

# Discrepancy and Halftoning

*Warning: Discrete Maths ahead!*

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1. Introduction to discrepancy theory.
2. Halftoning as linear discrepancy problem.
3. Dependent randomized rounding.

# Introduction to Discrepancy Theory

## Discrepancy Problems:

- a) Geometric discrepancy problem.
- b) Combinatorial discrepancy problem.
- c) Linear discrepancy and rounding problems.
- d) Game theoretic discrepancy problems: Liar games/noisy channels.

## Literature:

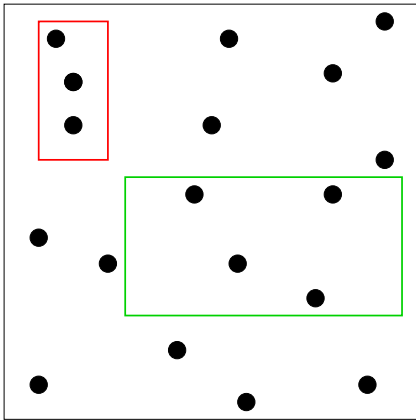
J. Beck, V. T. Sós, *Discrepancy Theory*, in *Handbook of Combinatorics*, 1995.

J. Matoušek, *Geometric Discrepancy*, 1999.

B. Chazelle, *The Discrepancy Method*, 2000.

# Geometric Discrepancies

Distribute  $n$  points *evenly* in the  $d$ -dimensional unit cube:  
Each axis-parallel rectangle  $R$  shall contain  $n \text{vol}(R)$  of the points.



$$d = 2$$

$$n = |P| = 18$$

$$\text{vol}(R_1) = \frac{2}{9} : |P \cap R| = 4 = n \text{vol}(R_1)$$

$$\text{vol}(R_2) = \frac{1}{18} : \left| |P \cap R| - n \text{vol}(R_2) \right| = |3 - 1| = 2$$

Observation: A perfect solution does not exist.

$\Rightarrow$  Minimize the discrepancy  $\text{disc}(P) := \sup_R \left| |P \cap R| - n \text{vol}(R) \right|$ .

## Geometric Discrepancy — 2

### Theorem:

$$\forall P \subseteq [0, 1]^d, |P| = n : \text{disc}(P) = \Omega_d((\log n)^{\frac{d-1}{2}}) \quad [\text{Roth (1954)}]$$

$$\exists P \subseteq [0, 1]^d, |P| = n : \text{disc}(P) = O_d((\log n)^{d-1}) \quad [\text{Halton, Hammersley (1960)}]$$

**Numerical Integration:** For given  $f : [0, 1]^d \rightarrow \mathbb{R}$ , estimate the integral by  $\frac{1}{n} \sum_{p \in P} f(p)$  for some  $n$ -point set  $P \subseteq [0, 1]^d$ .

**Koksma-Hlawka Inequality:** 
$$\left| \int_{[0,1]^d} f(x) dx - \frac{1}{n} \sum_{p \in P} f(p) \right| \leq \frac{1}{n} \text{disc}(P) V(f).$$

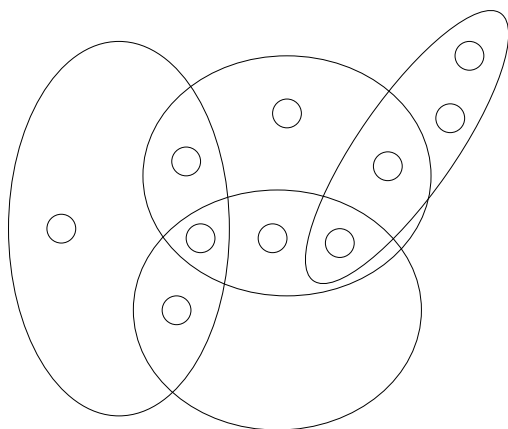
**Low-discrepancy point sets yield good estimates for the integral.**

# Combinatorial Discrepancy

**Def:** Hypergraph  $\mathcal{H} = (V, \mathcal{E})$

- $V$  finite set, ‘vertices’,
- $\mathcal{E} \subseteq 2^V$ , ‘(hyper)edges’.

Color the vertices of a hypergraph with  $k$  colors in a balanced manner:  
Each hyperedge  $E$  shall contain  $\frac{1}{k}|E|$  vertices in each color.



$|V| = 10$  vertices

$|\mathcal{E}| = 4$  hyperedges

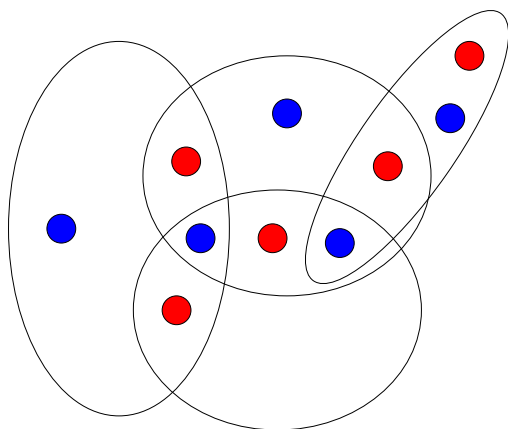
*Find a good solution for  $k = 2$ !*

# Combinatorial Discrepancy

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$|\mathcal{E}| = 4$  hyperedges

$k = 2$  colors

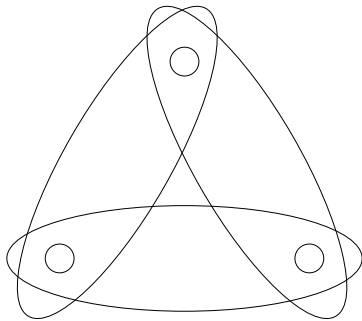
Perfect solution: Each edge  $E \in \mathcal{E}$   
contains  $\frac{1}{2}|E|$  red and blue vertices.

# Combinatorial Discrepancy

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Color the vertices of a hypergraph with  $k$  colors in a balanced manner:  
Each hyperedge  $E$  shall contain  $\frac{1}{k}|E|$  vertices in each color.



$|V| = 3$  vertices

$|\mathcal{E}| = 3$  hyperedges

$k = 2$  colors

*No perfect solution exists!*

## Combinatorial Discrepancy — 2

**Observation:** In general, a perfect solution does not exist.

**Combinatorial Discrepancy Problem:** Find a coloring  $\chi : V \rightarrow [k]^1$  minimizing

$$\text{disc}(\mathcal{H}, \chi) := \max_{i \in [k]} \max_{E \in \mathcal{E}} \left| |\chi^{-1}(i) \cap E| - \frac{1}{k}|E| \right|. \quad \text{Discrepancy of } \chi$$

**Theorem:** For all  $\mathcal{H}$  and  $k$ , there are  $\chi : V \rightarrow [k]$  such that

$$\text{disc}(\mathcal{H}, \chi) = O\left(\sqrt{\frac{1}{k}|V| \log |\mathcal{E}|}\right).$$

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<sup>1</sup> $[k] := \{1, \dots, k\}$

# Linear Discrepancy: Rounding Problems

Given:  $x \in [0, 1]^n$ ,  
 $A \in \mathbb{R}^{m \times n}$ .

Find  $y \in \{0, 1\}^n$  such that  $(Ay)_i \approx (Ax)_i$  for all  $i \in [m]$ . 'small rounding errors'

Linear Discrepancy of  $A$ :  $\text{lindisc}(A) := \max_{x \in [0, 1]^n} \min_{y \in \{0, 1\}^n} \|A(y - x)\|_\infty$ .

**Theorem<sup>1 2</sup>:**  $\text{lindisc}(A) \leq 2 \max_{x \in \{0, \frac{1}{2}\}^n} \min_{y \in \{0, 1\}^n} \|A(y - x)\|_\infty$ .

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<sup>1</sup>Hidden in: Beck, Spencer (1984)

<sup>2</sup>Explicit in: Lovász, Spencer, Vesztergombi (1986)

# Summary: Introduction to Discrepancy Theory

## Discrepancy Problems:

- a) **Geometric**: All rectangles shall contain the right number of points.
- b) **Combinatorial**: Each hyperedge has the same number of vertices in each color.
- c) **Linear**: All rounding errors shall be small.

## Common Characteristics:

- Achieve several objectives simultaneously / in a balanced manner.
- Approximate something large/continuous through smaller/discrete objects ('quantization').

# Discrepancy and Halftoning

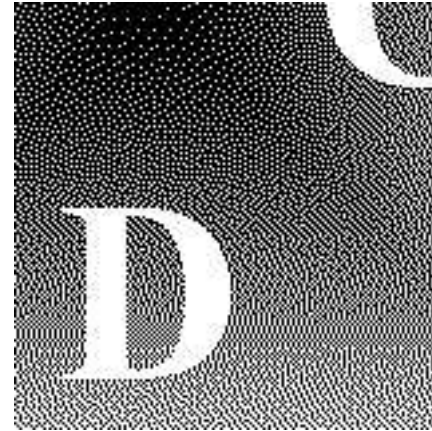
1. Introduction to discrepancy theory
  - Different problems
  - Common aspects: Balance, quantization
2. Halftoning as linear discrepancy problem
  - Halftoning problem
  - Error measure
3. Dependent randomized rounding

# Digital Halftoning Problem

Convert a continuous-tone image into a binary one that *looks similar*.



Input image



Output image

Input:  $X = (x_{ij}) \in [0, 1]^{m \times n}$  Continuous tone image

Output:  $Y = (y_{ij}) \in \{0, 1\}^{m \times n}$  Binary image

Aim:  $X$  and  $Y$  represent *similar* images.

**Problem:** What is similarity (in maths terms)?

# Digital Halftoning as Linear Discrepancy Problem

Input:  $X = (x_{ij}) \in [0, 1]^{m \times n}$  Continuous tone image

Output:  $Y = (y_{ij}) \in \{0, 1\}^{m \times n}$  Binary image

**Error measure:** Average error in the  $2 \times 2$  boxes.

$$d(X, Y) := \frac{1}{|\mathcal{R}|} \sum_{R \in \mathcal{R}} \left| \sum_{(i,j) \in R} (x_{ij} - y_{ij}) \right|,$$

where  $\mathcal{R} := \{ \{i, i+1\} \times \{j, j+1\} \mid i, j \dots \}$  is the set of all  $2 \times 2$  boxes.

**Claim<sup>3</sup>:**  $Y$  is a good halftoning of  $X$  if  $d(X, Y)$  is small.

$\Rightarrow$  Models the halftoning problem as  $L_1$  linear discrepancy problem.

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<sup>3</sup>T. Asano, N. Kato, K. Obokata, and T. Tokuyama, SIAM J. Computing (2003).

## Some Comments on this Error Measure

Average error in the  $2 \times 2$  boxes:  $d(X, Y) := \frac{1}{|\mathcal{R}|} \sum_{R \in \mathcal{R}} \left| \sum_{(i,j) \in R} (x_{ij} - y_{ij}) \right|$ .

- ⊕ General approach: Splits the problem into two.
  - What is a good error measure?
  - How to compute low-error approximations?
- ⊕ This error measure: Simple  $\Rightarrow$  hope that we can prove something.
- ⊖ Will model the human visual system not perfectly.

**Theorem [AMOT]:** For any  $X$ , a  $Y$  such that  $d(X, Y) \leq 0.75$  can be computed in quadratic time. [Lower bound: 0.5.]

# Discrepancy and Halftoning

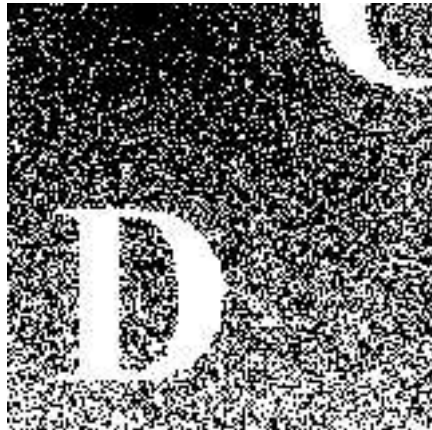
1. Introduction to discrepancy theory
2. Halftoning as linear discrepancy problem
  - Halftoning is a rounding problem
  - Error measure: Average rounding error in  $2 \times 2$  boxes  
 $\Rightarrow L_1$  linear discrepancy problem
3. Dependent randomized rounding
  - Randomized rounding (random dither) is unsuitable
  - Dependent randomized rounding does better.

# Independent Randomized Rounding (Random Dither)

For each  $i \in [m]$ ,  $j \in [n]$  independently round with probabilities

$$\Pr(y_{ij} = 1) = x_{ij},$$

$$\Pr(y_{ij} = 0) = 1 - x_{ij}.$$



Independent RR



Error Diff.

Expected error:  $Ed(X, Y) \leq 0.8294$ .

Run-time: linear.

## Why is Randomized Rounding so Bad?

**An example:** Let  $Y$  be an independent RR of  $X = \begin{pmatrix} 0.4 & 0.4 \\ 0.4 & 0.4 \end{pmatrix}$ .

$i = \sum Y^1$	$ \sum(X - Y)  =: e_i$	$\Pr(\sum Y = i) =: p_i$	$p_i e_i$
0	1.6	0.1296	<b>0.20736</b>
1	0.6	0.3456	0.20736
2	0.4	0.3456	0.13824
3	1.4	0.1536	0.21504
4	2.4	0.0256	0.06144
$\Sigma$		1.0	0.82944

**A 25% contribution to the expected error is caused by the possibility that we round *all* four entries down.**

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<sup>1</sup> $\sum Y := \sum_{i,j} y_{ij}$

# Joint Randomized Roundings

Let  $x = (x_1, \dots, x_k) \in [0, 1]^k$ . Then  $(y_1, \dots, y_k)$  is a *joint randomized rounding* of  $x$  if:

- For all  $i \in [k]$ ,  $y_i$  is a randomized rounding of  $x_i$ .
- $\sum_i y_i$  is a randomized rounding of  $\sum_i x_i$ :

$$\begin{aligned}\Pr(\sum_i y_i = \lfloor \sum_i x_i \rfloor + 1) &= \{\sum_i x_i\}^4 \\ \Pr(\sum_i y_i = \lfloor \sum_i x_i \rfloor) &= 1 - \{\sum_i x_i\}.\end{aligned}$$

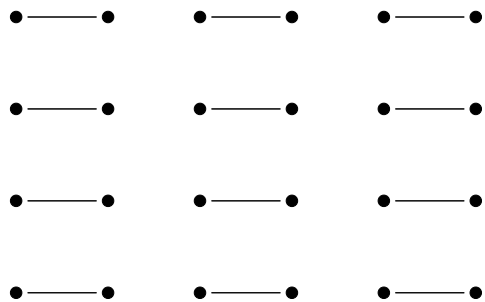
**Note:** This is *dependent randomized rounding*!

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<sup>4</sup> $\{r\} := r - \lfloor r \rfloor$ .

## Simple Application to Our Rounding Problem

- Partition  $X$  into horizontal pairs,
- round each pair independently as joint RR.



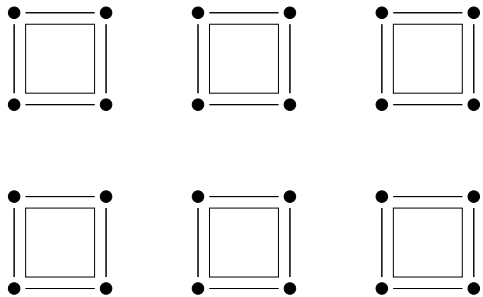
Expected error:  $Ed(X, Y) \leq 0.7111$ .

Run-time: linear.

# More Dependencies

Partition  $X$  into  $2 \times 2$  blocks. Round each block independently such that

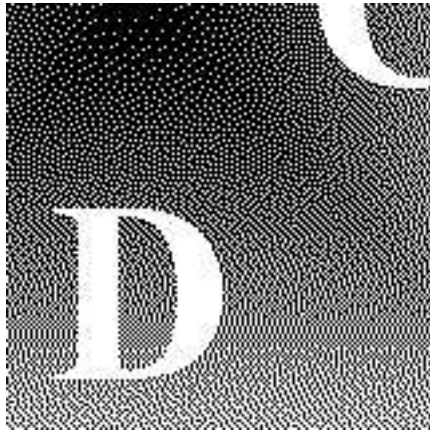
- each horizontal and vertical pair in the block is a joint RR,
- the whole block is a joint RR. **5 dependencies per block**



Expected error:  $Ed(X, Y) \leq 0.63$ .

Run-time: **linear**.

# Images



Error Diffusion



Dependent RR



Independent RR

- Dependent RR is **less grainy** than independent RR.
- Dependent RR produces **less artefacts** than error diffusion.

# Existence of Joint RRs: General Framework

Numbers  $x_i \in [0, 1], i \in I$

Hypergraph  $\mathcal{H} = (I, \mathcal{E})$  “dependency hypergraph”

For  $E \in \mathcal{E}$  put  $x_E := \sum_{i \in E} x_i$ .

Find random variables  $y_i, i \in I$ , such that “ $\mathcal{H}$ -randomized rounding”

$y_i$  is a RR of  $x_i$  for all  $i \in [n]$ ,

$y_E$  is a RR of  $x_E$  for all  $E \in \mathcal{E}$ .

**First matrix rounding example (pairs):**

$$I = [m] \times [n]$$

$$\mathcal{E} = \{\{(i, j), (i, j + 1)\} \mid i \in [m], j \in [n - 1] \text{ odd}\}.$$

## Existence of Joint RRs: Characterization

**Def:** A dependency hypergraph  $\mathcal{H} = (I, \mathcal{E})$  is *realizable*, if for all  $x_i \in [0, 1], i \in I$ , an  $\mathcal{H}$ -randomized rounding exists.

## Existence of Joint RRs: Characterization

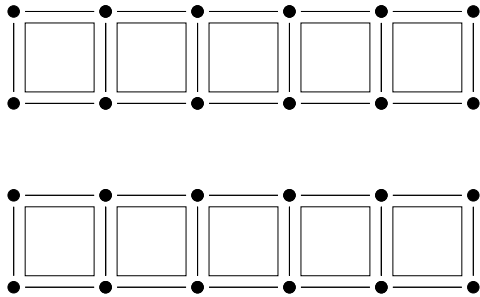
**Def:** A dependency hypergraph  $\mathcal{H} = (I, \mathcal{E})$  is *realizable*, if for all  $x_i \in [0, 1], i \in I$ , an  $\mathcal{H}$ -randomized rounding exists.

**Theorem:**  $\mathcal{H}$  is realizable if and only if  $\mathcal{H}$  is unimodular.

**Def:**  $\mathcal{H}$  is *unimodular* iff each square submatrix of the incidence matrix of  $\mathcal{H}$  has determinant  $-1, 0$  or  $1$ .

## Corollary

- A rounding  $Y$  of  $X$  such that all  $(y_{i,j}, y_{i,j+1}, y_{i+1,j}, y_{i+1,j+1})$ ,  $i$  odd,  $j$  arbitrary, are rounded as “blocks” is realizable.



- This  $Y$  satisfies  $Ed(X, Y) \leq 0.5463$ .<sup>5</sup>
- **Not a corollary (but true):** Such roundings can be computed in linear time.

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<sup>5</sup>In fact, we have  $Ed(X, Y) \leq 0.5368$ . This is sharp for these dependencies. [H. Schnieder, Diploma thesis, Kiel 2003]

# Summary

- **Discrepancy Problems:**
  - uniformly distributed point sets
  - balanced coloring of hypergraphs
  - rounding problems
- **Halftoning: An  $L_1$  linear discrepancy problem**
- **Dependent randomized rounding: Return of random dither?**
  - Low avg. error in  $2 \times 2$  boxes
  - Combines advantages of random dither (no artefacts) and error diffusion (low graininess).