

## A LAW OF THE ITERATED LOGARITHM FOR STABLE SUMMANDS

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Let  $x_n$  ( $n=1, 2, 3, \dots$ ) be mutually independent random variables, identically distributed according to the symmetric stable distribution with exponent  $\gamma$  ( $0 < \gamma \leq 2$ ), i.e.,  $E[\exp(itx_n)] = \exp(-|t|^\gamma)$ . Let  $S_n = \sum_{k=1}^n x_k$ . The classical "law of the iterated logarithm" (for the simplest exposition, see Feller [2, pp. 192–195]; see also [3] and [4]) tells us that for  $\gamma = 2$

$$P\left(\limsup_{n \rightarrow \infty} \frac{S_n}{\sqrt{(2n \log \log n)}} = 1\right) = 1.$$

That is, the variables  $(1/\sqrt{n})S_n$  again satisfy  $E[\exp(it(1/\sqrt{n})S_n)] = \exp(-|t|^2)$ , and to achieve a finite lim sup they must be cut down additionally (and multiplicatively) by the factors  $(2 \log \log n)^{-1/2}$ . For some reason the obvious corresponding statement for the case  $\gamma < 2$  does not seem to have been recorded, and it is the purpose of this note to do so.

For  $0 < \gamma < 2$ , the variables  $n^{-\gamma^{-1}}S_n$  again satisfy  $E[\exp(itn^{-\gamma^{-1}}S_n)] = \exp(-|t|^\gamma)$ . Since the corresponding distribution function  $F(x)$  has tail behavior  $F(-x) + 1 - F(x) \sim (\text{const})|x|^{-\gamma}$  as  $|x| \rightarrow \infty$ , instead of exponential decrease as in the  $\gamma = 2$  case, we can expect the "cut down factors" to appear otherwise than as multipliers.

**THEOREM.** *For  $\gamma < 2$*

$$P\left(\limsup_{n \rightarrow \infty} |n^{-\gamma^{-1}}S_n|^{(\log \log n)^{-1}} = e^{\gamma^{-1}}\right) = 1.$$

We sketch the proof. It suffices to show that for fixed  $\epsilon > 0$ , and for almost every sample point, we have

$$(1) \quad |n^{-\gamma^{-1}}S_n| > (\log n)^{(1+\epsilon)\gamma^{-1}} \quad \text{finitely often}$$

and

$$(2) \quad |n^{-\gamma^{-1}}S_n| > (\log n)^{(1-\epsilon)\gamma^{-1}} \quad \text{infinitely often.}$$

Now the proof proceeds almost exactly as for the  $\gamma = 2$  case. Thus, to show (1), let  $A_n$  be the event that  $|S_n| > n^{\gamma^{-1}}(\log n)^{(1+\epsilon)\gamma^{-1}}$ . Pick

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$\beta > 1$ , and for  $r = 1, 2, 3, \dots$ , let  $n_r$  denote  $[\beta^r]$ , the largest integer in  $\beta^r$ . Let  $B_r$  denote the event that  $|S_n| > (n_r)^{\gamma^{-1}} (\log n_r)^{(1+\epsilon)\gamma^{-1}}$  for some  $n$  with  $n_r \leq n < n_{r+1}$ . Then  $\limsup_{n \rightarrow \infty} A_n \subset \limsup_{r \rightarrow \infty} B_r$ ; and there exists a constant  $c > 0$  independent of  $r$  such that for all  $r$   $P(B_r) \leq cP(C_r)$ , where  $C_r$  is the event that

$$(n_{r+1} - 1)^{-\gamma^{-1}} |S_{n_{r+1}-1}| > \left(\frac{n_r}{n_{r+1} - 1}\right)^{\gamma^{-1}} (\log n_r)^{(1+\epsilon)\gamma^{-1}}.$$

Since the distribution for  $(n_{r+1}-1)^{-\gamma^{-1}}S_{n_{r+1}-1}$  has tail behavior  $\sim(\text{const})|x|^{-\gamma}$  (cf. [3, pp. 181-182]), we conclude that for some finite constant  $a > 0$ ,  $P(C_r) \leq ar^{-(1+\epsilon)}$ , and  $\sum_r P(B_r) < \infty$ . Hence by the Borel Cantelli lemma,  $P(\limsup_{n \rightarrow \infty} A_n) = P(\limsup_{r \rightarrow \infty} B_r) = 0$ , and (1) holds.

To prove (2), set  $D_r = S_{n_{r+1}} - S_{n_r}$ . These are independent variables, and by the Borel Cantelli lemma again we find that for almost every sample point,

$$(n_{r+1} - n_r)^{-\gamma^{-1}} |D_r| \geq (\log n_r)^{(1-\frac{1}{2}\epsilon)\gamma^{-1}}$$

for infinitely many  $r$ . Suppose that (2) does not hold on a set of positive probability. Then for almost every sample point in that set,

$$\begin{aligned} |n_{r+1}^{-\gamma^{-1}} S_{n_{r+1}}| &\geq \left(1 - \frac{n_r}{n_{r+1}}\right)^{\gamma^{-1}} |D_r| - \left(\frac{n_r}{n_{r+1}}\right)^{\gamma^{-1}} |S_{n_r}| \\ (3) \qquad &\geq \left(1 - \frac{n_r}{n_{r+1}}\right)^{\gamma^{-1}} (\log n_r)^{(1-\frac{1}{2}\epsilon)\gamma^{-1}} - \left(\frac{n_r}{n_{r+1}}\right)^{\gamma^{-1}} (\log n_r)^{(1-\epsilon)\gamma^{-1}} \end{aligned}$$

for infinitely many  $r$ . But for large  $r$  the last difference in (3) dominates  $(\log n_r)^{(1-\epsilon)\gamma^{-1}}$ ; so (2) does hold almost everywhere. For further details in this paraphrase of the classical case, we refer the reader to Feller [2], loc. cit.

REMARK. By stricting  $n$  to subsequences of the form  $n_k = [\beta^{k^\delta}]$  for fixed  $\beta > 1$  and  $\delta > 1$ , the proof shows that, with probability 1, every point in the interval  $[1, e^{\gamma^{-1}}]$  is a limit point of the sequence  $\{n^{-\gamma^{-1}}|S_n|^{(\log \log n)^{-1}}, n = 1, 2, 3, \dots\}$ . Now, at least for  $1 < \gamma < 2$ , 0 is also a limit point, as one can conclude from the general results of Chung and Fuchs (see [1, Theorem 4]). I do not know about the points in the interval  $(0, 1)$ .

*Added in proof.* V. Strassen has pointed out to us that the above theorem follows simply from a result of A. Khinchine, Mat. Sb. 45 (1938); p. 582. However, the present version of the log log law holds also if the common d. f.  $F$  of the  $x_n$  lies in that part of the domain of

normal attraction of a nonnormal stable d.f.  $G_\gamma$  ( $0 < \gamma < 2$ ) subject to conditions of the form

$$F(-x) = \frac{c_1}{x^\gamma} + \frac{d_1}{x^\delta} + r_1(x), \quad 1 - F(x) = \frac{c_2}{x^\gamma} + \frac{d_2}{x^\delta} + r_2(x),$$

where  $r_i(x) = O(1/x^\epsilon)$  and  $\gamma < \delta < \epsilon$  (and  $r_1(x) + r_2(x)$  are monotone as  $x \rightarrow \infty$  if  $\gamma < 1$ ). For under these conditions, H. Cramer has shown (*On asymptotic expansions for sums of independent random variables with a limiting stable distribution*, Sankhya Ser. A 25 (1963), 12–24) that for the d.f.  $F_n$  of  $S_n$  (suitably shifted and scaled),  $F_n(x) - G_\gamma(x) = O(1/n^\gamma)$  uniformly in  $x$ . Hence in the above proofs, we may replace tail estimates based on  $F_n$  by ones based on  $G_\gamma$  with an error of at most  $O(1/n^\gamma)$ . But on subsequences  $n_j \subset [c^j]$ ,  $c > 1$ , such errors will not affect the convergence or divergence of our series, and the proofs go through as before.

#### REFERENCES

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