

## ON LARGE DEVIATION PROBABILITIES OF U-STATISTICS IN NON I.I.D CASE

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**SUMMARY.** Under a rather stringent moment assumption on the kernel we compute large deviation probabilities of  $U$ -statistics.

### 1. INTRODUCTION

After the work of Hoeffding on limiting distribution of  $U$ -statistics, various authors studied the rates of convergence of  $U$ -statistics to normality see e.g. Grams and Serfling (1973), Bickel (1974), Chan and Wierman (1977), Callert and Janseen (1978) and Ghosh and Dasgupta (1980). However the problem of computing the large deviation probabilities for  $U$ -statistics has not received any attention. In this note using a simple technique we approximate the said probability in terms of that for independent summands. Our main result is stated below.

Let  $U_n$  be a  $U$ -statistic with kernel  $\phi$  and degree  $r$ , based on independent observations  $X_1, \dots, X_n$ . In the i.i.d case Hoeffding showed if  $E\phi(x_{i_1} \dots x_{i_r}) = 0$ ,  $\forall i_1, \dots, i_r$  then,

$$nU_n/(rs_n) = s_n^{-1} \sum_{l=1}^n \tilde{\psi}_n^{(l)}(X_l)(1 + o_p(1))$$

where

$$\tilde{\psi}_{i_2, \dots, i_r}^{(l)}(x_{i_1}) = E[\phi(X_{i_1} \dots X_{i_r}) / X_{i_1} = x_{i_1}]$$

$$\tilde{\psi}_n^{(l)}(X_l) = \binom{n-1}{r-1}^{-1} \sum_{1 < i_2, \dots, i_r < n} \tilde{\psi}_{i_2, \dots, i_r}^{(l)}(X_l); i_2 \neq i_1, \dots, i_r \neq i_1$$

and

$$s_n^2 = \sum_{l=1}^n E\tilde{\psi}_n^{(l)2}(X_l).$$

Suppose the kernel satisfies a certain moment condition (vide 3.6);

$$\inf_n n^{-1} s_n^2 > 0$$

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and

$$\lim n^{-1} \log P \left( s_n^{-1} \sum_{i=1}^n \bar{\psi}_n^{(1)}(X_i) > a\sqrt{n} \right) = \rho$$

is finite; then our main result is

$P(U_n/(rs_n) > a/\sqrt{n}) = P \left( s_n^{-1} \sum_{i=1}^n \psi_n^{(1)}(X_i) > a\sqrt{n} \right) (1+o(1))$  which implies that  $\lim n^{-1} \log P(U_n/(rs_n) > a/\sqrt{n}) = \rho$ .

## 2. ESTIMATE OF REMAINDER IN $U$ -STATISTICS

Let  $\{X_n, n \geq 1\}$  be a sequence of independent but not necessarily identically distributed random variables. A  $U$ -statistic with kernel  $\phi$  and degree  $r$ , based on  $X_1, X_2, \dots, X_n$  ( $n \geq r$ ), is defined by

$$U_n = \binom{n}{r}^{-1} \sum_{1 \leq i_1 < \dots < i_r \leq n} \phi(X_{i_1}, \dots, X_{i_r}) \quad \dots (2.1)$$

where the kernel  $\phi$  is symmetric in its arguments.

For the sake of completeness and further reference below (vide 2.9), we give a Hoeffding (1961) decomposition for  $U$ -statistics in the non i.i.d case (see also Ghosh and Dasgupta, 1980). We give the decomposition for the case  $r=3$ ; generalisation for other values of  $r$  follows easily. Without loss of generality let  $E\phi(X_{i_1}, X_{i_2}, X_{i_3}) = 0 \forall 1 \leq i_1 < i_2 < i_3 \leq n$ . Let

$$\begin{aligned} \psi_{i_2, i_3}^{i_1}(x_{i_1}) &= \phi_{i_2, i_3}^{i_1}(x_{i_1}) = E[\phi(X_{i_1}, X_{i_2}, X_{i_3}) | X_{i_1} = x_{i_1}] \\ & \quad 1 \leq i_1 \neq i_2 \neq i_3 \leq n. \quad \dots (2.2) \end{aligned}$$

$$\begin{aligned} \phi_{i_3}^{i_1, i_2}(x_{i_1}, x_{i_2}) &= E[\phi(X_{i_1}, X_{i_2}, X_{i_3}) | X_{i_1} = x_{i_1}, X_{i_2} = x_{i_2}] \\ & \quad 1 \leq i_1 \neq i_2 \neq i_3 \leq n; \quad \dots (2.3) \end{aligned}$$

$$\begin{aligned} \psi_{i_3}^{i_1, i_2}(x_{i_1}, x_{i_2}) &= \phi_{i_3}^{i_1, i_2}(x_{i_1}, x_{i_2}) - \psi_{i_2, i_3}^{i_1}(x_{i_1}) - \psi_{i_1, i_3}^{i_2}(x_{i_2}) \\ & \quad 1 \leq i_1 \neq i_2 \neq i_3 \leq n \quad \dots (2.4) \end{aligned}$$

$$\begin{aligned} \psi^{i_1, i_2, i_3}(x_{i_1}, x_{i_2}, x_{i_3}) &= \phi(x_{i_1}, x_{i_2}, x_{i_3}) - \psi_{i_2, i_3}^{i_1}(x_{i_1}) - \psi_{i_1, i_3}^{i_2}(x_{i_2}) \\ & \quad - \psi_{i_1, i_2}^{i_3}(x_{i_3}) - \psi_{i_3}^{i_1, i_2}(x_{i_1}, x_{i_2}) - \psi_{i_2}^{i_1, i_3}(x_{i_1}, x_{i_3}) - \psi_{i_1}^{i_2, i_3}(x_{i_2}, x_{i_3}) \\ & \quad 1 \leq i_1 \neq i_2 \neq i_3 \leq n. \quad \dots (2.5) \end{aligned}$$

Writing

$$\bar{V}_n^{(1)}(X_i) = \binom{n-1}{2}^{-1} \sum_{\substack{1 \leq j < l \leq n \\ j \neq i \\ l \neq i}} \psi_{j,l}^{(1)}(X_i).$$

$$\bar{V}_n^{(2)}(X_i, X_j) = (n-2)^{-1} \sum_{k=1, k \neq i, j}^n \psi_{i,k}^{(2)}(X_i, X_j) \quad \dots (2.6)$$

$$V_n^{(1)} = n^{-1} \sum_{i=1}^n \bar{V}_n^{(1)}(X_i),$$

$$V_n^{(2)} = \binom{n}{2}^{-1} \sum_{1 \leq i < j \leq n} \bar{V}_n^{(2)}(X_i, X_j) \quad \dots (2.7)$$

and

$$V_n^{(3)} = \binom{n}{3}^{-1} \sum_{1 < i_1 < i_2 < i_3 < n} \sum \sum \psi_{i_1, i_2, i_3}^{(3)}(X_{i_1}, X_{i_2}, X_{i_3}), \quad \dots (2.8)$$

one has the representation

$$U_n = 3V_n^{(1)} + 3V_n^{(2)} + V_n^{(3)}. \quad \dots (2.9)$$

The following facts can be easily verified

$$E\psi_{i_2, i_3}^{(1)}(X_{i_1}) = 0, \quad E[\psi_{i_2, i_3}^{(2)}(X_{i_1}, X_{i_2}) | X_{i_1} = x_{i_1}] = 0 \quad \text{a.e.}, \quad \dots (2.10)$$

$$E[\psi_{i_1, i_2, i_3}^{(3)}(X_{i_1}, X_{i_2}, X_{i_3}) | X_{i_1} = x_{i_1}, X_{i_2} = x_{i_2}] = 0 \quad \text{a.e.}, \quad \dots (2.11)$$

$$E[\psi_{i_1, i_2, i_3}^{(3)}(X_{i_1}, X_{i_2}, X_{i_3}) | X_{i_1} = x_{i_1}] = 0 \quad \text{a.e.} \quad \dots (2.12)$$

It follows from (2.10)-(2.12) that

$$E \left[ \psi_{i_2, i_3}^{(1)}(X_{i_1}) \psi_{i_1, i_2}^{(2)}(X_{i_1}, X_{i_2}) \right] = 0; \quad \dots (2.13)$$

for any  $1 \leq i_2 \neq i_3 \leq n$ ,  $1 \leq i_1 \neq i_2 \leq n$ ;

$$E \left[ \psi_{i_1, i_2}^{(2)}(X_{i_1}, X_{i_2}) \psi_{i_1, i_2}^{(2)}(X_{i_1}, X_{i_2}) \right] = 0, \quad \dots (2.14)$$

for any  $1 \leq i_1 \neq i_2 \leq n$ ,  $1 \leq i_2 \neq i_1 \leq n$ ;  $i_1 \neq i_3$ ;

$$E \left[ \psi_{i_2, i_3}^{(1)}(X_{i_1}) \psi_{i_1, i_2, i_3}^{(3)}(X_{i_1}, X_{i_2}, X_{i_3}) \right] = 0, \quad \dots (2.15)$$

for any  $1 \leq i_k \neq i_l \neq i_1 \leq n$ ,  $1 \leq i_1 \neq i_2 \neq i_3 \leq n$ ;

$$E \left[ \psi_{i_1}^{i_1 i_2 i_3} (X_{i_1}, X_{i_2}, X_{i_3}) \psi_{i_1 i_2 i_3}^{i_1 i_2 i_3} (X_{i_1}, X_{i_2}, X_{i_3}) \right] = 0, \quad \dots (2.16)$$

for any  $1 \leq i_r \neq i_1 \neq i_2 \leq n$ ,  $1 \leq i'_1 \neq i'_2 \neq i'_3 \leq n$ , whenever  $(i_1, i_2)$  and  $(i'_1, i'_2, i'_3)$  are disjoint;

$$E \left[ \psi_{i_1}^{i_1 i_2 i_3} (X_{i_1}, X_{i_2}, X_{i_3}) \psi_{i'_1 i'_2 i'_3}^{i'_1 i'_2 i'_3} (X_{i'_1}, X_{i'_2}, X_{i'_3}) \right] = 0 \quad \dots (2.17)$$

whenever  $(i_1, i_2, i_3) \neq (i'_1, i'_2, i'_3)$ .

Henceforth, unless otherwise mentioned, we work with  $U$ -statistics with kernel  $\phi$  and degree 3. The generalisation to an arbitrary  $r (> 3)$  is immediate. It is assumed without loss of generality that

$$E\phi(X_{i_1}, X_{i_2}, \dots, X_{i_r}) = 0, \quad 1 \leq i_1 \neq \dots \neq i_r \leq n. \quad \dots (2.18)$$

We now prove a lemma which gives moment bounds for  $V_n^{(2)}$  and  $V_n^{(3)}$  when  $\phi$  has  $(2m)$ -th moment.

Lemma 2.1: *If (2.18) holds and*

$$\delta_m = \sup_{n \geq 3} \binom{n}{3}^{-1} \sum_{1 \leq i_1 < i_2 < i_3 \leq n} E|\phi(X_{i_1}, X_{i_2}, X_{i_3})|^{2m} < \infty \quad \dots (2.19)$$

then

$$E(V_n^{(2)})^{2m} \leq n^{-2m} L^m m! \delta_m \quad \dots (2.20)$$

and

$$E(V_n^{(3)})^{2m} \leq n^{-3m} L^m m! \delta_m \quad \dots (2.21)$$

where in the above and in what follows  $L (> 0)$  is a generic constant independent of  $m$  and  $n$ .

*Proof:*

$$E(V_n^{(2)})^{2m} = \binom{n}{2}^{-2m} \sum_{1 \leq i_1 < j_1 < n} \sum_{1 \leq i_{2m} < j_{2m} < n} E[\tilde{\psi}_n^{(2)}(X_{i_1}, X_{j_1}) \dots \tilde{\psi}_n^{(2)}(X_{i_{2m}}, X_{j_{2m}})]. \quad \dots (2.22)$$

Note that if a pair of suffixes  $(i_k, j_k)$  occurs exactly once in  $((i_1, j_1), \dots, (i_{2m}, j_{2m}))$ , then in view of (2.14)

$$E[\tilde{\psi}_n^{(2)}(X_{i_1}, X_{j_1}) \dots \tilde{\psi}_n^{(2)}(X_{i_{2m}}, X_{j_{2m}})] = 0. \quad \dots (2.23)$$

Subject to the condition that each pair of suffixes  $(i_k, j_k)$  occurs at least twice, the maximum number of suffixes that can occur is  $2m$ , corresponding to  $m$  distinct pairs of suffixes.

If there are  $k$  distinct pairs, by repeated application of Hölders inequality, the product term inside the sum in (2.22) is

$$\begin{aligned} & |E(\bar{\psi}_n^{(i_1)}(X_{i_1}, X_{j_1}))^{l_1} \dots (\bar{\psi}_n^{(i_k)}(X_{i_k}, X_{j_k}))^{l_k}|; \quad l_1 + \dots + l_k = 2m \\ & \leq E^{l_1/2m} (\bar{\psi}_n^{(i_1)}(X_{i_1}, X_{j_1}))^{2m} \dots E^{l_k/2m} (\bar{\psi}_n^{(i_k)}(X_{i_k}, X_{j_k}))^{2m} \\ & \leq \frac{l_1}{2m} E(\bar{\psi}_n^{(i_1)}(X_{i_1}, X_{j_1}))^{2m} + \dots + \frac{l_k}{2m} E(\bar{\psi}_n^{(i_k)}(X_{i_k}, X_{j_k}))^{2m} \\ & \leq \sum_{p=1}^k E(\bar{\psi}_n^{(i_p)}(X_{i_p}, X_{j_p}))^{2m}; \text{ since } l_i \leq 2m, \forall i. \quad \dots (2.24) \end{aligned}$$

Now note that  $k$  pairs can be taken out of  $2m$  pairs in  $2m p_k$  ways,  $k = 1, \dots, m$ ,  $m$  being the maximum number of distinct pairs. Therefore from (2.22)

$$\begin{aligned} E(V_n^{(2)})^{2m} & \leq \binom{n}{2}^{-2m} \sum_{1 < i_1 < j_1 < n} \dots \sum_{1 < i_m < j_m < n} \\ & \times \left[ \sum_{k=1}^m \sum_{p=1}^k E |\bar{\psi}_n^{(i_p)}(X_{i_p}, X_{j_p})|^{2m-2m p_k} \right]. \quad \dots (2.25) \end{aligned}$$

Since  $2m p_k \leq L^m m!$  for  $k = 1, \dots, m$  and since the maximum variation of the indexes  $1 < i_1 < j_1 < n, \dots, 1 < i_m < j_m < n$  are in a total number of ways  $\leq n^{2m}$ , we have with an application of Jensen and  $C_{2m}$  inequalities

$$E(V_n^{(2)})^{2m} \leq \binom{n}{2}^{-2m} n^{2m} L^m m! m^2 \delta_m; \text{ from (2.19)}$$

and since  $p \leq k \leq m$ ,

$$\leq n^{-2m} L^m m! \delta_m.$$

Hence (2.20). Similarly (2.21) can be shown and the lemma follows.

3. RESULTS ON PROBABILITIES OF DEVIATIONS FOR  $U$ -STATISTICS

Now writing

$$n^{1/2}U_n/(3\sigma_n) = \sigma_n^{-1} \sum_{i=1}^n \tilde{\psi}_n^{(1)}(X_i) + R_n \quad \dots (3.1)$$

where

$$\delta_n^2 = \sum_{i=1}^n E \tilde{\psi}_n^{(1)2}(X_i), \quad \sigma_n^2 = n^{-1} \delta_n^2 \quad \dots (3.2)$$

and

$$R_n = n^{1/2} \sigma_n^{-1} \left( \mathcal{V}_n^{(2)} + \frac{1}{3} \mathcal{V}_n^{(3)} \right)$$

we have under

$$\inf_n \sigma_n^2 > 0, \quad \dots (3.3)$$

the following

$$E R_n^{2m} \leq n^{-m} L^m m! \delta_m. \quad \dots (3.4)$$

Also note that from (2.2), (2.6) using  $C_{2m}$  and Jensen's inequality for conditional expectation

$$\sup_n n^{-1} \sum_{i=1}^n E |\tilde{\psi}_n^{(1)}(X_i)|^{2m} \leq L^m \delta_m. \quad \dots (3.5)$$

The representation in (3.1) permits us to have large deviation results for  $U$ -statistics even for non i.i.d case. For i.i.d case under the assumption of existence of m.g.f. Chernoff (1952) has results on large deviation on sample mean which were generalised for independent random variables by Sievers (1969), Plachky and Stienebach (1975) etc. We may have similar results for  $U$ -statistics provided we show that the remainder has negligible contribution compared to the mean part in (3.1). Let

$$\delta_m \leq k^{-m} \cdot (m)! \text{ for all sufficiently large } m \quad \dots (3.6)$$

where  $k$  is fixed but may be taken arbitrary large. In i.i.d case this condition is equivalent to  $E \exp(t\psi^2) < \infty$  for large  $t$ . Then from (3.4) it is clear that m.g.f. of  $\sqrt{n}R_n$  exists for all values of  $t$  i.e.

$$f(t) = E \exp(t\sqrt{n}R_n) < \infty \quad \forall t \text{ real.} \quad \dots (3.7)$$

Hence by Marcov inequality we have the following

Theorem 1: Let  $\delta_m$  satisfies (3.8) and define

$$P_n^*(a) = P \left\{ s_n^{-1} \sum_{i=1}^n \tilde{\psi}_n^{(1)}(X_i) > a n^{1/2} \right\}.$$

If

$$\lim_n n^{-1} \log P_n^*(a) < \infty \text{ for some } a > 0. \quad \dots (3.8)$$

Then under (3.3), the following holds

$$P_n(a) = P_n^*(a) + o(P_n^*(a)) \quad \dots (3.9)$$

where  $P_n(a) = P\{U/(3\sigma_n) > a\}$ .

Comment: (3.8) is nothing but an assumption about existence of large deviation for independent random variables under quite a strong assumption  $2m$ -th moment is of order  $m$ !

It would be interesting to know if Theorem 1 holds under more natural condition  $\delta_m = O(2m)$ ! Sethuraman has a result similar to Theorem 1 independently. Since crude moment bounds are used, sharper results may not be possible by this technique.

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