

APPENDIX: STATISTICAL TESTS OF SIGNIFICANCE

BU-351-M

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Abstract

E. C. Pielou has proposed a new measure of association between the species occurring in a sample of  $N$  quadrats. When occurrence is measured by presence or absence the data may be displayed in an  $N \times k$  matrix of zeroes and ones, the  $i^{\text{th}}$  row sum  $s_i$  then denoting the number of different species occurring in the  $i^{\text{th}}$  quadrat, and the  $j^{\text{th}}$  column sum  $n_j$  denoting the number of quadrats in which the  $j^{\text{th}}$  species occurs. If the  $k$  species occur mutually independently then the conditional variance of the row sum  $s_i$ , given the column sums  $n_j = Np_j$ ,  $j=1, \dots, k$ , becomes

$$\text{Var}(s) = \sum_{j=1}^k p_j(1-p_j)$$

and Pielou has proposed that the difference

$$\frac{v(s)}{N} = \frac{1}{2}[m_2(s) - \text{Var}(s)]$$

between the observed row variance

$$m_2(s) = \frac{1}{N} \left[ \sum_{i=1}^N s_i^2 - \frac{1}{N} \left( \sum_{i=1}^N s_i \right)^2 \right]$$

and the variance predicted under the independence hypothesis be taken as a measure of dependence. The reduction in  $v/N$  obtained by deleting a specified subset ( $Y$ ) of species from the data matrix was further proposed as a statistic for testing the relation between  $Y$  and the remaining ( $X$ ) species.

This reduction in  $v/N$  is algebraically expressible as

$$\frac{v(x+y)}{N} - \frac{v(x)}{N} = \frac{v(y)}{N} + m_{11}(x,y)$$

where  $v(y)/N$  measures association within the Y-class and the product-moment  $m_{11}(x,y)$  measures association between the Y-class and the X-class. Separate, independent, large sample tests of these two different aspects of Pielou's null hypotheses are here derived in the form:

$$\frac{m_2(y)}{\text{Var}(y)}(N-1) \sim \chi^2_{(N-1)\text{d.f.}} \quad r^2_{xy}(N-1) \sim \chi^2_1 \text{ d.f.} \quad .$$

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If the collection of  $k$  species is partitioned into two classes, say the X-class and the Y-class, then the total number of species  $s_i$  appearing in the  $i^{\text{th}}$  quadrat is expressible as the sum  $s_i = x_i + y_i$  of the numbers in the two classes. The statistic  $v/N$  calculated from the complete data matrix, say  $v(x+y)/N$ , is then related to the corresponding statistics of the X- and Y-data matrices by the equation

$$\frac{v(x+y)}{N} = \frac{v(x)}{N} + \frac{v(y)}{N} + m_{11}(x,y)$$

where the product moment is defined by

$$m_{11}(x,y) = \frac{1}{N} [\Sigma xy - \frac{1}{N}(\Sigma x)(\Sigma y)] .$$

The reduction resulting from deletion of one class of species, say the Y-class,

$$\frac{v(x+y)}{N} - \frac{v(x)}{N} = \frac{v(y)}{N} + m_{11}(x,y)$$

will thus have expectation zero if each species in the Y-class is not only independent of all species in the X-class, implying  $m_{11}(x,y)$  has mean zero, but also independent of all other species in the Y-class, implying  $v(y)/N$  has mean zero. A hypothesis of no expected reduction is thus a composite of two null hypotheses, each of which is separately and independently testable.

If the Y-class is independent of the X-class then  $m_{11}$  has mean zero even when the expectation is conditioned on one of the order statistics, say

$$\{y\} = \{y_i | i=1,2,\dots,N\} = \text{unordered collection of } N \text{ } y\text{'s} .$$

Thus,

$$E_{H_0} [m_{11}(x,y) | (x), \{y\}] = 0$$

where the average is taken over the  $N!$  equally likely permutations of  $(y)$ .

For example, if the Y-class contains a single species then  $y_i = 0$  or 1 and

$$m_{11}(x,y) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x}_N) y_i = \frac{n}{N} (\bar{x}_n - \bar{x}_N)$$

where  $\bar{x}_n$  is the mean value of  $x$  in those  $n$  quadrats containing the Y-species.

The permutation distribution of  $m_{11}$  in this case is, in effect, the distribution of a mean of a sample of size  $n$  drawn randomly and without replacement from a finite population of size  $N$ . The normal approximation to this distribution gives

$$\frac{\left[ \frac{n}{N} (\bar{x}_n - \bar{x}_N) \right]^2}{\left( \frac{n}{N} \right)^2 \frac{N-n}{n(N-1)} m_2(x)} \sim \chi_1^2 \text{ d.f.} .$$

In the more general case we have

$$\text{Var} [m_{11}(x,y) | (x), \{y\}] = \frac{m_2(x)m_2(y)}{N-1}$$

and

$$\frac{[m_{11}(x,y)]^2}{m_2(x)m_2(y)} (N-1) = r_{xy}^2 (N-1) \sim \chi_1^2 \text{ d.f.} .$$

If the X- and Y-classes both contain a large number of species then the distribution of  $r_{xy}^2$  derived from bivariate (independent) normal theory might provide a better approximation than this chi-square distribution on one degree of freedom, but when one class is small the above approximation is the better of the two.

The statistical significance of  $v(y)/N$  for the  $k_Y$  species in the Y-class can be tested in a  $2^{k_Y}$  contingency table when  $k_Y$  is small, and can be tested by appealing to the Central Limit Theorem when  $k_Y$  is large. A row total  $y_i$  (see Table 1) is the sum of  $k_Y$  indicator variables, say

$$y_i = \sum_{j=1}^{k_Y} \delta_{ij}$$

which are independent under the null hypothesis, and hence as  $k_Y$  gets large the probability distribution of  $y_i$  approaches a normal distribution. The same may be said of the column totals

$$n_j = \sum_{i=1}^N \delta_{ij}$$

as  $N$  gets large, and hence the conditional distribution of the row totals, given the column totals, must approach multivariate normality. Since the conditional moments are

$$E_{H_0}(y_i | n_1, \dots, n_{k_Y}) = \sum_{j=1}^{k_Y} E_{H_0}(\delta_{ij} | n_j) = \sum_{j=1}^{k_Y} \frac{n_j}{N} = \sum_{j=1}^{k_Y} p_j$$

$$\text{Var}_{H_0}(y_i | n_1, \dots, n_{k_Y}) = \sum_{j=1}^{k_Y} \text{Var}_{H_0}(\delta_{ij} | n_j) = \sum_{j=1}^{k_Y} p_j(1-p_j)$$

$$\text{Cov}_{H_0}(y_i, y_i, |n_1, \dots, n_{k_Y}) = \sum_{j=1}^{k_Y} \text{Cov}(\delta_{ij}, \delta_{i',j} | n_j) = \frac{-1}{N-1} \sum_{j=1}^{k_Y} p_j(1-p_j)$$

then the quadratic form of any  $N-1$   $y$ 's, say  $\underline{y} = (y_1, \dots, y_{N-1})$ , reduces to

$$(\underline{y} - E(\underline{y} | \underline{n})) V^{-1} (\underline{y} - E(\underline{y} | \underline{n}))' = \frac{m_2(y)}{\frac{\sum_{j=1}^{k_Y} p_j(1-p_j)}{k_Y}} (N-1)$$

where  $V$  is the conditional covariance matrix of  $\underline{y}$ . For large  $k_Y$  this test statistic

$$\frac{m_2(y)}{\text{Var}(y)} (N-1) = \left[ 1 + \frac{2}{\text{Var}(y)} \frac{v(y)}{N} \right] (N-1) \sim \chi_{N-1}^2$$

is therefore approximately chi-square distributed on  $N-1$  degrees of freedom, and is asymptotically independent of  $\chi_1^2 \sim r_{xy}^2 (N-1)$  since the distribution of the latter is conditional on  $\{y\}$  and hence on  $m_2(y)$ . These two chi-squares could therefore be added to provide a test of the composite null hypothesis, but the separate tests of the two facets of this null hypothesis are more informative.