

CS 58500 – Theoretical Computer Science Toolkit

Lecture 18 (04/14)

Boolean Function Analysis (III)

https://ruizhezhang.com/course_spring_2026.html



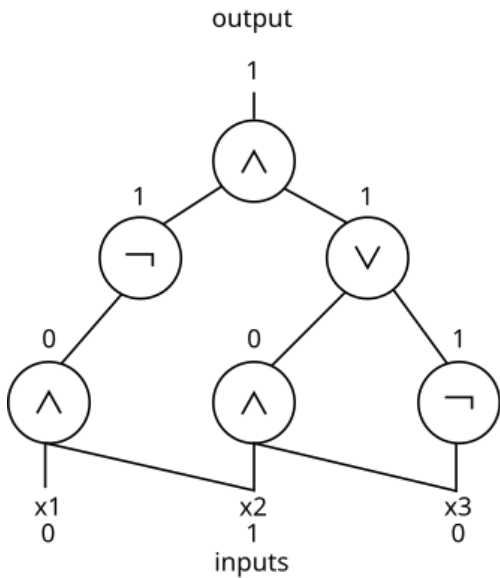
Today's Lecture

- Complexity of Boolean Functions
- Query Complexity vs. xyz
- Randomized Query Complexity
- The Sensitivity Theorem

Complexity of Boolean Functions

Let $f: \{0,1\}^n \rightarrow \mathbb{R}$ be a Boolean function. How do we measure the **complexity** of f ?

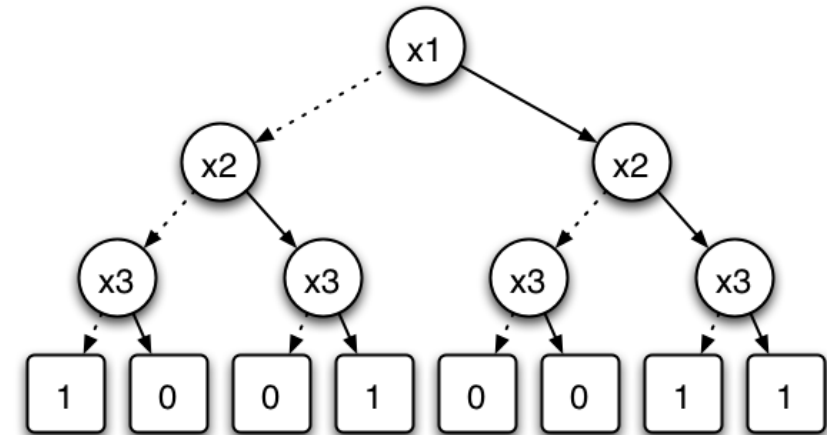
- For simplicity, we assume $f: \{0,1\}^n \rightarrow \{0,1\}$, i.e., a **decision problem** with n -bit input and “YES/NO” output. (You are encouraged to convert the results in this lecture to functions like $f: \{0,1\}^n \rightarrow \{-1,1\}$)



Circuit complexity



Kolmogorov complexity



Query complexity

Complexity of Boolean Functions

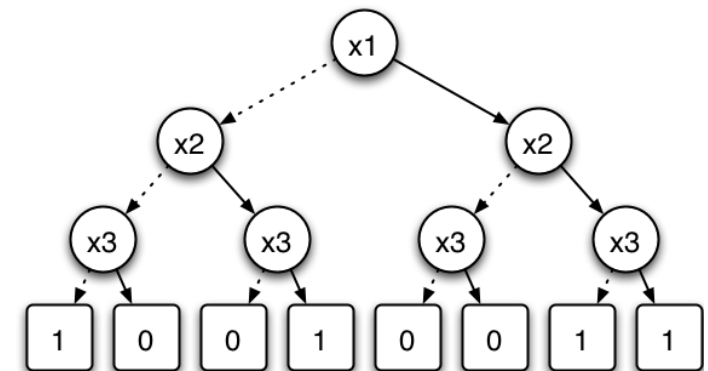
Theorem (Shannon '42). With probability at least $1 - o(1)$, a random function $f: \{0,1\}^n \rightarrow \{0,1\}$ requires a circuit (with bounded fan-in) of size $\Omega(2^n/n)$

Theorem (Lupanov '52). Any function $f: \{0,1\}^n \rightarrow \{0,1\}$ can be computed by a circuit using $(1 + o(1)) 2^n/n$ gates of fan-in ≤ 2

Complexity of Boolean Functions

Query complexity is also called the **decision tree complexity**

- A decision tree over variables x_1, \dots, x_n is a binary tree where each internal node has two children, left and right
- Each internal node is labelled with a variable, and each leaf is labelled with a value of 0 or 1
- To evaluate a decision tree at a point $x \in \{0,1\}^n$, we start from the root, and at each internal node with label x_i we query the value of x_i , go left if $x_i = 0$ and right if $x_i = 1$ until we reach a leaf. The leaf's value is the decision tree's output on x
- For a Boolean function $f: \{0,1\}^n \rightarrow \{0,1\}$, we let $D(f)$ denote the smallest **depth** of a decision tree computing f
- Trivially, $0 \leq D(f) \leq n$



Complexity of Boolean Functions

The goal of this lecture is to use **analytical measures** of a Boolean function to characterize its query complexity

- Degree $\deg(f)$
- Certificate complexity $C(f)$
- Sensitivity $s(f)$
- Block sensitivity $bs(f)$

Today's Lecture

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Query Complexity vs. Degree

Recall the Fourier transform of $f: \{0,1\}^n \rightarrow \{0,1\}$:

$$f(x) = \sum_S \hat{f}(S) \chi_S(x)$$

We can also use the monomial basis $\{\prod_{i \in S} x_i\}$ to expand f :

$$f(x) = \sum_S a_S \prod_{i \in S} x_i$$

How to use express a_S in terms of f ?

- By inclusion-exclusion formula, $a_S = \sum_{T \subseteq S} (-1)^{|S \setminus T|} f(\mathbf{1}_T) \implies a_S \in \mathbb{Z}$

How to use express a_S in terms of \hat{f} ?

$$a_S = (-2)^{|S|} \sum_{T \supseteq S} \hat{f}(T)$$

Query Complexity vs. Degree

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

$$f(x) = \sum_S \hat{f}(S) \chi_S(x) = \sum_S a_S \prod_{i \in S} x_i$$

we define the **(real) degree** of f as the

$$\deg(f) := \max\{|S| : a_S \neq 0\} = \max\{|S| : \hat{f}(S) \neq 0\}$$

Example:

$$\text{Parity}(x) = x_1 + \cdots + x_n \pmod{2} = \frac{1 - \chi_1(x)}{2}$$

- $\deg(\text{Parity}) = n$
- Its degree as a polynomial in \mathbb{F}_2 is 1

Query Complexity vs. Degree

Proposition. For every $f: \{0,1\}^n \rightarrow \{0,1\}$, we have $\deg(f) \leq D(f)$

Proof.

- If f can be expressed as a degree- d multilinear polynomial $\{0,1\}^n \rightarrow \mathbb{R}$, then $\deg(f) \leq d$
- Consider the decision tree that computes f with depth $D(f)$
- Let \mathcal{L}_1 be the set of leaves with label 1. And for each $x \in \{0,1\}^n$, let $\ell(x)$ be the leaf reached by the tree when computing $f(x)$

$$f(x) = \sum_{\ell \in \mathcal{L}_1} \mathbf{1}_{\ell(x)=\ell}$$

- For every leaf $\ell \in \mathcal{L}_1$, there is a unique path from the root to ℓ . Let T_ℓ and F_ℓ denote the indices of variables on this path that returned the value 1 and 0, respectively

Query Complexity vs. Degree

Proposition. For every $f: \{0,1\}^n \rightarrow \{0,1\}$, we have $\deg(f) \leq D(f)$

Proof.

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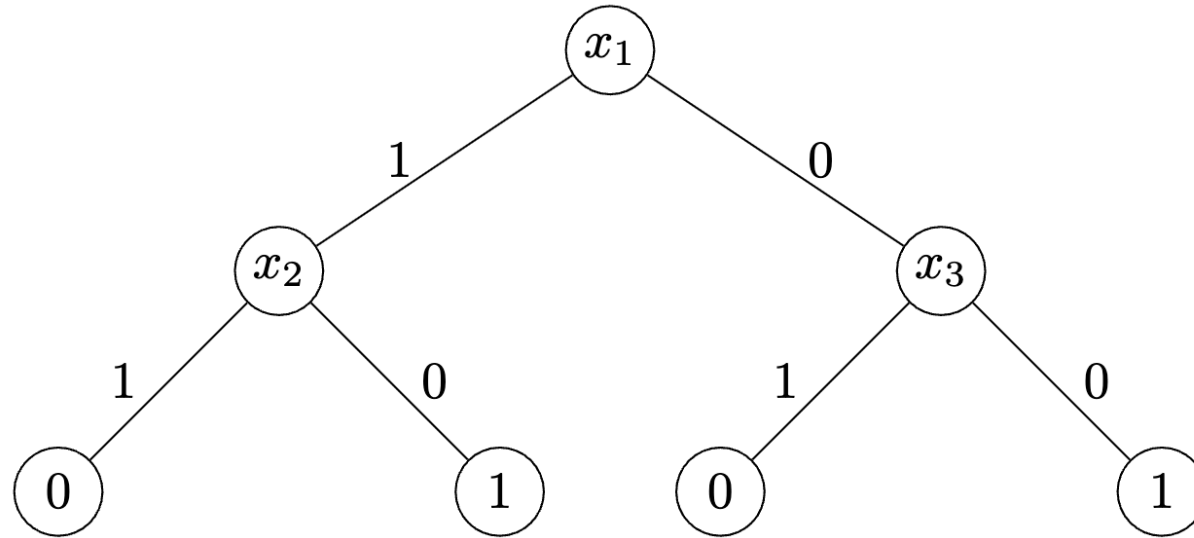
$$\mathbf{1}_{\ell(x)=\ell} \iff \left(\prod_{i \in T_\ell} x_i \right) \left(\prod_{j \in F_\ell} (1 - x_j) \right)$$

$$f(x) = \sum_{\ell \in \mathcal{L}_1} \left(\prod_{i \in T_\ell} x_i \right) \left(\prod_{j \in F_\ell} (1 - x_j) \right)$$

- $\deg(f) \leq \max_{\ell \in \mathcal{L}_1} (|T_\ell| + |F_\ell|) = D(f)$



Query Complexity vs. Degree



$$\begin{aligned} f(x_1, x_2, x_3) &= x_1(1 - x_2) + (1 - x_1)(1 - x_3) \\ &= (x_1 \wedge \neg x_2) \vee (\neg x_1 \wedge \neg x_3) \end{aligned}$$

Query Complexity vs. Certificate Complexity

A **certificate** for an input $x \in \{0,1\}^n$ to a Boolean function $f: \{0,1\}^n \rightarrow \{0,1\}$ is a set $S \subseteq [n]$ of indices such that f is **constant** on all inputs that match x_S

- $C_f(x)$ denotes the size of a smallest certificate for x
- The **certificate complexity** $C(f) := \max_x C_f(x)$

Example:

- $C(\text{Parity}) = n$
- $C(\text{AND}) = n$
- If f is a k -junta, then $C(f) = k$

Query Complexity vs. Certificate Complexity

Theorem. For every $f: \{0,1\}^n \rightarrow \{0,1\}$, we have $C(f) \leq D(f) \leq C(f)^2$

Proof.

- If there is a decision tree of depth $D(f)$ that computes f , then for any input x , the set of variables queried by the decision tree determines $f(x)$, which forms a certificate for x . Thus, $C(f) \leq D(f)$
- To prove $D(f) \leq C(f)^2$, observe that if $S \subseteq [n]$ is a certificate for $x \in f^{-1}(0)$ and $T \subseteq [n]$ is a certificate for $y \in f^{-1}(1)$, then $S \cap T \neq \emptyset$

- Define

$$C^0(f) := \max_{x \in f^{-1}(0)} C_f(x) \leq C(f), \quad C^1(f) := \max_{x \in f^{-1}(1)} C_f(x) \leq C(f)$$

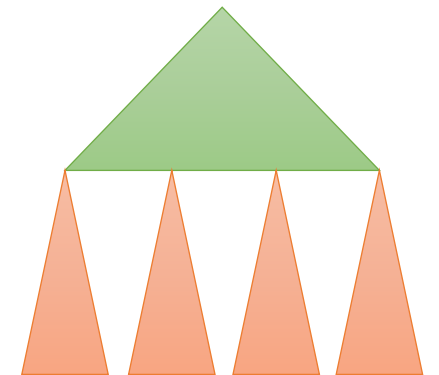
- We use induction on $C^1(f)$ to prove that $D(f) \leq C^0(f)C^1(f) \leq C(f)^2$
- If $C^1(f) = 0$, then $f \equiv 1$ and $D(f) = 0$

Query Complexity vs. Certificate Complexity

Theorem. For every $f: \{0,1\}^n \rightarrow \{0,1\}$, we have $C(f) \leq D(f) \leq C(f)^2$

Proof.

- Suppose $C^1(f) \neq 0$ and we pick any $x \in f^{-1}(0)$. Let S be a smallest certificate for x
- Construct a partial decision tree of depth $|S|$ by querying all the variables in S
- Each leaf ℓ in this partial decision tree corresponds to a function f_ℓ (a restriction of f)
- Since S intersects all the certificates for $y \in f^{-1}(1)$, we have
$$C^0(f_\ell) \leq C^0(f), \quad C^1(f_\ell) \leq C^1(f) - 1$$
- By induction, $D(f_\ell) \leq C^0(f)(C^1(f) - 1)$ for every ℓ
- Thus, $D(f) \leq C^0(f) + C^0(f)(C^1(f) - 1) = C^0(f)C^1(f)$



Query Complexity vs. Sensitivity

The sensitivity of $f: \{0,1\}^n \rightarrow \{0,1\}$ at a point x , denoted by $s_f(x)$, is the number of bits in x such that flipping any one of these bits changes the value of the function:

$$s_f(x) := |\{i \in [n] : f(x) \neq f(x + e_i)\}|$$

- The **sensitivity of f is $s(f) := \max_x s_f(x)$**

Example:

- $s(\text{Parity}) = n$
- $s(\text{AND}) = n$

Theorem (Nisan-Szegedy '94). Every $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $\deg(f) \geq \sqrt{s(f)/2}$

This result is proved using the “**Polynomial Method**”

Detour: Degree of Univariate Polynomials

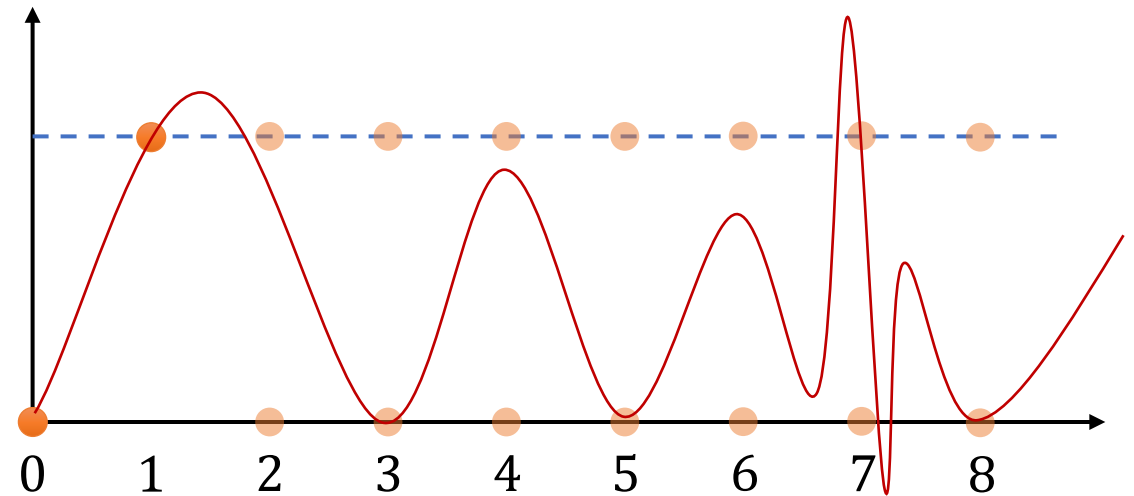
Theorem (Markov Brothers' Inequality). Let $q: \mathbb{R} \rightarrow \mathbb{R}$ be a univariate polynomial of degree d such that any real number $x \in [a_1, a_2]$ satisfies $q(x) \in [b_1, b_2]$. Then

$$|q'(x)| \leq d^2 \frac{b_2 - b_1}{a_2 - a_1} \quad \forall x \in [a_1, a_2]$$

Theorem. Let $q: \mathbb{R} \rightarrow \mathbb{R}$ be a univariate polynomial such that

1. $q(0) = 0$ and $q(1) = 1$
2. $0 \leq q(k) \leq 1$ for every $k \in [m]$

Then, $\deg(q) \geq \sqrt{m/2}$



Detour: Degree of Univariate Polynomials

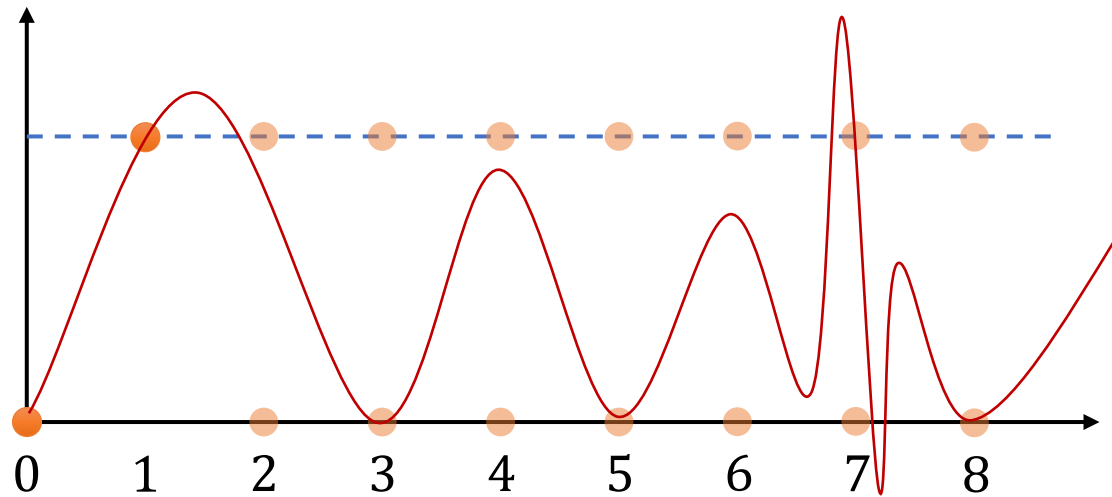
Theorem. Let $q: \mathbb{R} \rightarrow \mathbb{R}$ be a univariate polynomial such that: $q(0) = 0$, $q(1) = 1$, and $0 \leq q(k) \leq 1$ for every $k \in [m]$. Then $\deg(q) \geq \sqrt{m/2}$

Proof.

- By the mean value theorem, there exists a point $x \in [0,1]$ with $|q'(x)| \geq 1$
- Let $c := \max_{x \in [0,m]} |q'(x)|$, $c \geq 1$
- Since $0 \leq q(k) \leq 1$ for every $k \in [m]$, for every real number $x \in [0, m]$, the mean value theorem implies that $0 - c/2 \leq q(x) \leq 1 + c/2$
- Markov brothers' inequality: $c \leq d^2 \frac{1+c/2-(-c/2)}{m-0} = d^2 \frac{1+c}{m}$
- Thus, we get that $d \geq \sqrt{m \frac{c}{1+c}} \geq \sqrt{\frac{m}{2}}$ since $c \geq 1$



Detour: Degree of Univariate Polynomials



Degree lower bound



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



$$f(x) = \sum_S a_S x^S : \mathbb{R}^n \rightarrow \mathbb{R}$$
$$0 \leq f(x) \leq 1 \quad \forall x \in \{0,1\}^n$$

Detour: Symmetrization

We can symmetrize a multivariate polynomial $p: \mathbb{R}^n \rightarrow \mathbb{R}$ by averaging it over all permutations of the variables

$$p^{\text{sym}}(x_1, \dots, x_n) := \frac{1}{n!} \sum_{\pi \in \mathcal{S}_n} p(x_{\pi(1)}, \dots, x_{\pi(n)})$$

- $\deg(p^{\text{sym}}) \leq \deg(p)$

Theorem (Minsky-Paper '88). For every multilinear polynomial $p: \mathbb{R}^n \rightarrow \mathbb{R}$, there is a univariate polynomial $q: \mathbb{R} \rightarrow \mathbb{R}$ with $\deg(q) \leq \deg(p)$ such that

$$p^{\text{sym}}(x_1, \dots, x_n) = q(x_1 + \dots + x_n) \quad \forall x \in \{0,1\}^n$$

Detour: Symmetrization

Theorem (Minsky-Paper '88). For every multilinear polynomial $p: \mathbb{R}^n \rightarrow \mathbb{R}$, there is a univariate polynomial $q: \mathbb{R} \rightarrow \mathbb{R}$ with $\deg(q) \leq \deg(p)$ such that

$$p^{\text{sym}}(x_1, \dots, x_n) = q(x_1 + \dots + x_n) \quad \forall x \in \{0,1\}^n$$

Proof.

- Define the k -th elementary symmetric polynomial $e_k(x): \mathbb{R}^n \rightarrow \mathbb{R}$ as:

$$e_k(x) := \sum_{S \subseteq [n]: |S|=k} x^S$$

- $\{e_0, \dots, e_n\}$ forms a basis for symmetric polynomials
- Thus, $p^{\text{sym}} = c_0 + c_1 e_1 + \dots + c_d e_d$, where $\deg(p^{\text{sym}}) = d$
- Notice that if $x \in \{0,1\}^n$, then $e_k(x) = \binom{x_1 + \dots + x_n}{k}$, and we have

$$p^{\text{sym}}(x) = \underbrace{c_0 + c_1 \binom{t}{1} + \dots + c_d \binom{t}{d}}_{q(t)}, \quad t := x_1 + \dots + x_n \quad \forall x \in \{0,1\}^n$$



Detour: Symmetrization

Corollary. Let $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfy $f(0, \dots, 0) = 0$ and $f(e_1) = f(e_2) = \dots = f(e_n) = 1$.

Then $\deg(f) \geq \sqrt{n/2}$

Proof.

- Let $p^{\text{sym}}: \mathbb{R}^n \rightarrow \mathbb{R}$ be the symmetrization of f . Then $\deg(p^{\text{sym}}) \leq \deg(f)$
- Let $q: \mathbb{R} \rightarrow \mathbb{R}$ be the univariate polynomial provided by the previous theorem
- $q(0) = p^{\text{sym}}(0, \dots, 0) = f(0, \dots, 0) = 0$
- $q(1) = p^{\text{sym}}(e_1) = \frac{f(e_1) + \dots + f(e_n)}{n} = 1$
- $q(k) \in [0,1]$ for all $k \in [n]$
- Polynomial method implies that $\deg(q) \geq \sqrt{n/2}$



Query Complexity vs. Sensitivity

The sensitivity of $f: \{0,1\}^n \rightarrow \{0,1\}$ at a point x , denoted by $s_f(x)$, is the number of bits in x such that flipping any one of these bits changes the value of the function:

$$s_f(x) := |\{i \in [n] : f(x) \neq f(x + e_i)\}|$$

- The **sensitivity of f is $s(f) := \max_x s_f(x)$**

Theorem (Nisan-Szegedy '94). Every $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies **$\deg(f) \geq \sqrt{s(f)/2}$**

Proof.

- Let $y \in \{0,1\}^n$ with $s := s_f(y) = s(f)$, and let $i_1, \dots, i_s \in [n]$ be the sensitive coordinates
- We may assume $f(y) = 0$
- Define $g: \{0,1\}^s \rightarrow \{0,1\}$ as $g(z) := f(y + z_1 e_{i_1} + \dots + z_s e_{i_s})$

Query Complexity vs. Sensitivity

Theorem (Nisan-Szegedy '94). Every $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $\deg(f) \geq \sqrt{s(f)/2}$

Proof.

- Let $y \in \{0,1\}^n$ with $s := s_f(y) = s(f)$, and let $i_1, \dots, i_s \in [n]$ be the sensitive coordinates
- We may assume $f(y) = 0$
- Define $g: \{0,1\}^s \rightarrow \{0,1\}$ as $g(z) := f(y + z_1 e_{i_1} + \dots + z_s e_{i_s})$

$$g(z) = f(x_1, \dots, x_n), \quad x_i := \begin{cases} y_i & \text{if } i \notin \{i_1, \dots, i_s\} \\ z_i & \text{if } i \in \{i_1, \dots, i_s\}, y_i = 0 \\ 1 - z_i & \text{if } i \in \{i_1, \dots, i_s\}, y_i = 1 \end{cases}$$

- $\deg(g) \leq \deg(f)$, $g(0) = 0$, $g(e_i) = 1$ (by the definition of sensitivity)
- Thus, $\deg(g) \geq \sqrt{s/2}$



Query Complexity vs. Block Sensitivity

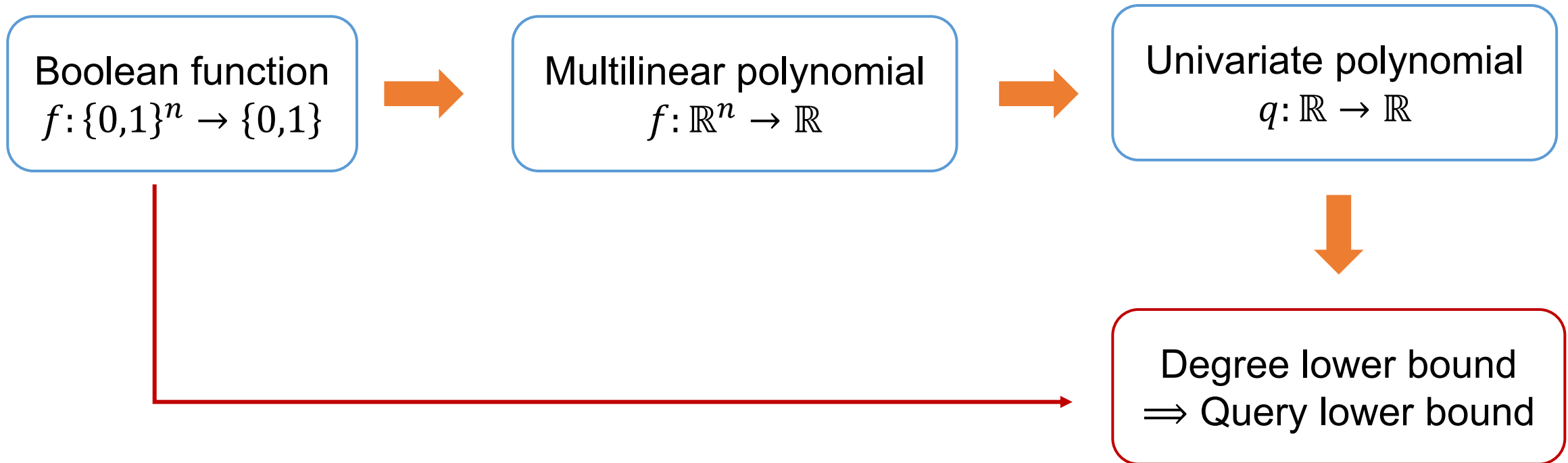
The block sensitivity of $f: \{0,1\}^n \rightarrow \{0,1\}$ at a point x , denoted by $\text{bs}_f(x)$, is the maximum number of disjoint subsets $B_1, \dots, B_k \subseteq [n]$ such that $f(x) \neq f(x + \mathbf{1}_{B_i})$ for all $i \in [k]$

- The **block sensitivity of f is $\text{bs}(f) := \max_x \text{bs}_f(x)$**
- $\text{bs}(f) \geq s(f)$ (we can take each block of size 1)

Theorem (Nisan-Szegedy '94). Every $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $\text{deg}(f) \geq \sqrt{\text{bs}(f)/2}$

- The proof is almost the same as the previous theorem

Polynomial Method



Query Complexity vs. Block Sensitivity

Theorem (Nisan '91). Every function $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $C(f) \leq s(f)bs(f)$

Proof.

- Let $x \in \{0,1\}^n$ with a maximal set of sensitive blocks $B_1, \dots, B_s \subseteq [n]$ and $s \leq bs(f)$
- Wlog, we may assume that B_i is minimal: $\forall j \in B_i, f(x) = f(x + \mathbf{1}_{B_i \setminus \{j\}})$
- Thus, on the input $x + \mathbf{1}_{B_i}$, each coordinate in B_i is sensitive. Hence, $|B_i| \leq s(f)$
- Since $\{B_1, \dots, B_s\}$ is maximal, fixing the values of the variables in $B = B_1 \cup \dots \cup B_s$ must determine the value of $f(x)$; otherwise, we could add one more sensitive block
- Thus, $C_f(x) \leq |B| = |B_1| + \dots + |B_s| \leq s(f)bs(f)$ for any $x \in \{0,1\}^n$ ■

Corollary. For any $f: \{0,1\}^n \rightarrow \{0,1\}$, we have

$$\deg(f) \leq D(f) \leq s(f)^2 bs(f)^2 \leq bs(f)^4 \lesssim \deg(f)^8$$

Randomized Query Complexity

A **randomized decision tree** \mathbf{T} of depth d is a random variable that takes values in the set of decision trees of depth at most d

The **randomized query complexity** of $f: \{0,1\}^n \rightarrow \{0,1\}$, denoted by $\mathbf{R}(f)$, is the smallest d such that there exists a randomized decision tree T of depth d such that

$$\Pr_{\mathbf{T}}[\mathbf{T}(x) \neq f(x)] \leq \frac{1}{3} \quad \forall x \in \{0,1\}^n$$

- Define $g(x) := \mathbb{E}[\mathbf{T}(x)] = \sum_T \mu(T)T(x)$, where μ is the probability distribution of \mathbf{T}
- $\|f - g\|_{\infty} \leq 1/3$ since

$$\begin{aligned} \|f - g\|_{\infty} &= \max_x \left| f(x) - \sum_T \mu(T)T(x) \right| \leq \max_x \sum_T \mu(T) |f(x) - T(x)| \\ &= \max_x \Pr[\mathbf{T}(x) \neq f(x)] \leq 1/3 \end{aligned}$$

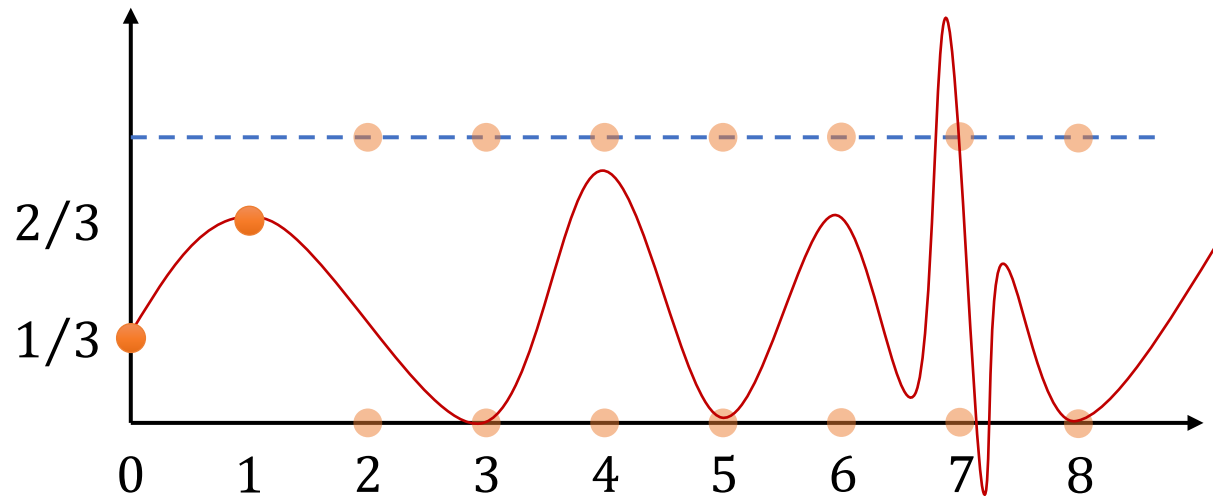
- Since $\deg(f) \leq D(f)$, we have $\deg(T) \leq d$ and $\deg(g) \leq d$

Randomized Query Complexity vs. Approximate Degree

The **approximate degree** of f , denoted by $\widetilde{\text{deg}}(f)$, is the smallest d such that there exists $g: \{0,1\}^n \rightarrow \mathbb{R}$ with $\text{deg}(g) \leq d$ and $\|f - g\|_\infty \leq 1/3$

Proposition. For every $f: \{0,1\}^n \rightarrow \{0,1\}$, we have $\widetilde{\text{deg}}(f) \leq R(f)$

Theorem (Nisan-Szegedy '94). Every function $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $\widetilde{\text{deg}}(f) \geq \sqrt{\text{bs}(f)/6}$



$$\text{deg}(q) \geq \sqrt{m/6}$$

Randomized Query Complexity vs. Approximate Degree

The **approximate degree** of f , denoted by $\widetilde{\text{deg}}(f)$, is the smallest d such that there exists $g: \{0,1\}^n \rightarrow \mathbb{R}$ with $\text{deg}(g) \leq d$ and $\|f - g\|_\infty \leq 1/3$

Proposition. For every $f: \{0,1\}^n \rightarrow \{0,1\}$, we have $\widetilde{\text{deg}}(f) \leq R(f)$

Theorem (Nisan-Szegedy '94). Every function $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $\widetilde{\text{deg}}(f) \geq \sqrt{\text{bs}(f)/6}$

- Since $D(f) \geq R(f)$ and $D(f) \leq \text{bs}(f)^4$, we have

$$D(f)^{\frac{1}{8}} \lesssim \sqrt{\text{bs}(f)} \lesssim \widetilde{\text{deg}}(f) \leq R(f) \leq D(f)$$

The following measures of Boolean functions are **polynomially equivalent**:

- Degree $\deg(f)$
- Certificate complexity $C(f)$
- Block sensitivity $bs(f)$
- Approximate degree $\widetilde{\deg}(f)$
- Deterministic query complexity $D(f)$
- Randomized query complexity $R(f)$

Can we add the sensitivity $s(f)$ to this list?

The Sensitivity Conjecture

- (Nisan-Szegedy '94) conjectured that the sensitivity of a Boolean function is polynomially equivalent to the degree, block sensitivity, query complexity, ...

- A quote from Scott Aaronson:

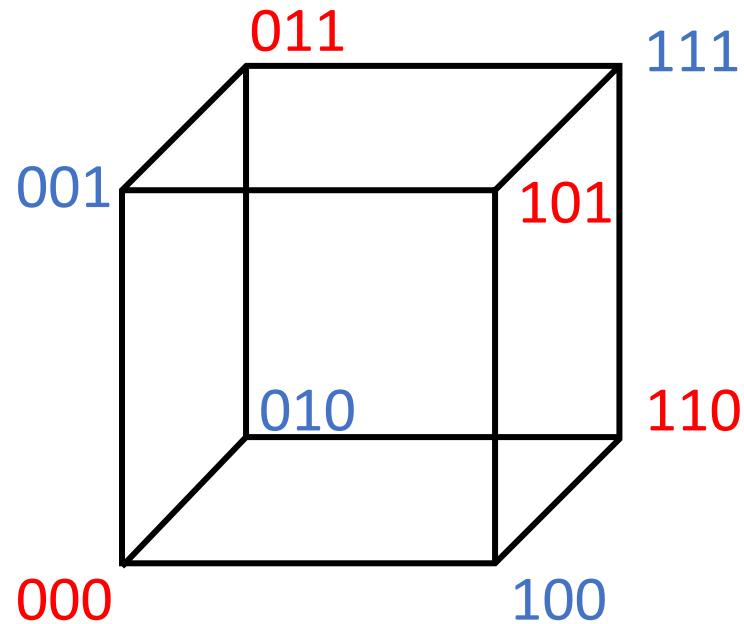
*Ever since it was posed by Nisan and Szegedy in 1989, this conjecture has stood as one of **the most frustrating and embarrassing open problems** in all of combinatorics and theoretical computer science. It seemed so easy, and so similar to other statements that had 5-line proofs. But a lot of the best people in the field sank months into trying to prove it.*

- Resolved by Hao Huang in 2019 (a beautiful 6-page paper)

Theorem. Every function $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $s(f) \geq \sqrt{\deg(f)}$



The Sensitivity Theorem

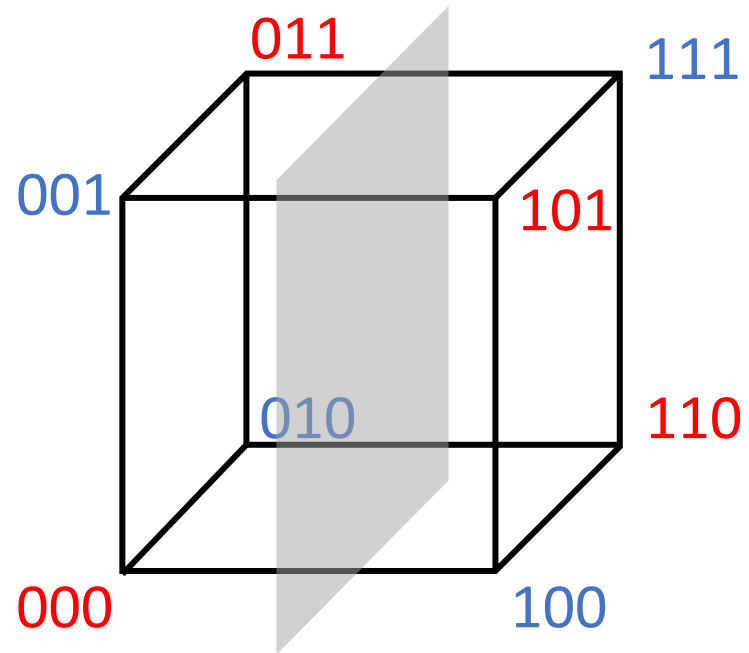


Define a bipartition of $\{0,1\}^n$:

$$V_{\text{even}} := \left\{ x \in \{0,1\}^n : \sum_{i \in [n]} x_i \equiv 0 \pmod{2} \right\}, \quad V_{\text{odd}} := \left\{ x \in \{0,1\}^n : \sum_{i \in [n]} x_i \equiv 1 \pmod{2} \right\}$$

Notice that the Boolean hypercube Q_n is a **bipartite graph** between V_{even} and V_{odd}

The Sensitivity Theorem



Adjacency matrix A_n of Q_n :

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

The Sensitivity Theorem

Theorem (Huang '19). For every $T \subseteq \{0, 1\}^n$ with $|T| > 2^{n-1}$, let $\mathcal{H} := Q_n[T]$ be the subgraph induced by Q_n on T . Then, the maximum degree of \mathcal{H} satisfies $\Delta(\mathcal{H}) \geq \sqrt{n}$

Proof.

- Define the **signed adjacency** matrix $\tilde{\mathbf{A}}_n$:

$$\tilde{\mathbf{A}}_1 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad \tilde{\mathbf{A}}_n = \begin{bmatrix} \tilde{\mathbf{A}}_{n-1} & \mathbf{I} \\ \mathbf{I} & -\tilde{\mathbf{A}}_{n-1} \end{bmatrix}$$

- Let \mathbf{B} denote the $T \times T$ principal submatrix of $\tilde{\mathbf{A}}_n$
- We have

$$\lambda_1(\mathbf{B}) \leq \max_{i \in T} \sum_{j \in T} |\mathbf{B}_{i,j}| = \max_{i \in T} \sum_{j \in T} |\tilde{\mathbf{A}}_{i,j}| = \max_{i \in T} \sum_{j \in T} |\mathbf{A}_{i,j}| = \max_{i \in T} \deg_{\mathcal{H}}(i) \leq \Delta(\mathcal{H})$$

(why?)

The Sensitivity Theorem

Theorem (Huang '19). For every $T \subseteq \{0, 1\}^n$ with $|T| > 2^{n-1}$, let $\mathcal{H} := Q_n[T]$ be the subgraph induced by Q_n on T . Then, the maximum degree of \mathcal{H} satisfies $\Delta(\mathcal{H}) \geq \sqrt{n}$

Proof.

- Define the **signed adjacency** matrix \tilde{A}_n :

$$\tilde{A}_1 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad \tilde{A}_n = \begin{bmatrix} \tilde{A}_{n-1} & I \\ I & -\tilde{A}_{n-1} \end{bmatrix}$$

- We can prove by induction that $(\tilde{A}_n)^2 = nI$:

$$\begin{bmatrix} \tilde{A}_{n-1} & I \\ I & -\tilde{A}_{n-1} \end{bmatrix} \cdot \begin{bmatrix} \tilde{A}_{n-1} & I \\ I & -\tilde{A}_{n-1} \end{bmatrix} = \begin{bmatrix} (\tilde{A}_{n-1})^2 + I & \mathbf{0} \\ \mathbf{0} & (\tilde{A}_{n-1})^2 + I \end{bmatrix}$$

- Thus, $\lambda_i(\tilde{A}_n) = \sqrt{n}$ or $-\sqrt{n}$ for any $i \in [N]$
- Since $\text{tr}[\tilde{A}_n] = 0$, we know that 2^{n-1} eigenvalues are \sqrt{n} and 2^{n-1} eigenvalues are $-\sqrt{n}$

Matrix Analysis: Eigenvalue Inequalities (Lecture 15)

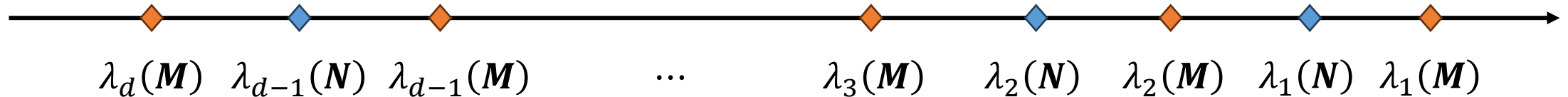
Theorem (Cauchy Interlacing Theorem). For any $\mathbf{M} \in \mathbb{S}^{d \times d}$ and $\mathbf{V} \in \mathbb{R}^{d \times r}$ with $\mathbf{V}^\top \mathbf{V} = \mathbf{I}_r$,

$$\lambda_{d-r+k}(\mathbf{M}) \leq \lambda_k(\mathbf{V}^\top \mathbf{M} \mathbf{V}) \leq \lambda_k(\mathbf{M}) \quad \forall k \in [r]$$

Corollary. For any $\mathbf{M} \in \mathbb{S}^{d \times d}$ and $\mathbf{N} \in \mathbb{S}^{r \times r}$ a principal submatrix of \mathbf{M} ,

$$\lambda_{d-r+k}(\mathbf{M}) \leq \lambda_k(\mathbf{N}) \leq \lambda_k(\mathbf{M}) \quad \forall k \in [r]$$

- If $r = d - 1$, then the eigenvalues of \mathbf{N} **interlace** the eigenvalues of \mathbf{M}



The Sensitivity Theorem

Theorem (Huang '19). For every $T \subseteq \{0, 1\}^n$ with $|T| > 2^{n-1}$, let $\mathcal{H} := Q_n[T]$ be the subgraph induced by Q_n on T . Then, the maximum degree of \mathcal{H} satisfies $\Delta(\mathcal{H}) \geq \sqrt{n}$

Proof.

- Let \mathbf{B} denote the $T \times T$ principal submatrix of $\tilde{\mathbf{A}}_n$
$$\Delta(\mathcal{H}) \geq \lambda_1(\mathbf{B})$$
- Thus, $\lambda_i(\tilde{\mathbf{A}}_n) = \sqrt{n}$ or $-\sqrt{n}$ for any $i \in [N]$
- Since $\text{tr}[\tilde{\mathbf{A}}_n] = 0$, we know that half of the eigenvalues are \sqrt{n} and half are $-\sqrt{n}$
- **Cauchy interlacing theorem** gives that

$$\lambda_1(\mathbf{B}) \geq \lambda_{2^n - |T| + 1}(\tilde{\mathbf{A}}_n) \geq \lambda_{2^{n-1}}(\tilde{\mathbf{A}}_n) = \sqrt{n}$$



The Sensitivity Theorem

Theorem (The Sensitivity Theorem). Every function $f: \{0,1\}^n \rightarrow \{0,1\}$ satisfies $s(f) \geq \sqrt{\deg(f)}$

Proof (via the reduction given by (Gotsman-Linial '92)).

- We may assume $\deg(f) = n$; otherwise, we can pick a $\deg(f)$ -degree monomial in f and restrict the remaining variables to 0. Let g be the restricted function. Then, $\deg(g) = \deg(f)$ (i.e., full degree) and $s(g) \leq s(f)$. Thus, if we prove that $s(g) \geq \sqrt{\deg(g)}$, then we also have $s(f) \geq \sqrt{\deg(f)}$

The Sensitivity Theorem

Proof (via a reduction given by (Gotsman-Linial '92)).

- We change the output domain of f from $\{0,1\}$ to $\{-1,1\}$, and we can write the its Fourier transform

$$f(x) = \sum_S \hat{f}(S) \chi_S(x)$$

- Since $\deg(f) = n$, $\hat{f}(\mathbf{1}) \neq 0$. We define $h(x) := f(x)\chi_{\mathbf{1}}(x) = f(x)(-1)^{x_1+\dots+x_n}$
- We have $\hat{h}(S) = \langle f\chi_{\mathbf{1}}, \chi_S \rangle = \hat{f}(\mathbf{1} + S)$. Thus, $\mathbb{E}[h] = \hat{h}(\mathbf{0}) = \hat{f}(\mathbf{1}) \neq 0$
- For any $i \in [n]$, $f(x) \neq f(x + e_i) \Leftrightarrow h(x) = h(x + e_i)$. Thus, $s_f(x) = |\{i \in [n] : h(x) = h(x + e_i)\}|$
- That is, $s_f(x) = \deg_{Q_n[T]}(x)$ where $T := \{y \in \{0,1\}^n : h(y) = h(x)\}$
- Since $|h^{-1}(1)| \neq |h^{-1}(-1)|$, we have $T > 2^{n-1}$ for some $x \in \{0,1\}^n$
- By [Huang's theorem](#), $\Delta(Q_n[T]) \geq \sqrt{n}$. Therefore, $s(f) \geq \sqrt{n} = \sqrt{\deg(f)}$



Table 1: Best known separations between complexity measures

	D	R ₀	R	C	RC	bs	s	λ	Q _E	deg	Q	$\widetilde{\text{deg}}$
D		2, 2 [ABB ⁺ 17]	2, 3 [ABB ⁺ 17]	2, 2 Λ ∘ V	2, 3 Λ ∘ V	2, 3 Λ ∘ V	3, 6 [BHT17]	4, 6 [ABB ⁺ 17]	2, 3 [ABB ⁺ 17]	2, 3 [GPW18]	4, 4 [ABB ⁺ 17]	4, 4 [ABB ⁺ 17]
R ₀	1, 1 ⊕		2, 2 [ABB ⁺ 17]	2, 2 Λ ∘ V	2, 3 Λ ∘ V	2, 3 Λ ∘ V	3, 6 [BHT17]	4, 6 [ABB ⁺ 17]	2, 3 [ABB ⁺ 17]	2, 3 [GJPW18]	3, 4 [ABB ⁺ 17]	4, 4 [ABB ⁺ 17]
R	1, 1 ⊕	1, 1 ⊕		2, 2 Λ ∘ V	2, 3 Λ ∘ V	2, 3 Λ ∘ V	3, 6 [BHT17]	4, 6 [ABB ⁺ 17]	$\frac{3}{2}, 3$ [ABB ⁺ 17]	2, 3 [GJPW18]	3, 4 [BS20] [SSW20]	4, 4 [ABB ⁺ 17]
C	1, 1 ⊕	1, 1 ⊕	1, 2 ⊕		2, 2 [GSS13]	2, 2 [GSS13]	2.22, 5 [BHT17]	2.44, 6 [BHT17] ^a	1.15, 3 [Amb13]	1.63, 3 [NW95]	2, 4 Λ	2, 4 Λ
RC	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕		$\frac{3}{2}, 2$ [GSS13]	2, 4 [Rub95]	2, 4 Λ	1.15, 2 [Amb13]	1.63, 2 [NW95]	2, 2 Λ	2, 2 Λ
bs	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕		2, 4 [Rub95]	2, 4 Λ	1.15, 2 [Amb13]	1.63, 2 [NW95]	2, 2 Λ	2, 2 Λ
s	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕		2, 2 Λ	1.15, 2 [Amb13]	1.63, 2 [NW95]	2, 2 Λ	2, 2 Λ
λ	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕		1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕
Q _E	1, 1 ⊕	1.33, 2 Λ-tree	1.33, 3 Λ-tree	2, 2 Λ ∘ V	2, 3 Λ ∘ V	2, 3 Λ ∘ V	3, 6 [BHT17]	4, 6 [ABK16]		2, 3 [ABK16]	2, 4 Λ	4, 4 [ABK16]
deg	1, 1 ⊕	1.33, 2 Λ-tree	1.33, 2 Λ-tree	2, 2 Λ ∘ V	2, 2 Λ ∘ V	2, 2 Λ ∘ V	2, 2 Λ ∘ V	2, 2 Λ	1, 1 ⊕		2, 2 Λ	2, 2 Λ
Q	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	2, 2 [ABK16]	2, 3 [ABK16]	2, 3 [ABK16]	3, 6 [BHT17]	4, 6 [ABK16]	1, 1 ⊕	2, 3 [ABK16]		4, 4 [ABK16]
$\widetilde{\text{deg}}$	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	2, 2 [BT17]	2, 2 [BT17]	2, 2 [BT17]	2, 2 [BT17]	2, 2 [BT17]	1, 1 ⊕	1, 1 ⊕	1, 1 ⊕	

(Aaronson-Ben-David-Kothari-Rao-Tal '21)

- An entry a, b in the row M_1 and column M_2 roughly means that there exists a function g with $M_1(g) \geq M_2(g)^{a-o(1)}$, and for all total functions f , $M_1(f) \leq M_2(f)^{b+o(1)}$ (see [ABK16])