Security and Fairness of Deep Learning

Generative Adversarial Networks

Spring 2020

Today

- Background discussions
  - “Latent” features
  - Autoencoders
  - Gradient descent variations
- Generative Adversarial Networks

“Latent” features

Recall: Linear score function

$$f(x_i, W) = Wx_i$$

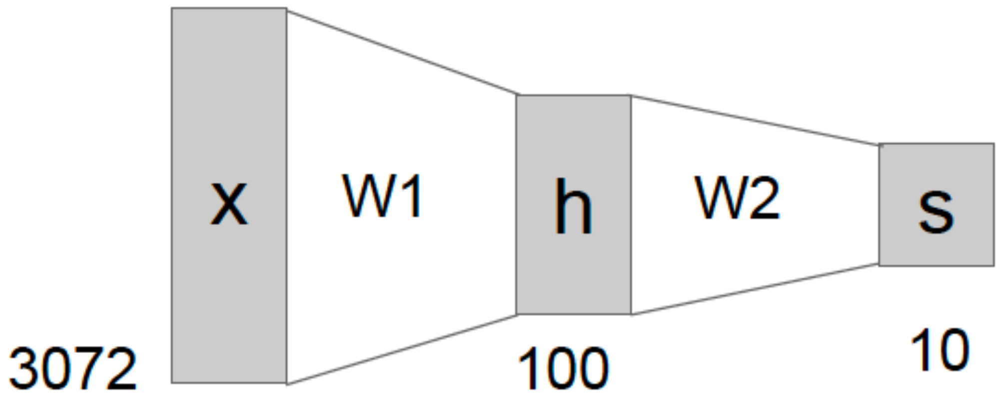
$$\underbrace{\begin{bmatrix} 0.2 & -0.5 & 0.1 & 2.0 \\ 1.5 & 1.3 & 2.1 & 0.0 \\ 0 & 0.25 & 0.2 & -0.3 \end{bmatrix}}_{W} \underbrace{\begin{bmatrix} 1.1 \\ 3.2 \\ -1.2 \end{bmatrix}}_{b} \quad \underbrace{\begin{bmatrix} 56 \\ 231 \\ 24 \\ 2 \\ 1 \end{bmatrix}}_{x_i}$$

For CIFAR:

W: 10 x 3072
x: 3072 x 1
10 class scores

2-Layer neural network

$$s = W_2 \max(0, W_1 x)$$



For CIFAR:

W1: 100 x 3072
W2: 10 x 100
x: 3072 x 1
10 class scores

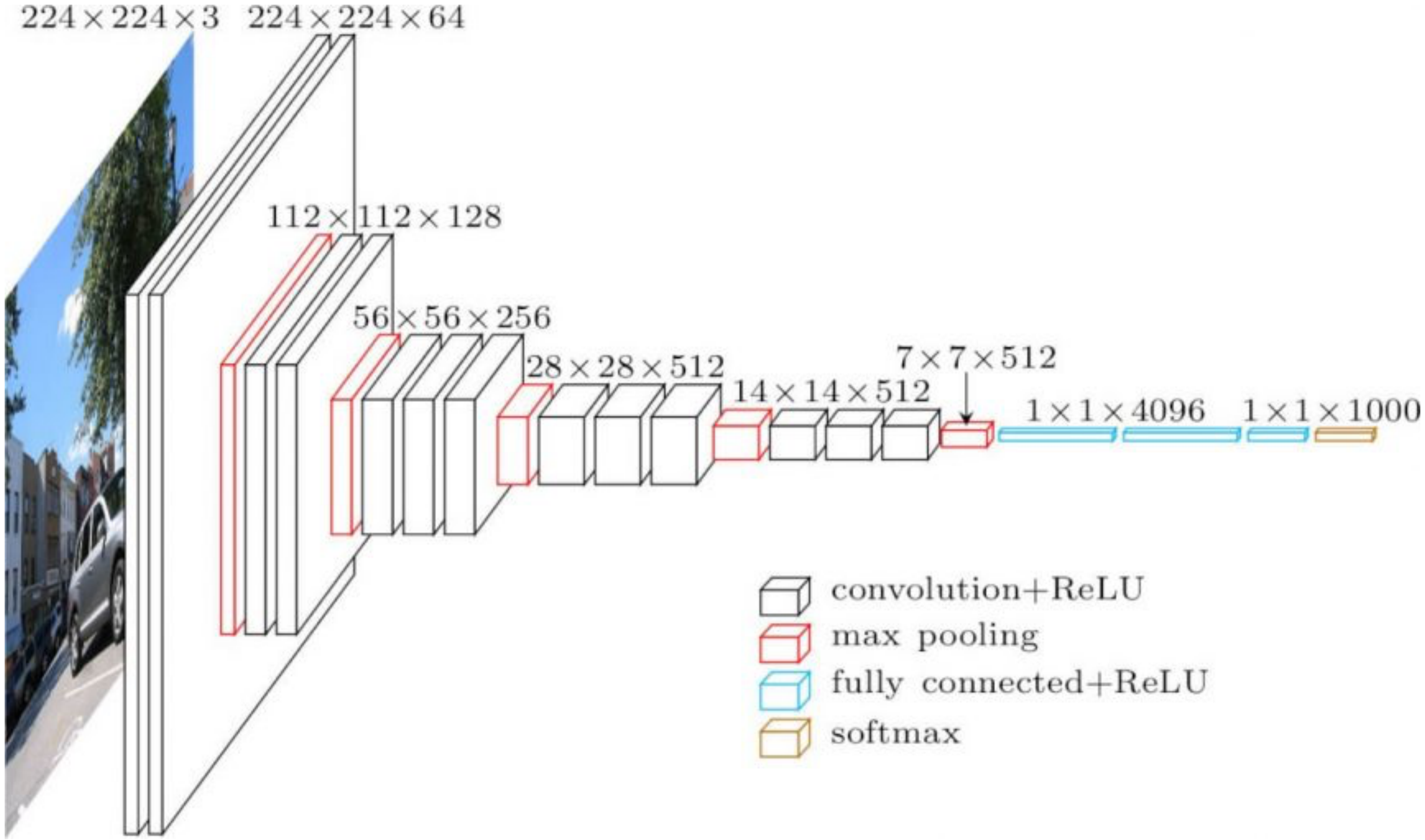
- Iterated construction: linear function followed by non-linear function
- Training network: learn W1, W2 using stochastic gradient descent; use backpropagation to compute gradients

“latent” features

- Unforced
  - Compare to input features, target class feature
- Uninterpretable
  - Visualization methods can help
- Feature extractors
  - “General purpose” vision models and “transfer learning”

VGG16 use-case

- Download pre-trained model up to the first fully connected layer.
- Add another fully connected layer to intended output.
- Train only the new parameters on your dataset.

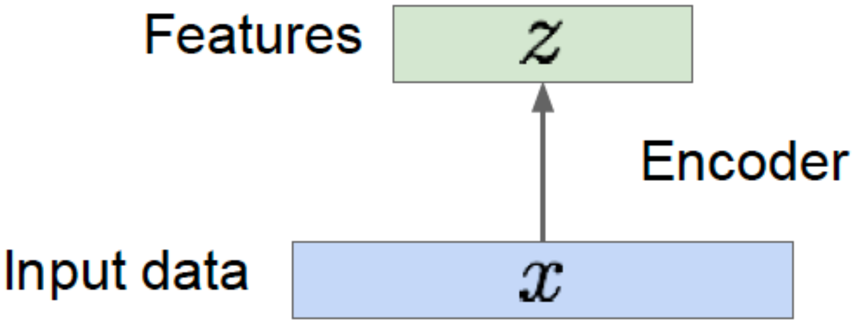


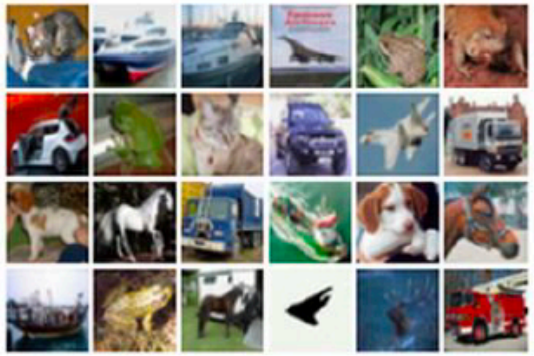
Example for 1000 classes.

Autoencoders

Autoencoders

Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data





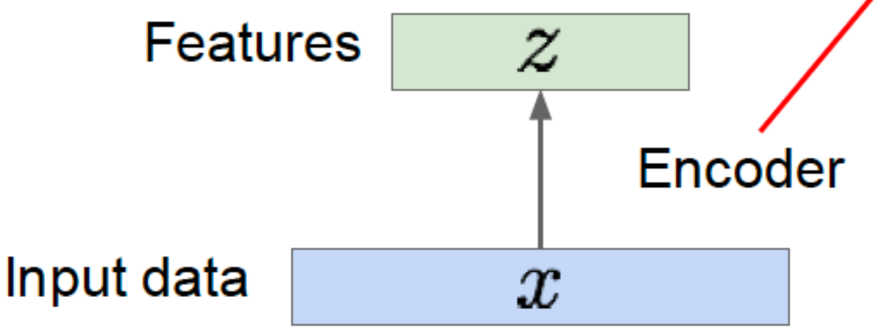
Autoencoders

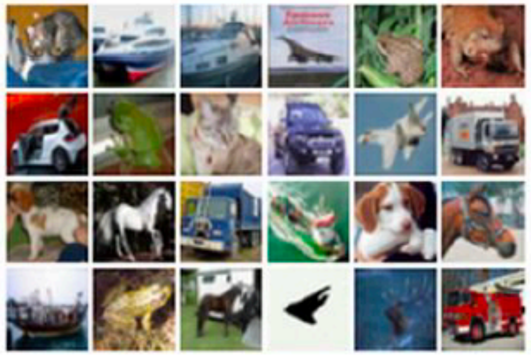
Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

z usually smaller than **x**
(dimensionality reduction)

Q: Why dimensionality reduction?

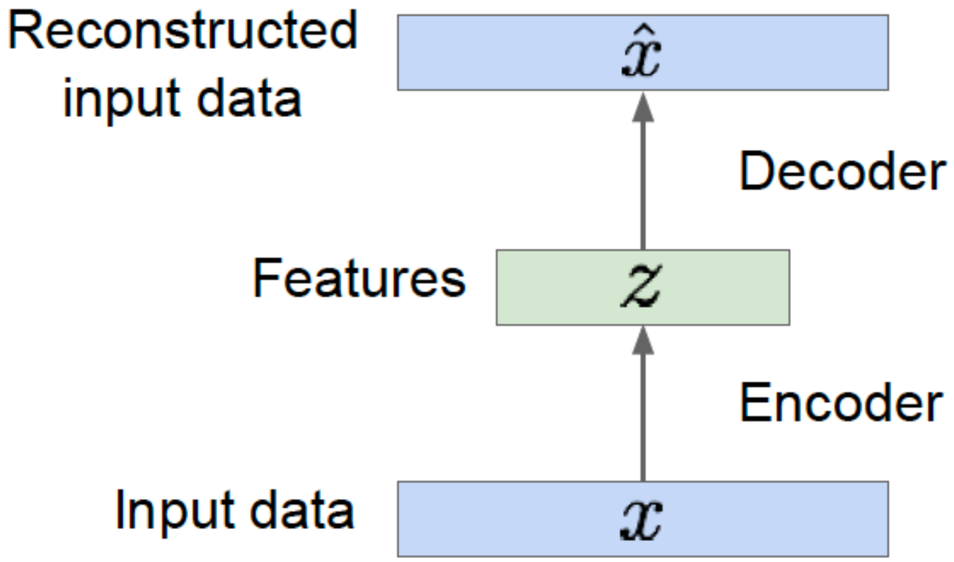
Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN

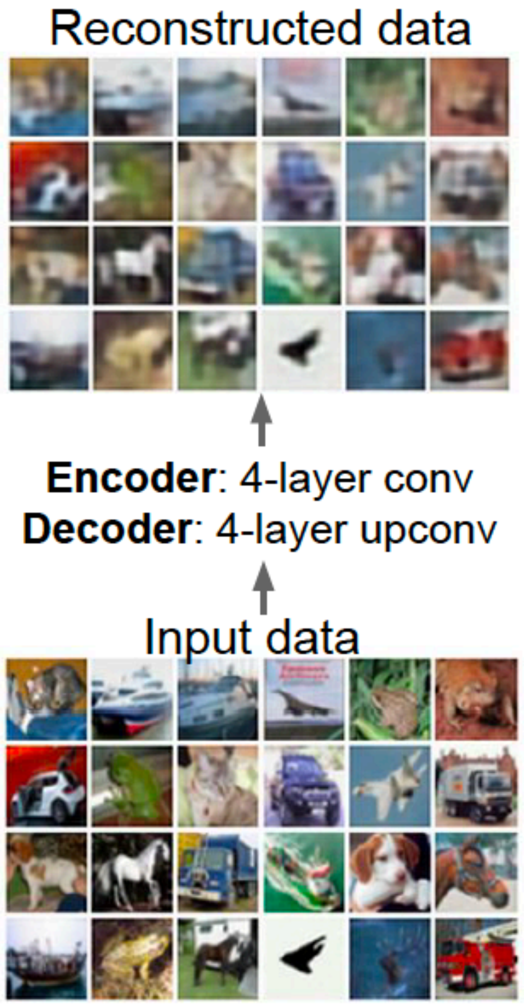




Autoencoders

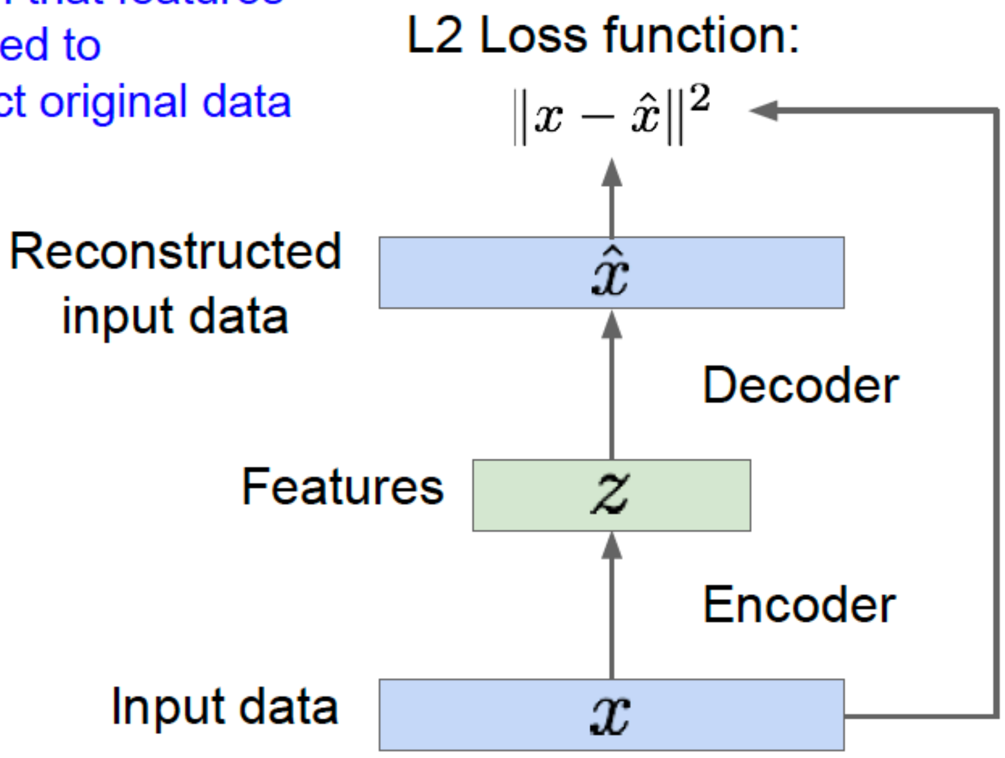
How to learn this feature representation?
Train such that features can be used to reconstruct original data
"Autoencoding" - encoding itself

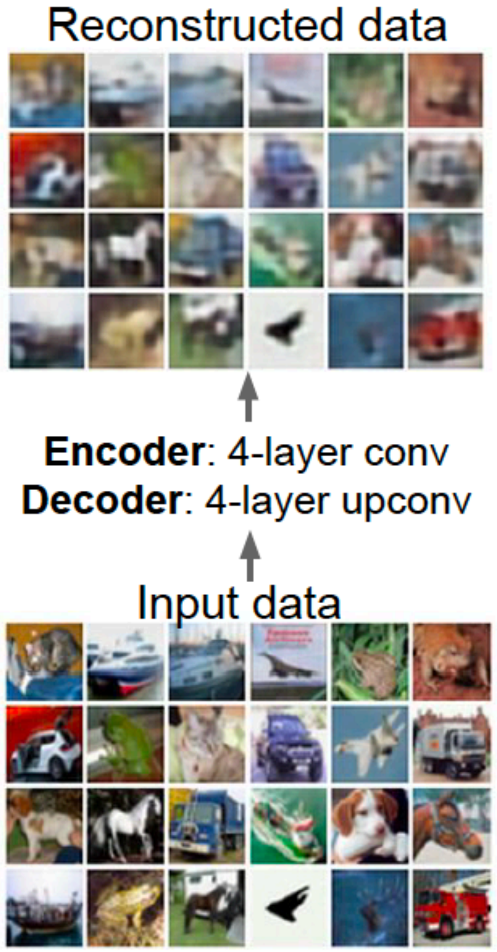




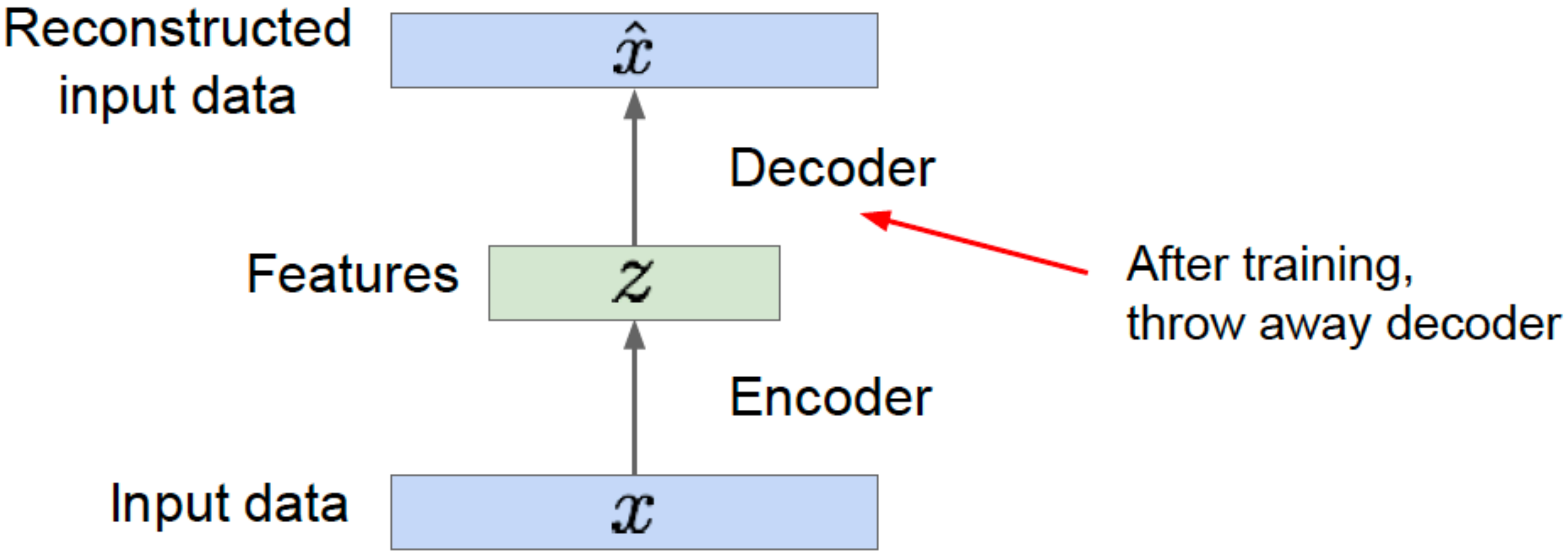
Autoencoders

Train such that features can be used to reconstruct original data



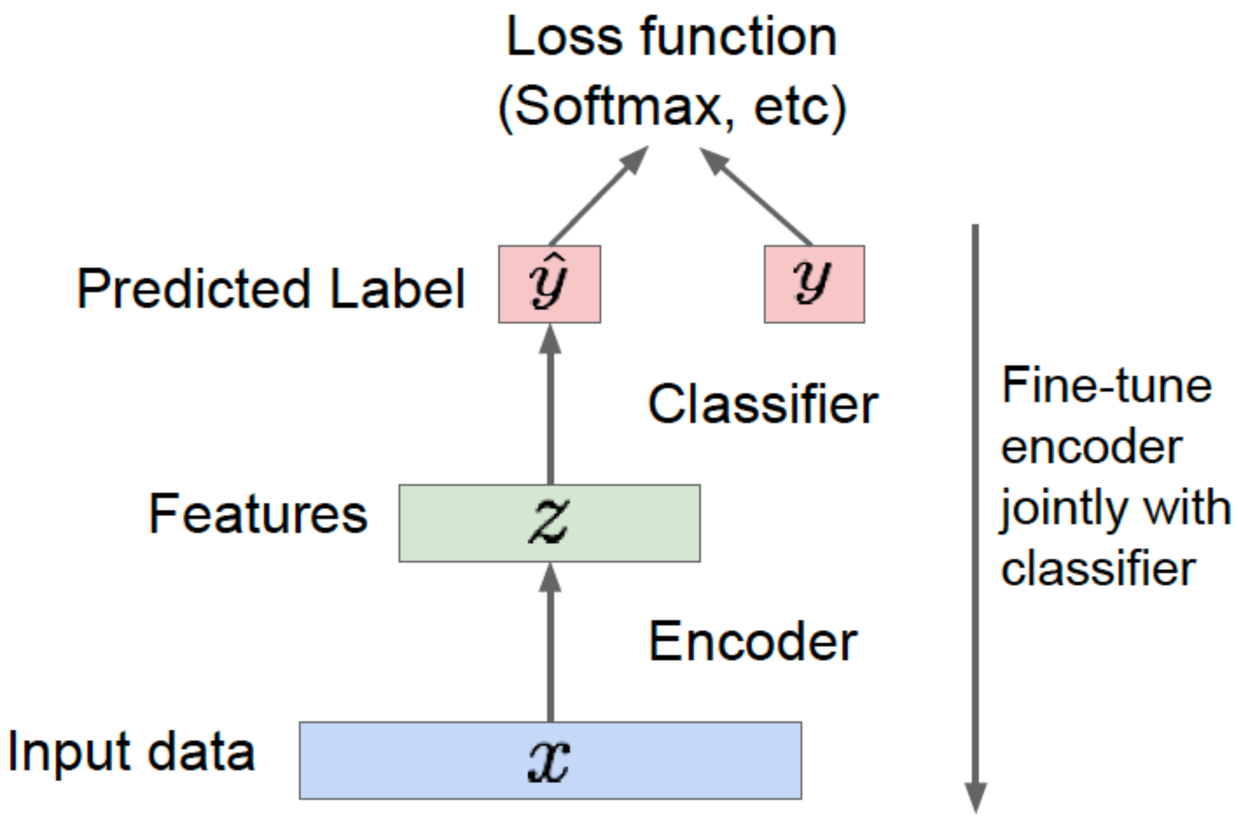


Autoencoders for unsupervised pretraining

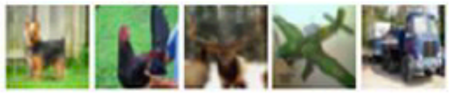


Autoencoders for unsupervised pretraining

Encoder can be used to initialize a **supervised** model



Train for final task (sometimes with small data)



Stacked auto-encoders: Bengio et al., [Greedy Layer-Wise Training of Deep Networks](), NIPS 2006

Gradient descent variations

More gradient descent variations

- Initialize:
  - θ -- parameters
- Do for epochs, instances, batches, …
  - $\theta \leftarrow \theta - \eta \nabla_\theta L(\theta, x, y)$

- Initialize:
  - $\theta = (\theta_1, \theta_2)$-- parameters
- Do for epochs, instances, batches, …
  - $\theta_1 \leftarrow \theta_1 - \eta \nabla_{\theta_1} L_{1(\theta,x,y)}$
  - $\theta_2 \leftarrow \theta_2 - \eta \nabla_{\theta_2} L_{2(\theta,x,y)}$

Variations

- Update in batches.
- Learning rate variations.

- Learning things other than parameters.
  - Adversarial examples.

- Update only a subset of parameters.
  - Transfer learning, unsupervised pre-training

- Multiple (competing) loss functions.
  - GAN (today)
  - Privacy/fairness applications (later)
    - Loss 1 = target class prediction loss
    - Loss 2 = - prediction of private/sensitive feature

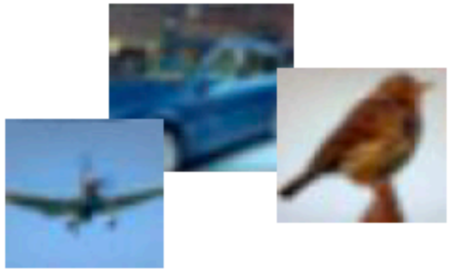
Generative Adversarial Networks

Generative models

- Collect large amount of data in some domain
- Train generative model to generate data like it
    - Compare to “discriminative”

Generative model

- Given training data generate samples from same distribution



Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

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

Source: Fei-Fei Li et al.

Key idea

- Generative models cannot memorize training data since they are not given enough parameters
- Forced to learn higher-level features from which they can reconstruct data

Why generative models?

- Long-term hope
  - Learn the “natural” features of a dataset

- Current applications
  - image denoising, inpainting, super-resolution, and neural network pretraining in cases where labeled data is expensive (will discuss today)

Generative models

- Generative adversarial networks (GAN)

- Other models
  - Variational autoencoders (see also: Variational fair autoencoder)
  - Boltzmann machines

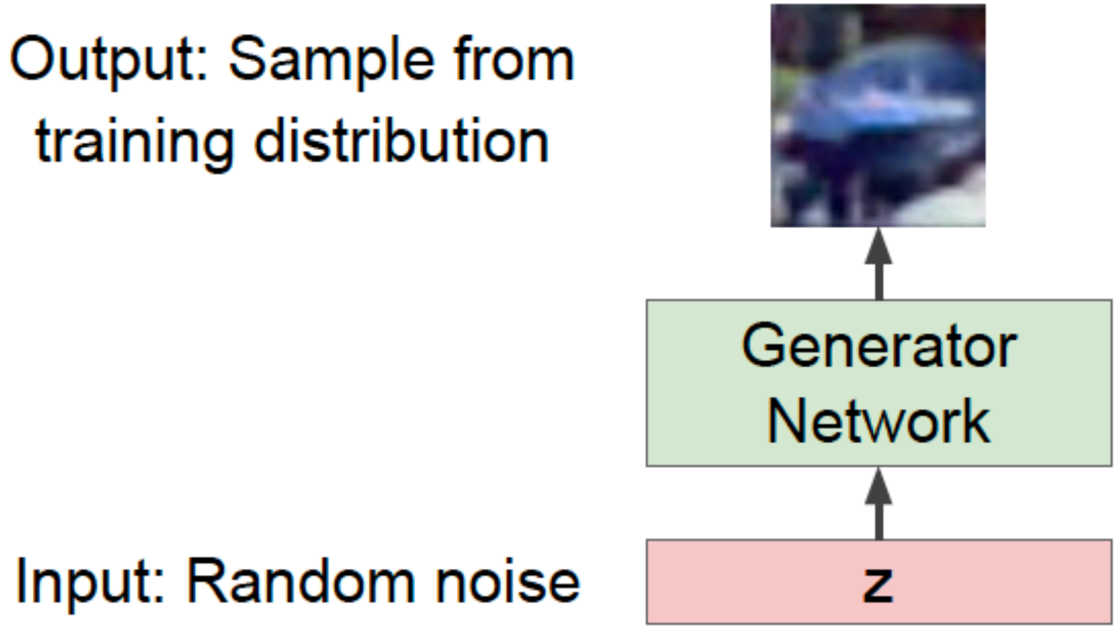
GANs

- Goal: Sample from complex, high-dimensional training distribution

- Approach
  - Sample from a simple distribution (e.g., random noise)
  - Learn transformation to training distribution

- Question
  - How to represent this complex transformation?
  - A neural network!

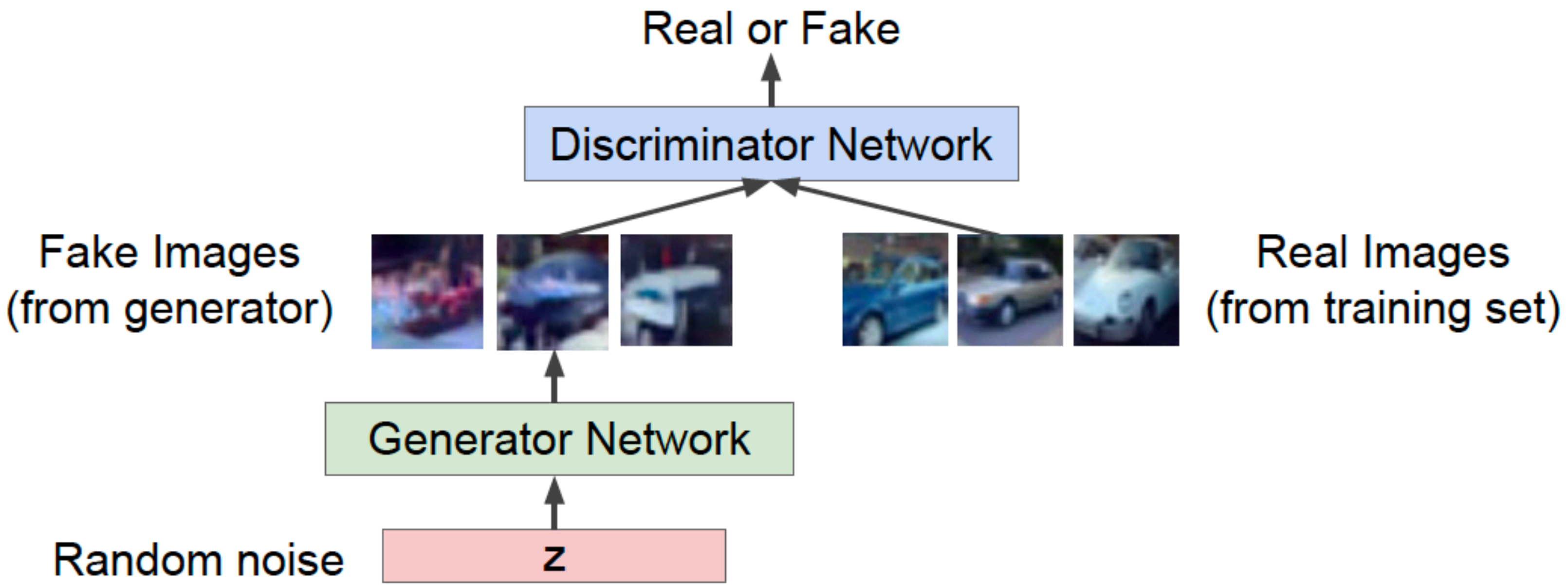
GANs



- Implicit density estimation
  - Can sample from training distribution without explicitly representing it

Training GANs

- Two player game
  - Generator: try to fool discriminator by generating real-looking images
  - Discriminator: try to distinguish between real and fake images



Training GANs

- Two player game
  - Generator: try to fool discriminator by generating real-looking images
  - Discriminator: try to distinguish between real and fake images

Train jointly in **minimax game**

Minimax objective function:

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

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

Training GANs

Train jointly in **minimax game**

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

Minimax objective function:

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

- Discriminator (θ_d) wants to **maximize objective** such that D(x) is close to 1 (real) and D(G(z)) is close to 0 (fake)

- Generator (θ_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

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

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

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

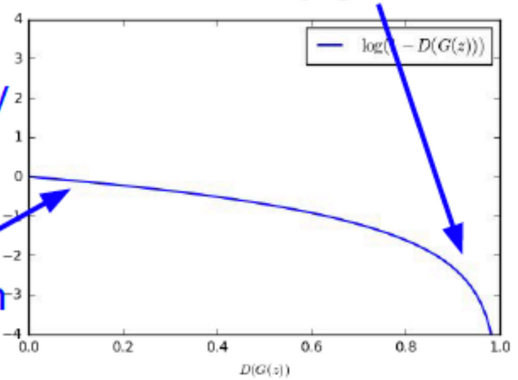
2. **Gradient descent** on generator

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

In practice, optimizing this generator objective does not work well!

When sample is likely fake, want to learn from it to improve generator. But gradient in this region is relatively flat!

Gradient signal dominated by region where sample is already good



Training GANs

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:

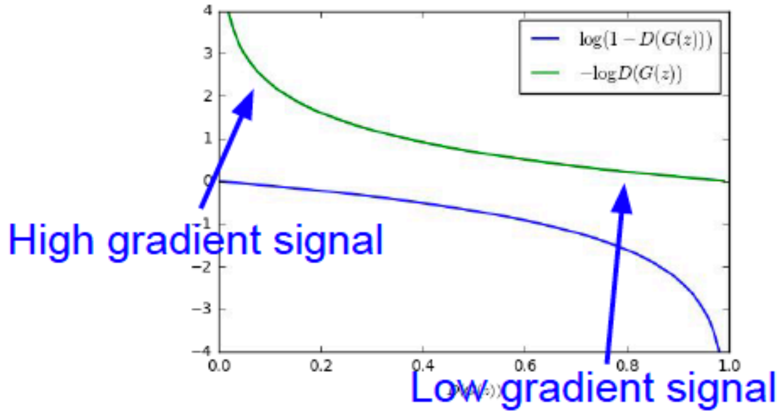
1. **Gradient ascent** on discriminator

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

2. **Instead: Gradient ascent** on generator, different objective

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

Instead of minimizing likelihood of discriminator being correct, now maximize likelihood of discriminator being wrong.
Same objective of fooling discriminator, but now higher gradient signal for bad samples => works much better! Standard in practice.



Training GANs

Putting it together: 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:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

  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 ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

Convergence theorem

- The training criterion allows one to recover the data generating distribution as G and D are given enough capacity

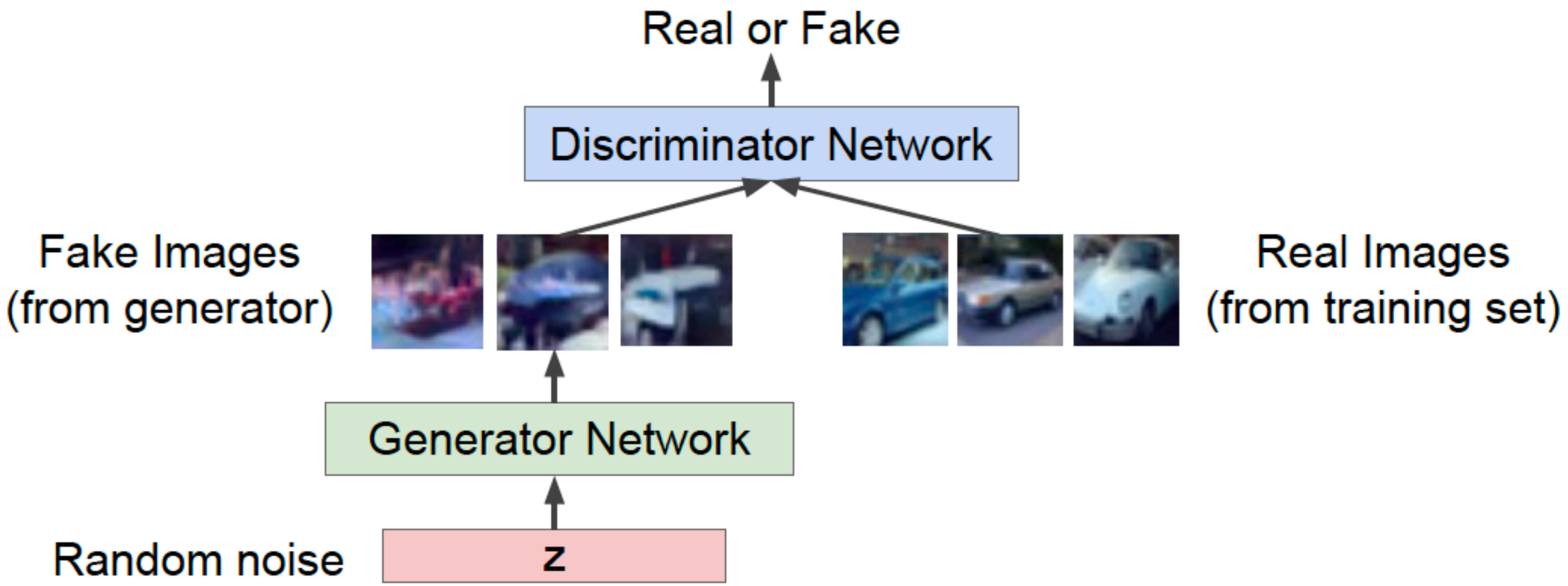
Proposition 2. *If G and D have enough capacity, and at each step of Algorithm 1, the discriminator is allowed to reach its optimum given G, and p_g is updated so as to improve the criterion*

$$\mathbb{E}_{\boldsymbol{x}\sim p_{data}}[\log D_G^*(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{x}\sim p_g}[\log(1 - D_G^*(\boldsymbol{x}))]$$

then p_g converges to p_{data}

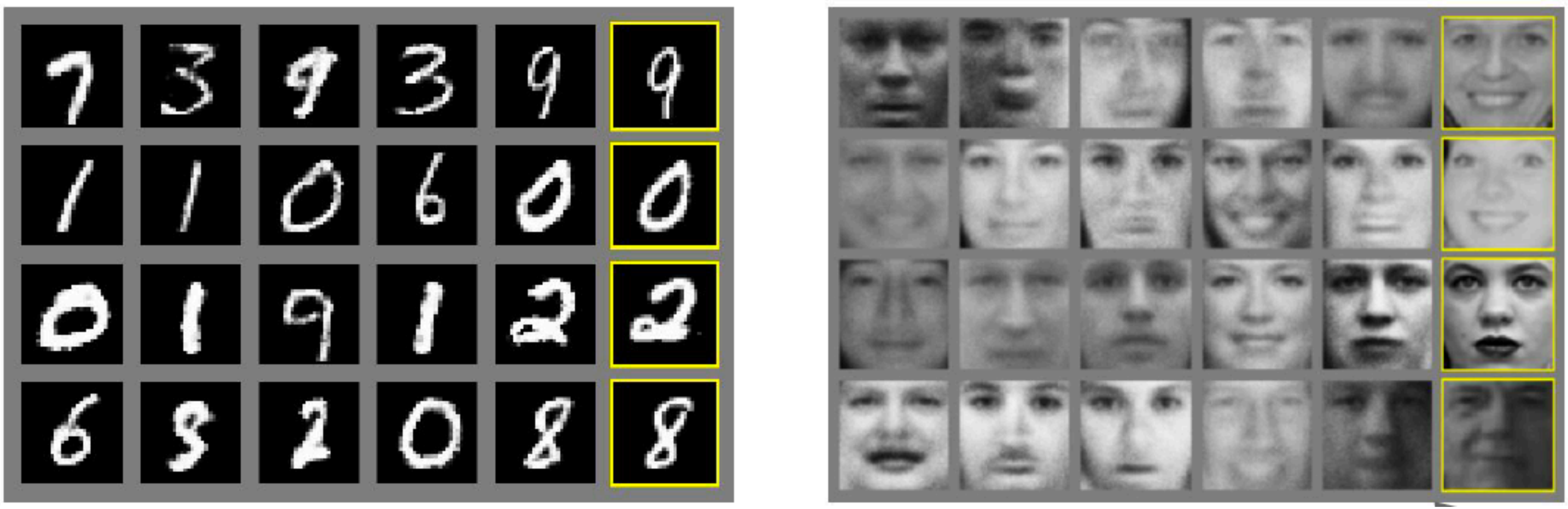
Training GANs

- Two player game
  - Generator: try to fool discriminator by generating real-looking images
  - Discriminator: try to distinguish between real and fake images



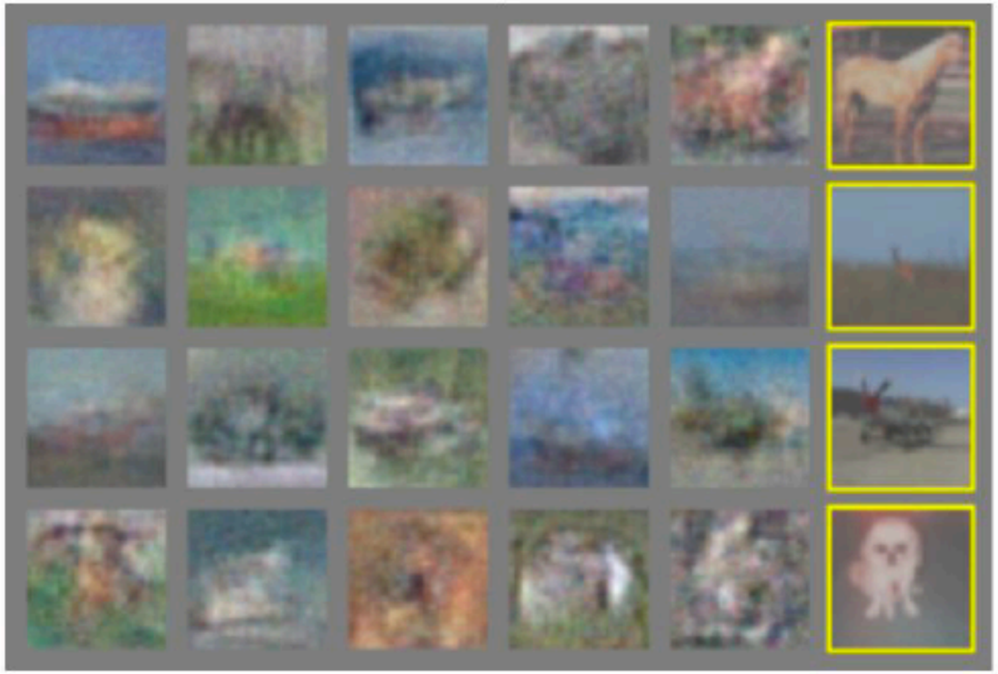
Generated samples

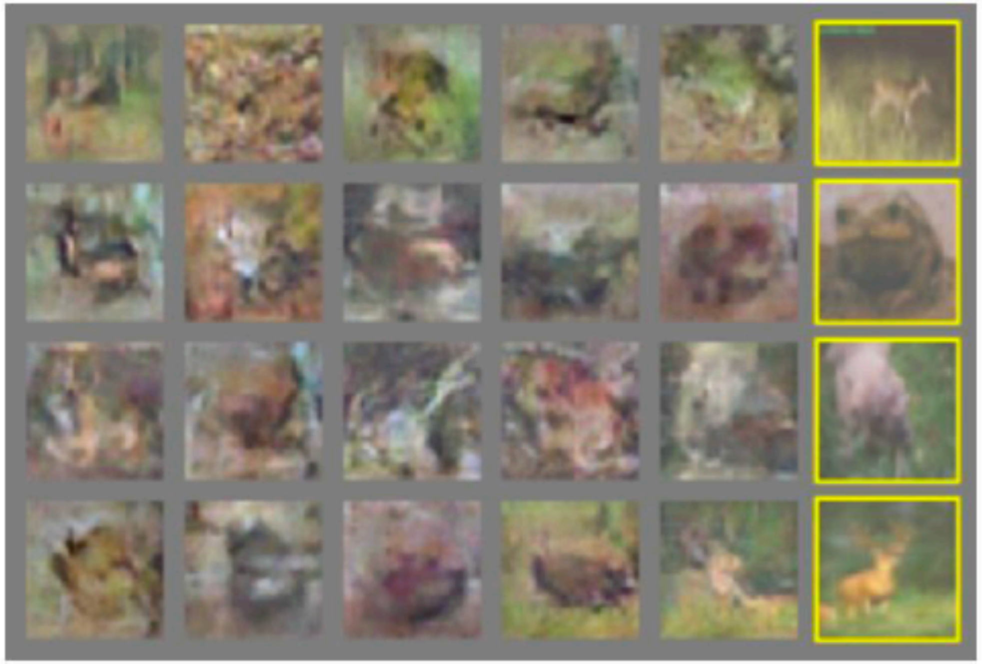
Generated samples



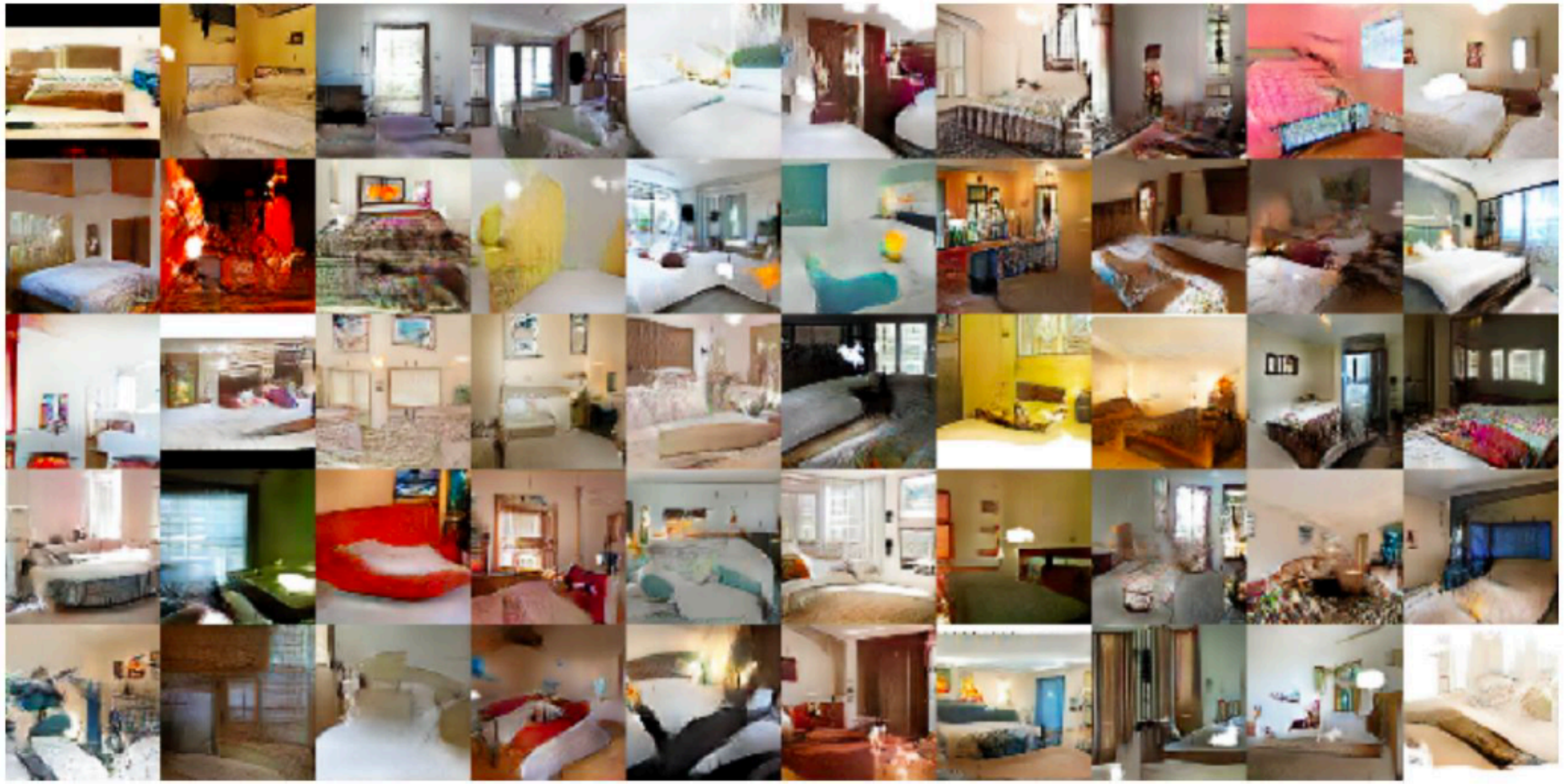
Generated samples

Generated samples (CIFAR-10)





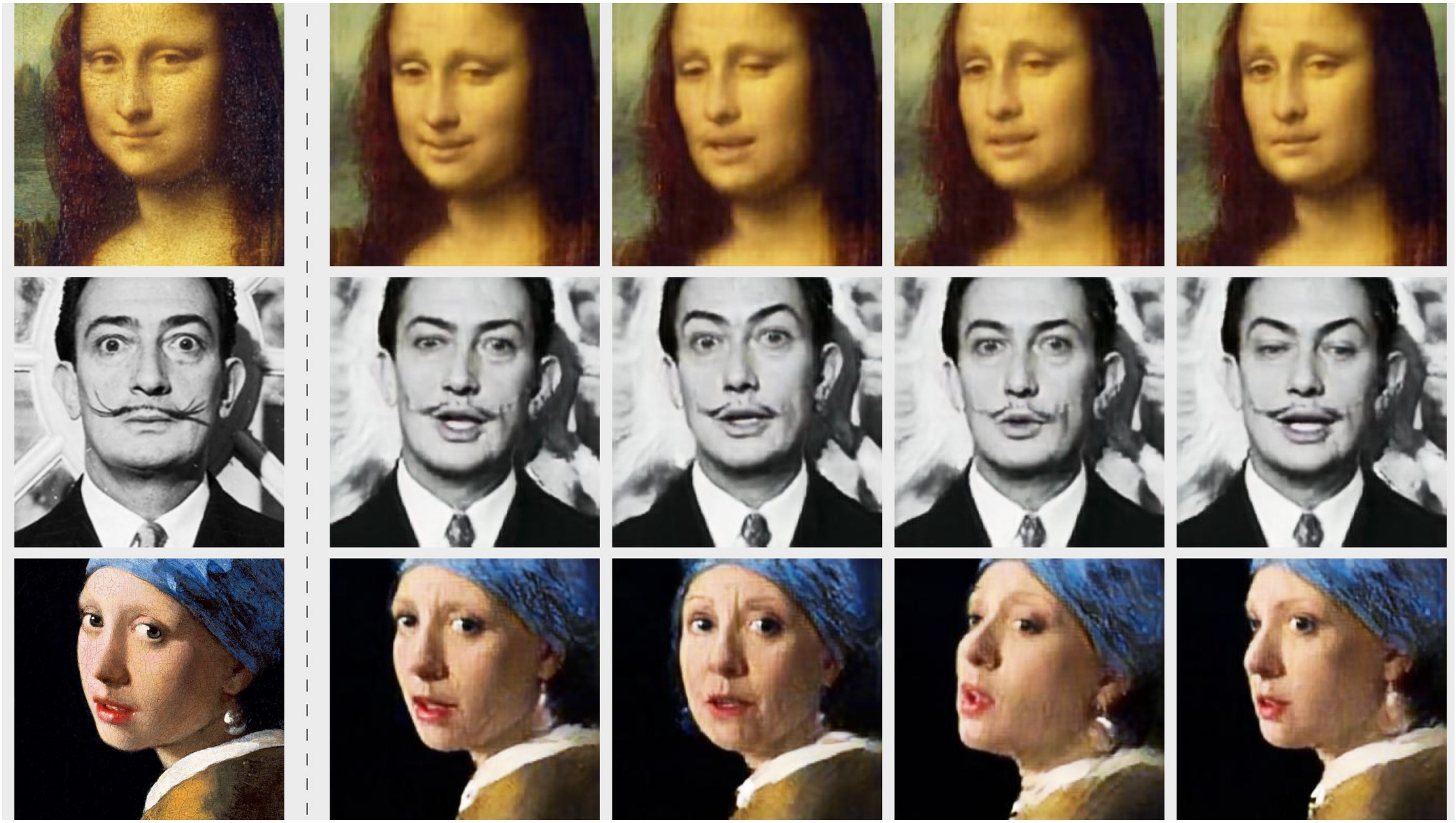
GANs: Convolutional architectures



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

GAN and company: implications

- Can generate and manipulate data/images that resemble a given distribution.



References and acknowledgments

- Fei-Fei Li et al.: Generative models
- OpenAI blog post on Generative Models
- Goodfellow et al.: Generative Adversarial Networks
- Spring 2018 Course

- Unsupervised pretraining reference
  - Erhan et al., Why Does Unsupervised Pre-training Help Deep Learning?, JMLR 11 (2010) 625-660