# The Local Limit Theorem and the Almost Sure Local Limit Theorem 

Rita Giuliano<br>Department of Mathematics "L. Tonelli"<br>University of Pisa<br>ITALY

## Outline

## Local Limit Theorems (LLT)

- The DeMoivre-Laplace theorem
- Gnedenko's Theorem
- Necessary and sufficient conditions for the LLT
- Necessary and sufficient conditions for the LLT with rate
- The general LLT for random variables in the domain of attraction of a stable distribution


## Outline

## Almost Sure Local Limit Theorems (ASLLT)

- Motivation: $\longrightarrow$ Almost Sure Central Limit Theorem (ASCLT)
- ASLLT for random sequences in the domain of attraction of the normal law
- ASLLT with rate (random sequences with moment $2+\epsilon$ )
- ASLLT for random sequences with second moment
- ASLLT for random sequences in the domain of attraction of a stable law with $\alpha<2$ (without second moment)


## The DeMoivre-Laplace theorem

## Theorem

Let $g_{n}(k)$ be the probability of getting $k$ heads in $n$ tosses of a coin which gives a head with probability $p$. Then

$$
\lim _{n \rightarrow \infty} \frac{g_{n}(k)}{\left(\frac{1}{\sqrt{2 n p q}} e^{-\frac{(k-n p)^{2}}{2 n p q}}\right)}=1
$$

uniformly for $k$ such that $\left|\frac{k-n p}{\sqrt{n p q}}\right|$ remains bounded.

- Abraham DeMoivre proved it only for a fair coin $(p=1 / 2)$ in Approximatio ad Summam Terminorum Binomii $(a+b)^{n}$ in Seriem expansi (1733).
- Pierre-Simon Laplace proved it in full generality in Théorie Analytique des probabilités (1812).

In the DeMoivre Theorem $\longrightarrow p=E\left[X_{1}\right]$ and $p q=\operatorname{Var} X_{1}$.
We could expect

## Theorem

Let $\left(X_{n}\right)_{n \geqslant 1}$ be a sequence of i.i.d. random variables, with $E\left[X_{1}\right]=\mu, \operatorname{Var} X_{1}=\sigma^{2}$. Then

$$
P\left(S_{n}=k\right) \approx \frac{1}{\sqrt{2 \pi n} \sigma} e^{-\frac{(k-n \mu)^{2}}{2 n \sigma^{2}}}
$$

if $\left|\frac{k-n \mu}{\sqrt{n p q}}\right|$ is bounded.

## A particular case

But certainly this cannot be true in general: if

$$
X_{1}=\left\{\begin{array}{cl}
-1 & \text { with probability } \frac{1}{2} \\
1 & \text { with probability } \frac{1}{2}
\end{array}\right.
$$

If $k$ is odd, then $P\left(S_{2 n}=k\right)=0$.
If $k$ is even, say $k=2 h$, we should obtain (with $2 n$ in place of $n$ and $2 h$ in place of $k, \mu=0, \sigma^{2}=1$ ).

$$
P\left(S_{2 n}=2 h\right) \approx \frac{1}{2 \sqrt{\pi n}} e^{-\frac{h^{2}}{n}}
$$

with $\frac{h}{\sqrt{n}}$ bounded.

## In particular

$\longrightarrow$ for $\left(h_{n}\right)$ such that $\frac{h_{n}}{\sqrt{n}} \rightarrow_{n} \frac{x}{\sqrt{2}}$ :

$$
\begin{equation*}
P\left(S_{2 n}=2 h_{n}\right) \approx \frac{1}{2 \sqrt{\pi n}} e^{-\frac{x^{2}}{2}} . \tag{1}
\end{equation*}
$$

## On the contrary

## Theorem

If $\frac{h_{n}}{\sqrt{n}} \rightarrow_{n} \frac{x}{\sqrt{2}}$

$$
\begin{equation*}
\lim _{n \rightarrow \infty} \sqrt{n} P\left(S_{n}=2 h_{n}\right)=\frac{1}{\sqrt{\pi}} e^{-\frac{x^{2}}{2}} . \tag{2}
\end{equation*}
$$

## A tentative statement

Hence a general theorem should roughly state that

$$
P\left(S_{n}=k\right) \approx \frac{c}{\sqrt{2 \pi n} \sigma} e^{-\frac{(k-n \mu)^{2}}{2 n \sigma^{2}}}
$$

if $k$ is a value of $S_{n}$ and $\left|\frac{k-n \mu}{\sqrt{n p q}}\right|$ is bounded, for a suitable $c$. But what is $c$ ? Comparing (1) and (2), we notice that the main difference is a factor of 2 in the second member of (2); where does it come from? We also notice that in this case the support of $S_{2 n}$ is concentrated on even integers, and two successive even integers differ by 2 . So one guesses that $c=2$ in our case, and in general $c$ is maybe connected with the gap between successive values of $S_{n}$.

## Preliminaries

$$
\mathcal{L}(a, \lambda):=a+\lambda \mathbb{Z}=\{a+\lambda k, k \in \mathbb{Z}\} .
$$

## Definition

A random variable $X$ has a lattice distribution if there exist two constant $a$ and $\lambda>0$ such that $P(X \in \mathcal{L}(a, \lambda))=1$.
$\phi=\mathbb{E}\left[e^{i t X}\right]=$ the characteristic function of $X$.
Link between lattice distribution and the behaviour $\phi$ :

## Theorem

There are only three possibilities:
(i) there exists a $t_{0}>0$ such that $\left|\phi\left(t_{0}\right)\right|=1$ and $|\phi(t)|<1$ for every $0<t<t_{0}$. In this case $X$ has a lattice distribution.
(ii) $|\phi(t)|<1$ for every $t \neq 0$ (non lattice distribution).
(iii) $|\phi(t)|=1$ for every $t \in \mathbb{R}$ : In this case $X$ is constant a.s. (degenerate distribution).

## Preliminaries

The proof shows in particular that

## Corollary

In case (i) of the preceding Theorem, we have

$$
\frac{2 \pi}{t_{0}}=\max \{\lambda>0: \exists a \in \mathbb{R}, P(X \in \mathcal{L}(a, \lambda))=1\}
$$

Hence

## Definition

In case (i) of the preceding Theorem, the number

$$
\Lambda=\frac{2 \pi}{t_{0}}=\max \{\lambda>0: \exists a \in \mathbb{R}, P(X \in \mathcal{L}(a, \lambda))=1\}
$$

is called the (maximal) span of the distribution of $X$.

## Some examples

- (i) Let

$$
X_{1}=\left\{\begin{aligned}
-1 & \text { with probability } \frac{1}{2} \\
1 & \text { with probability } \frac{1}{2}
\end{aligned}\right.
$$

Then $\phi(t)=\frac{1}{2}\left(e^{i t}+e^{-i t}\right)=\cos t$, and $|\phi(t)|=1$ if and only if $t=n \pi, n \in \mathbb{Z}$. Hence $t_{0}=\pi$, and the maximal span of the distribution is $\frac{2 \pi}{t_{0}}=2$.

- (ii) Let $X_{1}$ have standard gaussian law. Then $\phi(t)=e^{-\frac{t^{2}}{2}}$. In this case $|\phi(t)|=1$ only for $t=0$.
- (iii) If $X_{1}=c\left(c\right.$ some constant) we have $\phi(t)=e^{i t c}$, and $|\phi(t)|=1$ for every $t$.


## Gnedenko's Local Limit Theorem (1948)

$\left(X_{n}\right)_{n \geqslant 1}$ sequence of i.i.d random variables, $\mathbf{E}\left[X_{i}\right]=\mu, \operatorname{Var} X_{i}=\sigma^{2}$ (finite) with lattice distribution. $\Lambda=$ maximal span.

$$
S_{n}=X_{1}+\cdots+X_{n}
$$

$$
P\left(X_{i} \in \mathcal{L}(a, \Lambda)\right)=1 \Longrightarrow P\left(S_{n} \in \mathcal{L}(n a, \Lambda)=1\right.
$$

## Theorem

We have

$$
\lim _{n \rightarrow \infty} \sup _{N \in \mathcal{L}(n a, \Lambda)}\left|\frac{\sqrt{n}}{\Lambda} P\left(S_{n}=N\right)-\frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{(N-n \mu)^{2}}{2 n \sigma^{2}}}\right|=0
$$

## Gnedenko's Local Limit Theorem (1948)

Some heuristics $(\mu=0)$
By the CLT

$$
\begin{aligned}
& P\left(S_{n}=N\right) \approx P\left(N-\frac{\Lambda}{2} \leqslant S_{n} \leqslant N+\frac{\Lambda}{2}\right) \\
& =P\left(\frac{N}{\sqrt{n} \sigma}-\frac{\Lambda}{2 \sigma \sqrt{n}} \leqslant \frac{S_{n}}{\sigma \sqrt{n}} \leqslant \frac{N}{\sqrt{n} \sigma}-\frac{\Lambda}{2 \sigma \sqrt{n}}\right) \\
& \approx \int_{\frac{N}{\sqrt{n} \sigma}-\frac{\Lambda}{2 \sigma \sqrt{n}}}^{\frac{N}{\sqrt{n}}+\frac{\Lambda}{2 \sigma \sqrt{n}}} \frac{1}{\sqrt{2 \pi}} e^{-\frac{t^{2}}{2}} d t=\int_{\frac{N}{\sqrt{n}}-\frac{\Lambda}{2 \sqrt{n}}}^{\frac{N}{\sqrt{n}}+\frac{\Lambda}{\sqrt{n}}} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{t^{2}}{2 \sigma^{2}}} d t \\
& \approx \frac{\Lambda}{\sqrt{n}} \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{N^{2}}{2 n \sigma^{2}}} .
\end{aligned}
$$

## Gnedenko's Local Limit Theorem (necessary and sufficient conditions for the LLT)

Actually, the complete formulation of Gnedenko's result is

## Theorem

With the same assumptions as above, in order that

$$
\lim _{n \rightarrow \infty} \sup _{N \in \mathcal{L}(n a, \lambda)}\left|\frac{\sqrt{n}}{\lambda} P\left(S_{n}=N\right)-\frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{(N-n \mu)^{2}}{2 n \sigma^{2}}}\right|=0
$$

it is necessary and sufficient that $\lambda=\Lambda$.

## Necessary and sufficient conditions for the Local Limit

 Theorem with rateThe following result completes the theory

## Theorem

With the same assumptions as in Theorem 8, in order that

$$
\sup _{N \in \mathcal{L}(n a, \lambda)}\left|\frac{\sqrt{n}}{\lambda} P\left(S_{n}=N\right)-\frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{(N-n \mu)^{2}}{2 n \sigma^{2}}}\right|=O\left(n^{-\alpha}\right)
$$

with

$$
0<\alpha<\frac{1}{2}
$$

it is necessary and sufficient that the following conditions are satisfied
(i) $\lambda=\Lambda$;
(ii) if $F$ denotes the distribution function of $X_{1}$, then, as $u \rightarrow \infty$,
$\int_{|x| \geqslant 1} x^{2} F(d x)=O\left(u^{-2 \alpha}\right)$.

## Local Limit Theorem in the nonlattice case

$\left(X_{n}\right)_{n \geq 1}$ sequence of i.i.d. random variables . $\phi=$ characteristic function with $|\phi(t)|<1$ for every $t \neq 0$.

## Remark

In the nonlattice case, most characteristic functions verify the Cramer's condition, i.e.

$$
\limsup _{t \rightarrow \infty}|\phi(t)|<1
$$

## Local Limit Theorem in the nonlattice case

## Remark

There exist characteristic functions of nonlattice random variables, that do not verify Cramer's condition.

An example is

$$
\phi(t)=\prod_{k=1}^{\infty} \cos \left(\frac{t}{k!}\right)
$$

$|\phi(t)|=1 \Longleftrightarrow \frac{t}{k!}$ is a multiple of $\pi$ for each integer $k$ : impossible unless $t=0$.

But

$$
1-\phi(2 \pi N!) \rightarrow 0, \quad N \rightarrow \infty
$$

## Local Limit Theorem in the nonlattice case

The following result holds

## Theorem

Let $\left(X_{n}\right)_{n \geqslant 1}$ be sequence of i.i.d. nonlattice random variables, with $\mathbf{E}\left[X_{1}\right]=\mu, \operatorname{Var} X_{1}=\sigma^{2}<\infty$. If $\frac{x_{n}}{\sqrt{n}} \rightarrow x$ and $a<b$,

$$
\lim _{n \rightarrow \infty} \sqrt{n} P\left(S_{n}-n \mu \in\left(x_{n}+a, x_{n}+b\right)\right)=(b-a) \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{x^{2}}{2 \sigma^{2}}} .
$$

The heuristics are as before.

## Local Limit Theorem in the nonlattice case

With some further properties on $|\phi|$ :

## Theorem

If $|\phi|$ is integrable, then $\frac{S_{n}-n \mu}{\sigma \sqrt{n}}$ has a density $f_{n}$; moreover $f_{n}$ tends undiformly to the standard normal density

$$
\eta(x)=\frac{1}{\sqrt{2 \pi}} e^{-\frac{x^{2}}{2}} .
$$

## The general Local Limit Theorem for random variables in the domain of attraction of a stable distribution: preliminaries

$\left(X_{n}\right)_{n \geqslant 1}$ i.i.d. with (common) distribution $F$ (not necessarily lattice) and partial sums $S_{n}=X_{1}+\cdots+X_{n}$.
$G=$ distribution.

## Definition

The domain of attraction of $G$ is the set of distributions $F$ having the following property: there exists two sequences $\left(a_{n}\right)$ and ( $b_{n}$ ) of real numbers, with $b_{n} \rightarrow_{n} \infty$, such that

$$
\frac{S_{n}-a_{n}}{b_{n}} \xrightarrow{\mathcal{L}} G
$$

as $n \rightarrow \infty$.

# The general Local Limit Theorem for random variables in the domain of attraction of a stable distribution: stable distributions 

$G$ possesses a domain of attraction iff $G$ is stable, i.e.

## Definition

A non-degenerate distribution $G$ is stable if it satisfies the following property:
let $X_{1}$ and $X_{2}$ be independent variables with distribution $G$; for any constants $a>0$ and $b>0$ the random variable $a X_{1}+b X_{2}$ has the same distribution as $c X_{1}+d$ for some constants $c>0$ and $d$.

The general Local Limit Theorem for random variables in the domain of attraction of a stable distribution: alternative definition of stable distributions

## Definition

$G$ is stable if its characteristic function can be written as

$$
\varphi(t ; \mu, c, \alpha, \beta)=\exp \left[i t \mu-|c t|^{\alpha}(1-i \beta \operatorname{sgn}(t) \Phi)\right]
$$

where $\alpha \in(0,2], \mu \in \mathbb{R}, \beta \in[-1,1] ; \operatorname{sgn}(t)$ is just the sign of t and

$$
\Phi= \begin{cases}\tan \frac{\pi \alpha}{2} & \text { if } \alpha \neq 1 \\ -\frac{2}{\pi} \log |t| & \text { if } \alpha=1\end{cases}
$$

The parameter $\alpha$ is the exponent of the distribution.

## Remark

The normal law is stable with exponent $\alpha=2$.

# The general Local Limit Theorem for random variables in the domain of attraction of a stable distribution 

## Theorem

Let $X_{n}$ have lattice distribution with maximal span $\Lambda$. In order that, for some choice of constants $a_{n}$ and $b_{n}$

$$
\lim _{n \rightarrow \infty} \sup _{N \in \mathcal{L}(n a, \lambda)}\left|\frac{b_{n}}{\lambda} P\left(S_{n}=N\right)-g\left(\frac{N-a_{n}}{b_{n}}\right)\right|=0
$$

where $g$ is the density of some stable distribution $G$ with exponent $0<\alpha \leq 2$,
it is necessary and sufficient that
(i) the common distribution $F$ of the $X_{n}$ belongs to the domain of attraction of $G$;
(ii) $\lambda=\Lambda$ (i.e. maximal).

## Almost Sure Local Limit Theorems (ASLLT): the motivation (starting from the Almost Sure Central Limit Theorem)

$\left(X_{n}\right)_{n \geqslant 1}$ i.i.d with $\mathbf{E}\left[X_{1}\right]=\mu, \operatorname{Var} X_{1}=\sigma^{2}$.

$$
Z_{n}=\frac{S_{n}-n \mu}{\sigma \sqrt{n}}
$$

## Central Limit Theorem

## Theorem

For every $x \in \mathbb{R}$

$$
\mathbf{E}\left[1_{\left\{Z_{n} \leqslant x\right\}}\right]=P\left(Z_{n} \leqslant x\right) \underset{n}{\longrightarrow} \Phi(x):=\int_{-\infty}^{x} \frac{1}{\sqrt{2 \pi}} e^{-\frac{t^{2}}{2}} d t
$$

# Almost Sure Local Limit Theorems (ASLLT): the motivation (starting from the Almost Sure Central Limit Theorem) 

## Almost Sure Central Limit Theorem

## Theorem

$P-$ a. s., for every $x \in \mathbb{R}$

$$
\frac{1}{\log n} \sum_{h=1}^{n} \frac{1}{h} 1_{\left\{Z_{h} \leqslant x\right\}} \underset{n}{\longrightarrow} \Phi(x) .
$$

# By analogy (for the case of Gnedenko's Theorem) 

$$
\kappa_{n} \in \mathcal{L}(n a, \Lambda) \text { such that } \frac{\kappa_{n}-n \mu}{\sqrt{n}} \rightarrow \kappa
$$

Gnedenko's Theorem $\Longrightarrow$

$$
\mathbf{E}\left[\sqrt{n} 1_{\left\{S_{n}=\kappa_{n}\right\}}\right]=\sqrt{n} P\left(S_{n}=\kappa_{n}\right) \rightarrow \Lambda \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{\kappa^{2}}{2 \sigma^{2}}} .
$$

Comparing with the case of the Central Theorem:

## Tentative Almost Sure Local Limit Theorem

## Theorem

$P-a$. s.,

$$
\begin{aligned}
& \frac{1}{\log n} \sum_{h=1}^{n} \frac{1}{h}\left(\left(\sqrt{h} 1_{\left\{S_{h}=\kappa_{n}\right\}}\right)\right. \\
& =\frac{1}{\log n} \sum_{h=1}^{n} \frac{1}{\sqrt{h}} 1_{\left\{S_{h}=\kappa_{h}\right\}} \underset{n}{\longrightarrow} \Lambda \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{\kappa^{2}}{2 \sigma^{2}}} .
\end{aligned}
$$

## Some history

- In 1951 Chung and Erdös proved


## Theorem

Let $\left(X_{n}\right)_{n \geqslant 1}$ be a centered Bernoulli process with parameter $p$. Then

$$
\frac{1}{\log n} \sum_{h=1}^{n} \frac{1}{\sqrt{h}} 1_{\left\{S_{h}=0\right\}} \underset{n}{\longrightarrow} \frac{1}{\sqrt{2 \pi p(1-p)}}, \quad \text { a.s. }
$$

This is a particular case of our tentative ASLLT: just take $\kappa_{n}=n p$.

## Some history

- In 1993 Csáki, Földes and Révész proved


## Theorem

Let $\left(X_{n}\right)_{n \geqslant 1}$ be i.i.d. centered and with finite third moment. Then

$$
\frac{1}{\log n} \sum_{h=1}^{n} \frac{1}{p_{h}} 1_{\left\{a_{h} \leqslant S_{h} \leqslant b_{h}\right\}} \underset{n}{\longrightarrow} 1, \quad \text { a.s. }
$$

where $p_{n}=P\left(a_{n} \leqslant S_{n} \leqslant b_{n}\right)$.

This generalizes the Chung-Erdös Theorem: just take $a_{n}=b_{n}=0$ and recall Gnedenko's Theorem.

## The ASLLT for random sequences in the domain of attraction of the normal law

$\left(X_{n}\right)_{n \geqslant 1}$ i.i.d. having lattice distribution $F$ with maximal span $\Lambda$; $\mathbf{E}\left[X_{1}\right]=: \mu, \operatorname{Var} X_{1}=: \sigma^{2}$ (finite). We assume $\mu=0$ and $\sigma^{2}=1$ (no loss of generality).

## Definition

$\left(X_{n}\right)_{n \geqslant 1}$ satisfies an ASLLT if

$$
\lim _{n \rightarrow \infty} \frac{1}{\log n} \sum_{h=1}^{n} \frac{1}{\sqrt{h}} 1_{\left\{S_{h}=\kappa_{h}\right\}} \stackrel{\text { a.s. }}{=} \Lambda \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{\kappa^{2}}{2 \sigma^{2}}},
$$

for any sequence of integers $\left(\kappa_{n}\right)_{n \geqslant 1}$ in $\mathcal{L}(n a, \Lambda)$ such that

$$
\lim _{n \rightarrow \infty} \frac{\kappa_{n}-n \mu}{\sqrt{n}}=\kappa
$$

## ASLLT with rate

## Theorem

Let $\epsilon>0$ and assume that $\mathbf{E}\left[\left|X_{1}^{2+\epsilon}\right|\right]<\infty$. Then $\left(X_{n}\right)_{n \geqslant 1}$ satisfies an ASLLT. Moreover, if the sequence $\left(\kappa_{n}\right)_{n \geqslant 1}$ verifies the stronger condition

$$
\frac{\kappa_{n}-n \mu}{\sqrt{n}}=\kappa+O_{\delta}\left((\log n)^{-1 / 2+\delta}\right)
$$

then

$$
\sum_{h=1}^{n} \frac{1}{\sqrt{h}} 1_{\left\{S_{h}=\kappa_{h}\right\}}=\Lambda \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{\kappa^{2}}{2 \sigma^{2}}}+O_{\delta}\left((\log n)^{-1 / 2+\delta}\right)
$$

## ASLLT with rate

## Remark

If $\mathbf{E}\left[\left|X_{1}^{2+\epsilon}\right|\right]<\infty$ for some positive $\epsilon$, then the condition of Gnedenko's Theorem with rate, i.e.

$$
\begin{gathered}
\sup _{N \in \mathcal{L}(n a, \lambda)}\left|\frac{\sqrt{n}}{\lambda} P\left(S_{n}=N\right)-\frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{(N-n \mu)^{2}}{2 n \sigma^{2}}}\right|=O\left(n^{-\alpha}\right) \\
0<\alpha<\frac{1}{2}
\end{gathered}
$$

is satisfied with $\alpha=\epsilon / 2$. In fact

$$
\int_{|x| \geqslant u} x^{2} F(d x)=\int_{|x| \geqslant u}|x|^{2+\epsilon}|x|^{-\epsilon} F(d x) \leqslant \mathbf{E}\left[\left|X_{1}^{2+\epsilon}\right|\right] u^{-\epsilon}
$$

## Key ingredients for the proof

- (i) a suitable correlation inequality;
- (ii) Gnedenko's Theorem with rate;
- (iii) the notion of quasi orthogonal system.


## Correlation inequality

$$
Y_{h}=\sqrt{h}\left(1_{\left\{S_{h}=\kappa_{h}\right\}}-P\left(S_{h}=\kappa_{h}\right)\right) .
$$

## Proposition

Assume that

$$
\begin{aligned}
& r(n):=\sup _{N \in \mathcal{L}(n a, \Lambda)}\left|\frac{\sqrt{n}}{\Lambda} P\left(S_{n}=N\right)-\frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{(N-n \mu)^{2}}{2 n \sigma^{2}}}\right|=O\left(n^{-\alpha}\right), \\
& 0<\alpha<\frac{1}{2}
\end{aligned}
$$

Then there exists a constant $C$ such that, for all integers $m, n$ with $1 \leq m<n$

$$
\left|\operatorname{Cov}\left(Y_{m}, Y_{n}\right)\right| \leq C\left(\frac{1}{\sqrt{\frac{n}{m}}-1}+\sqrt{\frac{n}{n-m}} \cdot \frac{1}{(n-m)^{\alpha}}\right)
$$

## The notion of quasi orthogonal system

## Kac-Salem-Zygmund definition of quasi-orthogonal system

## Definition

A sequence of functions $\Psi:=\left(f_{n}\right)_{n \geqslant 1}$ defined on a Hilbert space $\mathcal{H}$ is said quasi-orthogonal if the quadratic form on $\ell^{2}$ : $\left(x_{n}\right) \mapsto \sum_{h, k}\left\langle f_{h}, f_{k}\right\rangle x_{h} x_{k}$ is bounded (as a quadratic form).

## Weber's criterion for quasi-orthogonality

## Lemma

In order that $\psi:=\left(f_{n}\right)_{n \geqslant 1}$ be a quasi-orthogonal system, it is sufficient that

$$
\sup _{h} \sum_{k}\left|\left\langle f_{h}, f_{k}\right\rangle\right|<\infty
$$

## The notion of quasi orthogonal system

## Remark

If $\mathcal{H}=L^{2}(T)$, where $(T, \mathcal{A}, \mu)$ is some probability space, then $\sum_{h, k}\left\langle f_{h}, f_{k}\right\rangle x_{h} x_{k}=\sum_{h, k}\left(\int f_{h} f_{k} d \mu\right) x_{h} x_{k}$. By
Rademacher-Menchov Theorem, it is seen that the series $\sum_{n} c_{n} f_{n}$ converges if for instance $c_{n}=n^{-\frac{1}{2}}(\log n)^{-b}$ with $b>\frac{3}{2}$.

## Main steps of the proof

(i) Any $\rho>1$ fixed.

The basic correlation inequality $\Longrightarrow$

$$
Z_{j}=\sum_{\rho^{j} \leqslant h<\rho^{j+1}} \frac{Y_{h}}{h} \text { is quasi-orthogonal. }
$$

(ii) By the preceding remark

$$
\sum_{j} \frac{z_{j}}{\sqrt{j}(\log j)^{b}} \text { converges as soon as } b>\frac{3}{2} .
$$

(iii) By Kronecker's Lemma

$$
\begin{aligned}
& \frac{1}{\sqrt{n}(\log n)^{b}} \sum_{j=1}^{n} Z_{j}=\frac{1}{\sqrt{n}(\log n)^{b}} \sum_{j=1}^{n} \sum_{\rho^{j} \leqslant h<\rho^{j+1}} \frac{Y_{h}}{h} \\
& =\frac{1}{\sqrt{n}(\log n)^{b}} \sum_{1 \leqslant h<\rho^{n+1}} \frac{Y_{h}}{h} \underset{n}{\longrightarrow} 0 .
\end{aligned}
$$

## Main steps of the proof

(iv) The preceding relation yields easily (details omitted)

$$
\begin{gathered}
\frac{\sqrt{\log t}}{(\log \log t)^{b}}\left(\frac{1}{\log t} \sum_{h \leqslant t} \frac{Y_{h}}{h}\right)=\frac{1}{\sqrt{\log t}(\log \log t)^{b}} \sum_{h \leqslant t} \frac{Y_{h}}{h} \underset{t}{\longrightarrow} 0 \\
\quad \text { since } \frac{\sqrt{\log t}}{(\log \log t)^{b}} \longrightarrow_{t} \infty, \text { this implies } \\
\frac{1}{\log t} \sum_{h \leqslant t} \frac{Y_{h}}{h}=\frac{1}{\log t} \sum_{h \leqslant t} \frac{1_{\left\{S_{h}=\kappa_{h}\right\}}}{\sqrt{h}}-\frac{1}{\log t} \sum_{h \leqslant t} \frac{\sqrt{h} P\left(S_{h}=\kappa_{h}\right)}{h} \underset{t}{\longrightarrow} 0
\end{gathered}
$$

(v) Last, by Gnedenko's Theorem

$$
\frac{1}{\log t} \sum_{h \leqslant t} \frac{\sqrt{h} P\left(S_{h}=\kappa_{h}\right)}{h} \underset{t}{\longrightarrow} \Lambda \frac{1}{\sqrt{2 \pi} \sigma} e^{-\frac{\kappa^{2}}{2 \sigma^{2}}}
$$

and the result follows.
The second part of the Theorem is proved similarly.

## ASLLT for random sequences with second moment

When only the second moment is available, the ASLLT with rate doen't hold (see remark). M. Weber proved the ASLLT afresh:
(1) with the additional assumption $\left(v_{k}, k \in \mathbb{Z}\right.$ are the elements of the lattice)

$$
\begin{equation*}
P\left(X=v_{k}\right) \wedge P\left(X=v_{k+1}\right)>0 \quad \text { for some } k \in \mathbb{Z} \tag{3}
\end{equation*}
$$

With (3), a basic correlation inequality holds, again for $Y_{h}=\sqrt{h}\left(1_{\left\{S_{h}=\kappa_{h}\right\}}-P\left(S_{h}=\kappa_{h}\right)\right):$

## Proposition

Assume that (3) holds. Then there exists a constant C (depending on the sequence $\left(\kappa_{n}\right)$ ) such that, for all integers $m$, $n$ with $1 \leq m<n$

$$
\left|\operatorname{Cov}\left(Y_{m}, Y_{n}\right)\right| \leq C\left(\frac{1}{\sqrt{\frac{n}{m}}-1}+\sqrt{\frac{n}{n-m}} \cdot \frac{1}{n-m}\right)
$$

(2) in the general case

## ASLLT for random sequences with second moment

Main ingredients similar to the previous ones:
(1) the above correlation inequality;
(2) Gnedenko's Theorem (without rate);
(3) the notion of quasi orthogonal system.

## ASLLT for random sequences in the domain of attraction of a stable law with $0<\alpha<2$.

Recent work by R. Giuliano and Z. Szewczak (work in progress).

- $\left(X_{n}\right)_{n \geq 1}$ sequence of i.i.d. random variables; common distribution $F$ is in the domain of attraction of a stable distribution $G$ (having density $g$ ) with exponent $\alpha$ ( $0<\alpha<2$ ).
- $\left(a_{n}\right)$ and $\left(b_{n}\right)$ as before; $b_{n}=L(n) n^{1 / \alpha}, L$ slowly varying in Karamata's sense.
- $X_{1}$ with lattice distribution; $\Lambda=$ maximal span.
- $F$ and $G$ symmetric $\Longrightarrow a_{n}=0$.


## IMPORTANT

Since $X_{1}$ doesn't possess second moment, the discussion of the preceding section doesn't work.

But we can use similar ingredients as before:
(1) a correlation inequality;
(2) General LLT Theorem (for stable distributions);
(3) Gaal-Koksma LLN.

The correlation inequality when $0<\alpha<2$

## Proposition

- For every pair $(m, n)$ of integers, with $1 \leq m<n$,

$$
\begin{aligned}
& b_{m} b_{n}\left|P\left(S_{m}=\kappa_{m}, S_{n}=\kappa_{n}\right)-P\left(S_{m}=\kappa_{m}\right) P\left(S_{n}=\kappa_{n}\right)\right| \\
& \leq C\left\{\left(\frac{n}{n-m}\right)^{1 / \alpha} \frac{L(n)}{L(n-m)}+1\right\} .
\end{aligned}
$$

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$$
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& \leq C \cdot L(n)\left\{n^{1 / \alpha}\left(\frac{1}{e^{(n-m) c}}+\frac{1}{e^{n c}}\right)+\frac{\frac{m}{n}}{\left(1-\frac{m}{n}\right)^{1+1 / \alpha}}+\right. \\
& \left.+\left(\frac{\frac{m}{n}}{\left(1-\frac{m}{2 n}\right)^{2}}\right)^{1 / \alpha}\right\}
\end{aligned}
$$

## Theorem

Let $\left(Z_{n}\right)_{n \geqslant 1}$ be a sequence of centered random variables with finite variance. Suppose that there exists a constant $\beta>0$ such that, for all integers $m \geq 0, n>0$,

$$
\begin{equation*}
E\left[\left(\sum_{i=m+1}^{m+n} Z_{i}\right)^{2}\right] \leq C\left((m+n)^{\beta}-m^{\beta}\right) \tag{4}
\end{equation*}
$$

for a suitable constant $C$ independent of $m$ and $n$. Then, for each $\delta>0$,

$$
\sum_{i=1}^{n} Z_{i}=O\left(n^{\beta / 2}(\log n)^{2+\delta}\right), \quad P-\text { a.s. }
$$

## ASLLT for random sequences without second moment

## Theorem

Let $\alpha>1$ and assume that there exists $\gamma \in(0,2)$ such that

$$
\sum_{k=a}^{b} \frac{L(k)}{k} \leq C\left(\log ^{\gamma} b-\log ^{\gamma} a\right)
$$

Then $\left(X_{n}\right)_{n \geqslant 1}$ satisfies an ASLLT, i.e.

$$
\lim _{N \rightarrow \infty} \frac{1}{\log N} \sum_{n=1}^{N} \frac{b_{n}}{n} 1_{\left\{S_{n}=\kappa_{n}\right\}}=\Lambda g(\kappa)
$$

## Main steps

We apply the above theorem to the sequence

$$
Z_{j}:=\sum_{h=\rho^{j-1}}^{\rho^{j}-1} \frac{Y_{h}}{h}
$$

where

$$
Y_{n}=b_{n}\left(1_{\left\{S_{n}=\kappa_{n}\right\}}-P\left(S_{n}=\kappa_{n}\right)\right)
$$

We obtain that

$$
\frac{1}{n} \sum_{1 \leqslant h \leqslant \rho^{n}} \frac{Y_{h}}{h} \rightarrow 0
$$

whence (as before)

$$
\frac{1}{\log n} \sum_{1 \leqslant h \leqslant n} \frac{Y_{h}}{h} \rightarrow 0
$$

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