Deep Unsupervised Learning pt 2

Unsupervised learning goals

1) Generative models

Autoregressive models

n-gram LM

PixCNN

VAE

RealNVP

GAN

2) Repr learning models

BERT

Word2Vec

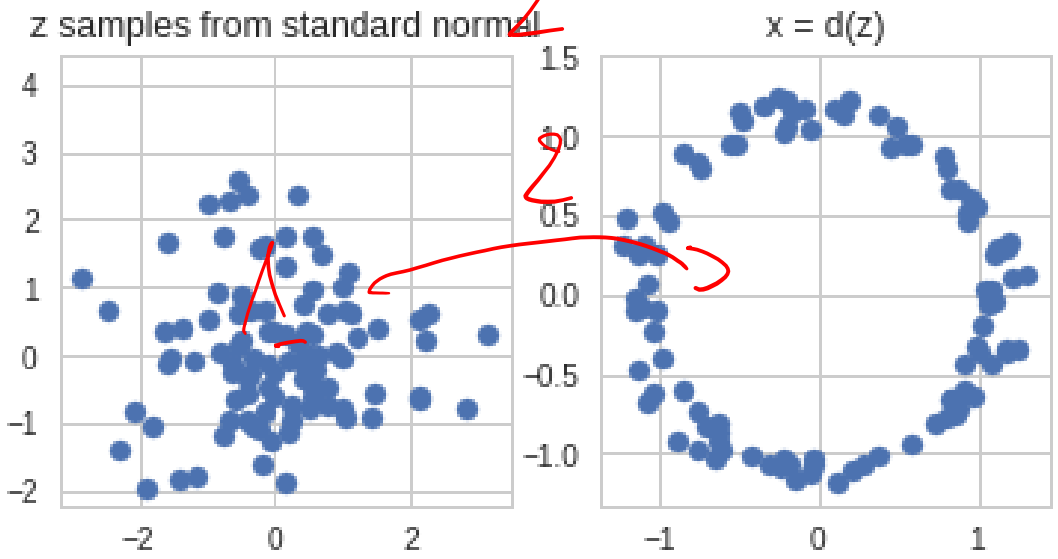
3) Self-supervised learning

VAE

Data Generation with Latent Variables: Intuitions

Intuition: to generate something complicated, do:

1. Sample something simple $z \sim \mathcal{N}(0,1)$
2. Transform it $x = \frac{z}{10} + \frac{z}{\|z\|}$



Latent variable model

Assume a 2 stage data generation process:

$z \sim \mathcal{N}(0,1)$ prior $p(z)$ assumed to be simple

$x \sim p(x|z)$ complicated transformation implemented with a neural network

How to train this model?

$$\log p(x) = \log \sum_z p(x|z)p(z)$$

$p(x,z)$

This is often intractable!

EM to the rescue!

Want:

$$\max \log p_\Theta(x) = \max \log \sum_z p_\Theta(x, z) = \max \log \sum_z p_\Theta(x|z) p_\Theta(z)$$

EM to the rescue!

Want:

$$\max \log p_\Theta(x) = \max \log \sum_z p_\Theta(x,z) = \max \log \sum_z p_\Theta(x|z)p_\Theta(z)$$

Iterate:

E-step: find $q_\Phi(z|x) = p_\Theta(z|x) = \frac{p_\theta(x,z)}{p_\theta(x)} = \frac{p_\theta(x|z)\, p_\theta(z)}{\sum_z p_\theta(x|z)\, p_\theta(z)}$

EM to the rescue!

Want:

$$\max \log p_\Theta(x) = \max \log \sum_z p_\Theta(x,z) = \max \log \sum_z p_\Theta(x|z)p_\Theta(z)$$

Iterate:

E-step: find $q_\Phi(z|x) = p_\Theta(z|x)$

M-step: $\max_\Theta \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z,x)}{q_\Phi(z|x)}\right)\right]$ (keep Φ fixed)

$\max_\theta \sum_i q_\phi(z|x) \log p_\theta(x|z)p_\theta(z)$

no sum under log !!

EASY !

EM to the rescue!

Want:

$$\max \log p_\Theta(x) = \max \log \sum_z p_\Theta(x,z) = \max \log \sum_z p_\Theta(x|z)p_\Theta(z)$$

Iterate:

E-step: find $q_\Phi(z|x) = p_\Theta(z|x)$

M-step: $\max_\Theta \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z,x)}{q_\Phi(z|x)}\right)\right]$ (keep Φ fixed)

Why?

$$\log p(x) = KL\big(q_\Phi(z|x) \,\|\, p_\Theta(z|x)\big) + \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z,x)}{q_\Phi(z|x)}\right)\right]$$

Proof

$$KL\left(q_\Phi(z|x) \parallel p_\Theta(z|x)\right) + \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z,x)}{q_\Phi(z|x)}\right)\right] =$$

$$= \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\frac{q_\Phi(z|x)}{p_\Theta(z|x)}\right] + \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z,x)}{q_\Phi(z|x)}\right)\right]$$

$$= \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\frac{q_\Phi(z|x)}{p_\Theta(z|x)}\frac{p_\Theta(z|x)p_\Theta(x)}{q_\Phi(z|x)}\right]$$

$$= \mathbb{E}_{z\sim q_\Phi(z|x)}\log p_\Theta(x) = \log p_\Theta(x)$$

ELBO: A lower bound on $\log p(x)$

We have shown that for any $q_\Phi(z|x)$

$$\log p_\Theta(x) = KL\left(q_\Phi(z|x) \| p_\Theta(z|x)\right) + \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z,x)}{q_\Phi(z|x)}\right)\right]$$

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$$\geq \mathbb{E}_{z\sim q_\Phi(z|x)}\left[\log\left(\frac{p_\Theta(z|x)p_\Theta(x)}{q_\Phi(z|x)}\right)\right]$$

$$= \mathbb{E}_{z\sim q_\Phi(z|x)}[\log p_\Theta(x|z)] - KL\left(q_\Phi(z|x) \,\|\, p_\Theta(z)\right)$$

The bound is tight for $p(z|x) = q(z|x)$.

Idea (VAE): Optimize ELBO using gradient techniques jointly over Θ and Φ

ELBO interpretation

ELBO, or evidence lower bound:

$$\log p(x) \geq \mathbb{E}_{z\sim q(z|x)}[\log p(x|z)] - KL\big(q(z|x) \,\|\, p(z)\big)$$

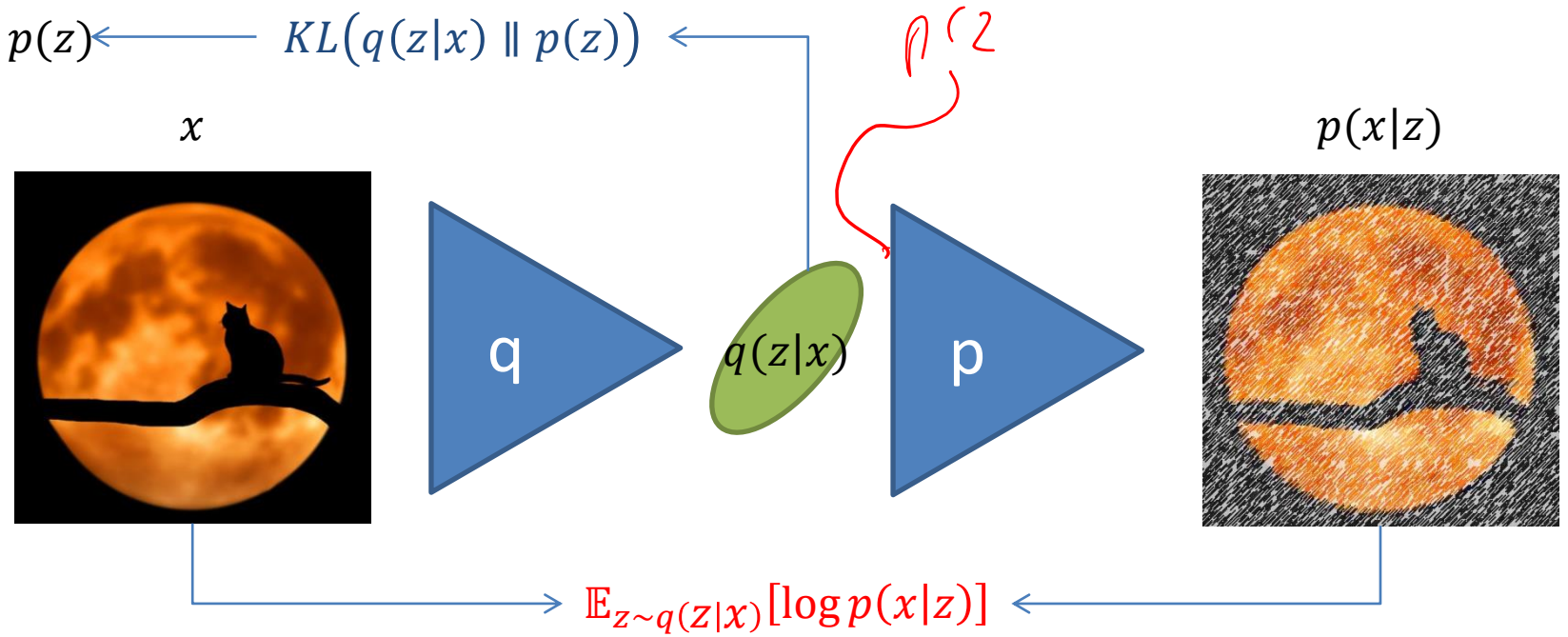
where:

$\mathbb{E}_{z\sim q(z|x)}[\log p(x|z)]$ reconstruction quality:
how many nats we need to reconstruct x,
when someone gives us $q(z|x)$

$KL\big(q(z|x) \,\|\, p(z)\big)$ code transmission cost:
how many nats we transmit about x in $q(z|x)$ rather than $p(z)$

Interpretation: do well at reconstructing x, limiting the amount of information about x encoded in z.

The Variational Autoencoder



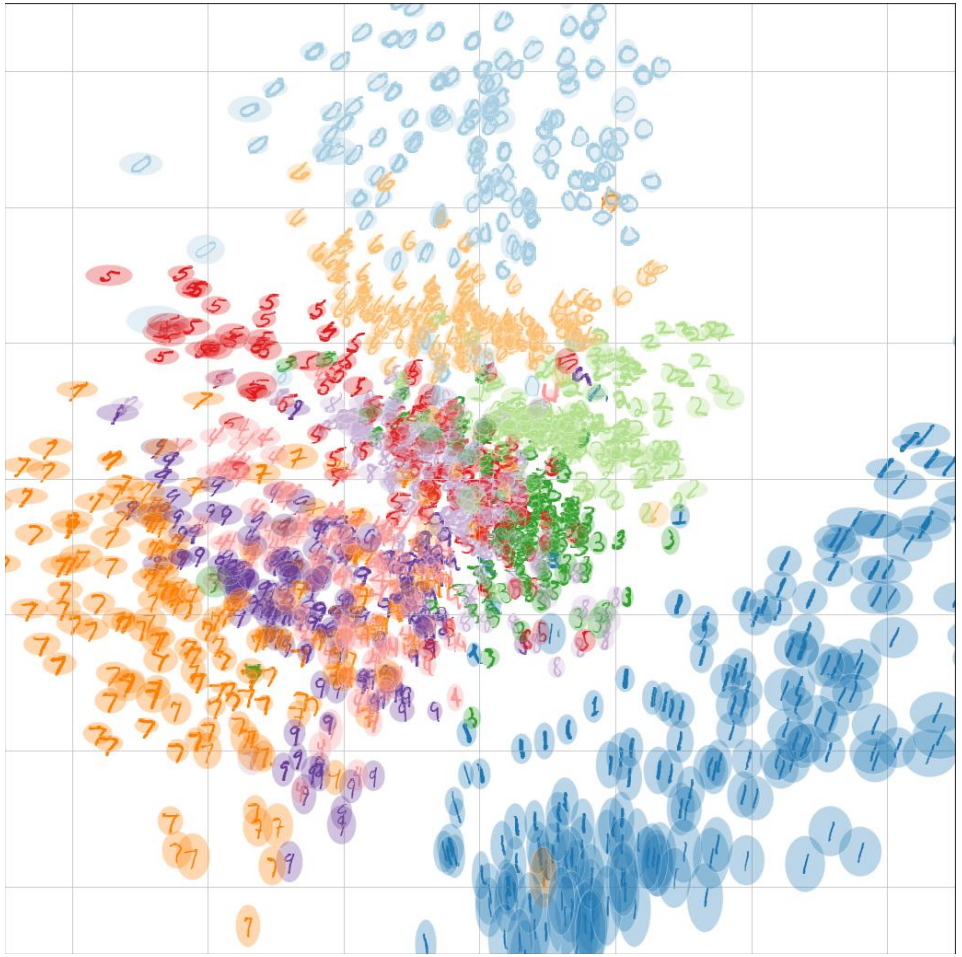
An input x is put through the q network to obtain a distribution over latent code z, $q(z|x)$.

Samples $z_1, \ldots, z_k$ are drawn from $q(z|x)$. They k reconstructions $p(x|z_k)$ are computed using the network p.

VAE is an Information Bottleneck

Each sample is represented as a Gaussian

This discards information (latent representation has low precision)



How to compute the ELBO?

Compute:

$$\log p(x) \geq \mathbb{E}_{z \sim q_\Phi(z|x)}[\log p_\Theta(x|z)] - KL\left(q_\Phi(z|x) p_\Theta(z)\right)$$

$KL\left(q_\Phi(z|x) \parallel p_\Theta(z)\right)$ has closed form for simple $q_\Phi(z|x)$

tractable to compute exactly.

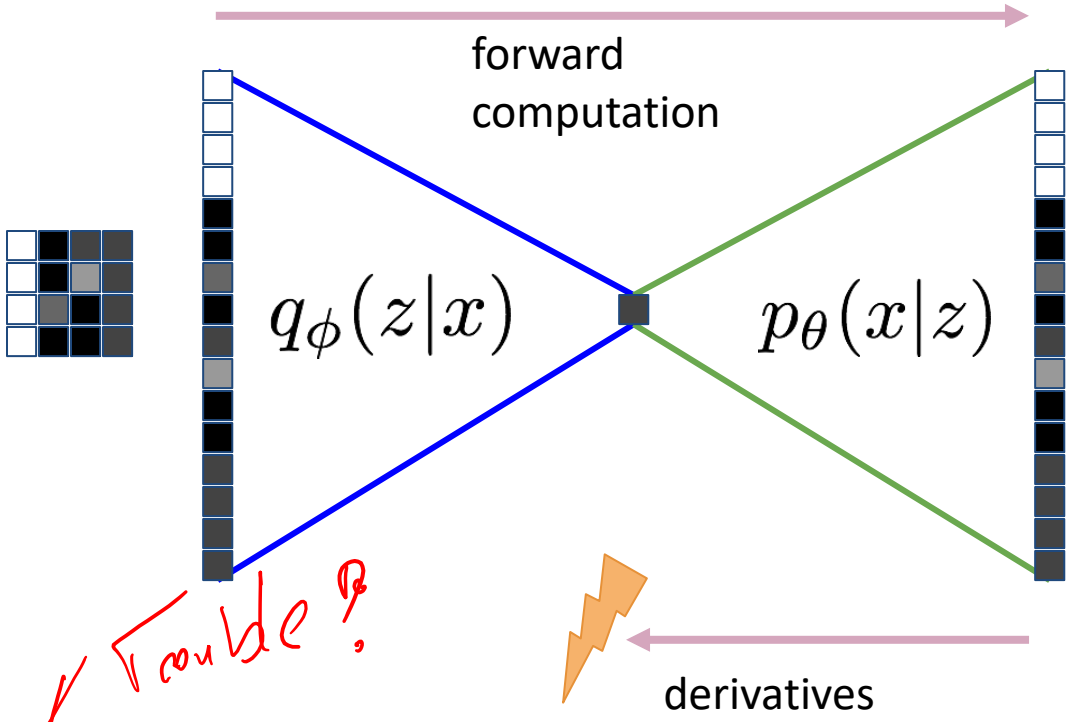
$\mathbb{E}_{z \sim q_\Phi(z|x)}[\log p_\Theta(x|z)]$ can be approximated using Monte Carlo:

$$\mathbb{E}_{z \sim q_\Phi(z|x)}[\log p_\Theta(x|z)] \approx \sum_i \log p_\Theta(x|z_i)$$

Where z_i drawn from $q_\Phi(z|x)$

Monte Carlo samples

How to train a VAE?



- $\log p(x) \geq \mathbb{E}_{z\sim q_\Phi(z|x)}[\log p_\Theta(x|z)] - KL\big(q_\Phi(z|x) \parallel p(z)\big)$
- Forward computation involves drawing samples
- Can't backprop (get $\frac{\partial \log p(x)}{\partial \Phi}$) ☹

Reparameterization exercise

Assume that $q_\Phi(z|x) = \mathcal{N}(\mu_z, \sigma_z)$.

Exercise:
you can sample from $\mathcal{N}(0,1)$

Q: how to draw samples from $\mathcal{N}(\mu_z, \sigma_z)$

Reparameterization exercise

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Exercise:
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Q: how to draw samples from $\mathcal{N}(\mu_z, \sigma_z)$

A:

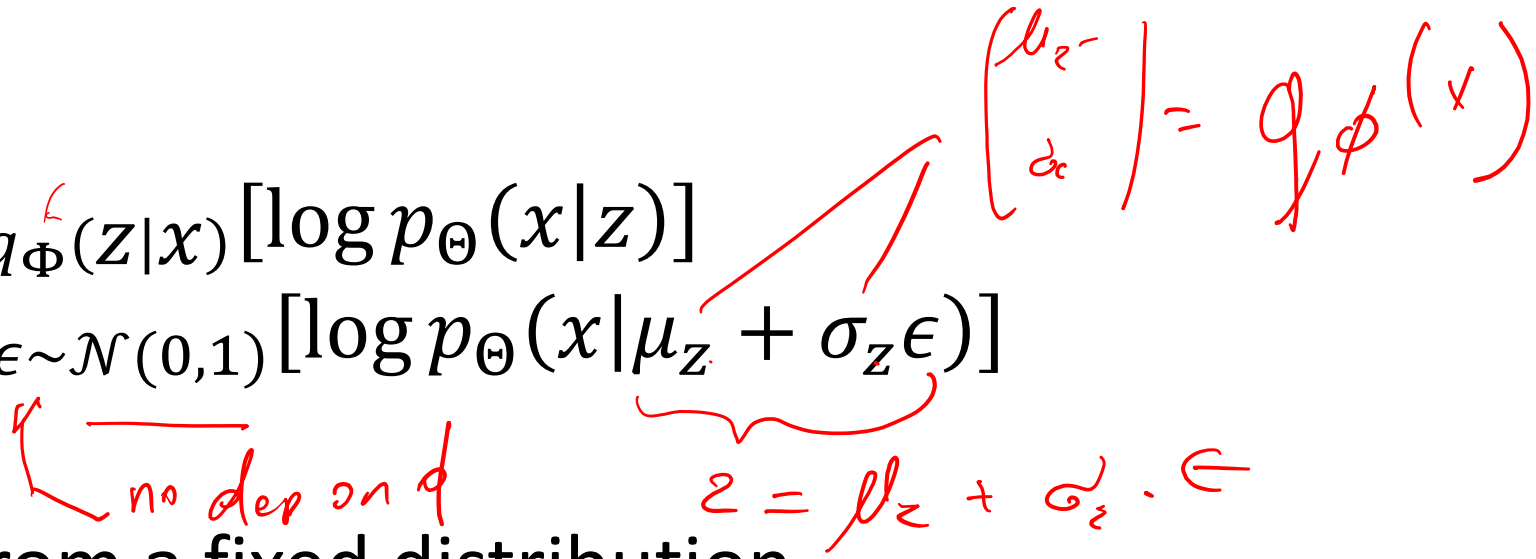
$$\epsilon_i \sim \mathcal{N}(0,1)$$
$$z_i = \mu_z + \sigma_z \epsilon$$

Reparametrization to the rescue

Assume that $q_\Phi(z|x) = \mathcal{N}(\mu_z, \sigma_z)$.

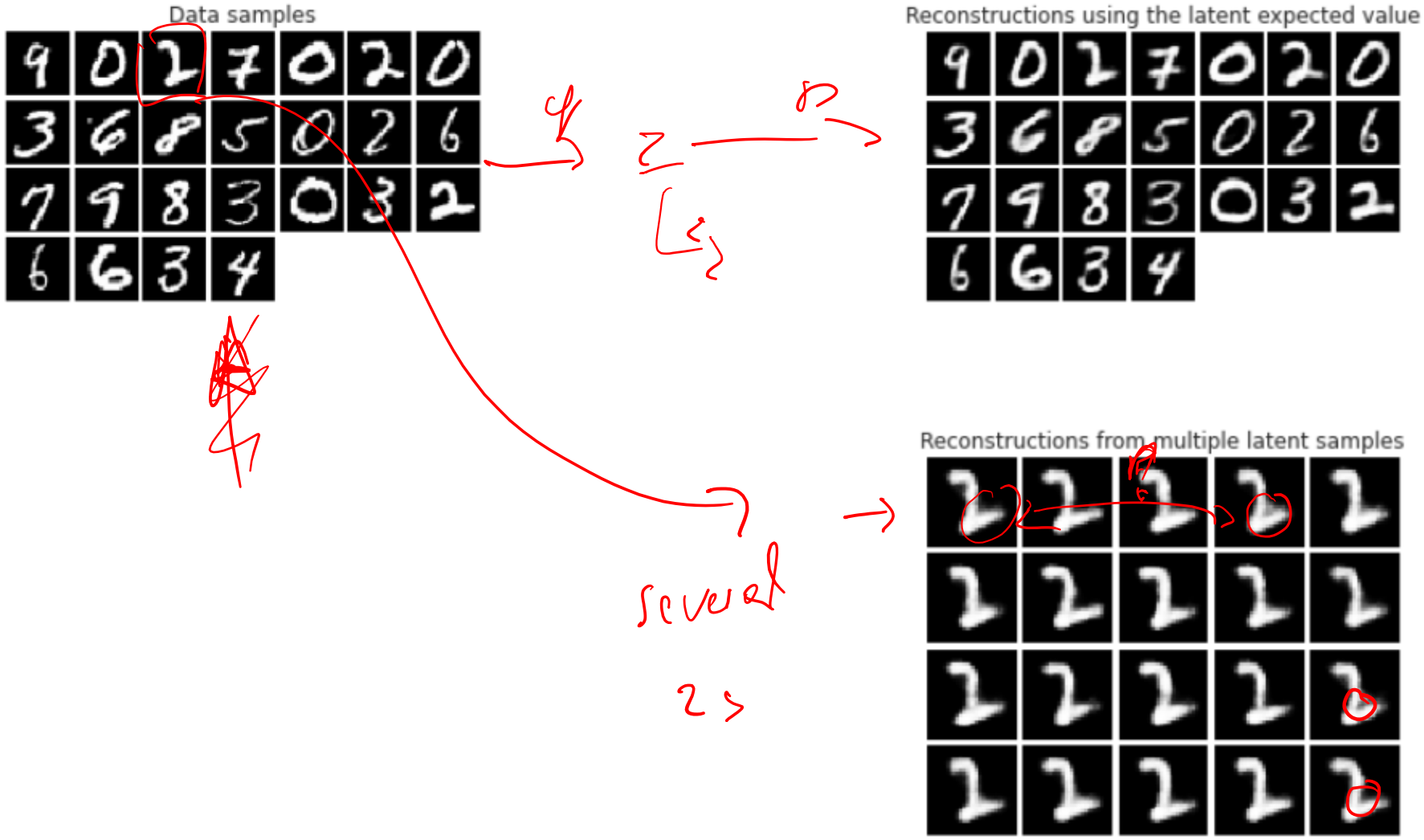
Then:

$$\mathbb{E}_{z\sim q_\Phi(z|x)}[\log p_\Theta(x|z)]$$
$$= \mathbb{E}_{\epsilon\sim\mathcal{N}(0,1)}[\log p_\Theta(x|\mu_z + \sigma_z\epsilon)]$$

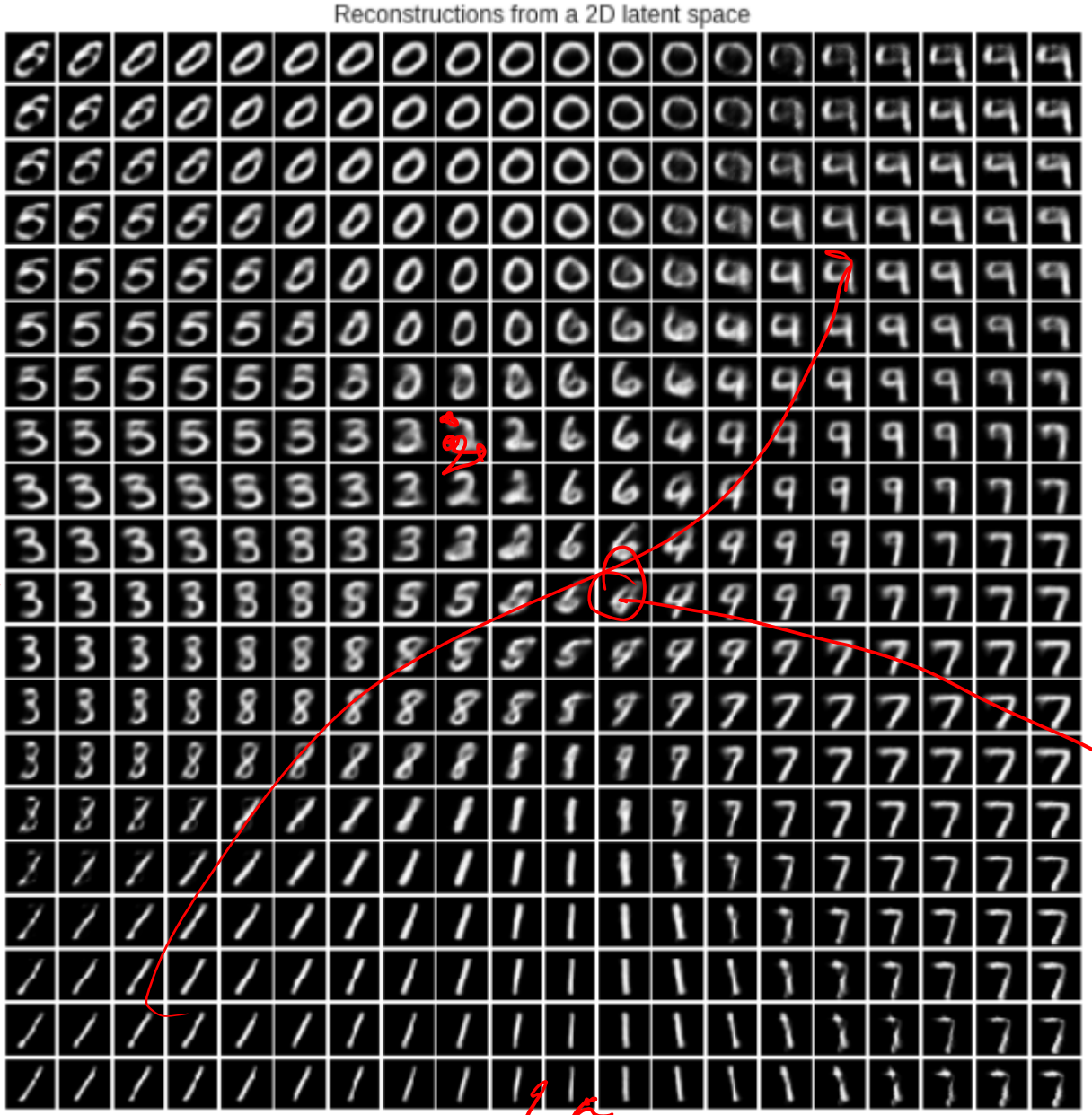


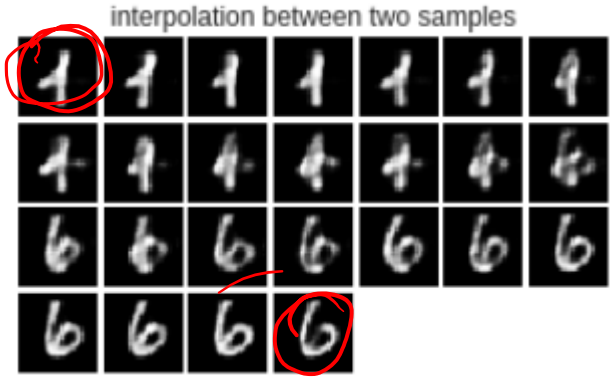
ϵ is drawn from a fixed distribution.
With ϵ given, the computation graph is deterministic -> we can backprop!

VAE in action



VAE in action





VAE in action

Gen samples

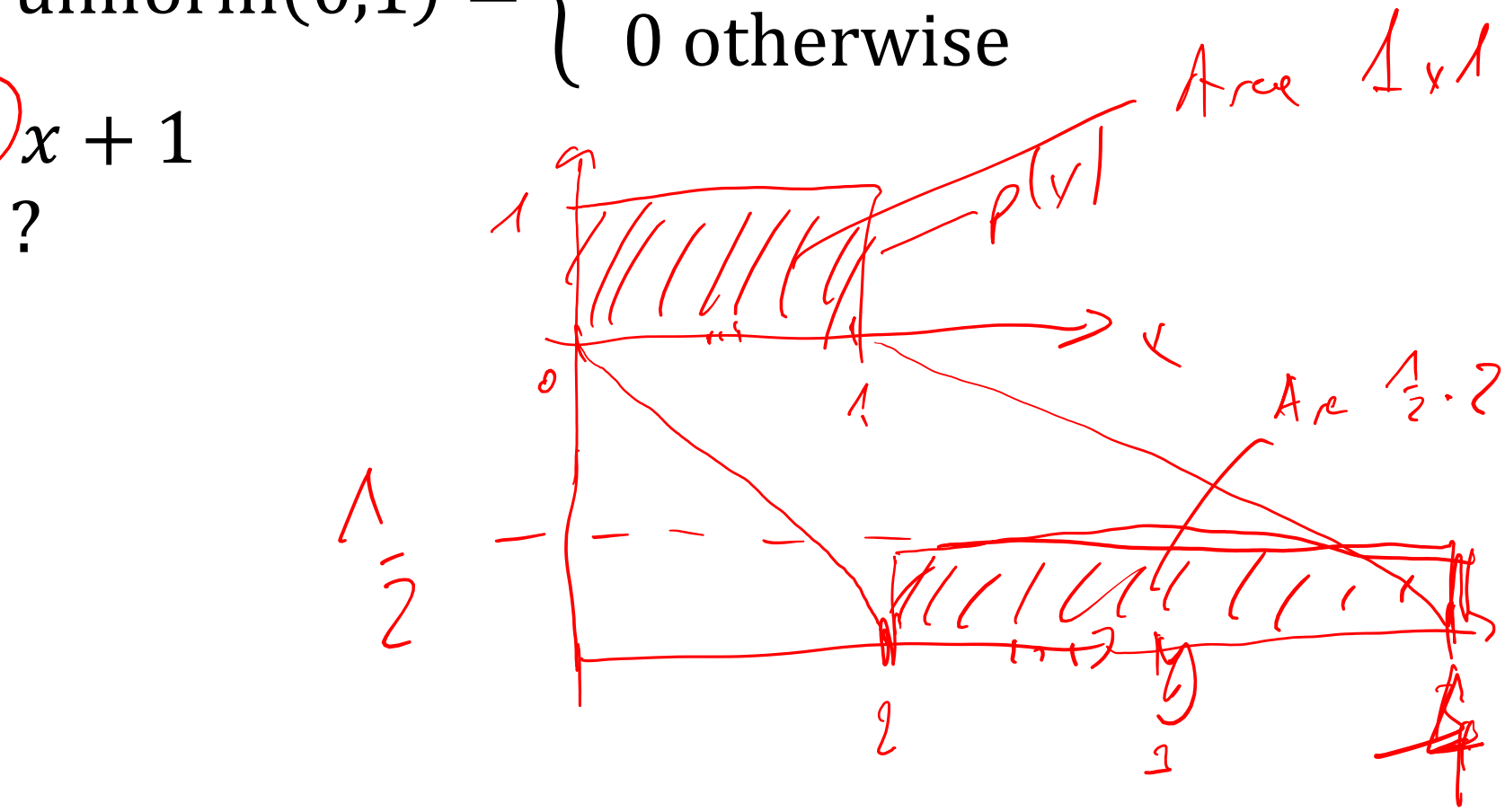
NORMALIZING FLOWS

Exercise

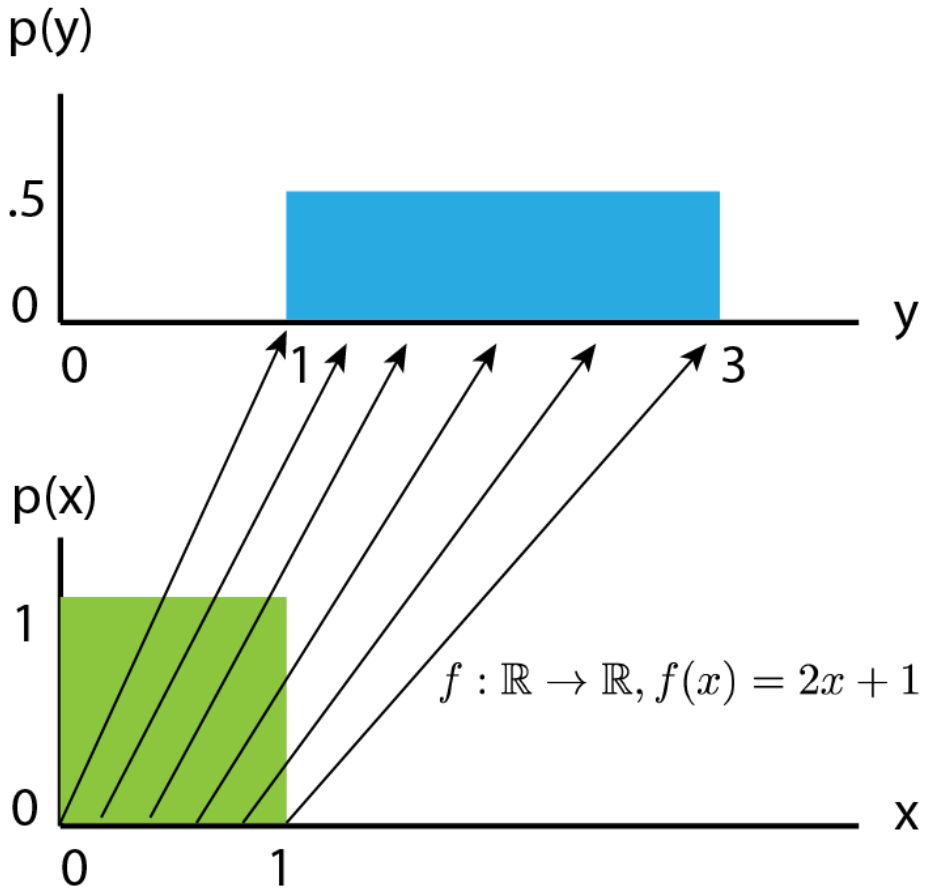
$$p(x) = \text{uniform}(0,1) = \begin{cases} 1 \text{ for } x \in (0,1) \\ 0 \text{ otherwise} \end{cases}$$

$$y = 2 * x + 1$$

$$p(y) = ?$$



Transforming distributions



y also has a uniform distribution!

$$p(y) = \text{uniform}(0,2) = \begin{cases} 1/2 \text{ for } y \in (1,3) \\ 0 \text{ otherwise} \end{cases}$$

E Jang https://blog.evjang.com/2018/01/nf1.html

The Jacobian: stretching space

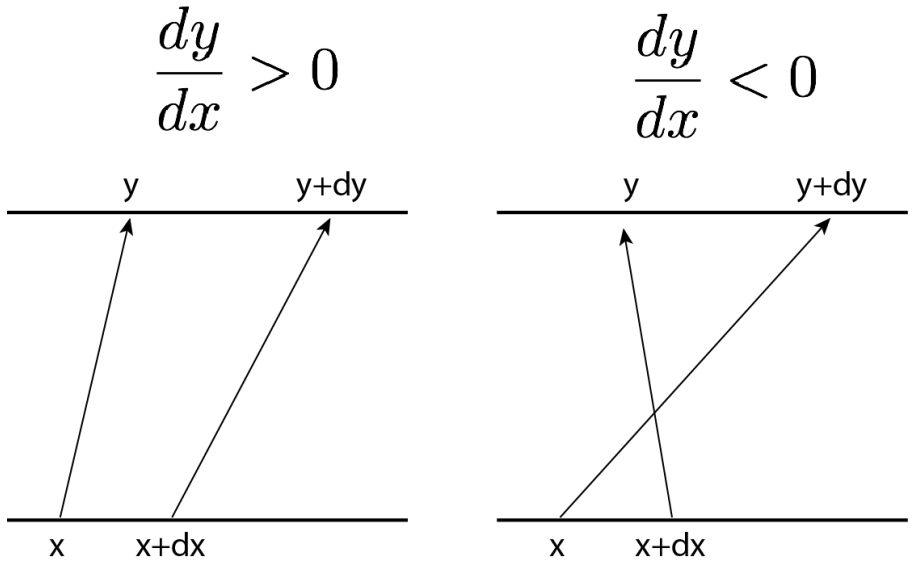
Let $y = f(x)$

Take a range $(x, x + \Delta x)$

Question:

How long is this range?

Δx



Question:

How long is $(f(x), f(x + \Delta x))$?

$$f(x + \Delta x) \approx f(x) + \frac{\partial f}{\partial x}\Delta x$$

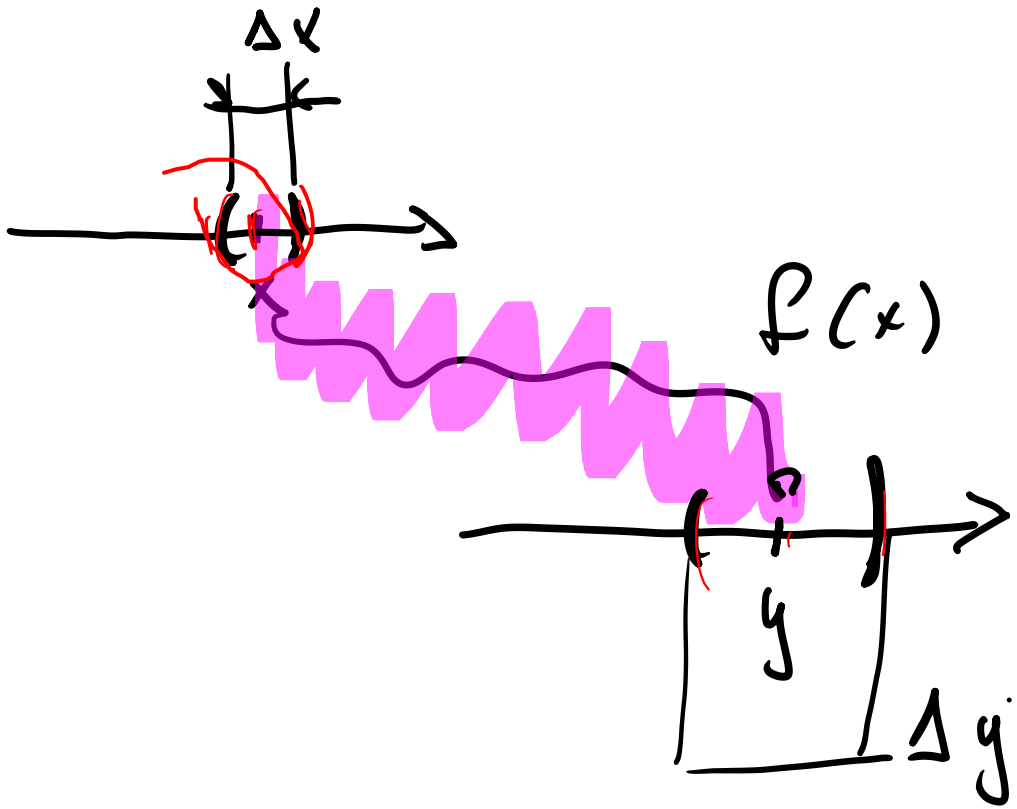
$$\left|\frac{\partial f}{\partial x}\Delta x\right|$$ ~ Det of Jacobian

https://blog.evjang.com/2018/01/nf1.html

Change of variables

$y = f(x), f$ is a bijection

$$p_x(x) = p_y(f(x)) \left| \det \frac{\partial f(x)}{\partial x} \right|$$



f transforms $x \pm \frac{\Delta x}{2}$ to y $\pm \frac{\Delta y}{2}$

The space is stretched by

$$\frac{\partial f(x)}{\partial x} \approx \frac{\Delta y}{\Delta x}$$

Idea

Start with $z \sim \mathcal{N}(0,1)$

Then $x = f^{-1}(z)$ (equivalently $z = f(x)$)

$$p_x(x) = p_z\big(f(x)\big)\left|\det \frac{\partial f(x)}{x}\right|$$

Tractable when:

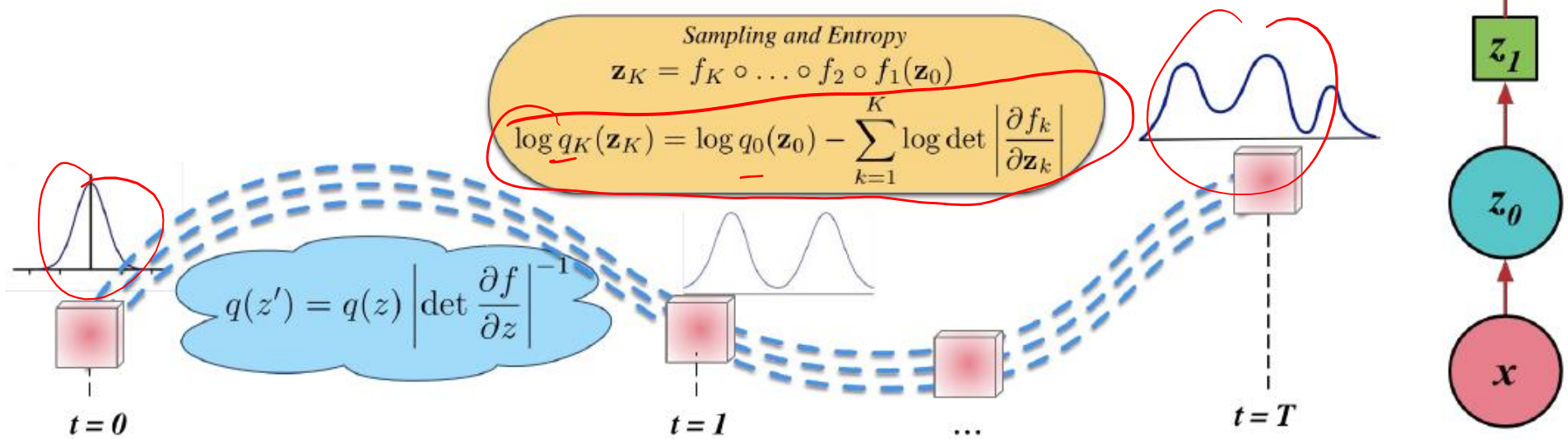
- f is easy to exactly invert
  f and f^{-1} form and exact auto-encoder!
- $\det \frac{\partial f(x)}{x}$ is easy to compute

=> We need special f!

Normalizing Flows

Exploit the rule for change of variables:

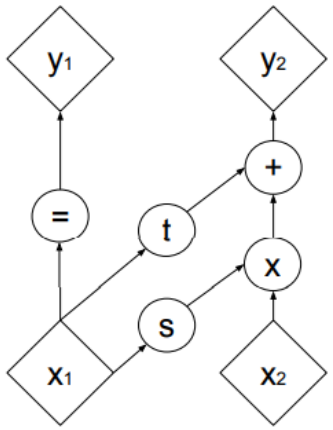
- Begin with an initial distribution
- Apply a sequence of K invertible transforms



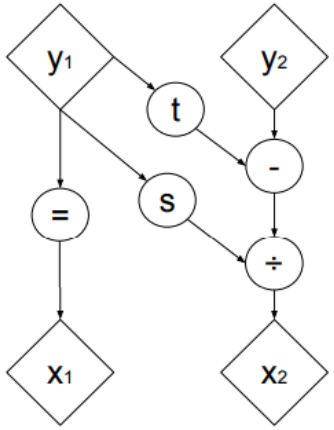
Distribution flows through a sequence of invertible transforms

Rezende and Mohamed, 2015

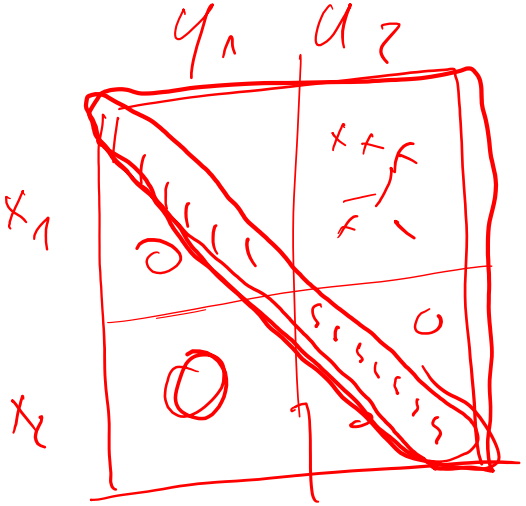
A special form of f

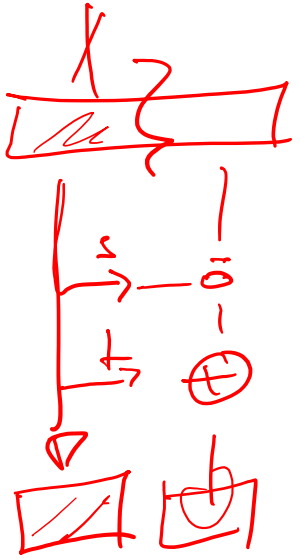


(a) Forward propagation



(b) Inverse propagation





$$x_1, x_2 = \text{split}(x)$$

$$y_1 = x_1$$

$$y_2 = x_2 s(x_1) + t(x_1)$$

Trivial to invert!

$\frac{\partial y}{\partial x}$ is diagonal, determinant is easy!

L. Dinh et al “NICE”, L. Dinh et al “Real NVP”

Normalizing flows in action

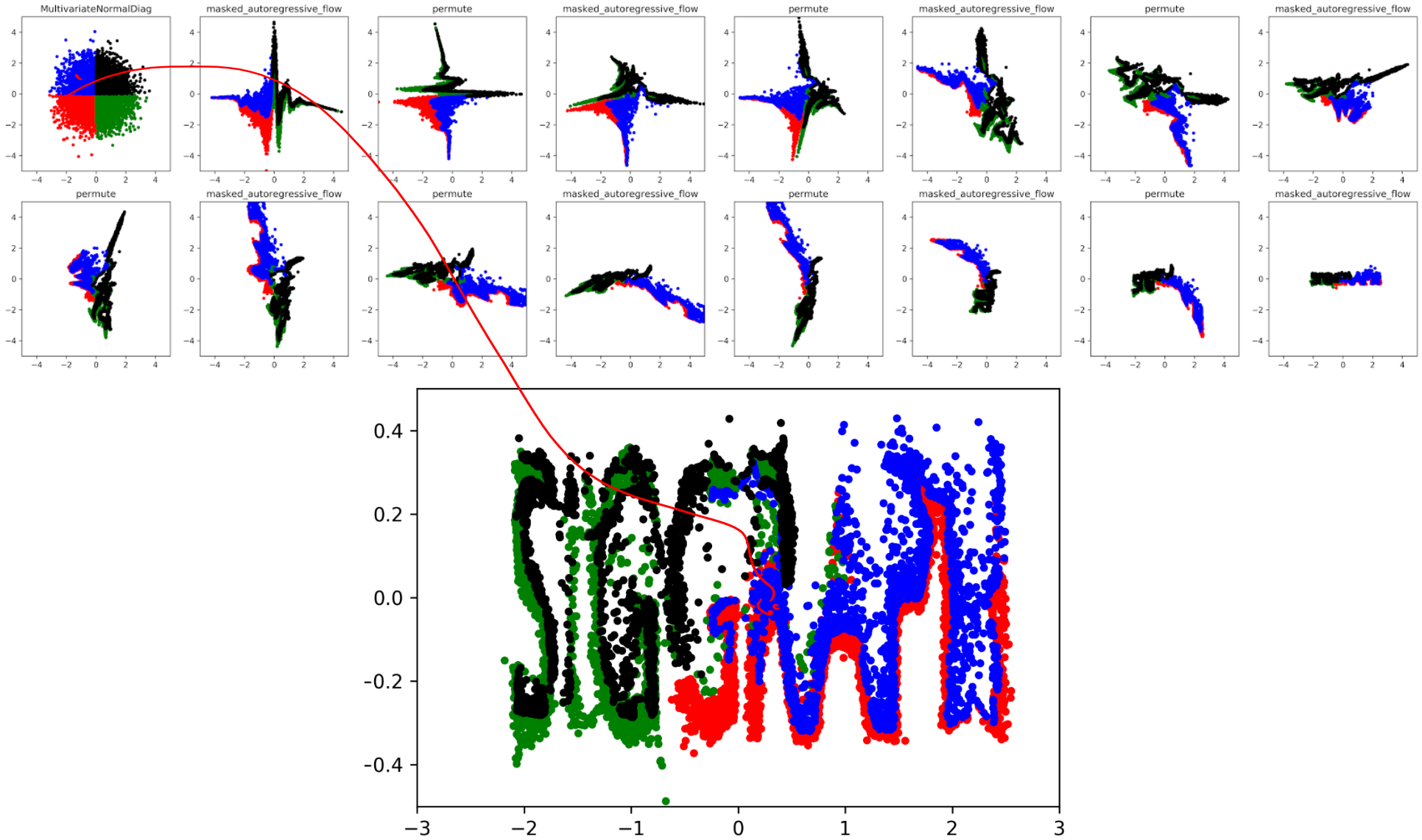
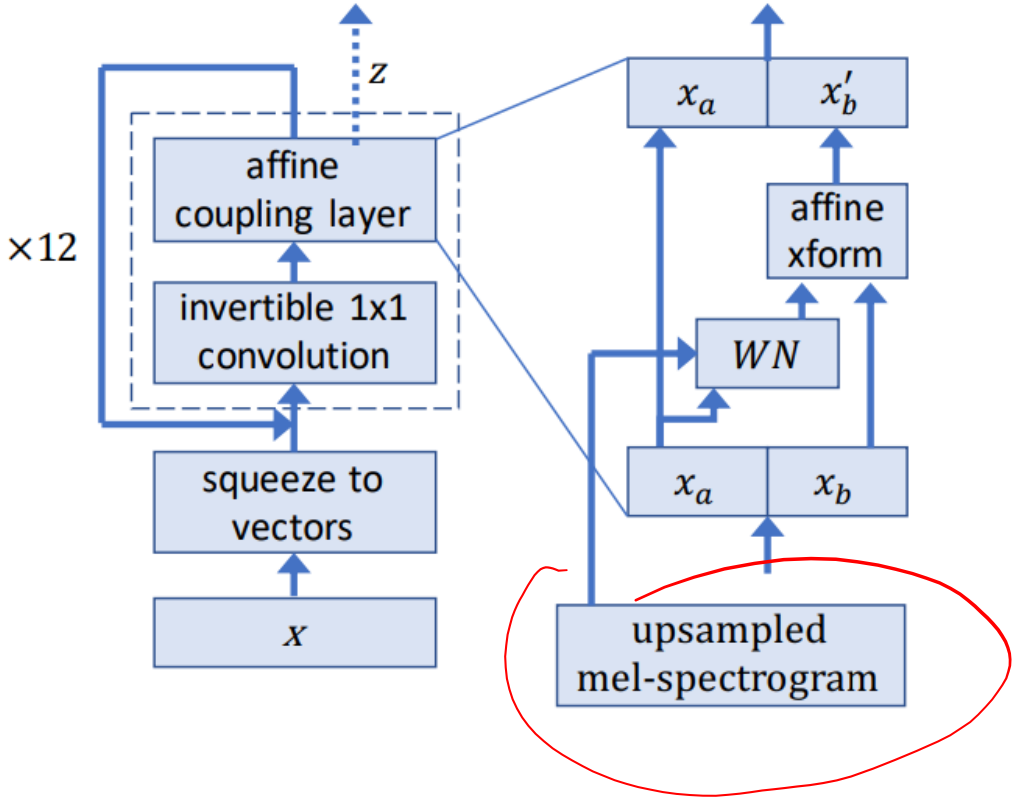


Image credit Eric Jang, https://blog.evjang.com/2018/01/nf2.html

Normalizing flows in action

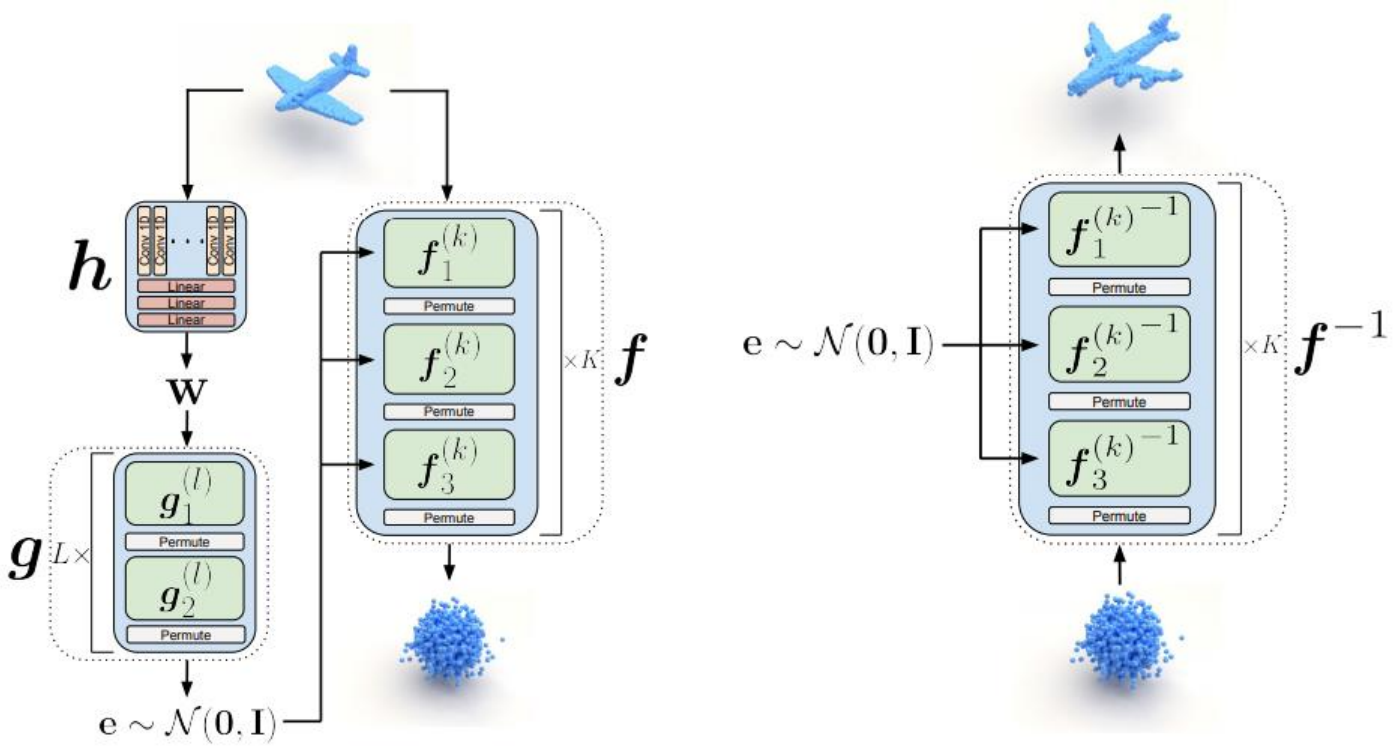
Kingma et al, “GLOW”



Prenger et al, “WAVEGLOW”

Normalizing Flows in Action

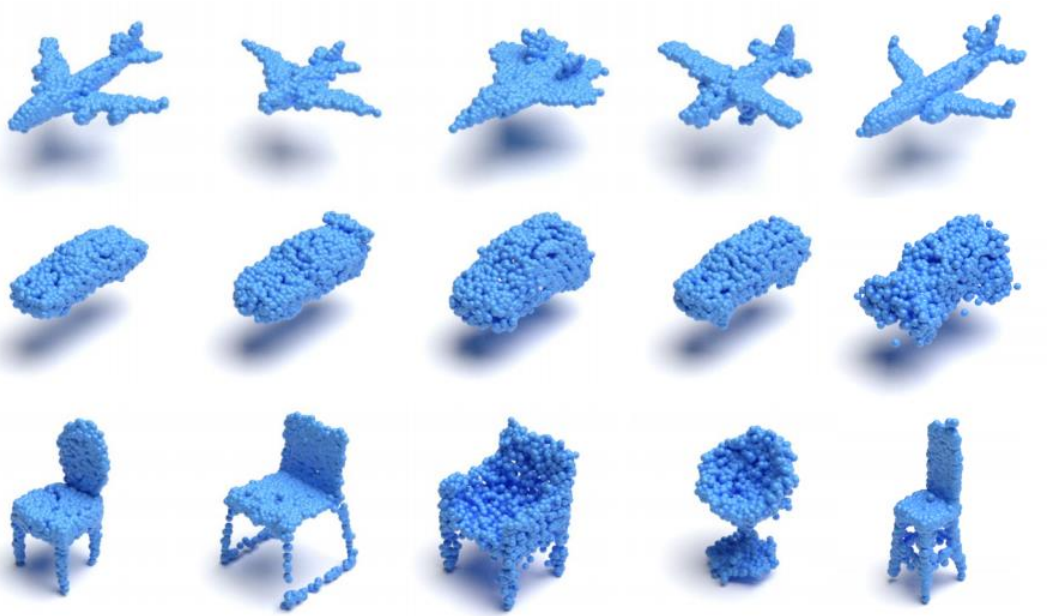
A generative model for point clouds:



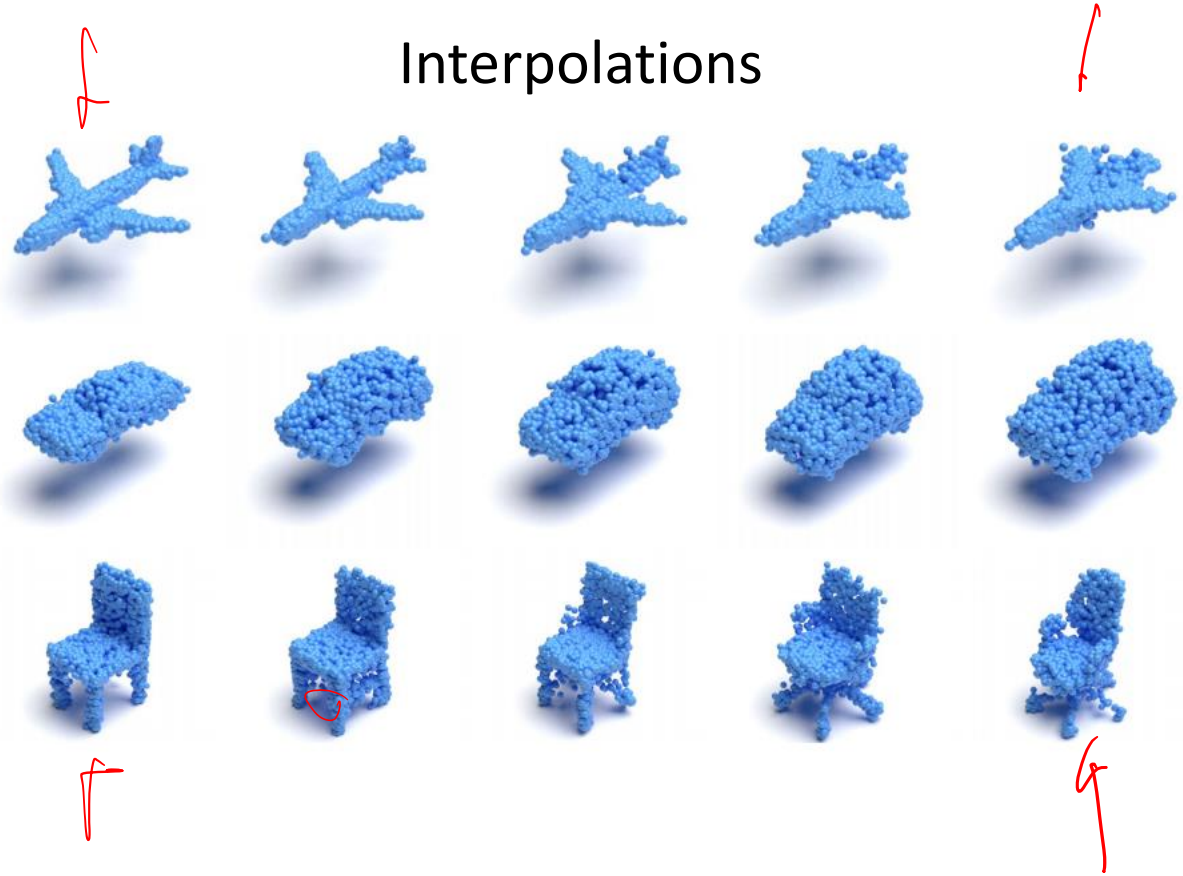
Work with Michał Stypułkowski, Kacper Kania, Maciej Zamorski, Maciej Zięba Tomasz Trzcinski

Normalizing Flows in Action

Samples



Interpolations

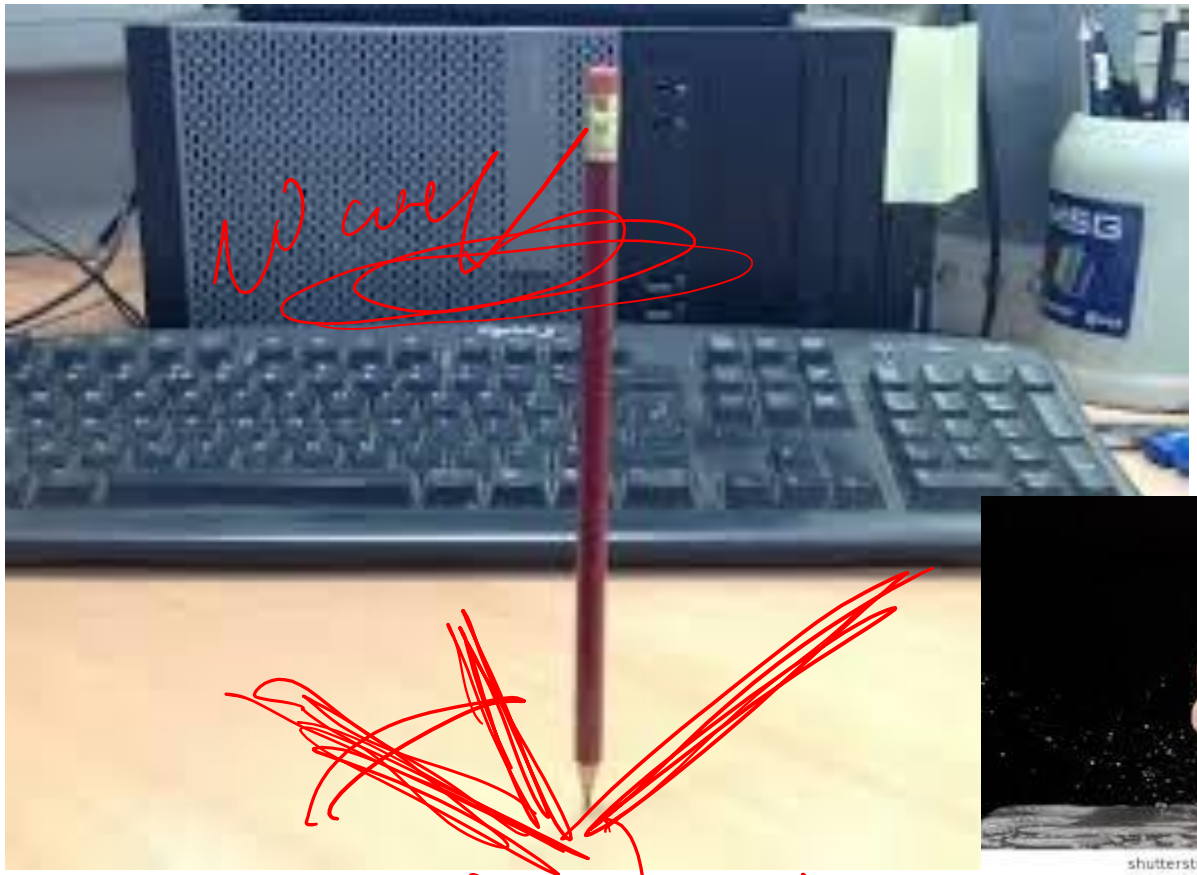


GAN

What will happen next?

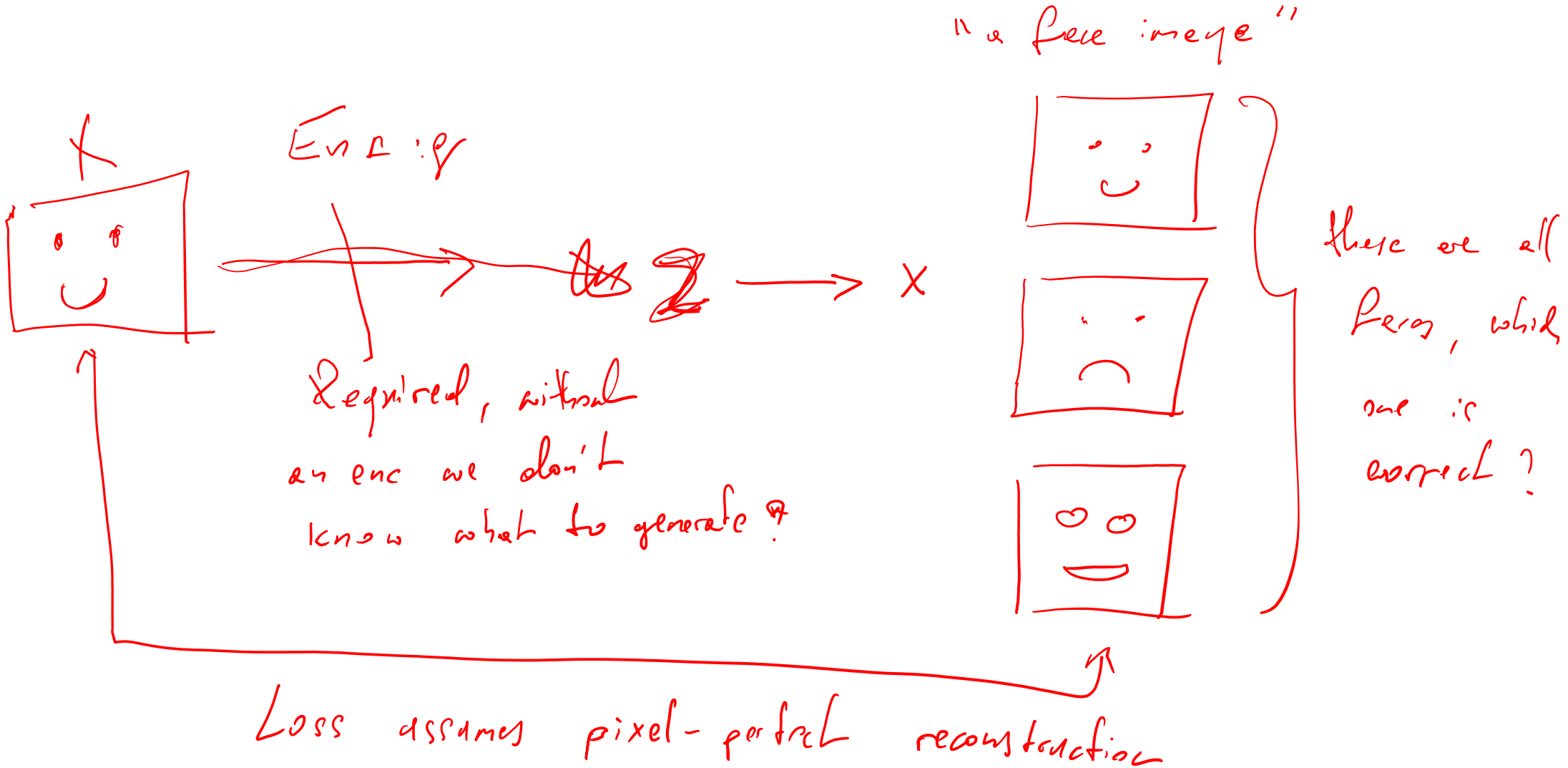
t_0

$p(t_2 \mid t_0, t_1)$



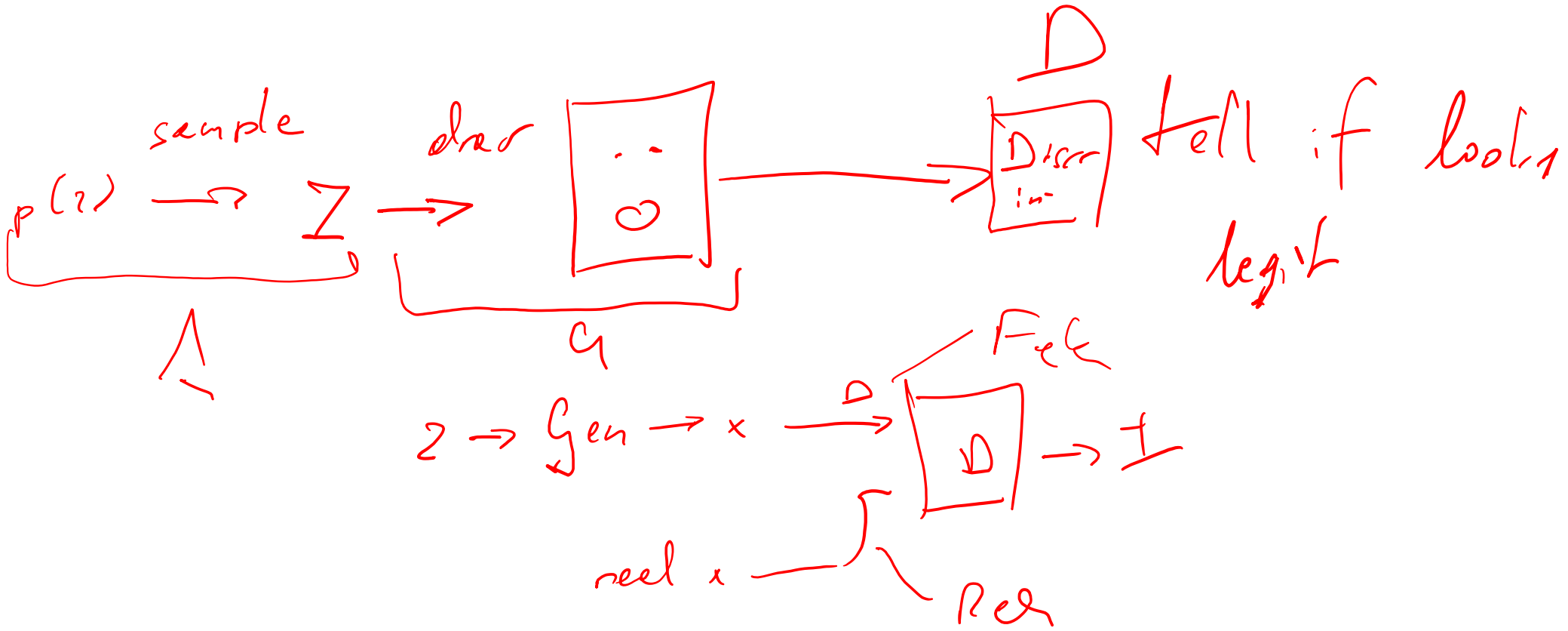
t_1

Trouble with autoencoders

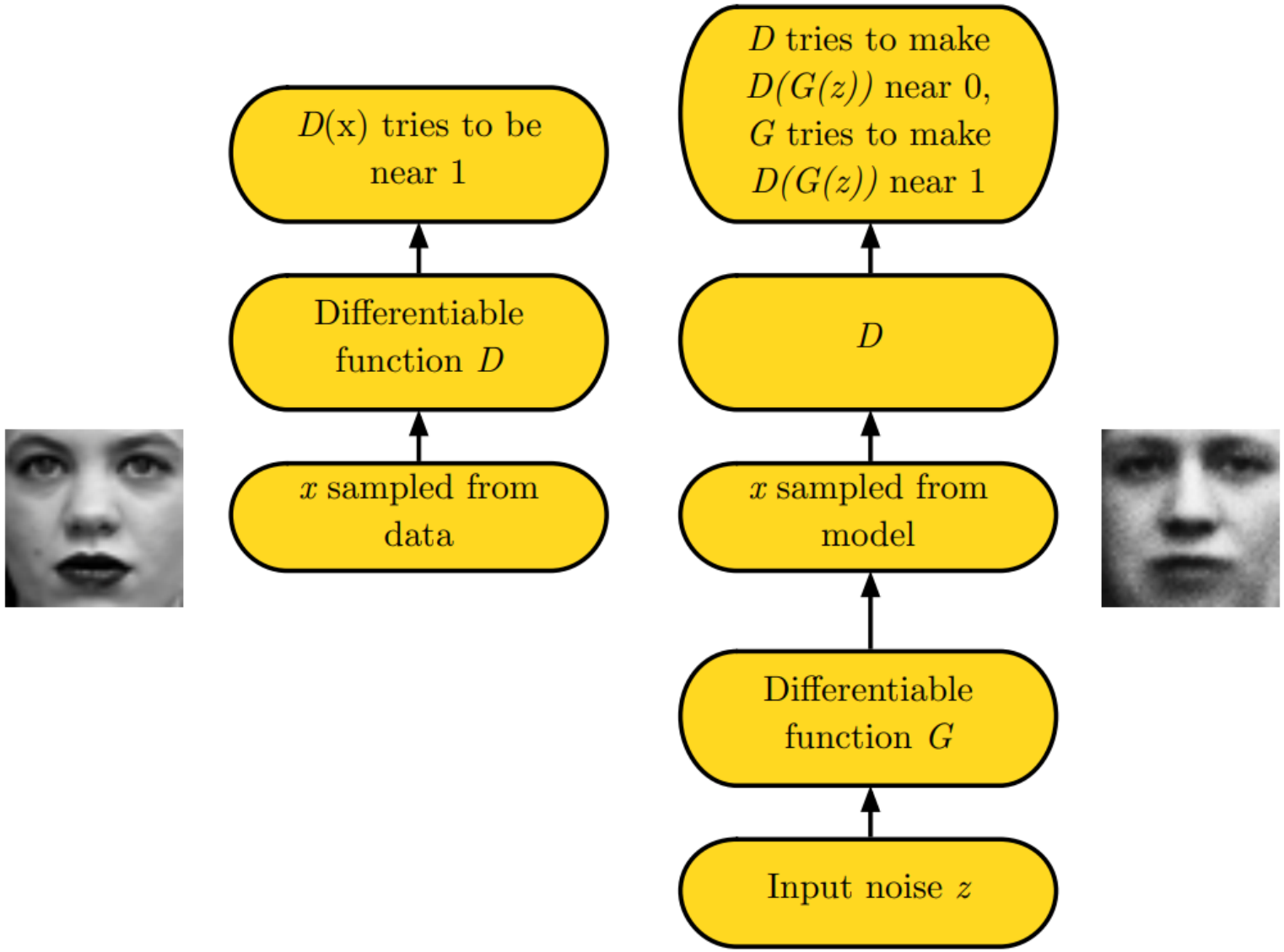


GAN idea

- Learn to tell plausible (i.e. like data) samples from other ones.



Adversarial Nets Framework

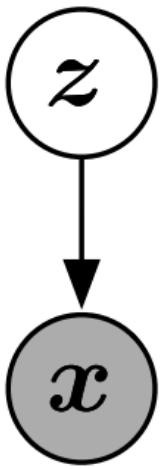


(Goodfellow 2016)

Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

Generator Network

$$\boldsymbol{x} = G(\boldsymbol{z}; \boldsymbol{\theta}^{(G)})$$



-Must be differentiable

- No invertibility requirement
- Trainable for any size of z
- Some guarantees require z to have higher dimension than x
- Can make x conditionally Gaussian given z but need not do so

Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

Training Procedure

- Use SGD-like algorithm of choice (Adam) on two minibatches simultaneously:
  - A minibatch of training examples
  - A minibatch of generated samples
- Optional: run k steps of one player for every step of the other player.

Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

Minimax Game

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

$$J^{(G)} = -J^{(D)}$$

- Equilibrium is a saddle point of the discriminator loss
- Resembles Jensen-Shannon divergence
- Generator minimizes the log-probability of the discriminator being correct

Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

Exercise 1

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

$$J^{(G)} = -J^{(D)}$$

- What is the solution to $D(x)$ in terms of p_{data} and $p_{\text{generator}}$?
- What assumptions are needed to obtain this solution?

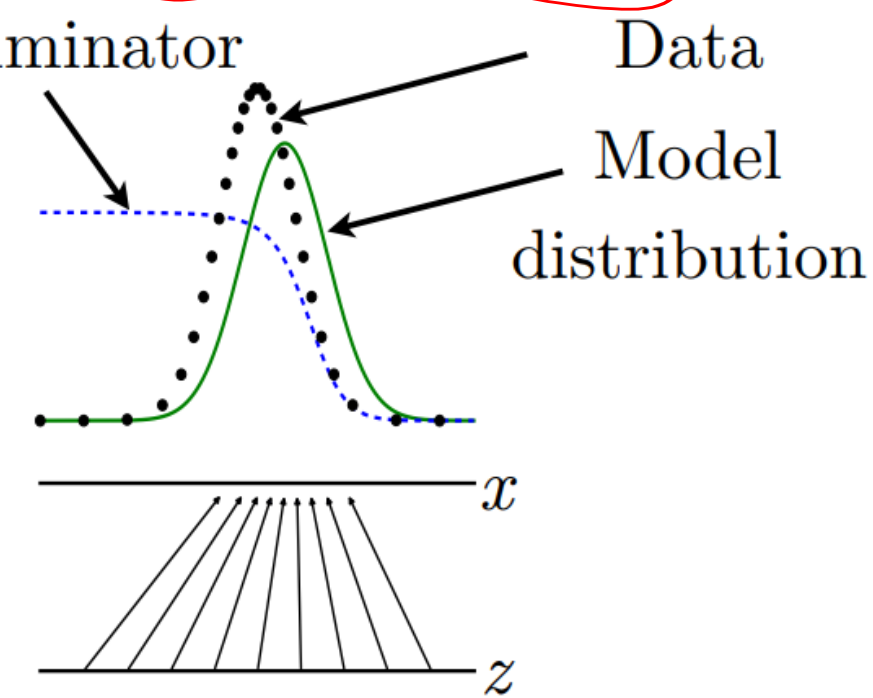
Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

Discriminator Strategy

Optimal $D(\boldsymbol{x})$ for any $p_{\text{data}}(\boldsymbol{x})$ and $p_{\text{model}}(\boldsymbol{x})$ is always

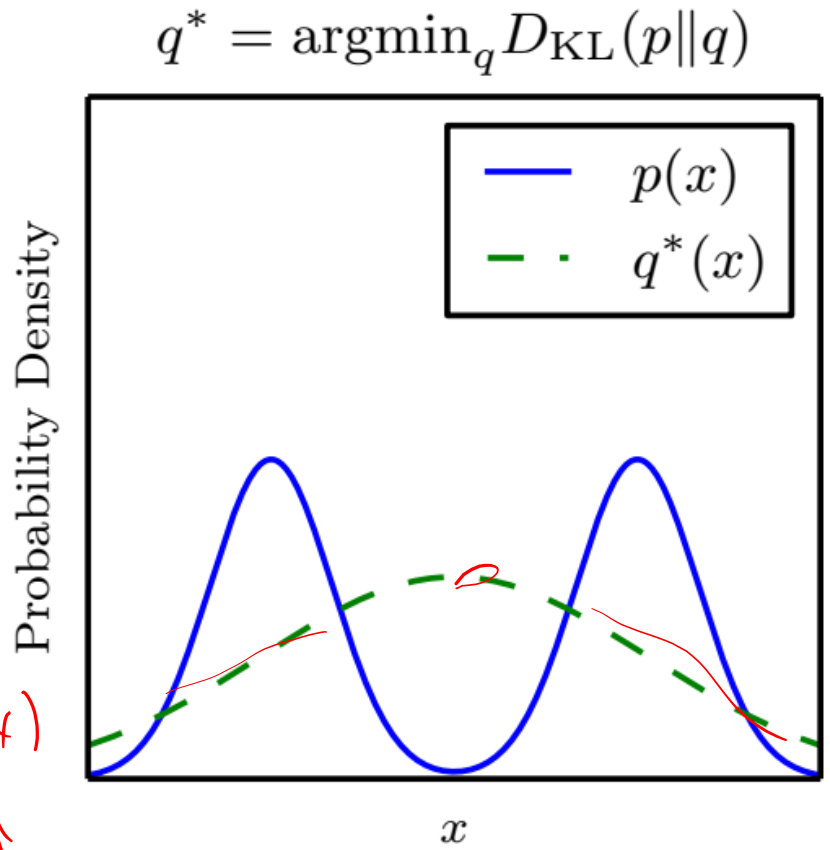
$$D(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x) + p_{\text{model}}(x)}$$

Estimating this ratio using supervised learning is the key approximation mechanism used by GANs

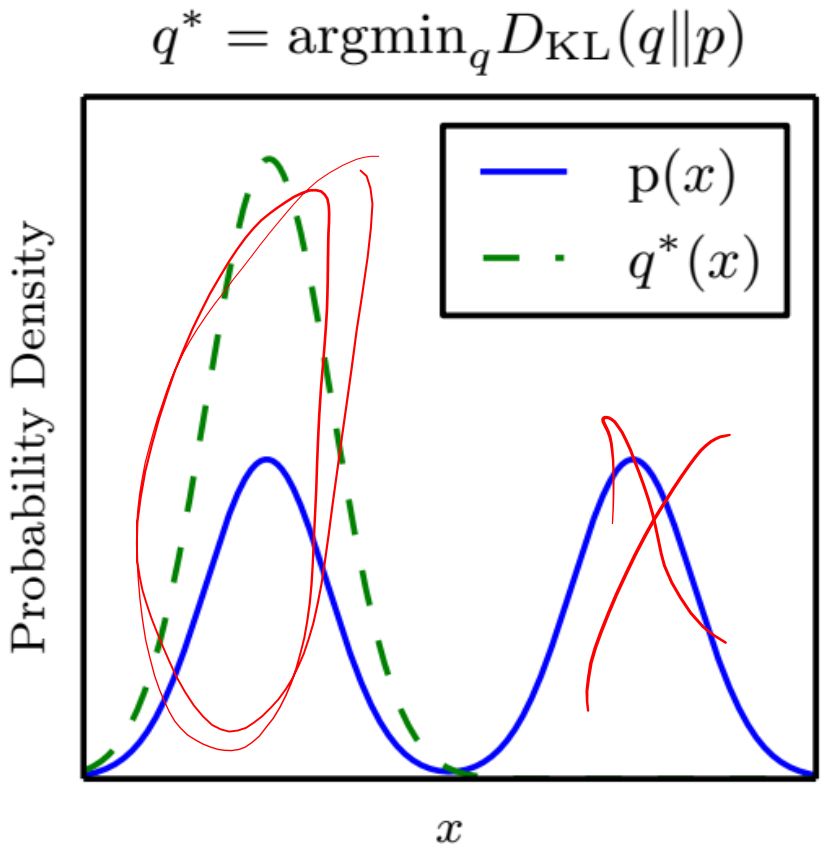


Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

Is the divergence important?



Maximum likelihood



Reverse KL

(Goodfellow et al 2016)

Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

GAN Trick

Non-saturating loss

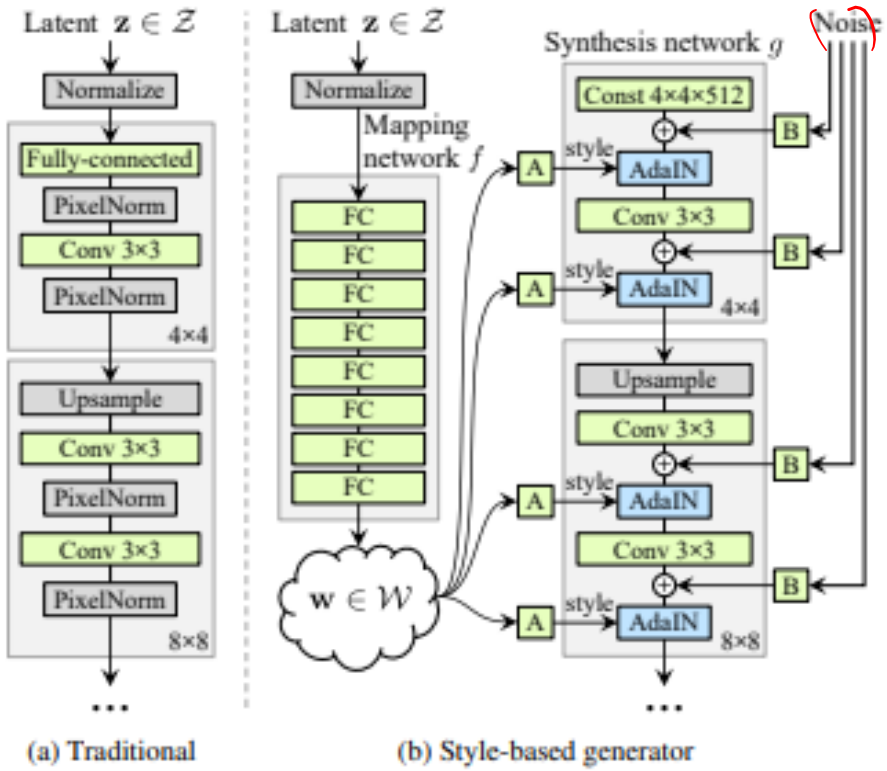
$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D\left(G(\boldsymbol{z})\right)$$

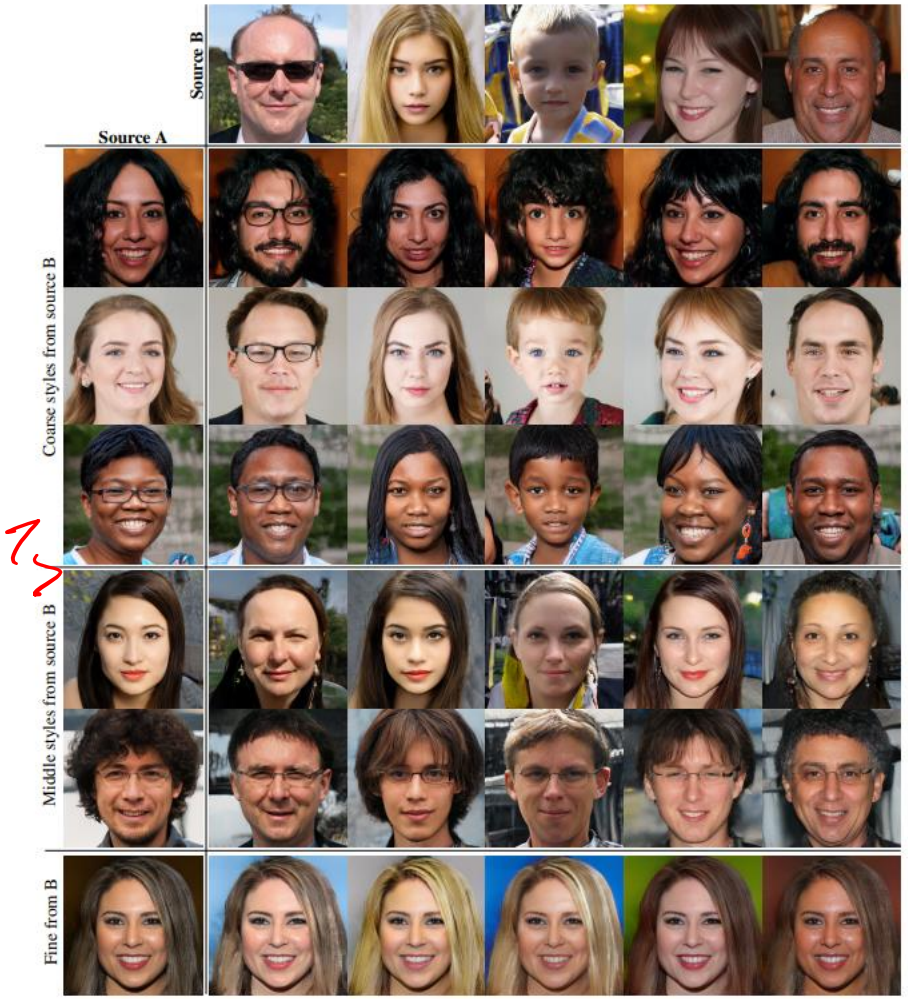
$J^G = -J^D - \frac{1}{2}\mathbb{E}_z(\log D(G(z)))$

Slide by Ian Goodfellow: https://media.nips.cc/Conferences/2016/Slides/6202-Slides.pdf

GAN Uses: image generation



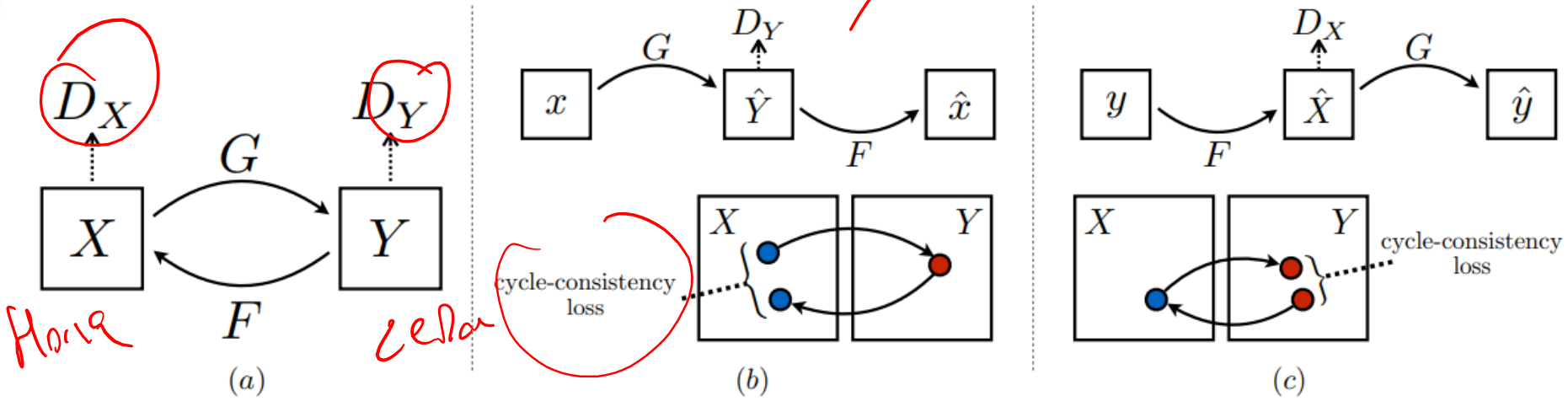
(a) Traditional (b) Style-based generator



https://arxiv.org/pdf/1812.04948.pdf

GAN Uses: unpaired image-image translation

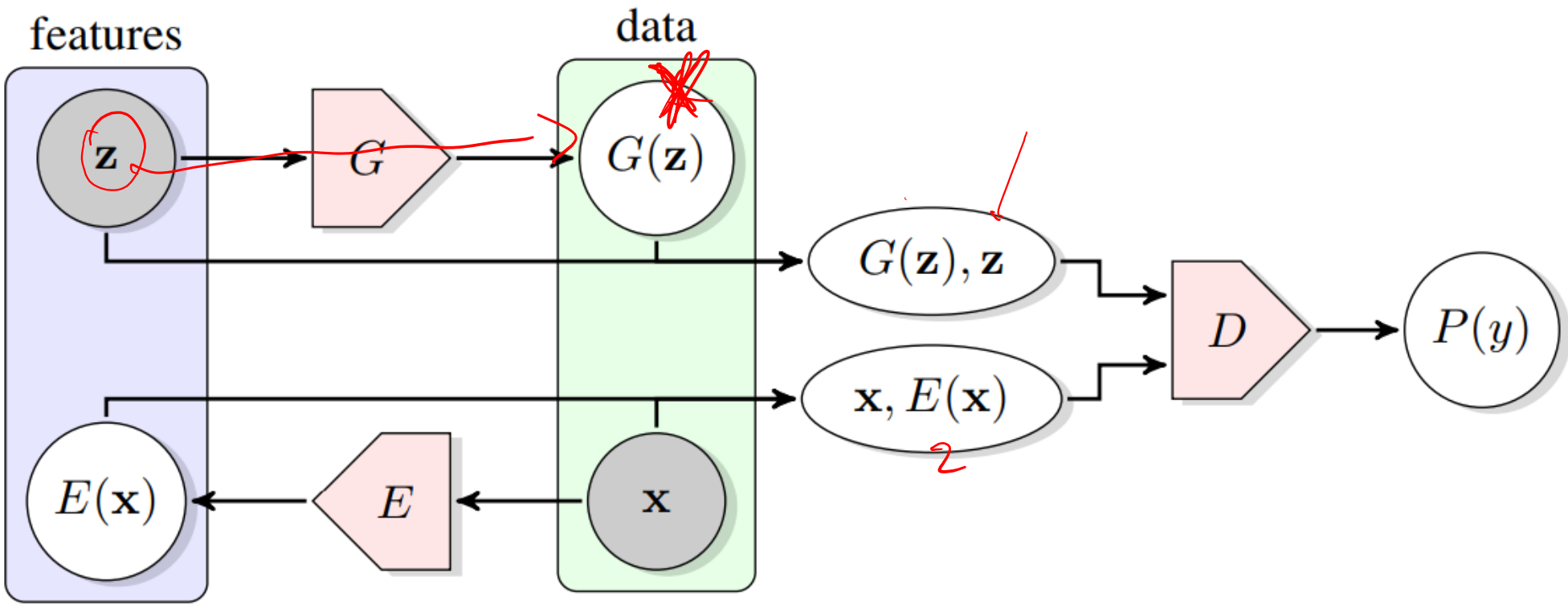
cycle GAN



https://arxiv.org/pdf/1703.10593.pdf

GANs and Latent Variables 1/3

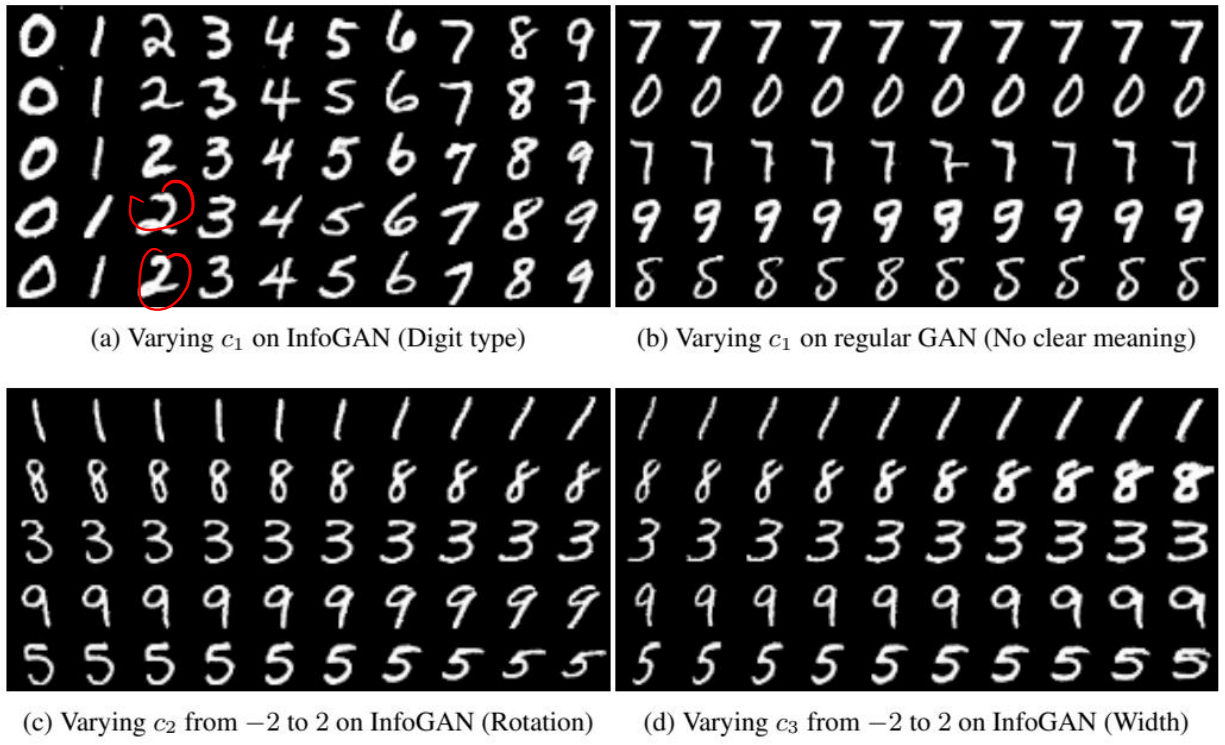
ADVERSARIALLY LEARNED INFERENCE (https://arxiv.org/pdf/1606.00704.pdf)
aka BiGAN (https://arxiv.org/abs/1605.09782)



GANs and Latent Variables 2/3

InfoGAN: https://arxiv.org/pdf/1606.03657.pdf

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I(c; G(z,c))$$



(a) Varying c_1 on InfoGAN (Digit type)

(b) Varying c_1 on regular GAN (No clear meaning)

(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

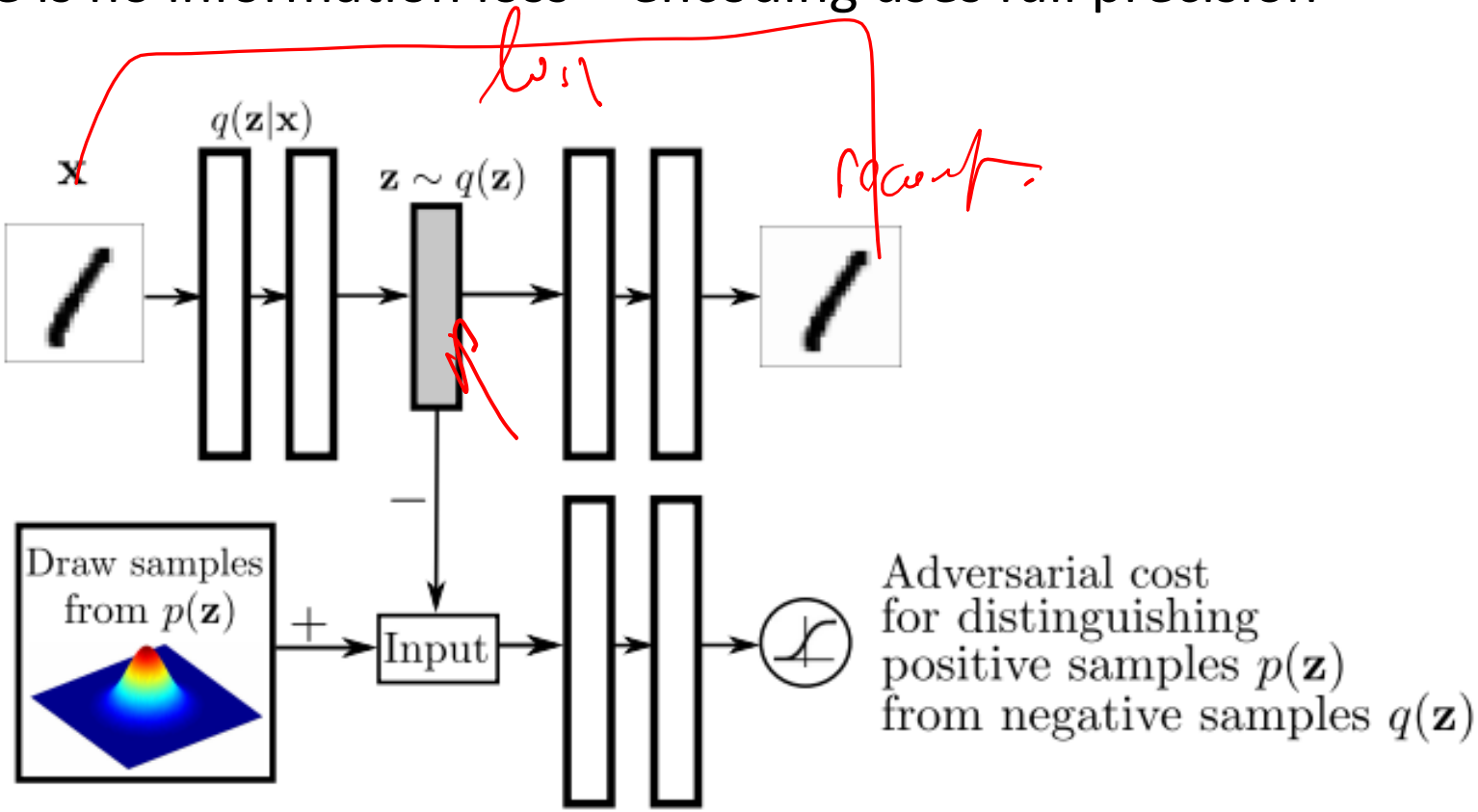
(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

GANs and Latent Variables 3/3

Adversarial Autoencoders (https://arxiv.org/pdf/1511.05644.pdf)

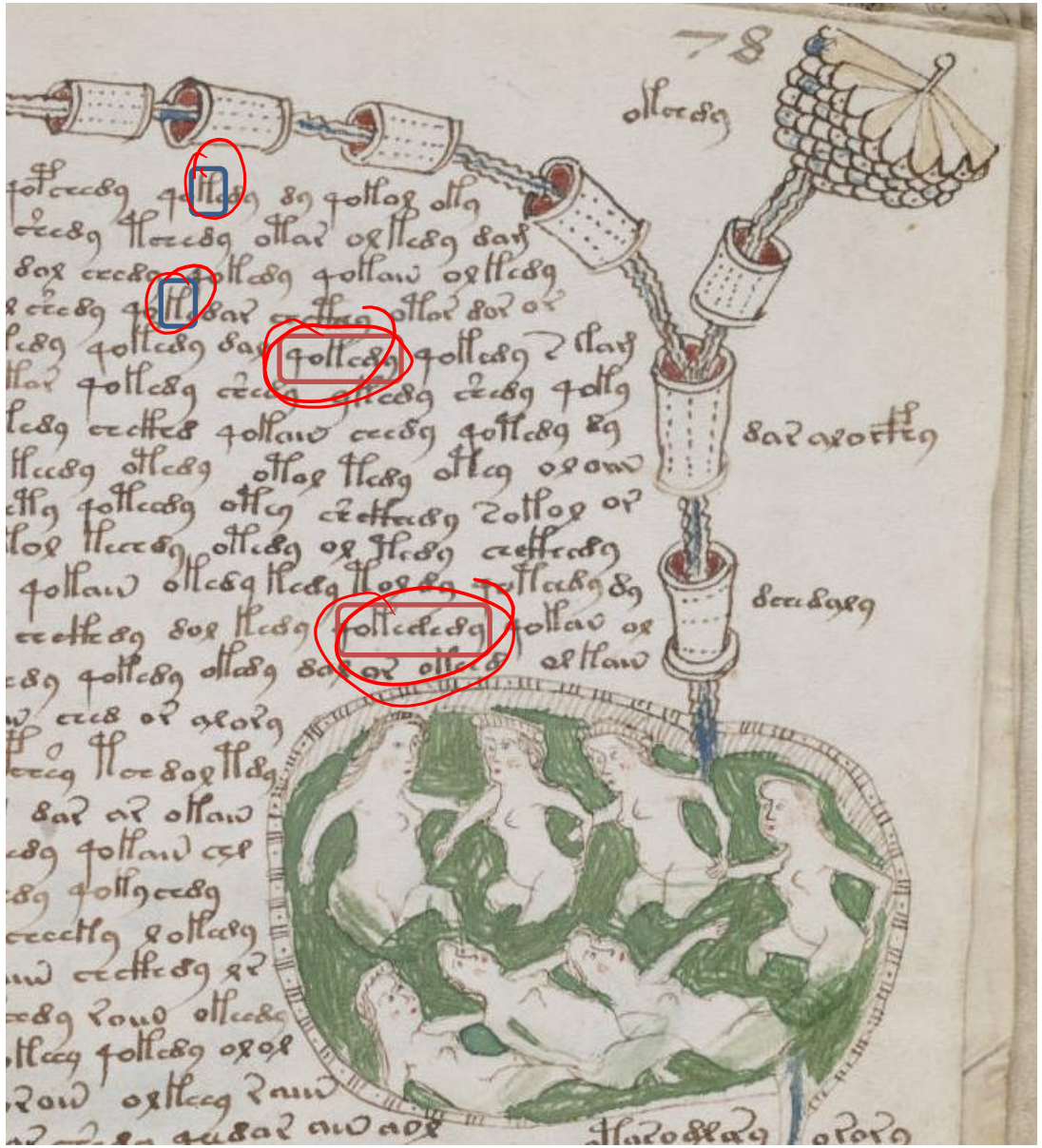
Like VAE, enforce latents to have a simple prior distribution

Unlike VAE, there is no information loss – encoding uses full precision



MY WORK:
VAE + AUTOREGRESSIVE DECODERS

Unlabeled data uses

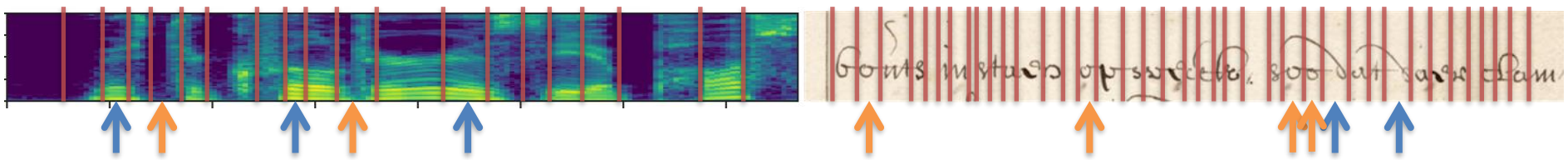


What can we learn without labels:

- Features (good data representations)
- Units (characters)
- Word types (sequences of units)
- Their co-occurrence patterns (structure, e.g. bigram stats)

Our goal

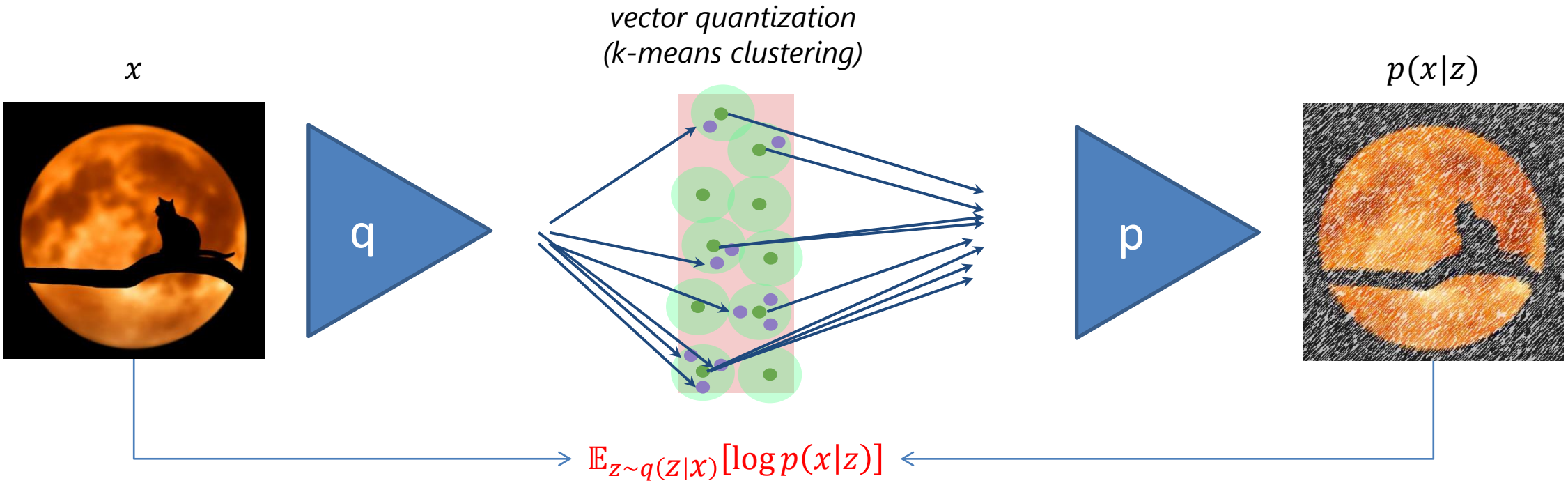
Unsupervised unit discovery
in speech and handwriting



1. Discover information-bearing units
   (cluster input segments)
2. Be invariant to other factors of variation
   (speaker/scribe, style, etc)

Extreme case of representation learning!
We will combine autoencoders with generative models.

The Vector Quantized Autoencoder



q produces a vector

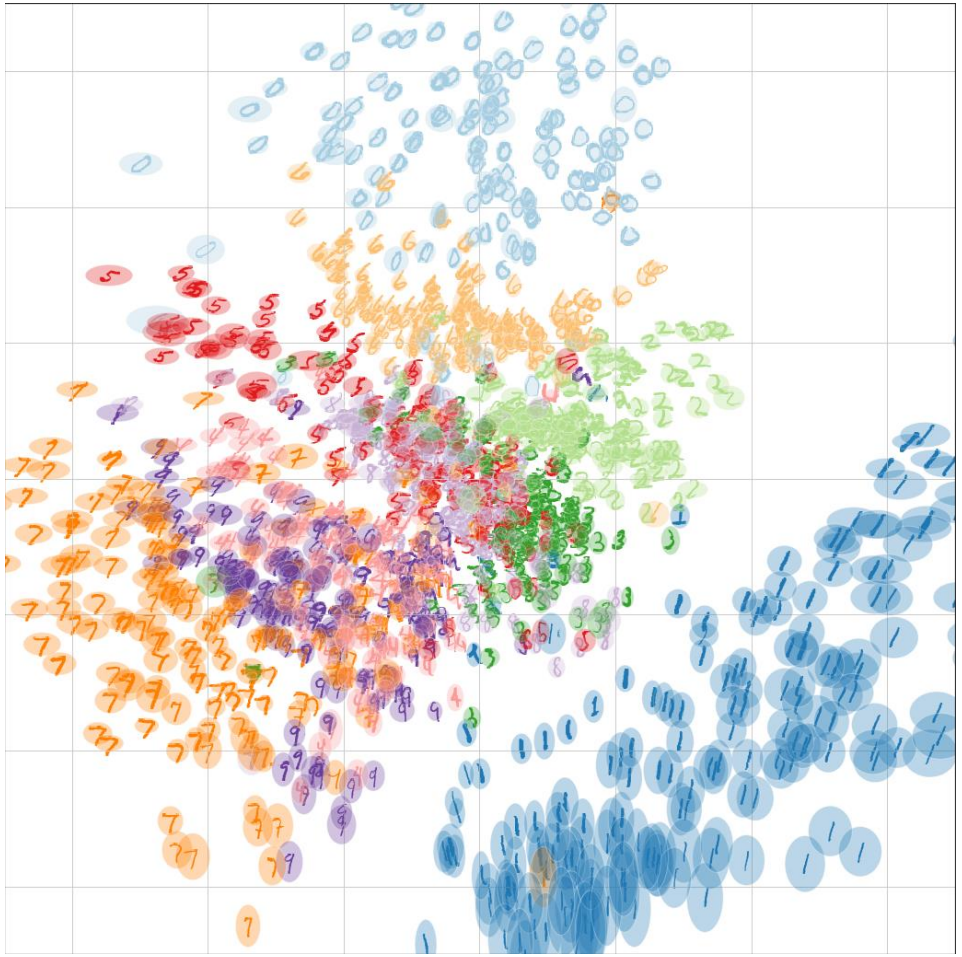
it is replaced by one of K prototypes

Information loss through quantization (rounding)

Recall: in VAE each z has a volume

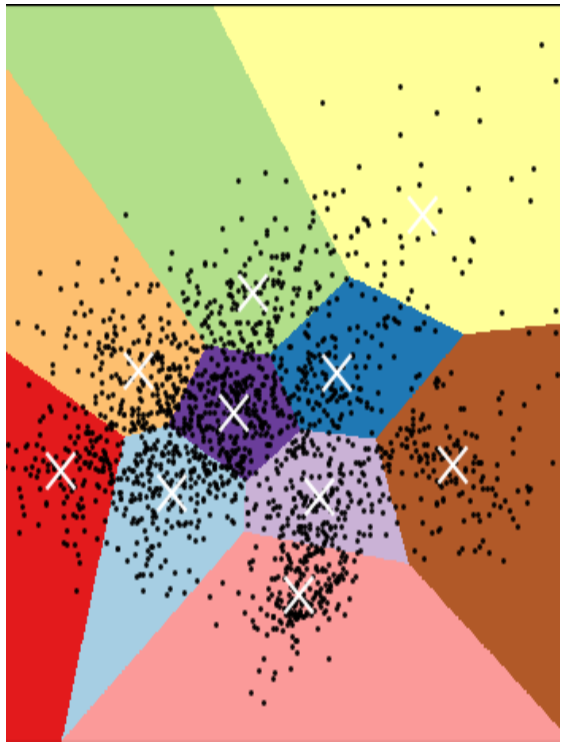
Each sample is represented as a Gaussian

This discards information (latent representation has low precision)



VQVAE – deterministic quantization, each z is rounded

Limit precision of the encoding by quantizing (round each vector to a nearest prototype).



Output can be treated:

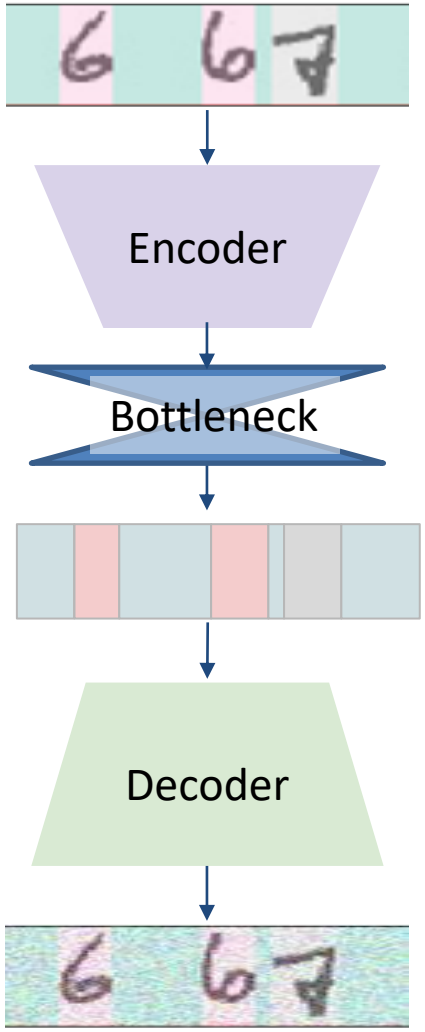
- As a sequence of discrete prototype ids (tokens)
- As a distributed representation (the prototypes themselves)

Train using the straight-through estimator,

with auxiliary losses:

$$\mathcal{L} = \log p(x \mid z_q(x)) + \|\mathrm{sg}(z_e(x)) - e_{q(x)}\|_2^2 + \gamma\|z_e(x) - \mathrm{sg}(e_{q(x)})\|_2^2$$

Autoencoders and missing information



Detailed input:
handwriting or speech

Encoder with bottleneck removes information, enforces segmentation, and quantizes the representation

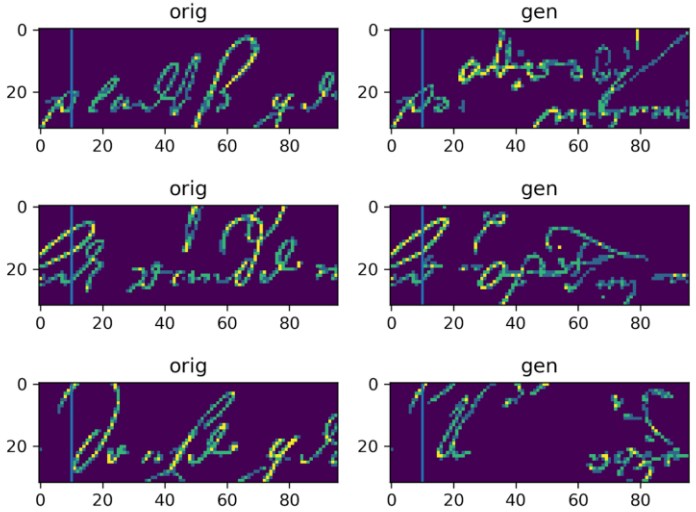
Latent encoding:
only high level features

Decoder regenerates the inputs.

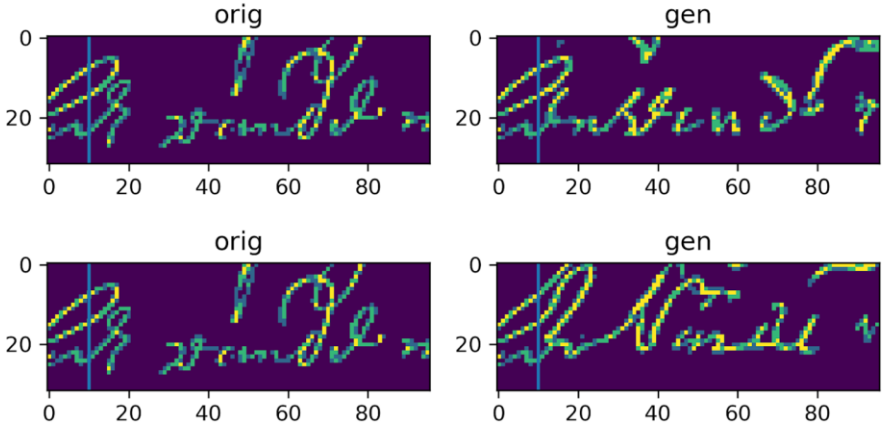
It learns $p(x|z)$ and it must fill in all discarded information.

Conditional PixelCNN can regenerate images.

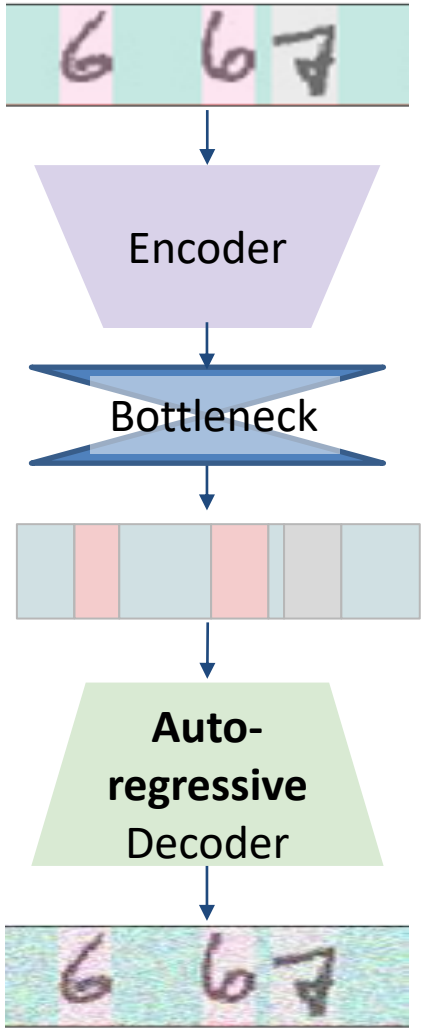
Unconditional



Conditioned on text



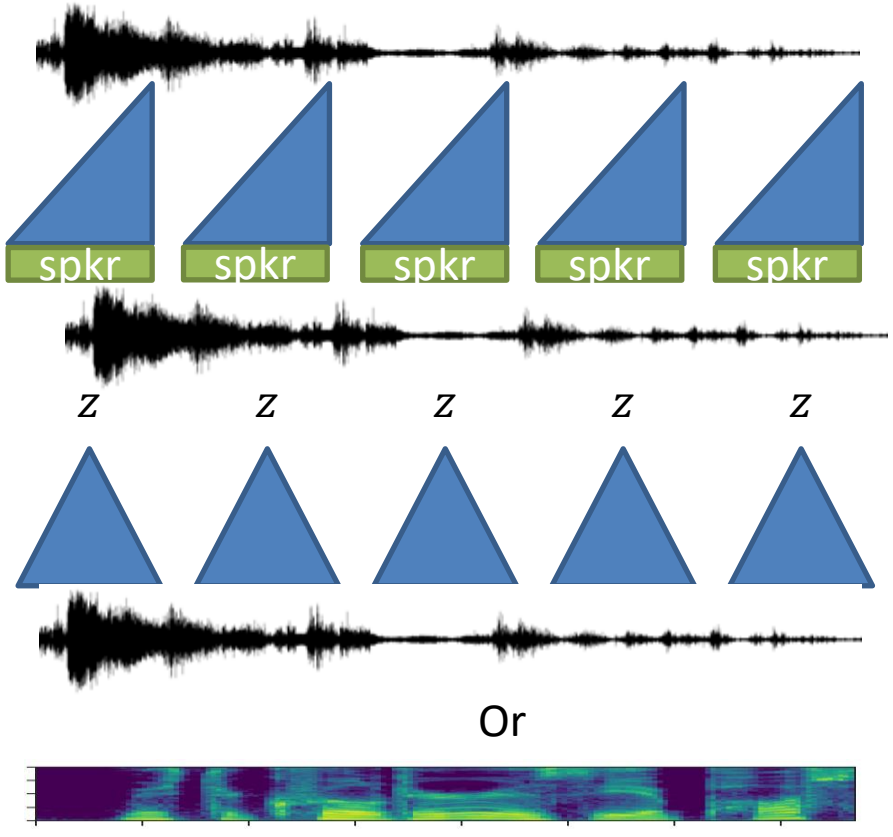
Our model:
Autoencoder + autoregressive decoder



Decoder computes a probability over input images/waveforms conditioned on the encoding.

It combines information from:
- latent representation
  (know what to reconstruct)
- neighboring sounds/pixels
  (recover details)
- other information (e.g. speaker id)

Experiments on Speech



WaveNet decoder conditioned on:

- latents extracted at 24Hz-50Hz
- speaker

3 bottleneck evaluated:

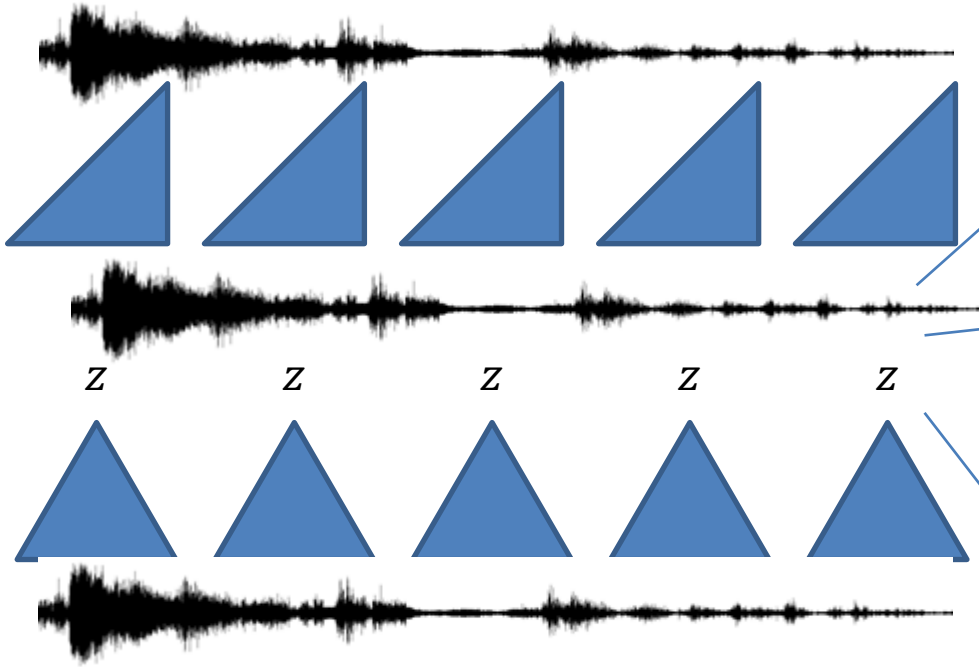
- Dimensionality reduction, max 32 bits/dim
- VAE, $KL\big(q(z|x) \parallel \mathcal{N}(0,1)\big)$ nats (bits)
- VQVAE with K protos: $\log_2 K$ bits

Input:

Waveforms, Mel Filterbanks, MFCCs

Representation probing points

We have inserted probing classifiers at 4 points in the network:



p_{cond}: several z codes mixed together using a convolution. The wavenet uses it for conditioning

p_{bn}: the latent codes

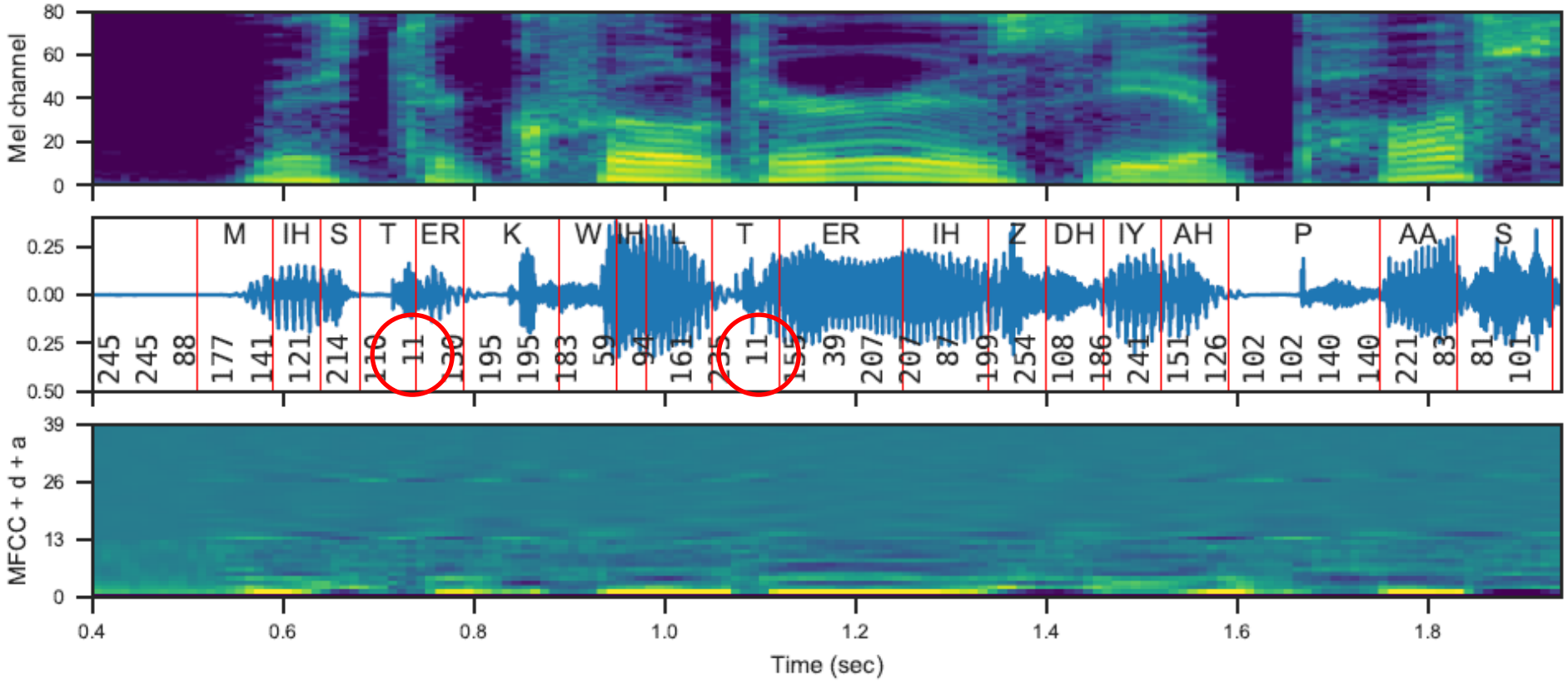
p_{proj}: low dimensional representation input to the bottleneck layer

p_{enc}: high dimensional representation coming out of the encoder

Experimental Questions #1

- What information is captured in the latent codes/probing points?
- What is the role of the bottleneck layer?
- How good is the representation on downstream tasks?
- What design choices affect it?

VQVAE Latent representation

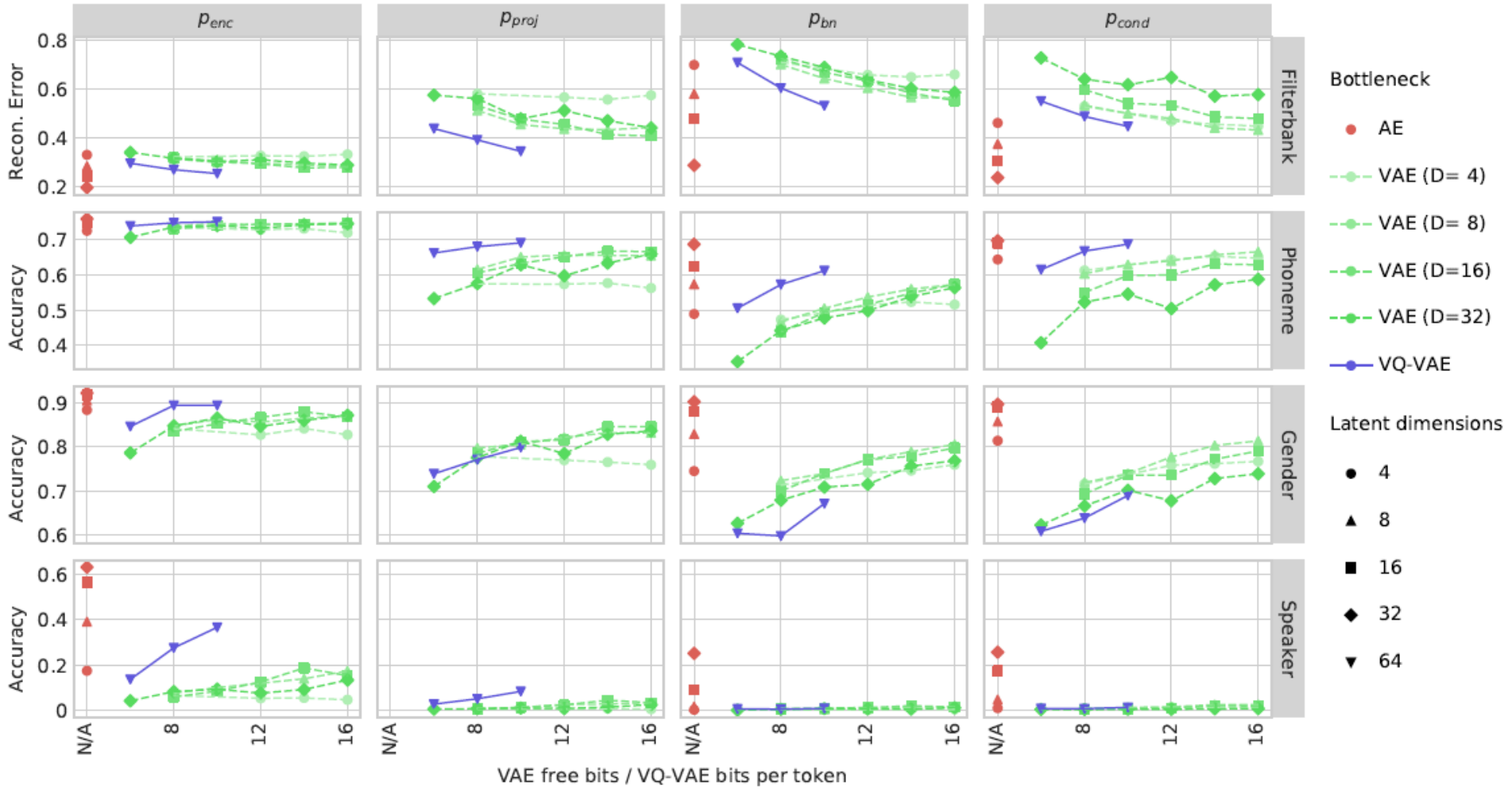


What information is captured in the latent codes?

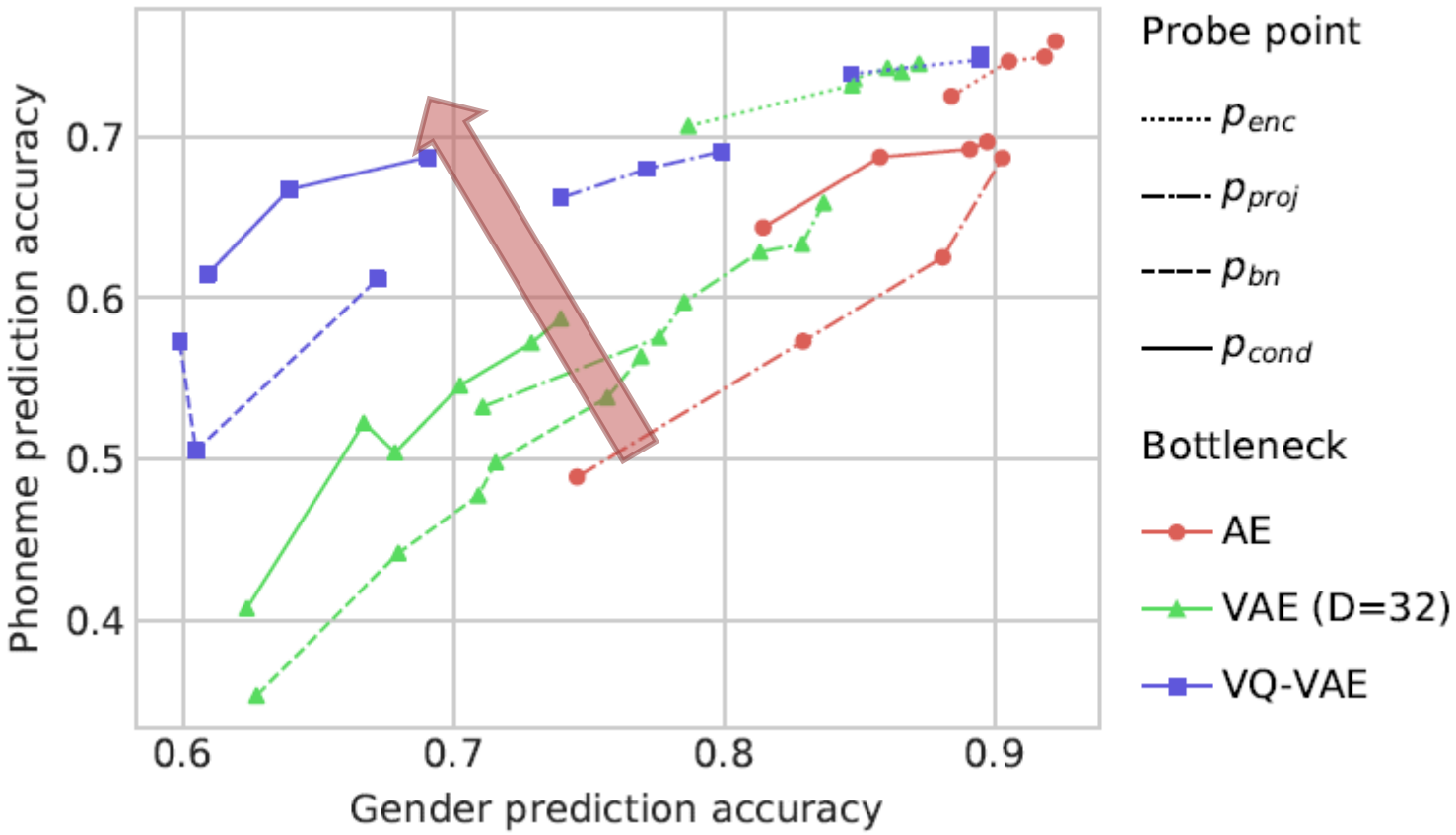
For each probing point, we have trained predictors for:

- Framewise phoneme prediction
- Speaker prediction
- Gender predicion
- Mel Filterbank reconstruction

Results


p_{enc}
p_{proj}
p_{bn}
p_{cond}
Filterbank
Phoneme
Gender
Speaker
Recon. Error
Accuracy
VAE free bits / VQ-VAE bits per token
N/A
8
12
16
Bottleneck
AE
VAE (D= 4)
VAE (D= 8)
VAE (D=16)
VAE (D=32)
VQ-VAE
Latent dimensions
4
8
16
32
64

Phonemes vs Gender tradeoff



Performance on ZeroSpeech 2017 unit discovery

	Within-speaker									Across-speaker								
	English (45h)			French (24h)			Mandarin (2.4h)			English (45h)			French (24h)			Mandarin (2.4h)		
Model	1s	10s	2m	1s	10s	2m	1s	10s	2m	1s	10s	2m	1s	10s	2m	1s	10s	2m
Unsupervised baseline	12.0	12.1	12.1	12.5	12.6	12.6	11.5	11.5	11.5	23.4	23.4	23.4	25.2	25.5	25.2	21.3	21.3	21.3
Supervised topline	6.5	5.3	5.1	8.0	6.8	6.8	9.5	4.2	4.0	8.6	6.9	6.7	10.6	9.1	8.9	12.0	5.7	5.1
VQ-VAE (per lang, p_{cond})	**5.6**	**5.5**	**5.5**	**7.3**	**7.5**	**7.5**	11.2	10.7	10.8	**8.1**	**8.0**	**8.0**	**11.0**	**10.8**	**11.1**	12.2	11.7	11.9
Heck et al. [57]	6.9	6.2	6.0	9.7	8.7	8.4	**8.8**	**7.9**	**7.8**	10.1	8.7	8.5	13.6	11.7	11.3	**8.8**	**7.4**	**7.3**
Chen et al. [58]	8.5	7.3	7.2	11.2	9.4	9.4	10.5	8.7	8.5	12.7	11.0	10.8	17.0	14.5	14.1	11.9	10.3	10.1
Ansari et al. [59]	7.7	6.8	N/A	10.4	N/A	8.8	10.4	9.3	9.1	13.2	12.0	N/A	17.2	N/A	15.4	13.0	12.2	12.3
Yuan et al. [60]	9.0	7.1	7.0	11.9	9.5	9.5	11.1	8.5	8.2	14.0	11.9	11.7	18.6	15.5	14.9	12.7	10.8	10.7

SOTA results in unsupervised phoneme discrimination Fr and EN ZeroSpeech challenge.

Mandarin shows limitation of the method:

- Too little training data (only2.4h unsup. speech)
- Tonal information is discarded.

English: VQVAE bottleneck adds speaker invariance

English	Within spkr.	Across spkr.
VQ-VAE (per lang, MFCC, p_{cond})	**5.6**	**8.0**
VQ-VAE (per lang, MFCC, p_{bn})	*6.2*	*8.8*
VQ-VAE (per lang, MFCC, p_{proj})	*5.9*	*9.0*
VQ-VAE (all lang, MFCC, p_{cond})	*5.8*	*8.6*
VQ-VAE (all lang, MFCC, p_{bn})	*6.3*	*9.2*
VQ-VAE (all lang, MFCC, p_{proj})	*5.8*	*9.3*
VQ-VAE (all lang, fbank, p_{proj})	*6.0*	*10.1*

The quantization discards speaker info, improving across-speaker results

MFCCs slightly better than FBanks

Mandarin: VQVAE bottleneck discards phone information

Mandarin	Within spkr.	Across spkr.
VQ-VAE (per lang, MFCC, p_{cond})	11.2	12.2
VQ-VAE (per lang, MFCC, p_{bn})	*10.8*	*11.9*
VQ-VAE (per lang, MFCC, p_{proj})	*9.9*	*11.0*
VQ-VAE (all lang, MFCC, p_{cond})	*9.2*	*10.3*
VQ-VAE (all lang, MFCC, p_{bn})	*9.0*	*9.9*
VQ-VAE (all lang, MFCC, p_{proj})	*7.4*	*8.6*
VQ-VAE (all lang, fbank, p_{proj})	*6.8*	*7.8*

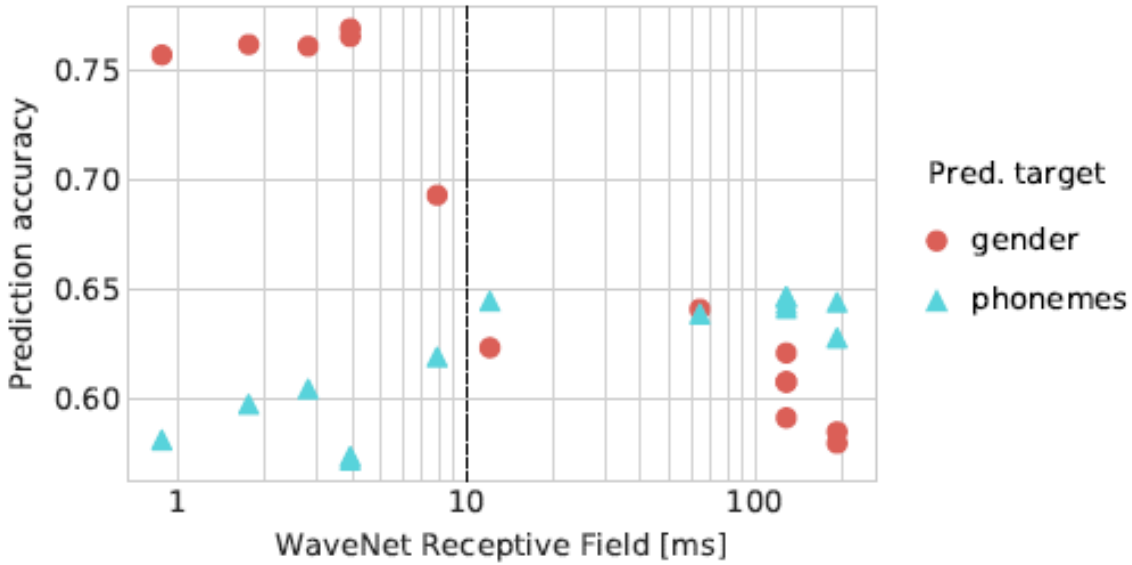
The quantization discards too much (tone insensitivity?)

MFCCs worse than FBanks

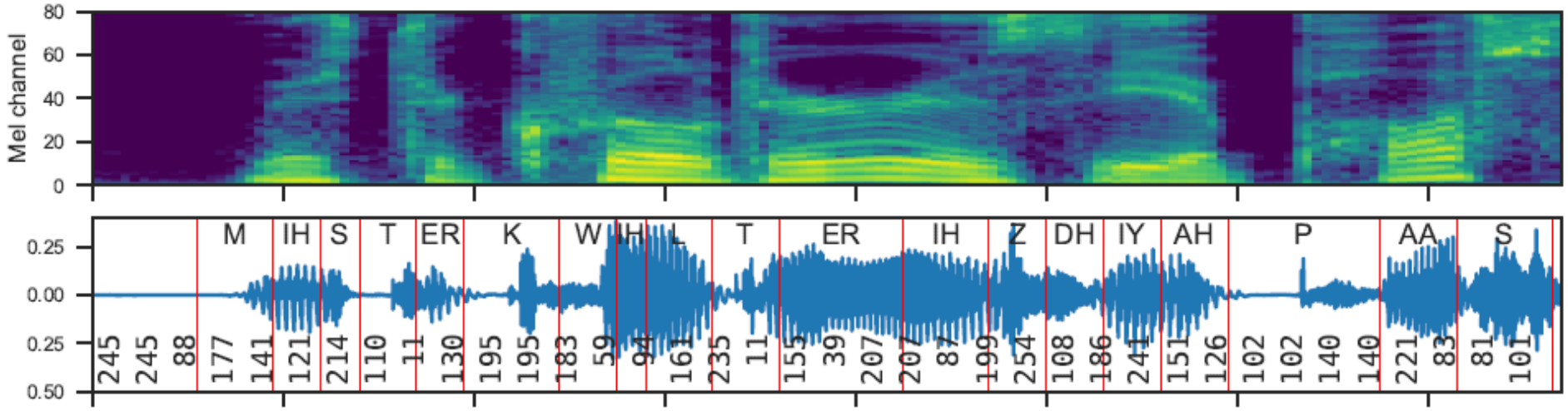
What impacts the representation?

Implicit time constant of the model:

- Input field of view of the encoder – optimum close to 0.3s
- WaveNet field of view - needs at minimum 10ms



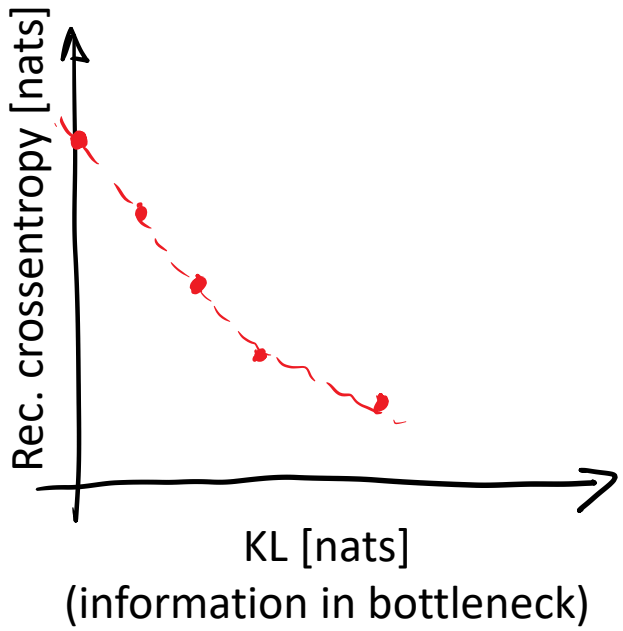
Experimental Questions #2



- Can we regularize the latent representation?
- How to promote latent code stability/segmentation?

VAE + autoregressive models: latent collapse danger

- Purely Autoregressive models: SOTA log-likelihoods
- Conditioning on latents:
  information passed through bottleneck
  lower reconstruction x-entropy
- In standard VAE model actively tries to
  - reduce information in the latents
  - maximally use autoregressive information
  => Collapse: latents are not used!
- Solution: stop optimizing KL term
  (free bits), make it a hyperparam (VQVAE)



Priors on latents promote collapse

Consider slow features:

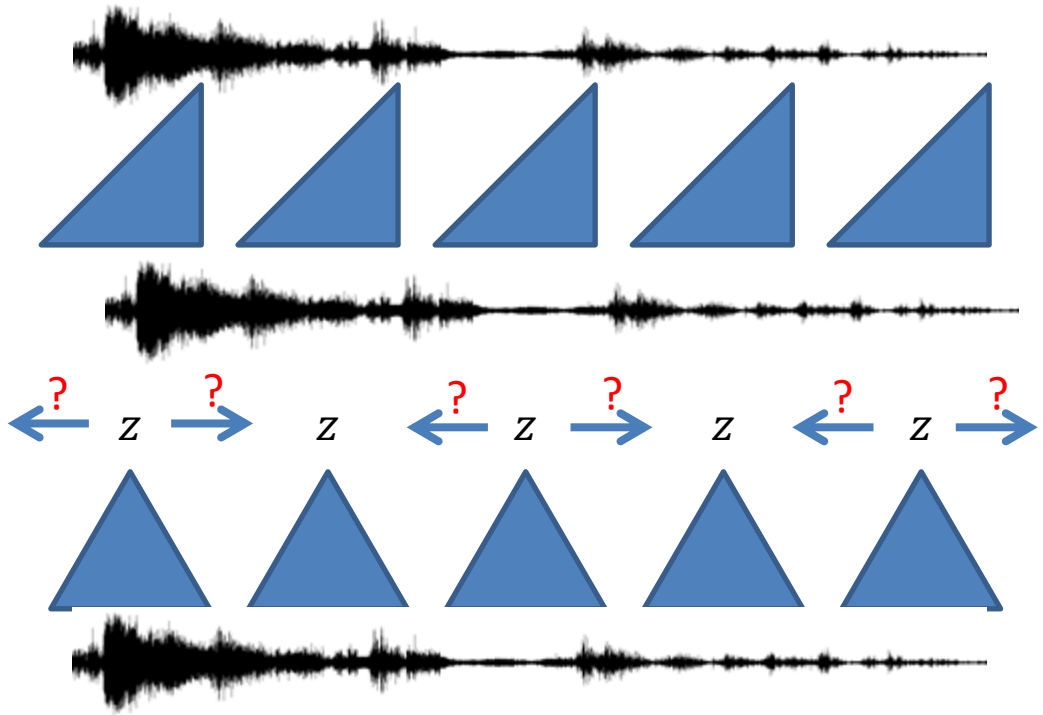
L1 penalty on the difference of neighboring codes

Promotes a constant encoding

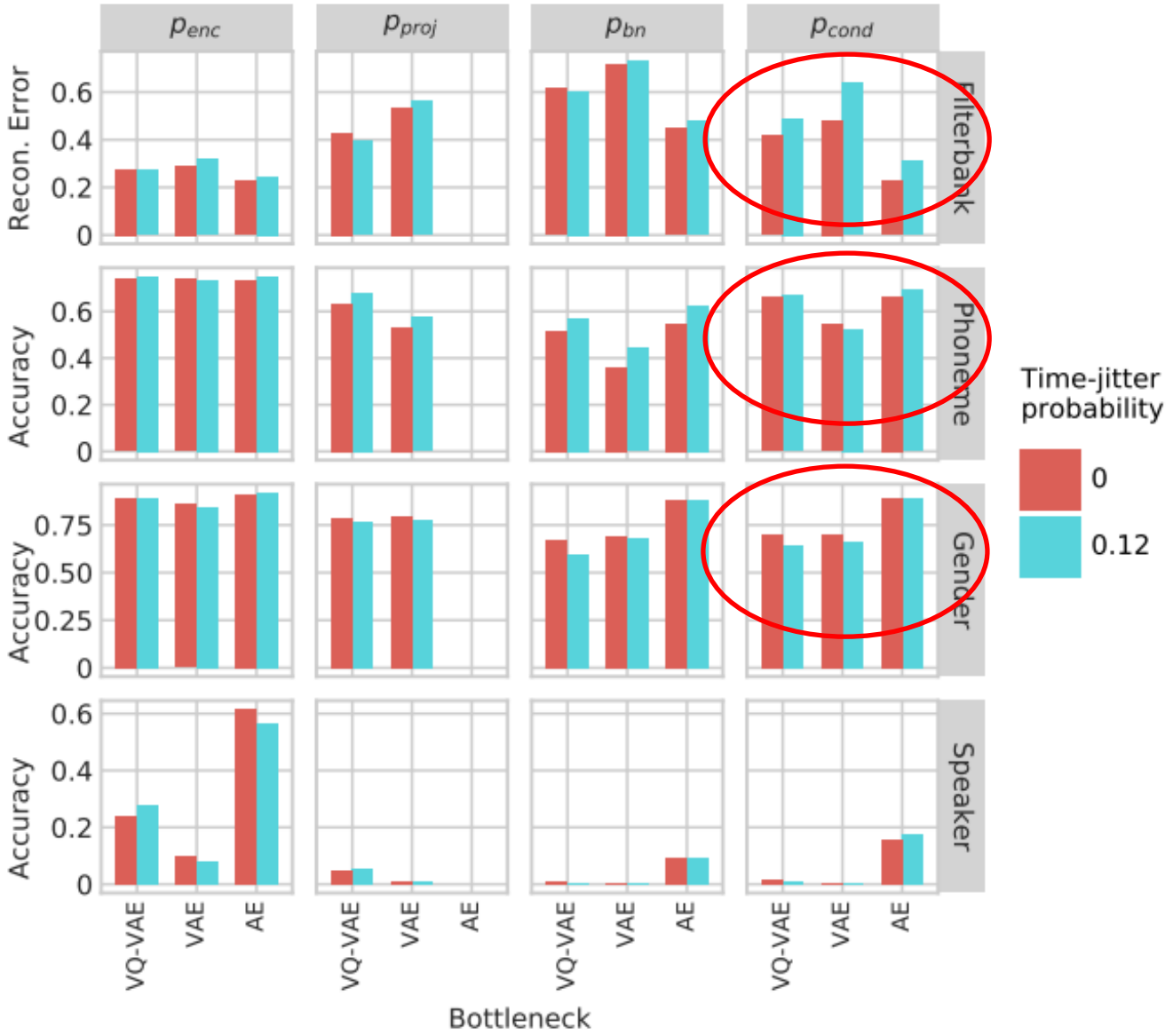
Leads to collapse

Randomized time jitter

Rather than putting a penalty on changes of the latent z vectors, add time jitter to them.
This forces the model to have a more stable representation over time.



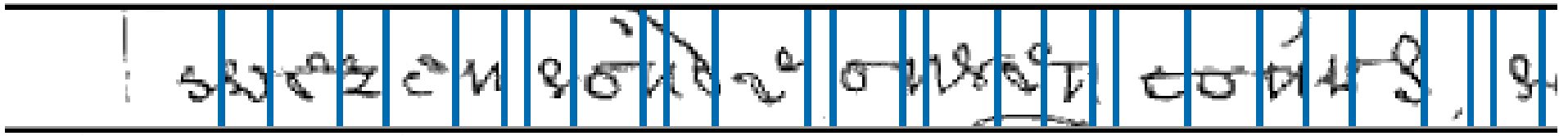
Randomized time jitter results



Segmenting auto-encoder

We extract a latent vector every 12 pixels

How to extract at every character?

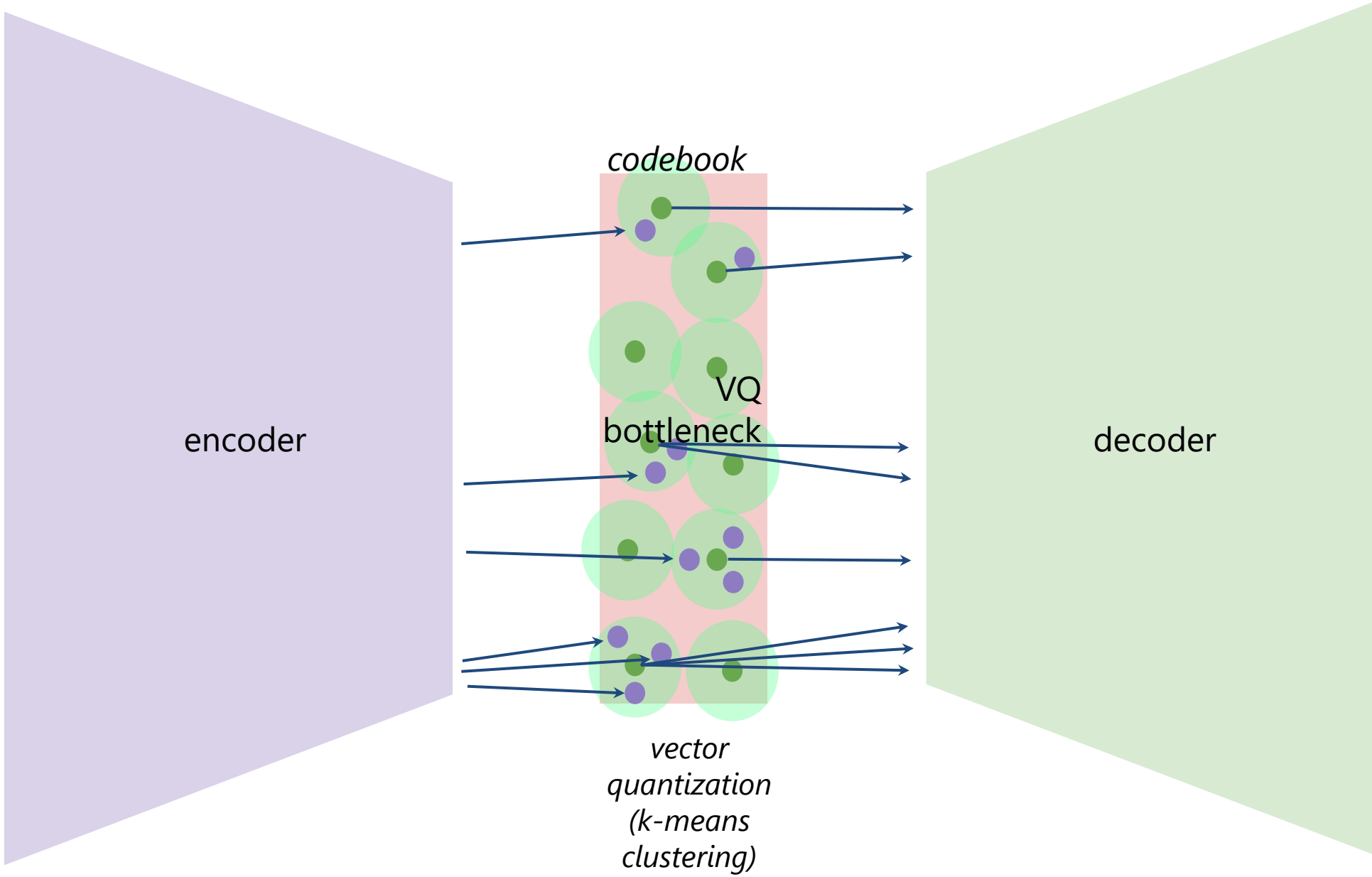


Enforce domain knowledge:

- timing
- average unit/state duration
- state and transition frequency modeling

Deep Learning value: bring hard constraints into smooth, differentiable models.

VQ-VAE


encoder
codebook
VQ
bottleneck
decoder
vector
quantization
(k-means
clustering)

Learning piecewise-constant representations

Quantization criterion:

$$\min \sum_{t=1}^{T} ||x_t - q_t|| \quad \text{subject to:} \sum_{t=1}^{T} [q_{t-1} \neq q_t] = K$$

encoder outputs

VQ tokens

expected # of characters

During training: enforce as a minibatch constraint

- easy to specify as a hyperparameter
- "large minibatch" statistics are close-ish to full data (our batches have many small chunks)
- fast with greedy merging algorithm (could be exact with Viterbi)

During inference: ?

Learning piecewise-constant representations

Quantization criterion:

$$\min \sum_{t=1}^{T} ||x_t - q_t|| \quad \text{subject to:} \sum_{t=1}^{T} [q_{t-1} \neq q_t] = K$$

Reformulate as:

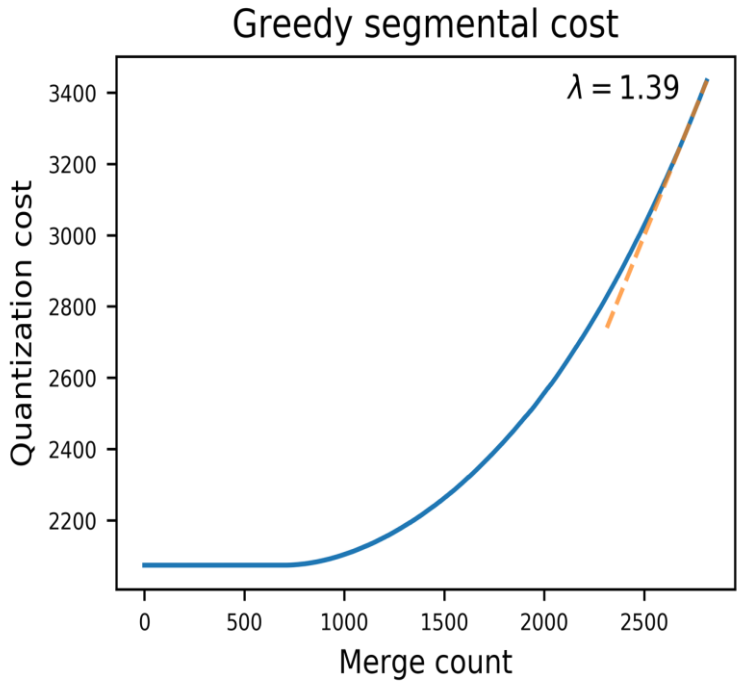
$$\min \sum_{t=1}^{T} ||x_t - q_t|| + \lambda \left(\sum_{t=1}^{T} [q_{t-1} \neq q_t] - K \right)$$

During training:

- estimate λ

During inference:

- use λ to balance the costs



Dual formulation and Markovian dynamics

Dual formulation resembles HMM cost:

$$\min \sum_{t=1}^{T} ||x_t - q_t|| + \lambda \left(\sum_{t=1}^{T} [q_{t-1} \neq q_t] - K \right)$$

state change cost

encoder outputs

Observed states: encoder outputs

Hidden states: sequence of VQ tokens

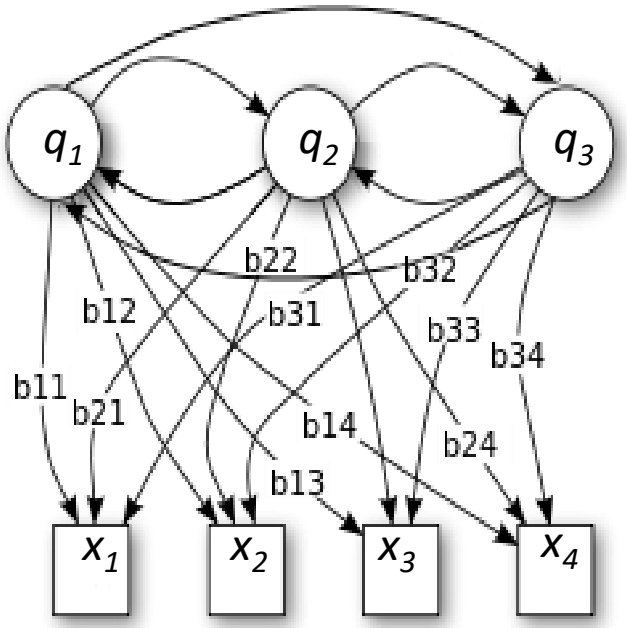


Image source: Wikipedia

Piecewise-constant results: Scribblelens

Dataset	*Model*	*Downstream CER*	*MLP Accuracy @Bottleneck*	*Token -> Char Accuracy*	*Rand score*	*Mutual information*
Single scribe Tasman	*Unsupervised base*	47%	54%	34%	0.15	0.15
	Piecewise-const VQ bottleneck	**30%**	**65%**	**57%**	**0.23**	**0.36**
All scribes	*Unsupervised base*	60%	42%	30%	0.13	0.10
	Piecewise-const VQ bottleneck	**51%**	**49%**	**39%**	**0.18**	**0.20**

THE FUTURE OF UNSUPERVISED: SELF-SUPERVISED LEARNING

Core Idea

Solve a task requiring data understanding, for which labels are easy to get.

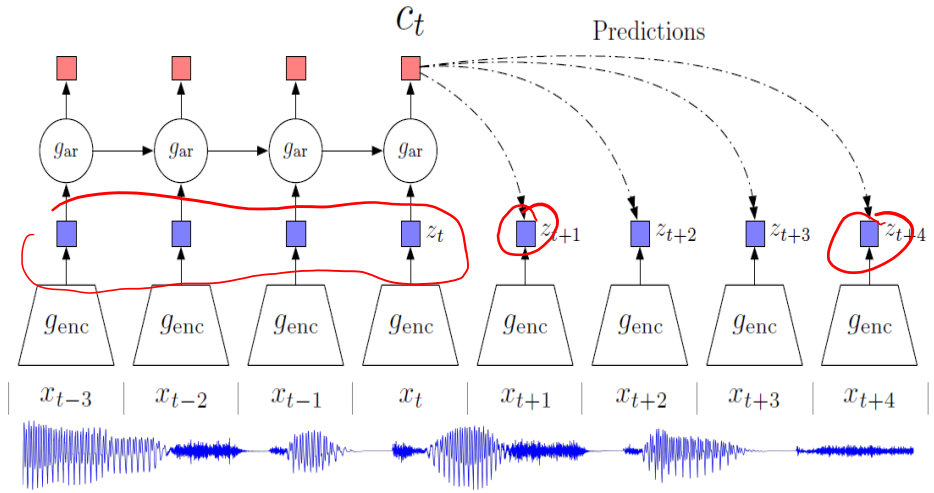
E.g. cut image into parts, predict their location.

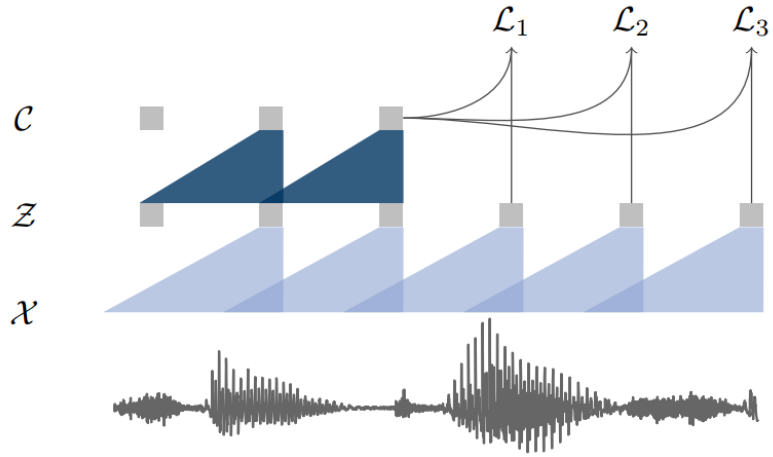
Or cut video into parts, predict time direction

Or cut sentence into words, predict neighbors (quick, what was the name of this model??)

Decoder-less approach: CPC

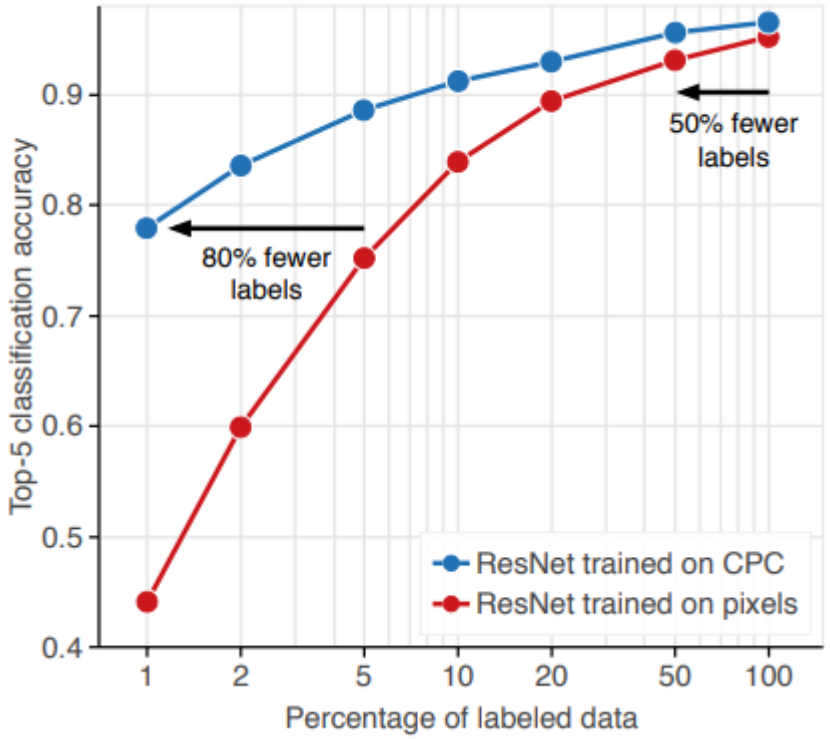
Contrastive coding learns representations that can tell a frame from a randomly sampled one



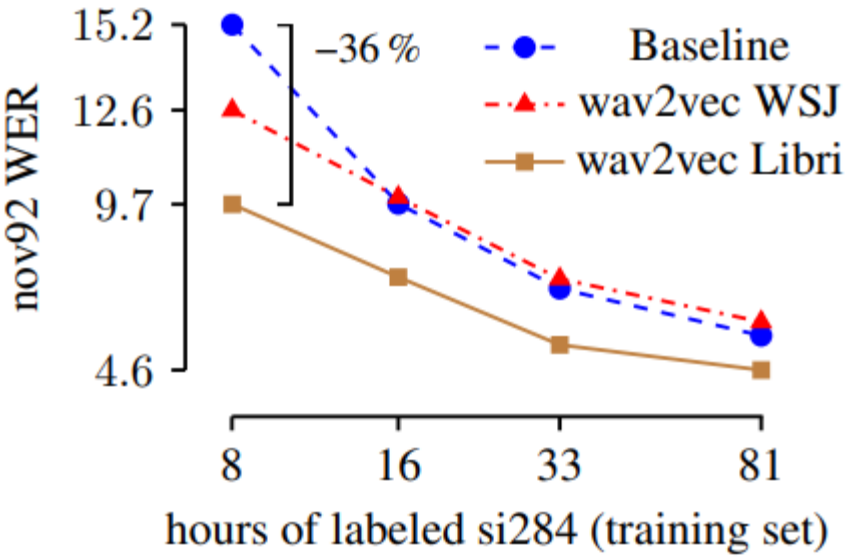


Oord et al. „Representation Learning with Contrastive Predictive Coding”
Schneider et al. „wav2vec: Unsupervised Pre-training for Speech Recognition”

CPC becomes practical



DATA-EFFICIENT IMAGE RECOGNITION WITH CONTRASTIVE PREDICTIVE CODING Olivier J. Henaff, Aravind Srinivas, Jeffrey De Fauw, Ali Razavi, ´ Carl Doersch, S. M. Ali Eslami, Aaron van den Oord



WAV2VEC: UNSUPERVISED PRE-TRAINING FOR SPEECH RECOGNITION Steffen Schneider, Alexei Baevski, Ronan Collobert, Michael Auli

Summary for unsupervised learning

- We gan generate nearly realistic samples with deep generative models!
- We can use unsupervised / self-supervised learning to learn good data representations
- We can approximately control the contents of the latent representation (e.g. separate phone/gender)

End of semester anouncements

- Grades!
  Make sure you have everything graded, if not ping me on discord -> I'll be grading A6 next week
- Project presentations
  They are mandatory, and you know it since a month!