and von Mises tests. A comparison of the power functions of these tests would be of great interest. Almost nothing is known of the small-sample power of any of these tests. The large-sample power of the chi-square test is known. It is the author’s conjecture that the limiting joint distribution of \(Q(n)\) and \(R_n(1; 1)\) is bivariate normal under the alternatives as well as under the hypothesis. If this conjecture could be proved, the asymptotic power of the proposed test would be known.

**TABLES FOR OBTAINING NON-PARAMETRIC TOLERANCE LIMITS**

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The general consideration of non-parametric tolerance limits had its origin with Wilks [10]. Wilks showed that for continuous populations, the distribution of \(P\), the proportion of the population between two order statistics from a random sample, was independent of the population sampled, and was in fact a function only of the particular order statistics chosen. Wald [9] and Tukey [8] extended the method to multivariate populations, Tukey being responsible for the term “statistically equivalent block.” Their work was extended further by Fraser [2], [3]. Murphy [4] presented graphs of minimum probable coverage by sample blocks determined by order statistics of a sample from a population with a continuous but unknown c.d.f. This note extends the results of Murphy, and tabularizes the results in a manner which eliminates or minimizes interpolation, particularly with respect to \(m\), in a large number of cases. The form of Table I parallels the tables of Eisenhart, Hastay and Wallis [1] “Tolerance Factors for Normal Distributions.”

Let \(P\) represent the proportion of the population between the \(r^{th}\) smallest and the \(s^{th}\) largest value in a random sample of \(n\) from a population having a continuous but unknown distribution function. Table I gives the largest value of \(m = r + s\) such that we have confidence of at least that 100 \(P\) percent of the population lies between the \(r^{th}\) smallest and \(s^{th}\) largest in the sample. Note, that we may choose any \(r, s \geq 0\) such that \(r + s = m\). We must, of course, decide upon the values of \(r\) and \(s\) independently of the observations in the sample. We obtain one-sided confidence intervals when we use \(r = 0\) or \(s = 0\) for a given \(m\). The values of \(m\) are the largest such that

\[
\gamma \leq I_{1-P}(m, n - \hat{m} + 1)
\]

where \(I\) is the incomplete Beta function tabulated in [5] and [7].

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