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Expectation-Maximisation. $x = x_1, x_2, \dots \rightarrow$ set of observed variables $z = z_1, z_2, \dots \rightarrow$ latent variables. $z_i \in \mathbb{Z} \rightarrow$ discrete $\theta \rightarrow$ parameter we wish to estimateTo find the MLE of θ , maximize the log marginal likelihood of the data

$$l(\theta) = \log p(x/\theta)$$

$$= \log \left[\sum_{z \in \mathbb{Z}} p(x, z/\theta) \right]$$

$$= \log \left[\sum_{z \in \mathbb{Z}} p(x/z, \theta) p(z/\theta) \right]$$



has no closed-form solution

- sum inside log makes partial diff. w.r.t θ difficult
- space of all possible θ & \mathbb{Z} is immense

So, we can construct a lower bound that can be easily optimise.

 $q \rightarrow$ a valid distr. function of z .

$$l(\theta) = \log \sum_{z \in \mathbb{Z}} \frac{p(x, z/\theta)}{q(z)} q(z)$$

$$= \log \left[E_{q(z)} \left(\frac{p(x, z/\theta)}{q(z)} \right) \right]$$

$$\geq E_{q(z)} \log(\cdot)$$

 \rightarrow Jensen for concave function.

$$= E_q(\log p - \log q)$$

$$= E_q[\log p(x, z|\theta)] + H(q)$$

$$= ELBO(\theta, q) \rightarrow \mathcal{Q}(\theta).$$

Now, finding θ that maximises ELBO is easier

$$\mathcal{Q}(\theta) = \sum_{z \sim q} q(z) \log p(x, z|\theta)$$

$\hookrightarrow \log$ is inside the sum

$H(q) \rightarrow$ doesn't depend on θ ,

it is sufficient to maximise $\mathcal{Q}(\theta)$

$$ELBO(q, \theta) = E_{q(z)} \left[\log \frac{p(x, z|\theta)}{q(z)} \right]$$

$$= E_{q(z)} \left[\log \frac{p(x, z|\theta) p(z|x, \theta)}{p(z|x, \theta) q(z)} \right]$$

$$= E_{q(z)} \left[\log \frac{p(z|x, \theta) p(x|\theta)}{p(z|x, \theta) q(z)} \right]$$

$$= E_q[\log p(x|\theta)] + E_q \left[\frac{p(x|\theta)}{q} \right]$$

$$= \text{maximum when } KL[q \| p(z|x, \theta)]$$

\rightarrow iterate b/w optimising ELBO w.r.t θ keeping q fixed.
 then " " " " " " $q(z)$ " " " " θ fixed