

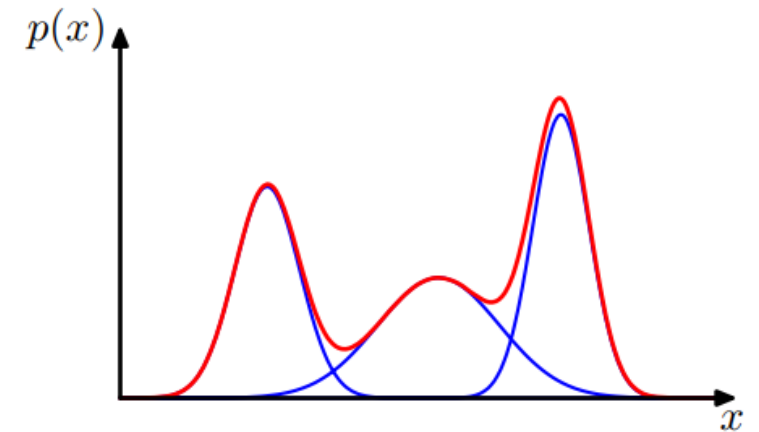
Generative neural networks

Romain Tavenard (Université de Rennes)
Deep Learning course @EDHEC

Generative models in a nutshell



- Goal: model $p(x)$ or $p(x|y)$
 - explicitly
 - eg. Gaussian Mixture Models
 - **implicitly**
 - at least allow for sampling (*i.e.* generate new data)
 - e.g. Variational Auto Encoders, Generative Adversarial Networks

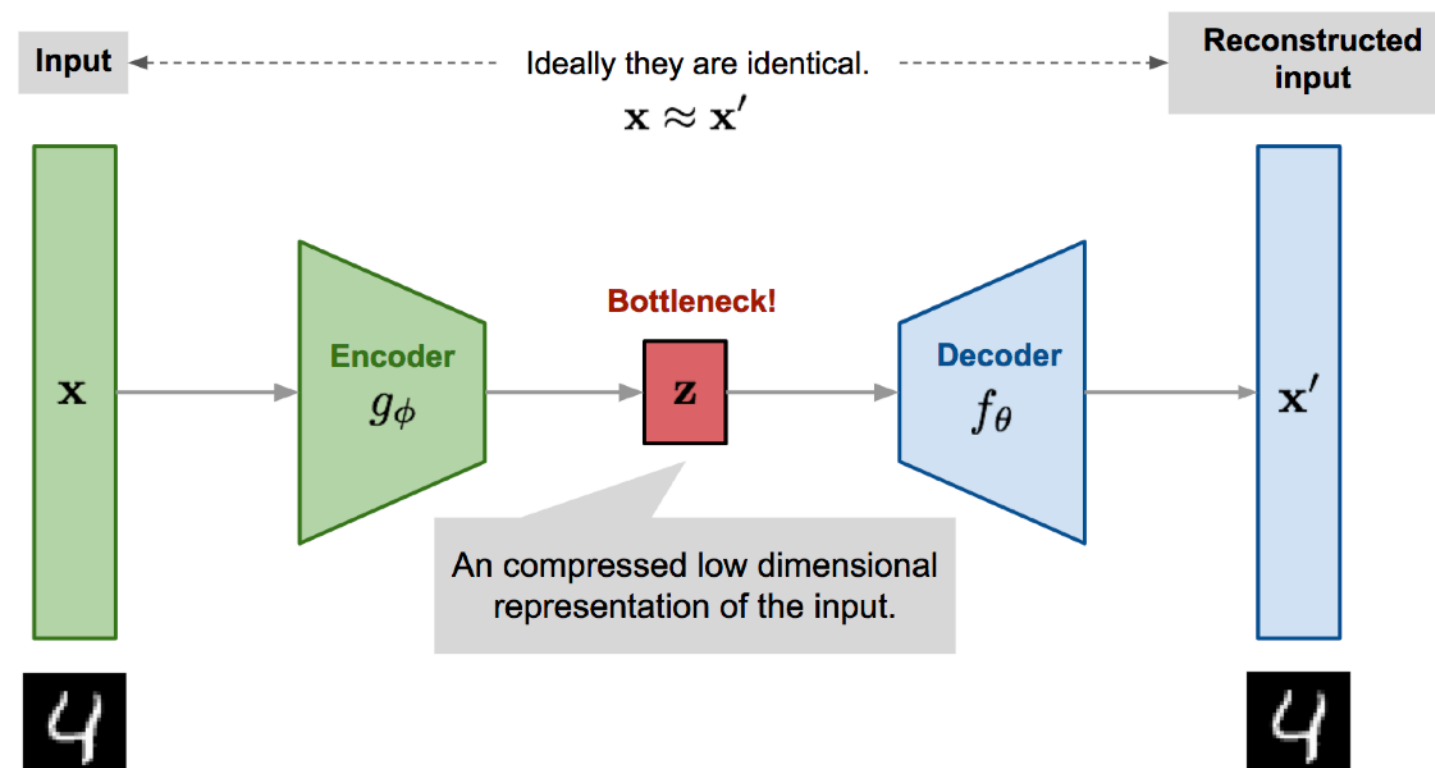


Auto-encoders

[Hinton & Salakhutdinov, 2006]



- Encode information in a latent space
 - typically lower-dimensional
 - similar in spirit to a non-linear PCA
 - not a generative model *per se*!

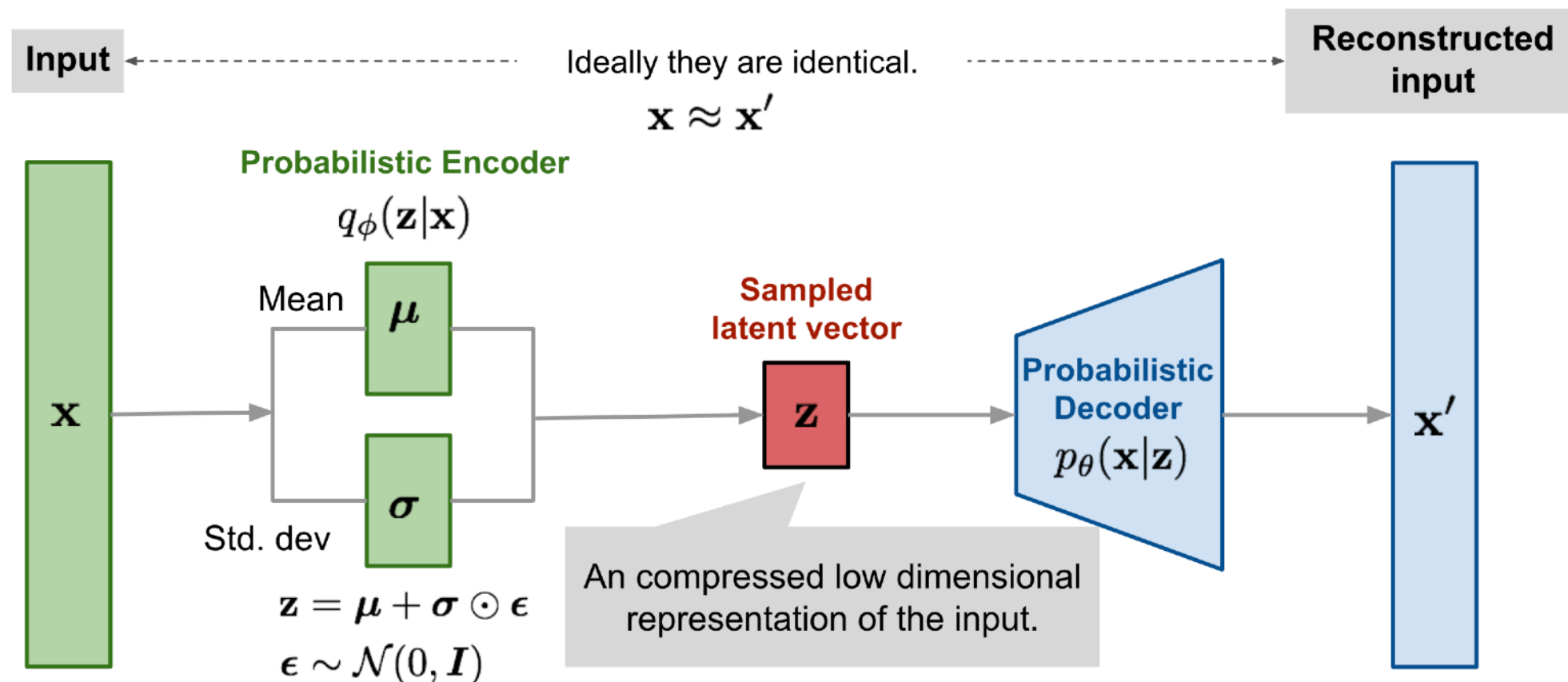


Variational auto-encoders

[Kingma & Welling, 2014]



- Goal: turn auto-encoders into generative models
- Idea: set a prior on the distribution of z (through penalization of the loss function)
- Generative process: draw z from the prior, and decode it

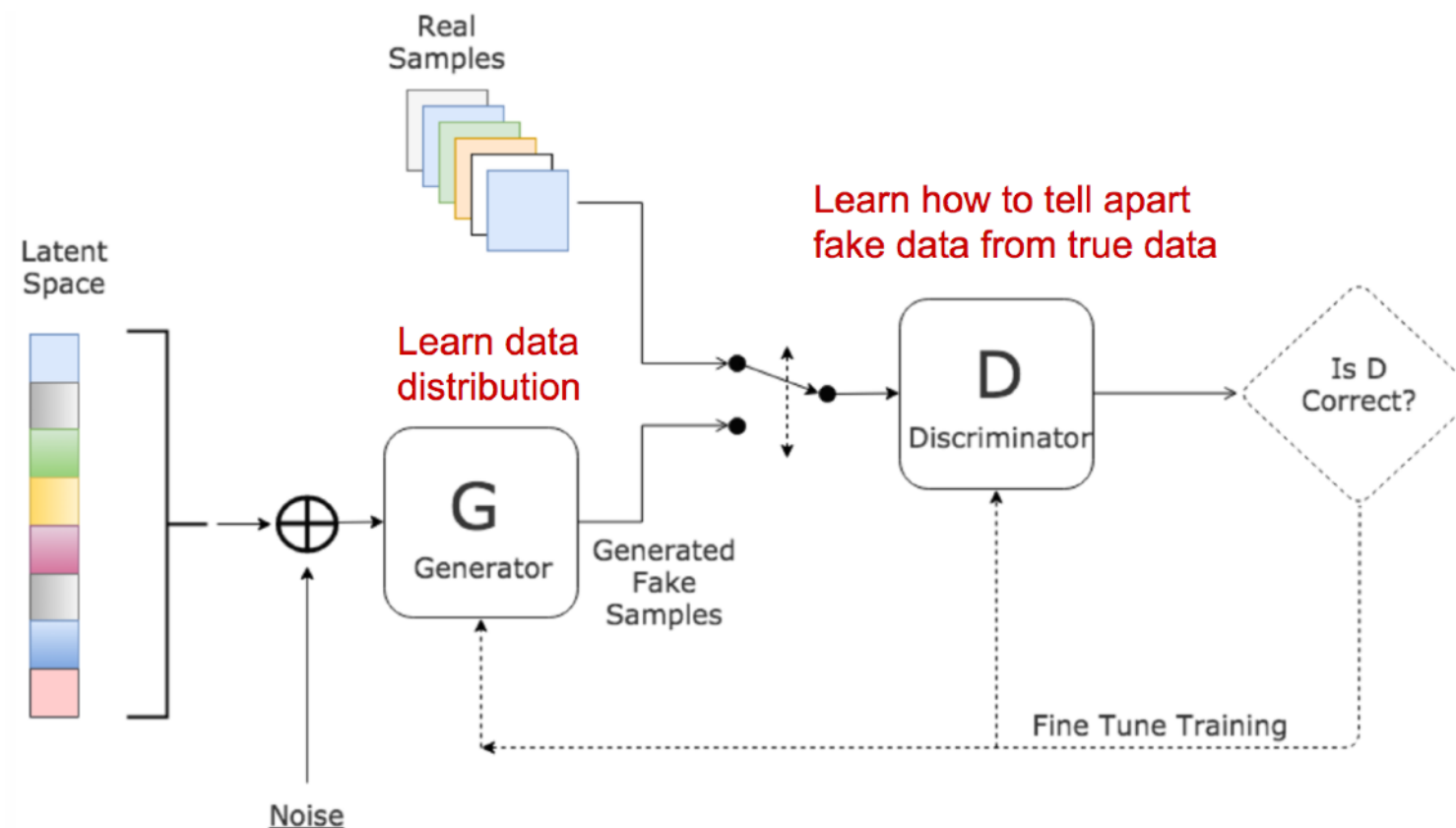


Generative Adversarial Networks

[Goodfellow *et al.*, 2014]



- Model:



Source: lilianweng.github.io

- Loss function:

$$\begin{aligned}\min_G \max_D L(D, G) &= \mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))] \\ &= \mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{x \sim p_z(x)} [\log(1 - D(x))]\end{aligned}$$

Generative Adversarial Networks

[Goodfellow *et al.*, 2014]



- Generative process
 - Draw z from p_z
 - Pass it to the generator to compute $G(z)$
- Optimization
 - Alternate between generator and discriminator
 - Very unstable process in practice

$$\begin{aligned}\min_G \max_D L(D, G) &= \mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))] \\ &= \mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{x \sim p_z(x)} [\log(1 - D(x))]\end{aligned}$$

Generative Adversarial Networks

- Many variants to the original model
 - Class-conditional variants
 - Different losses
 - Different structures
- Very realistic samples generated (BigGAN, StyleGAN)

