## Variational Inference

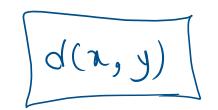
n: observed

z: Latent/hidden/unobserved

$$P(x) = \sum_{z} P(x,z)$$

$$q(z) \simeq p(z|x)$$
  
 $q'(z) = arg min \left(d(q(z), p(z|x))\right)$   
 $q(z) \in Q$ 

 $x \in X$ P(x)min |p(x) - q(x)| $\frac{1}{2} \left( p(x) - q(x) \right)^{2}$  distance



 $\bigcirc$  d(x,y) > 0

 $d(n,y) = 0 \Leftrightarrow n = y$ 

 $(4) d(x,y) + d(y,z) \geq d(x,z)$ 

$$d_1 = \sum_{x \in X} p(x) | p(x) - q(x) |$$

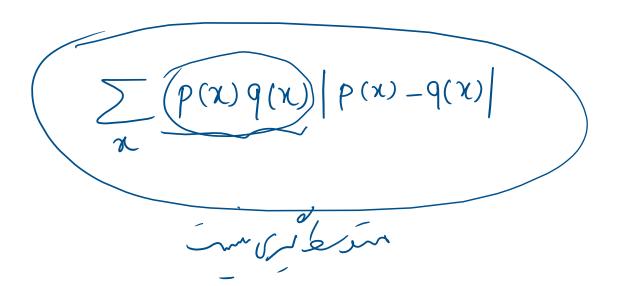
$$d_1 \neq d_2$$

$$d_2 = \sum_{x \in X} q(x) |p(x) - q(x)|$$

$$d(p,q) = \sum_{n} p(n) |p(n) - q(n)|$$

$$d(q, p) = \sum q(x) |p(x) - q(x)|$$





$$P(x) > 0$$

$$Q(x) > 0$$

$$\sum_{x} p(x) q(x) \neq 1$$

$$\rho(x) \approx q(x) = \epsilon$$

$$\rho(x) \approx q(x) = 1 - \epsilon$$

$$\sum_{\chi \in \chi} \log \left( \frac{p(\chi)}{q(\chi)} \right) p(\chi)$$

$$\rho(x) > 0$$
 $q(x) > 0$ 
 $\rho(x) = 10^{-1}$ 
 $q(x) = 10^{-10}$ 

$$KL(P||q) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)} > 0$$

$$KL(9|P) = \sum_{x \in X} q(x) \log \frac{q(x)}{p(x)} > 0$$

$$q^{*}(z) = avg min KL(q(z)||p(z|x))$$

$$q(z) \in Q$$

$$q^{*}(z) = \underset{=}{\text{arg min}} KL(p(z|x)||q(z))$$

$$KL(P||q) = \sum_{n} p(n) \log \frac{P(n)}{q(n)}$$

9(x) >0 9(x) >0

$$KL(911P) = \sum_{n=1}^{\infty} \varphi(n) \log \frac{\varphi(n)}{\varphi(n)}$$

$$p(x) > 0$$

$$q(x) > 0$$

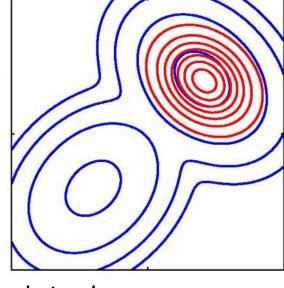
## KL divergence: M-projection vs. I-projection

Let P is mixture of two 2D Gaussians and Q be a 2D Gaussian distribution with arbitrary covariance matrix:

$$Q^* = \operatorname{argmin} \int P(\mathbf{z}) \log \frac{P(\mathbf{z})}{Q(\mathbf{z})} d\mathbf{z} \qquad P: \text{Blue} \qquad Q^*: \text{Red} \qquad Q$$

$$E_P[\mathbf{z}] = E_Q[\mathbf{z}] \qquad Cov_P[\mathbf{z}] = Cov_Q[\mathbf{z}]$$

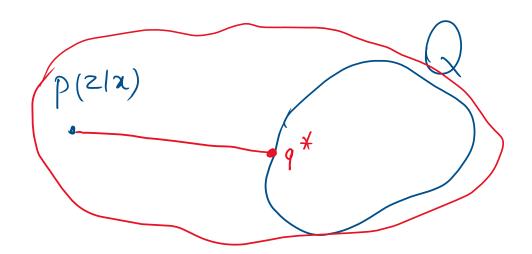
$$Q^* = \underset{O}{\operatorname{argmin}} \int Q(\mathbf{z}) \log \frac{Q(\mathbf{z})}{P(\mathbf{z})} d\mathbf{z}$$



two good solutions!

KL(911P)

[Bishop]





$$q^{*}(z) = arg min KL(q(z)||P(z|x)) P(z|x) = \frac{P(x,z)}{P(x)}$$

$$q(z) \in Q$$
?

$$KL\left(q(z) \parallel p(z|x)\right) = \sum_{z} q(z) \log \frac{q(z)}{p(z|x)}$$

$$= \sum_{z} q(z) (\log \frac{q(z) p(x)}{p(x,z)} = \sum_{z} q(z) (\log \frac{q(z)}{p(x,z)} + \log p(x))$$

$$= \sum_{z} q(z) \log \frac{q(z)}{p(x,z)} + \sum_{z} q(z) \log p(x)$$

$$= KL(q(z)||p(x,z)) + log P(x)$$

$$KL(q(z)||p(z|x)) = KL(q(z)||p(x,z)) + \log P(x)$$

$$\Rightarrow \log P(x) = -KL(q(z)||P(x,z)) + KL(q(z)||P(z|x))$$
const.

w.r.t q

$$q^{*}(z) = arg min KL(q(z)||p(z|x))$$

$$q(z)$$

$$= \operatorname{arg\ max} - KL(9(z) || P(x,z))$$

$$9(z)$$

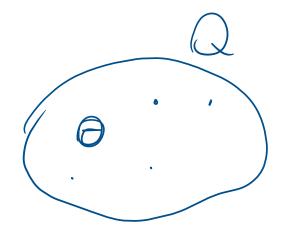
$$\frac{1}{\log(P(x))} = -KL(q(z) || P(x,z)) + KL(q(z) || P(z|x))$$

$$S = \chi UZ$$

Evidence Lower Bound

$$P(\chi) = \sum_{z} P(\chi, z)$$

$$\tilde{\theta} = \underset{\theta}{\text{arg man}} \quad \text{ELBO} \geq \underset{\theta}{\text{arg man}} - \text{KL}(q(z) || p(n_3 z))$$



VAE

man ELBO

WF

man Likelihood

log P(n)