

# Supplemental Notes



Thrm: ("Weak" law of large numbers, WLLN) If i.i.d.

$$X_1, X_2, \dots \text{ \& } \sigma_x^2 < \infty \text{ (r.s.) } \bar{X}_n \xrightarrow{P} \mu_x.$$

Pct:  $\forall \epsilon > 0$ :

$$\begin{aligned} \lim_{n \rightarrow \infty} P[|\bar{X}_n - \mu_x| > \epsilon] & \stackrel{\text{thm}}{=} \lim_{n \rightarrow \infty} P[|\bar{X}_n - E[\bar{X}_n]| > \epsilon]. \\ & \stackrel{\text{C.I.}}{\leq} \lim_{n \rightarrow \infty} \frac{V[\bar{X}_n]}{\epsilon^2} \\ & = \lim_{n \rightarrow \infty} \frac{\sigma_x^2}{n \cdot \epsilon^2} \\ & = 0 \end{aligned}$$

QED

optional

Thrm: ("Strong" LLN, SLLN)  $\bar{X}_n \xrightarrow{o} \mu_x$  if r.s.

Thrm: ("Mean-square" LLN, MSLLN)  $\bar{X}_n \xrightarrow{m} \mu$  if r.s.

Caewat: No such thing as a "law of averages"

Continuity Theorem: If  $g$  is continuous

$$\left. \begin{array}{l} X_n \xrightarrow{p} X \\ X_n \xrightarrow{P} X \\ X_n \xrightarrow{d} X \end{array} \right\} \Rightarrow \left. \begin{array}{l} g(X_n) \xrightarrow{p} g(X) \\ g(X_n) \xrightarrow{P} g(X) \\ g(X_n) \xrightarrow{d} g(X) \end{array} \right\}$$

Note:  $X_n \xrightarrow{m} X \not\Rightarrow g(X_n) \xrightarrow{m} g(X)$

Ex: WLLN  $\bar{X}_n \xrightarrow{P} \mu_x$  (iid,  $\sigma^2 < \infty$ )

put  $g(x) = x^2$

$\therefore (\bar{X}_n)^2 \xrightarrow{P} \mu_x^2$

Issue spotting

Suppose  $X_k \xrightarrow{P} X$

$$\lim_{n \rightarrow \infty} \sum_{k=1}^n g(X_k) = \lim_{n \rightarrow \infty} \overline{n \cdot g(X_n)} \xrightarrow{P} n E[g(X)]$$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{k=1}^n g(X_k) = \lim_{n \rightarrow \infty} \overline{g(X_n)} \xrightarrow{P} E[g(X)]$$

# Monte Carlo Simulation

"Monte-Carlo" casino in Monaco

2 types

① iid M.C.

- generate (simulate) random samples (iid)

- Use LLN:  $\bar{Y}_n \xrightarrow{\text{mopd}} (b-a) E_x[X]$

② "MCMC" Markov Chain MC (ETS17)

- Correlated samples (from a Markov process)

↳ converge to equilibrium pdf  $\pi_e$

- Problem with "Burn-in" and time to convergence

- Often use Gibbs Sampler (software: R or BUGS)

↳ Bayesian inference

## Monte-Carlo estimation

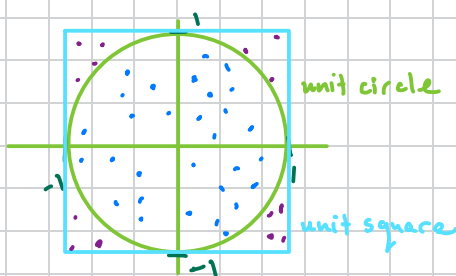
1942 Manhattan project

1945 Trinity (U.S.)  
MC too slow for "the Super"

1949 Joe1 (U.S.S.R.)

1952 Irv-Mike (U.S.)  
MCMC, "Metropolis"

Ex: estimate  $\pi$



Area circle,  $\pi r^2 = \pi$   
Area square, side<sup>2</sup> = 4.

$$\therefore \frac{A(c)}{A(s)} = \frac{\pi}{4}$$

$$\therefore \pi = 4 \cdot \frac{A(c)}{A(s)} = 4 \cdot \frac{\text{blue dots}}{\text{total dots}}$$

$\therefore$  use random sampling to compute ratio of areas.

$$\therefore P\left\{ \underbrace{(x,y)}_{\text{sampled from unit square}} \text{ in circle} \right\} = P\left\{ x^2 + y^2 \leq 1 \right\} = \frac{\pi}{4}$$

$\therefore$  So generate  $u_1, u_2 \sim U[-1, 1]$   
then count  $\# w / u_1^2 + u_2^2 \leq 1$ .  
divide by total  $\#$  of points.

## Ex: Monte Carlo Integration

Q: how to evaluate  $\int_a^b g(x) dx$  if  $g$  continuous but DON'T KNOW anti-derivative  $G$ ?

A: IID MC estimate

$$\begin{aligned} \textcircled{1} \int_a^b g(x) dx &= \frac{b-a}{b-a} \int_a^b g(x) dx && (a < b) \\ &= (b-a) \int_a^b g(x) \cdot \left(\frac{1}{b-a}\right) g(x) \\ &\stackrel{x \sim U[a,b]}{=} (b-a) \cdot E_x [g(x)]. \end{aligned}$$

② Compute:  $Y_k \stackrel{\Delta}{=} (b-a) \cdot g(X_k)$  ← simulate  
from iid draws  $X_k \sim U[a, b]$

$$\therefore \bar{Y}_n = \frac{1}{n} \sum_{k=1}^n Y_k = \frac{(b-a)}{n} \sum_{k=1}^n g(X_k)$$

$$\xrightarrow[\text{P}]{\text{LLN}} (b-a) E_x [g(x)] = \int_a^b g(x) dx$$

∴ consistent.

∴ Monte Carlo approach:

$$\int_a^b g(x) dx = (b-a) \int_a^b \frac{g(x)}{b-a} dx \quad \text{if } a < b.$$
$$= (b-a) \cdot E_x[g(X)] \quad \text{for r.v. } X \sim U[a, b].$$

∴ ① Draw iid  $X_1, \dots, X_N \sim U[a, b]$  random number generator

② Put  $Y_k = (b-a) \cdot g(X_k)$

③  $\bar{Y}_N \xrightarrow[\text{LLN}]{P, (b)}$   $(b-a) E_x[g(X)] = \int_a^b g(x) dx$

Ex: estimate  $\pi$ :  $4 \int_0^1 \sqrt{1-x^2} dx = \pi$

put  $a=0, b=1$ ;  $g(x) = 4\sqrt{1-x^2}$

∴  $\int_0^1 g(x) dx = (1-0) \cdot \int_0^1 \frac{g(x)}{1-0} dx = E_x[g(X)]$  for r.v.  $X \sim U[0, 1]$

① Draw iid  $X_1, \dots, X_N \sim U[0, 1]$

② Put  $Y_k = 4\sqrt{1-X_k^2} = g(X_k)$

∴  $\bar{Y}_N = \frac{1}{N} \sum_{k=1}^N Y_k = \frac{1}{N} \sum_{k=1}^N g(X_k) \xrightarrow[\text{LLN}]{P} E_x[g(X)]$

$$= \int_0^1 4\sqrt{1-x^2} dx = \pi$$

$$m \longrightarrow p \longrightarrow d. \quad \star$$

"Mom Paid Dad" (mnemonic)

- Often easier to prove  $m$  (or  $p$ ) than  $p$  (or  $d$ )

$$u \longrightarrow e \longrightarrow o \longrightarrow p \longrightarrow d.$$

"Uncle Ed Once Paid Dad"

-  $u$  implies all, even  $m$ .

Note:  $e \not\rightarrow m$

$$\text{Thm: } X_n \xrightarrow{m} X \quad \longrightarrow \quad X_n \xrightarrow{p} X$$

Prf: Say  $X_n \xrightarrow{m} X : \lim_{n \rightarrow \infty} E[(X_n - X)^2] = 0$ . Pick  $\varepsilon > 0$ .

$$\lim_{n \rightarrow \infty} P[|X_n - X| > \varepsilon] = \lim_{n \rightarrow \infty} P[(X_n - X)^2 > \varepsilon^2]$$

$$\stackrel{\text{M.I.}}{\leq} \lim_{n \rightarrow \infty} \frac{E[(X_n - X)^2]}{\varepsilon^2}$$

$$= 0 \quad (\text{by hypothesis})$$

QED.

Ex: Say  $X_n$  are similarly distributed as  $X_n \sim N(0, \frac{1}{n^2})$

( $\therefore$  not iid)

Define  $Y_n \triangleq \sqrt{n} \cdot X_n$ . Does  $Y_1, Y_2, \dots$  converge

redo at home w/  
 $n = 3, 4, \dots$

in probability to 0?

Q:  $Y_n \xrightarrow{P} 0$ ?

Method 1:  $m \rightarrow p \rightarrow d$  approach ( $m \rightarrow p$ )

$$Y_n \xrightarrow{m} 0 \text{ iff } \lim_{n \rightarrow \infty} E[Y_n^2] = 0$$

$$\therefore \lim_{n \rightarrow \infty} E[Y_n^2] = \lim_{n \rightarrow \infty} E[n \cdot X_n^2] = \lim_{n \rightarrow \infty} n \cdot E[X_n^2]$$

$$= \lim_{n \rightarrow \infty} n \cdot V[X_n] \quad \text{since } X_n \sim N(0, \frac{1}{n^2})$$

$$= \lim_{n \rightarrow \infty} \frac{n}{n^2} \quad \text{since } X_n \sim N(0, \frac{1}{n^2})$$

$$= \lim_{n \rightarrow \infty} \frac{1}{n} = 0$$

$\therefore Y_n \xrightarrow{P} 0$  by  $m \rightarrow p$  ( $m \rightarrow p \rightarrow d$ )

Method 2: (later)

Method 3: Directly by definition of  $Y_n \xrightarrow{P} Y$

pick  $\varepsilon > 0$ .

$$\therefore \lim_{n \rightarrow \infty} P[|Y_n - Y| > \varepsilon] = \lim_{n \rightarrow \infty} P[|\sqrt{n} X_n| > \varepsilon] = \lim_{n \rightarrow \infty} P[n X_n^2 > \varepsilon]$$

$$\stackrel{\text{M.I.}}{\leq} \lim_{n \rightarrow \infty} \frac{E[n X_n^2]}{\varepsilon^2} = \lim_{n \rightarrow \infty} \frac{n}{\varepsilon^2} E[X_n^2]$$

$$= \lim_{n \rightarrow \infty} \frac{n}{\varepsilon^2} \cdot V[X_n^2] \quad \text{since } X_n \sim N(0, \frac{1}{n^2})$$

$$= \lim_{n \rightarrow \infty} \frac{n}{n^2 \varepsilon^2} \quad \text{since } X_n \sim N(0, \frac{1}{n^2})$$

$$= \frac{1}{\varepsilon^2} \cdot \lim_{n \rightarrow \infty} \frac{1}{n} = 0$$

$\therefore Y_n \xrightarrow{P} 0$

Defn: Bias  $B$  of r.v. estimator  $\hat{\Theta}_n$

$$B = |E[\hat{\Theta}_n] - \Theta|$$

Defn:  $\hat{\Theta}_n$  is an unbiased estimator of  $\Theta$  iff (u.b.)

$$E[\hat{\Theta}_n] = \Theta \quad \forall n.$$

Ex:  $\bar{X}_n$  is unbiased because  $E[\bar{X}_n] = \mu_x$

$$(\because B = |E[\bar{X}_n] - \mu_x| = 0.)$$

Defn: The mean-square error (MSE) of  $\hat{\Theta}_n$ :  $MSE(\hat{\Theta}_n) = E[(\hat{\Theta}_n - \Theta)^2]$

Thm: ("Consistency")  $\hat{\Theta}_n$  is consistent for  $\Theta$  iff  $\hat{\Theta}_n \xrightarrow{P} \Theta$

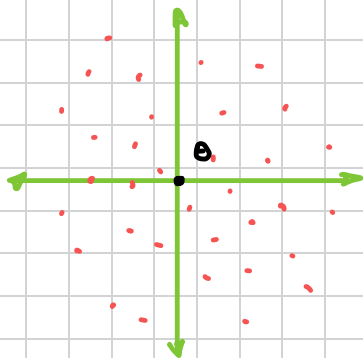
Ex:  $\bar{X}_n$  is consistent for  $\mu_x$  because  $\bar{X}_n \xrightarrow{P} \mu_x$   
(by WLLN)

Thm: ("Variance-Bias Decomposition")

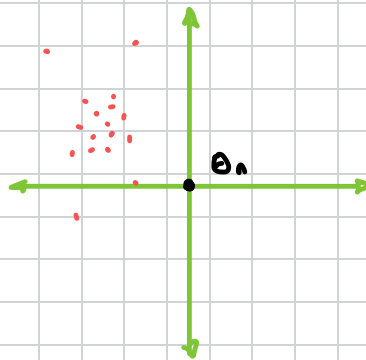
$$\text{MSE}[\hat{\theta}_n] = v[\hat{\theta}_n] + (E[\hat{\theta}_n] - \theta)^2$$

$$\text{for } \text{MSE}[\hat{\theta}_n] = E[(\hat{\theta}_n - \theta)^2].$$

V vs B tradeoff



V-high, B-low



V-low, B-high.

Prf:  $\text{MSE}[\hat{\theta}_n] = E[(\theta_n - \theta)^2]$

$$= E\left[\left((\theta_n - E[\theta_n]) + (E[\theta_n] - \theta)\right)^2\right].$$

$$= \underbrace{E[(\hat{\theta}_n - E[\hat{\theta}_n])^2]}_{v[\hat{\theta}_n]} + \underbrace{(E[\theta_n] - \theta)^2}_{B^2}$$

$$+ \cancel{2(E[\hat{\theta}_n - \theta] - \theta) \cdot \underbrace{E[\hat{\theta}_n - E[\hat{\theta}_n]]}_{E[\hat{\theta}_n] - E[\hat{\theta}_n] = 0}}.$$

$$= v[\hat{\theta}_n] + \text{Bias}^2[\hat{\theta}_n].$$

QED

Always ask: Is  $\hat{\Theta}_n$  unbiased?  
(if not is it asymptotically unbiased)

$\therefore$  Issue spotting sequence for m-p-d problems:

Use  $MS = V + B^2$  and  $m \rightarrow p \rightarrow d$

Q1: Is  $\hat{\Theta}_n$  unbiased (U.B.)? Asymptotically U.B.?

Q2: Is  $\hat{\Theta}_n$  consistent? (does  $V \downarrow 0$ )

If Q1 and Q2 yes: use  $m \rightarrow p \rightarrow d$  as problem dictates

Ex: (cont) Say  $X_n$  are similarly distributed as  $X_n \sim N(0, \frac{1}{n^2})$   
( $\therefore$  not iid)

Define  $Y_n \triangleq \sqrt{n} \cdot X_n$ . Does  $Y_1, Y_2, \dots$  converge

in probability to 0?

Q:  $Y_n \xrightarrow{P} 0$ ?

Method 2:  $MS = V + B^2$  and m-p-d.

$$E[Y_n] = E[\sqrt{n} X_n] = \sqrt{n} E[X_n] = 0 \quad \text{since } X_n \sim N(0, \frac{1}{n^2})$$

$\therefore Y_n$  is U.B. for 0

$$V[Y_n] = V[\sqrt{n} X_n] = n \cdot V[X_n] = \frac{n}{n^2} = \frac{1}{n} \quad \text{since } X_n \sim N(0, \frac{1}{n^2})$$

$$\begin{aligned} \therefore \lim_{n \rightarrow \infty} MSE[Y_n] &= \lim_{n \rightarrow \infty} \left( \underbrace{V[Y_n]}_{= \frac{1}{n}} + \underbrace{(E[Y_n] - 0)^2}_{= 0 \text{ (U.B.)}} \right) \\ &= \lim_{n \rightarrow \infty} \frac{1}{n} = 0 \end{aligned}$$

$\therefore Y_n \xrightarrow{m} 0 \quad \therefore Y_n \xrightarrow{P} 0$  by  $m \rightarrow p$ .

Thm: If iid  $X_1, \dots, X_n$  and  $E[|X|^4] < \infty$  then  
 ( $\therefore v[S^2]$  exists)

$S_n^2$  is unbiased for  $\sigma_x^2$ :  $E[S_n^2] = \sigma_x^2$ .

Prf:  $S_n^2 = \frac{1}{n-1} \sum_{k=1}^n (X_k - \bar{X}_n)^2$   $\therefore E\left[\frac{1}{n} (X_k - \bar{X}_n)^2\right] = \frac{n-1}{n} S_n^2$

$$= \frac{1}{n-1} \sum_{k=1}^n (X_k^2 + \bar{X}_n^2 - 2X_k\bar{X}_n)$$

$$= \frac{1}{n-1} \left( \sum_{k=1}^n X_k^2 + n \cdot \bar{X}_n^2 - 2\bar{X}_n \sum_{k=1}^n X_k \right)$$

$$= \frac{1}{n-1} \left( \sum_{k=1}^n X_k^2 + n \cdot \bar{X}_n^2 - 2n \bar{X}_n \left( \frac{1}{n} \sum_{k=1}^n X_k \right) \right)$$

$$= \frac{1}{n-1} \left( \sum_{k=1}^n X_k^2 + n \cdot \bar{X}_n^2 - 2n \cdot \bar{X}_n^2 \right)$$

$$= \frac{1}{n-1} \left( \sum_{k=1}^n X_k^2 - n \cdot \bar{X}_n^2 \right)$$

$\downarrow$   
 $\sigma_x^2$   
 $\therefore$  asymptotically unbiased  
 (reason for  $\frac{1}{n-1}$  vs  $\frac{1}{n}$ )

$$\therefore E[S_n^2] = \frac{1}{n-1} \left( \sum_{k=1}^n E[X_k^2] - n \cdot E[\bar{X}_n^2] \right)$$

$$= \frac{1}{n-1} \left( \sum_{k=1}^n (v[X_k] + E^2[X_k]) - n \cdot (v[\bar{X}_n] + E^2[\bar{X}_n]) \right)$$

since  $v[X] = E[X^2] - E^2[X]$  and finite 4<sup>th</sup> moment  $E[X^4]$ .

$$= \frac{1}{n-1} \left( \sum_{k=1}^n (\sigma_x^2 + \mu_x^2) - n \cdot \left( \frac{\sigma_x^2}{n} + \mu_x^2 \right) \right)$$

$$= \frac{1}{n-1} \left( n \cdot \sigma_x^2 + n \cdot \cancel{\mu_x^2} - \sigma_x^2 - n \cdot \cancel{\mu_x^2} \right)$$

$$= \frac{n\sigma_x^2 - \sigma_x^2}{n-1}$$

$$= \sigma_x^2 \cdot \frac{n-1}{n-1}$$

$$= \sigma_x^2$$

QED

Thm: iid  $X_1, X_2, \dots$  &  $\sigma_x^2 < \infty$  and  $E[X^4] < \infty$  ∴  $V[S_n^2] < \infty$

then  $S_n^2 \xrightarrow{P} \sigma_x^2$ . (∴  $S_n^2$  is consistent for  $\sigma_x^2$ )

Prf:

$$S_n^2 = \frac{1}{n-1} \sum_{k=1}^n (X_k - \bar{X}_n)^2$$

from prev.  $\left\{ \begin{aligned} &= \frac{1}{n-1} \sum_{k=1}^n (X_k^2 + \bar{X}_n^2 - 2 \cdot \bar{X}_n X_k) \\ &= \frac{1}{n-1} \left( \sum_{k=1}^n X_k^2 + n \cdot \bar{X}_n^2 - 2 \cdot \bar{X}_n \sum_{k=1}^n X_k \right) \cdot \frac{n}{n} \\ &= \frac{n}{n-1} \left( \frac{1}{n} \sum_{k=1}^n X_k^2 + \bar{X}_n^2 - 2 \bar{X}_n^2 \right) \\ &= \frac{n}{n-1} \left( \frac{1}{n} \sum_{k=1}^n X_k^2 - \bar{X}_n^2 \right) \end{aligned} \right.$ 

$\xrightarrow[\text{WLLN}]{P} 1 \cdot (E[X^2] - \mu_x^2) = \sigma_x^2$  ↙ continuity theorem since  $f(x) = x^2$  continuous.

$(\bar{X}_n)^2 \longrightarrow (\mu_x)^2$  QED.

Ex: iid  $X_1, \dots, X_n \sim N(\mu, \sigma^2)$ . (1) Does  $\bar{X}_n \xrightarrow{d} \mu_x$   
 (2) Does  $S_n^2 \xrightarrow{P} \sigma^2$  (consistency)

(1)  $MSE[\bar{X}_n] = V[\bar{X}_n] + (E[\bar{X}_n] - \mu_x)^2$

$\stackrel{\text{iid}}{\sim} \frac{\sigma^2}{n} + 0$  u.B. ∴  $\downarrow 0$  as  $n \uparrow \infty$

∴  $\bar{X}_n \xrightarrow{m} \mu$  ∴  $\bar{X}_n \xrightarrow{d} \mu$  by m.p.d

(2) Fact:  $V[S_n^2] = \frac{2\sigma^4}{n-1}$  if iid  $N(\mu, \sigma^2)$

earlier:  $S_n^2$  u.B. for  $\sigma^2$

∴  $MSE[S_n^2] = V[S_n^2] + (E[S_n^2] - \sigma^2)^2$

$= \frac{2\sigma^4}{n-1}$  ∴ 0 u.B.  $\downarrow 0$  as  $n \uparrow \infty$

∴  $S_n^2 \xrightarrow{m} \sigma^2$  ∴  $S_n^2 \xrightarrow{P} \sigma^2$  by m.p.d  
 ∴ Consistent

Q: Can you conclude  $S_n \xrightarrow{P} \sigma_x$ ?

A: Yes. since  $(\cdot)^2$  is continuous and so by continuity theorem.

$$\text{But: } E[S_n] = E[\sqrt{S_n^2}] \leq \sqrt{E[S_n^2]} = \sqrt{\sigma_x^2} = \sigma_x$$

( $<$ , strictly concave, by Jensen's ineq.)

$\therefore$  always biased (asymptotically unbiased)

optional

Thm: If  $X_n \xrightarrow{P} X$  and  $Y_n \xrightarrow{P} Y$  then  $X_n + Y_n \xrightarrow{P} X + Y$ .

Prf: Lemma: If  $a > 0$ ,  $b > 0$ , and  $c > 0$  then  
 $a + b > c \rightarrow (a > \frac{c}{2} \text{ or } b > \frac{c}{2})$

Prf: Say not.  $a + b > c$  and  $\sim (a > \frac{c}{2} \text{ OR } b > \frac{c}{2})$

$$\sim (a > \frac{c}{2} \text{ OR } b > \frac{c}{2}) \stackrel{\text{DeM}}{=} a \leq \frac{c}{2}, b \leq \frac{c}{2}$$

$$\therefore a + b \leq \frac{c}{2} + \frac{c}{2} = c$$

$\rightarrow \leftarrow$  contradiction

$\therefore a + b \leq c$  and  $a + b > c$ .

Pick  $\epsilon > 0$ :

$$\lim_{n \rightarrow \infty} P[|(X_n + Y_n) - (X + Y)| > \epsilon]$$

$$= \lim_{n \rightarrow \infty} P[|(X_n - X) + (Y_n - Y)| > \epsilon].$$

$$\leq \lim_{n \rightarrow \infty} P[|X_n - X| + |Y_n - Y| > \epsilon] \quad \begin{array}{l} \text{since } |a+b| \leq |a|+|b| \\ \text{and } P \text{ monotonicity} \end{array}$$

$$\stackrel{\text{Lemma}}{\leq} \lim_{n \rightarrow \infty} P\left[|X_n - X| > \frac{\epsilon}{2} \text{ OR } |Y_n - Y| > \frac{\epsilon}{2}\right]$$

$$\leq \underbrace{\lim_{n \rightarrow \infty} P\left[|X_n - X| > \frac{\epsilon}{2}\right]}_{= 0, \text{ since } X_n \xrightarrow{P} X} + \underbrace{\lim_{n \rightarrow \infty} P\left[|Y_n - Y| > \frac{\epsilon}{2}\right]}_{= 0, \text{ since } Y_n \xrightarrow{P} Y}.$$

$$= 0$$

$$\therefore X_n + Y_n \xrightarrow{P} X + Y$$

QED

optional

Thm: If  $X_n \xrightarrow{m} X$  and  $Y_n \xrightarrow{m} Y$  then  $X_n + Y_n \xrightarrow{m} X + Y$ .

Prf:  $\lim_{n \rightarrow \infty} E[(X_n + Y_n - (X + Y))^2]$

$$= \lim_{n \rightarrow \infty} E[((X_n - X) + (Y_n - Y))^2]$$

$$= \lim_{n \rightarrow \infty} E[(X_n - X)^2] + \lim_{n \rightarrow \infty} E[(Y_n - Y)^2]$$

$$+ \lim_{n \rightarrow \infty} 2 \cdot E[(X_n - X)(Y_n - Y)]$$

$$= 0 + 0 + \lim_{n \rightarrow \infty} 2 \cdot \sigma_{XY} \quad \text{since } X_n \xrightarrow{m} X \text{ and } Y_n \xrightarrow{m} Y.$$

$$\leq 2 \cdot \lim_{n \rightarrow \infty} \sigma_X \cdot \sigma_Y \quad \begin{array}{l} \text{(Cauchy-Schwartz)} \\ \text{by u.p. } E[UV] = \sqrt{E[U^2] \cdot E[V^2]} \end{array}$$

$$= 2 \cdot \lim_{n \rightarrow \infty} \sqrt{E[(X_n - X)^2]} \cdot \lim_{n \rightarrow \infty} \sqrt{E[(Y_n - Y)^2]}$$

$$= 2 \cdot \sqrt{\lim_{n \rightarrow \infty} E[(X_n - X)^2]} \cdot \sqrt{\lim_{n \rightarrow \infty} E[(Y_n - Y)^2]} \quad \text{since } f(x) = x^2 \text{ continuous.}$$

$$= 0 \quad \text{since } X_n \xrightarrow{m} X \text{ and } Y_n \xrightarrow{m} Y$$

$$\therefore X_n + Y_n \xrightarrow{m} X + Y$$

QED.

Caveat:  $X_n + Y_n \xrightarrow{d} X + Y$  even if  $X_n \xrightarrow{d} X$  and  $Y_n \xrightarrow{d} Y$ .

not in general

$p \rightarrow d$  only for one sequence  $X_1, X_2, X_3, \dots$

in general