

## Fall 2008 Math 541b Exam

1. Let  $X_1, \dots, X_n$  be i.i.d. from a normal distribution with unknown mean  $\mu$  and known variance 1. Suppose that negative values of  $X_i$  are truncated at 0, so that instead of  $X_i$  we actually observe

$$Y_i = \max\{0, X_i\}, \quad i = 1, \dots, n,$$

from which we would like to estimate  $\mu$ .

- (a) Explain how to use the EM algorithm to estimate  $\mu$  from  $Y_1, \dots, Y_n$ . Specifically, give the complete log-likelihood function  $\log L_c(\mu)$  (i.e., the log of the joint density of  $X_1, \dots, X_n$ ) and a recursive formula for the successive EM estimates  $\mu^{(k+1)}$ . Write these in terms of the density  $\phi$  and c.d.f.  $\Phi$  of the standard normal distribution. *Hint:* To simplify things, assume that  $X_1, \dots, X_m$  are not truncated, and  $X_{m+1}, \dots, X_n$  are.
- (b) Find the partial log-likelihood function  $\log L(\mu)$  (i.e., the log of the joint density of  $Y_1, \dots, Y_n$ ) and use it to write down a (nonlinear) equation which the MLE  $\hat{\mu}$  satisfies. Use this equation to manually verify that  $\hat{\mu}$  is indeed a fixed point of the recursion found in (a).
2. Let  $f$  denote the true density function of  $X$ , and consider testing the simple hypotheses

$$H_0 : f = f_0 \quad \text{vs.} \quad H_1 : f = f_1$$

for given densities  $f_0, f_1$ . For a fixed value  $\pi \in (0, 1)$ , suppose that the probabilities  $\pi_0 = \pi$  and  $\pi_1 = 1 - \pi$  can be assigned to  $H_0$  and  $H_1$  prior to the experiment. We will describe tests of  $H_0$  vs.  $H_1$  by their indicator functions

$$\psi(X) = \begin{cases} 1, & \text{the test rejects } H_0 \\ 0, & \text{the test accepts } H_0. \end{cases}$$

- (a) Show that the overall probability of an error resulting from using a test  $\psi$  is

$$\pi E_0 \psi(X) + (1 - \pi) E_1 [1 - \psi(X)]. \quad (1)$$

- (b) Call the test  $\psi^*$  minimizing (1) the *Bayes optimal* test. By writing (1) as a single  $E_0$  expectation using the “change of measure” technique

$$E_1(\cdot) = E_0 \left[ (\cdot) \frac{f_1(X)}{f_0(X)} \right],$$

show that the Bayes optimal test is equivalent to a simple likelihood ratio test. Also, give the value of the likelihood ratio test’s critical value.

- (c) Argue that the Bayes optimal test is hence most powerful for detecting  $f_1$  at a certain significance level. Write down an expression for this significance level, and also give an upper bound for it as a function of  $\pi$ .
- (d) The *posterior probability* of  $H_i$  is the conditional probability that  $H_i$  is true, given  $X = x$ . Show that the posterior probability of  $H_i$  is

$$\frac{\pi_i f_i(x)}{\pi_0 f_0(x) + \pi_1 f_1(x)}. \quad (2)$$

Show that the Bayes optimal test is also equivalent to choosing which hypothesis has the larger posterior probability.