

countably many points since F and G are cdfs. PM 60
Hence at all points by right continuity.

□

26] ^{know} Th: Let $g: \mathbb{R} \rightarrow \mathbb{R}$ be a continuous function, that does not depend on n .

a) If $X_n \xrightarrow{D} X$, then $g(X_n) \xrightarrow{D} g(X)$.

b) If $X_n \xrightarrow{P} X$, then $g(X_n) \xrightarrow{P} g(X)$.

c) If $X_n \xrightarrow{WPI} X$, then $g(X_n) \xrightarrow{WPI} g(X)$.

Note a) is the continuous mapping theorem. proved soon.

p340 ^{know}

27] Th: Suppose the X_n and X are RVS on the same probability space.

If $X_n \xrightarrow{WPI} X$, then $X_n \xrightarrow{P} X$.

If $X_n \xrightarrow{P} X$, then $X_n \xrightarrow{D} X$.

Note: in 27] If $X_n \xrightarrow{WPI} X$, then $X_n \xrightarrow{P} X$.

proof of 26c)

a) If $X_n(\omega) \rightarrow X(\omega)$, then $g(X_n(\omega)) \rightarrow g(X(\omega))$.
Since $X_n \xrightarrow{ae} X$, $g(X_n) \xrightarrow{ae} g(X)$, eg on a set A where $P(A)=1$.

28] Helly-Bray-Pormanteau Th

$X_n \xrightarrow{D} X$ iff $E[g(X_n)] \rightarrow E[g(X)]$

for every bounded, real, continuous function g .

Proof of continuous mapping Th If g is real

and continuous, then $\cos[tg(x)]$ and $\sin[tg(x)]$ are bounded real continuous functions.

Hence by the above theorem, for each $t \in \mathbb{R}$

$$\varphi_{g(X_n)}(t) = E[e^{itg(X_n)}] =$$

\uparrow
acts as a constant, $tg(x)$ is contin

$$E(\cos[tg(X_n)]) + i E(\sin[tg(X_n)])$$

$$\rightarrow E(\cos[tg(X)]) + i E(\sin[tg(X)]) = E[e^{itg(X)}]$$

$$= \varphi_{g(X)}(t), \text{ since } g(X_n) \xrightarrow{D} g(X) \text{ by}$$

the continuity th. \square

29] Notes for proving the CLT:

$$a) \varphi_X(t) = 1 + \sum_{j=1}^k \frac{E[\bar{x}^j]}{j!} (it)^j + O(t^k) \quad \leftarrow \text{little } o$$

is a Taylor series expansion of φ_X provided

$E[\bar{x}^k]$ exists. where the (error) remainder

$$R(t) = O(t^k) \text{ satisfies } \frac{O(t^k)}{t^k} \rightarrow 0 \text{ as } t \rightarrow 0.$$

$$b) \left(1 - \frac{a}{n}\right)^n \rightarrow e^{-a} \quad \therefore \left(1 - \frac{a \pm \varepsilon}{n}\right)^n \rightarrow e^{-(a \pm \varepsilon)}$$

and if $\varepsilon \rightarrow 0$, then $\left(1 - \frac{a \pm \varepsilon}{n}\right)^n \rightarrow e^{-a}$
even if ε is complex valued.

$$c) \varphi_{aX}(t) = E(e^{itax}) = \varphi_X(at).$$

If $\varphi_{X_n}(t) \rightarrow \varphi_X(t)$ for every t ,

then at is a t^* and $\varphi_{X_n}(at) = \varphi_{aX_n}(t)$

$\rightarrow \varphi_X(at) = \varphi_{aX}(t)$ for every t .

Hence if $z_n = \frac{\sqrt{n}(\bar{Y} - \mu)}{\sigma} = \frac{\bar{Y} - \mu}{\sigma/\sqrt{n}}$ satisfies

$\varphi_{z_n}(t) \rightarrow \varphi_z(t) = e^{-t^2/2}$, the $N(0,1)$ char fn,

then $\sigma z_n = \sqrt{n}(\bar{Y} - \mu)$ has $\varphi_{\sigma z_n}(t) \rightarrow \varphi_{\sigma z}(t) =$

$\varphi_z(\sigma t) = e^{-\sigma^2 t^2/2}$, the $N(0, \sigma^2)$ char fn,

and $\sigma z_n \xrightarrow{D} N(0, \sigma^2)$. So the CLT holds.

Proof of the CLT $z_n = \frac{\bar{Y} - \mu}{\sigma/\sqrt{n}} = \frac{\sum_{i=1}^n (Y_i - \mu)}{\sigma \sqrt{n}}$

$= \frac{\sum_{i=1}^n Y_i - n\mu}{\sigma \sqrt{n}} = \frac{\sum_{i=1}^n (Y_i - \mu)}{\sigma \sqrt{n}}$ where the

$Y_i - \mu$ are iid with char fn $\varphi_{Y-\mu}(t)$.

Hence the char fn of $\frac{Y_i - \mu}{\sigma \sqrt{n}}$ is $\varphi_{Y-\mu}\left(\frac{t}{\sigma \sqrt{n}}\right)$

and the char fn of z_n is $\varphi_{z_n}(t) \stackrel{iid}{=} \left[\varphi_{Y-\mu}\left(\frac{t}{\sigma \sqrt{n}}\right) \right]^n$.

$E[Y_i - \mu] = 0$ and $E(Y_i - \mu)^2 = \sigma^2$, so by

29 a) $\varphi_{Y-\mu}(t) = 1 - \frac{\sigma^2}{2} t^2 + o(t^2)$

and $\varphi_{Y-\mu}\left(\frac{t}{\sigma \sqrt{n}}\right) = 1 - \frac{t^2}{2n} + o\left(\frac{t^2}{n}\right)$.

(Cramer p90 Rao p90, 107)

where $\frac{o(\frac{t^2}{n})}{\frac{t^2}{n}} \rightarrow 0$ as $n \rightarrow \infty$.

Hence $n o(\frac{t^2}{n}) \rightarrow 0$ as $n \rightarrow \infty$.

Thus $\varphi_{z_n}(t) = \left[1 - \frac{t^2}{2n} + o(\frac{t^2}{n}) \right]^n =$

$$\left[1 - \frac{t^2/2 - n o(\frac{t^2}{n})}{n} \right]^n \rightarrow e^{-t^2/2} = \varphi_z(t) \quad \forall t$$

by 29b). $\therefore z_n \xrightarrow{D} z \sim N(0, 1)$ by the

continuity theorem, and $\sigma z_n = \sqrt{n}(\bar{Y}_n - \mu) \xrightarrow{D}$

$N(0, \sigma^2)$ by 29c).



30] Let e be the complex number
Let $c_n \in \mathbb{R}$ or \mathbb{C} . If $c_n \rightarrow c \in \mathbb{R}$, then

$$\lim_{n \rightarrow \infty} \left(1 + \frac{c_n}{n} \right)^n = e^c.$$

p35231] Some properties of characteristic functions]

i) $\varphi(0) = 1$ ← modulus

ii) $|\varphi(t)| \leq 1 \quad \forall t$ where $|a+ib| = \sqrt{a^2+b^2}$.

(iii) φ is continuous in t

(iv) $\varphi(t)$ is uniformly continuous.

(v) $\varphi^{(k)}(0) = i^k E(x^k)$ if $E(x^k)$ is finite.

32] Hence if $\varphi_n(t) \rightarrow h(t)$ and $h(t)$

is not continuous, then X_n does not converge in distribution to X by the continuity theorem.

See Hw 8.

33] If X has mgf $m(t)$ (exists

for $-s < t < s$ for some $s > 0$), then

$$E(x^k) < \infty \quad \forall k \in \mathbb{N} = \{1, 2, \dots\}.$$

34] Let $j, k \in \mathbb{N}$. If $E[x^k]$ is finite,

then $E(x^j)$ is finite for $1 \leq j \leq k$.

Proof] If $|y| \leq 1$, then $|y^j| = |y|^j \leq 1$

and if $|y| > 1$, then $|y|^j \leq |y|^k$.

Hence $|y|^j \leq |y|^k + 1$ and $|x|^j \leq |x|^k + 1$,
 $x = x(\omega)$

$$\therefore E[|x|^j] \leq E[|x|^k] + 1 < \infty.$$

35] The CLT for iid X_i is

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known as the Lindeberg-Lévy CLT.

36] $c(t) = \log[M(t)] =$ cumulant generating function
 $c'(0) = E(X)$, $c''(0) = V(X)$

L'Hôpital's rule: suppose $f(x) \rightarrow 0$ and $g(x) \rightarrow 0$
as $x \rightarrow d$, $x \rightarrow d$, $x \rightarrow d$, $x \rightarrow \infty$ or $x \rightarrow -\infty$.

If $\frac{f'(x)}{g'(x)} \rightarrow L$, then $\frac{f(x)}{g(x)} \rightarrow L$ as $x \rightarrow d$.

If the mgf exists, then $E(X^k)$ exists $\forall k \in \mathbb{N}$.

37] Proof of CLT if mgf exists.

Let Y_1, Y_2, \dots be iid with mean μ , variance σ^2
and mgf $m_Y(t)$ for $|t| < t_0$. Then

$Z_i = \frac{Y_i - \mu}{\sigma}$ has mean 0, variance 1 and

mgf $M_Z(t) = \exp\left(-\frac{t\mu}{\sigma}\right) m_Y\left(\frac{t}{\sigma}\right)$ for $|t| < \sigma t_0$.

want to show $W_n = \sqrt{n} \left(\frac{\bar{Y}_n - \mu}{\sigma} \right) \xrightarrow{D} N(0, 1)$.

$$W_n = n^{-\frac{1}{2}} \sum_{i=1}^n Z_i = n^{-\frac{1}{2}} \sum_{i=1}^n \left(\frac{Y_i - \mu}{\sigma} \right) =$$

$$n^{-\frac{1}{2}} \frac{\sum_{i=1}^n Y_i - n\mu}{\sigma} = \frac{n^{-\frac{1}{2}}}{\frac{1}{n}} \frac{\bar{Y}_n - \mu}{\sigma}$$

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$$\begin{aligned} \therefore M_{w_n}(t) &= E(e^{tw_n}) = E\left[\exp\left(t \sqrt{n} \sum_{i=1}^n z_i\right)\right] \\ &= E\left[\exp\left(\sum_{i=1}^n \frac{tz_i}{\sqrt{n}}\right)\right] \stackrel{\text{ind}}{=} \prod_{i=1}^n E\left[e^{tz_i/\sqrt{n}}\right] \end{aligned}$$

$$\stackrel{\text{iid}}{=} \prod_{i=1}^n M_z\left(\frac{t}{\sqrt{n}}\right) = \left[M_z\left(\frac{t}{\sqrt{n}}\right)\right]^n. \quad \text{Let}$$

$$C_z(x) = \log[M_z(x)]. \quad \text{Then } C_{w_n}(t) =$$

$$\log[M_{w_n}(t)] = n \log\left[M_z\left(\frac{t}{\sqrt{n}}\right)\right] = n C_z\left(\frac{t}{\sqrt{n}}\right)$$

$$= \frac{C_z\left(\frac{t}{\sqrt{n}}\right)}{\frac{1}{n}}. \quad \text{Now } C_z(0) = \log[M_z(0)] = \log(1) = 0.$$

\therefore by L'Hôpital's rule (deriv wrt n)

$$\lim_{n \rightarrow \infty} \log[M_{w_n}(t)] = \lim_{n \rightarrow \infty} \frac{C_z\left(\frac{t}{\sqrt{n}}\right)}{\frac{1}{n}} =$$

$$\frac{\lim_{n \rightarrow \infty} C_z'\left(\frac{t}{\sqrt{n}}\right) \left(\frac{-t}{2n^{3/2}}\right)}{-\frac{1}{n^2}} = \frac{t}{2} \lim_{n \rightarrow \infty} \frac{C_z'\left(\frac{t}{\sqrt{n}}\right)}{\frac{1}{\sqrt{n}}}$$

$$\text{Now } C_z'(0) = \frac{M_z'(0)}{M_z(0)} = \frac{E(z)}{1} = 0.$$

So L'Hôpital's rule can be applied again:

$$\lim_{n \rightarrow \infty} \log [M_{W_n}(t)] = \frac{t}{2} \frac{C_z''\left(\frac{t}{\sqrt{n}}\right) \left(\frac{-t}{2n^{3/2}}\right)}{\left(\frac{-1}{2n^{3/2}}\right)} =$$

$$\frac{t^2}{2} \lim_{n \rightarrow \infty} C_z''\left(\frac{t}{\sqrt{n}}\right) = \frac{t^2}{2} \underbrace{C_z''(0)}_{V(z)}$$

$$= \frac{t^2}{2} V(z) = \frac{t^2}{2}.$$

↑
EI rev 25)

$$\text{Thus } \lim_{n \rightarrow \infty} \log [M_{W_n}(t)] = \frac{t^2}{2} \text{ and}$$

$$\lim_{n \rightarrow \infty} M_{W_n}(t) = e^{t^2/2}, \text{ the } N(0,1) \text{ mgf.}$$

$$\therefore W_n = \sqrt{n} \left(\frac{\bar{Y}_n - \mu}{\sigma} \right) \xrightarrow{D} N(0,1)$$

by the continuity th. □

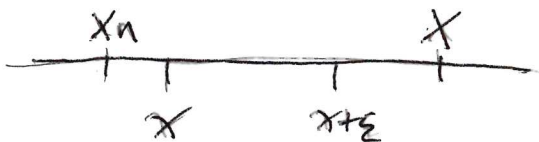
Remark: there is a proof for the CLT using similar techniques with $\varphi_Z(t)$. 645

Hoel, Port and Stone

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38] Prove $X_n \xrightarrow{P} X \Rightarrow X_n \xrightarrow{D} X$

proof] $F_n(x) = P(X_n \leq x) = P(X_n \leq x, X > x + \varepsilon) + P(X_n \leq x, X \leq x + \varepsilon)$ partition

$$\leq P(|X_n - X| \geq \varepsilon) + P(X \leq x + \varepsilon)$$

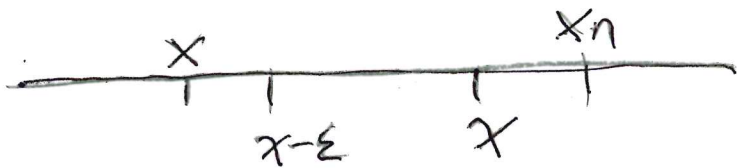


$$= P(|X_n - X| \geq \varepsilon) + F_X(x + \varepsilon).$$

$$F_X(x - \varepsilon) = P(X \leq x - \varepsilon) =$$

$$P(X \leq x - \varepsilon, X_n > x) + P(X \leq x - \varepsilon, X_n \leq x)$$
partition

$$\leq P(|X_n - X| \geq \varepsilon) + P(X_n \leq x)$$



$$= P(|X_n - X| \geq \varepsilon) + F_n(x).$$

$$\therefore F_X(x - \varepsilon) - P(|X_n - X| \geq \varepsilon) \leq F_n(x) \leq P(|X_n - X| \geq \varepsilon) + F_X(x + \varepsilon).$$