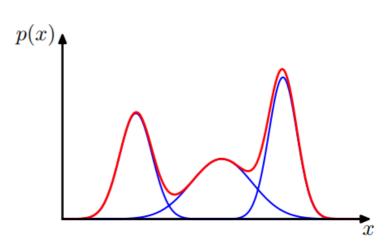
Generative neural networks

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- Goal: model p(x) or p(x|y)
 - explicitly
 - · eg. Gaussian Mixture Models



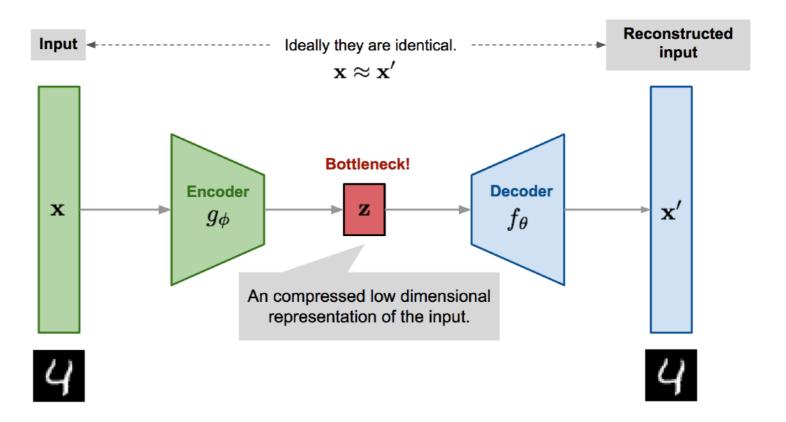
implicitly

- 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!

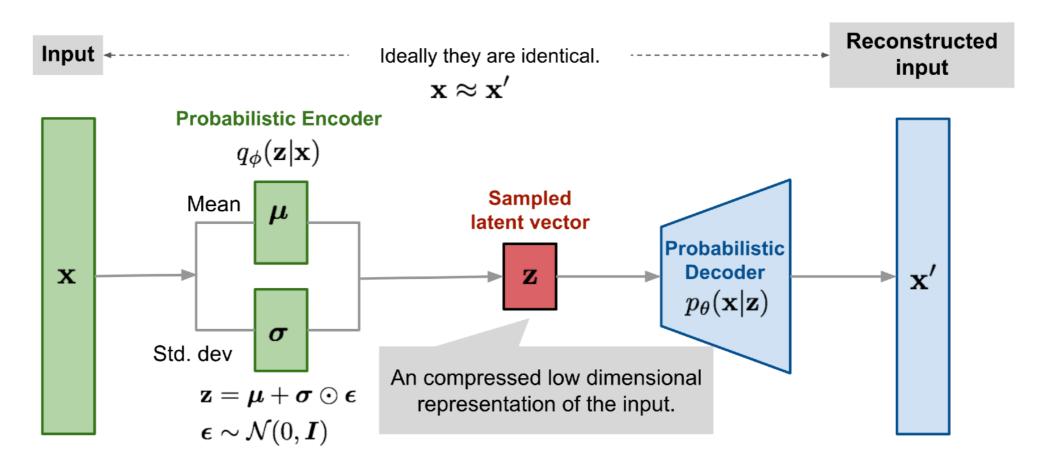


Source: <u>lilianweng.github.io</u>

Variational auto-encoders [Kingma & Welling, 2014]



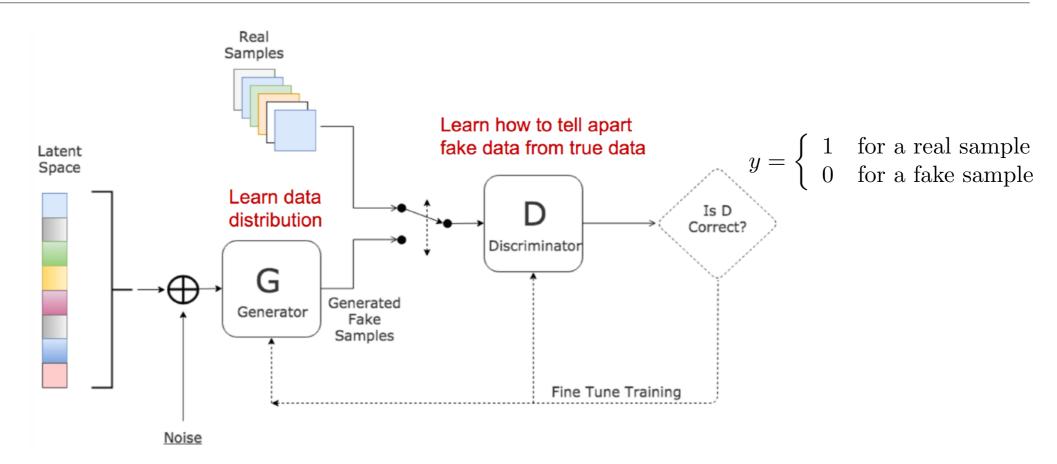
- Goal: turn auto-encoders into generative models
- <u>Idea:</u> set a prior on the distribution of z
 (through penalization of the loss function)
- Generative process: draw z from the prior, and decode it



Generative Adversarial Networks [Goodfellow et al., 2014]



Model:



Source: <u>lilianweng.github.io</u>

Loss function:

$$\min_{G} \max_{D} L(D, G) = \mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log (1 - D(G(z)))]$$
$$= \mathbb{E}_{x \sim p_r(x)} [\log D(x)] + \mathbb{E}_{x \sim p_q(x)} [\log (1 - D(x))]$$

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)



