

Sensitivity and block sensitivity

Definition: Given a boolean function $f : \{0, 1\}^n \rightarrow \{0, 1\}$. The local sensitivity $s(f, x)$ on the input x is defined as the number of indices i , such that $f(x) \neq f(x^{\{i\}})$, where $x^{\{i\}}$ is obtained by flipping the i -th bit of x . The sensitivity $s(f) := \max_{x \in \{0, 1\}^n} s(f, x)$.

Example: the *AND* function $f(x_1, \dots, x_n) = x_1 \wedge \dots \wedge x_n$.
 $s(f, \vec{0}) = 0, s(f, \vec{1}) = n, s(f) = n$.

Definition: The local block sensitivity $bs(f, x)$ on the input x is the maximum number of disjoint blocks B_1, \dots, B_k of $[n]$, such that for each $B_i, f(x) \neq f(x^{B_i})$. Here x^{B_i} is the n -bit string obtained from x by flipping its coordinates in B_i . The block sensitivity $bs(f) := \max_{x \in \{0, 1\}^n} bs(f, x)$.

Example: the *AND* function $f(x_1, \dots, x_n) = x_1 \wedge \dots \wedge x_n$.
 $bs(f, \vec{0}) = 1, bs(f, \vec{1}) = n, s(f) = n$.

Obviously, $bs(f, x) \geq s(f, x)$ for every x and thus $bs(f) \geq s(f)$. But does there exist a function f , such that $bs(f) > s(f)$?

The Rubinstein function

Define $f : \{0, 1\}^{n^2} \rightarrow \{0, 1\}$ as

$$f(x_{11}, \dots, x_{nn}) = \bigvee_{i=1}^n g(x_{i1}, \dots, x_{in}),$$

where $g(x_1, \dots, x_n) = 1$ if and only if $x_j = x_{j+1} = 1$ for some $1 \leq j \leq n-1$, and all other $x_k = 0$.

- $bs(f) \geq bs(f, \vec{0}) = \Omega(n^2)$.
- $s(f) = O(n)$.

◦ **Case 1:** $f(x) = 0$

Every row must output 0, there are at most two sensitive coordinates on each row, say when the row is

$$0 \quad \dots \quad 0 \quad 1 \quad 0 \quad \dots \quad 0.$$

So, $s(f, x) \leq 2n$.

◦ **Case 2:** $f(x) = 1$

If two rows output 1, $s(f, x) = 0$.

If only one row outputs 1, $s(f, x) \leq n$.

A quick summary: $s(f) \leq bs(f)$, and Rubinstein's example shows that $bs(f)$ could be quadratic in $s(f)$.

Sensitivity Conjecture[Nisan Szegedy 1992]

For every boolean function f , $bs(f) \leq poly(s(f))$.

Two complexity measures s_1 and s_2 of boolean functions are polynomially related if $\exists C_1, C_2 > 0$, such that for every boolean f :

$$s_2(f)^{C_1} \leq s_1(f) \leq s_2(f)^{C_2}.$$

The following measures are polynomially related:

- Block sensitivity $bs(f)$.
- Decision tree complexity $D(f)$.
- Certificate complexity $C(f)$.
- Degree (as real polynomial) $deg(f)$.
- Approximate degree $\tilde{deg}(f)$.
- Randomized query complexity $R(f)$.
- Quantum query complexity $Q(f)$.

In some sense, sensitivity measures how "smooth" a boolean function is, with respect to the Hamming distance. Low sensitivity means more smooth. The Sensitivity Conjecture asserts that

- Computationally, "smooth" (low-sensitivity) functions are easy to compute in some of the simplest models like the deterministic decision tree model.
- Algebraically, such functions have low degree.

Bounds proven: (Exponential)

- $bs(f) = O(s(f)4^{s(f)})$. (Simon 1983)
- $bs(f) \leq (e/\sqrt{2\pi})e^{s(f)}\sqrt{s(f)}$. (Kenyon, Kutin 2004)
- $bs(f) \leq 2^{s(f)-1}s(f)$ (Ambainis, Bavarian, Gao, Mao, Sun, Zuo 2013)

Separations constructed: (Quadratic)

- $bs(f) = \frac{1}{2}s(f)^2$. (Rubinstein 1995)
- $bs(f) = \frac{1}{2}s(f)^2 + s(f)$. (Virza 2011)
- $bs(f) = \frac{2}{3}s(f)^2 - \frac{1}{2}s(f)$. (Ambainis, Sun 2011)

The Gotsman-Linial equivalence

Theorem (Gotsman, Linial 1992)

The following are equivalent for any monotone function $h : \mathbb{N} \rightarrow \mathbb{R}$.

- For any induced subgraph H of Q^n with $|V(H)| \neq 2^{n-1}$, we have

$$\max\{\Delta(H), \Delta(Q^n - H)\} \geq h(n).$$

where Δ is the maximum degree of a graph.

- For any boolean function f , we have $s(f) \geq h(deg(f))$.

Showing (i) for $h(n) = n^c$ if and only if Sensitivity conjecture.

The Gostman-Linial correspondence was established via an intermediate statement:

- For any boolean function g of full degree n , $s(g) \geq h(n)$.

The direction we care about is $(i) \Rightarrow (iii) \Rightarrow (ii)$.

Proof of $(i) \Rightarrow (iii)$:

- Suppose there exists $g : \{0, 1\}^n \rightarrow \{-1, 1\}$, with $s(g) < h(n)$, $deg(g) = n$. Let $p(x) = (-1)^{x_1 + \dots + x_n}$.
- Consider the induced subgraph H with vertex set

$$V(H) = \{x : g(x) \cdot p(x) = 1\}.$$

- Obviously $s(g) = \max\{\Delta(H), \Delta(Q^n - H)\}$, and

$$(|V(H)| - |V(Q^n - H)|)/2^n = E[g(x)p(x)] = \hat{g}p(\phi) = \hat{g}([n]) \neq 0.$$

- The last inequality follows from $\deg(g) = n$.

Proof of (iii) \Rightarrow (ii):

Upper and lower bounds

Theorem (Chung, Furedi, Graham, Seymour 1988):

1. Q^n has a $(2^{n-1} + 1)$ -vertex induced subgraph of maximum degree $\lceil \sqrt{n} \rceil$. (quadratic separation)
2. Every $(2^{n-1} + 1)$ -vertex induced subgraph of Q^n has maximum degree at least $(1/2 - o(1)) \cdot \log_2 n$. (exponential upper bound)

The main theorem

Theorem (H. 2019+):

- Every $(2^{n-1} + 1)$ -vertex induced subgraph of Q^n contains a vertex of degree at least \sqrt{n} .

Corollary:

- For every boolean function f , $s(f) \geq \sqrt{\deg(f)}$

The **sensitivity conjecture** is true.

- $bs(f) \leq 2\deg(f)^2$ (Nisan, Szegedy 1992)
- $bs(f) \leq \deg(f)^2$ (Tal 2013)
- $bs(f) \leq \sqrt{2/3}\deg(f)^2 + 1$ (Wellens 2020)
- These result imply $bs(f) = O(s(f)^4)$.

Proof of the main theorem

Principal Submatrix: Given a $n \times n$ matrix A , a principal submatrix of A is obtained by deleting the same set of rows and columns from A .

Lemma 1 (Cauchy's Interlace Theorem): Let A be a symmetric $n \times n$ matrix, and B be a $m \times m$ principle submatrix of A , for some $m < n$. If the eigenvalues of A are $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$, and the eigenvalues of B are $\mu_1 \geq \mu_2 \geq \dots \geq \mu_m$, then for all $1 \leq i \leq m$,

$$\lambda_i \geq \mu_i \geq \lambda_{i+n-m}.$$

[You can find the proof here](#)

Lemma 2: We define a sequence of symmetric square matrices iteratively as follows,

$$A_1 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, A_n = \begin{bmatrix} A_{n-1} & I \\ I & -A_{n-1} \end{bmatrix}.$$

Then A_n is a $2^n \times 2^n$ matrix whose eigenvalues are \sqrt{n} of multiplicity 2^{n-1} , and $-\sqrt{n}$ of multiplicity 2^{n-1} .

Proof of Lemma 2:

- We prove by induction that $A_n^2 = nI$.
 - For $n = 1$, $A_1^2 = I$.
 - Suppose the statement holds for $n - 1$, that is $A_{n-1}^2 = (n - 1)I$, then

$$A_n^2 = \begin{bmatrix} A_{n-1}^2 + I & 0 \\ 0 & A_{n-1}^2 + I \end{bmatrix} = nI.$$

- Therefore, the eigenvalues of A_n are either \sqrt{n} or $-\sqrt{n}$.
 - Since $\text{trace}[A_n] = 0$, we know that A_n has exactly half of the eigenvalues being \sqrt{n} and the rest being $-\sqrt{n}$.
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Lemma 3: Suppose H is an m -vertex undirected graph, and A is a symmetric matrix whose entries are in $\{-1, 0, 1\}$ and whose rows and columns are indexed by $V(H)$, and whenever u and v are non-adjacent in H , $A_{u,v} = 0$. Then

$$\Delta(H) \geq \lambda_1 := \lambda_1(A).$$

Proof of Lemma 3:

- Suppose \vec{v} is the eigenvector corresponding to λ_1 , then $\lambda_1 \vec{v} = A\vec{v}$.
- WLOG, assume v_1 is the coordinate of \vec{v} that has the largest absolute value. Then

$$|\lambda_1 v_1| = |(A\vec{v})_1| = \left| \sum_{j=1}^m A_{1,j} v_j \right| = \left| \sum_{j \sim 1} A_{1,j} v_j \right| \leq \sum_{j \sim 1} |A_{1,j}| |v_1| \leq \Delta(H) |v_1|.$$

- Therefore $|\lambda_1| \leq \Delta(H)$.
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Proof of the main theorem:

- Let A_n be the sequence of matrices defined in lemma 2. When we changing every (-1) entry of A_n to 1, we get exactly the adjacency matrix of Q^n , and thus A_n and Q_n satisfy the conditions in lemma 3.
- A $(2^{n-1} + 1)$ -vertex induced subgraph H of Q^n and the principal submatrix A_H of A_n naturally induced by H also satisfy the conditions of lemma 3. So,

$$\Delta(H) \geq \lambda_1(A_H).$$

- From lemma 2, the eigenvalues of A_n are known to be

$$\sqrt{n}, \dots, \sqrt{n}, -\sqrt{n}, \dots, -\sqrt{n}.$$

- Note that A_H is a $(2^{n-1} + 1) \times (2^{n-1} + 1)$ submatrix of the $2^n \times 2^n$ matrix A_n . By Cauchy's Interlace Theorem,

$$\lambda_1(A_H) \geq \lambda_{1+2^{n-1}-1}(A_n) = \lambda_{2^{n-1}}(A_n) = \sqrt{n}.$$

- So, $\Delta(H) \geq \sqrt{n}$. complete our proof.