

# Hoeffding's Inequality: $a \leq X \leq b$ ①

$$\Rightarrow E(e^{t(X-E(X))}) \leq \exp\left(\frac{1}{8}t^2(b-a)^2\right), \text{ for } t > 0.$$

Proof: Since  $a \leq X \leq b$  we know

$$E(|X|) < \infty \quad \text{so} \quad a - E(X) \leq X - E(X) \leq b - E(X)$$

let  $a' = a - E(X)$ ,  $b' = b - E(X)$  then

$$a - b = a' - b'. \quad \text{So we assume } E(X) = 0$$

and  $a \leq X \leq b$ . This implies  $a \leq 0$

$b \geq 0$ .

If  $a \leq x \leq b$  then

$$x = \frac{x-a}{b-a} \cdot b + \frac{b-x}{b-a} \cdot a$$

$$tx = \frac{x-a}{b-a} (tb) + \frac{b-x}{b-a} (ta)$$

$$e^{tx} \leq \frac{x-a}{b-a} e^{tb} + \frac{b-x}{b-a} e^{ta}$$

$$\text{Thus } e^{tx} \leq \frac{x-a}{b-a} e^{tb} + \frac{b-x}{b-a} e^{ta}$$

$$E(e^{tx}) \leq \frac{b e^{ta} - a e^{tb}}{b-a}. \quad \text{So now we}$$

use calculus to prove

$$\frac{b e^{ta} - a e^{tb}}{b-a} \leq \exp\left(\frac{1}{8}t^2(b-a)^2\right) \text{ for}$$

all  $t$ .

② it suffices to show

$$\log \left[ \frac{be^{ta} - ae^{tb}}{b-a} \right] \leq \frac{[t(b-a)]^2}{8}$$

$$\log \left[ \frac{be^{ta} - ae^{tb}}{b-a} \right] = \log \left[ e^{ta} \cdot (b - ae^{t(b-a)}) (b-a)^{-1} \right]$$

$$= ta + \log(b - ae^{t(b-a)}) - \log(b-a)$$

$$= t(b-a) \frac{a}{b-a} + \log(b - ae^{t(b-a)}) - \log(b-a)$$

let  $x = t(b-a)$  and

$$f(x) = x \frac{a}{b-a} + \log(b - ae^x) - \log(b-a)$$

$$f(0) = 0$$

$$f'(x) = \frac{a}{b-a} - \frac{ae^x}{b - ae^x}, \quad f'(0) = 0$$

$$f''(x) = \frac{-abe^{2x}}{(b - ae^x)^2} \leq \frac{1}{4}$$

because  $-4abe^{2x} \leq (b - ae^x)^2$ . By

Lagrange's formula for the remainder in Taylor's series there is  $\theta$  between

0 and  $x$  such that

$$f(x) = f(0) + f'(0) \frac{x}{1!} + f''(\theta x) \frac{x^2}{2!} \leq \frac{x^2}{8}$$

$$\text{Hence } E(e^{tX}) \leq e^{t^2(b-a)^2/8} \quad (3)$$

## Hoeffding's Inequality, II

$X_1, \dots, X_n$  independent  $a_i \leq X_i \leq b_i$

$$k_i = b_i - a_i, \quad k = \sqrt{k_1^2 + \dots + k_n^2}, \quad \tilde{X}_i = X_i - E(X_i)$$

$$P\left(\sum_i \tilde{X}_i \geq t\right) = P\left(\lambda \sum_i \tilde{X}_i \geq \lambda t\right) \quad (\text{for } \lambda > 0)$$

$$= P\left(\exp\left(\lambda \sum_i \tilde{X}_i\right) \geq e^{\lambda t}\right)$$

$$\leq e^{-\lambda t} E\left(\exp\left(\sum_i \lambda \tilde{X}_i\right)\right)$$

$$= e^{-\lambda t} \prod E\left(e^{\lambda \tilde{X}_i}\right) = e^{-\lambda t} e^{\frac{\lambda^2}{8}(k_1^2 + \dots + k_n^2)}$$

$$= e^{-\lambda t} e^{\lambda^2 k^2/8}$$

$$P\left(-\sum_i \tilde{X}_i \geq t\right) \leq e^{-\lambda t} e^{\lambda^2 k^2/8}$$

$$P\left(\left|\sum_{i=1}^n \tilde{X}_i\right| \geq t\right) \leq e^{-\lambda t} e^{\lambda^2 k^2/8}, \quad \forall \lambda > 0.$$

choose  $\lambda > 0$  to minimize  $-\lambda t + \frac{\lambda^2 k^2}{8}$ :

$$\lambda = \frac{4t}{k^2}. \quad @ \lambda = \frac{4t}{k^2} \quad -\lambda t + \frac{\lambda^2 k^2}{8} = \frac{-2t^2}{k^2}$$

$$P\left(\left|\sum_{i=1}^n X_i - E(X_i)\right| \geq t\right) \leq 2e^{-2t^2/k^2}$$

## ④ Hoeffding's Inequality, III

$Z_1, \dots, Z_n$  independent complex valued random variables,  $|Z_i| \leq M_i$ ,  
 $M^2 = M_1^2 + \dots + M_n^2$ .

$$P\left(\left|\sum_{i=1}^n \dot{Z}_i\right| \geq t\right) \leq 4 e^{-t^2/(8M^2)}$$

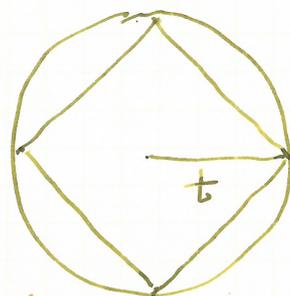
Proof:  $P\left(\left|\sum_{i=1}^n \dot{Z}_i\right| \geq t\right) \leq P\left(\left|\sum_{i=1}^n \operatorname{Re}(\dot{Z}_i)\right| \geq t/2\right)$

$$+ P\left(\left|\sum_{i=1}^n \operatorname{Im}(\dot{Z}_i)\right| \geq t/2\right)$$

$$\leq P\left(\left|\sum_{i=1}^n \operatorname{Re}(\dot{Z}_i)\right| \geq t/2\right)$$

$$+ P\left(\left|\sum_{i=1}^n \operatorname{Im}(\dot{Z}_i)\right| \geq t/2\right)$$

$$\leq 4 e^{-t^2/[4 \cdot 4 \cdot M^2]} = 4 e^{-t^2/(8M^2)}$$



## Fubini and Expectation

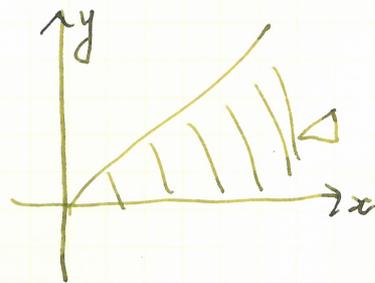
$X \geq 0$  with distribution  $\mu_X$ ,  $E(X) < \infty$

$$\Rightarrow E(X) = \int_0^{\infty} P(X \geq t) dt$$

Proof:  $E(X) = \int_0^{\infty} x d\mu_X(x) = \int_0^{\infty} \int_0^{\infty} \mathbb{I}_{\Delta}(x,y) dy d\mu_X(x)$

$$= \int_0^{\infty} \int_0^{\infty} \mathbb{I}_{\Delta}(x,y) d\mu_X(x) dy$$

$$= \int_0^{\infty} P(X \geq y) dy$$



# Lemma 2.3.1 (Tao)

(5)

Let  $X$  be a  $N \times N$  random matrix,  $X = (x_{ij})_{i,j=1}^N$  with  $E(x_{ij}) = 0$ ,  $|x_{ij}| \leq 1 \forall i, j$ . Suppose  $\xi \in \mathbb{C}^N$  with  $\|\xi\| = 1$ , and the random variables  $\{x_{ij}\}_{i,j=1}^N$  form an independent set. Then for  $\lambda > 0$  we have

$$P(\|X\xi\| \geq \lambda\sqrt{N}) \leq e^{-N(\lambda^2 - \log 32)}$$

Remark when  $\lambda > 3/2$   $\lambda < \lambda^2 - \log(32)$ .

Proof: Step I  $P(\|X_{i \cdot} \xi\| \geq \lambda) \leq 4e^{-\lambda^2/8}$

where  $X_{i \cdot} = \begin{bmatrix} x_{i1} \\ \vdots \\ x_{iN} \end{bmatrix}$  are the rows of  $X$ .

$$X_{i \cdot} \xi = \sum_{j=1}^N \xi_j x_{ij} \quad | \xi_j x_{ij} | \leq | \xi_j | \leq 1 \text{ so}$$

by Hoeffding III  $P(|X_{i \cdot} \xi| \geq \lambda) \leq 4e^{-\lambda^2/8}$ .

Step II  $E(e^{\|X_{i \cdot} \xi\|^2}) \leq 32$ .

$$\begin{aligned} E(e^{\|X_{i \cdot} \xi\|^2}) &= \int_0^\infty P(\|X_{i \cdot} \xi\|^2 \geq t) dt \quad \left\{ \begin{array}{l} \text{by} \\ \text{Fubini} \end{array} \right\} \\ &= \int_0^\infty P(\|X_{i \cdot} \xi\| \geq \sqrt{t}) dt = \int_0^\infty P(\|X_{i \cdot} \xi\| \geq s) 2s ds \\ &\leq \int_0^\infty 8 e^{-t^2/8} dt = 32 \int_0^\infty d(e^{-s^2/8}) = 32 \end{aligned}$$

Step III  $P(\|X\xi\| \geq \lambda\sqrt{N}) \leq e^{-N(\lambda^2 - 5\log 2)}$

$$\begin{aligned}
(6) \quad & P(\|X\xi\| \geq \lambda \sqrt{N}) = P(\|X\xi\|^2 \geq \lambda^2 N) \\
& = P(\exp(\|X\xi\|^2) \geq e^{\lambda^2 N}) \\
& \leq e^{-\lambda^2 N} E(e^{\|X_1 \cdot \xi\|^2} \dots e^{\|X_N \cdot \xi\|^2}) \\
& = e^{-\lambda^2 N} E(e^{\|X_1 \cdot \xi\|^2}) \dots E(e^{\|X_N \cdot \xi\|^2}) \\
& \leq e^{-\lambda^2 N} 32^N = e^{-N(\lambda^2 - \log 32)}.
\end{aligned}$$

### $\varepsilon$ -nets

Definition Let  $S$  be the unit sphere of  $\mathbb{C}^N$ .  
 $\Sigma \subseteq S$  is a maximal  $\varepsilon$ -net if

- (i)  $\forall \xi_1, \xi_2 \in \Sigma, \xi_1 \neq \xi_2, \|\xi_1 - \xi_2\| > \varepsilon$
- (ii)  $\forall \eta \in S \exists \xi \in \Sigma \text{ s.t. } \|\eta - \xi\| \leq \varepsilon$ .

Lemma Let  $X$  be a random  $N \times N$  matrix and  $\lambda > 0$  we have for  $\Sigma \subseteq S$ , a maximal  $\varepsilon$ -net

$$P(\|X\| > \lambda) \leq P\left(\bigvee_{\xi \in \Sigma} (\|X\xi\| > (1-\varepsilon)\lambda)\right).$$

Remark  $\{\omega \mid \|X(\omega)\| > \lambda\}$

$$= \{\omega \mid \exists \xi \in S \text{ s.t. } \|X(\omega)\xi\| > \lambda\}. \text{ We shall}$$

show

$$\{\omega \mid \exists \xi \in S \text{ s.t. } \|X(\omega)\xi\| > \lambda\}$$

$$\subseteq \{\omega \mid \exists \xi \in \Sigma, \text{ s.t. } \|X(\omega)\xi\| > (1-\varepsilon)\lambda\}.$$

Thus we have to show that  $\|X(\omega)\| > \lambda$  (7)

$\Rightarrow \exists \xi \in \Sigma$  s.t.  $\|X(\omega)\xi\| > (1-\varepsilon)\lambda$ . This is an easy application of the triangle inequality.

Proof: let  $\omega \in \Omega$  and suppose  $\|X(\omega)\| > \lambda$ .

Then  $\exists \xi_0 \in S$  such that  $\|X(\omega)\| = \|X(\omega)\xi_0\|$ . Then choose  $\xi \in \Sigma$  such that  $\|\xi - \xi_0\| \leq \varepsilon$ . Then  $\|X(\omega)\xi - X(\omega)\xi_0\| \leq \varepsilon\|X(\omega)\|$ . Hence

$$-\varepsilon\|X(\omega)\| \leq \|X(\omega)\xi\| - \|X(\omega)\xi_0\| = \|X(\omega)\xi\| - \|X(\omega)\|$$

$$\text{Thus } \|X(\omega)\xi\| \geq (1-\varepsilon)\|X(\omega)\| > (1-\varepsilon)\lambda.$$

Lemma Let  $\Sigma$  be an  $\varepsilon$ -net in  $S \subseteq \mathbb{C}^N$ . Then

$$|\Sigma| \leq (1+2\varepsilon^{-1})^N = e^{N \log(1+2\varepsilon^{-1})} \text{ for } \varepsilon \leq 1/2$$

Proof let  $B_r(\xi) = \{\eta \mid \|\eta - \xi\| \leq r\}$ .  $\text{vol}(B_r) = C_N r^N$

where  $C_N = \frac{\pi^{N/2}}{\Gamma(N/2+1)}$ .  $|\Sigma| \text{vol}(B_\varepsilon) \leq \text{vol}(B_{1+\varepsilon})$

$$\text{Thus } |\Sigma| \leq \left(\frac{1+\varepsilon}{\varepsilon}\right)^N = (1+2\varepsilon^{-1})^N$$

• each  $B_{\varepsilon/2}(\xi_1) \cap B_{\varepsilon/2}(\xi_2) = \emptyset$

$$\Rightarrow \|\xi_1 - \xi_2\| \leq \varepsilon.$$

## ⑧ GUE random matrices

$X \stackrel{\Delta}{\sim} \mathcal{N}_{\mathbb{R}}(0,1)$  means  $X$  is a normally distributed <sup>real</sup> random variable with mean 0 and variance 1,  $X \stackrel{\Delta}{\sim} \mathcal{N}_{\mathbb{C}}(0,1)$  means  $X$  is a complex random variable with real and imaginary parts that are independent, normally distributed, centred, with variance  $\frac{1}{2}$ .  
for such an  $X$   $E(X^2) = 0, E(X^2) = 0$ .

$X_N = \frac{1}{\sqrt{N}} (x_{ij})_{i,j=1}^N$  is a GUE random matrix if  $X_N = X_N^*$

•  $\{x_{11}, \dots, x_{NN}, \operatorname{Re}(x_{12}), \dots, \operatorname{Re}(x_{N-1,N}), \operatorname{Im}(x_{12}), \dots, \operatorname{Im}(x_{N-1,N})\}$  are independent and normally distributed such that  $x_{ii} \in \mathcal{N}_{\mathbb{R}}(0,1), x_{ij} \in \mathcal{N}_{\mathbb{C}}(0,1), i \neq j$ .

$$\operatorname{tr} = \frac{1}{N} \operatorname{Tr}$$

$$E(\operatorname{tr}(X_N^k)) \rightarrow \int_{-2}^2 t^k d\mu_0(t)$$

where  $d\mu_0(t) = \frac{\sqrt{4-t^2}}{2\pi} dt$  on  $[-2,2]$ ,

Wigner's semi-circle law.

Now suppose  $X_1, \dots, X_n$  are independent  $N \times N$  GOE random matrices and  $p \in \mathbb{C}\langle a_1, \dots, a_n \rangle$  the polynomials in the variables  $a_1, \dots, a_n$ , not assuming they commute. We say  $p$  is self-adjoint if <sup>when</sup> we put an involution  $*$  on  $\mathbb{C}\langle a_1, \dots, a_n \rangle$  by setting  $a_i^* = a_i$   $1 \leq i \leq n$  and  $(a_{i_1} \dots a_{i_r})^* = a_{i_r} \dots a_{i_1}$ , we have  $p^* = p$ . For example  $p = ia_1 a_2 a_3 + a_2 - ia_3 a_2 a_1$ .

} Theorem 4.1 (Chen, Garza-Vargas, van Handel, II)

Let  $q$  be the degree of  $p$ . There are constants  $C, c > 0$ , independent of  $n, q, N$ , and a sequence  $\{\nu_k\}_{k=0}^{\infty}$  of compactly distributed "distributions" (depending on  $p$ ) such that

for all  $h \in C^\infty(\mathbb{R})$   $1 \leq m \leq N/2$

$$\left| E\left(\frac{1}{n} \text{tr}(h(p(X_1, \dots, X_n)))\right) - \sum_{k=0}^{m-1} \frac{\nu_k(h)}{N^k} \right|$$

$$\leq \frac{(Cq)^{2m}}{m! N^m} \|f^{(2mt)}\|_{[0, 2\pi]}$$

$$+ C_r e^{-cN} \left\{ \|h\|_{\infty} + \|f'\|_{[0, 2\pi]} \right\}$$

where  $k = (C_r)^q \|p(x_1, \dots, x_r)\|$  and

$$f(\theta) = h(k \cos \theta).$$

By  $x_1, \dots, x_r \in \mathcal{B}(H)$  we mean a free semi-circular family