8 Sums of Independent Random Variables

We continue our study of sums of independent random variables, $S_n = X_1 + \cdots + X_n$. If each $X_i$ is square-integrable, with mean $\mu_i = \operatorname{E}X_i$ and variance $\sigma_i^2 = \operatorname{E}[(X_i - \mu_i)^2]$, then $S_n$ is square integrable too with mean $\operatorname{E}S_n = \mu_{\leq n} \equiv \sum_{i \leq n} \mu_i$ and variance $\operatorname{V}S_n = \sigma_{\leq n}^2 \equiv \sum_{i \leq n} \sigma_i^2$. But what about the actual probability distribution? If the $X_i$ have density functions $f_i(x_i)$ then so does $S_n$; for example, with $n = 2$, $S_2 = X_1 + X_2$ has CDF $F(s)$ and pdf $f(s) = F'(s)$ given by

$$
P[S_2 \leq s] = F(s) = \int_{x_1 + x_2 \leq s} f_1(x_1)f_2(x_2) \, dx_1dx_2 = \int_{-\infty}^{s} \int_{-\infty}^{s-x_2} f_1(x_1)f_2(x_2) \, dx_1dx_2$$

$$f(s) = F'(s) = \int_{-\infty}^{s} f_1(s-x_2)f_2(x_2) \, dx_2 = \int_{-\infty}^{s} f_1(x_1)f_2(s-x_1) \, dx_1,$$

the convolution of $f_1(x_1)$ and $f_2(x_2)$. Even if the distributions aren’t absolutely continuous, so no pdfs exist, $S_2$ has a distribution measure $\mu$ given by $\mu(ds) = \int_{\mathbb{R}} \mu_1(dx_1)\mu_2(ds-x_1)$. There is an analogous formula for $n = 3$, but it is quite messy; things get worse and worse as $n$ increases, so this is not a promising approach for studying the distribution of sums $S_n$ for large $n$.

If CDFs and pdfs of sums of independent RVs are not simple, is there some other feature of the distributions that is? The answer is Yes. What is simple about independent random variables is calculating expectations of products of the $X_i$, or products of any functions of the $X_i$; the exponential function will let us turn the partial sums $S_n$ into products $e^{S_n} = \prod e^{X_i}$ or, more generally, $e^{zS_n} = \prod e^{zX_i}$ for any real or complex number $z$. Thus for independent RVs $X_i$ and any number $z$ we can use independence to compute the expectation

$$Ee^{zS_n} = \prod_{i=1}^{n} Ee^{zX_i},$$

often called the “moment generating function” and denoted $M_X(z) = Ee^{zX}$ for any random variable $X$.

For real $z$ the function $e^{zX}$ becomes huge if $X$ becomes very large (for positive $z$) or very negative (if $z < 0$), so that even for integrable or square-integrable random variables $X$ the
expectation $M(z) = E e^{zX}$ may be infinite. Here are a few examples of $E e^{zX}$ for some familiar distributions:

- **Binomial:** $\text{Bi}(n, p)$
  \[ [1 + p(e^z - 1)]^n \quad z \in \mathbb{C} \]
- **Neg Bin:** $\text{NB}(\alpha, p)$
  \[ [1 - (p/q)(e^z - 1)]^{-\alpha} \quad z \in \mathbb{C} \]
- **Poisson:** $\text{Po}(\lambda)$
  \[ e^{\lambda(e^z - 1)} \quad z \in \mathbb{C} \]
- **Normal:** $\text{No}(\mu, \sigma^2)$
  \[ e^{z\mu + z^2\sigma^2/2} \quad z \in \mathbb{C} \]
- **Gamma:** $\text{Ga}(\alpha, \lambda)$
  \[ (1 - z/\lambda)^{-\alpha} \quad \Re(z) < \lambda \]
- **Cauchy:** $\frac{a}{\pi a^2 + (x-b)^2}$
  \[ e^{i\omega(x-b)} \quad \Re(z) = 0 \]

Aside from the problem that $M(z) = E e^{zX}$ may fail to exist for some $z \in \mathbb{C}$, the approach is promising: we can identify the probability distribution from $M(z)$, and we can even find important features about the distribution directly from $M$: if we can justify interchanging the limits implicit in differentiation and integration, then $M'(z) = E[X e^{zX}]$ and $M''(z) = E[X^2 e^{zX}]$, so (upon taking $z = 0$) $M'(0) = EX = \mu$ and $M''(0) = EX^2 = \sigma^2 + \mu^2$, so we can calculate the mean and variance (and other moments $EX^k = M^{(k)}(0)$) from derivatives of $M(z)$ at zero. We have two problems to overcome: discovering how to infer the distribution of $X$ from $M_X(z) = E e^{zX}$, and what to do about distributions for which $M(z)$ doesn’t exist.

### 8.1 Characteristic Functions

For complex numbers $z = x + iy$ the exponential $e^z$ can be given in terms of familiar real-valued transcendental functions as $e^{x+iy} = e^x \cos(y) + ie^x \sin(y)$. Since both $\sin(y)$ and $\cos(y)$ are bounded by one, for any real-valued random variable $X$ and real number $\omega$ the real and imaginary parts of the complex-valued random variable $e^{i\omega X}$ are bounded and hence integrable; thus it always makes sense to define the **characteristic function**

\[ \phi_X(\omega) = E e^{i\omega X} = \int_{\mathbb{R}} e^{i\omega x} \mu_X(dx), \quad \omega \in \mathbb{R}. \]

Of course this is just $\phi_X(\omega) = M_X(i\omega)$ when $M_X$ exists, but $\phi_X(\omega)$ exists even when $M_X$ does not; on the chart above you’ll notice that only the real part of $z$ posed problems, and $\Re(z) = 0$ was always OK, even for the Cauchy.

- **Binomial:** $\text{Bi}(n, p)$
  \[ \phi(\omega) = [1 + p(e^{i\omega} - 1)]^n \]
- **Neg Bin:** $\text{NB}(\alpha, p)$
  \[ \phi(\omega) = [1 - (p/q)(e^{i\omega} - 1)]^{-\alpha} \]
- **Poisson:** $\text{Po}(\lambda)$
  \[ \phi(\omega) = e^{\lambda(e^{i\omega} - 1)} \]
- **Normal:** $\text{No}(\mu, \sigma^2)$
  \[ \phi(\omega) = e^{i\omega\mu - \omega^2\sigma^2/2} \]
- **Gamma:** $\text{Ga}(\alpha, \lambda)$
  \[ \phi(\omega) = (1 - i\omega/\lambda)^{-\alpha} \]
- **Cauchy:** $\frac{a}{\pi a^2 + (x-b)^2}$
  \[ \phi(\omega) = e^{i\omega(x-b)} \]
8.1.1 Uniqueness

Suppose that two probability distributions $\mu_1(A) = P[X_1 \in A]$ and $\mu_2(A) = P[X_2 \in A]$ have the same Fourier transform $\hat{\mu}_1 \equiv \hat{\mu}_2$, where:

$$\hat{\mu}_j(\omega) = \mathbb{E}[e^{i\omega X_j}] = \int_{\mathbb{R}} e^{i\omega x} \mu_j(dx);$$

does it follow that $X_1$ and $X_2$ have the same probability distributions, i.e., that $\mu_1 = \mu_2$? The answer is yes; in fact, one can recover the measure $\mu$ explicitly from the function $\hat{\mu}(\omega)$. Thus we regard uniqueness as a corollary of the much stronger result, the Fourier Inversion Theorem.

Resnick (1999) has lots of interesting results about characteristic functions in Chapter 9, Grimmett and Stirzaker (2001) discuss related results in their Chapter 5, and Billingsley (1995) proves several versions of this theorem in his Section 26; I’m going to take a different approach, and stress the two special cases in which $\mu$ is discrete or has a density function, trying to make some connections with other encounters you might have had with Fourier transforms.

8.1.2 Positive Definiteness

Which functions $\phi(\omega)$ can be characteristic functions? We know that $\phi(0) = 1$ and $|\phi(\omega)| \leq 1$, and in a homework exercise you showed that $\phi(\omega)$ must be uniformly continuous—is that enough?

The answer is no. Each c.f. has the interesting property that it is “positive definite,” in the following sense:

**Definition 1** A function $\phi : \mathbb{R} \to \mathbb{C}$ is **positive definite** if for every $n \in \mathbb{N}$, $z \in \mathbb{C}^n$, and $\omega \in \mathbb{R}^n$,

$$\sum_{j,k=1}^{n} z_j \phi(\omega_j - \omega_k) \bar{z}_k \geq 0$$

or, equivalently, that each $n \times n$ matrix $A_{jk} = \phi(\omega_j - \omega_k)$ is a positive-definite matrix.
Here's a proof that $\phi(\omega) \equiv \int_{\mathbb{R}} e^{i\omega x} \mu(dx)$ is positive definite, for every distribution $\mu$ on $(\mathbb{R}, \mathcal{B})$:

$$\sum_{j,k=1}^{n} z_j \phi(\omega_j - \omega_k) \overline{z_k} = \sum_{j,k=1}^{n} \int_{\mathbb{R}} z_j e^{i \omega (\omega_j - \omega_k)} \mu(dx) \overline{z_k}$$

$$= \int_{\mathbb{R}} \left\{ \sum_{j=1}^{n} z_j e^{i \omega_j} \right\} \overline{\left\{ \sum_{k=1}^{n} z_k e^{i \omega_k} \right\}} \mu(dx)$$

$$= \int_{\mathbb{R}} \left\| \sum_{j=1}^{n} z_j e^{i \omega_j} \right\|^2 \mu(dx)$$

$$\geq 0.$$  

Interestingly, this condition is also sufficient:

**Theorem 1 (Bochner)** If $\phi : \mathbb{R} \to \mathbb{C}$ is continuous at zero, satisfies $\phi(0) = 1$, and is positive definite, then there exists a Borel probability measure $\mu$ on $(\mathbb{R}, \mathcal{B})$ such that $\phi(\omega) = \int_{\mathbb{R}} e^{i\omega x} \mu(dx)$ for each $\omega \in \mathbb{R}$.  

Here's a proof sketch for the special (but common) case where $\phi \in L_1(\mathbb{R}, d\omega)$. By positive definiteness, for any $\{\omega_j\} \subset \mathbb{R}$ and $\{z_j\} \subset \mathbb{C}$,

$$0 \leq \sum_{j,k} z_j \phi(\omega_j - \omega_k) \overline{z_k}$$

and in particular, for $x \in \mathbb{R}$, $\epsilon > 0$, and $z_j = \exp(-i \epsilon x \omega_j - \epsilon \omega_j^2/2),$

$$0 \leq \sum_{j} e^{-i \epsilon \omega_j} e^{-\epsilon (\omega_j + \omega_k^2)/2} \phi(\omega_j - \omega_k).$$

Taking $\omega_j = (j - n^2)/n$ for $0 \leq j \leq 2n^2$ and then taking the limit as $n \to \infty$,

$$0 \leq \int_{\mathbb{R}^2} e^{-i \epsilon (u - v) - \epsilon (u^2 + v^2)/2} \phi(u - v) \, du \, dv$$

Now change variables from $u$ to $\omega \equiv (u - v)$:

$$= \int_{\mathbb{R}^2} e^{-i \epsilon \omega - \epsilon [u^2 + (u^2 - 2uv + v^2)]/2} \phi(\omega) \, du \, d\omega$$

$$= \int_{\mathbb{R}} e^{-i \epsilon \omega - \epsilon \omega^2/2} \left\{ \int_{\mathbb{R}} e^{-\epsilon (u - \omega)^2 + \omega^2/4} \, du \right\} \phi(\omega) \, d\omega$$

$$= \sqrt{\pi}\epsilon \int_{\mathbb{R}} e^{-i \epsilon \omega - \epsilon \omega^2/4} \phi(\omega) \, d\omega$$

Re-scaling and then taking $\epsilon \to 0$, we find that $f(x) \equiv \frac{1}{2\pi} \int_{\mathbb{R}} e^{-ix\omega} \phi(\omega) \, d\omega \geq 0$ for every $x \in \mathbb{R}$ and can verify that $\phi(\omega) = \int_{\mathbb{R}} e^{i\omega x} \mu(dx)$ for the absolutely-continuous distribution given by $\mu(dx) = f(x) \, dx$.  

Page 4
8.1.3 Inversion: Integer-valued Discrete Case

Notice that the integer-valued discrete distributions always satisfy $\phi(\omega + 2\pi) = \phi(\omega)$ (and in particular are not integrable over $\mathbb{R}$), while the continuous ones satisfy $|\phi(\omega)| \to 0$ as $\omega \to \pm \infty$. For integer-valued random variables $X$ we can recover $p_k = \Pr[X = k]$ by inverting the Fourier series:

$$\phi(\omega) = \mathbb{E}[e^{i\omega X}] = \sum_{k} p_k e^{ik\omega}, \text{ so (by Fubini’s thm)}$$

$$p_k = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{-ik\omega} \phi(\omega) \, d\omega.$$

8.1.4 Inversion: Continuous Random Variables

Now let’s turn to the case of a distribution with a density function; first two preliminaries. For any real or complex numbers $a, b, c$ it is easy to compute (by completing the square) that

$$\int_{-\infty}^{\infty} e^{-a - bx - cx^2} \, dx = \sqrt{\frac{\pi}{c}} e^{-a + b^2 / 4c}$$

if $c$ has positive real part, and otherwise the integral is infinite. In particular, for any $\epsilon > 0$ the function $\gamma_\epsilon(x) \equiv \frac{1}{\sqrt{2\pi\epsilon}} e^{-x^2 / 2\epsilon}$ satisfies $\int \gamma_\epsilon(x) \, dx = 1$ (it’s just the normal pdf with mean 0 and variance $\epsilon$).

Let $\mu(dx) = f(x)dx$ be any probability distribution with density function $f(x)$ and ch.f. $\phi(\omega) = \hat{\mu}(\omega) = \int e^{i\omega x} f(x) \, dx$. Then $|\phi(\omega)| \leq 1$ so for any $\epsilon > 0$ the function $|e^{-iy\omega - \epsilon^2 / 2\epsilon} \phi(\omega)|$ is integrable and we can compute

$$\frac{1}{2\pi} \int_{\mathbb{R}} e^{-iy\omega - \epsilon^2 / 2\epsilon} \phi(\omega) \, d\omega = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-iy\omega - \epsilon^2 / 2\epsilon} \left[ \int_{\mathbb{R}} e^{ix\omega} f(x) \, dx \right] \, d\omega$$

$$= \frac{1}{2\pi} \int_{\mathbb{R}^2} e^{i(x-y)\omega - \epsilon^2 / 2\epsilon} f(x) \, dx \, d\omega$$

$$= \frac{1}{2\pi} \int_{\mathbb{R}} \left[ \int_{\mathbb{R}} e^{i(x-y)\omega - \epsilon^2 / 2\epsilon} \, d\omega \right] f(x) \, dx \quad (2)$$

$$= \frac{1}{2\pi} \int_{\mathbb{R}} \left[ \sqrt{\frac{2\pi}{\epsilon}} e^{-(x-y)^2 / 2\epsilon} \right] f(x) \, dx \quad (3)$$

$$= \frac{1}{\sqrt{2\pi\epsilon}} \int_{\mathbb{R}} e^{-(x-y)^2 / 2\epsilon} f(x) \, dx$$

$$\approx [\gamma_\epsilon \ast f](y) = [\gamma_\epsilon \ast \mu](y)$$

(Where the interchange of orders of integration in (2) is justified by Fubini’s theorem and the calculation in (3) by equation (1)), the convolution of the normal kernel $\gamma_\epsilon(\cdot)$ with $f(y)$. As $\epsilon \to 0$ this converges
• uniformly (and in $L_1$) to $f(y)$ if $f(\cdot)$ is bounded and continuous, the most common case;

• pointwise to $\frac{f(y^-)+f(y^+)}{2}$ if $f(x)$ has a jump discontinuity at $x = y$; and

• to infinity if $\mu(\{y\}) > 0$, i.e., if $\Pr[X = y] > 0$.

This is the Fourier Inversion Formula for $f(x)$: we can recover the density $f(x)$ from its Fourier transform $\phi(\omega) = \hat{\mu}(\omega)$ by

$$f(x) = \lim_{\varepsilon \to 0} \frac{1}{2\pi} \int e^{-i\omega x} \frac{1}{\varepsilon^2} \hat{\mu}(\omega) d\omega.$$ 

There are several interesting connections between the density function $f(x)$ and characteristic function $\phi(\omega)$. If $\phi(\omega)$ “wiggles” with rate approximately $\xi$, i.e., if $\phi(\omega) \approx a\cos(\omega\xi) + b\sin(\omega\xi) + c$, then $f(x)$ will have a spike at $x = \xi$ and $X$ will have a high probability of being close to $\xi$; if $\phi(\omega)$ is very smooth (i.e., has well-behaved continuous derivatives of high order) then it does not have high-frequency wiggles and $f(x)$ falls off quickly for large $|x|$, so $E[|X|^p] < \infty$ for large $p$. If $|\phi(\omega)|$ falls off quickly as $\omega \to \pm \infty$ then $\phi(\omega)$ doesn’t have large low-frequency components and $f(x)$ must be rather tame, without any spikes. Thus $\phi$ and $f$ both capture information about the distribution, but from different perspectives. This is often useful, for the vague descriptions of this paragraph can be made precise:

**Theorem 2** If $\int_{\mathbb{R}} |\hat{\mu}(\omega)| d\omega < \infty$ then $\mu_\varepsilon \equiv \mu * \gamma_\varepsilon$ converges a.s. to an $L_1$ function $f(x)$, $\hat{\mu}_\varepsilon(\omega)$ converges uniformly to $\hat{f}(\omega)$, and $\mu(A) = \int_A f(x) dx$ for each Borel $A \subset \mathbb{R}$. Also $f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-i\omega x} \hat{\mu}(\omega) d\omega$ for almost-every $x$.

**Theorem 3** For any $\mu$ and any $a < b$,

$$\mu(a, b) + \frac{1}{2} \mu(\{a, b\}) = \lim_{T \to \infty} \int_{-T}^T \frac{e^{-i\omega a} - e^{-i\omega b}}{2\pi i\omega} \hat{\mu}(\omega) d\omega.$$ 

**Theorem 4** If $\int_{\mathbb{R}} |x|^k \mu(dx) < \infty$ for an integer $k \geq 0$ then $\hat{\mu}(\omega)$ has continuous derivatives of order $k$ given by

$$\hat{\mu}^{(k)}(\omega) = \int_{\mathbb{R}} (ix)^k e^{i\omega x} \mu(dx).$$ (1)

Conversely, if $\hat{\mu}(\omega)$ has a derivative of finite even order $k$ at $\omega = 0$, then $\int_{\mathbb{R}} |x|^k \mu(dx) < \infty$ and

$$\mathbb{E}X^k = \int_{\mathbb{R}} x^k \mu(dx) = (-1)^{k/2} \hat{\mu}^{(k)}(0).$$ (2)
To prove (1) first note it’s true by definition for $k = 0$, then apply induction:

$$
\hat{\mu}^{(k+1)}(\omega) = \lim_{\epsilon \to 0} \int_{\mathbb{R}} (ix)^k \left( \frac{e^{i\epsilon x} - 1}{\epsilon} \right) e^{i\omega x} \mu(dx)
$$

$$
= \int_{\mathbb{R}} (ix)^{k+1} e^{i\omega x} \mu(dx)
$$

by LDCT since $|e^{i\epsilon x} - 1| \leq |\epsilon x|$.

By Theorem 3 the first few moments of the distribution, if they exist, can be determined from derivatives of the characteristic function or its logarithm $\log \phi(z)$ at $z = 0$: $\phi(0) = 1$, $\phi'(0) = iE[X]$, $\phi''(0) = -E[X^2]$, so

Mean: $\log \phi''(0) = \phi'(0)/\phi(0) = iE[X] = i\mu$

Variance: $\log \phi'''(0) = \phi''(0)/\phi(0)^2 = E[X]^2 - E[X^2] = -\sigma^2$

Etc.: $\log \phi^{(m)}(0) = \mathcal{O}(E[|X|^3])$

so by Taylor’s theorem we have:

$$
\log \phi(\omega) = 0 + i\mu \omega - \sigma^2 \omega^2 / 2 + \mathcal{O}(\omega^3)
$$

$$
\phi(\omega) \approx e^{i\mu \omega - \sigma^2 \omega^2 / 2 + \mathcal{O}(\omega^3)}
$$

8.1.5 Convergence in Distribution

In the Week 6 Notes we defined convergence in distribution of a sequence of distributions $\{\mu_n\}$ to a limiting distribution $\mu$ on a measurable space $(\mathcal{X}, \mathcal{E})$ (written $\mu_n \Rightarrow \mu$):

$$
(\forall \phi \in C_b(\mathcal{X})) \lim_{n \to \infty} \int_{\mathcal{X}} \phi(x) \mu_n(dx) = \int_{\mathcal{X}} \phi(x) \mu(dx)
$$

In fact requiring this convergence for all bounded continuous functions $\phi$ is more than what is necessary. For $\mathcal{X} = \mathbb{R}^d$, for example, it is enough to verify (3) for infinitely-differentiable $C_b^\infty$, or even just for complex exponentials $\phi_\omega(x) = \exp(i\omega \cdot x)$ for $\omega \in \mathbb{R}^d$, i.e.,

**Theorem 5** Let $\{\mu_n(dx)\}$ and $\mu(dx)$ be distributions on Euclidean space $(\mathbb{R}^d, \mathcal{B})$. Then $\mu_n \Rightarrow \mu$ if and only if the characteristic functions converge pointwise, i.e., if

$$
\phi_n(\omega) \equiv \int_{\mathbb{R}^d} e^{i\omega x} \mu_n(dx) \to \phi(\omega) \equiv \int_{\mathbb{R}^d} e^{i\omega x} \mu(dx)
$$

for all $\omega \in \mathbb{R}^d$.

How would you prove this?

**Examples**
Un: Let $X_n$ have the discrete uniform distribution on the points $j/n$, for $1 \leq j \leq n$. Then its ch.f. is

$$
\phi_n(\omega) = \frac{1}{n} \sum_{j=1}^{n} e^{i\omega j/n}
= \frac{e^{i\omega/n} - e^{i(n+1)\omega/n}}{n(1 - e^{i\omega/n})}
= \frac{1 - e^{i\omega}}{n(e^{-i\omega/n} - 1)}
\rightarrow \frac{1 - e^{i\omega}}{-i\omega} = \frac{e^{i\omega} - 1}{i\omega} = \int_{0}^{1} e^{i\omega x} \, dx,
$$

the ch.f. of the $Un(0, 1)$ distribution.

Po: Let $X_n$ have Binomial $Bi(n, p_n)$ distributions with success probabilities $p_n \sim 1/n$, so that $n p_n \rightarrow \lambda$ for some $\lambda > 0$ as $n \rightarrow \infty$. Then the ch.f.s satisfy

$$
\phi_n(\omega) = \left( 1 + p_n(e^{i\omega} - 1) \right)^n \rightarrow e^{(e^{i\omega} - 1)\lambda},
$$

the ch.f. of the $Po(\lambda)$ distribution.

No: Let $X_n$ have Binomial $Bi(n, p_n)$ distributions with success probabilities $p_n$ such that $\sigma_n^2 = n p_n(1 - p_n) \rightarrow \infty$ as $n \rightarrow \infty$, and set $\mu_n = n p_n$. Then the ch.f.s of $Z_n = (X_n - \mu_n)/\sigma_n$ satisfy

$$
\phi_n(\omega) = \left[ 1 + p_n(e^{i\omega/\sigma_n} - 1) \right]^n e^{-i\omega \mu_n/\sigma_n}
\approx \exp \left\{ \mu_n(e^{i\omega/\sigma_n} - 1) - p_n \mu_n(e^{i\omega/\sigma_n} - 1)^2/2 - i\omega \mu_n/\sigma_n \right\}
\approx \exp \left\{ i\mu_n \omega/\sigma_n - \mu_n \omega^2/2\sigma_n^2 - p_n \mu_n(-\omega^2/\sigma_n^2)/2 - i\omega \mu_n/\sigma_n \right\} \rightarrow e^{-\omega^2/2},
$$

the ch.f. of the $No(0, 1)$ distribution.

8.2 Limits of Partial Sums and the Central Limit Theorem

Let $\{X_i\}$ be iid and $L_2$, with common mean $\mu$ and variance $\sigma^2$, and set $S_n \equiv \sum_{i=1}^{n} X_i$ for $n \in \mathbb{N}$. We'll need to center and scale the distribution of $S_n$ before we can hope to make sense of $S_n$'s distribution for large $n$, so we'll need some facts about characteristic functions of linear combinations of independent RVs. For independent $X$ and $Y$, and real numbers $\alpha, \beta, \gamma$,

$$
\phi_{\alpha + \beta X + \gamma Y}(\omega) = E(e^{i\omega(\alpha + \beta X + \gamma Y)}) = E(e^{i\alpha \omega} E(e^{i\beta \omega X}) e^{i\gamma \omega Y}) = e^{i\alpha \omega} \phi_X(\omega \beta) \phi_Y(\omega \gamma)
$$
In particular, for iid $L_3$ random variables $\{X_i\}$ with characteristic function $\phi(t)$, the normalized sum $[S_n - n\mu]/\sqrt{n\sigma^2}$ has characteristic function

$$\phi_n(\omega) = \prod_{j=1}^{n} \left[ \phi(\omega/\sqrt{n\sigma^2})e^{-i\omega\mu/\sqrt{n\sigma^2}} \right]$$

Setting $s \equiv \omega/\sqrt{n\sigma^2}$, this is

$$= [\phi(s)e^{-i\omega\mu}]^n = e^{n[\log \phi(s)-i\omega\mu]}$$

with logarithm

$$\log \phi_n(\omega) = n[\log \phi(s) - i\omega\mu]$$

$$= n[0 + i\mu s - \sigma^2 s^2/2 + O(s^3)] - n\sigma \mu$$

$$= -n[\sigma^2(\omega^2/n\sigma^2)/2 + O(n^{-3/2})]$$

$$= -\omega^2/2 + O(n^{-1/2}),$$

so $\phi_n(\omega) \to e^{-\omega^2/2}$ for all $\omega \in \mathbb{R}$ and hence $Z_n \equiv [S_n - n\mu]/\sqrt{n\sigma^2} \Rightarrow \text{No}(0,1)$, the Central Limit Theorem.

**Note:** We assumed $X_i$ were iid with finite third moment $\gamma = \mathbb{E}|X_i|^3 < \infty$. Under those conditions one can prove the uniform “Berry-Esséen” bound $\sup_x |F_n(x) - \Phi(x)| \leq \gamma/[2\sigma^3 \sqrt{n}]$ for the CDF $F_n$ of $Z_n$. Another version of the CLT asserts weak convergence of $Z_n$ to $\text{No}(0,1)$ assuming only $\mathbb{E}[X^2] < \infty$, but with no bound on the difference of the CDFs. Another famous version, due to Lindeberg and Feller, asserts that

$$\frac{S_n}{s_n} \Rightarrow \text{No}(0,1)$$

for partial sums $S_n = X_1 + \cdots + X_n$ of independent mean-zero $L_2$ random variables $X_j$ that need not be identically distributed, but whose variances $\sigma_j^2 = \mathbb{V}[X_j]$ aren’t too extreme. The specific condition, for $s_n^2 \equiv \sigma_1^2 + \cdots + \sigma_n^2$, is

$$\frac{1}{s_n^2} \sum_{j=1}^{n} \mathbb{E} \left\{ X_j^2 1_{\{|X_j| > ts_n\}} \right\} \to 0$$

as $n \to \infty$ for each $t > 0$. This follows immediately for iid $\{X_j\} \subset L_2$ (where it becomes $s_j^2 \mathbb{E} [X_1^2 1_{\{|X_1| > nt\sigma^2\}}]$ which tends to zero as $n \to \infty$ by the DCT), but for applications it’s important to know that independent but non-iid summands still lead to a CLT.

This “Lindeberg Condition” implies both of

$$\max_{j \leq n} \frac{\sigma_j^2}{s_n^2} \to 0 \quad \quad \max_{j \leq n} \mathbb{P} \left\{ |X_j|/s_n > \epsilon \right\} \to 0$$
as $n \to \infty$, for any $\epsilon > 0$; roughly, no single $X_j$ is allowed to dominate the sum $S_n$. This condition follows from the easier-to-verify Liapunov Condition,

$$s_n^{-2+\delta} \sum_{j=1}^{n} \mathbb{E}|X_j|^{2+\delta} \to 0$$

Other versions of the CLT apply to non-identically distributed or nonindependent $\{X_j\}$, but $S_n$ cannot converge to a normally-distributed limit if $\mathbb{E}[X^2] = \infty$; ask for details (or read Gnedenko and Kolmogorov (1968)) if you’re interested.

Recently an interesting new approach to proving the Central Limit Theorem and related estimates with error bounds was developed by Charles Stein (Stein, 1972, 1986; Barbour and Chen, 2005), described later in these notes.

### 8.3 Compound Poisson Distributions

Let $X_j$ have independent Poisson distributions with means $\nu_j$ and let $u_j \in \mathbb{R}$; then the c.f. for $Y \equiv \sum u_j X_j$ is

$$\phi_Y(\omega) = \prod \exp \left[ \nu_j (e^{i\omega u_j} - 1) \right] = \exp \left[ \sum \left( e^{i\omega u_j} - 1 \right) \nu_j \right] = \exp \left[ \int_{\mathbb{R}} (e^{i\omega u} - 1) \nu(du) \right]$$

for the discrete measure $\nu(du) = \sum \nu_j \delta_{u_j}(du)$ that assigns mass $\nu_j$ to each point $u_j$. Evidently we could take a limit using a sequence of discrete measures that converges to a continuous measure $\nu(du)$ so long as the integral makes sense, i.e., $\int_{\mathbb{R}} |e^{i\omega u} - 1| \nu(du) < \infty$; this will follow from the requirement that $\int_{\mathbb{R}} (1 \wedge |u|) \nu(du) < \infty$. Such a distribution is called Compound Poisson, at least when $\nu(\mathbb{R}) < \infty$; in that case we can also write represent it in the form

$$Y = \sum_{i=1}^{N} X_i, \quad N \sim \text{Po}(\nu_+), \quad X_i \overset{i.i.d.}{\sim} \nu(dx)/\nu_+.$$ 

We’ll now see that it includes an astonishingly large set of distributions, each with c.f. of the form $\exp \left\{ \int (e^{i\omega u} - 1) \nu(du) \right\}$ with “Lévy measure” $\nu(du)$ as given:

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Log Ch Function</th>
<th>Lévy Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poisson $\text{Po}(\lambda)$</td>
<td>$\lambda(\exp i\omega - 1)$</td>
<td>$\lambda \delta_1(du)$</td>
</tr>
<tr>
<td>Gamma $\text{Ga}(\alpha, \lambda)$</td>
<td>$-\alpha \log(1 - i\omega / \lambda)$</td>
<td>$\alpha e^{-\lambda u} u^{-1} du$</td>
</tr>
<tr>
<td>Normal $\text{No}(0, \sigma^2)$</td>
<td>$-\omega^2 \sigma^2 / 2$</td>
<td>$-\sigma^2 \delta_0''(du)$</td>
</tr>
<tr>
<td>Neg Bin $\text{NB}(\alpha, p)$</td>
<td>$-\alpha \log[1 + \frac{p}{1 - \exp i\omega} - 1]$</td>
<td>$\sum_{k=1}^{\infty} \frac{\alpha \beta^k}{k} \delta_k(du)$</td>
</tr>
<tr>
<td>Cauchy $\text{Ca}(\gamma, 0)$</td>
<td>$-\gamma</td>
<td>\omega</td>
</tr>
<tr>
<td>Stable $\text{St}(\alpha, \beta, \gamma)$</td>
<td>$-\gamma</td>
<td>\omega</td>
</tr>
</tbody>
</table>
where \( c_\alpha \equiv \frac{2}{\pi} \Gamma(\alpha) \sin \frac{\pi \alpha}{2} \). Try to verify the measures \( \nu(du) \) for the Negative Binomial and Cauchy distributions. All these distributions share the property called infinite divisibility (“ID” for short), that for every integer \( n \in \mathbb{N} \) each can be written as a sum of \( n \) independent identically distributed terms. In 1936 the French probabilist Paul Lévy and Russian probabilist Alexander Ya. Khinchine discovered that every distribution with this property must have a ch.f. of a very slightly more general form than that given above,

\[
\log \phi(\omega) = i\omega - \frac{\sigma^2}{2} \omega^2 + \int_{\mathbb{R}} [e^{i\omega u} - 1 - i\omega h(u)] \nu(du),
\]

where \( h(u) \) is any bounded Borel function that acts like \( u \) for \( u \) close to zero (for example, \( h(u) = \arctan(u) \) or \( h(u) = \sin(u) \) or \( h(u) = u/(1 + u^2) \)). The measure \( \nu(du) \) need not quite be finite, but we must have \( u^2 \) integrable near zero and 1 integrable away from zero... one way to write this is to require that \( \int (1 \wedge u^2) \nu(du) < \infty \), another is to require \( \int \frac{u^2}{1+u^2} \nu(du) < \infty \). Some authors consider the finite measure \( \kappa(du) = \frac{u^2}{1+u^2} \nu(du) \) and write

\[
\log \phi(\omega) = i\omega a + \int_{\mathbb{R}} [e^{i\omega u} - 1 - i\omega h(u)] \frac{1+u^2}{u^2} \kappa(du),
\]

where now the Gaussian component \( -\frac{\sigma^2}{2} \omega^2 \) arises from a point mass for \( \kappa(du) \) of size \( \sigma^2 \) at \( u = 0 \).

If \( u \) is locally integrable, i.e., if \( \int_{-\infty}^{\infty} |u| \nu(du) < \infty \) for some (and hence every) \( \epsilon > 0 \), then the term “\(-i\omega h(u)\)” is unnecessary (it can be absorbed into \( i\omega a \)). This always happens if \( \nu(\mathbb{R}_-) = 0 \), i.e., if \( \nu \) is concentrated on the positive half-line. Every increasing stationary independent-increment stochastic process \( X_t \) (or subordinator) has increments which are infinitely divisible with \( \nu \) concentrated on the positive half-line and no Gaussian component \( (\sigma^2 = 0) \), so has the representation

\[
\log \phi(\omega) = i\omega a + \int_{0}^{\infty} [e^{i\omega u} - 1] \nu(du)
\]

for some \( a \geq 0 \) and some measure \( \nu \) on \( \mathbb{R}_+ \) with \( \int_{0}^{\infty} (1 \wedge u) \nu(du) < \infty \). In the compound Poisson example, \( \nu(du) = \sum \nu_j \delta_{u_j}(du) \) was the sum of point masses of size \( \nu_j \) at the possible jump magnitudes \( u_j \). This interpretation extends to help us understand all ID distributions: every ID random variable \( X \) may be viewed as the sum of a constant, a Gaussian random variable, and a compound Poisson random variable, the sum of independent Poisson jumps of sizes \( u \in E \subset \mathbb{R} \) with rates \( \nu(E) \).

### 8.3.1 Stable Limit Laws

Let \( S_n = X_1 + \ldots + X_n \) be the partial sum of iid random variables. IF the random variables are all square integrable, THEN the Central Limit Theorem applies and necessarily \( \frac{S_n - n \mu}{\sqrt{n \sigma^2}} \Rightarrow \text{No}(0,1) \). But what if each \( X_n \) is not square integrable? We have already seen that the CLT fails for Cauchy variables \( X_j \). Denote by \( F(x) = P[X_n \leq x] \) the common CDF of the \( \{X_n\} \).
Theorem 6 (Stable Limit Law) Let $S_n = \sum_{j \leq n} X_j$ be the sum of iid random variables. There exist constants $a_n > 0$ and $b_n \in \mathbb{R}$ and a non-trivial distribution $G$ for which the scaled and centered partial sums converge in distribution

$$\frac{S_n - b_n}{a_n} \xrightarrow{d} G$$

if and only if $\{X_j\} \subset L_2$ (in which case $a_n \sim \sqrt{n}$, $b_n = n\mu + O(\sqrt{n})$, and $G = \text{No}(\mu, \sigma^2)$ is the Normal distribution) or there are constants $0 < \alpha < 2$, $M^- \geq 0$, and $M^+ \geq 0$, with $M^- + M^+ > 0$, such that as $x \to \infty$ the following limits hold for every $\xi > 0$:

1. $\frac{F(-x)}{1 - F(x)} \to \frac{M^-}{M^+};$

2. $M^+ > 0 \Rightarrow \frac{1 - F(x\xi)}{1 - F(x)} \to \xi^{-\alpha}$

$M^- > 0 \Rightarrow \frac{F(-x\xi)}{F(-x)} \to \xi^{-\alpha}$.

In this case the limit is the $\alpha$-Stable Distribution, with index $\alpha$, with characteristic function

$$E[e^{i\omega Y}] = e^{i\delta \omega - \gamma|\omega|^\alpha [1 - i\beta \tan \frac{\pi \alpha}{2} \text{sgn}(\omega)]},$$

where $\beta = \frac{M^+ - M^-}{M^- + M^+}$ and $\gamma = (M^- + M^+)$. The sequence $A_n$ must be essentially $A_n \propto n^{1/\alpha}$ (more precisely, the sequence $C_n = n^{-1/\alpha}A_n$ is slowly varying in the sense that

$$1 = \lim_{n \to \infty} C_n / C_m$$

for every $c > 0$; thus partial sums converge to stable distributions at rate $n^{-1/\alpha}$, more slowly (much more slowly, if $\alpha$ is close to one) than in the $L_2$ (Gaussian) case of the central limit theorem. The limits in “2.” above are equivalent to the requirement that $F(x) = |x|^{-\alpha}\mathcal{L}_-(x)$ as $x \to -\infty$ and $F(x) = 1 - x^{-\alpha}\mathcal{L}_+(x)$ as $x \to +\infty$ for “slowly varying functions” $\mathcal{L}_\pm$.

The simplest case is the symmetric $\alpha$-stable ($\text{SOS}$). For $0 < \alpha < 2$ and $0 < \gamma < \infty$, the $\text{St}(\alpha, 0, \gamma, 0)$ has c.h.f. of the form

$$e^{-\gamma|\omega|^{\alpha}}$$

This includes the centered Cauchy ($\alpha = 1$, $\gamma = s$) and the centered Normal ($\alpha = 2$, $\gamma = \sigma^2/2$). The $\text{SOS}$ family interpolates between these (for $1 < \alpha < 2$) and extends them (for $0 < \alpha < 1$) even heavier-tailed distributions.

Although each Stable distribution has an absolutely continuous distribution with continuous unimodal probability density function $f(y)$, these two cases and the “inverse Gaussian” or “Lévy” distribution with $\alpha = 1/2$ and $\beta = \pm 1$ are the only ones where the pdf is available in closed form. Perhaps that’s the reason these are less studied than normal distributions; still, they are very useful for problems with “heavy tails”, i.e., where $P[X > u]$ does not die off quickly with increasing $u$. The symmetric ($\text{SOS}$) ones all have bell-shaped pdfs.
Moments are easy enough to compute but, for $\alpha < 2$, moments $E|X|^p$ are only finite for $p < \alpha$. In particular, means only exist for $\alpha > 1$ and none of them has a finite variance. The Cauchy has finite moments of order $p < 1$, but does not have a well-defined mean.

Condition 2. says that each tail must be fall off like a power (sometimes called Pareto tails), and the powers must be identical; Condition 1. gives the tail ratio. A common special case is $M^- = 0$, the “one-sided” or “fully skewed” Stable; for $0 < \alpha < 1$ these take only values in $[\delta, \infty)$ ($\mathbb{R}_+$ if $\delta = 0$). For example, random variables $X_n$ with the Pareto distribution (often used to model income) given by $P[X_n > t] = (k/t)^\alpha$ for $t \geq k$ will have a stable limit for their partial sums if $\alpha < 2$, and (by CLT) a normal limit if $\alpha \geq 2$. There are close connections between the theory of Stable random variables and the more general theory of statistical extremes. Ask me for references if you’d like to learn more about this exciting area.

Expression (5) for the $\alpha$-stable ch.f. behaves badly as $\alpha \to 1$ if $\beta \neq 0$, because the tangent function has a pole at $\pi/2$. For $\alpha \approx 1$ the complex part of the log ch.f. is:

$$
\Im \{\log E[e^{i\omega Y}]\} = i\delta \omega + i\beta \gamma \tan \frac{\pi \alpha}{2} |\omega|^\alpha \text{sgn}(\omega)
$$

$$
= i\delta \omega + i\beta \gamma \tan \frac{\pi \alpha}{2} |\omega|^{\alpha-1} \omega
$$

$$
= i\omega \left[ \delta + \beta \gamma \tan \frac{\pi \alpha}{2} \right] - i\beta \gamma \tan \frac{\pi \alpha}{2} \omega \left( 1 - |\omega|^{\alpha-1} \right)
$$

where the last term is bounded as $\alpha \to 1$ so (following V. M. Zolotarev, 1986) the $\alpha$-stable is often parametrized for $\alpha \neq 1$ as

$$
\log E[e^{i\omega Y}] = -\gamma |\omega|^\alpha + i\delta^* \omega - i\beta \gamma \tan \frac{\pi \alpha}{2} \omega \left( 1 - |\omega|^{\alpha-1} \right)
$$

with shifted “drift” term $\delta^* = \delta + \beta \gamma \tan(\pi \alpha / 2)$. You can find out more details by asking me or reading Breiman (1968, Chapter 9).

### 8.3.2 Key Idea of the Stable Limit Laws

The stable limit law Theorem 6 says that if there exist nonrandom sequences $a_n > 0$ and $b_n \in \mathbb{R}$ and a nondegenerate distribution $G$ such that the partial sum $S_n = \sum_{j \leq n} X_j$ of iid random variables $\{X_j\}$ satisfies

$$
\frac{S_n - b_n}{a_n} \Rightarrow G
$$

then $G$ must be either the normal distribution or an $\alpha$-stable distribution for some $0 < \alpha < 2$.

The key idea behind the theorem is that if a distribution $\mu$ with cdf $G$ satisfies (6) then also for any $n$ the distribution of the sum $S_n$ of $n$ independent random variables with cdf $G$ must also (after suitable shift and scale changes) have cdf $G$—i.e., that $c_n S_n + d_n \sim G$ for some constants $c_n > 0$ and $d_n \in \mathbb{R}$, so the characteristic function $\chi(\omega) = \int e^{i\omega x} G(dx)$ and
\[ \log \text{ ch.f. } \psi(\omega) = \log \chi(\omega) \text{ must satisfy} \]

\[
\chi(\omega) = \mathbb{E} \exp \{i\omega (c_n S_n + d_n)\} \\
= \exp(i\omega d_n) \chi(\omega c_n)^n \\
\psi(\omega) = i\omega d_n + n\psi(c_n \omega)
\]

(7)

whose only solutions are the normal and \( \alpha \)-stable distributions. Here’s a sketch of the proof for the symmetric (S\( \alpha \)S) case, where \( \psi(-\omega) = \psi(\omega) \) and so \( d_n = 0 \). Set \( \gamma = \psi(1) \) and note that (7) with \( \omega = c_n^k \) for \( k = 0, 1, \ldots \) implies successively:

\[
\psi(c_n) = \frac{\gamma}{n} \\
\psi(c_n^2) = \psi(c_n) \frac{1}{n} = \frac{\gamma}{n^2} \\
\vdots \\
\psi(c_n^k) = \frac{\gamma}{n^k}.
\]

Results from complex analysis imply this must hold for all \( k \geq 0 \), not just integers. Thus, with \( |w| = c_n^k \) and \( k = \log |w| / \log c_n \),

\[
\psi(w) = \gamma n^{-k} \\
= \gamma \exp \{- (\log |w|)(\log n) / (\log c_n)\} \\
= \gamma |w|^{-[\log n] / (\log c_n)} \\
= \gamma |w|^\alpha,
\]

where \( \alpha \) is the constant value of \( \frac{-\log n}{\log c_n} \) and so \( c_n = n^{-1/\alpha} \).
References


