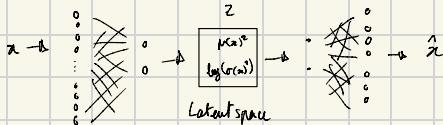


Problem scenario



* We can define the likelihood of our data

$$\text{as: } p(x) = \int p(x, z) dz$$

→ it's intractable, we would need to evaluate

this integral over all latent z .

we don't have
this ground
truth. This is
sth we want to
learn.

$$p(x|z) = \frac{p(x|z)p(z)}{p(x)}$$

$$\hookrightarrow \text{We could use } p(x) = \frac{p(x,z)}{p(z|x)}$$

Solution

We want to approximate our

true posterior $p_\theta(z|x) \approx q_\phi(z|x)$ approximate posterior

$$\log p_\theta(x) = \log p_\theta(z), \quad \text{why log? log-likelihood, turns products into sum}$$

$$= \log p_\theta(z) \int q_\phi(z|x) dz \\ = 1, \text{ integrated over the domain} \\ \text{probability distribution over } z$$

$$= \underbrace{\left[\log(p_\theta(z)) q_\phi(z|x) dz \right]}_{\mathbb{E}_{q_\phi(z|x)} [\log p_\theta(z)]} + \underbrace{\int c \cdot q(z) dz = c}_{c = \int q(z) dz}$$

$$= \mathbb{E}_{q_\phi(z|x)} \left[\log \left(\frac{p_\theta(z|x)}{q_\phi(z|x)} \right) \right]$$

$$= \mathbb{E}_{q_\phi(z|x)} \left[\log \frac{p_\theta(z|x) q_\phi(z|x)}{p_\theta(z|x) q_\phi(z|x)} \right]$$

$$= \mathbb{E}_{q_\phi(z|x)} \left[\log \frac{p_\theta(z|x)}{q_\phi(z|x)} \right] + \mathbb{E}_{q_\phi(z|x)} \left[\log \frac{q_\phi(z|x)}{p_\theta(z|x)} \right]$$

$$\log p_\theta(x) = \underbrace{\mathbb{E}_{q_\phi(z|x)} \left[\log \frac{p_\theta(z|x)}{q_\phi(z|x)} \right]}_{\text{ELBO}} + \underbrace{\mathbb{D}_{KL}(q_\phi(z|x) || p_\theta(z|x))}_{> 0}$$

$$\text{We know: } \log p_\theta(x) > \mathbb{E}_{q_\phi(z|x)} \left[\log \frac{p_\theta(z|x)}{q_\phi(z|x)} \right] = \mathbb{E}_{q_\phi(z|x)} \left[\log \frac{p_\theta(z|x) p_\theta(z)}{q_\phi(z|x)} \right]$$

$$\mathbb{D}_{KL}(q_\phi(z|x) || p_\theta(z)) = \int q(z|x) \log \frac{q(z|x)}{p_\theta(z)}$$

maximizing this = maximizing this

$$\begin{aligned} &= \mathbb{E}_{q_\phi(z|x)} \left[\log p_\theta(z|x) \right] + \mathbb{E}_{q_\phi(z|x)} \left[\log \frac{p_\theta(z)}{q_\phi(z|x)} \right] \\ &= \mathbb{E}_{q_\phi(z|x)} \left[\log p_\theta(z|x) \right] - \underbrace{\mathbb{D}_{KL}(q_\phi(z|x) || p_\theta(z))}_{\text{minimize}} \end{aligned}$$

$$\begin{aligned} &= \mathbb{E} \left[\log \frac{q(z|x)}{p(z)} \right] \\ &= -\mathbb{E} \left[\log \frac{p(z)}{q(z|x)} \right] \end{aligned}$$

Reparameterization Trick

Introducing new estimator, bc we can't run backpropagation over a stochastic process ($q_{\phi}(z|x)$)

$$\rightarrow \mathcal{L}(\theta, \phi, x) = \underbrace{\mathbb{E}_{q_{\phi}(z|x)}}_{\text{ELBO}} \left[\log \frac{p_{\theta}(x|z)}{q_{\phi}(z|x)} \right] = \mathbb{E}_{p(\epsilon)} \left[\log \frac{p_{\theta}(x, \epsilon)}{q_{\phi}(z|x)} \right] \quad \epsilon \approx p(\epsilon), z = g(\phi, x, \epsilon) \\ \epsilon \sim \mathcal{N}(0, I)$$

Loss function

$$\mathcal{L}(\theta, \phi; x) \approx \frac{1}{2} \sum_{j=1}^J (x_j - \mu_j^{(n)})^2 + \frac{1}{2} \sum_{i=1}^k \log p_{\theta}(x^{(i)} | z^{(i)}) \quad \text{where } z^{(i, \epsilon)} = \mu^{(i)} + \sigma^{(i)} \circ \epsilon^{(i)}, \epsilon^{(i)} \sim \mathcal{N}(0, I)$$