

# Lecture 4

## Linearity Testing

**Definition 1.** (BLR Test<sup>1</sup>) Want to test if  $f : \mathbb{F}_2^n \rightarrow \mathbb{F}_2$  is close to linear. Pick  $x, y \in \mathbb{F}_2^n$  u.a.r. Check whether  $f(x + y) = f(x) + f(y)$ .

**Theorem 1.** For all functions  $f$ , there exists a linear function  $g$  such that  $\text{dist}(f, g) := \Pr_n[f(n) \neq g(n)] \leq \frac{9}{2} \Pr[\text{BLR rejects } f]$ .<sup>2</sup>

**$\mathbb{F}_2$  Facts:**

1.  $+1 = -1 \pmod{2} \implies x + y = x - y, x + y + y = x$ .
2. Fix  $x \in \mathbb{F}_2^n$ .  $y \sim \mathbb{F}_2^n$  u.a.r.  $\implies x + y \sim \mathbb{F}_2^n$  u.a.r.
3. Fix  $v \neq 0$ .  $\Pr_x[\langle v, x \rangle \neq 0] = \frac{1}{2}$ .

Let  $g(x) := \text{Maj}_{z \in \mathbb{F}_2^n}(f(x + z) - f(z))$ . Recall that if  $f$  is linear, then  $f(x) = f(x + z) - f(z)$ . Intuitively, if only a few places in  $f$  are not linear, then most majority votes for  $g$  will be heavily lopsided.

**Claim 2.**  $g$  is a linear function if  $\delta := \Pr[\text{BLR rejects } f]$  is small ( $\leq \frac{1}{20}$ ).

**Claim 3.**  $\text{dist}(f, g) := \Pr_n[f(n) \neq g(n)] \leq 2\delta$ .

Combining Claims 2 and 3 yields proof for Theorem 1 for small  $\delta$ .

Let  $P_x := \Pr_y[g(x) = f(x + y) - f(y)]$ , i.e. how lopsided the majority vote for  $g$  is on the input  $x$ . Observe that  $P_x \geq \frac{1}{2}$  since it is always the winning majority of two candidates.

**Claim 4** ("Surprising" Claim).  $\forall x, P_x \geq 1 - 2\delta$ .

This is surprising since the BLR test, a "global" estimate of  $f$ 's linearity, gives a tight bound on the "local" exactness of  $g(x)$ .

*Proof.* Let event  $A(y, z) := \mathbb{1}\{f(x + y) - f(y) = f(x + z) - f(z)\}$ . Consider  $\Pr_{y, z}[A(y, z)]$  for a fixed  $x$ . WLOG, assume  $g(x) = 0$ .  $f(x + y) - f(y)$  and  $f(x + z) - f(z)$  are each bits with bias  $P_x$ . Then,  $\Pr[A] = P_x P_x + (1 - P_x)(1 - P_x) = P_x^2 + (1 - P_x)^2$ .

<sup>1</sup> M. Blum, M. Luby, and R. Rubinfeld. Self-testing/correcting with applications to numerical problems. In *Proceedings of the Twenty-Second Annual ACM Symposium on Theory of Computing*, STOC '90, page 73–83, New York, NY, USA, 1990. Association for Computing Machinery

<sup>2</sup>  $\frac{9}{2}$  can be eliminated by a different proof technique (Fourier Analysis).

Now, consider a different form of event  $A$ :  $f(x + y) + f(x + z) = f(y) + f(z)$  (by  $\mathbb{F}_2$  Fact #1, we can ignore  $\pm$ ). By using the BLR test, we can conclude that:

$$f(y) + f(z) = f(y + z) \text{ w.p. } (1 - \delta),$$

$$f(x + y) + f(x + z) = f(x + y + x + z) = f(y + z) \text{ w.p. } (1 - \delta).$$

Then, by a naive union bound of both sides evaluating to  $f(y + z)$ ,  $\Pr[A] \geq 1 - 2\delta$ . Substituting the previous result:

$$\begin{aligned} P_x^2 + (1 - P_x)^2 &\geq 1 - 2\delta \\ \implies 1 + 2P_x^2 - 2P_x &\geq 1 - 2\delta \\ \implies \delta &\geq P_x(1 - P_x) \geq \frac{1}{2}(1 - P_x) \\ \implies P_x &\geq 1 - 2\delta \end{aligned}$$

where the inequality in the third line holds due to  $P_x \geq \frac{1}{2}$ .  $\square$

Now, we are equipped to prove Claims 2 and 3.

*Proof.* (Claim 2) Our goal is to prove that  $g(x) + g(y) = g(x + y) \forall x, y$ . To do so, we first construct a "magic square" that relates

$$\begin{array}{rclcl} g(x) & = & f(x + z) & - & f(z) \\ + & & + & & + \\ g(y) & = & f(y + w) & - & f(w) \\ = & & = & & = \\ g(x + y) & = & f(x + y + z + w) & - & f(z + w) \end{array}$$

Table 1: "Magic Square"

functions  $f$  and  $g$ , as in Table . The key observation is that if all five red equalities hold, then the blue equality must also hold.

Due to the "Surprising" Claim 4, the following three equations:

$$g(x) = f(x + z) - f(z),$$

$$g(y) = f(y + w) - f(w),$$

$$g(x + y) = f(x + y + z + w) - f(z + w)$$

are satisfied with probability at least  $1 - 2\delta$ . The other two equations:

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

$$f(z) + f(w) = f(z + w)$$

are satisfied with probability at least  $1 - \delta$  due to the BLR test.

By taking a naive union bound, the probability that all are satisfied at the same time is at least  $1 - 8\delta$ . This gives the boundary condition to have a nonzero probability of satisfying  $g(x) + g(y) = g(x + y)$

be  $1 - 8\delta > 0 \implies \delta < \frac{1}{8}$ , which is always satisfied by a small  $\delta$  specified in the claim, say  $< \frac{1}{20}$ . If so, we can find  $z, w$  such that all equations are satisfied, which suffice to be witnesses to prove that  $g(x) + g(y) = g(x + y)$ .<sup>3</sup> Since this scheme is not dependent on the choice of  $x$  and  $y$ , we can generalize it  $\forall x, y$ .  $\square$

<sup>3</sup> A probabilistic method for existence.

*Proof.* (Claim 3) By the BLR test,

$$Pr_{x,y}[f(x) \neq f(x+y) - f(y)] = Pr_{x,y}[f(x) \neq f(x+y) - f(y)] = \delta.$$

Let  $BAD := \{x \mid f(x) \neq g(x)\}$ , the set of inputs that  $f$  and  $g$  disagree on. Then,  $Pr_y[f(x) \neq f(x+y) - f(y) \mid x \in BAD] \geq \frac{1}{2}$  since if  $x$  is in  $BAD$ ,  $f(x)$  must disagree with at least half of  $f(x+y) - f(y)$ .<sup>4</sup> Thus, the following inequality can be established:

<sup>4</sup> else,  $f(x)$  would have agreed with the majority and thus agreed with  $g(x)$ .

$$\begin{aligned} \delta &= Pr_{x,y}[f(x) \neq f(x+y) - f(y)] \\ &\geq Pr_{x,y}[f(x) \neq f(x+y) - f(y) \mid x \in BAD] \cdot Pr_x[x \in BAD] \\ &\geq \frac{1}{2} Pr_x[x \in BAD] \end{aligned}$$

where the first inequality is one partition of the probability space of  $x$  and the second inequality is due to the observation above.

It is easy to see from the first and last terms that  $dist(f, g) := Pr_x[f(x) \neq g(x)] = Pr_x[x \in BAD] \leq 2\delta$ .  $\square$

## Exponential PCP with Linearity Testing

**Recap:** The exponential-sized PCP testing is modeled with *QUADEQ*, where a solution  $l \in \mathbb{F}_2^n$  satisfies the system of quadratic equations:  $\{q_i(l) = 0 \mid i = 1 \dots m\}$ . The prover submits a proof in the form of:

- Hadamard encoding of  $l$  that admits a vector  $x$ ,  
 $\tilde{L}(x) := \langle l, x \rangle$ .
- Hadamard encoding of  $H := ll^\top$  that admits a matrix  $C$ ,  
 $\tilde{H}(C) := \sum_{i,j} C_{i,j} l_i l_j$ .

where  $\tilde{L}$  and  $\tilde{H}$  represent potentially false (nonlinear) proofs.

The process is largely split into four steps:

1. Test whether  $\tilde{L}$  is  $\epsilon$ -close to linear. If so, gain access to  $L$ .
2. Test whether  $\tilde{L}$  is  $\epsilon$ -close to linear. If so, gain access to  $H$ .
3. Test whether  $H$  and  $L$  agree.
4. Test a random sample of the constraints with  $H$  and  $L$ .

Steps 1 and 2 are done through BLR and reject with probability  $\Omega(\epsilon)$ . If  $\tilde{L}$  and  $\tilde{H}$  pass the BLR test, then we can safely assume that there exists a truly linear function  $L$  and  $H$  that we can access by self-correction with success probability  $\geq 1 - 2\epsilon$ . For step 3, we test whether  $H(xy^\top) = L(x) \cdot L(y)$  for a randomly sampled  $x, y \in \mathbb{F}_2^n$ . To analyze this step, we introduce another piece of useful  $\mathbb{F}_2$  fact.

**Another  $\mathbb{F}_2$  Fact:**

$$4. \forall M \neq 0, \Pr_{x,y}[x^\top My = \sum_{i,j} M_{i,j} x_i y_j \neq 0] \geq \frac{1}{4}.$$

*Proof.*  $M \neq 0 \implies \exists M_i \neq \vec{0}$  where  $M_i$  is a row of  $M$ . Since  $\forall M_i \neq \vec{0}$ ,  $\Pr_y[\langle M_i, y \rangle \neq 0] = \frac{1}{2}$ ,  $My \neq \vec{0}$  w.p.  $\geq \frac{1}{2}$ . Then,  $\Pr_x[\langle x, My \rangle \neq 0] \geq \Pr_{x,y}[\langle x, My \rangle \neq 0 \mid My \neq \vec{0}] \cdot \Pr_y[My \neq \vec{0}] \geq \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{4}$ .  $\square$

Now, we can manipulate the testing equation in step 3 in the following way:

$$H(xy^\top) - L(x) \cdot L(y) = x^\top Hy - x^\top l \cdot l^\top y = x^\top (H - ll^\top) y = 0.$$

If  $H - ll^\top$  indeed equals 0, then this test will always succeed. However, if not, by  $\mathbb{F}_2$  Fact #4,  $\Pr_{x,y}[x^\top (H - ll^\top) y \neq 0] \geq \frac{1}{4}$ . Thus, we can reject an inconsistent proof w.p.  $\geq \frac{1}{4}$ .

Finally, for step 4, we take a random linear combination of constraints  $\{q_i\}$  and expect it to equal 0. This can just be written as some  $\sum_{i,j} A_{i,j} l_i l_j + \sum_i b_i l_i + c = H(A) + L(b) + c = 0$ . If any of  $q_i(l) \neq 0$ , then w.p.  $\frac{1}{2}$ ,  $\Pr_l[\sum_i r_i q_i(l) \neq 0] \geq \frac{1}{2}$ .

**Remarks on Soundness Boosting:** For linearity testing, we can actually sample  $x, y \in \mathbb{F}_2^n$  multiple times to increase the chance of spotting inconsistent  $\tilde{L}$  and  $\tilde{H}$  early on. Say we sample  $x, y$   $t$  times, a total of  $6t$  bits. If  $f$  is  $\epsilon$ -far from linear,  $\Pr[\text{success}] \leq (1 - \epsilon)^t$ . In general, for  $t$  bits, the best possible soundness is  $O(\frac{1}{2^t})$ .

**Soundness of PCP:**

**Claim 5.** A PCP that reads  $t$  bits accepts a wrong proof w.p.  $O(\frac{2^t}{2^t})$ .

Rather than a proof, a sketch of the justification is as follows. Let  $S(\epsilon)$  be the statement that  $NP \subseteq PCP(t, \text{poly}(n), \epsilon)$ . This is equivalent to saying that there exists a CSP with constraints on  $t$  bits such that it is NP-Hard to approximate better than a  $\epsilon$ -factor. Also, for  $\epsilon = \frac{2^t}{2^t}$ , if  $S(\epsilon)$  is true, then for all CSPs with constraint on  $t$  bits, there exists a  $\frac{2^t}{2^t}$ -factor approximation algorithm.

## *Bibliography*

- [BLR90] M. Blum, M. Luby, and R. Rubinfeld. Self-testing/correcting with applications to numerical problems. In *Proceedings of the Twenty-Second Annual ACM Symposium on Theory of Computing*, STOC '90, page 73–83, New York, NY, USA, 1990. Association for Computing Machinery.