

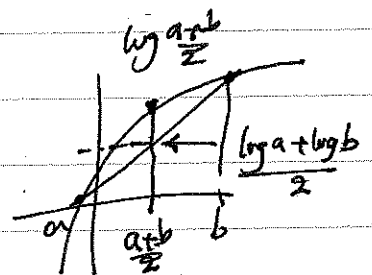
# ML:

$$\max_{\theta} P(X) = P(x) = \prod_{\theta} P(x_i)$$

$$\max_{\theta} \log P_{\theta}(X) = \sum_i \log P_{\theta}(x_i)$$

$$\log P(x) = \log \int P(x, z) dz$$

$$= \log \int P(x|z) P(z) dz$$

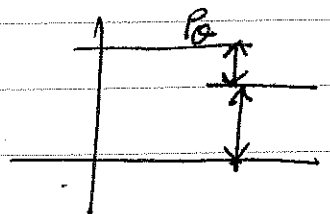


$$\geq \int \log [P(x|z) P(z)] dz$$

$$\frac{1}{2}(\log a + \log b) \leq \log \frac{a+b}{2}$$

$$\geq \int \log \frac{P_{\theta}(x|z) P(z)}{q(z)} q(z) dz$$

$$\underbrace{\qquad\qquad\qquad}_{\mathbb{E}_q \log \frac{P_{\theta}(x|z)}{q(z)}_{\psi}}$$



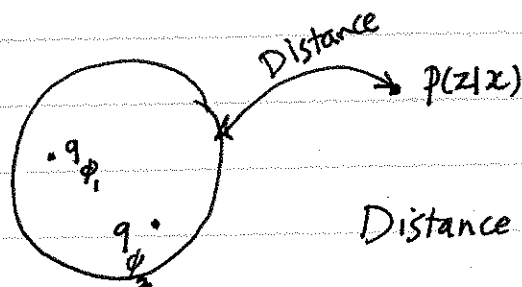
$$\max_{\theta, \psi} \mathbb{E} \log \frac{P_{\theta}(x|z)}{q_{\psi}(z)} \quad (\text{ELBO})$$

Another way of saying the same thing:

$P(Z|X)$        $\swarrow$  — interested

idea:

$$q_{\phi}(z) \quad \min_{\phi} \text{Distance} \left( q_{\phi}(z), p(z|x) \right)$$



Distance  $\equiv$  KL

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

~~$$= E[\log p(z|x)]$$~~

$$= \mathbb{E}_{\varphi} \left[ \log \frac{q_{\varphi}(z) p(x)}{p(x, z)} \right] = \mathbb{E}_{\varphi} \log \frac{q_{\varphi}(z)}{p(x, z)} + \log p(x)$$

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$$\log P(X) = \underbrace{KL(q_\phi(z), p(z|X))}_{\geq 0} - \mathbb{E}_{q_\phi} \log \frac{q_\phi(z)}{p(z, X)}$$

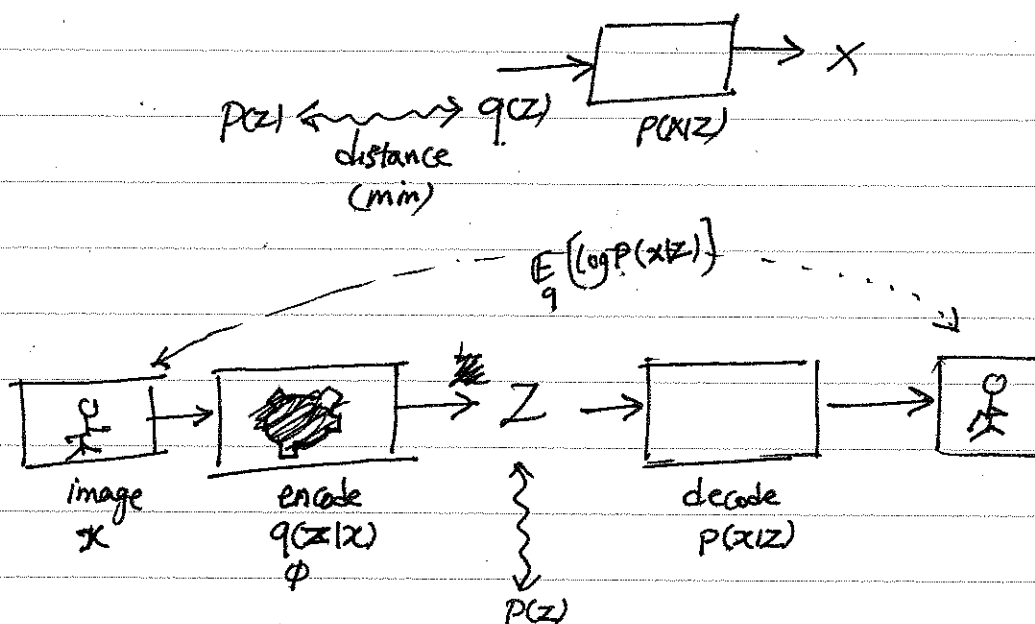
$$\log P(X) \geq \mathbb{E}_{q_\phi} \log \frac{P(z, X)}{q_\phi(z)} \quad (\text{ELBO})$$

Expand ELBO:

$$\mathbb{E}_{q_\phi} \log \frac{P(z, X)}{q_\phi(z)} = \mathbb{E}_{q_\phi} \log \frac{P(X|Z)}{q_\phi(z)} + \mathbb{E}_{q_\phi} \log \frac{P(z)}{q_\phi(z)}$$

$$= \mathbb{E}_{q_\phi} \log P(X|Z) - \underbrace{KL(q_\phi(z) \| p(z))}_{\text{distance to prior}}$$

decode — reconstruction as if  $q$  is generating



Challenges:

We have to find best  $\phi$  and  $\theta$  that max

$$\max_{\phi, \theta} -D_{KL}(q_{\phi}(Z|x) \| p_{\theta}(z)) + \mathbb{E}_{q_{\phi}(z|x^{(i)})} [\log p_{\theta}(x^{(i)}|z)]$$

$$\max_{\phi, \theta} -\mathbb{E}_q \log \frac{q(z|x)}{p_{\theta}(z)} + \mathbb{E}_q [\log p_{\theta}(x^{(i)}|z)]$$

$\nabla_{\theta}$  : easy!

$\nabla_{\phi}$  : No so much!

Let look closer:

$$\mathbb{E}_{q_{\phi}}[f(z)] = \int f(z) q_{\phi}(z) dz$$

$$\neq \nabla_{\phi} (//)$$

$$= \int \nabla f(z) q_{\phi}(z) dz = \int f(z) \underbrace{\nabla q_{\phi}(z)}_{\text{99\% you cannot do closed form}} dz$$

$$= \int f(z) \frac{\nabla q_{\phi}}{q_{\phi}} q_{\phi} dz$$

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$$\frac{\nabla_{\phi} q_{\phi}}{q_{\phi}} = \nabla_{\phi} \log q_{\phi}$$

$$(*) \int f(z) \nabla \log q_{\phi} q_{\phi} dz = \mathbb{E} [f(z) \nabla \log q_{\phi}]$$

$$\approx \frac{1}{L} \sum f(z_i) \nabla \log q_{\phi}(z)$$

(We know how to  
estimate but it has  
~~high~~ large variance!)

Remember ELBO:

$$\mathcal{L} = \int \log \frac{P(x, z)}{q(z|x)} q(z|x) dz = \mathbb{E} [\log P(x, z) - q(z|x)]$$

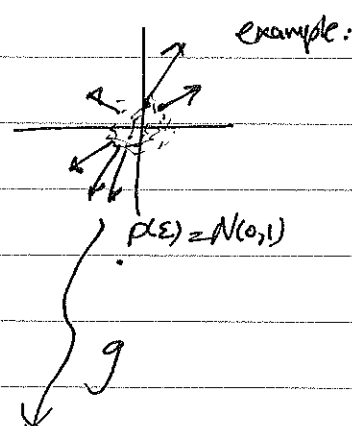
$$\approx \frac{1}{L} \sum_l \log (P(x, z^l) - q(z^l|x)) \quad (\text{I})$$

s.t.  $z^l \sim q(z|x)$

↓ how to generate this?

Sample  $\varepsilon^l \sim P(\varepsilon)$ 

$$z^l = g(\varepsilon^l, x)$$

↑  
a deterministic functionA. Let's look at example of  $g$ 

$$g(\varepsilon) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix}$$

↑  
2D

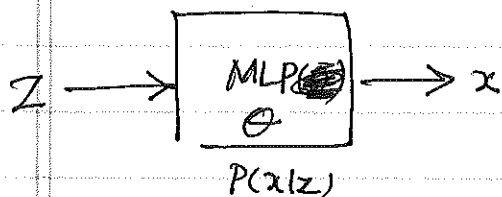
~~Approx~~ Estimation of  $\mathbb{E} q(\text{I})$  is fine but can have high variance

Let's compute anything that can be computed closed-form:

B.  $Z = g(\varepsilon) = \mu + \sigma \varepsilon$  - what's  $g(\varepsilon) = ?$   $P(Z) = ?$

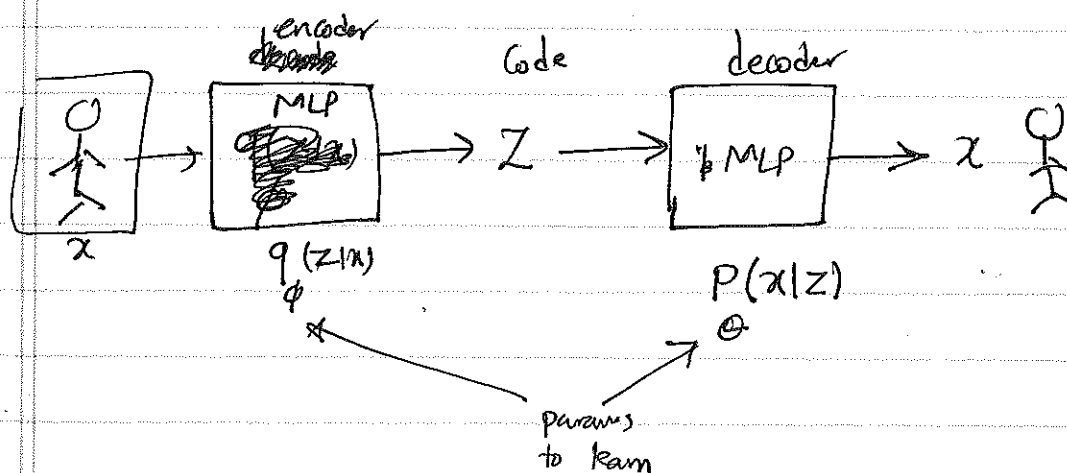
C.  $Z = g(\varepsilon) = \mu + A\varepsilon$  - what's  $P(Z) = ?$

our machine



$P(z|x)$  almost impossible to compute closed form

Remember decoder-encoder



How ~~we~~ are going to learn  $\phi, \Theta$ ?

- We set  $\phi$  to something, we pass the guy

to  $q(z|x)$ , how? remember  $z = g_\phi(x, \epsilon)$ !

Sample  $\epsilon$ , subst.  $\epsilon, x$  get  $z$ !

- Pass  $z$  to decoder get new  $\tilde{x}$ .

- Is  $x, \tilde{x}$  similar?  $\mathbb{E}_z \log P(x|z)$

log ~~log~~ example  $\log P(x|z) = \mu(x; \phi) + A(x; \phi)z$