

# Homework 1 Solution

## Problem 1

Pf:  $\inf_{\lambda > 0} \frac{E(e^{\lambda X})}{e^{\lambda \sigma}} = \inf_{\lambda > 0} \frac{E \sum_{k=0}^{\infty} \frac{\lambda^k X^k}{k!}}{\sum_{k=0}^{\infty} \frac{(\lambda \sigma)^k}{k!}} \quad (\text{by Taylor expansion}).$

$$(*) := \inf_{\lambda > 0} \lim_{n \rightarrow \infty} \frac{\sum_{k=0}^n \frac{\lambda^k EX^k}{k!}}{\sum_{k=0}^n \frac{(\lambda \sigma)^k}{k!}}$$

By applying the inequality, for any n.n.g. seqs.  $a_k, b_k \geq 0, k=1, \dots, n$ .

we have

$$\frac{\sum_{k=1}^n a_k}{\sum_{k=1}^n b_k} \geq \min_{k=1, \dots, n} \left( \frac{a_k}{b_k} \right)$$

$$(*) \geq \inf_{\lambda > 0} \lim_{n \rightarrow \infty} \left( \min_{k=0, \dots, n} \frac{\lambda^k EX^k / k!}{\lambda^k \sigma^k / k!} \right) = \lim_{n \rightarrow \infty} \left( \min_{k=0, \dots, n} \frac{EX^k}{\sigma^k} \right)$$

$$= \inf_{k=0, 1, 2, \dots} \frac{EX^k}{\sigma^k}$$

□

## Problem 2.

Pf:  $a \Rightarrow b$ .

$$\text{Let } G_0 = \frac{1}{b}, \text{ then } E e^{\lambda x} \leq e^{\frac{\lambda^2 V^2}{2}} \leq e^{\frac{G_0^2 V^2}{2}} < \infty.$$

$b \Rightarrow c$ .

By Chernoff bound

$$P(X > t) \leq \inf_{\lambda \in (0, G_0]} \frac{E e^{\lambda x}}{e^{\lambda t}} \leq E(e^{\frac{G_0 x}{2}}) \cdot e^{-\frac{G_0}{2} t} \text{ by taking } \lambda = G_0/2.$$

Let  $C_1' = E(e^{\frac{G_0}{2} x})$  and  $C_2' = \frac{G_0}{2}$ , then

$$P(X > t) \leq C_1' e^{-C_2' t}.$$

Similar arguments to another side,

$$P(X \leq -t) = P(-X \geq t) \leq \inf_{\lambda \in (0, G_0]} \frac{E e^{-\lambda x}}{e^{\lambda t}}$$

$$\leq E(e^{-\frac{G_0}{2} x}) \cdot e^{-\frac{G_0}{2} t}$$

by taking  $C_1'' = E e^{-\frac{G_0}{2} x}$ ,  $C_2'' = \frac{G_0}{2}$ .

Combine two pieces together,

$$P(|X| \geq t) \leq C_1 e^{-C_2 t},$$

where  $C_1 = \max(E e^{-\frac{G_0}{2} x}, E e^{\frac{G_0}{2} x})$ ,  $C_2 = \frac{G_0}{2}$ .

$$\underline{C \Rightarrow a.}$$

$$E e^{\lambda X} = E \sum_{k=0}^{\infty} \frac{\lambda^k X^k}{k!} = 1 + \sum_{k=2}^{\infty} \frac{|\lambda|^k E|X|^k}{k!}$$

$$E|X|^k = \int_0^{+\infty} P(|X|^k > t) dt = \int_0^{+\infty} k \cdot t^{k-1} P(|X| > t) dt$$

by applying (c).

$$\leq \int_0^{+\infty} k \cdot t^{k-1} C_1 e^{-C_2 t} dt = C_1 \cdot k P(k) C_2^{-k} = C_1 k! C_2^{-k}$$

plug in the  $E|X|^k$  to the above summation,

$$E e^{\lambda X} \leq 1 + \sum_{k=2}^{\infty} \frac{|\lambda|^k}{k!} C_1 k! C_2^{-k} = 1 + C_1 \sum_{k=2}^{\infty} \left(\frac{|\lambda|}{C_2}\right)^k$$

$$= 1 + \frac{C_1}{C_2} \frac{\lambda^2}{C_2 - |\lambda|} \quad \text{for all } |\lambda| < C_2.$$

Compare the term  $e^{\frac{\lambda^2 v^2}{2}} = 1 + \frac{\lambda^2 v^2}{2} + \sum_{k=2}^{\infty} \frac{(\frac{\lambda^2 v^2}{2})^k}{k!}$

There exist n.i.g numbers  $b$  and  $\nu$  s.t.

$$\frac{C_1}{C_2} \frac{1}{C_2 - |\lambda|} \leq \frac{C_1}{C_2} \frac{1}{C_2 - \frac{1}{b}} \leq \frac{\nu^2}{2}, \quad \text{for } |\lambda| \leq \frac{1}{b} < C_2.$$

$$\Rightarrow E e^{\lambda X} \leq e^{\frac{\lambda^2 \nu^2}{2}}, \quad \text{for } |\lambda| \leq \frac{1}{b}$$

□

### Problem 3.

(a) Define random variables  $g_i = \frac{X_i}{\sigma} \stackrel{i.i.d.}{\sim} N(0,1) \quad i=1, \dots, n$ .

It's equivalent to show  $\lim_{n \rightarrow \infty} \frac{E \max_{i=1, \dots, n} |g_i|}{\sqrt{2 \log n}} = 1$ .

It suffice to show  $\limsup_{n \rightarrow \infty} \frac{E \max_{i=1, \dots, n} |g_i|}{\sqrt{2 \log n}} \leq 1$  and

$$\liminf_{n \rightarrow \infty} \frac{E \max_{i=1, \dots, n} |g_i|}{\sqrt{2 \log n}} \geq 1.$$

First show the upper bound,

$$\begin{aligned} E \max_{i=1, \dots, n} |g_i| &= \int_0^{+\infty} P\left(\max_{i=1, \dots, n} |g_i| > t\right) dt \\ &= \int_0^{\sqrt{2 \log n}} P\left(\max_{i=1, \dots, n} |g_i| > t\right) dt + \int_{\sqrt{2 \log n}}^{+\infty} P\left(\max_{i=1, \dots, n} |g_i| > t\right) dt. \end{aligned}$$

by union bound

$$\begin{aligned} &\leq \sqrt{2 \log n} + n \int_{\sqrt{2 \log n}}^{+\infty} P(|g_i| > t) dt \\ &= \sqrt{2 \log n} + n \cdot \sqrt{\frac{2}{\pi}} \int_{\sqrt{2 \log n}}^{+\infty} \int_t^{+\infty} e^{-\frac{u^2}{2}} du dt \\ &= \sqrt{2 \log n} + n \sqrt{\frac{2}{\pi}} \int_{\sqrt{2 \log n}}^{+\infty} e^{-\frac{u^2}{2}} \int_{\sqrt{2 \log n}}^u dt du \\ &\leq \sqrt{2 \log n} + n \sqrt{\frac{2}{\pi}} e^{-\frac{2 \log n}{2}} - n \sqrt{\frac{2}{\pi}} \frac{2 \log n}{2 \log n + 1} e^{-\frac{2 \log n}{2}} = \sqrt{2 \log n} + n \sqrt{\frac{2}{\pi}} \frac{1}{2 \log n + 1} \cdot \frac{1}{n} \end{aligned}$$

$$\text{Thus } E \max_{1 \leq i \leq n} |g_i| \leq \sqrt{2 \log n} + \sqrt{\frac{2}{\lambda}} / (1 + 2 \log n).$$

$$\Rightarrow \limsup_{n \rightarrow \infty} \frac{E \max_{i=1, \dots, n} |g_i|}{\sqrt{2 \log n}} \leq 1$$

Now to check the other direction,

For  $t \leq \sqrt{(2-\delta) \log n}$ , for  $0 < \delta < 2$ ,

$$P(|g| > t) \geq \sqrt{\frac{2}{\lambda}} \frac{t}{t^2 + 1} e^{-\frac{t^2}{2}} \geq \sqrt{\frac{2}{\lambda}} \frac{\sqrt{(2-\delta) \log n}}{(2-\delta) \log n + 1} n^{-(2-\delta)/2}$$

$$P\left(\max_{i=1, \dots, n} |g_i| > t\right) = 1 - (1 - P(|g| > t))^n \quad \text{by apply } 1 - x \leq e^{-x} \text{ for all } x$$

$$\geq 1 - e^{-nP(|g| > t)} \rightarrow 1, \text{ as } n \rightarrow \infty \text{ for all } \delta \in (0, 2)$$

$$\text{Since } nP(|g| > t) \geq \sqrt{\frac{2}{\lambda}} \frac{\sqrt{(2-\delta) \log n}}{(2-\delta) \log n + 1} n^{\delta/2} \rightarrow +\infty \text{ as } n \rightarrow \infty \text{ for all } \delta \in (0, 2)$$

Then lower-bound the expectation

$$E \max_{i=1, \dots, n} |g_i| \geq \int_0^{\sqrt{(2-\delta) \log n}} P\left(\max_{i=1, \dots, n} |g_i| > t\right) dt$$

$$\geq \int_0^{\sqrt{(2-\delta) \log n}} (1 - e^{-nP(|g| > t)}) dt$$

$$= (1 - e^{-nP(|g| > t)}) \sqrt{(2-\delta) \log n}$$

$$\Rightarrow \liminf_{n \rightarrow \infty} \frac{E \max_{i=1, \dots, n} |g_i|}{\sqrt{(2-\delta) \log n}} \geq 1, \text{ Letting } \delta \rightarrow 0 \text{ Complete the proof. } \square$$

### Problem 3

(b) for any  $s > 0$ ,

$$\begin{aligned} E\left[\max_{i=1, \dots, n} X_i\right] &= \frac{1}{s} E\left(\log e^{s \max_{i=1, \dots, n} X_i}\right) \\ &\leq \frac{1}{s} \log E\left(e^{s \max_{i=1, \dots, n} X_i}\right) \quad \text{by Jensen's \#} \\ &= \frac{1}{s} \log E\left(\max_{i=1, \dots, n} e^{s X_i}\right) \\ &\leq \frac{1}{s} \log \left(\sum_{i=1}^n E e^{s X_i}\right) \\ &\leq \frac{1}{s} \log \left(n \cdot e^{\frac{\sigma^2 s^2}{2}}\right) = \frac{\log n}{s} + \frac{\sigma^2 s}{2} \quad \text{for all } s > 0. \end{aligned}$$

By taking  $s = \sqrt{2 \log n / \sigma^2}$  to minimize  $\frac{\log n}{s} + \frac{\sigma^2 s}{2} = \sigma \sqrt{2 \log n}$ .

$$\Rightarrow E\left(\max_{i=1, \dots, n} X_i\right) \leq \sigma \sqrt{2 \log n}.$$

□

# Problem 4.

Pf: To apply bounded difference inequality, first check

for points  $X = (x_1, \dots, x_k, \dots, x_n)$  and  $X' = (x_1, \dots, x_k', \dots, x_n)$  where  $x_k'$  is independent

copy of  $x_k$ , and consider  $F(x_1, \dots, x_n) = \|\hat{f} - f\|_1$

$$|F(x_1, \dots, x_k, \dots, x_n) - F(x_1, \dots, x_k', \dots, x_n)|$$

$$= \left| \int \left| \frac{1}{nh} \left( \sum_{i \neq k} K\left(\frac{x - x_i}{h}\right) + K\left(\frac{x - x_k}{h}\right) \right) - f(x) \right| dx \right.$$

$$\left. - \int \left| \frac{1}{nh} \left( \sum_{i \neq k'} K\left(\frac{x - x_i}{h}\right) + K\left(\frac{x - x_k'}{h}\right) \right) - f(x) \right| dx \right|$$

by applying  $||a| - |b|| \leq |a - b| \leq |a| + |b|$

$$\leq \int \frac{1}{nh} \left| K\left(\frac{x - x_k}{h}\right) - K\left(\frac{x - x_k'}{h}\right) \right| dx$$

$$\leq \int \frac{1}{nh} K\left(\frac{x - x_k}{h}\right) dx + \int \frac{1}{nh} K\left(\frac{x - x_k'}{h}\right) dx \quad \text{since } K(x) \geq 0.$$

$$\leq \frac{2}{nh} = L_K \quad \text{by change of variable}$$

$$\sum_{k=1}^n L_K^2 = n \left(\frac{2}{n}\right)^2 = \frac{4}{n}.$$

$$P(\|\hat{f} - f\|_1 \geq E(\|\hat{f} - f\|_1) + \delta) \leq e^{-\frac{2\delta^2}{4/n}} = e^{-n\delta^2/2} \leq e^{-n\delta^2/8}$$

□

Problem 5

(a) pf: Since  $X_1, X_2$  are indep.

$$\mathbb{E} e^{\lambda(X_1+X_2)} = \mathbb{E}_{X_1} e^{\lambda X_1} \mathbb{E}_{X_2} e^{\lambda X_2} \leq e^{\frac{\lambda^2 \sigma_1^2}{2}} e^{\frac{\lambda^2 \sigma_2^2}{2}} = e^{\frac{\lambda^2}{2}(\sigma_1^2 + \sigma_2^2)}$$

$\Rightarrow (X_1+X_2) \sim (\sigma_1^2 + \sigma_2^2)$  - sub gaussian.

(b), Applying Hölder's  $\dagger$  for  $p, q \geq 1$   $\frac{1}{p} + \frac{1}{q} = 1$

$$\begin{aligned} \mathbb{E} e^{\lambda(X_1+X_2)} &\leq (\mathbb{E}_{X_1} (e^{\lambda X_1})^p)^{\frac{1}{p}} \cdot (\mathbb{E}_{X_2} (e^{\lambda X_2})^q)^{\frac{1}{q}} \\ &\leq \left( e^{\frac{\sigma_1^2}{2} \lambda^2 p} \right)^{\frac{1}{p}} \left( e^{\frac{\sigma_2^2}{2} \lambda^2 q} \right)^{\frac{1}{q}} \\ &= e^{\frac{\lambda^2}{2} (p \sigma_1^2 + q \sigma_2^2)} \quad \text{since } q = \frac{p}{p-1} \end{aligned}$$

Then choose  $p \in (1, +\infty)$  such that minimize  $f(p) = p \sigma_1^2 + \frac{p}{p-1} \sigma_2^2$

$$\text{let } f'(p) = \sigma_1^2 - \frac{\sigma_2^2}{(p-1)^2} = 0 \Rightarrow p_* = 1 + \frac{\sigma_2}{\sigma_1}$$

Easy to check  $p_*$  is global minima, therefore  $q_* = 1 + \frac{\sigma_1}{\sigma_2}$

plug in  $p_*$  and  $q_*$  and obtain

$$\mathbb{E} e^{\lambda(X_1+X_2)} \leq e^{\frac{\lambda^2}{2} (\sigma_1 + \sigma_2)^2} \leq e^{\frac{\lambda^2}{2} (4\sigma_1^2 + 4\sigma_2^2)}$$

□



# Problem 5

(c). Since  $X_1, X_2$  independent.

$$E(e^{\lambda X_1 X_2}) = E_{X_2}(E_{X_1}(e^{\lambda X_1 X_2} | X_2))$$

$$\leq E \exp\left(\frac{(\lambda X_2)^2}{2} \sigma_1^2\right) \quad \text{by sub-gaussian property}$$

$$= 1 + \sum_{k=1}^{\infty} \frac{\left(\frac{\lambda \sigma_1}{2}\right)^2 E X_2^{2k}}{k!}$$

$$\leq 1 + \sum_{k=1}^{\infty} \frac{\left(\frac{1}{2} \lambda \sigma_1\right)^2 (2\sigma_2^2)^k \cdot 2k \cdot P(k)}{k!}$$

$$= 1 + 2 \sum_{k=1}^{\infty} \left(2 \cdot \frac{1}{2} \lambda^2 \sigma_1^2 \sigma_2^2\right)^k$$

$$= 1 + 2 \frac{\lambda^2 \sigma_1^2 \sigma_2^2}{1 - \lambda^2 \sigma_1^2 \sigma_2^2} \leq 1 + 4 \lambda^2 \sigma_1^2 \sigma_2^2 \quad \text{for } \lambda^2 \sigma_1^2 \sigma_2^2 \leq \frac{1}{2}$$

$$\leq e^{\frac{\lambda^2}{2} (8 \sigma_1^2 \sigma_2^2)} \quad \text{for } |\lambda| \leq \frac{1}{\sqrt{2} \sigma_1 \sigma_2}$$

$\Rightarrow X_1 X_2$  is sub-exponential with parameters  $(8 \sigma_1^2 \sigma_2^2, \sqrt{2} \sigma_1 \sigma_2)$ .

□