

# Analysis of Boolean Functions

Foundations and Applications in TCS.

A Boolean function is a function  $f: \{0,1\}^n \rightarrow \{0,1\}$ .

It can model:

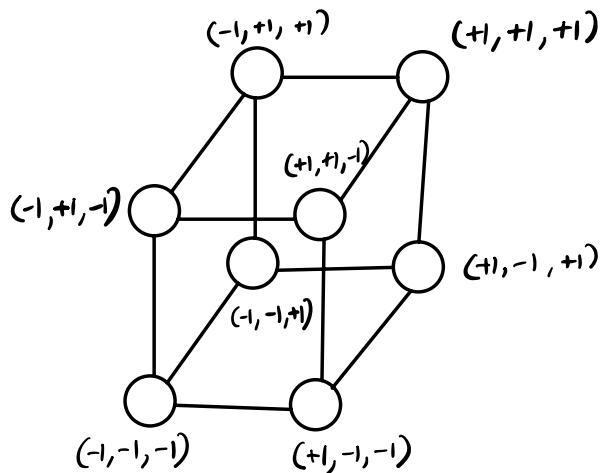
- Set systems in combinatorics  
 $A \subseteq \{0,1\}^n \rightarrow 1_A(x) = \begin{cases} 1 & x \in A \\ 0 & \text{otherwise.} \end{cases}$
- tests in cryptography / pseudorandomness  
We are trying to "fool".
- concepts and hypotheses in learning theory.
- Error correcting codes.
- Voting rules in social choice, e.g.,  
 $x \in \{0,1\}^n$  represents the  $n$  votes on a binary decision  
and  $f(x)$  represents the collective decision.
- Graph properties.  
and more...

The Boolean Domain: We'll realize the Boolean domain  $\{0,1\}$  as either  $\{\text{True}, \text{False}\}$  or  $\{+1, -1\}$

$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$
F	T	T	F

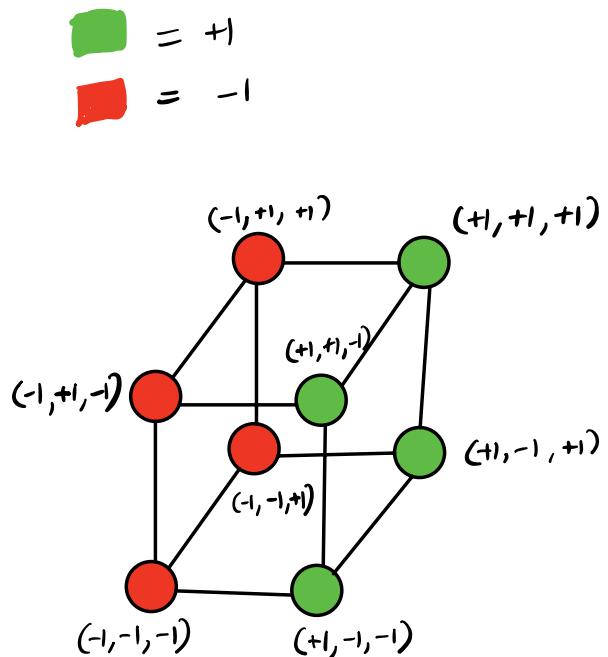
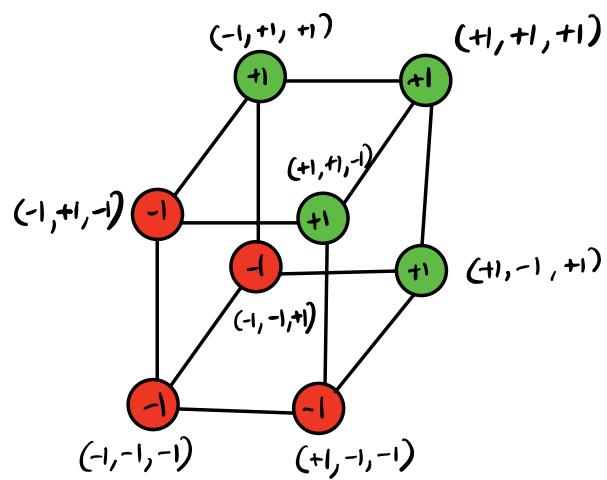
We'll be flexible, but will usually prefer the latter.

# The Boolean Hypercube (the domain)



$x \sim y$   
if they differ  
in exactly one  
coordinate.

# Examples of Boolean Functions

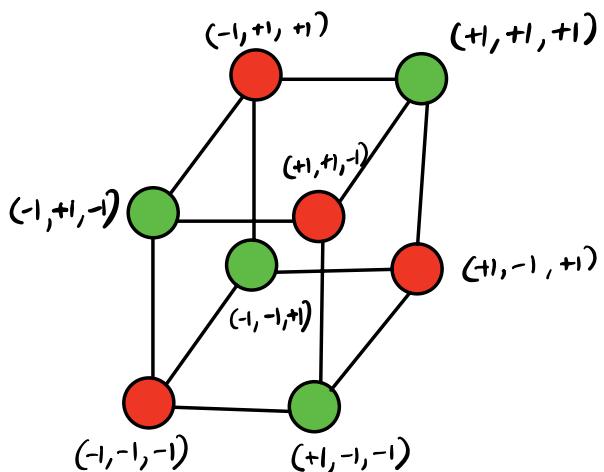


Majority vote

$$\text{Maj}_3(x_1, x_2, x_3) = \begin{cases} +1 & x_1 + x_2 + x_3 > 0 \\ -1 & \text{otherwise} \end{cases}$$

Dictatorship

$$f(x_1, x_2, x_3) = x_1$$



Parity

$$\text{Parity}_3(x_1, x_2, x_3) = x_1 \cdot x_2 \cdot x_3$$

## The Fundamental Theorem of Boolean Functions:

Every Boolean function  $f: \mathbb{F}_2^n \rightarrow \mathbb{F}_2$  can be uniquely represented as a multilinear polynomial

$$\text{over } \mathbb{R}: \quad f(x) = \sum_{\substack{S \subseteq \{1, \dots, n\} \\ i \in S}} c_S \cdot \prod_{i \in S} x_i$$

where  $c_s \in \mathbb{R}$

$$\text{E.g. } \text{Maj}_3(x_1, x_2, x_3) = \frac{1}{2}x_1 + \frac{1}{2}x_2 + \frac{1}{2}x_3 - \frac{1}{2}x_1 x_2 x_3$$

## First proof of Existence - Polynomial Interpolation

We construct the polynomial from the function truth-table

by interpolation. Example:  $\max_2(x_1, x_2)$

$x_1$	$x_2$	$\max_2(x_1, x_2)$	$\max_2(x_1, x_2) =$
-1	-1	-1	$\left(\frac{1-x_1}{2}\right)\left(\frac{1-x_2}{2}\right) \cdot (-1)$
-1	+1	+1	$+ \left(\frac{1-x_1}{2}\right)\left(\frac{1+x_2}{2}\right) \cdot (+1)$
+1	-1	+1	$+ \left(\frac{1+x_1}{2}\right)\left(\frac{1-x_2}{2}\right) \cdot (+1)$
+1	+1	+1	$+ \left(\frac{1+x_1}{2}\right)\left(\frac{1+x_2}{2}\right) \cdot (+1)$ .

More generally:

$$f(x) = \sum_{a \in \{ \pm 1 \}^n} f(a) \cdot \underbrace{\left( \frac{1+a_1 x_1}{2} \right) \cdots \left( \frac{1+a_n x_n}{2} \right)}_{\uparrow \text{ indicates that } x=a}$$

Note: The proof works for any  $f: \{ \pm 1 \}^n \rightarrow \mathbb{R}$ .

The Fundamental Theorem of Boolean Functions:

Every Boolean function  $f: \{ \pm 1 \}^n \rightarrow \mathbb{R}$  can be uniquely represented as a multilinear polynomial

over  $\mathbb{R}$ :

$$f(x) = \sum_{S \subseteq \{1, \dots, n\}} \hat{f}(S) \cdot \chi_S(x)$$

where  $\hat{f}(S) \in \mathbb{R}$  is called the  $S$ -Fourier coeff.  
 $\chi_S(x) = \prod_{i \in S} x_i$  is called the  $S$ -Fourier character.

Note:  $\chi_S$  is also a Boolean Function

$$\chi_S: \{ \pm 1 \}^n \rightarrow \{ \pm 1 \} \quad \chi_S(x_1, \dots, x_n) = \prod_{i \in S} x_i$$

Uniqueness:  $V_n = \{ f: \{ \pm 1 \}^n \rightarrow \mathbb{R} \}$  is

a vector space of dimension  $2^n$ .

The characters  $\{ \chi_S : S \subseteq [n] \}$  span  $V$ .

Since there are  $2^n$  of them, they form a basis.

$\Rightarrow$  the Fourier repr is unique. ■

## Second Proof of Fundamental Thm

Define the inner product of two functions  $f, g: \mathbb{F}^{\pm \mathbb{B}^n} \rightarrow \mathbb{R}$

as

$$\langle f, g \rangle \stackrel{\Delta}{=} \mathbb{E}_{\substack{x \in \mathbb{F}^{\pm \mathbb{B}^n}}} [f(x) \cdot g(x)]$$

Lemma: The characters  $\{x_s : s \subseteq [n]\}$  form an orthonormal basis of  $V_n$ .

Proof:

Let  $S, T \subseteq [n]$   $S \neq T$ .

$$\begin{aligned} \langle x_s, x_T \rangle &= \mathbb{E}_{\substack{x \in \mathbb{F}^{\pm \mathbb{B}^n}}} [x_s(x) \cdot x_T(x)] \\ &= \mathbb{E}_{\substack{x \in \mathbb{F}^{\pm \mathbb{B}^n}}} \left[ \prod_{i \in S} x_i \cdot \prod_{i \in T} x_i \right] \\ &= \mathbb{E}_{\substack{x \in \mathbb{F}^{\pm \mathbb{B}^n}}} \left[ \prod_{i \in S \Delta T} x_i \cdot \prod_{i \in S \cap T} x_i^2 \right] \\ &= \prod_{i \in S \Delta T} \mathbb{E}_{\substack{x \in \mathbb{F}^{\pm \mathbb{B}^n}}} [x_i] \quad \left( \text{since } x_1, \dots, x_n \text{ are independent} \right) \\ &= 0. \end{aligned}$$

$$\langle x_s, x_S \rangle = 1.$$

So  $\{x_s : s \subseteq [n]\}$  are orthonormal  $\Rightarrow$  linearly independent. As there are  $2^n$  of them  $\Rightarrow$  they form a basis for  $V_n$ . ■

Inversion Formula:  $\hat{f}(s) = \langle f, \chi_s \rangle$ .

Proof:  $\langle f, \chi_s \rangle = \left\langle \sum_{T \subseteq [n]} \hat{f}(T) \chi_T, \chi_s \right\rangle$

$$= \sum_{T \subseteq [n]} \hat{f}(T) \langle \chi_T, \chi_s \rangle$$
$$= \hat{f}(s).$$

Plancheral:  $\langle f, g \rangle = \sum_{S \subseteq [n]} \hat{f}(S) \hat{g}(S)$ .

Proof:  $\langle f, g \rangle = \left\langle \sum_{S \subseteq [n]} \hat{f}(S) \chi_S, \sum_{T \subseteq [n]} \hat{g}(T) \chi_T \right\rangle$

$$= \sum_{S, T \subseteq [n]} \hat{f}(S) \hat{g}(T) \langle \chi_S, \chi_T \rangle$$
$$= \sum_{S \subseteq [n]} \hat{f}(S) \cdot \hat{g}(S).$$

Parseval:  $\mathbb{E}_{\substack{x \in \{-1, 1\}^n}} [f(x)^2] = \langle f, f \rangle = \sum_{S \subseteq [n]} \hat{f}(S)^2$ .

Fourier coefficients are an alternative  
repr of a Boolean function compared to truth-table.

They encode "global" properties, e.g.

$$\hat{f}(\phi) = \langle f, \chi_\phi \rangle = \mathbb{E}_{\substack{x \in \{-1, 1\}^n}} [f(x) \cdot 1]$$

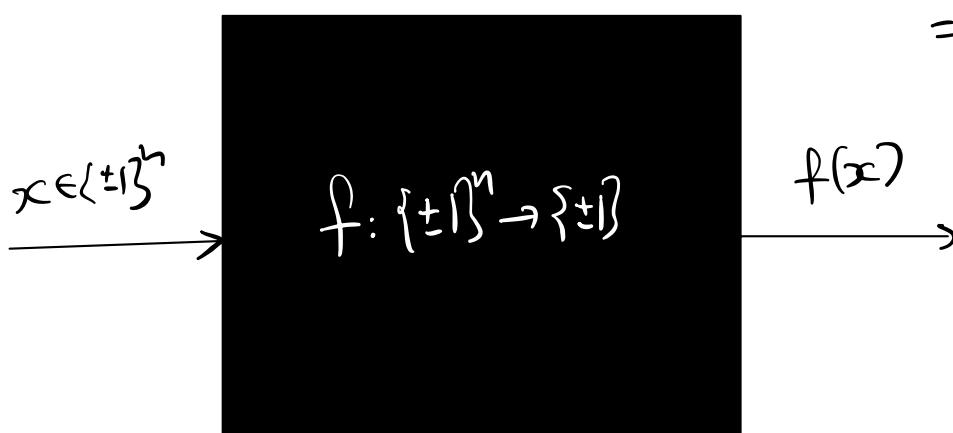
$$\text{Var}[f] = \mathbb{E}_{\substack{x \in \{-1, 1\}^n}} [f(x)^2] - \mathbb{E}_{\substack{x \in \{-1, 1\}^n}} [f(x)]^2 = \sum_{\phi \neq S \subseteq [n]} \hat{f}(S)^2$$

„ $\langle f, \chi_i \rangle = \mathbb{E}[f(x) \cdot x_i]$ “

$$\hat{f}(q_i) = \frac{\mathbb{E}[f(x) \mid x_i=1] - \mathbb{E}[f(x) \mid x_i=-1]}{2}$$

# Application: Linearity Testing

$$\chi_s(x) \cdot \chi_s(y) \\ = \chi_s(x+y)$$



Given Black-Box access to a Boolean function  $f$ ,  
 want to tell whether  $f$  is a character.

The characters are multiplicative over  $\{\pm 1\}$   
 $\Leftrightarrow$  linear over  $\mathbb{Z}_2$ .

**[BLR]:**  $\begin{array}{c} \text{Blum} \quad \text{Luby} \\ \diagup \quad \diagdown \\ \text{[BLR]} \end{array} \quad \text{Rubinfeld}$

- Pick random  $x, y \in \{\pm 1\}^n$  independently.
- check if  $f(x) \cdot f(y) = f(x+y)$ .

Defn:  $f, g: \{\pm 1\}^n \rightarrow \{\pm 1\}$   $\text{dist}(f, g) = \Pr_{x \in \{\pm 1\}^n} [f(x) \neq g(x)]$

Thm:

1. If  $f$  is a character, then the BLR test always accepts
2. If  $f$  is  $\varepsilon$ -far from all characters, then the BLR test rejects w.p.  $\geq \varepsilon$ .

Proof: (1) is clear. We prove (2).

Let  $f: \{ \pm B \}^n \rightarrow \{ \pm B \}$

$$1 - \varepsilon \leq \Pr[\text{BLR accepts } f]$$

$$= \Pr_{x,y} [f(x) \cdot f(y) = f(x \cdot y)]$$

$$= \mathbb{E}_{x,y} \left[ \frac{f(x) \cdot f(y) - f(x \cdot y)}{2} \right]$$

$x, y$

$$x_R(x) \cdot x_R(y)$$

||

By rearranging,

$$1 - 2\varepsilon \leq \mathbb{E}_{x,y} [f(x) \cdot f(y) - f(x \cdot y)]$$

$$= \mathbb{E}_{x,y} \left[ \sum_{S \subseteq [n]} \hat{f}(S) \cdot x_S(x) \cdot \sum_{T \subseteq [n]} \hat{f}(T) \cdot x_T(y) \cdot \sum_{R \subseteq [n]} \hat{f}(R) \cdot x_R(x \cdot y) \right]$$

$$= \sum_{S, T, R \subseteq [n]} \hat{f}(S) \cdot \hat{f}(T) \cdot \hat{f}(R) \cdot \mathbb{E}_x [x_S(x) x_R(x)] \mathbb{E}_y [x_T(y) x_R(y)]$$

$$= \sum_{S \subseteq [n]} \hat{f}(S)^3$$

$$\leq \max_{S: S \subseteq [n]} \hat{f}(S) \cdot \left( \sum_{S \subseteq [n]} \hat{f}(S)^2 \right) \stackrel{\text{Parseval}}{=} \max_{S: S \subseteq [n]} \hat{f}(S)$$

So, there exists a character  $x_S$  s.t.  $1 - 2\varepsilon \leq \langle f, x_S \rangle$ .

$$\begin{aligned} 1 - 2\varepsilon \leq \langle f, x_S \rangle &= \Pr_x [f(x) = x_S(x)] - \Pr_x [f(x) \neq x_S(x)] \\ &= 1 - 2 \cdot \Pr_x [f(x) \neq x_S(x)] = 1 - 2 \cdot \text{dist}(f, x_S) \end{aligned}$$

Thus,  $\text{dist}(f, x_S) \leq \varepsilon$ .

