

and

$\mathbf{v}_1, \dots, \mathbf{v}_K$ are the corresponding orthonormal eigenvectors.

The log-likelihood function in (7.2.19) is maximized for

$$\begin{aligned} \boldsymbol{\beta}' &= \tilde{\boldsymbol{\beta}}' := [\mathbf{v}_1, \dots, \mathbf{v}_r]' S_{11}^{-1/2}, \\ \boldsymbol{\alpha} &= \tilde{\boldsymbol{\alpha}} := \Delta Y M Y_{-1}' \tilde{\boldsymbol{\beta}} \left(\tilde{\boldsymbol{\beta}}' Y_{-1} M Y_{-1}' \tilde{\boldsymbol{\beta}} \right)^{-1} = S_{01} \tilde{\boldsymbol{\beta}} (\tilde{\boldsymbol{\beta}}' S_{11} \tilde{\boldsymbol{\beta}})^{-1}, \\ \boldsymbol{\Gamma} &= \tilde{\boldsymbol{\Gamma}} := (\Delta Y - \tilde{\boldsymbol{\alpha}} \tilde{\boldsymbol{\beta}}' Y_{-1}) \Delta X' (\Delta X \Delta X')^{-1}, \\ \Sigma_u &= \tilde{\Sigma}_u := (\Delta Y - \tilde{\boldsymbol{\alpha}} \tilde{\boldsymbol{\beta}}' Y_{-1} - \tilde{\boldsymbol{\Gamma}} \Delta X) (\Delta Y - \tilde{\boldsymbol{\alpha}} \tilde{\boldsymbol{\beta}}' Y_{-1} - \tilde{\boldsymbol{\Gamma}} \Delta X)' / T. \end{aligned}$$

The maximum is

$$\max \ln l = -\frac{KT}{2} \ln 2\pi - \frac{T}{2} \left[\ln |S_{00}| + \sum_{i=1}^r \ln(1 - \lambda_i) \right] - \frac{KT}{2}. \quad (7.2.20)$$

■

Proof: From Chapter 3, Section 3.4, it is known that for any fixed $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ the maximum of $\ln l$ is attained for

$$\tilde{\boldsymbol{\Gamma}}(\boldsymbol{\alpha}\boldsymbol{\beta}') = (\Delta Y - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1}) \Delta X' (\Delta X \Delta X')^{-1}.$$

Thus, we replace $\boldsymbol{\Gamma}$ in (7.2.19) by $\tilde{\boldsymbol{\Gamma}}(\boldsymbol{\alpha}\boldsymbol{\beta}')$ and get the concentrated log-likelihood

$$\begin{aligned} &-\frac{KT}{2} \ln 2\pi - \frac{T}{2} \ln |\Sigma_u| \\ &-\frac{1}{2} \text{tr} [(\Delta Y M - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1} M)' \Sigma_u^{-1} (\Delta Y M - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1} M)]. \end{aligned}$$

Hence, we just have to maximize this expression with respect to $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and Σ_u . We also know from Chapter 3 that, for given $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, the maximum is attained if

$$\tilde{\Sigma}(\boldsymbol{\alpha}\boldsymbol{\beta}') = (\Delta Y M - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1} M) (\Delta Y M - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1} M)' / T$$

is substituted for Σ_u . Consequently, we have to maximize

$$-\frac{T}{2} \ln |(\Delta Y M - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1} M) (\Delta Y M - \boldsymbol{\alpha}\boldsymbol{\beta}' Y_{-1} M)' / T|$$

or, equivalently, minimize the determinant with respect to $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. Thus, all results of Proposition 7.3 follow from Proposition A.7 of Appendix A.14. ■

The solutions $\tilde{\boldsymbol{\beta}}$ and $\tilde{\boldsymbol{\alpha}}$ of the optimization problem given in the proposition are not unique because, for any nonsingular $(r \times r)$ matrix Q , $\tilde{\boldsymbol{\alpha}} Q^{-1}$