

CONVERGENCE OF REDUCED EMPIRICAL AND QUANTILE  
PROCESSES WITH APPLICATION TO FUNCTIONS OF  
ORDER STATISTICS IN THE NON-I.I.D. CASE<sup>1</sup>

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Any triangular array of row independent rv's having continuous df's can be transformed naturally so that the empirical and quantile processes of the resulting rv's are relatively compact. Moreover, convergence (to a necessarily normal process) takes place if and only if a simple covariance function converges pointwise. Using these results we derive the asymptotic normality of linear combinations of functions of order statistics of non-i.i.d. rv's in the case of bounded scores.

**1. Notation and results.** Let  $\alpha_{n1}, \dots, \alpha_{nn}, n \geq 1$  be a triangular array of row independent rv's having continuous df's  $F_{n1}, \dots, F_{nn}, n \geq 1$ . Let  $F_n$  denote the empirical df of  $\alpha_{n1}, \dots, \alpha_{nn}$ . Using the left continuous version of the inverse of a df, we let

$$(1.1) \quad \beta_{ni} = F_n(\alpha_{ni}) \quad \text{and} \quad G_{ni} = F_{ni} \circ F_n^{-1} \quad \text{where} \quad F_n = n^{-1} \sum_1^n F_{ni}.$$

Then  $\beta_{ni}$  has absolutely continuous df  $G_{ni}$  on  $[0, 1]$  (in fact  $|G_{ni}(t) - G_{ni}(s)| \leq n|t - s|$ ) and also

$$(1.2) \quad n^{-1} \sum_1^n G_{ni}(t) = t \quad \text{for} \quad 0 \leq t \leq 1.$$

Let  $G_n$  denote the empirical df of  $\beta_{n1}, \dots, \beta_{nn}$ ; we will call  $G_n$  the *reduced empirical* df of  $\alpha_{n1}, \dots, \alpha_{nn}$ . Define the *reduced empirical process*  $X_n$  by

$$(1.3) \quad X_n(t) = n^{\frac{1}{2}}[G_n(t) - t] \quad \text{for} \quad 0 \leq t \leq 1.$$

Clearly  $X_n$  has mean value function 0 by (1.2). Also, if we define

$$(1.4) \quad K_n(s, t) = s \wedge t - n^{-1} \sum_1^n G_{ni}(s)G_{ni}(t) \quad \text{for} \quad 0 \leq s, t \leq 1,$$

then  $K_n$  is the covariance function of the  $X_n$  process since

$$\begin{aligned} \text{Cov}[X_n(s), X_n(t)] &= n^{-1} \sum_1^n [G_{ni}(s) \wedge G_{ni}(t) - G_{ni}(s)G_{ni}(t)] \\ &= K_n(s, t). \end{aligned}$$

The *reduced quantile process*  $Y_n$  is defined by

$$(1.5) \quad Y_n(t) = n^{\frac{1}{2}}[G_n^{-1}(t) - t] \quad \text{for} \quad 0 \leq t \leq 1.$$

Expressions for the exact mean value and covariance function of  $Y_n$  would be difficult; but the asymptotic behavior of  $Y_n$  is simply related to that of  $X_n$ .

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We wish to consider the weak convergence ( $\Rightarrow$ ) of the  $X_n$  and  $Y_n$  processes. Let  $C$  denote the collection of all continuous functions on  $[0, 1]$ ; and let  $\rho(x, y) = \sup_t |x(t) - y(t)|$  for functions  $x$  and  $y$  on  $[0, 1]$  or  $(-\infty, \infty)$ . *Weak convergence* and *relative compactness* of processes on  $(C, \rho)$  is as defined in Billingsley (1968).

We will write  $X_n \rightarrow_{r.d.} X$  as  $n \rightarrow \infty$  if the *finite dimensional distributions* of the  $X_n$  process converge to those of the  $X$  process. We will write  $\rightarrow_e$  to denote convergence at every point of the probability space; call this *everywhere convergence*.

For technical reasons it is convenient to define  $\bar{X}_n$  to be that process on  $(C, \rho)$  that equals  $X_n$  at each  $t$  in  $[0, 1]$  corresponding to one of  $\beta_{n1}, \dots, \beta_{nn}$  and that is linear on the intervals between these observations. Note that  $X_n$  and  $Y_n$  are not processes on  $(C, \rho)$ .

The theorems below show that convergence of the  $X_n$  process is equivalent to pointwise convergence of  $K_n$ ; and the limiting process must necessarily be normal. Moreover,  $X_n$  converges if and only if  $Y_n$  does, and the limits are simply related.

**THEOREM 1.** (i) *For any triangular array of row independent rv's  $\alpha_{n1}, \dots, \alpha_{nn}$ ,  $n \geq 1$  having continuous df's  $F_{n1}, \dots, F_{nn}$ ,  $n \geq 1$  we have both*

$$\rho(X_n, \bar{X}_n) \leq n^{-\frac{1}{2}} \rightarrow 0 \quad \text{as } n \rightarrow \infty$$

and

$$\{\bar{X}_n : n \geq 1\} \text{ is relatively compact on } (C, \rho).$$

(ii) *If*

$$(1.6) \quad K_n(s, t) \rightarrow K(s, t) \quad \text{as } n \rightarrow \infty \text{ for all } 0 \leq s, t \leq 1$$

*for some function  $K$ , then there exists a normal process  $X$  having sample paths in  $C$  and covariance function  $K$  for which*

$$\bar{X}_n \Rightarrow X \quad \text{on } (C, \rho) \quad \text{as } n \rightarrow \infty.$$

(iii) *Conversely, if  $X_n \rightarrow_{r.d.} X$  as  $n \rightarrow \infty$ , then  $X$  is necessarily a normal process; and if  $K$  denote the covariance function of  $X$ , then (1.6) must hold.*

**THEOREM 2.** *Let  $F_{n1}, \dots, F_{nn}$ ,  $n \geq 1$  be a triangular array of continuous df's for which (1.6) holds. Then there exists a triangular array of row independent rv's  $\alpha_{n1}, \dots, \alpha_{nn}$ ,  $n \geq 1$  having df's  $F_{n1}, \dots, F_{nn}$ ,  $n \geq 1$  and there exists a normal process  $X$  with sample paths in  $C$  and covariance function  $K$  for which*

$$\rho(X_n, X) \rightarrow_e 0 \quad \text{as } n \rightarrow \infty$$

and

$$\rho(Y_n, -X) \rightarrow_e 0 \quad \text{as } n \rightarrow \infty.$$

*Moreover, all finite dimensional moments ( $E[X_n(t_1)^{m_1} \dots X_n(t_k)^{m_k}]$  with  $0 \leq t_1, \dots, t_k \leq 1$  and  $k, m_1, \dots, m_k$  integers) of  $X_n$  converge to the corresponding moments of the limiting  $X$  process as  $n \rightarrow \infty$ .*

A *Brownian bridge* is a normal process on  $(C, \rho)$  having mean value function 0 and covariance function  $s \wedge t - st$  for  $0 \leq s, t \leq 1$ .

COROLLARY 1. Let  $F_{n1}, \dots, F_{nn}, n \geq 1$  be a triangular array of continuous df's for which

$$(1.7) \quad (\max_{1 \leq i, j \leq n}) \rho(F_{ni}, F_{nj}) \rightarrow 0 \quad \text{as } n \rightarrow \infty .$$

There there exists a triangular array of row independent rv's  $\alpha_{n1}, \dots, \alpha_{nn}, n \geq 1$  having df's  $F_{n1}, \dots, F_{nn}, n \geq 1$  and there exists a Brownian bridge  $X$  for which

$$\rho(X_n, X) \rightarrow_e 0 \quad \text{and} \quad \rho(Y_n, -X) \rightarrow_e 0 \quad \text{as } n \rightarrow \infty .$$

REMARK 1. Koul (1970) uses the methods of Billingsley (1968) to generalize the usual result on weak convergence of the empirical process of Uniform (0, 1) rv's. We use a different technique (the introduction of  $S_n$  below bypasses Theorems 12.1 and 12.2 of Billingsley) on a special case of Koul's problem and obtain stronger and cleaner results for our  $X_n$  (we could have considered the more general problem). The parallel results on  $Y_n$  are new and should prove highly useful. Application to the limiting distribution of linear combinations of functions of order statistics in the non i.i.d. case (see Shorack (1972) for the i.i.d. case) is discussed in Section 3.

2. **Proofs.** See pages 33, 34 and 56 of Hájek and Šidák (1967) for useful properties of  $F^{-1}$ .

PROOF OF THEOREM 1. (i) Let  $0 \leq s \leq t \leq 1$ . Let

$$\begin{aligned} \pi_{ni} &= 1 - p_{ni} & \text{if } s < \beta_{ni} \leq t \\ &= -p_{ni} & \text{if not,} \end{aligned}$$

where  $p_{ni} = G_{ni}(t) - G_{ni}(s)$ . Then using (1.2) we have

$$\begin{aligned} E[X_n(t) - X_n(s)]^4 &= n^{-2} E[\sum_i^n \pi_{ni}]^4 \\ &= n^{-2} [\sum_1^n E\pi_{ni}^4 + 3 \sum \sum_{i \neq j} E\pi_{ni}^2 E\pi_{nj}^2] \\ &= n^{-2} [3(\sum_1^n E\pi_{ni}^2)^2 + \sum_1^n (E\pi_{ni}^4 - 3E^2\pi_{ni}^2)] \\ (2.1) \quad &= 3[n^{-1} \sum_1^n p_{ni}(1 - p_{ni})]^2 \\ &\quad + n^{-2} \sum_1^n [p_{ni}(1 - p_{ni})(1 - 6p_{ni} + 6p_{ni}^2)] \\ &\leq 3[n^{-1} \sum_1^n p_{ni}]^2 + n^{-1} [n^{-1} \sum_1^n p_{ni}] \\ &= 3(t - s)^2 + (t - s)/n . \end{aligned}$$

Define  $S_n$  on  $(C, \rho)$  by setting  $S_n(i/n) = X_n(i/n)$  for  $0 \leq i \leq n$  and by letting  $S_n$  be linear on the intervals  $[(i - 1)/n, i/n]$ . We will demonstrate below that  $S_n$  satisfies

$$(2.2) \quad E|S_n(t) - S_n(s)|^4 \leq 144|t - s|^2 \quad \text{for all } 0 \leq s, t \leq 1$$

for all  $n \geq 1$ . For the time being we take (2.2) to be true. Thus  $\{S_n : n \geq 1\}$  is relatively compact on  $(C, \rho)$ ; see page 95 of Billingsley or (better yet for simplicity, and appreciation of  $S_n$ ) page 28 of Varadhan (1968). (The improvement of (2.2) over (2.1) is the most interesting part of this proof. Note (5.3) of Sen (1970).)

Now

$$(2.3) \quad \bar{X}_n = (\bar{X}_n - X_n) + (X_n - S_n) + S_n .$$

Note that  $\rho(\bar{X}_n, X_n) \leq n^{-1/2}$  so that

$$(2.4) \quad \rho(\bar{X}_n, X_n) \rightarrow_p 0 \quad \text{as } n \rightarrow \infty .$$

Also for  $n > (4/\epsilon)^2$  we have  $n^{1/2}|t - i/n| < \epsilon/4$  for all  $|t - i/n| \leq 1/n$ ; hence (recall (1.3) with  $G_n$  increasing)

$$\begin{aligned} P(\rho(X_n, S_n) > \epsilon) &= P(\max_{1 \leq i \leq n} (\sup_{i-1/n \leq t \leq i/n}) |X_n(t) - S_n(t)| > \epsilon) \\ &\leq P(\max_{0 \leq i \leq n} |\sup_{|t-i/n| \leq 1/n} |X_n(t) - X_n(i/n)| > \epsilon) \\ &\leq P(\max_{1 \leq i \leq n} n^{1/2} |G_n(i/n) - G_n((i-1)/n)| > 3\epsilon/4) \\ &\leq P(\max_{1 \leq i \leq n} |X_n(i/n) - X_n((i-1)/n)| > \epsilon/2) \\ &\leq \sum_1^n P(|X_n(i/n) - X_n((i-1)/n)| > \epsilon/2) , \end{aligned}$$

where the first inequality depends on the linearity of  $S_n$  in that

$$|X_n(t) - S_n(t)| \leq |X_n(t) - S_n(i/n)| \vee |X_n(t) - S_n((i-1)/n)|$$

for all  $(i-1)/n \leq t \leq i/n$ . Thus by (2.1) we have

$$\begin{aligned} P(\rho(X_n, S_n) > \epsilon) &\leq 16 \sum_1^n E[|X_n(i/n) - X_n((i-1)/n)|^4] / \epsilon^4 \\ &\leq (16/\epsilon^4)n(4/n^2) \rightarrow 0 . \end{aligned}$$

Thus

$$(2.5) \quad \rho(X_n, S_n) \rightarrow_p 0 \quad \text{as } n \rightarrow \infty .$$

Let  $\psi$  denote a bounded real functional on  $C$  that is uniformly continuous in the  $\rho$ -metric. Then on any subsequence  $n'$  where  $S_{n'}$  converges weakly (let  $S$  denote the limit) we have

$$\begin{aligned} |E\psi(\bar{X}_{n'}) - E\psi(S)| &\leq E|\psi(\bar{X}_{n'}) - \psi(X_{n'})| + E|\psi(X_{n'}) - \psi(S_{n'})| \\ &\quad + |E\psi(S_{n'}) - E\psi(S)| \\ &\rightarrow 0 + 0 + 0 = 0 \quad \text{as } n' \rightarrow \infty ; \end{aligned}$$

here (2.4), (2.5) and the uniform continuity of bounded  $\psi$  yield the first two zeroes. Thus  $\bar{X}_{n'} \Rightarrow S$  on  $(C, \rho)$  as  $n' \rightarrow \infty$  by page 12 of Billingsley. Thus  $\{\bar{X}_n : n \geq 1\}$  is relatively compact on  $(C, \rho)$ .

To complete the proof of (i), it remains only to establish (2.2). Let  $n \geq 1$  and  $0 \leq s, t \leq 1$ , be arbitrary, but fixed. Choose the integers  $i$  and  $j$  so that

$$(i-1)/n \leq s \leq i/n \quad \text{and} \quad (j-1)/n \leq t \leq j/n .$$

Let  $\Delta_{km} = |S_n(m/n) - S_n(k/n)|$  for integers  $k$  and  $m$ ; and note from (2.1) that

$$E\Delta_{km}^4 \leq [3|(m-k)/n|^2 + |(m-k)/n|/n] \leq 4[(m-k)/n]^2 .$$

Let  $e_{km} = 4[(m-k)/n]^2$ . We also let  $\Delta_{uv} = |S_n(v) - S_n(u)|$ .

Case 1.  $i < j - 1$ . Then

$$\Delta_{st} \leq \Delta_{i,j-1} \vee \Delta_{ij} \vee \Delta_{i-1,j-1} \vee \Delta_{i-1,j} ,$$

so that

$$\begin{aligned} E\Delta_{st}^4 &\leq e_{i,j-1} + e_{ij} + e_{i-1,j-1} + e_{i-1,j} \leq 4e_{i-1,j} \\ &= 16[(j - (i - 1))/n]^2 \leq 144(t - s)^2. \end{aligned}$$

*Case 2.*  $i = j$ . Since the change of a linear function on an interval of length  $t - s$  equals the slope times  $t - s$  we have

$$\Delta_{st} \leq n\Delta_{i-1,i}(t - s),$$

so that

$$E\Delta_{st}^4 \leq n^4(t - s)^4 e_{i-1,i} \leq 4n^2(t - s)^4 \leq 4(t - s)^2.$$

*Case 3.*  $i = j - 1$ . Then

$$\Delta_{st} \leq \Delta_{s,i/n} + \Delta_{i/n,t} \leq 2(\Delta_{s,i/n} \vee \Delta_{i/n,t}),$$

so that by Case 2 we have

$$\begin{aligned} E\Delta_{st}^4 &\leq 2^4(E\Delta_{s,i/n}^4 + E\Delta_{i/n,t}^4) \leq 2^4[4(i/n - s)^2 + 4(t - i/n)^2] \\ &\leq 2^7(t - s)^2. \end{aligned}$$

Thus (2.2) is established.

(ii) Suppose  $K_n \rightarrow K$ . The limit of covariance functions is necessarily a covariance function (page 468 of Loève (1963)); and since  $K$  is real there is a normal process  $X$  (we do not know yet that it has continuous sample paths) having covariance function  $K$  (page 467 of Loève). Thus for fixed  $k$ ,  $0 \leq t_1, \dots, t_k \leq 1$  and real  $a_1, \dots, a_k$  the variance of the rv  $\theta_n \equiv \sum_1^k a_i X_n(t_i)$  converges to the variance (denote it by  $c$ ) of the rv  $\theta \equiv \sum_1^k a_i X(t_i)$  as  $n \rightarrow \infty$ . If  $c = 0$ , then trivially  $\theta_n \rightarrow_p 0$  as  $n \rightarrow \infty$ . If  $c > 0$ , then  $\theta_n \rightarrow_d N(0, c)$  as  $n \rightarrow \infty$  by the Liapouov central limit theorem (this is again trivial since the summands are uniformly bounded and the sum of their variances goes to  $\infty$ ). We have shown that  $X_n \rightarrow_{f.d.} X$  as  $n \rightarrow \infty$  (see page 49 of Billingsley). Hence by (2.4) we have  $\bar{X}_n \rightarrow_{f.d.} X$  as  $n \rightarrow \infty$ . But  $\{\bar{X}_n : n \geq 1\}$  is relatively compact by (i); and if  $X_{n'} \Rightarrow Z$  on  $(C, \rho)$  as  $n' \rightarrow \infty$  for some subsequence  $n'$ , then  $X$  must have the same finite dimensional distributions as  $Z$ . Thus  $\bar{X}_n \Rightarrow X$  on  $(C, \rho)$  as  $n \rightarrow \infty$ .

(iii) It is easy that for all  $n \geq 1$  and all  $0 \leq t \leq 1$  we have  $EX_n^{2m}(t) \leq M_m$  for each  $m \geq 1$ , where  $M_m$  is a constant. The Cauchy-Schwarz inequality can be used to bound any finite dimensional moment by a product of powers of one dimensional moments. Application of the Corollary on page 184 of Loève then establishes convergence of the finite dimensional moment. In particular,  $K_n$  converges pointwise to  $K$  as  $n \rightarrow \infty$ . Thus  $X$  is a normal process by (ii).  $\square$

**PROOF OF THEOREM 2.** Using Theorem 1 (ii) and Item 3.1.1 of Skorokhod (1956) it is easy to construct the required  $\alpha_{ni}$ 's and  $X$  for which  $\rho(X_n, X) \rightarrow_e 0$  as  $n \rightarrow \infty$ . Now

$$(2.6) \quad Y_n = -X_n(G_n^{-1}) + n^{\frac{1}{2}}(G_n \circ G_n^{-1} - I),$$

where  $I$  denotes the identity function; so that

$$\begin{aligned} \rho(Y_n, -X) &\leq \rho(X_n(G_n^{-1}), X) + n^{\frac{1}{2}}\rho(G_n \circ G_n^{-1}, I) \\ &\leq \rho(X_n(G_n^{-1}), X(G_n^{-1})) + \rho(X(G_n^{-1}), X) + n^{-\frac{1}{2}} \\ &\leq \rho(X_n, X) + \rho(X(G_n^{-1}), X) + n^{-\frac{1}{2}}; \end{aligned}$$

and thus it suffices to show that  $\rho(X(G_n^{-1}), X) \rightarrow_e 0$  as  $n \rightarrow \infty$ . But since all sample paths of  $X$  are uniformly continuous on  $[0, 1]$ , it suffices to show that  $\rho(G_n^{-1}, I) \rightarrow_e 0$  as  $n \rightarrow \infty$ . But by symmetry

$$\rho(G_n^{-1}, I) = \rho(G_n, I) = n^{-\frac{1}{2}}\rho(X_n, 0) \leq n^{-\frac{1}{2}}[\rho(X_n, X) + \rho(X, 0)] \rightarrow_e 0$$

as  $n \rightarrow \infty$ , since every sample path of  $X$  is bounded. Thus  $\rho(Y_n, -X) \rightarrow_e 0$  as  $n \rightarrow \infty$ .

For the moment convergence, see the proof of Theorem 1 (iii).  $\square$

**PROOF OF COROLLARY 1.** Condition (1.7) implies  $(\max_{1 \leq i \leq n})\rho(F_{ni}, F_n) \rightarrow 0$  as  $n \rightarrow \infty$ . Hence  $(\max_{1 \leq i \leq n})\rho(G_{ni}, I) \rightarrow 0$  as  $n \rightarrow \infty$ . Hence (1.6) holds with  $K(s, t) = s \wedge t - st$ . Now apply Theorem 2.  $\square$

**3. Asymptotic normality of linear combinations of functions of order statistics in the non i.i.d. case.** We use the notation of Section 1. Consider

$$(3.1) \quad T_n = n^{-1} \sum_{i=1}^n c_{ni} h_n(\eta_{ni}) + \sum_{k=1}^k d_{nk} h_n(\eta_{n, [np_k] + 1})$$

where  $\eta_{n1} \leq \dots \leq \eta_{nn}$  are the ordered values of  $\alpha_{n1}, \dots, \alpha_{nn}$ , where the  $h_n$ 's are known functions, where  $0 < p_1 < \dots < p_k < 1$  and  $[ \ ]$  denotes the greatest integer function and where  $c_{n1}, \dots, c_{nn}, n \geq 1$  and  $d_{n1}, \dots, d_{nk}, n \geq 1$  are known constants. Let  $g_n = h_n(F_n^{-1})$ . Then

$$(3.2) \quad T_n = \int_0^1 g_n(G_n^{-1}(t)) J_n(t) dt + \sum_{k=1}^k d_{nk} g_n(G_n^{-1}(p_k)),$$

where  $J_n$  on  $[0, 1]$  is defined by  $J_n(t) = c_{ni}$  for  $(i - 1)/n < t \leq i/n$  and  $1 \leq i \leq n$  with  $J_n(0) = c_{n1}$ . Let

$$(3.3) \quad \mu_n = \int_0^1 g_n(t) J_n(t) dt + \sum_{k=1}^k d_k g_n(p_k)$$

for given constants  $d_1, \dots, d_k$ .

**THEOREM 3.** Suppose that for functions  $g$  and  $J$  either Assumptions 1, 2, 3, 4 or Assumption 1, 2', 3', 4 of Shorack (1972) are satisfied; where  $b_1 = b_2 = 0$  in Assumption 1 (thus  $J$  is a bounded function). Then

$$n^{\frac{1}{2}}(T_n - \mu_n) \rightarrow_d - \int_0^1 JX dg - \sum_{k=1}^k d_k g'(p_k) X(p_k) \quad \text{as } n \rightarrow \infty.$$

The limiting rv is  $(N(0, \sigma^2))$  where the formula for  $\sigma^2$  is (3) of Shorack (1972) with  $s \wedge t - st$  replaced by the covariance function  $K(s, t)$  of our present  $X$  process.

**PROOF.** Replace  $U_n, U, \xi_{ni}$  in the proofs of Theorem 1 and Corollary 2 of [6] by  $X_n, X, \beta_{n1}$ . For bounded  $J$ , Lemma A3 of [6] is not used to obtain a dominating function.  $\square$

The restriction to bounded  $J$  could be removed if an analog of Lemma A3 of

[6] could be proved for triangular arrays of continuous rv's; for some special triangular arrays such results are possible by deterministic manipulations of the  $G_{n_i}$ 's. Many of the most interesting  $J$ 's are bounded (those corresponding to trimmed, Winsorized and linearly weighted means for example).

Results similar to Theorem 3 obtained by the projection method appear in Stigler (1972).

## REFERENCES

- [1] BILLINGSLEY, P. (1968). *Convergence of Probability Measure*. Wiley, New York.
- [2] HÁJEK, J. and ŠIDÁK, Z. (1967). *Theory of Rank Tests*. Academic Press, New York.
- [3] KOUL, H. (1970). Some convergence theorems for ranks and weighted empirical cumulatives. *Ann. Math. Statist.* **41** 1768-1773.
- [4] LOÈVE, M. (1963). *Probability*. Van Nostrand, Princeton.
- [5] SEN, P. (1970). On the distribution of the one-sample rank order statistics. *Nonparametric Techniques in Statistical Inference*, ed. M. Puri. Cambridge Univ. Press.
- [6] SHORACK, G. (1970). Functions of order statistics. *Ann. Math. Statist.* **43** 412-427.
- [7] SKOROKHOD, A. (1956). Limit theorems for stochastic processes. *Theor. Probability Appl.* **1** 261-290.
- [8] STIGLER, S. (1972). Linear functions of order statistics with smooth weight functions. University of Wisconsin Technical Report.
- [9] VARADHAN S. (1968). *Stochastic Processes*. Courant Institute of Mathematical Sciences, New York Univ.

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