

Tail Inequalities (2)

SubExponential, Bernstein, McDiarmid, Levy

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Dec 2023

Outline

- 1 Subexponential random variables
- 2 Bernstein condition and inequality
- 3 McDiarmid's inequality and Levy's inequality

Subexponential random variable

A random variable X is $\text{SE}(\nu, \alpha)$ if $\mathbb{E}e^{\lambda(X-\mu)} \leq e^{\frac{\nu^2\lambda^2}{2}}$, $|\lambda| < 1/\alpha$.

Note that $\text{SG}(\sigma^2)$ random variable is subexponential with $\nu = \sigma$ and $\alpha = 0$.

Ex) Chi-square distribution

For $X \sim \chi^2(1)$, $X \in \text{SE}(\nu = 2, \alpha = 4)$.

pf) Note that $\mathbb{E}X = 1$. Let $Z \sim \text{N}(0, 1)$.

$$\begin{aligned}\mathbb{E}e^{X-1} &= \mathbb{E}e^{Z^2-1} = \int_{-\infty}^{\infty} e^{\lambda(z^2-1)} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz = e^{-\lambda} \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-(\frac{1}{2}-\lambda)z^2} dz \\ &= e^{-\lambda} \sigma \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{z^2}{2\sigma^2}} dz = e^{-\lambda\sigma} = e^{-\lambda} \frac{1}{\sqrt{1-2\lambda}},\end{aligned}$$

by choosing λ such that $1/2 - \lambda = 1/(2\sigma^2)$. $\sigma > 0 \iff \lambda < 1/2$.

Properties of subexponential random variable

Square of subGaussian is subexponential

Let X be zero-mean $\text{SG}(\sigma^2)$ random variable. Then, $X^2 \in \text{SE}(\nu = 16\sigma^2, \alpha = 16\sigma^2)$.

Subexponential tail bound

For $X \in \text{SE}(\nu, \alpha)$,

$$\mathbb{P}(|X - \mu| \geq t) \leq \begin{cases} 2e^{-t^2/(2\nu^2)} & \text{if } 0 \leq t \leq \nu^2/\alpha \\ 2e^{-t/(2\alpha)}, & \text{if } t > \nu^2/\alpha. \end{cases} \iff \mathbb{P}(|X - \mu| \geq t) \leq 2e^{-\frac{1}{2} \min(\frac{t}{\alpha}, \frac{t^2}{\nu^2})}.$$

Sum of independent subexponential random variables

Let X_1, \dots, X_n be independent $\text{SE}(\nu_i, \alpha_i)$ random variables. Then, for $\nu_* = \sqrt{\sum_{i=1}^n \nu_i^2}$ and $\alpha_* = \max_{i=1, \dots, n} \alpha_i$,

$$\sum_{i=1}^n (X_i - \mu_i) \in \text{SE}(\nu_*, \alpha_*)$$

$$\mathbb{P}\left(\frac{1}{n} \sum_{i=1}^n |X_i - \mu_i| \geq t\right) \leq \begin{cases} 2e^{-nt^2/(2\nu_*^2)} & \text{if } 0 \leq t \leq \nu_*^2/(n\alpha_*) \\ 2e^{-nt/(2\alpha_*)}, & \text{if } t > \nu_*^2/\alpha_*. \end{cases}$$

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Bernstein Condition

Suppose $|\mathbb{E}(X - \mu)^k| \leq \frac{1}{2} k! \sigma^2 b^{k-2}$, $k = 2, 3, \dots$. Then, X satisfies Bernstein condition with parameter b .
 Note that all bounded random variables $|X - \mu| \leq b$ satisfy this.

Bernstein implies subexponential

Let X satisfy Bernstein condition with parameter b . Then, Claim) $X \in \text{SE}(\sqrt{2}\sigma, 2b)$.

Pf)

$$\begin{aligned}
 \mathbb{E}e^{\lambda(X-\mu)} &= 1 + 0 + \frac{\lambda^2 \sigma^2}{2} + \sum_{k=3}^{\infty} \lambda^k \frac{\mathbb{E}(X - \mu)^k}{k!} \\
 &\leq 1 + \frac{\lambda^2 \sigma^2}{2} + \frac{\lambda^2 \sigma^2}{2} \sum_{k=3}^{\infty} (|\lambda| b)^{k-2} = 1 + \frac{\lambda^2 \sigma^2 / 2}{1 - b |\lambda|} \\
 &\leq e^{\frac{\lambda^2 \sigma^2 / 2}{1 - b |\lambda|}} \quad \because 1 + x \leq e^x, \forall x \in \mathbb{R} \\
 &\leq e^{\lambda^2 (\sqrt{2}\sigma)^2 / 2}.
 \end{aligned} \tag{1}$$

In expanding the geometric series, $|\lambda| < 1/b$ is assumed and the last inequality is based on the assumption of $|\lambda| < 1/(2b)$.

Bernstein type inequality

For X following Bernstein condition with parameter b ,

$$\begin{aligned}\mathbb{E}e^{\lambda(X-\mu)} &\leq e^{\frac{\lambda^2\sigma^2}{1-b|\lambda|}}, \quad \forall |\lambda| < 1/b, \\ \mathbb{P}(|X - \mu| \geq t) &\leq 2e^{-\frac{t^2}{2(\sigma^2+bt)}}, \quad t \geq 0.\end{aligned}\tag{2}$$

The first inequality is proven.

The second inequality is based on setting $\lambda = \frac{t}{bt+\sigma^2} \in [0, 1/b)$ in Chernoff bound.

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Bounded Difference Condition and McDiarmid's inequality

Bounded Difference Condition

For independent random variables X_1, \dots, X_n , the bounded difference condition denotes when $f : \mathbb{R}^n \rightarrow \mathbb{R}$ satisfies

$$|f(x_1, \dots, x_k, x_{k+1}, \dots, x_n) - f(x_1, \dots, x'_k, x_{k+1}, \dots, x_n)| \leq L_k, \quad \forall x, x' \in \mathbb{R}^n$$

McDiarmid's inequality

For random variables X_1, \dots, X_n , independent and satisfying bounded difference condition,

$$\mathbb{P}(|f(x_1, \dots, x_n) - \mathbb{E}f(x_1, \dots, x_n)| \geq t) \leq 2 \exp\left(-\frac{2t^2}{\sum_{i=1}^n L_k^2}\right).$$

The proof is quite involved.

Ex) Hoeffding's bound

Take $f(x) = \frac{1}{n} \sum_{i=1}^n x_i$ and each $X_i \in [a, b]$ almost surely. Then, $L_k = (b - a)/n$. Then,

$$\mathbb{P}\left(\frac{1}{n} \left| \sum_{i=1}^n (X_i - \mu_i) \right| \geq t\right) \leq 2 \exp\left(-\frac{2nt^2}{(b - a)^2}\right).$$

Levy's inequality: for Lipschitz smooth function of Gaussian random variable

Assume f satisfy

$$|f(x) - f(y)| \leq L\|x - y\|_2 \iff |f(x_1, \dots, x_n) - f(y_1, \dots, y_n)| \leq L\sqrt{\sum_{i=1}^n (x_i - y_i)^2}, \quad \forall x, y \in \mathbb{R}^n.$$

Further, if $X_1, \dots, X_n \stackrel{iid}{\sim} \mathcal{N}(0, 1)$,

$$\mathbb{P}(|f(x_1, \dots, x_n) - \mathbb{E}f(x_1, \dots, x_n)| \geq t) \leq 2\exp(-\frac{t^2}{2L^2}), \quad \forall t \geq 0.$$

Ex) Order statistic

Consider f as an order statistic (which is a function): $X_{(1)} \leq \dots \leq X_{(n)}$.

Then, for the iid sequence $Y_1, \dots, Y_n \stackrel{iid}{\sim} \mathcal{N}(0, 1)$,

$$|f(x_1, \dots, x_n) - f(y_1, \dots, y_n)| = |X_{(k)} - Y_{(k)}| \leq 1 \cdot \|X - Y\|_2, \quad \forall k = 1, \dots, n.$$

Therefore,

$$\mathbb{P}(|X_{(k)} - \mathbb{E}X_{(k)}| \geq t) \leq 2\exp(-\frac{t^2}{2}), \quad \forall t \geq 0.$$