G(E(**x**))

Want to learn more?

Donahue, et al. **Large Scale Adversarial Representation Learning.** Neural Information Processing Systems (**2019**)

BigBiGANs (Donahue et al.)

Want to learn more?

Donahue, et al. **Large Scale Adversarial Representation Learning.** Neural Information Processing Systems (**2019**)

- BiGANs at scale: **BigBiGANs** are BiGANs trained using the BigGAN G and D architectures
- ResNet-style encoders E
- Reconstructions exhibit clear high-level semantics of the input images (despite being unsupervised), while clearly not being memorised copies

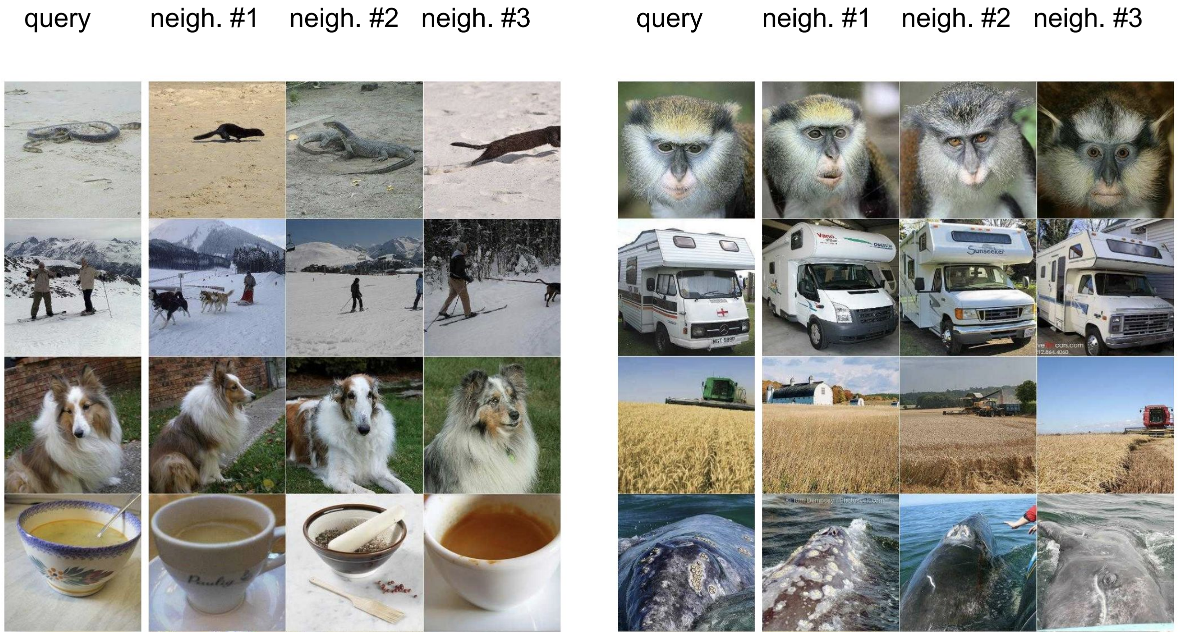
real data **x** (256x256)

BigBiGAN reconstructions G(E(**x**))

BigBiGANs (Donahue et al.)

- BigBiGAN encoder learns ImageNet representations competitive with other unsupervised / self-supervised approaches

- Nearest neighbors (right) in BigBiGAN encoder feature space show the semantics present in the learnt representations



Want to learn more?

Donahue, et al. **Large Scale Adversarial Representation Learning.** Neural Information Processing Systems (2019)

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3.3 GANs for Other Modalities & Problems

Pix2Pix (Isola et al.)

Want to learn more?

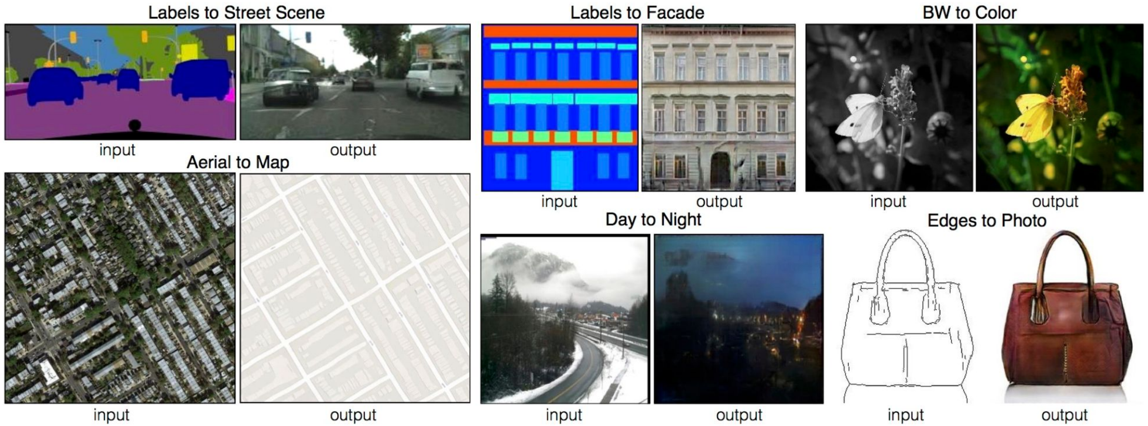
Isola, et al. **Image-to-Image Translation with Conditional Adversarial Networks.** IEEE Conference on Computer Vision and Pattern Recognition (**2017**)

- Train a generator to **translate** between images of two different domains
- Standard GAN objective combined with reconstruction error

$$\mathcal{L}_{GAN}(G,D) = \mathbb{E}_y[\log D(y)] + \mathbb{E}_{x,z}[\log(1 - D(G(x,z))].$$

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|_1].$$

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

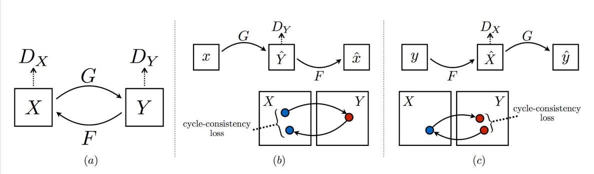


Example results on several image-to-image translation problems. In each case we use the same architecture and objective, simply training on different data.

CycleGAN (Zhu et al.)

- Train a generator to **translate** between images of two different domains

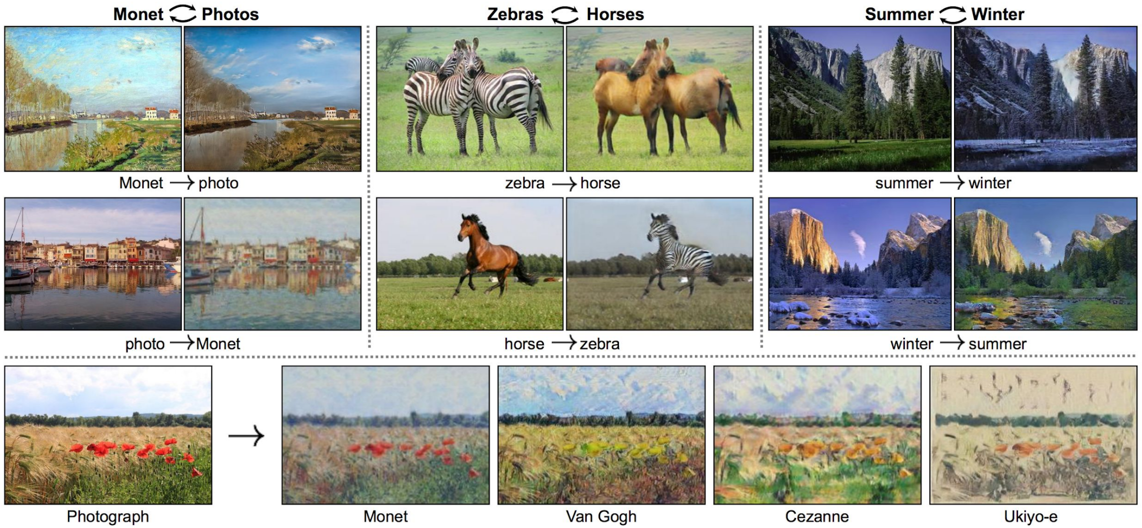
- But **without any paired samples**!



- Enforces **cycle consistency**:
  - Image **x** in domain A
  - Translate to domain B
  - Back to domain A -> **x'**
  - Enforce **x ≈ x'**

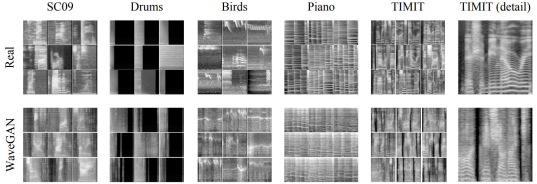
Want to learn more?

Zhu, et al. **Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks.** International Conference on Computer Vision (2017)

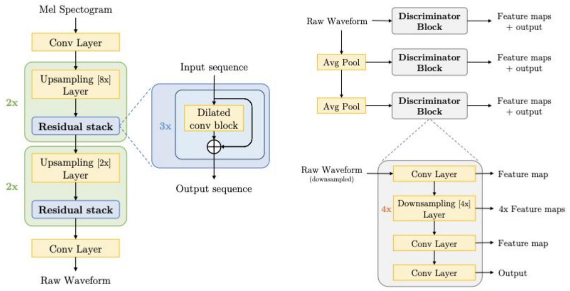


GANs for Audio Synthesis

WaveGAN (C. Donahue et al.)

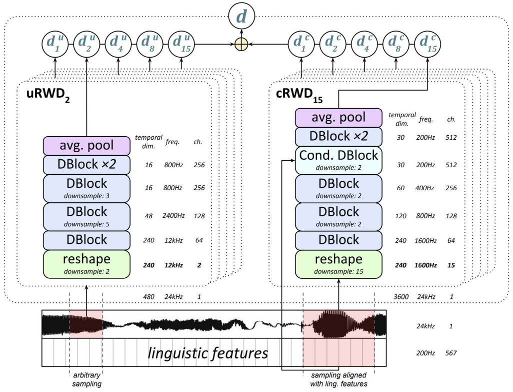


MelGAN (Kumar et al.)



(a) Generator
(b) Discriminator

GAN-TTS (Bińkowski et al.)



Want to learn more?

C. Donahue et al. **Adversarial Audio Synthesis.** International Conference on Learning Representations (2019)

Want to learn more?

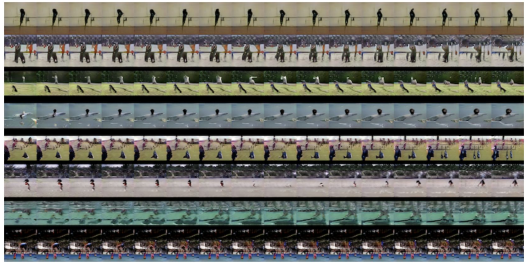
Kumar et al. **MelGAN: Generative Adversarial Networks for Conditional Waveform Synthesis.** Neural Information Processing Systems (2019)

Want to learn more?

Bińkowski et al. **High Fidelity Speech Synthesis with Adversarial Networks.** International Conference on Learning Representations (2020)

GANs for Video Synthesis & Prediction

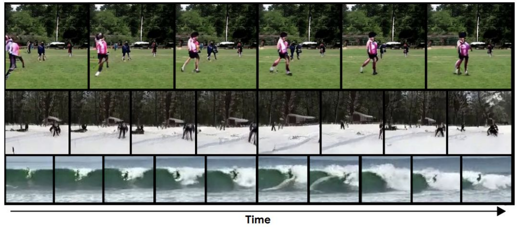
TGAN-v2 (Saito & Saito)



Want to learn more?

Saito and Saito. **TGANv2: Efficient Training of Large Models for Video Generation with Multiple Subsampling Layers.** arXiv:1811.09245 (**2018**)

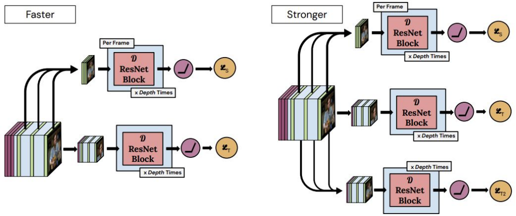
DVD-GAN (Clark et al.)



Want to learn more?

Clark et al. **Adversarial Video Generation on Complex Datasets.** arXiv:1907.06571 (**2019**)

TriVD-GAN (Luc et al.)

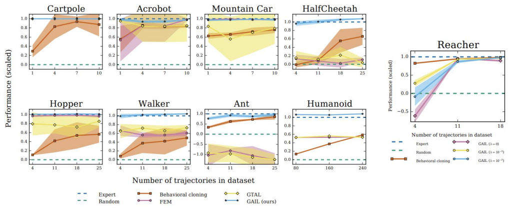


Want to learn more?

Luc et al. **Transformation-based Adversarial Video Prediction on Large-Scale Data.** arXiv:2003.04035 (**2020**)

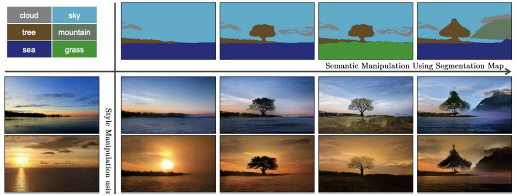
GANs Everywhere!

RL (Imitation Learning): **GAIL**



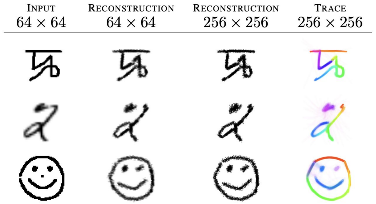
Ho and Erman. **Generative Adversarial Imitation Learning.** Neural Information Processing Systems (**2016**)

Image Editing: **GauGAN**



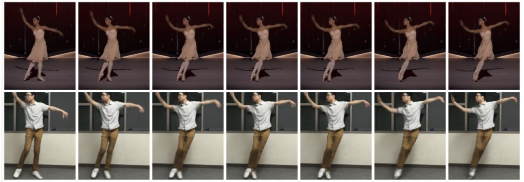
Park et al. **Semantic Image Synthesis with Spatially-Adaptive Normalization.** IEEE Conference on Computer Vision and Pattern Recognition (**2019**)

Program Synthesis: **SPIRAL**



Ganin et al. **Synthesizing Programs for Images using Reinforced Adversarial Learning.** International Conference on Machine Learning (**2018**)

Motion Transfer: **Everybody Dance Now**



Chan et al. **Everybody Dance Now.** International Conference on Computer Vision (**2019**)

Domain Adaptation: **DANN**

Ganin et al. **Domain-Adversarial Training of Neural Networks.** Journal of Machine Learning Research (**2016**)

Art: **Learning to See**

Akten. **Learning To See.** http://www.memo.tv/portfolio/learning-to-see/ (**2017**, accessed 2020)

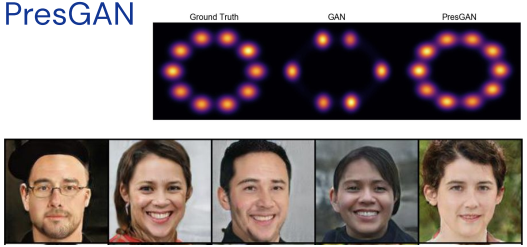
DeepMind

3.4 More GANs at DeepMind

(Updated: 1 July 2020)

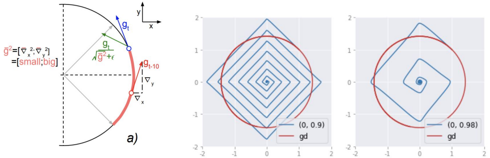
More GANs at DeepMind (2019)

PresGAN



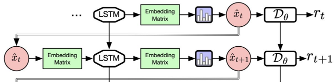
Dieng et al. **Prescribed Generative Adversarial Networks.** *arXiv:1910.04302* (2019)

Effectiveness of Adam on Cycles



Gemp & McWilliams. **The Unreasonable Effectiveness of Adam on Cycles.** *NeurIPS Smooth Games Optimization and Machine Learning Workshop* (2019)

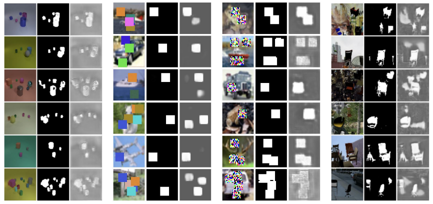
ScratchGAN



She ’ s that result she believes that for Ms . Marco Rubio ’ s candidate and that is still become smaller than ever .
I hadn ’ t been able to move on the surface – if grow through ,’ she said , given it at a time later that time .
If Iran wins business you have to win (Iowa) or Hillary Clinton ’ s survived nothing else since then , but also of all seeks to bring unemployment .
All the storm shows is incredible , most of the kids who are telling the girls the people we ’ re not turning a new study with a challenging group .
Six months before Britain were the UK leaving the EU we will benefit from the EU - it is meeting by auto , from London , so it ’ s of also fierce faith Freedom .

de Masson d'Autume et al. **Training language GANs from Scratch.** *Neural Information Processing Systems* (2019)

Copy-Pasting GAN



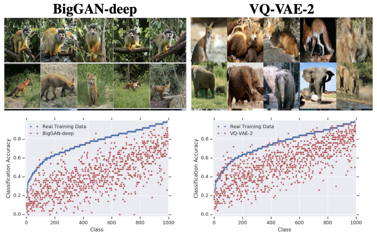
(a) CLEVR+bg (b) Squares (c) NoisySquares (d) Flying Chairs

Arandjelović & Zisserman. **Object Discovery with a Copy-Pasting GAN.** *arXiv:1905.11369* (2019)

Improved SPIRAL

Mellor et al. **Unsupervised Doodling and Painting with Improved SPIRAL.** *arXiv:1910.01007* (2019)

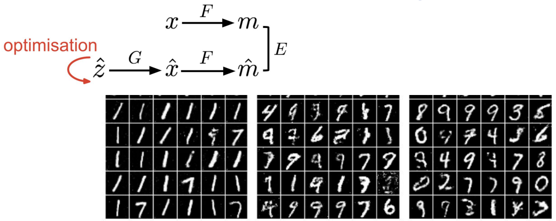
Classification Accuracy Score



Ravuri & Vinyals. **Classification Accuracy Score for Conditional Generative Models.** *Neural Information Processing Systems* (2019)

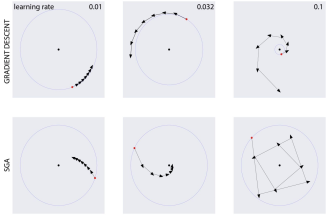
More GANs at DeepMind (2017-19)

Deep Compressed Sensing



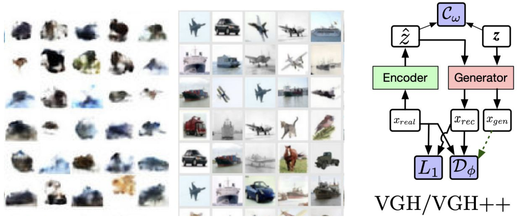
Wu et al. **Deep Compressed Sensing.** *International Conference on Machine Learning* (2019)

n-Player Differentiable Games



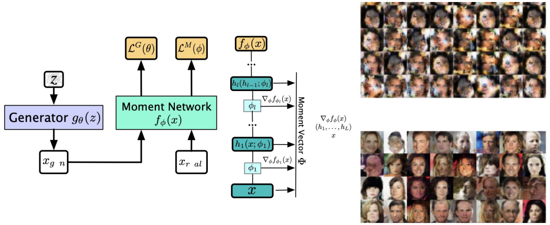
Balduzzi et al. **The Mechanics of n-Player Differentiable Games**. *International Conference on Machine Learning* (2018)

Variational GAN Hybrids



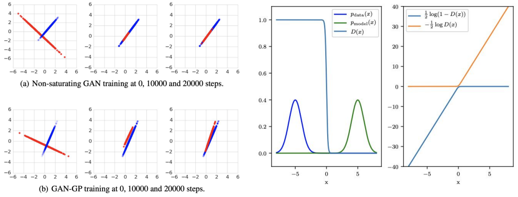
Rosca et al. **Distribution Matching in Variational Inference.** *arXiv:1802.06847* (2018)

Method of Learned Moments



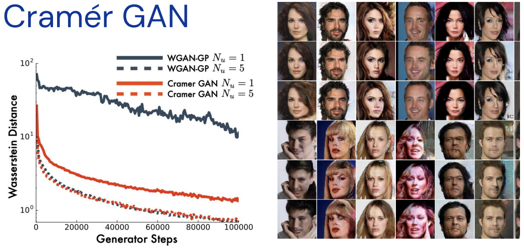
Ravuri et al. **Learning Implicit Generative Models with the Method of Learned Moments**. *International Conference on Machine Learning* (2018)

Many Paths to Equilibrium



Fedus et al. **Many Paths to Equilibrium: GANs Do Not Need to Decrease a Divergence At Every Step.** *International Conference on Learning Representations* (2017)

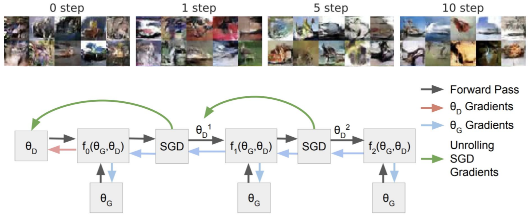
Cramér GAN



Bellemare et al. **The Cramer Distance as a Solution to Biased Wasserstein Gradients**. *arXiv:1705.10743* (2017)

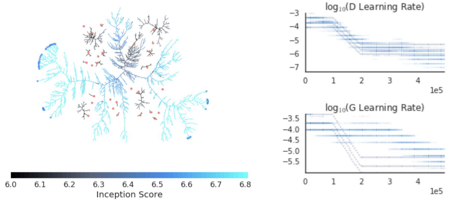
More GANs at DeepMind (2016-17)

Unrolled GAN



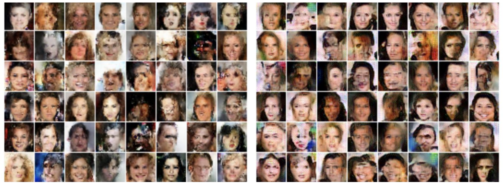
Metz et al. **Unrolled Generative Adversarial Networks.** *International Conference on Learning Representations* (2017)

Population Based Training



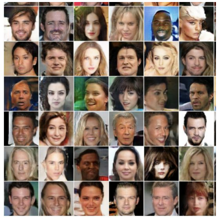
Jaderberg et al. **Population Based Training of Neural Networks.** *arXiv:1711.09846* (2017)

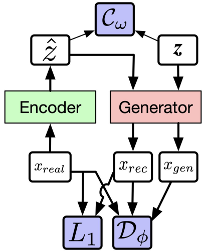
Likelihood vs. GAN NVP Training



Danihelka et al. **Comparison of Maximum Likelihood and GAN-based training of Real NVPs.** *arXiv:1705.05263* (2017)

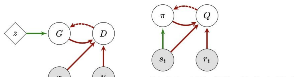
α-GAN





Rosca et al. **Variational Approaches for Auto-Encoding Generative Adversarial Networks.** *arXiv:1706.04987* (2017)

Connecting GANs & Actor-Critic



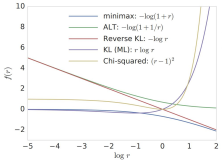
(a) Generative Adversarial Networks [4]

(b) Deterministic Policy Gradient [7] / SVG(0) [8] / Neurally-Fitted Q-learning with Continuous Actions [9]

Method	GANs	AC
Freezing learning	yes	yes
Label smoothing	yes	no
Historical averaging	yes	no
Minibatch discrimination	yes	no
Batch normalization	yes	yes
Target networks	n/a	yes
Replay buffers	no	yes
Entropy regularization	no	yes
Compatibility	no	yes

Pfau & Vinyals. **Connecting Generative Adversarial Networks and Actor-Critic Methods.** *NeurIPS Workshop on Adversarial Training* (2016)

Learning in Implicit Gen. Models



Loss	Objective Function ($\mathcal{D} := \mathcal{D}(\mathbf{x};\phi)$)
Bernoulli loss	$\pi\mathbb{E}_{p^*(\mathbf{x})}[-\log\mathcal{D}] + (1-\pi)\mathbb{E}_{q_\theta(\mathbf{x})}[-\log(1-\mathcal{D})]$
Brier score	$\pi\mathbb{E}_{p^*(\mathbf{x})}[(1-\mathcal{D})^2] + (1-\pi)\mathbb{E}_{q_\theta(\mathbf{x})}[\mathcal{D}^2]$
Exponential loss	$\pi\mathbb{E}_{p^*(\mathbf{x})}\left[\left(\frac{1-\mathcal{D}}{\mathcal{D}}\right)^{\frac{1}{2}}\right] + (1-\pi)\mathbb{E}_{q_\theta(\mathbf{x})}\left[\left(\frac{\mathcal{D}}{1-\mathcal{D}}\right)^{\frac{1}{2}}\right]$

Mohamed & Lakshminarayanan. **Learning in Implicit Generative Models.** *arXiv:1610.03483* (2016)

Thank you