

VAE (ch. 19 Bishop)

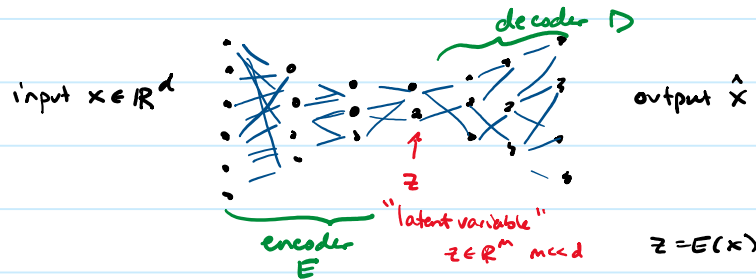
Wednesday, December 11, 2024 6:26 AM

ch. 18 (Bishop) Normalizing Flows

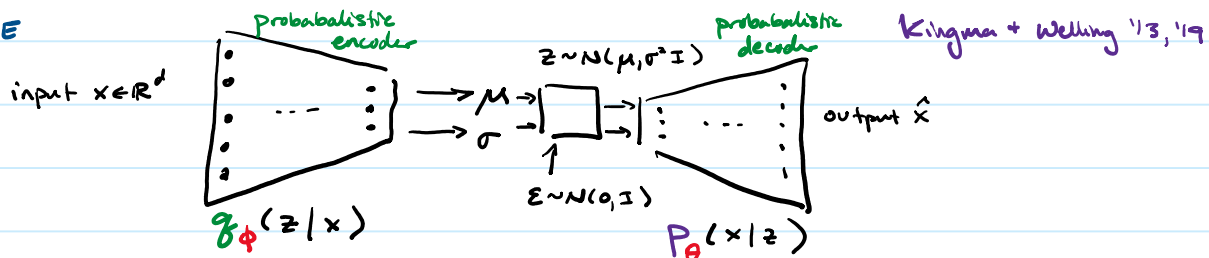
Also uses latent space, $x = f_w(z)$ and $z = g_w(x)$
 and use $p_x(x) = p_z(g(x)) \cdot |\det J(x)|$ — Jacobian, $\frac{dg}{dx}$
 popularized in ML by Rezende + Mohamed 2015
 Require to be invertible? so typically $\dim(z) = \dim(x)$
 Relation to neural ODEs

ch. 19 Autoencoders and Variational Autoencoders (VAE)

AE



VAE



Objective Function: maximum likelihood, $p(x)$ or $\log(p(x))$

$$\log(p(x)) = \int \underbrace{\log(p(x))}_{\text{Constant w.r.t. } z} g(z|x) dz + \int \log\left(\frac{p(z|x)}{g(z|x)}\right) g(z|x) dz + \int \log\left(\frac{g(z|x)}{p(z|x)}\right) g(z|x) dz \Bigg\} = 0$$

flip numerator/denominator

$$= \underbrace{\int \log\left(p(x) \frac{p(z|x)}{g(z|x)}\right) g(z|x) dz}_{\text{ELBO}} + \underbrace{\int \log\left(\frac{g(z|x)}{p(z|x)}\right) g(z|x) dz}_{\geq 0 \text{ intractable so ignore}}$$

can rewrite

$$\text{ELBO}(x; \phi, \theta) = \underbrace{E_{g_\phi} \log(p_\theta(x|z))}_{\text{Reconstruction}} - \underbrace{\text{KL}(g_\phi(z|x) \parallel p(z))}_{\text{Regularization}}$$

Fixed target

We want $g(z|x)$ to look like $p(z)$ so that

we can sample a new $z \sim p(z)$ later and it "could have come" from a datapoint x ... hence $p(x|z)$ is good

VAE (p. 2)

Wednesday, December 11, 2024

6:58 AM

3 key ideas to make VAE work:

① approximate likelihood function with ELBO

key trick in
"variational inference"

② amortized inference: encoder $g_\phi(z|x)$ approximates posterior distribution of z

③ reparameterization trick to make it implementable