# An Optimal Lower Bound for the Gap-Hamming-Distance Problem

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Joint work with Oded Regev, Tel Aviv University

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#### The Gap-Hamming-Distance Problem

Input: Alice gets  $x \in \{0,1\}^n$ , Bob gets  $y \in \{0,1\}^n$ .

Output:

- $\operatorname{GHD}(x,y) = 1$  if  $\Delta(x,y) > \frac{n}{2} + \sqrt{n}$
- $\operatorname{GHD}(x,y) = 0$  if  $\Delta(x,y) < \frac{n}{2} \sqrt{n}$

Want: randomized, constant error protocol

Cost: Worst case number of bits communicated

### **Data Stream Lower Bounds**

Data streams: two broad application scenarios

- Networks: Busy router, packets whizzing by
  - Web traffic statistics
  - Intrusion detection
- **Databases:** Huge DB, linear scan cheaper than random access
  - Query optimisation: join size estimation
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  - Query optimisation: join size estimation
  - Log analysis
- DB setting: Multiple passes meaningful

**GHD Motivation:** Obtain pass/space tradeoffs for some basic data stream problems [Indyk-Woodruff'03], [Woodruff'04], [C.-Cormode-McGregor'07]

### Data Stream Model

- Formally: input stream = n tokens, each token  $\in [m]$ 
  - Assume  $\log m = \Theta(\log n)$
- Compute some function of stream, using
  - Small space,  $s \ll m, n$  ... ideally,  $s = O(\log n)$
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  - Small space,  $s \ll m, n$  ... ideally,  $s = O(\log n)$
  - Small number of passes, p
- Give *\varepsilon*-approx:

$$\Pr\left[\left|\frac{\mathsf{output}}{\mathsf{answer}} - 1\right| \le \varepsilon\right] \ge \frac{2}{3}$$

- Distinct elements
- Frequency moments
- Empirical entropy

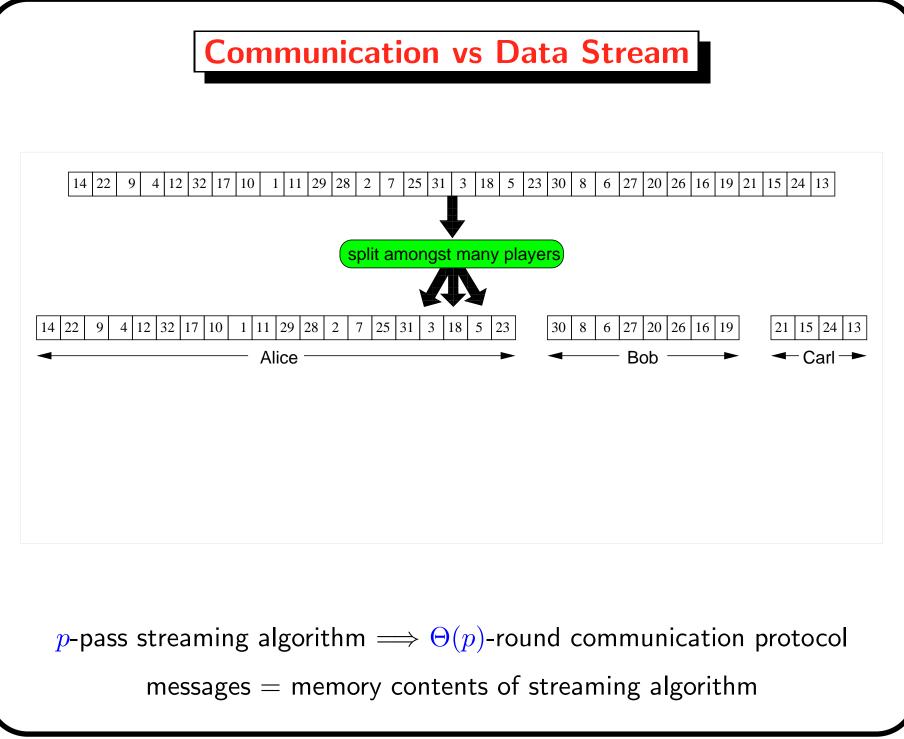
- Distinct elements ,  $F_0$
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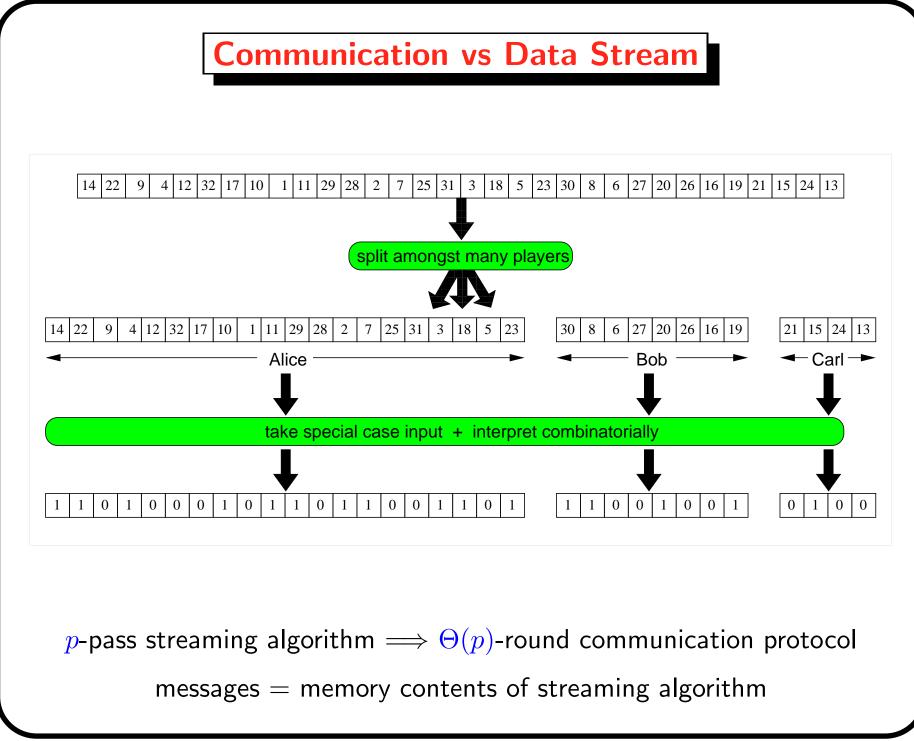
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  - In particular,  $\mathbf{R}^{\rightarrow}(\mathbf{GHD}) \longrightarrow 1$ -pass algorithms
  - Dependence of *s* on *n*: [A-M-S'96]; [C.-Khot-Sun'03]; [Gronemeier'09]

# Method: Reduce from Communication Complexity 14 22 4 12 32 17 10 1 11 29 28 2 7 25 31 3 18 5 23 30 8 6 27 20 26 16 19 21 15 24 13 9





### **The Reductions**

E.g., Distinct Elements (Other problems: similar)

Alice: 
$$x \mapsto \sigma = \langle (1, x_1), (2, x_2), \dots, (n, x_n) \rangle$$
  
Bob:  $y \mapsto \tau = \langle (1, y_1), (2, y_2), \dots, (n, y_n) \rangle$   
Notice:  $F_0(\sigma \circ \tau) = n + \Delta(x, y) = \begin{cases} < \frac{3n}{2} - \sqrt{n}, \text{ or} \\ > \frac{3n}{2} + \sqrt{n}. \end{cases}$  Set  $\varepsilon = \frac{1}{\sqrt{n}}$ .





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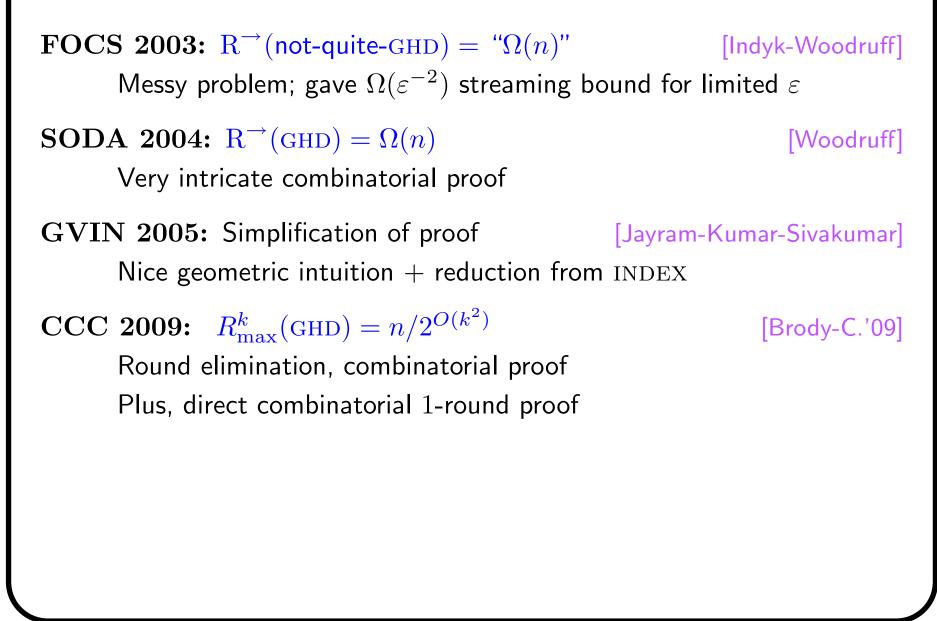
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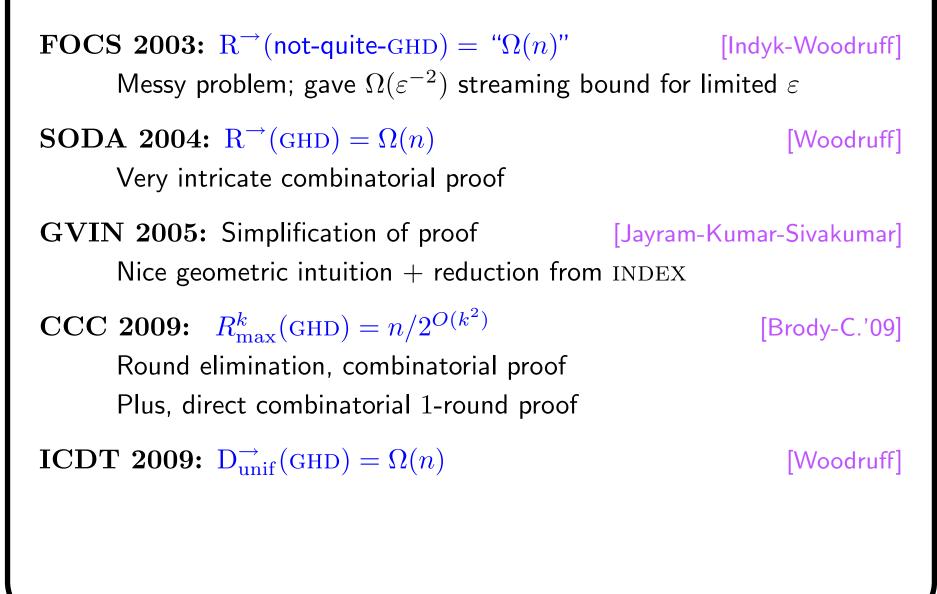


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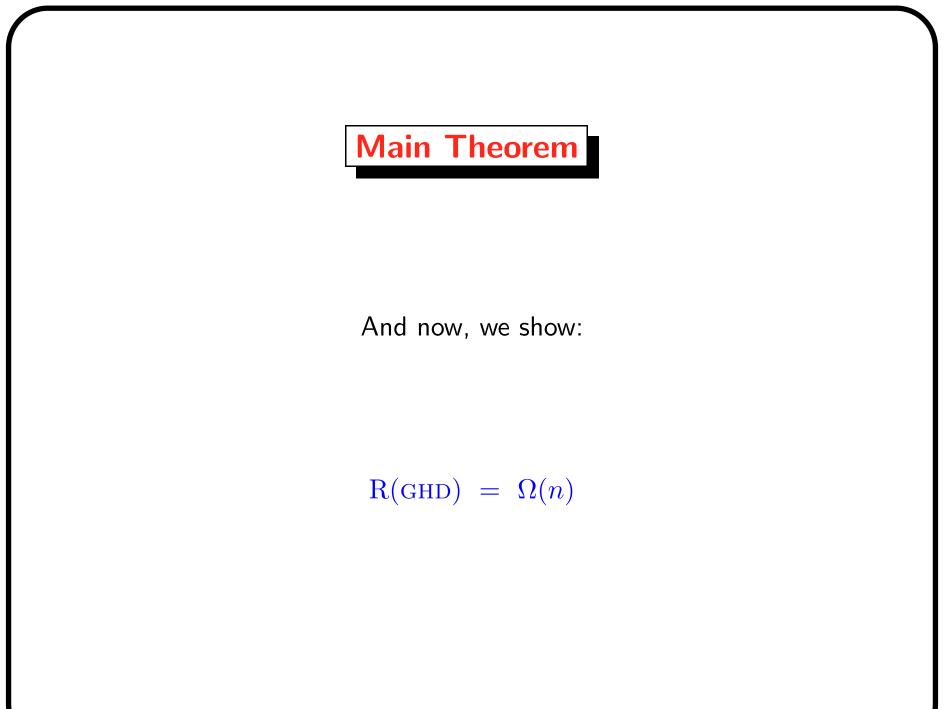








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CCC 2009:  $\mathbb{R}_{\max}^{k}(GHD) = n/2^{O(k^{2})}$  [Brody-C.'09]  
Round elimination, combinatorial proof  
Plus, direct combinatorial 1-round proof  
ICDT 2009:  $\mathbb{D}_{\text{unif}}^{\rightarrow}(GHD) = \Omega(n)$  [Woodruff]  
RND 2010:  $\mathbb{R}_{\max}^{k}(GHD) = \widetilde{\Omega}(n/k^{2})$  [Brody-C.-Regev-Vidick-deWolf]  
Better round elimination, geometric proof



### **GHD** Revisited

For  $x, y \in \{0, 1\}^n$ , define

bias
$$(x, y) = \frac{n/2 - \Delta(x, y)}{\sqrt{n}}$$

Then,

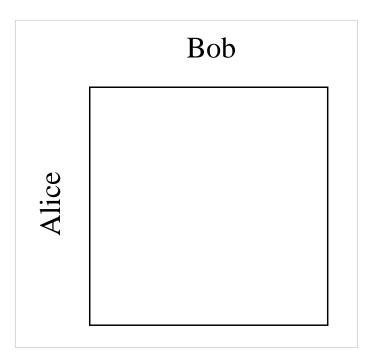
$$GHD(x,y) = \begin{cases} 0, & \text{if } \text{bias}(x,y) > 1, \\ 1, & \text{if } \text{bias}(x,y) < -1, \\ \star, & \text{otherwise.} \end{cases}$$

Alternative view (useful later): map  $b \in \{0, 1\} \mapsto (-1)^b / \sqrt{n}$ This maps  $x \in \{0, 1\}^n$  into  $\tilde{x} \in \mathbb{S}^{n-1}$  (unit sphere in  $\mathbb{R}^n$ )

 $bias(x,y) = \langle \widetilde{x}, \widetilde{y} \rangle \cdot \sqrt{n}/2$ 

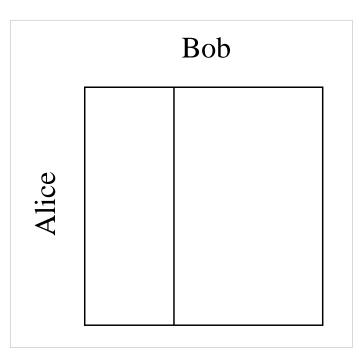
Let  $U = \{0,1\}^n \times \{0,1\}^n$  (input universe for Alice + Bob)

Take P deterministic protocol, communicating  $\leq c$  bits



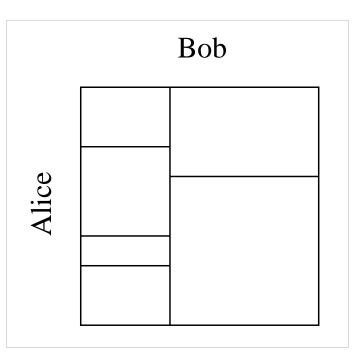
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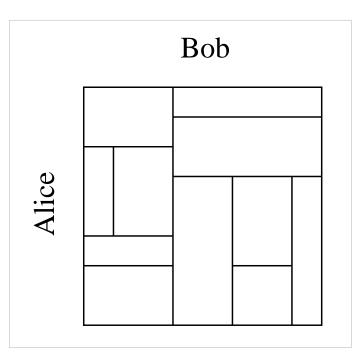
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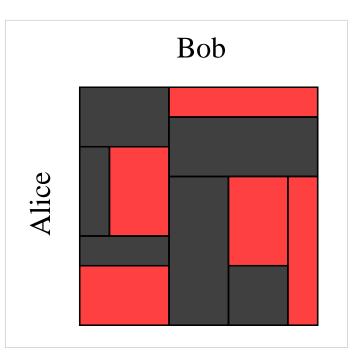
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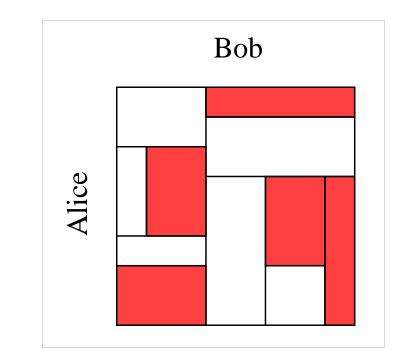
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Then P partitions U into  $\leq 2^c$  combinatorial rectangles (sets  $A \times B$ , where  $A, B \subseteq \{0, 1\}^n$ )



If P computes  $f: U \to \{0,1\}$ , then  $f^{-1}(0) = R_1 \cup R_2 \cup \cdots \cup R_{2^c}$ 

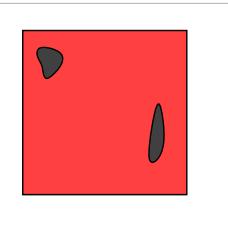
### **Discrepancy and Corruption**

We had:  $f^{-1}(1) = R_1 \cup R_2 \cup \cdots \cup R_{2^c}$ 

If P is a correct protocol, matrix of f contains 0-rectangle of size  $\geq 2^{2n-c}$ 

Basic method for lower bounding D(f): Show that f does *not* contain large 0-rectangle

To lower bound R(f), apply Yao's minimax principle



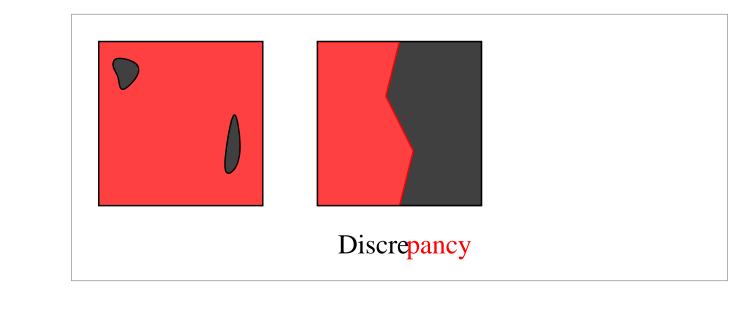
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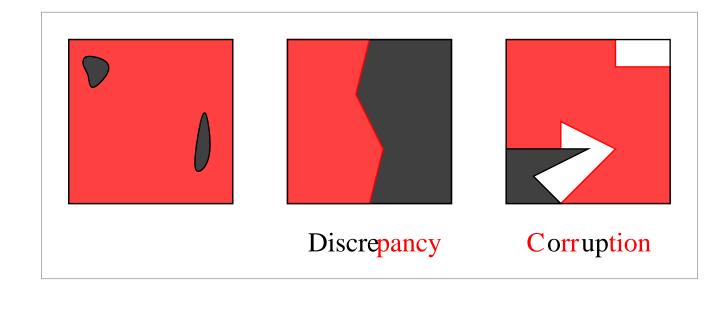
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There exist very large "uncorrupted" rectangles!

Consider:

$$A = B = \{0^{100\sqrt{n}}x : x \in \{0,1\}^{n-100\sqrt{n}}\}\$$

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 $\Pr_{(x,y)\in_R A\times B}[\operatorname{GHD}(x,y)=0] = \Pr_{(x,y)\in_R A\times B}[\operatorname{bias}(x,y)>1] = 1-2^{-\Omega(n)}$ 

Need a new technique?

### The Corruption Method: A Closer Look

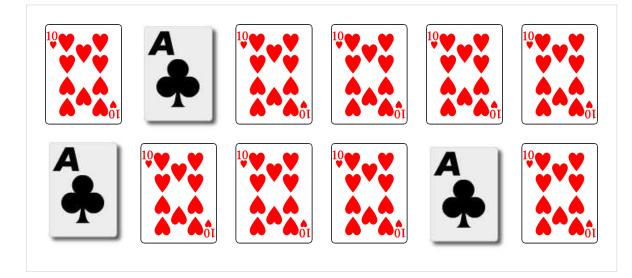
Pick distribs  $\mu_0, \mu_1$  on  $f^{-1}(0), f^{-1}(1)$ 

Argue that for all large rectangles R, we have

 $\mu_1(R) \geq \alpha \mu_0(R)$ 

Sum this over all 0-rectangles R; if protocol P is good for  $\mu_0, \mu_1$ :

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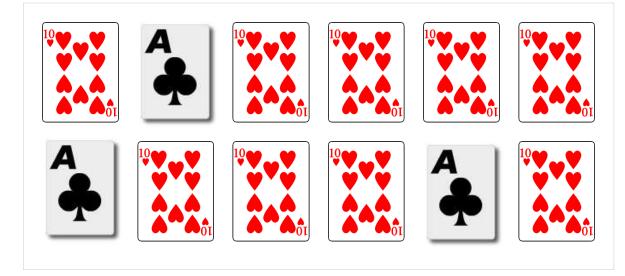
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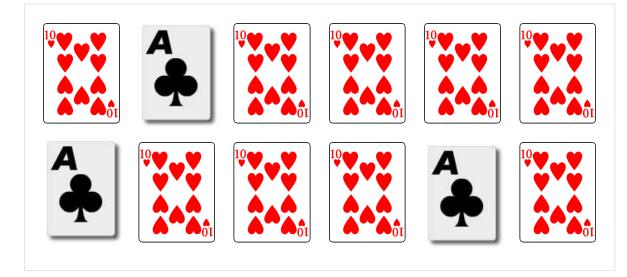
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**Jokers** 

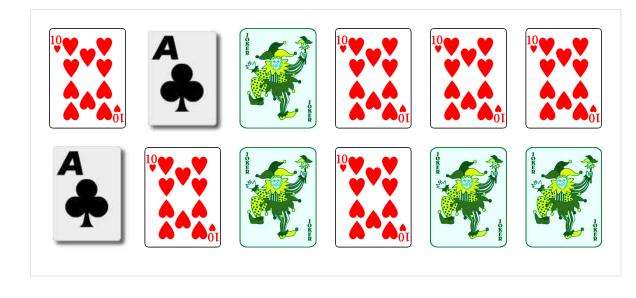
Pick distribs  $\mu_0, \mu_1$  on  $f^{-1}(0), f^{-1}(1)$ , and another distrib  $\mu_{\star}$ 

Argue that for all large rectangles R, we have

 $\mu_1(R) + \beta \,\mu_\star(R) \geq \alpha \,\mu_0(R) \qquad (\alpha > \beta)$ 

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 $\varepsilon + \beta \geq \mu_1(P_0) + \beta \mu_{\star}(P_0) \geq \alpha \mu_0(P_0) \geq \alpha(1 - \varepsilon)$ 





Consider slightly "shifted" version (doesn't really change anything)

$$GHD'(x,y) = \begin{cases} 0, & \text{if } \text{bias}(x,y) > -4, \\ 1, & \text{if } \text{bias}(x,y) < -6, \\ \star, & \text{otherwise.} \end{cases}$$

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**The Key Inequality:** For rectangles R of size  $\geq 2^{2n-0.01n}$ 

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Largeness crucial:

$$A = \{x \in \{0,1\}^{n/2}, |x| = n/4\}; \quad R = (0^{n/2} \cdot A) \times (A \cdot 0^{n/2})$$

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$$\begin{array}{rcl} A &=& \{x \in \{0,1\}^{n/2}, |x| = n/4\}; & R &=& (0^{n/2} \cdot A) \times (A \cdot 0^{n/2}) \\ & \mbox{then} & \forall (x,y) \in R: \mbox{bias}(x,y) = 0 & \mbox{and} & |R| \approx 2^n / \sqrt{n} \end{array}$$

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Do these jokers have any "meaning"?

- Yes! What we did here can be understood more deeply by studying a linear program (and its dual)
- Careful study of this type of generalization: "smooth rectangle bound" and "partition bound"

[Klauck'10] [Jain-Klauck'10]

## The Inequality: A Gaussian Version

Original inequality:  $|R| \ge 2^{1.99n} \implies \frac{1}{2}(\mu_1(R) + \mu_{\star}(R)) \ge 0.9\mu_0(R)$ 

Apply map from  $\{0,1\}^n$  to unit sphere  $\mathbb{S}^{n-1}$ 

Let  $\gamma = n$ -dimensional Gaussian distrib

Analogous inequality:

 $\gamma(A), \gamma(B) \ge 2^{-n/100}, \ x \leftarrow A, \ y \leftarrow B \implies$ distrib of  $\langle x, y \rangle / \sqrt{n}$  is "spread out" like N(0, 1)

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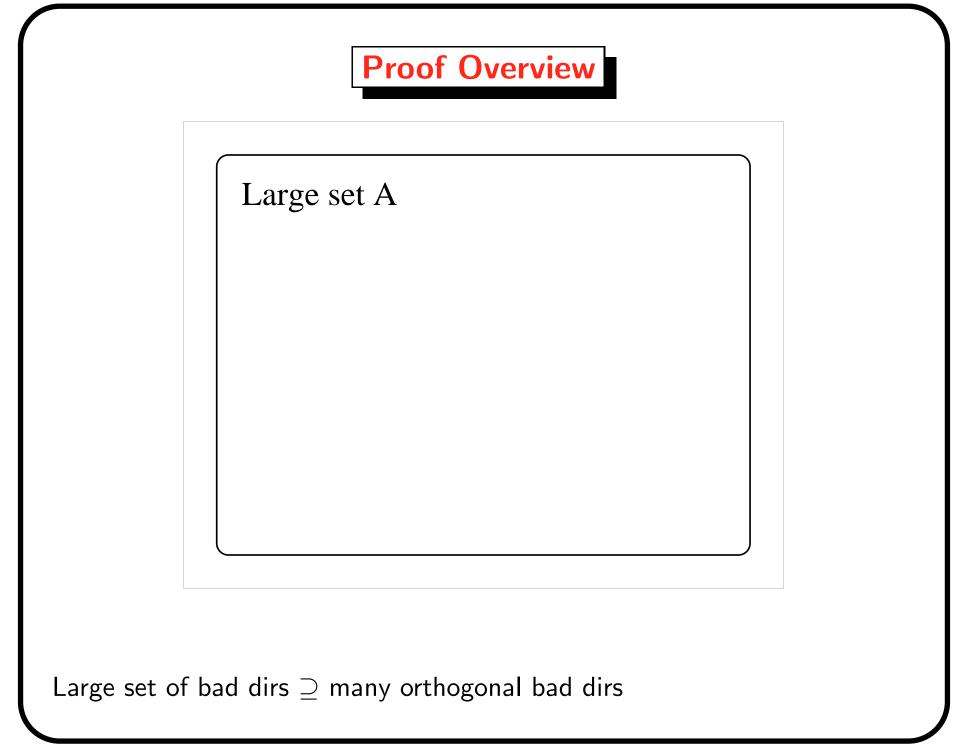
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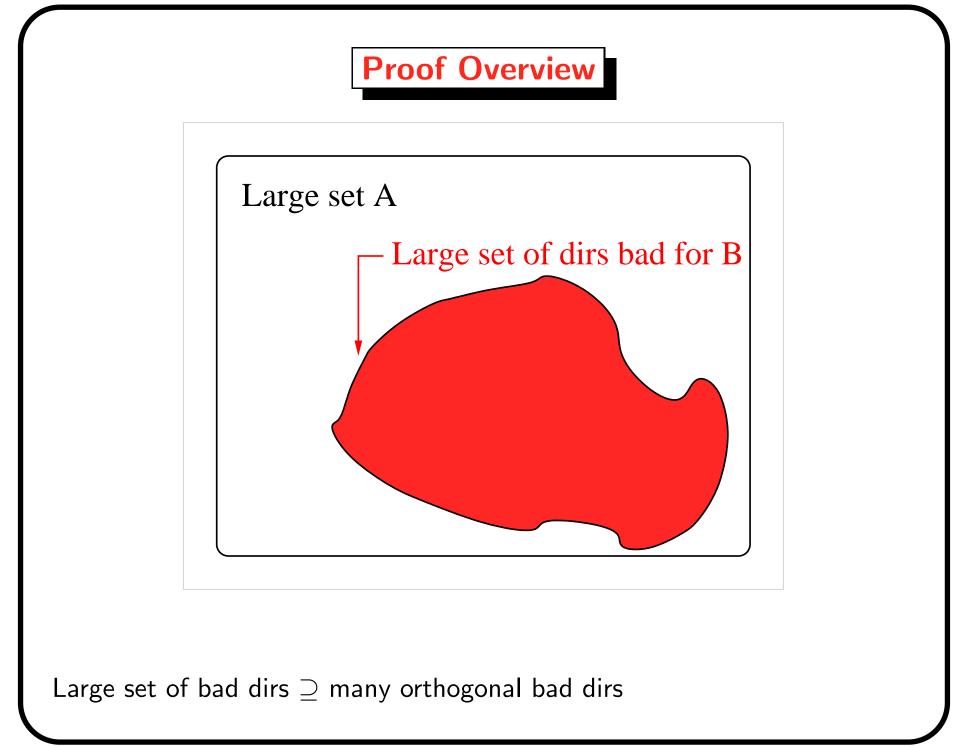
 $\gamma(A), \gamma(B) \ge 2^{-n/100}, x \leftarrow A, y \leftarrow B \implies$ distrib of  $\langle x, y \rangle / \sqrt{n}$  is "spread out" like N(0, 1)

[Can't just fix a direction  $x \in A$ : what if proj(B, x) sharply concentrated?]

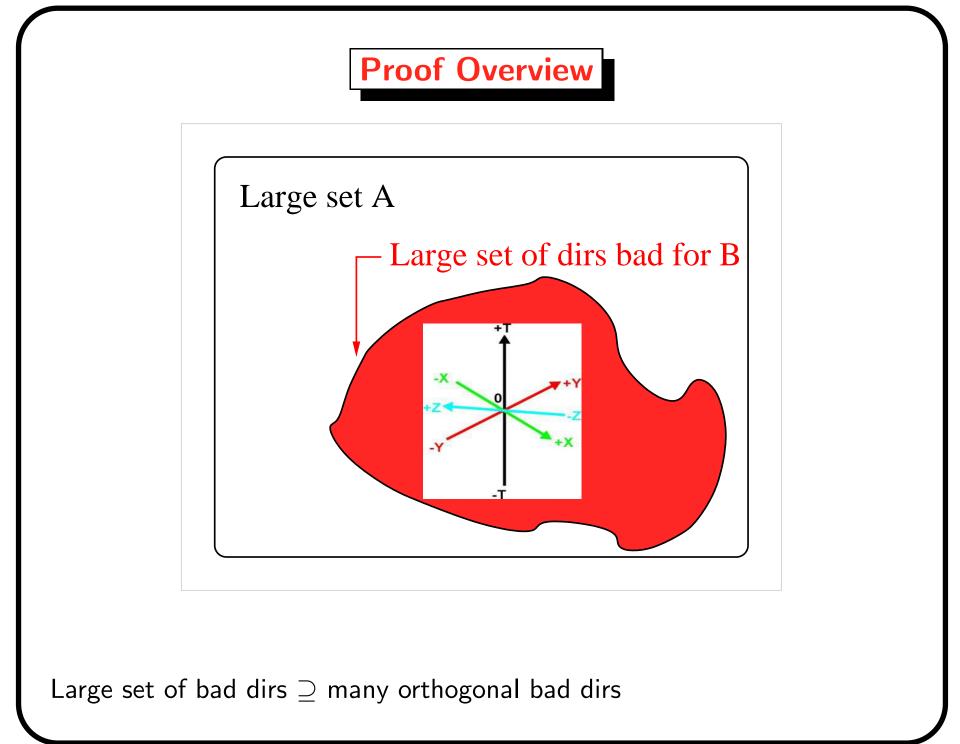
## A Stronger Statement

 $\gamma(B) \ge 2^{-n/100} \implies \text{projection of } B \text{ on all but } 2^{-n/50} \text{ of directions}$ distributed like N(0,1) + Z (i.e., mixture of normals with variance 1)





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## **Finding Orthogonal Bad Directions**

Want to show that A doesn't have many bad directions

We'll show: if it does, then  $\exists$  many *nearly orthogonal* bad directions

# **Finding Orthogonal Bad Directions** Want to show that A doesn't have many bad directions We'll show: if it does, then $\exists$ many *nearly orthogonal* bad directions A lemma from Raz: [Raz'99] Any set $A' \subseteq \mathbb{S}^{n-1}$ of at least $2^{-n/50}$ directions contains a set of $\frac{1}{10}$ -near-orthogonal vectors $x_1, \ldots, x_{n/2}$ , i.e., $\| \operatorname{proj}(x_i, \operatorname{span}(x_1, \dots, x_{i-1})) \| \le 1/10$ Proof via isoperimetric inequality

**Lemma 1:** Suppose  $B \subseteq \mathbb{R}^n$  is s.t.  $\gamma(B) \geq 2^{-n/100}$ . Let  $y \leftarrow B$ . Let directions  $x_1, \ldots, x_{n/2}$  be orthogonal. Then all of  $\langle y, x_1 \rangle, \ldots, \langle y, x_{n/2} \rangle$  cannot be sharply concentrated.

Precise statement: At least one (in fact, most) projection  $\langle y, x_k \rangle$  is close to N(0,1) (even when conditioned on  $\langle y, x_1 \rangle, \ldots, \langle y, x_{k-1} \rangle$ )

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**Proof Idea:** Complete to orthonormal basis:  $\{x_1, \ldots, x_n\}$ 

Then y is determined by  $\langle y, x_1 \rangle, \ldots, \langle y, x_n \rangle$ . Wave hands as follows:

 $0.99n \leq \mathrm{H}(y) \leq \mathrm{H}(\langle y, x_1 \rangle, \dots, \langle y, x_n \rangle)$ 

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 $\begin{array}{lll} 0.99n &\leq & \mathrm{H}(y) &\leq & \mathrm{H}(\langle y, x_1 \rangle, \dots, \langle y, x_n \rangle) \\ \\ & & = & \sum_{k=1}^{n/2} \mathrm{H}(\langle y, x_k \rangle \mid \langle y, x_1 \rangle, \dots, \langle y, x_{k-1} \rangle) \\ & & \quad + \sum_{k=n/2+1}^{n} \mathrm{H}(\langle y, x_k \rangle \mid \langle y, x_1 \rangle, \dots, \langle y, x_{k-1} \rangle) \end{array}$ 

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# Finishing the Proof

**Theorem:**  $\gamma(B) \ge 2^{-n/100} \implies$  projection of B on all but  $2^{-n/50}$  of directions distributed like N(0,1) + Z

#### **Proof Sketch:**

- Let  $A' = \{ \text{bad directions} \}$ ; suppose to the contrary that its measure is  $\geq 2^{-n/50}$
- Get near-orthogonal bad dirs  $x_1, \ldots, x_{n/2} \in A'$  by Raz's Lemma
- If these vectors were orthogonal, by Lemma 1,  $\exists k \text{ s.t. } \langle B, x_k \rangle$  is close to N(0, 1). So  $x_k$  is not bad. Contradiction.

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- Since they are only  $\frac{1}{10}$ -near-orthogonal, we instead get that  $\langle B, x_k \rangle$  is distributed like N(0, 1) + Z. Still a contradiction.

# Conclusions

- Settled communication complexity of GHD, proving a long-conjectured  $\Omega(n)$  bound
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# **Open Problem**

Apply the "jokers" idea (more generally, the smooth rectangle bound) to other interesting communication and query complexity problems.