Generative neural networks

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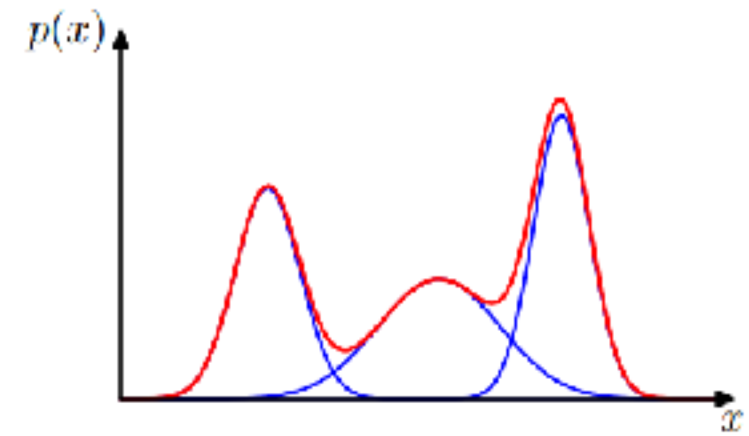
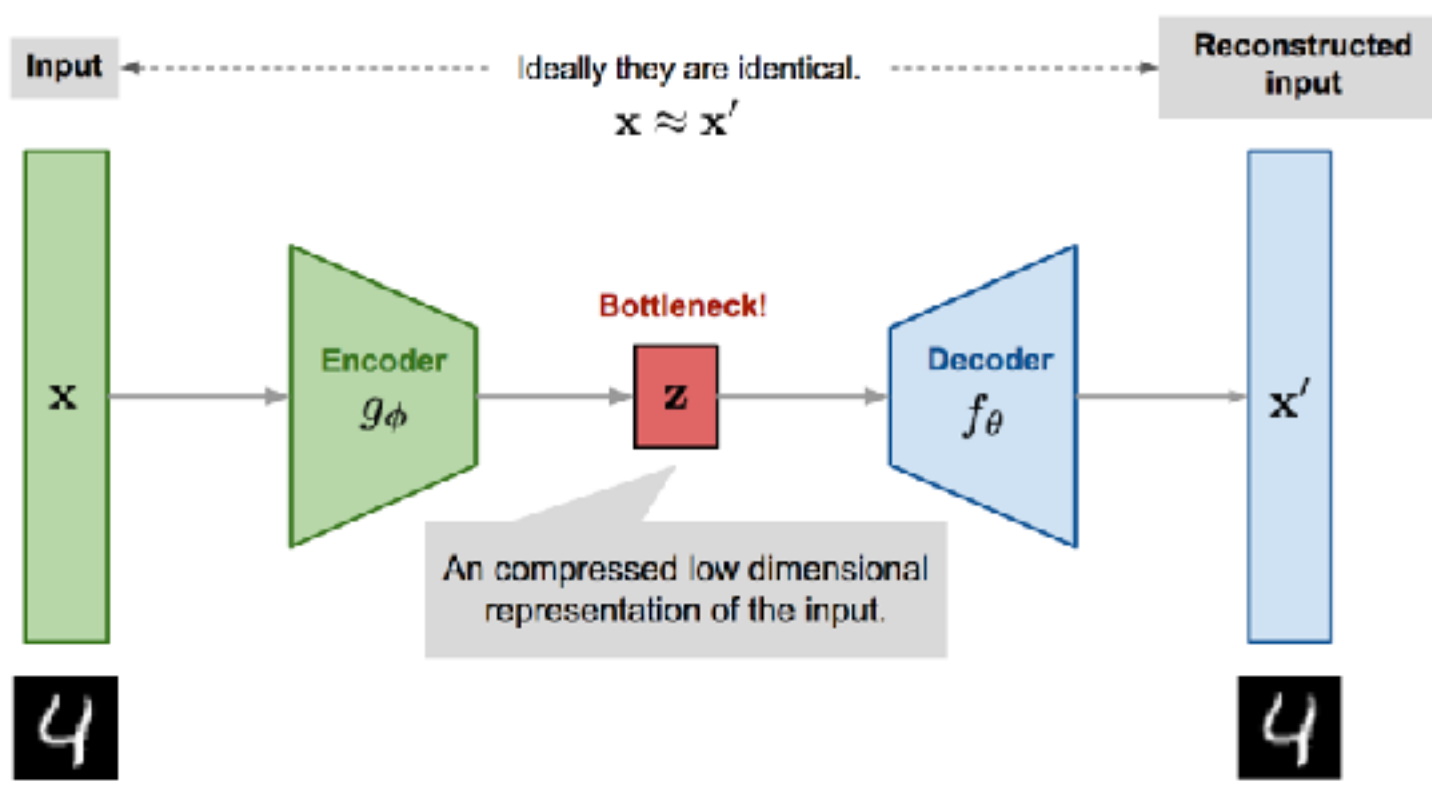
Generative models in a nutshell

- 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]

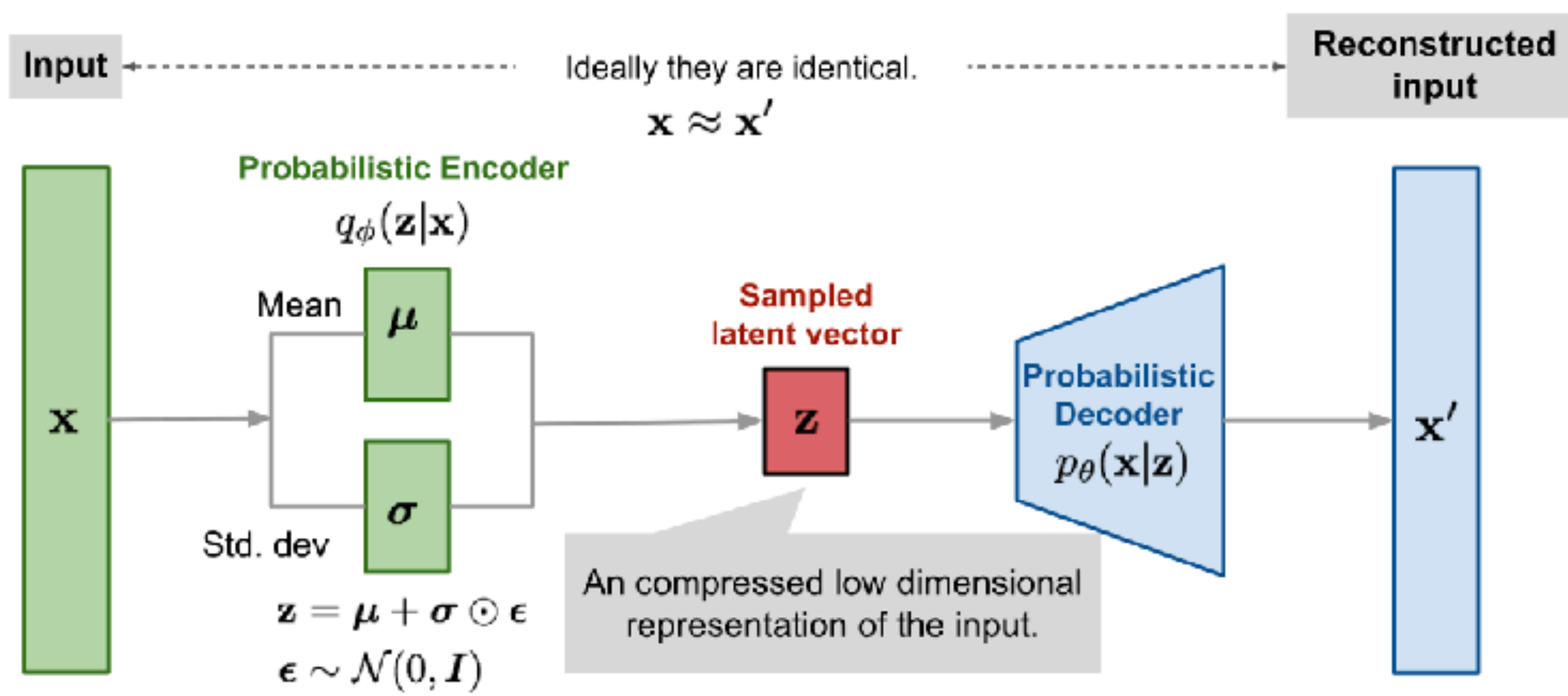
- Encode information in a latent space
  - typically lower-dimensional
  - similar in spirit to a non-linear PCA
  - not a generative model *per se*!



Source: lilianweng.github.io

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



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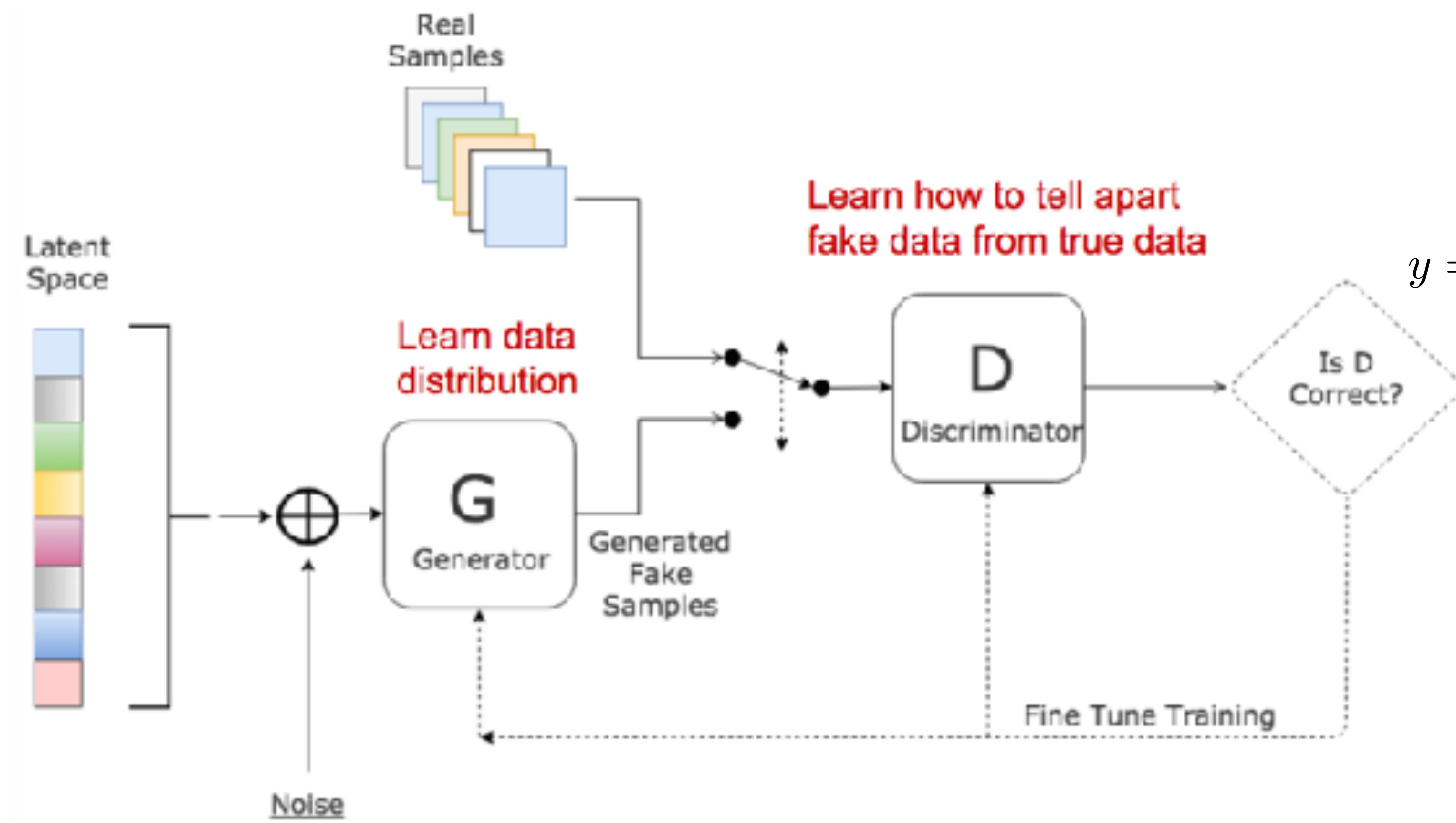
Generative Adversarial Networks [Goodfellow *et al.*, 2014]

- Model:



$$y = \begin{cases} 1 & \text{for a real sample} \\ 0 & \text{for a fake sample} \end{cases}$$

Source: lilianweng.github.io

- Loss function:

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

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

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Generative Adversarial Networks

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