

Exercise-1 :

(1)

(i) $\mu_n \sim \text{unif}([e^{-n}, e^n])$ easy.

(ii) $\mu_n = \text{Pois}(\frac{\lambda}{n})$ easy.

(iii) $\mu_n = (1 - \frac{1}{n})\delta_0 + \frac{1}{n}\delta_n \Rightarrow \delta_0$.

Take $I(x) = \begin{cases} 0 & x=0 \\ \infty & \text{else} \end{cases}$

I is a good rate function.

Lower bound: G open & $0 \notin G$. Then $\lim_{n \rightarrow \infty} \frac{1}{n} \log \mu_n(G) \geq -\inf_{x \in G} I(x) = -\infty$

Let $0 \in G$. $\Rightarrow \mu_n(G) \geq 1 - \frac{1}{n} \Rightarrow \lim_{n \rightarrow \infty} \frac{1}{n} \log \mu_n(G) \geq -\inf_{x \in G} I(x) = 0$.

Weak upper bound: K compact & $0 \notin K$. $\Rightarrow \mu_n(K) = 0$ for n large
as K is bounded. $\Rightarrow \overline{\lim}_n \frac{1}{n} \log \mu_n(K) = -\infty = -\inf_{x \in K} I(x)$

$0 \in K \Rightarrow \mu_n(K) = 1 - \frac{1}{n}$, n large $\Rightarrow \overline{\lim}_n \frac{1}{n} \log \mu_n(K) = 0 = -\inf_{x \in K} I(x)$

\Rightarrow weak LDP.

Take $F = [1, \infty)$ closed, but not compact.
But ~~we~~ check that upper bound does not hold. No Strong LDP.

Exercise 2:

(2)

This is simple:

A convex. This means, if

$$\frac{S_n}{n} \in A \text{ and } \frac{S_{n+m} - S_n}{n+m-n} \in A, \text{ then}$$

$$\frac{n}{m+n} \cdot \frac{S_n}{n} + \frac{m}{m+n} \cdot \frac{S_{n+m} - S_n}{n+m-n} \in A$$

$$\frac{S_n}{m+n} + \frac{S_{n+m} - S_n}{m+n} \in A$$

$$\frac{S_{n+m}}{m+n} \in A$$

Now use independence of $\frac{S_n}{n}$ and

$\frac{S_{n+m} - S_n}{n+m-n}$ to get the subadditive

bound.

Exercise 3:

By Cramér's ^{upper} bound, we know

$$P\left(\frac{S_n}{n} \in [x, \infty)\right) \leq 2 e^{-n \inf_{y \in [x, \infty)} \Lambda^*(y)}$$

But since Λ^* is a convex function and $x > m = E(X_1)$, we can show $\inf_{y \in [x, \infty)} \Lambda^*(y) > 0$. [See solution of Exercise 1 in Exercise sheet 3 for details.]

This justifies the exponential decay

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \log P\left(\frac{S_n}{n} \in [x, \infty)\right) < 0.$$

Exercise 4:

Enough to prove the claim for a standard normal vector $X_1 \sim N_{d \times d}\left(\underline{0}, \mathbf{I}_{d \times d}\right)$.

Otherwise, set the usual scaling, by writing, for $i=1, \dots, d$

$$\left(\tilde{X}_1\right)_i = \frac{(X_1)_i - \mu_i}{\sqrt{|\Sigma|}}$$

Tail estimate of a d-dimensional Gaussian:

$X \sim \mathcal{N}(\underline{0}, \text{Id}_{d \times d})$. Note that, this means

X has mean $\underline{\mu} = (0, \dots, 0) \in \mathbb{R}^d$ and

covariance matrix $\Sigma = \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix}$ which is positive definite. In this case, the

density function is

$$f_X(x_1, \dots, x_d) = \frac{1}{\sqrt{(2\pi)^d |\Sigma|}} \exp \left\{ -\frac{1}{2} (\underline{x} - \underline{\mu})^t \Sigma^{-1} (\underline{x} - \underline{\mu}) \right\}$$

$$\forall x \geq 0, \text{ Hence, } = \frac{1}{(2\pi)^{d/2}} e^{-\frac{1}{2} \|x\|^2}$$

$$\text{So, } P(\|X\| > x) = \frac{1}{(2\pi)^{d/2}} \int_{y \in B_x(0)^c} e^{-\frac{1}{2} \|y\|^2} dy$$

($y \mapsto e^{-\frac{1}{2} \|y\|^2}$ is a radial fct. so we change to polar coordinates)

$$= \frac{1}{(2\pi)^{d/2}} \int_x^\infty e^{-\frac{r^2}{2}} r^{d-1} dr$$

For $d=1$: we know what to do.

$$\int_x^\infty r e^{-r^2/2} dr = \int_{x^2/2}^\infty e^{-s} ds = e^{-x^2/2}$$

For $d=2$:

$$\int_x^\infty r^{d-2} \cdot r e^{-r^2/2}$$

& keep performing integration by parts till r^{d-2} disappears by differentiating. we'll get a term

$P(x) e^{-x^2/2}$ where $P(x)$ is a polynomial in x .