Stable Distributions

Lecture Notes

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ULM
2016
# Contents

1 Introduction 2

2 Properties of stable laws 7
   2.1 Equivalent definitions of stability 7
   2.2 Strictly stable laws 16
   2.3 Properties of stable laws 17
   2.4 Limit theorems 23
   2.5 Further properties of stable laws 28

3 Simulation of stable variables 34

4 Additional exercises 38

Literature 43
Forewords

These lecture notes are based on the bachelor course “Stable distributions” which originally took place at Ulm University during the summer term 2016.

In modern applications, there is a need to model phenomena that can be measured by very high numerical values which occur rarely. In probability theory, one talks about distributions with heavy tails. One class of such distributions are stable laws which (apart from the Gaussian one) do not have a finite variance. So, the aim of this course was to give an introduction into the theory of stable distributions, its basic facts and properties.

The choice of material of the course is selective and was mainly dictated by its introductory nature and limited lecture times. The main topics of these lecture notes are

1) Stability with respect to convolution
2) Characteristic functions and densities
3) Non-Gaussian limit theorem for i.i.d. random summands
4) Representations and tail properties, symmetry and skewness
5) Simulation.

For each topic, several exercises are included for deeper understanding of the subject. Since the target audience are bachelor students of mathematics, no prerequisites other than basic probability course are assumed.

You can find more information about this course at: https://www.uni-ulm.de/mawi/mawi-stochastik/lehre/ss16/stable-distributions/

The author hopes you find these notes helpful. If you notice an error or would like to discuss a topic further, please do not hesitate to contact the author at evgeny.spodarev@uni-ulm.de.

The author is also grateful to Dr. Vitalii Makogin for typesetting this lectures in LATEX, making illustrations, and the selection of exercises.

02.11.2016

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1 Introduction

Let \((\Omega, \mathcal{F}, \mathbb{P})\) be an abstract probability space. The property of stability of random variables with respect to (w.r.t.) convolution is known for you from the basic course of probability. Let \(X_1 \sim N(\mu_1, \sigma_1^2)\) and \(X_2 \sim N(\mu_2, \sigma_2^2)\) be independent random variables. Then \(X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)\). One can restate this property as follows. Let \(X_1 \overset{d}{=} X_2 \overset{d}{=} X \sim N(0, 1)\) and \(X, X_1, X_2\) are independent. Then \(\forall a, b \in \mathbb{R} aX_1 + bX_2 \sim N(0, a^2 + b^2)\), and so

\[
aX_1 + bX_2 = \frac{d}{c \geq 0} \sqrt{a^2 + b^2} X. \tag{1.0.1}
\]

Additionally, for any random variables \(X_1, \ldots, X_n\) i.i.d., \(X_i \overset{d}{=} X, \forall i = 1, \ldots, n\), it holds \(\sum_{i=1}^{n} X_i \overset{d}{=} \sqrt{n} X\). Property (1.0.1) rewrites in terms of cumulative distribution functions of \(X_1, X_2, X\) as \(\Phi\left(\frac{x}{\lambda}\right) \ast \Phi\left(\frac{y}{\lambda}\right) = \Phi\left(\frac{x+y}{\lambda}\right), x, y \in \mathbb{R}\), where \(\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-t^2/2} dt, x \in \mathbb{R}\), and \(\ast\) is the convolution operation.

It turns out that the normal law is not unique satisfying (1.0.1). Hence, it motivates the following definition.

**Definition 1.0.1**

A random variable \(X\) is stable if \(\forall a, b \in \mathbb{R} \exists c, d \in \mathbb{R}, c > 0 \) s.t.

\[
aX_1 + bX_2 = cX + d, \tag{1.0.2}
\]

where \(X_1, X_2\) are independent copies of \(X\). \(X\) as above is called strictly stable if \(d = 0\).

**Remark 1.0.1**

Let \(F_X\) be the cumulative distribution function (c.d.f.) of \(X\), i.e., \(F_X(y) = \mathbb{P}(X \leq y), y \in \mathbb{R}\). Then the property (1.0.2) rewrites as \(F_X\left(\frac{x}{\lambda}\right) \ast F_X\left(\frac{y}{\lambda}\right) = F_X\left(\frac{x+y}{\lambda}\right), y \in \mathbb{R}\), if \(a, b, c \neq 0\). The case \(c = 0\) corresponds to \(X \equiv \text{const a.s.}\), which is a degenerate case. Obviously, a constant random variable is always stable. The property (1.0.1) shows that \(X \sim N(0, 1)\) is strictly stable.

**Exercise 1.0.1**

Show that \(X \sim N(\mu, \sigma^2)\) is stable for any \(\mu \in \mathbb{R}, \sigma^2 > 0\). Find the parameters \(c\) and \(d\) in (1.0.2) for it. Prove that \(X \sim N(\mu, \sigma^2)\) is strictly stable if and only if (iff) \(\mu = 0\).

The notion of (strictly) stability has first introduced by Paul Lévy in his book *Calcul des probabilités* (1925). However, stable distributions (different from the normal ones), were known long before. Thus, French mathematicians Poisson and Cauchy some 150 years before Lévy found the distribution with density

\[
f_\lambda(x) = \frac{\lambda}{\pi(x^2 + \lambda^2)}, x \in \mathbb{R}, \tag{1.0.3}
\]

depending on parameter \(\lambda > 0\). Now this distribution bears the name of Cauchy, and it is known to be strictly stable. Its characteristic function \(\varphi_\lambda(t) = \int_{\mathbb{R}} e^{itx} f_\lambda(x) dx, t \in \mathbb{R}\) has the form \(\varphi_\lambda(t) = e^{-|t|}\).
In 1919 the Danish astronomer J. Holtsmark found a law of random fluctuation of gravitational field of some stars in space, which had characteristic function \( \varphi(t) = e^{-\lambda |t|^\alpha}, t \in \mathbb{R}^3 \), which led to the family of characteristic functions

\[
\varphi(t) = e^{-\lambda |t|^\alpha}, t \in \mathbb{R}, \lambda > 0.
\]

For \( \alpha = 3/2 \), it appeared to be strictly stable and now bears the name of Holtsmark. It needed some time till it has proven by P. Lévy in 1927 that \( \varphi(t) \) as in (1.0.4) is a valid characteristic function of some (strictly stable) distribution only for \( \alpha \in (0, 2] \). The theory of stable random variables took its modern form after 1938 when the books by P. Lévy and A. Khinchin where published.

Let us give further examples of stable laws and of their applications.

**Example 1.0.1 (Constants):**
Any constant \( c \) is evidently a stable random variable.

**Example 1.0.2 (Cauchy distribution in nuclear physics):**
Let a point source of radiation \( R \) be located at \((0, 0, 1)\) and radiate its elementary particles onto a screen \( S = \{ (x, y, 0), x, y \in \mathbb{R} \} \). The screen \( S \) is covered by a thin layer of metal so that it yields light flashes as the emitted particles reach it. Let \((u, v, 0)\) be the coordinates of one of these (random) flashes. Due to the symmetry of this picture (the whole process of radiation is rotationally symmetric around axis RA cf. Fig. 1.1) it is sufficient to find the distribution of one coordinate of \((u, v)\), say, \( u \sim v \). Project the whole picture onto the plane \((x, z)\). Let \( F_u(x) = \mathbb{P}(u \leq x) \) be the c.d.f. of \( U \). The angle \( \alpha \) to the ray \( RU \) varies in \((0, \pi)\) if it arrives at \( S \). It is logic to assume that \( \alpha \sim U[0, \pi] \). Since \( \tan\left(\alpha - \frac{\pi}{2}\right) = \frac{v}{u} = u \), it follows \( \alpha = \frac{\pi}{2} + \arctan x \). Then for any \( x > 0 \) \( \{U \leq x\} = \{\tan(\alpha - \pi/2) \leq x\} = \{\alpha \leq \pi/2 + \arctan x\} \). So,

\[
F_U(x) = \mathbb{P}(\alpha \leq \pi/2 + \arctan x) = \frac{\pi/2 + \arctan x}{\pi} = \frac{1}{2} + \frac{1}{\pi} \arctan x
\]

\[
= \int_{-\infty}^{x} \frac{1}{\sqrt{1+y^2}} \, dy = \int_{-\infty}^{x} f_1(y) \, dy,
\]

with \( f_1(\cdot) \) as in (1.0.3), \( \lambda = 1 \). So, \( U \sim \text{Cauchy}(0, 1) \). For instance, it describes the distribution of energy of unstable states on nuclear reactions (Lorenz law).
Example 1.0.3 (Theory of random matrices):
Let $A_nY_n = B_n$ be a random system of $n$ linear equations, where $A_n = \left(X_{ij}^{(n)}\right)_{i,j=1}^n$ be a random $(n \times n)$–matrices, and $B_n = \left(B_{ij}^{(n)}\right)_{i,j=1}^n$ be a random $n - \dim \text{vector in } \mathbb{R}^n$. If $\det(A_n) \neq 0$, its solution is $Y_n = A_n^{-1}B_n$ (for $\det(A_n) = 0$, put $Y_n = 0$ a.s.). As $n \to \infty$, the solution $Y_n$ is numerically very hard to compute. Then the following approximation (as $n \to \infty$) is helpful. Assume that for each $n \in \mathbb{N}$ $A_n$ and $B_n$ are mutually independent, $\mathbb{E}X_{ij}^{(n)} = \mathbb{E}B_{ij}^{(n)} = 0$, $\text{Var}X_{ij}^{(n)} = \text{Var}B_{ij}^{(n)} = 1 \forall i,j = 1,\ldots,n$. If $\sup_{n,i,j} \mathbb{E} \left(|X_{ij}^{(n)}|^5 + |B_{ij}^{(n)}|^5\right) < \infty$ then for any $1 \leq i,j \leq n$, $i \neq j \lim_{n \to \infty} \mathbb{P}(Y_{ij}^{(n)}) = \frac{1}{2} + \frac{1}{\pi} \arctan x, x > 0$, where $Y_n = (Y_{ij}^{(n)})_{i=1\ldots n}$. Hence, here again, $Y_{ij}^{(n)} \sim \text{Cauchy}(0,1), i = 1\ldots n$, compare Exercise 1.0.1

Exercise 1.0.2
Show that if $X \in \text{Cauchy}(0,1)$ then $X = \frac{Y_1}{\sqrt{2}}$, where $Y_1,Y_2$ are i.i.d. $N(0,1)$–distributed random variables.

Exercise 1.0.3
1) Prove that Cauchy distribution is stable. If it is centered, i.e., $X \sim \text{Cauchy}(0,\lambda)$, then it is strictly stable.
2) Show that if $X \sim \text{Cauchy}(0,\lambda)$ then $X = \frac{Y_1}{\lambda}$.

In fact, it can be shown that for $X \sim \text{Cauchy}(0,1)$, $X_1,\ldots,X_n$ i.i.d. and $X = \frac{Y_1}{\sqrt{2}}$, $\sum_{i=1}^n X_i = nX$, i.e., the constant $c$ in (1.0.2) is equal to 2 here. The property $\sum_{i=1}^n X_i = nX$ rewrites $\overline{X_n} := \frac{1}{n} \sum_{i=1}^n X_i \overset{d}{=} X$, i.e., the arithmetic mean of $X_i$ is distributed exactly as one of $X_i$.

Example 1.0.4 (Lévy distribution in branching processes):
Consider the following branching process in discrete time. A population of particles evolves in time as follows: at each time step, each particle (independently from others) dies with probability $p > 0$, doubles (i.e., is divided into two new similar particles) with probability $p > 0$, or simply stays untouched (with complimentary probability $1 - 2p$). Let $G(s) = p + (1 - 2p)s + ps^2,|s| \leq 1$ be the generating function describing this evolution in one step. Let $\nu_0(k)$ be the number of particles in generation $k - 1$, which died in $k$-th step. Let $\nu = \sum_{k=1}^\infty \nu_0(k)$ be the total number of died particles during the whole evolution of the process. Assuming that there is only one particle at time $k = 0$, put $\nu_0(0) = 0$, and denote $q_n = \mathbb{P}(\nu = n), n \in \mathbb{N}$. Let

$$\varphi(s) = \sum_{n=0}^\infty q_n s^n, \ |s| < 1 \quad (1.0.5)$$

be the generating probability function of $\nu$.

Exercise 1.0.4
Show that $\varphi(s) = G(\varphi(s)) + p(s-1), \ |s| < 1$.

From this evolution, it follows $\varphi(s) = \varphi(\varphi(s)) + ps^2(\varphi(s)+p(s-1))$, or $\varphi^2(s)-2\varphi(s)-s=0 \implies \varphi(s) = \frac{1}{2} \pm \sqrt{\frac{1}{2} + s}, \ |s| < 1$. Since $|\varphi(s)| \leq 1 \forall s : |s| < 1$, then $\varphi(s) = 1 - \sqrt{1-s} > 1$ is not a solution $\implies \varphi(s) = 1 - \sqrt{1-s}, |s| < 1$. Expanding it in the Taylor series, we get

$$\varphi(s) = \frac{1}{2\sqrt{n}} \sum_{n=1}^{\infty} \Gamma(n-1/2) n! s^n, \ |s| < 1, \quad (1.0.6)$$
which follows from $\varphi(0) = 0, \varphi'(0) = \frac{1}{2\sqrt{1-0}} = \frac{1}{2}, \varphi''(0) = \frac{3}{2}$, and so on: $\varphi^{(n)}(0) = \frac{\Gamma(n-1/2)}{2^{n-1}n(1/2)^n}, n \in \mathbb{N}$.

**Exercise 1.0.5**

Prove it inductively.

Recall the Stirling’s formula for Gamma function: $\forall x > 0 \quad \Gamma(x) = \sqrt{\frac{2\pi}{x}} (\frac{x}{e})^x e^{\mu(x)}$, where $0 < \mu < 1/12$. Comparing the form (1.0.5) and (1.0.6), we get

\[
q_n = \frac{\Gamma(n - 1/2)}{2\sqrt{\pi} \Gamma(n+1)} = \frac{\sqrt{\frac{2\pi}{n-1/2}} \left(\frac{n-1/2}{n}\right)^{n-1} e^{\mu(n-1/2)-\mu(n)}}{2\sqrt{\pi} \sqrt{\frac{2\pi}{n} n(\frac{n}{e})^n e^{\mu(n)}}} \\
= \frac{1}{2\sqrt{\pi}} \left(\frac{n-1/2}{n}\right)^{n-1} \sqrt{\frac{2\pi}{n}} e^{\mu(n-1/2)-\mu(n)} \sim \frac{1}{2\sqrt{\pi}} \left(1 - \frac{1}{2n}\right)^{n-1} \frac{1}{n^{3/2}} e^{1/2+\mu(n-1/2)-\mu(n)} \\
\sim \frac{n^{-3/2}}{\sqrt{2\pi}} \exp\left(\frac{1}{2} + (n-1) \log \left(1 - \frac{1}{2n}\right) + o(1)\right) \\
\sim \frac{n^{-3/2}}{\sqrt{2\pi}} \exp\left(\frac{1}{2} + (n-1) \left(-\frac{1}{2n}\right) + o(1)\right) \sim \frac{n^{-3/2}}{2\sqrt{\pi}}, n \to \infty.
\]

Summarizing, $q_n \sim \frac{n^{-3/2}}{2\sqrt{\pi}}, n \to \infty$.

Now assume that the whole process starts with $n$ particles at the initial moment of time $n = 0$. Then, the total number of died particles is a sum $\sum_{i=1}^{n} \nu_i$ of i.i.d. r.v.’s $\nu_i \overset{d}{=} \nu$. We will be able to show $\frac{1}{n^3} \sum_{i=1}^{n} \nu_i \overset{d}{=} X, n \to \infty$, where $X$ is a standard Lévy distributed random variable with density

\[
f_X(x) = \frac{1}{\sqrt{2\pi}} x^{-3/2} \exp\left(-\frac{1}{2x}\right), x > 0.
\]

**Exercise 1.0.6**

Let $X$ be as above. Then

1. $X \overset{d}{=} Y^{-2}$, where $Y \sim N(0,1)$.
2. $f_X(s) \sim \frac{1}{\sqrt{2\pi}} x^{-3/2}, x \to +\infty$.
3. $\mathbb{E}X = \text{Var}X = \infty$.
4. The standard Lévy distribution is strictly stable with $c = 4$ in (1.0.2), i.e., for independent $X_1 \overset{d}{=} X_2 \overset{d}{=} X : X_1 + X_2 \overset{d}{=} 4X$.

The graph of $f_X(\cdot)$ looks like it has its mode at $x = 1/3$, and $f(0) = 0$ by continuity, since $\lim_{x \to +0} f(x) = 0$. Relation (1.0.2) from Exercise 1.0.6(4) can be interpreted as $\frac{X_1+X_2}{2} \overset{d}{=} 2X$, the arithmetic mean of $X_1 \overset{d}{=} X_2 \overset{d}{=} X$ is distributed as $2X$. Compare with the same property of Cauchy distribution.
Figure 1.2: Graph of $f_X$
2 Properties of stable laws

2.1 Equivalent definitions of stability

Now we would like to give an number of further definitions of stability which appear to be equivalent. At the same time, they give important properties of stable laws.

**Definition 2.1.1**

A random variable $X$ is stable if there exists a family of i.i.d. r.v.’s $\{X_i\}_{i=1}^{\infty}$ and number sequences $\{a_n\}_{n \in \mathbb{N}}, \{b_n\}_{n \in \mathbb{N}}, b_n > 0 \forall n \in \mathbb{N}$ s.t.

$$
\frac{1}{b_n} \sum_{i=1}^{n} X_i - a_n \xrightarrow{d} X, n \to \infty. 
$$

(2.1.1)

**Remark 2.1.1**

Notice that this definition does not require the r.v. $X_1$ to have a finite variance or even a finite mean. But if $\sigma^2 = \text{Var} X_1 \in (0, +\infty)$ then $X \sim N(0, 1)$ according to the central limit theorem with $b_n = \sqrt{n} \sigma, a_n = \frac{\mu n}{\sqrt{n} \sigma} = \sqrt{n} \mu$, where $\mu = \mathbb{E} X_1$.

**Definition 2.1.2**

A non-constant random variable $X$ is stable if its characteristic function has the form

$$
\varphi_X(s) = e^{\eta(s)}, s \in \mathbb{R}, \quad \eta(s) = \lambda(is\gamma - |s|^\alpha + is\omega(s, \alpha, \beta)), s \in \mathbb{R}
$$

with

$$
\omega(s, \alpha, \beta) = \begin{cases} 
|s|^{\alpha-1} \beta \tan \left( \frac{\pi}{2} \alpha \right), & \alpha \neq 1, \\
-\beta \frac{s}{2} \log |s|, & \alpha = 1,
\end{cases}
$$

(2.1.2)

$\alpha \in (0, 2], \beta \in [-1, 1], \gamma \in \mathbb{R}, \lambda > 0$. Here $\alpha$ is called stability index, $\beta$ is the coefficient of skewness, $\lambda$ is the scale parameter, and $\mu = \lambda \gamma$ is the shift parameter.

We denote the class of all stable distributions with given above parameters $(\alpha, \beta, \lambda, \gamma)$ by $S_\alpha(\lambda, \beta, \gamma)$. Sometimes, the shift parameter $\mu$ is used instead of $\gamma$: $S_\alpha(\lambda, \beta, \mu)$. $X \in S_\alpha(\lambda, \beta, \gamma)$ means that $X$ is a stable r.v. with parameters $(\alpha, \beta, \lambda)$.

Unfortunately, the parametrisation of $\eta(s)$ in Definition 2.1.2 is not a continuous function of all parameters. It can be easily seen that $\omega(s, \alpha, \beta) \to \infty$ as $\alpha \to 1$ for any $\beta \neq 0$, instead of tending to $-\beta \frac{s}{2} \log |s|$. To remedy this, we can introduce an additive shift $+\lambda \beta \tan \left( \frac{\pi}{2} \alpha \right)$ to get $\eta(s) = \lambda(is\gamma - |s|^\alpha + is\omega_M(s, \alpha, \beta)), s \in \mathbb{R}$, where

$$
\gamma_M = \begin{cases} 
\gamma + \beta \tan \left( \frac{\pi}{2} \alpha \right), & \alpha \neq 1, \\
\gamma, & \alpha = 1,
\end{cases} \quad \omega_M(s, \alpha, \beta) = \begin{cases} 
(|s|^{\alpha-1} - 1) \beta \tan \left( \frac{\pi}{2} \alpha \right), & \alpha \neq 1, \\
-\beta \frac{s}{2} \log |s|, & \alpha = 1.
\end{cases}
$$

(2.1.3)

($M$ stands for “modified”)

**Exercise 2.1.1**

Check that this modified parametrisation is a continuous function of all parameters.
Another possibility to parametrise \( \eta(s) \) is given as follows:

\[
\eta(s) = \begin{cases} 
\exp\left(-i\frac{\pi}{2} \beta_B K(\alpha) \text{sign}(s)\right), & \alpha \neq 1, \\
\frac{s}{2} + i \beta_B \log|s| \text{sign}(s), & \alpha = 1,
\end{cases}
\]

where

\[
K(\alpha) = \alpha - 1 + \text{sign}(1 - \alpha),
\]

and for \( \alpha \neq 1 \):

\[
\lambda = \lambda_B \cos\left(\frac{\pi}{2} \beta_B K(\alpha)\right), \quad \gamma = \gamma_B / \cos\left(\frac{\pi}{2} \beta_B K(\alpha)\right),
\]

\[
\beta = \cot\left(\frac{\pi}{2} \alpha\right) \tan\left(\frac{\pi}{2} \beta_B K(\alpha)\right);
\]

for \( \alpha = 1 \):

\[
\lambda = \frac{\pi}{2} \lambda_B, \quad \gamma = \frac{2}{\pi} \gamma_B, \quad \beta = \beta_B.
\]

(B stays for “bounded” representation). In this form \( \eta(s) \) is again not continuous at \( \alpha = 1 \), but for \( \alpha \to 1, \alpha \neq 1 \) the whole function \( \eta(s) \) does not go to +\( \infty \) as in (2.1.2), but has a limiting finite form which corresponds to a characteristic function of a stable law with \( \eta(s) = \lambda_B (is (\gamma_B \pm \sin (\frac{\pi}{2} \beta_B)) - |s| \cos (\frac{\pi}{2} \beta_B)) \). Here, the “+” sign is chosen for \( \alpha \to 1 + 0 \), and “−” for \( \alpha \to 1 - 0 \).

**Exercise 2.1.2**

Show this convergence for \( \alpha \to 1 \pm 0 \).

Let us give two more definitions of stability.

**Definition 2.1.3**

A random variable \( X \) is stable if for the sequence of i.i.d. r.v.’s \( \{X_i\}_{i \in \mathbb{N}} \), \( X_i \overset{d}{=} X, \forall i \in \mathbb{N} \), for any \( n \geq 2 \exists c_n > 0 \) and \( d_n \in \mathbb{R} \) s.t.

\[
\sum_{i=1}^{n} X_i \overset{d}{=} c_n X + d_n. \tag{2.1.4}
\]

**Definition 2.1.4**

It turns out that this definition can be weakened. Thus, it is sufficient for stability of \( X \) to require (2.1.4) to hold only for \( n = 2, 3 \). We call it Definition 2.1.4.

Now let us formulate here equivalent statement.

**Theorem 2.1.1**

Definitions 1.0.1, 2.1.1-2.1.4 are all equivalent for a non-degenerate random variable \( X \) (i.e., \( X \neq \text{const} \)).

The proof of this result will require a number of auxiliary statements which now here to be formulated. The first of them is a limit theorem describing domains of attraction of infinitely divisible laws.

**Theorem 2.1.2 (Khinchin):**

Let \( \{X_{nj}, j = 1 \ldots k_n, n \in \mathbb{N}\} \) be the sequence of series of independent random variables with the property

\[
\lim_{n \to \infty} \max_{j=1 \ldots k_n} P(|X_{nj}| > \varepsilon) = 0, \forall \varepsilon > 0 \tag{2.1.5}
\]

and with c.d.f. \( F_{nj} \). Let \( S_n = \sum_{j=1}^{k_n} X_{nj} - a_n, n \in \mathbb{N} \). Then a random variable \( X \) with c.d.f. \( F_X \)
is a weak limit of $S_n$ ($S_n \xrightarrow{d} X, n \to \infty$) iff the characteristic function $\varphi_X$ of $X$ has the form

$$\varphi_X(s) = \exp\left(isa - bs^2 + \int_{\{|x| \neq 0\}} (e^{isx} - 1 - is \sin x) dH(x)\right), s \in \mathbb{R},$$

(2.1.6)

where $a \in \mathbb{R}, b > 0$, $H : \mathbb{R} \setminus \{0\} \to \mathbb{R}$ is non-decreasing on $\mathbb{R}_+$ and $\mathbb{R}_-$, $H(s) \to 0$, as $|x| \to +\infty$, and $\int_{0 < |x| < 1} x^2 dH(s) < \infty$.

This theorem will be given without proof.

**Remark 2.1.2**

1. The condition (2.1.5) is called the **asymptotic smallness condition** of $X_n$.

2. Representation (2.1.6) is called the **canonic representation of Lévy-Khintchin**.

3. Laws of $X$ with ch.f. $\varphi_X$ as in (2.1.6) are called infinitely divisible. For more properties of those, see lectures “Stochastics II”.

4. The function $H$ is called a **spectral density** of $X$.

**Exercise 2.1.3**

Show that CLT is a special case of Theorem (2.1.2): find $X_n$, and $a_n$.

Another important result was obtained by B.V. Gnedenko.

**Theorem 2.1.3 (Gnedenko):**

Consider $A_n(y) = \sum_{j=1}^{k_n} \mathbb{E}(X_{n_j} I(|X_{n_j}| < y)), n \in \mathbb{N}$, where $y \in \mathbb{R}$ is a number s.t. $y$ and $-y$ are continuity points of $H$ in (2.1.6). Introduce $\sigma_n^\varepsilon = \sum_{j=1}^{k_n} \text{Var}(X_{n_j} I(|X_{n_j}| < y)), \varepsilon > 0$. Let $F_X$ be a c.d.f. with ch.f. $\varphi_X$ as in (2.1.6). Take

$$a_n = A_n(y) - a - \int_{|u| < y} udH(u) + \int_{|u| \geq y} \frac{1}{u} dH(u), n \in \mathbb{N}.$$  

Then, $S_n \xrightarrow{d} X, n \to \infty$ (or $F_n \to F, n \to \infty$ weakly) iff

1) For each point $x$ of continuity of $H$ it holds

$$\lim_{n \to \infty} \sum_{j=1}^{k_n} \left(F_{n_j}(x) - \frac{1}{2}(1 + \text{sign}x)\right) = H(x).$$
2) \( \lim_{\varepsilon \to 0} \limsup_{n \to \infty} \sigma_n^\varepsilon = \lim_{\varepsilon \to 0} \liminf_{n \to \infty} \sigma_n^\varepsilon = 2b. \)

Without proof.

**Remark 2.1.3**

1. In order \( S_n = \frac{1}{b_n} \sum_{i=1}^n X_i - a_n \) from Definition 2.1.1 to fulfill condition (2.1.5), it is sufficient to require \( b_n \to \infty, n \to \infty \). Indeed, in this case \( X_{nj} = X_j/b_n \), and, since \( X_j \) are i.i.d., \( \lim_{n \to \infty} \max_{j=1...k_n} \mathbb{P}(X_{nj} > \varepsilon) = \lim_{n \to \infty} \mathbb{P}(\varepsilon b_n) = 0 \) if \( b_n \to \infty \).

2. Property (2.1.5) holds whenever \( F_n \to F_X \) weakly, where \( F_X \) is non-degenerate, i.e., \( X \neq \text{const} \) a.s. Indeed, let (2.1.5) does not hold, i.e., \( \lim_{n \to \infty} \max_{j=1...k_n} \mathbb{P}(X_{nj} > \varepsilon) = 0 \) for some \( \varepsilon > 0 \). Then \( \exists \) a subsequence \( n_k \to \infty \) as \( n \to \infty \) s.t. \( b_{n_k} = o(1) \). Since, \( S_n \to X, n \to \infty, \) s.t. \( \varphi_{S_{n_k}}(s) \to \varphi_X(s), k \to \infty, \) where

\[
\varphi_{S_{n_k}}(s) = \mathbb{E} e^{is \sum_{j=1}^{n_k} X_j/b_{n_k} - is a_{n_k}} = e^{-is a_{n_k}} \left( \varphi_{X_1} \left( \frac{s}{b_{n_k}} \right) \right)^{n_k}, s \in \mathbb{R},
\]

so, \( \varphi_{S_{n_k}}(s) = |\varphi_{X_1} \left( \frac{s}{b_{n_k}} \right) \right|^{n_k} (1 + o(1)), k \to \infty. \) Then for each small \( s \in B_6(0) \) \( |\varphi_{X_1}(s)| = |\varphi_{X} (sb_{n_k}) |^{1/n_k} (1 + o(1)) \to 1, k \to \infty, \) which can be only if \( |\varphi_{X_1}(s)| \equiv 1, \forall s \in \mathbb{R}, \) and hence \( \varphi_{X}(s) \equiv 1, \) which means \( X \equiv \text{const} \) a.s. This contradicts with our assumption \( \varepsilon \neq \text{const} \).

**Definition 2.1.5**

1) A function \( L : (0, +\infty) \to (0, +\infty) \) is called slowly varying at infinity if for any \( x > 0 \)

\[
\frac{L(tx)}{L(t)} \to 1, t \to +\infty.
\]

2) A function \( U : (0, +\infty) \to (0, +\infty) \) is called regularly varying at infinity if \( U(x) = x^\rho L(x), \forall x > 0, \) for some \( \rho \in \mathbb{R} \) and some slowly varying (at infinity) function \( L. \)

**Example 2.1.1**

1. \( L(x) = |\log(x)|^p, x > 0 \) is slowly varying for each \( p \in \mathbb{R}. \)

2. If \( \lim_{x \to +\infty} L(x) = p \) then \( L \) is slowly varying.

3. \( U(x) = (1 + x^2)^p, x > 0 \) is regularly varying for each \( p \in \mathbb{R} \) with \( \rho = 2p. \)

**Lemma 2.1.1**

A monotone function \( U : (0, +\infty) \to (0, +\infty) \) is regularly varying at infinity if \( U(tx)/U(t) \to +\infty \) on a dense subset \( A \) of \( (0, +\infty), \) and \( \psi(x) \in (0, +\infty) \) on an interval \( I \in \mathbb{R}_+. \)

**Proof**

Let \( X_1, X_2 \in A \cap I. \) For \( t \to +\infty \) we get

\[
\psi(x_1 x_2) \left( \frac{U(tx_1 x_2)}{U(t)} \right) \left( \frac{U(tx_2)}{U(t)} \right) \to \psi(x_1) \psi(x_2).
\]

Hence, \( \psi(x_1 x_2) = \psi(x_1) \psi(x_2). \) Since \( U \) is monotone, so is \( \psi. \) By monotonicity, define \( \psi \) anywhere by continuity from the right. Then \( \psi(x_1 x_2) = \psi(x_1) \psi(x_2) \) holds for any \( x_1, x_2 \in I. \) Set \( x = e^y, \psi(e^y) = \varphi(y). \) The above equation transforms to \( \varphi(y_1 + y_2) = \varphi(y_1) \varphi(y_2). \) One can easily show that if \( \psi \) has a unique (up to a constant \( \rho \)) solution bounded on any finite interval, and it is \( \varphi(y)e^{\rho y} \iff \psi(x) = x^\rho. \) \( \square \)

The proof of Theorem 2.1.1 will make use of the following important statement which is interesting on its own right.
Theorem 2.1.4
Let $X$ be a stable r.v. in the sense of Definition 2.1.1 with characteristic function $\varphi_X$ as in (2.1.6). Then its spectral function $H$ has the form

$$H(x) = \begin{cases} -c_1 x^{-\alpha}, & x > 0 \\ c_2 (-x)^{-\alpha}, & x < 0 \end{cases}, \quad \alpha \in (0, 2), c_1, c_2 \geq 0.$$ 

Proof Consider the non-trivial case of a non-degenerate distribution of $X$ (otherwise $c_1 = c_2 = 0$). Denote by $\mathcal{X}_H$ the set of all continuity points of the spectral function $H$.

Exercise 2.1.4
Prove that $\mathcal{X}_H$ is at most countable.

Since $X$ is stable in the sense of Definition 2.1.1, $\exists$ an i.i.d. sequence of r.v.’s $\{X_i\}_{i \in \mathbb{N}}$ and number sequences $\{a_n\}_{n \in \mathbb{N}}, \{b_n\}_{n \in \mathbb{N}}, b_n > 0 \forall n \in \mathbb{N}$ s.t. $S_n = \frac{1}{b_n} \sum_{i=1}^{n} X_i - a_n \rightarrow X, n \rightarrow \infty$. Using Theorem 2.1.3, condition 1), it means that $\forall x \in \mathcal{X}_H \ n(F(b_n x) - \frac{1}{2}(1 + \text{sign}x)) \rightarrow H(x), n \rightarrow \infty$, where $F(y) = \mathbb{P}(X_i \leq y), y \in \mathbb{R}$.

Consider the case $x > 0$. If $H(x) \neq 0$ on $\mathbb{R}_+$, then $\exists x_0 \in \mathcal{X}_H, x > 0$ with $q \triangleq -H(x_0) > 0$, compare Fig. 2.1 For each $t > 0$, find an $n = n(t) \in \mathbb{N}$ s.t. $n(t) = \min\{k : b_k x_0 \leq t < b_{k+1} x_0\}$. Since, $F(1 - F(x) \downarrow \mathbb{R}_+)$, we get

$$\frac{F(b_{n+1} x_0 x)}{F(b_n x_0)} \leq \frac{F(tx)}{F(t)} \leq \frac{F(b_n x_0 x)}{F(b_{n+1} x_0)}, \quad \forall x > 0. \quad (2.1.7)$$

Since, $n(t) \rightarrow \infty, t \rightarrow \infty, -(F(b_n(x)) - 1) \rightarrow H(x), x \rightarrow \infty$, we get for $x_0 x \in \mathcal{X}_H$

$$\frac{F(b_{n+1} x_0 x)}{F(b_n x_0)} \rightarrow \frac{-nF(b_{n+1} x_0 x)}{-nF(b_n x_0)} \rightarrow \frac{H(x_0 x)}{H(x_0)} = -\frac{H(x_0 x)}{q} := L(x).$$

The same holds for the right-hand side of (2.1.7). Hence, for any $x, y > 0$ s.t. $x_0 x, x_0 y, x_0 xy \in \mathcal{X}_H$ we have $\frac{F(xy)}{F(t)} \rightarrow L(xy), t \rightarrow +\infty$. Otherwise,

$$\frac{F(tx)}{F(t)} = \frac{F(ty)}{F(t)} \rightarrow L(x)L(y), t \rightarrow \infty$$

by the same reasoning. As a result, we get the separation $L(xy) = L(x)L(y)$ which holds for all $x, y > 0$. (may be except for a countable number of exceptions since $\mathcal{X}_H$ is at most countable.)

By definition of $L(x) := -\frac{H(x_0 x)}{q}, L : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is non-decreasing, $L(1) = 1, L(\infty) = 0$. It can be shown (cf. the proof of Lemma 2.1.1) that the solution of the equation

$$\begin{cases} L(xy) = L(x)L(y), \\ L(1) = 1, L(\infty) = 0 \end{cases}$$

is $L(x) = 1/x^\alpha, \alpha > 0$. Hence, for $x > 0 \ H(x) = -qL(x/x_0) = H(x_0)x^{-\alpha}/x_0^{-\alpha} = x_0^\alpha H(x_0)x^{-\alpha} = -c_1 x^{-\alpha}, c_1 \geq 0$. Since $\int_{0<|x|<1} x^2 dH(x) < \infty$ (cf. Theorem 2.1.2), it holds $\int_{0<|x|<1} x^{2-\alpha-1} dx < \infty \iff 2 - \alpha > 0 \iff \alpha < 2$. Hence, $0 < \alpha < 2, c_1 \geq 0$ can be arbitrary.

The case $x < 0$ is treated analogously and leads to the representation $H(x) = c_2 (-x)^{-\delta}, c_2 \geq 0, 0 < \delta < 2$. 

2 Properties of stable laws

11
Show that $\alpha = \delta$. Since $F(tx) \sim x^{-\alpha}, t \to \infty$ for $x > 0$, it means that $F(s)$ is regularly varying by Lemma 2.1.1. Hence, exists a slowly varying function $h_1 : (0, +\infty) \to (0, +\infty)$ s.t. $F(x) = x^{-\alpha} h_1(x), x > 0$. By property 1) of Theorem 2.1.3, $nF(b_nx) = nb_n^{-\alpha}x^{-\alpha} h_1(b_nx) \to H(x) = c_1x^{-\alpha}, n \to \infty$. Since, $\frac{h_1(b_n)}{h_1(b_nx)} \to 1, n \to \infty$, it holds
\[
c_1 \leftarrow nb_n^{-\alpha} h_1(b_nx) = nb_n^{-\alpha} h_1(b_n) \frac{h_1(b_n)}{h_1(b_nx)} \sim nb_n^{-\alpha} h_1(b_n), n \to \infty. \tag{2.1.8}
\]
Analogously, we get $F(x) = (-x)^{-\delta} h_2(-x), x < 0$, where $h_2 : (0, +\infty) \to (0, +\infty)$ is slowly varying, and $nb_n^{-\delta} h_1(b_n) \sim c_2$. Assuming $c_1, c_2 > 0$ (otherwise the statement get trivial since either $\alpha$ or $\delta$ can be chosen arbitrary), we get $b_n^{-\alpha+\delta} \frac{h_1(b_n)}{h_2(b_n)} \to \frac{c_1}{c_2} > 0, n \to \infty$, where $h_1/h_2$ is slowly varying at $+\infty$, which is possible only if $\alpha = \delta$.

**Corollary 2.1.1**

Under the conditions of Theorem 2.1.4, assume that $c_1 + c_2 > 0$. Then the normalizing sequence $b_n$ in Definition 2.1.1 behaves as $b_n \sim n^{1/\alpha} h(n)$, where $h : (0, +\infty) \to (0, +\infty)$ is slowly varying at $+\infty$.

**Proof** Assume, for simplicity, $c_1 > 0$. Then, formula (2.1.8) yields $n \sim c_1 b_n^{\alpha} h_1^{-1}(b_n), \alpha \in (0, 2)$. Hence, $b_n \sim n^{1/\alpha} c_1^{-1/\alpha}(h_1(b_n))^{\alpha} = n^{1/\alpha} h(n)$, where $h(n) = (c_1^{-1} h_1(b_n))^{\alpha}$ is slowly varying at $+\infty$ due to the properties of $h_1$.

**Proof of Theorem 2.1.1.** 1) Show the equivalence of Definitions 2.1.1 and 2.1.2.

Let $X$ be a non-constant r.v. with characteristic function $\varphi_X$ as in (2.1.6). Assume that $X$ is stable in the sense of Definition 2.1.1. By Theorem 2.1.4, its spectral function $H$ has the form $H(x) = \begin{cases} -c_1/|x|^{\alpha}, & x > 0, \\ c_2/|x|^{\alpha}, & x < 0 \end{cases}$, $\alpha \in (0, 2), c_1, c_2 \geq 0$. Put it into the formula (2.1.6):
\[
\log \varphi_X(x) = i sa - bs^2 + c_1 Q_\alpha(s) + c_2 Q_\alpha(s), \quad s \in \mathbb{R},
\]
where
\[
Q_\alpha(s) = -\int_0^{\infty} \left( e^{-isc} - 1 + is \sin x \right) dx^{-\alpha} = \text{Re} \left( \psi_\alpha(i,t) \right)_{t = -is},
\]
and $\psi_\alpha(z, t) = t \int_0^{\infty} (e^{-xz} - e^{-tx} ) x^{-\alpha} dx$ for $z, t \in \mathbb{C} : \text{Re} z, \text{Re} t > 0, \alpha \in (0, 2)$. Integrating by parts, we get
\[
\psi_\alpha(z, t) = \frac{t}{1 - \alpha} \int_0^{\infty} (ze^{-xz} - te^{-tx}) x^{1-\alpha} dx
\]
\[
= \frac{t}{1 - \alpha} \left( z^{a-1} \int_0^{\infty} e^{-zx} (z^{-a} d(z)) - t^{a-1} \int_0^{\infty} (e^{-tx}) (t^{-a} d(t)) \right) = \frac{z^{a-1}}{xt} = \frac{y}{y},
\]
\[
= \frac{t}{1 - \alpha} \left( z^{a-1} \int_0^{\infty} e^{-y} y^{2-a-1} dy - t^{a-1} \int_0^{\infty} e^{-y} y^{2-a-1} dy \right)
\]
\[
= \frac{t \Gamma(2 - \alpha)}{1 - \alpha} \left( z^{a-1} - t^{a-1} \right), \quad \text{for any } \alpha \neq 1, \text{Re} z, \text{Re} t > 0.
\]
For fixed $z, t \in \mathbb{C} : \text{Re} z, \text{Re} t > 0$ the function $\psi_\alpha(z, t) : (0, 2) \to \mathbb{C}$ as a function of $\alpha$ is
Then continuous on \((0, 2)\). Hence,

\[
\psi_1(z, t) = \lim_{\alpha \to 1} \psi_\alpha(z, t) = \lim_{\alpha \to 1} \frac{t \Gamma(2 - \alpha)}{1 - \alpha} (z^{\alpha - 1} - t^{\alpha - 1}) \\
= \lim_{1 - \alpha \to 0} t \frac{1 - \alpha}{1 - \alpha} (e^{(\alpha - 1)\log z} - e^{(\alpha - 1)\log t}) = |1 - \alpha = x| \\
= \lim_{x \to 0} t (1 - x \log z - 1 + x \log t + o(x)) = t (\log t - \log z) = t \log(t/z).
\]

Then for \(\alpha \neq 1\) we get

\[
Q_\alpha(s) = -\frac{is \Gamma(2 - \alpha)}{1 - \alpha} \left( \text{Re} (e^{i(\pi/2)\alpha^{1-\alpha})}) - (-is)^{1-\alpha} \right) \\
= -\frac{is \Gamma(2 - \alpha)}{1 - \alpha} \left( \text{Re} (e^{i(\pi/2)\alpha^{1-\alpha})}) - e^{i(\pi/2)}}\alpha^{1-\alpha}) \right) \\
= -is \Gamma(1 - \alpha) \left( \cos \left( \frac{\pi}{2} (\alpha - 1) \right) - i \text{signs} \sin \left( \frac{\pi}{2} (\alpha - 1) \right) \right) \\
= -is \left( \frac{\pi \alpha}{2} \right) \Gamma(1 - \alpha) - is \left( \frac{\pi \alpha}{2} \right) \Gamma(1 - \alpha) \cos \left( \frac{\pi \alpha}{2} \right) \\
= -\Gamma(1 - \alpha) \cos(\pi \alpha/2) |s|^{\alpha} - is(1 - |s|^{\alpha-1}) \Gamma(1 - \alpha) \sin(\pi \alpha/2).
\]

For \(\alpha = 1\)

\[
Q_\alpha(s) = -is \text{ Re} (\log(t/i))|_{t=-is} = -is \log |t/i||_{t=-is} = -is \log(-is) \\
= -is \log |s| + i(-\pi/2) \text{signs} = -|s| \frac{\pi}{2} - is \log |s|.
\]

Then

\[
|\varphi_X(s)| = \exp\{-bs^2 - d|s|^\alpha\}, \quad (2.1.9)
\]

where \(d = (c_1 + c_2) \frac{\Gamma(2 - \alpha)}{1 - \alpha} \sin \left( \frac{\pi}{2} (1 - \alpha) \right), \alpha \neq 1\). For \(\alpha = 1\) get limit as \(\alpha \to 1\) as a value of \(d:\) \((c_1 + c_2)\pi/2\). Show that \(bd = 0\).

If, for instance, \(d > 0\), then show that \(b = 0\). By Definition 2.1.1, \(\exists\) sequences \(\{a_n\}, \{b_n\} \subset \mathbb{R} : b_n \to \infty\) as \(n \to \infty\) and a characteristic function \(\varphi_X_1(s/b_n) \to \varphi_X(s), n \to \infty\), \(s \in \mathbb{R}\). Hence, \(|\varphi_X_1(s/b_n)|^{n} \to |\varphi_X(s)|, n \to \infty\) where \(b_n = n^{1/\alpha}h(n)\) by Corollary 2.1.1. Since, \(h\) is slowly varying, \(b_n, b_{nk} \to k^{-1/\alpha}, n \to \infty\) for any \(k \in \mathbb{N}\). Then

\[
|\varphi_X(s)| \xleftarrow{n \to \infty} \left| \varphi_X_1 \left( \frac{s}{b_{nk}} \right)^{nk} \right| = \left| \varphi_X_1 \left( \frac{s}{b_{nk}} b_{nk}^{-1} \right)^{nk} \right| \xrightarrow{n \to \infty} |\varphi_X (sk^{-1/\alpha})|^{k}, \forall k \in \mathbb{N},
\]

i.e., by (2.1.9), \(\exp\{-bs^2 - d|s|^\alpha\} = \exp\{-bs^2k^{-1-2/\alpha} - d|s|^\alpha\}\), which is only possible if \(b = 0\).

Now set

\[
\lambda = \begin{cases} 
  d, & \text{ if } c_1 + c_2 > 0, \\
  b, & \text{ if } c_1 + c_2 = 0 \text{ (Gaussian case)},
\end{cases}
\]

\[
\beta = \begin{cases} 
  (c_1 - c_2)/\lambda, & \text{ if } c_1 + c_2 > 0, \\
  0, & \text{ if } c_1 + c_2 = 0 \text{ (Gaussian case)},
\end{cases}
\]

\[
\gamma = \frac{1}{x}(a + \bar{a}), \text{ where } \bar{a} = \begin{cases} 
  (c_2 - c_1)\Gamma(1 - \alpha), \sin(\pi \alpha/2) & \text{ if } \alpha \neq 1, \\
  0, & \text{ if } \alpha = 1.
\end{cases}
\]
Then \( \varphi_X \) satisfies representation in Definition 2.1.2 with the above parameters \( \lambda, \beta, \gamma, \alpha \).

Vice versa, if \( \varphi_X \) satisfies Definition 2.1.2, then it can be represented as in (2.1.6) with spectral function \( H \) as in Theorem 2.1.4, see the formula (2.1.10), where \( c_1, c_2 \) can be restored from \( \lambda, \beta, \gamma \) uniquely. By theorem 2.1.2, the limit theorem \( S_n \overset{d}{\to} X, n \to \infty \) takes place.

Exercise 2.1.5
Show that \( \{X_n\} \) can be chosen here as in Definition 2.1.1 (since \( b_n = n^{1/\alpha} h(n) \) is clear, \( b_n \to \infty \), one has only to fix \( a_n \), cf. Remark 2.1.3)

2) Show the equivalence of Definitions 2.1.1 and 1.0.1.
Let \( X \) be stable in the sense of Definition 1.0.1. By induction, if follows from the relation \( aX_1 + bX_2 \overset{d}{=} cX + d \) of Definition 1.0.1 (with \( a = b = 1 \)) that for any \( n \geq 2 \) \exists \) constants \( b_n > 0, a_n \) s.t. for independent copies \( X_i, i = 1 \ldots n \) of \( X : X_1 + \cdots + X_n \overset{d}{=} b_nX + a_n \), or \( \frac{1}{b_n} \sum_{i=1}^{n} X_i - \frac{a_n}{b_n} d = X \). So, for \( n \to \infty \), the limiting distribution of the left-hand side coincides with that of \( X \), and Definition 2.1.1 holds.

Vice versa, we show that from Definition 2.1.2 (which is equivalent to Definition 2.1.1) it follows Definition 1.0.1. Definition 1.0.1 can be rewritten in terms of characteristic function as
\[
\varphi_X(as)\varphi_X(bs) = \varphi_X(cs)e^{isd},
\]
(2.1.11)
where \( a > 0 \) and \( b > 0 \) are arbitrary constants, and \( c > 0, d \in \mathbb{R} \) are chosen as in Definition 1.0.1, \( \varphi_X(s) = Ec^{is\lambda} \). By Definition 2.1.2, \( \varphi_X(s) = \exp\{\lambda(is\gamma - |s|^2 + is\omega(s, \alpha, \beta))\} \), \( s \in \mathbb{R} \) with \( \omega(s, \alpha, \beta) \) as in (2.1.2). It is quite easy to see that (2.1.2) follows with \( c = (a^\alpha + b^\beta)^{1/\alpha} \),
\[ d = \begin{cases} 
\lambda(\alpha a - b), & \alpha \neq 1 \\
\lambda\beta \frac{2}{\alpha}(a \log(a/c) + b \log(b/c)), & \alpha = 1.
\end{cases}
\]
3) Show the equivalence of Definitions 2.1.3 and Definition 1.0.1. Definition 2.1.3 follows from Definition 1.0.1 as it was shown in 2). Vise versa, from Definition 2.1.3 it follows Definition 2.1.1 (see 2), which is equivalent to Definition 1.0.1.
4) Show the equivalence of Definitions 2.1.3 and 2.1.4. In one direction (Definition 2.1.3 \( \Rightarrow \) Definition 2.1.4) it is evident, in the other direction, assume that \( X_1 + X_2 \overset{d}{=} c_2X + d_2 \), \( X_1 + X_2 + X_3 \overset{d}{=} c_3X + d_3 \) for some \( c_2, c_3 > 0, d_2, d_3 \in \mathbb{R} \). In order to show Definition 2.1.3, it is sufficient to check that
\[
n\eta(s) = \eta(cn) + isdn
\]
(2.1.12)
for any \( n \geq 4 \), some \( c_n > 0 \) and \( d_n \in \mathbb{R} \), where \( \eta(s) = \log \varphi_X(s), s \in \mathbb{R} \). Since (by assumption) (2.1.12) holds for \( n = 2, 3 \), it holds (by induction) for any \( n = \begin{cases} 2m & m \in \mathbb{N}, c_n = \left\{ \begin{array}{ll} c_2^m & \text{for} m \geq 1 \\
c_3^3 & \text{for} m = 0 \end{array} \right. 
\end{cases} \),
\[
d_n = \begin{cases} d_2(1 + c_2 + \cdots + c_2^{m-1}) & m \in \mathbb{N}, \text{Hence, the distribution of } X \text{ is infinitely divisible, and then } \left| \varphi(s) \right| \neq 0, \forall s \in \mathbb{R}. 
\end{cases}
\]
From the said above, it holds
\[
2^{3k} \eta(s) = \eta(c_2^j c_3^k s) + ia_{jk}s
\]
(2.1.13)
for some \( c_2, c_3 > 0, a_{jk} \in \mathbb{R}, j, k \in \mathbb{Z} \). The set \( \{2^{3k}j, k \in \mathbb{Z}\} \) is dense in \( \mathbb{R} \), since \( 2^{3k} = \exp(j \log 2 + k \log 3) \), and the set \( \{j + \omega k, j, k \in \mathbb{Z}\}, \omega \notin \mathbb{Q} \) is dense in \( \mathbb{R} \). Hence, for any \( n \in \mathbb{N} \),
\[n \eta(s) = \eta(c_2^j c_3^k s) + ia_{jk}s
\]
(2.1.13)
\[n \eta(s) = \eta(c_2^{-1} t) - is \frac{a_{jk}}{c_2}
\]
Similarly we get \( \frac{1}{2} \eta(t) = \eta(c_3^{-1} t) - is \frac{a_{jk}}{c_3} \).
So, formula (2.1.13) also holds for negative \( j, k \in \mathbb{Z} \).
sequence \( \{r_m\}_{m \in \mathbb{N}}, r_m \to n \) as \( m \to \infty \), and \( r_m = 2^m 3^{km} \). Let \( c_n(m) = c_2^m c_3^m, m \in \mathbb{N} \). Show that \( \{c_n(m)\}_{m \in \mathbb{N}} \) is bounded. It follows from (2.1.13) that \( r_m \Re(\eta(s)) = \Re(\eta(c_n(m)s)) \).

Assume that \( c_n(m) \) is unbounded, then 3 subsequence \( \{c_n(m')\} \) such that \( |c_n(m')| \to \infty, m' \to \infty \). Set \( s' = sc_n(m') \) in the last equation. Since \( r_m' \to n, m' \to \infty \), we get \( \Re \eta(s') = r_m' \Re \eta(c_n(m')) \to 0, m' \to \infty \). Hence, \( |\eta(s)| = 1 \), which can not be due to the assumption that \( X \not\equiv const. \)

Then \( \{c_n(m)\}_{m \in \mathbb{N}} \) is bounded, and \( \exists \) a subsequence \( \{c_n(m')\}_{m' \in \mathbb{N}} \) such that \( |c_n(m')| \to c_n, m' \to \infty \). Then \( a_{j,n,k,n'} \rightarrow \frac{1}{s}(\eta(c_n(m')) - r_m \eta(s)) \rightarrow \frac{1}{s}(\eta(c_n - m\eta(s)) := d_n \). Hence, \( \forall n \in \mathbb{N} \) and \( s \in \mathbb{R} \) it holds \( n\eta(s) = \eta(c_n s) + is\eta(d_n) \), which is the statement of equation (2.1.12), so we are done.

\[ \square \]

Remark 2.1.4

It follows from the proof of Theorem 2.1.1 1) that the parameter \( \beta = \frac{c_1 - c_2}{c_1 + c_2} \), if \( c_1 + c_2 > 0 \) in non-Gaussian case. Consider the extremal values of \( \beta = \pm 1 \). It is easy to see that for \( \beta = 1 \)
\( c_2 = 0 \), for \( \beta = -1 \)
\( c_1 = 0 \). This corresponds to the following situation in Definition 2.1.1:

\[ a) \text{Consider } \{X_n\}_{n \in \mathbb{N}} \text{ to be i.i.d. and positive a.s., i.e., } X_1 > 0 \text{ a.s. By Theorem 2.1.3,1) it follows that } H(x) = 0, x < 0 \implies c_2 = 0 \implies \beta = 1. \]

\[ b) \text{Consider } \{X_n\}_{n \in \mathbb{N}} \text{ to be i.i.d. and negative a.s. As above, we conclude } H(x) = 0, x > 0, \text{ and } c_1 = 0 \implies \beta = -1. \]

Although this relation can not be inverted (from \( \beta \pm 1 \) if does not follows that \( X > (<)0 \) a.s.), it explains the situation of total skewness of a non-Gaussian \( X \) as a limit of sums of positive or negative i.i.d. random variables \( S_n = \frac{1}{b_n} \sum_{i=1}^{n} X_i - a_n \).

Remark 2.1.5

One can show that \( c_n = n^{1/\alpha} \) in Definition 2.1.3, formula (2.1.4), for \( \alpha \in (0, 2] \).

**Proof** We prove it only for strictly stable laws. First, for \( \alpha = 2 \) (Gaussian case \( X, X_i \sim N(0, 1) \)) it holds \( \sum_{i=1}^{n} X_i \sim N(0, n) \) \( \frac{d}{\sqrt{n}} X \implies c_n = n^{1/\alpha} \) with \( \alpha = 2 \).

Now let \( \alpha \in (0, 2) \). Let \( X \) be strictly stable, s.t. \( \sum_{i=1}^{n} X_i \sim c_n X \). Take \( n = 2^k \), then
\[
S_n = \frac{(X_1 + X_2)}{X_1} + \frac{(X_3 + X_4)}{X_2} + \cdots + \frac{(X_{n-1} + X_n)}{X_{n/2}} = c_2(X_1' + X_2' + \cdots + X_{n/2}' = \cdots = c_2 X,
\]
from which it follows \( c_n = c_{2k} = c_2^k = c_2^{\log n/\log 2} \), so
\[
\log c_n = \frac{\log n}{\log 2} \log c_2 = \log \left(n^{\log c_2/\log 2}\right), \quad c_n = n^{1/\alpha_2}, \tag{2.1.14}
\]
where \( \alpha_2 = \log 2/\log c_2 \), for \( n = 2^k, k \in \mathbb{N} \). Generalizing the above approach to \( n = m^k \) turns, we get
\[
c_n = n^{1/\alpha_m}, \quad \alpha_m = \frac{\log m}{\log c_m}, n = m^k, k \in \mathbb{N}. \tag{2.1.15}
\]
To prove that \( c_n = n^{1/\alpha_0} \) it suffices to show that if \( c_\rho = r^{1/\beta} \) then \( \beta = \alpha_0 \). Now by (2.1.15) \( c_{r^j} = r^{j/\alpha_r} \) and \( c_{r^k} = r^{k/\alpha_r} \). But for each \( k \) there exists a \( j \) such that \( r^j < r^k \leq r^{j+1} \). Then
\[
(c_{r^j})^{\alpha_r/\alpha_0} < c_{r^k} = r^{k/\alpha_r} \leq r^{1/\alpha_r}(c_{r^j})^{\alpha_r/\alpha_0}. \tag{2.1.16}
\]
Note that $S_{m+n}$ is the sum of the independent variables $S_m$ and $S_{m+n} - S_m$ distributed, respectively, as $c_mX$ and $c_nX$. Thus for symmetric stable distributions $c_{m+n}X \overset{d}{=} c_mX_1 + c_nX_2$.

Next put $\eta = m + n$ and notice that due to the symmetry of the variables $X$, $X_1$, $X_2$ we have for $t > 0$ $2\mathbb{P}(X > t) \geq \mathbb{P}(X_2 > t\eta/c_n)$. It follows that for $\eta > n$ the ratios $c_n/c_\eta$ remain bounded. So, it follows from (2.1.16) that

$$r \geq (c_{\rho k})^{\alpha_{\rho} - \alpha_r} (c_{\rho k}/c_r)^{\alpha_r}$$

and hence $\alpha_r \geq \alpha_\rho$. Interchanging the roles of $r$ and $\rho$ we find similarly that $\alpha_r \leq \alpha_\rho$ and hence $\alpha_r = \alpha_\rho \equiv \alpha_0$ for any $r, \rho \in \mathbb{N}$.

We get the conclusion that $c_n = n^{1/\alpha_0}, n \in \mathbb{N}$. It can be further shown that $\alpha_0 = \alpha$. \qed

**Definition 2.1.6**

A random variable $X$ (or its distribution $\mathbb{P}_X$) is said to be symmetric if $X \overset{d}{=} -X$. $X$ is symmetric about $\mu \in \mathbb{R}$ if $X - \mu$ is symmetric. If $X$ is $\alpha-$stable and symmetric, we write $X \sim \alpha S$. This definition is justified by the property $X \sim \alpha (\lambda, \beta, \gamma)$, $X$--symmetric $\Leftrightarrow \gamma = \beta = 0$, which will be proven later.

### 2.2 Strictly stable laws

As it is clear from the definition of strict stability (Definition 1.0.1) $X$ is stable iff for any $a, b \in \mathbb{R}_+$ $\exists c > 0$ s.t. $\varphi_X(as)\varphi_X(bs) = \varphi_X(cs), s \in \mathbb{R}$, where $\varphi_X(s) = \mathbb{E}e^{isX}, s \in \mathbb{R}$.

**Theorem 2.2.1**

Let $X \not= \text{const}$ a.s. It is strictly stable if its characteristic function admits one of the following representations: $\forall s \in \mathbb{R}$

1. $\log \varphi_X(s) = \begin{cases} 
\lambda(-|s|^\alpha + is\omega(s, \alpha, \beta)) & \alpha \neq 1, \\
\lambda(is\gamma - |s|) & \alpha = 1,
\end{cases}$ i.e. $\begin{cases} 
\gamma = 0, & \alpha \neq 1, \\
\beta = 0, & \alpha = 1.
\end{cases}$

with $\omega(s, \alpha, \beta)$ as in (2.1.2).

2. (form C) $\log \varphi_X(s) = -\lambda_C|s|^\alpha \exp(-\frac{\pi}{2} \theta \text{sign}s), \alpha \neq 0\in (0, 2], \lambda_C > 0, \theta \leq \theta_\alpha = \min\{1, \frac{2}{\pi - 1}\}$.

**Proof 1.** In the proof of Theorem 2.1.1, 2) it is shown that

$$d = \begin{cases} 
\lambda \gamma(a + b - c), & \alpha \neq 1 \\
\lambda \beta^\frac{2}{\pi}(a \log(a/c) + b \log(b/c)), & \alpha = 1
\end{cases} = 0 \Leftrightarrow \begin{cases} 
\gamma = 0, & \alpha \neq 1 \\
\beta = 0, & \alpha = 1.
\end{cases}$$

2. Take the parametrisation (B) of $\varphi_X$ with parameters $\gamma, \beta$ as in 1, and left $\alpha$ unchanged,

$$\begin{cases} 
\theta = \beta B \frac{K(\alpha)}{\alpha}, \lambda_C = \lambda_B, \\
\theta = \frac{\pi}{2} \arctg\left(\frac{2}{\pi} \gamma B\right), \lambda_C = \lambda_B \left(\frac{x^2}{s^2} + \gamma^2_B\right)^{1/2},
\end{cases} \quad \alpha \neq 1, \quad \alpha = 1. \qed$$
2.3 Properties of stable laws

Here we consider further basic properties of $\alpha$--stable distributions.

Theorem 2.3.1
Let $X_i, i = 1, 2$ be $S_\alpha(\lambda_i, \beta_i, \gamma_i)$-distributed independent random variables, $X \sim S_\alpha(\lambda, \beta, \gamma)$. Then

1) $X$ has a density (i.e, has absolutely continuous distribution), which is bounded with all its derivatives.

2) $X_1 + X_2 \sim S_\alpha(\lambda, \beta, \gamma)$ with
\[
\lambda = \lambda_1 + \lambda_2, \quad \beta = \frac{\beta_1 \lambda_1 + \beta_2 \lambda_2}{\lambda_1 + \lambda_2}, \quad \gamma = \frac{\lambda_1 \gamma_1 + \lambda_2 \gamma_2}{\lambda_1 + \lambda_2}.
\]

3) $X + a \sim S_\alpha(\lambda, \beta, \gamma + a/\lambda)$, where $a \in \mathbb{R}$ is a constant.

4) For a real constant $a \neq 0$ it holds
\[
aX \sim \begin{cases}
S_\alpha ([|a|^\alpha, \text{sign}(a) \beta, \gamma |a|^{1-\alpha} \text{sign}(a)]), & \alpha \neq 1, \\
S_1 ([|a|, \lambda, \text{sign}(a) \beta), \text{sign}(a) \left(\gamma - \frac{\alpha}{2} (\log |a|) \beta\right)\), & \alpha = 1.
\end{cases}
\]

5) For $\alpha \in (0, 2)$, $X \sim S_\alpha(\lambda, \beta, 0) \iff -X \sim S_\alpha(\lambda, -\beta, 0)$.

6) $X$ is symmetric iff $\beta = \gamma = 0$. It is symmetric about $\lambda \gamma$ iff $\beta = 0$.

7) Let $\alpha \neq 1$. $X$ is strictly stable iff $\gamma = 0$.

Proof
1) Let $\varphi_X, \varphi_{X_i}$ be the characteristic function of $X, X_i, i = 1, 2$. It follows from Definition 2.1.2 that $|\varphi_X(s)| = e^{-\lambda |s|^\alpha}, s \in \mathbb{R}$. Take the inversion formula for the characteristic function. If $|\varphi_X|$ is integrable on $\mathbb{R}$ (which is here the case) then the density $f_X$ of $X$ exists and $f_X(s) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-isx} \varphi_X(x) dx, x \in \mathbb{R}$. Additionally, the $n$-th derivative of $f_X$ is
\[
\left|f_X^{(n)}(x)\right| \leq \frac{1}{2\pi} \int_{\mathbb{R}} |s|^{n} \frac{|\varphi_X(s)|}{\exp(-\lambda |s|^\alpha)} ds = \frac{\Gamma\left(\frac{n+1}{\alpha}\right)}{\pi \alpha} \lambda^{-\frac{n+1}{\alpha}} < \infty, x \in \mathbb{R}, n \in \mathbb{N}.
\]

2) Prove it for the case $\alpha \neq 1$, the case $\alpha = 1$ is treated similarly. Consider the characteristic function of $X_1 + X_2$, and take its logarithms:
\[
\log \varphi_{X_1 + X_2}(s) = \log(\varphi_{X_1}(s) \varphi_{X_2}(s)) = \log \varphi_{X_1}(s) + \log \varphi_{X_2}(s)
\]
\[
= \sum_{j=1}^{2} \lambda_j \left( is \gamma_j - |s|^\alpha + s|s|^{\alpha-1} i \beta_j \text{tg}(\pi \alpha/2) \right)
\]
\[
= -|s|^\alpha (\lambda_1 + \lambda_2) + i s (\lambda_1 \gamma_1 + \lambda_2 \gamma_2) + i s |s|^\alpha-1 (\lambda_1 \beta_1 + \lambda_2 \beta_2) \text{tg}(\pi \alpha/2)
\]
\[
= (\lambda_1 + \lambda_2) \left( is \frac{\lambda_1 \gamma_1 + \lambda_2 \gamma_2}{\lambda_1 + \lambda_2} - |s|^\alpha + i s |s|^{\lambda-1} \frac{\lambda_1 \beta_1 + \lambda_2 \beta_2}{\lambda_1 + \lambda_2} \right)
\]
\[
= \lambda (is \gamma - |s|^\alpha + is \omega(s, \alpha, \beta)),
\]
So, $X_1 + X_2 \sim S_\alpha(\lambda, \beta, \gamma)$ by Definition 2.1.2.

3) $\log \varphi_{X+a}(s) = isa + \lambda is\gamma - \lambda|s|^\alpha + is\omega(s, \alpha, \beta) = \lambda(is(\gamma + a/\lambda) - |s|^\alpha + is\omega(s, \lambda, \beta))$, hence $X + a \sim S_\alpha(\lambda, \beta, \gamma + a/\lambda)$.

4) Consider the case $\lambda \neq 1$.

$$
\log \varphi_{X}(s) = \lambda|a|^\alpha \left( is\gamma \frac{a}{|a|^\alpha} - |s|^\alpha + is\frac{|a|^\alpha - 1}{|a|^\alpha} |s|^\alpha - \beta \log(\pi \alpha / 2) \right)
$$

hence $aX \sim S_\alpha(\lambda|a|^\alpha, \text{sign}(a)\beta, \gamma |a|^{1-\alpha}\text{sign}(a))$.

For $\alpha = 1$, we have

$$
\log \varphi_{X}(s) = \lambda \left( is\gamma - |s| - \beta \frac{2}{\pi} \log |s| \right)
$$

hence $aX \sim S_1 \left( \lambda|a|, \text{sign}(a)\beta, \text{sign}(a) \left( \gamma - \beta \frac{2}{\pi} \log |a| \right) \right)$.

5) follows from 4) with $a = -1$.

6) $X$ is symmetric by definition iff $X \overset{d}{=} -X$, i.e., $\varphi_X(s) = \varphi_{-X}(s) = \varphi_X(-s), \forall s \in \mathbb{R}$, which is only possible if $\varphi_X(s) \in \mathbb{R}, s \in \mathbb{R}$. Indeed, $\mathbb{E}e^{isX} = \mathbb{E}\cos(sX) + i\mathbb{E}\sin(sX) = \mathbb{E}\cos(-sX) + i\mathbb{E}\sin(-sX) = \mathbb{E}\cos(sX) - i\mathbb{E}\sin(sX)$ if $2i\mathbb{E}\sin(sX) = 0, \forall s \in \mathbb{R}$. Using Definition 2.1.2, $\varphi_X(s)$ is real only if $\gamma = 0$ and $\omega(s, \alpha, \beta) = 0$, i.e., $\beta = 0$.

$X$ is symmetric around $\lambda\gamma$ by definition iff $X - \lambda\gamma \overset{d}{=} -(X - \lambda\gamma) = -X + \lambda\gamma$. By property 3) and 4), $X - \lambda\gamma \sim S_\alpha(\lambda, \beta, -\gamma - \gamma), -X + \gamma \sim S_\alpha(\lambda, -\beta, -\gamma + \gamma)$. So, $X - \lambda\gamma \overset{d}{=} -X + \lambda\gamma$ if $\beta = 0$.

7) Is already proven in Theorem 2.2.1. \hfill \Box

**Remark 2.3.1**

1) The analytic form of the density of a stable law $S_\alpha(\lambda, \beta, \gamma)$ is explicitly known only in the cases $\alpha = 2$ (Gaussian law), $\alpha = 1$ (Cauchy law), $\alpha = 1/2$ (Lévy law).

2) Due to Property 3) of Theorem 2.3.1, the parameter $\gamma$ (or sometimes $\lambda\gamma$) is called shift parameter.

3) Due to Property 4) of Theorem 2.3.1, the parameter $\lambda$ (or sometimes $\lambda^{1/\alpha}$) is called shape or scale parameter. Notice that this name is natural for $\alpha \neq 1$ or $\alpha = 1, \beta = 0$. In case $\alpha = 1, \beta \neq 0$, scaling of $X$ by $a$ results in a non-zero shift of the law of $X$ by $\frac{2}{\pi} \beta \log |a|$, hence the use of this name in this particular case can namely be recommended.

4) Due to properties 5)-6) of Theorem 2.3.1, parameter $\beta$ is called skewness parameter. If $\beta > 0 (\beta < 0)$ then $S_\alpha(\lambda, \beta, \gamma)$ is said to be skewed to the right (left). $S_\alpha(\lambda, \pm 1, \gamma)$ is said to be totally skewed to the right (for $\beta = 1$) or left (for $\beta = -1$).
5) It follows from Theorem 2.2.1 and Theorem 2.3.1, 3) that if \( X \sim S_\alpha(\lambda, \beta, \gamma), \alpha \neq 1 \), then 
\( X - \lambda \gamma \sim S_\alpha(\lambda, \beta, 0) \) is strictly stable.

6) It follows from Theorem 2.2.1 and Definition 2.1.2 that no non-strictly 1-stable random variable can be made strictly stable by shifting. Indeed, if \( S_1(\lambda, \beta, \gamma) \) is not strictly stable then \( \beta \neq 0 \), which can not be eliminated due to \( \alpha \) in \( \omega(s, \lambda, \beta) \). Analogously, every strictly 1-stable random variable can be made symmetric by shifting.

**Corollary 2.3.1**

Let \( X_1, i = 1, \ldots, n \) be i.i.d. \( S_\alpha(\lambda, \beta, \gamma) \)-distributed random variables, \( \alpha \in (0, 2] \). Then

\[
X_1 + \cdots + X_n = \begin{cases} 
  n^{1/\alpha}X_1 + \lambda \gamma(n - n^{1/\alpha}), & \text{if } \alpha \neq 1, \\
  nX_1 + \frac{2}{\pi} \lambda \beta n \log n, & \text{if } \alpha = 1.
\end{cases}
\]

This means, \( c_n \) and \( d_n \) of Definition 2.1.3 has values

\[
c_n = n^{1/\alpha}, \alpha \in (0, 2], \quad d_n = \begin{cases} 
  \lambda \gamma(n - n^{1/\alpha}), & \text{if } \alpha \neq 1, \\
  \frac{2}{\pi} \lambda \beta n \log n, & \text{if } \alpha = 1.
\end{cases}
\]

**Proof** It follows by induction from the proof of Theorem 2.1.1 2). There, it is shown \( aX_1 + bX_2 \overset{d}{=} cX_1 + d, \) with \( c = (a^\alpha + b^\alpha)^{1/\alpha}, d = \begin{cases} 
  \lambda \gamma(a + b - c), & \alpha \neq 1, \\
  \lambda \beta^2 c\pi(a \log(a/c) + b \log(b/c)), & \alpha = 1.
\end{cases} \) Take \( n = 2, a = b = 1 \Rightarrow c_2 = 2^{1/\alpha}, d_2 = \begin{cases} 
  \lambda \gamma(2 + 2^{1/\alpha}), & \alpha \neq 1, \\
  \lambda \beta^2 2 \log(2), & \alpha = 1.
\end{cases} \) The induction step is trivial. \( \square \)

**Corollary 2.3.2**

It follows from theorem 2.3.1, 2) and 3) that if \( X_1, X_2 \sim S_\alpha(\lambda, \beta, \gamma) \) are independent then \( X_1 - X_2 \sim S_\alpha(2\lambda, 0, 0) \) and \(-X_1 \sim S_\alpha(\lambda, -\beta, -\gamma)\).

**Proposition 2.3.1.** Let \( \{X_n\}_{n \in \mathbb{N}} \) be a sequence of random variables defined in the same probability space \( (\Omega, \mathcal{F}, \mathbb{P}) \), \( X_n \sim S_{\alpha_n}(\lambda_n^M, \beta_n^M, \gamma_n^M), n \in \mathbb{N} \), where \( \alpha_n \in (0, 2), \lambda_n^M > 0, \beta_n^M \in [-1, 1], \gamma_n^M \in \mathbb{R} \). Assume that \( \alpha_n \to \alpha, \lambda_n^M \to \lambda^M, \beta_n^M \to \beta^M \) as \( n \to \infty \) for some \( \alpha \in (0, 2), \lambda^M > 0, \beta^M \in [-1, 1], \gamma^M \in \mathbb{R} \). Then \( X_n \overset{d}{=} X \sim S_\alpha(\lambda^M, \beta^M, \gamma^M) \) as \( n \to \infty \). Here the superscript \( "M" \) means the modified parametrisation, cf. formula (2.1.3) after Definition 2.1.2.

**Proof** \( X_n \overset{d}{=} X \) as \( n \to \infty \) is equivalent to \( \varphi_{X_n}(s) \to \varphi_X(s), n \to \infty, s \in \mathbb{R} \), or, \( \log \varphi_{X_n}(s) = \lambda_n^M(is\gamma_n^M - |s|^\alpha + is\omega_M(s, \alpha_n, \beta_n^M)) \) as \( n \to \infty \) \( \lambda^M(is\gamma^M - |s|^\alpha + is\omega_M(s, \alpha, \beta^M)) \) which is straightforward by the continuity of the modified parametrisation w.r.t. its parameters. \( \square \)

Our aim now is to prove the following result.

**Proposition 2.3.2.** Let \( X \in S_\alpha(\lambda, 1, 0), \lambda > 0, \alpha \in (0, 1) \). Then \( X \geq 0 \) a.s.

This property justifies again the use of \( \beta \) as skewness parameter and brings a random variable \( X \in S_\alpha(\lambda, 1, 0) \) the name of stable subordinator. The above proposition will easily follows from the next theorem.

**Theorem 2.3.2**

1) For \( \alpha \in (0, 1) \), consider \( X_\delta = \sum_{k=1}^{N_\delta} U_{\delta,k} \) to be compound Poisson distributed, where \( N_\delta \) is
a Poisson($\delta^{-\alpha}$)—distributed random variable, $\delta > 0$, and \{\(U_{\delta,k}\)\}_{k \in \mathbb{N}} are i.i.d. positive random variables, independent of \(N\), with \(P(U_{\delta,k} > x) = \begin{cases} \delta^\alpha / x^\alpha, & x > \delta, \\ 0, & x \leq \delta. \end{cases}\)

Then \(X_\delta \sim X, \delta \to 0\), where \(X \sim S_\alpha(\lambda, 1, 0)\) with \(\lambda = \Gamma(1 - \alpha) \cos(\pi\alpha / 2)\).

2) Let \(X \sim S_\alpha(\lambda, 1, 0), \alpha \in (0, 1)\). Then its Laplace transform \(\hat{I}_X(s) := E e^{-sX}\) is equal to

\[
\hat{I}_X(s) = e^{-\Gamma(1 - \alpha)s\alpha}, s \geq 0.
\] (2.3.1)

**Proof** 1) Since the generating function of \(N \sim\) Poisson(a) is equal to \(\hat{g}_N(z) = E z^N = \sum_{k=0}^{\infty} z^k P(N = k) = e^{1/\delta_k} \int_0^\infty \delta_k e^{-x} dx = e^{-a} \sum_{k=0}^{\infty} (\alpha x)^k = e^{-a e^{\alpha x}} = e^{\alpha(z-1)}, z \in \mathbb{C}\), we have \(\hat{g}_N(z) = e^{\delta^{-\alpha}(z-1)}, z \in \mathbb{C}\), and hence

\[
\varphi_X(s) = \mathbb{E} e^{isX} = \mathbb{E} \left( \mathbb{E} e^{isN} | N_\delta \right) = \mathbb{E} \left( \mathbb{E} e^{is \sum_{k=0}^{\infty} U_{\delta,k} | N_\delta} \right) = \mathbb{E} \left( \prod_{k=1}^{N_\delta} \mathbb{E} e^{isU_{\delta,k}} \right) = \hat{g}_N(s) \varphi_U(s),
\]

where \(\varphi_U(s) = \int_0^\infty e^{isx} d\mathbb{P}(U_{\delta,k} \leq x) = \alpha \int_0^\infty e^{isx} \delta x^{-\alpha-1} dx\). So (since \(\alpha \int_0^\infty x^{-\alpha-1} dx = -\delta^{-\alpha}\))

\[
\varphi_X(s) = \exp \left( \alpha \int_0^\infty (e^{isx} - 1)x^{-\alpha-1} dx \right) \to \exp \left( \alpha \int_0^\infty (e^{isx} - 1)x^{-\alpha-1} dx \right),
\]

which is of the form (2.1.6) with \(H(x) = -c_1 x^{-\alpha} \Pi(x > 0)\) as in Theorem 2.1.4 (c2 = 0).

Consider \(\varphi_X(s) := \exp \left( \alpha \int_0^\infty (e^{isx} - 1)x^{-\alpha-1} dx \right)\), \(s \geq 0, \alpha \in (0, 1)\). Show that

\[
\int_0^\infty e^{isx} \frac{x^{-\alpha} - 1}{x^{\alpha+1}} dx = -\alpha \Gamma(1 - \alpha) e^{-ia\pi/2}.
\] (2.3.2)

If it is true then log \(\varphi_X(s) = -|s|^\alpha \Gamma(1 - \alpha) \cos(\pi\alpha / 2) - i \text{sign}(s) \sin(\pi\alpha / 2)\) since for \(s < 0\) we make the substitution \(s \rightarrow -s, i \rightarrow -i\). Then, log \(\varphi_X(s) = -|s|^\alpha \Gamma(1 - \alpha) \cos(\pi\alpha / 2)(1 - \text{sign}(s) \text{tg}(\pi\alpha / 2))\), \(s \in \mathbb{R}\), which means that, according to Definition 2.1.2, \(X \sim S_\alpha(\lambda, 1, 0)\). Now prove relation (2.3.2). It holds

\[
\int_0^\infty e^{isx} \frac{x^{-\alpha} - 1}{x^{\alpha+1}} dx = \lim_{\theta \to +0} \int_0^\infty e^{isx - \theta x} \frac{x^{-\alpha} - 1}{x^{\alpha+1}} dx = \lim_{\theta \to +0} \frac{1 - \theta + is}{\alpha} \int_0^\infty \frac{e^{-\theta x + isx} - 1}{x^\alpha} dx.
\]

\[
= \lim_{\theta \to +0} \frac{1}{\alpha} (e^{isx - \theta x} - 1) \frac{1}{x^\alpha} \left[ \frac{x^\alpha}{\Gamma(1 - \alpha)} \right]_0^\infty = -\theta + is \frac{1}{\alpha} \int_0^\infty e^{-\theta x + isx} x^{-\alpha} dx
\]

\[
= \lim_{\theta \to +0} -\theta + is \frac{1}{\alpha} \Gamma(1 - \alpha) \theta^{1-\alpha} \int_0^\infty e^{isx} x^{1-\alpha} e^{-\theta x} dx
\]

\[
= \lim_{\theta \to +0} \frac{1}{\alpha} \Gamma(1 - \alpha) \theta^{1-\alpha} \frac{1}{(1 - is/\theta)^{1-\alpha}} = \lim_{\theta \to +0} \frac{(\theta - is)^{1-1+\alpha}}{\alpha} \Gamma(1 - \alpha)
\]

\[
= \lim_{\theta \to +0} \frac{(\theta - is)^{1-1+\alpha}}{\alpha} \Gamma(1 - \alpha) = \frac{\Gamma(1 - \alpha)}{\alpha} \lim_{\theta \to +0} \left( \sqrt{\theta^2 + s^2 e^{\xi}} \right)^\alpha
\]

where \(\xi = \arg(\theta - is) \to -\pi/2\).
3) Similarly to said above,
\[ \hat{g}_X(s) = \mathbb{E}e^{-sX} = \exp \left\{ \alpha \int_{\delta}^{\infty} (e^{i\alpha x} - 1)x^{-\alpha-1} dx \right\} \]
(sup. \( y = sx \) = \( \exp \left\{ s^\alpha \int_{0}^{\infty} \alpha(e^{iy} - 1)y^{-\alpha-1} dy \right\} = \exp \left\{ -s^\alpha \Gamma(1 - \alpha) \right\}, s \geq 0. \)

\[ \square \]

Proof of Proposition 2.3.2 Since \( X_\delta \geq 0, X_\delta \to X \) as in Theorem 2.3.1) it holds \( X \geq 0. \) This means that the support of the density \( f \) of \( X \sim S_\alpha(\lambda, 1, 0) \) is contained in \( \mathbb{R}_+ \). Moreover, one can show that \( \text{supp} f := \{ x \in \mathbb{R} : f(x) > 0 \} = \mathbb{R}_+ \) by showing that \( \forall a, b > 0 : a^\alpha + b^\alpha = 1 \) it holds \( \text{asupp} f + b\text{supp} f = \text{supp} f \). It follows from this relation that \( \text{supp} f = \mathbb{R}_+ \) since it can not be \( \mathbb{R} \).

\[ \square \]

Exercise 2.3.1
Show this!

Remark 2.3.2
Actually, formula (2.3.1) is valid for all \( \alpha \neq 1, \alpha \in (0, 2] \) for \( X \sim S_\alpha(\lambda, 1, 0) \),
\[ \hat{l}_X(s) = \begin{cases} 
\exp \left\{ -\frac{\lambda}{\cos(\pi\alpha/2)} s^\alpha \right\}, & \alpha \neq 1, \alpha \in (0, 2], \\
\exp \left\{ -\lambda s \log s \right\}, & \alpha = 1,
\end{cases} 
\]
where \( \Gamma(1 - \alpha) = \frac{\lambda}{\cos(\pi\alpha/2)} \) for \( \alpha \neq 1 \). Here, \(-\frac{\lambda}{\cos(\pi\alpha/2)} = \begin{cases} 
< 0, & \alpha \in (0, 1), \\
 > 0, & \alpha \in (1, 2), \\
\lambda, & \alpha = 2.
\end{cases} \)

Proposition 2.3.3. The support of \( S_\alpha(\lambda, \beta, 0) \) is \( \mathbb{R} \), if \( \beta \in (-1, 1), \alpha \in (0, 2) \).

Proof Let \( X \sim S_\alpha(\lambda, 1, 0), \alpha \in (0, 2), \beta \in (-1, 1) \) with density \( f \). It follows from properties 2)-4) of Theorem 2.3.1 that \( \exists \) i.i.d. random variables \( Y_1, Y_2 \sim S_\alpha(\lambda, 1, 0) \) and constants \( a, b > 0, c \in \mathbb{R} \) s.t. \( X \overset{d}{=} \begin{cases} 
aY_1 - bY_2, & \alpha \neq 1, \\
aY_1 - bY_2 + c, & \alpha = 1.
\end{cases} \) Since, \( Y_1 \geq 0 \) and \( -Y_2 \leq 0 \) a.s. by Proposition 2.3.2, and their support is the whole \( \mathbb{R}_+ \) (\( \mathbb{R}_- \), resp.), it holds \( \text{supp} f = \mathbb{R} \).

\[ \square \]

Remark 2.3.3
One can prove that the support of \( S_\alpha(\lambda, \pm 1, 0) \) is \( \mathbb{R} \) as well, if \( \alpha \in [1, 2) \).

Now consider the tail behavior of stable random variables. In the Gaussian case \( \alpha = 2 \), it is exponential:

Proposition 2.3.4. Let \( X \sim N(0, 1) \). Then, \( \mathbb{P}(X < -x) = \mathbb{P}(X > x) \sim \frac{\varphi(x)}{x}, x \to \infty, \) where \( \varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \) is the standard normal density.
**Proof** Due to the symmetry of $X$, $P(X < -x) = P(X > x), \forall x > 0$. Prove the more accurate inequality

$$
\left(1 - \frac{1}{x^3}\right) \varphi(x) < P(X > x) < \frac{\varphi(x)}{x}, \forall x > 0. \tag{2.3.3}
$$

The asymptotic $P(X > x) \sim \frac{\varphi(x)}{x}, x \to +\infty$ follows immediately from it.

First prove the left relation in (2.3.3). Since $e^{-t^2/2} < e^{-t^2/2} \left(1 + \frac{1}{t^2}\right), \forall t > 0$, it holds for $x > 0: P(X > x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt \leq \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} \left(1 + \frac{1}{t^2}\right) dt = \frac{1}{\sqrt{2\pi}} \int_x^\infty \left(\frac{\varphi(x)}{x}\right)' dt$. Analogously, $e^{-t^2/2} \left(1 - \frac{3}{t^2}\right) < e^{-t^2/2}, \forall t > 0$, hence

$$
\left(1 - \frac{1}{x^3}\right) \varphi(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} \left(1 - \frac{3}{t^2}\right) dt \leq \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt = P(X > x), \tag{2.3.4}
$$

where again the left equality in (2.3.4) is proved by differentiation w.r.t. $x$.

**Remark 2.3.4**

If $X \in N(\mu, \sigma^2)$, then $P(X > x) \sim \frac{\varphi(x)}{x}, x \to +\infty$ accordingly.

However, for $\lambda \in (0, 2)$, the behaviour of right and left hand side tail probabilities is polynomial in $\frac{1}{x}$:

**Proposition 2.3.5.** Let $X \sim S_0(\lambda, \beta, \gamma), \alpha \in (0, 2)$. Then

$$
x^\alpha P(X > x) \to c_\alpha \frac{1 + \beta}{2} \lambda, \quad x^\alpha P(X < -x) \to c_\alpha \frac{1 - \beta}{2} \lambda, \quad as \ x \to +\infty,
$$

where

$$
c_\alpha = \left(\int_0^\infty \frac{\sin x}{x^n} dx\right)^{-1} = \begin{cases} \frac{\Gamma(1 - \alpha)\cos(\pi\alpha/2)}{2\pi}, & \alpha \neq 1 \\ \frac{\Gamma(1 - \alpha)}{2\pi}, & \alpha = 1. \end{cases}
$$

**Remark 2.3.5**

1) The above proposition states, for $\beta = \pm 1$, that for

- $X \sim S_0(\lambda, -1, 0)$, it holds $P(X > x)x^\alpha \to 0, x \to +\infty$, which means that the tails go to zero faster than $x^{-\alpha}$. But what is the correct asymptotic in this case? For $\alpha \in (0, 1)$ we know that $X$ is totally skewed to the left (right) and hence $P(X > x) = 0, \forall x > 0$ for $\beta = 1$ and $P(X < x) = 0, \forall x > 0$ for $\beta = 1$.

2) For $\alpha \geq 1$, this asymptotic is far from being trivial. Thus, it can be shown (see [6][Theorem 2.5.3]) that

$$
\begin{cases}
P(X > x) \sim \frac{1}{\sqrt{2\pi a_\alpha}} \left(\frac{x}{a_\alpha}\right)^{-\frac{\alpha}{2}} \exp \left(-\frac{(x - \lambda/\alpha a_\alpha)^2}{2}\right), & \alpha > 1, \\
P(X > x) \sim \frac{\exp \left(-\frac{(\pi/2)x^{2\alpha - 1}}{2} - e^{(\pi/2)x^{2\alpha - 1}}\right)}{\sqrt{2\pi}}, & \alpha = 1, \lambda = 1
\end{cases}
$$

where $a_\alpha = (\lambda/\cos(\pi(2 - \alpha)/2))^{1/\alpha}$.

3) In the specific case of $S_0S X$, i.e., $\beta = 0$, $X \sim S_0(\lambda, 0, 0)$, Proposition 2.3.5 yields

$$
P(X < x) = P(X > x) \sim \frac{\lambda c_\alpha}{2\pi} \frac{1}{x^{\alpha}}, x \to +\infty.
Proposition 2.3.5 will be proved later after we have proven important results, needed for it. Let us state now some corollaries.

Corollary 2.3.3
For any $X \sim S_\alpha(\lambda, \beta, \gamma), 0 < \alpha < 2$ it holds $\mathbb{E}|X|^p < \infty$ iff $p \in (0, \alpha)$. In particular, $\mathbb{E}|X|^\alpha = +\infty$.

Proof It follows immediately from the tail asymptotic of Proposition 2.3.5 and the formula $\mathbb{E}|X|^p = \int_0^\infty \mathbb{P}(|X|^p > x)dx$.

Proposition 2.3.6. Let $X \sim S_\alpha(\lambda, \beta, 0)$ for $0 < \alpha < 2$, and $\beta = 0$ if $\alpha = 1$. Then $(\mathbb{E}|X|^p)^{1/p} = c_{\alpha,\beta}(p)\lambda^{1/\alpha}$, where $\forall p \in (0, \alpha)$ and $c_{\alpha,\beta}(p)$ is a constant s.t.

$$c_{\alpha,\beta}(p) = \frac{2^{p-1}\Gamma(1-p/\alpha)}{p\int_0^\infty \frac{u^{-p-1}}{\sin^2 u}du} \left(1 + \beta^2 \tan^2 \left(\frac{\alpha\pi}{2}\right)\right)^{p/(2\alpha)} \cos \left(\frac{p}{\alpha} \arctg(\beta \tan(\alpha\pi/2))\right).$$

Proof We shall show only that $(\mathbb{E}|X|^p)^{1/p} = c_{\alpha,\beta}(p)\lambda^{1/\alpha}$, where $c_{\alpha,\beta}(p) = (\mathbb{E}|X_0|^p)^{1/p}$ with $X_0 \sim S_\alpha(1, \beta, 0)$. The exact calculation of $c_{\alpha,\beta}(p)$ will be left without proof. The first statement follows from Theorem 2.3.1, (4), namely, since $X \overset{d}{=} \lambda^{1/\alpha}X_0$. Then $(\mathbb{E}|X|^p)^{1/p} = \lambda^{1/\alpha}(\mathbb{E}|X_0|^p)^{1/p} = c_{\alpha,\beta}(p)$.

2.4 Limit theorems

Let us reformulate Definition 2.1.1 as follows.

Definition 2.4.1
We say that the distribution function $F$ belongs to the domain of attraction of distribution function $G$ if for a sequence of i.i.d. r.v.’s $\{X_n\}_{n \in \mathbb{N}}, X_n \sim F \exists$ sequences of constants $\{a_n\}_{n \in \mathbb{N}}, \{b_n\}_{n \in \mathbb{N}}: a_n \in \mathbb{R}, b_n > 0, \forall n \in \mathbb{N}$ s.t.

$$\frac{1}{b_n} \sum_{i=1}^n X_i - a_n \overset{d}{\rightarrow} X \sim G, n \rightarrow \infty.$$

Let us state and prove the following result.

Theorem 2.4.1
1) $G$ has a domain of attraction iff $G$ is a distribution function of a stable law.
2) $F$ belongs to the domain of attraction of $N(\mu, \sigma^2), \sigma > 0$ iff

$$\mu(x) := \int_{-\infty}^x y^2 F(dy), x > 0$$

is slowly varying at $\infty$. This holds, in particular, if $F$ has a finite second moment (then $\exists \lim_{x \rightarrow +\infty} \mu(x) = \mathbb{E}X_0^2$).
3) $F$ belongs to the domain of attraction of $\alpha$-stable law, $\alpha \in (0, 2)$, iff

$$\mu(x) \sim x^{2-\alpha}L(x),$$

where $L : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is slowly varying at $+\infty$ and it holds the tail balance condition

$$\mathbb{P}(X > x) = \frac{1 - F(x)}{1 - F(x) + F(-x)} \xrightarrow{x \to +\infty} p, \quad \mathbb{P}(X < -x) = \frac{F(-x)}{1 - F(x) + F(-x)} \xrightarrow{x \to +\infty} q$$

(2.4.2)
for some $p, q \geq 0 : p + q = 1$ with $X \sim F$.

4) Condition (2.4.1) equivalent to (2.4.3)

$$
\mathbb{P}(|X| > x) = 1 - F(x) + F(-x) \sim x^{-\alpha}L(x).
$$

(2.4.3)

**Remark 2.4.1**

a) In Definition 2.4.1, one can choose $b_n = \inf\{x : \mathbb{P}(|X| > x) \leq n^{-1}\}$, $a_n = n\mathbb{E}(X_1\mathbb{1}(|X_1| \leq b_n))$.

b) It is quite clear that statements 2) and 3) are special cases of the following one:

1) $F$ belongs to the domain of attraction of an $\alpha$-stable law, $\alpha \in (0, 2]$, iff (2.4.1) and (2.4.2) hold.

c) It can be shown that $\{b_n\}$ in Theorem 2.4.1 must satisfy the condition $\lim_{n \to \infty} \frac{nL(b_n)}{b_n^\alpha} = \lambda c_\alpha$, with $c_\alpha$ as in Proposition 2.3.5. Then $\{a_n\}$ can be chosen as

$$
a_n = \begin{cases}
0, & \alpha \in (0, 1), \\
\frac{n b_n^\alpha}{\int_{\mathbb{R}} \sin(x/b_n) dF(x)}, & \alpha = 1, \\
\frac{n b_n^\alpha}{\int_{\mathbb{R}} x dF(x)}, & \alpha (1, 2).
\end{cases}
$$

**Proof of Proposition 2.3.5** We just give the sketch of the proof. It is quite clear that $S_n(\lambda, \beta, \gamma)$ belongs to the domain of attraction of $S_\alpha(\lambda, \beta, 0)$ with $b_n = n^{1/\alpha}$, cf. Theorems 2.1.3, 2.1.4, Corollary 2.1.1 and Remark 2.1.5. Then the tail balance condition (2.4.2) holds with $p = \frac{1+\beta}{2}, q = \frac{1-\beta}{2}$. By Remark 2.4.1 c), putting $b_n = n^{1/\alpha}$ into it yields that $L(x)$ in (2.4.3) has the property $\lim_{x \to +\infty} L(x) = c_\alpha \lambda$. It follows from (2.4.2) and (2.4.3) of Theorem 2.4.1 that

$$
x^\alpha \mathbb{P}(X > x) \sim x^\alpha p \mathbb{P}(|X| > x) \sim p, x \to +\infty.
$$

$$
x^\alpha x^{-\alpha} \lim_{x \to +\infty} L(x) = pc_\alpha \lambda = c_\alpha \frac{1+\beta}{2} \lambda,
$$

$x^\alpha \mathbb{P}(X < -x) \sim q c_\alpha \lambda = c_\alpha \frac{1-\beta}{2} \lambda, x \to +\infty$ is shown analogously. $

**Proof of Theorem 2.4.1** $F$ belongs to the domain of attraction of a distribution function $G$ if, by Definition 2.4.1, $\exists$ i.i.d. r.v.'s $\{X_n\}_{n \in \mathbb{N}}, X_n \sim F$, $\{a_n\}_{n \in \mathbb{N}} \{b_n\}_{n \in \mathbb{N}} \subset \mathbb{R} : b_n > 0, \forall n$, s.t.

$$
S_n = \frac{1}{b_n} \sum_{i=1}^n X_i - a_n = \sum_{i=1}^n \frac{X_i - a_n b_n}{b_n} \xrightarrow{d} X \sim G, n \to \infty.
$$

Denote $c_n = a_n \frac{1}{n\alpha}, n \in \mathbb{N}$. In terms of characteristic functions, $\varphi_{S_n}(s) \xrightarrow{n \to \infty} \varphi_X(s)$ $\forall s \in \mathbb{R}$, where

$$
\varphi_{S_n}(s) = \mathbb{E} \exp \left( \sum_{k=1}^n \frac{X_k - c_n b_n}{b_n} \right) = \prod_{k=1}^n \mathbb{E} \exp \left( \frac{is X_k - c_n b_n}{b_n} \right) \xrightarrow{X_i \text{ i.i.d.}} \left( e^{-isc_n} \varphi_X(s/b_n) \right)^n.
$$

Put $\varphi_n(s) = \varphi_{X_1}(s/b_n), F_n(x) = F(b_n x)$. Then the statement of Theorem 2.4.1 is equivalent to

$$
\left( e^{-isc_n} \varphi_n(s) \right)^n \xrightarrow{n \to \infty} \varphi_X(s),
$$

(2.4.4)

where $X$ is stable.
Lemma 2.4.1
Under assumptions of Theorem 2.4.1, relation (2.4.4) is equivalent to
\[ n(\varphi_n(s) - 1 - ic_n s) \rightarrow \eta(s), n \rightarrow \infty \]  
(2.4.5)
where \( \eta(s) \) is a continuous function of the form \( \eta(s) = isa - bs^2 + \int_{x \neq 0} (e^{ixs} - 1 - is \sin x) dH(x) \) (cf. (2.1.6)) with \( H(\cdot) \) from Theorem 2.1.2 and \( \varphi_X(s) = e^{\eta(s)}, s \in \mathbb{R} \).

Proof
1) Show this equivalence in the symmetric case, i.e., if \( X_1 \overset{d}{=} -X_1 \). Then it is clear that we may assume \( c_n = 0, \forall n \in \mathbb{N} \). Show that
\[ \varphi_n^c(s) \xrightarrow{n \rightarrow \infty} e^{\eta(s)} \iff n(\varphi_n(s) - 1) \xrightarrow{n \rightarrow \infty} \eta(s), \]  
(2.4.7)
and \( \eta \) is continuous. First, if a characteristic function \( \varphi(s) \neq 0 \forall s : |s| < s_0 \), then \( \exists \) representation \( \varphi(s) = r(s)e^{i\theta(s)} \), where \( \theta(\cdot) \) is continuous and \( \theta(0) = 0 \). Hence, \( \log \varphi(s) = \log r(s) + i\theta(s) \) is well-defined, continuous, and \( \log \varphi(0) = \log r(0) + i\theta(0) = \log 1 + i0 = 0 \).

Let us show (2.4.7) \( \Rightarrow \) (2.4.6). It follows from (2.4.7) that \( \varphi_n(s) \xrightarrow{n \rightarrow \infty} 1 \) and by continuity theorem for characteristic functions, this convergence is uniform in any finite interval \( s \in (-s_0, s_0) \). Then, \( \log \varphi_n(s) \) is well-defined for large \( n \) (since \( \varphi_n(s) \neq 0 \) there). Since
\[ \log z = z - 1 + o((z - 1)^2) \text{ for } |z - 1| < 1, \]  
(2.4.8)
it follows \( \log \varphi_n^c(s) = n \log \varphi(s) = n(\varphi_n(s) - 1 + o((\varphi_n(s))^2)) \xrightarrow{n \rightarrow \infty} n(\varphi_n(s) - 1) \xrightarrow{n \rightarrow \infty} \eta(s) \) by (2.4.7). Then, \( \varphi_n^c(s) \xrightarrow{n \rightarrow \infty} e^{\eta(s)}, \forall s \in \mathbb{R} \) and (2.4.6) holds.

Let us show (2.4.6) \( \Rightarrow \) (2.4.7). Since \( \eta(0) = 0 \), then \( e^{\eta(s)} \neq 0 \ \forall s \in (-s_0, s_0) \) for some \( s_0 > 0 \). Since the convergence of characteristic functions is uniform by continuity theorem, \( \varphi_n(s) \neq 0 \) for all \( n \) large enough and for \( s \in (-s_0, s_0) \). Taking logarithms in (2.4.6), we get \( n \log \varphi_n(s) \xrightarrow{n \rightarrow \infty} \eta(s) \). Using Taylor expansion (2.4.8), we get \( n(\varphi_n(s) - 1) \xrightarrow{n \rightarrow \infty} \eta(s) \), and (2.4.7) holds.

2) Show this equivalence in the general case \( c_n \neq 0 \). More specifically, show that it holds if \( \varphi_n(s) \xrightarrow{n \rightarrow \infty} 1 \ \forall s \in \mathbb{R} \), and \( n\beta_n^2 \xrightarrow{n \rightarrow \infty} 0 \), where \( \beta_n = \int_{\mathbb{R}} \sin \left( \frac{x}{n} \right) F(dx) \). Then
\[ n(\beta_n - c_n) \xrightarrow{n \rightarrow \infty} a, \]  
(2.4.9)
and (2.4.5) writes equivalently as
\[ n(\varphi_n(s) - 1 - i\beta_n s) \xrightarrow{n \rightarrow \infty} \eta(s). \]  
(2.4.10)

Without loss of generality set \( a = 0 \).

Notice that the proof of 1) does not essentially depend on the symmetry of \( X_1 \), i.e., equivalence (2.4.6) \( \iff \) (2.4.7) holds for any characteristic functions \( \{\varphi_n\} \) s.t. \( \varphi_n(s) - 1 \xrightarrow{n \rightarrow \infty} 1 \ \forall s \in \mathbb{R} \). Applying this equivalence to \( \{\varphi_n(s)e^{-isc_n}\} \in \mathcal{N} \) leads to \( n(\varphi_n(s)e^{-isc_n} - 1) \xrightarrow{n \rightarrow \infty} \eta(s) = -bs^2 + \int_{x \neq 0} (e^{ixs} - 1 - is \sin x) dH(x) \). Since we assumed that \( \varphi_n(s) \xrightarrow{n \rightarrow \infty} 1 \) it follows \( c_n \xrightarrow{n \rightarrow \infty} 0 \), while \( b_n \xrightarrow{n \rightarrow \infty} \). Consider \( \text{Im} \left( n(\varphi_n(s) - e^{isc_n}) \right) \xrightarrow{n \rightarrow \infty} \text{Im} (e^{isc} \eta(s)) \) for \( s = 1 \). Since \( \eta(1) \in \mathbb{R} \) and \( c_n \xrightarrow{n \rightarrow \infty} 0 \), we get
\[ n(\text{Im} \varphi_n(1) - \sin c_n) \sim \eta(1) \sin c_n, \]  
since \( c_n \sim c_n \) as \( c_n \rightarrow 0 \), where
Im \( \varphi_n(1) = \text{Im} \left( \int_{\mathbb{R}} e^{is/b_n} dF(x) \right) \) on interval \( s = 1 \) equals \( \int_{\mathbb{R}} \sin(x/b_n) dF(x) = \beta_n \Rightarrow n(\beta_n - c_n) \to 0 \). Hence, relation \( n(\varphi_n(s)e^{-ic_n s} - 1) \to n(\eta(s) - 1) \to 0 \) one can write as \( n(\varphi_n(s)e^{-i\beta_n s} - 1) \to n(1 + i\beta_n s)e^{-i\beta_n s} - 1 \), since \( n((1 + i\beta_n s)e^{-i\beta_n s} - 1) = n((1 + \beta_n s)(1 - \beta_n s + o(b_n)) - 1) = n(1 + \beta_n^2 s^2 + o(b_n)) \to 0 \) by our assumption. We conclude that (2.4.4) \( \Rightarrow (2.4.5) \) holds.

Conversely, if (2.4.9) and (2.4.8) hold then reading the above reasoning in reverse order we go back to (2.4.4).

Now we have to show that \( \varphi_n(s) \to 1, n\beta_n^2 \to 0 \). The first statement is trivial since \( \varphi(s/b_n) \to \varphi(0) = 1 \), as \( b_n \to \infty \). Let us show \( n\beta_n^2 = n \left( \int_{\mathbb{R}} \sin(x/b_n) F(dx) \right)^2 \to 0 \).

By Corollary 2.1.1 \( b_n \sim n^{1/\alpha} h(n), n \to \infty \), where \( h(\cdot) \) is slowly varying at \( +\infty \). It follows from (2.4.3) that \( \mathbb{E}[X_1]^p < \infty \) for all \( p \in (0, \alpha) \). Then \( |\beta_n| \leq 2 \int_0^\infty \frac{p}{x^p} dF(x) = O(|\beta_n|^{-p}) = O(n^{-p/\alpha} h^{-p}(n)) \) and \( n\beta_n^2 = O(n^{1-2p/\alpha}) \to 0 \) if \( \beta \) is chosen s.t. \( p > \alpha/2 \).

Now prove the following.

**Lemma 2.4.2**

Conditions of Theorem 2.4.1 are necessary and sufficient for relation (2.4.5) to hold with some special sequences of constants \( \{b_n\}, \{c_n\} \).

If this lemma is proven, then the proof of Theorem 2.4.1 is complete, since by Lemma 2.4.1 relation (2.4.5) and (2.4.4) are equivalent, and thus \( F \) belongs to the domain of attraction of some \( \alpha \)-stable law.

**Proof of Lemma 2.4.2.** Let relation (2.4.5) holds with some \( b_n > 0 \) and \( a_n \). This means, equivalently, that \( S_n \xrightarrow{n \to \infty} X \sim G \). Since the case \( X \sim N(0, 1) \) is covered by the CLT, let us exclude it as well as the trivial case \( X \equiv \text{const} \). By Theorem 2.1.2-2.1.3 with \( k_n = nX_n \), \( a_n = A_n(y) = a - \int_{|u| < y} u dH(u) + \int_{|u| \geq y} \frac{1}{u} dH(u), X_1 \sim F \),

\[
A_n(y) = n \mathbb{E} \left( \frac{X_1}{b_n} \mathbb{I}(|X_1|/b_n < y) \right) = \frac{n}{b_n} \mathbb{E} (X_1 \mathbb{I}(|X_1| < b_n y)) \frac{y}{b_n} \int_{-y b_n}^{y b_n} x dF(x),
\]

\( \pm y \) being continuity points of \( H \), it follows that

\[
\begin{align*}
\limsup_{n \to \infty} \frac{n}{b_n} \int_{-\epsilon b_n}^{\epsilon b_n} x^2 dF(x) - \left( \int_{-\epsilon b_n}^{\epsilon b_n} x^2 dF(x) \right)^2 = b. 
\end{align*}
\]

1) Show that \( b_n \to \infty, \epsilon \to 0, \frac{b_n + \epsilon}{b_n} \to 1, \) if \( X \not\equiv \text{const} \) a.s. By Remark 2.1.3 2), it holds property (2.1.5), i.e., \( \lim_{n \to \infty} \mathbb{P}(|X_1| < c) = 1 \) then the central limit theorem can be applied to \( \{X_n\} \) with

\[
\frac{\sum_{i=1}^{n} X_i - n \mathbb{E} X_1}{\sqrt{n} \sqrt{\text{Var} X_1}} \xrightarrow{n \to \infty} N(0, 1)
\]
and it is not difficult to show (see Exercise 2.3.2 below) that \( b_n = \text{const}\sqrt{n} \to \infty \) in this case. If \( \exists c > 0 : \mathbb{P}(|X_1| < c) = 1 \) then \( b_n \neq O(1), n \to \infty \) since that would contradict \( \lim_{n \to \infty} \mathbb{P}(|X_1| > b_n) = 0 \Rightarrow \exists \{n_k\}, n_k \to \infty \) as \( k \to \infty : b_{n_k} \to +\infty \). W.l.o.g. identify sequences \( \{n\} \) and \( \{n_k\} \). Alternatively, one can agree that \( \{S_n\} \) is stochastically bounded (which is the case if \( S_n \xrightarrow{d} X \)) iff \( b_n \to +\infty \).

**Exercise 2.4.1**

Let \( \{F_n\}_{n \in \mathbb{N}} \) be a sequence of c.d.f.

s.t. \( F_n(\alpha_n + \beta_n) \xrightarrow{d} U(\cdot), n \to \infty, F_n(\gamma_n + \delta_n) \xrightarrow{d} V(\cdot), n \to \infty \) for some sequences \( \{\alpha_n\}, \{\beta_n\}, \{\gamma_n\}, \{\delta_n\} \) s.t. \( \alpha_n\gamma_n > 0 \), where \( U \) and \( V \) are c.d.f.’s, which are not concentrated at one point. Then

\[
\frac{\gamma_n}{\alpha_n} \to a \neq 0, \quad \frac{\delta_n - \beta_n}{\alpha_n} \to b
\]

and \( V(x) = U(ax + b), \forall x \in \mathbb{R} \).

Now show that \( \frac{b_{n+1}}{b_n} \to 1, n \to \infty \). Since \( S_n \xrightarrow{d} X \neq \text{const} \), it holds \( S_{n+1} \xrightarrow{d} X, \frac{X_{n+1}}{b_{n+1}} = S_{n+1} - S_n \xrightarrow{d} 0 \Rightarrow S_{n+1} \xrightarrow{p} 0, n \to \infty \). Thus, \( \frac{1}{b_{n+1}}S_n - a_{n+1} \xrightarrow{d} X \) and \( \frac{1}{b_n}S_n - a_n \xrightarrow{d} X \), which means by Exercise 2.4.1, that \( \frac{b_{n+1}}{b_n} \to 1 \).

2) Prove the following.

**Proposition 2.4.1.** Let \( \beta_n \xrightarrow{n \to \infty} +\infty, \frac{\alpha_{n+1}}{\alpha_n} \xrightarrow{n \to \infty} 1 \). Let \( U \) be a monotone function s.t.

\[
\lim_{n \to \infty} \alpha_n U(\beta_n x) \psi(x) = (2.4.12)
\]

exists on a dense subset of \( \mathbb{R}_+ \), where \( \psi(x) \in (0, +\infty) \) on some interval \( I \), then \( U \) is regularly varying at \( +\infty \), \( \psi(x) = cx^\rho, \rho \in \mathbb{R} \).

**Proof** W.l.o.g. set \( \psi(1) = 1 \), and assume that \( U \) is non-decreasing and \( (2.4.12) \) holds for \( x = 1 \) (otherwise, a scaling in \( x \) can be applied). Set \( n = \min\{k \in \mathbb{N}_0 : \beta_{k+1} > t\} \). Then it holds \( \beta_n \leq t < \beta_{n+1} \), and

\[
\psi(x) \sim \frac{\lambda_n U(\beta_n x)}{\lambda_n U(\beta_{n+1})} \xrightarrow{n \to \infty} \frac{U(\beta_n x)}{U(\beta_{n+1})} \leq \frac{U(\beta_{n+1})}{U(\beta_n)} \xrightarrow{n \to \infty} \frac{\lambda_n U(\beta_{n+1})}{\lambda_n U(\beta_n)} \xrightarrow{n \to \infty} \psi(x) = (2.4.12) \]

for all \( x \), for which \( (2.4.12) \) holds. The application of Lemma 2.1.1 finishes the proof. \( \square \)

3) Apply Proposition 2.4.1 to \( \begin{cases} n(F(x_{b_n}) - 1) \to H(x), & x > 0 \\ nF(-x_{b_n}) \to H(-x), & x > 0 \end{cases} \) as \( n \to \infty \) with \( \alpha_n = n, \beta_n = b_n \Rightarrow 1 - F(x) = \mathbb{P}(X_1 > x), F(-x) = \mathbb{P}(X_1 < -x) \) are regularly varying at \( +\infty \), and \( H(x) = c_1 x^{\rho_1}, H(-x) = c_2 x^{\rho_2} \),

\[
\mathbb{P}(X_1 > x) \sim x^{\rho_1} L_1(x), \quad \mathbb{P}(X_1 < -x) \sim x^{\rho_2} L_2(x), x \to +\infty \]

(2.4.13)

where \( L_1, L_2 \) are slowly varying at \( +\infty \).

Since \( (2.4.11) \) holds, \( \lim_{n \to \infty} \frac{1}{b_n^2} \left( \mu(\varepsilon b_n) - \left( f_{x_{b_n}}^x x \mu F(x) \right)^2 \right) \) is a bounded function of \( \varepsilon \) in the neighborhood of zero, hence by Proposition 2.4.1 with \( \alpha_n \equiv \frac{n}{b_n^2}, \beta_n = b_n, \mu(x) - \left( f_{-x}^x x \mu F(y) \right)^2 \)
is regularly varying at $+\infty$. By Theorem 2.1.4, $\rho_1 = \rho_2 = -\alpha$, $c_1 < 0$, $c_2 > 0$, and evidently, $\mathbb{P}(|X_1| > x) = 1 - F(x) + F(-x) \xrightarrow{x \to +\infty} x^{-\alpha} \frac{L_1(x) + L_2(x)}{L(x)}$, so (2.4.3) holds.

**Exercise 2.4.2**

Show that then $\mu(x) \sim x^{2-\alpha} L_3(x)$ is equivalent to (2.4.3). Show that tail balance condition (2.4.2) follows from (2.4.13) with $\rho_1 = \rho_2 = -\alpha$.

So we have proven that (2.4.5) $\Rightarrow$ (2.4.2),(2.4.3) (or, equivalently, (2.4.1),(2.4.2)). Now let us prove the inverse statement.

4) Let (2.4.1) hold. Since $L_1$ is slowly varying, one can find a sequence $\{b_n\}, b_n \to \infty, n \to \infty$ s.t. $\frac{n}{b_n} L(b_n) \to c > 0$ – some constant. (Compare Remark 2.4.1, c.) Then $\frac{n}{b_n} \mu(b_n x)^{2-\alpha} L(b_n x) = \frac{n}{b_n} L(b_n x) x^{-\alpha} \xrightarrow{n \to \infty} c x^{-\alpha}, x > 0$ and hence

$$n(F(xb_n) - 1) \xrightarrow{n \to \infty} c_1 x^{-\alpha},$$

$$nF(-xb_n) \xrightarrow{n \to \infty} c_2 x^{-\alpha}.$$ (2.4.14)

**Exercise 2.4.3**

1) Show the last relation. Then 1) of Theorem 2.1.3 holds.

2) Prove that 2) of Theorem 2.1.3 holds as well, as a consequence of $\frac{n}{b_n} \mu(b_n x)^{2-\alpha} L(b_n x) \xrightarrow{n \to \infty} c x^{-\alpha}$ and (2.4.14).

Then, by Theorem 2.1.3 $S_n \xrightarrow{d} X$, and (2.4.5) holds. Lemma 2.4.2 is proven.

The proof of Theorem 2.4.1 is thus complete. Part a) and the second half of part c) of Remark 2.4.1 will remain unproven.

### 2.5 Further properties of stable laws

**Proposition 2.5.1.** Let $X \sim S_\alpha(\lambda, \beta, \gamma)$ with $\alpha \in (1, 2]$. Then $\mathbb{E}X = \lambda \gamma$.

In addition to a proof a using the law of large numbers, (see Exercise 4.1.14) let us give an alternative proof here.

**Proof** By Corollary 2.3.3, $\mathbb{E}|X| < \infty$ if $\alpha \in (1, 2)$. For $\alpha = 2$ $X$ is Gaussian and hence $\mathbb{E}|X| < \infty$ is trivial. By Remark 2.3.1 5), $X - \alpha \gamma$ is strictly stable, i.e., $X_1 - \mu + X_2 - \mu \xrightarrow{d} c_2(X - \mu)$ by Definition 2.1.3, where $X_1 \xrightarrow{d} X_2 \xrightarrow{d} X$, all independent r.v.’s. Taking expectations on both sides yields $2\mathbb{E}(X - \mu) = c_2 \mathbb{E}(X - \mu)$. Since $c_n = n^{1/\alpha}$ by Remark 2.1.5, $c_2 = 2^{1/\alpha}$, and hence $\mathbb{E}(X - \mu) = 0 \Rightarrow \mathbb{E}X = \mu$.

Now we go on to show series representation of stable random variables. Some preparatory definitions are in order.

**Definition 2.5.1**

Let $X$ and $Y$ be two random variables defined possibly on different probability space. One says that $X$ is a representation of $Y$ if $X \xrightarrow{d} Y$. 

Definition 2.5.2
Let \( \{T_i\}_{i \in \mathbb{N}} \) be the sequence of i.i.d. \( \text{Exp}(\lambda) \)-distributed random variables with \( \lambda > 0 \). Set \( \tau_n = \sum_{i=1}^{n} T_i \forall n \in \mathbb{N}, \tau_0 = 0, \) and \( N(t) = \max\{n \in \mathbb{N} : \tau_n \leq t\}, t \geq 0. \) The random process \( N = \{N(t), t \geq 0\} \) is called Poisson with intensity \( \lambda \). Time instants \( T_i \) are called arrival times, \( \tau_i \) interarrival times.

Exercise 2.5.1
Prove the following properties of a Poisson process \( N \):

1. \( N(t) \sim \text{Poisson}(\lambda t), t > 0, \) and, in particular, \( \mathbb{E}N(t) = \text{Var}N(t) = \lambda t. \)
2. Let \( N_i = \{N_i(t), t \geq 0\} \) be two independent Poisson processes with intensities \( \lambda_i, i = 1, 2. \)
   Then \( \{N_1(t) + N_2(t), t \geq 0\} \) is a Poisson process with intensity \( \lambda_1 + \lambda_2 \) (which is called the superposition \( N_1 + N_2 \) of \( N_1 \) and \( N_2 \).)
3. \( T_n \sim \Gamma(n, \lambda), n \in \mathbb{N}, \) where \( \Gamma(n, \lambda) \) is a Gamma distribution with parameters \( n \) and \( \lambda, \) \( \mathbb{E}T_n = n/\lambda. \)

Clearly, all \( T_n \) are dependent random variables.

Proposition 2.5.2. Let \( N = \{N(t), t \geq 0\} \) be a Poisson process with intensity one \( (\lambda = 1) \) with arrival times \( \{T_n\}_{n \in \mathbb{N}} \). Let \( \{R_n\}_{n \in \mathbb{N}} \) be a sequence of i.i.d. random variables, independent of \( \{T_n\}_{n \in \mathbb{N}}. \) Then \( X = \sum_{n=1}^{\infty} T_n^{-1/\alpha} R_n \) is a strictly \( \alpha \)-stable random variable provided that \( \alpha \in (0, 2] \) and this series converges a.s.

Proof Let \( X_1 = \sum_{n=1}^{\infty} (T_n^{(i)})^{-1/\alpha} R_n^{(i)}, i = 1, 2, 3 \) be three independent copies of \( X, \) where \( \{R_n\} \overset{d}{=} \{R_n^{(i)}\}, i = 1, 2, 3, \) \( \{T_n\} \overset{d}{=} \{T_n^{(i)}\}, i = 1, 2, 3, \) and all three sequences are independent.

By Definition 2.1.4 and Remark 2.1.5, it suffices to show that:
\[
\begin{align*}
X_1 + X_2 & \overset{d}{=} 2^{1/\alpha} X, \\
X_1 + X_2 + X_3 & \overset{d}{=} 3^{1/\alpha} X,
\end{align*}
\]

\( 2^{1/\alpha} X = \sum_{n=1}^{\infty} (T_n/2)^{-1/\alpha} R_n, \) where \( \{T_n/2\}_{n \in \mathbb{N}} \) forms a Poisson process \( 2N \) with intensity \( \lambda = 2, \) since \( \tau_n/2 = (T_n - T_{n-1})/2 \forall n, \) and \( \mathbb{P}(\tau_n/2 \geq x) = \mathbb{P}(\tau_n \geq 2x) = \exp(-2x), x \geq 0. \)

It is clear that \( X_1 + X_2 = \sum_{n=1}^{\infty} (T_n')^{-1/\alpha} R_n', \) where \( \{T_n'\} \) are arrival times of the superposition \( N_1 + N_2 \) (being a Poisson process of intensity \( 2, \) cf. Exercise 2.5.1), and \( R_n' = \begin{cases} R_k^{(1)}, & \text{if } T_n' = T_k^{(1)} \text{ for some } k \in \mathbb{N} \\ R_k^{(2)}, & \text{if } T_n' = T_m^{(2)} \text{ for some } m \in \mathbb{N} \end{cases} \)

Since \( \{R_n\}_{n \in \mathbb{N}} \overset{d}{=} \{R_n'\}_{n \in \mathbb{N}}, \) and \( N_1 + N_2 \overset{d}{=} 2N, \) we have \( X_1 + X_2 \overset{d}{=} X, \) so we are done. For \( X_1 + X_2 + X_3, \) the proof is analogous. \( \square \)

In order to get a series representation of a \( S\alpha S \) random variable \( X, \) we’ll have to ensure the a.s. convergence of this series. For that, we impose restrictions on \( \alpha \in (0, 2) \) and on \( \{R_n\} : \) we assume \( R_n = \varepsilon_n W_n, \) where \( \varepsilon_n = \text{sign}(R_n) = \begin{cases} +1, & \text{if } R_n > 0, \\ -1, & \text{if } R_n < 0, \end{cases} \) \( W_n = |R_n|, \mathbb{E}W^\alpha < \infty. \)

Theorem 2.5.1 (LePage representation):
Let \( \{\varepsilon_n\}, \{W_n\}, \{T_n\} \) be independent sequences of random variables, where \( \{\varepsilon_n\}_{n \in \mathbb{N}} \) are i.i.d. Rademacher random variables, \( \varepsilon_n = \begin{cases} +1, & \text{with probability } 1/2, \\ -1, & \text{with probability } 1/2 \end{cases} \) \( \{W_n\}_{n \in \mathbb{N}} \) are i.i.d. random variables with \( \mathbb{E}|W_n|^\alpha < \infty, \alpha \in (0, 2), \) and \( \{T_n\}_{n \in \mathbb{N}} \) is the sequence of arrival times of a unit rate Poisson process \( N (\lambda = 1). \)
Then \( X \stackrel{a.s.}{=} \sum_{n=1}^{\infty} \varepsilon_n T_n^{-1/\alpha} W_n \sim S_\alpha(\sigma, 0, 0) \), where this series converges a.s., \( \sigma = \frac{\mathbb{E}|W_1|^{\alpha}}{c_0} \), and \( c_0 \) is a constant introduced in Proposition 2.3.5.

**Remark 2.5.1**

1) Proposition 2.5.2 yields the fact that \( X \sim S_\alpha \), but it does not give insights into the value of \( \sigma \).

2) Since the distribution of \( X \) depends only on \( \mathbb{E}|W_1|^{\alpha} \), it does not matter, which \( \{W_n\} \) we choose. A usual choice can be \( W_n \sim U[0,1] \), or \( W_n \sim N(0,1) \). Hence, \( W_n \) do not need to be non-negative, as in the comment before Theorem 2.5.1.

3) The LePage representation is not used to simulate stable variables, since the convergence of the series is rather slow. Indeed, methods in Chapter 3 are widely used.

4) Skewed stable variables have another series representation which will be given (without proof) in Theorem 2.5.3 below.

5) It follows directly from Theorem 2.5.1 that for any \( S_\alpha \) random variable \( X \sim S_\alpha(\lambda, 0, 0) \), it has the LePage representation \( X \stackrel{d}{=} \left( \frac{c_0 \lambda}{\mathbb{E}|W_1|^{\alpha}} \right)^{1/\alpha} \sum_{n=1}^{\infty} \varepsilon_n T_n^{-1/\alpha} W_n \), where sequences \( \{\varepsilon_n\} \), \( \{W_n\} \), \( \{T_n\} \) are chosen as above. In particular, choosing the law of \( W_1 \) s.t. \( \mathbb{E}|W_1|^{\alpha} = \lambda \) reduces the representation to \( X \stackrel{d}{=} c_0^{1/\alpha} \sum_{n=1}^{\infty} \varepsilon_n T_n^{-1/\alpha} W_n \). Since \( T_n \uparrow \) a.s. as \( n \to \infty \), the terms \( \varepsilon_n T_n^{-1/\alpha} W_n \downarrow \) stochastically, and one can show that the very first term \( \varepsilon_1 T_1^{-1/\alpha} W_1 \) dominates the whole tail behaviour of \( X \). In more details, by Proposition 2.3.5, it holds \( \mathbb{P}(X > x) \sim \frac{1}{2} c_0 \lambda x^{-\lambda} \) as \( x \to +\infty \), and it is not difficult to see that

\begin{align*}
a) & \quad \mathbb{P}(c_0^{1/\alpha} \varepsilon_1 T_1^{-1/\alpha} W_1 > x) \sim \frac{1}{2} c_0 \lambda x^{-\lambda} \quad \text{as} \quad x \to +\infty, \\
b) & \quad \mathbb{P}(\sum_{n=0}^{\infty} \varepsilon_n T_n^{-1/\alpha} W_n > x) = o(x^{-\alpha}) \quad \text{as} \quad x \to +\infty.
\end{align*}

**Exercise 2.5.2**

Prove the statement of the previous Remark 5,a).

**Proof of Theorem 2.5.1**

1) Let \( \{U_n\}_{n \in \mathbb{N}} \) be a sequence of i.i.d. \( U[0,1] \)-distributed random variables, independent of \( \{\varepsilon_n\}_{n \in \mathbb{N}} \) and \( \{W_n\}_{n \in \mathbb{N}} \). Then \( \{Y_n\}_{n \in \mathbb{N}} \) given by \( Y_n = \varepsilon_n U_n^{-1/\alpha} W_n, n \in \mathbb{N} \) is a sequence of symmetric i.i.d. random variables. Let us show that the law of \( Y_1 \) lies in the domain of attraction of a \( S_\alpha \) random variable. For that, compare its tail probability

\[
\mathbb{P}(|Y_1| > x) = \mathbb{P}(U_1^{-1/\alpha}|W_1| > x) = \mathbb{P}(U_1 < x^{-\alpha}|W_1|^{\alpha}) = \int_0^{\infty} \mathbb{P}(U_1 < x^{-\alpha} \omega^{\alpha}) dF_{|W_1|}(\omega) = \int_0^{\infty} x^{-\alpha} \omega^{\alpha} dF_{|W_1|}(\omega) + \int_\infty^{\infty} dF_{|W_1|}(\omega) = x^{-\alpha} \int_0^{\infty} \omega^{\alpha} dF_{|W_1|}(\omega) + \mathbb{P}(|W_1| > x),
\]

where \( F_{|W_1|}(x) = \mathbb{P}(|W_1| \leq x) \). So,

\[
\lim_{x \to +\infty} x^\alpha \mathbb{P}(|Y_1| > x) = \left[ \int_0^{\infty} \omega^{\alpha} dF_{|W_1|}(\omega) + \lim_{x \to +\infty} x^\alpha \mathbb{P}(|W_1| > x) \right] = \mathbb{E}|W_1|^{\alpha}.
\]

Hence, condition (2.4.3) of Theorem 2.4.1 is satisfied. Due to symmetry of \( Y_1 \), tail balance condition (2.4.2) is obviously true with \( p = q = 1/2 \). Then, by Theorem 2.4.1 and Corollary 2.1.1, it holds \( \frac{1}{n^{1/\alpha}} \sum_{k=1}^{n} Y_k \xrightarrow{d} X \sim S_\alpha(\sigma, 0, 0) \), where the parameters \( (\lambda, \beta, \gamma) \) of the limiting stable law come from the proof of Theorem 2.1.1 with \( c_1 = c_2 = \frac{\mathbb{E}|W_1|^{\alpha}}{2} \) (due to the symmetry of \( Y_1 \) and \( X \)).
2) Rewrite \( \frac{1}{n^{1/\alpha}} \sum_{k=1}^{n} Y_k \) to show that is limiting random variables \( X \) coincides with 
\( \sum_{k=1}^{\infty} \varepsilon_k T_k^{-1/\alpha} W_k \).

**Exercise 2.5.3**

Let \( N \) be the Poisson process with intensity \( \lambda > 0 \) built upon arrival times \( \{T_n\}_{n \in \mathbb{N}} \). Show that

a) under the condition \( \{T_{n+1} = t\} \) it holds \( (T_{1/t}, \ldots, T_{n/t}) \overset{d}{=} (u(1), \ldots, u(n)) \), where \( u(k), k = 1, \ldots, n \) are order statistics of a sample \( (u_1, \ldots, u_n) \) with \( u_k \sim U(0, 1) \) being i.i.d. random variables.

b) \( (T_{1/n}, \ldots, T_{n+1}) \overset{d}{=} (u(1), \ldots, u(n)) \).

Reorder the terms \( Y_k \) in the sum \( \sum_{k=1}^{n} Y_k \) in order of ascending \( u_k \), so to have \( \sum_{k=1}^{n} \varepsilon_k u_k^{-1/\alpha} W_k \).

Since \( W_k \) and \( \varepsilon_k \) are i.i.d., this does not change the distribution of the whole sum. Then

\[
\frac{1}{n^{1/\alpha}} \sum_{k=1}^{n} Y_k = \frac{1}{n^{1/\alpha}} \sum_{k=1}^{n} \varepsilon_k U_{(k)}^{1/\alpha} W_k = \frac{1}{n^{1/\alpha}} \sum_{k=1}^{n} \varepsilon_k \left( \frac{T_k}{T_{n+1}} \right)^{-1/\alpha} W_k
\]

by Exercise 2.5.3 b). Then, by part 1), \( \left( \frac{T_{n+1}}{n} \right)^{1/\alpha} \sum_{k=1}^{n} \varepsilon_k T_k^{-1/\alpha} W_k \overset{d}{\rightarrow} X \) with \( X \) as above.

3) Show that \( S_n \overset{d}{\rightarrow} \sum_{k=1}^{\infty} \varepsilon_k T_k^{-1/\alpha} W_k \), then we are done, since then \( S_n(\sigma, 0, 0) \sim X \overset{d}{=} \sum_{k=1}^{\infty} \varepsilon_k T_k^{-1/\alpha} W_k \). By the strong law of large numbers, it holds \( \frac{T_{n+1}}{n} = \frac{T_{n+1} + u + 1}{n+1} \overset{a.s.}{\rightarrow} \mathbb{E}T_1 = 1 \), as \( n \to \infty \), since the Poisson process \( N \) has the unit rate, and \( T_1 \sim \text{Exp}(1) \). Then \( \mathbb{P}(A) = 1 \), where \( A = \{\lim_{n \to \infty} \frac{T_n}{n} = 1\} \cap T_1 > 0 \). Let us show that \( \forall \omega \in A \), \( \sum_{k=1}^{\infty} \varepsilon_k(\omega)(T_k(\omega))^{-1/\alpha} W_k(\omega) < \infty \). Apply the following three-series theorem by Kolmogorov (without proof).

**Theorem 2.5.2 (Three-series theorem by Kolmogorov):**

Let \( \{Y_n\}_{n \in \mathbb{N}} \) be a sequence of independent random variables. Then \( \sum_{n=1}^{\infty} Y_n < \infty \) a.s. iff \( \forall s > 0 \)

a) \( \sum_{n=1}^{\infty} \mathbb{P}(|Y_n| > s) < \infty \)

b) \( \sum_{n=1}^{\infty} \mathbb{E}(Y_n 1(|Y_n| \leq s)) < \infty \)

c) \( \sum_{n=1}^{\infty} \mathbb{V}(Y_n 1(|Y_n| \leq s)) < \infty \)

See the proof in [1, Theorem IX.9.2.]

Let us check conditions a)-c) above. \( \forall s > 0 \)

a) \( \sum_{n=1}^{\infty} \mathbb{P}(|\varepsilon_n T_n^{-1/\alpha} W_n| > s) = \sum_{n=1}^{\infty} \mathbb{P}(|W_n|^\alpha > s^\alpha T_n) \leq \sum_{n=1}^{\infty} \mathbb{P}(|W_1|^\alpha > s^\alpha c_n) < \infty \),

since \( \exists c_1, c_2 > 0 : c_1 n \leq T_n(\omega) \leq c_2 n \forall n > N(\omega) \) (due to \( \frac{T_n(\omega)}{n} \overset{d}{\rightarrow} 1 \) \( \forall \omega \in A \)) and \( \mathbb{E}|W_1|^\alpha < \infty \) by assumptions.

b) It holds \( \mathbb{E} \left[ \varepsilon_n T_n^{-1/\alpha} W_n 1(|\varepsilon_n T_n^{-1/\alpha} W_n| \leq s) \right] = \mathbb{E} \left[ T_n^{-1/\alpha} W_n 1(|T_n^{-1/\alpha} W_n| \leq s) \right] = 0 \) by independence of \( \varepsilon_n \) from \( T_n \) and \( W_n \), and by symmetry of \( \{\varepsilon_n\} \). Then \( \sum_{n=1}^{\infty} \mathbb{E} \left[ \varepsilon_n T_n^{-1/\alpha} W_n 1(|\varepsilon_n T_n^{-1/\alpha} W_n| \leq s) \right] = 0 < \infty \).
Remark 2.5.2

Let \( W \in X \) be independent of \( \lambda \) and \( \beta \) as above, and \( \beta \) being a constant introducing in Proposition 2.3.5, \( \beta = \frac{\mathbb{E}[|W_1|^\alpha \text{sign}(W_1)]}{\mathbb{E}[|W_1|^\alpha]} \), and

\[
\kappa^{(\alpha)}_n = \begin{cases} 
0, & 0 < \alpha < 1, \\
\frac{\mathbb{E}\left(W_1 \left|\frac{|W_1|}{|W_1|^\alpha} \sin x \right.\right)}{\alpha - 1} - (n - 1) \left(\frac{n}{n - 1}\right) \mathbb{E}W_1, & \alpha > 1.
\end{cases}
\]

If \( \alpha = 1 \), then

\[
X := \sum_{n=1}^{\infty} \left( T_n^{-1}W_n - \mathbb{E}\left(W_1 \left|\frac{|W_1|}{|W_1|^\alpha} \sin x \right.\right) \right) \sim S_\alpha(\lambda, \beta, \gamma),
\]

(2.5.1)

with \( \lambda \) and \( \beta \) as above, and \( \gamma = -\frac{1}{\lambda} \mathbb{E}(W_1 \log |W_1|) \).

\textbf{Proof} see [3, §1.5.] \hfill \Box

Some remarks are in order.

\textbf{Remark 2.5.2}

1) The statement of Theorem 2.5.3 can be easily converted into a representation: a random variable \( X \sim S_\alpha(\lambda, \beta, \gamma), 0 < \alpha < 2 \), has a representation \( X \overset{d}{=} \lambda \gamma + \sum_{n=1}^{\infty} (T_n^{-1/\alpha}W_n - \kappa^{(\alpha)}_n) \), where the i.i.d. random variables \( \{W_n\}_{n \in \mathbb{N}} \) satisfy \( \mathbb{E}[|W_1|^\alpha] = c_\alpha \lambda, \mathbb{E}(|W_1|^2 \text{sign}(W_1)) = c_\alpha \beta \lambda \).

Apart from this restrictions on \( \{W_n\}_{n \in \mathbb{N}} \), the choice of their distribution is deliberate.

2) Theorem 2.5.1 is a special case of Theorem 2.5.3 if we replace \( W_n \) by \( \varepsilon_n W_n \), where \( \{\varepsilon_n\}_{n \in \mathbb{N}} \) are independent of \( \{W_n\}_{n \in \mathbb{N}} \) i.i.d. random variables.
3) The LePage representation of a stable subordinator $X \sim S_\alpha(\lambda, 1, 0), \lambda > 0, \alpha \in (0, 1)$, follows easily from Theorem 2.5.3. Indeed, set $W_n = 1, \forall n$. Then, $\sum_{n=1}^{\infty} T_n^{-1/\alpha} \sim S_\alpha(c_\alpha^{-1}, 1, 0)$, so $X \overset{d}{=} \lambda^{1/\alpha} c_\alpha^{1/\alpha} \sum_{n=1}^{\infty} T_n^{-1/\alpha}$.

4) For $\alpha \geq 1$, the series $\sum_{n=1}^{\infty} T_n^{-1/\alpha} W_n$ diverges in general, if $W_n$ are not symmetric. Hence, the correction $\kappa_\alpha^{(n)}$ is needed, which is of order of $E(W_n T_n^{-1/\alpha})$. Indeed, for $\lambda > 1$ $E(T_n^{-1/\alpha} W_n) = E T_n^{-1/\alpha} E W_n \sim n^{-1/\alpha} E W_1 \sim \kappa_\alpha^{(n)}$. Analogously, for $\alpha = 1$ $E(T_n^{-1} W_n) \sim n^{-1} E W_1 \sim \int_{1/n}^{1/(n-1)} \sin x dx \cdot E W_1$ as in (2.5.1).

The following result yields the integral form of the cumulative distribution function of a $S\alpha S$ law.

**Theorem 2.5.4**

1) Let $X \sim S_\alpha(1, 0, 0)$ be a $S\alpha S$ random variable, $\alpha \neq 1, \alpha \in (0, 2]$. Then

$$\frac{1}{\pi} \int_{0}^{\pi/2} \exp \left( -x^{\alpha-1} \kappa_\alpha(t) \right) dt = \begin{cases} P(0 \leq X \leq x), & \alpha \in (0, 1), \\ P(X > x), & \alpha \in (1, 2] \end{cases}$$

for $x > 0$, where

$$\kappa_\alpha(t) = \left( \frac{\sin(\alpha t)}{\cos t} \right)^{\alpha-1} \cos((1-\alpha)t), t \in \left(0, \frac{\pi}{2}\right].$$

2) Let $X \sim S_\alpha(1, 1, 0), \alpha \in (0, 1]$. Then

$$P(X \leq x) = \frac{1}{\pi} \int_{-\pi/2}^{\pi/2} \exp \left( -x^{\alpha-1} \bar{\kappa}_\alpha(t) \right) dt, x > 0,$$

where

$$\bar{\kappa}_\alpha(t) = \left( \frac{\sin(\alpha(\pi/2 + t))}{\sin(\pi/2 + t)} \right)^{\alpha-1} \frac{\sin((1-\alpha)(\pi/2 + t))}{\sin(\pi/2 + t)}, t \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right].$$

See [5, Remark 1 p.78.]
3 Simulation of stable variables

In general, the simulation of stable laws can be demanding. However, in some particular cases, it is quite easy.

**Proposition 3.0.1** (Lévy distribution). Let $X \sim S_{1/2}(\lambda, 1, \gamma)$. Then $X$ can be simulated by representation $X \overset{d}{=} \lambda^2 Y^{-2} + \lambda \gamma$, where $Y \sim N(0, 1)$.

**Proof** It follows from Exercise 1.0.6.1) and Theorem 2.3.1, 3),4).

**Proposition 3.0.2** (Cauchy distribution). Let $X \sim S_1(\lambda, 0, \gamma)$. Then $X$ can be simulated by representations
1) $X \overset{d}{=} \lambda Y_1^2 + \lambda \gamma$, where $Y_1$ and $Y_2$ are i.i.d. $N(0, 1)$ random variables,
2) $X \overset{d}{=} \lambda \text{tg}(\pi(U - 1/2)) + \lambda \gamma$, where $U \sim \text{Uniform}[0, 1]$.

**Proof** 1) Use Exercise 4.1.29 and the scaling properties of stable laws given in Theorem 2.3.1, 3),4).

2) By Example 1.0.2 it holds $\text{tg} d \overset{d}{=} Z, Y \sim U[-\pi/2, \pi/2] \overset{d}{=} \pi(U - 1/2), Z \sim \text{Cauchy}(0, 1) \sim S_1(1, 0, 0)$. Then use again Theorem 2.3.1, 3),4) to get $X \overset{d}{=} \lambda Z + \lambda \gamma$.

Now we reduced the simulation of Lévy and Cauchy laws to the simulation of $U[0,1]$ and $N(0,1)$ random variables. A realisation of a $U[0,1]$ is given by generators of pseudorandom numbers built into any programming language. The simulation of $N(0,1)$ is more involved, and we give it in the following Proposition 3.0.3 below. From this, it can be easily seen that the method of Proposition 3.0.2, 2) is much more efficient and fast than that of Proposition 3.0.2, 1).

**Proposition 3.0.3.** 1) Let $R$ and $\theta$ be independent random variables, $R^2 \sim \text{Exp}(1/2)$, $\theta \sim U[0, 2\pi]$. Then $X_1 = R \cos \theta$ and $X_2 = R \sin \theta$ are independent $N(0, 1)$-distributed random variables.

2) A random variable $X \sim N(u, \sigma^2)$ can be simulated by $X \overset{d}{=} \mu + \sigma \sqrt{2 \log U} \cos(2\pi V)$, where $U, V \sim U[0, 1]$ are independent.

**Proof** 1) For any $x, y \in \mathbb{R}$ consider
\[
P(X_1 \leq x, X_2 \leq y) = P(\sqrt{R^2 \cos \theta} \leq x, \sqrt{R^2 \sin \theta} \leq y)
= \frac{1}{2\pi} \int_0^{2\pi} \int_0^\infty (\sqrt{t} \cos \varphi \leq x, \sqrt{t} \sin \varphi \leq y) \frac{1}{2} e^{-t/2} dt d\varphi = |t = r^2|
= \frac{1}{2\pi} \int_0^{2\pi} \int_0^\infty (r \cos \varphi \leq x, r \sin \varphi \leq y) r e^{-r^2/2} dr d\varphi
= \frac{1}{2\pi} \int_0^\infty \int_0^\infty (x_1 \leq x, x_2 \leq y) e^{-x_1^2 + x_2^2}/x_2 dx_1 dx_2
= \frac{1}{\sqrt{2\pi}} \int_0^x e^{-x_1^2/2} dx_1 \frac{1}{\sqrt{2\pi}} \int_0^y e^{-x_2^2/2} dx_2 = \mathbb{P}(X_1 \leq x) \mathbb{P}(X_2 \leq y).
\]
Hence, \( X_1, X_2 \sim N(0,1) \) are independent.

2) If \( X \sim N(\mu, \sigma^2) \) then \( Y = \frac{X - \mu}{\sigma} \sim N(0,1) \). By 1), \( Y \overset{d}{=} R \cos \Theta \), where \( R^2 \sim \text{Exp}(1/2) \), \( \Theta \overset{d}{=} 2\pi V, V \sim U[0,1] \). Simulate \( R^2 \) by the inversion method, i.e. show that \( R \overset{d}{=} -2 \log U \), where \( U \sim U[0,1] \), independent of \( V \). Indeed, \( \mathbb{P}(-2 \log U \leq x) = \mathbb{P}(\log U \geq -x/2) = \mathbb{P}(U \geq e^{-x/2}) = 1 - e^{-x/2}, x \geq 0 \). Hence \( -2 \log U \sim \text{Exp}(1/2) \), then, it holds \( \frac{X - \mu}{\sigma} \overset{d}{=} \sqrt{-2 \log U} \cos(2\pi V) \), and we are done.

\[\square\]

**Remark 3.0.1 (Inverse function method):**

From the proof of Proposition 3.0.3, 2) it follows that for \( X \sim \text{Exp}(\lambda) \) it holds \( X \overset{d}{=} -1/\lambda \log U, U \sim U[0,1], \lambda > 0 \). This is the particular case of the so-called inverse function simulation method: for any random variable \( X \) with c.d.f. \( F_X(x) = \mathbb{P}(X \leq x) \) s.t. \( F_X \) is increasing on \((a,b)\) with \(-\infty \leq a < b < +\infty \), \( \lim_{x \to a^+} F_X(x) = 0, \lim_{x \to b^-} F_X(x) = 1 \) : it holds \( X \overset{d}{=} F_X^{-1}(U) \), where \( U \sim U[0,1], \) and \( F_X^{-1} \) is the quantile function of \( X \). Indeed, we may write \( \mathbb{P}(F_X^{-1}(U) \leq x) = \mathbb{P}(U \leq F_X(x)) = F_X(x), x \in (a,b) \), since \( \mathbb{P}(U \leq y) = y, \forall y \in [0,1] \).

**Theorem 3.0.1 (Simulation of \( S_\alpha(1,0,0) \)):**

Let \( X \sim S_\alpha(1,0,0), \alpha \in (0,2] \). Then \( X \) can be simulated by representation

\[
X \overset{d}{=} \frac{\sin(\alpha \pi(U - 1/2))}{(\cos(\pi(U - 1/2)))^{1/\alpha}} \left( \frac{\cos((1 - \alpha)\pi(U - 1/2))}{-\log V} \right)^{1/\alpha},
\]

where \( U, V \sim U[0,1] \) are independent random variables.

**Proof** Denote \( T = \pi(U - 1/2), W = -\log V \). By Remark 3.0.1 it is clear that \( T \sim U[-\pi/2, \pi/2], W \sim \text{Exp}(1) \). So (3.0.1) reduces to

\[
X \overset{d}{=} \frac{\sin(\alpha T)}{\cos(T)^{1/\alpha}} \left( \frac{\cos((1 - \alpha)T)}{W} \right)^{1/\alpha}.
\]

1) \( \alpha = 1 \) : Then (3.0.2) reduces to \( X \overset{d}{=} \text{tg}T \), which was proven in Proposition 3.0.2,2).

2) \( \alpha \in (0,1) \) : Under the condition \( T > 0 \), relation (3.0.2) rewrites as \( X \overset{d}{=} Y = \left( \frac{K_\alpha(T)}{W} \right)^{1/\alpha} \), where \( K_\alpha(T) = \left( \frac{\sin(\alpha T)}{\cos(T)} \right)^{1/\alpha} \cos((1 - \alpha)T)W^{1/\alpha} \) as in Theorem 2.5.1.

Then

\[
\mathbb{P}(0 \leq Y \leq x) = \mathbb{P}(0 \leq Y \leq x, T > 0) = |Y \geq 0 \Leftrightarrow T > 0| = \mathbb{P} \left( 0 \leq \left( \frac{K_\alpha(T)}{W} \right)^{1/\alpha} \leq x, T > 0 \right) = \mathbb{P}(W \geq K_\alpha(T)x^{-\alpha/\alpha}, T > 0) = \frac{1}{\pi} \int_0^{\pi/2} \mathbb{P}(W \geq K_\alpha(t)x^{-\alpha/\alpha})dt \overset{W \sim \text{Exp}(1)}{=} \frac{1}{\pi} \int_0^{\pi/2} \exp \left( -K_\alpha(t)x^{\alpha/\alpha} \right) dt.
\]

Hence, \( Y \sim S_\alpha(1,0,0) \) by Theorem 2.5.4 \( \Rightarrow X \overset{d}{=} Y \sim S_\alpha(1,0,0) \).

3) \( \alpha \in (1,2] \) is proven analogously as in 2) considering \( 1 - \alpha < 0 \) and \( \mathbb{P}(Y \geq x) = \mathbb{P}(Y \geq x, T > 0) \). 

\[\square\]
Remark 3.0.2
In the Gaussian case $\alpha = 2$, the formula (3.0.2) reduces to $X_d = \sqrt{W} \sin(T) = \sqrt{2 \sin T}$, so $2W \sim \text{Exp}(1/2)$. Hence, $X \sim N(0, 2)$ is generated by the algorithm 2) of Proposition 3.0.3, so formula (3.0.1) contains Proposition 2.4.7,2) as a special case.

Now let us turn to the general case of simulating a random variable $X \sim S_\alpha(\lambda, \beta, \gamma)$. We show first that, to this end, it sufficient to know how to simulate $X \sim S_\alpha(1, 1, 0)$.

Lemma 3.0.1
Let $X \sim S_\alpha(\lambda, \beta, \gamma), \alpha \in (0, 2)$. Then

$$X_d = \begin{cases} \lambda \gamma + \lambda^{1/\alpha} Y, & \alpha \neq 1, \\ \lambda \gamma + \frac{2}{\pi} \beta \lambda \log \lambda + \lambda Y, & \lambda = 1, \end{cases} \quad (3.0.3)$$

where $Y \sim S_\alpha(1, 1, 0)$ can be simulated by

$$Y_d = \begin{cases} \left(\frac{1+\beta}{2}\right)^{1/\alpha} Y_1 - \left(\frac{1-\beta}{2}\right)^{1/\alpha} Y_2, & \alpha \neq 1, \\ \left(\frac{1+\beta}{2}\right) Y_1 - \left(\frac{1-\beta}{2}\right) Y_2 + \frac{1}{\pi} \left(1 + \beta\right) \log \left(\frac{1+\beta}{2}\right) - \left(1 - \beta\right) \log \left(\frac{1-\beta}{2}\right), & \alpha = 1, \end{cases} \quad (3.0.4)$$

with $Y_1, Y_2 \sim S_\alpha(1, 1, 0)$ being independent random variables.

Proof Relation (3.0.4) follows from the proof of Proposition 2.3.3 and Exercise 4.1.28. Relation (3.0.3) follows easily from Theorem 2.3.1,3)-4).

Now let us simulate $X \sim S_\alpha(1, 1, 0)$. First, we do it for $\alpha \in (0, 1)$.

Lemma 3.0.2
Let $X \sim S_\alpha(1, 1, 0), \alpha \in (0, 1)$. Then $X$ can be simulated by $X \overset{d}{=} \frac{\sin(\alpha \theta)}{\sin \theta} \left(\frac{\sin((1-\alpha) \theta)}{\sin \theta}\right)^{1-\alpha}, \quad \text{where} \theta$ and $W$ are independent random variables, $\theta \sim U[0, \pi], W \sim \text{Exp}(1)$. As before, $\theta$ and $W$ can be simulated by $\theta \overset{d}{=} \pi U, U \sim U[0, 1], \text{where } W \overset{d}{=} -\log V, V \sim U[0, 1], \text{where } U$ and $V$ are independent.

Proof By Theorem 2.5.4, 2) we have true following representation formula for the c.d.f. $\mathbb{P}(X \leq x) = F_X(x)$:

$$F_X(x) = \frac{1}{\pi} \int_{-\pi/2}^{\pi/2} \exp \left(-\frac{x}{\pi} \frac{\alpha}{\sin \theta} \tilde{K}_\alpha(t) \right) dt, x > 0,$$

where

$$\tilde{K}_\alpha(t) = \left(\frac{\sin(\alpha (\pi/2 + t))}{\sin(\pi/2 + t)}\right)^{1-\alpha} \sin((1 - \alpha)(\pi/2 + t)) = \left(\frac{\sin(\alpha (\pi/2 + t))}{\sin(\pi/2 + t)}\right)^{1-\alpha} \sin(\pi/2 + t), t \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right).$$

The rest of the proof is exactly as in Theorem 3.0.1, 2).

Similar results can be proven for $\alpha \in [1, 2)$.\qed
Theorem 3.0.2

The random variable $X \sim S_{\alpha}(1, 1, 0), \alpha \in [1, 2)$ can be simulated by

$$X \overset{d}{=} \begin{cases} \frac{2}{\pi} \left( (\pi/2 + T)\tan T - \log \left( \frac{2W \cos T}{\pi + T} \right) \right), & \alpha = 1, \\ (1 + \tan^2 \left( \frac{\pi}{2} \alpha \right) ) \frac{1}{\alpha} \sin \left( \frac{(1-\alpha)T - \alpha \pi/2}{W} \right) \frac{1-\alpha}{\alpha} & \alpha \in (1, 2), \end{cases}$$

where $W \sim \text{Exp}(1)$ and $T \sim U[-\pi/2, \pi/2]$ are independent random variables.

Without proof.
4 Additional exercises

4.1

Exercise 4.1.1
Let $X_1, X_2$ be two i.i.d. r.v.’s with probability density $\varphi$. Find a probability density of $aX_1+bX_2$, where $a, b \in \mathbb{R}$.

Exercise 4.1.2
Let $X$ be a symmetric stable random variable and $X_1, X_2$ be its two independent copies. Prove that $X$ is a strictly stable r.v., i.e., for any positive numbers $A$ and $B$, there is a positive number $C$ such that $AX_1 + BX_2 \overset{d}{=} CX$.

Exercise 4.1.3
1. Prove that $\varphi = \{e^{-|x|}, x \in \mathbb{R}\}$ is a characteristic function. (Check Pólya’s criterion for characteristic functions.)

2. Let $X$ be a real r.v. with characteristic function $\varphi$. Is $X$ a stable random variable? (Verify definition.)

Exercise 4.1.4
Let real r.v. $X$ be Lévy distributed (see Exercise Sheet 1, Ex. 1-4). Find the characteristic function of $X$. Give parameters $(\alpha, \sigma, \beta, \mu)$ for the stable random variable $X$.

Hint: You may use the following formulas. \(^{2}\)

\[
\int_{0}^{\infty} \frac{e^{-1/(2x)}}{x^{3/2}} \cos(yx) dx = \sqrt{2\pi} e^{-\sqrt{|y|}} \cos(\sqrt{|y|}), \quad y \in \mathbb{R},
\]
\[
\int_{0}^{\infty} \frac{e^{-1/(2x)}}{x^{3/2}} \sin(yx) dx = \sqrt{2\pi} e^{-\sqrt{|y|}} \sin(\sqrt{|y|}) \text{sign} y, \quad y \in \mathbb{R}.
\]

Exercise 4.1.5
Let $Y$ be a Cauchy distributed r.v. Find the characteristic function of $Y$. Give parameters $(\alpha, \sigma, \beta, \mu)$ for the stable random variable $Y$.

Hint: Use Cauchy’s residue theorem.

Exercise 4.1.6
Let $X \sim S_1(\sigma, \beta, \mu)$ and $a > 0$. Is $aX$ stable? If so, define new $(\alpha_2, \sigma_2, \beta_2, \mu_2)$ of $aX$.

Exercise 4.1.7
Let $X \sim N(0, \sigma^2)$ and $A$ be a positive $\alpha$—stable r.v. Is the new r.v. $AX$ stable, strictly stable? If so, find its stability index $\alpha_2$.

---

1 Pólya’s theorem. If $\varphi$ is a real-valued, even, continuous function which satisfies the conditions $\varphi(0) = 1$, $\varphi$ is convex for $t > 0$, $\lim_{t \to \infty} \varphi(t) = 0$, then $\varphi$ is the characteristic function of an absolutely continuous symmetric distribution.

Exercise 4.1.8
Let $L$ be a positive slowly varying function, i.e., $\forall x > 0$

$$\lim_{t \to +\infty} \frac{L(tx)}{L(t)} = 1.$$  \hspace{1cm} (4.1.1)

1. Prove that $x^{-\varepsilon} \leq L(x) \leq x^\varepsilon$ for any fixed $\varepsilon > 0$ and all $x$ sufficiently large.

2. Prove that limit (4.1.1) is uniform in finite intervals $0 < a < x < b$.

Hint: Use a representation theorem:\(^3\)
A function $Z$ varies slowly iff it is of the form $Z(x) = a(x) \exp\left(\int x^{-\varepsilon(y)} dy\right)$, where $\varepsilon(x) \to 0$ and $a(x) \to c < \infty$ as $x \to \infty$.

Definition 4.1.1 (Infinitely divisible distributions):
A distribution function $F$ is called infinitely divisible if for all $n \geq 1$, there is a distribution function $F_n$ such that

$$Z \overset{d}{=} X_{n,1} + \cdots + X_{n,n},$$

where $Z \sim F$ and $X_{n,k}, 1 \leq k \leq n$ are i.i.d. r.v.’s with the distribution function $F_n$.

Exercise 4.1.9
For the following distribution functions check whether they are infinitely divisible.

1. (1 point) Gaussian distribution.
2. (1 point) Poisson distribution.
3. (1 point) Gamma distribution.

Exercise 4.1.10
Find parameters $(a, b, H)$ in the canonic Lévy-Khintchin representation of a characteristic function for

1. (1 point) Gaussian distribution.
2. (1 point) Poisson distribution.
3. (1 point) Lévy distribution.

Exercise 4.1.11
What is wrong with the following argument? If $X_1, \ldots, X_n \sim Gamma(\alpha, \beta)$ are independent, then $X_1 + \cdots + X_n \sim Gamma(n\alpha, \beta)$, so gamma distributions must be stable distributions.

Exercise 4.1.12
Let $X_i, i \in \mathbb{N}$ be i.i.d. r.v.’s with a density symmetric about 0 and continuous and positive at 0. Prove

$$\frac{1}{n} \left(\frac{1}{X_1} + \cdots + \frac{1}{X_n}\right) \overset{d}{\to} X, n \to \infty,$$

where $X$ is a Cauchy distributed random variable.

Hint: At first, apply Khintchin’s theorem (T.2.2 in the lecture notes). Then find parameters $a, b$ and a spectral function $H$ from Gnedenko’s theorem (T.2.3 in the lecture notes).

Exercise 4.1.13
Show that the sum of two independent stable random variables with different \( \alpha \)-s is not stable.

Exercise 4.1.14
Let \( X \sim S_\alpha(\lambda, \beta, \gamma) \). Using the weak law of large numbers prove that when \( \alpha \in (1, 2) \), the shift parameter \( \mu = \lambda \gamma \) equals \( \mathbb{E}X \).

Exercise 4.1.15
Let \( X \) be a standard Lévy distributed random variable. Compute its Laplace transform \( \mathbb{E} \exp(-\gamma X), \gamma > 0 \).

Exercise 4.1.16
Let \( X \sim S_\alpha'(\lambda', 1, 0) \), and \( A \sim S_{\alpha/\alpha'}(\lambda_A, 1, 0) \), \( 0 < \alpha < \alpha' < 1 \) be independent. The value of \( \lambda_A \) is chosen s.t. the shift parameter \( \mu = \lambda \gamma \) equals \( \mathbb{E}X \).

Exercise 4.1.17
Let \( X \sim S_\alpha(\lambda, 1, 0), \alpha < 1 \) and the Laplace transform of \( X \) be given by \( \mathbb{E} \exp(-\gamma X) = \exp(-c_\alpha \gamma^\alpha), \gamma > 0 \), where \( c_\alpha = \lambda^\alpha / \cos(\pi \alpha/2) \).

1. Show that \( \lim_{x \to \infty} x^{\alpha} \mathbb{P}\{X > x\} = C_\alpha \), where \( C_\alpha \) is a positive constant.

   Hint: Use the Tauberian theorem.\(^4\)

2. (2 points) Prove that

\[
\mathbb{E}|X|^p < \infty, \text{ for any } 0 < p < \alpha,
\]

\[
\mathbb{E}|X|^p = \infty, \text{ for any } p \geq \alpha.
\]

Exercise 4.1.18
Let \( X_1, X_2 \) be two independent \( \alpha \)-stable random variables with parameters \( (\lambda, \beta, \gamma) \). Prove that \( X_1 - X_2 \) is a stable random variable and find its parameters \( (\alpha_1, \lambda_1, \beta_1, \gamma_1) \).

Exercise 4.1.19
Let \( X_1, \ldots, X_n \) be i.i.d \( S_\alpha(\lambda, \beta, \gamma) \) distributed random variables and \( S_n = X_1 + \cdots + X_n \). Prove that the limiting distribution of

1. \( n^{-1/\alpha} S_n, n \to \infty, \text{ if } \alpha \in (0, 1) \);

2. \( n^{-1}(S_n - 2\pi^{-1}\lambda \beta n \log n - \lambda \gamma), n \to \infty, \text{ if } \alpha = 1 \);

3. \( n^{-1/\alpha}(S_n - n \lambda \gamma), n \to \infty, \text{ if } \alpha \in (1, 2] \);

\(^4\)(Feller 1971 Theorem XIII.5.4.) If \( L \) is slowly varying at infinity and \( \rho \in \mathbb{R}_+ \), the following relations are equivalent

\[
U(t) \sim \frac{1}{\Gamma(\rho + 1)} t\rho L(t), t \to \infty, \quad \int_0^\infty e^{-\tau x} dU(x) \sim \frac{1}{\tau^\rho} L \left( \frac{1}{\tau} \right), \tau \to 0.
\]
4 Additional exercises

Exercise 4.1.20
Let \( X_1, X_2, \ldots \) be a sequence of i.i.d. random variables and let \( p > 0 \). Applying the Borel-Cantelli lemmas, show that

1. \( \mathbb{E} |X_1|^p < \infty \) if and only if \( \lim_{n \to \infty} n^{1/p} X_n = 0 \) a.s.,
2. \( \mathbb{E} |X_1|^p = \infty \) if and only if \( \limsup_{n \to \infty} n^{1/p} X_n = \infty \) a.s.

Exercise 4.1.21
Let \( \xi \) be a non-negative random variable with the Laplace transform \( \mathbb{E} \exp(-\lambda \xi) = \exp(-\lambda \alpha) \), \( \lambda \geq 0 \). Prove that

\[
\mathbb{E} \xi = \frac{\Gamma(1-s)}{\Gamma(1-\alpha s)}\Gamma(1-s), s \in (0, 1).
\]

Exercise 4.1.22
Denote by \( \tilde{f}(s) := \int_0^\infty e^{-sx} f(x) \, dx \), the Laplace transform of a real function \( f \) defined for all \( s > 0 \), whenever \( \tilde{f}(s) \) is finite. For the following functions find the Laplace transforms (in terms of \( \tilde{f}(s) \)):

1. For \( a \in \mathbb{R} \) \( f_1(x) := f(x-a), x \in \mathbb{R}_+ \), and \( f(x) = 0, x < 0 \).
2. For \( b > 0 \) \( f_2(x) := f(bx), x \in \mathbb{R}_+ \).
3. \( f_3(x) := f'(x), x \in \mathbb{R}_+ \).
4. \( f_4(x) := \int_0^x f(u) \, du, x \in \mathbb{R}_+ \).

Exercise 4.1.23
Let \( \tilde{f}, \tilde{g} \) be Laplace transforms of functions \( f, g : \mathbb{R}_+ \to \mathbb{R}_+ \).

1. Find the Laplace transform of the convolution \( f * g \).
2. Prove the final value theorem: \( \lim_{s \to 0} s \tilde{f}(s) = \lim_{t \to \infty} f(t) \).

Exercise 4.1.24
Let \( \{X_n\}_{n \geq 0} \) be i.i.d. r.v.’s with a density symmetric about 0 and continuous and positive at 0. Applying the Theorem 2.8 from the lecture notes, prove that cumulative distribution function \( F(x) := \mathbb{P}(X_1^{-1} \leq x), x \in \mathbb{R} \) belongs to the domain of attraction of a stable law \( G \). Find its parameters \( (\alpha, \lambda, \beta, \gamma) \) and sequences \( a_n, b_n \) s.t. \( \frac{1}{b_n} \sum_{i=1}^n X_i^{-1} - a_n \xrightarrow{d} Y \sim G \) as \( n \to \infty \).

Exercise 4.1.25
Let \( \{X_n\}_{n \geq 0} \) be i.i.d. r.v.’s with for \( x > 1 \)

\[
\mathbb{P}(X_1 > x) = \theta x^{-\delta}, \quad \mathbb{P}(X_1 < -x) = (1 - \theta) x^{-\delta},
\]

where \( 0 < \delta < 2 \). Applying the Theorem 2.8 from the lecture notes, prove that c.d.f. \( F(x) := \mathbb{P}(X_1 \leq x), x \in \mathbb{R} \) belongs to the domain of attraction of a stable law \( G \). Find its parameters \( (\alpha, \lambda, \beta, \gamma) \) and sequences \( a_n, b_n \) s.t. \( \frac{1}{b_n} \sum_{i=1}^n X_i - a_n \xrightarrow{d} Y \sim G \) as \( n \to \infty \).

Exercise 4.1.26
Let \( X \) be a random variable with probability density function \( f(x) \). Assume that \( f(0) \neq 0 \) and that \( f(x) \) is continuous at \( x = 0 \). Prove that
1. if $0 < r \leq \frac{1}{2}$, then $|X|^{-r}$ belongs to the domain of attraction of a Gaussian law,

2. if $r > 1/2$ then $|X|^{-r}$ belongs to the domain of attraction of a stable law with stability index $1/r$.

**Exercise 4.1.27**

Find a distribution $F$ which has infinite second moment and yet it is in the domain of attraction of the Gaussian law.

**Exercise 4.1.28**

Prove the following statement which is used in the proof of Proposition 2.3.3.

Let $X \sim S_\alpha(\lambda, \beta, 0)$ with $\alpha \in (0, 2)$. Then there exist two i.i.d. r.v.’s $Y_1$ and $Y_2$ with common distribution $S_\alpha(\lambda, 1, 0)$ s.t.

$$X \overset{d}{=} \begin{cases} \left(\frac{1+\beta}{2}\right)^{1/\alpha} Y_1 - \left(\frac{1-\beta}{2}\right)^{1/\alpha} Y_2, & \text{if } \alpha \neq 1, \\ \left(\frac{1+\beta}{2}\right) Y_1 - \left(\frac{1-\beta}{2}\right) Y_2 + \frac{\lambda}{\alpha} \left((1 + \beta) \log \frac{1+\beta}{2} - (1 - \beta) \log \frac{1-\beta}{2}\right), & \text{if } \alpha = 1. \end{cases}$$

**Exercise 4.1.29**

Prove that for $\alpha \in (0, 1)$ and fixed $\lambda$, the family of distributions $S_\alpha(\lambda, \beta, 0)$ is stochastically ordered in $\beta$, i.e., if $X_\beta \sim S_\alpha(\lambda, \beta, 0)$ and $\beta_1 \leq \beta_2$ then $\mathbb{P}(X_{\beta_1} \geq x) \leq \mathbb{P}(X_{\beta_2} \geq x)$ for $x \in \mathbb{R}$.

**Exercise 4.1.30**

Prove the following theorem.

**Theorem 4.1.1**

A distribution function $F$ is in the domain of attraction of a stable law with exponent $\alpha \in (0, 2)$ if and only if there are constants $C_+, C_- \geq 0, C_+ + C_- > 0$, such that

1. $$\lim_{y \to +\infty} \frac{F(-y)}{1 - F(y)} = \begin{cases} C_- / C_+, & \text{if } C_+ > 0, \\ +\infty, & \text{if } C_+ = 0, \end{cases}$$

2. and for every $a > 0$

$$\begin{cases} \lim_{y \to +\infty} \frac{1 - F(ay)}{1 - F(y)} = a^{-\alpha}, & \text{if } C_+ > 0, \\ \lim_{y \to +\infty} \frac{F(-ay)}{F(-y)} = a^{-\alpha}, & \text{if } C_- > 0. \end{cases}$$
Bibliography


