

# Homework of Chapter 8

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## Ex. 8.1

*Solution.* Since  $\log$  function is a strictly concave function. Using Jensen's inequality, we have

$$\begin{aligned} & E_q \log[r(Y)/q(Y)] \\ & \leq \log E_q[r(Y)/q(Y)] \\ & = \log \int [r(y)/q(y)] q(y) dy \\ & = \log \int r(y) dy \\ & = \log 1 \\ & = 0 \end{aligned}$$

The Jensen's equality shows that  $E_q \log[r(Y)/q(Y)]$  is maximized as a function of  $r(y)$  when  $r(y) = q(y)$ .

According to the definition of (8.46), we have

$$\begin{aligned} R(\theta', \theta) &= E[\ell_1(\theta', \mathbf{Z}^M | \mathbf{Z}) | \mathbf{Z}, \theta] \\ &= E[\log \Pr(\mathbf{Z}^M | \mathbf{Z}, \theta') | \mathbf{Z}, \theta] \\ R(\theta, \theta) &= E[\ell_1(\theta, \mathbf{Z}^M | \mathbf{Z}) | \mathbf{Z}, \theta] \\ &= E[\log \Pr(\mathbf{Z}^M | \mathbf{Z}, \theta) | \mathbf{Z}, \theta] \end{aligned}$$

Then, using the equality we have just proved above, we can get

$$\begin{aligned} R(\theta', \theta) - R(\theta, \theta) &= E[\log \Pr(\mathbf{Z}^M | \mathbf{Z}, \theta') | \mathbf{Z}, \theta] - E[\log \Pr(\mathbf{Z}^M | \mathbf{Z}, \theta) | \mathbf{Z}, \theta] \\ &= E[\log(\Pr(\mathbf{Z}^M | \mathbf{Z}, \theta') / \Pr(\mathbf{Z}^M | \mathbf{Z}, \theta)) | \mathbf{Z}, \theta] \\ &\leq 0 \end{aligned}$$

Thus, we have proved  $R(\theta, \theta) \geq R(\theta', \theta)$ .

□

**Ex. 8.3**

*Solution.*

$$\begin{aligned} & E_{U_\ell^{(t)}}[Pr(u|U_\ell^{(t)}, \ell \neq k)] \\ &= \int Pr(u|u_\ell^{(t)}, \ell \neq k) Pr(u_\ell^{(t)}, \ell \neq k) d\ell \neq k \\ &= Pr_{U_k}(u) \end{aligned}$$

So, we have

$$\begin{aligned} E[\hat{Pr}_{U_k}(u)] &= E\left[\frac{1}{M-m+1} \sum_{t=m}^M Pr(u|U_\ell^{(t)}, \ell \neq k)\right] \\ &= \frac{1}{M-m+1} \sum_{t=m}^M E[Pr(u|U_\ell^{(t)}, \ell \neq k)] \\ &= Pr_{U_k}(u) \end{aligned}$$

Thus, we have justified the estimate (8.50).

□