

Proofs



$$\text{Markov} :- t \cdot \mathbb{1}_{x \geq t} \leq x \Rightarrow E[t \cdot \mathbb{1}_{x \geq t}] \leq E[x]$$

$$P(x \geq \alpha E[x]) \leq \frac{1}{\alpha} \Rightarrow t \cdot E[\mathbb{1}_{x \geq t}] \leq E[x] \Rightarrow P(x \geq t) \leq t' E[x]$$

Paley - Zygmund :- Cauchy-Schwarz

$$\begin{aligned} E[x]^2 &= E[x \cdot \mathbb{1}_{x > 0}]^2 \leq E[x^2] E[\mathbb{1}_{x > 0}] \\ &= E[x^2] P(x > 0) \quad \mu = E[x] \end{aligned}$$

$$E[x \cdot \mathbb{1}_{x > \alpha \mu}]^2 \leq E[x^2] P(x > \alpha \mu)$$

$$\begin{aligned} \mu &= E[x \cdot \mathbb{1}_{x > \alpha \mu}] + E[x \cdot \mathbb{1}_{x \leq \alpha \mu}] \\ &\leq E[x \cdot \mathbb{1}_{x > \alpha \mu}] + \alpha \mu \end{aligned}$$

$$\Rightarrow E[x \cdot \mathbb{1}_{x > \alpha \mu}] \geq (1-\alpha)\mu$$

$$\Rightarrow P(x > \alpha \mu) \geq \frac{(1-\alpha)^2 \mu^2}{E[x^2]}$$

$$\underline{\text{BC Lemmas}} \quad \limsup A_n = \inf_K \sup_{n > K} A_n$$

$$= \lim_{m \rightarrow \infty} \bigcup_{n=m}^{\infty} A_n$$

$$\liminf A_n = \sup_K \inf_{n > K} A_n = \lim_{m \rightarrow \infty} \bigcap_{n=m}^{\infty} A_n$$

Easier to calculate moments than probabilities  
(e.g. Mean, Variances)

BC-1  $\rightarrow$  Subadditivity

BC-2  $\rightarrow$  Easy.

### Zero one Laws

Proof:- Define  $T_n := \sigma(\cup_{k>n} F_k)$   $T = \cap_n T_n$

$F_1, F_2, \dots, F_n$  and  $T_n$  are independent.

$T \subseteq T_n \Rightarrow F_1, F_2, \dots, F_n, T$  are independent

$\Rightarrow T, \sigma(\cup_n F_n)$  are independent

$T \subseteq \sigma(\cup_n F_n) \Rightarrow T$  is independent of itself

$A \in T \quad P(A)^2 = P(A)P(A) \Rightarrow P(A) = 0, 1$

Proof: Fix  $\theta > 0$

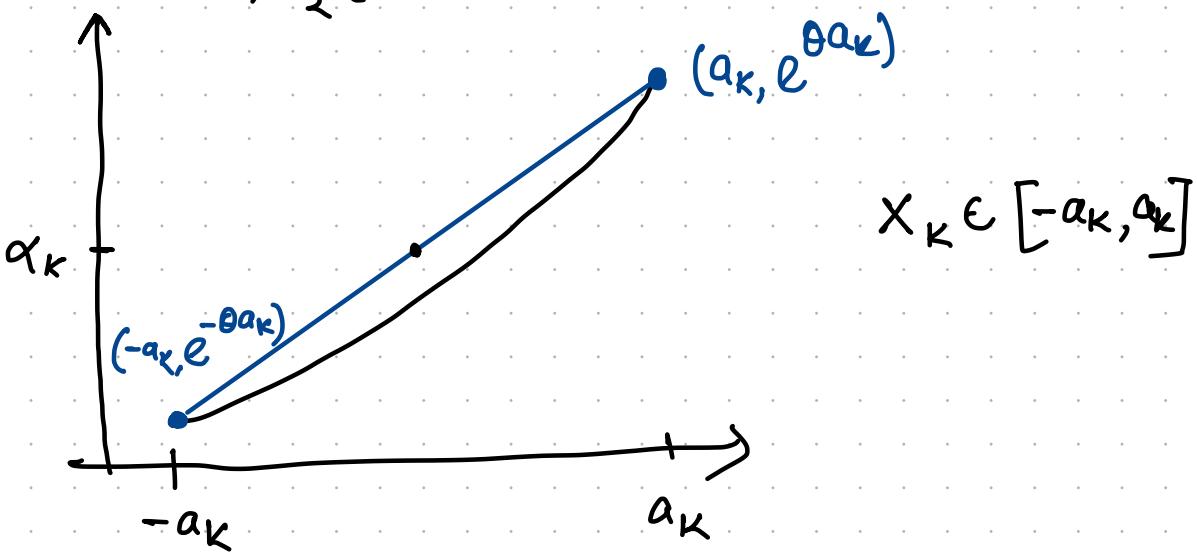
"Markov"

$$\begin{aligned} P\{S > tA\} &= P\{e^{\theta S} > e^{\theta tA}\} \leq e^{-\theta tA} E[e^{\theta S}] \\ &= e^{-\theta tA} E\left[\prod_{k=1}^n e^{\theta X_k}\right] \end{aligned}$$

$x \mapsto e^{\theta x}$  is convex on  $[-a_k, a_k]$

$$x \mapsto \frac{a_k - x}{2a_k} e^{-\theta a_k} + \frac{x + a_k}{2a_k} e^{\theta a_k}$$

$$\Rightarrow \frac{1}{2}(e^{\theta a_k} + e^{-\theta a_k}) + \frac{x}{2a_k}(e^{\theta a_k} - e^{-\theta a_k})$$



$$e^{\theta X_k} \leq \alpha_k + \beta_k X_k$$

$$\alpha_k = \frac{1}{2}(e^{\theta a_k} + e^{-\theta a_k})$$

$$\beta_k = \frac{1}{2a_k}(e^{\theta a_k} - e^{-\theta a_k})$$

$$\Rightarrow P\{S \geq tA\} \leq e^{-\theta tA} E\left[\prod_{k=1}^n (\alpha_k + \beta_k X_k)\right] = e^{-\theta tA} \prod_{k=1}^n \alpha_k$$

$$E[X_k] = 0 \quad \forall k$$

$$P\{S \geq tA\} \leq e^{-\theta t A} \prod_{k=1}^n \alpha_k$$

Wish to simplify bound over  $\theta$

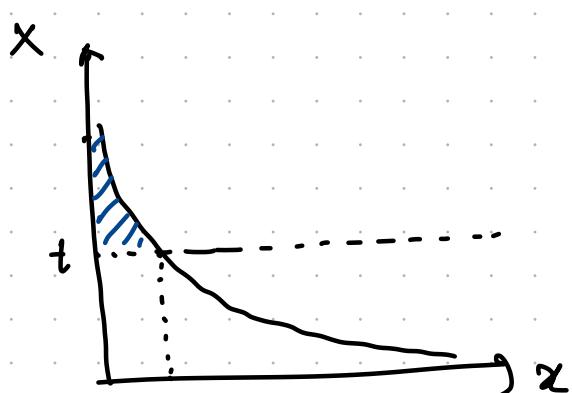
Consequently  $\alpha_k \leq e^{\theta^2 \alpha_k^2 / 2}$  (Follows from simple step)

$$\Rightarrow \prod_{k=1}^n \alpha_k \leq e^{\theta^2 A^2 / 2}$$

$$\begin{aligned} \Rightarrow P\{S \geq tA\} &\leq e^{-\theta t A + \theta^2 A^2 / 2} \\ &\leq e^{-t^2 / 2} \quad \text{Looks like Gaussian} \end{aligned}$$



### Kolmogorov's maximal inequality :-



$$X \sim \exp(\lambda)$$

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & \text{otherwise} \end{cases} \quad \lambda = 1$$

$$P(X_k > t) = e^{-t}$$

$$P\left(\max_{k \leq n} X_k > t\right) = 1 - (1 - e^{-t})^n$$

## Proof of Maximal inequality.

Stopping times

Fix  $n$  and let  $\tau = \inf\{k \leq n : |S_k| > t\}$

$$\mathbb{P}(\max_{k \leq n} |S_k| > t) = \mathbb{P}(|S_\tau| > t) \leq t^{-2} \underline{E[S_\tau^2]}$$

[Chebyshew inequality]

need to control  
this part

$$\begin{aligned} E[S_n^2] &= E[(S_\tau + (S_n - S_\tau))^2] \\ &= E[S_\tau^2] + E[(S_n - S_\tau)^2] + 2E[S_\tau(S_n - S_\tau)] \\ &\geq E[S_\tau^2] + 2E[S_\tau(S_n - S_\tau)] \end{aligned}$$

Evaluating 2nd term by splitting as per value of  $\tau$

$$S_n - S_\tau = 0 \text{ if } \tau = n$$

(martingale property)

$$\text{Also, } E[S_\tau(S_n - S_\tau)] = \sum_{k=1}^{n-1} E[1_{\tau=k} S_k (S_n - S_k)]$$

$$\begin{aligned} &= \sum_{k=1}^{n-1} E[1_{\tau=k} S_k] E[S_n - S_k] \text{ (independence)} \\ &= 0 \end{aligned}$$

$S_k 1_{\tau=k}$  depends only on  $x_1, \dots, x_k$

$S_n - S_k$  depends on  $x_{k+1}, \dots, x_n$

$$\mathbb{P}(\max_{k \leq n} |S_k| > t) \leq t^{-2} E[S_n^2]$$

Fix an integer  $t \geq 1$

$X_{t,k}$  = indicator that the  $k$ 'th book is not picked in first  $t$  days

$$\mathbb{P}(T_n > t) = \mathbb{P}(S_{t,n} \geq 1) \quad S_{t,n} = \sum_{k=1}^n X_{t,k} \quad (\text{No. of books that have not been picked in first } t \text{ days})$$

$$E[X_{t,k}] = \sum X_{t,k} \mathbb{P}(X_{t,k})$$

$$= 1 \cdot (1 - \gamma_n)^t + 0 \cdot (1 - (1 - \gamma_n)^t)$$

$$= (1 - \gamma_n)^t$$

$$E[X_{t,k} X_{t,l}] = (1 - \gamma_n)^t \quad k \neq l$$

$$E[S_{t,n}] = n (1 - \gamma_n)^t$$

Two useful inequalities

- $1-x \leq e^{-x} \forall x$

- $1-x \geq e^{-x-x^2}$

$$|x| < \frac{1}{2}$$

$$n e^{-t/\ln n - t^2/\ln n} \leq n (1 - \gamma_n)^t \leq n e^{-t/\ln n} \quad n > 2$$

$$E[S_{t,n}^2] = n (1 - \gamma_n)^t + n(n-1) (1 - \gamma_n)^t (1 - 2\gamma_n)^t \leq n e^{-t/\ln n} + \frac{n}{n(n-1)} e^{-2t/\ln n}$$

$$\text{Set } t = n \log n + n \theta_n$$

$$\begin{aligned} \mathbb{P}(T_n > n \log n + n \theta_n) &= \mathbb{P}(S_{t,n} \geq 1) \\ &\leq E[S_{t,n}] \leq n e^{-\frac{n \log n + n \theta_n}{n}} \\ &\leq e^{-\theta_n} = O(1) \end{aligned}$$

$$\text{Set } t = n \log n - n \theta_n \quad (\theta_n < \log n)$$

$$E[S_{t,n}^2] \leq e^{\theta_n} + e^{2\theta_n} \quad E[S_{t,n}] \geq e^{\theta_n - \frac{n \log n - \theta_n}{n}}$$

$$\mathbb{P}(T_n > n \log n - n\theta_n) = \mathbb{P}(S_{t,n} \geq 1) \geq \frac{\mathbb{E}[S_{t,n}]^2}{\mathbb{E}[S_{t,n}^2]} \geq \frac{e^{2\theta_n - 2 \frac{\log n - \theta_n}{n}}}{e^{\theta_n} + e^{2\theta_n}}$$

$$= 1 - o(1)$$

as  $n \rightarrow \infty$

$$\mathbb{P}(|T_n - n \log n| > n\theta_n) \rightarrow 0 \text{ as } \theta_n \rightarrow \infty$$

## # Branching process

$Z_n$ : G.W process     $Z_n$ : No of individual in  $n$ th gen.

$$Z_{n+1} = \begin{cases} \xi_1^{n+1} + \xi_2^{n+1} + \dots + \xi_{Z_n}^{n+1} & \text{if } Z_n > 0 \\ 0 & \text{if } Z_n = 0 \end{cases}$$

$$p_k = \mathbb{P}(\xi_i^n = k) \quad \mu = \mathbb{E} \xi_i^m \in (0, \infty)$$

Want to calculate extinction probability

#  $\mu \leq 1$     $\mathbb{P}(\xi_i^m = 1) < 1$  then  $Z_n = 0 \forall n$  sufficiently large

#  $\mu > 1$     $\mathbb{P}(Z_n \neq 0 \text{ for some } n) = p$ , the so called  $\varphi(p) = p$  which is called extinction probability.

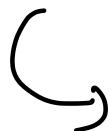
$$\varphi(s) = \sum_{k=0}^{\infty} p_k s^k \quad p_k = \mathbb{P}(\xi_i^n = k) \quad s \in [0, 1]$$

$$f_t(s) := \mathbb{E}[s^{Z_t}] = f^{(t)}(s) = \underbrace{f \circ f \circ \dots \circ f}_{t-\text{iterate of } f \text{ at } s}(s)$$

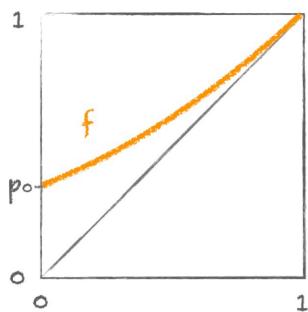
## Extinction Probability

no sol<sup>n</sup> other than 1

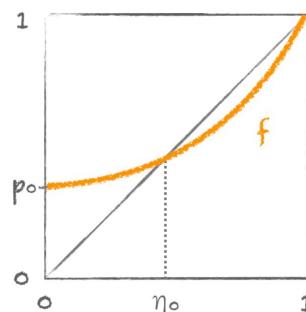
unique sol<sup>n</sup>



$$n < 1$$



$$n > 1$$



$$\phi(0) = p_0$$

$$\phi(1) = 1$$

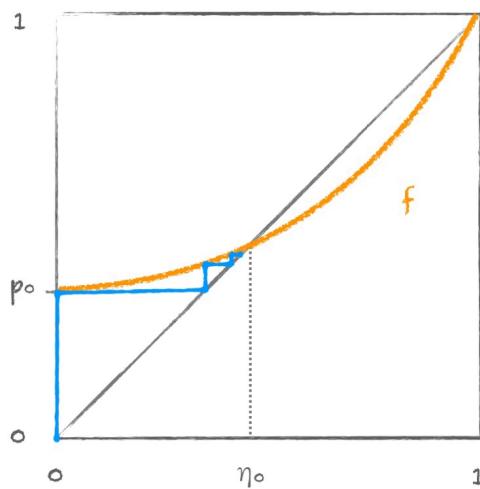


Figure 5.2: Convergence of iterates to a fixed point.

Credits: Notes  
(Sebastian Roch)

## Proof of WLLN:-

Step 1 :-  $X_i$  has finite variance  $\sigma^2$

$$\text{WLOG } E[X_1] = 0$$

$$\text{Chebychev inequality} \Rightarrow P\left(\left|\frac{S_n}{n}\right| > \delta\right) \leq \frac{1}{n^2 \delta^2} \text{Var}(S_n)$$

$$\text{Var}(S_n) = n \sigma^2 \Rightarrow P\left(\left|\frac{S_n}{n}\right| > \delta\right) \leq \frac{1}{n^2 \delta^2} (n \sigma^2)$$

Independence of  $X_i$ 's

$$= \frac{\sigma^2}{n \delta^2} \rightarrow 0$$

as  $n \rightarrow \infty$

$\delta$  fixed

Step 2 :- Let  $E[X_i] < \infty$  not necessarily higher moments  
let  $E[X_i] = 0$

$$\text{Fixing } n \quad X_k = Y_k + Z_k \quad Y_k := X_k \mathbb{1}_{|X_k| \leq A_n}$$

$$E[Y_k] = -E[Z_k] =: \mu_n \quad Z_k := X_k \mathbb{1}_{|X_k| > A_n}$$

which depends on  $A_n$  and goes to zero as  $A_n \rightarrow \infty$

$\mu_n \rightarrow 0$  as  $n \rightarrow \infty$

Fix  $\delta > 0$  choose  $n_0$  large enough  $|\mu_n| < \delta$  for  $n \geq n_0$

$$\text{As } |Y_1| \leq A_n \quad \text{Var}(Y_1) \leq E[Y_1^2] \leq A_n E[|X_1|]$$

$$P\left(\left|\frac{S_n}{n} - \mu_n\right| > \delta\right) \leq \frac{\text{Var}(Y_1)}{n \delta^2} \leq \frac{A_n E[|X_1|]}{n \delta^2}$$

If  $n \geq n_0$  then  $|\mu_n| < \delta$  if  $|\frac{1}{n} S_n + \mu_n| \geq \delta$ , then  
at least one of  $Z_1, Z_2, \dots, Z_n$  must be non zero

$$\mathbb{P}\left(\left|\frac{s_n^2}{n} + \mu_n\right| > \delta\right) \leq n \mathbb{P}(Z_1 \neq 0) = n \mathbb{P}(X_1 > A_n)$$

$$X_k = (Y_k - \mu_n) + (Z_k + \mu_n)$$

$$\mathbb{P}\left(\left|\frac{s_n}{n}\right| > 2\delta\right) \leq \mathbb{P}\left(\left|\frac{s_n^2}{n} - \mu_n\right| > \delta\right) + \mathbb{P}\left(\left|\frac{s_n^2}{n} - \mu_n\right| > \delta\right)$$

$$\leq \frac{A_n E[|X_1|]}{n \delta^2} + n \mathbb{P}(|X_1| > A_n)$$

$$\leq \frac{A_n E[|X_1|]}{n \delta^2} + \underbrace{\frac{n}{A_n} E[|X_1| \mathbf{1}_{|X_1| > A_n}]}$$

$$\text{Take } A_n = \frac{\delta^3}{E[|X_1|]} \cdot n \\ = \alpha n$$

This term  
is less than  
 $\delta$

$$\frac{n}{\alpha n} E[|X_1| \mathbf{1}_{|X_1| > \alpha n}]$$

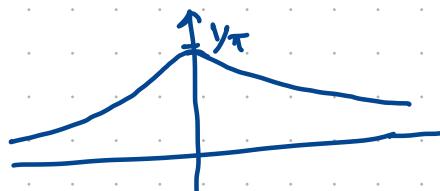
$$\Rightarrow \alpha^{-1} E[|X_1| \mathbf{1}_{|X_1| > \alpha n}]$$

$$= \frac{E[|X_1|]}{\delta^3} \cdot \underbrace{E[|X_1| \mathbf{1}_{|X_1| > \alpha n}]}_{\downarrow}$$

goes to zero  
as  $n \rightarrow \infty$

$$\Rightarrow \limsup_{n \rightarrow \infty} \mathbb{P}\left(\left|\frac{s_n}{n}\right| > 2\delta\right) \leq \delta$$

$$f(t) = \begin{cases} \frac{1}{\pi(1+t^2)} & -\infty < t < \infty \end{cases}$$



$$E[|X_1|] = \infty$$

## Weierstrass approximation :-

The set of polynomials is dense in the space of continuous functions.

$$\text{Pf: } f \in C[0,1], Q_{f,n}(p) = \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} p^k (1-p)^{n-k}$$

then,  $\|Q_{f,n}(p) - f(p)\| \rightarrow 0$  as  $n \rightarrow \infty$

$$Q_{f,n}(p) = E\left[f\left(\frac{s_n}{n}\right)\right] = \sum_{k=0}^n f\left(\frac{k}{n}\right) \mathbb{P}(S_n = k)$$

For  $p \in [0,1]$   $x_1, \dots, x_n \stackrel{\text{iid}}{\sim} \text{Ber}(p)$  random variables

$$\begin{aligned} |E_p\left[f\left(\frac{s_n}{n}\right)\right] - f(p)| &\leq E_p[|f\left(\frac{s_n}{n}\right) - f(p)|] \\ &= E_p\left[|f\left(\frac{s_n}{n}\right) - f(p)| \mathbb{1}_{\left|\frac{s_n}{n} - p\right| \leq \delta}\right] + \\ &\quad E_p\left[|f\left(\frac{s_n}{n}\right) - f(p)| \mathbb{1}_{\left|\frac{s_n}{n} - p\right| > \delta}\right] \\ &\leq \omega_f(\delta) + 2\|f\| \mathbb{P}\left(\left|\frac{s_n}{n} - p\right| > \delta\right) \end{aligned}$$

$$\omega_f(\delta) := \sup\{|f(x) - f(y)| : |x-y| < \delta\}$$

$$\mathbb{V}_{\text{Ber}_p}(X_i) = p(1-p) \quad \mathbb{P}_p\left(\left|\frac{s_n}{n} - p\right| > \delta\right) \leq \frac{p(1-p)}{n\delta^2} \leq \frac{1}{4n\delta^2}$$

$$\sup_{p \in [0,1]} |Q_{f,n}(p) - f(p)| \leq \omega_f(\delta) + \frac{\|f\|}{2\delta^2 n}$$

choosing  $\delta > 0$  s.t.  $\omega_f(\delta) < \epsilon$ , choosing  $n$  s.t.  $\frac{\|f\|}{2\delta^2 n} < \epsilon$

$$\Rightarrow \|Q_{f,n}(p) - f(p)\| < 2\epsilon$$

Q.E.D

## Monte-Carlo integration:

$f: [a, b] \rightarrow \mathbb{R}$  want to integrate

$x_1, \dots, x_n$  are  $\text{U}([a, b])$  iid  $y_k = f(x_k)$  are also iid

$$E[Y_1] = \int_a^b f(x) dx$$

By WLLN  $P\left(\left|\frac{1}{n} \sum_{k=1}^n f(x_k) - \int_a^b f(x) dx\right| > \delta\right) \rightarrow 0$

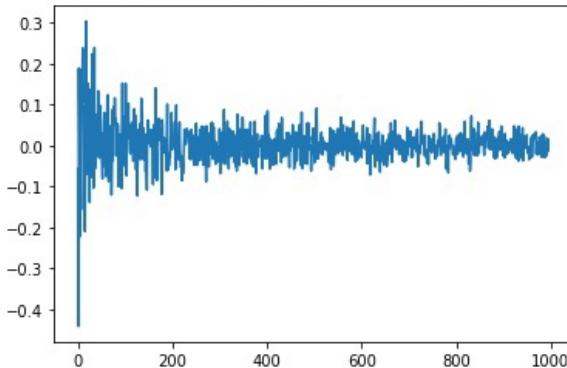
# Random points

Accuracy is bad

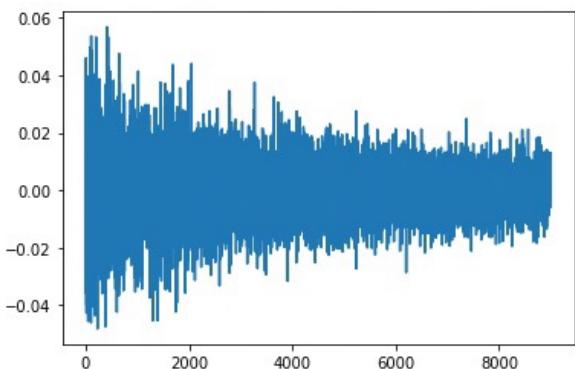
$\frac{1}{n} \sum_{k=1}^n f(x_k)$  has var  $O(1/n)$

$$\Rightarrow \text{sd} = O\left(\frac{1}{n^{1/2}}\right)$$

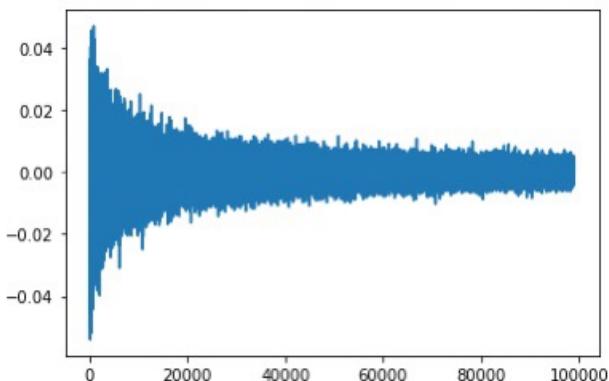
$$\pi = \int_0^1 \frac{4}{1+x^2} dx \approx \frac{1}{n} \sum_{k=1}^n \frac{4}{1+x_k^2}$$



1000 points  
Errors are plotted

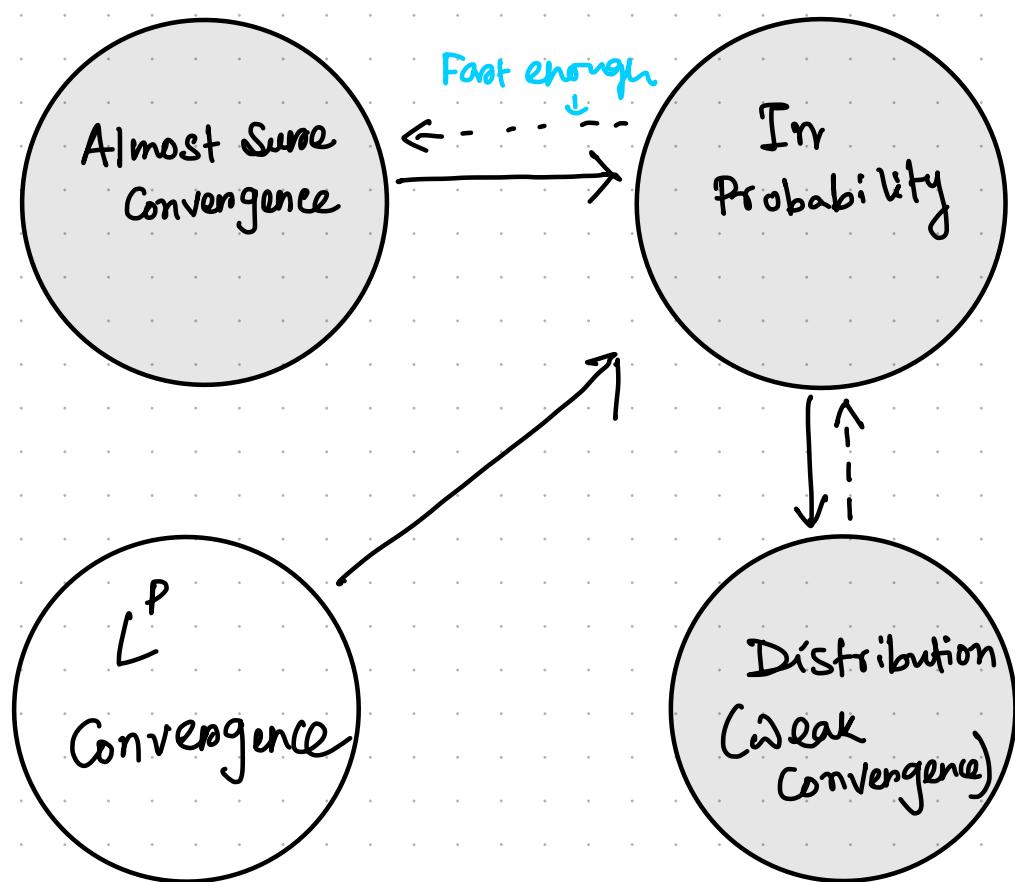


10000 points



100,000 points

- ①  $x_n \xrightarrow{\text{a.s.}} x \Rightarrow x_n \xrightarrow{P} x$
- ②  $x_n \xrightarrow{P} x \Rightarrow x_n \xrightarrow{d} x$
- ③  $x_n \xrightarrow{d} x \Rightarrow x_n \xrightarrow{P} x$   
 ↓  
 Constant a.s.



a.s. and in probability

$$\mathbb{P}(|x_n - x| > \delta) \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$\mathbb{P}(\omega : \lim x_n(\omega) = x(\omega)) = 1$$

$$1) \mathbb{1}_{A_n} \xrightarrow{P} 0 \iff \lim_{n \rightarrow \infty} \mathbb{P}(A_n) = 0$$

$$1) \mathbb{1}_{A_n} \xrightarrow{a.s.} 0 \iff \limsup \mathbb{P}(A_n) = 0$$

$$\mathbb{P}(\limsup A_n) \geq \limsup \mathbb{P}(A_n)$$

a.s  $\Rightarrow P$

$$\left. \begin{array}{l} P(A_n) = \gamma_n \\ \lim_{n \rightarrow \infty} \mathbb{P}(A_n) = 0 \end{array} \right\} \sum_n P(A_n) = \infty \quad (BC-2)$$

$$\mathbb{P}(\limsup A_n) = 1$$

$$x_n = \mathbb{1}_{[0, 1/n]} \quad x_n \xrightarrow{a.s} 0 \quad \mathbb{P}(x_n > \delta) \text{ is not summable}$$

$$x_n \xrightarrow{P} 0 \quad \text{for any } \delta > 0$$

no rate of convergence is assured.

Convergence in distributions :-

$$\text{let } x_n = 1 - x \quad \forall n$$

$x \sim \text{binomial}$

$$x_n \xrightarrow{d} x \quad x_n \not\xrightarrow{P} x$$

SLLN

Q: Does WLLN  $\xrightarrow{?}$  SLLN (i.e.  $P \xrightarrow{?} a.s.$ )

A: Possible if  $\sum_n P\left(\left|\frac{s_n}{n} - E[x_i]\right| > \delta\right) < \infty$  (i.e. summable) &  $\delta > 0$

Supposing  $\text{Var}(x_i) = \sigma^2 < \infty$  we get only a bound of

$\frac{\sigma^2}{n\delta^2}$  (chebyshev)  $P\left(\left|\frac{s_n}{n} - E[x_i]\right| > \delta\right) < \frac{\sigma^2}{n\delta^2}$   
which is not summable.

As we are at a "Borderline Summability".

Etemadi's version:-

Proof:  $x_i = x_i^+ - x_i^-$  then proving it for non neg r.v

Assume  $x_i$  are non neg r.v

Step 1 Truncate  $x_i$ 's to produce more tractable version

Define  $y_i := x_i \mathbb{1}_{\{x_i < i\}}$

$$\sum_{i=1}^{\infty} P(x_i \neq y_i) \leq \sum_{i=1}^{\infty} P(x_i \geq i) = \sum_{i=1}^{\infty} P(x_i \geq i) \leq E[x_i] < \infty$$

By BC-1  $P(x_i \neq y_i \text{ i.o.}) = 0$  [it suffices to show  $\sum_{i=1}^n y_i \xrightarrow{a.s.} \mu$ ]

Note  $E[y_i] - \mu = E[x_i; x_i \geq i] \rightarrow 0$  as  $i \rightarrow \infty$  by DCT

$$E[x_i; x_i \geq i] \leq E[x_i] < \infty$$

$$\therefore n^{\frac{1}{n}} \sum_{i=1}^n E[Y_i] \rightarrow \mu \text{ as } n \rightarrow \infty$$

Define  $Z_n := \frac{1}{n} \sum_{i=1}^n (Y_i - E[Y_i])$  Suffices to prove  
 $Z_n \rightarrow 0 \text{ a.s.}$

Take  $\alpha > 1$   $K_n := [\alpha^n]$

# For any choice of  $\alpha > 1$   $Z_{K_n} \rightarrow 0 \text{ a.s.}$

Take  $\epsilon > 0$   $X_i$ 's are pairwise independent

so are  $Y_i$   $\text{Cov}(Y_i, Y_j) = 0$  for any  $i \neq j$

$$P(|Z_{K_n}| > \epsilon) \leq \frac{1}{\epsilon^2 K_n^2} \sum_{i=1}^{K_n} \text{Var}(Y_i)$$

$$\begin{aligned} \sum_{n=1}^{\infty} P(|Z_{K_n}| > \epsilon) &\leq \sum_{n=1}^{\infty} \frac{1}{\epsilon^2 K_n^2} \sum_{i=1}^{K_n} \text{Var}(Y_i) \\ &= \frac{1}{\epsilon^2} \sum_{i=1}^{\infty} \text{Var}(Y_i) \sum_{n: K_n \geq i} \frac{1}{K_n^2} \end{aligned}$$

$\exists \beta > 1$  depending on  $\alpha$  s.t.  $K_{n+1}/K_n \geq \beta$  for all  $n$  large enough

$$\sum_{n: K_n \geq i} \frac{1}{K_n^2} \leq \frac{1}{\beta^2} \sum_{n=0}^{\infty} \frac{1}{\beta^n} \leq \frac{C}{\beta^2}$$

$$\sum_{n=1}^{\infty} P(|Z_{K_n}| > \epsilon) \leq \frac{C'}{\epsilon^2} E[X_1] < \infty$$

$$\text{B.C.} \Rightarrow P(|Z_{K_n}| > \epsilon \text{ i.o.}) = 0$$

$\Rightarrow Z_{K_n} \rightarrow 0$  as  $n \rightarrow \infty$  (we see this subsequence goes to 0 a.s.)

Final step  $Z_n \rightarrow 0 \text{ a.s.}$

Define  $T_n := \sum_{i=1}^n Y_i$        $K_n < m \leq K_{n+1}$

$$\frac{K_n}{K_{n+1}} \frac{T_{K_n}}{K_n} = \frac{T_{K_n}}{K_{n+1}} \leq \frac{T_m}{m} \leq \frac{T_{K_{n+1}}}{K_n} = \frac{T_{K_{n+1}}}{K_{n+1}} \frac{K_{n+1}}{K_n}$$

Let  $m \rightarrow \infty$      $\frac{K_{n+1}}{K_n} \rightarrow \alpha$      $\frac{T_{K_n}}{K_n} \xrightarrow{\text{a.s.}} \mu$  (Subsequence we shown above)  
 $K_n \rightarrow \infty$

$$\Rightarrow \frac{\mu}{\alpha} \leq \liminf_{m \rightarrow \infty} \frac{T_m}{m} \leq \limsup_{m \rightarrow \infty} \frac{T_m}{m} \leq \alpha \mu \text{ a.s.}$$

$\alpha > 1$  is arbitrary.

This completes the proof.