CS 1674: Generative Models

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Supervised vs Unsupervised Learning

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn a function to map x -> y

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

→ Cat

Classification

This image is CC0 public domain

Slide credit: Fei-Fei Li

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A cat sitting on a suitcase on the floor

Image captioning

Caption generated using neuraltalk2
Image is CC0 Public domain

Slide credit: Fei-Fei Li

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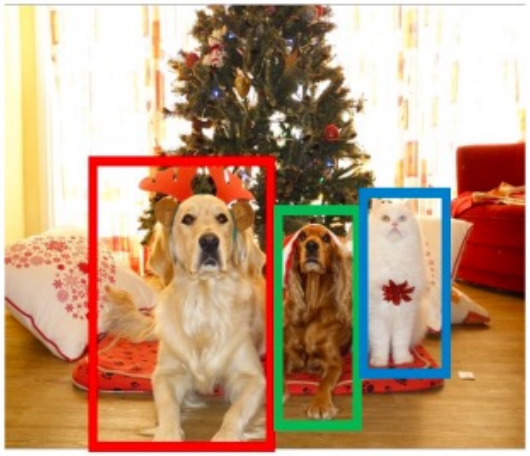

DOG, DOG, CAT

Object Detection

Slide credit: Fei-Fei Li

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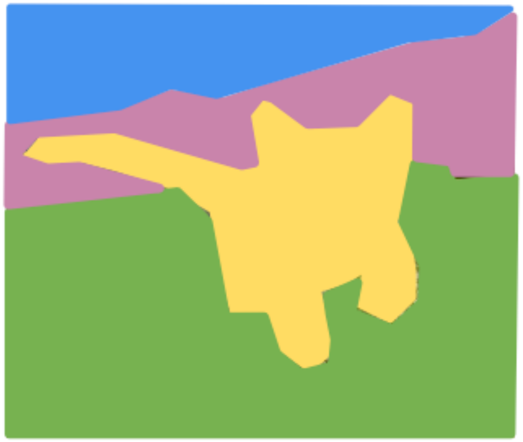


GRASS, CAT, TREE, SKY

Semantic Segmentation

Slide credit: Fei-Fei Li

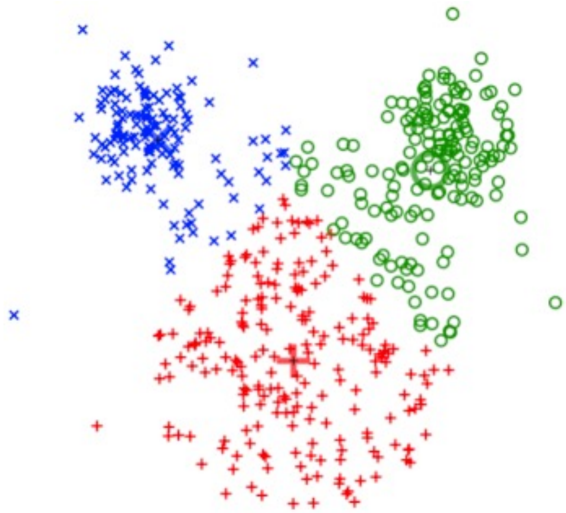
Supervised vs Unsupervised Learning

Unsupervised Learning

Data: x
Just data, no labels!

Goal: Learn some underlying hidden structure of the data

Examples: Clustering, dimensionality reduction, density estimation, etc.



K-means clustering

Slide credit: Fei-Fei Li

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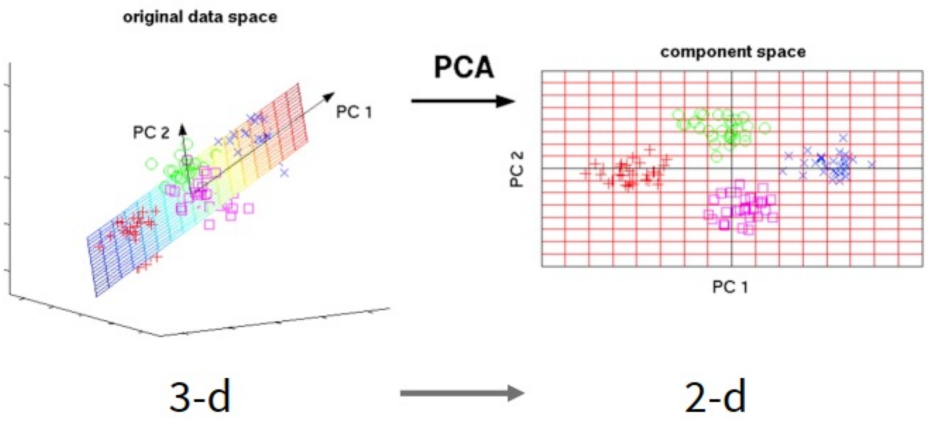
Goal: Learn some underlying hidden structure of the data

Examples: Clustering, dimensionality reduction, density estimation, etc.



Principal Component Analysis
(Dimensionality reduction)

Slide credit: Fei-Fei Li

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Unsupervised Learning

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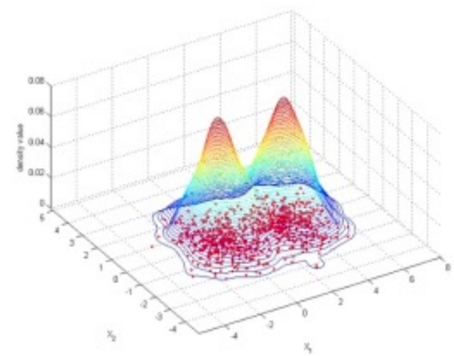
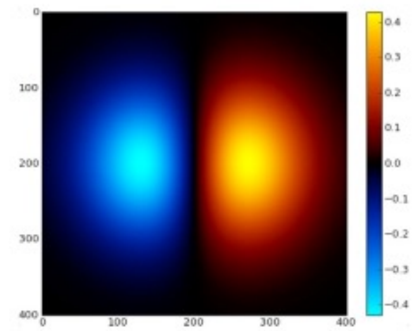
Just data, no labels!

Goal: Learn some underlying hidden structure of the data

Examples: Clustering, dimensionality reduction, density estimation, etc.





2-d density estimation

Modeling P(x)

2-d density images left and right are CC0 public domain

Slide credit: Fei-Fei Li

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

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Examples: Clustering, dimensionality reduction, density estimation, etc.

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Supervised vs Unsupervised Learning

Supervised Learning

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x is data, y is label

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x -> y

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

Unsupervised Learning

Data: x
Just data, no labels!

Goal: Learn some underlying hidden structure of the data

Examples: Clustering, dimensionality reduction, density estimation, etc.

Self-Supervised Learning

Data: (x, pseudo generated y)
No manual labels!

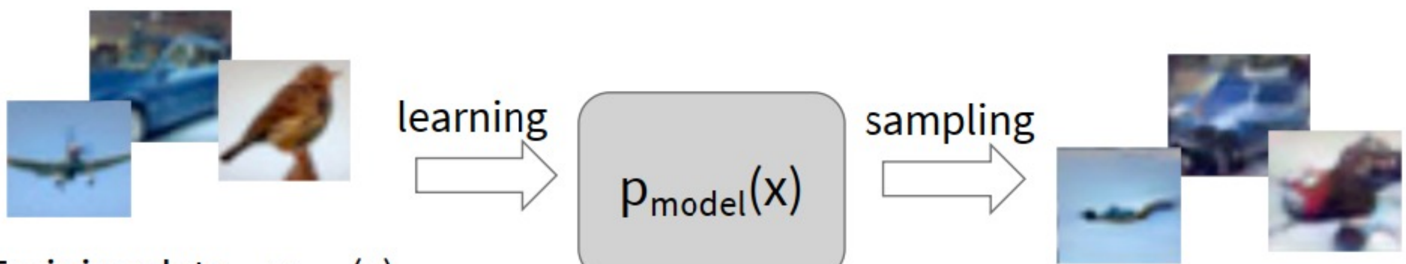
Goal: Learn to generate good features (reduce the data to useful/generic features)

Example: Classification in downstream applications where we have limited data

Slide credit: Fei-Fei Li

Generative Modeling

Given training data, generate new samples from same distribution



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

Generated Samples ~ $P_{model}(x)$

Objectives:

1. Learn $p_{model}(x)$ that approximates $p_{data}(x)$
2. Sampling new x from $p_{model}(x)$

Slide credit: Fei-Fei Li

Why Generative Models? Debiasing

Capable of uncovering **underlying features** in a dataset

Homogeneous skin color, pose

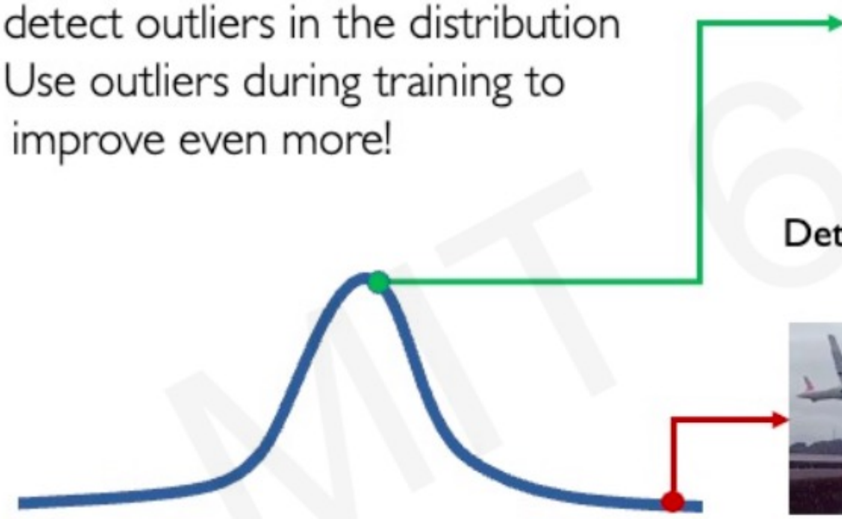
Diverse skin color, pose, illumination

How can we use this information to create fair and representative datasets?

Why Generative Models? Outlier Detection

- **Problem:** How can we detect when we encounter something new or rare?
- **Strategy:** Leverage generative models, detect outliers in the distribution
- Use outliers during training to improve even more!

95% of Driving Data:
(1) sunny, (2) highway, (3) straight road



Detect outliers to avoid unpredictable behavior when training

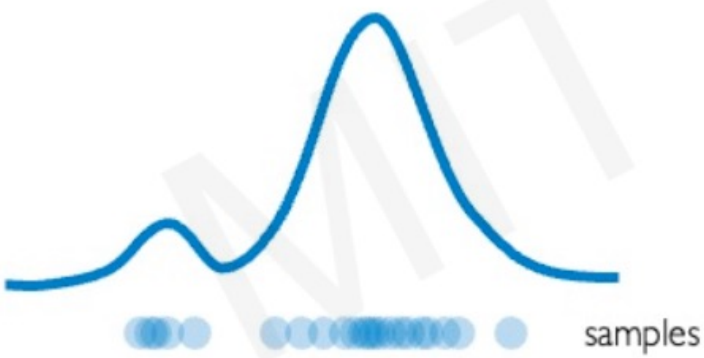
Edge Cases

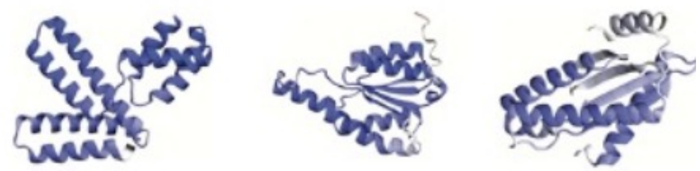
Harsh Weather

Pedestrians

Why Generative Models? Sample Generation

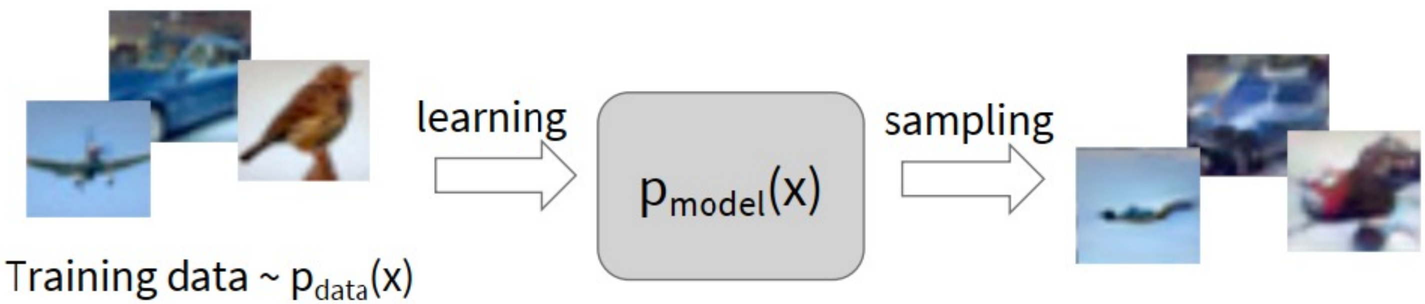
- **Generative models learn probability distributions**
- **Sampling** from that distribution → new data instances
- **Backbone of Generative AI:** generate language, images, and more





Generative Modeling

Given training data, generate new samples from same distribution



Formulate as density estimation problems:

- Explicit density estimation: explicitly define and solve for $p_{model}(x)$
- Implicit density estimation: learn model that can sample from $p_{model}(x)$ without explicitly defining it.

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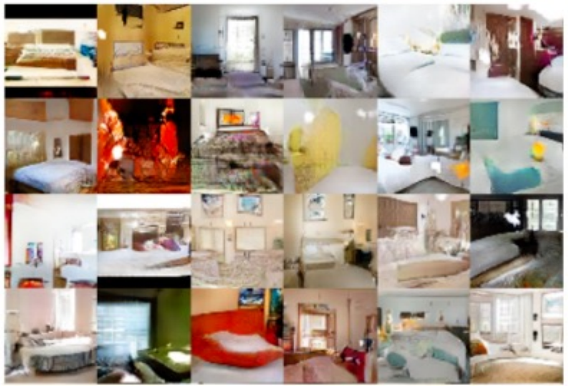
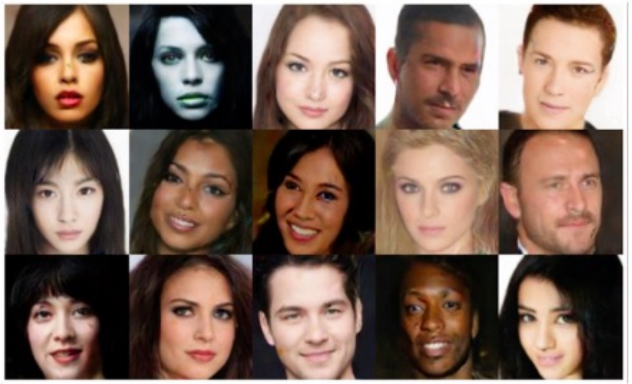
Generative Modeling: Applications





- Realistic samples for artwork, super-resolution, colorization, etc.
- Learn useful features for downstream tasks such as classification.
- Getting insights from high-dimensional data (physics, medical imaging, etc.)
- Modeling physical world for simulation and planning (robotics and reinforcement learning applications)
- Many more ...

Slide credit: Fei-Fei Li

Taxonomy of Generative Models

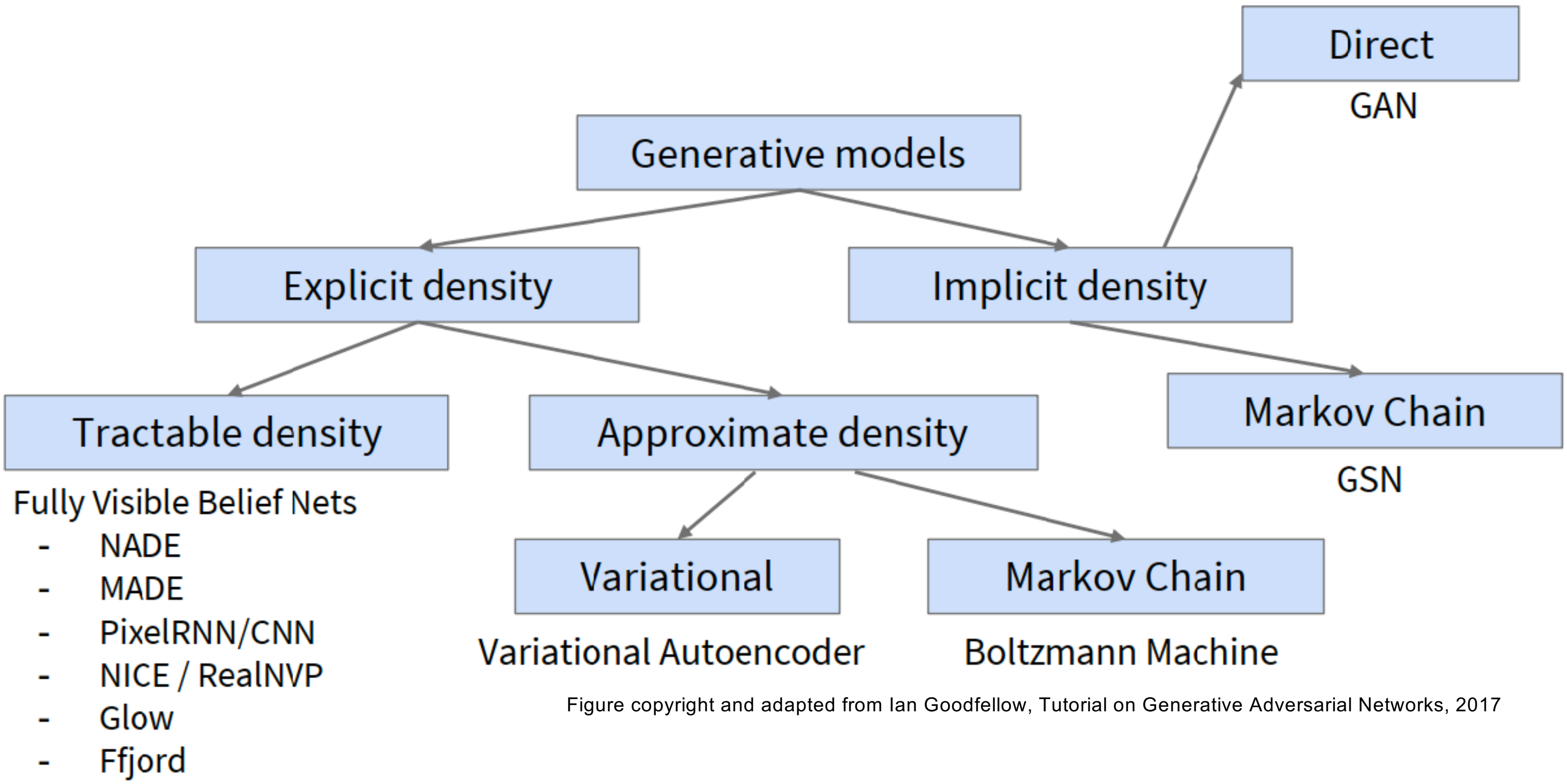


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017

Slide credit: Fei-Fei Li

PixelRNN and PixelCNN

Fully visible belief network (FVBN)

Explicit density model

$$\underset{\text{Likelihood of image x}}{p(x)} = \underset{\text{Joint likelihood of each pixel in the image}}{p(x_1, x_2, \ldots, x_n)}$$

Slide credit: Fei-Fei Li

Fully visible belief network (FVBN)

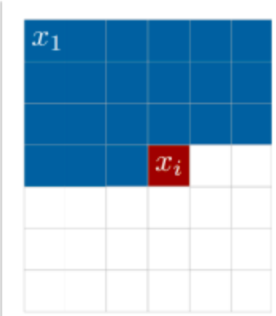
Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

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

Likelihood of image x

Probability of i'th pixel value given all previous pixels



Then maximize likelihood of training data

Slide credit: Fei-Fei Li

Fully visible belief network (FVBN)

Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

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Likelihood of image x

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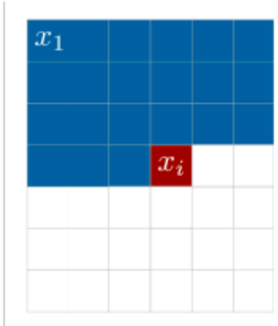
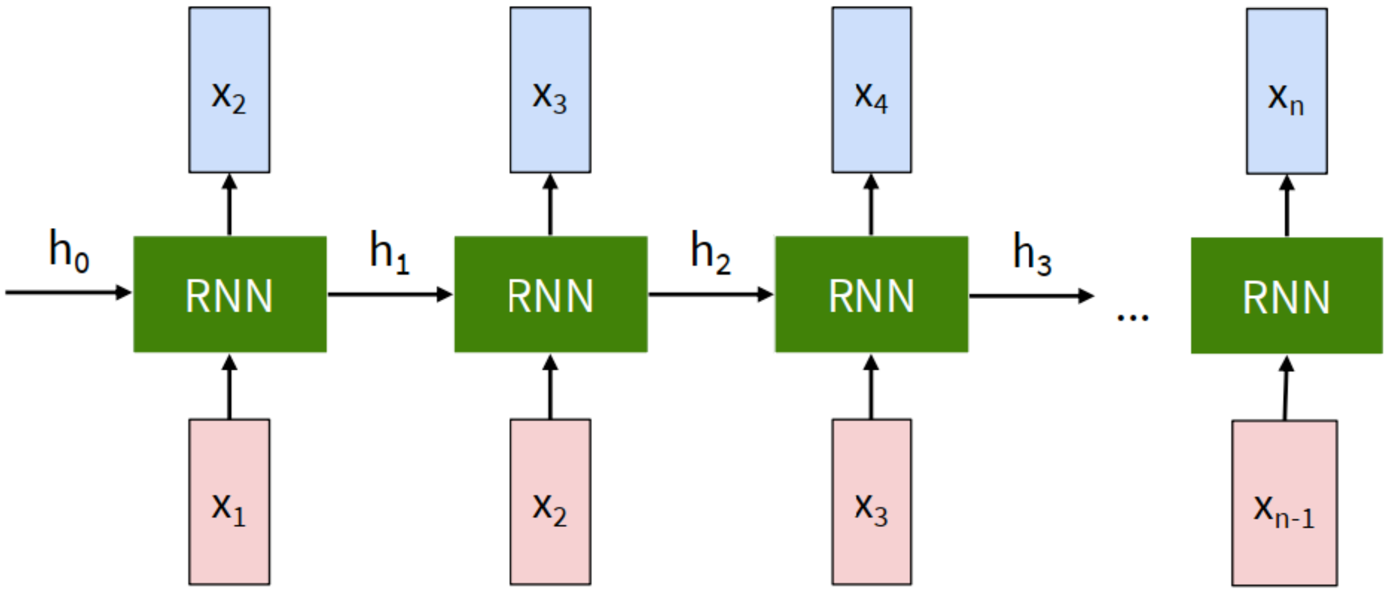


Complex distribution over pixel values => Express using a neural network!

Then maximize likelihood of training data

Slide credit: Fei-Fei Li

Another solution: Recurrent Neural Network



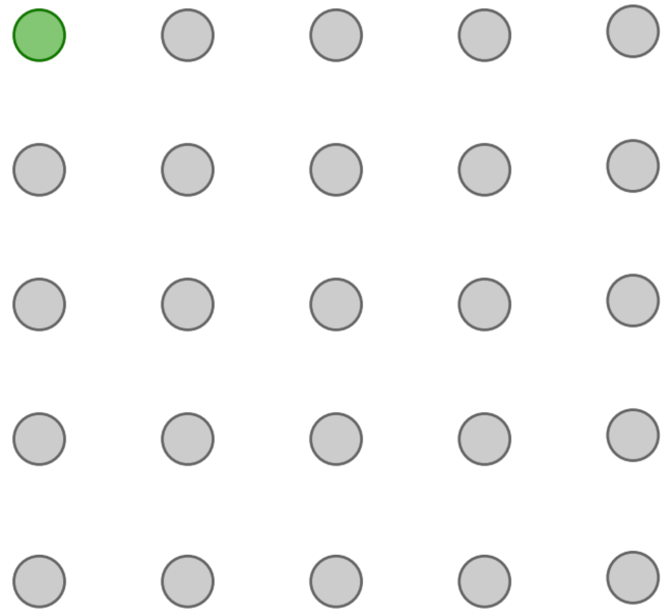
$$p(x_i | x_1, \ldots, x_{i-1})$$

Slide credit: Fei-Fei Li

PixelRNN [van der Oord et al. 2016]

Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)



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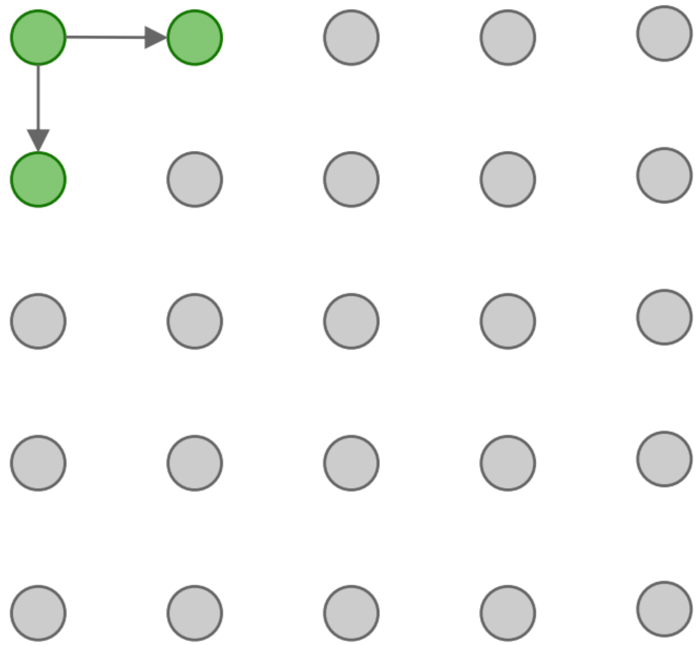

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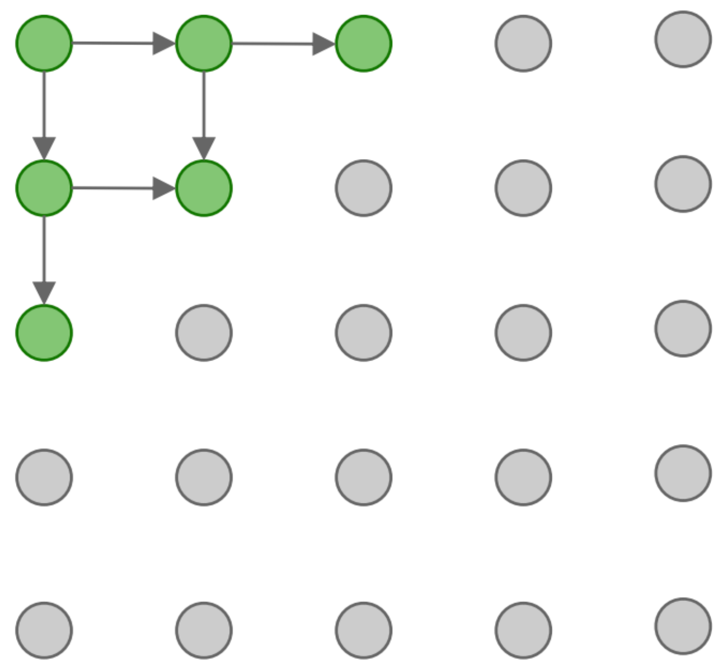

Slide credit: Fei-Fei Li

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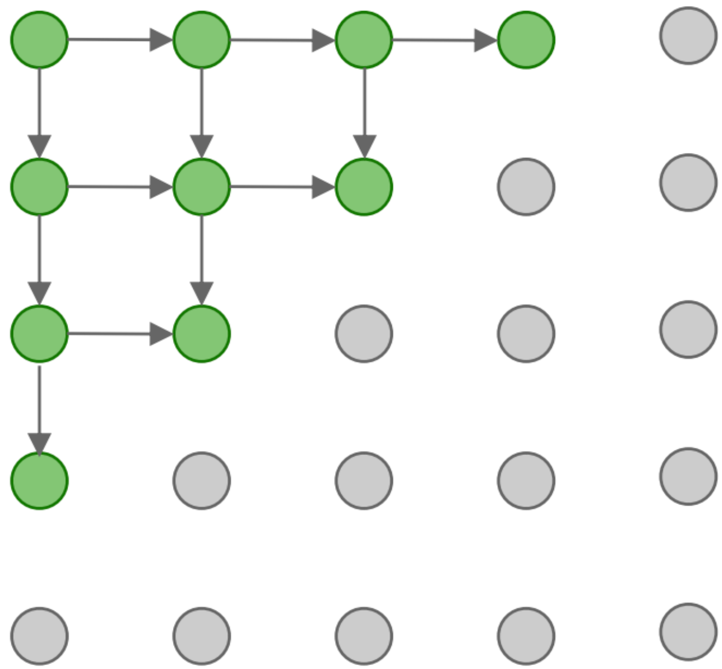
Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)

Drawback: sequential generation is slow in both training and inference!



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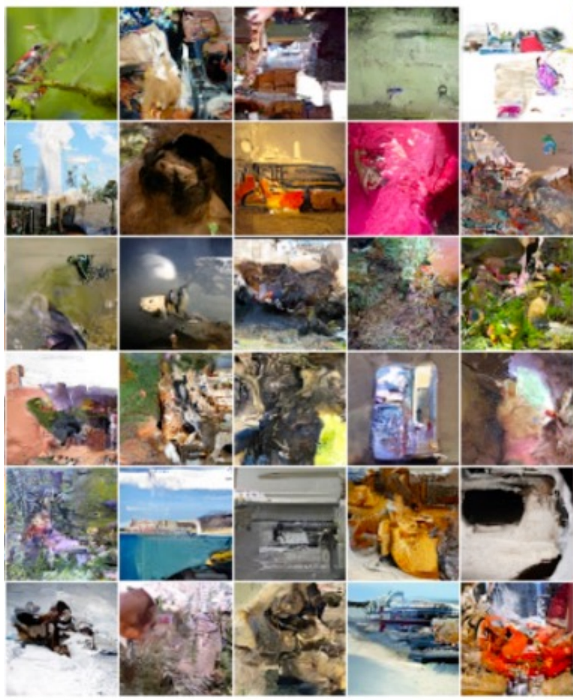
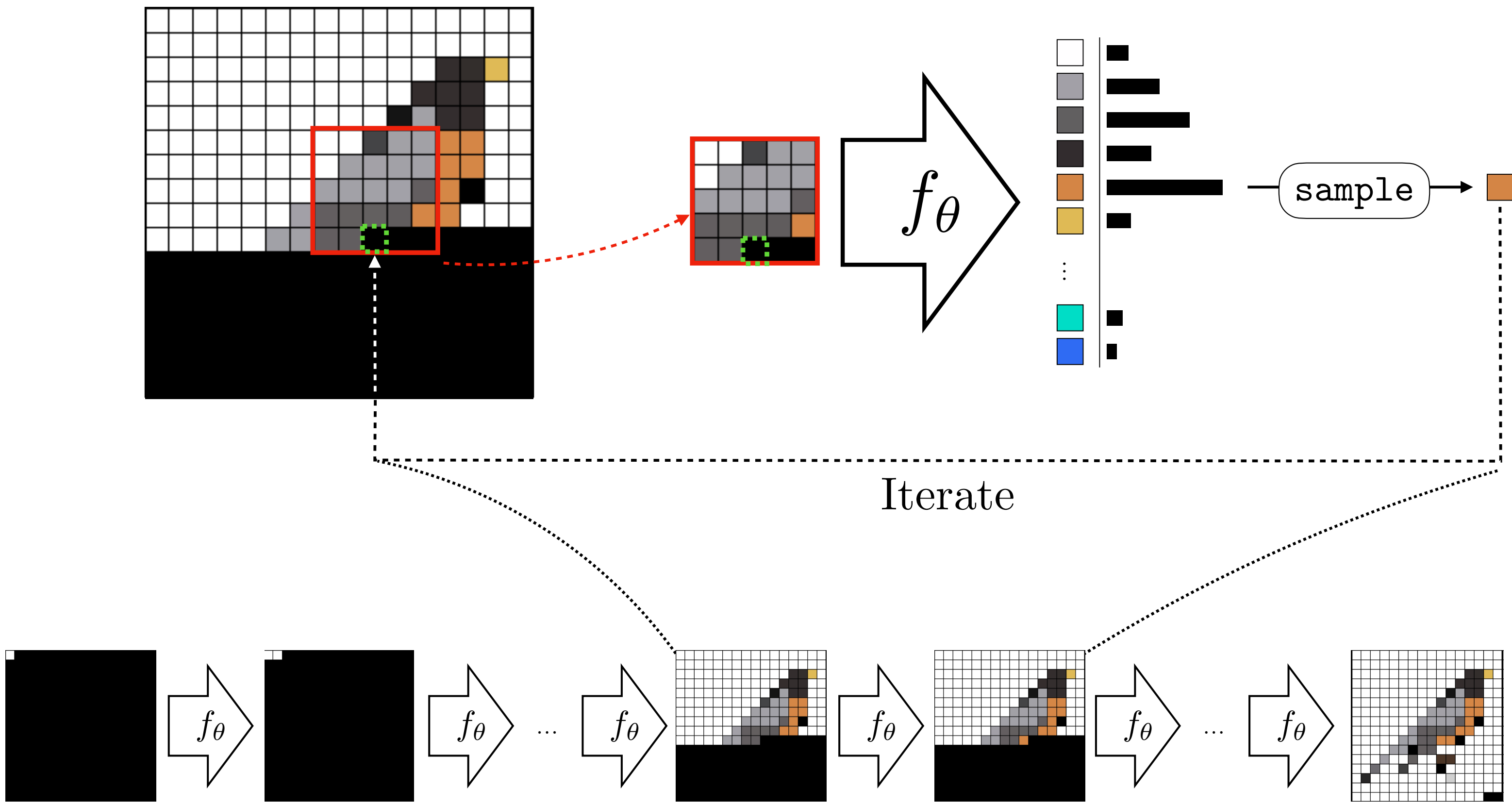


Samples from PixelRNN

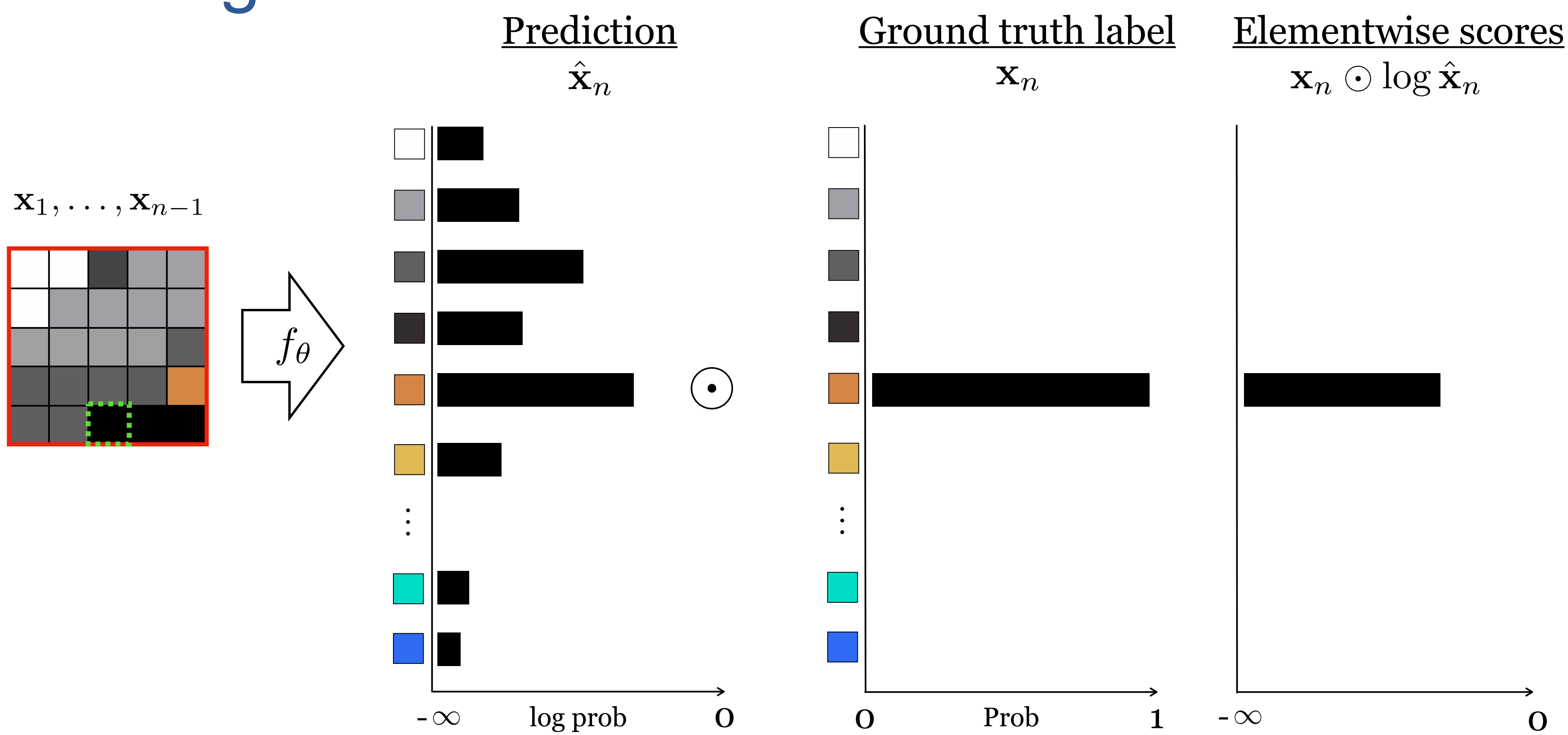
Image completions (conditional samples) from PixelRNN

[PixelRNN, van der Oord et al. 2016]

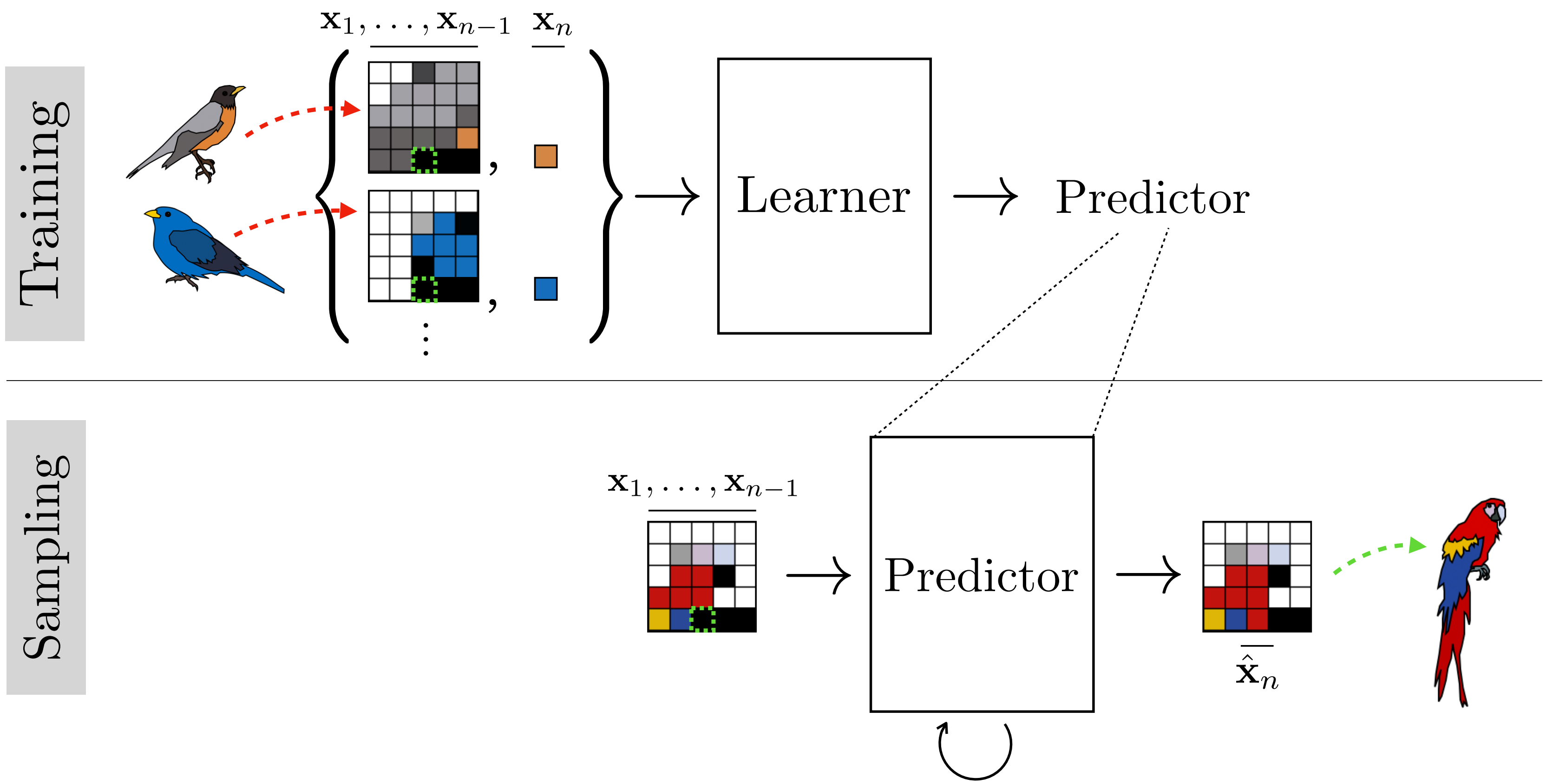
Autoregressive Model of Pixels



Autoregressive Model of Pixels



Autoregressive Model of Pixels



Taxonomy of Generative Models

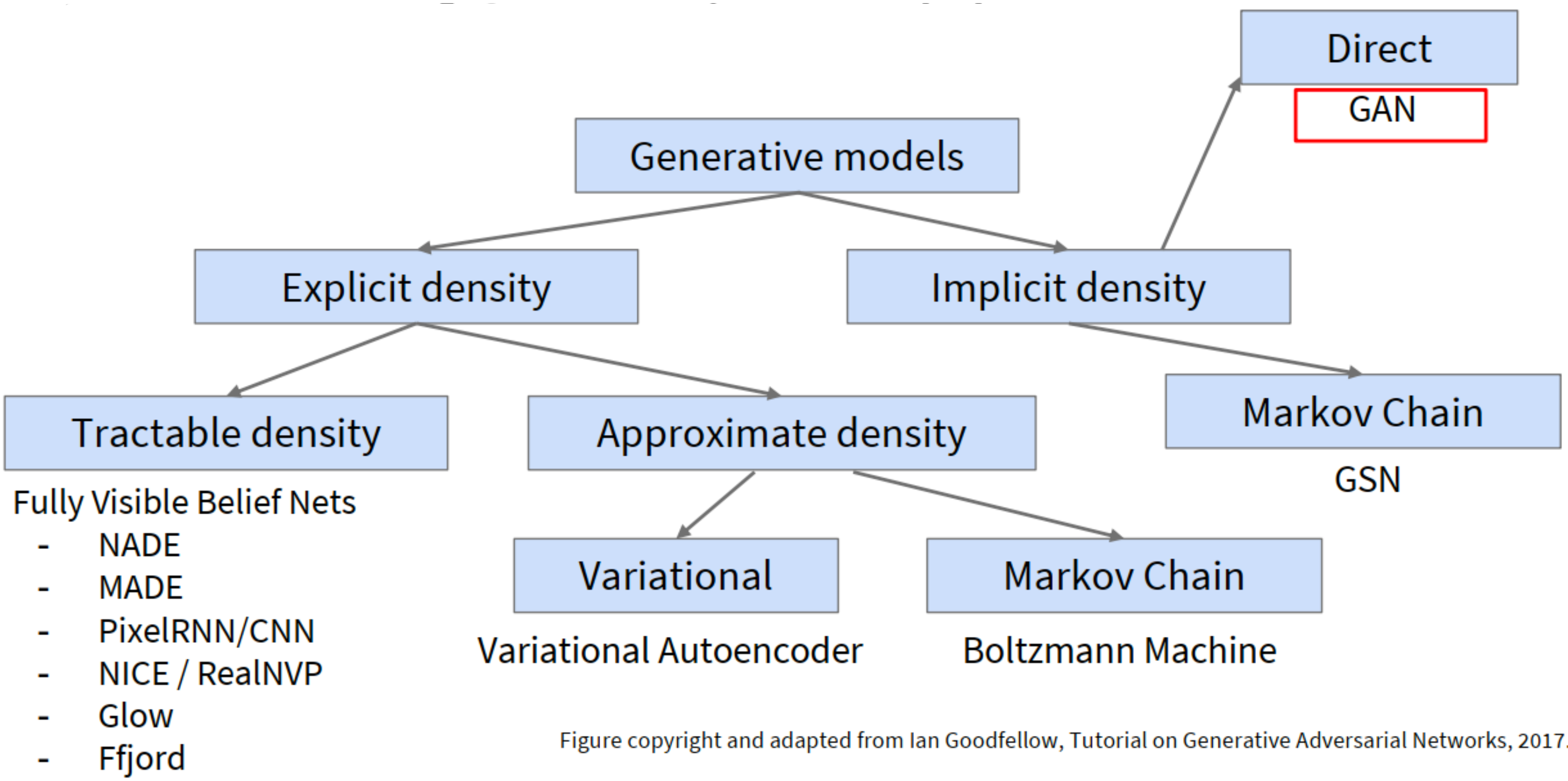


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Slide credit: Fei-Fei Li

Generative Adversarial Networks (GANs)

PixelRNN/CNNs define tractable density function, optimize likelihood of training data:

$$p_\theta(x) = \prod_{i=1}^{n} p_\theta(x_i | x_1, ..., x_{i-1})$$

VAEs define intractable density function with latent z:

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

Cannot optimize directly, derive and optimize lower bound on likelihood instead

What if we give up on explicitly modeling density, and just want ability to sample?

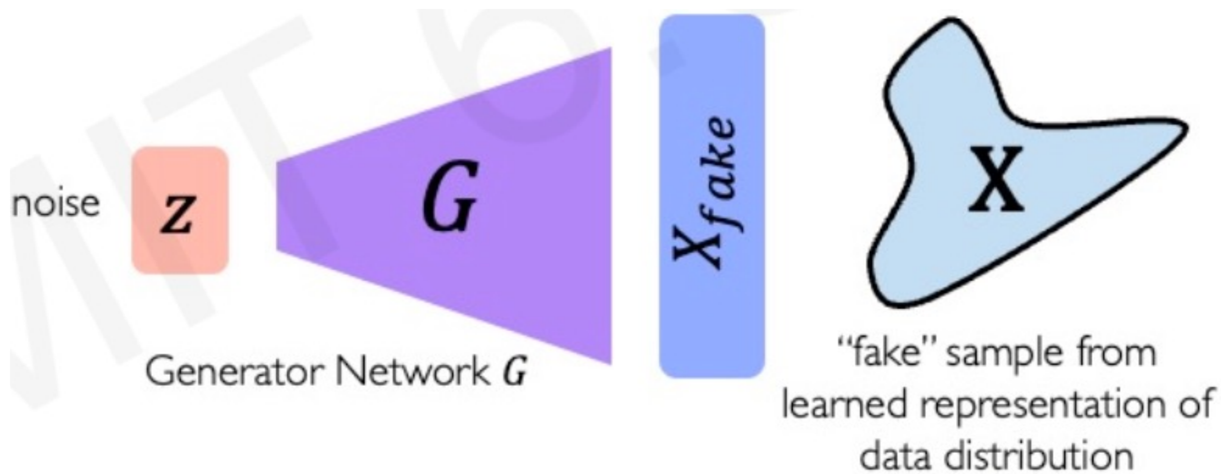
GANs: not modeling any explicit density function!

Slide credit: Fei-Fei Li

Generative Adversarial Networks (GANs)

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

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



https://introtodeeplearning.com/

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Slide credit: Fei-Fei Li

Generative Adversarial Networks (GANs)

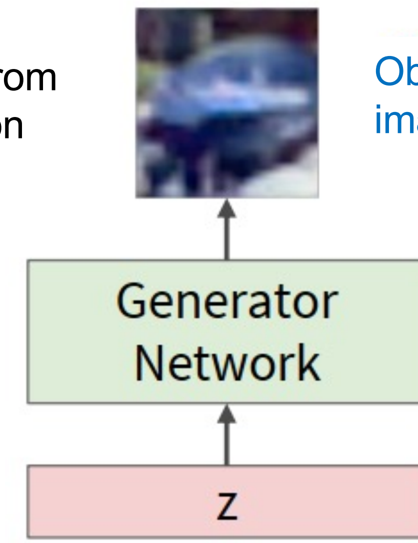
Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this!

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

But we don't know which sample z maps to which training image -> can't learn by reconstructing training images

Output: Sample from training distribution

Objective: generated images should look "real"



Input: Random noise

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

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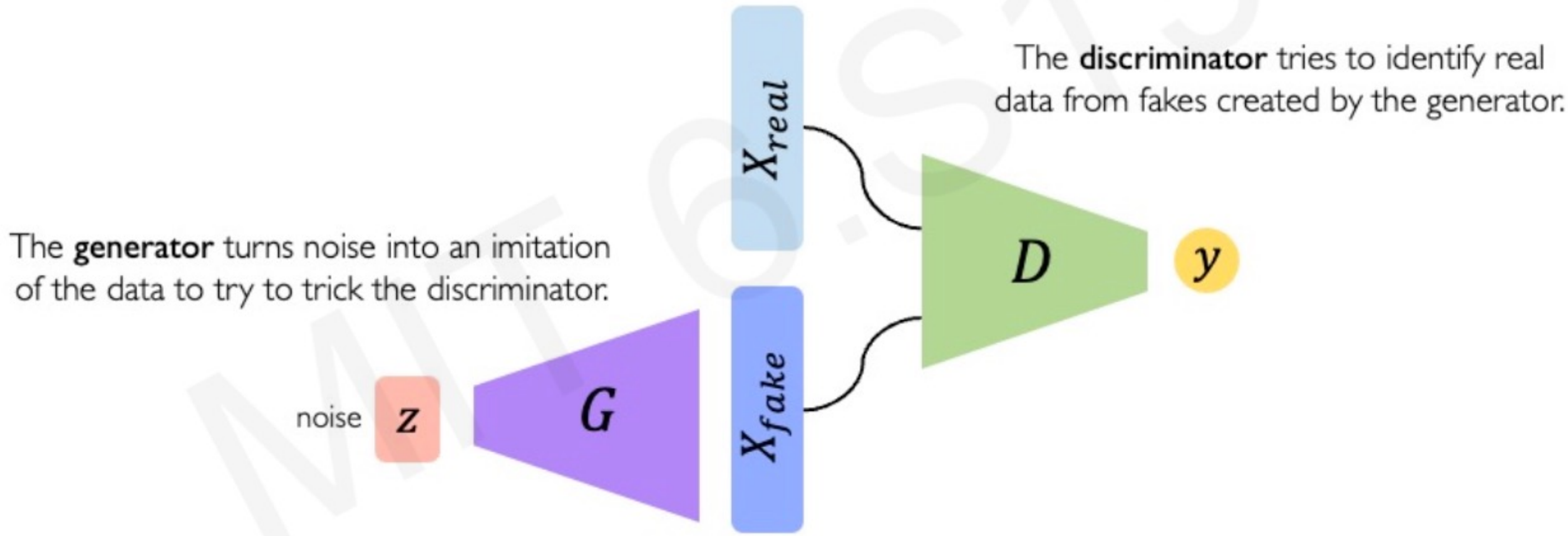
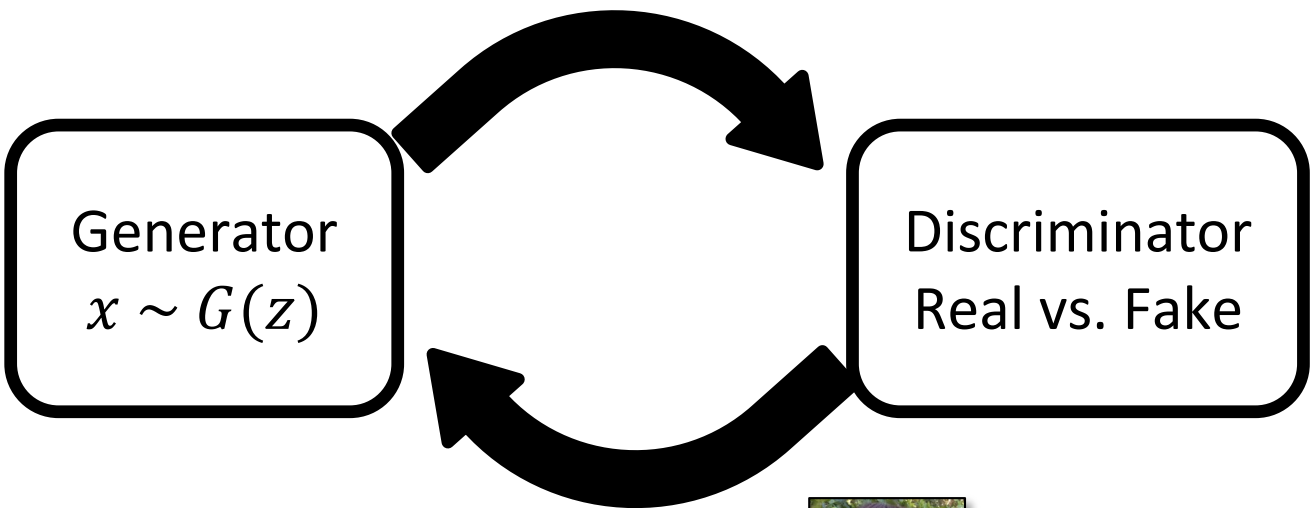
Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are a way to make a generative model by having two neural networks compete with each other.



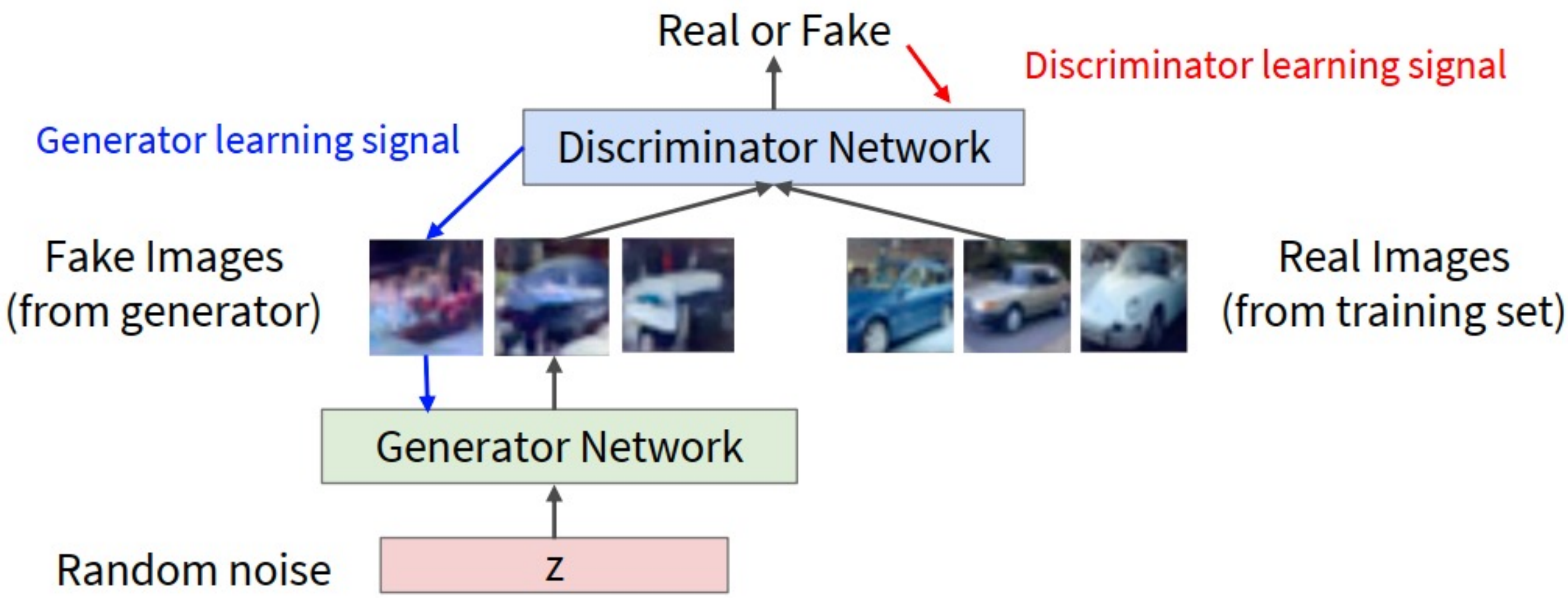
Adversarial Networks Framework



[Goodfellow et al. 2014]

Training GANs: Two-player game

Discriminator network: try to distinguish between real and fake images
Generator network: try to fool the discriminator by generating real-looking images



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

Slide credit: Fei-Fei Li

Training GANs: Two-player game

Discriminator network: try to distinguish between real and fake images
Generator network: try to fool the discriminator by generating real-looking images

Train jointly in minimax game

Minimax Objective Function:

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

Generator objective

Discriminator objective

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

Slide credit: Fei-Fei Li

Training GANs: Two-player game

Discriminator network: try to distinguish between real and fake images
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Train jointly in minimax game

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

Minimax objective function:

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

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- 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)

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Slide credit: Fei-Fei Li

Training GANs: Two-player game

Minimax objective function:

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

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

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

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

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Training GANs: Two-player game

Minimax objective function:

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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

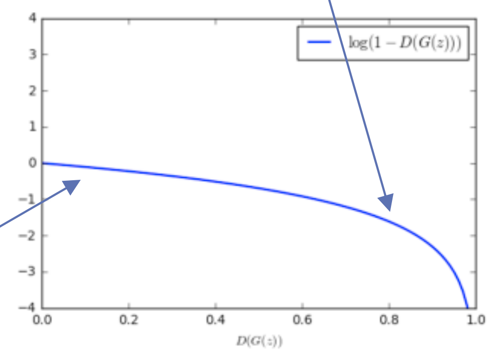
$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

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

Gradient signal dominated by region where sample is already good

When sample is likely fake, want to learn from it to improve generator (move to the right on X axis).

But gradient in this region is relatively flat!



Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Slide credit: Fei-Fei Li

Training GANs: Two-player game

Minimax objective function:

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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

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

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Slide credit: Fei-Fei Li

Training GANs: Two-player game

Putting it together: GAN training algorithm

for number of training iterations **do**

for $\boxed{k \text{ steps}}$ **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

Some find k=1 more stable, others use k > 1, no best rule.

Followup work (e.g. Wasserstein GAN, BEGAN) alleviates this problem, better stability!

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

Slide credit: Fei-Fei Li

Training GANs: Other Divergence

Least Squares GAN

$$\min_D V_{\text{LSGAN}}(D) = \frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}\left[(D(\boldsymbol{x})-1)^2\right] + \frac{1}{2}\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\left[(D(G(\boldsymbol{z})))^2\right]$$

$$\min_G V_{\text{LSGAN}}(G) = \frac{1}{2}\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\left[(D(G(\boldsymbol{z}))-1)^2\right].$$

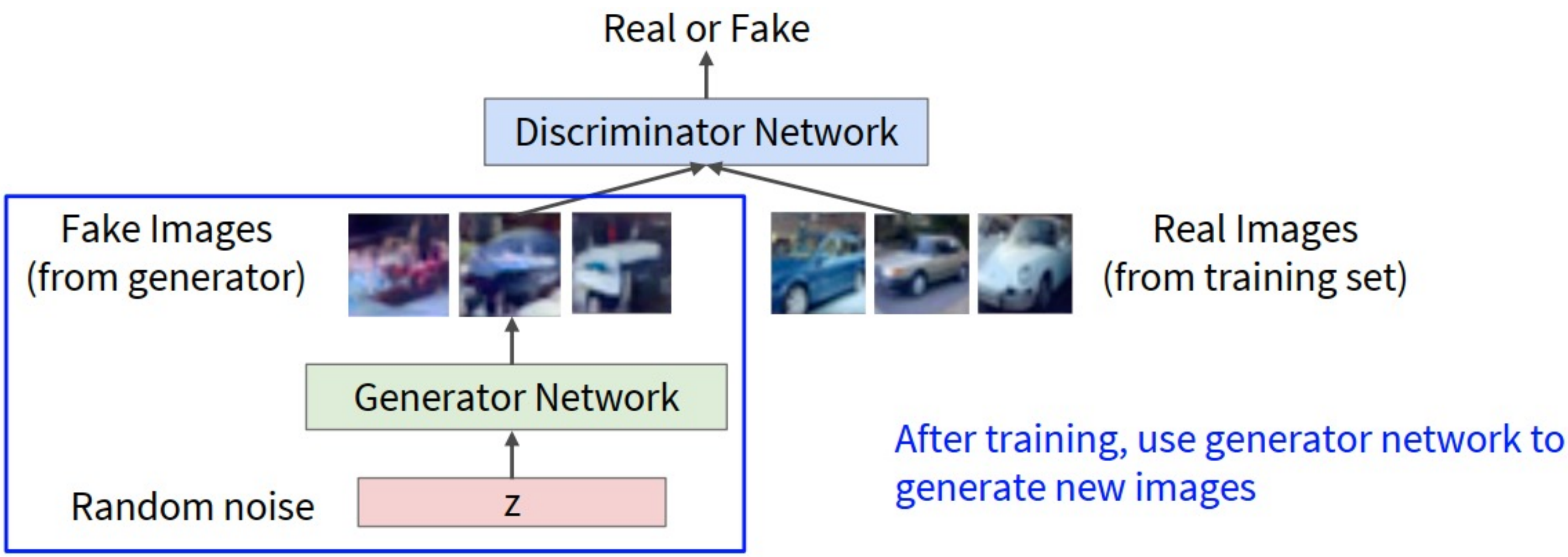
* Employed for our Assignment.

Xudong Mao et al., "Least Squares GAN", ICCV 2017

https://arxiv.org/pdf/1611.04076
https://sh-tsang.medium.com/review-lsgan-least-squares-generative-adversarial-networks-gan-bec12167e915

Training GANs: Two-player game

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

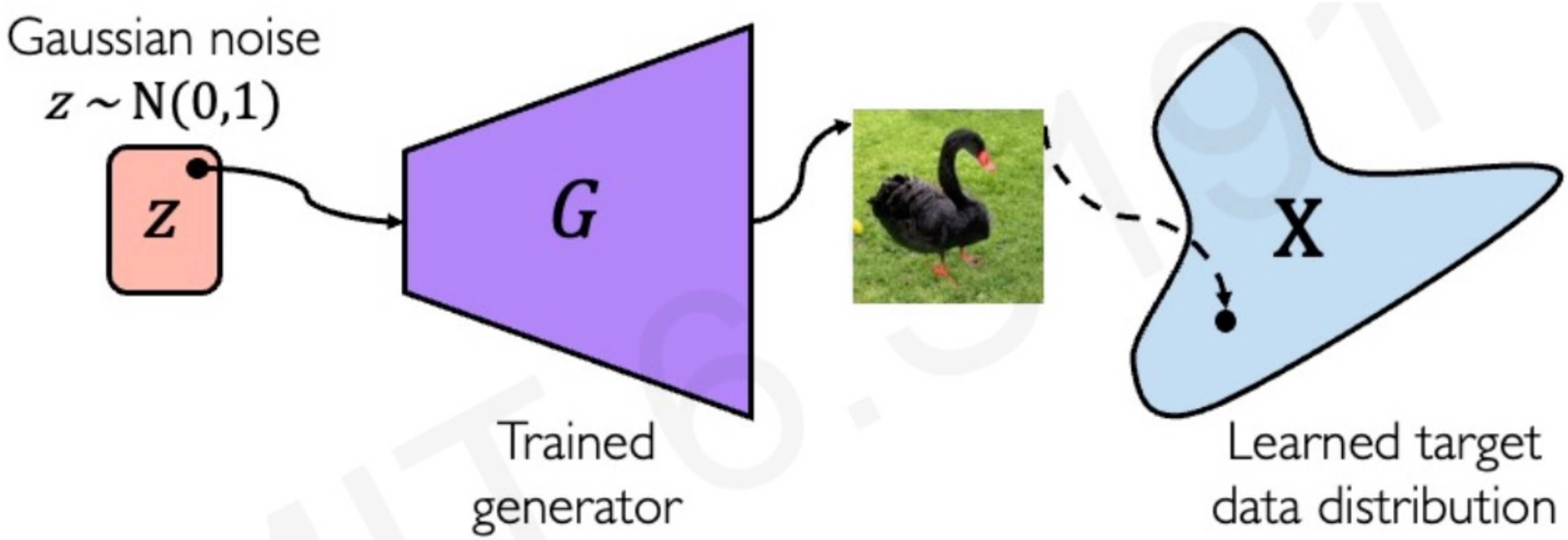


Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Slide credit: Fei-Fei Li

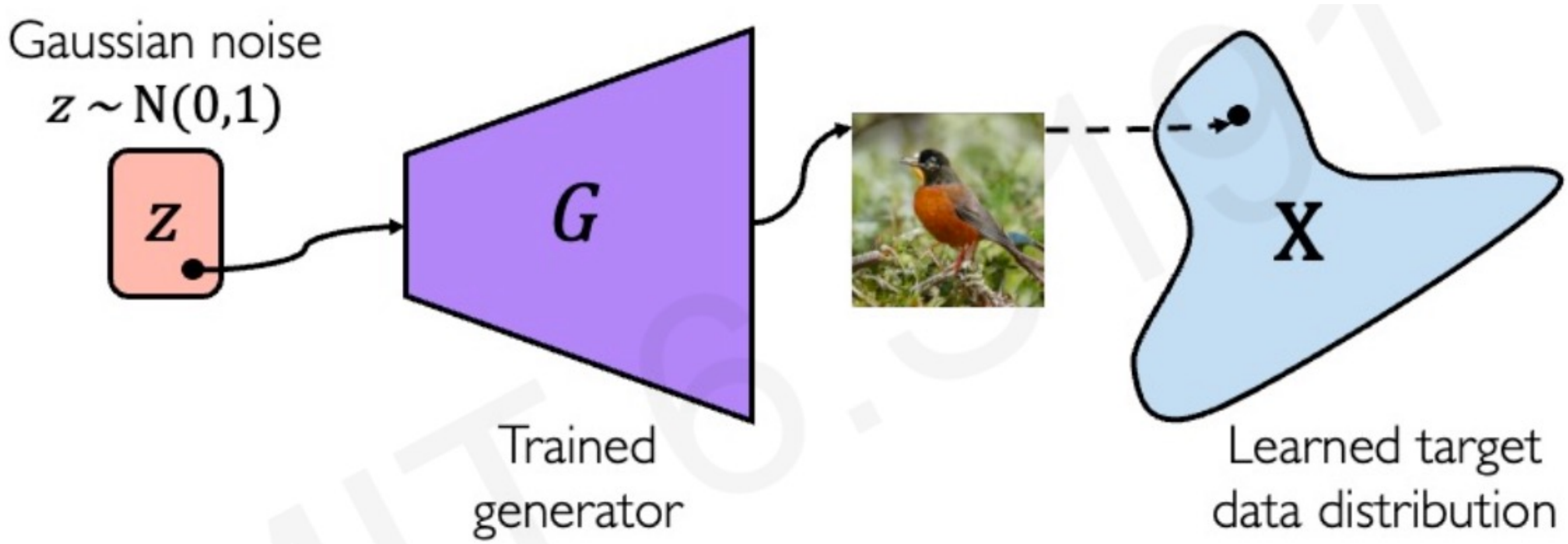
GANs: Generating New Data

GANs are Distribution Transformers



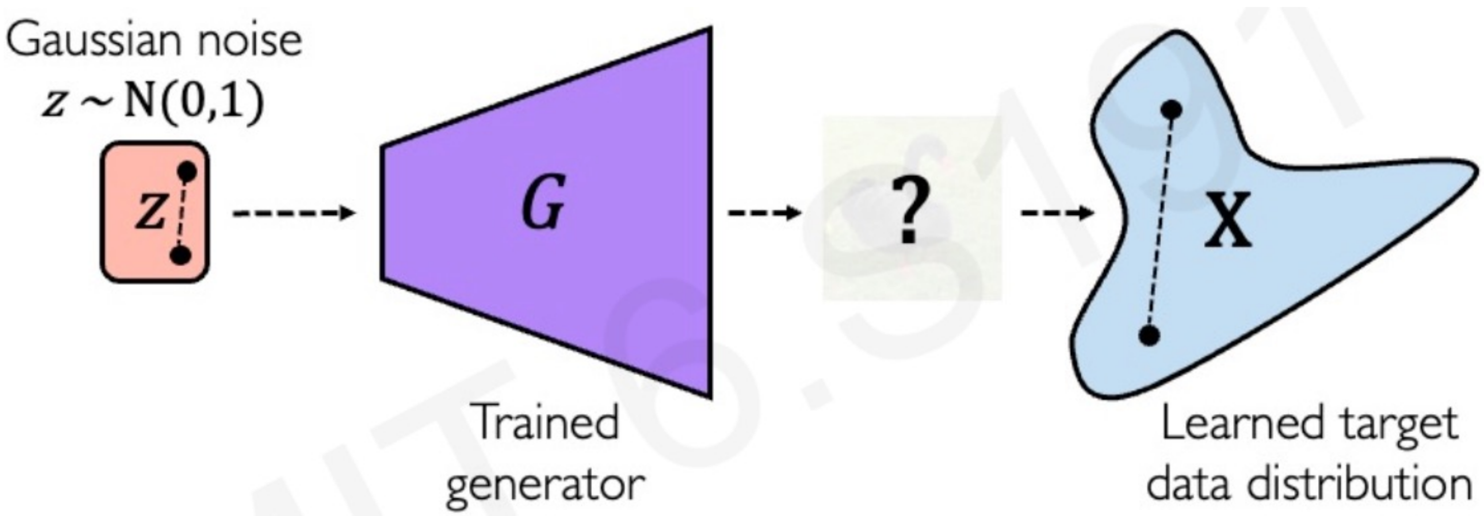
GANs: Generating New Data

GANs are Distribution Transformers



GANs: Generating New Data

GANs are Distribution Transformers

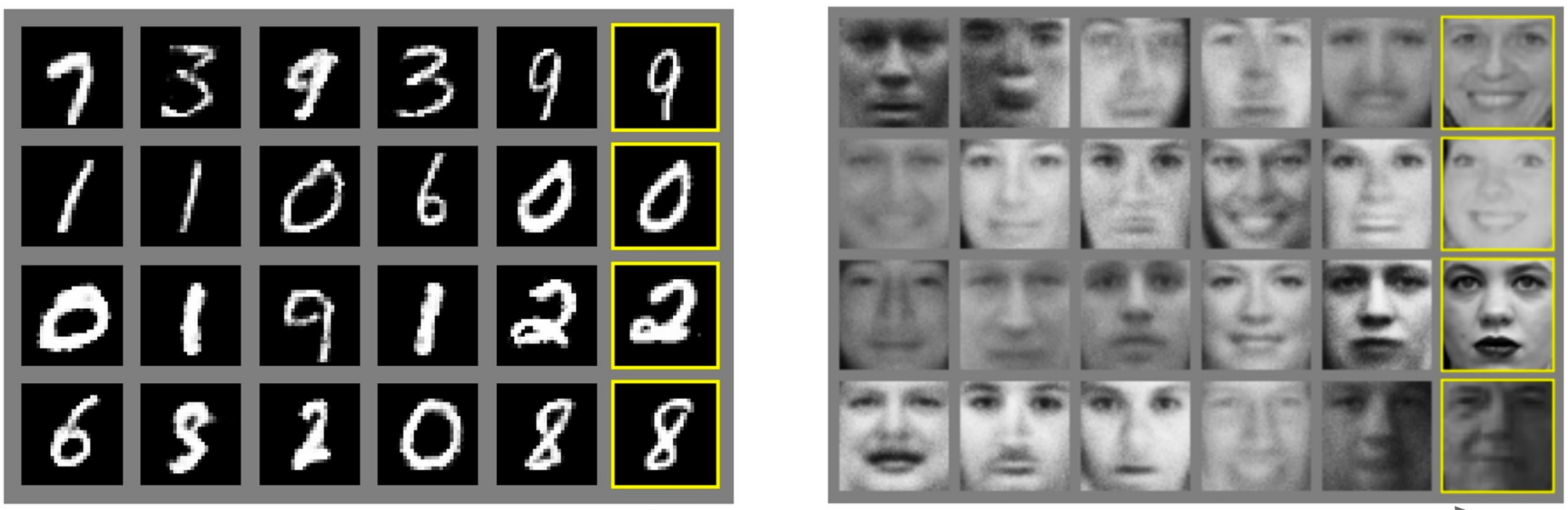


Lab 13a: Generative Adversarial Networks (GANs) for Digits

Duration: 10 min

Generative Adversarial Nets

Generated samples



Nearest neighbor from training set

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

Slide credit: Fei-Fei Li

Generative Adversarial Nets

Generated samples (CIFAR-10)

Nearest neighbor from training set

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

Slide credit: Fei-Fei Li

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

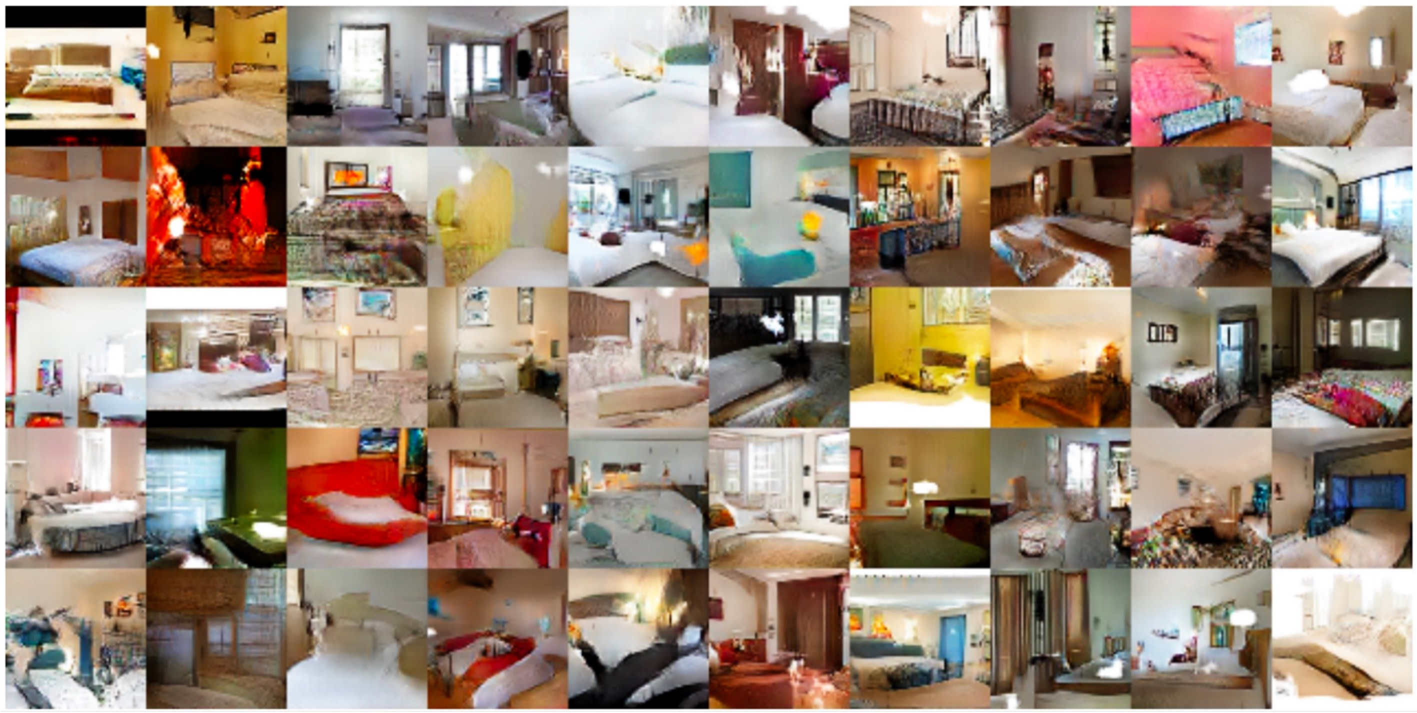
- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except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

Slide credit: Fei-Fei Li

Generative Adversarial Nets: Convolutional Architectures

Samples from the model look much better!



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

Slide credit: Fei-Fei Li

Generative Adversarial Nets: Convolutional Architectures

Interpolating between random points in latent space

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

Slide credit: Fei-Fei Li

GANs: Interpretable Vector Math

Radford et al, ICLR 2016

Smiling woman Neutral woman Neutral man

Samples from the model

Adapted from Serena Young

GANs: Interpretable Vector Math

Radford et al,
ICLR 2016

Adapted from Serena Young

2017: Explosion of GANs

"The GAN Zoo"

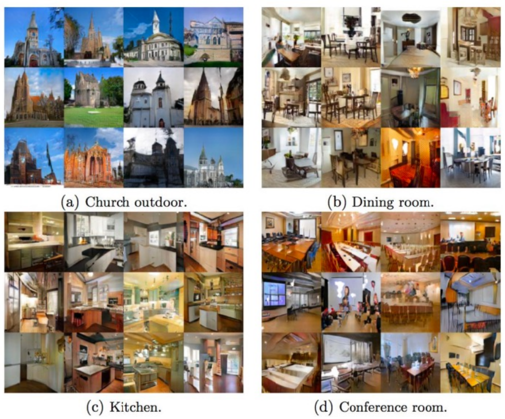
- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdaGAN - AdaGAN: 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 Categorial 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

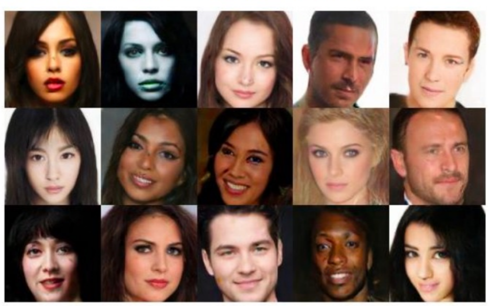
Adapted from Serena Young

2017: Explosion of GANs

Better training and generation



LSGAN. Mao et al. 2017.



BEGAN. Bertholet et al. 2017.

Adapted from Serena Young

Source->Target domain transfer

CycleGAN. Zhu et al. 2017.

Text -> Image Synthesis

Reed et al. 2017.

Many GAN applications

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

Summary: 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 samples!

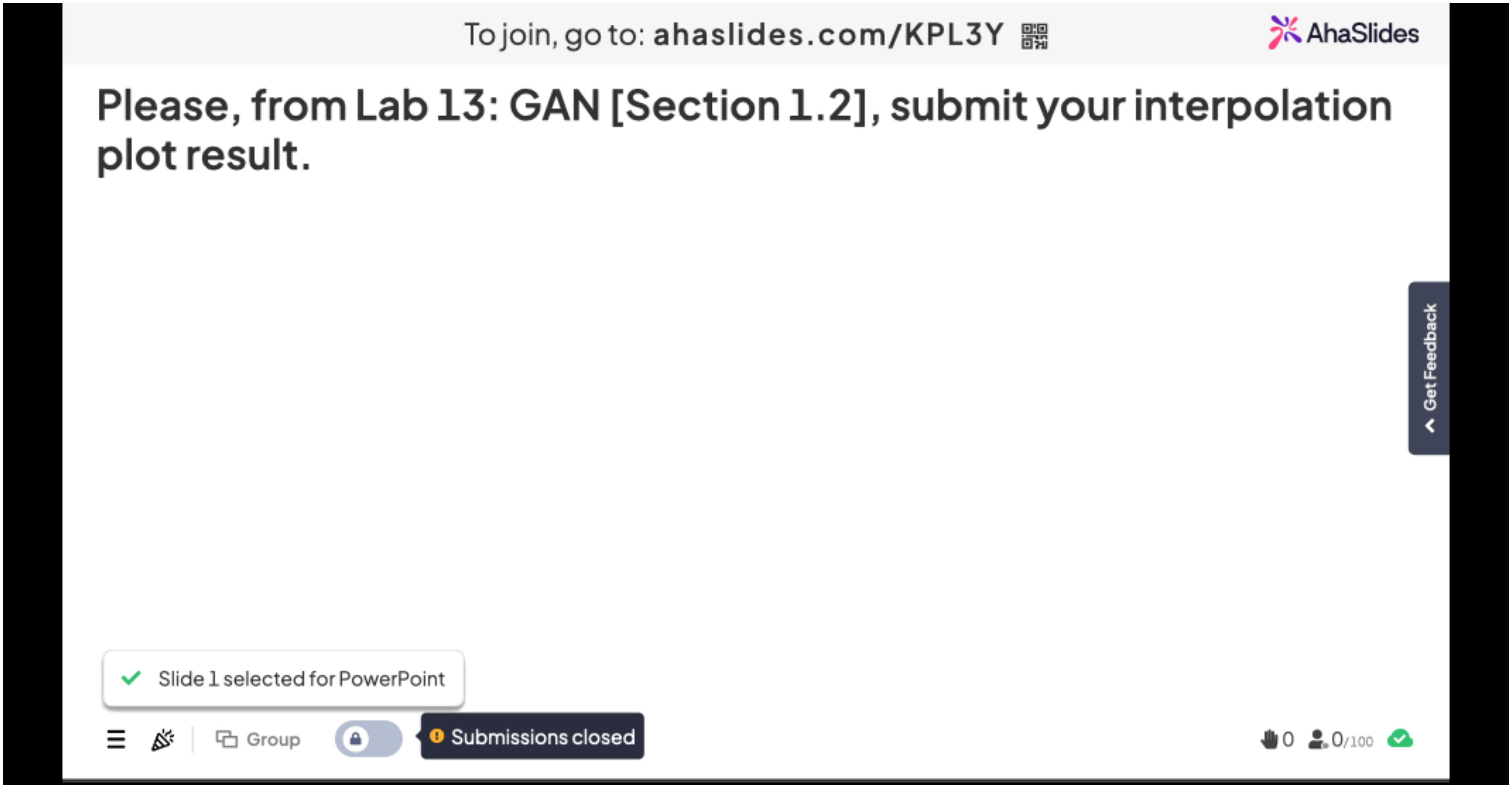
Cons:
- Trickier / more unstable to train
- Can't solve inference queries such as p(x), p(z|x)

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

Adapted from Serena Young

Lab 13b: Generative Adversarial Networks (GANs)

Duration: 10 min


To join, go to: ahaslides.com/KPL3Y
AhaSlides
Please, from Lab 13: GAN [Section 1.2], submit your interpolation plot result.
Get Feedback
Slide 1 selected for PowerPoint
Group
Submissions closed
0
0/100

Taxonomy of Generative Models

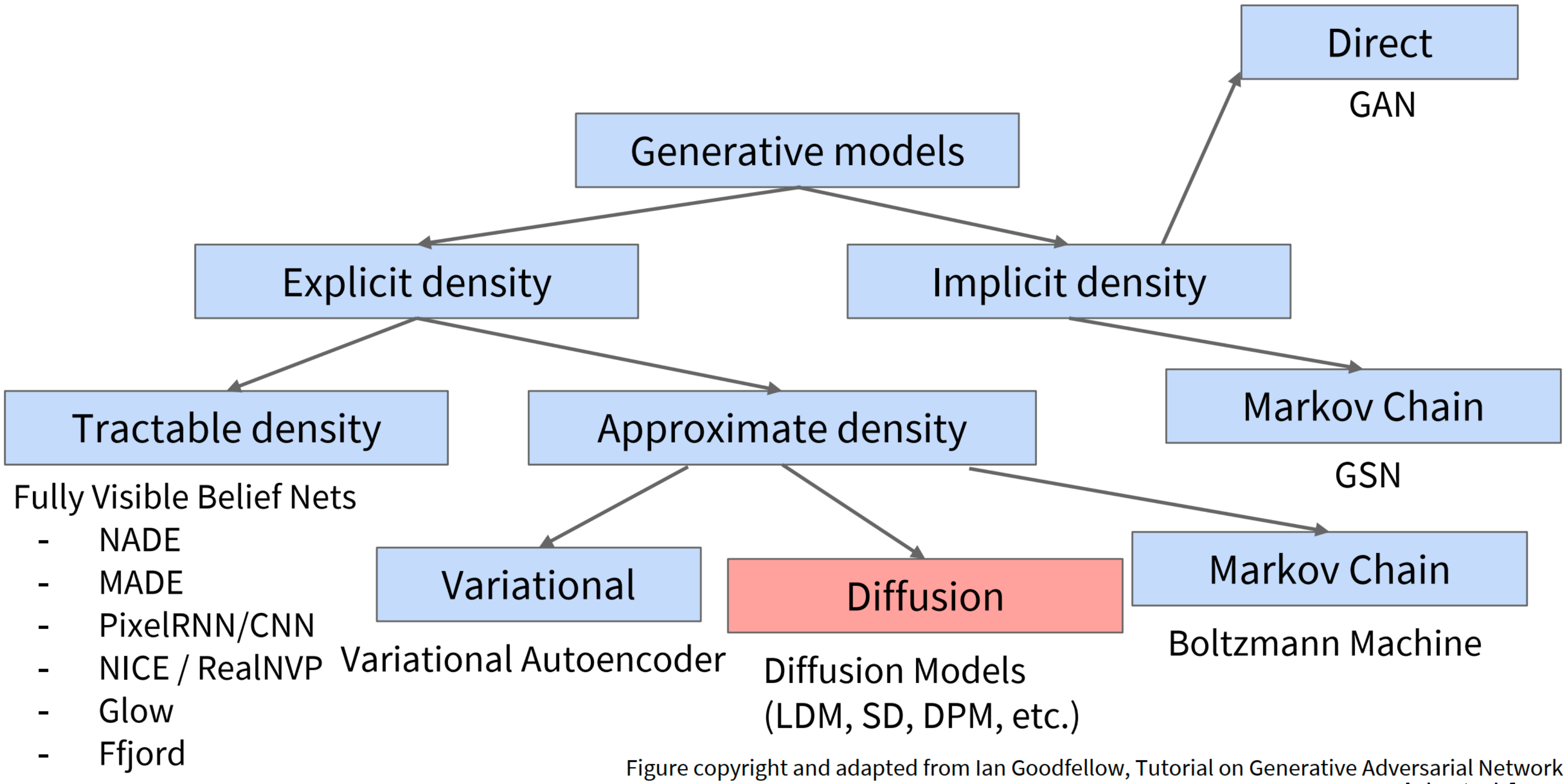


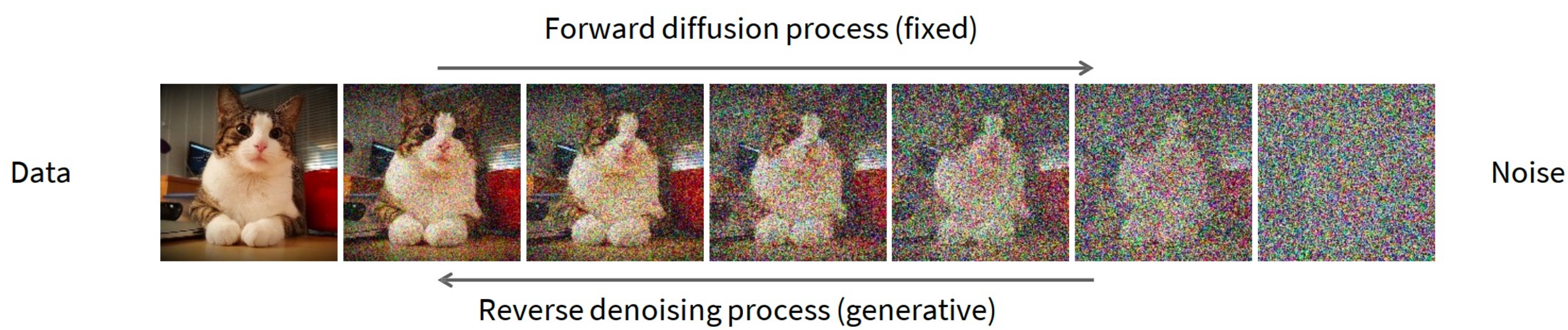
Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Network

Adapted from Fei-Fei Li

Denoising Diffusion Models

Learning to generate by denoising
Denoising diffusion models consist of two processes:

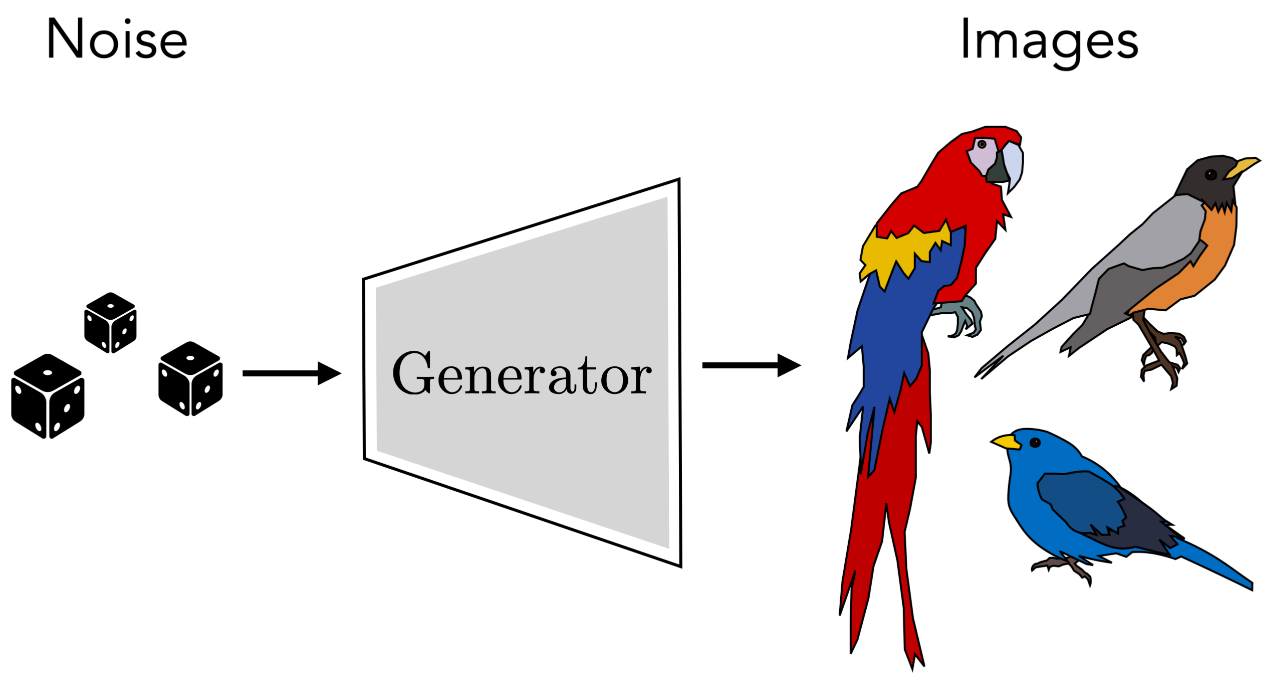
- Forward diffusion process that gradually adds noise to input
- Reverse denoising process that learns to generate data by denoising



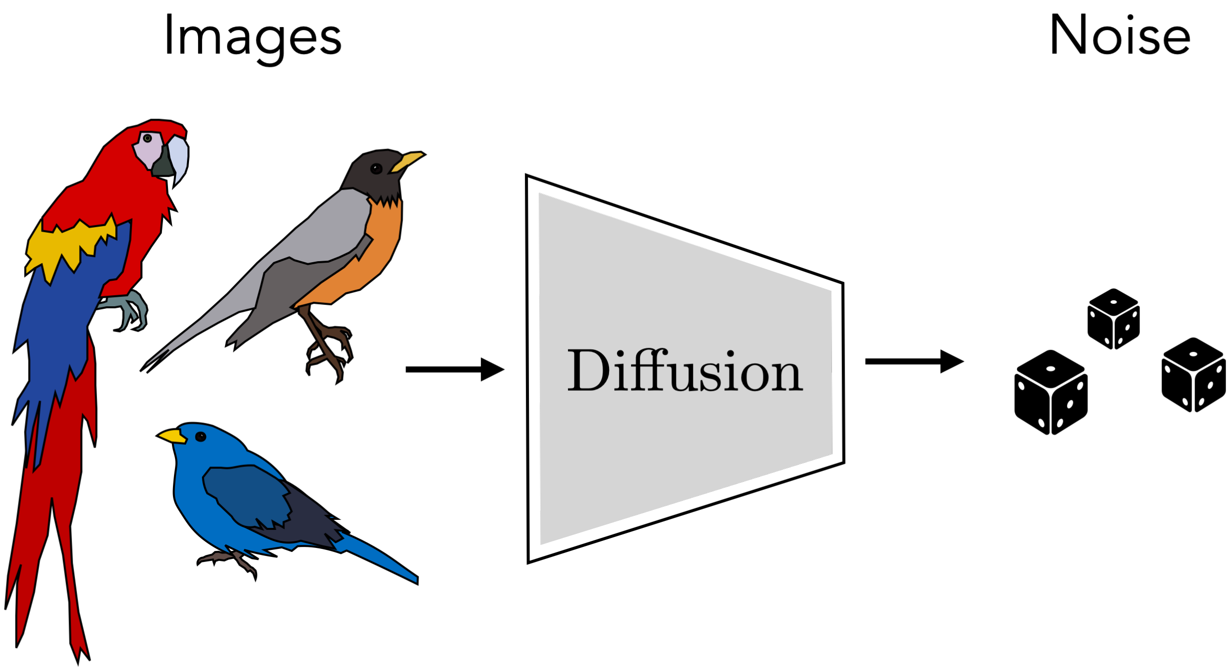
Sohl-Dickstein et al., Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML 2015 Ho et al., Denoising Diffusion Probabilistic Models, NeurIPS 2020
Song et al., Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021

slide from https://cvpr2022-tutorial-diffusion-models.github.io/
Courtesy of Ruiqi Gao

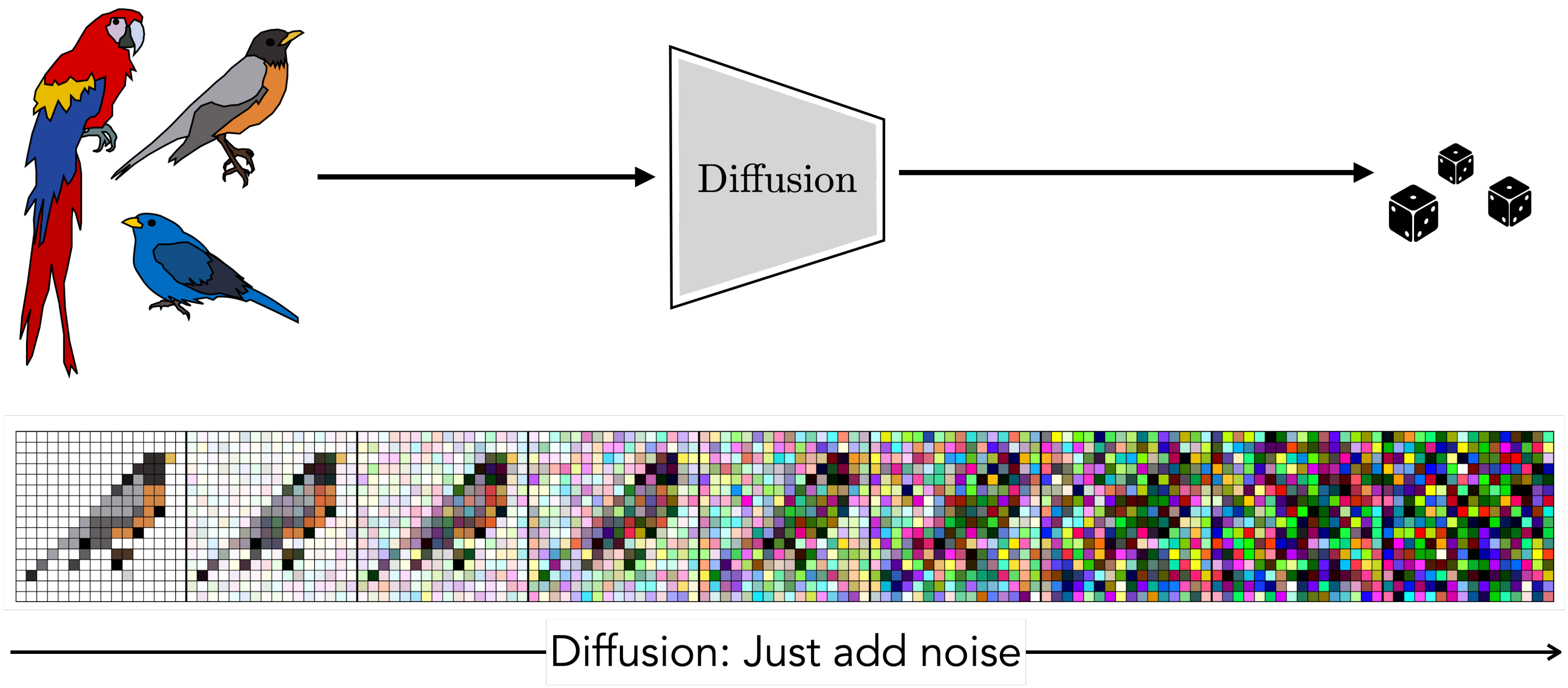
Diffusion Models



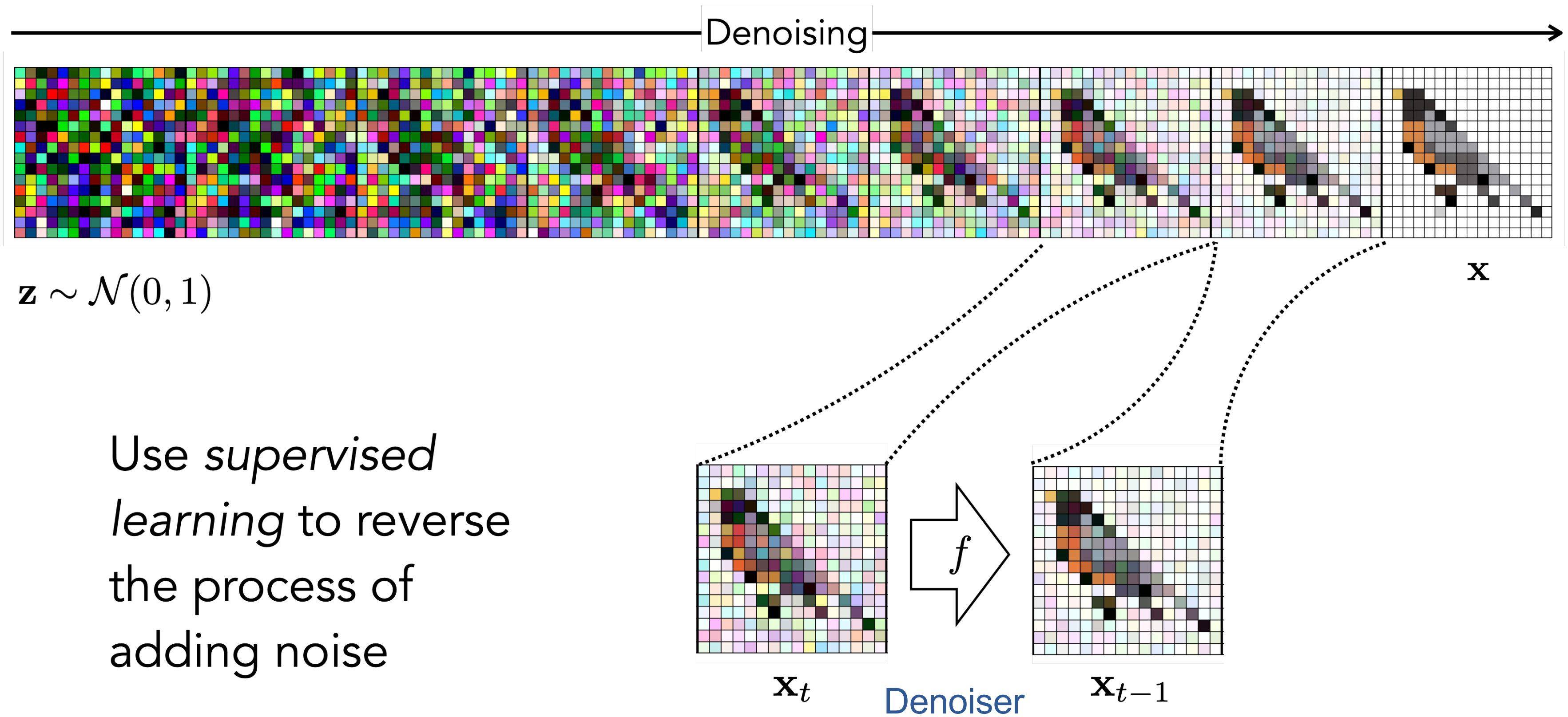
Diffusion Models



Diffusion Models

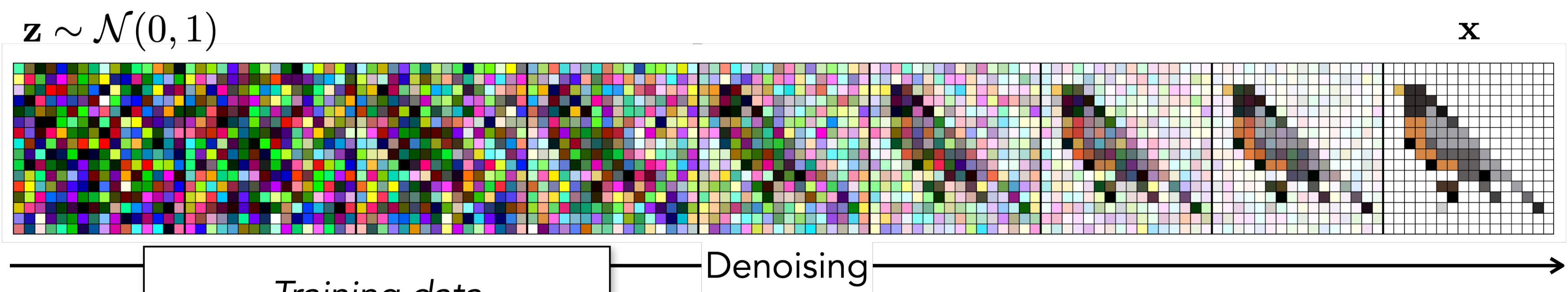


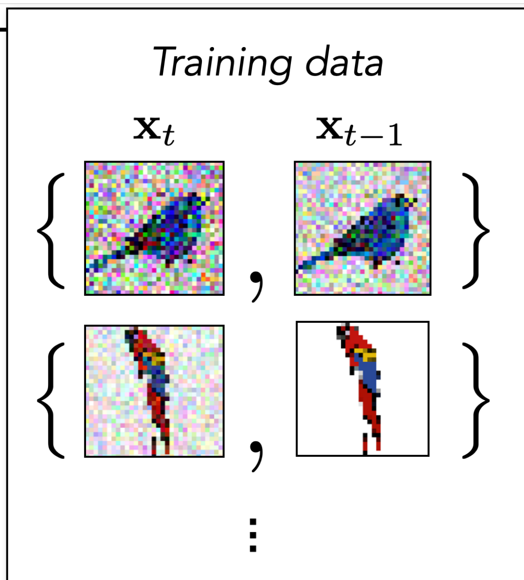
Diffusion Models



Use *supervised learning* to reverse the process of adding noise

Diffusion Models



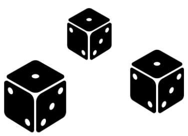


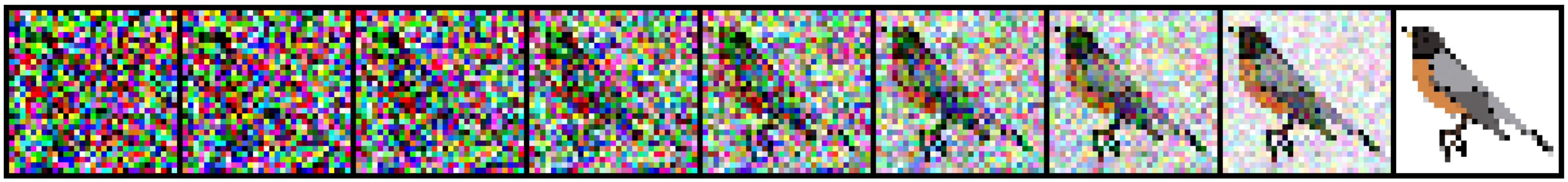
$$\arg\min_{f \in \mathcal{F}} \sum_{i=1}^{N} \mathcal{L}(f(\mathbf{x}_t), \mathbf{x}_{t-1})$$

Converts generative modeling into a bunch of supervised prediction problems

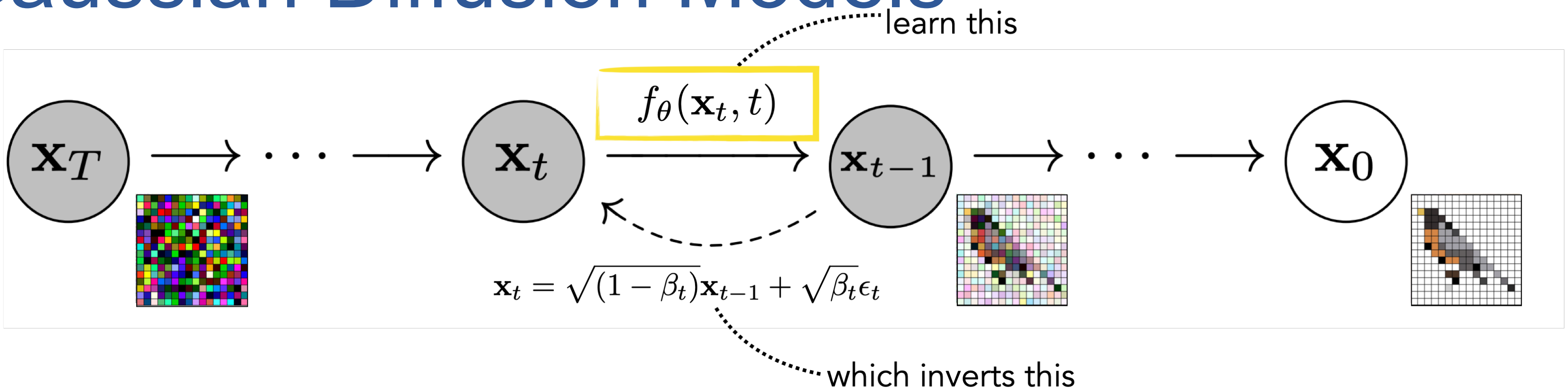
Diffusion Models

Different noise samples (dice rolls) result in different images





Gaussian Diffusion Models



Forward process:

$$\epsilon_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \qquad \mathbf{x}_t = \sqrt{(1-\beta_t)}\mathbf{x}_{t-1} + \sqrt{\beta_t}\epsilon_t$$

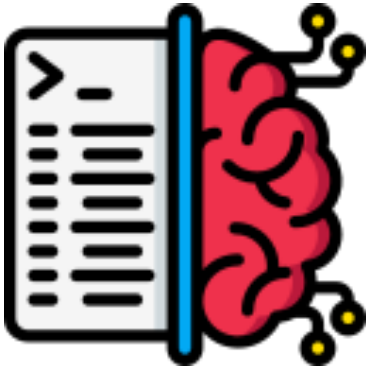
The variances, beta and sigma, are modeling choices. See Ho, Jain, and Abbeel for details.

Reverse process:

$$\mathbf{x}_{t-1} = f_\theta(\mathbf{x}_t, t)$$

Diffusion Models: Training

1. Generate Training data by corrupting a bunch of images (forward process; noising)
2. Train a neural net to invert each step of corruption (reverse process; denoising)



Diffusion Models: Training

Algorithm 1.2: Training a diffusion model.

Input: training data $\{\mathbf{x}^{(i)}\}_{i=1}^{N}$

Output: trained model f_θ

Forward Process. Noising

Generate training sequences via diffusion:

for $i = 1, \ldots, N$ **do**

  for $t = 1, \ldots, T$ **do**

    $\epsilon_t \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$

    $\mathbf{x}_t^{(i)} \leftarrow \sqrt{(1-\beta_t)}\mathbf{x}_{t-1}^{(i)} + \sqrt{\beta_t}\epsilon_t$

Reverse Process. Denoising

Train denoiser f_θ to reverse these sequences:

$\theta^* = \arg\min_\theta \sum_{i=1}^{N} \sum_{t=1}^{T} \mathcal{L}(f_\theta(\mathbf{x}_t^{(i)}, t), \mathbf{x}_{t-1}^{(i)})$

Return: f_{θ^*}

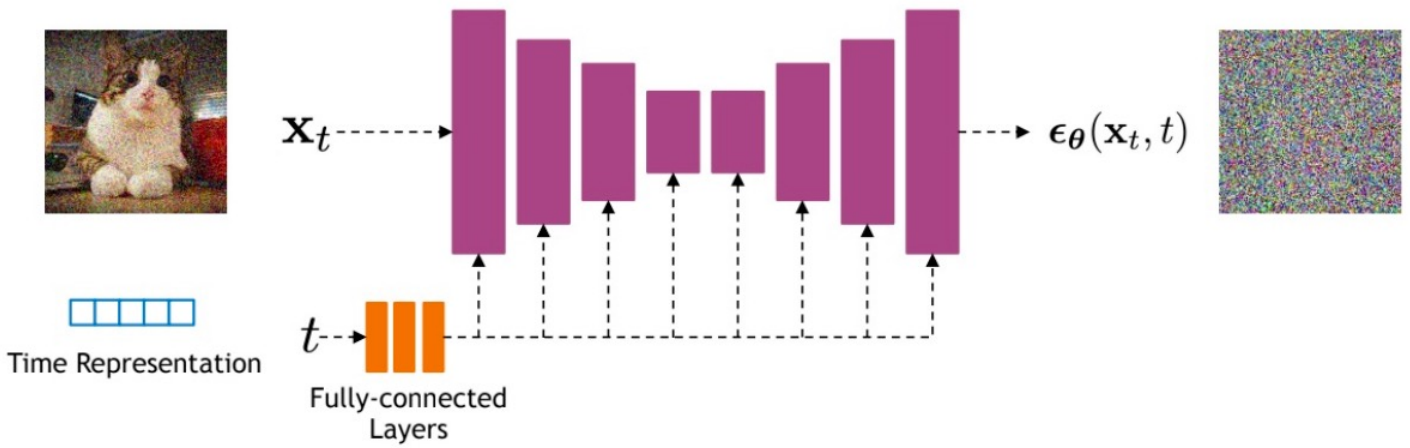
Lab 13c

Lab 13c: Diffusion Models

Duration: 10 min

Diffusion Models: Training – Unet model transition

Diffusion models often use U-Net architectures with ResNet blocks and self-attention layers to represent $\epsilon_\theta(\mathbf{x}_t, t)$

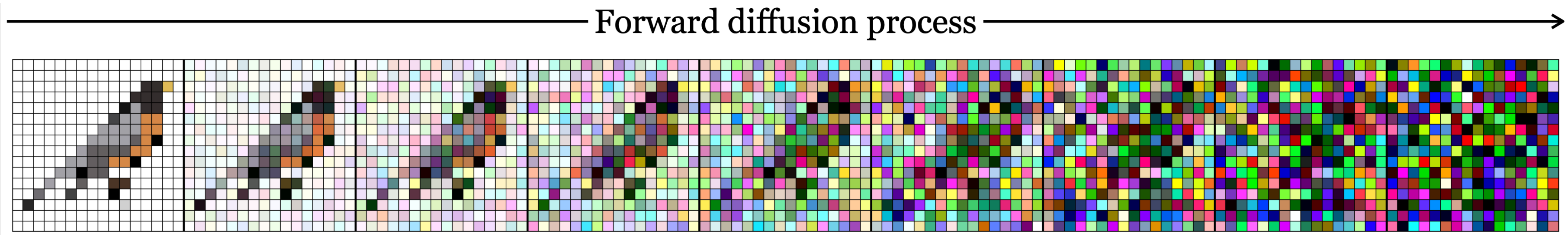


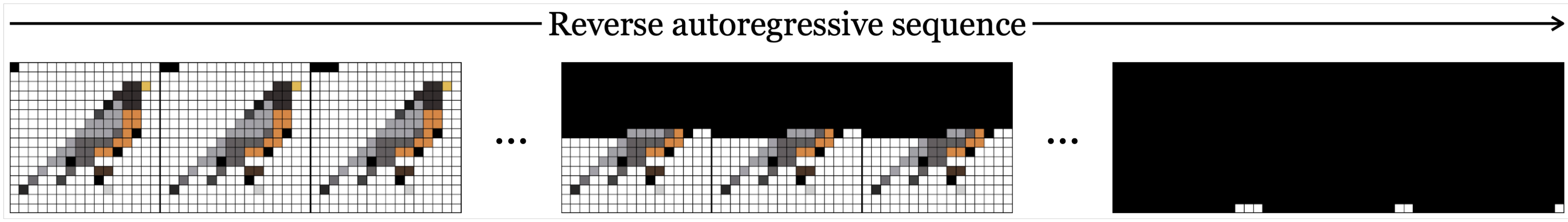
Time representation: sinusoidal positional embeddings or random Fourier features.

Time features are fed to the residual blocks using either simple spatial addition or using adaptive group normalization layers. (see Dharivwal and Nichol NeurIPS 2021)

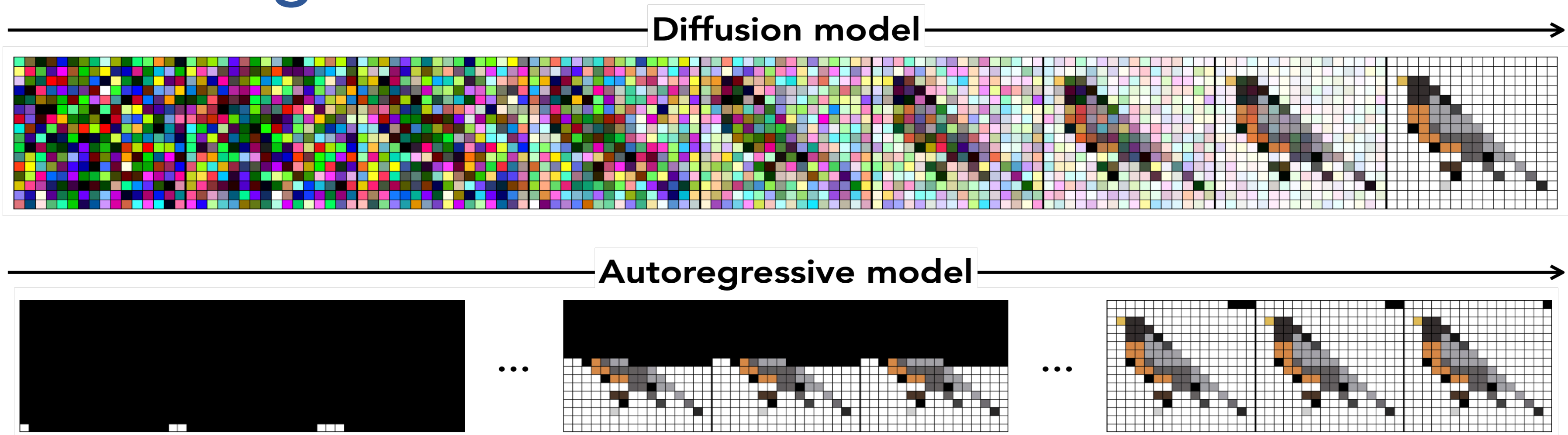
https://cvpr2022-tutorial-diffusion-models.github.io/

Autoregressive Modes vs Diffusion Models





Autoregressive Modes vs Diffusion Models



A common strategy is to turn generative modeling into a sequence of supervised learning problems

2022 / 2023 : The year of diffusion and generative modeling?

Parti
Pathways Autoregressive Text-to-Image Model

DALL·E 2

Stable Diffusion

slide from https://cvpr2022-tutorial-diffusion-models.github.io/
Courtesy of Ruiqi Gao

Useful Resources on Generative Models

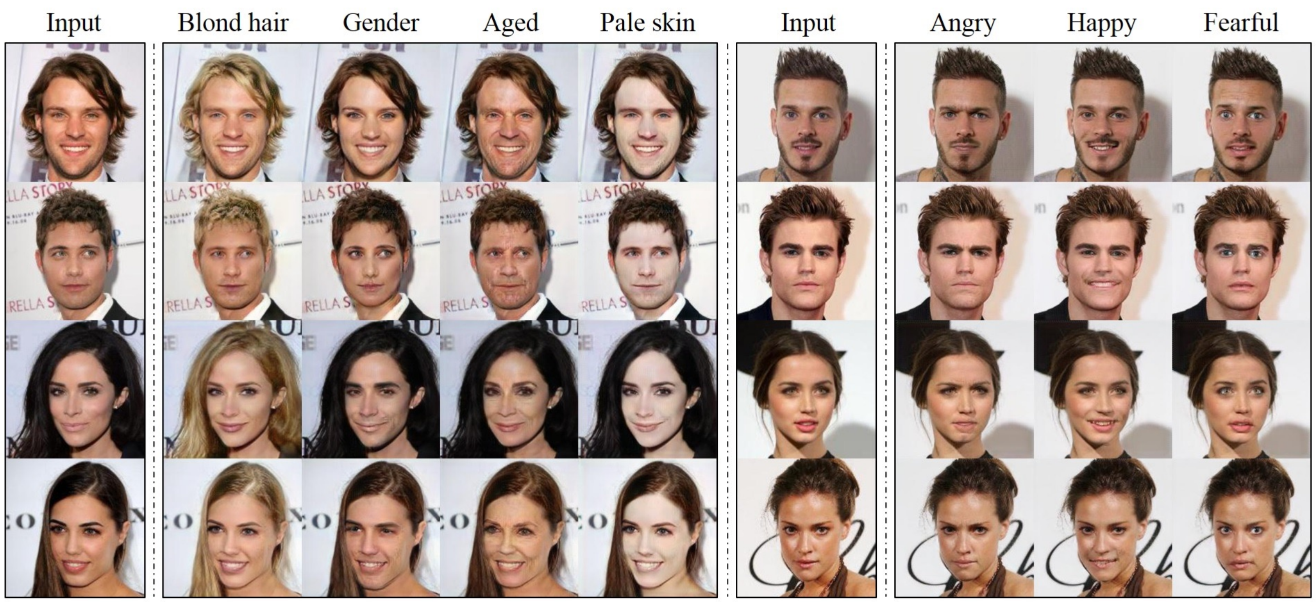
CS 236: Deep Generative Models (Stanford)

CS 294-158 Deep Unsupervised Learning (Berkeley)

Applications: Celebrities Who Never Existed

Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Applications: StarGAN



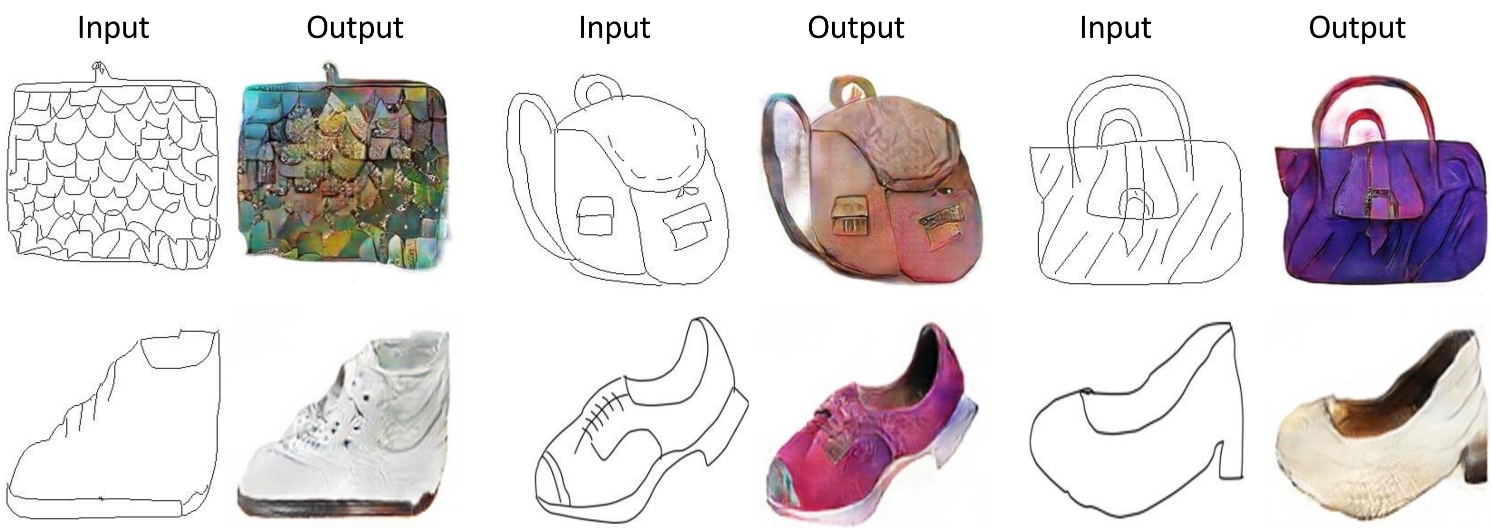
Choi et al., "StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation", CVPR 2018

Applications: Edges to Images

Edges from [Xie & Tu, 2015]

Pix2pix / CycleGAN

Applications: Sketches to Images



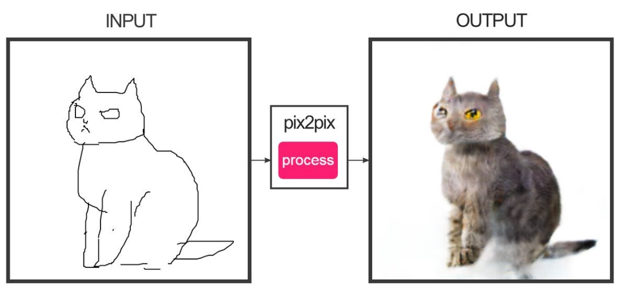
Trained on Edges → Images

Data from [Eitz, Hays, Alexa, 2012]

Pix2pix / CycleGAN

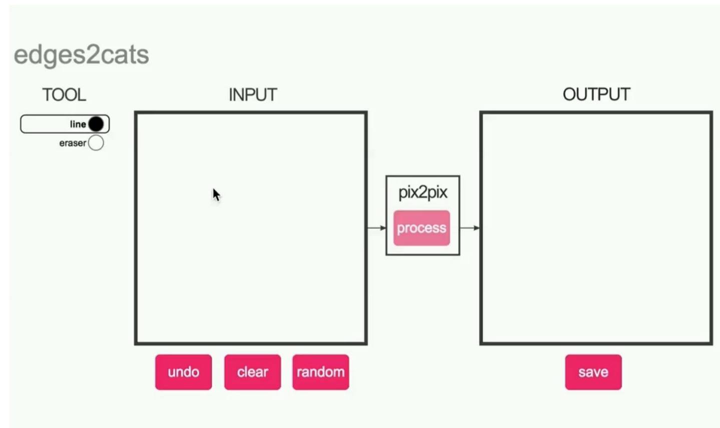
Applications: Edges to Images

#edges2cats [Christopher Hesse]



@gods_tail

Ivy Tasi @ivymyt



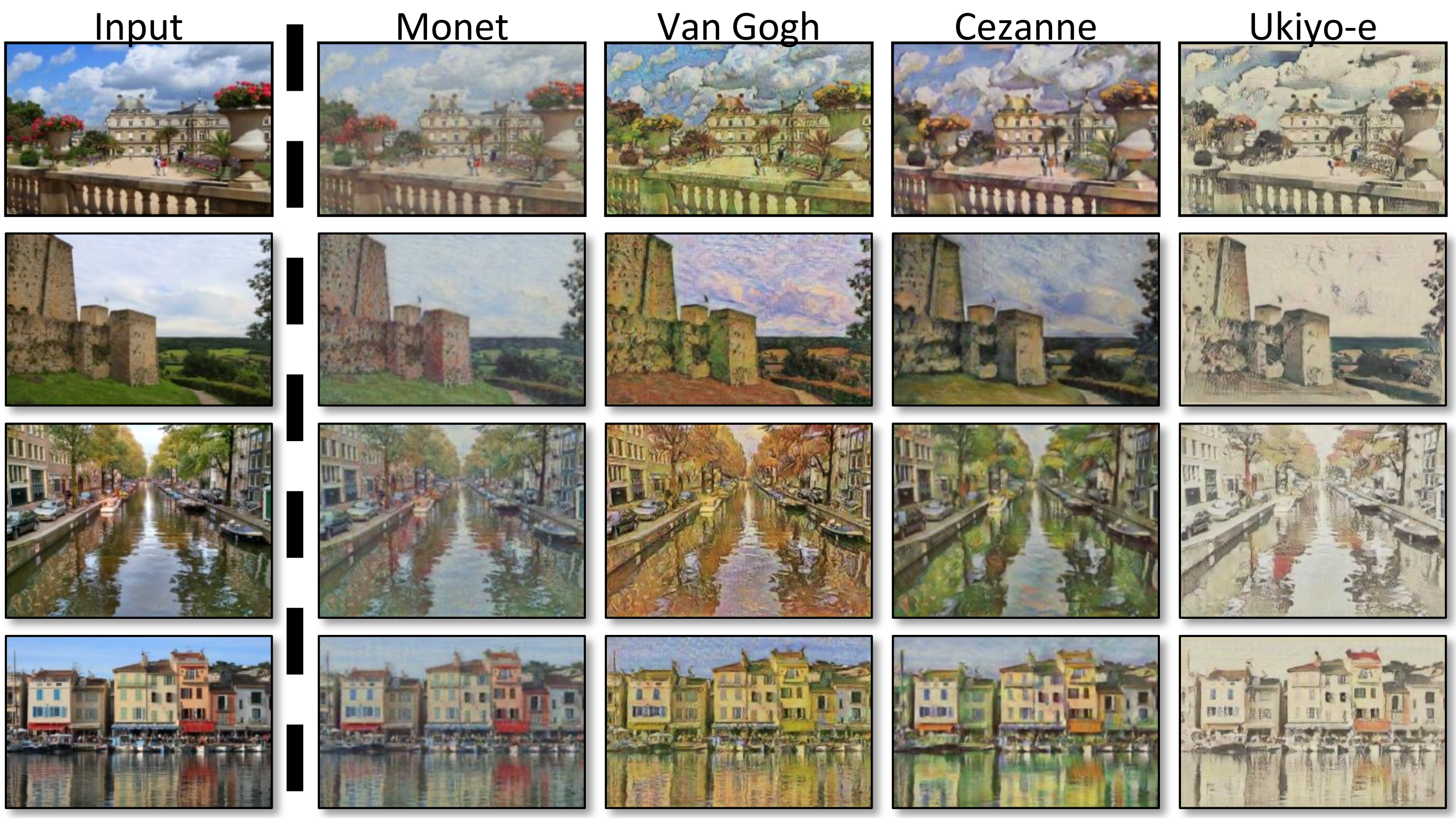
@matthematician

Vitaly Vidmirov @vvid

https://affinelayer.com/pixsrv/

Pix2pix / CycleGAN

Applications: Changing Artistic Style



Pix2pix / CycleGAN

Applications: Changing Seasons

Pix2pix / CycleGAN

Extra

Taxonomy of Generative Models

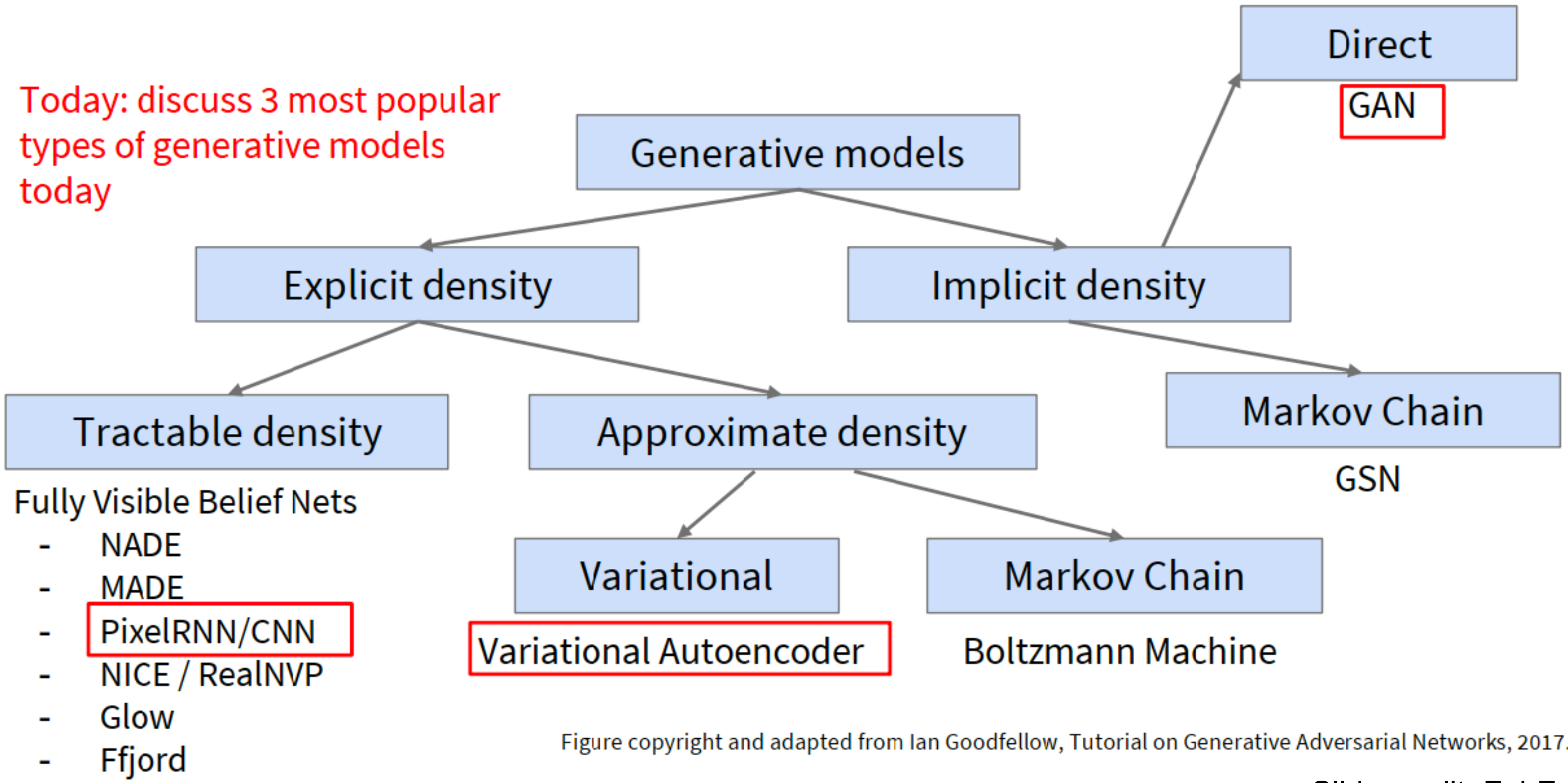


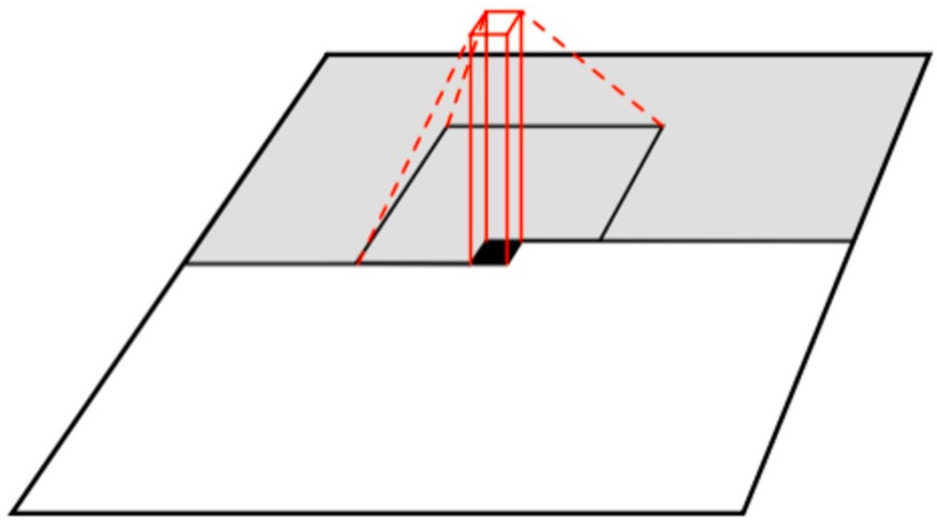
Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Slide credit: Fei-Fei Li

PixelCNN [van der Oord et al. 2016]

Still generate image pixels starting from corner

Dependency on previous pixels now model using a CNN over context region (masked convolution)



Slide credit: Fei-Fei Li

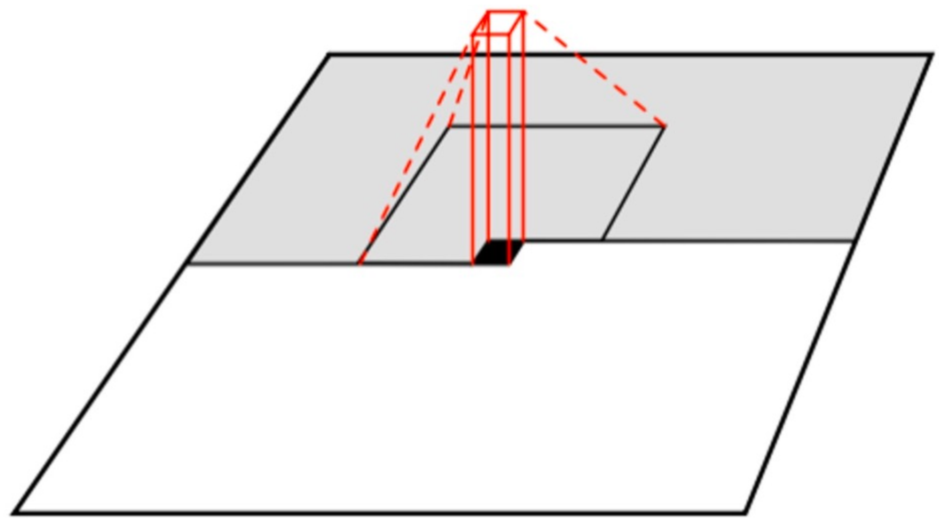
PixelCNN [van der Oord et al. 2016]

Still generate image pixels starting from corner

Dependency on previous pixels now model using a CNN over context region (masked convolution)

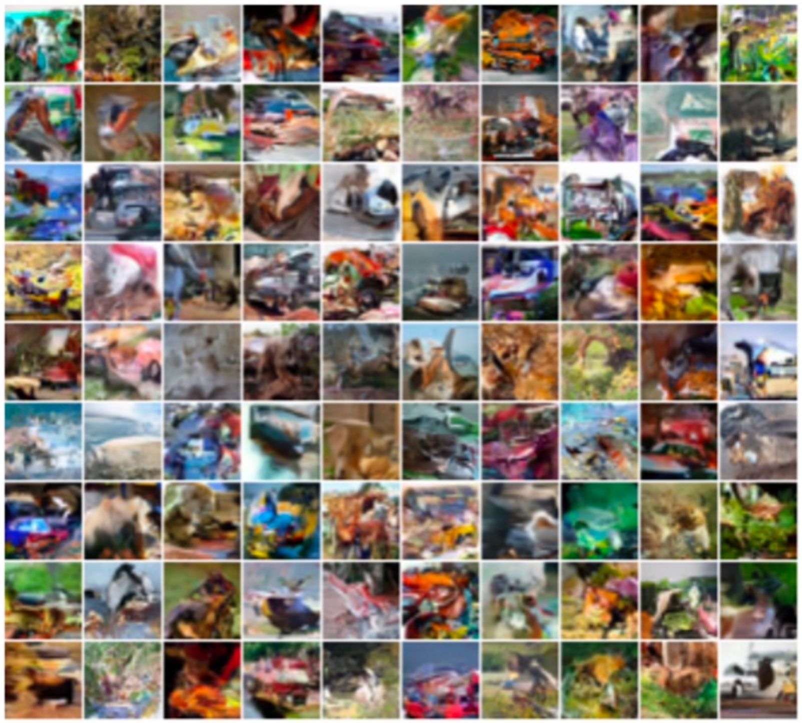
Training is faster than PixelRNN (can parallelize convolutions since context Region values known from training images)

Generation is still slow:
For a 32x32 image, we need to do forward passes of the network 1024 times for a single image

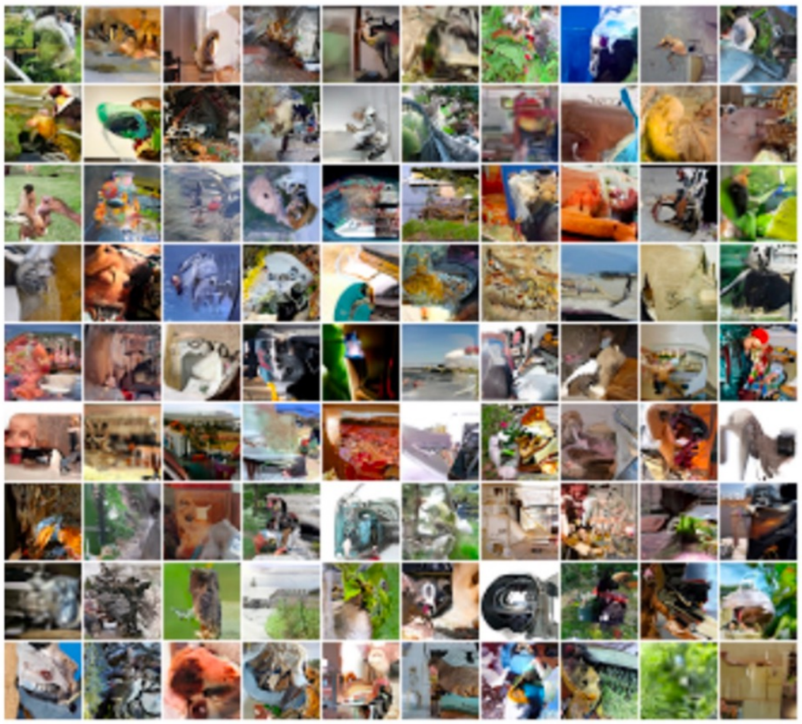


Slide credit: Fei-Fei Li

Generation Samples



32x32 CIFAR-10



32x32 ImageNet

Slide credit: Fei-Fei Li

PixelRNN and PixelCNN

Pros:

- Can explicitly compute likelihood p(x)
- Easy to optimize
- Good samples

Cons:
- Sequential generation => slow

Improving PixelCNN performance
- Gated convolutional layers
- Short-cut connections
- Discretized logistic loss
- Multi-scale
- Training tricks
- Etc…

See
- Van der Oord et al. NIPS 2016
- Salimans et al. 2017 (PixelCNN++)

Slide credit: Fei-Fei Li

How to improve PixelCNN?

What are the limitations of PixelCNN/RNN?

- Slow sampling time.
- May accumulate errors over multiple steps. (might not be a big issue for image completion)

How can we further improve results?

Slide credit: Jun-Yan Zhu - Learning-Based Image Synthesis

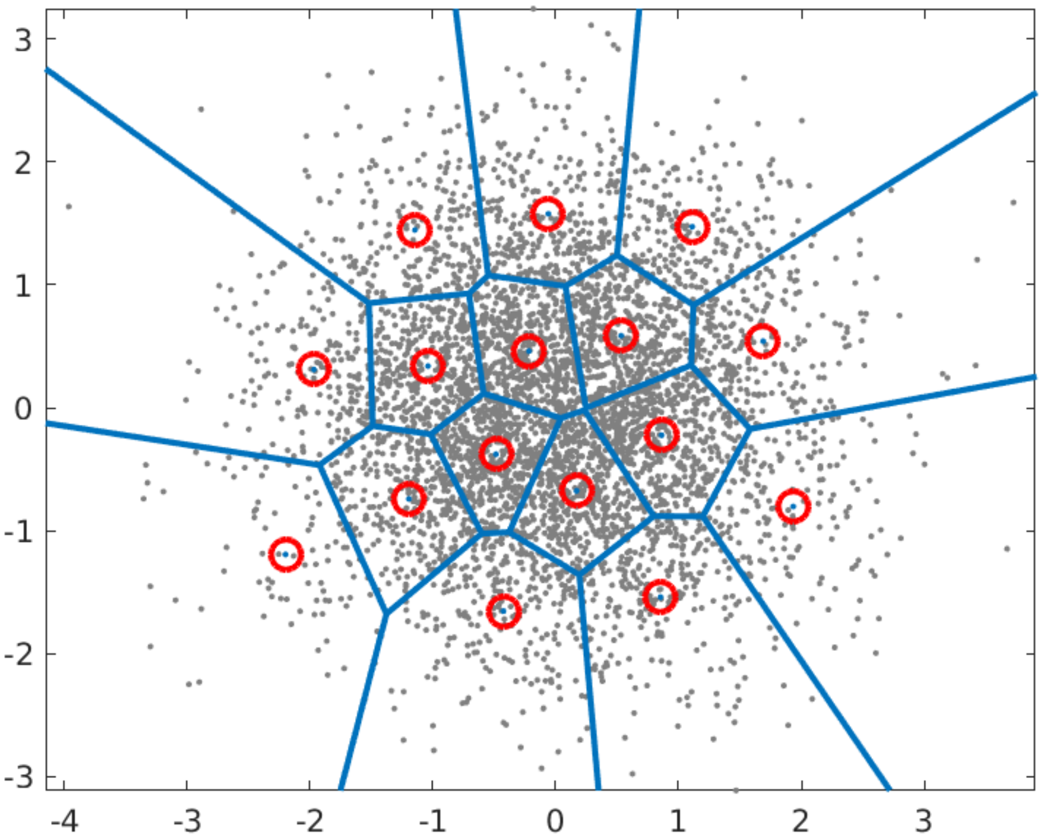
VQ-VAE-2 :VAE+PixelCNN

VQ (Vector quantization) maps continuous vectors into discrete codes

Common methods: clustering (e.g., k-means)

Generating Diverse High-Fidelity Images with VQ 45 -VAE-2 [Razavi et al., 2019]

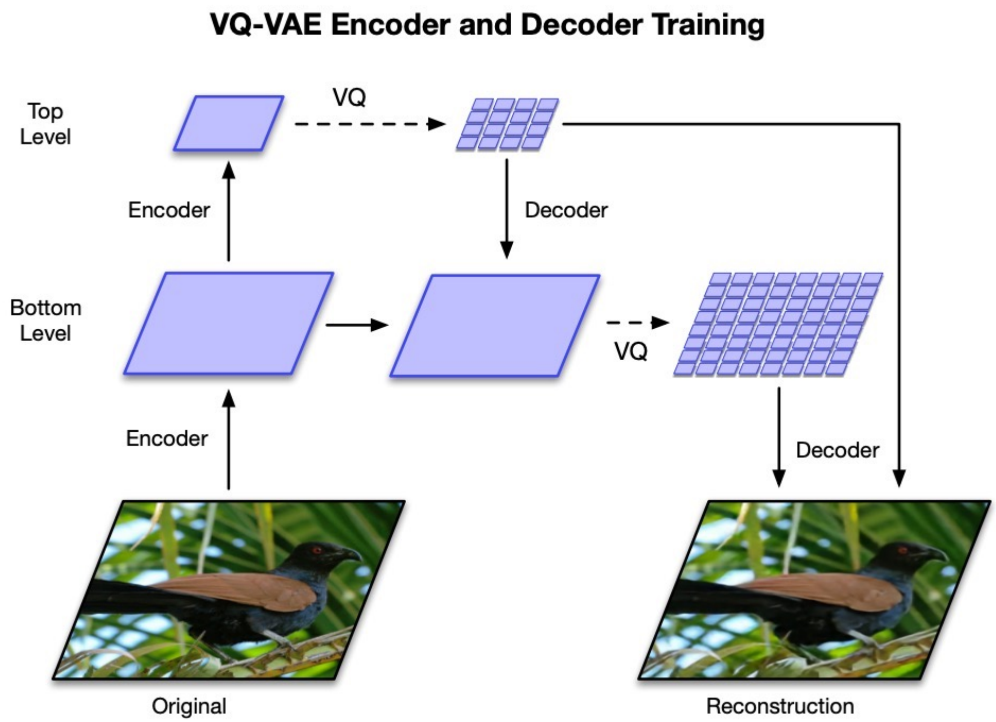
VQ-VAE-2 : Vector Quantization



K-means, EM (GMM), end-to-end learning

https://wiki.aalto.fi/pages/viewpage.action?pageId=149883153

VQ-VAE-2 :VAE+PixelCNN



VAE+VQ: learn a more compact codebook for PixelCNN (instead of pixels)
PixelCNN: use a more expressive bottleneck for VAE (instead of Gaussian

Generating Diverse High-Fidelity Images with VQ 45 -VAE-2 [Razavi et al., 2019]

Taxonomy of Generative Models

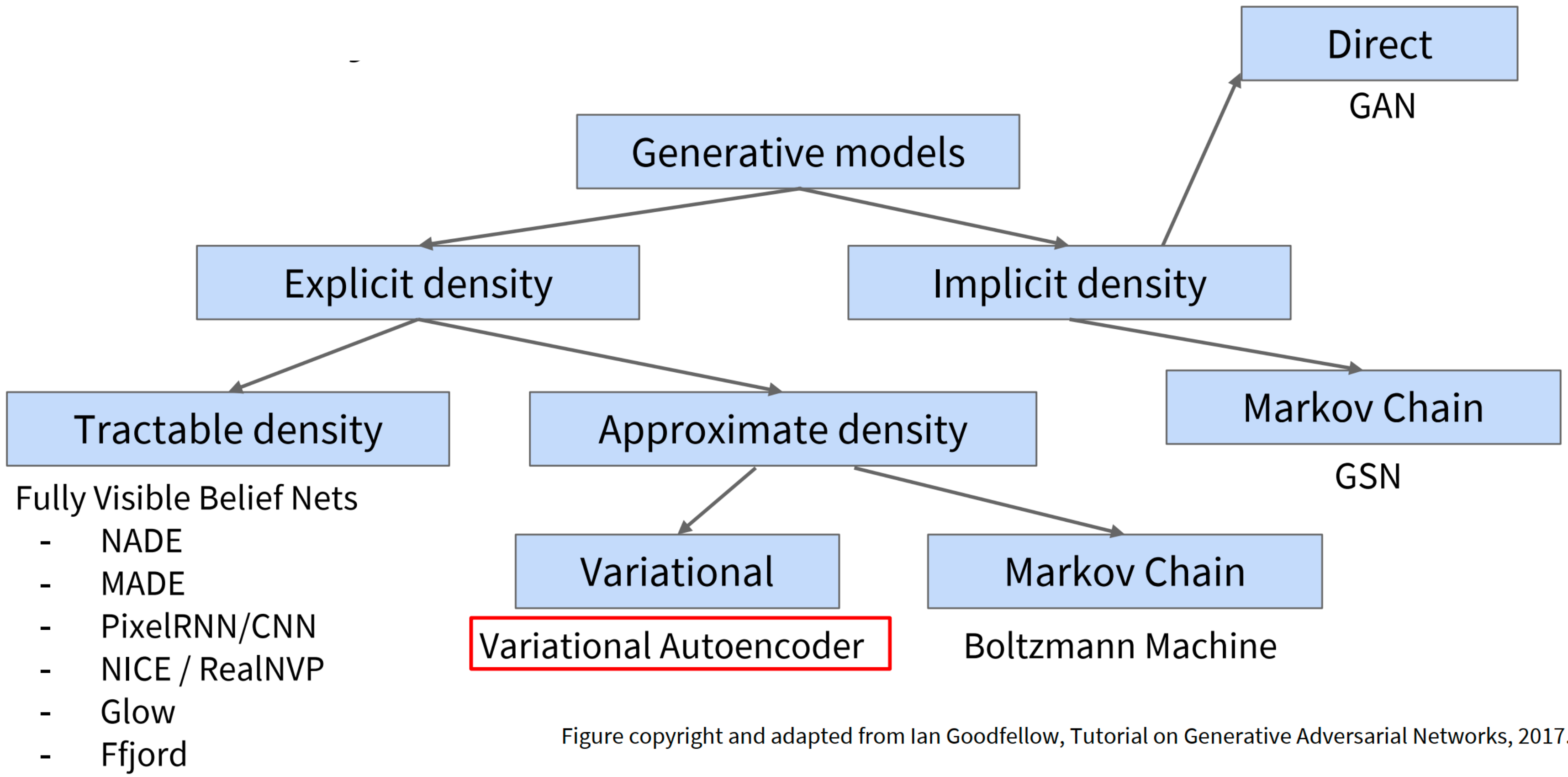


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Slide credit: Fei-Fei Li

The Myth of the Cave

https://www.youtube.com/watch?v=1RWOpQXTltA&ab_channel=TED-Ed

What is a Latent Variable?

https://en.wikipedia.org/wiki/Myth_of_the_Cave

The Myth of the Cave

https://en.wikipedia.org/wiki/Myth_of_the_Cave

Can we learn the **true explanatory factors** (e.g. latent variables) from only observed data?

Variational AutoEncoders (VAE)

PixelRNN/CNNs define tractable density function, optimize likelihood of training data:

$$p_\theta(x) = \prod_{i=1}^{n} p_\theta(x_i | x_1, ..., x_{i-1})$$

Variational Autoencoders (VAEs) define intractable density function with latent z:

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

No dependencies among pixels, can generate all pixels at the same time!

Cannot optimize directly, derive and optimize lower bound on likelihood instead

Why latent z?

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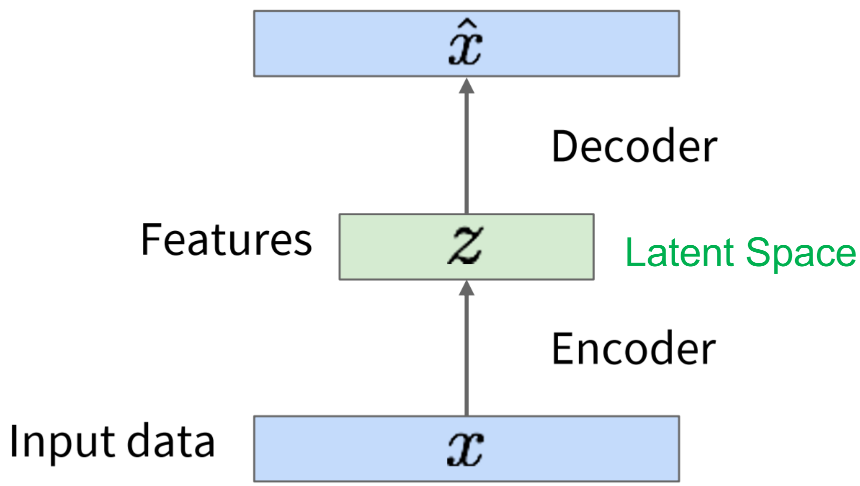
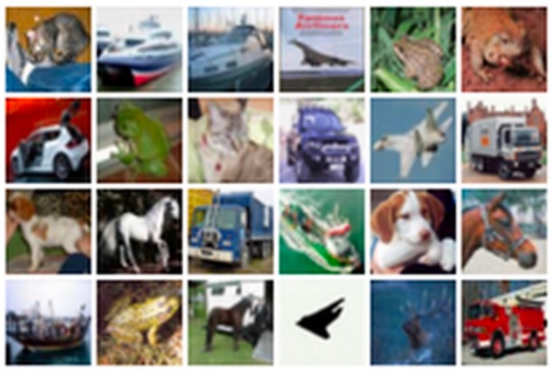
Background: AutoEncoders

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





Slide credit: Fei-Fei Li

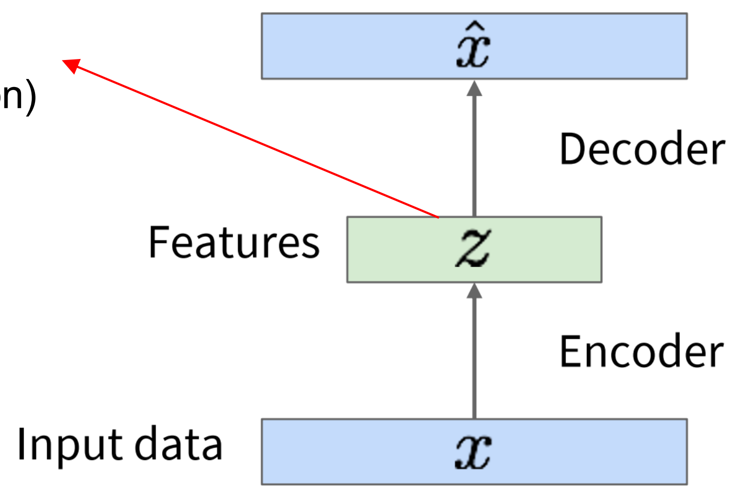
Background: AutoEncoders

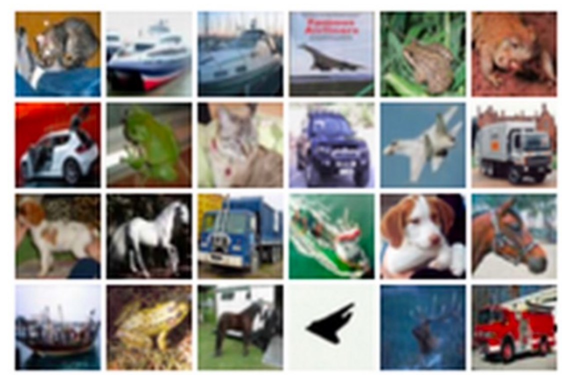
Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

z usually smaller than x
(dimensionality reduction)

Q: Why dimensionality reduction?

A: Want features to capture meaningful factors of variation in data



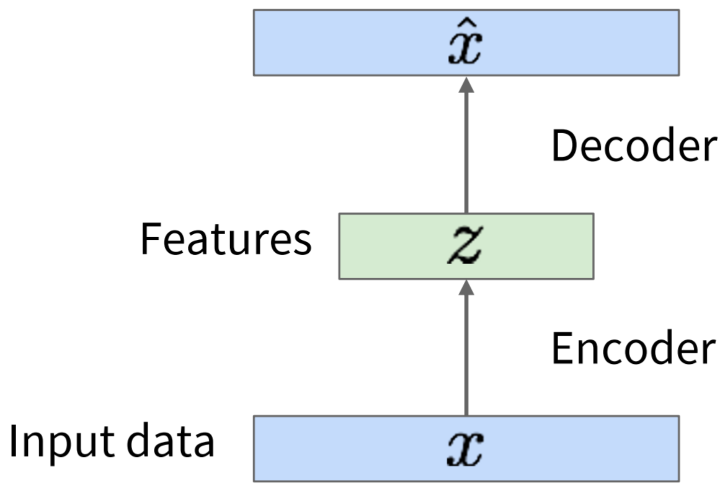


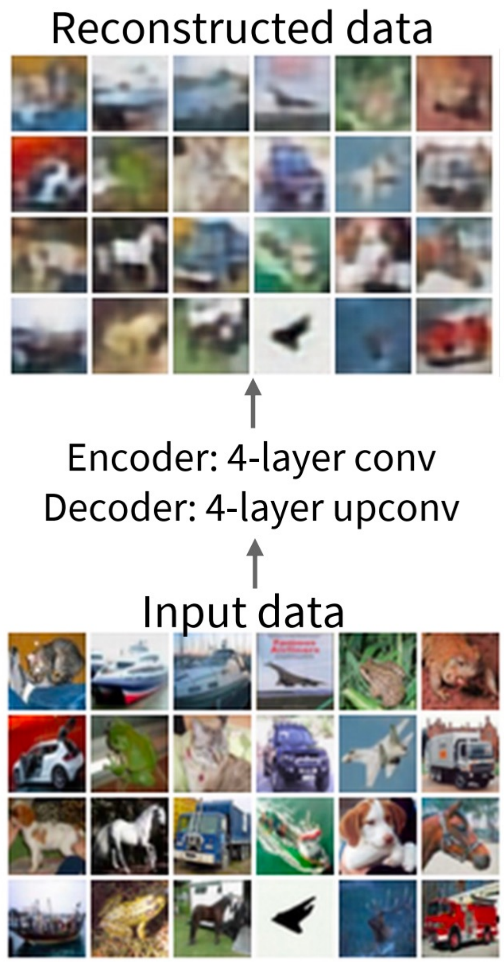
Slide credit: Fei-Fei Li

Background: AutoEncoders

How to learn this feature representation?

Train such that features can be used to reconstruct original data "Autoencoding" - encoding input itself





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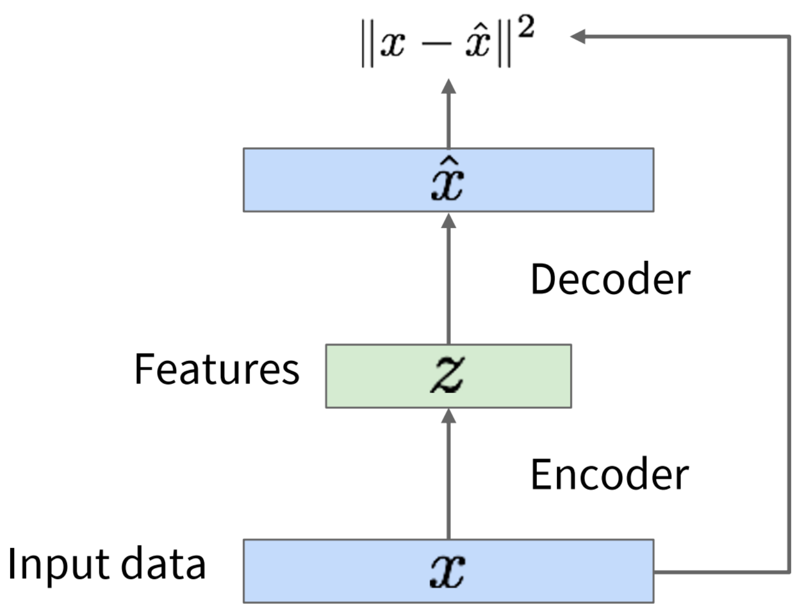
Background: AutoEncoders

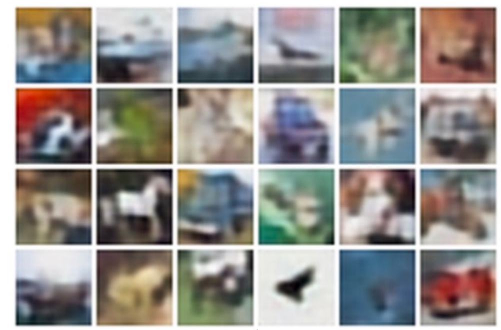
Train such that features can be used to reconstruct original data

Doesn't use labels!

L2 Loss function:

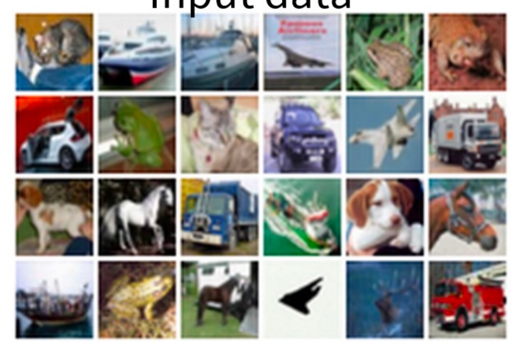


Reconstructed data



Encoder: 4-layer conv
Decoder: 4-layer upconv

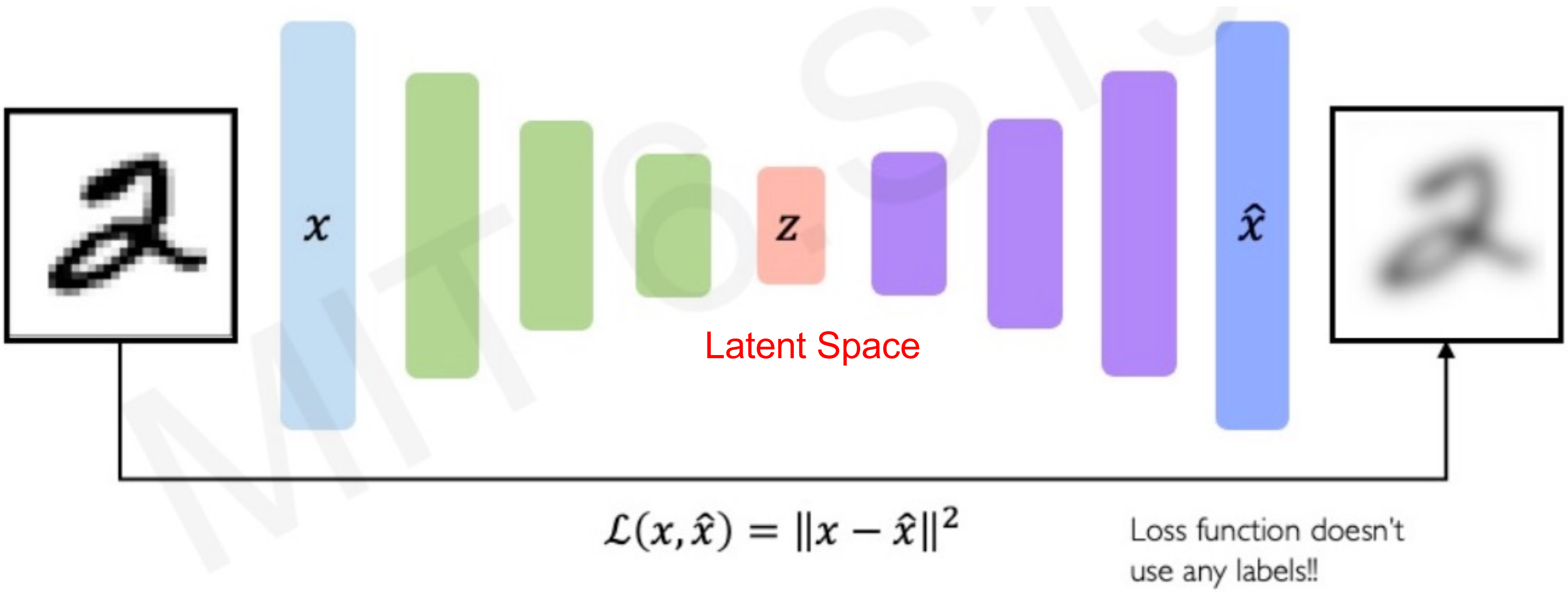
Input data



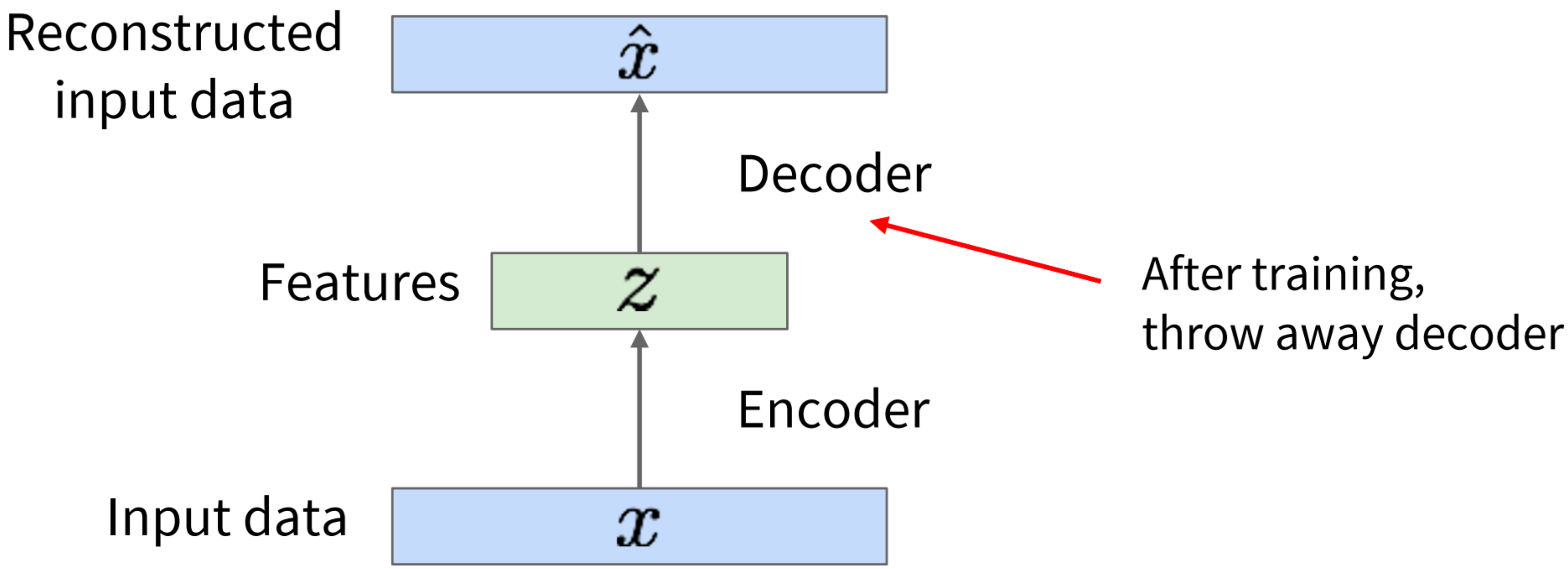
Slide credit: Fei-Fei Li

Background: AutoEncoders

How can we learn this latent space?
Train the model to use these features to **reconstruct the original data.**



Background: AutoEncoders



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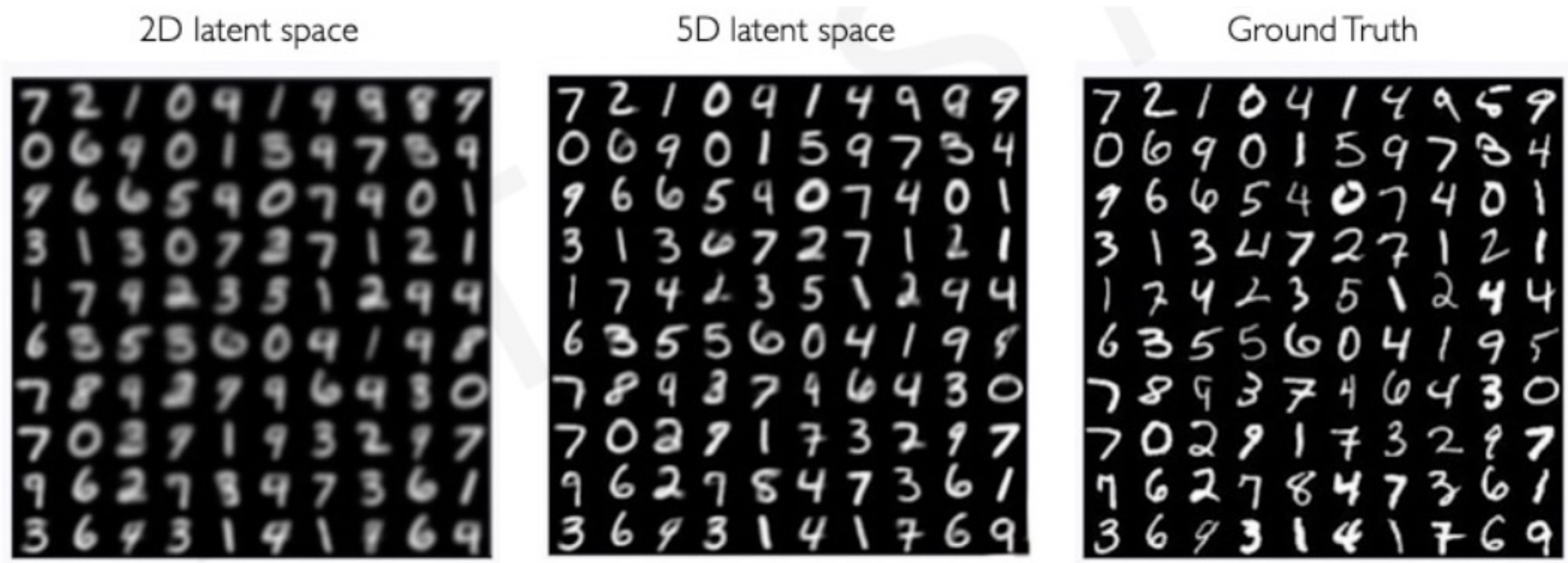
Background: AutoEncoders – Reconstruction Quality

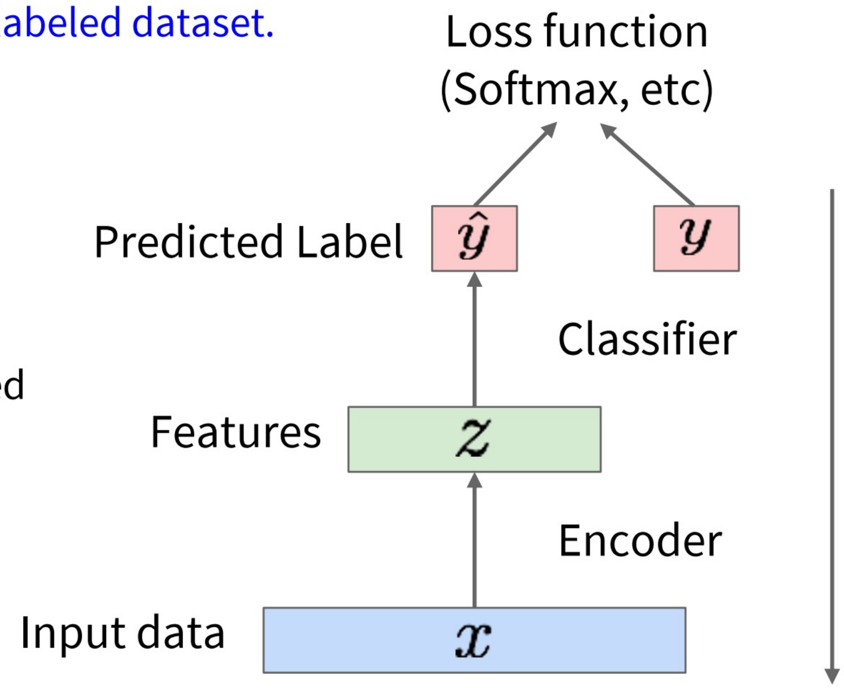
Autoencoding is a form of compression!
Smaller latent space will force a larger training bottleneck



Background: AutoEncoders

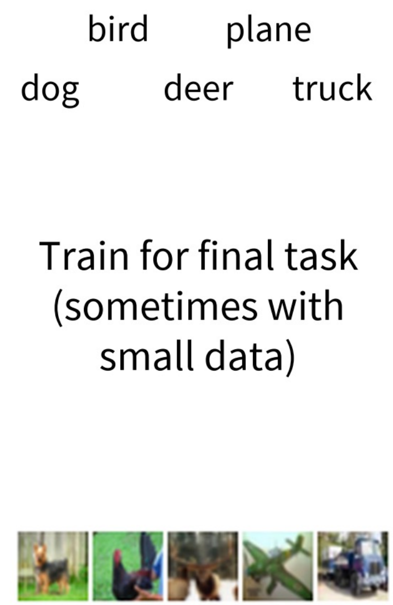
Transfer from large, unlabeled
dataset to small, labeled dataset.

Encoder can be used
to initialize a
supervised model



Fine-tune
encoder
jointly with
classifier

Train for final task
(sometimes with
small data)



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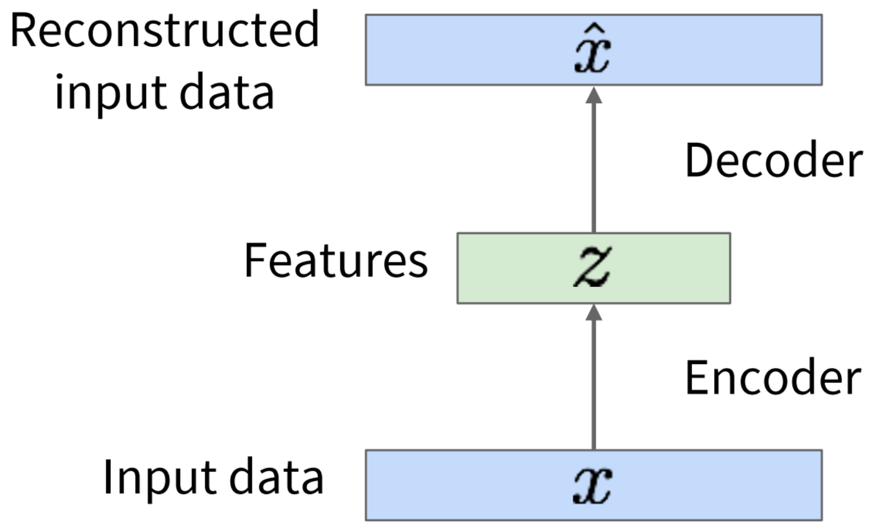
Background: AutoEncoders



Autoencoders can reconstruct data, and can learn features to initialize a supervised model

Features capture factors of variation in training data.

But we can't generate new images from an autoencoder because we don't know the space of z.

How do we make autoencoder a generative model?

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Variational AutoEncoders

Probabilistic spin on autoencoders - will let us sample from the model to generate data!

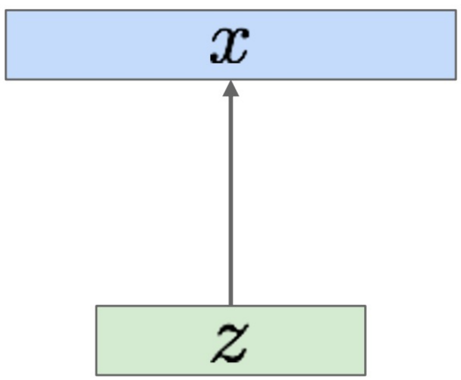
Assume training data $\{x^{(i)}\}_{i=1}^{N}$ is generated from the distribution of unobserved (latent) representation z

Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$

Sample from true prior

$z^{(i)} \sim p_{\theta^*}(z)$

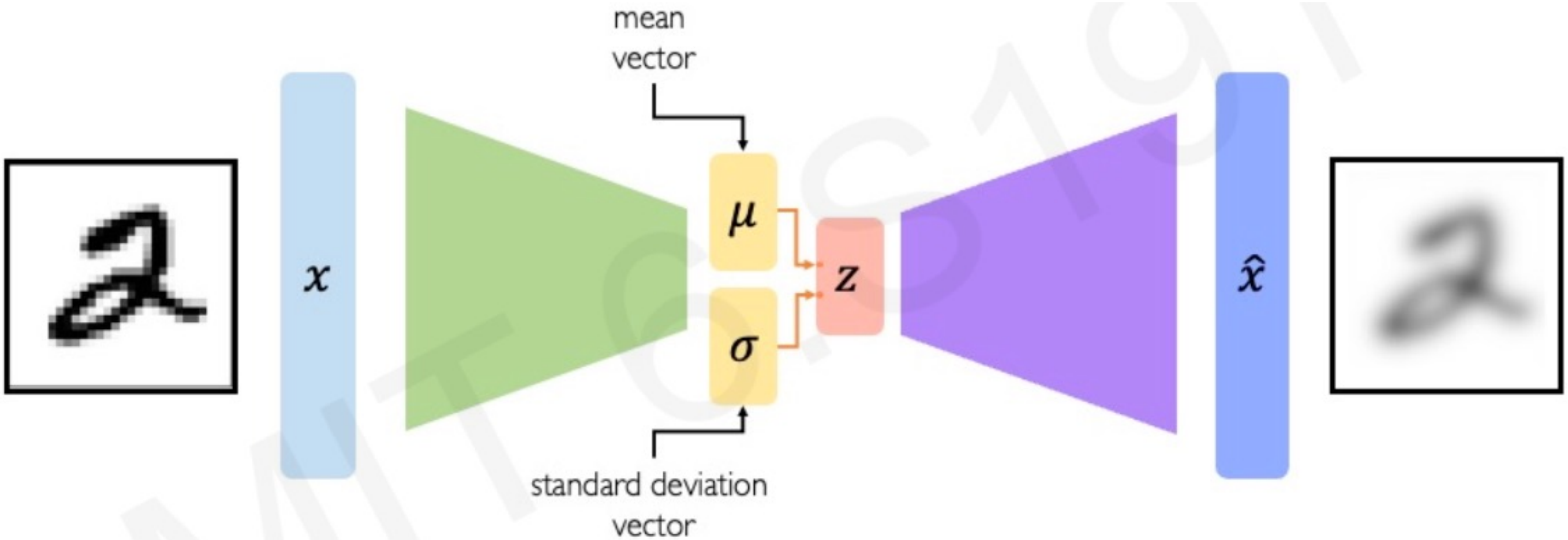


Intuition (remember from autoencoders!): x is an image, z is latent factors used to generate x: attributes, orientation, etc.

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders: Key Difference with AutoEncoders



Variational autoencoders are a probabilistic twist on autoencoders!
Sample from the mean and standard deviation to compute latent sample

Variational AutoEncoders

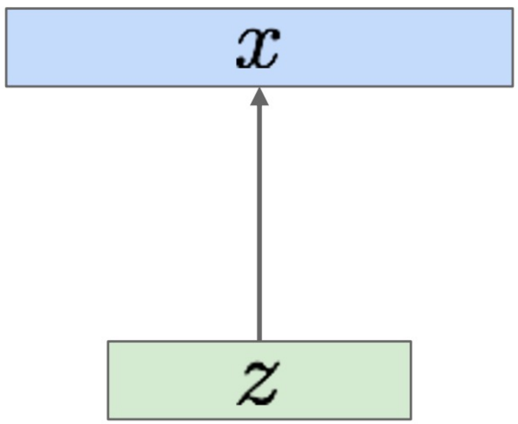
We want to estimate the true parameters θ^* of this generative model given training data x.

Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$

Sample from true prior

$z^{(i)} \sim p_{\theta^*}(z)$



How should we represent this model?

Choose prior p(z) to be simple, e.g. Gaussian. Reasonable for latent attributes, e.g. pose, how much smile.

Conditional p(x|z) is complex (generates image) => represent with neural network

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders

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Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$

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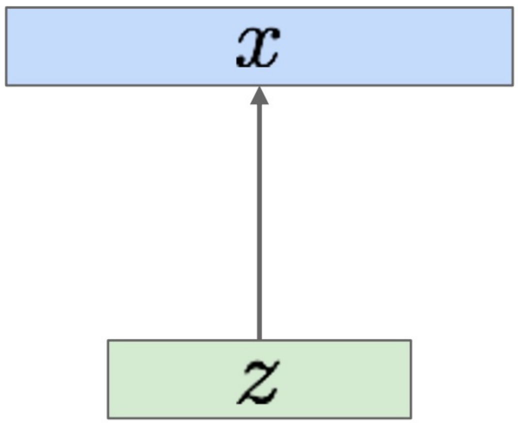

How to train the model?

Learn model parameters to maximize likelihood of training data

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

Q: What is the problem with this?

A: Intractable!

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders: Intractability

Data likelihood: $p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$

Simple Gaussian prior

Decoder neural network

Intractable to compute p(x|z) for every z!

☹

$$\log p(x) \approx \log \frac{1}{k} \sum_{i=1}^{k} p(x|z^{(i)}), \text{ where } z^{(i)} \sim p(z)$$

Monte Carlo estimation is too high variance

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Serena Young

Variational AutoEncoders: Intractability

Data likelihood: $p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$

Posterior density: $p_\theta(z|x) = p_\theta(x|z) p_\theta(z) / p_\theta(x)$

Intractable data likelihood

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

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Variational AutoEncoders: Intractability

Data likelihood: $p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$

Posterior density also intractable: $p_\theta(z|x) = p_\theta(x|z) p_\theta(z) / p_\theta(x)$

Solution: In addition to modeling $p_\theta(x|z)$, learn $q_\phi(z|x)$ that approximates the true posterior $p_\theta(z|x)$.

Will see that the approximate posterior allows us to derive a lower bound on the data likelihood that is tractable, which we can optimize.

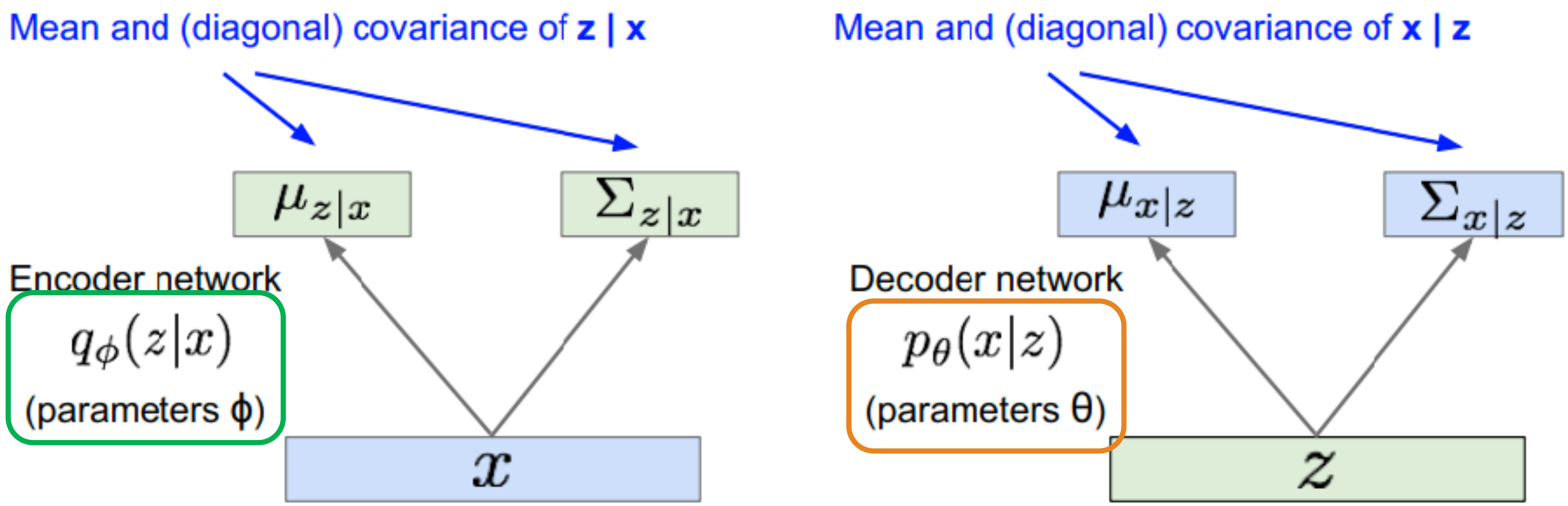
Variational inference is to approximate the unknown posterior distribution from only the observed data x

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders

Since we're modeling probabilistic generation of data, encoder and decoder networks are probabilistic



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Variational AutoEncoders

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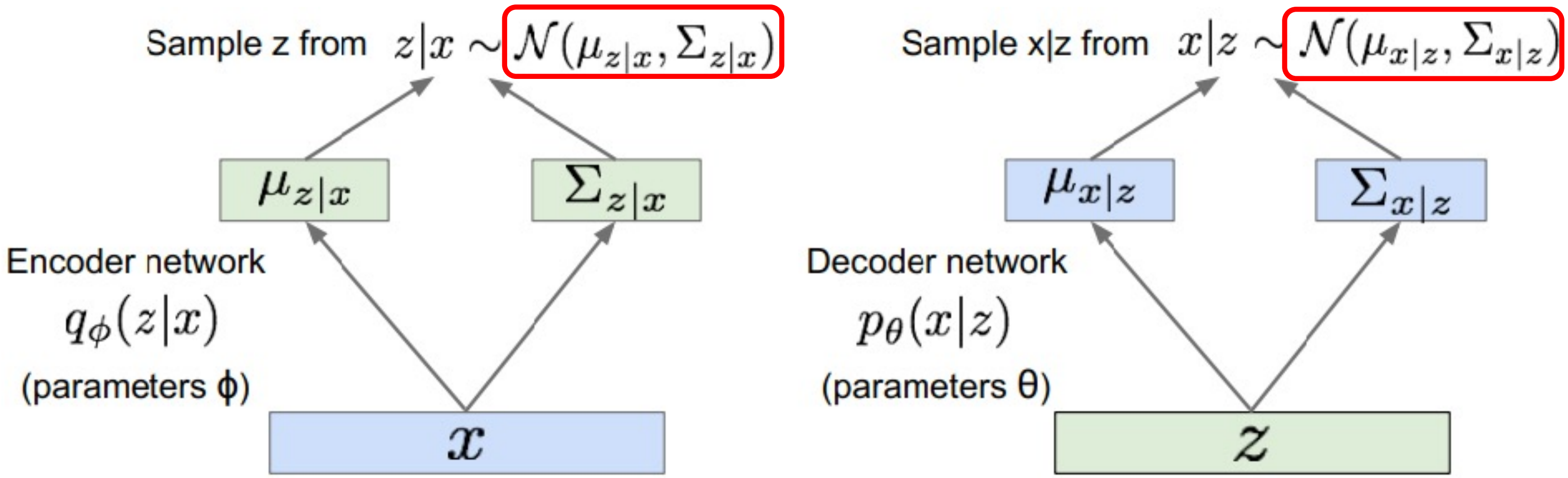

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Variational AutoEncoders

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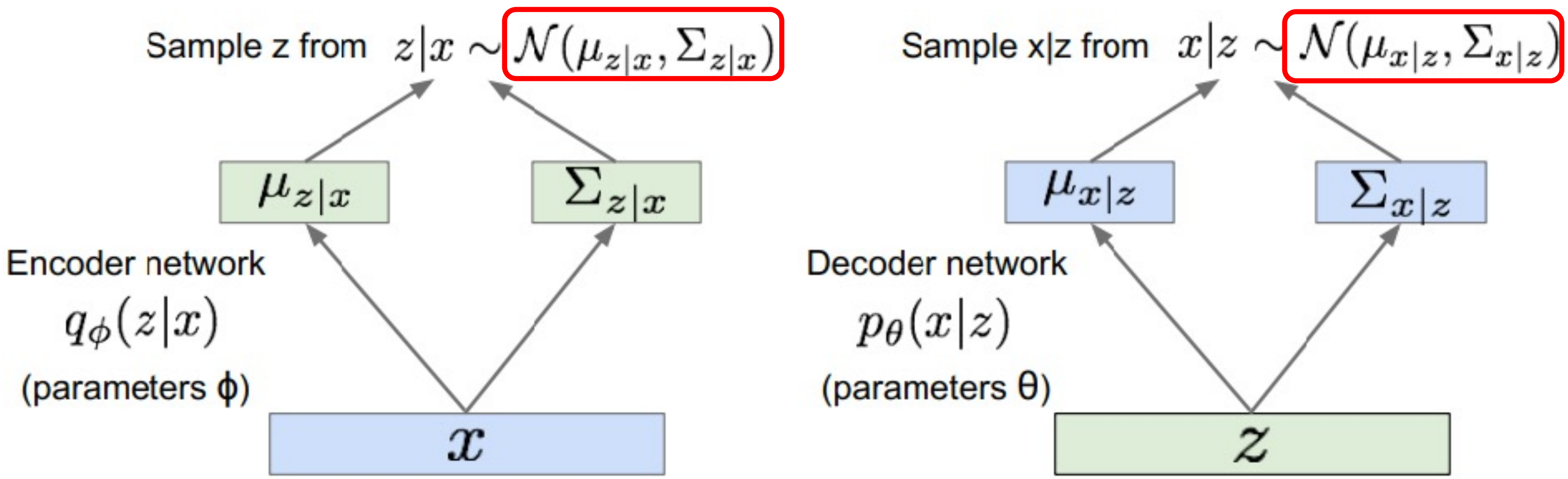


Encoder and decoder networks also called "recognition"/"inference" and "generation" networks

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders

Now equipped with our encoder and decoder networks, let's work out the (log) data likelihood:

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

Taking expectation wrt. z (using encoder network) will come in handy later

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Bayes' Rule)}$$

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})} \frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \quad \text{(Multiply by constant)}$$

$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Logarithms)}$$

$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z)) + D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))$$

The expectation wrt. z (using encoder network) let us write nice KL terms

Slide credit: Fei-Fei Li

Variational AutoEncoders

Now equipped with our encoder and decoder networks, let's work out the (log) data likelihood:

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

We want to maximize the Data likelihood

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Bayes' Rule)}$$

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})} \frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \quad \text{(Multiply by constant)}$$

$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Logarithms)}$$

$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z)) + D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, \boxed{p_\theta(z \mid x^{(i)})})$$

Decoder network gives pθ(x|z), can compute estimate of this term through sampling (need some trick to differentiate through sampling).

This KL term (between Gaussians for encoder and z prior) has nice closed-form solution!

pθ(z|x) intractable (saw earlier), can't compute this KL term :(But we know KL divergence always >= 0[1]

[1] https://statproofbook.github.io/P/kl-nonneg.html

Slide credit: Fei-Fei Li

Variational AutoEncoders

Now equipped with our encoder and decoder networks, let's work out the (log) data likelihood:

We want to maximize the Data likelihood

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Bayes' Rule)}$$

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \quad \text{(Multiply by constant)}$$

Encoder:
make approximate posterior distribution close to prior

Decoder:
reconstruct the input data

$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Logarithms)}$$

$$= \boxed{\underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{L(x(i), \theta, \phi)}} + \underbrace{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))}_{\boxed{>=0}}$$

Tractable lower bound which we can take gradient of and optimize! ($p_\theta(x|z)$ differentiable, KL term differentiable)

Slide credit: Fei-Fei Li

Variational AutoEncoders

Putting it all together: maximizing the likelihood lower bound

$$\underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \boxed{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}}_{\mathcal{L}(x^{(i)}, \theta, \phi)}$$

Let's look at computing the KL divergence between the estimated posterior and the prior given some data

Make approximate posterior distribution close to prior

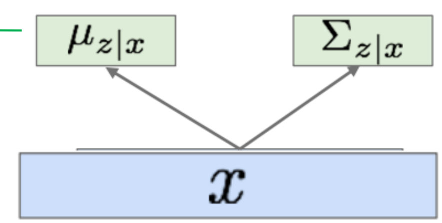
$$D_{KL}(\mathcal{N}(\mu_{z|x}, \Sigma_{z|x}) || \mathcal{N}(0, I))$$

Have analytical solution

Encoder network

$q_\phi(z|x)$

Input Data



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Variational AutoEncoders: KL Divergence

$$D_{KL}(\mathcal{N}(\mu_{z|x}, \Sigma_{z|x})||\mathcal{N}(0, I))$$

Inferred Latent Distribution

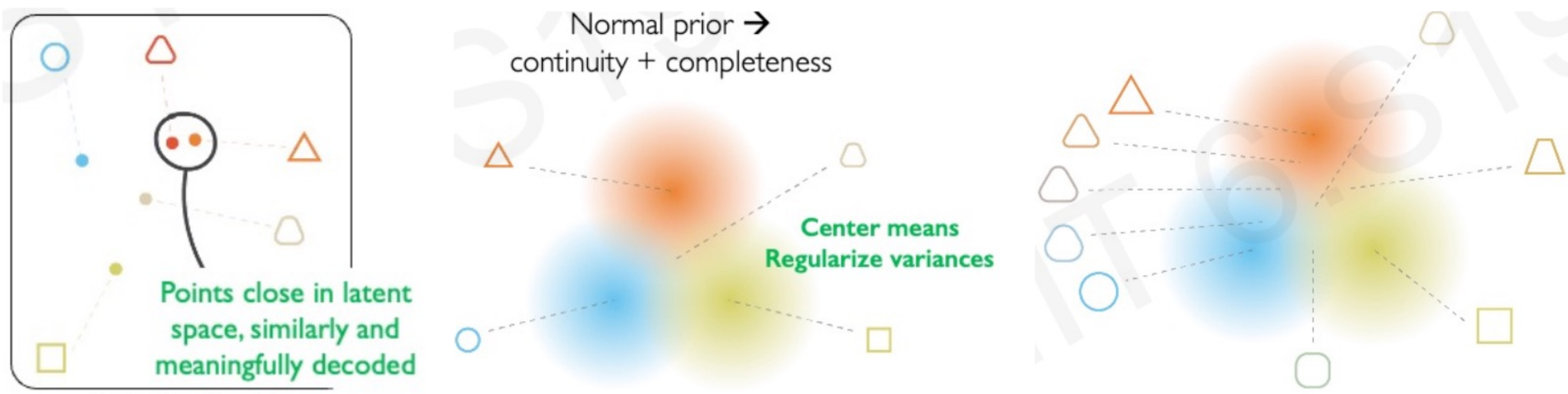
Fixed Prior on Latent Distribution

- Encourage encodings to distribute them evenly around the center of the latent space
- Penalize the network when it tries to “cheat” by clustering points in specific regions (i.e. memorizing data)

Variational AutoEncoders: KL Divergence

What properties do we want to achieve from KL Divergence?

1. Continuity: Points that are close in latent space → similar content after decoding
2. Completeness: sampling from latent space → "meaningful" content after decoding

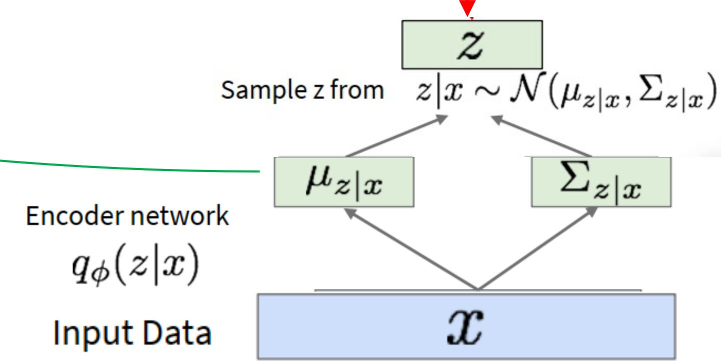


Variational AutoEncoders

Putting it all together: maximizing the likelihood lower bound

$$\underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \boxed{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}}_{\mathcal{L}(x^{(i)},\theta,\phi)}$$

Not part of the computation graph!



Make approximate posterior distribution close to prior

Slide credit: Fei-Fei Li

Variational AutoEncoders

Putting it all together: maximizing the likelihood lower bound

$$\underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \boxed{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}}_{\mathcal{L}(x^{(i)},\theta,\phi)}$$

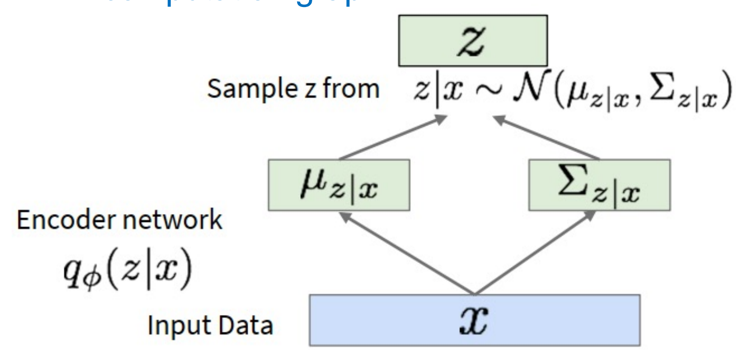
Reparameterization trick to make sampling differentiable:

Sample $\epsilon \sim \mathcal{N}(0, I)$

$$z = \boxed{\mu_{z|x}} + \boxed{\epsilon}\boxed{\sigma_{z|x}}$$

Part of computation graph

Input to the graph



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Variational AutoEncoders

Putting it all together: maximizing the likelihood lower bound

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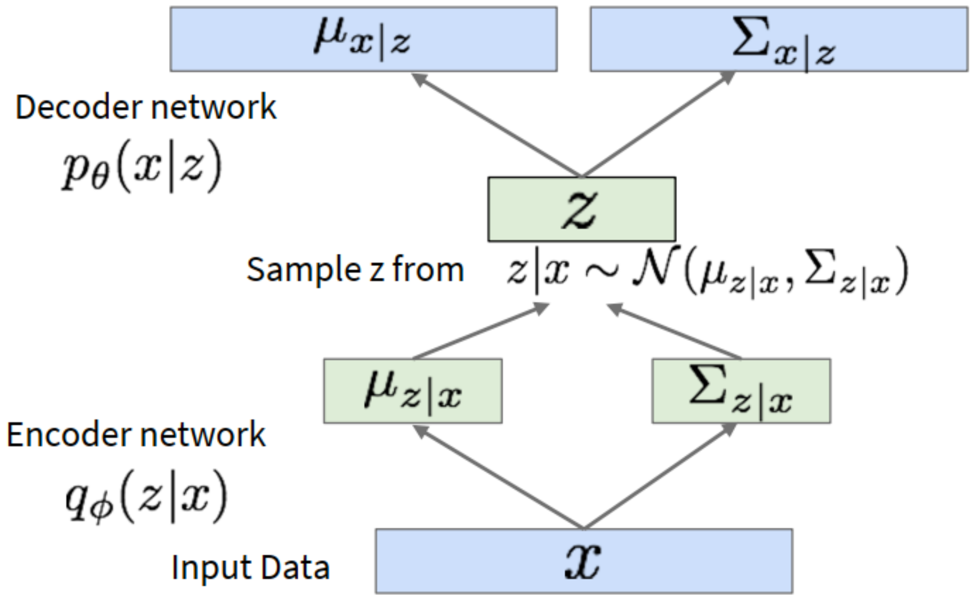

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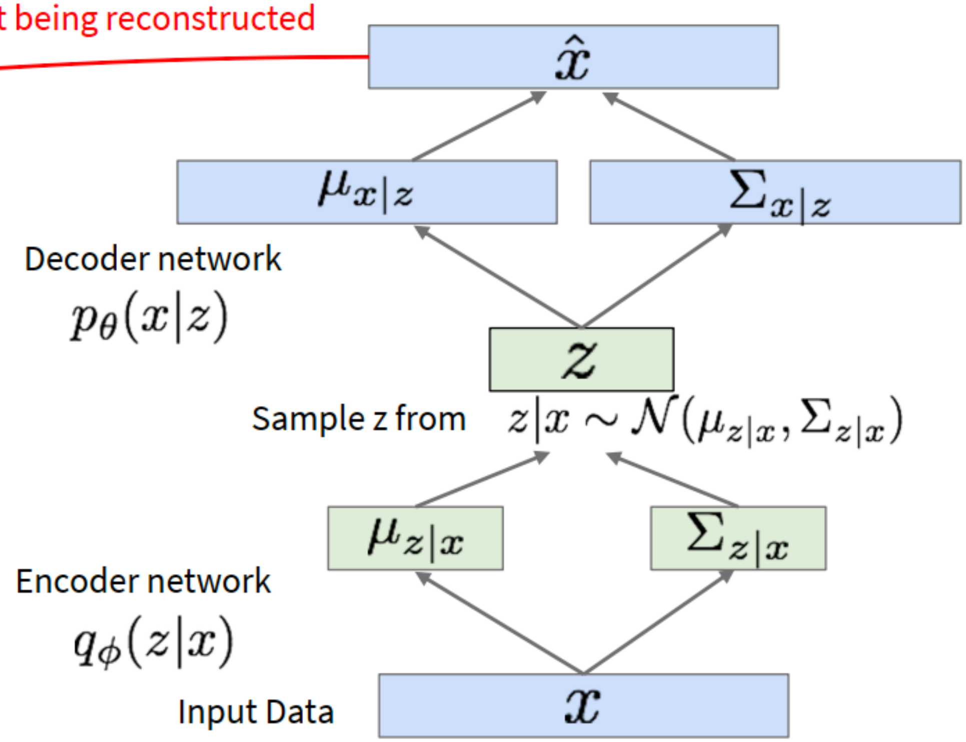
Variational AutoEncoders

Putting it all together: maximizing the likelihood lower bound

Maximize likelihood of original input being reconstructed

$$\underbrace{\boxed{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right]} - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)}, \theta, \phi)}$$



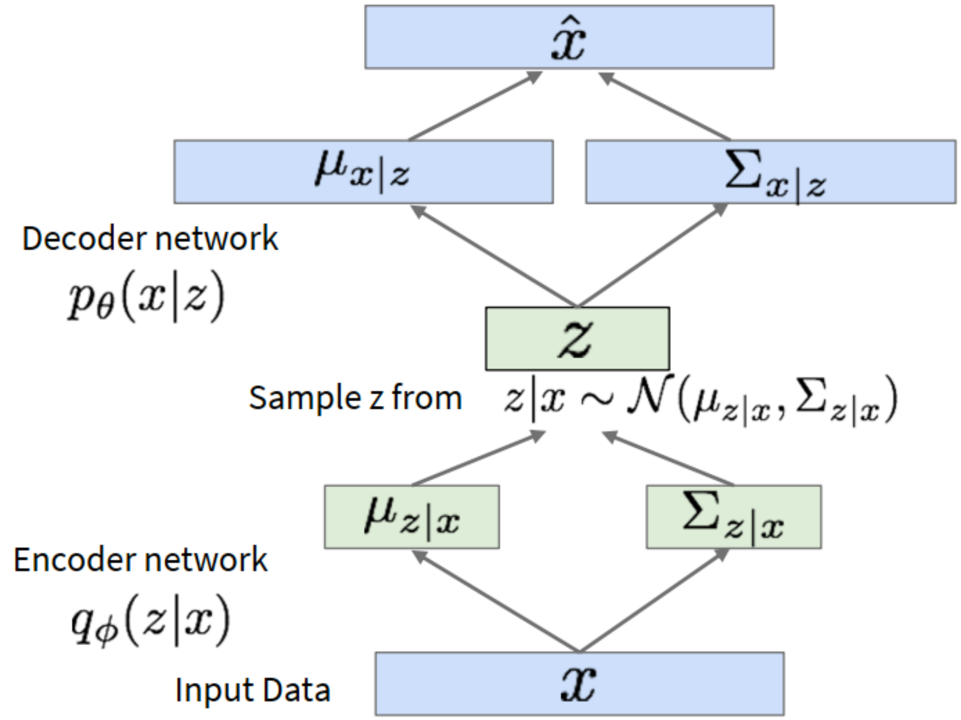
Slide credit: Fei-Fei Li

Variational AutoEncoders

Putting it all together: maximizing the likelihood lower bound

$$\underbrace{\boxed{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}}_{\mathcal{L}(x^{(i)}, \theta, \phi)}$$

For every minibatch of input data: compute this forward pass, and then backprop!



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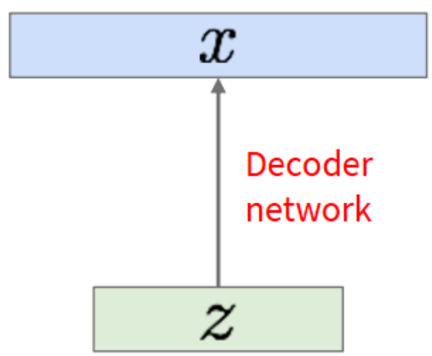
Variational AutoEncoders: Generating Data!

Our assumption about data generation process

Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$

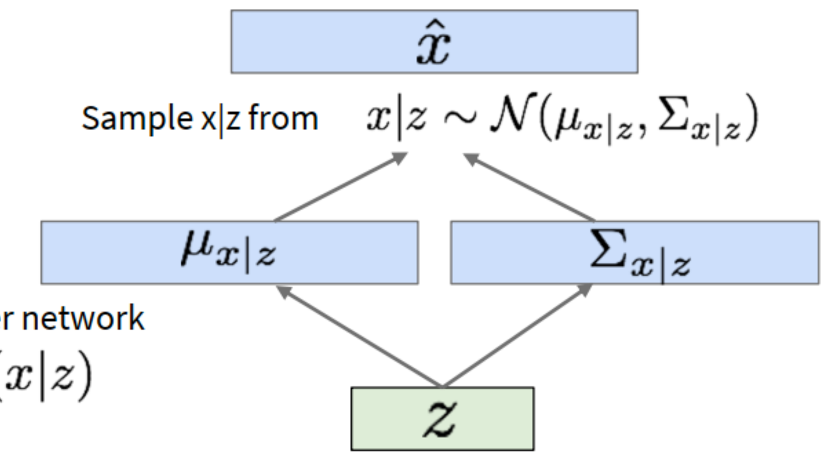


Sample from true prior

$z^{(i)} \sim p_{\theta^*}(z)$

Now given a trained VAE:
use decoder network & sample z from prior!

Sample x|z from $x|z \sim \mathcal{N}(\mu_{x|z}, \Sigma_{x|z})$



Decoder network $p_\theta(x|z)$

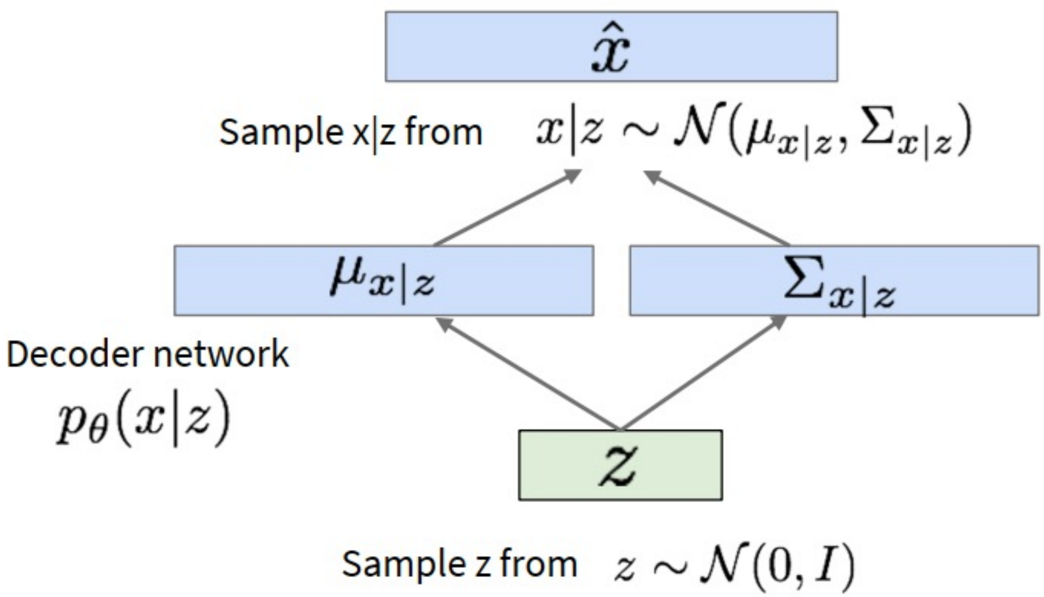
Sample z from $z \sim \mathcal{N}(0, I)$

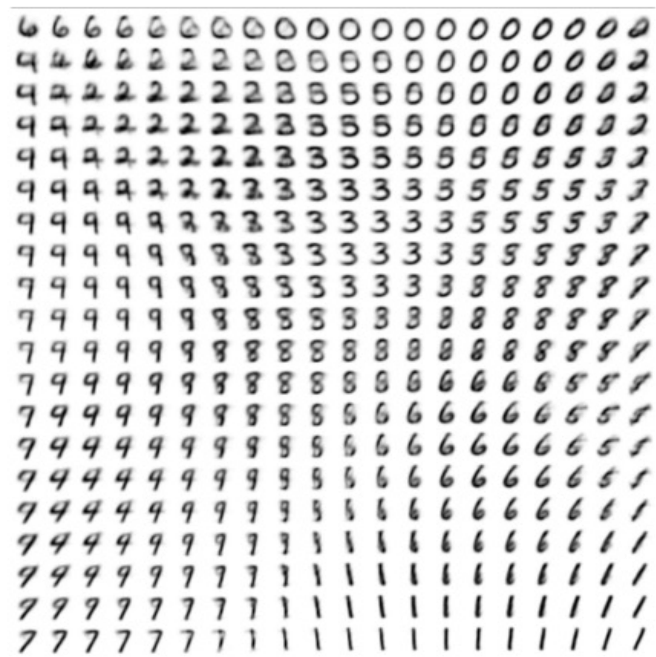
Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders: Generating Data!

Use decoder network. Now sample z from prior!



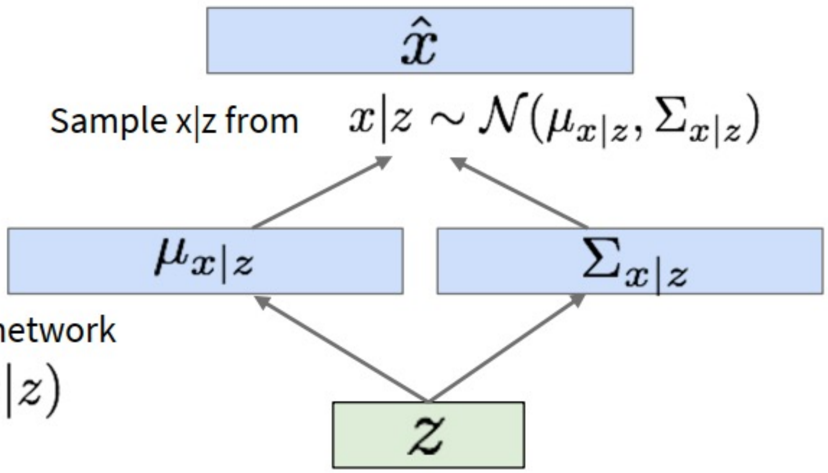


Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders: Generating Data!

Use decoder network. Now sample z from prior!



Sample x|z from $x|z \sim \mathcal{N}(\mu_{x|z}, \Sigma_{x|z})$

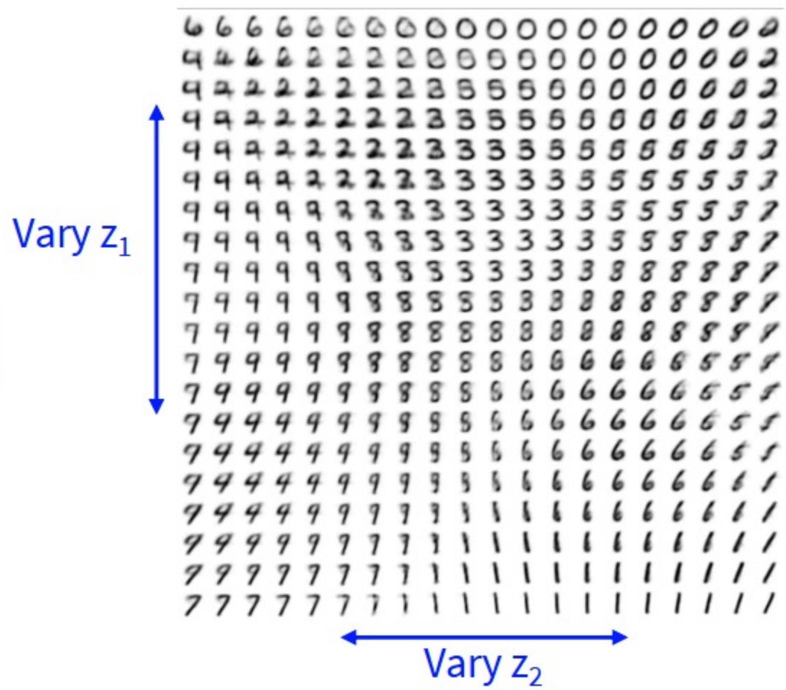
Decoder network

$p_\theta(x|z)$

Sample z from $z \sim \mathcal{N}(0, I)$

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Data manifold for 2-d z

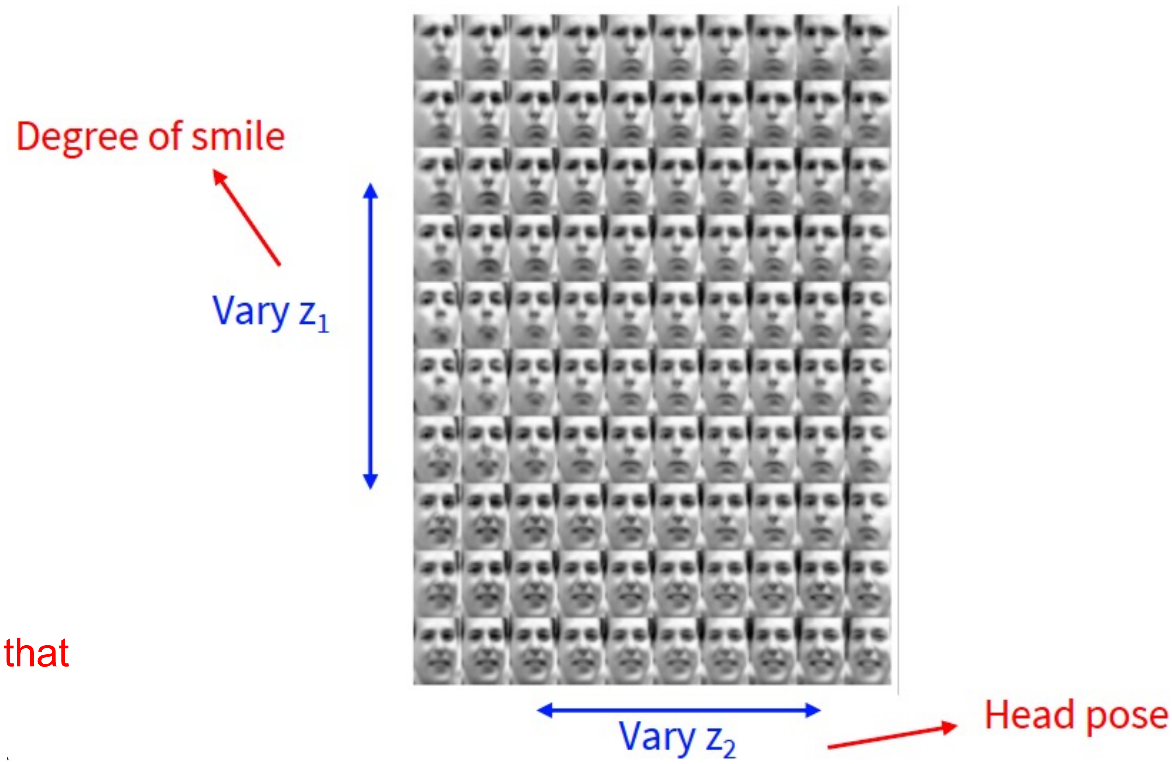


Slide credit: Fei-Fei Li

Variational AutoEncoders: Generating Data!

Diagonal prior on z
=> independent
latent variables

Different dimensions
of z encode
interpretable factors
of variation



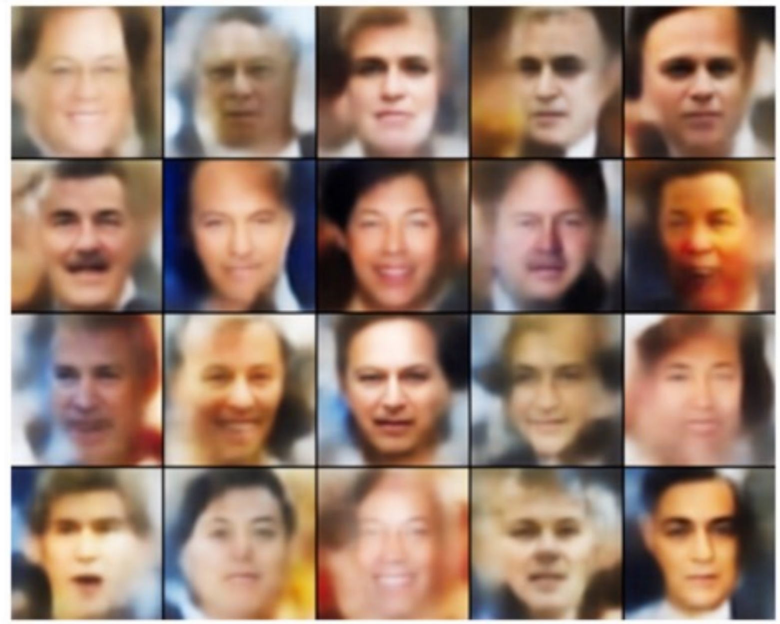
Also good feature representation that
can be computed using $q_\phi(z|x)$!

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Slide credit: Fei-Fei Li

Variational AutoEncoders: Generating Data!

32x32 CIFAR-10



Labeled Faces in the Wild

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Slide credit: Fei-Fei Li

Music VAE

https://magenta.tensorflow.org/music-vae

Variational AutoEncoders: Generating Data!

Probabilistic spin to traditional autoencoders => allows generating data
Defines an intractable density => derive and optimize a (variational) lower bound

Pros:
- Principled approach to generative models
- Interpretable latent space.
- Allows inference of q(z|x), can be useful feature representation for other tasks

Cons:
- Maximizes lower bound of likelihood: okay, but not as good evaluation as PixelRNN/PixelCNN
- Samples blurrier and lower quality compared to state-of-the-art (GANs)

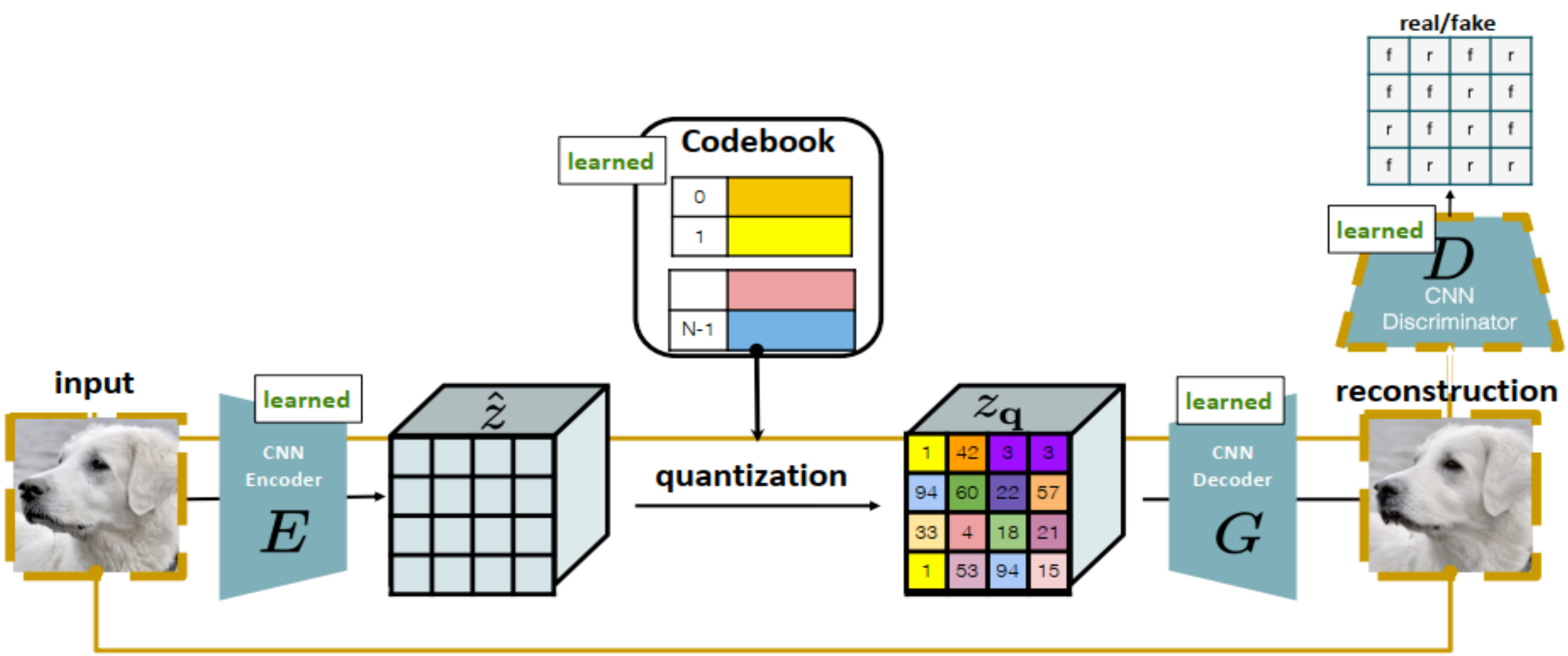
Active areas of research:
- More flexible approximations, e.g. richer approximate posterior instead of diagonal Gaussian, e.g., Gaussian Mixture Models (GMMs), Categorical Distributions.
- Learning disentangled representations.

Slide credit: Fei-Fei Li

GAN Example for Digits on Numpy

https://nbviewer.org/url/www.cs.toronto.edu/~rgrosse/courses/csc321_2018/tutorials/tut9_GAN.ipynb#

From VQ-VAE to VQGAN



$$\mathcal{L}_{\text{total}} = \mathcal{L}_{rec} + \mathcal{L}_{VQ} + \lambda \mathcal{L}_{GAN} \ \text{ where } \ \lambda = \frac{\nabla_{G_L}[\mathcal{L}_{rec}]}{\nabla_{G_L}[\mathcal{L}_{GAN}] + \delta}$$

Slide credit: Robin Rombach

From VQ-VAE to VQGAN

Slide credit: Robin Rombach

From VQ-VAE to VQGAN

Slide credit: Robin Rombach