

Expanding VAE Loss (ELBO : Evidence Lower Bound)

$$D_{KL}(q_{\phi}(z|x) || p_{\theta}(z|x))$$

Note: KL Divergence

$$D_{KL}(p(x)||q(x)) = \int p(x) \log \frac{p(x)}{q(x)} dx$$

$$= \int q_{\phi}(z|x) \log \frac{q_{\phi}(z|x)}{p_{\theta}(z|x)} dz$$

$$= \int q_{\phi}(z|x) \log \frac{q_{\phi}(z|x)}{p_{\theta}(z|x)/p_{\theta}(x)} dz$$

$$= \int q_{\phi}(z|x) \log \frac{q_{\phi}(z|x) p_{\theta}(x)}{p_{\theta}(z|x)} dz$$

$$= \int q_{\phi}(z|x) \left\{ \log p_{\theta}(x) + \log \frac{q_{\phi}(z|x)}{p_{\theta}(z|x)} \right\} dz$$

$$= \int q_{\phi}(z|x) \log p_{\theta}(x) dz + \int q_{\phi}(z|x) \log \frac{q_{\phi}(z|x)}{p_{\theta}(z|x)} dz$$

Note: Conditional Expectation

$$\mathbb{E}(x|y) = \int x f_{x|y}(x|y) dx$$

$$= \frac{1}{f_Y(y)} \int x f_{x,y}(x,y) dx$$

$$= \log p_{\theta}(x) + \int q_{\phi}(z|x) \log \frac{q_{\phi}(z|x)}{p_{\theta}(z|x)} dz$$

$$= \log p_{\theta}(x) + \int q_{\phi}(z|x) \log \frac{q_{\phi}(z|x)}{p_{\theta}(x|z) p_{\theta}(z)} dz \rightarrow D_{KL}(q_{\phi}(z|x) || p_{\theta}(z))$$

$$= \log p_{\theta}(x) + \int q_{\phi}(z|x) \left\{ \log \frac{q_{\phi}(z|x)}{p_{\theta}(z)} - \log p_{\theta}(x|z) \right\} dz$$

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

$$= \log p_{\theta}(x) + D_{KL}(q_{\phi}(z|x) || p_{\theta}(z)) - \mathbb{E}_{z \sim q_{\phi}(z|x)} [\log p_{\theta}(x|z)]$$

$$\therefore D_{KL}(q_{\phi}(z|x) || p_{\theta}(z|x)) = \log p_{\theta}(x) + D_{KL}(q_{\phi}(z|x) || p_{\theta}(z)) - \mathbb{E}_{z \sim q_{\phi}(z|x)} \log p_{\theta}(x|z)$$

Objective

Minimize: $D_{KL}(q_{\phi}(z|x) || p_{\theta}(z|x)) - \log p_{\theta}(x)$

= minimize difference between approx & true posterior distributions

= maximize likelihood of generating x

$$D_{KL} \geq 0$$

$$-L_{VAE} = +\log p_{\theta}(x) - D_{KL}(q_{\phi}(z|x) || p_{\theta}(z|x)) \leq \log p_{\theta}(x)$$

↑ Lower Bound!