Observations on the Computational Procedure for Maximum-Likelihood Estimates

by Herman Rubin July 27, 1948

In his thesis, the author found that

(1)
$$-\frac{\partial \log L}{\partial A_{yx}} = S^{-1} AM - R^{-1} AW$$
,

(2)
$$-\frac{\partial^{2} \log L}{\partial (\text{vec}_{p}^{A} yx)^{2}} - s^{-1} \otimes (M - MA^{*}S^{-1}AM) - R^{-1} \otimes (W - WA^{*}R^{-1}AW) - (MA^{*}S^{-1}) \otimes (S^{-1}AM) + (WA^{*}R^{-1}) \otimes (R^{-1}AW).$$

If A strung out as a vector is $\hat{a}_q \Phi$, where \hat{a}_q is the vector of essential parameters, we obtain

(3)
$$-\frac{\partial \log L}{\partial \bar{a}} - \text{veo}_{p} (8^{-1}\text{AM-R}^{-1}\text{AW}) \bar{\Phi}'$$

(4)
$$-\frac{\int^2 \log L}{\int \frac{R^2}{q}} = \underbrace{\Phi} \left\{ s^{-1} \mathscr{Q} \left(M - MA'S^{-1}AM \right) - R^{-1} \mathscr{Q} \left(W - WA'R^{-1}AW \right) - \left(MA'S^{-1} \right) \mathscr{Q} \left(S^{-1}AM \right) + \left(WAR^{-1} \right) \mathscr{Q} \left(R^{-1}AW \right) \right\} \underbrace{\Phi}' = L_{da}$$

In this

- (5) $S = AMA^{\dagger}$
- (6) R = AWA 1.

This reduces to the usual formulas for a complete system, as

and

However, the ph method gives a positive "second derivative" matrix, which insures an increase for small h. The ph-method uses S⁻¹ M instead of (2) above.

Suppose, however, we use $S^{-1} \otimes (M-W)$. This is also positive. Furthermore, the roots of $/L_{qq} - \lambda \not \equiv (S^{-1} \otimes (M-W)) \not \equiv // = 0$ are asymptotically 1, which means a p_1 method should converge rapidly for large samples.