

# High-Dimensional Probability

Lectured by [Hao Ge](#)

L<sup>A</sup>T<sub>E</sub>Xed by [Chengxin Gong](#)

December 8, 2023

## Contents

<a href="#">0</a>	<a href="#">Appetizer</a>	<a href="#">2</a>
<a href="#">1</a>	<a href="#">Preliminaries on random variables</a>	<a href="#">2</a>
<a href="#">2</a>	<a href="#">Concentration of sums of independent random variables</a>	<a href="#">2</a>
<a href="#">3</a>	<a href="#">Random vectors in high dimensions</a>	<a href="#">4</a>
<a href="#">4</a>	<a href="#">Random matrices</a>	<a href="#">5</a>
<a href="#">5</a>	<a href="#">Concentration without independence</a>	<a href="#">7</a>
<a href="#">6</a>	<a href="#">Quadratic forms, symmetrization, contraction</a>	<a href="#">9</a>
<a href="#">7</a>	<a href="#">Random processes</a>	<a href="#">10</a>
<a href="#">8</a>	<a href="#">Chaining</a>	<a href="#">11</a>

[Reference](#) [High-Dimensional Probability: An Introduction with Applications in Data Science \(Roman Vershynin\)](#)

## 0 Appetizer

- Convex combination: For  $z_1, z_2, \dots, z_m \in \mathbb{R}^n$ , the form of  $\sum_{i=1}^m \lambda_i z_i$  with  $\lambda_i \geq 0, \sum_{i=1}^m \lambda_i = 1$ . Convex hull of  $T \subset \mathbb{R}^n$ :  $\text{conv}(T) = \{\text{convex combinations of } z_1, \dots, z_m \in T, m \in \mathbb{N}\}$ .
- Caratheodory's theorem: Every point in the convex hull of a set  $T \subset \mathbb{R}^n$  can be expressed as a convex combination of at most  $n + 1$  points from  $T$ .
- Approximate Caratheodory's theorem: Consider  $T \subset \mathbb{R}^n$ ,  $\text{diam}(T) = \sup\{\|s - t\|_2, s, t \in T\} < 1$ . Then for any  $x \in \text{conv}(T)$  and any  $k$ , one can find points  $x_1, x_2, \dots, x_k \in T$  such that  $\|x - \frac{1}{k} \sum_{i=1}^k x_i\|_2 \leq \frac{1}{\sqrt{k}}$  (repetition is allowed).

*Proof* WLOG assume  $\|t\|_2 \leq 1, \forall t \in T$ . Fix  $x \in \text{conv}(T), x = \sum_{i=1}^m \lambda_i z_i, z_i \in T$ . Define  $Z, \mathbb{P}(Z = z_i) = \lambda_i, \mathbb{E}Z = x$ . Consider i.i.d.  $Z_1, Z_2, \dots$  of  $Z, \frac{1}{n} \sum_{j=1}^n Z_j \rightarrow x$  a.s.  $n \rightarrow +\infty$ .  $\mathbb{E}\|x - \frac{1}{k} \sum_{j=1}^k Z_j\|_2^2 = \frac{1}{k^2} \sum_{j=1}^k \mathbb{E}\|Z_j - x\|_2^2 = \frac{1}{k^2} \sum_{j=1}^k (\mathbb{E}\|Z_j\|_2^2 - \|\mathbb{E}Z_j\|_2^2) \leq \frac{1}{k} \Rightarrow \exists$  a realization of  $Z_1, \dots, Z_k$  such that  $\|x - \frac{1}{k} \sum_{j=1}^k Z_j\|_2 \leq \frac{1}{\sqrt{k}}$ .  $\square$

- Corollary (Covering polytopes by balls):  $P$  is a polytope in  $\mathbb{R}^n$  with  $N$  vertices,  $\text{diam}(P) \leq 1$ . Then  $P$  can be covered by at most  $N^{\lceil 1/\epsilon^2 \rceil}$  Euclidean balls of radii  $\epsilon > 0$ .

## 1 Preliminaries on random variables

- Jensen's inequality: convex  $\phi, \phi(\mathbb{E}X) \leq \mathbb{E}\phi(X). \Rightarrow \|X\|_{L^p} \leq \|X\|_{L^q}$  for  $p \leq q$ .
- Minkowski inequality:  $p \geq 1, \|X + Y\|_{L^p} \leq \|X\|_{L^p} + \|Y\|_{L^p}$ .
- Cauchy-Schwarz inequality:  $\mathbb{E}|XY| \leq \|X\|_{L^2} \|Y\|_{L^2}$ .
- Holder inequality:  $p, q \in (1, +\infty), \frac{1}{p} + \frac{1}{q} = 1$  or  $p = 1, q = \infty, \mathbb{E}\|XY\| \leq \|X\|_{L^p} \|Y\|_{L^q}$ .
- $X \geq 0$ , then  $\mathbb{E}X = \int_0^{+\infty} \mathbb{P}(X > t) dt$ .
- Markov inequality:  $X \geq 0, t > 0, \mathbb{P}(X \geq t) \leq \frac{\mathbb{E}X}{t}$ .
- LLN:  $X_1, \dots, X_n, \dots$  i.i.d.,  $\mathbb{E}X_i = \mu, \text{Var}(X_i) = \sigma^2, S_N = X_1 + X_2 + \dots + X_N$ . Then: (WLLN)  $\mathbb{P}(|\frac{S_N}{N} - \mu| > \epsilon) \rightarrow 0, \forall \epsilon > 0$ ; (SLLN)  $\mathbb{P}(\frac{S_N}{N} \rightarrow \mu, N \rightarrow +\infty) = 1$ .
- CLT:  $Z_N = \frac{S_N - \mathbb{E}S_N}{\sqrt{\text{Var}(S_N)}} \xrightarrow{d} \mathcal{N}(0, 1)$ .
- $X_{N,i}, 1 \leq i \leq N$  independent  $\text{Ber}(p_{N,i}), \max_{i \leq N} p_{N,i} \rightarrow 0, S_N = \sum_{i=1}^N X_{N,i}, \mathbb{E}S_N \rightarrow \lambda < +\infty$ . Then  $S_N \xrightarrow{d} \text{Poisson}(\lambda)$ .

## 2 Concentration of sums of independent random variables

- Question:  $N$  times,  $\mathbb{P}(\text{head} \geq \frac{3}{4}N) = ?$  Let  $S_N$  be the number of heads,  $\mathbb{E}S_N = \frac{N}{2}, \text{Var}(S_N) = \frac{N}{4}$ . (1) Chebyshev's inequality:  $\mathbb{P}(S_N \geq \frac{3}{4}N) \leq \mathbb{P}(|S_N - \frac{N}{2}| \geq \frac{N}{4}) \leq \frac{4}{N}$ ; (2)  $Z_N = \frac{S_N - \frac{N}{2}}{\sqrt{N/4}}$ , expect:  $\mathbb{P}(Z_N \geq \sqrt{N/4}) \approx \mathbb{P}(g \geq \sqrt{N/4}) \leq \frac{1}{\sqrt{2\pi}} e^{-N/8}$  where  $g \sim \mathcal{N}(0, 1)$ .
- For all  $t > 0, (\frac{1}{t} - \frac{1}{t^3}) \frac{1}{\sqrt{2\pi}} e^{-t^2/2} \leq \mathbb{P}(g \sim \mathcal{N}(0, 1) \geq t) \leq \frac{1}{t} \frac{1}{\sqrt{2\pi}} e^{-t^2/2}$ .
- Berry-Esseen bound:  $|\mathbb{P}(Z_N \geq t) - \mathbb{P}(g \geq t)| \leq \frac{\rho}{\sqrt{N}}$  where  $\rho = \mathbb{E}|X_1 - \mu|^3 / \sigma^3$ . And in general, no improvement since  $\mathbb{P}(S_N = \frac{N}{2}) \sim \frac{1}{\sqrt{N}} \Rightarrow \mathbb{P}(Z_N = 0) \sim \frac{1}{\sqrt{N}}$  but  $\mathbb{P}(g = 0) = 0$ .
- Hoeffding's inequality:  $X_1, \dots, X_N$  i.i.d. symmetric Bernoulli ( $\mathbb{P}(X = 1) = \mathbb{P}(X = -1) = \frac{1}{2}$ ),  $a = (a_1, \dots, a_N) \in \mathbb{R}^N$ . Then  $\forall t \geq 0, \mathbb{P}(\sum_{i=1}^N a_i X_i \geq t) \leq e^{-t^2/2\|a\|_2^2}, \mathbb{P}(|\sum_{i=1}^N a_i X_i| \geq t) \leq 2e^{-t^2/2\|a\|_2^2}$ .

*Proof* WLOG,  $\|a\|_2^2 = 1$ . For  $\lambda > 0, \mathbb{P}(\sum_{i=1}^N a_i X_i \geq t) = \mathbb{P}(e^{\lambda \sum_{i=1}^N a_i X_i} \geq e^{\lambda t}) \leq e^{-\lambda t} \mathbb{E}e^{\lambda \sum_{i=1}^N a_i X_i} = e^{-\lambda t} \prod_{i=1}^N \mathbb{E}e^{\lambda a_i X_i} = e^{-\lambda t} \prod_{i=1}^N \cosh(\lambda a_i) \leq e^{-\lambda t} \prod_{i=1}^N e^{\lambda^2 a_i^2 / 2} = e^{-\lambda t + \frac{\lambda^2}{2}} \Rightarrow \mathbb{P}(\sum_{i=1}^N a_i X_i \geq t) \leq \inf_{\lambda \geq 0} e^{-\lambda t + \frac{\lambda^2}{2}} = e^{-\frac{t^2}{2}} (\lambda = t). \quad \square$

- Bounded r.v.s:  $X_1, \dots, X_N$  independent,  $X_i \in [m_i, M_i]$ . Then  $\forall t \geq 0, \mathbb{P}(\sum_{i=1}^N (X_i - \mathbb{E}X_i) \geq t) \leq e^{-\frac{2t^2}{\sum_{i=1}^N (M_i - m_i)^2}}$ .
- Chernoff's inequality:  $X_i \sim \text{Ber}(p_i)$  independent,  $S_N = \sum_{i=1}^N X_i, \mu = \mathbb{E}S_N \Rightarrow \forall t > \mu, \mathbb{P}(S_N \geq t) \leq e^{-\mu(\frac{t}{\mu})^t}$ .  
*Proof*  $\mathbb{P}(S_N \geq t) \leq e^{-\lambda t} \prod_{i=1}^N \mathbb{E}e^{\lambda X_i}$ .  $\mathbb{E}e^{\lambda X_i} = e^{\lambda p_i} + (1 - p_i) = 1 + (e^\lambda - 1)p_i \leq e^{(e^\lambda - 1)p_i} \Rightarrow \mathbb{P}(S_N \geq t) \leq e^{-\lambda t} e^{(e^\lambda - 1)\mu}$ . Take  $\lambda^* = \log(t/\mu)$ .  $\square$
- $d = (n - 1)p$  is the expected degree. There is an absolute constant  $C$  s.t. for  $G(n, p)$ ,  $d \geq C \log n$ . Then with high prob (for example 0.9), all vertices of  $G$  have degrees between  $0.9d$  and  $1.1d$ .  
*Proof* Ex 2.3.5  $\Rightarrow \mathbb{P}(|d_i - d| \geq \delta d) \leq 2e^{-c\delta^2 d}$ . Union bound:  $\mathbb{P}(\exists i, |d_i - d| \geq \delta d) \leq n \cdot 2e^{-c\delta^2 d} \leq n \cdot 2 \dots n^{-C\delta^2} = 2n^{1-C\delta^2} \leq 1 - p^*$  (let  $C\delta^2 > 1$ ).  $\square$
- Sub-gaussian properties: The following are equivalent: (i)  $\mathbb{P}(|X| \geq t) \leq 2e^{-t^2/k_1^2}$  for all  $t \geq 0$ ; (ii)  $\|X\|_{L^p} = (\mathbb{E}|X|^p)^{1/p} \leq k_2\sqrt{p}$  for all  $p \geq 1$ ; (iii)  $\mathbb{E}e^{\lambda^2 X^2} \leq e^{k_3^2 \lambda^2}$  for all  $\lambda$  s.t.  $|\lambda| \leq \frac{1}{k_3}$ ; (iv)  $\mathbb{E}e^{X^2/k_4^2} \leq 2$ ; (v)  $\mathbb{E}e^{\lambda X} \leq e^{k_5^2 \lambda^2}$ , for all  $\lambda \in \mathbb{R}$  (if  $\mathbb{E}X = 0$ ).  
*Proof* (i)  $\Rightarrow$  (ii): WLOG  $k_1 = 1$ .  $\mathbb{E}|X|^p = \int_0^{+\infty} \mathbb{P}(|X| \geq t) p t^{p-1} dt \leq \int_0^{+\infty} 2e^{-t^2} p t^{p-1} dt = p \Gamma(\frac{p}{2}) \leq \frac{\Gamma(x) \leq 3x^x \text{ for } x \geq \frac{1}{2}}{3p(\frac{p}{2})^{p/2}} \Rightarrow \|X\|_p \leq \frac{1}{\sqrt{2}}(3p)^{1/p} p^{1/2} \leq 3\sqrt{p}$ .  
(ii)  $\Rightarrow$  (iii): WLOG  $k_2 = 1$ .  $\mathbb{E}e^{\lambda^2 X^2} = \mathbb{E}[1 + \sum_{p=1}^{+\infty} \frac{(\lambda^2 X^2)^p}{p!}]$ .  $\mathbb{E}|X|^{2p} \leq (2p)^p, p! \geq (\frac{p}{e})^p \Rightarrow \mathbb{E}e^{\lambda^2 X^2} \leq 1 + \sum_{p=1}^{+\infty} \frac{(2\lambda^2 p)^p}{(\frac{p}{e})^p} = \frac{1}{1 - 2e\lambda^2}$  (if  $2e\lambda^2 < 1$ )  $\leq e^{4e\lambda^2}$  (if  $2e\lambda^2 \leq 1/2 \Leftrightarrow \lambda \leq \frac{1}{2\sqrt{e}}$ ).  
(iii)  $\Rightarrow$  (iv): trivial.  
(iv)  $\Rightarrow$  (i):  $\mathbb{P}(|X| \geq t) = \mathbb{P}(e^{X^2} \leq e^{t^2}) \leq e^{-t^2} \mathbb{E}e^{X^2} \leq 2e^{-t^2}$ .  
(iii)  $\Rightarrow$  (v): WLOG  $k_3 = 1$ . If  $|\lambda| \leq 1$ , then  $\mathbb{E}e^{\lambda X} \leq \mathbb{E}(\lambda X + e^{\lambda^2 X^2}) = \mathbb{E}e^{\lambda^2 X^2} \leq e^{\lambda^2}$ . If  $|\lambda| \geq 1$ , then  $\mathbb{E}e^{\lambda X} \leq e^{\frac{\lambda^2}{2}} \mathbb{E}e^{\frac{X^2}{2}} e^{\frac{\lambda^2}{2}} e^{\frac{1}{2}} \leq e^{\lambda^2}$ .  
(v)  $\Rightarrow$  (i): mimic the proof of (iv)  $\Rightarrow$  (i).  $\square$
- Sub-gaussian r.v.: satisfy the above sub-gaussian properties.  $\|X\|_{\psi_2} = \inf\{t > 0 : \mathbb{E}e^{X^2/t^2} \leq 2\}$ . Thus  $\mathbb{P}(|X| \geq t) \leq 2e^{-ct^2/\|X\|_{\psi_2}^2}$ ;  $\|X\|_{L^p} \leq C\|X\|_{\psi_2}\sqrt{p}$ ; if  $\mathbb{E}X = 0$  then  $\mathbb{E}e^{\lambda X} \leq e^{C\lambda^2\|X\|_{\psi_2}^2}$ .
- Let  $X_1, \dots, X_N$  be independent and mean zero sub-gaussian, then  $\|\sum_{i=1}^N X_i\|_{\psi_2}^2 \leq C \cdot \sum_{i=1}^N \|X_i\|_{\psi_2}^2$ .  
*Proof*  $\forall \lambda \in \mathbb{R}, \mathbb{E}e^{\lambda \sum_{i=1}^N X_i} = \prod_{i=1}^N \mathbb{E}e^{\lambda X_i} \leq \prod_{i=1}^N e^{c\lambda^2\|X_i\|_{\psi_2}^2} = e^{c\lambda^2 \sum_{i=1}^N \|X_i\|_{\psi_2}^2}$   $\square$
- Centering:  $X$  is sub-gaussian  $\Rightarrow X - \mathbb{E}X$  is sub-gaussian and  $\|X - \mathbb{E}X\|_{\psi_2} \leq C\|X\|_{\psi_2}$ .  
*Proof*  $\|\mathbb{E}X\|_{\psi_2} \leq C_1\|\mathbb{E}X\| \leq C_1\mathbb{E}|X| = C_1\|X\|_{L^1} \leq C_1C_2\|X\|_{\psi_2}$ .  $\square$
- Sub-exponential properties: The following are equivalent: (1)  $\mathbb{P}(|X| \geq t) \leq 2e^{-t/k_1}, \forall t \geq 0$ ; (2)  $\|X\|_{L^p} \leq k_2 p, p \geq 1$ ; (3)  $\mathbb{E}e^{\lambda|X|} \leq e^{k_3\lambda}$  for all  $0 \leq \lambda \leq \frac{1}{k_3}$ ; (4)  $\mathbb{E}e^{|X|/k_4} \leq 2$ ; (5) if  $\mathbb{E}X = 0, \mathbb{E}e^{\lambda X} \leq e^{k_5^2 \lambda^2}$  for  $|\lambda| \leq \frac{1}{k_5}$ .  
*Proof* (2)  $\Rightarrow$  (5):  $k_2 = 1, \mathbb{E}e^{\lambda X} = 1 + \sum_{p=2}^{+\infty} \frac{\lambda^p \mathbb{E}X^p}{p!} \leq 1 + \sum_{p=2}^{+\infty} \frac{\lambda^p p^p}{(p/e)^p} = 1 + \frac{(e\lambda)^2}{1 - e\lambda} (|e\lambda| < 1)$ . If  $|e\lambda| \leq \frac{1}{2}, 1 + \frac{(e\lambda)^2}{1 - e\lambda} \leq 1 + 2e^2\lambda^2 \leq e^{4e^2\lambda^2}$ , i.e.  $k_5 = 2e$ .  
(5)  $\Rightarrow$  (1):  $k_5 = 1, |x|^p \leq p^p(e^x + e^{-x}) \Rightarrow \mathbb{E}|X|^p \leq p^p(\mathbb{E}e^X + \mathbb{E}e^{-X}) \leq 2ep^p$ .  $\square$
- $\|X\|_{\psi_1} = \inf\{t > 0 : \mathbb{E}e^{|X|/t} \leq 2\}$ .  $X$  is sub-gaussian  $\Leftrightarrow X^2$  is sub-exponential.  $\|X^2\|_{\psi_1} = \|X\|_{\psi_2}^2$ .
- $X, Y$  are sub-gaussian  $\Rightarrow XY$  is sub-exponential and  $\|XY\|_{\psi_1} \leq \|X\|_{\psi_2}\|Y\|_{\psi_2}$ .  
*Proof* WLOG  $\|X\|_{\psi_2} = \|Y\|_{\psi_2} = 1$ .  $\mathbb{E}e^{XY} \leq \mathbb{E}e^{\frac{X^2+Y^2}{2}} = \mathbb{E}[e^{\frac{X^2}{2} + \frac{Y^2}{2}}] \leq \frac{1}{2}(\mathbb{E}e^{X^2} + \mathbb{E}e^{Y^2}) = 2$ .  $\square$
- Orlicz function/space:  $\psi : [0, +\infty) \rightarrow [0, +\infty)$ , convex, increasing,  $\psi(0) = 0, \psi(x) \rightarrow +\infty, x \rightarrow +\infty$ .  $\|X\|_\psi := \inf\{t > 0 : \mathbb{E}\psi(|X|/t) \leq 1\}$ .  $L_\psi := \{X : \|X\|_\psi < +\infty\}$  is Banach space. Examples: (1)  $L_p : \psi(x) = x^p, p \geq 1$ ; (2)  $L_{\psi_2} : \psi_2(x) = e^{x^2} - 1, L_\infty \subset L_{\psi_2} \subset L_p$ .
- Bernstein's inequality:  $X_1, \dots, X_N$  independent, mean zero and sub-exponential. Then for  $t \geq 0, \mathbb{P}(|\sum_{i=1}^N X_i| \geq t) \leq 2e^{-c \min(\frac{t^2}{\sum_{i=1}^N \|X_i\|_{\psi_1}^2}, \max_i \frac{t}{\|X_i\|_{\psi_1}})}$ .

*Proof*  $S = \sum_{i=1}^N X_i$ .  $\mathbb{P}(S \geq t) \leq e^{-\lambda t} \prod_{i=1}^N \mathbb{E} e^{\lambda X_i}$ .  $\mathbb{E} e^{\lambda X_i} \leq e^{c\lambda^2 \|X_i\|_{\psi_1}^2}$  if  $|\lambda| \leq \frac{c}{\max \|X_i\|_{\psi_1}}$ . Then  $\mathbb{P}(S \geq t) \leq e^{-\lambda t + c\lambda^2 \sigma^2}$  where  $\sigma^2 := \sum_{i=1}^N \|X_i\|_{\psi_1}^2$ . The following is to find the minimum of a quadratic function with the restriction  $|\lambda| \leq \frac{c}{\max \|X_i\|_{\psi_1}}$ .  $\square$

- Corollary 1:  $\mathbb{P}(|\sum_{i=1}^N a_i X_i| \geq t) \leq 2e^{-c \min(\frac{t^2}{K^2 \|a\|_2^2}, \frac{t}{K \|a\|_\infty})}$  where  $K = \max_i \|X_i\|_{\psi_1}$ .
- Corollary 2:  $|X_i| \leq K$ , then  $\mathbb{P}(|\sum_{i=1}^N X_i| \geq t) \leq 2 \exp(-\frac{t^2/2}{\sigma^2 + Kt/3})$  where  $\sigma^2 = \sum_{i=1}^N \mathbb{E} X_i^2$ .

### 3 Random vectors in high dimensions

- $X \in \mathbb{R}^n$ , independent sub-gaussian coordinate  $X_i$ ,  $\mathbb{E} X_i^2 = 1$ . Then  $\|X\|_2 - \sqrt{n} \leq CK^2$ ,  $K = \max_i \|X_i\|_{\psi_2}$ .  
*Proof*  $\mathbb{E} X_i^2 = 1 \Rightarrow K \geq 1$ .  $\|X_i^2 - 1\|_{\psi_1} \leq C\|X_i^2\|_{\psi_1} = C\|X_i\|_{\psi_2}^2 \leq CK^2$ . Bernstein's inequality:  $\mathbb{P}(|\frac{1}{n}\|X\|_2^2 - 1| \geq u) = \mathbb{P}(|\frac{1}{n}\sum_{i=1}^n (X_i^2 - 1)| \geq u) \leq 2e^{-cn \min(\frac{u^2}{K^4}, \frac{u}{K^2})} \leq 2e^{-\frac{cn}{K^4} \min(u^2, u)}$ . For any  $\delta > 0$ ,  $\mathbb{P}(|\frac{1}{\sqrt{n}}\|X\|_2 - 1| \geq \delta) \leq \mathbb{P}(|\frac{1}{n}\|X\|_2^2 - 1| \geq \max(\delta, \delta^2)) \leq 2e^{-\frac{cn}{K^4} \delta^2} \Rightarrow \mathbb{P}(|\|X\|_2 - \sqrt{n}| \geq t) \leq 2e^{-ct^2/K^4}$ .  $\square$
- Isotropy:  $\Sigma(X) = \mathbb{E} X X^T = I$ . If  $\Sigma \neq I_n$ , then let  $Z = \Sigma^{-1/2} X$ .  $X$  is isotropic  $\Leftrightarrow \mathbb{E} \langle X, x \rangle^2 = \|x\|_2^2$  for any  $x \in \mathbb{R}^n$ .  
*Proof*  $\mathbb{E} \langle X, x \rangle^2 = \mathbb{E}(x^T X X^T x) = x^T (\mathbb{E} X X^T) x$ .  $\|x\|_2^2 = x^T I_n x \Rightarrow \mathbb{E} X X^T = I_n$ .  $\square$
- $X$  is isotropic  $\Rightarrow \mathbb{E} \|X\|_2^2 = n$ . If  $X, Y$  are independent and isotropic  $\Rightarrow \mathbb{E} \langle X, Y \rangle^2 = n$ .  
*Proof*  $\mathbb{E} \|X\|_2^2 = \mathbb{E}(X^T X) = \mathbb{E}(\text{tr}(X^T X)) = \text{tr}(\mathbb{E} X X^T) = n$ .  
 $\mathbb{E} \langle X, Y \rangle^2 = \mathbb{E}(X^T Y Y^T X) = \mathbb{E}(\text{tr}(X^T Y Y^T X)) = \mathbb{E}(\text{tr}(X X^T Y Y^T)) = \text{tr}((\mathbb{E} X X^T)(\mathbb{E} Y Y^T)) = n$ .  $\square$
- Examples:  $X \sim U(\sqrt{n}\mathbb{S}^{n-1})$ ,  $X \sim U(\{-1, 1\}^n)$ ,  $X = (X_1, \dots, X_n)$  i.i.d.,  $\mathbb{E} X_i = 0$ ,  $\text{Var}(X_i) = 1$  are all isotropic.
- $g \sim \mathcal{N}(0, I_n)$ , then  $\mathbb{P}(|\|g\|_2 - \sqrt{n}| \geq t) \leq 2e^{-ct^2}$ .
- Frame:  $\{u_i\}_{i=1}^N \subset \mathbb{R}^n$ , Approximate Parseval's identity:  $A\|x\|_2^2 \leq \sum_{i=1}^N \langle u_i, x \rangle^2 \leq B\|x\|_2^2$ .  $A, B$ : frame bounds.  $A = B$ : tight frame ( $\Leftrightarrow \sum_{i=1}^N u_i u_i^T = A I_n$ ) and in this case,  $\sum_{i=1}^N \langle u_i, x \rangle u_i = Ax$ .
- (a) Tight frame  $\{u_i\}_{i=1}^N$ ,  $A = B$ ,  $X = \text{Unif}\{u_i, i = 1, 2, \dots, N\}$ , then  $(\frac{N}{A})^{1/2} X$  is isotropic. (b)  $X$  is isotropic,  $\mathbb{P}(X = x_i) = p_i, i = 1, 2, \dots, N$ . Then  $u_i = \sqrt{p_i} x_i$  form a tight frame with  $A = B = 1$ .
- Isotropic convex sets:  $X \sim \text{Unif}(K)$ ,  $K \subset \mathbb{R}^n$  convex, bounded, non-empty interior (convex body). Assume  $\mathbb{E} X = 0, \Sigma = \text{Cov}(X)$ . Then  $Z = \Sigma^{-1/2} X$  is isotropic and  $Z \sim \text{Unif}(\Sigma^{-1/2} K)$ .
- $X \in \mathbb{R}^n$  is sub-gaussian  $\Leftrightarrow \forall X \in \mathbb{R}^n, \langle X, x \rangle$  are sub-gaussian.  $\|X\|_{\psi_2} = \sup_{x \in \mathbb{S}^{n-1}} \|\langle X, x \rangle\|_{\psi_2}$ .
- $X = (X_1, \dots, X_n)$  independent, mean zero, sub-gaussian coordinate. Then  $X$  is sub-gaussian with  $\|X\|_{\psi_2} \leq C \max_{i \leq n} \|X_i\|_{\psi_2}$ .  
*Proof*  $\|\langle X, x \rangle\|_{\psi_2}^2 = \|\sum X_i x_i\|_{\psi_2}^2 \leq C \sum_{i=1}^n x_i^2 \|X_i\|_{\psi_2}^2 \leq C \max_{i \leq n} \|X_i\|_{\psi_2}^2$ .  $\square$
- Gaussian dist:  $X \sim \mathcal{N}(0, I_n)$ ,  $\|X\|_{\psi_2} \leq C$ .
- Discrete dist:  $X \sim \text{Unif}\{\sqrt{n}e_i, i = 1, 2, \dots, n\}$ ,  $\|X\|_{\psi_2} \simeq \sqrt{\frac{n}{\log n}}$ .
- Uniform dist:  $X \sim \text{Unif}\{\sqrt{n}\mathbb{S}^{n-1}\}$ ,  $\|X\|_{\psi_2} \leq C$ .  
*Proof*  $g \sim \mathcal{N}(0, I_n)$ ,  $X \stackrel{d}{=} \frac{\sqrt{ng}}{\|g\|_2}$ .  $p(t) := \mathbb{P}(|X_1| \geq t) = \mathbb{P}(\frac{|g_1|}{\|g\|_2} \geq \frac{t}{\sqrt{n}})$ .  $\|g\|_2 - \sqrt{n} \leq C \Rightarrow \mathbb{P}(\|g\|_2 \leq \frac{\sqrt{n}}{2}) \leq 2e^{-cn}$ . Need to show that all one-dimensional marginals  $\langle X, x \rangle$  are sub-gaussian. By rotation invariance, we may assume that  $x = (1, 0, \dots, 0)$ . Let  $\mathcal{E} = \{\|g\|_2 \geq \frac{\sqrt{n}}{2}\} \Rightarrow p(t) \leq \mathbb{P}(\frac{|g_1|}{\|g\|_2} \geq \frac{t}{\sqrt{n}}, \mathcal{E}) + \mathbb{P}(\mathcal{E}) \leq \mathbb{P}(|g_1| \geq \frac{t}{2}, \mathcal{E}) + 2e^{-cn} \leq 2e^{-t^2/8} + 2e^{-cn} \stackrel{t \leq \sqrt{n}}{\leq} 4e^{-ct^2}$ .  $\square$
- Grothendieck's inequality:  $A = \{a_{ij}\}_{m \times n}$  of real numbers. Assume  $\forall x_i, y_i \in \{-1, 1\}$ , we have  $|\sum_{i,j} a_{ij} x_i y_j| \leq 1$ . Then for any Hilbert space  $\mathcal{H}$ , any  $u_i, v_j \in \mathcal{H}$  satisfying  $\|u_i\| = \|v_j\| = 1$ , we have  $|\sum_{i,j} a_{ij} \langle u_i, v_j \rangle| \leq K$  with  $K \leq 1.783$ .

*Proof* (1) Reduction. For any  $u_i, v_j \in \mathbb{R}^N$  s.t.  $\|u_i\|_2 = \|v_j\|_2 = 1, K_{u,v} := \sum_{i,j} a_{ij} \langle u_i, v_j \rangle, K = \sup_{\|u\|_2=\|v\|_2=1} K_{u,v}$ .

(2) Introduce randomness.  $g \sim \mathcal{N}(0, I_N), U_i = \langle g, u_i \rangle, V_j = \langle g, v_j \rangle, \mathbb{E} U_i V_j = \langle u_i, v_j \rangle$ .  $K_{u,v} = \mathbb{E}(\sum_{i,j} a_{ij} U_i V_j) \Rightarrow K_{u,v} \leq R^2$  if  $|U_i| \leq R, |V_j| \leq R$ .

(3) Truncation. Given  $R \geq 1, U_i = U_i^- + U_i^+, U_i^- = U_i 1_{\{|U_i| \leq R\}}, V_j = V_j^- + V_j^+, |U_i^-| \leq R, |V_j^-| \leq R$ .  $\|U_i^+\|_{L^2}^2 \leq 2(R + \frac{1}{R}) \frac{1}{\sqrt{2\pi}} e^{-R^2/2} < \frac{4}{R^2} (R > 1)$ .

(4) Breaking up the sum.  $\mathbb{E} \sum a_{ij} U_i V_j = \mathbb{E} \sum a_{ij} U_i^- V_j^- + \mathbb{E} \sum a_{ij} U_i^+ V_j^- + \mathbb{E} \sum a_{ij} U_i^- V_j^+ + \mathbb{E} \sum a_{ij} U_i^+ V_j^+ := S_1 + S_2 + S_3 + S_4$ .  $S_1 \leq R^2, S_2 \leq K \max \|U_i^+\|_2 \max \|V_j^-\|_2 \leq K \frac{2}{R}, S_3 \leq K \frac{2}{R}, S_4 \leq K \frac{4}{R^2}$ .

(5) Putting everything together.  $K_{u,v} \leq R^2 + \frac{4K}{R} + \frac{4K}{R^2} \Rightarrow K \leq R^2 + \frac{4K}{R} + \frac{4K}{R^2} \Rightarrow K \leq \frac{R^2}{1 - \frac{4}{R} - \frac{4}{R^2}}$ .  $\square$

- Remark: The assumption can be equivalently stated as  $|\sum_{i,j} a_{ij} x_i y_j| \leq \max_i |x_i| \max_j |y_j|$ . The conclusion can be equivalently stated as  $|\sum_{i,j} a_{ij} \langle u_i, v_j \rangle| \leq K \max_i \|u_i\| \max_j \|v_j\|$ .
- Semidefinite programming:  $\max \langle A, X \rangle$  s.t.  $X \succeq 0, \langle B_i, X \rangle = b_i, A, B_i n \times n, b_i$  real number,  $\langle A, X \rangle = \text{tr}(A^T X) = \sum_{i,j=1}^n A_{ij} X_{ij}$ .
- Semidefinite relaxation:  $\max \sum_{i,j=1}^n A_{ij} x_i x_j, x_i = \pm 1, A n \times n$  symmetric matrix. Relax to  $\max \sum_{i,j=1}^n A_{ij} \langle X_i, X_j \rangle, \|X_i\|_2 = 1, X_i \in \mathbb{R}^n$ .
- A positive semidefinite,  $\text{INT}(A) := \max \sum_{i,j=1}^n A_{ij} x_i x_j, x_i = \pm 1, \text{SDP}(A) := \max \sum_{i,j=1}^n A_{ij} \langle X_i, X_j \rangle, \|X_i\|_2 = 1$ . Then  $\text{INT}(A) \leq \text{SDP}(A) \leq 2K \cdot \text{INT}(A)$ .
- Maximum cut:  $G = (V, E)$  finite simple,  $V \rightarrow V_1 + V_2$ , cut number of edges crossing between  $V_1$  and  $V_2$ . MAX-CUT( $G$ ): NP-hard. Adjacency matrix  $A = \{A_{ij}\}_{n \times n}, A_{ij} = \begin{cases} 1, & i \leftrightarrow j \\ 0, & \text{otherwise} \end{cases}$ . Partition:  $X = (x_i)_{n \times 1}, x_i = \pm 1$ .  $\text{CUT}(G, X) = \frac{1}{4} \sum_{i,j=1}^n A_{ij} (1 - x_i x_j)$ .  $\text{MAX-CUT}(G) = \frac{1}{4} \max \{ \sum_{i,j} A_{ij} (1 - x_i x_j) : x_i = \pm 1 \}$ .
- 0.5-approximation algorithm: Partition at random,  $\mathbb{E} \text{CUT}(G, X) = 0.5|E| \geq 0.5 \text{MAX-CUT}(G)$ .
- 0.878-approximation algorithm:  $\text{SDP}(G) = \frac{1}{4} \max \{ \sum_{i,j=1}^n A_{ij} (1 - \langle X_i, X_j \rangle), x_i \in \mathbb{R}^n, \|X_i\|_2 = 1 \}$ .  $X_1, \dots, X_n \rightarrow x_1, \dots, x_n : g \sim \mathcal{N}(0, I_n), x_i := \text{sgn}(\langle X_i, g \rangle)$ .  $\mathbb{E} \text{CUT}(G, X) \geq 0.878 \text{SDP}(G) \geq 0.878 \text{MAX-CUT}(G)$ .

*Proof*  $\mathbb{E} \text{CUT}(G, X) = \frac{1}{4} \sum_{i,j=1}^n A_{ij} (1 - \mathbb{E} x_i x_j)$  and  $1 - \mathbb{E} x_i x_j = 1 - \mathbb{E} \text{sgn} \langle g, X_i \rangle \text{sgn} \langle g, X_j \rangle = 1 - \frac{2}{\pi} \arcsin \langle X_i, X_j \rangle \geq 0.878 (1 - \langle X_i, X_j \rangle)$ .  $\square$

- $u, v \in \mathbb{S}^{n-1}, \mathbb{E} \text{sgn}(\langle g, u \rangle) \text{sgn}(\langle g, v \rangle) = \frac{2}{\pi} \arcsin \langle u, v \rangle$ .
- There exists a Hilbert space  $\mathcal{H}$  and  $\phi, \psi : \mathbb{S}^{n-1} \rightarrow \mathbb{S}(\mathcal{H})$  s.t.  $\frac{2}{\pi} \arcsin \langle \phi(u), \psi(v) \rangle = \beta \langle u, v \rangle$  for all  $u, v \in \mathbb{S}^{n-1}$  and  $\beta = \frac{2}{\pi} \log(1 + \sqrt{2})$ .

*Proof*  $\langle \phi(u), \psi(v) \rangle = \sin(\frac{\beta\pi}{2} \langle u, v \rangle)$ . Ex 3.7.6  $\Rightarrow \exists \mathcal{H}, \phi, \psi$ .  $\sin t = t - \frac{t^3}{3!} + \frac{t^5}{5!} - \dots, \sinh t = t + \frac{t^3}{3!} + \frac{t^5}{5!} + \dots, \|\phi(u)\|_2^2 = \|\psi(u)\|_2^2 = \sinh(\frac{\beta\pi}{2}) = 1$  for all  $u \in \mathbb{S}^{n-1} \Rightarrow \beta = \frac{2}{\pi} \log(1 + \sqrt{2})$ .

*Proof of Grothendieck's inequality with  $K \leq \frac{1}{\beta} \approx 1.783$  WLOG  $u_i, v_j \in \mathbb{S}^{N-1}$ , then  $\frac{2}{\pi} \arcsin \langle u'_i, v'_j \rangle = \beta \langle u_i, v_j \rangle, \mathcal{H} = \mathbb{R}^M, g \sim \mathcal{N}(0, I_M)$ .  $\beta \sum a_{ij} \langle u_i, v_j \rangle = \sum_{i,j} a_{ij} \frac{2}{\pi} \arcsin \langle u'_i, v'_j \rangle = \sum_{i,j} a_{ij} \mathbb{E} \text{sgn} \langle g, u'_i \rangle \text{sgn} \langle g, v'_j \rangle \leq 1$ .  $\square$*

## 4 Random matrices

- Singular vector decomposition:  $A_{m \times n} = U_{m \times m} \Sigma_{m \times n} V_{n \times n}^T = \sum_{i=1}^n s_i U_i V_i^T, \Sigma = \text{diag}(s_1, s_2, \dots, s_r), s_i \geq 0$  singular values.  $s_i = \sqrt{\lambda_i(AA^T)} = \sqrt{\lambda_i(A^T A)}$ . If  $A$  is symmetric,  $s_i = |\lambda_i(A)|$ .
- Courant-Fisher's min-max theorem:  $\lambda_i(A) = \max_{\dim E=i} \min_{x \in \mathbb{S}(E)} \langle Ax, x \rangle, s_i(A) = \max_{\dim E=i} \min_{x \in \mathbb{S}(E)} \|Ax\|_2$ .
- Operator norm/spectral norm:  $\|A\| = \max_{x \in \mathbb{R}^n \setminus \{0\}} \frac{\|Ax\|_2}{\|x\|_2} = \max_{x \in \mathbb{S}^{n-1}} \|Ax\|_2 = s_1(A)$ . Or equivalently,  $\|A\| = \max_{x \in \mathbb{S}^{n-1}, y \in \mathbb{S}^{m-1}} \langle Ax, y \rangle$ .
- $s_n(A) > 0 \Leftrightarrow m \geq n = \text{rank}(A), s_n(A) = \frac{1}{\|A^+\|}$  where  $A^+$  is pseudo-inverse (the norm of  $A^{-1}$  restriction to the image of  $A$ ).

- Frobenius norm:  $\|A\|_F = (\sum_{i=1}^n \sum_{j=1}^n A_{ij}^2)^{\frac{1}{2}} = (\sum_{i=1}^n s_i^2(A))^{\frac{1}{2}}$ .
- Low-rank approximation:  $\text{rank}(A) = r, k < r, A_k := \sum_{i=1}^k s_i u_i v_i^T, \|A - A_k\| = \min_{\text{rank}(A') \leq k} \|A - A'\|$  (holds for  $\|\cdot\|, \|\cdot\|_F$ ).
- Approximate isometries:  $m\|x\|_2 \leq \|Ax\|_2 \leq n\|x\|_2$  where  $m = s_n(A), n = s_1(A)$ , or  $s_n\|x - y\|_2 \leq \|Ax - Ay\|_2 \leq s_1\|x - y\|_2$ .
- $A_{m \times n}, \delta > 0$ . If  $\|A^T A - I_n\| \leq \max(\delta, \delta^2)$ , then  $(1 - \delta)\|x\|_2 \leq \|Ax\|_2 \leq (1 + \delta)\|x\|_2$  for all  $x$ .  
*Proof* WLOG  $\|x\|_2 = 1$ .  $|\|Ax\|_2^2 - 1| = |\langle (A^T A - I_n)x, x \rangle| \leq \max(\delta, \delta^2) \Rightarrow \max(|\|Ax\|_2 - 1|, (\|Ax\|_2 - 1)^2) \leq \max(\delta, \delta^2) \Rightarrow |\|Ax\|_2 - 1| \leq \delta$ .  $\square$
- $Q_{n \times m}, QQ^T = I_n \Leftrightarrow P = Q^T Q$  is an orthogonal proj in  $\mathbb{R}^m$  onto a subspace with  $\dim n$ .
- $\epsilon$ -net:  $(T, d)$  a metric space,  $K \subset T, \epsilon > 0$ .  $\mathcal{N} \subset K$  is an  $\epsilon$ -net of  $K$  if  $\forall x \in K, \exists x_0 \in \mathcal{N}$  s.t.  $d(x, x_0) \leq \epsilon$ . Covering number: smallest  $|\mathcal{N}| = |\mathcal{N}(K, d, \epsilon)|$ .
- Compactness:  $\mathcal{N}(K, d, \epsilon) < +\infty$  for all  $\epsilon > 0$ .
- $\epsilon$ -separated:  $\mathcal{P} \subset T$  is  $\epsilon$ -separated if  $d(x, y) > \epsilon$  for all  $x, y \in \mathcal{P}$ . Packing number: largest  $|\mathcal{P}| = |\mathcal{P}(K, d, \epsilon)|$ .
- $\mathcal{P}$  is a maximal  $\epsilon$ -separated subset  $\Rightarrow \mathcal{P}$  is a  $\epsilon$ -net of  $K$ .
- $\mathcal{P}(K, d, 2\epsilon) \leq \mathcal{N}(K, d, \epsilon) \leq \mathcal{P}(K, d, \epsilon)$ .

*Proof* The upper bound follows from the previous lemma. For the lower bound, choose an  $2\epsilon$ -separated subset  $\mathcal{P} = \{x_i\}$  in  $K$  and an  $\epsilon$ -net  $\mathcal{N} = \{y_j\}$  of  $K$ .  $\forall x_i, \exists y_j \in \mathcal{N}$ , s.t.  $|x_i - y_j| < \epsilon$ .  $\forall y_j$ , there exists at most a  $x_j \in \mathcal{P}$  s.t.  $|x_i - y_j| < \epsilon$ .  $\square$

- Minkowski sum:  $A, B \in \mathbb{R}^n, A + B := \{a + b, a \in A, b \in B\}$ .
- $K \subset \mathbb{R}^n, \epsilon > 0, \frac{|K|}{|B_2^n|} \leq \mathcal{N}(K, \epsilon) \leq \mathcal{P}(K, \epsilon) \leq \frac{|K + \frac{\epsilon}{2} B_2^n|}{|\frac{\epsilon}{2} B_2^n|}$  where  $|\cdot|$  denotes the volume in  $\mathbb{R}^n$ ,  $B_2^n$  denotes the unit Euclidean ball in  $\mathbb{R}^n$ .
- Corollary: Let  $K = B_2^n$ .  $|B_2^n| = \epsilon^n |K|, |K + \frac{\epsilon}{2} B_2^n| = (1 + \frac{\epsilon}{2})^n |K| \Rightarrow (\frac{1}{\epsilon})^n \leq \mathcal{N}(B_2^n, \epsilon) \leq (1 + \frac{2}{\epsilon})^n$ .  $\epsilon \in (0, 1] \Rightarrow (\frac{1}{\epsilon})^n \leq \mathcal{N}(B_2^n, \epsilon) \leq (\frac{3}{\epsilon})^n$ .
- Hamming cube:  $x, y \in \{0, 1\}^n, d_H(x, y) := \#\{i : x(i) \neq y(i)\}$ .
- $(T, d)$  a metric space,  $K \subset T$ ,  $\mathcal{C}(K, d, \epsilon)$  the smallest number of bits sufficient specify every points  $x \in K$  with accuracy  $\epsilon$  in the metric  $d$ . Then  $\log_2 \mathcal{N}(K, d, \epsilon) \leq \mathcal{C}(K, d, \epsilon) \leq \log_2 \mathcal{N}(K, d, \frac{\epsilon}{2})$ .  $\log_2 \mathcal{N}(K, \epsilon)$  is often called the metric entropy of  $K$ .

*Proof* Lower bound. Assume  $\mathcal{C}(K, d, \epsilon) \leq N$ . There exists a transformation of  $x \in K$  into bit strings of length  $N$ . A partition of  $K$  into at most  $2^N$  subsets.

Upper bound. Assume  $\log_2 \mathcal{N}(K, d, \frac{\epsilon}{2}) \leq N$ . There exists an  $\frac{\epsilon}{2}$ -net  $\mathcal{N}$  with  $|\mathcal{N}| \leq 2^N$ . To every point  $x \in K$ , assign a point  $x_0 \in \mathcal{N}$  that is closest to  $x$ . The encoding  $x \mapsto x_0$  represents points in  $K$  with accuracy  $\epsilon$ .  $\square$

- Error correcting code: Fix integers  $k, n$  and  $r$ . Encoder  $\{0, 1\}^k \rightarrow \{0, 1\}^n$ , Decoder  $\{0, 1\}^n \rightarrow \{0, 1\}^k$ ,  $D(y) = x$  if  $x \in \{0, 1\}^k, y \in \{0, 1\}^n$  and  $d_H(E(x), y) \leq r$ .
- If  $\log_2 \mathcal{P}(\{0, 1\}^n, d_H, 2r) \geq k$ , then there exists an error correcting code,  $k$  bits  $\rightarrow n$  bits, correct  $r$  error.  
*Proof*  $\exists \mathcal{P} \in \{0, 1\}^n, |\mathcal{P}| = 2^k$  s.t closed balls centered at  $\mathcal{P}$  with radii  $r$  are disjoint.  $E : \{0, 1\}^k \rightarrow \mathcal{N}$  one to one;  $D : \{0, 1\}^n \rightarrow \{0, 1\}^k$  nearest-neighbor decodes.  $\square$
- If  $n \geq k + 2r \log_2(\frac{en}{2r})$ , then there exists an error correcting code that encodes  $k$ -bit strings into  $n$ -bit strings and can correct  $r$  errors.

*Proof*  $\mathcal{P}(\{0, 1\}^n, d_H, 2r) \geq \mathcal{N}(\{0, 1\}^n, d_H, 2r) \geq \frac{2^n}{\sum_{k=0}^{2r} C_n^k} \geq 2^n (\frac{2r}{en})^{2r} \geq 2^k$ .  $\square$

- $A_{m \times n}, \epsilon \in [0, 1)$ . Then for any  $\epsilon$ -set  $\mathcal{N}$  of  $\mathbb{S}^{n-1}$ ,  $\sup_{x \in \mathcal{N}} \|Ax\|_2 \leq \|A\| \leq \frac{1}{1-\epsilon} \sup_{x \in \mathcal{N}} \|Ax\|_2$ .

*Proof* Fix  $x \in \mathbb{S}^{n-1}$ ,  $\|A\| = \|Ax\|_2$ .  $\exists x_0 \in \mathcal{N}, \|x - x_0\|_2 \leq \epsilon$ ,  $\|Ax - Ax_0\|_2 \leq \|A\| \|x - x_0\|_2 \leq \epsilon \|A\| \Rightarrow \|Ax_0\|_2 \geq \|Ax\|_2 - \epsilon \|A\| \Rightarrow \|A(x - x_0)\|_2 \geq \|A\| - \epsilon \|A\|$ .  $\square$

- $A_{m \times n} = \{A_{ij}\}$ ,  $A_{ij}$  independent mean zero sub-gaussian,  $K = \max_{i,j} \|A_{ij}\|_{\psi_2}$ . Then for any  $t > 0$ ,  $\mathbb{P}(\|A\| \leq CK(\sqrt{m} + \sqrt{n} + t)) \geq 1 - 2e^{-t^2}$ .

*Proof* Step 1: Approximation. Choose  $\epsilon = 1/4$  and  $\epsilon$ -net  $\mathcal{N}$  of  $\mathbb{S}^{n-1}$ ,  $\epsilon$ -net  $\mathcal{M}$  of  $\mathbb{S}^{m-1}$  with  $|\mathcal{N}| \leq 9^n, |\mathcal{M}| \leq 9^m$ . Ex 4.4.3  $\Rightarrow \|A\| \leq 2 \max_{x \in \mathcal{N}, y \in \mathcal{M}} \langle Ax, y \rangle$ .

Step 2: Concentration.  $\langle Ax, y \rangle = \sum_{i,j} A_{ij} x_i y_j, \|\langle Ax, y \rangle\|_{\psi_2}^2 \leq C \sum_{i,j} \|A_{ij}\|_{\psi_2}^2 x_i^2 y_j^2 \leq CK^2 \Rightarrow \mathbb{P}(\langle Ax, y \rangle \geq u) \leq 2e^{-cu^2/K^2}$ .

Step 3: Union bound.  $\mathbb{P}(\max_{x \in \mathcal{N}, y \in \mathcal{M}} \langle Ax, y \rangle \geq u) \leq \sum_{x \in \mathcal{N}, y \in \mathcal{M}} \mathbb{P}(\langle Ax, y \rangle \geq u) \leq 9^{n+m} 2e^{-cu^2/K^2}$ . Take  $u = CK(\sqrt{m} + \sqrt{n} + t), u^2 \geq C^2 K^2 (m + n + t^2)$ .  $C$  sufficiently large s.t.  $cu^2/K^2 \geq 3(n + m + t^2)$ .  $\square$

- $A_{n \times n}$  symmetric,  $A_{ij}, i \leq j$  independent mean zero sub-gaussian. Then for  $t \geq 0, \mathbb{P}(\|A\| \leq CK(\sqrt{n} + t)) \geq 1 - 4e^{-t^2}$ .

*Proof*  $A = \underbrace{A^+ + A^-}_{\text{upper + lower triangular matrix}}, \mathbb{P}(\|A^+\| \leq CK(\sqrt{n} + t)) \geq 1 - 2e^{-4t^2} \geq 1 - 2e^{-t^2}, \mathbb{P}(\|A^-\| \leq CK(\sqrt{n} + t)) \geq 1 - 2e^{-4t^2} \geq 1 - 2e^{-t^2}, \mathbb{P}(\|A\| \leq CK(\sqrt{n} + t)) \geq \mathbb{P}(\|A^+\| \leq \frac{C}{2}K(\sqrt{n} + t), \|A^-\| \leq \frac{C}{2}K(\sqrt{n} + t)) \geq 2(1 - 2e^{-t^2}) - 1 = 1 - 4e^{-t^2}$ .  $\square$

- Stochastic block model (SBM):  $G(n, p, q), p > q$ ,  $n$  vertices, two community of size  $n/2$ ,  $x, y \in$  same community  $\Rightarrow \mathbb{P}(x \sim y) = p$ , otherwise  $\mathbb{P}(x \sim y) = q$ .  $A = \{A_{ij}\}, A_{ij} = 1$  if  $i \sim j$  otherwise 0.  $A = \mathbb{E}A + R := D + R, \|D\| = \frac{p+q}{2} \cdot n, \mathbb{P}(\|R\| \leq C\sqrt{n}) \geq 1 - 4e^{-n}$ .

- Weyl's inequality: Symmetric matrices  $S$  and  $T$  with same dim,  $\max_i |\lambda_i(S) - \lambda_i(T)| \leq \|S - T\|$ .

- Davis-Kahan: Fix  $i, \min_{j \neq i} |\lambda_i(S) - \lambda_j(S)| = \delta > 0$ . Then  $\sin \angle(v_i(S), v_i(T)) \leq \frac{\|S - T\|}{\delta} \Rightarrow \exists \theta \in \{-1, 1\}, \|v_i(S) - \theta v_i(T)\|_2 \leq \frac{\|S - T\|}{\delta} \cdot 2^{3/2}$ .

- Spectral clustering: Recall SBM  $A = D + R$  and let  $S = D, T = A = D + R$  in Davis-Kahan.  $\delta = \min(\lambda_2, \lambda_2 - \lambda_1) = \min(\frac{p-q}{2}, q)n := \mu n$ .  $\mathbb{P}(\|R\| = \|T - S\| \leq C\sqrt{n}) \geq 1 - 4e^{-n} \Rightarrow \exists \theta \in \{\pm 1\}, \|v_2(D) - \theta v_2(A)\| \leq \frac{C}{\mu\sqrt{n}}$ . Let  $u_2(D) = (1, 1, \dots, 1, -1, -1, \dots, -1) \Rightarrow \|u_2(D) - \theta u_2(A)\| \leq \frac{C}{\mu} \Rightarrow \sum_{j=1}^n |u_2(D)_j - \theta u_2(A)_j|^2 \leq \frac{C}{\mu^2}$ . Thus the number of disagreeing signs between  $u_2(D)$  and  $u_2(A)$  must be bounded by  $\frac{C}{\mu^2}$ .

- $A_{m \times n}$ , rows  $A_i$  independent mean zero sub-gaussian, isotropic. Then for any  $t \geq 0, \sqrt{m} - CK^2(\sqrt{n} + t) \leq s_n(A) \leq s_1(A) \leq \sqrt{m} + CK^2(\sqrt{n} + t)$  with prob  $\geq 1 - 2e^{-t^2}$ . Here  $K = \max_i \|A_i\|_{\psi_2}$ .

*Proof* Only need to prove  $\|\frac{1}{m} A^T A - I_n\| \leq \epsilon := K^2 \max\{\delta, \delta^2\}, \delta = C(\frac{\sqrt{n}}{\sqrt{m}} + \frac{t}{\sqrt{m}})$ .

Step 1: Approximation. Find an  $\frac{1}{4}$ -net  $\mathcal{N}$  of the unit space  $\mathbb{S}^{n-1}, |\mathcal{N}| \leq 9^n$ .  $\|\frac{1}{m} A^T A - I_n\| \leq 2 \max_{x \in \mathcal{N}} |\langle \frac{1}{m} A^T A - I_n, x \rangle| = 2 \max_{x \in \mathcal{N}} |\frac{1}{m} \|Ax\|_2^2 - 1|$ .

Step 2: Concentration.  $X_i := \langle A_i, x \rangle$  independent, mean zero,  $\|X_i\|_{\psi_2} \leq K, \mathbb{E}X_i^2 = 1$ .  $\mathbb{P}(|\frac{1}{m} \|Ax\|_2^2 - 1| \geq \frac{\epsilon}{2}) \leq 2e^{-c_1 \delta^2 m} \leq 2e^{-c_1 C^2 (n+t^2)}$ .

Step 3: Union bound.  $\mathbb{P}(|\frac{1}{m} \|Ax\|_2^2 - 1| \geq \frac{\epsilon}{2}) \leq 9^n \cdot 2e^{-c_1 C^2 (n+t^2)} \leq 2e^{-t^2}$ .  $\square$

- $X \in \mathbb{R}^n$  sub-gaussian.  $\mathbb{E}X = 0, \Sigma = \mathbb{E}XX^T, X_i \stackrel{d}{=} X$  i.i.d.,  $\Sigma_m = \frac{1}{m} \sum_{i=1}^m X_i X_i^T$ . Assume there exists  $K \geq 1$  s.t.  $\|\langle X, x \rangle\|_{\psi_2}^2 \leq K^2 \|\langle X, x \rangle\|_{L^2}^2$ . Then for  $m, \mathbb{E}\|\Sigma_m - \Sigma\| \leq CK^2(\sqrt{\frac{n}{m}} + \frac{n}{m})\|\Sigma\|$ .

*Proof*  $Z_i = \Sigma^{-1/2} X_i, Z = \Sigma^{-1/2} X, \mathbb{E}Z_i Z_i^T = I_n, \|Z\|_{\psi_2} \leq K, \|Z_i\|_{\psi_2} \leq K$ . Then  $\|\Sigma_m - \Sigma\| = \|\Sigma^{1/2} R_m \Sigma^{1/2}\| \leq \|R_m\| \|\Sigma\|$  where  $R_m = \frac{1}{m} \sum_{i=1}^m Z_i Z_i^T - I$ . Consider an  $m \times n$  random matrix  $A$  whose rows are  $Z_i^T$ .  $\mathbb{E}\|R_m\| = \mathbb{E}\|\frac{1}{m} A^T A - I\| \leq CK^2(\sqrt{\frac{n}{m}} + \frac{n}{m})$ .  $\square$

## 5 Concentration without independence

- $(X, d_X) \xrightarrow{f} (Y, d_Y), d_Y(f(u), f(v)) \leq L \cdot d_X(u, v), \forall u, v \in X$ . The infimum of all  $L$  in this definition is called the Lipschitz norm of  $f$  and is denoted  $\|f\|_{\text{Lip}}$ .

- $\epsilon > 0, A_\epsilon = A + \epsilon B_2^n, A \subset \mathbb{R}^n$ ,  $\min_A$  volume of  $A_\epsilon$  with volume  $A$  fixed is achieved when  $A$  is a ball.

- $\sigma_{n-1}(A)$  normalized area on  $\mathbb{S}^{n-1}$ ,  $\epsilon > 0$ . With given  $\sigma_{n-1}(A)$ ,  $\min_A \sigma_{n-1}(A_\epsilon)$  is achieved when  $A$  is a spherical cap.

- $A \subset \sqrt{n}\mathbb{S}^{n-1}$ . If  $\sigma(A) \geq \frac{1}{2}$ , then  $\forall t \geq 0, \sigma(A_t) \geq 1 - 2e^{-ct^2}$ .

*Proof* Let  $H = \{x \in \sqrt{n}\mathbb{S}^{n-1}, x_1 \leq 0\}$ .  $\sigma(A) \geq \frac{1}{2}\sigma(H)$ . Thm 5.1.6  $\Rightarrow \sigma(A_t) \geq \sigma(H_t) = \mathbb{P}(X \in H_t)$ .  $H_t \supset \{x \in \sqrt{n}\mathbb{S}^{n-1}, x_1 \leq \frac{t}{\sqrt{2}}\} \Rightarrow \sigma(H_t) \geq \mathbb{P}(X_1 \leq \frac{t}{\sqrt{2}})$ .  $\|X_1\|_{\psi_2} \leq C \Rightarrow \mathbb{P}(X_1 \leq \frac{t}{\sqrt{2}}) \geq 1 - 2e^{-ct^2}$ .  $\square$

- $X \sim \text{Unif}(\sqrt{n}\mathbb{S}^{n-1})$ ,  $f : \sqrt{n}\mathbb{S}^{n-1} \rightarrow \mathbb{R}$ . Then  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq C\|f\|_{\text{Lip}}$ .

*Proof* WLOG  $\|f\|_{\text{Lip}} = 1$ ,  $\mathbb{P}(f(X) \geq M) \geq \frac{1}{2}$ ,  $\mathbb{P}(f(X) \leq M) \geq \frac{1}{2}$ .  $A := \{x \in \sqrt{n}\mathbb{S}^{n-1} : f(x) \leq M\}$ .  $\mathbb{P}(X \in A) \geq \frac{1}{2} \Rightarrow \mathbb{P}(A_t) \geq 1 - 2e^{-ct^2} \Rightarrow \mathbb{P}(f(X) \leq M + t) \geq 1 - 2e^{-ct^2}$ . By centering,  $f(X) - \mathbb{E}f(X) = f(X) - M - (\mathbb{E}f(X) - M)$  is sub-gaussian.  $\square$

- $X \sim \mathcal{N}(0, I_n)$ ,  $\gamma_n(A) = \mathbb{P}(X \in A)$ ,  $\epsilon > 0$ ,  $\gamma_n(A)$  given, half spaces minimize  $\gamma_n(A_\epsilon)$ .
- $X \sim \mathcal{N}(0, I_n)$ ,  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $\|f\|_{\text{Lip}} < \infty$ . Then  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq C\|f\|_{\text{Lip}}$ .
- Hamming cube,  $d(x, y) = \frac{1}{n}|\{i : x_i \neq y_i\}|$ ,  $\mathbb{P}(A) = \frac{|A|}{2^n}$ .  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq \frac{C\|f\|_{\text{Lip}}}{\sqrt{n}}$ .
- $S_n : n!$  permutation of  $n$  symbols.  $d(\pi, \rho) = \frac{1}{n}|\{i : \pi(i) \neq \rho(i)\}|$ ,  $\mathbb{P}(A) = \frac{|A|}{n!}$ .  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq \frac{C\|f\|_{\text{Lip}}}{\sqrt{n}}$ .
- Special orthogonal group  $\text{SO}(n)$ , determinant = 1,  $d = \|\cdot\|_F$ ,  $\mathbb{P}$  is uniform measure.  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq \frac{C\|f\|_{\text{Lip}}}{\sqrt{n}}$ .
- $G_{n,m}$  all  $m$ -dim subspaces of  $\mathbb{R}^n$  ( $\simeq P_{G_{n,m}}$  orthogonal projections),  $d(E, F) = \|P_E - P_F\|$ ,  $\mathbb{P}$  is uniform measure. A random subspace  $E$  can be constructed by computing the column span (i.e. the image) of a random  $n \times m$  Gaussian random matrix  $G$  with i.i.d.  $\mathcal{N}(0, 1)$  entries.  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq \frac{C\|f\|_{\text{Lip}}}{\sqrt{n}}$ .
- A random vector  $X$  in  $\mathbb{R}^n$  with density  $p(x) = e^{-U(x)}$ , Hess  $U(x) \succeq \kappa I_n$ .  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq \frac{C\|f\|_{\text{Lip}}}{\sqrt{\kappa}}$ .
- $X = (X_1, \dots, X_n)$  independent coordinates,  $|X_i| \leq 1$  a.s.,  $f$  convex and Lipschitz.  $\|f(X) - \mathbb{E}f(X)\|_{\psi_2} \leq C\|f\|_{\text{Lip}}$ .
- $E \sim \text{Unif}(G_{n,m})$ ,  $z \in \mathbb{R}^n$ ,  $\epsilon > 0$ . Then (a)  $(\mathbb{E}\|P_E z\|_2^2)^{\frac{1}{2}} = \sqrt{\frac{m}{n}}\|z\|_2$ ; (b)  $\mathbb{P}(|\|P_E z\|_2 - \sqrt{\frac{m}{n}}\|z\|_2| \leq \epsilon\sqrt{\frac{m}{n}}\|z\|_2) \geq 1 - 2e^{-c\epsilon^2 m}$ .

*Proof* (a): WLOG  $\|z\|_2 = 1$ . Rotational invariance:  $\mathbb{P}(E \in A) = \mathbb{P}(U(E) \in A)$  where  $U$  is  $n \times n$  orthogonal  $\Rightarrow$  The dist. of  $P_E z$  is the same if we fix  $E$ ,  $z \in \text{Unif}(\mathbb{S}^{n-1})$ . WLOG  $Pz = (z_1, \dots, z_m, 0, \dots, 0)$ .  $\mathbb{E}\|Pz\|_2^2 = m\mathbb{E}z_i^2 = \frac{m}{n}$ .

(b):  $f : z \rightarrow \|Pz\|_2$ ,  $\|f\|_{\text{Lip}} = 1 \Rightarrow \|\|Pz\|_2 - \mathbb{E}\|Pz\|_2\|_{\psi_2} \leq \frac{C}{\sqrt{n}}$   $\square$

- Johnson-Lindenstrauss lemma:  $\mathcal{X}$  a set of  $N$  points in  $\mathbb{R}^n$ ,  $\epsilon > 0$ ,  $m \geq \frac{C}{\epsilon^2} \log N$ ,  $E \sim \text{Unif}(G_{n,m})$ ,  $Q = \sqrt{\frac{n}{m}}P_E$ . Then  $\mathbb{P}(|\|Qx - Qy\|_2 - \|x - y\|_2| \leq \epsilon\|x - y\|_2 \text{ for any } x, y \in \mathcal{X}) \geq 1 - 2e^{-c\epsilon^2 m}$ .

*Proof* Let  $\mathcal{X} - \mathcal{X} := \{x - y : x, y \in \mathcal{X}\}$ . The latest lemma  $\Rightarrow \forall z, \mathbb{P}((1 - \epsilon)\sqrt{\frac{m}{n}}\|z\|_2 \leq \|Pz\|_2 \leq (1 + \epsilon)\sqrt{\frac{m}{n}}\|z\|_2) \geq 1 - 2e^{-c\epsilon^2 m}$ . Union bound:  $\mathbb{P}(\dots \text{ for any } z \in \mathcal{X} - \mathcal{X}) \geq 1 - N^2 \cdot 2e^{-c\epsilon^2 m} \geq 1 - 2e^{-c'\epsilon^2 m}$ .  $\square$

- $f : \mathbb{R} \rightarrow \mathbb{R}$ ,  $X = \sum_{i=1}^n \lambda_i u_i u_i^T$ , define  $f(X) = \sum_{i=1}^n f(\lambda_i) u_i u_i^T$ .

- P.S.D. order:  $X \succeq 0$ ,  $X \succeq Y$  if  $X - Y \succeq 0$ .

- Golden-Thompson inequality:  $\text{tr}(e^{A+B}) \leq \text{tr}(e^A e^B)$ .

- Lieb's inequality:  $H : n \times n$  symmetric matrix,  $X$  P.D.,  $f(X) = \text{tr}(e^{H+\log X})$ . Then  $f$  is concave.

- $X$  is a random P.D. matrix  $\Rightarrow \mathbb{E}f(X) \leq f(\mathbb{E}X)$ .  $X = e^Z$ ,  $Z$  symmetric. Then  $\mathbb{E}\text{tr}(e^{H+Z}) \leq \text{tr}(e^{H+\log \mathbb{E}e^Z})$ .

- $X_1, \dots, X_N$  independent mean zero  $n \times n$  symmetric random matrices,  $\|X_i\| \leq K$  a.s. for all  $i$ . Then for  $\forall t \geq 0$ ,  $\mathbb{P}(\|\sum_{i=1}^N X_i\| \geq t) \leq 2ne^{-\frac{t^2/2}{\sigma^2 + Kt/3}}$  where  $\sigma^2 = \|\sum_{i=1}^N \mathbb{E}X_i^2\|$ .

*Proof* Step 1: Reduction to MGF.  $S := \sum_{i=1}^N X_i$ .  $\|S\| = \max_i |\lambda_i(S)| = \max(\lambda_{\max}(S), \lambda_{\max}(-S))$ .  $\mathbb{P}(\lambda_{\max}(S) \geq t) \leq e^{-\lambda t} \mathbb{E}e^{\lambda \lambda_{\max}(S)}$ .  $E := \mathbb{E}e^{\lambda \lambda_{\max}(S)} = \mathbb{E}\lambda_{\max}(e^{\lambda S}) \Rightarrow E \leq \mathbb{E}\text{tr}(e^{\lambda S})$ .

Step 2: Apply Lieb's inequality.  $\mathbb{E}\text{tr}(e^{\lambda S}) = \mathbb{E}\text{tr}(e^{\sum_{i=1}^{N-1} \lambda X_i + \lambda X_N}) \leq \mathbb{E}\text{tr}(e^{\sum_{i=1}^{N-1} \lambda X_i + \log \mathbb{E}e^{\lambda X_N}}) \leq \text{tr}(e^{\sum_{i=1}^{N-1} \log \mathbb{E}e^{\lambda X_i}})$ .

Step 3: Lemma:  $X$  is an  $n \times n$  symmetric mean zero random matrix,  $\|X\| \leq K$  a.s. Then  $e^{\lambda X} \preceq e^{g(\lambda)\mathbb{E}X^2}$  where  $g(\lambda) = \frac{\lambda^2/2}{1 - |\lambda|K/3}$ ,  $|\lambda| < 3/K$ .



*Proof*  $e^z \leq 1 + z + \frac{1}{1-|z|/3} \frac{z^2}{2}$  if  $|z| < 3$ .  $z = \lambda x$ . If  $|x| \leq K, |\lambda| < \frac{3}{K}$ ,  $e^{\lambda x} \leq 1 + \lambda x + g(\lambda)x^2$ . (b) of Ex. 5.4.5  $\Rightarrow$  If  $\|X\| \leq K, |\lambda| < 3/K$ ,  $\mathbb{E}e^{\lambda X} \leq I + g(\lambda)\mathbb{E}X^2$  (since  $\mathbb{E}X = 0$ )  $\leq e^{g(\lambda)\mathbb{E}X^2}$ .  $\square$

Step 4:  $E \leq \text{tr}(e^{\sum_{i=1}^N \log \mathbb{E}e^{\lambda X_i}})$ . The latest lemma + (g) of Ex.5.4.5  $\Rightarrow \log \mathbb{E}e^{\lambda X_i} \leq g(\lambda)\mathbb{E}X_i^2 \Rightarrow \sum_{i=1}^N \log \mathbb{E}e^{\lambda X_i} \leq g(\lambda) \cdot Z$  where  $Z := \sum_{i=1}^N \mathbb{E}X_i^2$  and  $\sigma^2 = \|Z\|$ . (e) of Ex.5.4.5  $\Rightarrow \text{tr}(e^{\sum_{i=1}^N \log \mathbb{E}e^{\lambda X_i}}) \leq \text{tr}(e^{g(\lambda)Z}) \Rightarrow E \leq \text{tr}(e^{g(\lambda)Z}) \leq n\lambda_{\max}(e^{g(\lambda)Z}) = ne^{g(\lambda)\|Z\|} = ne^{g(\lambda)\sigma^2}$ . Minimize for  $\lambda$  as a function of  $t$  with  $0 < \lambda < 3/K$ .  $\square$

- $X \in \mathbb{R}^n, \Sigma = \mathbb{E}XX^T, \Sigma_m = \frac{1}{m} \sum_{i=1}^m X_i X_i^T, X_i \stackrel{\text{i.i.d.}}{\sim} X, \|X\|_2 \leq K(\mathbb{E}\|X\|_2^2)^{\frac{1}{2}}$  a.s.. Then  $\mathbb{E}\|\Sigma_m - \Sigma\| \leq C(\sqrt{\frac{K^2 n \log n}{m}} + \frac{K^2 n \log n}{m})\|\Sigma\|$ .

*Proof*  $\mathbb{E}\|X\|_2^2 = \mathbb{E}XX^T = \mathbb{E}\text{tr}(X^T X) = \mathbb{E}\text{tr}(XX^T) = \text{tr}(\Sigma) \Rightarrow \|X\|_2^2 \leq K^2 \text{tr}(\Sigma)$  a.s.. Ex 5.4.11  $\Rightarrow \mathbb{E}\|\Sigma_m - \Sigma\| = \frac{1}{m} \mathbb{E}\|\sum_{i=1}^m (X_i X_i^T - \Sigma)\| \lesssim \frac{1}{m}(\sigma\sqrt{\log n} + M \log n)$  where  $\sigma^2 = \|\sum_{i=1}^m \mathbb{E}(X_i X_i^T - \Sigma)^2\| = m\|\mathbb{E}(XX^T - \Sigma)^2\|$  and  $M$  is chosen s.t.  $\|XX^T - \Sigma\| \leq M$  a.s.. Then  $\mathbb{E}(XX^T - \Sigma)^2 = \mathbb{E}(XX^T)^2 - \Sigma^2 \leq \mathbb{E}(XX^T)^2 = \mathbb{E}(\|X\|_2^2 XX^T) \leq K^2 \text{tr}(\Sigma)\Sigma \Rightarrow \sigma^2 \leq K^2 m \text{tr}(\Sigma)\|\Sigma\|$ .  $\|XX^T - \Sigma\| \leq \|X\|_2^2 + \|\Sigma\| \leq K^2 \text{tr}(\Sigma) + \|\Sigma\| \leq 2K^2 \text{tr}(\Sigma) := M$  (since  $K \geq 1$  and  $\|\Sigma\| \leq \text{tr}(\Sigma)$ ). Substitute our bounds for  $\sigma^2$  and  $M$  into the previous bound  $\frac{1}{m}(\sigma\sqrt{\log n} + M \log n)$ .  $\square$

## 6 Quadratic forms, symmetrization, contraction

- $Y \perp Z, \mathbb{E}Z = 0$ , then  $\mathbb{E}F(Y) \leq \mathbb{E}F(Y + Z)$ .

*Proof*  $F(y) = F(\mathbb{E}(y + Z)) \leq \mathbb{E}F(y + Z) \Rightarrow \mathbb{E}F(Y) = \mathbb{E}(\mathbb{E}(F(Y + \mathbb{E}Z)|Y)) = \mathbb{E}(\mathbb{E}(F(\mathbb{E}(Y + Z))|Y)) \leq \mathbb{E}(\mathbb{E}(F(Y + Z)|Y)) = \mathbb{E}F(Y + Z)$ .  $\square$

- Decoupling:  $A_{n \times n}$  diagonal-free (i.e. the diagonal entries of  $A$  equal zero),  $X = (X_1, \dots, X_n)$  independent mean zero. Then for every convex function  $F : \mathbb{R} \rightarrow \mathbb{R}$ ,  $\mathbb{E}F(X^T A X) \leq \mathbb{E}F(4X^T A X')$  where  $X' \stackrel{d}{=} X, X' \perp X$ .

*Proof*  $\delta_1, \dots, \delta_n \stackrel{\text{i.i.d.}}{\sim} \text{Ber}(1, \frac{1}{2}), I = \{i : \delta_i = 1\}, \mathbb{E}\delta_i(1 - \delta_j) = \frac{1}{4}, X^T A X = \sum_{i \neq j} a_{ij} X_i X_j = 4\mathbb{E}_\delta \sum_{i,j} \delta_i(1 - \delta_j) a_{ij} X_i X_j = 4\mathbb{E}_I \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j \Rightarrow \mathbb{E}_X F(X^T A X) = \mathbb{E}_X F(4\mathbb{E}_I \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j) \leq \mathbb{E}_I \mathbb{E}_X F(4 \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j)$ . There exists an  $I$  s.t.  $\mathbb{E}_X F(4 \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j') = \mathbb{E}_X F(4 \sum_{(i,j) \in I \times I^c} a_{ij} X_i X_j) \geq \mathbb{E}F(X^T A X)$ . LHS  $\leq \mathbb{E}_X F(4 \sum_{i,j} a_{ij} X_i X_j')$  by the latest lemma since  $\mathbb{E}[(\sum_{(i,j) \in I \times I} + \sum_{(i,j) \in I^c \times I^c} + \sum_{(i,j) \in I^c \times I} a_{ij} X_i X_j') | \{X_i, i \in I\}, \{X_j', j \in I^c\}] = 0$ .  $\square$

- $X, X' \sim \mathcal{N}(0, I_n), X \perp X'$ , then  $\mathbb{E}e^{\lambda X^T A X'} \leq e^{C\lambda^2 \|A\|_F^2}, |\lambda| \leq \frac{c}{\|A\|}$ .

*Proof*  $A = \sum_i s_i u_i v_i^T, X^T A X' = \sum_i s_i \underbrace{\langle u_i, X \rangle}_{:=g_i} \underbrace{\langle v_i, X' \rangle}_{:=g'_i}$ .  $(g_1, \dots, g_n) \perp (g'_1, \dots, g'_n) \sim \mathcal{N}(0, I_n) \Rightarrow \mathbb{E}e^{\lambda X^T A X'} = \prod_{i=1}^n \mathbb{E}e^{\lambda s_i g_i g'_i} = \prod_{i=1}^n \mathbb{E}e^{\lambda^2 s_i^2 g_i^2 / 2} \leq \prod_{i=1}^n e^{C\lambda^2 s_i^2 (\lambda^2 s_i^2 \leq c)} \leq e^{C\lambda^2 \|A\|_F^2} (\lambda^2 \leq \frac{c}{\max_i s_i^2} = \frac{c}{\|A\|^2})$ .  $\square$

- $X, X'$  independent sub-gaussian mean zero,  $\|X\|_{\psi_2} \leq K, \|X'\|_{\psi_2} \leq K$ .  $g, g' \sim \mathcal{N}(0, I_n), g \perp g'$ . Then  $\mathbb{E}e^{\lambda X^T A X'} \leq \mathbb{E}e^{CK^2 \lambda g^T A g'}$ .

*Proof* Conditioned on  $X'$ ,  $\mathbb{E}_X e^{\lambda X^T A X'} \leq e^{C\lambda^2 K^2 \|A X'\|_2^2}, \mathbb{E}_g e^{\mu g^T A X'} = e^{\frac{\mu^2 \|A X'\|_2^2}{2}}$ .  $\mu = \sqrt{2cK}\lambda \Rightarrow \mathbb{E}_X e^{\lambda X^T A X'} \leq \mathbb{E}_g e^{\sqrt{2cK}\lambda g^T A X'} \Rightarrow \mathbb{E}e^{\lambda X^T A X'} \leq \mathbb{E}e^{\sqrt{2cK}\lambda g^T A g'} \leq \mathbb{E}e^{2cK^2 \lambda g^T A g'}$ .  $\square$

- Hanson-Wright inequality:  $X = (X_1, \dots, X_n)$  independent mean zero sub-gaussian, then  $\mathbb{P}(|X^T A X - \mathbb{E}X^T A X| \geq t) \leq 2e^{-c \min(\frac{t^2}{K^4 \|A\|_F^2}, \frac{t}{K^2 \|A\|})}$ .

*Proof* WLOG  $K = 1$ .  $X^T A X = \sum_{i,j} a_{ij} X_i X_j, \mathbb{E}X^T A X = \sum_i a_{ii} \mathbb{E}X_i^2, X^T A X - \mathbb{E}X^T A X = \sum_i a_{ii} (X_i^2 - \mathbb{E}X_i^2) + \sum_{i \neq j} a_{ij} X_i X_j$ .  $p := \mathbb{P}(X^T A X - \mathbb{E}X^T A X \geq t) \leq \mathbb{P}(\sum_i a_{ii} (X_i^2 - \mathbb{E}X_i^2) \geq \frac{t}{2}) + \mathbb{P}(\sum_{i \neq j} a_{ij} X_i X_j \geq \frac{t}{2}) := p_1 + p_2$ .

Step 1:  $\|X_i^2 - \mathbb{E}X_i^2\|_{\psi_1} \lesssim 1$ . Bernstein  $\Rightarrow p_1 \leq e^{-c \min(\frac{t^2}{\sum_i a_{ii}^2}, \frac{t}{\max_i |a_{ii}|})} \leq e^{-c \min(\frac{t^2}{\|A\|_F^2}, \frac{t}{\|A\|})}$ .

Step 2:  $S := \sum_{i \neq j} a_{ij} X_i X_j$ .  $p_2 \leq e^{-\frac{\lambda t}{2}} \mathbb{E}e^{\lambda S}, \mathbb{E}e^{\lambda S} \leq \mathbb{E}e^{4\lambda X^T A X'} \leq \mathbb{E}e^{c_1 \lambda g^T A g'} \leq e^{C\lambda^2 \|A\|_F^2}$  (with  $\lambda \leq \frac{c}{\|A\|}$ ).  $\square$

- $B_{m \times n}, X \in \mathbb{R}^n, \{X_i\}$  independent mean-zero, unit-variance, sub-gaussian. Then  $|\|BX\|_2 - \|B\|_F|_{\psi_2} \leq CK^2 \|B\|, K = \max_i \|X\|_{\psi_2}$ .

*Proof*  $A = B^T B, X^T A X = \|BX\|_2^2, \mathbb{E}X^T A X = \|B\|_F^2, \|A\| = \|B\|^2, \|A\|_F = \|B^T B\|_F \leq \|B^T\| \|B\|_F = \|B\| \|B\|_F$ . Thus  $\forall u \geq 0$ ,  $\mathbb{P}(|\|BX\|_2^2 - \|B\|_F^2| \geq u) \leq e^{-\frac{c}{K^4} \min(\frac{u^2}{\|B\|^2 \|B\|_F^2}, \frac{u}{\|B\|^2})}$ . Let  $u = \epsilon \|B\|_F^2, \mathbb{P}(|\|BX\|_2^2 - \|B\|_F^2| \geq \epsilon \|B\|_F^2) \leq 2e^{-c \min(\epsilon^2, \epsilon) \frac{\|B\|_F^2}{K^4 \|B\|^2}}$ . Let  $\delta^2 = \min(\epsilon^2, \epsilon)$ , then  $\epsilon = \max(\delta, \delta^2), |\|BX\| - \|B\|_F| \geq \delta \|B\|_F \Rightarrow |\|BX\|_2^2 - \|B\|_F^2| \geq \epsilon \|B\|_F^2 \Rightarrow \mathbb{P}(|\|BX\|_2 - \|B\|_F| \geq \delta \|B\|_F) \leq 2e^{-c\delta^2 \frac{\|B\|_F^2}{K^4 \|B\|^2}}$ .  $\square$

- Symmetrization:  $X_1, X_2, \dots, X_N$  independent, mean zero in a normed space,  $\epsilon_1, \epsilon_2, \dots, \epsilon_N$  a sequence of independent symmetric Bernoulli random variables. Then  $\frac{1}{2}\mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\| \leq \mathbb{E}\|\sum_{i=1}^N X_i\| \leq 2\mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\|$ .

*Proof* Upper bound.  $X' \perp X, X' \stackrel{d}{=} X$ .  $p = \mathbb{E}\|\sum_{i=1}^N X_i\| \leq \mathbb{E}\|\sum_{i=1}^N X_i - \sum_{i=1}^N X'_i\| = \mathbb{E}\|\sum_{i=1}^N \epsilon_i(X_i - X'_i)\| \leq \mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\| + \mathbb{E}\|\sum_{i=1}^N \epsilon_i X'_i\| = 2\mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\|$ .  $\square$

- $A_{n \times n}$  symmetric independent mean zero. Then  $\mathbb{E}\|A\| \leq C\sqrt{\log n} \mathbb{E} \max \|A_i\|_2$  where  $A_i$  is  $i$ -th row of  $A$ .

*Proof*  $A = \sum_{i \leq j} Z_{ij}$  independent mean zero symmetric where  $Z_{ij} = \begin{cases} A_{ij}(e_i e_j^T + e_j e_i^T), & i \leq j \\ A_{ii} e_i e_i^T & i = j \end{cases} \Rightarrow \mathbb{E}\|A\| \leq 2\mathbb{E}\|\sum_{i \leq j} \epsilon_{ij} Z_{ij}\|$ .

Ex 5.4.3(a)  $\Rightarrow$  Conditioned on  $\{Z_{ij}\}, \mathbb{E}_\epsilon \|\sum_{i \leq j} \epsilon_{ij} Z_{ij}\| \leq C\sqrt{\log n} \|\sum_{i \leq j} Z_{ij}^2\|^{\frac{1}{2}} \Rightarrow \mathbb{E}\|\sum_{i \leq j} \epsilon_{ij} Z_{ij}\| \leq C\sqrt{\log n} \mathbb{E}\|\sum_{i \leq j} Z_{ij}^2\|^{\frac{1}{2}}$ ,  $\sum_{i \leq j} Z_{ij}^2 = \sum_{i=1}^n (\sum_{j=1}^n A_{ij}^2) e_i e_i^T = \sum_{i=1}^n \|A_i\|_2^2 e_i e_i^T \Rightarrow \|\sum_{i \leq j} Z_{ij}^2\|^{\frac{1}{2}} = \max \|A_i\|_2$ .  $\square$

- Matrix completion:  $X_{n \times n}, \text{rank}(X) = r \ll n, Y_{ij} = \delta_{ij} X_{ij}, \delta_{ij} \sim \text{Ber}(p), p = \frac{m}{n^2}, \hat{X} = \arg \min_{\text{rank}(A') \leq r} \|p^{-1}Y - A'\|$ . Then  $\mathbb{E} \frac{1}{n} \|\hat{X} - X\|_F \leq C\sqrt{\frac{rn \log n}{m}} \|X\|_\infty$ .

*Proof* Step 1.  $\|\hat{X} - X\| \leq \|\hat{X} - p^{-1}Y\| + \|p^{-1}Y - X\| \leq 2\|p^{-1}Y - X\| = \frac{2}{p}\|Y - pX\|$ .  $(Y - pX)_{ij} = (\delta_{ij} - p)X_{ij}$  independent mean zero, Ex 6.5.2  $\Rightarrow \mathbb{E}\|Y - pX\| \leq C\sqrt{\log n} (\mathbb{E} \max_i \|(Y - pX)_i\|_2 + \mathbb{E} \max_j \|(Y - pX)^j\|_2)$ .  $\|(Y - pX)_i\|_2^2 = \sum_{j=1}^n (\delta_{ij} - p)^2 X_{ij}^2 \leq \sum_{j=1}^n (\delta_{ij} - p)^2 \|X\|_\infty^2$ . Ex 6.6.2  $\Rightarrow \mathbb{E} \max_i \sum_{j=1}^n (\delta_{ij} - p)^2 \leq Cpn \Rightarrow \frac{2}{p}\|Y - pX\| \leq C\sqrt{\frac{n \log n}{p}} \|X\|_\infty$ .

Step 2.  $\text{rank}(X) \leq r, \text{rank}(\hat{X}) \leq r, \text{rank}(\hat{X} - X) \leq 2r$ .  $\|\hat{X} - X\|_F \leq \sqrt{2r} \|\hat{X} - X\| \Rightarrow \mathbb{E}\|\hat{X} - X\|_F \leq C\sqrt{\frac{rn \log n}{p}} \|X\|_\infty$ .  $\square$

- Contraction principle:  $X_1, \dots, X_N$  vectors in some normed space,  $a = (a_1, \dots, a_N) \in \mathbb{R}^N$ . Then  $\mathbb{E}\|\sum_{i=1}^N a_i \epsilon_i X_i\| \leq \|a\|_\infty \mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\|$ .

*Proof* WLOG  $\|a\|_\infty \leq 1, f(a) = \mathbb{E}\|\sum_{i=1}^N a_i \epsilon_i X_i\|$  is convex, which implies the maximum of  $f$  is attained at the boundary. Thus  $f(a) \leq f(a^*) = \mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\|$  with  $a_i^* = 1$  or  $-1$ .  $\square$

- Symmetrization with gaussians:  $X_1, \dots, X_N$  independent mean zero,  $g_1, \dots, g_N \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1), \frac{C}{\sqrt{\log N}} \mathbb{E}\|\sum_{i=1}^N g_i X_i\| \leq \mathbb{E}\|\sum_{i=1}^N X_i\| \leq 3\mathbb{E}\|\sum_{i=1}^N g_i X_i\|$ .

*Proof* Upper:  $\mathbb{E}\|\sum_{i=1}^N X_i\| \leq 2\mathbb{E}\|\sum_{i=1}^N \epsilon_i X_i\| = 2\sqrt{\frac{\pi}{2}} \mathbb{E}_{X, \epsilon} \|\sum_{i=1}^N \epsilon_i \mathbb{E}_g |g_i| X_i\| \leq 2\sqrt{\frac{\pi}{2}} \mathbb{E}\|\sum_{i=1}^N \epsilon_i |g_i| X_i\| = 2\sqrt{\frac{\pi}{2}} \mathbb{E}\|\sum_{i=1}^N g_i X_i\|$ .

Lower:  $\mathbb{E}\|\sum_{i=1}^N g_i X_i\| = \mathbb{E}\|\sum_{i=1}^N \epsilon_i g_i X_i\| \leq \mathbb{E}_g \mathbb{E}_X (\|g\|_\infty \mathbb{E}_\epsilon \|\sum_{i=1}^N \epsilon_i X_i\|) = \mathbb{E}_g \|g\|_\infty \mathbb{E}_{X, \epsilon} \|\sum_{i=1}^N \epsilon_i X_i\| \leq 2\mathbb{E}_g \|g\|_\infty \mathbb{E}_X \|\sum_{i=1}^N X_i\| \leq C\sqrt{\log N} \mathbb{E}_X \|\sum_{i=1}^N X_i\|$ .  $\square$

## 7 Random processes

- Basic concepts:  $\{X_t\}_{t \in T \subset \mathbb{R}^n}, \mathbb{E}X_t = 0, \forall t \in T, \Sigma(t, s) = \text{Cov}(X_t, X_s) = \mathbb{E}X_t X_s, d(t, s) = \|X_t - X_s\|_{L^2} = (\mathbb{E}(X_t - X_s)^2)^{\frac{1}{2}}$  (increments).

- Gaussian process:  $T_0 \subset T, |T_0| < \infty, \{X_t\}_{t \in T_0}$  has normal distribution.

- $Y$  is a mean zero Gaussian r.v. in  $\mathbb{R}^n$ . Then there exists  $t_1, \dots, t_n \in \mathbb{R}^n$  s.t.  $Y \stackrel{d}{=} (\langle g, t_i \rangle)_{i=1}^n, g \sim \mathcal{N}(0, I_n)$ .

- Gaussian integration by parts:  $X \sim \mathcal{N}(0, 1)$ . Then for  $f$  differentiable,  $\mathbb{E}f'(X) = \mathbb{E}Xf(X)$ .

*Proof*  $f$  has bounded support:  $\mathbb{E}f(X) = \int_{\mathbb{R}} f'(x)\phi(x)dx = -\int_{\mathbb{R}} f(x)\phi'(x)dx$ . General  $f: f_n \rightarrow f$ .  $\square$

- $X \sim \mathcal{N}(0, \Sigma), f: \mathbb{R}^n \rightarrow \mathbb{R}$ . Then  $\mathbb{E}Xf(X) = \Sigma \cdot \mathbb{E}\nabla f(X)$ .

- $X \sim \mathcal{N}(0, \Sigma^X), Y \sim \mathcal{N}(0, \Sigma^Y), X \perp Y, Z(u) = \sqrt{u}X + \sqrt{1-u}Y, u \in [0, 1]$ . Then  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  twice-differentiable,  $\frac{d}{du} \mathbb{E}f(Z(u)) = \frac{1}{2} \sum_{i,j=1}^n (\Sigma_{ij}^X - \Sigma_{ij}^Y) \mathbb{E}[\frac{\partial^2 f}{\partial x_i \partial x_j}(Z(u))]$ .

*Proof*  $\frac{d}{du} \mathbb{E}f(Z(u)) = \frac{1}{2} \sum_{i=1}^n \mathbb{E} \frac{\partial f}{\partial x_i}(Z(u)) (\frac{X_i}{\sqrt{u}} - \frac{Y_i}{\sqrt{1-u}})$ .  $\sum_{i=1}^n \frac{1}{\sqrt{u}} \mathbb{E}X_i \frac{\partial f}{\partial x_i}(Z(u)) := \sum_{i=1}^n \frac{1}{\sqrt{u}} \mathbb{E}X_i g_i(X)$  (conditioned on  $Y$ ) where  $g_i(X) := \frac{\partial f}{\partial x_i}(\sqrt{u}X + \sqrt{1-u}Y)$ .  $\mathbb{E}X_i g_i(X) = \sum_{j=1}^n \Sigma_{ij}^X \mathbb{E} \frac{\partial g_i}{\partial x_j}(X) = \sum_{j=1}^n \Sigma_{ij}^X \mathbb{E} \frac{\partial^2 f}{\partial x_i \partial x_j}(\sqrt{u}X + \sqrt{1-u}Y) \sqrt{u}$ .  $\square$

- $\mathbb{E}X_i^2 = \mathbb{E}Y_i^2, \mathbb{E}(X_i - X_j)^2 \leq \mathbb{E}(Y_i - Y_j)^2, \frac{\partial^2 f}{\partial x_i \partial x_j} \geq 0, \forall i \neq j$ . Then  $\mathbb{E}f(X) \geq \mathbb{E}f(Y)$ .

- Slepian's inequality: Let  $\{X_t\}_{t \in T}$  and  $\{Y_t\}_{t \in T}$  be two mean zero Gaussian processes. Assume  $\mathbb{E}X_t^2 = \mathbb{E}Y_t^2, \mathbb{E}(X_t - X_s)^2 \leq \mathbb{E}(Y_t - Y_s)^2$ . Then for every  $t \in \mathbb{R}, \mathbb{P}(\sup_{t \in T} X_t \geq t) \leq \mathbb{P}(\sup_{t \in T} Y_t \geq t)$  and  $\mathbb{E} \sup_{t \in T} X_t \leq \mathbb{E} \sup_{t \in T} Y_t$ .

*Proof* Let  $f(x) \approx 1_{\{\max x_i < t\}} = \prod_{i=1}^n 1_{\{x_i < t\}}$  and use the latest lemma.  $\square$

- Sudakov-Fernique's inequality: Let  $\{X_t\}_{t \in T}$  and  $\{Y_t\}_{t \in T}$  be two mean zero Gaussian processes. Assume  $\mathbb{E}(X_t - X_s)^2 \leq \mathbb{E}(Y_t - Y_s)^2$ . Then  $\mathbb{E} \sup_{t \in T} X_t \leq \mathbb{E} \sup_{t \in T} Y_t$ .

*Proof* Let  $f(x) = \frac{1}{\beta} \log \sum_{i=1}^n e^{\beta x_i}$ .  $f(x) \rightarrow \max x_i$  as  $\beta \rightarrow \infty$ .  $\frac{\partial^2 f}{\partial x_i \partial x_j} \leq 0$ .  $\square$

- $A_{m \times n}$  independent  $\mathcal{N}(0, 1)$  entries. Then  $\mathbb{E} \|A\| \leq \sqrt{m} + \sqrt{n}$ .

*Proof*  $\max_{u \in \mathbb{S}^{n-1}, v \in \mathbb{S}^{m-1}} \langle Au, v \rangle := \max_{(u,v) \in T} X_{uv}$  where  $T = \mathbb{S}^{n-1} \times \mathbb{S}^{m-1}$  and  $X_{uv} \sim \mathcal{N}(0, 1)$ .  $\mathbb{E}(X_{uv} - X_{wz})^2 = \mathbb{E}(\langle Au, v \rangle - \langle Aw, z \rangle)^2 = \mathbb{E}(\sum_{i,j} A_{ij}(u_j v_i - w_j z_i))^2 = \sum_{i,j} (u_j v_i - w_j z_i)^2 = \|uv^T - wz^T\|_F^2 \leq \|u - w\|_2^2 + \|v - z\|_2^2$ . Define  $Y_{uv} = \langle g, u \rangle + \langle h, v \rangle$ ,  $g \sim \mathcal{N}(0, I_n)$ ,  $h \sim \mathcal{N}(0, I_m)$ ,  $g \perp h$ .  $\mathbb{E}(Y_{uv} - Y_{wz})^2 = \|u - w\|_2^2 + \|v - z\|_2^2$ . Then  $\mathbb{E} \|A\| = \mathbb{E} \sup_{(u,v) \in T} X_{uv} \leq \mathbb{E}_{(u,v) \in T} Y_{uv} = \mathbb{E} \sup_{u \in \mathbb{S}^{n-1}} \langle g, u \rangle + \mathbb{E} \sup_{v \in \mathbb{S}^{m-1}} \langle h, v \rangle = \mathbb{E} \|g\|_2 + \mathbb{E} \|h\|_2 \leq \sqrt{n} + \sqrt{m}$ .  $\square$

- $\mathbb{P}(\|A\| \geq \sqrt{m} + \sqrt{n} + t) \leq 2e^{-ct^2}$ .

*Proof*  $A \sim \mathcal{N}(0, I_{nm})$ ,  $f(A) = \|A\| \leq \|A\|_2 \Rightarrow \|f\|_{\text{Lip}} \leq 1 \Rightarrow \|f(A) - \mathbb{E}f(A)\|_{\psi_2} \leq C$ .  $\square$

- Sudakov's minoration inequality:  $\{X_t\}_{t \in T}$  mean zero Gaussian process.  $\forall \epsilon > 0$ ,  $\mathbb{E} \sup_{t \in T} X_t \geq C\epsilon \sqrt{\log \mathcal{N}(T, d, \epsilon)}$ .

*Proof* Assume  $\mathcal{N}(T, d, \epsilon) = N < \infty$ . Let  $\mathcal{N}$  be a maximal  $\epsilon$ -separated subset of  $T$ .  $|\mathcal{N}| \geq N$ . It suffices to show  $\mathbb{E} \sup_{t \in \mathcal{N}} X_t \geq C\epsilon \sqrt{\log N}$ .  $Y_t := \frac{\epsilon}{\sqrt{2}} g_t$ ,  $g_t \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1)$ .  $\mathbb{E}(X_t - X_s)^2 = d(t, s)^2 \geq \epsilon^2 = \mathbb{E}(Y_t - Y_s)^2 \Rightarrow \mathbb{E} \sup_{t \in \mathcal{N}} X_t \geq \mathbb{E} \sup_{t \in \mathcal{N}} Y_t = C\epsilon \sqrt{\log N}$ .  $\square$

- $X_t = \langle g, t \rangle$ ,  $g \sim \mathcal{N}(0, I_n)$ ,  $d(s, t) = \|t - s\|_2$ ,  $\mathbb{E} \sup_{t \in T} \langle g, t \rangle \geq C\epsilon \sqrt{\log \mathcal{N}(T, \epsilon)}$ .

- $P$  a polytope in  $\mathbb{R}^n$  with  $N$  vertices, diameter is bounded by 1. Then for  $\epsilon > 0$ ,  $\mathcal{N}(P, \epsilon) \leq N^{c/\epsilon^2}$ .

*Proof*  $x_1, x_2, \dots, x_N$  vertices of  $P$ ,  $\mathbb{E} \sup_{t \in P} \langle g, t \rangle = \mathbb{E} \sup_{i \leq N} \langle g, x_i \rangle \leq C\sqrt{\log N}$ .  $\square$

- Gaussian width:  $\omega(T) := \mathbb{E} \sup_{x \in T} \langle g, x \rangle$ ,  $g \sim \mathcal{N}(0, I_n)$ .

- Properties of Gaussian width: (a)  $\omega(T) < \infty \Leftrightarrow T$  is bounded; (b) For every orthogonal matrix  $U$  and vector  $y$ ,  $\omega(UT + y) = \omega(T)$ ; (c)  $\omega(\text{conv}(T)) = \omega(T)$ ; (d)  $\omega(T + S) = \omega(T) + \omega(S)$ ,  $\omega(aT) = |a|\omega(T)$ ; (e)  $\omega(T) = \frac{1}{2}\omega(T - T) = \frac{1}{2}\mathbb{E} \sup_{x, y \in T} \langle g, x - y \rangle$ ; (f)  $\frac{1}{\sqrt{2\pi}} \text{diam}(T) \leq \omega(T) \leq \frac{\sqrt{n}}{2} \text{diam}(T)$ .

*Proof* (e):  $\omega(T) = \frac{1}{2}(\omega(T) + \omega(T)) = \frac{1}{2}(\omega(T) + \omega(-T)) \stackrel{(d)}{=} \frac{1}{2}\omega(T - T)$ .

(f): Lower bound. Fix  $x, y \in T$ ,  $x - y, y - x \in T - T$ ,  $\omega(T) \geq \frac{1}{2}\mathbb{E} \max(\langle x - y, g \rangle, \langle y - x, g \rangle) = \frac{1}{2}\mathbb{E} |\langle x - y, g \rangle| = \sqrt{\frac{1}{2\pi}} \|x - y\|_2$ .

Upper bound.  $\omega(T) = \frac{1}{2}\mathbb{E} \sup_{x, y \in T} \langle g, x - y \rangle \leq \frac{1}{2}\mathbb{E} \sup_{x, y \in T} \|g\|_2 \|x - y\|_2 = \frac{1}{2}\mathbb{E} \|g\|_2 \text{diam}(T)$  and  $\mathbb{E} \|g\|_2 \leq (\mathbb{E} \|g\|_2^2)^{\frac{1}{2}} = \sqrt{n}$ .  $\square$

- Spherical width:  $\omega_{\mathbb{S}}(T) = \mathbb{E} \sup_{x \in T} \langle \theta, x \rangle$ ,  $\theta \sim \text{Unif}(\mathbb{S}^{n-1})$ .

- $(\sqrt{n} - C)\omega_{\mathbb{S}}(T) \leq \omega(T) \leq (\sqrt{n} + C)\omega_{\mathbb{S}}(T)$ .

*Proof*  $g = \|g\|_2 \cdot \frac{g}{\|g\|_2} := r \cdot \theta$ ,  $r \perp \theta$ .  $\omega(T) = \mathbb{E} \sup_{x \in T} \langle r\theta, x \rangle = \mathbb{E} r \mathbb{E} \sup_{x \in T} \langle \theta, x \rangle = \mathbb{E} \|g\|_2 \omega_{\mathbb{S}}(T)$ . Ex 3.1.4  $\Rightarrow |\mathbb{E} \|g\|_2 - \sqrt{n}| \leq C$ .  $\square$

- Squared version of the Gaussian width:  $h(T)^2 = \mathbb{E} \sup_{t \in T} \langle g, t \rangle^2$ ,  $g \sim \mathcal{N}(0, I_n)$ .

- Stable dimension: bounded  $T \subset \mathbb{R}^n$ ,  $d(T) = \frac{h(T-T)^2}{\text{diam}^2(T)} \asymp \frac{\omega^2(T)}{\text{diam}^2(T)}$ .

- $d(T) \leq \dim(T)$ .

*Proof* Let  $\dim(T) = k$  and  $T \subset \mathbb{R}^k$ .  $h(T - T)^2 = \mathbb{E} \sup_{x, y \in T} \langle g, x - y \rangle^2$ .  $x - y = \text{diam}(T) \cdot z$  for some  $z \in B_2^k$ .  $\therefore h(T - T)^2 \leq \text{diam}^2(T) \mathbb{E} \sup_{z \in B_2^k} \langle g, z \rangle^2 = \text{diam}^2(T) \mathbb{E} \|g\|_2^2 = \text{diam}^2(T) \cdot k$ .  $\square$

- Stable rank:  $A_{m \times n}$ ,  $r(A) := \frac{\|A\|_F^2}{\|A\|^2} = d(AB_2^n) \leq \text{rank}(A) = \dim(AB_2^n)$ .

- Gaussian complexity:  $\gamma(T) := \mathbb{E} \sup_{x \in T} |\langle g, x \rangle|$ ,  $g \sim \mathcal{N}(0, I_n)$ .

- $T \subset \mathbb{R}^n$ ,  $\mathcal{P}$  project to a random  $m$ -dim subspace.  $\forall m \leq n$ , with prob at least  $1 - 2e^{-m}$ ,  $\text{diam}(\mathcal{P}T) \leq C[\omega_{\mathbb{S}}(T) + \sqrt{\frac{m}{n}} \text{diam}(T)]$ .

## 8 Chaining