

A structure theorem for Boolean functions with small total influences

Hamed Hatami

School of Computer Science
McGill University

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Influences

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- The influence of the j -th variable on f is

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- $I_f = \sum_{j=1}^n I_j(f)$ is called the **total influence** of f .

Some Examples

Example

- Let $X = (\{0, 1\}, \mu)$ be the uniform distribution on $\{0, 1\}$.
- Let $f : \{0, 1\}^n \rightarrow \{0, 1\}$ be parity

$$f(x_1, \dots, x_n) = x_1 + \dots + x_n \pmod{2}.$$

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- Total influence of f is $n/2$.

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- Total influence $I_f \leq 2(n-1)/n \approx 2$.

Main Question

What can we say about the structure of functions $f : X^n \rightarrow \{0, 1\}$ with $I_f = O(1)$?

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 - ▶ 3-SAT exhibits a sharp threshold.
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- Bourgain 2000: Partially extended this to general setting $f : X^n \rightarrow \{0, 1\}$.

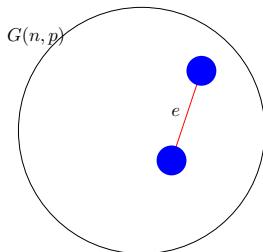
Phase Transitions

Erdős-Rényi graph

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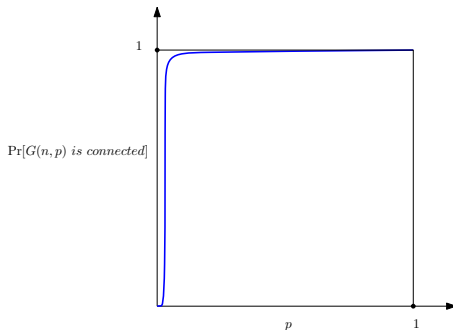
- In early sixties Erdős and Rényi invented the notion of a random graph $G(n, p)$:
- Every edge is present independently with probability p .



$$\Pr[e \in G(n, p)] = p$$

Thresholds

They observed that some fundamental graph properties such as connectivity exhibit a threshold as p increases.



sharpness of threshold

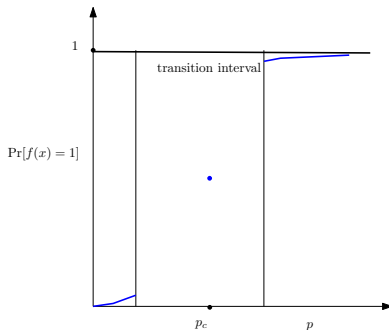
One of the main questions that arises in studying phase transitions is:

- “How sharp is the threshold?”

sharpness of threshold

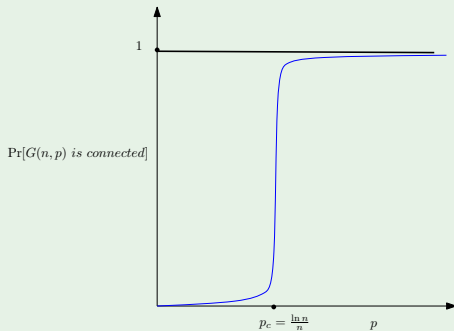
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- That is how short is the interval in which the transition occurs.



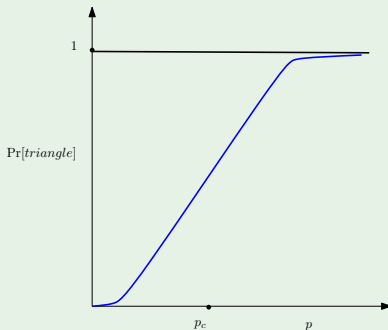
Example

Connectivity exhibits a sharp threshold.



Example

Containing a triangle does not exhibit a sharp threshold.



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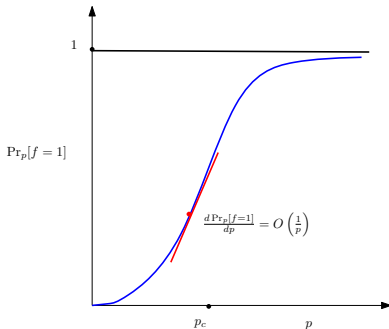
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Is there a general approach to such questions?

Observation

If $f : \{0, 1\}^n \rightarrow \{0, 1\}$ does not exhibit a sharp threshold, then $\frac{d \Pr_p[f(x)=1]}{dp} = O\left(\frac{1}{p}\right)$, for some p in the transition interval.



Question [Coarse Threshold]

Which functions $f : \{0, 1\}^n \rightarrow \{0, 1\}$ satisfy $\frac{d \Pr_p[f(x)=1]}{dp} = O\left(\frac{1}{p}\right)$?

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Russo-Margulis Lemma

The sharpness of the threshold is controlled by the total influence of the indicator function of the property:

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Question Rephrased

Which functions $f : (\{0, 1\}^n, \mu_\rho) \rightarrow \{0, 1\}$ satisfy $I_f = O(1)$?

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More general question

What is the structure of the functions $f : X^n \rightarrow \{0, 1\}$ with bounded total influence?

Bounded Total Influence

Functions with Small Total Influence

Juntas

Definition (Junta)

The value of $f(x_1, \dots, x_n)$ depends on a small set of variables $\{x_{i_1}, \dots, x_{i_k}\}$:

$$f(x) := g(x_{i_1}, \dots, x_{i_k}).$$

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- Juntas have total influence $O(1)$.

Direct theorem

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Theorem (More precisely)

Let $f : \{0, 1\}^n \rightarrow \{0, 1\}$ have total influence $O(1)$. Then for every $\epsilon > 0$, there exists a $O_\epsilon(1)$ -junta $g : \{0, 1\}^n \rightarrow \{0, 1\}$ such that

$$\Pr[f(x) \neq g(x)] \leq \epsilon.$$

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- For the applications in phase transition, the range $p \lesssim n^{-c}$ is the most interesting case.
 - ▶ connectivity
 - ▶ satisfiability of 3-SAT
 - ▶ 3-colorability of graphs....

Pseudo-Juntas

$$f : X^n \rightarrow \{0, 1\}$$

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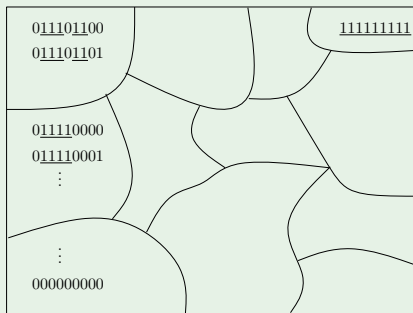
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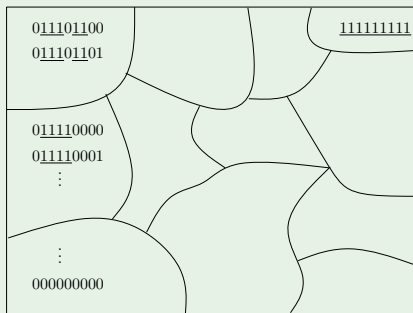


Definition (Pseudo-junta)

If $f : X^n \rightarrow \{0, 1\}$ is measurable w.r.t. $\mathcal{F}_{\mathcal{J}}$, then f is called a **k -pseudo-junta** provided that

$$\mathbb{E}[\text{number of active coordinates of } x] \leq k.$$

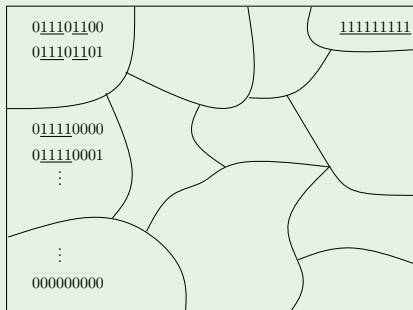
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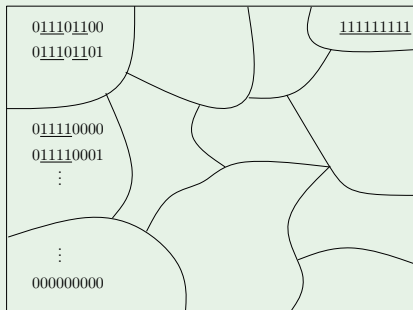
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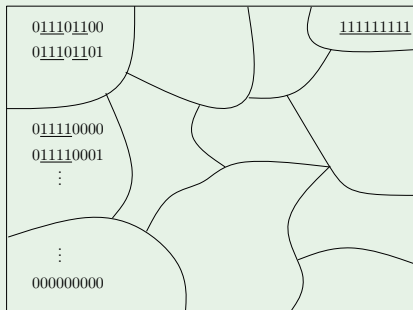
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- $j \notin J_{\mathcal{F}}(x) \cup J_{\mathcal{F}}(y) \Leftrightarrow x$ and y are atom-mates.

Example (The partition $\mathcal{F}_{\mathcal{J}}$ of X^n)



Theorem (Direct Theorem)

Let $f : X^n \rightarrow \{0, 1\}$ be a k -pseudo-junta. Then $I_f \leq 2k$.

$$\begin{aligned} I_f &= \sum_{j \in [n]} \Pr[f(x_1, \dots, x_j, \dots, x_n) \neq f(x_1, \dots, y_j, \dots, x_n)] \\ &\leq \sum_{j \in [n]} \Pr[j \in J_{\mathcal{J}}(x_1, \dots, x_j, \dots, x_n) \cup J_{\mathcal{J}}(x_1, \dots, y_j, \dots, x_n)] \end{aligned}$$

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Theorem (Recall - Direct Theorem)

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*If the total influence of a **graph** property f is $O(1)$ on $G(n, p)$, then f is essentially a pseudo-junta.*

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- It is only applicable to p -biased distribution.

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- does not come with a corresponding direct theorem.
- does not tell anything about the global structure of f .

Main Theorem

Theorem (H. 2011, Inverse Theorem)

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Theorem (More precisely:)

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

Theorem (H. 2011, Inverse Theorem)

If the total influence of $f : X^n \rightarrow \{0, 1\}$ is $O(1)$, then f is essentially a pseudo-junta.

Theorem (More precisely:)

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

- There exists a $\exp(10^{15}\epsilon^{-3}\lceil I_f \rceil^3)$ -pseudo-junta $h : X^n \rightarrow \{0, 1\}$ such that*

$$\Pr[f(x) \neq h(x)] \leq \epsilon.$$

Proof Sketch

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Proof plan:

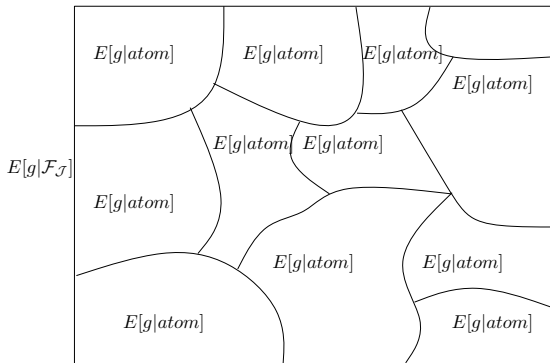
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- So

$$f \approx \sum_{S: |S| < k} F_S =: g.$$

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Bourgain 2000

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- **But** we want

$$\int |f - \mathbb{E}[f|\mathcal{F}_J]|^2 = \int \left| \sum (F_S - \mathbb{E}[F_S|\mathcal{F}_J]) \right|^2 \approx 0.$$

Note bounding $\mathbb{E}[|J_{\mathcal{J}}|]$ is easy:

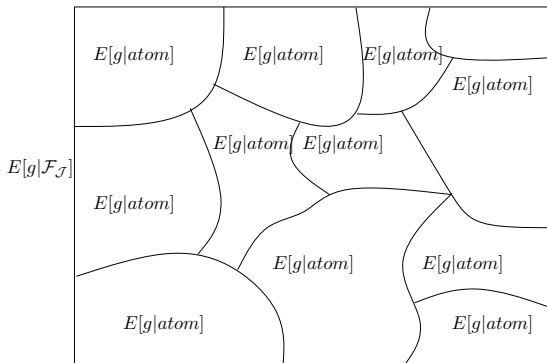
$$\begin{aligned}\mathbb{E}[|J_{\mathcal{J}}(x)|] &\leq \sum |\mathcal{S}| \times \Pr[J_{\mathcal{S}}(x) = 1] \\ &\leq k \sum \int J_{\mathcal{S}}(x) \\ &\leq k \sum \int \epsilon_1^{-1} |F_{\mathcal{S}}|^2 \leq \epsilon_1^{-1} k = O(1).\end{aligned}$$

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- To remedy this we define some auxiliary σ -algebras \mathcal{F}_S (activate coordinates only if x_S activates them, E.g.

$$\underbrace{(1, 1, 0, 1, 1, 0, 0)}_S \quad \text{vs.} \quad \underbrace{(1, 1, 0, 1, 1, 0, 0)}_S$$

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- Since \mathcal{F}_S is coarser than \mathcal{F}_J :

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- We get

$$\begin{aligned} \|g - \mathbb{E}[g|\mathcal{F}_{\mathcal{J}}]\|_2^2 &\lesssim \int \sum |F_S - \mathbb{E}[F_S|\mathcal{F}_S]|^2 \\ &+ \sum_{\substack{S_1, S_2 \in \mathcal{S} \\ S_1 \cap S_2 \neq \emptyset, S_1 \neq S_2}} \left| \int \mathbb{E}[F_{S_1}|\mathcal{F}_{S_1}] \mathbb{E}[F_{S_2}|\mathcal{F}_{S_2}] \right|. \end{aligned}$$

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- First sum is small by Bourgain's inequality.
- Second term is analyzed by considering $T := S_1 \cap S_2$:

$$\int \mathbb{E}[F_{S_1}(x_T, \cdot)|\mathcal{F}_{S_1}] \mathbb{E}[F_{S_2}(x_T, \cdot)|\mathcal{F}_{S_2}] = \int \mathbb{E}[F_{S_1}(x_T, \cdot)|\mathcal{F}_{S_1}] \times \int \mathbb{E}[F_{S_2}(x_T, \cdot)|\mathcal{F}_{S_2}].$$

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$$J_T(y) := \begin{cases} 1 & \max_{R \subseteq T} \delta_0^{-2|T \setminus R|} \int \xi_T(y_R, x_{T \setminus R}) dx_{T \setminus R} \geq 1, \\ 0 & \text{otherwise.} \end{cases}$$

where

$$\xi_T(y) := \begin{cases} 1 & \sum_{R \subseteq T} \sum_{S \in \mathcal{S}: S \supseteq T} \int a_S(y_R, x_{S \setminus R}) dx_{S \setminus R} > \epsilon_2, \\ 0 & \text{otherwise.} \end{cases}$$

where

$$a_S(y) := 2^{3k} \delta^{-2k} \sum_{T \subseteq S} \int 1_{[|F_S(y_{S \setminus T}, x_T)| > \epsilon_1]} dx_T.$$

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 - ▶ G_S shares the nice properties of F_S .
 - ▶ $\sum \|F_S - G_S\|_2^2$ is small.
 - ▶ $\sum_{|S| \leq k} \|G_S\|_1 = O(1)$.

Increasing Functions

Friedgut 2000

For an **increasing** graph property f , if $I_f = O(1)$, then there exists a small set of coordinates J such that

$$\mathbb{E}[f(x) | x_J = \vec{1}] \geq 1 - \epsilon.$$

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If $I_f = O(1)$ for an **increasing** $f : (\{0, 1\}^n, \mu_p) \rightarrow \{0, 1\}$, then $\exists \delta > 0$ and a small J such that

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H 2011

Under the above assumptions

$$\mathbb{E}[f(x)|x_J = \vec{1}] \geq 1 - \epsilon.$$

Open problem

Conjecture[Friedgut]

If $I_f = O(1)$ for an **increasing** $f : (\{0, 1\}^n, \mu_p) \rightarrow \{0, 1\}$, then

$$f \approx O(1) - \text{Monotone DNF.}$$

Conjecture

If $f : [0, 1]^n \rightarrow \{0, 1\}$ is increasing, and $I_f = O(1)$, then there is $|J| = O_\epsilon(1)$ such that either

$$\mathbb{E}[f(x) | x_J = \vec{1}] \geq 1 - \epsilon,$$

or

$$\mathbb{E}[f(x) | x_J = \vec{0}] \leq \epsilon.$$

Thank you!