On Sums of Independent Random Variables without Power Moments

S. V. Nagaev^a and V. I. Vakhtel^b

1. Let X, X_1, \ldots be independent identically distributed random variables. Assume that $V(x) = P(X \ge x)$ is a slowly varying function as $x \to \infty$; i.e.,

$$\lim_{x \to \infty} \frac{V(cx)}{V(x)} = 1 \tag{1}$$

for any c > 0. This condition implies that $E\{X^t; X > 0\} = \infty$ for any t > 0; i.e., all the power moments are infinite.

Define
$$S_n = X_1 + X_2 + ... + X_n$$
 and $\overline{X}_n = \max_{k < n} X_k$.

Let X_n^* be the maximum term in absolute value; i.e., $|X_n^*| = \max |X_k|$.

It was P. Lévy who noted that, under condition (1), the absolute value of the difference $S_n - X_n^*$ is small compared to X_n^* ; i.e., X_n^* makes an overwhelming contribution to S_n [1] (see also [2, p. 212]). Assuming additionally that $X \ge 0$, it is seems rather plausible that

$$P(S_n < x) \sim P(\overline{X}_n < x) = (1 - V(x))^n.$$
 (2)

If n and x are related by nV(x) = y, where y is a fixed positive constant, we obtain the approximate equality

$$P(S_n < x) \sim e^{-y}.$$

Setting $x = V^{-1}\left(\frac{y}{n}\right)$, where V^{-1} is the inverse of V, we conclude that

$$\lim_{n \to \infty} P(nV(S_n) > y) = e^{-y}.$$

e-mail: vakhtel@wias-berlin.de

Thus, we have convergence to a nondegenerate distribution under the functional normalization in terms of V(x). This approach was realized by Darling [3] with the constraint $X \ge 0$ not being required.

Theorem A (Darling). If $X \ge 0$ or P(X < -x) = o(V(x)), then

$$\lim_{n \to \infty} P(nV(S_n) < y; S_n \ge 0) = 1 - e^{-y}.$$
 (3)

If the left tail is comparable with the right one, i.e.,

$$\frac{V(x)}{V(x) + P(X < -x)} \to p \in (0, 1), \tag{4}$$

then

$$\lim_{n \to \infty} P(nW(S_n) < y) = 1 - pe^{-y/p} - qe^{-y/q}, \quad (5)$$

where q = 1 - p and $W(x) = V(x)I(x \ge 0) + P(X < x)I(x < 0)$.

In what follows, we need the following notation:

$$g^+(s) = E\{e^{-sX} | X \ge 0\}, \quad g^-(s) = E\{e^{sX} | X < 0\},$$

$$L^{+}(x) = \left[1 - g^{+}\left(\frac{1}{x}\right)\right] P(X \ge 0),$$

$$L^{-}(x) = \left[1 - g^{-}\left(\frac{1}{x}\right)\right] P(X < 0).$$

Let $R^{\pm}(x)$ denote the inverse of $L^{\pm}(x)$.

In these terms, Theorem A can be restated as follows.

Theorem 1. Assume that $L^+(x)$ is a slowly varying function such that

$$\lim_{x \to \infty} \frac{L^+(x)}{L^-(x)} = \frac{p^+}{p^-} \tag{6}$$

for some $p \in (0, 1)$, where $p^+ = p$ and $p^- = 1 - p$.

^a Sobolev Institute of Mathematics, Siberian Division, Russian Academy of Sciences, Universitetskii pr. 4, Novosibirsk, 630090 Russia

e-mail: nagaev@math.nsc.ru

b Weierstrass Institute for Applied Analysis and Stochastics, Berlin, Germany

Then, for any x > 0,

$$\lim_{x \to \infty} P\left(\pm S_n > R^{\pm}\left(\frac{x}{n}\right)\right) = \lim_{n \to \infty} P(nL^{\pm}(\pm S_n) < x; \pm S_n > 0)$$

$$= p^{\pm}\left(1 - \exp\left\{-\frac{x}{p^{\pm}}\right\}\right). \tag{7}$$

If $L^{\pm}(x)$ varies slowly and

$$L^{\mathrm{T}}(x) = o(L^{\pm}(x)), \tag{8}$$

then

$$\lim_{x \to \infty} P\left(\pm S_n > R^{\pm}\left(\frac{x}{n}\right)\right) = \lim_{n \to \infty} P(nL^{\pm}(\pm S_n) < x; \pm S_n > 0)$$

$$= 1 - e^{-x}$$
(9)

Note that Theorem 1 is stated in terms of the Laplace transforms of the positive and negative parts of X rather than in terms of its distribution function. The fact is that, according to the Tauberian theorem in [4, p. 503, formula (5.22)], the function $V^{\pm}(x) := P(\pm X > x)$ is slowly varying if and only if $L^{\pm}(x)$ has the same property and

$$\lim_{x \to \infty} \frac{V^{\pm}(x)}{L^{\pm}(x)} = 1. \tag{10}$$

It follows that conditions (4) and (6) are equivalent. The use of the normalization of $L^{\pm}(x)$ is explained by the fact that $L^{\pm}(x)$ is a continuous strictly decreasing function, which prevents us from difficulties associated with the inversion of $V^{\pm}(x)$.

For any fixed c, the domain $\{y: nL^{\pm}(y) > c\}$ can be viewed as a region of normal deviations. Accordingly, $\{y: nL^{\pm}(y) < \varepsilon_n\}$, where $\varepsilon_n \to 0$ as $n \to 0$, can be viewed as a region of large deviations.

The following assertion concerns the asymptotic behavior of large-deviation probabilities for S_n .

Theorem 2. Suppose that condition (6) or (8) holds and $n, y \to \infty$ so that $nL^{\pm}(y) \to 0$. Then

$$\lim_{n,y\to\infty} \frac{P(\pm S_n > y)}{nL^{\pm}(y)} = 1. \tag{11}$$

If $L(x) = L^+(x) + L^-(x)$ varies slowly and $nL(y) \rightarrow 0$, then

$$\lim_{n, y \to \infty} \frac{P(|S_n| > y)}{nL(y)} = 1.$$
 (12)

Note that (11) can be written as

$$\frac{\mathrm{P}(L^{\pm}(\pm S_n) < L^{\pm}(y))}{nL^{\pm}(y)} \to 1.$$

Furthermore,

$$\frac{p^{\pm}(1 - e^{-nL^{\pm}(y)/p^{\pm}})}{nL^{\pm}(y)} \to 1$$

if $nL^{\pm}(y) \rightarrow 0$.

Now setting $x = nL^{\pm}(y)$, we conclude that

$$P(nL^{\pm}(\pm S_n) < x) \sim p^{\pm} \left(1 - \exp\left\{-\frac{x}{p^{\pm}}\right\}\right)$$

as $x \to 0$. Thus, formula (12) also applies to large-deviation probabilities for S_n .

The proof of Theorem 1 is based on the following result, which relates the weak convergence of distributions to the convergence of the corresponding Laplace transforms.

Let ξ_n be an arbitrary sequence of nonnegative random variables, and let L(x) be a continuous monotone slowly varying function. The inverse of L(x) is denoted by R(x). Suppose that a_n is a positive number sequence and $\varphi(x)$ is a nondecreasing function.

Theorem 3. If L(x) increases and $a_n \to \infty$, then

$$\lim_{n \to \infty} \operatorname{Eexp} \left\{ -\frac{\xi_n}{R(a_n x)} \right\} = \varphi(x)$$
 (13)

holds on the set continuity of ϕ if and only if

$$\lim_{n \to \infty} P(a_n^{-1} L(\xi_n) < x) = \varphi(x)$$
 (14)

holds on the set continuity of ϕ .

If L(x) decreases and $a_n \to 0$, then (13) holds if and only if

$$\lim_{n \to \infty} P(a_n^{-1} L(\xi_n) < x) = 1 - \varphi(x)$$
 (15)

is true on the set continuity of φ.

The direct assertion in Theorem 3 for increasing L(x) was stated (in a somewhat different form) and proved in [5].

Theorem 1 is deduced easily from Theorem 3 if $X \ge 0$. The general case is reduced to this special one. The proof of Theorem 2 makes use of the upper bounds for $P(S_n \ge x)$ and $P(|S_n| \ge x)$ derived in [6] and the lower bounds for these probabilities obtained in [7, 8]. Since $P(X \ge x)$ and $P(|X| \ge x)$ are slowly varying

functions, these bounds approach each other and give an asymptotically sharp result.

ACKNOWLEDGMENTS

This work was supported by the INTAS, project 03-51-5018.

REFERENCES

- 1. P. Lévy, J. Math. 14, 347–402 (1935).
- 2. P. Lévy, *Théorie de l'addition des variables aléatoires* (Paris, 1937).

- 3. D. A. Darling, Trans. Am. Math. Soc. **73**, 95–107 (1952).
- 4. W. Feller, *An Introduction to Probability Theory and Its Applications* (Wiley, New York, 1968; Mir, Moscow, 1984), Vol. 2.
- 5. I. L. Hudson and E. Seneta, J. Appl. Probab. **14**, 836–842 (1977).
- 6. D. Kh. Fuk and S. V. Nagaev, Teor. Veroyatn. Ee Primen. **16**, 660–675 (1971).
- 7. A. A. Borovkov, Sib. Mat. Zh. 41, 997–1038 (2000).
- 8. S. V. Nagaev, Mat. Zametki 34, 309-313 (1983).