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ABSTRACTS OF PAPERS

(*Abstracts of papers presented at the Annual meeting, Madison, Wisconsin, August 26–30, 1968. Additional abstracts appeared in earlier issues.*)

90. Bayesian analysis of growth curves. SEYMOUR GEISSER, State University of New York at Buffalo. (Invited)

From a Bayesian viewpoint, we initiate the study of the generalized growth model of (Potthoff and Roy, *Biometrika* **51** (1964)). The model asserts $E(Y_{p\times N}) = X_{p\times m}\tau_{m\times r}A_{r\times N}$, where X is a known matrix of rank $m \leqq p$, A is a known matrix of rank $r \leqq N$, τ is unknown and the columns of Y are independent p-dimensional multinormal variates having a common unknown arbitrary covariance matrix Σ. A Bayesian justification is presented for the Rao (*Proc. Fifth Berkeley Symp. Math. Statist. Prob.* **1** (1967)) adjusted estimator $\hat{\tau}$ of τ the set of unknown parameters, as well as an estimating region for τ. Using only an augmented location model we also obtain a Bayesian vindication for the unadjusted estimator of τ that is necessarily different in character from the frequentist exculpation since this latter pertains to a restricted covariance structure. The problem of estimating regions for future observations from this model, given a preliminary sample, is also discussed. (Received 12 August 1968.)

91. A unified derivation of tests of goodness of fit based on spacings. B. K. KALE, University of Manitoba.

Let $(x_1, x_2, \cdots, x_n)$ be a random sample from a continuous df F and suppose we wish to test the null hypothesis that $F = F_0$ where F_0 is a completely specified df. Let $x_{(0)} = -\infty < x_{(1)} < x_{(2)} \cdots < x_{(n)} < x_{(n+1)} = +\infty$ denote the order statistics of the sample and let $v_i = F_0[x_{(i)}] - F_0[x_{(i-1)}]$, $i = 1, 2, \cdots, n + 1$, be the spacings. Several tests of goodness of fit based on spacings are known in the literature. By using the set of observations and the hypothesized df F_0, we first derive a simple estimate $\Phi_n(x)$ of the underlying df and show that for large n, $\Phi_n(x)$ is close to $F_n(x)$ the usual sample df or empirical df. By giving various definitions of "closeness", essentially using directed distances, we show that $\Phi_n(x)$ is the df which is as "close" as possible to F_0 and therefore most difficult to discriminate from F_0 on the basis of the given sample. Using the rule to reject $F = F_0$ if Φ_n and F_0 are sufficiently apart, we derive several different tests based on spacings v_i corresponding to different definitions of "closeness". (Received 19 August 1968.)

(*An abstract of a paper presented at the European meeting, Amsterdam, Netherlands, September 2–7, 1968. Additional abstracts appeared in earlier issues.*)

14. Nonparametric confidence and tolerance bounds and intervals when sampling from a finite population. H. S. KONIJN, Tel Aviv University.

Nonparametric confidence intervals and bounds for fractiles and tolerance intervals and bounds have been obtained by Wilks for samples of n independent observations from a continuous population. Tukey and others have made some assertions with respect to applicability of these results to discrete populations. Wilks also gives some incomplete results for the case of simple random sampling from a finite discrete population without replacement in which all members of the population take on different values. This paper gives complete and exact results for this case and examines also the case of sampling with replacement. It turns out that the argument is essentially more elementary than that for continuous populations; the latter may then, of course, be obtained from the former by a limiting process. The only quite intractable case is that of tolerance intervals in sampling