

Discrepancy and SDPs

Nikhil Bansal

(TU Eindhoven, Netherlands)

Outline

Discrepancy Theory

- What is it
- Basic Results (non-constructive)

SDP connection

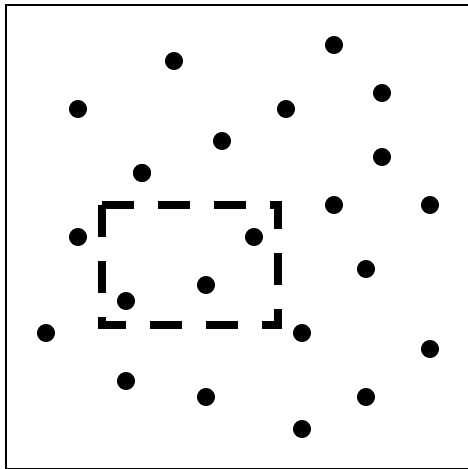
- Algorithms for discrepancy
- New methods in discrepancy (upper/lower bounds)
- Approximation

Discrepancy: Example

Input: n points placed **arbitrarily** in a grid.

Color them **red/blue** such that each axis-parallel rectangle is colored as evenly as possible

Discrepancy: \max over rect. R $(| \# \text{red in } R - \# \text{blue in } R |)$



Random has about $O(n^{1/2} \log^{1/2} n)$

Can achieve $O(\log^{2.5} n)$

Why do we care?

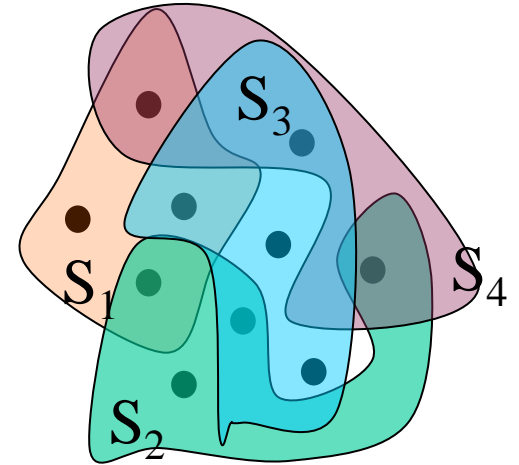
Combinatorial Discrepancy

Universe: $U = [1, \dots, n]$

Subsets: S_1, S_2, \dots, S_m

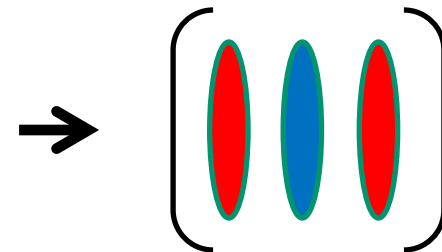
Find $\chi: [n] \rightarrow \{-1, +1\}$ to

Minimize $|\chi(S)|_1 = \max_S \left| \sum_{i \in S} \chi(i) \right|$



If A is a $m \times n$ matrix.

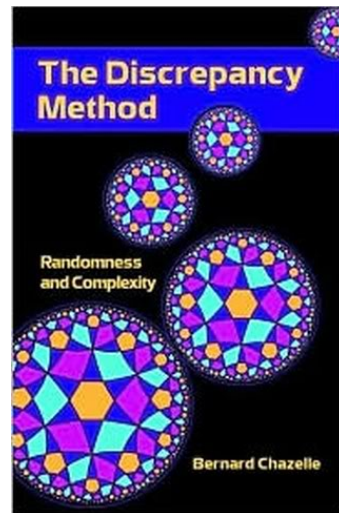
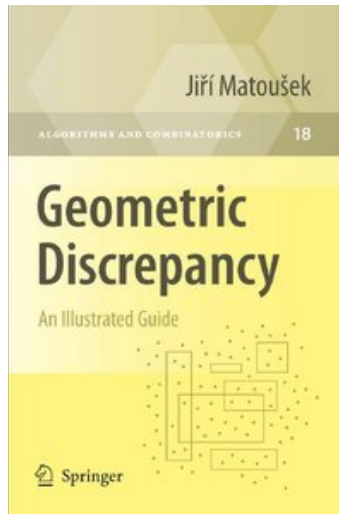
$$\text{Disc}(A) = \min_{x \in \{-1, 1\}^n} \|Ax\|_\infty$$



Applications

CS: Computational Geometry, Comb. Optimization, Monte-Carlo simulation, Machine learning, Complexity, Pseudo-Randomness, ...

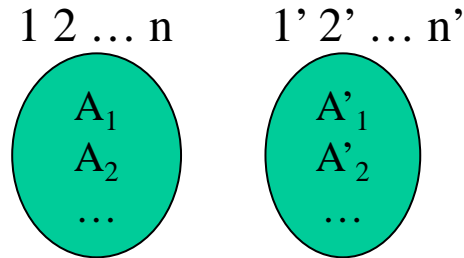
Math: Dynamical Systems, Combinatorics, Mathematical Finance, Number Theory, Ramsey Theory, Algebra, Measure Theory, ...



Hereditary Discrepancy

Discrepancy a useful measure of complexity of a set system

But not so **robust**



$$S_i = A_i \cup A'_i$$

Discrepancy = 0

Hereditary discrepancy:

$$\text{herdisc}(U, S) = \max_{U' \subseteq U} \text{disc}(U', S|_{U'})$$

Robust version of discrepancy

(How to certify $\text{herdisc} < D$? In **NP**?)

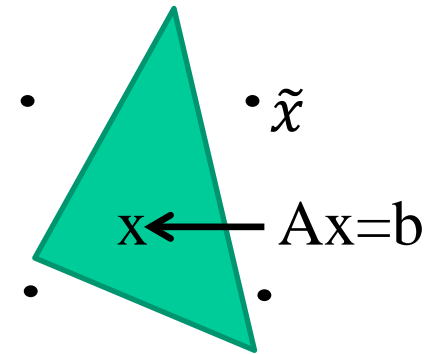
Some Applications

Rounding

Lovasz-Spencer-Vesztermgombi'86: Given any matrix A , and $x \in R^n$, can **round** x to $\tilde{x} \in Z^n$ s.t.

$$|Ax - A\tilde{x}|_{\infty} < \text{Herdisc}(A)$$

Proof: Round the bits of x one by one.



$$x_1: \text{blah } .0101101 \leftarrow (-1)$$

$$x_2: \text{blah } .1101010$$

...

$$x_n: \text{blah } .0111101 \leftarrow (+1)$$

Key Point: Low discrepancy coloring **guides** our updates!

$$\text{Error} = \text{herdisc}(A) \left(\frac{1}{2^k} \right)$$

Rounding

LSV'86 result guarantees existence of good rounding.

How to find it **efficiently**?

Thm [B'10]. Can round efficiently, so that

$$\text{Error} \leq O(\sqrt{\log m \log n}) \text{Herdisc}(A)$$

Use SDPs, basic method

Refinements

Spencer'85: Any 0-1 matrix ($n \times n$) has $\text{disc} \leq 6\sqrt{n}$

Non-constructive **Entropy method** (very powerful technique)

B.'10: **Algorithmic** $O(\sqrt{n})$ (SDP + Entropy method)

Lovett-Meka'12: (much simpler)

Better variant of “entropy method”

Extends **iterated rounding**.

Bin-packing: Rothvoss'13: $\text{Alg} \leq \text{LP} + O(\log \text{OPT} \log \log \text{OPT})$

Karmarkar-Karp'82: $\text{Alg} \leq \text{LP} + O(\log^2 \text{OPT})$

Dynamic Data Structures

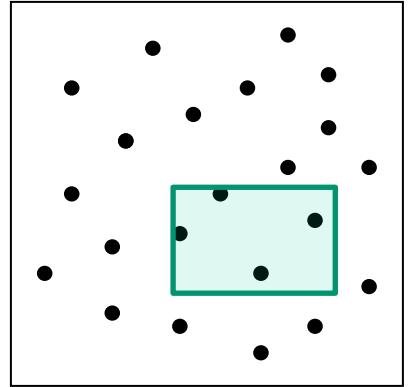
N weighted points in a 2-d region.

Weights updated over time.

Query: Given an axis-parallel rectangle R , determine the total weight on points in R .

Goal: Preprocess (in a data structure)

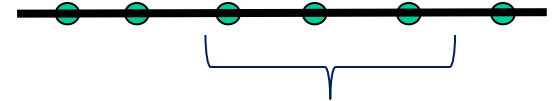
- 1) Low **query** time
- 2) Low **update** time (upon weight change)



Example

Line: Interval queries

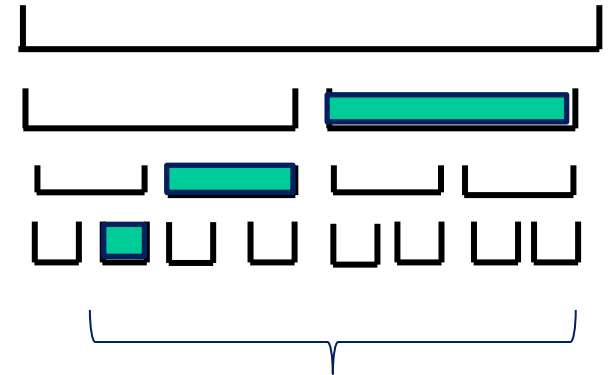
Trivial: Query Time = $O(n)$ Update Time = 1



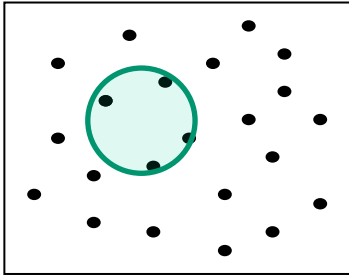
Query time = 1 Update time = $O(n^2)$ (Table of entries $W[a,b]$)

Query = $O(\log n)$ Update = $O(\log n)$

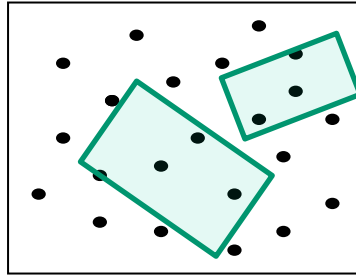
Recursively for 2-d.
 $O(\log^2 n, \log^2 n)$



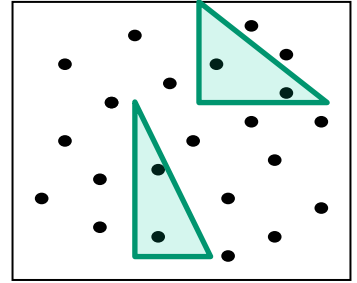
What about other queries?



Circles



arbitrary rectangles



aligned triangle

Turns out $t_q t_u \geq \frac{n^{1/2}}{\log^2 n}$

Reason: Set system S formed by query sets & points has large **discrepancy** (about $n^{1/4}$)

Larsen-Green'11: $t_q t_u \geq \frac{\text{disc}(S)^2}{\log^2 n}$

Lower Bounds

Various methods: Spectral, Fourier analytic, ...

Determinant lower bound:

$$\text{detlb}(A) \leq \text{herdisc}(A) \quad [\text{Lovasz et al. 86}]$$

$$\text{herdisc}(A) \leq \text{polylog}(n,m) \text{detlb}(A) \quad [\text{Matousek'11}]$$

(SDP duality)

Polylog **approximation** for $\text{herdisc}(A)$ [Nikolov, Talwar, Zhang'13]

SDP Connection

Vector Discrepancy

Exact: Min t

$$-t \leq \sum_j a_{ij} x_j \leq t \quad \text{for all rows } i$$

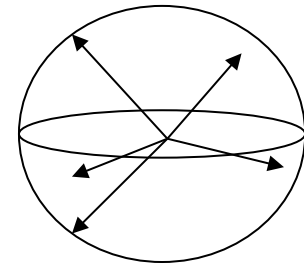
$$x_j \in \{-1, 1\} \quad \text{for each } j$$

SDP: $\text{vecdisc}(A)$

min t

$$\left| \sum_i a_{ij} v_j \right|_2 \leq t \quad \text{for all rows } i$$

$$\|v_j\|_2 = 1 \quad \text{for each } j$$



Is vecdisc a good relaxation?

Not directly. $\text{vecdisc}(A) = 0$ even if $\text{disc}(A)$ very large

[Charikar, Newman, Nikolov'11]

NP-Hard: $\text{disc}(A) = 0$ or $\text{disc}(A)$ very large ?

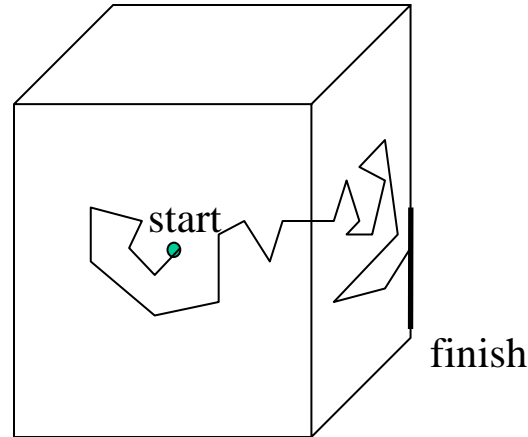
Let $\text{hervecdisc}(A) = \max_S \text{vecdisc}(A|_S)$

Thm [B'10]: $\text{disc}(A) = O(\sqrt{\log m \log n}) \text{hervecdisc}(A)$

Pf: Algorithm

Algorithm (at high level)

Cube: $\{-1,+1\}^n$



Each **dimension**: An Element
Each **vertex**: A Coloring

Algorithm: “Sticky” random walk

Each step generated by rounding a suitable SDP

Move in various dimensions correlated, e.g. $\delta_1^t + \delta_2^t \approx 0$

Analysis: Few steps to reach a vertex (walk has **high** variance)

$\text{Disc}(S_i)$ does a random walk (with **low** variance)

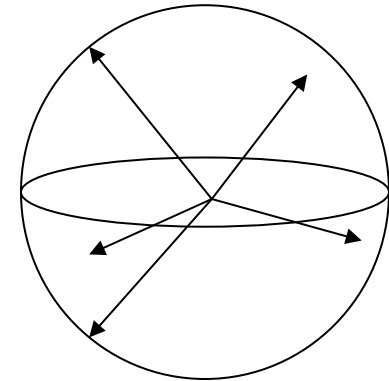
An SDP

Hereditary disc. λ) the following SDP is feasible

SDP: **Low discrepancy**

$$|\sum a_{ij} v_j|^2 \leq \lambda^2 \quad \text{for each row } i.$$

$$|v_j|^2 = 1 \quad \text{for each element } j.$$



Obtain $v_j \in \mathbb{R}^n$

Perhaps v_j can **guide** us how to update color of element j ?

Trouble: v_j is a vector. Need a **real number**.

Project on random vector vector g ($\eta_i = g \cdot v_i$)

Seems promising: $\sum_j a_{ij} \eta_j = g \cdot (\sum_j a_{ij} v_j)$

Properties of Rounding

Lemma: If $g \in \mathbb{R}^n$ is a random Gaussian, for any $v \in \mathbb{R}^n$,
 $g \cdot v$ is distributed as $N(0, |v|^2)$

1. Each $\eta_j \gg N(0,1)$

2. For each row i ,

$$\sum_j a_{ij} \eta_j = g \cdot (\sum_j a_{ij} v_j) \gg N(0, \cdot \lambda^2)$$

(std deviation $\cdot \lambda$)

SDP:

$$|v_j|^2 = 1$$

$$|\sum_j a_{ij} v_j|^2 \cdot \lambda^2$$

η 's will **guide** our updates to x .

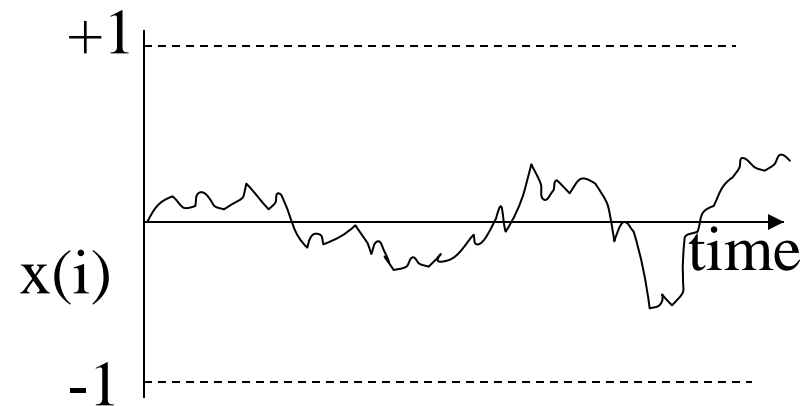
Algorithm Overview

Construct coloring **iteratively**.

Initially: Start with coloring $x_0 = (0,0,0, \dots, 0)$ at $t = 0$.

At Time t : Update coloring as $x_t = x_{t-1} + \gamma (\eta_1^t, \dots, \eta_n^t)$

(γ tiny: say $1/n$)



$$x_t(j) = \gamma (\eta_j^1 + \eta_j^2 + \dots + \eta_j^t)$$

Color of element j : Does **random walk** over time with step size $\frac{1}{n} \gamma N(0,1)$

Fixed if reaches -1 or $+1$.

Disc(row i): $\sum_j a_{ij} x_t(j)$ does a **random walk w/ step** $\gamma N(0, \lambda^2)$

Analysis

At time $T = O(1/\gamma^2)$

- 1: With prob. $1/2$, an element reaches -1 or $+1$.
- 2: Each row has **discrepancy** in expectation.

At time $T = O((\log n)/\gamma^2)$

1. Most likely all elements fixed
2. **Expected discrepancy** for a row = $\lambda\sqrt{\log n}$
(By Chernoff, all have discrepancy $O(\lambda\sqrt{\log n \log m})$)

New Entropy Method

Entropy method

Very **powerful** method to prove discrepancy upper bounds

[Beck, Spencer 80's]: Given an $m \times n$ matrix A , there is a partial coloring satisfying $|a_i x| \leq \lambda_i |a_i|_2$

provided $\sum_i g(\lambda_i) \leq \frac{n}{5}$

$$g(\lambda_i) \approx \ln\left(\frac{1}{\lambda_i}\right) \quad \text{if } \lambda_i < 1$$
$$\approx e^{-\lambda_i^2} \quad \text{if } \lambda_i \geq 1$$

E.g. can ask for partial coloring with 0 discrepancy on $n/\log n$ rows, and reasonable amount on others.

Lovett Meka Algorithm

Do a sticky random walk.

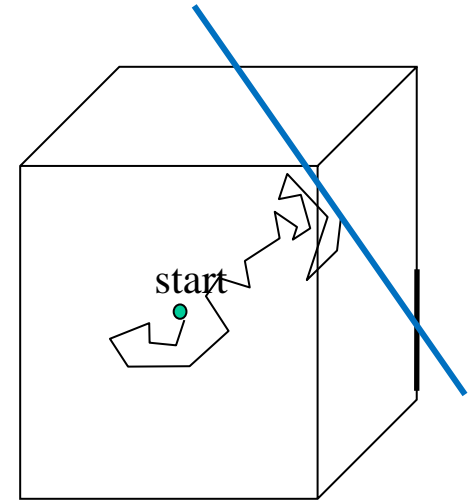
If some row A_i gets **tight** ($\text{disc}(A_i) = \lambda_i |a_i|_2$)

Move in space $A_i x = 0$

Make progress as long
as **dimension** = $\Omega(n)$

$$\sum_i \exp(-\lambda_i^2) \leq \frac{n}{2} \quad (\text{better than entropy method})$$

Guarantees a **partial coloring**, even if $n/4$ λ_i 's are 0.



Comparison with iterated rounding

Fact: If n variables, but $\leq n/2$ constraints $Ax = b$ (rest: $0 \leq x \leq 1$)

There exists a **basic feasible solution** with $> n/2$ variables 0-1.

Iterated rounding: LP with m constraints, drop except $n/2$.

(no control on dropped constraints ($a_i x \leq b_i$), error up to $|a_i|_1$)

Lovett-Meka Lemma: Can find solution with $\geq n/2$ integral variables with error $\leq \lambda_i |a_i|_2$).

E.g. Can set $n/10$ constraints to have 0 error, and controlled bounds on others

Lower Bounds

Discrepancy

If $\text{disc}(A) > D$

$$|Ax|_{\infty} \geq D \text{ for all } x \in \{-1,1\}^n$$

(say A : $n \times n$ matrix for convenience)

If $\sigma_{\min}(A) \geq D$

$$|Ax|_2 \geq \sigma_{\min}(A) |x|_2$$

Could be very weak bound.

Can consider $\sigma_{\min}(PA)$

P :diag, $\text{tr}(P) = n$

Determinant Lower Bound

Thm (Lovasz Spencer Vesztergombi'86): $\text{herdisc}(A) \geq \text{detlb}(A)$

$$\text{detlb}(A): \max_k \max_{\{k \times k \text{ submatrix } B \text{ of } A\}} \det(B)^{1/k}$$

(simple geometric argument)

Conjecture (LSV'86): $\text{Herdisc} \leq O(1) \text{ detlb}$

Remark: For TU Matrices, $\text{Herdisc}(A) = 1$, $\text{detlb} = 1$

(every submatrix has $\det -1, 0$ or $+1$)

Hoffman's example

Hoffman: $\text{Detlb}(A) \leq 2$

$$\text{herdisc}(A) \geq \left(\frac{\log n}{\log \log n} \right)$$

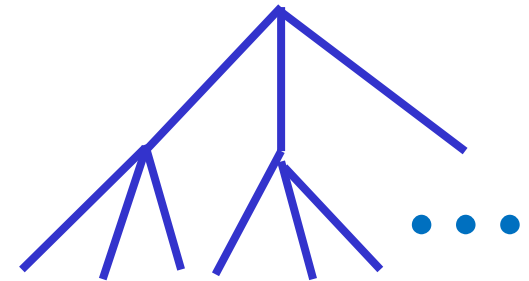
Palvolgyi'11: $\Omega(\log n)$ gap

T: k -ary tree of depth k .

$\approx k^k$ nodes.

S: All edges out of a node.

S': All leaf to root paths.



Both S and S' are TU.

Claim: $\text{Detlb}(S \cup S') \leq 2$ (Expand determinant)

$$\text{Herdisc}(S \cup S') = k$$

Matousek'11: $\text{herdisc}(A) \leq O(\log n \sqrt{\log m}) \det b.$

Idea: SDP Duality \rightarrow **Dual Witness** for large $\text{herdisc}(A)$.

Dual Witness \rightarrow Submatrix with large determinant.

Other implications:

$$\text{herdisc}(A_1 \cup \dots \cup A_t) \leq O(\log n \sqrt{\log m}) \sqrt{t} \max_i \text{herdisc}(A_i)$$

Matousek's result

Thm: $\text{Herdisc}(A) = O(\log n \sqrt{\log m}) \det_{\text{lb}}(A)$

Pf: Recall, $\text{Disc}(A) = O(\sqrt{\log m \log n}) \text{Hervecdisc}(A)$

Some S , s.t. $\text{Vecdisc}(A_{|S}) = \text{Herdisc}(A) / O(\sqrt{\log m \log n})$

Will show: $\text{vecdisc}(A_{|S}) \leq O(\sqrt{\log n}) \det_{\text{lb}}(A_{|S})$

Let us use A for $A_{|S}$

SDP Duality

If $\text{vecdisc}(A) \geq D$, there exist

weights $w_1, \dots, w_m \geq 0$ with $\sum_i w_i \leq 1$

And $z_1, \dots, z_n \geq 0$ such that $\sum_j z_j \geq D^2$

$$w_i \begin{pmatrix} z_j \\ \vdots \\ \end{pmatrix}$$

$$\sum_i w_i \left(\sum_j a_{ij} x_j \right)^2 \geq \sum_j z_j x_j^2 \quad \text{for all } x \in R^n.$$

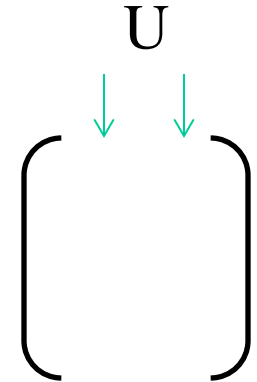
Why is this a **witness**?

Proof Sketch

As $\sum_j z_j \geq D^2$

There exists a subset of **variables U** such that

$$z_j \in \left[\frac{D^2}{4|U| \log n}, \frac{D^2}{2|U| \log n} \right]$$



$$\sum_i w_i \left(\sum_{j \in U} a_{ij} x_j \right)^2 \geq \frac{D^2}{4|U| \log n} \sum_{j \in U} x_j^2 \quad \text{for all } x \in R^n.$$

$W^{1/2} A|_U$ has **large σ_{\min}**

Use Cauchy-Binet to show that A has large sub-determinant

Concluding Remarks

SDP view has been extremely useful in discrepancy

Various open problems in discrepancy

Beck Fiala Conjecture

Discrepancy of points and rectangles

Constructive version of Banaszczyk's theorem?

...

Tightness of detlb bound (\log vs $\log^{3/2}$)

$O(1)$ approximation for herdisc

Thanks!