

# Day 5 Talk 1

Alexander Litvak

"The smallest singular value of a  $d$ -regular random square matrix"

Motivation

$$3 \leq d \leq n/2$$

$M = \{m_{ij}\}_{n \times n}$  adjacency matrix of random  $d$ -regular directed graph with  $n$ -vertices (uniform probability).

Conjecture Vu '08, Frieze, Vu ICM-talk '14:

$M$  non-singular with high probability

$$P \rightarrow 1$$

$n \rightarrow \infty$ .

RK if  $d=1$   $M$  is a permutation matrix  
 $\Rightarrow$  invertible

$d=2$  conjecture fails

$d=d_0, d=n-d_0$  are essentially the same

Thm Cook '14 (arxiv date)

Conjecture true for  $d \gg \ln^2 n$  with probability  $1 - \frac{1}{d^c}$

Rk  $d \gg \ln^2 n$  means  $d/\ln^2 n \rightarrow \infty$  as  $n \rightarrow \infty$

|| Thm (LLTP, '15)

Conjecture  $C \leq d \leq n/\ln^2 n$  with ~~probability~~ probability  $1 - C \ln^2 d / \sqrt{d}$

Q: Quantitative estimates for smallest singular value  $s_n(M)$ ?

• Thm above says  $s_n(M) \neq 0$  w.h. probability

• Bound  $s_n(M)$  from below?

Some bounds for  $s_n(M)$  by BR '15 for Erdős-Rényi

Theorem Cook '16

$$P(s_n(M) \geq n^{-c \ln n / \ln d}) \geq 1 - \ln^2 n / \sqrt{d}$$

Thm LLTP '17

$C < d < n / \log^2 n$ . Then

$$P(s_n(M) \geq 1/n^6) \geq 1 - \ln^2 d / \sqrt{d}$$

Proof ideas:

- Remove "bad events" with small probability

(Switch to blackboard)

$$S_n(M) > \lambda_0 \iff \forall x \in S^{n-1} \quad \|Mx\| \geq \lambda_0$$

$\rightsquigarrow$  splitting sphere

Rk: Goal estimate  
 $Mx \forall x$ , treat differently

Main idea: splitting sphere  $\rightarrow$  goes back Kashin-Kononov

Schechtman  
 L.P.R.T.  $\rightarrow$  R.V.

split sphere to  
 { sparse + close  
 { other vectors

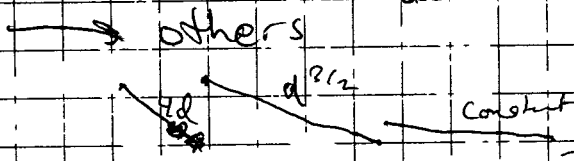
- Introduce
- Almost constant vectors (flat)
- Steep vectors
- Sloping vectors

Intuitive:  
 Steep:  $x \in S^{n-1}$

$\{x_i\}^*$

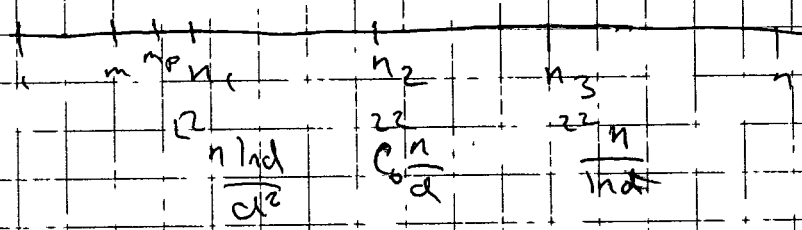
decreasing rearrangement of coordinates

Sloping:



jumps  $p = \sqrt{\frac{\alpha}{ln d}}$

Steep:

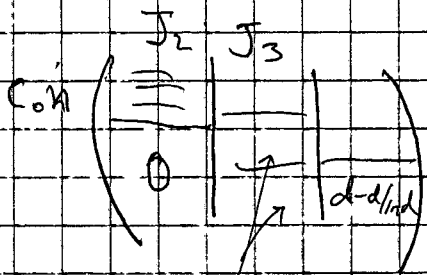


$$B(p) = \text{almost const} = \{x \in S^{n-1} \mid \exists \lambda \text{ s.t. } |\{i : |x_i - \lambda| < p\}| > n - n_3\}$$

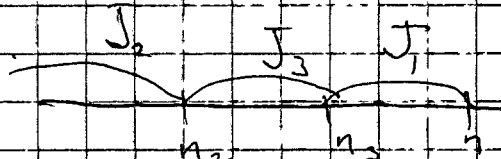
# Two steps in proof

(1) Almost constant  $\beta(p)$    
 ↗ steep   
 ↘ sloping

(2) other vectors

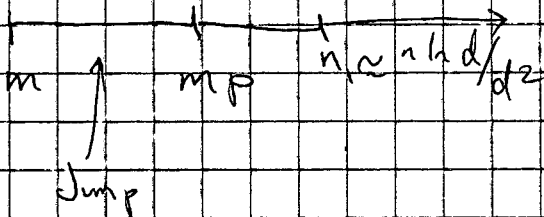
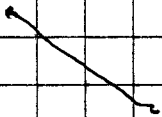


# of rows with many 1's not large

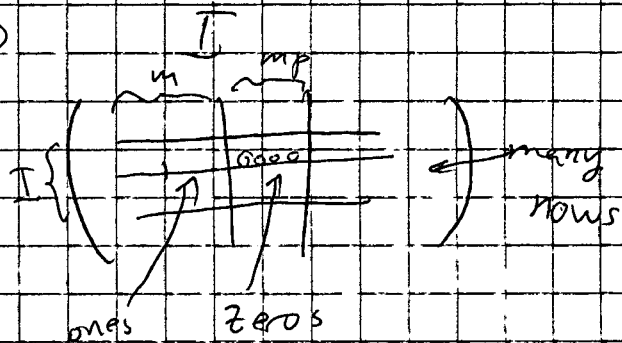


$M_x \rightarrow \langle R_{i,x} \rangle$  — big

$\leadsto$  gives bound for case (1)



in most matrices can find  $\leadsto$



$$(R_{i,x}) = x_{j_0} + \sum_{k=1}^{d-1} x_{j_k}$$

$\leadsto$  many rows where

$(R_{i,x})$  separated from zero

For  $\frac{a_{i_1} \dots a_{i_n}}{n_1 \dots n_n}$  Apply union bound

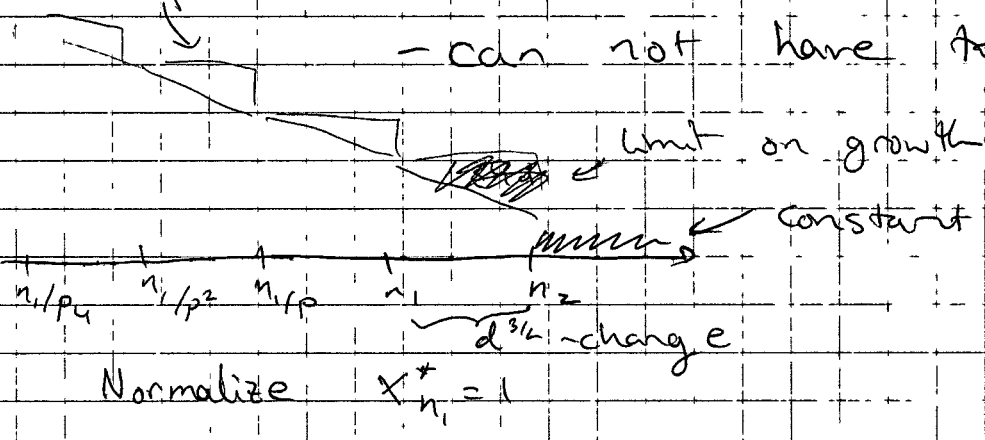
$$\|Mx\| \leq \epsilon_0$$

Need bound for all  $x$ , but infinite.

- So need a good net, union bound.

- can not have too large a net

Not enough

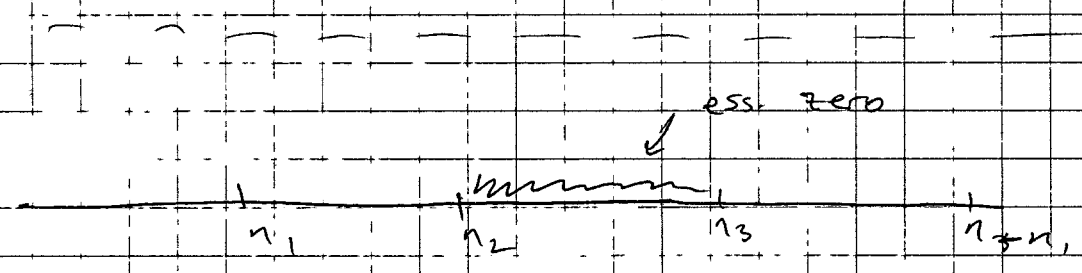


Construct net piece by piece:

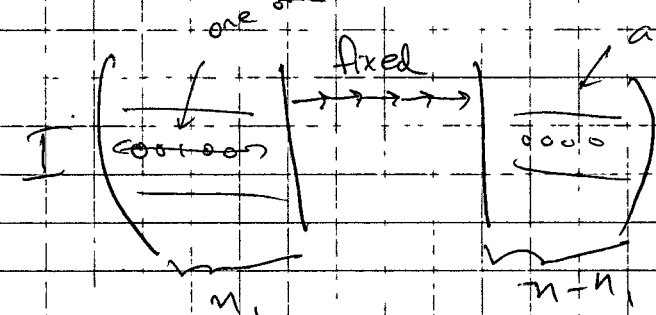
If good net:  $d^{3/4}$ -net in  $\ell_\infty$ -norm

$$|N| \leq e^{10n_1 d} \leq e^{n_2 d/k}$$

↑  
net



going to split matrix



if  $\|Mx\|/k$  small

Estimate  $\langle R_i, x \rangle > \frac{1}{4}$

Estimate probability that many  $\langle R_i, x \rangle < \frac{1}{4}$

$$P(n, \epsilon) \rightarrow e^{-n_2 d / \epsilon} \quad \leftarrow \text{kills /ok with } \epsilon\text{-net size.}$$

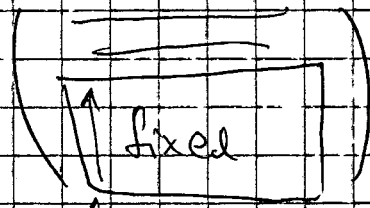
What if vectors  $x$  is not almost constant

~~Just~~ Just main idea!

$x$  - not almost constant case

bound for

$$S_n(M) \longleftrightarrow \langle R_i, x \rangle \geq \frac{1}{4}$$

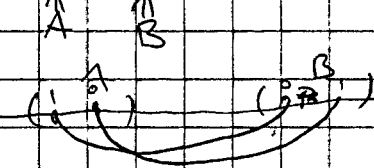


exactly  $d$  ones

(2d)  
(d)

$A, B$  - large

$$|x_i - x_j| > \epsilon/16$$



# The smallest singular value of a $d$ -regular random square matrix

Alexander Litvak

University of Alberta

based on a joint work with

A. Lytova, K. Tikhomirov, N. Tomczak-Jaegermann, and P. Youssef

MSRI, Berkeley, 2017

# Motivation

We consider adjacency matrices of random  $d$ -regular directed graphs (digraphs) on  $n$  vertices, which can be also seen as bipartite graphs (bigraphs).



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**Remark 2.** If  $d = 2$  the conjecture fails (see e.g., Vu, Cook).

**Remark 3.** The cases  $d = d_0$  and  $d = n - d_0$  are essentially the same (by interchanging zeros and ones).

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Sparse matrices are very important in statistics, neural network, electrical engineering, wireless communications, and in many other fields. In standard iid model we refer to recent works by [Tao–Vu](#), [Götze–A.Tikhomirov](#), [Wood](#), [Basak–Rudelson](#).



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## Theorem (BR, 2015)

In Erdos–Renyi model with  $p_n = d/n$  one has

$$\mathbb{P} \left( s_n(M) \geq \varepsilon c_{n,d} \frac{\sqrt{d}}{n} \right) \geq 1 - \varepsilon - e^{-d},$$

where  $c_{n,d} = \exp \left( -\frac{c \ln(n/d)}{\ln d} \right)$ .

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Let  $d > \ln^c n$ . Let  $M$  be  $d$ -regular random square matrix. Then

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there exist  $k$  columns such that cardinality of union of their supports is  $\leq (1 - \varepsilon)dk$ .

(Of course, **2** is a partial case of **3** with  $k = 2$ .)