

**A BOUND ON TAIL PROBABILITIES FOR QUADRATIC FORMS  
 IN INDEPENDENT RANDOM VARIABLES<sup>1</sup>**

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Let  $X_i$  for  $i = 0, \pm 1, \dots$  be independent random variables whose distributions are symmetric about zero and such that

$$(1) \quad P\{|X_i| \geq x\} \leq M \int_x^\infty e^{-t^2} dt$$

for all  $i$  and all  $x \geq 0$  where  $M$  and  $\gamma$  are positive constants. Suppose  $a_{ij}$  for  $i, j = 0, \pm 1, \dots$  are real numbers such that  $a_{ij} = a_{ji}$  for all  $i$  and  $j$ , and such that

$$(2) \quad \Lambda^2 = \sum_{i,j} a_{ij}^2 < \infty.$$

Let  $A$  denote the matrix  $((|a_{ij}|))_{i,j=0,\pm 1,\dots}$ , and let  $\|A\|$  be the norm of  $A$  considered as an operator on  $l_2$ , the index on the sequences in  $l_2$  taking on the values  $0, \pm 1, \dots$ . Define

$$(3) \quad S = \sum_{i,j} a_{ij}(X_i X_j - EX_i X_j).$$

The purpose of this paper is to prove:

**THEOREM.** *Under the assumptions stated above,  $S$  exists as a limit, both in quadratic mean and almost surely, of the sequence*

$$\{S_N = \sum_{i,j=-N}^N a_{ij}(X_i X_j - EX_i X_j)\},$$

and there exist constants  $C_1$  and  $C_2$  depending on  $M$  and  $\gamma$  (but not on the coefficients  $a_{ij}$ ) such that for every  $\varepsilon > 0$

$$(4) \quad P\{S \geq \varepsilon\} \leq \exp(-\min\{C_1 \varepsilon / \|A\|, C_2 \varepsilon^2 / \Lambda^2\}).$$

If  $\{Y_k = \sum_v \alpha_v X_{k-v}\}$  is a moving average, then quadratic sums of the form (3) occur naturally when estimating its spectral density. This was the original motivation behind our work.

We would very much like to remove the restriction that the distributions of the  $X$ 's be symmetric. Unfortunately, our proof depends heavily on this symmetry.

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PROOF OF THEOREM. Let

$$(5) \quad \begin{aligned} a_{ij}^{(N)} &= a_{ij} && \text{if } -N \leq i, j \leq N, \\ &= 0 && \text{otherwise;} \end{aligned}$$

and let

$$(6) \quad A_N = ((|a_{ij}^{(N)}|))_{i,j=0,=1,\dots}$$

Define

$$(7) \quad \Lambda_N^2 = \sum_{i,j} (a_{ij}^{(N)})^2.$$

A minor re-indexing of our  $X$ 's enables us to use Theorems 1 and 2 of Varberg [2] to obtain both types of convergence of  $S_N$  to  $S$ .

The main part of our proof consists, first, of showing that (4) holds with  $S$ ,  $A$ , and  $\Lambda$  replaced by  $S_N$ ,  $A_N$ , and  $\Lambda_N$  respectively, and second, of a "continuity" argument which removes the subscripts.

Before proceeding with the main part of the proof we establish several lemmas.

LEMMA 1. *If  $EX^2 = \sigma^2 < \infty$ , then for  $n = 0, 1, 2, \dots$  and  $k = 1, 3, 5, \dots$  we have*

$$EX^{2n}(X^2 - \sigma^2)^k \geq \sigma^{2n}E(X^2 - \sigma^2)^k$$

*if both sides exist and are finite.*

LEMMA 2. *If  $Z$  is  $N(0, 1)$  (i.e., normal with  $EZ = 0$  and  $EZ^2 = 1$ ), then*

$$EZ^{2n} = \frac{(2n)!}{n!2^n}$$

*for  $n = 0, 1, 2, \dots$ .*

LEMMA 3. *If  $Z$  is  $N(0, 1)$  and  $n \geq 2$ , then  $E(Z^2 - 1)^n \geq 1$ .*

PROOF. For  $n \geq 2$  we have (using Lemma 2)

$$\begin{aligned} E(Z^2 - 1)^n &= \sum_{\alpha} [ \binom{n}{2\alpha} EZ^{2(n-2\alpha)} - \binom{n}{2\alpha+1} EZ^{2(n-2\alpha-1)} ] \\ &\geq \binom{n}{0} EZ^{2n} - \binom{n}{1} EZ^{2n-2} \\ &= [(2n-1) - n] EZ^{2n-2} \geq 1. \end{aligned}$$

LEMMA 4. *If  $Z$  is  $N(0, 1)$  and  $X$  satisfies (1) then there exists  $\lambda$  depending only on  $M$  and  $\gamma$  such that*

$$|EX^{2n}(X^2 - EX^2)^v| \leq \lambda^{2n+2v} EZ^{2n}(Z^2 - 1)^v$$

*for  $n = 0, 1, \dots$  and  $v = 0, 1, \dots$ .*

PROOF. Case  $v = 0$ . Setting  $x = y/(2\gamma)^{\frac{1}{2}}$  we get

$$\begin{aligned} EX^{2n} &\leq \int_0^\infty x^{2n} M e^{-\gamma x^2} dx = (2\gamma)^{-n-\frac{1}{2}} M \int_0^\infty y^{2n} e^{-y^2/2} dy \\ &= (2\gamma)^{-n} (M\pi^{\frac{1}{2}}/2\gamma^{\frac{1}{2}}) \int_{-\infty}^\infty (2\pi)^{-\frac{1}{2}} y^{2n} e^{-y^2/2} dy. \end{aligned}$$

The desired inequality holds if

$$\lambda \geq \lambda_1 = (2\gamma)^{-\frac{1}{2}}(1 + M\pi^{\frac{1}{2}}/2\gamma^{\frac{1}{2}}).$$

Case  $v = 1, n = 0$ . The conclusion of this lemma is  $0 = 0$ .

Case  $v = 1, n \geq 1$ . Using Lemma 2 we get

$$EZ^{2n}(Z^2 - 1)^1 \geq 1 > P\{|Z| \geq 2\}.$$

[Proof continued below.]

Case  $v \geq 2, v$  odd. Using Lemma 1 and then Lemma 3 we get

$$EZ^{2n}(Z^2 - 1)^v \geq E(Z^2 - 1)^v \geq 1 > P\{|Z| \geq 2\}.$$

[Proof continued below.]

Case  $v \geq 2, v$  even.  $EZ^{2n}(Z^2 - 1)^v \geq P\{|Z| \geq 2\}$ . We now continue the proof for these last three cases. The symbols  $a, b,$  and  $C$  will denote various constants whose exact values do not matter, and which may depend on  $M$  and  $\gamma$  but not on  $n$  and  $v$ . The inequality  $1 + C \leq C$  demonstrates our usage. Setting  $\tau^2 = EX^2$  and  $x = y/(2\gamma)^{\frac{1}{2}}$  we get

$$\begin{aligned} |EX^{2n}(X^2 - \tau^2)^v| &\leq C^{n+v} + \int_{\tau}^{\infty} x^{2n} |x^2 - \tau^2|^v M e^{-\gamma x^2} dx \\ &\leq C^{n+v} [1 + a \int_{\tau(2\gamma)^{1/2}}^{\infty} y^{2n} |y^2 - 2\gamma\tau^2|^v e^{-y^2/2} dy] \\ &\leq C^{n+v} \left[ b + a \int_{2+2\tau\gamma^{1/2}}^{\infty} y^{2n} (y^2 - 1)^v \left( \frac{y^2 - 2\gamma\tau^2}{y^2 - 1} \right)^v e^{-y^2/2} dy \right] \\ &\leq aC^{n+v} [1 + \int_{2+2\tau\gamma^{1/2}}^{\infty} y^{2n} (y^2 - 1)^v e^{-y^2/2} dy] \\ &\leq bC^{n+v} [1 + EZ^{2n}(Z^2 - 1)^v + \int_0^{2+2\tau\gamma^{1/2}} y^{2n} |y^2 - 1|^v e^{-y^2/2} dy]. \\ &\leq aC^{n+v} [1 + EZ^{2n}(Z^2 - 1)^v]. \end{aligned}$$

In the three cases under consideration we have  $1 \leq EZ^{2n}(Z^2 - 1)^v/P\{|Z| \geq 2\}$  so in these cases

$$|EX^{2n}(X^2 - \tau^2)^v| \leq bC^{n+v}EZ^{2n}(Z^2 - 1)^v.$$

If  $\lambda \geq \max \{\lambda_1, (1+b)C^{\frac{1}{2}}\}$  where  $b$  and  $C$  come from the inequality above, and  $\lambda_1$  comes from the case  $v = 0$ , then the conclusion of the lemma holds.

LEMMA 5. *If  $A$  is a real symmetric  $n \times n$  matrix, then there exists a real  $n \times n$  orthogonal matrix  $D$  such that*

$$D^TAD \equiv B = \text{diag}(b_1, \dots, b_n)$$

where  $b_1, \dots, b_n$  are the eigenvalues of  $A$ . It follows that  $\text{tr } A = \text{tr } B, \text{tr } A^2 = \text{tr } B^2,$  and  $\|A\| = \max |b_i|.$

LEMMA 6. *If  $X$  is a random variable with  $EX = 0$  and  $Ee^{\theta X}$  defined and finite for  $\theta$  in some open interval about zero, then there exist  $\tau > 0$  and  $C > 0$  such that for  $|\theta| \leq \tau$  we have  $Ee^{\theta X} \leq e^{C\theta^2}$ .*

PROOF. See Lemma 3 in [1] and note that the tails of a distribution go down at least exponentially fast if and only if its moment generating function is finite in some open interval about zero.

We now proceed with the main part of our proof. We will use  $A_N$  both as defined in (6) and as the matrix  $((|a_{ij}|))_{i,j=-N,\dots,N}$ . For all  $\theta \geq 0$ ,  $P\{S_N \geq \varepsilon\} \leq E e^{\theta(S_N - \varepsilon)}$  which equals

$$(8) \quad e^{-\varepsilon\theta} \sum_{k=0}^{\infty} \frac{\theta^k}{k!} E \left[ \sum_{i,j=-N}^N a_{ij}(X_i X_j - EX_i X_j) \right]^k$$

for  $|\theta|$  less than the radius of convergence of the series. Terms in the expansion of  $E[\sum_{i,j=-N}^N a_{ij}(X_i X_j - EX_i X_j)]^k$  are of the form  $\prod_{v=1}^k a_{i_v, j_v} \prod_{i=-N}^N EX_i^{\alpha_i} (X_i^2 - EX_i^2)^{\beta_i}$  since the  $X_i$ 's are independent and  $EX_i \equiv 0$ . Using  $\lambda$  from Lemma 4 and letting  $\{Z_i\}$  be an i.i.d. sequence of  $N(0, 1)$  random variables we have

(i)  $EX_i^{\alpha_i} (X_i^2 - EX_i^2)^{\beta_i} = \lambda^{\alpha_i + 2\beta_i} EZ_i^{\alpha_i} (Z_i^2 - 1)^{\beta_i} = 0$  from symmetry if  $\alpha_i$  is odd, and

(ii)  $|EX_i^{\alpha_i} (X_i^2 - EX_i^2)^{\beta_i}| \leq \lambda^{\alpha_i + 2\beta_i} EZ_i^{\alpha_i} (Z_i^2 - 1)^{\beta_i}$  from Lemma 4 if  $\alpha_i$  is even so that (8) is bounded by

$$(9) \quad e^{-\varepsilon\theta} \sum_{k=0}^{\infty} \frac{\theta^k \lambda^{2k}}{k!} E \left[ \sum_{i,j=-N}^N |a_{ij}| (Z_i Z_j - EZ_i Z_j) \right]^k$$

$$(10) \quad = e^{-\varepsilon\theta} E \exp [\theta \lambda^2 \sum_{i,j=-N}^N |a_{ij}| (Z_i Z_j - EZ_i Z_j)]$$

for  $0 \leq \theta <$  the radius of convergence of the series in (9). Now let  $Z$  be the vector  $(Z_{-N}, \dots, Z_N)$ , let  $D$  be a matrix such as is guaranteed by Lemma 5 for  $A_N$ , let  $W = (W_{-N}, \dots, W_N) = ZD$ , and let  $B = D^T A_N D$ . Then  $W_{-N}, \dots, W_N$  are independent  $N(0, 1)$  random variables and

$$\begin{aligned} \sum_{i,j=-N}^N |a_{ij}| (Z_i Z_j - EZ_i Z_j) &= Z A_N Z^T - \text{tr } A_N \\ &= (ZD)(D^T A_N D)(D^T Z^T) - \text{tr}(D^T A_N D) = W B W^T - \text{tr } B \\ &= \sum_{i=-N}^N b_i (W_i^2 - 1). \end{aligned}$$

Expression (10) becomes

$$(11) \quad e^{-\varepsilon\theta} \prod_{k=-N}^N E \exp [\theta \lambda^2 b_k (W_k^2 - 1)]$$

since the random variables  $W_k^2$  are independent, each having the Chi-squared distribution with one degree of freedom. Since  $E(W_k^2 - 1) = 0$  we can apply Lemma 6 to obtain  $\tau > 0$  and  $C > 0$  such that (11) is bounded by

$$(12) \quad e^{-\varepsilon\theta} \exp \{C\theta^2 \lambda^4 \sum_{k=-N}^N b_k^2\}$$

for  $0 \leq \theta \lambda^2 \max_k |b_k| \leq \tau$ . (Incidentally, a “backwards” inspection of our proof shows that everything we have done so far is valid for  $\theta$  in this range.) Since  $\sum_{i,j=-N}^N a_{ij}^2 = \text{tr } A_N^2$ , from Lemma 5 we see that (12) can be rewritten

$$(13) \quad \exp[-\varepsilon\theta + C\theta^2\lambda^4\Lambda_N^2]$$

which is minimized if  $\theta = \varepsilon/2C\lambda^4\Lambda_N^2$  if that is a permissible value of  $\theta$ . Set

$$\theta_0 = \min \{ \varepsilon/2C\lambda^4\Lambda_N^2, \tau/\lambda^2 \|A_N\| \}$$

and recall from Lemma 5 that  $\|A_N\| = \max_{|i| \leq N} |b_i|$ . Then (13), and therefore (8), is bounded by

$$\exp \{ -\theta_0(\varepsilon - C\theta_0\lambda^4\Lambda_N^2) \} \leq e^{-\theta_0\varepsilon/2}.$$

Set  $C_1 = \tau/2\lambda^2$  and  $C_2 = 1/4C\lambda^4$  and the theorem is proved in the special case  $S = S_N$ .

Since  $S_N \rightarrow S$  in quadratic mean,  $S_N \rightarrow S$  in probability so

$$P\{S \geq \varepsilon\} \leq \liminf_N \exp[-\min \{ C_1(\varepsilon - \delta)/\|A_N\|, C_2(\varepsilon - \delta)^2/\Lambda_N^2 \}]$$

for every  $0 < \delta < \varepsilon$ . We know  $\Lambda_N^2 \rightarrow \Lambda^2$  and if we can show that  $\|A_N\| \rightarrow \|A\|$  we can let  $N \rightarrow \infty$  and then  $\delta \downarrow 0$  and be done. Now  $\|A_N\|$  has the same value whether  $A_N$  is considered to be an operator on  $2N+1$  dimensional Hilbert space or an operator on  $l_2$ . If  $T = ((t_{ij}))$  then  $\|T\| \leq [\sum_{i,j} t_{ij}^2]^{1/2}$ . Thus

$$\|A - A_N\|^2 \leq \sum_{|i| > N \text{ and/or } |j| > N} a_{ij}^2 \rightarrow 0.$$

It follows that  $\|A_N\| \rightarrow \|A\|$ .

REFERENCES

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