

# Matrix Bernstein $\neq$

Note Title

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Recall: (scalar) Bernstein  $\neq$  for bounded r.v.'s:

Thm (Bernstein  $\neq$ ) Let  $X_1, \dots, X_n$  be ind., zero-mean, r.v.'s. Suppose:

$$|X_i| \leq K \text{ a.s.}, \quad \sum_{i=1}^n \mathbb{E} X_i^2 \leq \sigma^2.$$

Then,

$$P\left(\left|\sum_{i=1}^n X_i\right| > t\right) \leq 2 \exp\left(\frac{-\frac{1}{2}t^2}{\sigma^2 + \frac{Kt}{3}}\right)$$

$$\sim 2 \exp\left(-c \min\left(\frac{t^2}{\sigma^2}, \frac{t}{K}\right)\right).$$

Sub-Gauss.

Sub-exp.

(we proved a slightly diff. version.)

Similar result holds for sums of random matrices:

Thm (Matrix Bernstein  $\neq$ ) Let  $X_1, \dots, X_m$  be ind. self adjoint, mean-zero,  $n \times n$  random matrices. Suppose:

$$\max_i \|X_i\| \leq K \text{ a.s.}, \quad \left\| \sum_{i=1}^m \mathbb{E} X_i^2 \right\| \leq \sigma^2.$$

Then,

$$P\left(\left\| \sum_{i=1}^m X_i \right\| > t\right) \leq 2n \exp\left(\frac{-t^2/2}{\sigma^2 + Kt/3}\right)$$

Remarks:

① Spectral norm,  $\|A\| = \sigma_1(A) = \max_{i=1, \dots, n} |\lambda_i(A)|$

= largest eigenvalue since  $A$  is self-adjoint.

② Matrix version recovers scalar version when  $n=1$ .

③ If  $X_i$  are not self adjoint, replace them w/  
 $\begin{bmatrix} 0 & X_i \\ X_i^T & 0 \end{bmatrix}$ .

We will prove thm using MGF as before. Set

$$S_m = \sum_{i=1}^m X_i.$$

$$P(S_m > t) \stackrel{?}{\leq} P(\mathbb{E} e^{\lambda S_m} > e^{\lambda t})$$

$\uparrow$  matrix       $\uparrow$  scalar

Self adjoint matrix relations:

① Partial ordering:

•  $A \leq B \stackrel{\text{def}}{\iff} B - A \succeq 0$  i.e.  $B - A$  is PSD  
 i.e. all eigenvals of  $B - A$  are  $\geq 0$ .

② Exponent:  $e^A := \sum_{k=0}^{\infty} \frac{A^k}{k!} = \sum_{k=0}^{\infty} \frac{1}{k!} \sum_{i=1}^n \lambda_i^k u_i u_i^* = \sum_{i=1}^n e^{\lambda_i} u_i u_i^*$

$\uparrow$  eigen-val,       $\uparrow$  eigen-vecs

(exponentiate eigenvalues)

③ Unfortunately  $e^{A+B} \neq e^A e^B$ .

But,  $\boxed{\text{tr}(e^{A+B}) \leq \text{tr}(e^A e^B)}$

"Golden Thompson  $\neq$ " See T. Tao "What's new" blog post for proof.

Proof (of matrix Bernstein  $\neq$ )

$$\|S_m\| \leq t \iff -tI_n \leq S_m \leq tI_n \quad (\text{All eig-vals} \in [-t, t])$$

$\downarrow$  identity

$$\iff e^{-\lambda t I_n} \leq e^{\lambda S_m} \leq e^{\lambda t I_n} \quad (\lambda > 0)$$

We show  $**$  holds wh.p. (Replace  $S_m$  w/  $-S_m$  to control  $*$ .)

(\*)

$$P(e^{\lambda S_m} \not\leq e^{\lambda t I}) \leq P(\text{tr}(e^{\lambda S_m}) \geq e^{\lambda t}) \leq \frac{\mathbb{E} \text{tr}(e^{\lambda S_m})}{e^{\lambda t}}$$

$\uparrow$  "an eigen-val.  $> e^{\lambda t}$ "       $\uparrow$  "sum of eig.vals.  $> e^{\lambda t}$ "       $\uparrow$  Markov  $\neq$

It suffices to bound  $\mathbb{E} \text{tr}(e^{\lambda S_m})$ .

$$\mathbb{E} \operatorname{tr}(e^{\lambda S_m}) = \mathbb{E} \operatorname{tr}(e^{\lambda X_m + \lambda S_{m-1}})$$

$$\leq \mathbb{E} \operatorname{tr}(e^{\lambda X_m} e^{\lambda S_{m-1}}) \quad (\text{By Golden Thompson})$$

$$= \operatorname{tr}(\mathbb{E} e^{\lambda X_m} \cdot \mathbb{E} e^{\lambda S_{m-1}})$$

$$\leq \|\mathbb{E} e^{\lambda X_m}\| \cdot \operatorname{tr}(\mathbb{E} e^{\lambda S_{m-1}}) \quad (\text{Exercise})$$

$$\leq \dots \leq \quad (\text{Continue by induction})$$

$$\prod_{i=1}^m \|\mathbb{E} e^{\lambda X_i}\| \operatorname{tr} \underbrace{\mathbb{E} e^0}_{\substack{I_n \\ n}}$$

$$= n \prod_{i=1}^m \|\mathbb{E} e^{\lambda X_i}\|$$

Now bound  $\|\mathbb{E} e^{\lambda X_i}\|$ . Assume  $k=1$ , i.e.,  $\|X_i\| \leq 1$ .

Enforce  $0 < \lambda \leq 1$ .  $\Rightarrow \|\lambda X_i\| \leq 1$ . Let  $Z = \lambda X_i$

Then,

$$\mathbb{E} e^Z \leq \mathbb{E}(I_n + Z + Z^2) \quad \text{Taylor series}$$

$$= I_n + Z^2$$

$$\leq e^{\mathbb{E} Z^2}$$

Exercise Justify above steps

$$\Rightarrow \mathbb{E} e^{\lambda X_i} \leq e^{\lambda^2 \mathbb{E} X_i^2}$$

$$\Rightarrow \|\mathbb{E} e^{\lambda X_i}\| \leq e^{\lambda^2 \|\mathbb{E} X_i^2\|}$$

We have shown that

$$P(S_n \notin t I_n) \leq n e^{-\lambda t} \exp \lambda^2 \sum_{i=1}^n \|\mathbb{E} X_i^2\|$$

Set  $\sigma^2 = \sum_{i=1}^n \|\mathbb{E} X_i^2\|$ . Then,

$$P(S_n \notin t I_n) \leq n \exp(-\lambda t + \lambda^2 \sigma^2)$$

Optimize over  $\lambda \in (0, 1]$ . QED.

We have proven slightly weaker version

$$\begin{array}{ccc} \text{w/} & \sigma^2 = \sum_{i=1}^n \|E X_i\|^2 & \text{not} & \sigma^2 = \left\| \sum_{i=1}^n E X_i \right\|^2 \\ & \uparrow & & \uparrow \\ & [\text{Ahlsveds-Winter}] & & [\text{R. Oliveira}], [\text{Tropp}] \end{array}$$

Literature: [Joel Tropp, "User-friendly..."]