

Section 1.6 of Gallager's book

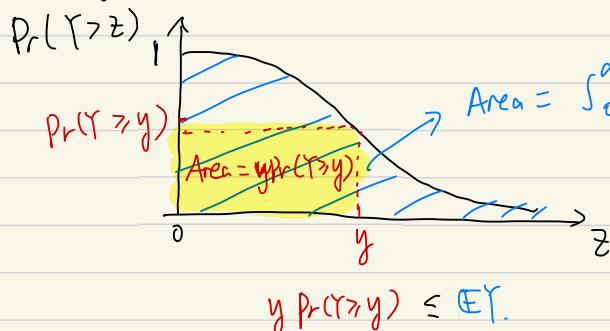
- Markov's inequality
- Chebyshhev's inequality
- Chernoff bounds

Markov's Inequality.

LEM: Let T be non-negative rv. with mean of $\mathbb{E}T$ then for any $y > 0$

$$\Pr(T \geq y) \leq \frac{\mathbb{E}T}{y}.$$

Complementary CDF of T :



$$\text{Area} = \int_0^\infty \Pr(T > z) dz = \mathbb{E}T.$$

(Fact: Layer-cake Representation
in Lecture 2)

$$\lim_{y \rightarrow \infty} y \Pr(T \geq y) = 0 \text{ if } \mathbb{E}T < \infty$$

Ex: If T represents height of a random student in the class. $\mathbb{E}T = 1.6\text{m}$. What's the chance that T exceeds $1.5\mathbb{E}T$?

$$\Pr(T \geq 1.5\mathbb{E}T) \leq \frac{\mathbb{E}T}{1.5\mathbb{E}T} = \frac{2}{3}$$

2.4m.

Ex: If $X \in \{0, 5\}$, $\Pr(X=0) = \frac{24}{25}$, $\Pr(X=5) = \frac{1}{25}$

$\mathbb{E}X = \frac{1}{25} \cdot 5 = \frac{1}{5}$. What's the chance that $X \geq 5$?

$$\Pr(X \geq 5) \leq \frac{\mathbb{E}X}{5} = \frac{1}{25} = \Pr(X=5) \Rightarrow \text{tight}$$

(no better bound using only Ex)

$$\text{Pf: } \{T > y\} \leq \frac{1}{y}, \forall y > 0. \quad \left\{ \begin{array}{l} \text{if } T > y, \frac{T}{y} \geq 1 = \mathbb{I}\{T > y\}. \\ \text{if } T \leq y, \frac{T}{y} \geq 0 = \mathbb{I}\{T \leq y\}. \end{array} \right.$$

$$\begin{aligned} \text{Take expectations on both sides} \Rightarrow \mathbb{E}[\mathbb{I}\{T > y\}] &\leq \frac{\mathbb{E}T}{y} \\ \Rightarrow \Pr[T > y] &\leq \frac{\mathbb{E}T}{y}. \end{aligned}$$

— Chebyshev's Inequality.

Lem: Let Z is a rv. with finite mean $\mathbb{E}Z$ & finite variance $\text{Var}(Z) = b_z^2$

Then

$$\Pr((Z - \mathbb{E}Z)^2 \geq y) \leq \frac{b_z^2}{y}, \forall y > 0.$$

Rmk: Chebyshev's ineq. applies to rv. with finite mean & variance
 first moment first and second moment.
 Markov's ineq applies to non-negative rv with finite mean
 (Variance can be too)

\Rightarrow the more moments we use, the tighter the results we can get in general

Rmk: What's the prob that Z deviates from $\mathbb{E}Z$ by $\geq cb_z$ for some $c > 0$?
 $\Pr(|Z - \mathbb{E}Z| \geq cb_z) = \Pr((Z - \mathbb{E}Z)^2 \geq c^2 b_z^2) \leq \frac{1}{c^2}$

Pf: Apply Markov's ineq. to non-negative rv. $\Pr((Z - \mathbb{E}Z)^2 \geq y) \leq \frac{\mathbb{E}[(Z - \mathbb{E}Z)^2]}{y} = \frac{\text{Var}Z}{y} = \frac{b_z^2}{y}.$ ■

— Chernoff bounds

Let X_1, X_2, \dots, X_n be iid Bernoulli rv where $\Pr[X_i = 1] = p, \Pr[X_i = 0] = 1-p$
 Fix $\varepsilon > 0, \Pr\left(\left|\frac{1}{n} \sum_{i=1}^n X_i - p\right| > \varepsilon\right) = \Pr\left(\left(\frac{1}{n} \sum_{i=1}^n X_i - p\right)^2 > \varepsilon^2\right)$
 $\leq \frac{\mathbb{E}\left[\left(\frac{1}{n} \sum_{i=1}^n X_i - p\right)^2\right]}{\varepsilon^2}$ (Markov's ineq)
 $= \frac{\frac{1}{n^2} \sum_{i=1}^n \mathbb{E}[X_i^2] + \frac{1}{n^2} \sum_{i,j} \mathbb{E}[X_i X_j] - 2p \frac{1}{n} \sum_{i=1}^n \mathbb{E}[X_i] + p^2}{\varepsilon^2}$
 $= \frac{p(1-p)}{n \varepsilon^2}$

$$\text{Let } p = \frac{1}{2} \quad \& \quad \varepsilon = 0.01$$

$$\text{Let } \Pr\left(\left|\frac{1}{n}\sum_{i=1}^n X_i - p\right| > \varepsilon\right) \leq 0.01 \Rightarrow n \geq 2000 \text{ samples}$$

Do we need this # of samples to get $\Pr(\dots) \leq 0.01$?

} Yes, if further moments don't exist
 } No, if more moments exist.

$$\text{MGF of } n. X. \quad g_X(r) = \mathbb{E}[e^{rx}], \quad \forall r \in \mathbb{R}$$

Assume that $g_X(r)$ exists for all r in a neighbourhood of 0

$$\text{Note that } g_X(0) = 1$$

$$g'_X(r) = \mathbb{E}[X e^{rx}], \quad g''_X(r) = \mathbb{E}[X^2 e^{rx}], \quad \dots, \quad g_X^{(k)}(r) = \mathbb{E}[X^k e^{rx}]$$

$$g_X^{(k)}(0) = \mathbb{E}[X^k]$$

Thus, the MGF $g_X(r) \Rightarrow$ the moments $\mathbb{E}[X^k]$ of X .

For any rv. Z , Markov's inequality to get

$$\Pr(e^{rz} \geq y) \leq \frac{\mathbb{E}[e^{rz}]}{y} = \frac{g_Z(r)}{y}. \quad (e^{rz} > 0)$$

$$\text{Replace } y \text{ by } e^{rb} \text{ for some } b \in \mathbb{R} \Rightarrow \Pr(e^{rz} \geq e^{rb}) \leq \exp(-rb) g_Z(r)$$

$$\Pr(Z \geq b) \quad (\forall r > 0)$$

In the other direction, for $r < 0$.

$$\Pr(Z \leq b) = \Pr(e^{rz} \geq e^{rb}) \leq \exp(-rb) g_Z(r), \quad \forall r < 0.$$

- Go back to the original problem, if consider X_i 's iid with $\mathbb{E}X = 0$ and $g_X(r)$ exists

$$\text{Fix } r > 0. \quad \Pr\left(\frac{1}{n}\sum_{i=1}^n X_i > \varepsilon\right) = \Pr\left(\sum_{i=1}^n X_i > n\varepsilon\right)$$

(one-sided version)

$$= \Pr\left(\exp\left(r\sum_{i=1}^n X_i\right) > \exp(n\varepsilon)\right)$$

$$\leq \exp(-n\varepsilon) \mathbb{E}\left[\exp\left(r\sum_{i=1}^n X_i\right)\right]$$

$$= (\mathbb{E}[\exp(rx)])^n \exp(-n\varepsilon)$$

$$= (g_x(r))^n \exp(-nr\epsilon)$$

Define the semi-invariant MGF (also called cumulant generating function)
 $\gamma_x(r) := \ln g_x(r)$

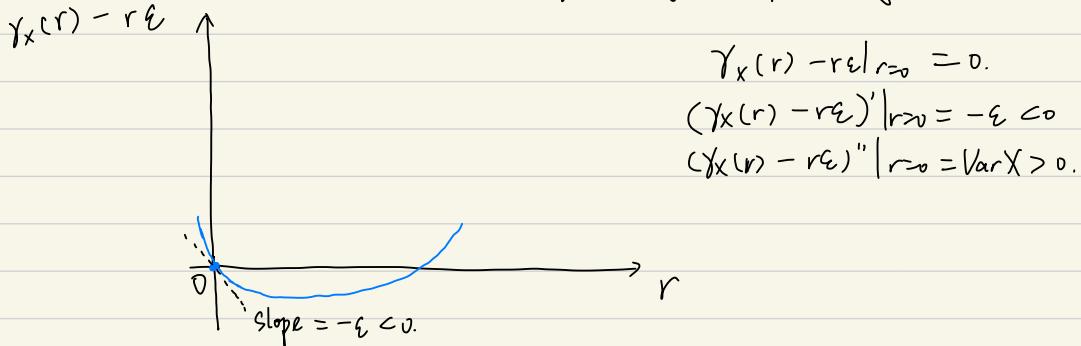
$$\Rightarrow \Pr\left(\frac{1}{n} \sum_{i=1}^n X_i > \epsilon\right) \leq \exp(n(\gamma_x(r) - r\epsilon))$$

This bound is exponential in n for fixed ϵ and fixed r .

To obtain the smallest upper bound, we minimize $\gamma_x(r) - r\epsilon$ over all $r > 0$.

Note that $\gamma_x(r) - r\epsilon|_{r=0} = 0$, $\frac{d}{dr} \gamma_x(r) - r\epsilon|_{r=0} = \mathbb{E}X - \epsilon = -\epsilon < 0$.

This means that $\gamma_x(r) - r\epsilon$ must be negative for sufficiently small r .



Thm: (Chernoff Bounds)

Let $\{X_i\}_{i=0}^\infty$ be iid rv. & $S_n = X_1 + \dots + X_n$.

Assume MGF $g_x(r)$ exists $\forall r \in \mathbb{R}$. Then

$$\Pr(S_n \geq n\epsilon) \leq \exp(n\mu_x(\epsilon)) \text{ where}$$

$$\mu_x(\epsilon) = \inf_{r>0} \{\gamma_x(r) - r\epsilon\}$$

Furthermore, $\mu_x(\epsilon) \rightarrow 0$ for $\epsilon < \mathbb{E}X$ & $\mu_x(\epsilon) = 0$ for $\epsilon \geq \mathbb{E}X$

Rank: Compared with Markov's ineq & Chebyshev's ineq.

Chernoff bounds make use of all moments since we assume $g_x(r) = \mathbb{E}[e^{rx}]$ exist.
 By Taylor expansion: $\mathbb{E}[e^{rx}] = \sum_{k=0}^{\infty} \mathbb{E}\left[\frac{(rx)^k}{k!}\right] = \sum_{k=0}^{\infty} \frac{r^k}{k!} \mathbb{E}[X^k]$.

Ex : $X \in \{0, 1\}$, $\Pr(X=1) = p$, $\Pr(X=0) = 1-p=q$.

$$g_X(r) = q + pe^r, \forall r \in \mathbb{R}, \quad \gamma_X(r) = \ln(g + pe^r)$$

$$\text{Consider } \Pr(S_n > n(pt+\epsilon)) = \Pr\left(\frac{1}{n} \sum_{i=1}^n X_i > pt + \epsilon\right)$$

According to the Chernoff bounds, this prob $\leq \exp(n \ln(g + pe^r))$

$$\begin{aligned} M_X(pt+\epsilon) &= \inf_{r>0} \{ \gamma_X(r) - r(pt+\epsilon) \} \\ &= \inf_{r>0} \{ \ln(q + pe^r) - r(pt+\epsilon) \} \end{aligned}$$

$$\text{After some differentiations: } r^* = \ln \frac{(pt+\epsilon)(1-p)}{(1-p-\epsilon)p}$$

For $\epsilon > 0$, this $r^* > 0$. achieving them with over $r > 0$.

$$\begin{aligned} M_X(pt+\epsilon) &= (pt+\epsilon) \ln \frac{p}{pt+\epsilon} + (1-p-\epsilon) \ln \frac{1-p}{1-p-\epsilon} = -D(pt+\epsilon || p) \leq 0, \\ \Rightarrow \Pr\left(\frac{1}{n} \sum_{i=1}^n X_i > pt + \epsilon\right) &\leq \exp(-n D(pt+\epsilon || p)) \end{aligned}$$

If we want \downarrow to be ≤ 0.05 & $\epsilon = 0.01$, $p=q=\frac{1}{2}$
we need $n \geq \frac{\ln 200}{D(pt+\epsilon || p)} \approx 263$ samples.

prob ≤ 0.01 , we need 1500 samples.

- Quiz 1:
- Next Friday from 8pm - 9pm.
 - One sheet of handwritten notes (both sides)
 - Everyone must show up in LT1 to take the quiz
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Sec 1.7 Laws of large numbers.

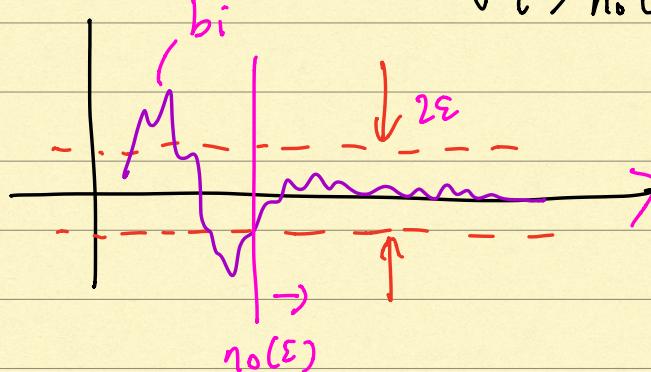
Let $\{b_i\}_{i=1}^{\infty} \subset \mathbb{R}$ be a sequence of real numbers.

$$b_i \rightarrow b \text{ as } i \rightarrow \infty$$

$$\Leftrightarrow \forall \varepsilon > 0, \exists n_0 = n_0(\varepsilon) \in \mathbb{N} \text{ s.t. } |b_i - b| < \varepsilon \quad \forall i > n_0(\varepsilon).$$

e.g. $b_i = \frac{1}{i} \quad (\frac{1}{1}, \frac{1}{2}, \frac{1}{3}, \dots) \quad b_i \rightarrow 0 = b$

$$\underline{\varepsilon = 10^{-6}}, \quad n_0(\varepsilon) = 10^6 + 1, \quad \frac{1}{i} < 10^{-6} \quad \forall i > n_0(\varepsilon) = 10^6 + 1$$



Recall that rvs X_n are functions from the sample space Ω to \mathbb{R} (i.e., $X_n(\omega) \in \mathbb{R}$).

Hence there are many ways a seq. of rvs $\{X_n\}$ can converge to a limiting rv.

Weak law of large numbers,
(WLLN)

Thm: If $n \geq 1$, let $S_n = X_1 + \dots + X_n$ be the sum of n i.i.d. rvs each with finite variance $\sigma^2 < \infty$.

Then $\forall \varepsilon > 0$

$$\lim_{n \rightarrow \infty} \Pr \left(\left| \frac{1}{n} S_n - \mathbb{E} X \right| > \varepsilon \right) = 0$$

Empirical average

In other words, emp. av. $\frac{1}{n} S_n$ "converges in probability" to $\mathbb{E} X$.

$$\Leftrightarrow \frac{1}{n} S_n = \frac{1}{n} \sum_{i=1}^n X_i \xrightarrow{P} \mathbb{E} X. \quad (n \rightarrow \infty)$$

$$(\text{Ex: } \sigma^2 < \infty \Rightarrow \mathbb{E} X < \infty)$$

If: By Chebychev's Ineq.

$$\begin{aligned} \Pr \left(\left| \frac{1}{n} \sum_{i=1}^n (X_i - \mathbb{E} X) \right|^2 > \varepsilon^2 \right) \\ \leq \frac{\mathbb{E} \left[\frac{1}{n^2} \left| \sum_{i=1}^n (X_i - \mathbb{E} X) \right|^2 \right]}{\varepsilon^2} \end{aligned}$$

$$= \frac{n\sigma^2}{n^2\bar{\varepsilon}^2} = \frac{\sigma^2}{n\bar{\varepsilon}^2}. \quad \boxed{\begin{matrix} \text{Var } Y = \mathbb{E}(Y^2) \\ Y \text{ z.m.} \end{matrix}}$$

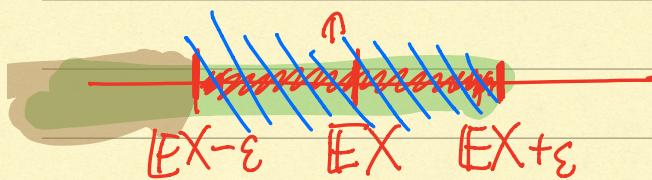
$$\mathbb{E}\left[\left(\sum_{i=1}^n (X_i - \mathbb{E}X)^2\right)\right] = \text{Var}\left(\sum_{i=1}^n (X_i - \mathbb{E}X)\right)$$

$$= \sum_{i=1}^n \text{Var}(X_i - \mathbb{E}X) = n\sigma^2$$

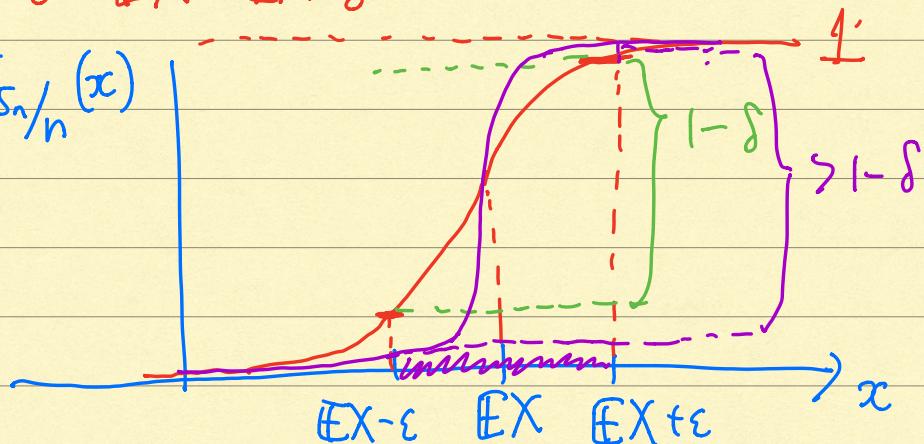
$$P\left(\left|\left(\frac{1}{n}\sum_{i=1}^n X_i\right) - \mathbb{E}X\right| > \varepsilon\right) \leq \frac{\sigma^2}{n\varepsilon^2} = O\left(\frac{1}{n}\right) \xrightarrow{\text{///}} 0.$$

$$P\left(\left|\underbrace{\left(\frac{1}{n}\sum_{i=1}^n X_i\right)}_{S_n/n} - \mathbb{E}X\right| \leq \varepsilon\right) = F_{S_n/n}(\mathbb{E}X + \varepsilon) - F_{S_n/n}(\mathbb{E}X - \varepsilon)$$

$$P\left(\frac{S_n}{n} \leq \mathbb{E}X + \varepsilon\right)$$



$$F_{S_n/n}(x)$$



Rmk: The bound $\frac{\sigma^2}{n\epsilon^2}$ is extremely loose in practice.
 \Longleftarrow chebyshev

In fact for X s.t. MGF $g_X(r)$ exists.

$$\Pr\left(\left|\frac{1}{n}S_n - \mathbb{E}X\right| > \epsilon\right) \leq \exp(n\mu_X(\mathbb{E}X + \epsilon)) + \exp(n\mu_X(\mathbb{E}X - \epsilon))$$

||

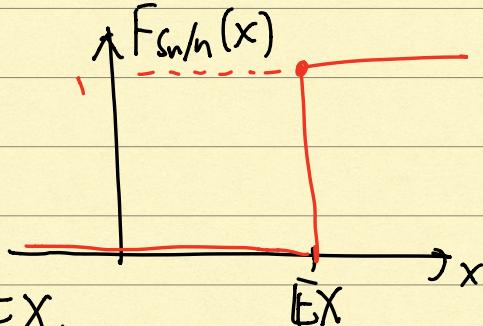
$$\Pr\left(\frac{1}{n}S_n > \mathbb{E}X + \epsilon\right) + \Pr\left(\frac{1}{n}S_n < \mathbb{E}X - \epsilon\right)$$

$$\sim \exp(-nc) \quad c > 0.$$

\uparrow Chernoff. exponentially fast decay.

Central Limit Thm

What does $F_{S_n/n}(x)$ look like when $n \rightarrow \infty$?



A step function that jumps at $\mathbb{E}X$.
 Not interesting.

$$\{X_i\}_{i=1}^{\infty} \text{ i.i.d.} \quad Z_n := \frac{1}{\sqrt{n}\sigma} \sum_{i=1}^n (X_i - \mathbb{E}X)$$

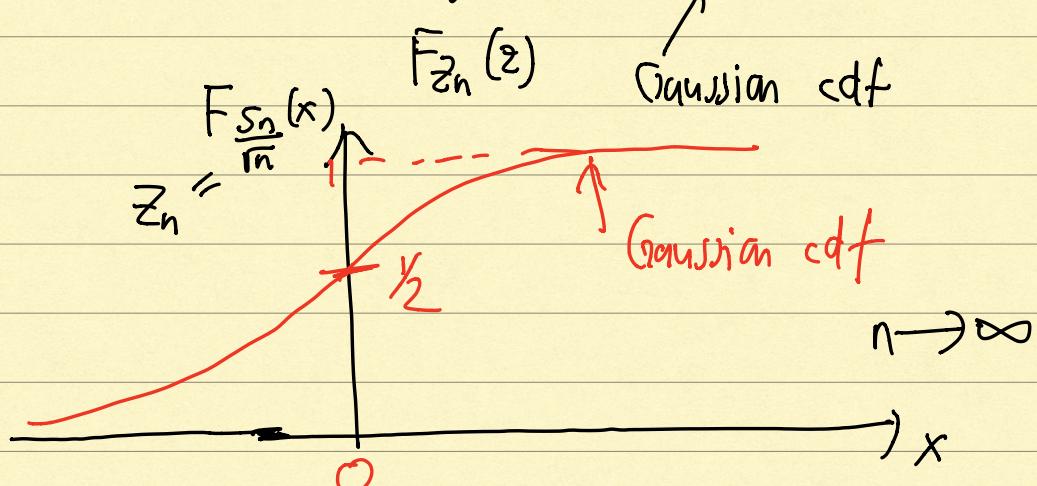
Rmk: $\mathbb{E}X = 0$, $\sigma = 1$, $Z_n = \sqrt{n} \left(\frac{S_n}{n} \right)$

$$\mathbb{E}Z_n = \frac{1}{\sqrt{n}\sigma} \sum_{i=1}^n \mathbb{E}[X_i - \mathbb{E}X] = 0.$$

$$\text{Var } Z_n = \frac{1}{n\sigma^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{1}{n\sigma^2} (n\sigma^2) = 1$$

Thm: (CLT) $\{X_i\}_{i=1}^{\infty}$ i.i.d. $\mathbb{E}X, \sigma^2 < \infty$.

$$\forall z \in \mathbb{R}, \quad \lim_{n \rightarrow \infty} \Pr \underbrace{\left(Z_n \leq z \right)}_{\rightarrow} = \Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy.$$



$$\left(\text{Ex: } Y > 0, \frac{S_n}{n^{1/k+Y}} \rightarrow 0 \text{ in prob. if } E[X] = 0 \right)$$

$Z_n \xrightarrow{d} N(0, 1)$. " Z_n converges to a standard Gaussian in dist".

Pf sketch of CLT: $E(X) = 0$, $\text{Var}(X) = 1$.

$$\mathbb{E}[e^{rZ_n}] = \mathbb{E}\left[e^{\frac{r}{\sqrt{n}}\sum_{i=1}^n X_i}\right] = \left(g_X\left(\frac{r}{\sqrt{n}}\right)\right)^n$$

$$\mathbb{E}\left[\prod_{i=1}^n e^{X_i}\right] = \prod_{i=1}^n \mathbb{E}[e^{X_i}]$$

$$\log \mathbb{E}[e^{rZ_n}] = \underbrace{\log g_X(\frac{r}{\sqrt{n}})}$$

Semi-invariant MGF

$$g_X(\frac{r}{\sqrt{n}}) \approx g_X(0) + \cancel{g_X'(0)} \frac{r}{\sqrt{n}} + \frac{g_X''(0)}{2} \frac{r^2}{n}.$$

$$\approx 1 + \frac{1}{2} \frac{r^2}{n}.$$

$$\log \mathbb{E}[e^{rZ_n}] = \log \left(1 + \frac{1}{2} \frac{r^2}{n} \right) \approx \frac{r^2}{2n}.$$

$$\log(1+\varepsilon) \approx \varepsilon$$

$$\mathbb{E}[e^{rZ_n}] \approx \left(e^{\frac{r^2}{2n}} \right)^n = e^{r^2/2}$$

MGF of $Z_n \rightarrow$ MGF $N(0, 1)$

MGF of $N(0, 1)$.

Levi's continuity theorem \downarrow

pointwise

$$F_{Z_n}(z) \rightarrow F(z) \quad \forall z \in \mathbb{R}$$

$$\text{Recall} \quad \frac{1}{\sqrt{n}} (X_1 + \dots + X_n) \xrightarrow{d} N(0, 1)$$

if $\mathbb{E} X_i = 0$ & $\text{Var } X_i = 1$.

More generally.

X_i i.i.d.

Def: A sequence of rvs $\{Z_n\}_{n=1}^{\infty}$ converge in distribution Z if

$$\lim_{n \rightarrow \infty} F_{Z_n}(z) = F_Z(z)$$

for all points of continuity of
 $F_Z(z)$

By CLT: $\left\{ Z_n = \frac{1}{\sigma n} \sum_{i=1}^n (X_i - \mathbb{E}X) \right\}_{n=1}^{\infty}$
 $Z_n \xrightarrow{d} N(0, 1)$

Def: A sequence of rvs $\{Z_n\}_{n=1}^{\infty}$ converges in probability to Z if

$$\forall \varepsilon > 0, \quad \lim_{n \rightarrow \infty} \Pr(|Z_n - z| > \varepsilon) = 0$$

Eg: $Z_n = \frac{1}{n} S_n \xrightarrow{P} \mathbb{E}X \quad (\sigma^2 < \infty)$

$X_1 + \dots + X_n$ i.i.d

Fact: Conv. in prob \Rightarrow Conv. in distribution. (HW).

Def: A sequence of rvs $\{Z_n\}_{n=1}^{\infty}$ converges in mean square to Z if

$$\lim_{n \rightarrow \infty} \mathbb{E}[(Z_n - z)^2] = 0$$

Fact: $\frac{S_n}{n} \rightarrow \mathbb{E}X$ in ms. ($r^2 < \infty$)

$$S_n = X_1 + \dots + X_n \quad (X_i \text{ iid})$$

Pf: $\mathbb{E}\left[\left(\frac{S_n}{n} - \mathbb{E}X\right)^2\right] = \text{Var}\left(\frac{S_n}{n}\right) \rightarrow 0.$
has zero mean

$$\mathbb{E}\left[\frac{S_n}{n}\right] = \frac{1}{n} \mathbb{E}[X_1 + \dots + X_n] = \mathbb{E}X.$$

$$\begin{aligned} \text{Var}\left(\frac{S_n}{n}\right) &= \frac{1}{n^2} \text{Var}(X_1 + \dots + X_n) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) \\ &= \frac{\sigma^2}{n} \rightarrow 0. \end{aligned}$$

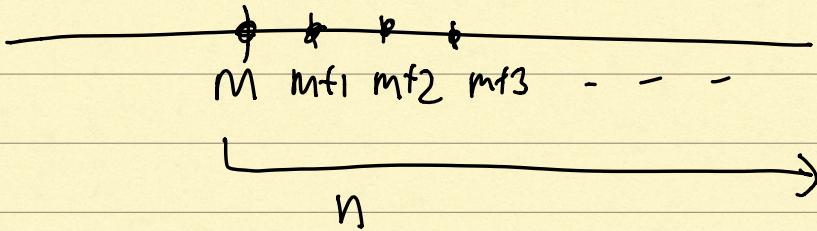
Def: $\{Z_n\}_{n=1}^{\infty}$ converges to Z with probability 1
 (almost surely) if

$$\Pr\left(\left\{w \in \Omega : \lim_{n \rightarrow \infty} Z_n(w) = Z(w)\right\}\right) = 1.$$

$$Z_n \xrightarrow{\text{a.s.}} Z \quad Z_n \rightarrow Z \text{ wp 1.}$$

Fact: $Z_n \xrightarrow{\text{a.s.}} Z$ if $\forall \varepsilon > 0,$

$$\lim_{m \rightarrow \infty} \Pr(\underline{|Z_n - Z| < \varepsilon \text{ for all } n \geq m}) = 1$$



Rmk: Conv w.p 1 means that the set of sample paths, $w \in \Omega$, that $Z_n(w)$ converges to $Z(w)$ (in the sense of a sequence of numbers converging to a limit) has prob. 1.

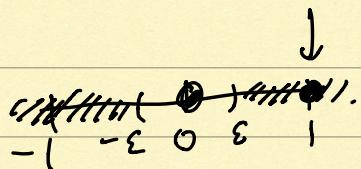
$$\text{Ex: } X_n = \begin{cases} 0 & \text{w.p. } 1 - \frac{1}{n} \\ 1 & \text{w.p. } \frac{1}{n} \end{cases}$$

$\{X_n\}$ independent.

Claim: i) $X_n \xrightarrow{P} 0$.

ii) $X_n \xrightarrow{\text{ms}} 0$.

iii) $X_n \rightarrow 0$ a.s.



If of i) $P(|X_n - 0| \geq \varepsilon) \quad \varepsilon \in (0, 1)$

$$= P(X_n = 1) = \frac{1}{n} \rightarrow 0.$$

By the def² of conv. in prob. $X_n \xrightarrow{P} 0$. //

ii) $E[(X_n - 0)^2] = E X_n = 0 \cdot (1 - \frac{1}{n}) + 1 \cdot \frac{1}{n}$
 $= \frac{1}{n} \rightarrow 0.$

By the def² of conv. in ms. $X_n \xrightarrow{\text{ms}} 0$.

iii) $\Pr_{\varepsilon \text{ small}}(|X_n - 0| < \varepsilon \text{ for all } n \geq m) =: a_m.$

$$a_m = \Pr(X_n = 0 \text{ for all } n \geq m)$$

$$= \Pr(X_m = 0, X_{m+1} = 0, X_{m+2} = 0, \dots)$$

$$a_m = \lim_{k \rightarrow \infty} \prod_{n=m}^k \Pr(X_n = 0)$$

$$= \lim_{k \rightarrow \infty} \prod_{n=m}^k \left(1 - \frac{1}{n}\right) = \lim_{k \rightarrow \infty} \prod_{n=m}^k \frac{n-1}{n}$$

$$= \lim_{k \rightarrow \infty} \frac{m-1}{m} \cdot \frac{m}{m+1} \cdot \frac{m+1}{m+2} \cdots \frac{k-1}{k}$$

$$= \lim_{k \rightarrow \infty} \frac{m-1}{K} = 0 \quad \text{for every fixed } m \in \mathbb{N}.$$

$$a_m = \Pr(X_n = 0 \text{ for all } n \geq m) = 0 \quad \forall m \in \mathbb{N}.$$

$$\lim_{m \rightarrow \infty} a_m = 0 \neq 1.$$

MS conv



a.s conv (w.p. 1) \Rightarrow conv in prob $\xrightarrow[\text{HW}]{} \text{conv dist}^{\Omega}.$

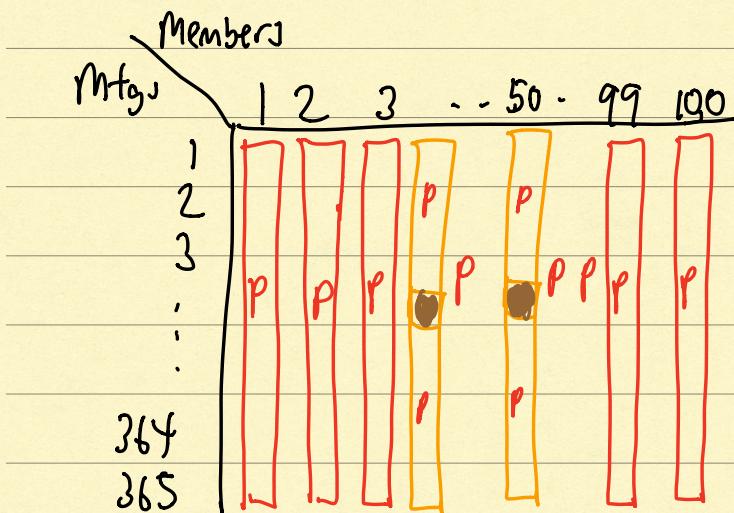
Analogue: Committee of 100 members.

Each member is represented by $w \in \Omega$.

One mtg involving the committee everyday throughout the year.

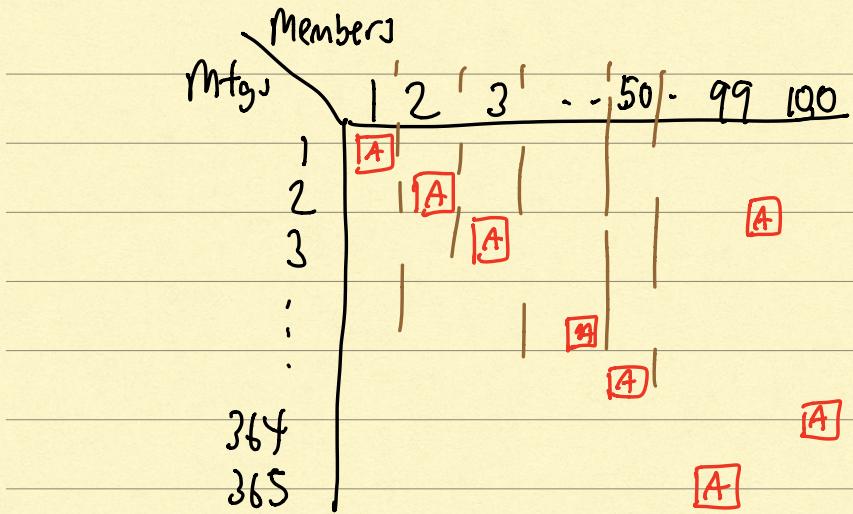
Interested in the attendance of the committee members

Conv. a.s. \Rightarrow Almost all members have perfect attendance over the 365 days.



$$\Pr(\{\omega \in \Omega : \lim_{n \rightarrow \infty} X_n(\omega) = X(\omega)\}) = 1.$$

Conv. in prob: All meetings were almost all full.



Set of elements $w \in \Omega$ for which $X_n(w) \approx X(w)$
 has prob $\rightarrow 1$

Note that if all mtgs were nearly full, it may not be the case that any member has perfect attendance.

$$\prod_{i=1}^{\infty} a_i = \lim_{k \rightarrow \infty} \prod_{i=1}^k a_i$$

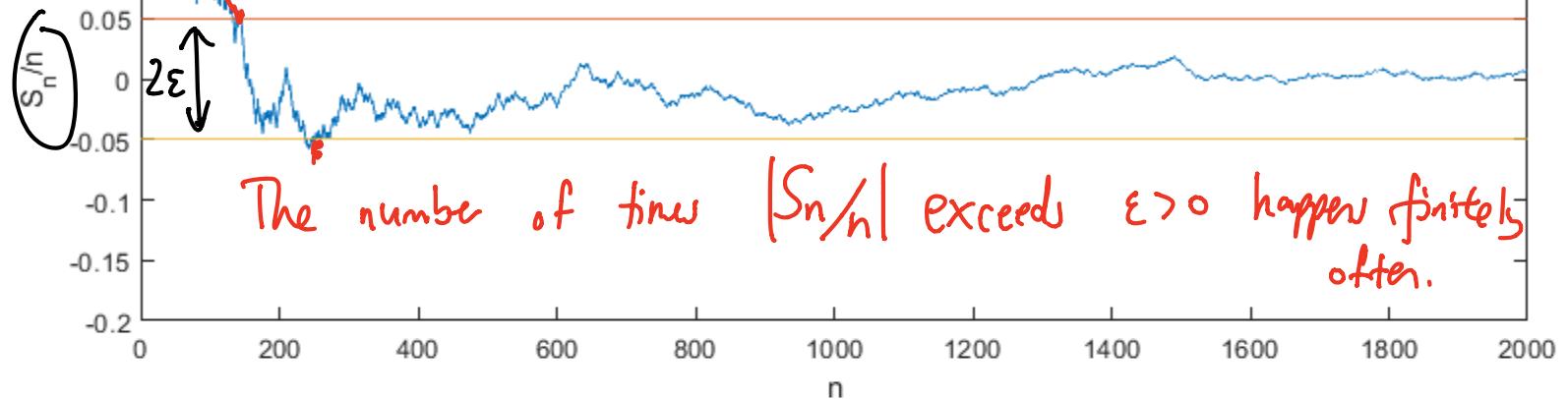
$$\sum_{i=1}^{\infty} a_i = \lim_{k \rightarrow \infty} \sum_{i=1}^k a_i$$

$$X_n = \begin{cases} 1 & \frac{1}{2} \\ -1 & \frac{1}{2} \end{cases}$$

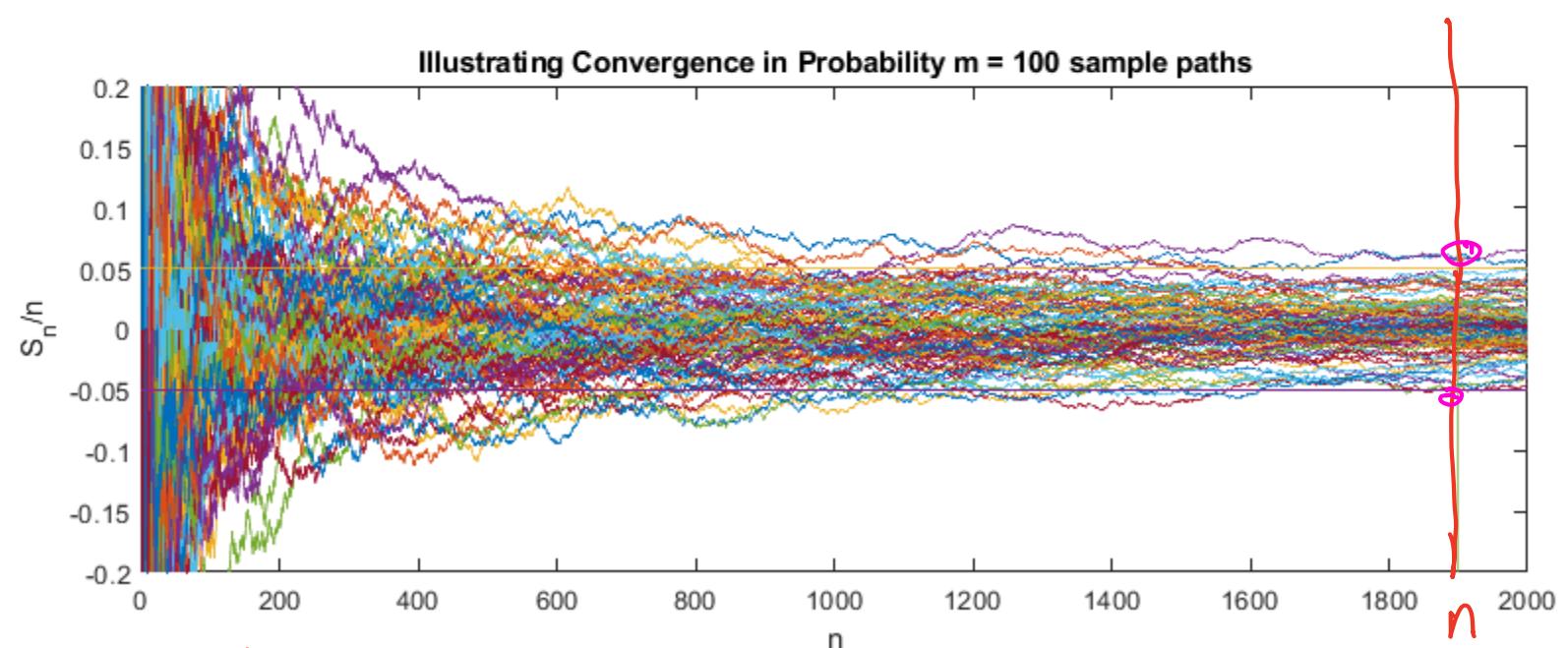
$$S_n = \frac{1}{n} \sum_{i=1}^n X_i$$

Illustrating Almost Sure Convergence

$$\Pr \left(\lim_{n \rightarrow \infty} \frac{S_n}{n} = 0 \right) = 1.$$



Illustrating Convergence in Probability $m = 100$ sample paths



$$\lim_{n \rightarrow \infty} \Pr \left(\left| \frac{S_n}{n} - 0 \right| > \varepsilon \right) = 0.$$

The fraction of sample paths that exceed $\pm\varepsilon$ is small