Bock & Bargmann

Case I: The Quasi-Simplex

For repeated measurements (learning trials—the example variables involve scores at stages of learning on a two-hand coordination task):

"According to the simplex model, each of these variables incorporates a new component of skill at that stage of practice. These components are assumed to combine additively to determine the score of each subject at the respective stage of practice."

Bock & Bargmann, p. 523

Algebraically, that gives a model for the test scores

$$m{y}_i = m{\mu} + m{A}m{\xi}_i + m{\epsilon}_i$$

for person *i*, in which $\boldsymbol{\xi}_i$ is a latent variable and \boldsymbol{A} is fixed and known:

	1	0	0	• • •	0 -
	1	1	0		0
A =	1	1	1		0
	÷	:	:		÷
	1	1	1		1

$oldsymbol{y}_i = oldsymbol{\mu} + oldsymbol{A}oldsymbol{\xi}_i + oldsymbol{\epsilon}_i$

implies that the observed variables as distributed in multivariate normal form with mean μ and covariance matrix:

$$\Sigma = A \Phi A' + \Gamma$$

Case I, the only one we'll discuss, restricts the latent variables to be uncorrelated,

$$\mathbf{\Phi} = \operatorname{diag}[\phi_1, \phi_2, \dots, \phi_m]$$

and the error variances to be homoscedastic:

 $\Gamma = \gamma I$

The multivariate normal likelihood is:

$$L = \prod_{i=1}^{N} \frac{|\mathbf{\Sigma}|^{-1/2}}{(2\pi)^{p/2}} \exp[-\frac{1}{2} (\mathbf{y}_{i} - \boldsymbol{\mu})' \mathbf{\Sigma}^{-1} (\mathbf{y}_{i} - \boldsymbol{\mu})]$$

The maximum likelihood estimate of μ is (either) obviously (or see Anderson, 1958, p. 47) the mean vector $y_{.}$ If we let the sum of products of the N observations corrected to the sample mean be

$$N \cdot \boldsymbol{S} = \sum_{i=1}^{N} \boldsymbol{y} \boldsymbol{y}' - N \boldsymbol{y} \boldsymbol{y} \boldsymbol{y}',$$

and the loglikelihood to be maximized to estimate the parameters that yield Σ is:

$$\log L = -\frac{Np}{2}\log 2\pi - \frac{N}{2}\log |\boldsymbol{\Sigma}| - \frac{N}{2}\operatorname{tr}\boldsymbol{\Sigma}^{-1}\boldsymbol{S}.$$

Bock and Bargmann show how to figure the derivatives of that loglikelihood, and use a Newton-Raphson algorithm to find parameter estimates that maximize it.

Here we'll look at:

- Derivative-free R
- R with derivatives
- C++ (with derivatives; no choice here)