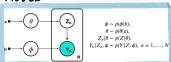


MODEL



Let $\Psi = [\phi, \theta, z, \dots, z_w]$

Variational Family $Q = \{q(\Psi|\lambda) | \lambda \in \Delta\}$

Goal: $\lambda^* = \arg \min_{\lambda} D_{KL}[p(\Psi|Data) || q(\Psi|\lambda)]$

Problem: we don't know $q(\Psi|\lambda)$ and we can't evaluate it!

Solution: instead of min. D_{KL} we max ELBO

$$\arg \max_{\lambda} \mathbb{E}_{\Psi \sim q(\Psi|\lambda)} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right]$$

Why? ELBO involves the joint:
 $p(\Psi, Data) = p(Data|\Psi)p(\Psi)$

The joint is tractable while posterior is not.

Assumptions: mean-field

$$q(\Psi|\lambda) = \prod_{i=1}^n q(\Psi_i|\lambda_i)$$

How: right now we can only optimize Φ ns analytically, so we do coordinate-ascent on ELBO, because this is easier!

iterate:

$$\max_{\lambda_i} \text{ELBO}(\Psi_i|\lambda_i)$$

Claim: $\mathbb{E}[\dots] = \mathbb{E}[\mathbb{E}[\dots]]$
 $\Psi \sim q(\Psi|\lambda) \quad \Psi_i \sim q(\Psi_i|\lambda_i) \quad \Psi_{-i} \sim q(\Psi_{-i}|\lambda_{-i})$

$$\begin{aligned} \mathbb{E} \left[\log \left(\frac{p(\Psi|Data)}{q(\Psi|\lambda)} \right) \right] &= \int_{\Psi} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right] q(\Psi|\lambda) d\P \\ &= \int_{\Psi_i} \int_{\Psi_{-i}} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right] q(\Psi|\lambda) d\P_{-i} d\P_i \\ &= \int_{\Psi_i} \int_{\Psi_{-i}} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right] q(\Psi_{-i}|\lambda_{-i}) q(\Psi_i|\lambda_i) d\P_{-i} d\P_i \\ &= \mathbb{E} \left[\mathbb{E} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right] \right] \end{aligned}$$

In fact, with a bit more algebra, we can show that:

$$\max_{\lambda_i} \mathbb{E} \left[\mathbb{E} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right] \right] = \max_{\lambda_i} \mathbb{E} \left[\mathbb{E} \left[\log \left(\frac{p(\Psi, Data|\Psi_i)}{q(\Psi_i|\lambda_i)} \right) \right] \right]$$

Claim: $\max_{\lambda_i} \mathbb{E}[\dots] = \min_{\lambda_i} D_{KL}[\dots]$

$$\begin{aligned} \max_{\lambda_i} \mathbb{E} \left[\mathbb{E} \left[\log \left(\frac{p(\Psi, Data|\Psi_i)}{q(\Psi_i|\lambda_i)} \right) \right] \right] &\stackrel{\text{algebra}}{=} \max_{\lambda_i} \mathbb{E} \left[\mathbb{E} \left[\log p(\Psi_i, Data|\Psi_i) - \log q(\Psi_i|\lambda_i) \right] \right] \\ &\stackrel{\text{algebra}}{=} \max_{\lambda_i} \mathbb{E} \left[\log \left(\exp \left\{ \mathbb{E} \left[\log p(\Psi_i, Data|\Psi_i) - \log q(\Psi_i|\lambda_i) \right] \right\} \right) \right] \\ &\equiv \min_{\lambda_i} \mathbb{E} \left[\log \left(\frac{q(\Psi_i|\lambda_i)}{\exp \left\{ \mathbb{E} \left[\log p(\Psi_i, Data|\Psi_i) \right] \right\}} \right) \right] \\ &\quad \text{looks like DKL but denominator is not a pdf!} \\ &= \min_{\lambda_i} \mathbb{E} \left[\log \left(\frac{q(\Psi_i|\lambda_i)}{\underbrace{\mathbb{E} \left[\exp \left\{ \log p(\Psi_i, Data|\Psi_i) \right\} \right]}_{\text{make denominator into pdf with normalizing constant Z!}}} \right) \right] \\ &= \min_{\lambda_i} \mathbb{E} \left[\log \left(\frac{q(\Psi_i|\lambda_i)}{\mathbb{E} \left[\exp \left\{ \log p(\Psi_i, Data|\Psi_i) \right\} \right]} \right) \right] + \log(Z) \\ &\equiv \min_{\lambda_i} D_{KL} \left[q(\Psi_i|\lambda_i) || \mathbb{E} \left[\exp \left\{ \log p(\Psi_i, Data|\Psi_i) \right\} \right] \right] \end{aligned}$$

Lesson: we solve for $\lambda^* = \arg \max_{\lambda} \mathbb{E} \left[\log \left(\frac{p(\Psi, Data)}{q(\Psi|\lambda)} \right) \right]$ by coordinate ascent

each time updating λ_i by

$$\lambda_i^* = \arg \max_{\lambda_i} \text{ELBO}(\lambda_i, \lambda_{-i})$$

$$q(\Psi_i|\lambda_i^*) \propto \exp \left\{ \mathbb{E} \left[\log p(\Psi_i, Data|\Psi_i) \right] \right\}$$