

Asymptotic bounds for infinitely divisible sequences

Stanisław Kwapień * Jan Rosiński †

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In memory of Kazimierz Urbanik

Abstract

We give asymptotic bounds for sample paths of discrete time infinitely divisible processes and prove the optimality of such bounds.

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1 Preliminaries and the main result

Consider a stochastic process

$$(1.1) \quad X(t) = \int_{\mathbb{R}} g(t, s) Z(ds) \quad t \in \mathbb{R},$$

where Z is a Lévy process and g is a deterministic kernel. Suppose that we sample this process at discrete times t_n , which are not far apart from each other. Formally, we state such condition as

$$(1.2) \quad \int_{\mathbb{R}} \int_{\mathbb{R}} (v^2 \sup_n g(t_n, s)^2 \wedge 1) \Pi_Z(dv) ds < \infty,$$

where Π_Z is the Lévy measure of $Z(1)$. Note that (1.2), without the supremum, is necessary for the integral (1.1) to exist (see, e.g., [6]). We will characterize an extremal sample behavior of $X(t_n)$ as $n \rightarrow \infty$. Roughly speaking, we show that possible heavy tails of $X(t)$ have small influence on

*Department of Mathematics, Warsaw University, ul. Banacha 2, Warsaw 02097, Poland (kwapstan@mimuw.edu.pl). Research supported, in part, by the Polish Grant KBN 2P03A 02722. The work was begun during his visit at the University of Tennessee, Knoxville.

†Department of Mathematics, University of Tennessee, Knoxville, TN 37996-1300, USA (rosinski@math.utk.edu) Research supported, in part, by a grant from the National Science Foundation.

the variation of the sequence $(X(t_n))$ and its behavior depends mostly on small jumps of Z (see Examples 7 and 8). We quantify this dependence. We will put and solve this problem in a general framework and then apply the solution to special cases as above.

Our work extends and refines a result of Braverman [2] given for symmetric stable processes. The technique is based on series representations of infinitely divisible processes combined with precise estimates for the tail of a Rademacher series related to an infinitely divisible distribution. We further develop this technique in Section 2. Section 3 contains the proof of the main result and some applications. The proof uses series representations and methods developed in [4] as well.

A sequence $\mathbf{X} = (X_n)_{n \in \mathbb{N}}$ is said to be infinitely divisible if for every $n \in \mathbb{N}$ the random vector (X_1, \dots, X_n) has an infinitely divisible distribution in \mathbb{R}^n . It follows from Maruyama [5] that every infinitely divisible sequence has the Lévy-Khintchine representation

$$\mathbb{E}e^{i\langle \mathbf{y}, \mathbf{X} \rangle} = \exp \left\{ \langle \mathbf{y}, \mathbf{b} \rangle - \frac{1}{2}Q(\mathbf{y}) + \int_{\mathbb{R}^{\mathbb{N}}} (e^{i\langle \mathbf{y}, \mathbf{x} \rangle} - 1 - i\langle \mathbf{y}, [\mathbf{x}] \rangle) \nu(d\mathbf{x}) \right\},$$

where $\mathbf{y} \in \mathbb{R}^{\mathbb{N}}$ has only finitely many nonzero components, $\langle \mathbf{y}, \mathbf{x} \rangle := \sum_n y_n x_n$, and $[\mathbf{x}] \in \mathbb{R}^{\mathbb{N}}$, $[\mathbf{x}]_n := x_n / (|x_n| \vee 1)$. Here $\mathbf{b} \in \mathbb{R}^{\mathbb{N}}$ is a drift, Q is a Gaussian covariance, and ν is a Lévy measure. I. e., ν is a Borel measure on $\mathbb{R}^{\mathbb{N}}$ such that $\nu(\{0\}) = 0$ and $\int (|x_n|^2 \wedge 1) \nu(d\mathbf{x}) < \infty$ for every $n \in \mathbb{N}$.

We will assume in the sequel that \mathbf{X} is an infinitely divisible sequence with no Gaussian component or drift, i.e., $Q = 0$ and $\mathbf{b} = 0$. In this case the characteristic function of \mathbf{X} simplifies to

$$(1.3) \quad \mathbb{E}e^{i\langle \mathbf{y}, \mathbf{X} \rangle} = \exp \left\{ \int_{\mathbb{R}^{\mathbb{N}}} (e^{i\langle \mathbf{y}, \mathbf{x} \rangle} - 1 - i\langle \mathbf{y}, [\mathbf{x}] \rangle) \nu(d\mathbf{x}) \right\}.$$

The condition corresponding to (1.2) is of the form

$$(1.4) \quad \int_{\mathbb{R}_0^{\mathbb{N}}} (\|\mathbf{x}\|_{\infty}^2 \wedge 1) \nu(d\mathbf{x}) < \infty,$$

where $\|\mathbf{x}\|_{\infty} := \sup_n |x_n|$. Our main result is the following.

Theorem 1 *Let $\mathbf{X} = (X_n)_{n \in \mathbb{N}}$ be an infinitely divisible sequence satisfying (1.3)–(1.4). Let $\theta : (0, \infty) \mapsto [0, \infty)$ be a left continuous non-increasing function such that for some $u_0 > 0$*

$$(1.5) \quad \nu(\{\mathbf{x} : \|\mathbf{x}\|_{\infty} \geq u\}) \leq \theta(u) \quad u \in (0, u_0).$$

Put

$$(1.6) \quad \kappa_{\theta}(t) = \int_0^t (\theta^{-1}(s) \wedge 1) ds + \sqrt{t} \left(\int_t^{\infty} ((\theta^{-1}(s))^2 \wedge 1) ds \right)^{\frac{1}{2}} \quad t \geq 0,$$

where θ^{-1} is the right continuous inverse of θ . Then

$$(1.7) \quad \limsup_{n \rightarrow \infty} \frac{|X_n|}{\kappa_{\theta}(\log n)} < \infty \quad a.s.$$

This asymptotic bound of \mathbf{X} is sharp in the following sense. For every left continuous non-increasing function $\theta : (0, \infty) \mapsto [0, \infty)$ with $\int (u^2 \wedge 1) (-d\theta(u)) \in (0, \infty)$ there exists an infinitely divisible

sequence \mathbf{X} with Lévy measure ν satisfying (1.3), (1.4) and (1.5) such that

$$(1.8) \quad \limsup_{n \rightarrow \infty} \frac{|X_n|}{\kappa_\theta(\log n)} > 0$$

with positive probability.

In order to use (1.7) we need information about the asymptotic behavior of κ_θ . This is possible, to a large extent, when θ is regularly varying function at zero. We will write $f(t) \asymp g(t)$ ($t \rightarrow \infty$) when $C^{-1}g(t) \leq f(t) \leq Cg(t)$ for some positive constant C and all t sufficiently large.

Lemma 2 *Suppose θ is a regularly varying function with index $-\alpha$ at zero. If $\alpha < 1$ then κ_θ is bounded. If $\alpha = 1$ then*

$$(1.9) \quad \kappa_\theta(t) \asymp \int_1^t \theta^{-1}(s) ds.$$

If $1 < \alpha < 2$ then

$$(1.10) \quad \kappa_\theta(t) \asymp t\theta^{-1}(t).$$

If $\alpha = 2$ then

$$(1.11) \quad \kappa_\theta(t) \asymp \left(t \int_t^\infty (\theta^{-1}(s))^2 ds \right)^{\frac{1}{2}}.$$

If $\alpha > 2$, then $\kappa_\theta(t) = \infty$.

Example 3 If $\theta(u) = u^{-\alpha}$ then $\kappa_\theta(t) \asymp t^{1-1/\alpha}$ when $1 < \alpha < 2$ and $\kappa_\theta(t) \asymp \log t$ when $\alpha = 1$. If $\theta(u) = u^{-\alpha}\ell(u^{-\alpha})$, where ℓ is slowly varying at infinity, then

$$\theta^{-1}(t) \asymp t^{-\frac{1}{\alpha}}(\ell^\#(t))^{-\frac{1}{\alpha}}.$$

Here $\ell^\#$ is de Bruijn conjugate of ℓ defined by

$$\ell(t)\ell^\#(t\ell(t)) \rightarrow 1, \quad \ell^\#(t)\ell(t\ell^\#(t)) \rightarrow 1 \quad (t \rightarrow \infty)$$

(see [1], Proposition 1.5.15). Combining these facts with Lemma 2 we can evaluate the asymptotic behavior of κ_θ in many cases. For example, if $\theta(u) = u^{-\alpha} \prod_{k=1}^n (\log^{(k)}(u^{-1}))^{\beta_k}$ ($u \rightarrow 0$), where $\log^{(k)}$ is the k -th iterate of \log and $\beta_k \in \mathbb{R}$, then for $1 < \alpha < 2$

$$\kappa_\theta(t) \asymp t^{1-\frac{1}{\alpha}} \left(\prod_{k=1}^n (\log^{(k)} t)^{\beta_k} \right)^{\frac{1}{\alpha}}$$

(cf. [1], Appendix 5).

2 Rademacher series related to infinitely divisible distributions

Our first aim is to recall precise estimates for the tail of a Rademacher series. If $\mathbf{a} = (a_i)$ is a bounded sequence of real numbers then $\mathbf{a}^* = (a_i^*)$ will stand for the nonincreasing rearrangement of $(|a_i|)$ and $\|\mathbf{a}\|_p = (\sum_{i=1}^{\infty} |a_i|^p)^{1/p}$. Let (ϵ_i) denote the Rademacher sequence, i.e. a sequence of i.i.d. symmetric random variables taking on values ± 1 . Assume that $\|\mathbf{a}\|_2 < \infty$ and let $S = \sum_{i=1}^{\infty} \epsilon_i a_i$ denote the corresponding Rademacher series.

For each $t > 0$ we consider the following quasi norms of $\mathbf{a} = (a_i)$

$$(2.1) \quad \begin{aligned} M_{\mathbf{a}}(t) &:= (E|S|^t)^{\frac{1}{t}}, \\ K_{\mathbf{a}}(t) &:= \inf \left\{ \|a'\|_1 + \sqrt{t} \|a''\|_2 : a = a' + a'' \right\}, \end{aligned}$$

and

$$(2.2) \quad H_{\mathbf{a}}(t) := \sum_{i \leq t} a_i^* + \sqrt{t} \left(\sum_{i > t} a_i^{*2} \right)^{\frac{1}{2}},$$

Then the following inequalities hold for each $t > 0$ (see [3])

$$(2.3) \quad P(|S| > eM_{\mathbf{a}}(t)) \leq e^{-t} \leq 2e^2 P(|S| > M_{\mathbf{a}}(t))^{\frac{1}{2}}$$

and

$$(2.4) \quad \frac{1}{4} H_{\mathbf{a}}(t) \leq M_{\mathbf{a}}(t) \leq K_{\mathbf{a}}(t) \leq H_{\mathbf{a}}(t).$$

Finally, let

$$(2.5) \quad \psi_{\mathbf{a}}(s) := K_{\mathbf{a}}^{-1} \left(\frac{s}{2e} \right).$$

Since $t \mapsto K_{\mathbf{a}}(t)$ is a concave function (as the infimum of concave functions) and $K_{\mathbf{a}}(0) = 0$, the function $s \mapsto \psi_{\mathbf{a}}(s)$ is convex with $\psi_{\mathbf{a}}(0) = 0$. (Note that when $K_{\mathbf{a}}(\infty) < \infty$, $\psi_{\mathbf{a}}(s) = \infty$ for large $|s|$; this occurs if and only if $\|\mathbf{a}\|_1 < \infty$). (2.3)–(2.5) yield the following estimates on the tail of S :

$$(2.6) \quad (4e^4)^{-1} e^{-\psi_{\mathbf{a}}(8es)} \leq P(|S| > s) \leq e^{-\psi_{\mathbf{a}}(2s)}, \quad s > 0.$$

Now we consider a real symmetric infinitely divisible random variable X with characteristic function given by

$$Ee^{iuX} = \exp \left(- \int_0^{\infty} (1 - \cos ux) \tau(dx) \right)$$

where τ is a Borel measure on \mathbb{R}_+ such that $\int_0^{\infty} (x^2 \wedge 1) \tau(dx) < \infty$. Let $\theta(x) := \tau([x, \infty))$, $x > 0$ and define

$$(2.7) \quad \theta^{-1}(t) := \inf \{ x > 0 : \theta(x) \leq t \}, \quad t > 0.$$

θ^{-1} is the right-continuous inverse of θ ; θ^{-1} is a nonincreasing function. Let $\{\Gamma_i\}$ be the sequence of arrival times in a Poisson process with rate 1 independent of the Rademacher sequence $\{\epsilon_j\}$. Then we have the following representation of X in distribution

$$(2.8) \quad X \stackrel{d}{=} \sum_{i=1}^{\infty} \epsilon_i \theta^{-1}(\Gamma_i)$$

(see, e.g., [7]). By the Strong Law of Large Numbers $i^{-1}\Gamma_i \rightarrow 1$ a.s.. Therefore, (2.8) is closely related to the Rademacher series

$$(2.9) \quad S := \sum_{i=1}^{\infty} \epsilon_i \theta^{-1}(i).$$

We want to express bounds for the tail of S explicitly as a function of θ . To this end we introduce the function

$$(2.10) \quad \kappa_{\theta}(t) = \int_0^t (\theta^{-1}(s) \wedge 1) ds + \sqrt{t} \left(\int_t^{\infty} ((\theta^{-1}(s))^2 \wedge 1) ds \right)^{\frac{1}{2}}, \quad t > 0$$

and $\kappa_{\theta}(0) = 0$, as in (1.6). Equivalently,

$$\kappa_{\theta}(t) = \int_{\theta^{-1}(t)}^{\infty} (x \wedge 1) \tau(dx) + \sqrt{t} \left(\int_0^{\theta^{-1}(t)} (x^2 \wedge 1) \tau(dx) \right)^{\frac{1}{2}}.$$

The following estimates play the key role.

Lemma 4 *Let $\mathbf{a} = (\theta^{-1}(i))_{i \in \mathbb{N}}$ and let $\psi_{\mathbf{a}}$ be given by (2.5). Then for all $t > 0$*

$$(2.11) \quad c\kappa_{\theta}(t) \leq \psi_{\mathbf{a}}^{-1}(t) \leq C\kappa_{\theta}(t)$$

where $c = \frac{\epsilon}{8}(\theta^{-1}(1) \wedge 1)$ and $C = 4e(\theta^{-1}(1) \vee 1)$.

Proof By (2.4) it is enough to estimate $H_{\mathbf{a}}$ in (2.2). For $t \geq 1$ we have

$$\begin{aligned} H_{\mathbf{a}}(t) &= \sum_{i \leq t} \theta^{-1}(i) + \sqrt{t} \left(\sum_{i > t} (\theta^{-1}(i))^2 \right)^{\frac{1}{2}} \\ &\leq \theta^{-1}(1) + \int_1^t \theta^{-1}(s) ds + \sqrt{t} \left(\int_t^{\infty} (\theta^{-1}(s))^2 ds + (\theta^{-1}(t))^2 \right)^{\frac{1}{2}} \\ &\leq \theta^{-1}(1) + \int_1^t \theta^{-1}(s) ds + \sqrt{t} \left(\int_t^{\infty} (\theta^{-1}(s))^2 ds \right)^{\frac{1}{2}} + \sqrt{t} \theta^{-1}(t). \end{aligned}$$

It is easy to verify the following bounds for $t \geq 1$

$$\begin{aligned} \theta^{-1}(1) + \int_1^t \theta^{-1}(s) ds &\leq (\theta^{-1}(1) \vee 1) \int_0^t (\theta^{-1}(s) \wedge 1) ds, \\ \int_t^{\infty} (\theta^{-1}(s))^2 ds &\leq ((\theta^{-1}(1))^2 \vee 1) \int_t^{\infty} ((\theta^{-1}(s))^2 \wedge 1) ds \end{aligned}$$

and

$$\sqrt{t} \theta^{-1}(t) \leq t \theta^{-1}(t) \leq (\theta^{-1}(1) \vee 1) \int_0^t (\theta^{-1}(s) \wedge 1) ds.$$

Hence we get

$$(2.12) \quad H_{\mathbf{a}}(t) \leq 2(\theta^{-1}(1) \vee 1) \kappa_{\theta}(t) \quad \text{for } t \geq 1.$$

If $t < 1$ then

$$H_{\mathbf{a}}(t) = \sqrt{t} \left(\sum_{i=1}^{\infty} (\theta^{-1}(i))^2 \right)^{1/2} \leq \sqrt{t} \left(\int_1^{\infty} (\theta^{-1}(s))^2 ds + (\theta^{-1}(1))^2 \right)^{\frac{1}{2}}.$$

We have the following elementary bounds for $t < 1$

$$\begin{aligned} \int_1^{\infty} (\theta^{-1}(s))^2 ds &\leq ((\theta^{-1}(1))^2 \vee 1) \int_t^{\infty} ((\theta^{-1}(s))^2 \wedge 1) ds, \\ (\theta^{-1}(1))^2 &\leq 2((\theta^{-1}(1))^2 \vee 1) \int_t^{\infty} ((\theta^{-1}(s))^2 \wedge 1) ds \quad \text{if } t \in (0, 1/2], \end{aligned}$$

and

$$\sqrt{t}\theta^{-1}(1) \leq \sqrt{2t}\theta^{-1}(1) \leq \sqrt{2}(\theta^{-1}(1) \vee 1) \int_0^t (\theta^{-1}(s) \wedge 1) ds \quad \text{if } t \in (1/2, 1).$$

It follows that

$$(2.13) \quad H_{\mathbf{a}}(t) \leq \sqrt{3}(\theta^{-1}(1) \vee 1) \kappa_{\theta}(t) \quad \text{if } t < 1.$$

Combining (2.12) and (2.13) we prove the upper bound in (2.11).

Now we will prove the lower bound in (2.11). For $t < 1$ we have

$$\begin{aligned} \kappa_{\theta}(t) &= \int_0^t (\theta^{-1}(s) \wedge 1) ds + \sqrt{t} \left(\int_t^{\infty} ((\theta^{-1}(s))^2 \wedge 1) ds \right)^{\frac{1}{2}} \\ &\leq t + \sqrt{t} \left(1 + \sum_{i=1}^{\infty} (\theta^{-1}(i))^2 \right)^{\frac{1}{2}} \leq 2\sqrt{t} + H_{\mathbf{a}}(t) \\ &\leq \left(\frac{2}{\theta^{-1}(1)} + 1 \right) H_{\mathbf{a}}(t). \end{aligned}$$

For $t \geq 1$ we obtain

$$\begin{aligned} \kappa_{\theta}(t) &\leq 1 + \sum_{i \leq t} \theta^{-1}(i) + \sqrt{t} \left((\theta^{-1}(t))^2 + \sum_{i > t} (\theta^{-1}(i))^2 \right)^{\frac{1}{2}} \\ &\leq \left(\frac{1}{\theta^{-1}(1)} + 1 \right) \sum_{i \leq t} \theta^{-1}(i) + \sqrt{t} \left(\sum_{i > t} (\theta^{-1}(i))^2 \right)^{\frac{1}{2}} + \sqrt{t}\theta^{-1}(t). \end{aligned}$$

Since $t \geq 1$, we get $\sum_{i \leq t} \theta^{-1}(i) \geq \frac{t}{2}\theta^{-1}(t) \geq \frac{\sqrt{t}}{2}\theta^{-1}(t)$. Hence, for $t \geq 1$ we have

$$\kappa_{\theta}(t) \leq \left(\frac{1}{\theta^{-1}(1)} + 3 \right) H_{\mathbf{a}}(t).$$

Using (2.4) we obtain the lower bound in (2.11). The proof of Lemma 4 is complete. \square

Lemma 5 (i). *For every $k > 0$ there exists a constant L such that*

$$\kappa_{\theta}(kt) \leq L\kappa_{\theta}(t) \quad t \geq 0.$$

(ii). *Suppose that $\theta_1(u) \leq k\theta_2(u)$ for all $u \in (0, u_0)$ and some $k, u_0 > 0$. Then there exists a constant L such that*

$$\kappa_{\theta_1}(t) \leq L\kappa_{\theta_2}(t) \quad t \geq 0.$$

Proof (i). If $k \leq 1$, then by (2.11) and the fact that $\psi_{\mathbf{a}}^{-1}$ is nonincreasing, $\kappa_{\theta}(kt) \leq c^{-1}\psi_{\mathbf{a}}^{-1}(kt) \leq c^{-1}\psi_{\mathbf{a}}^{-1}(t) \leq Cc^{-1}\kappa_{\theta}(t)$. If $k > 1$, then by the concavity of $\psi_{\mathbf{a}}^{-1}$, $\psi_{\mathbf{a}}^{-1}(0) = 0$, and (2.11) we have

$$\kappa_{\theta}(kt) \leq c^{-1}\psi_{\mathbf{a}}^{-1}(kt) \leq c^{-1}k\psi_{\mathbf{a}}^{-1}(t) \leq Cc^{-1}k\kappa_{\theta}(t).$$

(ii). Put $\theta_3 = k\theta_2$. We have $\theta_1^{-1}(t) \leq \theta_3^{-1}(t)$ for all $t > \theta_3(u_0)$ and $\theta_1^{-1}(t) \wedge 1 \leq (\theta_3^{-1}(t) \wedge 1)/(u_0 \wedge 1)$ for all $t \leq \theta_3(u_0)$. Using (i) and the definition of κ_{θ} we have

$$\kappa_{\theta_1}(t) \leq (u_0 \wedge 1)^{-1}\kappa_{\theta_3}(t) = (u_0 \wedge 1)^{-1}k\kappa_{\theta_2}(k^{-1}t) \leq L\kappa_{\theta_2}(t).$$

□

3 Proof of Theorem 1 and some applications

Proof of the Theorem 1: Let N be a Poisson random measure on $\mathbb{R}^{\mathbb{N}}$ with intensity measure ν . Define $f_n : \mathbb{R}^{\mathbb{N}} \mapsto \mathbb{R}$ by $f_n(\mathbf{x}) = x_n$ and $f(\mathbf{x}) := \sup_n f_n(\mathbf{x}) = \|\mathbf{x}\|_{\infty}$. Put

$$X'_n = \int_{\mathbb{R}^{\mathbb{N}}} f_n(\mathbf{x}) (N(d\mathbf{x}) - (|f_n(\mathbf{x})| \vee 1)^{-1}\nu(d\mathbf{x})) \quad n \in \mathbb{N}.$$

The sequence $\mathbf{X}' = (X'_n)$ is well defined and its characteristic function is the same as of \mathbf{X} . Therefore, we may further assume that $\mathbf{X}' = \mathbf{X}$. Then we decompose X_n as follows

$$X_n = a_n + \int_{f \leq 1} f_n d(N - \nu) + \int_{f > 1} f_n dN$$

where

$$a_n = - \int_{f > 1} f_n (|f_n| \vee 1)^{-1} d\nu.$$

From (1.4) $\nu(f > 1) < \infty$. Hence

$$\sup_n |a_n| \leq \nu(f > 1) < \infty$$

and

$$\sup_n \left| \int_{f > 1} f_n dN \right| \leq \int_{f > 1} |f_n| dN \leq \int_{f > 1} f dN < \infty \quad a.s$$

because the last integral is a finite sum. Therefore, the asymptotic behavior of X_n is determined by

$$Y_n := \int_{f \leq 1} f_n d(N - \nu).$$

From now on we may and do assume that ν is concentrated on $\{f \leq 1\}$, that is, all f_n 's are uniformly bounded by 1.

Let $Y'_n := \int f_n d(N' - \nu)$, where N' is an independent copy of N . Let $\tilde{N} = N - N'$ be the symmetrization of N and let

$$(3.1) \quad \tilde{Y}_n = Y_n - Y'_n = \int f_n d\tilde{N}$$

be the corresponding symmetrization of Y_n . We will use series representation of (\tilde{Y}_n) given in [4], Section 5.1. Namely, let $\sum_i \delta_{s_i}$ be a Poisson point process on $S := \mathbb{R}^{\mathbb{N}}$ with intensity measure 2ν independent of the Rademacher sequence $\{\epsilon_i\}$. Then $\tilde{N} \stackrel{d}{=} \sum_i \epsilon_i \delta_{s_i}$ and $(\tilde{Y}_n)_{n \in \mathbb{N}} \stackrel{d}{=} (\sum_i \epsilon_i f_n(s_i))_{n \in \mathbb{N}}$. Without loss of generality, we may and do assume that

$$\tilde{Y}_n = \sum_{i=1}^{\infty} \epsilon_i f_n(s_i).$$

Put

$$\tilde{\theta}(u) = 2\nu(f \geq u) \quad u > 0$$

and let $\tilde{\theta}^{-1}$ denote the right continuous inverse of $\tilde{\theta}$ given by (2.7). Recall that $(a_i^*)_{i \in \mathbb{N}}$ stands for the nonincreasing rearrangement of any sequence $(|a_i|)_{i \in \mathbb{N}}$. Let

$$(3.2) \quad T = \sup \{i \geq 1 : f^*(s_i) > u_i\}$$

where

$$u_i := \tilde{\theta}^{-1} \left(\frac{1}{2} i \right).$$

Write

$$(3.3) \quad \tilde{Y}_n \stackrel{d}{=} \sum_{i \leq T} \epsilon_i f_n^*(s_i) + \sum_{i > T} \epsilon_i f_n^*(s_i) =: V_n + W_n.$$

Since $|f_n(s_i)| \leq f(s_i)$, we have $f_n^*(s_i) \leq f^*(s_i) \leq 1$ ($f \leq 1$ by our assumption). Therefore

$$(3.4) \quad |V_n| \leq T f^*(s_1) \leq T.$$

We will show that T has some exponential moment finite, so that $T < \infty$ a.s. Observe that for every $k \geq 1$

$$T \geq k \iff \exists i \geq k : \text{Card}\{j : f(s_j) > u_i\} \geq i.$$

Since $\sum_i \delta_{s_i}$ is a Poisson point process with intensity 2ν , $\sum_j \delta_{f(s_j)}$ is a Poisson point process on \mathbb{R}_+ with intensity measure $\mu = (2\nu) \circ f^{-1}$. Therefore, for each Borel set $A \subset \mathbb{R}_+$

$$\text{Card}\{j : f(s_j) \in A\} \stackrel{d}{=} M(\mu(A)),$$

where $M(t)$, $t \geq 0$ is the usual Poisson process with parameter 1. Hence

$$\begin{aligned} P(T \geq k) &\leq \sum_{i=k}^{\infty} P(M(\mu(u_i, \infty)) \geq i) = \sum_{i=k}^{\infty} P\left(M(\tilde{\theta}(u_i+)) \geq i\right) \\ &\leq \sum_{i=k}^{\infty} P\left(M\left(\frac{1}{2}i\right) \geq i\right) \end{aligned}$$

because $\tilde{\theta}(\tilde{\theta}^{-1}(t)+) \leq t$. Applying a large deviations estimate $P\left(\left|\frac{M(t)}{t} - 1\right| > \frac{1}{3}\right) \asymp \exp(-\alpha t)$ for certain $\alpha > 0$ as $t \rightarrow \infty$, we get that

$$(3.5) \quad Ee^{\beta T} < \infty \quad \text{for some } \beta > 0.$$

Now we consider W_n in (3.3). Using the contraction principle conditionally $\{s_i\}$ we obtain

$$\begin{aligned}
P_\epsilon(|W_n| > t) &\leq 2P_\epsilon\left(\left|\sum_{i>T} \epsilon_i f^*(s_i)\right| > t\right) \leq 4P_\epsilon\left(\left|\sum_{i=2}^{\infty} \epsilon_i \tilde{\theta}^{-1}\left(\frac{i}{2}\right)\right| > t\right) \\
&\leq 4P_\epsilon\left(\left|\sum_{i=1}^{\infty} \epsilon_i \tilde{\theta}^{-1}(i)\right| > \frac{t}{2}\right) + 4P_\epsilon\left(\left|\sum_{i=1}^{\infty} \epsilon_i \tilde{\theta}^{-1}\left(i + \frac{1}{2}\right)\right| > \frac{t}{2}\right) \\
&\leq 12P_\epsilon\left(\left|\sum_{i=1}^{\infty} \epsilon_i \tilde{\theta}^{-1}(i)\right| > \frac{t}{2}\right).
\end{aligned}$$

Hence

$$(3.6) \quad P(|W_n| > t) \leq 12P\left(\left|\sum_{i=1}^{\infty} \epsilon_i \tilde{\theta}^{-1}(i)\right| > \frac{t}{2}\right) \quad t > 0.$$

Using (3.6) and (2.6) for $\mathbf{a} = (\tilde{\theta}^{-1}(i))_{i \in \mathbb{N}}$ we get for every $x > 0$

$$\begin{aligned}
P\left(\sup_{n \geq 2} \frac{|W_n|}{\kappa_{\tilde{\theta}}(\log n)} > x\right) &\leq \sum_{n=2}^{\infty} P(|W_n| > x \kappa_{\tilde{\theta}}(\log n)) \\
&\leq 12 \sum_{n=2}^{\infty} P\left(\left|\sum_{i=1}^{\infty} \epsilon_i \tilde{\theta}^{-1}(i)\right| > \frac{x}{2} \kappa_{\tilde{\theta}}(\log n)\right) \\
&\leq 12 \sum_{n=2}^{\infty} \exp(-\psi_{\mathbf{a}}(x \kappa_{\tilde{\theta}}(\log n))).
\end{aligned}$$

Applying (2.11) we get

$$\psi_{\mathbf{a}}(x \kappa_{\tilde{\theta}}(\log n)) \geq \psi_{\mathbf{a}}\left(\frac{x}{C} \psi_{\mathbf{a}}^{-1}(\log n)\right) \geq \frac{x}{C} \log n.$$

The last inequality follows from the concavity of $\psi_{\mathbf{a}}^{-1}$, provided $x \geq C$. Consequently,

$$P\left(\sup_{n \geq 2} \frac{|W_n|}{\kappa_{\tilde{\theta}}(\log n)} > x\right) \leq \sum_{n=2}^{\infty} n^{-x/C}$$

for $x > C$. In particular, this shows that

$$(3.7) \quad \mathbb{E}\left(\sup_{n \geq 2} \frac{|W_n|}{\kappa_{\tilde{\theta}}(\log n)}\right) < \infty,$$

which together with (3.3), (3.4) and (3.5) yields

$$\mathbb{E}\left(\sup_{n \geq 2} \frac{|\tilde{Y}_n|}{\kappa_{\tilde{\theta}}(\log n)}\right) < \infty.$$

Recall (3.1), i.g., \tilde{Y}_n is the symmetrization of Y_n and $\mathbb{E}Y_n = 0$. Hence

$$\mathbb{E}\left(\sup_{n \geq 2} \frac{|Y_n|}{\kappa_{\tilde{\theta}}(\log n)}\right) = \mathbb{E}\left(\sup_{n \geq 2} \frac{|Y_n - \mathbb{E}_Y(Y'_n)|}{\kappa_{\tilde{\theta}}(\log n)}\right) \leq \mathbb{E}\left(\sup_{n \geq 2} \frac{|\tilde{Y}_n|}{\kappa_{\tilde{\theta}}(\log n)}\right) < \infty.$$

Combining this with the first part of the proof we get

$$(3.8) \quad \sup_{n \geq 2} \frac{|X_n|}{\kappa_{\tilde{\theta}}(\log n)} < \infty.$$

By (1.5) we have $\tilde{\theta}(u) \leq 2\theta(u)$ for $u < u_0$. Since, by Lemma 5(ii), $\kappa_{\tilde{\theta}}(t) \leq L\kappa_{\theta}(t)$, (3.8) implies (1.7).

Now we will prove the optimality of the sequence $b_n = \kappa_{\theta}(\log n)$. Let θ be fixed and let τ be a measure on \mathbb{R}_+ with $\tau([u, \infty)) = \theta(u)$. Let $(\epsilon_{in})_{i,n \in \mathbb{N}}$ be an array of independent symmetric random variables taking values ± 1 . Consider

$$(3.9) \quad X_n := \sum_{i=1}^{\infty} \epsilon_{in} \theta^{-1}(\Gamma_i),$$

where (Γ_i) are arrival times in a Poisson process with rate 1 independent of (ϵ_{in}) . It is well known that given the condition on θ , series (3.9) converges a.s., defining an infinitely divisible sequence $\mathbf{X} = (X_n)$ (see, e.g. [7]). The Lévy measure ν of \mathbf{X} is the push-forward of the product of τ and $(\frac{1}{2}\delta_{-1} + \frac{1}{2}\delta_1)^{\otimes \mathbb{N}}$ by the map $(u, \mathbf{x}) \mapsto u\mathbf{x}$. Therefore,

$$\nu(\mathbf{x} : \|\mathbf{x}\|_{\infty} \geq u) = \theta(u).$$

By the first part of Theorem 1,

$$(3.10) \quad \limsup_{n \rightarrow \infty} \frac{|X_n|}{b_n} < \infty \quad a.s.$$

Using the mentioned above large deviation estimate for a Poisson process we infer that there exists a constant $d > 1$ such that the event

$$A = \{\Gamma_i \leq di, \forall i \in \mathbb{N}\}$$

has positive probability. Consider an i.i.d. sequence

$$S_n := \sum_{i=1}^{\infty} \epsilon_{in} \theta^{-1}(di).$$

We will show that there exists a constant $L > 0$ such that

$$(3.11) \quad \limsup_{n \rightarrow \infty} \frac{|S_n|}{b_n} \geq L \quad a.s.$$

Indeed, by (2.6) for $\mathbf{a} = (\theta^{-1}(di))_{i \in \mathbb{N}}$

$$\sum_n P(|S_n| > Lb_n) = \sum_n P(|S_1| > Lb_n) \geq (4e^4)^{-1} \sum_n \exp(-\psi_{\mathbf{a}}(8eLb_n)).$$

By Lemmas 5 and 4

$$b_n = \kappa_{\theta}(\log n) \leq L_1 \kappa_{d^{-1}\theta}(\log n) \leq L_1 c^{-1} \psi_{\mathbf{a}}^{-1}(\log n).$$

Hence

$$\sum_n P(|S_n| > Lb_n) \geq \sum_n \exp(-\psi_{\mathbf{a}}(8eLL_1c^{-1}\psi_{\mathbf{a}}^{-1}(\log n))) = \sum_n \frac{1}{n} = \infty$$

when $L = (8eL_1)^{-1}c$. By Borel–Cantelli Lemma (3.11) holds.

Fix positive integers $m > k > 1$ and let (\mathbf{e}_n) denote the standard basis in l_∞^m . We have

$$\sup_{k \leq n \leq m} \frac{|S_n|}{b_n} = \left\| \sum_{n=k}^m b_n^{-1} S_n \mathbf{e}_n \right\|_\infty = \left\| \sum_{i=1}^{\infty} \theta^{-1}(di) \mathbf{y}_i \right\|_\infty$$

where

$$\mathbf{y}_i = \sum_{n=k}^m b_n^{-1} \epsilon_{in} \mathbf{e}_n.$$

(\mathbf{y}_i) are independent symmetric random vectors with $\|\mathbf{y}_i\|_\infty = b_k^{-1}$. By the contraction principle we have

$$\begin{aligned} P \left(\sup_{k \leq n \leq m} \frac{|S_n|}{b_n} \geq L \right) &= P \left(\left\| \sum_{i=1}^{\infty} \theta^{-1}(di) \mathbf{y}_i \right\|_\infty \geq L \mid A \right) \\ &\leq 2P \left(\left\| \sum_{i=1}^{\infty} \theta^{-1}(\Gamma_i) \mathbf{y}_i \right\|_\infty \geq L \mid A \right) \\ &= 2P \left(\sup_{k \leq n \leq m} \frac{|X_n|}{b_n} \geq L \mid A \right). \end{aligned}$$

Letting $m \rightarrow \infty$ and then $k \rightarrow \infty$ and applying (3.11) we get

$$1 \leq 2P \left(\limsup_{n \rightarrow \infty} \frac{|X_n|}{b_n} \geq L \mid A \right).$$

This proves (1.8) and completes the proof of Theorem 1. \square

Remark 6 Somewhat more explicit but equivalent form of the sequence (X_n) constructed in the second part of the theorem is as follows. Let $Z(t)$, $t \geq 0$ be a symmetric Lévy process with Lévy measure

$$\Pi_Z(x : |x| \geq u) = \theta(u).$$

Let $h_n(t) = \text{sign}(\sin(2^n t))$ be the Rademacher functions. Then

$$X_n = \int_0^1 h_n(t) dZ(t).$$

If $\Pi_Z(\mathbb{R}) = \infty$, then a 0-1 law for subspaces of paths together with (1.8) imply that

$$\limsup_{n \rightarrow \infty} \frac{|X_n|}{\kappa_\theta(\log n)} > 0 \quad a.s.$$

(see, e.g., [8]). If also $\int_{|x| \leq 1} |x| \Pi_Z(dx) = \infty$, then $\kappa_\theta(\log n) \rightarrow \infty$. In this case one can show by the Hewitt-Savage 0-1 law applied to the representation (3.9) that

$$\limsup_{n \rightarrow \infty} \frac{|X_n|}{\kappa_\theta(\log n)} = \text{Constant} > 0 \quad a.s.$$

Proof of Lemma 2: Notice that

$$(3.12) \quad \kappa_\theta(t) = \theta(1) + \int_{\theta(1)}^t \theta^{-1}(s) ds + \sqrt{t} \left(\int_t^\infty (\theta^{-1}(s))^2 ds \right)^{\frac{1}{2}} \quad t \geq \theta(1).$$

The function $\theta^{-1}(t)$ is $(\frac{-1}{\alpha})$ -regularly varying and $(\theta^{-1}(t))^2$ is $(\frac{-2}{\alpha})$ -regularly varying at infinity, see [1], Proposition 1.5.15, page 29. By Karamata Theorem (see [1], Theorem 1.5.15 page 28) we obtain that

$$(3.13) \quad \int_1^t \theta^{-1}(s) ds \asymp t\theta^{-1}(t) \quad \text{if } \alpha > 1$$

and

$$(3.14) \quad \int_t^\infty (\theta^{-1}(s))^2 ds \asymp t(\theta^{-1}(t))^2 \quad \text{if } \alpha < 2.$$

This and (3.12) imply (1.10). If $\alpha = 1$, then (3.14) and $\int_1^t \theta^{-1}(s) ds \geq \frac{1}{2}t\theta^{-1}(t)$ for $t > 2$ yield (1.9). If $\alpha = 2$, then (3.13) and $\int_t^\infty (\theta^{-1}(s))^2 ds \geq t(\theta^{-1}(2t))^2 > \frac{1}{3}t(\theta^{-1}(t))^2$ for t large enough yield (1.11). The cases $\alpha < 1$ and $\alpha > 2$ are obvious. \square

Now we will return to our original question concerning infinitely divisible sequences defined by a stochastic integral.

Example 7 Let $X(t)$, $t \in \mathbb{R}$ be a stochastic process as in (1.1)–(1.2), where Z is a Lévy process with no Gaussian part. For simplicity we assume that $\mathbb{E}|Z(1)| < \infty$ with $\mathbb{E}Z(1) = 0$ or $Z(1)$ is symmetric. Then we write

$$X(t_n) = b_n + X_n$$

where $\mathbf{X} = (X_n)_{n \in \mathbb{N}}$ satisfies (1.3) with ν being the push-forward of the product of Π_Z and the Lebesgue measure on \mathbb{R} by the map $(s, x) \mapsto (xg(t_n, s))_{n \in \mathbb{N}}$ and

$$b_n = - \int_{\mathbb{R}} \int_{\mathbb{R}} \text{sign}(vg(t_n, s)) I(|vg(t_n, s)| > 1) \Pi_Z(dv) dt$$

or $b_0 = 0$ when Z is symmetric (cf. [6]).

By (1.2) sequence $(b_n)_{n \in \mathbb{N}}$ is bounded. Define

$$(3.15) \quad \theta(u) = \int_{\mathbb{R}} \Pi_Z(\{v \in \mathbb{R} : |v| \sup_n |g(t_n, s)| \geq u\}) ds$$

for small $u > 0$, otherwise θ can be arbitrary. By Theorem 1

$$(3.16) \quad \limsup_{n \rightarrow \infty} \frac{|X(t_n)|}{\kappa_\theta(\log n)} < \infty \quad a.s.$$

For example, if Z is an α -stable process with $\Pi_Z(dv) = (a|v|^{-\alpha-1}I(v < 0) + bv^{-\alpha-1}I(v > 0))dv$, then condition (1.2) becomes

$$c := \int_{\mathbb{R}} \sup_n |g(t_n, s)|^\alpha ds < \infty$$

and (3.15) gives

$$\theta(u) = \alpha^{-1}(a + b)cu^{-\alpha}.$$

Consider $1 \leq \alpha < 2$ (assume $\mathbb{E}Z(1) = 0$ when $1 < \alpha < 2$ and $Z(1)$ symmetric when $\alpha = 1$). Then by Example 3 and (3.16)

$$(3.17) \quad \limsup_{n \rightarrow \infty} \frac{|X(t_n)|}{(\log n)^{1-\frac{1}{\alpha}}} < \infty \quad a.s. \quad \text{when } 1 < \alpha < 2$$

and

$$(3.18) \quad \limsup_{n \rightarrow \infty} \frac{|X(t_n)|}{\log(\log n)} < \infty \quad a.s. \quad \text{when } \alpha = 1.$$

(3.17)-(3.18) were obtained by Braverman [2] for symmetric stable processes. Observe that smaller value of α produces less variability in $(X(t_n))$.

Naturally, one may consider more general infinitely divisible processes defined by stochastic integral with respect to an infinitely divisible random measure. The conclusion of Theorem 1 does not depend on a representation of an infinitely divisible process.

Example 8 Let M be an independently scattered divisible random measure on \mathbb{R} with finite control measure m and no Gaussian part. Assume that M is symmetric and

$$\mathbb{E}e^{iuM(A)} = e^{-m(A)\psi(u)},$$

where $\psi(u) = \int_0^\infty (1 - \cos uv) \Pi(du)$ with Π being a Lévy measure. Consider a harmonizable process

$$X(t) = \int_{\mathbb{R}} e^{itu} M(du) \quad t \in \mathbb{R}.$$

Condition (1.4) of Theorem 1 holds for the real and imaginary parts of $X(t_n)$ for any sequence $(t_n)_{n \in \mathbb{N}}$. In this case we take

$$\theta(u) = m(\mathbb{R})\Pi([u, \infty))$$

and conclude that

$$(3.19) \quad \limsup_{n \rightarrow \infty} \frac{|X(t_n)|}{\kappa_\theta(\log n)} < \infty \quad a.s.$$

Given that $X(t_n)$ may have heavy tails and the sequence $\kappa_\theta(\log n)$ may converge to infinity very slowly (as in the case of 1-stable processes, $\kappa_\theta(\log n) = \log(\log n)$), (3.19) indicates that the sequence $(X(t_n))$ will be strongly dependent for any sequence $(t_n)_{n \in \mathbb{N}}$. This reinforces the fact that the process $(X(t))$ is never ergodic, see [5].

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