

## Complete Convergence and Some Maximal Inequalities for Weighted Sums of Random Variables

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### Abstract

Let  $\{X_n\}$  be a sequence of arbitrary random variables with  $EX_n = 0$  and  $EX_n^2 < \infty$ , for every  $n \geq 1$  and  $\{a_{nk}\}$  be an array of real numbers. We will obtain two maximal inequalities for partial sums and weighted sums of random variables and also, we will prove complete convergence for weighted sums  $\sum_{j=1}^n a_{nj}X_j$ , under some conditions on  $a_{nj}$  and sequence  $\{X_n, n \geq 1\}$ .

**Keywords:** Complete convergence; Weighted sums; Maximal inequalities; Pair-wise negative dependence

### 1. Introduction

The concept of complete convergence of a sequence of random variables was introduced by Hsu and Robins [4], as follows. A sequence  $\{X_n, n \geq 1\}$  of random variables converges completely to a constant  $a$  (denoted  $\lim_{n \rightarrow \infty} X_n = a$ , completely), if

$$\sum_{n=1}^{\infty} P[|X_n - a| > \varepsilon] < \infty \text{ for all } \varepsilon > 0.$$

From then on, there are many authors who devote the study to the complete convergence for partial sums and weighted sums of independent random variables such as Taylor [13], Hu *et al.* [6], Sung *et al.* [11], Weideng and Zhengran [15] and Sung [12]. Several authors extended this convergence to partial sums and weighted sums of negatively dependent and negatively associated random variables namely Liang and Su [10], Liang [9], Huang and Xu [5] and Amini, and Bozorgnia [1]. In this paper

first, we prove two maximal inequalities for partial sums and weighted sums of arbitrary random variables and then present various conditions on  $\{a_{nj}\}$  and  $\{X_n\}$  for which  $\sum_{j=1}^n a_{nj}X_j$  converges completely.

In addition we consider  $\{X_n, n \geq 1\}$  as a sequence of random variables with zero means such that

$$P[|X_n| \geq x] \leq M \int_x^{+\infty} e^{-\gamma t^2} dt, \quad (1)$$

for all  $n$  and all  $x \geq 0$ , where  $M$  and  $\gamma$  are positive constants. Hanson and Wright [3], obtained a bound on tail probabilities for quadratic forms in independent random variables using condition (1). Wright [16] proved that the bound established by Hanson and Wright [3] for independent symmetric random variables also holds when the random variables are not symmetric but condition (1) is valid.

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**Definition.** ([2]) The sequence  $\{X_n, n \geq 1\}$  of random variables is said to be pair-wise negative dependent (PND) if for every  $x_i, x_j \in \mathbb{R}$

$$P[X_i \leq x_i, X_j \leq x_j] \leq P[X_i \leq x_i]P[X_j \leq x_j].$$

**Lemma 1.** ([2]) If the sequence  $\{X_n, n \geq 1\}$  is PND, then

$$E(X_i X_j) \leq E(X_i)E(X_j) \quad \text{for all } i \neq j.$$

**Lemma 2.** If  $Z \sim N(0, 1)$ , and  $X$  satisfies (1), then there exists  $\lambda$  such that

$$EX^2 \leq \lambda^2 EZ^2.$$

**Proof.** By condition (1), we get

$$\begin{aligned} EX^2 &= \int_0^{+\infty} 2xP[|X| > x]dx \\ &\leq M \int_0^{+\infty} 2x \left( \int_x^{+\infty} e^{-t^2} dt \right) \\ &= M \int_0^{+\infty} t^2 e^{-t^2} dt \leq \lambda^2 EZ^2, \end{aligned}$$

Where  $\frac{\sqrt{M} \sqrt[4]{\pi}}{2\gamma^{\frac{3}{4}}} \leq \lambda < \infty$ .

**Lemma 3.** ([8]) The sequence  $\{X_n, n \geq 1\}$  converges almost surely if and only if

$$\lim_{n \rightarrow \infty} P[\sup_{k \geq 1} |X_{n+k} - X_n| > \varepsilon] = 0,$$

for every  $\varepsilon > 0$ .

**Theorem 1.** ([7]) If  $\{(X_n, F_n), n \geq 1\}$  is a non-negative sub-martingale, then

$$E(\max_{0 \leq k \leq n} X_k)^p \leq \left(\frac{p}{p-1}\right)^p EX_n^p, \text{ when } p > 1.$$

### 2.The Maximal Inequalities

In this section, we prove two maximal inequalities and extend Kolomogorov's convergence criterion of strong law of large numbers and we obtain some other useful results.

**Theorem 2.** Let  $\{X_n, n \geq 1\}$  be a sequence of random variables with  $E(X_n) = 0, EX_n^2 < \infty,$

$n \geq 1$ , then for the given  $\varepsilon > 0$ ,

$$P[\max_{1 \leq k \leq n} |S_k| \geq \varepsilon] \leq \frac{32}{\varepsilon^2} \left(\sum_{j=1}^n \sigma_j\right)^2 \tag{2}$$

Where  $S_k = \sum_{i=1}^k X_i$  and  $\sigma_i = \sqrt{\text{var}(X_i)}$ .

**Proof.** Set  $S_{1n} = \sum_{k=1}^n X_k^+$  and  $S_{2n} = \sum_{k=1}^n X_k^-$ , where  $X^+ = \max\{0, X\}$  and  $X^- = \max\{0, -X\}$ . Since  $E[S_{1n} | F_{n-1}] \geq S_{1(n-1)}$ , a.e. and  $E[S_{2n} | F_{n-1}] \geq S_{2(n-1)}$ , a.e. hence the sequences  $\{S_{1n}, F_n, n \geq 1\}$  and  $\{S_{2n}, F_n, n \geq 1\}$  are nonnegative sub-martingales where  $F_n = \sigma(X_1, \dots, X_n)$  for all  $n \geq 1$ , where  $\sigma(X_1, X_2, \dots, X_n)$  is the smallest sigma filed produced by  $X_1, X_2, \dots, X_n$ . Then, we get by Markov's inequality and Theorem 1 for  $p = 2$ , that

$$\begin{aligned} P[\max_{1 \leq k \leq n} S_{1k} > \varepsilon] &\leq \frac{1}{\varepsilon^2} E[\max_{1 \leq k \leq n} S_{1k}]^2 \\ &\leq \frac{4ES_{1n}^2}{\varepsilon^2} \leq \frac{4}{\varepsilon^2} \left(\sum_{j=1}^n \sigma_j\right)^2 \quad \text{for all } \varepsilon > 0, \end{aligned}$$

the last inequality is true by the following statement

$$ES_{1n}^2 \leq \sum_{k=1}^n \sigma_k^2 + \sum_{i \neq j} \sigma_i \sigma_j = \left(\sum_{k=1}^n \sigma_k\right)^2.$$

Similarly, one can show that

$$P[\max_{1 \leq k \leq n} S_{2k} > \varepsilon] \leq \frac{4}{\varepsilon^2} \left(\sum_{j=1}^n \sigma_j\right)^2.$$

Combining these two inequalities and  $|S_n| \leq S_{1n} + S_{2n}$ , we obtain

$$\begin{aligned} P[\max_{1 \leq k \leq n} |S_k| \geq \varepsilon] &\leq P[\max_{1 \leq k \leq n} S_{1k} \geq \frac{\varepsilon}{2}] \\ &\quad + P[\max_{1 \leq k \leq n} S_{2k} \geq \frac{\varepsilon}{2}] \\ &\leq \frac{32}{\varepsilon^2} \left(\sum_{j=1}^n \sigma_j\right)^2 \quad \text{for all } \varepsilon > 0, \end{aligned}$$

The following corollary is an extension of Kolomogorov's convergence criterion of strong law of large numbers for arbitrary random variables.

**Corollary 1.** Let  $\{X_n, n \geq 1\}$  be as in Theorem 2.

i) If  $\sum_{n=1}^{\infty} \sigma_n < \infty$ , then the series  $\sum_{n=1}^{\infty} X_n$

converges a.e.

ii) If  $\sum_{n=1}^{\infty} \frac{\sigma_n}{b_n} < \infty$ , then the following statements

hold.

$$\frac{1}{b_n} \sum_{k=1}^n X_k \rightarrow 0 \text{ a.e. as } n \rightarrow \infty, \quad (3)$$

and

$$E \left( \sup_{n \geq 1} \frac{|S_n|}{b_n} \right)^\beta < \infty \text{ for all } 0 < \beta \leq 2 \quad (4)$$

where  $\{b_n\}$  is a sequence of positive increasing real numbers such that

$$b_n \rightarrow \infty \text{ as } n \rightarrow \infty.$$

**Proof.**

i) By applying Lemma 2, Theorem 2 and Lemma 3, we have

$$\begin{aligned} P[\sup_{k \geq 1} |S_{n+k} - S_n| > \varepsilon] &= \\ \lim_{m \rightarrow \infty} P[\sup_{1 \leq k \leq m} |S_{n+k} - S_n| > \varepsilon] & \\ \leq \frac{32}{\varepsilon^2} \left( \sum_{j=n+1}^{\infty} \sigma_j \right)^2, \text{ for all } \varepsilon > 0, & \end{aligned}$$

Since  $\sum_{n=1}^{\infty} \sigma_n < \infty$ , it follows that

$$\lim_{m \rightarrow \infty} P[\sup_{k \geq 1} |S_{n+k} - S_n| > \varepsilon] = 0,$$

this completes the proof.

ii) Taking  $Y_n = \frac{X_n}{b_n}$ , we get (3) and (4) by

Keronecker's Lemma, Lemma 3 and Theorem 2.

**Corollary 2.** Let  $\{X_n, n \geq 1\}$  be as in Theorem 2.

i) If  $\sum_{n=1}^{\infty} \sigma_n < \infty$ , then for the given  $\varepsilon > 0$  and for  $\alpha > 0$ , the following statements hold

$$\sum_{n=1}^{\infty} n^{2\alpha-2} P[\max_{1 \leq k \leq n} |S_k| > n^\alpha \varepsilon] < \infty, \quad (5)$$

and

$$\sum_{n=1}^{\infty} n^{2\alpha-2} P[\sup_{k \geq n} \frac{|S_k|}{k^\alpha} > \varepsilon] < \infty, \quad (6)$$

ii) If  $\sum_{n=1}^{\infty} n^{\beta-2} \left( \sum_{j=1}^n \sigma_j \right)^2 < \infty$ , for some  $\beta > 0$ , then for every  $\varepsilon > 0$ ,

$$\sum_{n=1}^{\infty} n^\beta P[\max_{1 \leq k \leq n} |S_k| > n\varepsilon] < \infty \text{ for all } \varepsilon > 0. \quad (7)$$

In particular, if  $\sum_{j=1}^n \sigma_j = O(n^{1-\frac{\alpha+\beta}{2}})$ , for some  $\beta > 0$  and  $\alpha > 1$ , then we can obtain (5).

iii) If  $\{X_n\}$  satisfies condition (1), then  $\sum_{j=1}^n \alpha_j = O(n)$ , and for  $0 < \beta < 1$ , we have

$$\sum_{n=1}^{\infty} n^{\beta-2} \left( \sum_{j=1}^n \sigma_j \right)^2 < \infty$$

**Theorem 3.** Let  $\{X_n, n \geq 1\}$  be an arbitrary sequence of random variables with  $E(X_n) = 0, EX_n^2 < \infty, n \geq 1$ . Suppose that  $\{a_{nj}, 1 \leq j \leq n, n \geq 1\}$  be an array of real numbers, then

$$\begin{aligned} P[\max_{1 \leq k \leq n} |T_k| > \varepsilon] &\leq \\ \frac{32}{\varepsilon^2} \left( \sum_{j=1}^n |a_{nj}| \sigma_j \right)^2 &\text{ for all } \varepsilon > 0, \end{aligned} \quad (8)$$

where  $T_n = \sum_{k=1}^n a_{nk} X_k$ .

**Proof.** Set  $T_{1n} = \sum_{k=1}^n |a_{nk}| X_k^+$  and  $T_{2n} = \sum_{k=1}^n |a_{nk}| X_k^-$ . Since  $E[T_{1n} | F_{n-1}] \geq T_{1(n-1)}$ , a.e. and  $E[T_{2n} | F_{n-1}] \geq T_{2(n-1)}$ , a.e. it follows that the sequences  $\{T_{1n}, F_n, n \geq 1\}$  and  $\{T_{2n}, F_n, n \geq 1\}$  are nonnegative sub-martingales, where  $F_n = \sigma(X_1, \dots, X_n)$  for all  $n \geq 1$ . Since  $|T_n| \leq T_{1n} + T_{2n}$  for all  $n \geq 1$ , the proof of (8) follows from the same argument as that in the proof of Theorem 2. Hence

$$\begin{aligned} P[\max_{1 \leq k \leq n} |T_k| \geq \varepsilon] &\leq P[\max_{1 \leq k \leq n} T_{1k} \geq \frac{\varepsilon}{2}] \\ &+ P[\max_{1 \leq k \leq n} T_{2k} \geq \frac{\varepsilon}{2}] \\ &\leq \frac{32}{\varepsilon^2} \left( \sum_{j=1}^n |a_{nj}| \sigma_j \right)^2 \text{ for all } \varepsilon > 0. \end{aligned}$$

**Corollary 3.** Let  $\{X_n, n \geq 1\}$  and  $\{a_{nj}\}$  be as in Theorem 3,

i) If  $\sum_{n=1}^{\infty} n^{\beta-2} \left( \sum_{j=1}^n |a_{nj}| \sigma_j \right)^2 < \infty$ , for some  $\beta > 0$ , then we have

$$\sum_{n=1}^{\infty} n^{\beta-2} P[\max_{1 \leq k \leq n} |T_k| > \varepsilon] < \infty \text{ for all } \varepsilon > 0. \quad (9)$$

ii) If  $\{X_n\}$  satisfies condition (1) and  $\sum_{j=1}^n |a_{nj}| = O(n^{\alpha/2})$  for all  $\alpha > 0$ , then (9) holds.

### 3. Complete Convergence for Weighted Sums

Using results of Section 2, we obtain complete convergence for weighted sums  $\sum_{j=1}^n a_{nj} X_j$  of random variables that satisfy (1) under some conditions on  $a_{nj}$ .

**Theorem 4.** Let  $\{X_n, n \geq 1\}$  be an arbitrary sequence of random variables and  $\{a_{nj}, 1 \leq j \leq n, n \geq 1\}$  be an array of real numbers such that

$$\sum_{j=1}^n |a_{nj} - a_{n(j+1)}| = O(n^\beta) \text{ for some } \beta > 0,$$

where  $a_{n(n+1)} = 0$ .

i) If  $\{X_n, n \geq 1\}$  satisfies in condition (1), then

$$\sum_{j=1}^n a_{nj} X_j \rightarrow 0, \text{ completely as } n \rightarrow \infty. \tag{10}$$

ii) If  $\sum_{k=1}^n \sigma_k = O(n^\alpha)$  for some  $\alpha > 0$ , then (10) holds.

**Proof.** Using Abel's partial summation rule we get

$$\begin{aligned} \left| \sum_{j=1}^n a_{nj} X_j \right| &\leq \max_{1 \leq i \leq n} |S_i| \left( \sum_{j=1}^n |a_{nj} - a_{n(j+1)}| \right) \\ &\leq C n^{-\beta} \max_{1 \leq i \leq n} |S_i| \text{ for some } \beta > 0. \end{aligned} \tag{11}$$

From Theorem 2, we conclude that

$$\begin{aligned} \sum_{n=1}^{\infty} P(n^{-\beta} \max_{1 \leq i \leq n} |S_i| > \varepsilon) \\ \leq \frac{32}{\varepsilon^2} \sum_{n=1}^{\infty} n^{-2\beta} \left( \sum_{j=1}^n \sigma_j \right)^2 \text{ for all } \varepsilon > 0. \end{aligned} \tag{12}$$

Hence (11) and (12) yield

$$\begin{aligned} \sum_{n=1}^{\infty} P\left[ \left| \sum_{j=1}^n a_{nj} X_j \right| > \varepsilon \right] &\leq \sum_{n=1}^{\infty} P(n^{-\beta} \max_{1 \leq i \leq n} |S_i| > \varepsilon) \\ &\leq \frac{32}{\varepsilon^2} \sum_{n=1}^{\infty} n^{-2\beta} \left( \sum_{j=1}^n \sigma_j \right)^2. \end{aligned}$$

i) Condition (1) implies that

$$\begin{aligned} \sum_{n=1}^{\infty} n^{-2\beta} \left( \sum_{j=1}^n \sigma_j \right)^2 \\ \leq \lambda^2 \sum_{n=1}^{\infty} \frac{1}{n^{2\beta-2}} < \infty \text{ for all } \beta > 3/2. \end{aligned}$$

ii) If  $\sum_{k=1}^n \sigma_k = O(n^\alpha)$  for some  $\alpha > 0$ , then

$$\begin{aligned} \sum_{n=1}^{\infty} n^{-2\beta} \left( \sum_{j=1}^n \sigma_j \right)^2 \\ < M \sum_{n=1}^{\infty} \frac{1}{n^{2\beta-2\alpha}} < \infty \text{ for all } \beta > 1/2 + \alpha. \end{aligned}$$

Where  $0 < M < \infty$ , this completes the proof.

**Theorem 5.** Let  $\{X_n, n \geq 1\}$  be an arbitrary sequence of random variables with zero means that satisfies (1) and  $\{a_{nj}\}$  be as in Theorem 4. Then, there exists  $\lambda > 0$  such that

$$P\left[ \left| \sum_{j=1}^n a_{nj} X_j \right| > \varepsilon \right] \leq \frac{\lambda^2}{\varepsilon^2} \left( \sum_{j=1}^n |a_{nj}| \right)^2 \text{ for all } \varepsilon > 0.$$

**Proof.** Applying Markov's inequality, Cauchy-Schwarz's inequality and Lemma 2, we have

$$\begin{aligned} P\left[ \left| \sum_{j=1}^n a_{nj} X_j \right| > \varepsilon \right] &\leq \frac{1}{\varepsilon^2} E \left( \sum_{j=1}^n a_{nj} X_j \right)^2 \\ &\leq \frac{1}{\varepsilon^2} \left( \sum_{j=1}^n (a_{nj})^2 EX_j^2 + \sum_{i \neq j} |a_{ni}| |a_{nj}| E|X_i X_j| \right) \\ &\leq \frac{1}{\varepsilon^2} \left( \sum_{j=1}^n (a_{nj})^2 EX_j^2 + \sum_{i \neq j} |a_{ni}| |a_{nj}| \sqrt{EX_i^2 EX_j^2} \right) \\ &\leq \frac{1}{\varepsilon^2} \left( \sum_{j=1}^n |a_{nj}| \sigma_j \right)^2 \\ &\leq \frac{\lambda^2}{\varepsilon^2} \left( \sum_{j=1}^n |a_{nj}| \right)^2 \text{ for all } \varepsilon > 0. \end{aligned}$$

**Corollary 4.** Let  $\{X_n, n \geq 1\}$  and  $\{a_{nj}\}$  be as in Theorem 5.

i) If  $\sum_{i=1}^n |a_{ni}| = O(1)$ , then for all  $\beta > \frac{1}{2}$ ,

$$n^{-\beta} \sum_{j=1}^n a_{nj} X_j \rightarrow 0, \text{ completely as } n \rightarrow \infty.$$

ii) If  $\max_{1 \leq i \leq n} |a_{ni}| = O(n^{-\frac{\delta}{2}})$ ,  $0 < \delta < 2$ , then for all  $\beta > 1 - \frac{\delta}{2}$ , we have

$$n^{-\beta} \sum_{j=1}^n a_{nj} X_j \rightarrow 0, \quad \text{completely as } n \rightarrow \infty.$$

**Theorem 6.** Let  $\{X_n, n \geq 1\}$  be a sequence of PND random variables with zero means that satisfies (1). Let  $\{a_{nj}\}$  be an array of positive real numbers with  $\sum_{i=1}^n a_{ni}^2 = O(n^\delta)$ , for all  $\delta \geq 0$ . Then for all  $\beta > \frac{1+\delta}{2}$ , we have

$$n^{-\beta} \sum_{j=1}^n a_{nj} X_j \rightarrow 0, \quad \text{completely as } n \rightarrow \infty.$$

**Proof.** By Markov's inequality, Lemmas 1 and 2, we get

$$\begin{aligned} & \sum_{n=1}^{\infty} P[n^{-\beta} |\sum_{j=1}^n a_{nj} X_j| > \varepsilon] \\ & \leq \sum_{n=1}^{\infty} \frac{1}{n^{2\beta} \varepsilon^2} E \left( \sum_{j=1}^n a_{nj} X_j \right)^2 \\ & \leq \sum_{n=1}^{\infty} \frac{1}{n^{2\beta} \varepsilon^2} \left( \sum_{j=1}^n a_{nj}^2 EX_j^2 + \sum_{i \neq j} \sum_{i,j} a_{ni} a_{nj} EX_i EX_j \right) \\ & \leq \sum_{n=1}^{\infty} \frac{\lambda^2}{n^{2\beta} \varepsilon^2} \sum_{j=1}^n a_{nj}^2 \\ & \leq \sum_{n=1}^{\infty} \frac{\lambda^2}{n^{2\beta-\delta} \varepsilon^2} < \infty \quad \text{for all } \varepsilon > 0. \end{aligned}$$

This completes the proof.

#### 4. Examples

In the following we have several examples that satisfy the conditions of Theorem 2, and Corollaries 1 and 2.

1. Let  $\{X_n, n \geq 1\}$  be a sequence of arbitrary random variables.

i) If  $X_n \sim \exp(\lambda_n)$  for all  $n \geq 1$  and  $\sum_{n=1}^{\infty} \frac{1}{\lambda_n} < \infty$ , then  $\sum_{n=1}^{\infty} X_n$  converges a.e. In particular if  $\lambda_n = n^\alpha$  for all  $\alpha > 1$ , then  $\sum_{n=1}^{\infty} X_n$  converges

a.e.

ii) Let  $P[X_n = 0] = 1 - \frac{1}{n^\alpha}$  and  $P[X_n = \mp n] = \frac{1}{2n^\alpha}$  for all  $\alpha > 4$ . Since  $\sum_{n=1}^{\infty} \sigma_n = \sum_{n=1}^{\infty} \frac{1}{n^{\frac{\alpha-1}{2}}} < \infty$ , it

follows that  $\sum_{n=1}^{\infty} X_n$  converges a.e.

iii) If  $X_n \sim U(-a_n, a_n)$ ,  $0 < a_n < 1$  for all  $n \geq 1$ , and  $\sum_{n=1}^{\infty} a_n < \infty$ , then  $\sum_{n=1}^{\infty} X_n$  converges a.e.

iv) Let  $X_n \sim \Gamma(m_0, n^\alpha)$ , for all  $\alpha > 0$ . Since  $\sum_{n=1}^{\infty} \frac{\sigma_n}{n} < \infty$ , it follows that

$$\frac{1}{n} \sum_{k=1}^n (X_k - EX_k) \rightarrow 0 \quad \text{a.e.}$$

2. Let  $\{X_n\}$  be a sequence of i.i.d. random variables with distribution  $U[0, 1]$ . Set  $Y_n = \prod_{k=1}^n X_k$  and  $\sigma_n = \sqrt{\text{Var}(Y_n)}$ . It is obvious that  $EY_n = \frac{1}{2^n}$  and  $\text{Var}(Y_n) < \frac{1}{3^n}$ , for all  $n \geq 1$ . Since  $\sum_{n=1}^{\infty} \sigma_n < \infty$ , from Corollary 1.i, we conclude that  $\sum_{n=1}^{\infty} (Y_n - EY_n)$  converges a.e. Next, note that  $\sum_{n=1}^{\infty} EY_n < \infty$  a.e. hence

$$\sum_{n=1}^{\infty} \prod_{k=1}^n X_k, \quad \text{converges a.e.}$$

Also, the conditions of Corollary 2.i are valid for the sequence  $\{Y_n\}$ . Thus (5) and (6) hold.

3. Let  $\{X_n\}$  be a sequence of random variables with the probability function,

$$P[X_n = 0] = P[X_n = 2] = \frac{1}{2} \quad \text{for all } n \geq 1.$$

It is obvious that conditions of Corollaries 1 and 2 are valid for the sequence  $\{\frac{X_n}{3^n}\}$ , hence  $\sum_{n=1}^{\infty} \frac{X_n}{3^n}$  converges a.e. and the statements (5) and (6) are true.

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### References

1. Amini M. and Bozorgnia A. Complete convergence for ND random variables. *Journal of App. Math. and Stoch. Analysis.*, **16**(2): 121-126 (2003).
2. Bozorgnia A., Patterson R.F., and Taylor R.L. Limit theorems for dependent random variables: World Congress Nonlinear Analysts'92. p. 1639-1650 (1996).
3. Hanson D.L. and Wright F.T. A bound for tail probabilities for quadratic forms in independent random variables. *Ann. Math. Statist.*, **42**: 1079-1083 (1971).
4. Hsu P.L. and Robbins H. Complete convergence and the law of large numbers. *Proc. Nat. Acad. Sci.*, **33**: 25-31 (1947).
5. Huang W.T. and Xu B. Some maximal inequalities and complete convergence of NA random sequences. *Statistics & Probability Letters*, **57**: 183-191 (2002).
6. Hu T.C., Szynal D., and Volodin A.I. A note on complete convergence for arrays. *Ibid.*, **38**: 27-31 (1998).
7. Gut A. *Probability: A Graduate Course*. Springer, New York (2005).
8. Karr F.A. *Probability*. Springer Verlage, New York (1993).
9. Liang H.Y. Complete convergence for weighted sums of negatively dependent random variables. *Statistics & Probability Letters*, **48**: 317-325 (2000).
10. Liang H.Y. and Su C. Complete convergence for weighted sums of NA sequences. *Ibid.*, **45**: 85-95 (1999).
11. Sung S.H., Volodin A.I., and Hu T.C. More on complete convergence for arrays. *Ibid.*, **71**: 303-311 (2005).
12. Sung S.H. Complete convergence for weighted sums of r.v.'s. *Ibid.*, **77**: 303-311 (2007).
13. Taylor R.L. Complete convergence for weighted sums of array of random elements. *J. Math. I & Math. Science.*, **6**(1): 69-79 (1983).
14. Teicher H. Almost certain convergence in double array. *Z. Wahsch. Vern. Gebiete.*, **69**: 331-345 (1985).
15. Weideng L. and Zhengran L. A supplement to the complete convergence. *Statistics & Probability Letters.*, **76**: 748-754 (2006).
16. Wright F.T. A bound on tail probabilities for quadratic forms in independent random variables whose distributions are not necessarily symmetric. *The Annals of Probability*, **1**(6): 1068-1070 (1973).