

Problem 1

Total: 95/100 (A).

(a) For $X > 0$ essentially and $u > 0$, for any $\lambda > 0$,

$$E[e^{\lambda \frac{X}{u}}] = E\left[\sum_{i=0}^{\infty} \left(\frac{\lambda X}{u}\right)^i \frac{1}{i!}\right]$$

Monotone
Convergence Thm, $\sum_{i=0}^{\infty} E\left[\left(\frac{X}{u}\right)^i\right] \frac{\lambda^i}{i!}$

Yes $\rightarrow \geq \sum_{i=0}^{\infty} \frac{\lambda^i}{i!} \inf_{\substack{k \geq 0 \\ k \in \mathbb{Z}}} E\left[\left(\frac{X}{u}\right)^k\right]$

$$= e^{\lambda} \inf_{\substack{k \geq 0 \\ k \in \mathbb{Z}}} E\left[\left(\frac{X}{u}\right)^k\right], \quad \text{For all } \lambda > 0.$$

therefore $\inf_{\lambda > 0} E[e^{\lambda \frac{X}{u}}] \geq \inf_{\lambda > 0} e^{\lambda} \inf_{\substack{k \geq 0 \\ k \in \mathbb{Z}}} E\left[\left(\frac{X}{u}\right)^k\right]$
 $\geq \inf_{\substack{k \geq 0 \\ k \in \mathbb{Z}}} E\left[\left(\frac{X}{u}\right)^k\right]$ \square

(+)

(b) $M_X(\lambda) e^{-\lambda u} = \frac{1}{2} M_X(\lambda) e^{-\lambda u} + \frac{1}{2} M_X(\lambda) e^{-\lambda u}$ by symmetric.

$$= E\left[\frac{1}{2} \sum_{i=0}^{\infty} \left(-\frac{\lambda X}{u}\right)^i \frac{1}{i!} + \frac{1}{2} \sum_{i=0}^{\infty} \left(\frac{\lambda X}{u}\right)^i \frac{1}{i!}\right]$$

$$= E\left[\sum_{i=0}^{\infty} \left(\frac{\lambda X}{u}\right)^{2i} \frac{1}{(2i)!}\right]$$

Now that
the summands
are all ≥ 0

Monotone
Convergence
Theorem, $\sum_{i=0}^{\infty} \frac{\lambda^{2i}}{(2i)!} E\left[\left(\frac{X}{u}\right)^{2i}\right]$

$$\geq \sum_{i=0}^{\infty} \frac{\lambda^{2i}}{(2i)!} \inf_{\substack{k \in \mathbb{Z} \\ k \geq 0}} E\left[\left(\frac{X}{u}\right)^k\right]$$

$$\geq \frac{1}{2} \inf_{\substack{k \in \mathbb{Z} \\ k \geq 0}} E\left[\left(\frac{X}{u}\right)^k\right] \quad \text{for all } \lambda > 0. \quad (+) \quad \square$$

I wonder if
they still teach
cosh & sinh
in high school :)

Problem 2

Assume X is a discrete random variable, point mass $\{p_i\}_{i=1}^k$

$$\frac{d}{dt} K_X(t) = \frac{d}{dt} \log E[e^{tX}] = \frac{1}{E[e^{tX}]} E[Xe^{tX}]$$

$$\frac{d^2}{dt^2} K_X(t) = \frac{E[X^2 e^{tX}] E[e^{tX}] - E[Xe^{tX}]^2}{E[e^{tX}]^2}$$

Apply Young's inequality with conjugate pair $(\frac{1}{2}, \frac{1}{2}) =$

$$\sum_{i=1}^k |p_i x_i e^{tx_i}| = \sum_{i=1}^k |p_i^{\frac{1}{2}} x_i e^{\frac{1}{2}tx_i} p_i^{\frac{1}{2}} e^{\frac{1}{2}tx_i}| \quad (\frac{1}{p}, \frac{1}{q})$$

[Also works, yes] $\leq \left(\sum_{i=1}^k p_i x_i^2 e^{tx_i} \right)^{\frac{1}{2}} \left(\sum_{i=1}^k p_i e^{tx_i} \right)^{\frac{1}{2}}$

therefore $E[Xe^{tX}]^2 \leq E[X^2 e^{tX}] E[e^{tX}]$

$$\leq \left(\sum_{i=1}^k p_i e^{tx_i} x_i^2 \right) \left(\sum_{i=1}^k p_i e^{tx_i} \right)$$

$$= E[X^2 e^{tX}] E[e^{tX}]$$

we have $\frac{d^2}{dt^2} K_X(t) \geq 0$ for all t . $\Rightarrow K_X(t)$ is \oplus convex.

Problem 3

$$(a) \int_u^\infty \phi(t) dt = \int_u^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

$$= \frac{1}{\sqrt{2\pi}} \int_{t \geq u} \frac{1}{t} e^{-\frac{t^2}{2}} dt^2$$

$$(\text{since } u \geq 0) \leq \frac{1}{\sqrt{2\pi}} \int_{t \geq u} \frac{1}{2u} e^{-\frac{t^2}{2}} dt^2 = \frac{1}{\sqrt{2\pi}} \frac{1}{u} e^{-\frac{u^2}{2}}$$

$$= \frac{1}{u} \phi(u)$$

Now show the other bound.

$$\int_u^\infty \phi(t) dt = \frac{1}{\sqrt{2\pi}} \int_{t \geq u} -\frac{1}{t} d e^{-\frac{t^2}{2}}$$

$$(\text{int. by parts}) = \frac{1}{\sqrt{2\pi}} \left(-\frac{1}{t} e^{-\frac{t^2}{2}} \Big|_u^\infty + \int_{t \geq u} e^{-\frac{t^2}{2}} d \left(\frac{1}{t} \right) \right)$$

$$= \frac{1}{\sqrt{2\pi}} \frac{1}{u} e^{-\frac{u^2}{2}} + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} -\frac{1}{t^2} e^{-\frac{t^2}{2}} dt$$

$$= \frac{1}{u} \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} -\frac{1}{2t^2} e^{-\frac{t^2}{2}} dt^2$$

$$\geq \frac{1}{u} \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} -\frac{1}{2u^2} e^{-\frac{t^2}{2}} dt^2$$

$$= \frac{1}{u} \phi(u) + \frac{1}{\sqrt{2\pi}} \frac{1}{u^2} e^{-\frac{u^2}{2}}$$

$$= \left(\frac{1}{u} - \frac{1}{u^3} \right) \phi(u)$$



3. (b) As shown in 3(a), we have

$$\begin{aligned}\int_u^\infty \phi(t) dt &= \frac{1}{u} \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} -\frac{1}{2t^3} e^{-\frac{t^2}{2}} dt^2 \\ &= \frac{1}{u} \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} \frac{1}{t^3} d e^{-\frac{t^2}{2}}\end{aligned}$$

$$\begin{aligned}(\text{int. by parts}) &= \frac{1}{u} \phi(u) + \frac{1}{\sqrt{2\pi}} \left(e^{-\frac{t^2}{2}} \frac{1}{t^3} \Big|_u^\infty - \int_{t \geq u} e^{-\frac{t^2}{2}} d \frac{1}{t^3} \right) \\ &= \left(\frac{1}{u} - \frac{1}{u^3} \right) \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} \frac{3}{t^4} e^{-\frac{t^2}{2}} dt \\ &= \left(\frac{1}{u} - \frac{1}{u^3} \right) \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} \frac{3}{t^5} d e^{-\frac{t^2}{2}} \\ &\leq \left(\frac{1}{u} - \frac{1}{u^3} \right) \phi(u) + \frac{1}{\sqrt{2\pi}} \int_{t \geq u} \frac{3}{t^5} d e^{-\frac{t^2}{2}}\end{aligned}$$

$$\oplus = \left(\frac{1}{u} - \frac{1}{u^3} + \frac{1}{u^5} \right) \phi(u).$$

□

$$3.2 \quad \frac{1}{2} - \Phi(u) = \int_0^u \phi(t) dt \quad (\text{Assume } u \geq 0)$$

$$\begin{aligned}&= \int_0^1 u \phi(tu) dt \\ &= \int_0^1 \frac{u}{\sqrt{2\pi}} \sum_{i=0}^{\infty} \frac{\left(-\frac{(tu)^2}{2}\right)^i}{i!} dt \\ &= \int_0^1 \frac{1}{\sqrt{2\pi}} \sum_{i=0}^{\infty} \frac{(-1)^i u^{2i+1} t^{2i}}{2^i i!} dt\end{aligned}$$

$$\text{since } \sum_{i=0}^{\infty} \left| \frac{(-1)^i u^{2i+1} t^{2i}}{2^i i!} \right| \leq u \exp\left(\frac{u^2}{2} t^2\right) \leq u \exp\left(\frac{u^2}{2}\right) \text{ on } t \in [0, 1]$$

By dominated convergence theorem,

$$\oplus \quad \frac{1}{2} - \Phi(u) = \frac{1}{\sqrt{2\pi}} \sum_{i=0}^{\infty} \frac{(-1)^i u^{2i+1}}{2^i i!} \int_0^1 t^{2i} dt = \frac{1}{\sqrt{2\pi}} \sum_{k=0}^{\infty} \frac{(-1)^k u^{2k+1}}{2^k k! (2k+1)}$$

Well done!

Problem 4

(i) First, by Cauchy inequality,

$$\begin{aligned} E[X 1_{\{X \geq (1-t)EX\}}]^2 &\leq E[X^2] E[1_{\{X \geq (1-t)EX\}}^2] \\ &= E[X^2] P(X \geq (1-t)EX) \quad (*) \end{aligned}$$

Also, notice that

$$(1-t)EX \geq E[X 1_{\{X \leq (1-t)EX\}}] \quad + \text{ (Note that } X \geq 0 \text{ is used here)}$$

$$\text{which is } EX - tEX \geq EX - E[X 1_{\{X \geq (1-t)EX\}}]$$

$$\text{therefore } tEX \leq E[X 1_{\{X \geq (1-t)EX\}}] \quad +$$

$$\begin{aligned} \text{since } X \geq 0, \quad t^2(EX)^2 &\leq E[X 1_{\{X \geq (1-t)EX\}}]^2 \\ (\text{by } *) &\leq E[X^2] P(X \geq (1-t)EX) \quad + \oplus \end{aligned}$$

$$(ii) \text{ To show } P(X \geq (1-t)EX) \geq \frac{t^2(EX)^2}{t^2(EX)^2 + \text{Var}(X)} \quad \square.$$

$$\text{it is the same to show } P(X < (1-t)EX) \leq \frac{\text{Var}(X)}{\text{Var}(X) + t^2(EX)^2}.$$

Notice that $P(X - EX - \frac{\text{Var}(X)}{tEX} < -tEX - \frac{\text{Var}(X)}{tEX}) \leq 0$

Agreed $\leq P((X - EX - \frac{\text{Var}(X)}{tEX})^2 > (tEX + \frac{\text{Var}(X)}{tEX})^2)$

$$\begin{aligned} (\text{Markov ineq}) &\leq \frac{E[(X - EX - \frac{\text{Var}(X)}{tEX})^2]}{(tEX + \frac{\text{Var}(X)}{tEX})^2} \quad + \\ &= \frac{\text{Var}(X) + \frac{\text{Var}(X)^2}{(tEX)^2}}{(tEX + \frac{\text{Var}(X)}{tEX})^2} \end{aligned}$$

$$\text{Smart (shorter than the one I've seen before)} \quad = \frac{\text{Var}(X)}{t^2(EX)^2 + \text{Var}(X)} \quad + \oplus$$

So the Cantelli inequality is proved.

Bravo! \oplus

4(iii) Use Hölder Ineq. Here q satisfies $\frac{1}{p} + \frac{1}{q} = 1$


$$E[|X| \mathbb{1}_{\{X \geq (1-t)EX\}}] \leq E[|X|^p]^{\frac{1}{p}} E[\mathbb{1}_{\{X \geq (1-t)EX\}}^q]^{\frac{1}{q}}$$

Since $X \geq 0$, $E[X \mathbb{1}_{\{X \geq (1-t)EX\}}]^p \leq E[|X|^p] \cancel{E[X \mathbb{1}_{\{X \geq (1-t)EX\}}]}$

$$P(X \geq (1-t)EX)^{p-1}$$

Again notice that $E[X \mathbb{1}_{\{X \geq (1-t)EX\}}] \geq tEX$
(argument made in 4(i))

we have $(tEX)^p \leq E[|X|^p] P(X \geq (1-t)EX)^{p-1}$

which is exactly $P(X \geq (1-t)EX) \geq \left(\frac{t^p (EX)^p}{E[|X|^p]} \right)^{\frac{1}{p-1}}$ 

Problem 5

(a) let $X \sim \chi^2_2$, then $X = Z_1^2 + Z_2^2$ where Z_1, Z_2 independent std normal

$$M_X(t) = E[e^{tX}] = E[e^{tZ_1^2 + tZ_2^2}]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{t(x^2+y^2)} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dx dy$$

$$= \int_0^{\infty} \int_0^{2\pi} \frac{1}{2\pi} e^{tr^2} e^{-\frac{1}{2}r^2} r d\theta dr$$

$$= \int_0^{\infty} r \exp\left((t - \frac{1}{2})r^2\right) dr = \frac{1}{2t-1} \cdot (-1) = \frac{1}{1-2t}$$

(+)

Assume $t < \frac{1}{2}$.

if $t \geq \frac{1}{2}$, then the integral $\int_0^{\infty} r e^{(t-\frac{1}{2})r^2} dr$ diverges.

Therefore, $M_X(t) = \frac{1}{1-2t}$, $t < \frac{1}{2}$.

$$\text{Also } M_{2d}(t) = E[e^{t \sum_{i=1}^{2d} Z_i^2}] \stackrel{i.i.d}{=} E[e^{tZ_1^2 + tZ_2^2}]^d = \left(\frac{1}{1-2t}\right)^d$$

$$(b) P(X > x) \stackrel{q.s.}{=} P(e^{tx} > e^{tX}) \leq \frac{E[e^{tX}]}{e^{tx}} = \frac{e^{-tx}}{(1-2t)^d}$$

Now improve the bound by picking t . for $0 < t < \frac{1}{2}$.

$$\log \frac{e^{-tx}}{(1-2t)^d} = -tx - d \cdot \log(1-2t), \text{ take derivative w.r.t. } t$$

the derivative is $-x + \frac{2d}{1-2t}$, 2nd order derivative is

$$\text{Stationary point } t^* = \frac{1}{2} - \frac{d}{x} \in (0, \frac{1}{2})$$

$$\left(\frac{4d}{(1-2t)^2}\right) > 0$$

$$\text{so } P(X > x) \leq \frac{e^{-t^*x}}{(1-2t^*)^d} = \left(\frac{x}{2d}\right)^d \exp\left(d - \frac{x}{2}\right) = \exp\left(d \log\left(\frac{x}{2d}\right) - \frac{x-2d}{2}\right)$$

(+)

Problem 5. (c)*

(i) Claim: $\log(1+u) \leq u - \frac{1}{4} \min\{u, u^2\}$, $\forall u \geq 0$

indeed, when $0 \leq u \leq 1$, $\min\{u, u^2\} = u^2$

$$g(u) = \log(1+u) - u + \frac{1}{4} u^2$$

$$g'(u) = \frac{1}{1+u} - 1 + \frac{u}{2} = \frac{u^2 + u + 2 - 2u - 2}{2(1+u)} = \frac{u^2 - u}{2(1+u)}$$

so $g(u) \leq g(0) = 0$ on $u \in [0, 1]$. $+$ $= \frac{u^2 - u}{2(1+u)} \leq 0$

when $u \geq 1$, $u \leq u^2$, then

$$h(u) = \log(1+u) - u + \frac{3}{4} u = \log(1+u) - \frac{1}{4} u$$

$$h'(u) = \frac{1}{1+u} - \frac{1}{4} < 0, \text{ so } g(u) \leq g(1) \leq 0, \forall u \geq 1$$

so the claim holds. $+$

$$P(X - 2d > z) \leq \exp\left(d \log\left(1 + \frac{z}{2d}\right) - \frac{z}{2}\right)$$

$$\leq \exp\left(d \cdot \left(\frac{z}{2d} - \frac{1}{4} \min\left\{\frac{z}{2d}, \left(\frac{z}{2d}\right)^2\right\}\right) - \frac{z}{2}\right)$$

$$= \exp\left(-\frac{d}{4} \min\left\{\left(\frac{z}{2d}\right)^2, \frac{z}{2d}\right\}\right)$$

$$= \begin{cases} \exp\left(-\frac{z^2}{16d}\right), & \text{if } 0 \leq \frac{z}{2d} \leq 1, \\ \exp\left(-\frac{1}{8} z\right), & \text{if } \frac{z}{2d} > 1. \end{cases}$$

$+$

Problem 6

$$\begin{aligned}
 (a) \quad \text{Risk}(sX) &= E[\|sX - \mu\|^2] \\
 &= s^2 E[\|X - \frac{\mu}{s}\|^2 + \|\frac{\mu}{s} - \mu\|^2] \\
 &= s^2 \cdot d + s^2 \cdot (\frac{1}{s} - 1)^2 \|\mu\|^2 \\
 &= s^2 d + (s-1)^2 \|\mu\|^2.
 \end{aligned}$$

For $s < 0$, $\text{Risk}(-sX) \leq \text{Risk}(sX)$, so $-s$ is always better.

~~For~~ So we can restrict discussion to $s \in [0, \infty)$.

For $s > 1$, $s-1$ is always better, so we can restrict discussion to $s \in [0, 1]$. +

$$(b) \quad \text{Risk}(sX) = (d + \|\mu\|^2)s^2 - 2\|\mu\|^2 s + \|\mu\|^2$$

The stationary point of this quadratic form is

$$s^* = \frac{\|\mu\|^2}{d + \|\mu\|^2} = 1 - \frac{d}{d + \|\mu\|^2}. \quad \text{span style="color: red;">+}$$

(c) Because s^* is not known, it involves true value μ .

For $(1 - \frac{d}{\|X\|^2})X = \hat{\mu}$, it approximates $\|\mu\|^2$ using the observation we have, which is $\|X\|^2$. +

Question 6(d)*.

$$\mu^\delta = (1 - \frac{\delta}{\|x\|^2})x$$

denote $g_i(x) = (1 - \frac{\delta}{\|x\|^2})x_i$, then

$$\frac{\partial g_i(x)}{\partial x_j} = \begin{cases} 1 - \frac{\delta}{\|x\|^2} + \frac{2\delta x_i^2}{\|x\|^4}, & \text{if } i=j \\ \frac{2x_i \delta x_j}{\|x\|^4}, & \text{otherwise} \end{cases}$$

$$\begin{aligned} \textcircled{1} \quad E\left[\left|\frac{\partial g_i(x)}{\partial x_j}\right|\right] &\leq \max\left\{E\left[1 - \frac{\delta}{\|x\|^2} + \frac{2\delta x_i^2}{\|x\|^4}\right], \right. \\ &\quad \left. |2\delta| E\left[\frac{x_i x_j}{\|x\|^4}\right]\right\} \\ &\leq \max\left\{1 + 3|\delta| E\left[\frac{1}{\|x\|^2}\right], 2|\delta| E\left[\frac{1}{\|x\|^2}\right]\right\} \\ &= 1 + 3|\delta| E\left[\frac{1}{\|x\|^2}\right]. \end{aligned}$$

For $d \geq 3$, $\|x\|^2$ is a chi-squared random variable with shifted degree of freedom > 2 ,

therefore the integral exists, $E\left[\frac{1}{\|x\|^2}\right] < \infty$

For $d=1,2$, $\frac{\delta}{\|x\|^2}$ is not integrable. +

② Also, $|g_i(x)(x_j - \mu_j)|$ is integrable. $\forall i, j$.

By Stein's lemma, $E[(x_j - \mu_j) g_i(x)] = E\left[\frac{\partial}{\partial x_i} g_i(x)\right]$.

$$= 1 - \delta E\left[\frac{1}{\|x\|^2}\right] + 2\delta E\left[\frac{x_i^2}{\|x\|^4}\right].$$

+

Also expand the left hand side, we get

$$E \left[\sum_{i=1}^d \left(1 - \frac{\delta}{\|x\|^2}\right) x_i^2 - \mu_i x_i \left(1 - \frac{\delta}{\|x\|^2}\right) \right] = d - d\delta E \left[\frac{1}{\|x\|^2} \right] + 2\delta E \left[\frac{\sum_{i=1}^d x_i^2}{\|x\|^4} \right].$$

that is,

$$E \left[\|x\|^2 \right] - \delta - \sum_{i=1}^d \mu_i^2 + \delta E \left[\frac{\sum_{i=1}^d \mu_i x_i}{\|x\|^2} \right] = d - d\delta E \left[\frac{1}{\|x\|^2} \right] + 2\delta E \left[\frac{\sum_{i=1}^d x_i^2}{\|x\|^4} \right]$$

Expand $E \left[\|x\|^2 \right] = \sum_{i=1}^d \mu_i^2 + d$, we have

$$-\delta + \delta E \left[\frac{\sum_{i=1}^d \mu_i x_i}{\|x\|^2} \right] = (2-d)\delta E \left[\frac{1}{\|x\|^2} \right].$$

$$\Rightarrow \boxed{-1 + E \left[\frac{\mu^T x}{\|x\|^2} \right] = (2-d) E \left[\frac{1}{\|x\|^2} \right].} \quad (+) (*)$$

Now we look at the risk function of $\hat{\mu}^\delta$.

$$\text{Risk}(\hat{\mu}^\delta) = E \left[\|\hat{\mu}^\delta - \mu\|^2 \right]$$

$$= E \left[\left(1 - \frac{\delta}{\|x\|^2}\right)^2 x^2 - 2x^T \mu \left(1 - \frac{\delta}{\|x\|^2}\right) + \|\mu\|^2 \right]$$

$$= E \left[\frac{\delta^2}{\|x\|^4} - 2\delta + \frac{2x^T \mu \delta}{\|x\|^2} + x^2 - 2x^T \mu + \mu^2 \right]$$

$$= \delta^2 E \left[\frac{1}{\|x\|^4} \right] + \delta (-2 + 2E \left[\frac{\mu^T x}{\|x\|^2} \right]) + E \left[x^2 \right] - 2E \left[x^T \mu \right] + \mu^2.$$

View the risk function as a quadratic form of δ , then

the minimizer is $\delta^* = \frac{-2 + 2E \left[\frac{\mu^T x}{\|x\|^2} \right]}{-2E \left[\frac{1}{\|x\|^4} \right]}$

Using (*), we have $\delta^* = d-2$. (+)

Now $\text{Risk}(\hat{\mu}^{\delta^*})$ is strictly convex w.r.t. μ .

Problem 7

Reference : Math.StackExchange.com

Lol, OK :)

"Why can a Venn diagram for 4+ sets not be constructed using circles?"

① $F_n = |\text{power}(\{1, 2, \dots, n\})| = 2^n$ because each

$I \subseteq \{1, 2, \dots, n\}$ represents a face, in particular, \emptyset is the outer region. +

② $V_n = 2 \cdot \binom{n}{2}$ because for any two i, j circle,

they must intersect on two distinct points, otherwise they ~~cannot~~ cannot create a face for $A_i \cap A_j$. +

③ Every Vertex has degree 4. *Not the way I did it but ok...*
otherwise, there should be 3 circles sharing one intersection point.

Then not all intersections $\{A_1 \cap A_2, A_1 \cap A_3, A_2 \cap A_3, A_1 \cap A_2 \cap A_3\}$ are present as faces.

$$\sum_{i \in V_n} \deg(i) = 2 |E_n| \quad \text{for simple graph, so } E_n = 2V_n.$$

For $n=4$, $F_4 + V_4 - E_4 = 16 - 12 = 4 \neq 2$ contradicts Euler form.
therefore cannot draw Venn diagram for $n=4$.

Then, of course, cannot draw for $n \geq 4$, since

+ removing one circle from n -Venn diagram results in a $(n-1)$ -Venn diagram.