Deep Learning Concepts

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1 Deep Learning
- Basic idea
- Supervised learning
- Unsupervised learning

Deep Learning

Basic idea

Key principle

Suppose we want to find some function $y(x)$.

Concept of learning

1. construct some model $y = f(x, \theta)$ using basic building blocks

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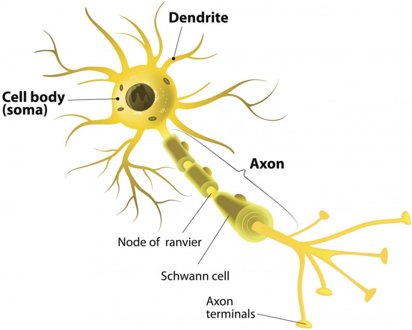
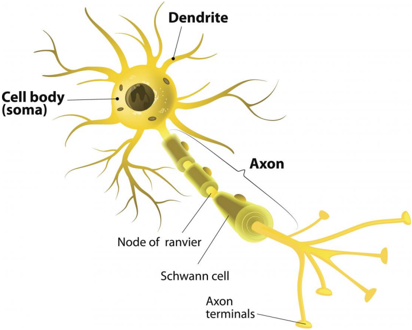
2. select some differentiable scalar criterion to optimize $L(f)$
3. select optimization procedure (i.e. gradient descent)
4. solve $\theta^* = \min\limits_{\theta} L(f)$

Neurons


Dendrite
Cell body
(soma)
Axon
Node of ranvier
Schwann cell
Axon
terminals

Neurons



input: $x \in \{0,1\}^n$

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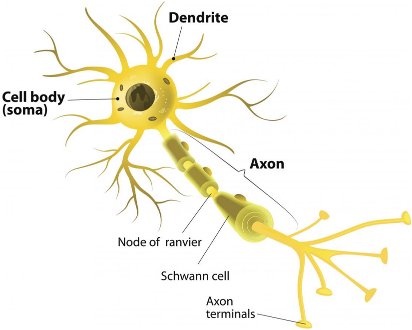

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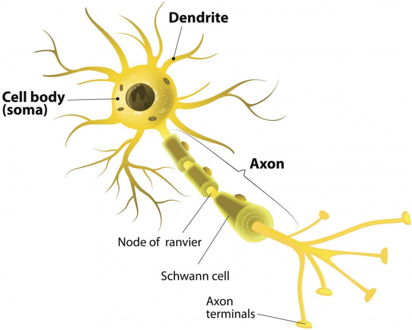

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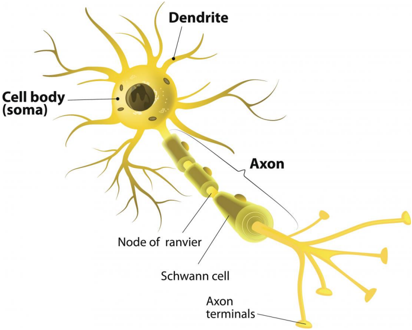

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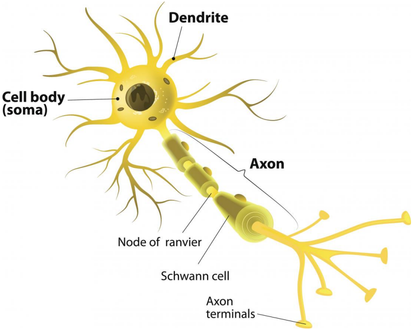

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1. **i-th signal:** $w_i x_i$
2. **accumulation:** $\sum_i w_i x_i$
3. **output:** $\sum_i w_i x_i > b$

Artificial neurons

$$y(x) = \mathbb{I}[\langle w, x \rangle - b > 0]$$

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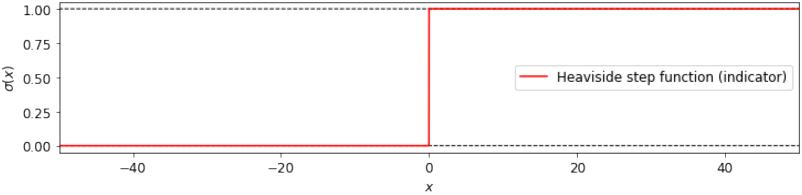

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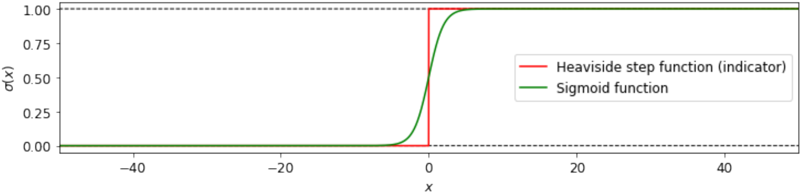
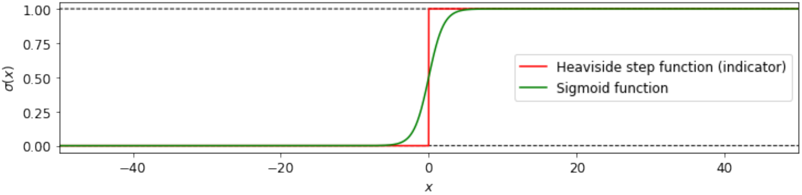


General idea

Everything discrete can be smoothed!

Artificial neurons

$$y(x) = \sigma\left(\langle w, x \rangle - b\right)$$



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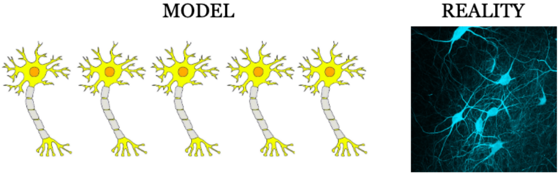
Sigmoid function:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Fully-connected layer

Standard building block for neural networks:

$$y(x) = \sigma(Wx - b)$$



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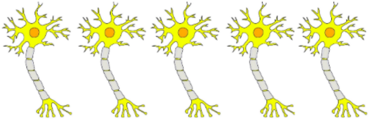

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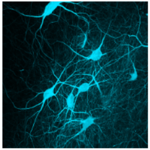

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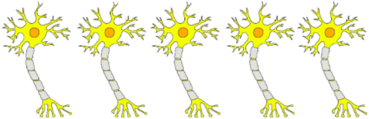

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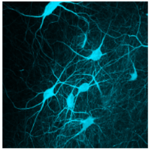

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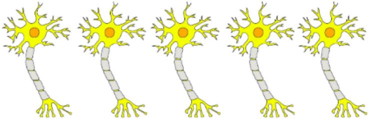

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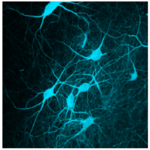

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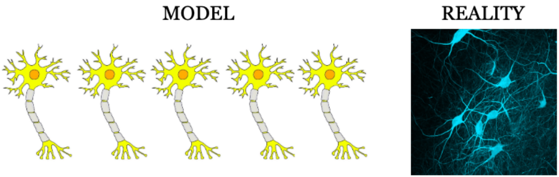
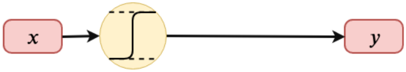


- 😇 universal approximation properties!
- 😈 if there is infinite number of neurons...
- 😇 stack more layers!
- 😈 gradient vanishing / exploding problem!

Stacking a lot of layers



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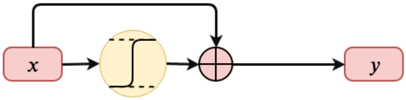

Residual connections

$$y = x + \sigma(Wx - b)$$

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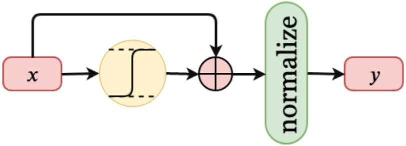

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Layer normalization

$$\mu = \frac{1}{m}\sum_{i}^{n} x_i \qquad s^2 = \frac{1}{m}\sum_{i}^{n}(x_i - \mu) \qquad y = (x - \mu)/s$$

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- uninterpretable («black box» model)

Deep Learning

Supervised learning

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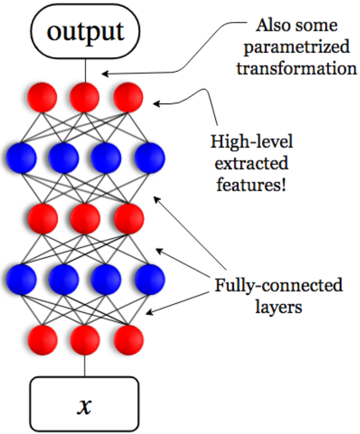

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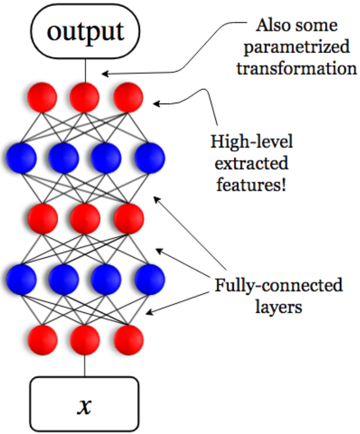

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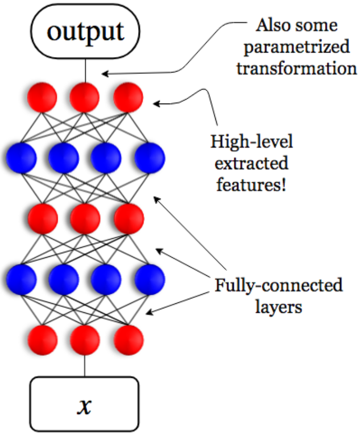

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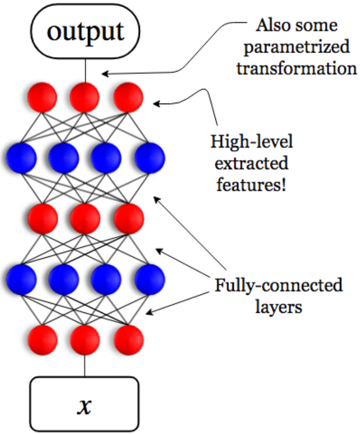

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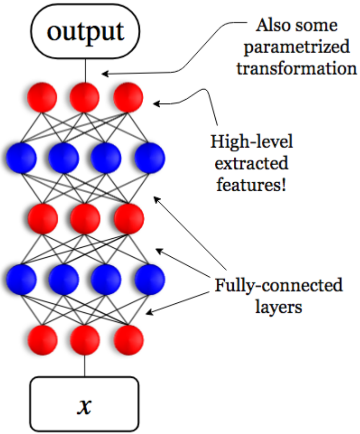

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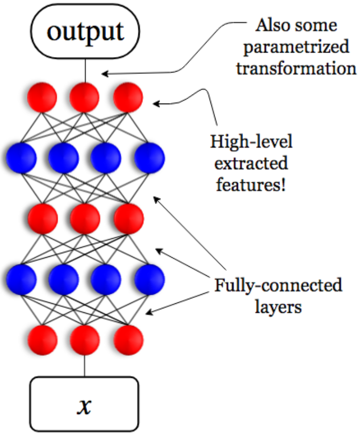

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4. $L(f) = \frac{1}{N}\sum\limits_i \text{Loss}(y_i, \hat{y}(z(x_i)))$

Final decision rules

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  - **Linear layer + softmax:** $\hat{y} = \text{softmax}\left(\langle w, z \rangle + b\right)$
    (softmax = exp + normalize)

Loss functions

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$$p(y \mid x) — ?$$

Our neural network actually defines approximating distribution $q(y \mid x, \theta)$. What to do next?

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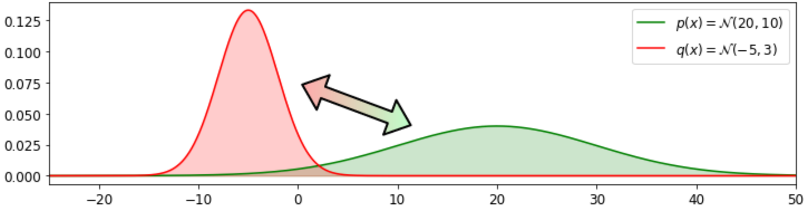
- **Bayesian inference:** seek for $p(\theta \mid X, Y)$

Divergences



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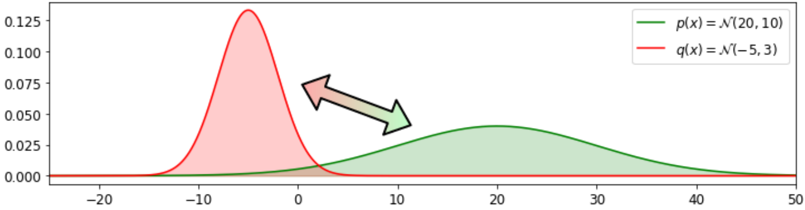

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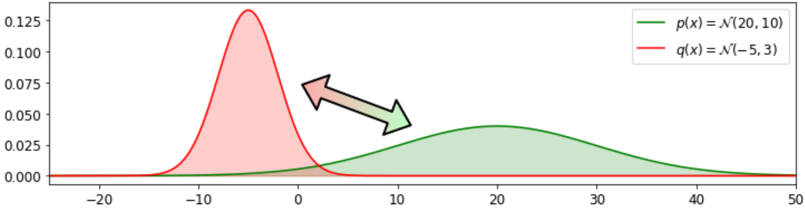

- **Kullback-Leibler divergence — the chosen one!**
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Const(θ) terms can be ignored!

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$$-\mathbb{E}_{p(y \mid x)} \log q(y_i \mid x_i, \theta) \to \min_{\theta}$$

Const(θ) terms can be ignored!

Motivation behind Kullback-Leibler

Recall our task:

$$\mathrm{KL}(p(y \mid x) \parallel q(y_i \mid x_i, \theta)) \to \min_{\theta}$$

Using definition:

$$-\mathbb{E}_{p(y|x)} \log q(y_i \mid x_i, \theta) \to \min_{\theta}$$

Const(θ) terms can be ignored!

Implicit expectation minimization

We do not know $p(y \mid x)$, but ability to sample from it is enough!

Monte-Carlo gradient estimation

How to calculate gradient for optimization methods in such case?

$$L(f) = \mathbb{E}_{p(x,y)} \operatorname{Loss}(x, y, \theta) \to \min_{\theta}$$

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Monte-Carlo estimation

$$\mathbb{E}_{p(x,y)} \nabla_\theta \operatorname{Loss}(x, y, \theta) \approx \frac{1}{M} \sum_{i}^{M} \nabla_\theta \operatorname{Loss}(x_i, y_i, \theta)$$

where x_i, y_i are samples from $p(x, y)$.

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where x_i, y_i are samples from $p(x, y)$.

- ✓ an **unbiased** estimation (gives true gradient in expectation)

Stochastic gradient descent

Use unbiased estimations of gradient instead of true gradients!

Algorithm 1 SGD

Initialize θ_0 randomly
for $t = 0, 1, 2, \dots$ **do**
    Sample M pairs $x_i, y_i \sim p(x, y)$
    $g_t \leftarrow \frac{1}{M} \sum_i^M \nabla_\theta \operatorname{Loss}(x_i, y_i, \theta_t)$
    $\theta_{t+1} \leftarrow \theta_t - \alpha_t g_t$
end for

Stochastic gradient descent

Use unbiased estimations of gradient instead of true gradients!

Algorithm 2 SGD

1: Initialize θ_0 randomly
2: **for** $t = 0, 1, 2, \dots$ **do**
3: Sample M pairs $x_i, y_i \sim p(x, y)$
4: $g_t \leftarrow \frac{1}{M}\sum_i^M \nabla_\theta \operatorname{Loss}(x_i, y_i, \theta_t)$
5: $\theta_{t+1} \leftarrow \theta_t - \alpha_t g_t$
6: **end for**

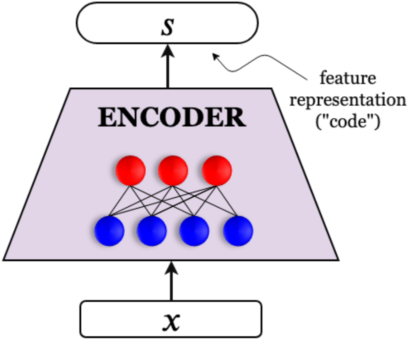
SGD converges to local optima if

$$\sum_t \alpha_t = +\infty \quad \sum_t \alpha_t^2 < +\infty$$

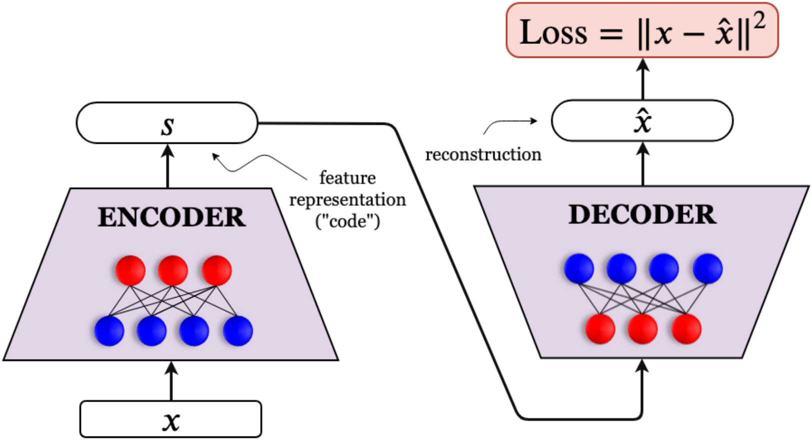
Deep Learning

Unsupervised learning

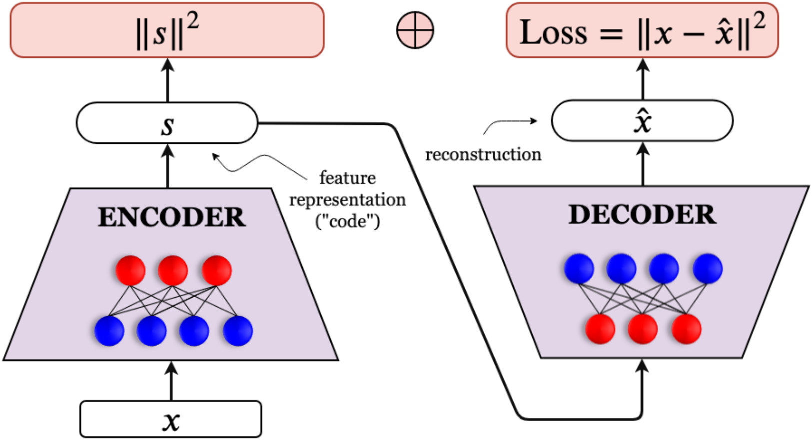
Autoencoder



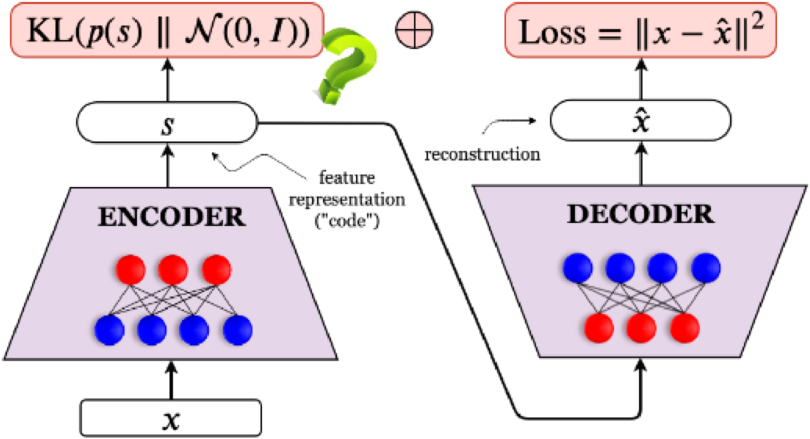
Autoencoder



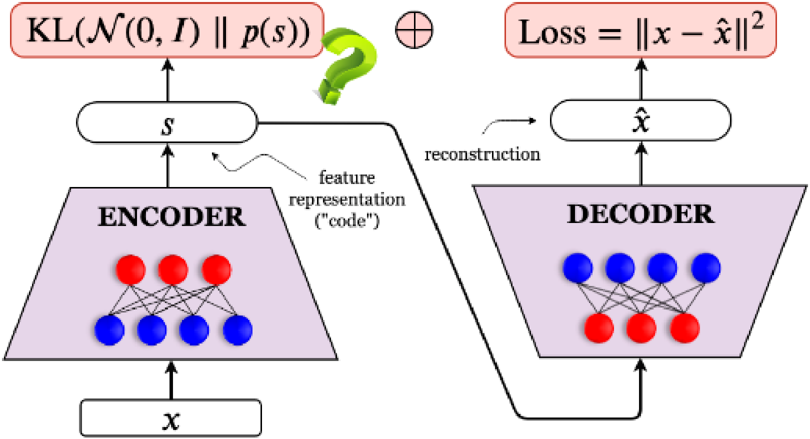
Shaping latent representation



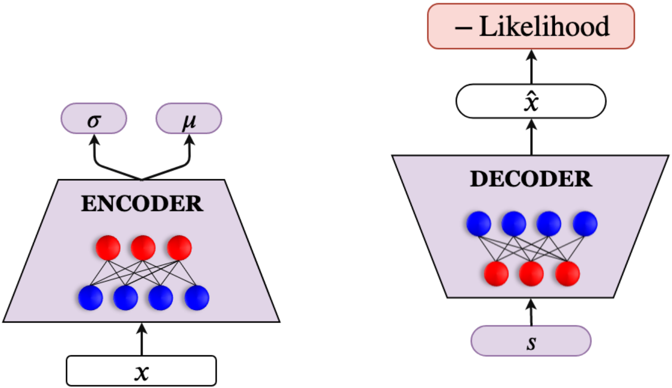
Shaping latent representation



Shaping latent representation



VAE



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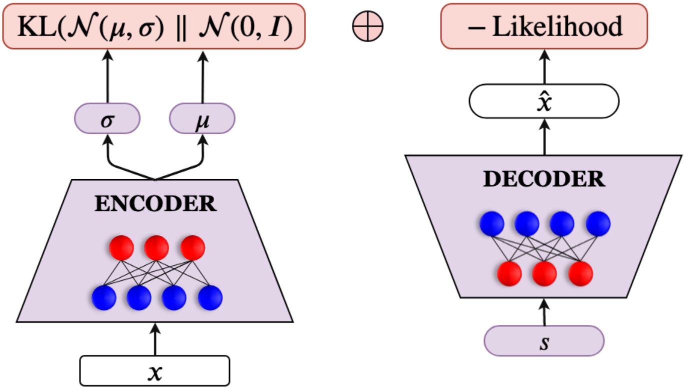
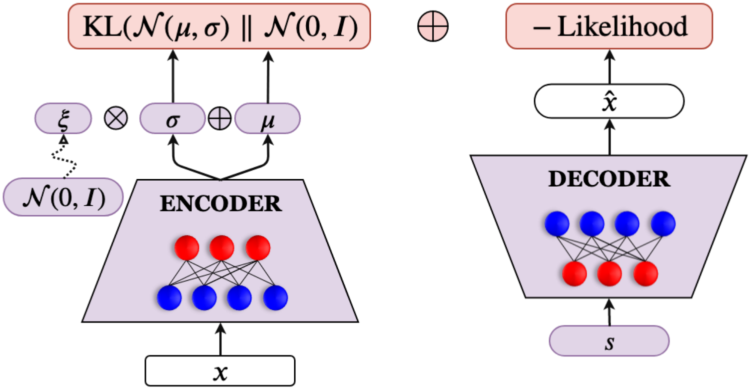


$\mathrm{KL}(\mathcal{N}(\mu, \sigma) \,||\, \mathcal{N}(0, I))$
$\oplus$
$-$Likelihood
σ
μ
ENCODER
x
$\hat{x}$
DECODER
s

VAE



$\mathrm{KL}(\mathcal{N}(\mu, \sigma) \,||\, \mathcal{N}(0, I))$
$\oplus$
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ENCODER
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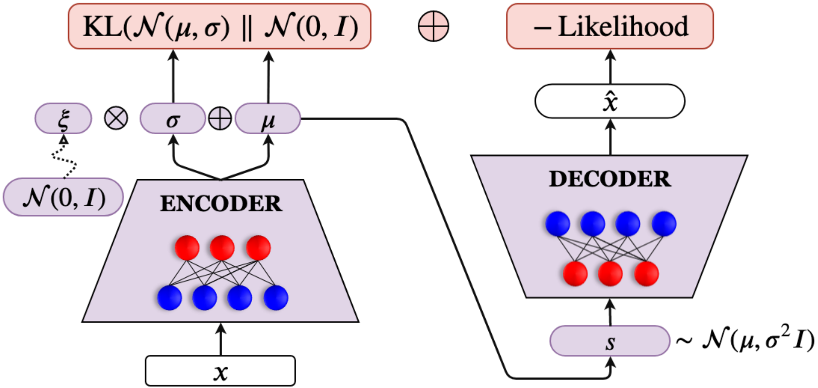
s

VAE


KL($\mathcal{N}(\mu, \sigma)$ || $\mathcal{N}(0, I)$)
$\oplus$
– Likelihood
$\hat{x}$
ξ
$\otimes$
σ
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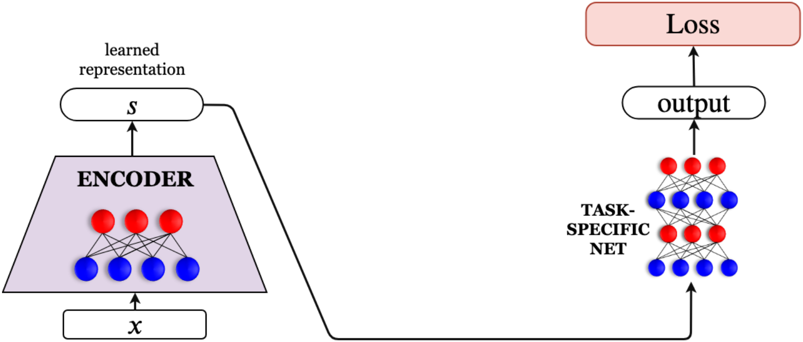
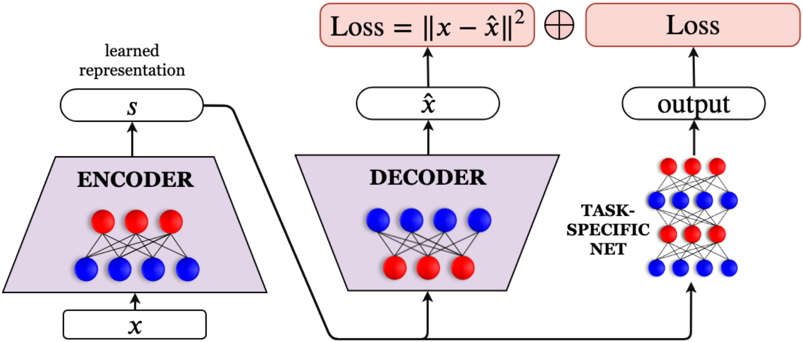
μ
$\mathcal{N}(0, I)$
ENCODER
DECODER
x
s
$\sim \mathcal{N}(\mu, \sigma^2 I)$

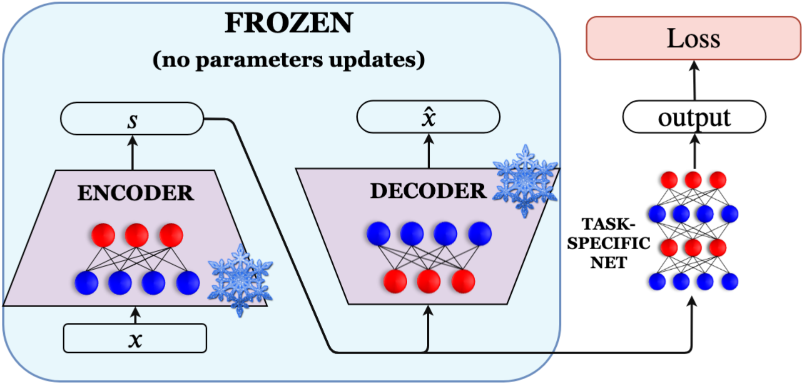
Possible usage



Possible usage



Transfer learning



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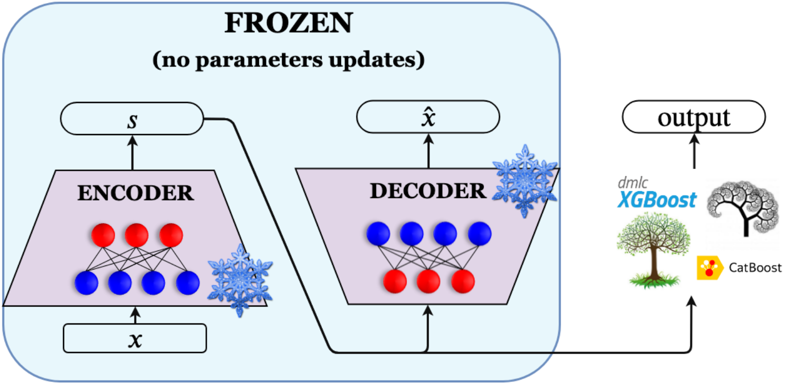
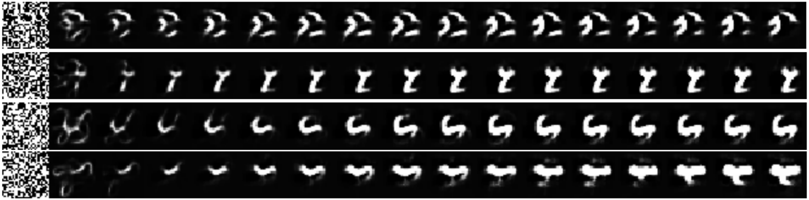


Example: digits that are not[1]



[1] https://arxiv.org/abs/1606.04345

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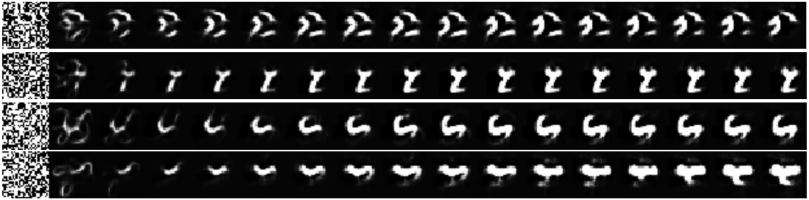

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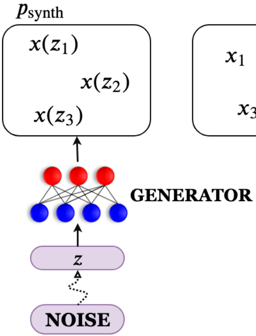
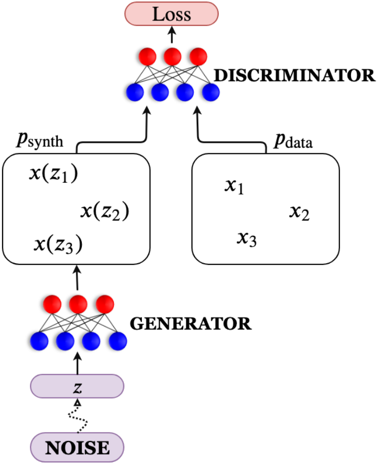
Generative Adversarial Networks (GAN)



Generative Adversarial Networks (GAN)



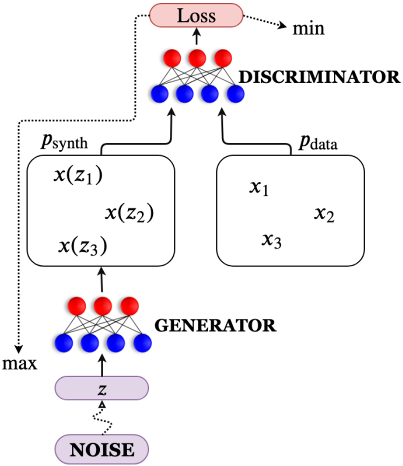
Training discriminator D:

$$\text{Loss}(D, G) :=$$

$$-\mathbb{E}_{x \sim p_{\text{real}}} \log D(x) -$$

$$-\mathbb{E}_{x \sim p_{\text{synth}}} \log(1 - D(x)) \to \min_D$$

Generative Adversarial Networks (GAN)



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Training generator G:

$$\text{Loss}(D, G) \to \max_G$$

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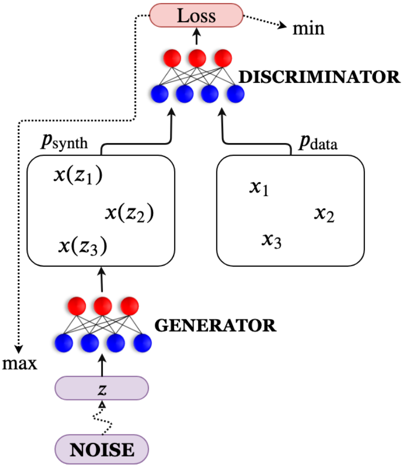

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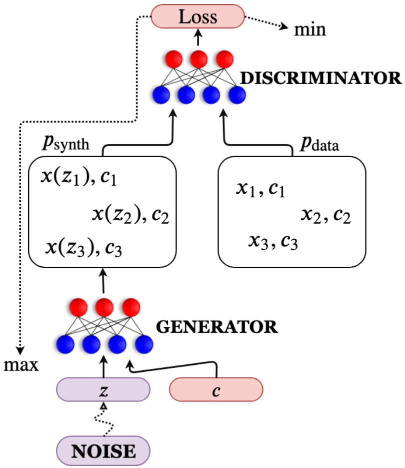
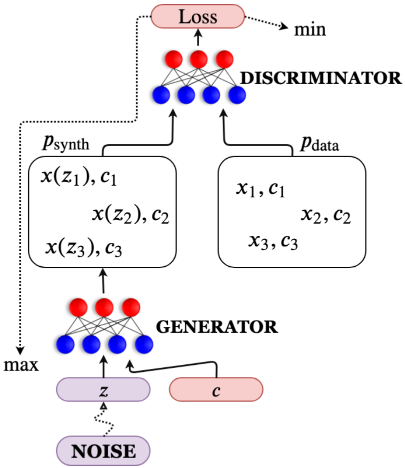
Conditional GAN (cGAN)



Train $p_{\text{synth}}(x \mid c)$
to imitate $p_{\text{data}}(x \mid c)$!

Conditional GAN (cGAN)



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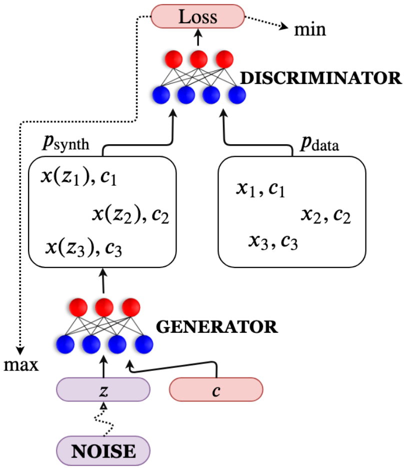

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✓ condition can be of any complexity!

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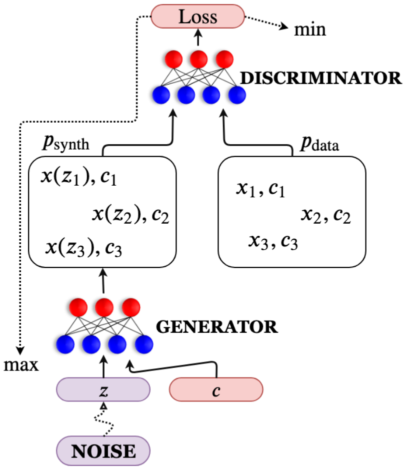

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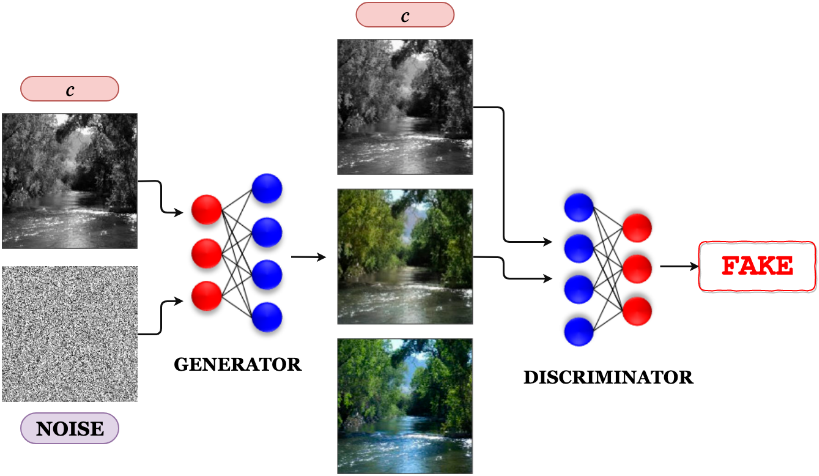
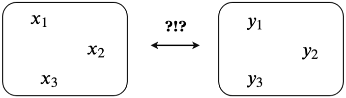
- ✓ condition can be of any complexity!
- ✓ can be viewed as **loss function learning** when output is complex

cGAN: Example

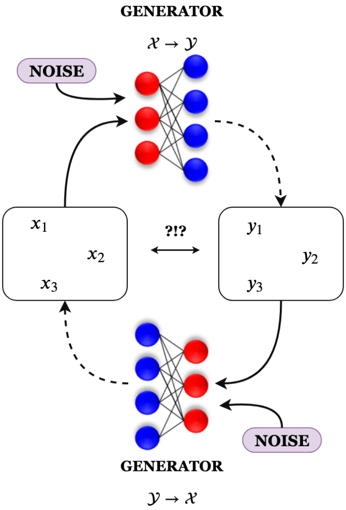
cGAN: Example



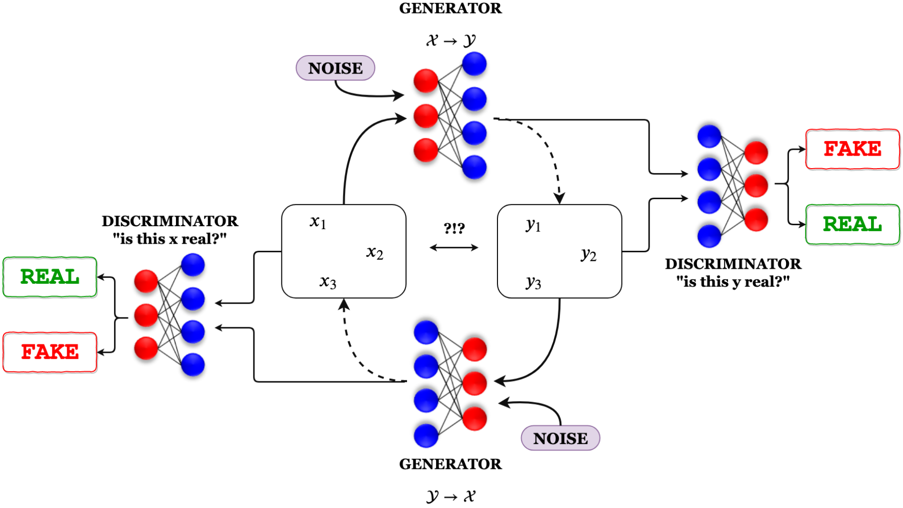
Unpaired learning



Unpaired learning



Unpaired learning



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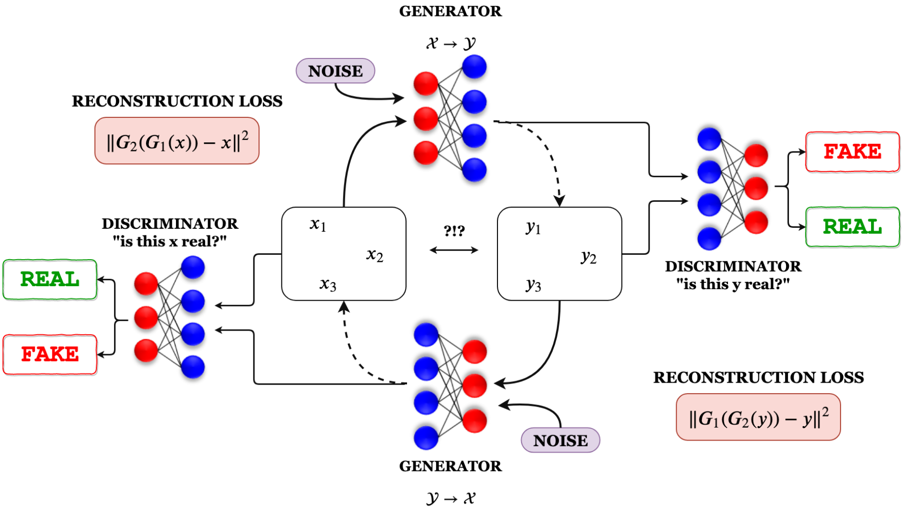

CycleGAN: Example