NORMAL SAMPLES WITH LINEAR CONSTRAINTS AND GIVEN VARIANCES

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1. Summary. In Biometrika (1948) a paper [1] by H. L. Seal contained a theorem applying to "n random variables normally distributed about zero mean with unit variance, these variables being connected by means of k linear relations."[1] Arising from this is the question of how to obtain a set of normal variates connected by k linear relations and such that each variate has unit variance: or, more generally, connected by k linear relations and such that each variate has a given variance. The procedure for obtaining such a set of variates when existent from a set of independent normal deviates with unit variances is given in §**5**. In §§**2**, **3** and **4**, we shall consider various conditions necessary for the existence and construction of such a set.

2. Normal distribution in a linear subspace. Let $(x_1, x_2, \ldots, x_n)$ designate a point in an n-dimensional Euclidean space R^n. A set of variates $x_1, x_2, \ldots, x_n$ can be considered as a random point in R^n. In the present problem we shall assume the set has a multivariate normal distribution.

Consider k homogeneous and independent linear relations

$$\sum_{j=1}^{n} a_{pj}x_j = 0 \qquad (p = n-k+1, \ldots, n).$$

A variate satisfying these relations and these only will belong to an $(n-k)$-dimensional linear subspace. By taking linear combinations of the above k relations, an equivalent set of k relations can be obtained such that they are orthogonal and normalized:

$$\sum_{j=1}^{n} b_{pj}x_j = 0 \qquad (p = n-k+1, \ldots, n),$$

and

$$\sum_{j=1}^{n} b_{pj}b_{qj} = \delta_{pq}.$$

By adding $n-k$ rows, the matrix $||b_{pj}||$ can be completed to an n by n matrix $||b_{ij}||$ $(i, j, = 1, 2, \ldots, n)$ satisfying the orthogonality conditions

$$\sum_{k=1}^{n} b_{ik}b_{jk} = \delta_{ij}.$$

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[1]It is to be noted that the statement of the theorem in [1] is incorrect. The theorem applies to the *residuals* of n normal variables after fitting k linear constraints.

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This matrix can now be considered as the matrix of an orthogonal rotation of n-space. Consider coordinates $y_1, y_2, \ldots, y_n$ with respect to the new axes: then

$$y_i = \sum_{j=1}^{n} b_{ij}x_j.$$

Since normality is invariant under linear transformations, a set of normally distributed x variates yields a set of normally distributed y variates, and conversely. A set of variates $(x_1, x_2, \ldots, x_n)$ satisfying k linear relations

$$\sum_{j=1}^{n} a_{pj}x_j = 0$$

is transformed by the above to set a of variates $(y_1, y_2, \ldots, y_{n-k})$ satisfying no linear constraints where $y_{n-k+1}, \ldots, y_n$ are identically zero.

3. Conditions on the variance. We have solved the problem of linear constraints by working in an $(n - k)$-dimensional subspace. How do we interpret in this subspace the original variance conditions:

$$\operatorname{var}\{x_i\} = v_i \qquad (i = 1, 2, \ldots, n),$$

with

$$y_r = \sum_{j=1}^{n} b_{rj}x_j,$$

$$x_i = \sum_{r=1}^{n-k} b_{ri}y_r.$$

Each x_i is seen to be a linear combination of the $n - k$ variates y_r and consequently the variance of x_i can be expressed in terms of the elements of the variance covariance matrix of the y_r. Consider now a multivariate normal distribution in the subspace with covariance matrix $||\tau_{rs}||$ with respect to the axes $y_1, y_2, \ldots, y_{n-k}$.

Thus the variance conditions after rotation into the subspace become

$$\sum_{r,s=1}^{n-k} b_{ri}\tau_{rs}b_{si} = v_i \qquad (i = 1, 2, \ldots, n).$$

4. Existence. Our problem has now reduced itself to that of finding a multivariate normal distribution in $n - k$ dimensions with covariance matrix $||\tau_{rs}||$ such that

$$\sum_{r,s=1}^{n-k} b_{ri}\tau_{rs}b_{si} = v_i \qquad (i = 1, 2, \ldots, n),$$

or

$$\sum_{r,s=1}^{n-k} c_{ri}\tau_{rs}c_{si} = 1 \qquad (i = 1, 2, \ldots, n)$$

where $c_{ri} = v_i^{-\frac{1}{2}}b_{ri}$.

We have n equations with $\binom{n-k+1}{2}$ unknowns. If $\binom{n-k+1}{2} \geqslant n$, a solution will exist and can best be obtained by solving the equation directly. If $\binom{n-k+1}{2} < n$, an application of linear regression theory would be indicated.

To find a matrix $||\tau_{rs}||$, if one exists, is equivalent to finding a generalized ellipsoid

$$\sum_{r,s=1}^{n-k} z_r \tau_{rs} z_s = 1$$

passing through the n points

$$(c_{1i}, \ldots, c_{n-k,i}) \qquad (i = 1, 2, \ldots, n).$$

This is accomplished using linear regression theory by fitting to the constant 1 the functions $z_r z_s$ $(r,s = 1, 2, \ldots, n-k)$ for the n "sample" values given above of the vector $(z_1, z_2, \ldots, z_{n-k})$. If the sum of squares for residuals is zero then a quadratic surface exists. However, to have a solution to our distribution problem, the matrix of the quadratic form must be positive. If it is not positive definite, then our variance conditions have imposed a further linear constraint on the set of variates.

5. Conclusions. The problem may be stated: to find normal variables $x_1, x_2, \ldots, x_n$ satisfying k homogeneous and independent linear relations

$$\sum_{j=1}^{n} a_{pj} x_j = 0 \qquad (p = n-k+1, \ldots, n),$$

and with

$$\text{var}\{x_i\} = v_i \qquad (i = 1, 2, \ldots, n).$$

The solution can be described in five steps.

5.1. Find a matrix $||b_{pj}||$ with $p = n-k+1, \ldots, n$ and $j = 1, 2, \ldots n$ with orthogonal and normalized rows equivalent to $||a_{pj}||$ as described in §2.

5.2. Complete $||b_{pj}||$ to an orthogonal matrix $||b_{ij}||$ $(i, j = 1, 2, \ldots, n)$.

5.3. Find a quadratic equation

$$\sum_{r,s=1}^{n-k} z_r \tau_{rs} z_s = 1$$

satisfied by the n points

$$(b_{1i} v_i^{-\frac{1}{2}}, \ldots, b_{n-ki} v_i^{-\frac{1}{2}}) \qquad (i = 1, 2, \ldots, n),$$

if it exists, directly or by regression theory as in §4. If the equation does not exist or if it exists with a non-positive matrix then the problem has no solution.

5.4. If the matrix $||\tau_{rs}||$ is positive, then find random variates $y_1, y_2, \ldots, y_{n-k}$ with zero means and $||\tau_{rs}||$ as covariance matrix. (If $||\tau_{rs}||$ is positive

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definite, take the square root matrix of $||\tau_{rs}||$ and apply as a linear transformation to $n - k$ independent normal variates with means 0 and variances 1. If positive but not definite, then the previous method will work in a subspace of $y_1, y_2, \ldots, y_{n-k}$.)

5.5. Obtain the set of x variates, thus solving the problem, by applying the transformation

$$x_i = \sum_{r=1}^{n-k} b_{ri} y_r$$

to the y variates obtained in 5.4.

References

1. H. L. Seal, *A note on the χ^2 smooth test*, Biometrika, vol. 35 (1948), 202.

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