

# COMP547

## DEEP UNSUPERVISED LEARNING

Lecture #7 – Variational Autoencoders

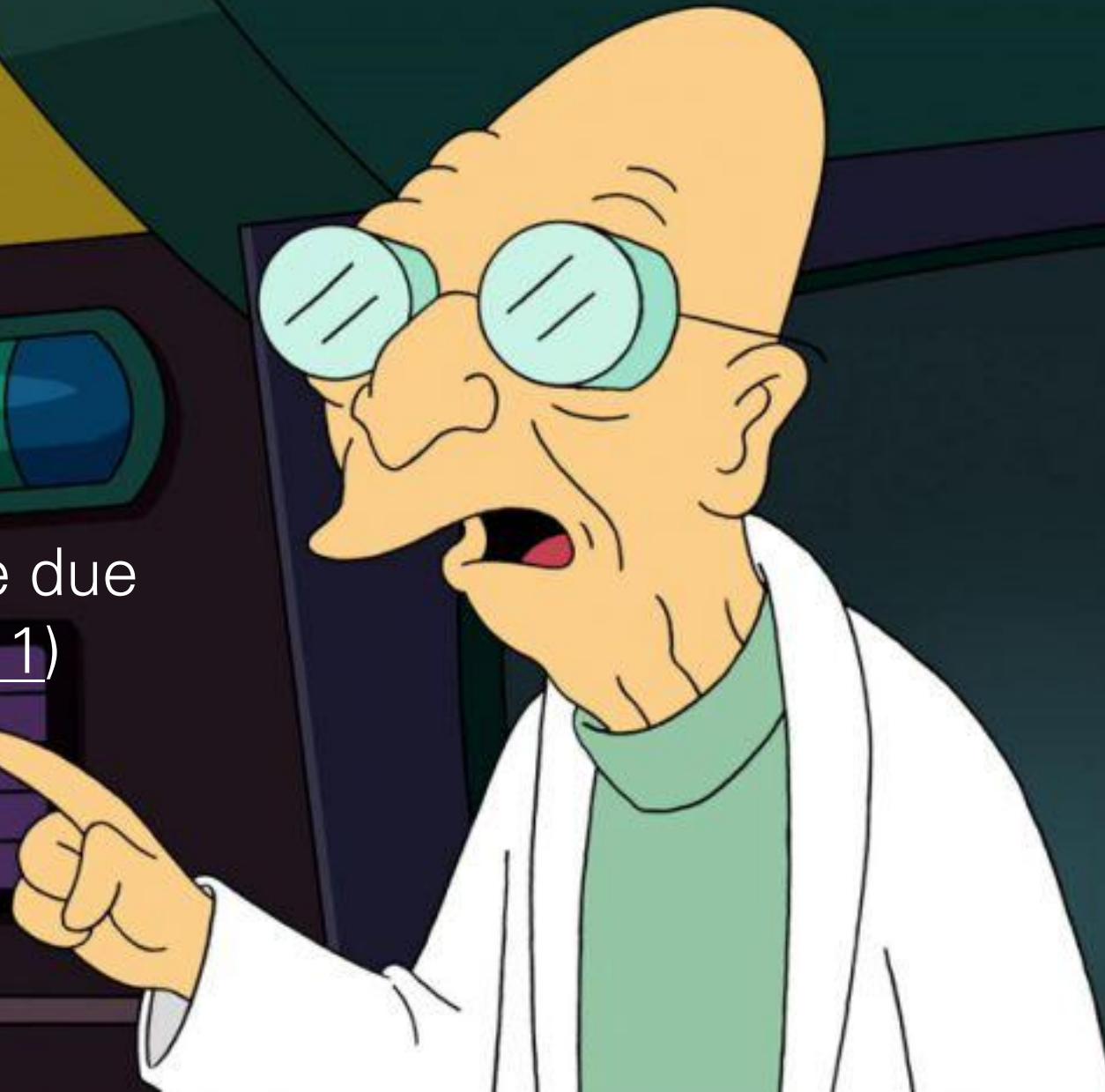


KOÇ  
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Aykut Erdem // Koç University // Spring 2021

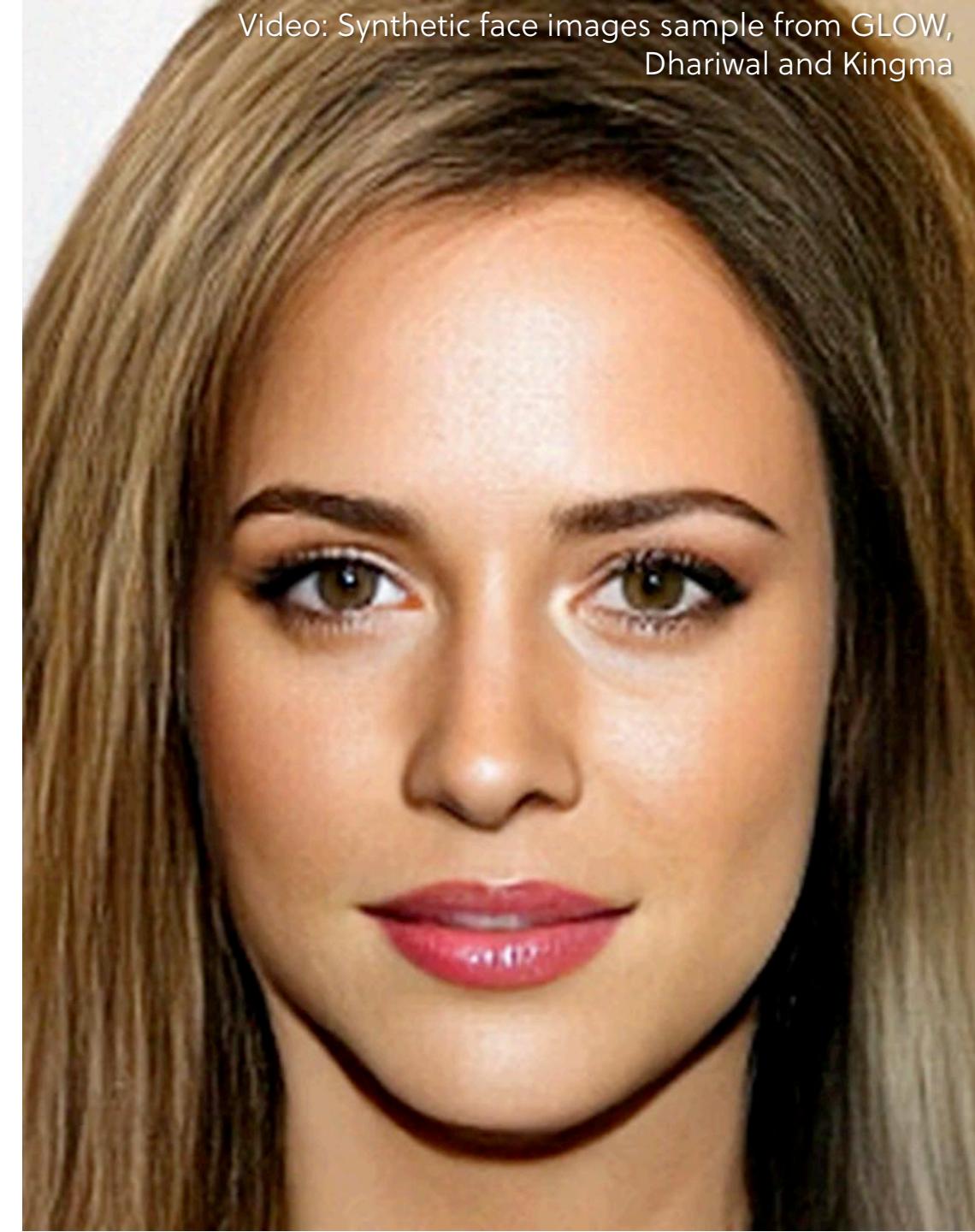
# Good news, everyone!

- Assignment 1 is due  
March 17, 23:59!
- Project proposals are due  
in one month (April 11)



# Previously on COMP547

- Foundations of Flows (1-D)
- 2-D Flows
- N-D Flows
- Dequantization



# Lecture overview

- Motivation
- Training Latent Variable Models (including VAE and IWAE)
- Variations:
- Related ideas

**Disclaimer:** Much of the material and slides for this lecture were borrowed from

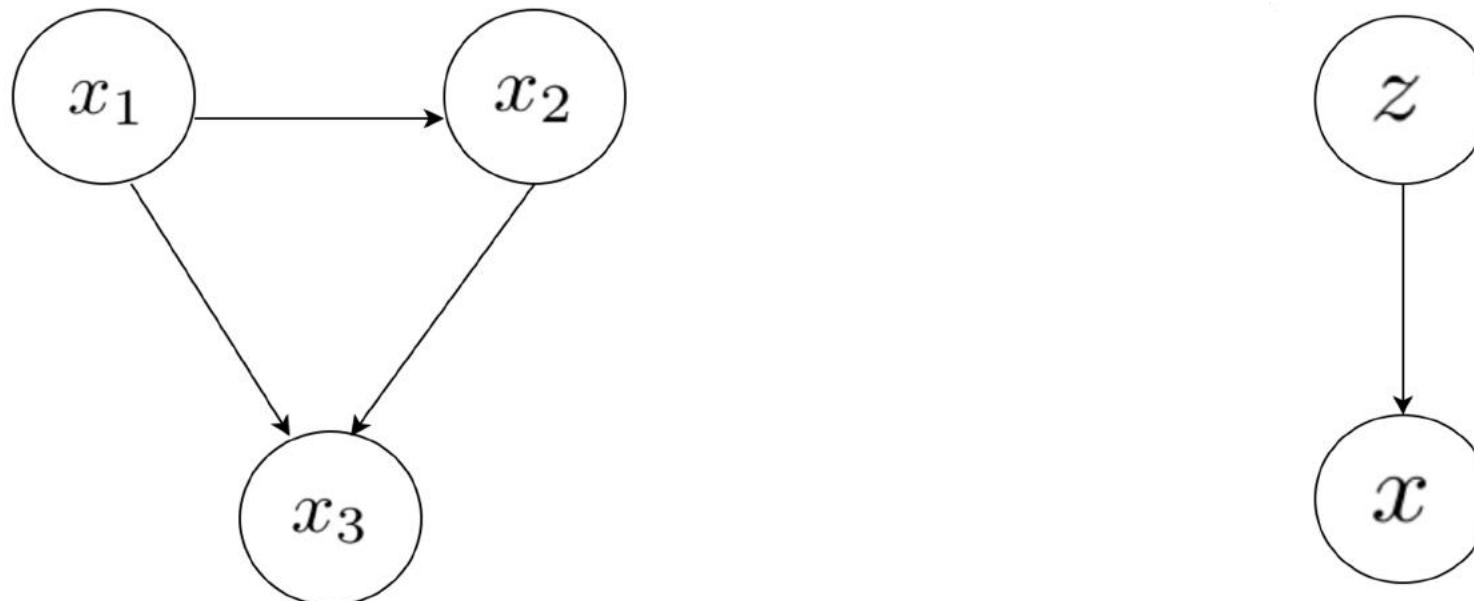
- Pieter Abbeel, Peter Chen, Jonathan Ho, Aravind Srinivas' Berkeley CS294-158 class
- David McAllester's TTIC 31230 class
- Jimmy Ba's UToronto CSC413/2516 class

# Lecture overview

- Motivation
- Training Latent Variable Models (including VAE and IWAE)
- Variations:
- Related ideas

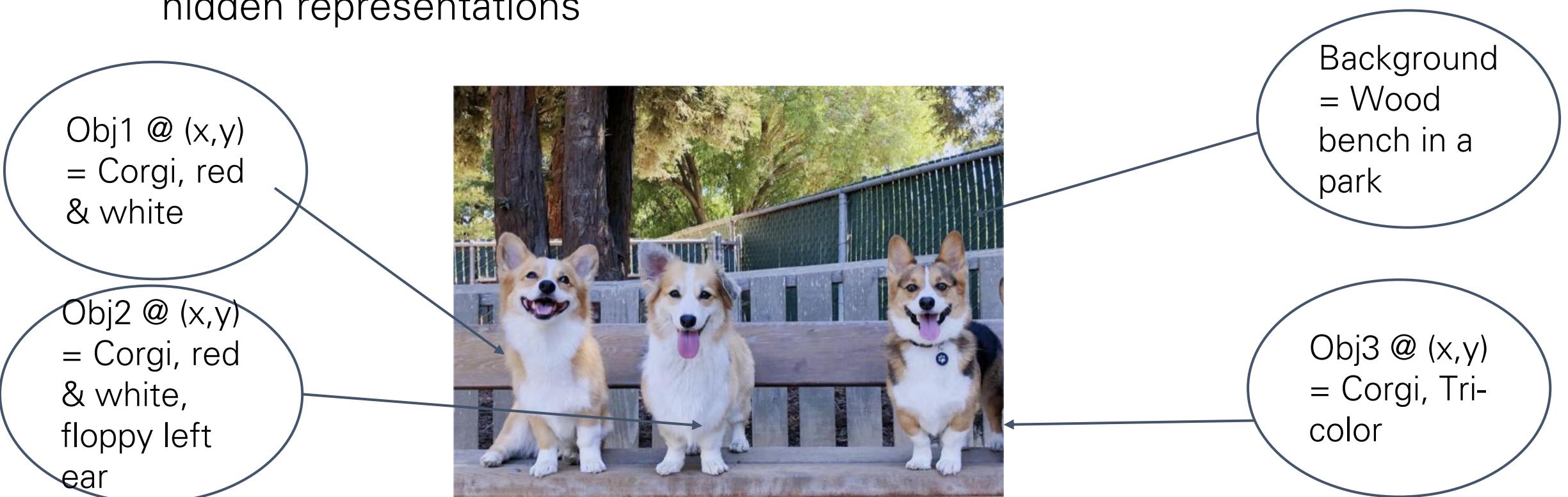
# Latent Variable Models

- Autoregressive models + Flows
  - All random variables are observed
- Latent Variable Models (LVMs):
  - Some random variables are hidden - we do not get to observe



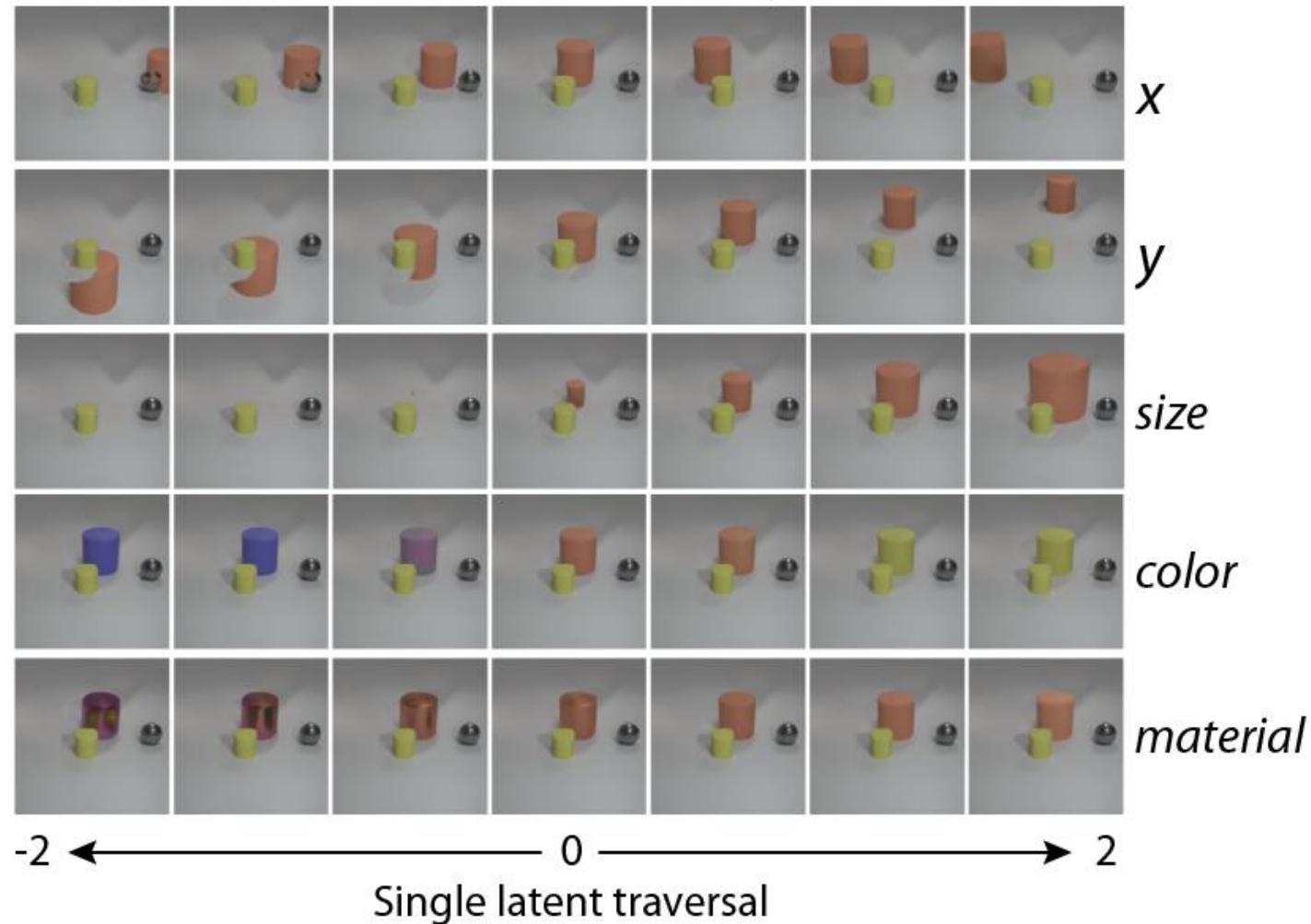
# Why Latent Variable Models?

- Simpler, lower-dimensional representations of data often possible
  - Latent variable models hold the promise of automatically identifying those hidden representations



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  - Latent variable models hold the promise of automatically identifying those hidden representations

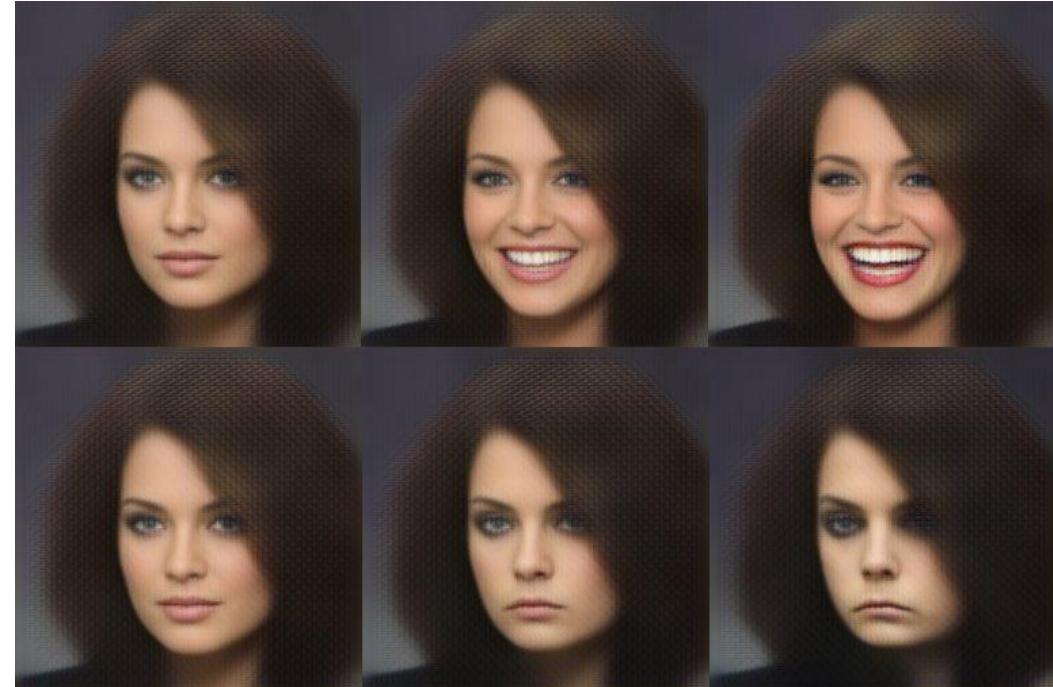


# Why Latent Variable Models?

- AR models are slow to sample because all pixels (observation dims) are assumed to be dependent on each other
- We can make part of observation space independent **conditioned on some latent variables**
  - Latent variable models can have faster sampling by exploiting statistical patterns

# Latent Variable Models

- Sometimes, it's possible to design a latent variable model with an understanding of the causal process that generates data
- In general, we don't know what are the latent variables and how they interact with observations
  - Most popular models make little assumption about what are the latent variables
  - Best way to specify latent variables is still an active area of research

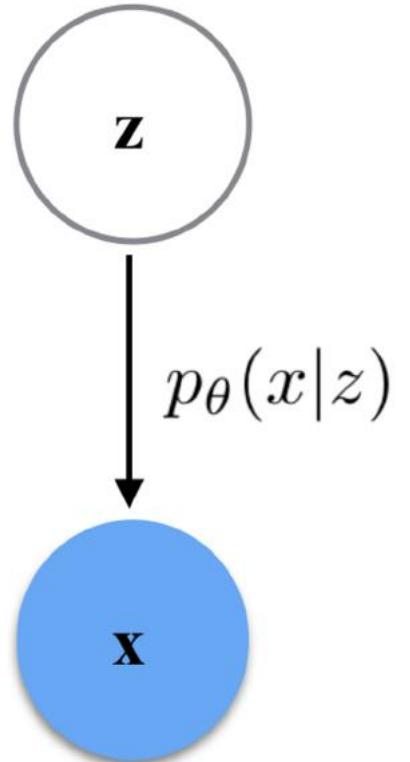


Modifying the latent code in the direction of a smile vector, producing a range of versions of the original, from smiling to sadness (White, 2016)

# Example Latent Variable Model

$$z = (z_1, z_2, \dots, z_K) \sim p(z; \beta) = \prod_{k=1}^K \beta_k^{z_k} (1 - \beta_k)^{1-z_k}$$

$$x = (x_1, x_2, \dots, x_L) \sim p_\theta(x|z) \Leftrightarrow \text{Bernoulli}(x_i; \text{DNN}(z))$$



# Latent Variable Model

- Sample

$$z \sim p_Z(z)$$

$$x \sim p_\theta(x | z)$$

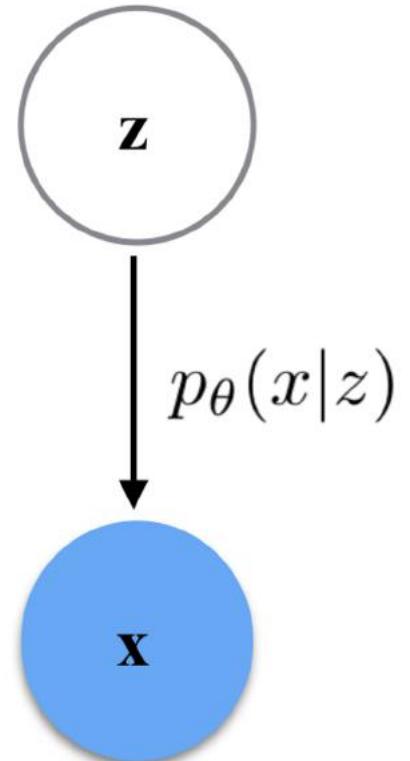
- Evaluate likelihood

$$p_\theta(x) = \sum_z p_Z(z)p_\theta(x | z)$$

- Train

$$\max_{\theta} \sum_i \log p_\theta(x^{(i)}) = \sum_i \log \sum_z p_Z(z)p_\theta(x^{(i)} | z)$$

$$x \rightarrow z$$



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  - Objective
    - Exact
    - Prior Sampling
    - Importance Sampling
    - Variational Lower Bound (VLB) / Evidence Lower BOund (ELBO)
  - Optimization
    - Likelihood Ratio Gradients vs. Reparameterization Trick Gradients
    - Optimizing the VLB/ELBO
- Variations
- Related ideas

# Training Latent Variable Models

- Objective:



$$\max_{\theta} \sum_i \log p_{\theta}(x^{(i)}) = \sum_i \log \sum_z p_Z(z) p_{\theta}(x^{(i)} | z)$$

- Scenario 1:  $z$  can only take on a small number of values  $\rightarrow$  exact objective tractable
- Scenario 2:  $z$  can take on an impractical number of values to enumerate  $\rightarrow$  approximate

How about optimizing  $p_z(z)$ ? = “learning the prior” and sometimes done [more later]

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# Exact Likelihood Objective

**Example:** mixture of 3 Gaussians, with uniform prior over components

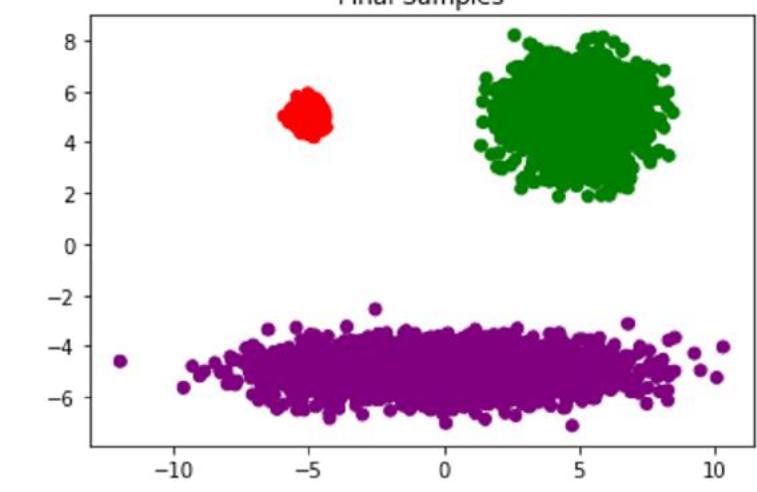
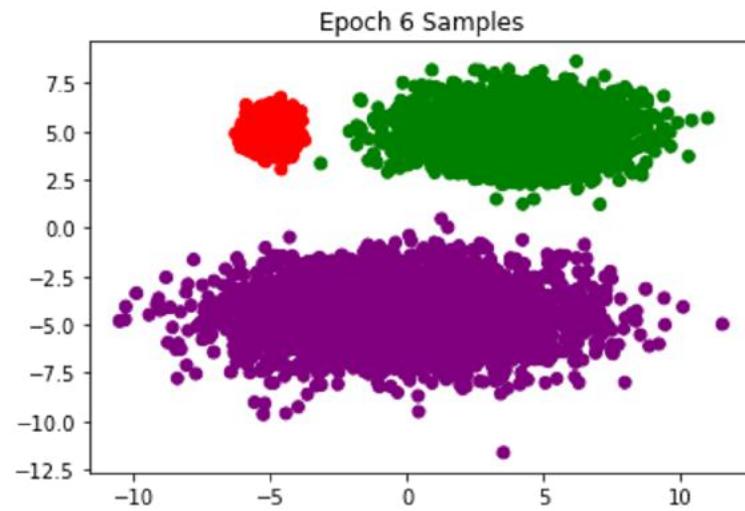
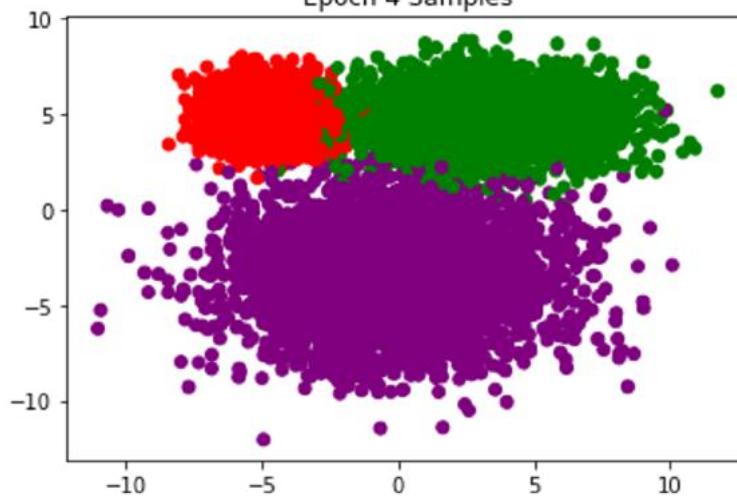
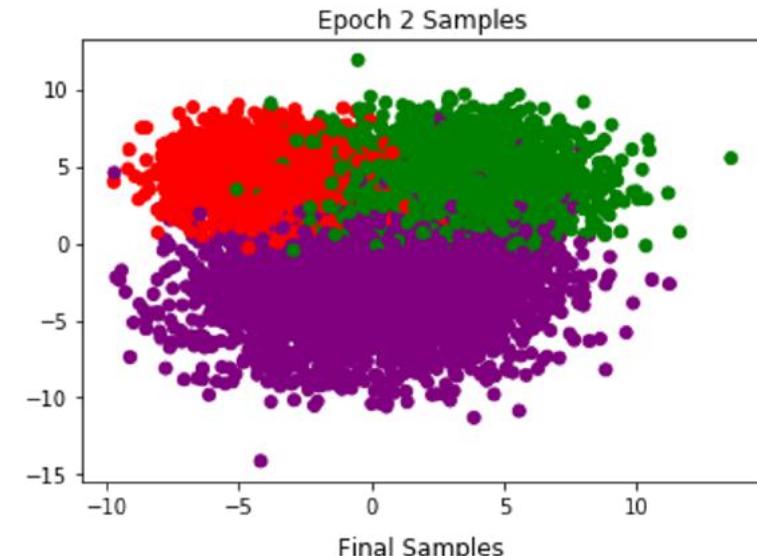
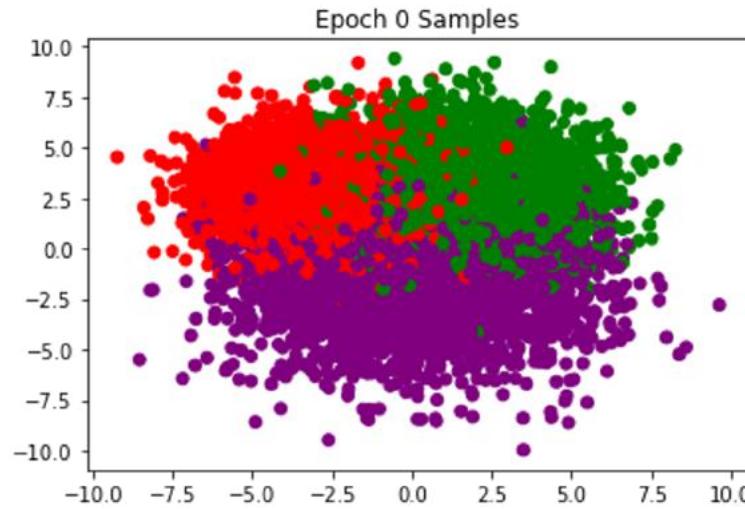
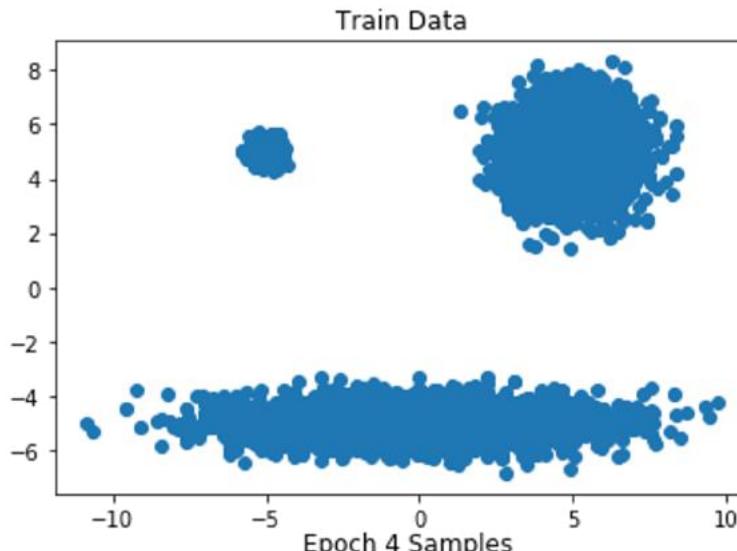
$$p_{\theta}(x) = \sum_z p_Z(z)p_{\theta}(x | z) \quad p_Z(z = A) = p_Z(z = B) = p_Z(z = C) = \frac{1}{3}$$

$$p_{\theta}(x | z = k) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_k|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x - \mu_k)^\top \Sigma_k^{-1} (x - \mu_k)\right)$$

**Training objective:**  $\max_{\theta} \sum_i \log p_{\theta}(x^{(i)})$

$$\begin{aligned} &= \max_{\mu, \Sigma} \sum_i \log [ & \frac{1}{3} & \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_A|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x^{(i)} - \mu_A)^\top \Sigma_A^{-1} (x^{(i)} - \mu_A)\right) \\ & & + \frac{1}{3} & \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_B|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x^{(i)} - \mu_B)^\top \Sigma_B^{-1} (x^{(i)} - \mu_B)\right) \\ & & + \frac{1}{3} & \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_C|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x^{(i)} - \mu_C)^\top \Sigma_C^{-1} (x^{(i)} - \mu_C)\right) ] \end{aligned}$$

# 2-D mixture of Gaussians



# Prior Sampling

Main idea: if  $z$  can take on many values  $\rightarrow$  sample  $z$

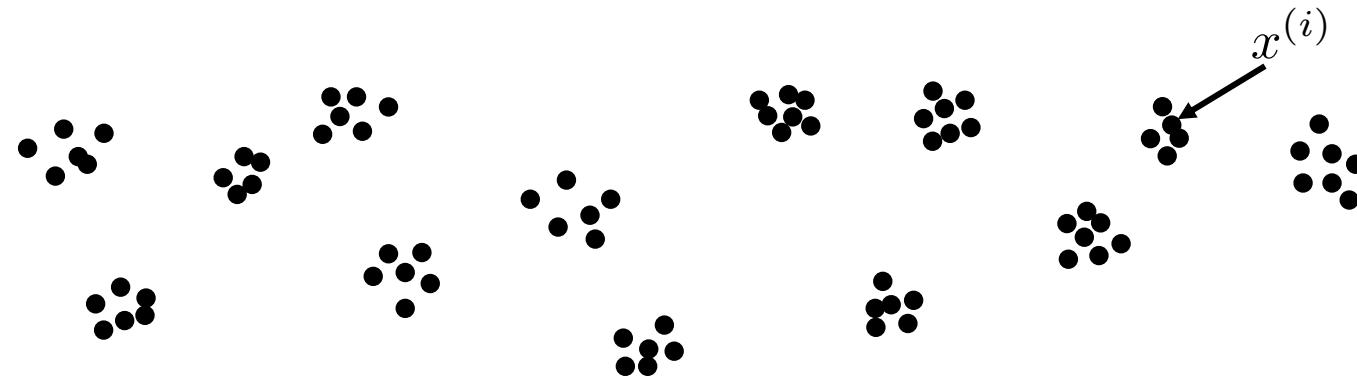
$$\sum_i \log \sum_z p_Z(z) p_\theta(x^{(i)} | z) \approx \sum_i \log \frac{1}{K} \sum_{k=1}^K p_\theta(x^{(i)} | z_k^{(i)}) \quad z_k^{(i)} \sim p_Z(z)$$

---

$\rightarrow$  run Stochastic Gradient Descent (SGD) on the approximate objective

# Prior Sampling – Example + Challenge

Consider data in N clusters:



Sampling  $z$  uniformly results in only  $1/N$  terms being useful.

**Recall:**  $z$  might correspond to many high level properties, e.g., 100 high level properties, probably of correct  $z$  for given  $x$ :  $0.5^{100}$

**Issue:** When going to higher dimensional data, it becomes near impossible to be lucky enough that a sampled  $z$  is a good match for a data point  $x^{(i)}$

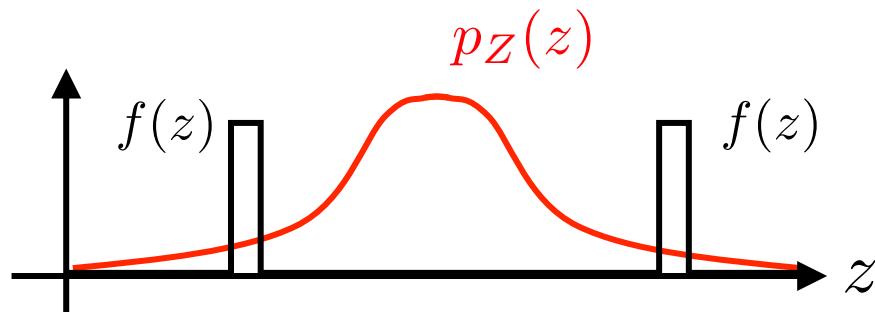
# Importance Sampling – Motivation

## Problem setting:

Want to compute  $\mathbb{E}_{z \sim p_Z(z)} [f(z)]$

But: (1) hard to sample from  $p_Z(z)$   
and/or (2) samples from  $p_Z(z)$  are not very informative

Example of (2):



Note: our Latent Variable Model objective is also example of (2)

# Importance Sampling – Algorithm

Formulation:

$$\begin{aligned}\mathbb{E}_{z \sim p_Z(z)} [f(z)] &= \sum_z p_Z(z) f(z) \\ &= \sum_z \frac{q(z)}{q(z)} p_Z(z) f(z) \\ &= \mathbb{E}_{z \sim q(z)} \left[ \frac{p_Z(z)}{q(z)} f(z) \right] \\ &\approx \frac{1}{K} \sum_{k=1}^K \frac{p_Z(z^{(k)})}{q(z^{(k)})} f(z^{(k)}) \quad \text{with } z^{(k)} \sim q(z)\end{aligned}$$

→ Can sample from  $q$  to compute expectation w.r.t.  $p$

# Importance Sampling for Latent Variable Model

## Training Objective:

$$\sum_i \log \sum_z p_Z(z) p_\theta(x^{(i)} | z) \approx \sum_i \log \frac{1}{K} \sum_{k=1}^K \frac{p_Z(z_k^{(i)})}{q(z_k^{(i)})} p_\theta(x^{(i)} | z_k^{(i)}) \quad \text{with } z_k^{(i)} \sim q(z_k^{(i)})$$

## Good proposal distribution $q(z)$ ?

We want samples compatible with  $x^{(i)}$

$$\rightarrow \text{How about } q(z) = p_\theta(z | x^{(i)}) = \frac{p_\theta(x^{(i)} | z) p_Z(z)}{p_\theta(x^{(i)})}$$

**Issue:** not clear how to sample from this distribution...

# Importance Sampling Proposal Distribution

## General Principle of Variational Approach:

We can't directly use  $p$  we want

So, instead, we propose a parameterized distribution  $q$  we know we can work with easily (in this case, sample from easily), and try to find a parameter setting that makes it as good as possible.

E.g. find  $q(z) = \mathcal{N}(z; \mu, \sigma^2)$  as close as possible to

$$p_\theta(z | x^{(i)}) = \frac{p_\theta(x^{(i)} | z)p_Z(z)}{p_\theta(x^{(i)})}$$

# Importance Sampling Proposal Distribution

## Variational Approach to Finding q:

We can't directly use  $p$  we want

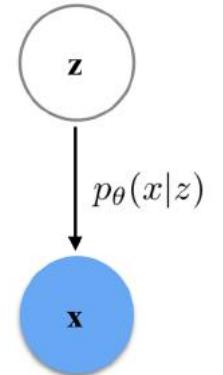
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E.g. find  $q(z) = \mathcal{N}(z; \mu, \sigma^2)$  as close as possible to

$$p_\theta(z | x^{(i)}) = \frac{p_\theta(x^{(i)} | z)p_Z(z)}{p_\theta(x^{(i)})}$$

# Importance Sampling Proposal Distribution

$$\begin{aligned} & \min_{q(z)} \text{KL}(q(z) \| p_\theta(z | x^{(i)})) \\ = & \min_{q(z)} \mathbb{E}_{z \sim q(z)} \log \left( \frac{q(z)}{p_\theta(z | x^{(i)})} \right) \\ = & \min_{q(z)} \mathbb{E}_{z \sim q(z)} \log \left( \frac{q(z)}{p_\theta(x^{(i)} | z) p_Z(z) / p_\theta(x^{(i)})} \right) \\ = & \min_{q(z)} \mathbb{E}_{z \sim q(z)} [\log q(z) - \log p_Z(z) - \log p_\theta(x^{(i)} | z)] + \log p_\theta(x^{(i)}) \\ = & \min_{q(z)} \mathbb{E}_{z \sim q(z)} [\log q(z) - \log p_Z(z) - \log p_\theta(x^{(i)} | z)] + \text{constant independent of } z \end{aligned}$$



→ optimize to find q

Note: all needed quantities in the objective readily computable

# Amortized Inference

**General Idea of Amortization:** if same inference problem needs to be solved many times, can we parameterize a neural network to solve it?

**Our case:** for all  $x^{(i)}$  we want to solve:

$$\min_{q(z)} \text{KL}(q(z) \| p_\theta(z \mid x^{(i)}))$$

**Amortized formulation:**

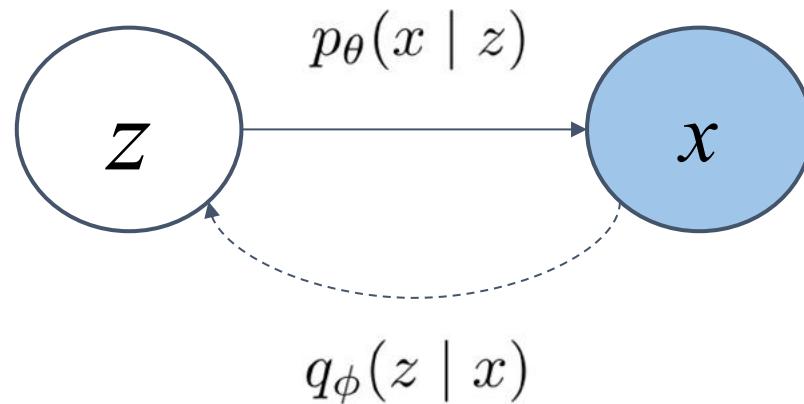
$$\min_{\phi} \sum_i \text{KL}(q_\phi(z \mid x^{(i)}) \| p_\theta(z \mid x^{(i)}))$$

**Trade-off:** + : faster, regularization; - : not as precise

# Amortized Inference

Amortized formulation:

$$\min_{\phi} \sum_i \text{KL}(q_{\phi}(z | x^{(i)}) \| p_{\theta}(z | x^{(i)}))$$



E.g:

$$q_{\phi}(z | x) = \mathcal{N}(\mu_{\phi}(x), \sigma_{\phi}^2(x))$$

Equivalently:  $z = \mu_{\phi}(x) + \varepsilon \sigma_{\phi}(x)$  with  $\varepsilon \sim \mathcal{N}(0, I)$

# Importance Weighted AutoEncoder (IWAE)

**Objective:**  $\sum_i \log \frac{1}{K} \sum_{k=1}^K \frac{p_Z(z_k^{(i)})}{q(z_k^{(i)})} p_\theta(x^{(i)} \mid z_k^{(i)})$  with  $z_k^{(i)} \sim q(z_k^{(i)})$

And:  $\min_{\phi} \sum_i \text{KL}(q_\phi(z \mid x^{(i)}) \| p_\theta(z \mid x^{(i)}))$

→ maximize term1 – term2

# Importance Weighted AutoEncoder (IWAE)

**Theorem 1.** *For all  $k$ , the lower bounds satisfy*

$$\log p(\mathbf{x}) \geq \mathcal{L}_{k+1} \geq \mathcal{L}_k.$$

*Moreover, if  $p(\mathbf{h}, \mathbf{x})/q(\mathbf{h}|\mathbf{x})$  is bounded, then  $\mathcal{L}_k$  approaches  $\log p(\mathbf{x})$  as  $k$  goes to infinity.*

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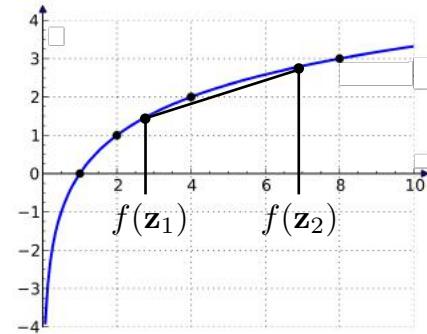
# VLB: Derivation 1 (Jensen)

$$\begin{aligned}
 \max_{\theta} \sum_i \log p_{\theta}(x^{(i)}) &= \max_{\theta} \sum_i \log \left( \sum_z p_z(z) \cdot p_{\theta}(x^{(i)}|z) \right) \\
 &\max_{\theta} \sum_i \log \left( \sum_z \frac{q(z)}{q(z)} p_z(z) \cdot p_{\theta}(x^{(i)}|z) \right) \\
 &\geq \max_{\theta} \sum_i \mathbb{E}_{z \sim q(z)} \log \frac{p_z(z)}{q(z)} p_{\theta}(x^{(i)}|z) \\
 &= \max_{\theta, q} \sum_i \mathbb{E}_{z \sim q(z)} \log p_z(z) \\
 &\quad + \mathbb{E}_{z \sim q(z)} \log p_{\theta}(x^{(i)}|z) \\
 &\quad - \mathbb{E}_{z \sim q(z)} q(z)
 \end{aligned}$$

Jensen Inequality (for concave functions)

- $\log$  is a concave function

$$\log(\mathbb{E}_{\mathbf{z} \sim q(\mathbf{z})}[f(\mathbf{z})]) = \log\left(\sum_{\mathbf{z}} q(\mathbf{z})f(\mathbf{z})\right) \geq \sum_{\mathbf{z}} q(\mathbf{z}) \log f(\mathbf{z})$$



If  $q(z) \propto p_z(z)p_{\theta}(x^{(i)}|z)$   
 $p_{\theta}(z|x^{(i)})$ ,  
we have equality

**VLB: Variational Lower Bound**  
**ELBO: Evidence Lower Bound**

# VLB: Derivation 2 (KL)

$$\begin{aligned} D_{\text{KL}} [q_x(z) \parallel p(z|x)] &= \mathbb{E}_{z \sim q_x(z)} [\log q_x(z) - \log p(z|x)] \\ &= \mathbb{E}_{z \sim q_x(z)} \left[ \log q_x(z) - \log \frac{p(z, x)}{p(x)} \right] \\ &= \mathbb{E}_{z \sim q_x(z)} [\log q_x(z) - \log p(z) - \log p(x|z) + \log p(x)] \\ &= \underbrace{\mathbb{E}_{z \sim q_x(z)} [\log q_x(z) - \log p(z) - \log p(x|z)]}_{\text{Only this part depends on } z} + \log p(x) \end{aligned}$$

$$\log p(x) = \mathbb{E}_{z \sim q_x(z)} [-\log q_x(z) + \log p(z) + \log p(x | z)] + D_{KL} [q_x(z) \| p(z | x)]$$

Same as with Jensen's, but now we know the gap = KL

# Variational Lower Bound (VLB)

- We now have an objective amenable to stochastic optimization

$$D_{\text{KL}} [q_x(z) \parallel p(z|x)] = \mathbb{E}_{z \sim q_x(z)} [\log q_x(z) - \log p(z) - \log p(x|z)] + \log p(x)$$

- Turns out we can get more out of this exercise

$$\begin{aligned} \log p(x) &= -\mathbb{E}_{z \sim q_x(z)} [\log q_x(z) - \log p(z) - \log p(x|z)] + D_{\text{KL}} [q_x(z) \parallel p(z|x)] \\ &= \underbrace{\mathbb{E}_{z \sim q_x(z)} [\log p(z) + \log p(x|z) - \log q_x(z)]}_{\text{Variational Lower Bound}} + \underbrace{D_{\text{KL}} [q_x(z) \parallel p(z|x)]}_{\geq 0} \end{aligned}$$

- note: the optimal  $q_x(z)$  of VLB is  $p(z|x)$ , at which point VLB is tight ( $= \log p(x)$ )

# VLB Maximization

- Given a data distribution  $\mathbf{x} \sim p_{\text{data}}$ , we can know train the generative model by maximizing the VLB under data distribution

$$\begin{aligned} & \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}} \left[ \mathbb{E}_{\mathbf{z} \sim q_x(\mathbf{z})} [\log p(\mathbf{z}) + \log p(\mathbf{x}|\mathbf{z}) - \log q_x(\mathbf{z})] \right] \\ & \leq \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}} [\log p(\mathbf{x})] \end{aligned}$$

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# Gradients of Expectations

Two major types of gradient estimators for  $\nabla_{\phi} \mathbb{E}_{q_{\phi}(\mathbf{z})}[f(\mathbf{z})]$  :

- REINFORCE / likelihood-ratio estimator
  - Very general
    - Applicable to both discrete and continuous latent variables
    - Can handle non-differentiable functions  $f(\mathbf{z})$
  - Tends to have relatively high variance: needs variance reduction.
- Reparameterization / pathwise estimator
  - Less general
    - Applicable only to continuous latent variables
    - Requires  $f(\mathbf{z})$  to be differentiable
  - Tends to have relatively low variance

# Likelihood Ratio Gradient

$$\max_{\phi} \mathbb{E}_{z \sim q_{\phi}(z)} [f(z)] \quad z^{(i)} \sim q_{\phi}(z)$$

$$\max_{\phi} \mathbb{E}_z [q_{\phi}(z) f(z)]$$

$$\nabla_{\phi} \left( \max_{\phi} \mathbb{E}_z [q_{\phi}(z) f(z)] \right) = \sum_z \nabla_{\phi} [q_{\phi}(z) f(z)]$$

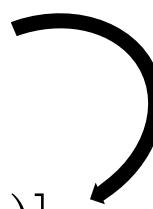
$$= \sum_z \frac{q_{\phi}(z)}{q_{\phi}(z)} \nabla_{\phi} [q_{\phi}(z) f(z)]$$

$$= \mathbb{E}_{z \sim q_{\phi}(z)} \frac{\nabla_{\phi} q_{\phi}(z)}{q_{\phi}(z)} f(z)$$

$$= \mathbb{E}_{z \sim q_{\phi}(z)} [\nabla_{\phi} \log q_{\phi}(z) f(z)] \approx \frac{1}{k} \sum_{i=1}^k \nabla_{\phi} \log q_{\phi}(z) f(z)$$

~~$\mathbb{E}_{z \sim q_{\phi}(z)} [f(z)] \approx \frac{1}{k} \sum_{i=1}^k f(z^{(i)})$~~

cannot compute  $\nabla_{\phi} \left( \frac{1}{k} \sum_{i=1}^k f(z^{(i)}) \right)$

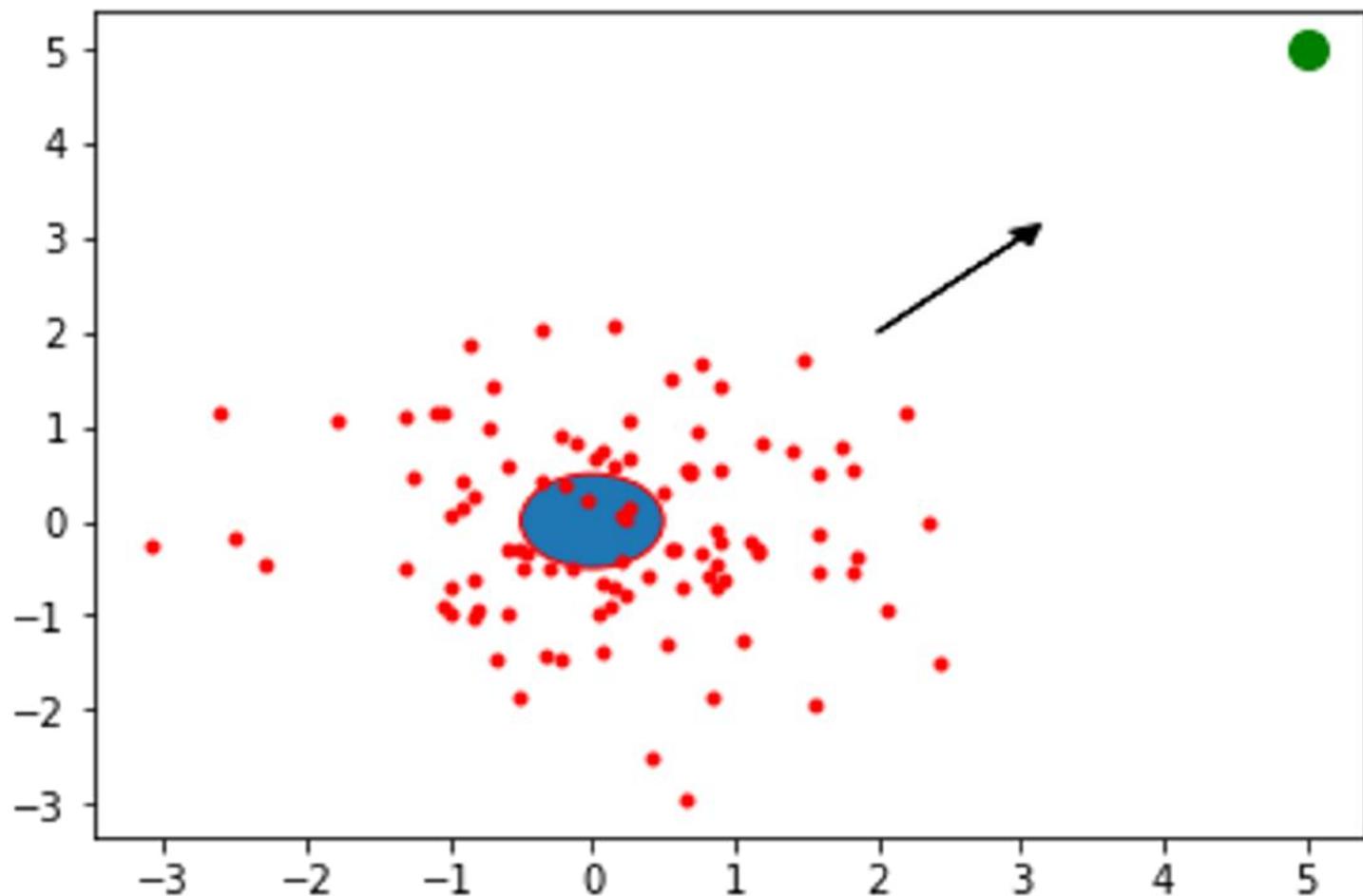


We need to turn this into  
an expectation

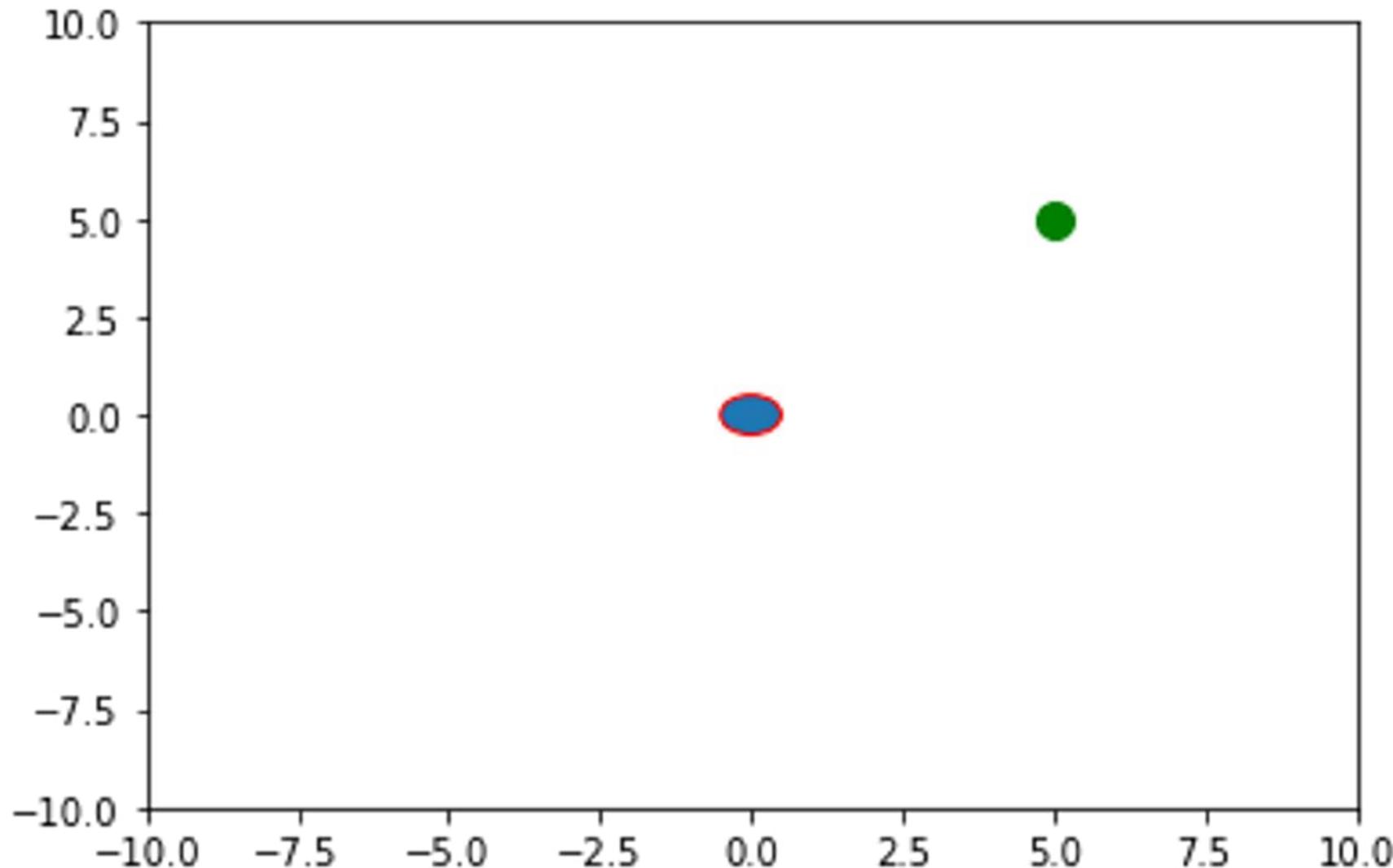
# Likelihood Ratio Gradient – Toy Problem

Learn  $\mu \in \mathbb{R}^2$  to minimize the objective below to reach the green point

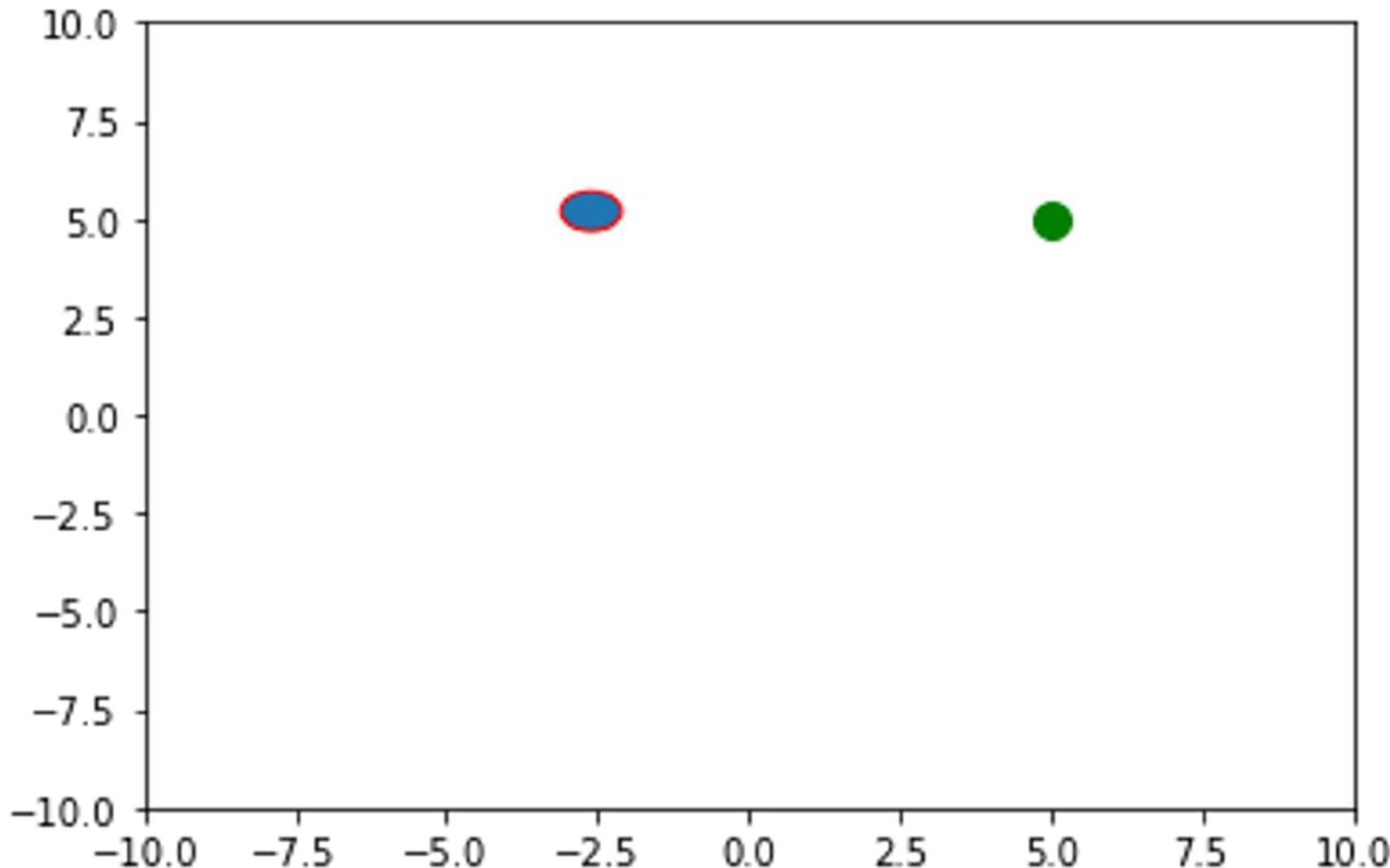
$$\mathcal{L} = \mathbb{E}_{x \sim N(\mu, I)} \|x - \begin{bmatrix} 5 \\ 5 \end{bmatrix}\|_2^2$$



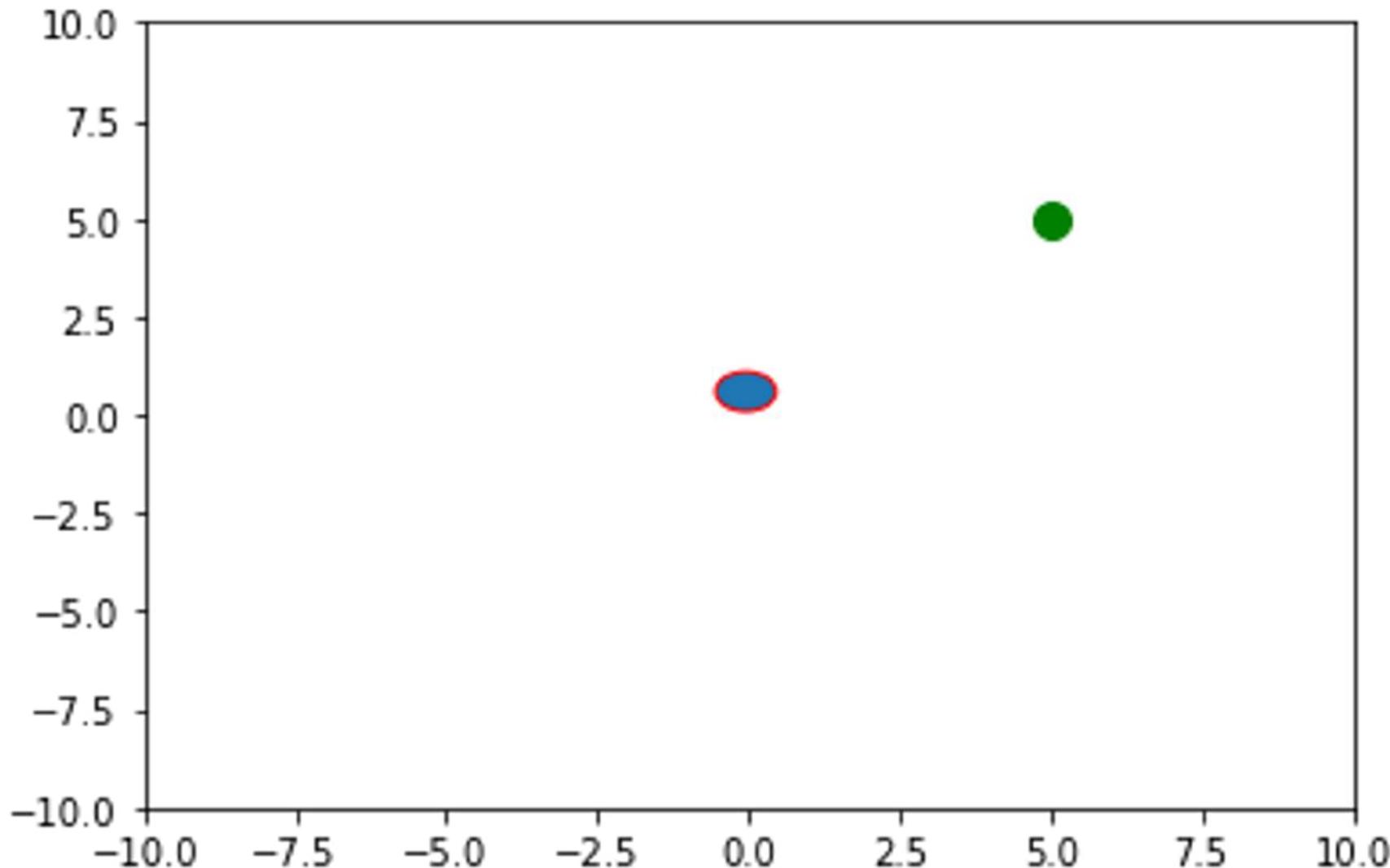
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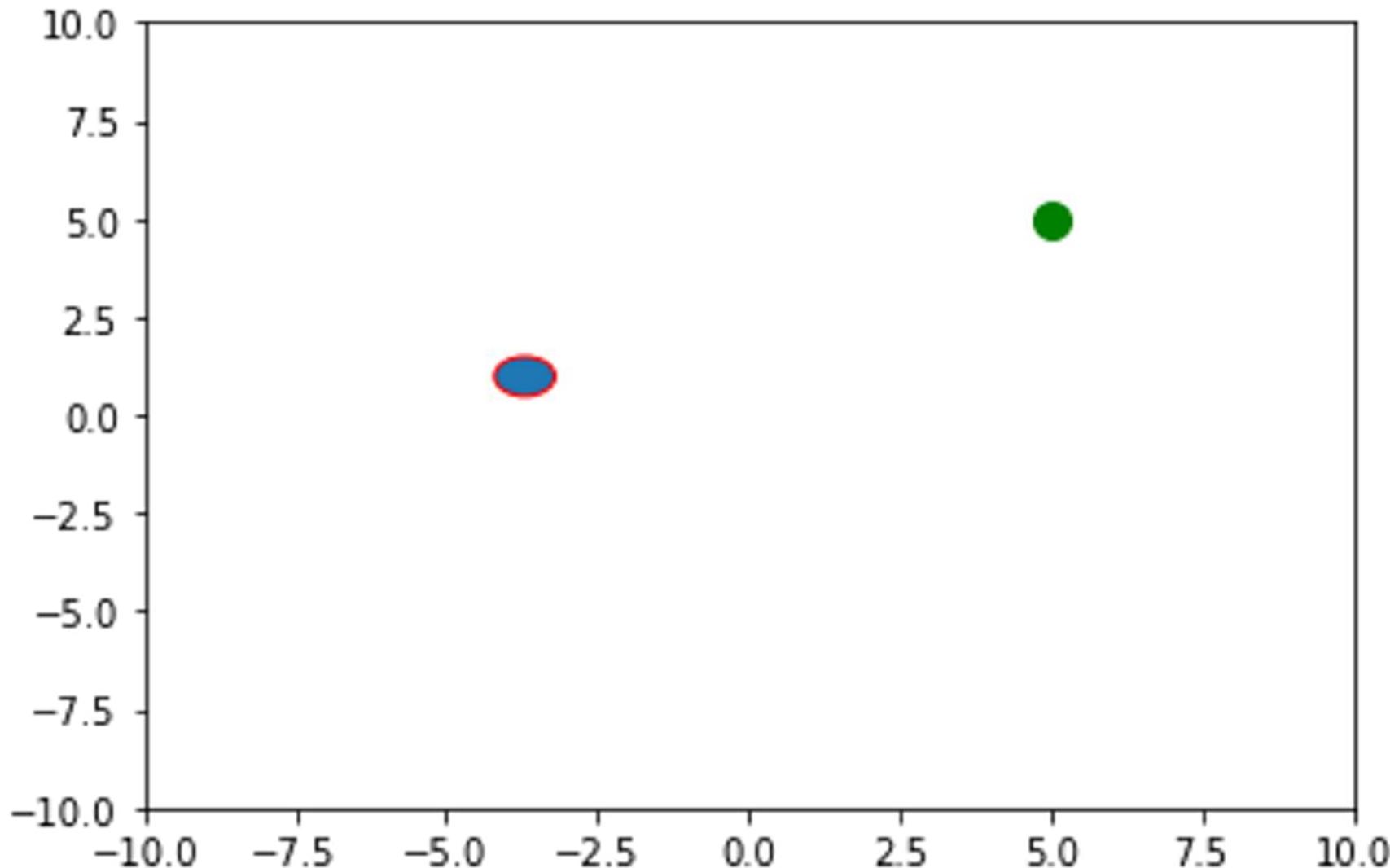
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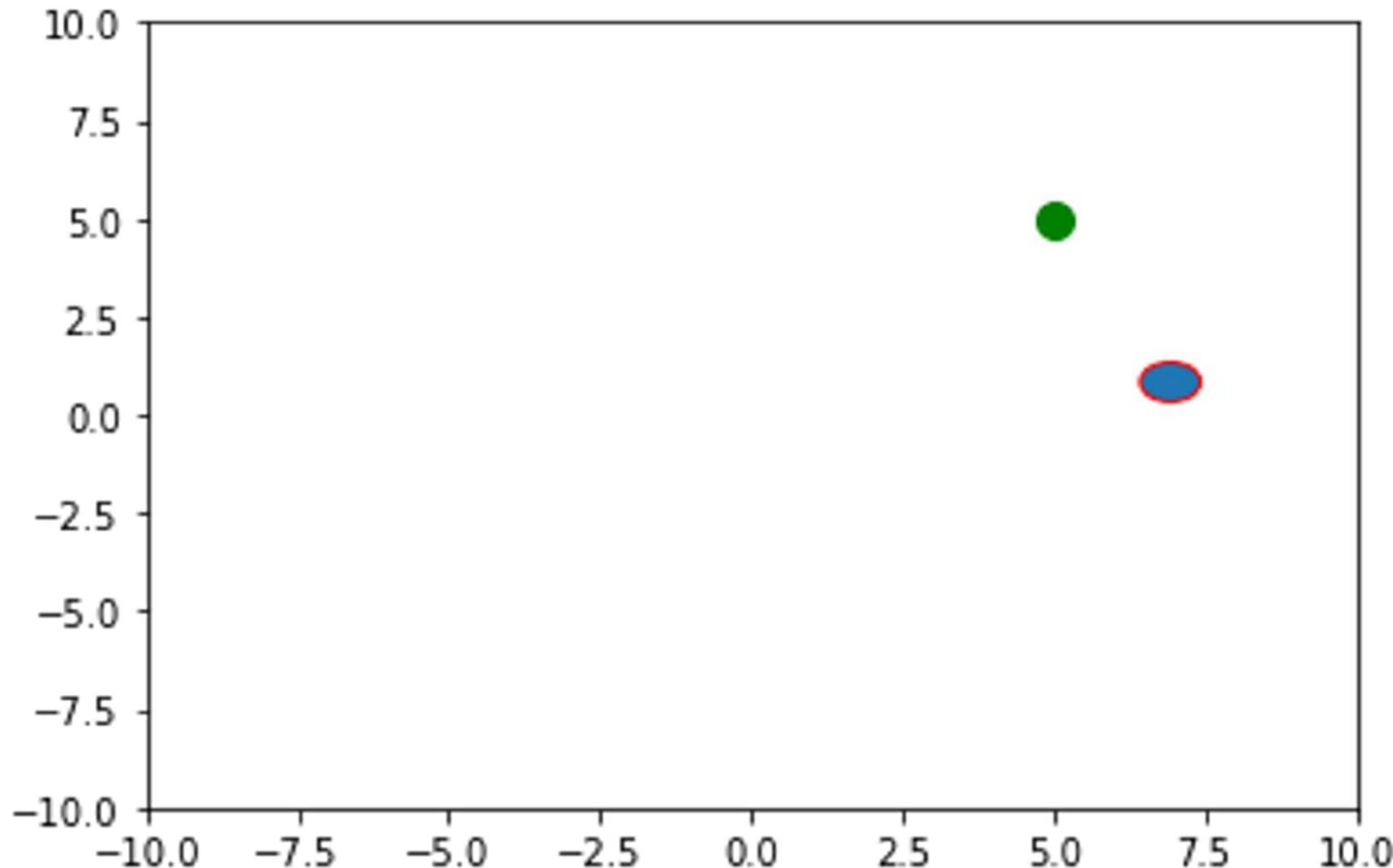
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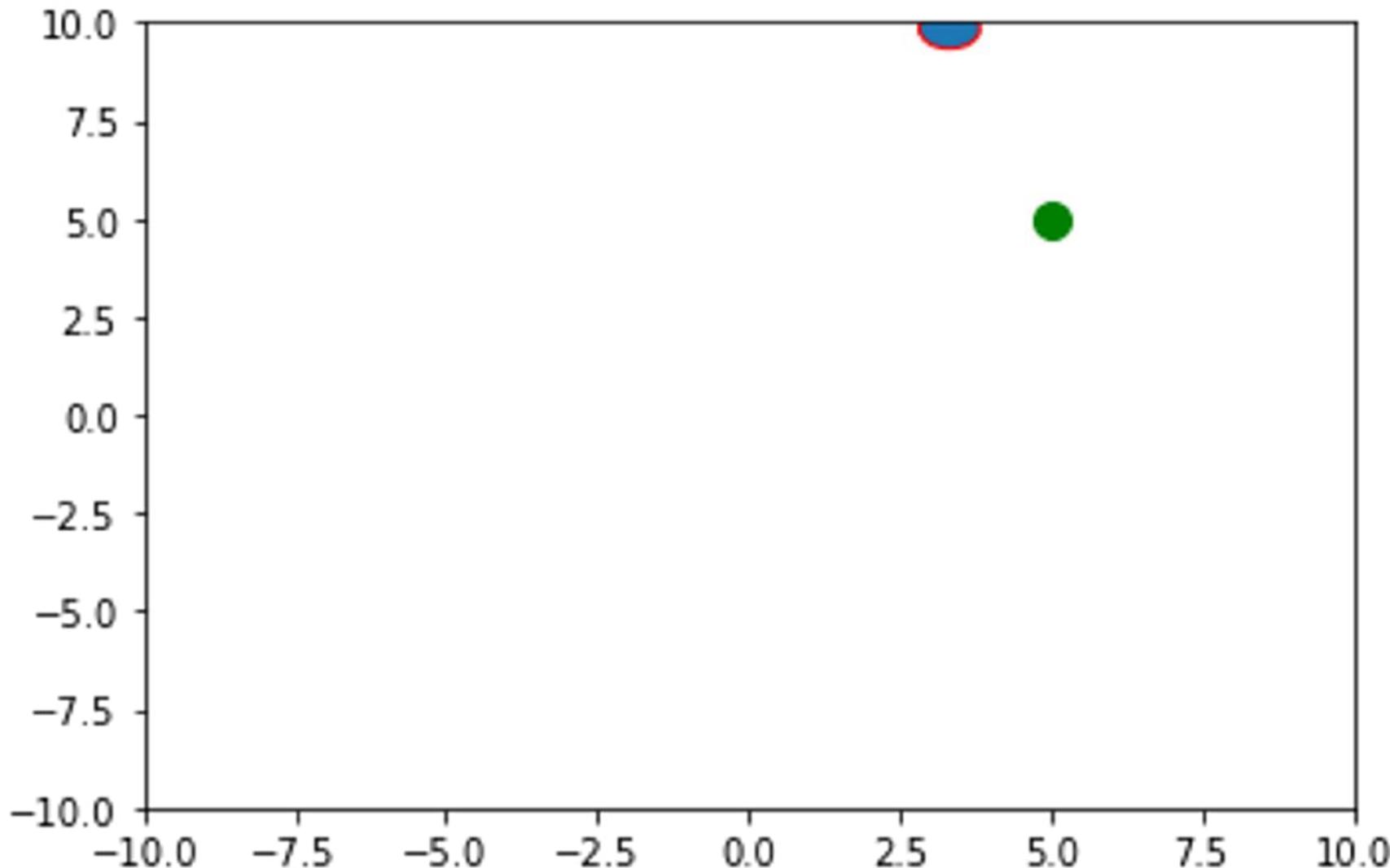
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# Likelihood Ratio Gradient – Toy Problem



# Likelihood Ratio Gradient – Toy Problem



# Pathwise Derivative / Reparameterization Trick

$$\mathbb{E}_{z \sim q_\phi(z)}[f(z)] \quad q_\phi(z) = \mathcal{N}(\mu, \sigma^2)$$

$$z = \mu + \epsilon \cdot \sigma \quad \epsilon \sim \mathcal{N}(0, 1)$$

$$= \mathbb{E}_{\epsilon \sim \mathcal{N}(0, 1)}[f(\mu + \epsilon \sigma)]$$

no  $\phi$  here

$$\approx \frac{1}{k} \sum_{i=1}^k f(\mu + \epsilon^{(i)} \sigma)$$

- We can then compute  $\nabla_{\mu, \sigma} \left( \frac{1}{k} \sum_{i=1}^k f(\mu + \epsilon^{(i)} \sigma) \right)$

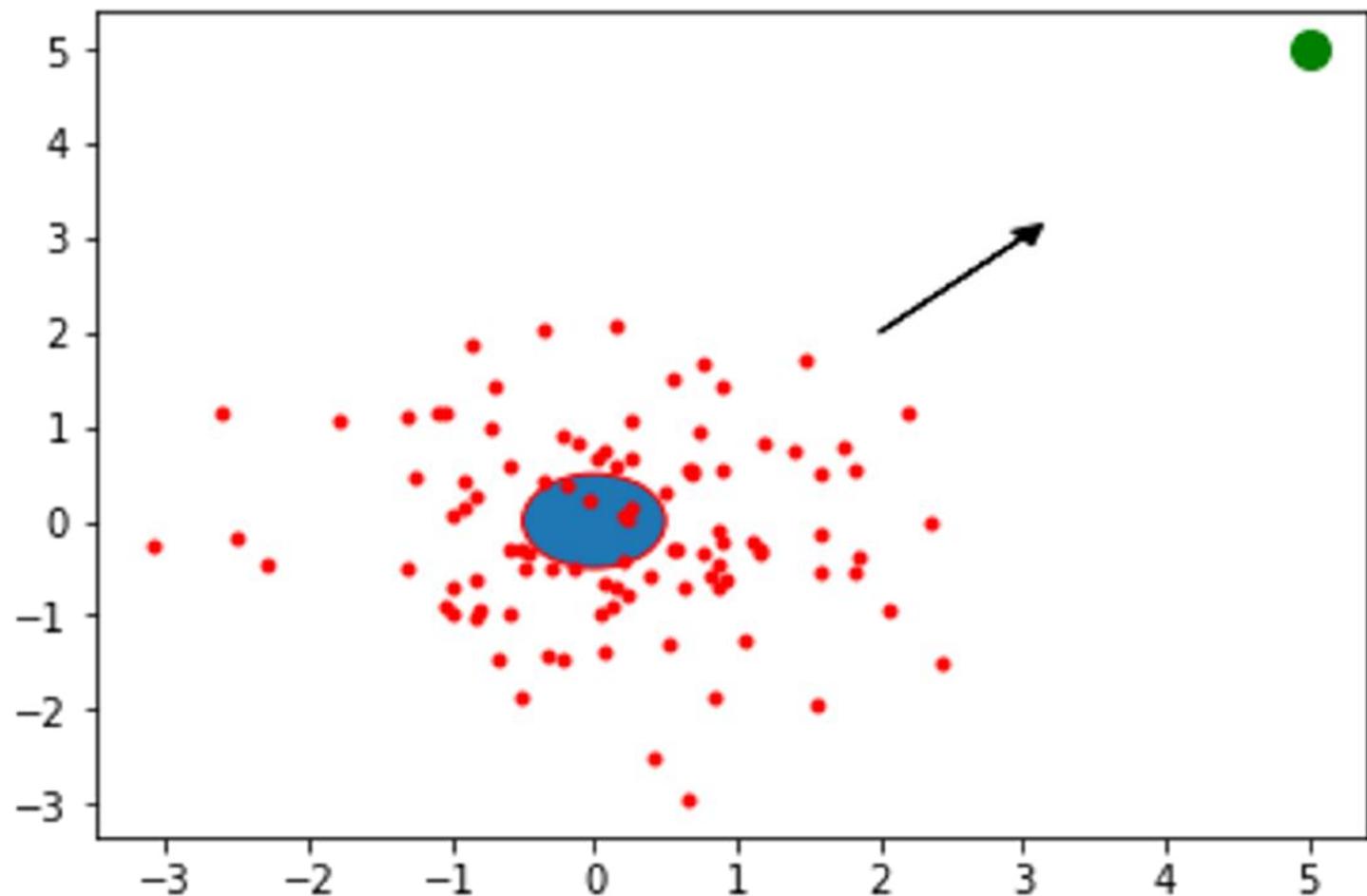
# Pathwise Derivative (PD)

- Stochastic gradient possible if  $z$  is continuous now (more technical condition?)
  - Common choice:  $\epsilon \sim \mathcal{N}, f(\epsilon) = \mu + \sigma\epsilon$
  - Any flow that you just learned!
- Also known as **reparameterization trick**
- Can work with only 1~2 samples

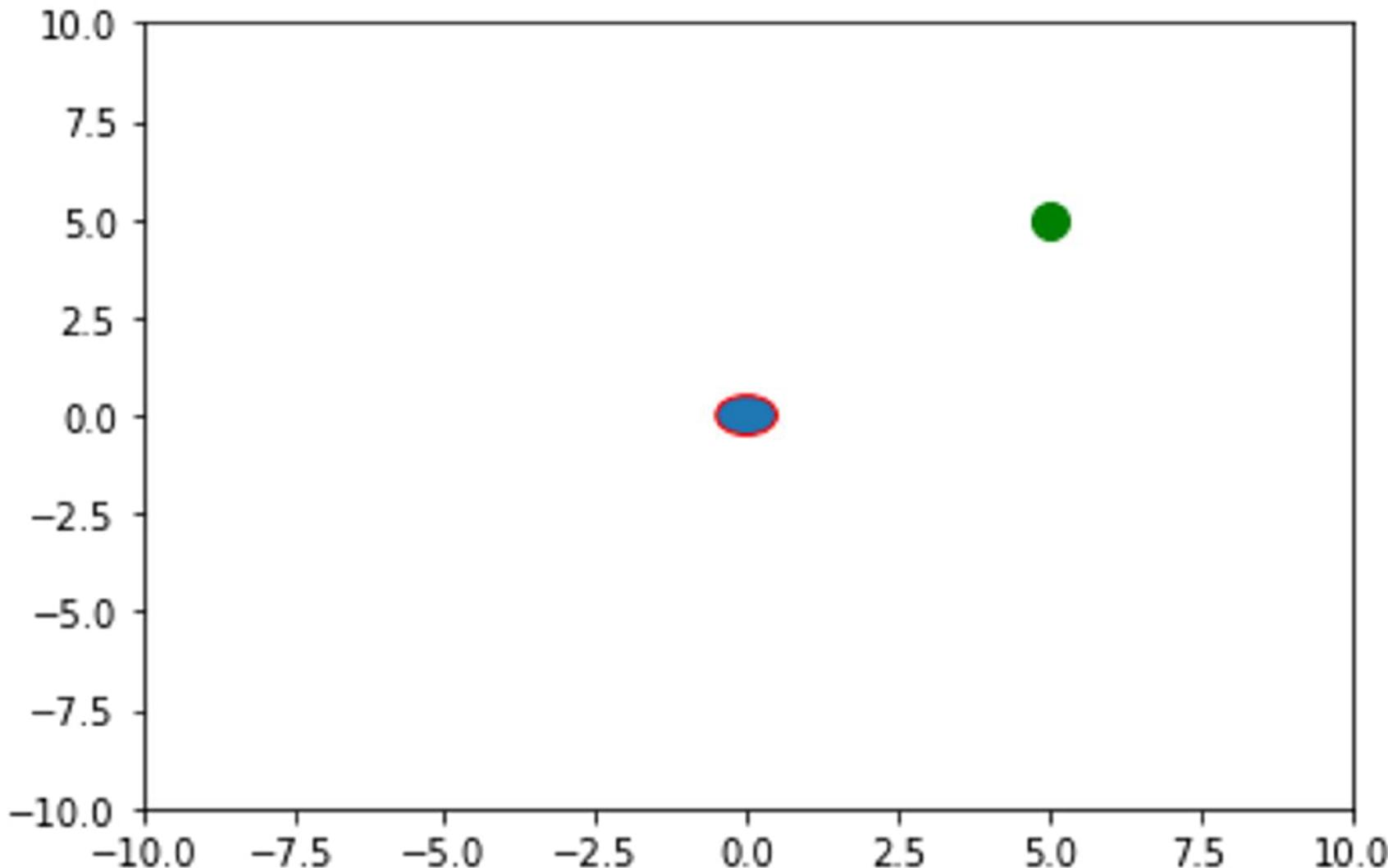
# Pathwise Derivative – Toy Problem

Learn  $\mu \in \mathbb{R}^2$  to  
minimize the objective  
below to reach the  
green point

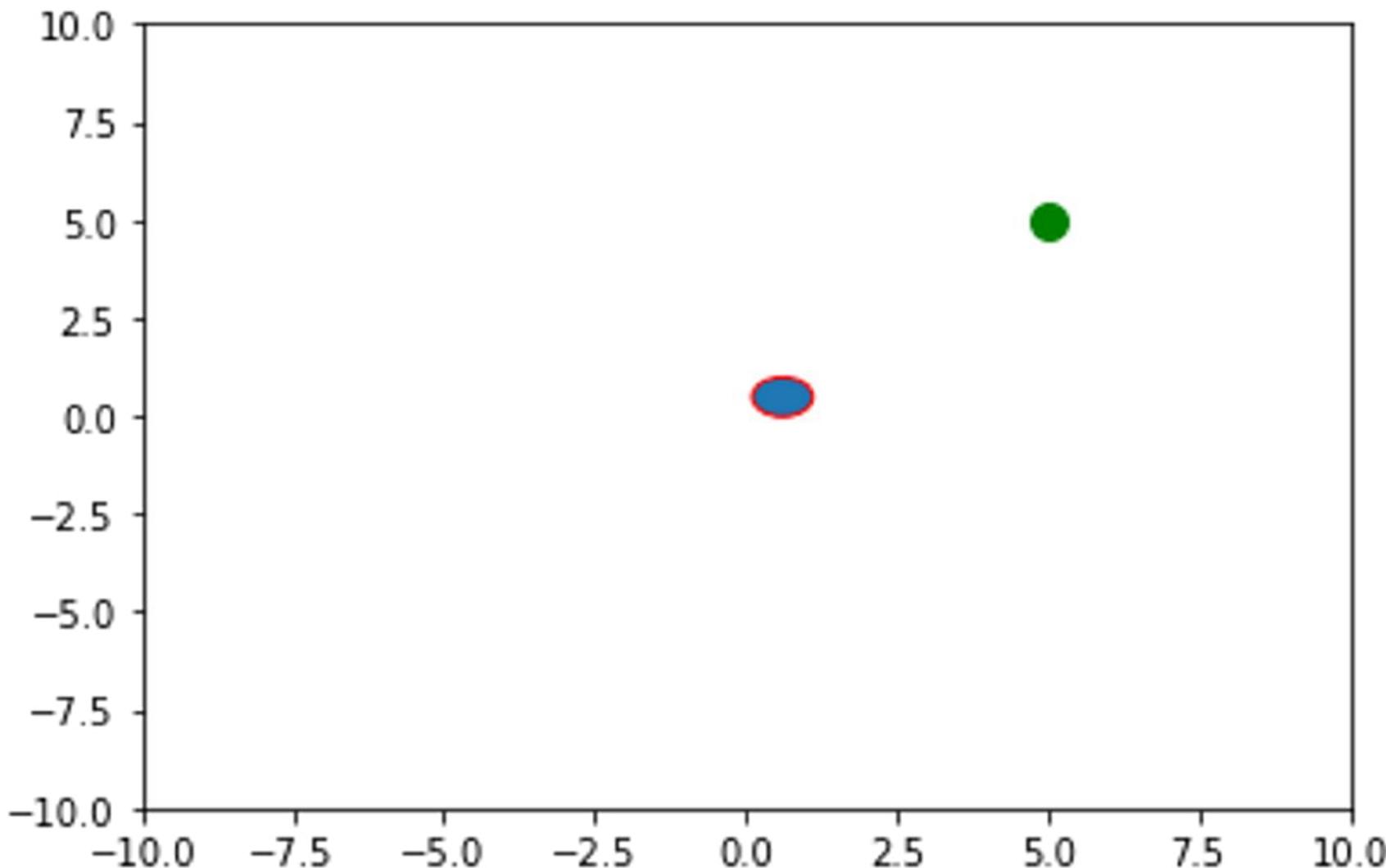
$$\mathcal{L} = \mathbb{E}_{x \sim N(\mu, I)} \|x - \begin{bmatrix} 5 \\ 5 \end{bmatrix}\|_2^2$$



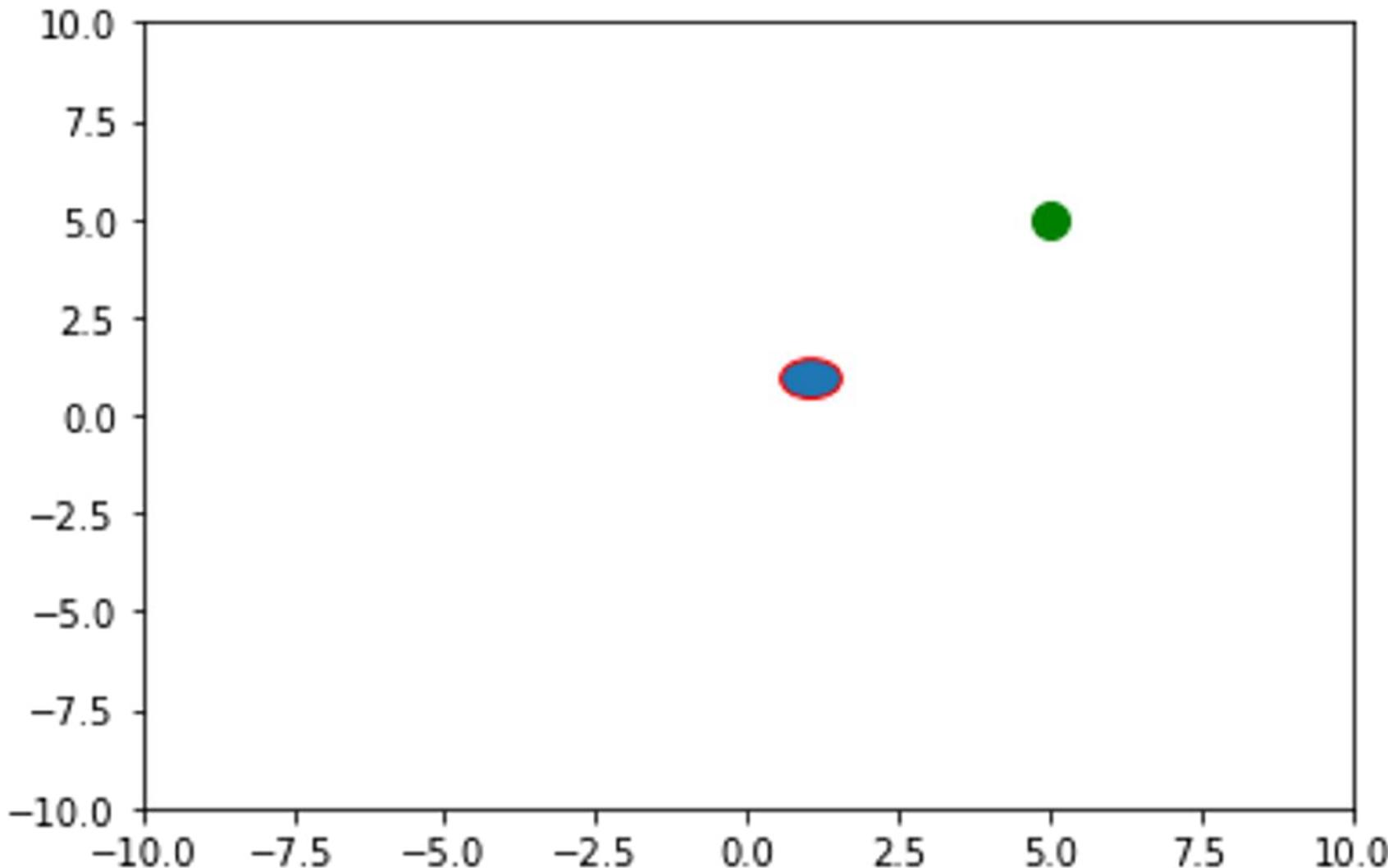
# Pathwise Derivative – Toy Problem



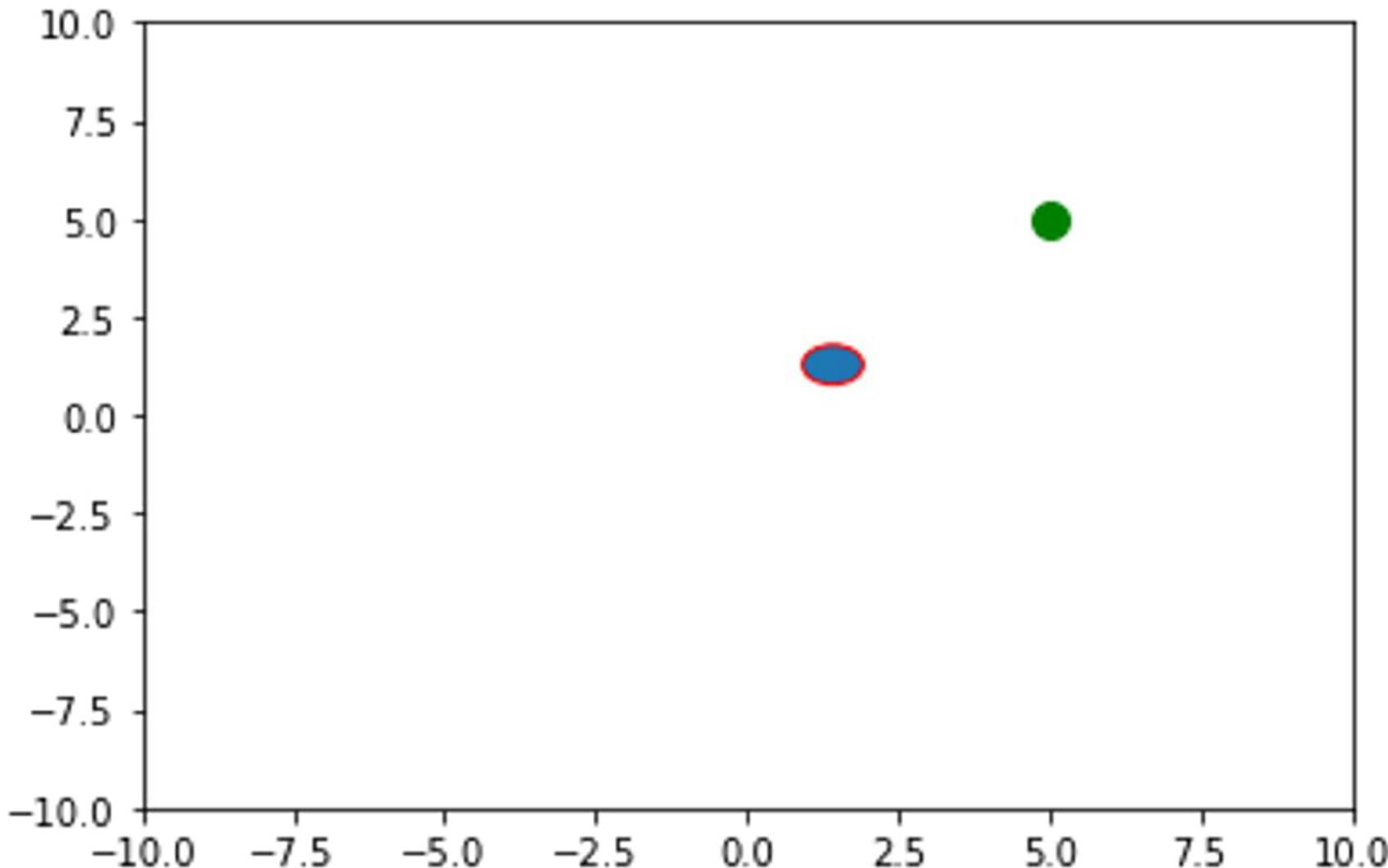
# Pathwise Derivative – Toy Problem



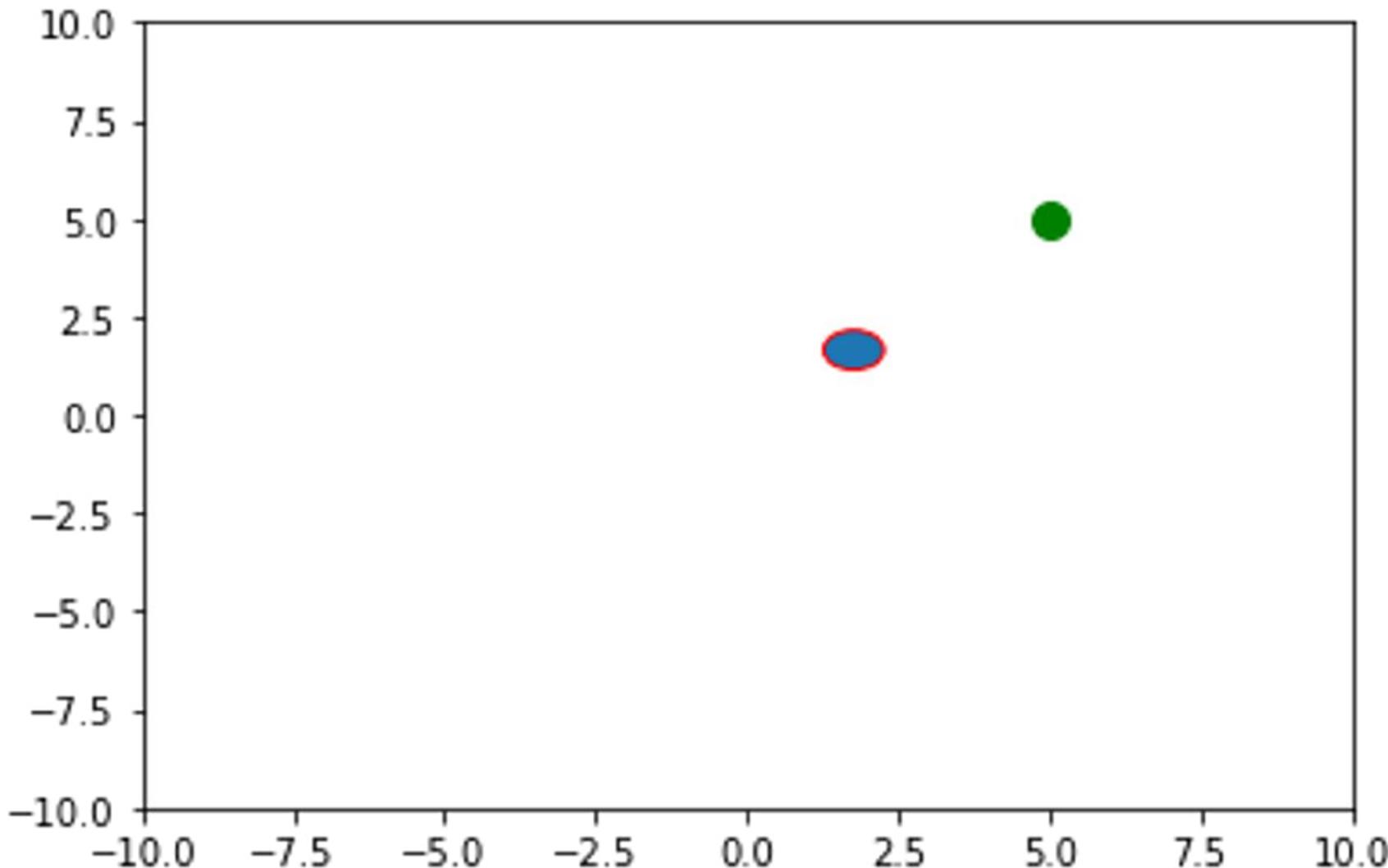
# Pathwise Derivative – Toy Problem



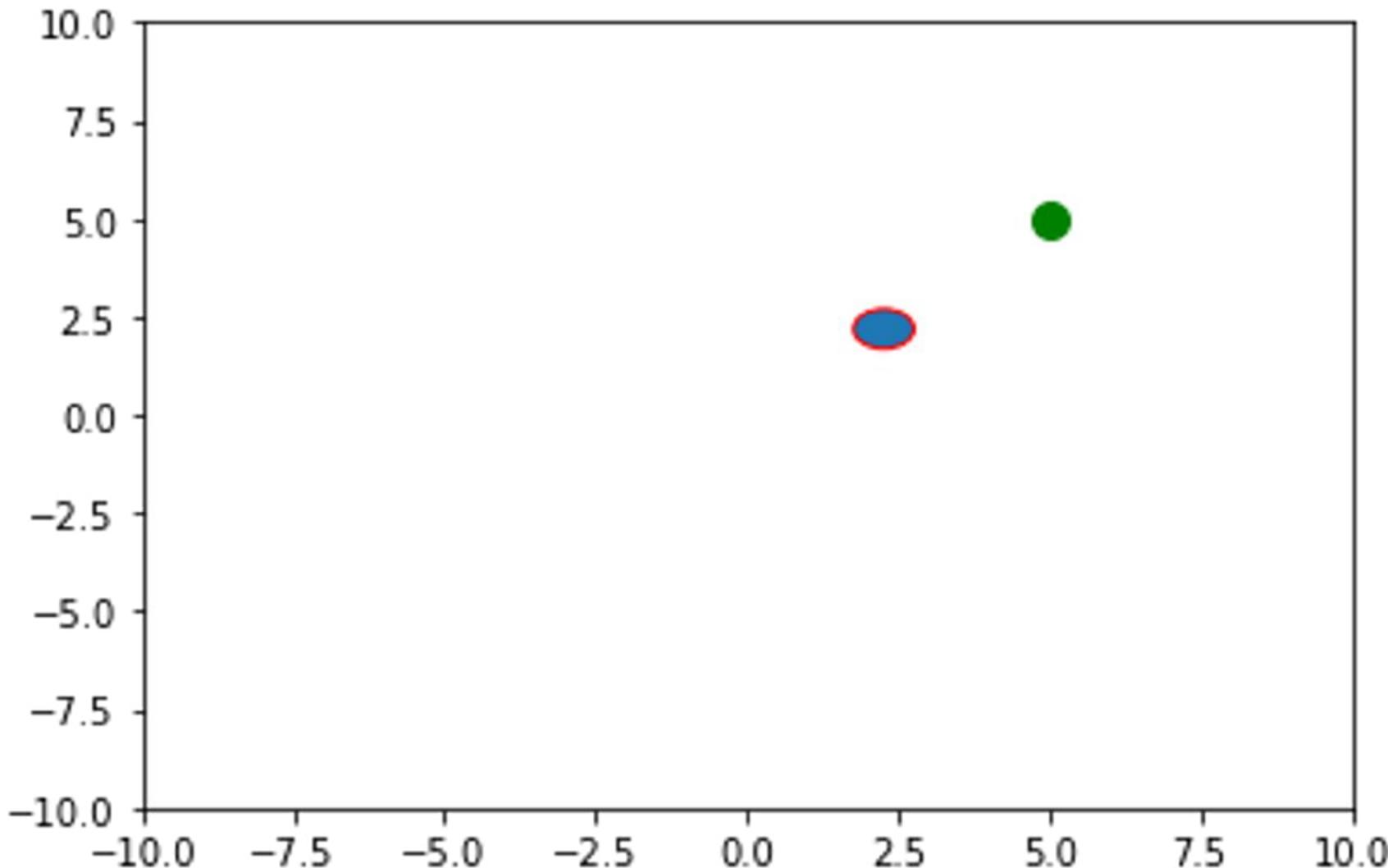
# Pathwise Derivative – Toy Problem



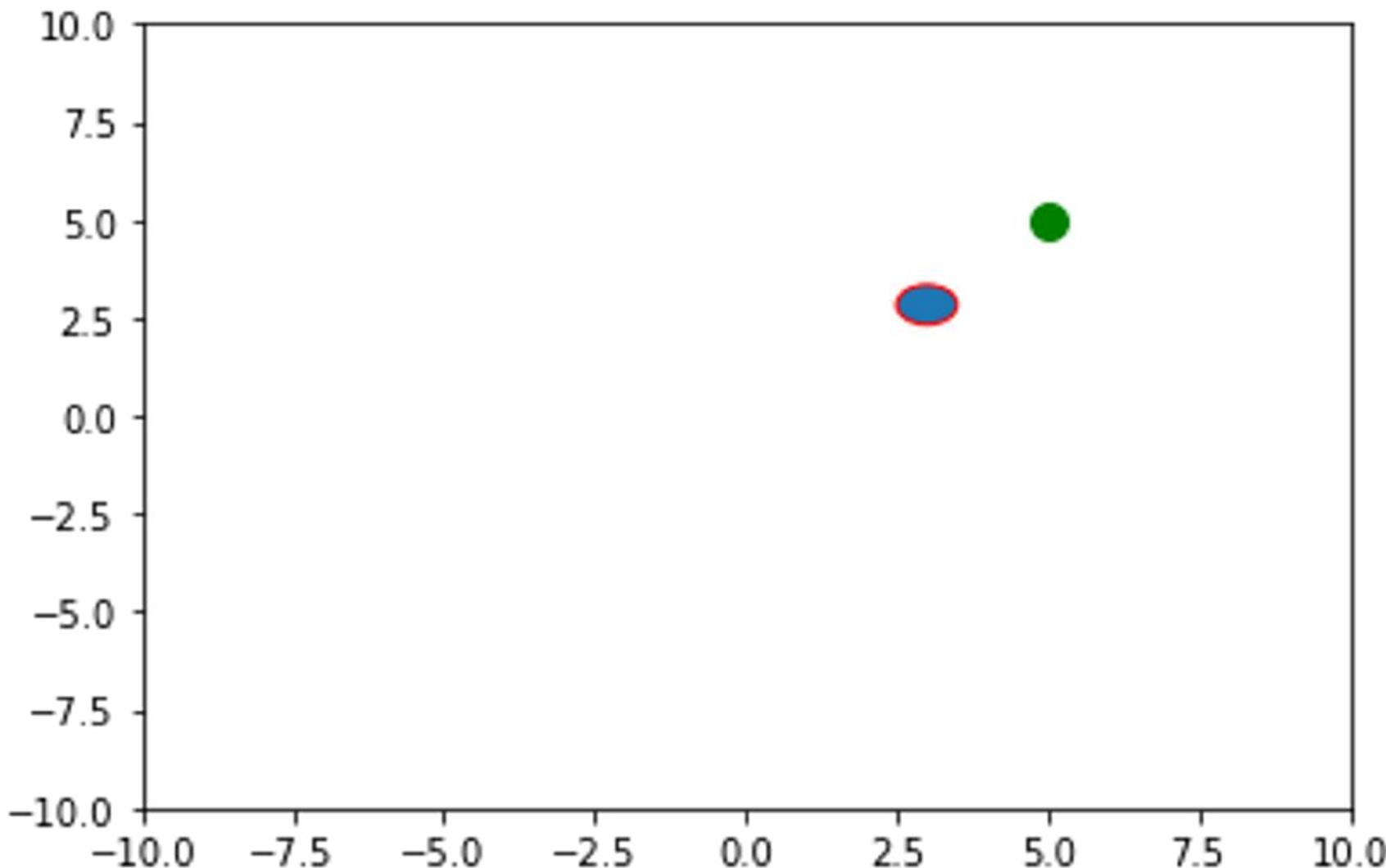
# Pathwise Derivative – Toy Problem



# Pathwise Derivative – Toy Problem



# Pathwise Derivative – Toy Problem



# Pathwise Derivative (PD)

One other way to optimize this objective when  $z$  is continuous is to cast  $z$  as a function of a simple fixed noise such as standard gaussian.

$$z = g(\epsilon, \phi), \epsilon \sim \mathcal{N}(0, I)$$

$$\mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)] = \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [f(g(\epsilon, \phi))]$$

When  $f$  is differentiable,

$$\nabla_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)] = \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [\nabla_\phi f(g(\epsilon, \phi))]$$

# Reparameterizing distributions

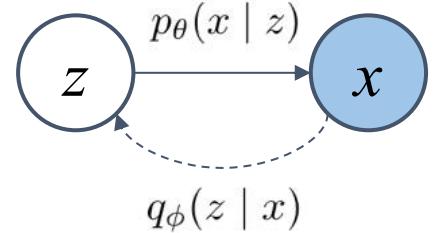
- Any distribution in the scale-location family (Laplace, Cauchy, Student's t, etc.) can be reparameterized in the same way.
- Distributions like Gamma and Dirichlet can be parameterized using implicit reparameterization.
- Not every distribution can be reparameterized in a differentiable way.
  - For example, discrete variables are not reparameterizable in this way.
- Deep learning frameworks such as TensorFlow and PyTorch support reparameterization for many continuous distributions, making it easy to propagate gradients through samples.

# VAE and Likelihood Ratio Gradient

$$\max_{\theta, \phi} \mathbb{E}_{z \sim q_\phi(z|x^{(i)})} [\log p_z(z) + \log p_\theta(x^{(i)}|z) - \log q_\phi(z|x^{(i)})]$$

$$\nabla_\theta(\cdot) = \nabla_\theta \mathbb{E}_{z \sim q_\phi(z|x^{(i)})} [\log p_\theta(x^{(i)}|z)] \approx \frac{1}{K} \sum_{k=1}^K \nabla_\theta \log p_\theta(x^{(i)}|z^{(k)})$$

$z^{(k)} \sim q_\phi(z|x^{(i)})$



$$\begin{aligned} \nabla_\phi(\cdot) &= \mathbb{E}_{z \sim q_\phi(z|x^{(i)})} \nabla_\phi \log q_\phi(z|x^{(i)}) [\log p_z(z) + \log p_\theta(x^{(i)}|z) - \log q_\phi(z|x^{(i)})] \\ &\quad + \underbrace{\mathbb{E}_{z \sim q_\phi(z|x^{(i)})} [-\nabla_\phi \log q_\phi(z|x^{(i)})]}_{\mathbb{E}_{z \sim q_\phi(z|x^{(i)})} \left[ -\frac{\nabla_\phi q_\phi(z|x^{(i)})}{q_\phi(z|x^{(i)})} \right]} \\ &= \mathbb{E}_z \left[ -q_\phi(z|x^{(i)}) \frac{\nabla_\phi q_\phi(z|x^{(i)})}{q_\phi(z|x^{(i)})} \right] \\ &= \nabla_\phi \sum_z q_\phi(z|x^{(i)}) = 1 \end{aligned}$$

# Likelihood Ratio Estimator

We are interested in  $\operatorname{argmax}_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)]$

How do we compute  $\nabla_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)]$  ?

$$\nabla_\phi \sum_z q_\phi(z|x) f(z) = \sum_z \nabla_\phi q_\phi(z|x) f(z) = \sum_z \underbrace{\frac{\nabla_\phi q_\phi(z|x)}{q_\phi(z|x)}}_{f(z)q_\phi(z|x)}$$

$$\Rightarrow \nabla_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)] = \sum_z (\nabla_\phi \log q_\phi(z|x) f(z)) q_\phi(z|x) = \mathbb{E}_{z \sim q_\phi(\cdot|x)} [\nabla_\phi \log q_\phi(z|x) f(z)]$$

$$\phi \leftarrow \phi + \alpha \nabla_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [\nabla_\phi \log q_\phi(z|x) f(z)]$$

**Issue:** High variance gradients, needs many samples of z to form a good estimate

# VAE and Pathwise Derivative

One other way to optimize this objective when  $z$  is continuous is to cast  $z$  as a function of a simple fixed noise such as standard gaussian.

$$z = g(\epsilon, \phi), \epsilon \sim \mathcal{N}(0, I)$$

$$\mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)] = \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [f(g(\epsilon, \phi))]$$

When  $f$  is differentiable,

$$\nabla_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)] = \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [\nabla_\phi f(g(\epsilon, \phi))]$$

# PD applied to VI

## Variational AutoEncoder

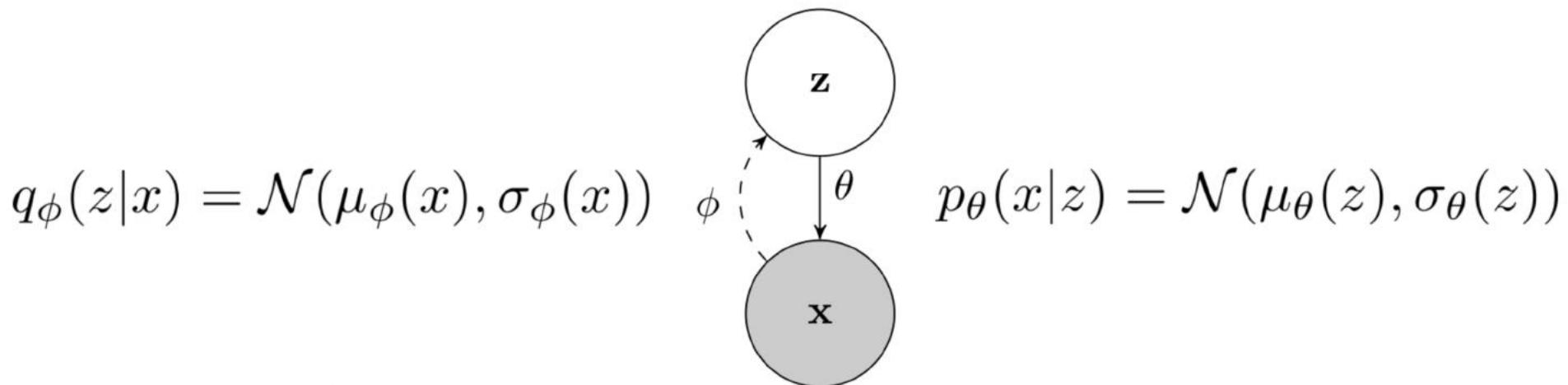
$q_\phi(z|x)$  is modeled as a Gaussian with parameters  $\mu$  and  $\sigma$  a DNN encoder (parameters  $\phi$ ) of  $x$ . The DNN decoder  $p_\theta(x|z)$  is differentiable.

$$\text{Let } z = \Sigma^{1/2}(x; \phi)\epsilon + \mu(x; \phi)$$

$$\begin{aligned} \text{VLB} &= \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [\log p_\theta(x|z) - \log q_\phi(z|x) + \log p(z)] \\ &= \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [\log p_\theta(x|z)] - KL(q_\phi(z|x) || p(z)) \end{aligned}$$

$\nabla_\theta$  [VLB] and  $\nabla_\phi$  [VLB] can now be efficiently computed with SGD.

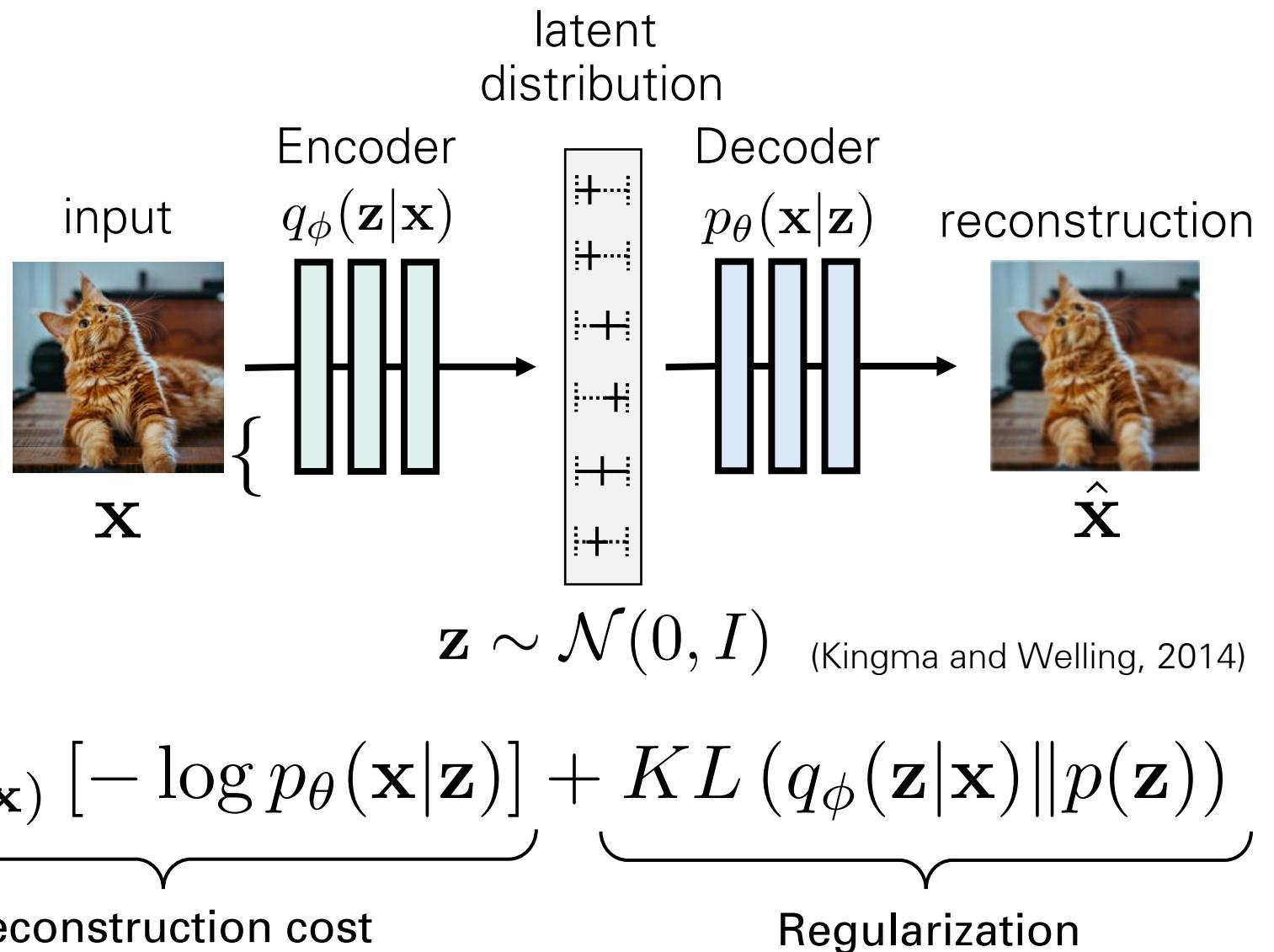
# VAE



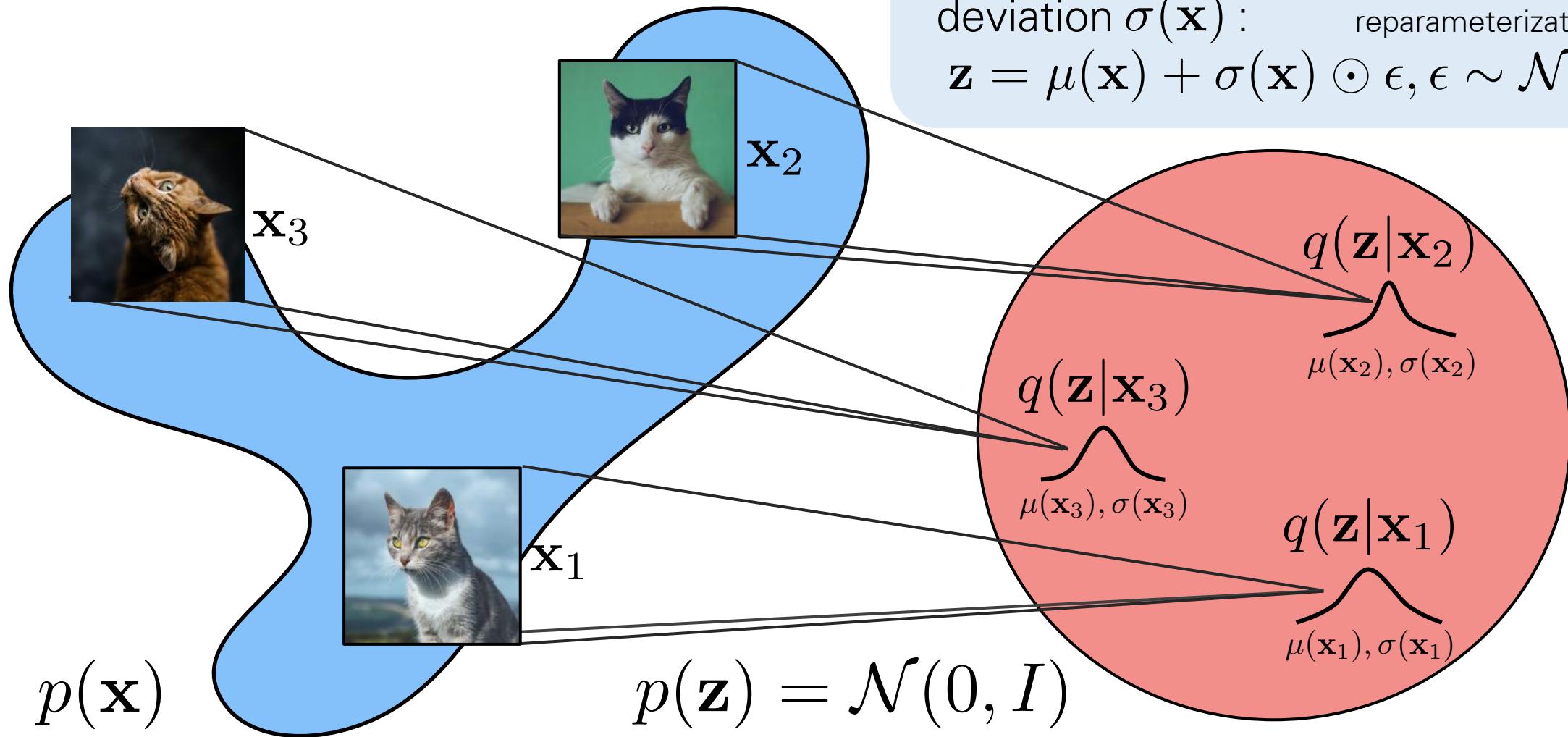
- Prior:  $p(\mathbf{z}) = \mathcal{N}(0, I)$
- Likelihood / decoder:
  - For binary data:  $p_\theta(\mathbf{x}|\mathbf{z}) = \text{Bernoulli}(\text{NN}_\theta(\mathbf{z}))$
  - For real-valued data:  $p_\theta(\mathbf{x}|\mathbf{z}) = \mathcal{N}(\text{NN}_\theta(\mathbf{z}), \text{diag}(\text{NN}_\theta(\mathbf{z})))$
- Variational posterior / encoder:  $q_\phi(\mathbf{z}|\mathbf{x}) = \mathcal{N}(\text{NN}_\phi(\mathbf{x}), \text{diag}(\text{NN}_\phi(\mathbf{x})))$
- Can also use other types of neural nets (e.g. ConvNets) instead of fully-connected neural networks.

# VAEs in a Nutshell

- Assume a known distribution (e.g. Normal distribution) on the latent space,  $p(\mathbf{z})$ .
- Parametrize the conditional probability  $p(\mathbf{x}|\mathbf{z})$  by a neural network.
- Approximate  $p(\mathbf{z}|\mathbf{x})$  using a variational distribution  $q(\mathbf{z}|\mathbf{x})$ , also parametrized by a neural network.



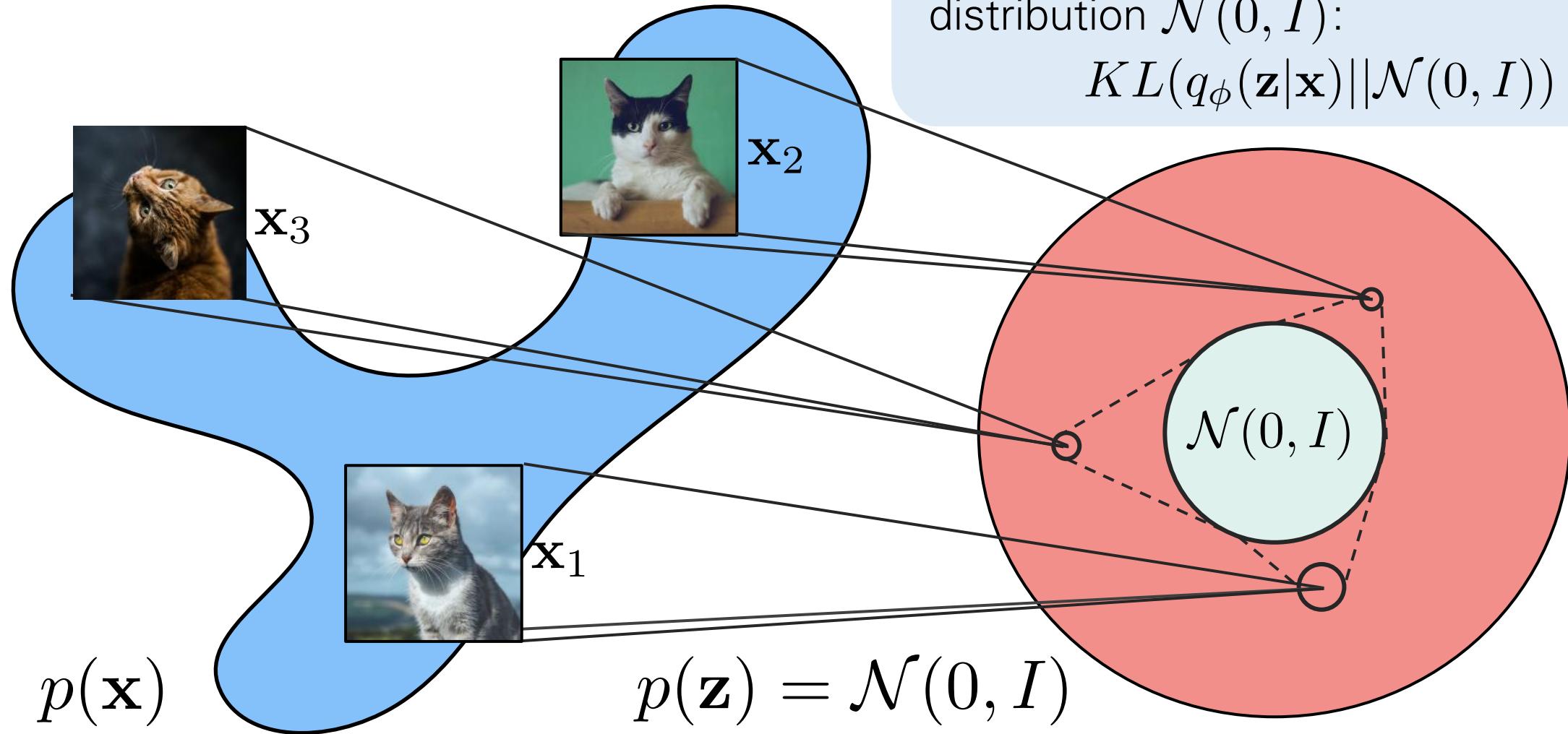
# Intuition behind VAEs



To get the latent code  $\mathbf{z}$ , we sample from the mean  $\mu(\mathbf{x})$  and the standard deviation  $\sigma(\mathbf{x})$ : reparameterization trick  
$$\mathbf{z} = \mu(\mathbf{x}) + \sigma(\mathbf{x}) \odot \epsilon, \epsilon \sim \mathcal{N}(0, I)$$

$$\mathcal{L}_{VAE}(\mathbf{x}; \theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [-\log p_\theta(\mathbf{x}|\mathbf{z})] + KL(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z}))$$

# Intuition behind VAEs

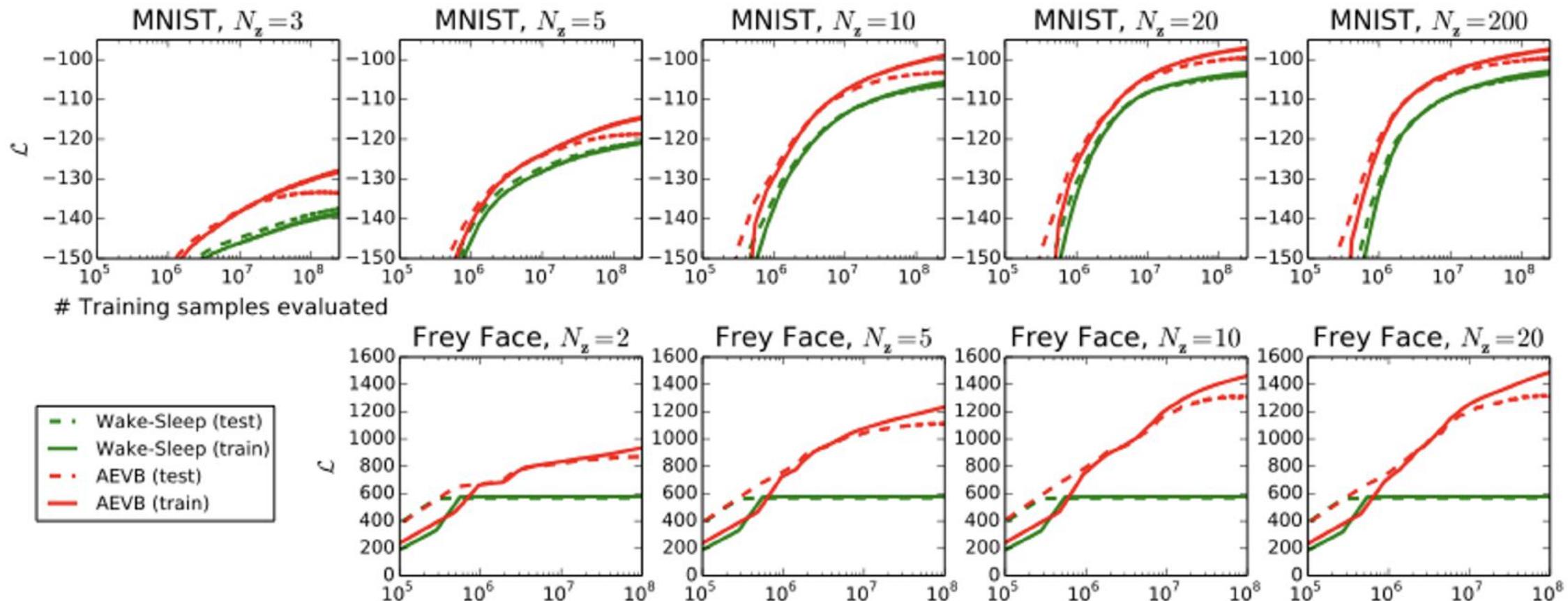


Minimize the Kullback-Leibler distance between each  $q(\mathbf{z}|\mathbf{x})$  and the normal distribution  $\mathcal{N}(0, I)$ :

$$KL(q_\phi(\mathbf{z}|\mathbf{x})||\mathcal{N}(0, I))$$

$$\mathcal{L}_{VAE}(\mathbf{x}; \theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [-\log p_\theta(\mathbf{x}|\mathbf{z})] + KL(q_\phi(\mathbf{z}|\mathbf{x})||\mathcal{N}(0, I))$$

# VAE



# VAE

2	8	3	1	3	8	5	7	3	8
8	3	8	2	7	9	8	5	3	8
3	5	9	9	4	3	9	5	1	6
1	9	1	8	3	3	3	4	9	7
2	7	3	6	4	3	0	2	0	3
5	9	7	0	5	9	3	3	4	5
6	9	4	3	6	2	8	5	7	2
8	4	9	0	8	0	7	3	8	6
7	4	3	6	3	0	3	6	0	3
2	1	2	0	4	7	1	0	5	0

# Evolutions of VAEs

- 5 years of VAE progress on face generation



2014



2015



2016



2017



2018



2019

D.P. Kingma and M. Welling. **Auto-Encoding Variational Bayes**. ICLR 2014.

A. Radford. **Conv/Deconv Variational Autoencoder**. 2015.

A. Boesen L. Larsen, S.K. Sønderby, H. Larochelle, O. Winther. **Autoencoding beyond pixels using a learned similarity metric**. ICML 2016.

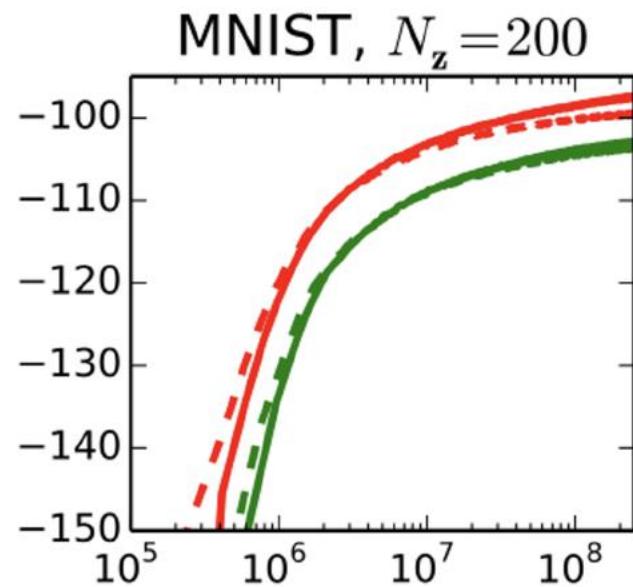
L.M. Mescheder, S. Nowozin, A. Geiger. **Adversarial Variational Bayes: Unifying Variational Autoencoders and Generative Adversarial Networks**. ICML 2017.

H. Huang, Z. Li, R. He, Z. Sun, T. Tan. **IntroVAE: Introspective Variational Autoencoders for Photographic Image Synthesis**. NeurIPS 2018.

A. Razavi, A. van den Oord, O. Vinyals. **Generating Diverse High-Resolution Images with VQ-VAE-2**. NeurIPS 2019.

# Compared to AR

- We now have a family of trainable latent variable models!
- But performance is lacking



Model	NLL Test
DBM 2hl [1]:	$\approx 84.62$
DBN 2hl [2]:	$\approx 84.55$
NADE [3]:	88.33
EoNADE 2hl (128 orderings) [3]:	85.10
EoNADE-5 2hl (128 orderings) [4]:	84.68
DLGM [5]:	$\approx 86.60$
DLGM 8 leapfrog steps [6]:	$\approx 85.51$
DARN 1hl [7]:	$\approx 84.13$
MADE 2hl (32 masks) [8]:	86.64
DRAW [9]:	$\leq 80.97$
PixelCNN:	81.30

# Why is it called an autoencoder?

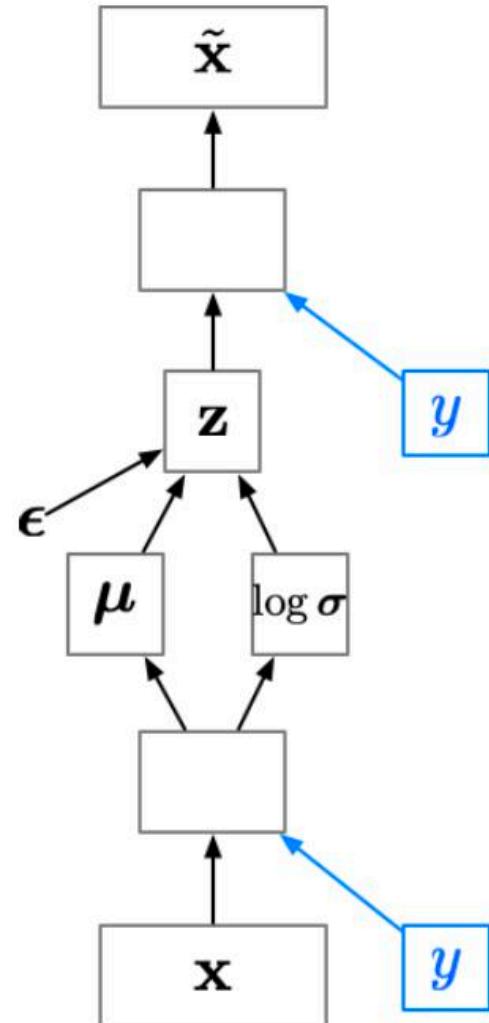
- We have seen that a variational autoencoder is a latent variable model with Gaussian prior  $p(z)$  and approximate posterior  $q(z|x)$ .
  - Why is it called an “autoencoder”?

$$\log p_\theta(x) \geq \underbrace{\left( E_{z \sim q_x(z)} \log p_\theta(x|z) \right)}_{\text{Reconstruction loss}} - \underbrace{KL(q_\phi(z|x) || p(z))}_{\text{Regularization}}$$

$\overbrace{\hspace{30em}}$   
 $L(\theta, \phi) - \text{VAE objective}$

# Class-Conditional VAE

- So far, we haven't used the labels  $y$ . A **class-conditional VAE** provides the labels to both the encoder and the decoder.
- Since the latent code  $z$  no longer has to model the image category, it can focus on modeling the stylistic features.
- If we're lucky, this lets us **disentangle** style and content. (Note: disentanglement is still a dark art.)
- See Kingma et al., "Semi-supervised learning with deep generative models."



# Class-Conditional VAE

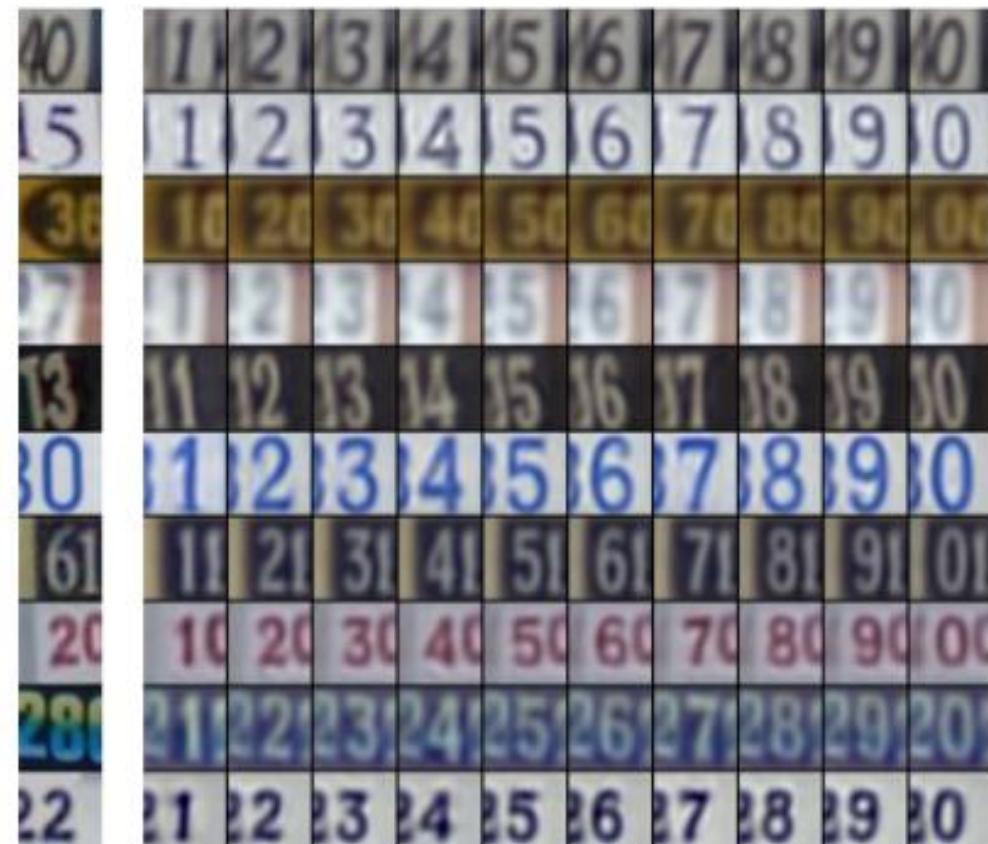
- By varying two **latent dimensions** (i.e. dimensions of  $z$ ) while holding  $y$  fixed, we can visualize the **latent space**.



# Class-Conditional VAE

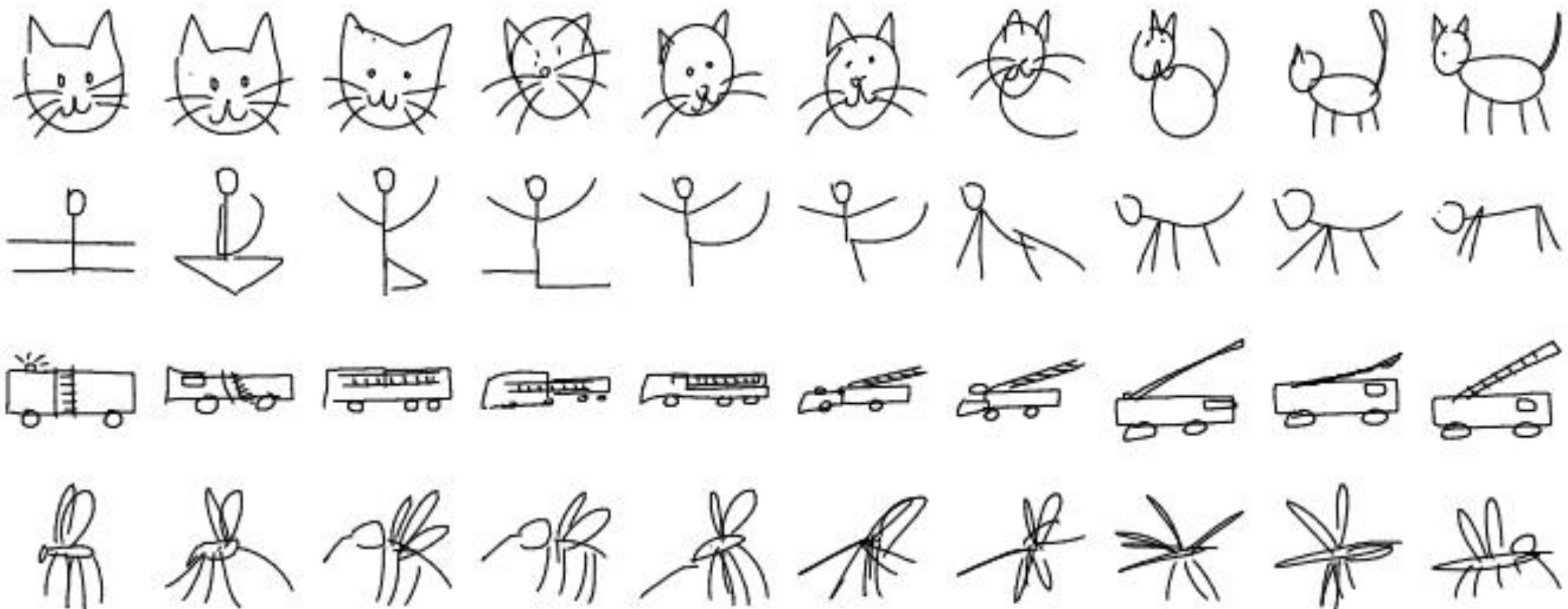
- By varying the label  $y$  while holding  $z$  fixed, we can solve image analogies.

4 0 1 2 3 4 5 6 7 8 9  
9 0 1 2 3 4 5 6 7 8 9  
5 0 1 2 3 4 5 6 7 8 9  
4 0 1 2 3 4 5 6 7 8 9  
2 0 1 2 3 4 5 6 7 8 9  
7 0 1 2 3 4 5 6 7 8 9  
5 0 1 2 3 4 5 6 7 8 9  
1 0 1 2 3 4 5 6 7 8 9  
7 0 1 2 3 4 5 6 7 8 9  
1 0 1 2 3 4 5 6 7 8 9



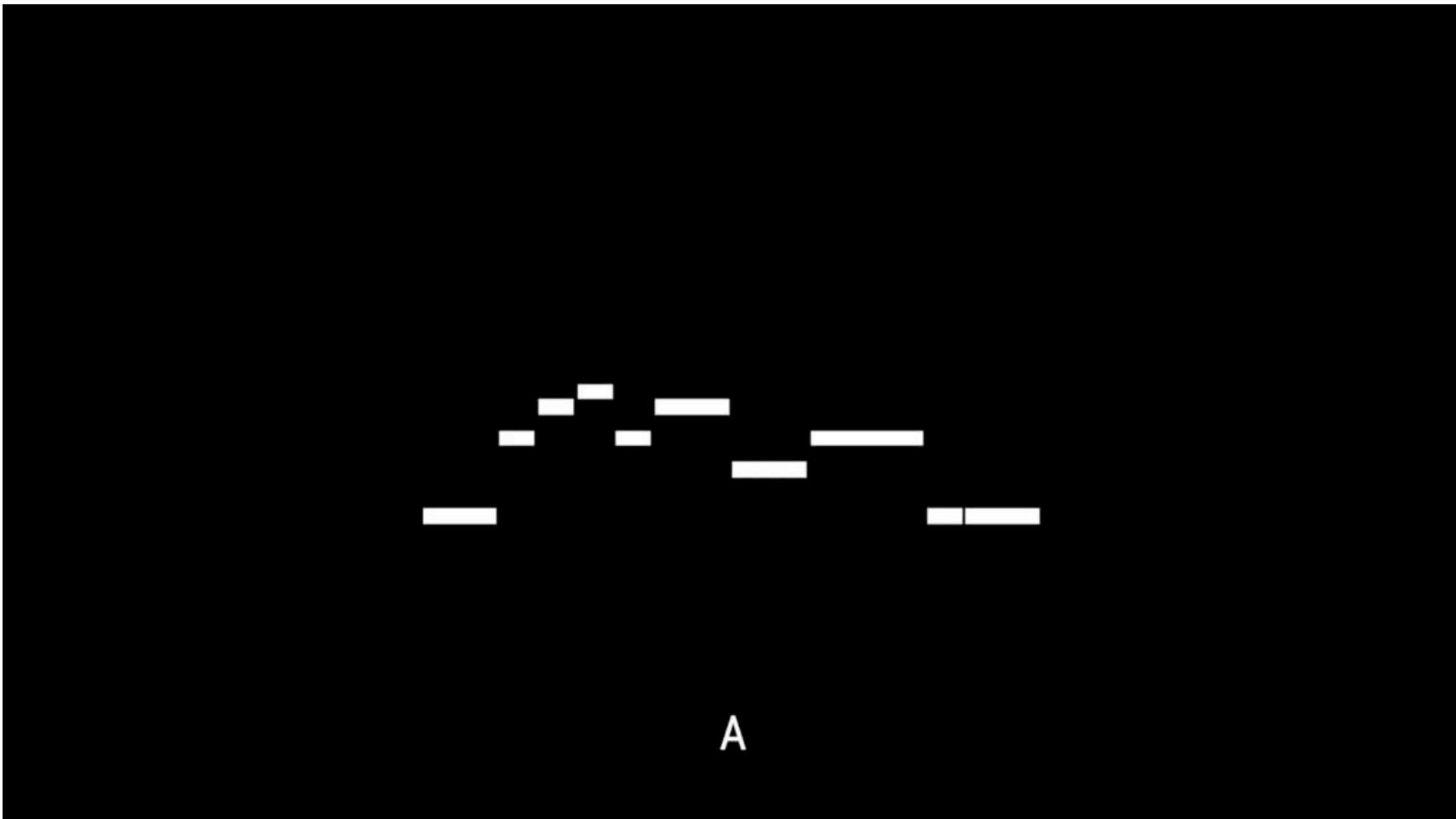
# Latent Space Interpolations

- You can often get interesting results by interpolating between two vectors in the latent space:



# Latent Space Interpolations

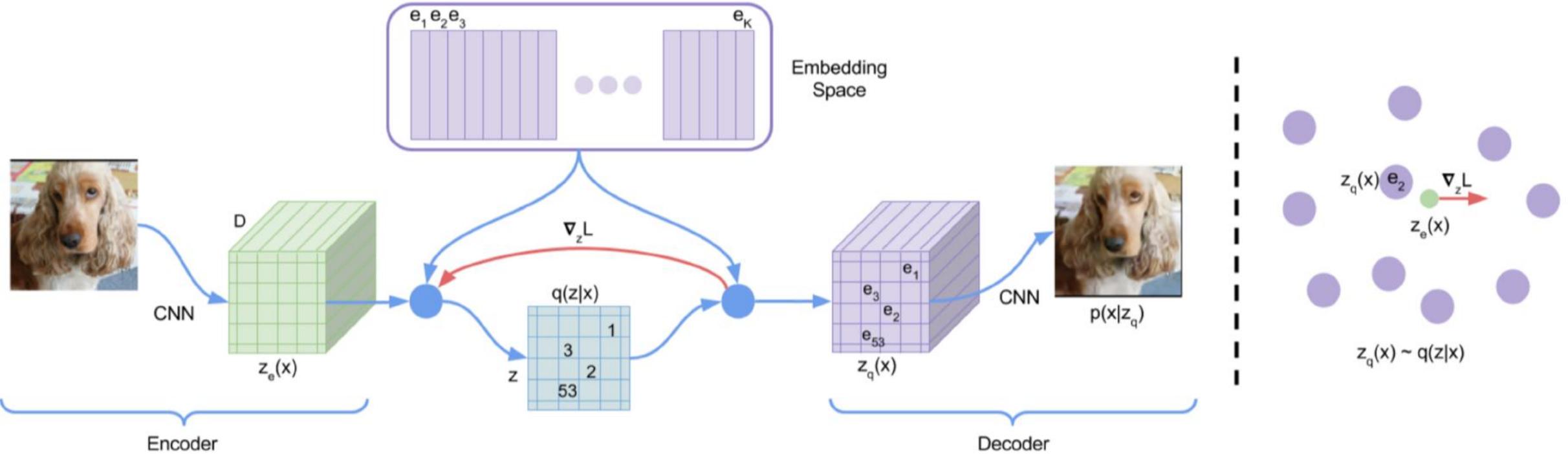
- Latent space interpolation of music:



# Lecture overview

- Motivation
- Training Latent Variable Models (including VAE and IWAE)
- Variations
  - SOTA: VQ-VAE, VQ-VAE 2.0, Nouveau VAE
  - AR + VAE: Variational Lossy AutoEncoder, PixelVAE
  - Disentanglement: Beta VAE
- Related ideas

# VQ-VAE



$$L = \log p(x|z_q(x)) + \|\text{sg}[z_e(x)] - e\|_2^2 + \beta \|z_e(x) - \text{sg}[e]\|_2^2$$

# VQ-VAE – Experiments



Figure 2: Left: ImageNet 128x128x3 images, right: reconstructions from a VQ-VAE with a 32x32x1 latent space, with K=512.

# VQ-VAE – Experiments

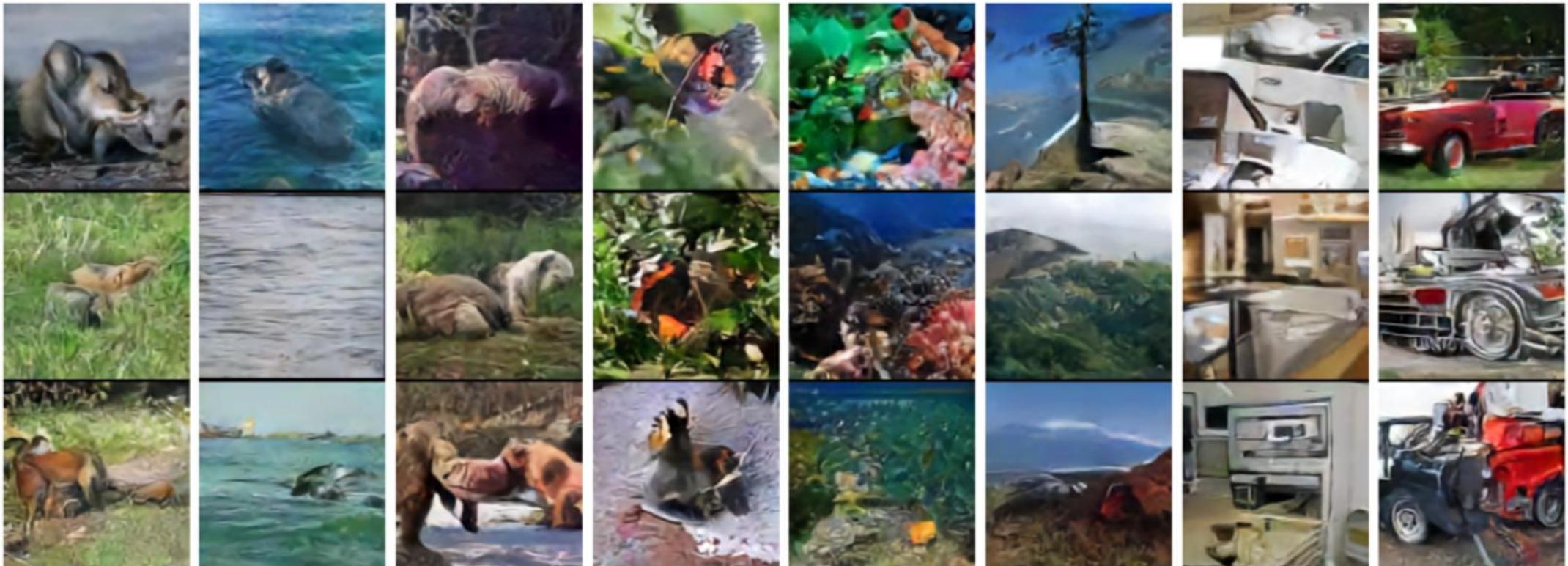
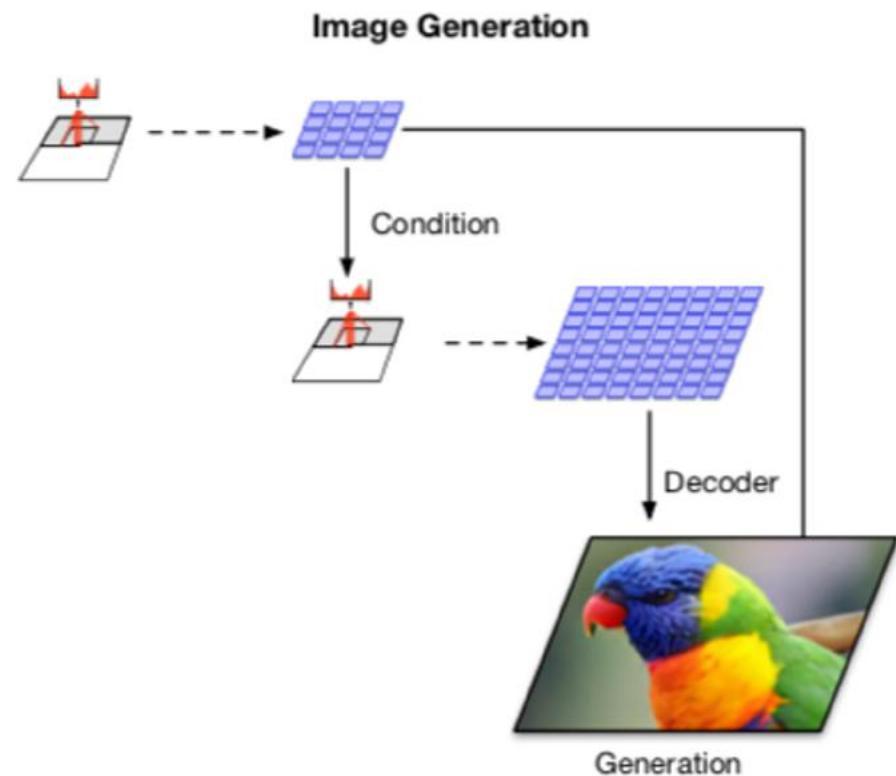
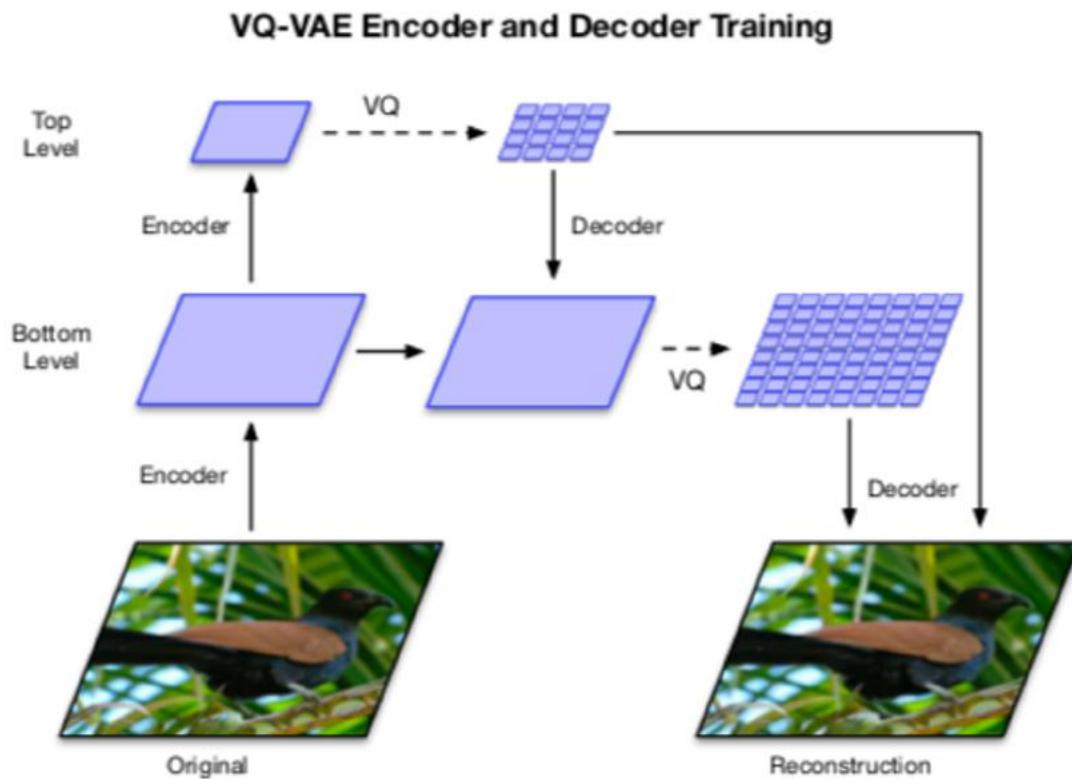
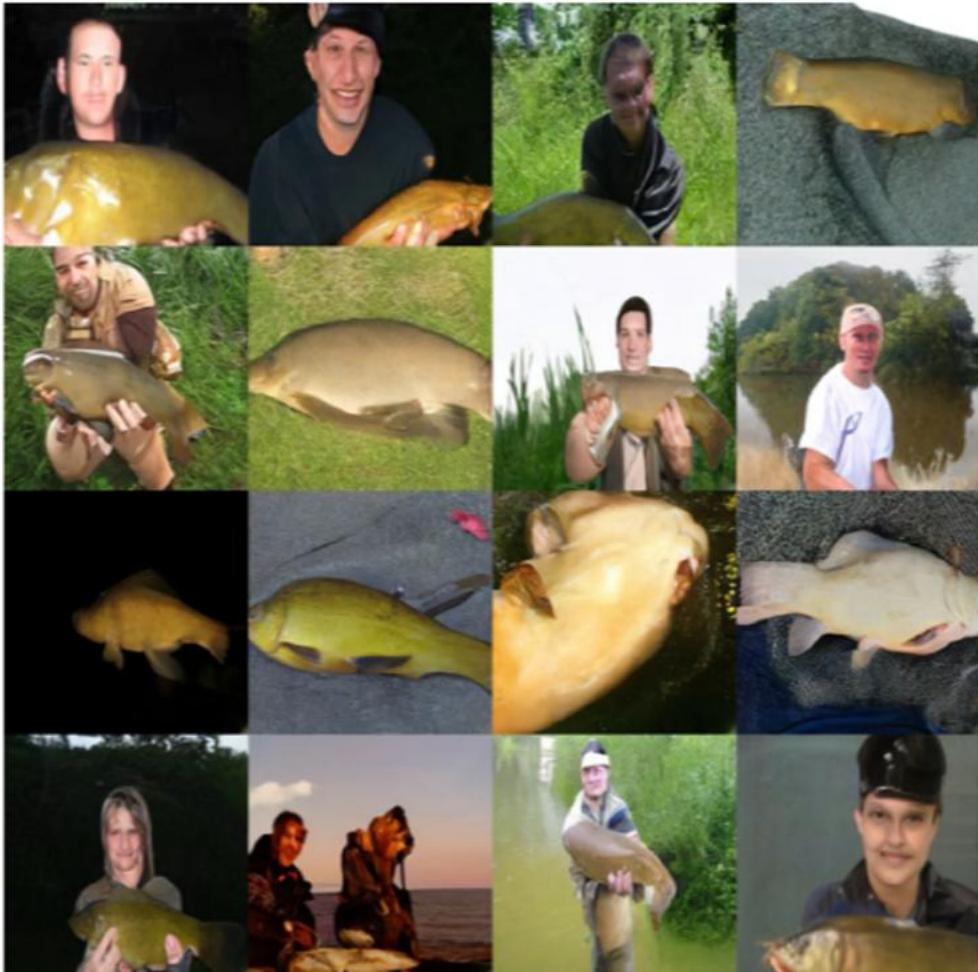


Figure 3: Samples (128x128) from a VQ-VAE with a PixelCNN prior trained on ImageNet images. From left to right: kit fox, gray whale, brown bear, admiral (butterfly), coral reef, alp, microwave, pickup.

# VQ-VAE 2.0



# VQ-VAE 2.0 – Experiments

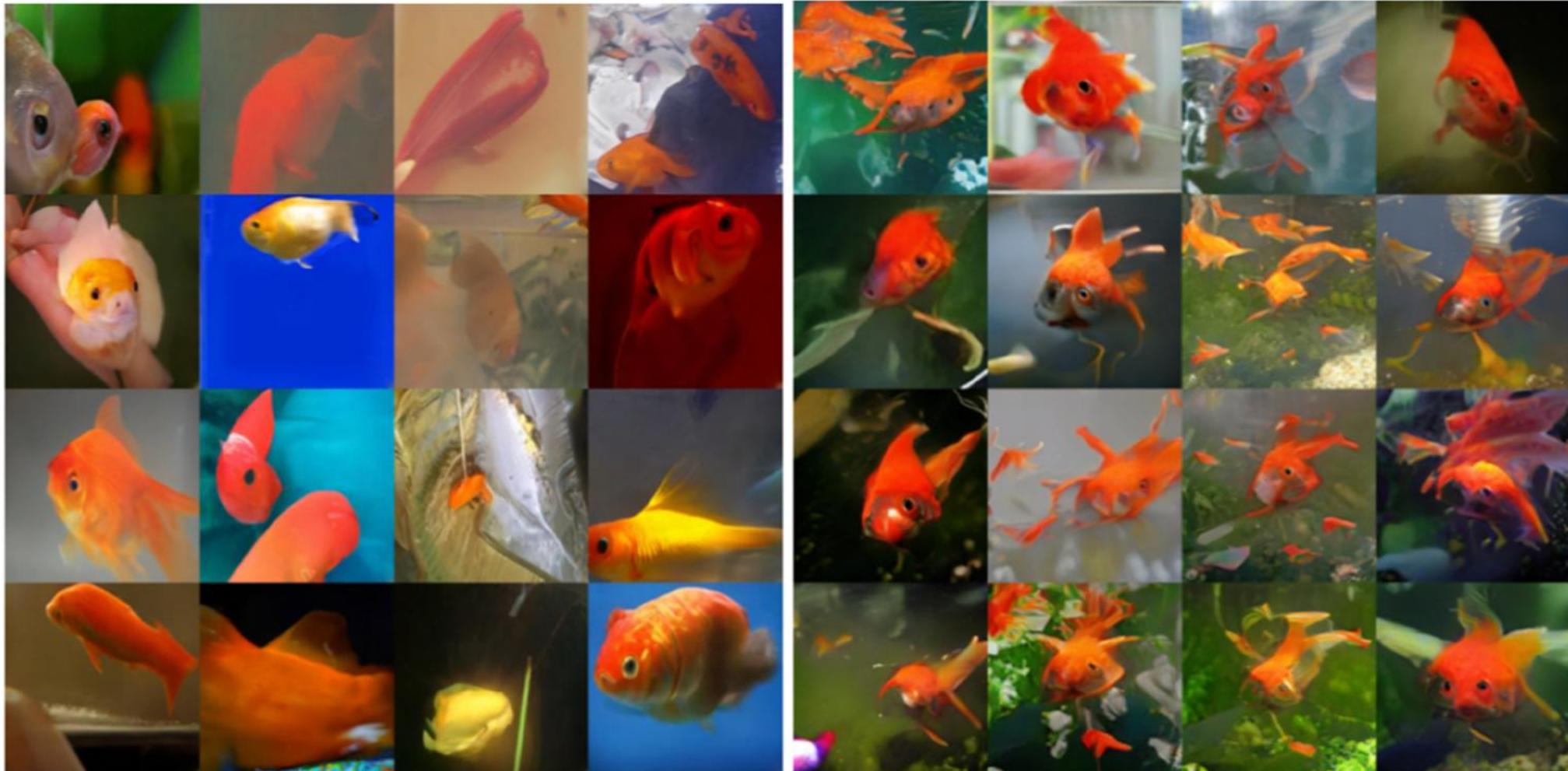


VQ-VAE 2.0



BigGAN Deep

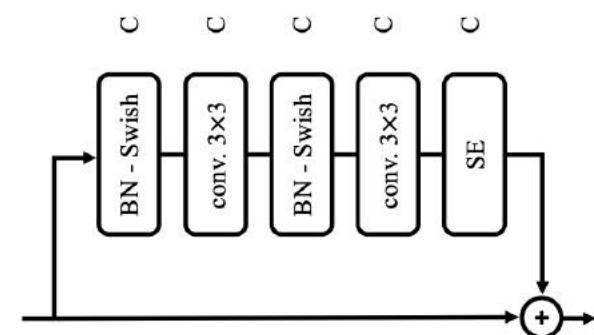
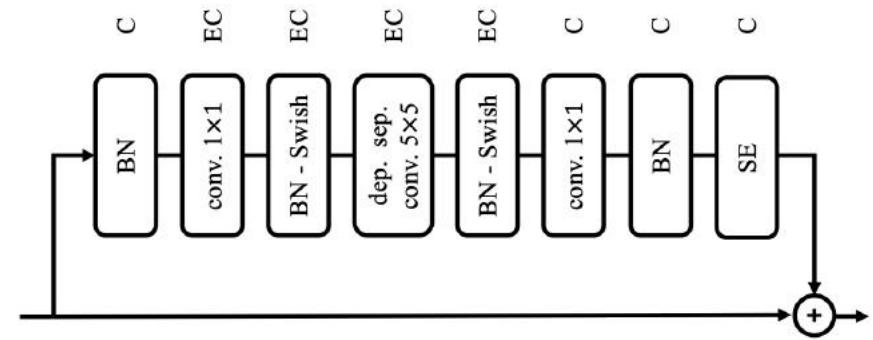
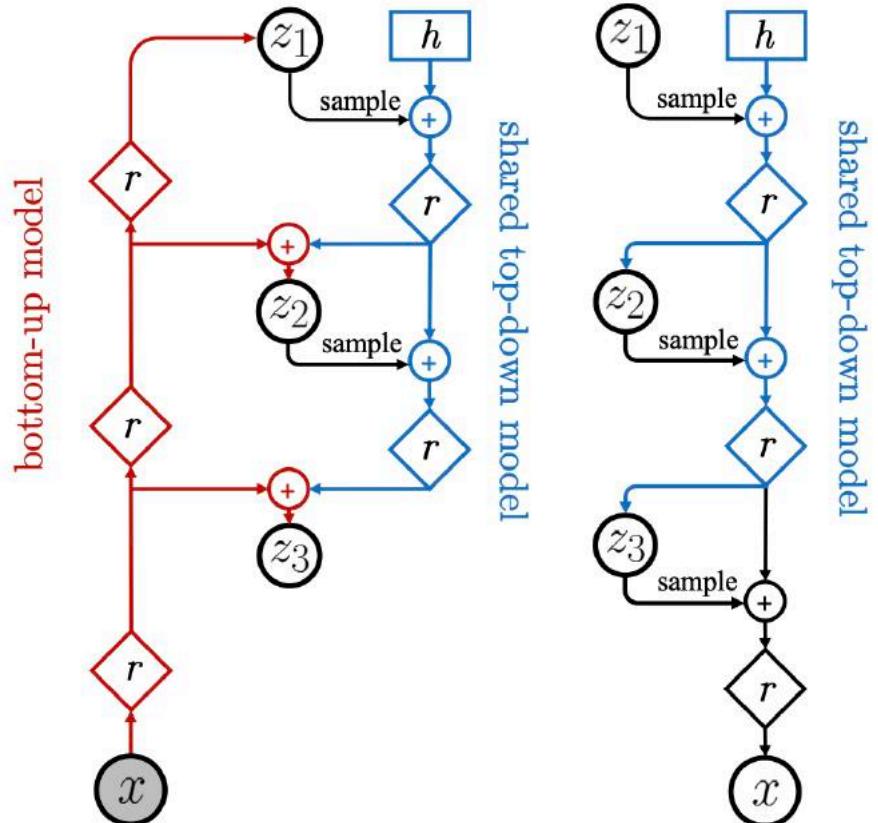
# VQ-VAE 2.0 – Experiments



VQ-VAE 2.0

BigGAN Deep

# NVAE



$$\mathcal{L}_{\text{VAE}}(\mathbf{x}) := \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} [\log p(\mathbf{x}|\mathbf{z})] - \text{KL}(q(\mathbf{z}_1|\mathbf{x})||p(\mathbf{z}_1)) - \sum_{l=2}^L \mathbb{E}_{q(\mathbf{z}_{<l}|\mathbf{x})} [\text{KL}(q(\mathbf{z}_l|\mathbf{x}, \mathbf{z}_{<l})||p(\mathbf{z}_l|\mathbf{z}_{<l}))]$$

$$q(\mathbf{z}_{<l}|\mathbf{x}) := \prod_{i=1}^{l-1} q(\mathbf{z}_i|\mathbf{x}, \mathbf{z}_{<i})$$

# NVAE – Experiments



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- Related ideas

# Decoder distribution

- So far all models use simple distribution for  $p(x|z)$
- Due to lack of expressivity itself, all entropy is pushed to  $z$  and  $z$  needs to convey a lot of information

# Powerful decoder

- What's the maximum VLB?

$$\begin{aligned}\mathbb{E}_{x \sim p_{\text{data}}(x)} [VLB] &\leq \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log p_{\theta}(x)] \\ &\leq \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log p_{\text{data}}(x)]\end{aligned}$$

- What if  $p(x|z) = p_{\text{data}}(x)$ ?

$$\begin{aligned}\mathbb{E}_{x \sim p_{\text{data}}(x)} [VLB] &= \mathbb{E}_{x \sim p_{\text{data}}(x), z \sim q(z|x)} [\log p(x|z) + \log p(z) - \log q(z|x)] \\ &= \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log p_{\text{data}}(x) + \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log p(z) - \log q(z|x)]]\end{aligned}$$

- $q(z|x)$  would be set to  $p(z) \rightarrow z$  has no information

# Powerful decoder

- Having information in  $z$  incurs VLB penalty of  $KL(q||p)$  which is usually non-zero
- “Ignoring latent code” problems well documented in literature
  - (Fabius & van Amersfoort, 2014; Chung et al., 2015; Bowman et al., 2015; Serban et al., 2016; Fraccaro et al., 2016; Xu & Sun, 2016)
  - Many proposed solutions

# Weakening models

- Adding dropout in autoregressive conditioning (Bowman et al., 2015)
- PixelCNN with limited receptive field (Chen et al., 2016)
- Constant bit rate.  $D_{KL}(q_\phi(z|x) || p_\theta(z)) = c$  (Guu et al., 2017),  
(Xu & Durrett, 2018), (Davidson et al., 2018)
- Minimum bit rate  $D_{KL}(q_\phi(z|x) || p_\theta(z)) \geq \delta$  (Razavi et al., 2019)

# Changing training dynamics

- $D_{KL}(q_\phi(z|x) || p_\theta(z))$  warmup (Bowman et al., 2015); (Yang et al., 2017); (Kim et al., 2018); (Gulrajani et al., 2016)
- “Free-bits” (Kingma et al., 2016); (Chen et al., 2016)
- More training updates to  $q(z|x)$  (He et al., 2019)

# Lecture overview

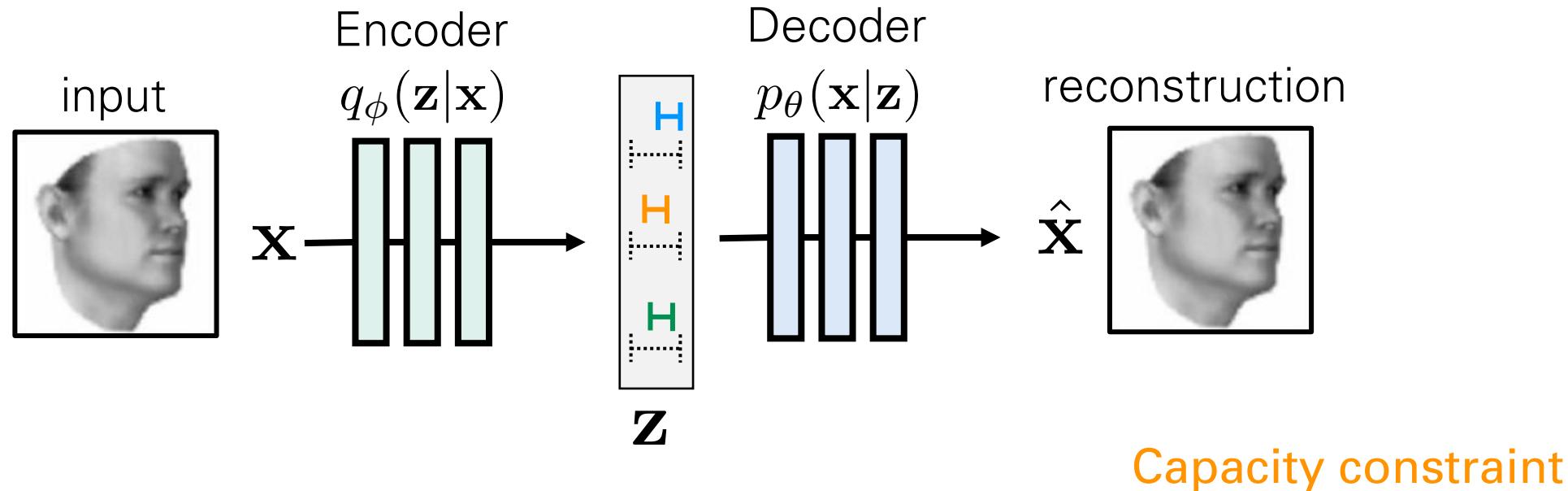
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- Related ideas

# $\beta$ -VAE

The Beta-VAE objective is identical to the VAE objective when beta = 1

$$\mathcal{L} = \mathbb{E}_{q_\phi(z|x)} [\log p_\theta(x|z)] - \beta D_{KL}(q_\phi(z|x) || p(z))$$

# Disentangled Representations with $\beta$ -VAE



$$\mathcal{L}_{\beta-\text{VAE}}(\theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [\log p_\theta (\mathbf{x}|\mathbf{z})] - \beta KL [q_\phi (\mathbf{z}|\mathbf{x}) \| p (\mathbf{z})]$$

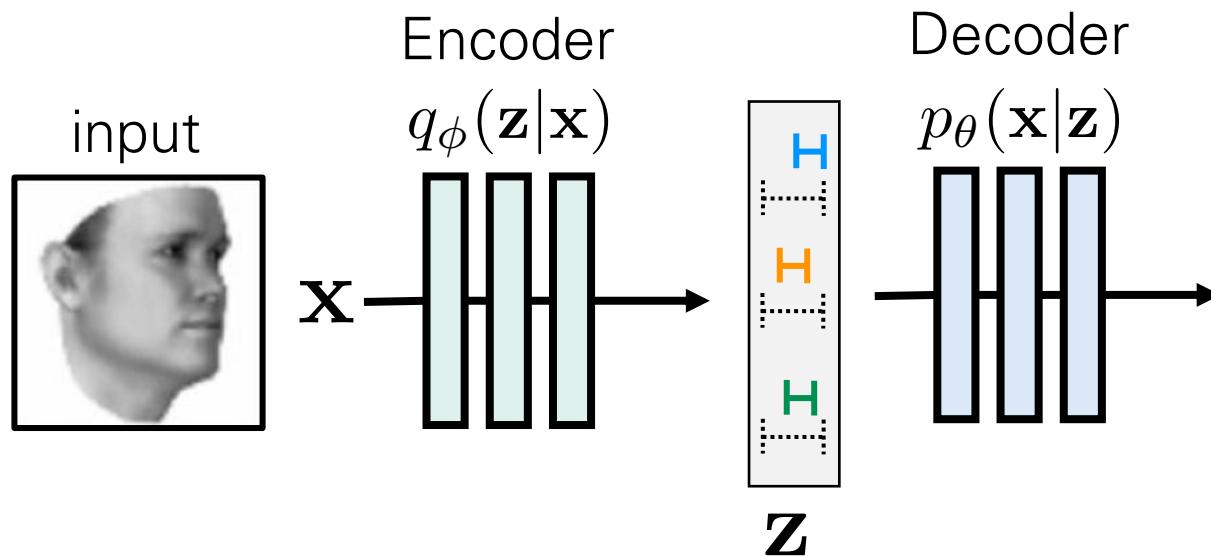
Reconstruction cost

(Higgins et al., 2017)

# Disentangled Representations with $\beta$ -VAE

- What do individual features learn?

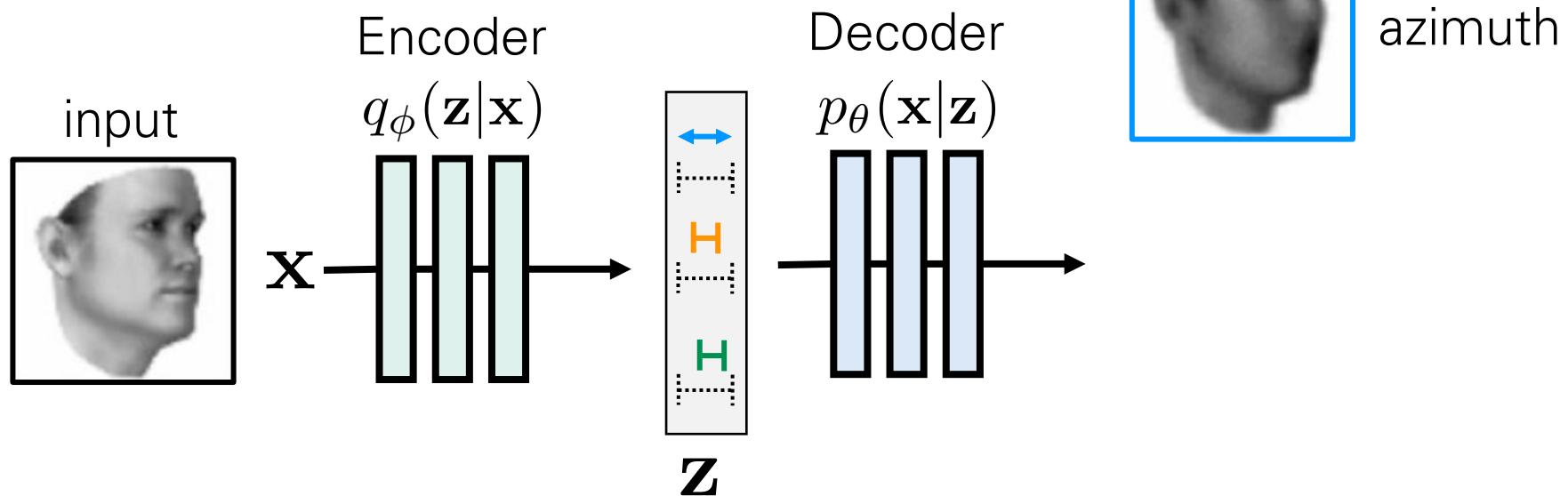
Latent traversal



# Disentangled Representations with $\beta$ -VAE

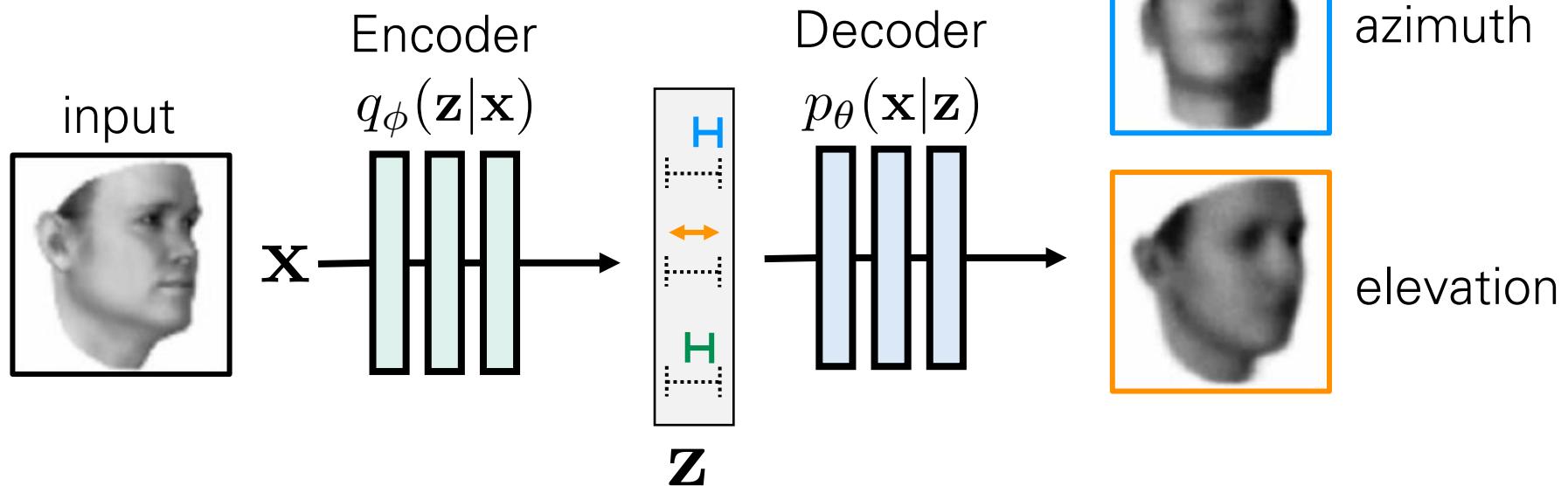
- What do individual features learn?

Latent traversal



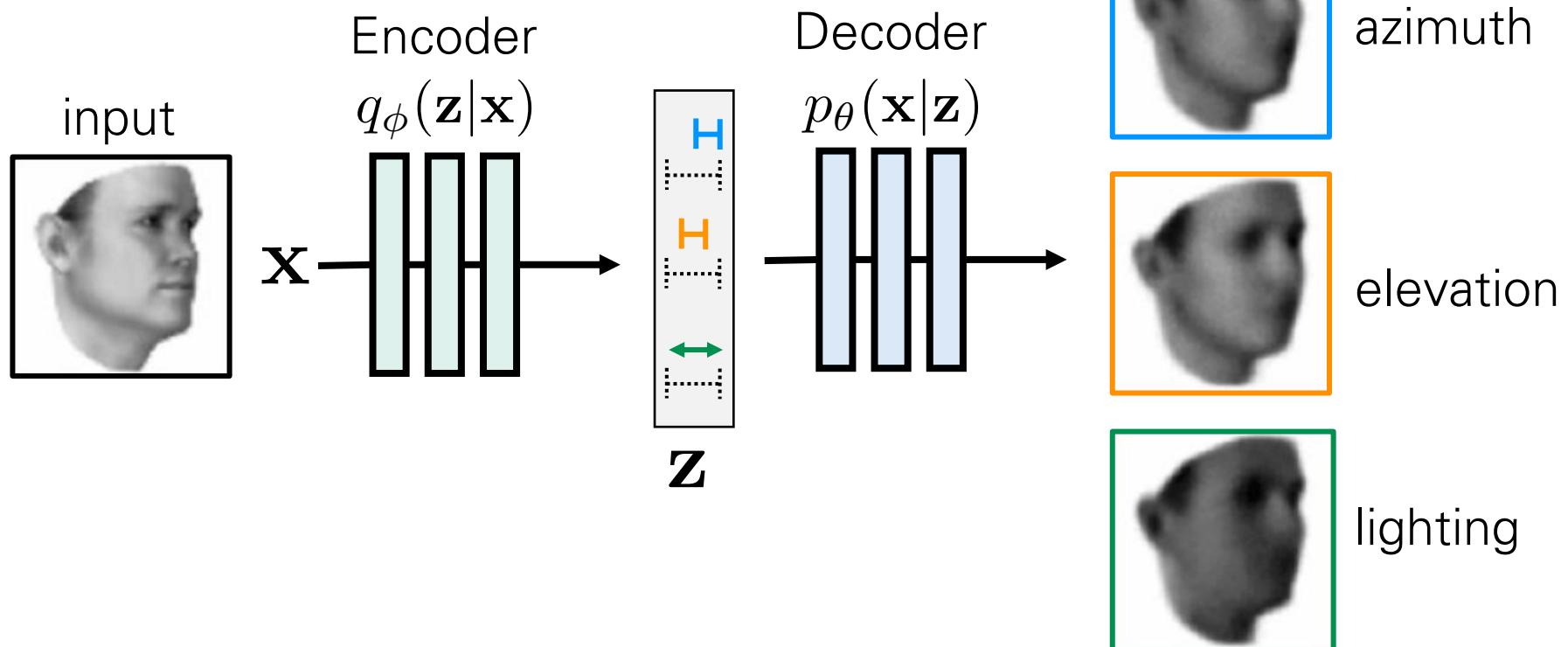
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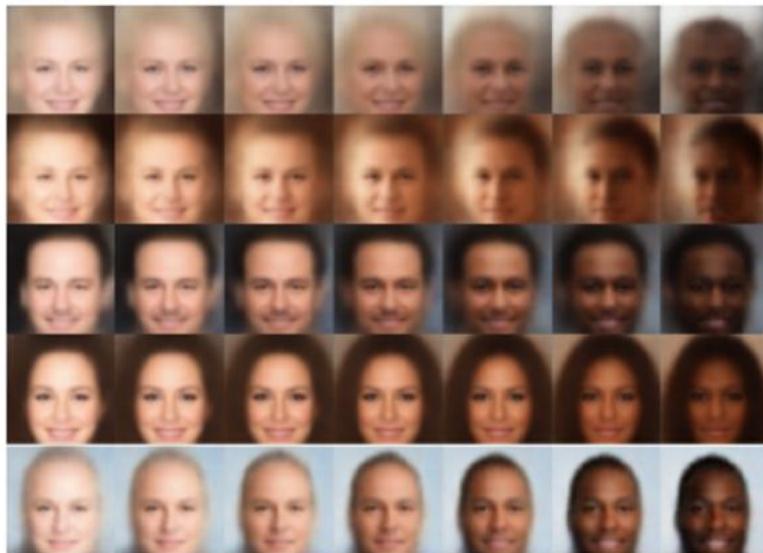
# Disentangled Representations with $\beta$ -VAE

- What do individual features learn?

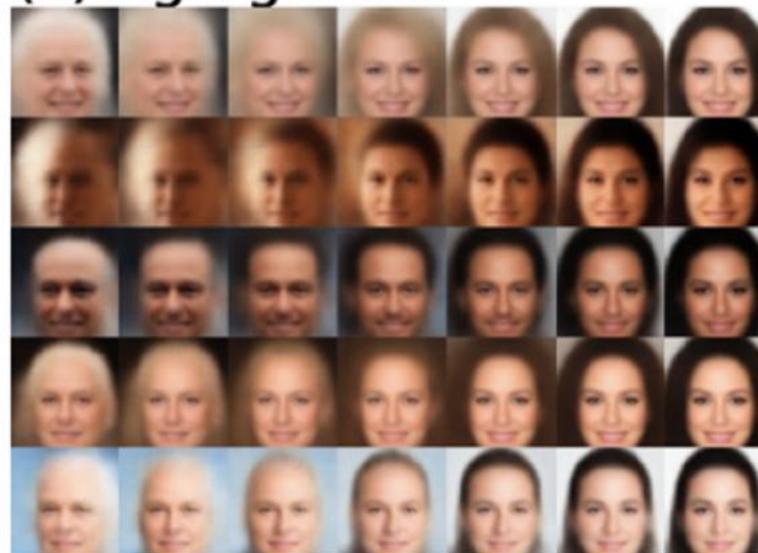


# $\beta$ -VAE – Experiments

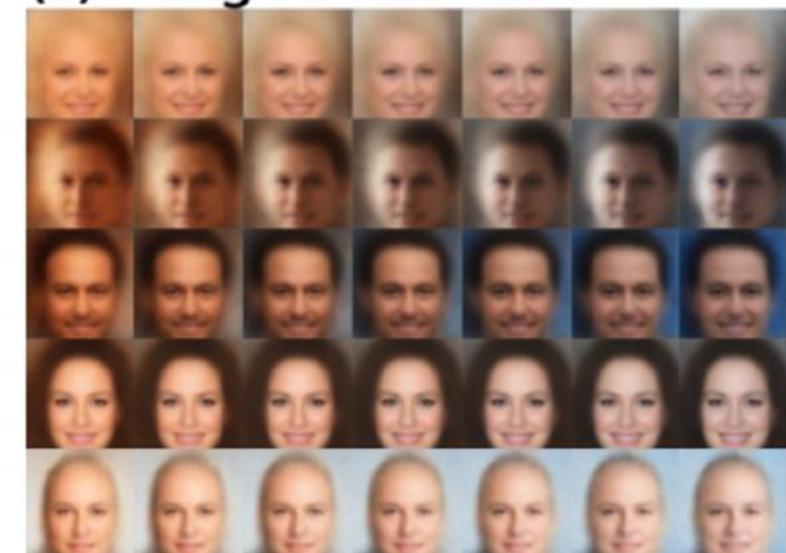
(a) Skin colour



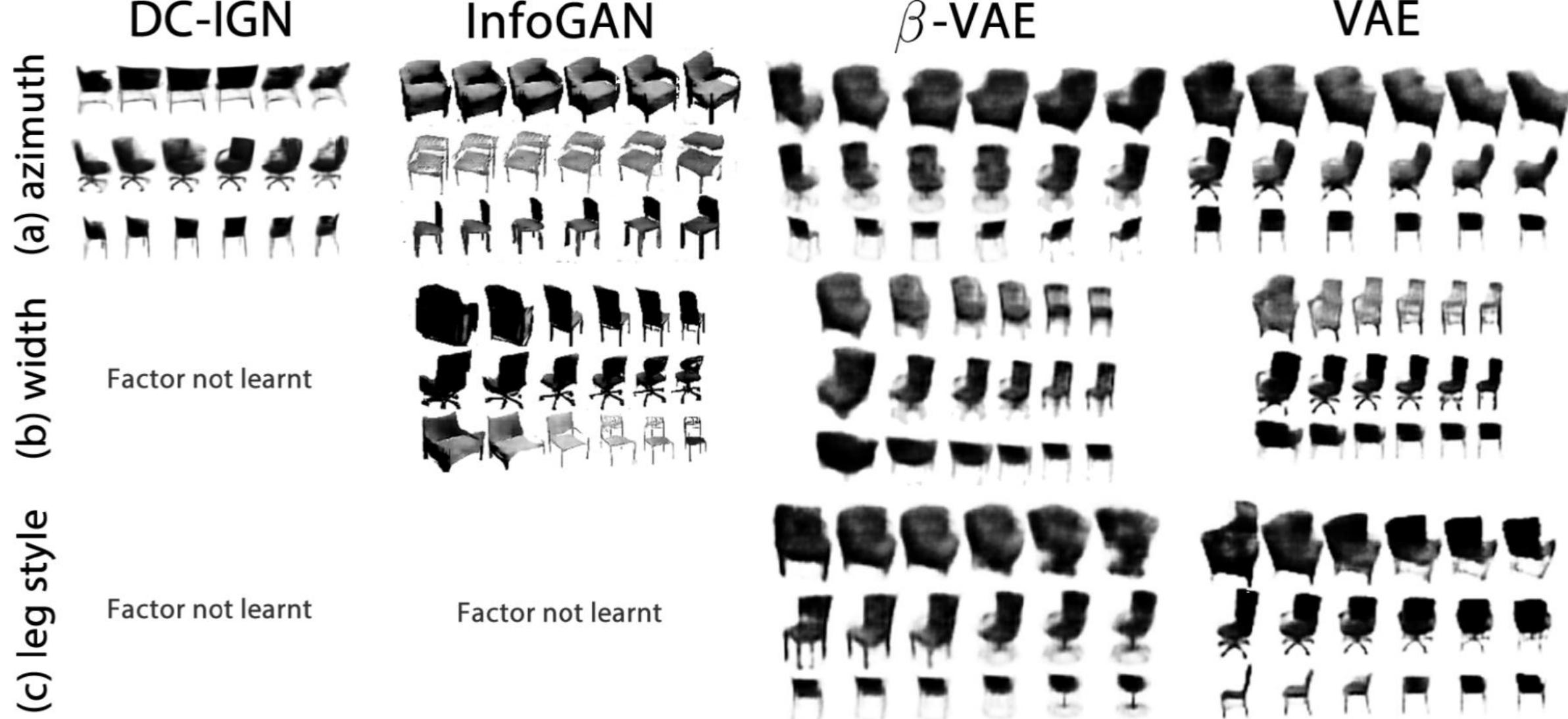
(b) Age/gender



(c) Image saturation



# $\beta$ -VAE – Experiments



# Lecture overview

- Motivation
- Training Latent Variable Models (including VAE and IWAE)
- Variations
- Related ideas
  - Variational Dequantization (flow++)

# Recap: Uniform Dequantization

- **Uniform Dequantization.** Add noise to data.

$$\mathbf{x} \in \{0, 1, 2, \dots, 255\}$$

- We draw noise  $\mathbf{u}$  uniformly from  $[0, 1)^D$

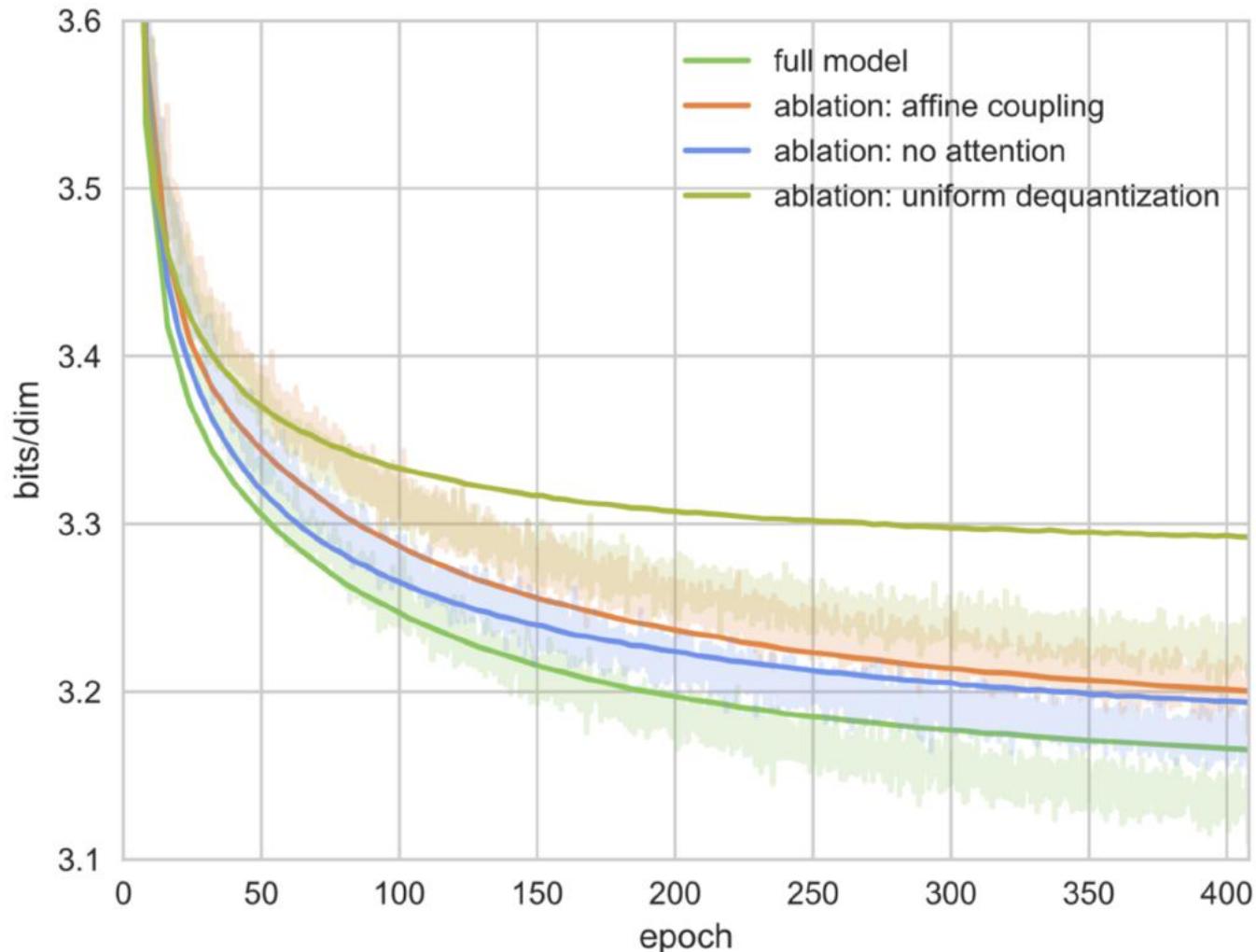
$$\begin{aligned}\mathbb{E}_{\mathbf{y} \sim p_{\text{data}}} [\log p_{\text{model}}(\mathbf{y})] &= \sum_{\mathbf{x}} P_{\text{data}}(\mathbf{x}) \int_{[0,1)^D} \log p_{\text{model}}(\mathbf{x} + \mathbf{u}) d\mathbf{u} \\ &\leq \sum_{\mathbf{x}} P_{\text{data}}(\mathbf{x}) \log \int_{[0,1)^D} p_{\text{model}}(\mathbf{x} + \mathbf{u}) d\mathbf{u} \\ &= \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} [\log P_{\text{model}}(\mathbf{x})]\end{aligned}$$

# Variational Dequantization

- **Variational Dequantization.** Add a learnable noise  $q$  to data.

$$\begin{aligned}\mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} [\log P_{\text{model}}(\mathbf{x})] &= \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} \left[ \log \int_{[0,1)^D} q(\mathbf{u}|\mathbf{x}) \frac{p_{\text{model}}(\mathbf{x} + \mathbf{u})}{q(\mathbf{u}|\mathbf{x})} d\mathbf{u} \right] \\ &\geq \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} \left[ \int_{[0,1)^D} q(\mathbf{u}|\mathbf{x}) \log \frac{p_{\text{model}}(\mathbf{x} + \mathbf{u})}{q(\mathbf{u}|\mathbf{x})} d\mathbf{u} \right] \\ &= \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} \mathbb{E}_{\mathbf{u} \sim q(\cdot|\mathbf{x})} \left[ \log \frac{p_{\text{model}}(\mathbf{x} + \mathbf{u})}{q(\mathbf{u}|\mathbf{x})} \right]\end{aligned}$$

# Variational Dequantization on CIFAR



**Next lecture:**  
**Generative Adversarial**  
**Networks**