

Stat 543 2-11-05

Recall $k=4$ outcomes possible in each of
 $n=10$ trials

$$X_i = (X_{i1}, X_{i2}, X_{i3}, X_{i4})$$

$$X = (X_1, X_2, \dots, X_{10})$$

$$Y_i = X_i \text{ for } i=1, 2, 4, 5, 7, 9, 10$$

$$Y_3 = (X_{31}, X_{33}, X_{32} + X_{34})$$

$$Y_6 = (X_{61}, X_{64}, X_{62} + X_{63})$$

$$Y_8 = (X_{83}, X_{84}, X_{81} + X_{82})$$

$$Y = (Y_1, Y_2, \dots, Y_{10})$$

$$Y = S(X)$$

maximum likelihood based on Y is "hard" while
 maximum likelihood based on X is "easy"

$$l_X(p) = n_1 \log p_1 + n_2 \log p_2 + n_3 \log p_3 \\ + n_4 \log (1 - p_1 - p_2 - p_3)$$

Given that $Y = \text{data in hand}$, this is

$$\left\langle \begin{aligned} &(2 + X_{21}) \log p_1 + (2 + X_{32} + X_{62} + X_{82}) \log p_2 \\ &+ (2 + X_{63}) p_3 + (1 + X_{34}) \log (1 - p_1 - p_2 - p_3) \end{aligned} \right.$$

For any particular $p_0 = (p_{01}, p_{02}, p_{03}, p_{04})$

$$E_{p_0} [X_{21} \mid Y = \text{data in hand}] = \frac{p_{01}}{p_{01} + p_{02}}$$

$$E_{P_0} [X_{32} | Y = \text{data in hand}] = \frac{P_{02}}{P_{02} + P_{04}}$$

$$E_{P_0} [X_{62} | \quad] = \frac{P_{02}}{P_{02} + P_{03}}$$

$$E_{P_0} [X_{82} | \quad] = \frac{P_{02}}{P_{01} + P_{02}}$$

$$E_{P_0} [X_{63} | \quad] = \frac{P_{03}}{P_{02} + P_{03}}$$

$$E_{P_0} [X_{34} | \quad] = \frac{P_{04}}{P_{02} + P_{04}}$$

Based on these, perhaps a sensible estimation algorithm is the following

① pick some starting p_0 (say $(\frac{2}{7}, \frac{2}{7}, \frac{2}{7}, \frac{1}{7})$)
from "complete cases" / where $Y_i = X_i$)

"E" step { Find $E_{p_0} [l_X(p) \mid Y = \text{data in hand}]$
for the current iterate p_0

Here this is $a(p_0)$ $b(p_0)$

$$\left(2 + \frac{p_{01}}{p_{01} + p_{02}}\right) \log p_1 + \left(2 + p_{02} \left(\frac{1}{p_{02} + p_{04}} + \frac{1}{p_{02} + p_{03}} + \frac{1}{p_{01} + p_{02}}\right)\right) \log p_2$$

$$+ \left(2 + \frac{p_{03}}{p_{02} + p_{03}}\right) \log p_3 + \left(1 + \frac{p_{04}}{p_{02} + p_{04}}\right) \log (1 - p_1 - p_2 - p_3)$$

$c(p_0)$ $d(p_0)$

note $a(p_0) + b(p_0) + c(p_0) + d(p_0) = 10 = n$

this is the p_0 conditional expected X loglikelihood given $Y = \text{data in hand}$

② Maximize $E_{p_0} [l_X(p) \mid Y = \text{data in hand}]$
 as a function of p — call the maximizer p^*

M-step

In our example the p_0 conditional expected log-likelihood is simple (i.e. of the form of log-likelihood for a complete data problem) and I know how to maximize it

$$p^* = \left(\frac{a(p_0)}{10}, \frac{b(p_0)}{10}, \frac{c(p_0)}{10}, \frac{d(p_0)}{10} \right)$$

③ replace current p_0 with p^* and return to ①

Iterate ①, ②, ③ until convergence

In our example this amounts to

$$P_0^{l+1} = \left(\frac{a(P_0^l)}{10}, \frac{b(P_0^l)}{10}, \frac{c(P_0^l)}{10}, \frac{d(P_0^l)}{10} \right)$$

$l+1$ st
iterate

and iterating to find a fixed point and hope that it is a solution to the original (X) likelihood equation

The general E-M algorithm is: for observable Y with nasty loglikelihood $l_Y(\theta)$, sometimes it is possible to dream up X s.t. $Y = S(X)$ and optimization of $l_X(\theta)$ is easy and computation of

$\rightarrow E_{\theta_0} [l_X(\theta) \mid Y = \text{data in hand}]$

is feasible - If so I can

① pick some starting θ_0

② Find

E-step

$E_{\theta_0} [l_X(\theta) \mid Y = \text{data in hand}]$

for current θ_0 .

- M-step ② Optimize with θ^* the optimizer
- ③ Replace θ_0 with θ^* and return to ①
- iterating to convergence

B+D give some arguments as to why E-M might work - see in particular Lemma 2.9.1 that says that at each step $l_y(\theta)$ never decreases -

The standard complaint w/ the E-M algorithm is that its convergence is often slow - you need a good starting point and where other methods are possible they may be better -