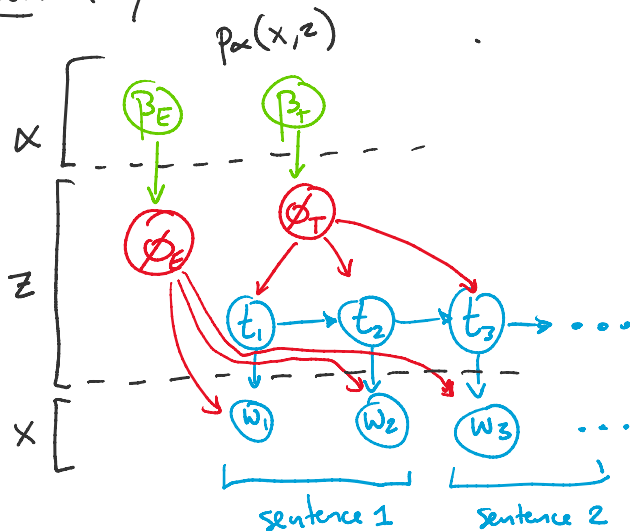


Ex: Unsupervised POS Tagging

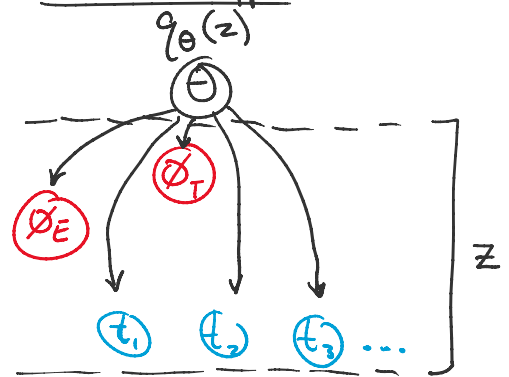
Given: sentences only (concatenated together)

Goal: infer tags for unlabeled sentences

Model: Bayesian HMM



Mean Field Approx



Training Objective

$$\log p(x|\alpha) = \log \sum_z p(x, z|\alpha) = \log \sum_z \sum_{\theta_E} \sum_{\theta_T} p(\tilde{w}, \tilde{t}, \phi_E, \phi_T | \beta_E, \beta_T)$$

Using the ELBO:

$$\log p(x|\alpha) \geq \text{ELBO}(q_\theta) = E_{q_\theta}[\log p(x, z)] - E_{q_\theta}[\log q_\theta(z)]$$

$$\rightarrow E_{q_\theta}[\log p(w, t, \phi_E, \phi_T | \beta_E, \beta_T)] - E_{q_\theta}[\log q_\theta(t, \phi_E, \phi_T)]$$

Variational inference gives:

$$q_\theta(z) \approx p_\alpha(z|x) \Rightarrow q_\theta(\tilde{t}) \approx p(\tilde{t}|\beta) \quad q_\theta(\phi_E) \approx p(\phi_E|\beta) \quad q_\theta(\phi_T) \approx p(\phi_T|\beta)$$

Problem: How to estimate α ?

★ New Idea ★: Jointly find p_α and q_θ to make ELBO as large as possible.

Two Approximations:

(i) Approximate Learning: choosing α for p / can't compute by assumption

Two Approximations:

- ① Approximate Learning: choosing α for p
 - really want to maximize $\log p(x|\alpha)$
 - instead maximize a variational lower bound
- ② Approximate Inference: choosing θ for q
 - after reaching a (local) maximum w.r. (p_α, q_θ) query q_θ approximately about z
 - ↖ b/c directly querying p_α about z is intractable

Key Idea: jointly optimize ELBO as a function of both α and θ

Variational EM

Apply Block Coordinate Ascent to ELBO

Algo:

while not converged:

① Variational E-step:

adjust q_θ given current p_α

i.e. run V.I. to minimize $KL(q_\theta \| p_\alpha)$ for θ only
maximize $ELBO(q_\theta; p_\alpha)$

$$\theta = \underset{\theta}{\operatorname{argmax}} ELBO(q_\theta; p_\alpha) = \operatorname{run}\text{-variational}\text{-inf}(q_\theta, p_\alpha)$$

② Variational M-step:

adjust p_α given current q_θ

i.e. improve $ELBO(q_\theta; p_\alpha)$ for α only

↪ only one term involves α
 $E_{q_\theta}[\log p_\alpha(x, z)]$

$$\alpha = \underset{\alpha}{\operatorname{argmax}} ELBO(q_\theta; p_\alpha) = \underset{\alpha}{\operatorname{argmax}} E_{q_\theta}[\log p_\alpha(x, z)]$$

Key Difference between Standard EM and Variational EM

We say that the "variational gap" in Standard EM is zero.

i.e. $q_n(z)$ perfectly estimates $p_n(z|x)$

Standard EM is zero. - '

i.e. $q_{\theta}(z)$ perfectly estimates $p_{\alpha}(z|x)$ _p