67939 - Topics in Learning Theory **(Due: 16/06/24)**

Exercise 1

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Exercise 1

The moment generating function (MGF) of a random variable X is $M_X(\lambda) = \mathbb{E}[e^{\lambda X}]$. Assume that M_X is defined for any λ in a non-empty segment $(-a, a)$. Show that

1. $M_X^{(k)}(0) = \mathbb{E}[X^k]$

   Using the definition of the moment-generating function, we can write:

$$M_X^{(k)}(t) = \frac{d^k}{d\lambda^k}\mathbb{E}[e^{\lambda X}]$$

   Using the power series expansion of the exponential function

$$e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$$

   we can write

$$M_X^{(k)}(t) = \frac{d^k}{d\lambda^k}\mathbb{E}\left(\sum_{m=0}^{\infty} \frac{\lambda^m X^m}{m!}\right)$$

   Because the expected value is a linear operator, we have:

$$M_X^{(k)}(t) = \frac{d^k}{d\lambda^k}\sum_{m=0}^{\infty} \mathbb{E}\left(\frac{\lambda^m X^m}{m!}\right) = \sum_{m=0}^{\infty} \frac{d^k}{d\lambda^k}\left(\frac{\lambda^m}{m!}\right)\mathbb{E}[X^m]$$

   Using the k-th derivative of the m-th power

$$\frac{d^k}{d\lambda^k}\lambda^m = \begin{cases} \tilde{m}^k \lambda^{m-k}, & \text{if } k \le m \\ 0, & \text{if } k > m \end{cases}$$

   when

$$\tilde{m}^k = \prod_{i=0}^{k-1}(m-i) = \frac{m!}{(m-k)!}$$

   then we have

$$\begin{aligned} M_X^{(k)}(\lambda) &= \sum_{m=0}^{\infty} \frac{d^k}{d\lambda^k}\left(\frac{\lambda^m}{m!}\right)\mathbb{E}[X^m] = \sum_{m=k}^{\infty} \frac{\tilde{m^k}\lambda^{m-k}}{m!}\mathbb{E}[X^m] = \sum_{m=k}^{\infty} \frac{m!\lambda^{m-k}}{(m-k)!m!}\mathbb{E}[X^m] \\ &= \sum_{m=k}^{\infty} \frac{\lambda^{m-k}}{(m-k)!}\mathbb{E}[X^m] = \frac{t^{n-n}}{(n-n)!}\mathbb{E}[X^n] + \sum_{m=k+1}^{\infty} \frac{\lambda^{m-k}}{(m-k)!}\mathbb{E}[X^m] \\ &= \mathbb{E}[X^k] + \sum_{m=k+1}^{\infty} \frac{\lambda^{m-k}}{(m-k)!}\mathbb{E}[X^m] \end{aligned}$$

   Setting $\lambda = 0$ in the above equation, we get

$$M_X^{(k)}(0) = \mathbb{E}[X^k] + \sum_{m=k+1}^{\infty} \frac{0^{m-k}}{(m-k)!}\mathbb{E}[X^m] = \mathbb{E}[X^k]$$

   which completes the proof.

2. Show that for a centered Gaussian X with variance σ^2, $M_X(\lambda) = e^{\frac{\lambda^2\sigma^2}{2}}$. In other words, being σ-SubGaussian is equivalent to having MGF that is bounded by the MGF of a centered Gaussian with variance σ^2.

   Let X be a centered Gaussian random variable with mean $\mathbb{E}[X] = 0$ and variance $\text{var}(X) = \sigma^2$. The moment generating function (MGF) of X is defined as:

$$M_X(\lambda) = \mathbb{E}[e^{\lambda X}].$$

   Since X is Gaussian, X has the probability density function:

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

   Therefore, the MGF $M_X(\lambda)$ is:

$$M_X(\lambda) = \int_{-\infty}^{\infty} e^{\lambda x} f_X(x)\, dx = \int_{-\infty}^{\infty} e^{\lambda x} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}\, dx$$

   Combining the exponents, we get:

$$M_X(\lambda) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\lambda x - \frac{x^2}{2\sigma^2}}\, dx$$

   Completing the square in the exponent:

$$\lambda x - \frac{x^2}{2\sigma^2} = -\frac{1}{2\sigma^2}\left(x^2 - 2\sigma^2\lambda x\right) = -\frac{1}{2\sigma^2}\left(x^2 - 2\sigma^2\lambda x + \sigma^4\lambda^2 - \sigma^4\lambda^2\right) = -\frac{1}{2\sigma^2}\left((x-\sigma^2\lambda)^2 - \sigma^4\lambda^2\right).$$

   Thus, the integral becomes:

$$M_X(\lambda) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\sigma^2\lambda)^2} e^{\frac{\sigma^2\lambda^2}{2}}\, dx$$

   Since the first term inside the integral is a normal distribution that integrates to 1, we get:

$$M_X(\lambda) = e^{\frac{\sigma^2\lambda^2}{2}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\sigma^2\lambda)^2}\, dx = e^{\frac{\sigma^2\lambda^2}{2}}$$

   Therefore, the MGF of X is:

$$M_X(\lambda) = e^{\frac{\lambda^2\sigma^2}{2}}$$

   This shows that being σ-SubGaussian is equivalent to having an MGF that is bounded by the MGF of a centered Gaussian with variance σ^2.

3. Show that if X is uniform over $[a, b]$ then $M_X(\lambda) = \frac{e^{\lambda b} - e^{\lambda a}}{\lambda(b-a)}$.

   Let X be a random variable uniformly distributed over the interval $[a, b]$. The probability density function of X is:

$$f_X(x) = \frac{1}{b-a}, \quad \text{for } a \leq x \leq b$$

   The moment generating function (MGF) of X is defined as:

$$M_X(\lambda) = \mathbb{E}[e^{\lambda X}] = \int_a^b e^{\lambda x} f_X(x)\, dx$$

   Substituting the PDF of X:

$$M_X(\lambda) = \int_a^b e^{\lambda x} \frac{1}{b-a}\, dx$$

   Since $\frac{1}{b-a}$ is a constant, we can factor it out:

$$M_X(\lambda) = \frac{1}{b-a} \int_a^b e^{\lambda x}\, dx$$

   To solve the integral, we use the antiderivative of $e^{\lambda x}$:

$$\int e^{\lambda x}\, dx = \frac{1}{\lambda} e^{\lambda x} + C$$

   Evaluating this from a to b, we get:

$$\int_a^b e^{\lambda x}\, dx = \frac{1}{\lambda} e^{\lambda x} + C \Big|_a^b = \frac{1}{\lambda}\left(e^{\lambda b} - e^{\lambda a}\right).$$

   Therefore,

$$M_X(\lambda) = \frac{1}{b-a} \cdot \frac{1}{\lambda}\left(e^{\lambda b} - e^{\lambda a}\right) = \frac{e^{\lambda b} - e^{\lambda a}}{\lambda(b-a)}.$$

   This completes the proof that the moment generating function of a uniform random variable over $[a, b]$ is:

$$M_X(\lambda) = \frac{e^{\lambda b} - e^{\lambda a}}{\lambda(b-a)}$$

Exercise 2

1. Show that if X_i is σ_i-SubGaussian for $i = 1, 2$ then $X_1 + X_2$ is $(\sigma_1 + \sigma_2)$-SubGaussian [1].

   Let X_1 and X_2 be σ_1-SubGaussian and σ_2-SubGaussian random variables, respectively. This means that for any $\lambda \in \mathbb{R}$,

$$\mathbb{E}\left[e^{\lambda(X_1-\mathbb{E}[X_1])}\right] \leq e^{\frac{\lambda^2\sigma_1^2}{2}} \quad \text{and} \quad \mathbb{E}\left[e^{\lambda(X_2-\mathbb{E}[X_2])}\right] \leq e^{\frac{\lambda^2\sigma_2^2}{2}}$$

   We need to show that $X_1 + X_2$ is $(\sigma_1 + \sigma_2)$-SubGaussian, i.e.,

$$\mathbb{E}\left[e^{\lambda(X_1+X_2-\mathbb{E}[X_1+X_2])}\right] \leq e^{\frac{\lambda^2(\sigma_1+\sigma_2)^2}{2}}$$

   Consider the expectation:

$$\mathbb{E}\left[e^{\lambda(X_1+X_2-\mathbb{E}[X_1]-\mathbb{E}[X_2])}\right] = \mathbb{E}\left[e^{\lambda(X_1-\mathbb{E}[X_1])}e^{\lambda(X_2-\mathbb{E}[X_2])}\right]$$

   Using Hölder's inequality with $p = q = 2$ (since $\frac{1}{p} + \frac{1}{q} = 1$ and $p, q \geq 0$), we get:

$$\mathbb{E}\left[e^{\lambda(X_1-\mathbb{E}[X_1])}e^{\lambda(X_2-\mathbb{E}[X_2])}\right] \leq \left(\mathbb{E}\left[e^{2\lambda(X_1-\mathbb{E}[X_1])}\right]\right)^{1/2}\left(\mathbb{E}\left[e^{2\lambda(X_2-\mathbb{E}[X_2])}\right]\right)^{1/2}$$

   Since X_1 is σ_1-SubGaussian and X_2 is σ_2-SubGaussian, we have:

$$\mathbb{E}\left[e^{2\lambda(X_1-\mathbb{E}[X_1])}\right] \leq e^{2\lambda^2\sigma_1^2} \quad \text{and} \quad \mathbb{E}\left[e^{2\lambda(X_2-\mathbb{E}[X_2])}\right] \leq e^{2\lambda^2\sigma_2^2}$$

   Therefore,

$$\mathbb{E}\left[e^{\lambda(X_1+X_2-\mathbb{E}[X_1+X_2])}\right] \leq \left(e^{2\lambda^2\sigma_1^2}\right)^{1/2}\left(e^{2\lambda^2\sigma_2^2}\right)^{1/2} = e^{\lambda^2\sigma_1^2}e^{\lambda^2\sigma_2^2} = e^{\lambda^2(\sigma_1^2+\sigma_2^2)}.$$

   To show that $X_1 + X_2$ is $(\sigma_1 + \sigma_2)$-SubGaussian, we use the triangle inequality for the variance:

$$\sigma_1^2 + \sigma_2^2 \leq (\sigma_1 + \sigma_2)^2$$

   Thus,

$$\mathbb{E}\left[e^{\lambda(X_1+X_2-\mathbb{E}[X_1+X_2])}\right] \leq e^{\lambda^2(\sigma_1+\sigma_2)^2}.$$

   Hence, $X_1 + X_2$ is $(\sigma_1 + \sigma_2)$-SubGaussian.

[1] Use the Hölder inequality ($\mathbb{E}[XY] \leq (\mathbb{E}[X^p])^{1/p}(\mathbb{E}[Y^q])^{1/q}$ if $\frac{1}{p} + \frac{1}{q} = 1$ and $p, q \geq 0$) on $\mathbb{E}[e^{\lambda(X-\mathbb{E}[X])}e^{\lambda(Y-\mathbb{E}[Y])}]$

2. For a sub-Gaussian random variable X, define $\|X\|_{vp}$ as the minimal σ for which X is σ-SubGaussian. Show that $\|\cdot\|_{vp}$ is a norm on the space of centered sub-Gaussian random variables. This norm is called the Proxy Variance norm and $\|X\|_{vp}$ is called the optimal proxy variance of X.

To show that $\|\cdot\|_{vp}$ is a norm, we need to verify the following properties for all centered sub-Gaussian random variables X and Y:

(a) **Positivity**: $\|X\|_{vp} \geq 0$ and $\|X\|_{vp} = 0$ if and only if $X = 0$ almost surely.
(b) **Homogeneity**: $\|aX\|_{vp} = |a|\|X\|_{vp}$.
(c) **Triangle Inequality**: $\|X + Y\|_{vp} \leq \|X\|_{vp} + \|Y\|_{vp}$.

Positivity By definition, $\|X\|_{vp}$ is the minimal σ such that X is σ-SubGaussian.

Since the variance of X is non-negative, σ must also be non-negative. Therefore, $\|X\|_{vp} \geq 0$.

If $X = 0$ almost surely, then X is deterministically zero, meaning it has no variability and does not deviate from its mean. Therefore, it is trivially σ-SubGaussian for any σ, and hence $\|X\|_{vp} = 0$.

Conversely, if $\|X\|_{vp} = 0$, then by definition, for all $\lambda \in \mathbb{R}$,

$$\mathbb{E}\left[e^{\lambda X}\right] \leq e^{\frac{\lambda^2 \cdot 0^2}{2}} = 1$$

The moment generating function of X, $\mathbb{E}\left[e^{\lambda X}\right]$, being less than or equal to 1 for all λ implies that X must be zero almost surely. This is because the only random variable with this property is the constant zero. If X had any non-zero value with non-zero probability, the expectation $\mathbb{E}\left[e^{\lambda X}\right]$ would exceed 1 for some λ. Hence, $\|X\|_{vp} = 0$ implies that $X = 0$ almost surely.

Homogeneity Let $a \in \mathbb{R}$ and X be a centered sub-Gaussian random variable. We need to show that $\|aX\|_{vp} = |a|\|X\|_{vp}$.

Step 1: $\|aX\|_{vp} \leq |a|\|X\|_{vp}$

Assume $\|X\|_{vp} = \sigma$. This means that for all $\lambda \in \mathbb{R}$,

$$\mathbb{E}\left[e^{\lambda X}\right] \leq e^{\frac{\lambda^2 \sigma^2}{2}}$$

We need to show that aX is $|a|\sigma$-SubGaussian. Consider the moment generating function of aX:

$$\mathbb{E}\left[e^{\lambda(aX)}\right] = \mathbb{E}\left[e^{a\lambda X}\right]$$

Using the sub-Gaussian property of X and the fact that a is a constant and $a\lambda$ spans that same range as λ, we have:

$$\mathbb{E}\left[e^{a\lambda X}\right] \leq e^{\frac{(a\lambda)^2\sigma^2}{2}} = e^{\frac{\lambda^2 a^2 \sigma^2}{2}} = e^{\frac{\lambda^2(|a|\sigma)^2}{2}}$$

This shows that aX is $|a|\sigma$-SubGaussian. Therefore, $\|aX\|_{vp} \leq |a|\|X\|_{vp}$.

Step 2: $\|aX\|_{vp} \geq |a|\|X\|_{vp}$

If $a = 0$, then $aX = 0$ almost surely, and $\|aX\|_{vp} = 0 = |a|\|X\|_{vp}$.

Otherwise, Assume aX is τ-SubGaussian for some $\tau \geq 0$. This means that for all $\lambda \in \mathbb{R}$,

$$\mathbb{E}\left[e^{\lambda(aX)}\right] \leq e^{\frac{\lambda^2\tau^2}{2}}.$$

Consider $\lambda' = \frac{\lambda}{a}$:

$$\mathbb{E}\left[e^{\lambda X}\right] = \mathbb{E}\left[e^{\lambda' aX}\right] \leq e^{\frac{(\lambda')^2\tau^2}{2}} = e^{\frac{\lambda^2\tau^2}{2a^2}}$$

By the definition of the sub-Gaussian property of X, we must have:

$$\frac{\tau^2}{a^2} \geq \sigma^2 \quad \Rightarrow \quad \tau \geq |a|\sigma.$$

Therefore, $\|aX\|_{vp} \geq |a|\|X\|_{vp}$.

Combining both steps, we have shown that $\|aX\|_{vp} = |a|\|X\|_{vp}$.

Triangle Inequality Let X and Y be centered sub-Gaussian random variables with $\|X\|_{vp} = \sigma_X$ and $\|Y\|_{vp} = \sigma_Y$.

From Exercise 2.1, we know that if X is σ_X-SubGaussian and Y is σ_Y-SubGaussian, then $X + Y$ is $(\sigma_X + \sigma_Y)$-SubGaussian. Therefore, the proxy variance norm satisfies the triangle inequality:

$$
\begin{aligned}
&\mathbb{E}\left[e^{\lambda(X+Y)}\right] \leq e^{\frac{\lambda^2(\sigma_X+\sigma_Y)^2}{2}} \Rightarrow \\
&\|X+Y\|_{vp} := \min\{\sigma \mid \forall\lambda \in \mathbb{R}, \quad \mathbb{E}\left[e^{\lambda(X+Y)}\right] \leq e^{\frac{\lambda^2\sigma^2}{2}}\} \leq \sigma_X + \sigma_Y \Rightarrow \\
&\|X+Y\|_{vp} \leq \|X\|_{vp} + \|Y\|_{vp}
\end{aligned}
$$

Since the Proxy Variance operator $\|\cdot\|_{vp}$ satisfies positivity, homogeneity, and the triangle inequality, it is a norm on the space of centered sub-Gaussian random variables.

Exercise 3

1. Let X be a σ-SubGaussian random variable. Show that [2] $\sigma \geq \sqrt{\text{var}(X)}$.

Let $Y = X - \mathbb{E}[X]$. Note that Y is a centered random variable, i.e., $\mathbb{E}[Y] = 0$, and since X is σ-SubGaussian, Y is also σ-SubGaussian. This is because the sub-Gaussian property is invariant under shifts by the mean. Hence,

$$\mathbb{E}\left[e^{\lambda Y}\right] \leq e^{\frac{\lambda^2\sigma^2}{2}} \quad \text{for all } \lambda \in \mathbb{R}.$$

Define the function $f(\lambda) = \mathbb{E}[e^{\lambda Y}]$ and $g(\lambda) = e^{\frac{\lambda^2\sigma^2}{2}}$.

We need to show that:

$$\sqrt{\text{var}(X)} \leq \sigma.$$

To do this, consider the Taylor expansions of $f(\lambda)$ and $g(\lambda)$ around $\lambda = 0$.

The Taylor expansions of $f(\lambda)$ and $g(\lambda)$ are:

$$f(\lambda) = f(0) + f'(0)\lambda + \frac{f''(0)}{2}\lambda^2 + O(\lambda^3)$$
$$g(\lambda) = g(0) + g'(0)\lambda + \frac{g''(0)}{2}\lambda^2 + O(\lambda^3)$$

Now, calculate the derivatives at $\lambda = 0$, utilizing the result from question 1.1:

$$f(0) = \mathbb{E}[e^0] = 1$$
$$f'(0) = \frac{d}{d\lambda}\mathbb{E}[e^{\lambda Y}]\Big|_{\lambda=0} \overset{1.1}{=} \mathbb{E}[Y] = 0$$
$$f''(0) = \frac{d^2}{d\lambda^2}\mathbb{E}[e^{\lambda Y}]\Big|_{\lambda=0} = \mathbb{E}[Y^2] = \text{var}(Y) \overset{\text{Shifting R.V by constant}}{=} \text{var}(X)$$
$$g(0) = e^0 = 1$$
$$g'(0) = \frac{d}{d\lambda}e^{\frac{\lambda^2\sigma^2}{2}}\Big|_{\lambda=0} = \lambda\sigma^2 e^{\frac{\lambda^2\sigma^2}{2}}\Big|_{\lambda=0} = 0$$
$$g''(0) = \frac{d^2}{d\lambda^2}e^{\frac{\lambda^2\sigma^2}{2}}\Big|_{\lambda=0} = \frac{d}{d\lambda}\left(\lambda\sigma^2 e^{\frac{\lambda^2\sigma^2}{2}}\right)\Big|_{\lambda=0} = \sigma^2 e^{\frac{\lambda^2\sigma^2}{2}} + \lambda\sigma^2\left(\sigma^2 e^{\frac{\lambda^2\sigma^2}{2}}\right)\Big|_{\lambda=0} = \sigma^2$$

From the given hint, since $f(0) = g(0)$, $f'(0) = g'(0)$, and $f(\lambda) \leq g(\lambda)$ for all $\lambda \in \mathbb{R}$, we have:

$$f''(0) \leq g''(0).$$

Therefore,

$$\text{var}(X) \leq \sigma^2.$$

Taking the square root of both sides, we get:

$$\sqrt{\text{var}(X)} \leq \sigma.$$

This completes the proof.

[2]Hint: You can use the fact that for twice differentiable f and g, we have that if $f(0) = g(0)$, $f'(0) = g'(0)$ and $f(x) \leq g(x)$ then $f''(0) \leq g''(0)$

2. If $\|X\|_{vp} = \sqrt{\mathrm{var}(X)}$, then X is called strictly sub-Gaussian. Show that if X is uniform on $\{-1, 1\}$, then it is strictly sub-Gaussian. Conclude that the bound in Hoeffding's lemma is optimal.

First, let's show that if X is uniform on $\{-1, 1\}$, then it is strictly sub-Gaussian.
Given X is uniform on $\{-1, 1\}$, the probability mass function is:

$$\mathbb{P}(X = -1) = \mathbb{P}(X = 1) = \frac{1}{2}.$$

The mean and variance of X are:

$$\mathbb{E}[X] = 0, \quad \mathrm{var}(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2 = 1.$$

The moment generating function (MGF) of X is:

$$M_X(\lambda) = \mathbb{E}[e^{\lambda X}] = \frac{1}{2}e^{\lambda} + \frac{1}{2}e^{-\lambda} = \cosh(\lambda).$$

For X to be σ-SubGaussian, we need for all $\lambda \in \mathbb{R}$:

$$\cosh(\lambda) \le e^{\frac{\lambda^2\sigma^2}{2}}.$$

For this inequality to hold for all λ, we need to equate the exponents on both sides. Consider $\lambda = 0$:

$$\cosh(0) = e^0 = 1.$$

Next, consider the general case for $\lambda \neq 0$. Use the Taylor series expansions to equate terms:
1. The Taylor series expansion for $\cosh(\lambda)$ is:

$$\cosh(\lambda) = 1 + \frac{\lambda^2}{2!} + \frac{\lambda^4}{4!} + \cdots.$$

2. The Taylor series expansion for $e^{\frac{\lambda^2\sigma^2}{2}}$ is:

$$e^{\frac{\lambda^2\sigma^2}{2}} = 1 + \frac{\lambda^2\sigma^2}{2!} + \frac{(\lambda^2\sigma^2)^2}{4!} + \cdots.$$

For the series to be equal for all λ, each term in the expansion must match. Let's equate the coefficients of λ^2:

$$\frac{\lambda^2}{2} = \frac{\lambda^2\sigma^2}{2}.$$

Solving for σ:

$$\frac{1}{2} = \frac{\sigma^2}{2} \quad \Rightarrow \quad \sigma^2 = 1 \quad \Rightarrow \quad \sigma = 1.$$

Therefore, the equality $(*)$:

$$\frac{e^{\lambda} + e^{-\lambda}}{2} = e^{\frac{\lambda^2\sigma^2}{2}}$$

holds for all λ if and only if $\sigma = 1$.
Thus, X is strictly sub-Gaussian with $\sigma = 1$, meaning $\|X\|_{vp} = \sqrt{\mathrm{var}(X)} = 1$. This shows that if X is uniform on $\{-1, 1\}$, then it is strictly sub-Gaussian.
Let $a \le X \le b$ be a random variable. Hoeffding's lemma states that X is $\frac{(a-b)}{2}$-SubGaussian, i.e., for all $\lambda \in \mathbb{R}$,

$$\mathbb{E}\left[e^{\lambda(X - \mathbb{E}[X])}\right] \le e^{\frac{\lambda^2(b-a)^2}{8}}.$$

Lets substitute X to both sides of the inequality:
The left side becomes:

$$\mathbb{E}\left[e^{\lambda(X - \mathbb{E}[X])}\right] = \mathbb{E}\left[e^{\lambda X}\right] = cosh(\lambda)$$

The right side becomes:

$$e^{\frac{\lambda^2(b-a)^2}{8}} = e^{\frac{\lambda^2(1-(-1))^2}{8}} = e^{\frac{\lambda^2 4}{8}} = e^{\frac{\lambda^2(\mathrm{Var}(X))}{2}}$$

and we have seen in $(*)$ a case where the inequality holds with equality. Therefore, the bound in Hoeffding's lemma is optimal.

3. Show that a linear combination of independent strictly sub-Gaussians is strictly sub-Gaussian.

Let $X_1, X_2, \ldots, X_n$ be independent strictly sub-Gaussian random variables, and let $a_1, a_2, \ldots, a_n$ be real coefficients. We need to show that the linear combination $Y = \sum_{i=1}^n a_i X_i$ is strictly sub-Gaussian.

Since X_i are strictly sub-Gaussian, we have $\|X_i\|_{vp} = \sqrt{\text{var}(X_i)}$ for all i. By definition, this means that for each X_i,

$$\mathbb{E}[e^{\lambda X_i}] \le e^{\frac{\lambda^2 \text{var}(X_i)}{2}} \quad \text{for all } \lambda \in \mathbb{R}$$

Because the X_i are independent, the moment generating function (MGF) of their linear combination Y is:

$$M_Y(\lambda) = \mathbb{E}[e^{\lambda Y}] = \mathbb{E}\left[e^{\lambda \sum_{i=1}^n a_i X_i}\right] = \mathbb{E}\left[e^{\sum_{i=1}^n \lambda a_i X_i}\right] = \mathbb{E}\left[\prod_{i=1}^n e^{\lambda a_i X_i}\right] \overset{independency}{=} \prod_{i=1}^n \mathbb{E}\left[e^{\lambda a_i X_i}\right].$$

For each X_i, since it is strictly sub-Gaussian, we have:

$$\mathbb{E}\left[e^{\lambda a_i X_i}\right] \le e^{\frac{\lambda^2 a_i^2 \text{var}(X_i)}{2}}$$

Therefore,

$$M_Y(\lambda) \le \prod_{i=1}^n e^{\frac{\lambda^2 a_i^2 \text{var}(X_i)}{2}} = e^{\frac{\lambda^2}{2} \sum_{i=1}^n a_i^2 \text{var}(X_i)}.$$

From question 1.1, being σ-SubGaussian is equivalent to having an MGF that is bounded by the MGF of a centered Gaussian with variance σ^2. Therefore, Y is sub-Gaussian with variance parameter $\sum_{i=1}^n a_i^2 \text{var}(X_i)$

Next, we need to show that Y is strictly sub-Gaussian. To do this, we calculate the variance of Y:

$$\text{var}(Y) = \text{var}\left(\sum_{i=1}^n a_i X_i\right)$$

Since the X_i are independent, the variance of their linear combination is:

$$\text{var}(Y) = \sum_{i=1}^n a_i^2 \text{var}(X_i).$$

Since we already showed that:

$$M_Y(\lambda) \le e^{\frac{\lambda^2 \text{var}(Y)}{2}},$$

we have:

$$\mathbb{E}[e^{\lambda Y}] \le e^{\frac{\lambda^2 \text{var}(Y)}{2}} \quad \text{for all } \lambda \in \mathbb{R}.$$

Therefore, the variance proxy norm of Y is:

$$\|Y\|_{vp} = \sqrt{\text{var}(Y)}.$$

Hence, Y is strictly sub-Gaussian.

4. Show that for any $M \geq 1$, there is a random variable X with $\text{var}(X) = 1$ and $\|X\|_{vp} = M$.

Exercise 4

Show that there is a universal constant $C > 0$ for which the following holds. If X is a random variable such that for any $t \geq 0$,

$$\Pr(X - \mathbb{E}[X] \geq t) \leq e^{-\frac{t^2}{2\sigma^2}} \quad \text{and} \quad \Pr(X - \mathbb{E}[X] \leq -t) \leq e^{-\frac{t^2}{2\sigma^2}}$$

then X is $(C\sigma)$-SubGaussian[3].

[3]Hint: You may use the fact that for a non-negative random variable Y, $\mathbb{E}[Y] = \int_0^\infty \Pr(Y \geq x)dx$