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 $r^{\text{th}}$ smallest and the $s^{\text{th}}$ 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 $r^{\text{th}}$ smallest and $s^{\text{th}}$ largest in the sample. Note, that we may choose any $r, s \geqq 0$ 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

$$\gamma \leqq I_{1-P}(m, n - m + 1)$$

where $I$ is the incomplete Beta function tabulated in [5] and [7].

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