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Asymptotic Multinormality and Remainder Terms of Linear Rank Vectors Under Alternatives

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## 0. Summary

Asymptotic multinormality of linear rank statistics based on independent vector valued random variables is obtained. Under suitable assumptions, weak estimates for the remainder terms for convergence to normality are also obtained. Results on asymptotic normality are related to Hajek (1968) and Puri and Sen (1969). Results on the remainder terms are related to those of Jurečkova and Puri (1975), Bergström and Puri (1977), and Huškova (1977).

## 1. Preliminaries

Let  $\underline{x}_{Ni} = (x_{Ni}^{(1)}, \dots, x_{Ni}^{(p)})'$ , i=1,..., N be a sequence of independent p-variate (p ≥ 1) random vectors having continuous cumulative distribution functions (cdf)  $F_{Ni}(\underline{x})$ ,

 $x = (x^{(1)}, \dots, x^{(p)})'$ , i=1,..., N respectively. Consider now the random matrix  $\underline{X}_{N}$  corresponding to  $(\underline{X}_{N1}, \dots, \underline{X}_{NN})$ , i.e.,

(1.1)

 $\underline{x}_{N} = ((\underline{x}_{Ni}^{(v)}))_{\substack{i=1,...,N;\\v=1,...,p}}; \underline{x}_{Ni} = (\underline{x}_{Ni}^{(1)},...,\underline{x}_{Ni}^{(p)})'$ 

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and observe that each row of  $\chi_N$  is composed of N independent univariate random variables. Let  $R_{Ni}^{(\nu)}$  be the rank of  $\chi_{Ni}^{(\nu)}$  among  $(\chi_{N1}^{(\nu)}, \ldots, \chi_{NN}^{(\nu)})$  for each  $\nu = 1, \ldots, p$ . Then corresponding to the observation matrix  $\chi_N$ , we have a rank collection matrix  $R_N$ , where

(1.2) 
$$R_{Ni} = ((R_{Ni}^{(v)}))$$
  
 $\sim N = ((R_{Ni}^{(v)}))$   
 $i=1,...,N;$   
 $v=1,...,p.$ 

Consider now p sets of scores  $(a_{Ni}^{(\nu)}, 1 \le i \le N), 1 \le \nu \le p$ generated by known functions  $\varphi_{V}$ :  $(0,1) \rightarrow R$  in either of the following ways:

(1.3) 
$$a_{Ni}^{(v)} = \varphi_{v} (i/(N+1), i=1,...,N; v=1,...,p)$$

 $a_{Ni}^{(v)} = E\phi_v(U_N^{(i)}), i=1,...,N; v=1,...,p$ where  $U_N^{(i)}$  is the i<sup>th</sup> order statistic in a random sample of size N from the uniform distribution over (0,1). Consider

now the simple linear rank vector  $S_N$  corresponding to  $X_N$  (or  $R_N) where$ 

$$S_{N} = (S_{N}^{(1)}, \dots, S_{N}^{(p)}) , S_{N}^{(v)} = \sum_{i=1}^{N} C_{Ni}^{(v)} a_{N}^{(v)} (R_{Ni}^{(v)}), 1 \le v \le p$$

and where  $(C_{Ni}^{(v)}, 1 \le i \le N), 1 \le v \le p$  are p-sets of known (regression) constants.

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In the next section we establish the asymptotic normality of  $S_N$  by following the methods of Chernoff-Savage (1958) and Puri-Sen (1971). For a different approach, see Hajek (1968) and Puri-Sen (1969). In Section 3 we obtain the estimates for the order of normal approximation for  $S_N$ . This constitutes the generalizations of the results of Jurečková-Puri (1975), Bergstrom-Puri (1977), Puri-Rajaram (1977), and Hušková (1977b) where the problems are treated in the univariate set-ups. The multivariate extensions in the generality of our paper do not appear to exist in the literature so far. (For a rather special multivariate case, the reader is referred to Hušková (1977a)).

<u>Asymptotic Normality of</u>  $S_N$ . We now establish the asymptotic 2. normality of  $S_N$  defined in (1.5). We make the following assumptions: 6 \_3/2 8 -13

(2.1) 
$$|\phi_{v}(t)| \leq K\{(1-t)\}$$
,  $|\phi_{v}'(t)| \leq K\{t(1-t)\}$ ; 0\max\_{Ni} |c\_{Ni}^{(v)}|

 $= 0(N^{\frac{1}{2}}), 1 \le v \le p$ 8.,

where

(2.3)

 $g_{v}^{2} = \text{Var } S_{N}^{(v)}, 1 \leq v \leq p$ For convenience we shall take  $S_N = \left(\frac{S_N^{(1)}}{S_1}, \dots, \frac{S_N^{(p)}}{S_n}\right)$ , where the  $\mathbf{s}_{v}$ 's are given by (2.3).

We then have the following theorem.

Theorem 2.1 Let the scores  $a_{Ni}^{(\vee)}$ ,  $1 \le \nu \le p$  be defined by (1.3). Then, under the assumptions (2.1) and (2.2), for every vector  $\lambda \quad \underline{in} \quad \mathbb{R}^{p}, \quad \lambda' (\underline{s}_{N} - \underline{u}_{N}) / (\underline{\lambda}' \underline{v}_{N} \underline{\lambda})^{\frac{1}{2}} \quad \underline{has asymptotically} \quad (as \quad N \rightarrow \infty)$ the n(0,1) distribution where  $u_N$  and  $v_N$  are defined by

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(2.4) 
$$\underline{\mu}_{N} = (\underline{\mu}_{N}^{(1)}, \dots, \underline{\mu}_{N}^{(p)})', \ \underline{\mu}_{N}^{(v)} = \sum_{i=1}^{N} C_{Ni}^{(v)} \int_{-\infty}^{\infty} \varphi_{v}(H^{(v)}(\mathbf{x}) dF_{Ni}^{(v)}(\mathbf{x}), 1 \leq v \leq p)$$

(2.5) 
$$H^{(\nu)}(x) = N^{-1} \sum_{i=1}^{N} F_{Ni}^{(\nu)}(x); F_{Ni}^{(\nu)}(x) = P(X_{Ni}^{(\nu)} \le x), 1 \le \nu \le p$$

(2.6) 
$$\mathbf{v}_{\underline{\mathbf{N}}} = \left( \left( \frac{\mathbf{g}_{\underline{\mu}\nu}}{\mathbf{g}_{\underline{\mu}}\mathbf{g}_{\nu}} \right) \right) , \mathbf{1} \leq \mu, \nu \leq p$$

and

and

 $I(x \le y) = 1$  if  $x \le y$ , and 0 otherwise

Proof:

Let  $(a_1, a_2, \dots, a_p)$  be a set of fixed but arbitrary constants. By the Cramer-Wold criterion, it suffices to show that

(2.10) 
$$\sum_{\nu=1}^{p} \alpha_{\nu} \frac{s_{N}^{(\nu)}}{s_{\nu}} = U_{N}, \text{ say is asymptotically normal.}$$

We introduce the following representation for  $S_N^{(\nu)}$ . Let

(2.11) 
$$H_{N}^{(v)}(x) = N^{-1} \sum_{i=1}^{N} I(X_{Ni}^{(v)} \le x)$$

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$$H^{(\nu)}(\mathbf{x}) \text{ is already defined. (See (2.4) above.)}$$

$$(2.12) \quad C_{N}^{(\nu)}(\mathbf{x}) = \sum_{i=1}^{N} C_{Ni}^{(\nu)} \text{ I } (\mathbf{x}_{Ni}^{(\nu)} \le (\mathbf{x}))$$

$$(2.13) \quad C^{(\nu)}(\mathbf{x}) = \sum_{i=1}^{N} C_{Ni}^{(\nu)} F_{Ni}^{(\nu)}(\mathbf{x}) = E[C_{N}^{(\nu)}(\mathbf{x})]$$

We shall adhere to the convention of denoting stochastic variables  $(H_N^{(\nu)}, C_N^{(\nu)})$  with subscripts and non-random functions  $(H^{(\nu)}, C^{(\nu)})$ without subscripts, although depending upon N. Then the following inequalities are immediate: (2.14)  $|C_N^{(\nu)}(x)| \le N \max_{1\le i\le N} |C_{Ni}^{(\nu)}| H_N^{(\nu)}(x)$ (2.15)  $|C^{(\nu)}(x)| \le N \max_{1\le i\le N} |C_{Ni}^{(\nu)}| H^{(\nu)}(x), 1 \le \nu p$ We shall use the representation.

(2.16) 
$$s_{N}^{(\nu)} = \int_{-\infty}^{\infty} \varphi_{\nu} \left( \frac{N}{N+1} H_{N}^{(\nu)}(x) \right) dC_{N}^{(\nu)}(x) = \mu_{N}^{(\nu)} + \beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)} + \frac{3}{\Sigma} D_{jN}^{(\nu)}$$
  
where  $\mu_{N}^{(\nu)}$  is given by (2.3).

$$(2.17) \quad \beta_{1N}^{(\nu)} = \int_{-\infty}^{\infty} \varphi_{\nu} (H^{(\nu)}(x)) d (C_{N}^{(\nu)}(x) - C^{(\nu)}(x))$$

$$(2.18) \quad \beta_{2N}^{(\nu)} = \int_{-\infty}^{\infty} (H_{N}^{(\nu)}(x) - H^{(\nu)}(x)) \varphi_{\nu}^{'} (H^{(\nu)}(x)) dC^{(\nu)}(x)$$

$$(2.19) \quad D_{1N}^{(\nu)} = \frac{-1}{N+1} \int_{-\infty}^{\infty} H_{N}^{(\nu)}(x) \varphi_{\nu}^{'} (H^{(\nu)}(x)) dC_{N}^{(\nu)}(x)$$

$$(2.20) \quad D_{2N}^{(\nu)} = \int_{-\infty}^{\infty} (H_{N}^{(\nu)}(x) - H^{(\nu)}(x)) \varphi_{\nu} (H^{(\nu)}(x)) d(C_{N}^{(\nu)}(x) - C^{(\nu)}(x))$$

$$(2.21) \quad D_{3N}^{(\nu)} = \int_{-\infty}^{\infty} \{\varphi_{\nu}(\frac{N}{N+1} - H_{N}^{(\nu)}(x)) - \varphi_{\nu}(H^{(\nu)}(x)) - (\frac{N}{N+1} - H_{N}^{(\nu)}(x) - H^{(\nu)}(x)) \} dC_{N}^{(\nu)}(x)$$

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Substituting (2.16) in (2.10), we have

(2.22) 
$$\mathbf{U}_{\mathbf{N}} = \sum_{\nu=1}^{\mathbf{p}} \frac{\alpha_{\nu}}{s_{\nu}} \left\{ \boldsymbol{\mu}_{\mathbf{N}}^{(\nu)} + \left(\boldsymbol{\beta}_{\mathbf{1N}}^{(\nu)} + \boldsymbol{\beta}_{\mathbf{2N}}^{(\nu)}\right) + \sum_{\mathbf{j}=1}^{3} \mathbf{D}_{\mathbf{jN}}^{(\nu)} \right\}$$

The proof will be accomplished if we show the following:

(A)  $\mu_{N}^{(v)}$  is finite. (B)  $\sum_{\nu=1}^{p} \alpha_{\nu} \frac{\left(\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)}\right)}{\mathbf{s}_{\nu}}$  is asymptotically normal. (C)  $\sum_{\nu=1}^{p} \frac{\alpha_{\nu}}{\mathbf{s}_{\nu}} \frac{3}{\sum_{j=1}^{p} D_{jN}^{(\nu)}} \rightarrow 0$  in probability.

Proof of (A): Observe that

$$|\mu_{N}^{(\nu)}| = |\int_{-\infty}^{\infty} \varphi_{\nu}(H^{(\nu)}(x)) dC^{(\nu)}(x)|$$
  
$$\leq N \max_{\substack{1 \leq i \leq N}} |C_{Ni}^{(\nu)}| \int_{-\infty}^{\infty} \varphi_{\nu}(H^{(\nu)}(x)) dH^{(\nu)}(x) < +\infty \text{ for each } N$$

by assumptions (2.1) and (2.15).

<u>Proof of (B)</u>: For a fixed v, we shall verify the Liapunov criterion for the normality of  $(\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)}) g_{\nu}^{-1}$  and then do the same

for the sum  $\sum_{\nu=1}^{p} \alpha_{\nu}(\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)}) g_{\nu}^{-1}$ , by an extension of the  $C_r$ -inequality.

In fact we do so separately for  $\beta_{1N}^{(\nu)} g_{\nu}^{-1}$  and  $\beta_{2N}^{(\nu)} g_{\nu}^{-1}$  and use the  $C_r$ -inequality.

Since we are considering a fixed v, we can drop the indexing variable v and simplify our notation substantially.

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Consider (2.18)

$$\beta_{2N} = \int_{-\infty}^{\infty} (H_N(x) - H(x)) \phi'(H(x)) dC(x)$$

Integration by parts yields,

(2.23) 
$$\beta_{2N} = B(x) \{H_N(x) - H(x)\} \Big|_{-\infty}^{+\infty} - \int_{-\infty}^{\infty} B(x) d(H_N(x) - H(x))$$

where

(2.24) 
$$B(x) = \int_{x_0}^{x} \phi'(H(x)) dC(x)$$
,  $x_0$  arbitrary but  $H(x_0) > 0$ 

We shall later prove that the first term in (2.23) is

$$O_p(g)$$
,  $g = g$ .

The second term of the same can be written as

(2.25) 
$$\int_{-\infty}^{\infty} B(x) d(H_{N}(x) - H(x)) N^{-1} \sum_{i=1}^{N} \left\{ B(X_{Ni}) - E (X_{Ni}) \right\}$$

We shall show that

 $(2.26)(SN)^{-(2+\epsilon)}\sum_{i=1}^{N} E|\beta(X_{Ni}) - E\beta(X_{Ni})|^{2+\epsilon} \to 0, \text{ as } N \to \infty \text{ for some } \epsilon > 0.$ 

In fact, it suffices to verify,

(2.27) 
$$(SN)^{(2+\epsilon)} \sum_{i=1}^{N} E|\beta(X_{Ni})|^{2+\epsilon} \rightarrow 0$$

which by the C, and Jensen inequalities implies (2.26).

Next, choose an  $\epsilon > 0$  such that  $(2 + \epsilon)(\delta - \frac{1}{2}) > -1$  for the  $\delta$  given by the constraints on  $\varphi$ . Then,

$$(2.28) (SN)^{-1} (2+\epsilon)^{N} \sum_{i=1}^{N} |\beta(X_{Ni})|^{2+\epsilon} = (SN)^{-1} (2+\epsilon) \sum_{i=1}^{N} E|B(X_{Ni})|^{2+\epsilon}$$

$$\leq (SN)^{-(2+\epsilon)} \sum_{i=1}^{N} N^{2+\epsilon} \max_{\substack{|x| \leq i \leq N}} |C_{Ni}|^{2+\epsilon} \int_{-\infty}^{\infty} |\int_{X_{0}}^{X} \varphi'(H(y)) dH(y)| dF_{Ni}(x)$$

$$= \{ \max_{\substack{|x| \leq N}} |\overline{S}^{1}| |C_{Ni}| \} \sum_{\substack{|x| = 1 \\ i = 1}}^{\infty} \int_{-\infty}^{\infty} \{ |\varphi(H(x))| + |\varphi(H(x_{0}))| \}^{2+\epsilon} dF_{Ni}(x)$$

$$= 0(N^{-\epsilon/2}) \int_{-\infty}^{\infty} \{ |\varphi(H(x))| + |\varphi(H(x_{0}))| \}^{2+\epsilon} dH(x) \neq 0, \text{ as } N \neq \infty.$$

because  $(2+\varepsilon)(\delta - \frac{1}{2}) > -1$  and  $\varphi(H(x_0))$  is a constant. Observe that we have used the fact  $\max_{\substack{nx \\ 1 \le i \le N}} \frac{|C_{Ni}|^{2+\varepsilon}}{g^{2+\varepsilon}} = O(N^{-1-\varepsilon/2})$ .

It remains to be shown that in (2.23),

$$\frac{\beta(\mathbf{x})}{g} \int_{-\infty}^{\infty} = \frac{B(\mathbf{x})}{g} \left\{ H_{\mathbf{N}}(\mathbf{x}) - H(\mathbf{x}) \right\} \left\{ \int_{-\infty}^{+\infty} = \circ_{\mathbf{p}}(1) \\ \left| \frac{\beta(\mathbf{x})}{g} \right| = \sqrt{N} \left| H_{\mathbf{N}}(\mathbf{x}) - H(\mathbf{x}) \right| \frac{1}{\sqrt{Ng}} \left| \int_{\mathbf{x}_{0}}^{\mathbf{x}} \varphi'(H(\mathbf{y})) \right| dH(\mathbf{y}) \right|$$

$$\leq \sqrt{N} \left| H_{\mathbf{N}}(\mathbf{x}) - H(\mathbf{x}) \right| 0(1) \left| \int_{\mathbf{x}_{0}}^{\mathbf{x}} \varphi'(H(\mathbf{y})) \right| dH(\mathbf{y}) \right|$$

 $\leq K \sqrt{N|H_N(x) - H(x)|} \{H(x)(1 - H(x))\}^{\delta^{-\frac{1}{2}}}$ 

since  $\varphi(H(x_0))$  is a constant.

By Puri-Sen (1971), given any  $\varepsilon$ ,  $\delta'$  positive, there is a constant  $C(\varepsilon, \delta')$  independent of N such that, with probability > 1- $\varepsilon$ ,

$$N^{\frac{1}{2}}|H_{N}(x) - H(x)| \leq C(\varepsilon, \delta') \left\{H(x)(1 - H(x))\right\}^{\frac{1}{2} - \delta'}$$
  
Thus,

$$\left|\overline{\mathfrak{g}}^{1}_{\beta}(\mathbf{x})\right| \leq K \left\{ H(\mathbf{x}) \left(1 - H(\mathbf{x})\right) \right\}^{\delta - \delta'} C(\varepsilon, \delta') \to 0$$

as  $x \rightarrow \pm \infty$ , by choosing  $0 < \delta' < \delta$ 

The verification of the Liapunov condition for  $\overline{s}^{1}\beta_{1N}$  is similar, in fact, easier and is therefore not given here. The

C -inequality yields the Liapunov condition for  $\overline{s}^{1}(\beta_{1N} + \beta_{2N})$ Consider next the normalized sum,

 $\sum_{\nu=1}^{p} \alpha_{\nu} \overline{s}_{\nu}^{1} (\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)}) .$ 

We need to verify the Liapunov condition for the above expression.

Let  $\sigma^2 = \operatorname{Var}\left(\sum_{\nu=1}^{p} \alpha_{\nu} \overline{s}_{\nu}^{1}(\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)})\right)$ .

We shall assume that  $\sigma^2$  is bounded away from zero for all N. (If not, the sum is trivially degenerate normal as  $N \rightarrow +\infty$ .)

Write 
$$\beta_{1N}^{(v)} + \beta_{2N}^{(v)} = \sum_{i=1}^{N} \beta_{Ni}^{(v)}$$

where  $\beta_{\text{Ni}}^{(\nu)}$  are independent random variables (as already done earlier). We have to show

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(2.29) 
$$\lim_{N \to \infty} \sigma^{-(2+\epsilon)} \sum_{\substack{i=1 \\ i=1}}^{N} E \left| \sum_{\substack{j=1 \\ j=1}}^{p} \alpha_{j} \frac{\beta_{Ni}}{g} \right| = 0$$

We have already shown that

(2.30) 
$$\lim_{N \to \infty} (g_{v})^{(2+\epsilon)} \sum_{i=1}^{N} |\beta_{i}|^{(v)}|^{2+\epsilon} = 0$$

(2.29) follows from (2.30) upon noting that there is a constant  $C(p,\epsilon)$ , depending only upon p and  $\epsilon$  such that

$$\mathbf{E} \left| \begin{array}{c} \mathbf{p} \\ \Sigma \\ \mathbf{v}=1 \end{array} \right|^{\left( \mathbf{v} \right)} \mathbf{s}_{\mathcal{V}}^{2+\epsilon} = \mathbf{C}(\mathbf{p},\epsilon) \begin{array}{c} \mathbf{p} \\ \Sigma \\ \mathbf{v}=1 \end{array} \left| \mathbf{a}_{\mathcal{V}}^{\prime} \delta_{\mathcal{V}} \right|^{2+\epsilon} = \left| \mathbf{B}_{\mathbf{N}\mathbf{i}}^{(\mathbf{v})} \right|^{2+\epsilon}$$

(Generalized  $C_r$ -inequality.)

This establishes (B). We note that  $\varepsilon$  depends only upon  $\delta$  and hence the same choice of  $\varepsilon$  works for all  $\nu$  .

Proof of (C): Recall that we have to establish

$$\sum_{\nu=1}^{p} \alpha_{\nu} s_{\nu}^{-1} \sum_{j=1}^{3} D_{jN}^{(\nu)} = o_{p}^{(1)}.$$

Clearly, it suffices to prove for a particular v since we have a finite sum (1,...,p). Again, we shall drop the index v.

Consider, 
$$|\overline{g}^{1}D_{1N}| = |-(N+1)\overline{g}^{1}| \int_{-\infty}^{\infty} H_{N}(x) \varphi'(H(x)) dC_{N}(x)|$$
  

$$\leq (gN)\overline{b} \sum_{\Sigma} |\varphi'(H(X_{Ni}))| C_{Ni}| = \frac{1}{N} \sum_{i=1}^{N} V_{Ni}$$

where

$$V_{Ni} = |\phi'(H(X_{Ni})) \ \bar{s}^{1} C_{Ni}| .$$

To prove

 $\sum_{\substack{\Sigma \\ i=1}}^{N} V_{Ni} \rightarrow 0 \quad \text{in probability,}$ 

it suffices to show that

N  $\Sigma \tilde{N}^{\alpha} E |V_{Ni}|^{\alpha} < +\infty$ , for all N, for some  $\alpha$ ,  $0 < \alpha < 1$ . i=1

(By particular case 1°, page 241, Loéve (1963)).

Take 
$$\alpha = 2/3$$
:  
 $\mathbf{N}^{-2/3} \sum_{i=1}^{N} E|V_{Ni}|^{2/3} \le K \mathbf{N}^{-2/3} \sum_{i=1}^{N} |\frac{C_{Ni}}{g}|^{2/3} E|H(X_{Ni})(1 - H(X_{Ni}))|^{(\delta - 3/2)}$ 

$$\leq N^{1/3} \max_{\substack{1 \leq i \leq N}} (g^{-1} | C_{Ni} |)^{2/3} \sum_{i=1}^{N} \int_{-\infty}^{\infty} \{H(x) (1 - H(x))\}^{\frac{20}{3} - 1} dF_{Ni}(x)$$

$$= K \cdot 0(1) \int_{-\infty}^{\infty} \{H(x) (1 - H(x))\}^{\frac{2\delta}{3} - 1} dH(x) < +\infty ;$$

where we have used the fact that

$$\max_{1 \le i \le N} |\overline{s}^{1}C_{Ni}|^{2/3} = O(N^{-1/3}) .$$

Consider next,

$$D_{2N} = \int_{-\infty}^{\infty} (H_{N}(x) - H(x))_{\varphi}' (H(x)) d(C_{N}(x) - C(x))$$

By Puri-Sen (1971), given any  $\varepsilon > 0$ ,  $0 < \delta' < \frac{1}{2}$ , there is a constant  $C(\varepsilon, \delta')$ , independent of N such that with probability  $> 1 - \varepsilon$ ,

$$N^{\frac{1}{2}}|H_{N}(x) - H(x)| < C(\varepsilon, \delta') \left\{H(x)(1 - H(x))\right\}^{\frac{1}{2}-\delta'}$$

Thus with probability  $> 1 - \epsilon$ ,

$$|H_{N}(x) - H(x)|_{\phi}'(H(x))| \leq KC(e, \delta') N^{\frac{1}{2}} \{H(x)(1 - H(x))\}^{\delta''-1}$$

taking  $\delta' < \delta$  and setting  $\delta^* = \delta - \delta'$ .

It suffices to show that

$$\overline{s}^{1} \overline{N}^{\frac{1}{2}} \int_{-\infty}^{\infty} \left\{ H(x) \left( 1 - H(x) \right) \right\}^{\delta^{*} - 1} d(C_{N}(x) - C(x)) \to 0 \quad \text{in probability.}$$

We shall use the Liapunov criterion for degenerate convergence (page 275, Loeve (1963)).

$$\overline{g}^{1} \overline{N}^{\frac{1}{2}} \int_{-\infty}^{\infty} \left\{ H(x) (1 - H(x)) \right\}^{\delta^{*} - 1} dC_{N}(x)$$

$$= \overline{g}^{1} \overline{N}^{\frac{1}{2}} \sum_{i=1}^{N} C_{Ni} \left\{ H(X_{Ni}) (1 - H(X_{Ni})) \right\}^{\delta^{*} - 1}$$

Set

$$v_{\rm Ni} = N^{\frac{1}{2}} g^{-1} C_{\rm Ni} \left\{ H(X_{\rm Ni}) (1 - H(X_{\rm Ni})) \right\}^{\delta^{*-1}}$$

Then,

$$\overline{g}^{1} \overline{N}^{\frac{1}{2}} \sum_{i=1}^{N} C_{Ni} \left\{ H(X_{Ni}) \left( 1 - H(X_{Ni}) \right) \right\}^{\delta^{\frac{1}{2}} - 1} = \overline{N}^{-1} \sum_{i=1}^{N} V_{Ni}$$

It remains to prove,  $N^{-1} \sum_{i=1}^{N} (V_{Ni} - EV_{Ni}) \rightarrow 0$  in probability. i=1 This will be accomplished if we can show that for some  $\alpha > 0$ ,

(2.31) 
$$\overline{N}^{(1+\alpha)} \sum_{i=1}^{N} E |V_{Ni}|^{1+\alpha} \neq 0$$

Choose  $\alpha > 0$  such that,  $(1 + \alpha)(\delta^* - 1) > -1$ ; that is,  $0 < \alpha < \frac{\delta^*}{1 - \delta^*}$ . Then,

$$\begin{split} & \bar{N}^{(1+\alpha)} \sum_{\substack{i=1\\i=1}}^{N} E |V_{Ni}|^{1+\alpha} \\ & \leq \bar{N}^{1(1+\alpha)} |\frac{\sqrt{N \max |C_{Ni}|}}{\frac{1 \leq i \leq N}{3}} |\frac{1+\alpha}{1 \leq i \leq N} | \frac{N}{\sum_{i=1}^{N} E \left\{ H(X_{Ni}) (1-H(X_{Ni})) \right\}^{(1+\alpha)(\delta^{*}-1)}}{\sum_{i=1}^{N} E \left\{ H(X_{Ni}) (1-H(X_{Ni})) \right\}^{(1+\alpha)(\delta^{*}-1)}} \\ & = O(1) \bar{N}^{\alpha} \int_{0}^{\infty} \left\{ H(x) (1-H(x)) \right\}^{(1+\alpha)(\delta^{*}-1)} dH(x) = O(N^{-\alpha}) \end{split}$$

which proves (2.31).

Next consider

$$\overline{g}^{\frac{1}{2}}D_{3N} = \overline{g}^{1} \int_{-\infty}^{\infty} \left\{ \varphi\left(\frac{NH_{N}(x)}{N+1}\right) - \varphi\left(H(x)\right) - \left(\frac{NH_{N}(x)}{N+1} - H(x)\right) \varphi'(H(x)) \right\} dC_{N}(x) .$$

We have to show that  $S^{-1}D_{3N} \rightarrow o$  in probability.

The following substitution will simplify the proof. Let

(2.32) 
$$C_{3N} = \frac{D_{3N}}{g \sqrt{N}}$$

Then it suffices to prove  $C_{3N} = O_p(N^{-\frac{1}{2}})$ 

Observe that, since  $\max_{\substack{l \le i \le N}} |\frac{C_{Ni}}{\sqrt{NS}}| = O(N^{-1})$ 

we have

$$\leq 0(1) \int_{-\infty}^{\infty} \left| \varphi \left( \frac{N}{N+1} H_{N}(x) \right) - \varphi \left( H(x) \right) - \left( \frac{N H_{N}(x)}{N+1} - H(x) \right) \varphi' \left( H(x) \right) \left| d H_{N}(x) \right| \right|$$

The proof that the right hand side of (2.36) is  $\circ_p(N^{-\frac{1}{2}})$  can be found in Puri-Sen (1971), pages 401-405.

This proves Theorem 2.1.

For a different approach, as well as the derivation of some tests for linear hypothesis based on  $S_N$ , see Puri-Sen (1969).

<u>Computation of</u>  $V_N$ : It is clear that the variance contribution is from the term  $\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)}$ . It is easy to check that

(2.34) 
$$\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)} = \sum_{i=1}^{N} \left\{ A_{Ni}^{(\nu)} (X_{Ni}^{(\nu)}) - E A_{Ni}^{(\nu)} (X_{Ni}^{(\nu)}) \right\}$$

where

$$A_{Ni}^{(\nu)}(x) = \frac{1}{N} \sum_{j=1}^{N} (C_{Ni}^{(\nu)} - C_{Nj}^{(\nu)}) \int_{x_{0}}^{x} \varphi_{\nu}^{(H^{(\nu)}(y))} dF_{Nj}^{(\nu)}(y) ; x_{0} \text{ arbitrary.}$$

Centering  $A_{Ni}^{(v)}(x)$  at its expectations, we note that

(2.35) 
$$\beta_{1N}^{(\nu)} + \beta_{2N}^{(\nu)} = \sum_{i=1}^{N} A_{Ni}^{(\nu)} (X_{Ni}^{(\nu)})$$

where

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$$A_{Ni}^{(v)}(x) = \frac{1}{N} \sum_{j=1}^{N} (C_{Ni}^{(v)} - C_{Nj}^{(v)}) \int_{-\infty}^{\infty} \{I(x \le y) - F_{Ni}^{(v)}(y)\} \varphi_{v}'(H^{(v)}(y)) dF_{Nj}^{(v)}(y)$$

which yields the desired approximation (2.7).

We next give a corollary which extends these results to the case when the scores are generated according to (1.7)(b).

Corollary 2.2: Let  $\varphi_{V}$  be the inverse of a distribution function. Let  $S_{N}^{*}$  be the linear rank vector defined as in (1.8) but with the scores generated according to (1.4). Then, under the conditions of Theorem 2.1,  $S_{N}^{*}$  is asymptotically multinormal with the same parameters  $\psi_{N}$  and  $V_{N}$ .

Proof: Let

(2.36) 
$$s_{N}^{*} = \left(\frac{s_{N}^{*(1)}}{s_{1}}, \dots, \frac{s_{N}^{*(p)}}{s_{p}}\right)$$

Clearly, it suffices to prove (2.37)  $s_N^{*(v)} - s_N^{(v)} = o_p(\mathbf{s}_v)$ ,  $1 \le v \le p$ which then entails  $S_N^* - S_N \rightarrow 0$  in probability. Again, since v is fixed,  $1 \le v \le p$ , we shall drop this index. We define

(2.38) 
$$\varphi_{N}(t) = \sum_{i=1}^{[Nt]} (a_{N}(i) - a_{N}(i-1)), a_{N}(0) = 0, 0 < t < 1$$

where  $[\alpha]$  is the greatest integer not exceeding  $\alpha$ .

It is easy to check that

(2.39) 
$$S_N^* = \int_{-\infty}^{\infty} \varphi_N \left( \frac{N H_N(x)}{N+1} \right) dC_N(x)$$

The proof of Corollary 2.2 will be accomplished if we prove the following:

Lemma 2.3: Under the hypotheses of Theorem 2.1 and Corollary 2.2, we have

(i) 
$$\lim_{N \to +\infty} \varphi_{N}(t) = \varphi(t)$$
  
(ii) 
$$\left| \int_{-\infty}^{\infty} \left\{ \varphi_{N} \left( \frac{N}{N+1} H_{N}(x) \right) - \varphi \left( \frac{N}{N+1} H_{N}(x) \right) \right\} dC_{N}(x) \right\} = O_{p}(g)$$

<u>Proof of Lemma 2.3</u>: We shall only prove (ii) since the proof of (i) can be found in pages 408-409 of Puri-Sen (1971).

By inequality (2.14), we have

(2.40) 
$$\left|\int_{-\infty}^{\infty} \left\{\varphi_{N}\left(\frac{NH_{N}(x)}{N+1}\right) - \varphi\left(\frac{NH_{N}(x)}{N+1}\right)\right\} d C_{N}(x)\right|$$

$$\leq \max_{\substack{\mathbf{l} \leq \mathbf{i} \leq \mathbf{N}}} |C_{\mathbf{N}\mathbf{i}}| \sum_{\mathbf{i}=1}^{\mathbf{N}} |\varphi_{\mathbf{N}}(\frac{\mathbf{i}}{\mathbf{N}+1}) - \varphi(\frac{\mathbf{i}}{\mathbf{N}+1})| .$$

Hence it follows that

$$(2.41) \max_{\substack{1 \leq i \leq N}} \left| \frac{C_{Ni}}{g} \right| \sum_{\substack{i=1\\i=1}}^{N} \left| \varphi_{N} \left( \frac{i}{N+1} \right) - \varphi \left( \frac{i}{N+1} \right) \right|$$
$$= O(1) N^{-\frac{1}{2}} \sum_{\substack{i=1\\i=1}}^{N} \left| \varphi_{N} \left( \frac{i}{N+1} \right) - \varphi \left( \frac{i}{N+1} \right) \right| = A_{N}, \text{ say}$$

But,  $\lim_{N \to +\infty} A_{N} = 0$ , by Puri-Sen (1971), pages 409-411. This immediately entails  $\frac{S_{N} - S_{N}^{*}}{g} \rightarrow 0$  in probability, which proves Corollary 2.2.

A consequence of Corollary 2.2 is that in many cases of practical interest (such as the normal scores), asymptotic normality holds with the same centering sequence  $\mu_N$ , whether the scores are given by (1.3) or (1.4) . Thus theorem 2.1 and corollary 2.2 serve to unify the results of Hajek (1968) and Hoeffding (1973), and also to some extent simplify the results of the latter paper.

3. <u>Remainder Terms of</u>  $S_N$ : In this section, we obtain an estimate for the remainder in the normal approximation to  $S_{\sim N}$ 

Recall that we can write

(3.1) 
$$\underset{\sim}{\mathbf{S}_{\mathbf{N}}} - \underset{\sim}{\boldsymbol{\mu}_{\mathbf{N}}} = \underset{i=1}{\overset{\mathbf{N}}{\Sigma}} \underset{\sim}{\overset{\mathbf{A}_{\mathbf{N}i}}{\overset{\mathbf{N}}{\sim}}} (\mathbf{X}_{\mathbf{N}i}) + \underset{\sim}{\overset{\mathbf{D}}{\sim}} \mathbf{N}$$

where

Normalization by  $g_v$  is of no consequence and was introduced there merely to simplify the details of the proof. We shall not use it here.

We shall simplify the notation somewhat and also express it in a form so that we can use Corollary 17.2, page 165 of Bhattacharya-Ranga Rao (1976).

We can write,

(3.3) 
$$\underline{T}_{Ni} = N^{\frac{1}{2}} \underline{A}_{Ni}(X_{Ni})$$
,  $V_{i} = Cov(\underline{T}_{Ni})$ .

Then,

(3.4) 
$$S_{N} = N^{-\frac{1}{2}} \sum_{i=1}^{N} \mathcal{I}_{Ni} + \mathcal{D}_{N}$$

Let

(3.5) 
$$V = N^{-1} \sum_{i=1}^{N} V_i$$
.

Comparing (3.5) to (2.7) and (2.8), it is clear that the elements of V are  $g_{\mu\nu}$ . Let, for  $x = (x^{(1)}, \dots, x^{(p)})$ ,

(3.6) 
$$F_{N}(\underline{x}) = P(S_{N}^{(1)} - \mu_{N}^{(1)} \le x^{(1)}, \dots, S_{N}^{(p)} - \mu_{N}^{(p)} \le x^{(p)})$$

We then have the following theorem:

Theorem: Let the conditions of Theorem 2.1 be satisfied. Let in addition,

(3.7) Sup 
$$|\phi_{v}(t)| = ||\phi_{v}|| < +\infty$$
,  $1 \le v \le p$ ,  
 $0 \le t \le 1$ 

and V be positive definite.

(3.8) 
$$\sup_{\substack{x \in \mathbb{R}^{p}}} |F_{N}(x) - \Phi_{0,v}(x)| \le C(p) \lambda^{-3/2} \rho_{3} N^{-\frac{1}{2}} + \Delta_{N}$$

where

(3.9)  $\Phi_{0,v}(x)$  is the distribution function (p-variate) of a Gaussian random vector with mean 0 and dispersion matrix V; (3.10)  $\lambda =$ smallest eigenvalue of V;

(3.11)  $\rho_3 = \frac{1}{N} \sum_{i=1}^{N} E \| T_{Ni} \|^3$ , the norm being the euclidean norm;

and  $A_N \rightarrow 0$  pointwise.

Furthermore

(3.12)  $\mathbf{N}^{\frac{1}{2}}\Delta_{\mathbf{N}} = O_{\mathbf{p}}\left(\sum_{\nu=1}^{\mathbf{p}} \|\boldsymbol{\varphi}_{\nu}\| \mathbf{s}_{\nu}^{-1}\left[\sum_{i=1}^{\mathbf{N}} |\mathbf{c}_{\mathbf{N}i}^{(\nu)}|\right]\right)$ 

<u>Remark</u>. Since  $\Delta_N \rightarrow 0$ , it would be of interest to have an estimate for the fluctuations of  $\Delta_N$ . But in view of the generality of the situation and the fact that we are dealing with the multivariate set up, it is not easy to secure a purely numerical estimate. (3.12) gives a probabilistic bound. The problem of obtaining a sharp bound remains open.

<u>Proof</u>: Writing  $T_N = N^{\frac{1}{2}} \sum_{i=1}^{N} T_{Ni}$ , we have

 $(3.13) \quad \underset{\sim}{\mathbb{S}}_{\mathbb{N}} - \underset{\sim}{\mathbb{H}}_{\mathbb{N}} = \underset{\sim}{\mathbb{T}}_{\mathbb{N}} + \underset{\sim}{\mathbb{D}}_{\mathbb{N}} .$ 

Let  $G_N$  be the distribution function (p-variate) of  $\underline{T}_N$ . Then (3.14)  $F_N(\underline{x}) = G_N(\underline{x} - \underline{D}_N)$ .

Hence,

$$(3.15) |F_{N}(x) - \Phi_{0,v}(x)| \le |G_{N}(x - D_{N}) - \Phi_{0,v}(x - D_{N})| + |\Phi_{0,v}(x - D_{N}) - \Phi_{0,v}(x)|$$

We estimate the two quantities on the right hand side separately.

First, an application of Corollary 17.2 (page 172) of Bhattacharya-Ranga Rao (1976) yields,

(3.16) 
$$|G_N(x - D_N) - \phi_{0,v}(x - D_N)| \le C(p) \lambda^{-3/2} \rho_3 N^{-\frac{1}{2}}$$
  
uniformly in x, wherein all the quantities have already been  
defined.  $||g'|| < +\infty$  ensures the existence of  $\rho_2$ .

Estimating the second term is rather more involved. However, since  $\Phi_{0,v}$  is continuous, the convergence of the distribution functions is uniform and hence

(3.17)  $\sup_{\mathbf{x}\in\mathbf{IR}^{\mathbf{p}}} | \mathbf{\hat{e}}_{0,\nu} (\mathbf{x} - \mathbf{D}_{\mathbf{N}}) - \mathbf{\hat{e}}_{0,\nu} (\mathbf{x}) | = \Delta_{\mathbf{N}}$ 

converges to zero pointwise. We only need to obtain (3.12).

Note that, by the Mean Value Theorem (in  $\mathbb{R}^p$ ), there is a point  $\xi$  on the Line segment joining  $x - D_N$  and x such that

(3.18)  $\Phi_{0,\nu}(\underline{x}) - \Phi_{0,\nu}(\underline{x} - \underline{D}_{N}) = \underline{D}_{N}' L(\underline{g})$ 

where  $L(\xi)$  is the differential of  $\Phi_{0,v}$  at  $\xi$ .

Next, for the right hand side of (3.18), we have

(3.19) 
$$\mathbf{D}_{\mathbf{N}} \mathbf{L}(\underline{\mathbf{g}}) = \sum_{\nu=1}^{\mathbf{p}} \mathbf{D}_{\mathbf{N}}^{(\nu)} \frac{\delta}{\delta \mathbf{x}^{(\nu)}} \mathbf{e}_{0,\nu}(\underline{\mathbf{x}}) |$$
  
$$\mathbf{x} = \underline{\mathbf{g}}$$

Further, for each v,  $l \leq v \leq p$ , it is easy to check that

$$\left|\frac{\delta \Phi_{0,v}}{\delta x^{(v)}}\right|$$
 is dominated by the v<sup>th</sup> marginal density.

Hence, 
$$\left|\frac{\delta \Phi_{0,v}}{\delta x^{(v)}}\right| \leq \$_{v}^{-1}(2\pi)^{-\frac{1}{2}}$$

Consequently,

(3.19) 
$$|\Delta_{\mathbf{N}}| \leq \sum_{\nu=1}^{p} \mathbf{s}_{\nu}^{-1} |D_{\mathbf{N}}^{(\nu)}| (2\pi)^{-\frac{1}{2}}$$
.

Thus, (3.12) will be established if we show that for each  $\nu$ ,

(3.20) 
$$\sqrt{N} D_{N}^{(v)} = 0 (\|\varphi_{v}'\| \sum_{i=1}^{N} |C_{Ni}^{(v)}|)$$

Again, we shall drop the index v in the rest of the proof. Rearranging terms of  $D_N$ , we get,

$$(3.21) \quad D_{N} = \int_{-\infty}^{\infty} \left\{ \varphi \left( \frac{N}{N+1} H_{N}(x) \right) - \varphi \left( H(x) \right) \right\} dC_{N}(x)$$
$$- \int_{-\infty}^{\infty} \left( H_{N}(x) - H(x) \right) \varphi' \left( H(x) \right) dC(x) .$$

In order to simplify the proof, we shall drop the factor  $\frac{N}{N+1}$ . In view of the fact that  $\phi'$  is bounded, the conclusion will not be affected.

Consider  $\varphi(H_N(x)) - \varphi(H(x))$ . By the Mean Value Theorem,

$$\varphi(H_{N}(x)) - \varphi(H(x)) = (H_{N}(x) - H(x)) \varphi'(g_{N}(x))$$

for some \$ (\*).

Hence,

$$(3.22) | \sqrt{N} \int_{-\infty}^{\infty} (H_N(x) - H(x)) \varphi' (\xi_N(x)) dC_N(x) |$$
  
$$\leq ||\varphi'|| \int_{-\infty}^{\infty} \sqrt{N} |H_N(x) - H(x)| d|C_N|(x)$$

Let  $\varepsilon > 0$  be given. Then by Puri-Sen (1971), there is a constant  $C(\varepsilon)$  independent of N such that with probability  $> 1 - \varepsilon$ 

$$\sqrt{N|H_{N}(x) - H(x)|} < C(\varepsilon)$$
.

Thus in (3.22), with probability > 1 -  $\varepsilon$ ,

$$(3.23) \quad \left| \int \sqrt{N} \left( H_{N}(x) - H(x) \right) \varphi' \left( \xi_{N}(x) \right) dC_{N}(x) \right| \leq C(\epsilon) \left\| \varphi' \right\| \sum_{i=1}^{N} |C_{Ni}|$$

The proof of

(3.24) 
$$\left|\int_{-\infty}^{\infty} \sqrt{N} \left(H_{N}(x) - H(x)\right) \varphi'(H(x)) dC(x)\right| \leq C(\varepsilon) \|\varphi'\| \sum_{i=1}^{\infty} |C_{Ni}|$$

in probability is identical.

(3.23) and (3.24) establish (3.20) and (3.19), which in turn entail (3.12). The proof is completed.

<u>Remark</u>: From the expressions for  $g_{\mu\nu}$  and  $g_{\nu}^2$ , it is clear that  $\lambda$  is extremely hard to compute. Recall that  $\lambda$  is the smallest eigenvalue of the dispersion matrix V. However, if the components  $X_{Ni}^{(\nu)}$  of the vectors  $X_{Ni}$  satisfy the condition of "weak dependence" in the sense

(3.25) 
$$s_{\nu}^{2} - \sum_{\mu \neq \mu} |s_{\mu}| > 0$$
,  $\nu = 1, ..., p$ ;

the classical Grischgorin theorem (cf. Dahlquist-Björek, (1974)), permits us to replace  $\lambda$  by much simpler expression (3.25), assuming without loss of generality,  $\lambda > 0$ . If one is prepared to work numerically, much better estimates for  $\lambda$  can be obtained (op.cit. Dahlquist-Björck).

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