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2 Central limit theorem

2a Introduction

Discrete probability spaces are enough here as long as all random variables are discrete (otherwise $\Omega = \mathbb{R}^n$ fits); to this end use triangle arrays.

Let X_1, X_2, \dots be independent identically distributed random variables, and $S_n = X_1 + \dots + X_n$.

2a1 Theorem. ¹ Let $\mathbb{E} X_1 = 0$ and $\mathbb{E} X_1^2 = 1$. Then

$$\mathbb{P}(a\sqrt{n} < S_n < b\sqrt{n}) \rightarrow \frac{1}{\sqrt{2\pi}} \int_a^b e^{-x^2/2} dx \quad \text{as } n \rightarrow \infty$$

whenever $-\infty \leq a \leq b \leq \infty$.

Clearly, the De Moivre-Laplace Theorem 1a20 is a special case.

More than 10 proofs are well-known. Some use Stirling formula. Some use Brownian motion. Some prove convergence to the normal distribution. Some prove first convergence to some distribution, and then identify it.

Moment method: first, find $\lim_n \mathbb{E} \left(\frac{S_n}{\sqrt{n}}\right)^k$ assuming all moments finite (otherwise, truncate); then approximate the indicator of an interval by polynomials.

Fourier transform (“characteristic function”): first, $\lim_n \mathbb{E} \exp(i\lambda \frac{S_n}{\sqrt{n}}) = \exp(-\frac{\lambda^2}{2})$; then approximate the indicator of an interval by trigonometric sums.

Smooth test functions (Lindeberg): first, $\mathbb{E} f(\frac{S_n}{\sqrt{n}}) - \mathbb{E} f(\frac{\tilde{S}_n}{\sqrt{n}}) \rightarrow 0$ as $n \rightarrow \infty$ for $f \in C^3$; then approximate the indicator of an interval by such smooth functions. This will be done here.

¹[KS, Sect. 10.1, Th. 10.5]; [D, Sect. 2.4, Theorem (4.1)].

2b Convolution

The convolution $\nu * f$ of a probability distribution ν on \mathbb{R} and a bounded continuous function $f : \mathbb{R} \rightarrow \mathbb{R}$ is a function $\mathbb{R} \rightarrow \mathbb{R}$ defined by¹

$$(\nu * f)(x) = \int f(x + y) \nu(dy).$$

For a discrete ν the convolution is a linear combination of shifts. In general it may be thought of as an integral combination of shifts. Probabilistically, $(P_X * f)(a) = \mathbb{E} f(a + X)$.

2b1 Lemma. If f is bounded and continuous² then also $\mu * f$ is, and $\|\mu * f\| \leq \|f\|$.

Here and below the norm is supremal (rather than L_2):

$$\|f\| = \sup_{x \in \mathbb{R}} |f(x)|.$$

Proof. Boundedness: $|\mathbb{E} f(a + X)| \leq \sup |f(\cdot)|$. Continuity: if $a_n \rightarrow a$ then $f(a_n + x) \rightarrow f(a + x)$ pointwise, thus $\mathbb{E} f(a_n + X) \rightarrow \mathbb{E} f(a + X)$ by the bounded convergence theorem. \square

For independent X, Y we have $P_{X+Y} * f = P_Y * P_X * f$ (it means, $(P_Y * (P_X * f))$), since

$$\begin{aligned} (P_{X+Y} * f)(a) &= \mathbb{E} f(a + X + Y) = \iint f(a + x + y) P_X(dx) P_Y(dy) = \\ &= \int \left(\int f(a+x+y) P_X(dx) \right) P_Y(dy) = \int (P_X * f)(a+y) P_Y(dy) = (P_Y * (P_X * f))(a). \end{aligned}$$

We define the convolution of two probability distributions μ, ν by $(\mu * \nu)(B) = (\mu \times \nu)(\{(x, y) : x + y \in B\})$, then $P_{X+Y} = P_X * P_Y$ for independent X, Y , and we may interpret $P_Y * P_X * f$ as $(P_Y * P_X) * f$ equally well.

Convolution for discrete:

$$\begin{aligned} (P_X * f)(a) &= \sum_x p_X(x) f(a + x); \\ p_{X+Y}(a) &= \sum_{(x,y):x+y=a} p_X(x) p_Y(y) = \sum_x p_X(x) p_Y(a - x). \end{aligned}$$

¹The definition generalizes easily to finite signed measures and bounded Borel functions, but we do not need it.

²Well, it is required by the definition above...

Convolution for absolutely continuous:

$$(P_X * f)(a) = \int p_X(x) f(a+x) dx ;$$

$$p_{X+Y}(a) = \int p_X(x) p_Y(a-x) dx .$$

Some examples:

$$\text{Binom}(m, p) * \text{Binom}(n, p) = \text{Binom}(m+n, p) , \quad \text{--- binomial}$$

$$N(a_1, \sigma_1^2) * N(a_2, \sigma_2^2) = N(a_1 + a_2, \sigma_1^2 + \sigma_2^2) . \quad \text{--- normal}$$

The latter equality can be checked by integration, or obtained from the former by a limiting procedure, but better note that the standard two-dimensional normal distribution $N(0, 1) \times N(0, 1)$ has the density¹

$$\frac{1}{\sqrt{2\pi}} e^{-x^2/2} \cdot \frac{1}{\sqrt{2\pi}} e^{-y^2/2} = \frac{1}{2\pi} e^{-(x^2+y^2)/2}$$

invariant under rotations; thus, $X \cos \alpha + Y \sin \alpha \sim N(0, 1)$ for all α .

2b2 Lemma. If f has a bounded and continuous derivative, then also $\mu * f$ has, and $(\mu * f)' = \mu * f'$.

Proof. We have a bounded continuous g satisfying $f(b) = f(a) + \int_a^b g(x) dx$. Thus,

$$\begin{aligned} (\mu * f)(b) &= \int f(b+y) \mu(dy) = \int \left(f(a+y) + \int_{a+y}^{b+y} g(x) dx \right) \mu(dy) = \\ &= \int f(a+y) \mu(dy) + \int \left(\int_a^b g(x+y) dx \right) \mu(dy) = \\ &= (\mu * f)(a) + \int_a^b \left(\int g(x+y) \mu(dy) \right) dx = (\mu * f)(a) + \int_a^b (\mu * g)(x) dx . \end{aligned}$$

□

The same holds for f'' and f''' .²

¹In addition, integrating it in polar coordinates we get $\frac{1}{2\pi} (\int_0^\infty e^{-r^2/2} r dr) (\int_0^{2\pi} d\varphi) = 1$, which shows that $1/\sqrt{2\pi}$ is the right coefficient for the density of $N(0, 1)$. (See also Proof of 1a20.)

²And so on, of course, but we need only three derivatives.

2c The initial distribution does not matter

Let μ, ν be two probability distributions on \mathbb{R} satisfying

$$\int x \mu(dx) = \int x \nu(dx) = 0, \quad \int x^2 \mu(dx) = \int x^2 \nu(dx) = 1.$$

We consider independent random variables X_1, \dots, X_n distributed μ , and independent random variables Y_1, \dots, Y_n distributed ν . Note that $\mathbb{E} X_1 = \mathbb{E} Y_1 = 0$ and $\mathbb{E} X_1^2 = \mathbb{E} Y_1^2 = 1$.

2c1 Proposition. If f, f', f'', f''' are continuous and bounded on \mathbb{R} then

$$\mathbb{E} f\left(\frac{X_1 + \dots + X_n}{\sqrt{n}}\right) - \mathbb{E} f\left(\frac{Y_1 + \dots + Y_n}{\sqrt{n}}\right) \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

The proof will be given after a corollary.

2c2 Corollary.

$$\mathbb{E} f\left(\frac{X_1 + \dots + X_n}{\sqrt{n}}\right) \rightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} f(x) e^{-x^2/2} dx.$$

Proof of the corollary. Let Y_1 be normal $N(0, 1)$, then $Y_1 + \dots + Y_n$ is also normal, thus

$$\mathbb{E} f\left(\frac{Y_1 + \dots + Y_n}{\sqrt{n}}\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} f(x) e^{-x^2/2} dx \quad \text{for all } n.$$

□

We start proving the proposition.

We have $\int (a + bx + cx^2) \mu(dx) = \int (a + bx + cx^2) \nu(dx)$ for all $a, b, c \in \mathbb{R}$. Similarly,

$$\int (a + bx + cx^2) \mu_n(dx) = \int (a + bx + cx^2) \nu_n(dx);$$

here and below μ_n is the distribution of X_1/\sqrt{n} , and ν_n — of Y_1/\sqrt{n} ; that is, $\int f\left(\frac{x}{\sqrt{n}}\right) \mu(dx) = \int f d\mu_n$ (and the same for ν). These μ_n, ν_n are useful, since

$$(2c3) \quad \mathbb{E} f\left(\frac{X_1 + \dots + X_n}{\sqrt{n}}\right) = (\mu_n * \dots * \mu_n * f)(0) = (\mu_n^{*n} * f)(0),$$

and the same for Y and ν .

2c4 Lemma. There exist $\varepsilon_n \rightarrow 0$ such that for every f (as in 2c1) and every n ,

$$\left| \int f \, d\mu_n - \int f \, d\nu_n \right| \leq \frac{\varepsilon_n}{n} (\|f''\| + \|f'''\|).$$

2c5 Remark. These ε_n depend on μ, ν (but not f). If μ, ν have third moments then moreover

$$\left| \int f \, d\mu_n - \int f \, d\nu_n \right| \leq \frac{1}{6n^{1.5}} \|f'''\| (\mathbb{E}|X_1|^3 + \mathbb{E}|Y_1|^3).$$

Proof of the lemma. We define g by

$$f(x) = f(0) + f'(0)x + \frac{1}{2}f''(0)x^2 + g(x);$$

g is continuous but not bounded;

$$|g(x)| \leq \|f'''\| \cdot \frac{1}{6}|x|^3.$$

We have $\int (f - g) \, d\mu_n = \int (f - g) \, d\nu_n$, therefore

$$\left| \int f \, d\mu_n - \int f \, d\nu_n \right| \leq \int |g| \, d\mu_n + \int |g| \, d\nu_n,$$

which leads immediately to 2c5, but we need an argument that does not require the third moments. We note that $|\frac{1}{2}f''(0)x^2 + g(x)| \leq \frac{1}{2}\|f''\|x^2$, therefore

$$|g(x)| \leq \|f''\| \cdot |x|^2,$$

and split the integral:¹

$$\begin{aligned} \int |g| \, d\mu_n &= \int \left| g\left(\frac{x}{\sqrt{n}}\right) \right| \mu(dx) \leq \\ &\leq \underbrace{\int_{|x| \leq n^{1/12}} \|f'''\| \cdot \frac{1}{6} \left| \frac{x}{\sqrt{n}} \right|^3 \mu(dx)}_{O(n^{-7/6})} + \underbrace{\int_{|x| > n^{1/12}} \|f''\| \cdot \left| \frac{x}{\sqrt{n}} \right|^2 \mu(dx)}_{o(1/n)} \leq \\ &\leq \frac{\varepsilon_n}{n} (\|f''\| + \|f'''\|) \quad \text{where} \\ \varepsilon_n &= \max \left(\frac{1}{24n^{1/6}}, \int_{|x| > n^{1/12}} x^2 \mu(dx) \right); \end{aligned}$$

the same holds for $\int |g| \, d\nu_n$. □

¹The exponent 1/12 may be replaced with any other number between 0 and 1/6.

Proof of Proposition 2c1. By (2c3) it is sufficient to prove that $|(\mu_n^{*n} * f)(0) - (\nu_n^{*n} * f)(0)| \rightarrow 0$. Applying Lemma 2c4 to a shifted function $x \mapsto f(a+x)$ we get

$$\|\mu_n * f - \nu_n * f\| \leq \frac{\varepsilon_n}{n} (\|f''\| + \|f'''\|).$$

We turn μ_n^{*n} into ν_n^{*n} gradually:

$$\begin{aligned} \mu_n^{*n} * f - \nu_n^{*n} * f &= \sum_{k=0}^{n-1} (\mu_n^{*(n-k)} * \nu_n^{*k} * f - \mu_n^{*(n-k-1)} * \nu_n^{*(k+1)} * f) = \\ &= \sum_{k=0}^{n-1} \mu_n^{*(n-k-1)} * (\mu_n * f_k - \nu_n * f_k), \end{aligned}$$

where $f_k = \nu_n^{*k} * f$. Now, $\|f_k''\| \leq \|f''\|$, $\|f_k'''\| \leq \|f'''\|$, and $\|\mu_n^{*(n-k-1)} * (\dots)\| \leq \|(\dots)\|$; thus,

$$\|\mu_n^{*n} * f - \nu_n^{*n} * f\| \leq \sum_{k=0}^{n-1} \frac{\varepsilon_n}{n} (\|f''\| + \|f'''\|) = \varepsilon_n (\|f''\| + \|f'''\|) \rightarrow 0$$

as $n \rightarrow \infty$. □

2d From smooth functions to indicators

2d1 Lemma. There exists a function $\varphi : \mathbb{R} \rightarrow \mathbb{R}$ having three bounded derivatives and such that $\varphi(x) = 0$ for all $x \leq -1$, $\varphi(x) = 1$ for all $x \geq 0$.

Proof. The function $\psi(x) = (1 - x^2)^4$ for $|x| \leq 1$, otherwise 0, has two (in fact, three) continuous derivatives. We take $\varphi(x) = \frac{1}{c} \int_{-\infty}^{2x+1} \psi(t) dt$ where $c = \int_{-\infty}^{\infty} \psi(t) dt$. □

Let X_1, \dots, X_n be as in 2c1. By 2c2, for every $a \in \mathbb{R}$ and $\varepsilon > 0$,

$$\mathbb{E} \varphi \left(\frac{1}{\varepsilon} \left(\frac{X_1 + \dots + X_n}{\sqrt{n}} - a \right) \right) \rightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \varphi \left(\frac{1}{\varepsilon} (x - a) \right) e^{-x^2/2} dx$$

as $n \rightarrow \infty$. Taking into account that

$$\mathbb{P} \left(\frac{X_1 + \dots + X_n}{\sqrt{n}} \geq a \right) \leq \mathbb{E} \varphi \left(\frac{1}{\varepsilon} \left(\frac{X_1 + \dots + X_n}{\sqrt{n}} - a \right) \right)$$

we get

$$\limsup_{n \rightarrow \infty} \mathbb{P} \left(\frac{X_1 + \dots + X_n}{\sqrt{n}} \geq a \right) \leq \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \varphi \left(\frac{1}{\varepsilon} (x - a) \right) e^{-x^2/2} dx.$$

The right-hand side converges to $\frac{1}{\sqrt{2\pi}} \int_a^\infty e^{-x^2/2} dx$ as $\varepsilon \rightarrow 0$. Thus, $\limsup \mathbb{P}(X_1 + \dots + X_n \geq a\sqrt{n}) \leq \mathbb{P}(\xi \geq a)$ where $\xi \sim N(0, 1)$; or equivalently, $\liminf \mathbb{P}(X_1 + \dots + X_n < a\sqrt{n}) \geq \mathbb{P}(\xi < a)$. Similarly, $\limsup \mathbb{P}(-X_1 - \dots - X_n \geq a\sqrt{n}) \leq \mathbb{P}(\xi \geq a)$, that is, $\limsup \mathbb{P}(X_1 + \dots + X_n \leq -a\sqrt{n}) \leq \mathbb{P}(\xi \leq -a)$, or equivalently, $\limsup \mathbb{P}(X_1 + \dots + X_n \leq a\sqrt{n}) \leq \mathbb{P}(\xi \leq a)$. We have

$$\begin{aligned} \mathbb{P}(\xi < a) &\leq \liminf \mathbb{P}(X_1 + \dots + X_n < a\sqrt{n}) \leq \\ &\leq \limsup \mathbb{P}(X_1 + \dots + X_n \leq a\sqrt{n}) \leq \mathbb{P}(\xi \leq a) = \mathbb{P}(\xi < a), \end{aligned}$$

therefore

$$\lim_{n \rightarrow \infty} \mathbb{P}(X_1 + \dots + X_n < a\sqrt{n}) = \mathbb{P}(\xi < a).$$