

Put  $y = A_a(n)\gamma_n$ . We introduce a parameter  $h$  with

$$\frac{c_1}{H_n} \leq h \leq c_2 \frac{A_a(n)}{H_n^2}.$$

Further, using the method proposed in [9], we obtain relations (2.6) or (2.1) of Theorem 5 or Theorem 1.

### References

- [1] S. A. B o o k, *Large deviation probabilities for weighted sums*, Ann. Math. Statist. (1972), pp. 1221–1234.
- [2] —, *A large deviation theorem for weighted sums*, Z. Wahrscheinlichkeitstheorie und verw. Gebiete (1973), pp. 43–49.
- [3] V. P e t r o v *A generalization of Cramér's limit theorem*, Uspehi Mat. Nauk 9 (1954), pp. 195–202 (in Russian).
- [4] L. S a u l i s *An asymptotic expansion for probabilities of large deviations*, Litovski Mat. Sb. 9 (1969), pp. 605–625 (in Russian).
- [5] —, *The limit theorems which allow large deviations if Ju. V. Linnik's condition is satisfied*, ibid. 12 (1973), ibid. (1973), pp. 173–194 (in Russian).
- [6] L. S a u l i s, V. S t a t u l e v i č i u s, *On large deviations in the scheme of summing of weighted random variables*, ibid. (1976), pp. 145–154 (in Russian).
- [7] W. W o l f, *Große Abweichungen im zentralen Grenzwertsatz*, Wiss. Z. Techn. Univ. Dresden (1975), pp. 393–398.
- [8] —, *On the probability of large deviations in the case where Cramér's condition is not satisfied*, Math. Nachr. (1976), pp. 197–215 (in Russian).
- [9] —, *Asymptotische Entwicklungen für Wahrscheinlichkeiten großer Abweichungen*, Preprints TU Dresden Sektion Mathematik 07-01-76, 07-02-76; Z. Wahrscheinlichkeitstheorie und verw. Gebiete (in print 1977).

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### ROBUSTNESS: A QUANTITATIVE APPROACH

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According to Box and Anderson [1] who introduced the notion, a test is “robust” if it is “sensitive to change, of a magnitude likely to occur in practice, in extraneous factors”. Furthermore, a test is said to be “powerful” if it is “sensitive to change in the specific factor tested”. In the note a real valued function on the parameter space of a statistical problem is constructed which measures robustness of a test similarly as the power function measures its “sensitivity to change in the factor tested”.

More precisely, given a statistical structure  $M_0 = (\mathcal{X}, \mathcal{A}, \mathcal{P}_0)$ ,  $\mathcal{P}_0 \subset \mathcal{P}$ ,  $\mathcal{P}$  being the set of all probability measures on  $\mathcal{A}$ , we will use a larger structure  $M_1 \supset M_0$  to express “changes, of a magnitude likely to occur in practice, in extraneous factors”. Let  $\pi: \mathcal{P}_0 \rightarrow 2^{\mathcal{P}}$  be a function such that  $\pi(P) \ni P$  and define  $M_1 = (\mathcal{X}, \mathcal{A}, \mathcal{P}_1)$  with  $\mathcal{P}_1 = \bigcup_{P \in \mathcal{P}_0} \pi(P)$ . Let  $t$  be a fixed statistic and  $q$  a real valued function on  $\mathcal{P}_1$ ,  $\mathcal{P}_1^t = \{P^t(\cdot) = P((t^{-1}(\cdot)))$ ,  $P \in \mathcal{P}_1\}$ . A function  $r_t: \mathcal{P}_0 \rightarrow R^1$  defined as

$$r_t(P) = \sup\{q(Q^t): Q \in \pi(P)\} - \inf\{q(Q^t): Q \in \pi(P)\}$$

is called  $q$ -robustness of the statistic  $t$  in the extension  $M_1$  of  $M_0$ .

EXAMPLE. Let  $d$  be a metric in the space  $\mathcal{P}$  and for a given statistic  $t$  let  $d_t$  be a metric in  $\mathcal{P}^t$ . For a given statistical structure  $M_0 = (\mathcal{X}, \mathcal{A}, \mathcal{P}_0)$  consider  $M_1$  defined as  $\varepsilon$ -extension of  $M_0$  constructed by the mapping  $\pi(P) = \{Q \in \mathcal{P}: d(P, Q) < \varepsilon\}$ . The distribution-robustness of the statistic  $t$  in  $\varepsilon$ -extension of  $M_0$  is given by

$$r_{t,\varepsilon}(P) = \sup\{d_t(P^t, Q^t): Q \in \pi(P)\},$$

A qualitative Hampel's [2] definition of robustness is:  $t$  is robust in a neighbourhood of  $P$  if for any  $\delta > 0$  there exists  $\varepsilon > 0$  such that  $r_{t,\varepsilon}(P) < \delta$ ;  $t$  is robust in the structure  $M_0$  if for any positive  $\delta$  there exists  $\varepsilon > 0$  such that  $\sup_{\mathcal{P}_0} r_{t,\varepsilon}(P) < \delta$ .

The full text containing some further discussion and examples (power-robustness of the two-sided Student test with respect to change of variance; a risk-robustness of sample mean and sample median in estimating expected value of a normal dis-

tribution; power-robustness of a test with respect to unequal probabilities in Bernoulli trials; size-robust tests) appeared in [3].

### References

- [1] G. E. P. Box and S. L. Anderson, *Permutation theory in the derivation of robust criteria and the study of departures from assumptions*, J. Roy. Statist. Soc. Ser. B 17 (1955), pp. 1–34.  
 [2] F. R. Hampel, *A general qualitative definition of robustness*, Ann. Math. Statist. 42 (1971), pp. 1887–1896.  
 [3] R. Zieliński, *Robustness: A quantitative approach*, Bull. Acad. Pol. Sci., Sér. math., astr. et phys. 25(1977), pp. 1281–1286.

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## COMPLETENESS FOR A FAMILY OF NORMAL DISTRIBUTIONS

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### 1. Introduction

In this paper the problem of completeness of minimal sufficient statistics for a family of multivariate normal distributions  $\mathcal{P} = \{N(\mu, \Sigma): \mu \in \mathcal{X}, \Sigma \in \mathcal{V}\}$  is considered. Here  $\mathcal{X}$  is a subspace of  $n$ -dimensional Euclidean space  $R^n$  and  $\mathcal{V}$  is a set of  $n \times n$  positive definite matrices containing non-empty open set relative to the  $\text{sp } \mathcal{V}$  (the smallest linear space containing  $\mathcal{V}$ ).

For special cases this problem has been considered by Graybill and Hultquist [1] and Seely [3], [4].

### 2. Minimal sufficient statistics

Without loss of generality we assume that the identity operator  $I$  belongs to  $\mathcal{V}$ . Let  $\mathcal{W} = \{\Sigma^{-1}: \Sigma \in \mathcal{V}\}$  and let  $W_1, \dots, W_k$  form a basis for  $\text{sp } \mathcal{W}$ . Then for  $W \in \mathcal{W}$  we have

$$(1) \quad W = \sum_{i=1}^k w_i(\Sigma) W_i,$$

where  $w(\Sigma) = (w_1(\Sigma), \dots, w_k(\Sigma))'$  is the vector of linearly independent functions from  $\mathcal{W}$  to  $R^1$ . Let  $\mathcal{B}$  be the smallest subspace of  $R^n$  such that  $\Sigma^{-1}\mathcal{X} \subset \mathcal{B}$  for all  $\Sigma \in \mathcal{V}$ . Note that  $\mathcal{X} \subset \mathcal{B}$ , because  $I \in \mathcal{V}$ . Let  $x_1, \dots, x_p$  and  $x_1, \dots, x_p, x_{p+1}, \dots, x_r$  be a basis for  $\mathcal{X}$  and  $\mathcal{B}$ , respectively. Moreover, let for  $\mu \in \mathcal{X}$  and  $\Sigma \in \mathcal{V}$ ,  $f(y|\mu, \Sigma)$  denote the  $N(\mu, \Sigma)$  density functions with respect to Lebesgue's measure.

LEMMA 1. *The functions  $T(y) = (x_1'y, \dots, x_r'y)'$  and  $W(y) = (y'W_1y, \dots, y'W_ky)$  are minimal sufficient statistics for  $\mathcal{P}$ .*

*Proof.* Let  $R$  denote the  $n \times r$  matrix  $[x_1 \dots x_r]$ . Since  $R(R'R)^{-1}R'$  is the orthogonal projection on  $\mathcal{B}$ , we have

$$\Sigma^{-1}\mu = R(R'R)^{-1}R'\Sigma^{-1}\mu = Ra(\Sigma, \mu),$$