

MA3K0 - High-Dimensional Probability

Lecture Notes

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Notes are in final version - proofreading not completed yet! Typos and errors will be updated on a regular basis

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Preface

Introduction

We discuss an elegant argument that showcases the usefulness of probabilistic reasoning in geometry. First recall that a *convex combination* of points $z_1, \dots, z_m \in \mathbb{R}^n$ is a linear combination with coefficients that are non-negative and sum to 1, i.e., it is a sum of the form

$$\sum_{i=1}^m \lambda_i z_i \quad \text{where} \quad \lambda_i \geq 0 \quad \text{and} \quad \sum_{i=1}^m \lambda_i = 1. \quad (0.1)$$

Given a set $M \subset \mathbb{R}^n$, the *convex hull* of M is the set of all convex combinations of all finite collections of points in M , defined as

$$\text{conv}(M) := \{\text{convex combinations of } z_1, \dots, z_m \in M \text{ for } m \in \mathbb{N}\}.$$

The number m of elements defining a convex combination in \mathbb{R}^n is not restricted a priori. The classical theorem of Caratheodory states that one always take $m \leq n + 1$. For the convenience of the reader we briefly state that classical theorem.

Theorem 0.1 (Caratheodory's theorem) *Every point in the convex hull of a set $M \subset \mathbb{R}^n$ can be expressed as a convex combination of at most $n + 1$ points from M .*

Unfortunately the bound $n + 1$ cannot be improved (it is clearly attained for a simplex M)¹ This is some bad news. However, in most applications we only want to *approximate* a point $x \in \text{conv}(M)$ rather than to represent it exactly as a convex combination.

Can we do this with fewer than $n + 1$ points?

We now show that it is possible, and actually the number of required points does not need to depend on the dimension n at all! This is certainly brilliant news for any applications in mind - in particular for those where the dimension of the data set is extremely high (data science and machine learning and high-dimensional geometry and statistical mechanics models).

Theorem 0.2 (Approximate form Caratheodory's theorem) *Consider a set $M \subset \mathbb{R}^n$ whose diameter $\text{diam}(M) := \sup\{\|x - y\| : x, y \in M\}$ is bounded by 1. Then, for every point $x \in \text{conv}(M)$ and every positive integer k , one can find points $x_1, \dots, x_k \in M$ such that*

$$\|x - \frac{1}{k} \sum_{j=1}^k x_j\| \leq \frac{1}{\sqrt{k}}.$$

Here $\|x\| = \sqrt{x_1^2 + \dots + x_n^2}$, $x = (x_1, \dots, x_n) \in \mathbb{R}^n$, denotes the Euclidean norm on \mathbb{R}^n .

¹A simplex is a generalisation of the notion of a triangle to arbitrary dimensions. Specifically, a k -simplex S is the convex hull of its $k + 1$ vertices: Suppose $u_0, \dots, u_k \in \mathbb{R}^k$ are affinely independent, which means that $u_1 - u_0, \dots, u_k - u_0$ are linearly independent. Then, the simplex determined by these vertices is the set of points

$$S = \left\{ \lambda_0 u_0 + \dots + \lambda_k u_k : \sum_{i=0}^k \lambda_i = 1, \lambda_i \geq 0 \text{ for } i = 0, \dots, k \right\}.$$

Remark 0.3 We have assumed $\text{diam}(M) \leq 1$ for simplicity. For a general set M , the bound in the theorem changes to $\text{diam}(M)/\sqrt{k}$.

Why is this result surprising?

First, the number of points k in convex combinations does not depend on the dimension n . Second, the coefficients of convex combinations can be made all equal.

Proof. The argument upon which our proof is based is known as the *empirical method* of B. Maurey. W.l.o.g., we may assume that not only the diameter but also the *radius* of M is bounded by 1, i.e.,

$$\|w\| \leq 1 \quad \text{for all } w \in M.$$

We pick a point $x \in \text{conv}(M)$ and express it as a convex combination of some vectors $z_1, \dots, z_m \in M$ as in (0.1). Now we consider the numbers λ_i in that convex combination as probabilities that a random vector Z takes the values $z_i, i = 1, \dots, m$, respectively. That is, we define

$$\mathbb{P}(Z = z_i) = \lambda_i, \quad i = 1, \dots, m.$$

This is possible by the fact that the weights $\lambda_i \in [0, 1]$ and sum to 1. Consider now a sequence $(Z_j)_{j \in \mathbb{N}}$ of copies of Z . This sequence is an independent identically distributed sequence of \mathbb{R}^n -valued random variables. By the strong law of large numbers,

$$\frac{1}{k} \sum_{j=1}^k Z_j \rightarrow x \quad \text{almost surely as } k \rightarrow \infty.$$

We shall now get a quantitative version of this limiting statement, that is, we wish to obtain an error bound. For this we shall compute the variance of $\frac{1}{k} \sum_{j=1}^k Z_j$. We obtain

$$\begin{aligned} \mathbb{E} \left[\left\| x - \frac{1}{k} \sum_{j=1}^k Z_j \right\|^2 \right] &= \frac{1}{k^2} \mathbb{E} \left[\left\| \sum_{j=1}^k (Z_j - x) \right\|^2 \right] \quad (\text{since } \mathbb{E}[Z_i - x] = 0) \\ &= \frac{1}{k^2} \sum_{j=1}^k \mathbb{E}[\|Z_j - x\|^2]. \end{aligned}$$

The last identity is just a higher-dimensional version of the basic fact that the variance of a sum of independent random variables equals the sum of the variances. To bound the variances of the single terms we compute using that Z_j is copy of Z and that $\|Z\| \leq 1$ as $Z \in M$,

$$\mathbb{E}[\|Z_j - x\|^2] = \mathbb{E}[\|Z - \mathbb{E}[Z]\|^2] = \mathbb{E}[\|Z\|^2] - \|\mathbb{E}[Z]\|^2 \leq \mathbb{E}[\|Z\|^2] \leq 1,$$

where the second equality follows from the well-known property of the variance, namely, for $n = 1$,

$$\mathbb{E}[\|Z - \mathbb{E}[Z]\|^2] = \mathbb{E}[(Z - \mathbb{E}[Z])^2] = \mathbb{E}[Z^2 - 2Z\mathbb{E}[Z] + \mathbb{E}[Z]^2] = \mathbb{E}[Z^2] - \mathbb{E}[Z]^2,$$

and the cases for $n > 1$ follow similarly. We have thus shown that

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

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Therefore, there exists a realisation of the random variables Z_1, \dots, Z_k such that

$$\left\| x - \frac{1}{k} \sum_{j=1}^k Z_j \right\|^2 \leq \frac{1}{k}.$$

Since by construction each Z_j takes values in M , the proof is complete. □

We shall give one application of Theorem 0.2 in computational geometry. Suppose that we are given a subset $P \subset \mathbb{R}^n$ (say a polygon²) and asked to cover it by balls of a given radius $\varepsilon > 0$. What is the smallest number of balls needed, and how should we place them?

Corollary 0.4 (Covering polytopes by balls) *Let P be a polytope in \mathbb{R}^n with N vertices and whose diameter is bounded by 1. Then P can be covered by at most $N^{\lceil 1/\varepsilon^2 \rceil}$ Euclidean balls of radii $\varepsilon > 0$.*

Proof. We shall define the centres of the balls as follows. Let $k := \lceil 1/\varepsilon^2 \rceil$ and consider the set

$$\mathcal{N} := \left\{ \frac{1}{k} \sum_{j=1}^k x_j : x_j \text{ are vertices of } P \right\}.$$

The polytope P is the convex hull of the set of its vertices, which we denote by M . We then apply Theorem 0.2 to any point $x \in P = \text{conv}(M)$ and deduce that x is within a distance $1/\sqrt{k} \leq \varepsilon$ from some point in \mathcal{N} . This shows that the ε -balls centred at \mathcal{N} do indeed cover P . □

In this lecture we will learn several other approaches to the covering problem in relation to packing, entropy and coding, and random processes.

²In geometry, a polytope is a geometric object with 'flat' sides. It is a generalisation of the three-dimensional polyhedron which is a solid with flat polygonal faces, straight edges and sharp corners/vertices. Flat sides mean that the sides of a $(k + 1)$ -polytope consist of k -polytopes.

1 Preliminaries on Probability Theory

In this chapter we recall some basic concepts and results of probability theory. The reader should be familiar with most of this material some of which is taught in elementary probability courses in the first year. To make these lectures self-contained we review the material mostly without proof and refer the reader to basic chapters of common undergraduate textbooks in probability theory, e.g. [Dur19] and [Geo12]. In Section 1.1 we present basic definitions for probability space and probability measure as well as random variables along with expectation, variance and moments. Vital for the lecture will be the review of all classical inequalities in Section 1.2. Finally, in Section 1.3 we review well-know limit theorems.

1.1 Random variables

A probability space (Ω, \mathcal{F}, P) is a triple consisting of a set Ω , a σ -algebra \mathcal{F} and a probability measure P . We write $\mathcal{P}(\Omega)$ for the power set of Ω which is the set of all subsets of Ω .

Definition 1.1 (σ -algebra) Suppose $\Omega \neq \emptyset$. A system $\mathcal{F} \subset \mathcal{P}(\Omega)$ satisfying

- (a) $\Omega \in \mathcal{F}$
- (b) $A \in \mathcal{F} \Rightarrow A^c := \Omega \setminus A \in \mathcal{F}$
- (c) $A_1, A_2, \dots \in \mathcal{F} \Rightarrow \bigcup_{i \geq 1} A_i \in \mathcal{F}$.

is called σ -algebra (or σ -field) on Ω . The pair (Ω, \mathcal{F}) is then called an event space or measurable space.

Example 1.2 (Borel σ -algebra) Let $\Omega = \mathbb{R}^n$, $n \in \mathbb{N}$ and

$$\mathcal{G} = \left\{ \prod_{i=1}^n [a_i, b_i] : a_i < b_i, a_i, b_i \in \mathbb{Q} \right\}$$

be the system consisting of all compact rectangular boxes in \mathbb{R}^n with rational vertices and edges parallel to the axes. In honour of Émile Borel (1871–1956), the system $\mathcal{B}^n = \sigma(\mathcal{G})$ is called the Borel σ -algebra on \mathbb{R}^n , and every $A \in \mathcal{B}^n$ a Borel set. Here, $\sigma(\mathcal{G})$ denotes the smallest σ -algebra generated by the system \mathcal{G} . Note that the \mathcal{B}^n can also be generated by the system of open or half-open rectangular boxes, see [Dur19, Geo12].



The decisive point in the process of building a stochastic model is the next step: For each $A \in \mathcal{F}$ we need to define a value $P(A) \in [0, 1]$ that indicates the probability of A . Sensibly, this should be done so that the following holds.

(N) *Normalisation:* $P(\Omega) = 1$.

(A) *σ -Additivity:* For pairwise disjoint events $A_1, A_2, \dots \in \mathcal{F}$ one has

$$P\left(\bigcup_{i \geq 1} A_i\right) = \sum_{i \geq 1} P(A_i).$$

Definition 1.3 (Probability measure) Let (Ω, \mathcal{F}) be a measurable space. A function $P: \mathcal{F} \rightarrow [0, 1]$ satisfying the properties (N) and (A) is called a probability measure or a probability distribution, in short a distribution (or, a little old-fashioned, a probability law) on (Ω, \mathcal{F}) . Then the triple (Ω, \mathcal{F}, P) is called a probability space.

Theorem 1.4 (Construction of probability measures via densities) (a) *Discrete case: For countable Ω , the relations*

$$P(A) = \sum_{\omega \in A} \varrho(\omega) \text{ for } A \in \mathcal{P}(\Omega), \quad \varrho(\omega) = P(\{\omega\}) \text{ for } \omega \in \Omega$$

establish a one-to-one correspondence between the set of all probability measures P on $(\Omega, \mathcal{P}(\Omega))$ and the set of all sequences $\varrho = (\varrho(\omega))_{\omega \in \Omega}$ in $[0, 1]$ such that $\sum_{\omega \in \Omega} \varrho(\omega) = 1$.

(b) *Continuous case: If $\Omega \subset \mathbb{R}^n$ is Borel, then every function $\varrho: \Omega \rightarrow [0, \infty)$ satisfying the properties*

$$(i) \{x \in \Omega: \varrho(x) \leq c\} \in \mathcal{B}_\Omega^n \text{ for all } c > 0,$$

$$(ii) \int_\Omega \varrho(x) \, dx = 1$$

determines a unique probability measure on $(\Omega, \mathcal{B}_\Omega^n)$ via

$$P(A) = \int_A \varrho(x) \, dx \text{ for } A \in \mathcal{B}_\Omega^n$$

(but not every probability measure on $(\Omega, \mathcal{B}_\Omega^n)$ is of this form).

Proof. See [Dur19, Geo12]. □

Definition 1.5 A sequence or function ϱ as in Theorem 1.4 above is called a density (of P) or, more explicitly (to emphasise normalisation), a probability density (function), often abbreviated as *pdf*. If a distinction between the discrete and continuous case is required, a sequence $\varrho = (\varrho(\omega))_{\omega \in \Omega}$ as in case (a) is called a discrete density, and a function ϱ in case (b) a Lebesgue density.

In probability theory one often considers the transition from a measurable space (event space) (Ω, \mathcal{F}) to a coarser measurable (event) space (Ω', \mathcal{F}') . In general such a mapping should satisfy the requirement

$$A' \in \mathcal{F}' \Rightarrow X^{-1}A' := \{\omega \in \Omega: X(\omega) \in A'\} \in \mathcal{F}. \quad (1.1)$$

Definition 1.6 Let (Ω, \mathcal{F}) and (Ω', \mathcal{F}') be two measurable (event) spaces. The every mapping $X: \Omega \rightarrow \Omega'$ satisfying property (1.1) is called a random variable from (Ω, \mathcal{F}) to (Ω', \mathcal{F}') , or a random element of Ω' . Alternatively (in the terminology of measure theory), X is said to be measurable relative to \mathcal{F} and \mathcal{F}' .

In probability theory it is common to write $\{X \in A'\} := X^{-1}A'$.

Theorem 1.7 (Distribution of a random variable) *If X is a random variable from a probability space (Ω, \mathcal{F}, P) to a measurable space (Ω', \mathcal{F}') , then the prescription*

$$P'(A') := P(X^{-1}A') = P(\{X \in A'\}) \quad \text{for } A' \in \mathcal{F}'$$

defines a probability measure P' on (Ω', \mathcal{F}') .

Definition 1.8 (a) The probability measure P' in Theorem 1.7 is called the distribution of X under P , or the image of P under X , and is denoted by $P \circ X^{-1}$. (In the literature, one also finds the notations P_X or $\mathcal{L}(X; P)$. The letter \mathcal{L} stands for the more traditional term law, or loi in French.) (b) Two random variables are said to be identically distributed if they have the same distribution.

We are considering real-valued or \mathbb{R}^n -valued random variables in the following and we just call them random variables for these cases.

In basic courses in probability theory, one learns about the two most important quantities associated with a random variable X , namely the expectation³ (also called the mean) and variance. They will be noted in this lecture by

$$\mathbb{E}[X] \quad \text{and} \quad \text{Var}(X) := \mathbb{E}[(X - \mathbb{E}(X))^2].$$

The distribution of a real-valued random variable X is determined by the cumulative distribution function (CDF) of X , defined as

$$F_X(t) = \mathbb{P}(X \leq t) = \mathbb{P}((-\infty, t]), \quad t \in \mathbb{R}. \quad (1.2)$$

It is often more convenient to work with the tails of random variables, namely with

$$\mathbb{P}(X > t) = 1 - F_X(t). \quad (1.3)$$

Here we write \mathbb{P} for the generic distribution of the random variable X which is given by the context. For any real-valued random variable the *moment generating function (MGF)* is defined

$$M_X(\lambda) := \mathbb{E}[e^{\lambda X}], \quad \lambda \in \mathbb{R}. \quad (1.4)$$

When M_X is finite for all λ in a neighbourhood of the origin, we can easily compute all moments by taking derivatives (interchanging differentiation and expectation (integration) in the usual way).

Lemma 1.9 (Integral Identity) *Let X be a real-valued non-negative random variable. Then*

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

³In measure theory the expectation $\mathbb{E}[X]$ of a random variable on a probability space (Ω, \mathcal{F}, P) is the Lebesgue integral of the function $X: \Omega \rightarrow \mathbb{R}$. This makes theorems on Lebesgue integration applicable in probability theory for expectations of random variables

Proof. We can write any non-negative real number x via the following identity using indicator function ⁴:

$$x = \int_0^x 1 \, dt = \int_0^\infty \mathbb{1}_{\{t < x\}}(t) \, dt.$$

Substitute now the random variable X for x and take expectation (with respect to X) on both sides. This gives

$$\mathbb{E}[X] = \mathbb{E}\left[\int_0^\infty \mathbb{1}_{\{t < X\}}(t) \, dt\right] = \int_0^\infty \mathbb{E}[\mathbb{1}_{\{t < X\}}] \, dt = \int_0^\infty \mathbb{P}(t < X) \, dt.$$

To change the order of expectation and integration in the second inequality, we used the Fubini-Tonelli theorem. \square

Exercise 1.10 (Integral identity) Prove the extension of Lemma 1.9 to any real-valued random variable (not necessarily positive):

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



1.2 Classical Inequalities

In this section fundamental classical inequalities are presented. Here, classical refers to typical estimates for analysing stochastic limits.

Proposition 1.11 (Jensen's inequality) Suppose that $\Phi: I \rightarrow \mathbb{R}$, where $I \subset \mathbb{R}$ is an interval, is a convex function. Let X be a real-valued random variable. Then

$$\Phi(\mathbb{E}[X]) \leq \mathbb{E}[\Phi(X)].$$

Proof. See [Dur19] or [Geo12] using either the existence of sub-derivatives for convex functions or the definition of convexity with the epi-graph of a function. The epi-graph of a function $f: I \rightarrow \mathbb{R}$, $I \subset$ some interval, is the set

$$\text{epi}(f) := \{(x, f(x)) \in \mathbb{R}^2: x \in I\}.$$

A function $f: I \rightarrow \mathbb{R}$ is convex if, and only if $\text{epi}(f)$ is a convex set in \mathbb{R}^2 . \square

A consequence of Jensen's inequality is that $\|X\|_{L^p}$ is an increasing function in the parameter p , i.e.,

$$\|X\|_{L^p} \leq \|X\|_{L^q} \quad 0 \leq p \leq q \leq \infty.$$

This follows from the convexity of $\Phi(x) = x^{\frac{q}{p}}$ when $q \geq p$.

Proposition 1.12 (Minkowski's inequality) For $p \in [1, \infty]$, let $X, Y \in L^p$, then

$$\|X + Y\|_{L^p} \leq \|X\|_{L^p} + \|Y\|_{L^p}.$$

⁴ $\mathbb{1}_A$ denotes the indicator function of the set A , that is, $\mathbb{1}_A(t) = 1$ if $t \in A$ and $\mathbb{1}_A(t) = 0$ if $t \notin A$.

Proposition 1.13 (Cauchy-Schwarz inequality) For $X, Y \in L^2$,

$$|\mathbb{E}[XY]| \leq \|X\|_{L^2} \|Y\|_{L^2}.$$

Proposition 1.14 (Hölder's inequality) For $p, q \in (1, \infty)$ with $1/p + 1/q = 1$ let $X \in L^p$ and $Y \in L^q$. Then

$$\mathbb{E}[XY] \leq \mathbb{E}[|XY|] \leq \|X\|_{L^p} \|Y\|_{L^q}.$$

Lemma 1.15 (Linear Markov's inequality) For non-negative random variables X and $t > 0$ the tail is bounded as

$$\mathbb{P}(X > t) \leq \frac{\mathbb{E}[X]}{t}.$$

Proof. Pick $t > 0$. Any positive number x can be written as

$$x = x \mathbb{1}_{\{X \geq t\}} + x \mathbb{1}_{\{X < t\}}.$$

As X is non-negative, we insert X into the above expression and take the expectation (integral) to obtain

$$\mathbb{E}[X] = \mathbb{E}[X \mathbb{1}_{\{X \geq t\}}] + \mathbb{E}[X \mathbb{1}_{\{X < t\}}] \geq \mathbb{E}[t \mathbb{1}_{\{X \geq t\}}] = t \mathbb{P}(X \geq t).$$

□

This is one version of the Markov inequality which provides linear decay in t . In the following proposition we obtain the general version which will be used frequently throughout the lecture.

Proposition 1.16 (Markov's inequality) Let Y be a real-valued random variable and $f: [0, \infty) \rightarrow [0, \infty)$ an increasing function. Then, for all $\varepsilon > 0$ with $f(\varepsilon) > 0$,

$$\mathbb{P}(|Y| \geq \varepsilon) \leq \frac{\mathbb{E}[f \circ |Y|]}{f(\varepsilon)}.$$

Proof. Clearly, the composition $f \circ |Y|$ is a positive random variable such that

$$f(\varepsilon) \mathbb{1}_{\{|Y| \geq \varepsilon\}} \leq f \circ |Y|.$$

Taking the expectation on both sides of that inequality gives

$$f(\varepsilon) \mathbb{P}(|Y| \geq \varepsilon) = \mathbb{E}[f(\varepsilon) \mathbb{1}_{\{|Y| \geq \varepsilon\}}] \leq \mathbb{E}[f \circ |Y|].$$

□

The following version of the Markov inequality is often called Chebyshev's inequality.

Corollary 1.17 (Chebyshev's inequality, 1867) For all $Y \in L^2$ with $\mathbb{E}[Y] \in (-\infty, \infty)$ and $\varepsilon > 0$,

$$\mathbb{P}\left(|Y - \mathbb{E}[Y]| \geq \varepsilon\right) \leq \frac{\text{Var}(Y)}{\varepsilon^2}$$

1.3 Limit Theorems

Definition 1.18 (Variance and covariance) Let $X, Y \in L^2$ be real-valued random variables.

(a)

$$\text{Var}(X) := \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

is called the **variance**, and $\sqrt{\text{Var}(X)}$ the **standard deviation** of X with respect to \mathbb{P} .

(b)

$$\text{cov}(X, Y) := \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$$

is called the **covariance** of X and Y . It exists since $|XY| \leq X^2 + Y^2$.

(c) If $\text{cov}(X, Y) = 0$, then X and Y are called **uncorrelated**.

Recall that two independent random variables are uncorrelated, but two uncorrelated are not necessarily independent as the following example shows.

Example 1.19 Let $\Omega = \{1, 2, 3\}$ and let P the uniform distribution on Ω . Define two random variables by their images, that is,

$$(X(1), X(2), X(3)) = (1, 0, -1) \quad \text{and} \quad (Y(1), Y(2), Y(3)) = (0, 1, 0).$$

Then $XY = 0$ and $\mathbb{E}[XY] = 0$, and therefore $\text{cov}(X, Y) = 0$, but

$$\mathbb{P}(X = 1, Y = 1) = 0 \neq \frac{1}{9} = \mathbb{P}(X = 1)\mathbb{P}(Y = 1).$$

Hence X and Y are not independent. ♣

Theorem 1.20 (Weak law of large numbers, L^2 -version) Let $(X_i)_{i \in \mathbb{N}}$ be a sequence of uncorrelated (e.g. independent) real-valued random variables in L^2 with bounded variance, in that $v := \sup_{i \in \mathbb{N}} \text{Var}(X_i) < \infty$. Then for all $\varepsilon > 0$

$$\mathbb{P}\left(\left|\frac{1}{N} \sum_{i=1}^N (X_i - \mathbb{E}[X_i])\right| \geq \varepsilon\right) \leq \frac{v}{N\varepsilon^2} \xrightarrow{N \rightarrow \infty} 0,$$

and thus

$$\frac{1}{N} \sum_{i=1}^N (X_i - \mathbb{E}[X_i]) \xrightarrow[N \rightarrow \infty]{\mathbb{P}} 0,$$

($\xrightarrow[N \rightarrow \infty]{\mathbb{P}}$ means convergence in probability). In particular, if $\mathbb{E}[X_i] = \mathbb{E}[X_1]$ holds for all $i \in \mathbb{N}$, then

$$\frac{1}{N} \sum_{i=1}^N X_i \xrightarrow{\mathbb{P}} \mathbb{E}[X_1].$$

We now present a second version of the weak law of large numbers, which does not require the existence of the variance. To compensate we must assume that the random variables, instead of being pairwise uncorrelated, are even pairwise independent and identically distributed.

Theorem 1.21 (Weak law of large numbers, L^1 -version) *Let $(X_i)_{i \in \mathbb{N}}$ be a sequence of pairwise independent, identically distributed real-valued random variables in L^1 . Then*

$$\frac{1}{N} \sum_{i=1}^N X_i \xrightarrow[N \rightarrow \infty]{\text{P}} \mathbb{E}[X_1].$$

Theorem 1.22 (Strong law of large numbers) *If $(X_i)_{i \in \mathbb{N}}$ is a sequence of pairwise uncorrelated real-valued random variables in L^2 with $v := \sup_{i \in \mathbb{N}} \text{Var}(X_i) < \infty$, then*

$$\frac{1}{N} \sum_{i=1}^N (X_i - \mathbb{E}[X_i]) \rightarrow 0 \text{ almost surely as } N \rightarrow \infty.$$

Theorem 1.23 (Central limit theorem; A.M. Lyapunov 1901, J.W. Lindeberg 1922, P. Leévy 1922) *Let $(X_i)_{i \in \mathbb{N}}$ be a sequence of independent, identically distributed real-valued random variables in L^2 with $\mathbb{E}[X_i] = m$ and $\text{Var}(X_i) = v > 0$. Then, as $N \rightarrow \infty$,*

$$S_N^* := \frac{1}{\sqrt{N}} \sum_{i=1}^N \frac{X_i - m}{\sqrt{v}} \xrightarrow{d} \text{N}(0, 1).$$

The normal distribution is defined as follows.

A real-valued random variable X is **normally** distributed with mean μ and variance $\sigma^2 > 0$ if

$$\mathbb{P}(X > x) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_x^\infty e^{-\frac{(u-\mu)^2}{2\sigma^2}} du, \quad \text{for all } x \in \mathbb{R}.$$

We write $X \sim \text{N}(\mu, \sigma^2)$. We say that X is standard normal distributed if $X \sim \text{N}(0, 1)$.

A random vector $X = (X_1, \dots, X_n)$ is called a **Gaussian random vector** if there exists an $n \times m$ matrix A , and an n -dimensional vector $b \in \mathbb{R}^n$ such that $X^T = AY + b$, where Y is an m -dimensional vector with independent standard normal entries, i.e. $Y_i \sim \text{N}(0, 1)$ for $i = 1, \dots, m$. Likewise, a random variable $Y = (Y_1, \dots, Y_m)$ with values in \mathbb{R}^m has the m -dimensional standard Gaussian distribution if the m coordinates are standard normally distributed and independent. The covariance matrix of $X = AY + b$ is then given by

$$\text{cov}(Y) = \mathbb{E}[(Y - \mathbb{E}[Y])(Y - \mathbb{E}[Y])^T] = AA^T.$$

Lemma 1.24 *If A is an orthogonal $n \times n$ matrix, i.e. $AA^T = \mathbb{1}$, and X is a n -dimensional standard Gaussian vector, then AX is also a n -dimensional standard Gaussian vector.*

Lemma 1.25 *Let X_1 and X_2 be independent and normally distributed with zero mean and variance $\sigma^2 > 0$. Then $X_1 + X_2$ and $X_1 - X_2$ are independent and normally distributed with mean 0 and variance $2\sigma^2$.*

Proposition 1.26 *If X and Y are n -dimensional Gaussian vectors with $\mathbb{E}[X] = \mathbb{E}[Y]$ and $\text{cov}(X) = \text{cov}(Y)$, then X and Y have the same distribution.*

Corollary 1.27 *A Gaussian random vector X has independent entries if and only if its covariance matrix is diagonal. In other words, the entries in a Gaussian vector are uncorrelated if and only if they are independent.*

Bernoulli: $p \in [0, 1]$, then $X \sim \text{Ber}(p)$ if $\mathbb{P}(X = 1) = p$ and $\mathbb{P}(X = 0) = 1 - p =: q$. If $X \sim \text{Ber}(p)$, then $\mathbb{E}[X] = p$ and $\text{Var}(X) = pq$.

Binomial: $S_N = \sum_{i=1}^N X_i \sim \text{B}(N, p)$ if $X_i \sim \text{Ber}(p)$ and $(X_i), i = 1, \dots, N$, independent family. $\mathbb{E}[S_N] = Np$ and $\text{Var}(S_N) = Npq$.

Poisson: $\lambda > 0$, then $X \sim \text{Poi}(\lambda)$ if

$$\mathbb{P}(X = k) = \frac{e^{-\lambda} \lambda^k}{k!} \quad k \in \mathbb{N}_0,$$

$\text{Poi}(\lambda) \in \mathcal{M}_1(\mathbb{N}_0, \mathcal{P}(\mathbb{N}_0))$. Here, $\mathcal{M}_1(\Omega)$ denotes the set of probability measures on Ω .

Exponential: A random variable X taking positive real value is exponentially distributed with parameter $\alpha > 0$ when the probability density function is

$$f_X(t) = \alpha e^{-\alpha t} \quad \text{for } t \geq 0.$$

We write $X \sim \text{Exp}(\alpha)$. If $X \sim \text{Exp}(\alpha)$, then $\mathbb{E}[X] = \frac{1}{\alpha}$ and $\text{Var}(X) = \frac{1}{\alpha^2}$.

Theorem 1.28 (Poisson limit theorem) *Let $X_i^{(N)}, i = 1, \dots, N$, be independent Bernoulli random variables $X_i^{(N)} \sim \text{Ber}(p_i^{(N)})$, and denote $S_N = \sum_{i=1}^N X_i^{(N)}$ their sum. Assume that, as $N \rightarrow \infty$,*

$$\max_{1 \leq i \leq N} \{p_i^{(N)}\} \xrightarrow{N \rightarrow \infty} 0 \quad \text{and} \quad \mathbb{E}[S_N] = \sum_{i=1}^N p_i^{(N)} \xrightarrow{N \rightarrow \infty} \lambda \in (0, \infty).$$

Then, as $N \rightarrow \infty$,

$$S_N \longrightarrow \text{Poi}(\lambda) \quad \text{indistribution.}$$

2 Concentration inequalities for independent random variables

2.1 Why concentration inequalities

Suppose a random variable X has mean μ , then, for any $t \geq 0$,

$$\mathbb{P}(|X - \mu| > t) \leq \text{something small}$$

is a concentration inequality. One is interested in cases where the bound on the right hand side decays with increasing parameter $t \geq 0$. We now discuss a very simple example to demonstrate that we need better concentration inequalities than the ones obtained for example from the central limit theorem (CLT). Toss a fair coin N times. What is the probability

that we get at least $3N/4$ heads? Recall that $\mathbb{E}[S_N] = \frac{N}{2}$ and $\text{Var}(S_N) = \frac{N}{4}$ in conjunction with Corollary 1.17 gives the bound

$$\mathbb{P}\left(S_N \geq \frac{3}{4}N\right) \leq \mathbb{P}\left(\left|S_N - \frac{N}{2}\right| \geq \frac{N}{4}\right) \leq \frac{4}{N}.$$

This concentration bound vanishes linearly in N . One may wonder if we can do better using the CLT. The De Moivre Laplace limit theorem (variant of the CLT for Binomial distributions) states that the distribution of the normalised number of heads

$$Z_N = \frac{S_N - N/2}{\sqrt{N/4}}$$

converges to the standard normal distribution $N(0, 1)$. We therefore expect to get the following concentration bound

$$\mathbb{P}\left(S_N \geq \frac{3}{4}N\right) = \mathbb{P}\left(Z_N \geq \sqrt{N/4}\right) \approx \mathbb{P}(Y \geq \sqrt{N/4}), \quad (2.1)$$

where $Y \sim N(0, 1)$. To obtain explicit bounds we need estimates on the tail of the normal distribution.

Proposition 2.1 (Tails of the normal distribution) *Let $Y \sim N(0, 1)$. Then, for all $t > 0$, we have*

$$\left(\frac{1}{t} - \frac{1}{t^3}\right) \frac{1}{\sqrt{2\pi}} e^{-t^2/2} \leq \mathbb{P}(Y \geq t) \leq \frac{1}{t} \frac{1}{\sqrt{2\pi}} e^{-t^2/2}.$$

Proof. Denote $f(x) := \exp(-x^2/2)$. For the upper bound we use $x \geq t$ to get the estimate

$$\int_t^\infty f(x) \, dx \leq \int_t^\infty \frac{x}{t} e^{-x^2/2} \, dx = \frac{1}{t} e^{-t^2/2}.$$

For the lower bound we use integration by parts (IBP):

$$\begin{aligned} \int_t^\infty e^{-x^2/2} \, dx &= \int_t^\infty \frac{1}{x} x e^{-x^2/2} \, dx = \left[-\frac{1}{x} e^{-x^2/2} \right]_t^\infty - \int_t^\infty \frac{1}{x^2} e^{-x^2/2} \, dx \\ &= \frac{1}{t} e^{-t^2/2} - \int_t^\infty \frac{1}{x^3} x e^{-x^2/2} \, dx = \frac{1}{t} e^{-t^2/2} - \left[-\frac{1}{x^3} e^{-x^2/2} \right]_t^\infty \\ &\quad + \int_t^\infty \frac{3}{x^4} e^{-x^2/2} \, dx. \end{aligned}$$

Hence

$$\int_t^\infty e^{-x^2/2} \, dx = \left(\frac{1}{t} - \frac{1}{t^3}\right) e^{-t^2/2} + \int_t^\infty \frac{3}{x^4} e^{-x^2/2} \, dx,$$

and, as the integral on the right hand side is positive,

$$\mathbb{P}(Y \geq t) \geq \frac{1}{\sqrt{2\pi}} (1/t - 1/t^3) e^{-t^2/2}.$$

□

The lower bound in Proposition 2.1 is lower than the tail lower bound in Lemma C.5 in the appendix.

Lemma 2.2 (Lower tail bound for normal distribution) *Let $Y \sim N(0, 1)$. Then, for all $t \geq 0$,*

$$\mathbb{P}(Y \geq t) \geq \left(\frac{t}{t^2 + 1}\right) \frac{1}{\sqrt{2\pi}} e^{-t^2/2}.$$

Proof. Define

$$g(t) := \frac{1}{\sqrt{2\pi}} \left(\int_t^\infty e^{-x^2/2} dx - \frac{t}{t^2 + 1} e^{-t^2/2} \right).$$

Then $g(0) > 0$ and $g'(t) = \frac{-2e^{-t^2/2}}{(t^2+1)^2} < 0$. Thus g is strictly decreasing with $\lim_{t \rightarrow \infty} g(t) = 0$ implying that $g(t) > 0$ for all $t \in \mathbb{R}$. \square

Using the tail estimates in Proposition 2.1 we expect to obtain an exponential bound for the right hand side of (2.1), namely that the probability of having at least $3N/4$ heads seems to be smaller than $\frac{1}{\sqrt{2\pi}} e^{-N/8}$. However, we have not taken into account the approximation errors of \approx in (2.1). Unfortunately, it turns out that the error decays too slowly, actually even more slowly than linearly in N . This can be seen from the following version of the CLT which we state without proof, see for example [Dur19].

Theorem 2.3 (Berry-Esseen CLT) *In the setting of Theorem 1.23, for every N and every $t \in \mathbb{R}$, we have*

$$|P(Z_N \geq t) - \mathbb{P}(Y \geq t)| \leq \frac{\varrho}{\sqrt{N}},$$

where $Y \sim N(0, 1)$ and $\varrho = \mathbb{E}[|X_1 - m|^3]/\sigma^3$.

Can we improve the approximation error ' \approx ' in (2.1) by simply computing the probabilities with the help of Stirling's formula? Suppose that n is even. Then

$$\mathbb{P}(S_N = N/2) = 2^{-N} \binom{N}{N/2} \sim \frac{1}{\sqrt{N}} \quad \text{and} \quad \mathbb{P}(Z_N = 0) \sim \frac{1}{\sqrt{N}},$$

but $\mathbb{P}(Y = 0) = 0$. We thus see that we shall get a better concentration bound. This is the content of the next section.

2.2 Hoeffding's Inequality

In this section we study sums of *symmetric Bernoulli random variables* defined as follows.

Definition 2.4 A random variable Z taking values in $\{-1, +1\}$ with

$$\mathbb{P}(Z = -1) = \mathbb{P}(Z = +1) = \frac{1}{2}$$

is called symmetric Bernoulli random variable.

Note that the 'standard' Bernoulli random variable X takes values in $\{0, 1\}$, and one easily switch between both via $Z = 2X - 1$.

Theorem 2.5 (Hoeffding's inequality) *Suppose that X_1, \dots, X_N , are independent symmetric Bernoulli random variables and let $a = (a_1, \dots, a_N) \in \mathbb{R}^N$. Then, for any $t \geq 0$, we have*

$$\mathbb{P}\left(\sum_{i=1}^N a_i X_i \geq t\right) \leq \exp\left(-\frac{t^2}{2\|a\|_2^2}\right).$$

Proof. Without loss of generality we can put $\|a\|_2 = 1$, namely, if $\|a\|_2 \neq 1$, then define $\tilde{a}_i = a_i/\|a\|_2, i = 1, \dots, N$, to obtain the bound for

$$\mathbb{P}\left(\sum_{i=1}^N \tilde{a}_i X_i \geq \|a\|_2 t\right).$$

Let $\lambda > 0$, then, using Markov's inequality, obtain

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

To bound the right hand side use first that the random variables are independent,

$$\mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^N a_i X_i\right)\right] = \prod_{i=1}^N \mathbb{E}[e^{\lambda a_i X_i}]$$

and then compute for $i \in \{1, \dots, N\}$,

$$\mathbb{E}[e^{\lambda a_i X_i}] = \frac{e^{\lambda a_i} + e^{-\lambda a_i}}{2} = \cosh(\lambda a_i).$$

We are left to find a bound for the hyperbolic cosine. There are two ways to get the upper bound

$$\cosh(x) \leq e^{x^2/2}.$$

1.) Simply write down both Taylor series and compare term by term, that is,

$$\cosh(x) = 1 + \frac{x^2}{2!} + \frac{x^4}{4!} + \frac{x^6}{6!} + \dots$$

and

$$e^{x^2/2} = \sum_{k=0}^{\infty} \frac{(x^2/2)^k}{k!} = 1 + \frac{x^2}{2} + \frac{x^4}{2^2 2!} + \dots$$

2.) Use the product expansion (complex analysis – not needed for this course, just as background information)

$$\cosh(x) = \prod \left(1 + \frac{4x^2}{\pi^2(2k-1)^2}\right) \leq \exp\left(\sum_{k=1}^{\infty} \frac{4x^2}{\pi^2(2k-1)^2}\right) = e^{x^2/2}.$$

In any case, we obtain

$$\mathbb{E}[e^{\lambda a_i X_i}] \leq e^{\lambda^2 a_i^2/2},$$

and thus

$$\mathbb{P}\left(\sum_{i=1}^N a_i X_i \geq t\right) \leq \exp\left(-\lambda t + \frac{\lambda^2}{2} \|a\|_2^2\right).$$

Using $\|a\|_2 = 1$, and optimising over the value of λ we get $\lambda = t$ and thus the right hand is simply $\exp(-t^2/2)$. \square

With Hoeffding's inequality in Theorem 2.5 we are now in the position to answer our previous question on the probability for a fair coin to have at least $3/4N$ times with heads. The fair coin is a standard Bernoulli random variable Y with $\mathbb{P}(Y = 1) = \mathbb{P}(Y = 0) = \frac{1}{2}$, and the symmetric one is just $Z = 2Y - 1$. Thus we obtain the following bound,

$$\begin{aligned} \mathbb{P}\left(\sum_{i=1}^N X_i \geq 3/4N\right) &= \mathbb{P}\left(\sum_{i=1}^N \frac{Z_i + 1}{2} \geq 3/4N\right) = \mathbb{P}\left(\sum_{i=1}^N \frac{Z_i}{2} \geq 1/4N\right) \\ &= \mathbb{P}\left(\sum_{i=1}^N \frac{Z_i}{\sqrt{N}} \geq \frac{1}{2}\sqrt{N}\right) \leq \exp\left(-\frac{1}{2 \cdot 4}N\right). \end{aligned}$$

This shows that Hoeffding's inequality is the a good concentration estimate avoiding the approximating error using the CLT. We also get two-sided tail / concentration estimates for $S = \sum_{i=1}^n a_i X_i$ using Theorem 2.5 writing

$$\mathbb{P}(|S| \geq t) = \mathbb{P}(S \geq t) + \mathbb{P}(-S \geq t).$$

Theorem 2.6 (Two-sided Hoeffding's inequality) *Suppose that X_1, \dots, X_N , are independent symmetric Bernoulli random variables and let $a = (a_1, \dots, a_N) \in \mathbb{R}^N$. Then, for any $t \geq 0$, we have*

$$\mathbb{P}\left(\left|\sum_{i=1}^N a_i X_i\right| \geq t\right) \leq 2 \exp\left(-\frac{t^2}{2\|a\|_2^2}\right).$$

As the reader may have realised, the proof of Hoeffding's inequality, Theorem 2.5, is quite flexible a sit is based on bounding the moment generating function. For example, the following version of Hoeffding's inequality is valid for general bounded random variables. The proof will be given as an exercise.

Theorem 2.7 (Hoeffding's inequality for general bounded random variables) *Let X_1, \dots, X_N be independent random variable with $X_i \in [m_i, M_i]$, $m_i < M_i$, for $i = 1, \dots, N$. Then, for any $t \geq 0$, we have*

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

Example 2.8 Let X_1, \dots, X_N non-negative independent random variables with continuous distribution (i.e., having a density with respect to the Lebesgue measure). Assume that the probability density functions f_i of X_i are uniformly bounded by 1. Then the following holds.

(a) For all $i = 1, \dots, N$,

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

(b) For any $\varepsilon > 0$, we have

$$\mathbb{P}\left(\sum_{i=1}^N X_i \leq \varepsilon N\right) \leq (e\varepsilon)^N. \quad (2.2)$$

To show (2.2), we use Markov's inequality for some $\lambda > 0$, the independence, and part (a) to arrive at

$$\mathbb{P}\left(\sum_{i=1}^N \left(\frac{-X_i}{\varepsilon}\right) \geq N\right) \leq e^{\lambda N} \prod_{i=1}^N \mathbb{E}[e^{-\lambda/\varepsilon X_i}] \leq e^{\lambda N} \left(\frac{\varepsilon}{\lambda}\right)^N = e^{\lambda N} e^{N \log(\varepsilon/\lambda)}.$$

Minimising over $\lambda > 0$ gives $\lambda = 1$ and thus the desired statement.



2.3 Chernoff's Inequality

Hoeffding's inequality is already good but it does not produce good results in case the success probabilities/parameter p_i are very small. In that case one knows that the sum S_N of N Bernoulli random variables has an approximately Poisson distribution. The Gaussian tails are not good enough to match Poisson tails as we will see later.

Theorem 2.9 (Chernoff's inequality) *Let X_i be independent Bernoulli random variables with parameter $p_i \in [0, 1]$, i.e., $X_i \sim \text{Ber}(p_i)$, $i = 1, \dots, N$. Denote $S_N = \sum_{i=1}^N X_i$ their sum and $\mu = \mathbb{E}[S_N]$ its mean. Then, for any $t > \mu$, we have*

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

Proof. Let $\lambda > 0$, then Markov's inequality gives

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

We need to bound the MGF of each Bernoulli random variable X_i separately. Using $1 + x \leq e^x$, we get

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

Thus

$$\prod_{i=1}^N \mathbb{E}[\exp(\lambda X_i)] \leq \exp\left(\left(e^\lambda - 1\right) \sum_{i=1}^N p_i\right) = \exp\left(\left(e^\lambda - 1\right)\mu\right),$$

and therefore

$$\mathbb{P}(S_N \geq t) \leq e^{-\lambda t} \exp((e^\lambda - 1)\mu) \quad \text{for all } \lambda > 0.$$

Optimising over $\lambda > 0$ we obtain $\lambda = \log(t/\mu)$ as $t > \mu$ for the minimal upper bound. \square

Exercise 2.10 In the setting of Theorem 2.9, prove that, for any $t < \mu$,

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



Solution. We get

$$\mathbb{P}(S_N \leq t) = \mathbb{P}(-S_N \geq -t) \leq \mathbb{E}[e^{-\lambda S_N}]e^{\lambda t}$$

and

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

Thus

$$\mathbb{P}(S_N \leq t) \leq e^{\lambda t} \exp((e^{-\lambda} - 1)\mu).$$

Minimising over $\lambda > 0$, gives $-\lambda = \log(t/\mu)$ which is valid as $t < \mu$. \odot

We shall now discuss some example on random graphs where concentration inequalities provide sufficient bounds.

Example 2.11 (Degrees of Random Graphs) We consider the Erdős-Rényi random graph model. This is the simplest stochastic model for large, real-world networks. The random graph $G(n, p)$ consists of n vertices, and each pair of distinct vertices is connected independently (from all other pairs) with probability $p \in [0, 1]$. The degree of a vertex is the (random) number of edges incident to that vertex. The expected degree of every vertex i (we label the n vertices by numbers $1, \dots, n$), is

$$d(i) = \mathbb{E}[D(i)] = (n - 1)p \quad i = 1, \dots, n.$$

Note that $d(i) = d(j)$ for all $i \neq j, i, j = 1, \dots, n$, and thus we simply write d in the following. We call the random graph dense when $d \geq \log n$ holds, and the graph is denoted regular if the degree of all vertices approximately equal d .

Proposition 2.12 (Dense graphs are almost regular) *There is an absolute constant $C > 0$ such that the following holds: Suppose that $G(n, p)$ has expected degree $d \geq C \log n$. Then, with high probability, all vertices of $G(n, p)$ have degrees between $0.9d$ and $1.1d$.*

Proof. Pick a vertex i of the graph, the the degree is simply a sum of Bernoulli random variables, i.e.,

$$D(i) = \sum_{k=1}^{n-1} X_k \quad X_k \sim \text{Ber}(p).$$

We are using the two-sided version of the Chernoff bound in Theorem 2.9, see Exercise 2(a) Example Sheet 1:

$$\mathbb{P}(|D(i) - d| \geq 0.1d) \leq 2e^{-cd} \quad \text{for some absolute constant } c > 0.$$

We can now 'unfix' i by taking the union bound over all vertices of the graph:

$$\mathbb{P}(\exists i \in \{1, \dots, n\}: |D(i) - d| \geq 0.1d) \leq \sum_{i=1}^n \mathbb{P}(|D(i) - d| \geq 0.1d) \leq 2ne^{-cd}$$

If $d \geq C \log n$ for a sufficiently large absolute constant C , the probability on the left hand side is bounded as

$$\mathbb{P}(\exists i \in \{1, \dots, n\}: |D(i) - d| \geq 0.1d) \leq 2ne^{-cC \log n} = 2n^{1-cC} \leq 0.1.$$

This means that, with probability 0.9, the complementary event occurs and we have

$$\mathbb{P}(\forall i \in \{1, \dots, n\}: |D(i) - d| < 0.1d) \geq 0.9.$$

□



2.4 Sub-Gaussian random variables

In this section we introduce a family of random variables, the so-called *sub-Gaussian random variables*, who show exponential concentration bounds similar to the Normal distribution (Gaussian). Before we define this class via various properties, we discuss some facts on Chernoff bounds.

Suppose the real-valued random variable X has mean $\mu \in \mathbb{R}$ and there is some constant $b > 0$ such that the function

$$\Phi(\lambda) := \mathbb{E}[e^{\lambda(X - \mathbb{E}[X])}] \tag{2.3}$$

the so-called *centred moment generating function* exists for all $|\lambda| \leq b$. For $\lambda \in [0, b]$, we may apply Markov's Inequality in Theorem 1.16 to the random variable $Y = e^{\lambda(X - \mathbb{E}[X])}$, thereby obtaining the upper bound

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

Optimising our choice of λ so as to obtain the tightest results yields the so-called *Chernoff bound*, namely. the inequality

$$\log \mathbb{P}((X - \mu) \geq t) \leq \inf_{\lambda \in [0, b]} \{ \log \Phi(\lambda) - \lambda t \}. \tag{2.4}$$

Example 2.13 (Gaussian tail bounds) Let $X \sim N(\mu, \sigma^2)$, $\mu \in \mathbb{R}$, $\sigma^2 > 0$, and recall the probability density function (p.d.f) of X ,

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}.$$

The moment generating function (MGF) is easily computed as

$$\begin{aligned} M_X(\lambda) &= \mathbb{E}[e^{\lambda X}] = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{\mathbb{R}} e^{-\frac{(x-\mu)^2}{2\sigma^2} + \lambda x} dx = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{\mathbb{R}} e^{-y^2/2\sigma^2 + \lambda y} dy \\ &= e^{\lambda\mu + \lambda^2\sigma^2/2} < \infty \end{aligned}$$

for all $\lambda \in \mathbb{R}$. We obtain the Chernoff bound by optimising over $\lambda \geq 0$ using $\Phi(\lambda) = e^{-\lambda\mu} M_X(\lambda) = e^{\lambda^2\sigma^2/2}$,

$$\inf_{\lambda \geq 0} \{ \log \Phi(\lambda) - \lambda t \} = \inf_{\lambda \geq 0} \left\{ \frac{\lambda^2\sigma^2}{2} - \lambda t \right\} = -\frac{t^2}{2\sigma^2}.$$

Thus any $N(\mu, \sigma^2)$ random variable X satisfies the *upper deviation inequality*

$$\mathbb{P}(X \geq \mu + t) \leq \exp\left(-\frac{t^2}{2\sigma^2}\right), \quad t \geq 0,$$

and the two-sided version

$$\mathbb{P}(|X - \mu| \geq t) \leq 2 \exp\left(-\frac{t^2}{2\sigma^2}\right), \quad t \geq 0.$$



Exercise 2.14 (Moments of the normal distribution) Let $p \geq 1$ and $X \sim N(0, 1)$. Then

$$\begin{aligned} \|X\|_{L^p} &= (\mathbb{E}[|X|^p])^{1/p} = \left(\frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} |x|^p e^{-x^2/2} dx\right)^{1/p} = \left(\frac{2}{\sqrt{2\pi}} \int_0^\infty x^p e^{-x^2/2} dx\right)^{1/p} \\ &\stackrel{(x^2/2=w)}{=} \left(\int_0^\infty (\sqrt{2}\sqrt{w})^p e^{-w} \frac{\sqrt{2}}{\sqrt{w}} \frac{1}{2} dw\right)^{1/p} = \left(\frac{2}{\sqrt{2\pi}} \frac{\sqrt{2}^p \sqrt{2}}{2} \Gamma(p/2 + 1/2)\right)^{1/p} \\ &= \sqrt{2} \left(\frac{\Gamma(p/2 + 1/2)}{\Gamma(1/2)}\right)^{1/p}. \end{aligned}$$

Hence

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



We also note that the MGF of $X \sim N(0, 1)$ is given as $M_X(\lambda) = e^{\lambda^2/2}$. In the following proposition we identify equivalent properties for a real-valued random variable which exhibits similar tail bounds, moment bounds and MGF estimates than a Gaussian random variable does.

Proposition 2.15 (Sub-Gaussian properties) *Let X be a real-valued random variable. Then there are absolute constants $C_i > 0, i = 1, \dots, 5$, such that the following statements are equivalent:*

(i) **Tails of X :**

$$\mathbb{P}(|X| \geq t) \leq 2 \exp(-t^2/C_1^2) \quad \text{for all } t \geq 0.$$

(ii) **Moments:**

$$\|X\|_{L^p} \leq C_2 \sqrt{p} \quad \text{for all } p \geq 1.$$

(iii) **MGF of X^2 :**

$$\mathbb{E}[\exp(\lambda^2 X^2)] \leq \exp(C_3^2 \lambda^2) \quad \text{for all } \lambda \text{ with } |\lambda| \leq \frac{1}{C_3}.$$

(iv) **MGF bound:**

$$\mathbb{E}[\exp(X^2/C_4^2)] \leq 2.$$

Moreover, if $\mathbb{E}[X] = 0$, then the statements (i)-(iv) are equivalent to the following statement

(v) **MGF bound of X :**

$$\mathbb{E}[\exp(\lambda X)] \leq \exp(C_5^2 \lambda^2) \quad \text{for all } \lambda \in \mathbb{R}.$$

Proof. (i) \Rightarrow (ii): Without loss of generality we can assume that $C_1 = 1$ for property (i). This can be seen by just multiplying the parameter t with C_1 which corresponds to multiply X by $1/C_1$. The integral identity in Lemma 1.9 applied to the non-negative random variable $|X|^p$ gives

$$\begin{aligned} \mathbb{E}[|X|^p] &= \int_0^\infty \mathbb{P}(|X|^p > t) dt \stackrel{t=up}{=} \int_0^\infty \mathbb{P}(|X| \geq u) p u^{p-1} du \stackrel{(i)}{\leq} \int_0^\infty 2e^{-u^2} p u^{p-1} du \\ &\stackrel{u^2=s}{=} p \Gamma\left(\frac{p}{2}\right) \leq p \left(\frac{p}{2}\right)^{p/2}, \end{aligned}$$

where we used the property $\Gamma(x) \leq x^x$ of the Gamma function.⁵ Taking the p th root gives $\sqrt[p]{p} \sqrt[p]{p} \sqrt{1/2}$ and $\sqrt[p]{p} \leq 2$ gives (ii) with some $C_2 \leq 2$. To see that $\sqrt[p]{p} \leq 2$ recall that $\lim_{n \rightarrow \infty} \sqrt[n]{n} = 1$. More precisely, in that proof one takes $\sqrt[n]{n} = 1 + \delta_n$ and shows with the binomial theorem that $0 < \delta_n < \sqrt{\frac{2}{n-1}}$.

(ii) \Rightarrow (iii): Again with loss of generality we can assume that $C_2 = 1$. Taylor expansion of the exponential function and linearity of the expectation gives

$$\mathbb{E}[\exp(\lambda^2 X^2)] = 1 + \sum_{k=1}^{\infty} \frac{\lambda^{2k} \mathbb{E}[X^{2k}]}{k!}.$$

Property (ii) implies that $\mathbb{E}[X^{2k}] \leq (2k)^k$ and Stirling's formula⁶ we get that $k! \geq \left(\frac{k}{e}\right)^k$. Thus

$$\mathbb{E}[\exp(\lambda^2 X^2)] \leq 1 + \sum_{k=1}^{\infty} \frac{(2\lambda^2 k)^k}{(k/e)^k} = \sum_{k=0}^{\infty} (2e\lambda^2)^k = \frac{1}{1 - 2e\lambda^2},$$

provided that $2e\lambda^2 < 1$ (geometric series). To bound the right hand side, i.e., to bound $1/(1 - 2e\lambda^2)$, we use that

$$\frac{1}{1-x} \leq e^{2x} \quad \text{for all } x \in [0, 1/2].$$

⁵ $\Gamma(n) = (n-1)!, n \in \mathbb{N}$.

$$\begin{aligned} \Gamma(z) &:= \int_0^\infty x^{z-1} e^{-x} dx \quad \text{for all } z = x + iy \in \mathbb{C} \text{ with } x > 0, \\ \Gamma(z+1) &= z\Gamma(z), \\ \Gamma(1) &= 1, \\ \Gamma\left(\frac{1}{2}\right) &= \sqrt{\pi}. \end{aligned}$$

⁶Stirling's formula:

$$N! \sim \sqrt{2\pi N} e^{-N} N^N \quad \text{where } \sim \text{ means quotient goes to zero when } N \rightarrow \infty.$$

Alternatively,

$$N! \sim \sqrt{2\pi N} e^{-N} N^N \left(1 + \frac{1}{12N} + O\left(\frac{1}{N^2}\right)\right).$$

For all $|\lambda| \leq \frac{1}{2\sqrt{e}}$ we have $2e\lambda^2 < \frac{1}{2}$, and thus

$$\mathbb{E}[\exp(\lambda^2 X^2)] \leq \exp(4e\lambda^2) \quad \text{for all } |\lambda| \leq \frac{1}{2\sqrt{e}},$$

and (iii) follows with $C_3 = 2\sqrt{e}$.

(iii) \Rightarrow (iv): Trivial and left as an exercise.

(iv) \Rightarrow (i): Again, we assume without loss of generality that $C_4 = 1$. Using Markov's inequality 1.16 with $f = \exp \circ x^2$, we obtain

$$\mathbb{P}(|X| \geq t) = \mathbb{P}(e^{X^2} \geq e^{t^2}) \leq e^{-t^2} \mathbb{E}[e^{X^2}] \stackrel{(iv)}{\leq} 2e^{-t^2}.$$

Suppose now that $\mathbb{E}[X] = 0$. We show that **(iii) \Rightarrow (v)** and **(v) \rightarrow (i)**.

(iii) \Rightarrow (v): Again, we assume without loss of generality that $C_3 = 1$. We use the well-known inequality

$$e^x \leq x + e^{x^2}, \quad x \in \mathbb{R},$$

to obtain

$$\mathbb{E}[e^{\lambda X}] \leq \mathbb{E}[\lambda X + e^{\lambda^2 X^2}] = \mathbb{E}[e^{\lambda^2 X^2}] \stackrel{(iii)}{\leq} e^{\lambda^2} \quad \text{if } |\lambda| \leq 1,$$

and thus we have (v) for the range $|\lambda| \leq 1$. Now, assume $|\lambda| \geq 1$. This time, use the inequality $2\lambda x \leq \lambda^2 + x^2$, $\lambda, x \in \mathbb{R}$, to arrive at

$$\mathbb{E}[e^{\lambda X}] \leq e^{\lambda^2/2} \mathbb{E}[e^{X^2/2}] \leq e^{\lambda^2/2} \exp(1/2) \leq e^{\lambda^2} \quad \text{as } |\lambda| \geq 1.$$

(v) \rightarrow (i): Again, assume that $C_5 = 1$. Let $\lambda \geq 0$.

$$\mathbb{P}(X \geq t) = \mathbb{P}(e^{\lambda X} \geq e^{\lambda t}) \leq e^{-\lambda t} \mathbb{E}[e^{\lambda X}] \leq e^{-\lambda t} e^{\lambda^2} = \exp(-\lambda t + \lambda^2).$$

Optimising over $\lambda \geq 0$, we obtain $\lambda = t/2$, and thus $\mathbb{P}(x \geq t) \leq e^{-t^2/4}$. Now we repeat the argument for $-X$ and obtain $\mathbb{P}(X \leq -t) \leq e^{-t^2/4}$, and thus

$$\mathbb{P}(|X| \geq t) \leq 2e^{-t^2/4},$$

and $C_1 = 2$ implies (i). □

Definition 2.16 (Sub-Gaussian random variable, first definition) A random real-valued variable X that satisfies one of the equivalent statements (i)-(iv) in Proposition 2.15 is called *sub-Gaussian random variable*. Define, for any sub-Gaussian random variable

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

Exercise 2.17 (Sub-Gaussian norm) Let X be a sub-Gaussian random variable and define

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

Show that $\|\cdot\|_{\psi_2}$ is indeed a norm on the space of sub-Gaussian random variables. ♣

Example 2.18 (Examples of Sub-Gaussian random variables) (a) $X \sim N(0, 1)$ is sub-Gaussian random variable: pick $t > 0$ with $1 > \frac{2}{t^2}$ and set $a(t) := 1 - \frac{2}{t^2}$. Then

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

shows that there is an absolute constant $C > 0$ with $\|X\|_{\psi_2} \leq C$.

(b) Let X be a symmetric Bernoulli random variable, $\|X\| = 1$.

$$\mathbb{E}[e^{X^2/t^2}] = e^{1/t^2} \leq 2 \Leftrightarrow \frac{1}{\log 2} \leq t^2.$$

Thus $\|X\|_{\psi_2} = 1/\sqrt{\log 2}$.

(c) Let X be a real-valued, bounded random variable, that is, $|X| \leq b = \|X\|_{\infty}$. Thus

$$\mathbb{E}[e^{X^2/t^2}] \leq e^{\|X\|_{\infty}^2/t^2} \leq 2 \Leftrightarrow t \geq \|X\|_{\infty}/\sqrt{\log 2},$$

and $\|X\|_{\psi_2} = \|X\|_{\infty}/\sqrt{\log 2}$. ♣

Recall that the sum of independent normal random variables $X_i \sim N(\mu_i, \sigma_i^2), i = 1, \dots, N$, is normally distributed, that is,

$$S_N = \sum_{i=1}^N X_i \sim N\left(\sum_{i=1}^N \mu_i, \sum_{i=1}^N \sigma_i^2\right).$$

For a proof see [Dur19] or [Geo12]. We then may wonder if the sum of independent sub-Gaussian random variables is sub-Gaussian as well. There are different statements on this depending whether $\mu_i = 0$ for all $i = 1, \dots, N$, as done in the book [Ver18], or not. We shall follow the general case here. It proves useful to have the following equivalent definition of sub-Gaussian random variables.

Definition 2.19 (Sub-Gaussian random variables, second definition) A real-valued random variable X with mean $\mu = \mathbb{E}[X]$ is a sub-Gaussian random variable if there is a positive number σ such that

$$\mathbb{E}[e^{\lambda(X-\mu)}] \leq e^{\sigma^2 \lambda^2/2} \quad \text{for all } \lambda \in \mathbb{R}. \quad (2.5)$$

The constant σ satisfying (2.5) is referred to as the *sub-Gaussian parameter*; for instance, we say that X is sub-Gaussian with parameter σ when (2.5) holds.

Remark 2.20 (Sub-Gaussian definitions:) It is easy to see that our two definitions are equivalent when the random variable X has zero mean $\mu = 0$: use statement (v) of Proposition 2.15. If $\mu \neq 0$ and X satisfies (2.5), we obtain the following tail bound

$$\mathbb{P}(|X| \geq t) \leq 2 \exp\left(-\frac{1}{2\sigma^2}(t - \mu)^2\right) \quad \text{for all } t \geq 0. \quad (2.6)$$

This tail bound is not exactly the statement (i) of Proposition 2.15 as the parameter $t \geq 0$ is chosen with respect to the mean. In most cases, one is solely interested in tail estimates away from the mean. Thus the definitions are equivalent in case $\mu \neq 0$ if we limit the range for parameter t to $t \geq |\mu|$. In the literature and in applications Definition 2.19 is widely used and sometimes called sub-Gaussian for centred random variables. We use both definitions synonymously. \diamond

Proposition 2.21 (Sum of independent sub-Gaussian random variables) *Let X_1, \dots, X_N be independent sub-Gaussian random variables with sub-Gaussian parameters $\sigma_i, i = 1, \dots, N$, respectively. Then $S_N = \sum_{i=1}^N X_i$ is a sub-Gaussian random variable with sub-Gaussian parameter $\sqrt{\sum_{i=1}^N \sigma_i^2}$.*

Proof.

$$\mathbb{E}\left[\exp\left(\lambda \sum_{i=1}^N (X_i - \mu_i)\right)\right] = \prod_{i=1}^N \mathbb{E}\left[\exp\left(\lambda(X_i - \mu_i)\right)\right] \leq \exp\left(\lambda^2/2 \sum_{i=1}^N \sigma_i^2\right) \quad \text{for all } \lambda \in \mathbb{R}.$$

□

This allows us to obtain a Hoeffding bound for independent sum of sub-Gaussian random variables.

Proposition 2.22 (Hoeffding bounds for sums of independent sub-Gaussian random variables) *Let X_1, \dots, X_N be real-valued independent sub-Gaussian random variables with sub-Gaussian parameter σ_i and mean $\mu_i, i = 1, \dots, N$, respectively. Then, for all $t \geq 0$,*

$$\mathbb{P}\left(\sum_{i=1}^N (X_i - \mu_i) \geq t\right) \leq \exp\left(-\frac{t^2}{2 \sum_{i=1}^N \sigma_i^2}\right).$$

Proof. Set $\tilde{S}_N := \sum_{i=1}^N (X_i - \mu_i)$. Using again the exponential version of the Markov inequality in Proposition 1.16, we obtain

$$\mathbb{P}(\tilde{S}_N \geq t) \leq \mathbb{E}[e^{\lambda \tilde{S}_N}] e^{-\lambda t} = e^{-\lambda t} \prod_{i=1}^N \mathbb{E}[e^{\lambda(X_i - \mu_i)}] \leq \exp\left(-\lambda t + \lambda^2/2 \sum_{i=1}^N \sigma_i^2\right).$$

Optimising over λ , we obtain $\lambda = t / \sum_{i=1}^N \sigma_i^2$, and conclude with the statement. \square

Example 2.23 (Bounded random variables) Let X be a real-valued random variable with mean-zero and (bounded) supported on $[a, b]$, $a < b$. Denote X' an identical independent copy of X , i.e., $X \sim X'$. For any $\lambda \in \mathbb{R}$, using Jensen's inequality 1.11,

$$\mathbb{E}_X[e^{\lambda X}] = \mathbb{E}_X[e^{\lambda(X - \mathbb{E}_{X'}[X'])}] \leq \mathbb{E}_{X, X'}[e^{\lambda(X - X')}],$$

where $\mathbb{E}_{X, X'}$ is expectation with respect to the two independent and identically distributed random variables X and X' . Suppose ε is an independent (from X and X' Rademacher function, that is ε is a symmetric Bernoulli random variable. Then $(X - X') \sim \varepsilon(X - X')$. For Rademacher functions/symmetric Bernoulli random variables ε we estimate the moment generating function as

$$\begin{aligned} \mathbb{E}[e^{\lambda \varepsilon}] &= \frac{1}{2}(e^\lambda + e^{-\lambda}) = \frac{1}{2} \left(\sum_{k=0}^{\infty} \frac{(\lambda)^k}{k!} + \sum_{k=0}^{\infty} \frac{(-\lambda)^k}{k!} \right) = \sum_{k=0}^{\infty} \frac{\lambda^{2k}}{(2k)!} \\ &\leq 1 + \sum_{k=1}^{\infty} \frac{\lambda^{2k}}{2^k k!} = e^{\lambda^2/2}. \end{aligned}$$

Thus

$$\begin{aligned} \mathbb{E}_{X, X'}[e^{\lambda(X - X')}] &= \mathbb{E}_{X, X'}[\mathbb{E}_\varepsilon[e^{\lambda \varepsilon(X - X')}]] \leq \mathbb{E}_{X, X'}[\exp(\lambda^2(X - X')^2/2)] \\ &\leq \mathbb{E}_{X, X'}[\exp(\lambda^2(b - a)^2/2)], \end{aligned}$$

as $|X - X'| \leq b - a$. Thus X sub-Gaussian with sub-Gaussian parameter $\sigma = b - a > 0$, see Definition 2.19. \clubsuit

As discussed above in Remark 2.20, in many situations and results we encounter later, we typically assume that the random variables have zero means. Then the two definitions are equivalent. In the next lemma we simply show that centering does not harm the sub-Gaussian property. This way we can see that we can actually use both our definitions for sub-Gaussian random variables.

Lemma 2.24 (Centering) *If X is sub-Gaussian random variable then $X - \mathbb{E}[X]$ is sub-Gaussian too with*

$$\|X - \mathbb{E}[X]\|_{\psi_2} \leq C\|X\|_{\psi_2}$$

for some absolute constant $C > 0$.

Proof. We use the fact that $\|\cdot\|_{\psi_2}$ is norm. Triangle inequality gives

$$\|X - \mathbb{E}[X]\|_{\psi_2} \leq \|X\|_{\psi_2} + \|\mathbb{E}[X]\|_{\psi_2}.$$

For any $a \in \mathbb{R}$ one can find $t \geq \frac{|a|}{\log 2}$ such that $\mathbb{E}[\exp(a^2/t^2)] \leq 2$, thus

$$\|a\|_{\psi_2} = \frac{|a|}{\log 2} \leq c|a|$$

for some constant $c > 0$. Hence

$$\|\mathbb{E}[X]\|_{\psi_2} \leq c|\mathbb{E}[X]| \leq c\mathbb{E}[|X|] = c\|X\|_{L^1} \leq C\|X\|_{\psi_2}$$

using $\|X\|_{L^p} \leq C\|X\|_{\psi_2} \sqrt{p}$ for all $p \geq 1$.

□

2.5 Sub-Exponential random variables

Suppose $Y = (Y_1, \dots, Y_N) \in \mathbb{R}^N$ is a random vector with independent coordinates $Y_i \sim \mathcal{N}(0, 1)$, $i = 1, \dots, N$. We expect that the Euclidean norm $\|Y\|_2$ exhibits some form of concentration as the square of the norm $\|Y\|_2^2$ is the sum of independent random variables Y_i^2 . However, although the Y_i are sub-Gaussian random variables, the Y_i^2 are not. Recall our tail estimate for the Gaussian random variables and note that

$$\mathbb{P}(Y_i^2 > t) = \mathbb{P}(|Y_i| > \sqrt{t}) \leq C \exp(-\sqrt{t}^2/2) = C \exp(-t/2).$$

The tails are like those for the exponential distribution. To see that, suppose that $X \sim \text{Exp}(\lambda)$, $\lambda > 0$, i.e., the probability density function (pdf) is $f_X(t)\lambda e^{-\lambda t} \mathbb{1}\{t \geq 0\}$. Then, for all $t \geq 0$,

$$\mathbb{P}(X \geq t) = \int_t^\infty \lambda e^{-\lambda t} dt = e^{-\lambda t}.$$

We can therefore use our general Hoeffding bound. The following proposition summarises properties of a new class of random variables.

Proposition 2.25 (Sub-exponential properties) *Let X be a real-valued random variable. Then the following properties are equivalent for absolute constant $C_i > 0$, $i = 1, \dots, 5$:*

(i) **Tails:**

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

(ii) **Moments:**

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

(iii) **Moment generating function (MGF) of $|X|$:**

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

(iv) **MGF of $\|X\|$ bounded at some point:**

$$\mathbb{E}[\exp(|X|/C_4)] \leq 2.$$

Moreover, if $\mathbb{E}[X] = 0$, the properties (i)-(iv) are also equivalent to (v):

(v) **MGF of X :**

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

Definition 2.26 (Sub-exponential random variable, first definition) A real-valued random variable X is called *Sub-exponential* if it satisfies one of the equivalent properties (i)-(iv) of Proposition 2.25 (respectively properties (i)-(v) when $\mathbb{E}[X] = 0$). Define $\|X\|_{\psi_1}$ by

$$\|X\|_{\psi_1} := \inf\{t > 0: \mathbb{E}[\exp(|X|/t)] \leq 2\}. \quad (2.7)$$

Lemma 2.27 Equation (2.7) defines the sub-exponential norm $\|X\|_{\psi}$ on the set of all sub-exponential random variables X .

Proof. Supportclass. □

Lemma 2.28 A real-valued random variable X is sub-Gaussian if and only if X^2 is sub-exponential. Moreover,

$$\|X^2\|_{\psi_1} = \|X\|_{\psi_1}^2. \quad (2.8)$$

Proof. Suppose X is sub-Gaussian and $t \geq 0$. Then

$$\mathbb{P}(|X|^2 \geq t) = \mathbb{P}(|X| \geq \sqrt{t}) \leq 2 \exp(-\sqrt{t}^2/C_1^2),$$

and thus X^2 is sub-exponential according to Proposition 2.25 (i). If X^2 is sub-exponential we have

$$\mathbb{P}(|X| \geq t) = \mathbb{P}(|X|^2 \geq t^2) \leq 2 \exp(-t^2/C_1),$$

and thus X is sub-Gaussian. As for the norms, recall that $\|X^2\|_{\psi_1}$ is the infimum of all numbers $C > 0$ satisfying $\mathbb{E}[\exp(X^2/C)] \leq 2$, whereas $\|X\|_{\psi_2}$ is the infimum of all numbers $K > 0$ satisfying $\mathbb{E}[\exp(X^2/K^2)] \leq 2$. Putting $C = K^2$, one obtains $\|X^2\|_{\psi_1} = \|X\|_{\psi_2}^2$. □

Lemma 2.29 (Product of sub-Gaussians) Let X and Y real-valued sub-Gaussian random variables. Then XY is sub-exponential and

$$\|XY\|_{\psi_1} \leq \|X\|_{\psi_2} \|Y\|_{\psi_2}.$$

Proof. Suppose that $0 \neq \|X\|_{\psi_2}$ (if $\|X\|_{\psi_2} = 0$ and/or $\|Y\|_{\psi_2} = 0$ the statement trivially holds). Then $\tilde{X} = X/\|X\|_{\psi_2}$ is sub-Gaussian with $\|\tilde{X}\|_{\psi_2} = \frac{1}{\|X\|_{\psi_2}} \|X\|_{\psi_2} = 1$. Thus we assume without loss of generality that $\|X\|_{\psi_2} = \|Y\|_{\psi_2} = 1$. To prove the statement in the lemma we shall show that $\mathbb{E}[\exp(X^2)] \leq 2$ and $\mathbb{E}[\exp(Y^2)] \leq 2$ both imply that $\mathbb{E}[\exp(|XY|)] \leq 2$, where $\mathbb{E}[\exp(|XY|)] \leq 2$ implies that $\|XY\|_{\psi_1} \leq 1$. We are going to use *Young's inequality* :

$$ab \leq \frac{a^2}{2} + \frac{b^2}{2} \quad \text{for } a, b \in \mathbb{R}.$$

Thus

$$\begin{aligned} \mathbb{E}[\exp(|XY|)] &\leq \mathbb{E}\left[\exp\left(\frac{X^2}{2} + \frac{Y^2}{2}\right)\right] = \mathbb{E}\left[\exp\left(\frac{X^2}{2}\right) \exp\left(\frac{Y^2}{2}\right)\right] \quad \text{Young's inequality} \\ &\leq \frac{1}{2} \mathbb{E}\left[\exp(X^2) + \exp(Y^2)\right] = \frac{1}{2}(2 + 2) = 2 \quad \text{Young's inequality.} \end{aligned}$$

□

Example 2.30 (Exponential random variables) Suppose $X \sim \text{Exp}(\alpha)$, $\alpha > 0$. Then $\mathbb{E}[X] = \frac{1}{\alpha}$ and $\text{Var}(X) = \frac{1}{\alpha^2}$. We compute for every $t \neq \frac{1}{\alpha}$ to get

$$\mathbb{E}[\exp(|X|/t)] = \int_0^\infty \alpha e^{x/t} e^{-\alpha x} dx = \left[\frac{-\alpha}{(\alpha - 1/t)} e^{-x(\alpha - 1/t)} \right]_0^\infty = \frac{\alpha}{(\alpha - 1/t)} \leq 2$$

if and only if $t \geq 2/\alpha$. Hence $\|X\|_{\psi_1} = \frac{2}{\alpha}$.



Example 2.31 (Sub-exponential but not sub-Gaussian) Suppose that $Z \sim N(0, 1)$, and define $X := Z^2$. Then $\mathbb{E}[X] = 1$. For $\lambda < \frac{1}{2}$ we have

$$\mathbb{E}[e^{\lambda(X-1)}] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\lambda(z^2-1)} e^{-z^2/2} dz = \frac{e^{-\lambda}}{\sqrt{1-2\lambda}},$$

whereas for $\lambda > \frac{1}{2}$ we have $\mathbb{E}[e^{\lambda(X-1)}] = +\infty$. Thus X is not sub-Gaussian. In fact one can show, after some computation, that

$$\frac{e^{-\lambda}}{\sqrt{1-2\lambda}} \leq e^{2\lambda^2} = e^{4\lambda^2/2} \quad \text{for all } |\lambda| < \frac{1}{4}.$$

This motivates the following alternative definition of sub-exponential random variables which corresponds to the second definition for sub-Gaussian random variables in Definition 2.19.



Definition 2.32 (Sub-exponential random variables, second definition) A real-valued random variable X with mean $\mu \in \mathbb{R}$ is *sub-exponential* if there exist non-negative parameters (ν, α) such that

$$\mathbb{E}[\exp(\lambda(X - \mu))] \leq e^{\nu^2 \lambda^2 / 2} \quad \text{for all } |\lambda| < \frac{1}{\alpha}. \quad (2.9)$$

Remark 2.33 (a) The random variable X in Example 2.31 is sub-exponential with parameters $(\nu, \alpha) = (2, 4)$.

(b) It is easy to see that our two definitions are equivalent when the random variable X has zero mean $\mu = 0$: use statement (v) of Proposition 2.25. If $\mu \neq 0$ and X satisfies (2.9), we obtain the following tail bound

$$\mathbb{P}(|X| \geq t) \leq 2 \exp\left(-\frac{1}{2\nu^2}(t - \mu)^2\right) \quad \text{for all } t \geq 0. \quad (2.10)$$

This tail bound is not exactly the statement (i) of Proposition 2.25 as the parameter $t \geq 0$ is chosen with respect to the mean. In most cases, one is solely interested in tail estimates away from the mean. Thus the definitions are equivalent in case $\mu \neq 0$ if we limit the range for parameter t to $t \geq |\mu|$. In the literature and in applications Definition 2.32 is widely used and sometimes called sub-exponential for centred random variables. We use both definitions synonymously.



Example 2.34 (Bounded random variable) Let X be a real-valued, mean-zero and bounded random variable support on the compact interval $[a, b]$, $a < b$. Furthermore, let X' be an independent copy of X and let ε be an independent (from both X and X') *Rademacher function*, that is, ε is a symmetric Bernoulli random variable with $\mathbb{P}(\varepsilon = -1) = \mathbb{P}(\varepsilon = 1) = \frac{1}{2}$. Using Jensen's inequality for X' we obtain

$$\mathbb{E}_X[e^{\lambda X}] = \mathbb{E}_X[e^{\lambda(X - \mathbb{E}_{X'}[X'])}] \leq \mathbb{E}_{X, X'}[e^{\lambda(X - X')}] = \mathbb{E}_{X, X'}[\mathbb{E}_\varepsilon[e^{\lambda\varepsilon(X - X')}]],$$

where we write $\mathbb{E}_{X, X'}$ for the expectation with respect to X and X' , \mathbb{E}_ε for the expectation with respect to ε , and where we used that $(X - X') \sim \varepsilon(X - X')$. Here, \sim means that both random variables have equal distribution. Hold $\alpha := (X - X')$ fixed and compute

$$\begin{aligned} \mathbb{E}_\varepsilon[e^{\lambda\varepsilon\alpha}] &= \frac{1}{2}[e^{-\lambda\alpha} + e^{\lambda\alpha}] = \frac{1}{2}\left(\sum_{k=0}^{\infty} \frac{(-\lambda\alpha)^k}{k!} + \sum_{k=0}^{\infty} \frac{(\lambda\alpha)^k}{k!}\right) = \sum_{k=0}^{\infty} \frac{(\lambda\alpha)^{2k}}{(2k)!} \\ &\leq 1 + \sum_{k=1}^{\infty} \frac{(\lambda\alpha)^{2k}}{2^k k!} = e^{\lambda^2\alpha^2/2}. \end{aligned}$$

Inserting this result in the previous one leads to

$$\mathbb{E}_X[e^{\lambda X}] \leq \mathbb{E}_{X, X'}\left[e^{\lambda^2(X - X')^2/2}\right] \leq e^{\lambda^2(b-a)^2/2}$$

as $|X - X'| \leq b - a$. ♣

Proposition 2.35 (Sub-exponential tail-bound) Let X be a real-valued sub-exponential random variable with parameters (ν, α) and mean $\mu = \mathbb{E}[X]$. Then, for every $t \geq 0$,

$$\mathbb{P}(X - \mu \geq t) \leq \begin{cases} e^{-\frac{t^2}{2\nu^2}} & \text{for } 0 \leq t < \nu^2/\alpha, \\ e^{-\frac{t}{2\alpha}} & \text{for } t \geq \nu^2/\alpha. \end{cases} \quad (2.11)$$

Proof. Recall Definition 2.32 and obtain

$$\mathbb{P}(X - \mu \geq t) \leq e^{-\lambda t} \mathbb{E}[e^{\lambda(X - \mu)}] \leq \exp\left(-\lambda t + \frac{\lambda^2\nu^2}{2}\right) \quad \text{for } \lambda \in [0, \alpha^{-1}).$$

Define $g(\lambda, t) := -\lambda t + \lambda^2\nu^2/2$. We need to determine $g^*(t) = \inf_{\lambda \in [0, \alpha^{-1})} \{g(\lambda, t)\}$. Suppose that t is fixed, then $\partial_\lambda g(\lambda, t) = -t + \lambda\nu^2 = 0$ if and only if $\lambda = \lambda^* = \frac{t}{\nu^2}$. If $0 \leq t < \nu^2/\alpha$, then the infimum equals the unconstrained one and $g^*(t) = -t^2/2\nu^2$ for $t \in [0, \nu^2/\alpha)$. Suppose now that $t \geq \nu^2/\alpha$. As $g(\cdot, t)$ is monotonically decreasing on $[0, \lambda^*)$, the constrained infimum is achieved on the boundary $\lambda^* = \alpha^{-1}$, and hence $g^*(t) = -t/2\alpha$. \square

Definition 2.36 (Bernstein condition) A real-valued random variable X with mean $\mu \in \mathbb{R}$ and variance $\sigma^2 \in (0, \infty)$ satisfies the *Bernstein condition* with parameter $b > 0$ if

$$|\mathbb{E}[(X - \mu)^k]| \leq \frac{1}{2}k!\sigma^2 b^{k-2} \quad k = 2, 3, 4, \dots \quad (2.12)$$

Exercise 2.37 (a) Show that a bounded random variable X with $|X - \mu| \leq b$ satisfies the *Bernstein condition* (2.12).

(b) Show that the bounded random variable X in (a) is sub-exponential and derive a bound on the centred moment generating function

$$\mathbb{E}[\exp(\lambda(X - \mathbb{E}[X]))].$$



Solution. (a) From our assumption we have $|\mathbb{E}[(x - \mu)^2]| \leq \sigma^2$. Using Hölder's inequality we obtain

$$\mathbb{E}[|X - \mu|^{k-2}|X - \mu|^2] \leq \sigma^2 \mathbb{E}[|X - \mu|^{k-2}] \leq \sigma^2 b^{k-2} \frac{1}{2} k!$$

for all $k \in \mathbb{N}, k \geq 2$.

(b) By power series expansion we have (using the Bernstein bound from (a)),

$$\begin{aligned} \mathbb{E}[e^{\lambda(X-\mu)}] &= 1 + \frac{\lambda^2 \sigma^2}{2} + \sum_{k=3}^{\infty} \lambda^k \frac{\mathbb{E}[(X-\mu)^k]}{k!} \\ &\leq 1 + \frac{\lambda^2 \sigma^2}{2} + \frac{\lambda^2 \sigma^2}{2} \sum_{k=3}^{\infty} (|\lambda|b)^{k-2}, \end{aligned}$$

and for $|\lambda| < 1/b$ we can sum the geometric series to obtain

$$\mathbb{E}[e^{\lambda(X-\mu)}] \leq 1 + \frac{\lambda^2 \sigma^2 / 2}{1 - b|\lambda|} \leq \exp\left(\frac{\lambda^2 \sigma^2 / 2}{1 - b|\lambda|}\right)$$

by using $1 + t \leq e^t$.

Thus X is sub-exponential as we obtain

$$\mathbb{E}[e^{\lambda(X-\mu)}] \leq \exp(\lambda^2 (\sqrt{2}\sigma)^2 / 2)$$

for all $|\lambda| < 1/2b$.

□

Exercise 2.38 (general Hoeffding inequality) Let X_1, \dots, X_N independent mean-zero sub-Gaussian real-valued random variables, and let $a = (a_1, \dots, a_N) \in \mathbb{R}^N$. Then, for every $t \geq 0$, we have

$$\mathbb{P}\left(\left|\sum_{i=1}^N a_i X_i\right| \geq t\right) \leq 2 \exp\left(-\frac{ct^2}{K^2 \|a\|_2^2}\right),$$

where $K = \max_{1 \leq i \leq N} \{\|X_i\|_{\psi_2}\}$.



Hint: Use the fact that X_i sub-Gaussian, $i = 1, \dots, N$ implies that $\sum_{i=1}^N X_i$ is sub-Gaussian with

$$\left\|\sum_{i=1}^N X_i\right\|_{\psi_2}^2 \leq C \sum_{i=1}^N \|X_i\|_{\psi_2}^2.$$

3 Random vectors in High Dimensions

We study random vectors $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ and aim to obtain concentration properties of the Euclidean norm of random vectors X .

3.1 Concentration of the Euclidean norm

Suppose $X_i, i = 1, \dots, n$, are independent \mathbb{R} -valued random variables with $\mathbb{E}[X_i] = 0$ and $\text{Var}(X_i) = 1$. Then

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

We thus expect that the expectation of the Euclidean norm is approximately \sqrt{n} . We will now see in a special case that X is indeed very close to \sqrt{n} with high probability.

Theorem 3.1 (Concentration of the norm) *Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with independent sub-Gaussian coordinates X_i that satisfy $\mathbb{E}[X_i^2] = 1$. Then*

$$\|\|X\|_2 - \sqrt{n}\|_{\psi_2} \leq CK^2,$$

where $K := \max_{1 \leq i \leq n} \{\|X_i\|_{\psi_2}\}$ and $C > 0$ an absolute constant.

The following two exercises are used in the proof of the theorem.

Exercise 3.2 (Centering for sub-exponential random variables) Show the centering lemma for sub-exponential random variables. This is an extension of Lemma 2.24 to sub-exponential random variables: Let X be a real-valued sub-exponential random variable. Then

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



Exercise 3.3 (Bernstein inequality) Let X_1, \dots, X_N be independent mean-zero sub-exponential real-valued random variables. Then, for every $t \geq 0$, we have

$$\mathbb{P}\left(\left|\frac{1}{N} \sum_{i=1}^N X_i\right| \geq t\right) \leq 2 \exp\left(-c \min\left\{\left(\frac{t^2}{K^2}\right), \left(\frac{t}{K}\right)\right\}N\right),$$

for some absolute constant $c > 0$ and where $K := \max_{1 \leq i \leq N} \{\|X_i\|_{\psi_1}\}$.



Solution. $S_N := \frac{1}{N} \sum_{i=1}^N X_i$. As usual we start with

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

and (v) in Proposition 2.25 implies that, writing $\tilde{X}_i = X_i/N$,

$$\mathbb{E}[e^{\lambda \tilde{X}_i}] \leq \exp(c\lambda^2 \|\tilde{X}_i\|_{\psi_1}^2) \quad \text{for } |\lambda| \leq \frac{c}{K},$$

and $\|\tilde{X}_i\|_{\psi_1}^2 = 1/N^2\|X_i\|_{\psi_1}^2$. Thus

$$\mathbb{P}(S_N \geq t) \leq \exp\left(-\lambda t + c\lambda \sum_{i=1}^N \left(\frac{1}{N}\right)^2 \|X_i\|_{\psi_1}^2\right) \quad \text{for } |\lambda| \leq \frac{c}{\max_{1 \leq i \leq N} \{\|X_i\|_{\psi_1}\}}.$$

Optimising over λ one obtains

$$\lambda = \min \left\{ \left(\frac{t^2}{2c\tilde{\sigma}^2} \right), \left(\frac{c}{\max_{1 \leq i \leq N} \{\|\tilde{X}_i\|_{\psi_1}\}} \right) \right\},$$

where $\tilde{\sigma}^2 = \sum_{i=1}^N 1/N^2 \|X_i\|_{\psi_1}^2$. Thus

$$\mathbb{P}(S_N \geq t) \leq \exp \left(-c \min \left\{ \left(\frac{t^2}{2c\tilde{\sigma}^2} \right), \left(\frac{c}{\max_{1 \leq i \leq N} \{\|\tilde{X}_i\|_{\psi_1}\}} \right) \right\} \right),$$

and finally

$$\mathbb{P}(S_N \geq t) \leq \exp \left(-c \min \left\{ \left(\frac{t^2}{K^2} \right), \left(\frac{t}{K} \right) \right\} N \right).$$

☺

Remark 3.4 With high probability, e.g., with probability 0.99 (adjust the absolute constants $c > 0$ and $K > 0$ accordingly) X stays within a constant distance from the sphere of radius \sqrt{n} . $S_n := \|X\|_2^2$ has mean n and standard deviation $O(\sqrt{n})$:

$$\text{Var}(\|X\|_2^2) = \mathbb{E} \left[\sum_{i,j=1}^n (X_i X_j)^2 \right] - n^2 = \sum_{i=1}^n \mathbb{E}[X_i^4] + \sum_{1 \leq i < j \leq n} \mathbb{E}[(X_i X_j)^2] - n^2.$$

For any $i \neq j$ we have $\mathbb{E}[(X_i X_j)^2] = 1$, and $\mathbb{E}[X_i^4] = O(1)$ (follows from (ii) in Proposition 2.15). Thus $\text{Var}(\|X\|_2^2) = (n + (n-1)^2 - n^2)O(1)$, and therefore $\sqrt{\text{Var}(\|X\|_2^2)} = O(\sqrt{n})$. Hence $\|X\|_2 = \sqrt{S_n}$ deviates by $O(1)$ around \sqrt{n} . Note that this follows from

$$\sqrt{n \pm O(\sqrt{n})} = \sqrt{n} \pm O(1).$$

◇

Proof of Theorem 3.1. We assume again without loss of generality that $K \geq 1$.

$$\frac{1}{n} \|X\|_2^2 - 1 = \frac{1}{n} \sum_{i=1}^n (X_i^2 - 1).$$

X_i sub-Gaussian implies that $X_i^2 - 1$ is sub-exponential (Lemma 2.29). The centering property of Exercise 3.2 shows that there is an absolute constant $C > 0$ such that

$$\|X_i^2 - 1\|_{\psi_1} \leq C \|X_i^2\|_{\psi_1} \stackrel{\text{Lemma 2.28}}{=} C \|X_i\|_{\psi_2}^2 \leq CK^2.$$

We now apply the Bernstein inequality in Exercise 3.3 to obtain, for every $u \geq 0$,

$$\mathbb{P}\left(\left|\frac{1}{n}\|X\|_2^2 - 1\right| \geq u\right) \leq 2 \exp\left(-\frac{cn}{K^4} \min\{u^2, u\}\right), \quad (3.1)$$

where we used that $K \geq 1$ implies $K^4 \geq K^2$. Note that for $z \geq 0$ inequality $|z - 1| \geq \delta$ implies the inequality

$$|z^2 - 1| \geq \max\{\delta, \delta^2\}.$$

To see that, consider first $z \geq 1$ which implies that $z + 1 \geq z - 1 \geq \delta$ and thus $|z^2 - 1| = |z - 1||z + 1| \geq \delta^2$. For $0 \leq z < 1$ we have $z + 1 \geq 1$ and thus $|z^2 - 1| \geq \delta$. We apply this finding, (3.1) with $u = \max\{\delta, \delta^2\}$ to obtain

$$\mathbb{P}\left(\left|\frac{1}{\sqrt{n}}\|X\|_2 - 1\right| \geq \delta\right) \leq \mathbb{P}\left(\left|\frac{1}{n}\|X\|_2^2 - 1\right| \geq \max\{\delta, \delta^2\}\right) \leq 2 \exp\left(-\frac{cn}{K^4} \delta^2\right).$$

We used that $v = \min\{u, u^2\} = \delta$ when $u = \max\{\delta, \delta^2\}$. To see that, note that $\delta \geq \delta^2$ implies $\delta \leq 1$ and thus $u = \delta$ and $v = \delta^2$. If $\delta > 1$ we have $\delta \gg \delta^2$ and thus $u = \delta^2$ and thus $v = \delta^2$. Setting $t = \delta\sqrt{n}$ we finally conclude with

$$\mathbb{P}(|\|X\|_2 - \sqrt{n}| \geq t) \leq 2 \exp\left(-\frac{ct^2}{K^4}\right),$$


which shows that $\|X\|_2 - \sqrt{n}$ is sub-Gaussian. \square

Exercise 3.5 (Small ball probabilities) Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with independent coordinates X_i having continuous distribution with probability density functions $f_i: \mathbb{R} \rightarrow \mathbb{R}$ (Radon-Nikodym density with respect to the Lebesgue measure) satisfying

$$|f_i(x)| \leq 1, \quad i = 1, \dots, n, \quad \text{for all } x \in \mathbb{R}.$$

Show that, for any $\varepsilon > 0$, we have

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

for some absolute constant $C > 0$. 

Solution.


$$\mathbb{P}(\|X\|_2^2 \leq \varepsilon^2 n) = \mathbb{P}(-\|X\|_2^2 \geq -\varepsilon^2 n) \leq e^{\lambda \varepsilon^2 n} \mathbb{E}[\exp(-\lambda \|X\|_2^2)] = e^{\lambda \varepsilon^2 n} \prod_{i=1}^n \mathbb{E}[\exp(-\lambda X_i^2)],$$

and inserting

$$\mathbb{E}[\exp(-\lambda X_i^2)] \leq \int_{\mathbb{R}} e^{-\lambda x^2} |f_i(x)| dx \leq \int_{\mathbb{R}} e^{-\lambda x^2} dx = \sqrt{\frac{\pi}{\lambda}},$$

we obtain

$$\mathbb{P}(\|X\|_2^2 \leq \varepsilon^2 n) \leq \exp\left(\lambda \varepsilon^2 n - \frac{n}{2} \log(\lambda/\pi)\right) \leq (C\varepsilon)^n,$$

where the last inequality follows by optimising over λ and getting $\lambda = \frac{1}{2\varepsilon^2}$. 

3.2 Covariance matrices and Principal Component Analysis (PCA)

Definition 3.6 Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector. Define the random matrix XX^T as the $(n \times n)$ matrix

$$XX^T := \begin{pmatrix} X_1 \\ \cdot \\ \cdot \\ X_n \end{pmatrix} (X_1 \cdot \cdot \cdot X_n) = \begin{pmatrix} X_1^2 & X_1X_2 & \cdot & \cdot & X_1X_n \\ X_2X_1 & X_2^2 & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ X_nX_1 & \cdot & \cdot & \cdot & X_n^2 \end{pmatrix}.$$

Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with mean $\mu = \mathbb{E}[X]$ and matrix $\mu\mu^T = (\mu_i\mu_j)_{i,j=1,\dots,n}$. Then the *covariance matrix*, which is defined as

$$\text{cov}(X) := \mathbb{E}[(X - \mu)(X - \mu)^T] = \mathbb{E}[XX^T] - \mu\mu^T, \quad (3.2)$$

is a $(n \times n)$ symmetric positive-semidefinite matrix with entries

$$\text{cov}(X)_{i,j} = \mathbb{E}[(X_i - \mu_i)(X_j - \mu_j)], \quad i, j = 1, \dots, n. \quad (3.3)$$

The *second moment matrix* of a random vector $X \in \mathbb{R}^n$ is simply

$$\Sigma = \Sigma(X) = \mathbb{E}[XX^T] = (\mathbb{E}[X_iX_j])_{i,j=1,\dots,n}, \quad (3.4)$$

and $\Sigma(X)$ is symmetric and positive-semidefinite matrix which can be written as the spectral decomposition

$$\Sigma(X) = \sum_{i=1}^n s_i \mathbf{u}_i \mathbf{u}_i^T, \quad (3.5)$$


where $\mathbf{u}_i \in \mathbb{R}^n$ are the eigenvectors of $\Sigma(X)$ for the eigenvalues s_i . The second moment matrix allows the principal component analysis (PCA). We order the eigenvalues of $\Sigma(X)$ according to their size: $s_1 \geq s_2 \geq \dots \geq s_n$. For large values of the dimension n one aims to identify a few principal directions. These directions correspond to the eigenvectors with the largest eigenvalues. For example, suppose that the first m eigenvalues are significantly larger than the remaining $n - m$ ones. This allows to reduced the dimension of the given data to \mathbb{R}^m by neglecting all contributions from directions with eigenvalues significantly smaller than the chosen principal ones.

Definition 3.7 A random vector $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ is called *isotropic* if

$$\Sigma(X) = \mathbb{E}[XX^T] = \mathbb{1}_n,$$

where $\mathbb{1}_n := \text{id}_n$ is the identity operator/matrix in \mathbb{R}^n .

Exercise 3.8 (a) Let Z be an isotropic mean-zero random vector in \mathbb{R}^n , $\mu \in \mathbb{R}^n$, and Σ be a $(n \times n)$ positive-semidefinite matrix. Show that then $X := \mu + \Sigma^{1/2}Z$ has mean μ and covariance matrix $\text{cov}(X) = \Sigma$.

(b) Let $X \in \mathbb{R}^n$ be a random vector with mean μ and invertible covariance matrix $\Sigma = \text{cov}(X)$. Show that then $Z := \Sigma^{-1/2}(X - \mu)$ is an isotropic mean-zero random vector. 

Lemma 3.9 (Isotropy) *A random vector $X \in \mathbb{R}^n$ is isotropic if and only if*

$$\mathbb{E}[\langle X, x \rangle^2] = \|x\|_2^2 \quad \text{for all } x \in \mathbb{R}^n.$$

Proof. X is isotropic if and only if $(\mathbb{E}[X_i X_j])_{i,j=1,\dots,n} = (\delta_{i,j})_{i,j=1,\dots,n} = \mathbb{1}_n$. For every $x \in \mathbb{R}^n$ we have

$$\mathbb{E}[\langle X, x \rangle^2] = \sum_{i,j=1}^n \mathbb{E}[x_i X_i x_j X_j] = \sum_{i,j=1}^n x_i \mathbb{E}[X_i X_j] x_j = \langle x, \Sigma(X)x \rangle = \|x\|_2^2$$

if and only if $\Sigma(X) = \mathbb{1}_n$. □

It suffices to show $\mathbb{E}[\langle X, e_i \rangle^2] = 1$ for all basis vectors $e_i, i = 1, \dots, n$. Note that $\langle X, e_i \rangle$ is a one-dimensional marginal of the random vector X . Thus X is isotropic if and only if all one-dimensional marginals of X have unit variance. An isotropic distribution is evenly extended in all spatial directions.

Lemma 3.10 *Let X be an isotropic random vector in \mathbb{R}^n . Then*

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

Moreover, if X and Y are two independent isotropic random vectors in \mathbb{R}^n , then

$$\mathbb{E}[\langle X, Y \rangle^2] = n.$$

Proof. For the first statement we view $X^T X$ as a 1×1 matrix and take advantage of the cyclic property of the trace operation on matrices:

$$\begin{aligned} \mathbb{E}[\|X\|_2^2] &= \mathbb{E}[X^T X] = \mathbb{E}[\text{Trace}(X^T X)] = \mathbb{E}[\text{Trace}(X X^T)] = \text{Trace}(\mathbb{E}[X X^T]) \\ &= \text{Trace}(\mathbb{1}_n) = n. \end{aligned}$$

We fix a realisation of Y , that is, we consider the conditional expectation of X with respect to Y which we denote \mathbb{E}_X . The law of total expectation says that

$$\mathbb{E}[\langle X, Y \rangle^2] = \mathbb{E}_Y[\mathbb{E}_X[\langle X, Y \rangle^2 | Y]],$$

where \mathbb{E}_Y denotes the expectation with respect to Y . To compute the innermost expectation we use Lemma 3.9 with $x = Y$ and obtain using the previous part that

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

□

Suppose $X \perp Y$ are isotropic vectors in \mathbb{R}^n , and consider the normalised versions $\bar{X} := X/\|X\|_2$ and $\bar{Y} := Y/\|Y\|_2$. From the concentration results in this chapters we know that with high probability, $\|X\|_2 \sim \sqrt{n}$, $\|Y\|_2 \sim \sqrt{n}$, and $\langle X, Y \rangle \sim \sqrt{n}$. Thus, with high probability,

$$|\langle \bar{X}, \bar{Y} \rangle| \sim \frac{1}{\sqrt{n}}.$$

Thus, in high dimensions, independent and isotropic random vector are almost orthogonal.

3.3 Examples of High-Dimensional distributions

Definition 3.11 (Spherical distribution) A random vector X is called spherically distributed if it is uniformly distributed on the Euclidean sphere with radius \sqrt{n} and centre at the origin, i.e.,

$$X \sim \text{Unif}(\sqrt{n}S^{n-1}),$$

where

$$S^{n-1} = \left\{ x = (x_1, \dots, x_n) \in \mathbb{R}^n : \sum_{i=1}^n x_i^2 = 1 \right\} = \{x \in \mathbb{R}^n : \|x\|_2 = 1\}$$

is the *unit sphere* of radius 1 and centre at the origin.

Exercise 3.12 $X \sim \text{Unif}(\sqrt{n}S^{n-1})$ is isotropic but the coordinates $X_i, i = 1, \dots, n$, of X are not independent due to the condition $X_1^2 + \dots + X_n^2 = n$. ☕☕

Solution. We give a solution for $n = 2$. The solution for higher dimensions is similar and use high-dimensional versions of the Polar coordinates. We use Polar coordinates to represent X as

$$X = \sqrt{n} \begin{pmatrix} \cos(\theta) \\ \sin(\theta) \end{pmatrix}, \quad \theta \in [0, 2\pi].$$

Let e_1 and e_2 the two unit basis vectors in \mathbb{R}^2 . It suffices to show $\mathbb{E}[\langle X, e_i \rangle^2] = 1, i = 1, 2$, as any vector can be written as a linear combination of the two basis vectors. Without loss of generality we pick e_1 (the proof for e_2 is just analogous):

$$\mathbb{E}[\langle X, e_1 \rangle^2] = \mathbb{E}[(\sqrt{n} \cos(\theta))^2] = \frac{n}{2\pi} \int_0^{2\pi} \cos^2(\theta) d\theta = \frac{2}{2\pi} \left[\frac{\theta}{2} + \frac{\sin(2\theta)}{4} \right]_0^{2\pi} = \frac{2\pi}{2} \pi = 1.$$

☺

An example of a discrete isotropic distribution in \mathbb{R}^n is the *symmetric Bernoulli distribution* in \mathbb{R}^n . We say that a random vector $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ is symmetric Bernoulli distributed if the coordinates X_i are independent, symmetric, Bernoulli random variables. A random variable ε is symmetric if $\mathbb{P}(\varepsilon = -1) = \mathbb{P}(\varepsilon = +1) = \frac{1}{2}$. Equivalently, we may say that X is uniformly distributed on the unit cube in \mathbb{R}^n :

$$X \sim \text{Unif}(\{-1, +1\}^n).$$

The symmetric Bernoulli distribution is isotropic. This can be easily seen again by checking $\mathbb{E}[\langle X, e_i \rangle^2] = 1$ for all $i = 1, \dots, n$, or for any $x \in \mathbb{R}^n$ by checking that

$$\mathbb{E}[\langle X, x \rangle^2] = \mathbb{E}\left[\sum_{i=1}^n X_i^2 x_i^2\right] + \mathbb{E}\left[2 \sum_{1 \leq i < j \leq n} X_i X_j x_i x_j\right] = \|x\|_2^2,$$

as the second term vanishes as the X_i independent mean-zero random variables .

Any random vector $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ with independent mean-zero coordinates X_i with unit variance $\text{Var}(X_i) = 1$ is an isotropic random vector in \mathbb{R}^n .

For the following recall the definition of the normal distribution. See also the appendix sheets distributed at the begin of the lecture for useful Gaussian calculus formulae.

Definition 3.13 (Multivariate Normal / Gaussian distribution) We say a random vector $Y = (Y_1, \dots, Y_n) \in \mathbb{R}^n$ has standard normal distribution in \mathbb{R}^n , denoted

$$Y \sim \mathbf{N}(0, \mathbb{1}_n),$$

if the coordinates $Y_i, i = 1, \dots, n$, are independent, \mathbb{R} -valued standard normally distributed random variables, i.e., $Y_i \sim \mathbf{N}(0, 1)$. The probability density function (pdf) for Y is just the product

$$f_Y(x) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-x_i^2/2} = \frac{1}{(2\pi)^{n/2}} e^{-\|x\|_2^2/2}. \quad (3.6)$$

It is easy to check that Y is isotropic. Furthermore, as the density (3.6) only depends on the Euclidean norm, that is, the standard normal distribution in \mathbb{R}^n only depends on the length and not on the direction. In other words, the standard normal distribution in \mathbb{R}^n is rotation invariant. This reasoning is rigorously stated in the next proposition.

Proposition 3.14 Let $Y \sim \mathbf{N}(0, \mathbb{1}_n)$ and U be a $n \times n$ orthogonal matrix (i.e., $U^T U = U U^T = \mathbb{1}_n$, or equivalently, $U^{-1} = U^T$). Then

$$UY \sim \mathbf{N}(0, \mathbb{1}_n).$$

Proof. For $Z := UY$ we have

$$\|Z\|_2^2 = Z^T Z = X^T U^T U X = X^T X = \|X\|_2^2.$$

Furthermore, $|\det(U)| = |\det(U^T)| = 1$, and thus for any vector $J \in \mathbb{C}^n$ (characteristic functions/Laplace transform),

$$\begin{aligned} \mathbb{E}_Z[e^{\langle J, Z \rangle}] &= \frac{1}{(2\pi)^{n/2}} \int_{\mathbb{R}^n} \exp\left(-\frac{1}{2}\langle z, z \rangle + \langle J, x \rangle\right) \prod_{i=1}^n dz_i \\ &= \frac{1}{(2\pi)^{n/2}} \int_{\mathbb{R}^n} \exp\left(-\frac{1}{2}\langle x, x \rangle + \langle U^T J, x \rangle\right) \prod_{i=1}^n dx_i \\ &= \frac{1}{(2\pi)^{n/2}} \exp\left(\frac{1}{2}\langle U^T J, U^T J \rangle\right) = \mathbb{E}_Y[e^{\langle J, Y \rangle}]. \end{aligned}$$

□

Let Σ be a symmetric positive-definite $n \times n$ matrix and $X \in \mathbb{R}^n$ random vector with mean $\mu = \mathbb{E}[X]$. Then

$$\begin{aligned} X \sim \mathbf{N}(\mu, \Sigma) &\Leftrightarrow Z = \Sigma^{-1/2}(X - \mu) \sim \mathbf{N}(0, \mathbb{1}_n) \\ &\Leftrightarrow f_X(x) = \frac{1}{(2\pi)^{n/2} \det(\Sigma)^{1/2}} \exp\left(-\frac{1}{2}\langle X - \mu, \Sigma^{-1}(X - \mu) \rangle\right), \quad x \in \mathbb{R}^n. \end{aligned}$$

For large values of n the standard normal distribution $\mathbf{N}(0, \mathbb{1}_n)$ is not concentrated around the origin, instead it is concentrated in a thin spherical shell around the sphere of radius \sqrt{n} around the origin (shell with width of order $O(1)$). From Theorem ?? we obtain for $Y \sim \mathbf{N}(0, \mathbb{1}_n)$,

$$\mathbb{P}(|\|Y\|_2 - \sqrt{n}| \geq t) \leq 2 \exp(-Ct^2), \quad \text{for all } t \geq 0$$

and an absolute constant $C > 0$. Therefore with high probability $\|Y\|_2 \approx \sqrt{n}$ and

$$Y \approx \sqrt{n}\Theta \sim \text{Unif}(\sqrt{n}\mathbb{S}^{n-1}),$$

with $\Theta = Y/\|Y\|_2$. Henceforth, with high probability,

$$\mathbf{N}(0, \mathbb{1}_n) \approx \text{Unif}(\sqrt{n}\mathbb{S}^{n-1}).$$

3.4 Sub-Gaussian random variables in higher dimensions

Definition 3.15 (Sub-Gaussian random vectors) A random vector $X \in \mathbb{R}^n$ is sub-Gaussian if the one-dimensional marginals $\langle X, x \rangle$ are sub-Gaussian real-valued random variables for all $x \in \mathbb{R}^n$. Moreover,

$$\|X\|_{\psi_2} := \sup_{x \in \mathbb{S}^{n-1}} \{\|\langle X, x \rangle\|_{\psi_2}\}.$$

Lemma 3.16 Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with independent mean-zero sub-Gaussian coordinates X_i . Then X is sub-Gaussian and

$$\|X\|_{\psi_2} \leq C \max_{1 \leq i \leq n} \{\|X_i\|_{\psi_2}\},$$

for some absolute constant $C > 0$.

Proof. Let $x \in \mathbb{S}^{n-1}$. We are using Proposition 2.21 for the sum of independent sub-Gaussian random variables:

$$\|\langle X, x \rangle\|_{\psi_2}^2 = \left\| \sum_{i=1}^n x_i X_i \right\|_{\psi_2}^2 \stackrel{\text{Prop. 2.21}}{\leq} C \sum_{i=1}^n x_i^2 \|X_i\|_{\psi_2}^2 \leq C \max_{1 \leq i \leq n} \{\|X_i\|_{\psi_2}^2\},$$

where we used that $\sum_{i=1}^n x_i^2 = 1$, □

Theorem 3.17 (Uniform distribution on the sphere) Let $X \in \mathbb{R}^n$ be a random vector uniformly distributed on the Euclidean sphere in \mathbb{R}^n with centre at the origin and radius \sqrt{n} , i.e.,

$$X \sim \text{Unif}(\sqrt{n}S^{n-1}).$$

Then X is sub-Gaussian, and $\|X\|_{\psi_2} \leq C$ for some absolute constant $C > 0$.

We will actually present two different proofs of this statement. The first uses concentration properties whereas the second employs a geometric approach.

Proof of Theorem 3.17 - Version I. See [Ver18] page 53-54. □

Proof of Theorem 3.17 - Version II.

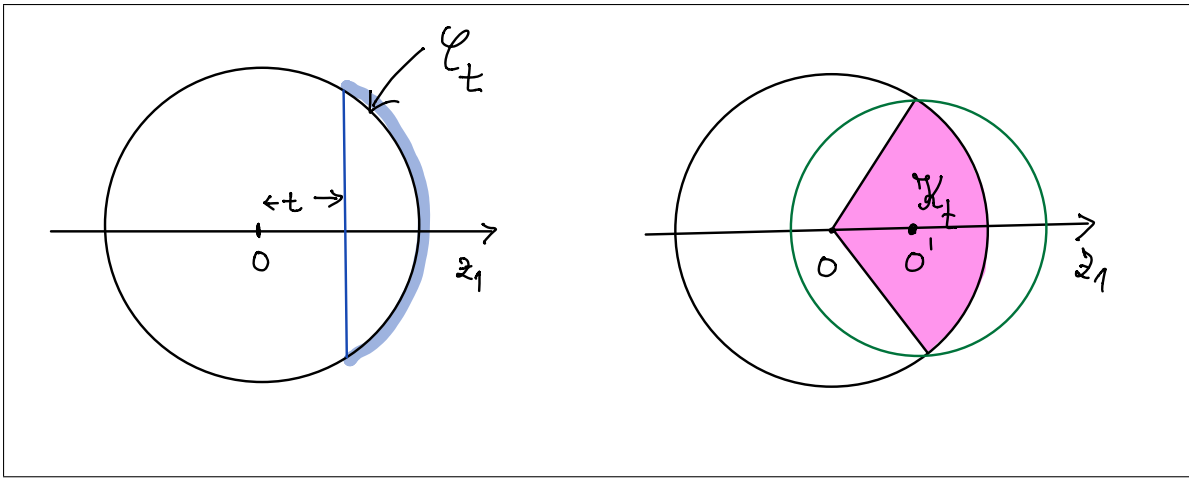


Figure 1:

For convenience we will work on the unit sphere, so let us rescale

$$Z := \frac{X}{\sqrt{n}} \sim \text{Unif}(S^{n-1}).$$

It suffices to show that $\|Z\|_{\psi_2} \leq C/\sqrt{n}$, which by definition means that $\|\langle Z, x \rangle\|_{\psi_2} \leq C$ for all unit vectors x . By rotation invariance, all marginals $\langle Z, x \rangle$ have the same distribution, and hence without loss of generality, we may prove our claim for $x = e_1 = (1, 0, \dots, 0) \in \mathbb{R}^n$. In other words, we shall show that

$$\mathbb{P}(|Z_1| \geq t) \leq 2 \exp(-ct^2n) \quad \text{for all } t \geq 0.$$

We use the fact that

$$P(Z_1 \geq t) = \mathbb{P}(Z \in \mathcal{C}_t) \quad \text{with the spherical cap } \mathcal{C}_t = \{z \in S^{n-1} : z_1 \geq t\}.$$

Denote by \mathcal{K}_t the "ice-cream" cone when we connect all points in \mathcal{C}_t to the origin, see Figure 1. The fraction of \mathcal{C}_t in the unit sphere (in terms of area) is the same as the fraction of \mathcal{K}_t in the unit ball $B(0, 1) = \{x \in \mathbb{R}^n : x_1^2 + \dots + x_n^2 \leq 1\}$. Thus

$$\mathbb{P}(Z_1 \in \mathcal{C}_t) = \frac{\text{Vol}(\mathcal{K}_t)}{\text{Vol}(B(0, 1))}.$$

The set \mathcal{K}_t is contained in a ball $B(O', \sqrt{1-t^2})$ with radius $\sqrt{1-t^2}$ centred at $O' = (t, 0, \dots, 0)$. We get

$$\mathbb{P}(Z_1 \geq t) = (\sqrt{1-t^2})^n \leq \exp(-t^2 n/2) \quad \text{for } 0 \leq t \leq 1/\sqrt{2},$$

and we can easily extend this bound to all t by loosening the absolute constant (note that for $t \geq 1$ is trivially zero). Indeed, in the range $1/\sqrt{2} \leq t \leq 1$,

$$\mathbb{P}(Z_1 \geq t) \leq P(Z_1 \geq 1/\sqrt{2}) \leq \exp(-n/4) \leq \exp(-t^2 n/4)$$

We proved that $\mathbb{P}(Z_1 \geq t) \leq \exp(-t^2 n/4)$. By symmetry, the same inequality holds for $-Z_1$. Taking the union bound, we obtain the desired sub-Gaussian tail. \square

Remark 3.18 The so-called *Projective Central Limit Theorem* tells us that marginals of the uniform distribution on the sphere in \mathbb{R}^n become asymptotically normally distributed as the dimension n increases. For any fixed unit vector $u \in \mathbb{R}^n$:

$$X \sim \text{Unif}(\sqrt{n}S^{n-1}) \longrightarrow \text{N}(0, 1) \text{ in distribution as } n \rightarrow \infty.$$

\diamond

3.5 Application: Grothendieck's inequality

See Chapter 3.5 in [Ver18].

4 Random Matrices

4.1 Geometrics concepts

Definition 4.1 Let (T, d) be a metric space, $K \subset T$, and $\varepsilon > 0$.

(a) **ε -net:** A subset $\mathcal{N} \subset K$ is an ε -net of K if for every point of K is within a distance ε of some point of \mathcal{N} ,

$$\forall x \in K \exists x_0 \in \mathcal{N} : d(x, x_0) \leq \varepsilon.$$

(b) **Covering number:** The smallest possible cardinality of an ε -net of K is the *covering number* of K and is denoted $\mathcal{N}(K, d, \varepsilon)$. Equivalently, $\mathcal{N}(K, d, \varepsilon)$ is the smallest number of closed balls with centres in K and radii ε whose union covers K .

(c) **ε -separated sets:** A subset $\mathcal{N} \subset T$ is ε -separated if $d(x, y) > \varepsilon$ for all distinct points $x, y \in \mathcal{N}$.

(d) **Packing numbers:** The largest possible cardinality of an ε -separated subset of K is called the *packing number* of K and denoted $\mathcal{P}(K, d, \varepsilon)$.

Lemma 4.2 Let (T, d) be a metric space. Suppose that \mathcal{N} is a maximal ε separated subset of $K \subset T$. Here maximal means that adding any new point $x \in K$ to the set \mathcal{N} destroys the ε -separation property. Then \mathcal{N} is an ε -net.

Proof. Let $x \in K$. If $x \in \mathcal{N} \subset K$, then choosing $x_0 = x$ we have $d(x_0, x_0) = 0 \leq \varepsilon$. Suppose $x \notin \mathcal{N}$. Then the maximality assumption implies that $\mathcal{N} \cup \{x\}$ is not ε -separated, thus $d(x, x_0) \leq \varepsilon$ for some $x_0 \in \mathcal{N}$. \square

Lemma 4.3 (Equivalence of packing and covering numbers) *Let (T, d) be a metric space. For any $K \subset T$ and any $\varepsilon > 0$, we have*

$$\mathcal{P}(K, d, 2\varepsilon) \leq \mathcal{N}(K, d, \varepsilon) \leq \mathcal{P}(K, d, \varepsilon). \quad (4.1)$$

Proof. Without loss of generality we consider Euclidean space $T = \mathbb{R}^n$ with $d = \|\cdot\|_2$. For the upper bound one can show that $\mathcal{P}(K, \|\cdot\|_2, \varepsilon)$ is the largest number of closed disjoint balls with centres in K and radii $\varepsilon/2$. Furthermore, $\mathcal{P}(K, \|\cdot\|_2, \varepsilon)$ is the largest cardinality of an ε -separated subset, any ε -separated set \mathcal{N} with $\#\mathcal{N} = \mathcal{P}(K, \|\cdot\|_2, \varepsilon)$ is maximal, and hence an ε -net according to Lemma 4.2. Thus $\mathcal{N}(K, \|\cdot\|_2, \varepsilon) \leq \#\mathcal{N}$. Pick an 2ε -separated subset $\mathcal{P} = \{x_i\}$ in K and an ε -net $\mathcal{N} = \{y_j\}$ of K . Each $x_i \in K$ belongs to some closed ball $\overline{B_\varepsilon(y_j)}$ with radius ε around some y_j . Any such ball $\overline{B_\varepsilon(y_j)}$ may contain at most one point of the x_i 's. Thus $|\mathcal{P}| = \#\mathcal{P} \leq |\mathcal{N}| = \#\mathcal{N}$. \square

In the following we return to the Euclidean space \mathbb{R}^n with its Euclidean norm, $d(x, y) = \|x - y\|_2$.

Definition 4.4 (Minkowski sum) $A, B \subset \mathbb{R}^n$.

$$A + B := \{a + b : a \in A, b \in B\}.$$

Proposition 4.5 (Covering numbers of the Euclidean ball) (a) *Let $K \subset \mathbb{R}^n$ and $\varepsilon > 0$. Denote $|K|$ the volume of K and denote $B^{(n)} = \{x \in \mathbb{R}^n : \|x\|_2 \leq 1\}$ the closed unit Euclidean ball. Then*

$$\frac{|K|}{|\varepsilon B^{(n)}|} \leq \mathcal{N}(K, \|\cdot\|_2, \varepsilon) \leq \mathcal{P}(K, \|\cdot\|_2, \varepsilon) \leq \frac{|(K + \varepsilon/2 B^{(n)})|}{|\varepsilon/2 B^{(n)}|}.$$

(b)

$$\left(\frac{1}{\varepsilon}\right)^n \leq \mathcal{N}(B^{(n)}, \|\cdot\|_2, \varepsilon) \leq \left(\frac{2}{\varepsilon} + 1\right)^n.$$

Proof.

(a) The centre inequality follows from Lemma 4.3. Lower bound: Let $N := \mathcal{N}(K, \|\cdot\|_2, \varepsilon)$. Then we can cover K by N balls with radii ε . Then $|K| \leq N|\varepsilon B^{(n)}|$. Upper bound: Let $N := \mathcal{P}(K, \|\cdot\|_2, \varepsilon)$ and construct N closed disjoint balls $B_{\varepsilon/2}(x_i)$ with centres $x_i \in K$ and radii $\varepsilon/2$. These balls might not fit entirely into the set K , but certainly into the extended set $K + \frac{\varepsilon}{2}B^{(n)}$. Thus

$$N\left|\frac{\varepsilon}{2}B^{(n)}\right| \leq \left|K + \frac{\varepsilon}{2}B^{(n)}\right|.$$

(b) The statement follows easily with part (a) and is left as an exercise. \square

Remark 4.6 To simplify the bound in Proposition 4.5, note that in the nontrivial range $\varepsilon \in (0, 1]$ we have

$$\left(\frac{1}{\varepsilon}\right)^n \leq \mathcal{N}(B^n, \|\cdot\|_2, \varepsilon) \leq \left(\frac{3}{\varepsilon}\right)^n.$$

◇

Definition 4.7 (Hamming cube) The *Hamming cube* \mathcal{H} is the set of binary strings of length n , i.e.,

$$\mathcal{H} = \{0, 1\}^n.$$

Define the *Hamming distance* $d_{\mathcal{H}}$ between two binary strings as the number of bits where they disagree, i.e.,

$$d_{\mathcal{H}}(x, y) := \#\{i \in \{1, \dots, n\} : x(i) \neq y(i)\}, \quad x, y \in \{0, 1\}^n.$$

Exercise 4.8 Show that $d_{\mathcal{H}}$ is a metric on \mathcal{H} . 

4.2 Concentration of the operator norm of random matrices

Definition 4.9 Let A be an $m \times n$ matrix with real entries. The matrix A represents a linear map $\mathbb{R}^n \rightarrow \mathbb{R}^m$.

(a) The *operator norm* or *simply the norm* of A is defined as

$$\|A\| := \max_{x \in \mathbb{R}^n \setminus \{0\}} \left\{ \frac{\|Ax\|_2}{\|x\|_2} \right\} = \max_{x \in \mathbb{S}^{n-1}} \{\|Ax\|_2\}.$$

Equivalently,

$$\|A\| = \max_{x \in \mathbb{S}^{n-1}, y \in \mathbb{S}^{m-1}} \{\langle Ax, y \rangle\}.$$

(b) The *singular values* $s_i = s_i(A)$ of the matrix A are the square roots of the eigenvalues of both AA^T and $A^T A$,

$$s_i(A) = \sqrt{\lambda_i(AA^T)} = \sqrt{\lambda_i(A^T A)},$$

and one orders them $s_1 \geq s_2 \geq \dots \geq s_n \geq 0$. If A is symmetric, then $s_i(A) = |\lambda_i(A)|$.

(c) Suppose $r = \text{rank}(A)$. The singular value decomposition of A is

$$A = \sum_{i=1}^r s_i u_i v_i^T,$$

where $s_i = s_i(A)$ are the singular values of A , the vectors $u_i \in \mathbb{R}^m$ are the left singular vectors, and the vectors $v_i \in \mathbb{R}^n$ are the right singular vectors of A .

Remark 4.10 (a) In terms of its spectrum, the operator norm of A equals the largest singular value of A ,

$$s_1(A) = \|A\|.$$

(b) The extreme singular values $s_1(A)$ and $s_r(A)$ are respectively the smallest number M and the largest number m such that

$$m\|x\|_2 \leq \|Ax\|_2 \leq M\|x\|_2, \quad \text{for all } x \in \mathbb{R}^n.$$

Thus

$$s_n(A)\|x - y\|_2 \leq \|Ax - Ay\|_2 \leq s_1(A)\|x - y\|_2 \quad \text{for all } x, y \in \mathbb{R}^n.$$

◇

Lemma 4.11 (Operator norm on a net) Let $\varepsilon \in [0, 1)$ and A be an $m \times n$ matrix. Then, for any ε -net \mathcal{N} of S^{n-1} , we have

$$\sup_{x \in \mathcal{N}} \{\|Ax\|_2\} \leq \|A\| \leq \frac{1}{1 - \varepsilon} \sup_{x \in \mathcal{N}} \{\|Ax\|_2\}.$$

Proof. The lower bound is trivial as $\mathcal{N} \subset S^{n-1}$. For the upper bound pick an $x \in S^{n-1}$ for which $\|A\| = \|Ax\|_2$ and choose $x_0 \in \mathcal{N}$ for this x such that $\|x - x_0\|_2 \leq \varepsilon$. Then

$$\|Ax - Ax_0\|_2 \leq \|A\|\|x - x_0\|_2 \leq \varepsilon\|A\|.$$

The triangle inequality implies that

$$\|Ax_0\|_2 \geq \|Ax\|_2 - \|Ax - Ax_0\|_2 \geq (1 - \varepsilon)\|A\|,$$

and thus $\|A\| \leq \|Ax_0\|_2 / (1 - \varepsilon)$. □

Exercise 4.12 Let \mathcal{N} be an ε -net of S^{n-1} and \mathcal{M} be an ε -net of S^{m-1} . Show that for any $m \times n$ matrix A one has

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

☹

Exercise 4.13 (Isometries) Let A be an $m \times n$ matrix with $m \geq n$. Prove the following equivalences:

$$\begin{aligned} A^T A = \mathbb{1}_n &\Leftrightarrow A \text{ isometry, i.e., } \|Ax\|_2 = \|x\|_2 \text{ for all } x \in \mathbb{R}^n \\ &\Leftrightarrow s_n(A) = s_1(A). \end{aligned}$$

☹☹

Theorem 4.14 (Norm of sub-Gaussian random matrices) *Let A be an $m \times n$ random matrix with independent mean-zero sub Gaussian random entries $A_{ij}, i = 1, \dots, m, j = 1, \dots, n$. Then, for every $t > 0$, we have*

$$\|A\| \leq CK(\sqrt{m} + \sqrt{n} + t),$$

with probability at least $1 - 2 \exp(-t^2)$, where $K := \max_{\substack{1 \leq i \leq m, \\ 1 \leq j \leq n}} \{\|A_{ij}\|_{\psi_2}\}$ and where $C > 0$ is an absolute constant.

Proof. We use an ε -net argument for our proof.

Step 1: Using Proposition 4.5 (b) we can find for $\varepsilon = \frac{1}{4}$ an ε -net $\mathcal{N} \subset \mathbb{S}^{n-1}$ and an ε -net $\mathcal{M} \subset \mathbb{S}^{m-1}$ with

$$|\mathcal{N}| \leq 9^n \text{ and } |\mathcal{M}| \leq 9^m.$$

By Exercise 4.12, the operator norm of A can be bounded using our nets as follows

$$\|A\| \leq 2 \max_{x \in \mathcal{N}, y \in \mathcal{M}} \{\langle Ax, y \rangle\}.$$

Step 2: Concentration Pick $x \in \mathcal{N}$ and $y \in \mathcal{M}$. We compute (using the fact that the entries and sub-Gaussians with their norm bounded by K)

$$\|\langle Ax, y \rangle\|_{\psi_2}^2 \leq C \sum_{i=1}^m \sum_{j=1}^n \|A_{ij} x_i y_j\|_{\psi_2}^2 \leq CK^2 \sum_{i=1}^m \sum_{j=1}^n y_j^2 x_i^2 = CK^2,$$

for some absolute constant $C > 0$. We therefore obtain a tail bound for $\langle Ax, y \rangle$, i.e., for every $u \geq 0$,

$$\mathbb{P}(\langle Ax, y \rangle \geq u) \leq 2 \exp(-cu^2/K^2),$$

for some absolute constant $c > 0$.

Step 3: Union bound We unfix the choice of x and y in Step 2 by a union bound.

$$\mathbb{P}\left(\max_{x \in \mathcal{N}, y \in \mathcal{M}} \{\langle Ax, y \rangle\} \geq u\right) \leq \sum_{x \in \mathcal{N}, y \in \mathcal{M}} \mathbb{P}(\langle Ax, y \rangle \geq u) \leq 9^{n+m} 2 \exp(-cu^2/K^2).$$

We continue the estimate by choosing $u = CK(\sqrt{n} + \sqrt{m} + t)$ which leads to a lower bound $u^2 \geq C^2 K^2(n + m + t^2)$, and furthermore, adjust the constant $C > 0$ such $cu^2/K^2 \geq 3(n + m) + t^2$. Inserting these choices we get

$$\mathbb{P}\left(\max_{x \in \mathcal{N}, y \in \mathcal{M}} \{\langle Ax, y \rangle\} \geq u\right) \leq 9^{n+m} 2 \exp(-3(n + m) - t^2) \leq 2 \exp(-t^2),$$

and thus

$$\mathbb{P}(\|A\| \geq 2u) \leq 2 \exp(-t^2).$$

□

Corollary 4.15 *Let A be an $n \times n$ random matrix whose entries on and above the diagonal are independent mean-zero sub-Gaussian random variables. Then, for every $t > 0$, we have*

$$\|A\| \leq CK(\sqrt{n} + t)$$

with probability at least $1 - 4 \exp(-t^2)$ and $K := \max_{1 \leq i, j \leq n} \{\|A_{ij}\|_{\psi_2}\}$.

Proof. Exercise. Decompose the matrix into an upper-triangular part and a lower-triangular part and use the proof of the previous theorem. \square

We can actually improve the statement in Theorem 4.14 in two ways. First we obtain a two-sided bound, and, secondly, we can relax the independence assumption. As this is a refinement of our previous statement we only state the result and omit its proof. The statement is used in covariance estimation below.

Theorem 4.16 *Let A be an $m \times n$ matrix whose rows $A_i, i = 1, \dots, m$, are independent mean-zero sub-Gaussian isotropic random vectors in \mathbb{R}^n . Then, for every $t > 0$, we have*

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

with probability at least $1 - 2 \exp(-t^2)$ and $K := \max_{1 \leq i \leq m} \{\|A_i\|_{\psi_2}\}$. Furthermore,

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

4.3 Application: Community Detection in Networks

See Chapter 4.5 in [Ver18].

4.4 Application: Covariance Estimation and Clustering

Suppose that $X^{(1)}, \dots, X^{(N)}$ are empirical samples (random outcomes) of a random vector $X \in \mathbb{R}^n$. We do not have access to the full distribution, only to the empirical measure

$$L_N = \frac{1}{N} \sum_{i=1}^N \delta_{X^{(i)}},$$

which is a random (depending on the N random outcomes $X^{(i)}$) probability measure on \mathbb{R}^n . Here, the symbol δ_X is the Kronecker-delta measure or point measure defined as

$$\delta_X(y) = \begin{cases} 1 & \text{if } X = y, \\ 0 & \text{if } y \neq X, \end{cases} \quad y \in \mathbb{R}^n.$$

We assume for simplicity that $\mathbb{E}[X] = 0$ and recall $\Sigma = \Sigma(X) = \mathbb{E}[X X^T]$.

Definition 4.17 Let $X \in \mathbb{R}^n$ with N random outcomes/random samples $X^{(1)}, \dots, X^{(N)}$.

(a) The *empirical measure* of $X^{(1)}, \dots, X^{(N)}$ is the probability measure on \mathbb{R}^n ,

$$L_N := \frac{1}{N} \sum_{i=1}^N \delta_{X^{(i)}}.$$

(b) The *empirical covariance* of $X^{(1)}, \dots, X^{(N)}$ is the random matrix

$$\Sigma_N := \frac{1}{N} \sum_{i=1}^N (X^{(i)})(X^{(i)})^T.$$

Note that $X_i \sim X$ implies that $\mathbb{E}[\Sigma_N] = \Sigma$. The law of large numbers yields

$$\Sigma_N \rightarrow \Sigma \quad \text{almost surely as } N \rightarrow \infty.$$

Theorem 4.18 (Covariance estimation) Let X be a sub-Gaussian random vector in \mathbb{R}^n , and assume that there exist $K \geq 1$ such that

$$\|\langle X, x \rangle\|_{\psi_2} \leq K \|\langle X, x \rangle\|_{L^2}, \quad \text{for all } x \in \mathbb{R}^n.$$

Then, for every $N \in \mathbb{N}$,

$$\mathbb{E}[\|\Sigma_N - \Sigma\|] \leq CK^2 \left(\sqrt{\frac{n}{N}} + \frac{n}{N} \right) \|\Sigma\|.$$

Proof. First note that

$$\|\langle X, x \rangle\|_{L^2}^2 = \mathbb{E}[|\langle X, x \rangle|^2] = \mathbb{E}[\langle X, x \rangle^2] = \langle \Sigma x, x \rangle.$$

We bring $X, X^{(1)}, \dots, X^{(N)}$ all into isotropic position. That is, there exist independent isotropic random vectors $Z, Z^{(1)}, \dots, Z^{(N)}$ such that

$$X = \Sigma^{1/2} Z \quad \text{and} \quad X^{(i)} = \Sigma^{1/2} Z^{(i)}.$$

We have from our assumptions that

$$\|Z\|_{\psi_2} \leq K \quad \text{and} \quad \|Z^{(i)}\|_{\psi_2} \leq K.$$

Then

$$\|\Sigma_N - \Sigma\| = \|\Sigma^{1/2} R_N \Sigma^{1/2}\| \leq \|R_N\| \|\Sigma\|,$$

where

$$R_N = \frac{1}{N} \sum_{i=1}^N (Z^{(i)})(Z^{(i)})^T - \mathbb{1}_n.$$

Suppose now that A is the $N \times n$ matrix whose rows are $(Z^{(i)})^T$, that is,

$$\frac{1}{N} A^T A - \mathbb{1}_n = R_N,$$

and Theorem 4.16 for A implies that

$$\mathbb{E}[\|R_N\|] \leq CK^2 \left(\sqrt{\frac{n}{N}} + \frac{n}{N} \right),$$

and we conclude with our statement. \square

Remark 4.19 For all $\varepsilon \in (0, 1)$ we have

$$\mathbb{E}[\|\Sigma_N - \Sigma\|] \leq \varepsilon \|\Sigma\|,$$

if we take a sample of size $N \sim \varepsilon^{-2}n$. \diamond

5 Concentration of measure - general case

We study now general concentration of measure phenomena and aim in particular to include cases where the random variables are not necessarily independent. This assumptions made our concentration results relatively easy to develop. In the first section we summarise concentration results by entropy techniques before studying dependent random variables in the remaining sections.

5.1 Concentration by entropic techniques

In the following assume that $\varphi: \mathbb{R} \rightarrow \mathbb{R}$ is a convex function, X an \mathbb{R} -valued random variable such that $\mathbb{E}[X]$ and $\mathbb{E}[\varphi(X)]$ are finite unless otherwise stated. The random variable is a measurable map from some probability space $(\Omega, \mathcal{F}, \mathbb{P})$ to \mathbb{R} and distributed with law $P_X = \mathbb{P} \circ X^{-1} \in \mathcal{M}_1(\mathbb{R})$.

Definition 5.1 (Entropy) The entropy of the random variable X for the convex function φ is

$$H_\varphi(X) = \mathbb{E}[\varphi(X)] - \varphi(\mathbb{E}[X]).$$

Corollary 5.2 By Jensen's inequality, $\varphi(\mathbb{E}[X]) \leq \mathbb{E}[\varphi(X)]$, we see that $H_\varphi(X) \geq 0$.

Example 5.3 (i) $\varphi(u) = u^2, u \in \mathbb{R}$, then the entropy of X ,

$$H_\varphi(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2 = \text{Var}(X)$$

is the variance of X .

(ii) $\varphi(u) = -\log u, u > 0$, and for X real-valued random variable we have that $Z := e^{\lambda X} > 0$ is a strictly positive real-valued random variable.

$$H_\varphi(Z) = -\lambda \mathbb{E}[X] + \log \mathbb{E}[e^{\lambda X}] = \log \mathbb{E}[e^{\lambda(X - \mathbb{E}[X])}].$$

1. $\varphi(u) = u \log u, u > 0$, and $\varphi(0) := 0$. φ is convex function on \mathbb{R}_+ . For any non-negative random variable $Z \geq 0$, the φ -entropy is

$$H_\varphi(Z) = \mathbb{E}[Z \log Z] - \mathbb{E}[Z] \log \mathbb{E}[Z].$$



In the following we will drop the index φ for the entropy whenever we take $\varphi(u) = u \log u$ as in Example 5.3 (iii). There are several reasons why this choice is particular useful. In the next remark we show some connection of that entropy to other entropy concepts in probability theory.

Remark 5.4 Suppose that Ω is a finite sample space, and let $p, q \in \mathcal{M}_1(\Omega)$ be two probability measures (vectors) such that $q(\omega) = 0$ implies $p(\omega) = 0$. Define

$$X: \Omega \rightarrow \mathbb{R}, \omega \mapsto X(\omega) = \begin{cases} \frac{p(\omega)}{q(\omega)} & \text{if } q(\omega) > 0, \\ 0 & \text{if } q(\omega) = p(\omega) = 0, \end{cases}$$

with distribution $q \in \mathcal{M}_1(\Omega)$. Then $X \geq 0$ with

$$\mathbb{E}[X] = \sum_{\omega \in \Omega} X(\omega)q(\omega) = \sum_{\omega \in \Omega} p(\omega) = 1.$$

$$\begin{aligned} H(X) &= \sum_{\omega \in \Omega} X(\omega)q(\omega) \log X(\omega) - \mathbb{E}[X] \log \mathbb{E}[X] = \sum_{\omega \in \Omega} p(\omega) \log \frac{p(\omega)}{q(\omega)} \\ &=: H(p|q) =: D(p||q), \end{aligned}$$

where $H(p|q)$ is the *relative entropy of p with respect to q* , a widely used function probability theory (e.g. large deviation theory) and information theory, and where $D(p||q)$ is the *Kullback-Leibler divergence* of p and q used in information theory. \diamond

For any real-valued random variable X , $Z = \exp(\lambda X)$, $\lambda \in \mathbb{R}$, is a positive random variable and the entropy can be written with the moment generating function of X , recall the definition of the moment generating function (MGF) in (1.4) (we assume again that the expectations are finite for all $\lambda \in \mathbb{R}$),

$$H(e^{\lambda X}) = \lambda M'_X(\lambda) - M_X(\lambda) \log M_X(\lambda). \quad (5.1)$$

Example 5.5 (Entropy - Gaussian random variable) Suppose $X \sim N(0, \sigma^2)$, $\sigma > 0$. Then $M_X(\lambda) = \exp(\lambda^2 \sigma^2 / 2)$, and $M'_X(\lambda) = \lambda \sigma^2 M_X(\lambda)$, and therefore

$$H(e^{\lambda X}) = \lambda^2 \sigma^2 M_X(\lambda) - \lambda^2 \sigma^2 / 2 M_X(\lambda) = \frac{1}{2} \lambda^2 \sigma^2 M_X(\lambda).$$

♣

A bound on the entropy leads to a bound of the centred moment generating function Φ , see (2.3), this is the content of the so-called *Herbst argument*.

Proposition 5.6 (Herbst argument) *Let X be a real-valued random variable and suppose that, for $\sigma > 0$,*

$$H(e^{\lambda X}) \leq \frac{1}{2} \sigma^2 \lambda^2 M_X(\lambda)$$

for $\lambda \in I$ with interval I being either $[0, \infty)$ or \mathbb{R} . Then

$$\log \mathbb{E}[\exp(\lambda(X - \mathbb{E}[X]))] \leq \frac{1}{2} \lambda^2 \sigma^2 \quad \text{for all } \lambda \in I. \quad (5.2)$$

Remark 5.7 (a) When $I = \mathbb{R}$, then the bound (5.2) is equivalent to asserting that the centred random variable $X - \mathbb{E}[X]$ is sub-Gaussian with parameter $\sigma > 0$.

(b) For $I = [0, \infty)$, the bound (5.2) leads immediately to the one-sided tail estimate

$$\mathbb{P}(X \geq \mathbb{E}[X] + t) \leq \exp(-t^2/2\sigma^2), \quad t \geq 0,$$

and $I = \mathbb{R}$ provides the corresponding two-sided estimate. ◇

Proof of Proposition 5.6. Suppose that $I = [0, \infty)$. Using (5.1), our assumption turns into a differential inequality for the moment generating function,

$$\lambda M'_X(\lambda) - M_X(\lambda) \log M_X(\lambda) \leq \frac{1}{2} \sigma^2 \lambda^2 M_X(\lambda) \quad \text{for all } \lambda \geq 0. \quad (5.3)$$

Define now a function $G(\lambda) := \frac{1}{\lambda} \log M_X(\lambda)$ for $\lambda \neq 0$, and then extend the function to 0 by continuity

$$G(0) := \lim_{\lambda \rightarrow 0} G(\lambda) = \left. \frac{d}{d\lambda} \log M_X(\lambda) \right|_{\lambda=0} = \mathbb{E}[X].$$

Our assumptions on the existence of the MGF imply differentiability with respect to the parameter λ . Hence

$$G'(\lambda) = \frac{1}{\lambda} \frac{M'_X(\lambda)}{M_X(\lambda)} - \frac{1}{\lambda^2} \log M_X(\lambda),$$

and thus we can rewrite our differential inequality (5.3) as

$$G'(\lambda) \leq \frac{1}{2} \sigma^2 \quad \text{for all } \lambda \in I = [0, \infty).$$

For any $\lambda_0 > 0$ we can integrate both sides of the previous inequality to arrive at

$$G(\lambda) - G(\lambda_0) \leq \frac{1}{2} \sigma^2 (\lambda - \lambda_0).$$

Now, letting $\lambda_0 \downarrow 0$ and using the above definition of $G(0)$, we get

$$G(\lambda) - \mathbb{E}[X] = \frac{1}{\lambda} \left(\log M_X(\lambda) - \log e^{\lambda \mathbb{E}[X]} \right) \leq \frac{1}{2} \sigma^2 \lambda,$$

and we conclude with the statement in (5.2). □

Proposition 5.8 (Bernstein entropy bound) *Suppose there exist $B > 0$ and $\sigma > 0$ such that the real-valued random variable X satisfies the following entropy bound*

$$H(e^{\lambda X}) \leq \lambda^2 (B M'_X(\lambda) + M_X(\lambda) (\sigma^2 - B \mathbb{E}[X])) \quad \text{for all } \lambda \in [0, B^{-1}).$$


Then

$$\log \mathbb{E}[e^{\lambda(X - \mathbb{E}[X])}] \leq \sigma^2 \lambda^2 (1 - B\lambda)^{-1} \quad \text{for all } \lambda \in [0, B^{-1}). \quad (5.4)$$

Remark 5.9 As a consequence of the Chernoff argument, Proposition 5.8 implies that X satisfies the upper tail bound

$$\mathbb{P}(X \geq \mathbb{E}[X] + \delta) \leq \exp\left(\frac{\delta}{4\sigma^2 + 2B\delta}\right), \quad \text{for all } \delta \geq 0. \quad (5.5)$$

◇

Exercise 5.10 Prove the tail bound (5.5). 

Proof of Proposition 5.8. We skip the proof of this statement as it employs similar techniques as in the proof of Proposition 5.6. □

So far, the entropic method has not provided substantial new insight as all concentration results are done via the usual Chernoff bound. We shall now study concentration for functions of many random variables.

Definition 5.11 (a) A function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is *separately convex* if, for every index $k \in \{1, \dots, n\}$, the univariate function

$$f_k: \mathbb{R} \rightarrow \mathbb{R}, \\ y_k \mapsto f_k(y_k) := f(x_1, \dots, x_{k-1}, y_k, x_{k+1}, \dots, x_n),$$

is convex for each vector $(x_1, \dots, x_{k-1}, x_{k+1}, \dots, x_n) \in \mathbb{R}^{n-1}$.

(b) A function $f: X \rightarrow Y$ for metric spaces (X, d_X) and (Y, d_Y) is *Lipschitz continuous* (sometimes called *locally Lipschitz continuous*) if for every $x \in X$ there exists a neighbourhood $U \subset X$ such that $f|_U$ is globally Lipschitz continuous. Here $f|_U: U \rightarrow Y$ is the restriction of f to U .

(c) A function $f: X \rightarrow Y$ for metric spaces (X, d_X) and (Y, d_Y) is *L-Lipschitz continuous* (sometimes called *globally Lipschitz continuous*) if there exists $L \in \mathbb{R}$ such that

$$d_Y(f(x), f(y)) \leq L d_X(x, y) \quad \text{for all } x, y \in X. \quad (5.6)$$

The smallest constant $L > 0$ satisfying (5.6) is denoted $\|f\|_{\text{Lip}}$. In the following some statements hold for global Lipschitz continuity and some only for local Lipschitz continuity.

Theorem 5.12 (Tail-bound for Lipschitz functions) Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with independent random coordinates X_i supported on the interval $[a, b]$, $a < b$, and let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be separately convex and L -Lipschitz continuous with respect to the Euclidean norm $\|\cdot\|_2$. Then, for every $t \geq 0$,

$$\mathbb{P}(f(X) \geq \mathbb{E}[f(X)] + t) \leq \exp\left(-\frac{t^2}{4L^2(b-a)^2}\right). \quad (5.7)$$

Example 5.13 (Operator norm of a random matrix) Let $M \in \mathbb{R}^{n \times d}$ be a $n \times d$ matrix with independent identically distributed mean-zero random entries $M_{ij}, i \in \{1, \dots, n\}, j \in \{1, \dots, d\}$ supported on the interval $[-1, 1]$.

$$\|M\| = \max_{\nu \in \mathbb{R}^d: \|\nu\|_2=1} \{\|M\nu\|_2\} = \max_{\substack{\nu \in \mathbb{R}^d: \\ \|\nu\|_2=1}} \max_{\substack{u \in \mathbb{R}^n: \\ \|u\|_2=1}} \{\langle u, M\nu \rangle\}.$$

$M \mapsto \|M\|$ is a function $f: \mathbb{R}^{n \times d} \rightarrow \mathbb{R}, f(M) = \|M\|$. To apply Theorem 5.12 above we shall show that f is Lipschitz and separately convex. The operator norm is the max/min/supremum of functions that are linear in the entries of the matrix M , and thus any such function is convex and as such separately convex. Moreover, for $M, M' \in \mathbb{R}^{n \times d}$,

$$\left| \|M\| - \|M'\| \right| \leq \|M - M'\| \leq \|M - M'\|_F,$$

where $\|M\|_F := \sqrt{\sum_{i=1}^n \sum_{j=1}^d M_{ij}^2}$ is the Euclidean norm of all entries of the matrix, called the Frobenius norm of the matrix M . The first inequality shows that $f := \|\cdot\|$ is 1-Lipschitz continuous. Thus Theorem 5.12 implies that, for every $t \geq 0$,

$$\mathbb{P}(\|M\| \geq \mathbb{E}[\|M\|] + t) \leq e^{-t^2/16}.$$

♣

Key ingredients for the proof of Theorem 5.12 are the following two lemmas.

Lemma 5.14 (Entropy bound for univariate functions) Let X and Y two independent, identically distributed \mathbb{R} -valued random variables. Denote by $\mathbb{E}_{X,Y}$ the expectation with respect to X and Y . For any function $g: \mathbb{R} \rightarrow \mathbb{R}$ the following statements hold:

(a)

$$\mathbb{H}(e^{\lambda g(X)}) \leq \lambda^2 \mathbb{E}_{X,Y} \left[\left(g(X) - g(Y) \right)^2 e^{\lambda g(X)} \mathbb{1} \left\{ g(X) \geq g(Y) \right\} \right], \quad \text{for all } \lambda > 0.$$

(b) If in addition the random variable X is supported on $[a, b], a < b$, and the function g is convex and Lipschitz continuous, then

$$\mathbb{H}(e^{\lambda g(X)}) \leq \lambda^2 (b - a)^2 \mathbb{E} \left[(g'(X))^2 e^{\lambda g(X)} \right], \quad \text{for all } \lambda > 0.$$

Lemma 5.15 (Tensorisation of the entropy) Let X_1, \dots, X_n be independent real-valued random variables and $f: \mathbb{R}^n \rightarrow \mathbb{R}$ a given function. Then

$$\mathbb{H}(e^{\lambda f(X_1, \dots, X_n)}) \leq \mathbb{E} \left[\sum_{k=1}^n \mathbb{H} \left(e^{\lambda f_k(X_k)} \middle| \bar{X}^k \right) \right], \quad \text{for all } \lambda > 0, \quad (5.8)$$

where f_k is the function introduced in Definition 5.11 and

$$\bar{X}^k = (X_1, \dots, X_{k-1}, X_{k+1}, \dots, X_n).$$

The entropy on the right hand side is computed with respect to X_k for $k = 1, \dots, n$, by holding the remaining \bar{X}^k fixed. That is,

$$\mathbb{H} \left(e^{\lambda f_k(X_k)} \middle| \bar{X}^k \right) = \mathbb{E}_{X_k} \left[e^{\lambda f_k(X_k)} \lambda f_k(X_k) \right] - \mathbb{E}_{X_k} \left[\exp(\lambda f_k(X_k)) \right] \log \mathbb{E}_{X_k} \left[\exp(\lambda f_k(X_k)) \right]$$

is still a function of \bar{X}^k and is integrated with respect to \mathbb{E} on the right hand side of (5.8).

We first finish the proof of theorem 5.12.

Proof of Theorem 5.12. For $k \in \{1, \dots, n\}$ and every vector (fixed) $\bar{X}^k \in \mathbb{R}^{n-1}$ the f_k is convex, and hence Lemma 5.14 implies for all $\lambda > 0$ that

$$\begin{aligned} \mathbb{H}\left(e^{\lambda f_k(X_k)} \middle| \bar{X}^k\right) &\leq \lambda^2(b-a)^2 \mathbb{E}_{X_k} \left[(f'_k(X_k))^2 e^{\lambda f_k(X_k)} \middle| \bar{X}^k \right] \\ &\leq \lambda^2(b-a)^2 \mathbb{E}_{X_k} \left[\left(\frac{\partial f(X_1, \dots, X_k, \dots, X_n)}{\partial x_k} \right)^2 \exp(\lambda f(X_1, \dots, X_k, \dots, X_n)) \right]. \end{aligned}$$

With Lemma 5.15 one obtains writing $X = (X_1, \dots, X_n)$,

$$\begin{aligned} \mathbb{H}\left(e^{\lambda f(X)}\right) &\leq \lambda^2(b-a)^2 \mathbb{E} \left[\sum_{k=1}^n \mathbb{E}_{X_k} \left[\left(\frac{\partial f(X)}{\partial x_k} \right)^2 \exp(\lambda f(X)) \right] \right] \\ &\leq \lambda^2(b-a)^2 L^2 \mathbb{E}[e^{\lambda f(X)}], \end{aligned}$$

where we used the Lipschitz continuity leading

$$\|\nabla f(X)\|_2^2 = \sum_{k=1}^n \left(\frac{\partial f(X)}{\partial x_k} \right)^2 \leq L^2 \quad \text{almost surely.}$$

The tail bound then follows from the Herbst argument in Proposition 5.6. \square

Proof of Lemma 5.14. Using the fact that X and Y are independent and identical distributed we have

$$\mathbb{H}(e^{\lambda g(X)}) = \mathbb{E}_X[\lambda g(X) e^{\lambda g(X)}] - \mathbb{E}_X[e^{\lambda g(X)}] \log \mathbb{E}_Y[e^{\lambda g(Y)}].$$

By Jensen's inequality,

$$\log \mathbb{E}_Y[e^{\lambda g(Y)}] \geq \mathbb{E}_Y[\lambda g(Y)],$$

and thus, using the symmetry between X and Y , we obtain (we write $\mathbb{E}_{X,Y}$ for the expectation with respect to both, X and Y when we want to distinguish expectations with respect to the single random variables. Note that we can easily replace $\mathbb{E}_{X,Y}$ by \mathbb{E}),

$$\begin{aligned} \mathbb{H}(e^{\lambda g(X)}) &\leq \mathbb{E}_X[\lambda g(X) e^{\lambda g(X)}] - \mathbb{E}_{X,Y}[e^{\lambda g(X)} \lambda g(Y)] \\ &= \frac{1}{2} \mathbb{E}_{X,Y}[\lambda (g(X) - g(Y)) (e^{\lambda g(X)} - e^{\lambda g(Y)})] \\ &\stackrel{\text{Symmetry}}{=} \lambda \mathbb{E}[(g(X) - g(Y)) (e^{\lambda g(X)} - e^{\lambda g(Y)}) \mathbb{1}\{g(X) \geq g(Y)\}] \end{aligned} \tag{5.9}$$

For all $s, t \in \mathbb{R}$ we have $e^s - e^t \leq e^s(s-t)$. To see that, assume without loss of generality that $s \geq t$ and recall that $e^x \geq 1+x$, to see that

$$e^s(1 - e^{t-s}) \leq e^s(1 - (1 + (t-s))) = e^s(s-t).$$

For $s \geq t$, we obtain therefore

$$(s-t)(e^s - e^t) \mathbb{1}\{s \geq t\} \leq (s-t)^2 e^s \mathbb{1}\{s \geq t\}.$$

Applying this bound with $s = \lambda g(X)$ and $t = \lambda g(Y)$ to the inequality (5.9) yields

$$\mathsf{H}(e^{\lambda g(X)}) \leq \lambda^2 \mathbb{E}[(g(X) - g(Y))^2 e^{\lambda g(X)} \mathbb{1}\{g(X) \geq g(Y)\}].$$

If in addition the function g is convex, then we have the upper bound

$$g(x) - g(y) \leq g'(x)(x - y),$$

and hence, for $g(x) \geq g(y)$,

$$(g(x) - g(y))^2 \leq (g'(x))^2 (x - y)^2$$

which finishes the proof of the statement in Lemma 5.14. \square

Proof of Lemma 5.15. Their key ingredient is the variational representation of the entropy (5.13), see Proposition 5.16 and Remark 5.17 below:

$$\mathsf{H}(e^{\lambda f(X)}) = \sup_{g \in \mathcal{G}} \{\mathbb{E}[g(X)e^{\lambda f(X)}]\}, \quad (5.10)$$

where $\mathcal{G} = \{g: \Omega \rightarrow \mathbb{R}: e^g \leq 1\}$. The proof now amounts to some computation once the following notations are introduced.

For each $j \in \{1, \dots, n\}$ define $\bar{X}_j = (X_j, \dots, X_n)$, and for any $g \in \mathcal{G}$ define the functions $g^i, i = 1, \dots, n$, as follows using $X = (X_1, \dots, X_n)$ and $\mathbb{E}[\cdot | \bar{X}_j]$ denote expectation with respect to X conditions on fixing \bar{X}_j :

$$\begin{aligned} g^1(X_1, \dots, X_n) &:= g(X) - \log \mathbb{E}[e^{g(X)} | \bar{X}_2], \\ g^k(X_k, \dots, X_n) &:= \log \frac{\mathbb{E}[e^{g(X)} | \bar{X}_k]}{\mathbb{E}[e^{g(X)} | \bar{X}_{k+1}]}, \quad \text{for } k = 2, \dots, n. \end{aligned}$$

It is easy to see that by construction we have,

$$\sum_{k=1}^n g^k(X_k, \dots, X_n) = g(X) - \log \mathbb{E}[e^{g(X)}] \geq g(X), \quad (5.11)$$

and

$$\mathbb{E}[\exp(g^k(X_k, \dots, X_n) | X_{k+1})] = 1.$$

We use this decomposition within the variational representation (5.10) leading to the following chain of upper bounds:

$$\begin{aligned} \mathbb{E}[g(X)e^{\lambda f(X)}] &\stackrel{(5.11)}{\leq} \sum_{k=1}^n \mathbb{E}[g^k(X_k, \dots, X_n)e^{\lambda f(X)}] \\ &= \sum_{k=1}^n \mathbb{E}_{\bar{X}^k} [\mathbb{E}_{X_k} [g^k(X_k, \dots, X_n)e^{\lambda f(X)} | \bar{X}^k]] \\ &\stackrel{(5.10)}{\leq} \sum_{k=1}^n \mathbb{E}_{\bar{X}^k} [\mathsf{H}(e^{\lambda f_k(X_k)} | \bar{X}^k)]. \end{aligned}$$

We conclude with the statement by optimising over the function $g \in \mathcal{G}$. \square

Proposition 5.16 (Duality formula of the Entropy) *Let Y be a non-negative \mathbb{R} -valued random variable defined on a probability space (Ω, \mathcal{F}, P) such that $\mathbb{E}[\Phi(Y)] < \infty$, where $\Phi(u) = u \log u$ for $u \geq 0$. Then*

$$H(Y) = \sup_{g \in \mathcal{U}} \{\mathbb{E}[gY]\}, \quad (5.12)$$

where $\mathcal{U} = \{g: \Omega \rightarrow \mathbb{R} \text{ measurable with } \mathbb{E}[e^g] = 1\}$.

Proof. Denote $Q = e^g P$ the probability measure with Radon-Nikodym density $\frac{dQ}{dP} = e^g$ with respect to P for some $g \in \mathcal{U}$. Denote \mathbb{E} the expectation with respect to P and \mathbb{E}_Q the expectation with respect to Q , and we write H_Q we we compute the entropy with respect to the probability measure Q . Then

$$\begin{aligned} H_Q(Ye^{-g}) &= \mathbb{E}_Q[Ye^{-g}(\log Y - g)] - \mathbb{E}_Q[Ye^{-g}] \log \mathbb{E}_Q[Ye^{-g}] \\ &= \mathbb{E}[Y \log Y] - \mathbb{E}[Yg] - \mathbb{E}[Y] \log \mathbb{E}[Y] \\ &= H(Y) - \mathbb{E}[Yg], \end{aligned}$$

and as $H_Q(Ye^{-g}) \geq 0$ (entropy is positive due to Corollary 5.2) we get that

$$H(Y) \geq \mathbb{E}[Yg].$$

The equality in (5.12) follows by setting $e^g = Y/\mathbb{E}[Y]$, i.e., $g = \log Y = \log \mathbb{E}[Y]$. \square

Remark 5.17 (Variational representation of the entropy) One can easily extend the variational formula (5.12) in Proposition to the set $\mathcal{G} = \{g: \Omega \rightarrow \mathbb{R}: e^g \leq 1\}$, namely

$$H(Y) = \sup_{g \in \mathcal{G}} \{\mathbb{E}[gY]\}. \quad (5.13)$$

\diamond

5.2 Concentration via Isoperimetric Inequalities

We will see that Lipschitz functions concentrate well on S^{n-1} . In the following, when we consider the sphere S^{n-1} or $\sqrt{b}S^{n-1}$ we use the Euclidean metric in \mathbb{R}^n instead of the geodesic metric of the spheres.

Theorem 5.18 (Concentration of Lipschitz functions on the sphere) *Let $f: \sqrt{n}S^{n-1} \rightarrow \mathbb{R}$ be a Lipschitz function and*

$$X \sim \text{Unif}(\sqrt{n}S^{n-1}).$$

Then

$$\|f(X) - \mathbb{E}[f(X)]\|_{\psi_2} \leq C \|f\|_{\text{Lip}},$$

for some absolute constant $C > 0$.

The statement of Theorem 5.18 amounts to the following concentration result, for every $t \geq 0$,

$$\mathbb{P}(|f(X) - \mathbb{E}[f(X)]| \geq t) \leq 2 \exp\left(-\frac{Ct^2}{\|f\|_{\text{Lip}}^2}\right), \quad (5.14)$$

for some absolute constant $C > 0$. We already know this statement for linear functions, see Theorem 3.17 saying that when $X \sim \sqrt{n}(\mathcal{S}^{n-1})$ we have that X (or any linear map) is sub-Gaussian. To prove the extension to any nonlinear Lipschitz function we need two fundamental results, the so-called isoperimetric inequalities, which we can only state in order not to overload the lecture.

Definition 5.19 Suppose $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is some function. Its *level-sets* (or *sub-level sets*) are

$$\mathcal{L}_f(c) := \{x \in \mathbb{R}^n: f(x) \leq c\}, \quad c \in \mathbb{R}.$$

Theorem 5.20 (Isoperimetric inequality on \mathbb{R}^n) Among all subsets $A \subset \mathbb{R}^n$ with given volume, Euclidean balls have minimal surface area. Moreover, for any $\varepsilon > 0$, Euclidean balls minimise the volume of the ε -neighbourhood of A ,

$$A_\varepsilon := \{x \in \mathbb{R}^n: \exists y \in A: \|x - y\|_2 \leq \varepsilon\} = A + \varepsilon B^{(n)},$$

where $B^{(n)}$ is the unit ball in \mathbb{R}^n .

Theorem 5.21 (Isoperimetric inequality on the sphere) Let $\varepsilon > 0$. Then, among all $A \subset \mathcal{S}^{n-1}$ with given area $\sigma_{n-1}(A)$, the spherical caps minimise the area of the ε -neighbourhood $\sigma_{n-1}(A_\varepsilon)$,

$$A_\varepsilon := \{x \in \mathcal{S}^{n-1}: \exists y \in A: \|x - y\|_2 \leq \varepsilon\}.$$

A spherical cap $C(a, \varepsilon)$ centred at a point $a \in \mathcal{S}^{n-1}$ is the set

$$C(a, \varepsilon) := \{x \in \mathcal{S}^{n-1}: \|x - a\|_2 \leq \varepsilon\}.$$

For the proof of Theorem 5.18 the following lemma is a crucial step.

Lemma 5.22 (Blow-up) For any $A \subset \sqrt{n}\mathcal{S}^{n-1}$, denote σ the normalised area on the sphere. If $\sigma(A) \geq \frac{1}{2}$, then, for every $t \geq 0$,

$$\sigma(A_t) \geq 1 - 2 \exp(-ct^2)$$

for some absolute constant $c > 0$.

Proof. For the hemisphere $H = \{x \in \sqrt{n}\mathcal{S}^{n-1}: x_1 \leq 0\}$, we have $\sigma(A) \geq \frac{1}{2} = \sigma(H)$. The t -neighbourhood H_t of the hemisphere H is a spherical cap, and the isoperimetric inequality in Theorem 5.21 gives

$$\sigma(A_t) \geq \sigma(H_t).$$

We continue with Theorem 3.17 but noting that the normalised measure σ is the uniform probability measure on the sphere such that

$$\sigma(H_t) = \mathbb{P}(X \in H_t).$$

Because of

$$H_t \supset \left\{ x \in \sqrt{n}\mathcal{S}^{n-1}: x_1 \leq \frac{t}{\sqrt{2}} \right\}$$

we have

$$\sigma(H_t) \geq \mathbb{P}(X_1 \leq t/\sqrt{2}) = 1 - \mathbb{P}(X_1 > t/\sqrt{2}) \leq 1 - 2 \exp(-ct^2),$$

for some absolute constant $c > 0$. □

Proof of Theorem 5.18. Without loss of generality we assume that $\|f\|_{\text{Lip}} = 1$. Let M denote the median of $f(X)$, that is,

$$\mathbb{P}(f(X) \leq M) \geq \frac{1}{2} \quad \text{and} \quad \mathbb{P}(f(X) \geq M) \geq \frac{1}{2}.$$

The set $A = \{x \in \sqrt{n}\mathcal{S}^{n-1} : f(x) \leq M\}$ is a level (sub-level) set of f with $\mathbb{P}(X \in A) \geq \frac{1}{2}$. Lemma 5.22 implies that $\mathbb{P}(X \in A_t) \geq 1 - 2 \exp(-Ct^2)$ for some absolute constant $C > 0$. We claim that, for every $t \geq 0$,

$$\mathbb{P}(X \in A_t) \leq \mathbb{P}(f(X) \leq M + t). \quad (5.15)$$

To see (5.15), note that $X \in A_t$ implies $\|X - y\|_2 \leq t$ for some point $y \in A$. By our definition of the set A , $f(y) \leq M$. As $\|f\|_{\text{Lip}} = 1$, we have

$$f(X) - f(y) \leq |f(X) - f(y)| \leq \|X - y\|_2$$

and thus

$$f(X) \leq f(y) + \|X - y\|_2 \leq M + t.$$

Hence

$$\mathbb{P}(f(X) \leq M + t) \geq 1 - 2 \exp(-Ct^2).$$

We now repeat our argument for $-f$: $\tilde{A} = \{x \in \sqrt{n}\mathcal{S}^{n-1} : -f(x) \leq M\}$. Then $\mathbb{P}(X \in \tilde{A}) \geq 1/2$ and thus $\mathbb{P}(X_t \in \tilde{A}_t) \geq 1 - 2 \exp(-Ct^2)$. Now $X \in \tilde{A}$ implies $\|X - y\|_2 \leq t$ for some $y \in \tilde{A}$, and $f(y) \geq M$ by definition of \tilde{A} .

$$-f(X) - (-f(y)) \leq \|X - y\|_2 \leq t \Rightarrow f(X) \geq f(y) - t \geq M - t,$$

and thus $\mathbb{P}(f(X) \geq M - t) \geq 1 - 2 \exp(-\tilde{C}t^2)$ for some absolute constant $\tilde{C} > 0$. Combining our two estimates we obtain

$$\mathbb{P}(|f(X) - M| \leq t) \geq 1 - 2 \exp(-\hat{C}t^2)$$

for some absolute constant $\hat{C} > 0$, and thus the immediate tail estimate shows that

$$\|f(X) - M\|_{\psi_2} \leq C$$

for some absolute constant $C > 0$. To replace the median M by the expectation $\mathbb{E}[f(X)]$ note that although the median is not unique it is a fixed real number determined by the distribution of the random variable X and the function f . We use the centering Lemma 2.24 to get

$$\begin{aligned} \left| \|f(X)\|_{\psi_2} - \|M\|_{\psi_2} \right| &\leq \|f(X) - M\|_{\psi_2} \leq C \\ \|M\|_{\psi_2} &\leq \tilde{C} \Rightarrow -\tilde{C} + \|f(X)\|_{\psi_2} \leq C \\ &\Rightarrow \|f(x)\|_{\psi_2} \leq \tilde{C} + C \\ &\Rightarrow \|f(X) - \mathbb{E}[f(X)]\|_{\psi_2} \leq C. \end{aligned}$$

□

Definition 5.23 (Isoperimetric problem) Let (E, d) be a metric space and $\mathcal{B}(E)$ its Borel- σ algebra, and $P \in \mathcal{M}_1(E, \mathcal{B}(E))$ some given probability measure and X an E -valued random variable.

Isoperimetric problem: Given $p \in (0, 1)$ and $t > 0$, find the sets A with $P(X \in A) \geq p$ for which $P(d(X, A) \geq t)$ is maximal, where

$$d(X, A) := \inf_{y \in A} \{d(x, y)\}.$$

Concentration function:

$$\alpha(t) := \sup_{\substack{A \subset E: \\ P(A) \geq 1/2}} \{P(d(X, A) \geq t)\} = \sup_{\substack{A \subset E: \\ P(A) \geq 1/2}} \{P(A_t^c)\},$$

where A_t is the t -blowup of the set A , $A_t = \{x \in E : d(x, A) < t\}$. For a given function $f : E \rightarrow \mathbb{R}$ denote the median of $f(X)$ by $Mf(X)$.

There are many isoperimetric inequalities, we only mention the Gaussian isoperimetric inequality as it is widely used. Recall that the Gaussian (standard normal distribution) is given by the probability measure $p \in \mathcal{M}_1(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$,

$$\gamma_n(A) = \int_A (2\pi)^{-n/2} e^{-\|x\|^2/2} dx_1 \cdots dx_n, \quad A \subset \mathcal{B}(\mathbb{R}^n).$$

The concentration function for the one-dimensional Gaussian ($n = 1$) is just $\alpha(t) = 1 - \Phi(t)$ with $\Phi(t) = \frac{1}{\sqrt{2\pi}} \int_t^\infty e^{-u^2/2} du$. In the following statement half-spaces are sets of the form

$$A = \{x \in \mathbb{R}^n : \langle x, u \rangle < \lambda\}, \quad u \in \mathbb{R}^n, \lambda \in \mathbb{R}, \text{ or } A = \{x \in \mathbb{R}^n : x_1 \leq z\}, \quad z \in \mathbb{R}.$$

Theorem 5.24 (Gaussian isoperimetric inequality) Let $\varepsilon > 0$ be given. Among all $A \subset \mathbb{R}^n$ with fixed Gaussian measure $\gamma_n(A)$, the half-spaces minimise the Gaussian measure of the ε -neighbourhood $\gamma_n(A_\varepsilon)$.

From this we can obtain the following concentration results. The proof is using similar steps as done above, and leave the details as exercise for the reader.

Theorem 5.25 (Gaussian concentration) Suppose $X \sim N(0, \mathbb{I}_n)$, and let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a Lipschitz continuous function. Then

$$\|f(X) - \mathbb{E}[f(X)]\|_{\psi_2} \leq C \|f\|_{\text{Lip}}$$

for some absolute constant $C > 0$.

5.3 Some matrix calculus and covariance estimation

Theorem 5.26 (Matrix Bernstein inequality) *Let X_1, \dots, X_N be independent mean-zero random $n \times n$ symmetric matrices such that $\|X_i\| \leq K$ almost surely for all $i = 1, \dots, N$. Then, for every $t \geq 0$, we have*

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

where $\sigma^2 = \left\|\sum_{i=1}^N \mathbb{E}[X_i^2]\right\|$ is the norm of the matrix variance of the sum.

For the proof we shall introduce a few well-known facts about matrix calculus.

Definition 5.27 (a) For any symmetric $n \times n$ matrix X with eigenvalues $\lambda_i = \lambda_i(X)$ and corresponding eigenvectors u_i the function of a matrix for any given $f: \mathbb{R} \rightarrow \mathbb{R}$ is defined as the $n \times n$ matrix

$$f(X) := \sum_{i=1}^n f(\lambda_i) u_i u_i^T.$$

(b) Suppose X is a $n \times n$ matrix. We write $X \succcurlyeq 0$ if X is positive-semidefinite. Equivalently, $X \succcurlyeq 0$ if all eigenvalues of X are positive, i.e., $\lambda_i \geq 0$. For $Y \in \mathbb{R}^{n \times n}$, we set $X \succcurlyeq Y$ and $Y \preccurlyeq X$ if $X - Y \succcurlyeq 0$.

We borrow the following trace inequalities from linear algebra. Recall the notion of the trace of a matrix.

Golden-Thompson inequality: For any $n \times n$ symmetric matrices A and B we have

$$\text{Trace}(e^{A+B}) \leq \text{Trace}(e^A e^B).$$

Lieb's inequality: Suppose H is a $n \times n$ symmetric matrix and define the function on matrices

$$f(X) := \text{Trace}(\exp(H + \log X)).$$

Then f is concave on the space of positive-definite $n \times n$ matrices.

In principle one can prove the Matrix Bernstein inequality in Theorem 5.26 with these two results from matrix analysis. If X is a random positive-definite matrix then Lieb's and Jensen's inequality imply that

$$\mathbb{E}[f(X)] \leq f(\mathbb{E}[X]).$$

We now apply this with $X = e^Z$ for some $n \times n$ symmetric matrix Z :

Lemma 5.28 (Lieb's inequality for random matrices) *Let H be a fixed $n \times n$ symmetric matrix and Z be a random $n \times n$ symmetric matrix. Then*

$$\mathbb{E}[\text{Trace}(\exp(H + Z))] \leq \text{Trace}(\exp(H + \log \mathbb{E}[e^Z])). \quad (5.16)$$

The proof of Theorem 5.26 follows below and is based on the following bound of the moment generating function (MGF).

Lemma 5.29 (Bound on MGF) *Let X be an $n \times n$ symmetric mean-zero random matrix such that $\|X\| \leq K$ almost surely. Then*

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

Proof of Lemma 5.29. For $z \in \mathbb{C}$ we can easily obtain the following estimate

$$e^z \leq 1 + z + \frac{1}{1 - |z|/3} \frac{z^2}{2} \quad \text{for } |z| < 3.$$

This can be easily derived from the Taylor series of the exponential function in conjunction with the lower bound $p! \geq 2 \times 3^{p-2}$ and the geometric series. Details are left to the reader. Now with $z = \lambda x$, $|x| \leq K$, $|\lambda| < 3/K$, we then obtain

$$e^{\lambda x} \leq 1 + \lambda x + g(\lambda)x^2.$$

Now we transfer this inequality from scalar to matrices:

$$e^{\lambda X} \preceq \mathbb{1}_n + \lambda X + g(\lambda)X^2,$$

and then, after taking the expectation and using $\mathbb{E}[X] = 0$, to arrive at

$$\mathbb{E}[e^{\lambda X}] \leq \mathbb{1}_n + g(\lambda)\mathbb{E}[X^2].$$

To finish, use the inequality $1 + z \leq e^z$ to conclude with

$$\mathbb{E}[e^{\lambda X}] \leq \exp(g(\lambda)\mathbb{E}[X^2]).$$

□

Proposition 5.30 (Expectation bound via the Bernstein Theorem) *Under all the assumptions in Theorem 5.26 we have the tail bound*

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

Then

$$\mathbb{E}\left[\left\|\sum_{i=1}^N X_i\right\|\right] \leq 2\sigma\left(\frac{\sqrt{2\pi}}{2} + \sqrt{\log(2n)}\right) + \frac{4}{3}K\left(1 + \log(2n)\right). \quad (5.17)$$

Proof. Define $b := \frac{K}{3}$. Then the right hand side in Theorem 5.26 reads as

$$2n \exp\left(-\frac{t^2}{2(\sigma^2 + bt)}\right).$$

We will use a crude union-type bound on the tail probability itself by observing that either $\sigma^2 \leq bt$ or $\sigma^2 \geq bt$. Define $Z := \sum_{i=1}^N X_i$. For every $t \geq 0$,

$$\begin{aligned} \mathbb{P}(\|Z\| \geq t) &\leq 2n \exp\left(-\frac{t^2}{2(\sigma^2 + bt)}\right) \leq 2n \max\left\{\exp\left(-\frac{t}{4b}\right), \exp\left(-\frac{t^2}{4\sigma^2}\right)\right\} \\ &\leq 2n \exp\left(-\frac{t}{4b}\right) + 2n \exp\left(-\frac{t^2}{4\sigma^2}\right). \end{aligned}$$

We shall combine this with the trivial inequality $\mathbb{P}(\|X\| \geq t) \leq 1$. Thus

$$\mathbb{P}(\|Z\| \geq t) \leq 1 \wedge 2n \exp\left(-\frac{t}{4b}\right) + 1 \wedge 2n \exp\left(-\frac{t^2}{4\sigma^2}\right),$$

and

$$\mathbb{E}[\|Z\|] = \int_0^\infty \mathbb{P}(\|Z\| \geq t) dt =: I_1 + I_2,$$

with $I_1 = \int_0^\infty 1 \wedge 2n \exp(-t/(4b)) dt$ and $I_2 = \int_0^\infty 1 \wedge 2n \exp(-t^2/(4\sigma^2)) dt$. Solve $2n \exp(-t_1/(4b)) = 1$ to obtain $t_1 = 4b \log(2n)$, and then

$$I_1 = \int_0^{t_1} 1 dt + \int_{t_1}^\infty (2n) \exp(-t/(4b)) dt = t_1 + 4b = 4b(1 + \log(2n)).$$

Solve $2n \exp(-t^2/(4\sigma^2)) = 1$ to obtain $t_2 = 2\sigma\sqrt{\log(2n)}$, and then

$$\begin{aligned} I_2 &= \int_0^{t_2} 1 dt + \int_{t_2}^\infty (2n) \exp(-t^2/(4\sigma^2)) dt \stackrel{\tilde{t}=t/2\sigma}{=} t_2 + 2\sigma \int_{\sqrt{\log(2n)}}^\infty (2n) e^{-\tilde{t}^2/2} d\tilde{t} \\ &\leq 2\sigma(\sqrt{\log(2n)} + \sqrt{\pi}), \end{aligned}$$

where we used another transformation for the inequality, namely, $x = \tilde{t} - \sqrt{\log(2n)}$. Equivalently, we may use $2n e^{-\tilde{t}^2/2} \leq e^{-x^2}$ for all $t \geq \sqrt{\log(2n)}$. We arrive at

$$\mathbb{E}[\|Z\|] \leq 2\sigma\left(\frac{\sqrt{\pi}}{2} + \sqrt{\log(2n)}\right) + 4b(1 + \log(2n)).$$

□

Proof of Theorem 5.26.

Step 1: Define $S := \sum_{i=1}^N X_i$ and $\lambda_m(S) := \max_{1 \leq i \leq n} \lambda_i(S)$ the largest eigenvalue of S . Then $\|S\| = \max\{\lambda_m(S), \lambda_m(-S)\}$.

$$\mathbb{P}(\lambda_m(S) \geq t) = \mathbb{P}(e^{\lambda_m(S)} \geq e^{t}) \leq e^{-\lambda t} \mathbb{E}[e^{\lambda_m(S)}].$$

The eigenvalues of $e^{\lambda S}$ are $e^{\lambda \lambda_i(S)}$, and thus

$$E := \mathbb{E}[e^{\lambda \lambda_m(S)}] = \mathbb{E}[\lambda_m(e^{\lambda S})].$$

All eigenvalues of $e^{\lambda S}$ are positive, hence the maximal eigenvalue of $e^{\lambda S}$ is bounded by the sum of all eigenvalues, that is, by the trace of $e^{\lambda S}$. Henceforth

$$E \leq \mathbb{E}[\text{Trace}(e^{\lambda S})]. \quad (5.18)$$

Step 2: We now turn to bound the expectation of the trace using Lieb's inequality, in particular Lemma 5.28. We write the exponent of $e^{\lambda S}$ separately, namely splitting off the last term of the sum, writing

$$\text{Trace} \left(e^{\sum_{i=1}^{N-1} \lambda X_i + \lambda X_N} \right). \quad (5.19)$$

When we take the expectation of (5.19) we condition on X_1, \dots, X_{N-1} and apply Lieb's inequality (Lemma 5.28 for the fixed matrix $H := \sum_{i=1}^N \lambda X_i$), and obtain

$$E \leq \mathbb{E} \left[\text{Trace} \left(\exp \left(\sum_{i=1}^{N-1} \lambda X_i + \log \widehat{\mathbb{E}}[\exp(\lambda X_N)] \right) \right) \right],$$

where $\widehat{\mathbb{E}}$ is the conditional expectation. We repeat this application of Lemma 5.28 successively for $\lambda X_{N-1}, \dots, \lambda X_1$, to arrive at

$$E \leq \text{Trace} \left(\exp \left(\sum_{i=1}^N \log \mathbb{E} \left[e^{\lambda X_i} \right] \right) \right).$$

Step 3: We use Lemma 5.29 to bound $\mathbb{E}[e^{\lambda X_i}]$ for each $X_i, i = 1, \dots, N$.

Step 4: With Step 3 we get

$$E \leq \text{Trace} \left(\exp(g(\lambda)Z) \right),$$

where $Z := \sum_{i=1}^N \mathbb{E}[X_i^2]$. The trace of $\exp(g(\lambda)Z)$ is a sum of n positive eigenvalues,

$$E \leq n \lambda_m(\exp(g(\lambda)Z)) = n \exp(g(\lambda)\lambda_m(Z)) = n \exp(g(\lambda)\|Z\|) = n \exp(g(\lambda)\sigma^2).$$

Thus, with Step 1 and Lemma 5.29,

$$\mathbb{P}(\lambda_m(S) \geq t) \leq n \exp(-\lambda t + g(\lambda)\sigma^2) \quad \text{for } |\lambda| < 3/K.$$

The minimum in the exponent is attained for $\lambda = t/(\sigma^2 + 2Kt/3)$. We finally conclude with

$$\mathbb{P}(\lambda_m(S) \geq t) \leq n \exp \left(-\frac{t^2/2}{\sigma^2 + 2Kt/3} \right),$$

and repeating our steps for $\lambda_m(-S)$ we conclude with the statement of the theorem. \square

6 Basic tools in high-dimensional probability

6.1 Decoupling

Definition 6.1 Let X_1, \dots, X_n be independent real-valued random variables and $a_{ij} \in \mathbb{R}, i, j = 1, \dots, n$. The random quadratic form

$$\sum_{i,j=1}^n a_{ij} X_i X_j = X^T A X = \langle X, A X \rangle, \quad X = (X_1, \dots, X_n) \in \mathbb{R}^n, A = (a_{ij}),$$

is called *chaos* in probability theory.

For simplicity, we assume in the following that the random variables X_i have mean-zero and unit variances,

$$\mathbb{E}[X_i] = 0, \quad \text{Var}(X_i) = 1, \quad i = 1, \dots, n.$$

Then

$$\mathbb{E}[\langle X, AX \rangle] = \sum_{i,j=1}^n a_{ij} \mathbb{E}[X_i X_j] = \sum_{i=1}^m a_{ii} = \text{Trace}(A).$$

We shall study concentration properties for chaos. This time we need to develop tools to overcome the fact that we have sum of not necessarily independent random variables. The idea is to use the *decoupling technique*. The idea is to study the following random quadratic form,

$$\sum_{i,j=1}^n a_{ij} X_i X'_j = X^T A X' = \langle X, A X' \rangle, \quad (6.1)$$

where $X' = (X'_1, \dots, X'_n)$ is a random vector independent of X but with the same distribution as X . Obviously, the bilinear form in (6.1) is easier to study, e.g., when we condition on X' we simply obtain a linear form for the random vector X . The vector X' is called an independent copy of X , and conditioning on X' ,

$$\langle X, A X' \rangle = \sum_{i=1}^n c_i X_i \quad \text{with } c_i = \sum_{j=1}^n a_{ij} X'_j,$$

is a random linear form for X depending on the condition of the independent copy.

Lemma 6.2 *Let Y and Z be independent random vectors in \mathbb{R}^n such that $\mathbb{E}_Y[Y] = \mathbb{E}_Z[Z] = 0$ (we write indices when we want to stress the expectation for a certain random variable). Then, for every convex function $F: \mathbb{R}^n \rightarrow \mathbb{R}$, one has*

$$\mathbb{E}[F(Y)] \leq \mathbb{E}[F(Y + Z)].$$

Proof. Fix $y \in \mathbb{R}^n$ and use $\mathbb{E}_Z[Z] = 0$ and the convexity to get

$$F(y) = F(y + \mathbb{E}_Z[Z]) \leq \mathbb{E}_Z[F(y + Z)].$$

We choose $y = Y$ and take expectation with respect to Y ,

$$\mathbb{E}_Y[F(Y)] = \mathbb{E}_Y[F(Y + \mathbb{E}_Z[Z])] = \mathbb{E}_Y[F(\mathbb{E}_Z[Y + Z])] \leq \mathbb{E}_Y \otimes \mathbb{E}_Z[F(Y + Z)].$$

□

Theorem 6.3 (Decoupling) *Let A be an $n \times n$ diagonal-free (i.e., diagonal entries vanish) and $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with independent mean-zero coordinates X_i , and X' an independent copy of X . Then, for every convex function $F: \mathbb{R} \rightarrow \mathbb{R}$, one has*

$$\mathbb{E}[F(\langle X, AX \rangle)] \leq \mathbb{E}[F(4\langle X, A X' \rangle)]. \quad (6.2)$$

Proof. The idea is to study partial chaos

$$\sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j$$

with a randomly chosen subset $I \subset \{1, \dots, n\}$. Let $\delta_1, \dots, \delta_n$ be independent Bernoulli random variables with $\mathbb{P}(\delta_i = 0) = \mathbb{P}(\delta_i = 1) = \frac{1}{2}$. Then set $I = \{i: \delta_i = 1\}$. We condition on the random variable X and obtain for $i \neq j$ using $a_{ii} = 0$ and $\mathbb{E}[\delta_i(1 - \delta_j)] = 1/4$,

$$\langle X, AX \rangle = \sum_{i \neq j} a_{ij} X_i X_j = 4\mathbb{E}_\delta \left[\sum_{i \neq j} \delta_i(1 - \delta_j) a_{ij} X_i X_j \right] = 4\mathbb{E}_I \left[\sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j \right],$$

where \mathbb{E}_δ is expectation with respect to the Bernoulli random variables and \mathbb{E}_I is expectation with respect to the Bernoulli random variables for $I = \{i: \delta_i = 1\}$. Apply F on both sides and use Jensen (w.r.t. to \mathbb{E}_I) and Fubini to get

$$\mathbb{E}_X[F(\langle X, AX \rangle)] \leq \mathbb{E}_I \mathbb{E}_X \left[F \left(4 \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j \right) \right].$$

There is a realisation of a random set I such that

$$\mathbb{E}_X[F(\langle X, AX \rangle)] \leq \mathbb{E} \left[F \left(4 \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j \right) \right]. \quad (6.3)$$

We fix such an realisation of I until the end. We now replace $X_i, j \in I^c$, by X'_j on the right hand side of (6.3). It remains to show that

$$\text{R.H.S. of (6.3)} \leq \mathbb{E} \left[F \left(4 \sum_{(i,j) \in [n] \times [n]} a_{ij} X_i X'_j \right) \right], \quad (6.4)$$

where $[n] = \{1, \dots, n\}$. We now split the argument of the function F on the right hand side of (6.4) into three terms,

$$\sum_{(i,j) \in [n] \times [n]} a_{ij} X_i X'_j =: Y + Z_1 + Z_2,$$

with

$$Y := \sum_{(i,j) \in I \times I^c} a_{ij} X_i X'_j, \quad Z_1 := \sum_{(i,j) \in I \times I} a_{ij} X_i X'_j, \quad Z_2 := \sum_{(i,j) \in I^c \times [n]} a_{ij} X_i X'_j.$$

We now condition on all random variables except $(X'_j)_{j \in I}$ and $(X_i)_{i \in I^c}$. We denote the corresponding conditional expectation by $\tilde{\mathbb{E}}$. The conditioning already fixes Y . Furthermore, Z_1 and Z_2 have zero expectation. Applications of Lemma 6.2 leads to

$$F(4Y) \leq \tilde{\mathbb{E}}[F(4Y + 4Z_1 + 4Z_2)],$$

and thus

$$\mathbb{E}[F(4Y)] \leq \mathbb{E}[F(4Y + 4Z_1 + 4Z_2)].$$

This proves (6.4) and finishes the argument by taking the final expectation with respect to I .

□

Theorem 6.4 (Hanson-Wright inequality) *Let $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ be a random vector with independent mean-zero sub-Gaussian coordinates and A be an $n \times n$ matrix. Then, for every $t \geq 0$,*

$$\mathbb{P}\left(|\langle X, AX \rangle - \mathbb{E}[\langle X, AX \rangle]| \geq t\right) \leq 2 \exp\left(-c \min\left\{\left(\frac{t^2}{K^4 \|A\|_F^2}\right), \left(\frac{t}{K^2 \|A\|}\right)\right\}\right),$$

where $K := \max_{1 \leq i \leq n} \{\|X_i\|_{\psi_2}\}$.

We prepare the proof with the following two lemmas.

Lemma 6.5 (MGF of Gaussian chaos) *Let $X, X' \sim \mathcal{N}(0, \mathbb{1}_n)$, X and X' be independent, and let A be an $n \times n$ matrix. Then*

$$\mathbb{E}[\exp(\lambda \langle X, AX' \rangle)] \leq \exp(C\lambda^2 \|A\|_F), \quad \text{for all } |\lambda| \leq C/\|A\|,$$

for some absolute constant $C > 0$.

Proof. We use the singular value decomposition of the matrix A , see Definition 4.9:

$$\begin{aligned} A &= \sum_{i=1}^n s_i u_i v_i^T \\ \langle X, AX' \rangle &= \sum_{i=1}^n s_i \langle u_i, X \rangle \langle v_i, X' \rangle \\ \langle X, AX' \rangle &= \sum_{i=1}^n s_i Y_i Y_i', \end{aligned}$$

where $Y = (\langle u_1, X \rangle, \dots, \langle u_n, X \rangle) \sim \mathcal{N}(0, \mathbb{1}_n)$ and $Y' = (\langle v_1, X' \rangle, \dots, \langle v_n, X' \rangle) \sim \mathcal{N}(0, \mathbb{1}_n)$. Independence yields

$$\mathbb{E}[\exp(\lambda \langle X, AX' \rangle)] = \prod_{i=1}^n \mathbb{E}[\exp(\lambda s_i Y_i Y_i')].$$

For each $i \in \{1, \dots, n\}$ we compute (taking the expectation with respect to Y')

$$\mathbb{E}[\exp(\lambda s_i Y_i Y_i')] = \mathbb{E}[\exp(\lambda^2 s_i^2 Y_i^2 / 2)] \leq \exp(C\lambda^2 s_i^2), \quad \text{provided } \lambda^2 s_i^2 \leq C.$$

Thus

$$\mathbb{E}[\exp(\lambda \langle X, AX' \rangle)] \leq \exp\left(C\lambda^2 \sum_{i=1}^n s_i^2\right), \quad \text{provided } \lambda \leq \frac{C}{\max_{1 \leq i \leq n} \{s_i^2\}}.$$

We conclude with $\sum_{i=1}^n s_i^2 = \|A\|_F^2$ and $\max_{1 \leq i \leq n} \{s_i\} = \|A\|$. \square

Lemma 6.6 (Comparison) *Let X and X' be independent mean-zero sub-Gaussian random vectors in \mathbb{R}^n with $\|X\|_{\psi_2} \leq K$ and $\|X'\|_{\psi_2} \leq K$. Furthermore, let Y, Y' be independent normally distributed random vectors $Y, Y' \sim \mathcal{N}(0, \mathbb{1}_n)$, and A be an $n \times n$ matrix. Then*

$$\mathbb{E}[\exp(\lambda \langle X, AX' \rangle)] \leq \mathbb{E}[\exp(CK^2 \lambda \langle Y, AY' \rangle)].$$

Proof. We condition on X' and take the expectation with respect to X (denoted by \mathbb{E}_X). Then $\langle X, AX' \rangle$ is conditionally sub-Gaussian and

$$\mathbb{E}_X[\exp(\lambda\langle X, AX' \rangle)] \leq \exp(C\lambda^2 K^2 \|AX'\|_2^2), \quad \lambda \in \mathbb{R}.$$

We now replace X by Y but still conditioning on X' (we replace one at a time),

$$E_Y[\exp(\mu\langle Y, AX' \rangle)] = \exp(\mu^2 K^2 \|AX'\|_2^2 / 2), \quad \mu \in \mathbb{R}.$$

Choosing $\mu = \sqrt{2C}\lambda$, we can match our estimates to get

$$\mathbb{E}_X[\exp(\lambda\langle X, Ax' \rangle)] \leq E_Y[\exp(\sqrt{2C}\lambda\langle Y, AX' \rangle)].$$

We can now take the expectation with respect to X' on both sides and see that we have successfully replaced X by Y . We can now repeat the same procedure for X' and Y' to obtain our statement. \square

Proof of Theorem 6.4. Without loss of generality, $K = 1$. It suffices to show the one-sided tail estimate. Denote

$$p = \mathbb{P}(\langle X, AX \rangle - \mathbb{E}[\langle X, AX \rangle] \geq t).$$

Write

$$\langle X, AX \rangle - \mathbb{E}[\langle X, AX \rangle] = \sum_{i=1}^n a_{ii}(X_i^2 - \mathbb{E}[X_i^2]) + \sum_{i,j: i \neq j} a_{ij}X_iX_j,$$

and thus the problem reduces to estimating diagonal and off-diagonal sums:

$$p \leq \mathbb{P}\left(\sum_{i=1}^n a_{ii}(X_i^2 - \mathbb{E}[X_i^2]) \geq t/2\right) + \mathbb{P}\left(\sum_{i,j: i \neq j} a_{ij}X_iX_j \geq t/2\right) =: p_1 + p_2.$$

Diagonal sum: $X_i^2 - \mathbb{E}[X_i^2]$ are independent mean-zero sub-exponential random variables. Thus, using centering (see Exercise 3.2) and Lemma 2.28 we have

$$\|X_i^2 - \mathbb{E}[X_i^2]\|_{\psi_1} \leq C\|X_i^2\|_{\psi_1} \leq C\|X_i\|_{\psi_2}^2 \leq C.$$

Then Bernstein's inequality (see Exercise 3.3 using it with $1/N$ replaced by A_{ii}) implies that

$$p_1 \leq \exp\left(-C \min\left\{\left(\frac{t^2}{\sum_{i=1}^n a_{ii}^2}\right), \left(\frac{t}{\max_{1 \leq i \leq n}\{|a_{ii}|}\right)}\right\}\right).$$

Off-diagonal sum: $S := \sum_{i \neq j} a_{ij}X_iX_j$ and $\lambda > 0$. Then

$$\mathbb{E}[\exp(\lambda S)] \leq \mathbb{E}[\exp(4\lambda\langle X, AX' \rangle)] \leq \exp(C\lambda^2 \|A\|_F^2) \quad \text{provided } |\lambda| \leq C/\|A\|.$$

Thus

$$p_2 \leq \exp(-\lambda t/2) \mathbb{E}[\exp(\lambda S)] \leq \exp(-\lambda t/2 + C\lambda t^2 \|A\|_F^2).$$

Optimising over $0 \leq \lambda \leq C/\|A\|$, we get

$$p_2 \leq \exp\left(-C \min\left\{\left(\frac{t^2}{\|A\|_F^2}\right), \left(\frac{t}{\|A\|}\right)\right\}\right).$$

\square

6.2 Concentration for Anisotropic random vectors

We now study anisotropic random vectors, which have the form BX where B is a fixed matrix and where X is an isotropic random vector.

Exercise 6.7 Let B be an $m \times n$ matrix and X be an isotropic random vector in \mathbb{R}^b . Show that

$$\mathbb{E}[\|BX\|_2^2] = \|B\|_F^2.$$



Theorem 6.8 (Concentration for random vectors) Let B be an $m \times n$ matrix and $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ a random vector with independent mean-zero unit variance sub-Gaussian coordinates. Then

$$\left| \|BX\|_2 - \|B\|_F \right|_{\psi_2} \leq CK^2 \|B\|, \quad K := \max_{1 \leq i \leq n} \{\|X_i\|_{\psi_2}\},$$

for some absolute constant $C > 0$.

Remark 6.9 (a) We have, according to Exercise 6.7,

$$\mathbb{E}[\|BX\|_2^2] = \|B\|_F^2.$$

(b) Recall that we have already proved a version with $B = \mathbb{1}_n$ in Theorem 3.1, namely,

$$\left| \|X\|_2 - \sqrt{n} \right|_{\psi_2} \leq CK^2.$$



Proof of Theorem 6.8. Without loss of generality we assume that $K \geq 1$ and we write $A = B^T B$ and apply Hanson-Wright inequality (Theorem 6.4) with the following.

$$\begin{aligned} \langle X, AX \rangle &= \|BX\|_2^2, \\ \mathbb{E}[\langle X, AX \rangle] &= \|B\|_F^2; \|A\| = \|B\|^2, \\ \|B^T B\|_F &\leq \|B^T\| \|B\|_F = \|B\| \|B\|_F. \end{aligned}$$

Thus, for every $u \geq 0$,

$$\mathbb{P}\left(\left| \|BX\|_2^2 - \|B\|_F^2 \right| \geq u\right) \leq 2 \exp\left(-\frac{C}{K^4} \min\left\{\left(\frac{u^2}{\|B\|^2 \|B\|_F^2}\right), \left(\frac{u}{\|B\|^2}\right)\right\}\right).$$

Setting $u = \varepsilon \|B\|_F^2$ with $\varepsilon \geq 0$, we obtain

$$\mathbb{P}\left(\left| \|BX\|_2^2 - \|B\|_F^2 \right| \geq \varepsilon \|B\|_F^2\right) \leq 2 \exp\left(-C \min\{\varepsilon^2, \varepsilon\} \frac{\|B\|_F^2}{K^4 \|B\|^2}\right).$$

We now set $\delta^2 = \min\{\varepsilon^2, \varepsilon\}$, or, equivalently $\varepsilon = \max\{\delta, \delta^2\}$, and we recall our reasoning in the proof of Theorem 3.1, namely, that for $z \geq 0$, the bound $|z - 1| \geq \delta$ implies $|z^2 - 1| \geq \max\{\delta, \delta^2\}$.

$$\left| \|BX\|_2 - \|B\|_F \right| \geq \delta \|B\|_F \Rightarrow \left| \|BX\|_2^2 - \|B\|_F^2 \right| \geq \varepsilon \|B\|_F^2.$$

Thus

$$\mathbb{P}\left(\left|\|BX\|_2 - \|B\|_F\right| \geq \delta\|B\|_F\right) \leq 2 \exp\left(-C\delta^2 \frac{\|B\|_F^2}{K^4\|B\|^2}\right),$$

and setting $t = \delta\|B\|_F$, we obtain the tail-estimate

$$\mathbb{P}\left(\left|\|BX\|_2 - \|B\|_F\right| \geq t\right) \leq 2 \exp\left(-\frac{Ct^2}{K^4\|B\|^2}\right).$$

□

6.3 Symmetrisation

Definition 6.10 (symmetric random variables) A real-valued random variable X is called *symmetric* if X and $-X$ have the same distribution.

Exercise 6.11 Let X be a real-valued random variable independent of some symmetric Bernoulli random variable ε , i.e., $\mathbb{P}(\varepsilon = -1) = \mathbb{P}(\varepsilon = 1) = \frac{1}{2}$. Show the following statements.

- (a) εX and $\varepsilon|X|$ are symmetric random variables and εX and $\varepsilon|X|$ have the same distribution.
- (b) X symmetric \Rightarrow distribution of εX and $\varepsilon|X|$ equal the distribution of X .
- (c) Suppose X' is an independent copy of X , then $X - X'$ is a symmetric random variable.

Lemma 6.12 (Symmetrisation) Let X_1, \dots, X_N be independent mean-zero random vectors in a normed space $(E, \|\cdot\|)$ and let $\varepsilon_1, \dots, \varepsilon_N$ be independent symmetric Bernoulli random variables (that is, they are not only independent of each other but also of any $X_i, i = 1, \dots, N$). Show that

$$\frac{1}{2}\mathbb{E}\left[\left\|\sum_{i=1}^N \varepsilon_i X_i\right\|\right] \leq \mathbb{E}\left[\left\|\sum_{i=1}^N X_i\right\|\right] \leq 2\mathbb{E}\left[\left\|\sum_{i=1}^N \varepsilon_i X_i\right\|\right].$$

Proof.

Upper bound: Let (X'_i) be an independent copy of the random vector (X_i) . Since $\sum_{i=1}^N X'_i$ has zero mean,

$$p := \mathbb{E}\left[\left\|\sum_{i=1}^N X_i\right\|\right] \leq \mathbb{E}\left[\left\|\sum_{i=1}^N X_i - \sum_{i=1}^N X'_i\right\|\right] = \mathbb{E}\left[\left\|\sum_{i=1}^N (X_i - X'_i)\right\|\right],$$

where the inequality stems from an application of Lemma 6.2), namely, if $\mathbb{E}[Z] = 0$ then $\mathbb{E}[\|Y\|] \leq \mathbb{E}[\|Y + Z\|]$.

Since all $(X_i - X'_i)$ are symmetric random vectors, they have the same distribution as $\varepsilon_i(X_i - X'_i)$, see Exercise 6.11. Application of the triangle inequality and our assumptions conclude the upper bound

$$p \leq \mathbb{E} \left[\left\| \sum_{i=1}^N \varepsilon_i (X_i - X'_i) \right\| \right] \leq \mathbb{E} \left[\left\| \sum_{i=1}^N \varepsilon_i X_i \right\| \right] + \mathbb{E} \left[\left\| \sum_{i=1}^N \varepsilon_i X'_i \right\| \right] = 2\mathbb{E} \left[\left\| \sum_{i=1}^N \varepsilon_i X_i \right\| \right]$$

Lower bound: By conditioning on ε_i and the triangle inequality,

$$\begin{aligned} \mathbb{E} \left[\left\| \sum_{i=1}^N \varepsilon_i X_i \right\| \right] &\leq \mathbb{E} \left[\left\| \sum_{i=1}^N \varepsilon_i (X_i - X'_i) \right\| \right] = \mathbb{E} \left[\left\| \sum_{i=1}^N (X_i - X'_i) \right\| \right] \\ &\leq \mathbb{E} \left[\left\| \sum_{i=1}^N X_i \right\| \right] + \mathbb{E} \left[\left\| \sum_{i=1}^N X'_i \right\| \right] = 2\mathbb{E} \left[\left\| \sum_{i=1}^N X_i \right\| \right]. \end{aligned}$$

□

7 Random Processes

Definition 7.1 A *random process* is a collection of random variables $X := (X_t)_{t \in T}$ of random variables X_t defined on the same probability space, which are indexed by the elements t of some set T .

Example 7.2 (a) $T = \{1, \dots, n\}$, then $X = (X_1, \dots, X_n) \in \mathbb{R}^n$ random vector.

(b) $T = \mathbb{N}$, then $X = (X_n)_{n \in \mathbb{N}}$ with

$$X_n = \sum_{i=1}^n Z_i, \quad Z_i \text{ independent identically distributed,}$$

is the discrete time random walk.

(c) When the dimension of the index set is greater than one, e.g., $T \subset \mathbb{R}^n$ or $T \subset \mathbb{Z}^n$, we often call the process a *random field* $(X_t)_{t \in T}$.

♣

Definition 7.3 Let $(X_t)_{t \in T}$ be a random process with $\mathbb{E}[X_t] = 0$ for all $t \in T$. The *covariance function* of the process is defined as

$$\Sigma(t, s) := \text{cov}(X_t, X_s), \quad t, s \in T.$$

The *increments* of the process are defined as

$$d(t, s) := \|X_t - X_s\|_{L^2} = (\mathbb{E}[(X_t - X_s)^2])^{1/2}, \quad t, s \in T.$$

Definition 7.4 (Gaussian process) (a) A random process $(X_t)_{t \in T}$ is called a *Gaussian process* if, for any finite subset $T_0 \subset T$, the random vector $(X_t)_{t \in T_0}$ has normal distribution. Equivalently, $(X_t)_{t \in T}$ is called a *Gaussian process* if every finite linear combination

$$\sum_{t \in T_0} a_t X_t, \quad a_t \in \mathbb{R},$$

is a normally distributed random variable.

(b) Suppose $T \subset \mathbb{R}^n$ and let $Y \sim N(0, \mathbb{1}_n)$, and define

$$X_t := \langle Y, t \rangle, \quad t \in T \subset \mathbb{R}^n.$$

We call the random process $(X_t)_{t \in T}$ the *canonical Gaussian process in \mathbb{R}^n* .

To compute the increments of a canonical Gaussian process, recall that $\langle Y, t \rangle \sim N(0, \|t\|_2^2)$ for any $t \in \mathbb{R}^n$. Then one show that (easy exercise) the increments are

$$d(t, s) = \|X_t - X_s\|_{L^2} = \|t - s\|_2 \quad t, s \in \mathbb{R}^n,$$

where $\|\cdot\|_2$ denotes the Euclidean norm in \mathbb{R}^n .

Lemma 7.5 *Let $X \in \mathbb{R}^n$ be a mean-zero Gaussian random vector. Then there exist points $t_1, \dots, t_n \in \mathbb{R}^n$ such that*

$$X := (\langle Y, t_i \rangle)_{i=1, \dots, n} \in \mathbb{R}^n, \quad \text{with } Y \sim N(0, \mathbb{1}_n).$$

Proof. Left as an exercise to the reader. □

Theorem 7.6 (Slepian's inequality) *Let $(X_t)_{t \in T}$ and $(Y_t)_{t \in T}$ be two mean-zero Gaussian processes. Assume that, for all $t, s \in T$, we have*

$$(i) \mathbb{E}[X_t^2] = \mathbb{E}[Y_t^2] \quad (ii) \mathbb{E}[(X_t - X_s)^2] \leq \mathbb{E}[(Y_t - Y_s)^2]. \quad (7.1)$$

Then, for every $\tau \in \mathbb{R}$, we have

$$\mathbb{P}\left(\sup_{t \in T} \{X_t\} \geq \tau\right) \leq \mathbb{P}\left(\sup_{t \in T} \{Y_t\} \geq \tau\right), \quad (7.2)$$

and, consequently,

$$\mathbb{E}\left[\sup_{t \in T} \{X_t\}\right] \leq \mathbb{E}\left[\sup_{t \in T} \{Y_t\}\right].$$

Whenever (7.2) holds, we say that the process $(X_t)_{t \in T}$ is *stochastically dominated* by the process $(Y_t)_{t \in T}$. The proof of Theorem 7.6 follows combining the two versions of Slepian's inequality which we will discuss below. To prepare these statements we introduce the method of *Gaussian interpolation* first.

Suppose T is finite, e.g., $|T| = n$. Let $X = (X_t)_{t \in T}$ and $Y = (Y_t)_{t \in T}$ be two Gaussian random vectors (without loss of generality we may assume that they X and Y are independent). We define the Gaussian interpolation as

$$Z(u) := \sqrt{u}X + \sqrt{1-u}Y \quad u \in [0, 1]. \quad (7.3)$$

It is easy to see (following exercise) that the covariance matrix of the interpolation interpolates linearly between the covariance matrices of X and Y .

Exercise 7.7 Show that

$$\Sigma(Z(u)) = u\Sigma(X) + (1 - u)\Sigma(Y) \quad t \in [0, 1].$$



For a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$, we shall study how the expectation $\mathbb{E}[f(Z(u))]$ varies with $u \in [0, 1]$. Suppose, for example, that $f(x) := \mathbb{1}\{\max_{1 \leq i \leq n} \{x_i\} \leq u\}$. Then one can easily show that $\mathbb{E}[f(Z(u))]$ increases with u leading to

$$\mathbb{E}[f(Z(1))] \geq \mathbb{E}[f(Z(0))],$$

and henceforth

$$\mathbb{P}(\max_{1 \leq i \leq n} \{X_i\} < \tau) \geq \mathbb{P}(\max_{1 \leq i \leq n} \{Y_i\} < \tau).$$

The following three lemmas collect basic facts about Gaussian random variables and their proofs will be left as an exercise (homework).

Lemma 7.8 (Gaussian integration by parts) Suppose $X \sim \mathcal{N}(0, 1)$. Then, for any differentiable function $f: \mathbb{R} \rightarrow \mathbb{R}$,

$$\mathbb{E}[f'(X)] = \mathbb{E}[Xf(X)].$$

Proof. Exercise for the reader. Solution see Lemma 7.2.3 in [Ver18]. □

Similarly, $X \sim \mathcal{N}(0, \sigma^2)$, $\sigma > 0$ implies $\mathbb{E}[Xf(X)] = \sigma^2 \mathbb{E}[f'(X)]$.

Lemma 7.9 (Gaussian integration by parts) Suppose $X \sim \mathcal{N}(0, \Sigma)$, $X \in \mathbb{R}^n$, Σ an $n \times n$ symmetric positive semi-definite matrix. Then, for any differentiable function $f: \mathbb{R}^n \rightarrow \mathbb{R}$,

$$\mathbb{E}[Xf(X)] = \Sigma \mathbb{E}[\nabla f(X)].$$

Proof. Exercise for the reader (homework Sheet 4). □

Lemma 7.10 (Gaussian interpolation) Consider two independent Gaussian random vectors $X \sim \mathcal{N}(0, \Sigma^X)$ and $Y \sim \mathcal{N}(0, \Sigma^Y)$ in \mathbb{R}^n . Define the interpolation Gaussian random vector as

$$Z(u) := \sqrt{u}X + \sqrt{1-u}Y, \quad u \in [0, 1]. \quad (7.4)$$

Then for any twice-differentiable function $f: \mathbb{R}^n \rightarrow \mathbb{R}$, we have

$$\frac{d}{du} \mathbb{E}[f(Z(u))] = \frac{1}{2} \sum_{i,j=1}^n (\Sigma_{ij}^X - \Sigma_{ij}^Y) \mathbb{E} \left[\frac{\partial^2 f}{\partial x_i \partial x_j} (Z(u)) \right]. \quad (7.5)$$

Proof. Exercise for the reader (homework Sheet 4). Solution see Lemma 7.2.7 in [Ver18]. □

We now prove a first version of Slepian's inequality (Theorem 7.6).

Lemma 7.11 (Slepian's inequality, functional form) *Let $X, Y \in \mathbb{R}^n$ be two mean-zero Gaussian random vectors. Assume that for all $i, j = 1, \dots, n$,*

$$(i) \mathbb{E}[X_i^2] = \mathbb{E}[Y_i^2], \quad (ii) \mathbb{E}[(X_i - X_j)^2] \leq \mathbb{E}[(Y_i - Y_j)^2], \quad (7.6)$$

and let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be twice-differentiable such that

$$\frac{\partial^2 f}{\partial x_i \partial x_j}(x) \geq 0 \quad \text{for all } i \neq j.$$

Then

$$\mathbb{E}[f(X)] \geq \mathbb{E}[f(Y)].$$

Proof. We have, using $\Sigma_{ii}^X = \Sigma_{ii}^Y$ and $\Sigma_{ij}^X \geq \Sigma_{ij}^Y$,

$$\mathbb{E}[(X_i - X_j)^2] \leq \mathbb{E}[Y_i^2 - 2Y_i Y_j + Y_j^2].$$

We assume without loss of generality that X and Y are independent. The Lemma 7.10 shows that

$$\frac{d}{du} \mathbb{E}[f(Z(u))] \geq 0,$$

and hence that $\mathbb{E}[f(Z(u))]$ increases in u . Thus $\mathbb{E}[f(Z(1))] = \mathbb{E}[f(X)] \geq \mathbb{E}[f(Y)] = \mathbb{E}[f(Z(0))]$. \square

We can now prove Theorem 7.6 with the following results for Gaussian vectors.

Theorem 7.12 *Let X and Y be two mean-zero Gaussian random vectors in \mathbb{R}^n as in Lemma 7.11. Then, for every $\tau \in \mathbb{R}$, we have*

$$\mathbb{P}\left(\max_{1 \leq i \leq n} \{X_i\} \geq \tau\right) \leq \mathbb{P}\left(\max_{1 \leq i \leq n} \{Y_i\} \geq \tau\right).$$

Consequently,

$$\mathbb{E}\left[\max_{1 \leq i \leq n} \{X_i\}\right] \leq \mathbb{E}\left[\max_{1 \leq i \leq n} \{Y_i\}\right].$$

Proof. The key idea is to use Lemma 7.11 for some appropriate approximation of the maximum. For that to work, let $h: \mathbb{R} \rightarrow [0, 1]$ be a twice-differentiable approximation of the indicator function of the interval $(-\infty, \tau)$, that is, $h(t) \approx \mathbb{1}_{(-\infty, \tau)}(t)$, $t \in \mathbb{R}$. Define $f(x) := h(x_1) \cdots h(x_n)$ for $x = (x_1, \dots, x_n) \in \mathbb{R}^n$. The second partial derivatives

$$\frac{\partial^2 f}{\partial x_i \partial x_j}(x) = h'(x_i)h'(x_j) \prod_{k \neq i, j} h(x_k)$$

are positive. It follows that $\mathbb{E}[f(X)] \geq \mathbb{E}[f(Y)]$. Thus, by the above approximations, according to Lemma 7.11,

$$\mathbb{P}\left(\max_{1 \leq i \leq n} \{X_i\} < \tau\right) \geq \mathbb{P}\left(\max_{1 \leq i \leq n} \{Y_i\} < \tau\right),$$

and thus

$$\mathbb{E}\left[\max_{1 \leq i \leq n} \{X_i\}\right] \leq \mathbb{E}\left[\max_{1 \leq i \leq n} \{Y_i\}\right],$$

and the statement. \square

The following theorem improves Slepian's inequality by using a different approximation in the proof.

Theorem 7.13 (Sudakov-Fernique inequality) Let $(X_t)_{t \in T}$ and $(Y_t)_{t \in T}$ be two random processes. Assume that, for all $t, s \in T$, we have

$$(i) \quad \mathbb{E}[(X_t - X_s)^2] \leq \mathbb{E}[(Y_t - Y_s)^2].$$

Then

$$\mathbb{E}[\sup_{t \in T} \{X_t\}] \leq \mathbb{E}[\sup_{t \in T} \{Y_t\}].$$

Proof. We shall prove the statement for Gaussian random vectors $X, Y \in \mathbb{R}^n$ with the help of Theorem 7.12. The idea is that this time we use an approximation of the maximum itself and not for the indicator function. For $\beta > 0$, define

$$f(x) := \frac{1}{\beta} \log \sum_{i=1}^n e^{\beta x_i} \quad x \in \mathbb{R}^n.$$

One can easily show that

$$f(x) \xrightarrow{\beta \rightarrow \infty} \max_{1 \leq i \leq n} \{x_i\}.$$

Inserting the function into the Gaussian interpolation formula (7.5) we can obtain that

$$\frac{d}{du} \mathbb{E}[f(Z(u))] \leq 0,$$

and conclude with our statement. □

We now combine feature of the index space with the random process.

Definition 7.14 (Canonical metric) Suppose $X = (X_t)_{t \in T}$ is a random process with index set T . We define the *canonical metric of the process* by

$$d(t, s) := \|X_t - X_s\|_{L^2} = \left(\mathbb{E} \left[\left(X_t - X_s \right)^2 \right] \right)^{1/2} \quad t, s \in T.$$

We can now study the question if we can evaluate the expectation $\mathbb{E}[\sup_{t \in T} \{X_t\}]$ by using properties of the geometry, in particular using covering numbers of the index metric space (T, d) of a given random process. Via this approach we obtain a lower bound of the expectation of the supremum.

Theorem 7.15 (Sudakov's minorisation inequality) Let $X = (X_t)_{t \in T}$ be a mean-zero Gaussian process. Then, for any $\varepsilon \geq 0$, we have

$$\mathbb{E}[\sup_{t \in T} \{X_t\}] \geq C\varepsilon \sqrt{\log \mathcal{N}(T, d, \varepsilon)},$$

where d is the canonical metric of the process, $C > 0$ an absolute constant and $\mathcal{N}(T, d, \varepsilon)$ the covering number for T (recall Definition 4.1).

Proof. Assume that $\mathcal{N}(T, d, \varepsilon) = N < \infty$ is finite. When T is not compact, one can show that the expectation of the supremum is infinite (we skip this step). Let \mathcal{M} be a maximal ε -separated subset of T . Then \mathcal{M} is an ε -net according to Lemma 4.2, and thus $|\mathcal{M}| \geq N$. It suffices to show

$$\mathbb{E}[\sup_{t \in \mathcal{M}} \{X_t\}] \geq C\varepsilon\sqrt{\log N}. \quad (7.7)$$

To show (7.7), we compare the process $(X_t)_{t \in \mathcal{M}}$ with a simpler process $(Y_t)_{t \in \mathcal{M}}$.

$$Y_t := \frac{\varepsilon}{\sqrt{2}}G_t, \quad G_t \sim \mathbf{N}(0, 1), \quad G_t \text{ independent of } G_s \text{ for all } t \neq s.$$

For $t, s \in \mathcal{M}$ fixed we have

$$\mathbb{E}[(X_t - X_s)^2] = d(t, s)^2 \geq \varepsilon^2,$$

while

$$\mathbb{E}[(Y_t - Y_s)^2] = \frac{\varepsilon^2}{2}\mathbb{E}[(G_t - G_s)^2] = \varepsilon^2.$$

Thus

$$\mathbb{E}[(X_t - X_s)^2] \geq \mathbb{E}[(Y_t - Y_s)^2] \quad \text{for all } t, s \in \mathcal{M}.$$

We now obtain with Theorem 7.13,

$$\mathbb{E}[\sup_{t \in \mathcal{M}} \{X_t\}] \geq \mathbb{E}[\sup_{t \in \mathcal{M}} \{Y_t\}] = \frac{\varepsilon}{\sqrt{2}}\mathbb{E}[\max_{i \in \mathcal{M}} \{G_i\}] \geq C\varepsilon\sqrt{\log N},$$

where we used Proposition 7.16 below. □

Proposition 7.16 *Let $Y_i \sim \mathbf{N}(0, 1)$, $i = 1, \dots, N$, be independent normally distributed real-valued random variables. Then the following holds.*

(a)

$$\mathbb{E}\left[\max_{1 \leq i \leq N} \{Y_i\}\right] \leq \sqrt{2 \log N}.$$

(b)

$$\mathbb{E}\left[\max_{1 \leq i \leq N} \{|Y_i|\}\right] \leq \sqrt{2 \log(2N)}.$$

(c)

$$\mathbb{E}\left[\max_{1 \leq i \leq N} \{Y_i\}\right] \geq C\sqrt{2 \log N} \quad \text{for some absolute constant } C > 0.$$

Proof. (a) Let $\beta > 0$. Using Jensen's inequality, we obtain

$$\begin{aligned} \mathbb{E}[\max_{1 \leq i \leq n} Y_i] &= \frac{1}{\beta} \mathbb{E}[\log e^{\beta \max_{1 \leq i \leq n} \{Y_i\}}] \leq \frac{1}{\beta} \mathbb{E}[\log \sum_{i=1}^N e^{\beta Y_i}] \leq \frac{1}{\beta} \log \sum_{i=1}^N \mathbb{E}[e^{\beta Y_i}] \\ &= \frac{1}{\beta} \log \left(N e^{\beta^2/2} \right) = \frac{\beta}{2} + \frac{\log N}{\beta}. \end{aligned}$$

The claim is proved by taking $\beta = \sqrt{2 \log N}$.

(b) We repeat the steps in (a),

$$\mathbb{E}[\max_{1 \leq i \leq n} |Y_i|] = \dots \leq \frac{1}{\beta} \sum_{i=1}^N \mathbb{E}[e^{\beta Y_i} + e^{-\beta Y_i}] = \frac{\beta}{2} + \frac{\log(2N)}{\beta}.$$

Taking $\beta = \sqrt{2 \log(2N)}$, we conclude with the statement.

(c) The lower bound is slightly more involved and needs some preparation:

(i) The Y_i 's are symmetric (Gaussian), and hence, by symmetry,

$$\mathbb{E}[\max_{1 \leq i, j \leq N} \{|Y_i - Y_j|\}] = \mathbb{E}[\max_{1 \leq i, j \leq N} \{(Y_i - Y_j)\}] = 2\mathbb{E}[\max_{1 \leq i \leq N} \{Y_i\}].$$

(ii) For every $k \in \{1, \dots, N\}$, using (i),

$$\begin{aligned} \mathbb{E}[\max_{1 \leq i \leq N} \{Y_i\}] &\leq \mathbb{E}[\max_{1 \leq i \leq N} \{|Y_i|\}] \leq \mathbb{E}[|Y_k|] + \mathbb{E}[\max_{1 \leq i, j \leq N} \{|Y_i - Y_j|\}] \\ &= \mathbb{E}[|Y_k|] + 2\mathbb{E}[\max_{1 \leq i \leq N} \{Y_i\}]. \end{aligned}$$

To obtain an lower bound we exploit the fact that our Gaussian random variables Y_i are independent and identically distributed. Then, for every $\delta > 0$,

$$\mathbb{E}[\max_{1 \leq i \leq N} \{|Y_i|\}] \geq \int_0^\delta [1 - (1 - \mathbb{P}(|Y_1| > t))^N] dt \geq \delta[1 - (1 - \mathbb{P}(|Y_1| > \delta))^N].$$

Now, we obtain with the lower tail bound of the normal distribution (see Proposition 2.1),

$$\mathbb{P}(|Y_1| > \delta) = \sqrt{\frac{2}{\pi}} \int_\delta^\infty \exp(-t^2/2) dt \geq \sqrt{\frac{2}{\pi}} \exp(-(\delta+1)^2/2).$$

Now we choose $\delta = \sqrt{\log N}$ with N large enough so that

$$\mathbb{P}(|Y_1| > \delta) \geq \frac{1}{N},$$

and hence

$$\mathbb{E}[\max_{1 \leq i \leq N} \{Y_i\}] \geq \delta[1 - (1 - \frac{1}{N})^N] \geq \delta(1 - \frac{1}{e}).$$

We conclude with statement (c) using

$$\mathbb{E}[\max_{1 \leq i \leq N} \{|Y_i|\}] \leq \mathbb{E}[|Y_1|] + 2\mathbb{E}[\max_{1 \leq i \leq N} \{Y_i\}].$$

□

Definition 7.17 The *Gaussian width* of a subset $T \subset \mathbb{R}^n$ is defined

$$W(T) := \mathbb{E} \left[\sup_{x \in T} \langle Y, x \rangle \right] \quad \text{with } Y \sim \mathbf{N}(0, \mathbb{I}_n).$$

Exercise 7.18 Suppose $X_i, i = 1, \dots, N$, are sub-Gaussian random variables, and $K = \max_{1 \leq i \leq N} \|X_i\|_{\psi_2}$. Show that, for any $N \geq 2$,

$$\mathbb{E}[\max_{1 \leq i \leq N} \{|X_i|\}] \leq CK\sqrt{\log N}.$$



We summarise a few simple properties of the Gaussian width. We skip the proof as it involves mostly elementary properties of the norm and the Minkowski sum.

Proposition 7.19 (Properties of Gaussian width) (a) $W(T)$ is finite $\Leftrightarrow T$ is bounded.

(b) $W(T + S) = W(T) + W(S)$ $S, T \subset \mathbb{R}^n$.

(c)

$$\frac{1}{\sqrt{2\pi}} \text{diam}(T) \leq W(T) \leq \frac{\sqrt{n}}{2} \text{diam}(T).$$

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