

## Variational Autoencoders (VAEs)

- Decoder :  $p(x|z, \theta)$  (e.g.  $N(\mu^\theta(z); \Sigma^\theta(z))$ )
- Encoder :  $q(z|x, \phi)$  (e.g.  $N(\mu^\phi(x); \Sigma^\phi(x))$ )

- likelihood of  $x$  given  $\theta$

$$\begin{aligned}\log P(x|\theta) &= \log \int P(x|z, \theta) dP(z|\theta) \\ &= \log \int \frac{P(x|z, \theta) P(z|\theta)}{Q(z|x, \phi)} dQ(z|x, \phi)\end{aligned}$$

Jensen's inequality  $\rightarrow$

$$\geq \int \log \left( \frac{P(x|z, \theta) P(z|\theta)}{Q(z|x, \phi)} \right) dQ(z|x, \phi)$$

$$= \mathbb{E}^{Q_\phi} \left[ \log P(x|z, \theta) \right]$$

reconstruction loss

$$- \mathbb{E}^{Q_\phi} \left[ \log \left( \frac{Q(z|x, \phi)}{P(z|\theta)} \right) \right]$$

Kullback-Leibler distance  
acts as a regularizer

NB: The quantities of interest in the ELBO depend heavily on the distributions  $P, Q$ .

## Optimization procedure

Let  $\phi, \theta$  be artificial neural networks (ANNs) for respectively the encoder and decoder.

1. Process  $x$  through ANN  $\phi$   
↳ gives  $\mu^\phi(x)$  and  $\Sigma^\phi(x)$ .
2. Sample  $z$  from  $q_\phi(\cdot | x)$   
↳ gives  $z$ 's drawn from the encoder.
3. Process  $z$  through ANN  $\theta$   
↳ gives  $\mu^\theta(z)$  and  $\Sigma^\theta(z)$ .
4. Compute Monte-Carlo estimates of ELBO

$$\log P(x|z, \theta(z)) - \log \left( \frac{Q(z|x, \phi(x))}{P(z|\theta(z))} \right).$$

5. Maximize the ELBO with respect to  $\phi, \theta$ .  
↳ updates both ANNs
6. Repeat until convergence.