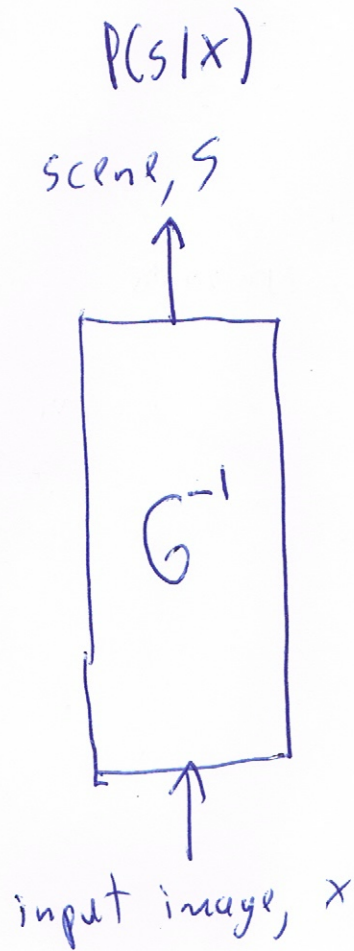


discriminative approach

①

(supervised)

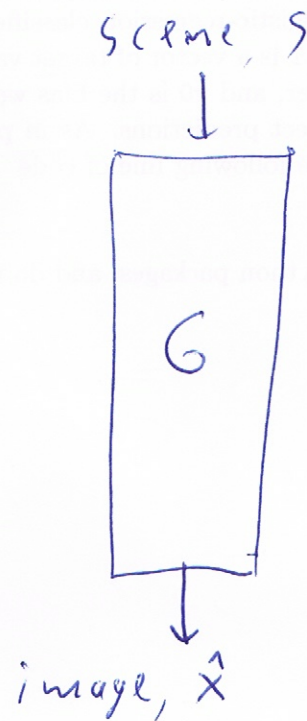


$$\dim(s) \ll \dim(x)$$

s = scene representation.

Generative Approach (unsupervised)

(2)



input image, x

find s that makes $\hat{x} \approx x$.

more generally, find $P(s|x)$.

~~the closer \hat{x} is to x , the more like~~
 $P(s|x)$ is high iff $\hat{x} \approx x$, ~~etc~~

Intractable in general.

use variational approximations (later).

Note:

Use Bayes Rule to compute $P(s|x)$:

$$P(s|x) = \frac{P(x|s) \cdot P(s)}{P(x)} \quad \leftarrow \text{prior on scenes,}$$

$$P(x) = \sum_s P(x, s) = \sum_s P(x|s) \cdot P(s)$$

$$P(x|s) = P(x|\hat{x}(s))$$

usually simple
(eg, Gaussian)

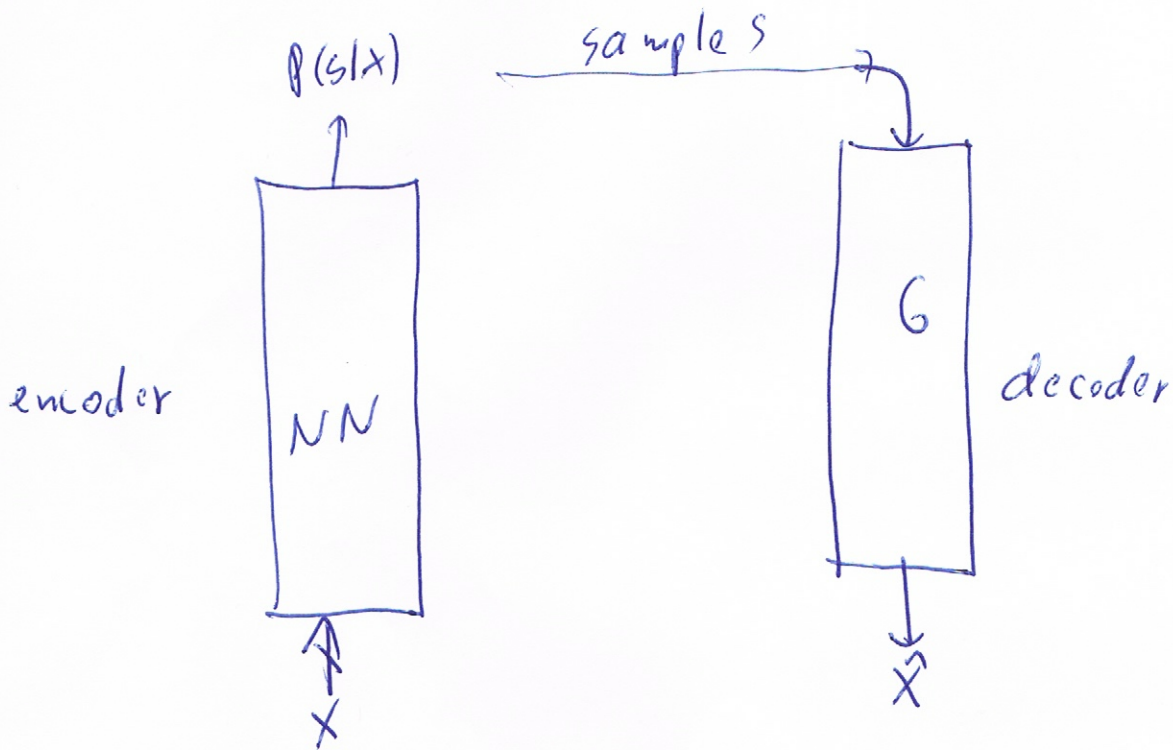
~~$P(x|s)$~~ eg, $P(x|\hat{x}) = \frac{e^{-||x-\hat{x}||^2/2\sigma^2}}{\sqrt{2\pi}\sigma}$

Variational Autoencoder

(3)

Simplifying assumption:

~~$p(s|x)$~~ Train a NN to compute
(an approximation to) $p(s|x)$



train NN to make $\hat{x} \approx x$ (for all training points)

~~can train~~ G can be given or can be trained
with ~~NN~~ simultaneously with NN

Note: ~~must~~

Note: must perform gradient descent ⁽⁴⁾
through both G & NN (at the sampling
operation).

No problem if G is a NN .

If G is a graphics program, we
must be able to differentiate it.
(Hence "differentiable rendering").

Note: unlike discriminative approach,
vae is unsupervised.

No ~~scene~~ labels needed.