

# EM test

Sunday, June 24, 2018 1:03 PM

1. Recall the derivation of EM algorithm. In our notation,  $X$  is observable data,  $Z$  is latent variable and  $\theta$  is a vector of model parameters. We introduced  $q(Z)$  — an arbitrary distribution over the latent variable. Choose the correct expressions for the marginal log-likelihood  $\log p(X|\theta)$ :

☐  $\int q(Z) \log \frac{p(X, Z|\theta)}{q(Z)} dZ + \int q(Z) \log \frac{q(Z)}{p(Z|X, \theta)} dZ$  ?

This should be selected

☒  $\log \int p(X, Z|\theta) dZ$

Correct

$Z$  is integrated out:

$\log \int p(X, Z|\theta) dZ = \log p(X|\theta)$

☐  $\mathbb{E}_{q(Z)} \log p(X, Z|\theta) - \mathbb{E}_{q(Z)} \log p(Z|X, \theta)$  ?

This should be selected

☐  $\int q(Z) \log p(X|\theta) dZ$  }

This should be selected

2. In EM algorithm, we maximize variational lower bound  $\mathcal{L}(q, \theta) = \log p(X|\theta) - \text{KL}(q||p)$  with respect to  $q$  (E-step) and  $\theta$  (M-step) iteratively. Why is the maximization of lower bound on E-step equivalent to minimization of KL divergence?

- ☐ Because uncomplete likelihood does not depend on  $q(Z)$  ?
- ☐ Because we cannot maximize lower bound w.r.t.  $q(Z)$
- ☐ Because posterior becomes tractable
- ☒ Because of Jensen's inequality

This should not be selected

Revise [E-step details](#) video



6. Imagine that you want to pat your friend's cat Becky. Cats are really random creatures.

Becky might get grumpy and scratch you with probability  $p$  or curl up and start purring (with prob.  $1 - p$ ). You don't know Becky well yet, so you estimate prior on  $p$  to be distributed as  $\text{Beta}(2, 2)$ . Within one evening, Becky has scratched you 6 times and only 2 times she purred. What will be the parameters for posterior distribution over  $p$ ? What is the MAP-estimate for  $p$ ?

Enter your answers separated by comma: e.g. if you think that correct answer is  $\text{Beta}(1, 0.2)$  and MAP is 3, you should enter 1,0.2,3. Express real numbers as decimals with dot as delimiter.

8,4,0.7

Correct Response

1. Recall the derivation of EM algorithm. In our notation,  $X$  is observable data,  $Z$  is latent variable and  $\theta$  is a vector of model parameters. We introduced  $q(Z)$  — an arbitrary distribution over the latent variable. Choose the correct expressions for the marginal log-likelihood  $\log p(X|\theta)$ :

☒  $\int q(Z) \log \frac{p(X, Z|\theta)}{q(Z)} dZ + \int q(Z) \log \frac{q(Z)}{p(Z|X, \theta)} dZ$

Correct

$$\begin{aligned} & \int q(Z) \log \frac{p(X, Z|\theta)}{q(Z)} dZ + \int q(Z) \log \frac{q(Z)}{p(Z|X, \theta)} dZ = \\ & \int q(Z) \log p(X, Z|\theta) dZ - \int q(Z) \log q(Z) dZ + \\ & + \int q(Z) \log q(Z) dZ - \int q(Z) \log p(Z|X, \theta) dZ = \\ & = \int q(Z) \log \frac{p(X, Z|\theta)}{p(Z|X, \theta)} dZ = \int q(Z) \log p(X|\theta) dZ = \log p(X|\theta) \end{aligned}$$

☒  $\log \int p(X, Z|\theta) dZ$

Correct

$Z$  is integrated out:

$\log \int p(X, Z|\theta) dZ = \log p(X|\theta)$

☒  $\mathbb{E}_{q(Z)} \log p(X, Z|\theta) - \mathbb{E}_{q(Z)} \log p(Z|X, \theta)$

Correct

$$\begin{aligned} & \mathbb{E}_{q(Z)} \log p(X, Z|\theta) - \mathbb{E}_{q(Z)} \log p(Z|X, \theta) = \\ & = \mathbb{E}_{q(Z)} \log \frac{p(X, Z|\theta)}{p(Z|X, \theta)} = \mathbb{E}_{q(Z)} \log p(X|\theta) = \log p(X|\theta) \end{aligned}$$

☒  $\int q(Z) \log p(X|\theta) dZ$

Correct

$\log p(X|\theta)$  does not depend on  $Z$ .

$\int q(Z) \log p(X|\theta) dZ = \log p(X|\theta)$

$\int q(Z) dZ \cdot \log p(X|\theta)$

$$\begin{aligned} \Rightarrow \mathcal{L}(y|\theta) &= \prod_{i=1}^n \theta^{y_i} (1-\theta)^{1-y_i} \\ &= \theta^{\sum y_i} (1-\theta)^{n-\sum y_i} \\ &= \theta^6 (1-\theta)^2 \end{aligned}$$

$$\begin{aligned} p(y|\theta) &= \theta^6 (1-\theta)^2 \\ p(\theta) &= \frac{\Gamma(2)\Gamma(2)}{\Gamma(2+2)} \theta^{2-1} (1-\theta)^{2-1} \end{aligned}$$

$$p(\theta|y) = \frac{p(y|\theta) p(\theta)}{\int p(y|\theta) p(\theta) d\theta}$$

$$\begin{aligned} & \propto p(y|\theta) p(\theta) \\ & \propto \theta^{2+6-1} (1-\theta)^{2+2-1} \\ & = \theta^{2+6-1} (1-\theta)^{2+2-1} \end{aligned}$$

Calculate  $= \text{Beta}(8, 4)$   
Mode, not mean

Mode of Beta dist

$$\frac{\alpha - 1}{\alpha + \beta - 2} = \frac{8 - 1}{8 + 4 - 2} = \frac{7}{10}$$