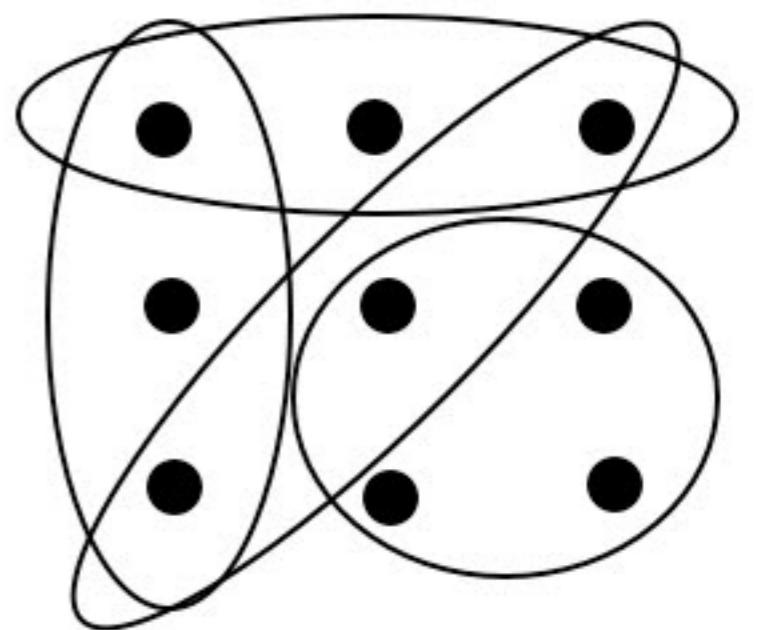


Algorithm for Komlós discrepancy problem matching Banaszczyk's bound

Nikhil Bansal (TU Eindhoven)
Daniel Dadush (CWI, Amsterdam)
Shashwat Garg (TU Eindhoven)

Combinatorial discrepancy

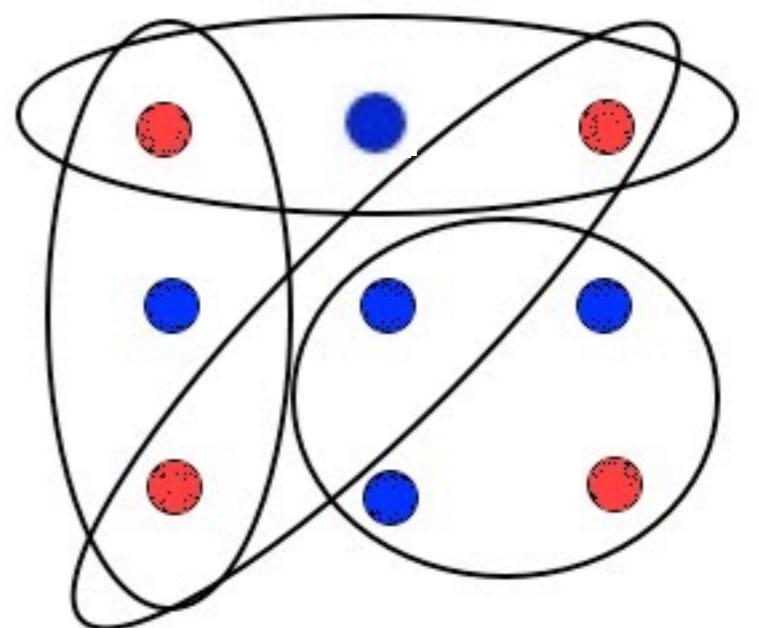
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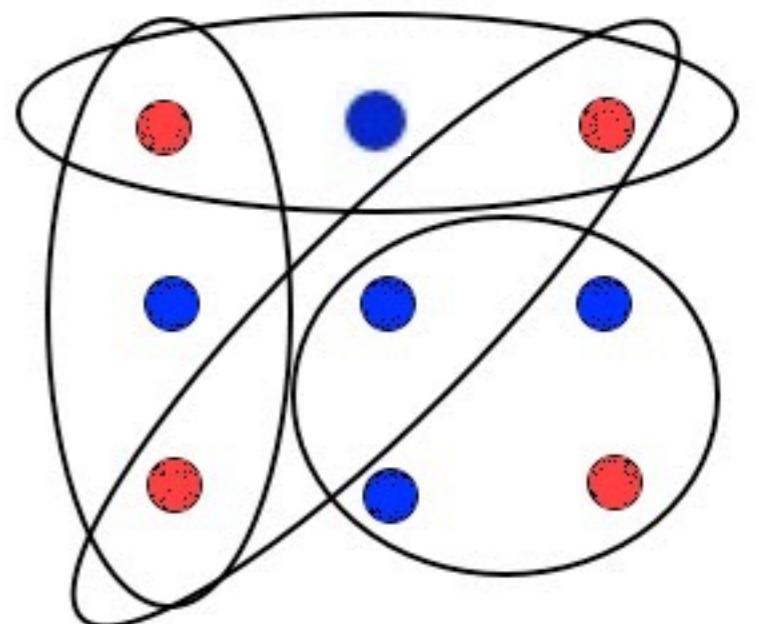
Color each point $\chi_i = -1$ or $+1$



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$$disc(S_j, \chi) = \left| \sum_{i \in S_j} \chi_i \right|$$

$$disc(\mathcal{S}, \chi) = \max_j disc(S_j, \chi)$$

$$disc(\mathcal{S}) = \min_{\chi} \max_j disc(S_j, \chi)$$

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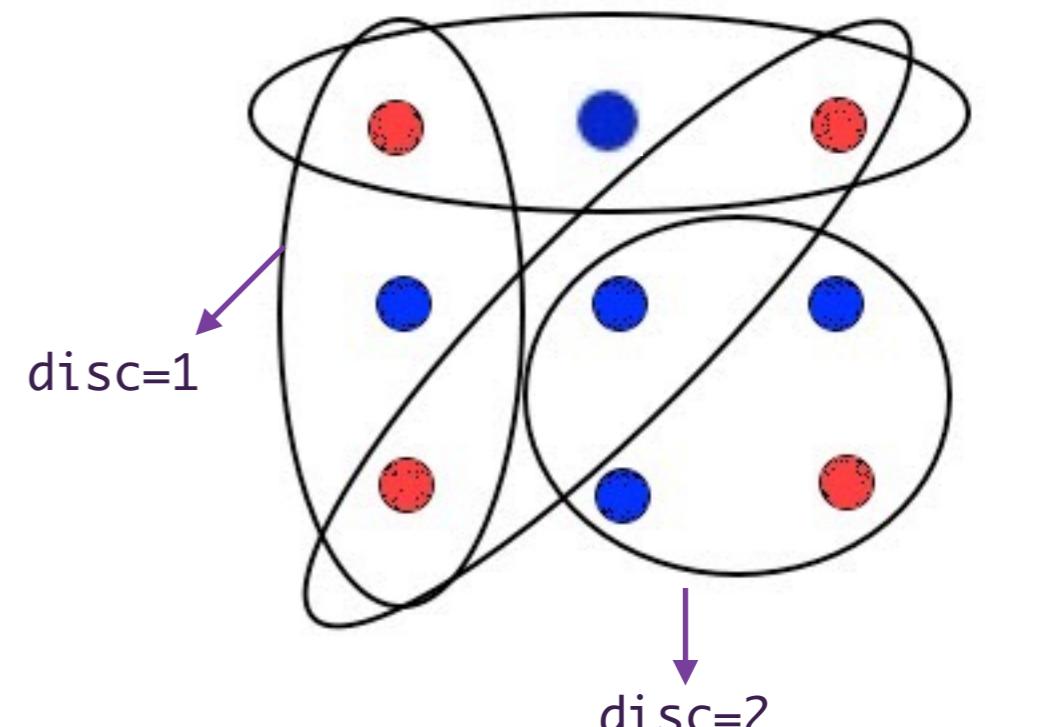
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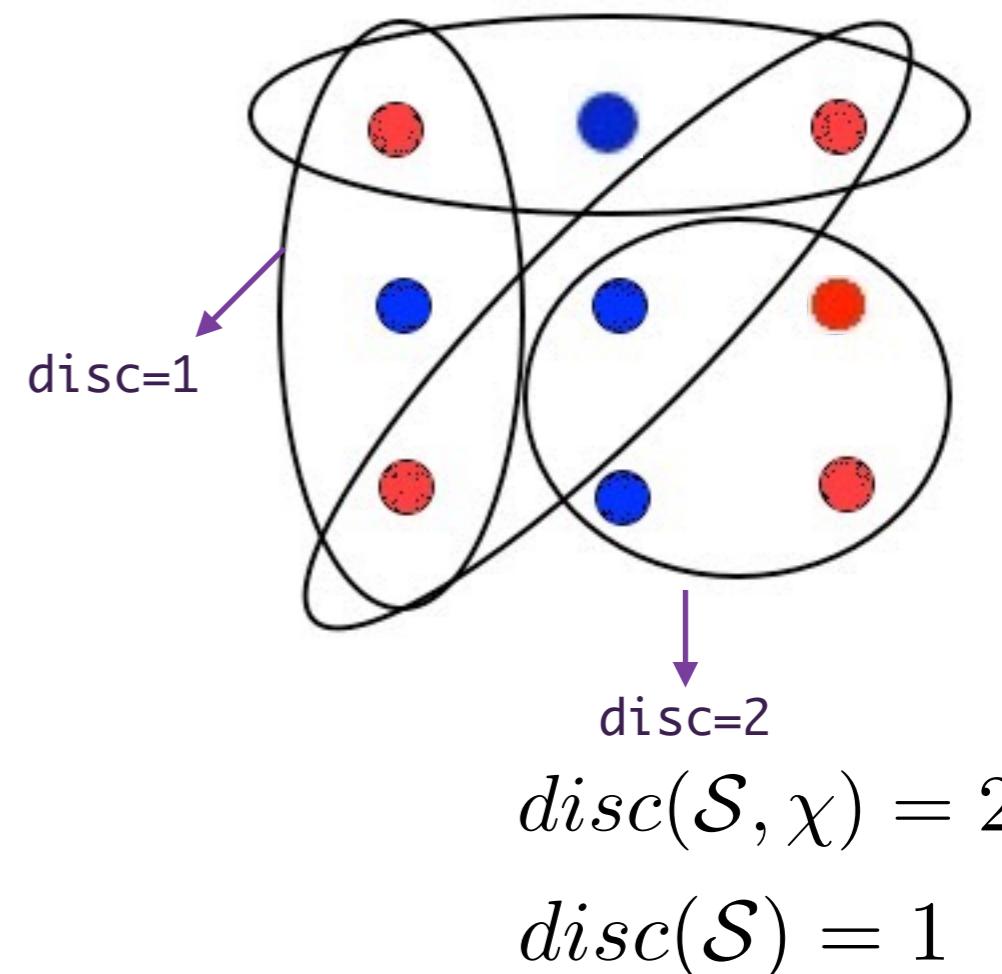
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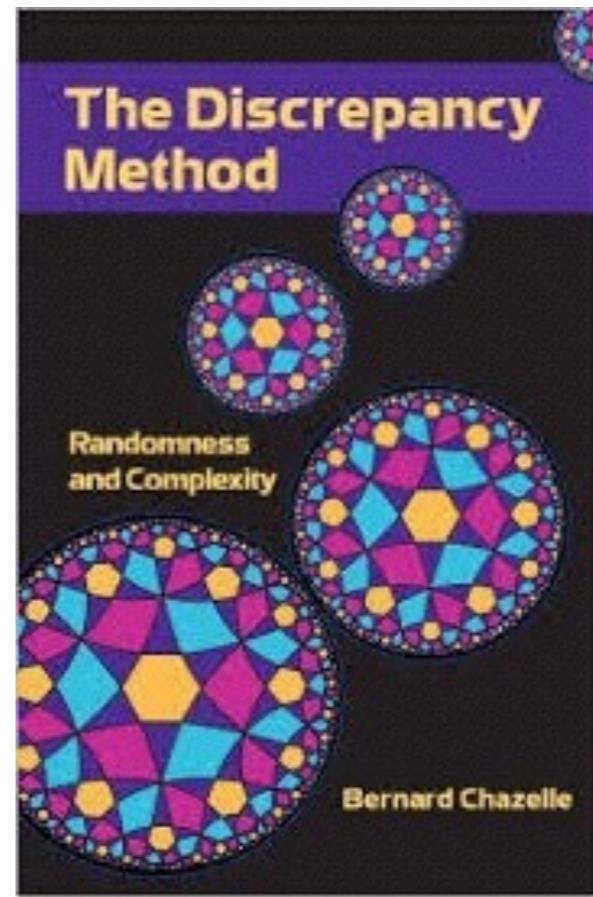
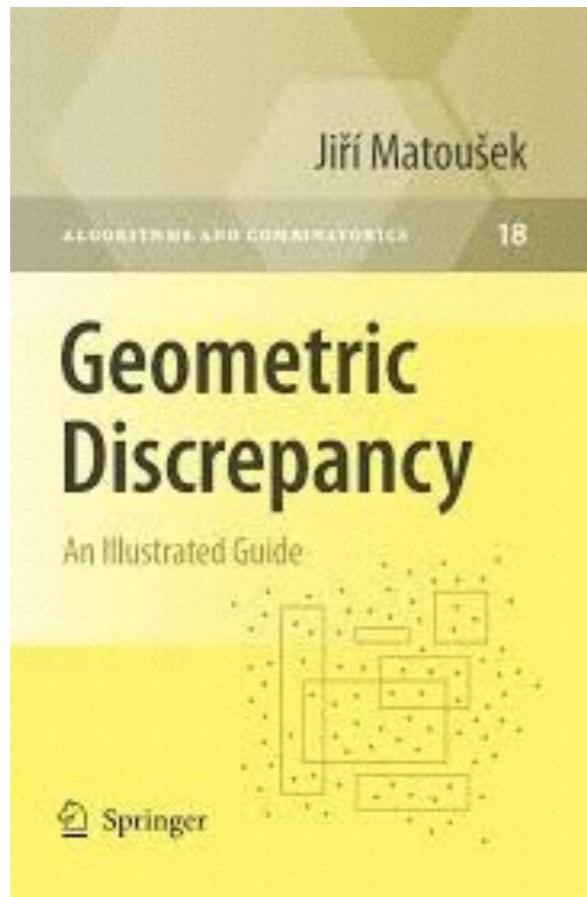


Matrix Notation

Incidence matrix $A = \begin{pmatrix} 1 & 0 & \cdots & 1 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 0 \end{pmatrix}$

Coloring $\chi \in \{-1, +1\}^n$ to minimize $\|A\chi\|_\infty$

Applications



Approximation algorithms: Bin Packing [Rothvoss'13]

Data structures [Larsen'11]

many more ...

Beck-Fiala Setting

- ◆ Every point lies in at most t sets
- ◆ Beck-Fiala[’81] showed $2t-1$ discrepancy
- ◆ Conjecture $O(\sqrt{t})$

Beck-Fiala Setting

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Komlós:

- ♦ Vectors of A of length at most 1
- ♦ conjecture $O(1)$

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Banaszczyk[‘98]:

- ◆ Komlós: $O(\sqrt{\log n})$
- ◆ Beck-Fiala: $O(\sqrt{t \log n})$

Earlier work

- $2t - 1$ (**constructive** [Beck-Fiala'81])
- $O(\sqrt{t} \log n)$ (**non-constructive**)
[Srinivasan'97]: entropy method
- $O(\sqrt{t} \log n)$ (**constructive**) : based on partial colorings
[Bansal'10]: SDP based random walk
[Lovett-Meka'12]: simplified random walk without SDP
[Rothvoß'14]: random sample and project
[Harvey, Schwartz, Singh'14], [Eldan, Singh'14]
- $O(\sqrt{t \log n})$ (**non-constructive** [Banaszczyk'98])

Our main result

There is an algorithm which returns a coloring of discrepancy $O(\sqrt{t \log n})$ in Beck-Fiala setting w.h.p.

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Also extends to Komlós with discrepancy $O(\sqrt{\log n})$

Earlier approaches

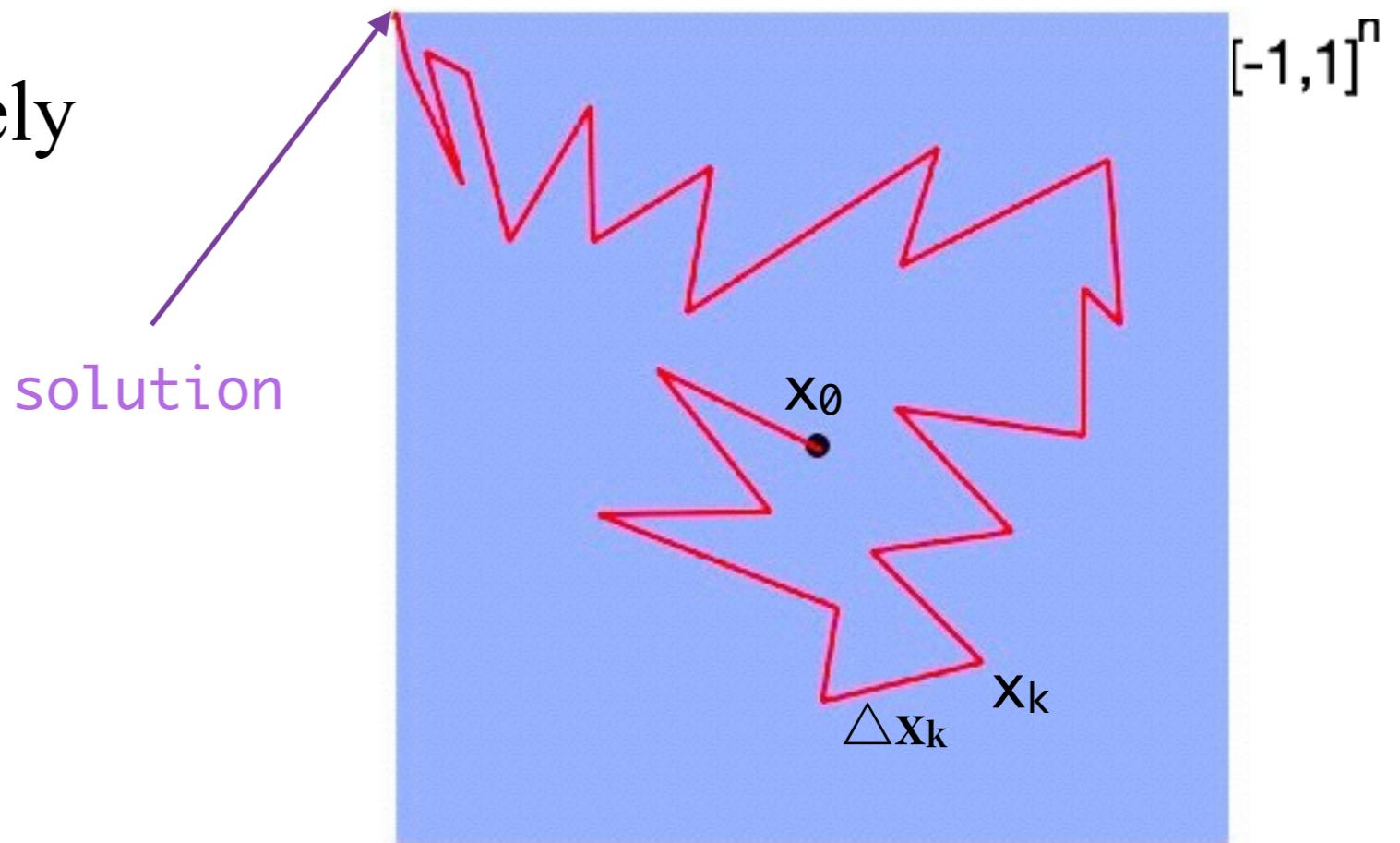
- ♦ Based on partial coloring
 - ♦ Color half the points globally
 - ♦ Discrepancy = \sqrt{t}
 - ♦ Repeat $\log n$ times
 - ♦ Total discrepancy = $\sqrt{t} \log n$

Earlier approaches

- ♦ Based on partial coloring
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 - ♦ Discrepancy = \sqrt{t}
 - ♦ Repeat $\log n$ times
 - ♦ Total discrepancy = $\sqrt{t} \log n$
- ♦ Obstacle: Partial coloring can give discrepancy \sqrt{t} to set S while coloring only few points of S

Main idea

- ♦ Random walk cleverly
- ♦ Use SDP to get a finer control over how discrepancy of each set evolves
- ♦ Choose updates steps wisely



Overcoming $\sqrt{t \log n}$ barrier

a) Zero discrepancy for big sets ($> 100t$)

 at most $n/100$ of these
 $m \geq n$

Also possible in earlier approaches

Overcoming $\sqrt{t \log n}$ barrier

Partial coloring can give discrepancy \sqrt{t} to set S
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Overcoming $\sqrt{t \log n}$ barrier

Partial coloring can give discrepancy \sqrt{t} to set S while coloring only few elements of S

b) Proportional discrepancy

$$\left(\sum_{i \in S} \Delta x_k(i)\right)^2 \leq \sum_{i \in S} \Delta x_k(i)^2$$

$$(\Delta \text{discrepancy})^2$$



energy injected into S at time k

energy of $S = \sum_{i \in S} x_k(i)^2$



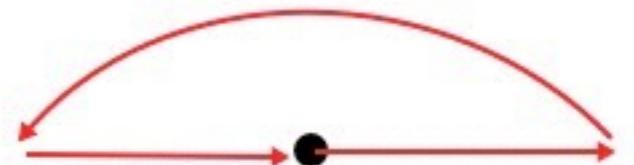
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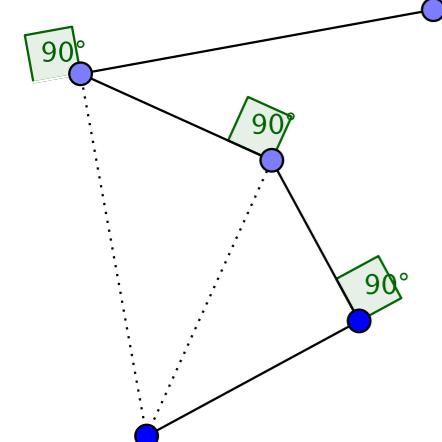
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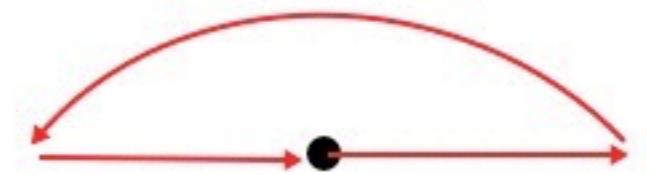
c) Orthogonality constraints

$$\left(\sum_{i \in S} x_{k-1}(i) \Delta x_k(i) \right)^2 \leq \sum_{i \in S} \Delta x_k(i)^2$$



(fluctuations)²

energy injected into S at time k



Summing it up

- 1.sets only start incurring discrepancy when their size at most $100t$
- 2.after that, $(\text{disc})^2 < \text{total energy injected}$
- 3.and total energy injected $< |S| < 100t$

Thus, discrepancy of $S \leq 10\sqrt{t}$

Lose a factor of $\sqrt{\log n}$ in union bound

Capturing this via SDP

zero discrepancy for big sets: $A_k = \text{elements not yet frozen}$

$$\left\| \sum_{i \in S} u_i \right\|_2^2 = 0 \quad \text{if } |S \cap A_k| > 100t$$

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(disc)² < energy injected:

$$\left\| \sum_{i \in S} u_i \right\|_2^2 \leq 2 \sum_{i \in S} \|u_i\|_2^2 \quad \text{if } |S \cap A_k| \leq 100t$$

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make large progress:

$$\text{maximize} \sum_{i \in A_k} \|u_i\|_2^2$$

Algorithm

$x_0 = 0^n$

for $k=1, \dots, T$:

solve SDP

$$x_k(i) = x_{k-1}(i) + \gamma \langle r_k, u_i \rangle$$

small step size

random \pm

if for some i , $|x_k(i)| \geq 1 - 1/n$

freeze i

remove it from A_k

T is chosen large enough s.t. all elements are frozen by time T w.h.p.

Proof strategy

1. at each time k , SDP has value $\Omega(A_k)$
thus we make a large move at each step
2. all properties are satisfied and $\text{disc}(S) = \sqrt{t \log n}$
whp till time T
3. all elements are frozen by time T whp

SDP has large value

maximize $\sum_{i \in A_k} \|u_i\|_2^2$ subject to

$$\left\| \sum_{i \in S} u_i \right\|_2^2 = 0 \quad \text{if } |S \cap A_k| > 100t$$

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$$\left\| \sum_{i \in S} x_{k-1}(i) u_i \right\|_2^2 \leq 2 \sum_{i \in S} \|u_i\|_2^2 \quad \text{if } |S \cap A_k| \leq 100t$$

$$\|u_i\|_2^2 \leq 1$$

A_k = elements not yet frozen

SDP has large value

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A_k = elements not yet frozen

Theorem: strong duality holds.

Dual SDP

$$\text{Minimize} \quad \sum_{i \in A_k} b_i \quad \text{s.t.}$$

$$\sum_{i \in A_k} b_i e_i e_i^T + \sum_{S \in \text{big sets}} \alpha_S v_S v_S^T + \sum_{S \in \text{small sets}} (\beta_S (v_S v_S^T - 2I_S) + \beta_S^x (x_S x_S^T - 2I_S)) \succeq I$$

$$b_i \geq 0 \quad \forall i \in A_k$$

$$\alpha_S \in \mathbb{R} \quad \forall \text{big sets } S$$

$$\beta_S, \beta_S^x \geq 0 \quad \forall \text{small sets } S$$

indicator vector of set S

Dual SDP

$$\begin{aligned} \text{Minimize} \quad & \sum_{i \in [n]} b_i \quad \text{s.t.} \\ & \sum_{i \in [n]} b_i e_i e_i^T + \sum_{S \in \text{big sets}} \alpha_S v_S v_S^T + \sum_{S \in \text{small sets}} (\beta_S (v_S v_S^T - 2I_S) + \beta_S^x (x_S x_S^T - 2I_S)) \succeq I \end{aligned}$$

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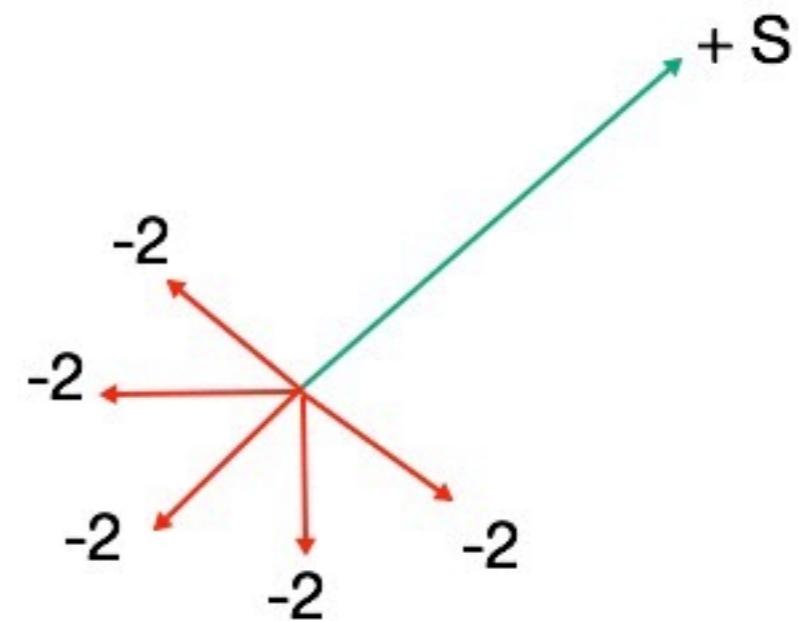
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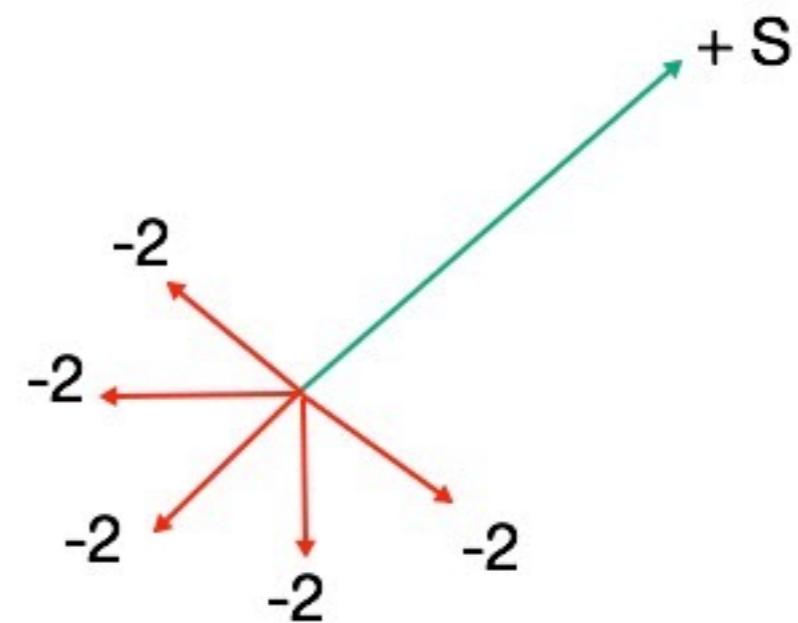
↓

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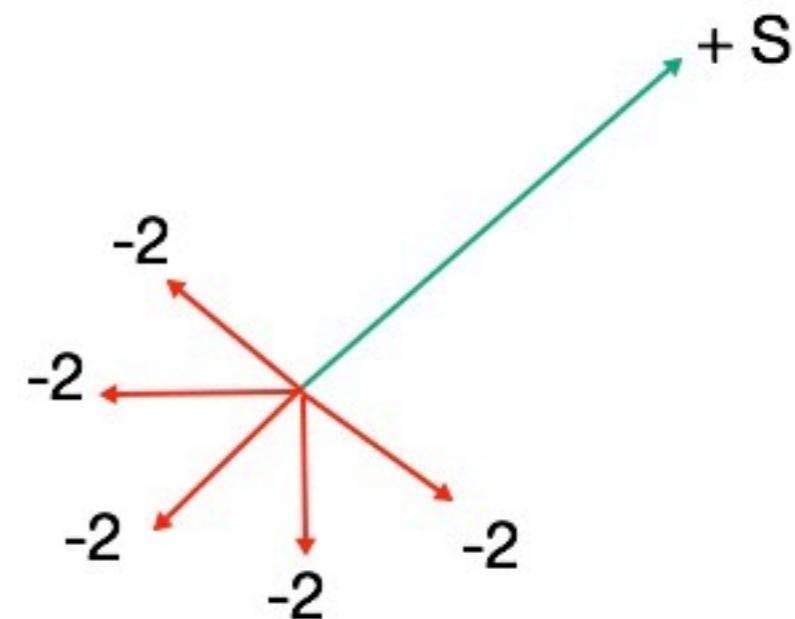


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$$\frac{n}{2} - \frac{n}{100} \quad \dim \leq \frac{n}{100} \quad \preceq 0 \text{ on } \dim \geq n/2$$



Theorem: Let $B = \sum_v (vv^T - 2\text{diag}(vv^T))$. Then, $y^T By \leq 0$ for $y \in W$ and $\dim(W) \geq n/2$.

Proof:

$$M = \begin{pmatrix} & & & \textcolor{violet}{i} \\ & \vdots & & \\ v_i & & \cdots & \textcolor{violet}{v} \\ & & & \\ & \vdots & & \\ & \sqrt{\sum_v v_i^2} & & \cdots \end{pmatrix}$$

$$D = \begin{pmatrix} & & & \textcolor{violet}{i} \\ & \downarrow \text{diagonal} & & \\ & \vdots & & \\ & \sqrt{\sum_v v_i^2} & & \cdots \end{pmatrix}$$

$$\begin{aligned} y^T By &\leq 0 \\ \Leftrightarrow \|My\|_2^2 &\leq 2\|Dy\|_2^2 \\ \Leftrightarrow \|MD^{-1}y\|_2^2 &\leq 2\|y\|_2^2 \end{aligned}$$

\downarrow
columns of length ≤ 1

Lemma: Given $m \times n$ matrix M will all columns of ℓ_2 -norm ≤ 1 . Then,
 $\|My\|_2^2 \leq 2\|y\|_2^2$ for all $y \in W$ where $\dim(W) \geq n/2$.

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Sum of squared-singular values of M is at most n .

$$\sum_i \sigma_i^2 = \text{Tr}[M^T M] = \|M\|_F^2 \leq n$$

Thus, half of the singular values are at most $\sqrt{2}$.

■

Bounding discrepancy

- ♦ How does $disc_k(S)$ evolve?

$$disc_k(S) = disc_{k-1}(S) + \sum_{i \in S} \gamma \langle r_k, u_i \rangle$$

Bounding discrepancy

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$$disc_k(S) = disc_{k-1}(S) + \sum_{i \in S} \gamma \langle r_k, u_i \rangle$$

- ♦ It is a martingale.
- ♦ Use martingale concentration inequalities

Freedman's inequality: very strong !

Bounding discrepancy

Freedman: Given a martingale X_0, \dots, X_T , with $|X_t - X_{t-1}| \leq M$ and $W = \sum_t \mathbb{E}_{t-1}[(X_t - X_{t-1})^2]$,

$$\Pr[X_T \geq \lambda \text{ and } W \leq \sigma^2] \leq 2\exp\left(-\frac{\lambda^2}{2(\sigma^2 + M\lambda/3)}\right)$$

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- W roughly equal to total energy injected

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$disc_k(S)$ is a martingale with:

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$$\Pr[disc_T(S) \geq \lambda] \approx \exp(-\lambda^2/100t)$$

Put $\lambda = O(\sqrt{t \log n})$ and union bound over $\leq nt$ sets

Komlós setting

- ♦ Matrix A with columns of length ≤ 1 . Find $x \in \{-1, 1\}^n$ to minimise $\|Ax\|_\infty$
- ♦ Our algorithm also extends here with guarantee $O(\sqrt{\log n})$.

$$\Pr[(Ax_T)_i \geq \lambda] \approx \exp(-\lambda^2/100)$$

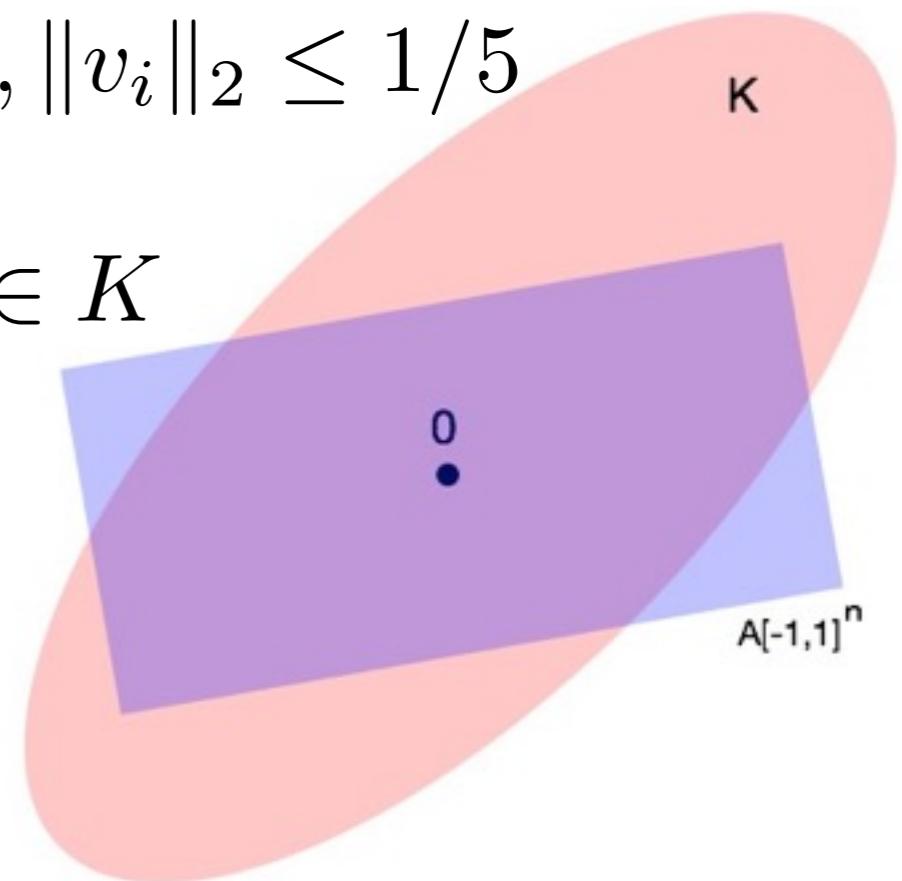


final coloring

Open Problem: General Banaszczyk

Theorem: Given $v_1, v_2, \dots, v_n \in \mathbb{R}^m$, $\|v_i\|_2 \leq 1/5$ and convex body K , $\gamma_m(K) \geq 1/2$.

There exists coloring ϵ_i s.t. $\sum_{i=1}^n \epsilon_i v_i \in K$



- ♦ We only proved the special case of $K = \sqrt{\log n}$ cube
- ♦ An algorithm for general K will imply
 - constructive approximation for hereditary discrepancy [Matousek,Nikolov,Talwar'15]
 - improved algorithm for Steinitz conjecture

Thank you for your attention

Any questions?