

<https://ThisPersonDoesNotExist.com>

# Lecture 11: Generative Models

# Supervised vs Unsupervised Learning

## Supervised Learning

**Data:**  $(x, y)$

$x$  is data,  $y$  is label

**Goal:** Learn a *function* to map  $x \rightarrow y$

**Examples:** Classification,  
regression, object detection,  
semantic segmentation, image  
captioning, etc.



→ Cat

Classification

This image is CC0 public domain

# Supervised vs Unsupervised Learning

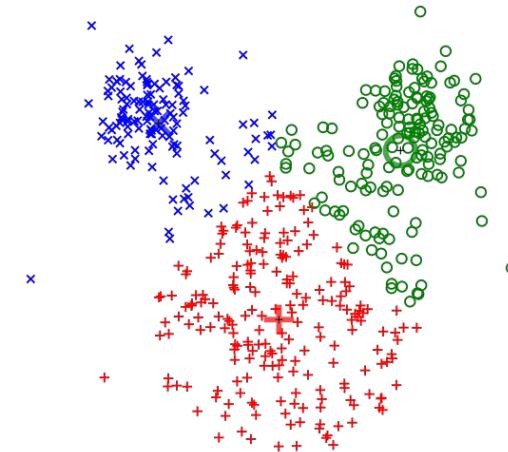
## Unsupervised Learning

**Data:**  $x$

Just data, no labels!

**Goal:** Learn some underlying hidden *structure* of the data

**Examples:** Clustering, dimensionality reduction, feature learning, density estimation, etc.



K-means clustering

This image is CC0 public domain

# Supervised vs Unsupervised Learning

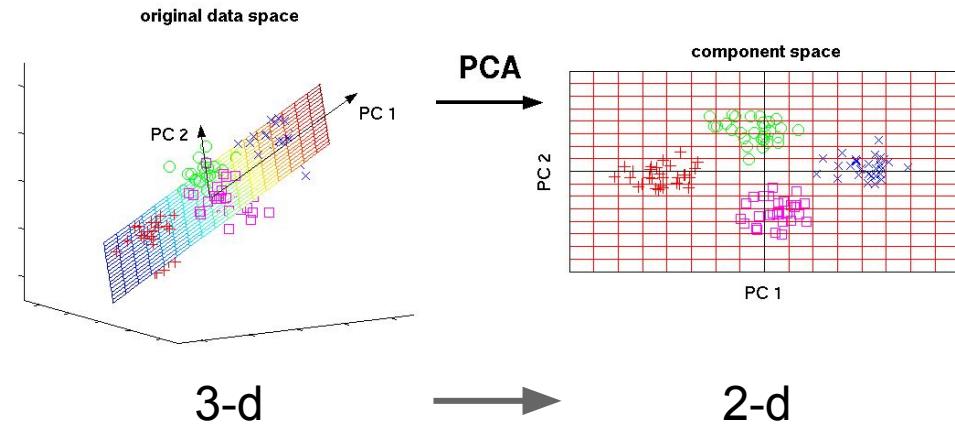
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Principal Component Analysis  
(Dimensionality reduction)

This image from Matthias Scholz  
is CC0 public domain

# Supervised vs Unsupervised Learning

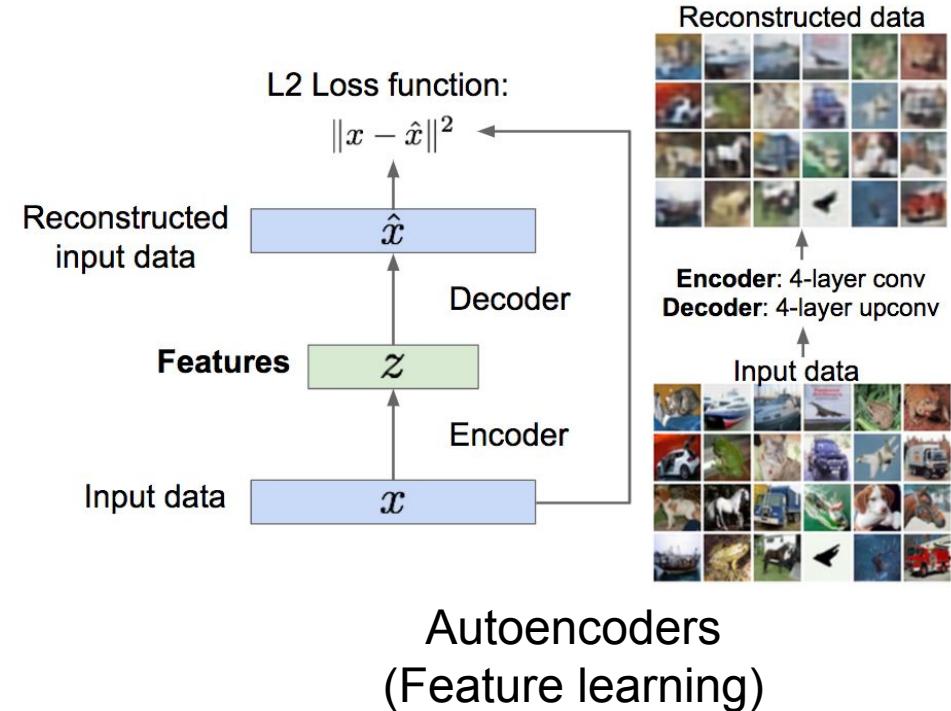
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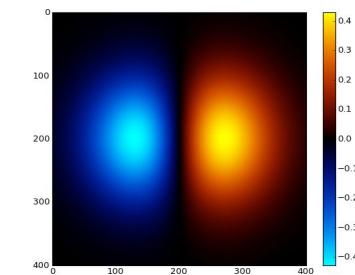
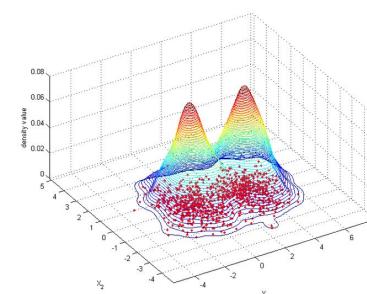
**Goal:** Learn some underlying hidden *structure* of the data

**Examples:** Clustering, dimensionality reduction, feature learning, density estimation, etc.



Figure copyright Ian Goodfellow, 2016. Reproduced with permission.

1-d density estimation



2-d density estimation

2-d density images [left](#) and [right](#)  
are CC0 public domain

# Supervised vs Unsupervised Learning

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# Supervised vs Unsupervised Learning

## Supervised Learning

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**Examples:** Classification,  
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semantic segmentation, image  
captioning, etc.

## Unsupervised Learning

Training data is cheap

**Data:**  $x$

Just data, no labels!

**Goal:** Learn some underlying  
hidden *structure* of the data

Holy grail: Solve  
unsupervised learning  
 $\Rightarrow$  understand structure  
of visual world

# Generative Models

Given training data, generate new samples from same distribution



Training data  $\sim p_{\text{data}}(x)$



Generated samples  $\sim p_{\text{model}}(x)$

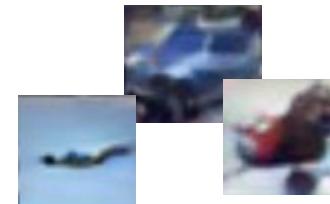
Want to learn  $p_{\text{model}}(x)$  similar to  $p_{\text{data}}(x)$

# Generative Models

Given training data, generate new samples from same distribution



Training data  $\sim p_{\text{data}}(x)$



Generated samples  $\sim p_{\text{model}}(x)$

Want to learn  $p_{\text{model}}(x)$  similar to  $p_{\text{data}}(x)$

Addresses density estimation, a core problem in unsupervised learning

## Several flavors:

- Explicit density estimation: explicitly define and solve for  $p_{\text{model}}(x)$
- Implicit density estimation: learn model that can sample from  $p_{\text{model}}(x)$  w/o explicitly defining it

# Why Generative Models?

- Realistic samples for artwork, super-resolution, colorization, etc.



- Generative models of time-series data can be used for simulation and planning (reinforcement learning applications!)
- Training generative models can also enable inference of latent representations that can be useful as general features

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# Taxonomy of Generative Models

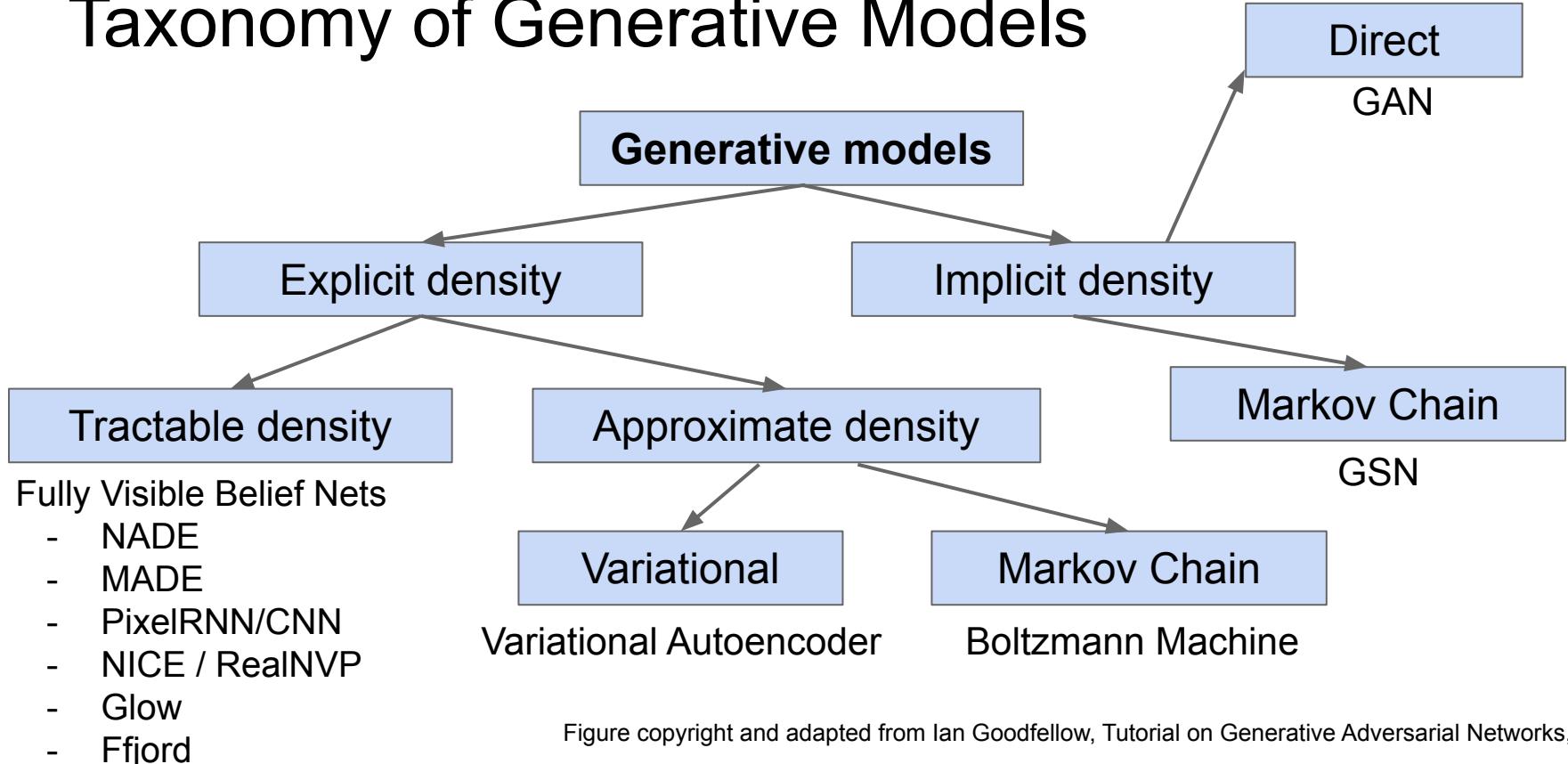


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

# Generative Adversarial Networks (GAN)

# Generative Adversarial Networks

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

14

Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this!

Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.

Q: What can we use to represent this complex transformation?

# Generative Adversarial Networks

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

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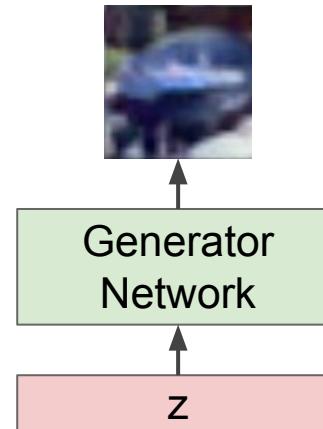
Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.

Q: What can we use to represent this complex transformation?

A: A neural network!

Output: Sample from training distribution

Input: Random noise



# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

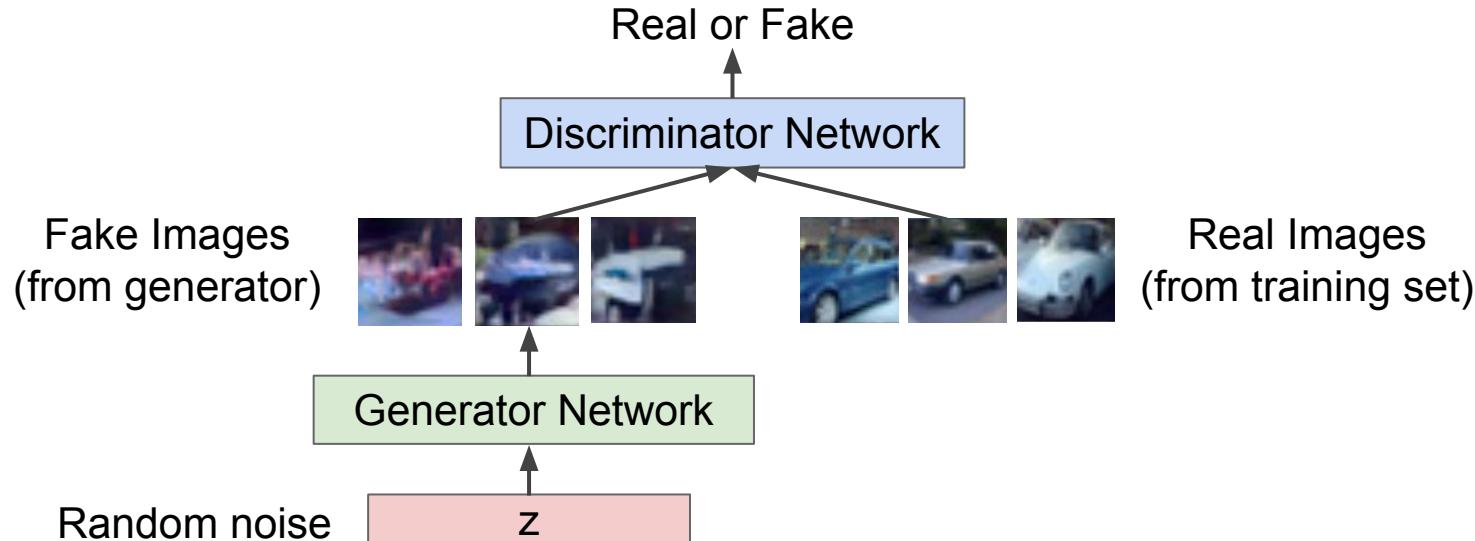
**Generator network:** try to fool the discriminator by generating real-looking images

**Discriminator network:** try to distinguish between real and fake images

# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

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Fake and real images copyright Emily Denton et al. 2015. Reproduced with permission.

# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

**Generator network:** try to fool the discriminator by generating real-looking images

**Discriminator network:** try to distinguish between real and fake images

Train jointly in **minimax game**

Minimax objective function:

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

# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

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

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

Discriminator output for real data x

Discriminator output for generated fake data G(z)

# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

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- Discriminator ( $\theta_d$ ) wants to **maximize objective** such that  $D(x)$  is close to 1 (real) and  $D(G(z))$  is close to 0 (fake)
- Generator ( $\theta_g$ ) wants to **minimize objective** such that  $D(G(z))$  is close to 1 (discriminator is fooled into thinking generated  $G(z)$  is real)

# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Minimax objective function:

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

Alternate between:

1. **Gradient ascent** on discriminator

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

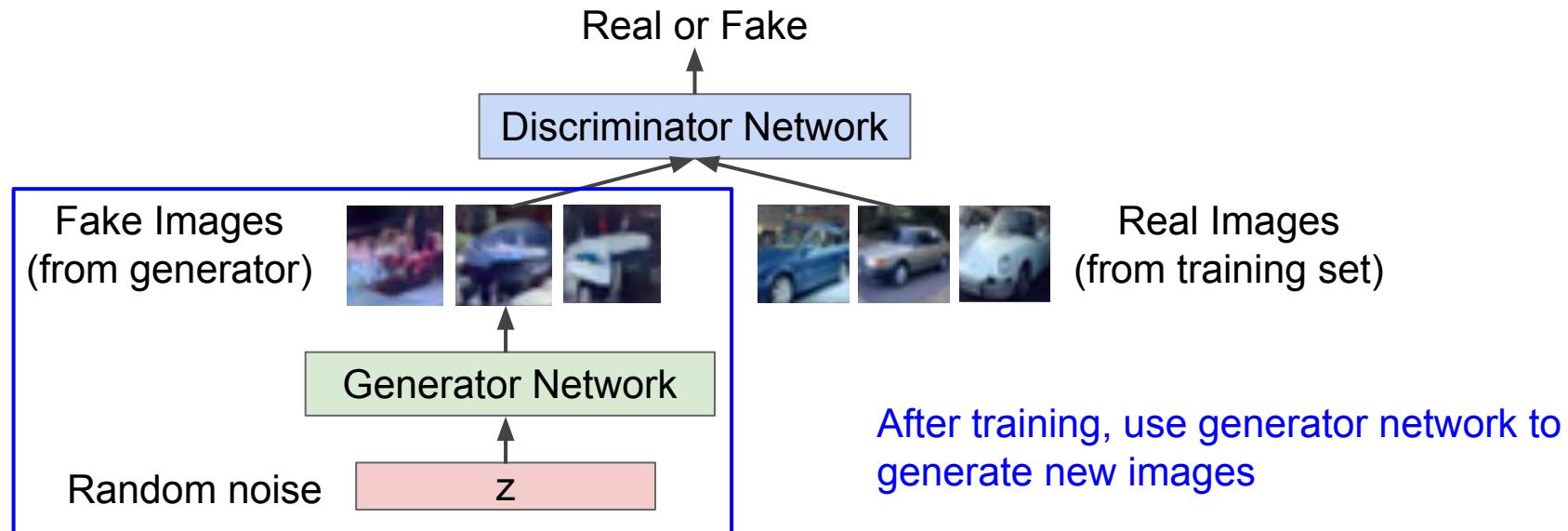
2. **Gradient descent** on generator

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

# Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

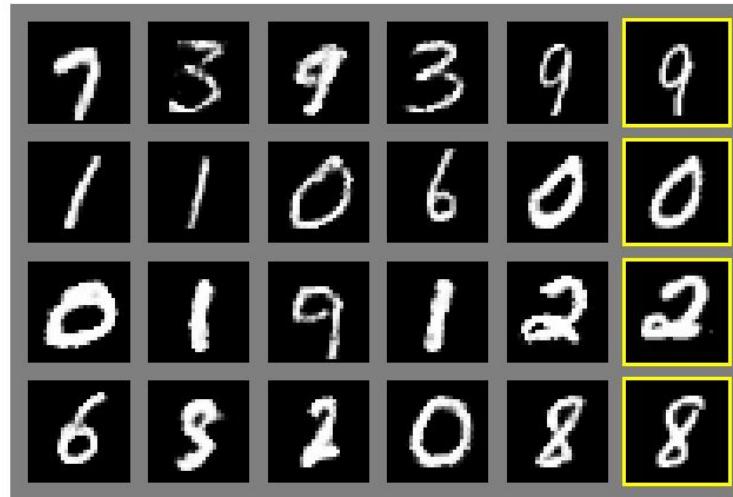
**Generator network:** try to fool the discriminator by generating real-looking images  
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Fake and real images copyright Emily Denton et al. 2015. Reproduced with permission.

# Generative Adversarial Nets

Generated samples

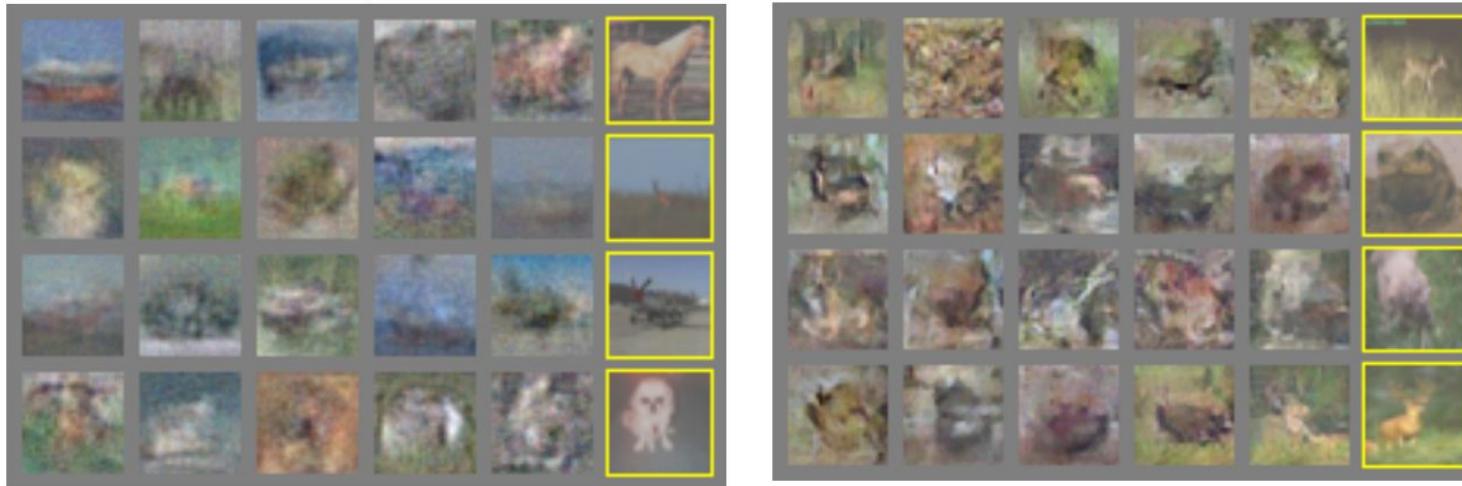


Nearest neighbor from training set

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# Generative Adversarial Nets

Generated samples (CIFAR-10)



Nearest neighbor from training set

Figures copyright Ian Goodfellow et al., 2014. Reproduced with permission.

# Generative Adversarial Nets: Convolutional Architectures

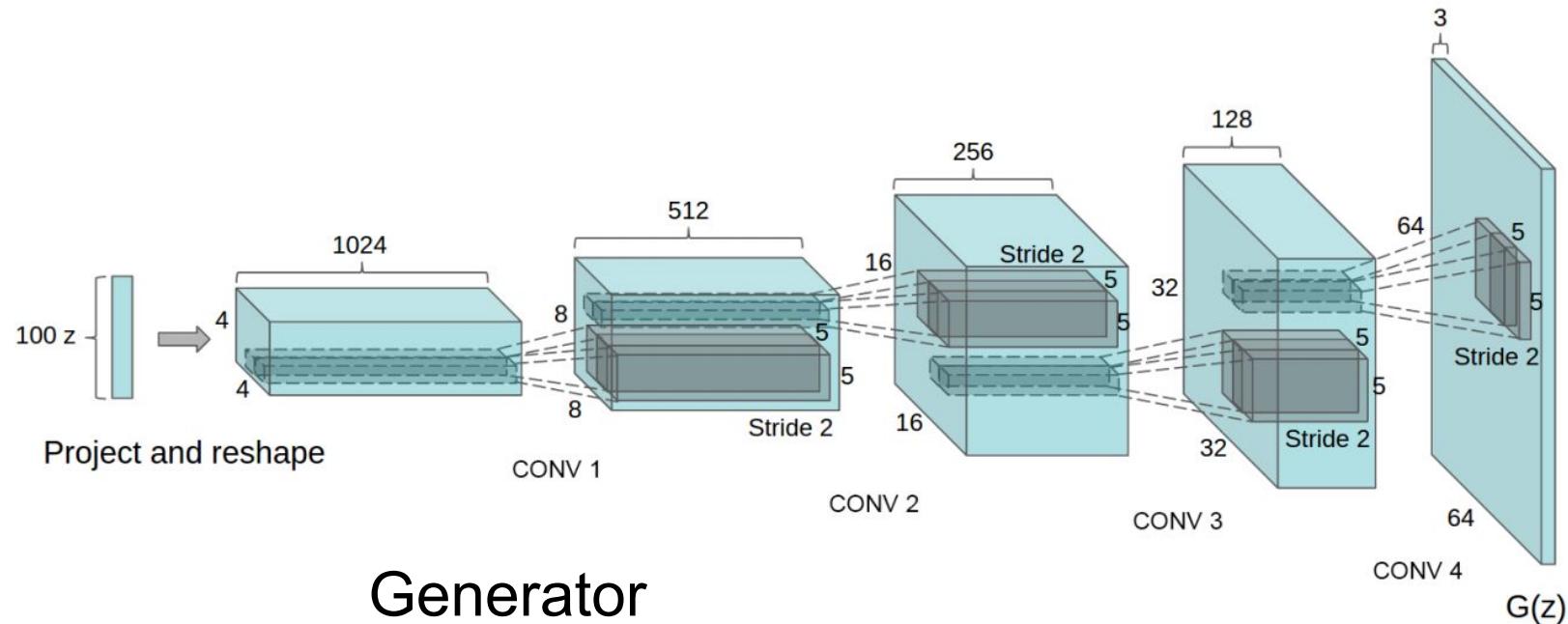
Generator is an upsampling network with fractionally-strided convolutions  
Discriminator is a convolutional network

Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

# Generative Adversarial Nets: Convolutional Architectures



Generator

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

# Generative Adversarial Nets: Convolutional Architectures

Samples from the model look much better!



Radford et al,  
ICLR 2016

# Generative Adversarial Nets: Convolutional Architectures

Interpolating  
between  
random  
points in latent  
space



Radford et al,  
ICLR 2016

# Generative Adversarial Nets: Interpretable Vector Math

Smiling woman



Neutral woman



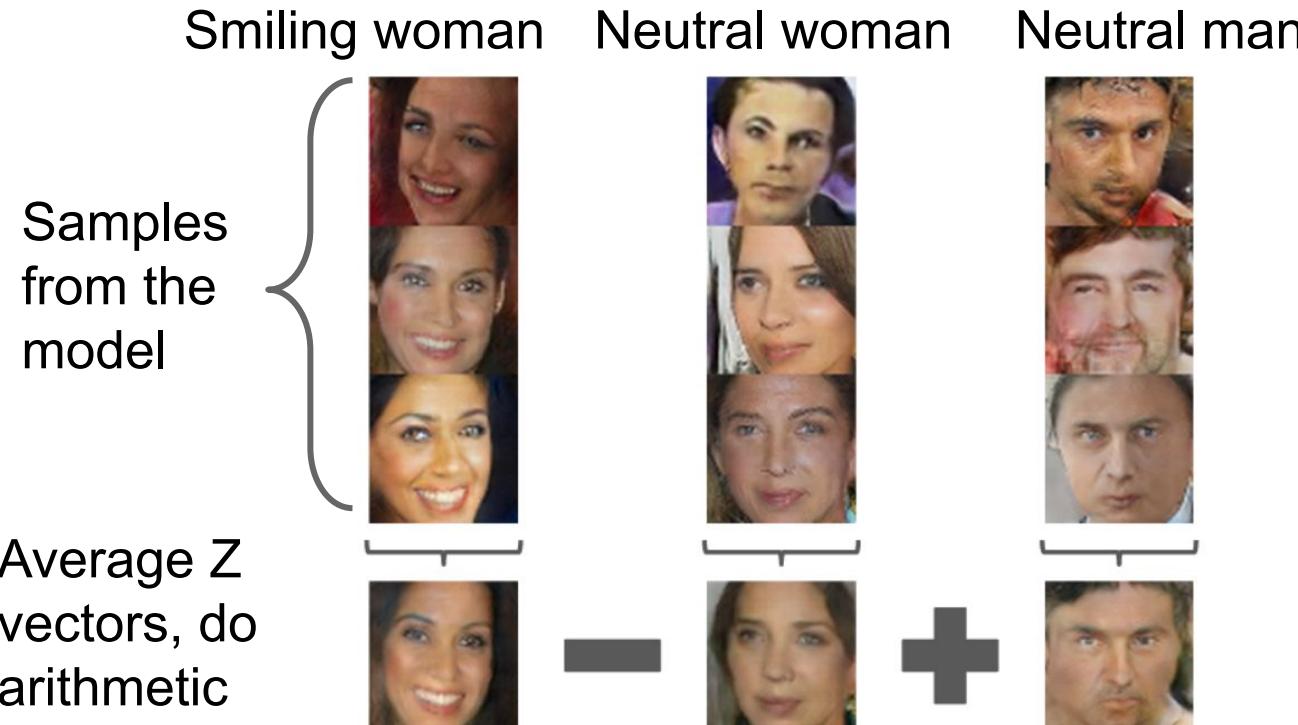
Neutral man



Samples  
from the  
model

Radford et al, ICLR 2016

# Generative Adversarial Nets: Interpretable Vector Math

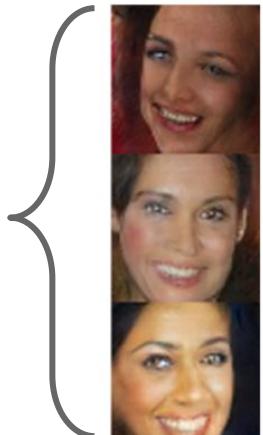


Radford et al, ICLR 2016

# Generative Adversarial Nets: Interpretable Vector Math

Smiling woman   Neutral woman   Neutral man

Samples  
from the  
model



Average Z  
vectors, do  
arithmetic



Radford et al, ICLR 2016

Smiling Man

# Generative Adversarial Nets: Interpretable Vector Math

Glasses man



No glasses man



No glasses woman



Radford et al,  
ICLR 2016



# Generative Adversarial Nets: Interpretable Vector Math

Glasses man



No glasses man



No glasses woman



Radford et al,  
ICLR 2016

Woman with glasses



# 2017: Explosion of GANs

## “The GAN Zoo”

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdAGAN - AdaGAN: Boosting Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorical GANs
- b-GAN - b-GAN: Unified Framework of Generative Adversarial Networks
- Bayesian GAN - Deep and Hierarchical Implicit Models
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks
- CCGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CoGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
- DTN - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DR-GAN - Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- EBGAN - Energy-based Generative Adversarial Network
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- GAWWN - Learning What and Where to Draw
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data
- Geometric GAN - Geometric GAN
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending
- IAN - Neural Photo Editing with Introspective Adversarial Networks
- iGAN - Generative Visual Manipulation on the Natural Image Manifold
- IcGAN - Invertible Conditional GANs for image editing
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- Improved GAN - Improved Techniques for Training GANs
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
- LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis
- LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

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

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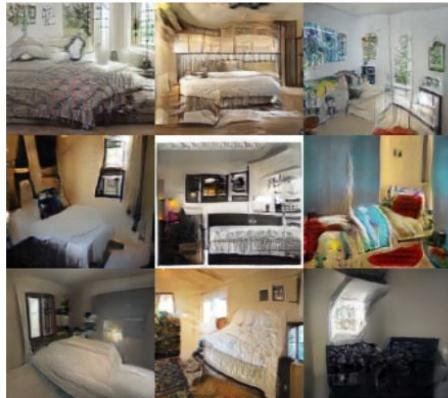
See also: <https://github.com/soumith/ganhacks> for tips and tricks for trainings GANs

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# 2017: Explosion of GANs

Better training and generation



LSGAN, Zhu 2017.



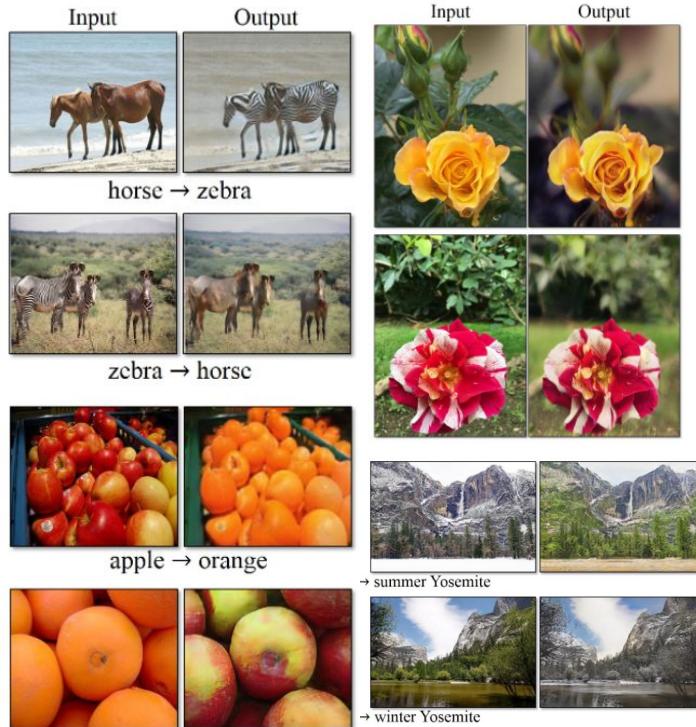
Wasserstein GAN,  
Arjovsky 2017.  
Improved Wasserstein  
GAN, Gulrajani 2017.



Progressive GAN, Karras 2018.

# 2017: Explosion of GANs

Source->Target domain transfer



CycleGAN. Zhu et al. 2017.

## Text -> Image Synthesis

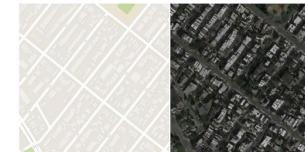
this small bird has a pink breast and crown, and black primaries and secondaries.

this magnificent fellow is almost all black with a red crest, and white cheek patch.



Reed et al. 2017.

## Many GAN applications



Pix2pix. Isola 2017. Many examples at <https://phillipi.github.io/pix2pix/>

# 2019: BigGAN



Brock et al., 2019

# GANs

Don't work with an explicit density function

Take game-theoretic approach: learn to generate from training distribution through 2-player game

Pros:

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

Cons:

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

Active areas of research:

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

# Useful Resources on Generative Models

CS 236: [Deep Generative Models](#) (Stanford)

CS 294-158 [Deep Unsupervised Learning](#) (Berkeley)