

# 1 Review

**Theorem 1.1** (Convergence Theorem). *Let  $X_n$  have characteristic function  $\phi_n$ .*

*If  $\phi_n(t) \rightarrow \phi_\infty(t)$  as  $n \rightarrow \infty$ , each  $t$ , and if  $\phi_\infty(t)$  is the characteristic function of some  $X_\infty$ , then  $X_n \xrightarrow{d} X_\infty$ .*

**Lemma 1.2** (Technical bound using moments). *Suppose  $\mathbb{E}|X|^n < \infty$ . Then*

$$\left| \phi_X(t) - \sum_{m=0}^n \frac{\mathbb{E}[itX]^m}{m!} \right| = o(|t|^n) \text{ as } t \rightarrow \infty \quad (1.1)$$

$$n = 1 \implies |\phi_X(s) - (1 + is\theta)| = o(|s|) \quad (1.2)$$

$$n = 2 \implies \left| \phi_X(s) - \left( 1 + \frac{s^2\sigma^2}{2} \right) \right| = o(s^2) \quad (1.3)$$

# 2 Using CFs

To demonstrate the technique we will use in more elaborate forms later on.

**Theorem 2.1** (Weak law of large numbers). *Let  $X_1, X_2, \dots$  be IID with  $\mathbb{E}X = \theta < \infty$ ,  $S_n = \sum_{i=1}^n X_i$ . Then  $n^{-1}S_n \xrightarrow{d} \theta$ , and hence (because  $\theta$  is a constant)  $n^{-1}S_n \xrightarrow{p} \theta$ .*

*Proof.* Prob. meas.  $\delta_\theta$  has CF  $e^{i\theta t}$  so by theorem 1.1 suffices to show  $\phi_{n^{-1}S_n}(t) \rightarrow e^{i\theta t}$  as  $n \rightarrow \infty$ ,  $t$  fixed.

Motivated by  $z_n \rightarrow z \in \mathbb{C} \implies (1 + n^{-1}z_n)^n \rightarrow e^z$ , write

$$\phi_{n^{-1}S_n}(t) = \left( \phi_X(n^{-1}t) \right)^n \quad (2.1)$$

$$= \left( 1 + \frac{n(\phi_X(n^{-1}t) - 1)}{n} \right)^n \quad (2.2)$$

So it suffices to show  $n(\phi_X(n^{-1}t) - 1) \rightarrow i\theta t$ . Applying lemma 1.2 with  $s = t/n$

$$n(\phi_X(n^{-1}t) - 1) = n \left( i \frac{t}{n} \theta + o \left( \frac{|t|}{n} \right) \right) \quad (2.3)$$

$$= it\theta + no \left( \frac{|t|}{n} \right) \rightarrow i\theta t \quad (2.4)$$

□

*Remark 2.2.* Proof shows that  $\phi'_X(0) = \theta$  is sufficient for WLLN. In fact (not obvious), this is also necessary.

*Remark 2.3.*  $\mathbb{E}X = \theta \implies \phi'_X(0) = \theta$ , but not conversely.

**Theorem 2.4** (IID Central Limit Theorem).  $(X_i, i \geq 1)$  IID,  $\mathbb{E}X = \mu$ ,  $\text{Var}(X) = \sigma^2 < \infty$ . Then

$$\frac{S_n - n\mu}{\sqrt{n}} \xrightarrow{d} N(0, \sigma^2) \quad (2.5)$$

*Proof.* WLOG take  $\mu = 0$ . Suffices to show  $\phi_{n^{-1/2}S_n}(t) \rightarrow \exp(-\sigma^2 t^2/2)$ .

$$\phi_{n^{-1/2}S_n}(t) = \left(\phi_X(n^{-1/2}t)\right)^n = \left(1 + \frac{n(\phi_X(n^{-1/2}t) - 1)}{n}\right)^n \quad (2.6)$$

So by definition of  $e$  suffices to show  $n(\phi_X(n^{-1/2}t) - 1) \rightarrow \sigma^2 t^2/2$ . Taking  $s = n^{-1/2}t$  in lemma 1.2

$$n(\phi_X(n^{-1/2}t) - 1) = n \left( \frac{t^2 \sigma^2}{n} + o\left(\frac{t^2}{n}\right) \right) \quad (2.7)$$

$$= t^2 \sigma^2/2 + o\left(\frac{t^2}{n}\right) \rightarrow t^2 \sigma^2/2 \quad (2.8)$$

□

There are many variations of CLT, one modification removes the identical distribution assumption.

**Theorem 2.5** (Lindeberg's Theorem). For each  $n$  let  $X_{n,1}, X_{n,2}, \dots, X_{n,n}$  be independent,  $\mathbb{E}X_{n,m} = 0$ ,  $\text{Var}X_{n,m} = \sigma_{n,m}^2 < \infty$ .

Write  $S_n = \sum_{m=1}^n X_{n,m}$ , so  $\mathbb{E}S_n = 0$  and  $\sigma_n^2 = \sum_{m=1}^n \sigma_{n,m}^2 = \text{Var}(S_n)$ .

Suppose

(a)  $\sigma_n^2 \rightarrow \sigma^2 < \infty$  as  $n \rightarrow \infty$

(b) (Lindenbergs condition or uniformly asymptotically negligible, UAN)

$$\lim_{n \rightarrow \infty} \sum_{m=1}^n \mathbb{E}[X_{n,m}^2 1_{|X_{n,m}| > \varepsilon}] = 0, \quad \forall \varepsilon > 0 \quad (2.9)$$

Then  $S_n \xrightarrow{d} N(0, \sigma^2)$ .

*Proof.* Let  $\phi_{n,m}(t)$  be the CF of  $X_{n,m}$ .

From last time (Durrett 3.3.7), we know

$$\left| \phi_{n,m}(t) - \left(1 - \frac{t^2 \sigma_{n,m}^2}{2}\right) \right| \leq \mathbb{E} \min \left( \frac{|tX_{n,m}|^3}{6}, |tX_{n,m}|^2 \right) \quad (2.10)$$

Cheap trick: if  $|X| \leq \varepsilon$ , then  $|X|^3 \leq \varepsilon X^2$ . Splitting  $X_{n,m}$  into two parts, one where  $X_{n,m} < \varepsilon$  and another where  $X_{n,m} \geq \varepsilon$

$$\left| \phi_{n,m}(t) - \left( 1 - \frac{t^2 \sigma_{n,m}^2}{2} \right) \right| \leq \frac{\varepsilon |t|^3}{6} \mathbb{E}[X_{n,m}^2] + |t|^2 \mathbb{E}[X_{n,m}^2 1_{|X_{n,m}| \geq \varepsilon}] \quad (2.11)$$

$$\limsup_n \underbrace{\sum_{m=1}^n \left| \phi_{n,m}(t) - \left( 1 - \frac{t^2 \sigma_{n,m}^2}{2} \right) \right|}_{B_n(t)} \leq \frac{\varepsilon |t|^3}{6} \sigma^2 + 0 \quad (2.12)$$

where the  $+0$  comes from 2.9. After letting  $\varepsilon \downarrow 0$ , we have  $B_n(t) \rightarrow 0$  as  $n \rightarrow \infty$ .

**Claim.** (i)  $\max_m \sigma_{n,m}^2 \rightarrow 0$  as  $n \rightarrow \infty$

(ii)  $\sum_m \sigma_{n,m}^4 \rightarrow 0$  as  $n \rightarrow \infty$

*Proof.* (i):

$$\sigma_{n,m}^2 = \mathbb{E} X_{n,m}^2 1_{|X_{n,m}| \geq \varepsilon} + \mathbb{E} X_{n,m}^2 1_{|X_{n,m}| \leq \varepsilon} \quad (2.13)$$

$$\leq \sum_m [\cdot] + \varepsilon^2 \quad (2.14)$$

$$\limsup_n \max_m \sigma_{n,m}^2 \leq \underbrace{0}_{\text{by 2.9}} + \varepsilon^2 \quad (2.15)$$

Let  $\varepsilon \downarrow 0$

(ii):

$$\sum_m \sigma_{n,m}^4 \leq \left( \max_m \sigma_{n,m}^2 \right) \sum_m \sigma_{n,m}^2 \rightarrow 0 \quad (2.16)$$

by (a). □

**Lemma 2.6.** If  $w_i, z_i \in \mathbb{C}$ ,  $|w_i| \leq 1$ ,  $|z_i| \leq 1$ , then

$$\left| \prod_{i=1}^n z_i - \prod_{i=1}^n w_i \right| \leq \sum_{i=1}^n |w_i - z_i| \quad (2.17)$$

*Proof.*

$$|z_1 z_2 \dots z_i w_{i+1} \dots w_n - z_1 \dots z_{i+1} w_{i+2} \dots w_n| = |(z_{i+1} - w_{i+1}) \cdot A| \quad (2.18)$$

$$\leq |z_{i+1} - w_{i+1}| \quad (2.19)$$

where  $|A| \leq 1$ . □

Consider  $\phi_{S_n}(t) = \prod_{m=1}^n \phi_{n,m}(t)$ . Lemma 2.6 implies

$$\left| \phi_{S_n}(t) - \prod_{m=1}^n \left( 1 - \frac{t^2 \sigma_{n,m}^2}{2} \right) \right| \leq B_n(t) \rightarrow 0 \quad (2.20)$$

using (i).

The goal is to prove  $\phi_{S_n}(t) \rightarrow \exp(-t^2\sigma^2/2)$ , so it's enough to prove

$$\prod_{m=1}^n \left(1 - \frac{t^2\sigma_{n,m}^2}{2}\right) \rightarrow \exp(-t^2\sigma^2/2) \quad (2.21)$$

**Lemma 2.7.** *Let  $a_{n,m} \in \mathbb{R}$ . If*

$$(1) \sum_m a_{n,m} \rightarrow a \text{ as } n \rightarrow \infty$$

$$(2) \sum_m a_{n,m}^2 \rightarrow 0$$

*Then  $\prod_{m=1}^n (1 - a_{n,m}) \rightarrow e^{-a}$ .*

*Proof.* We know  $\max_m |a_{n,m}| \rightarrow 0$  by (2), so

$$|\log(1 - x) + x| \leq Cx^2 \quad \text{for } |x| \leq \frac{1}{2} \quad (2.22)$$

$$\implies \left| \sum_{m=1}^n \log(1 - a_{n,m}) + \sum_{m=1}^n a_{n,m} \right| \leq C \sum_m a_{n,m}^2 \quad \text{for large } n \quad (2.23)$$

$$\rightarrow 0 \text{ as } n \rightarrow \infty \quad (2.24)$$

$$\implies \log \prod_{m=1}^n (1 - a_{n,m}) \rightarrow -a \quad (2.25)$$

$$\implies \prod_{m=1}^n (1 - a_{n,m}) \rightarrow e^{-a} \quad (2.26)$$

□

(1) of lemma is assumption (a) of theorem and (2) of lemma is (ii) of claim, so applying the lemma to  $a_{n,m} = -t^2\sigma_{n,m}^2/2$  yields the desired result. □

**Theorem 2.8** (Equivalent form of Lindeberg CLT). *For each  $n$ , let  $X_{n,m}$ ,  $1 \leq m \leq n$ , be independent,  $\mathbb{E}X_{n,m} = 0$ . Let  $S_n = \sum_{m=1}^n X_{n,m}$  and  $s_n^2 = \text{Var}(S_n) = \sum_{m=1}^n \text{Var}(X_{n,m})$ .*

*Suppose*

$$\sum_{m=1}^n \mathbb{E} \left( \frac{X_{n,m}^2}{s_n^2} 1_{|X_{n,m}| \geq \varepsilon s_n} \right) \rightarrow 0 \quad \text{as } n \rightarrow \infty \quad (2.27)$$

*Then  $\frac{S_n}{s_n} \xrightarrow{d} N(0, 1)$ .*

This follow from previous theorem applied with  $\hat{X}_{n,m} = \frac{X_{n,m}}{s_n}$ .  
Looks more like IID version.