

# Math 525: Lecture 15

March 6, 2018

Today, we finally prove the central limit theorem (CLT). Recall that for a “sufficiently nice” sequence of i.i.d. random variables  $(X_n)_n$ , the law of large numbers told us

$$\frac{S_n}{n} \equiv \frac{X_1 + \cdots + X_n}{n} \rightarrow \mathbb{E}X_1 \text{ a.s.}$$

The CLT will tell us about the distribution of  $S_n/n$ . Namely,

$$\sqrt{n} \left( \frac{S_n}{n} - \mathbb{E}X_1 \right) \xrightarrow{\mathcal{D}} Y \tag{1}$$

where  $Y \sim \mathcal{N}(0, \text{Var}(X_1))$ . Before we give the CLT, let’s review normal random variables.

## 1 Normal random variables

**Definition 1.1.** We say  $X$  is a *normal random variable* with mean  $\mu$  and variance  $\sigma^2$  if its probability density is

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

In this case, we write  $X \sim \mathcal{N}(\mu, \sigma^2)$ .

**Proposition 1.2.** *The characteristic function of  $X \sim \mathcal{N}(0, 1)$  random variable is*

$$\phi_X(t) = e^{-t^2/2}.$$

*Proof.* Note that

$$\begin{aligned} \phi_X(t) = \mathbb{E} [e^{itX}] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} e^{itx} dx \\ &= \frac{1}{\sqrt{2\pi}} \left( \int_{-\infty}^0 e^{-\frac{x^2}{2}} e^{itx} dx + \int_0^{\infty} e^{-\frac{x^2}{2}} e^{itx} dx \right) \\ &= \frac{1}{\sqrt{2\pi}} \left( \int_0^{\infty} e^{-\frac{x^2}{2}} e^{-itx} dx + \int_0^{\infty} e^{-\frac{x^2}{2}} e^{itx} dx \right) \\ &= \frac{2}{\sqrt{2\pi}} \int_0^{\infty} e^{-\frac{x^2}{2}} \cos(tx) dx. \end{aligned}$$

Now, take the derivative with respect to  $t$  to get

$$\phi'_X(t) = -\frac{2}{\sqrt{2\pi}} \int_0^\infty e^{-\frac{x^2}{2}} x \sin(tx) dx.$$

Integrate by parts to get

$$\begin{aligned} \phi'_X(t) &= \frac{2}{\sqrt{2\pi}} \left( e^{-\frac{x^2}{2}} \sin(tx) \Big|_0^\infty - t \int_0^\infty e^{-\frac{x^2}{2}} \cos(tx) dx \right) \\ &= -\frac{2t}{\sqrt{2\pi}} \int_0^\infty e^{-\frac{x^2}{2}} \cos(tx) dx \\ &= -t\phi_X(t). \end{aligned}$$

Note that

$$\phi'(t) = -t\phi(t)$$

is an ordinary differential equation with

$$\phi(t) = C_0 \exp\left(-\frac{t^2}{2}\right)$$

where  $C_0$  is some constant. Since  $\phi$  is a characteristic function, we must have  $\phi(0) = 1$ . This implies that  $C_0 = 1$ .  $\square$

## 2 Classical CLT

Just like with the law of large numbers, there are various versions of the CLT. Here is the first version we encounter:

**Proposition 2.1.** *Let  $(X_j)_j$  be a sequence of i.i.d. random variables. Let  $\mu = \mathbb{E}[X_1]$ ,  $\sigma^2 = \text{Var}(X_1)$ , and  $S_n = X_1 + \dots + X_n$ . Then,*

$$\frac{\sqrt{n}}{\sigma} \left( \frac{S_n}{n} - \mu \right) \xrightarrow{\mathcal{D}} \mathcal{N}(0, 1)$$

(note that this is identical to (1) if we multiply both sides by  $\sigma$ ).

In establishing Levy's continuity theorem, we have actually done all the hard work already to prove this fact.

*Proof.* First, note that

$$\frac{\sqrt{n}}{\sigma} \left( \frac{S_n}{n} - \mu \right) = \frac{(X_1 - \mu) + \dots + (X_n - \mu)}{\sqrt{n}\sigma} = \frac{Y_1 + \dots + Y_n}{\sqrt{n}}$$

where

$$Y_n = \frac{X_n - \mu}{\sigma}.$$

Note that

$$\begin{aligned}\mathbb{E}Y_n &= \frac{\mathbb{E}X_n - \mu}{\sigma} = 0 \\ \text{Var}(Y_n) &= \text{Var}\left(\frac{X_n - \mu}{\sigma}\right) = 1.\end{aligned}$$

For brevity, let  $S'_n = Y_1 + \cdots + Y_n$ .

The characteristic function of  $Y_n$  is

$$\begin{aligned}\phi(t) &= \mathbb{E}[e^{itY_n}] \\ &= \mathbb{E}\left[\sum_{k \geq 0} \frac{(it)^k}{k!} Y_n^k\right] \\ &= \mathbb{E}[Y^0] + (it)\mathbb{E}[Y^1] + \frac{(it)^2}{2}\mathbb{E}[Y^2] + \cdots \\ &= 1 - \frac{t^2}{2} + \cdots\end{aligned}$$

More precisely,

$$\phi(t) = 1 - \frac{t^2}{2} + h(t^2)$$

where  $h$  denotes a function that satisfying  $h(cx)/x \rightarrow 0$  as  $x \rightarrow 0$  (corresponding to the higher order terms in the Taylor expansion). Now, let

$$S'_n = \frac{Y_1 + \cdots + Y_n}{\sqrt{n}}.$$

Note that

$$\begin{aligned}\phi_{S'_n}(t) &= \mathbb{E}\left[\exp\left(it\frac{Y_1 + \cdots + Y_n}{\sqrt{n}}\right)\right] \\ &= \mathbb{E}\left[\exp\left(it\frac{Y_1}{\sqrt{n}}\right) \cdots \exp\left(it\frac{Y_n}{\sqrt{n}}\right)\right] \\ &= \mathbb{E}\left[\exp\left(it\frac{Y_1}{\sqrt{n}}\right)\right] \cdots \mathbb{E}\left[\exp\left(it\frac{Y_n}{\sqrt{n}}\right)\right] \\ &= \phi\left(\frac{t}{\sqrt{n}}\right) \cdots \phi\left(\frac{t}{\sqrt{n}}\right) \\ &= \left(\phi\left(\frac{t}{\sqrt{n}}\right)\right)^n \\ &= \left(1 - \frac{t^2}{2n} + o\left(\frac{t^2}{n}\right)\right)^n. \\ &= \left(1 + \frac{z_n}{n}\right)^n\end{aligned}$$

where we have defined

$$z_n = -\frac{t^2}{2} + nh\left(\frac{t^2}{n}\right).$$

Let  $c = t^2$  and  $x = 1/n$ . Then,

$$nh \left( \frac{t^2}{n} \right) = \frac{h(cx)}{x} \rightarrow 0 \quad \text{as} \quad x \rightarrow 0.$$

Therefore,

$$\phi_{S'_n}(t) \rightarrow e^{t^2/2}.$$

By Lévy's continuity theorem,  $S'_n$  converges to a standard normal random variable.  $\square$

**Exercise 2.2.**  $n$  numbers are rounded to the nearest integer and then summed. Suppose that the individual roundoff errors are uniformly distributed over  $[-0.5, 0.5]$ . What is the probability that the roundoff error exceeds the exact sum by more than  $x$ ?

Hint: let  $Y_j$  be the  $j$ -th number and  $[Y_j]$  be the result from rounding. Then,

$$X_j = Y_j - [Y_j] \sim U[-0.5, 0.5].$$

Therefore,

$$\mathbb{E}X_j = 0 \quad \text{and} \quad \sigma^2 = \text{Var}(X_j) = \mathbb{E}X_j^2 = \int_{-1/2}^{1/2} x^2 dx = \frac{1}{12}.$$

Let  $S_n = X_1 + \cdots + X_n$ . Then,

$$\begin{aligned} \mathbb{P}\{|S_n| > x\} &= 1 - \mathbb{P}\{|S_n| \leq x\} \\ &= 1 - \mathbb{P}\left\{\frac{|S_n|}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\} \\ &= 1 - \mathbb{P}\left\{-\frac{x}{\sqrt{n}\sigma} \leq \frac{S_n}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\} \\ &= 1 - \left(\mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\} - \mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} < -\frac{x}{\sqrt{n}\sigma}\right\}\right) \\ &= 1 - \left(\mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\} - \left(1 - \mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} \geq -\frac{x}{\sqrt{n}\sigma}\right\}\right)\right) \\ &\approx 1 - \left(\mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\} - \left(1 - \mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\}\right)\right) \\ &= 2 \left(1 - \mathbb{P}\left\{\frac{S_n}{\sqrt{n}\sigma} \leq \frac{x}{\sqrt{n}\sigma}\right\}\right) \end{aligned}$$

Since we expect  $\frac{S_n}{\sqrt{n}\sigma}$  to be normally distributed, letting  $F$  denote the distribution function of  $\mathcal{N}(0, 1)$ ,

$$\mathbb{P}\{|S_n| > x\} \approx 2 \left(1 - F\left(\frac{x}{\sqrt{n}\sigma}\right)\right).$$

For example, if  $n = 10$  and  $x = 1$ , then

$$\mathbb{P}\{|S_{10}| > 1\} \approx 2 \left(1 - F\left(\frac{\sqrt{12}}{\sqrt{10}}\right)\right) \approx 0.27.$$

### 3 Confidence intervals

The discussion in this section is very hand wavy, so take it with a grain of salt.

Consider conducting a sequence of trials represented as i.i.d. random variables  $(X_j)_j$ . For example, we may repeatedly toss an unfair coin repeatedly in order to determine its distribution. In practice, we will not have access to the variance of  $X_1$ .

Letting  $S_n = X_1 + \dots + X_n$ , and consider the random variable

$$Z_n = \frac{\sqrt{n}}{\sigma} \left( \frac{S_n}{n} - \mu \right).$$

Then,

$$\mathbb{P}(-z \leq Z_n \leq z) = \mathbb{P} \left( \mu - z \frac{\sigma}{\sqrt{n}} \leq \frac{S_n}{n} \leq \mu + z \frac{\sigma}{\sqrt{n}} \right).$$

Now, fix  $\alpha \in [0, 1]$ . Pick  $z$  such that

$$\mathbb{P}(-z \leq Z_n \leq z) = 1 - \alpha.$$

Since  $Z_n \xrightarrow{\mathcal{D}} \mathcal{N}(0, 1)$ ,

$$\begin{aligned} \mathbb{P}(-z \leq Z_n \leq z) &= \mathbb{P}(Z_n \leq z) - \mathbb{P}(Z_n < -z) \\ &= \mathbb{P}(Z_n \leq z) - (1 - \mathbb{P}(Z_n \geq -z)) \\ &\approx \mathbb{P}(Z_n \leq z) - (1 - \mathbb{P}(Z_n \leq z)) \\ &= 2\mathbb{P}(Z_n \leq z) - 1 \end{aligned}$$

where we have used the approximation

$$\mathbb{P}(Z_n \geq -z) \approx \mathbb{P}(Z_n \leq z)$$

which is a consequence of  $Z_n$  being nearly normal. Therefore,

$$\mathbb{P}(Z_n \leq z) \approx 1 - \frac{\alpha}{2}$$

and hence

$$z \approx F^{-1} \left( 1 - \frac{\alpha}{2} \right).$$

This tells us that our sample mean  $S_n/n$  is “very likely” to be within

$$\pm F^{-1} \left( 1 - \frac{\alpha}{2} \right) \frac{\sigma}{\sqrt{n}}$$

of the actual mean. However, this estimate is not so useful since we may not have access to  $\sigma$ . So instead, we make another approximation, substituting the sample variance:

$$F^{-1} \left( 1 - \frac{\alpha}{2} \right) \frac{\sigma_n}{\sqrt{n}}$$

where

$$\sigma_n = \frac{1}{n} \sum_{j=1}^n \left( X_j - \frac{S_n}{n} \right)^2.$$

**Example 3.1.** We toss a coin 100 times. The result of the  $j$ -th toss is  $X_j$ . Suppose we observe 53 heads so that

$$\frac{S_n(\omega)}{n} = 0.53 \quad \text{and} \quad \sigma_n^2 \approx 0.25$$

where we have written  $S_n(\omega)$  above to stress that 0.53 is an observation. Let  $\alpha = 0.05$ , corresponding to a confidence interval of  $1 - \alpha = 0.95$ . Then,

$$F^{-1}\left(1 - \frac{\alpha}{2}\right) = F^{-1}(0.975) = 1.96.$$

Moreover,

$$1.96 \cdot \frac{\sigma_n}{\sqrt{n}} \approx 0.1$$

The confidence interval is

$$[0.53 - 0.1, 0.53 + 0.1] = [0.43, 0.63].$$

## 4 Lyapunov's CLT

The problem with the classical CLT is that it requires the variables to be identically distributed. Lyapunov's CLT relaxes this assumption:

**Proposition 4.1.** *Let  $(X_j)_j$  be a sequence independent, mean zero random variables such that  $X_j^3$  is integrable. Let  $\sigma_j^2 = \text{Var}(X_j)$ ,  $\hat{\gamma}_j = \mathbb{E}[X_j^3]$ , and  $\gamma_j = \mathbb{E}[|X_j|^3]$ . Let  $S_n = X_1 + \cdots + X_n$  and  $s_n = \sigma_1^2 + \cdots + \sigma_n^2$ . Suppose that*

$$\frac{\gamma_1 + \cdots + \gamma_n}{s_n^3} \rightarrow 0 \quad \text{as} \quad n \rightarrow \infty.$$

Then,

$$\frac{S_n}{s_n} \xrightarrow{\mathcal{D}} \mathcal{N}(0, 1) \quad \text{as} \quad n \rightarrow \infty.$$