

## Lecture 11

### Sub-Exponential Random Variables

In the previous lecture, we explored sub-Gaussian random variables and observed their limitations. Specifically, we encountered simple random variables that did not fall under the sub-Gaussian category. Additionally, we saw that Hoeffding's Lemma, while useful, has limitations due to its invariance to variance. To address these limitations, we now introduce the concept of sub-exponential random variables. These variables offer a more nuanced approach to characterizing random variables and their concentration properties, particularly in scenarios where sub-Gaussianity proves insufficient.

Recall from the last lecture that for  $|\lambda| \leq 1/4$ , we have:

$$\mathbf{E}\left[e^{Z^2-1}\right] \leq e^{2\lambda^2},$$

where  $Z \sim \mathcal{N}(0, 1)$  was a standard normal distribution.

The definition of sub-exponential random variables is inspired by the behavior of  $Z^2$ . Like  $Z^2$ , sub-exponential random variables have moment generating functions (MGFs) that are bounded for a range of  $\lambda$  values. In fact, we define a sub-exponential random variable with this property:

**Definition 1.** A random variable  $X$  with mean  $\mu = \mathbf{E}[X]$  is sub-exponential if there are non-negative parameters  $(\nu^2, \alpha)$  such that

$$\mathbf{E}\left[e^{\lambda(X-\mu)}\right] \leq e^{\nu^2\lambda^2/2} \quad \text{for all } \lambda \text{ for which } |\lambda| \leq \frac{1}{\alpha}.$$

We write  $X \in \text{subE}(\nu^2, \alpha)$ .

These variables also exhibit heavier tails than sub-Gaussian random variables, decaying at a rate  $e^{-t}$ , similar to that of  $Z^2$ . This slower tail decay distinguishes sub-exponential random variables from sub-Gaussian ones and makes them suitable for modeling distributions with heavier tails.

**Lemma 2.** If  $X \in \text{subE}(\nu^2, \alpha)$ , then we have:

$$\Pr[X - \mathbf{E}[X] \geq t] \leq \begin{cases} e^{\frac{-t^2}{2\nu^2}} & 0 \leq t \leq \frac{\nu^2}{\alpha} \\ e^{\frac{-t}{2\alpha}} & t \geq \frac{\nu^2}{\alpha} \end{cases} \quad (1)$$

The same bound holds for the tail of  $\mathbf{E}[X] - X$ . Alternatively, we can write:

$$\begin{aligned}\Pr[X - \mathbf{E}[X] \geq t] &\leq \exp\left(-\min\left\{\frac{t^2}{2\nu^2}, \frac{t}{2\alpha}\right\}\right) \\ &\leq \exp\left(-\frac{t^2/2}{\nu^2 + t\alpha}\right)\end{aligned}$$

*Proof.* To establish this tail bound, we employ the Cramér-Chernoff method. This method leverages the fact that for any strictly increasing function  $f$  and any  $x, y \in \mathbb{R}$ ,  $x \geq y$  if and only if  $f(x) \geq f(y)$ . This implies that  $\Pr[X \geq Y] = \Pr[f(X) \geq f(Y)]$ . For any  $\lambda > 0$ , the function  $f(x) = e^{\lambda x}$  is strictly increasing. Therefore, we get:

$$\begin{aligned}\Pr[X - \mathbf{E}[X] \geq t] &= \Pr[e^{\lambda(X - \mathbf{E}[X])} \geq e^{\lambda t}] \\ &\leq \frac{\mathbf{E}[e^{\lambda(X - \mathbf{E}[X])}]}{e^{\lambda t}}. \quad (\text{by Markov's inequality})\end{aligned}$$

The expected value in the numerator is the moment generating function (MGF) of the centered random variable  $X - \mathbf{E}[X]$ . Since  $X$  is sub-exponential, we can bound this MGF as follows:

$$\Pr[X - \mathbf{E}[X] \geq t] \leq \frac{\mathbf{E}[e^{\lambda(X - \mathbf{E}[X])}]}{e^{\lambda t}} \leq \frac{e^{\frac{\nu^2 \lambda^2}{2}}}{e^{\lambda t}} = \exp\left(\frac{\nu^2 \lambda^2}{2} - \lambda t\right).$$

This bound holds for all  $\lambda \in (0, \frac{1}{\alpha}]$ . Thus, we have:

$$\Pr[X - \mathbf{E}[X] \geq t] \leq \inf_{\lambda \in (0, \alpha^{-1}]} \exp\left(\frac{\nu^2 \lambda^2}{2} - \lambda t\right).$$

To obtain the tightest upper bound, we minimize the exponent over this range. The exponent is a quadratic function in  $\lambda$ :

$$g(\lambda) := \frac{\nu^2 \lambda^2}{2} - \lambda t = \lambda \left(\frac{\nu^2}{2} \lambda - t\right).$$

This quadratic has roots at  $\lambda = 0$  and  $\lambda = \frac{2t}{\nu^2}$ , and it attains its minimum at the midpoint,  $\lambda_{\min} = \frac{t}{\nu^2}$ . Now, we consider two cases based on whether  $\lambda_{\min}$  is in  $(0, \alpha^{-1}]$  or not:

**Case 1:**  $\lambda_{\min} \leq \frac{1}{\alpha}$ . In this case, the minimum is within the allowed range for  $\lambda$ , and we have:

$$\Pr[X - \mathbf{E}[X] \geq t] \leq \exp\left(\frac{\nu^2 \lambda_{\min}^2}{2} - \lambda_{\min} t\right) = \exp\left(-\frac{t^2}{2\nu^2}\right).$$

**Case 2:**  $\lambda_{\min} > \frac{1}{\alpha}$ . Here, the minimum falls outside the allowed range. Since  $g(\lambda)$  is decreasing for  $\lambda < \lambda_{\min}$ , the minimum value within the allowed range is achieved at  $\lambda = \frac{1}{\alpha}$ :

$$\begin{aligned} \Pr[X - \mathbf{E}[X] \geq t] &\leq \exp\left(\frac{\nu^2}{2\alpha^2} - \frac{t}{\alpha}\right) \leq \exp\left(\frac{t}{2\alpha} - \frac{t}{\alpha}\right) \quad (\text{using } t > \frac{\nu^2}{\alpha}) \\ &= \exp\left(-\frac{t}{2\alpha}\right). \end{aligned}$$

The above bounds together imply Equation (1). To see that the same bound applies to the other tail,  $\Pr[\mathbf{E}[X] - X \geq t]$ , we simply note that if  $X$  is sub-exponential, then so is  $-X$  with the same parameters. Applying the above argument to  $-X$  yields the desired bound.

The alternative form of the bound can be easily derived from the above cases, and we leave its proof as an exercise.  $\square$

This lemma reveals that sub-exponential random variables exhibit tail behavior similar to sub-Gaussian random variables near their mean. However, as we move further away from the mean, their tail behavior transitions to an  $e^{-t}$  decay. The parameter  $\nu$  acts as a variance parameter, while  $\alpha$  serves as an inverse width parameter, controlling the range over which the sub-Gaussian-like tail behavior holds.

## Alternative Definitions

It is worth noting that alternative definitions of sub-exponential random variables exist (e.g., Section 2.7 in [Ver18]), using roughly the same parameters for both  $\nu$  and  $\alpha$ . For these alternative definitions, we have an analogous lemma to sub-Gaussians establishing equivalent properties.

**Lemma 3** (Equivalent Properties of Sub-Exponential Random Variables). *The following properties are equivalent (up to constant factors, with the  $C_i$ 's differing by at most an absolute constant factor) for a random variable  $X$ :*

1. **Tail Bound:** *The tail probability of  $X$  satisfies*

$$\Pr[|X| \geq t] \leq 2 \exp(-t/C_1) \quad \text{for all } t \geq 0.$$

2. **Moment bound:** *The moments of  $X$  satisfy*

$$\|X\|_{L_p} := (\mathbf{E}[|X|^p])^{1/p} \leq C_2 p \quad \text{for all } p \geq 1.$$

3. **MGF of  $|X|$ :** *The moment generating function of  $|X|$  satisfies the following bound:*

$$\mathbf{E}[e^{\lambda|X|}] \leq \exp(C_3 \lambda) \quad \text{for all } \lambda \text{ such that } 0 \leq \lambda \leq \frac{1}{C_3}.$$

4. **MGF of  $|X|$ :** The moment generating function of  $|X|$  is bounded at some point. For some  $C_4$ , we have:

$$\mathbf{E}[e^{|X|/C_4}] \leq 2.$$

5. **MGF of  $X$ :** If  $X$  is centered ( $\mathbf{E}[X] = 0$ ), then the moment generating function of  $X$  satisfies:

$$\mathbf{E}[e^{\lambda X}] \leq \exp(C_5^2 \lambda^2) \quad \text{for all } \lambda \text{ such that } |\lambda| \leq \frac{1}{C_5}.$$

### Deriving MGF Bound from Moment Bound: Proof of 2 $\Rightarrow$ 5

*Proof.* Suppose  $X$  is a zero mean random variable with bounded moments. For all  $p \geq 1$ , we have:

$$\|X\|_{L_p} := (\mathbf{E}[|X|^p])^{1/p} \leq C_2 p.$$

Our goal is to bound the moment generating function of  $X$ . We start by the Taylor expansion of the exponential function:

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

Using this, we can write the MGF of  $X$  as:

$$\begin{aligned} \mathbf{E}[e^{\lambda X}] &= \mathbf{E}\left[\sum_{p=0}^{\infty} \frac{(\lambda X)^p}{p!}\right] \leq \mathbf{E}\left[1 + \lambda X + \sum_{p=2}^{\infty} \frac{(\lambda X)^p}{p!}\right] \\ &= 1 + \lambda \mathbf{E}[X] + \sum_{p=2}^{\infty} \frac{\lambda^p \mathbf{E}[X^p]}{p!} = 1 + \sum_{p=2}^{\infty} \frac{\lambda^p \mathbf{E}[X^p]}{p!}, \end{aligned}$$

where we used the fact that  $\mathbf{E}[X] = 0$  in the last equality. Now, we can use the moment bound to bound the terms in the summation:

$$\begin{aligned} \mathbf{E}[e^{\lambda X}] &\leq 1 + \sum_{p=2}^{\infty} \frac{\lambda^p \mathbf{E}[X^p]}{p!} \leq 1 + \sum_{p=2}^{\infty} \frac{\lambda^p (C_2 p)^p}{p!} \\ &\leq 1 + \sum_{p=2}^{\infty} \frac{(\lambda C_2 p)^p}{(p/e)^p} \quad (\text{using Stirling's approximation: } p! \geq (p/e)^p) \\ &= 1 + \sum_{p=2}^{\infty} (C_2 \lambda e)^p = 1 + \frac{(C_2 \lambda e)^2}{1 - C_2 \lambda e} \quad (\text{for } |C_2 \lambda e| < 1) \end{aligned}$$

Note that the series in the last line converges only when  $|C_2 \lambda e|$  is bounded away from one. The denominator in the last term can get arbitrarily close to zero, which makes the bound useless. Here, we set  $\lambda$  in a way that the denominator is at most a constant. (Remember that we have control in determining the range of  $\lambda$ .) Let's assume  $\lambda$  is in a range for which we have  $|C_2 \lambda e|$  at most  $1/2$ . Then, we obtain:

$$\begin{aligned}\mathbf{E}[e^{\lambda X}] &\leq 1 + 2(C_2 \lambda e)^2 \leq \exp(2(C_2 \lambda e)^2) && (\text{for all } |\lambda| < \frac{1}{2C_2 e}) \\ &\leq \exp((2e C_2)^2 \lambda^2) .\end{aligned}$$

This shows that the MGF of  $X$  is bounded as described in Definition 5 for  $C_5 = 2C_2 e$ .  $\square$

### Bibliographic Note

The content of this lecture was derived from Section 2.7 of [Ver18], and the lecture notes of Prof. Sasha Rakhlin for “Mathematical Statistics: A Non-Asymptotic Approach”, which can be found [here](#) [Rak22].

### References

- [Rak22] Alexander Rakhlin. Mathematical statistics: A non-asymptotic approach, 2022. Lecture notes for MIT course IDS.160, Spring 2022.
- [Ver18] Roman Vershynin. *High-Dimensional Probability: An Introduction with Applications in Data Science*. Cambridge University Press, 2018.