NLP course

Lecture 12:
Knowledge Distillation and Generative Adversarial Networks for texts

Radoslav Neychev

MADE, Moscow

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Outline

1. Knowledge Distillation
2. Bonus: generative models overview
3. Outro

Based on: Distilling the Knowledge in a Neural Network

Knowledge Distillation

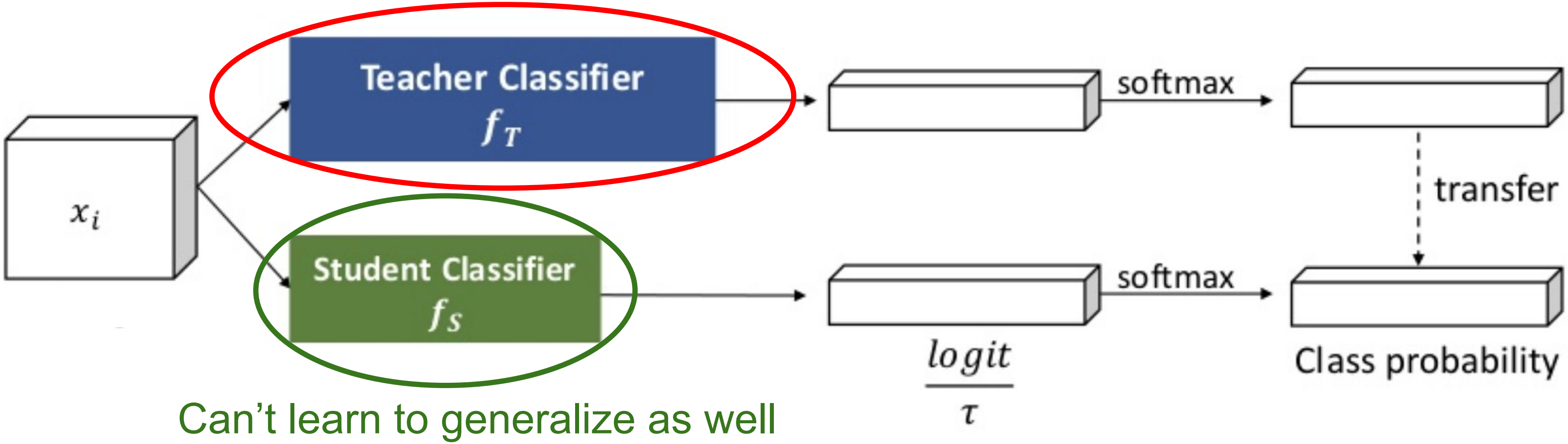
Cerura Vinula in caterpillar and butterfly forms

Do they have the same “life purpose”
and solve the same problems?

Image credits: commons.wikimedia.org (left), Ben Sale/Flickr.com (right), copied from
https://nat-geo.ru/nature/insects/bylo-stalo-kak-vyglyadyat-babochki-i-ikh-gusenitsy/

Knowledge distillation

Learns to generalize
and perform well



Can’t learn to generalize as well
as the teacher,
but still can perform well

Source: https://www.slideshare.net/NaverEngineering/relational-knowledge-distillation

Knowledge distillation

Denote **teacher** and **student** models.

Student model has logits z_i and corresponding probabilities q_i , derived with the softmax operation:

$$q_i = \frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$

where *T* stays for the temperature.

Teacher model has logits v_i and corresponding probabilities p_i .

Source: Distilling the Knowledge in a Neural Network

Knowledge distillation

Let’s derive the cross-entropy gradient on **student** logits using the **teacher** predictions as targets:

$$\frac{\partial C}{\partial z_i} = \frac{1}{T}(q_i - p_i) = \frac{1}{T}\left(\frac{e^{z_i/T}}{\sum_j e^{z_j/T}} - \frac{e^{v_i/T}}{\sum_j e^{v_j/T}}\right)$$

If the temperature is high, the following equation takes place:

$$\frac{\partial C}{\partial z_i} \approx \frac{1}{T}\left(\frac{1 + z_i/T}{N + \sum_j z_j/T} - \frac{1 + v_i/T}{N + \sum_j v_j/T}\right)$$

Source: Distilling the Knowledge in a Neural Network

Knowledge distillation

Logits can be centered, so

$$\sum_j z_j = \sum_j v_j = 0$$

Then the gradient takes form:

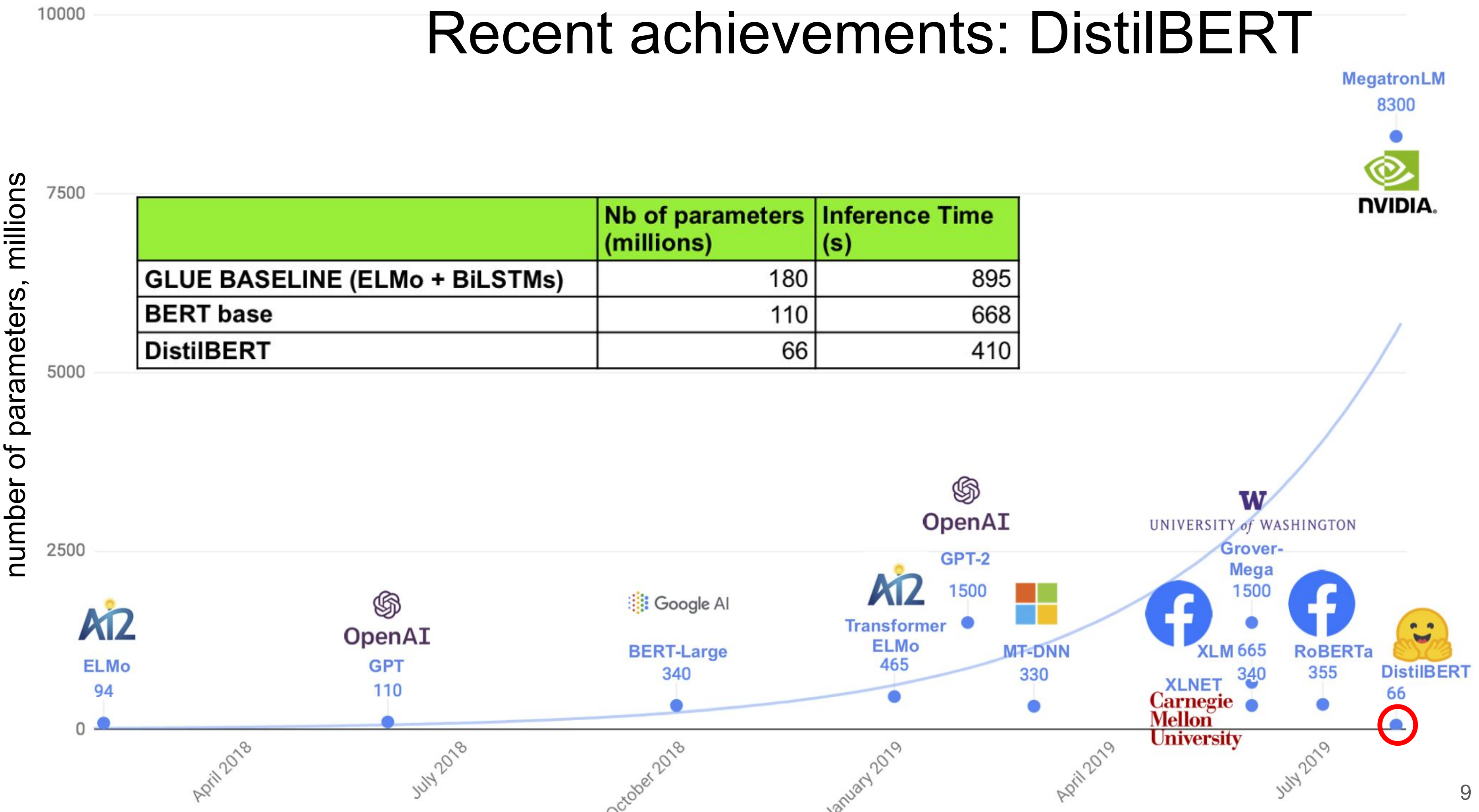
$$\frac{\partial C}{\partial z_i} \approx \frac{1}{T}\left(\frac{1+z_i/T}{N+\sum_j z_j/T} - \frac{1+v_i/T}{N+\sum_j v_j/T}\right) \approx \frac{1}{NT^2}(z_i - v_i)$$

Constant

$$\frac{dC}{dz_i} = \frac{1}{NT^2}(z_i - v_i) \sim (z_i - v_i) = M\frac{d(z_i - v_i)^2}{dz_i}$$

Source: Distilling the Knowledge in a Neural Network

Recent achievements: DistilBERT



	Nb of parameters (millions)	Inference Time (s)
GLUE BASELINE (ELMo + BiLSTMs)	180	895
BERT base	110	668
DistilBERT	66	410

Image source: [Smaller, faster, cheaper, lighter: Introducing DistilBERT, a distilled version of BERT]

Main ideas

- DistilBERT is initialized from its teacher, BERT, by taking one layer out of two, leveraging the common hidden size.
  - *Comment: Training a sub-network is not only about the architecture. It is also about finding the right initialization for the sub-network to converge.*

- DistilBERT is trained on very large batches leveraging gradient accumulation (up to 4000 examples per batch), with dynamic masking and removed the next sentence prediction objective.
  - *Comment: the way BERT is trained is crucial for its final performance.*

- DistilBERT was trained on eight 16GB V100 GPUs for approximately three and a half days using the concatenation of Toronto Book Corpus and English Wikipedia (same data as original BERT).

Image source: [Smaller, faster, cheaper, lighter: Introducing DistilBERT, a distilled version of BERT]()

Generative Models

Generative models taxonomy

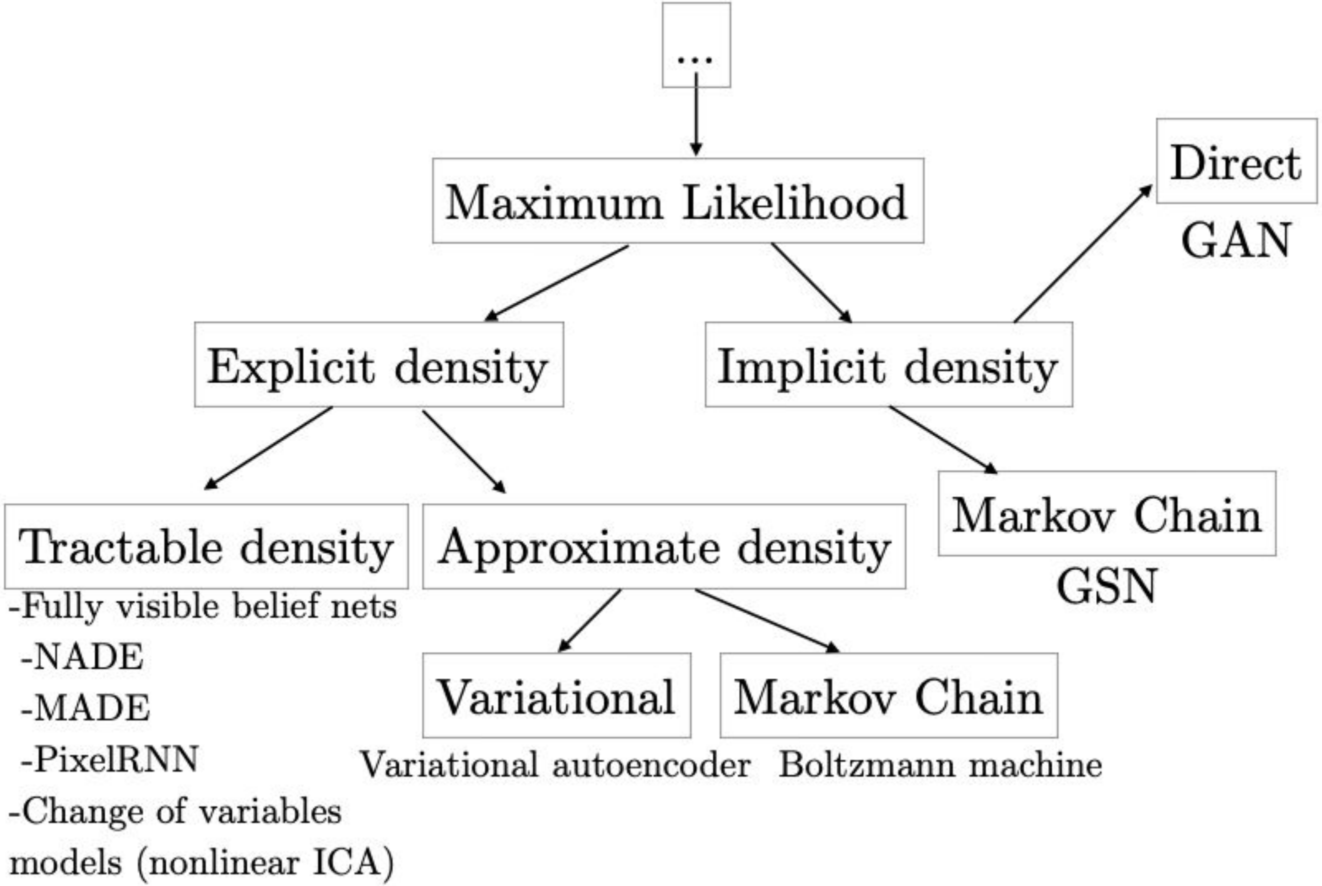


Image source: [Tutorial on Generative Adversarial Networks, Ian Goodfellow, NIPS, 2016]

Generative models taxonomy

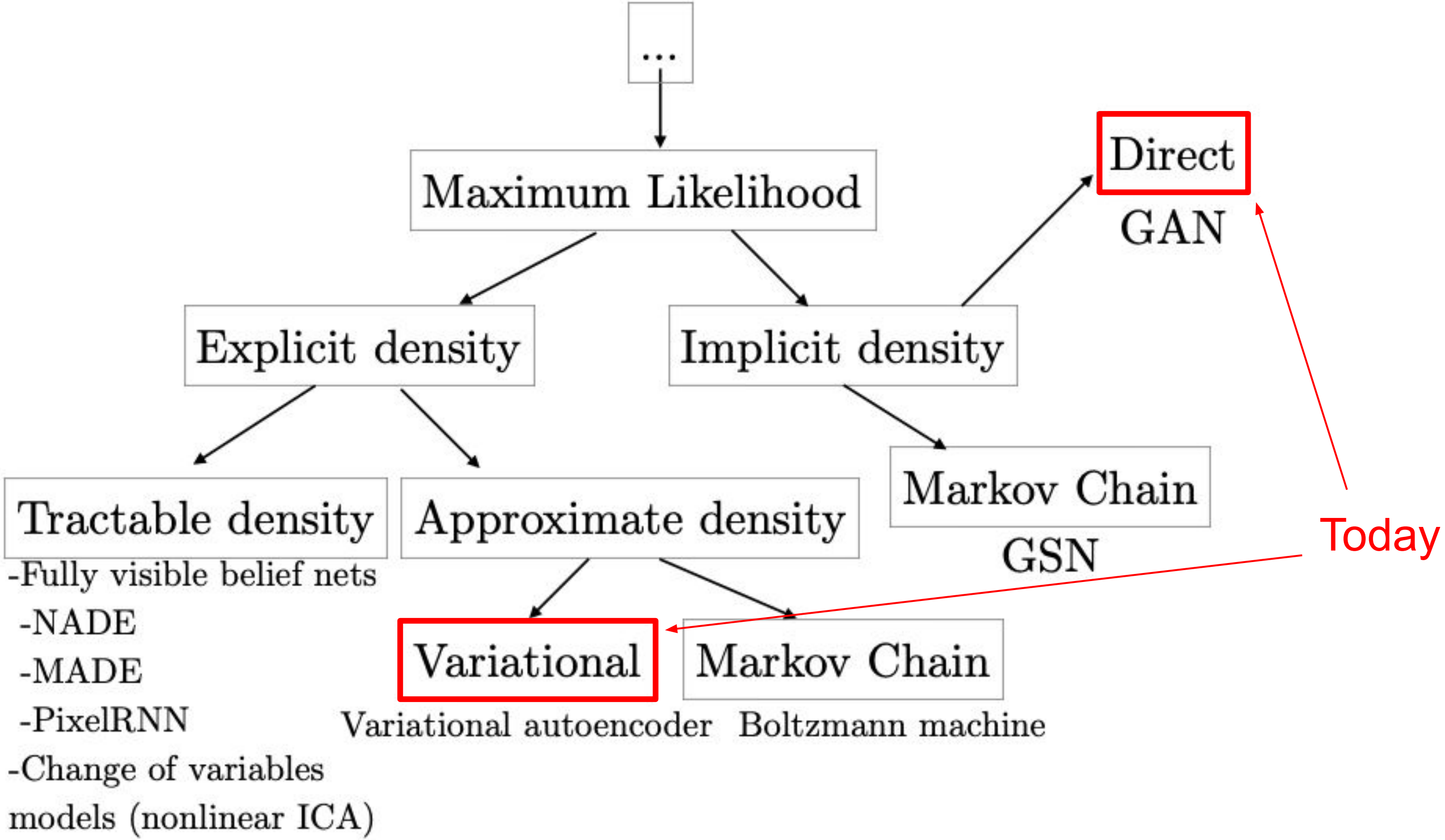


Image source: Tutorial on Generative Adversarial Networks, Ian Goodfellow, NIPS, 2016

Autoencoders

Denote **z** as encoded with encoder E input **x**

$$\mathbf{z} = E(\mathbf{x}, \boldsymbol{\theta}_E)$$

Decoder D recovers **x** from latent representation

$$\hat{\mathbf{x}} = D(\mathbf{z}, \boldsymbol{\theta}_D)$$

Optimal parameters learned w.r.t. loss function L

$$[\boldsymbol{\theta}_E, \boldsymbol{\theta}_D] = \arg\min L(\hat{\mathbf{x}}, \mathbf{x})$$

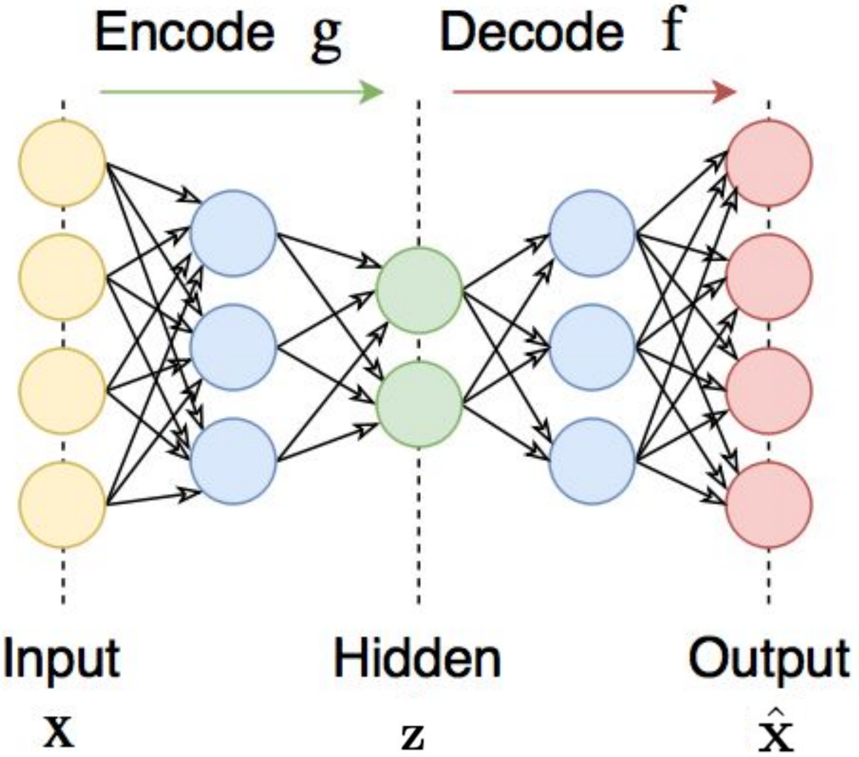


Image source: Habr post on autoencoders and GANs

Autoencoders

Denote **z** as encoded with encoder E input **x**

$$\mathbf{z} = E(\mathbf{x}, \boldsymbol{\theta}_E)$$

Decoder D recovers **x** from latent representation

$$\hat{\mathbf{x}} = D(\mathbf{z}, \boldsymbol{\theta}_D)$$

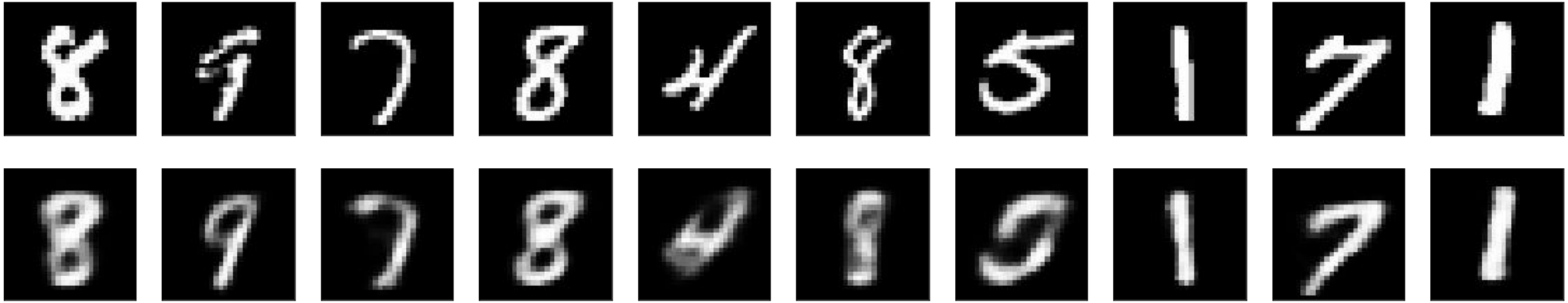
Simple example: PCA

Optimal parameters learned w.r.t. loss function L

$$[\boldsymbol{\theta}_E, \boldsymbol{\theta}_D] = \arg\min L(\hat{\mathbf{x}}, \mathbf{x})$$

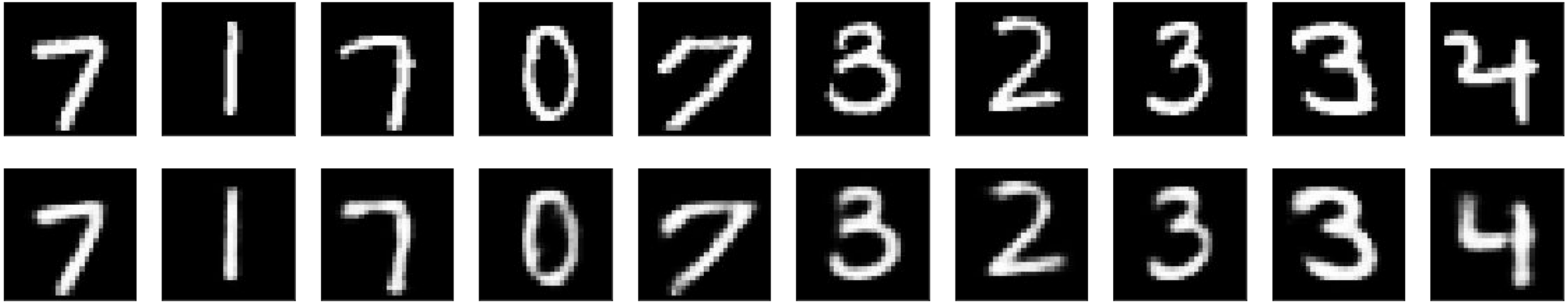
Image source: Habr post on autoencoders and GANs

PCA performance on MNIST



16 components

Convolutional performance on MNIST

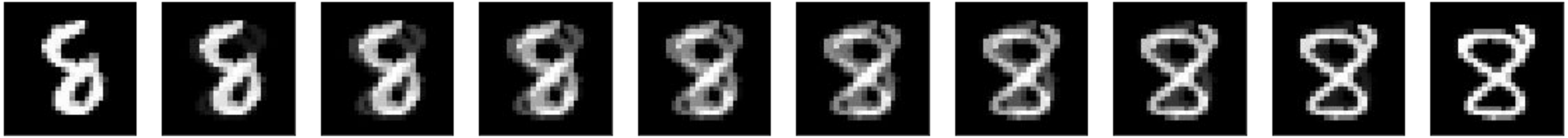


7 x 7 latent space

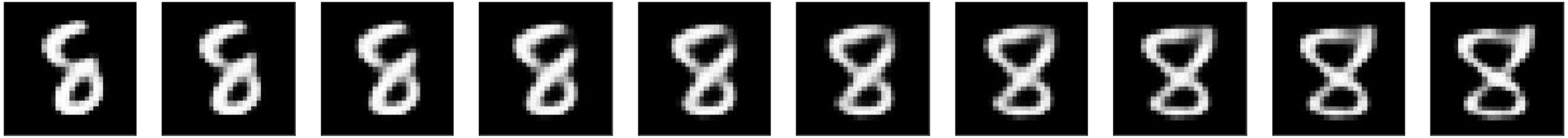
Homotopy between samples

10 steps between samples

- In original feature space (28 x 28):



- In latent space (7 x 7):



Latent space structure

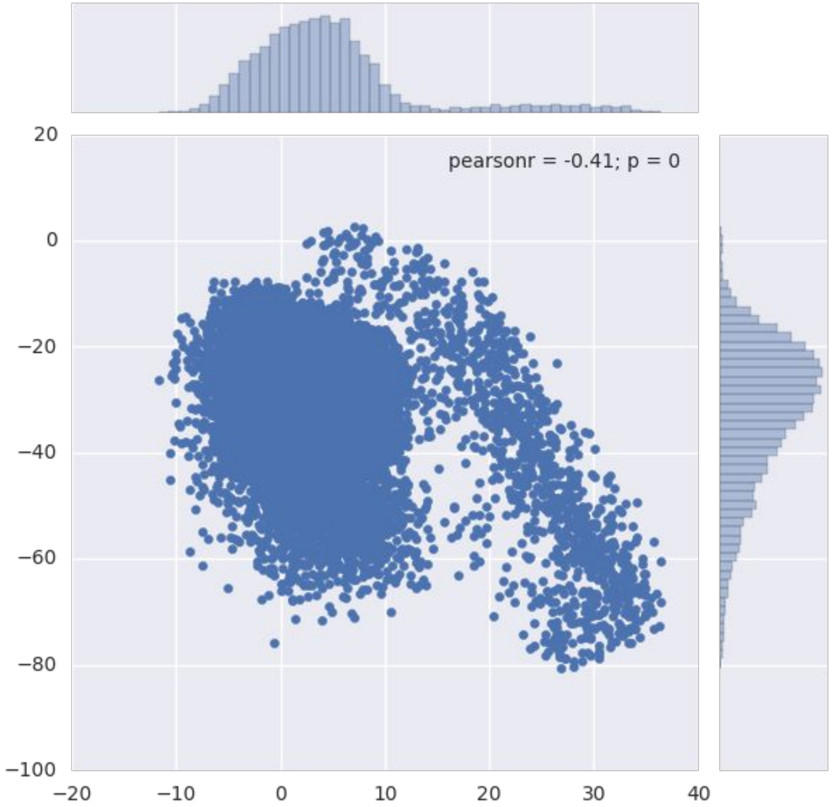


Image source: Habr post on autoencoders and GANs

VAE intuition

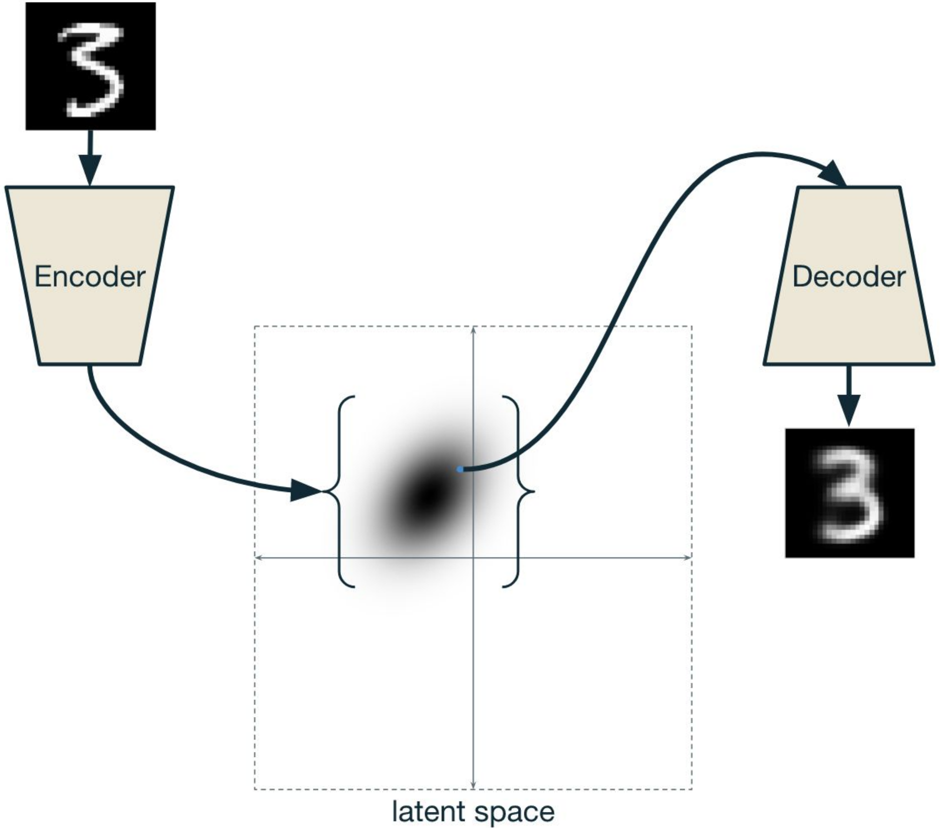


Image source: Conditional Variational Autoencoders by Isaac Dykeman, 2016

KL divergence

Denote distributions $Q(z)$ and $P(z|X)$.

Kullback–Leibler divergence is defined as

$$\mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(z|X)\right]$$

KL divergence

$$\mathcal{D}\left[Q(z)\|P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(z|X)\right]$$

Applying the Bayes rule:

$$\mathcal{D}\left[Q(z)\|P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(X|z) - \log P(z)\right] + \log P(X)$$

KL divergence

$$\mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(z|X)\right]$$

Applying the Bayes rule:

$$\mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(X|z) - \log P(z)\right] + \log P(X)$$

$$\log P(X) - \mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z\sim Q}\left[\log P(X|z)\right] - \mathcal{D}\left[Q(z) \| P(z)\right]$$

KL divergence

$$\mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z \sim Q}\left[\log Q(z) - \log P(z|X)\right]$$

Applying the Bayes rule:

$$\mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z \sim Q}\left[\log Q(z) - \log P(X|z) - \log P(z)\right] + \log P(X)$$

$$\log P(X) - \mathcal{D}\left[Q(z) \| P(z|X)\right] = E_{z \sim Q}\left[\log P(X|z)\right] - \mathcal{D}\left[Q(z) \| P(z)\right]$$

$$\boxed{\log P(X) - \mathcal{D}\left[Q(z|X) \| P(z|X)\right] = E_{z \sim Q}\left[\log P(X|z)\right] - \mathcal{D}\left[Q(z|X) \| P(z)\right]}$$

This equation is the core of Variational Autoencoders

Structure of the latent space

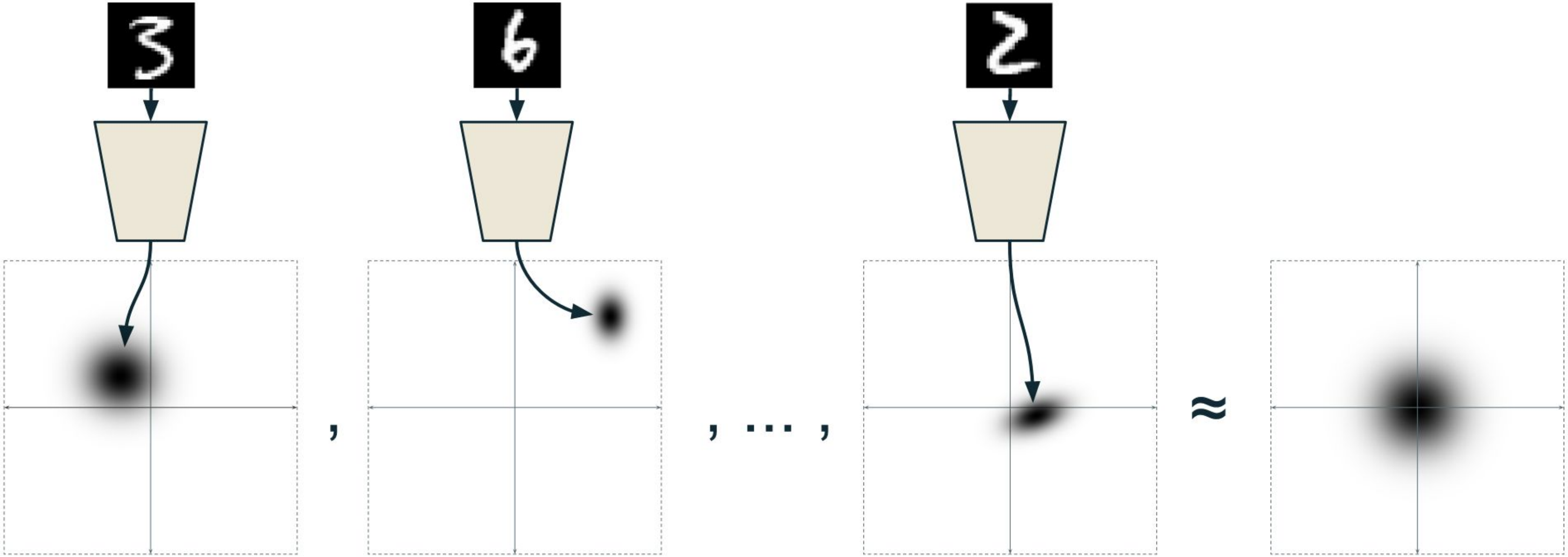
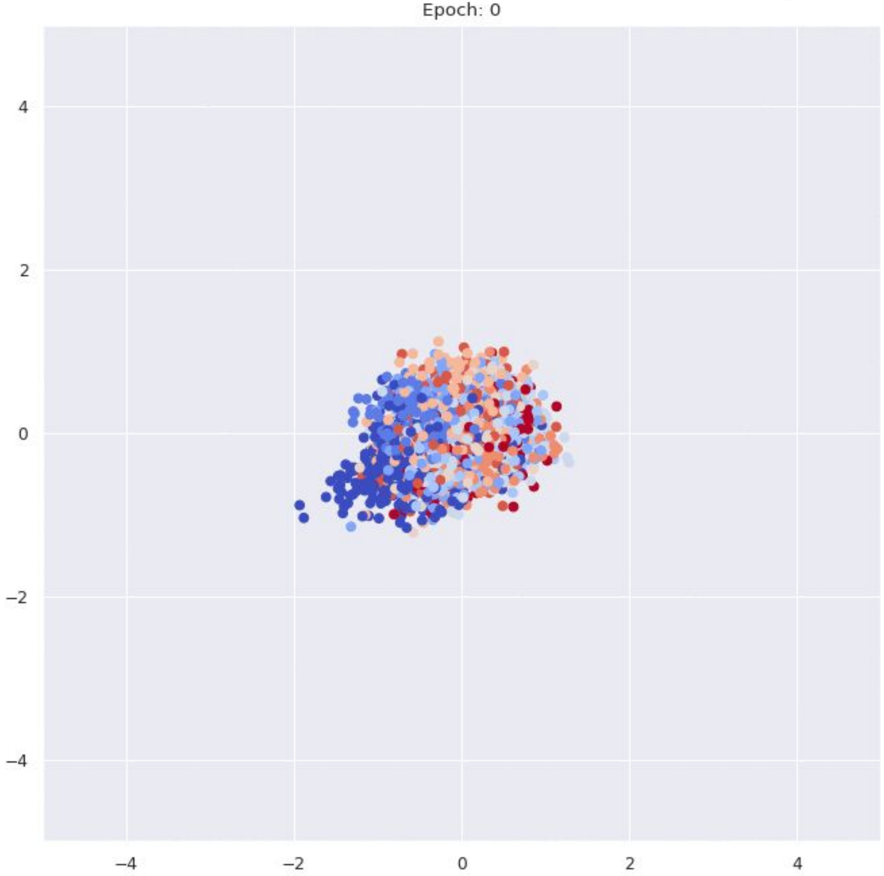


Image source: Conditional Variational Autoencoders by Isaac Dykeman, 2016

VAE latent space distribution



VAE so far

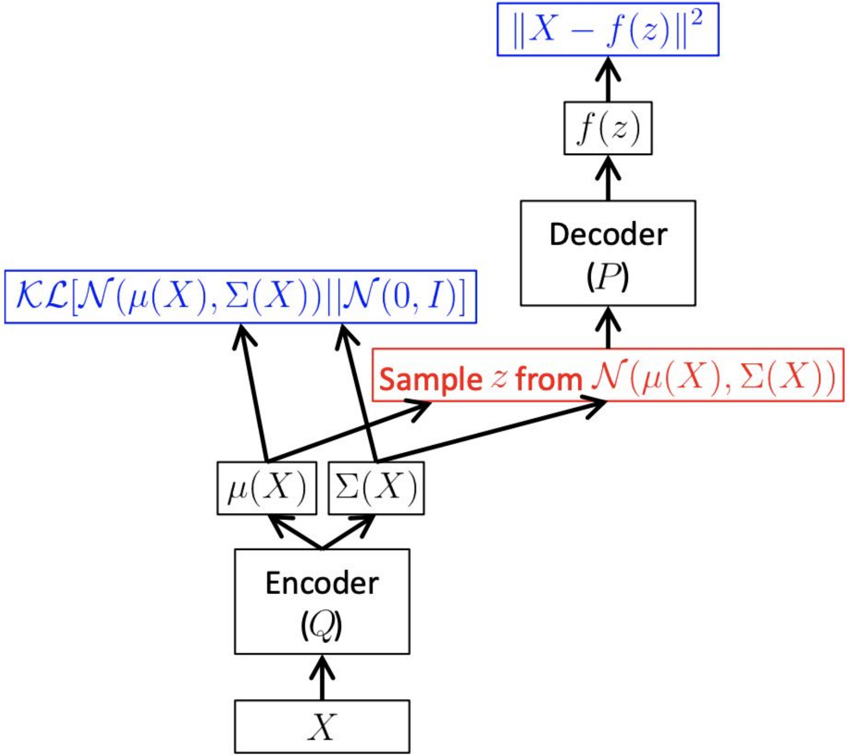

$\|X - f(z)\|^2$
$f(z)$
Decoder
(P)
$\mathcal{KL}[\mathcal{N}(\mu(X), \Sigma(X)) || \mathcal{N}(0, I)]$
Sample z from $\mathcal{N}(\mu(X), \Sigma(X))$
$\mu(X)$
$\Sigma(X)$
Encoder
(Q)
X

Image source: Tutorial on Variational Autoencoders by Carl Doersch, 2016

VAE so far

$$\mathcal{D}[\mathcal{N}(\mu(X),\Sigma(X))\|\mathcal{N}(0,I)] = \frac{1}{2}\left(\mathrm{tr}\left(\Sigma(X)\right) + \left(\mu(X)\right)^{\top}\left(\mu(X)\right) - k - \log\det\left(\Sigma(X)\right)\right)$$

Try to derive it by yourself

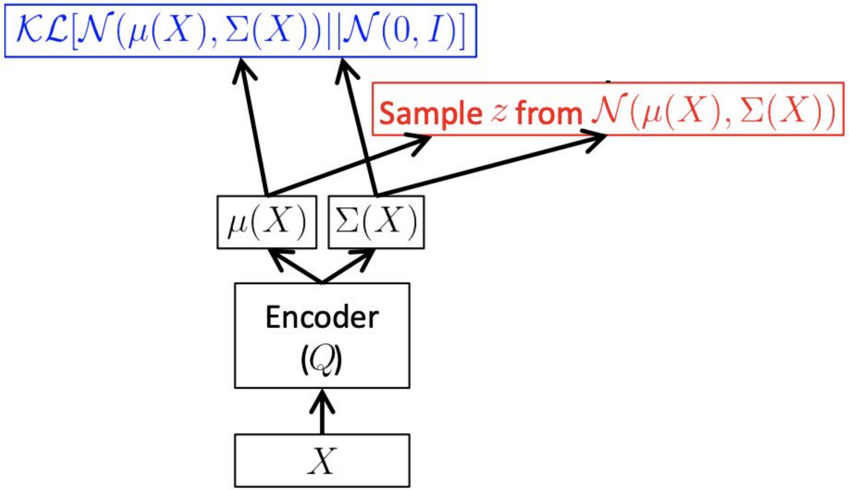
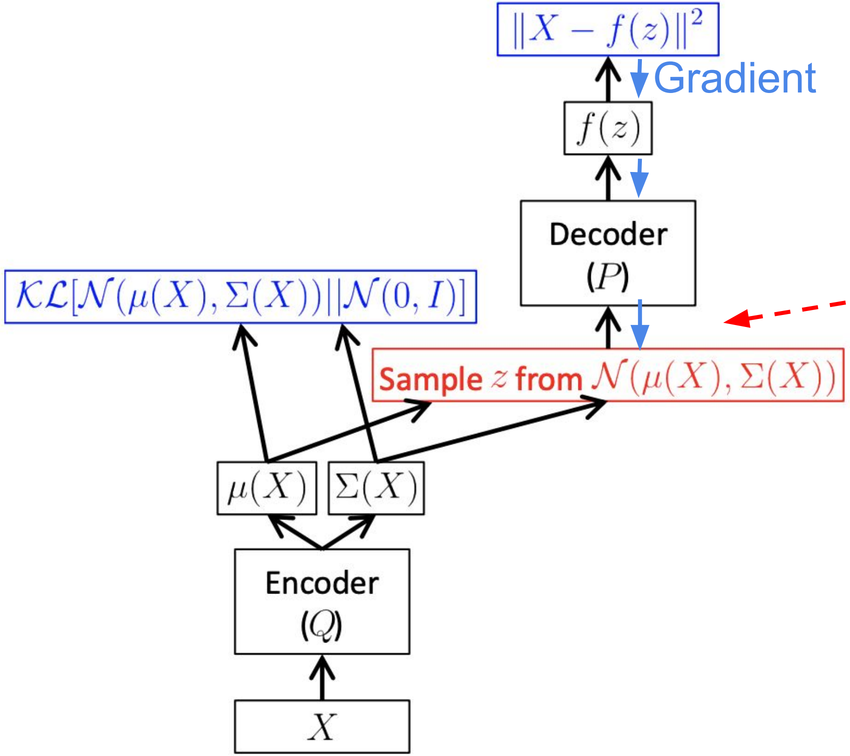

$\mathcal{KL}[\mathcal{N}(\mu(X),\Sigma(X))||\mathcal{N}(0,I)]$
Sample z from $\mathcal{N}(\mu(X),\Sigma(X))$
$\mu(X)$
$\Sigma(X)$
Encoder (Q)
X

Image source: Tutorial on Variational Autoencoders by Carl Doersch, 2016

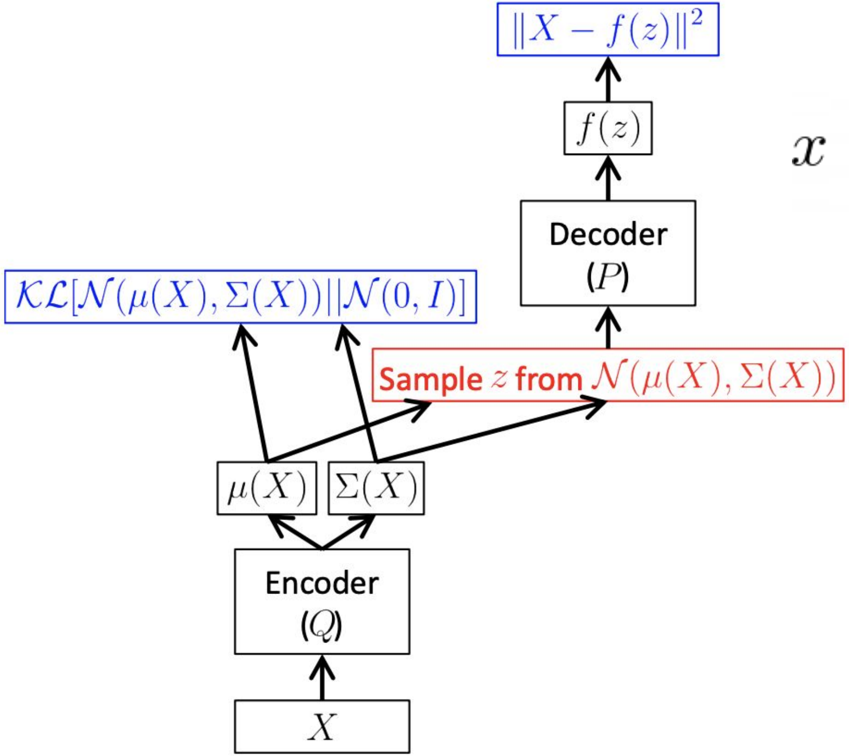
VAE so far


$\|X - f(z)\|^2$
Gradient
$f(z)$
Decoder
(P)
$\mathcal{KL}[\mathcal{N}(\mu(X), \Sigma(X))||\mathcal{N}(0, I)]$
Sample z from $\mathcal{N}(\mu(X), \Sigma(X))$
$\mu(X)$
$\Sigma(X)$
Encoder
(Q)
X

Gradient flow is broken!

Image source: Tutorial on Variational Autoencoders by Carl Doersch, 2016

Reparametrization trick


$\|X - f(z)\|^2$
$f(z)$
Decoder
(P)
$\mathcal{KL}[\mathcal{N}(\mu(X),\Sigma(X))||\mathcal{N}(0,I)]$
Sample z from $\mathcal{N}(\mu(X),\Sigma(X))$
$\mu(X)$
$\Sigma(X)$
Encoder
(Q)
X

$$x \sim \mathcal{N}(\mu, \sigma^2), \quad z = \frac{x-\mu}{\sigma} \sim \mathcal{N}(0,1)$$

$$\Rightarrow x = \sigma(z+\mu) \sim \mathcal{N}(\mu, \sigma^2)$$

Image source: Tutorial on Variational Autoencoders by Carl Doersch, 2016

Reparametrization trick

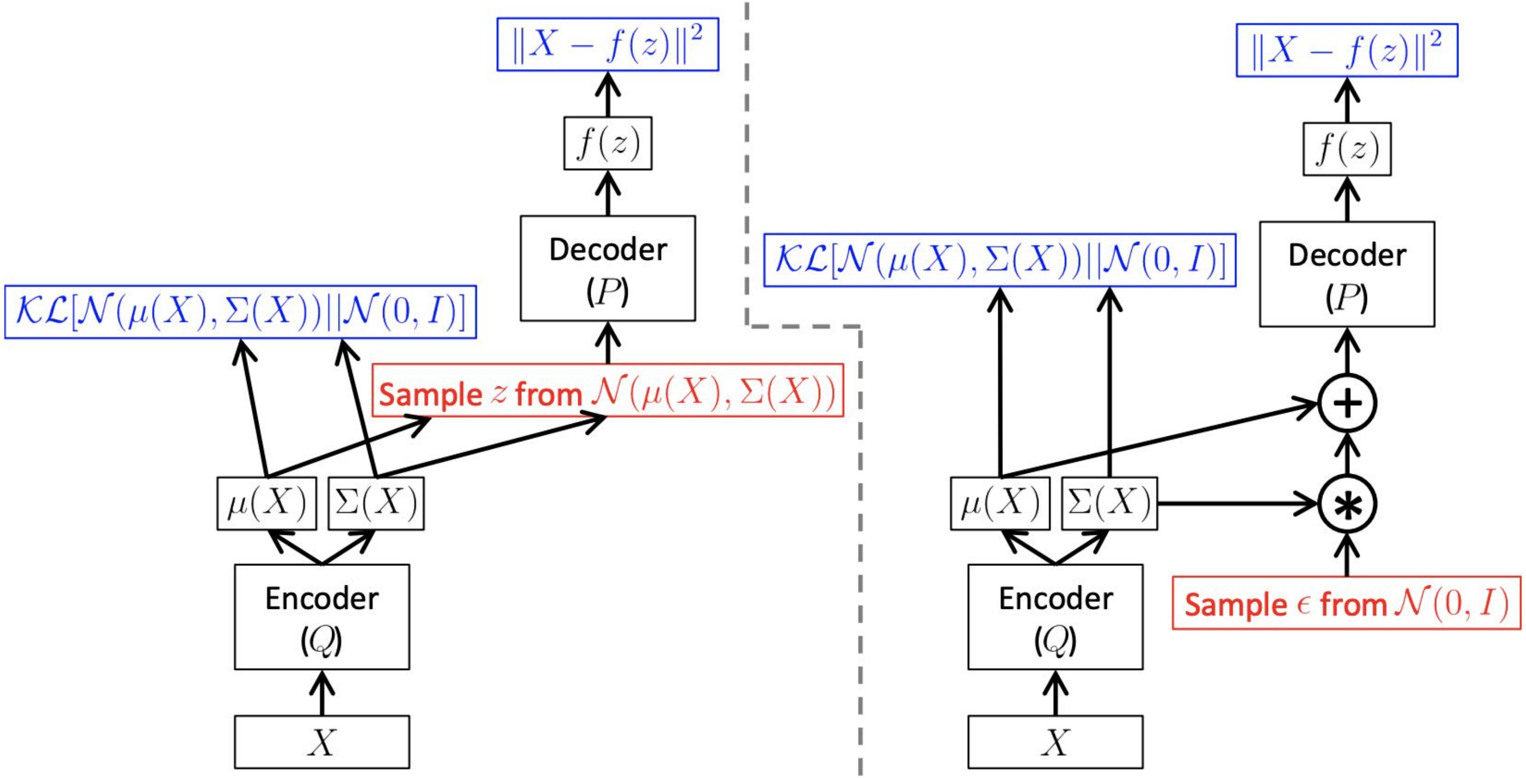
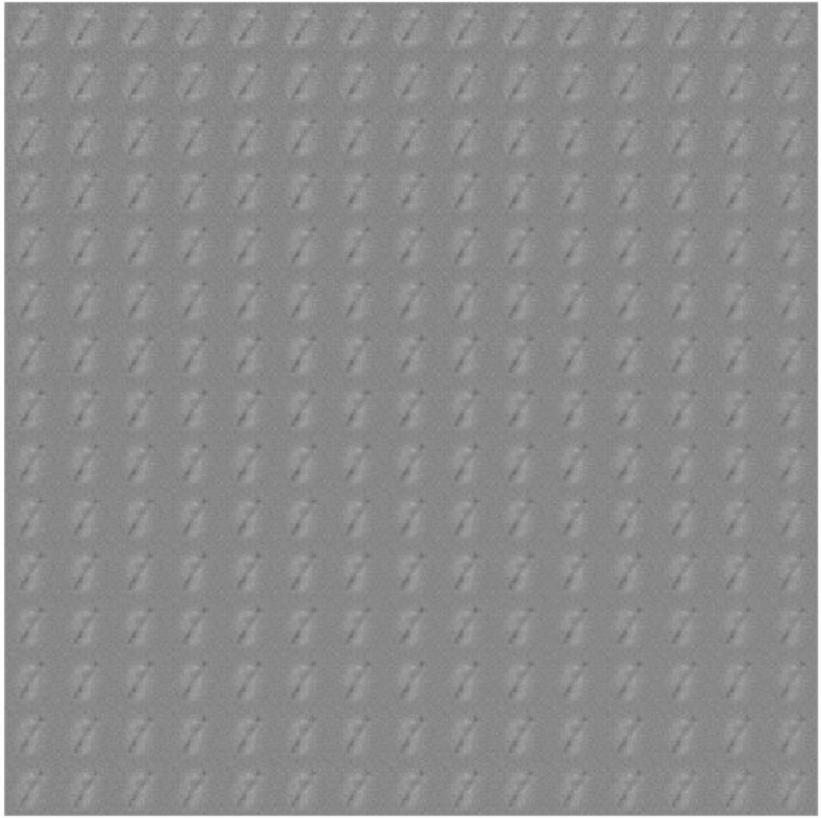

$\|X - f(z)\|^2$
$f(z)$
Decoder (P)
$\mathcal{KL}[\mathcal{N}(\mu(X), \Sigma(X)) \| \mathcal{N}(0, I)]$
Sample z from $\mathcal{N}(\mu(X), \Sigma(X))$
$\mu(X)$
$\Sigma(X)$
Encoder (Q)
X
$\|X - f(z)\|^2$
$f(z)$
$\mathcal{KL}[\mathcal{N}(\mu(X), \Sigma(X)) \| \mathcal{N}(0, I)]$
Decoder (P)
$+$
$*$
$\mu(X)$
$\Sigma(X)$
Encoder (Q)
Sample ϵ from $\mathcal{N}(0, I)$
X

Image source: Tutorial on Variational Autoencoders by Carl Doersch, 2016

VAE manifold

Epoch: 0



Structure of the latent space

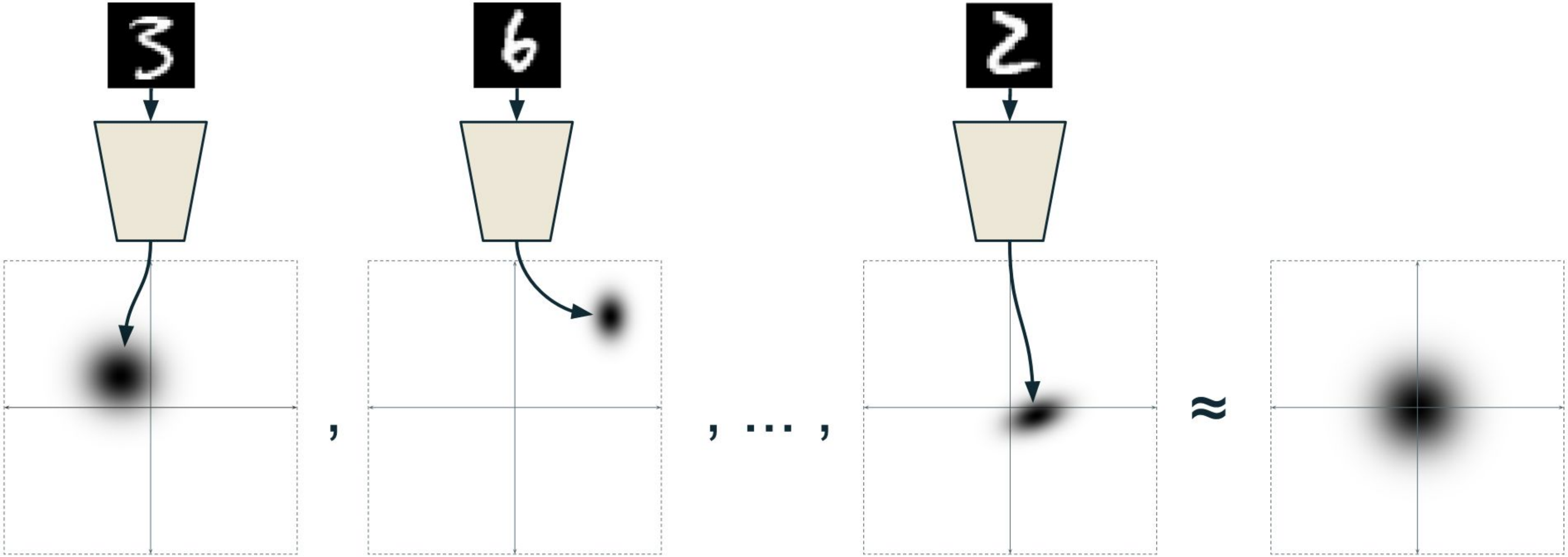


Image source: Conditional Variational Autoencoders by Isaac Dykeman, 2016

Conditional VAE intuition

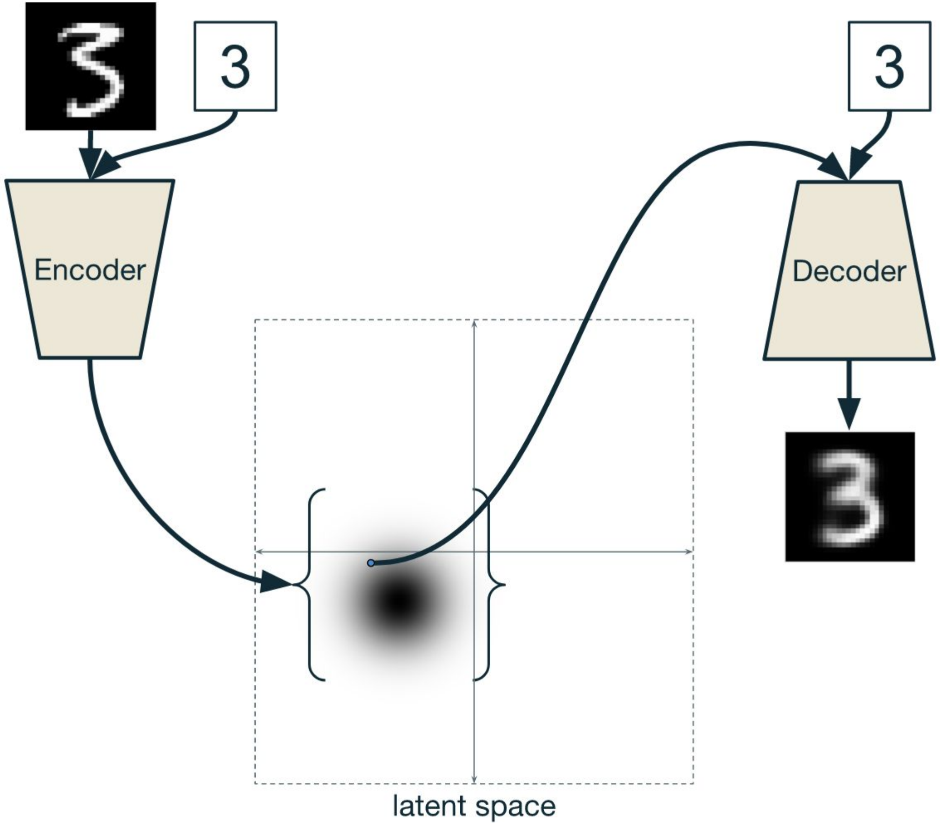
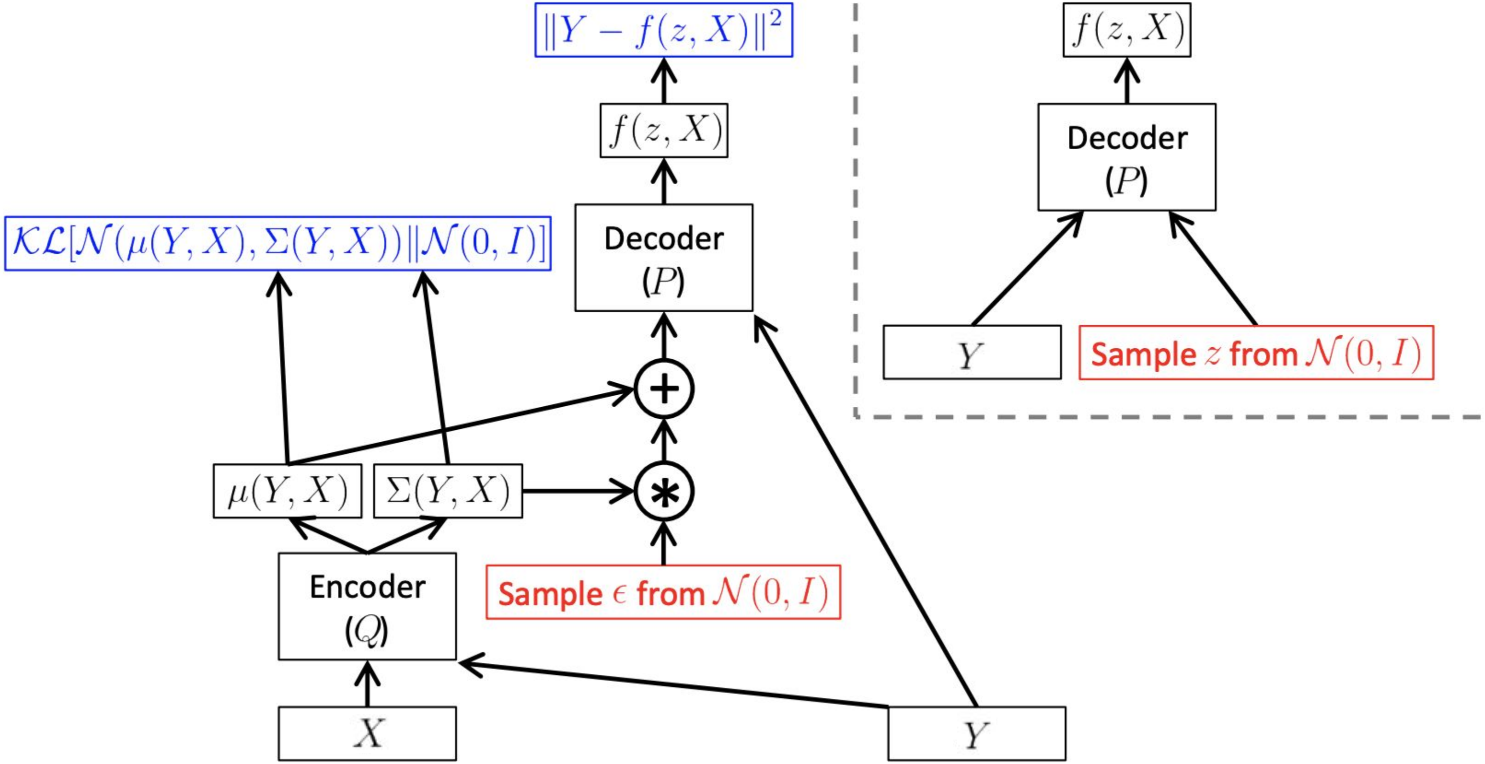


Image source: Conditional Variational Autoencoders by Isaac Dykeman, 2016

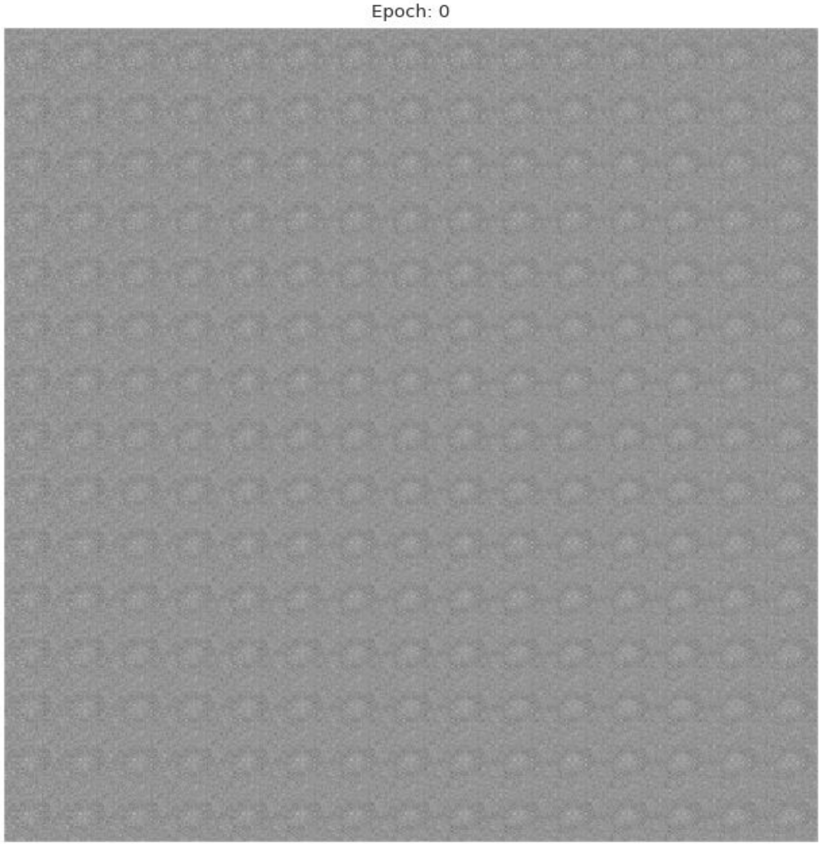
Conditional VAE



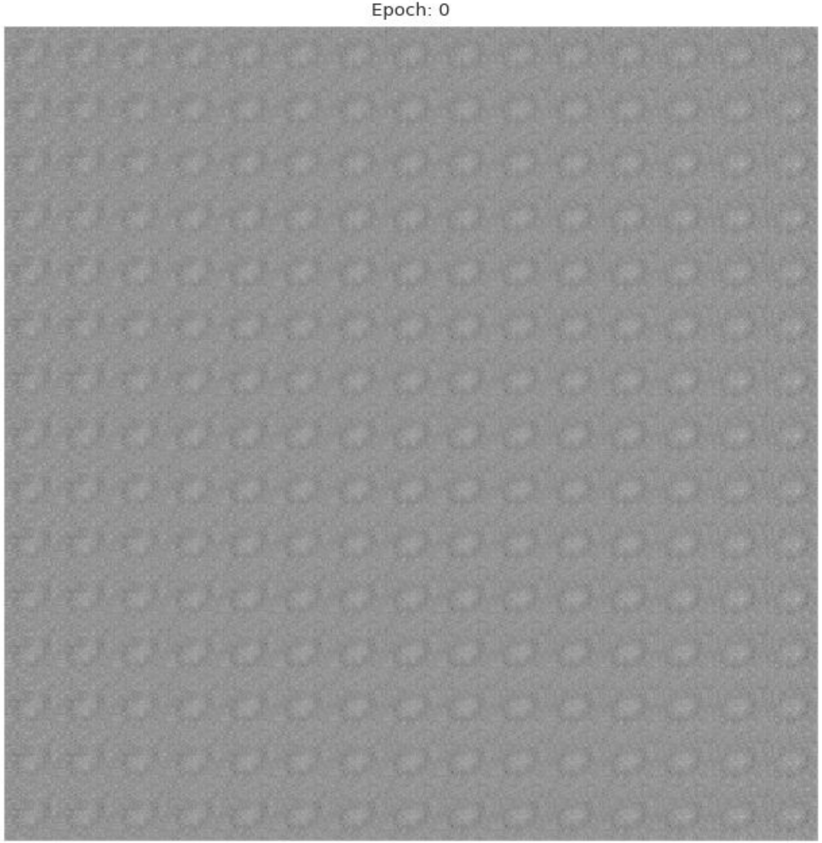
$\|Y - f(z, X)\|^2$
$f(z, X)$
Decoder (P)
$\mathcal{KL}[\mathcal{N}(\mu(Y, X), \Sigma(Y, X)) \| \mathcal{N}(0, I)]$
+
$\mu(Y, X)$
$\Sigma(Y, X)$
*
Encoder (Q)
Sample ϵ from $\mathcal{N}(0, I)$
X
Y
$f(z, X)$
Decoder (P)
Y
Sample z from $\mathcal{N}(0, I)$

Image source: Tutorial on Variational Autoencoders by Carl Doersch, 2016

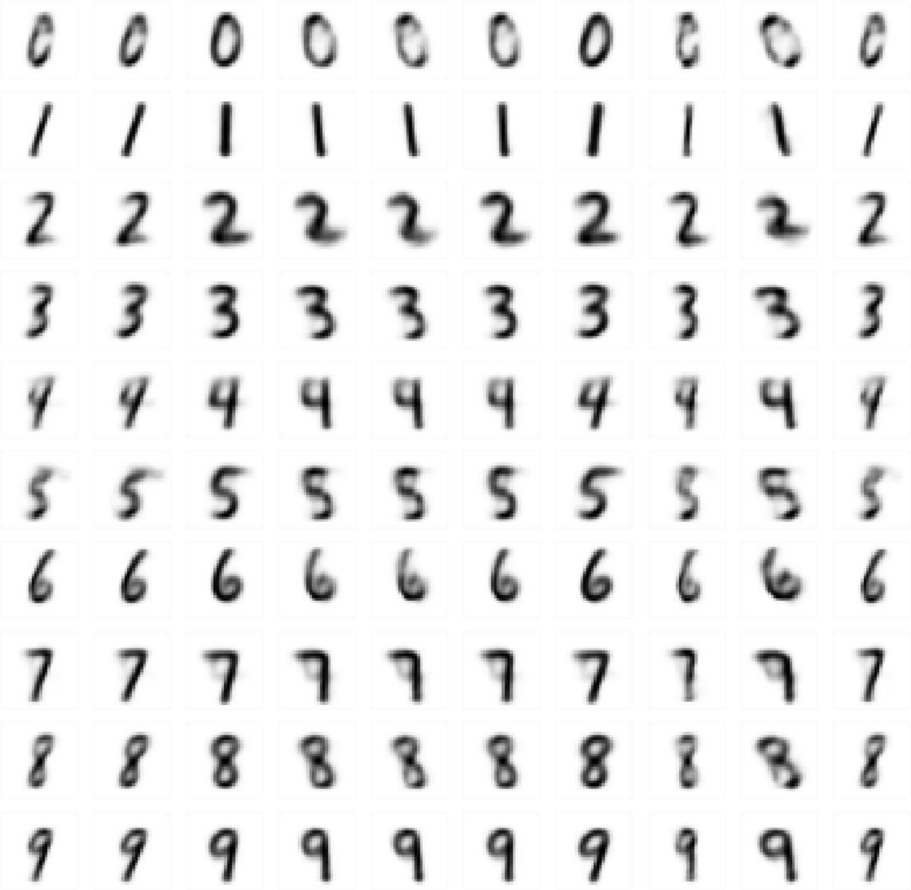
cVAE manifold



cVAE manifold



Transferring style with cVAE



Seed label is 1

Once again

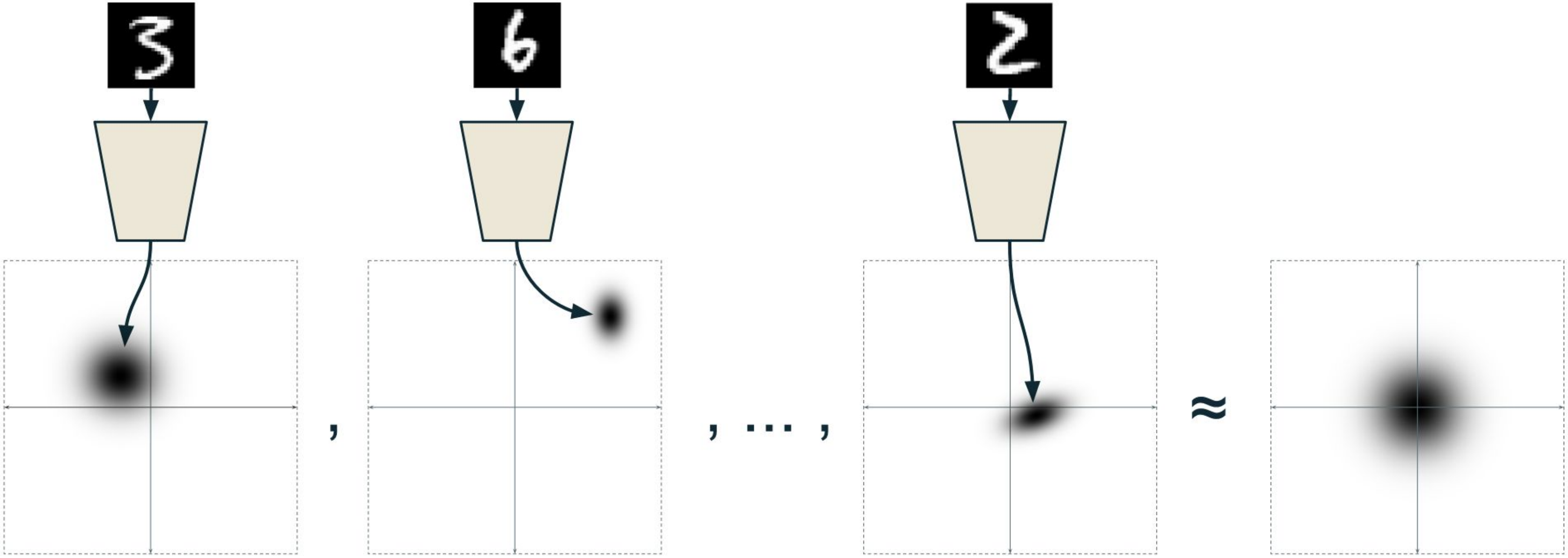
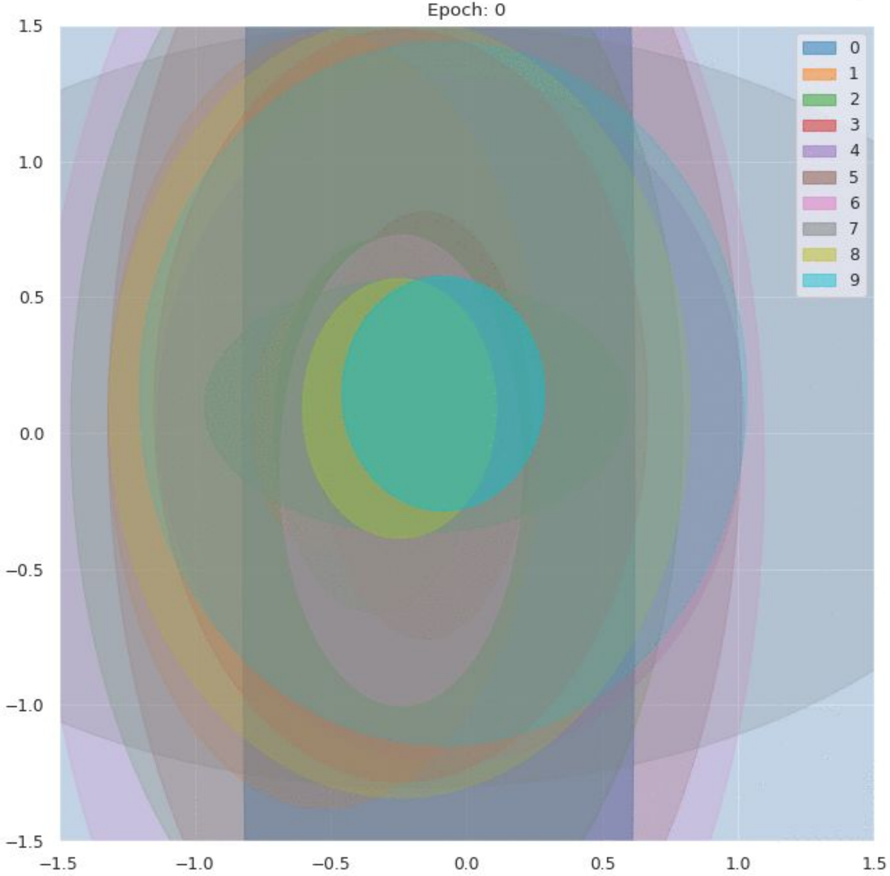


Image source: Conditional Variational Autoencoders by Isaac Dykeman, 2016

cVAE latent space distribution



GAN

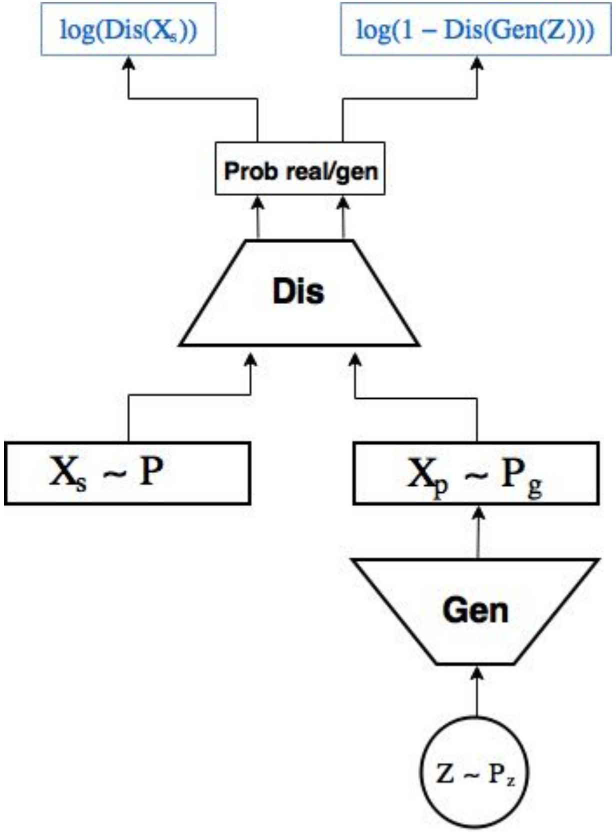
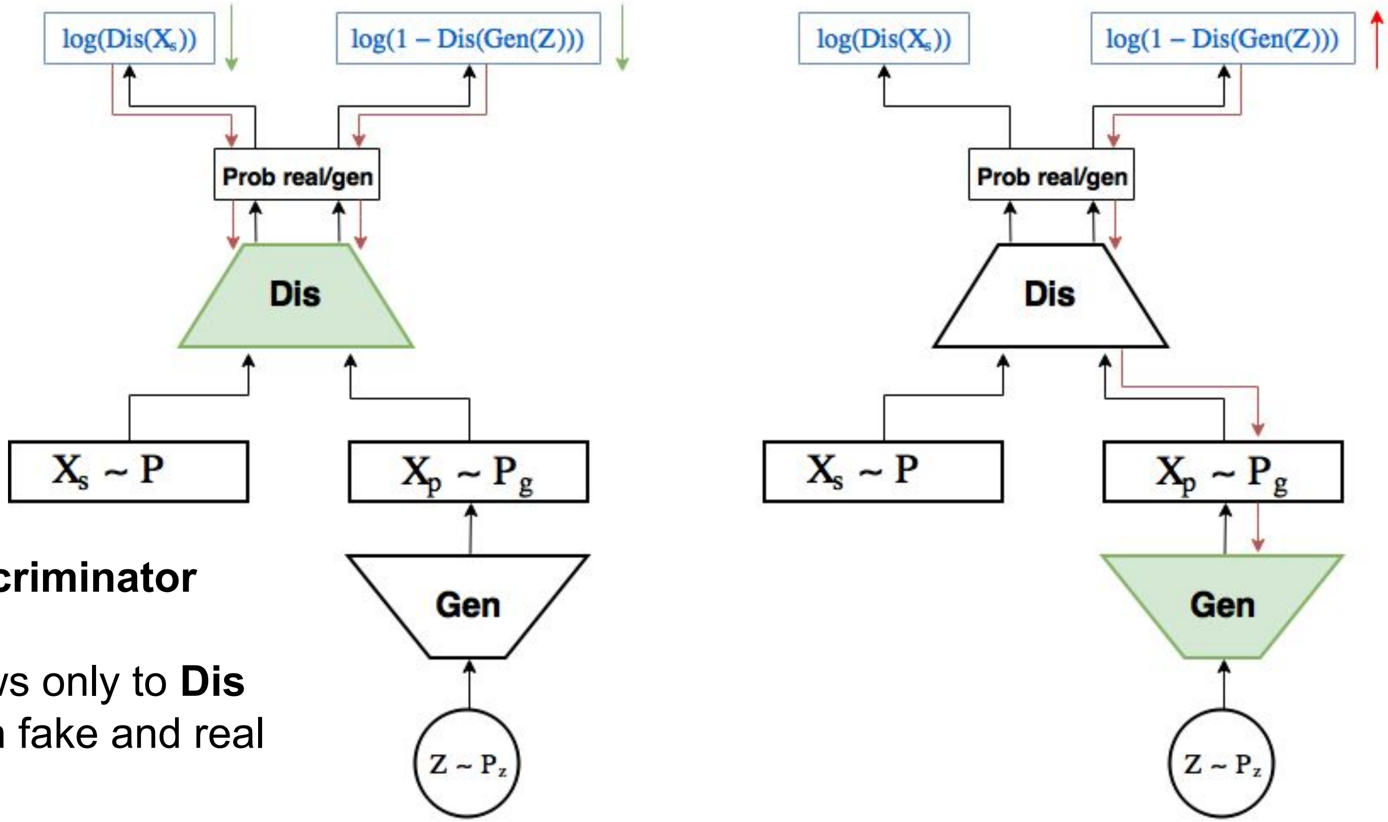

$\log(\mathrm{Dis}(X_s))$
$\log(1 - \mathrm{Dis}(\mathrm{Gen}(Z)))$
Prob real/gen
Dis
$X_s \sim P$
$X_p \sim P_g$
Gen
$Z \sim P_z$

Image source: Habr post on autoencoders and GANs

Training GAN

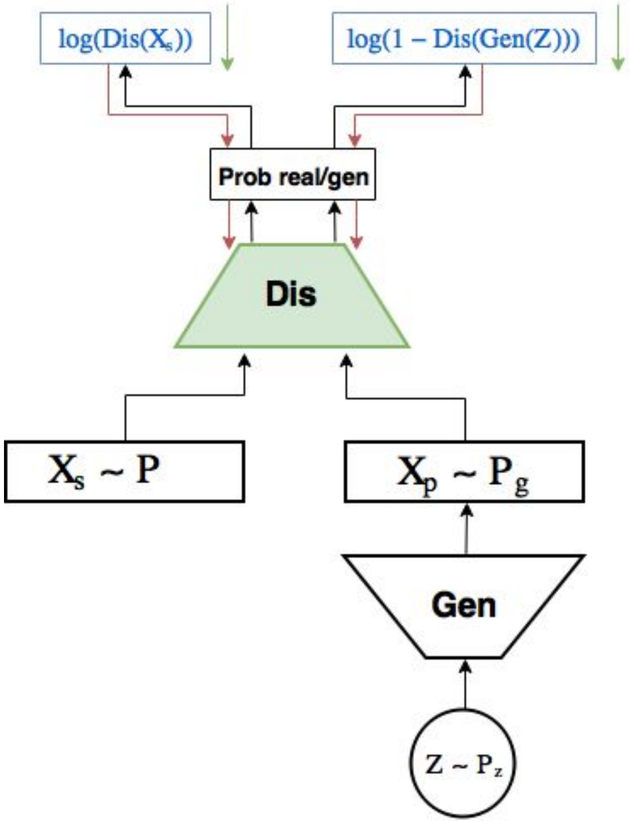


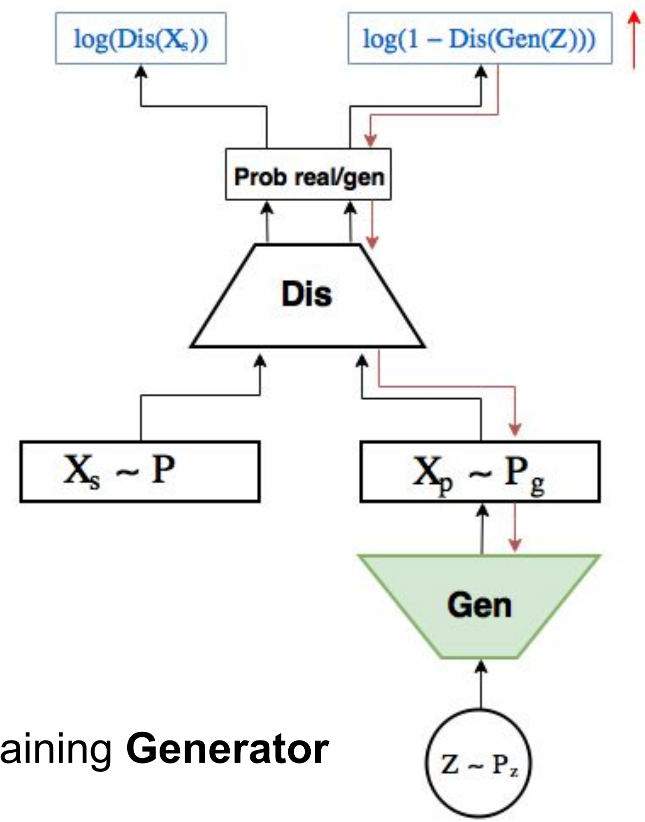
Training **Discriminator**

Gradient flows only to **Dis** to distinguish fake and real examples

Image source: Habr post on autoencoders and GANs

Training GAN



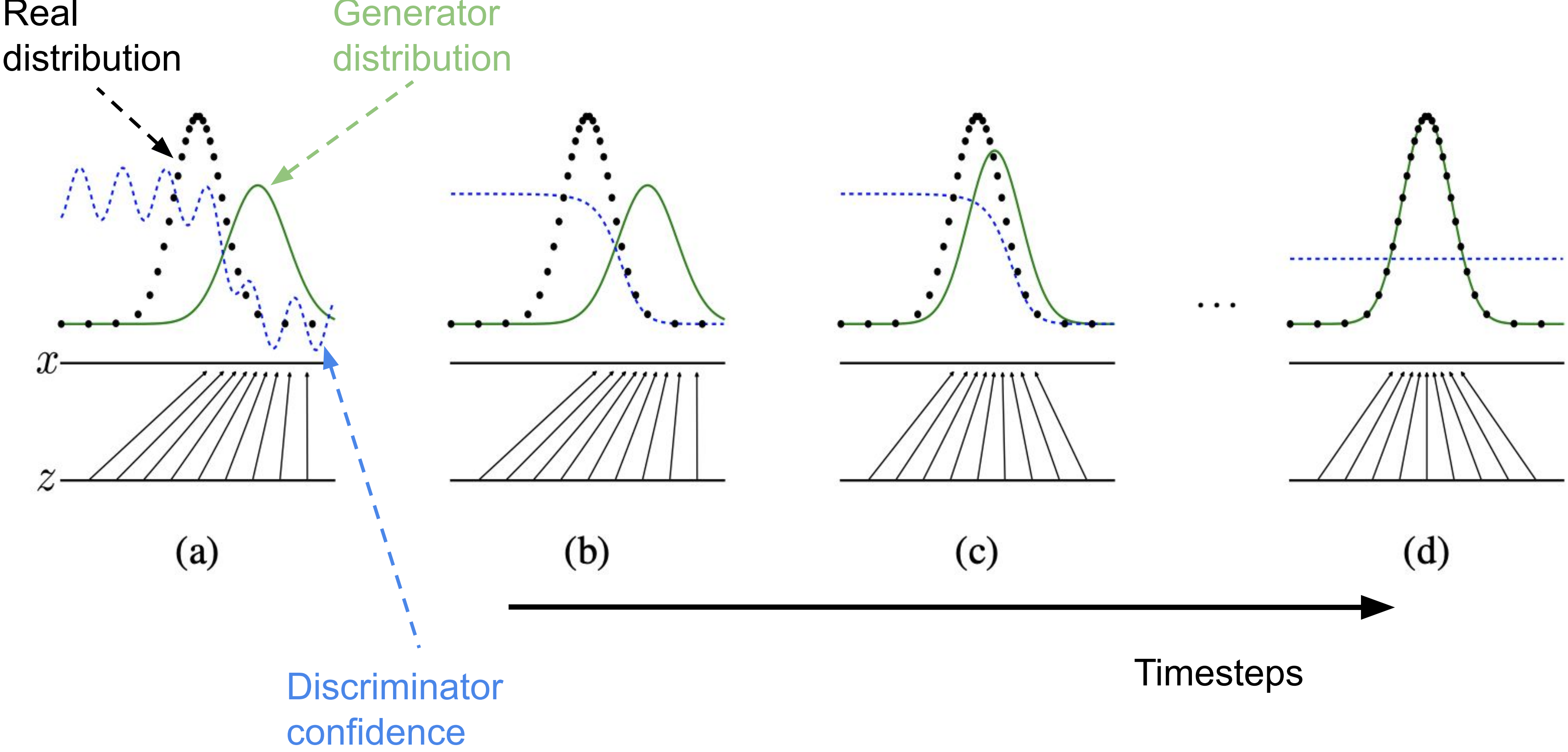


Training **Generator**

Gradient flows to **Gen** with **Dis** weights freezed to fool the Discriminator

Image source: Habr post on autoencoders and GANs

Optimization process in GAN



Real distribution

Generator distribution

Discriminator confidence

Timesteps

Image source: Generative Adversarial Nets, Ian J. Goodfellow et al, 2014

GAN manifold

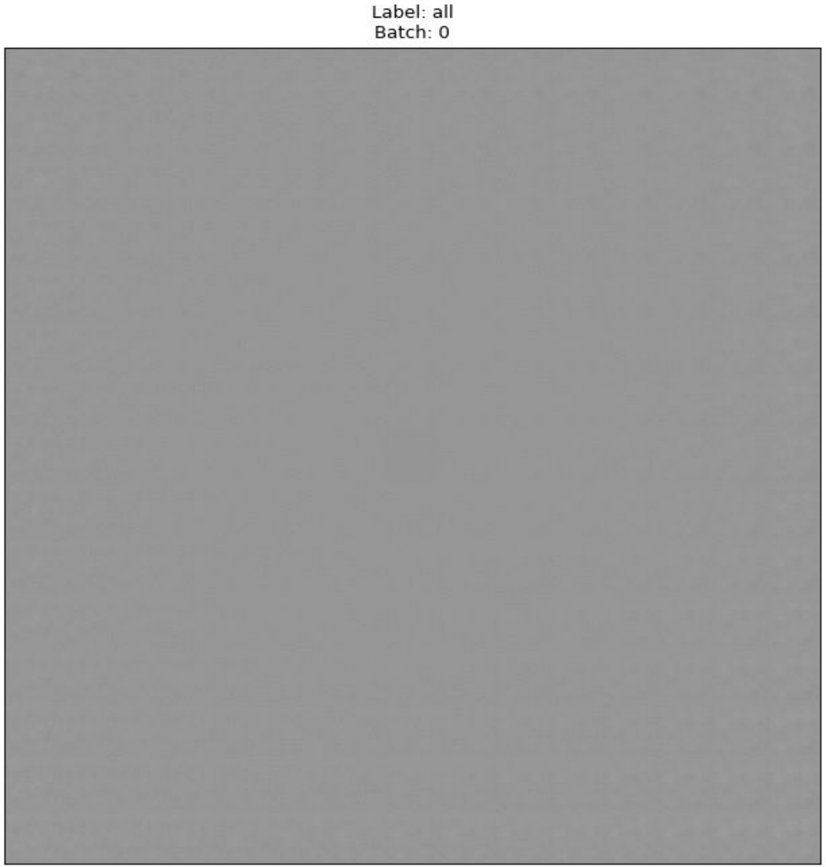


Image source: Habr post on autoencoders and GANs

Conditional GAN

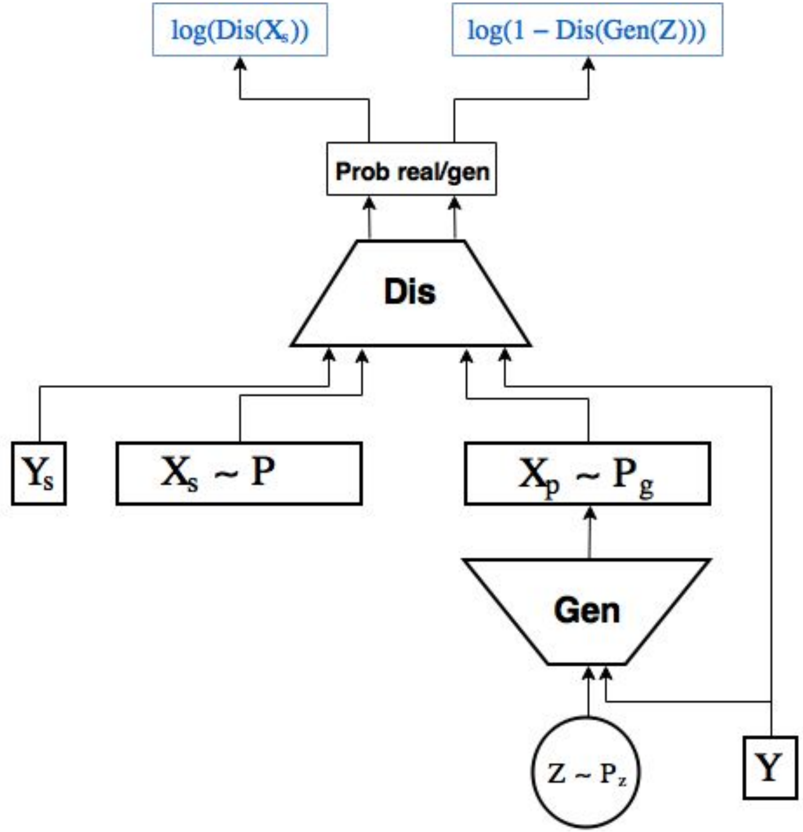
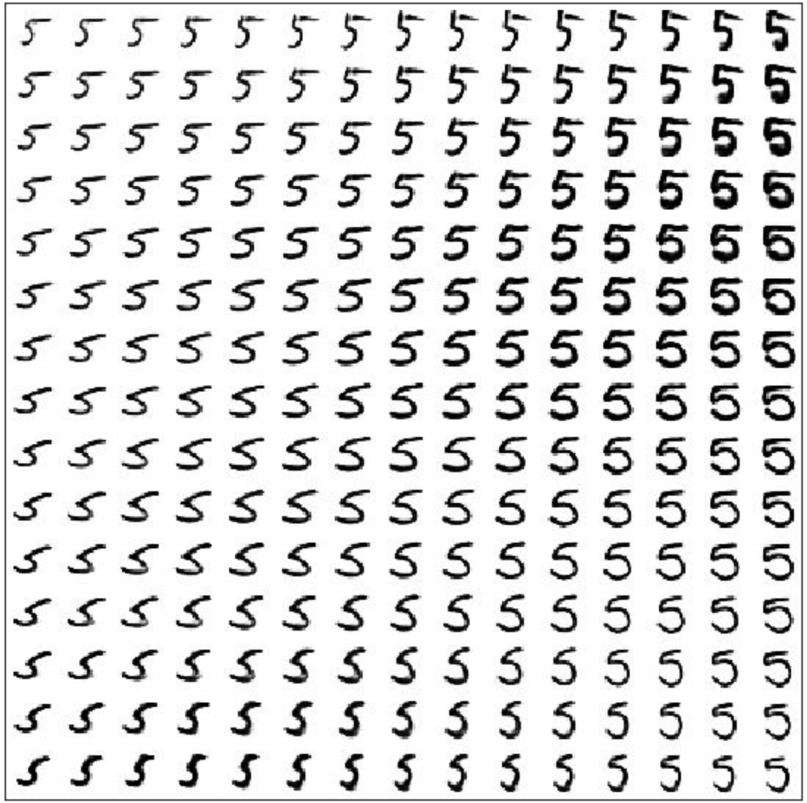


Image source: Habr post on autoencoders and GANs

cGAN manifolds



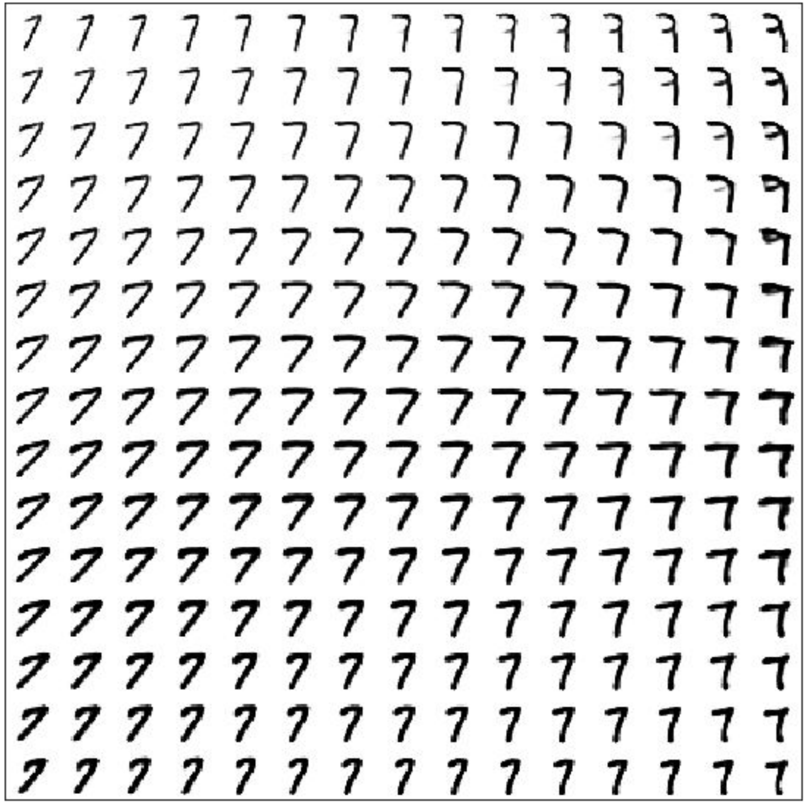


Image source: Habr post on autoencoders and GANs

Some more combinations

VAE

learning latent distribution

GAN

looking for good latent distribution

Image source: Guiness World Records blog, original video PIKOTARO - PPAP (Pen Pineapple Apple Pen)

Simple GAN

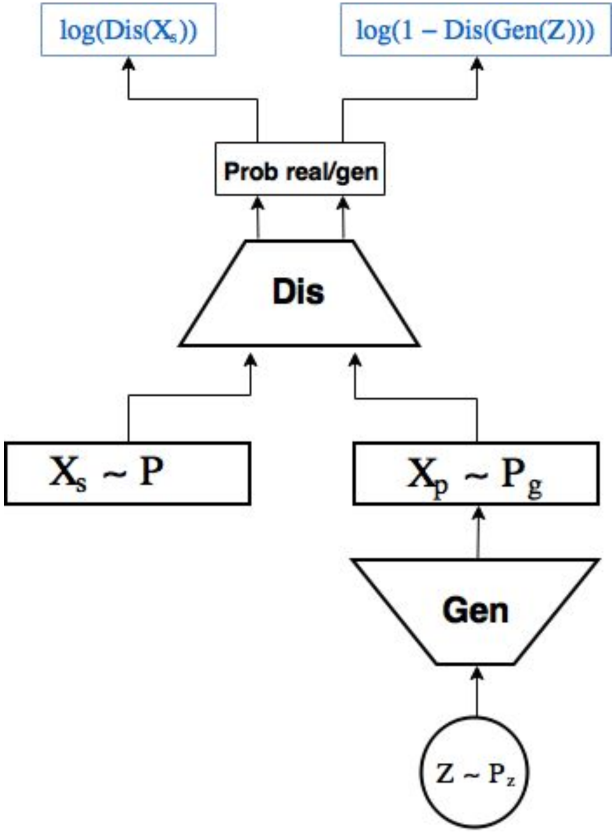
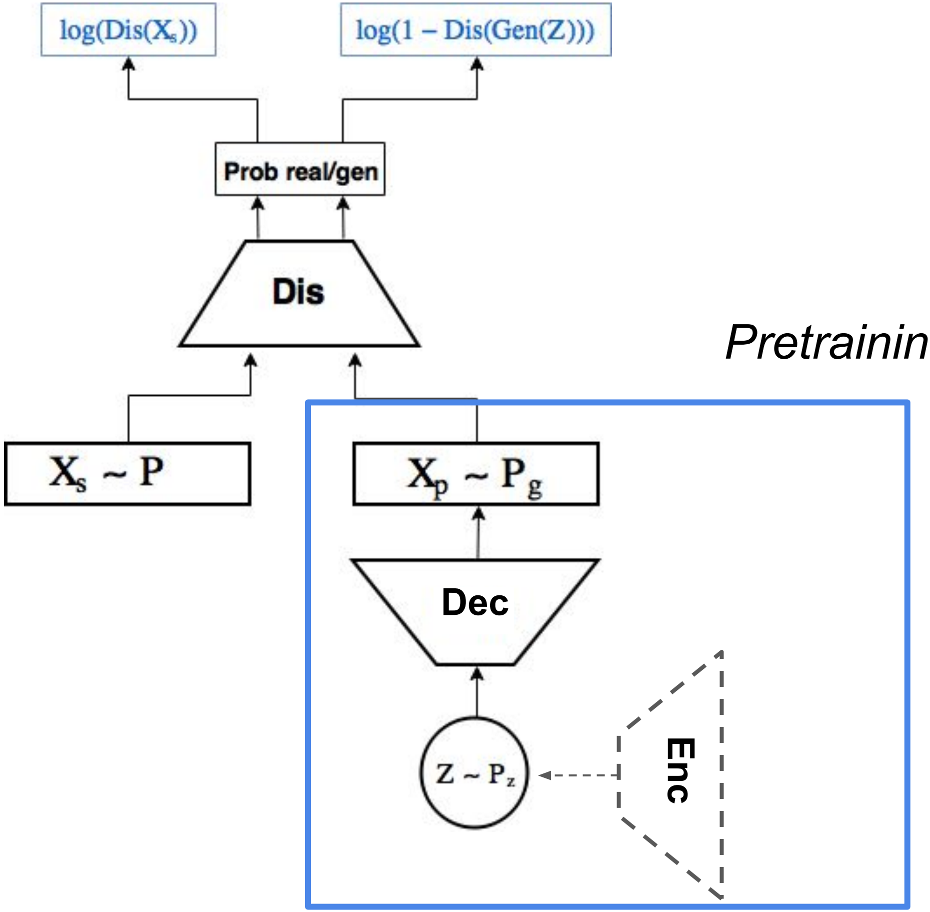


Image source: Habr post on autoencoders and GANs

VAE/GAN



Partial image source: [Habr post on autoencoders and GANs]

VAE/GAN original illustration

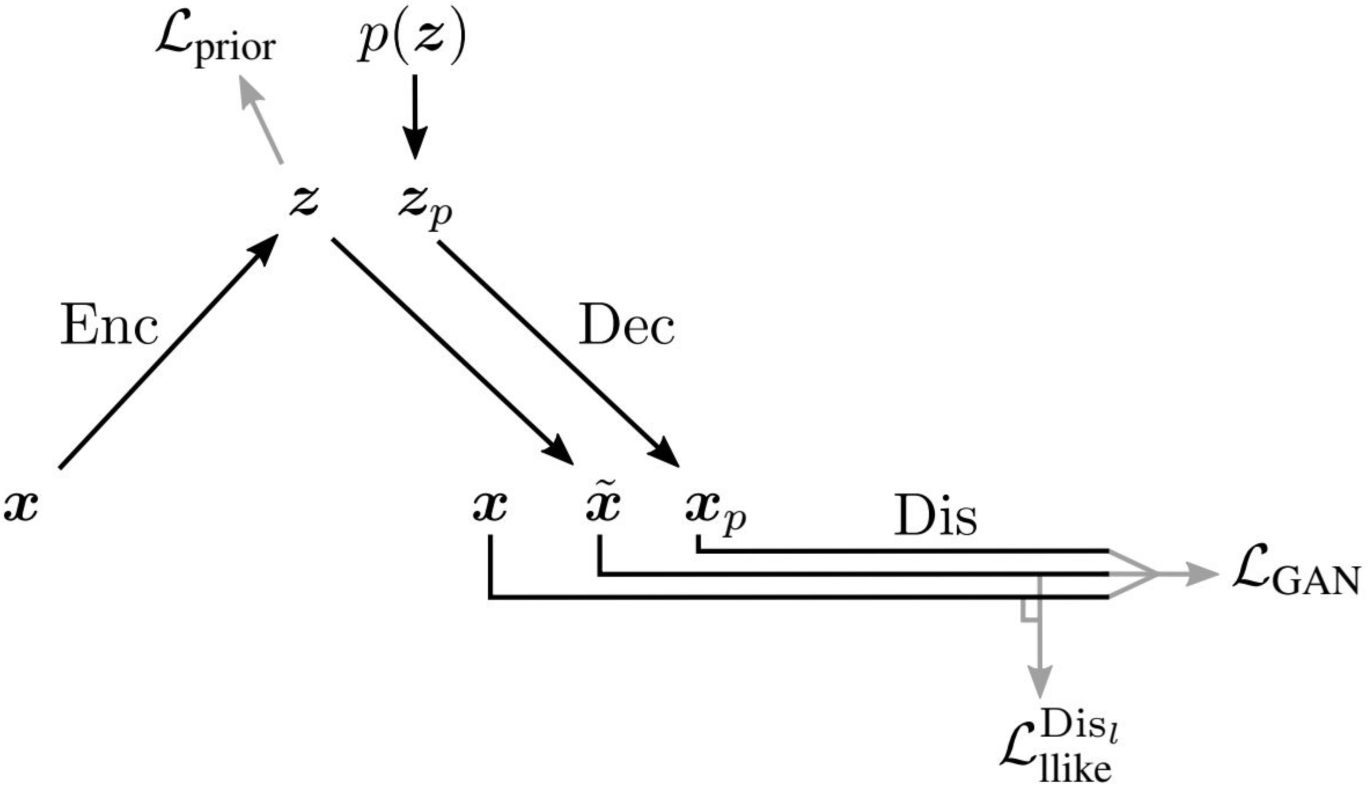
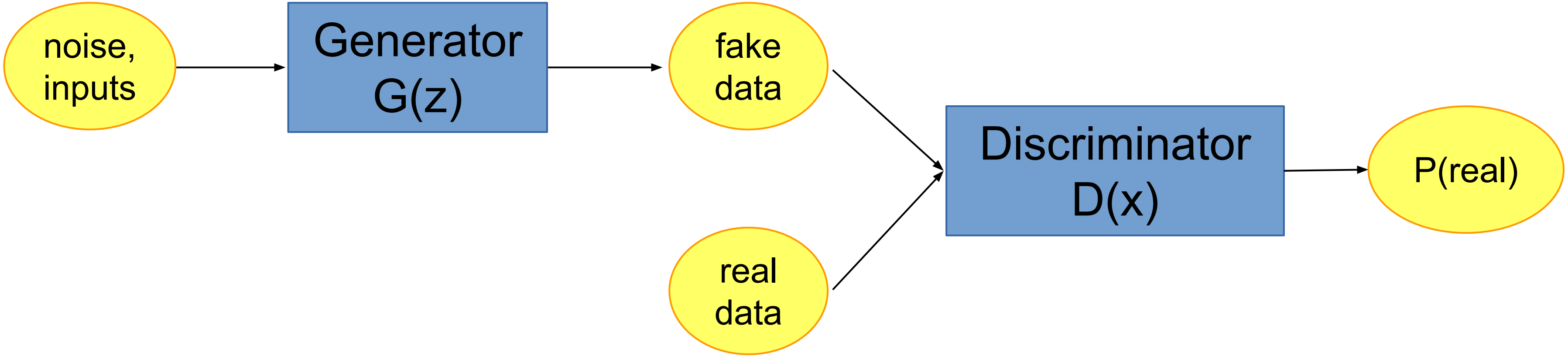


Image source: Autoencoding beyond pixels using a learned similarity metric, Anders Boesen Lindbo Larsen et al, 2016

Bonus: discrete GANs

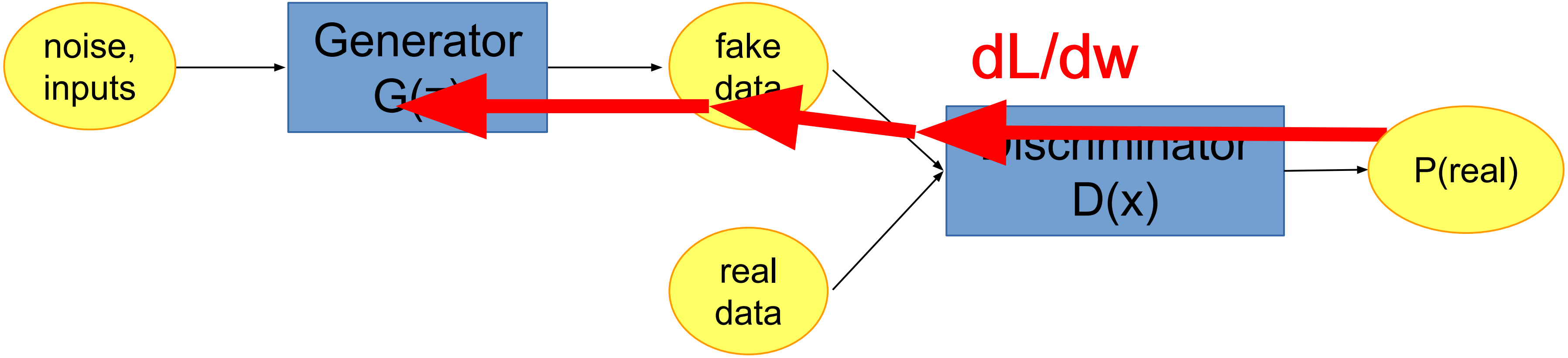
Generalized GAN scheme



source: [Practical RL week07]()

Bonus: discrete GANs

Generalized GAN scheme

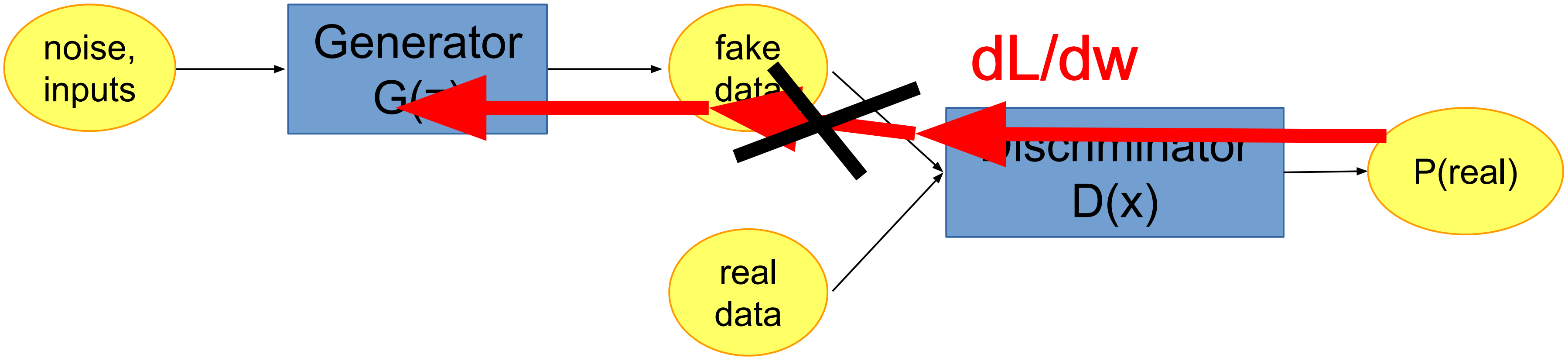


source: Practical RL week07

Bonus: discrete GANs

Standard scheme fails if G(z) is discrete

- generating text
- generating music notes
- generating molecules
- binary image masks



source: Practical RL week07

Bonus: discrete GANs

We can train generator with Reinforcement Learning methods!

$$\nabla J = \mathop{E}_{\substack{z \sim p(z) \\ x \sim P(x|G_\theta(z))}} \nabla \log P(x|G_\theta(z)) D(x)$$

source: Practical RL week07