

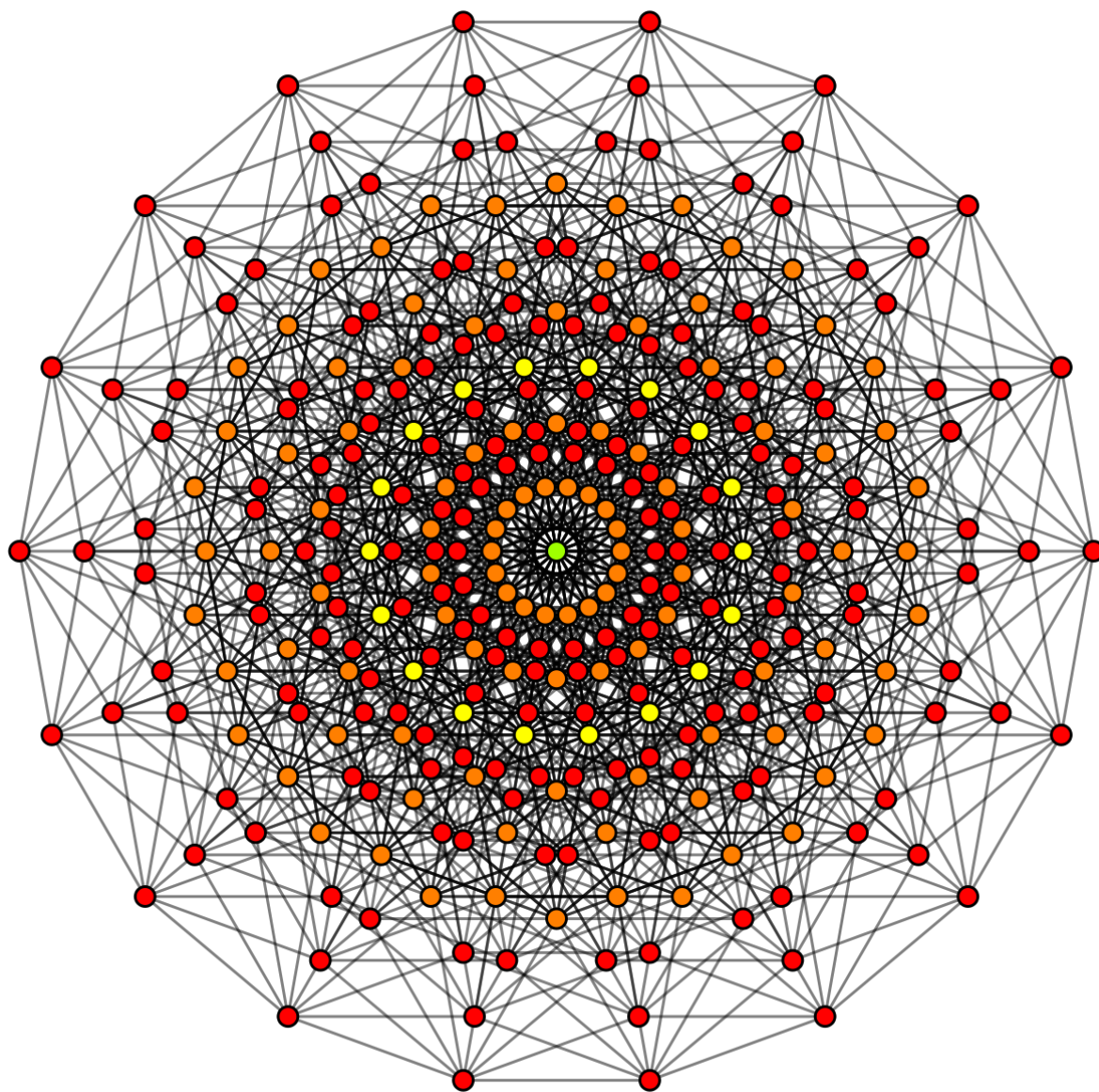
# High-Dimensional Probability Solution Manual

Pingbang Hu

June 30, 2024

## Abstract

This is the solution I write when organizing the reading group on [Roman Vershynin's \*High Dimensional Probability\*](#) [Ver24]. While we aim to solve all the exercises, occasionally we omit some due to either 1.) simplicity; 2.) difficulty; or 3.) skipped section. Additionally, it may contain factual and/or typographic errors.



The reading group started from Spring 2024, and the date on the cover page is the last updated time.

# Contents

<b>Appetizer: using probability to cover a geometric set</b>	<b>2</b>
<b>1 Preliminaries on random variables</b>	<b>4</b>
1.1 Basic quantities associated with random variables . . . . .	4
1.2 Some classical inequalities . . . . .	4
1.3 Limit theorems . . . . .	5
<b>2 Concentration of sums of independent random variables</b>	<b>6</b>
2.1 Why concentration inequalities? . . . . .	6
2.2 Hoeffding's inequality . . . . .	6
2.3 Chernoff's inequality . . . . .	10
2.4 Application: degrees of random graphs . . . . .	13
2.5 Sub-gaussian distributions . . . . .	15
2.6 General Hoeffding's and Khintchine's inequalities . . . . .	19
2.7 Sub-exponential distributions . . . . .	21
2.8 Bernstein's inequality . . . . .	25
<b>3 Random vectors in high dimensions</b>	<b>27</b>
3.1 Concentration of the norm . . . . .	27
3.2 Covariance matrices and principal component analysis . . . . .	29
3.3 Examples of high-dimensional distributions . . . . .	30
3.4 Sub-gaussian distributions in higher dimensions . . . . .	33
3.5 Application: Grothendieck's inequality and semidefinite programming . . . . .	36
3.6 Application: Maximum cut for graphs . . . . .	37
3.7 Kernel trick, and tightening of Grothendieck's inequality . . . . .	37
<b>4 Random matrices</b>	<b>40</b>
4.1 Preliminaries on matrices . . . . .	40
4.2 Nets, covering numbers and packing numbers . . . . .	42
4.3 Application: error correcting codes . . . . .	44
4.4 Upper bounds on random sub-gaussian matrices . . . . .	45
4.5 Application: community detection in networks . . . . .	47
4.6 Two-sided bounds on sub-gaussian matrices . . . . .	49
4.7 Application: covariance estimation and clustering . . . . .	51
<b>5 Concentration without independence</b>	<b>52</b>
5.1 Concentration of Lipschitz functions on the sphere . . . . .	52
5.2 Concentration on other metric measure spaces . . . . .	52
5.3 Application: Johnson-Lindenstrauss Lemma . . . . .	52
5.4 Matrix Bernstein's inequality . . . . .	52

# Appetizer: using probability to cover a geometric set

## Week 1: Appetizer and Basic Inequalities

19 Jan. 2024

**Problem (Exercise 0.0.3).** Check the following variance identities that we used in the proof of Theorem 0.0.2.

(a) Let  $Z_1, \dots, Z_k$  be independent mean zero random vectors in  $\mathbb{R}^n$ . Show that

$$\mathbb{E} \left[ \left\| \sum_{j=1}^k Z_j \right\|_2^2 \right] = \sum_{j=1}^k \mathbb{E} [\|Z_j\|_2^2].$$

(b) Let  $Z$  be a random vector in  $\mathbb{R}^n$ . Show that

$$\mathbb{E} [\|Z - \mathbb{E}[Z]\|_2^2] = \mathbb{E} [\|Z\|_2^2] - \|\mathbb{E}[Z]\|_2^2.$$

**Answer.** (a) If  $Z_1, \dots, Z_k$  are independent mean zero random vectors in  $\mathbb{R}^n$ , then

$$\mathbb{E} \left[ \left\| \sum_{j=1}^k Z_j \right\|_2^2 \right] = \mathbb{E} \left[ \sum_{i=1}^n \left( \sum_{j=1}^k (Z_j)_i \right)^2 \right] = \sum_{i=1}^n \mathbb{E} \left[ \left( \sum_{j=1}^k (Z_j)_i \right)^2 \right].$$

From the assumption,  $\mathbb{E} [(Z_j)_i (Z_{j'})_i] = \mathbb{E} [(Z_j)_i] \mathbb{E} [(Z_{j'})_i] = 0$ , hence

$$\sum_{i=1}^n \mathbb{E} \left[ \left( \sum_{j=1}^k (Z_j)_i \right)^2 \right] = \sum_{i=1}^n \mathbb{E} \left[ \sum_{j=1}^k (Z_j)_i^2 \right] = \sum_{j=1}^k \mathbb{E} \left[ \sum_{i=1}^n (Z_j)_i^2 \right] = \sum_{j=1}^k \mathbb{E} [\|Z_j\|_2^2],$$

proving the result.

(b) If  $Z$  is a random vector in  $\mathbb{R}^n$ , then

$$\begin{aligned} \mathbb{E} [\|Z - \mathbb{E}[Z]\|_2^2] &= \mathbb{E} \left[ \sum_{i=1}^n (Z_i - \mathbb{E}[Z_i])^2 \right] \\ &= \sum_{i=1}^n \mathbb{E} [Z_i^2 - 2Z_i \mathbb{E}[Z_i] + (\mathbb{E}[Z_i])^2] \\ &= \sum_{i=1}^n \mathbb{E} [Z_i^2] - 2 \sum_{i=1}^n \mathbb{E}[Z_i] \mathbb{E}[Z_i] + \sum_{i=1}^n \mathbb{E}[Z_i]^2 \\ &= \mathbb{E} [\|Z\|_2^2] - \|\mathbb{E}[Z]\|_2^2. \end{aligned}$$

⊛

**Problem (Exercise 0.0.5).** Prove the inequalities

$$\left(\frac{n}{m}\right)^m \leq \binom{n}{m} \leq \sum_{k=0}^m \binom{n}{k} \leq \left(\frac{en}{m}\right)^m$$

for all integers  $m \in [1, n]$ .

**Answer.** Fix some  $m \in [1, n]$ . We first show  $(n/m)^m \leq \binom{n}{m}$ . This is because

$$\frac{(n/m)^m}{\binom{n}{m}} = \prod_{j=0}^{m-1} \left( \frac{n}{m} \frac{m-j}{n-j} \right) \leq 1$$

as  $\frac{n-j}{m-j} \geq \frac{n}{m}$  for all  $j$ . The second inequality  $\binom{n}{m} \leq \sum_{k=0}^m \binom{n}{k}$  is trivial since  $\binom{n}{k} \geq 1$  for all  $k$ . The last inequality is due to

$$\frac{\sum_{k=0}^m \binom{n}{k}}{\left(\frac{n}{m}\right)^m} \leq \sum_{k=0}^n \binom{n}{k} \left(\frac{m}{n}\right)^k = \left(1 + \frac{m}{n}\right)^n \leq e^m.$$

⊛

**Problem (Exercise 0.0.6).** Check that in Corollary 0.0.4,

$$(C + C\epsilon^2 N)^{\lceil 1/\epsilon^2 \rceil}$$

suffice. Here  $C$  is a suitable absolute constant.

**Answer.** Omit.

⊛

# Chapter 1

## Preliminaries on random variables

### 1.1 Basic quantities associated with random variables

No Exercise!

### 1.2 Some classical inequalities

**Problem (Exercise 1.2.2).** Prove the following extension of Lemma 1.2.1, which is valid for any random variable  $X$  (not necessarily non-negative):

$$\mathbb{E}[X] = \int_0^\infty \mathbb{P}(X > t) dt - \int_{-\infty}^0 \mathbb{P}(X < t) dt.$$

**Answer.** Separating  $X$  into the plus and minus parts would do the job. Specifically, let  $X = X_+ - X_-$  where  $X_+ = \max(X, 0)$  and  $X_- = \max(-X, 0)$ , both are non-negative. Then, we see that by applying Lemma 1.2.1,

$$\begin{aligned} \mathbb{E}[X] &= \mathbb{E}[X_+] - \mathbb{E}[X_-] \\ &= \int_0^\infty \Pr(t < X_+) dt - \int_0^\infty \Pr(t < X_-) dt \\ &= \int_0^\infty \Pr(X > t) dt - \int_0^\infty \Pr(X < -t) dt \\ &= \int_0^\infty \Pr(X > t) dt - \int_{-\infty}^0 \Pr(X < t) dt. \end{aligned}$$

⊛

**Problem (Exercise 1.2.3).** Let  $X$  be a random variable and  $p \in (0, \infty)$ . Show that

$$\mathbb{E}[|X|^p] = \int_0^\infty pt^{p-1} \mathbb{P}(|X| > t) dt$$

whenever the right-hand side is finite.

**Answer.** Since  $|X|^p$  is non-negative, from Lemma 1.2.1, we have

$$\mathbb{E}[|X|^p] = \int_0^\infty \Pr(t < |X|^p) dt = \int_0^\infty pt^{p-1} \Pr(|X| > t) dt$$

where we let  $t \leftarrow t^p$ , hence  $dt \leftarrow pt^{p-1}dt$ .

⊛

## Week 2: Basic Inequalities and Limit Theorems

24 Jan. 2024

**Problem (Exercise 1.2.6).** Deduce Chebyshev's inequality by squaring both sides of the bound  $|X - \mu| \geq t$  and applying Markov's inequality.

**Answer.** From Markov's inequality, for any  $t > 0$ ,

$$\Pr(|X - \mu| \geq t) = \Pr(|X - \mu|^2 \geq t^2) \leq \frac{\mathbb{E}[|X - \mu|^2]}{t^2} = \frac{\sigma^2}{t^2}.$$

⊛

### 1.3 Limit theorems

**Problem (Exercise 1.3.3).** Let  $X_1, X_2, \dots$  be a sequence of i.i.d. random variables with mean  $\mu$  and finite variance. Show that

$$\mathbb{E} \left[ \left| \frac{1}{N} \sum_{i=1}^N X_i - \mu \right| \right] = O \left( \frac{1}{\sqrt{N}} \right) \text{ as } N \rightarrow \infty.$$

**Answer.** We see that

$$\mathbb{E} \left[ \left| \frac{1}{N} \sum_{i=1}^N X_i - \mu \right| \right] \leq \sqrt{\mathbb{E} \left[ \left| \frac{1}{N} \sum_{i=1}^N X_i - \mu \right|^2 \right]} = \sqrt{\text{Var} \left[ \frac{1}{N} \sum_{i=1}^N X_i \right]} = \frac{\sigma}{\sqrt{N}}.$$

As  $\sigma < \infty$  is a constant, the rate is exactly  $O(1/\sqrt{N})$ .

⊛

## Chapter 2

# Concentration of sums of independent random variables

### Week 3: More Powerful Concentration Inequalities

#### 2.1 Why concentration inequalities?

2 Feb. 2024

**Problem (Exercise 2.1.4).** Let  $g \sim \mathcal{N}(0, 1)$ . Show that for all  $t \geq 1$ , we have

$$\mathbb{E}[g^2 \mathbb{1}_{g>t}] = t \cdot \frac{1}{\sqrt{2\pi}} e^{-t^2/2} + \mathbb{P}(g > t) \leq \left(t - \frac{1}{t}\right) \frac{1}{\sqrt{2\pi}} e^{-t^2/2}.$$

**Answer.** Denote the standard normal density as

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}.$$

Since we have  $\Phi'(x) = -x\Phi(x)$ , by integration by part,

$$\begin{aligned} \mathbb{E}[g^2 \mathbb{1}_{g>t}] &= \int_0^\infty x^2 \mathbb{1}_{x>t} \Phi(x) \, dx \\ &= - \int_t^\infty x \Phi'(x) \, dx \\ &= -x\Phi(x)|_t^\infty + \int_t^\infty \Phi(x) \, dx \\ &= t \cdot \frac{1}{\sqrt{2\pi}} e^{-t^2/2} + \mathbb{P}(g > t), \end{aligned}$$

which gives the first equality. Furthermore, as  $t \geq 1$ , we trivially have

$$\int_t^\infty \Phi(x) \, dx \leq \int_t^\infty \frac{x}{t} \Phi(x) \, dx = \frac{1}{t} \int_t^\infty -\Phi'(x) \, dx = \frac{\Phi(t)}{t},$$

implying that

$$\mathbb{E}[g^2 \mathbb{1}_{g>t}] = t \cdot \frac{1}{\sqrt{2\pi}} e^{-t^2/2} + \int_t^\infty \Phi(x) \, dx \leq \left(t + \frac{1}{t}\right) \frac{1}{\sqrt{2\pi}} e^{-t^2/2},$$

which gives the second inequality. ⊗

#### 2.2 Hoeffding's inequality



**Problem (Exercise 2.2.3).** Show that

$$\cosh(x) \leq \exp(x^2/2) \text{ for all } x \in \mathbb{R}.$$

**Answer.** Omit. \*

The next exercise is to prove Theorem 2.2.5 ([Hoeffding's inequality for general bounded random variables](#)), which we restate it for convenience.

**Theorem 2.2.1** (Hoeffding's inequality for general bounded random variables). Let  $X_1, \dots, X_N$  be independent random variables. Assume that  $X_i \in [m_i, M_i]$  for every  $i$ . Then, for any  $t > 0$ , we have

$$\mathbb{P}\left(\sum_{i=1}^N (X_i - \mathbb{E}[X_i]) \geq t\right) \leq \exp\left(-\frac{2t^2}{\sum_{i=1}^N (M_i - m_i)^2}\right).$$

**Problem (Exercise 2.2.7).** Prove the [Hoeffding's inequality for general bounded random variables](#), possibly with some absolute constant instead of 2 in the tail.

**Answer.** Since raising both sides to  $p$ -th power doesn't work since we're now working with sum of random variables, so we instead consider the MGF trick (also known as Crarmer-Chernoff method):

**Lemma 2.2.1** (Crarmer-Chernoff method). Given a random variable  $X$ ,

$$\mathbb{P}(X - \mu \geq t) = \mathbb{P}(e^{\lambda(X-\mu)} \geq e^{\lambda t}) \leq \inf_{\lambda > 0} \frac{\mathbb{E}[e^{\lambda(X-\mu)}]}{e^{\lambda t}}.$$

**Proof.** This directly follows from the Markov's inequality. ■

Hence, we see that

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^N (X_i - \mathbb{E}[X_i]) \geq t\right) &\leq \inf_{\lambda > 0} e^{-\lambda t} \mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^N (X_i - \mathbb{E}[X_i])\right)\right] \\ &= \inf_{\lambda > 0} e^{-\lambda t} \prod_{i=1}^N \mathbb{E}\left[\exp(\lambda(X_i - \mathbb{E}[X_i]))\right]. \end{aligned}$$

So now everything left is to bound  $\mathbb{E}[\exp(\lambda(X_i - \mathbb{E}[X_i]))]$ . Before we proceed, we need one lemma.

**Lemma 2.2.2.** For any bounded random variable  $Z \in [a, b]$ ,

$$\text{Var}[Z] \leq \frac{(b-a)^2}{4}.$$

**Proof.** Since

$$\text{Var}[Z] = \text{Var}\left[Z - \frac{a+b}{2}\right] \leq \mathbb{E}\left[\left(Z - \frac{a+b}{2}\right)^2\right] \leq \frac{(b-a)^2}{4}.$$
■

**Claim.** Given  $X \in [a, b]$  such that  $\mathbb{E}[X] = 0$ , for all  $\lambda \in \mathbb{R}$ ,

$$\mathbb{E}[e^{\lambda X}] \leq \exp\left(\lambda^2 \frac{(b-a)^2}{8}\right).$$

**Proof.** We first define  $\psi(\lambda) = \ln \mathbb{E}[e^{\lambda X}]$ , and compute

$$\psi'(\lambda) = \frac{\mathbb{E}[X e^{\lambda X}]}{\mathbb{E}[e^{\lambda X}]}, \quad \psi''(\lambda) = \frac{\mathbb{E}[X^2 e^{\lambda X}]}{\mathbb{E}[e^{\lambda X}]} - \left( \frac{\mathbb{E}[X e^{\lambda X}]}{\mathbb{E}[e^{\lambda X}]} \right)^2.$$

Now, observe that  $\psi''$  is the variance under the law of  $X$  re-weighted by  $\frac{e^{\lambda X}}{\mathbb{E}[e^{\lambda X}]}$ , i.e., by a change of measure, consider a new distribution  $\mathbb{P}_\lambda$  (w.r.t. the original distribution  $\mathbb{P}$  of  $X$ ) as

$$d\mathbb{P}_\lambda(x) := \frac{e^{\lambda x}}{\mathbb{E}_\mathbb{P}[e^{\lambda X}]} d\mathbb{P}(x),$$

then

$$\psi'(\lambda) = \frac{\mathbb{E}_\mathbb{P}[X e^{\lambda X}]}{\mathbb{E}_\mathbb{P}[e^{\lambda X}]} = \int \frac{x e^{\lambda x}}{\mathbb{E}_\mathbb{P}[e^{\lambda X}]} d\mathbb{P}(x) = \mathbb{E}_{\mathbb{P}_\lambda}[X]$$

and

$$\psi''(\lambda) = \frac{\mathbb{E}_\mathbb{P}[X^2 e^{\lambda X}]}{\mathbb{E}_\mathbb{P}[e^{\lambda X}]} - \left( \frac{\mathbb{E}_\mathbb{P}[X e^{\lambda X}]}{\mathbb{E}_\mathbb{P}[e^{\lambda X}]} \right)^2 = \mathbb{E}_{\mathbb{P}_\lambda}[X^2] - \mathbb{E}_{\mathbb{P}_\lambda}[X]^2 = \text{Var}_{\mathbb{P}_\lambda}[X].$$

From [Lemma 2.2.2](#), since  $X$  under the new distribution  $\mathbb{P}_\lambda$  is still bounded between  $a$  and  $b$ ,

$$\psi''(\lambda) = \text{Var}_{\mathbb{P}_\lambda}[X] \leq \frac{(b-a)^2}{4}.$$

Then by Taylor's theorem, there exists some  $\tilde{\lambda} \in [0, \lambda]$  such that

$$\psi(\lambda) = \psi(0) + \psi'(0)\lambda + \frac{1}{2}\psi''(\tilde{\lambda})\lambda^2 = \frac{1}{2}\psi''(\tilde{\lambda})\lambda^2$$

since  $\psi(0) = \psi'(0) = 0$ . By bounding  $\psi''(\tilde{\lambda})\lambda^2/2$ , we finally have

$$\ln \mathbb{E}[e^{\lambda X}] = \psi(\lambda) \leq \frac{1}{2} \cdot \frac{(b-a)^2}{4} \lambda^2 = \lambda^2 \frac{(b-a)^2}{8},$$

raising both sides by  $e$  shows the desired result.  $\circledast$

Say given  $X_i \in [m_i, M_i]$  for every  $i$ , then  $X_i - \mathbb{E}[X_i] \in [m_i - \mathbb{E}[X_i], M_i - \mathbb{E}[X_i]]$  with mean 0 for every  $i$ . Then given any of the two bounds, for all  $\lambda \in \mathbb{R}$ ,

$$\mathbb{E}\left[e^{\lambda(X_i - \mathbb{E}[X_i])}\right] \leq \exp\left(\lambda^2 \frac{(M_i - m_i)^2}{8}\right).$$

Then we simply recall that

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^N (X_i - \mathbb{E}[X_i]) \geq t\right) &= \inf_{\lambda > 0} e^{-\lambda t} \prod_{i=1}^N \exp(\lambda(X_i - \mathbb{E}[X_i])) \\ &\leq \inf_{\lambda > 0} \exp\left(-\lambda t + \sum_{i=1}^N \lambda^2 \frac{(M_i - m_i)^2}{8}\right) \\ &= \exp\left(-\frac{4t^2}{\sum_{i=1}^N (M_i - m_i)^2} + \frac{2t^2}{\sum_{i=1}^N (M_i - m_i)^2}\right) \\ &= \exp\left(-\frac{2t^2}{\sum_{i=1}^N (M_i - m_i)^2}\right) \end{aligned}$$

since infimum is achieved at  $\lambda = 4t/(\sum_{i=1}^N (M_i - m_i)^2)$ .  $\circledast$

**Problem (Exercise 2.2.8).** Imagine we have an algorithm for solving some decision problem (e.g., is a given number  $p$  a prime?). Suppose the algorithm makes a decision at random and returns the correct answer with probability  $\frac{1}{2} + \delta$  with some  $\delta > 0$ , which is just a bit better than a random guess. To improve the performance, we run the algorithm  $N$  times and take the majority vote. Show that, for any  $\epsilon \in (0, 1)$ , the answer is correct with probability at least  $1 - \epsilon$ , as long as

$$N \geq \frac{1}{2\delta^2} \ln\left(\frac{1}{\epsilon}\right).$$

**Answer.** Consider  $X_1, \dots, X_N \stackrel{\text{i.i.d.}}{\sim} \text{Ber}(\frac{1}{2} + \delta)$ , which is a series of indicators indicating whether the random decision is correct or not. Note that  $\mathbb{E}[X_i] = \frac{1}{2} + \delta$ .

We see that by taking majority vote over  $N$  times, the algorithm makes a mistake if  $\sum_{i=1}^N X_i \leq N/2$  (let's not consider tie). This happens with probability

$$\mathbb{P}\left(\sum_{i=1}^N X_i \leq \frac{N}{2}\right) = \mathbb{P}\left(\sum_{i=1}^N (X_i - \mathbb{E}[X_i]) \leq -N\delta\right) \leq \exp\left(-\frac{2(N\delta)^2}{N}\right) = e^{-2N\delta^2}$$

from Hoeffding's inequality.<sup>a</sup> Requiring  $e^{-2N\delta^2} \leq \epsilon$  is equivalent to requiring  $N \geq \frac{1}{2\delta^2} \ln(1/\epsilon)$ .  $\circledast$

<sup>a</sup>Note that the sign is flipped. However, Hoeffding's inequality still holds (why?).

**Problem (Exercise 2.2.9).** Suppose we want to estimate the mean  $\mu$  of a random variable  $X$  from a sample  $X_1, \dots, X_N$  drawn independently from the distribution of  $X$ . We want an  $\epsilon$ -accurate estimate, i.e., one that falls in the interval  $(\mu - \epsilon, \mu + \epsilon)$ .

- Show that a sample of size  $N = O(\sigma^2/\epsilon^2)$  is sufficient to compute an  $\epsilon$ -accurate estimate with probability at least  $3/4$ , where  $s^2 = \text{Var}[X]$ .
- Show that a sample of size  $N = O(\log(\delta^{-1})\sigma^2/\epsilon^2)$  is sufficient to compute an  $\epsilon$ -accurate estimate with probability at least  $1 - \delta$ .

**Answer.** (a) Consider using the sample mean  $\hat{\mu} = \frac{1}{N} \sum_{i=1}^N X_i$  as an estimator of  $\mu$ . From the Chebyshev's inequality,

$$\mathbb{P}(|\hat{\mu} - \mu| > \epsilon) \leq \frac{\sigma^2/N}{\epsilon^2}.$$

By requiring  $\sigma^2/(N\epsilon^2) \leq 1/4$ , i.e.,  $N \geq 4\sigma^2/\epsilon^2 = O(\sigma^2/\epsilon^2)$ , suffices.

- Consider gathering  $k$  estimator from the above procedure, i.e., we now have  $\hat{\mu}_1, \dots, \hat{\mu}_k$  such that each are an  $\epsilon$ -accurate mean estimator with probability at least  $3/4$ . This requires  $k \cdot 4\sigma^2/\epsilon^2 = O(k\sigma^2/\epsilon^2)$  samples. We claim that the median  $\hat{\mu} := \text{median}(\hat{\mu}_1, \dots, \hat{\mu}_k)$  is an  $\epsilon$ -accurate mean estimator with probability at least  $1 - \delta$  for some  $k$  (depends on  $\delta$ ). Consider a series of indicators  $X_i = \mathbb{1}_{|\hat{\mu}_i - \mu| > \epsilon}$ , indicating if  $\hat{\mu}_i$  is not  $\epsilon$ -accurate. Then  $X_i \sim \text{Ber}(1/4)$ . Then, our median estimator  $\hat{\mu}$  fails with probability

$$\mathbb{P}(|\hat{\mu} - \mu| > \epsilon) = \mathbb{P}\left(\sum_{i=1}^k X_i > \frac{k}{2}\right) = \mathbb{P}\left(\sum_{i=1}^k (X_i - \mathbb{E}[X_i]) > \frac{k}{4}\right)$$

as  $\mathbb{E}[X_i] = 1/4$ . From Hoeffding's inequality, the above probability is bounded above by  $\exp(-2(k/4)^2/k)$ , setting it to be less than  $\delta$  we have

$$\exp\left(-\frac{2(k/4)^2}{k}\right) \leq \delta \Leftrightarrow \ln\left(\frac{1}{\delta}\right) \geq \frac{k}{8} \Leftrightarrow k = O(\ln(\delta^{-1})),$$

i.e., the total number of samples required is  $O(k\sigma^2/\epsilon^2) = O(\ln(\delta^{-1})\sigma^2/\epsilon^2)$ .

$\circledast$

**Problem (Exercise 2.2.10).** Let  $X_1, \dots, X_N$  be *non-negative* independent random variables with continuous distributions. Assume that the densities of  $X_i$  are uniformly bounded by 1.

(a) Show that the MGF of  $X_i$  satisfies

$$\mathbb{E}[\exp(-tX_i)] \leq \frac{1}{t} \text{ for all } t > 0.$$

(b) Deduce that, for any  $\epsilon > 0$ , we have

$$\mathbb{P}\left(\sum_{i=1}^N X_i \leq \epsilon N\right) \leq (e\epsilon)^N.$$

**Answer.** (a) Since  $X_i$ 's are non-negative and the densities  $f_{X_i} \leq 1$  uniformly, for every  $t > 0$ ,

$$\mathbb{E}[\exp(-tX_i)] = \int_0^\infty e^{-tx} f_{X_i}(x) dx \leq \int_0^\infty e^{-tx} dx = -\frac{1}{t} e^{-tx} \Big|_0^\infty = \frac{1}{t}.$$

(b) From [Chernoff's inequality](#), for any  $\epsilon > 0$ ,

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^N X_i \leq \epsilon N\right) &= \mathbb{P}\left(\sum_{i=1}^N -\frac{X_i}{\epsilon} \geq -N\right) \\ &\leq \inf_{\lambda > 0} e^{\lambda N} \mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^N -\frac{X_i}{\epsilon}\right)\right] \\ &= \inf_{\lambda > 0} e^{\lambda N} \prod_{i=1}^N \mathbb{E}\left[\exp\left(-\lambda \frac{X_i}{\epsilon}\right)\right] \\ &\leq \inf_{\lambda > 0} e^{\lambda N} \prod_{i=1}^N \frac{\epsilon}{\lambda} && \text{Part (a) with } t = \lambda/\epsilon \\ &= \inf_{\lambda > 0} \left(e^\lambda \frac{\epsilon}{\lambda}\right)^N \\ &= (e\epsilon)^N \end{aligned}$$

since the infimum is achieved when  $\lambda = 1$ .

⊛

## 2.3 Chernoff's inequality

**Problem (Exercise 2.3.2).** Modify the proof of Theorem 2.3.1 to obtain the following bound on the lower tail. For any  $t < \mu$ , we have

$$\mathbb{P}(S_N \leq t) \leq e^{-\mu} \left(\frac{e\mu}{t}\right)^t.$$

**Answer.** A direct modification is that considering for any  $\lambda > 0$ ,

$$\mathbb{P}(S_N \leq t) = \mathbb{P}(-S_N \geq -t) = \mathbb{P}(e^{-\lambda S_N} \geq e^{-\lambda t}) \leq e^{\lambda t} \prod_{i=1}^N \mathbb{E}[\exp(-\lambda X_i)].$$

A direct computation gives

$$\mathbb{E}[\exp(-\lambda X_i)] = e^{-\lambda} p_i + (1 - p_i) = 1 + (e^{-\lambda} - 1)p_i \leq \exp((e^{-\lambda} - 1)p_i),$$

hence

$$\mathbb{P}(S_N \leq t) \leq e^{\lambda t} \prod_{i=1}^N \exp((e^{-\lambda} - 1)p_i) = e^{\lambda t} \exp((e^{-\lambda} - 1)\mu) = \exp(\lambda t + (e^{-\lambda} - 1)\mu).$$

Minimizing the right-hand side, we see that

$$t + (-\mu e^{-\lambda}) = 0 \Leftrightarrow t = \mu e^{-\lambda} \Leftrightarrow \lambda = \ln \frac{\mu}{t}$$

achieves the infimum. And since  $t < \mu$ ,  $\lambda > 0$  as required, which gives

$$\mathbb{P}(S_N \leq t) \leq \exp\left(t \ln \frac{\mu}{t} + \left(\frac{t}{\mu} - 1\right)\mu\right) = \exp\left(t \ln \frac{\mu}{t} + t - \mu\right) = e^{-\mu} \left(\frac{e\mu}{t}\right)^t.$$

⊛

**Problem (Exercise 2.3.3).** Let  $X \sim \text{Pois}(\lambda)$ . Show that for any  $t > \lambda$ , we have

$$\mathbb{P}(X \geq t) \leq e^{-\lambda} \left(\frac{e\lambda}{t}\right)^t.$$

**Answer.** From [Chernoff's inequality](#), for any  $\theta > 0$ , we have

$$\mathbb{P}(X \geq t) \leq e^{-\theta t} \mathbb{E}[\exp(\theta X)].$$

Then the Poisson moment can be calculated as

$$\mathbb{E}[\exp(\theta X)] = \sum_{k=0}^{\infty} e^{\theta k} \cdot e^{-\lambda} \frac{\lambda^k}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{(e^{\theta} \lambda)^k}{k!} = e^{-\lambda} \exp(e^{\theta} \lambda) = \exp((e^{\theta} - 1)\lambda),$$

hence

$$\mathbb{P}(X \geq t) \leq e^{-\theta t} \exp((e^{\theta} - 1)\lambda) = \left(\frac{\lambda}{t}\right)^t \exp(t - \lambda) = e^{-\lambda} \left(\frac{e\lambda}{t}\right)^t$$

where we take the minimizing  $\theta = \ln(t/\lambda) > 0$  as  $t > \lambda$ .

⊛

Alternatively, we can also solve [Exercise 2.3.3](#) directly as follows.

**Answer.** Consider a series of independent Bernoulli random variables  $X_{N,i}$  for a fixed  $N$  such that the Poisson limit theorem applies to approximate  $X \sim \text{Pois}(\lambda)$ , i.e., as  $N \rightarrow \infty$ ,  $\max_{i \leq N} p_{N,i} \rightarrow 0$  and  $\lambda_N := \mathbb{E}[S_N] \rightarrow \lambda < \infty$ ,  $S_N \rightarrow \text{Pois}(\lambda)$ . From Chernoff's inequality, for any  $t > \lambda_N$ ,

$$\mathbb{P}(S_N > t) \leq e^{-\lambda_N} \left(\frac{e\lambda_N}{t}\right)^t.$$

We then see that

$$\mathbb{P}(X > t) = \lim_{N \rightarrow \infty} \mathbb{P}(S_N > t) \leq \lim_{N \rightarrow \infty} e^{-\lambda_N} \left(\frac{e\lambda_N}{t}\right)^t = e^{-\lambda} \left(\frac{e\lambda}{t}\right)^t$$

since  $\lambda_N \rightarrow \lambda$  as  $N \rightarrow \infty$ .

⊛

## Week 4: Chernoff's Inequality and Degree Concentration

**Problem (Exercise 2.3.5).** Show that, in the setting of Theorem 2.3.1, for  $\delta \in (0, 1]$  we have

$$\mathbb{P}(|S_N - \mu| \geq \delta \mu) \leq 2e^{-c\mu\delta^2}$$

where  $c > 0$  is an absolute constant.

7 Feb. 2024

**Answer.** From Chernoff's inequality (right-tail), for  $t = (1 + \delta)\mu$ , we have

$$\begin{aligned}\ln \mathbb{P}(S_N \geq (1 + \delta)\mu) &\leq -\mu + (1 + \delta)\mu(1 + \ln \mu - \ln(1 + \delta) - \ln \mu) \\ &= \delta\mu - (1 + \delta)\mu(\ln(1 + \delta)) \\ &= \mu(\delta - (1 + \delta)\ln(1 + \delta)).\end{aligned}$$

A classic bound for  $\ln(1 + \delta)$  is the following.

**Claim.** For all  $x > 0$ ,

$$\frac{2x}{2+x} \leq \ln(1+x).$$

**Proof.** As  $(1 + x/2)^2 = 1 + x + x^2/4 \geq 1 + x$ ,

$$[\log(1+x)]' = \frac{1}{1+x} \geq \frac{1}{(1+x/2)^2} = \left(\frac{x}{1+x/2}\right)'.$$

Note that  $\log(1+x) = x/(1+x/2) = 0$  at  $x = 0$ , so for all  $x > 0$

$$\log(1+x) \geq \frac{x}{1+x/2}.$$

⊗

Hence, as our  $\delta \in (0, 1]$ , we have

$$\ln \mathbb{P}(S_N \geq (1 + \delta)\mu) \leq \mu(\delta - (1 + \delta)\ln(1 + \delta)) \leq \mu\delta - \mu(1 + \delta)\frac{2\delta}{2 + \delta} = -\frac{\mu\delta^2}{2 + \delta} \leq -\frac{\mu\delta^2}{3}.$$

Similarly, from Chernoff's inequality (left-tail), for  $t = (1 - \delta)\mu$ , we have

$$\begin{aligned}\ln \mathbb{P}(S_N \leq (1 - \delta)\mu) &\leq -\mu + (1 - \delta)\mu(1 + \ln \mu - \ln(1 - \delta) - \ln \mu) \\ &= -\delta\mu - (1 - \delta)\mu \ln(1 - \delta) \\ &= \mu(-\delta - (1 - \delta)\ln(1 - \delta)).\end{aligned}$$

Another classic bound for  $\ln(1 - \delta)$  is the following.

**Claim.** For all  $x \in [-1, 1)$ ,

$$-x - \frac{x^2}{2} \leq \ln(1 - x).$$

**Proof.** This one is even easier: since  $\ln(1 - x) = -x - x^2/2 - x^3/3 - \dots$

⊗

Hence, if  $\delta \in (0, 1]$ ,<sup>a</sup> we have

$$\ln \mathbb{P}(S_N \leq (1 - \delta)\mu) \leq \mu(-\delta - (1 - \delta)\ln(1 - \delta)) \leq -\mu\delta - \mu(1 - \delta)\left(-\delta - \frac{\delta^2}{2}\right) \leq -\frac{\mu\delta^2}{2}.$$

Combining two tails, we then see that

$$\begin{aligned}\mathbb{P}(|S_N - \mu| > \delta\mu) &\leq \mathbb{P}(S_N \geq (1 + \delta)\mu) + \mathbb{P}(S_N \leq (1 - \delta)\mu) \\ &\leq \exp\left(-\frac{\mu\delta^2}{3}\right) + \exp\left(-\frac{\mu\delta^2}{2}\right) \\ &\leq 2\exp\left(-\frac{\mu\delta^2}{3}\right),\end{aligned}$$

which almost complete the proof for  $c = 1/3$ .

⊗

<sup>a</sup>When  $\delta = 1$ ,  $\ln \mathbb{P}(S_N \leq (1 - \delta)\mu) \leq -\frac{\mu\delta^2}{2}$  holds trivially since  $\mathbb{P}(S_N = 0) \leq \exp(-\mu/2)$ .

**Problem (Exercise 2.3.6).** Let  $X \sim \text{Pois}(\lambda)$ . Show that for  $t \in (0, \lambda]$ , we have

$$\mathbb{P}(|X - \lambda| \geq t) \leq 2 \exp\left(-\frac{ct^2}{\lambda}\right).$$

**Answer.** Fix some  $t =: \delta\lambda \in (0, \lambda]$  for some  $\delta \in (0, 1]$  first. Consider a series of independent Bernoulli random variables  $X_{N,i}$  for a fixed  $N$  such that the Poisson limit theorem applies to approximate  $X \sim \text{Pois}(\lambda)$ , i.e., as  $N \rightarrow \infty$ ,  $\max_{i \leq N} p_{N,i} \rightarrow 0$  and  $\lambda_N := \mathbb{E}[S_N] \rightarrow \lambda < \infty$ ,  $S_N \rightarrow \text{Pois}(\lambda)$ . From multiplicative form of Chernoff's inequality, for  $t_N := \delta\lambda_N$ ,

$$\mathbb{P}(|S_N - \lambda_N| \geq t_N = \delta\lambda_N) \leq 2 \exp\left(-\frac{ct_N^2}{\lambda_N}\right).$$

It then follows that from the Poisson limit theorem,

$$\mathbb{P}(|X - \lambda| \geq t) = \lim_{N \rightarrow \infty} \mathbb{P}(|S_N - \lambda_N| \geq t_N) = \lim_{N \rightarrow \infty} 2 \exp\left(-\frac{ct_N^2}{\lambda_N}\right) = 2 \exp\left(-\frac{ct^2}{\lambda}\right)$$

since  $t_N = \delta\lambda_N \rightarrow \delta\lambda = t$ . \*

**Problem (Exercise 2.3.8).** Let  $X \sim \text{Pois}(\lambda)$ . Show that, as  $\lambda \rightarrow \infty$ , we have

$$\frac{X - \lambda}{\sqrt{\lambda}} \xrightarrow{D} \mathcal{N}(0, 1).$$

**Answer.** Since  $X := \sum_{i=1}^{\lambda} X_i \sim \text{Pois}(\lambda)$  if  $X_i \stackrel{\text{i.i.d.}}{\sim} \text{Pois}(1)$  for all  $i$ , from Lindeberg-Lévy central limit theorem, we have

$$\frac{X - \mathbb{E}[X]}{\sqrt{\text{Var}[X]}} = \frac{X - \lambda}{\sqrt{\lambda}} \xrightarrow{d} \mathcal{N}(0, 1)$$

as  $\mathbb{E}[X_i] = \text{Var}[X_i] = 1$ . \*

## 2.4 Application: degrees of random graphs

**Problem (Exercise 2.4.2).** Consider a random graph  $G \sim G(n, p)$  with expected degrees  $d = O(\log n)$ . Show that with high probability (say, 0.9), all vertices of  $G$  have degrees  $O(\log n)$ .

**Answer.** Since  $d = O(\log n)$ , there exists an absolute constant  $M > 0$  such that  $d = (n-1)p \leq M \log n$  for all large enough  $n$ . Now, consider some  $C > 0$  such that  $eM/C =: \alpha < 1$ . From Chernoff's inequality,

$$\mathbb{P}(d_i \geq C \log n) \leq e^{-d} \left(\frac{ed}{C \log n}\right)^{C \log n} \leq e^{-d} \left(\frac{eM}{C}\right)^{C \log n} \leq \alpha^{C \log n}.$$

Hence, from union bound, we have

$$\mathbb{P}(\forall i: d_i \leq C \log n) \geq 1 - n\alpha^{C \log n},$$

which can be arbitrarily close to 1 as  $C$  is sufficiently large. \*

**Problem (Exercise 2.4.3).** Consider a random graph  $G \sim G(n, p)$  with expected degrees  $d = O(1)$ . Show that with high probability (say, 0.9), all vertices of  $G$  have degrees

$$O\left(\frac{\log n}{\log \log n}\right).$$

**Answer.** Since now  $d = (n-1)p \leq M$  for some absolute constant  $M > 0$  for all large  $n$ , from Chernoff's inequality,

$$\mathbb{P}\left(d_i \geq C \frac{\log n}{\log \log n}\right) \leq e^{-d} \left(\frac{ed}{C \frac{\log n}{\log \log n}}\right)^{C \frac{\log n}{\log \log n}} \leq e^{-d} \left(\frac{eM \log \log n}{C \log n}\right)^{C \frac{\log n}{\log \log n}}$$

for some  $C > 0$ . This implies that

$$\mathbb{P}\left(\forall i: d_i \leq C \frac{\log n}{\log \log n}\right) \geq 1 - ne^{-d} \left(\frac{eM \log \log n}{C \log n}\right)^{C \frac{\log n}{\log \log n}}.$$

Now, considering  $C = M$ , we have

$$ne^{-d} \left(\frac{eM \log \log n}{C \log n}\right)^{C \frac{\log n}{\log \log n}} \leq ne^{-d} \left(\frac{e \log \log n}{\log n}\right)^{M \frac{\log n}{\log \log n}}.$$

Taking logarithm, we observe that

$$\begin{aligned} & \log n - d + M \frac{\log n}{\log \log n} (1 + \log \log \log n - \log \log n) \\ &= (1 - M) \log n - d + M \frac{\log n}{\log \log n} (1 + \log \log \log n) \\ &= \left[1 - M \left(1 + \frac{1}{\log \log n} + \frac{\log \log \log n}{\log \log n}\right)\right] \log n - d \rightarrow -\infty \end{aligned}$$

as  $n \rightarrow \infty$ , i.e.,

$$ne^{-d} \left(\frac{eM \log \log n}{C \log n}\right)^{C \frac{\log n}{\log \log n}} \rightarrow 0,$$

which is what we want to prove.  $\ast$

**Problem (Exercise 2.4.4).** Consider a random graph  $G \sim G(n, p)$  with expected degrees  $d = o(\log n)$ . Show that with high probability, (say, 0.9),  $G$  has a vertex with degree  $10d$ .

**Answer.** Omit.  $\ast$

**Problem (Exercise 2.4.5).** Consider a random graph  $G \sim G(n, p)$  with expected degrees  $d = O(1)$ . Show that with high probability, (say, 0.9),  $G$  has a vertex with degree

$$\Omega\left(\frac{\log n}{\log \log n}\right).$$

**Answer.** Firstly, note that the question is ill-defined in the sense that if  $d = (n-1)p = O(1)$ , it can be  $d = 0$  (with  $p = 0$ ), which is impossible to prove the claim. Hence, consider the non-degenerate case, i.e.,  $d = \Theta(1)$ .

We want to prove that there exists some absolute constant  $C > 0$  such that with high probability  $G$  has a vertex with degree at least  $C \log n / \log \log n$ . First, consider separate the graph randomly into two parts  $A, B$ , each of size  $n/2$ . It's then easy to see by dropping every inner edge in  $A$  and  $B$ , the graph becomes bipartite such that now  $A$  and  $B$  forms independent sets. Consider working on this new graph (with degree denoted as  $d'$ ), we have

$$\begin{aligned} \mathbb{P}(d'_i = k) &= \binom{n/2}{k} \left(\frac{d}{n-1}\right)^k \left(1 - \frac{d}{n-1}\right)^{n/2-k} \geq \left(\frac{n}{2k}\right)^k \cdot \frac{d^k}{n^k} \cdot e^{-d} \\ &= d^k n^{-k} \left(\frac{n}{2k}\right)^k e^{-d} = \left(\frac{d}{2k}\right)^k e^{-d}. \end{aligned}$$



Let  $k = C \log n / \log \log n$  such that  $d/2k > 1/\log n$  for large enough  $n$ ,<sup>a</sup> we have

$$\begin{aligned} \mathbb{P}\left(d'_i = \frac{C \log n}{\log \log n}\right) &\geq e^{-d} \left(\frac{d}{2k}\right)^k \geq e^{-d} (\log n)^{-k} = \exp(-d - k \log \log n) \\ &= \exp(-d - C \log n) = e^{-d} n^{-C}. \end{aligned}$$

Let this probability be  $q$ , and focus on  $A$ . We can then define  $X_i = \mathbb{1}_{d'_i=k}$  for  $i \in A$ , and note that  $X_i$  are all independent as  $A$  being an independent set. Then, the number of vertices in  $A$ , denoted as  $X$ , with degree exactly  $k$  follows  $\text{Bin}(n/2, q)$  with  $X = \sum_{i \in A} X_i$  and mean  $nq/2$ , variance  $nq(1-q)/2$ . From Chebyshev's inequality,

$$\mathbb{P}(X = 0) \leq \mathbb{P}(|X - \mu| \geq \mu) \leq \frac{\sigma^2}{\mu^2} = \frac{nq(1-q)/2}{(nq/2)^2} = 2 \frac{1-q}{nq} \leq \frac{2}{nq} \leq \frac{2}{ne^{-d} n^{-C}} = \frac{2e^d}{n^{1-C}}.$$

Now, by setting  $C < 1$ , say  $1/2$ , then

$$\mathbb{P}(X = 0) \leq 2e^d n^{-1/2} \rightarrow 0$$

as  $n \rightarrow \infty$ , which means  $\mathbb{P}(X \geq 1) \rightarrow 1$ , i.e., with probability 1, there are at least one point with degree  $\log n / 2 \log \log n$ . Now, by considering the deleting edges in the beginning, we conclude that there will be a vertex with degree

$$\Omega\left(\frac{\log n}{\log \log n}\right)$$

with overwhelming probability. ⊛

<sup>a</sup>Since this is equivalent as  $k < d \log n / 2$ . As  $k$  has a  $\log \log n \rightarrow \infty$  factor in the denominator, the claim holds.

## Week 5: Sub-Gaussian Random Variables

### 2.5 Sub-gaussian distributions

16 Feb. 2024

**Problem (Exercise 2.5.1).** Show that for each  $p \geq 1$ , the random variable  $X \sim \mathcal{N}(0, 1)$  satisfies

$$\|X\|_{L^p} = (\mathbb{E}[|X|^p])^{1/p} = \sqrt{2} \left( \frac{\Gamma((1+p)/2)}{\Gamma(1/2)} \right)^{1/p}.$$

Deduce that

$$\|X\|_{L^p} = O(\sqrt{p}) \text{ as } p \rightarrow \infty.$$

**Answer.** We see that for  $p \geq 1$ , we have

$$(\mathbb{E}[|X|^p])^{1/p} = \left( \int_{-\infty}^{\infty} |x|^p \cdot \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \right)^{1/p} = \left( 2 \int_0^{\infty} |x|^p \cdot \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \right)^{1/p}$$

from the symmetry around 0. Next, consider a change of variable  $x^2 =: u$ , we have

$$= \left( 2 \frac{1}{\sqrt{2\pi}} \int_0^{\infty} u^{p/2} e^{-u/2} \frac{1}{2\sqrt{u}} du \right)^{1/p} = \left( \frac{1}{\sqrt{2\pi}} \int_0^{\infty} u^{(p-1)/2} e^{-u/2} du \right)^{1/p}$$

with another change of variable  $u/2 =: t$ ,

$$\begin{aligned} &= \left( \frac{1}{\sqrt{2\pi}} \int_0^{\infty} (2t)^{(p-1)/2} e^{-t} 2 dt \right)^{1/p} = \left( \frac{1}{\sqrt{2\pi}} \cdot 2^{(p-1)/2} \cdot 2 \int_0^{\infty} t^{(p-1)/2} e^{-t} dt \right)^{1/p} \\ &= \left( \frac{1}{\sqrt{2\pi}} 2^{(p+1)/2} \Gamma\left(\frac{p+1}{2}\right) \right)^{1/p} = \left( \frac{1}{\sqrt{2}} \sqrt{2^{p+1}} \frac{\Gamma((p+1)/2)}{\Gamma(1/2)} \right)^{1/p} \end{aligned}$$

as  $\Gamma(1/2) = \sqrt{\pi}$ , we finally have

$$= \sqrt{2} \left( \frac{\Gamma((p+1)/2)}{\Gamma(1/2)} \right)^{1/p},$$

where we recall that

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt.$$

To show that  $\|X\|_{L^p} = O(\sqrt{p})$  as  $p \rightarrow \infty$ , we first note the following.

**Lemma 2.5.1.** We have that for  $p \geq 1$ ,

$$\Gamma\left(\frac{1+p}{2}\right) = \begin{cases} 2^{-p/2} \sqrt{\pi} (p-1)!!, & \text{if } p \text{ is even;} \\ 2^{-(p-1)/2} (p-1)!!, & \text{if } p \text{ is odd.} \end{cases}$$

**Proof.** Consider the Legendre duplication formula, i.e.,

$$\Gamma(z)\Gamma(z+1/2) = 2^{1-2z} \sqrt{\pi} \Gamma(2z).$$

We see that for  $p$  being even,  $(1+p)/2 = p/2 + 1/2$ , by letting  $z := p/2 \in \mathbb{N}$ ,

$$\begin{aligned} \Gamma((1+p)/2) &= \frac{2^{1-p} \sqrt{\pi} \Gamma(p)}{\Gamma(p/2)} = 2^{1-p} \sqrt{\pi} \frac{(p-1)!}{(p/2-1)!} \\ &= 2^{1-p} \sqrt{\pi} \frac{(p-1)!}{(1/2)^{p/2-1} (p-2)!!} = 2^{-p/2} \sqrt{\pi} (p-1)!!. \end{aligned}$$

For odd  $p$ , recall the identity  $\Gamma(z+1) = z\Gamma(z)$ . We then have

$$\begin{aligned} \Gamma((1+p)/2) &= \frac{p-1}{2} \cdot \Gamma((p-1)/2) \\ &= \frac{(p-1)(p-3)}{2^2} \cdot \Gamma((p-3)/2) \\ &\vdots \\ &= \frac{(p-1)(p-3) \dots (p-(p-2))}{2^{(p-1)/2}} \cdot \Gamma(1) & 2 = (p - (p-2)) \\ &= 2^{-(p-1)/2} (p-1)(p-3) \dots (2) \\ &= 2^{-(p-1)/2} (p-1)!!. \end{aligned}$$

■

We then see that as  $p \rightarrow \infty$ ,

$$\|X\|_{L^p} = \sqrt{2} \left( \frac{\Gamma((1+p)/2)}{\Gamma(1/2)} \right)^{1/p} \lesssim ((p-1)!!)^{1/p} = O(\sqrt{p}^{1/p}) = O(\sqrt{p}).$$

⊛

**Problem (Exercise 2.5.4).** Show that the condition  $\mathbb{E}[X] = 0$  is necessary for property v to hold.

**Answer.** Since if  $\mathbb{E}[\exp(\lambda X)] \leq \exp(K_5^2 \lambda^2)$  for all  $\lambda \in \mathbb{R}$ , we see that from Jensen's inequality,

$$\exp(\mathbb{E}[\lambda X]) \leq \mathbb{E}[\exp(\lambda X)] \leq \exp(K_5^2 \lambda^2),$$

i.e.,

$$\lambda \mathbb{E}[X] \leq K_5^2 \lambda^2.$$

Since this holds for every  $\lambda \in \mathbb{R}$ , if  $\lambda > 0$ ,  $\mathbb{E}[X] \leq K_5^2 \lambda$ ; on the other hand, if  $\lambda < 0$ ,  $\mathbb{E}[X] \geq K_5^2 \lambda$ . In either case, as  $\lambda \rightarrow 0$  (from both sides, respectively),  $0 \leq \mathbb{E}[X] \leq 0$ , hence  $\mathbb{E}[X] = 0$ . ⊛

**Problem (Exercise 2.5.5).** (a) Show that if  $X \sim \mathcal{N}(0, 1)$ , the function  $\lambda \mapsto \mathbb{E}[\exp(\lambda^2 X^2)]$  is only finite in some bounded neighborhood of zero.

- (b) Suppose that some random variable  $X$  satisfies  $\mathbb{E}[\exp(\lambda^2 X^2)] \leq \exp(K\lambda^2)$  for all  $\lambda \in \mathbb{R}$  and some constant  $K$ . Show that  $X$  is a bounded random variable, i.e.,  $\|X\|_\infty < \infty$ .

**Answer.** (a) If  $X \sim \mathcal{N}(0, 1)$ , we see that

$$\mathbb{E}[\exp(\lambda^2 X^2)] = \int_{-\infty}^{\infty} \exp(\lambda^2 x^2) \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \exp((\lambda^2 - 1/2)x^2) dx.$$

It's obvious that if  $\lambda^2 - 1/2 \geq 0$ , the above integral doesn't converge simply because  $e^{\epsilon x^2}$  for any  $\epsilon \geq 0$  is unbounded. On the other hand, if  $\lambda^2 - 1/2 < 0$ , then this is just a (scaled) Gaussian integral, which converges. Hence, this function is only finite in  $\lambda \in (-1/\sqrt{2}, 1/\sqrt{2})$ .

- (b) Simply because that for any  $t$ , we have that for any  $\lambda$ ,

$$\mathbb{P}(|X| > t) \leq \frac{\mathbb{E}[\exp(\lambda^2 X^2)]}{\exp(\lambda^2 t^2)} \leq \frac{\exp(K\lambda^2)}{\exp(\lambda^2 t^2)} = \exp(\lambda^2(K - t^2)).$$

Now, let's pick  $t > \sqrt{K}$  (as  $K$  being a constant,  $t$  can be any constant greater than  $t > \sqrt{K}$ ), so  $\lambda^2(K - t^2) < 0$ . By letting  $\lambda \rightarrow \infty$ , we see that  $\mathbb{P}(|X| > t) = 0$ , i.e.,  $\mathbb{P}(|X| \leq t) = 1$ . Since we're in one-dimensional,  $|X| = \|X\|_\infty$ , hence we're done.

⊛

**Problem (Exercise 2.5.7).** Check that  $\|\cdot\|_{\psi_2}$  is indeed a norm on the space of sub-gaussian random variables.

**Answer.** It's clear that  $\|X\|_{\psi_2} = 0$  if and only if  $X = 0$ . Also, for any  $\lambda > 0$ ,  $\|\lambda X\|_{\psi_2} = \lambda\|X\|_{\psi_2}$  is obvious. Hence, we only need to verify triangle inequality, i.e., for any sub-gaussian random variables  $X$  and  $Y$ ,

$$\|X + Y\|_{\psi_2} \leq \|X\|_{\psi_2} + \|Y\|_{\psi_2}.$$

Firstly, we observe that since  $\exp(x)$  and  $x^2$  are both convex (hence their composition),

$$\begin{aligned} \exp\left(\left(\frac{X + Y}{\|X\|_{\psi_2} + \|Y\|_{\psi_2}}\right)^2\right) &\leq \frac{\|X\|_{\psi_2}}{\|X\|_{\psi_2} + \|Y\|_{\psi_2}} \exp((X/\|X\|_{\psi_2})^2) \\ &\quad + \frac{\|Y\|_{\psi_2}}{\|X\|_{\psi_2} + \|Y\|_{\psi_2}} \exp((Y/\|Y\|_{\psi_2})^2). \end{aligned}$$

Then, by taking expectation on both sides,

$$\mathbb{E}\left[\exp\left(\left(\frac{X + Y}{\|X\|_{\psi_2} + \|Y\|_{\psi_2}}\right)^2\right)\right] \leq 2 \frac{\|X\|_{\psi_2}}{\|X\|_{\psi_2} + \|Y\|_{\psi_2}} + 2 \frac{\|Y\|_{\psi_2}}{\|X\|_{\psi_2} + \|Y\|_{\psi_2}} = 2.$$

Now, we see that from the definition of  $\|X + Y\|_{\psi_2}$  and  $t := \|X\|_{\psi_2} + \|Y\|_{\psi_2}$ , the above implies

$$\|X + Y\|_{\psi_2} \leq \|X\|_{\psi_2} + \|Y\|_{\psi_2},$$

hence the triangle inequality is verified.

⊛

**Problem (Exercise 2.5.9).** Check that Poisson, exponential, Pareto and Cauchy distributions are not sub-gaussian.

**Answer.** Omit.

⊛

**Problem (Exercise 2.5.10).** Let  $X_1, X_2, \dots$ , be a sequence of sub-gaussian random variables, which

are not necessarily independent. Show that

$$\mathbb{E} \left[ \max_i \frac{|X_i|}{\sqrt{1 + \log i}} \right] \leq CK,$$

where  $K = \max_i \|X_i\|_{\psi_2}$ . Deduce that for every  $N \geq 2$  we have

$$\mathbb{E} \left[ \max_{i \leq N} |X_i| \right] \leq CK \sqrt{\log N}.$$

**Answer.** Let  $Y_i := |X_i|/K\sqrt{1 + \log i}$  (which is always positive) for all  $i \geq 1$ . Then for all  $t \geq 0$ ,

$$\begin{aligned} \mathbb{P}(Y_i \geq t) &= \mathbb{P} \left( \frac{|X_i|}{K\sqrt{1 + \log i}} \geq t \right) \\ &= \mathbb{P} \left( |X_i| \geq tK\sqrt{1 + \log i} \right) \\ &\leq 2 \exp \left( -\frac{ct^2 K^2 (1 + \log i)}{\|X_i\|_{\psi_2}^2} \right) \leq 2 \exp(-ct^2(1 + \log i)) = 2(ei)^{-ct^2} \end{aligned}$$

as  $K := \max_i \|X_i\|_{\psi_2}$ . Then, our goal now is to show that  $\mathbb{E}[\max_i Y_i] \leq C$  for some absolute constant  $C$ . Consider  $t_0 := \sqrt{1/c}$ , then we have

$$\begin{aligned} \mathbb{E} \left[ \max_i Y_i \right] &= \int_0^\infty \mathbb{P} \left( \max_i Y_i \geq t \right) dt \\ &\leq \int_0^{t_0} \mathbb{P} \left( \max_i Y_i \geq t \right) dt + \int_{t_0}^\infty \sum_{i=1}^\infty \mathbb{P}(Y_i \geq t) dt && \text{union bound} \\ &\leq t_0 + \int_{t_0}^\infty \sum_{i=1}^\infty 2(ei)^{-ct^2} dt \\ &\leq \sqrt{1/c} + 2 \int_{t_0}^\infty e^{-ct^2} \sum_{i=1}^\infty i^{-2} dt \\ &\leq \sqrt{1/c} + 2 \cdot \frac{\pi^2}{6} \int_0^\infty e^{-ct^2} dt = \sqrt{1/c} + \frac{\pi^2}{3} \cdot \frac{\sqrt{\pi}}{2\sqrt{c}} = \frac{1 + \frac{\pi^{5/2}}{6}}{\sqrt{c}} =: C. \end{aligned}$$

Finally, for every  $N \geq 2$ ,

$$\mathbb{E} \left[ \max_{i \leq N} \frac{|X_i|}{\sqrt{1 + \log N}} \right] \leq \mathbb{E} \left[ \max_{i \leq N} \frac{|X_i|}{\sqrt{1 + \log i}} \right] \leq \mathbb{E} \left[ \max_i \frac{|X_i|}{\sqrt{1 + \log i}} \right] \leq CK,$$

i.e.,  $\mathbb{E}[\max_{i \leq N} |X_i|] \leq CK\sqrt{1 + \log N} \leq CK\sqrt{2 \log N}$  for all  $N \geq 2$ . By letting  $C' := \sqrt{2}C$ ,

$$\mathbb{E} \left[ \max_{i \leq N} |X_i| \right] \leq C'K\sqrt{\log N},$$

which is exactly what we want. \*

**Problem (Exercise 2.5.11).** Show that the bound in [Exercise 2.5.10](#) is sharp. Let  $X_1, X_2, \dots, X_N$  be independent  $\mathcal{N}(0, 1)$  random variables. Prove that

$$\mathbb{E} \left[ \max_{i \leq N} X_i \right] \geq c\sqrt{\log N}.$$

**Answer.** Again, let's first write

$$\mathbb{E} \left[ \max_{i \leq N} X_i \right] = \int_0^\infty \mathbb{P} \left( \max_{i \leq N} X_i \geq t \right) dt,$$

and observe that for any  $t \geq 0$ ,

$$\begin{aligned}\mathbb{P}(X_i \geq t) &= \int_t^\infty \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx \\ &= \frac{1}{\sqrt{2\pi}} \int_0^\infty \exp\left(-\frac{(x+t)^2}{2}\right) dx && x \leftarrow x+t \\ &\geq \frac{1}{\sqrt{2\pi}} \int_0^1 \exp\left(-\frac{(x+t)^2}{2}\right) dx \\ &\geq Ce^{-t^2}\end{aligned}$$

for some constant  $C > 0$ . Since  $X_i$ 's are i.i.d.,

$$\mathbb{P}\left(\max_{i \leq N} X_i \geq t\right) = 1 - (\mathbb{P}(X_1 < t))^N = 1 - (1 - \mathbb{P}(X_1 \geq t))^N,$$

so

$$\begin{aligned}\mathbb{E}\left[\max_{i \leq N} X_i\right] &= \int_0^\infty 1 - (1 - \mathbb{P}(X_1 \geq t))^N dt \\ &\geq \int_0^\infty 1 - (1 - Ce^{-t^2})^N dt \\ &= \sqrt{\log N} \int_0^\infty 1 - \left(1 - \frac{C}{Nu^2}\right)^N du. && t =: \sqrt{\log N} u\end{aligned}$$

Finally, as the final integral can be further bounded below by some absolute constant  $c$  depending only on  $C$ , hence we obtain the desired result.  $\circledast$

## Week 6: Hoeffding's and Khintchine's Inequalities

### 2.6 General Hoeffding's and Khintchine's inequalities

21 Feb. 2024

**Problem (Exercise 2.6.4).** Deduce Hoeffding's inequality for bounded random variables (Theorem 2.2.6) from Theorem 2.6.3, possibly with some absolute constant instead of 2 in the exponent.

**Answer.** Omit.  $\circledast$

**Problem (Exercise 2.6.5).** Let  $X_1, \dots, X_N$  be independent sub-gaussian random variables with zero means and unit variances, and let  $a = (a_1, \dots, a_N) \in \mathbb{R}^N$ . Prove that for every  $p \in [2, \infty)$  we have

$$\left(\sum_{i=1}^N a_i^2\right)^{1/2} \leq \left\|\sum_{i=1}^N a_i X_i\right\|_{L^p} \leq CK\sqrt{p} \left(\sum_{i=1}^N a_i^2\right)^{1/2}$$

where  $K = \max_i \|X_i\|_{\psi_2}$  and  $C$  is an absolute constant.

**Answer.** From Jensen's inequality,

$$\left\|\sum_{i=1}^N a_i X_i\right\|_{L^p} \geq \left\|\sum_{i=1}^N a_i X_i\right\|_{L^2} = \left[\mathbb{E}\left[\left(\sum_{i=1}^N a_i X_i\right)^2\right]\right]^{1/2}.$$

Then, observe that since  $\mathbb{E}[X_i] = 0$ ,

$$\text{Var}\left[\sum_{i=1}^N a_i X_i\right] = \mathbb{E}\left[\left(\sum_{i=1}^N a_i X_i\right)^2\right] - \left(\mathbb{E}\left[\sum_{i=1}^N a_i X_i\right]\right)^2 = \mathbb{E}\left[\left(\sum_{i=1}^N a_i X_i\right)^2\right],$$

and at the same time, as  $\text{Var}[X_i] = 1$ ,  $\text{Var}\left[\sum_{i=1}^N a_i X_i\right] = \sum_{i=1}^N a_i^2 \text{Var}[X_i] = \sum_{i=1}^N a_i^2 = \|a\|^2$ , hence we have

$$\left\|\sum_{i=1}^N a_i X_i\right\|_{L^p} \geq [\|a\|^2]^{1/2} = \|a\|,$$

which is the desired lower-bound. For the upper-bound, we see that

$$\begin{aligned} \left\|\sum_{i=1}^N a_i X_i\right\|_{L^p}^2 &\leq C^2 \sqrt{p}^2 \left\|\sum_{i=1}^N a_i X_i\right\|_{\psi_2}^2 \\ &\leq C' p \sum_{i=1}^N \|a_i X_i\|_{\psi_2}^2 = C'' p \sum_{i=1}^N a_i^2 \|X_i\|_{\psi_2}^2 \leq C'' K^2 p \|a\|^2, \end{aligned}$$

where  $C, C', C''$  are all absolute constant (might depend on each other). Taking square root on both sides, we obtain the desired result.  $\circledast$

**Problem (Exercise 2.6.6).** Show that in the setting of [Exercise 2.6.5](#), we have

$$c(K) \left(\sum_{i=1}^N a_i^2\right)^{1/2} \leq \left\|\sum_{i=1}^N a_i X_i\right\|_{L^1} \leq \left(\sum_{i=1}^N a_i^2\right)^{1/2}.$$

Here  $K g \max_i \|X_i\|_{\psi_2}$  and  $c(K) > 0$  is a quantity which may depend only on  $K$ .

**Answer.** Skip, as this is a special case of [Exercise 2.6.7](#).  $\circledast$

**Problem (Exercise 2.6.7).** State and prove a version of Khintchine's inequality for  $p \in (0, 2)$ .

**Answer.** The Khintchine's inequality for  $p \in (0, 2)$  can be stated as

$$c(K, p) \left(\sum_{i=1}^N a_i^2\right)^{1/2} \leq \left\|\sum_{i=1}^N a_i X_i\right\|_{L^p} \leq \left(\sum_{i=1}^N a_i^2\right)^{1/2}.$$

Here  $K = \max_i \|X_i\|_{\psi_2}$  and  $c(K, p) > 0$  is a quantity which depends on  $K$  and  $p$ . We first recall the generalized Hölder inequality.

**Theorem 2.6.1 (Generalized Hölder inequality).** For  $1/p + 1/q = 1/r$  where  $p, q \in (0, \infty]$ ,

$$\|fg\|_{L^r} \leq \|f\|_{L^p} \|g\|_{L^q}.$$

**Proof.** The classical case is when  $r = 1$ . By considering  $|f|^r \in L^{p/r}$  and  $|g|^r \in L^{q/r}$ ,  $r/p + r/q = 1$ . Then the standard Hölder inequality implies

$$\begin{aligned} \|fg\|_{L^r}^r &= \int |fg|^r = \int |f|^r |g|^r \leq \| |f|^r \|_{L^{p/r}} \| |g|^r \|_{L^{q/r}} \\ &= \left( \int (|f|^r)^{p/r} \right)^{r/p} \left( \int (|g|^r)^{q/r} \right)^{r/q} = \|f\|_{L^p}^r \|g\|_{L^q}^r, \end{aligned}$$

implying the result.  $\blacksquare$

Now, take  $r = 2$ ,  $p = q = 4$ , we get

$$\|XY\|_{L^2} \leq \|X\|_{L^4} \|Y\|_{L^4} = (\mathbb{E}[|X|^4])^{1/4} (\mathbb{E}[|Y|^4])^{1/4}.$$

Let  $X = |Z|^{p/4}$  and  $Y = |Z|^{(4-p)/4}$ , we see that

$$\|Z\|_{L^2} \leq (\mathbb{E}[|Z|^p])^{1/4} (\mathbb{E}[|Z|^{4-p}])^{1/4} = \|Z\|_{L^p}^{p/4} \|Z\|_{L^{4-p}}^{(4-p)/4},$$

implying

$$\|Z\|_{L^p} \geq \left( \frac{\|Z\|_{L^2}}{\|Z\|_{L^{4-p}}^{(4-p)/4}} \right)^{4/p} = \frac{\|Z\|_{L^2}^{4/p}}{\|Z\|_{L^{4-p}}^{(4-p)/p}}.$$

Finally, by letting  $Z = \sum_{i=1}^N a_i X_i$ ,

$$\left\| \sum_{i=1}^N a_i X_i \right\|_{L^p} \geq \left\| \sum_{i=1}^N a_i X_i \right\|_{L^2}^{4/p} / \left\| \sum_{i=1}^N a_i X_i \right\|_{L^{4-p}}^{(4-p)/p}.$$

Observe that from [Exercise 2.6.5](#):

- $\|\sum_{i=1}^N a_i X_i\|_{L^2} = \|a\|$ ;
- $\|\sum_{i=1}^N a_i X_i\|_{L^{4-p}} \leq CK\sqrt{4-p}\|a\|$  (as  $4-p > 2$  from  $p \in (0, 2)$ ),

hence

$$\left\| \sum_{i=1}^N a_i X_i \right\|_{L^p} \geq \|a\|^{4/p} / \left( CK\sqrt{4-p}\|a\| \right)^{(4-p)/p} = \left( CK\sqrt{4-p} \right)^{-\frac{p}{4-p}} \|a\|.$$

Hence, we see that by letting  $c(K, p) := (CK\sqrt{4-p})^{-p/(4-p)}$ , the lower-bound is established. The upper-bound is essentially the same as [Exercise 2.6.5](#) (in there we use have the lower-bound since  $p \geq 2$ ), where this time we use  $\|\cdot\|_{L^p} \leq \|\cdot\|_{L^2}$  since  $p \leq 2$ .<sup>a</sup> Hence, we're done.  $\circledast$

<sup>a</sup>Note that although  $\|\cdot\|_{L^p}$  for  $p \in [0, 1)$  is not a norm, this inequality still holds.

**Remark.** [Exercise 2.6.6](#) is just a special case with  $c(K, 1) = (CK\sqrt{3})^{-1/3}$ .

**Problem** ([Exercise 2.6.9](#)). Show that unlike (2.19), the centering inequality in Lemma 2.6.8 does not hold with  $C = 1$ .

**Answer.** Consider the random variable  $X := \sqrt{\log 2} \cdot \epsilon$  where  $\epsilon$  is a Rademacher random variable with parameter  $p$ , i.e.,

$$X = \begin{cases} \sqrt{\log 2}, & \text{w.p. } p; \\ -\sqrt{\log 2}, & \text{w.p. } 1-p. \end{cases}$$

Since  $\mathbb{E}[\exp(X^2)] = 2$ , we know that  $\|X\|_{\psi_2}$  is exactly 1. We now want to show that  $\|X - \mathbb{E}[X]\|_{\psi_2} > \|X\|_{\psi_2} = 1$  for some  $p$ . It amounts to show that  $\mathbb{E}[\exp(|X - \mathbb{E}[X]|^2)] > 2$ . Now, we know that  $\mathbb{E}[X] = \sqrt{\log 2}(2p - 1)$ , and hence

$$X - \mathbb{E}[X] = \begin{cases} 2(1-p)\sqrt{\log 2}, & \text{w.p. } p; \\ -2p\sqrt{\log 2}, & \text{w.p. } 1-p. \end{cases}$$

Hence, we have that

$$\mathbb{E}[\exp(|X - \mathbb{E}[X]|^2)] = p \cdot 2^{4(1-p)^2} + (1-p)2^{4p^2}.$$

A quick numerical optimization gives the desired result with  $p \approx 0.236$ .  $\circledast$

## Week 7: Sub-Exponential Random Variables

### 2.7 Sub-exponential distributions

1 Mar. 2024

**Problem (Exercise 2.7.2).** Prove the equivalence of properties a-d in Proposition 2.7.1 by modifying the proof of Proposition 2.5.2.

**Answer.** This is a special case of Exercise 2.7.3 with  $\alpha = 1$ . \*

**Problem (Exercise 2.7.3).** More generally, consider the class of distributions whose tail decay is of the type  $\exp(-ct^\alpha)$  or faster. Here  $\alpha = 2$  corresponds to sub-gaussian distributions, and  $\alpha = 1$ , to sub-exponential. State and prove a version of Proposition 2.7.1 for such distributions.

**Answer.** The generalized version of Proposition 2.7.1 is known to be the so-called *Sub-Weibull distributions* [Vla+20]: Let  $X$  be a random variable. Then the following properties are equivalent; the parameters  $K_i > 0$  appearing in these properties differ from each other by at most an absolute constant factor.

(a) The tails of  $X$  satisfy

$$\mathbb{P}(|X| \geq t) \leq 2 \exp(-t^\alpha/K_1) \text{ for all } t \geq 0.$$

(b) The moments of  $X$  satisfy

$$\|X\|_{L^p} = (\mathbb{E}|X|^p)^{1/p} \leq K_2 p^{1/\alpha} \text{ for all } p \geq 1.$$

(c) The MGF of  $|X|$  satisfies

$$\mathbb{E}[\exp(\lambda^\alpha |X|^\alpha)] \leq \exp(\lambda^\alpha K_3^\alpha) \text{ for all } \lambda \text{ such that } 0 \leq \lambda \leq \frac{1}{K_3}.$$

(d) The MGF of  $|X|$  is bounded at some point, namely

$$\mathbb{E}[\exp(|X|^\alpha/K_4^\alpha)] \leq 2.$$

**Claim.** (a)  $\Rightarrow$  (b)

**Proof.** Without loss of generality, let  $K_1 = 1$ . Then, we have

$$\begin{aligned} \|X\|_{L^p}^p &= \int_0^\infty \mathbb{P}(|X|^p \geq t) dt \\ &= \int_0^\infty p u^{p-1} \mathbb{P}(|X| \geq u) du && u := t^{1/p} \\ &\leq 2p \int_0^\infty u^{p-1} e^{-u^\alpha} du && \text{from our assumption} \\ &= \frac{2p}{\alpha} \int_0^\infty t^{p/\alpha-1} e^{-t} dt && t := u^\alpha \\ &= 2 \frac{p}{\alpha} \Gamma(p/\alpha) = 2\Gamma(p/\alpha + 1) \lesssim (p/\alpha + 1)^{p/\alpha+1} \end{aligned}$$

for some constant  $C$  from Stirling's approximation. Hence,

$$\|X\|_{L^p} \lesssim \left(\frac{p}{\alpha} + 1\right)^{\frac{1}{\alpha} + \frac{1}{p}} = \left(\frac{p}{\alpha} + 1\right)^{\frac{1}{\alpha}} \left(\frac{p}{\alpha} + 1\right)^{\frac{1}{p}} \lesssim p^{1/\alpha}$$

as we desired. \*

**Claim.** (b)  $\Rightarrow$  (c)



**Proof.** Firstly, from Taylor's expansion, we have

$$\mathbb{E}[\exp(\lambda^\alpha |X|^\alpha)] = 1 + \sum_{k=1}^{\infty} \frac{\lambda^{\alpha k} \mathbb{E}[|X|^{\alpha k}]}{k!} \leq 1 + \sum_{k=1}^{\infty} \frac{\lambda^{\alpha k} \mathbb{E}[|X|^{\alpha k}]}{k!}.$$

From (b), when  $\alpha k \geq 1$ , we have  $\mathbb{E}[|X|^{\alpha k}] \leq (K_2(\alpha k)^{1/\alpha})^{\alpha k} = K_2^{\alpha k} (\alpha k)^k$ . On the other hand, for any given  $\alpha > 0$ , there are only finitely many  $k \geq 1$  such that  $\alpha k < 1$ . Hence, there exists some  $\tilde{K}_2$  such that

$$\mathbb{E}[|X|^{\alpha k}] \leq \tilde{K}_2^{\alpha k} (\alpha k)^k$$

for all  $k \geq 1$ . With  $k! \geq (k/e)^k$  from Stirling's approximation, we further have

$$1 + \sum_{k=1}^{\infty} \frac{\lambda^{\alpha k} \mathbb{E}[|X|^{\alpha k}]}{k!} \leq 1 + \sum_{k=1}^{\infty} \frac{\lambda^{\alpha k} \tilde{K}_2^{\alpha k} (\alpha k)^k}{(k/e)^k} = 1 + \sum_{k=1}^{\infty} \lambda^{\alpha k} \tilde{K}_2^{\alpha k} (\alpha e)^k = 1 + \sum_{k=1}^{\infty} (\tilde{K}_2^\alpha \lambda^\alpha \alpha e)^k.$$

Observe that if  $0 < \tilde{K}_2^\alpha \lambda^\alpha \alpha e < 1$ , we then have

$$\mathbb{E}[\exp(\lambda^\alpha |X|^\alpha)] \leq 1 + \sum_{k=1}^{\infty} (\tilde{K}_2^\alpha \lambda^\alpha \alpha e)^k = \frac{1}{1 - \tilde{K}_2^\alpha \lambda^\alpha \alpha e}.$$

As  $(1-x)e^{2x} \geq 1$  for all  $x \in [0, 1/2]$ , the above is further less than

$$\exp\left(2(\tilde{K}_2^\alpha \lambda^\alpha \alpha e)\right) = \exp\left(\left[(2\alpha e)^{1/\alpha} \tilde{K}_2\right]^\alpha \lambda^\alpha\right).$$

By letting  $K_3 := (2\alpha e)^{1/\alpha} \tilde{K}_2$ , we have the desired result whenever  $\tilde{K}_2^\alpha \lambda^\alpha \alpha e < 1$ , or equivalently,

$$0 < \lambda^\alpha < \frac{1}{\tilde{K}_2^\alpha \alpha e} \Leftrightarrow 0 < \lambda < \frac{1}{\tilde{K}_2 (\alpha e)^{1/\alpha}}.$$

Hence, if  $0 < \lambda \leq \frac{1}{\tilde{K}_2 (\alpha e)^{1/\alpha}} = \frac{1}{K_3}$ , the above is satisfied.  $\circledast$

**Claim.** (c)  $\Rightarrow$  (d)

**Proof.** Assuming (c) holds, then (d) is obtained by taking  $\lambda := 1/K_4$  where  $K_4 := K_3(\ln 2)^{-1/\alpha}$ . In this case,  $\lambda = 1/K_3 \cdot (\ln 2)^{1/\alpha}$ , hence

$$\mathbb{E}[\exp(\lambda^\alpha |X|^\alpha)] = \mathbb{E}[\exp(|X|^\alpha / K_4^\alpha)] \leq \exp(\lambda^\alpha K_3^\alpha)$$

for all  $0 \leq \lambda = 1/K_4 \leq 1/K_3$  from (d) gives

$$\mathbb{E}[\exp(|X|^\alpha / K_4^\alpha)] \leq \exp\left(\ln 2 \cdot \frac{1}{K_3^\alpha} \cdot K_3^\alpha\right) = 2.$$

$\circledast$

**Claim.** (d)  $\Rightarrow$  (a)

**Proof.** Let  $K_4 = 1$  without loss of generality. Then, we have

$$\mathbb{P}(|X| \geq t) = \mathbb{P}(\exp(|X|^\alpha) \geq \exp(t^\alpha)) \leq \frac{\mathbb{E}[\exp(|X|^\alpha)]}{\exp(t^\alpha)} \leq 2 \exp(-t^\alpha),$$

hence  $K_1 := 1$  proves the result.  $\circledast$

$\circledast$

**Problem (Exercise 2.7.4).** Argue that the bound in property c can not be extended for all  $\lambda$  such that  $|\lambda| \leq 1/K_3$ .

**Answer.** It's easy to see that in the proof of Exercise 2.7.3, when we prove (b)  $\Rightarrow$  (c), the condition for  $\lambda$  essentially comes from:

- whether  $1 + \sum_{k=1}^{\infty} (\tilde{K}_2^\alpha \lambda^\alpha \alpha e)^k = 1 + \sum_{k=1}^{\infty} (\tilde{K}_2 \lambda e)^k$  as  $\alpha = 1$  converges; and
- the numerical inequality  $(1 - x)e^{2x} \geq 1$  for  $x \in [0, 1/2]$  such that  $x := \tilde{K}_2 \lambda e$ .

For the first condition, we only need  $|\tilde{K}_2 \lambda e| < 1$ , hence we don't need positivity for  $\lambda$  at first; however, the second condition indeed requires  $\lambda \geq 0$ , and it's impossible to remove as this is tight.

FROM THE MAKERS OF WOLFRAM LANGUAGE AND MATHEMATICA



$(1-x)e^{2x}$  x in  $(-1/2, 1/2)$

NATURAL LANGUAGE

MATH INPUT

EXTENDED KEYBOARD

EXAMPLES

UPLOAD

RANDOM

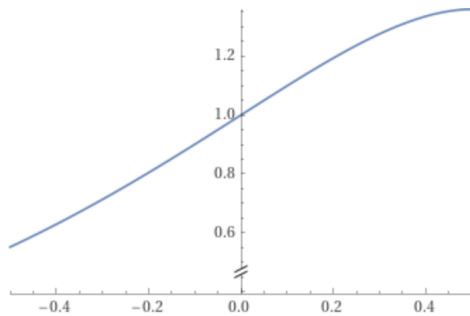
Input interpretation

plot

$(1-x)e^{2x}$

$x = -\frac{1}{2}$  to  $\frac{1}{2}$

Plot



⊗

**Problem (Exercise 2.7.10).** Prove an analog of the Centering Lemma 2.6.8 for sub-exponential random variables  $X$ :

$$\|X - \mathbb{E}[X]\|_{\psi_1} \leq C\|X\|_{\psi_1}.$$

**Answer.** Since  $\|\cdot\|_{\psi_2}$  is a norm, we have  $\|X - \mathbb{E}[X]\|_{\psi_1} \leq \|X\|_{\psi_1} + \|\mathbb{E}[X]\|_{\psi_1}$  such that

$$\begin{aligned} \|\mathbb{E}[X]\|_{\psi_1} &\lesssim \|\mathbb{E}[X]\| & \|a\|_{\psi_1} = \inf_{t>0} \{\mathbb{E}[e^{|a|/t}] \leq 2\} &\lesssim |a| \\ &\leq \mathbb{E}[|X|] & &\text{Jensen's inequality} \\ &= \|X\|_{L^1} \lesssim \|X\|_{\psi_1} \end{aligned}$$

from Proposition 2.7.1 (b) with  $p = 1$ , i.e.,

$$\|X\|_{L^1} \leq K_2 \cong \|X\|_{\psi_1}$$

since  $K_i \cong \|X\|_{\psi_1} = K_4$ .

⊗

## Week 8: Bernstein's Inequality

6 Mar. 2024

**Problem (Exercise 2.7.11).** Show that  $\|X\|_\psi$  is indeed a norm on the space  $L_\psi$ .

**Answer.** Clearly,  $\|X\|_\psi \geq 0$ . To check  $\|X\|_\psi = 0$  if and only if  $X = 0$  a.s., we first see that  $\|0\|_\psi = 0$  as  $\psi(0) = 0$ . On the other hand, if  $\|X\|_\psi = 0$ , then by the monotone convergence theorem, we have

$$\begin{aligned} 1 &\geq \lim_{t \rightarrow 0} \mathbb{E}[\psi(|X|/t)] = \mathbb{E} \left[ \lim_{t \rightarrow 0} \psi(|X|/t) \right] \\ &= \int_0^\infty \mathbb{P} \left( \lim_{t \rightarrow 0} \psi(|X|/t) > u \right) du \\ &= \mathbb{P}(|X| > 0) \int_0^\infty \mathbb{P} \left( \lim_{t \rightarrow 0} \psi(|X|/t) > u \mid |X| > 0 \right) du \\ &= \mathbb{P}(|X| > 0) \int_0^\infty du \\ &= \infty \cdot \mathbb{P}(|X| > 0), \end{aligned}$$

since if  $|X| = 0$ ,  $\psi(|X|/t) = \psi(0) = 0$  for all  $t > 0$ , and

$$\mathbb{P} \left( \lim_{t \rightarrow 0} \psi(|X|/t) > u \mid |X| > 0 \right) = 1$$

since  $\psi(x) \rightarrow \infty$  for  $x \rightarrow \infty$ , and in this case,  $x = |X|/t$ , which indeed goes to  $\infty$  as  $t \rightarrow 0$ . Overall, this implies  $\mathbb{P}(|X| > 0) = 0$ , i.e.,  $X = 0$  almost surely, hence we conclude that  $\|X\|_\psi = 0$  if and only if  $X = 0$  a.s. The other two properties follow the same proof of [Exercise 2.5.7](#).  $\circledast$

## 2.8 Bernstein's inequality

**Problem (Exercise 2.8.5).** Let  $X$  be a mean-zero random variable such that  $|X| \leq K$ . Prove the following bound on the MGF of  $X$ :

$$\mathbb{E}[\exp(\lambda X)] \leq \exp(g(\lambda)\mathbb{E}[X^2]) \text{ where } g(\lambda) = \frac{\lambda^2/2}{1 - |\lambda|K/3},$$

provided that  $|\lambda| < 3/K$ .

**Answer.** From the hint, we first check the following.

**Claim.** For all  $|x| < 3$ ,

$$e^x \leq 1 + x + \frac{x^2/2}{1 - |x|/3}.$$

**Proof.** From Taylor's expansion,

$$e^x = 1 + x + \frac{x^2}{2} \sum_{k=0}^{\infty} \frac{x^k}{(2+k)!/2} \leq 1 + x + \frac{x^2}{2} \sum_{k=0}^{\infty} \frac{x^k}{3^k} = 1 + x + \frac{x^2/2}{1 - |x|/3}$$

where the last equality follows for all  $|x| < 3$ .  $\circledast$

Now, for a random variable  $X$  such that  $|X| \leq K$  and  $|\lambda| < 3/K$ , we have

$$\mathbb{E}[\exp(\lambda X)] \leq \mathbb{E} \left[ 1 + \lambda X + \frac{\lambda^2 X^2/2}{1 - |\lambda X|/3} \right] = 1 + \frac{\lambda^2 \mathbb{E}[X^2]/2}{1 - |\lambda|K/3} \leq \exp \left( \frac{\lambda^2 \mathbb{E}[X^2]/2}{1 - |\lambda|K/3} \right),$$

where we let  $x := \lambda X$  and apply the claim. Finally, note that the right-hand side is exactly  $\exp(g(\lambda)\mathbb{E}[X^2])$ , we're done.  $\circledast$

**Problem (Exercise 2.8.6).** Deduce Theorem 2.8.4 from the bound in [Exercise 2.8.5](#).

**Answer.** From Markov's inequality, for every  $t \geq 0$ ,

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^N X_i \geq t\right) &\leq \inf_{\lambda > 0} \frac{\mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^N X_i\right)\right]}{\exp(\lambda t)} \\ &= \inf_{\lambda > 0} e^{-\lambda t} \prod_{i=1}^N \mathbb{E}[\exp(\lambda X_i)] \leq \inf_{\lambda > 0} e^{-\lambda t} \exp\left(g(\lambda) \sum_{i=1}^N \mathbb{E}[X_i^2]\right) \end{aligned}$$

from [Exercise 2.8.5](#), if  $|\lambda| < 3/K$ . Denote  $\sigma^2 = \sum_{i=1}^N \mathbb{E}[X_i^2]$ , we further have

$$\mathbb{P}\left(\sum_{i=1}^N X_i \geq t\right) \leq \inf_{\lambda > 0} \exp(-\lambda t + g(\lambda)\sigma^2).$$

Let  $0 \leq \lambda = \frac{t}{\sigma^2 + tK/3} < 3/K$ , we see that

$$\mathbb{P}\left(\sum_{i=1}^N X_i \geq t\right) \leq \exp\left(-\frac{t^2}{\sigma^2 + tK/3} + \frac{\sigma^2 \lambda^2 / 2}{1 - |\lambda|K/3}\right) = \exp\left(-\frac{t^2/2}{\sigma^2 + tK/3}\right).$$

Applying the same argument for  $-X_i$ , we get

$$\mathbb{P}\left(\left|\sum_{i=1}^N X_i\right| \geq t\right) \leq 2 \exp\left(-\frac{t^2/2}{\sigma^2 + tK/3}\right).$$

⊛

# Chapter 3

## Random vectors in high dimensions

### Week 9: Concentration Inequalities of Random Vectors

#### 3.1 Concentration of the norm

15 Mar. 2024

**Problem (Exercise 3.1.4).** (a) Deduce from Theorem 3.1.1 that

$$\sqrt{n} - CK^2 \leq \mathbb{E}[\|X\|_2] \leq \sqrt{n} + CK^2.$$

(b) Can  $CK^2$  be replaced by  $o(1)$ , a quantity that vanishes as  $n \rightarrow \infty$ ?

**Answer.** (a) From Jensen's inequality, we have

$$|\mathbb{E}[\|X\|_2 - \sqrt{n}]| \leq \mathbb{E}[|\|X\|_2 - \sqrt{n}|] \leq \|\|X\|_2 - \sqrt{n}\|_{\psi_2} \leq CK^2$$

from Theorem 3.1.1 and

$$\|Z\|_{\psi_2} = \inf\{t > 0: \mathbb{E}[\exp(Z^2/t^2)] \leq 2\} \geq \|Z\|_{L^1}$$

as  $\mathbb{E}[\exp(Z^2/(\mathbb{E}[\|Z\|^2]))] \geq 1 + \mathbb{E}[Z^2]/(\mathbb{E}[\|Z\|^2]) \geq 2$ , again from Jensen's inequality.

(b) We first observe that  $\mathbb{E}[\|X\|_2] \leq \sqrt{\mathbb{E}[\|X\|_2^2]} = \sqrt{n}$ , hence we only need to deal with lower-bound. Consider the following non-negative function

$$f(x) = \sqrt{x} - \frac{1}{2}(1 + x - (x - 1)^2) \geq 0$$

for  $x \geq 0$ . Then, for  $x = \|X\|_2^2/n \geq 0$ , we have

$$\begin{aligned} \sqrt{\frac{\|X\|_2^2}{n}} &\geq \frac{1}{2} \left( 1 + \frac{\|X\|_2^2}{n} - \left( \frac{\|X\|_2^2}{n} - 1 \right)^2 \right) \\ \Rightarrow \|X\|_2 &\geq \frac{\sqrt{n}}{2} \left( 1 + \frac{\|X\|_2^2}{n} - \left( \frac{\|X\|_2^2}{n} - 1 \right)^2 \right) \\ \Rightarrow \mathbb{E}[\|X\|_2] &\geq \frac{\sqrt{n}}{2} \left( 1 + \frac{n}{n} \right) - \frac{\sqrt{n}}{2} \mathbb{E} \left[ \left( \frac{\|X\|_2^2 - \mathbb{E}[\|X\|_2^2]}{n} \right)^2 \right] \\ \Rightarrow \mathbb{E}[\|X\|_2] &\geq \sqrt{n} - \frac{1}{2n^{3/2}} \text{Var}[\|X\|_2^2]. \end{aligned}$$

Expanding the variance, we see that

$$\text{Var}[\|X\|_2^2] = \sum_{i=1}^n \text{Var}[X_i^2] = \sum_{i=1}^n (\mathbb{E}[X_i^4] - \mathbb{E}[X_i^2]^2) \leq n \cdot \max_{1 \leq i \leq n} \mathbb{E}[X_i^4] = n \cdot \max_{1 \leq i \leq n} \|X_i\|_{L^4}^4,$$

and from the sub-gaussian property, this is  $\lesssim n \cdot \max_{1 \leq i \leq n} \|X_i\|_{\psi_2}^4 = nK^4$ . Overall,

$$\mathbb{E}[\|X\|_2] \gtrsim \sqrt{n} - \frac{1}{2n^{3/2}} nK^4 = \sqrt{n} - \frac{K^4}{\sqrt{n}} = \sqrt{n} + o(1),$$

if  $K \geq 1$ . Otherwise, when  $K < 1$ , we replace  $K^4$  by 1, the result holds still.

⊛

**Problem (Exercise 3.1.5).** Deduce from Theorem 3.1.1 that

$$\text{Var}[\|X\|_2] \leq CK^4.$$

**Answer.** From the definition and the fact that the mean minimizes the MSE,

$$\text{Var}[\|X\|_2] = \mathbb{E}[(\|X\|_2 - \mathbb{E}[\|X\|_2])^2] \leq \mathbb{E}[(\|X\|_2 - \sqrt{n})^2],$$

then from the proof of Exercise 3.1.4, as  $\mathbb{E}[\|X\|_2 - \sqrt{n}] \leq cK^2$  for some  $c$ ,

$$\text{Var}[\|X\|_2] \leq \mathbb{E}[(\|X\|_2 - \sqrt{n})^2] \leq c^2 K^4,$$

and by letting  $c^2 =: C$ , we're done.

⊛

**Problem (Exercise 3.1.6).** Let  $X = (X_1, \dots, X_n) \in \mathbb{R}^n$  be a random vector with independent coordinates  $X_i$  that satisfy  $\mathbb{E}[X_i^2] = 1$  and  $\mathbb{E}[X_i^4] \leq K^4$ . Show that

$$\text{Var}[\|X\|_2] \leq CK^4.$$

**Answer.** Firstly, observe that with our new assumption, Exercise 3.1.4 (b) again gives  $\mathbb{E}[\|X\|_2] \gtrsim \sqrt{n} - K^4/\sqrt{n}$ . Then from the same reason as stated in Exercise 3.1.5,

$$\text{Var}[\|X\|_2] \leq \mathbb{E}[(\|X\|_2 - \sqrt{n})^2] = 2n - 2\sqrt{n}\mathbb{E}[\|X\|_2] \lesssim 2n - 2\sqrt{n} \left( \sqrt{n} - \frac{K^4}{\sqrt{n}} \right) = 2K^4,$$

proving the result.

⊛

**Problem (Exercise 3.1.7).** Let  $X = (X_1, \dots, X_n) \in \mathbb{R}^n$  be a random vector with independent coordinates  $X_i$  with continuous distributions. Assume that the densities of  $X_i$  are uniformly bounded by 1. Show that, for any  $\epsilon > 0$ , we have

$$\mathbb{P}(\|X\|_2 \leq \epsilon\sqrt{n}) \leq (C\epsilon)^n.$$

**Answer.** We want to bound

$$\mathbb{P}(\|X\|_2 \leq \epsilon\sqrt{n}) = \mathbb{P}(\|X\|_2^2 \leq \epsilon^2 n) = \mathbb{P}\left(\sum_{i=1}^n X_i^2 \leq \epsilon^2 n\right).$$

Follow the same argument as Exercise 2.2.10,<sup>a</sup> i.e., first we bound  $\mathbb{E}[\exp(-tX_i^2)]$  for all  $t > 0$ . We have

$$\mathbb{E}[\exp(-tX_i^2)] = \int_0^\infty e^{-tx^2} f_{X_i}(x) dx \leq \int_0^\infty e^{-tx^2} dx = \frac{1}{2} \sqrt{\frac{\pi}{t}}$$

from the Gaussian integral. Then, from the MGF trick, we have

$$\mathbb{P}(\|X\|_2 \leq \epsilon\sqrt{n}) = \mathbb{P}(-\|X\|_2^2 \geq -\epsilon^2 n) \leq \inf_{t>0} \frac{\mathbb{E}[\exp(-t\|X\|_2^2)]}{\exp(-t\epsilon^2 n)} \leq \inf_{t>0} \left( \frac{1}{2} \sqrt{\frac{\pi}{t}} \right)^n e^{t\epsilon^2 n}.$$

Let  $t = \epsilon^{-2}$ , we have

$$\mathbb{P}(\|X\|_2 \leq \epsilon\sqrt{n}) \leq \left(\frac{\sqrt{\pi}}{2}\epsilon \cdot e\right)^n =: (C\epsilon)^n$$

by letting  $C := \sqrt{\pi}e/2$ . \*

<sup>a</sup>The result does not directly follow from this because  $\epsilon$  is replaced by  $\epsilon^2$ , and a bound on the density of  $X_i$  doesn't give a bound on the density of  $X_i^2$ .

## 3.2 Covariance matrices and principal component analysis

**Problem (Exercise 3.2.2).** (a) Let  $Z$  be a mean zero, isotropic random vector in  $\mathbb{R}^n$ . Let  $\mu \in \mathbb{R}^n$  be a fixed vector and  $\Sigma$  be a fixed  $n \times n$  symmetric positive semidefinite matrix. Check that the random vector

$$X := \mu + \Sigma^{1/2}Z$$

has mean  $\mu$  and covariance matrix  $\text{Cov}[X] = \Sigma$ .

(b) Let  $X$  be a random vector with mean  $\mu$  and invertible covariance matrix  $\Sigma = \text{Cov}[X]$ . Check that the random vector

$$Z := \Sigma^{-1/2}(X - \mu)$$

is an isotropic, mean zero random vector.

**Answer.** (a) Firstly,

$$\mathbb{E}[X] = \mathbb{E}[\mu] + \mathbb{E}[\Sigma^{1/2}Z] = \mu + \Sigma^{1/2}\mathbb{E}[Z] = \mu$$

Moreover,

$$\begin{aligned} \text{Cov}[X] &= \text{Cov}[\mu + \Sigma^{1/2}Z] \\ &= \mathbb{E}[(\mu + \Sigma^{1/2}Z)(\mu + \Sigma^{1/2}Z)^\top] - \mu\mu^\top \\ &= \mathbb{E}[(\mu + \Sigma^{1/2}Z)Z^\top(\Sigma^{1/2})^\top] \\ &= \mathbb{E}[\mu Z^\top(\Sigma^{1/2})^\top] + \mathbb{E}[\Sigma^{1/2}ZZ^\top(\Sigma^{1/2})^\top] \\ &= 0 + \Sigma^{1/2}\mathbb{E}[ZZ^\top](\Sigma^{1/2})^\top \\ &= \Sigma^{1/2}I_n(\Sigma^{1/2})^\top \\ &= \Sigma \end{aligned}$$

as  $\Sigma$  is positive-semidefinite.

(b) Similarly,

$$\mathbb{E}[Z] = \Sigma^{-1/2}\mathbb{E}[X - \mu] = \Sigma^{-1/2}(\mu - \mu) = 0,$$

and moreover,

$$\begin{aligned} \text{Cov}[Z] &= \text{Cov}[\Sigma^{-1/2}(X - \mu)] \\ &= \mathbb{E}\left[(\Sigma^{-1/2}(X - \mu))(\Sigma^{-1/2}(X - \mu))^\top\right] \\ &= \Sigma^{-1/2}\mathbb{E}[(X - \mu)(X - \mu)^\top](\Sigma^{-1/2})^\top \\ &= \Sigma^{-1/2}\Sigma(\Sigma^{-1/2})^\top \\ &= I_n, \end{aligned}$$

hence  $Z$  is also isotropic. \*

**Problem (Exercise 3.2.6).** Let  $X$  and  $Y$  be independent, mean zero, isotropic random vectors in  $\mathbb{R}^n$ .

Check that

$$\mathbb{E}[\|X - Y\|_2^2] = 2n.$$

**Answer.** This directly follows from

$$\mathbb{E}[\|X - Y\|_2^2] = \mathbb{E}[\langle X - Y, X - Y \rangle] = \mathbb{E}[\langle X, X \rangle] - 2\mathbb{E}[\langle X, Y \rangle] + \mathbb{E}[\langle Y, Y \rangle] = n - 0 + n = 2n.$$

⊛

## Week 10: Common High-Dimensional Distributions

### 3.3 Examples of high-dimensional distributions

20 Mar. 2024

**Problem (Exercise 3.3.1).** Show that the spherically distributed random vector  $X$  is isotropic. Argue that the coordinates of  $X$  are not independent.

**Answer.** Firstly, from the spherical symmetry of  $X$ , for any  $x \in \mathbb{R}^n$ ,  $\langle X, x \rangle \stackrel{D}{=} \langle X, \|x\|_2 e \rangle$  for all  $e \in S^{n-1}$ . Hence, to show  $X$  is isotropic, from Lemma 3.2.3, it suffices to show that for any  $x \in \mathbb{R}^n$ ,

$$\mathbb{E}[\langle X, x \rangle^2] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\langle X, \|x\|_2 e_i \rangle^2] = \frac{1}{n} \mathbb{E} \left[ \sum_{i=1}^n (\|x\|_2 X_i)^2 \right] = \|x\|_2^2 \mathbb{E} \left[ \frac{1}{n} \sum_{i=1}^n X_i^2 \right] = \|x\|_2^2,$$

where  $e_i$  denotes the  $i^{\text{th}}$  standard unit vector. The last equality holds from the fact that

$$\mathbb{E} \left[ \frac{1}{n} \sum_{i=1}^n X_i^2 \right] = \frac{1}{n} \mathbb{E}[\|X\|_2^2] = \frac{1}{n} n = 1$$

as  $X \sim \mathcal{U}(\sqrt{n}S^{n-1})$ . On the other hand, clearly  $X_i$ 's can't be independent since the first  $n-1$  coordinates determines the last coordinate. ⊛

**Problem (Exercise 3.3.3).** Deduce the following properties from the rotation invariance of the normal distribution.

(a) Consider a random vector  $g \sim \mathcal{N}(0, I_n)$  and a fixed vector  $u \in \mathbb{R}^n$ . Then

$$\langle g, u \rangle \sim \mathcal{N}(0, \|u\|_2^2).$$

(b) Consider independent random variables  $X_i \sim \mathcal{N}(0, \sigma_i^2)$ . Then

$$\sum_{i=1}^n X_i \sim \mathcal{N}(0, \sigma^2) \text{ where } \sigma^2 = \sum_{i=1}^n \sigma_i^2.$$

(c) Let  $G$  be an  $m \times n$  Gaussian random matrix, i.e., the entries of  $G$  are independent  $\mathcal{N}(0, 1)$  random variables. Let  $u \in \mathbb{R}^n$  be a fixed unit vector. Then

$$Gu \sim \mathcal{N}(0, I_m).$$

**Answer.** (a) Without loss of generality, we may assume  $\|u\|_2 = 1$  and prove

$$\langle g, u \rangle \sim \mathcal{N}(0, 1)$$

for any fixed unit vector  $u \in \mathbb{R}^n$ . But this is clear as there must exist  $u_1, \dots, u_{n-1}$  such that  $\{u, u_1, \dots, u_{n-1}\}$  forms an orthonormal basis of  $\mathbb{R}^n$ , and  $U := (u, u_1, \dots, u_{n-1})^\top$  is



orthonormal. From Proposition 3.3.2, we have

$$Ug \sim \mathcal{N}(0, I_n),$$

which implies  $(Ug)_1 \sim \mathcal{N}(0, 1)$ . With  $(Ug)_1 = u^\top g = \langle g, u \rangle$ , we're done.

(b) For independent  $X_i \sim \mathcal{N}(0, \sigma_i^2)$ , we have  $X_i/\sigma_i \sim \mathcal{N}(0, 1)$ . We want to show

$$\sum_{i=1}^n X_i \sim \mathcal{N}(0, \sigma^2)$$

where  $\sigma^2 = \sum_{i=1}^n \sigma_i^2$ . Firstly, we have  $g := (X_1/\sigma_1, \dots, X_n/\sigma_n) \sim \mathcal{N}(0, I_n)$ , then by considering  $u := (\sigma_1, \dots, \sigma_n) \in \mathbb{R}^n$ , we have

$$\langle g, u \rangle = \sum_{i=1}^n X_i \sim \mathcal{N}(0, \|u\|_2^2) = \mathcal{N}\left(0, \sum_{i=1}^n \sigma_i^2\right) = \mathcal{N}(0, \sigma^2)$$

from (a).

(c) For any fixed unit vector  $u$ ,  $(Gu)_i = \sum_{j=1}^n g_{ij}u_j = \langle g_i, u \rangle$  where  $g_i = (g_{i1}, g_{i2}, \dots, g_{in})$  for all  $i \in [m]$ . It's clear that  $g_i \sim \mathcal{N}(0, I_n)$ , and from (a),  $\langle g_i, u \rangle \sim \mathcal{N}(0, 1)$ . This implies

$$Gu = (\langle g_1, u \rangle, \dots, \langle g_m, u \rangle) \sim \mathcal{N}(0, I_m)$$

as desired.

⊛

**Problem (Exercise 3.3.4).** Let  $X$  be a random vector in  $\mathbb{R}^n$ . Show that  $X$  has a multivariate normal distribution if and only if every one-dimensional marginal  $\langle X, \theta \rangle$ ,  $\theta \in \mathbb{R}^n$ , has a (univariate) normal distribution.

**Answer.** This is an application of Cramér-Wold device and Exercise 3.3.3 (a). Omit the details. ⊛

**Problem (Exercise 3.3.5).** Let  $X \sim \mathcal{N}(0, I_n)$ .

(a) Show that, for any fixed vectors  $u, v \in \mathbb{R}^n$ , we have

$$\mathbb{E}[\langle X, u \rangle \langle X, v \rangle] = \langle u, v \rangle.$$

(b) Given a vector  $u \in \mathbb{R}^n$ , consider the random variable  $X_u := \langle X, u \rangle$ . From Exercise 3.3.3 we know that  $X_u \sim \mathcal{N}(0, \|u\|_2^2)$ . Check that

$$\|X_u - X_v\|_{L^2} = \|u - v\|_2$$

for any fixed vectors  $u, v \in \mathbb{R}^n$ .

**Answer.** (a) It's because

$$\mathbb{E}[\langle X, u \rangle \langle X, v \rangle] = \mathbb{E}[(u^\top X)(X^\top v)] = u^\top \mathbb{E}[XX^\top]v = u^\top I_n v = \langle u, v \rangle$$

from the fact that  $X$  is isotropic.

(b) Since  $X_u - X_v = \langle X, u \rangle - \langle X, v \rangle = \langle X, u - v \rangle = X_{u-v}$  from linearity of inner product. Hence,

$$\|X_u - X_v\|_{L^2} = \sqrt{\langle X_{u-v}, X_{u-v} \rangle} = \sqrt{\mathbb{E}[X_{u-v}^2]} = \sqrt{\mathbb{E}[\langle X, u - v \rangle^2]}.$$

From (a),  $\mathbb{E}[\langle X, u - v \rangle^2] = \langle u - v, u - v \rangle = \|u - v\|_2^2$ , hence

$$\|X_u - X_v\|_{L^2} = \sqrt{\|u - v\|_2^2} = \|u - v\|_2.$$

⊗

**Problem (Exercise 3.3.6).** Let  $G$  be an  $m \times n$  Gaussian random matrix, i.e., the entries of  $G$  are independent  $\mathcal{N}(0, 1)$  random variables. Let  $u, v \in \mathbb{R}^n$  be unit orthogonal vectors. Prove that  $G_u$  and  $G_v$  are independent  $\mathcal{N}(0, I_m)$  random vectors.

**Answer.** It's clear that  $G_u$  and  $G_v$  are both  $\mathcal{N}(0, I_m)$  random vectors from Exercise 3.3.3 (c). It remains to show that  $G_u$  and  $G_v$  are independent, i.e.,  $(G_u)_i$  and  $(G_v)_j$  are independent random variables.

For  $i \neq j$ , this is clear since  $(G_u)_i = e_i^\top (Gu)$  and  $(G_v)_j = e_j^\top (Gv)$ , and  $e_i^\top G$  gives the  $i^{\text{th}}$  row of  $G$ , while  $e_j^\top G$  gives the  $j^{\text{th}}$  row of  $G$ . The fact that  $G$  has independent rows proves the result for the case of  $i \neq j$ .

For  $i = j$ , let  $e_i^\top G =: g^\top$  where  $g \sim \mathcal{N}(0, I_n)$ , and we want to show independence of  $(G_u)_i = g^\top u$  and  $(G_v)_j = g^\top v$ . This is still easy since

$$\begin{pmatrix} g^\top u \\ g^\top v \end{pmatrix} = (u, v)^\top g \sim \mathcal{N}(0, (u, v)^\top I_n (u, v)) = \mathcal{N}(0, I_2)$$

as  $u, v$  are unit orthogonal vectors.

⊗

**Problem (Exercise 3.3.7).** Let us represent  $g \sim \mathcal{N}(0, I_n)$  in polar form as

$$g = r\theta$$

where  $r = \|g\|_2$  is the length and  $\theta = g/\|g\|_2$  is the direction of  $g$ . Prove the following:

- (a) The length  $r$  and direction  $\theta$  are independent random variables.
- (b) The direction  $\theta$  is uniformly distributed on the unit sphere  $S^{n-1}$ .

**Answer.** For any measurable  $M \subseteq \mathbb{R}^n$ , given the normal density  $f_G(g)$  of  $g$ , some elementary calculus gives the polar coordinate transformation  $dg = r^{n-1} dr d\sigma(\theta)$ , hence

$$\begin{aligned} \mathbb{P}(g \in M) &= \int_M f_G(g) dg = \int_A \int_B f_G(r\theta) d\sigma(\theta) r^{n-1} dr \\ &= \frac{\omega_{n-1}}{(2\pi)^{n/2}} \int_A r^{n-1} e^{-r^2/2} dr \int_B d\sigma(\theta) = \mathbb{P}(r \in A, \theta \in B) \end{aligned} \quad (3.1)$$

for some  $A \subseteq [0, \infty)$  and  $B \subseteq S^{n-1}$  generating  $M$ , where  $\sigma$  is the surface area element on  $S^{n-1}$  such that  $\int_{S^{n-1}} d\sigma = \omega_{n-1}$ , i.e.,  $\omega_{n-1}$  is the surface area of the unit sphere  $S^{n-1}$ .

- (a) From Equation 3.1, it's possible to write

$$\mathbb{P}(g \in M) = \mathbb{P}(r \in A, \theta \in B) =: f(A)g(B)$$

such that  $g(S^{n-1}) = 1$  with appropriate constant manipulation. Hence, with  $B = S^{n-1}$ ,

$$\mathbb{P}(r \in A, \theta \in S^{n-1}) = \mathbb{P}(r \in A) = f(A),$$

implying  $f([0, \infty)) = 1$  as well. This further shows that by considering  $A = [0, \infty)$ ,

$$\mathbb{P}(r \in [0, \infty), \theta \in B) = \mathbb{P}(\theta \in B) = g(B).$$

Such a separation of probability proves the independence.

- (b) From Equation 3.1, we see that for any  $B \subseteq S^{n-1}$ , the density is uniform among  $d\sigma(\theta)$ , hence  $\theta$  is uniformly distributed on  $S^{n-1}$ .

⊛

**Problem (Exercise 3.3.9).** Show that  $\{u_i\}_{i=1}^N$  is a tight frame in  $\mathbb{R}^n$  with bound  $A$  if and only if

$$\sum_{i=1}^N u_i u_i^\top = A I_n.$$

**Answer.** Recall that for two symmetric matrices  $A, B \in \mathbb{R}^{n \times n}$ ,  $A = B$  if and only if  $x^\top A x = x^\top B x$  for all  $x \in \mathbb{R}^n$ . Hence,

$$\sum_{i=1}^N u_i u_i^\top = A I_n \Leftrightarrow x^\top \left( \sum_{i=1}^N u_i u_i^\top \right) x = x^\top (A I_n) x$$

for all  $x \in \mathbb{R}^n$ . We see that

- The left-hand side:

$$x^\top \left( \sum_{i=1}^N u_i u_i^\top \right) x = \sum_{i=1}^N (x^\top u_i)(u_i^\top x) = \sum_{i=1}^N \langle u_i, x \rangle^2,$$

- The right-hand side:

$$x^\top A I_n x = A x^\top x = A \|x\|_2^2.$$

Hence,  $\sum_{i=1}^N u_i u_i^\top = A I_n$  if and only if  $\sum_{i=1}^N \langle u_i, x \rangle^2 = A \|x\|_2^2$ , i.e.,  $\{u_i\}_{i=1}^N$  being a tight frame. ⊛

## Week 11: High-Dimensional Sub-Gaussian Distributions

### 3.4 Sub-gaussian distributions in higher dimensions

29 Mar. 2024

**Problem (Exercise 3.4.3).** This exercise clarifies the role of independence of coordinates in Lemma 3.4.2.

1. Let  $X = (X_1, \dots, X_n) \in \mathbb{R}^n$  be a random vector with sub-gaussian coordinates  $X_i$ . Show that  $X$  is a sub-gaussian random vector.
2. Nevertheless, find an example of a random vector  $X$  with

$$\|X\|_{\psi_2} \gg \max_{i \leq n} \|X_i\|_{\psi_2}.$$

**Answer.** 1. We see that

$$\|X\|_{\psi_2} = \sup_{x \in S^{n-1}} \|\langle X, x \rangle\|_{\psi_2} \leq \sup_{x \in S^{n-1}} \sum_{i=1}^n \|x_i X_i\|_{\psi_2} \leq \sup_{x \in S^{n-1}} \|X_i\|_{\psi_2} < \infty.$$

2. Just consider  $X_i = Z$  are the same where  $Z \sim \mathcal{N}(0, 1)$ . Then, we see that

$$\max_i \|X_i\|_{\psi_2} = \|Z\|_{\psi_2} = \sqrt{8/3}$$

as  $\mathbb{E}[\exp(Z^2/t^2)] = 1/\sqrt{1-2/t^2}$ . On the other hand,

$$\|X\|_{\psi_2} \geq \|\langle X, \mathbb{1}_n/\sqrt{n} \rangle\|_{\psi_2} = \|\sqrt{n}Z\|_{\psi_2} = \sqrt{8n/3}.$$

⊛

**Problem (Exercise 3.4.4).** Show that

$$\|X\|_{\psi_2} \asymp \sqrt{\frac{n}{\log n}}.$$

**Answer.** Since we not only want an upper-bound, but a tight, non-asymptotic behavior, we need to calculate  $\|X\|_{\psi_2}$  as precise as possible. We note that

$$\|X\|_{\psi_2} = \sup_{x \in S^{n-1}} \|\langle X, x \rangle\|_{\psi_2} = \sup_{x \in S^{n-1}} \inf\{t > 0: \mathbb{E}[\exp(\langle X, x \rangle^2/t^2)] \leq 2\},$$

and clearly the supremum is attained when  $x = e_i$  for some  $i$ . In this case,

$$\|X\|_{\psi_2} = \inf\{t > 0: \mathbb{E}[\exp(X_i^2/t^2)] \leq 2\}.$$

Note that since  $X \sim \mathcal{U}(\{\sqrt{n}e_i\}_i)$ , we see if we focus on a particular coordinate  $i$ ,

$$X_i = \begin{cases} 0, & \text{w.p. } \frac{n-1}{n}; \\ \sqrt{n}, & \text{w.p. } \frac{1}{n}. \end{cases}$$

Hence, for any  $t > 0$ ,

$$\mathbb{E}[\exp(X_i^2/t^2)] = \frac{n-1}{n} + \frac{1}{n} \exp\left(\frac{n}{t^2}\right).$$

Equating the above to be exactly 2 and solve it w.r.t.  $t$ , we have

$$\frac{n-1}{n} + \frac{1}{n} \exp\left(\frac{n}{t^2}\right) = 2 \Leftrightarrow n-1 + e^{n/t^2} = 2n \Leftrightarrow \ln(n+1) = \frac{n}{t^2} \Leftrightarrow t = \sqrt{\frac{n}{\ln(n+1)}},$$

meaning that

$$\|X\|_{\psi_2} = \inf\{t > 0: \mathbb{E}[\exp(X_i^2/t^2)] \leq 2\} = \sqrt{\frac{n}{\ln(n+1)}} \asymp \sqrt{\frac{n}{\log n}}.$$

⊛

**Problem (Exercise 3.4.5).** Let  $X$  be an isotropic random vector supported in a finite set  $T \subseteq \mathbb{R}^n$ . Show that in order for  $x$  to be sub-gaussian with  $\|X\|_{\psi_2} = O(1)$ , the cardinality of the set must be exponentially large in  $n$ :

$$|T| \geq e^{cn}.$$

**Answer.** This is a hard one. See [here](#) for details.

⊛

**Problem (Exercise 3.4.7).** Extend Theorem 3.4.6 for the uniform distribution on the Euclidean ball  $B(0, \sqrt{n})$  in  $\mathbb{R}^n$  centered at the origin and with radius  $\sqrt{n}$ . Namely, show that a random vector

$$X \sim \mathcal{U}(B(0, \sqrt{n}))$$

is sub-gaussian, and

$$\|X\|_{\psi_2} \leq C.$$

**Answer.** For  $X \sim \mathcal{U}(B(0, \sqrt{n}))$ , consider  $R := \|X\|_2 / \sqrt{n}$  and  $Y := X/R = \sqrt{n}X/\|X\|_2 \sim \mathcal{U}(\sqrt{n}S^{n-1})$ . From Theorem 3.4.6,  $\|Y\|_{\psi_2} \leq C$ . It's clear that  $R \leq 1$ , hence for any  $x \in S^{n-1}$ ,

$$\mathbb{E}[\exp(\langle X, x \rangle^2 / t^2)] = \mathbb{E}[\exp(R^2 \langle Y, x \rangle^2 / t^2)] \leq \mathbb{E}[\exp(\langle Y, x \rangle^2 / t^2)],$$

which implies  $\|\langle X, x \rangle\|_{\psi_2} \leq \|\langle Y, x \rangle\|_{\psi_2}$ . Hence,  $\|X\|_{\psi_2} \leq \|Y\|_{\psi_2} \leq C$ .  $\circledast$

**Problem (Exercise 3.4.9).** Consider a ball of the  $\ell_1$  norm in  $\mathbb{R}^n$ :

$$K := \{x \in \mathbb{R}^n : \|x\|_1 \leq r\}.$$

- (a) Show that the uniform distribution on  $K$  is isotropic for some  $r \asymp n$ .
- (b) Show that the subgaussian norm of this distribution is *not* bounded by an absolute constant as the dimension  $n$  grows.

**Answer.** (a) Observe that for  $i \neq j$ ,  $(X_i, X_j) \stackrel{D}{=} (X_i, -X_j)$ , hence  $\mathbb{E}[X_i] = 0$  and  $\mathbb{E}[X_i X_j] = 0$  for  $i \neq j$ . Hence, for  $X$  to be isotropic, we need  $\mathbb{E}[X_i^2] = 1$ . Now, we note that  $\mathbb{P}(|X_i| > x) = (r - x)^n / r^n = (1 - x/r)^n$  for  $x \in [0, r]$ , hence

$$\mathbb{E}[X_i^2] = \int_0^\infty 2x \mathbb{P}(|X_i| > x) dx = 2r^2 \int_0^r \frac{x}{r} \left(1 - \frac{x}{r}\right)^n \frac{dx}{r} = 2r^2 \int_0^1 t(1-t)^n dt,$$

which with some calculation is  $2r^2/(n^2 + 3n + 2)$ . Equating this with 1 gives  $r \asymp n$ .

- (b) It suffices to show that  $\|X_i\|_{L^p} > C\sqrt{p}$ , which in turns blow up the sub-Gaussian property in terms of  $L^p$  norm. We see that

$$\begin{aligned} \|X_i\|_{L^p}^p &= \int_0^\infty px^{p-1} \mathbb{P}(|X_i| > x) dx \\ &= pr^p \int_0^r \left(\frac{x}{r}\right)^{p-1} \left(1 - \frac{x}{r}\right)^n \frac{dx}{r} = pr^p \int_0^1 t^{p-1} (1-t)^n dt = pr^p \cdot B(p, n+1), \end{aligned}$$

where  $B$  is the Beta function. From the Beta function,

$$\|X_i\|_{L^p}^p = pr^p \cdot \frac{\Gamma(p)\Gamma(n+1)}{\Gamma(p+n+1)},$$

hence  $\|X_i\|_{L^p} > C\sqrt{p}$  is evident from the Stirling's formula.  $\circledast$

**Problem (Exercise 3.4.10).** Show that the concentration inequality in Theorem 3.1.1 may not hold for a general isotropic sub-gaussian random vector  $X$ . Thus, independence of the coordinates of  $X$  is an essential requirement in that result.

**Answer.** We want to show that  $\|\|X\|_2 - \sqrt{n}\|_{\psi_2} \leq C \max \|X_i\|_{\psi_2}^2$  does not hold for a general isotropic sub-Gaussian random vector  $X$  with  $\mathbb{E}[X_i^2] = 1$ . Let  $0 < a < 1 < b$  such that  $a^2 + b^2 = 2$ , and define

$$X := (aZ)^\epsilon (bZ)^{1-\epsilon},$$

where  $\epsilon \sim \text{Bern}(1/2)$  and  $Z \sim \mathcal{N}(0, I_n)$ . In human language, consider  $X$  has a distribution

$$F_X := \frac{1}{2}F_{aZ} + \frac{1}{2}F_{bZ}.$$

With this construction,  $X$  is isotropic since

$$\begin{aligned}\mathbb{E}[XX^\top] &= \frac{1}{2}\mathbb{E}[(aZ)(aZ)^\top] + \frac{1}{2}\mathbb{E}[(bZ)(bZ)^\top] \\ &= \frac{1}{2}a^2\mathbb{E}[ZZ^\top] + \frac{1}{2}b^2\mathbb{E}[ZZ^\top] = \left(\frac{a^2}{2} + \frac{b^2}{2}\right)I_n = I_n,\end{aligned}$$

and  $\mathbb{E}[X_i^2] = 1$  with a similar calculation. Moreover, for any vector  $x \in S^{n-1}$ ,

$$\mathbb{E}[\exp(\langle X, x \rangle^2 / t^2)] = \frac{1}{2\sqrt{1-2a^2/t^2}} + \frac{1}{2\sqrt{1-2b^2/t^2}} < 2$$

when  $t$  is large enough (compared to  $a, b$ ). This shows  $\|\langle X, x \rangle\|_{\psi_2} \leq t$ , and since  $a, b$  is taken to be constants,  $X$  is indeed a sub-Gaussian random vector.

Now, we show that the norm of  $X$  actually deviates away from  $\sqrt{n}$  at a non-vanishing rate of  $n$ . In particular, consider  $t = (b-1)\sqrt{n}/2$ , then

$$\begin{aligned}2\mathbb{E}[\exp(\|X\|_2 - \sqrt{n})^2 / t^2] &> \mathbb{E}[\exp((\|bZ\|_2 - \sqrt{n})^2 / t^2)] \\ &> \mathbb{E}[\exp((\|bZ\|_2 - \sqrt{n})^2 / t^2) \mathbb{1}_{\|Z\|_2^2 > n}] \\ &> \exp((b\sqrt{n} - \sqrt{n})^2 / t^2) \mathbb{P}(\|Z\|_2^2 > n) \quad \text{since } b > 1 \\ &= e^4 \mathbb{P}(\|Z\|_2^2 > n) \\ &\rightarrow e^4 / 2 > 4\end{aligned}$$

since  $\mathbb{P}(\|Z\|_2^2 > n) = \mathbb{P}(\sum_{i=1}^n Z_i^2 > n)$ , and with  $\mathbb{E}[Z_i^2] = \text{Var}[Z_i] = 1$ , and  $\text{Var}[Z_i^2] = \mathbb{E}[Z_i^4] - \mathbb{E}[Z_i^2]^2 = 3 - 1 = 2 < \infty$ ,

$$\frac{\frac{1}{n} \sum_{i=1}^n Z_i^2 - 1}{\sqrt{2}/\sqrt{n}} = \frac{1}{\sqrt{2n}} \left( \sum_{i=1}^n Z_i^2 - n \right) \xrightarrow{D} \mathcal{N}(0, 1)$$

by the central limit theorem, hence, the asymptotic distribution of  $\sum_{i=1}^n Z_i^2 - n$  is symmetric around 0, meaning that  $\mathbb{P}(\sum_{i=1}^n Z_i^2 > n) = \mathbb{P}(\sum_{i=1}^n Z_i^2 - n > 0) = 1/2$ . This implies that for all large enough  $n$ ,

$$\|\|X\|_2 - \sqrt{n}\|_{\psi_2} \geq t = (b-1)\frac{\sqrt{n}}{2} \rightarrow \infty.$$

⊛

## Week 12: High-Dimensional Sub-Gaussian Distributions

### 3.5 Application: Grothendieck's inequality and semidefinite programming

3 Apr. 2024

**Problem (Exercise 3.5.2).** 1. Check that the assumption of Grothendieck's inequality can be equivalently stated as follows:

$$\left| \sum_{i,j} a_{ij} x_i y_j \right| \leq \max_i |x_i| \cdot \max_j |y_j|$$

for any real numbers  $x_i$  and  $y_j$ .

2. Show that the conclusion of Grothendieck's inequality can be equivalently stated as follows:

$$\left| \sum_{i,j} a_{ij} \langle u_i, v_j \rangle \right| \leq K \max_i \|u_i\| \cdot \max_j \|v_j\|$$

for any Hilbert space  $H$  and any vectors  $u_i, v_j \in H$ .

**Answer.** Omit. \*

**Problem (Exercise 3.5.3).** Deduce the following version of Grothendieck's inequality for symmetric  $n \times n$  matrices  $A = (a_{ij})$  with real entries. Suppose that  $A$  is either positive semidefinite or has zero diagonal. Assume that, for any numbers  $x_i \in \{-1, 1\}$ , we have

$$\left| \sum_{i,j} a_{ij} x_i x_j \right| \leq 1.$$

Then, for any Hilbert space  $H$  and any vectors  $u_i, v_j \in H$  satisfying  $\|u_i\| = \|v_j\| = 1$ , we have

$$\left| \sum_{i,j} a_{ij} \langle u_i, v_j \rangle \right| \leq 2K,$$

where  $K$  is the absolute constant from Grothendieck's inequality.

**Answer.** Omit. \*

**Problem (Exercise 3.5.5).** Show that the optimization (3.21) is equivalent to the following semidefinite program:

$$\max \langle A, X \rangle : X \succeq 0, \quad X_{ii} = 1 \text{ for } i = 1, \dots, n.$$

**Answer.** Omit. \*

**Problem (Exercise 3.5.7).** Let  $A$  be an  $m \times n$  matrix. Consider the optimization problem

$$\max \sum_{i,j} A_{ij} \langle X_i, Y_j \rangle : \|X_i\|_2 = \|Y_j\|_2 = 1 \text{ for all } i, j$$

over  $X_i, Y_j \in \mathbb{R}^k$  and  $k \in \mathbb{N}$ . Formulate this problem as a semidefinite program.

**Answer.** Omit. \*

### 3.6 Application: Maximum cut for graphs

**Problem (Exercise 3.6.4).** For any  $\epsilon > 0$ , given an  $(0.5 - \epsilon)$ -approximation algorithm for maximum cut, which is always *guaranteed* to give a suitable cut, but may have a random running time. Give a bound on the expected running time.

**Answer.** Omit. \*

**Problem (Exercise 3.6.7).** Prove Grothendieck's identity.

**Answer.** Omit. \*

### 3.7 Kernel trick, and tightening of Grothendieck's inequality

**Problem (Exercise 3.7.4).** Show that for any vectors  $u, v \in \mathbb{R}^n$  and  $k \in \mathbb{N}$ , we have

$$\langle u^{\otimes k}, v^{\otimes k} \rangle = \langle u, v \rangle^k.$$

**Answer.** This is immediate from the definition, i.e.,

$$\langle u^{\otimes k}, v^{\otimes k} \rangle = \sum_{i_1, \dots, i_k} u_{i_1 \dots i_k} v_{i_1 \dots i_k} = \sum_{i_1, \dots, i_k} u_{i_1} \dots u_{i_k} v_{i_1} \dots v_{i_k} = \left( \sum_{i=1}^n u_i v_i \right)^k$$

by observation (and probably term-matching).  $\circledast$

**Problem (Exercise 3.7.5).** (a) Show that there exist a Hilbert space  $H$  and a transformation  $\Phi: \mathbb{R}^n \rightarrow H$  such that

$$\langle \Phi(u), \Phi(v) \rangle = 2\langle u, v \rangle^2 + 5\langle u, v \rangle^3 \text{ for all } u, v \in \mathbb{R}^n.$$

(b) More generally, consider a polynomial  $f: \mathbb{R} \rightarrow \mathbb{R}$  with non-negative coefficients, and construct  $H$  and  $\Phi$  such that

$$\langle \Phi(u), \Phi(v) \rangle = f(\langle u, v \rangle) \text{ for all } u, v \in \mathbb{R}^n.$$

(c) Show the same for any *real analytic function*  $f: \mathbb{R} \rightarrow \mathbb{R}$  with non-negative coefficients, i.e., for any function that can be represented as a convergent series

$$f(x) = \sum_{k=0}^{\infty} a_k x^k, \quad x \in \mathbb{R} \quad (3.2)$$

and such that  $a_k \geq 0$  for all  $k$ .

**Answer.** (a) Consider  $H = \mathbb{R}^{n \times n} \oplus \mathbb{R}^{n \times n \times n}$ . Then, consider  $\Phi(x) := (\sqrt{2}x^{\otimes 2}, \sqrt{5}x^{\otimes 3})$ , and we have

$$\begin{aligned} \langle \Phi(u), \Phi(v) \rangle &= \langle (\sqrt{2}u^{\otimes 2}, \sqrt{5}u^{\otimes 3}), (\sqrt{2}v^{\otimes 2}, \sqrt{5}v^{\otimes 3}) \rangle \\ &= 2\langle u^{\otimes 2}, v^{\otimes 2} \rangle + 5\langle u^{\otimes 3}, v^{\otimes 3} \rangle = 2\langle u, v \rangle^2 + 5\langle u, v \rangle^3, \end{aligned}$$

where the last equality follows from [Exercise 3.7.4](#).

(b) Consider an  $m$ -order polynomial of  $\langle u, v \rangle$ , which we write  $f(\langle u, v \rangle) = \sum_{k=0}^m a_k \langle u, v \rangle^k$ . Then, by noting that  $a_k \geq 0$ , we may define

$$H := \bigoplus_{k=0}^m \mathbb{R}^{n^k}, \text{ and } \Phi(x) := \bigoplus_{k=0}^m \sqrt{a_k} x^{\otimes k} = (\sqrt{a_0}, \sqrt{a_1}x, \sqrt{a_2}x^{\otimes 2}, \dots, \sqrt{a_m}x^{\otimes m}).$$

Then by a similar calculation as [\(a\)](#), we have  $\langle \Phi(u), \Phi(v) \rangle = f(\langle u, v \rangle)$  for all  $u, v \in \mathbb{R}^n$ .

(c) In this case, we just let  $m = \infty$  in [\(b\)](#), i.e., consider

$$H := \bigoplus_{k=0}^{\infty} \mathbb{R}^{n^k}, \text{ and } \Phi(x) := \bigoplus_{k=0}^{\infty} \sqrt{a_k} x^{\otimes k},$$

where the limit is allowed as  $f$  converges everywhere. Note that  $a_k \geq 0$ , hence  $\sqrt{a_k}$  is also well-defined.  $\circledast$

**Problem (Exercise 3.7.6).** Let  $f: \mathbb{R} \rightarrow \mathbb{R}$  be any real analytic function (with possibly negative coefficients in [Equation 3.2](#)). Show that there exist a Hilbert space  $H$  and transformation  $\Phi, \Psi: \mathbb{R}^n \rightarrow H$  such that

$$\langle \Phi(u), \Psi(v) \rangle = f(\langle u, v \rangle) \text{ for all } u, v \in \mathbb{R}^n.$$



Moreover, check that

$$\|\Phi(u)\|^2 = \|\Psi(u)\|^2 = \sum_{k=0}^{\infty} |a_k| \|u\|_2^{2k}.$$

**Answer.** Again, similar to [Exercise 3.7.5 \(c\)](#), we construct

$$H := \bigoplus_{k=0}^{\infty} \mathbb{R}^{n^k}, \text{ and } \Phi(x) := \bigoplus_{k=0}^{\infty} \sqrt{a_k} x^{\otimes k}, \text{ and } \Psi(x) := \bigoplus_{k=0}^{\infty} \text{sgn}(a_k) \sqrt{|a_k|} x^{\otimes k}.$$

Then,  $\langle \Phi(u), \Psi_v \rangle = f(\langle u, v \rangle)$  since the sign of  $a_k$  is now taking care by  $\Psi$ . The norm can be calculated as

$$\begin{aligned} \|\Phi(u)\|^2 &= \langle \Phi(u), \Phi_u \rangle = \sum_{k=0}^{\infty} \langle \sqrt{|a_k|} u^{\otimes k}, \sqrt{|a_k|} u^{\otimes k} \rangle \\ &= \sum_{k=0}^{\infty} |a_k| \langle u^{\otimes k}, u^{\otimes k} \rangle = \sum_{k=0}^{\infty} |a_k| \langle u, u \rangle^k = \sum_{k=0}^{\infty} |a_k| \|u\|_2^{2k}, \end{aligned}$$

where the last equality follows from [Exercise 3.7.4](#). A similar calculation can be carried out for  $\|\Psi(u)\|^2$ . \*

## Chapter 4

# Random matrices

### 4.1 Preliminaries on matrices

**Problem (Exercise 4.1.1).** Suppose  $A$  is an invertible matrix with singular value decomposition

$$A = \sum_{i=1}^n s_i u_i v_i^\top.$$

Check that

$$A^{-1} = \sum_{i=1}^n \frac{1}{s_i} v_i u_i^\top.$$

**Answer.** Let  $A = U\Sigma V^*$ , and it suffices to check that

$$A \left( \sum_{i=1}^n \frac{1}{s_i} v_i u_i^\top \right) = I_n.$$

Indeed, by plugging  $A$ , we have

$$\left( \sum_{i=1}^n s_i u_i v_i^\top \right) \left( \sum_{i=1}^n \frac{1}{s_i} v_i u_i^\top \right) = \sum_{i=1}^n \frac{s_i}{s_i} u_i v_i^\top v_i u_i^\top = \sum_{i=1}^n u_i u_i^\top = U U^\top = I_n,$$

where all the cross-terms vanish since  $v_i^\top v_j = 0$  as  $V$  is orthonormal, and  $\sum_{i=1}^n u_i u_i^\top = U U^\top = I_n$  since  $U$  is again orthonormal. \*

**Problem (Exercise 4.1.2).** Prove the following bound on the singular values  $s_i$  of any matrix  $A$ :

$$s_i \leq \frac{1}{\sqrt{i}} \|A\|_F.$$

**Answer.** We have seen that  $\|A\|_F = \|s\|_2 = \sqrt{\sum_k s_k^2}$ , hence

$$\|A\|_F^2 = \sum_{k=1}^r s_k^2 \geq \sum_{k=1}^i s_k^2 \geq i s_i^2$$

since we arrange  $s_k$ 's in the decreasing order. This proves the result. \*

**Problem (Exercise 4.1.3).** Let  $A_k$  be the best rank  $k$  approximation of a matrix  $A$ . Express  $\|A - A_k\|^2$  and  $\|A - A_k\|_F^2$  in terms of the singular values  $s_i$  of  $A$ .

**Answer.** From Eckart-Young-Mirsky theorem, we have

$$A_k = \sum_{i=1}^k s_i u_i v_i^\top,$$

hence

$$A - A_k = \sum_{i=k+1}^n s_i u_i v_i^\top.$$

This implies, the singular values of the matrix  $A - A_k$  are just  $s_{k+1}, \dots, s_n$ ,<sup>a</sup> implying

$$\|A - A_k\|^2 = s_{k+1}^2,$$

and

$$\|A - A_k\|_F^2 = \sum_{i=k+1}^n s_i^2.$$

⊛

<sup>a</sup>This can be seen from the fact that the same  $U$  and  $V$  still work, but now  $s_i = 0$  for all  $1 \leq i \leq k$ .

**Problem (Exercise 4.1.4).** Let  $A$  be an  $m \times n$  matrix with  $m \geq n$ . Prove that the following statements are equivalent.

- (a)  $A^\top A = I_n$ .
- (b)  $P := AA^\top$  is an *orthogonal projection*<sup>a</sup> in  $\mathbb{R}^m$  onto a subspace of dimension  $n$ .
- (c)  $A$  is an *isometry*, or isometric embedding of  $\mathbb{R}^n$  into  $\mathbb{R}^m$ , which means that

$$\|Ax\|_2 = \|x\|_2 \text{ for all } x \in \mathbb{R}^n.$$

- (d) All singular values of  $A$  equal 1; equivalently

$$s_n(A) = s_1(A) = 1.$$

<sup>a</sup>Recall that  $P$  is a projection if  $P^2 = P$ , and  $P$  is called orthogonal if the image and kernel of  $P$  are orthogonal subspaces.

**Answer.** It's easy to see that (a), (c), and (d) are all equivalent. Indeed, for (a) and (c), we want  $\|Ax\|_2^2 = (Ax)^\top(Ax) = xA^\top Ax = x^\top x = \|x\|_2^2$ , and the equivalency lies in the equality  $xA^\top Ax = x^\top x$ . If  $\|Ax\|_2 = \|x\|_2$  holds for all  $x$ , since  $A^\top A$  is a symmetric matrix, we know that this means  $A^\top A = I_n$ . On the other hand, if  $A^\top A = I_n$ , then we clearly have the equality. For (c) and (d), noting the Equation 4.5 suffices. Now, we focus on proving the equivalence between (a) and (b).

- (a) $\Rightarrow$ (b): Suppose  $A^\top A = I_n$ . Then  $P = AA^\top$  is a projection since  $P^2 = AA^\top AA^\top = AI_n A^\top = AA^\top = P$ . Moreover, observe that  $P^\top = P$ , hence  $P$  is also an orthogonal projection.<sup>a</sup>

Finally, we need to show that  $\text{rank}(P) = \text{rank}(AA^\top) = n$ . But since  $A^\top A = I_n$ ,

$$n = \text{rank}(I_n) = \text{rank}(A^\top A) \leq \text{rank}(A) \leq n$$

as matrix multiplication can only reduce the rank, hence  $\text{rank}(A) = n$ . This also implies  $\text{rank}(A^\top) = n$ , hence we're left to check whether  $\text{Im } A^\top \cap \ker A = \emptyset$ . If this is true, then  $\text{rank}(AA^\top) = n$  as well, and we're done. But it's well-known that  $\text{Im } A^\top = (\ker A)^\perp$ , which completes the proof.

- (b) $\Rightarrow$ (a): We want to show that if  $P = AA^\top$  is an orthogonal projection on a subspace of

dimension  $n$ , then  $A^\top A = I_n$ . Observe that since  $P^2 = P$ ,

$$(AA^\top)(AA^\top) = AA^\top \Leftrightarrow A(A^\top A - I_n)A^\top = 0.$$

Now, we use the fact that  $\text{rank}(P) = \text{rank}(AA^\top) = n$ . From the previous argument, we know that  $\text{rank}(A) = \text{rank}(A^\top) = n$ , and hence

$$A(A^\top A - I_n)A^\top = 0 \Rightarrow A(A^\top A - I_n) = 0$$

as  $A^\top$  spans all  $\mathbb{R}^n$ . Taking the transpose, we again have

$$(A^\top A - I_n)^\top A^\top = 0 \Rightarrow (A^\top A - I_n)^\top = 0$$

since again,  $A^\top$  spans all  $\mathbb{R}^n$ . We hence have  $A^\top A = I_n$  as desired.

⊛

<sup>a</sup>Note that such a characterization is standard. See [here](#) for example.

**Problem (Exercise 4.1.6).** Prove the following converse to Lemma 4.1.5: if (4.7) holds, then

$$\|A^\top A - I_n\| \leq 3 \max(\delta, \delta^2).$$

**Answer.** Firstly, by the quadratic maximizing characterization, we have

$$\begin{aligned} \|A^\top A - I_n\| &= \max_{x \in S^{n-1}, y \in S^{n-1}} \langle (A^\top A - I_n)x, y \rangle \\ &\leq \max_{x \in S^{n-1}} |x^\top (A^\top A - I_n)x| = \max_{x \in S^{n-1}} |\|Ax\|_2^2 - 1|. \end{aligned}$$

Since we assume that  $\|Ax\|_2 \in [1 - \delta, 1 + \delta]$  (with  $x \in S^{n-1}$  now),

$$\|A^\top A - I_n\| \leq \max|(1 \pm \delta)^2 - 1| = \max|\delta^2 \pm 2\delta| \leq 3 \max(\delta, \delta^2).$$

⊛

**Problem (Exercise 4.1.8).** Canonical examples of isometries and projections can be constructed from a fixed unitary matrix  $U$ . Check that any sub-matrix of  $U$  obtained by selecting a subset of columns is an isometry, and any sub-matrix obtained by selecting a subset of rows is a projection.

**Answer.** Consider a tall sub-matrix  $A_{n \times k}$  of  $U_{n \times n}$  for some  $k < n$ . We know that  $A$  is an isometry if and only if  $A^\top$  is a projection. From Remark 4.1.7, it suffices to check  $A^\top A = I_k$ . But this is trivial since  $U$  is unitary, and we're basically computing pair-wise inner products between some columns (selected in  $A$ ) of  $U$ .

On the other hand, consider a fat sub-matrix  $B_{k \times n}$  of  $U_{n \times n}$  for some  $k < n$ . We want to show that  $B^\top B$  is an orthogonal projection (of dimension  $k$ ). From Exercise 4.1.4, it's equivalent to showing  $B^\top$  is an isometry, and from the above, it reduces to show that  $U^\top$  is also unitary since  $B^\top$  can be viewed as a tall sub-matrix of  $U^\top$ . But this is true by definition. ⊛

## Week 13: Covering and Packing Numbers

### 4.2 Nets, covering numbers and packing numbers

12 Apr. 2024

**Problem (Exercise 4.2.5).** (a) Suppose  $T$  is a normed space. Prove that  $\mathcal{P}(K, d, \epsilon)$  is the largest number of closed disjoint balls with centers in  $K$  and radii  $\epsilon/2$ .

(b) Show by example that the previous statement may be false for a general metric space  $T$ .

**Answer.** (a) Consider any  $\epsilon$ -separated subset of  $K$ . Then,  $\overline{B}(x_i, \epsilon/2)$ 's are disjoint since if not, then there exists  $y \in \overline{B}(x_i, \epsilon/2) \cap \overline{B}(x_j, \epsilon/2)$  such that

$$\epsilon < d(x_i, x_j) \leq d(x_i, y) + d(x_j, y) \leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon,$$

a contradiction. On the other hand, if  $d(x_i, x_j) \leq \epsilon$  then

$$\frac{x_i + x_j}{2} \in \overline{B}(x_i, \epsilon/2) \cap \overline{B}(x_j, \epsilon/2),$$

hence, there is a one-to-one correspondence between  $\epsilon$ -separated subset of  $K$  and families of closed disjoint balls with centers in  $K$  and radii  $\epsilon/2$ , proving the result.

(b) Let  $T = \mathbb{Z}$  and  $d(x, y) = \mathbb{1}_{x \neq y}$ . For  $K = \{0, 1\}$  and  $\epsilon = 1$ , we have  $\mathcal{P}(K, d, 1) = 1$ . On the other hand,  $\overline{B}(0, 1/2) = \{0\}$  and  $\overline{B}(1, 1/2) = \{1\}$  are disjoint. If the result of (a) holds, then at least  $\mathcal{P}(K, d, 1) = 2$  as there are exactly two such disjoint closed balls.

⊛

**Problem (Exercise 4.2.9).** In our definition of the covering numbers of  $K$ , we required that the centers  $x_i$  of the balls  $B(x_i, \epsilon)$  that form a covering lie in  $K$ . Relaxing this condition, define the *exterior covering number*  $\mathcal{N}^{\text{ext}}(K, d, \epsilon)$  similarly but without requiring that  $x_i \in K$ . Prove that

$$\mathcal{N}^{\text{ext}}(K, d, \epsilon) \leq \mathcal{N}(K, d, \epsilon) \leq \mathcal{N}^{\text{ext}}(K, d, \epsilon/2).$$

**Answer.** The lower bound is trivial. We focus on the upper bound. Consider an exterior cover  $\{\overline{B}(x_i, \epsilon/2)\}$  of  $K$  where  $x_i$  might not lie in  $K$ . Now, for every  $i$ , choose exactly one  $y_i$  from  $\overline{B}(x_i, \epsilon/2) \cap K$  if it's non-empty. Then,  $\{\overline{B}(y_i, \epsilon)\}$  covers  $K$  since

$$\overline{B}(x_i, \epsilon/2) \cap K \subseteq \overline{B}(y_i, \epsilon)$$

from  $d(x, y_i) \leq d(x, x_i) + d(x_i, y_i) \leq \epsilon/2 + \epsilon/2 = \epsilon$  for any  $x \in \overline{B}(x_i, \epsilon/2)$ . Hence, by taking the union over  $i$ ,  $\{\overline{B}(y_i, \epsilon)\}$  indeed cover  $K$ , so the upper bound is proved. ⊛

**Problem (Exercise 4.2.10).** Give a counterexample to the following monotonicity property:

$$L \subseteq K \text{ implies } \mathcal{N}(L, d, \epsilon) \leq \mathcal{N}(K, d, \epsilon).$$

Prove an approximate version of monotonicity:

$$L \subseteq K \text{ implies } \mathcal{N}(L, d, \epsilon) \leq \mathcal{N}(K, d, \epsilon/2).$$

**Answer.** The problem lies in the fact that we're not allowing exterior covering. Consider  $K = [-1, 1]$  and  $L = \{-1, 1\}$ . Then,  $\mathcal{N}(L, d, 1) = 2 > 1 = \mathcal{N}(K, d, 1)$  for  $d(x, y) = |x - y|$ .

The approximate version of monotonicity can be proved with a similar argument as [Exercise 4.2.9](#): specifically, consider an  $\epsilon/2$ -covering  $\{x_i\}$  of  $K$  with size exactly  $\mathcal{N}(K, d, \epsilon/2)$ . Now, for every  $i$ , choose one  $y_i \in \overline{B}(x_i, \epsilon/2) \cap L$  if the latter is non-empty. It turns out that  $\{\overline{B}(y_i, \epsilon)\}$  covers  $L$ . Indeed,  $\overline{B}(x_i, \epsilon/2) \cap L \subseteq \overline{B}(y_i, \epsilon)$  since

$$d(x, y_i) \leq d(x, x_i) + d(x_i, y_i) \leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$$

for all  $x \in \overline{B}(x_i, \epsilon/2)$ . ⊛

**Intuition.** The fundamental idea is just every such  $\overline{B}(y_i, \epsilon)$  can cover  $\overline{B}(x_i, \epsilon/2)$ .

**Problem (Exercise 4.2.15).** Check that  $d_H$  is indeed a metric.

**Answer.** We check the following.

- $d_H(x, x) = 0$  for all  $x$  and  $d_H(x, y) > 0$  for all  $x \neq y$ : Trivial.
- $d_H(x, y) = d_H(y, x)$  for all  $x, y$ : Trivial.
- $d_H(x, y) \leq d_H(x, z) + d_H(y, z)$  for all  $x, y, z$ : Suppose  $x$  and  $y$  initially disagree at  $d_H(x, y)$  places, and denote the set of those disagreeing indices as  $I$ . Then for any  $z$ , as long as  $z$  and  $x$  (hence  $y$ ) disagree at an index outside  $I$ ,  $d_H(x, z) + d_H(y, z)$  increases by 2. There's no way to exist a  $z$  such that  $d_H(x, z) + d_H(y, z)$  can decrease, at best  $z$  and  $x$  (or  $y$ ) disagree at an index in  $I$ , then it'll coincide with  $y$  (or  $x$ ), contributing the same amount to  $d_H(x, y)$ .

⊛

**Problem (Exercise 4.2.16).** Let  $K = \{0, 1\}^n$ . Prove that for every integer  $m \in [0, n]$ , we have

$$\frac{2^n}{\sum_{k=0}^m \binom{n}{k}} \leq \mathcal{N}(K, d_H, m) \leq \mathcal{P}(K, d_H, m) \leq \frac{2^n}{\sum_{k=0}^{\lfloor m/2 \rfloor} \binom{n}{k}}.$$

**Answer.** The middle inequality follows from Lemma 4.2.8. Now, for  $K = \{0, 1\}^n$ , we first note that we have  $|K| = 2^n$ . Furthermore, observe the following.

**Claim.** For any  $x \in K$ , we have

$$|\{y \in K : d_H(x, y) \leq m\}| = \sum_{k=0}^m |\{y \in K : d_H(x, y) = k\}| = \sum_{k=0}^m \binom{n}{k}.$$

We then see the following.

- Lower bound: observe that  $|K| \leq \mathcal{N}(K, d_H, m) |\{y \in K : d_H(x_i, y) \leq m\}|$  where  $\{x_i\}$  is an  $m$ -net of  $K$  of size  $\mathcal{N}(K, d_H, m)$ .
- Upper bound: observe that  $|K| \geq \mathcal{P}(K, d_H, m) |\{y \in K : d_H(x_i, y) \leq \lfloor m/2 \rfloor\}|$  where  $\{x_i\}$  is  $m$ -packing of size  $\mathcal{P}(K, d_H, m)$ .

Plugging the above calculation complete the proof of both bounds.

⊛

**Remark.** Unlike Proposition 4.2.12, we don't have the issue of "going outside  $K$ " since we're working with a hamming cube, i.e., the entire universe is exactly the collection of  $n$ -bits string. Moreover, for the upper bound, we use  $\lfloor m/2 \rfloor$  since  $m \in \mathbb{N}$ , and taking the floor makes sure that  $\{y \in K : d_H(x, y) \leq \lfloor m/2 \rfloor\}$ 's are disjoint for  $\{x_i\}$  being  $m$ -separated. Hence, the total cardinality is upper bounded by  $|K|$ .

## Week 14: Random Sub-Gaussian Matrices

### 4.3 Application: error correcting codes

17 Apr. 2024

**Problem (Exercise 4.3.7).** (a) Prove the converse to the statement of Lemma 4.3.4.

- (b) Deduce a converse to Theorem 4.3.5. Conclude that for any error correcting code that encodes  $k$ -bit strings into  $n$ -bit strings and can correct  $r$  errors, the rate must be

$$R \leq 1 - f(\delta)$$

where  $f(t) = t \log_2(1/t)$  as before.

**Answer.** Omit. \*

## 4.4 Upper bounds on random sub-gaussian matrices

**Problem (Exercise 4.4.2).** Let  $x \in \mathbb{R}^n$  and  $\mathcal{N}$  be an  $\epsilon$ -net of the sphere  $S^{n-1}$ . Show that

$$\sup_{y \in \mathcal{N}} \langle x, y \rangle \leq \|x\|_2 \leq \frac{1}{1 - \epsilon} \sup_{y \in \mathcal{N}} \langle x, y \rangle.$$

**Answer.** The lower bound is again trivial. On the other hand, for any  $x \in \mathbb{R}^n$ , consider an  $x_0 \in \mathcal{N}$  such that  $\|x_0 - x/\|x\|_2\|_2 \leq \epsilon$  (normalization is necessary since  $\mathcal{N}$  is an  $\epsilon$ -net of  $S^{n-1}$ , while  $x \in \mathbb{R}^n$ ). Now, observe that from the Cauchy-Schwarz inequality, we have

$$\|x\|_2 - \langle x, x_0 \rangle = \left\langle x, \frac{x}{\|x\|_2} - x_0 \right\rangle \leq \|x\|_2 \left\| \frac{x}{\|x\|_2} - x_0 \right\| \leq \epsilon \|x\|_2,$$

which implies  $\langle x, x_0 \rangle \geq (1 - \epsilon)\|x\|_2$ . This proves the upper bound. \*

**Problem (Exercise 4.4.3).** Let  $A$  be an  $m \times n$  matrix and  $\epsilon \in [0, 1/2)$ .

(a) Show that for any  $\epsilon$ -net  $\mathcal{N}$  of the sphere  $S^{n-1}$  and any  $\epsilon$ -net  $\mathcal{M}$  of the sphere  $S^{m-1}$  we have

$$\sup_{x \in \mathcal{N}, y \in \mathcal{M}} \langle Ax, y \rangle \leq \|A\| \leq \frac{1}{1 - 2\epsilon} \cdot \sup_{x \in \mathcal{N}, y \in \mathcal{M}} \langle Ax, y \rangle.$$

(b) Moreover, if  $m = n$  and  $A$  is symmetric, show that

$$\sup_{x \in \mathcal{N}} |\langle Ax, x \rangle| \leq \|A\| \leq \frac{1}{1 - 2\epsilon} \cdot \sup_{x \in \mathcal{N}} |\langle Ax, x \rangle|.$$

**Answer.** (a) The lower bound is again trivial. On the other hand, denote  $x^* \in S^{n-1}$  and  $y^* \in S^{m-1}$  such that  $\|A\| = \langle Ax^*, y^* \rangle$ . Pick  $x_0 \in \mathcal{N}$  and  $y_0 \in \mathcal{M}$  such that  $\|x^* - x_0\|_2, \|y^* - y_0\|_2 \leq \epsilon$ . We then have

$$\begin{aligned} \langle Ax^*, y^* \rangle - \langle Ax_0, y_0 \rangle &= \langle A(x^* - x_0), y^* \rangle + \langle Ax_0, y^* - y_0 \rangle \\ &\leq \|A\|(\|x^* - x_0\|_2 \|y^*\|_2 + \|x_0\|_2 \|y^* - y_0\|_2) \leq 2\epsilon \|A\| \end{aligned}$$

as  $\|y^*\| = \|x_0\|_2 = 1$ . Rewrite the above, we have

$$\|A\| - \langle Ax_0, y_0 \rangle \leq 2\epsilon \|A\| \Rightarrow \|A\| \leq \frac{1}{1 - 2\epsilon} \langle Ax_0, y_0 \rangle \leq \frac{1}{1 - 2\epsilon} \sup_{x \in \mathcal{N}, y \in \mathcal{M}} \langle Ax, y \rangle.$$

(b) Following the same argument as (a), with  $y^* := x^*$  and  $y_0 := x_0$ . To be explicit to handle the absolute value, we see that

$$|\langle Ax^*, x^* \rangle| - |\langle Ax_0, x_0 \rangle| \leq |\langle Ax^*, x^* \rangle - \langle Ax_0, x_0 \rangle| \leq 2\epsilon \|A\|,$$

from the same argument. The result follows immediately. \*

**Problem (Exercise 4.4.4).** Let  $A$  be an  $m \times n$  matrix,  $\mu \in \mathbb{R}$  and  $\epsilon \in [0, 1/2)$ . Show that for any  $\epsilon$ -net  $\mathcal{N}$  of the sphere  $S^{n-1}$ , we have

$$\sup_{x \in S^{n-1}} |\|Ax\|_2 - \mu| \leq \frac{C}{1 - 2\epsilon} \cdot \sup_{x \in \mathcal{N}} |\|Ax\|_2 - \mu|.$$

**Answer.** Let  $\mu = 1$ . Firstly, for  $x \in S^{n-1}$ , observe that we can write

$$|\|Ax\|_2^2 - 1| = \langle Rx, x \rangle$$

for a symmetric  $R = A^\top A - I_n$ . Secondly, there exists  $x^*$  such that  $\|R\| = \langle Rx^*, x^* \rangle$ , consider  $x_0 \in \mathcal{N}$  such that  $\|x_0 - x^*\| \leq \epsilon$ . Now, from a numerical inequality  $|z - 1| \leq |z^2 - 1|$  for  $z > 0$ , we have

$$\begin{aligned} \sup_{x \in S^{n-1}} |\|Ax\|_2 - 1| &\leq \sup_{x \in S^{n-1}} |\|Ax\|_2^2 - 1| = \|R\| \\ &\leq \frac{1}{1 - 2\epsilon} \sup_{x \in \mathcal{N}} |\langle Rx, x \rangle| = \frac{1}{1 - 2\epsilon} \sup_{x \in \mathcal{N}} |\|Ax\|_2^2 - 1|, \end{aligned}$$

where the last inequality follows from [Exercise 4.4.3](#). Further, factoring  $|\|Ax\|_2^2 - 1|$  get

$$\sup_{x \in S^{n-1}} |\|Ax\|_2 - 1| \leq \frac{1}{1 - 2\epsilon} \sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| (\|Ax\|_2 + 1).$$

If  $\|A\| \leq 2$ , then  $\|Ax\|_2 + 1 \leq 3$ , and  $C = 3$  suffices.

On the other hand, if  $\|A\| > 2$ , consider directly computing the left-hand side

$$\sup_{x \in S^{n-1}} |\|Ax\|_2 - 1| = \|A\| - 1$$

where the maximum is attained at some  $x' \in S^{n-1}$ . With the existence of  $x'' \in \mathcal{N} \cap \{x: \|x - x'\|_2 \leq \epsilon\}$ , the supremum over  $\mathcal{N}$  can be lower bounded as

$$\sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| \geq \|Ax''\|_2 - 1 \geq \|Ax'\|_2 - \|A(x'' - x')\|_2 - 1 \geq \|A\|(1 - \epsilon) - 1 > 1 - 2\epsilon.$$

The above implies the following.

- $\|A\| \leq \frac{1}{1 - \epsilon} (\sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| + 1).$
- $\sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| > 1 - 2\epsilon.$

This allows us to conclude that

$$\begin{aligned} \sup_{x \in S^{n-1}} |\|Ax\|_2 - 1| &= \|A\| - 1 \leq \frac{1}{1 - \epsilon} \left( \sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| + 1 \right) - 1 \\ &= \frac{1}{1 - \epsilon} \left( \sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| + \epsilon \right) \leq \frac{3}{1 - 2\epsilon} \sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1|, \end{aligned}$$

provided that

$$C := 3 \geq \sup_{d > 1 - 2\epsilon} \frac{1 - 2\epsilon}{1 - \epsilon} \left( 1 + \frac{\epsilon}{d} \right) \geq \frac{1 - 2\epsilon}{1 - \epsilon} \frac{\sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1| + \epsilon}{\sup_{x \in \mathcal{N}} |\|Ax\|_2 - 1|},$$

which is true since the middle supremum is just 1. The case that  $\mu \neq 1$  can be easily generalized by considering  $R = A^\top A - \mu I_n$ . \*

**Problem (Exercise 4.4.6).** Deduce from Theorem 4.4.5 that

$$\mathbb{E}[\|A\|] \leq CK(\sqrt{m} + \sqrt{n}).$$

**Answer.** From Theorem 4.4.5, for any  $t > 0$ , we have

$$\mathbb{P}(\|A\| - CK(\sqrt{m} + \sqrt{n}) > CKt) \leq 2 \exp(-t^2).$$



Then we immediately have

$$\begin{aligned}\mathbb{E}[\|A\| - CK(\sqrt{m} + \sqrt{n})] &= \mathbb{E}[\|A\|] - CK(\sqrt{m} + \sqrt{n}) \\ &= \int_0^\infty \mathbb{P}(\|A\| - CK(\sqrt{m} + \sqrt{n}) > CKt) CK dt \\ &\leq 2CK \int_0^\infty \exp(-t^2) dt = CK\sqrt{\pi},\end{aligned}$$

hence  $\mathbb{E}[\|A\|] \leq CK(\sqrt{m} + \sqrt{n} + \sqrt{\pi})$ , and choosing a large enough  $C$  subsumes  $\sqrt{\pi}$ .  $\circledast$

**Problem (Exercise 4.4.7).** Suppose that in Theorem 4.4.5 the entries  $A_{ij}$  have unit variances. Prove that for sufficiently large  $n$  and  $m$  one has

$$\mathbb{E}[\|A\|] \geq \frac{1}{4}(\sqrt{m} + \sqrt{n}).$$

**Answer.** Clearly, by choosing  $x = e_1 \in S^{n-1}$ ,

$$\|A\| = \sup_{x \in S^{n-1}} \|Ax\|_2 \geq \|(A_{i1})_{1 \leq i \leq m}\|_2.$$

On the other hand, by picking  $x = (A_{11}/\|(A_{1j})_{1 \leq j \leq n}\|_2, \dots, A_{1n}/\|(A_{1j})_{1 \leq j \leq n}\|_2) \in S^{n-1}$  and  $y = e_1 \in S^{m-1}$ , we have

$$\|A\| = \sup_{x \in S^{n-1}, y \in S^{m-1}} \langle Ax, y \rangle \geq \sum_{j=1}^n \frac{A_{1j}}{\|(A_{1j})_{1 \leq j \leq n}\|_2} A_{1j} = \|(A_{1j})_{1 \leq j \leq n}\|_2.$$

Hence,  $\|A\|$  is lower bounded by the norm of the first row and column, i.e.,

$$\|A\| \geq \max(\|(A_{i1})_{1 \leq i \leq m}\|_2, \|(A_{1j})_{1 \leq j \leq n}\|_2).$$

**Exercise 3.1.4 (b)**, the expectation of  $\|A\|$  is then greater than or equal to  $\max(\sqrt{m} - o(1), \sqrt{n} - o(1))$  by Thus,  $\mathbb{E}[\|A\|] \geq (\sqrt{m} + \sqrt{n} - o(1))/2$ .  $\circledast$

**Remark.** An easier way to deduce the second (i.e., lower bounded by the norm of the first row) is to note that  $\|A^\top\| = \|A\|$  by some elementary (functional) analysis.

## Week 15: Stochastic Block Model and Community Detection

### 4.5 Application: community detection in networks

8 Jun. 2024

**Problem (Exercise 4.5.2).** Check that the matrix  $D$  has rank 2, and the non-zero eigenvalues  $\lambda_i$  and the corresponding eigenvectors  $u_i$  are

$$\lambda_1 = \left(\frac{p+q}{2}\right)n, \quad u_1 = \begin{bmatrix} \mathbb{1}_{n/2 \times 1} \\ \mathbb{1}_{n/2 \times 1} \end{bmatrix}, \quad \lambda_2 = \left(\frac{p-q}{2}\right)n, \quad u_2 = \begin{bmatrix} \mathbb{1}_{n/2 \times 1} \\ -\mathbb{1}_{n/2 \times 1} \end{bmatrix}.$$

**Answer.** Let  $n$  be an even number. Firstly, for any  $D \in \mathbb{R}^{n \times n}$ , columns 1 to  $n/2$  are identical, same for columns  $n/2 + 1$  to  $n$ . Furthermore, since  $p > q$ , column 1 and  $n/2 + 1$  are linear independent, so  $\text{rank}(D) = 2$ .

Instead of solving the characteristic equation and find the eigenvalues, and find the corresponding eigenvectors later, since we know that  $\text{rank}(D) = 2$ , it's immediate that there are only 2 non-zero

eigenvalues. Hence, we directly verify that

$$\lambda_1 = \left(\frac{p+q}{2}\right)n, \quad u_1 = \mathbb{1}_{n \times 1}, \quad \lambda_2 = \left(\frac{p-q}{2}\right)n, \quad u_2 = \begin{pmatrix} \mathbb{1}_{1 \times n/2} \\ -\mathbb{1}_{1 \times n/2} \end{pmatrix}^\top.$$

For  $\lambda_1$ , indeed, since

$$Du_1 = \lambda_1 u_1 \Rightarrow \begin{pmatrix} \frac{p+q}{2}n \\ \frac{p+q}{2}n \\ \vdots \\ \frac{q+p}{2}n \\ \frac{q+p}{2}n \end{pmatrix} = \left(\frac{p+q}{2}\right)n \cdot \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \\ 1 \end{pmatrix}.$$

On the other hand, for  $\lambda_2$ , we have

$$Du_2 = \lambda_2 u_2 \Rightarrow \begin{pmatrix} \frac{p-q}{2}n \\ \frac{p-q}{2}n \\ \vdots \\ \frac{q-p}{2}n \\ \frac{q-p}{2}n \end{pmatrix} = \left(\frac{p-q}{2}\right)n \cdot \begin{pmatrix} 1 \\ 1 \\ \vdots \\ -1 \\ -1 \end{pmatrix},$$

which again holds. \*

**Problem (Exercise 4.5.4).** Deduce Weyl's inequality from the Courant-Fisher's min-max characterization of eigenvalues.

**Answer.** We have that from the Courant-Fisher's min-max characterization,

$$\lambda_i(A) = \max_{\dim E=i} \min_{x \in S(E)} \langle Ax, x \rangle.$$

Now, as  $\lambda_i(A) = -\lambda_{n-i+1}(-A)$ , we see that

$$\lambda_i(A) = -\lambda_{n-i+1}(-A) = -\max_{\dim E=n-i+1} \min_{x \in S(E)} \langle -Ax, x \rangle = \min_{\dim E=n-i+1} \max_{x \in S(E)} \langle Ax, x \rangle.$$

We now show the [Weyl's inequality](#).

**Theorem 4.5.1 (Weyl's inequality).**  $\lambda_{i+j-1}(A+B) \leq \lambda_i(A) + \lambda_j(B) \leq \lambda_{i+j-n}(A+B)$ .

**Proof.** We first show the lower-bound. From the Courant-Fisher's min-max characterization, it suffices to show that for any  $E$  with  $\dim E = i+j-1$ , there exists some  $x \in S(E)$  such that  $\langle (A+B)x, x \rangle \leq \lambda_i(A) + \lambda_j(B)$ .

We first analyze  $\lambda_i(A)$ . We know that from the max-min characterization,

$$\lambda_i(A) = \min_{\dim E=n-i+1} \max_{x \in S(E)} \langle Ax, x \rangle,$$

i.e., there exists some  $E_A$  with  $\dim E_A = n-i+1$  such that  $\lambda_i(A) = \max_{x \in S(E_A)} \langle Ax, x \rangle$ . Similarly, there exists some  $E_B$  with  $\dim E_B = n-j+1$  satisfying the same property. Hence, it suffices to find some unit vector  $x$  in  $E_A \cap E_B \cap E$ . We see that

$$\dim(E_A \cap E_B) \geq \dim E_A + \dim E_B - n = n-i-j+2,$$

which implies that  $E_A \cap E_B$  will have a non-trivial intersection with  $E$  since  $\dim E = i+j-1$ , hence we're done. For the upper-bound, taking the negative gives the result. ■

To obtain the spectral stability, we see that from [Weyl's inequality](#), we have

$$\begin{cases} \lambda_i(A+B) \leq \lambda_i(A) + \lambda_1(B); \\ \lambda_i(A+B) \geq \lambda_i(A) + \lambda_n(B); \end{cases} \Rightarrow \lambda_n(B) \leq \lambda_i(A+B) - \lambda_i(A) \leq \lambda_1(B).$$

Given any symmetric  $S, T$ , by setting  $A := T$  and  $B := S - T$ , the upper-bound yields

$$\lambda_i(S) - \lambda_i(T) \leq \lambda_1(S - T) = \|S - T\|.$$

On the other hand, by setting  $A := S$  and  $B := T - S$ , the upper-bound again yields

$$\lambda_i(T) - \lambda_i(S) \leq \lambda_1(T - S) = \|T - S\| = \|S - T\|.$$

As this holds for every  $i$ , we have

$$\max_i |\lambda_i(S) - \lambda_i(T)| \leq \|S - T\|$$

as we desired. \*

## Week 16: Tighter Bounds on Sub-Gaussian Matrices

### 4.6 Two-sided bounds on sub-gaussian matrices

13 Jun. 2024

**Problem (Exercise 4.6.2).** Deduce from (4.22) that

$$\mathbb{E} \left[ \left\| \frac{1}{m} A^\top A - I_n \right\| \right] \leq CK^2 \left( \sqrt{\frac{n}{m}} + \frac{n}{m} \right).$$

**Answer.** We have that for any  $t \geq 0$ , with probability at least  $1 - 2 \exp(-t^2)$ ,

$$\left\| \frac{1}{m} A^\top A - I_n \right\| \leq K^2 \max(\delta, \delta^2), \text{ where } \delta = C \left( \sqrt{\frac{n}{m}} + \frac{t}{\sqrt{m}} \right),$$

and we want to prove

$$\mathbb{E} \left[ \left\| \frac{1}{m} A^\top A - I_n \right\| \right] \leq CK^2 \left( \sqrt{\frac{n}{m}} + \frac{n}{m} \right).$$

Firstly, we know that with  $u := K^2 \left( \left( \frac{C}{\sqrt{m}} + \frac{2C^2\sqrt{n}}{m} \right) t + \frac{C^2}{m} t^2 \right)$ , we get exactly

$$\mathbb{P} \left( \left\| \frac{1}{m} A^\top A - I_n \right\| > K^2 \left( C \sqrt{\frac{n}{m}} + C^2 \frac{n}{m} \right) + u \right) \leq 2e^{-t^2}.$$

Then, from the integral identity with the substitution  $v := u + K^2(C\sqrt{\frac{n}{m}} + C^2\frac{n}{m})$ ,

$$\begin{aligned} & \mathbb{E} \left[ \left\| \frac{1}{m} A^\top A - I_n \right\| \right] \\ &= \left( \int_0^{K^2(C\sqrt{\frac{n}{m}} + C^2\frac{n}{m})} + \int_{K^2(C\sqrt{\frac{n}{m}} + C^2\frac{n}{m})}^\infty \right) \mathbb{P} \left( \left\| \frac{1}{m} A^\top A - I_n \right\| > v \right) dv \\ &\leq \int_0^{K^2(C\sqrt{\frac{n}{m}} + C^2\frac{n}{m})} 1 dv + \int_{K^2(C\sqrt{\frac{n}{m}} + C^2\frac{n}{m})}^\infty \mathbb{P} \left( \left\| \frac{1}{m} A^\top A - I_n \right\| > v \right) dv \\ &= K^2 \left( C \sqrt{\frac{n}{m}} + C^2 \frac{n}{m} \right) + \int_0^\infty \mathbb{P} \left( \left\| \frac{1}{m} A^\top A - I_n \right\| > K^2 \left( C \sqrt{\frac{n}{m}} + C^2 \frac{n}{m} \right) + u \right) du \end{aligned}$$

plugging back  $v = u + K^2(C\sqrt{\frac{n}{m}} + C^2\frac{n}{m})$ ,

$$\begin{aligned} &\leq K^2 \left( C\sqrt{\frac{n}{m}} + C^2\frac{n}{m} \right) + \int_0^\infty 2e^{-t^2} du \\ &= K^2 \left( C\sqrt{\frac{n}{m}} + C^2\frac{n}{m} \right) + \int_0^\infty 2e^{-t^2} K^2 \left( \frac{C}{\sqrt{m}} + \frac{2C^2\sqrt{n}}{m} + \frac{2C^2}{m}t \right) dt \\ &= K^2 \left( C\sqrt{\frac{n}{m}} + C^2\frac{n}{m} \right) + K^2 \left( \sqrt{\pi} \left( \frac{C}{\sqrt{m}} + \frac{2C^2\sqrt{n}}{m} \right) + \frac{2C^2}{m} \right), \end{aligned}$$

which is asymptotically  $\asymp K^2(\sqrt{\frac{n}{m}} + \frac{n}{m})$ .  $\circledast$

**Problem (Exercise 4.6.3).** Deduce from Theorem 4.6.1 the following bounds on the expectation:

$$\sqrt{m} - CK^2\sqrt{n} \leq \mathbb{E}[s_n(A)] \leq \mathbb{E}[s_1(A)] \leq \sqrt{m} + CK^2\sqrt{n}.$$

**Answer.** From Theorem 4.6.1, for any  $t \geq 0$ ,

$$\sqrt{m} - CK^2(\sqrt{n} + t) \leq s_n(A) \leq s_1(A) \leq \sqrt{m} + CK^2(\sqrt{n} + t)$$

with probability at least  $1 - 2\exp(-t^2)$ . We want to show that

$$\sqrt{m} - CK^2\sqrt{n} \leq \mathbb{E}[s_n(A)] \leq \mathbb{E}[s_1(A)] \leq \sqrt{m} + CK^2\sqrt{n}.$$

Consider

$$\xi := \frac{\max(0, \sqrt{m} - CK^2\sqrt{n} - s_n(A), s_1(A) - \sqrt{m} - CK^2\sqrt{n})}{CK^2} \geq 0,$$

then from the integral identity,

$$\mathbb{E}[\xi] = \int_0^\infty \mathbb{P}(\xi > t) dt \leq \int_0^\infty 2e^{-t^2} dt = \sqrt{\pi},$$

which proves the result.  $\circledast$

**Problem (Exercise 4.6.4).** Give a simpler proof of Theorem 4.6.1, using Theorem 3.1.1 to obtain a concentration bound for  $\|Ax\|_2$  and Exercise 4.4.4 to reduce to a union bound over a net.

**Answer.** From the proof of Theorem 4.6.1, we know that  $S^{n-1}$  admits a  $1/4$ -net  $\mathcal{N}$  such that  $|\mathcal{N}| \leq 9^n$ . Furthermore, for any  $x \in \mathcal{N}$ , we have

- $\mathbb{E}[\langle A_i, x \rangle] = \langle \mathbb{E}[A_i], x \rangle = \langle 0, x \rangle = 0$ ;
- $\mathbb{E}[\langle A_i, x \rangle^2] = x^\top \mathbb{E}[A_i^\top A_i] x = x^\top I_n x = 1$  ( $x \in S^{n-1}$  too);
- $\|\langle A_i, x \rangle\|_{\psi_2} \leq \|A_i\|_{\psi_2} \leq K$  for all  $i$ ,

by Theorem 3.1.1, we have  $\| \|Ax\|_2 - \sqrt{m} \|_{\psi_2} \leq CK^2$ . From Proposition 2.5.2 (i), for any  $t > 0$ ,

$$\begin{aligned} &\mathbb{P} \left( \| \|Ax\|_2 - \sqrt{m} \| > CK(\sqrt{n \log 9} + t) \right) \\ &\leq 2 \exp \left( -(\sqrt{n \log 9} + t)^2 \right) \leq 2 \exp \left( -(n \log 9 + t^2) \right) = 2 \cdot 9^{-n} \cdot e^{-t^2}. \end{aligned}$$

Finally, from Exercise 4.4.4, with a union bound over  $\mathcal{N}$ , we have

$$\mathbb{P} \left( \neg \left\{ \sqrt{m} - 2CK^2(\sqrt{n \log 9} + t) \leq s_n(A) \leq s_1(A) \leq \sqrt{m} + 2CK^2(\sqrt{n \log 9} + t) \right\} \right)$$

by the definition of  $s_n(A)$  and  $s_1(A)$ , we have

$$\begin{aligned}
 &\leq \mathbb{P} \left( \max_{x \in S^{n-1}} |\|Ax\|_2 - \sqrt{m}| > 2CK^2(\sqrt{n \log 9} + t) \right) \\
 &\leq \mathbb{P} \left( 2 \max_{x \in \mathcal{N}} |\|Ax\|_2 - \sqrt{m}| > 2CK^2(\sqrt{n \log 9} + t) \right) \\
 &\leq \sum_{x \in \mathcal{N}} \mathbb{P} \left( |\|Ax\|_2 - \sqrt{m}| > CK^2(\sqrt{n \log 9} + t) \right) \\
 &\leq 9^n \cdot 2 \cdot 9^{-n} \cdot e^{-t^2} = 2e^{-t^2}.
 \end{aligned}$$

Scaling  $C$  accommodates the additional  $\log 9$  factor finishes the proof.  $\circledast$

## 4.7 Application: covariance estimation and clustering

**Problem (Exercise 4.7.3).** Our argument also implies the following high-probability guarantee. Check that for any  $u \geq 0$ , we have

$$\|\Sigma_m - \Sigma\| \leq CK^2 \left( \sqrt{\frac{n+u}{m}} + \frac{n+u}{m} \right) \|\Sigma\|$$

with probability at least  $1 - 2e^{-u}$ .

**Answer.** Omit  $\circledast$

**Problem (Exercise 4.7.6).** Prove Theorem 4.7.5 for the spectral clustering algorithm applied for the Gaussian mixture model. Proceed as follows.

- Compute the covariance matrix  $\Sigma$  of  $X$ ; note that the eigenvector corresponding to the largest eigenvalue is parallel to  $\mu$ .
- Use results about covariance estimation to show that the sample covariance matrix  $\Sigma_m$  is close to  $\Sigma$ , if the sample size  $m$  is relatively large.
- Use the Davis-Kahan Theorem 4.5.5 to deduce that the first eigenvector  $v = v_1(\Sigma_m)$  is close to the direction of  $\mu$ .
- Conclude that the signs of  $\langle \mu, X_i \rangle$  predict well which community  $X_i$  belongs to.
- Since  $v \approx \mu$ , conclude the same for  $v$ .

**Answer.** Omit  $\circledast$

# Chapter 5

## Concentration without independence

### Week 17

#### 5.1 Concentration of Lipschitz functions on the sphere

22 Jun. 2024

#### 5.2 Concentration on other metric measure spaces

#### 5.3 Application: Johnson-Lindenstrauss Lemma

### Week 18: Tighter Bounds on Sub-Gaussian Matrices

#### 5.4 Matrix Bernstein's inequality

29 Jun. 2024

**Problem** (Exercise 5.4.3).

**Answer.**

⊛

**Problem** (Exercise 5.4.5).

**Answer.**

⊛

**Problem** (Exercise 5.4.6).

**Answer.**

⊛

**Problem** (Exercise 5.4.11).

**Answer.**

⊛

**Problem** (Exercise 5.4.12).

**Answer.**

⊛

**Problem** (Exercise 5.4.13).

**Answer.**

⊛

**Problem (Exercise 5.4.14).** Let  $X$  be an  $n \times n$  random matrix that takes values  $e_k e_k^\top$ ,  $k = 1, \dots, n$ , with probability  $1/n$  each. (Here  $(e_k)$  denotes the standard basis in  $\mathbb{R}^n$ .) Let  $X_1, \dots, X_N$  be independent copies of  $X$ . Consider the sum  $S = \sum_{i=1}^N X_i$ , which is a diagonal matrix.

- Show that the entry  $S_{ii}$  has the same distribution as the number of balls in  $i$ -th bin when  $N$  balls are thrown into  $n$  bins independently.
- Relating this to the classical coupon collector's problem, show that if  $N \asymp n$ , then

$$\mathbb{E}\|S\| \asymp \frac{\log n}{\log \log n}.$$

Deduce that the bound in [Exercise 5.4.11](#) would fail if the logarithmic factors were removed from it.

**Answer.** (a) We see that  $X = e_k e_k^\top$  with  $k$  being chosen uniformly randomly among  $[n]$ , where  $e_k e_k^\top$  is a matrix with all 0's except the  $k^{\text{th}}$  diagonal element being 1. Hence, by interpreting each  $X_i$  as “throwing a ball into  $n$  bins,”  $S_{kk}$  records the number of balls in the  $k^{\text{th}}$  bin when  $N$  balls are thrown into  $n$  bins independently.

- We first observe that since  $S$  is diagonal,  $\|S\| = \lambda_1(S) = \max_k S_{kk}$  as all the diagonal elements are eigenvalues of  $S$ . We first answer the question of how this related to the coupon collector's problem. Firstly, let's introduce the problem formally:

**Problem 5.4.1 (Coupon collector's problem).** Say we have  $n$  different types of coupons to collect, and we buy  $N$  boxes, where each box contains a (uniformly) random type of coupon. The classical *coupon collector problem* asks for the expected number of boxes (i.e.,  $N$ ) we need in order to collect all coupons.

With the interpretation of (a), we can view  $S_{kk}$  as the number of coupons we have collected for the  $k^{\text{th}}$  type of the coupon, where  $N$  is the number of boxes we have bought. Hence, the coupon collector's problem asks for the expected  $N$  we need for  $\lambda_n(S) = \min_k S_{kk} > 0$ .

Compared to our original problem, we see that it is *different* from the classical coupon collector's problem: we're asked for the expected number of *the most frequent* coupons (i.e.,  $\max_k S_{kk}$ ) we will see when buying only  $N \asymp n$  boxes.

To proceed, we need to recall the following theorems.

**Theorem 5.4.1 (Poisson limit theorem).** Let  $X_{N,i}$ ,  $1 \leq i \leq N$ , be independent random variables  $X_{N,i} \sim \text{Ber}(p_{N,i})$ , and let  $S_N := \sum_{i=1}^N X_{N,i}$ . Assume that as  $N \rightarrow \infty$ ,  $\max_{i \leq N} p_{N,i} \rightarrow 0$  and  $\mathbb{E}[S_N] \rightarrow \lambda < \infty$ . Then, as  $N \rightarrow \infty$ ,  $S_N \xrightarrow{D} \text{Pois}(\lambda)$ .<sup>a</sup>

<sup>a</sup>Recall that  $Z \sim \text{Pois}(\lambda)$  means  $\mathbb{P}(Z = k) = e^{-\lambda} \lambda^k / k!$  for  $k = 0, 1, \dots$

Also, we need the following.

**Theorem 5.4.2 (Skorokhod's representation theorem).** If  $X_N \xrightarrow{D} X$ , then there exists  $(\Omega, \mathcal{F}, \mathbb{P})$  on which we can define random variables  $(Y_n)$  and  $Y$  such that  $Y_N \stackrel{D}{=} X_N$  for all  $n$  and  $Y \stackrel{D}{=} X$ , and  $\mathbb{P}(Y_N \rightarrow Y) = 1$ .

Now, consider the following random  $n \times n$  matrix (slightly different from  $S$ )

$$T := \sum_{i=1}^N \sum_{k=1}^n b_{ik}^{(N)} e_k e_k^\top,$$

where  $b_{ik}^{(N)} \stackrel{\text{i.i.d.}}{\sim} \text{Ber}(1/N)$ . Using the above theorems, we can show the following.

**Claim.** As  $N \rightarrow \infty$ , with  $Z_k \sim \text{Pois}(1)$ , we have

$$\mathbb{E}[\lambda_1(T)] = \mathbb{E} \left[ \max_{1 \leq k \leq n} T_{kk} \right] \rightarrow \mathbb{E} \left[ \max_{1 \leq k \leq n} Z_k \right] = \Theta \left( \frac{\log n}{\log \log n} \right).$$

**Proof.** For every  $k \in [n]$ , we apply the [Poisson limit theorem](#) since as  $N \rightarrow \infty$ ,  $p_{N,ik} = 1/N \rightarrow 0$  and  $\mathbb{E}[S_N^k] = \mathbb{E}[\sum_{i=1}^N b_{ik}^{(N)}] = 1 =: \lambda$  as  $N \rightarrow \infty$ . So as  $N \rightarrow \infty$ ,  $S_N^k \xrightarrow{D} \text{Pois}(1)$ . Here, with a similar interpretation as in (a), we can interpret  $S_N^k = \sum_{i=1}^N b_{ik}^{(N)}$  as the value of the  $k^{\text{th}}$  diagonal element of  $T$ , i.e.,  $T_{kk}$ . Hence, as  $N \rightarrow \infty$ , for all  $k$ ,  $T_{kk} \xrightarrow{D} Z_k$  where  $Z_k \stackrel{\text{i.i.d.}}{\sim} \text{Pois}(1)$ . By using the [Skorokhod's representation theorem](#), we can establish that  $T \xrightarrow{\text{a.s.}} \text{diag}(Z_1, \dots, Z_n)$ ,<sup>a</sup> therefore

$$\mathbb{E}[\lambda_1(T)] = \mathbb{E} \left[ \max_{1 \leq k \leq n} T_{kk} \right] \rightarrow \mathbb{E} \left[ \max_{1 \leq k \leq n} Z_k \right].$$

Finally, the expectation of maximum of independent Poisson is thoroughly studied [[Kim83](#); [BSP09](#)], which is highly concentrated exactly around  $\log n / \log \log n$ . ⊗

<sup>a</sup>Note that  $X_n \xrightarrow{D} X$  and  $Y_n \xrightarrow{D} Y$  doesn't imply  $(X_n, Y_n) \xrightarrow{D} (X, Y)$ .

**Remark.** We note that the above claim doesn't require  $n$  to vary with  $N$ .

Finally, the bound in [Exercise 5.4.11](#) will fail if the logarithmic factors were removed becomes obvious after a direct substitution. Indeed, since  $\|X_i\| = 1 =: K$ , [Exercise 5.4.11](#) states that

$$\mathbb{E} \left[ \left\| \sum_{i=1}^N X_i \right\| \right] \lesssim \left\| \sum_{i=1}^N \mathbb{E}[X_i^2] \right\|^{1/2},$$

where the logarithmic factors were removed along with  $K = 1$ . Now, using the bound for  $S := \sum_{i=1}^N X_i$  we have, with the observation that  $X_i^2 = X_i$  and  $\mathbb{E}[X_i^2] = \mathbb{E}[X_i] = \text{diag}(1/n, \dots, 1/n)$ , we see that the bound becomes

$$\frac{\log n}{\log \log n} \lesssim \sqrt{\frac{N}{n}},$$

which is clear not valid. ⊗

**Problem (Exercise 5.4.15).** Let  $X_1, \dots, X_N$  be independent, mean zero,  $m \times n$  random matrices, such that  $\|X_i\| \leq K$  almost surely for all  $i$ . Prove that for  $t \geq 0$ , we have

$$\mathbb{P} \left( \left\| \sum_{i=1}^N X_i \right\| \geq t \right) \leq 2(m+n) \exp \left( -\frac{t^2/2}{\sigma^2 + Kt/3} \right),$$

where

$$\sigma^2 = \max \left( \left\| \sum_{i=1}^N \mathbb{E}[X_i^\top X_i] \right\|, \left\| \sum_{i=1}^N \mathbb{E}[X_i X_i^\top] \right\| \right).$$

**Answer.** Consider the following  $N$  independent  $(m+n) \times (m+n)$  symmetric, mean 0 matrices

$$X'_i := \begin{pmatrix} 0_{n \times n} & X_i^\top \\ X_i & 0_{m \times m} \end{pmatrix}.$$

To apply the matrix Bernstein's inequality (Theorem 5.4.1), we need to show that  $\|X'_i\| \leq K'$  for



some  $K'$ , where we know that  $\|X_i\| \leq K$ . However, it's easy to see that since  $\|X_i\| = \|X_i^\top\|$ , we have  $\|X'_i\| \leq K$  as well since the characteristic equation for  $X'_i$  is

$$\det(X'_i - \lambda I) = \det\left(\begin{pmatrix} -\lambda I & X_i^\top \\ X_i & -\lambda I \end{pmatrix}\right) = \det(\lambda^2 I - X_i^\top X_i) = 0,$$

so  $\|X'_i\| = \sqrt{\|X_i^\top X_i\|} \leq K$ . Hence, from matrix Bernstein's inequality, for every  $t \geq 0$ ,

$$\mathbb{P}\left(\left\|\sum_{i=1}^N X_i\right\| \geq t\right) \leq 2(m+n) \exp\left(-\frac{t^2/2}{\sigma^2 + Kt/3}\right),$$

where  $\sigma^2 = \|\sum_{i=1}^N \mathbb{E}[(X'_i)^2]\|$ . A quick calculation reveals that

$$(X'_i)^2 = \begin{pmatrix} 0 & X_i^\top \\ X_i & 0 \end{pmatrix} \begin{pmatrix} 0 & X_i^\top \\ X_i & 0 \end{pmatrix} = \begin{pmatrix} X_i^\top X_i & 0 \\ 0 & X_i X_i^\top \end{pmatrix},$$

hence we have

$$\sigma^2 = \max\left(\left\|\sum_{i=1}^N \mathbb{E}[X_i^\top X_i]\right\|, \left\|\sum_{i=1}^N \mathbb{E}[X_i X_i^\top]\right\|\right),$$

which completes the proof. \*

# Bibliography

- [BSP09] K. M. Briggs, L. Song, and T. Prellberg. *A note on the distribution of the maximum of a set of Poisson random variables*. 2009. arXiv: [0903.4373 \[math.PR\]](https://arxiv.org/abs/0903.4373). URL: <https://arxiv.org/abs/0903.4373>.
- [Kim83] AC Kimber. “A note on Poisson maxima”. In: *Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete* 63.4 (1983), pp. 551–552.
- [Ver24] Roman Vershynin. *High-Dimensional Probability*. Vol. 47. Cambridge University Press, 2024. URL: <https://www.math.uci.edu/~rvershyn/papers/HDP-book/HDP-book.html>.
- [Vla+20] Mariia Vladimirova et al. “Sub-Weibull distributions: Generalizing sub-Gaussian and sub-Exponential properties to heavier tailed distributions”. In: *Stat* 9.1 (Jan. 2020). ISSN: 2049-1573. DOI: [10.1002/sta4.318](https://doi.org/10.1002/sta4.318). URL: <http://dx.doi.org/10.1002/sta4.318>.