

Record all answers in the blue books. Show your work.

1. Consider a generic missing data problem in which data  $X$  and missing data  $Z$  have a joint probability density function,  $p(x, z|\theta)$ , determined by a parameter  $\theta$ . Let

$$Q_m(\theta) = E \{ \log p(x, Z|\theta) \mid X = x, \theta_m \}$$

be as constructed in the E step of the EM algorithm, at iteration  $m$  when the current parameter value is  $\theta_m$ . Let  $H_m(\theta) = l(\theta) - Q_m(\theta)$ , where  $l(\theta) = \log p(x|\theta)$  is the ordinary log likelihood. Taking  $\Delta_m(\theta) = H_m(\theta) - H_m(\theta_m)$ , argue that  $\Delta_m(\theta) \geq 0$  for all  $\theta$ , and therefore that  $l(\theta_{m+1}) \geq l(\theta_m)$  upon taking an M step to position  $\theta_{m+1}$ . [Do not be overly concerned with regularity conditions on the densities that would allow various manipulations to be valid, but do state the rationale for each step taken.]

2. The following model is a simplification of one arising in the study of how neurotransmitters mediate their effects. We have a collection of mutually independent random variables: for each  $i = 1, 2, \dots, n$ , we have two Poisson-distributed variables  $U_i, V_i$  with common rate  $\lambda > 0$ , and we also have a Bernoulli trial  $W_i$  having success probability  $\alpha$ . The observable count  $X_i = U_i + V_i W_i$ . Set up an EM algorithm to compute the maximum likelihood estimate of  $\theta = (\lambda, \alpha)$  on the basis of realized values  $x_1, \dots, x_n$ . [Recall the mass function of a Poisson-distributed variable  $U$  is  $e^{-\lambda} \lambda^u / u!$  for  $u = 0, 1, 2, \dots$  ] Also, find an easily computed method of moments estimate that may be used to initiate the algorithm.