

Lecture 6: Subexponential RVs

Ex: Let $Z \sim N(0,1)$. Let's compute

$$\begin{aligned}\mathbb{E}[e^{\lambda(Z^2-1)}] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\lambda(x^2-1)} e^{-x^2/2} dx \\ &= \frac{e^{-\lambda}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-(1-2\lambda)x^2/2} dx \\ &= \begin{cases} \frac{e^{-\lambda}}{\sqrt{1-2\lambda}} & \text{if } \lambda \leq \frac{1}{2} \\ +\infty & \text{if } \lambda > \frac{1}{2} \end{cases}\end{aligned}$$

Defn: X with mean $\mu = \mathbb{E}X$ is subexponential with parameters (σ, α) if $\mathbb{E}[e^{\lambda(X-\mu)}] \leq e^{\frac{\sigma^2 \lambda^2}{2}} \forall |\lambda| \leq \frac{1}{\alpha}$

Back to example $Z \sim N(0,1)$

$$\mathbb{E}[e^{\lambda(Z^2-1)}] \leq \frac{e^{-\lambda}}{\sqrt{1-2\lambda}} \leq e^{\frac{4\lambda^2}{2}} \quad \forall |\lambda| < \frac{1}{4}$$

So Z^2 is $(2, 4)$ -subexponential.

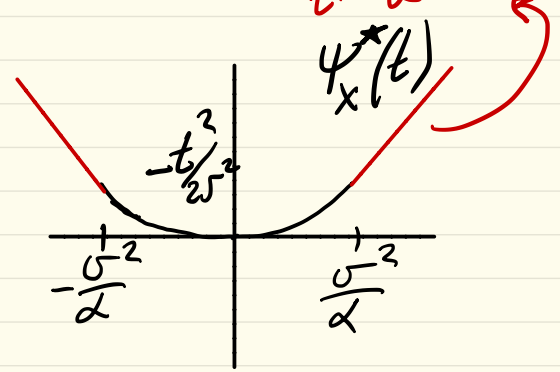
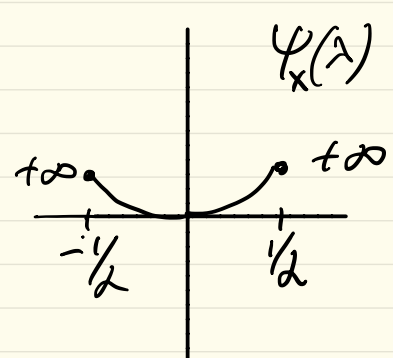
Thm (Subexponential tail bound)
 Let X be subexponential with (σ, α) .
 Then

$$P[X - \mu \geq t] \leq \begin{cases} e^{-\frac{t^2}{2\sigma^2}}, & \text{if } |t| \leq \frac{\sigma^2}{\alpha} \\ e^{-\frac{t}{\alpha} + \frac{\sigma^2}{2\alpha^2}}, & \text{o.w.} \end{cases}$$

pf: Back to Chernoff
 $\log P[X - \mu \geq t] \leq -\Psi_X^*(t)$

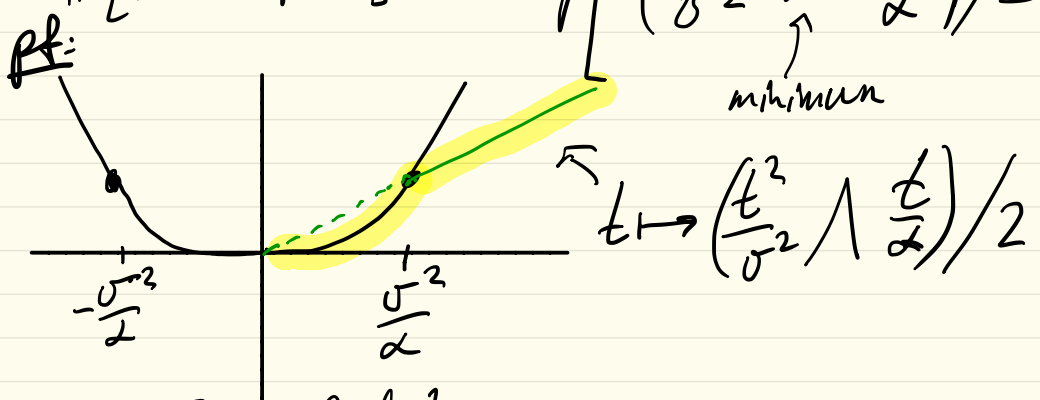
where $\Psi_X(\lambda) = \log \mathbb{E} e^{\lambda(X - \mu)}$
 $= \begin{cases} \frac{\sigma^2 \lambda^2}{2}, & \text{if } |\lambda| \leq \frac{1}{\alpha} \\ +\infty, & \text{o.w.} \end{cases}$

$t \mapsto \frac{t}{\alpha} - \frac{\sigma^2}{2\alpha^2}$
 $\Psi_X^*(t)$



Thm: (Bernstein) Let X be subexponential with parameter (σ, α) and mean $\mu = \mathbb{E}X$. Then

$$P[|X - \mu| \geq t] \leq 2 \exp\left[-\left(\frac{t^2}{\sigma^2} \wedge \frac{t}{\alpha}\right) / 2\right]$$



Lemma: [Sum Rule]

X_i are (σ_i, α_i) -subexp independent $\forall i=1, \dots, n \Rightarrow \sum_{i=1}^n X_i$ is $(\|\sigma\|_2, \|\alpha\|_\infty)$ -subexp

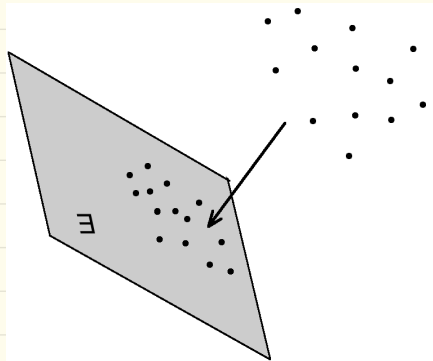
Thm (Bernstein for sums) Let X_1, \dots, X_n be independent subexponential with parameters (σ_i, α_i) , and with mean $\mu_i = \mathbb{E}X_i$.

Then

$$P\left[\left|\sum_{i=1}^n (X_i - \mu_i)\right| \geq t\right] \leq 2 \exp\left[-\frac{1}{2} \left(\frac{t^2}{\|\sigma\|_2^2} \wedge \frac{t}{\|\alpha\|_\infty}\right)\right]$$

Application: Dimensionality Reduction

Given $u_1, \dots, u_m \in \mathbb{R}^d$ with $m \ll d$,
can one map u_1, \dots, u_m into a
lower dimensional space with low distortion?



Thm: (Johnson-Lindenstrauss)

Fix $\epsilon, \delta \in (0, 1)$, a set $U \subseteq \mathbb{R}^d$ of m
points and a number $n > \frac{16 \ln(\frac{m^2}{\delta})}{\epsilon^2}$.

Let $X \in \mathbb{R}^{n \times d}$ consist of i.i.d $N(0, 1)$ entries.

Then with probability $1 - \delta$, the map $f(u) = \frac{1}{\sqrt{n}} Xu$
satisfies

$$1 - \epsilon \leq \frac{\|f(u) - f(v)\|_2^2}{\|u - v\|_2^2} \leq 1 + \epsilon \quad \forall u, v \in U.$$

pt: Observe \leftarrow i th row of X

$$\frac{\|Xu\|_2^2}{\|u\|_2^2} = \sum_{i=1}^n \underbrace{\left\langle x_i, \frac{u}{\|u\|} \right\rangle^2}_{\text{i.i.d } \mathcal{N}(0,1)}$$

$\Rightarrow \frac{\|Xu\|_2^2}{\|u\|_2^2}$ is $(25n, 4)$ -subexponential

\Rightarrow Bernstein:

$$P\left[\left|\frac{\|Xu\|_2^2}{n\|u\|_2^2} - 1\right| > \varepsilon\right] \leq 2 \exp\left[-\left(\frac{n\varepsilon^3}{8} \wedge \frac{n\varepsilon}{8}\right)\right]$$

So for any i , get $= 2 \exp\left(-\frac{n\varepsilon^3}{8}\right) \forall 0 \leq \varepsilon \leq 1$

$$P\left[\frac{\|f(u_i, -u_i)\|_2^2}{\|u_i, -u_i\|_2^2} \notin [1-\varepsilon, 1+\varepsilon]\right] \leq 2e^{-n\varepsilon^3/8}$$

Take union bound over $\binom{m}{2}$ pairs of points

$$2\binom{m}{2}e^{-n\varepsilon^3/8} \leq m^2 e^{-n\varepsilon^3/8} = \delta \quad \square$$

Question: What if $m \rightarrow \infty$ but u has few "degrees of freedom"?