

Concentration Inequalities : Exercises solutions

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Contents

2 Basic Inequalities	2
Exercise 1.	2
Exercise 2.	2
Exercise 3. (Chebyshev-Cantelli Inequality)	3
Exercise 4. (Paley-Zigmond Inequality)	4
Exercise 5. (Moments VS. Chernoff Bounds)	5
Exercise 6.	6
Exercise 7.	7
Exercise 9. (Sub-Gaussian lower tail for nonnegative random variables) .	8
Exercise 16.	9

Chapter 2

Basic Inequalities

Exercise 2.1

Let $\mathbf{M}Z$ be a median of the square integrable variable Z (i.e $\mathbb{P}[Z \geq \mathbf{M}Z] \geq \frac{1}{2}$ and $\mathbb{P}[Z \leq \mathbf{M}Z] \geq \frac{1}{2}$). Show that :

$$|\mathbb{E}[Z] - \mathbf{M}Z| \leq \sqrt{\text{Var}(Z)}$$

Solution : We have the following inequalities :

$$\begin{aligned} |\mathbb{E}[Z] - \mathbf{M}Z| &= |\mathbb{E}[Z - \mathbf{M}Z]| \\ &\leq \mathbb{E}[|Z - \mathbf{M}Z|] \\ &\leq \mathbb{E}[|Z - \mathbb{E}[Z]|] \\ &\leq \sqrt{\mathbb{E}[(Z - \mathbb{E}[Z])^2]} \end{aligned}$$

Where the second inequality comes from the optimality of the median for the mean absolute error ($\mathbf{M}Z \in \arg \min_{c \in \mathbf{R}} \mathbb{E}[|Z - c|]$) and the third inequality is Cauchy-Schwarz. \square

Exercise 2.2

Let X be a random variable with median $\mathbf{M}X$, such that there exist positive constants a and b such that for all $t \geq 0$,

$$\mathbb{P}[|X - \mathbf{M}X| > t] \leq a \exp -\frac{t^2}{b}$$

Show that $|\mathbf{M}X - \mathbb{E}[X]| \leq \min\left(\sqrt{ab}, a\sqrt{b\pi}/2\right)$

Solution : We have the following :

$$\begin{aligned}
|\mathbb{E}[X] - \mathbf{M}X| &= |\mathbb{E}[X - \mathbf{M}X]| \\
&\leq \mathbb{E}[|X - \mathbf{M}X|] \\
&= \int_0^\infty \mathbb{P}[|X - \mathbf{M}X| > t] dt \\
&\leq \int_0^\infty a \exp -\frac{t^2}{b} \\
&\leq a \cdot \sqrt{b\pi}/2
\end{aligned}$$

For the second inequality, we will bound the variance and use the first exercise. We know that

$$Var(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \min_{c \in \mathbf{R}} \mathbb{E}[(X - c)^2]$$

In particular, plugging in the value of the median as c , we get :

$$\begin{aligned}
Var(X) &\leq \mathbb{E}[(X - \mathbf{M}X)^2] \\
&= \int_0^\infty \mathbb{P}[(X - \mathbf{M}X)^2 > t] dt \\
&= \int_0^\infty \mathbb{P}[|X - \mathbf{M}X| > \sqrt{t}] dt \\
&\leq \int_0^\infty a \cdot \exp -\frac{t}{b} dt \\
&\leq ab
\end{aligned}$$

Then using the result of the first exercise we have :

$$|\mathbb{E}[X] - \mathbf{M}X| \leq \sqrt{Var(X)} \leq \sqrt{ab}$$

□

Exercise 2.3 (CHEBYSHEV-CANTELLI INEQUALITY)

Prove the following one-sided improvement of Chebyshev's inequality : for any real-valued random variable Y and $t > 0$,

$$\mathbb{P}[Y - \mathbb{E}[Y] \geq t] \leq \frac{Var(Y)}{Var(Y) + t^2}$$

Solution : We start by defining $Z := Y - \mathbb{E}[Y]$ and $v := \mathbb{E}[Z^2] = Var(Y)$

We are now trying to prove $\mathbb{P}[Z \geq t] \leq \frac{v}{v+t^2}$. We have for any $u \geq 0$

$$\begin{aligned}\mathbb{P}[Z \geq t] &= \mathbb{P}[Z + u \geq t + u] \\ &\leq \mathbb{P}[(Z + u)^2 \geq (t + u)^2] \\ &\stackrel{(\text{Markov})}{\leq} \frac{\mathbb{E}[(Z + u)^2]}{(t + u)^2} \\ &\leq \frac{v + u^2}{(t + u)^2}\end{aligned}$$

We're now going to optimize the value of this fraction over u . Let

$$\begin{aligned}\varphi : \mathbf{R}^+ &\longrightarrow \mathbf{R} \\ u &\longmapsto \frac{v + u^2}{(t + u)^2}\end{aligned}$$

We compute it's derivative :

$$\begin{aligned}\varphi'(u) &= \frac{2u \cdot (t + u)^2 - (v + u^2) \cdot 2(t + u)}{(t + u)^4} \\ &= \frac{(t + u) \cdot (2ut - 2v)}{(t + u)^4}\end{aligned}$$

In particular, φ reaches its minimum in $u^* := \frac{v}{t}$. We plug that value in the previous inequality :

$$\begin{aligned}\mathbb{P}[Z \geq t] &\leq \varphi(u^*) = \frac{v + \frac{v^2}{t}}{(t + \frac{v}{t})^2} \\ &= \frac{v \cdot (t^2 + v)}{(t^2 + v)^2} \\ &= \frac{v}{v + t^2}\end{aligned}$$

□

Exercise 2.4 (PALEY-ZIGMUND INEQUALITY)

Show that if Y is a nonnegative random variable, then for any $a \in (0, 1)$,

$$\mathbb{P}[Y - \mathbb{E}[Y]] \geq (1 - a)^2 \frac{(\mathbb{E}[Y])^2}{\mathbb{E}[Y^2]}$$

Solution : We have :

$$\begin{aligned}
\mathbb{E}[Y] &= \mathbb{E}[Y \mathbb{I}_{Y < a\mathbb{E}[Y]}] + \mathbb{E}[Y \mathbb{I}_{Y \geq a\mathbb{E}[Y]}] \\
&\leq \mathbb{E}[a\mathbb{E}[Y] \mathbb{I}_{Y < a\mathbb{E}[Y]}] + \sqrt{\mathbb{E}[Y^2] \cdot \mathbb{E}[\mathbb{I}_{Y \geq a\mathbb{E}[Y]}^2]} \\
&\leq a\mathbb{E}[Y] + \sqrt{\mathbb{E}[Y^2] \cdot \mathbb{P}[Y \geq a\mathbb{E}[Y]]} \\
(1-a)\mathbb{E}[Y] &\leq \sqrt{\mathbb{E}[Y^2] \cdot \mathbb{P}[Y \geq a\mathbb{E}[Y]]}
\end{aligned}$$

Where the first inequality comes from Cauchy Schwarz on the right term. Taking the square and rearranging, we get the claimed result. \square

Exercise 2.5 (MOMENTS VS. CHERNOFF BOUNDS)

Show that moment bounds for tail probabilities are always better than Cramér-Chernoff bounds. More precisely, let Y be a nonnegative random variable and let $t > 0$. The best moment bound for the tail probability $\mathbb{P}[Y \geq t]$ is $\min_q \mathbb{E}[Y^q] t^{-q}$ where the minimum is taken over all positive integers. The best Cramér-Chernoff bound is $\inf_{\lambda > 0} \mathbb{E}[\exp \lambda(Y - t)]$. Prove that :

$$\min_q \mathbb{E}[Y^q] t^{-q} \leq \inf_{\lambda > 0} \mathbb{E}[\exp \lambda(Y - t)]$$

Solution : We denote $m := \min_q \mathbb{E}[Y^q] t^{-q}$. In particular, we have that for any integer q , $\mathbb{E}[Y^q] \geq m \cdot t^q$. We will now fix a $\lambda > 0$. We have :

$$\begin{aligned}
\mathbb{E}[\exp \lambda(Y - t)] &= e^{-\lambda t} \mathbb{E} \left[\sum_{q=0}^{\infty} \frac{(\lambda Y)^q}{q!} \right] \\
&\stackrel{\text{(Fubini-Tonelli)}}{=} e^{-\lambda t} \sum_{q=0}^{\infty} \frac{(\lambda^q \mathbb{E}[Y^q])}{q!} \\
&\geq e^{-\lambda t} \sum_{q=0}^{\infty} \frac{(\lambda^q \cdot m \cdot t^q)}{q!} \\
&= m \cdot e^{-\lambda t} \sum_{q=0}^{\infty} \frac{(\lambda^q t^q)}{q!} \\
&= m \cdot e^{-\lambda t} \cdot e^{\lambda t} \\
&= m
\end{aligned}$$

\square

Exercise 2.6

Let Z be a real-valued random variable. Show that the set of positive numbers $S = \{\lambda > 0 : \mathbb{E}[e^{\lambda Z}] < \infty\}$ is either empty or an interval with left end point equal to 0. Let $b = \sup S$. Show that $\varphi_Z(\lambda) = \log \mathbb{E}[e^{\lambda Z}]$ is convex and infinitely many times differentiable on $I = (0, b)$ with $\varphi'_Z(0) = \varphi_Z(0) = 0$ and the Cramér transform of Z equals $\varphi_Z^* = \sup_{\lambda \in I} (\lambda t - \varphi_Z(\lambda))$

Solution : We start with the first claim, we are going to prove that:

$$\text{For any } 0 < \lambda < \mu, \quad \mu \in S \implies \lambda \in S$$

This will prove that S is either empty or an interval with left end point equal to 0. Let $0 < \lambda < \mu$ with $\mu \in S$. We have :

$$\begin{aligned} \mathbb{E}[e^{\lambda Z}] &= \mathbb{E}[e^{\lambda Z} \mathbb{I}_{Z \leq 0} + e^{\lambda Z} \mathbb{I}_{Z > 0}] \\ &= \mathbb{E}[1 \cdot \mathbb{I}_{Z \leq 0}] + \mathbb{E}[e^{\mu Z}] \\ &< \infty \end{aligned}$$

Now for the differentiability, let $0 < \alpha < \beta < b$, $\lambda \in (\alpha, \beta)$ and $k \in \mathbb{N}$. We have :

$$\frac{d^k}{d\lambda} e^{\lambda Z} = Z^k e^{\lambda Z}$$

To prove the differentiability of φ on (α, β) , it is enough to provide a domination of $\frac{d^k}{d\lambda}$ on (α, β) . We have :

$$\begin{aligned} |Z^k e^{\lambda Z}| &\leq |Z|^k e^{\lambda Z} \mathbb{I}_{Z \leq 0} + |Z|^k e^{\lambda Z} \mathbb{I}_{Z > 0} \\ &\leq |Z|^k e^{\alpha Z} \mathbb{I}_{Z \leq 0} + (|Z|^k \cdot e^{-\frac{b-\beta}{2} Z})(e^{\frac{b+\beta}{2} Z} \mathbb{I}_{Z > 0}) \end{aligned}$$

The left term is integrable because it is bounded and the right term is integrable as the product of a bounded function and an integrable function. Now since $\mathbb{E}[e^{\lambda Z} > 0]$ on S , we have proven that φ is infinitely differentiable on I .

To prove convexity, we use the previous result and compute the 2nd order derivative of φ . For any $\lambda \in I$:

$$\begin{aligned} \varphi'(\lambda) &= \frac{\mathbb{E}[Z e^{\lambda Z}]}{\mathbb{E}[e^{\lambda Z}]} \\ \varphi'' &= \frac{\mathbb{E}[Z^2 e^{\lambda Z}] \cdot \mathbb{E}[e^{\lambda Z}] - \mathbb{E}[Z e^{\lambda Z}]^2}{\mathbb{E}[e^{\lambda Z}]^2} \stackrel{(C.S)}{\geq} 0 \end{aligned}$$

Where the second inequality comes from Cauchy-Schwarz Inequality. This proves the convexity of φ .

To finish the exercise, it remains to study the case in which the expectation of Z is 0. To prove that φ is continuously differentiable on $[0, b)$, we simply need to verify that its derivative has a right limit in 0. It is clear that $Ze^{\lambda Z} \xrightarrow{\lambda \rightarrow 0} Z$. Then :

$$\begin{aligned}\mathbb{E} [Ze^{\lambda Z}] &= \mathbb{E} [Ze^{\lambda Z} \mathbb{I}_{Z \leq 0}] + \mathbb{E} [Ze^{\lambda Z} \mathbb{I}_{Z > 0}] \\ &\xrightarrow{\lambda \rightarrow 0} \mathbb{E} [Z \mathbb{I}_{Z \leq 0}] + \mathbb{E} [Z \mathbb{I}_{Z > 0}] = \mathbb{E} [Z] = 0\end{aligned}$$

Where the left expectation converges because of dominated convergence and the right one because of monotonic convergence. We have proven continuous differentiability of φ on $[0, b)$ and that $\varphi(0) = \varphi'(0) = 0$. \square

Exercise 2.7

Prove that if Z is a centered normal random variable with variance σ^2 , then

$$\sup_{t>0} \left(\mathbb{P} [Z \geq t] \exp \frac{t^2}{2\sigma^2} \right) = \frac{1}{2}$$

Solution : Without loss of generality, we assume that $\sigma = 1$. Let $t > 0$, we have

$$\begin{aligned}\mathbb{P} [Z \geq t] &= \int_t^{+\infty} \frac{1}{\sqrt{2\pi}} \exp -\frac{u^2}{2} du \\ &= \int_0^{+\infty} \frac{1}{\sqrt{2\pi}} \exp -\frac{(u+t)^2}{2} du \\ &= \exp -\frac{t^2}{2} \cdot \int_0^{\infty} \frac{1}{\sqrt{2\pi}} \exp (-ut) \exp (-\frac{u^2}{2}) du \\ \mathbb{P} [Z \geq t] \cdot \exp \left(\frac{t^2}{2} \right) &= \int_0^{\infty} \frac{1}{\sqrt{2\pi}} \exp (-ut) \exp (-\frac{u^2}{2}) du\end{aligned}$$

Then we notice that $\exp(-ut) \xrightarrow{t \rightarrow \infty} 1$ pointwise. More importantly it converges in an increasing manner and since everything inside the integral is nonnegative, we can use the monotone convergence theorem to conclude

that :

$$\begin{aligned}
\sup_{t>0} \mathbb{P}[Z \geq t] \cdot \exp\left(\frac{t^2}{2}\right) &= \sup_{t>0} \int_0^{+\infty} \frac{1}{\sqrt{2\pi}} \exp(-ut) \exp\left(-\frac{u^2}{2}\right) du \\
&= \lim_{t \rightarrow \infty} \int_0^{+\infty} \frac{1}{\sqrt{2\pi}} \exp(-ut) \exp\left(-\frac{u^2}{2}\right) du \\
&= \int_0^{+\infty} \lim_{t \rightarrow \infty} \frac{1}{\sqrt{2\pi}} \exp(-ut) \exp\left(-\frac{u^2}{2}\right) du \\
&= \int_0^{+\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{u^2}{2}\right) du = \frac{1}{2}
\end{aligned}$$

□

Exercise 2.9 (SUB-GAUSSIAN LOWER TAIL FOR NONNEGATIVE RANDOM VARIABLES)

Let X be a nonnegative random variable with finite second moment. Show that for any $\lambda > 0$, $\mathbb{E}[e^{-\lambda(X - \mathbb{E}[X])}] \leq e^{\lambda^2 \mathbb{E}[X^2]/2}$. In particular, if X_1, \dots, X_n are independent nonnegative random variables, then for any $t \geq 0$,

$$\mathbb{P}[S \leq -t] \leq \exp\left(-\frac{t^2}{v}\right)$$

where $S = \sum_{i=1}^n (X_i - \mathbb{E}[X_i])$ and $v = \sum_{i=1}^n \mathbb{E}[X_i^2]$

Solution : We have the following elementary inequalities :

$$\begin{aligned}
\forall x \geq 0, \exp -x &\leq 1 - x + \frac{x^2}{2} \\
\forall x \in \mathbb{R}, 1 + x &\leq \exp x
\end{aligned}$$

Using this we get :

$$\begin{aligned}
\mathbb{E}[e^{-\lambda(X - \mathbb{E}[X])}] &= e^{\lambda \mathbb{E}[X]} \cdot \mathbb{E}[e^{-\lambda X}] \\
&\leq e^{\lambda \mathbb{E}[X]} \cdot \mathbb{E}\left[1 - \lambda X + \frac{\lambda^2 X^2}{2}\right] \\
&\leq e^{\lambda \mathbb{E}[X]} \cdot \left(1 + \left(-\lambda \mathbb{E}[X] + \frac{\lambda^2}{2} \mathbb{E}[X^2]\right)\right) \\
&\leq e^{\lambda \mathbb{E}[X]} \cdot e^{-\lambda \mathbb{E}[X] + \frac{\lambda^2}{2} \mathbb{E}[X^2]} \\
&= e^{\lambda^2 \mathbb{E}[X^2]/2}
\end{aligned}$$

□

Exercise 2.16

Prove that if X is a sub-Gaussian random variable with variance factor v then $\text{Var}(X) \leq v$.

Solution : We define $\phi(\lambda) := \log \mathbb{E} [e^{\lambda X}]$ the log moment generating function of X . The subgaussian condition can be written as

$$\forall \lambda \in \mathbb{R}, \phi(\lambda) \leq \frac{\lambda^2 v}{2}$$

We also have that $\phi(0) = \phi'(0)$ and $\phi''(0) = \text{Var}(X)$ we can now use a Taylor expansion around 0 to get the following result :

$$\begin{aligned} 0 &\leq \frac{\lambda^2 v}{2} - \phi(\lambda) \\ &= \frac{\lambda^2}{2} \cdot (v - \text{Var}(X)) + o(\lambda^2) \\ &\sim \frac{\lambda^2 v}{2} \cdot (v - \text{Var}(X)) \end{aligned}$$

This is only possible if $\text{Var}(X) \leq v$

□

Bibliography