

# MATRIX RIGIDITY

## REVIEW OF PART I

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# TOOLS USED IN PART I

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## LAST LECTURE

Take a random object  
Prove  $\Pr[\text{GOOD}] > 0$   
 $\Pr[\text{BAD}] < 1$   $\Rightarrow$   $\exists$  exists GOOD obj

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we proved  $\exists$  rigid matrices

- Probabilistic Method
- Algebraic Independence

Alg ind is often as good as randomness (or even better)

Matrix w alg ind entries is rigid.

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Step 1

- showed that all  $N$  polynomials are linearly independent
- subspace  $V$  generated by  $N$  poly,  $\dim(V) = N$

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  - defined a polynomial for each zero pattern

Step 1 • showed that all  $N$  polynomials are linearly independent

Step 2 • but they live in a low-dimensional space

$\dim(U)$  is low

$N = \dim(U)$

↳ is small

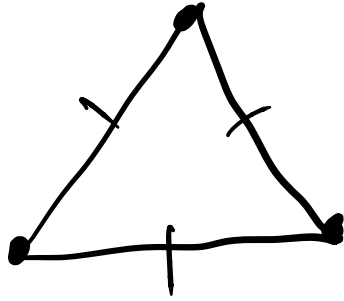
# POLYNOMIAL METHOD

- In order to prove an upper bound on the number  $N$  of zero-patterns, we
  - defined a polynomial for each zero pattern
  - showed that all  $N$  polynomials are linearly independent
  - but they live in a low-dimensional space
  - hence, an upper bound on  $N$



$\mathbb{R}^2$ 

$n$  points s.t. all pairwise distances are **same**

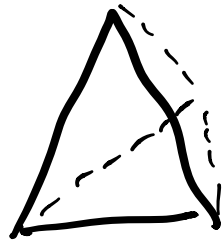


$$n=3$$

 $\mathbb{R}^d$ 

regular simplex in  $\mathbb{R}^d$

$$n = d + 1$$

 $\mathbb{R}^2$ 

$n$  points s.t. all pairwise distances are  $\{a, b\}$



$$n=5$$

$\mathbb{R}^d$ two distances  $\{a, b\}$ 

$$n \approx \Omega(d^2)$$

$$P_1, \dots, P_n \in \{0, 1\}^d$$

 $\|P_i\|_1 = 2$  - has exactly two ones.

$$n = \binom{d}{2}$$

$$P_i \begin{array}{|c|c|c|c|c|c|c|c|} \hline 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ \hline \end{array} \quad \text{dist}=2$$

$$P_j \begin{array}{|c|c|c|c|c|c|c|c|} \hline 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ \hline \end{array}$$

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$$P_i \begin{array}{|c|c|c|c|c|c|c|c|} \hline 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ \hline \end{array} \quad \text{dist}=\sqrt{2}$$

$$P_j \begin{array}{|c|c|c|c|c|c|c|c|} \hline 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline \end{array}$$

$\mathbb{R}^d$  two distances (a, b)  
Prove an Upper Bound on n

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$$p_1, \dots, p_n \in \mathbb{R}^d$$

$$f_1, \dots, f_n \text{ - poly } f_i(x) \quad x \in \mathbb{R}^d$$

⋮  
 $f_i(x_1, \dots, x_d)$

$$f_i(x) = (\|x - p_i\|_2^2 - a^2) \cdot (\|x - p_i\|_2^2 - b^2)$$

$$f_i(p_i) = a^2 \cdot b^2 \neq 0$$

$$i \neq j: f_i(p_j) = (\|p_j - p_i\|_2^2 - a^2) (\|p_j - p_i\|_2^2 - b^2) \\ = 0$$

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Poly method 

Step 1: prove polys are lin ind

Step 2: dim(span) is small

Step 1:  $f_i$  are lin ind.

$$\sum_{i=1}^n f_i \cdot \alpha_i = 0 \stackrel{\text{WTS}}{\implies} \text{all } \alpha_i = 0$$

$\forall x$

$$\sum_{i=1}^n f_i(x) \cdot \alpha_i = 0$$

$x = p_j \quad \forall j \in \{1, \dots, n\}$

$$\sum_{i=1}^n f_i(p_j) \cdot \alpha_i = 0$$

$$\Downarrow$$
$$f_j(p_j) \cdot \alpha_j = 0$$

$$\Downarrow$$
$$\alpha_j = 0 \quad \forall j \in \{1, \dots, n\}$$

$$\begin{aligned} f_i(p_j) &= 0 \\ \text{iff } i &\neq j \\ f_j(p_j) &\neq 0 \end{aligned}$$

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$V$  - subspace real funs  $\mathbb{R}^d \rightarrow \mathbb{R}$   
spanned  $f_1 \dots f_n$

$$\dim(V) = n$$

It remains to show  $\dim(V)$  is small

$$\begin{aligned}
 F_i(x_1, \dots, x_d) &= (\|x - p_i\|^2 - a^2) \cdot (\|x - p_i\|^2 - b^2) \\
 &= \left( \sum_{j=1}^d (x_j - p_{ij})^2 - a^2 \right) \left( \sum_{j=1}^d (x_j - p_{ij})^2 - b^2 \right) \\
 &\quad - \text{poly of deg 4 in } x_1, \dots, x_d.
 \end{aligned}$$

1	}	basis	1
$x_1, \dots, x_d$		$d$	
$x_1^2, x_1 x_2, x_1 x_3, \dots, x_d^2$		$d^2$	
$x_1^3, x_1^2 x_2, \dots, x_d^3$		$d^3$	
$x_1 x_2 x_3 x_4, x_1^4, \dots$	$d^4$		

$$n = \dim(V) \leq \text{size of the basis} = O(d^4)$$

In our case

basis	# of polys
1	1
$x_1, \dots, x_d$	$d$
$x_1^2, \dots, x_d^2$	$d^2$
$x_j \sum_{i=1}^d x_i^2 \quad \forall j \in [d]$	$d$
$(\sum x_i^2)^2$	1

$= O(d^2)$   
 $\Downarrow$   
 $n \leq O(d^2)$

# POLYNOMIAL METHOD. EXAMPLE

## Theorem

Let  $x_1, \dots, x_n \in \mathbb{R}^d$  be points such that the pairwise distances between them take *two* values. Then

$$n = O(d^2).$$

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- We showed that a graph without bipartite cliques is not dense

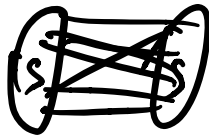


# ZARANKIEWICZ PROBLEM

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Theorem [KST]

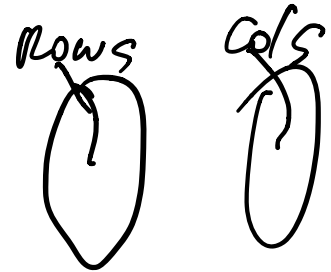
Let  $s \in \mathbb{N}$  be a constant. The number of edges in a  $K_{s,s}$ -free graph is  $O(n^{2-1/s})$ .



vs  $\Theta(n^2)$  in complete graph

# ZARANKIEWICZ PROBLEM

- Concluded that a few changes in a matrix leave an untouched matrix of size  $s \times s$



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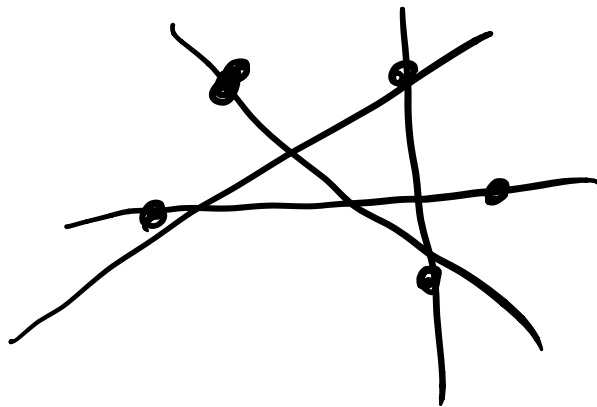
- Concluded that a few changes in a matrix leave an untouched matrix of size  $s \times s$
- Thus, matrices with non-zero minors are (moderately) rigid

# ZARANKIEWICZ PROBLEM. EXAMPLE

Theorem (Szemerédi–Trotter theorem)

$n$  points and  $n$  lines in the plane have  $O(n^{4/3})$  point-line incidences.

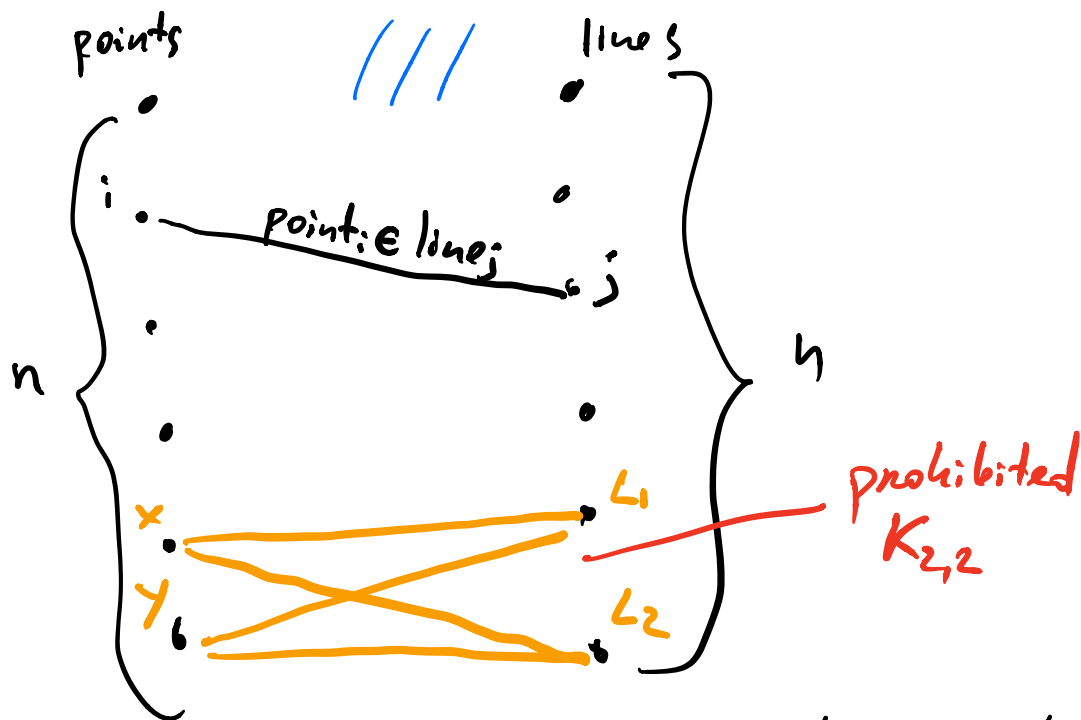
$\mathbb{R}^2$



(point, line) s.t.  
point  $\in$  line

# point-line  
incidences  $\in n^2$

# (point-line)-incidences  $\leq O(n^{3/2})$



Upper bound on # edges in the graph



Zarankiewicz: no  $K_{s,s}$   
 $\Rightarrow$  #edges  $O(n^{2-1/s})$

COR: no  $K_{2,2} \Rightarrow$  #edges  $O(n^{3/2})$

# HÖLDER'S INEQUALITY

## Theorem

For any  $x, y \in \mathbb{C}^n$ , any  $p, q \in [1, \infty]$  with  $1/p + 1/q = 1$ :

$$\sum_{i=1}^n |x_i y_i| \leq \|x\|_p \|y\|_q.$$

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$$\sum d_i^s \leq \text{Bound}$$

- Connects different  $L_p$  norms
- In Kővári-Sós-Turán Theorem, we had a bound on sth moment of vertices' degrees, needed bound on number of edges

$$|E| \leq \sum d_i^s \leq \text{Bound}'$$



# HÖLDER'S INEQUALITY. EXAMPLE

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WTS:

$$\|v\|_1 \leq \sqrt{n} \cdot \|v\|_2$$

$$x_i = v_i \quad y_i = 1 \quad p = q = 2 \quad \frac{1}{p} + \frac{1}{q} = 1$$

$$\|v\|_1 = \sum_{i=1}^n |v_i| = \sum |x_i y_i|$$

Hölder

$$\leq \|x\|_p \cdot \|y\|_q = \|v\|_2 \cdot \sqrt{n}$$

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$$\|v\|_2 \leq \sqrt{\|v\|_1 \cdot \|v\|_\infty}$$

$$p=1 \quad q=\infty \quad \frac{1}{p} + \frac{1}{q} = 1$$

$$x_i = y_i = v_i$$

$$\|v\|_2^2 = \sum v_i^2 = \sum |x_i y_i|$$

Hölder

$$\leq \|x\|_p \cdot \|y\|_q = \|v\|_1 \cdot \|v\|_\infty$$

# HÖLDER'S INEQUALITY. EXAMPLE

## Theorem

For  $v \in \mathbb{C}^n$ :

$$\frac{\|v\|_1}{\sqrt{n}} \leq \|v\|_2 \leq \sqrt{\|v\|_1 \|v\|_\infty}.$$

## Theorem

For  $v \in \mathbb{C}^n$ :

$$\|v\|_r \leq n^{1/r-1/s} \|v\|_s.$$

This is tight

$$r=1$$
$$s=1$$
$$\sqrt{n}$$

# SIGN-RANK

Let  $A \in \{1, -1\}^{n \times n}$ . Then  $\text{signrk}(A)$  is the minimum rank of  $B$  s.t.  $\text{sign}(b_{ij}) = a_{ij}$  for all  $i, j \in [n]$ .

# Unbounded-error communication complexity

$$F: \{0,1\}^n \times \{0,1\}^n \rightarrow \{0,1\}$$

$$F(x, y)$$

Alice gets  $x$   $\rightsquigarrow$   $F(x, y)$   
Bob gets  $y$   $\rightsquigarrow$

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det  
non-det  
rand  
quant w/ ent  
quant w/ ent

comm models

---

Unbounded-error comm.

compute  $F(x, y)$  with prob  $> \frac{1}{2}$   
say,  $\frac{1}{2} + \frac{1}{2^n}$

Alice & Bob use **private** randomness

If we had shared randomness,

1011011111

Alice  $\rightarrow$   $\leftarrow$  Bob

Then  $CC(\text{every problem}) \leq 1$

Alice:

sends 1 iff first  $n$  bits of randomness

$= x$

sends 0.

Bob:

receives 1. Knows  $x \Rightarrow f(x, y)$

else. Random bit.

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Prob of success:

$$2^{-n} + (1 - 2^{-n}) \cdot \frac{1}{2} = \frac{1}{2} + \frac{1}{2^{n+1}} > \frac{1}{2}$$

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Important: Randomness is Private

# SIGN-RANK

Let  $A \in \{1, -1\}^{n \times n}$ . Then signrk(A) is the minimum rank of  $B$  s.t.  $\text{sign}(b_{ij}) = a_{ij}$  for all  $i, j \in [n]$ .

## Theorem (Paturi, Simon)

*Unbounded-error communication complexity of a problem is  $\log(\text{signrk}(A))$  of its communication matrix  $A$ .*

$\text{signrk}(A)$

$A \in \{\pm 1\}^{n \times n}$

$B \in \mathbb{R}^{n \times n}$

$\text{sign}(b_{ij}) = a_{ij}$

$\min \text{rk } B \leftarrow \text{signrk}(A)$

$B_0 = A$

$$A \begin{bmatrix} 1 & 1 \\ -1 & -1 \end{bmatrix}$$

$$B_1 \begin{bmatrix} 7 & 0.5 \\ -3 & -1 \end{bmatrix}$$

$$B_2 \begin{bmatrix} 0.1 & 11 \\ -1 & -1 \end{bmatrix}$$

Sometimes  $\text{signrk}(A) < \text{rk}(A)$

Ex.

A

$$\begin{bmatrix} 1 & -1 & -1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & 1 & 1 & -1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

$$\begin{aligned} \text{rk}(A) &\geq n-1 \\ \text{rk}(A+J) &= \\ &= \text{rk}(2 \cdot \text{Tr}) \\ &= n \end{aligned}$$

B

$$\begin{bmatrix} 1 & -1 & -3 & -5 \\ 3 & 1 & -1 & -3 \\ 5 & 3 & 1 & -1 \\ 7 & 5 & 3 & 1 \end{bmatrix}$$

$$\begin{array}{cccc} 1 & -1 & -3 & -5 \\ 2 & 2 & 2 & 2 \\ \text{rk}(B) = 2 \end{array}$$



$$\text{rk}(A) = n - 1$$

$$\text{signrk}(A) = 2$$

$$\text{signrk}(A) \ll \ll \ll \text{rk}(A)$$

---

Unbounded error Comm Comp

$$= \log_2(\text{signrk}(A)) \pm 1$$

# ZERO-PATTERNS

- A vector  $\sigma \in \{0, 1\}^n$  is a zero-pattern of polynomials  $p_1, \dots, p_n$  if there exists  $\underline{x} \in \mathbb{R}^t$  s.t.  $\underline{p_i(x)} = 0$  iff  $\underline{\sigma_i} = 0$   
*n polys of t variables*

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- The number of zero-patterns is  $\leq 2^n$

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- The number of zero-patterns is  $\leq \underline{\underline{2^n}}$

## Theorem

For constant degree polynomials, the number of zero-patterns is  $\leq \boxed{n^t} \ll \underline{\underline{2^n}}$  (for small  $t$ )

$n$  - # polys  
 $t$  - # var

# ZERO-PATTERNS

- Non-rigid  $M$ :

$$\square = \text{sparse} + \begin{matrix} \text{low-} \\ \text{rank} \end{matrix}$$

# ZERO-PATTERNS

- Non-rigid  $M$ :

$$\begin{aligned} \square &= \square_{\text{sparse}} + \square_{\text{low-rank}} \\ &= \square_{\text{sparse}} + \begin{matrix} R \\ | \\ n \end{matrix} \times \begin{matrix} n \\ | \\ R \end{matrix} \end{aligned}$$

The diagram illustrates the decomposition of a matrix  $M$  into a sparse matrix and a low-rank matrix. The first equation shows  $M$  as the sum of a sparse matrix and a low-rank matrix. The second equation shows  $M$  as the sum of a sparse matrix and the product of two matrices: a vertical matrix of size  $n \times R$  and a horizontal matrix of size  $R \times n$ .

# ZERO-PATTERNS

- Non-rigid  $M$ :

The diagram illustrates the decomposition of a matrix  $M$  into two parts. The first part is a square box with a single black dot in the top-left corner, representing a sparse matrix. This is followed by an equals sign, then another square box with the word "sparse" in orange text, followed by a plus sign, and then a square box with the words "low-rank" in orange text. Below this, the same square box with the dot is followed by an equals sign, then a square box with the word "sparse" in orange text, followed by a plus sign, and then a vertical rectangular box with a thick black line at the top, followed by a multiplication sign, and then a horizontal rectangular box with a thick black line on the left. A curved line underlines the vertical and horizontal boxes, indicating they are multiplied together.

- Each (out of  $n^2$ ) entries on the **left** is a degree-2 polynomial of the entries on the **right**

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- By the zero-pattern theorem, there are only a few zero-non-zero matrices low-degree polynomials can generate
- In particular, only a few  $\{0, 1\}$ -matrices
- Therefore, a random  $\{0, 1\}$ -matrix is rigid

Brute Force  $2^{n^2}$

# SIGN-PATTERNS. EXAMPLE

## Theorem

The number of sign-patterns of  $n$  constant-degree polynomials of  $t$  variables is (also)  $\leq n^t$

# SIGN-PATTERNS. EXAMPLE

## Theorem

The number of *sign*-patterns of  $n$  constant-degree polynomials of  $t$  variables is (also)  $\leq n^t$ .

## Theorem [Alon et al 1985]

There exist matrices of high *sign*-rank. (There exist problems of high unbounded-error communication complexity.)