

THE BIVARIATE ORTHOGONAL INVERSE EXPANSION AND THE MOMENTS OF ORDER STATISTICS

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1. Introduction

The orthogonal inverse expansion has been introduced in my previous paper [9] to obtain the universal upper bounds and the approximation for the moments of order statistics. For the same purpose two other series have been introduced by David and Johnson [2] and Plackett [6] and the error of the approximation of $E(X_{r/n})$ is evaluated by Saw [8] and Plackett [6].

In this paper we shall derive the universal upper bounds and the approximation for $E(X_{r/n}^i X_{s/n}^j)$ ($i, j=1, 2$) together with the error of the approximation by means of the bivariate orthogonal inverse expansion.

2. Some preliminaries

First we restate for convenience the following Proposition in [9].

Proposition 1. *Let H be a pre-Hilbert space and $\{\varphi_\nu\}_{\nu=0,1,\dots}$ be any orthonormal system in H . Put $a_\nu=(f, \varphi_\nu)$ and $b_\nu=(g, \varphi_\nu)$ for any elements f, g in H . Then we have*

$$(2.1) \quad |(f, g) - \sum_{\nu=0}^k a_\nu b_\nu| \leq \{ \|f\|^2 - \sum_{\nu=0}^k a_\nu^2 \}^{1/2} \{ \|g\|^2 - \sum_{\nu=0}^k b_\nu^2 \}^{1/2},$$

where equality holds if and only if $f, g, \varphi_0, \dots, \varphi_k$ are linearly dependent.

We also use the following well-known Proposition concerning a bivariate orthonormal system in a rectangular domain. The proof is found, for example, in Courant and Hilbert [1].

Proposition 2. *Let $L^2(0, 1)$ and $L^2(R)$ be the Hilbert spaces of all functions square integrable in the interval $(0, 1)$ and the square $R = \{(u, v) | 0 \leq u, v \leq 1\}$, respectively. If $\{\varphi_\nu(u)\}_{\nu=0,1,\dots}$ is a complete orthonormal system in $L^2(0, 1)$, then $\{\varphi_\lambda(u)\varphi_\nu(v)\}_{\lambda,\nu=0,1,\dots}$ is a complete orthonormal system in $L^2(R)$.*

EXAMPLE 1. Legendre polynomials in $(0, 1)$:

$$(2.2) \quad \varphi_\nu(u) = \frac{\sqrt{2\nu+1}}{\nu!} \frac{d^\nu}{du^\nu} u^\nu (u-1)^\nu \quad (\nu = 0, 1, \dots)$$

constitute a complete orthonormal system in $L^2(0, 1)$, so we can get a complete orthonormal system in $L^2(R)$ by Proposition 2.

To get the results corresponding to Example 3 in [9], we decompose $L^2(R)$ into the following four subspaces:

$$(2.3) \quad \begin{aligned} L_{e,e}^2(R) &= \{f(u, v) | f \in L^2(R) \text{ and } f(u, v) = f(1-u, v) = f(u, 1-v)\}, \\ L_{e,0}^2(R) &= \{f(u, v) | f \in L^2(R) \text{ and } f(u, v) = f(1-u, v) = -f(u, 1-v)\}, \\ L_{0,e}^2(R) &= \{f(u, v) | f \in L^2(R) \text{ and } f(u, v) = -f(1-u, v) = f(u, 1-v)\}, \\ L_{0,0}^2(R) &= \{f(u, v) | f \in L^2(R) \text{ and } f(u, v) = -f(1-u, v) = -f(u, 1-v)\}. \end{aligned}$$

Proposition 3. *Let $\{\varphi_\nu(u)\}_{\nu=0,1,\dots}$ be any complete orthonormal system in $L^2(0, 1)$ satisfying $\varphi_\nu(u) = (-1)^\nu \varphi_\nu(1-u)$. Then*

$$(2.4) \quad \begin{aligned} \{\varphi_{2\lambda}(u)\varphi_{2\nu}(v)\}_{\lambda,\nu=0,1,\dots} &\in L_{e,e}^2(R), \quad \{\varphi_{2\lambda}(u)\varphi_{2\nu+1}(v)\}_{\lambda,\nu=0,1,\dots} \in L_{e,0}^2(R), \\ \{\varphi_{2\lambda+1}(u)\varphi_{2\nu}(v)\}_{\lambda,\nu=0,1,\dots} &\in L_{0,e}^2(R), \quad \{\varphi_{2\lambda+1}(u)\varphi_{2\nu+1}(v)\}_{\lambda,\nu=0,1,\dots} \in L_{0,0}^2(R) \end{aligned}$$

and each subsystem is complete and orthonormal in the corresponding subspace.

The proof of Proposition 3 is straightforward. The completeness follows from Parseval's equation as in Example 3 of [9].

REMARK 1. Legendre polynomials cited in Example 1 satisfy the assumption of Proposition 3 and will be used in section 4.

Proposition 4. *Suppose that a random variable X has a distribution function $F(x)$ absolutely continuous with respect to the Lebesgue measure and that $E(X^2) < \infty$. Put $u = F(x)$, and then the inverse function $x(u) = F^{-1}(u)$ is defined almost everywhere u and*

$$(2.5) \quad x(u)x(v) \in L^2(R).$$

If further $F(x)$ is symmetric, then

$$(2.6) \quad x(u)x(v) \in L_{0,0}^2(R).$$

Proof.

$$\begin{aligned} \iint_R [x(u)x(v)]^2 dudv &= \int_0^1 [x(u)]^2 du \int_0^1 [x(v)]^2 dv \\ &= \left(\int_{-\infty}^{\infty} x^2 dF(x) \right)^2 < \infty, \end{aligned}$$

which shows (2.5). Symmetricity of $F(x)$ means that $x(u) = -x(1-u)$, which implies (2.6).

3. Universal upper bounds and approximation for $E(X_{r/n}^i X_{s/n}^j)$ ($i, j=1, 2$)

The following Theorem is an extension of Theorem 1 in [9] to the bivariate case.

Theorem 1. *Let $X_{i/n}$ be the i th (smallest) order statistic in a random sample of size n with distribution function $F(x)$ absolutely continuous with respect to the Lebesgue measure having mean μ and finite variance σ^2 . Let $\{\varphi_\nu(u)\}_{\nu=0,1,\dots}$ ($\varphi_0(u)=1$) be any complete orthonormal system in $L^2(0, 1)$ and let for any pair r, s ($1 \leq r < s \leq n$)*

$$(3.1) \quad a_\lambda = \int_0^1 x(u)\varphi_\lambda(u)du ,$$

$$(3.2) \quad b_{\lambda,\nu} = \frac{1}{B(r, s-r, n-s+1)} \iint_{0 < u < v < 1} u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s}\varphi_\lambda(u)\varphi_\nu(v)dudv ,$$

then

$$(3.3) \quad \left| E(X_{r/n}X_{s/n}) - \mu E(X_{r/n} + X_{s/n}) + \mu^2 - \frac{1}{2} \sum_{\lambda,\nu=1}^k a_\lambda a_\nu (b_{\lambda,\nu} + b_{\nu,\lambda}) \right| \\ \leq \left\{ \sigma^4 - \sum_{\lambda,\nu=1}^k a_\lambda^2 a_\nu^2 \right\}^{1/2} \left\{ \frac{B(2r-1, 2s-2r-1, 2n-2s+1)}{2[B(r, s-r, n-s+1)]^2} \right. \\ - \frac{B(2r-1, 2n-2r+1)}{2[B(r, n-r+1)]^2} - \frac{B(r+s-1, 2n-r-s+1)}{B(r, n-r+1)B(s, n-s+1)} \\ \left. - \frac{B(2s-1, 2n-2s+1)}{2[B(s, n-s+1)]^2} + 1 - \frac{1}{4} \sum_{\lambda,\nu=1}^k (b_{\lambda,\nu} + b_{\nu,\lambda})^2 \right\}^{1/2} ,$$

where

$$(3.4) \quad B(p, q, r) = \frac{\Gamma(p)\Gamma(q)\Gamma(r)}{\Gamma(p+q+r)} .$$

Proof. It holds that

$$(3.5) \quad E(X_{r/n}X_{s/n}) = \frac{1}{B(r, s-r, n-s+1)} \iint_{-\infty < x < y < \infty} xy[F(x)]^{r-1} \\ \times [F(y)-F(x)]^{s-r-1}[1-F(y)]^{n-s}dF(x)dF(y) \\ = \frac{1}{B(r, s-r, n-s+1)} \iint_{0 < u < v < 1} x(u)x(v)u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s}dudv \\ = \frac{1}{B(r, s-r, n-s+1)} \iint_{0 < v < u < 1} x(u)x(v)v^{r-1}(u-v)^{s-r-1}(1-u)^{n-s}dudv \\ = \iint_{\mathbb{R}} f(u, v)g(u, v)dudv ,$$

where

$$(3.6) \quad f(u, v) = x(u)x(v),$$

$$(3.7) \quad g(u, v) = \begin{cases} \frac{1}{2B(r, s-r, n-s+1)} u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s} & 0 < u < v < 1, \\ \frac{1}{2B(r, s-r, n-s+1)} v^{r-1}(u-v)^{s-r-1}(1-u)^{n-s} & 0 < v < u < 1. \end{cases}$$

Since

$$(3.8) \quad \begin{aligned} \|f\|^2 &= \iint_R [x(u)x(v)]^2 dudv = (\mu^2 + \sigma^2)^2 < \infty, \\ \|g\|^2 &= \frac{B(2r-1, 2s-2r-1, 2n-2s+1)}{2[B(r, s-r, n-s+1)]^2} < \infty, \end{aligned}$$

we can apply the Proposition 1 to (f, g) in (3.5). Replacing $\{\mathcal{P}_v\}_{v=0,1,\dots,k}$ by $\{\mathcal{P}_0(u)\mathcal{P}_v(v)\}_{v=0,1,\dots} \cup \{\mathcal{P}_\lambda(u)\mathcal{P}_0(v)\}_{\lambda=1,2,\dots} \cup \{\mathcal{P}_\lambda(u)\mathcal{P}_v(v)\}_{\lambda,v=1,2,\dots,k}$ in Proposition 1, we have

$$(3.9) \quad \begin{aligned} &|E(X_{r/n}X_{s/n}) - \sum_{\lambda=0}^{\infty} a_{\lambda,0}^* b_{\lambda,0}^* - \sum_{v=0}^{\infty} a_{0,v}^* b_{0,v}^* + a_{0,0}^* b_{0,0}^* - \sum_{\lambda,v=1}^k a_{\lambda,v}^* b_{\lambda,v}^*| \\ &\leq \{ \|f\|^2 - \sum_{\lambda=0}^{\infty} a_{\lambda,0}^{*2} - \sum_{v=0}^{\infty} a_{0,v}^{*2} + a_{0,0}^{*2} - \sum_{\lambda,v=1}^k a_{\lambda,v}^{*2} \}^{1/2} \{ \|g\|^2 - \sum_{\lambda=0}^{\infty} b_{\lambda,0}^{*2} - \sum_{v=0}^{\infty} b_{0,v}^{*2} \\ &\quad + b_{0,0}^{*2} - \sum_{\lambda,v=1}^k b_{\lambda,v}^{*2} \}^{1/2}, \end{aligned}$$

where $a_{\lambda,v}^*$ and $b_{\lambda,v}^*$ are the Fourier coefficients of f and g in R , that is,

$$(3.10) \quad \begin{aligned} a_{\lambda,v}^* &= \iint_R x(u)x(v)\mathcal{P}_\lambda(u)\mathcal{P}_v(v)dudv = a_\lambda a_v, \\ b_{\lambda,v}^* &= \iint_R g(u, v)\mathcal{P}_\lambda(u)\mathcal{P}_v(v)dudv \\ &= \frac{1}{2B(r, s-r, n-s+1)} \iint_{0 < u < v < 1} u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s} \\ &\quad \times [\mathcal{P}_\lambda(u)\mathcal{P}_v(v) + \mathcal{P}_\lambda(v)\mathcal{P}_v(u)]dudv \\ &= \frac{b_{\lambda,v} + b_{v,\lambda}}{2}, \end{aligned}$$

because of (3.1) and (3.2). This implies

$$(3.11) \quad \begin{aligned} a_{0,0}^* &= a_0^2 = \mu^2, & a_{\lambda,v}^* &= a_{v,\lambda}^*, \\ b_{0,0}^* &= 1, & b_{\lambda,v}^* &= b_{v,\lambda}^*, \end{aligned}$$

and hence

$$(3.12) \quad \sum_{v=0}^{\infty} a_{0,v}^{*2} = \sum_{\lambda=0}^{\infty} a_{\lambda,0}^{*2} = \mu^2 \sum_{v=0}^{\infty} a_v^2 = \mu^2(\mu^2 + \sigma^2).$$

We calculate each term in (3.9). If we put $\lambda=0$ in (3.2) and transform the variable u to t by $u=vt$, then

$$(3.13) \quad b_{0,v} = \frac{1}{B(r, s-r, n-s+1)} \int_0^1 v^{s-1}(1-v)^{n-s} \varphi_v(v) dv \int_0^1 t^{r-1}(1-t)^{s-r-1} dt$$

$$= \frac{1}{B(s, n-s+1)} \int_0^1 v^{s-1}(1-v)^{n-s} \varphi_v(v) dv,$$

and similarly

$$(3.14) \quad b_{\lambda,0} = \frac{1}{B(r, n-r+1)} \int_0^1 u^{r-1}(1-u)^{n-r} \varphi_{\lambda}(u) du.$$

We have already met with (3.13) in Theorem 1 and 2 in [9] in dealing with $E(X_{s/n})$. From (3.10), (3.13), (3.14) and the completeness of $\{\varphi_v(u)\}_{v=0,1,\dots}$ in $L^2(0, 1)$, it follows that

$$(3.15) \quad \sum_{v=0}^{\infty} a_{0,v}^* b_{0,v}^* = \frac{\mu}{2} \sum_{v=0}^{\infty} a_v(b_{0,v} + b_{v,0})$$

$$= \frac{\mu}{2} E(X_{r/n} + X_{s/n}),$$

$$(3.16) \quad \begin{cases} \sum_{\lambda=0}^{\infty} b_{\lambda,0}^2 &= \frac{B(2r-1, 2n-2r+1)}{[B(r, n-r+1)]^2}, \\ \sum_{v=0}^{\infty} b_{0,v}^2 &= \frac{B(2s-1, 2n-2s+1)}{[B(s, n-s+1)]^2}, \\ \sum_{v=0}^{\infty} b_{0,v} b_{v,0} &= \frac{B(r+s-1, 2n-r-s+1)}{B(r, n-r+1)B(s, n-s+1)}, \end{cases}$$

whence we can calculate

$$(3.17) \quad \sum_{v=0}^{\infty} b_{0,v}^{*2} = \sum_{\lambda=0}^{\infty} b_{\lambda,0}^{*2} = \frac{1}{4} \left(\sum_{\lambda=0}^{\infty} b_{\lambda,0}^2 + 2 \sum_{v=0}^{\infty} b_{0,v} b_{v,0} + \sum_{v=0}^{\infty} b_{0,v}^2 \right).$$

Substituting (3.11), (3.12) and (3.15)~(3.17) into (3.9), we can get Theorem 1.

Corollary 1. *For any distribution absolutely continuous with respect to the Lebesgue measure with mean zero and variance one and for any r, s ($1 \leq r < s \leq n$),*

$$(3.18) \quad |E(X_{r,n} X_{s/n})| \leq \left\{ \frac{B(2r-1, 2s-2r-1, 2n-2s+1)}{2[B(r, s-r, n-s+1)]^2} \right\}$$

$$\begin{aligned} & -\frac{B(2r-1, 2n-2r+1)}{2[B(r, n-r+1)]^2} - \frac{B(r+s-1, 2n-r-s+1)}{B(r, n-r+1)B(s, n-s+1)} \\ & - \left. \frac{B(2s-1, 2n-2s+1)}{2[B(s, n-s+1)]^2} + 1 \right\}^{1/2} \quad (= a, \text{ say}), \end{aligned}$$

and equality holds if and only if

$$(3.19) \quad x(u)x(v) = \pm \frac{1}{a} \left\{ 1 + g(u, v) - \frac{u^{r-1}(1-u)^{n-r} + v^{r-1}(1-v)^{n-r}}{2B(r, n-r+1)} \right. \\ \left. - \frac{u^{s-1}(1-u)^{n-s} + v^{s-1}(1-v)^{n-s}}{2B(s, n-s+1)} \right\},$$

where $g(u, v)$ is defined by (3.7).

Proof. We get (3.18) from Theorem 1 by excluding the terms corresponding to $\{\varphi_\lambda(u)\varphi_\nu(v)\}_{\lambda, \nu=1, 2, \dots, k}$ in (3.9). Equality holds from Proposition 1 if and only if

$$(3.20) \quad x(u)x(v) = \alpha + \beta g(u, v) + \sum_{\nu=1}^{\infty} \gamma_\nu \varphi_\nu(u) + \sum_{\nu=1}^{\infty} \delta_\nu \varphi_\nu(v),$$

for some constants $\alpha, \beta, \gamma_\nu$ and $\delta_\nu (\nu=1, 2, \dots)$. Integrating (3.20) by u and v , we get

$$(3.21) \quad \begin{aligned} \alpha + \beta \int_0^1 g(u, v) du + \sum_{\nu=1}^{\infty} \delta_\nu \varphi_\nu(v) &= 0, \\ \alpha + \beta \int_0^1 g(u, v) dv + \sum_{\nu=1}^{\infty} \gamma_\nu \varphi_\nu(u) &= 0, \\ \alpha + \beta &= 0. \end{aligned}$$

From (3.7) we have

$$(3.22) \quad \begin{aligned} \int_0^1 g(u, v) du &= \frac{1}{2B(r, s-r, n-s+1)} \left\{ \int_0^v u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s} du \right. \\ & \left. + \int_v^1 v^{r-1}(u-v)^{s-r-1}(1-u)^{n-s} du \right\} \\ &= \frac{v^{r-1}(1-v)^{n-r}}{2B(r, n-r+1)} + \frac{v^{s-1}(1-v)^{n-s}}{2B(s, n-s+1)}, \end{aligned}$$

$$(3.23) \quad \int_0^1 g(u, v) dv = \frac{u^{r-1}(1-u)^{n-r}}{2B(r, n-r+1)} + \frac{u^{s-1}(1-u)^{n-s}}{2B(s, n-s+1)}.$$

From (3.21)~(3.23) and $\|x(u)x(v)\|^2=1$, we can determine $\alpha, \beta, \sum_{\nu=1}^{\infty} \gamma_\nu \varphi_\nu(u)$ and $\sum_{\nu=1}^{\infty} \delta_\nu \varphi_\nu(v)$. Substituting these relations into (3.20), we have (3.19).

In particular, when $r=n-1$ and $s=n$ in Corollary 1, we get

$$(3.24) \quad |E(X_{n-1/n}X_{n/n})| \leq \frac{n-2}{2} \sqrt{\frac{n-1}{2n-1}}.$$

This exhibits a universal upper bound for $E(X_{n-1/n}X_{n/n})$ when the distribution is required to have mean zero and variance one. By the way, under the same assumption as above, the upper bound due to Gumbel [3] and Hartley and David [4] is

$$(3.25) \quad |E(X_{n/n})| \leq \sqrt{\frac{n-1}{2n-1}}.$$

Some numerical values for $n=5$ in Corollary 1 are shown in the second column of Table 1. The third column is calculated from Corollary 2 (i.e. universal upper bounds for symmetric population). The last three columns give the values of $E(X_{r/5}X_{s/5})$ from the uniform distribution in the interval $(-\sqrt{3}, \sqrt{3})$, exponential distribution with the density $e^{-(x+1)}$ ($x \geq -1$), and the standard normal distribution, the values being calculated from Sarhan and Greenberg [7].

Table 1. Some special values of $E(X_{r/5}X_{s/5})$ and the upper bounds.

(r, s)	upper bound		true distribution		
	any distribution	symmetric distribution	uniform	exponential	normal
(4, 5)	1	0.8696	0.8571	0.8272	0.8000
(3, 5)	0.6667	0.2795	0.1429	-0.0645	0.1482
(2, 5)	0.8729	0.6512	-0.5714	-0.6006	-0.4699
(1, 5)	1.3244	1.3025	-1.2857	-0.9867	-1.2783
(3, 4)	0.6667	0.4812	0.2857	-0.4003	0.2084
(2, 4)	0.4543	0.3660	-0.1429	-0.0533	-0.0951

Now we shall consider, as in Moriguti [5], the case when the distribution is known to be symmetric. This additional information is expected to reduce the upper bound as is the case with $E(X_{r/n})$ in [9]. For this purpose we shall define

$$(3.26) \quad I(p_1, p_2, p_3, q_1, q_2) = \iint_{\substack{0 < u < v < 1 \\ u+v < 1}} u^{p_1-1} v^{p_2-1} (1-v)^{p_3-1} (v-u)^{q_1-1} (1-u-v)^{q_2-1} dudv,$$

where p_1, p_2, p_3, q_1, q_2 are positive integers.

Lemma 1. *The following relations for $I(p_1, p_2, p_3, q_1, q_2)$ hold:*

$$(3.27) \quad I(p_1, p_2, p_3, q_1, q_2) = \sum_{i=0}^{p_2-1} \sum_{j=0}^{p_3-1} \binom{p_2-1}{i} \binom{p_3-1}{j} \times B(q_1+i, q_2+j, p_1+p_2+p_3-i-j-2) 2^{-(p_1+p_2+p_3-i-j-2)},$$

$$(3.28) \quad I(p_1, p_2, p_3, q_1, q_2) = I(p_1, p_3, p_2, q_2, q_1).$$

Proof. Binomial expansion of $v^{p_2-1}(1-v)^{p_3-1} = \{(v-u)+u\}^{p_2-1}\{(1-u-v)+u\}^{p_3-1}$ yields

$$\begin{aligned} I(p_1, p_2, p_3, q_1, q_2) &= \sum_{i=0}^{p_2-1} \sum_{j=0}^{p_3-1} \binom{p_2-1}{i} \binom{p_3-1}{j} \\ &\quad \times \iint_{\substack{0 < u < v < 1 \\ u+v < 1}} u^{p_1+p_2+p_3-i-j-3} (v-u)^{q_1+i-1} (1-u-v)^{q_2+j-1} dudv. \end{aligned}$$

After transforming the variable v to t by $v=u+(1-2u)t$, we can see that the right side of the equation is equal to

$$\begin{aligned} &\sum_{i=0}^{p_2-1} \sum_{j=0}^{p_3-1} \binom{p_2-1}{i} \binom{p_3-1}{j} \int_0^{\frac{1}{2}} u^{p_1+p_2+p_3-i-j-3} (1-2u)^{q_1+q_2+i+j-1} du \\ &\quad \times \int_0^1 t^{q_1+i-1} (1-t)^{q_2+j-1} dt, \end{aligned}$$

which proves (3.27). (3.28) is obvious from (3.27).

Theorem 2. Let $X_{i/n}$ be the i th (smallest) order statistic in a random sample of size n with symmetric distribution $F(x)$ absolutely continuous with respect to the Lebesgue measure with finite variance σ^2 . Let $\{\varphi_\nu(u)\}_{\nu=0,1,\dots}$ ($\varphi_0(u)=1$) be any complete orthonormal system in $L^2(0,1)$ satisfying $\varphi_\nu(u) = (-1)^\nu \varphi_\nu(1-u)$ for $\nu=1, 2, \dots$. Putting a_λ and $b_{\lambda,\nu}$ as in (3.1) and (3.2), we have for any r, s ($1 \leq r < s \leq n$)

$$(3.29) \quad \begin{aligned} &|\mathbb{E}(x_{r/n} x_{s/n}) - \frac{1}{2} \sum_{\lambda,\nu=0}^k a_{2\lambda+1} a_{2\nu+1} (b_{2\lambda+1,2\nu+1} + b_{2\nu+1,2\lambda+1})| \\ &\leq \{\sigma^4 - \sum_{\lambda,\nu=0}^k a_{2\lambda+1}^2 a_{2\nu+1}^2\}^{1/2} \{A_1 - B_1 - \frac{1}{4} \sum_{\lambda,\nu=0}^k (b_{2\lambda+1,2\nu+1} + b_{2\nu+1,2\lambda+1})^2\}^{1/2}, \end{aligned}$$

where

$$(3.30) \quad \begin{aligned} A_1 &= \frac{B(2r-1, 2s-2r-1, 2n-2s+1) + B(n+r-s, n+r-s, 2s-2r-1)}{8[B(r, s-r, n-s+1)]^2}, \\ B_1 &= \frac{I(2r-1, n-s+1, n-s+1, s-r, s-r) + 2I(n+r-s, r, n-s+1)}{8[B(r, s-r, n-s+1)]^2} \\ &\quad \frac{s-r, s-r + I(2n-2s+1, r, r, s-r, s-r)}{8[B(r, s-r, n-s+1)]^2} \end{aligned}$$

and $I(p_1, p_2, p_3, q_1, q_2)$ is defined by (3.27).

Proof. Since (3.5)~(3.8) hold also in this case for $\mu=0$, we substitute $\{\varphi_{2\lambda}(u)\varphi_\nu(v), \varphi_{2\lambda+1}(u)\varphi_{2\nu}(v)\}_{\lambda,\nu=0,1,\dots} \cup \{\varphi_{2\lambda+1}(u)\varphi_{2\nu+1}(v)\}_{\lambda,\nu=0,1,\dots,k}$ for $\{\varphi_\nu\}_{\nu=0,1,\dots,k}$ in Proposition 1 to get

$$\begin{aligned}
 (3.31) \quad & |E(X_{r/n}X_{s/n}) - \sum_{\lambda, \nu=0}^{\infty} (a_{2\lambda, \nu}^* b_{2\lambda, \nu}^* + a_{2\lambda+1, 2\nu}^* b_{2\lambda+1, 2\nu}^*) - \sum_{\lambda, \nu=0}^k a_{2\lambda+1, 2\nu+1}^* b_{2\lambda+1, 2\nu+1}^*| \\
 & \leq \{ \|f\|^2 - \sum_{\lambda, \nu=0}^{\infty} (a_{2\lambda, \nu}^{*2} + a_{2\lambda+1, 2\nu}^{*2}) - \sum_{\lambda, \nu=0}^k a_{2\lambda+1, 2\nu+1}^{*2} \}^{1/2} \\
 & \quad \times \{ \|g\|^2 - \sum_{\lambda, \nu=0}^{\infty} (b_{2\lambda, \nu}^{*2} + b_{2\lambda+1, 2\nu}^{*2}) - \sum_{\lambda, \nu=0}^k b_{2\lambda+1, 2\nu+1}^{*2} \}^{1/2},
 \end{aligned}$$

where $a_{\lambda, \nu}^*$ and $b_{\lambda, \nu}^*$ are defined by (3.10). Since $x(u)x(v) \in L^2_{0,0}(R)$ by Proposition 4, from Proposition 3 and (3.10) we have

$$(3.32) \quad a_{2\lambda, \nu}^* = a_{2\lambda+1, 2\nu}^* = 0$$

and by Proposition 2 and (3.7), (3.10)

$$(3.33) \quad \|g\|^2 - \sum_{\lambda, \nu=0}^{\infty} (b_{2\lambda, \nu}^{*2} + b_{2\lambda+1, 2\nu}^{*2}) = \sum_{\lambda, \nu=0}^{\infty} b_{2\lambda+1, 2\nu+1}^{*2}.$$

Hence the essential part of this proof consists in calculating $\sum_{\lambda, \nu=0}^{\infty} b_{2\lambda+1, 2\nu+1}^{*2}$. From (3.10) we have

$$\begin{aligned}
 & b_{2\lambda+1, 2\nu+1}^* \\
 & = \frac{1}{2B(r, s-r, n-s+1)} \left\{ \iint_{0 < u < v < 1} u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s} \varphi_{2\lambda+1}(u) \varphi_{2\nu+1}(v) dudv \right. \\
 & \quad \left. + \iint_{0 < v < u < 1} u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s} \varphi_{2\lambda+1}(v) \varphi_{2\nu+1}(u) dudv \right\}.
 \end{aligned}$$

Transforming the variable (u, v) to $(1-v, 1-u)$ in the second integral, we can rewrite the right-hand side as

$$\begin{aligned}
 & \frac{1}{2B(r, s-r, n-s+1)} \iint_{0 < u < v < 1} \{ (u^{r-1}(1-v)^{n-s} + u^{n-s}(1-v)^{r-1}) \\
 & \quad \times (v-u)^{s-r-1} \varphi_{2\lambda+1}(u) \varphi_{2\nu+1}(v) dudv,
 \end{aligned}$$

which becomes after transforming (u, v) to $(1-u, 1-v)$

$$\begin{aligned}
 & \frac{1}{2B(r, s-r, n-s+1)} \iint_{0 < v < u < 1} \{ (1-u)^{r-1}v^{n-s} + (1-u)^{n-s}v^{r-1} \} \\
 & \quad \times (u-v)^{s-r-1} \varphi_{2\lambda+1}(u) \varphi_{2\nu+1}(v) dudv.
 \end{aligned}$$

So if we put

$$(3.34) \quad \xi(u, v) = \begin{cases} \frac{1}{4B(r, s-r, n-s+1)} \{ u^{r-1}(1-v)^{n-s} + u^{n-s}(1-v)^{r-1} \} (v-u)^{s-r-1} & 0 < u < v < 1, \\ \frac{1}{4B(r, s-r, n-s+1)} \{ (1-u)^{r-1}v^{n-s} + (1-u)^{n-s}v^{r-1} \} (u-v)^{s-r-1} & 0 < v < u < 1, \end{cases}$$

$$(3.35) \quad \eta(u, v) = \frac{1}{2} \{ \xi(u, v) - \xi(u, 1-v) \},$$

then we can see $\xi(u, v) = \xi(v, u) = \xi(1-u, 1-v)$ and $\eta(u, v) \in L_{0,0}^2(R)$. Since

$$(3.36) \quad b_{2\lambda+1, 2\nu+1}^* = \iint_R \eta(u, v) \varphi_{2\lambda+1}(u) \varphi_{2\nu+1}(v) dudv,$$

from Proposition 3 we have

$$(3.37) \quad \begin{aligned} \sum_{\lambda, \nu=0}^{\infty} b_{2\lambda+1, 2\nu+1}^{*2} &= \int_0^1 \int_0^1 [\eta(u, v)]^2 dudv \\ &= \frac{1}{2} \int_0^1 \int_0^1 [\xi(u, v)]^2 dudv - \frac{1}{2} \int_0^1 \int_0^1 \xi(u, v) \xi(u, 1-v) dudv. \end{aligned}$$

After some calculation the last two integrals are expressed as follows:

$$(3.38) \quad \begin{aligned} \int_0^1 \int_0^1 [\xi(u, v)]^2 dudv &= 2A_1, \\ \int_0^1 \int_0^1 \xi(u, v) \xi(u, 1-v) dudv &= 2B_1. \end{aligned}$$

Substituting (3.32), (3.33), (3.37) and (3.38) into (3.31), we have (3.29).

Similarly we can get

$$(3.39) \quad \begin{aligned} \sum_{\lambda, \nu=0}^{\infty} b_{2\lambda, 2\nu}^{*2} &= \frac{1}{2} \int_0^1 \int_0^1 [\xi(u, v)]^2 dudv + \frac{1}{2} \int_0^1 \int_0^1 \xi(u, v) \xi(u, 1-v) dudv, \\ \sum_{\lambda, \nu=0}^{\infty} b_{2\lambda, 2\nu+1}^{*2} &= \sum_{\lambda, \nu=0}^{\infty} b_{2\lambda+1, 2\nu}^{*2} \\ &= \frac{B(2r-1, 2s-2r-1, 2n-2s+1) - B(n+r-s, n+r-s, 2s-2r-1)}{8[B(r, s-r, n-s+1)]^2}, \end{aligned}$$

which is available to check (3.33) and will be used in the proof of Theorem 3.

Corollary 2. *For any symmetric distribution absolutely continuous with respect to the Lebesgue measure with mean zero and variance one,*

$$(3.40) \quad \begin{aligned} |E(X_{r/n} X_{s/n})| &\leq \frac{1}{2\sqrt{2B(r, s-r, n-s+1)}} \\ &\times \{ B(2r-1, 2s-2r-1, 2n-2s+1) \\ &+ B(n+r-s, n+r-s, 2s-2r-1) \\ &- I(2r-1, n-s+1, n-s+1, s-r, s-r) \\ &- 2I(n+r-s, r, n-s+1, s-r, s-r) \\ &- I(2n-2s+1, r, r, s-r, s-r) \}^{1/2} \quad (= b, \text{ say}), \end{aligned}$$

where $I(p_1, p_2, p_3, q_1, q_2)$ is defined by (3.27), and equality holds if and only if

$$(3.41) \quad x(u)x(v) = \pm \frac{1}{b} \eta(u, v),$$

where $\eta(u, v)$ is defined by (3.35).

Proof. We get (3.40) from Theorem 2 by excluding the term corresponding to $\{\mathcal{P}_{2\lambda+1}(u)\mathcal{P}_{2\nu+1}(v)\}_{\lambda, \nu=0,1,\dots,k}$ in (3.31). An analogous argument as in Corollary 1 leads us to (3.41).

It is to be noted that the upper bound for $E(X_{r/n}X_{s/n})$ is identical to the one for $E(X_{n-s+1/n}X_{n-r+1/n})$ both in Corollary 1 and 2. The simplest form in Corollary 2 appears when $r=1$ and $s=n$, that is,

$$(3.42) \quad |E(X_{1/n}X_{n/n})| \leq \frac{n}{2} \left\{ \frac{n-1}{2(2n-3)} - \frac{1}{\binom{2n-2}{n-1}} \right\}^{1/2}.$$

This is the universal upper bound for $E(X_{1/n}X_{n/n})$ when the distribution is required to be symmetric with mean zero and variance one. The corresponding upper bound in Corollary 1 is

$$(3.43) \quad |E(X_{1/n}X_{n/n})| \leq n \left\{ \frac{n-1}{4(2n-3)} - \frac{(n-1)^2}{n^2(2n-1)} - \frac{1}{(2n-1)\binom{2n-2}{n-1}} \right\}^{1/2}.$$

This is the universal upper bound when the distribution is required only to have mean zero and variance one.

The third column in Table 1 is calculated by (3.40), which, in comparison with the second, shows the effect of the restriction to symmetric populations.

A quite analogous argument as in the proof of Theorem 1 and 2 leads us to the following Theorem, the proof of which may be found in [10].

Theorem 3. Suppose $E(X^4) < \infty$, then under the same assumption and notation as in Theorem 2 we have

$$(3.44) \quad |E(X_{r/n}^2 X_{s/n}^2) - \sigma^2 E(X_{r/n}^2 + X_{s/n}^2) + \sigma^4 - \frac{1}{2} \sum_{\lambda, \nu=1}^{\infty} a'_{2\lambda} a'_{2\nu} (b_{2\lambda, 2\nu} + b_{2\nu, 2\lambda})|$$

$$\leq \{ (E(X^4) - \sigma^2)^2 - \sum_{\lambda, \nu=1}^k a'_{2\lambda} a'_{2\nu} \}^{1/2} \{ A_2 + B_2 - C_2 + 1$$

$$- \frac{1}{4} \sum_{\lambda, \nu=1}^k (b_{2\lambda, 2\nu} + b_{2\nu, 2\lambda})^2 \}^{1/2},$$

where

$$(3.45) \quad a'_\lambda = \int_0^1 [x(u)]^2 \varphi_\lambda(u) du,$$

$$A_2 = A_1,$$

$$B_2 = B_1,$$

$$(3.46) \quad C_2 = \frac{B(2r-1, 2n-2r+1)+B(n, n)}{4[B(r, n-r+1)]^2} + \frac{B(2s-1, 2n-2s+1)+B(n, n)}{4[B(s, n-s+1)]^2} \\ + \frac{B(r+s-1, 2n-r-s+1)+B(n+r-s, n-r+s)}{2B(r, n-r+1)B(s, n-s+1)}.$$

Theorem 4. *Under the same assumption and notation as in Theorem 3, the following two inequalities hold for any r, s ($1 \leq r < s \leq n$).*

$$(3.47) \quad |E(X_{r/n}^2 X_{s/n}) - \sigma^2 E(X_{s/n}) - \sum_{\lambda, \nu=0}^k a'_{2\lambda+2} a_{2\nu+1} b_{2\lambda+2, 2\nu+1}| \\ \leq \{\sigma^2 E(X^4) - \sigma^6 - \sum_{\lambda, \nu=0}^k a'_{2\lambda+2} a_{2\nu+1}^2\}^{1/2} \{A_3 - B_3 - \sum_{\lambda, \nu=0}^k b_{2\lambda+2, 2\nu+1}^2\}^{1/2},$$

$$(3.48) \quad |E(X_{r/n} X_{s/n}^2) - \sigma^2 E(X_{r/n}) - \sum_{\lambda, \nu=0}^k a_{2\lambda+1} a'_{2\nu+2} b_{2\lambda+1, 2\nu+2}| \\ \leq \{\sigma^2 E(X^4) - \sigma^2 - \sum_{\lambda, \nu=0}^k a_{2\lambda+1}^2 a_{2\nu+2}^2\}^{1/2} \{A_4 - B_4 - \sum_{\lambda, \nu=0}^k b_{2\lambda+1, 2\nu+2}^2\}^{1/2},$$

where

$$(3.49) \quad \left\{ \begin{array}{l} A_3 = \frac{B(2r-1, 2s-2r-1, 2n-2s+1)}{4[B(r, s-r, n-s+1)]^2} - \frac{B(2s-1, 2n-2s+1)-B(n, n)}{2[B(s, n-s+1)]^2}, \\ B_3 = \frac{I(2r-1, n-s+1, n-s+1, s-r, s-r) - I(2n-2s+1, r, r, s-r, s-r)}{4[B(r, s-r, n-s+1)]^2}, \\ A_4 = \frac{B(2r-1, 2s-2r-1, 2n-2s+1)}{4[B(r, s-r, n-s+1)]^2} - \frac{B(2r-1, 2n-2r+1)-B(n, n)}{2[B(r, n-r+1)]^2}, \\ B_4 = -B_3. \end{array} \right.$$

Proof. We shall sketch the proof of (3.47), leaving the details to [10]. From (3.5) we have

$$E(X_{r/n}^2 X_{s/n}) = \frac{1}{B(r, s-r, n-s+1)} \iint_{0 < u < v < 1} [x(u)]^2 x(v) u^{r-1} (v-u)^{s-r-1} (1-v)^{n-s} dudv,$$

which is written by transforming the variable (u, v) to $(1-u, 1-v)$ as

$$\frac{-1}{B(r, s-r, n-s+1)} \iint_{0 < v < u < 1} [x(u)]^2 x(v) (1-u)^{r-1} (u-v)^{s-r-1} v^{n-s} dudv.$$

Putting

$$(3.50) \quad \begin{aligned} f_1(u, v) &= [x(u)]^2 x(v), \\ g_1(u, v) &= \begin{cases} \frac{1}{2B(r, s-r, n-s+1)} u^{r-1}(v-u)^{s-r-1}(1-v)^{n-s} & 0 < u < v < 1, \\ \frac{-1}{2B(r, s-r, n-s+1)} (1-u)^{r-1}(u-v)^{s-r-1}v^{n-s} & 0 < v < u < 1, \end{cases} \end{aligned}$$

we have from Proposition 1

$$(3.51) \quad \begin{aligned} &|E(X_{r/n}^2 X_{s/n}) - \sum_{\nu=0}^{\infty} c_{0,2\nu+1} d_{0,2\nu+1} - \sum_{\lambda,\nu=0}^k c_{2\lambda+2,2\nu+1} d_{2\lambda+2,2\nu+1}| \\ &\leq \{ \|f_1\|^2 - \sum_{\nu=0}^{\infty} c_{0,2\nu+1}^2 - \sum_{\lambda,\nu=0}^k c_{2\lambda+2,2\nu+1}^2 \}^{1/2} \\ &\quad \times \{ \sum_{\lambda,\nu=0}^{\infty} d_{2\lambda,2\nu+1}^2 - \sum_{\nu=0}^{\infty} d_{0,2\nu+1}^2 - \sum_{\lambda,\nu=0}^k d_{2\lambda+2,2\nu+1}^2 \}^{1/2}, \end{aligned}$$

where

$$(3.52) \quad \begin{aligned} c_{\lambda,\nu} &= \int_0^1 \int_0^1 [x(u)]^2 x(v) \varphi_{\lambda}(u) \varphi_{\nu}(v) du dv \\ &= a'_{\lambda} a_{\nu}, \\ d_{2\lambda,2\nu+1} &= \int_0^1 \int_0^1 g_1(u, v) \varphi_{2\lambda}(u) \varphi_{2\nu+1}(v) du dv \\ &= \frac{1}{2} \int_0^1 \int_0^1 \{g_1(u, v) - g_1(u, 1-v)\} \varphi_{2\lambda}(u) \varphi_{2\nu+1}(v) du dv. \end{aligned}$$

Since $g_1(u, v) - g_1(u, 1-v) \in L^2_{e,0}(R)$, we have

$$(3.53) \quad \sum_{\lambda,\nu=0}^{\infty} d_{2\lambda,2\nu+1}^2 = \frac{1}{4} \|g_1(u, v) - g_1(u, 1-v)\|^2,$$

which after some calculation turns out to be equal to

$$(3.54) \quad \frac{B(2r-1, 2n-2s+1, 2s-2r-1) - I(2r-1, n-s+1, n-s+1, s-r, s-r)}{4[B(r, s-r, n-s+1)]^2} + \frac{I(2n-2s+1, r, r, s-r, s-r)}{4[B(r, s-r, n-s+1)]^2}.$$

We can also see

$$(3.55) \quad \sum_{\nu=0}^{\infty} d_{0,2\nu+1}^2 = \frac{B(2s-1, 2n-2s+1) - B(n, n)}{2[B(s, n-s+1)]^2}.$$

Substituting (3.52), (3.54) and (3.55) into (3.51), we have (3.47).

4. The values of $E(X_{r/n} X_{s/n})$ in normal sample

As an application of Theorem 2, we shall calculate $E(X_{r/n} X_{s/n})$ for

the standard normal population. Adopting Legendre polynomials as $\varphi_\nu(u)$ in Theorem 2 and putting

$$(4.1) \quad \varphi_\lambda(u) = \sum_i \alpha_{\lambda,i} u^i,$$

we have

$$(4.2) \quad \varphi_\lambda(u)\varphi_\nu(v) = \sum_{i,j} (-1)^j \alpha_{\lambda,i} \alpha_{\nu,j} u^i (1-v)^j,$$

$$(4.3) \quad a_{\lambda,\nu} = \sum_{i,j} \frac{\alpha_{\lambda,i} \alpha_{\nu,j}}{(i+1)(j+1)} E(X_{i+1/i+1}) E(X_{j+1/j+1}),$$

$$b_{\lambda,\nu} = \sum_{i,j} (-1)^j \alpha_{\lambda,i} \alpha_{\nu,j} \frac{\Gamma(r+i)\Gamma(n-s+1+j)\Gamma(n+1)}{\Gamma(r)\Gamma(n-s+1)\Gamma(n+i+j+1)}.$$

Some numerical values of $\alpha_{\lambda,i}$ and $E(X_{i+1/i+1})$ are shown in [9]. From these relations we get Table 2.

Table 2. Values of $E(X_{r/5} X_{s/5})$ for standard normal population.

(r, s)	first approximation $a_1^2 b_{11}$	second approximation $a_1^2 b_{11} + \frac{1}{2} a_1 a_3 (b_{13} + b_{31})$	exact value
(4, 5)	0.818 ± 0.043	0.7990 ± 0.0193	0.8000
(3, 5)	0.136 ± 0.071	0.1494 ± 0.0364	0.1482
(2, 5)	-0.546 ± 0.093	-0.4676 ± 0.0075	-0.4699
(1, 5)	-1.228 ± 0.062	-1.2798 ± 0.0050	-1.2783
(3, 4)	0.273 ± 0.115	0.2013 ± 0.0411	0.2084
(2, 4)	-0.136 ± 0.100	-0.0844 ± 0.0415	-0.0951

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