

Since $X_n \xrightarrow{P} X$, $P(|X_n - X| \geq \epsilon) \rightarrow 0$ as $n \rightarrow \infty$.

If $F_X(x)$ is continuous at X , then

$F_X(x-\epsilon) \rightarrow F_X(x)$ and $F_X(x+\epsilon) \rightarrow F_X(x)$ as $\epsilon \rightarrow 0$.

Taking limsup and liminf gives

$$F_X(x-\epsilon) \leq \liminf F_n(x) \leq \limsup F_n(x) \leq F_X(x+\epsilon).$$

$\therefore F_n(x) \rightarrow F_X(x)$ if $F_X(x)$ is contin at x .



Ash stat

39] a) If $\underbrace{E[(X_n - X)^2]}_{X_n \xrightarrow{P} X} \rightarrow 0$ as $n \rightarrow \infty$, then $X_n \xrightarrow{P} X$.

b) If $E[X_n] \rightarrow E(X)$ and $V(X_n - X) \rightarrow 0$, then $X_n \xrightarrow{P} X$.

know c) If $X \in C$, b) is $E[X_n] \rightarrow c$, $V(X_n) \rightarrow 0 \Rightarrow X_n \xrightarrow{P} c$.

proof: a) By Generalized Chebyshev's Inequality,

$$P(|X_n - X| \geq \epsilon) = P\left[\sqrt{(X_n - X)^2} \geq \epsilon\right] \leq \frac{E[(X_n - X)^2]}{\epsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

$$E(W^2) = V(W) + [E(W)]^2$$

$$b) E[(X_n - X)^2] = V(X_n - X) + [E(X_n - X)]^2$$

$$= V(X_n - X) + [E(X_n) - E(X)]^2 \rightarrow 0$$

as $n \rightarrow \infty$.



$$P[W^2 \geq \epsilon^2] \leq \frac{E(W^2)}{\epsilon^2}$$

$$40] X_n \xrightarrow{P} c \iff X_n \xrightarrow{D} c$$

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proof] showed $X_n \xrightarrow{P} c \implies X_n \xrightarrow{D} c$ in 38].

$$P[|X_n - c| \geq \epsilon] = P(X_n \geq c + \epsilon) + P(X_n \leq c - \epsilon)$$

$$= 1 - P(X_n < c + \epsilon) + P(X_n \leq c - \epsilon) = \text{RHS}$$

Now $P(X_n < c + \epsilon) \geq P(X_n \leq c + \frac{\epsilon}{2}) \dots$

$$P[|X_n - c| \geq \epsilon] = \text{RHS} \leq 1 - P(X_n \leq c + \frac{\epsilon}{2}) + P(X_n \leq c - \epsilon)$$

$$= 1 - \underbrace{F_n(c + \frac{\epsilon}{2})}_{\rightarrow 1} + \underbrace{F_n(c - \epsilon)}_{\rightarrow 0}$$

$F_n(t) \rightarrow F_X(t)$ for $t \neq c$ where $F_X(t) = \begin{cases} 1 & t \geq c \\ 0 & t < c \end{cases}$ } justification

$$\therefore P[|X_n - c| \geq \epsilon] \rightarrow 1 - 1 + 0 = 0 \text{ as } n \rightarrow \infty.$$



41] p346 RVS X_n are tight or bounded in probability if for each $\epsilon > 0$,

$$\exists x_\epsilon \text{ and } y_\epsilon \quad \exists F_n(x_\epsilon) < \epsilon \text{ and } F_n(y_\epsilon) > 1 - \epsilon \quad \forall n \geq 1, |z| \leq \epsilon$$

iff $\forall \epsilon > 0 \exists$ constants D_ϵ and N_ϵ s.t.

$$P(|X_n| \leq D_\epsilon) \geq 1 - \epsilon \quad \forall n \geq N_\epsilon. \quad \left. \vphantom{P(|X_n| \leq D_\epsilon)} \right\} \text{Increase}$$

D_ε to D'_ε so $P(|x_n| \leq D'_\varepsilon) \geq 1-\varepsilon$
 $\forall n \geq 1.$)

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If X_n is not tight, then "mass escapes to ∞ or $-\infty$."

42] ^{p346} Tightness is a necessary and sufficient condition that for every sequence $\{F_{n_k}\}$ there exists a further subsequence $\{F_{n_{k(j)}}\}$ such that $X_{n_{k(j)}} \xrightarrow{D} X_j$ for some RV X_j .

Remark] Hence if the X_n are not tight, X_n can't converge in distribution to

some RV X . (Take $\{F_n\}$ to be the seq.)

If $X_n \xrightarrow{D} X$, then the X_n are tight.

43] If $n^\delta (X_n - c) \xrightarrow{D} X$ where $0 < \delta \leq 1$,

then $X_n \xrightarrow{P} c$. In particular,

if $\sqrt{n} (X_n - c) \xrightarrow{D} N(0, \sigma^2)$, $X_n \xrightarrow{P} c$.

44] Slutsky's Theorem] If $Y_n \xrightarrow{D} Y$ and $w_n \xrightarrow{P} c$, ^{66.5}

then a) $Y_n + w_n \xrightarrow{D} Y + c$

b) $Y_n w_n \xrightarrow{D} cY$

c) $Y_n / w_n \xrightarrow{D} \frac{Y}{c}$ if $c \neq 0$.

Note: $c_n \rightarrow c$ as $n \rightarrow \infty \Rightarrow c_n \xrightarrow{ae} c \Rightarrow c_n \xrightarrow{P} c$.

Note: $w_n \xrightarrow{P} c \Leftrightarrow w_n \xrightarrow{D} c$.

45] If $X_n \xrightarrow{r} X$, then $X_n \xrightarrow{P} X$ and $X_n \xrightarrow{D} X$.

Showed $X_n \xrightarrow{z} X \Rightarrow X_n \xrightarrow{P} X$.

46] $X_n \xrightarrow{r} X \Rightarrow X_n \xrightarrow{k} X \quad 0 < k < r$.

proof of 45] $|X_n - X|^r \geq |X_n - X|^r \underbrace{I(|X_n - X| \geq \varepsilon)}_{1 \text{ or } 0}$
 $\geq \varepsilon^r I[|X_n - X| \geq \varepsilon]$

So for any $\varepsilon > 0$,

$$E[|X_n - X|^r] \geq E[|X_n - X|^r I(|X_n - X| \geq \varepsilon)]$$

$$\geq E[\varepsilon^r I(|X_n - X| \geq \varepsilon)]$$

$$= \varepsilon^r P(|X_n - X| \geq \varepsilon).$$

$$\text{So } P[|X_n - X| \geq \varepsilon] \leq \frac{E[|X_n - X|^r]}{\varepsilon^r} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

□

47) $X_n \xrightarrow{P} X \Rightarrow X_n$ is close to X .

$X_n \xrightarrow{D} X$ does not imply that X_n is close to X .

48) (Hw 2) Jensen's Inequality:

$g(E(X)) \leq E[g(X)]$ if the expected values exist and g is convex on an interval containing the range of X .

49) ^{see p44} Proof that $X_n \xrightarrow{D} X \Rightarrow X_n \xrightarrow{K} X, 0 < K < r$.

Let $U_n = |X_n - X|^r$ and $W_n = |X_n - X|^k$.

Then $U_n = W_n^t$ where $t = \frac{r}{k} > 1$ and

$g(x) = x^t$ is convex on $[0, \infty)$. By

Jensen's inequality,

$$E[|X_n - X|^r] = E[U_n] = E[W_n^t]$$

$$\geq (E[W_n])^t = \left(E[|X_n - X|^k]\right)^{\frac{r}{k}}, \quad r > k,$$

$$\therefore \lim_{n \rightarrow \infty} E[|X_n - X|^r] = 0 \Rightarrow \lim_{n \rightarrow \infty} E[|X_n - X|^k] = 0, \quad 0 < k < r,$$

□

50) Let X_n have pdf $f_{X_n}(x)$ and let X have pdf $f_X(x)$.

a) If $f_{X_n}(x) \rightarrow f_X(x) \quad \forall x$, then $X_n \xrightarrow{D} X$.

b) If $f_{X_n}(x) \rightarrow f_X(x) \quad a.e. \lambda$,
 Lebesgue measure
 then $X_n \xrightarrow{D} X$.
 for X outside a set of Lebesgue measure 0

51) Suppose $g: \mathbb{R} \rightarrow \mathbb{R}$ is continuous a.t.c.

a) If $X_n \xrightarrow{D} c$, $g(X_n) \xrightarrow{D} c$

b) If $X_n \xrightarrow{P} c$, $g(X_n) \xrightarrow{P} c$

c) If $X_n \xrightarrow{w.p.1} c$, $g(X_n) \xrightarrow{w.p.1} c$.

52) Suppose X_n and X are integer valued RVs.

Then $X_n \xrightarrow{D} X$ iff $P(X_n = k) \rightarrow P(X = k)$

for every integer k .

iff $\underbrace{P_{X_n}(x)}_{\text{pmfs}} \rightarrow P_X(x) \quad \forall \text{ real } x$

Basu's

pmfs

53] Billingsley's proof of CLT

$$\varphi_x(t) = E[e^{itx}] = E[\cos(tx)] + i E[\sin(tx)]$$

$$|\varphi_x(t)| \leq 1 \quad \forall t \quad \text{since}$$

$$E[e^{itx}] \leq E[|e^{itx}|] = E[1]$$

↑
even for complex RV

$$e^{itx} = \cos(tx) + i \sin(tx)$$

$$\text{so } |e^{itx}| = \sqrt{\cos^2(tx) + \sin^2(tx)} = \sqrt{1}$$

Lemma: Let z_1, \dots, z_m and w_1, \dots, w_m be complex numbers of modulus at most 1. Then

$$|(z_1 \dots z_m) - (w_1 \dots w_m)| \leq \sum_{k=1}^m |z_k - w_k|.$$

proof: see HW 8.

$$\text{Let } z_n = \sqrt{n} \left(\frac{\bar{y}_n - \mu}{\sigma} \right) = \sum_{i=1}^n \frac{y_i - \mu}{\sigma \sqrt{n}}$$

$$\varphi_{z_n}(t) = \left[\varphi_{\frac{y-\mu}{\sigma \sqrt{n}}}\left(\frac{t}{\sigma \sqrt{n}}\right) \right]^n.$$

$$\varphi_{y-\mu}(t) = 1 - \frac{\sigma^2}{2} t^2 + R(t),$$

$$R(t) = O(t^2), \quad \frac{R(t)}{t^2} \rightarrow 0 \text{ as } t^2 \rightarrow 0$$

$$\varphi_{\frac{y-\mu}{\sigma \sqrt{n}}}\left(\frac{t}{\sigma \sqrt{n}}\right) = 1 - \frac{t^2}{2n} + R\left(\frac{t}{\sigma \sqrt{n}}\right)$$

$$\text{So } \left| \varphi_{Y-\mu}\left(\frac{t}{\sigma\sqrt{n}}\right) - \left(1 - \frac{t^2}{2n}\right) \right| = \left| R\left(\frac{t}{\sigma\sqrt{n}}\right) \right| = o\left(\frac{t^2}{\sigma^2 n}\right)$$

$$\frac{R\left(\frac{t}{\sigma\sqrt{n}}\right)}{\frac{t^2}{\sigma^2 n}} \rightarrow 0 \text{ so } \left| \frac{R\left(\frac{t}{\sigma\sqrt{n}}\right)}{\frac{t^2}{\sigma^2 n}} \right| \rightarrow 0$$

$$n o\left(\frac{t^2}{\sigma^2 n}\right) \rightarrow 0 \quad \therefore$$

$$n \left| \varphi_{Y-\mu}\left(\frac{t}{\sigma\sqrt{n}}\right) - \left(1 - \frac{t^2}{2n}\right) \right| \rightarrow 0.$$

By lemma with n so large that $0 < \frac{t^2}{2n} < 1 < 2$,

$$z_i = \varphi_{Y-\mu}\left(\frac{t}{\sigma\sqrt{n}}\right), \quad w_i = 1 - \frac{t^2}{2n},$$

$$\left| \left[\varphi_{Y-\mu}\left(\frac{t}{\sigma\sqrt{n}}\right) \right]^n - \left(1 - \frac{t^2}{2n}\right)^n \right| \leq n \left| \varphi_{Y-\mu}\left(\frac{t}{\sigma\sqrt{n}}\right) - \left(1 - \frac{t^2}{2n}\right) \right| \rightarrow 0.$$

$$\therefore \varphi_{Z_n}(t) = \left[\varphi_{Y-\mu}\left(\frac{t}{\sigma\sqrt{n}}\right) \right]^n \rightarrow \lim_n \left(1 - \frac{t^2/2}{n}\right)^n = \underbrace{e^{-t^2/2}}_{\varphi_Z(t), Z \sim N(0,1)} \quad \forall t.$$

$$\therefore Z_n \xrightarrow{D} N(0,1).$$

54] A complex RV Z has the

form $Z = X + iY$ where X and Y

are ordinary RVs. $E[Z] = E[X] + iE[Y]$,

and Z is integrable if $E[|Z|] = E[\sqrt{X^2 + Y^2}] < \infty$.

Linearity, LDCT and key inequalities remain valid, including $|E[Z]| \leq E[|Z|]$.

$Z = e^{itX}$ is the main complex RV in this class.

55] p360 Th If $\lim_{n \rightarrow \infty} \varphi_{X_n}(t) = g(t) \wedge^t$ where

g is continuous at $t=0$, then $g(t) = \varphi_X(t)$

is a characteristic function and $X_n \xrightarrow{D} X$.

Note: Hence continuity at $t=0 \Rightarrow$ continuity everywhere

Since $g(t) = \varphi_X(t)$ is continuous,

If $g(t)$ is not continuous at $t=0$, then

X_n does not converge in distribution.

§27 56] For each n , let

W_{n1}, \dots, W_{nrn} be independent.

The probability space may change with n .

Let $E[W_{nk}] = 0, V(W_{nk}) = E[W_{nk}^2] = \sigma_{nk}^2$

and $\Delta_n^2 = \sum_{k=1}^{r_n} \sigma_{nk}^2 = V\left[\sum_{k=1}^{r_n} W_{nk}\right], z_n = \frac{\sum_{k=1}^{r_n} W_{nk}}{\Delta_n}$ is

the z-score of $\sum_{k=1}^{r_n} W_{nk}$.

57) Lyapounov's CLT:

Under 56),

assume the $|W_{nk}|^{2+s}$ are integrable for some $s > 0$.

Assume Lyapounov's

condition: $\lim_n \sum_{k=1}^{r_n} \frac{E[|W_{nk}|^{2+s}]}{\Delta_n^{2+s}} = 0.$

Then $z_n = \frac{\sum_{k=1}^{r_n} W_{nk}}{\Delta_n} \xrightarrow{D} N(0, 1).$

58) special cases: i) $r_n = n, W_{nk} = w_k$

has w_1, \dots, w_n, \dots independent.

ii) $w_{nk} = X_{nk} - E(X_{nk}) = X_{nk} - \mu_{nk}$

has $\frac{\sum_{k=1}^{r_n} (X_{nk} - \mu_{nk})}{\Delta_n} \xrightarrow{D} N(0, 1).$

iii) suppose X_1, X_2, \dots are ind

with $E(x_i) = \mu_i$, $V(x_i) = \sigma_i^2$.

Let $Z_n = \frac{\sum_{i=1}^n x_i - \sum_{i=1}^n \mu_i}{\left(\sum_{i=1}^n \sigma_i^2\right)^{1/2}}$ be the

Z score of $\sum_{i=1}^n x_i$. Hence $E(Z_n) = 0$, $V(Z_n) = 1$.

Assume $E[|x_i - \mu_i|^3] < \infty$ for $i \in \mathbb{N}$

and $\lim_{n \rightarrow \infty} \frac{\sum_{i=1}^n E[|x_i - \mu_i|^3]}{\left(\sum_{i=1}^n \sigma_i^2\right)^{3/2}} = 0$. (*)

Then $Z_n \xrightarrow{D} N(0, 1)$.

Proof of (ii): Take $w_{nk} = x_k - \mu_k$, $s = 1$

$\Delta_n = \sqrt{\sum_{i=1}^n \sigma_i^2}$ and apply Lyapounov's CLT.

Note that $\left(\sum_{i=1}^n \sigma_i^2\right)^{3/2} = (\Delta_n^2)^{3/2} = \Delta_n^3 = \Delta_n^{2+1}$.

59] The (Lindeberg - Lévy) CLT

70.5

has the X_i iid with $V(X_i) = \sigma^2 < \infty$.

The Lyapounov CLT in 58 iii) has

the X_i independent (not necessarily identically distributed) with $E[|X_i|^3] < \infty$ and satisfies (*).

ex] **Qual Problem** suppose the X_i iid $\text{Ber}(p_i)$ and

$$\sum_{i=1}^{\infty} p_i q_i = \infty \quad \text{where } q_i = 1 - p_i, \quad V(X_i) = p_i q_i.$$

$$\text{claim } \bar{Z}_n = \frac{\sum_{i=1}^n X_i - \sum_{i=1}^n p_i}{\left(\sum_{i=1}^n p_i q_i\right)^{\frac{1}{2}}} \xrightarrow{D} N(0,1).$$

Proof: Let $Y_i = |W_i| = |X_i - p_i|$

x	1	0
y	$1 - p_i$	p_i
$P(y)$	p_i	q_i

$X_i - p_i = W$	$1 - p_i$	$-p_i$
$P(W)$	p_i	q_i

$$E[|X_i - p_i|^3] =$$

$$E[|W_i|^3] = E[Y_i^3] = \sum_y y^3 P(y) = (1 - p_i)^3 p_i + p_i^3 q_i$$

$$= q_i^3 p_i + p_i^3 q_i = p_i q_i \underbrace{(p_i^2 + q_i^2)}_{\leq (p_i + q_i)^2 = 1} \leq p_i q_i$$