

The Gowers Norm in the Testing of Boolean Functions

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- 1 Introduction
 - Dictatorship testing
 - Testing graph free
- 2 Technique overview
- 3 Design & analysis of dictatorship test
- 4 Design & analysis of graph free test

Property testing

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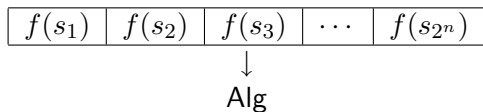
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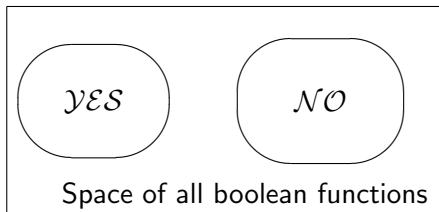
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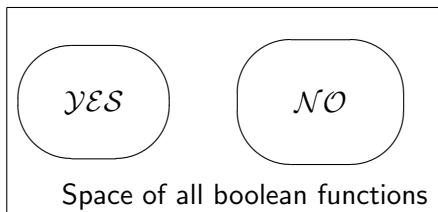
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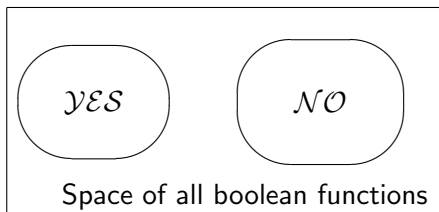


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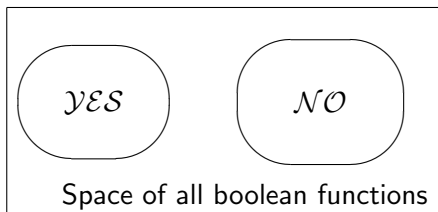


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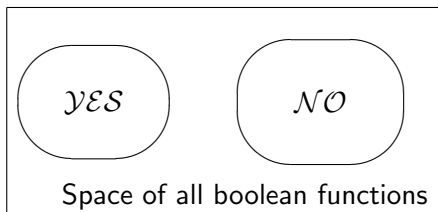


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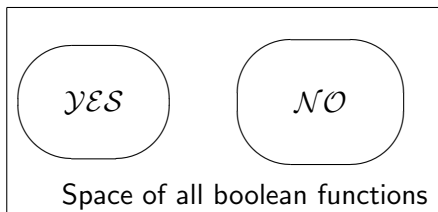


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accepts w.p. $\text{poly}(q) \cdot 2^{-q}$

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“meta theorem”

Under the unique games conjecture, a (q, c, s) dictatorship test translates into a PCP system with q queries, completeness $0.99c$, and soundness s .

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- [DS, KKMO]: one that has an “influential variable”

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 - $f(x) = x_1 + \text{Maj}(x_2, \dots, x_n)$. $I_1(T_\rho(f)) > 0$.
- Upshot: any function has a finite number of variables with positive ρ -attenuated influence

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Theorem (C08)

A q -query (adaptive) dictatorship test with completeness 1 and soundness $O(q^3 \cdot 2^{-q})$.

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i.e., no x, y such that $f(x) = f(y) = f(x + y) = 1$

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Our result: joint with Bhattacharyya, Sudan, Xie

Let G be a graph with k edges. There is a k -query “ G -free” test with completeness 1 and soundness < 1 .

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- No. Property of triangle-free is linear-invariant & non-linear

Removal lemma for graphs

(folklore) If a graph on n vertices has $o(n^3)$ triangles, then $o(n^2)$ edges can be removed so that the graph has no triangle.

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- main tool: Szemerédi's regularity lemma
- applications: additive combinatorics, e.g. arithmetic progressions

Green's removal lemma for functions

Theorem (Green)

Let $A = \{x : f(x) = 1\}$. $N = 2^n$. If A has $o(N^2)$ Schur triples, then $o(N)$ points can be removed from A so that A has no Schur triple.

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- motivated by a number theoretic conjecture

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- **similarities**: regularity lemmas, notions of pseudorandomness

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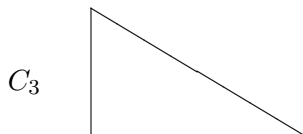
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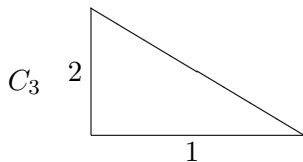
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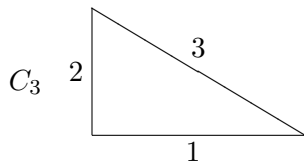
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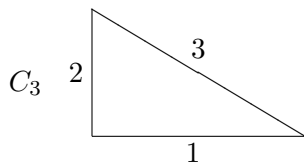
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- each edge is associated with an integer from $[k]$
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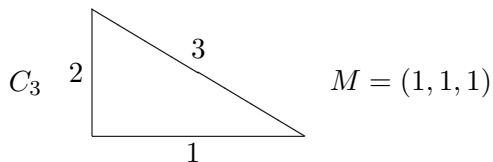
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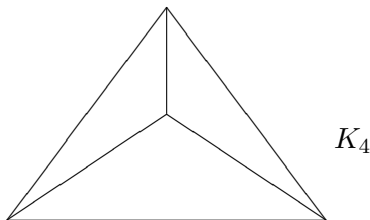
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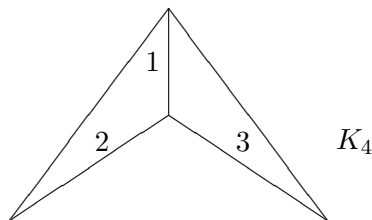
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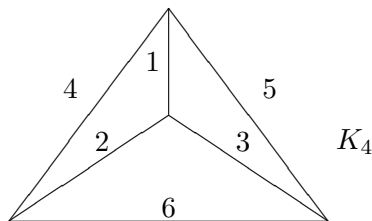
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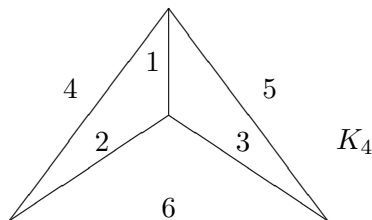


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$$M = \begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 \end{pmatrix}$$



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Can only guarantee $\tau(\epsilon) \geq 2^{-O(W(\frac{1}{\epsilon}))}$,
where $W(t)$ denotes a tower of twos with height t

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Test T :

- selects a random local structure.
- accepts iff f has no structure.

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where $\Phi(f)$ is some “extension of f ” dependent on $(\mathcal{YES}, \mathcal{NO})$

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roughly: due to values of d , field characteristic, roots of unity, etc

The Gowers uniformity norm $\|f\|_{U_d}$

Definition

- $\|f\|_{U_2} = \|\hat{f}\|_4$
i.e., U_2 norm is the L_4 norm of f 's Fourier transform
- Inductively, define $\|f\|_{U_{d+1}}^{2^{d+1}} = \mathbb{E}_h \|\Delta_h f\|_{U_d}^{2^d}$,
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where $\Delta_h f(x) = f(x)f(x+h)$ denotes the discrete derivative of f .
- Expanding, $\|f\|_{U_2}^4 = \mathbb{E}_{x,y,z} [f(x)f(x+y)f(x+z)f(x+y+z)]$
- monotonicity: $\|f\|_{U_2} \leq \|f\|_{U_3} \leq \dots$

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If $\|1_A - \delta\|_{U_{k-1}} = o(1)$, then A has approximately $\delta^k N^2$ k -term AP.

Generalized von-Neumann type theorems

- statements that show certain “estimations of f ” are bounded above by the Gowers norm of f
- [Samorodnitsky, S.&Trevisan06]: The acceptance probability of the AKKLR test for degree d polynomials is bounded above by the $(d + 1)$ -th Gowers norm

Generalized von-Neumann type theorems

- statements that show certain “estimations of f ” are bounded above by the Gowers norm of f
- [Green&Tao:] A system of linear equations with “complexity d ” is bounded above by the $(d + 1)$ -th Gowers norm

System of linear equations with low complexity

Theorem (Green & Tao)

Suppose the system of linear equations L_1, \dots, L_k over variables x_1, \dots, x_m has “complexity d .”

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$$\mathbb{E}_{x_1, \dots, x_m} \left[\prod_{i \in [k]} f_i(L_i(x_1, \dots, x_m)) \right] \leq \min_{i \in [k]} \|f_i\|_{U_{d+1}}$$

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- Find a basic dictatorship test that has completeness 1 and soundness $\frac{1}{2}$.

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ST Lemma:

For balanced function f , if for all $i \in [n]$ $I_i(f) = o(1)$, then for all $d \in \mathbb{Z}^+$, $\|f\|_{U_d} = o(1)$.

Basic test with completeness 1

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- monomial testing: Parnas, Ron, Samorodnitsky 02
- essentially checks if $f(y) \wedge f(z) = f(y \wedge z)$.

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$$f(x_i)f(x_j)(f(y) \wedge f(z)) = f(x_i + x_j + y \wedge z)$$

[Håstad & Khot 02]; too inefficient for us

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[Håstad 97]; imperfect completeness

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[GLST 98]

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- We will use a complete hypergraph following [ST06]

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$$\prod_{i \in e} [f(x_i)] = f\left(\sum_{i \in e} x_i\right).$$

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accepts large parities, $f(x) = (-1)^{x_1 + \dots + x_n}$

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H-Test, with access to $f : \{0, 1\}^n \rightarrow \{-1, 1\}$

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“Extension” Φ_ρ

For every $f : \{0, 1\}^n \rightarrow \{-1, 1\}$, define $\Phi_\rho(f) : \{0, 1\}^{2n} \rightarrow [-1, 1]$ to be

$$\Phi_\rho(f)(x, y) = \mathbb{E}_{z \in \mathcal{D}_\rho} f(x + y \wedge z)$$

- for $i \in [n]$, $I_i(T_\rho(f)) \approx I_i(\Phi_\rho(f))$.

Analysis continued

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- By generalized von-Neumann,

$$\Pr[k\text{-deg AKKLR test accepts } \Phi_\rho(f)] \leq \|\Phi_\rho(f)\|_{U_{k+1}}$$

Outline

- 1 Introduction
 - Dictatorship testing
 - Testing graph free
- 2 Technique overview
- 3 Design & analysis of dictatorship test
- 4 Design & analysis of graph free test

M -free test

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If f is M -free, test always accepts.

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H is a subspace of $\{0,1\}^n$

f_{g+H} is the restriction of f to the affine subspace $g + H$

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Let $\epsilon > 0$, $f : \{0,1\}^n \rightarrow \{0,1\}$.

There exists a subspace H of constant co-dimension such that

$\Phi(f) = \{f_{g+H}\}$ is ϵ -pseudorandom.

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- 2 Else, set $f_{g+H}^R = f_{g+H}$.

- Since $\delta(f, f^R) \leq \epsilon$, there exist x_1, \dots, x_k such that $f^R(x_1), \dots, f^R(x_k) = 1$.

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If M is graphic, then the rows of M form a complexity 1 system of linear forms.

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- By generalized von-Neumann, this is \approx the expected number of M patterns in a random function, which is > 0
- Since H has constant co-dimension, test rejects with positive probability.

Open question:

- a q -query PCP with completeness 1, soundness $\text{poly}(q) \cdot 2^{-q}$?

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- prove some form of inverse for Gowers norm
a low-degree polynomial test with soundness $\frac{1}{2}$.