# Robust tests for the common principal components model

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#### 1 Introduction

In multivariate analysis we often deal with situations involving several populations, such as discriminant analysis, where the assumption of equality of scatter matrices is usually assumed. Yet sometimes, this assumption is not adequate but problems related to an excessive number of parameters will arise if we estimate the scatter matrices separately for each population. In many practical situations this problem can be avoided if the scatter matrices of the different populations exhibit some common structure. Several authors, as for instance Flury (1988), have studied models for common structure dispersion. One such basic common structure assumes that the k scatter matrices have different eigenvalues but identical eigenvectors, *i.e.*, the matrices are pairwise commutable and may be simultaneously diagonalizable. That is, there is a  $(p \times p)$ -orthogonal matrix  $\boldsymbol{\beta}: \boldsymbol{\Sigma}_i = \boldsymbol{\beta} \boldsymbol{\Lambda}_i \boldsymbol{\beta}^{\mathrm{T}}, i = 1, \dots, k$  where  $\boldsymbol{\Sigma}_i$  is the  $(p \times p)$ -scatter matrix of the *i*-th population and  $\Lambda_i = \text{diag}(\lambda_{i1}, ..., \lambda_{ip})$ . This model, proposed by Flury (1984), became known as the Common Principal Components (CPC) model. The more restrictive proportionality model assumes that the scatter matrices are equal up to a proportionality constant, i.e.,  $\Sigma_i = \rho_i \Sigma_1$ , for  $1 \le i \le k$  and  $\rho_1 = 1$ . In Flury (1988) a unified study of the maximum likelihood estimators under a CPC model and under a proportionality model is given and likelihood ratio tests for a hierarchy of models is studied. However, as it is well known, the likelihood ratio test are in most situations affected by anomalous observations. In this work we propose robust procedures for testing the relationship between scatter matrices. An robust statistic for testing proportionality against a common principal components model is considered. Also, the null hypothesis of a CPC model versus no restrictions on the scatter matrices is studied.

## 2 The proposal for testing proportionality

Supose that we wish to test

$$H_0: \Sigma_i = \rho_i \Sigma_1$$
, with  $\rho_1 = 1$ , versus  $H_1: \Sigma_i = \beta \Lambda_i \beta^{\mathrm{T}}$ ,  $1 \le i \le k$ .

Let  $c_{ij} = \frac{\lambda_{ij}}{\lambda_{i1}}$ , and  $\mathbf{c}_i = (c_{i2}, \ldots, c_{ip})$ , then under  $H_0$   $c_{ij} = c_{1j}$ , for all *i* and *j*. On the other hand, under  $H_1$ ,  $c_{ij} = c_{1j}$  for all *i* and *j* entail that  $H_0$  is true. Our test will be based on robust estimators, obtained by plug-in or by projection -pursuit (see Boente and Orellana, 2001 and Boente, Pires and Rodrigues, 2002, 2005), of the eigenvalues of the matrices  $\Sigma_i$  assuming a CPC model.

## 3 The proposal for testing CPC

The next level in the hierarchy discussed in Flury (1988) corresponds to test

$$H_0: \Sigma_i = \beta \Lambda_i \beta^{\mathrm{T}}$$
, versus  $H_1: \Sigma_i$  arbitrary positive definite scatter matrices,  $1 \leq i \leq k$ .

#### 2 Guidelines for Preparing an Abstract

The test statistic to test this hypothesis is given by

$$\sum_{i=1}^{k} n_i \log \left[ \frac{\det\left(\widehat{\mathbf{A}}_i\right)}{\det\left(\mathbf{S}_i\right)} \right]$$

where  $\widehat{\mathbf{\Lambda}}_i$  is the diagonal matrix of the eigenvalues estimated under  $H_0$ , and  $\mathbf{S}_i$  is the covariance matrix of the *i*-th population.

The idea beyond this statistic is that under  $H_0$  it should be expected that  $\hat{\boldsymbol{\beta}}^{\mathrm{T}} \mathbf{S}_i \hat{\boldsymbol{\beta}}$  will be approximately a diagonal matrix. This idea can be used to robustify the test statistic by considering

$$T_{\text{CPC}} = \sum_{i=1}^{k} n_i \log \left[ \frac{\det\left(\operatorname{diag}\left(\widehat{\boldsymbol{\beta}}^{\mathrm{T}} \mathbf{V}_i \widehat{\boldsymbol{\beta}}\right)\right)}{\det\left(\widehat{\boldsymbol{\beta}}^{\mathrm{T}} \mathbf{V}_i \widehat{\boldsymbol{\beta}}\right)} \right] = \sum_{i=1}^{k} n_i \log \left[ \frac{\det\left(\operatorname{diag}\left(\widehat{\boldsymbol{\beta}}^{\mathrm{T}} \mathbf{V}_i \widehat{\boldsymbol{\beta}}\right)\right)}{\det\left(\mathbf{V}_i\right)} \right]$$

where  $\mathbf{V}_i$  are independent robust affine equivariant scatter estimates which are asymptotically normally distributed and spherically invariant.

#### 4 Monte Carlo study

Through a Monte Carlo study, we evaluate the finite sample behaviour, in level an power, of both tests statistics for normal and contaminated samples.

#### References

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