

Theorem: (Cramér's Large Deviation Theorem)

Let  $\{X_n\}_{n=1}^{\infty}$  be iid. exponentially integrable random variables.

Let  $\dot{X}_n = X_n - \mathbb{E}[X_n]$ , and  $\dot{S}_n = \dot{X}_1 + \dots + \dot{X}_n$ . For any  $\varepsilon > 0$ ,

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(\dot{S}_n > n\varepsilon) = -\underline{\Psi}_{\dot{X}_1}^*(\varepsilon) \leq 0.$$

We have already proved that

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(\dot{S}_n > n\varepsilon) \leq -\underline{\Psi}_{\dot{X}_1}^*(\varepsilon).$$

Thus, it suffices to prove that

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(\dot{S}_n > n\varepsilon) \geq -\underline{\Psi}_{\dot{X}_1}^*(\varepsilon).$$

For the sake of readability, set  $\underline{\Psi}(t) := \underline{\Psi}_{\dot{X}_1}(t)$        $M(t) := M_{\dot{X}_1}(t)$   
 $\underline{\Psi}^*(\varepsilon) := \underline{\Psi}_{\dot{X}_1}^*(\varepsilon)$

Observations about  $\Psi^*$ :

- Since  $\Psi = \log M$  is smooth, and convex,

$$\Psi^*(\eta) = \sup_{t \geq 0} (\eta t - \Psi(t)) = \eta t_\eta - \Psi(t_\eta) \quad \text{for some maximizer } t_\eta > 0.$$

Useful trick:

Given exponentially integrable  $Y$  (w.r.t.  $(\Omega, \mathcal{F}, \mathbb{P})$ ),

for each  $t$  define a new probability measure  $\mathbb{P}_t$  on  $(\Omega, \mathcal{F})$ :

$$d\mathbb{P}_t = \frac{e^{tY}}{M_Y(t)} d\mathbb{P}$$

In the proof, we will use independent samples from  $\mathbb{P}_t$   
with  $t = t_\eta$  (maximizer defining  $\Psi_{X_1}^*(\eta)$ )

Prop. For all  $\varepsilon > 0$ ,

$$\liminf_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(\hat{S}_n > n\varepsilon) \geq -\Psi^*(\varepsilon).$$

Pf. Any maximizer  $t_\varepsilon$  of  $t \mapsto \varepsilon t - \Psi(t)$  is a solution of

$$\Psi'(t) = \varepsilon.$$

I.e.  $t = t_\varepsilon$  is characterized by the requirement that

Let  $\{w_n\}_{n=1}^{\infty}$  be iid. random variables with

$$w_n \stackrel{d}{=} \dot{X}_1 * P_t$$

$$\mathbb{E}_{P_t}[\dot{X}_1] = \varepsilon$$

$$\Rightarrow \mathbb{E}_P[w_n] = \varepsilon$$

$$\therefore \mu_{w_n}(dx) = \frac{e^{tx}}{M(t)} \mu_{\dot{X}_1}(dx) \quad \therefore \mu_{\dot{X}_1}(dx) = M(t) e^{-tx} \mu_{w_n}(dx)$$

Then for measurable  $f: \mathbb{R}^n \rightarrow [0, \infty]$ ,

$$\mathbb{E}[f(\dot{X}_1, \dots, \dot{X}_n)]$$

Let  $T_n = W_1 + \dots + W_n$ .

$\therefore$  We've shown that, for measurable  $f: \mathbb{R}^n \rightarrow [0, \infty]$ ,

$$\mathbb{E}[f(\overset{\circ}{X}_1, \dots, \overset{\circ}{X}_n)] = M(t)^n \mathbb{E}[f(W_1, \dots, W_n) e^{-tT_n}]$$

Apply this with  $f(x_1, \dots, x_n) = \mathbb{1}_{x_1 + \dots + x_n > n\varepsilon}$ .

$$\mathbb{P}(\hat{S}_n > n\varepsilon) \geq e^{-n\Phi^*(\varepsilon)} e^{-nt_\varepsilon\delta} \mathbb{P}(n\varepsilon \leq T_n \leq n(\varepsilon+\delta))$$

$$\therefore \liminf_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(\hat{S}_n > n\varepsilon) \geq -\Phi^*(\varepsilon) - t_\varepsilon\delta$$

$$+ \liminf_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{P}(n\varepsilon \leq T_n \leq n(\varepsilon+\delta)) \quad (\star)$$

for any  $\delta > 0$ .

To complete the proof, we want to let  $\delta \downarrow 0$ . This means we have to show that  $(\star)$  is well-behaved as  $n \rightarrow \infty$ .

Note:  $\mathbb{E}[W_n] = \varepsilon$ , so  $\mathbb{E}[T_n] = \mathbb{E}[W_1 + \dots + W_n] = n\varepsilon$ .

$$\therefore \mathbb{P}(n\varepsilon \leq T_n \leq n(\varepsilon+\delta))$$

\* Flash Forward \*

$$\text{CLT} : \mathbb{P}\left(\frac{T_n - n\varepsilon}{\sqrt{n \text{Var}(W_1)}} \geq 0\right) \xrightarrow{n \rightarrow \infty} \int_0^\infty \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = \frac{1}{2}$$