

## Probabilistically checkable proofs (II): the BLR linearity test

The previous lecture introduced probabilistically checkable proofs (PCPs) and explained why the PCP theorem has strong consequences for hardness of approximation. A recurring technical theme in PCP constructions is that the verifier wants to check that a long proof string behaves like a codeword of some error-correcting code. This motivates the study of *property testing* problems in which the verifier has oracle access to a function and must distinguish the case that the function has a desired algebraic structure from the case that it is “far” from every structured function.

This lecture focuses on the simplest and most fundamental example: testing whether a Boolean function is linear over  $\mathbb{F}_2$ . This is exactly the consistency check needed for the Hadamard code. We present the celebrated Blum–Luby–Rubinfeld (BLR) *linearity test* and give two soundness proofs. The first uses Fourier analysis on  $\{0, 1\}^n$  and explains the test in terms of the Fourier spectrum. The second is a combinatorial “majority decoding” argument that also hints at the local self-correction property of the Hadamard code.

### 7.1 The BLR linearity test

We view  $\{0, 1\}^n$  as the vector space  $\mathbb{F}_2^n$ . Throughout, addition  $x + y$  denotes bitwise XOR.

**DEFINITION 7.1** (linear functions). A function  $\ell : \{0, 1\}^n \rightarrow \{0, 1\}$  is *linear* if  $\ell(0) = 0$  and  $\ell(x) + \ell(y) = \ell(x + y)$  for all  $x, y \in \{0, 1\}^n$ , where addition on the right-hand side is in  $\mathbb{F}_2$ . Equivalently, there exists  $a \in \{0, 1\}^n$  such that  $\ell(x) = \langle a, x \rangle \pmod{2}$ , where  $\langle a, x \rangle = \sum_i a_i x_i$  is the  $\mathbb{F}_2$  inner product.

**DEFINITION 7.2** (distance and “far”). For functions  $f, g : \{0, 1\}^n \rightarrow \{0, 1\}$ , define the (relative) Hamming distance

$$\Delta(f, g) := \Pr_{x \in \{0, 1\}^n} [f(x) \neq g(x)].$$

Let  $\text{LIN}$  denote the set of linear functions  $\{0, 1\}^n \rightarrow \{0, 1\}$ . We say that  $f$  is  $\varepsilon$ -far from linear if  $\Delta(f, \text{LIN}) := \min_{\ell \in \text{LIN}} \Delta(f, \ell) \geq \varepsilon$ .

DEFINITION 7.3 (BLR test). Given oracle access to  $f : \{0, 1\}^n \rightarrow \{0, 1\}$ , the *BLR linearity test* is:

1. Sample  $x, y \in \{0, 1\}^n$  independently and uniformly at random.
2. Query  $f(x), f(y), f(x + y)$ .
3. **Accept** iff  $f(x) + f(y) = f(x + y)$  in  $\mathbb{F}_2$ .

If  $f$  is linear, the test always accepts (perfect completeness). The main content is soundness: if  $f$  is far from linear, then the test rejects with noticeable probability.

THEOREM 7.4 (BLR soundness). *If  $f$  is  $\varepsilon$ -far from linear, then the BLR test rejects with probability  $\Omega(\varepsilon)$ . Equivalently, if the BLR test accepts with probability at least  $1 - \varepsilon$ , then there exists a linear function  $\ell$  with  $\Delta(f, \ell) \leq \varepsilon$ .*

We next prove this theorem in two different ways.

## 7.2 Fourier analysis preliminaries

For Fourier analysis it is convenient to work with  $\{\pm 1\}$ -valued functions. Given  $f : \{0, 1\}^n \rightarrow \{0, 1\}$ , define its  $\pm 1$  encoding by

$$F(x) := (-1)^{f(x)} \in \{\pm 1\}.$$

Under this encoding, the BLR acceptance condition  $f(x) + f(y) = f(x + y)$  becomes  $F(x)F(y) = F(x + y)$ , or equivalently  $F(x)F(y)F(x + y) = 1$ .

For each subset  $S \subseteq [n]$ , define the Fourier character

$$\chi_S(x) := (-1)^{\sum_{i \in S} x_i} = \prod_{i \in S} (-1)^{x_i}.$$

If we identify  $S$  with its indicator vector  $a \in \{0, 1\}^n$ , this is also  $\chi_S(x) = (-1)^{\langle a, x \rangle}$ .

DEFINITION 7.5 (Fourier coefficients). For a function  $h : \{0, 1\}^n \rightarrow \mathbb{R}$ , its Fourier coefficient at  $S$  is

$$\widehat{h}(S) := 2^{-n} \sum_{x \in \{0, 1\}^n} h(x) \chi_S(x).$$

The collection  $\{\widehat{h}(S)\}_{S \subseteq [n]}$  is the *Fourier spectrum*.

PROPOSITION 7.6 (basic Fourier facts). *Let  $\langle f, g \rangle := \sum_{x \in \{0, 1\}^n} f(x)g(x)$  denote the unnormalized inner product. Then:*

1. **Orthogonality:**  $\langle \chi_S, \chi_T \rangle = 0$  for  $S \neq T$ , and  $\langle \chi_S, \chi_S \rangle = 2^n$ .
2. **Coefficient formula:**  $\widehat{h}(S) = 2^{-n} \langle \chi_S, h \rangle$ .
3. **Parseval/Plancherel:**  $2^{-n} \langle f, g \rangle = \sum_{S \subseteq [n]} \widehat{f}(S) \widehat{g}(S)$ . In particular, if  $f : \{0, 1\}^n \rightarrow \{\pm 1\}$  then  $\sum_S \widehat{f}(S)^2 = 1$ .

EXAMPLE 7.7 (Fourier expansion of a simple Boolean function). Consider the OR function on  $\{\pm 1\}^n$  defined by  $\text{OR}(\tilde{x}) = 1$  iff  $\tilde{x} = 1^n$  and  $\text{OR}(\tilde{x}) = -1$  otherwise. As a polynomial over the reals,

$$\text{OR}(\tilde{x}) = 2 \prod_{i=1}^n \frac{1 + \tilde{x}_i}{2} - 1 = 1 + \sum_{\emptyset \neq S \subseteq [n]} 2^{1-|S|} \prod_{i \in S} \tilde{x}_i.$$

If  $\tilde{x}_i = (-1)^{x_i}$  for  $x \in \{0, 1\}^n$ , then  $\prod_{i \in S} \tilde{x}_i = \chi_S(x)$ . So this is exactly a Fourier expansion.

Fourier analysis makes linear functions easy to recognize. If  $\ell(x) = \langle a, x \rangle + b \pmod{2}$  is an affine function, then its  $\pm 1$  encoding is  $L(x) = (-1)^{\langle a, x \rangle + b}$ . The next calculation (from the notes) shows that its Fourier spectrum is supported on a single character.

FACT 7.8 (Fourier spectrum of a linear/affine function). *Let  $L(x) = (-1)^{\langle a, x \rangle + b}$ . Let  $S \subseteq [n]$  be the set corresponding to  $a$ . Then  $\widehat{L}(S) = (-1)^b$  and  $\widehat{L}(T) = 0$  for all  $T \neq S$ .*

*Proof.* Using the coefficient formula,

$$\widehat{L}(S) = 2^{-n} \sum_x (-1)^{\langle a, x \rangle + b} \chi_S(x) = 2^{-n} \sum_x (-1)^{\langle a, x \rangle + b} (-1)^{\langle a, x \rangle} = 2^{-n} \sum_x (-1)^b = (-1)^b.$$

For  $T \neq S$ , orthogonality gives  $\widehat{L}(T) = 2^{-n} \langle L, \chi_T \rangle = 2^{-n} (-1)^b \langle \chi_S, \chi_T \rangle = 0$ .  $\square$

### 7.3 Fourier-analytic proof of BLR

Fix  $F : \{0, 1\}^n \rightarrow \{\pm 1\}$ . Suppose the BLR test accepts with probability at least  $1 - \varepsilon$ , i.e.

$$\Pr_{x,y}[F(x)F(y) = F(x+y)] \geq 1 - \varepsilon.$$

Equivalently,

$$\Pr_{x,y}[F(x)F(y)F(x+y) = 1] \geq 1 - \varepsilon.$$

Since the random variable  $F(x)F(y)F(x+y)$  takes values in  $\{\pm 1\}$ , the above implies

$$\mathbb{E}_{x,y}[F(x)F(y)F(x+y)] \geq 1 - 2\varepsilon. \tag{7.1}$$

Define the (normalized) convolution of two functions  $g, f : \{0, 1\}^n \rightarrow \mathbb{R}$  by

$$(g * f)(x) := \mathbb{E}_{y \in \{0,1\}^n} [g(y)f(x+y)].$$

Then the left-hand side of (7.1) can be rewritten as

$$\mathbb{E}_x [F(x) \mathbb{E}_y [F(y)F(x+y)]] = \mathbb{E}_x [F(x) (F * F)(x)].$$

FACT 7.9 (Fourier of convolution). *For all  $g, f$  and all  $S \subseteq [n]$ ,  $\widehat{g * f}(S) = \widehat{g}(S) \widehat{f}(S)$ .*

*Proof from the notes.* Expand  $g$  and  $f$  in the Fourier basis:  $g(y) = \sum_S \widehat{g}(S) \chi_S(y)$  and  $f(x+y) = \sum_T \widehat{f}(T) \chi_T(x+y)$ . Using  $\chi_T(x+y) = \chi_T(x) \chi_T(y)$ , we obtain

$$\begin{aligned} (g * f)(x) &= \mathbb{E}_y \left[ \sum_S \widehat{g}(S) \chi_S(y) \sum_T \widehat{f}(T) \chi_T(x) \chi_T(y) \right] \\ &= \sum_{S,T} \widehat{g}(S) \widehat{f}(T) \chi_T(x) \mathbb{E}_y [\chi_{S \Delta T}(y)]. \end{aligned}$$

The expectation  $\mathbb{E}_y [\chi_{S \Delta T}(y)]$  equals 0 unless  $S = T$ , in which case it equals 1. Hence  $(g * f)(x) = \sum_S \widehat{g}(S) \widehat{f}(S) \chi_S(x)$ , so  $\widehat{g * f}(S) = \widehat{g}(S) \widehat{f}(S)$ .  $\square$

Apply Parseval with  $f = F$  and  $g = F * F$ :

$$\mathbb{E}_x [F(x)(F * F)(x)] = \sum_S \widehat{F}(S) \widehat{F * F}(S) = \sum_S \widehat{F}(S)^3,$$

where the last equality uses the convolution fact with  $g = f = F$ . Combining with (7.1),

$$\sum_{S \subseteq [n]} \widehat{F}(S)^3 \geq 1 - 2\varepsilon. \quad (7.2)$$

Since  $\sum_S \widehat{F}(S)^2 = 1$ , we can upper bound the left-hand side of (7.2) by

$$\sum_S \widehat{F}(S)^3 \leq \left( \max_T \widehat{F}(T) \right) \sum_S \widehat{F}(S)^2 = \max_T \widehat{F}(T).$$

Therefore there exists  $S^*$  such that  $\widehat{F}(S^*) \geq 1 - 2\varepsilon$ .

Finally, note that  $\widehat{F}(S) = \mathbb{E}_x [F(x) \chi_S(x)]$ . If  $F$  and  $\chi_{S^*}$  are  $\pm 1$ -valued, then

$$\Pr_x [F(x) = \chi_{S^*}(x)] = \frac{1 + \mathbb{E}_x [F(x) \chi_{S^*}(x)]}{2} = \frac{1 + \widehat{F}(S^*)}{2} \geq 1 - \varepsilon.$$

Thus  $F$  agrees with a character on all but an  $\varepsilon$  fraction of inputs. Translating back to  $\{0, 1\}$ -valued functions,  $f$  is  $\varepsilon$ -close to the corresponding linear function. This proves BLR soundness.

## 7.4 Combinatorial proof and majority decoding

We now sketch the combinatorial proof from the notes. Here it is more convenient to use  $\{0, 1\}$ -valued functions and write all additions in  $\mathbb{F}_2$ . Assume the BLR test accepts  $f$  with probability  $1 - \varepsilon$ , i.e.  $\Pr_{x,y} [f(x) + f(y) = f(x+y)] = 1 - \varepsilon$ .

Define a new function  $g : \{0, 1\}^n \rightarrow \{0, 1\}$  by *majority decoding*: for each  $x$ , let  $g(x)$  be the plurality value of  $f(y) + f(y+x)$  over random  $y$ . Equivalently,

$$g(x) \in \arg \max_{v \in \{0,1\}} |\{y \in \{0,1\}^n : f(y) + f(y+x) = v\}|.$$

CLAIM 7.10.  $\Pr[\text{BLR rejects } f] \geq \frac{1}{2} \Delta(f, g)$ .

*Proof.* Fix  $x$ . The BLR test (with this  $x$ ) accepts iff  $f(y) + f(x+y) = f(x)$ . If  $f(x) \neq g(x)$ , then by definition of  $g(x)$  the event  $f(y) + f(x+y) = g(x)$  occurs with probability at least  $1/2$  over random  $y$ . On that event, the test must reject because  $g(x) \neq f(x)$ . Therefore

$$\Pr[\text{reject}] \geq \Pr_x[f(x) \neq g(x)] \cdot \frac{1}{2} = \frac{1}{2} \Delta(f, g).$$

□

The next claim says that for any fixed direction  $x$ , the “derivative”  $f(y) + f(y+x)$  is usually consistent across different base points  $y$ .

CLAIM 7.11. *For every fixed  $x \in \{0, 1\}^n$ ,*

$$\Pr_{y,z}[f(y) + f(y+x) = f(z) + f(z+x)] \geq 1 - 2\varepsilon.$$

*Proof from the notes.* Fix  $x$ . Define the set  $T$  of pairs  $(y, z)$  such that both of the following BLR constraints hold:

$$f(y) + f(y+z) = f(z), \quad f(x+y) + f(y+z) = f(x+z).$$

Each displayed equality is of the BLR form  $f(a)+f(b) = f(a+b)$  for a uniformly random pair  $(a, b)$ : namely  $(a, b) = (y, y+z)$  in the first and  $(a, b) = (x+y, y+z)$  in the second. Therefore each fails with probability at most  $\varepsilon$ , and by the union bound  $\Pr_{y,z}[(y, z) \in T] \geq 1 - 2\varepsilon$ .

If  $(y, z) \in T$ , then adding the two equalities gives

$$f(y) + f(x+y) = f(z) + f(x+z),$$

which is exactly the desired conclusion. □

Now fix  $x$  and write  $p := \Pr_y[f(y) + f(y+x) = g(x)]$ . By definition of majority,  $p \geq 1/2$ . Since the quantity  $f(y) + f(y+x)$  is a single bit, we have

$$\Pr_{y,z}[f(y) + f(y+x) = f(z) + f(z+x)] = p^2 + (1-p)^2.$$

Combining with the previous claim yields  $p^2 + (1-p)^2 \geq 1 - 2\varepsilon$ . Rearranging gives  $p(1-p) \leq \varepsilon$ . Since  $p \geq 1/2$ , this implies  $1-p \leq 2\varepsilon$ , i.e.

$$\Pr_y[f(y) + f(y+x) = g(x)] \geq 1 - 2\varepsilon \quad \text{for all } x. \quad (7.3)$$

CLAIM 7.12. *If  $\varepsilon < \frac{1}{8}$ , then  $g$  is linear.*

*Proof from the notes.* Fix  $x, z \in \{0, 1\}^n$ . Consider the following three events over a random  $y$ :

$$\begin{aligned} f(y) + f(y+x) &= g(x), \\ f(y) + f(y+z) &= g(z), \\ f(y+x) + f(y+z) &= g(x+z). \end{aligned}$$

Each event has probability at least  $1 - 2\varepsilon$  by (7.3) (the third event is (7.3) for shift  $x+z$  and base point  $y' = y+x$ , which is uniform when  $y$  is). By the union bound, all three events

hold simultaneously with probability at least  $1 - 6\varepsilon$ . If  $\varepsilon < 1/6$ , there exists a  $y$  for which all three equalities hold. Adding them in  $\mathbb{F}_2$  cancels all  $f(\cdot)$  terms (each appears twice), leaving  $g(x) + g(z) + g(x + z) = 0$ , i.e.  $g(x) + g(z) = g(x + z)$ . Since this holds for all  $x, z$ ,  $g$  is linear.  $\square$

Combining linearity of  $g$  with the first claim gives a distance bound. If the BLR test rejects with probability  $\varepsilon$ , then  $\Delta(f, g) \leq 2\varepsilon$ , and (for  $\varepsilon < 1/6$ ) this shows that  $f$  is  $O(\varepsilon)$ -close to a linear function. Taking contrapositives yields the BLR soundness statement.