

# General Cramer Theory

Let  $(E, \mathcal{B})$  is a measure space.  $I: E \rightarrow \mathbb{R}^+$   
 s.t.  $\forall L > 0. \{I(x) \leq L\} \subset_{cpt} E$ . good rate func.

Def: i) LDP with rate func.  $I$  for  $\{\mu_\varepsilon\}_{\varepsilon>0}$   
 is: For  $\forall G \subset E$  open.  $\forall F \subset E$  closed.

$$\liminf_{\varepsilon \rightarrow 0} \varepsilon \log \mu_\varepsilon(G) \geq -\inf_G I$$

$$\limsup_{\varepsilon \rightarrow 0} \varepsilon \log \mu_\varepsilon(F) \leq -\inf_F I$$

ii) Weak LDP with rate  $I$  if  $\forall K \subset_{cpt} E$   
 $\limsup_{\varepsilon \rightarrow 0} \varepsilon \log \mu_\varepsilon(K) \leq -\inf_K I$ .

Recall tightness of  $\{\mu_\varepsilon\}_{\varepsilon>0} \Leftrightarrow \{\mu_\varepsilon\}$  is cpt  
 in  $(\mu_+^*, \text{Weak-top})$ . And we can choose  
 $K_\delta \subset_{cpt} E$ . s.t.  $\sup_\varepsilon \mu_\varepsilon(K_\delta^c) < \delta$ . Next, we  
 extend it to exponential type:

Def:  $\{\mu_\varepsilon\}$  satisfies exponential tightness

if  $\forall \delta > 0. \exists K_\delta \subset_{cpt} E$ . s.t. We have:

$$\limsup_{\varepsilon \rightarrow 0} \varepsilon \log \mu_\varepsilon(K_\delta^c) \leq -1/\delta.$$

Claim: weak LDP + exp. tightness  $\Rightarrow$   
Strong upper bound.

Prmk: We want to restrict on  
cpt set  $K_\delta$ .

Pf: 
$$\begin{aligned} \mathbb{E} \log \mu_\varepsilon(F) &\leq \mathbb{E} \log (\mu_\varepsilon(F \cap K_\delta) + \mu_\varepsilon(K_\delta^c)) \\ &\leq -\inf_{F \cap K_\delta} I \vee -1/\delta + \mathbb{E} \log 2. \text{ Let } \delta \downarrow 0. \end{aligned}$$

Challenge is that now in Banach space  $E$ , s.t.  $\dim E = +\infty$ . Then  $\overline{B}(x, r)$  isn't cpt.

Prmk: But sometimes  $\exists \| \cdot \|_1 \gg \| \cdot \|_2$ . s.t.  $\overline{B}$   
may be cpt in  $(E, \| \cdot \|_1)$ . eg:

$$E = C([0, 1]) \cap \{f(0) = 0\} \text{ with } \| \cdot \|_\infty.$$

$\{ \| f \|_\infty \leq 1 \}$  isn't cpt. But if we

consider  $\| \cdot \|_\alpha$ ,  $\alpha$ -Hölder norm. then:

$$\{ \| f \|_\alpha \leq 1 \} \stackrel{\text{cpt}}{\subseteq} \overline{E}.$$

$$\text{If } \exists \beta > 0. \text{ s.t. } \Lambda(\beta) = \overline{\lim}_{\varepsilon \downarrow 0} \mathbb{E} \log \mathbb{E} \mu_\varepsilon$$

$$(\exp(\beta \| x \|_\alpha / \varepsilon)) < \infty. \text{ Then we can}$$

Conclude it satisfies exp. tight:

$$K_\delta := \{ \|x\|_x \leq 1/\delta \} \subseteq E.$$

$$\mu_z(K_\delta) \stackrel{\text{Ch. by skew}}{\leq} \mathbb{E}_{\mu_z} \left( \exp \left( \beta \|x\|_x / \varepsilon \right) \right) / e^{\beta/\varepsilon}.$$

$$\Rightarrow \mathbb{E} \log \mu_z(K_\delta) \leq \mathbb{E} \log \mathbb{E}_{\mu_z} - \beta/\varepsilon.$$

Remark: It's kind of Fernique Thm.

As for weak LDP. we claim it can come from:  $\forall x \in E, I(x) < \infty$ . then,

$$\lim_{\delta \downarrow 0} \lim_{\varepsilon \rightarrow 0} \mathbb{E} \log \mu_z(B(x, \delta)) \leq -I(x).$$

Pf: Note  $K \subseteq E, \forall \delta > 0, \exists \bigcup_{i=1}^N B(x_i, \delta) \supseteq K$ .

$$\begin{aligned} \Rightarrow \mathbb{E} \log(\mu_z(K)) &\leq \mathbb{E} \log \left( \sum_{i=1}^N \mu_z(B(x_i, \delta)) \right) \\ &\leq \mathbb{E} \log N + \max_i \mathbb{E} \log \mu_z(B(x_i, \delta)) \end{aligned}$$

We've copied with upper bound above. And

for lower bound, It's from Varadhan Lem:

Lem.  $\{\mu_z\}_{z \in \mathbb{R}}$  satisfies LDP with rate  $I(x)$

If  $F: E \rightarrow \mathbb{R}$  is conti. Then:

$$\lim_{\varepsilon \rightarrow 0} \mathbb{E} \log \mathbb{E}_{\mu_z} e^{F(x)/\varepsilon} = \sup_E (F(z) - I(z))$$

Cor. If  $I(x)$  is convex. Then:

$$I(x) = \Lambda^*(x). \quad * \text{ is Legendre transf.}$$

Pf: Let  $F(x) = \langle \lambda, x \rangle$ .

$$\text{We have RHS above} = \Lambda^*(x).$$

Prop: For  $\Lambda(\lambda)$  convex.  $\Rightarrow \Lambda^*$  convex.

if additionally  $\Lambda(\lambda)$  is l.s.c.

$$\Rightarrow \Lambda^{**} = \Lambda.$$

Contraction Principle:

For  $(\mu, I)$  LDP with  $I$ .  $\phi \in C(E, \tilde{E})$ .

Let  $\tilde{\mu} = \mu \circ \phi^{-1}$ . Then:  $\tilde{\mu}$  satisfies

LDP with  $\tilde{I}(y) = \inf_{x: \phi(x)=y} I(x)$ .

Prop: If  $\phi$  isn't conti. Then we need

some exponential approxi.  $(\phi_\delta(x))_{\delta>0}$

$\in C(E, \tilde{E})$ , s.t.  $\forall \delta > 0$

$$\lim_{\delta \rightarrow 0} \frac{1}{\delta} \log \mu_\delta(\|\phi_\delta - \phi\| > \delta) = -\infty.$$

Variance: (For lower bound)

Consider  $L_N(x) = \frac{1}{N} \sum_{k=1}^N \delta_{x_k}$ .  $\mu_N = (L_N)_* P$ .

Next, we assume  $(X_k)$  is stationary. Then:

by ergodic Thm,  $L_N \xrightarrow{w} \mu$ . ( $X_k \sim \mu$ )

i.e.  $\lim_{N \rightarrow \infty} P_N(L_N \in B(\mu, \varepsilon)) = 1$ .  $\forall \varepsilon > 0$ .

( $P_N$  is p.m. restricted on  $\mathcal{S}([X_k]_N)$ )

The idea to derive its LDP is to find

$Q_N$ . s.t.  $Q_N \sim P_N$  and  $Q_N$  is stationary for

$\theta \in \mathcal{H}$ . i.e.  $\exists \varepsilon > 0$ , s.t.  $Q_N(L_N \in B(\theta, \varepsilon)) \rightarrow 1$ .

We set  $F_N = dQ_N / dP_N$ .  $H(\theta | P) := \lim_{N \rightarrow \infty} \frac{H(Q_N | P_N)}{N}$

where  $H(v | \mu) = \int \frac{d\nu}{d\mu} \log \frac{d\nu}{d\mu} d\mu$

Remark. For  $X_k$  i.i.d. we have  $H(Q_N | P_N) =$   
 $N H(\theta | P)$ .

$$1) \log (P_N(L_N \in B(\theta, \varepsilon)) / Q_N(L_N \in B(\theta, \varepsilon)))$$

$$= \log \left[ \int_B F_N^{-1} dQ_N(\cdot | L_N \in B(\theta, \varepsilon)) \right].$$

$$\stackrel{\text{Jensen}}{\geq} \int_B (\log F_N^{-1}) dQ_N(\cdot | P) \stackrel{\text{take } E(\cdot)}{=} - \int_B \log F_N \cdot F_N dP_N.$$

$\log +$

$$= \int -\varphi(L_N) dP_N - \int \varphi(L_N) I_{\{L_N \leq 0\}} dP_N$$

$$\geq -H(Q_N \| P_N) - \frac{1}{\epsilon} \quad (-\varphi(t) \geq -\frac{1}{\epsilon}.)$$

$$2) \text{ So } \lim_{N \rightarrow \infty} \frac{1}{N} \log P_N(L_N \in G) \geq$$

$$\lim_{N \rightarrow \infty} \frac{1}{N} \log P_N(L_N \in B(\theta, \epsilon)) \geq$$

$$\lim_{N \rightarrow \infty} \frac{1}{N} \left\{ -H(Q_N \| P_N) - \frac{1}{\epsilon} - \log Q_N(\dots) \right\}$$

$$= -H(Q \| P)$$

Remark: It can be applied in SDE by Girsanov

Then (which derive the shifted p.m.)