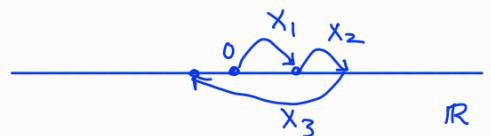


- ∅  $X$  is a rv s.t.  $\mathbb{E} e^{sx} < \infty \forall s \in \mathbb{R}$ .  
 $\Rightarrow \mathbb{E} e^{sx} \leq e^{s^2/2} \forall |s| \leq s_0$   
 $\Rightarrow X$  is subexponential.

$\leftarrow \bullet \circ$

- $X_n$  iid  $X$  and  $S_n = \sum_{i=1}^n X_i$ .



$$\mathbb{P}(S_n - n\mu \geq c_n) \leq \exp\left(-\frac{kc_n^2}{n}\right)$$

- Typical value  $\approx \sqrt{n}$        $S_n = O_p(\sqrt{n})$   
 $\Leftrightarrow \forall \varepsilon > 0, \exists C$  s.t.  
 $\mathbb{P}(S_n \geq C\sqrt{n}) \leq \varepsilon$ .

$$\mathbb{P}\left(\frac{S_n}{n} - \mu \geq c\right) \leq \exp(-k_c n)$$

Prove SLLN!

[Exc: Use Borel Cantelli Lemma I]

Largest  $k_c$  possible

•  $\checkmark$   $\text{poly}(n) \exp(-k_c n) \leq \mathbb{P}\left(\frac{S_n}{n} - \mu \geq c\right) \leq \text{poly}(n) \exp(-k_c n)$

Exact rate of decay.      Large Deviation Event.

- ★ Cramer-Chernoff bound:  $X_n$  iid  $X$ ,  $\mathbb{E} e^{sx} < \infty \forall s \in \mathbb{R}$ ,  $\mu = \mathbb{E} X$ .

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^n X_i \geq an\right) &\quad \begin{matrix} \nearrow \text{Should decay exponentially for } a \geq \mathbb{E} X \\ \nearrow 1 - e^{-n} \text{ if } a < \mathbb{E} X \end{matrix} \\ &= \mathbb{P}\left(e^{\lambda \sum_{i=1}^n X_i} \geq e^{\lambda an}\right) \quad \forall \lambda > 0 \\ &\leq e^{-\lambda an} \mathbb{E} e^{\lambda \sum_{i=1}^n X_i} = e^{-\lambda an} (\mathbb{E} e^{\lambda X})^n, \text{ let } \psi_X(\lambda) = \log \mathbb{E} e^{\lambda X} \\ &= \exp\left(-\lambda an + n \psi_X(\lambda)\right) = \exp\left(-n(\lambda a - \psi_X(\lambda))\right) \end{aligned}$$

∴  $\boxed{\mathbb{P}\left(\sum_{i=1}^n X_i \geq an\right) \leq \exp\left(-n \sup_{\lambda > 0} (\lambda a - \psi_X(\lambda))\right)}$

Observations: 1.  $\Psi_X(\lambda)$  - strictly convex, so long as  $\text{Var}(X) > 0$ .

Assume

$$\psi \in C^2$$

$$\begin{aligned} \cdot \quad \underline{\Psi''_X(\lambda)} &= \mathbb{E}\left[X^2 \frac{e^{\lambda X}}{\mathbb{E} e^{\lambda X}}\right] - \left(\mathbb{E}\left[X \frac{e^{\lambda X}}{\mathbb{E} e^{\lambda X}}\right]\right)^2 \leftarrow \\ &= \underline{\text{Var}_{\mu}(X)} > 0 \end{aligned}$$

$$2. \sup_{\lambda \in \mathbb{R}} (\lambda a - \underline{\Psi(\lambda)}) = \underline{\psi^*(a)} \leftarrow \begin{array}{l} \text{Convex dual of } \psi. \\ \text{Convex fn.} \end{array}$$

$$\begin{array}{l} \text{Max. at} \\ \left| \begin{array}{l} \psi'(\lambda^*) = a \\ \psi'(0) = \mathbb{E}X \end{array} \right. \end{array}$$

$$\psi'(\lambda) = \mathbb{E}\left[X \frac{e^{\lambda X}}{\mathbb{E} e^{\lambda X}}\right]$$

Since  $\psi$  is strictly convex,  $\psi'$  is strictly ↑.

$$\therefore \lambda^* > 0.$$

$$\therefore \boxed{\mathbb{P}\left(\frac{S_n}{n} \geq a\right) \leq \exp(-n\psi^*(a))} \rightarrow \boxed{a > \mathbb{E}X} \rightarrow \text{Chernoff Cramer bound}$$

Right Tail  
Chernoff bd

$$\text{egs: } 1. \quad X \sim N(0,1), \quad \Psi_X(\lambda) = \frac{\lambda^2}{2}, \quad \lambda = a$$

$$\psi_X^*(a) = \sup_{\lambda \in \mathbb{R}} \left\{ \lambda a - \frac{\lambda^2}{2} \right\} = \frac{a^2}{2}$$

$$\mathbb{P}\left(\frac{S_n}{n} \geq a\right) \leq \exp\left(-n \frac{a^2}{2}\right) \leftarrow$$

Left Tail:

$$\mathbb{P}\left(\frac{S_n}{n} \leq a\right) \text{ for } a < \mathbb{E}X$$

$$= \mathbb{P}\left(e^{\lambda S_n} \geq e^{\lambda a n}\right) \text{ for } \lambda < 0$$

$$= \exp\left(-n \sup_{\lambda < 0} (\lambda a - \Psi(\lambda))\right), \quad a < \mathbb{E}X$$

$$= \exp\left(-n \sup_{\lambda \in \mathbb{R}} (\lambda a - \Psi(\lambda))\right) = \exp(-n \psi_X^*(a))$$

⊕

$$\mathbb{P}(S_n \geq an) \leq \exp(-n \underline{\psi(a)}) \quad \text{if } a > \mathbb{E}X$$

$$\mathbb{P}(S_n \leq an) \leq \exp(-n \underline{\psi(a)}) \quad \text{if } a < \mathbb{E}X$$

Automatically gives  
us SLLN

0<sup>th</sup> result of  
Large Deviation Theory.

$$\rightarrow \lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(S_n \geq an) = -\psi^*(a)$$

★ Thm (Cramer's theorem):  $\mathbb{E}e^{sX} < \infty \quad \forall |s| \leq s_0$ , then

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(S_n \geq an) = -\psi^*(a) \quad \begin{matrix} \text{Large dev. event} \\ \text{LD rate } f_n \end{matrix} \quad \forall a > \mathbb{E}X$$

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(S_n \leq an) = -\psi^*(a) \quad \forall a < \mathbb{E}X.$$

eg: 1. If  $X \sim N(0,1)$ ,

$$S_n = \sum_{i=1}^n X_i, \quad X_i \text{ iid } N(0,1)$$

$$\left(\frac{1}{a} - \frac{1}{a^3}\right) e^{-\frac{a^2}{2}} \leq \mathbb{P}(X \geq a) \leq \frac{1}{a} e^{-\frac{a^2}{2}}$$

$$\mathbb{P}(S_n \geq na) = \mathbb{P}\left(\frac{S_n}{\sqrt{n}} \geq \sqrt{n}a\right), \quad \frac{S_n}{\sqrt{n}} \sim N(0,1)$$

$$\cdot \quad \left(\frac{1}{\sqrt{n}a} - \frac{1}{(\sqrt{n}a)^3}\right) e^{-\frac{na^2}{2}} \leq \cdot \leq \frac{1}{\sqrt{n}a} e^{-\frac{na^2}{2}}$$

★ Ex:  $Ber(p)$ ,  $Poisson(\lambda)$ ,  $Exp(\lambda)$ , ...

For these, try to the Cramer-Chernoff bds.

$$\star \quad \mathbb{P} \left( \frac{s_n}{n} \in [a, \infty) \right) \rightsquigarrow \mathbb{P} \left( \frac{s_n}{n} \in [a, b] \right)$$

$$= \mathbb{P} \left( \frac{s_n}{n} \in [a, \infty) \right) - \mathbb{P} \left( \frac{s_n}{n} \in [b, \infty) \right)$$

$$\approx (-)^e e^{-n\psi^*(a)} - (-)^e e^{-n\psi^*(b)}$$

$$\psi^*(a) < \psi^*(b) \longrightarrow \text{Rate of decay} = -\psi^*(a)$$

•  $\frac{1}{n} \log \left( \mathbb{P} \left( \frac{s_n}{n} \in A \right) \right) \stackrel{\text{sufficiently regular}}{=} - \inf_{x \in A} \psi^*(x) \longrightarrow \text{Large Deviation Principle.}$

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## ② Concentration Inequalities for $X_1 + \dots + X_n$ :

1. Chebychev's Ineq: Variance bounds  $\Rightarrow$  Conc. ineq.
2. Exponential Conc. Ineq.  $\xrightarrow{\text{Hoeffding}}$  Depends on  $L_1$  norm  
 $\xrightarrow{\text{Bernstein}}$  Depends on Variance
3. Cramer Chernoff method  $\rightarrow$  More direct exp.conc. ✓

II.  $\mathbb{P}(|f(X_1, X_2, \dots) - \mathbb{E} f(X_1, \dots)| \geq c_n) = o(1)$

e.g.:  $f = \frac{X_1 + \dots + X_n}{n}$ ,  $\frac{X_1^2 + \dots + X_n^2}{n}$ , ... what others

<sup>66</sup>  $f(X_1, \dots, X_n)$  conc around its mean if  
 $\rightarrow$  i)  $X_1, \dots, X_n$  are weakly dependent  
ii)  $f$  depends weakly on each of  $X_1, \dots, X_n$ .

## 3. Martingales:

Defn:  $X_0, X_1, X_2, \dots$  is a collection of random variables. Then a collection  $(M_t)_{t \in \mathbb{N} \cup \{0\}}$  is called a Martingale w.r.t  $X_0, X_1, X_2, \dots$  if

- ✓ i)  $X_0, \dots, X_t$  completely determines  $M_t$  Amount of money gained
- ✓ ii)  $\mathbb{E}|M_t| < \infty$  and
- iii)  $\mathbb{E}[M_{t+1} | X_0, X_1, \dots, X_t] = M_t$

e.g. 1.  $X_1, \dots$  iid  $X$ ,  $\mathbb{E}X = \mu$ .

$$\text{Then } M_n = (X_1 + \dots + X_n) - n\mu$$

$$\begin{aligned} \mathbb{E}[M_{t+1} | X_1, \dots, X_t] &= \mathbb{E}[X_1 + \dots + X_t + \underbrace{X_{t+1}}_{-(t+1)\mu} | X_1 + \dots + X_t] \\ &= (X_1 + \dots + X_t) + \mathbb{E}[X_{t+1}] - (t+1)\mu \\ &= M_t \end{aligned}$$

∴ This a martingale.

• Property:  $\mathbb{E}M_t = \mathbb{E}M_0$ ,  $t$  a fixed time.

Proof:  $\mathbb{E}M_{t+1} = \mathbb{E}\mathbb{E}M_t = \dots$  (use Tower law).

2.  $M_n = S_n^2 - n\sigma^2$  if  $\text{Var } X = \sigma^2 < \infty \rightarrow$  Also defines a martingale.

Defn: 1. Supermartingale :  $\mathbb{E}\overbrace{[M_{t+1} | X_0, \dots, X_t]}^{\mathcal{F}_t} \leq M_t$   
 Submartingale :  $\mathbb{E}[M_{t+1} | \mathcal{F}_t] \geq M_t$

Sup :  $\mathbb{E}M_0 \leq \mathbb{E}M_1 \leq \dots$

Sub :  $\mathbb{E}M_0 \geq \dots$

Defn: 1. Stopping time : A stopping time  $X_0, X_1, X_2, \dots$  is a random variable  $T$  s.t.  $\{\tau \leq t\}$  is completely determined by  $X_0, \dots, X_t$ .

2. Predictable process:  $(A_t)_{t \geq 0}$  s.t.  $A_t$  is compl. det. by  $X_0, X_1, \dots, X_{t-1}$ .

e.g. Let  $f(x_0, x_1, \dots)$   
 Let  $Y$  be a rv depending upon  $x_0, x_1, x_2, \dots$ , assume  $E|Y| < \infty$ .  
 Then,  $M_t = \mathbb{E}[Y | x_0, \dots, x_t]$  is a martingale.

$$\begin{aligned} \mathbb{E}[M_t | x_0, \dots, x_{t-1}] &= \mathbb{E}\left[\underbrace{\mathbb{E}[Y | x_0, \dots, x_t]}_{\text{Tower Law}}\right] | x_0, \dots, x_{t-1} \\ &= \mathbb{E}[Y | x_0, \dots, x_{t-1}] = M_{t-1}. \end{aligned}$$

(Doob's Martingale OR Information Exposure Martingale)

\* Property:  $M_0, M_1, \dots$  are martingales wrt  $X_0, X_1, \dots$ , then

- $\text{Cov}(M_k - M_\ell, M_s - M_t) = 0 \quad \text{if}$



so long as  $[k, \ell] \cap [s, t] = \emptyset$ . [Exercise]

Idea:  $(-f(x_1, x_2, \dots, x_n) + \mathbb{E}f(x_1, x_2, \dots, x_n))$

$$\begin{aligned} &= (\underbrace{\mathbb{E}f(\underline{x}) - \mathbb{E}[f(\underline{x}) | x_1]}_{\dots} + \dots + \underbrace{(\mathbb{E}[f(\underline{x}) | x_1, x_2] - \mathbb{E}[f(\underline{x}) | x_1, x_2, \dots, x_{n-1}])}_{\dots}) \end{aligned}$$

①  $f - \mathbb{E}f = \text{Sum of uncorrelated random variables.}$   
 (using Doob's Martingale).

- $\mathbb{E}e^{x_1+x_2} = \mathbb{E}e^{x_1} \mathbb{E}e^{x_2}$

→ We would get around these difficulties using monotonicity of Submartingale.

Thm: (Optional Stopping Theorem):

- $(M_t)$  is a submartingale. Then

$$\mathbb{E} M_T \geq \mathbb{E} M_0$$

Requires some cond<sup>n</sup>s  
i)  $T$  is bounded ✓  
ii)  
iii)  
iv)  $M_t \geq 0$

Real q<sub>??</sub>:

$$\boxed{\mathbb{E} M_T \geq \mathbb{E} M_0 ? \quad \forall \text{ sub } M}$$

Let  $(M_t)$  be a  $M$ , then  $M_t$  &  $-M_t$  are both sub  $M$

$$\mathbb{E}[-M_T] \geq \mathbb{E}[-M_0], \quad \mathbb{E} M_T \geq \mathbb{E} M_0$$

$$\Rightarrow \boxed{\mathbb{E} M_T = \mathbb{E} M_0}$$



Week 1

Week 2

Week 3 -

{ Week 4 - 9/06, 12/06  
- 16/06 19/06 ] → No classes

Weeks 5 - ~~30/06~~ . . .

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Week 8 -