

On the Series of Some Independent Random Variables.

By

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1. Let $\{X_n\}$ be a sequence of independent random variables with a common distribution function $F(x)$ and $\{a_n\}$ be a decreasing sequence of positive numbers. Further let us put

$$P_0 = \text{Prob.} \left[\sum_n |a_n X_n| < +\infty \right]$$

$$P_1 = \text{Prob.} \left[\sum_n a_n X_n \text{ converges} \right]$$

and

$$P_2 = \text{Prob.} \left[\sum_n a_n \left(X_n - \int_{|a_n x| \leq 1} x dF(x) \right) \text{ converges} \right].$$

It is seen that each of

$$(1.1) \quad P'_0 = \text{Prob.} \left[\overline{\lim}_{n \rightarrow \infty} a_n \sum_{i=1}^n |X_i| \leq 1 \right] = 1,$$

and

$$(1.2) \quad P'_1 = \text{Prob.} \left[\overline{\lim}_{n \rightarrow \infty} \left| a_n \sum_{i=1}^n X_i \right| \leq 1/2 \right] = 1$$

implies

$$(1.3) \quad \text{Prob.} \left[\overline{\lim}_{n \rightarrow \infty} |a_n X_n| \leq 1 \right] = 1$$

and therefore, by the Borel-Cantelli lemma, (1.1) and also (1.2) imply

$$(1.4) \quad \sum_n \text{Prob.} \left[|X_n| > \frac{1}{a_n} \right] = \sum_n \int_{|x| > \frac{1}{a_n}} dF(x) < +\infty.$$

In this note we prove that under some conditions on $\{a_n\}$, (1.4) implies $P_i = 1$ ($i=0, 1, 2$). Especially, by Knopp's theorem in the theory of series, $P_0 = 1$ (or $P_1 = 1$) implies $P'_0 = 1$ (or $P'_1 = 1$).

2. THEOREM 1. If for some $\lambda > 1$

$$(2.1) \quad \frac{a_{n+1}}{a_n} \leq \left(\frac{n}{n+1} \right)^\lambda \quad n = 1, 2, \dots,$$

then (1.4) implies $P_0 = 1$.

PROOF. By the three series theorem, it is sufficient to show that

$$\sum_n V_n = \sum_n \left[\int_{|a_n x| \leq 1} (a_n x)^2 dF(x) - \left(\int_{|a_n x| \leq 1} |a_n x| dF(x) \right)^2 \right] < +\infty$$

and

$$\sum_n \bar{M}_n = \sum_n \int_{|a_n x| \leq 1} |a_n x| dF(x) < +\infty.$$

On the other hand, it may be seen that

$$0 \leq V_n \leq \int_{|a_n x| \leq 1} |a_n x|^2 dF(x) \leq \bar{M}_n$$

and hence, it is sufficient to prove that $\sum_n \bar{M}_n < +\infty$.

We have

$$\begin{aligned} \sum_{n=1}^{\infty} \int_{|a_n x| \leq 1} |a_n x| dF(x) &= \sum_{n=1}^{\infty} a_n \sum_{m=1}^n \int_{\frac{1}{a_{m-1}} < |x| \leq \frac{1}{a_m}} |x| dF(x) \\ &\leq \sum_{n=1}^{\infty} a_n \sum_{m=1}^n \frac{1}{a_m} \int_{\frac{1}{a_{m-1}} < |x| \leq \frac{1}{a_m}} dF(x) = \sum_{m=1}^{\infty} \frac{1}{a_m} \int_{\frac{1}{a_{m-1}} < |x| \leq \frac{1}{a_m}} dF(x) \sum_{n=m}^{\infty} a_n, \end{aligned}$$

where

$$\frac{1}{a_0} \equiv 0.$$

From (2.1), we have

$$a_n \leq a_m \left(\frac{m}{n}\right)^\lambda \quad \text{for } n \geq m,$$

and we have

$$\sum_{n=m}^{\infty} a_n \leq a_m m^\lambda \sum_{n=m}^{\infty} \left(\frac{1}{n}\right)^\lambda \leq A a_m m$$

where A is a constant independent of m .

Therefore, it follows that

$$\begin{aligned} \sum_{n=1}^{\infty} \bar{M}_n &\leq A \sum_{m=1}^{\infty} m \int_{\frac{1}{a_{m-1}} < |x| \leq \frac{1}{a_m}} dF(x) \\ &= A \sum_{m=1}^{\infty} \left[\int_{|x| > \frac{1}{a_m}} dF(x) + \int_{\frac{1}{a_{m-1}} < |x| \leq \frac{1}{a_m}} dF(x) \right] < +\infty. \end{aligned}$$

THEOREM 2. Let $F(x)$ be a symmetric distribution function and for some $\lambda > 1/2$

$$(2.2) \quad \frac{a_{n+1}}{a_n} \leq \left(\frac{n}{n+1}\right)^\lambda \quad n = 1, 2, \dots$$

Then (1.4) implies $P_1 = 1$.

PROOF. It is sufficient to show that

$$\sum_n \int_{|a_n x| \leq 1} (a_n x)^2 dF(x) < +\infty$$

and this can be proved by the same way as the proof of $\sum_n \bar{M}_n < +\infty$.

THEOREM 3. If for some $\lambda > 1/2$

$$(2.3) \quad \frac{a_{n+1}}{a_n} \leq \left(\frac{n}{n+1}\right)^\lambda \quad n = 1, 2, \dots,$$

then (1.4) implies $P_2 = 1$.

PROOF. Let us define random variables Y_n and Z_n as follows.

$$Y_n = \begin{cases} 0, & \text{if } |X_n| > \frac{1}{a_n} \\ X_n, & \text{if } |X_n| \leq \frac{1}{a_n} \end{cases}$$

and

$$Z_n = \begin{cases} X_n, & \text{if } |X_n| > \frac{1}{a_n} \\ 0, & \text{if } |X_n| \leq \frac{1}{a_n} \end{cases} \quad n = 1, 2, \dots$$

From (1.4) and the above definitions, it follows that

$$(2.4) \quad \text{Prob.} \left[\sum_n |a_n Z_n| < +\infty \right] = 1,$$

and

$$D_n = E \left[(a_n Y_n)^2 \right] - \left[E(a_n Y_n) \right]^2 = \int_{|a_n x| \leq 1} (a_n x)^2 dF(x) - \left(\int_{|a_n x| \leq 1} a_n x dF(x) \right)^2$$

$$M_n = E(a_n Y_n) = \int_{|a_n x| \leq 1} a_n x dF(x).$$

As the proof of Theorem 2, we can show that

$$0 \leq \sum_n D_n \leq \sum_n \int_{|a_n x| \leq 1} (a_n x)^2 dF(x) < +\infty.$$

On the other hand, the random variable $(a_n Y_n - M_n)$ has the mean value zero and the dispersion D_n . Hence, by Khintchine-Kolmogoroff's theorem, we have

$$(2.5) \quad \text{Prob.} \left[\sum_n (a_n Y_n - M_n) \text{ converges} \right] = 1.$$

From (2.4) and (2.5), we get the required result.

3. 1°. Suppose that

$$(3.1) \quad \text{Prob.} \left[\sum_n \left| \frac{1}{n} X_n \right| < +\infty \right] = 1.$$

Then, by the Borel-Cantelli lemma, it follows that for any constant $c > 0$,

$$\sum_n \text{Prob.} \left[|X_n| > cn \right] < +\infty.$$

Therefore, we have

$$\int_{-\infty}^{+\infty} |x| dF(x) < +\infty,$$

and the strong law of large numbers shows that

$$\text{Prob.} \left[\frac{1}{n} \sum_{k=1}^n |X_k| \rightarrow \int_{-\infty}^{+\infty} |x| dF(x) \right] = 1.$$

On the other hand, from (3.1), we have

$$\text{Prob.} \left[\frac{1}{n} \sum_{k=1}^n |X_k| \rightarrow 0 \right] = 1.$$

Hence, we have

$$\int_{-\infty}^{+\infty} |x| dF(x) = 0$$

and this is equivalent to

$$(3.2) \quad \text{Prob.} \left[X_n = 0 \right] = 1 \quad n = 1, 2, \dots$$

Therefore, λ in Theorem 1 can not be replaced by 1 except a trivial case (3.2).

2°. Let $F(x)$ be symmetric and

$$(3.3) \quad \text{Prob.} \left(\sum_n \frac{1}{\sqrt{n}} X_n \text{ converges} \right) = 1.$$

Then we have, by the same way as 1°,

$$\int_{-\infty}^{+\infty} x^2 dF(x) < +\infty,$$

and from the central limit theorem and (3.3), we have

$$\int_{-\infty}^{+\infty} x^2 dF(x) = 0.$$

This shows that (3.3) implies (3.2). Therefore, λ in Theorem 2 can not be replaced by $\frac{1}{2}$ except a trivial case (3.2).

3°. Let

$$\text{Prob.} \left[\sum_n \frac{1}{\sqrt{n}} \left(X_n - \int_{|x| \leq \sqrt{n}} x dF(x) \right) \text{ converges} \right] = 1$$

and \bar{X}_n denote the symmetrized random variable of X_n .

Then we have

$$\text{Prob.} \left[\sum_n \frac{1}{\sqrt{n}} \bar{X}_n \text{ converges} \right] = 1.$$

Therefore, by the discussion in 2°, we have

$$\text{Prob.} \left[\bar{X}_n = 0 \right] = 1 \quad n=1, 2, \dots$$

This shows that

$$(3.4) \quad \text{Prob.} \left[X_n = m \right] = 1 \quad n = 1, 2, \dots$$

where m is a constant independent of n .

Hence λ in Theorem 3 can not be replaced by $\frac{1}{2}$ except a trivial case (3.4).