

# Coverings of random ellipsoids, and invertibility of matrices with i.i.d. heavy-tailed entries

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# Invertibility problem

## Theorem (Rudelson, Vershynin)

Let  $n \geq n_0$  and let  $A = (a_{ij})$  be an  $n \times n$  random matrix with i.i.d mean zero *subgaussian* entries. Then for any  $\varepsilon > 0$  we have

$$\mathbb{P}\{s_n(A) \leq \varepsilon n^{-1/2}\} \leq L\varepsilon + u^n,$$

where  $L > 0$  and  $u \in (0, 1)$  depend only on the distribution of  $a_{ij}$ .

## Definition

A random variable  $\xi$  is called subgaussian, if for any  $t > 0$

$$\mathbb{P}\{|\xi| > t\} \leq C \exp(-ct^2).$$

# Invertibility problem

## Theorem (R, Tikhomirov)

Let  $n \geq n_0$  and let  $A = (a_{ij})$  be an  $n \times n$  random matrix with i.i.d mean zero  $\mathbb{E}a_{ij}^2 = 1$  entries. Then for any  $\varepsilon > 0$  we have

$$\mathbb{P}\{s_n(A) \leq \varepsilon n^{-1/2}\} \leq L\varepsilon + u^n,$$

where  $L > 0$  and  $u \in (0, 1)$  depend only on the distribution of  $a_{ij}$ .

Corollary: i.i.d. matrices with heavy-tailed entries (as well as subgaussian) are well-invertible, as

$$\|A^{-1}\| = s_{\max}(A^{-1}) = 1/s_n(A) \sim \sqrt{n}.$$

# Subgaussian case, idea of the proof

$$s_n(A) := s_{\min}(A) = \min_{x \in S^{n-1}} \|Ax\|$$

Approximation by the  $\varepsilon$ -net  $\mathcal{N} \subset S^{n-1}$ .

For any  $x \in S^{n-1}$  find the closest  $y \in \mathcal{N}$ :

$$\|Ax\| \geq \|Ay\| - \|A(x-y)\| \geq \|Ay\| - \|A\| \|x-y\| \geq \inf_{y \in \mathcal{N}} \|Ay\| - \sqrt{n} \cdot \varepsilon$$

**Lemma (norm of a subgaussian matrix  $\sim \sqrt{n}$ )**

For  $A$  be an  $n \times n$  random matrix with i.i.d. subgaussian entries.

$$\mathbb{P}\{\|A\| \geq t\sqrt{n}\} \leq \exp(-c_0 t^2 n) \quad \text{for } t > C_0.$$

Challenge: find an  $\varepsilon$ -net with the sufficiently low cardinality

$$|\mathcal{N}| \sim \left( \frac{c}{\varepsilon\sqrt{n}} \right)^n.$$

# Heavy-tailed case

$$s_n(A) := s_{\min}(A) = \min_{x \in S^{n-1}} \|Ax\|$$

Approximation by the  $\varepsilon$ -net  $\mathcal{N} \subset S^{n-1}$ .

For any  $x \in S^{n-1}$  find the closest  $y \in \mathcal{N}$ :

$$\|Ax\| \geq \|Ay\| - \|A(x-y)\| \geq \|Ay\| - \|A\| \|x-y\| \geq ???$$

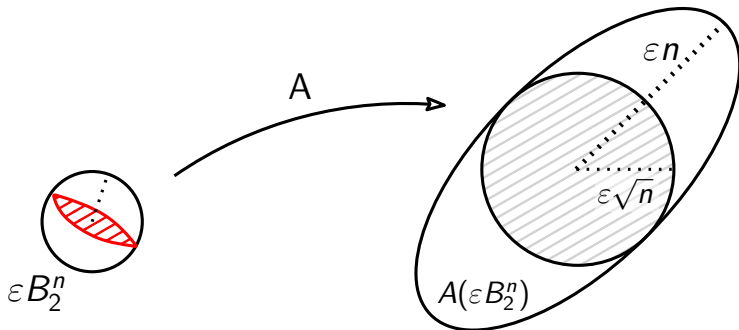
Norm is too large:

$$\|A\| \sim n \gg \sqrt{n}$$

New challenge: obtain an estimate  $\|A(x-y)\| \leq \sqrt{n}\varepsilon$ , where  $x, y$  are in the same  $\varepsilon$ -net element.

So, for any  $x, y$  taken from one net element we would like to have

$$\|A(x - y)\| \leq \sqrt{n}\varepsilon$$



The net should be refined without blowing up of cardinality  $|\mathcal{N}|$ . It is possible as  $A$  cannot have too many large directions!

(\*) Our model:  $A$  is an  $n \times n$  random matrix with i.i.d  $\mathbb{E}a_{ij} = 0$  and  $\mathbb{E}a_{ij}^2 = 1$  entries.

### Definition

We call a diagonal matrix  $D = (d_{ij})_{i,j=1}^n$  with  $d_{ii} \in (0, 1)$  a (positive diagonal) *contraction*.

### Key proposition

Let  $\delta \in (0, 1]$  and  $A$  satisfies (\*). Then with probability  $1 - 4 \exp(-\delta n/8)$  there exists a contraction  $D$ , such that (1)  $\det D \geq \exp(-\delta n)$  and (2)  $\|AD\|_{\infty \rightarrow 2} \leq \frac{C}{\sqrt{\delta}} n$ .

Then the shifts of parallelepiped  $D(n^{-\frac{1}{2}} B_{\infty}^n)$  can serve as "diluted net elements":

$$\|AD(n^{-\frac{1}{2}} B_{\infty}^n)\| \leq \frac{1}{\sqrt{n}} \|AD\|_{\infty \rightarrow 2} \leq \frac{C}{\sqrt{\delta}} \sqrt{n},$$

# Consequences of the key proposition

1) This solves an **invertibility problem** for heavy-tailed matrices: there is a net refinement of cardinality  $|\mathcal{N}'| \leq C^n \left(\frac{c}{\varepsilon\sqrt{n}}\right)^n$  such that  $\|A(x - y)\| \sim \sqrt{n}\varepsilon$  for every  $A$  with high probability.

2) Also, it implies the following geometric theorem about the existence of a good **covering** for a **random ellipsoid**:

## Theorem A

*For any  $\delta \in (0, 1/4]$  there is a subset  $\mathcal{N} \subset B_2^n$  of cardinality at most  $\exp(C_\delta n)$ , such that for any random matrix  $A$  satisfying (\*) with probability at least  $1 - 4\exp(-n\delta/32)$  we have*

$$A(B_2^n) \subset \bigcup_{y \in A(\mathcal{N})} (y + c_\delta \sqrt{n} B_2^n).$$



# Proof of key proposition

## Key proposition

Let  $\delta \in (0, 1]$  and  $A$  satisfies (\*). Then with probability  $1 - 4 \exp(-\delta n/8)$  there exists a contraction  $D$ , such that (1)  $\det D \geq \exp(-\delta n)$  and (2)  $\|AD\|_{\infty \rightarrow 2} \leq \frac{C}{\sqrt{\delta}} n$ .

Construction of  $D$ :

- 1 Step 1: construct  $D$  with the following properties:
  - Euclidean norms of all the rows of  $AD$  are bounded by  $C_\delta \sqrt{n}$
  - $\det D \geq \exp(-\delta n)$
- 2 Step 2: show that the norms of the rows condition implies that  $\|AD\|_{\infty \rightarrow 2} \leq C'_\delta n$  with high probability

## Step 1: Bernoulli case, for one row

Suppose a vector  $X := (a_{i1}^2, \dots, a_{in}^2)$  has Bernoulli coordinates.  
We define  $D_i$  for  $X$ :

$$\begin{cases} d_{ii} := \frac{Cn}{\|X\|_1} \cdot \mathbb{I}_{\{x_i \neq 0\}} & \text{if } \|X\|_1 > Cn \\ d_{ii} := 1 & \text{otherwise} \end{cases}$$

Then  $\|\langle X, D_i \rangle\|_1 \leq Cn$  and  $\det D_i \geq \exp(-\delta)$ .

Example 1 (making  $l_1$  norm a bad row to be at most 2):

$$\begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & d & 0 & 0 & 0 \\ 0 & 0 & d & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & d \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & d & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & d & d & 0 & d \\ 1 & 0 & 0 & 0 & d \end{bmatrix}$$

# Step 1: Bernoulli case, for a matrix

Define

$$D := \prod_{i=1}^n D_i$$

Then

- $\|\langle X, D \rangle\|_1 \leq Cn$  for every row  $X = (a_{i1}^2, \dots, a_{in}^2)$
- $\det D = \prod (\det D_i) \geq \exp(-\delta n)$ .

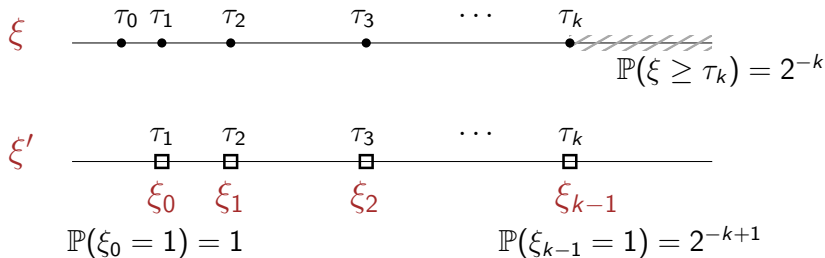
Example 2 (making  $l_1$  norm of every row be at most 2):

$$\begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} d_1 \cdot 1 & 0 & 0 & 0 & 0 \\ 0 & d_1 d_2 & 0 & 0 & 0 \\ 0 & 0 & 1 \cdot d_2 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & d_1 d_2 \end{bmatrix} = \begin{bmatrix} d_1 & 0 & 0 & 1 & 0 \\ 0 & d_1 d_2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & d_1 d_2 & d_2 & 0 & d_1 d_2 \\ d_1 & d_1 d_2 & 0 & 0 & d_1 d_2 \end{bmatrix}$$

# Step 1: General distribution case

Main idea: any random variable  $\xi$  (for us  $\xi = a_{ij}^2$ ) can be almost surely approximated above by the sum of Bernoulli random variables  $\xi_i$ , such that  $\mathbb{P}(\xi_i = 1) = 2^{-i}$ ,

$$\xi' := \sum_{i=1}^{\infty} \tau_i \xi_i \geq \xi, \quad \text{and} \quad \mathbb{E} \xi' \leq 2 \mathbb{E} \xi.$$



## Step 3: from bounded rows to bounded $\|\cdot\|_{\infty \rightarrow 2}$ norm

### Lemma

Let  $A$  has symmetrically distributed entries and satisfies (\*). If there exists  $D \in \mathcal{F}$  (any countable subset of the set of contractions), such that Euclidean norms of the rows  $AD$  are at most  $K\sqrt{n}$ , then

$$\|AD\|_{\infty \rightarrow 2} \leq CKn$$

with exponentially high probability.

Main idea: as

$$\|AD\|_{\infty \rightarrow 2}^2 = \sup_{v \in \text{Vert}(B_{\infty}^n)} \|ADv\|^2 = \sum \langle ADv, e_i \rangle^2,$$

after conditioning on  $|A|$  and on  $D$  (only signs of the entries matter) we can use Bernstein's inequality to bound the norm.

## References and related work

- E. Rebrova, K. Tikhomirov, Coverings of random ellipsoids, and invertibility of matrices with i.i.d. heavy-tailed entries Preprint. arXiv:1508.06690
- Tikhomirov K. E. The smallest singular value of random rectangular matrices with no moment assumptions on entries. Israel Journal of Mathematics, 2016. DOI: 10.1007/s11856-016-1287-8.
- Rudelson, M.; Vershynin, R. The Littlewood-Offord problem and invertibility of random matrices. Adv. Math. 218 (2008), no. 2, 600–633.
- M. Rudelson, Lecture notes on non-asymptotic random matrix theory, Notes from the AMS Short Course on Random Matrices, 2013

Thanks for your attention!  
Please share your questions and comments with me.  
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