

SDS 384 11: Theoretical Statistics

Lecture 4: Sub-gaussian and sub-exponential random variables

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Sub-Gaussian random variables

Theorem

For X_1, \dots, X_n independent sub-gaussian random variables with sub-gaussian parameters σ_i^2 and $E[X_i] = \mu_i$, for $\forall t > 0$,

$$P\left(\sum_i (X_i - \mu_i) \geq t\right) \leq e^{-\frac{t^2}{2\sum_i \sigma_i^2}}$$

- If $X_i \in [a, b]$, $E[X_i] = 0$, using Hoeffding's lemma we have:
 $\sigma_i^2 = (b - a)^2 / 4$.
- So, the above theorem immediately gives the original Hoeffding inequality back.

$$P\left(\sum_i X_i \geq t\right) \leq e^{-\frac{2t^2}{n(b-a)^2}}$$

Sub-exponential random variables

Definition

X is sub-exponential with parameters (ν, b) if, $\forall |\lambda| < 1/b$,

$$\log M_{X-\mu}(\lambda) \leq \frac{\lambda^2 \nu^2}{2}$$

Examples:

- Sub-Gaussian X with parameter σ^2 is sub-exponential with parameters $(\sigma^2, b) \forall b > 0$.
- How about the converse?

Sub-exponential but not sub-gaussian

Example

Let $Z \sim N(0, 1)$ and consider the random variable $X = Z^2$. For $\lambda < 1/2$, we have:

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Let $Z \sim N(0, 1)$ and consider the random variable $X = Z^2$. For $\lambda < 1/2$, we have:

$$\begin{aligned} E[e^{\lambda(X-1)}] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\lambda(z^2-1)} e^{-z^2/2} dz \\ &= e^{-\lambda} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-z^2(1-2\lambda)/2} dz \\ &= \frac{e^{-\lambda}}{\sqrt{1-2\lambda}} \\ &\leq e^{2\lambda^2} \quad \forall |\lambda| < 1/4 \end{aligned}$$

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The MGF is only defined for $\lambda < 1/2$. So this is a sub-exponential random variable with parameter $(2, 4)$, but not a sub-gaussian random variable.

Theorem

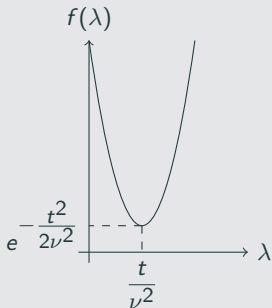
Let X be a sub-exponential random variable with parameters (ν, b) . Then,

$$P(X \geq \mu + t) \leq \begin{cases} e^{-\frac{t^2}{2\nu^2}} & \text{if } 0 \leq t \leq \frac{\nu^2}{b} \\ e^{-\frac{t}{2b}} & \text{if } t \geq \frac{\nu^2}{b} \end{cases}$$

- For small t this is sub-gaussian in nature, whereas for large t the exponent decays linearly with t .

Proof.

$$\begin{aligned}
 P(X \geq t) &\leq \inf_{\lambda \geq 0} e^{-\lambda t} E[e^{\lambda X}] \\
 &\leq \inf_{\lambda \geq 0} \underbrace{e^{-\lambda t + \lambda^2 \nu^2 / 2}}_{f(\lambda)} \quad \text{When } 0 \leq \lambda < 1/b
 \end{aligned}$$



- If $\frac{t}{\nu^2} \leq \frac{1}{b}$,

$$\inf_{\lambda \geq 0} f(\lambda) = f(t/\nu^2) = e^{-\frac{t^2}{2\nu^2}}$$

□

- If $\frac{t}{\nu^2} > \frac{1}{b}$, then $f(\lambda)$ is minimized at the boundary $\lambda' = 1/b$.

$$f(\lambda') = e^{-\lambda'/b + \lambda'^2 \nu^2 / 2} \leq e^{-\frac{t}{2b}}$$

A moment condition

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A random variable with mean μ and variance σ^2 satisfies the Bernstein condition with parameter $b > 0$, if $E[|X - \mu|^k] \leq \frac{1}{2} k! \sigma^2 b^{k-2}$ for $k \geq 2$.

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- A bounded random variable with $E[|X - \mu|] \leq b$ satisfies the above.

Bernstein's condition and the sub-exponential property

Theorem

If X ($E[X] = \mu$, $\text{var}(X) = \sigma^2$) satisfies the Bernstein condition with parameter $b > 0$, then X is sub-exponential with $(\sqrt{2}\sigma, 2b)$.

Proof.

$$\begin{aligned} E[e^{\lambda(X-\mu)}] &= \sum_{k=0}^{\infty} \frac{\lambda^k E[(X-\mu)^k]}{k!} \\ &= 1 + \frac{\lambda^2 \sigma^2}{2} + \sum_{k=3}^{\infty} \frac{|\lambda|^k \sigma^2 b^{k-2}}{2} \\ &= 1 + \frac{\lambda^2 \sigma^2}{2} \left(1 + \sum_{k=1}^{\infty} (|\lambda|b)^k \right) \\ &= 1 + \frac{\lambda^2 \sigma^2}{2(1 - |\lambda|b)} \quad \text{For } |\lambda| < 1/b \\ &\leq e^{\frac{\lambda^2 \sigma^2}{2(1 - |\lambda|b)}} \leq e^{\lambda^2 \sigma^2} = e^{\frac{\lambda^2 (\sqrt{2}\sigma)^2}{2}} \quad \text{For } |\lambda| < 1/2b \end{aligned}$$

Bernstein's inequality

Theorem

If X with mean μ and variance σ^2 satisfies the Bernstein condition with parameter $b > 0$, then

$$P(|X - \mu| \geq t) \leq 2e^{-\frac{t^2}{2(\sigma^2 + bt)}} \quad (1)$$

- Why not use Hoeffding?

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- Why not use Hoeffding?
- For small t , Bernstein gives us a subgaussian tail with parameter σ
- In contrast, Hoeffding always gives us a subgaussian tail with parameter $b \geq \sigma$.

Bernstein's inequality

Proof.

$$\begin{aligned} P(X - \mu \geq t) &\leq \inf_{\lambda \in [0, 1/b)} e^{-\lambda t + M_{X-\mu}(\lambda)} \\ &= \inf_{\lambda \in [0, 1/b)} e^{-\lambda t + \frac{\lambda^2 \sigma^2 / 2}{1 - b\lambda}} \\ &= e^{-\frac{t^2}{2(bt + \sigma^2)}} \quad \text{Setting } \lambda = \frac{t}{bt + \sigma^2} \in [0, 1/b) \end{aligned}$$



sub-exponential property

- The sub-exponential property is preserved under summation of independent random variables.
- Consider $X_k, k = 1, \dots, n$ independent sub-exponential (ν_k, b_k) random variables with $E[X_k] = \mu_k$.
-

$$\begin{aligned} E \left[e^{\lambda \sum_k (X_k - \mu_k)} \right] &= \prod_{i=1}^n E \left[e^{\lambda (X_i - \mu_i)} \right] \\ &\leq \prod_{i=1}^n e^{\frac{\lambda^2 \nu_i^2}{2}} \quad \text{For } |\lambda| \leq 1 / \max_i b_i \end{aligned}$$

- So $\sum_k (X_k - \mu_k) / n$ is sub-exponential with parameters (ν_*, b_*) .

$$b_* = \max_k b_k, \text{ and } \nu_*^2 = \sum_i \nu_i^2 / n \quad (2)$$

Application: the wonders of Johnson-Lindenstrauss embedding

- Given m data points $u_i, i = 1 : m$ in \mathbb{R}^d , one wants to compute low dimensional projections $F(u_i), F : \mathbb{R}^d \rightarrow \mathbb{R}^n$ with $n \ll d$.
- The goal is to preserve distances, so that distance-based algorithms can work “almost as well” on the low dimensional space.

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- We define “almost as well” by:

$$\|u_i - u_j\|(1 - \epsilon) \leq \|F(u_i) - F(u_j)\| \leq \|u_i - u_j\|(1 + \epsilon) \quad (3)$$

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- Construct a random matrix $X \in \mathbb{R}^{n \times d}$ with $X_{ij} \sim N(0, 1)$.
- Define $F(u)$ as Xu/\sqrt{n}

- **Theorem**

As long as $m > 2$, and $u_i \neq u_j, \forall i \neq j$ and $n = \Omega(\log(m/\delta)/\epsilon^2)$, Equation (3) is satisfied with probability at least $1 - \delta$.

We can do this easily with our tools

Proof.

- $u' = u/\|u\|$. We will assume that $u \neq 0$.
- Let $Y := \frac{\|F(u)\|}{\|u\|} = \sum_i (Xu'_i)^2$.
- But $Y_i := (Xu'_i) = \sum_j X_{ij}u'_j \sim N(0, 1)$
- Note that Y_i^2 is sub-exponential with parameters $(2, 4)$. So by the summation property, Y is sub-exponential $(2\sqrt{n}, 4)$.
- So $P\left(\left|\frac{Y}{n} - 1\right| \geq t\right) \leq 2e^{-\frac{nt^2}{8}}$ for $t \in (0, 1)$.
- $P\left(\frac{\|F(u_i - u_j)\|}{\|u_i - u_j\|} \geq \epsilon\right) \leq 2\binom{m}{2}e^{-\frac{n\epsilon^2}{8}}$
- If $m \geq 2$ and $n > \frac{16}{\epsilon^2} \log(m/\delta)$, the above probability can be made as small as δ .