On the Sensitivity Conjecture

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Abstract

The sensitivity of a Boolean function $f : \{0,1\}^n \to \{0,1\}$ is the maximal number of neighbors a point in the Boolean hypercube has with different f-value. Roughly speaking, the block sensitivity allows to flip a set of bits (called a block) rather than just one bit, in order to change the value of f. The sensitivity conjecture, posed by Nisan and Szegedy (CC, 1994), states that the block sensitivity, $bs(f)$, is at most polynomial in the sensitivity, $s(f)$, for any Boolean function f. A positive answer to the conjecture will have many consequences, as the block sensitivity is polynomially related to many other complexity measures such as the certificate complexity, the decision tree complexity and the degree. The conjecture is far from being understood, as there is an exponential gap between the known upper and lower bounds relating $bs(f)$ and $s(f)$.

We continue a line of work started by Kenyon and Kutin (Inf. Comput., 2004), studying the ℓ-block sensitivity, $bs_\ell(f)$, where ℓ bounds the size of sensitive blocks. While for $bs_2(f)$ the picture is well understood with almost matching upper and lower bounds, for $bs_3(f)$ it is not. We show that any development in understanding $bs_3(f)$ in terms of $s(f)$ will have great implications on the original question. Namely, we show that either $bs(f)$ is at most sub-exponential in $s(f)$ (which improves the state of the art upper bounds) or that $bs_3(f) \geq s(f)^{3-\varepsilon}$ for some Boolean functions (which improves the state of the art separations).

We generalize the question of $bs(f)$ versus $s(f)$ to bounded functions $f : \{0,1\}^n \to [0,1]$ and show an analog result to that of Kenyon and Kutin: $bs_\ell(f) = O(s(f))^\ell$. Surprisingly, in this case, the bounds are close to being tight. In particular, we construct a bounded function $f : \{0,1\}^n \to [0,1]$ with $bs(f) \geq n/\log n$ and $s(f) = O(\log n)$, a clear counterexample to the sensitivity conjecture for bounded functions.

Finally, we give a new super-quadratic separation between sensitivity and decision tree complexity by constructing Boolean functions with $\mathrm{DT}(f) \geq s(f)^{2.115}$. Prior to this work, only quadratic separations, $\mathrm{DT}(f) = s(f)^2$, were known.

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1 Introduction

A long-standing open problem in complexity and combinatorics asks what is the relationship between two complexity measures of Boolean functions: the sensitivity and block-sensitivity. We first recall the definition of the two complexity measures.

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▶ **Definition 1.** Let $f : \{0,1\}^n \to \{0,1\}$ be a Boolean function and $x \in \{0,1\}^n$ be a point. The sensitivity of f at x is the number of neighbors y of x in the Hamming cube such that $f(y) \neq f(x)$, i.e., $s(f,x) \triangleq |\{i \in [n] : f(x) \neq f(x \oplus e_i)\}|$.[1] The (maximal) sensitivity of f is defined as $s(f) \triangleq \max_{x\in\{0,1\}^n} s(f,x)$.

▶ **Definition 2.** Let $f : \{0,1\}^n \to \{0,1\}$ be a Boolean function and $x \in \{0,1\}^n$ be a point. For a block $B \subseteq [n]$, denote by $\mathbb{1}_B \in \{0,1\}^n$ its characteristic vector, i.e., $(\mathbb{1}_B)_i = 1$ iff $i \in B$. We say that a block B is sensitive for f on x if $f(x) \neq f(x \oplus \mathbb{1}_B)$. The block-sensitivity of f at x $x \in \{0,1\}^n$ is the maximal number of disjoint sensitive blocks for f at x, i.e.,

$$bs(f,x) = \max\{r : \exists \text{ disjoint } B_1, B_2, \ldots, B_r \subseteq [n]\ , f(x) \neq f(x \oplus \mathbb{1}_{B_i})\}\ .$$

The (maximal) block-sensitivity of f is defined as $bs(f) \triangleq \max_{x\in\{0,1\}^n} bs(f,x)$.

For shorthand, we will denote $(x \oplus e_i)$ and $(x \oplus \mathbb{1}_B)$ by $(x + e_i)$ and $(x + B)$ respectively. By definition, the block-sensitivity is at least the sensitivity by considering only blocks of size 1. The sensitivity conjecture, posed by Nisan and Szegedy [14], asks if a relation in the other direction holds as well.

▶ **Conjecture 3** (The Sensitivity Conjecture). $\exists d\ \forall f :\ bs(f) \leq s(f)^d$.

A stronger variant of the conjecture states that d can be taken to be 2. Despite much work on the problem [13, 14, 15, 12, 8, 20, 4, 11, 6, 1, 2, 5, 3, 9, 17, 10] there is still an exponential gap between the best known separations and the best known relations connecting the two complexity measures.

Known Separations. An interesting example due to Rubinstein [15] shows a quadratic separation between the two measures: $bs(f) = \frac{1}{2} \cdot s(f)^2$. This example was improved by [20] and then by [4] to $bs(f) = \frac{2}{3} \cdot s(f)^2 \cdot (1 - o(1))$ which is current state of the art.

Known Relations. Simon [16] proved (implicitly) that $bs(f)$ is at most $4^{s(f)} \cdot s(f)$. The upper bound was improved by Kenyon and Kutin [12] who showed that $bs(f) \leq O(e^{s(f)} \cdot \sqrt{s(f)})$. Recently, Ambainis et al. [1] improved this bound to $bs(f) \leq 2^{s(f)-1} \cdot s(f)$. Even more recently, Ambainis et al. [3] improved this bound slightly to $bs(f) \leq 2^{s(f)-1} \cdot (s(f) - 1/3)$.

To sum up, while the best known upper bound on the block-sensitivity in terms of sensitivity is exponential, the best known lower bound is quadratic. Indeed, we seem far from understanding the right relation between the two complexity measures.

1.1 ℓ-block sensitivity

All mentioned examples that exhibit quadratic separations between the sensitivity and block sensitivity ([15, 20, 4]) have the property that the maximal block sensitivity is achieved on blocks of size at most 2. For this special case, Kenyon and Kutin [12] showed that the block sensitivity is at most $2 \cdot s(f)^2$. Hence, these examples are essentially tight for this subcase.

Kenyon and Kutin introduced the notion of ℓ-block sensitivity (denoted $bs_\ell(f)$): the maximal number of disjoint sensitive blocks where each block is of size at most ℓ. Note that without loss of generality we may consider only sensitive blocks that are minimal with respect to set-inclusion (since otherwise we could of picked smaller blocks that are still disjoint). A

[1] e_i is the vector whose i-th entry equals 1 and all other entries equal 0.

well-known fact (cf. [7, Lemma 3]) asserts that any minimal sensitive block for f is of size at most $s(f)$, thus $bs(f) = bs_{s(f)}(f)$. Kenyon and Kutin proved the following inequalities relating the ℓ-block sensitivity of different ℓ-s:

$$bs_\ell(f) \le \frac{4}{\ell} \cdot s(f) \cdot bs_{\ell-1}(f) \tag{1}$$

$$bs_\ell(f) \le \frac{e}{(\ell-1)!} \cdot s(f)^\ell \tag{2}$$

for all $2 \le \ell \le s(f)$. Plugging $\ell = s(f)$ gives the aforementioned bound $bs(f) \le O(e^{s(f)} \cdot \sqrt{s(f)})$.

1.2 Our Results

1. In the full version [19], we refine the argument of Kenyon and Kutin giving a better upper bound on the ℓ-block sensitivity in terms of $(\ell-1)$-block sensitivity. We show that

$$bs_\ell(f) \le \frac{e}{\ell} \cdot s(f) \cdot bs_{\ell-1}(f) \tag{3}$$

   improving the bound in Eq. (1). On the other hand, Kenyon and Kutin gave examples with $bs_\ell(f) \ge \frac{1}{\ell} \cdot s(f) \cdot bs_{\ell-1}(f)$. Hence, Eq. (3) (and in fact, also Eq. (1)) is tight up to a constant. Interestingly, our analysis uses (a very simple) ordinary differential equation.
2. In Section 2, we put focus on understanding $bs_3(f)$ in terms of the sensitivity. We show that an upper bound of the form $bs_3(f) \le s(f)^{3-\varepsilon}$ for some constant ε implies a sub-exponential upper bound for the sensitivity conjecture: $\forall f : bs(f) \le 2^{s(f)^{1-\delta}}$, for $\delta > 0$. On the other hand, the best known separation (i.e., the aforementioned example by [4]) gives examples with $bs_3(f) \ge bs_2(f) \ge \Omega(s(f)^2)$. Thus, improving either the upper or lower bound for $bs_3(f)$ in terms of $s(f)$ will imply a breakthrough in our understanding of the sensitivity conjecture.
3. In Section 3, we consider an extension of the sensitivity conjecture to bounded functions $f : \{0,1\}^n \to [0,1]$. We show that while Kenyon and Kutin's approach works in this model, it is almost tight, i.e., we give functions for which $bs_\ell(f) = \Omega((s(f)/\ell)^\ell)$. In particular, we give a function with sensitivity $O(\log n)$ and block sensitivity $\Omega(n/\log n)$ – a clear counterexample for the sensitivity conjecture in this model.
4. In Section 4, we find better-than-quadratic separations between the sensitivity and the decision tree complexity. We construct functions based on minterm cyclic functions (as coined by Chakraborty [8]), that were found using computer search. In particular, we give an infinite family of functions $\{f_n\}_{n\in I}$ with $\mathrm{DT}(f_n) = n$ and $s(f_n) = O(n^{0.48})$. In addition, we give an infinite family of functions $\{g_n\}_{n\in I}$ with $s(g_n) = O(\mathrm{DT}(g_n)^{0.473})$.

2 Understanding $bs_3(f)$ is Important

As the upper and lower bounds for $bs_2(f)$ are almost matching, it seems that the next challenge is understanding the asymptotic behavior of $bs_3(f)$. A more modest challenge is the following.

▶ **Open Problem 4.** *Improve either the upper or lower bound on $bs_3(f)$.*

Recall that the upper bound on $bs_3(f)$ is $O(s(f)^3)$ (see Eq. (2)) and the lower bound is $(2/3) \cdot s(f)^2 \cdot (1 - o(1))$. It is somewhat surprising that any slight improvement on either the lower or upper bound on bs_3 would be a significant step forward in our understanding of the general question. The following claim shows that a slightly better than quadratic gap on a single example implies a better than quadratic gap on an infinite family of examples.

▶ **Claim 5.** *If there exists a function such that $bs_3(f) > s(f)^2$ then there exists a family of functions $\{f_n\}_{n\in\mathbb{N}}$ with $bs(f_n) > s(f_n)^{2+\varepsilon}$ for some constant $\varepsilon > 0$ (dependant on f).*

This family is simply $f_1 = f$, $f_n = f \circ f_{n-1}$ where $\circ$ stands for Boolean function composition as in [18]. Next, we prove a theorem exhibiting the self-reducibility nature of the problem.

▶ **Theorem 6.** *Let $k, \ell, a \in \mathbb{N}$ such that $\ell > k$ and let $T : \mathbb{N} \to \mathbb{R}$ be a monotone function. If $\forall f :\ bs_\ell(f) \le T(bs_k(f))$, then $\forall f' :\ bs_{\ell a}(f') \le T(bs_{ka}(f'))$.*

Proof. Assume by contradiction that there exists a function f' such that $bs_{\ell a}(f') > T(bs_{ka}(f'))$. We will show that there exists a function f such that $bs_\ell(f) > T(bs_k(f))$. We shall assume WLOG that the maximal $bs_{\ell a}$ of f' is achieved on $\vec{0}$. Let $B_1, B_2, \dots, B_m$ be a family of disjoint sensitive blocks for f at $\vec{0}$, each B_i of size at most ℓa. Split every block B_i to ℓ sets $B_{i,1}, \dots, B_{i,\ell}$ of size at most a. The function f will have a variable $x_{i,j}$ corresponding to every set $B_{i,j}$ of size at most a. The value of $f(x_{1,1}, \dots, x_{m,\ell})$ is defined to be the value of f' where the variable in each $B_{i,j}$ equal $x_{i,j}$, and all other variables equal 0. $bs_\ell(f, \vec{0}) \ge bs_{\ell a}(f', \vec{0})$, since for any sensitive block $B_1, \dots, B_m$ for f', there exists a corresponding sensitive block $B'_1, \dots, B'_m$ for f of size ℓ, where $B'_i = \{x_{i,j} : j \in [\ell]\}$.

On the other hand, any set of disjoint sensitive blocks of size at most k for f corresponds to a disjoint set of sensitive blocks of size at most ka for f'. Thus $bs_k(f) \le bs_{ka}(f')$, giving

$$T(bs_k(f)) \le T(bs_{ka}(f')) < bs_{\ell a}(f') \le bs_\ell(f) ,$$

where we used the monotonicity of T in the first inequality. ◀

Using Theorem 6 we get that any upper bound of the form $bs_\ell(f) \le s(f)^{\ell-\varepsilon}$ implies a sub-exponential upper bound on $bs(f)$ in terms of $s(f)$.

▶ **Theorem 7.** *Let $k \in \mathbb{N}, \varepsilon > 0$ be constants. If for all Boolean functions $bs_k(f) \le s(f)^{k-\epsilon}$, then for the constant $\gamma = \frac{\log(k-\varepsilon)}{\log(k)} < 1$ it holds that $bs(f) \le 2^{O(s(f)^\gamma \cdot \log s(f))}$ for all f.*

For example, Theorem 7 shows that if $\forall f : bs_3(f) \le s(f)^2$, then $\forall f : bs(f) \le 2^{O(s^{0.631} \cdot \log(s))}$.

Proof. Using the hypothesis and Theorem 6 one can show by induction on t that

$$\forall f : bs_{k^t}(f) \le s(f)^{(k-\epsilon)^t} . \tag{4}$$

The base case $t = 1$ is simply the hypothesis. We assume the claim is true for $1, \dots, t-1$, and show the claim is true for t. Using Theorem 6 with $T(x) = x^{k-\epsilon}$ and $a = k^{t-1}$ we get $bs_{k^t}(f) \le T(bs_{k^{t-1}}(f)) = (bs_{k^{t-1}}(f))^{k-\epsilon}$. By induction $bs_{k^{t-1}}(f) \le s(f)^{(k-\epsilon)^{t-1}}$. Hence, we get $bs_{k^t}(f) \le s(f)^{(k-\epsilon)^t}$, which finishes the induction proof.

Fix f and let $s = s(f)$. Recall that $bs(f) = bs_s(f)$ since each minimal block that flips the value of f is of size at most s. Hence,

$$\begin{aligned} bs(f) &= bs_s(f) = bs_{k^{\lceil \log_k(s) \rceil}}(f) \\ &\le s^{(k-\epsilon)^{\lceil \log_k(s) \rceil}} \le s^{(k-\epsilon)^{\log_k(s)+1}} = 2^{\log(s) \cdot s^{\log(k-\epsilon)/\log(k)} \cdot (k-\epsilon)} = 2^{O(s^\gamma \cdot \log(s))} . \end{aligned}$$ ◀

3 The Sensitivity Conjecture for Bounded Functions

In this section, we generalize the definitions of sensitivity and block sensitivity to bounded functions $f : \{0,1\}^n \to [0,1]$, extending the definitions for Boolean functions. We generalize the result of Kenyon and Kutin to this setting (after removing some trivial obstucles). Given that, one may hope that the sensitivity conjecture holds also for bounded functions, i.e., that the block-sensitivity is at most polynomial in the sensitivity. However, we give a counterexample to this question, by constructing functions on n variables with sensitivity $O(\log n)$ and block sensitivity $n/\log(n)$. In fact, we show that the result of Kenyon and Kutin is essentially tight by giving examples for which $bs_\ell(f) = n/\ell$ and $s(f) = O(\ell \cdot n^{1/\ell})$ for any $\ell \leq \log n$.

We begin by generalizing the definitions of sensitivity and block-sensitivity. For $f : \{0,1\}^n \to [0,1]$ and $x \in \{0,1\}^n$, we denote the sensitivity of f at a point x by

$$s(f,x) = \sum_{i=1}^{n} |f(x) - f(x \oplus e_i)|. \tag{5}$$

Similarly we define the block sensitivity and ℓ-block sensitivity as

$$bs(f,x) = \max\left\{ \sum_i |f(x) - f(x+B_i)| \ : \ B_1, \ldots, B_k \subseteq [n] \text{ are disjoint} \right\}. \tag{6}$$

and

$$bs_\ell(f,x) = \max\left\{ \sum_i |f(x) - f(x+B_i)| \ : \ B_1, \ldots, B_k \subseteq [n] \text{ are disjoint and } \forall i. |B_i| \leq \ell \right\}.$$

Naturally we denote by $s(f) = \max_x s(f,x)$, by $bs(f) = \max_x bs(f,x)$ and by $bs_\ell(f) = \max_x bs_\ell(f,x)$. It is easy to see that for a Boolean function these definitions match the standard definitions of sensitivity, block sensitivity and ℓ-block sensitivity.

We wish to prove an analog of Kenyon-Kutin result, showing that $bs_\ell(f) \leq c_\ell \cdot s(f)^\ell$. However, stated as is the claim is false for a "silly" reason. Take any Boolean function f with a gap between the sensitivity and the ℓ-block sensitivity and take $g(x) = f(x)/s(f)$. Then, we get $s(g) = 1$ and $bs_\ell(g) = bs_\ell(f)/s(f)$. As there are examples with $bs_2(f) = n/2$ and $s(f) = \sqrt{n}$, we get that $bs_2(g) = \sqrt{n}/2$ while $s(g) = 1$, where n grows to infinity. This seems to rule out any relation between the sensitivity and block sensitivity (and even 2-block sensitivity) in the case of bounded functions. To overcome this triviality, we insist that the block sensitivity is close to n, or alternatively that changing each block dramatically changes the value of the function. Surprisingly, under this requirement we are able to retrieve known relations between sensitivity and block sensitivity that were established in the Boolean setting by Kenyon and Kutin [12].

▶ **Theorem 8.** *Let $c > 0$ and $f : \{0,1\}^n \to [0,1]$. Assume that there exists a point $x_0 \in \{0,1\}^n$ and disjoint blocks $B_1, \ldots, B_k$ of size at most ℓ such that $|f(x_0) - f(x_0 + B_i)| \geq c$ for all $i \in k$. Furthermore, assume that $2 \leq \ell \leq \log(k)$. Then, $s(f) \geq \Omega(k^{1/\ell} \cdot c)$.*

We get the following corollary, whose proof is deferred to Appendix A.

▶ **Corollary 9.** *Let $f : \{0,1\}^n \to [0,1]$ with $bs(f) \geq n/\ell$. Then, $s(f) \geq \Omega(n^{1/2\ell}/\ell)$.*

Unlike in the Boolean case, we are able to show that Theorem 8 is essentially tight! That is, for any ℓ and n we have a construction with $bs_\ell(f) \geq n/\ell$ and $s(f) = O(\ell \cdot n^{1/\ell})$. In particular, picking $\ell = \log(n)$ gives an exponential separation between block sensitivity (which is at least $n/\log n$) and sensitivity (which is $O(\log n)$).

▶ **Theorem 10.** *Let $\ell, n \in \mathbb{N}$ with $2 \leq \ell \leq n$. Then, there exists a function $h : \{0,1\}^n \to [0,1]$ with $bs_\ell(h) \geq \lfloor n/\ell \rfloor$ and $s(h) \leq 3 \cdot \ell \cdot n^{1/\ell}$.*

3.1 Proof of Kenyon-Kutin Result for Bounded Functions

Proof Overview. We start by giving a new proof for Kenyon-Kutin result, based on random walks on the hypercube. We assume by contradiction that $f(x_0) = 0$ and $f(x_0 + B_i) = 1$ for all $i \in [k]$ and that the sensitivity is $o(k^{1/\ell})$. Taking a random walk of length $r = n/k^{1/\ell}$ starting from x_0 will end up in point y where with high probability $f(y) = f(x_0)$. This is true since in each step with probability at least $1 - s(f)/n$ we are maintaining the value of f, hence by union bound with probability at least $1 - r \cdot s(f)/n$ we maintain the value of f in the entire walk. On the contrast, choosing a random $i \in [k]$ and starting a random walk of length $r - |B_i|$ starting from $(x_0 + B_i)$ will lead to a point y' where with high probability $f(y') = f(x_0 + B_i) = 1$. However, as we show in the proof below, the distributions of y and y' are similar (close in statistical distance). This leads to a contradiction as $f(y)$ tends to be equal to 0 and $f(y')$ tends to be equal to 1.

A simple observation, which allows us to generalize the argument above to bounded functions, is that for a given point $x \in \{0,1\}^n$ and a random neighbor in the hypercube, $y \sim x$, the expected value of $f(y)$ is close to $f(x)$. This follows from Eq. (5). Thus, the only difference in the argument for bounded functions will be that $\mathbf{E}[f(y)]$ is close to 0 and $\mathbf{E}[f(y')]$ is close to 1, leading to a contradiction as well.

Proof of Theorem 8. First, we make a few assumptions that are without loss of generality, in order to make the argument later clearer. We assume $x_0 = 0^n$ and $f(x_0) = 0$. We assume $n = k \cdot \ell$ and that the blocks are given by $B_i = \{(i-1)\ell + 1, \ldots, i\ell\}$ for $i \in [k]$. We assume that $c = 1$, since for $c < 1$ one can take $f'(x) = \min\{f(x)/c, 1\}$, and note that f' is a bounded function with $f'(x_0 + B_i) = 1$. Proving the theorem for f' gives $s(f) \geq s(f') \cdot c \geq \Omega(c \cdot k^{1/\ell})$.

Let $r = \lfloor \frac{n}{(2k)^{1/\ell}} \rfloor$, by the assumption $2 \leq \ell \leq \log(k)$ we have $\sqrt{n} \leq r \leq n/2$. Assume by contradiction that $s(f) \leq \varepsilon \cdot k^{1/\ell}$ for some sufficiently small constant $\varepsilon > 0$ to be determined later. Consider the following two random processes.

Algorithm 1 Process A

1: $X_0 \leftarrow 0^n$
2: **for** $t = 1, \ldots, r$ **do**
3: Select a random $i \in [n]$ among the coordinates for which X_{t-1} is 0 and let $X_t \leftarrow X_{t-1} + e_i$.
4: **end for**

Algorithm 2 Process B

1: Select uniformly $i \in [k]$ and let $Y_0 \leftarrow B_i$
2: **for** $t = 1, \ldots, r - \ell$ **do**
3: Select a random $i \in [n]$ among the coordinates for which Y_{t-1} is 0 and let $Y_t \leftarrow Y_{t-1} + e_i$.
4: **end for**

For each $t \in \{0, \ldots, r-1\}$, we claim that

$$\mathbf{E}[f(X_{t+1}) - f(X_t)] = \mathbf{E}\left[\frac{1}{n-t} \cdot \sum_{i:(X_t)_i = 0} f(X_t + e_i) - f(X_t)\right]$$
$$\leq \frac{1}{n-t} \cdot \mathbf{E}[s(f(X_t))] \leq \frac{s(f)}{n-t}\,.$$

By telescoping this implies that

$$\mathbf{E}[f(X_r)] = \mathbf{E}[f(X_0)] + \sum_{t=0}^{r-1} \mathbf{E}[f(X_{t+1}) - f(X_t)] \leq 0 + \frac{r \cdot s(f)}{n-r} \leq O(\varepsilon) .$$

In a symmetric fashion, for each $t \in \{1, \ldots, r-\ell\}$ we have $\mathbf{E}[f(Y_{t+1}) - f(Y_t)] \geq -\frac{s(f)}{n-t-\ell}$. Again, telescoping implies that

$$\mathbf{E}[f(Y_{r-\ell})] \geq \mathbf{E}[f(Y_0)] - \frac{(r-\ell) \cdot s(f)}{n-r} \geq 1 - \frac{r \cdot s(f)}{n-r} \geq 1 - O(\varepsilon) .$$

So it seems that the distribution of X_r and $Y_{r-\ell}$ are very different from one another. However, we shall show that conditioned on a probable event, X_r and $Y_{r-\ell}$ are identically distributed. To define the event, consider the sets

$$U_i = \{\mathbb{1}_A \mid A \subseteq [n], |A| = r, B_i \subseteq A, \forall j \neq i : B_j \nsubseteq A\}$$

for $i \in [k]$ and their union

$$U = \bigcup_{i=1}^{k} U_i = \{\mathbb{1}_A \mid A \subseteq [n], |A| = r, \exists! i \in [k] : B_i \subseteq A\} .$$

Let E_X be the event that $X_r \in U$, and E_Y be the event that $Y_{r-\ell} \in U$. We show that

▶ **Claim 11.** *The following hold:*

1. $X_r|E_X$ *is identically distributed as* $Y_{r-\ell}|E_Y$.
2. $\mathbf{Pr}[E_Y] = \Omega(1)$
3. $\mathbf{Pr}[E_X] = \Omega(1)$

We defer the proof of Claim 11 for later. We derive a contradiction from all of the above by showing that $\mathbf{E}[f(X_r)|E_X] < \mathbf{E}[f(Y_{r-\ell})|E_Y]$ (this is indeed a contradiction because by the claim $X_r|E_X$ and $Y_{r-\ell}|E_Y$ should be identically distributed and hence the expected values of $f(\cdot)$ on each of them should be the same). To show this, we note that

$$\begin{aligned}\mathbf{E}[f(X_r)|E_X] &= \mathbf{E}[f(X_r) \cdot \mathbb{1}_{E_X}]/\,\mathbf{Pr}[E_X] \\ &\leq \mathbf{E}[f(X_r)]/\,\mathbf{Pr}[E_X] = O(\mathbf{E}[f(X_r)]) = O(\varepsilon) .\end{aligned}$$

On the other hand

$$\begin{aligned}\mathbf{E}[f(Y_{r-\ell})|E_Y] &= 1 - \mathbf{E}[1 - f(Y_{r-\ell})|E_Y] \\ &\geq 1 - \mathbf{E}[1 - f(Y_{r-\ell})]/\,\mathbf{Pr}[E_Y] = 1 - O(\mathbf{E}[1 - f(Y_{r-\ell})]) = 1 - O(\varepsilon) .\end{aligned}$$

Choosing ε to be a small enough constant implies that $\mathbf{E}[f(X_r)|E_X] < \mathbf{E}[f(Y_{r-\ell})|E_Y]$, which completes the proof. ◀

Proof of Claim 11. We shall use in the proof of Items 2 and 3 the fact that $1/3 \leq \frac{r^\ell k}{n^\ell} \leq 1/2$ which follows from the choice of $r = \lfloor \frac{n}{(2k)^{1/\ell}} \rfloor$ (for large enough n and k).

1. First note that X_r is distributed uniformly over the set of vectors in $\{0,1\}^n$ with hamming weight r. In particular, conditioning that X_r is in a set U of such vectors, makes it uniform over U. We are left to show that $Y_{r-\ell}|E_Y$ is distributed uniformly over U. Given that $Y_0 = B_i$, we have that $Y_{r-\ell}$ is the OR of $\mathbb{1}_{B_i}$ with a random vector of weight $r - \ell$ on $[n] \setminus B_i$. Conditioned on E_Y the only way to reach U_i is if $Y_0 = B_i$, hence, by the above, all points in U_i are attained with the same probability. Using symmetry, all points in $U = \bigcup_i U_i$ are attained with the same probability.

2. Let B_i be the block selected in the first step of Process B. We analyze the probability that all indices in B_j for some $j \neq i$ are chosen in the $r - \ell$ iterations of Process B.

$$\begin{aligned}\mathbf{Pr}[B_j \text{ is selected}] &= \frac{(\#\text{ of sequences where } B_j \text{ is selected})}{(\#\text{ of sequences})} \\ &= \frac{(r-\ell)^{\underline{\ell}} \cdot (n-2\ell)^{\underline{r-2\ell}}}{(n-\ell)^{\underline{r-\ell}}} = \frac{(r-\ell)!(n-2\ell)!(n-r)!}{(r-2\ell)!(n-r)!(n-\ell)!} \\ &= \frac{(r-\ell)!(n-2\ell)!}{(r-2\ell)!(n-\ell)!} = \frac{(r-\ell)\cdots(r-2\ell+1)}{(n-\ell)\cdots(n-2\ell+1)} \leq \left(\frac{r}{n}\right)^{\ell}\end{aligned}$$

(recall that $n^{\underline{k}} \triangleq \frac{n!}{(n-k)!}$). Hence, $\mathbf{Pr}[\exists j \neq i : B_j \text{ is selected}] \leq k \cdot (r/n)^{\ell} \leq 1/2$ and we have $\mathbf{Pr}[E_Y] \geq 1/2$.

3. Let $\pi_1, \ldots, \pi_r \in [n]$ be the sequence of choices made by Process A. For $i \in [k]$, let $E_{X,i}$ be the event that $X_r \in U_i$. By the uniqueness of the block contained in X_r the events $E_{X,i}$ are disjoint, hence $\mathbf{Pr}[E_X] = \sum_{i=1}^{k} \mathbf{Pr}[E_{X,i}]$. By symmetry, $\mathbf{Pr}[E_X] = k \cdot \mathbf{Pr}[E_{X,1}]$. The event $E_{X,1}$ is simply the event that there exists a set $S \subseteq [r]$ of size ℓ such that $\{\pi_j\}_{j \in S} = B_1$ and the sequence $\{\pi_j : j \in [r] \setminus S\}$ is a sequence of choices for which E_Y holds, when starting Process B from $Y_0 = B_1$. This shows that $\mathbf{Pr}[E_{X,1}] = \mathbf{Pr}[E_Y | Y_0 = B_1] \cdot \mathbf{Pr}[B_1 \subseteq \{\pi_1, \ldots, \pi_r\}]$. By Symmetry, $\mathbf{Pr}[E_Y | Y_0 = B_i] = \mathbf{Pr}[E_Y] = \Omega(1)$ from the previous item. In addition,

$$\begin{aligned}\mathbf{Pr}[B_1 \subseteq \{\pi_1, \ldots, \pi_r\}] &= \frac{r^{\underline{\ell}} \cdot (n-\ell)^{\underline{r-\ell}}}{n^{\underline{r}}} = \frac{r!(n-\ell)!(n-r)!}{(r-\ell)!(n-r)!n!} \\ &= \frac{r!(n-\ell)!}{(r-\ell)!n!} = \frac{r \cdots (r-\ell+1)}{n \cdots (n-\ell+1)} \geq \left(\frac{r-\ell}{n}\right)^{\ell} \\ &= \left(\frac{r}{n}\right)^{\ell} \cdot (1-\ell/r)^{\ell} = \left(\frac{r}{n}\right)^{\ell} \cdot (1-o(1))\end{aligned}$$

where $(1-\ell/r)^{\ell} = 1 - o(1)$ follows from $\ell \leq \log(k)$ and $r \geq \sqrt{n} \geq \sqrt{k}$. Thus,

$$\begin{aligned}\mathbf{Pr}[E_X] = k \cdot \mathbf{Pr}[E_{X,1}] &= k \cdot \mathbf{Pr}[B_1 \text{ is selected}] \cdot \mathbf{Pr}[E_Y | Y_0 = B_1] \\ &\geq k \cdot \left(\frac{r}{n}\right)^{\ell} \cdot (1-o(1)) \cdot \frac{1}{2} \geq \frac{1}{3} \cdot (1-o(1) \cdot \frac{1}{2} = \Omega(1)\,.\end{aligned}$$ ◀

3.2 Separating Sensitivity and Block Sensitivity of Bounded Functions

The Lattice Variant of The Sensitivity Conjecture

The proof of Theorem 10 is more natural in the lattice-variant of the sensitivity conjecture as suggested by Aaronson (see [6]). In this variant, instead of talking about functions over $\{0,1\}^n$ we are considering functions over $\{0,1,\ldots,\ell\}^k$ for $\ell, k \in \mathbb{N}$. Given a function $g : \{0,1,\ldots,\ell\}^k \to \mathbb{R}$ one can define a Boolean function $f : \{0,1\}^{\ell \cdot k} \to \mathbb{R}$ by the following equation:

$$f(x_{1,1}, \ldots, x_{k,\ell}) = g\left(\sum_{i=1}^{\ell} x_{1,i}, \ldots, \sum_{i=1}^{\ell} x_{k,i}\right). \tag{7}$$

For a point $y \in \{0,1,\ldots,\ell\}^k$ and function $g : \{0,\ldots,\ell\}^k \to \mathbb{R}$ one can define the sensitivity of g at y as

$$s(g,y) = \sum_{y' \sim y} |g(y') - g(y)|$$

where $y' \sim y$ if $y' \in \{0,\dots,\ell\}^k$ is a neighbor of y in the grid $\{0,\dots,\ell\}^k$, i.e., if y and y' agree on all coordinates except for one coordinate, say $j \in [k]$, on which $|y_j - y'_j| = 1$. The following claim relates the sensitivity of f to that of g.

▶ **Claim 12.** *Let $g : \{0,\dots,\ell\}^k \to \mathbb{R}$ and let f be the function defined by Eq. (7). Then $s(f) \le \ell \cdot s(g)$.*

Proof. Let $x = (x_{1,1},\dots,x_{k,\ell}) \in \{0,1\}^{kl}$ and and let $x' \in \{0,1\}^{kl}$ be a neighbor of x, obtained by flipping the (i,j)-th coordinate. Let $y = (\sum_{i=1}^{\ell} x_{1,i},\dots,\sum_{i=1}^{\ell} x_{k,i})$ and similarly let $y' = (\sum_{i=1}^{\ell} x'_{1,i},\dots,\sum_{i=1}^{\ell} x'_{k,i})$. Then y and y' differ only on the i-th coordinate, and on this coordinate they differ by a ± 1. If $y'_i = y_i + 1$, then the number of neighbors $x' \sim x$ that are mapped to y' by $y' = (\sum_i x'_{1,i},\dots,\sum_i x'_{k,i})$ equals the number of zeros in the i-th block of x, i.e., it equals $\ell - y_i$. Similarly, in the case $y'_i = y_i - 1$ the number of $x' \sim x$ that are mapped to y' equals y_i. In both cases, there are between 1 to ℓ points $x' \sim x$ that are mapped to each neighbor $y' \sim y$. Thus,

$$\sum_{x'\sim x} |f(x') - f(x)| = \sum_{x'\sim x} |g(y') - g(y)| \le \ell \cdot \sum_{y'\sim y} |g(y') - g(y)| \,. \qquad ◀$$

Construction of a Separation. Let k,ℓ be integers. We construct $f : \{0,1,\dots,\ell\}^k \to [0,1]$ such that $f(0) = 0$, $f(e_i \cdot \ell) = 1$ for all $i \in [k]$ and $s(f) \le O(k^{1/\ell})$.

Define a weight function $w : \{0,1,\dots,\ell\} \to [0,1]$ as follows: $w(a) = k^{a/\ell}/k$ for $a \in \{1,\dots,\ell\}$ and $w(0) = 0$. Take $g : \{0,\dots,\ell\}^k \to \mathbb{R}^+$ to be the function $g(x_1,\dots,x_n) = \sum_{i=1}^{k} w(x_i)$ and take $f : \{0,\dots,\ell\}^k \to [0,1]$ to be $f(x) = \min\{1, g(x)\}$. Then $f(0^k) = 0$ and $f(\ell \cdot e_i) = 1$ for all $i \in [k]$.

▶ **Theorem 13.** $s(f) \le 3 \cdot k^{1/\ell}$.

Proof. Let $x \in \{0,1,\dots,\ell\}^k$ be a point in the lattice. We distinguish between two cases $g(x) \ge 2$ and $g(x) < 2$. In the first case, all neighbors $x' \sim x$ have $g(x') \ge 1$ since the sums $\sum_i w(x_i)$ and $\sum_i w(x'_i)$ differ by at most 1. Since both $g(x)$ and $g(x')$ are at least 1 we get that $f(x) = f(x') = 1$ and the sensitivity of f at x is 0.

In the latter case, $g(x) < 2$, we bound the sensitivity as well. For ease of notation we extend w to be defined over $\{-1,\dots,\ell+1\}$ by taking $w(\ell+1) = w(\ell)$ and $w(-1) = w(0)$. We extend also g to $\{-1,0,\dots,\ell+1\} \to \mathbb{R}^+$ by taking $g(x_1,\dots,x_n) = \sum_i w(x_i)$. We have

$$\begin{aligned}
s(f,x) \le s(g,x) &= \sum_{i=1}^{k} |g(x+e_i) - g(x)| + |g(x) - g(x-e_i)| \\
&= \sum_{i=1}^{k} |w(x_i+1) - w(x_i)| + |w(x_i) - w(x_i-1)| \\
&= \sum_{i=1}^{k} w(x_i+1) - w(x_i-1) && (w \text{ is monotone}) \\
&\le \sum_{i=1}^{k} w(x_i+1) && (w \text{ is non-negative}) \\
&\le \sum_{i:x_i=0} w(1) + \sum_{i:x_i>0} w(x_i) \cdot k^{1/\ell} \\
&\le k \cdot \frac{k^{1/\ell}}{k} + \sum_i w(x_i) \cdot k^{1/\ell} \\
&= k^{1/\ell} + g(x) \cdot k^{1/\ell} \le 3k^{1/\ell}. && ◀
\end{aligned}$$

We show that Theorem 10 is a corollary of Theorem 13.

Proof of Theorem 10. Let $k = n/\ell$. Let $f : \{0, 1, \dots, \ell\}^k \to [0, 1]$ be the function in Theorem 13. Take $h(x_{1,1}, \dots, x_{k,\ell}) = f\left(\sum_{i=1}^{\ell} x_{1,i}, \dots, \sum_{i=1}^{\ell} x_{n,i}\right)$. For $x = 0^n$, there are k disjoint blocks $B_1, \dots, B_k$ of size ℓ each such that $h(x + B_i) = 1$. Hence, $bs_\ell(h) \geq k = n/\ell$. By Claim 12, the sensitivity of h is at most $s(f) \cdot \ell \leq 3 \cdot k^{1/\ell} \cdot \ell \leq 3 \cdot n^{1/\ell} \cdot \ell$ which completes the proof. ◀

4 New Separations between Decision Tree Complexity and Sensitivity

We report a new separation between the decision tree complexity and the sensitivity of Boolean functions. We construct an infinite family of Boolean functions with

$$\mathrm{DT}(f_n) \geq s(f_n)^{1+\log_{14}(19)} \geq s(f_n)^{2.115}.$$

Our functions are transitive functions, and are inspired by the work of Chakraborty [8].

Our construction is based on finding a "gadget" Boolean function f, defined over a constant number of variables, such that $s^0(f) = 1$, $s^1(f) = k$ and $\mathrm{DT}(f) = \ell$ for $\ell > k$ (recall that $s^0(f) = \max_{x:f(x)=0} s(f, x)$ and similarly $s^1(f) = \max_{x:f(x)=1} s(f, x)$). Given the gadget f, we construct an infinite family of functions with super-quadratic gap between the sensitivity and the decision tree complexity using compositions (which is a well-used trick in query complexity separations, cf. [18]).

▶ **Lemma 14.** *Let $f : \{0, 1\}^c \to \{0, 1\}$ such that $s^0(f) = 1$, $s^1(f) = k$ and $\mathrm{DT}(f) = \ell > k$. Then, there exists an infinite family of functions $\{g_i\}_{i\in\mathbb{N}}$ such that $s(g_i) = k^i$ and $\mathrm{DT}(g_i) = (k\ell)^i = s(g_i)^{1+\log(k)/\log(\ell)}$.*

Proof. Take $g = \mathrm{OR}_k \circ f$. It is easy to verify that $s(g) = k$, and that $\mathrm{DT}(g) = \mathrm{DT}(\mathrm{OR}_k) \cdot \mathrm{DT}(f) = k\ell$ (for the latter, one can use [18, Lemma 3.1]). For $i \in \mathbb{N}$, we take $g_i = g^i$. It is well-known (cf. [18, Lemma 3.1]) that $s(g^i) \leq s(g)^i$ and that $\mathrm{DT}(g^i) = \mathrm{DT}(g)^i$, which completes the proof. ◀

4.1 Finding a Good Gadget

The gadget f will be a minterm-cyclic function. Roughly speaking, a function $f : \{0, 1\}^n \to \{0, 1\}$ is minterm-cyclic if there exists pattern $p \in \{0, 1, *\}^n$ such that the function f simply checks if x matches one of the cyclic shifts of p. The formal definition follows

▶ **Definition 15.** A pattern $p \in \{0, 1, *\}^n$ is a partial assignment to the variables $x_1, \dots, x_n$. We say that a point $x \in \{0, 1\}^n$ matches the pattern p, denoted by $p \subseteq x$, if for all $i \in [n]$ such that $p_i \in \{0, 1\}$ we have $p_i = x_i$. Given a pattern p, let $CS(p) = \{p^1, \dots, p^n\}$ be the set of cyclic shifts of p, where the i-th cyclic shift of p is given by $p^i = (p_i, p_{i+1}, \dots, p_n, p_1, \dots, p_{i-1})$. For a pattern $p \in \{0, 1, *\}^n$ we denote by $f_p : \{0, 1\}^n \to \{0, 1\}$ the function defined by

$$f_p(x) = 1 \quad \Leftrightarrow \quad \exists p^i \in CS(p) : p^i \subseteq x$$

and call f_p the minterm cyclic function defined by p.

For example, the pattern $p =$ `0011**` defines a function f_p that checks if there's a sequence of two zeros followed by two ones in x, when x is viewed as a cyclic string. We say that two patterns $p, q \in \{0, 1, *\}^n$ disagree on a coordinate i if both p_i and q_i are in $\{0, 1\}$ and $p_i \neq q_i$.

▶ **Claim 16.** *Let $p \in \{0,1,*\}^n$ be a pattern defining $f_p : \{0,1\}^n \to \{0,1\}$. Assume that any two different cyclic-shifts of p disagree on at least 3 coordinates. Then, $s^0(f_p) = 1$.*

Proof. Let $x \in \{0,1\}^n$ with $f_p(x) = 0$ and assume by contradiction that $s(f_p, x) \geq 2$. In such a case, there are two indices i and j such that $f_p(x + e_i) = 1$ and $f_p(x + e_j) = 1$. Let q and q' be the patterns among $CS(p)$ that $x+e_i$ and $x+e_j$ satisfy respectively. If $q = q'$, then since both $x + e_i$ and $x + e_j$ satisfy q and they differ on coordinates i and j, it must be the case that $q_i = q_j = *$. However, this implies that x satisfy q as well, which is a contradiction. If $q \neq q'$, then we get that q and q' may disagree only on coordinates i and j, which is also a contradiction. ◀

The following fact is easy to verify.

▶ **Fact 17.** *Let $p \in \{0,1,*\}^n$ be a pattern defining $f_p : \{0,1\}^n \to \{0,1\}$. Then, $s^0(f_p) \leq c^0(f_p) \leq |\{i \in [n] : p_i \in \{0,1\}\}|$.*

Next, we demonstrate a simple example with better-than-quadratic separation between $\mathrm{DT}(f)$ and $s(f)$. Take the pattern $p = *001011$. Denote by $p^1, \ldots, p^7$ all the cyclic shifts of p, where in p^i the i-th coordinate equals $*$. It is easy to verify that any p^i and p^j for $i \neq j$ disagree on at least 3 coordinates. Hence, $s^0(f_p) = 1$ and $s^1(f_p) \leq 6$. We wish to show that any decision tree T for f_p is of depth 7. Let x_i be the first coordinate read by a decision tree T for f_p. Our adversary will answer 0, and will continue to answer as if x matches p^i. Assume the decision tree made a decision before reading the entire input. The decision tree must decide 1 since the adversary answered according to x which satisfies p^i. However, if the decision tree hasn't read the entire input, there is still an unread coordinate j, where $j \neq i$. Let $x' = x + e_j$. Then, the decision tree answers 1 on x' as well. However x' does not match pattern p^i as $(p^i)_j \in \{0,1\}$ and it must be the case that $x_j = (p^i)_j \neq x'_j$.

We also need to rule out that x' matches some other pattern. Indeed, if x' matches some other pattern p^k it means that p^k and p^i disagree only on at most one coordinate, which as discussed above cannot happen.

Using Lemma 14 the function f_p can be turned into an infinite family of functions g_i with $\mathrm{DT}(g_i) = (6 \cdot 7)^i$ and $s(g_i) \leq 6^i$. This gives a super-quadratic separation since

$$\mathrm{DT}(g_i) \geq s(g_i)^{1+\log(7)/\log(6)} \geq s(g_i)^{2.086}.$$

In a similar fashion, one can show that for the pattern $p =$ `**0*10000*101` after reading any two input bits from the input there exists a cyclic shift p^i of the pattern from which no $\{0,1\}$ coordinate has been read yet. However, to verify that the input x matches p^i we must read all $\{0,1\}$ positions in p^i, which gives $\mathrm{DT}(f_p) \geq 9 + 2$ where 9 is the number of $\{0,1\}$-s in the pattern p.

The decision tree complexity analysis for the other patterns written below is more involved. We computed it using a computer program written to calculate the decision tree complexity in this special case. In the list below, we report several patterns yielding super-quadaratic separations. For each pattern p we report its length n, the decision tree complexity of f_p, the maximal sensitivity of f_p (which equals the number of $\{0,1\}$-s in p) and the resulting exponent one get by using Lemma 14 (i.e., $1 + \frac{\log \mathrm{DT}(f_p)}{\log s(f_p)}$).

```
p = *001011,                          n = 7,  DT = 7,  s = 6,  exp = 2.086
p = **0*10000*101,                    n = 13, DT = 11, s = 9,  exp = 2.091
p = ******01*1*01100000,              n = 19, DT = 14, s = 11, exp = 2.100
p = ******00*0*0010**1*00*011,        n = 25, DT = 17, s = 13, exp = 2.104
p = ******1**0**0**1**0**00*0*10*1011, n = 33, DT = 19, s = 14, exp = 2.115
```

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A Proof of Corollary 9

Proof. Let $x \in \{0,1\}^n$ and $B_1, \dots, B_m$ be the blocks that achieve $bs(f)$. Assume without loss of generality that $B_1, \dots, B_{m'}$ are of size at most 2ℓ and that $B_{m'+1}, \dots, B_m$ are of size larger than 2ℓ. Then, by the disjointness of $B_{m'+1}, \dots, B_m$ we have that $m - m' \le \frac{n}{2\ell}$. Thus,

$$\begin{aligned} bs_\ell(f,x) &\ge \sum_{i=1}^{m'} |f(x) - f(x+B_i)| = \sum_{i=1}^{m} |f(x) - f(x+B_i)| - \sum_{i=m'+1}^{m} |f(x) - f(x+B_i)| \\ &\ge bs(f,x) - (m - m') \ge bs(f,x) - \frac{n}{2\ell} \ge \frac{n}{2\ell}\,. \end{aligned}$$

Assume without loss of generality that $B_1, \dots, B_{m''}$ are blocks such that $|f(x) - f(x+B_i)| \ge \frac{1}{4\ell}$ and that $B_{m''+1}, \dots, B_{m'}$ are not. Then, $\sum_{i=m''+1}^{m'} |f(x) - f(x+B_i)| \le \frac{m''-m'}{4\ell} \le \frac{n}{4\ell}$. This implies that $\sum_{i=1}^{m''} |f(x) - f(x+B_i)| \ge \frac{n}{4\ell}$, and in particular that $m'' \ge \frac{n}{4\ell}$. Thus, there are $m'' \ge n/4\ell$ disjoint blocks of size at most 2ℓ which change the value of f by at least $\frac{1}{4\ell}$. Theorem 8 gives that $s(f) \ge \Omega((m'')^{1/2\ell}/\ell) \ge \Omega(n^{1/2\ell}/\ell)$. ◀