(Big)GANs

Jeff Donahue
DeepMind

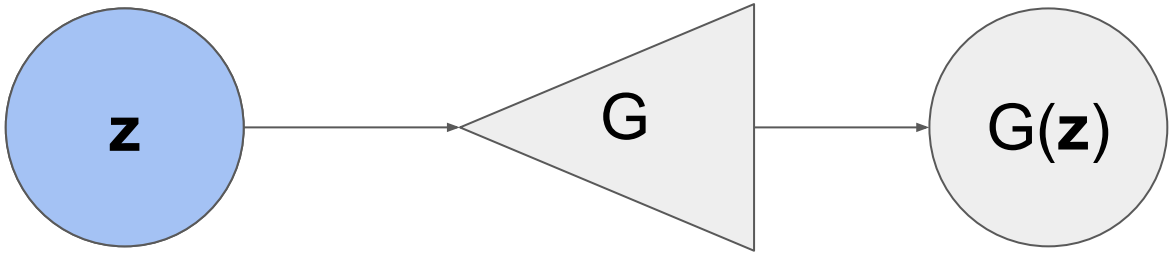
Generative Adversarial Networks (GAN)

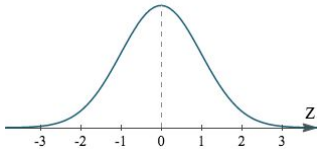
The Generator

latent (“noise”) vector
z ~ P(**z**)

generator G:
a deep neural network
(usually)

generated data
G(**z**)

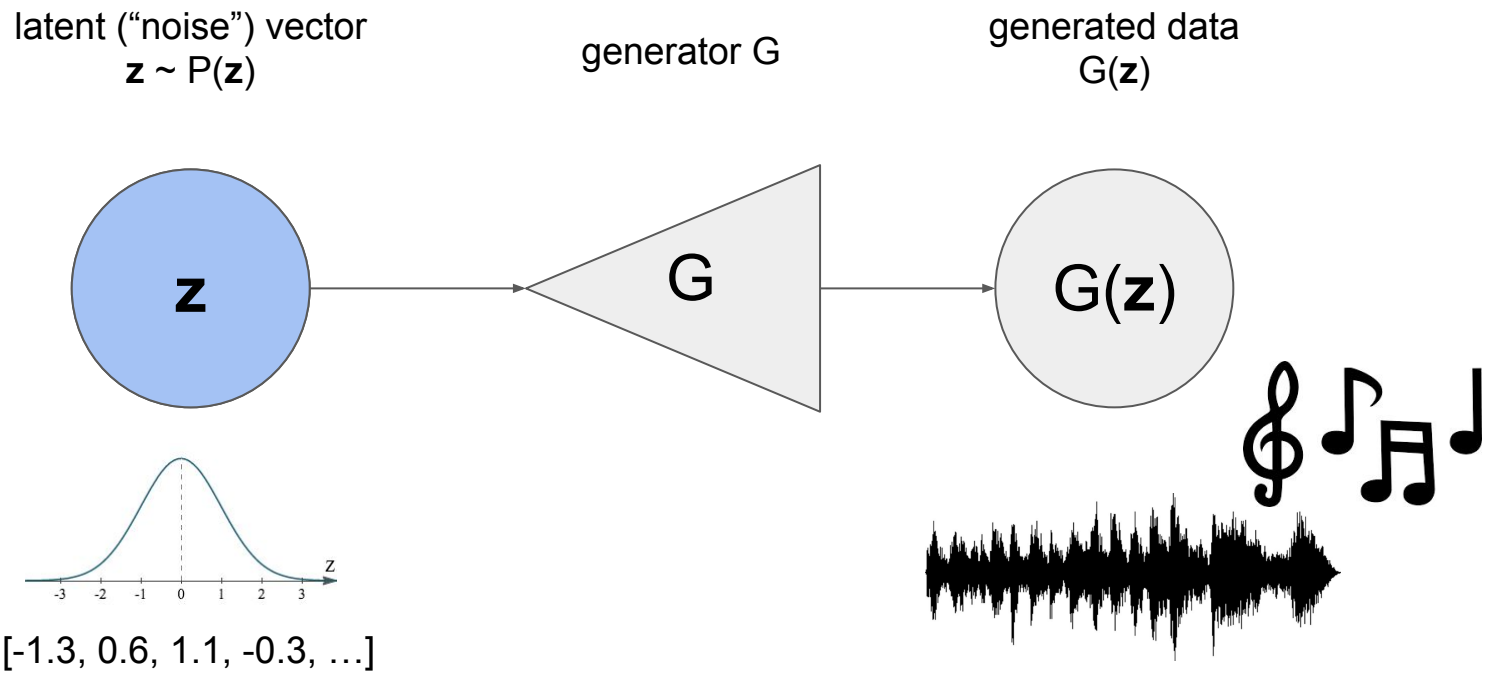




[-1.3, 0.6, 1.1, -0.3, …]

Generative Adversarial Networks (GAN)

The Generator



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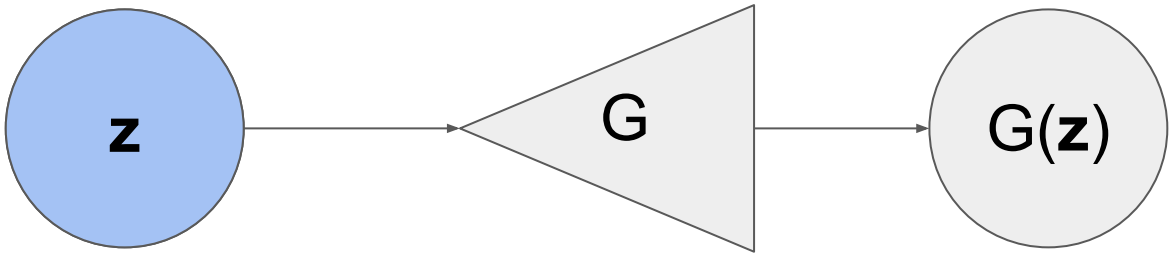

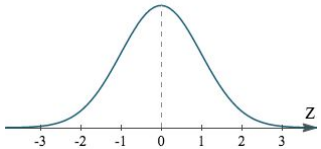

[-1.3, 0.6, 1.1, -0.3, …]

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

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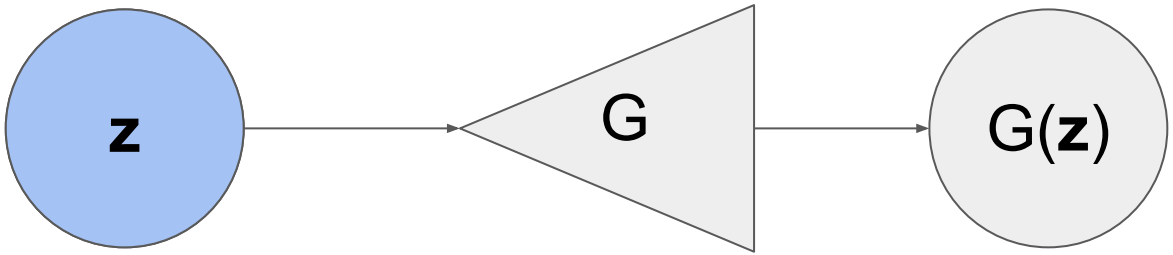
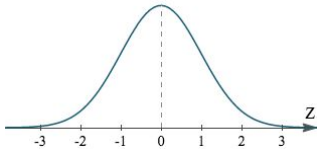




[-1.3, 0.6, 1.1, -0.3, …]

Any kind of data you want!

Generative Adversarial Networks (GAN)

The Discriminator

real data **x** ~ P(**x**)

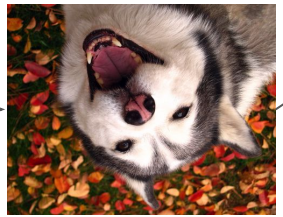
D

Predict 0-1:
real (1)
or
generated (0)?

generator G

G

generated data
G(**z**)



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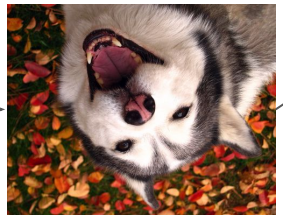

Discriminator's objective:
predict whether my inputs are real or generated as accurately as possible

Generative Adversarial Networks (GAN)

The Discriminator

Generator's objective: "fool" the discriminator into believing my generated data are real

real data **x** ~ P(**x**)

D

Predict 0-1:
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or
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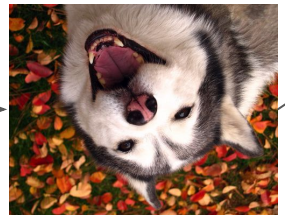
generator G

G

generated data
G(**z**)



Discriminator's objective: predict whether my inputs are real or generated as accurately as possible

Generative Adversarial Networks (GAN)

The ~~Discriminator~~ **Teacher** (a less “adversarial” view)

Generator’s objective:
~~“fool” the discriminator~~
make the teacher happy
by making my generated data look real

real data **x** ~ P(**x**)

D

Predict 0-1:
real (1)
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generator G

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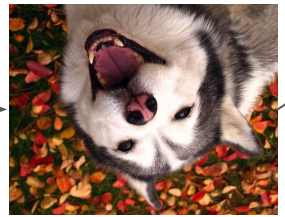
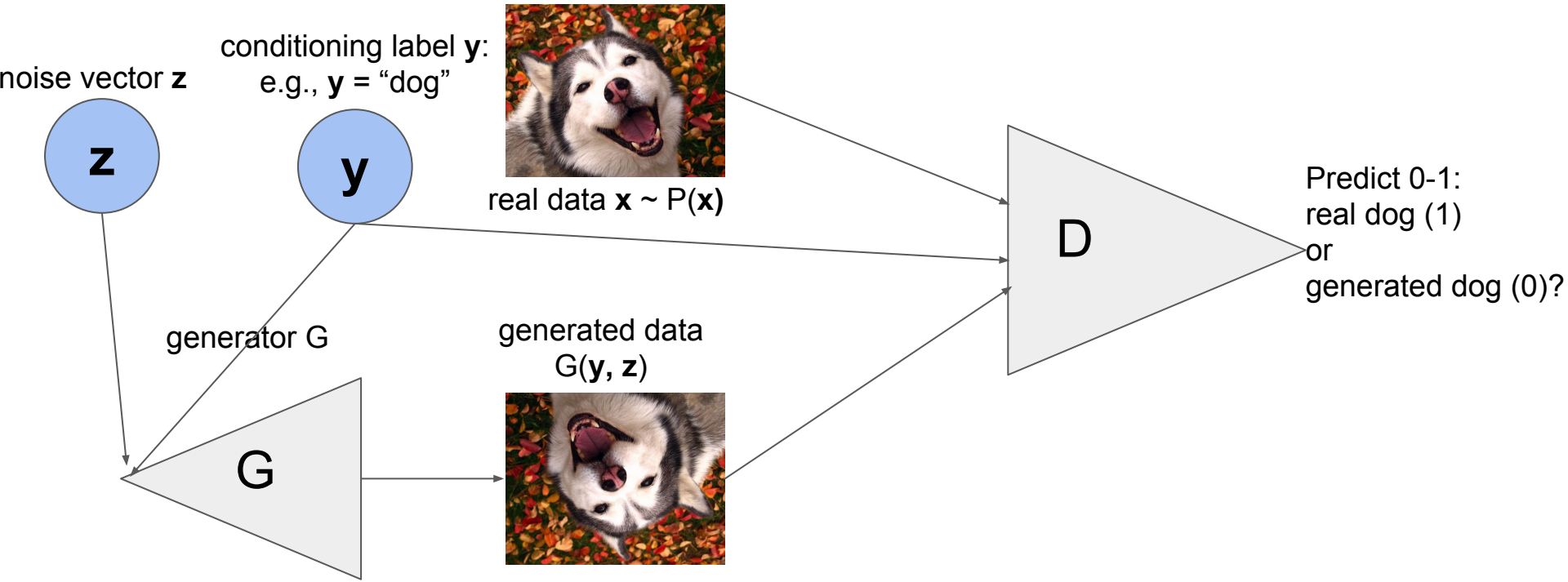
generated data
G(**z**)



Teacher’s objective:
predict whether my inputs are real or generated as accurately as possible, **so that I can tell the generator how to improve them**

Generative Adversarial Networks (GAN)

Conditional version



Generative Adversarial Networks (GAN)

The Game

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

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

GANs. Goodfellow et al., 2014. https://arxiv.org/abs/1406.2661

Generative Adversarial Networks (GAN)

Training Algorithm

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

GANs. Goodfellow et al., 2014. https://arxiv.org/abs/1406.2661

Generative Adversarial Networks (GAN)

What happens at convergence?

Theorem 1. *The global minimum of the virtual training criterion $C(G)$ is achieved if and only if $p_g = p_{data}$.*

In other words, the generator is **perfect** if the objective we train towards is perfectly satisfied: its outputs are **indistinguishable** from the dataset we trained it to mimic.

The discriminator simply predicts ½ probability of being real for all inputs, real or generated. **The generator "wins"**!

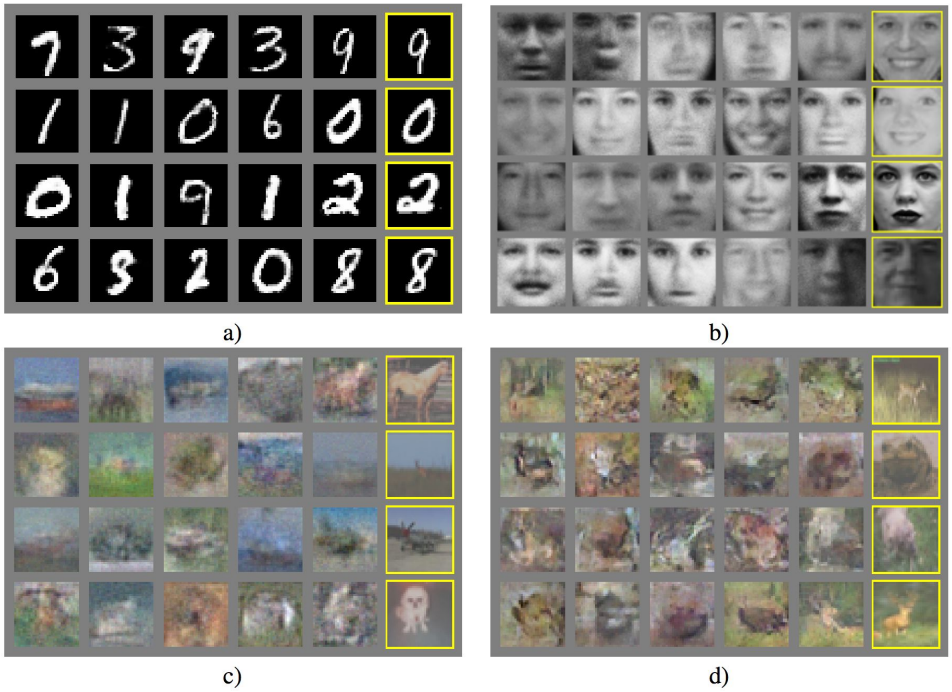
GANs. Goodfellow et al., 2014. https://arxiv.org/abs/1406.2661

Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

First results from original GAN paper:

- simple data (~32x32 images)
- simple models
- both G and D were (basically) ReLU networks
- In (a) & (b), G's output and D's input were both **flat vectors** (displayed as 2D images here)
  - ignored spatial structure: adjacent pixels treated the same as far away pixels



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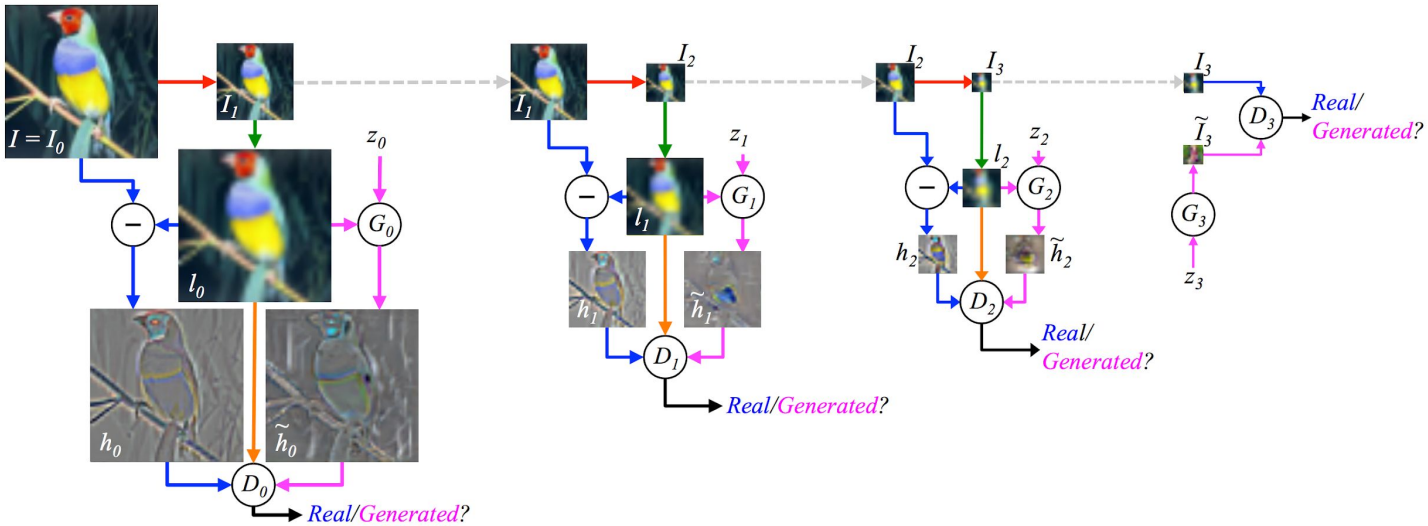
Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

LAPGANs
(Laplacian GANs)

Starting from a tiny image, upsample to larger image and generate the difference (or Laplacian)



LAPGANs. Denton et al., 2015. https://arxiv.org/abs/1506.05751

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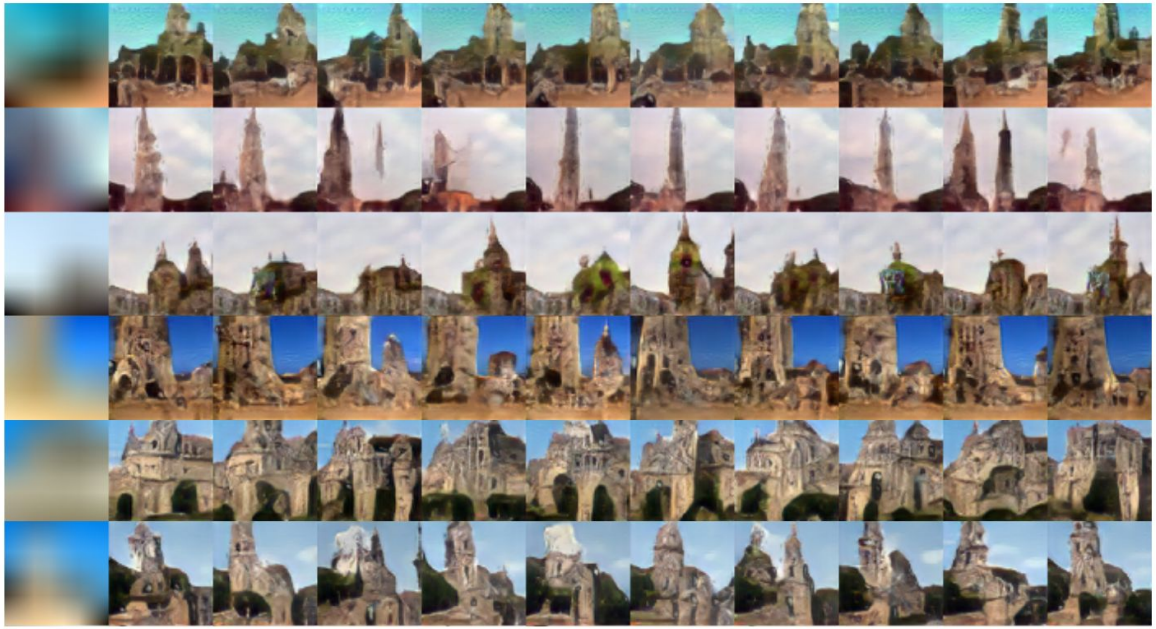

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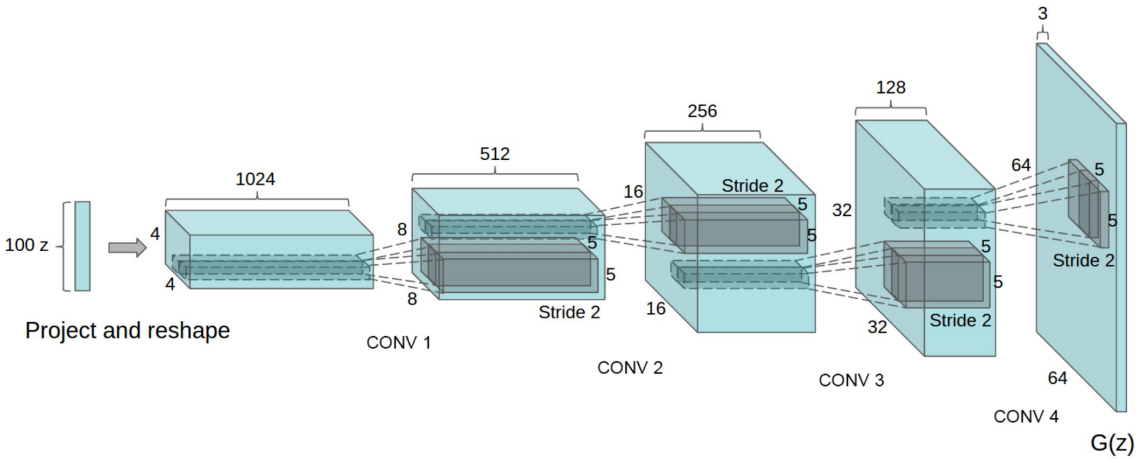
Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

"**DCGAN**" (deep convolutional GANs)

- simply use deep convnets for G and D
- importantly, **batch normalization** (Ioffe and Szegedy, 2015) helps to stabilize notoriously difficult learning process



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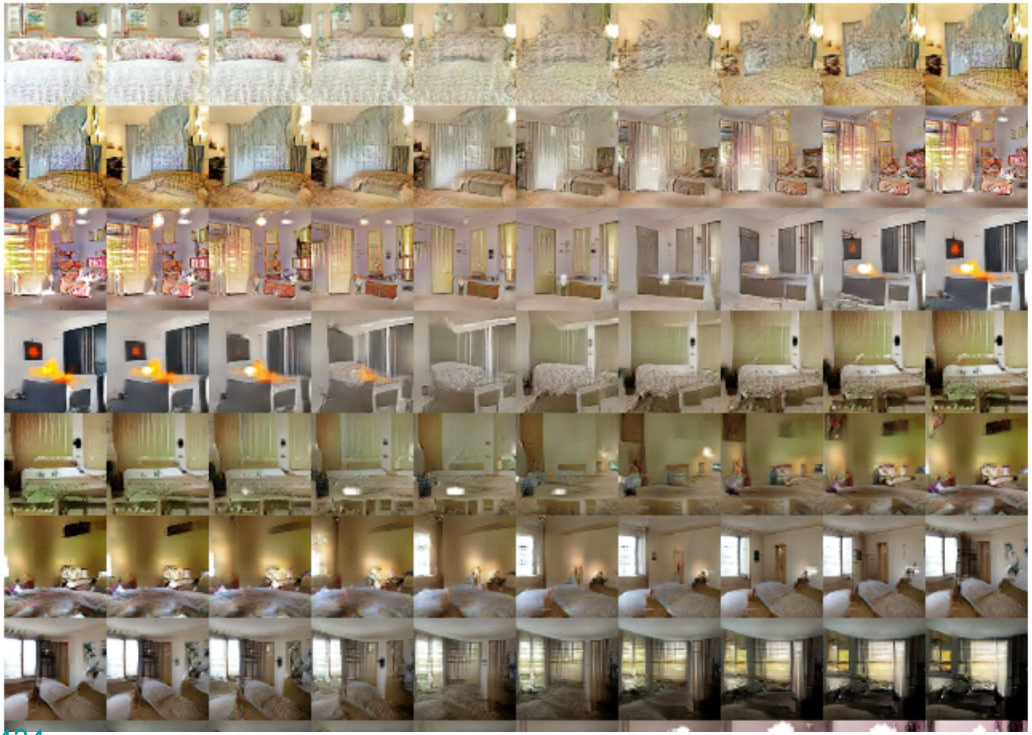

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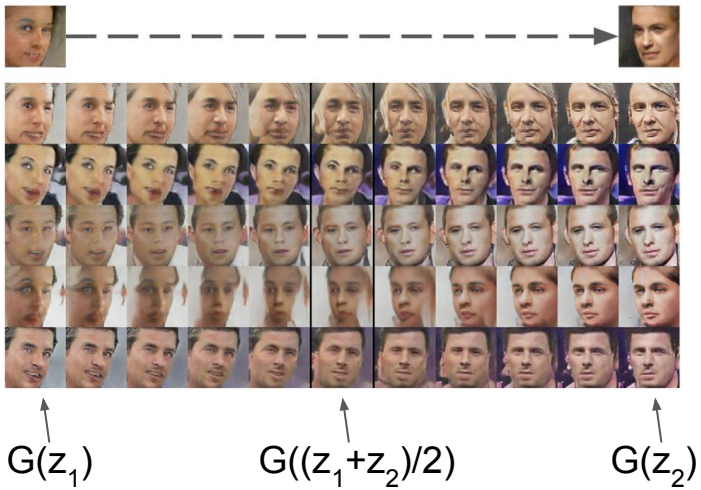
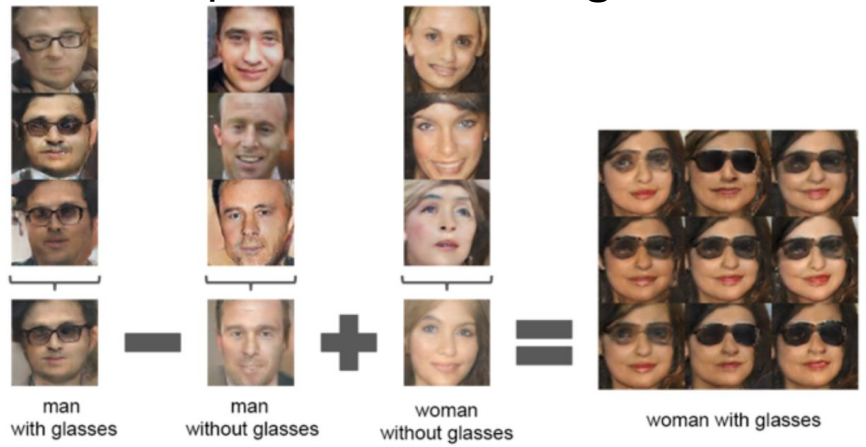
Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

DCGAN: observed that the generator's noise/latent space has **meaningful semantics**





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Generative Adversarial Networks (GAN)
Evolution: from MNIST to ImageNet, and beyond

ACGAN: improved class-conditional discriminator with auxiliary classifier

$$L_S = E[\log P(S = real \mid X_{real})] + E[\log P(S = fake \mid X_{fake})]$$

$$L_C = E[\log P(C = c \mid X_{real})] + E[\log P(C = c \mid X_{fake})]$$

D: maximize $L_S + L_C$

G: maximize $L_C - L_S$

Trained on **ImageNet**:
1.28M images, 1000 categories

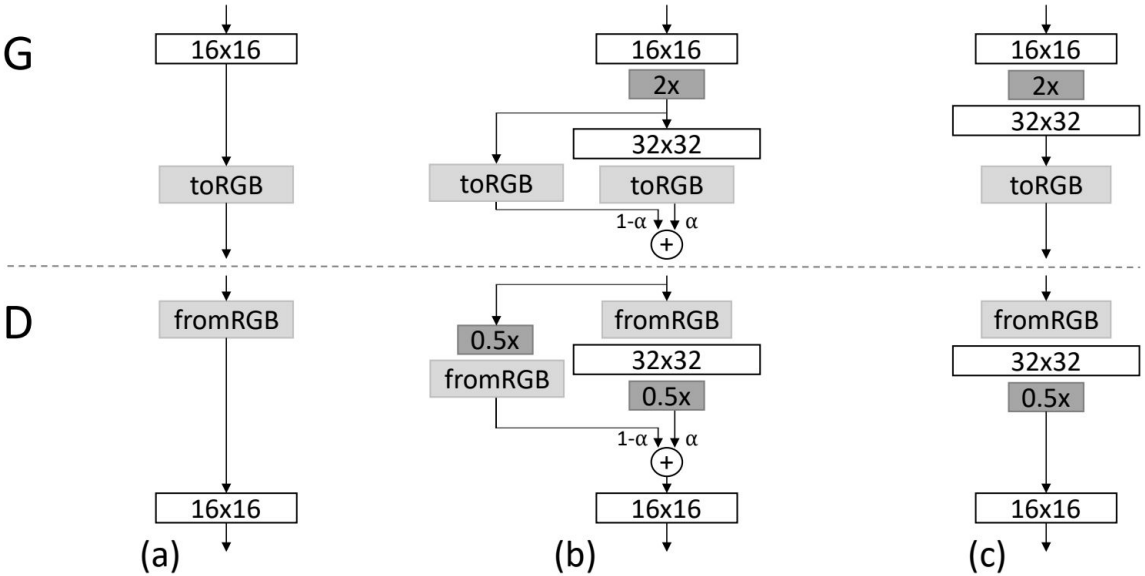
Odena et al., 2016. https://arxiv.org/abs/1610.09585

Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

Progressive GANs

- first, train a GAN to generate tiny (4x4) images
- after convergence, add a new layer to generate 8x8 resolution images, then 16x16, then 32x32, ..., repeat until 1024x1024
- compelling results in a restricted domain (faces)



Karras et al., 2018. https://arxiv.org/abs/1802.05637

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Evolution: from MNIST to ImageNet, and beyond

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Generative Adversarial Networks (GAN)
Evolution: from MNIST to ImageNet, and beyond

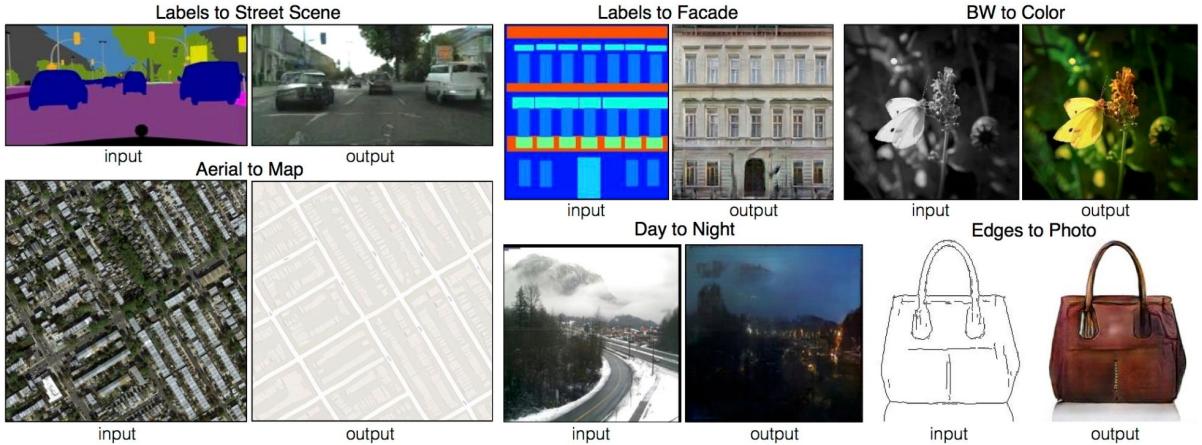
pix2pix

Given paired examples of images in two different domains, train a generator to translate between them

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

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

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



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

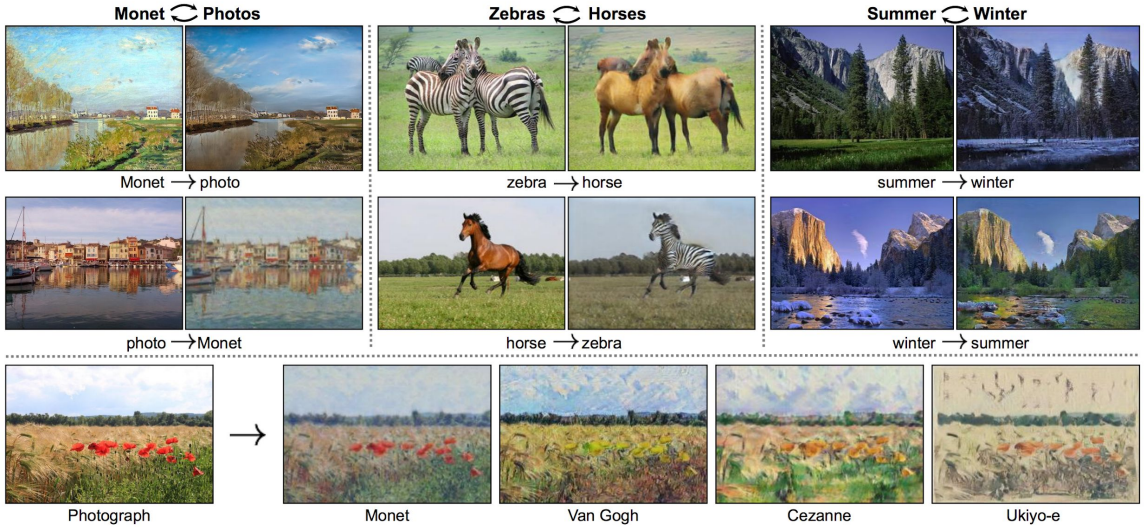
Isola et al., 2016. https://arxiv.org/abs/1611.07004

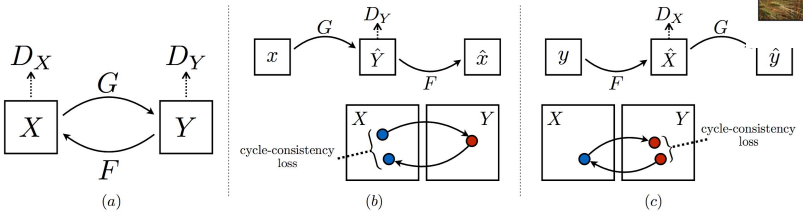
Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

CycleGAN

Given **unpaired** examples of images in two different domains, train a generator to translate between them





Zhu et al., 2017. https://arxiv.org/abs/1703.10593

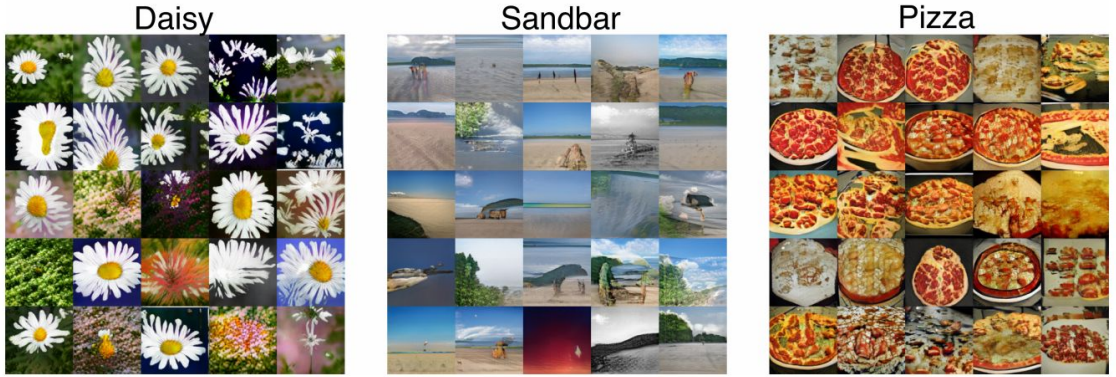
Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

SNGAN: stabilized training by clamping the singular values of D's weights to 1

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

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



Miyato et al., 2018. https://arxiv.org/abs/1802.05957

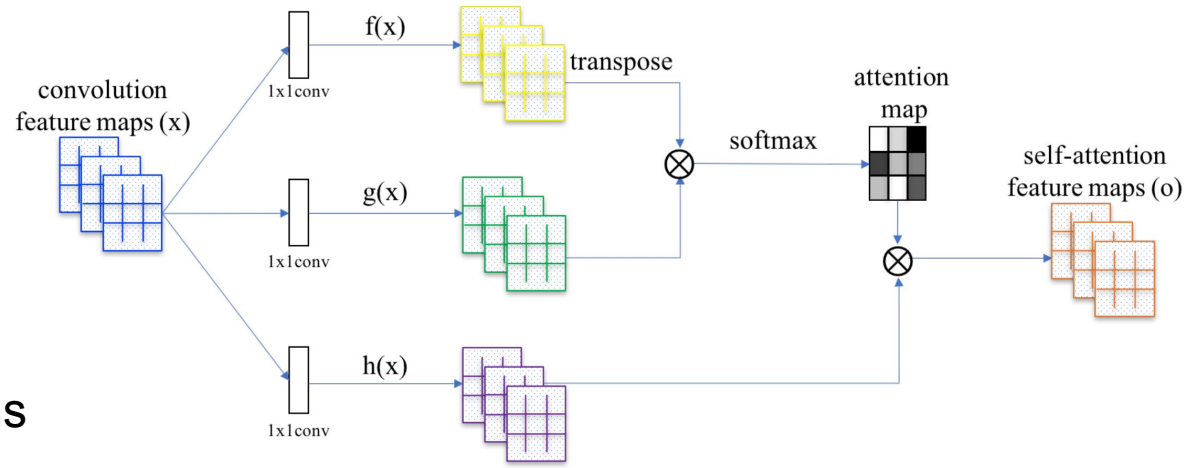
Generative Adversarial Networks (GAN)

Evolution: from MNIST to ImageNet, and beyond

Self-attention GAN (SAGAN)

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

- self-attention is a recent advance that has made a bit impact in many domains
  - especially language modeling, translation



Zhang et al., 2018. https://arxiv.org/abs/1805.08318

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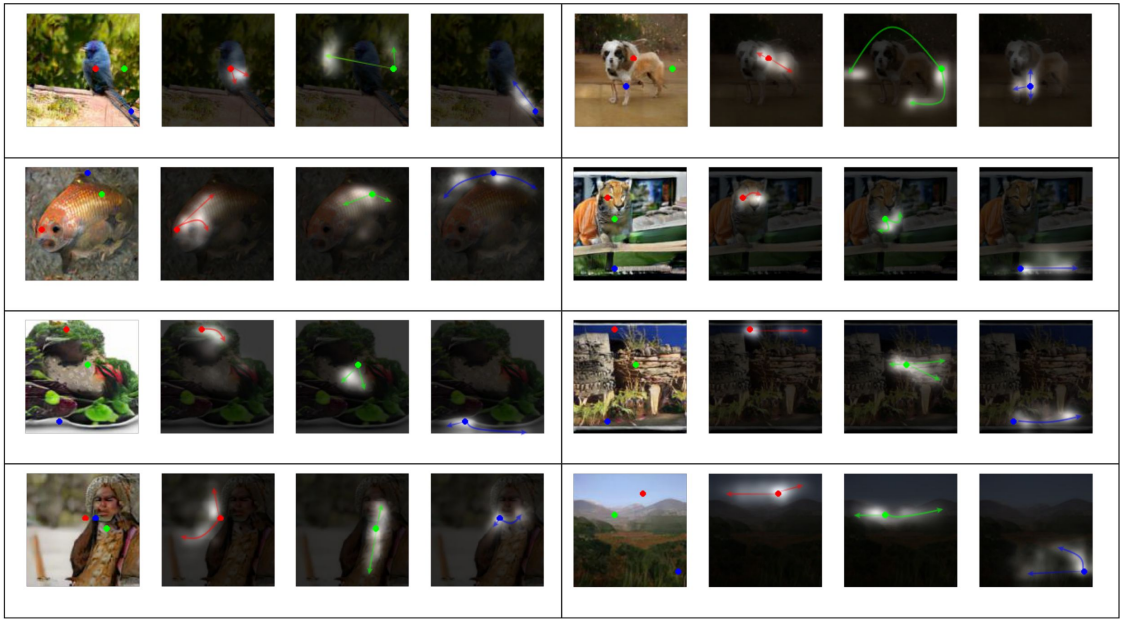

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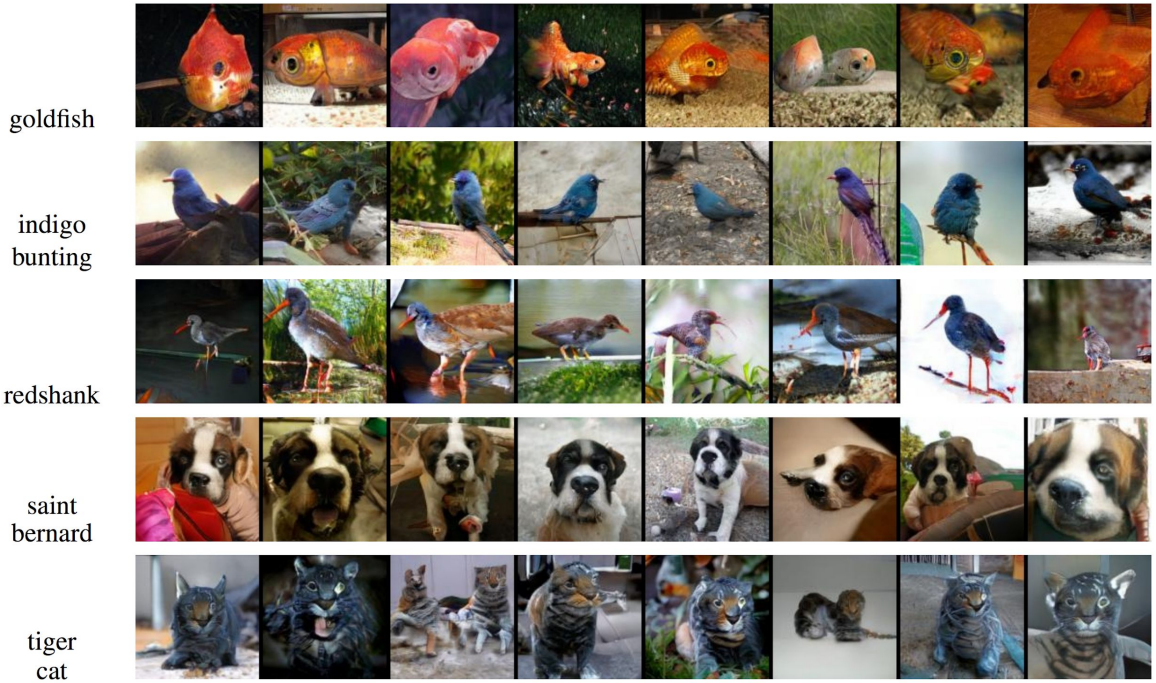

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BigGAN

Main idea: make GANs really, really big

- big **batches** (2048 images -- 8-32x larger than typical previous models)
- big **models**: first layer features in G are 4x4x1536 = ~24K
- big **datasets**:
  - ImageNet (1.28M images)
  - JFT (internal Google dataset, 300M images)
- big **resolution**: up to 512x512

Brock, Donahue, & Simonyan, 2018.
https://arxiv.org/abs/1809.11096

BigGAN

How did we get there?

- explored just about every trick from prior work, and kept the ones that worked
  - hinge loss
  - spectral normalization
  - self-attention
  - projection discriminator
- and added a few new ones
  - orthogonal regularization
  - “skip connections” from noise
  - shared class label embedding




Brock, Donahue, & Simonyan, 2018.
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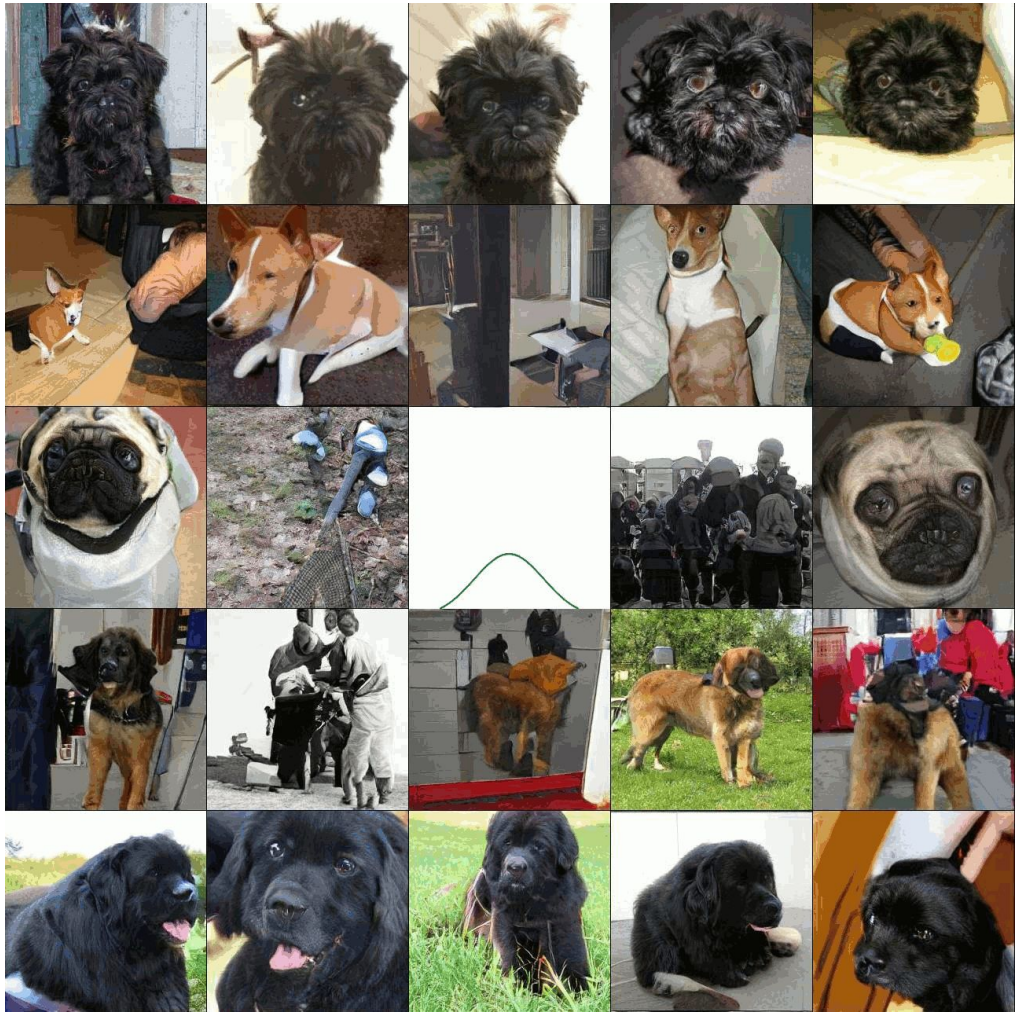
BigGAN

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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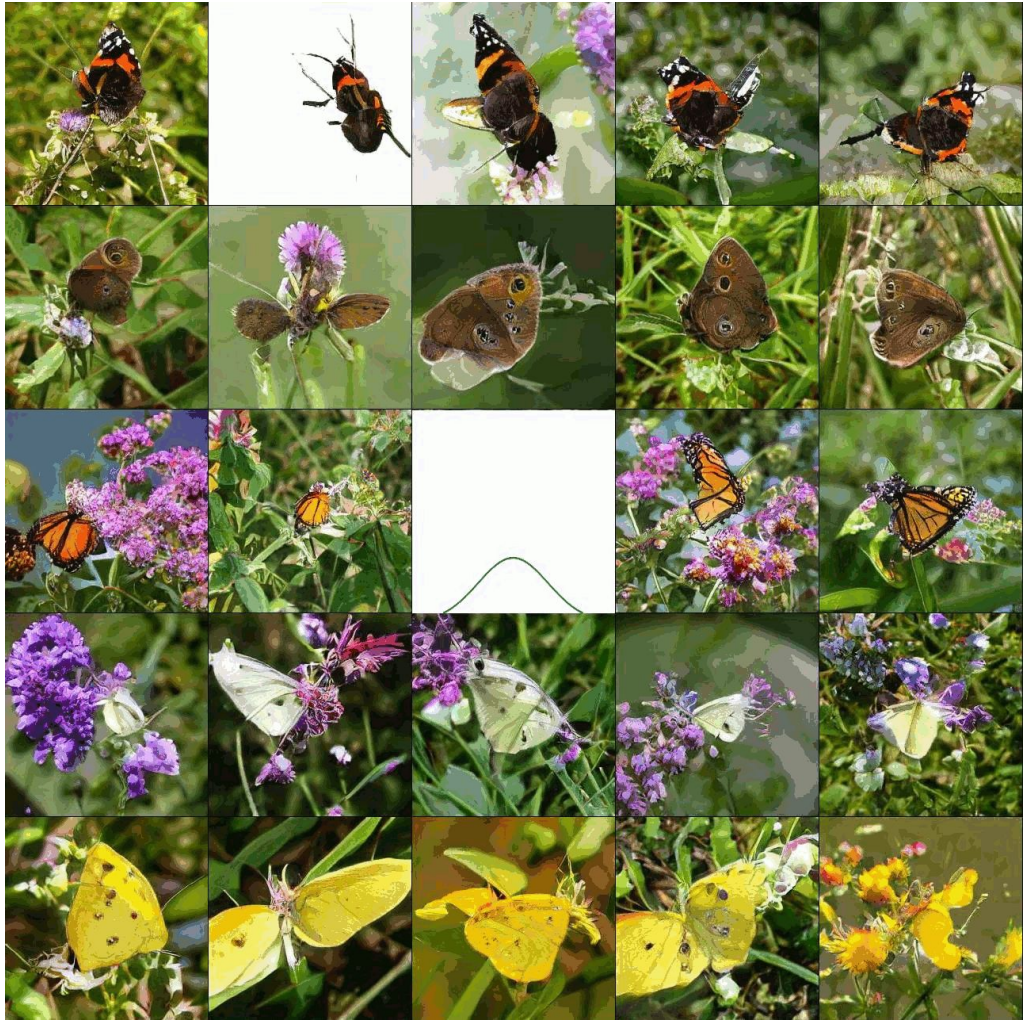

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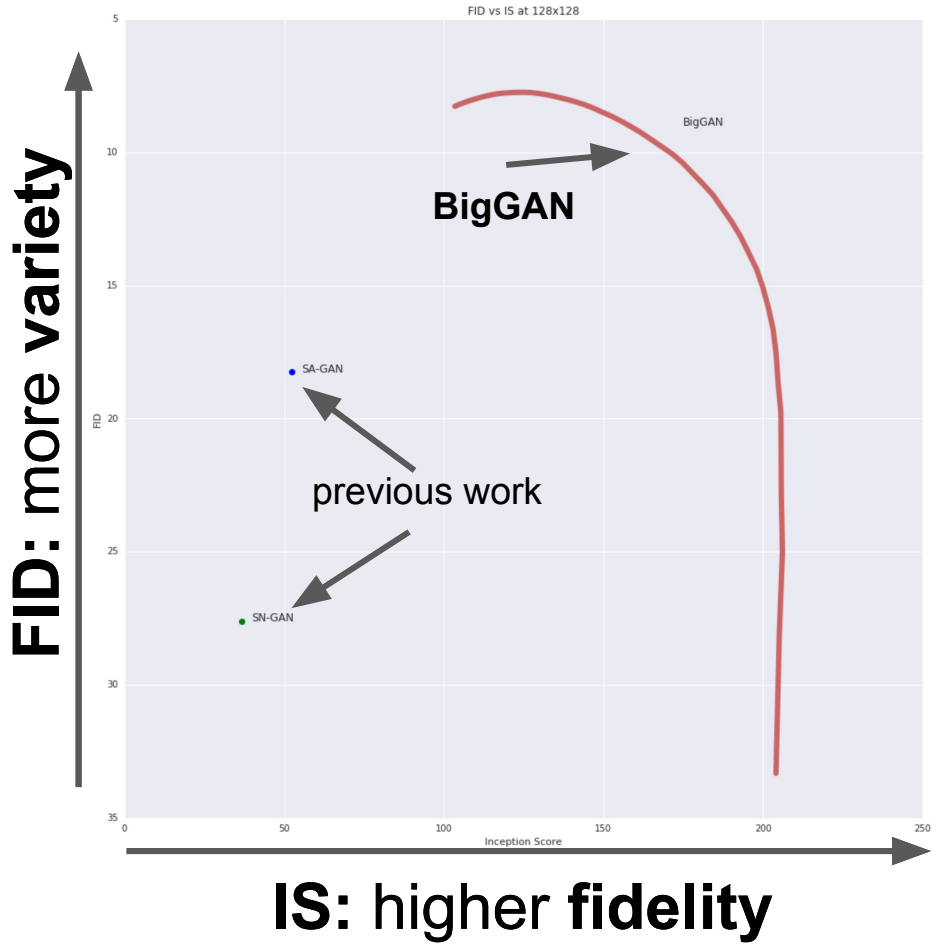
BigGAN

Metrics: how do we know it works?

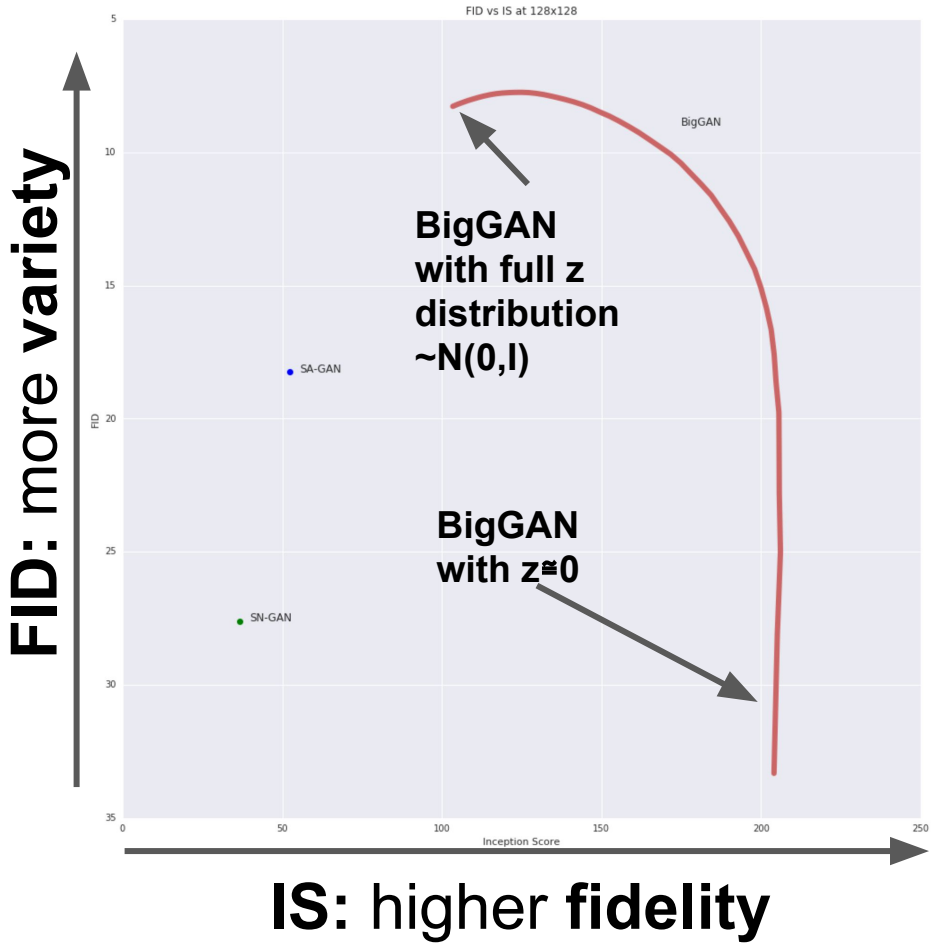
- GANs are difficult to evaluate
- Standard metrics use a **classifier** pretrained for image classification
- Inception Score (Salimans et al., 2016)
  - how **confident** is the classifier in its predictions for the generated images?
- Fréchet Inception Distance (FID) (Heusel et al., 2017)
  - how similar is the overall **distribution** of generated images to that of real images?



Brock, Donahue, & Simonyan, 2018.
https://arxiv.org/abs/1809.11096

BigGAN

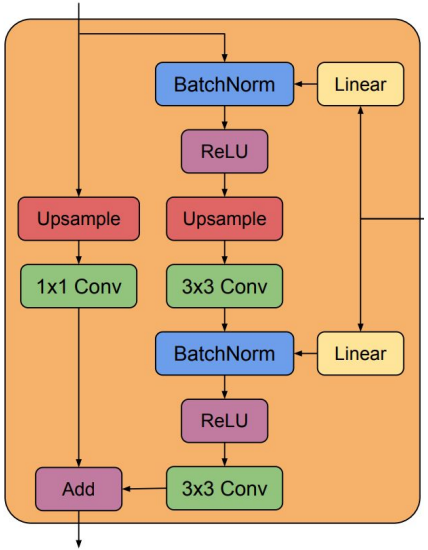
The **truncation trick** lets us trade-off between more fidelity (better IS) and more variety (better FID)



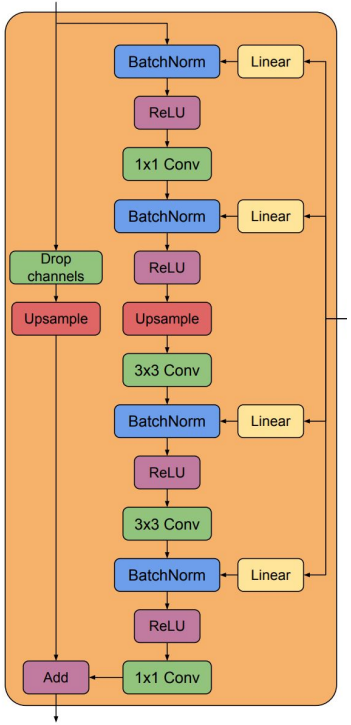
BigGAN-deep: latest results

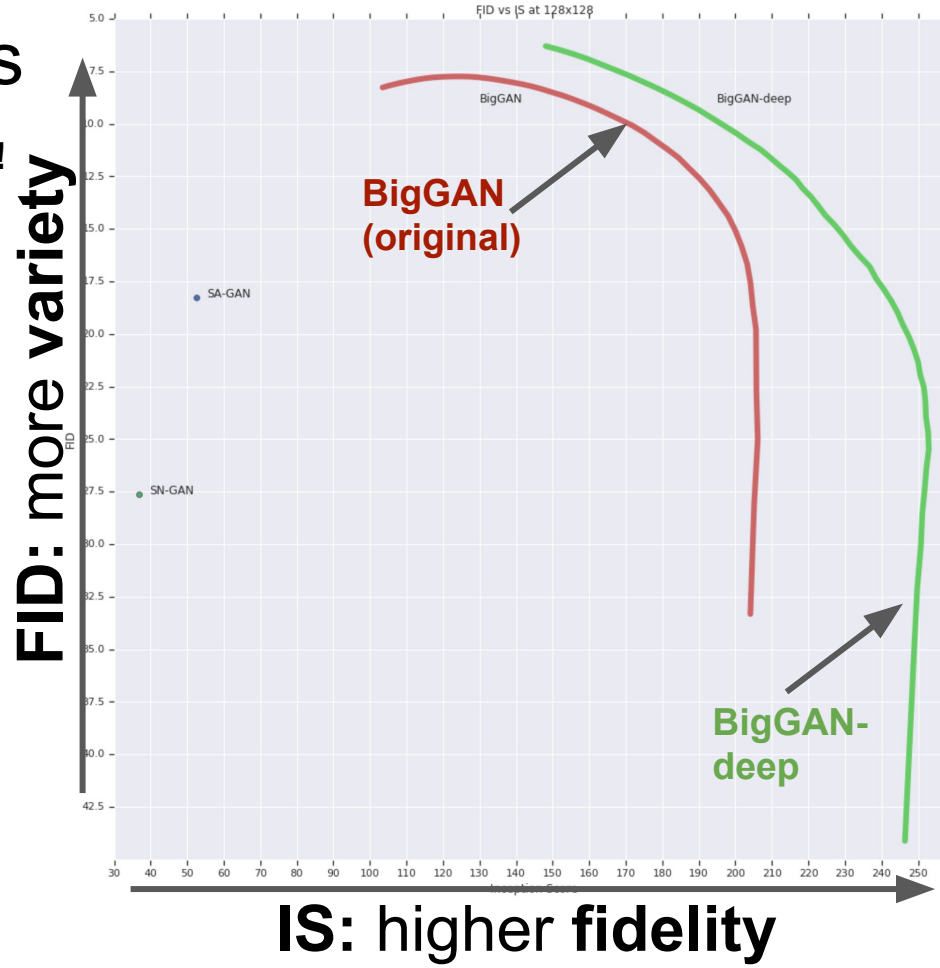
4x deeper, but more efficient!

BigGAN (original) Block



BigGAN-deep Block





Brock, Donahue, & Simonyan, 2018.
https://arxiv.org/abs/1809.11096

BigGAN: memorization?

Is it just memorizing the dataset? No!

For a given BigGAN generated image, we check the nearest neighbors -- the most similar images -- from the dataset it was trained to mimic.

We rarely/never see near-duplicates of images from the training set.

Brock, Donahue, & Simonyan, 2018.
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BigGAN generated image

Nearest neighbors: most similar real images

Brock, Donahue, & Simonyan, 2018.
https://arxiv.org/abs/1809.11096

BigGAN: failure modes

Dogball

An example of “class leakage”

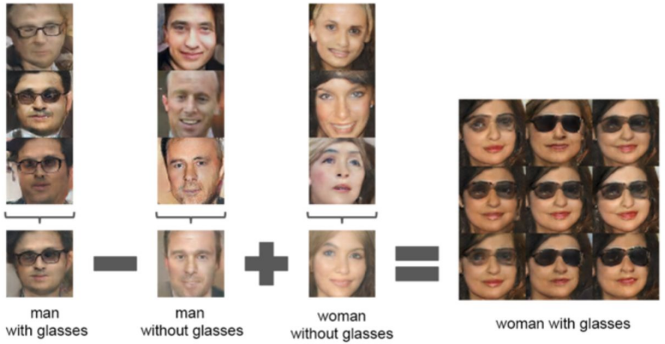
BigGAN: failure modes

Difficult classes:

- Complex structure
- Complex scenes
- Under-represented in dataset

Why train GANs? (Or any generative models?)

- Because it’s fun! (Reason enough?)
- If you can generate it, you understand it
- Planning for agents
  - GANs are particularly efficient samplers
  - Use to “imagine” the outcomes of different decisions and act accordingly
- Unsupervised learning
  - Latent space of a GAN encodes interesting semantic attributes with no labels
  - Learn from huge unlabeled databases?

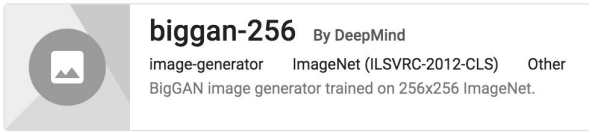


BigGAN: Colab demo (time permitting)

(1) Go to tfhub.dev

(2) Search for **biggan**

(3) Click on any of the 3 results (e.g., **biggan-256**)



(4) Click  (right side of the page)