

# EM algorithm

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# EM algorithm

- For non-Gaussian mixture
- a broader view of the EM algorithm

# Jensen's inequality

- Consider a convex function,  $f$  and a random variable,  $X$
- Theorem:  $\mathbb{E}[f(X)] \geq f(\mathbb{E}[X])$

# The EM algorithm

- Want to know:  $p(x, z; \theta)$ 
  - Marginalization:  $p(x; \theta) = \sum_z p(x, z; \theta)$

- Log-likelihood:  $\ell(\theta) = \sum_i \log(x^{(i)}; \theta)$

$$\ell(\theta) = \sum_i \log \sum_z (x^{(i)}, z^{(i)}; \theta)$$

- For simpler exposition: drop  $i$

$$\ell(\theta) = \log \sum_z (x, z; \theta)$$

# The EM algorithm (cont.)

- Assume a distribution of the latent variable,  $Q(z)$
- Lower bound:

$$\begin{aligned} p(x; \theta) &= \log \sum_z p(x, z; \theta) \\ &= \log \sum_z Q(z) \frac{p(x, z; \theta)}{Q(z)} \\ &\geq \sum_z Q(z) \log \frac{p(x, z; \theta)}{Q(z)} \end{aligned}$$

- Jensen's inequality

$$f \left( \mathbb{E}_{z \sim Q} \left[ \frac{p(x, z; \theta)}{Q(z)} \right] \right) \geq \mathbb{E}_{z \sim Q} \left[ f \left( \frac{p(x, z; \theta)}{Q(z)} \right) \right]$$

# The EM algorithm (cont.)

- To get tight bound,  $\frac{p(x, z; \theta)}{Q(z)} = c$

- Using the fact  $\sum_z Q(z) = 1$

$$Q(z) = p(z|x; \theta)$$

- Now one can verify that

$$\sum_z Q(z) \log \frac{p(x, z; \theta)}{Q(z)} = \log p(x; \theta)$$

- Evidence Lower Bound (ELBO):

$$\log p(x; \theta) \geq \text{ELBO}(x; Q, \theta) = \sum_z Q(z) \log \frac{p(x, z; \theta)}{Q(z)}$$

# The EM algorithm (cont.)

- Interpretation:

$$\forall Q, \theta, x, \quad \log p(x; \theta) \geq \text{ELBO}(x; Q, \theta)$$

- E-step: fix  
set

$$Q(z) = p(z|x; \theta)$$

- M-step: fix  
maximize

# More on ELBO

- Interpretation:

$$\text{ELBO}(x; Q, \theta) = \sum_z Q(z) \log \frac{p(x, z; \theta)}{Q(z)}$$

- Decomposition:

$$\begin{aligned}\text{ELBO}(x; Q, \theta) &= \mathbb{E}_{z \sim Q} [p(x, z; \theta)] - \mathbb{E}_{z \sim Q} [\log Q(z)] \\ &= \mathbb{E}_{z \sim Q} [p(x, z; \theta)] - D_{\text{KL}}(Q \| p_z)\end{aligned}$$

$$\text{ELBO}(x; Q, \theta) = \log p(x) - D_{\text{KL}}(Q \| p_{z|x})$$



# Variational Inference

- Extension of EM
  - Continuous latent variable, non-Gaussian, ...

- ELBO:

$$\text{ELBO}(Q, \theta) = \sum_{i=1}^n \text{ELBO}(x^{(i)}; Q_i, \theta) = \sum_i \sum_{z^{(i)}} Q_i(z^{(i)}) \log \frac{p(x^{(i)}, z^{(i)}; \theta)}{Q_i(z^{(i)})}$$

- Mean-field assumption:

$$Q_i(z) = Q_i^1(z) Q_i^2(z) \dots Q_i^k(z)$$

- Example: Gaussian with diagonal covariance

$$Q_i = \mathcal{N}(q(x^{(i)}; \phi), \text{diag}(v(x^{(i)}; \psi))^2)$$