

Berry-Esseen Theorem

$$\cdot X_1, X_2, \dots \text{ i.i.d. } E|X_1|^3 < \infty$$

$$\cdot \left| P\left(\frac{S_n - nEX_1}{\sqrt{n}\sigma} \leq x\right) - \Phi(x) \right| \leq C \frac{E|X_1 - EX_1|^3}{\sigma^3 \sqrt{n}}$$

$$\text{where } C \leq 2$$

$$X_1, X_2, \dots \text{ i.i.d. Bernoulli}(p)$$

$$S_n \stackrel{D}{=} \text{Binomial}(n, p)$$

$$\begin{aligned} P(S_n > x) &= P\left(\frac{S_n - np}{\sqrt{np(1-p)}} > \frac{x - np}{\sqrt{np(1-p)}}\right) \\ &\approx P\left(N(0,1) > \frac{x - np}{\sqrt{np(1-p)}}\right) \end{aligned}$$

$$\text{e.g. choose } x = n$$

$$P(S_n > n) = 0$$

relative error of Normal approx. is terrible for $x = n$

How to fix this?

$$P(S_n > x) = 1 - \Phi\left(\frac{x - nEX_1}{\sqrt{n}\sigma}\right) + O\left(\frac{1}{\sqrt{n}}\right)$$

if

$$\bar{\Phi}\left(\frac{x - nEX_1}{\sqrt{n}\sigma}\right) = O\left(\frac{1}{\sqrt{n}}\right)$$

the error term dominates

↓

Normal approximation no longer works

$$P(S_n > nEX_1 + \frac{x - nEX_1}{\sqrt{n}} \sigma)$$

↑
when x is too big
normal approx will be poor

$$F(x)$$

$$\bar{F}(x) = 1 - F(x)$$

What do we use to replace Normal Approx when x is large?

$$P(S_n > nEX_1 + x\sqrt{n}\sigma)$$

↑ make x a func of n

Large Deviations

$$X_n = O(\sqrt{n})$$

• X_1, X_2, \dots i.i.d

• $P(S_n > na)$ ($a > EX_1$)

• $E \exp(\theta X_1) < \infty$. $\theta > 0$ "light-tailed"

$$P(S_n > na) \approx e^{-nI(a)}$$

↑ rate function

Heavy-tailed Setting

If the X_i 's are heavy-tailed, we get different behavior:

$$P(X_1 > x) = (1+x)^{-\alpha}, \quad x \geq 0$$

$$\Rightarrow P(X_1 > na) \sim n^{-\alpha} x^{-\alpha} \text{ as } n \rightarrow \infty$$

↑
asymptotic to

$$P(S_n > x) \sim n P(X_1 > x) \text{ as } x \rightarrow \infty$$

↑
any x very big

The sum gets large when a single one of the X_i 's is big (heavy-tailed).

$$a_n \sim b_n$$

iff $a_n/b_n \rightarrow 1$ as $n \rightarrow \infty$

"single big jump"

Light-tailed Setting

$$P(S_n > na) \approx e^{-nI(a)}$$

$$\frac{1}{n} \log P(S_n > na) \rightarrow -I(a) \text{ as } n \rightarrow \infty$$

Markov Inequality:

$$P(W > w) \leq \exp(-\theta w) E \exp(\theta W) \quad , \quad \theta > 0$$

$$\Rightarrow P(S_n > na) \leq \exp(-\theta na) E \exp(\theta S_n)$$

$$\begin{aligned} E \exp(\theta S_n) &= E \exp\left(\theta \sum_{i=1}^n X_i\right) \\ &= \prod_{i=1}^n E \exp(\theta X_i) \\ &= (E \exp(\theta X_1))^n \\ &= e^{n \phi(\theta)} \end{aligned}$$

$$\phi(\theta) = \log E \exp(\theta X_1)$$

"cumulant generating fun"

$$P(S_n > na) \leq \exp(-n(a - \phi(\theta)))$$

Choose θ to maximize $a - \phi(\theta)$

$$\frac{d}{d\theta} = a - \phi'(\theta(a)) = 0$$

$$\boxed{\phi'(\theta(a)) = a}$$

$$P(S_n > na) \leq \exp(-nI(a))$$

$$I(a) \triangleq a - \phi(\theta(a))$$

$$\phi(\theta) = \log E e^{\theta X_1}$$

$$\phi'(\theta) = \frac{1}{E e^{\theta X_1}} \frac{d}{d\theta} E e^{\theta X_1}$$

$$= \frac{1}{E e^{\theta X_1}} E X_1 e^{\theta X_1}$$

Dominated Convergence Thm
 \rightarrow bring d into E

$$\phi'(\theta) = \frac{\int_{\mathbb{R}} x e^{\theta x} F(dx)}{\int_{\mathbb{R}} e^{\theta x} F(dx)}$$

$$= \int_{\mathbb{R}} x F_{\theta}(dx)$$

$$\bar{F}_\theta(dx) = \frac{e^{\theta x} F(dx)}{\int_{\mathbb{R}} e^{\theta y} F(dy)}$$

"exponentially tilted
version of $F(\cdot)$ "

($f(x) \Rightarrow e^{\theta x} f(x)$, exponentially more likely)

$$\theta > 0 \quad , \quad \int_{\mathbb{R}} x \bar{F}_\theta(dx) > \int_{\mathbb{R}} x F(dx)$$

$$\varphi'(\theta) = \int_{\mathbb{R}} x \bar{F}_\theta(dx)$$

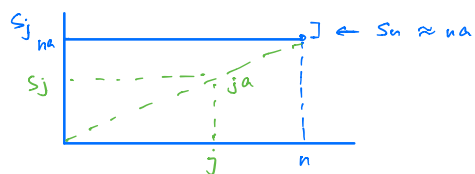
$$\varphi'(\theta(a)) = a$$

means

$$\int x \bar{F}_{\theta(a)}(dx) = a$$

In other words ,

$$E_{\theta(a)} X_1 = a$$



$$P(S_n > na) \leq \exp(-n(\overbrace{a\theta(a) - \varphi(\theta(a))}^{I(a) > 0}))$$

$\{S_n > na\}$ very rare

$$E(X_1 | S > na)$$

$$\approx E(X_1 | S \approx na)$$

$$\approx E(X_1 | S = na)$$

$$E(X_1, \dots, X_n | S_n = na) = na$$

$$\underbrace{\sum_{i=1}^n E(X_i | S_n = na)}$$

$$n E(X_1 | S_n = na) = na$$

$$E(X_1 | S_n = na) = a$$

We've seen the exponential tilts arise in the upper bound

for $P(S_n > na)$

Maybe it appears intrinsically in deciding the lower bound

on $P(S_n > na)$

$$P(S_n \in B) = \int_{\{x_1, \dots, x_n \in B\}} f(x_1) f(x_2) \dots f(x_n) dx_1 \dots dx_n$$

$$= \int_{\{x_1, \dots, x_n \in B\}} \frac{\prod_{i=1}^n f(x_i)}{\prod_{i=1}^n f_\theta(x_i)} \prod_{i=1}^n f_\theta(x_i) dx_i$$

$$= E_\theta I(S_n \in B) \prod_{i=1}^n \frac{f(x_i)}{f_\theta(x_i)}$$

$$\frac{f(x)}{f_\theta(x)} = \frac{f(x)}{e^{\theta x} f(x)} e^{-\phi(\theta)} = e^{-\theta x + \phi(\theta)}$$

$$\Rightarrow P(S_n \in B) = E_\theta I(S_n \in B) e^{-\theta \sum_{i=1}^n x_i + n \phi(\theta)}$$

$$= E_\theta I(S_n \in B) e^{-\theta S_n + n \phi(\theta)}$$

$$P(S_n > na) = E_\theta I(S_n > na) e^{-\theta S_n + n \phi(\theta)}$$

$$\text{Choose } \theta = \theta(a)$$

$$P(S_n > na) = E_{\theta(a)} I(S_n > na) e^{-\theta(a) S_n + n \phi(\theta(a))}$$

Under $P_{\theta(a)}$, x_1, \dots, x_n i.i.d.

with common tilted $F_{\theta(a)}(\cdot)$

$$\frac{x_1 + \dots + x_n}{n} \xrightarrow{P} E_{\theta(a)} x_1 = a$$

$$S_n \approx na$$

"Change of Measure"

We modified the measure from the "nominal" measure

to a specially chosen prob. that makes the calculation easier