

COMP547

DEEP UNSUPERVISED LEARNING

Lecture #7 – Latent Variable Models



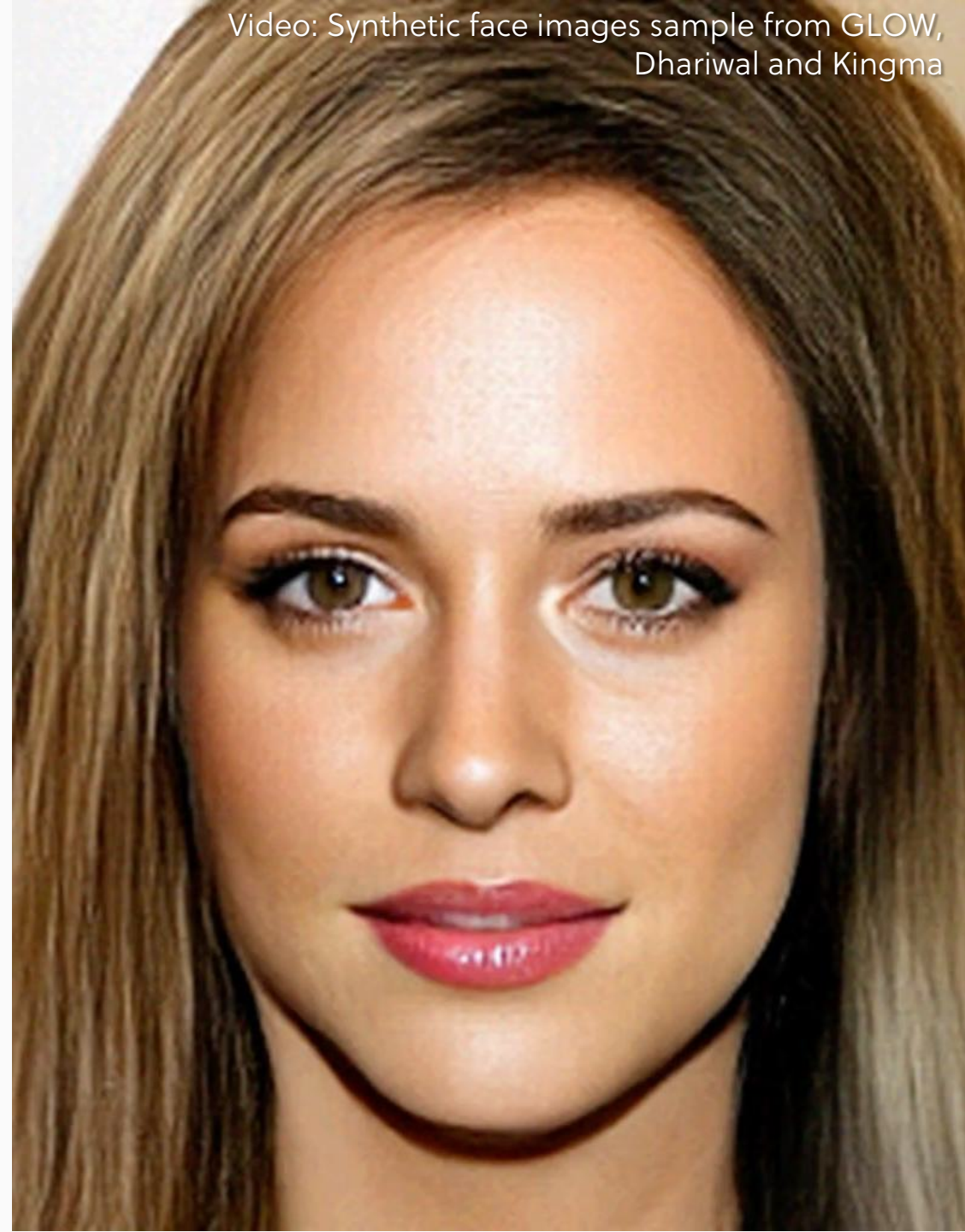
**KOÇ
UNIVERSITY**

Aykut Erdem // Koç University // Spring 2026

Previously on COMP547

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

Video: Synthetic face images sample from GLOW,
Dhariwal and Kingma



Lecture overview

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

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

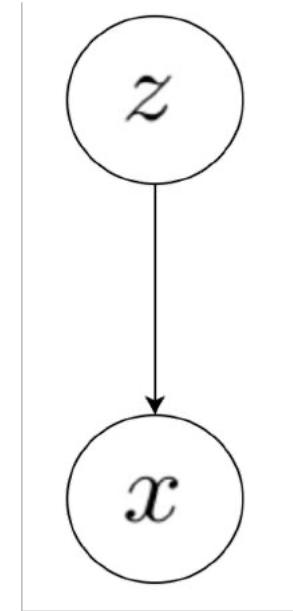
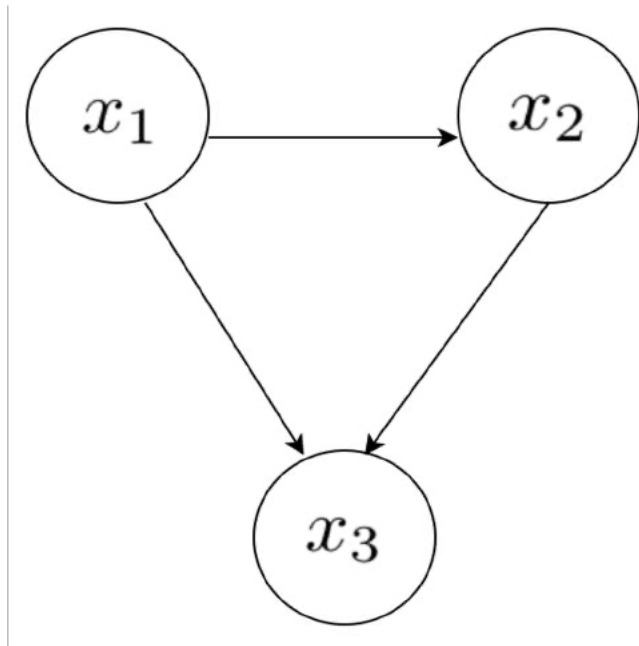
- Pieter Abbeel, Peter Chen, Jonathan Ho, Aravind Srinivas' Berkeley CS294-158 class
- David McAllester's TTIC 31230 class
- Aaron van den Oord's talk on "Neural Discrete Representation Learning"
- Jimmy Ba's UToronto CSC413/2516 class

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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

Obj1 @ (x,y)
= Corgi, red
& white

Obj2 @ (x,y)
= Corgi, red
& white,
floppy left
ear

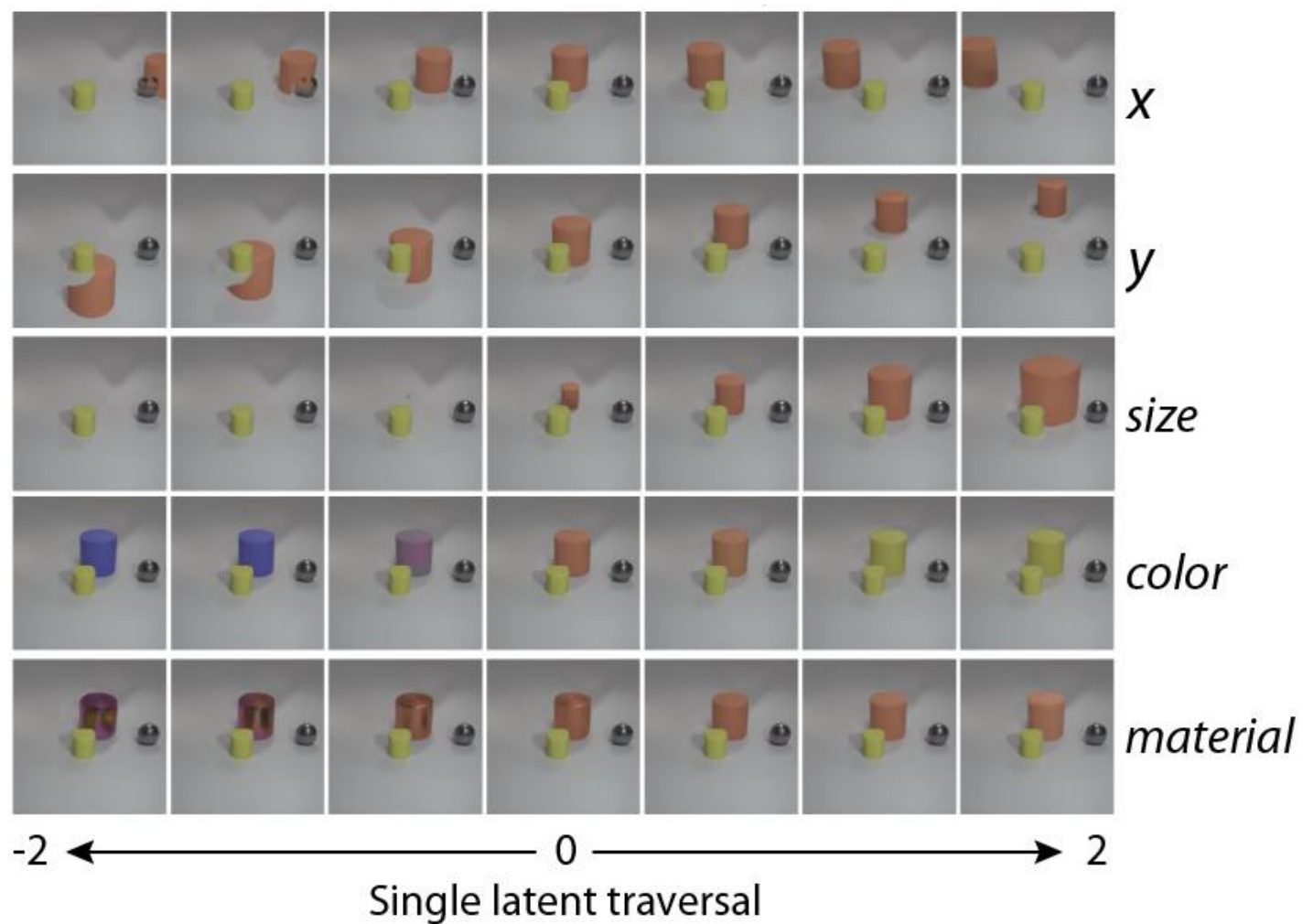


Background
= Wood
bench in a
park

Obj3 @ (x,y)
= Corgi, Tri-
color

Why Latent Variable Models?

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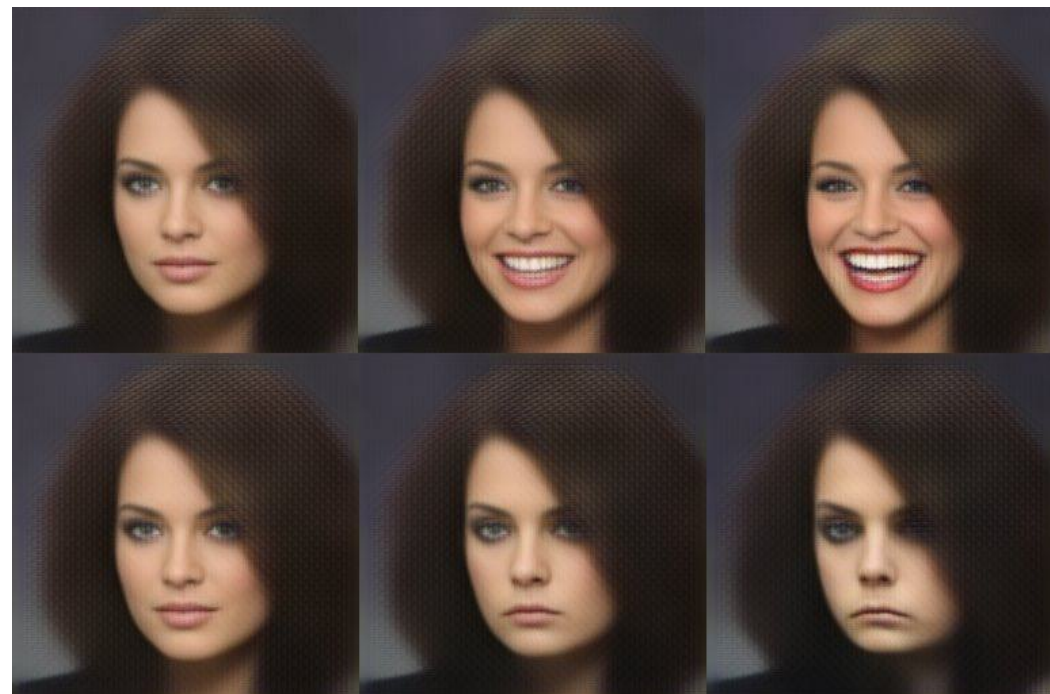


Why Latent Variable Models?

- 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

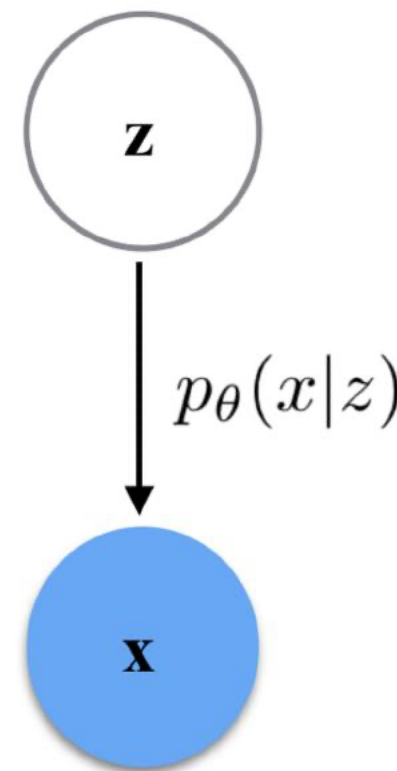


Modifying the latent code in the direction of a smile vector, producing a range of versions of the original, from smiling to sadness (White, 2016)

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

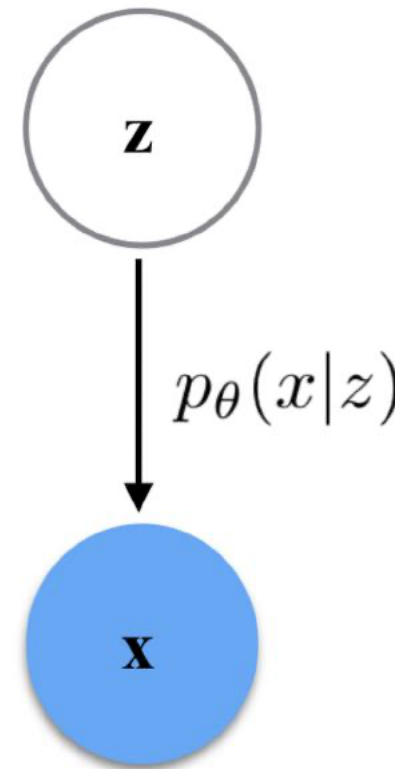
$$p_\theta(x) = \sum_z p_Z(z) p_\theta(x | z)$$

- Train

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

- Representation

$$x \rightarrow z$$



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 - Prior Sampling
 - Importance Sampling
 - Variational Lower Bound (VLB) / Evidence Lower Bound (ELBO)
 - Optimization
 - Likelihood Ratio Gradients vs. Reparameterization Trick Gradients
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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

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

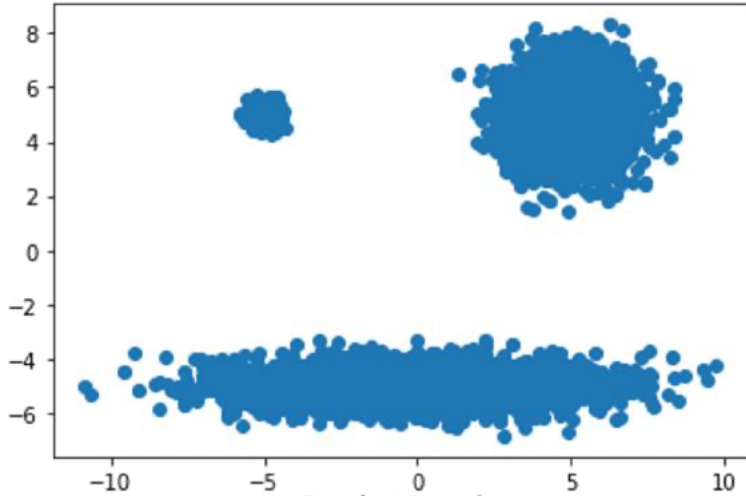
$$p_{\theta}(x | z = k) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_k|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x - \mu_k)^{\top} \Sigma_k^{-1} (x - \mu_k)\right)$$

Training objective:

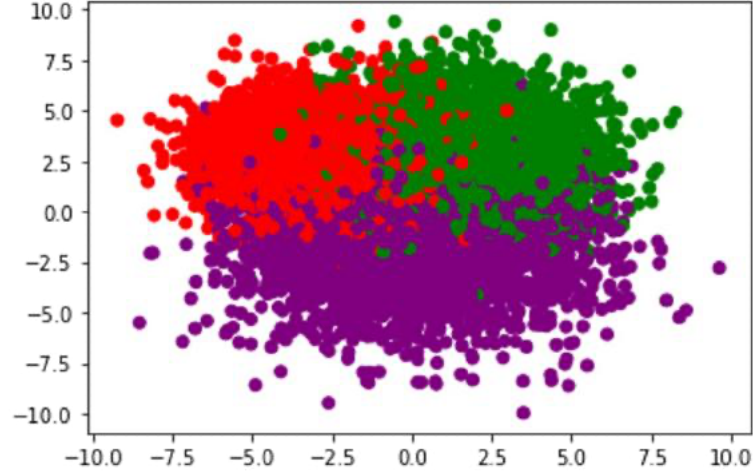
$$\begin{aligned} & \max_{\theta} \sum_i \log p_{\theta}(x^{(i)}) \\ &= \max_{\mu, \Sigma} \sum_i \log \left[\frac{1}{3} \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_A|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x^{(i)} - \mu_A)^{\top} \Sigma_A^{-1} (x^{(i)} - \mu_A)\right) \right. \\ & \quad + \frac{1}{3} \frac{1}{(2\pi)^{\frac{n}{2}}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

2-D mixture of Gaussians

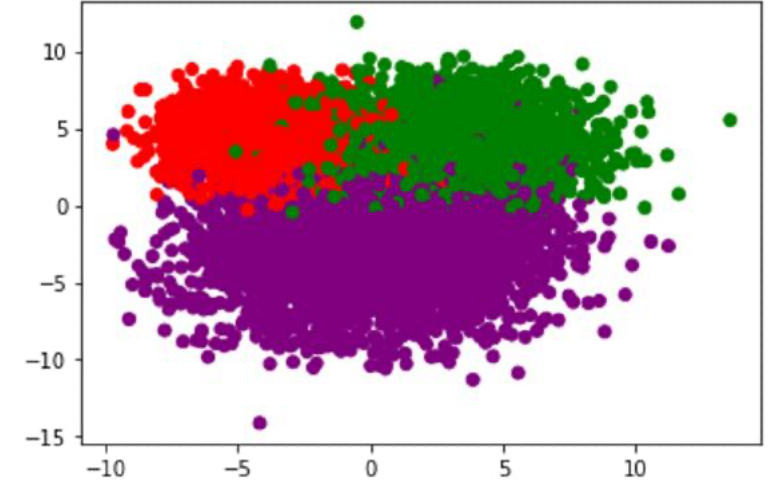
Train Data



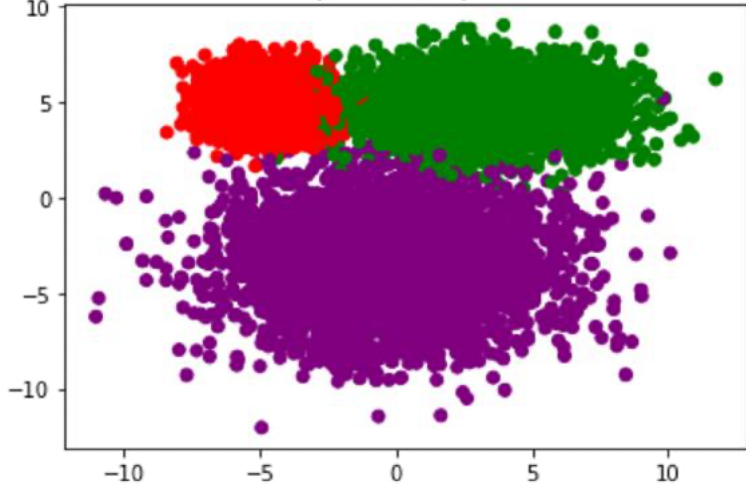
Epoch 0 Samples



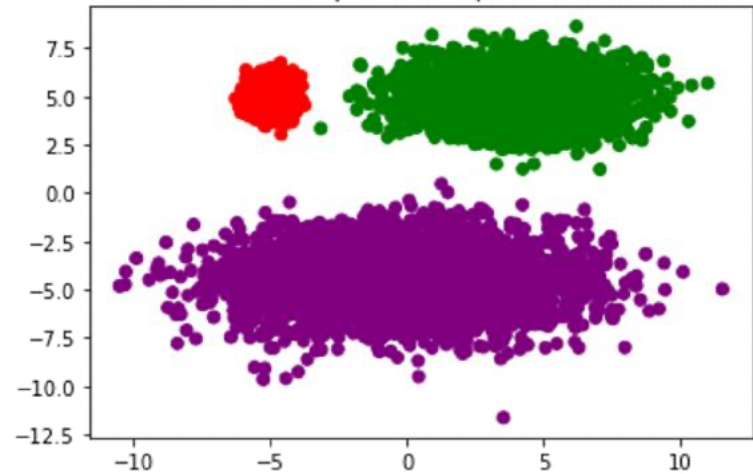
Epoch 2 Samples



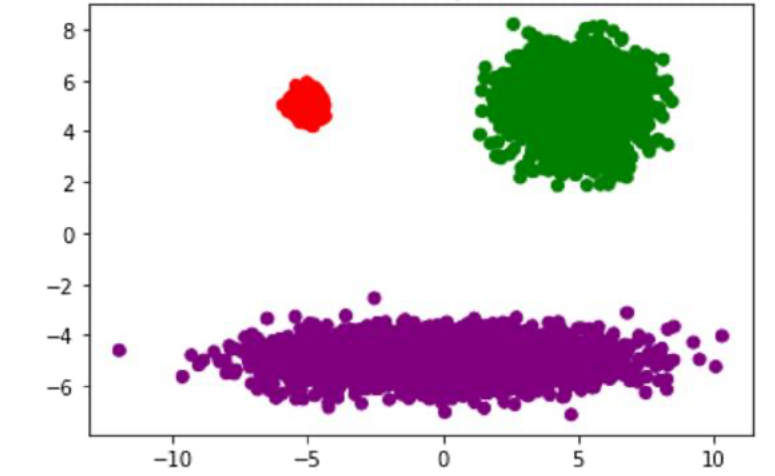
Epoch 4 Samples



Epoch 6 Samples



Final Samples



Prior Sampling

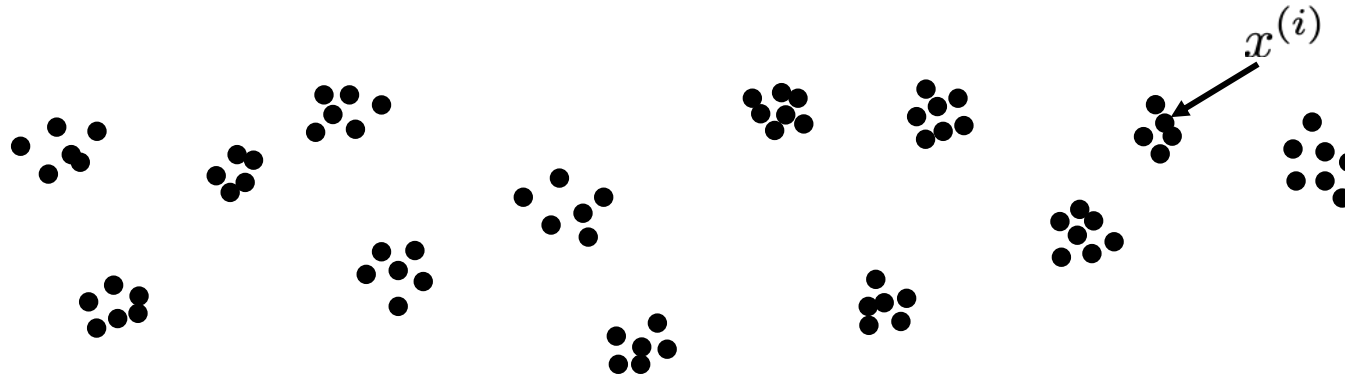
Main idea: if z can take on many values \rightarrow sample z

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

\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 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

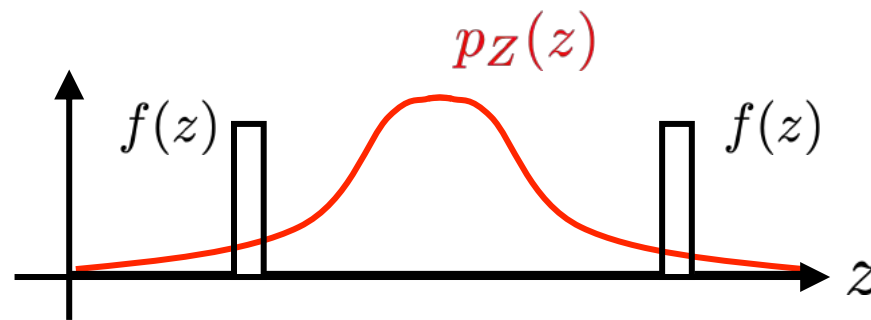
Problem setting:

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

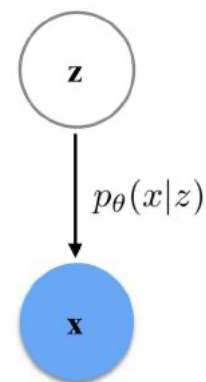
So, instead, we propose a parameterized distribution q we know we can work with easily (in this case, sample from easily), and try to find a parameter setting that makes it as good as possible.

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

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



→ 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:

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

Amortized formulation:

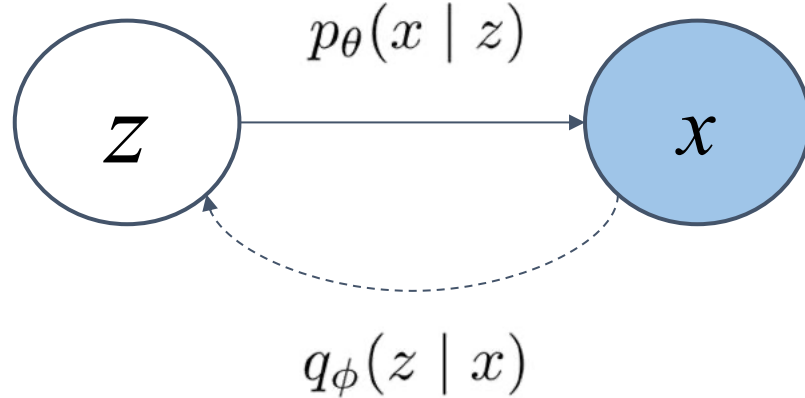
$$\min_{\phi} \sum_i \text{KL}(q_{\phi}(z \mid x^{(i)}) \parallel p_{\theta}(z \mid x^{(i)}))$$

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

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

→ 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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- Related ideas

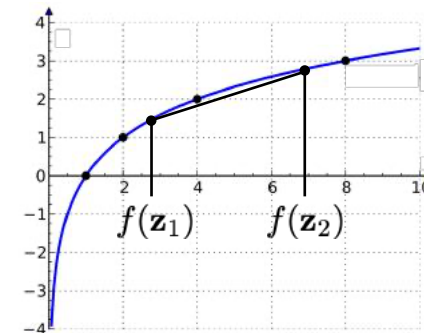
VLB: Derivation 1 (Jensen)

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

Jensen Inequality (for concave functions)

- log is a concave function)

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



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)

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

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

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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Likelihood Ratio Gradient

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

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

~~$$\mathbb{E}_{z \sim q_{\phi}(z)} [f(z)] \approx \frac{1}{k} \sum_{i=1}^k f(z^{(i)})$$~~
~~cannot compute $\nabla_{\phi} \left(\frac{1}{k} \sum_{i=1}^k f(z^{(i)}) \right)$~~

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

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

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

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

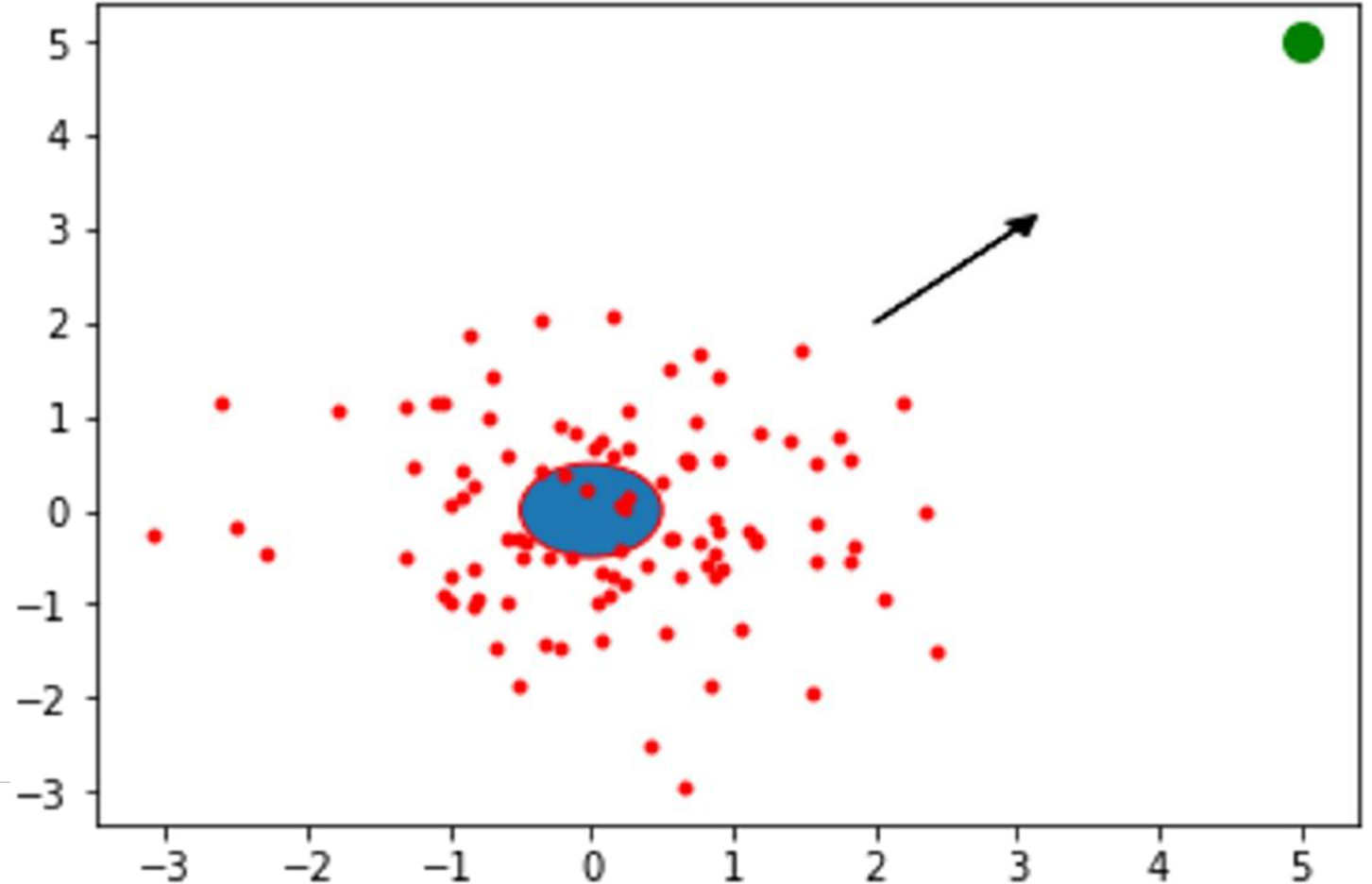
$$= \mathbb{E}_{z \sim q_{\phi}(z)} [\nabla_{\phi} \log q_{\phi}(z) f(z)] \approx \frac{1}{k} \sum_{i=1}^k \nabla_{\phi} \log q_{\phi}(z) f(z)$$

We need to turn this into an expectation

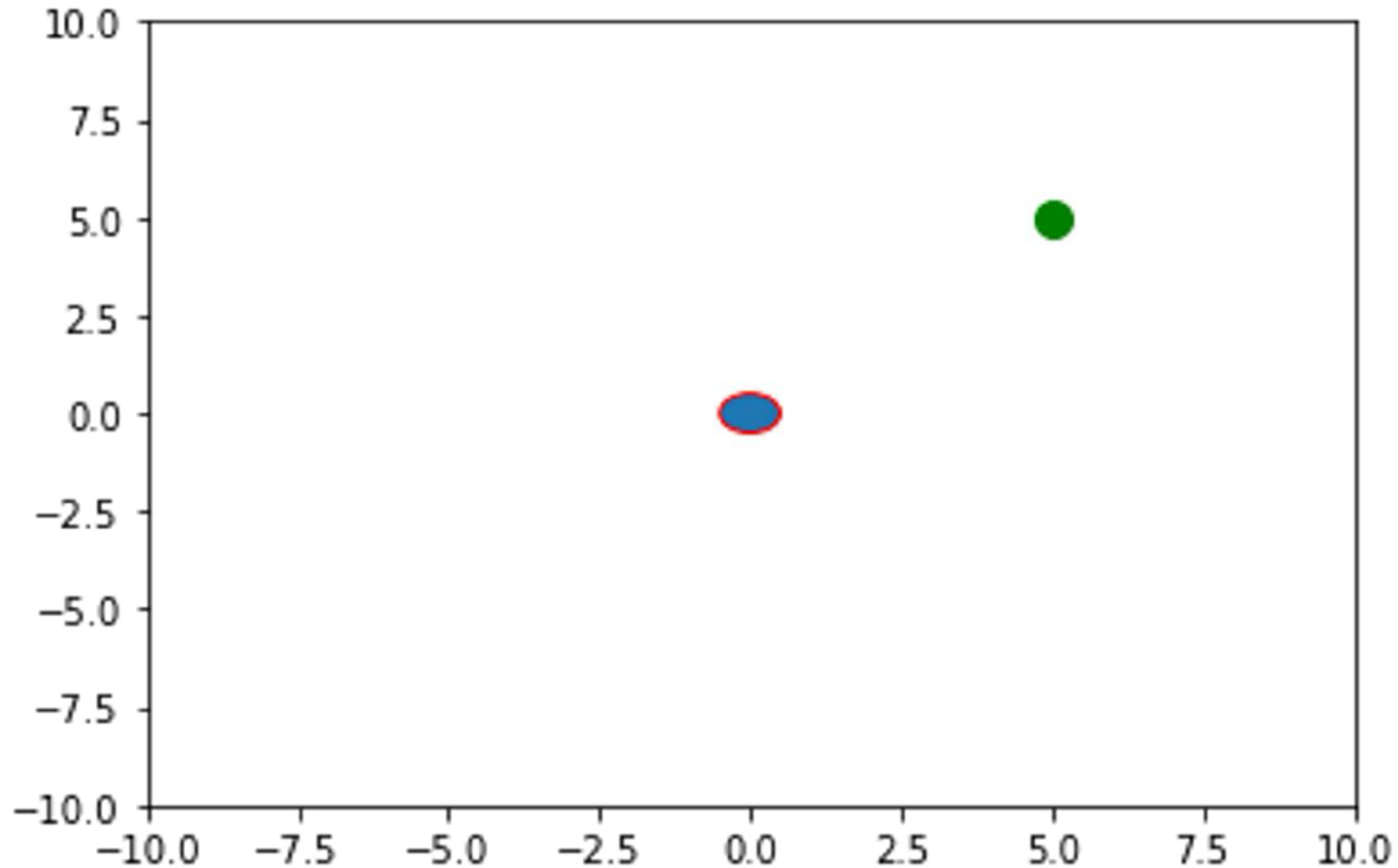
Likelihood Ratio Gradient – Toy Problem

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

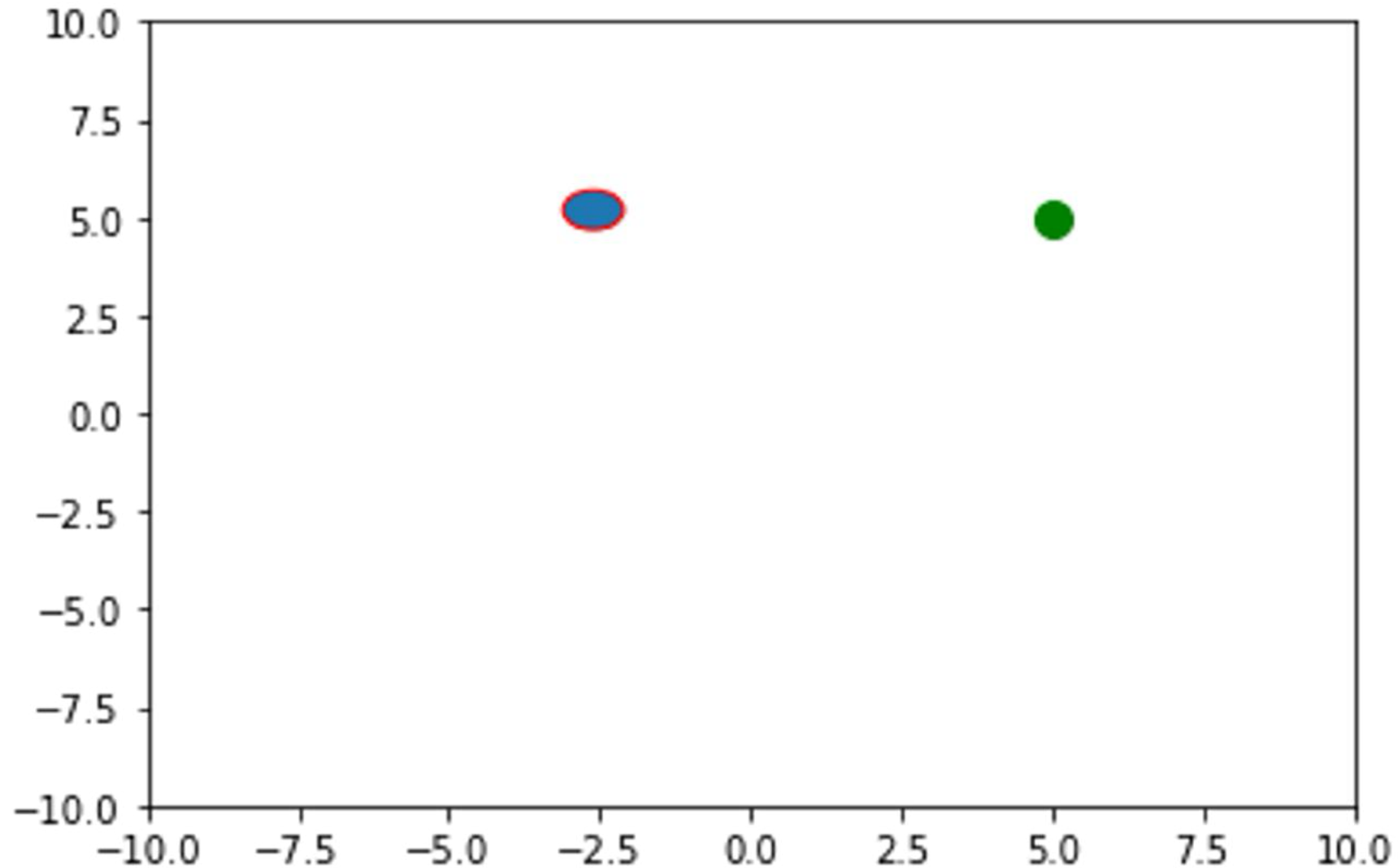
$$\mathcal{L} = \mathbb{E}_{x \sim N(\mu, I)} \left\| x - \begin{bmatrix} 5 \\ 5 \end{bmatrix} \right\|_2^2$$



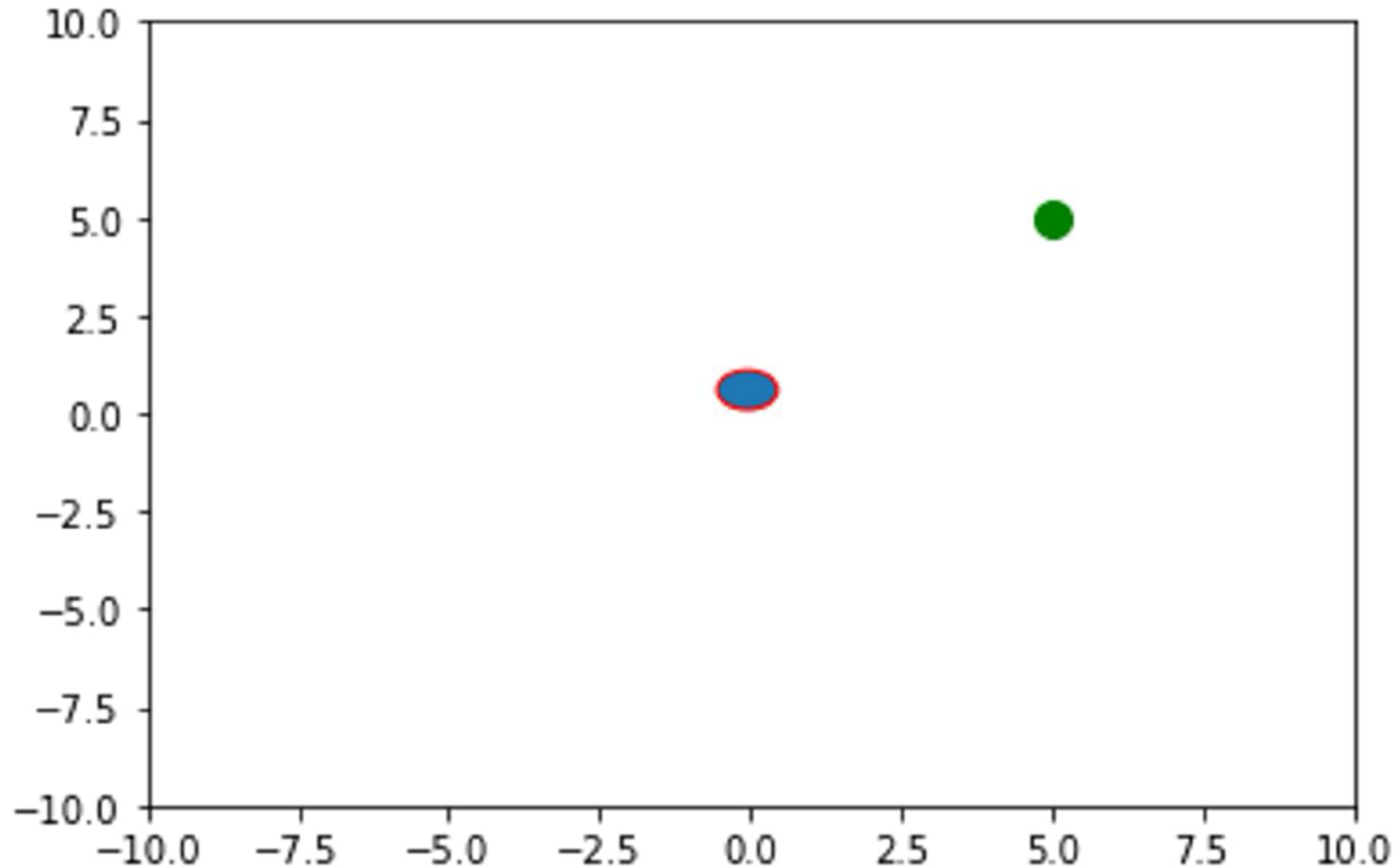
Likelihood Ratio Gradient – Toy Problem



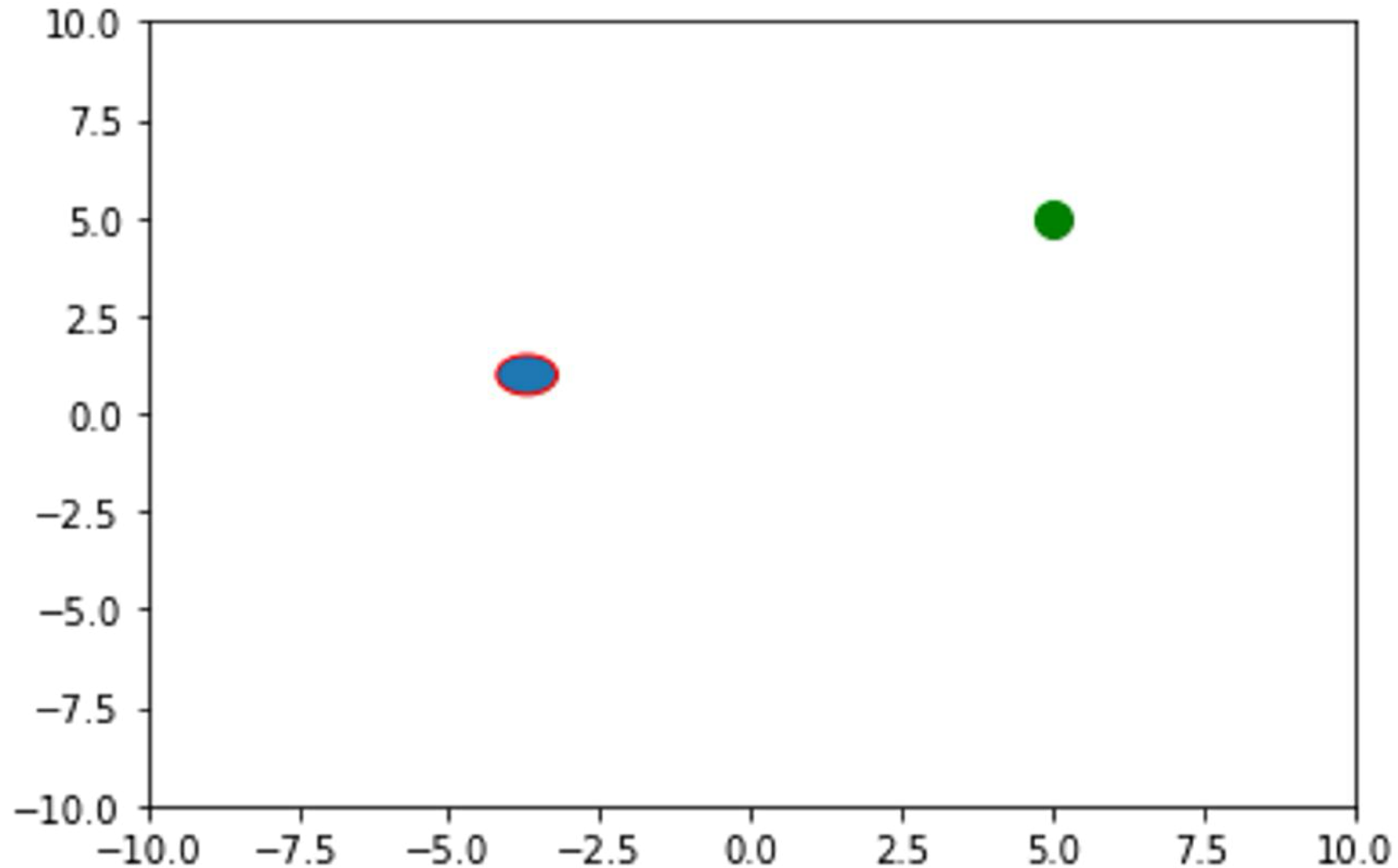
Likelihood Ratio Gradient – Toy Problem



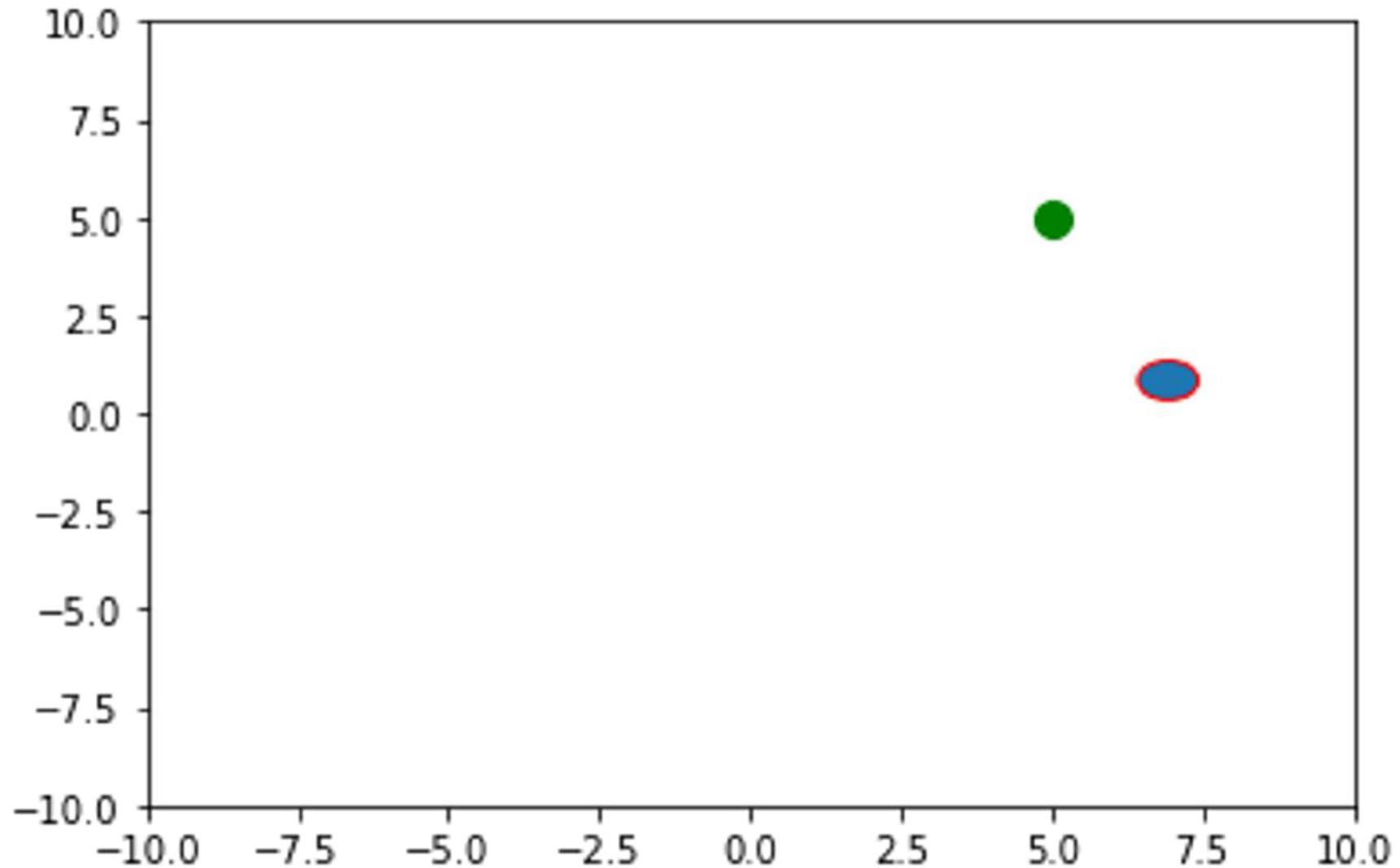
Likelihood Ratio Gradient – Toy Problem



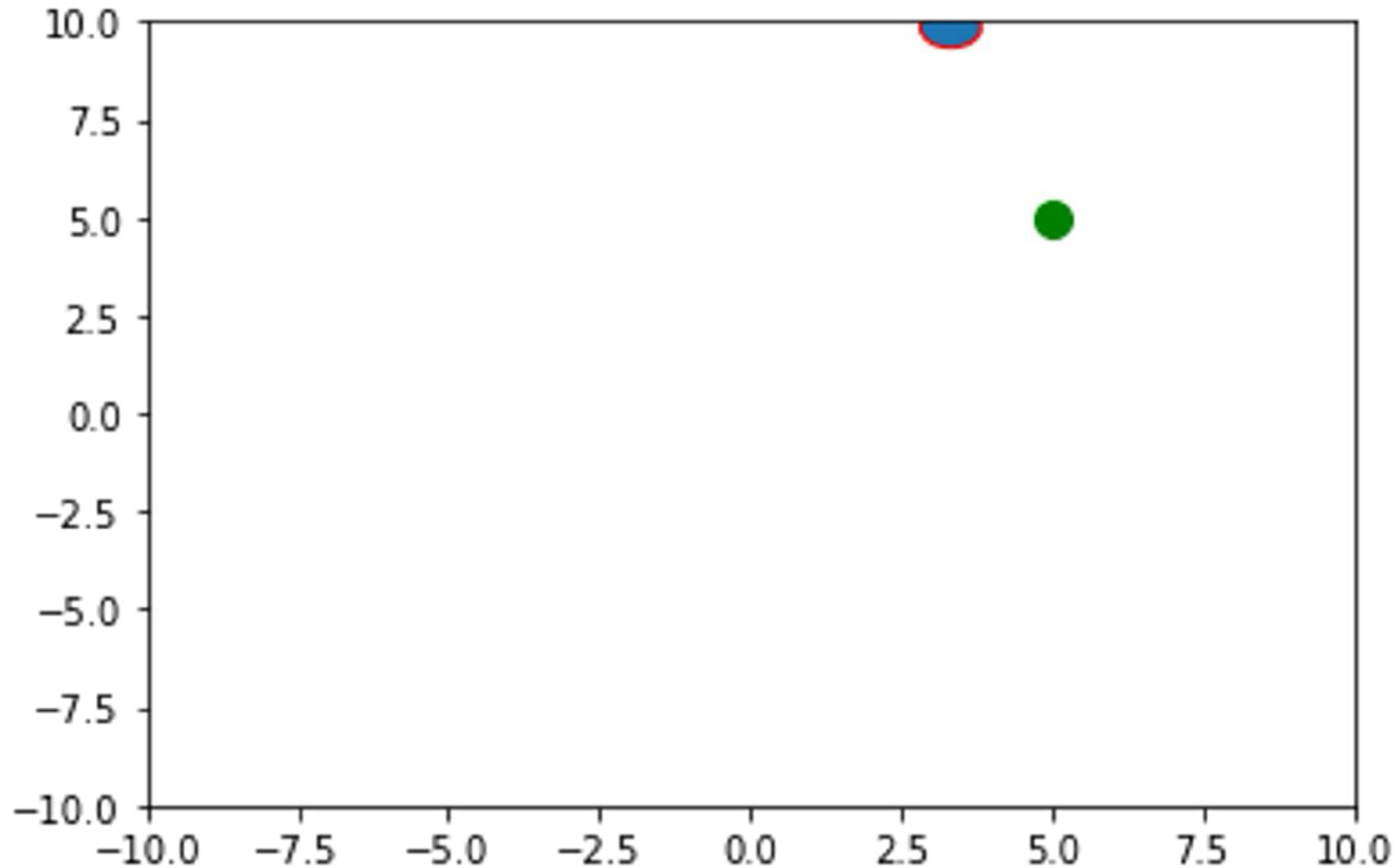
Likelihood Ratio Gradient – Toy Problem



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 ϕ here

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

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

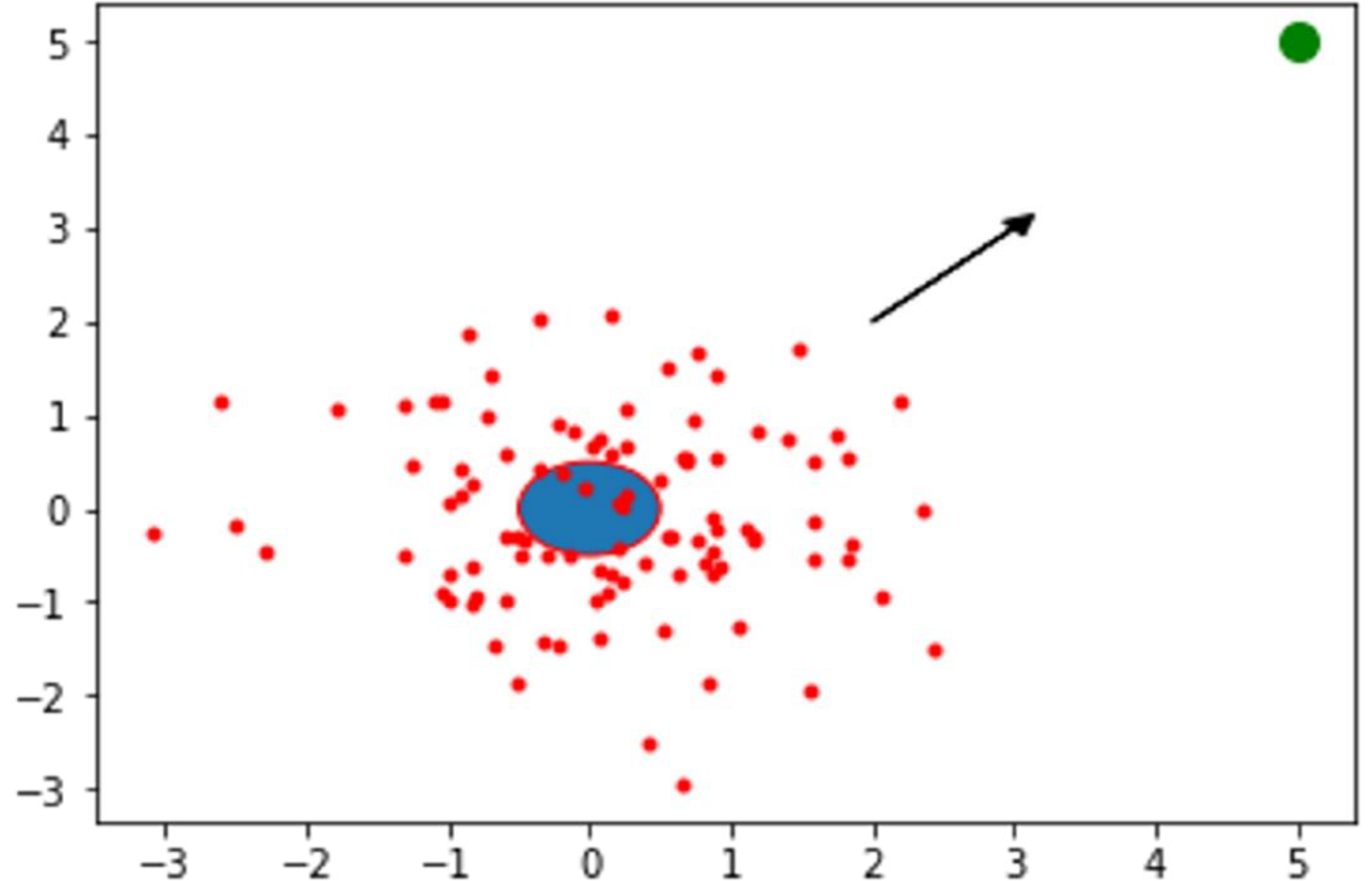
Pathwise Derivative (PD)

- 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

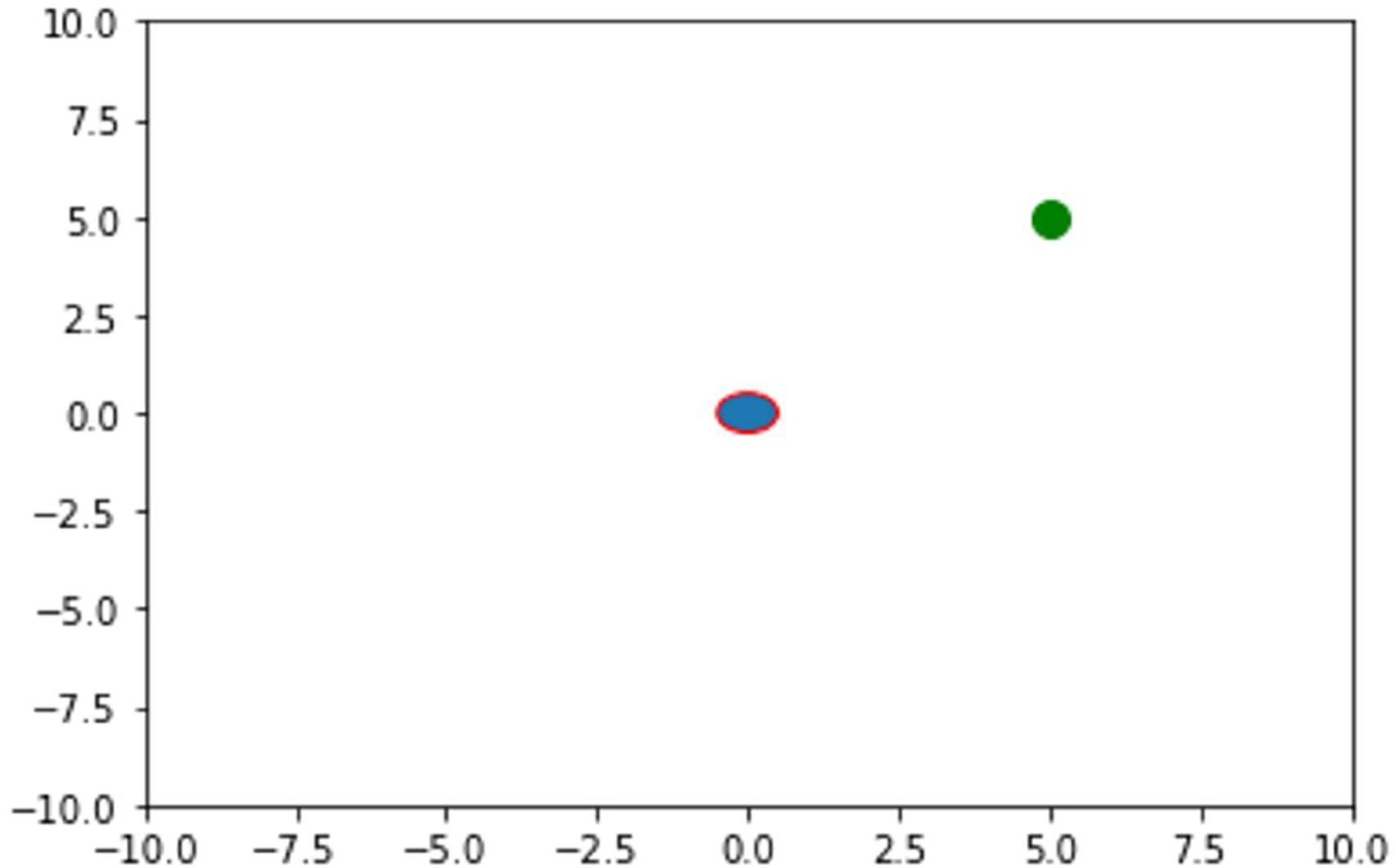
Pathwise Derivative – Toy Problem

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

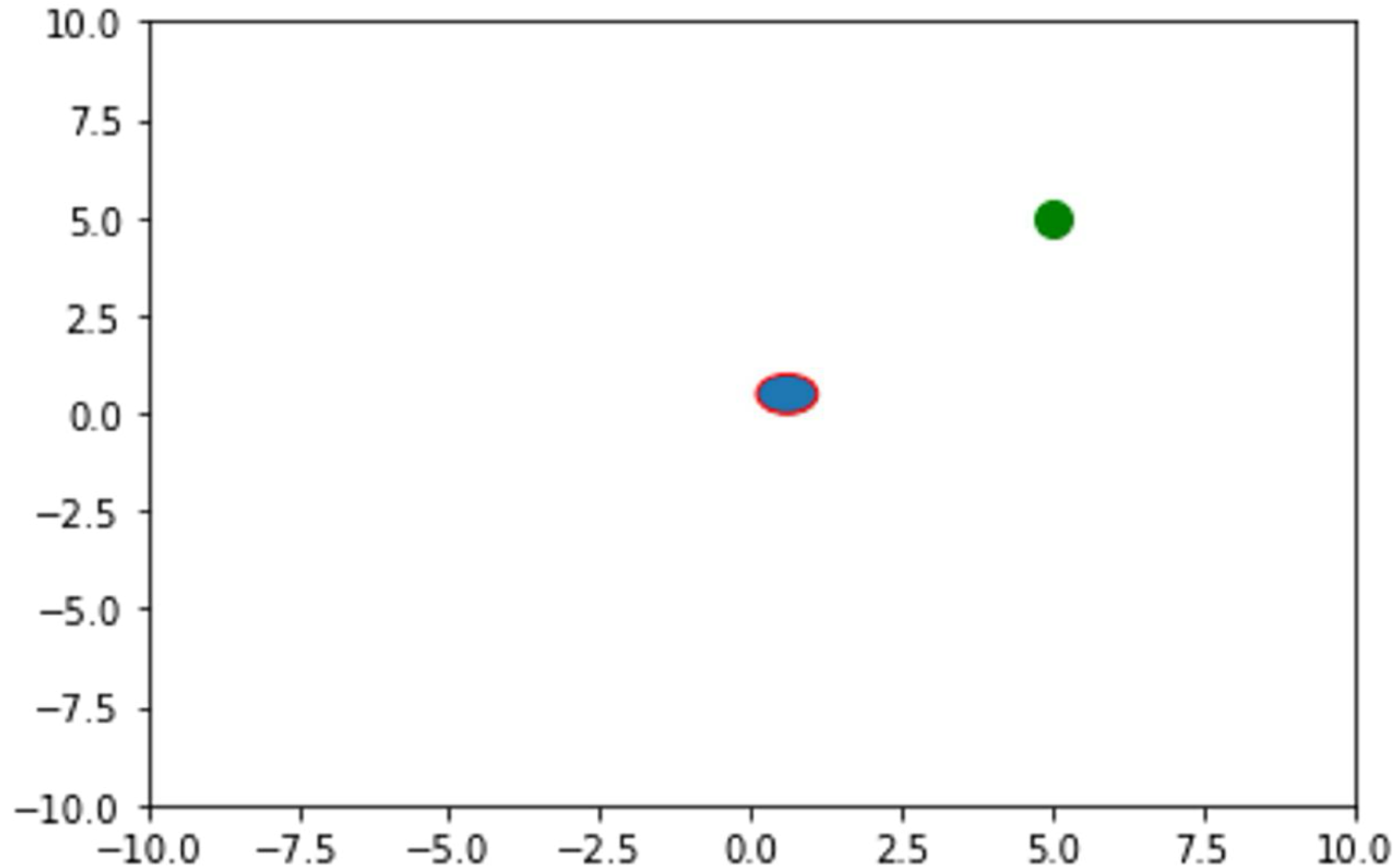
$$\mathcal{L} = \mathbb{E}_{x \sim N(\mu, I)} \left\| x - \begin{bmatrix} 5 \\ 5 \end{bmatrix} \right\|_2^2$$



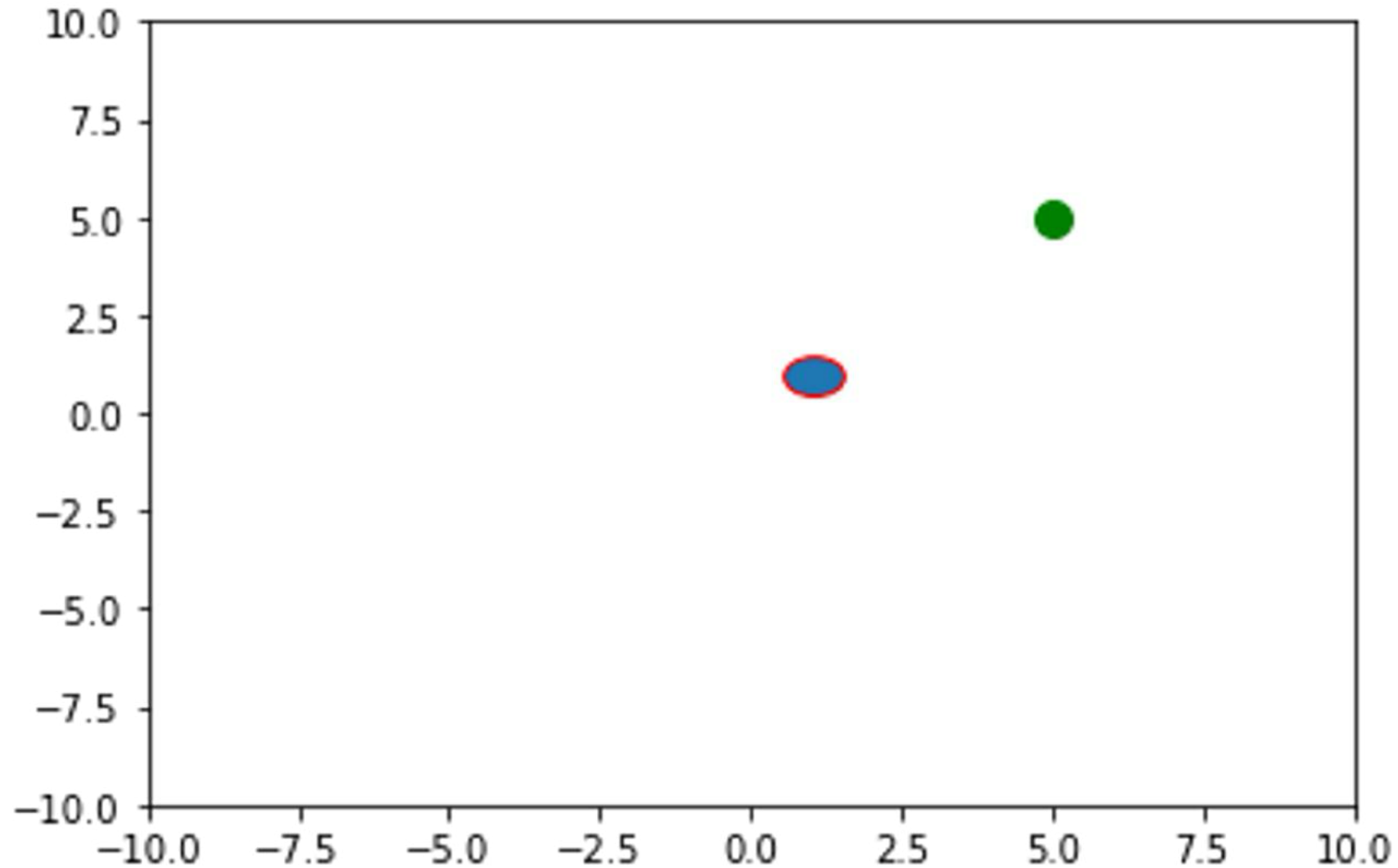
Pathwise Derivative – Toy Problem



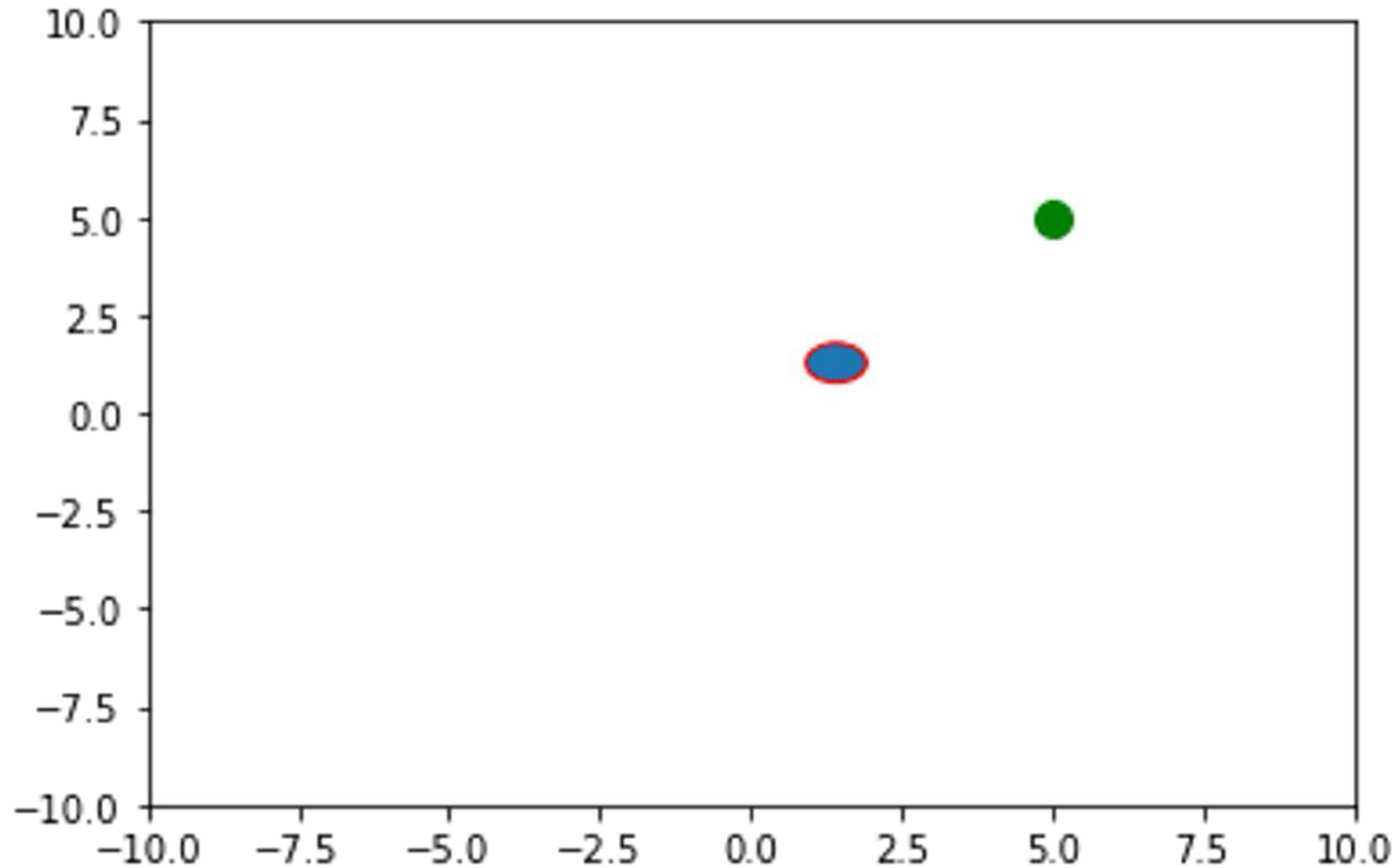
Pathwise Derivative – Toy Problem



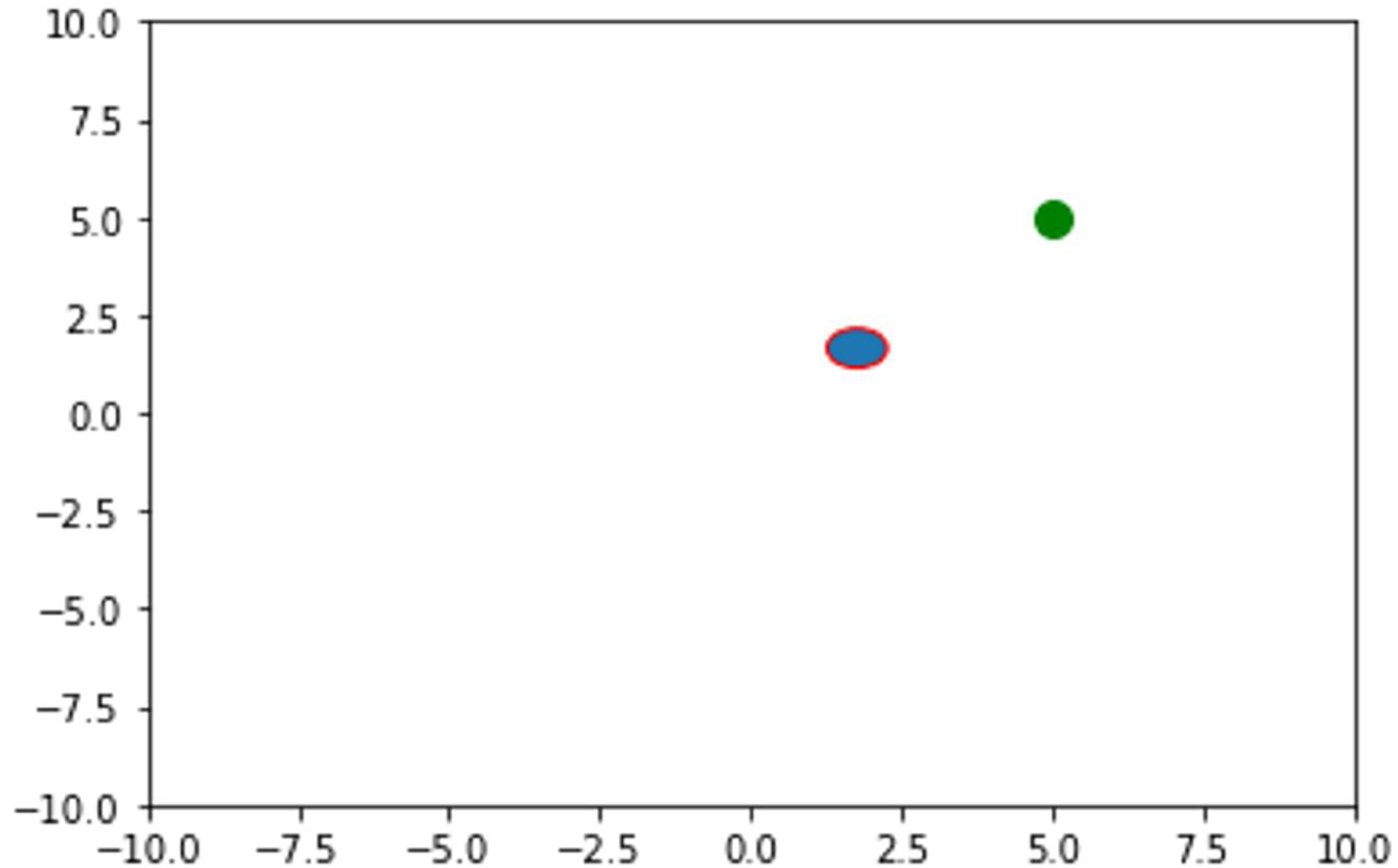
Pathwise Derivative – Toy Problem



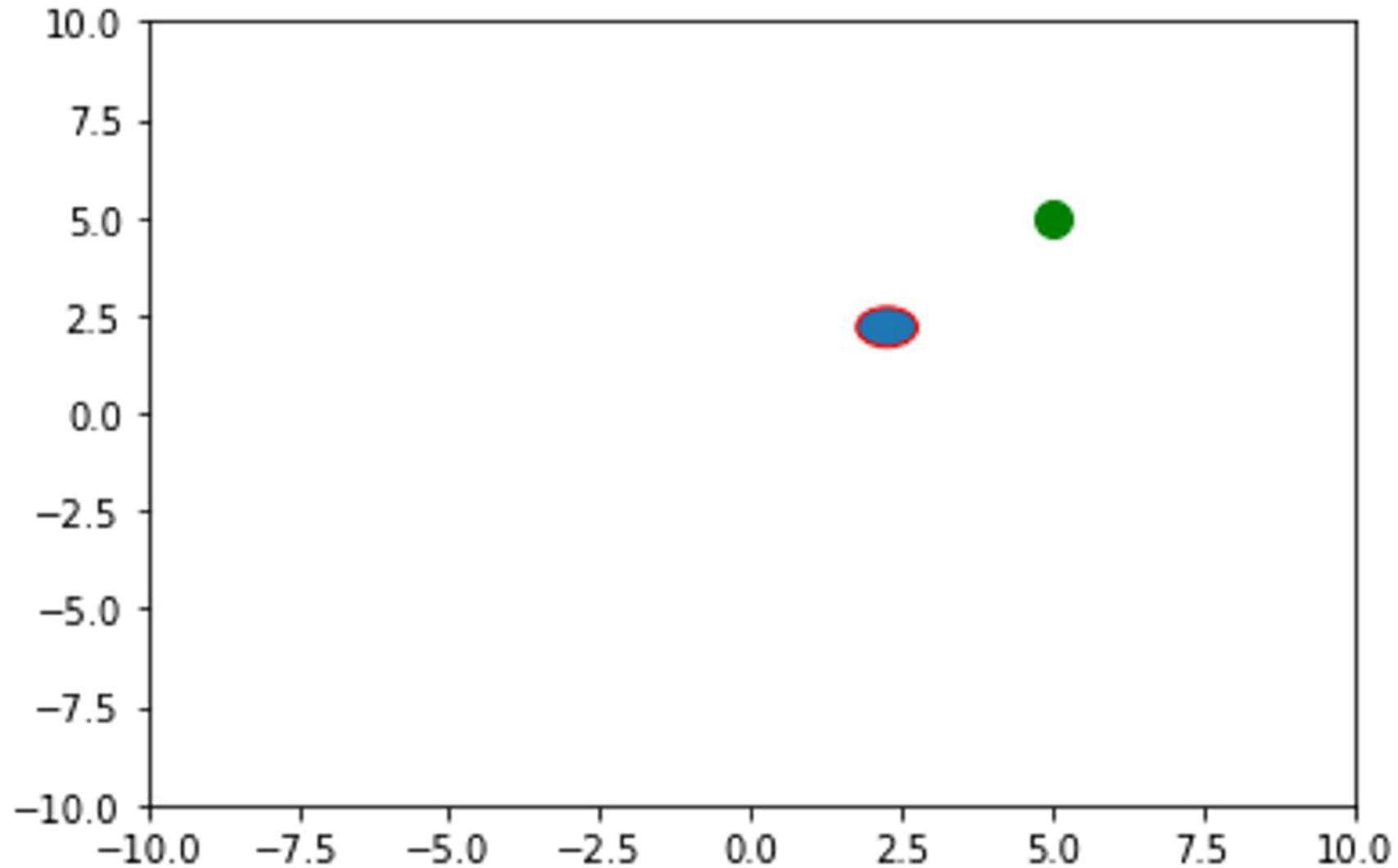
Pathwise Derivative – Toy Problem



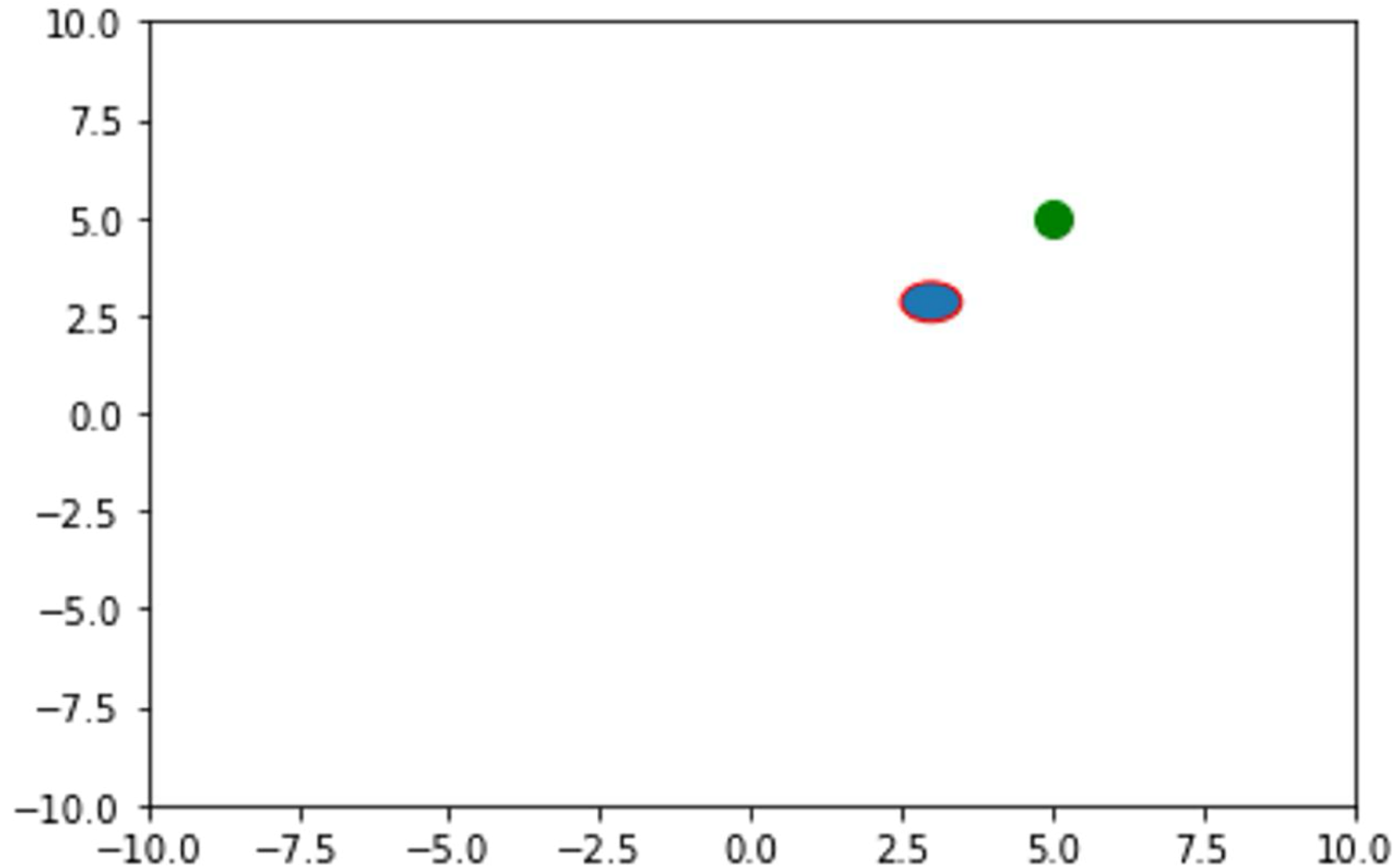
Pathwise Derivative – Toy Problem



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,

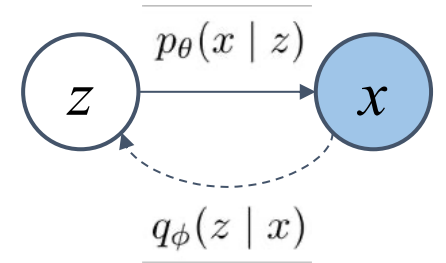
$$\nabla_\phi \mathbb{E}_{z \sim q_\phi(\cdot|x)} [f(z)] = \mathbb{E}_{\epsilon \sim \mathcal{N}(0, I)} [\nabla_\phi f(g(\epsilon, \phi))]$$

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

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



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

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

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

$$+ \underbrace{\mathbb{E}_{z \sim q_{\phi}(z|x^{(i)})} [-\nabla_{\phi} \log q_{\phi}(z|x^{(i)})]}$$

$$\mathbb{E}_{z \sim q_{\phi}(z|x^{(i)})} \left[-\frac{\nabla_{\phi} q_{\phi}(z|x^{(i)})}{q_{\phi}(z|x^{(i)})} \right] = \mathbb{E}_z \left[-q_{\phi}(z|x^{(i)}) \frac{\nabla_{\phi} q_{\phi}(z|x^{(i)})}{q_{\phi}(z|x^{(i)})} \right]$$

$$= \nabla_{\phi} \sum_z q_{\phi}(z|x^{(i)}) = 1$$

Likelihood Ratio Estimator

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

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

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

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

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

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

PD applied to VLB

Variational AutoEncoder

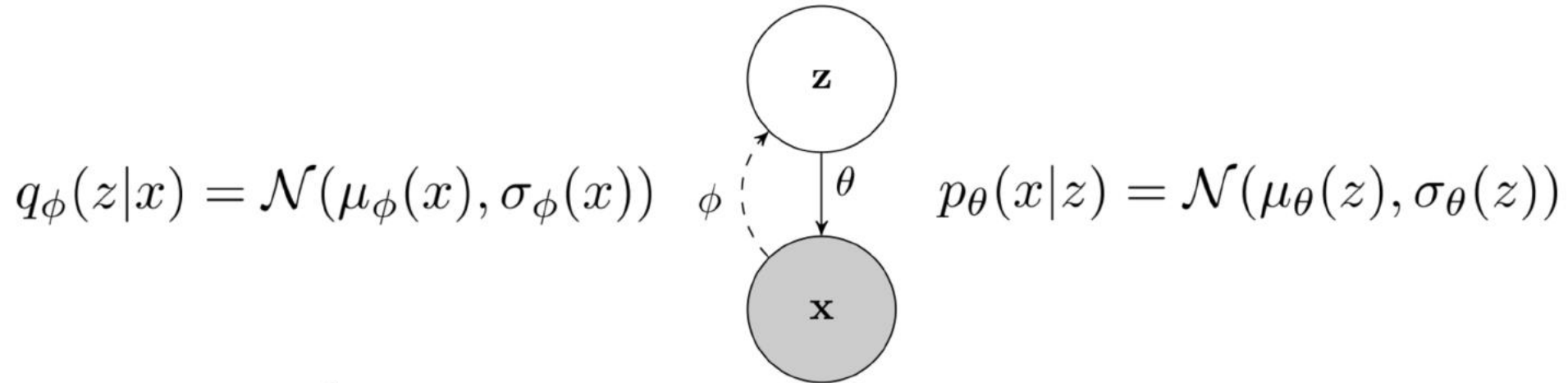
$q_\phi(z|x)$ is modeled as a Gaussian with parameters μ and σ a DNN encoder (parameters ϕ) of x . The DNN decoder $p_\theta(x|z)$ is differentiable.

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

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

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

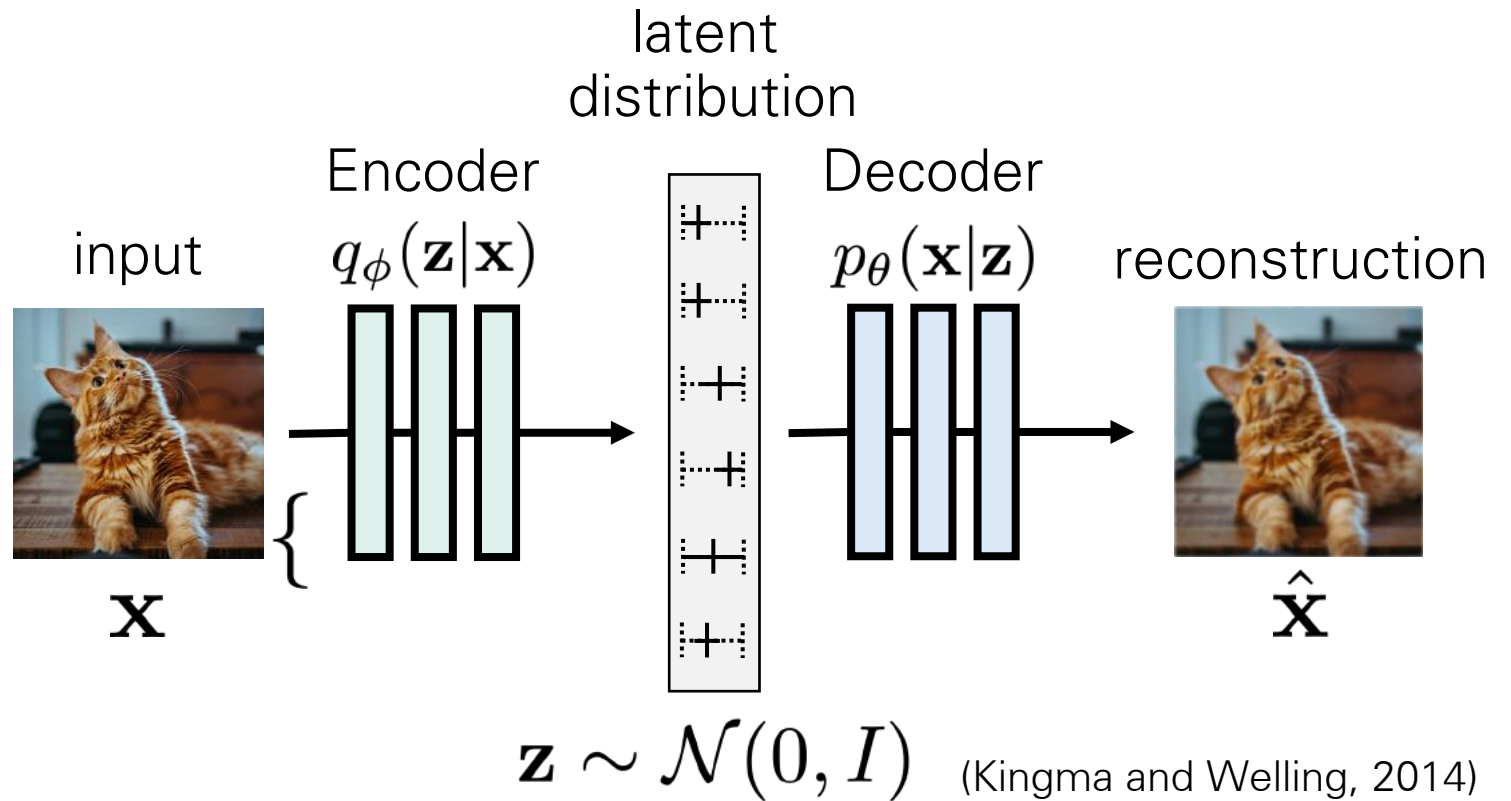
VAE



- **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

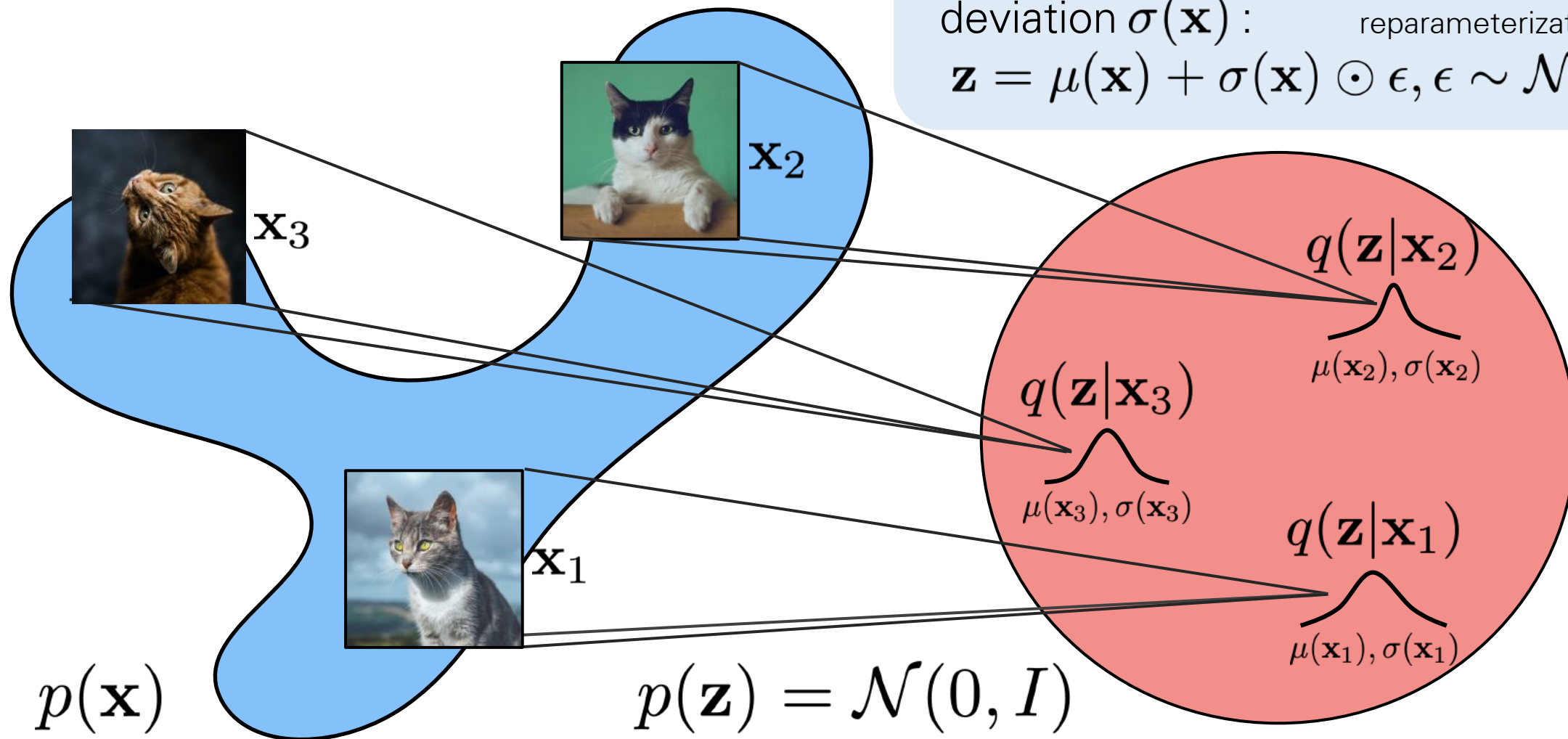
- Assume a known distribution (e.g. Normal distribution) on the latent space, $p(\mathbf{z})$.
- Parametrize the conditional probability $p(\mathbf{x}|\mathbf{z})$ by a neural network.
- Approximate $p(\mathbf{z}|\mathbf{x})$ using a variational distribution $q(\mathbf{z}|\mathbf{x})$, also parametrized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



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

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
 $\mathbf{z} = \mu(\mathbf{x}) + \sigma(\mathbf{x}) \odot \epsilon, \epsilon \sim \mathcal{N}(0, I)$

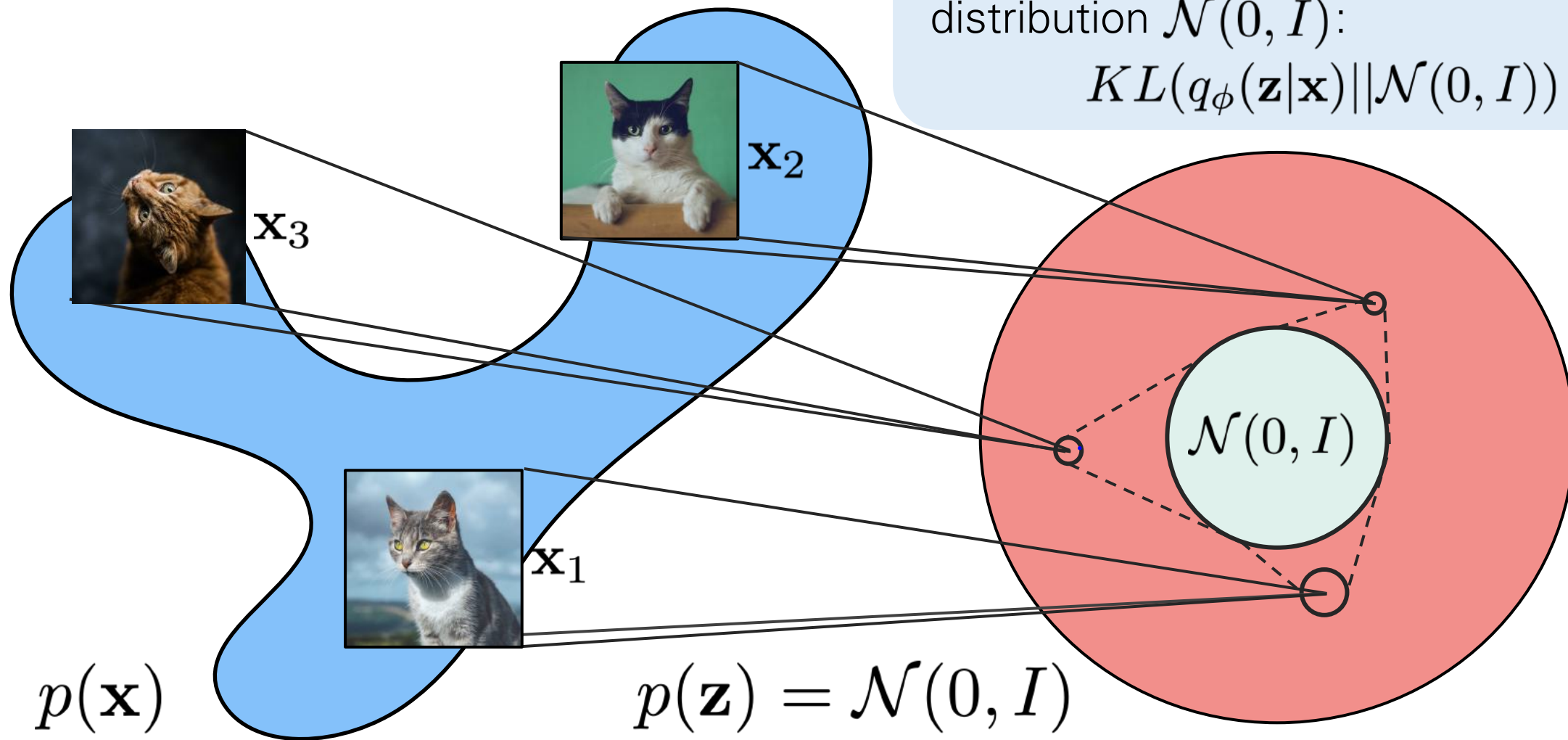


$$\mathcal{L}_{VAE}(\mathbf{x}; \theta, \phi) = \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} [-\log p_{\theta}(\mathbf{x}|\mathbf{z})] + KL(q_{\phi}(\mathbf{z}|\mathbf{x}) || p(\mathbf{z}))$$

Intuition behind VAEs

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

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



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

Evolutions of VAEs

- 6 years of VAE progress on face generation



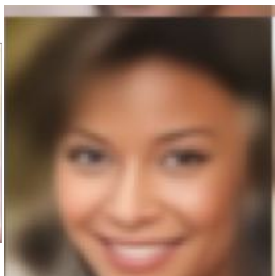
2014



2015



2016



2017



2018



2019



2020

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.

A. Vahdat and J. Kautz. **NVAE: A Deep Hierarchical Variational Autoencoder**. NeurIPS 2020.

Why is it called an autoencoder?

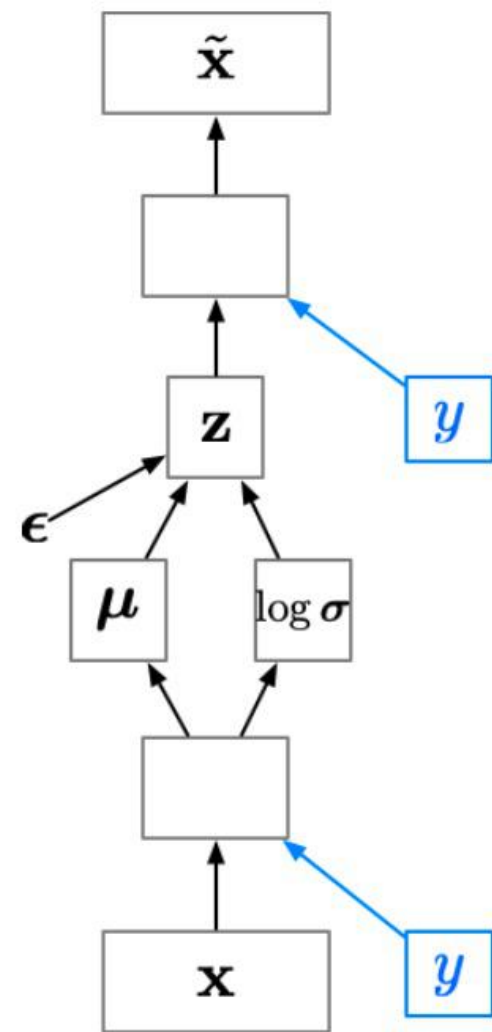
- We have seen that a variational autoencoder is a latent variable model with Gaussian prior $p(z)$ and approximate posterior $q(z|x)$.
 - Why is it called an “autoencoder”?

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

$L(\theta, \phi)$ - 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**.



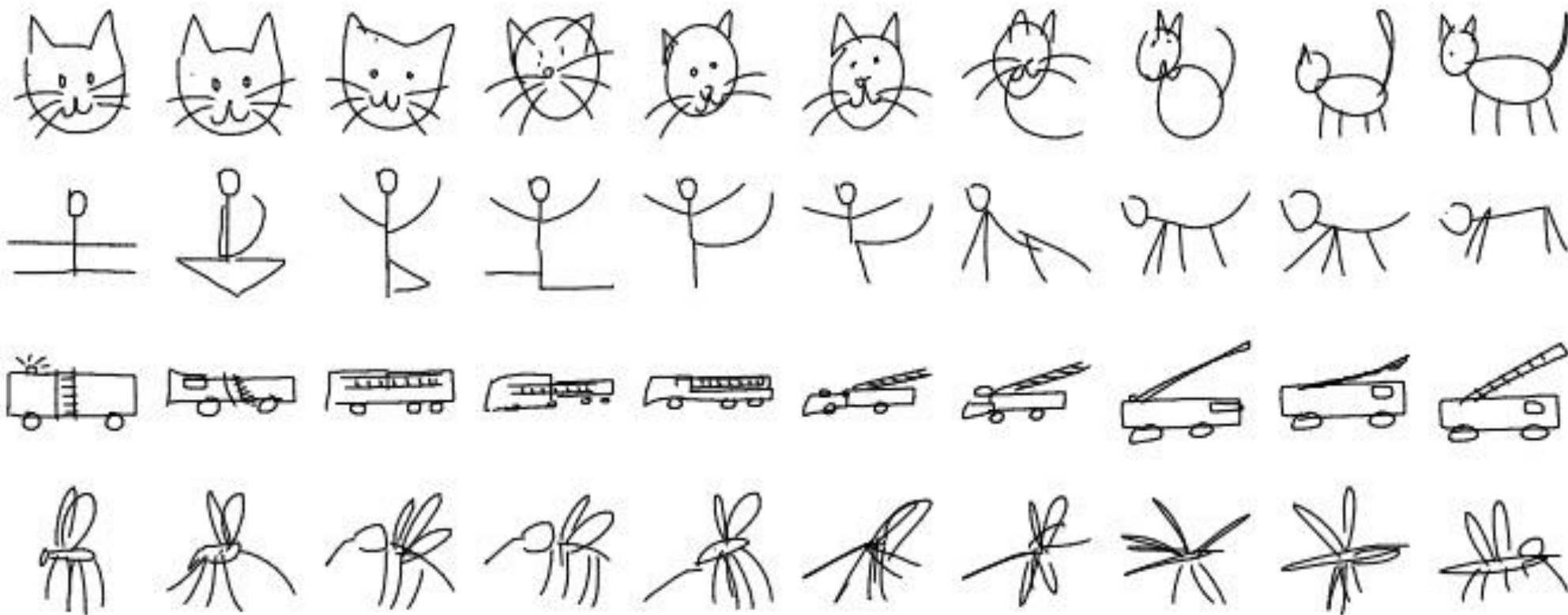
Class-Conditional VAE

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



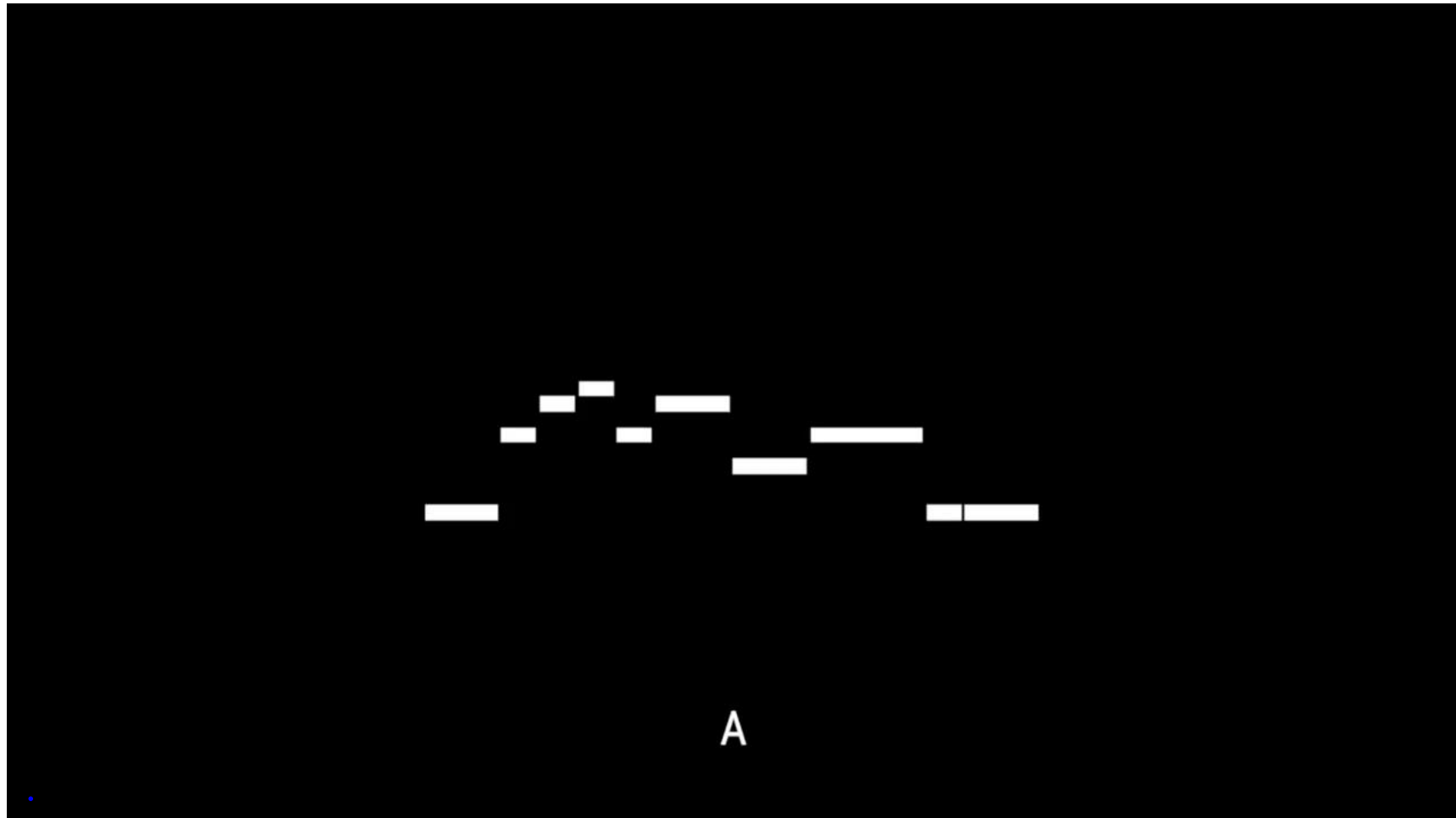
Latent Space Interpolations

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



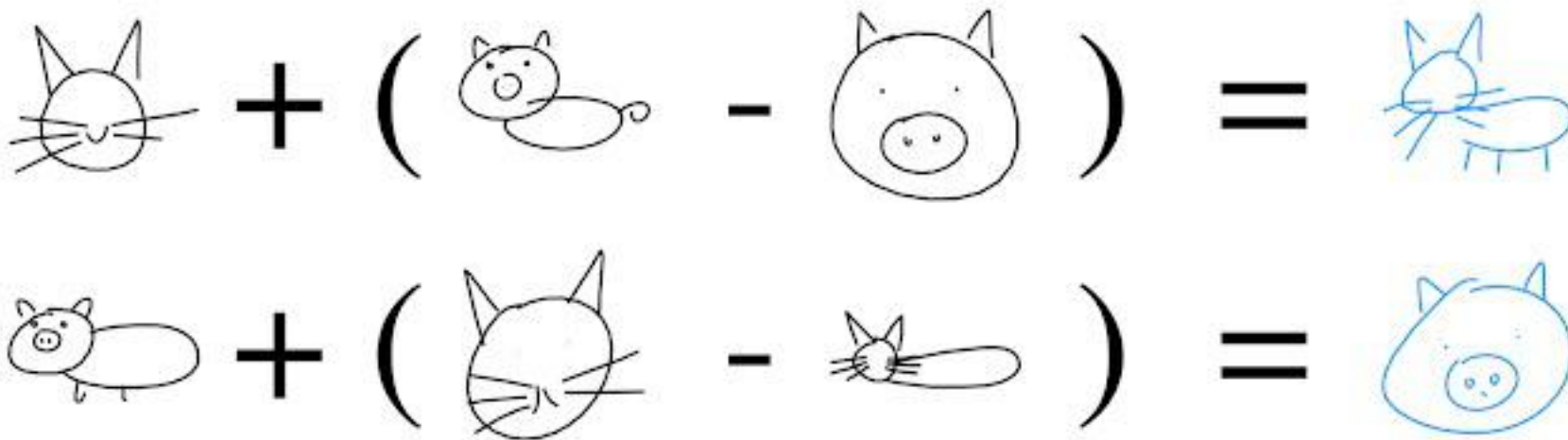
Latent Space Interpolations

- Latent space interpolation of music:



Latent Space Arithmetic

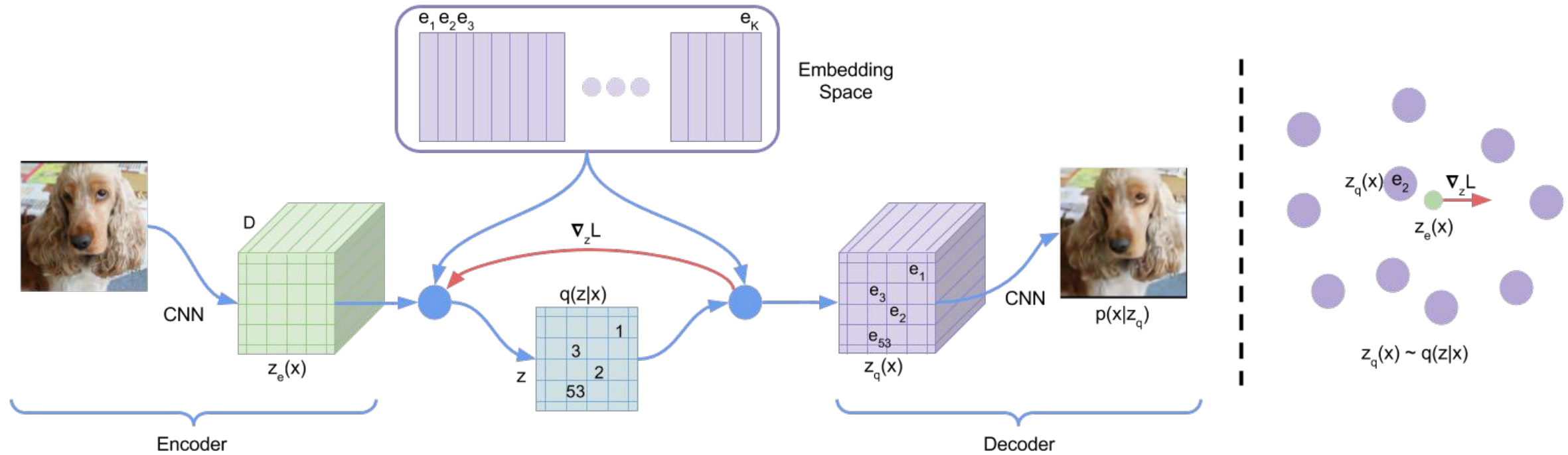
- You can even perform vector arithmetic on latent vectors:



Lecture overview

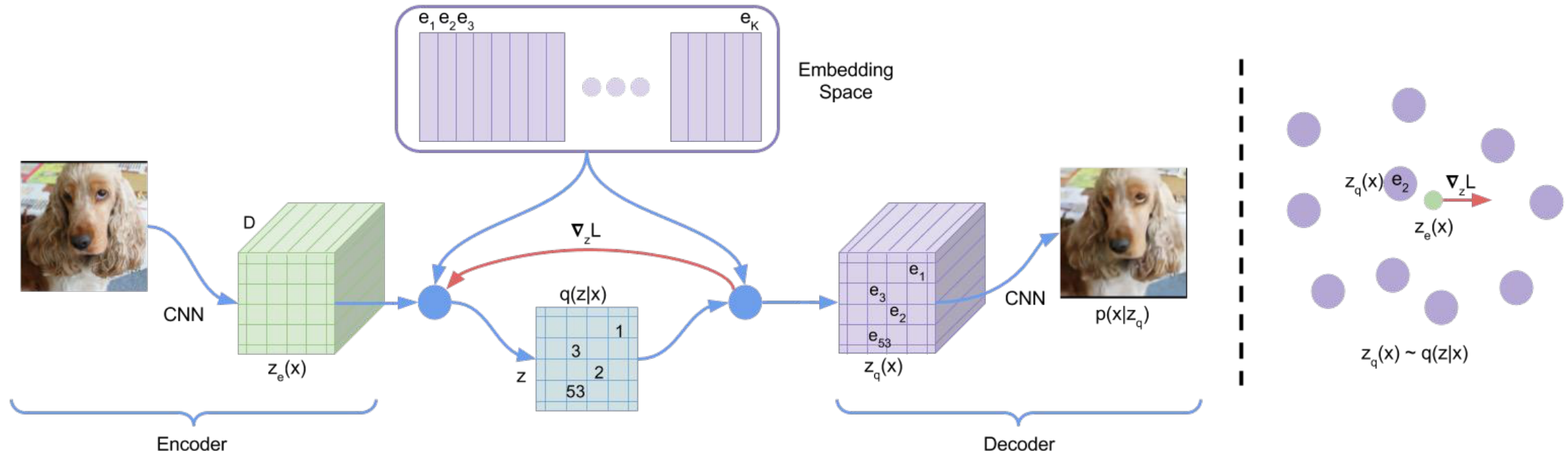
- Motivation
- Training Latent Variable Models (including VAE and IWAE)
- **Variations**
 - **SOTA: VQ-VAE, VQ-VAE 2.0, NVAE**
 - AR + VAE: Variational Lossy AutoEncoder, PixelVAE
 - Disentanglement: Beta VAE

VQ-VAE



- A latent embedding space $e \in \mathbb{R}^{K \times D}$ where K is the size of the discrete latent space (K-way categorical distribution)
- Encoder output $z_e(x)$ is mapped to discrete latent code z by a nearest neighbour look-up using the shared embedding space e

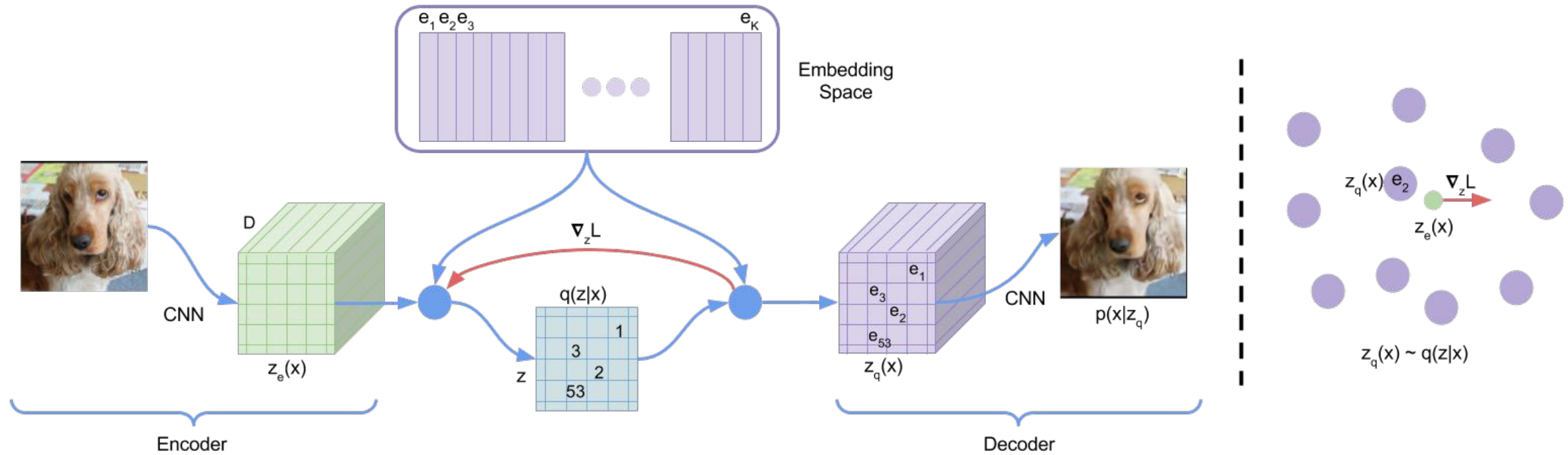
VQ-VAE



- The posterior categorical distribution $q(z|x)$ probabilities are defined as one-hot as:

$$q(z = k | x) = \begin{cases} 1 & \text{for } k = \operatorname{argmin}_j \|z_e(x) - e_j\|_2 \\ 0 & \text{otherwise} \end{cases}$$

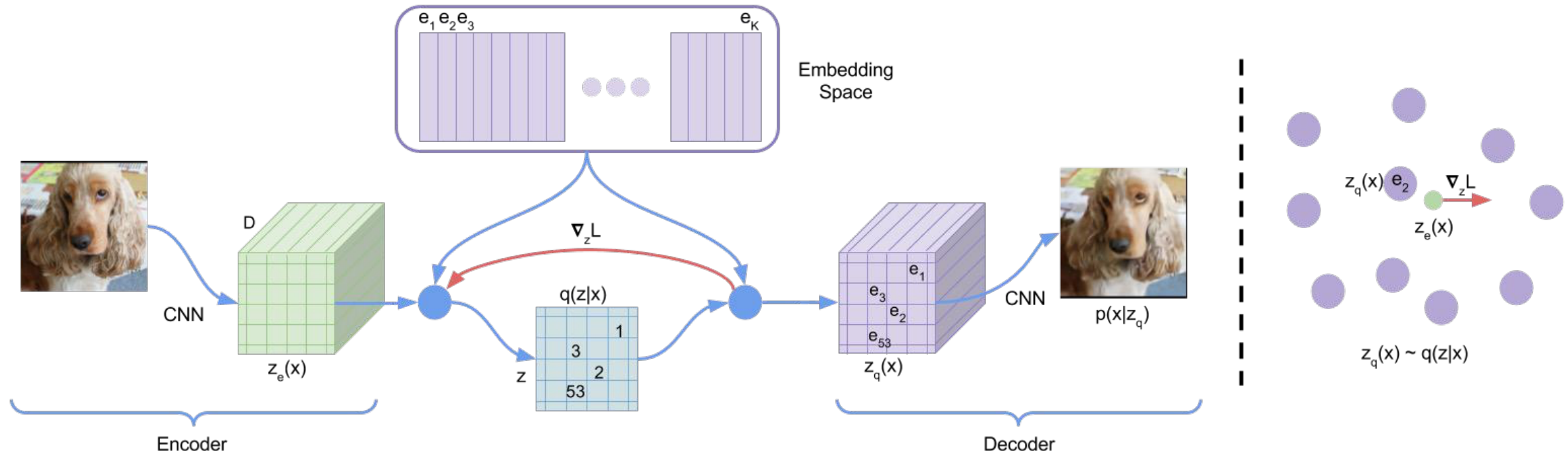
VQ-VAE



- This model can be seen as a VAE in which the proposal distribution $q(z = k|x)$ is deterministic.
- The representation $z_e(x)$ is passed through the discretization bottleneck followed by mapping onto the nearest element of embedding e

VQ-VAE

sg stands for the **stopgradient** operator that is defined as identity at forward computation time and has zero partial derivatives, thus effectively constraining its operand to be a non-updated constant.

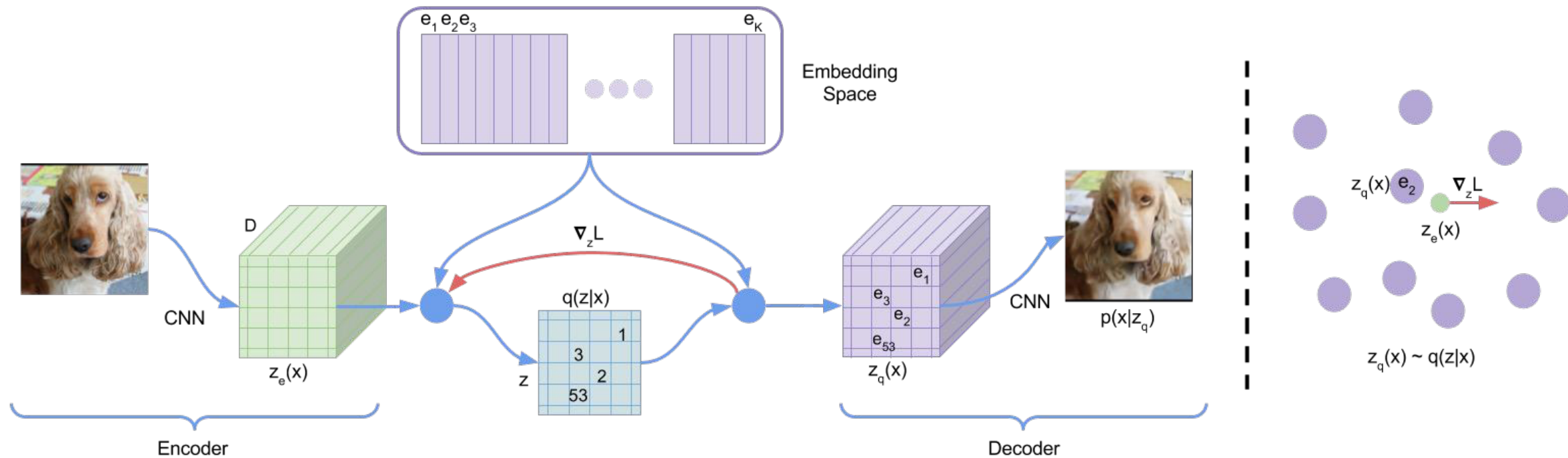


$$z_q(x) = e_k, \quad \text{where} \quad k = \operatorname{argmin}_j \|z_e(x) - e_j\|_2$$

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

VQ-VAE

sg stands for the **stopgradient** operator that is defined as identity at forward computation time and has zero partial derivatives, thus effectively constraining its operand to be a non-updated constant.

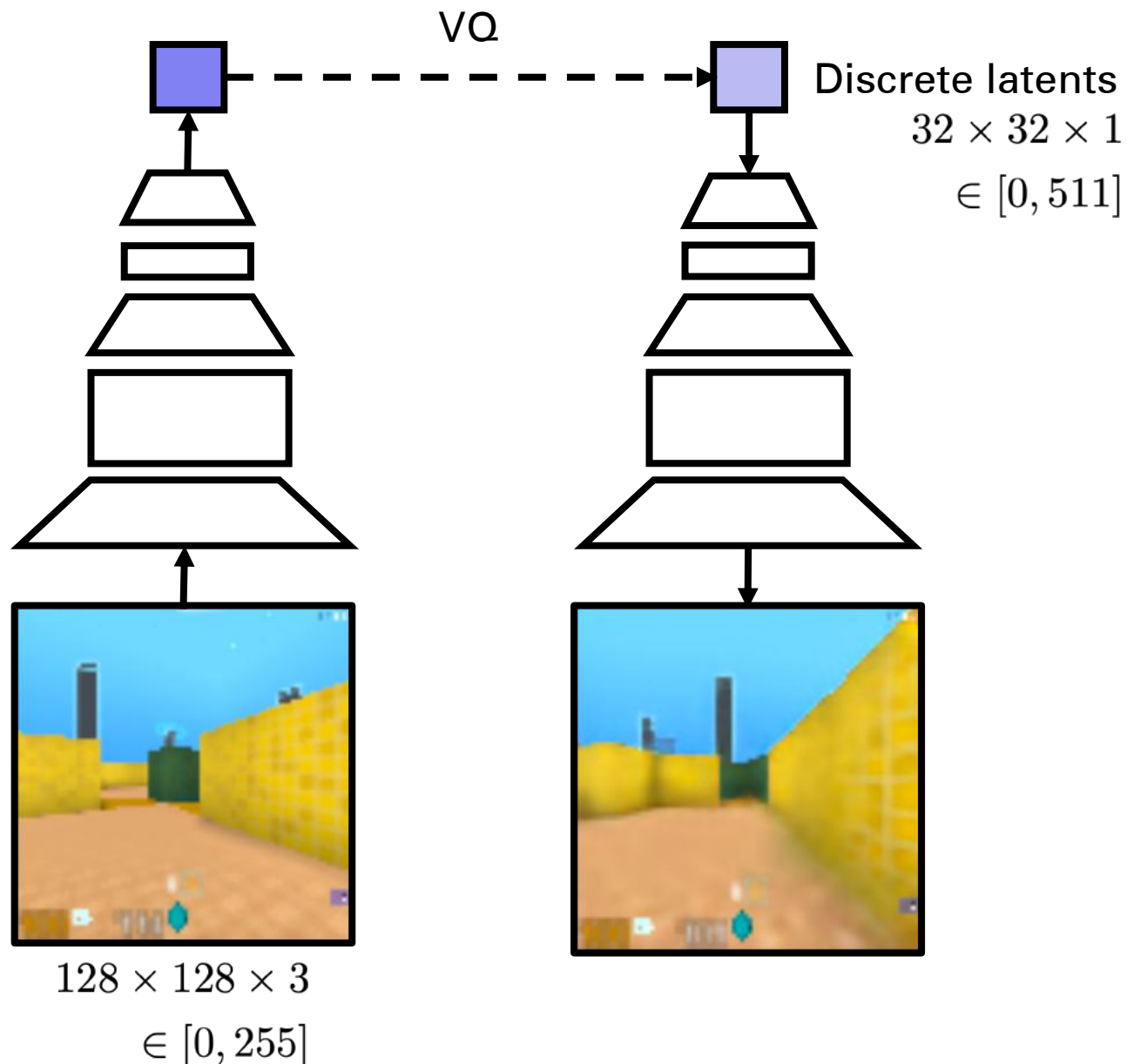


$$L = \log p(x | z_q(x)) + \|\text{sg}[z_e(x)] - e\|_2^2 + \beta \|z_e(x) - \text{sg}[e]\|_2^2$$

The embedding space is learned via Vector Quantization (VQ), whose objective uses the l_2 error to move the embedding vectors e_i towards the encoder outputs $z_e(x)$

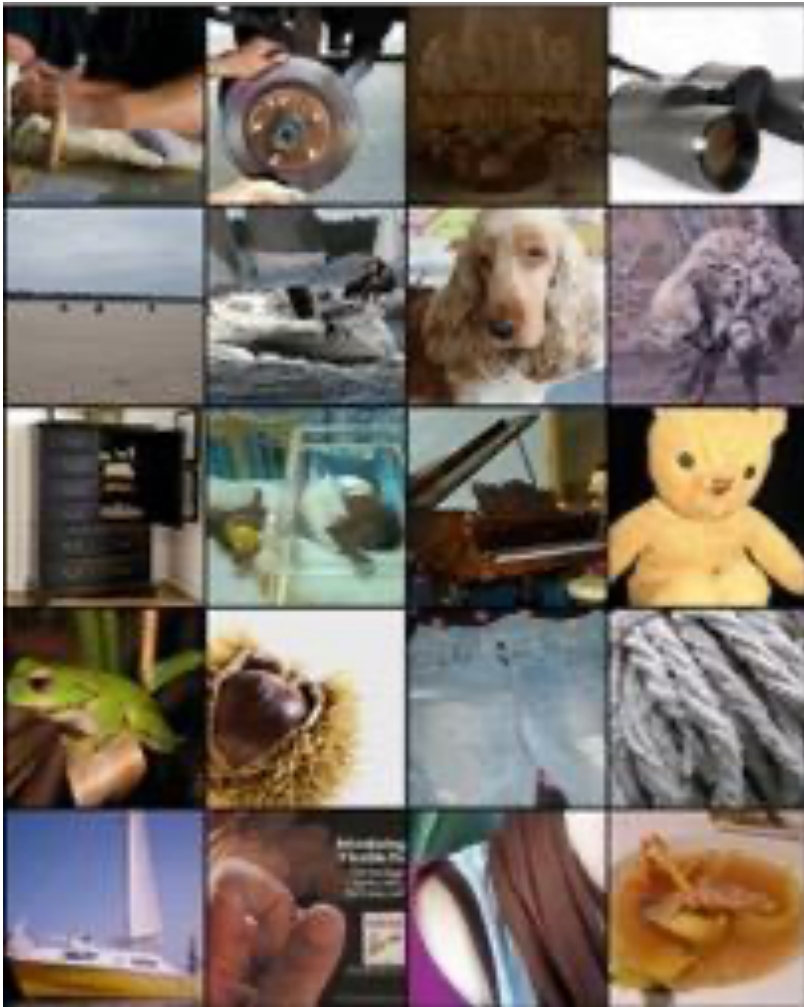
VQ-VAE

- For speech, image and videos one can respectively extract a 1D, 2D and 3D latent feature spaces
- 32 x 32 latents for ImageNet, or 8 x 8 x 10 for CIFAR10
- 512-dimensional latents for VCTK and LibriSpeech

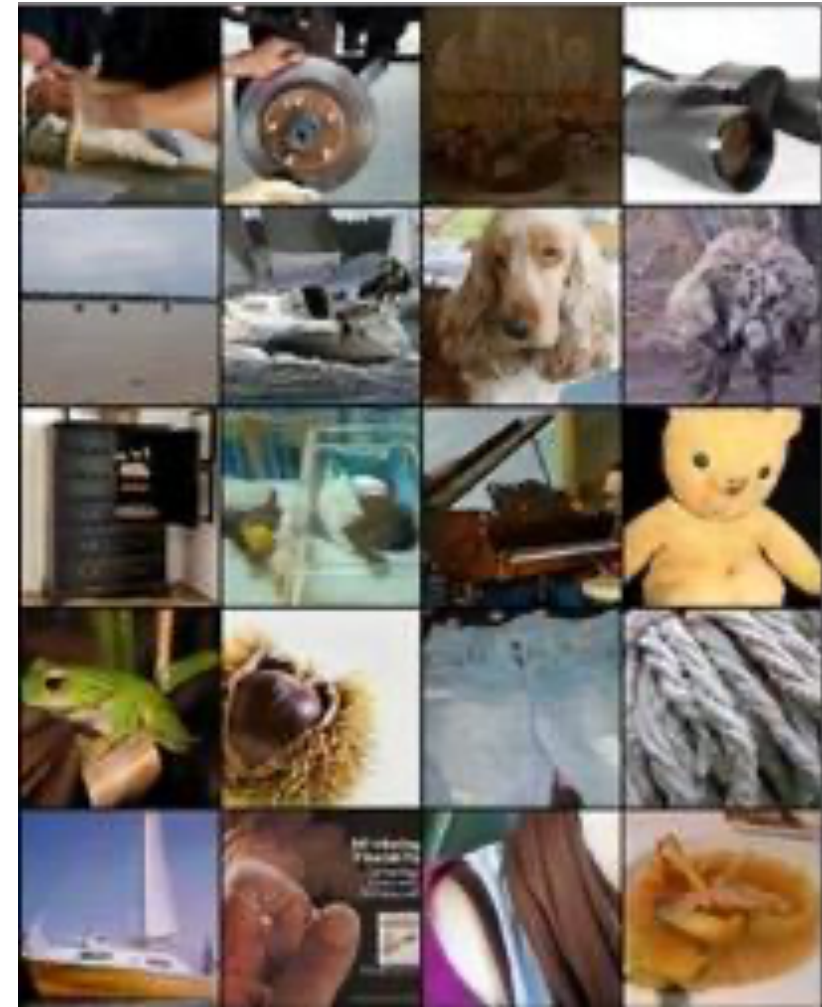


VQ-VAE ImageNet Reconstructions

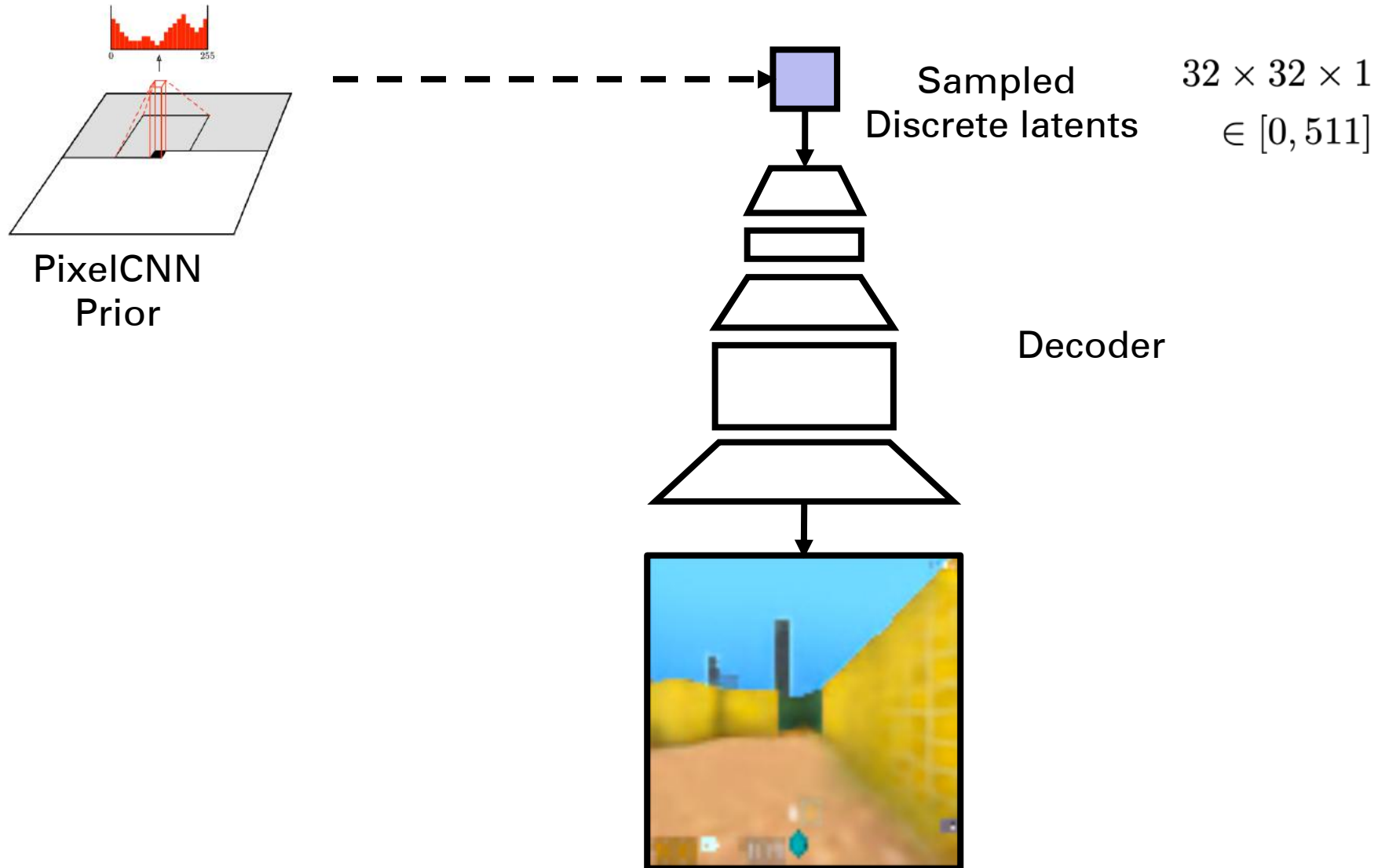
Original 128 x 128 images



Reconstructions



VQ-VAE Sampling from prior



VQ-VAE ImageNet Samples

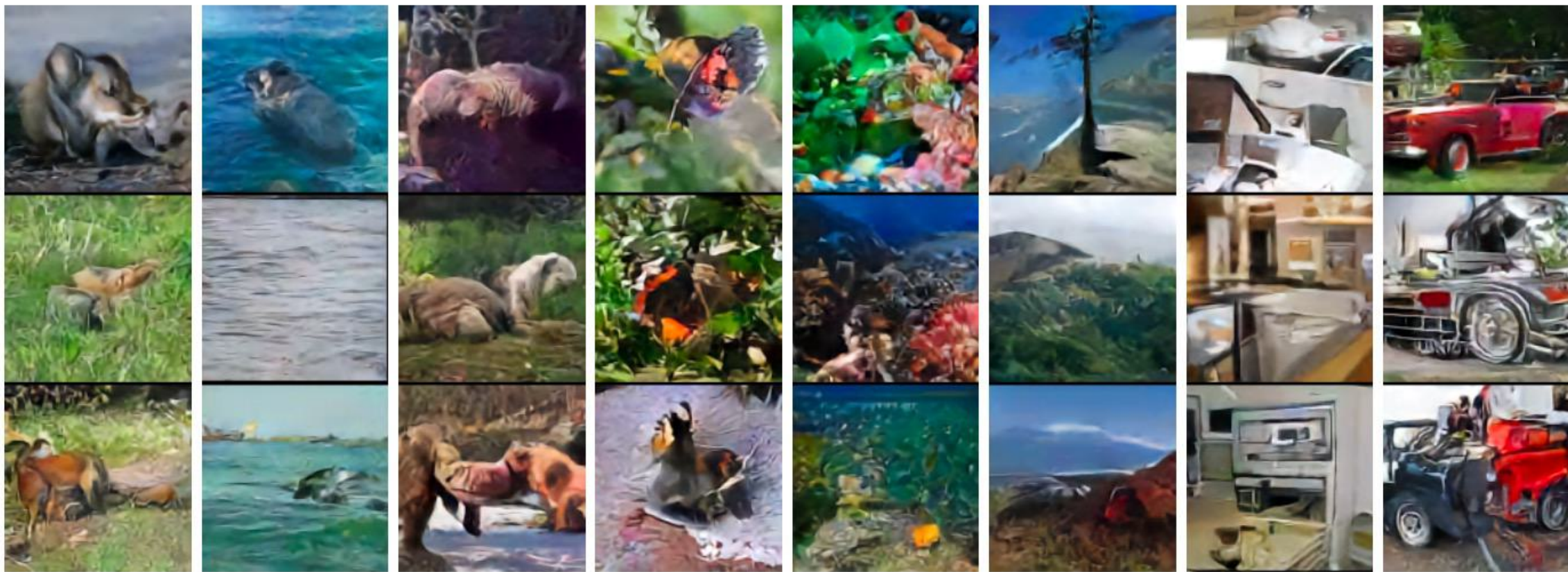
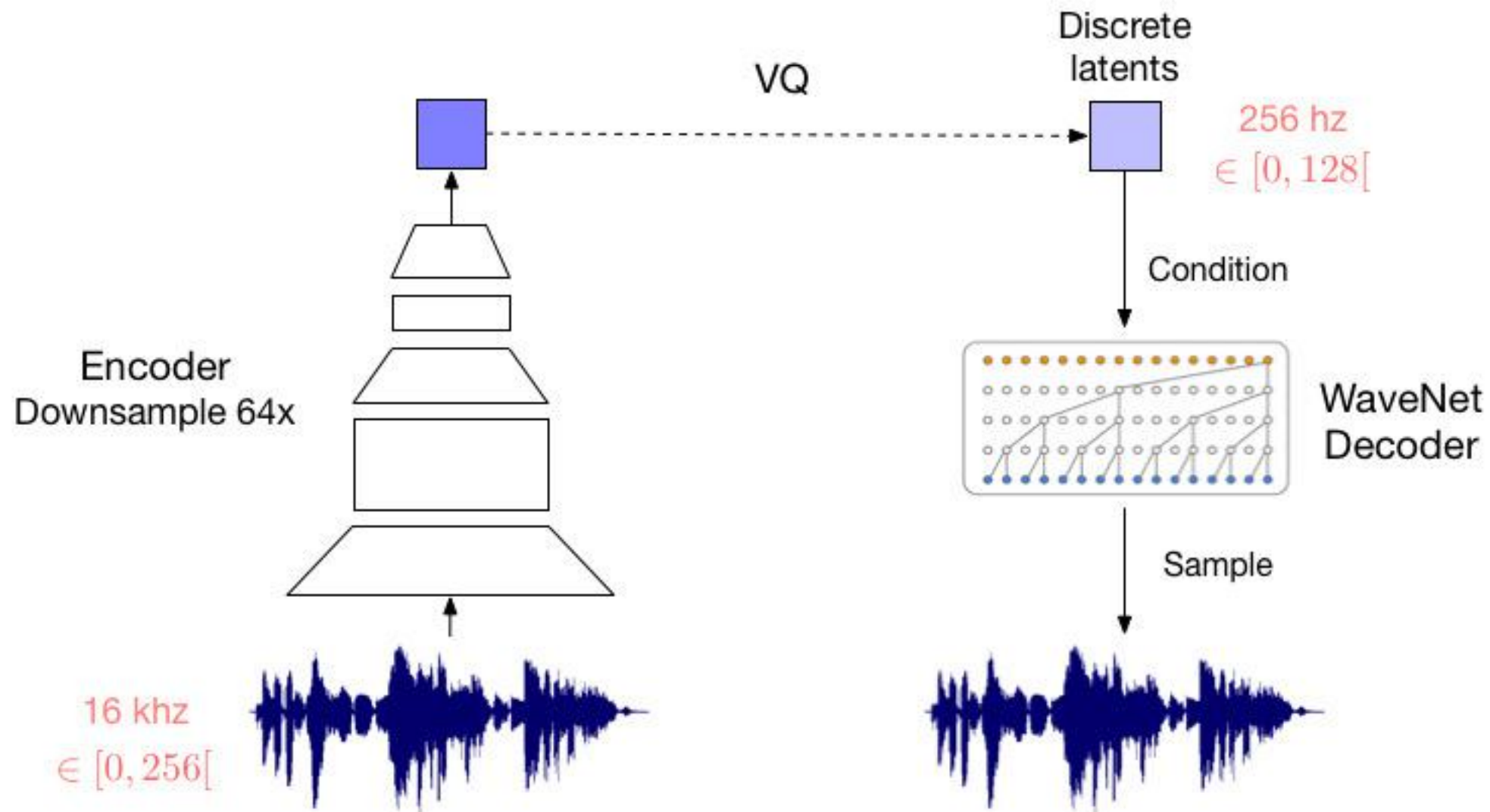
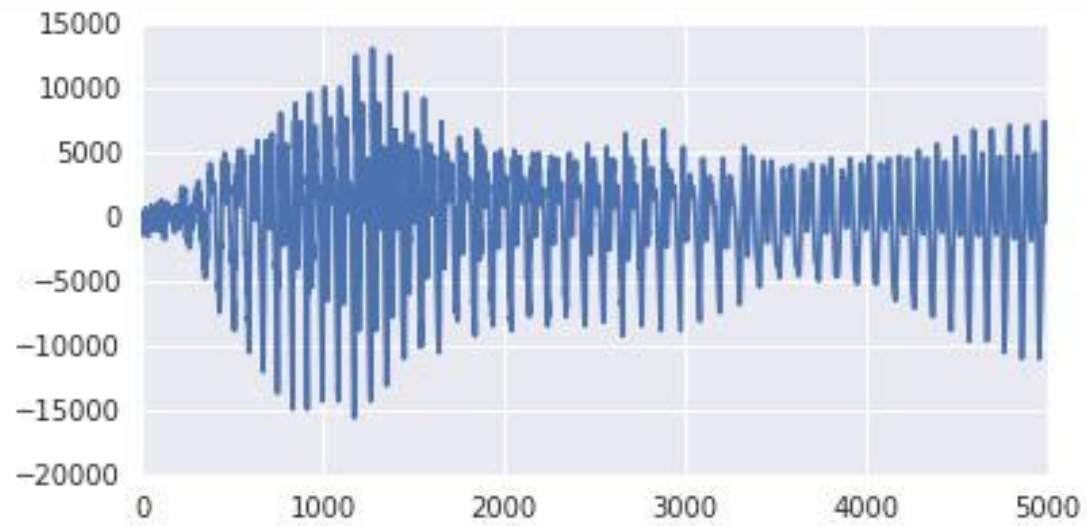


Figure 3: Samples (128x128) from a VQ-VAE with a PixelCNN prior trained on ImageNet images. From left to right: kit fox, gray whale, brown bear, admiral (butterfly), coral reef, alp, microwave, pickup.

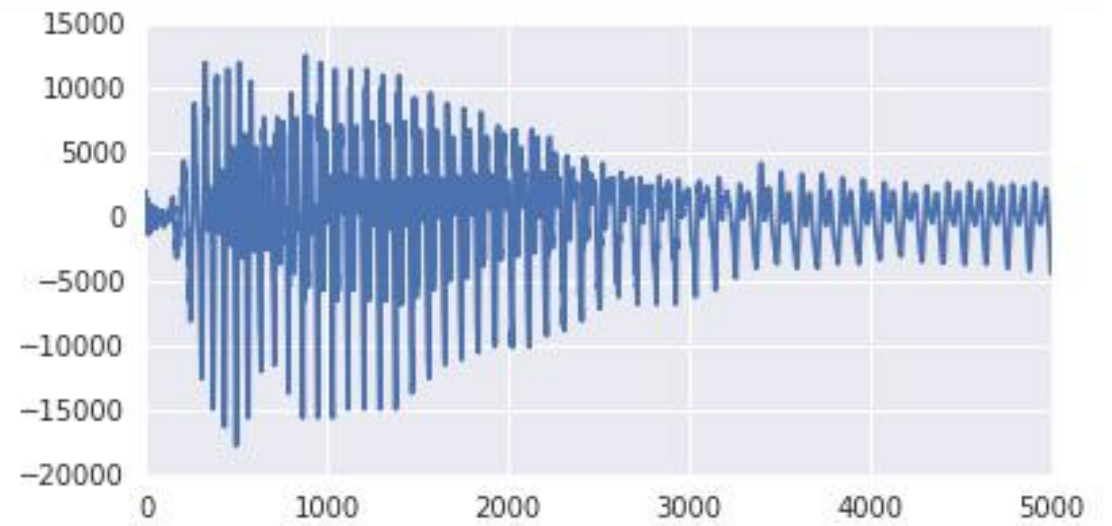
VQ-VQA Speech Modeling



VQ-VQA VCTK Reconstructions

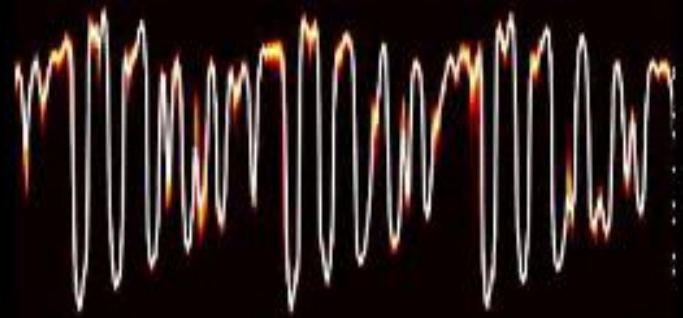
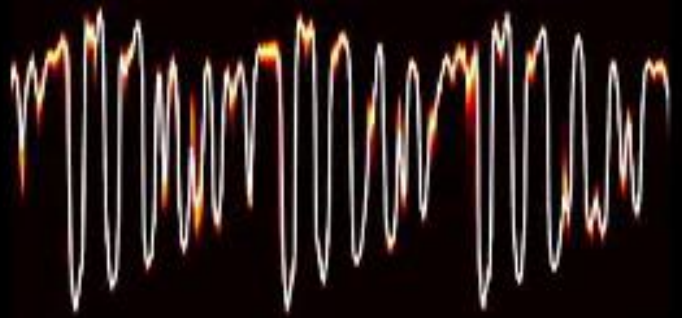


Original

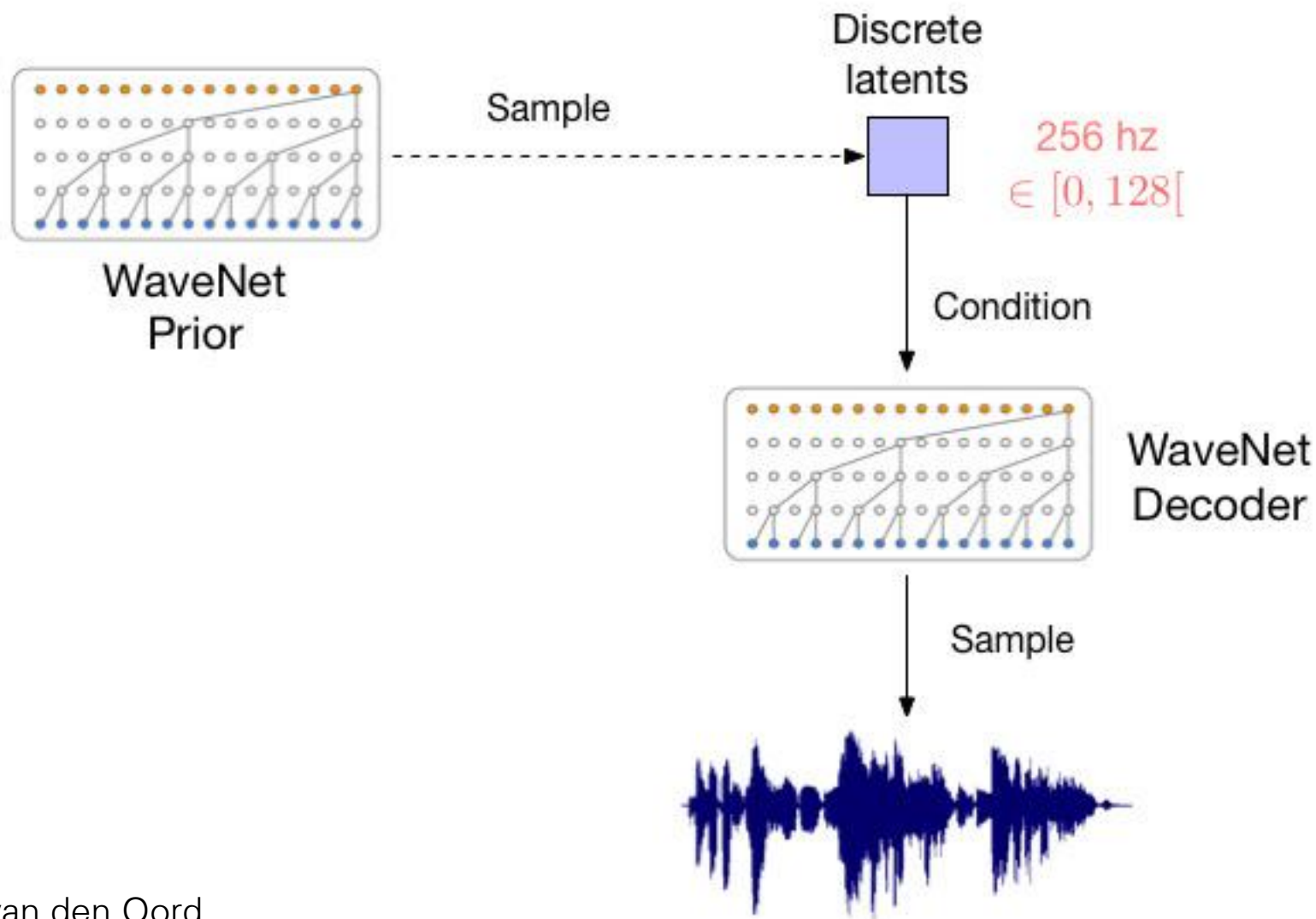


Reconstruction

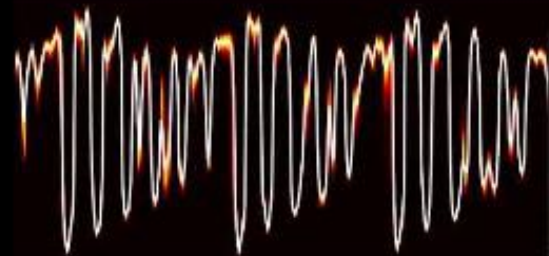
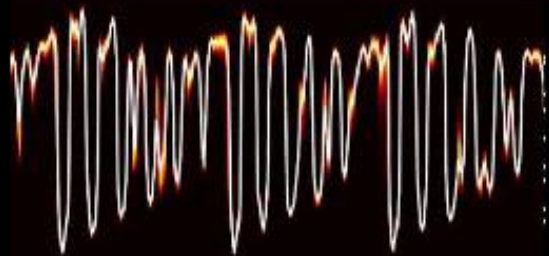
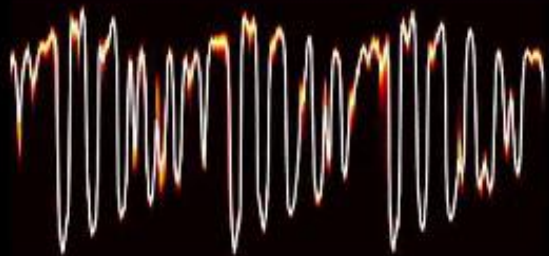
VQ-VAE Reconstructions



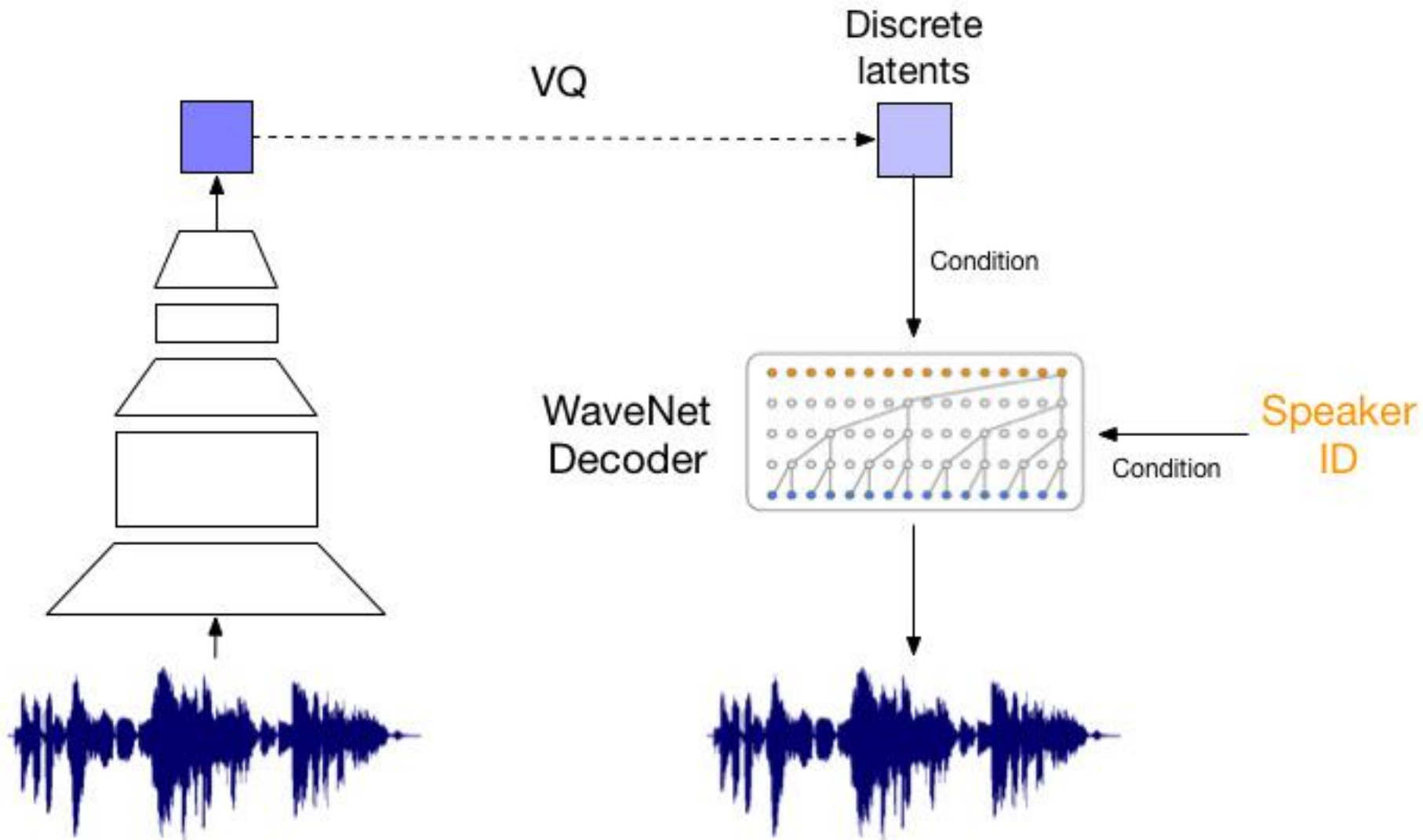
VQ-VAE Sampling from prior



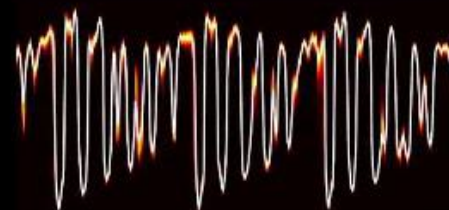
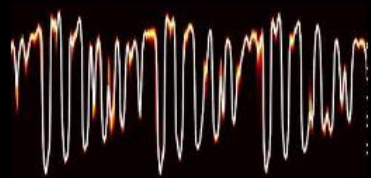
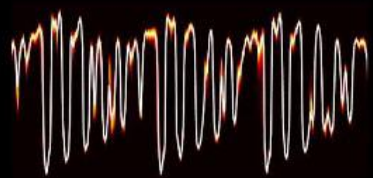
VQ-VAE Samples



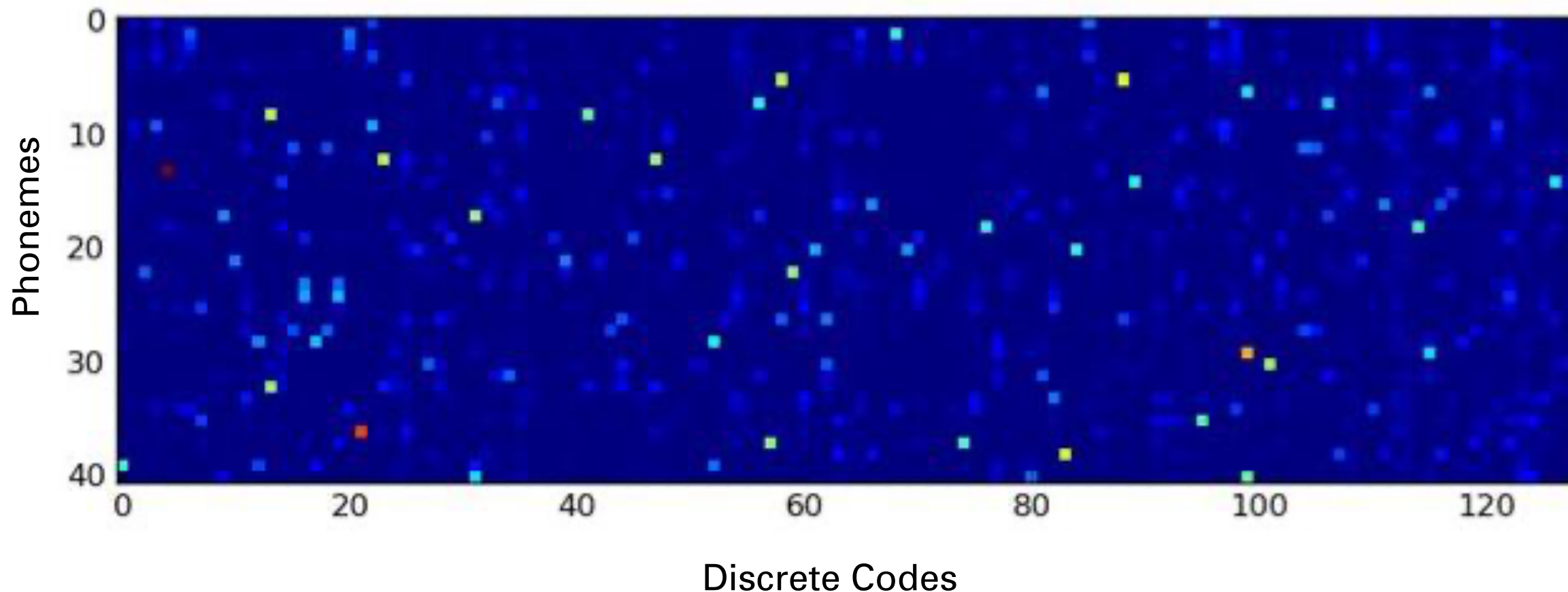
VQ-VAE Voice Style-Transfer



VQ-VAE Voice Style-Transfer Results



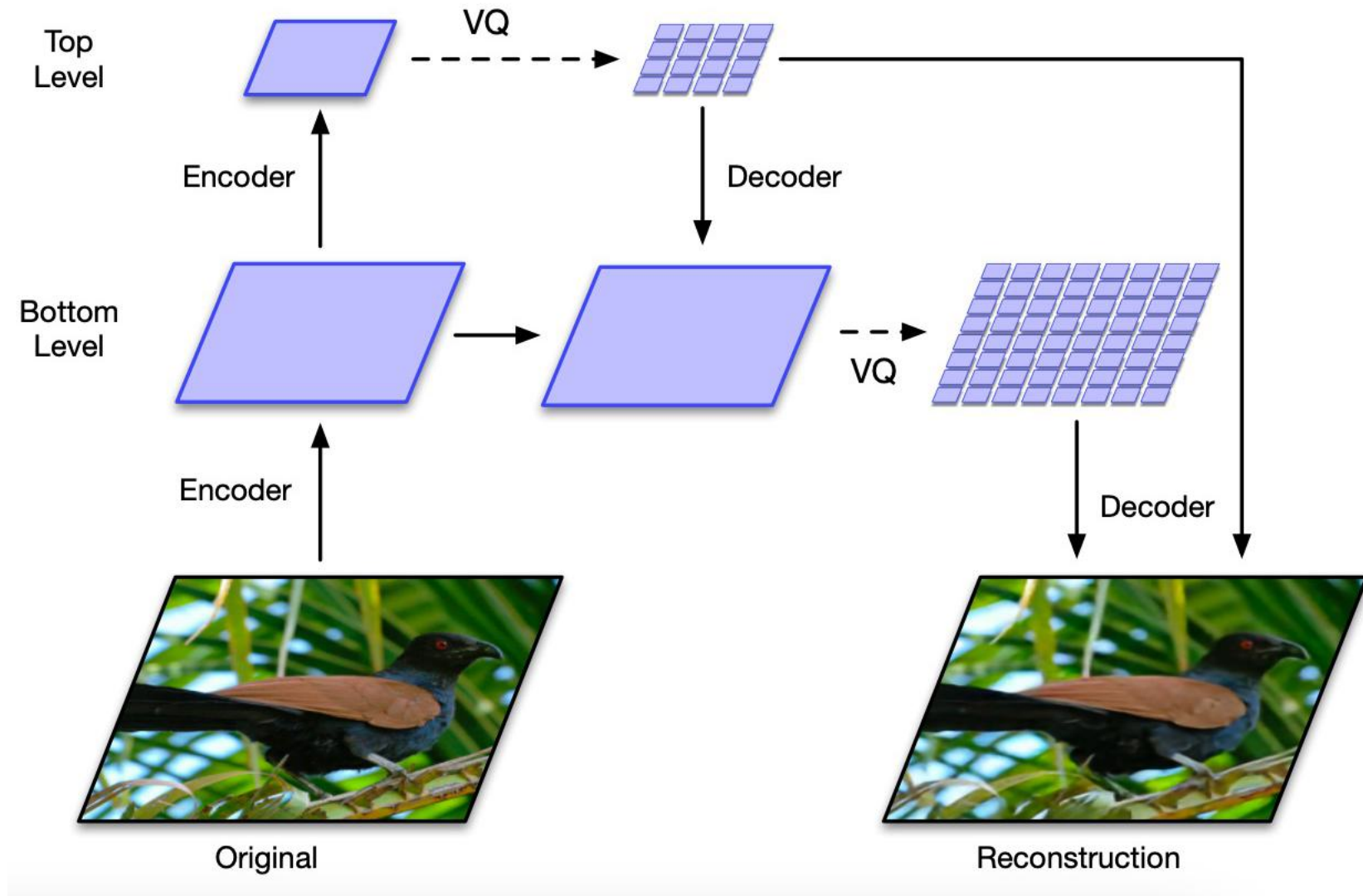
Unsupervised Learning of Phonemes



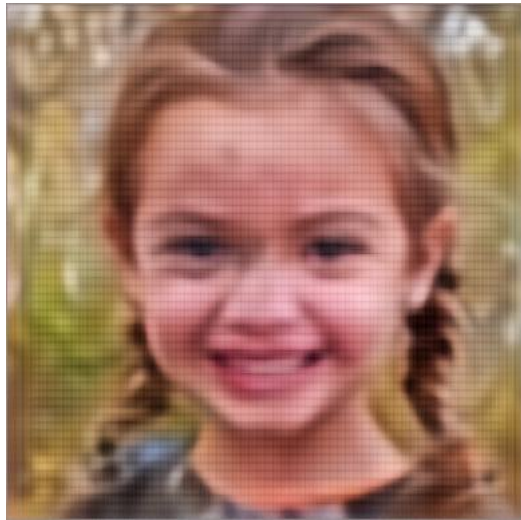
- 41-way classification
- 49.3% accuracy **fully unsupervised**

VQ-VAE-2

- The input 256×256 image is compressed to quantized latent maps of size 64×64 and 32×32
- The decoder reconstructs the image from the two latent maps.



VQ-VAE-2 Reconstructions



h_{top}



$h_{\text{top}}, h_{\text{middle}}$



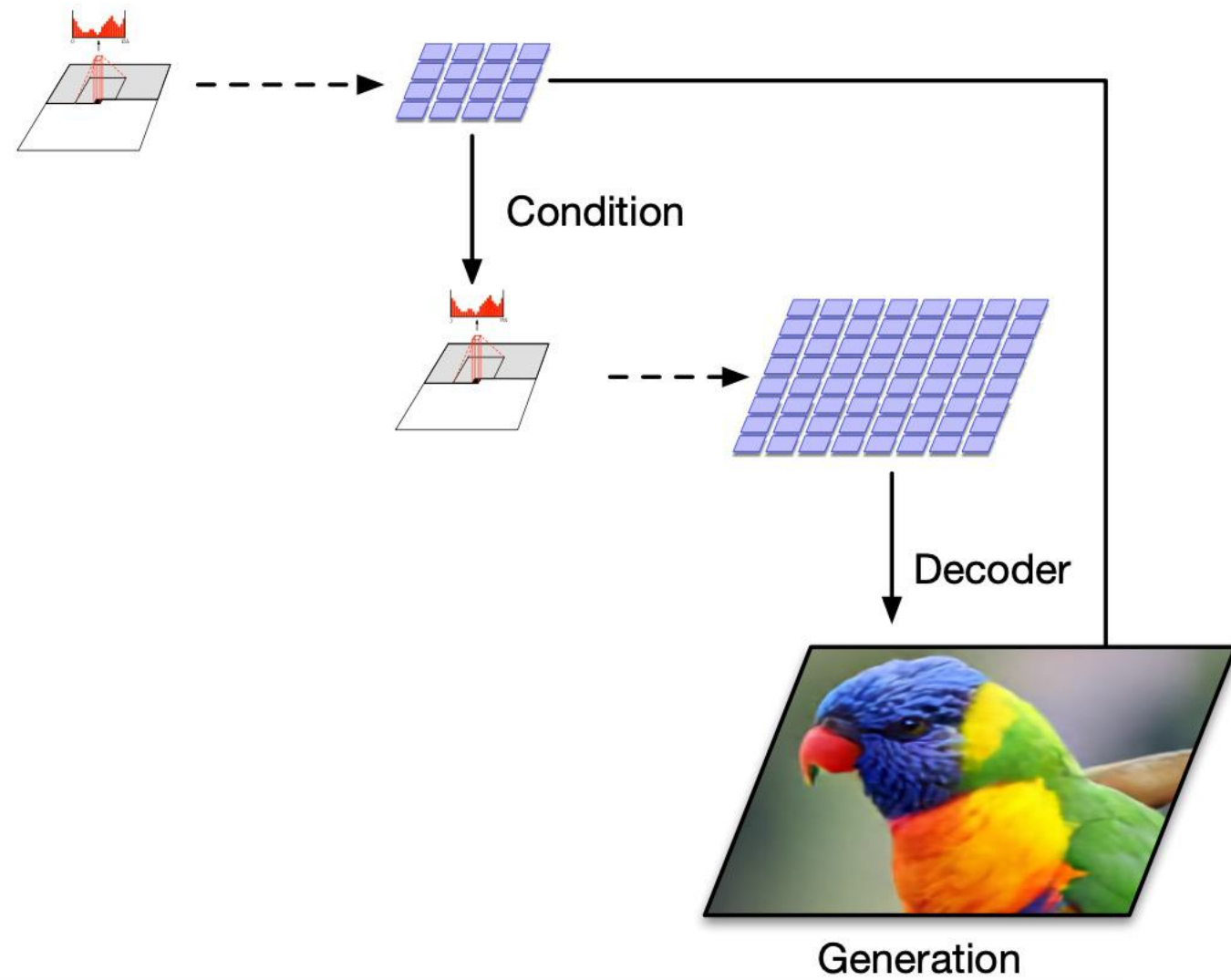
$h_{\text{top}}, h_{\text{middle}}, h_{\text{bottom}}$



Original

- Each latent map adds extra detail to the reconstruction.
- These latent maps are approximately 3072x, 768x, 192x times smaller than the original image, respectively.

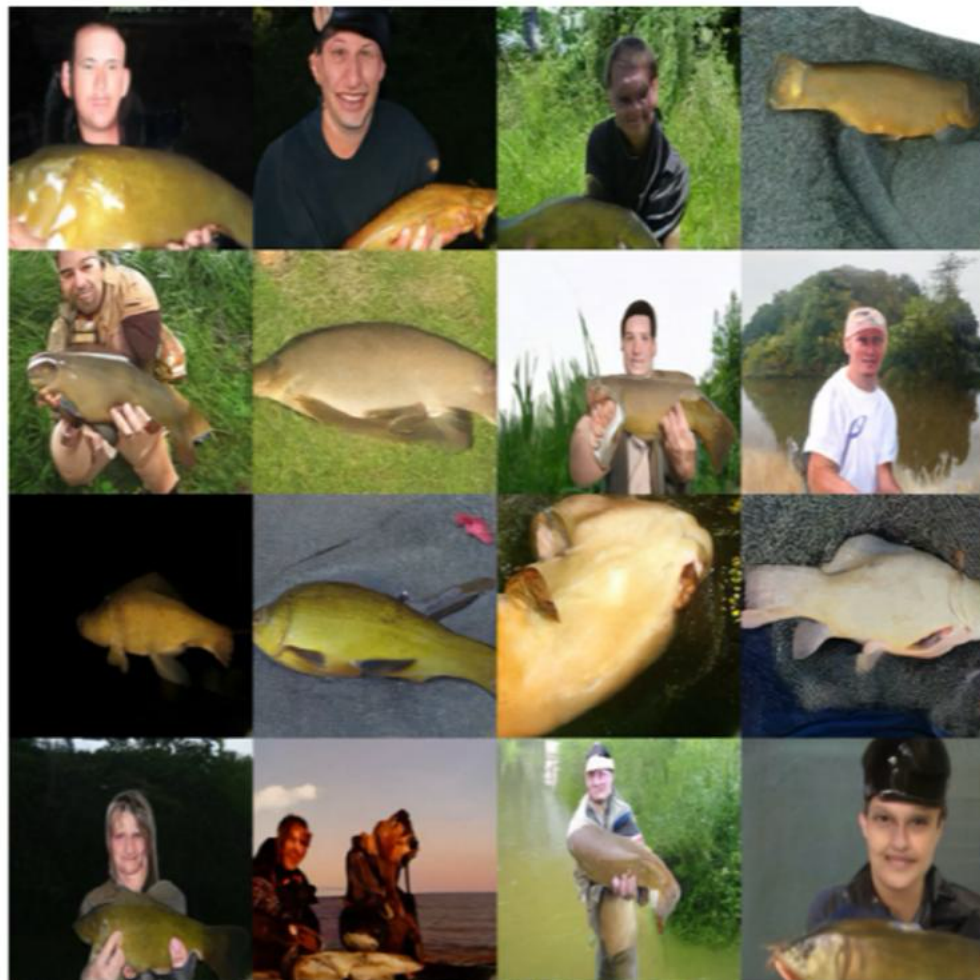
VQ-VAE-2



VQ-VAE-2 FFHQ-2014 Samples



VQ-VAE ImageNet Samples

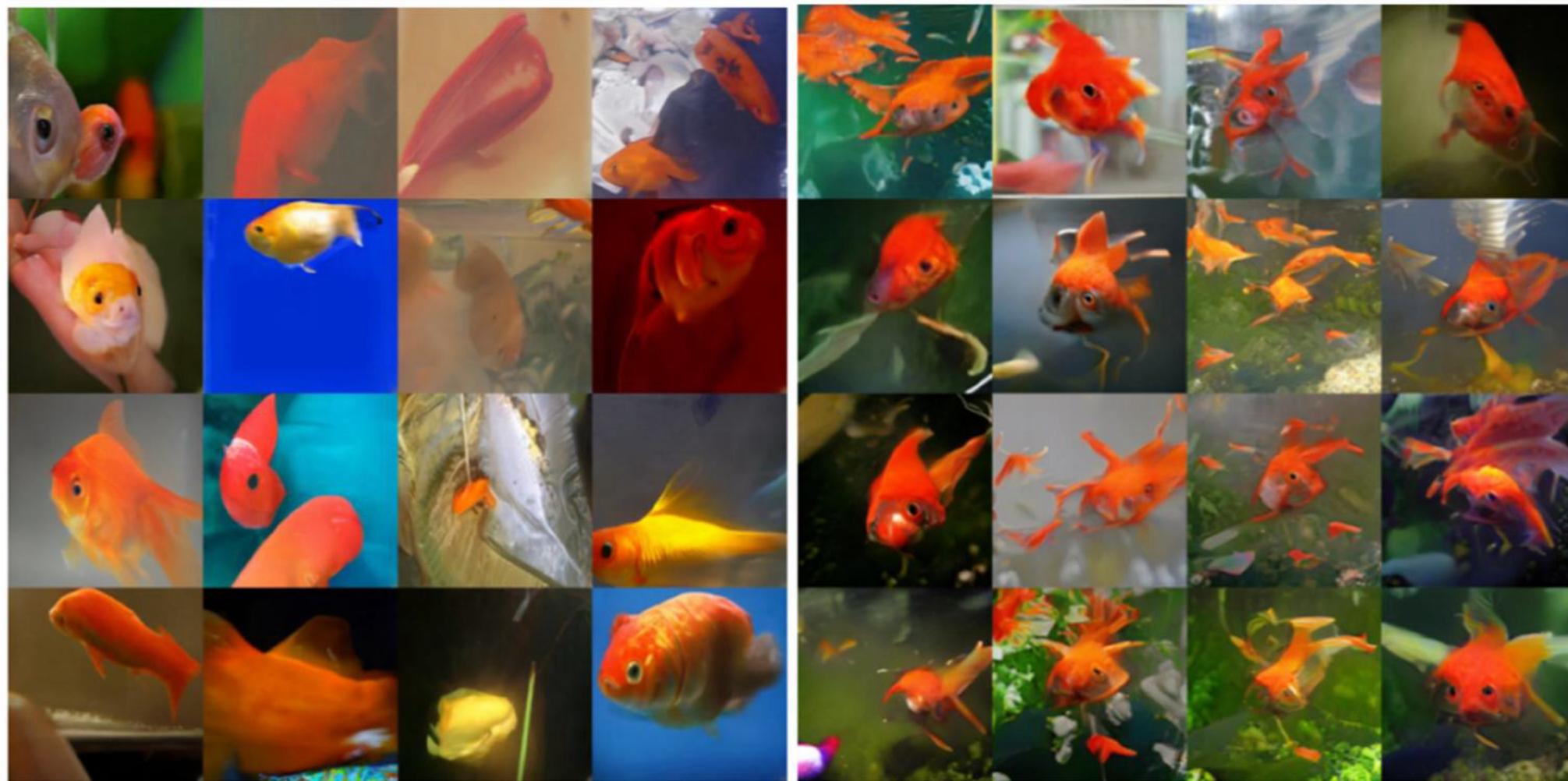


VQ-VAE 2.0



BigGAN Deep

VQ-VAE ImageNet Samples



VQ-VAE 2.0

BigGAN Deep

VQ-VAE ImageNet Samples



VQ-VAE 2.0

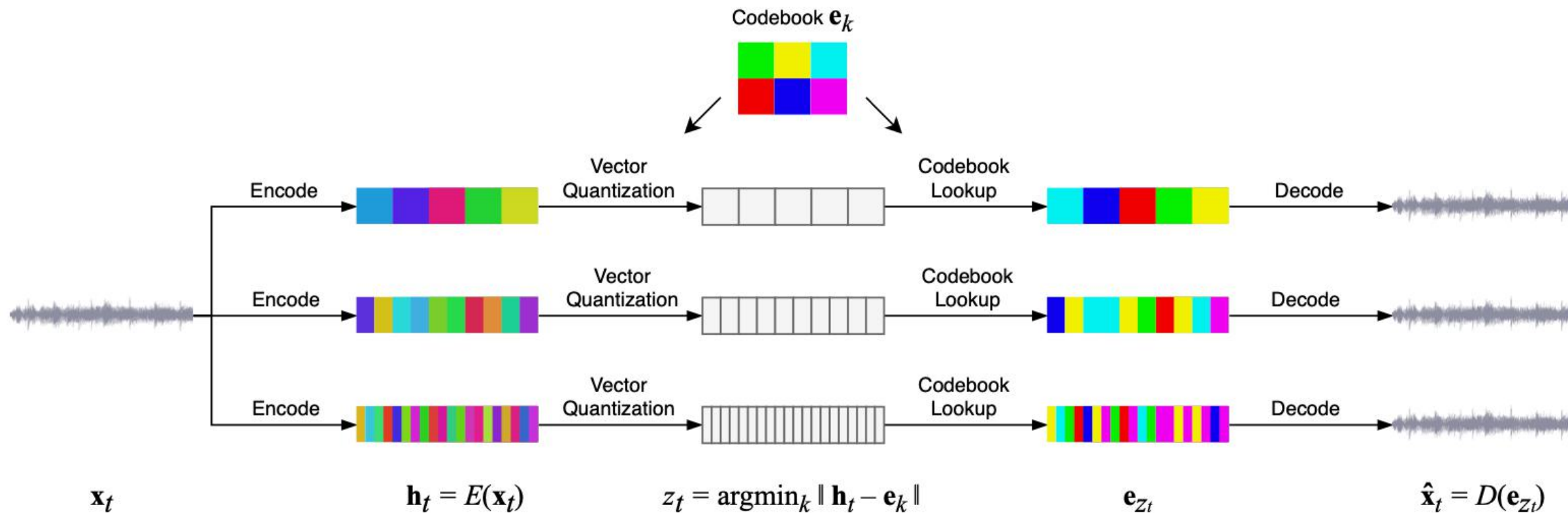
BigGAN Deep

VQ-VAE-2 Quantitative Evaluation

- The VQ-VAE-2 paper reports a classification accuracy score (CAS) for class-conditional image generation.
- Generate image-class pairs from the generative model trained on the ImageNet training data.
- Train an image classifier from the generated pairs and measure its accuracy on the ImageNet test set.

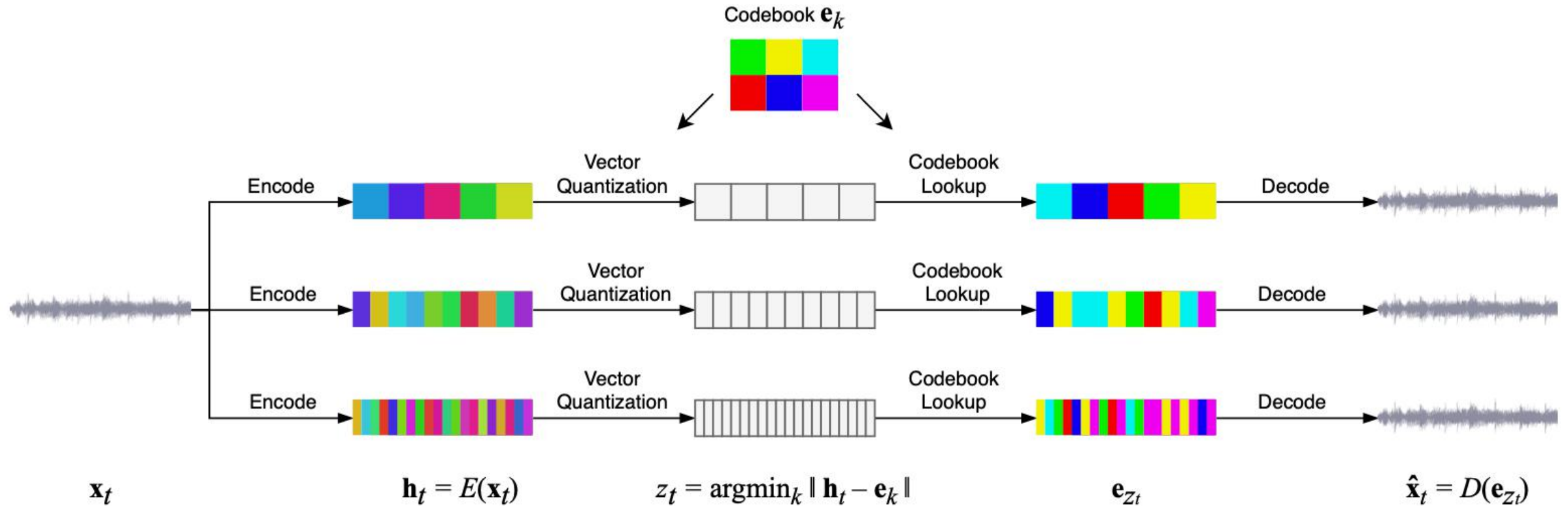
	Top-1 Accuracy	Top-5 Accuracy
BigGAN deep	42.65	65.92
VQ-VAE	54.83	77.59
VQ-VAE after reconstructing	58.74	80.98
Real data	73.09	91.47

VQ-VAE-2 for Music Generation



- Three separate VQ-VAE models with different temporal resolutions

VQ-VAE-2 for Music Generation



- Three separate VQ-VAE models with different temporal resolutions

Jukebox

We're introducing Jukebox, a neural net that generates music, including rudimentary singing, as raw audio in a variety of genres and artist styles. We're releasing the model weights and code, along with a tool to explore the generated samples.

[📄 READ PAPER](#)[🔗 VIEW CODE](#)

<https://openai.com/blog/jukebox/>

April 30, 2020

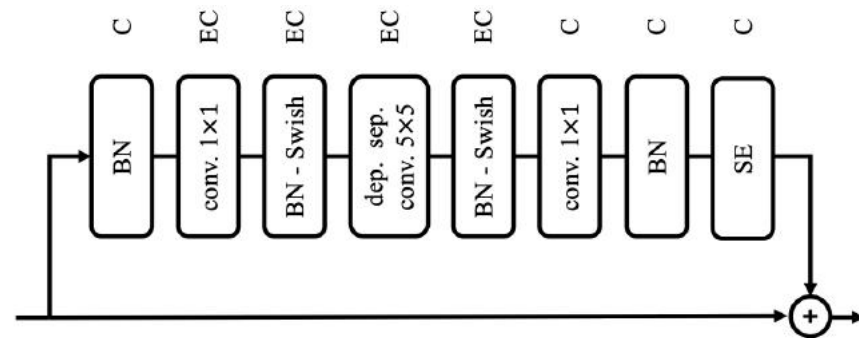
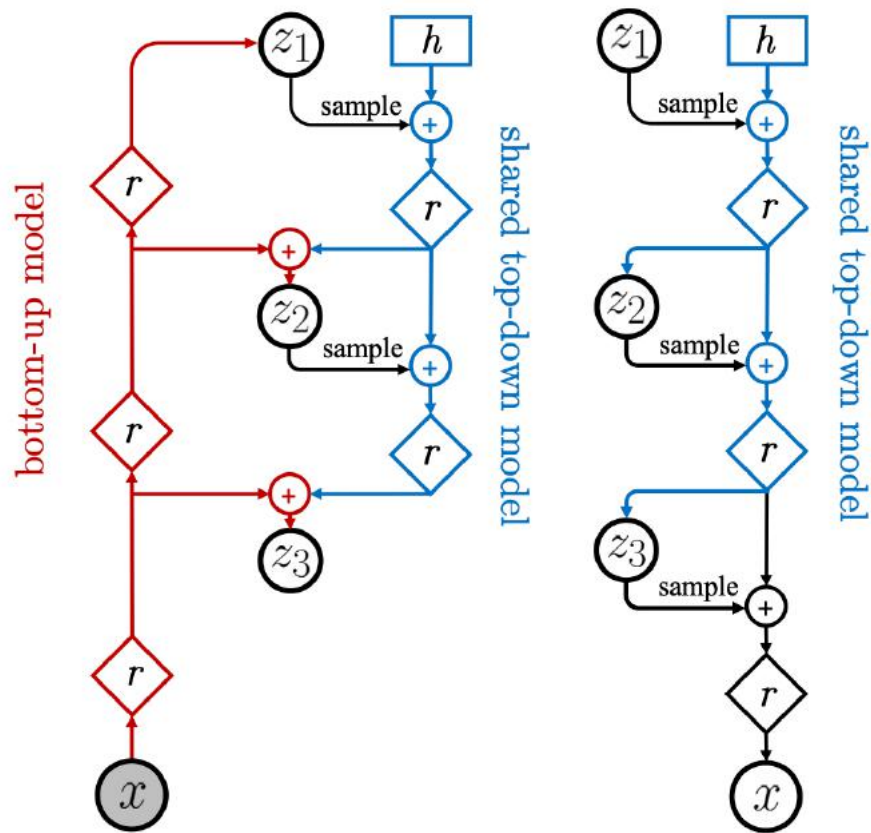
12 minute read, 10 day listen



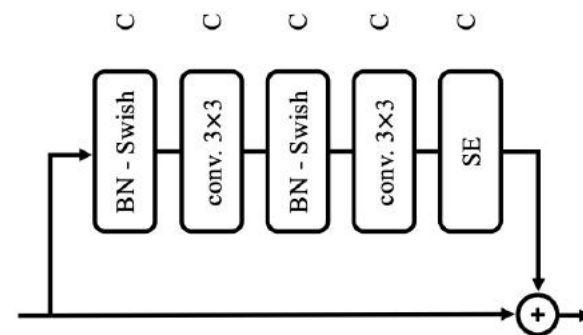
Lecture overview

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

NVAE



(a) Residual Cell for NVAE Generative Model

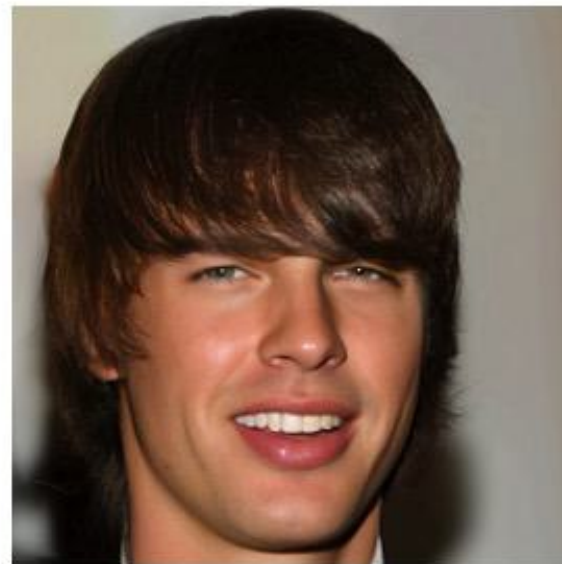


(b) Residual Cell for NVAE Encoder

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

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

NVAE – Experiments



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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

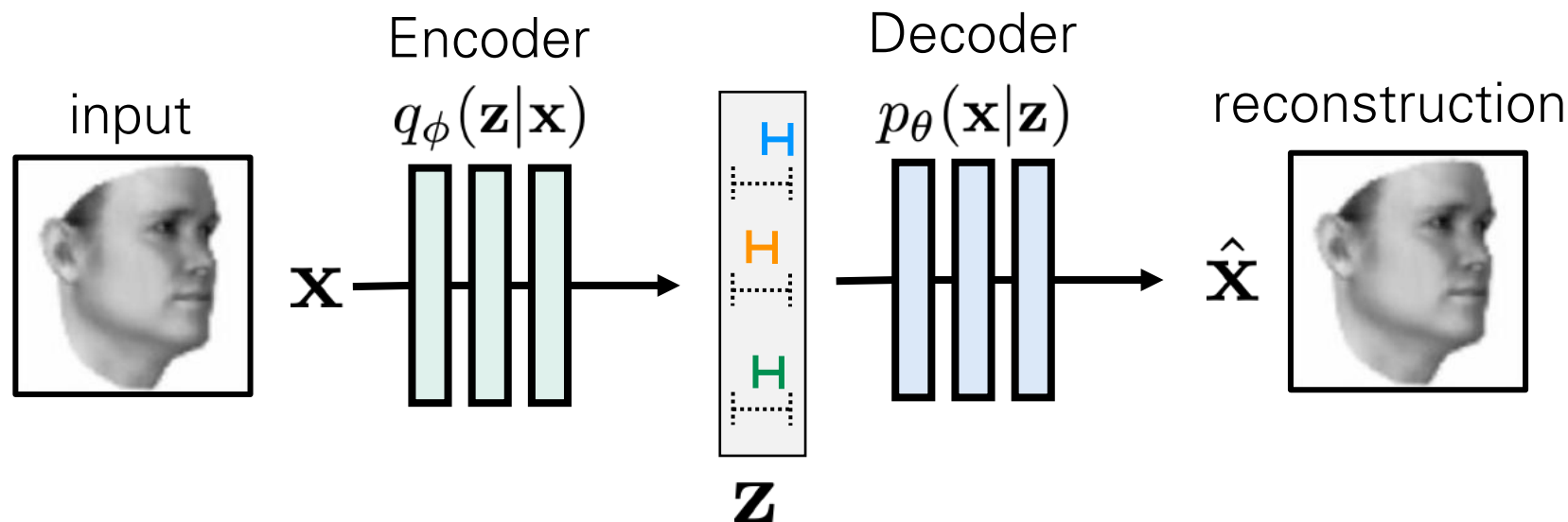
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 - **Disentanglement: β -VAE**

β -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 β -VAE



Capacity constraint

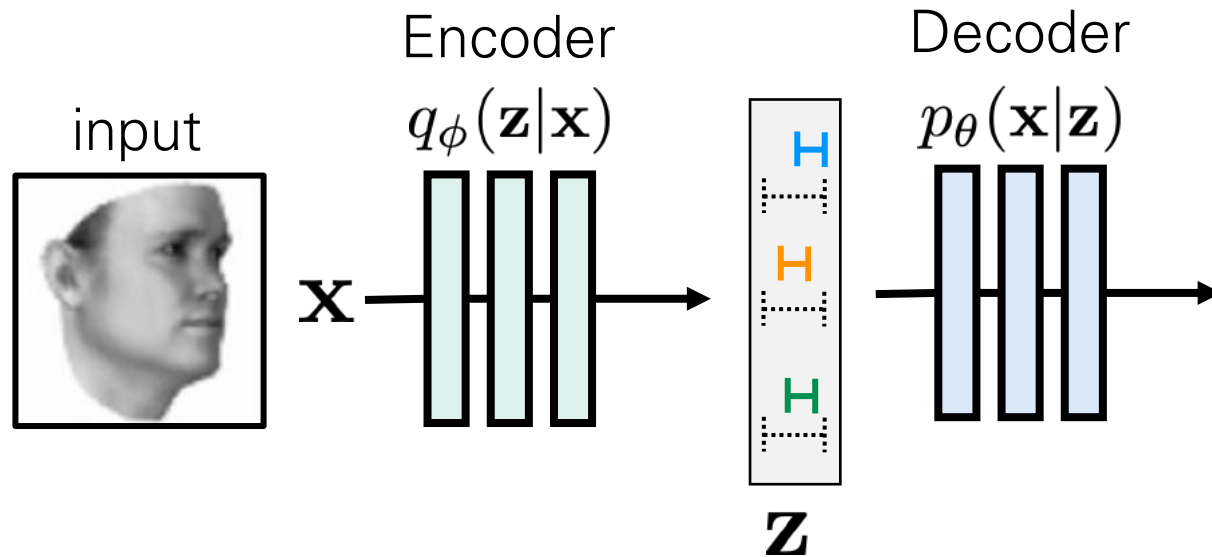
$$\mathcal{L}_{\beta\text{-VAE}}(\theta, \phi) = \underbrace{\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [\log p_\theta(\mathbf{x}|\mathbf{z})]}_{\text{Reconstruction cost}} - \beta \text{KL} [q_\phi(\mathbf{z}|\mathbf{x}) || p(\mathbf{z})]$$

Reconstruction cost

Disentangled Representations with β -VAE

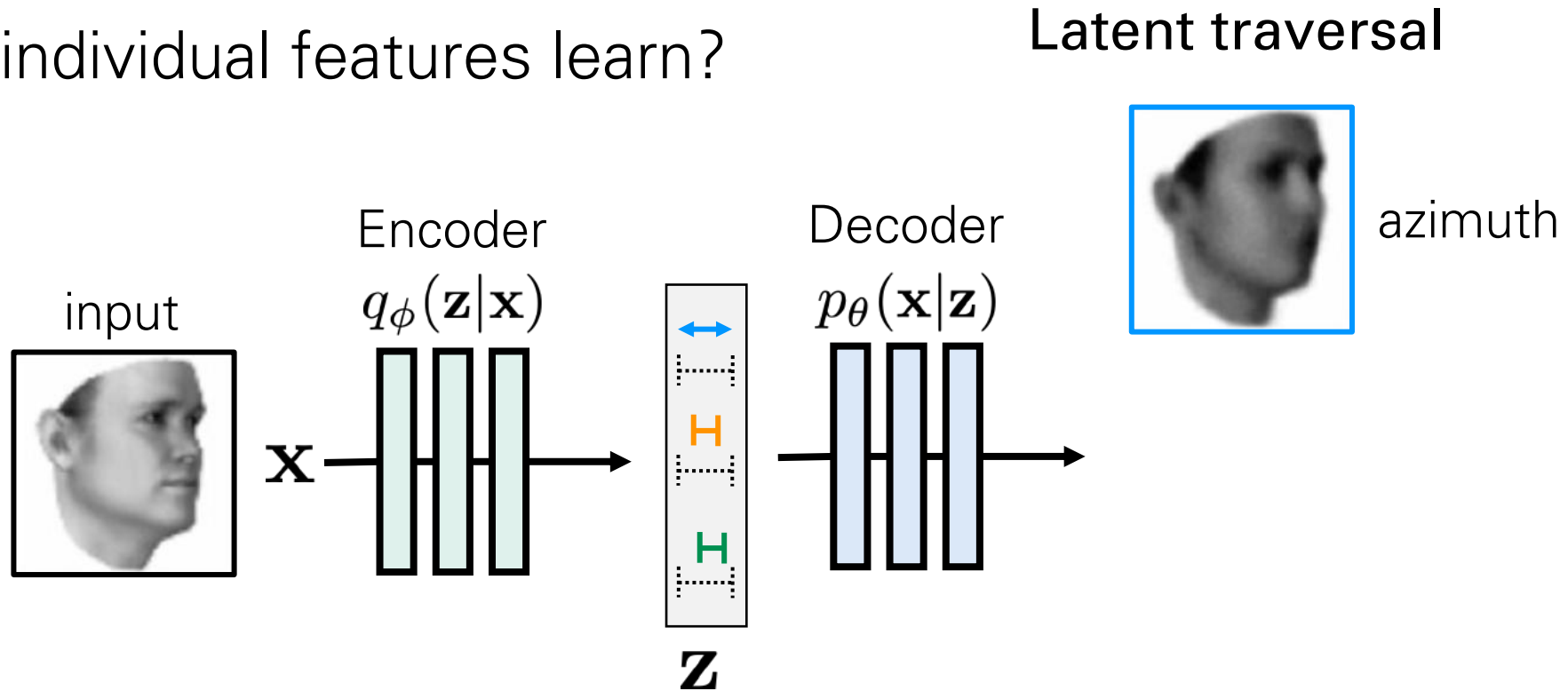
- What do individual features learn?

Latent traversal



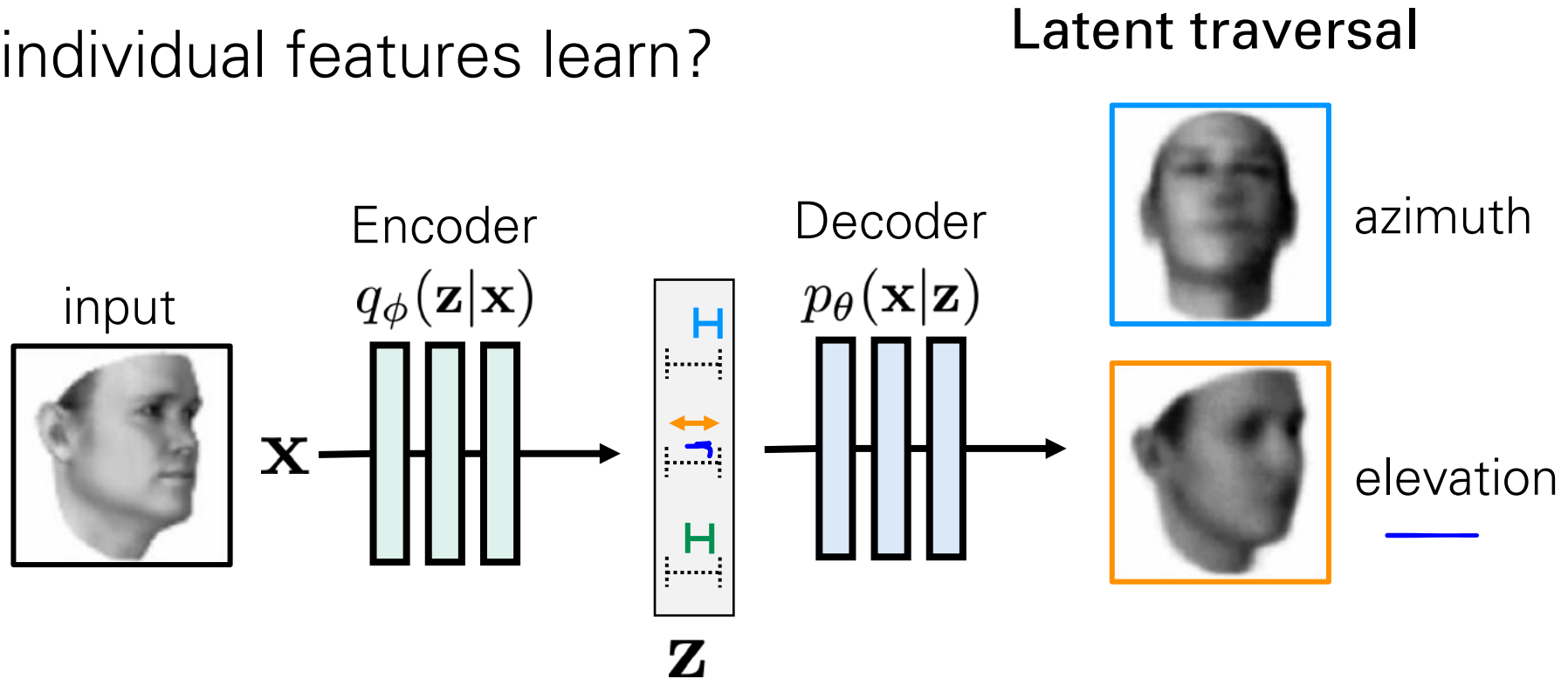
Disentangled Representations with β -VAE

- What do individual features learn?



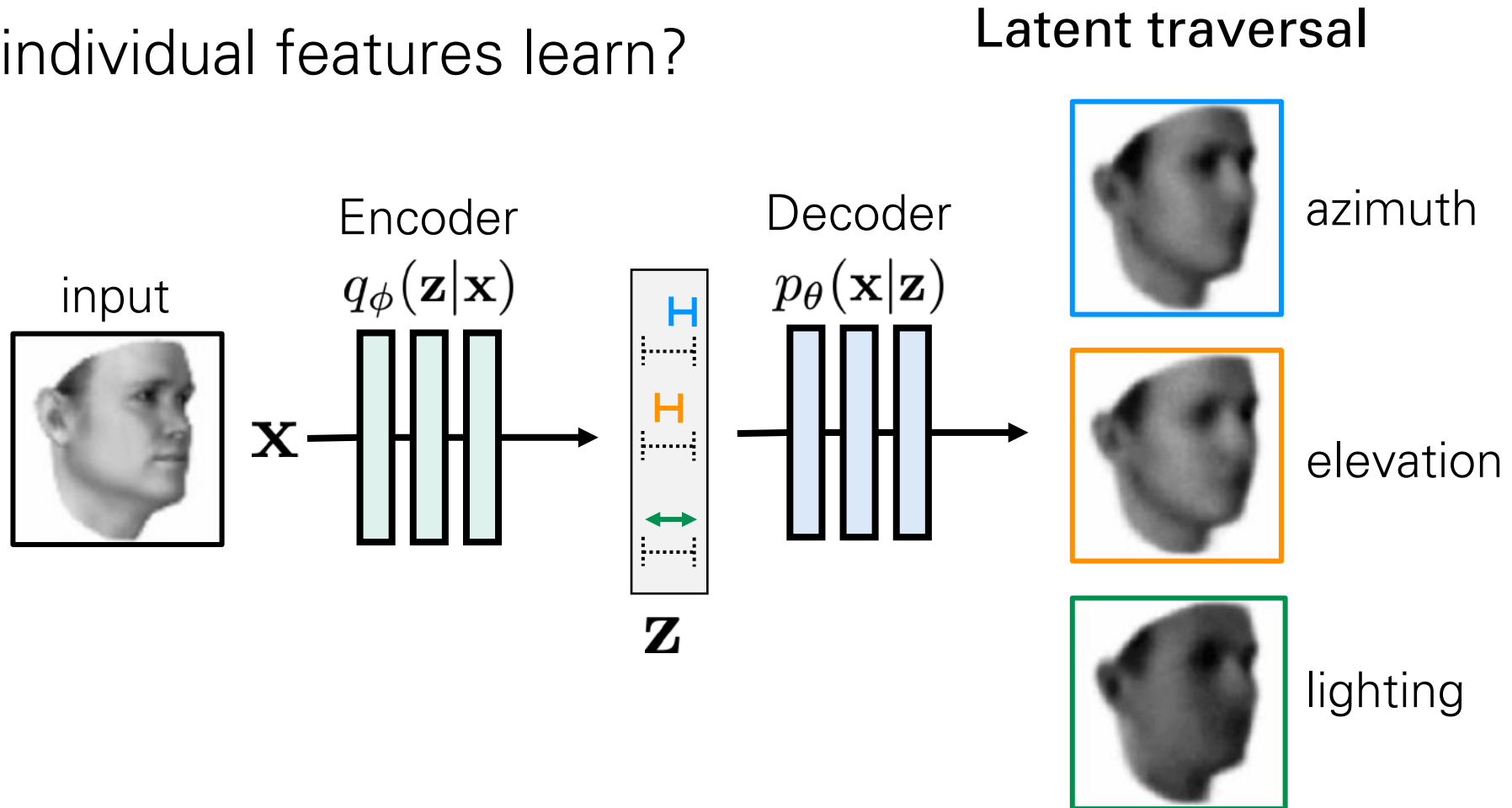
Disentangled Representations with β -VAE

- What do individual features learn?



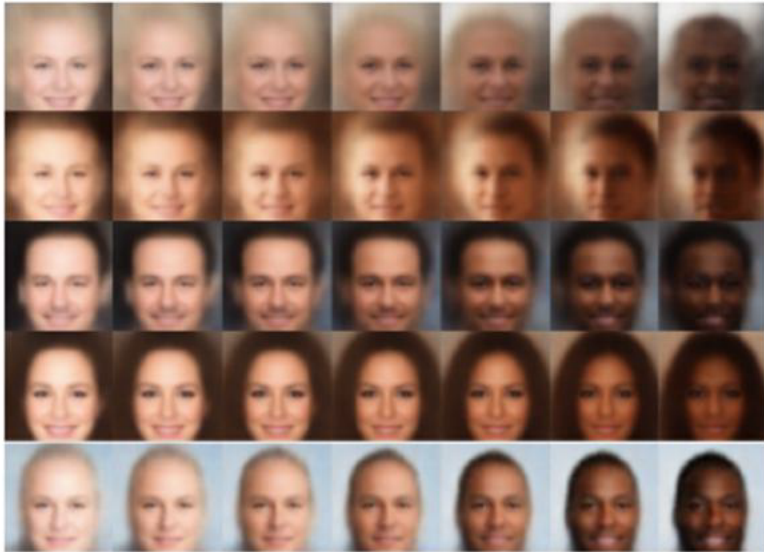
Disentangled Representations with β -VAE

- What do individual features learn?



β -VAE – Experiments

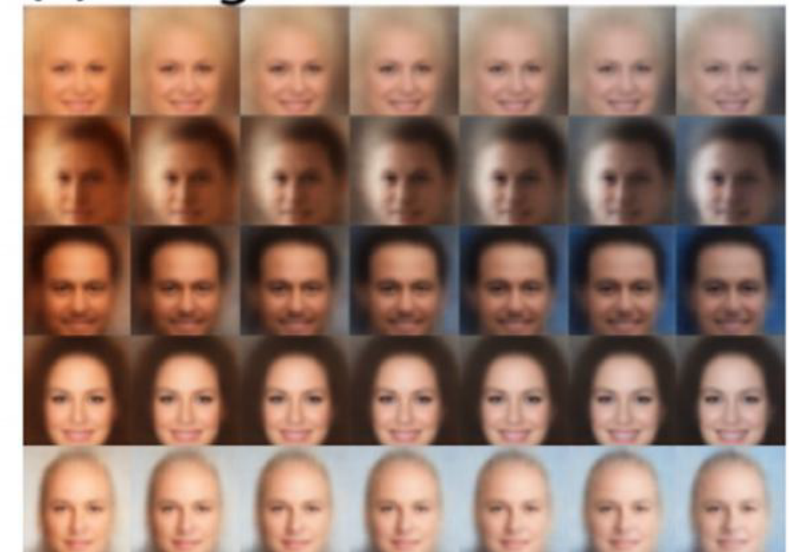
(a) Skin colour



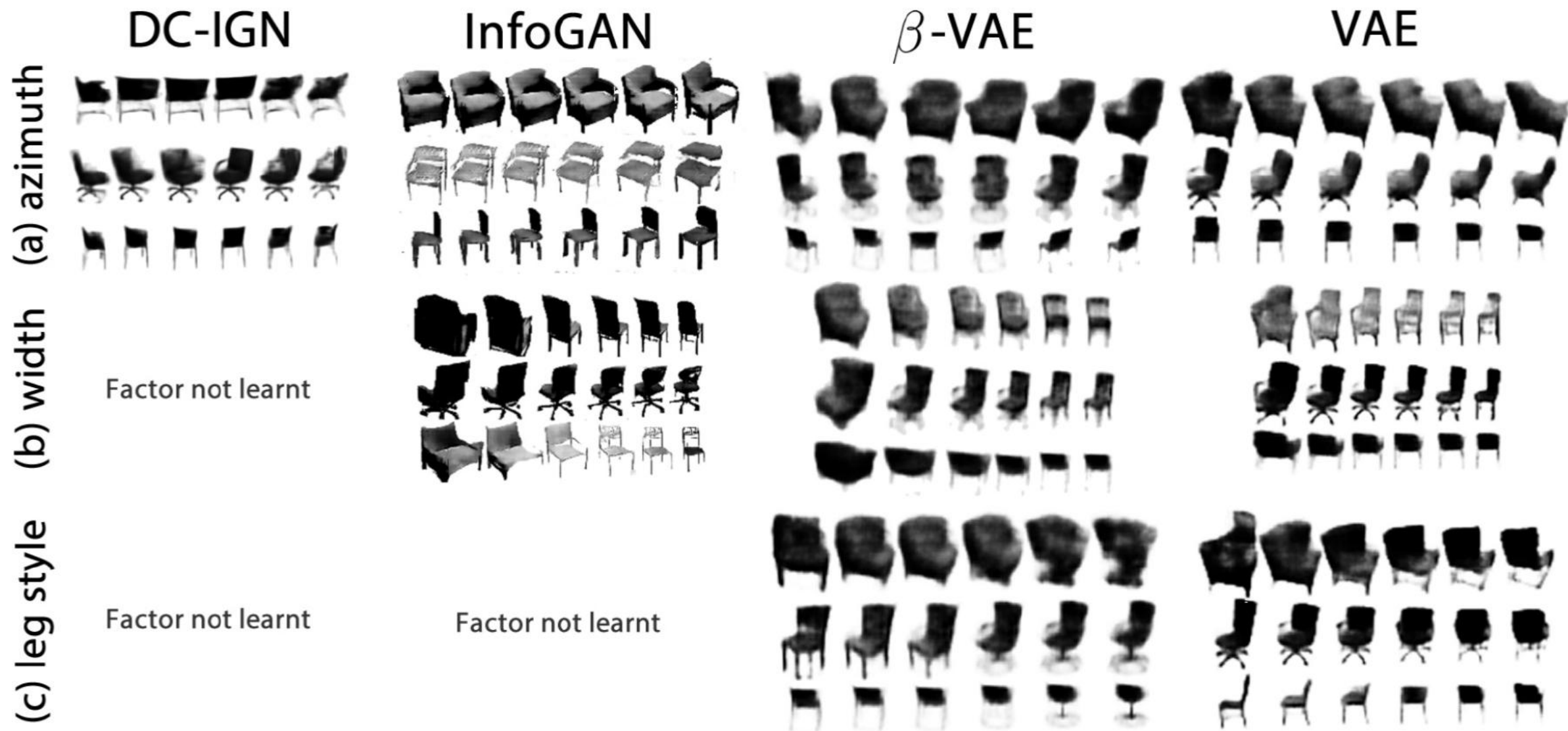
(b) Age/gender



(c) Image saturation



β -VAE – Experiments



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**Next lecture:
Generative Adversarial
Networks**