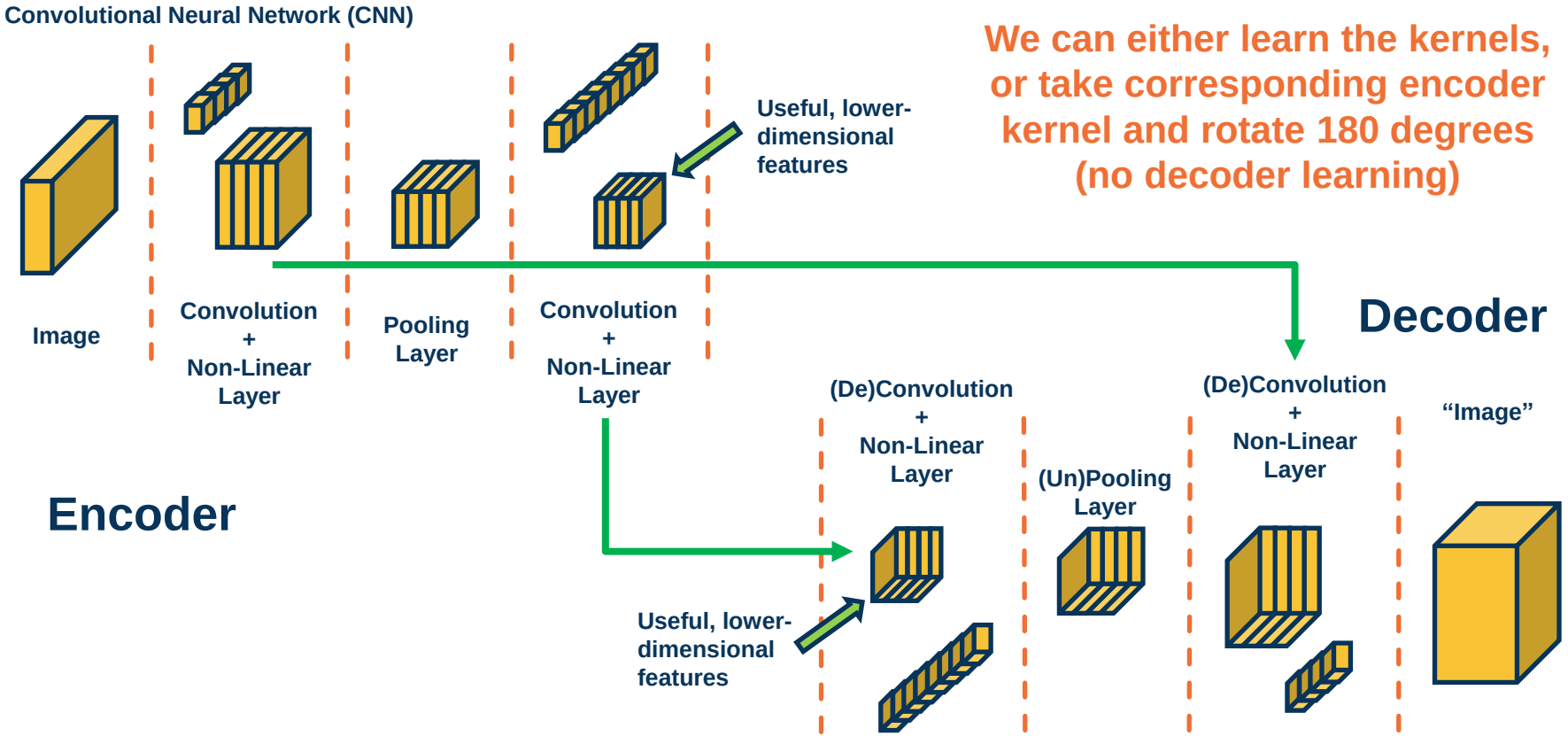
Topics:

- Generative Adversarial Networks

CS 4644-DL / 7643-A
ZSOLT KIRA

- **Assignment 3**
  - Due **March 8th 11:59pm EST**
- **Projects**
  - Project proposal due **March 14th**
- Next Meta office hours 03/14 3pm ET on machine translation

W9: Mar 3	Generative Models (Part I): Generative Adversarial Networks	• Generative Adversarial Networks ;
W9: Mar 5	Project Planning Session	
W10: Mar 10	Generative Models (Part II): Diffusion Models PS3/HW3 due Mar 8th 11:59pm (grace period Mar 10th), PS4/HW4 out (due Mar 30th)	
W10: Mar 12	Variational Autoencoders (VAEs) Project Check-in Due March 14th 11:59pm (grace period until March 16th)	• Tutorial on Variational Autoencoders
W11: Mar 17	Spring Break	
W11: Mar 19	Spring Break	



Symmetry in Encoder/Decoder

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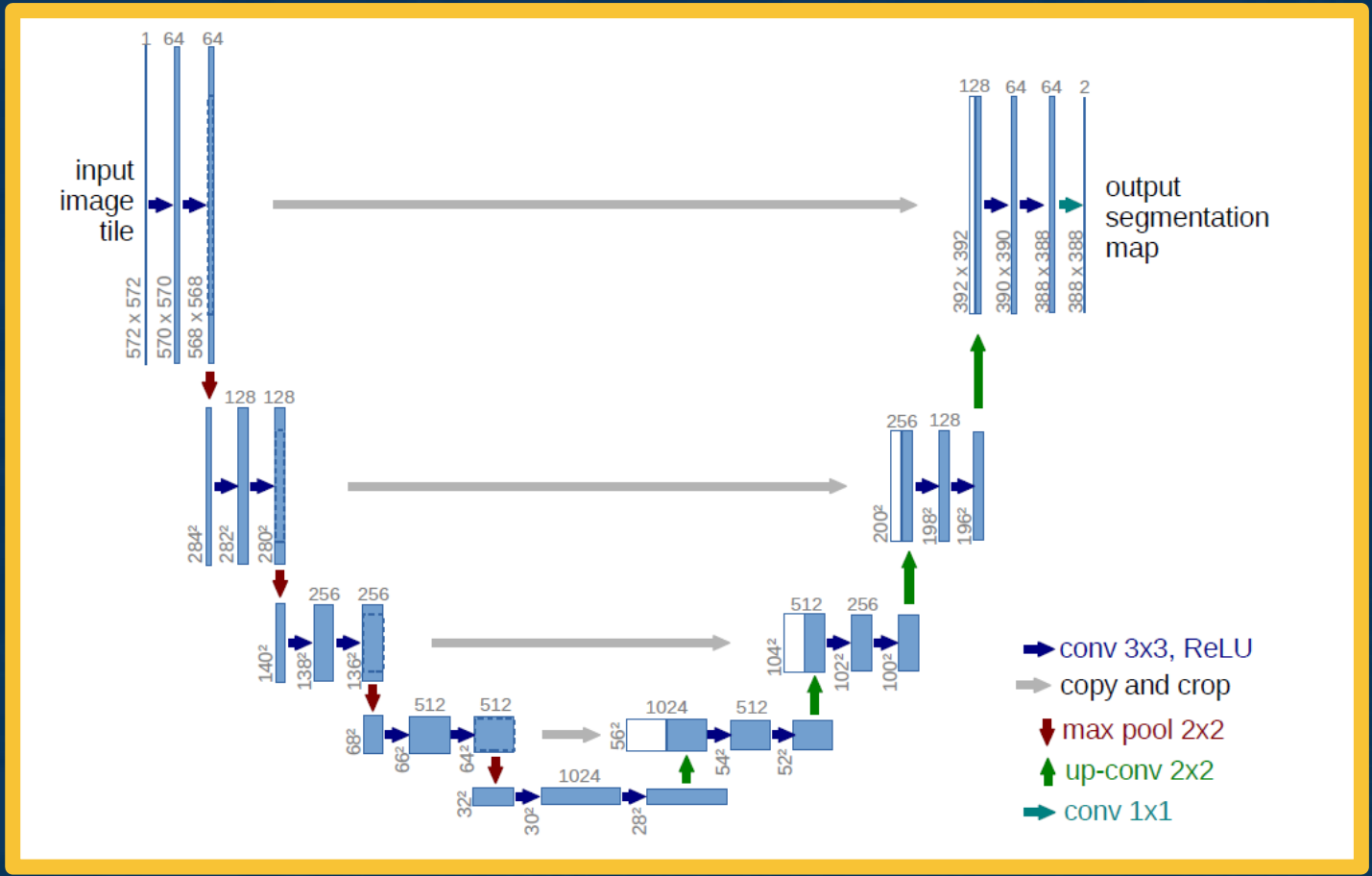
U-Net

You can have skip connections to bypass bottleneck!

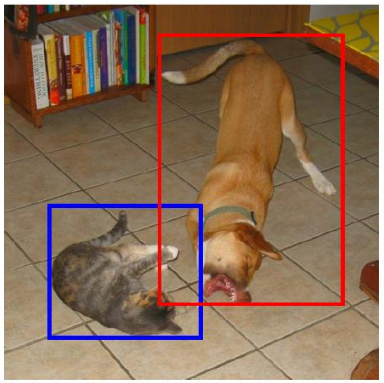


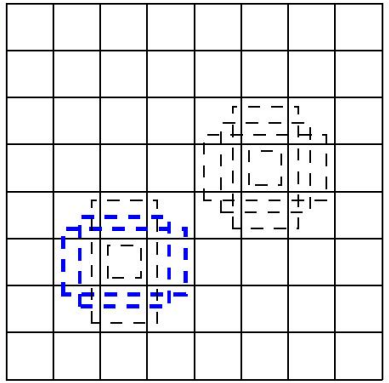
Ronneberger, et al., "U-Net: Convolutional Networks for Biomedical Image Segmentation", 2015

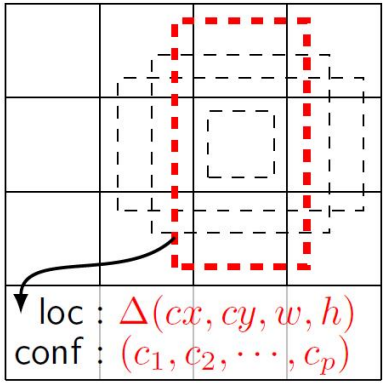
Georgia Tech

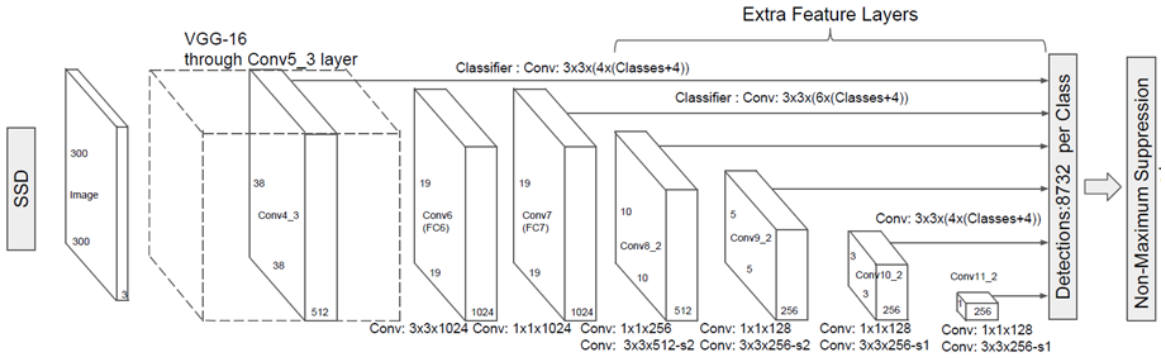
Single-shot detectors use an idea of **grids** as anchors, with different scales and aspect ratios around them

- Various tricks used to increase the resolution (decrease subsampling ratio)









Liu, et al., "SSD: Single Shot MultiBox Detector", 2015

Single-Shot Detector (SSD)

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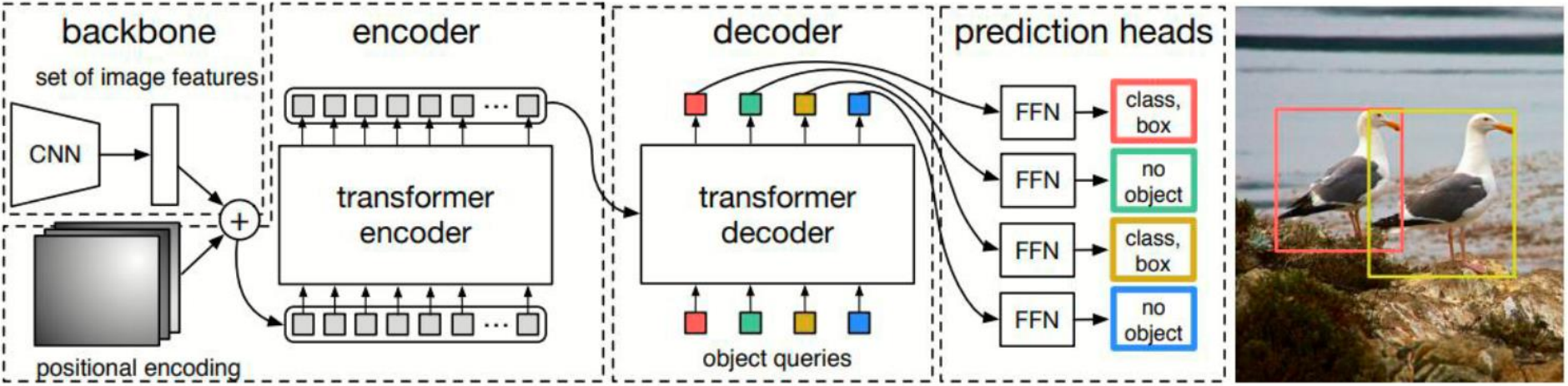
DEtector TRansformer - DETR overview



Generative Models: Introduction

Supervised Learning

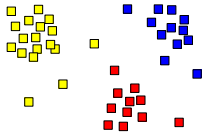
- Train Input: $\{X, Y\}$
- Learning output: $f : X \rightarrow Y$, $P(y|x)$
- e.g. classification

Sheep
Dog
Cat
Lion
Giraffe

Less Labels

Unsupervised Learning

- Input: $\{X\}$
- Learning output: $P(x)$
- Example: Clustering, density estimation, etc.



Spectrum of Low-Labeled Learning

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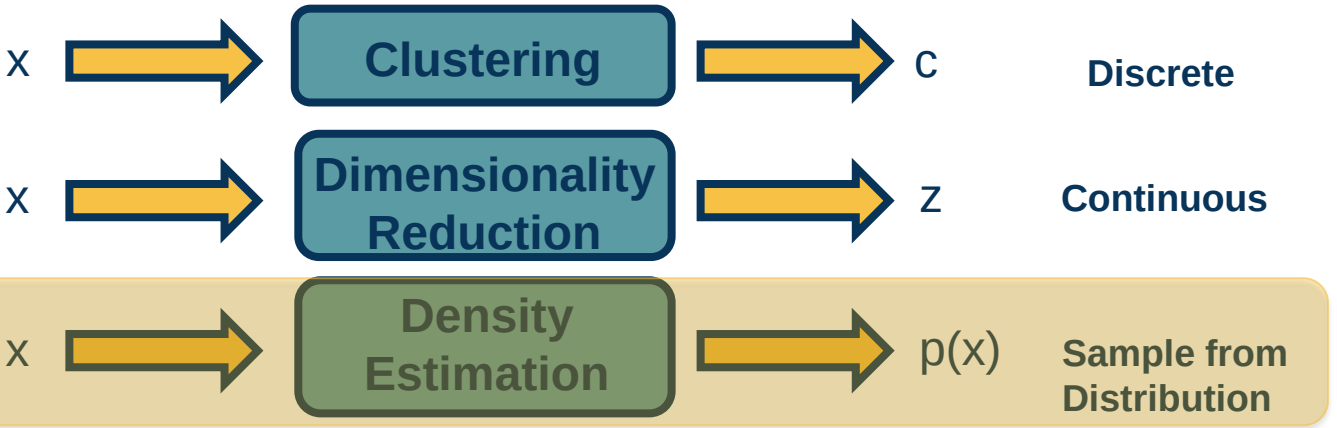
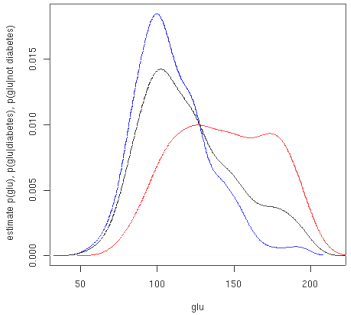
Supervised Learning

Unsupervised Learning



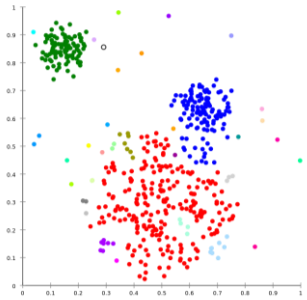
Traditional unsupervised learning methods:



Density estimation

Modeling $P(x)$

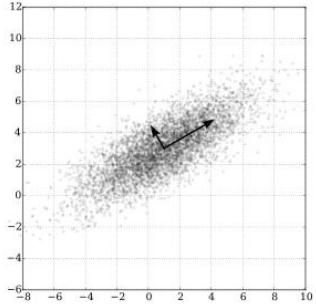
Deep Generative Models



Clustering

Comparing/ Grouping

Metric learning & clustering



Principal Component Analysis

Representation Learning

Almost all deep learning!

Similar in deep learning, but **from neural network/learning perspective**

Discriminative vs. Generative Models

- Discriminative models model $P(y|x)$
  - Example: Model this via neural network, SVM, etc.

- Generative models model $P(x)$

Goodfellow, NeurIPS 2016 Tutorial: Generative Adversarial Networks

Discriminative vs. Generative Models

- Discriminative models model $P(y|x)$
  - Example: Model this via neural network, SVM, etc.

- Generative models model $P(x)$
- We can parameterize our model as $P(x, \theta)$ and use maximum likelihood to optimize the parameters given an unlabeled dataset:

$$\begin{aligned}\boldsymbol{\theta}^* &= \arg\max_{\boldsymbol{\theta}} \prod_{i=1}^{m} p_{\text{model}}\left(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}\right) \\ &= \arg\max_{\boldsymbol{\theta}} \log \prod_{i=1}^{m} p_{\text{model}}\left(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}\right) \\ &= \arg\max_{\boldsymbol{\theta}} \sum_{i=1}^{m} \log p_{\text{model}}\left(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}\right).\end{aligned}$$

- They are called generative because they can often generate *samples*
  - Example: Multivariate Gaussian with estimated parameters $\boldsymbol{\mu}, \boldsymbol{\sigma}$

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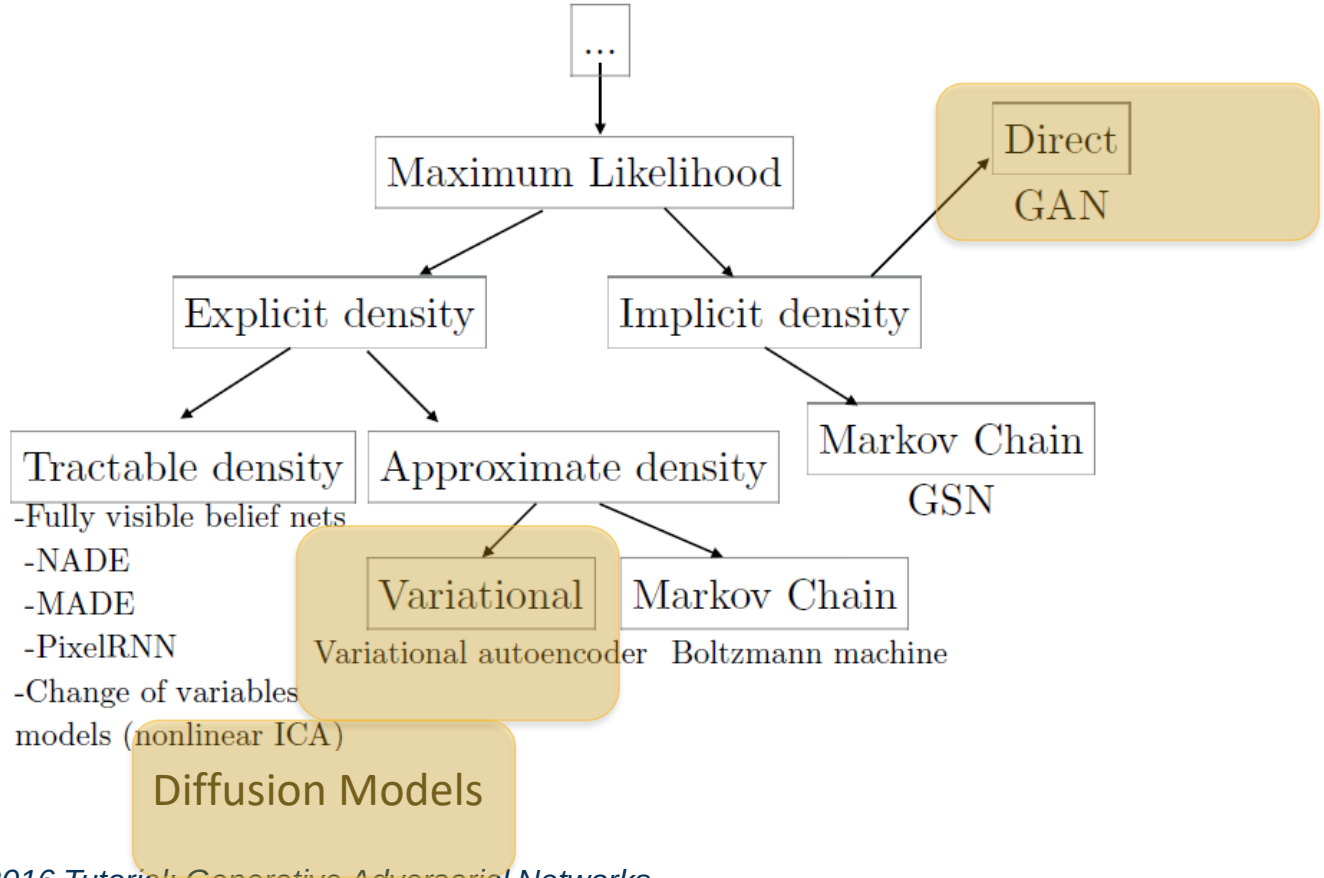
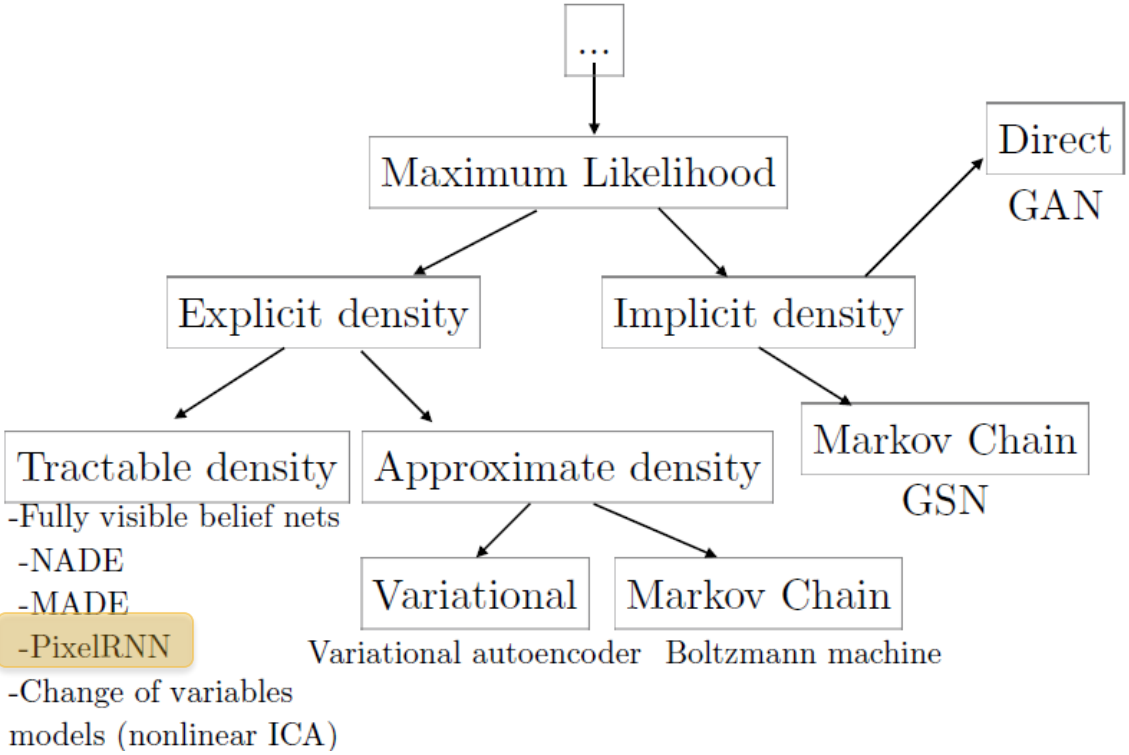


Goodfellow, NeurIPS 2016 Tutorial: Generative Adversarial Networks

Generative Models

PixelRNN & PixelCNN



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Generative Models

We can use chain rule to decompose the joint distribution

- Factorizes joint distribution into a product of conditional distributions
  - Similar to Bayesian Network (factorizing a joint distribution)
  - Similar to language models!

$$p(x) = \prod_{i=1}^{n^2} p(x_i | x_1, \ldots, x_{i-1})$$

Same as language modeling!

$$p(s) = \prod_{i} p(w_i \mid w_{i-1}, \ldots, w_1)$$

i: next word; $w_{i-1}, \ldots, w_1$: history

- Requires some *ordering* of variables (edges in a probabilistic graphical model)
- We can estimate this conditional distribution as a neural network

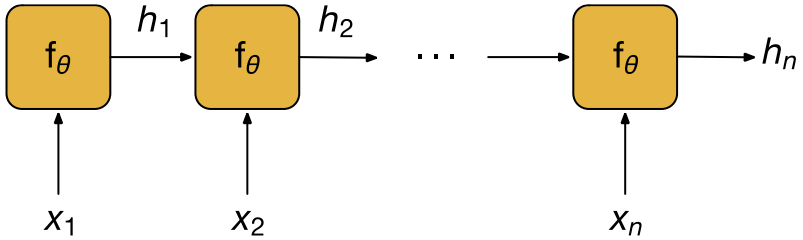
Oord et al., Pixel Recurrent Neural Networks

- Language modeling involves estimating a probability distribution over sequences of words.

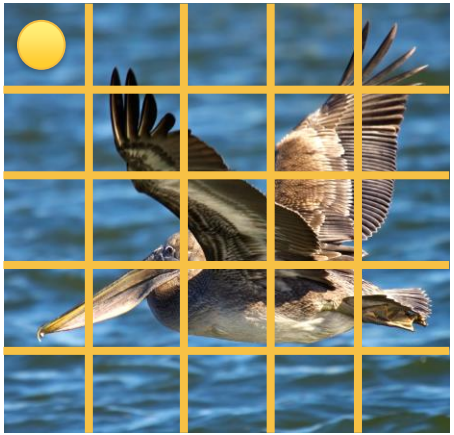
$$\mathrm{p}(\boldsymbol{s}) = \mathrm{p}(w_1, w_2, \ldots, w_n) = \prod_i \mathrm{p}(w_i \mid w_{i-1}, \ldots, w_1)$$

i: next word; $w_{i-1}, \ldots, w_1$: history

- RNNs are a family of neural architectures for modeling sequences.



Language Models as an RNN



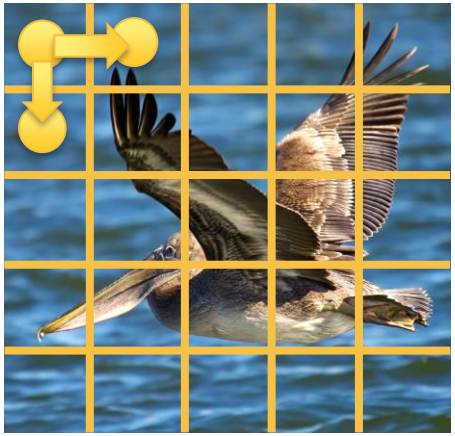
$$p(x) = \prod_{i=1}^{n^2} p(x_i | x_1, \ldots, x_{i-1})$$

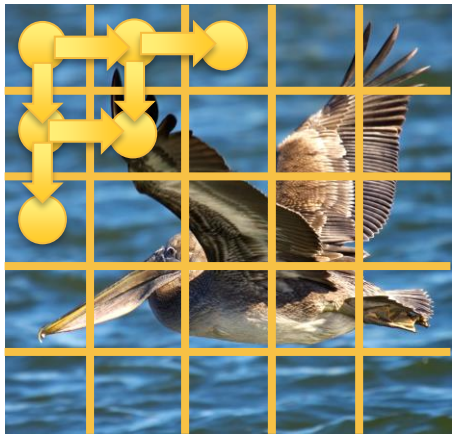
$$p(x) = p(x_1) \prod_{i=2}^{n^2} p(x_i | x_1, \ldots, x_{i-1})$$

1. Choose ordering (upper left, top to bottom, left to right.

Separate out pixel 1

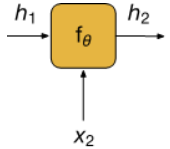
Oord et al., Pixel Recurrent Neural Networks





$$p(x) = p(x_1)p(x_2|x_1)p(x_3|x_1)\prod_{i=1}^{n^2} p(x_i|x_1, \ldots, x_{i-1})$$

- Model this as RNN with parameters

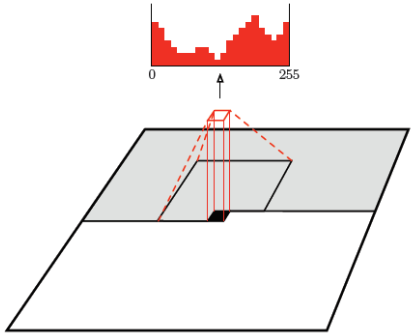


- Training:
  - We can train similar to language models:
  - Maximum likelihood approach

Downsides?

- Downsides:
  - Slow sequential generation process
  - Only considers few context pixels

Oord et al., Pixel Recurrent Neural Networks



1	1	1	1	1
1	1	1	1	1
1	1	0	0	0
0	0	0	0	0
0	0	0	0	0

- **Idea:** Represent conditional distribution as a convolution layer!
  - Because of spatial locality in images
- Considers larger context (receptive field)
- Practically can be implemented by applying a mask, zeroing out “future” pixels
- Faster training but still slow generation
  - Limited to smaller images

Oord et al., Conditional Image Generation with PixelCNN Decoders

Pixel CNN

Oord et al., Conditional Image Generation with PixelCNN Decoders

Example Results: Image Completion (PixelRNN)

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Geyser

Hartebeest

Grey whale

Tiger

Can we update this to modern times?

Oord et al., Conditional Image Generation with PixelCNN Decoders

Example Images (PixelCNN)

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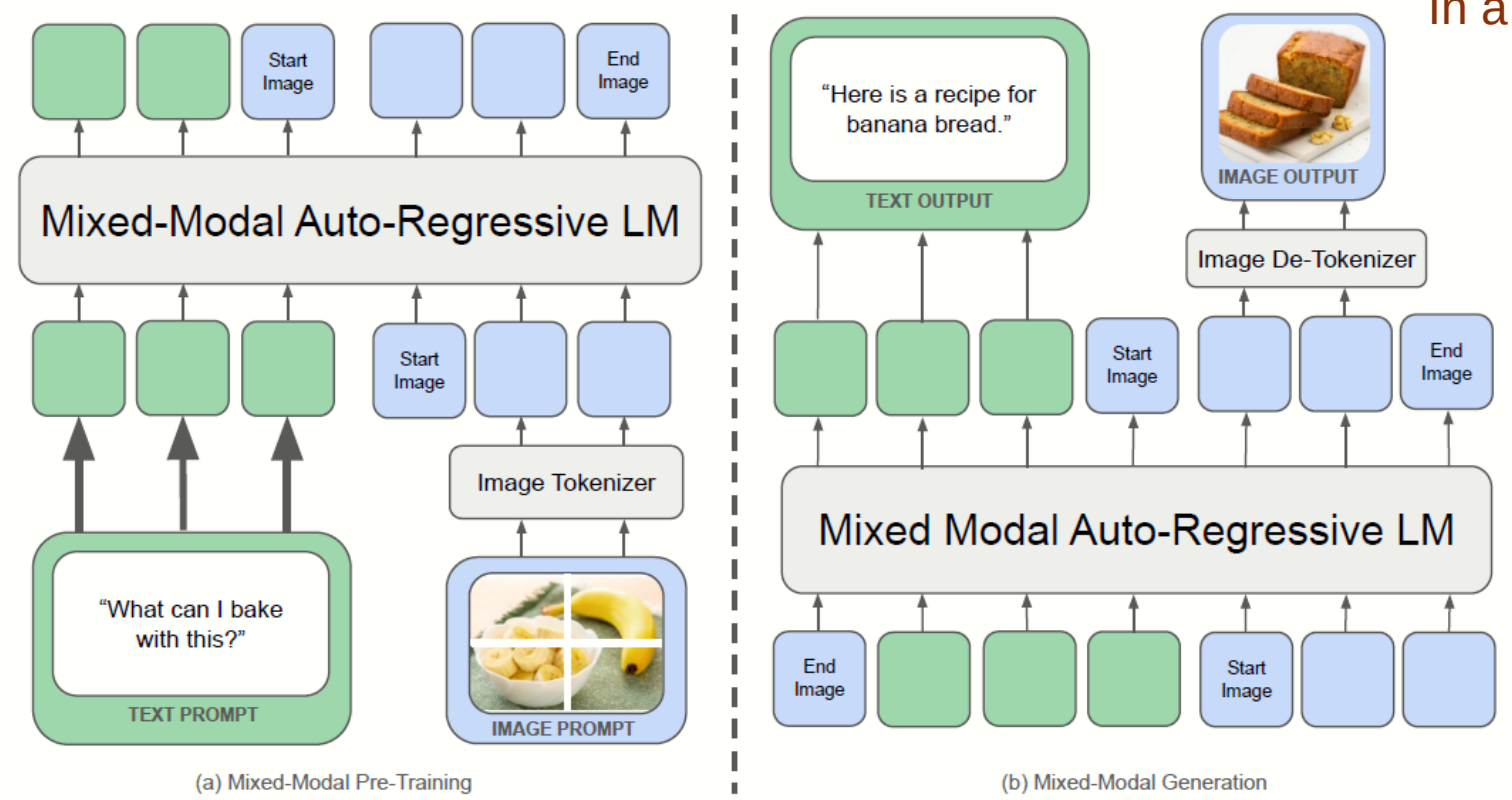
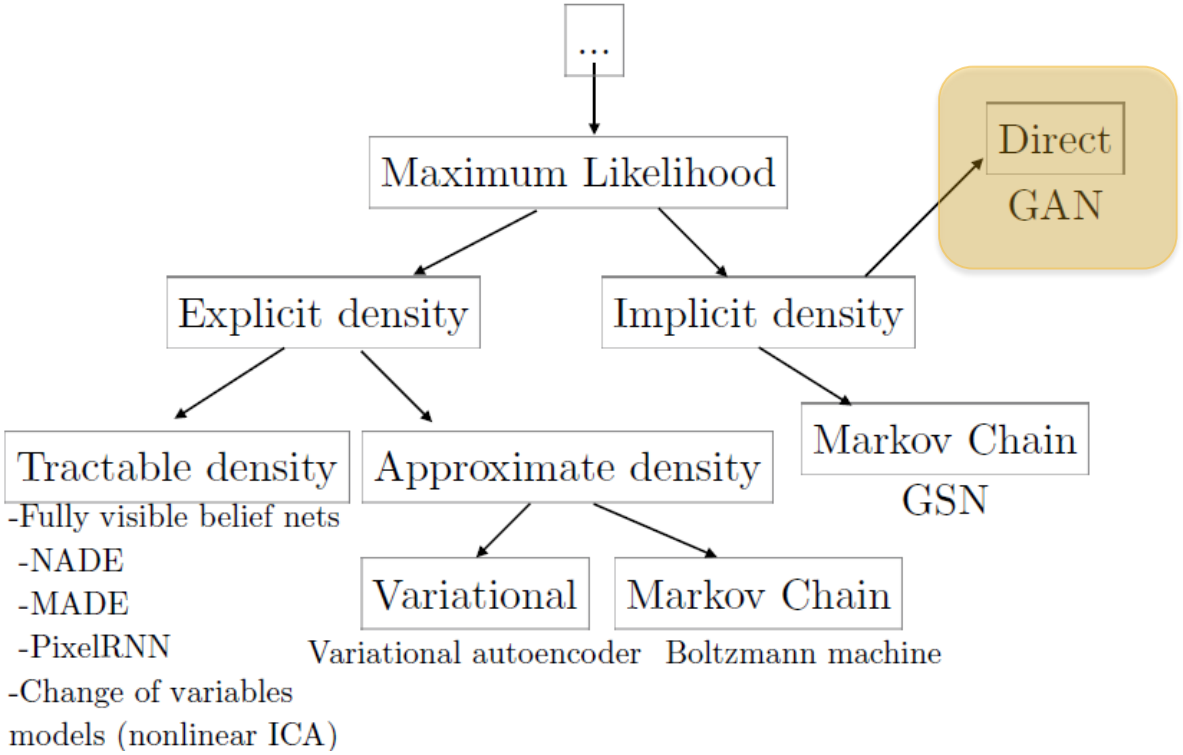
In a few weeks



Chameleon: Mixed-Modal Early-Fusion Foundation Models

Generative Adversarial Networks (GANs)



Goodfellow, NeurIPS 2016 Tutorial: Generative Adversarial Networks

Generative Models

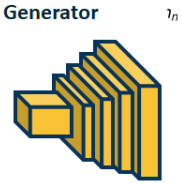
- *Implicit* generative models do not actually learn an explicit model for $\boldsymbol{p(x)}$

- Instead, learn to *generate samples* from $\boldsymbol{p(x)}$
  - Learn good feature representations
  - Perform data augmentation
  - Learn world models (a simulator!) for reinforcement learning

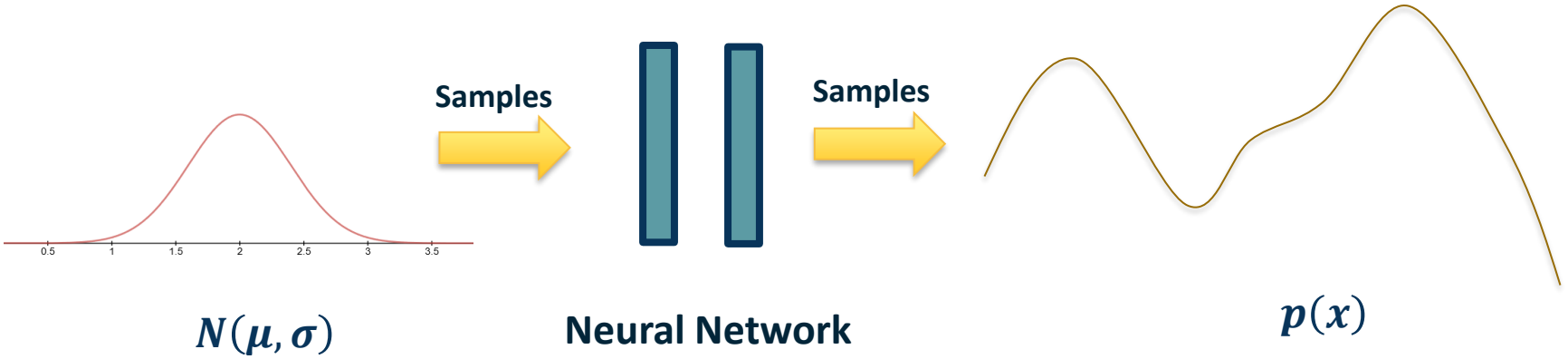
- How?
  - **Decode architecture**
  - **Learn to sample** from a neural network output

What architecture lets us generate images?

How do we generate a different image every time?

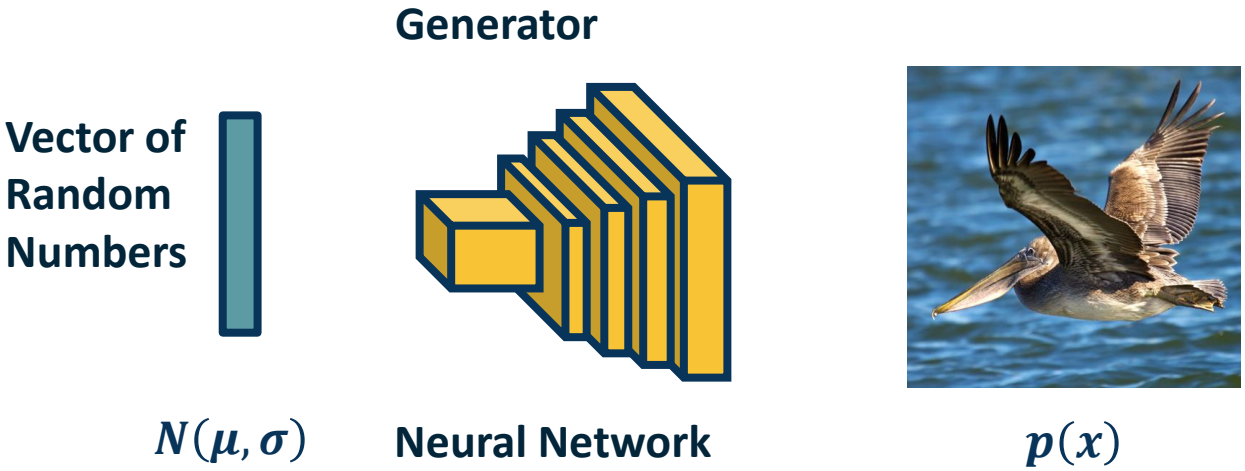


- We would like to *sample* from $\boldsymbol{p(x)}$ using a neural network
- **Idea:**
  - Sample from a simple distribution (Gaussian)
  - Transform the sample to $\boldsymbol{p(x)}$



Learning to Sample

- Input can be a vector with (independent) Gaussian random numbers
- We can use a CNN to generate images!

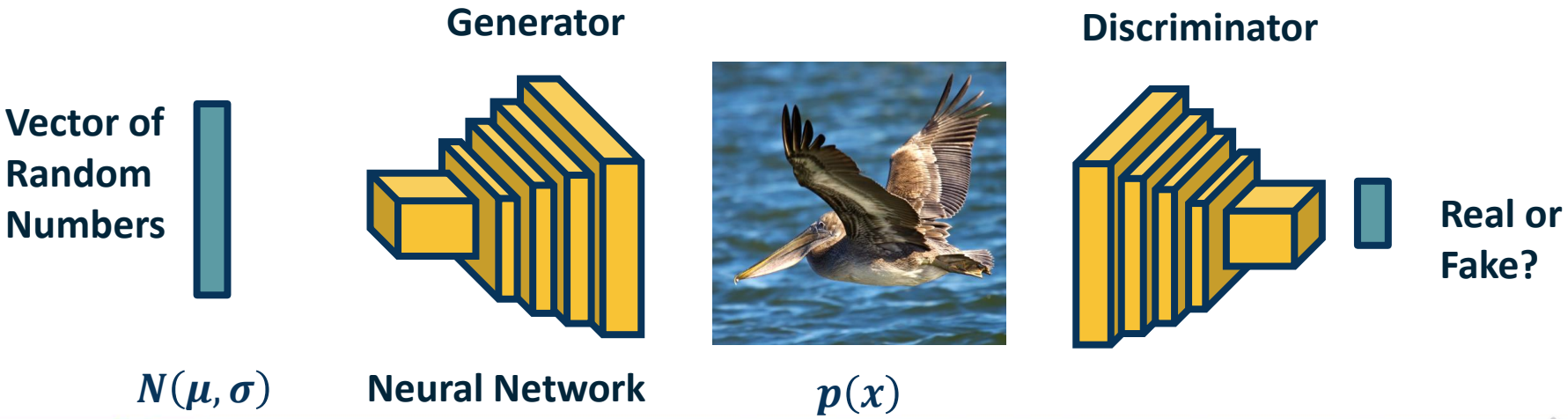


How do we train this (loss)?

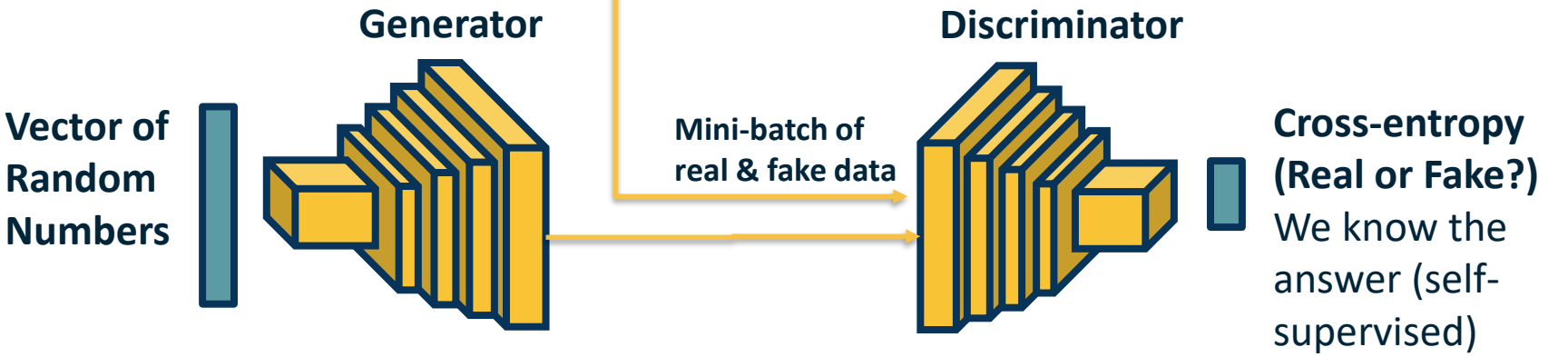
- Instead, learn to *generate samples* from $\boldsymbol{p(x)}$

- How?
  - **Adversarial training** that uses one network's predictions to train the other (dynamic loss function!)
  - **Lots of tricks** to make the optimization more stable

- **Goal:** We would like to generate *realistic* images. How can we drive the network to learn how to do this?
- **Idea:** Have *another* network try to distinguish a real image from a generated (fake) image
  - **Why?** Signal can be used to determine how well it's doing at generation
    - Can be seen as a dynamic (adversarial) loss!



- **Generator:** Update weights to improve realism of generated images
- **Discriminator:** Update weights to better discriminate



Question: What loss functions can we use (for each network)?

- Since we have two networks competing, this is a mini-max two player game
  - Ties to game theory
  - Not clear what (even local) Nash equilibria are for this game

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Mini-max Two Player Game

- Since we have two networks competing, this is a mini-max two player game
  - Ties to game theory
  - Not clear what (even local) Nash equilibria are for this game

- The full mini-max objective is:

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

Sample from real **Sample from fake**

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

- where $D(x)$ is the discriminator outputs probability ([0,1]) of **real** image
- x is a **real image** and $G(z)$ is a **generated** image

- The discriminator wants to **maximize** this:
  - $D(x)$ is pushed up (to 1) because x is a real image
  - $1 - D\big(G(z)\big)$ is also pushed up to 1 (so that $\mathrm{D}\big(\mathrm{G}(\mathrm{z})\big)$ is pushed down to 0)
  - In other words, discriminator wants to classify real images as real (1) and fake images as fake (0)

Discriminator Perspective

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

- where $D(x)$ is the discriminator outputs probability ([0,1]) of **real** image
- x is a **real image** and $G(z)$ is a **generated** image

- The generator wants to **minimize** this:
  - First term: G(..) doesn't appear in it!
  - $1 - D\big(G(z)\big)$ is pushed down to 0 (so that $\mathrm{D}\big(\mathrm{G}(\mathrm{z})\big)$ is pushed up to 1)
  - This means that the generator is **fooling** the discriminator, i.e. succeeding at generating images that the discriminator can't discriminate from real

Generator Perspective

- Since we have two networks competing, this is a mini-max two player game
  - Ties to game theory
  - Not clear what (even local) Nash equilibria are for this game

- The full mini-max objective is:

Sample from fake

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

Generator *minimizes*

How well discriminator does (0 for fake)

  - where $D(x)$ is the discriminator outputs probability ([0,1]) of **real** image
  - x is a **real image** and $G(z)$ is a **generated** image

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Sample from real **Sample from fake**

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

Discriminator *maximizes*

How well discriminator does (1 for real)

How well discriminator does (0 for fake)

  - where $D(x)$ is the discriminator outputs probability ([0,1]) of **real** image
  - x is a **real image** and $G(z)$ is a **generated** image

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Generator

Discriminator

Vector of Random Numbers

Mini-batch of real & fake data

Cross-entropy (Real or Fake?)
We know the answer (self-supervised)

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

Generator Loss

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log \left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

Discriminator Loss

Generative Adversarial Networks (GANs)

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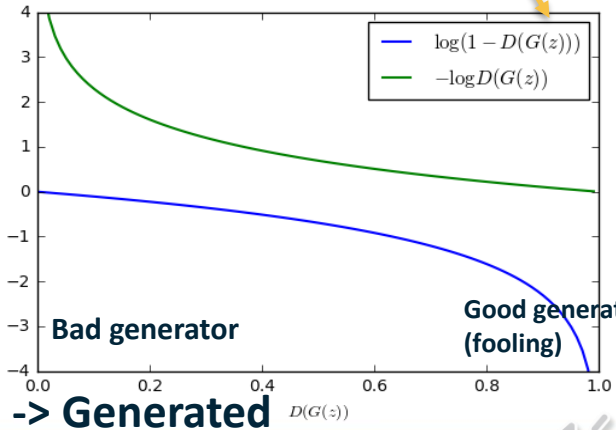
- The generator part of the objective does not have good gradient properties

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

  - High gradient when $D(G(z))$ is high (that is, discriminator is wrong)
  - We want it to improve when samples are *bad* (discriminator is right)



- Alternative objective, ***maximize***:

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

Plot from CS231n, Fei-Fei Li, Justin Johnson, Serena Yeung

Converting to Max-Max Game

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

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:

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

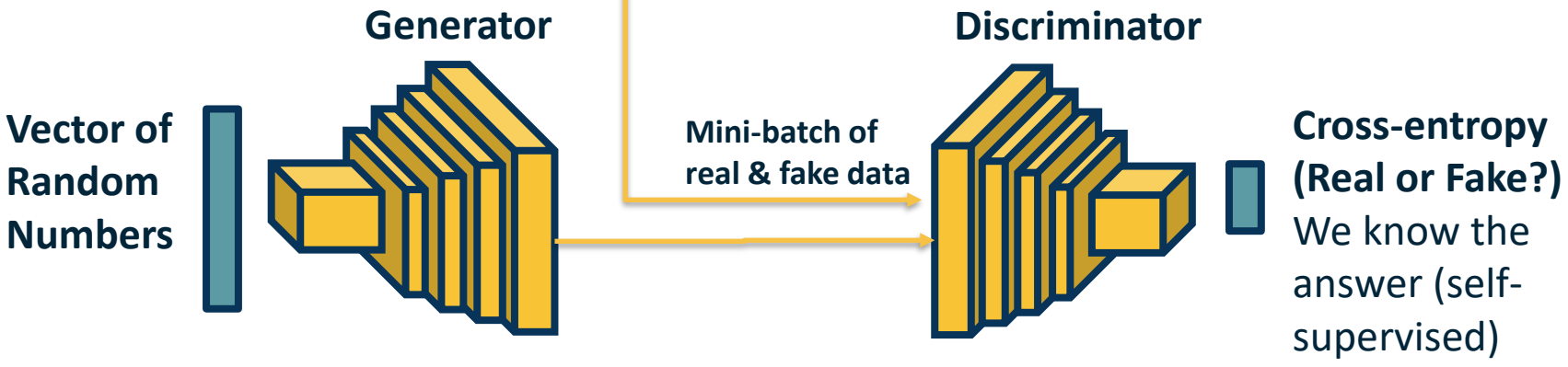
end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

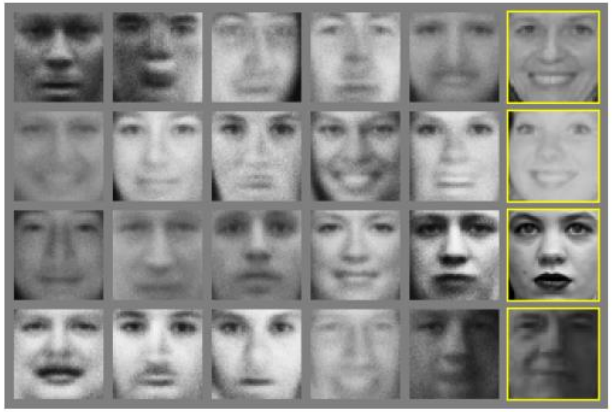
Goodfellow, NeurIPS 2016 Generative Adversarial Nets

Final Algorithm

- At the end, we have:
  - An *implicit* generative model!
  - Features from discriminator

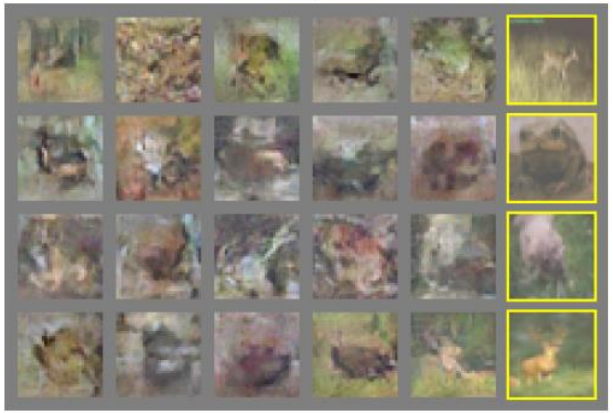


a)



b)

c)



d)

- Low-resolution images but look decent!
- Last column are nearest neighbor matches in dataset

Early Results

- GANs are very difficult to train due to the mini-max objective

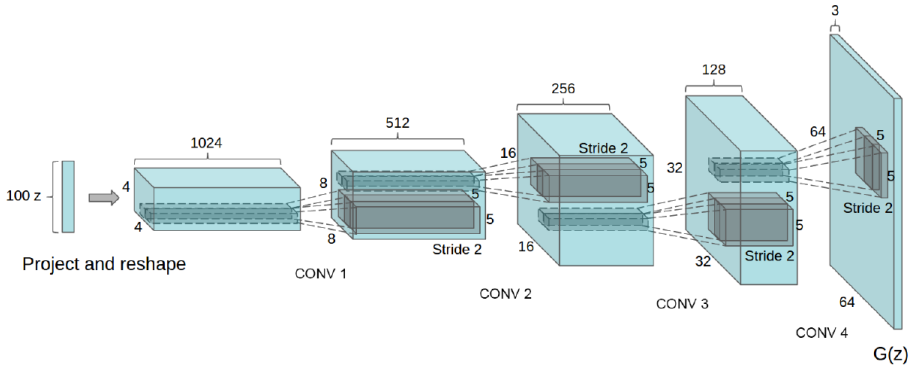
- Advancements include:
  - More stable architectures
  - Regularization methods to improve optimization
  - Progressive growing/training and scaling

Goodfellow, NeurIPS 2016 Generative Adversarial Nets

Difficulty in Training

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

DCGAN

- Training GANs is difficult due to:
  - Minimax objective – For example, what if generator learns to memorize training data (no variety) or only generates part of the distribution?
  - Mode collapse – Capturing only some modes of distribution

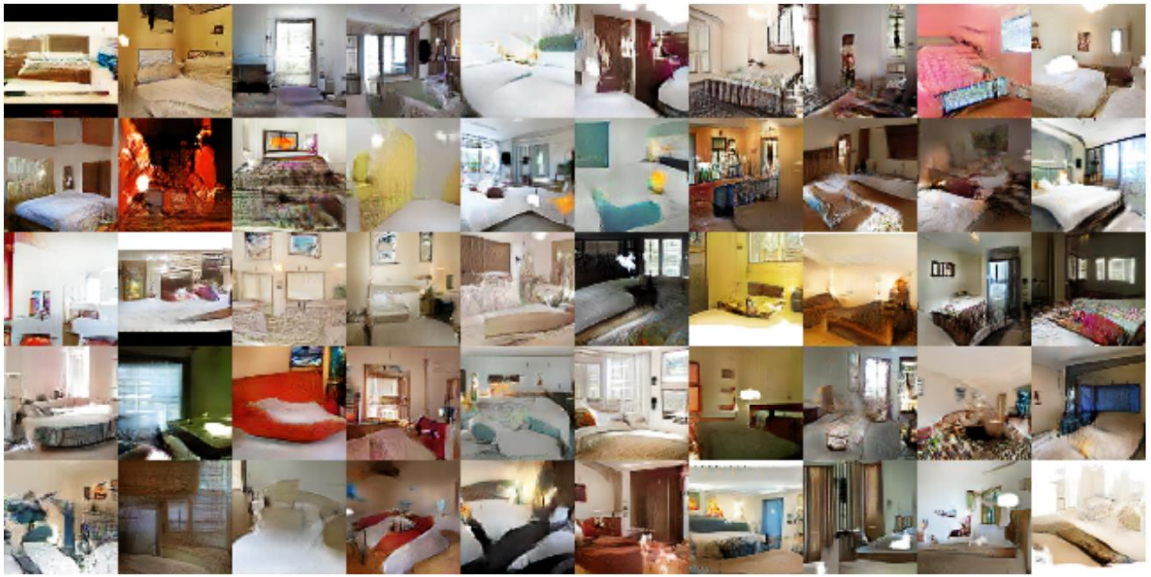
- Several theoretically-motivated regularization methods
  - Simple example: Add noise to real samples!

$$\lambda \cdot \mathbb{E}_{x \sim P_{real}, \delta \sim N_d(0, cI)} \left[\|\nabla_{\mathbf{x}} D_\theta(x + \delta)\| - k \right]^2$$

Kodali et al., On Convergence and Stability of GANs (also known as How to Train your DRAGAN)

Generative Adversarial Nets: Convolutional Architectures

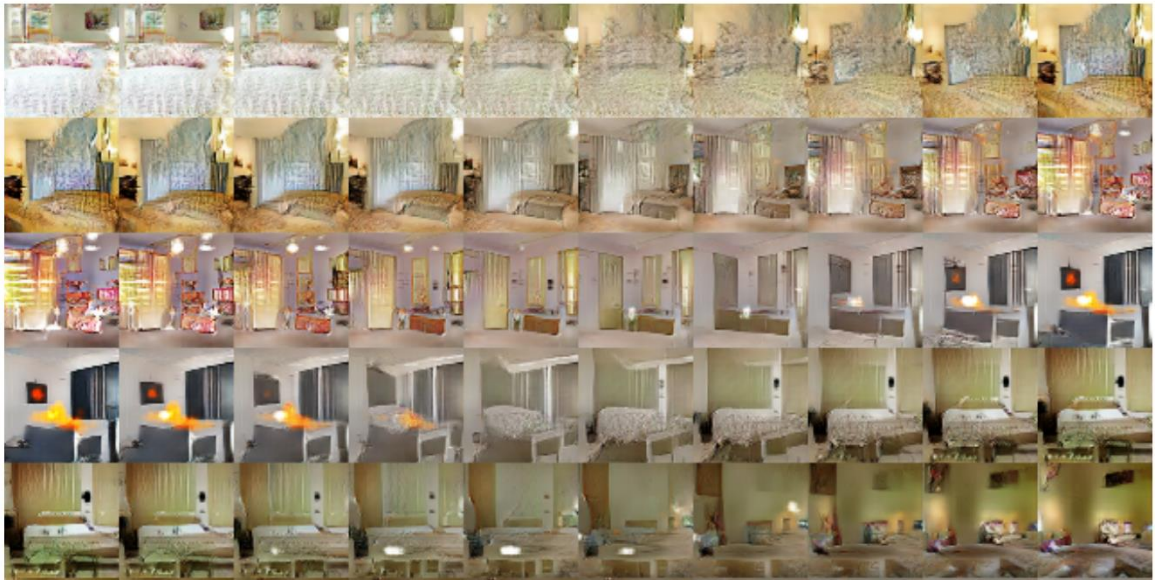
Samples from the model look much better!



Radford et al, ICLR 2016

Generative Adversarial Nets: Convolutional Architectures

Interpolating between random points in latent space



Radford et al, ICLR 2016

Brock et al., Large Scale GAN Training for High Fidelity Natural Image Synthesis

Example Generated Images - BigGAN

Georgia Tech

(a) 128×128 (b) 256×256 (c) 512×512 (d)

Figure 4: Samples from our model with truncation threshold 0.5 (a-c) and an example of class leakage in a partially trained model (d).

Brock et al., Large Scale GAN Training for High Fidelity Natural Image Synthesis

Failure Examples - BigGAN

Georgia Tech

https://www.youtube.com/watch?v=PCBTZh41Ris

Video Generation

Georgia Tech

- Generative Adversarial Networks (GANs) can produce amazing images!

- Several drawbacks
  - High-fidelity generation heavy to train
  - Training can be unstable
  - No explicit model for distribution

- Larger number of extensions:
  - GANs conditioned on labels or other information
  - Adversarial losses for other applications

Summary

Comparison of Methods