

# Boolean Functions II

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Review: Boolean function is  $f: \{-1, 1\}^n \rightarrow \{-1, 1\}$

Basically, assigning  $\pm 1$  to each vertex of  $n$ -cube

We can model a function  $f$  as a polynomial!

Note that  $(\frac{1}{2} + \frac{x_1}{2})(\frac{1}{2} + \frac{x_2}{2})(\frac{1}{2} + \frac{x_3}{2})$  only has nonzero value at  $(1, 1, 1)$ . So (assume  $n=3$  for simplicity)

$$f = \left(\frac{1}{2} + \frac{x_1}{2}\right)\left(\frac{1}{2} + \frac{x_2}{2}\right)\left(\frac{1}{2} + \frac{x_3}{2}\right) f(1, 1, 1) \\ + \left(\frac{1}{2} + \frac{x_1}{2}\right)\left(\frac{1}{2} + \frac{x_2}{2}\right)\left(-\frac{1}{2} + \frac{x_3}{2}\right) f(1, 1, -1) \\ + \dots$$

$$= \left[ \text{some multilinear (all exponents are 0 or 1) poly.} \right]$$

We define  $\hat{f}(S)$  for  $S \subseteq [n]$  to be the coefficient of  $\prod_{i \in S} x_i$  in this Fourier expansion.

E.g.  $\hat{f}(\{1, 2, 3\}) = 3$  for  $f = 3x_1x_2x_3 + 2x_1x_2 + 5x_3 + 4x_2x_3$ .

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Inner Product:  $\langle f, g \rangle = \mathbb{E}_{x \in \{-1, 1\}^n} [f(x)g(x)]$

(also equal to  $1 - 2\Pr_x [f(x) \neq g(x)]$ )

Parseval's Theorem: For  $f$  and  $g$ ,

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

(end of review)

Influence: "Probability that individual bit affects outcome"

Formally: We call coordinate  $i \in [n]$  pivotal for fn.  $f$  and input  $x$  if  $f(x) \neq f(x^{\oplus i})$

$x^{\oplus i} = (x_1, x_2, \dots, x_{i-1}, -x_i, x_{i+1}, \dots)$  (flip the bit with index  $i$ )

The influence of coordinate  $i$  on  $f: \{-1, 1\}^n \rightarrow \{-1, 1\}$

is:

$$\text{Inf}_i[f] = \Pr_{x \in \{-1, 1\}^n} [f(x) \neq f(x^{\oplus i})]$$

(probability that  $i$  is pivotal for a random input)

EXAMPLES ON PG. 4

We claim that this also equals  $\sum_{\substack{S \subseteq [n] \\ S \ni i}} \hat{f}(S)^2$ .

For simplicity, let  $f(x^{\oplus i}) = g(x)$ .

Note that  $\Pr [f(x) \neq g(x)]$  is equivalent to

$$\frac{1}{4} E \left( (f(x) - g(x))^2 \right)$$

$$= \frac{1}{4} E \left( f(x)^2 + g(x)^2 - 2f(x)g(x) \right)$$

$$= \frac{1}{4} + \frac{1}{4} - \frac{1}{2} E(f(x)g(x)) \quad \text{since } E(f(x)^2) = 1$$

$$= \frac{1}{2} - \frac{1}{2} \langle f, g \rangle \quad \text{since } \langle f, g \rangle = E(f(x)g(x))$$

$$= \frac{1}{2} \langle f, f \rangle - \frac{1}{2} \langle f, g \rangle \quad \text{since } 1 = E(f(x)^2) = \langle f, f \rangle$$

$$= \frac{1}{2} \sum_{s \in [n]} \hat{f}(s)^2 - \frac{1}{2} \sum_{s \in [n]} \hat{f}(s) \hat{g}(s) \quad \text{by Parseval's}$$

$$= \frac{1}{2} \sum_{s \neq i} \hat{f}(s)^2 + \frac{1}{2} \sum_{s \ni i} \hat{f}(s)^2 - \frac{1}{2} \sum_{s \neq i} \hat{f}(s) \hat{g}(s) - \frac{1}{2} \sum_{s \ni i} \hat{f}(s) \hat{g}(s)$$

Note that if  $i \notin s$ ,  $\hat{f}(s) = \hat{g}(s)$  and if  $i \in s$ ,  $\hat{f}(s) = -\hat{g}(s)$ .

This is because  $g = f^{\oplus i}$ , meaning the Fourier expansion of  $g$  is exactly that of  $f$ , except with all  $(x_i)$ 's turned into  $(-x_i)$ 's. So:

$$= \frac{1}{2} \sum_{s \neq i} \hat{f}(s)^2 + \frac{1}{2} \sum_{s \ni i} \hat{f}(s)^2 - \frac{1}{2} \sum_{s \neq i} \hat{f}(s)^2 + \frac{1}{2} \sum_{s \ni i} \hat{f}(s)^2$$

$$= \sum_{s \ni i} \hat{f}(s)^2.$$

## Influence examples

- Dictator function:  $f(x_1, x_2, x_3, \dots, x_n) = x_d$  for some  $d$

What is  $\text{Inf}_i[f]$  for  $i \neq d$ ? ...  $\Pr[f(x) \neq f(x^{\oplus i})]$

Since  $f(x) = x_d$ , this probability is 0.

Similarly,  $\text{Inf}_d[f] = 1$ , since  $f(x)$  always  $\neq f(x^{\oplus d})$ .

- Parity function:  $f(x_1, x_2, x_3, \dots, x_n) = \prod_i x_i$

What is  $\text{Inf}_i[f]$ ?

Changing bit  $i$  will always flip the value of  $f$ , so

$\text{Inf}(i) = 1$  for all  $i$ .

- Majority function:  $f(x_1, x_2, \dots, x_n) = \begin{cases} +1 & \text{if majority } x_i = +1 \\ -1 & \text{otherwise} \end{cases}$   
( $n$  is odd)

Changing bit  $i$  will flip the value of  $f$  only if the other bits are split evenly between  $\pm 1$ .

For a random  $x$ , this has probability  $\frac{\binom{n-1}{n/2}}{2^{n-1}}$ .

Stirling's formula:  $m! \sim \left(\frac{m}{e}\right)^m \sqrt{2\pi m}$

$$\Rightarrow \text{Inf}_i[f] \sim \frac{1}{2^{n-1}} \frac{\left(\frac{n-1}{e}\right)^{n-1} \sqrt{2\pi(n-1)}}{\left(\frac{n-1}{2e}\right)^{n-1} 2\pi \frac{n-1}{2}} = \frac{1}{2^{n-1}} 2^{n-1} \frac{\sqrt{2}}{\sqrt{\pi} \sqrt{n-1}}$$

$$= O\left(\frac{1}{\sqrt{n}}\right)$$

Noise Stability: "Probability that noise in the bits affects the output of the function"

Formally: Let  $p \in [-1, 1]$ . For input  $x \in \{-1, 1\}^n$ , let  $y$  be a string drawn such that:

$$y_i = \begin{cases} x_i & \text{with probability } \frac{1}{2} + \frac{1}{2}p \\ -x_i & \text{with probability } \frac{1}{2} - \frac{1}{2}p \end{cases}$$

We say that  $y$  is  $p$ -correlated to  $x$ .

The noise stability of  $f$  at  $p$  is:

$$\begin{aligned} \text{Stab}_p[f] &= E_{\substack{(x,y) \\ p\text{-correlated}}} [f(x) f(y)] = 2 \cdot \Pr[f(x) = f(y)] - 1 \\ &= 1 - 2 \cdot \Pr[f(x) \neq f(y)] \end{aligned}$$

• Dictator function:  $f(x_1, x_2, \dots, x_n) = x_i$  for some  $i$

$f(y) \neq f(x)$  only if  $y_i \neq x_i$ , since no other  $y_j$  matters.  $\Pr[y_i \neq x_i] = (\frac{1}{2} - \frac{1}{2}p)$

$$\Rightarrow \text{Stab}_p[f] = 1 - 2(\frac{1}{2} - \frac{1}{2}p) = p$$

• Majority function: harder!

$$\text{Stab}_p[\text{Maj}_n] = E[\text{Maj}_n x \cdot \text{Maj}_n y]$$

$$= E\left[\text{sign}\left(\sum \frac{1}{\sqrt{n}} x_i\right) \cdot \text{sign}\left(\sum \frac{1}{\sqrt{n}} y_i\right)\right]$$

$$= 1 - 2 \cdot \Pr\left[\text{sign}\left(\sum \frac{1}{\sqrt{n}} x_i\right) \neq \text{sign}\left(\sum \frac{1}{\sqrt{n}} y_i\right)\right]$$

For  $n \rightarrow \infty$ ,  $\sum \frac{1}{\sqrt{n}} x_i \rightarrow g_1$ , and  $\sum \frac{1}{\sqrt{n}} y_i \rightarrow g_2$   
 where  $g_1, g_2$  are  $\rho$ -correlated Gaussians.

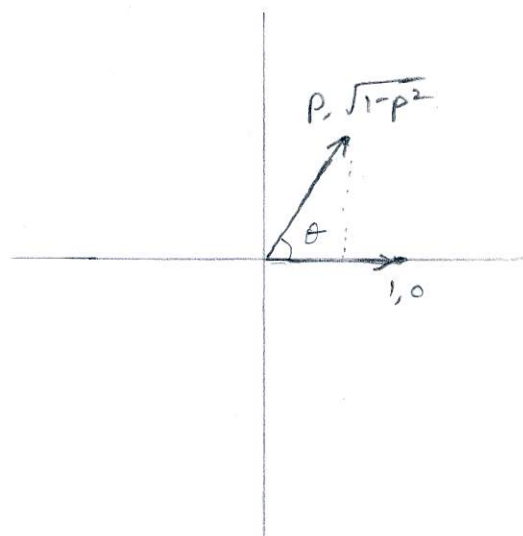
$$\begin{pmatrix} g_1 \\ g_2 \end{pmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) \quad (\text{mean, cov. matrix})$$

i.e.  $E[g_1] = E[g_2] = 0$ ,  $E[g_1^2] = E[g_2^2] = 1$ ,  
 and  $E[g_1 g_2] = \rho$

This is equivalent to  $g_1 = z_1$ ,  $g_2 = \rho z_1 + \sqrt{1-\rho^2} z_2$   
 for independent  $z_1, z_2 \sim N(0, 1)$ . You can verify  
 that all expected values check out!

So  $g_1 = (1, 0) \cdot (z_1, z_2)$  and  $g_2 = (\rho, \sqrt{1-\rho^2}) \cdot (z_1, z_2)$ .

$g_1$  and  $g_2$  will have opposite signs  
 iff the normal vector to  $(z_1, z_2)$   
 cuts through the angle  $\theta$ .



The angle of  $(z_1, z_2)$  is uniformly  
 random, and  $\theta$  here equals  
 $\arccos(\rho)$ , so the probability is

$\frac{1}{\pi} \arccos(\rho)$ . This gives us:

$$\begin{aligned} \text{Stab}_\rho[\text{Maj}_n] &= 1 - \frac{2}{\pi} \arccos \rho \\ &= \frac{2}{\pi} \arcsin \rho \end{aligned}$$

Majority is Stablest: For  $0 < p < 1$  and  
 $f: \{-1, 1\}^n \rightarrow \{-1, 1\}$ , if:

1.  $E[f(x)] = 0$  for random  $x$ , and
2.  $\text{Inf}_i[f] \leq \epsilon$  for any  $i \in [n]$ , then

$$\text{Stab}_p[f] \leq \frac{2}{\pi} \arcsin(p) + O\left(\frac{\log \log \frac{1}{\epsilon}}{\log \epsilon}\right)$$

So  $\text{Maj}_p[f]$  is the 'stablest' function!

Note that conditions 1) and 2) are necessary.

- If 1) is taken away, the constant function  $f(x) = 1$  gives trivial 1 stability.
- If 2) is taken away, the dictator function  $f(x) = x_i$  gives easy  $p$  stability.