

Assignment Levy processes

Abstract

We elaborate some results from chapter 25 of Sato's *Lévy processes and infinitely divisible distributions* Sato 2013. Additions are denoted in blue, while deletions are signified in red.

Proof of Existence of Moments from Smoothness of Characteristic Function

Definition 0.0.1 (Δ_h^k)

We define $\forall h > 0 : \Delta_h$ (h -central difference) of $f : \mathbb{R} \rightarrow \mathbb{R}$ as follows:

$$\Delta_h f(t) = f(t+h) - f(t-h), \quad (1)$$

and $\forall k \in \mathbb{N} : \Delta_h^k$ is defined as applying Δ_h applying k times and $k = 0$ as the identity. Note that Δ_h^k is a linear operator. We will always take differences in respect to the t variable.

Lemma 0.0.2 ($\Delta_h^k e^{at}$)

$$\forall k \in \mathbb{N} : \Delta_h^k e^{at} = e^{at} (e^{ah} - e^{-ah})^k. \quad (2)$$

Proof. This follows simply by induction. $k = 0$ is trivial. Base case:

$$\Delta_h e^{at} = (e^{a(t+h)} - e^{a(t-h)}) \quad (3)$$

$$= e^{at} (e^{ah} - e^{-ah}). \quad (4)$$

Induction hypothesis:

$$\Delta_h^{k-1} e^{at} = e^{at} (e^{ah} - e^{-ah})^{k-1}. \quad (5)$$

Induction step:

$$\Delta_h^k e^{at} = \Delta_h \Delta_h^{k-1} e^{at} \quad (6)$$

$$= \Delta_h \left(e^{at} (e^{ah} - e^{-ah})^{k-1} \right) \quad (7)$$

$$= \Delta_h (e^{at}) (e^{ah} - e^{-ah})^{k-1} \quad (8)$$

$$= e^{at} (e^{ah} - e^{-ah}) (e^{ah} - e^{-ah})^{k-1} \quad (9)$$

$$= e^{at} (e^{ah} - e^{-ah})^k. \quad (10)$$

□

Theorem 0.0.3 (central finite difference formula)

$\forall k \in \mathbb{N} \forall$ k -continuously differentiable f 's at 0:

$$f^{(k)}(0) = \lim_{h \rightarrow 0} \frac{\Delta_h^k f(t)|_{t=0}}{(2h)^k}. \quad (11)$$

Proof. Follows by the mean value theorem.

$$\lim_{h \rightarrow 0} \frac{\Delta_h^k f(t)|_{t=0}}{(2h)^k} \quad (12)$$

$$= \lim_{h \rightarrow 0} \frac{\Delta_h \Delta_h^{k-1} f(t)|_{t=0}}{(2h)^k} \quad (13)$$

$$= \lim_{h \rightarrow 0} \frac{\Delta_h^{k-1} f(t)(|_{t=h} - |_{t=-h})}{(2h)^k} \quad (14)$$

$$= \lim_{h \rightarrow 0} \frac{2h(\Delta_h^{k-1} f(t))'|_{t=z_h^1}, z_h^1 \in [-h, h]}{(2h)^k} \quad (15)$$

$$= \lim_{h \rightarrow 0} \frac{\Delta_h^{k-1} f'(t)|_{t=z_h^1}, z_h^1 \in [-h, h]}{(2h)^{k-1}} \quad (16)$$

$$= \lim_{h \rightarrow 0} \frac{\Delta_h^{k-2} f^{(2)}(t)|_{t=z_h^2}, z_h^2 \in [z_h^1 - h, z_h^1 + h] \subset [-2h, 2h]}{(2h)^{k-2}} \quad (17)$$

$$\dots \quad (18)$$

$$= \lim_{h \rightarrow 0} f^{(k)}(t)|_{t=z_h^k}, z_h^k \in [-kh, kh] \quad (19)$$

$$= \lim_{h \rightarrow 0} f^{(k)}(z_h^k) = f^{(k)}(0). \quad (20)$$

Last line follows because $f^{(k)}$ is continuous at 0. □

Lemma 0.0.4

$\forall k \in \mathbb{N} : \phi_X(t)$ is $2k$ -time continuous differentiable $\Rightarrow E[X^{2k}] < \infty$

Proof. Use the central finite difference formula and previous lemma:

$$|\phi_X^{(2k)}(0)| = \left| \lim_{h \rightarrow 0} \frac{\Delta_h^{2k} \phi_X(t)|_{t=0}}{(2h)^{2k}} \right| \quad (21)$$

$$= \left| \lim_{h \rightarrow 0} \frac{\Delta_h^{2k} |_{t=0} E[e^{itX}]}{(2h)^{2k}} \right| \quad (22)$$

$$= \left| \lim_{h \rightarrow 0} \frac{E[\Delta_h^{2k} |_{t=0} e^{itX}]}{(2h)^{2k}} \right| \quad (23)$$

$$= \left| \lim_{h \rightarrow 0} \frac{E[e^{itX}|_{t=0} (e^{ihX} - e^{-ihX})^{2k}]}{(2h)^{2k}} \right| \quad (24)$$

$$= \left| \lim_{h \rightarrow 0} \frac{E[(e^{ihX} - e^{-ihX})^{2k}]}{(2h)^{2k}} \right| \quad (25)$$

$$= \left| \lim_{h \rightarrow 0} \frac{1}{i^{2k}} E \left[\frac{(e^{ihX} - e^{-ihX})^{2k}}{(2h)^{2k}} \right] \right| \quad (26)$$

$$= \lim_{h \rightarrow 0} E \left[\frac{\sin(Xh)^{2k}}{h^{2k}} \right] \quad (27)$$

$$= \lim_{h \rightarrow 0} E \left[X^{2k} \frac{\sin(Xh)^{2k}}{X^{2k} h^{2k}} \right] \quad (28)$$

$$= \lim_{h \rightarrow 0} E \left[X^{2k} \text{sinc}(Xh)^{2k} \right] \quad (29)$$

$$\geq E \left[X^{2k} \right] \quad (30)$$

Where last line follows by Fatou's lemma. \square

25. Moments

We define the g -moment of a random variable and discuss finiteness of the g -moment of X_t for a Lévy process $\{X_t\}$.

DEFINITION 25.1. Let $g(x)$ be a nonnegative measurable function on \mathbb{R}^d . We call $\int g(x)\mu(dx)$ the g -moment of a measure μ on \mathbb{R}^d . We call $E[g(X)]$ the g -moment of a random variable X on \mathbb{R}^d .

DEFINITION 25.2. A function $g(x)$ on \mathbb{R}^d is called submultiplicative if it is nonnegative and there is a constant $a > 0$ such that

$$g(x+y) \leq ag(x)g(y) \text{ for } x, y \in \mathbb{R}^d \quad (25.1)$$

A function bounded on every compact set is called locally bounded.

LEMMA 25.1 Let $g(x)$ be a submultiplicative with constant a then:

$$\forall (x_i)_i \subset \mathbb{R}^d : g \left(\sum_{i=1}^n x_i \right) \leq a^{n-1} \prod_{i=1}^n g(x_i).$$

Proof. This follows by induction on n .

Base case: $n = 2$ is true by submultiplicativity.

Induction hypothesis: assume $2 \leq n \leq k$.

Induction step: $n = k + 1$:

$$\begin{aligned} & \forall (x_i)_i \subset \mathbb{R}^d : \\ & g \left(\sum_{i=1}^{k+1} x_i \right) = g \left(\sum_{i=1}^k x_i + x_{k+1} \right) \\ & \leq ag \left(\sum_{i=1}^k x_i \right) g(x_{k+1}) \text{ by submultiplicativity} \\ & \leq aa^{k-1} \prod_{i=1}^k g(x_i) g(x_{k+1}) \text{ by induction hypothesis} \\ & \leq a^k \prod_{i=1}^{k+1} g(x_i). \end{aligned}$$

\square

THEOREM 25.3 (g -Moment). Let g be a submultiplicative, locally bounded, measurable function on \mathbb{R}^d . Then, finiteness of the g -moment is not a time dependent distributional property in the class of Lévy processes. Let $\{X_t\}$ be a Lévy process on \mathbb{R}^d with

Lévy measure ν . Then, X_t has finite g -moment for every $t > 0$ if and only if $[\nu]_{\{|x|>1\}}$ has finite g -moment.

The following facts indicate the wide applicability of the theorem.

PROPOSITION 25.4.

- (i) The product of two submultiplicative functions is submultiplicative.
- (ii) If $g(x)$ is submultiplicative on \mathbb{R}^d , then so is $g(cx + \gamma)^\alpha$ with $c \in \mathbb{R}$, $\gamma \in \mathbb{R}^d$, and $\alpha > 0$.
- (iii) Let $0 < \beta \leq 1$. Then the following functions are submultiplicative:

$$\begin{aligned} & |x| \vee 1, |x_j| \vee 1, x_j \vee 1, \exp(|x|^\beta), \exp(|x_j|^\beta) \\ & \exp((x_j \vee 0)^\beta), \log(|x| \vee e), \log(|x_j| \vee e), \log(x_j \vee e) \\ & \log \log(|x| \vee e^e), \log \log(|x_j| \vee e^e), \log \log(x_j \vee e^e) \end{aligned}$$

Here x_j is the j th component of x .

Proof. (i) **Immediate from the definition.**

Let $g, h : \mathbb{R}^d \rightarrow \mathbb{R}$ be submultiplicative functions then:

$$\forall x, y \in \mathbb{R}^d : g(x+y)h(x+y) \leq a_1 g(x)g(y)a_2 h(x)h(y) \leq a_1 a_2 g(x)h(x)g(y)h(y).$$

So $gh : \mathbb{R}^d \rightarrow \mathbb{R}$ is submultiplicative.

- (ii) Let $g_1(x) = g(cx)$, $g_2(x) = g(x + \gamma)$, and $g_3(x) = g(x)^\alpha$. **Then it follows from (25.1) that $g_1(x+y) \leq a g_1(x)g_1(y)$, $g_2(x+y) \leq a^2 g(-\gamma)g_2(x)g_2(y)$, and $g_3(x+y) \leq a^\alpha g_3(x)g_3(y)$.**

$$\forall x, y \in \mathbb{R}^d :$$

$$\begin{aligned} g_1(x+y) &= g(c(x+y)) = g(cx + cy) \leq a g(cx)g(cy) = a g_1(x)g_1(y) \\ g_2(x+y) &= g(x+y+\gamma) = g(x+\gamma+y+\gamma-\gamma) \leq a^2 g(-\gamma)g(x+\gamma)g(y+\gamma) \\ &\leq a^2 g(-\gamma)g_2(x)g_2(y) \\ g_3(x+y) &= g(x+y)^\alpha \leq (a g(x)g(y))^\alpha = a^\alpha g(x)^\alpha g(y)^\alpha = a^\alpha g_3(x)g_3(y). \end{aligned}$$

- (iii) Let $h(u)$ be a positive increasing function on \mathbb{R} such that, for some $b \geq 0$, $h(u)$ is **constant** on $(-\infty, b]$ and $\log h(u)$ is concave on $[b, \infty)$. Then $h(u)$ is submultiplicative on \mathbb{R} . In fact, for $u, v \geq b \geq 0$, **by concaveness** the function $f(u) = \log h(u)$ satisfies

$$\begin{aligned} \frac{f(u+b) - f(u)}{b} &\leq \frac{f(2b) - f(b)}{b} \Leftrightarrow f(u+b) - f(u) \leq f(2b) - f(b) \\ \frac{f(u+v) - f(v)}{u} &\leq \frac{f(u+b) - f(b)}{u} \Leftrightarrow f(u+v) - f(v) \leq f(u+b) - f(b) \end{aligned}$$

the first line is for $b \neq 0$, $b = 0$ is trivial and hence

$$\begin{aligned} f(u+v) &\leq f(u+b) - f(b) + f(v) \leq f(2b) - 2f(b) + f(u) + f(v) \Leftrightarrow \\ h(u+v) &\leq \frac{h(2b)}{h(b)^2} h(u)h(v) \end{aligned}$$

which shows

$$h(u+v) \leq \text{const } h(u)h(v) \tag{25.2}$$

It follows (we miss the cases for $u \geq b \geq v, b \geq u, v$) that (25.2) holds for all $u, v \in \mathbb{R}$. The functions $u \vee 1, \exp((u \vee 0)^\beta), \log(u \vee e)$, and $\log \log(u \vee e)$ fulfil the conditions on $h(u)$. By (25.2) and by the increasingness of h , the functions $h(|x|), h(|x_j|)$, and $h(x_j)$ are submultiplicative on \mathbb{R}^d . \square

We prove Theorem 25.3 after three lemmas.

LEMMA 25.5. If $g(x)$ is submultiplicative and locally bounded, then

$$g(x) \leq be^{c|x|} \quad (25.3)$$

with some $b > 0$ and $c > 0$.

Proof. Choose b in such a way that $\sup_{|x| \leq 1} g(x) \leq b$ and $ab > 1$. If $n-1 < |x| \leq n$, then $\exists b : \sup_{|x| \leq 1} g(x) \leq b$ and $ab > 1$ because g is locally bounded. $\forall x$ set $n_x = \lceil |x| \rceil$ implying $n_x - 1 < |x| \leq n_x, \frac{x}{n_x} \in \{u \mid |u| \leq 1\}$, then

$$g(x) = g\left(\sum_{i=1}^{n_x} \frac{x}{n_x}\right) \leq a^{n_x-1} g\left(\frac{x}{n_x}\right)^{n_x} \leq a^{n_x-1} b^{n_x} \leq b(ab)^{|x|} \leq be^{\ln(ab)|x|}$$

which shows (25.3). \square

LEMMA 25.6. Let μ be an infinitely divisible distribution on \mathbb{R}^d with Lévy measure ν supported on a bounded set S . Then $\hat{\mu}(t)$ can be extended to an entire function on \mathbb{C}^d .

Proof. There is a finite $a > 0$ such that $S_\nu \subset [-a, a]$. The Lévy representation of $\hat{\mu}(t)$ is written as

$$\hat{\mu}(t) = \exp \left[-\frac{1}{2} \langle t, At \rangle + \int_S \left(e^{i \langle t, x \rangle} - 1 - i \langle t, x \rangle \right) \nu(dx) + i \langle \gamma', t \rangle \right]$$

with some $\gamma' \in \mathbb{R}^d$. The right-hand side is meaningful even if t is complex. Denote this function by $\Phi(t)$. Then $\Phi(t)$ is an entire function in each of its variables, since we can exchange the order of integration and differentiation and innerproducts are analytical. Thereby $\Phi(t)$ is also entire by Hartogs's theorem. \square

LEMMA 25.7. If μ is a probability measure on \mathbb{R} and $\hat{\mu}(z)$ is extendible to an entire function on \mathbb{C} , then μ has finite exponential moments, that is, it has finite $e^{c|x|}$ -moment for every $c > 0$.

Proof. It follows from Proposition 2.5(x) (see 0.0.4) that $\alpha_n = \int x^n \mu(dx)$ and $\beta_n = \int |x|^n \mu(dx)$ are finite for any $n \geq 1$. Since $\frac{d^n \hat{\mu}}{dz^n}(0) = i^n \alpha_n$, we have

$$\hat{\mu}(z) = \sum_{n=0}^{\infty} \frac{1}{n!} i^n \alpha_n z^n$$

the radius of convergence of the right-hand side being infinite. Notice that $\beta_{2k} = \alpha_{2k}$ and $\beta_{2k+1} \leq \frac{1}{2} (\alpha_{2k+2} + \alpha_{2k})$, since $|x|^{2k+1} \leq \frac{1}{2} (x^{2k+2} + x^{2k})$. It follows that

$$\int e^{|x|} \mu(dx) = \sum_{n=0}^{\infty} \frac{1}{n!} \beta_n c^n < \infty$$

completing the proof. \square

Proof of Theorem 25.3. Let $\nu_0 = [\nu]_{\{|x| \leq 1\}}$ and $\nu_1 = [\nu]_{\{|x| > 1\}}$. Construct independent Lévy processes $\{X_t^0\}$ and $\{X_t^1\}$ on \mathbb{R}^d such that $\{X_t\} =_d \{X_t^0 + X_t^1\}$ and $\{X_t^1\}$ is compound Poisson with Lévy measure ν_1 . Let μ_0^t and μ_1^t be the distributions of X_t^0 and X_t^1 , respectively.

Suppose that X_t has finite g -moment for some $t > 0$. It follows from

$$E[g(X_t)] = E[g(X_t^0 + X_t^1)] = \iint g(x+y) \mu_0^t(dx) \mu_1^t(dy)$$

that $\int g(x+y) \mu_1^t(dy) < \infty$ for some x . This means (see (24.1) in sato)

$$\sum_{n=0}^{\infty} \frac{t^n}{n!} \int g(x+y) \nu_1^n(dy) < \infty$$

Since $g(y) \leq ag(-x)g(x+y) \leq abe^{c|x|}g(x+y)$ by Lemma 25.5, we get

$$\sum_{n=0}^{\infty} \frac{t^n}{n!} \int g(y) \nu_1^n(dy) < \infty \quad (25.4)$$

Hence $\int g(y) \nu_1(dy) < \infty$.

Conversely, suppose that $\int g(y) \nu_1(dy) < \infty$. Let us prove that $E[g(X_t)] < \infty$ for every t . By the submultiplicativity,

$$\begin{aligned} \int g(y) \nu_1^n(dy) &= \int \cdots \int g(y_1 + \cdots + y_n) \nu_1(dy_1) \cdots \nu_1(dy_n) \\ &\leq a^{n-1} \left(\int g(y) \nu_1(dy) \right)^n \end{aligned}$$

Hence we have (25.4) for every t . That is, X_t^1 has finite g -moment. Since

$$E[g(X_t)] \leq E[g(X_t^0 + X_t^1)] \leq abE[e^{c|X_t^0|}] E[g(X_t^1)]$$

by (25.1) and (25.3), it remains only to show that $E[e^{c|X_t^0|}] < \infty$. Let $X_j^0(t)$, $1 \leq j \leq d$, be the components of X_t^0 . Then

$$\begin{aligned} E[e^{c|X_t^0|}] &\leq E \left[\exp \left(c \sum_{j=1}^d |X_j^0(t)| \right) \right] \leq E \left[\prod_{j=1}^d \left(e^{cX_j^0(t)} + e^{-cX_j^0(t)} \right) \right] \\ &\leq E \left[\sum_{\alpha_j \in \{-1,1\}} e^{c \sum_{j=1}^d \alpha_j X_j^0(t)} \right] \leq \sum_{\alpha_j \in \{-1,1\}} E \left[e^{c \sum_{j=1}^d \alpha_j X_j^0(t)} \right] \end{aligned}$$

which is written as a sum of a finite number of terms of the form $E[\exp X_t^\sharp]$ with X_t^\sharp being a linear combination of $X_j^0(t)$, $1 \leq j \leq d$. Since $\{X_t^\sharp\}$ is a Lévy process on \mathbb{R} with Lévy measure supported on a bounded set (use Proposition 11.10), $E[\exp X_t^\sharp]$ is finite by virtue of Lemmas 25.6 and 25.7. This proves all statements in the theorem.

Since X_t^0 is a Lévy process with a Lévy measure supported on a bounded set, $X_j^0(t)$ is a Lévy process on \mathbb{R} with a Lévy measure supported on a bounded set therefore it has finite (exponential) moments by (25.7) and so do any linear combinations $\sum_{j=1}^d \alpha_j X_j^0(t)$. I.e. $E[e^{c|X_t^0|}] \leq E[e^{c \sum_{j=1}^d \alpha_j X_j^0(t)}] < \infty$. \square

Corollary 25.8. Let $\alpha > 0, 0 < \beta \leq 1$, and $\gamma \geq 0$. None of the properties $\int |x|^\alpha \mu(dx) < \infty$, $\int (0 \vee \log |x|)^\alpha \mu(dx) < \infty$, and $\int |x|^\gamma e^{\alpha|x|^\beta} \mu(dx) < \infty$ is time dependent in the class of Lévy processes. For a Lévy process on \mathbb{R}^d with Lévy measure ν , each of the properties is expressed by the corresponding property of $[\nu]_{\{|x|>1\}}$.

Proof. This follows from Theorem 25.3 and Proposition 25.4. \square

EXAMPLE 25.12. Let $\{X_t\}$ be a Lévy process on \mathbb{R}^d generated by (A, ν, γ) . In components, $X_t = (X_j(t))$, $\gamma = (\gamma_j)$, and $A = (A_{jk})$. Then X_t has finite mean for $t > 0$ if and only if $\int_{\{|x|>1\}} |x| \nu(dx) < \infty$. When this condition is met, we can find $m_j(t) = E[X_j(t)]$ expressed as

$$m_j(t) = t \left(\int_{|x|>1} x_j \nu(dx) + \gamma_j \right) = t \gamma_{1,j}, \quad j = 1, \dots, d \quad (25.7)$$

differentiating $\hat{\mu}(z)$ (Proposition 2.5(ix) , $m_j(t) = \frac{1}{t} \partial z_j|_{z=0} \hat{\mu}_t(z)$).

$$\begin{aligned} \hat{\mu}_t(z) &= \exp \left[-t \left(\frac{1}{2} \langle z, Az \rangle + i \langle \gamma, z \rangle + \int_{\mathbb{R}^d} (\exp(i \langle z, x \rangle) - 1 - i \langle z, x \rangle I_D(x)) \nu(dx) \right) \right], \\ \partial z_j|_{z=0} \left(-\frac{1}{2} \langle z, Az \rangle \right) &= -\frac{1}{2} \langle \partial z_j(z), Az|_{z=0} \rangle - \frac{1}{2} \langle z|_{z=0}, A \partial z_j(z) \rangle = 0, \\ \partial z_j|_{z=0} (i \langle \gamma, z \rangle) &= i \langle \gamma, \partial z_j|_{z=0}(z) \rangle = i \langle \gamma, e_j \rangle = i \gamma_j, \\ \partial z_j|_{z=0} \left(\int_{\mathbb{R}^d} (\exp(i \langle z, x \rangle) - 1 - i \langle z, x \rangle I_D(x)) \nu(dx) \right) &= \int_{\mathbb{R}^d} (ix_j - ix_j I_D(x)) \nu(dx) \\ &= i \int_{D^c} x_j \nu(dx) \end{aligned}$$

Here $\gamma_{1,j}$ is the j th component of the center γ_1 in (8.8). Similarly, $E[|X_t|^2] < \infty$ for all $t > 0$ if and only if $\int_{|x|>1} |x|^2 \nu(dx) < \infty$. In this case,

$$\begin{aligned} v_{jk}(t) &= E[(X_j(t) - m_j(t))(X_k(t) - m_k(t))], \quad j, k = 1, \dots, d \\ &= E[X_j(t)X_k(t)] - m_j(t)m_k(t) \\ &= -\partial z_j \partial z_k \hat{\mu}_t(z)|_{z=0} - m_j(t)m_k(t) \\ &= -\partial z_j (\partial z_k (\ln \hat{\mu}_t(z)) \hat{\mu}_t(z))|_{z=0} - m_j(t)m_k(t) \\ &= -\partial z_j \partial z_k|_{z=0} (\ln \hat{\mu}_t(z)) \hat{\mu}_t(z) - \partial z_j (\ln \hat{\mu}_t(z)) \partial z_k (\ln \hat{\mu}_t(z)) \hat{\mu}_t(z)|_{z=0} - m_j(t)m_k(t) \\ &= -\partial z_j \partial z_k|_{z=0} (\ln \hat{\mu}_t(z)) \hat{\mu}_t(z) - \underbrace{\partial z_j (\ln \hat{\mu}_t(z))}_{\xrightarrow{im_j(t)}} \underbrace{\partial z_k (\ln \hat{\mu}_t(z))}_{\xrightarrow{im_k(t)}} \underbrace{\hat{\mu}_t(z)}_{\xrightarrow{1}}|_{z=0} - m_j(t)m_k(t) \\ &= -\partial z_j \partial z_k|_{z=0} (\ln \hat{\mu}_t(z)) \end{aligned}$$

the (j, k) elements of the covariance matrix of $X(t)$ **calculated with the cumulant generating function**, are expressed as

$$v_{jk}(t) = t \left(A_{jk} + \int_{\mathbb{R}^d} x_j x_k \nu(dx) \right) \quad (25.8)$$

$$-\partial z_j \partial z_k \left(-\frac{t}{2} \langle z, Az \rangle \right) = \frac{t}{2} \partial z_j (\langle e_k, Az \rangle + \langle z, A e_k \rangle)$$

$$\begin{aligned}
&= \frac{t}{2} (\langle e_k, Ae_j \rangle + \langle e_j, Ae_k \rangle) \\
&= tA_{jk} \\
-\partial z_j \partial z_k (i \langle \gamma, z \rangle) &= -i \partial z_j \langle \gamma, e_k \rangle \\
&= 0 \\
-\partial z_j \partial z_k|_{z=0} &\left(t \int_{\mathbb{R}^d} (\exp(i \langle z, x \rangle) - 1 - i \langle z, x \rangle I_D(x)) \nu(dx) \right) \\
&= -t \int_{\mathbb{R}^d} \partial z_j \partial z_k|_{z=0} \exp(i \langle z, x \rangle) \nu(dx) \\
&= t \int_{\mathbb{R}^d} x_j x_k \nu(dx)
\end{aligned}$$

Theorem 25.3 shows that, for a Lévy process $\{X_t\}$ with Lévy measure ν , the tails of P_{X_t} and ν have a kind of similarity. Are they actually equivalent in some class of Lévy processes? This question was answered by Embrecht, Goldie, and Veraverbeke [109] for subordinators. We state their result without proof in two remarks below.

THEOREM 25.17 (Exponential moment). Let $\{X_t\}$ be a Lévy process on \mathbb{R}^d generated by (A, ν, γ) . Let

$$C = \left\{ c \in \mathbb{R}^d : \int_{|x|>1} e^{\langle c, x \rangle} \nu(dx) < \infty \right\}$$

- (i) The set C is convex and contains the origin.
- (ii) $c \in C$ if and only if $E e^{\langle c, X_t \rangle} < \infty$ for some $t > 0$ or, equivalently, for every $t > 0$.
- (iii) If $w \in \mathbb{C}^d$ is such that $\operatorname{Re} w \in C$, then

$$\Psi(w) = \frac{1}{2} \langle w, Aw \rangle + \int_{\mathbb{R}^d} \left(e^{\langle w, x \rangle} - 1 - \langle w, x \rangle 1_D(x) \right) \nu(dx) + \langle \gamma, w \rangle \quad (25.11)$$

is definable, $E |e^{\langle w, X_t \rangle}| < \infty$, and

$$E \left[e^{\langle w, X_t \rangle} \right] = e^{t\Psi(w)} \quad (25.12)$$

Proof. (i) Obviously C contains the origin. If c_1 and c_2 are in C , then, for any $0 < r < 1$ and $s = 1 - r$,

$$\int_{|x|>1} e^{\langle rc_1 + sc_2, x \rangle} \nu(dx) \leq \left(\int_{|x|>1} e^{\langle c_1, x \rangle} \nu(dx) \right)^r \left(\int_{|x|>1} e^{\langle c_2, x \rangle} \nu(dx) \right)^s < \infty$$

by Hölder's inequality. Hence C is convex.

(ii) The function $g(x) = e^{\langle c, x \rangle}$ is clearly submultiplicative. Hence Theorem 25.3 gives the assertion.

(iii). Any linear transformation U of \mathbb{R}^d to \mathbb{R}^d can be uniquely extended to a linear transformation of \mathbb{C}^d to \mathbb{C}^d . Regarding U as a $d \times d$ matrix, it is easy to see that $\langle w, Uv \rangle = \langle U'w, v \rangle$ for $w, v \in \mathbb{C}^d$, where U' is the transpose of U . Now let $\operatorname{Re} w \in C$.

Then $\int_{|x|>1} |e^{\langle w, x \rangle}| \nu(dx) = \int_{|x|>1} e^{\langle \operatorname{Re} w, x \rangle} \nu(dx) < \infty$, which shows that $\Psi(w)$ of (25.11) is definable and finite. Also, $E |e^{\langle w, X_t \rangle}| = E e^{\langle \operatorname{Re} w, X_t \rangle} < \infty$ by (ii). Let us show (25.12) in three steps.

Step 1. Let e_1 be the unit vector with first component 1. Assume that $e_1 \in C$. Let us prove (25.12) for all $w = (w_j)_{1 \leq j \leq d}$ with $\operatorname{Re} w_1 \in [0, 1]$ and $\operatorname{Re} w_j = 0, 2 \leq j \leq d$. Fix $t > 0$ and $w_2, \dots, w_d \in \mathbb{C}$ with $\operatorname{Re} w_j = 0, 2 \leq j \leq d$, and regard w_1 as variable in $F = \{w_1 \in \mathbb{C} : \operatorname{Re} w_1 \in [0, 1]\}$. Consider $f(w_1) = E e^{\langle w, X_t \rangle}$. Then $f(w_1)$ is continuous on F , since

$$\left| e^{\langle w, X(t) \rangle} \right| = e^{(\operatorname{Re} w_1) X_1(t)} \leq (\operatorname{Re} w_1) e^{X_1(t)} + (1 - \operatorname{Re} w_1) \leq e^{X_1(t)} + 1$$

by the convexity of $e^{u X_1(t)}$ in u , where $X_1(t)$ is the first component of $X(t)$. Moreover, $f(w_1)$ is analytic in the interior of F , since it is the limit of the analytic functions $E [e^{\langle v, X_t \rangle}; |X_t| \leq n]$ as $n \rightarrow \infty$. Similarly, $h(w_1) = e^{\operatorname{tw}(w)}$ is continuous on F and analytic in the interior of F . If $\operatorname{Re} w_1 = 0$, then $f(w_1) = h(w_1)$, which is the Lévy-Khintchine representation of P_{X_i} . Therefore, as in the proof of Theorem 24.11, the principle of reflection and the uniqueness theorem yield (25.12) when $\operatorname{Re} w_1 \in [0, 1]$.

Step 2. Let U be a linear transformation from \mathbb{R}^d onto \mathbb{R}^d . Let $Y_t = U X_t$. Then $\{Y_t\}$ is a Lévy process with generating triplet (A_U, ν_U, γ_U) by Proposition 11.10. Write

$$C_U = \left\{ c \in \mathbb{R}^d : \int_{|x|>1} e^{\langle c, x \rangle} \nu_U(dx) < \infty \right\}$$

Since $\nu_U = \nu U^{-1}$, we have $C_U = (U')^{-1} C$. Given $w \in \mathbb{C}^d$ satisfying $\operatorname{Re} w \in C$, let $v = (U')^{-1} w$. Then $\operatorname{Re} v \in C_U$. Define

$$\Psi_U(v) = \frac{1}{2} \langle v, A_U v \rangle + \int_{\mathbb{R}^d} \left(e^{\langle v, x \rangle} - 1 - \langle v, x \rangle 1_D(x) \right) \nu_U(dx) + \langle \gamma_U, v \rangle$$

We claim that if

$$E \left[e^{\langle v_i Y_t \rangle} \right] = e^{t \Psi_U(v)} \quad (25.13)$$

then w satisfies (25.12). In fact, $\langle v, Y_t \rangle = \left\langle \langle U^{-1} \rangle' w, Y_t \right\rangle = \langle w, X_t \rangle$ and

$$\begin{aligned} \Psi_U(v) &= \frac{1}{2} \langle U' v, A U' v \rangle + \int \left(e^{\langle v, Ux \rangle} - 1 - \langle v, Ux \rangle 1_D(x) \right) \nu(dx) + \langle U \gamma, v \rangle \\ &= \Psi(w) \end{aligned}$$

by (11.8)-(11.10). That is, (25.13) is identical with (25.12).

Step 3. Given $w \in \mathbb{C}^d$ satisfying $\operatorname{Re} w \in C$, we shall show (25.12). If $\operatorname{Re} w = 0$, there is nothing to prove. Assume $\operatorname{Re} w \neq 0$. Choose a linear transformation U from \mathbb{R}^d onto \mathbb{R}^d such that $\operatorname{Re} w = U' e_1$. Consider the Lévy process $Y_t = U X_t$. Since $C_U = (U')^{-1} C$, we have $e_1 \in C_U$. We know, by Step 1, that, if $v \in \mathbb{C}^d$ satisfies $\operatorname{Re} v = e_1$, then (25.13) holds. Hence, by the result of Step 2, w satisfies (25.12). \square

We close this section with a discussion of the g -moments of $\sup_{s \in [0, t]} |X_s|$

THEOREM 25.18. Let $\{X_t\}$ be a Lévy process on \mathbb{R}^d . Define

$$X_t^* = \sup_{s \in [0, t]} |X_s| \quad (25.14)$$

Let $g(r)$ be a nonnegative continuous submultiplicative function on $[0, \infty)$, increasing to ∞ as $r \rightarrow \infty$. Then the following four statements are equivalent.

(1) $E[g(X_t^*)] < \infty$ for some $t > 0$.

(2) $E[g(X_t^*)] < \infty$ for every $t > 0$.

(3) $E[g(|X_t|)] < \infty$ for some $t > 0$.

(4) $E[g(|X_t|)] < \infty$ for every $t > 0$.

Proof. Since $g(|x|)$ is submultiplicative on \mathbb{R}^d , (3) and (4) are equivalent by Theorem 25.3. As $|X_t| \leq X_t^* \implies g(|X_t|) \leq g(X_t^*)$, all we have to show is that, for any fixed $t > 0$, $E[g(|X_t|)] < \infty$ implies $E[g(X_t^*)] < \infty$. We claim that, for any $a > 0$ and $b > 0$,

$$P[X_t^* > a + b] \leq P[|X_t| > a] / P[X_t^* \leq b/2] \quad (25.15)$$

Fix t and let $t_{n,j} = jt/2^n$ for $j = 1, \dots, 2^n$ and $X_{(n)}^* = \max_{1 \leq j \leq 2^n} |X_{t_{n,j}}|$. Choosing $Z_j(s) = Z_j = X_{t_{n,j}} - X_{t_{n,j-1}}$ in Lemma 20.2 and using Remark 20.3, we have

$$P[X_{(n)}^* > a + b] \leq P[|X_t| > a] / P[X_{(n)}^* \leq b/2]$$

in (20.2). Hence, letting $n \rightarrow \infty$, we get (25.15). Choose $b > 0$ such that $P[X_t^* \leq b/2] > 0$. Let $\tilde{g}(r)$ be a continuous increasing function on $[0, \infty)$ such that $\tilde{g}(0) = 0$ and $\tilde{g}(r) = g(r)$ for $r \geq 1$. Apply Lemma 17.6 to $k(r) = 1 - P[|X_t| \leq r]$ and $l(r) = \tilde{g}(r)$. Then

$$\int_{0+}^{\infty} P[|X_t| > r] d\tilde{g}(r) = \int_{(0, \infty)} \tilde{g}(r) P[|X_t| \in dr] = E[\tilde{g}(|X_t|)]$$

14 follows from (25.15) that

$$\int_{0+}^{\infty} P[X_t^* > r + b] d\tilde{g}(r) \leq E[\tilde{g}(|X_t|)] / P[X_t^* \leq b/2]$$

The integral in the left-hand side equals

$$\int_{(0, \infty)} \tilde{g}(r) P[X_t^* - b \in dr] = E[\tilde{g}(X_t^* - b); X_t^* > b]$$

similarly. Hence, if $E[g(|X_t|)] < \infty$, then $E[g(X_t^* - b); X_t^* > b] < \infty$ and, by the submultiplicativity of g , $E[g(X_t^*)] < \infty$.

□

References

Sato, Ken-iti (2013). *Lévy processes and infinitely divisible distributions*. en. Revised edition, corrected paperback edition. Cambridge studies in advanced mathematics 68. Cambridge: Cambridge Univ. Press. ISBN: 978-0-521-55302-5 978-1-107-65649-9.