

$p$ -STATISTICS  
OR  
SOME GENERALISATIONS IN ANALYSIS OF VARIANCE  
APPROPRIATE TO MULTIVARIATE PROBLEMS

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INTRODUCTION.

In an earlier paper<sup>1</sup> worked out by the author jointly with Mr. R. C. Bose the problem of discrimination between and classification of different multi-variate normal populations (with the same set of variances and covariances but with different sets of means) was sought to be tackled by defining the Studentized  $D^2$ -statistic and obtaining its sampling distribution. But the problem yet remained to be attacked when the populations differ in the sets of variances and covariances and when it is sought to discriminate between and classify them in the light of these sets. It is the object of the present paper to take a first step towards answering the following question. Can the two multi-variate normal populations from which two samples have been drawn be reasonably (*i.e.* on a given probability level) supposed to have the same set of variances and covariances or to have distinct sets? For the uni-variate case the question is completely answered by the sampling distribution of  $s_1/s_2$  and Fisher's  $z$ .

In the earlier paper<sup>1</sup> by the author already quoted it was noted that if following Fisher one started from a linear compound with arbitrary coefficients, of the variates and so chose the compounding coefficients as to make a maximum the ratio between the square of the difference of the sample means (for the compound character) and the within variance of the samples for the same character, one could easily see after maximisation that this ratio is proportional to the studentised  $D^2$ -statistic referred to in that paper. In the present paper starting from a similar linear compound of the variates and so choosing the compounding coefficients as to make a maximum the ratio of the variance of the first sample (for the compound character) and the variance of the second sample for the same character one finds that the quest for the maximised value of the ratio spoken of above, leads one in the case of  $p$ -variate populations to as many as  $p$  studentised statistics instead of to merely one studentised statistic as in the previous case. Of these statistics it is found that one is a true maximum, another is a true minimum and the rest are what are known in analysis as stationary values. The invariance under linear transformations of these statistics is then shown. Next a geometrical interpretation is given of these  $p$ -statistics connecting them up with the  $p$  critical angles between two definite hyper-planes, one of

$p$  dimensions and the other of  $n'-1$  dimensions (where  $n'-1$ , is of course greater than  $p$ ,  $n'$  being the size of one of the samples). Finally, partly with the help of the geometrical interpretation and partly with the help of earlier results derived by the author jointly with Mr. R. C. Bose in two previous papers<sup>2,3</sup> the joint sampling distribution of the statistics is worked out for the case where the two populations in question are identical in the sets of variances and covariances. The statistic corresponding to the maximum value of the ratio is here called the maximum statistic and that for the minimum value the minimum statistic. Either the maximum or the minimum statistic or another specified statistic would serve according to circumstances to be set forth in the concluding section of this paper, to distinguish best between two samples drawn from a multi-variate normal population. The sampling distribution of either of these can be obtained by considering the joint distribution of the  $p$ -statistics and integrating out for all the others between suitable limits. Work has been carried up to this point in the present paper. New tables are needed to make the result available for practical purposes, *i.e.* for testing the hypothesis whether the two populations from which the two samples have been drawn are identical or distinct on any given probability level so far as the set of variances and covariances is concerned. The problem of analysis of variance is of course closely connected with the above problem and both are really solved together.

In the next paper which is to shortly appear in this Journal the incomplete probability integral for the distribution of the maximum, or the minimum or the other specified statistic would be given in a form which facilitates the construction of suitable tables. It is further proposed in that paper to work out the sampling distribution of these statistics for the non-zero case, *i.e.* when the two populations sampled are distinct in the sets of variances and covariances; this, too, is proposed to be given in a form suitable for the construction of appropriate tables. As distinguished from the problem of discrimination this will, of course, solve, so far as the dispersion matrix is concerned, the problem of classification of multi-variate normal populations; the need for and significance of this problem was pointed out in the introduction to the earlier paper by the author already referred to.

### §1. DERIVATION OF THE $p$ -STATISTICS BY MAXIMISATION.

I shall take over now certain definitions and notations from the previous paper.

Consider two samples  $\Sigma$  and  $\Sigma'$  of sizes  $n$  and  $n'$  from two  $p$ -variate normal populations  $\Pi$  and  $\Pi'$  with the same set of variances and co-variances,  $a_{ij}$  ( $i, j=1, 2, \dots, p$ ) where  $a_{ij} = \rho_{ij} \cdot \sigma_i \cdot \sigma_j$ ,  $\sigma_i$ ,  $\sigma_j$  and  $\sigma_j$  being the standard deviations for the  $i^{\text{th}}$  and  $j^{\text{th}}$  characters respectively, and  $\rho_{ij}$  the correlations between the  $i^{\text{th}}$  and the  $j^{\text{th}}$  character. The matrix  $||a_{ij}||$  will be said to be the common dispersion matrix for the two populations. Let  $a_i, a'_i$  ( $i, j=1, 2, \dots, p$ ) denote the respective variances, and co-variances of the samples  $\Sigma$  and  $\Sigma'$  so that  $||a_{ij}||$  and  $||a'_i||$  are their respective dispersion matrices. Let  $\bar{a}_i, \bar{a}'_i$  ( $i=1, 2, \dots, p$ ) be the mean for the  $i^{\text{th}}$  character for the populations  $\Pi$  and  $\Pi'$  and let  $a_i$  and  $a'_i$  denote corresponding quantities for the samples  $\Sigma$  and  $\Sigma'$ . Let the sample readings for the sample  $\Sigma$  be  $x_{ik}$  ( $i=1, 2, \dots, p$ ;  $k=1, 2, \dots, n$ ) and those for the sample  $\Sigma'$  be  $x'_{ik}$  ( $i=1, 2, \dots, p$ ;  $k'=1, 2, \dots, n'$ ) the first suffix in both cases referring to the character and the second to the individual.

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Then

$$\left. \begin{aligned} a_i &= \frac{1}{n} \sum_{k=1}^n x_{ik} \quad (i=1, 2, \dots, p) \\ a'_i &= \frac{1}{n'} \sum_{k'=1}^{n'} x'_{ik'} \quad (i=1, 2, \dots, p) \\ a_{ij} &= \sum_{k=1}^n (x_{ik} - a_i)(x_{jk} - a_j)/n \quad (i, j=1, 2, \dots, p) \\ a'_{ij} &= \sum_{k'=1}^{n'} (x'_{ik'} - a'_i)(x'_{jk'} - a'_j)/n' \quad (i, j=1, 2, \dots, p) \end{aligned} \right\} \dots (1.1)$$

Let the compounding co-efficients be  $\lambda_i$  ( $i=1, 2, \dots, p$ ); from the point of view of the compound character the sample  $\Sigma$  is now represented by the  $n$  readings  $\sum_{i=1}^p \lambda_i x_{ik}$  ( $k=1, 2, \dots, n$ ) and the sample  $\Sigma'$  by the  $n'$  readings  $\sum_{i=1}^p \lambda_i x'_{ik'}$  ( $k'=1, 2, \dots, n'$ ); if we now denote by  $b$  and  $b'$  the variances of the samples  $\Sigma$  and  $\Sigma'$  for the compound character then it is easily seen from (1.1) that

$$\left. \begin{aligned} b &= \sum_{i,j=1}^p \lambda_i \lambda_j a_{ij} \\ \text{and} \\ b' &= \sum_{i,j=1}^p \lambda_i \lambda_j a'_{ij} \end{aligned} \right\} \dots (1.2)$$

Let us set the ratio of  $b/b' = K^2$  ... (1.3)

Then maximising this  $K$  with regard to the arbitrary co-efficients  $\lambda_i$  ( $i=1, 2, \dots, p$ ) we are easily led on to the system of  $p$  equations.

$$\sum_{j=1}^p \lambda_j (a_{ij} - K^2 a'_{ij}) = 0, \quad (i=1, 2, \dots, p) \quad \dots (1.4)$$

Eliminating  $\lambda_j$  ( $j=1, 2, \dots, p$ ) between these  $p$  equations we get the following  $p$ -fold determinantal equation in  $K^2$  whose  $p$  roots give the stationary values for  $K$

$$| a_{ij} - K^2 a'_{ij} | \quad (1.5)$$

It can be shown from algebra as well as from certain geometrical considerations to be given in a later section that of these  $p$  roots one corresponds to the maximum  $K$ , the other to the minimum  $K$  and the rest to stationary values of  $K$ .

§2. INVARIANCE OF THE  $p$ -STATISTICS.

As in the previous paper we shall now show that if from the primary  $p$  statistical variates we obtain a new set of  $p$  variates by linear transformation with matrix  $|| \lambda_{ij} ||$  of rank  $p$ , then the  $p$ -statistics given by the  $p$ -roots of the equation (1.5) remain unchanged

If  $a_{ij}$  goes over to  $b_{ij}$ , it is easily seen that

$$b_{ij} = \lambda_{i1} \lambda_{j1} a_{11} + \dots + \lambda_{i,p} \lambda_{j,p} a_{pp} + (\lambda_{i1} \lambda_{j2} + \lambda_{i2} \lambda_{j1}) a_{12} + \dots + (\lambda_{i,p-1} \lambda_{j,p} + \lambda_{i,p} \lambda_{j,p-1}) a_{p-1,p} \quad (2.1)$$

Thus

$$| | b_{ij} | | = | | \lambda_{ij} | | \cdot | | a_{ij} | | \cdot | | \lambda_{ij} | | \quad \dots (2.2)$$

where  $||\lambda_{ij}||$  is the matrix obtained from  $||\lambda_{ij}||$  by interchanging the rows and columns. Similarly if  $a'_{ij}$  goes over to  $b'_{ij}$  then we get a formula similar to (2.1). A similar relation holds for the corresponding determinants. Thus

$$\text{and } \left. \begin{aligned} |b_{ij}| &= |a_{ij}| \cdot |\lambda_{ij}|^2 \\ |b'_{ij}| &= |a'_{ij}| \cdot |\lambda_{ij}|^2 \end{aligned} \right\} \dots (2.3)$$

From (2.1) we easily see that if  $K$  be any arbitrary quantity,  $||b_{ij} - K^2 b'_{ij}||$  transforms to  $S_n |a_{ij} - K^2 a'_{ij}| \bar{S}_n$ , where  $S_n$  denotes the transformation matrix  $||\lambda_{ij}||$ , and  $\bar{S}_n$  the matrix obtained from it by interchanging the row and columns. Therefore  $|b_{ij} - K^2 b'_{ij}|$  transforms to  $|a_{ij} - K^2 a'_{ij}| \cdot |\lambda_{ij}|^2$ ; it should be noted that  $K^2$  is the same in all these expressions. Hence the  $p$  roots of the equation  $|b_{ij} - K^2 b'_{ij}| = 0$  are both formally and numerically the same as the  $p$  roots of the equation  $|a_{ij} - K^2 a'_{ij}| = 0$ . Hence the  $p$ -statistics are invariant under any linear transformation.

### §3. GEOMETRICAL INTERPRETATION OF THE $p$ -STATISTICS.

The sample  $\Sigma$  with the readings  $x_{ik}$  ( $i=1, 2, \dots, p; k=1, 2, \dots, n$ ) can be represented in the usual Fisherian space  $S_n$  of  $n$  dimensions by the  $p$  points with co-ordinates.

$$(x_{i1}, x_{i2}, \dots, x_{in}), (i=1, 2, \dots, p) \dots (3.1)$$

or by  $p$  vectors  $x_i$  joining the points to the origin. We may take another space  $S'_n$  of  $n'$  dimensions absolutely orthogonal to the former space, and represent in it the sample  $\Sigma'$  by  $p$  other similar vectors  $x'_i$ . Let

$$y_{ik} = x_{ik} - a_i, y'_{ik} = x'_{ik} - a'_i \dots (3.2)$$

where  $i=1, 2, \dots, p; k=1, 2, \dots, n; k'=1, 2, \dots, n'$  and  $a_i$  and  $a'_i$  have been already defined in (1.1)

Let  $y_i, y'_i$  denote the vectors, with components  $(y_{i1}, y_{i2}, \dots, y_{in})$  and  $(y'_{i1}, y'_{i2}, \dots, y'_{in'})$  lying in the spaces  $S_n$  and  $S'_n$  respectively. Then it is easily seen from (3.2) that the vectors  $y_i$  lie in a flat space  $S_{n-1}$  of  $n-1$  dimensions, perpendicular to the equiangular line in  $S_n$ . Similar considerations apply to the vectors  $y'_i$ . Denoting now the scalar product of  $y_i$  and  $y_j$  by  $y_i \cdot y_j$  we have clearly

$$a_{ij} = (y_i \cdot y_j) / n, a'_{ij} = (y'_i \cdot y'_j) / n' \dots (3.3)$$

Let us form the resultant of the vectors  $y_i$  and  $y'_i$  and call it  $u_i$  ( $i=1, 2, \dots, p$ ). The  $p$  vectors  $u_i$  form a flat of  $p$ -dimensions which makes with the flat  $S_{n-1}$  containing the  $p$  vectors  $y'_i$ ,  $p$  critical angles which let us call  $\varphi_i$  ( $i=1, 2, \dots, p$ ). The significance and properties of these critical angles are, of course, well known to students of hyperspace geometry, we shall show that the  $p$  roots of the equation (1.5) are also equal to  $n'/n$  times the squares of the tangents of the  $p$  critical angles. That is to say,

$$K_i = \tan \varphi_i \sqrt{n'/n} \quad (i=1, 2, \dots, p) \dots (3.4)$$

where  $K'_i$  ( $i=1, 2, \dots, p$ ) are the  $p$  roots of the equation (1.5). This can be shown as follows.

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Let us denote the flat space containing the vectors  $\nu_i$  by  $S_p$ . Then it is well known that if we take a line in  $S_p$  and any line in  $S_{p-1}$ , then a stationary value of the angle between these lines, obtained by taking appropriate positions of the two lines, is called a critical angle.

Any vector in the flat  $S_p$  is given by  $\sum_{i=1}^p \lambda_i \nu_i$ , where  $\lambda_i$ 's are arbitrary co-efficients.

The projection of this on the flat  $S_{p-1}$  is clearly equal to  $\sum_{i=1}^p \lambda_i \gamma_i$  and that on the flat  $S_{p-1}$  which is absolutely orthogonal to  $S_{p-1}$  is  $\sum_{i=1}^p \lambda_i \nu_i$ ; therefore, if the angle between the vector  $\sum_{i=1}^p \lambda_i \nu_i$  and the flat  $S_{p-1}$  is  $\phi$ , then it must be given by

$$\tan^2 \phi = \frac{\sum_{i,j=1}^p \lambda_i \lambda_j \gamma_i \cdot \gamma_j}{\sum_{i,j=1}^p \lambda_i \lambda_j \nu_i \cdot \nu_j} = \frac{n}{n'} \cdot \frac{\sum_{i,j=1}^p \lambda_i \lambda_j a_{ij}}{\sum_{i,j=1}^p \lambda_i \lambda_j a'_{ij}} \quad \text{from (3.3)} \quad \dots (3.5)$$

Differentiating this with the regard to  $\lambda_i$ 's we easily see that the critical angles are given by the  $p$  roots of the  $p$ -fold determinantal equation.

$$\left| a_{ij} - \frac{n'}{n} \tan^2 \phi \cdot a'_{ij} \right| \quad \dots (3.6)$$

Thus it is seen that the  $p$  roots of the equation (3.6) in  $\frac{n'}{n} \tan^2 \phi$  are the same as the  $p$  roots of the equation (1.5) in  $K^2$  giving the  $p$ -statistics. Let us denote the vectors  $\sum_{i=1}^p \lambda_i \nu_i$ ,  $\sum_{i=1}^p \lambda_i \gamma_i$ ,  $\sum_{i=1}^p \lambda_i \nu_i$  by  $L_i$ ,  $M_i$ ,  $N_i$  respectively. Then there are  $p$  such triads, each triad, of course, determining one ordinary plane; it is well known and can also be very easily proved that each such plane is perpendicular to all other planes, i.e.,  $L_i, M_i, N_i$  are each perpendicular to each of  $L_j, M_j, N_j$  ( $i \neq j$ ,  $i, j = 1, 2, \dots, p$ ).

§4. THE DISTRIBUTION OF THE  $p$ -STATISTICS  $K_i$  ( $i = 1, 2, \dots, p$ ) FOR THE CASE WHERE THE TWO POPULATIONS SAMPLED HAVE IDENTICAL DISPERSION MATRICES

In an earlier paper<sup>3</sup> published by the author jointly with Mr. R. C. Bose the joint sampling distribution of  $a_{ij}$ 's for a sample  $\Sigma$  drawn from a  $p$ -variate normal population  $\Pi$  was given in the form

$$\text{const. } e^{-\frac{n}{2} \sum_{i,j=1}^p a_{ij} a_{ij}} |a_{ij}|^{(n-p-2)/2} \prod da_{ij} \quad \dots (4.1)$$

where  $\Pi da_{ij}$  is the product  $da_{11}, da_{12}, \dots, da_{pp}, da_{12}, \dots, da_{p-1,p}$  and  $a^{ij}$  is the minor of  $a_{ij}$  in the determinant  $|a_{ij}|$  divided by the determinant itself. By an entirely different method this distribution was also obtained by Wishart<sup>4</sup> in an earlier paper.

Similarly the joint distribution of  $a'_u$ 's for the sample  $\Sigma'$  would be given by

$$\text{const. } e^{-\frac{n'}{2} \sum_{u=1}^p a'^u a'_u} |a'_u|^{(n'-p-2)/2} \prod da'_u \quad \dots (4.2)$$

Therefore the joint distribution of  $a_u$  and  $a'_u$  would be given by

$$\text{const. } e^{-\frac{1}{2} \sum_{u=1}^p a^u (n a_u + n' a'_u)} |a_u|^{(n-p-2)/2} |a'_u|^{(n'-p-2)/2} \prod da_u \prod da'_u \quad \dots (4.3)$$

In the flat  $S_p$  let us refer the vectors  $v_i$  to  $p$  orthogonal axes along the directions of the critical vectors  $L_i$  ( $i=1, 2, \dots, p$ ); let us call the projections of the vectors  $v_i$  along these directions,  $v_{ij}$  ( $j=1, 2, \dots, p$ ); the vectors  $v_i$  are now replaced by the  $p^2$  component vectors  $v_{ij}$  ( $i, j=1, 2, \dots, p$ ); where the first suffix refers to the vector and the second suffix to its component along the axis in the direction of the critical vector  $L_j$ . The projection of  $v_i$  in the direction of  $L_j$ , when regarded as a vector shall be denoted by  $v_{ij}$  and its magnitude will be denoted simply by  $v_{ij}$ . It now follows from the considerations given at the end of Section 3 that

$$\begin{aligned} y'_i &= \text{projection of } v_i \text{ on } S'_{p-1} \\ &= \text{vector sum of the projections of } v_{ij} (j=1, 2, \dots, p) \text{ on } S'_{p-1} \\ &= \sum_{j=1}^p v_{ij} \cos \phi_j \text{ (the summation being of course a vector summation)} \end{aligned} \quad \dots (4.4)$$

the different vectors  $v_{ij} \cos \phi_j$  being in the orthogonal directions  $N_j$ ,

$$\text{Similarly } y_i = \sum_{j=1}^p v_{ij} \sin \phi_j \quad \dots (4.5)$$

the summation being a vector summation and the different vectors  $v_{ij} \sin \phi_j$  ( $j=1, 2, \dots, p$ ) being in the orthogonal directions  $M_j$ . Hence it is easily seen from (3.3) (4.4) and (4.5) that

$$\left. \begin{aligned} a_{ij} &= (y_i, y_j) / n = \sum_{k=1}^p v_{ik} v_{jk} \sin^2 \phi_k / n \\ a'_{ij} &= (y'_i, y'_j) / n' = \sum_{k=1}^p v_{ik} v_{jk} \cos^2 \phi_k / n' \end{aligned} \right\} \quad \dots (4.6)$$

Therefore,  $n a_{ij} + n' a'_{ij}$  which occurs in the density factor of the distribution (4.1) is easily seen to be given by

$$n a_{ij} + n' a'_{ij} = \sum_{k=1}^p v_{ik} v_{jk} \quad \dots (4.61)$$

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In the joint distribution (4.1) let us now transform from  $a_{ij}$  and  $a'_{ij}$  to the new variates  $v_{ij}$  ( $i, j = 1, 2, \dots, p$ ) and  $\varphi_j$  ( $j = 1, 2, \dots, p$ ). It should be noted that the total number of variates in the previous case is  $\frac{p(p+1) \cdot 2}{2}$  and in the latter case it is  $p^2 + p = p(p+1)$ . They are, therefore, the same as they should be.

$$\begin{aligned} \text{From (4.6) } |a_{ij}| &= \left| \sum_{k=1}^p v_{ik} v_{jk} \sin^2 \varphi_k / n \right| \\ &= (\sin \varphi_1 \sin \varphi_2 \dots \sin \varphi_p)^2 \cdot \left| \sum_{k=1}^p v_{ik} v_{jk} \right| / n^p \\ &= \prod_{i=1}^p \sin^2 \varphi_i |v_{ij}|^2 / n^p \quad \dots (4.62) \end{aligned}$$

and

$$\begin{aligned} |a'_{ij}| &= \left| \sum_{k=1}^p v_{ik} v_{jk} \cos^2 \varphi_k / n \right| \\ &= (\cos \varphi_1 \cos \varphi_2 \dots \cos \varphi_p)^2 \cdot \left| \sum_{k=1}^p v_{ik} v_{jk} \right| / n^p \\ &= \prod_{i=1}^p \cos^2 \varphi_i |v_{ij}|^2 / n^p \quad \dots (4.63) \end{aligned}$$

Again from (4.6), the Jacobian

$$\frac{\partial (a_{ij}, a'_{ij})}{\partial (v_{ij}, \varphi_j)} \quad (i, j = 1, 2, \dots, p; a_{ij} = a_{ji}, a'_{ij} = a'_{ji}, \text{ but } v_{ij} \neq v_{ji})$$

is easily seen to be given by the determinant.

$$\begin{aligned} \text{const. } & \begin{vmatrix} \frac{\partial a'_{11}}{\partial v_{11}} & \dots & \frac{\partial a'_{11}}{\partial v_{1p}} & \dots & \frac{\partial a'_{11}}{\partial v_{p1}} & \dots & \frac{\partial a'_{11}}{\partial v_{pp}} & \frac{\partial a'_{11}}{\partial \varphi_1} & \dots & \frac{\partial a'_{11}}{\partial \varphi_p} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \frac{\partial a'_{1p}}{\partial v_{11}} & \dots & \frac{\partial a'_{1p}}{\partial v_{1p}} & \dots & \frac{\partial a'_{1p}}{\partial v_{p1}} & \dots & \frac{\partial a'_{1p}}{\partial v_{pp}} & \frac{\partial a'_{1p}}{\partial \varphi_1} & \dots & \frac{\partial a'_{1p}}{\partial \varphi_p} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \frac{\partial a'_{pp}}{\partial v_{11}} & \dots & \frac{\partial a'_{pp}}{\partial v_{1p}} & \dots & \frac{\partial a'_{pp}}{\partial v_{p1}} & \dots & \frac{\partial a'_{pp}}{\partial v_{pp}} & \frac{\partial a'_{pp}}{\partial \varphi_1} & \dots & \frac{\partial a'_{pp}}{\partial \varphi_p} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \frac{\partial a_{11}}{\partial v_{11}} & \dots & \frac{\partial a_{11}}{\partial v_{1p}} & \dots & \frac{\partial a_{11}}{\partial v_{p1}} & \dots & \frac{\partial a_{11}}{\partial v_{pp}} & \frac{\partial a_{11}}{\partial \varphi_1} & \dots & \frac{\partial a_{11}}{\partial \varphi_p} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \frac{\partial a_{1p}}{\partial v_{11}} & \dots & \frac{\partial a_{1p}}{\partial v_{1p}} & \dots & \frac{\partial a_{1p}}{\partial v_{p1}} & \dots & \frac{\partial a_{1p}}{\partial v_{pp}} & \frac{\partial a_{1p}}{\partial \varphi_1} & \dots & \frac{\partial a_{1p}}{\partial \varphi_p} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \frac{\partial a_{pp}}{\partial v_{11}} & \dots & \frac{\partial a_{pp}}{\partial v_{1p}} & \dots & \frac{\partial a_{pp}}{\partial v_{p1}} & \dots & \frac{\partial a_{pp}}{\partial v_{pp}} & \frac{\partial a_{pp}}{\partial \varphi_1} & \dots & \frac{\partial a_{pp}}{\partial \varphi_p} \end{vmatrix} \\ &= J \text{ (Suppose)} \quad \dots (4.64) \end{aligned}$$

Therefore, by virtue of the relations (4.61), (4.62), (4.63) and (4.64) the joint distribution (4.3) now reduces to

$$\text{const. } c \cdot \frac{1}{n^p} \sum_{i=1}^p a_i^n \sum_{k=1}^p v_{ik} v_{jk} \left| \sum_{k=1}^p v_{ik} v_{jk} \right|^{p-1} \left( \prod_{i=1}^p \sin \varphi_i \right)^{p-p+2} \left( \prod_{i=1}^p \cos \varphi_i \right)^{p-p+2} \prod_{i=1}^p d v_{ij} \prod_{j=1}^p d \varphi_j \quad (4.65)$$

where  $J$  is of course given by (4.64)

Let us for convenience put

$$\sin \varphi_i = s_i \text{ and } \cos \varphi_i = c_i \quad (i = 1, 2, \dots, p) \quad \dots (4'66)$$

Then (4'65) reduces to

$$\text{const. } \epsilon \quad \left| v_{ij} \right| \quad \left( \prod_{i=1}^p s_i \right)^{n-p-1} \left( \prod_{i=1}^p c_i \right)^{n-p-2} \prod_{i=1}^p d v_i \prod_{i=1}^p d \varphi_i \quad \dots (4'67)$$

We have now to calculate J given by (4'64)

From the relations given by (4'6) the determinant J is easily seen to reduce to

$$\text{const.} \begin{vmatrix} 2v_{11}c_1^2 & \dots & 2v_{1p}c_p^2 & 0 & \dots & 0 & -2v_{11}^2c_1s_1 & \dots & -2v_{1p}^2c_p s_p \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ v_{p1}c_1^2 & \dots & v_{pp}c_p^2 & 0 & \dots & v_{11}c_1^2 & \dots & v_{1p}c_p^2 & -2v_{11}v_{p1}c_1s_1 & \dots & -2v_{1p}v_{pp}c_p s_p \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & 0 & 2v_{11}c_1^2 & \dots & 2v_{pp}c_p^2 & -2v_{p1}^2c_1s_1 & \dots & -2v_{1p}^2c_p s_p \\ 2v_{11}s_1^2 & \dots & 2v_{1p}s_p^2 & 0 & 0 & 0 & 0 & 2v_{11}^2c_1s_1 & \dots & 2v_{1p}^2c_p s_p \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ v_{p1}s_1^2 & \dots & v_{pp}s_p^2 & 0 & \dots & v_{11}s_1^2 & \dots & v_{1p}s_p^2 & 2v_{11}v_{p1}c_1s_1 & \dots & 2v_{1p}v_{pp}c_p s_p \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & 0 & 2v_{p1}s_1^2 & \dots & 2v_{pp}s_p^2 & 2v_{p1}^2c_1s_1 & \dots & 2v_{pp}^2c_p s_p \end{vmatrix}$$

This is a determinant of the order  $p^2 + p$ . Now adding to the first row the  $\left\{ \frac{p(p+1)}{2} + 1 \right\}$ th row, to the second row the  $\left\{ \frac{p(p+1)}{2} + 2 \right\}$ th row and so on, and taking common  $c_1 s_1$  out of the  $(p^2 + 1)$ th column,  $c_2 s_2$  out of the  $(p^2 + 2)$ th column and so on this determinant J (by virtue of the relation  $c_i^2 + s_i^2 = 1$ ) reduces to

$$\text{const.} \begin{vmatrix} v_{11} & \dots & v_{1p} & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ v_{p1} & \dots & v_{pp} & 0 & \dots & v_{11} & \dots & v_{1p} & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & 0 & v_{p1} & \dots & v_{pp} & 0 & \dots & 0 \\ v_{11}s_1^2 & \dots & v_{1p}s_p^2 & 0 & 0 & \dots & 0 & v_{11}^2 & \dots & v_{1p}^2 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ v_{p1}s_1^2 & \dots & v_{pp}s_p^2 & 0 & \dots & v_{11}s_1^2 & \dots & v_{1p}s_p^2 & 2v_{11}v_{p1} & \dots & 2v_{1p}v_{pp} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & 0 & \dots & v_{p1}s_1^2 & \dots & v_{pp}s_p^2 & v_{p1}^2 & \dots & v_{pp}^2 \end{vmatrix} \cdot \prod_{i=1}^p c_i s_i$$

This Jacobian determinant might be reduced in an elegant manner by the use of the advanced algebra of determinants and matrices. But in the present paper I purposely adopt more elementary and pedestrian methods to make the whole derivation simple and obvious, though rather lengthy. I reserve the more elegant and condensed treatment for a later paper where a purely geometrical method will also be given of deriving the distribution in view. With this remark I take to the more elementary method proposed.



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To illustrate the method by which this determinant may be reduced let us take for simplicity the case of three variates. The method is, of course, perfectly general and it would be obvious from what follows that we could immediately generalise from 3 to  $p$  variates. In the case of 3 variates let us set down for convenience

$$\left. \begin{aligned} v_{11} &= x_{11}, & v_{12} &= x_{21}, & v_{13} &= x_{31} \\ v_{21} &= y_{11}, & v_{22} &= y_{21}, & v_{23} &= y_{31} \\ v_{31} &= z_{11}, & v_{32} &= z_{21}, & v_{33} &= z_{31} \end{aligned} \right\} \dots \quad (4.65)$$

Rearrange the rows as if the Jacobian determinant had been laid out by differentiating ( $a_{11}, a_{01}$ ) row after row in the following order:  $a'_{11}, a'_{21}, a'_{31}, a'_{12}, a'_{22}, a'_{32}, a_{11}, a_{21}, a_{31}, a_{12}, a_{22}, a_{32}$ . Then the determinant  $J$  is easily seen to be given in the present case by

$$J = \text{const.} \prod_{i=1}^3 c_i s_i$$

$$x \begin{vmatrix} x_1 & x_2 & x_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & y_1 & y_2 & y_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & z_1 & z_2 & z_3 & 0 & 0 & 0 \\ y_1 & y_2 & y_3 & x_1 & x_2 & x_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ z_1 & z_2 & z_3 & 0 & 0 & 0 & x_1 & x_2 & x_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ x_1^2 s_1^2 & x_2^2 s_2^2 & x_3^2 s_3^2 & 0 & 0 & 0 & 0 & 0 & 0 & x_1^2 & x_2^2 & x_3^2 \\ 0 & 0 & 0 & y_1^2 s_1^2 & y_2^2 s_2^2 & y_3^2 s_3^2 & 0 & 0 & 0 & y_1^2 & y_2^2 & y_3^2 \\ 0 & 0 & 0 & 0 & 0 & 0 & z_1^2 s_1^2 & z_2^2 s_2^2 & z_3^2 s_3^2 & z_1^2 & z_2^2 & z_3^2 \\ y_1^2 s_1^2 & y_2^2 s_2^2 & y_3^2 s_3^2 & x_1^2 s_1^2 & x_2^2 s_2^2 & x_3^2 s_3^2 & 0 & 0 & 0 & 2x_1 y_1 & 2x_2 y_2 & 2x_3 y_3 \\ z_1^2 s_1^2 & z_2^2 s_2^2 & z_3^2 s_3^2 & 0 & 0 & 0 & x_1^2 s_1^2 & x_2^2 s_2^2 & x_3^2 s_3^2 & 2x_1 z_1 & 2x_2 z_2 & 2x_3 z_3 \\ 0 & 0 & 0 & z_1^2 s_1^2 & z_2^2 s_2^2 & z_3^2 s_3^2 & y_1^2 s_1^2 & y_2^2 s_2^2 & y_3^2 s_3^2 & 2y_1 z_1 & 2y_2 z_2 & 2y_3 z_3 \end{vmatrix} \quad (4.63)$$

The reduction of this determinant will be shown in some detail as it will immediately make obvious the reduction in the general case of  $p$ -variates. Denote the columns by (1), (2), (3), (4) etc. now multiply (2) by  $x_1$  and subtract from it  $x_2$ , (1); multiply (3) by  $x_1$  and subtract from it  $x_3$ , (1); treat the columns (4), (5) (6) similarly, taking the multipliers to be  $(y_1, y_2, y_3)$ ; then the columns (7), (8), (9) taking as multipliers  $(z_1, z_2, z_3)$ . To keep the determinant unaltered in value each multiplication will have to be balanced by a corresponding division. In all that follows such divisions will always be understood to have been made. The determinant (leaving out the factor

$\prod_{i=1}^3 c_i s_i$ ) now reduces to

$$\text{const.} \frac{1}{x_1 y_1 z_1}$$

$$x \begin{vmatrix} (y_2 x_1) & (y_3 x_1) & (x_2 y_1) & (x_3 y_1) & 0 & 0 & 0 & 0 & 0 \\ (z_2 x_1) & (z_3 x_1) & 0 & 0 & (x_1 z_1) & (x_2 z_1) & (x_3 z_1) & 0 & 0 & 0 \\ 0 & 0 & (z_2 y_1) & (z_3 y_1) & (y_1 z_1) & (y_2 z_1) & (y_3 z_1) & 0 & 0 & 0 \\ x_1^2 x_2^2 s_{21}^2 & x_1^2 x_3^2 s_{31}^2 & 0 & 0 & 0 & 0 & 0 & x_1^2 & x_2^2 & x_3^2 \\ 0 & 0 & y_1^2 y_2^2 s_{21}^2 & y_1^2 y_3^2 s_{31}^2 & 0 & 0 & 0 & y_1^2 & y_2^2 & y_3^2 \\ (y_2 x_1^2 s_2^2) & (y_3 x_1^2 s_3^2) & (x_2 y_1^2 s_{21}^2) & (x_3 y_1^2 s_{31}^2) & 0 & 0 & 2x_1 y_1 & 2x_1 y_2 & 2x_1 y_3 \\ (z_2 x_1^2 s_2^2) & (z_3 x_1^2 s_3^2) & 0 & 0 & (x_1 z_1^2 s_{11}^2) & (x_2 z_1^2 s_{21}^2) & (x_3 z_1^2 s_{31}^2) & 2x_1 z_1 & 2x_1 z_2 & 2x_1 z_3 \\ 0 & 0 & (z_2 y_1^2 s_{21}^2) & (z_3 y_1^2 s_{31}^2) & (y_2 z_1^2 s_{21}^2) & (y_3 z_1^2 s_{31}^2) & 2y_1 z_1 & 2y_1 z_2 & 2y_1 z_3 \end{vmatrix}$$

where\*

$$\left. \begin{aligned} s_{31} &= s_2^2 - s_1^2, \quad s_{31}^2 = s_3^2 - s_1^2; \\ (y_2, x_1) &\text{ stands for } y_2 x_1 - x_2 y_1 \text{ and similar meanings attach to } (y_2, x_1) \text{ etc.} \\ (y_1, x_1, s_1^2) &\text{ stands for } y_2 x_1 s_1^2 - x_2 y_1 s_1^2 \text{ and similar meanings attach to } \dots \end{aligned} \right\} \dots (4.605)$$

Adding to column (1), columns (3) and (5), and to column (2) columns (4) and (6), and taking out the factor  $(s_2^2 - s_1^2)$  from the first column and  $(s_2^2 - s_1^2)$  from the second column, the determinant reduces to

$$\text{const. } \frac{s_{31}^2 s_{21}^2}{x_1 y_1 z_1} \times \begin{vmatrix} 0 & 0 & (x_2 y_1) & (x_2 y_1) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & (x_2 z_1) & (x_2 z_1) & 0 & 0 & 0 \\ 0 & 0 & (z_2 y_1) & (z_2 y_1) & (y_2 z_1) & (y_2 z_1) & 0 & 0 & 0 \\ x_1 x_2 & x_1 x_2 & 0 & 0 & 0 & 0 & x_1^2 & x_2^2 & x_3^2 \\ y_1 y_2 & y_1 y_2 & y_1 y_2 s_{31}^2 & y_1 y_2 s_{21}^2 & 0 & 0 & y_1^2 & y_2^2 & y_3^2 \\ z_1 z_2 & z_1 z_2 & 0 & 0 & z_1 z_2 s_{31}^2 & z_1 z_2 s_{21}^2 & z_1^2 & z_2^2 & z_3^2 \\ [x_1, y_2] & [x_1, y_2] & (x_2 y_1 s_2^2) & (x_2 y_1 s_1^2) & 0 & 0 & 2x_1 y_1 & 2x_2 y_2 & 2x_3 y_3 \\ [x_1, z_2] & [x_1, z_2] & 0 & 0 & (x_2 z_1 s_2^2) & (x_2 z_1 s_1^2) & 2x_1 z_1 & 2x_2 z_2 & 2x_3 z_3 \\ [y_1, z_2] & [y_1, z_2] & (z_2 y_1 s_2^2) & (z_2 y_1 s_1^2) & (y_2 z_1 s_2^2) & (y_2 z_1 s_1^2) & 2y_1 z_1 & 2y_2 z_2 & 2y_3 z_3 \end{vmatrix}$$

where  $[x_1, y_2]$  stands for  $x_1 y_2 + y_1 x_2$ , and similar meanings attach to  $[x_1, z_2]$  etc. (4.606)

From row (7) subtract row (1) multiplied by  $s_1^2$ , from row (8) subtract row (2) multiplied by  $s_1^2$ , and from row (9) subtract row (3) multiplied by  $s_1^2$ . The determinant now becomes

$$\text{const. } \frac{s_{31}^2 s_{21}^2}{x_1 y_1 z_1} \times \begin{vmatrix} 0 & 0 & (x_2 y_1) & (x_2 y_1) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & (x_2 z_1) & (x_2 z_1) & 0 & 0 & 0 \\ 0 & 0 & (z_2 y_1) & (z_2 y_1) & (y_2 z_1) & (y_2 z_1) & 0 & 0 & 0 \\ x_1 x_2 & x_1 x_2 & 0 & 0 & 0 & 0 & x_1^2 & x_2^2 & x_3^2 \\ y_1 y_2 & y_1 y_2 & y_1 y_2 s_{31}^2 & y_1 y_2 s_{21}^2 & 0 & 0 & y_1^2 & y_2^2 & y_3^2 \\ z_1 z_2 & z_1 z_2 & 0 & 0 & z_1 z_2 s_{31}^2 & z_1 z_2 s_{21}^2 & z_1^2 & z_2^2 & z_3^2 \\ [x_1, y_2] & [x_1, y_2] & x_2 y_1 s_{31}^2 & x_2 y_1 s_{21}^2 & 0 & 0 & 2x_1 y_1 & 2x_2 y_2 & 2x_3 y_3 \\ [x_1, z_2] & [x_1, z_2] & 0 & 0 & x_2 z_1 s_{31}^2 & x_2 z_1 s_{21}^2 & 2x_1 z_1 & 2x_2 z_2 & 2x_3 z_3 \\ [y_1, z_2] & [y_1, z_2] & z_2 y_1 s_{31}^2 & z_2 y_1 s_{21}^2 & y_2 z_1 s_{31}^2 & y_2 z_1 s_{21}^2 & 2y_1 z_1 & 2y_2 z_2 & 2y_3 z_3 \end{vmatrix}$$

\* These abbreviations are introduced to keep within the available space.

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Denote by  $(\bar{x}_1, \bar{x}_2, \bar{x}_3, \bar{y}_1, \bar{y}_2, \bar{z}_1, \bar{z}_2, \bar{z}_3)$  the co-factors of  $(x_1, x_2, x_3, y_1, y_2, y_3, z_1, z_2, z_3)$  in the determinant D given by

$$D = \begin{vmatrix} x_1 & x_2 & x_3 \\ y_1 & y_2 & y_3 \\ z_1 & z_2 & z_3 \end{vmatrix}$$

Then in the 9th order determinant just preceding it multiply column (4) by  $-\bar{z}_3$  and column (6) by  $\bar{y}_3$  and subtract from them respectively column (3) multiplied by  $\bar{z}_1$  and column (5) multiplied by  $-\bar{y}_2$ . The determinant D then becomes, by virtue of the relations  $\bar{x}_1 \bar{z}_3 - \bar{x}_3 \bar{z}_1 = y_1 D$  and  $\bar{x}_2 \bar{y}_3 - \bar{x}_3 \bar{y}_2 = z_1 D$ ,

$$\text{const. } \frac{s_{31}^2 - s_{31}^2 \cdot D}{x_1}$$

$$\times \begin{vmatrix} 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ x_1 x_2 & x_1 x_3 & 0 & 0 & x^2_1 & x^2_2 & x^2_3 \\ y_1 y_2 & y_1 y_3 & -y_1 \bar{z}_2 s^2_{31} - y_2 \bar{z}_3 s^2_{31} & 0 & y^2_1 & y^2_2 & y^2_3 \\ z_1 z_2 & z_1 z_3 & 0 & z_2 \bar{y}_3 s^2_{31} + z_3 \bar{y}_2 s^2_{31} & z^2_1 & z^2_2 & z^2_3 \\ [x_1 y_2] & [x_1 y_3] & -x_2 \bar{z}_2 s^2_{31} - x_3 \bar{z}_3 s^2_{31} & 0 & 2x_1 y_1 & 2x_2 y_1 & 2x_3 y_1 \\ [x_1 z_2] & [x_1 z_3] & 0 & x_2 \bar{y}_3 s^2_{31} + x_3 \bar{y}_2 s^2_{31} & 2x_1 z_1 & 2x_1 z_2 & 2x_1 z_3 \\ [y_1 z_2] & [y_1 z_3] & -z_2 \bar{z}_2 s^2_{31} - z_3 \bar{z}_3 s^2_{31} & y_2 \bar{y}_3 s^2_{31} + y_3 \bar{y}_2 s^2_{31} & 2y_1 z_1 & 2y_2 z_2 & 2y_3 z_3 \end{vmatrix}$$

Subtracting now column (4) from column (3) this is easily seen to reduce to

$$\text{const. } \frac{s_{31}^2 - s_{31}^2 \cdot D}{x_1}$$

$$\times \begin{vmatrix} x_1 x_2 & x_1 x_3 & 0 & x^2_1 & x^2_2 & x^2_3 \\ y_1 y_2 & y_1 y_3 & -y_2 \bar{z}_2 s^2_{31} - y_3 \bar{z}_3 s^2_{31} & y^2_1 & y^2_2 & y^2_3 \\ z_1 z_2 & z_1 z_3 & -z_2 \bar{y}_3 s^2_{31} - z_3 \bar{y}_2 s^2_{31} & z^2_1 & z^2_2 & z^2_3 \\ [x_1 y_2] & [x_1 y_3] & -x_2 \bar{z}_2 s^2_{31} - x_3 \bar{z}_3 s^2_{31} & 2x_1 y_1 & 2x_2 y_2 & 2x_3 y_3 \\ [x_1 z_2] & [x_1 z_3] & -x_2 \bar{y}_3 s^2_{31} - x_3 \bar{y}_2 s^2_{31} & 2x_1 z_1 & 2x_2 z_2 & 2x_3 z_3 \\ [y_1 z_2] & [y_1 z_3] & -(z_2 \bar{z}_2 + y_2 \bar{y}_2) s^2_{31} - (z_3 \bar{z}_3 + y_3 \bar{y}_3) s^2_{31} & 2y_1 z_1 & 2y_2 z_2 & 2y_3 z_3 \end{vmatrix}$$

Subtracting from column (3), column (2) multiplied by  $(s^2_2 - s^2_1)$ , and adding to column (3), column (1) multiplied by  $(s^2_3 - s^2_1)$  the determinant is easily seen to reduce to

$$\text{const. } s^2_{12} s^2_{13} s^2_{23} \cdot D$$

$$\times \begin{vmatrix} x_1 x_2 & x_1 x_3 & x_2 x_3 & x^2_1 & x^2_2 & x^2_3 \\ y_1 y_2 & y_1 y_3 & y_2 y_3 & y^2_1 & y^2_2 & y^2_3 \\ z_1 z_2 & z_1 z_3 & z_2 z_3 & z^2_1 & z^2_2 & z^2_3 \\ [x_1 y_2] & [x_1 y_3] & [x_2 y_3] & 2x_1 y_1 & 2x_2 y_2 & 2x_3 y_3 \\ [x_1 z_2] & [x_1 z_3] & [x_2 z_3] & 2x_1 z_1 & 2x_2 z_2 & 2x_3 z_3 \\ [y_1 z_2] & [y_1 z_3] & [y_2 z_3] & 2x_1 z_1 & 2x_2 z_2 & 2x_3 z_3 \end{vmatrix}$$

Multiply columns (2), (3), (4) and (5) respectively by  $x_2, x_1, x_2, x_1$  and subtract from them respectively column (1) multiplied by  $x_2, x_1, x_2, x_1$ ; also multiply column (6) by  $x_1$  and subtract from it column (2) multiplied by  $x_2$ . The above expression then reduces (after substitution from 4'695 and 4'696) to

$$\text{const.} - \frac{(s_1^2 - s_2^2)(s_1^2 - s_2^2)(s_2^2 - s_3^2) D}{x_1^2 x_2}$$

$$\times \begin{vmatrix} y_1 \bar{z}_1 & -y_2 \bar{z}_2 & y_1 \bar{z}_3 & y_1 \bar{z}_3 & -y_1 \bar{z}_3 \\ -z_1 \bar{y}_1 & z_2 \bar{y}_2 & -z_1 \bar{y}_1 & -z_2 \bar{y}_2 & z_1 \bar{y}_1 \\ x_1 \bar{z}_1 & -x_2 \bar{z}_2 & x_1 \bar{z}_2 & x_1 \bar{z}_2 & -x_2 \bar{z}_2 \\ -x_1 \bar{y}_1 & x_2 \bar{y}_2 & -x_1 \bar{y}_2 & -x_2 \bar{y}_2 & x_2 \bar{y}_2 \\ z_1 \bar{z}_1 - y_1 \bar{y}_1 & -z_2 \bar{z}_2 + y_2 \bar{y}_2 & z_1 \bar{z}_2 + y_1 \bar{y}_2 & z_2 \bar{z}_2 - y_1 \bar{y}_2 & -z_2 \bar{z}_2 + y_2 \bar{y}_2 \end{vmatrix}$$

Multiply column (2) by  $y_1 z_1$  and subtract from it column (1) multiplied by  $-y_2 \bar{z}_2$ , multiply columns (3), (4), (5) respectively by  $\bar{z}_1, -\bar{z}_2, y_2$  and subtract from them respectively column (1) multiplied by  $\bar{z}_2$ , column (2) multiplied by  $\bar{z}_1$  and column (2) multiplied by  $y_2$ .

Remembering<sup>7</sup> the property (2) that a minor of the order  $m$  formed out of the inverse constituents is equal to the complementary of the corresponding minor of the original determinant  $D$  multiplied by the  $(m-1)$ th power of  $D$ , the above expression is easily seen to reduce to

$$\text{const.} \frac{(s_1^2 - s_2^2)(s_1^2 - s_2^2)(s_2^2 - s_3^2) D^2}{y_1 x_1 y_2 z_1^2 z_2^2}$$

$$\times \begin{vmatrix} y_1 \bar{z}_1 & 0 & 0 & 0 & 0 \\ -z_1 \bar{y}_1 & y_1 z_1 y_2 \bar{z}_1 - z_1 y_2 z_2 \bar{y}_1 & z_1 & z_2 & \bar{y}_2 \bar{y}_1 \\ x_1 \bar{z}_1 & +z_2 z_1 z_2 & 0 & 0 & +z_2 z_1 \\ -x_1 \bar{y}_1 & y_1 x_2 z_1 \bar{y}_2 - x_1 y_2 z_1 \bar{z}_2 & x_1 & x_2 & -\bar{y}_2 z_1 \\ -z_1 \bar{z}_1 - y_1 \bar{y}_1 & \bar{y}_2 z_1 z_2 - y_1 y_2 x_2 D & y_1 & y_2 & -z_2 \bar{y}_1 \end{vmatrix}$$

e. to

$$\text{const.} \frac{(s_1^2 - s_2^2)(s_1^2 - s_2^2)(s_2^2 - s_3^2) D^2}{x_1 y_2 z_1 z_2}$$

$$\times \begin{vmatrix} \bar{y}_2 \bar{y}_2 \bar{z}_1 - x_2 z_1 y_1 D & z_1 & z_2 & \bar{y}_2 \bar{y}_1 \\ -z_1 z_2 z_2 & 0 & 0 & -z_2 z_1 \\ -z_2 z_1 \bar{y}_1 - x_1 y_2 x_2 D & x_1 & x_2 & -\bar{y}_2 z_1 \\ \bar{y}_2 z_1 z_2 - y_1 y_2 x_1 D & y_1 & y_2 & z_2 \bar{y}_1 \end{vmatrix}$$

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i.e. to

$$\text{const.} \frac{(s_1^2 - s_2^2) s_1^2 - s_2^2) (s_2^2 - s_3^2) D^3}{x_1 y_1 z_1}$$

$$\times \begin{vmatrix} \bar{N}_2 \bar{y}_2 & z_1 & z_2 & \bar{y}_2 \bar{N}_1 \\ \bar{z}_2 \bar{z}_2 & 0 & 0 & \bar{z}_2 \bar{z}_1 \\ -\bar{y}_2 \bar{z}_2 & x_1 & x_2 & -\bar{y}_2 \bar{z}_1 \\ -\bar{N}_2 \bar{z}_2 & y_1 & y_2 & -\bar{z}_2 \bar{N}_1 \end{vmatrix}$$

Multiplying column (4) by  $\bar{z}_1$  and subtracting from it column (1) multiplied by  $\bar{z}_1$  this easily becomes

$$\text{const.} \frac{(s_1^2 - s_2^2) (s_1^2 - s_2^2) (s_2^2 - s_3^2) D^4}{\lambda_1}$$

$$\times \begin{vmatrix} z_1 & z_2 & \bar{y}_2 \\ x_1 & x_2 & 0 \\ y_1 & y_2 & -\bar{z}_2 \end{vmatrix}$$

$$\text{Or, const.} \frac{(s_1^2 - s_2^2) (s_1^2 - s_2^2) (s_2^2 - s_3^2)}{x_1} D^4 \cdot (\bar{y}_2 \bar{z}_1 - \bar{z}_2 \bar{y}_2)$$

$$\text{Or, const.} (s_1^2 - s_2^2) (s_1^2 - s_2^2) (s_2^2 - s_3^2) D^3$$

(absorbing everywhere the negatives into the const)

Therefore, from (4.69) the determinant J would be given by

$$J = \text{const.} \prod_{i=1}^p c_i s_i (s^2 - s_1^2) (s^2 - s_2^2) (s^2 - s_3^2) \dots \quad \dots \quad (4.7)$$

From what has been given above it would be obvious that this method of evaluating J and finally reducing it to the form (4.7) is perfectly general and in the case of  $p$ -variates, J would be evidently given by

$$J = \text{const.} \prod_{i=1}^p c_i s_i (s^2 - s_1^2) \dots (s^2 - s_{p-1}^2) (s^2 - s_p^2) \dots (s^2 - s_p^2) | \tau_U |^{p+1} \dots \quad (4.71)$$

From the relations (4.61), (4.62), (4.63) and (4.71), the joint distribution (4.3) transforms to

$$\begin{aligned} & -\frac{1}{2} \sum_{i=1}^p a^{(i)} \sum_{k=1}^p v_{ik} v_{jk} \\ \text{const. } e & | \tau_U |^{p+1} | \tau_U |^{p+1} \prod_{i=1}^p s_i^{p+1} c_i^{s_i - p + 1} \\ & \times (s^2 - s_1^2) \dots (s^2 - s_{p-1}^2) (s^2 - s_p^2) \dots (s^2 - s_p^2) \dots (s^2 - s_{p-1}^2) \dots | \tau_U |^{p+1} \prod_{i=1}^p c_i s_i \\ & \times \prod_{i=1}^p d v_U \prod_{i=1}^p d \phi_i \quad \dots \quad (4.72) \end{aligned}$$

Or to

$$\text{const. } e^{-\frac{1}{2} \sum_{i=1}^p a_{ii} \sum_{k=1}^p v_{ik} v_{jk}} |v_{ij}|^{n+n'-p-2} \prod_{i=1}^p c_i^{n'-p-1} s_i^{n-p-1} \times (s_1^2 - s_2^2) \dots (s_{p-1}^2 - s_p^2) \prod_{i=1}^p dv_i \prod_{i=1}^p d\varphi_i \dots \quad (4.73)$$

Integrating out over  $v_u$ 's we have the joint distribution of  $\varphi_i$ 's in the form

$$\text{const. } \prod_{i=1}^p c_i^{n'-p-1} s_i^{n-p-1} \times (s_1^2 - s_2^2) \dots (s_{p-1}^2 - s_p^2) \prod_{i=1}^p d\varphi_i \dots \quad (4.74)$$

where of course  $c_i$  and  $s_i$  are given by (4.66)

Therefore from (3.4), (4.66) and (7.74) the joint distribution of  $K_i$ 's (where  $K_i$ 's are the roots of equation (1.5) and are accordingly our  $\beta$ -statistics) is obtained in the form

$$\text{const. } \prod_{i=1}^p \frac{K_i^{n-p-1}}{(1+c^2 K_i^2)^{(n+n'-2)/2}} \times (K_1^2 - K_2^2) \dots (K_{p-1}^2 - K_p^2) \prod_{i=1}^p dK_i \dots \quad (4.75)$$

where  $c^2 = n/n'$  ... (4.76)

It should be noted that if we put  $\beta=1$  then the above can be shown to reduce as it should to

$$\text{const. } \frac{K^{n-2} dK}{(1+c^2 K^2)^{(n+n'-2)/2}} \dots \quad (4.77)$$

### §5 CONCLUSION.

The hypothesis to be tested is that the two samples  $\Sigma$  and  $\Sigma'$  have come from two populations  $\Pi$  and  $\Pi'$  with the same set of variances and covariances. With that end in view we proceed as follows.

It has been noted at the end of section 3 that of these  $K_i$ 's, one is a true maximum, one is a true minimum and the others are stationary. It is evident from (1.5), (4.3) and from the geometrical considerations in section 3 and section 4 that  $K_i$ 's might each be taken to vary from 0 to  $\alpha$ .

Let us assume that in any particular case  $K_1$  is the maximum statistic,  $K_p$  the minimum and  $K_s$  is the one nearest to unity. In any given case all these can of course be calculated to any desired degree of approximation by any suitable method, say, Horner's method.

To obtain the sampling distribution of  $K_1$ , the maximum statistic, we integrate out (4.75) successively over  $K_2, K_3, \dots, K_p$ , each from 0 to  $K_1$ . This will be done in the second paper which is to appear shortly in the next issue of this journal. Suppose this distribution is

$$\text{const. } F(K_1) dK_1 \dots \quad (5.1)$$

## GENERALIZATIONS IN ANALYSIS OF VARIANCE

To obtain the sampling distribution of  $K_p$ , we proceed otherwise; changing the order of integration, i.e., integrating out (4.75) successively over  $K_1, K_2, \dots, K_{p-1}$  each from  $K_p$  to  $\infty$ , the distribution of  $K_p$ , the minimum statistic would be obtained, say, in the form

$$\text{const. } f(K_p) d(K_p) \quad \dots \quad (5.2)$$

The sampling distribution of  $K_r$ , the statistic which or whose reciprocal is nearest to unity can be similarly obtained by integrating out over the others between suitable limits. Suppose it is of the general form

$$\text{const. } \phi(K_r) dK_r \quad \dots \quad (5.3)$$

The suitable limits involved in the derivation (5.3) as well as the general forms of  $F(K_r)$ ,  $f(K_r)$  and  $\phi(K_r)$  given in (5.1), (5.2) and (5.3) will be shown in detail in the next paper. Each of the functions  $F(K_r)$ ,  $f(K_r)$  and  $\phi(K_r)$  is the sum of a number of terms each of which involves the product of incomplete  $\Gamma$ -functions.

(i) To accept the hypothesis with safety (on any level of significance) we use either  $K_1$  and (5.1), or  $K_p$  and (5.2) according as  $K_1$  is greater or less than  $1/K_p$ . The underlying logic is that we now look at the samples from a point of view which puts them farthest apart. If even from such a point of view the difference looks insignificant we are entitled to assert with safety that the difference is in fact really insignificant (on a certain level of course). What is precisely implied is this. When we assert in such a situation that the difference is insignificant on the 5% level we are really putting a maximum limit to the margin of error involved in our assertion, which is here 5%. The error may be in fact less than this.

(ii) To reject the hypothesis with safety (on a given level of course) we have recourse to  $K_r$  and its sampling distribution given in (5.3). The underlying logic again is that we now look at the samples from a point of view which puts them closest to each other. If even from such a point of view the difference looks significant then it is in fact really significant. More precisely speaking, when we assert in such a situation that the difference is significant on the 5% level we are again putting a maximum limit to the error involved in our assertion, which is here 5%. Here also the error may in fact be much less than this.

For (5.1), (5.2) and (5.3) a transformation to a new set of variates has been found to be mathematically convenient, the new variates being defined by

$$Z_i \quad (i=1, 2, \dots, p); \quad \dots \quad (5.4) \\ K_i = e^{-Z_i}$$

In practice these new variates and their sampling distributions should be preferred to the  $K_i$ 's. The changes consequent upon this transformation will come out in the next paper already referred to.

Starting from the joint distribution of  $K_1, K_2, \dots, K_p$  given in (4.75) we can, however, tackle the problem of testing of hypothesis in an entirely different way, by considering a space of  $p$  dimensions (such that a point in it has the co-ordinates  $K_1, K_2, \dots, K_p$ ) the family of equiprobability surfaces  $\mu = \text{const.}$ , where  $\mu$  is given by the relation

$$\mu = \text{const.} \quad \prod_{i=1}^p \frac{K_i^{p-1}}{(1+e^{Z_i} K_i^2)^{(p+1)/2}} \\ \times (K_1^2 - K_2^2) \dots (K_1^2 - K_p^2) (K_2^2 - K_3^2) \dots (K_2^2 - K_p^2) \dots (K_{p-1}^2 - K_p^2) \quad \dots \quad (5.5)$$

The expression on the right hand side of 55 is really the density factor in (475).

This latter method of testing of hypothesis will be dealt with in a later paper.

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