

Sub-exponential Variables and the Azuma–Hoeffding Inequality

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1 Recall

We begin by recalling the Johnson–Lindenstrauss lemma and equivalent characterizations of sub-exponential random variables. These results will be used to derive concentration inequalities for martingale difference sequences.

Lemma 1.1 (Johnson–Lindenstrauss lemma). *Suppose that we are given $N \geq 2$ distinct vectors*

$$\{u^1, u^2, \dots, u^N\} \subset \mathbb{R}^d.$$

Consider the random map

$$F : \mathbb{R}^d \longrightarrow \mathbb{R}^m, \quad F(u) = \frac{Xu}{\sqrt{m}},$$

where $X \in \mathbb{R}^{m \times d}$ has independent and identically distributed $N(0, 1)$ entries. If

$$m > \frac{16}{\delta^2} \log \left(\frac{N}{\varepsilon} \right),$$

then, with probability at least $1 - \varepsilon$,

$$1 - \delta \leq \frac{\|F(u^i) - F(u^j)\|_2^2}{\|u^i - u^j\|_2^2} \leq 1 + \delta \quad \text{for every } i \neq j.$$

Theorem 1.2 (Equivalent characterizations of sub-exponential random variables). *For a mean-zero random variable X , the following conditions are equivalent.*

(i) *There exist non-negative parameters (ν, α) such that*

$$\mathbb{E} [e^{\lambda X}] \leq e^{\nu^2 \lambda^2 / 2} \quad \text{for all } |\lambda| \leq \frac{1}{\alpha}.$$

(ii) *There exist constants $c_0, c_0 > 0$ such that*

$$\mathbb{E} [e^{\lambda X}] \leq c_0 \quad \text{for all } |\lambda| \leq c_0.$$

(iii) *There exist constants $c_1, c_2 > 0$ such that*

$$\mathbb{P}(|X| \geq t) \leq c_1 e^{-c_2 t} \quad \text{for all } t \geq 0.$$

(iv) *The quantity*

$$\gamma := \sup_{k \geq 2} \left(\frac{\mathbb{E} [|X|^k]}{k!} \right)^{1/k}$$

is finite.

Remark 1.3. A sub-exponential tail bound decays more slowly than a sub-Gaussian tail bound for large t , so the sub-exponential class permits heavier tails.

2 Martingale-Based Methods

Definition 2.1 (Martingale difference sequence). An adapted sequence $\{(D_k, \mathcal{F}_k)\}_{k=0}^\infty$ is called a *martingale difference sequence* if, for every $k \geq 1$,

$$\mathbb{E}[|D_k|] < \infty \quad \text{and} \quad \mathbb{E}[D_k \mid \mathcal{F}_{k-1}] = 0.$$

Equivalently, after shifting the index, $\mathbb{E}[D_{k+1} \mid \mathcal{F}_k] = 0$.

Remark 2.2. Here, D_k denotes the difference and $\mathcal{F}_k$ denotes the associated sigma-algebra.

Example 2.3. Let $\{(Y_k, \mathcal{F}_k)\}_{k \geq 0}$ be a martingale and define

$$D_k := Y_k - Y_{k-1}, \quad k \geq 1.$$

Then D_k is $\mathcal{F}_k$ -measurable and

$$\mathbb{E}[D_{k+1} \mid \mathcal{F}_k] = \mathbb{E}[Y_{k+1} \mid \mathcal{F}_k] - Y_k = 0 \quad \text{a.s.}$$

Moreover,

$$Y_k - Y_0 = \sum_{i=1}^k D_i.$$

Theorem 2.4. Let $\{(D_k, \mathcal{F}_k)\}$ be a martingale difference sequence. Suppose that, for every $k = 1, \dots, n$,

$$\mathbb{E}[e^{\lambda D_k} \mid \mathcal{F}_{k-1}] \leq e^{\lambda^2 \nu_k^2 / 2} \quad \text{for all } |\lambda| < \frac{1}{\alpha_k}.$$

Define

$$\alpha_* := \max_{1 \leq k \leq n} \alpha_k.$$

Then the following statements hold.

(a) $\sum_{k=1}^n D_k$ is sub-exponential with parameters $\left(\sqrt{\sum_{k=1}^n \nu_k^2}, \alpha_*\right)$.

$$(b) \quad \mathbb{P}(|\sum_{k=1}^n D_k| \geq t) \leq \begin{cases} 2 \exp\left(-\frac{t^2}{2 \sum_{k=1}^n \nu_k^2}\right), & 0 \leq t \leq \frac{\sum_{k=1}^n \nu_k^2}{\alpha_*}, \\ 2 \exp\left(-\frac{t}{2\alpha_*}\right), & t > \frac{\sum_{k=1}^n \nu_k^2}{\alpha_*}. \end{cases}$$

Remark 2.5. The moment-generating-function assumption in Theorem 2.4 is a conditional sub-exponential condition. Part (a) is the martingale-difference analogue of the standard result that a sum of independent sub-exponential random variables is sub-exponential.

Proof. First, the tower property gives

$$\mathbb{E}[D_k] = \mathbb{E}[\mathbb{E}[D_k \mid \mathcal{F}_{k-1}]] = 0,$$

and hence $\mathbb{E}[\sum_{k=1}^n D_k] = 0$.

For $|\lambda| < 1/\alpha_*$, condition successively on the filtration:

$$\begin{aligned}
\mathbb{E} \left[e^{\lambda \sum_{k=1}^n D_k} \right] &= \mathbb{E} \left[\mathbb{E} \left[e^{\lambda \sum_{k=1}^n D_k} \mid \mathcal{F}_{n-1} \right] \right] \\
&= \mathbb{E} \left[e^{\lambda \sum_{k=1}^{n-1} D_k} \mathbb{E} \left[e^{\lambda D_n} \mid \mathcal{F}_{n-1} \right] \right] \\
&\leq \mathbb{E} \left[e^{\lambda \sum_{k=1}^{n-1} D_k} e^{\lambda^2 \nu_n^2 / 2} \right], \quad |\lambda| < \frac{1}{\alpha_n} \\
&= e^{\lambda^2 \nu_n^2 / 2} \mathbb{E} \left[e^{\lambda \sum_{k=1}^{n-1} D_k} \right], \quad |\lambda| < \frac{1}{\alpha_n} \\
&\leq e^{\lambda^2 \nu_n^2 / 2} e^{\lambda^2 \nu_{n-1}^2 / 2} \mathbb{E} \left[e^{\lambda \sum_{k=1}^{n-2} D_k} \right], \quad |\lambda| < \frac{1}{\alpha_n}, |\lambda| < \frac{1}{\alpha_{n-1}} \\
&\leq \dots \leq e^{\lambda^2 \nu_n^2 / 2} \dots e^{\lambda^2 \nu_1^2 / 2}, \quad |\lambda| < \frac{1}{\alpha_n}, \dots, |\lambda| < \frac{1}{\alpha_1} \\
&= \exp \left(\frac{\lambda^2}{2} \sum_{k=1}^n \nu_k^2 \right), \quad |\lambda| < \frac{1}{\max_{1 \leq k \leq n} \alpha_k}.
\end{aligned}$$

This proves part (a). Part (b) follows from the standard two-regime sub-exponential tail bound. $\square$

Remark 2.6. If the D_k were independent, the MGF would factor as $\prod_{k=1}^n \mathbb{E}[e^{\lambda D_k}]$. For a martingale difference sequence, conditional expectation replaces this factorization. Given $\mathcal{F}_{n-1}$, the partial sum $\sum_{k=1}^{n-1} D_k$ is $\mathcal{F}_{n-1}$ -measurable and therefore acts as a constant inside the conditional expectation.

2.1 Azuma–Hoeffding Inequality

Corollary 2.7 (Azuma–Hoeffding). *Let $\{(D_k, \mathcal{F}_k)\}$ be a martingale difference sequence. Suppose there are constants $\{(a_k, b_k)\}_{k=1}^\infty$ such that*

$$D_k \in [a_k, b_k] \quad \text{a.s. for every } k.$$

Then, for every $t \geq 0$,

$$\mathbb{P} \left(\left| \sum_{k=1}^n D_k \right| \geq t \right) \leq 2 \exp \left(- \frac{2t^2}{\sum_{k=1}^n (b_k - a_k)^2} \right).$$

Proof. Conditioned on $\mathcal{F}_{k-1}$, the random variable D_k still lies in $[a_k, b_k]$ almost surely. By the conditional form of Hoeffding's lemma, D_k is conditionally $(b_k - a_k)/2$ -sub-Gaussian and is therefore conditionally sub-exponential with parameters

$$\left(\frac{b_k - a_k}{2}, 0 \right).$$

By Theorem 2.4(a),

$$\sum_{k=1}^n D_k \text{ is } \left(\sqrt{\sum_{k=1}^n \frac{(b_k - a_k)^2}{4}}, 0 \right) \text{ sub-exponential } \rightarrow \left(\sqrt{\sum_{k=1}^n \frac{(b_k - a_k)^2}{4}} \right) \text{ sub-Gaussian.}$$

The stated tail bound follows. $\square$

Remark 2.8. Conditional expectation preserves inequalities: if $X \leq b$, then $\mathbb{E}[X \mid \mathcal{F}] \leq \mathbb{E}[b \mid \mathcal{F}] = b$. Also, every sub-Gaussian random variable is sub-exponential.

2.2 Bounded Differences

Definition 2.9 (Bounded difference property). We say that a function f satisfies the bounded difference property with parameters $(L_1, \dots, L_n)$ if, for every $k = 1, \dots, n$,

$$|f(x_1, \dots, x_n) - f(x_1, \dots, x_{k-1}, x'_k, x_{k+1}, \dots, x_n)| \leq L_k$$

for all $x_1, \dots, x_n, x'_k$.

Example 2.10. For $x, y \in \mathbb{R}^n$, define the Hamming distance by

$$d_H(x, y) := \sum_{i=1}^n \mathbf{1}\{x_i \neq y_i\}.$$

If f is L -Lipschitz with respect to d_H , meaning that

$$|f(x) - f(y)| \leq L d_H(x, y),$$

then changing only the k th coordinate gives

$$|f(x_1, \dots, x_n) - f(x_1, \dots, x_{k-1}, x'_k, x_{k+1}, \dots, x_n)| \leq L \cdot 1 = L.$$

Thus, f has the bounded difference property with $L_k = L$ for every k .

Corollary 2.11 (Bounded difference inequality). *Suppose f satisfies the bounded difference property with parameters $(L_1, \dots, L_n)$ and that $X = (X_1, \dots, X_n)$ has independent components. Then, for every $t \geq 0$,*

$$\mathbb{P}(|f(X) - \mathbb{E}[f(X)]| \geq t) \leq 2 \exp\left(-\frac{2t^2}{\sum_{k=1}^n L_k^2}\right).$$

Partial proof. Let

$$\mathcal{F}_k := \sigma(X_1, \dots, X_k), \quad Y_k := \mathbb{E}[f(X) \mid \mathcal{F}_k].$$

Since $\mathcal{F}_n$ is generated by all the components of X ,

$$Y_n = \mathbb{E}[f(X) \mid \mathcal{F}_n] = f(X),$$

while

$$Y_0 = \mathbb{E}[f(X) \mid \mathcal{F}_0] = \mathbb{E}[f(X)].$$

Therefore,

$$f(X) - \mathbb{E}[f(X)] = Y_n - Y_0 = \sum_{k=1}^n D_k, \quad D_k := Y_k - Y_{k-1}.$$

The sequence $\{(D_k, \mathcal{F}_k)\}$ is a martingale difference sequence.

To obtain conditional bounds for D_k , define

$$\begin{aligned} A_k &:= \inf_x \mathbb{E}[f(X) \mid X_1, \dots, X_{k-1}, X_k = x] - \mathbb{E}[f(X) \mid X_1, \dots, X_{k-1}] \\ &= \inf_x \mathbb{E}[f(X_1, \dots, X_{k-1}, x, X_{k+1}, \dots, X_n) \mid X_1, \dots, X_{k-1}] - \mathbb{E}[f(X) \mid X_1, \dots, X_{k-1}], \\ B_k &:= \sup_x \mathbb{E}[f(X) \mid X_1, \dots, X_{k-1}, X_k = x] - \mathbb{E}[f(X) \mid X_1, \dots, X_{k-1}] \\ &= \sup_x \mathbb{E}[f(X_1, \dots, X_{k-1}, x, X_{k+1}, \dots, X_n) \mid X_1, \dots, X_{k-1}] - \mathbb{E}[f(X) \mid X_1, \dots, X_{k-1}]. \end{aligned}$$

Conditioning on $X_1, \dots, X_{k-1}$ is equivalent to conditioning on $\mathcal{F}_{k-1}$.

Because $X_1, \dots, X_n$ are independent, these bounds can also be written as

$$A_k = \inf_x \mathbb{E}_{X_{k+1}, \dots, X_n} [f(X_1, \dots, X_{k-1}, x, X_{k+1}, \dots, X_n)] - \mathbb{E}_{X_k, \dots, X_n} [f(X_1, \dots, X_n)],$$

$$B_k = \sup_x \mathbb{E}_{X_{k+1}, \dots, X_n} [f(X_1, \dots, X_{k-1}, x, X_{k+1}, \dots, X_n)] - \mathbb{E}_{X_k, \dots, X_n} [f(X_1, \dots, X_n)].$$

Both A_k and B_k are random because they depend on $X_1, \dots, X_{k-1}$.

The proof will be continued in the next lecture.

References

- [1] M. J. Wainwright, *High-Dimensional Statistics: A Non-Asymptotic Viewpoint*, Cambridge University Press, 2019.