

Polynomials and Combinatorial Definitions of Languages

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Abstract

Using polynomials to represent languages and Boolean functions has opened up a new vein of mathematical insight into fundamental problems of computational complexity theory. Many notable advances in the past ten years have been obtained by working directly with these polynomials. This chapter surveys important results and open problems in this area, with special attention to low-level circuit classes and to the issues of “strong” vs. “weak” representations raised by Barrington, Smolensky, and others. Other combinatorial representations for languages besides polynomials are worthy of attention, and a new example characterizing parity-of-(ands-of)-threshold circuits is presented in the last section.

1 Introduction

Turing machines and complexity measures are great for *defining* classes of languages, but many researchers are finding that they are not so hot for *analyzing* these classes, especially for lower bounds. As formal tools they mostly stand by themselves; they do not build on or easily link to the great progression of mathematical concepts and tools. Turing machines are unstructured; their work environment is a *tabula rasa*; their computational process is not known to have anything like the overt properties and hooks for analysis of other mathematical processes. Even chaos is structured. These remarks apply to other general machine models, and in large part to Boolean circuits.

Machine-independent characterizations of complexity classes seek to answer these concerns. A prominent main line of research has been “capturing” these classes by systems of first and second-order logic. The chapter by Barrington and Immerman in this volume covers some of this, and some recent successes in lower and upper bounds

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may be found in [AF90, FSV93, Sch94]. Here we try to characterize languages and complexity notions for entities that have been studied for a long time.

Polynomials over various rings and fields have had notable advances over the past ten years. The main idea of polynomials is that of *degree*, which in turn is a chief algebraic measure of complexity. The results covered here show how well it compares with other measures for the languages and functions represented. They had been used as early as 1968 by Minsky and Papert [Min68] on *perceptrons*, polynomials really erupted onto the scene in [Raz87], Smolensky¹ [Smo87], and Toda [Tod89, Tod90]. In this case, the polynomials not only captured the problem, but also provided algebraic techniques that solved the problems. A polynomial method [All89, AH90, Sze90, Sze93, Yao90, BT91, BT94, TBR91b, BRS95, Bar92, BBR92, BBR94, NS92, NS94] “polynomial method” and expanded its significance.

Although polynomials have deservedly gotten the most attention here, there are other combinatorial objects that combine issues of complexity theory with areas of mathematics where more answers are known. Space allows us only to introduce one such notion with a more geometrical flavor that takes polynomials and thresholds one step further, and proving results.

This survey covers much of the same ground as the previous one, but with a different set of emphases. First, we emphasize the “strong” versus “weak” representations, and set up the effect of both the underlying ring or field and the underlying class of languages defined. Second, we try to build on this framework, continuing the foundations laid by polynomials, and tradeoffs in the theory of *error-correcting codes* in [Reg93]. Finally, we emphasize applications for the small classes of languages, and the geometrical notion in Section 8 to the whole. Some of this is from the author’s joint papers [GKR⁺95] and [NRS95], and some is new.

2 Polynomials

Multi-variable polynomials are perhaps the simplest objects that are capable of representing languages. Let R be a ring with operations $+, * : R \times R \rightarrow R$. Then any arithmetic

¹This author was greatly saddened by the news of Roman Smolensky’s death in 1995. He had been working on his study of Smolensky’s papers themselves, but I hope that this will encourage others to continue his work and contribute to the “problem of representations,” which Smolensky highlighted in his paper [Smo87]. It is a problem that will stay in memory and spur interest in the goals toward which he was working.

u_1, \dots, u_n ($n \geq 0$) and elements of R defines an n -variable polynomial p over R , written $p \in R[u_1, \dots, u_n]$. If $+$ is associative and commutative, has an identity $0 \in R$, and gives every element an additive inverse—and if $*$ is associative and distributes on both left and right over $+$, then $\mathcal{R} = (R, +, *)$ is a *ring*. If $*$ is also commutative and has an identity $1 \in R$, then \mathcal{R} is a *commutative ring with identity*, and further if every non-0 element has a multiplicative inverse, then \mathcal{R} is a *field*. The complex numbers \mathbf{C} , the real numbers \mathbf{R} , the rational numbers \mathbf{Q} , and the integers modulo q (denoted by \mathbf{Z}_q) for prime q are fields, but the integers \mathbf{Z} , and \mathbf{Z}_m for composite $m \geq 2$, are “merely” commutative rings with identity. For any $k \geq 1$ and prime q , the *Galois field* $\text{GF}(q^k)$ is defined with $R = (\mathbf{Z}_q)^k$ using vector addition and a $*$ operation whose definition does not concern us here; for more on all the above, see [Jac51]. Every finite field is isomorphic to some $\text{GF}(q^k)$. $\text{GF}(q)$ is the same as \mathbf{Z}_q , but for $k \geq 2$, $\text{GF}(q^k)$ should not be confused with \mathbf{Z}_{q^k} , which is not a field.

One perhaps counter-intuitive import of current research is that the more properties one adds to \mathcal{R} , the *weaker* the power of polynomials over \mathcal{R} to represent languages. Indeed, the most recent fundamental work has been on polynomials (and generalizations of polynomials) defined over structures weaker than rings—see [BT88, BST90, MPT91, Nis91, AJ93, MV94]. However, our reasons for emphasizing rings come out in Section 4. Unless otherwise specified, languages are defined over the alphabet $\{0, 1\}$.

Definition 1. Given $\mathcal{R} = (R, +, *)$, let e_0 and e_1 be fixed elements of R , and let S_1 and S_0 be nonempty disjoint subsets of R . A sequence of polynomials $\{p_n : n \geq 1\}$, with each $p_n \in R[u_1, \dots, u_n]$, is said to represent a language L with scheme (e_1, e_0, S_1, S_0) if for all n and $x \in \{0, 1\}^n$,

$$\begin{aligned} x \in L &\implies p_n(x) \in S_1, \\ x \notin L &\implies p_n(x) \in S_0. \end{aligned}$$

Here $p_n(x)$ is defined by substituting, for each i ($1 \leq i \leq n$), e_0 for u_i if x_i (i.e., the i th bit of x) is a 0, and e_1 for u_i if x_i is a 1.

This definition “promises” that for all x , $p_n(x) \in S_0 \cup S_1$. When $S_0 = R \setminus S_1$, no promise is needed, and every sequence $\{p_n\}$ represents a unique language. Given e_1 and e_0 , the negation of a Boolean variable u_i is expressed by $(e_1 + e_0 - u_i)$. By analogy with a *term* in a DNF Boolean formula, we call a product of factors of the form u_i or $(e_1 + e_0 - u_i)$ a *schematic term*.

The following “complexity measures” for polynomials spring to mind.

- (1) *Degree*: $\deg_p(n) =$ the degree of p_n .
- (2) *Size*: Here there are three main notions:
 - (2a) *Number of monomials*: $m_p(n) =$ the number of monomials when p_n is “multiplied out” via the distributive law.
 - (2b) *Number of schematic terms*: $s_p(n) =$ the minimum number of schematic terms needed to write p_n as a sum of schematic terms.

(2c) *Formula size*: $F_p(n) =$ the minimum number of terms in p_n .

(3) *Coefficient Size*: $C_p(n) =$ the maximum number of nonzero coefficients in p_n .

The coefficient size comes into play for the first two complexity measures. For formula size, we have a measure of the number of terms in p_n . Computing the other complexity measures besides formula size, for p_n , can present difficulties. Counting the monomials in p_n is straightforward since our given formulas are “multiplied out” via the distributive law, but minimum number-of-schematic-terms and minimum number-of-terms are not so easy. Even in seemingly favorable cases, such as where p_n is a Boolean formula, the number of nonzero values and all of them are given. (See [GJ79] for a survey of Boolean formulas, called MINIMUM EQUIVALENT DISJUNCTIVE NORMAL FORM, in [GJ79].)

In order to focus on these complexity measures, we will focus on functions themselves, with regard to various properties and dependence on representation scheme.

3 Representation Schemes and Complexity Measures

Nearly all the results in our references use one of the following representation schemes. Sign outputs are not applicable for the first two. Definitions (1) and (2) are adapted from Beigel’s survey [Bei93], and (3) follows the nomenclature in [Bar92, Smo93, BBR94].

Definition 2. Chief representation schemes for languages are:

- (1) Standard input, sign output: $e_0 = 0$, $e_1 = 1$, $S_0 = \{r \in R : r < 0\}$.
- (2) Fourier input, sign output: $e_0 = +1$, $e_1 = -1$, $S_0 = \{r \in R : r < 0\}$.
- (3) Strong representation: $e_0 = 0$, $e_1 = 1$, $S_1 = \{r \in R : r > 0\}$.
- (4) Standard nonzero representation: $e_0 = 0$, $e_1 = 1$, $S_0 = \{r \in R : r = 0\}$ (so zero stands for $x \notin L$, everything else for $x \in L$).
- (5) Weak representation: $e_0 = 0$, $e_1 = 1$, and $p_n(x) \in S_0$ for all $x \in R$. This is complementary to strong representation.
- (6) Truly weak representation: $e_0 = 0$, $e_1 = 1$, $p_n(x) \in S_0$ for all $x \in R$ and different n , and $S_0 = R \setminus S_1$.

With standard inputs as in (1), multiplication corresponds to logical AND, while with Fourier inputs as in (2), multiplication carries out XOR. Fourier inputs can also be used in place of standard inputs in (3)–(6). A major point of both these input schemes is that $x^2 = x$ holds in the former, $x^2 = 1$ in the latter. Hence the only polynomials we need to consider are *multilinear*, and the maximum degree involved is n .

The promise $p_n \neq 0$ in (1) and (2) is not important—one can meet it from the case $S_0 = R \setminus S_1$ by forming $2p_n(x) - 1$. It also makes no difference if we let a negative sign stand for true, positive for false. Hence (3) is the only one with a real promise condition, justifying Barrington’s name “strong representation” for it. Taking $a = 1$ in (5) makes it clear that *all* of the other output schemes are met by polynomials obeying (3). Smolensky [Smo93] identifies (4) with Barrington’s (5), but we prefer to think of (4) as loosely analogous to “NP,” (5) to “coNP,” and (3) to “P.” Truly weak representation is equivalent to saying that we have polynomials p_n such that for all $x, y \in \{0, 1\}^n$ with $x \in L$ and $y \notin L$, $p_n(x) \neq p_n(y)$. Note that no distinction between L and its complement is made in this condition.

Definition 3. Two representation schemes over a ring \mathcal{R} are equivalent if for every $\{p_n\}$ representing a language L using one scheme, there exist polynomials $\{q_n\}$ that represent L using the other scheme, such that $\deg_q(n) = O(\deg_p(n))$, $F_q(n) = O(F_p(n))$, and $C_q(n) = O(nC_p(n))$.

The condition on $C_q(n)$ is just strong enough to preserve polynomial coefficient size. Now we observe that all representation schemes over finite fields are equivalent to (3), and we use the basic idea to reduce the other cases as much as possible. We need the following technical provision, which holds in many cases.

Definition 4. Given disjoint $S_1, S_0 \subseteq \mathcal{R}$ and disjoint $T_1, T_0 \subseteq \mathcal{R}$, say that (S_1, S_0) is polynomially mappable to (T_1, T_0) if there is a polynomial g in one variable over \mathcal{R} such that $g(S_1) \subseteq T_1$ and $g(S_0) \subseteq T_0$. Call (S_1, S_0) and (T_1, T_0) inter-mappable if (T_1, T_0) is likewise mappable into (S_1, S_0) .

Now suppose we want to convert a polynomial p over \mathcal{R} with scheme (a_1, a_0, S_1, S_0) into a polynomial q that represents the same language with scheme (b_1, b_0, T_1, T_0) , where we are given g mapping (S_1, S_0) into (T_1, T_0) . If $b_1 - b_0$ has an inverse in \mathcal{R} , then we can use the linear formula

$$q(\vec{x}) = g(p(\frac{(a_1 - a_0)\vec{x} + a_0b_1 - a_1b_0}{b_1 - b_0})). \quad (1)$$

To verify: if a variable x_i of q is assigned b_0 , then the corresponding variable of p gets the value $((a_1 - a_0)b_0 + a_0b_1 - a_1b_0)/(b_1 - b_0) = a_0(b_1 - b_0)/(b_1 - b_0) = a_0$, and similarly an assignment of b_1 to an argument of q puts a_1 into the corresponding argument for the evaluation of p . This leads to a nice “robustness” theorem for fields, especially finite fields.

Proposition 0.1. (a) Every two inter-mappable representation schemes over a field are equivalent.

(b) All representation schemes over a finite field F are equivalent to strong representation; i.e., to (3) above.

Proof. Part (a) follows by Equation (1) and gives a formula size of $p(\vec{x})$ is at most 7 times the formula size of g . Applying g to \vec{x} gives at most another constant-factor overhead. If (e_1, e_0, S_1, S_0) and a polynomial p be given. It suffices to find a polynomial g such that $g(r) = 1$ for $r \in S_1$ and $g(r) = 0$ otherwise. We have

$$g(r) = 1 - [\prod_{s \in S_1} (r - s)]$$

since every non-zero element raised to the power m is 1.

$$q(\vec{x}) = g(p((e_1 - e_0)\vec{x}))$$

This yields a strong representation, and $\deg(q) \leq \deg(p)$. To reduce to any other scheme (b_1, b_0, T_1, T_0) , fix any $a \in T_0$ and

$$q'(\vec{x}) = (b - a)q(\frac{x - a}{b_1 - b_0})$$

Now we observe that the construction in (a) works in fields, but also in many other cases. It works:

- When $b_1 - b_0$ has an inverse in \mathcal{R} —for instance, if $b_1 - b_0$ is prime to m .
- When the function g can be multiplied by a polynomial h such that h maps S into T and the complement of S into the complement of T . Then $h(b_1 - b_0)^{\deg(p)}$ cancels all denominators in the formula.

Corollary 0.1. (a) For sign output, all representation schemes over a field are equivalent for polynomials over \mathbf{Z} , as well as the four schemes in (3)–(6).

(b) Fourier inputs are equivalent to standard inputs over a field if m is odd, in each of (3)–(6).

(c) When S_0 and S_1 are fixed for outputs, low-degree polynomials over a field apply to all other representation schemes.

Proof. (a) If $(b_1 - b_0)$ is positive, then $S = \{x \in \mathbf{Z}^n \mid (b_1 - b_0) \mid x\}$ is the set of multiples of $(b_1 - b_0)$, as is its complement. If $(b_1 - b_0)$ is negative, then $S = \{x \in \mathbf{Z}^n \mid (b_1 - b_0) \nmid x\}$ is the set of non-multiples of $(b_1 - b_0)$, as is its complement. The coefficient size stays within the bounds of the proof of (3)–(6).

(b) holds because 2 is relatively prime to m when m is odd.

p_n representing L with a scheme (a_1, a_0, S) can be converted to $(1, 0, S)$ because then $b_1 - b_0 = 1$. \square

Note that we left the term-counting and monomial-counting measures out of the definition of equivalence. The above results do not preserve the latter—they can blow up to exponentially many monomials. We do not know what happens in general for schematic terms. However, Equation (1) does preserve the ability to wire Boolean inputs into small circuit gadgets that give the corresponding values in the ring, so that wherever “number of terms” is used in the following results, robustness does hold. Several authors use “terms” as synonymous with monomials or leave the meaning vague; we pin it down to “schematic terms” if need be. Call $\{p_n\}$ *sparse* if the p_n can be written with polynomially many schematic terms.

To describe various kinds of *circuits* and circuit classes, we adopt and adapt the notations of Goldmann, Håstad, and Razborov [GHR92] and Maciel and Thérien [MT93, Mac95] as follows: A *stratified circuit* of *depth* d has inputs labeled x_1, \dots, x_n together with their negations $\bar{x}_1, \dots, \bar{x}_n$, and then has d *levels*. Gates at each level receive inputs from the previous level (the inputs are level 0), and all gates at the same level have the same type. The gate types we consider are:

- AND gates (A) and OR gates (O), of unbounded fan-in;
- “Small” AND gates (AND_{small}), defined to have fan-in $(\log n)^{O(1)}$;
- Mod_k gates (Mod_k), standardly defined to output *true* iff the number of *true* inputs is zero modulo k ;
- Parity gates (P) or (Parity), which are the same as Mod_2 gates;
- Large Threshold gates (LT), each of which has a threshold t and integer weights w_i associated to its 0-1 valued input lines e_i , and outputs *true* iff $\sum_i w_i e_i > t$.
- Small Threshold gates (T) have $t, w_i = r^{O(1)}$, where r is the fan-in.
- Majority gates (MAJ) have all $w_i = 1$ and $t = r/2$. We also include the negation of a MAJ gate under this heading.
- Midbit gates (Midbit): a Midbit gate of fan-in r returns the $\lceil \log_2 r \rceil$ th bit of the number m of *true* inputs, where m is in binary notation.
- General symmetric gates (SYM) are any gates whose output depends only on the number of input lines that are *true*. This designation includes all of the above except T and LT gates.

The major classes defined by polynomial-size, constant-depth circuit families are AC^0 , where the circuits have unbounded fan-in AND, OR, and NOT gates, ACC^0 , where they may also have Mod_k gates (with k fixed for the family), and TC^0 , where they may instead have LT gates. Since an LT gate can be simulated by a depth-two, n^{13} -sized gadget of MAJ gates [Hof96] (see also [GHR92]), TC^0 can also be defined

via T gates or MAJ gates. Also for each $k \geq 1$, \mathbf{NC}^k is accepted by *bounded* fan-in Boolean circuit families of depth k , and $\mathbf{NC} = \cup_k \mathbf{NC}^k$. We skirt issues of uniformity of computation in this chapter by Barrington and Immerman in this volume, and focus on background in what follows. The known inclusions

$$\text{AC}^0 \subset \text{ACC}^0 \subseteq \text{TC}^0 \subseteq \text{NC}^1 \subseteq \text{NC}^2$$

Only the first inclusion is known to be proper
unknown!

The stratified-circuit notation allows us to do above. For example, $\text{MAJ} \circ A$ stands for polynomial gate connected to one layer of AND gates at the top, and may have a large threshold gate at the output in the middle. We denote proper subclasses of TC^0 (see [GHR92, Ma94]) by adding classes to polynomials.

Theorem 1 (cf. [Bei93]). (a) Let L be representable over \mathbf{Q} or \mathbf{R} having polynomial formula and coefficients. Then $L \in \text{NC}^2$.

- (b) If the p_n are sparse, then $L \in \text{LI} \circ \text{A}$. Conversely, every language in $\text{LI} \circ \text{A}$ has sparse polynomial formulae of size $2^{\text{polylog}(n)}$.
- (c) If standard inputs are used and the coefficients of the polynomial magnitude (that is, have $O(\log n)$ bits) are sparse, then every language in $\text{MAJ} \circ \text{A}$ has sparse polynomial formulae of size $2^{\text{polylog}(n)}$.
- (d) If L is represented by p_n over a finite ring \mathcal{R} , then $L \in \text{NC}^1$. Moreover, every $L \in \text{NC}^1$ has sparse polynomial formulae of size $2^{\text{polylog}(n)}$.
- (e) In (d), if the p_n are sparse, then $L \in \text{AC}^0$. Conversely, every language in AC^0 has sparse polynomial formulae of size $2^{\text{polylog}(n)}$.

Proof Sketch. The main point of (a) is the fact that formulas can be effectively “rebalanced” into arithmetic and log depth (see [Spi71, Bre74, MP92]). Since the p_n , all intermediate values have polynomially many operations, and since each operation is in (Boolean) NC^1 , the whole is in NC^1 . The monomial becomes a weight on a line into a three-line gate, which can duplicate gates below the inputs and add due to the fact that the weight is a monomial. This is clear by the reasoning in (a), and the converse follows from the fact that every formula can be converted into an equivalent Boolean formula. The first part of (e) is immediate from the fact that every formula can be converted into an equivalent Boolean formula.

extend it to other finite rings. The second part is due to Beigel and Tarui [BT91], and is bundled into Theorem 12 below. \square

Cases (c) and (e) correspond to “Theorem 2” in [Bei93]. In (e), if the ring is \mathbf{Z}_m and weak representation (5) in Definition 2 is used with $a = 0$, then the output gate becomes a Mod_k gate.

Curiously, these basic relationships with circuit classes say nothing by themselves about the *degree* measure. Degree corresponds to the *order* of a *perceptron*, as formalized and studied by Minsky and Papert [MP68]. The equivalence of perceptrons to polynomials with bounded coefficients (and with the number of monomials plus one equal to the *size* of the perceptron) is shown by Beigel [Bei93] and treated further in [Bei94a]. One remark is that an order- d perceptron of order d , size s , and weights of magnitude w can be converted into an order- d perceptron of size $2^d s$ and weight sw that has no negated inputs and no duplicate AND gates (see [Bei94b, MP68]); this corresponds to the obvious relationship between number of schematic terms and number of monomials. We do not discuss perceptrons further here. The impact of having low-degree polynomials comes out in other simulations described below. In contrast to the lack of good lower bounds for familiar machine-based complexity measures, the degree measure lends itself to tight lower and upper bounds in a number of important cases.

4 Strong Versus Weak Representation

First, we note that to every Boolean function $f(x_1, \dots, x_n)$ we can associate a canonical polynomial σ_f , such that σ_f represents f over *any* ring \mathcal{R} under strong representation. For every assignment $\vec{a} = (a_1, \dots, a_n)$ in $\{0, 1\}^n$, let $M_{\vec{a}}(\vec{x}) = \prod_i (2a_i x_i - x_i - a_i + 1)$. This is zero except when $\vec{x} = \vec{a}$, when it is 1. Then let σ_f be the sum of $M_{\vec{a}}$ over all \vec{a} such that $f(\vec{a}) = \text{true}$. As explained by Tarui [Tar91], because \mathcal{R} is a ring and not a weaker structure, the \mathcal{R} -module $\mathcal{F}_n(\mathcal{R})$ of functions from $\{0, 1\}^n$ to \mathcal{R} behaves much like a 2^n -dimensional vector space—even if \mathcal{R} is not a field. In particular, the 2^n multilinear monomials form a basis for this space, so every function in $\mathcal{F}_n(\mathcal{R})$ can be written uniquely as a linear combination (with coefficients in \mathcal{R}) of these monomials. (Since 0 and 1 commute with every element of a ring, we do not even need \mathcal{R} to be a commutative ring, and the above features hold also for Fourier inputs.) Hence σ_f is the unique strong representation of f . If we know the degree and size measures of σ_f , that’s it—no strong representation can do better.

Now define Z_f to be the set of polynomials that compute f (over a given \mathcal{R}) under the standard nonzero representation. Proposition 0.1(b) now says that over a finite field \mathcal{F} , all members of Z_f have degree within a factor of $|\mathcal{F}| - 1$ of that of σ_f . Over \mathbf{Z}_m with m composite, however, there can be drastic differences. Barrington [Bar92] gives this example with $m = 6$:

$$L = (0^*(10^*)^6)^*.$$

L is weakly represented over \mathbf{Z}_6 by the degree-one polynomial $x_1 + \dots + x_6$. However, the unique strong representations have different degrees.

The differences emerge even for the basic AND and OR. For example, AND and OR respectively, are represented by linear polynomials over \mathbf{Z}_6 ; viz., OR by $x_1 + \dots + x_6$ and AND by $x_1 \cdot \dots \cdot x_6$. The known bounds are different.

Theorem 2. *For polynomials over \mathbf{Z}_m , $m \geq 2$:*

- (a) [Tar91, BST90] (Beigel [Bei93] adds “folklore”) *AND and OR require degree n .*
- (b) [BBR94] *Under the standard nonzero representation, AND has degree n , but OR is representable in degree $\lceil n/m \rceil$ if m has k distinct prime factors of n . The best known upper bound is $\Omega(\log^{1/(k-1)} n)$ [TB95].*
- (c) [Smo87, BST90, BBR94] *If m is a prime power, then OR is representable in degree $\lceil n/m - 1 \rceil$, and this is best possible.*
- (d) *Under weak representation, (b) and (c) hold with the degrees reversed. In particular, there is no degree n such that OR is representable in standard nonzero representation and its complement NOT OR is representable in degree n .*

Proof. (a) We have $\sigma_{\text{AND}}(u_1, \dots, u_n) = u_1 \cdots u_n$. Those are the unique strong representations, and the unique weak representation p of AND maps all of $\{0, 1\}^n$ to $\{0, 1\}$. The function $p(1^n) = a$ determines the whole function—it is 1 if $a = 1$ and 0 if $a = 0$. Since p has degree n , and by the reasoning for σ_f above, this has degree n , and by the reasoning for σ_f above, this has degree n . The other part of (b), see [Bei93] or [BBR94].

(c) For the upper bound, let $d = \lceil n/m - 1 \rceil$, and let

$$g(u) = (u_1 \cdots u_d) + (u_{d+1} \cdots u_{2d}) + \dots$$

Then g has $m - 1$ monomials, each of degree d , and g represents $\text{OR}(x_1, \dots, x_n)$ under the complementary representation. For the lower bound, note that the converse of (a) is not true, since \mathbf{Z}_m is a field and multiplies the degree by m . The lower bound cannot be lower than d . Part (d) follows from the same reasoning.

The polynomials constructed in [BBR94] to achieve the upper bound in (b) are symmetric, and a matching lower bound for standard nonzero representation of OR is proved in [BBR94]. We will see that the lower bound for standard nonzero representation improves considerably when we go to *probabilistic* representation. First we examine bounds for some simple functions.

5 Known Upper and Lower Bounds on Degree

The following results are taken from Beigel's survey [Bei93], where full proofs may be found. By the robustness results and usages established in the last section, we can be fairly brief in stating the hypotheses.

Theorem 3 ([MP68]). *The parity language $0^*1(0^*10^*1)^*0^*$ requires degree n over \mathbf{Z} , \mathbf{Q} , and \mathbf{R} .*

Note that the parity function $x_1 + x_2 + \dots + x_n \pmod{2}$ is a degree-one polynomial over $\text{GF}(2)$. Over \mathbf{Z}_m with $m = 2k$ one can use $kx_1 + \dots + kx_n$ to get a degree-one representation with $S_0 = \{0\}$ and $S_1 = \{k\}$. The case of odd m is different.

Theorem 4 ([Smo87]). *Parity requires degree $\Omega(n^{1/2})$ over \mathbf{Z}_m for any odd $m \geq 3$.*

Now, following [BBR94], define $\text{Mod}_k(x_1, \dots, x_n)$ to be *false* if $x_1 + \dots + x_n \equiv 0 \pmod{k}$, and *true* otherwise. Write $\delta(f, m)$ for the minimum degree of a standard nonzero representation of f over \mathbf{Z}_m , and $\Delta(f, m)$ for that of a “truly weak” representation. Recall that the minimum degree of f under weak representation (i.e., with $S_1 = \{0\}$) is the same as $\delta(\neg f, m)$.

Theorem 5. (a) [Smo87] *When $m = p$ is prime and k is not a power of p , $\delta(\text{Mod}_k, p) = \Omega(n)$.*

(b) [BBR94] *If k has a prime divisor that is not a divisor of m , then $\delta(\text{Mod}_k, m) = n^{\Omega(1)}$ and also $\delta(\neg \text{Mod}_k, m) = n^{\Omega(1)}$.*

(c) (see [BBR94]) *If the set of prime divisors of k is contained in that of m , then $\delta(\text{Mod}_k, m) = O(1)$ and $\delta(\neg \text{Mod}_k, m) = O(1)$.*

(d) [Tsa93] *If m is not a prime power, then $\delta(\neg \text{Mod}_m, m) = \Omega(n)$.*

(e) [Tsa93] *If m is not a prime power, and k has a prime divisor that does not divide m , then $\delta(\text{Mod}_k, m)$ and $\delta(\neg \text{Mod}_k, m)$ are both $\Omega(n)$.*

The results by Tsai [Tsa93] improved $n^{\Omega(1)}$ bounds in [BBR94] in the case where m is not square-free. Green [Gre95] improved the results of [BBR94, Tsa93] further by showing that under standard nonzero representation, for all k there is a constant C_k such that for all m that are relatively prime to k , $\delta(\text{Mod}_k, m) \geq C_k n$. That is, the constant in “ $\delta(\text{Mod}_k, m) = \Omega(n)$ ” is independent of m so long as the modulus m is prime to k . This holds even if Definition 2(4) is made weaker by requiring only that the polynomial p is not identically zero but gives zero whenever $x \notin L$ (i.e., the Boolean function concerned, here Mod_k , is false). However, none of these bounds are known at all for the degrees $\Delta(\text{Mod}_k, m)$ under “truly weak” representation. Tsai also proved the following theorem.

Theorem 6 ([Tsa93]). *For any integer $m \geq 2$:*

(a) $\delta(\text{MAJ}, m) \geq n/2$.

(b) $\delta(\text{Midbit}, m) = \Omega(n^{1/2})$.

Some functions that (unlike parity and Mod) require more than polylog degree over the infinite field \mathbf{R} are the following.

Theorem 7 ([MP68]). *Over \mathbf{Z} , \mathbf{Q} , and \mathbf{R} , $f(x_0, \dots, x_{4m^3-1}) = (\forall i \in [0 \dots m-1])(\exists j \in [0 \dots 3m^2-1])x_{4im^3+j} = 1$. Hence with $n = 4m^3$, the degree is $\Omega(n^{1/3})$.*

For representation by polynomials over \mathbf{R} , it is known that the function $f(x_0, \dots, x_{4m^3-1}) = (\forall i \in [0 \dots m-1])(\exists j \in [0 \dots 3m^2-1])x_{4im^3+j} = 1$ requires degree $\Omega(n)$. Nisan and Szegedy [NS94] showed that this representation is polynomially related to that of the parity function, and hence for every Boolean function f , every polynomial representation of f over \mathbf{R} has degree at least $c(\deg(\sigma_f))^{1/8}$, where the constant c depends on f . In fact, they showed that both measures are polynomially related to the complexity of f . Similar techniques were used by Beigel and Furst [BF93] to show that every Boolean function f has a polynomial representation over \mathbf{R} with degree at most $\text{poly}(\deg(f))$.

$$L = (00 + 01 + 10 + 11) \oplus \dots$$

(called ODDMAXBIT in [Bei93]), which is represented by a polynomial $\sum_{i=1}^n (-2)^i x_n$ with linear-sized coefficients. It is known that this function can be represented over \mathbf{Q} or \mathbf{R} by low-degree polynomials with small coefficients. However, it cannot be done in degree $n^{o(1)}$ with coefficients of size $n^{o(1)}$. In particular, this language is not recognizable by a polynomial-time algorithm with exponential weight, and quasipolynomial size (i.e., $n^{o(n)}$).

Several of the lower bounds show that all polynomial representations of a function fail to represent a given Boolean function on a large fraction of the domain, such as a constant fraction of them. The next theorem is an example of this.

Theorem 8 ([ABFR94]). *For all d , n , and m , there is a polynomial p over \mathbf{Z} whose sign represents Parity on $\{0, 1\}^n$ and $m \leq \sum_{0 \leq k < (n+d+1)/2} \binom{n}{k}$.*

In particular, to compute parity correctly on a large fraction of the domain, one needs degree $\Omega(\sqrt{n})$. Now define L_k ($k \geq 1$) to be the set of x formed by concatenating some number m of “blocks” of length k such that $\sum_{i=1}^m r_i \neq 0$ modulo k . Using polynomials over \mathbf{R} and Straubing [BS94] obtained the following theorem.

Theorem 9 ([BS94]). *There exists δ depending on d and n such that for any $m \geq \sum_{0 \leq k < (n+d+1)/2} \binom{n}{k}$, there is a polynomial p over \mathbf{R} representing L_k (by sign over \mathbf{Z}) on a $1 - \delta$ proportion of the domain.*

The most basic non-approximability results for the Parity function are the following lemma, versions of which may be found in [Bar92, ABFR94].

Lemma 9.1. *Every polynomial $p(x_1, \dots, x_n)$ of degree d is either constant, or takes value 0 on at least $2^{n-d}(1 - \delta)$ of the domain.*

In consequence, a degree- d polynomial over \mathbf{Z}_2 must disagree with OR on at least $2^{n-d} - 1$ arguments, and straightforward constructions show that this bound is tight. Barrington [Bar92] proved a generalization.

Theorem 10 ([Bar92]). *Let p have degree d and take at most r distinct values in a field \mathcal{F} . Then p has value 0 on at least $2^{n-d(r-1)}$ 0-1 arguments.*

For arbitrary rings \mathcal{R} in place of \mathcal{F} , Barrington proved that the statement of Theorem 10 holds if $d = 1$ or $r = 2$, and that the weaker Lemma 9.1 holds for all d in \mathbf{Z}_{p^k} , for any prime p and all k [Bar92]. However, an example credited to Applegate, Aspnes, and Rudich in [Bar92] shows that the statement fails for $\mathcal{R} = \mathbf{Z}_6$ with $d = 3$ and $n = 27$: Let

$$p(x) = s_3(x) + 5s_2(x) + 5s_1(x),$$

where s_i stands for the mod-6 sum of all monomials of degree i . This polynomial is a standard nonzero representation of OR in \mathbf{Z}_6 , and meets the prescribed bounds from Theorem 2(b). For a full explanation of the failure, see [BBR94].

Smolensky [Smol93] used *Hubert functions* to prove several other non-approximability results in fields of finite characteristic.

Theorem 11 ([Sm093]). *Using asymptotic notation that depends only on the characteristic c and not on the size of a field \mathcal{F} , and using standard non-zero representation:*

- (a) Every polynomial of degree $o(n^{1/2})$ differs from MAJ on at least $2^{n-1} - o(2^n)$ Boolean arguments.
- (b) If $c \neq 2$, then every polynomial of degree $o(n^{1/2})$ differs from Parity on at least $2^{n-1} - o(2^n)$ Boolean arguments.
- (c) If q is prime and $c \neq q$, then every polynomial of degree $o(n^{1/2})$ differs from $\neg\text{Mod}_q$ on at least $(1/q)2^n - o(2^n)$ Boolean arguments.

6 Polynomials For Closure Properties

Polynomials have also been used to prove relationships among complexity classes. Instead of n variables standing for bits in an input string, the polynomials used here may have just one or two variables standing for numerical quantities used in defining the classes. The first striking application of this kind was given by Toda [Tod91] in proving that the polynomial hierarchy is contained in $\text{P}^{\#P}$. He constructed single-variable polynomials P_d over \mathbf{Z} that have the following *modulus-amplifying* property for all integers $k \geq 1$ and $x \geq 0$:

$$x \equiv 0 \pmod{k} \implies P_d(x) \equiv 0 \pmod{k^d}, \quad (2)$$

$$x \equiv -1 \pmod{k} \implies P_d(x) \equiv -1 \pmod{k^d}. \quad (3)$$

Toda used $P_2(x) = 3x^4 + 4x^3$ and inductively defined $P_{2d}(x) = P_2(P_{d-1}(x))$ for $d \geq 2$, using only moduli a power of 2. Yao [Yao90] improved the degree and showed that

ACC^0 circuits can be simulated by probabilistic S polynomial (i.e., $2^{\text{polylog}(n)}$ size, where the ANDs have polylogarithmic size) and this makes Yao's circuits deterministic without increasing the size of the circuit. This is done by following polynomials P_d of optimal degree $2d - 1$ such that

$$P_d(x) = 1 - (1-x)^d \left(\sum_{j=0}^{d-1} \right)$$

(These satisfy $x \equiv +1 \pmod k \implies P_d(x) \equiv +1$ easy to convert between these conditions, and this Green, Köbler, and Torán [GKT92], following on the theorem in [RS92], replaced the arbitrary SYM gate, and obtained the following theorem.

Theorem 12 ([GKT92, GKR⁺95]). *Every language in $\text{AND}_{\text{small}}$ has circuits of quasipolynomial size.*

Proof Sketch. Let $L \in \text{Midbit} \circ \text{ACC}^0$. The gates in the ACC^0 part of the circuits defining $\text{Mod}_m \circ \text{AND}_{\text{small}}$ sub-circuits, where as before, gates of polylog fan-in. Since only polylog-many gates are in the ACC^0 part of the circuits defining $\text{Mod}_m \circ \text{AND}_{\text{small}}$ sub-circuits, this part can be simulated by many deterministic $\text{Mod}_m \circ \text{AND}_{\text{small}}$ circuits. The small ANDs can be interchanged with Mod_m gates in one layer of small ANDs at the inputs. Then the circuit is split into two parts: one between the Midbit-of-sum and the small ANDs, and one between the small ANDs and the outputs. In the first part, where each level uses Mod_k gates for some prime k , the Midbit gate can “swallow up” a sum of Mod_k gates. Pushing the small ANDs beyond the next level (i.e., for different k) toward the inputs (as before) leaves a sum of Mod_k gates. The process is repeated until all the Mod_k gates are gone, for the Midbit-of-sum-of- Mod_k part in full since it is a polynomial.

Lemma 12.1. *Let k be prime and let $\{b_n\}$ be a sequence of integers. Then there exists a polynomial r where for each n , b_n is of the form $r(n)$.*

$$b_n(x_1, \dots, x_n) = \sum_{i=1}^w c_i(x)$$

where each c_i is a $\text{Mod}_k \circ \text{AND}_{\text{small}}$ circuit and we can assume that there are polynomials p and q and a family of polynomials r_i such that for each n ,

$$b_n(x_1, \dots, x_n) \equiv (h_n(x_1, \dots, x_n) \text{ div } 2^q)$$

Proof. To simplify notation, let p, p', q, r, s , and t denote $p(\log n), p'(\log n), q(\log n), r(\log n), s(\log n)$, and $t(\log n)$, respectively. Each $\text{Mod}_k \circ \text{AND}_{\text{small}}$ circuit c_i outputs 1 if and only if a certain sum σ_i of the AND-gates is nonzero mod k . Now each σ_i can be regarded as a polynomial in variables (x_1, \dots, x_n) over \mathbf{Z}_k of degree equal to the fan-in of the small ANDs, and since k is prime, we may arrange via Lemma 0.1 that $\sigma_i(\vec{x})$ is always 0 or 1 (mod k). Now using the “Toda polynomials” P_d in (4) above, it follows that

$$b_n(x) = \sum_{i=1}^w [P_d(\sigma_i) \bmod k^d].$$

We choose $d = p'(\log n)$ where p' is a polynomial such that $k^{p'} > 2^{r+t+2}$. Then $b_n(x) \leq 2^r < k^{p'}$. Now the outer sum in the equation above for b_n is less than $k^{p'}$, so the “mod” can be moved outside; i.e.,

$$b_n(x) \equiv \left[\sum_{i=1}^w P_{p'}(\sigma_i) \right] \pmod{k^{p'}}.$$

Writing $f_n(x) = \sum_{i=1}^w P_{p'}(\sigma_i)$, we have

$$f_n(x) = a_n(x)k^{p'} + b_n(x)$$

for some $a_n(x)$. Note that for some polynomial s , $f_n(x) < 2^s$. Also note that since σ_i is a polynomial of polylog degree, there is some polynomial p such that f_n is a polynomial of degree $p(\log n)$ in the variables x_1, \dots, x_n . Define the degree $p(\log n)$ polynomial h_n as follows:

$$h_n(x) = i(n) \left\lceil 2^q/k^{p'} \right\rceil f_n(x) + 2^q f_n(x),$$

where $i(n) \equiv -k^{p'} \pmod{2^t}$ and q is a polynomial such that $q \geq s+t+2$. Then $\lceil 2^q/k^{p'} \rceil f_n(x) = a_n(x)2^q + b'_n(x)$, where $b'_n(x) < 2^{q-t-1}$. Hence

$$h_n(x) \equiv 2^q b_n(x) + i(n) b'_n(x) \pmod{2^{q+t}},$$

where $i(n) b'_n(x) < 2^{q-1}$. This completes the proof of Lemma 12.1 and the sketch of Theorem 12. \square

The class MP (also called MidbitP) introduced in [RS92, GKR⁺95] was motivated to find the sharpest upper bound for the polynomial hierarchy in Toda’s theorem. A language L belongs to MP if there exists a polynomial-time NTM N such that for all strings x , $x \in L \iff$ the middle bit of the standard binary representation of $\#\text{acc}_N(x)$ is a “1.” Here $\#\text{acc}_N(x)$ stands for the number of accepting computations of N on input x , while $\text{Gap}_N(x)$ (see [FFK91]) stands for $\#\text{acc}_N(x)$ minus the number of non-accepting computations. A useful equivalent definition of MP is obtained by combining observations in [GKR⁺95] and [FFL93]. Say that an integer r is “top

modulo 2^k ” if $(r \bmod 2^k)$ belongs to $[2^{k-1} \dots 2^k - 1]$ and a polynomial-time computable function g such that

$$x \in L \iff \text{Gap}_N(x) \text{ is top}$$

This compares well with the standard definition such that for some N and all x ,

$$x \in L \iff \text{Gap}_N(x) > 0$$

Both PP and MP are closed under complementation. The proof of the first part of this section follows via (6) from the existence of an integer r such that for all polynomial-time NTMs N_1 and N_2 and all strings x ,

$$h(\text{Gap}_{N_1}(x), \text{Gap}_{N_2}(x), x) > 0 \iff \text{Gap}_{N_1}(x) > 0 \wedge \text{Gap}_{N_2}(x) < 0$$

and such that there is a polynomial-time NTM N such that $\text{Gap}_N(x) = h(\text{Gap}_{N_1}(x), \text{Gap}_{N_2}(x), x)$ equals the left-hand side of (7). One would like to find such an r for all integers r and s , $A(r, s) > 0 \iff r > 0 \wedge s < 0$. However, we only need this to hold for those r and s such that $A_m(r, s) > 0$ for all m such that $|m| \leq \max(|r|, |s|)$. For some k depending on N , $A_m(r, s) > 0$ for all $m \in [-2^m \dots 2^m]$, where $m = |x|^k$. The following construction of $A_m(r, s)$ were found by Beigel, Reingold, and Spielman [BRS95] and on one-variable rational functions (i.e., quotients of polynomials) on similar ranges found by Newman [New95].

$$\begin{aligned} A_m(r, s) &:= \frac{1}{4} (P_m(r) + P_m(-r))(P_m(s) + P_m(-s)) - \\ &= \frac{1}{4} (3P_m(r) - P_m(-r))(3P_m(s) - P_m(-s)) \end{aligned}$$

where

$$P_m(r) = (r - 1) \prod_{i=1}^m (r - 2^i)$$

For more details, see [BRS95]. Unlike the Toda polynomials, the A_m polynomials do not belong to \mathbf{Z} . However, all values on integers r and s are A_m integer-valued, and the degree of A_m is polynomial in m . This suffices for constructing the required polynomial-time NTM. Reingold extended this construction to show that the class MP is closed under polynomial-time truth-table reductions [FR91]. Ogiwara [Ogi94] used A_m polynomials to show that the log-space analogue PL is closed under polynomial-time truth-table reductions [Ogi94].

Now let us turn attention to the problem of showing that $\text{PP} \subseteq \text{PL}$. This section. This time, what we want is a polynomial-time computable function g such that for all strings x ,

In terms of k , what is the minimum degree of an integer-valued polynomial $p(x, y)$ such that for some polynomial t and all x and y , $p(x, y)$ is top modulo $2^{t(k)}$ \iff both x and y are top modulo 2^k ?

Note that p may have rational coefficients so long as it is integer-valued. The simplest polynomial we know that satisfies this congruence relation (with $t(k) = k$) is $p(x, y) = \binom{x}{2^{k-1}} \binom{y}{2^{k-1}} 2^{k-1}$, which has degree 2^k . M. Coster and A. Odlyzko [personal communication, 3/91] found solutions with degree $O(\phi^k)$, where ϕ is the golden ratio $1.618\dots$, and with coefficients likewise appreciably smaller than the above. If such p can be found with degree polynomial in k , then p can be written as a polynomial-sized sum of small binomial coefficients in x and y , which can then be used in building the polynomial-time NTM needed to show MP closed under intersection.

A related question is: What is the minimum degree required to achieve, with all quantities defined modulo m ,

$$p(x, y) = 0 \iff (x = 0 \wedge y = 0)?$$

With integer coefficients, this is possible iff m is square-free—and then p can have degree 2. For the case $m = 2^k$ (and rational coefficients), D.A.M. Barrington [personal communication, 11/95] gives an argument that makes an $\Omega(\sqrt{m}) = \Omega(2^{k/2})$ lower bound on degree highly plausible, for both this and the “top mod 2^k ” problem with $t(k) = k$. The main idea is that there is a unique way to write $p(x, y)$ in the form $\sum_{i,j} a_{i,j} \binom{x}{i} \binom{y}{j}$ with integral $a_{i,j}$. A well-known fact is that $\binom{2^k}{i}$ is divisible by $2^k / \text{ord}_2(i)$, where $\text{ord}_2(i)$ stands for the largest power of 2 dividing i . With $x = y = m/2$, all the terms with both $\text{ord}_2(i)$ and $\text{ord}_2(j)$ at most $\sqrt{m}/2$ are divisible by m . Thus in particular, all terms with $1 \leq i, j \leq \sqrt{m}/2$ disappear in the congruence mod m . The only low-degree terms that can squeak through this analysis are those with $i = 0$ or $j = 0$, and these give us single-variable polynomials (with zero constant term) $q(x)$ and $r(y)$ such that $p(m/2, m/2)$ is congruent to $p(0, 0) + q(m/2) + r(m/2)$ modulo m . If the q and r terms can be made to “go away,” we have the desired contradiction.

Note that this would not contradict the above upper bound since it amounts to $\Omega(1.414\dots^k)$. The tantalizing aspect, however, is that even this argument has no effect when $t(k) \geq 2k$. It may yet be possible to build two-variable “modulus-shifting” polynomials to meet the above requirement for closure of MP under intersection, and a direct and efficient-enough construction might collapse some counting classes between $\text{PP}^{\oplus \text{P}}$ and P^{PP} , as discussed at the end of Section 3 of [GKR⁺95].

7 Probabilistic Polynomials

A *probabilistic polynomial* in n variables over a ring \mathcal{R} is formally defined, following Tarui [Tar93], as a mapping σ from a *sample space* U to the set $\mathcal{R}[x_1, \dots, x_n]$ of polynomials in variables x_1, \dots, x_n with coefficients in \mathcal{R} . The *degree* of σ is defined

to be the maximum, over all $j \in U$, of the degree $\Pr_{j \in U}[\dots]$ to indicate sampling according to the distribution $\Pr_{j \in U}[\dots]$.

Definition 5. A probabilistic polynomial σ represents a sampling distribution using scheme (e_1, e_0, S_1, S_0) , if for all n and $x \in \mathcal{R}^n$,

$$\begin{aligned} x \in L &\implies \Pr_{j \in U}[\sigma_j(x) \in S_1] = e_1 \\ x \notin L &\implies \Pr_{j \in U}[\sigma_j(x) \in S_0] = e_0 \end{aligned}$$

Here we will use the standard $(1, 0)$ input representation for inputs, and the strong and weak representation for outputs. We will also use the field $\text{GF}(2^k)$ and k may increase with n , so the number of wires to the inputs of an AND gate becomes a factor. However, we will then convert the standard representation over $\text{GF}(2^k)$ to representations over $\text{GF}(2)$, where standard AND gates are replaced by $\text{Mod}_m \circ \text{AND}$ gates. In this representation, schematic terms are products of x_i and x_i^m , and the “terms” are the terms of the polynomial. The following two results are well-known.

Proposition 12.1 (see [Tar93]). *Let σ be a probabilistic polynomial over \mathbf{Z}_m (with standard nonzero representation) $\{0, 1\}^r$, and such that for each j , σ_j is written using an equivalent $\text{Mod}_m \circ \text{AND}$ circuit C with n “active” wires, and r “random” wires, such that the AND layer has at most $c2^r$ gates, etc.*

Proof. Each possible value of j can be regarded as a configuration of n wires to σ_j and each term in σ_j involving variables x_{i_1}, \dots, x_{i_r} can be regarded as a configuration of r wires to the inputs. The first d wires go to the AND gate, the next r wires go to the wires that appear in the term, and the other r wires go to the wires that appear in the term complement, each according to whether the corresponding clause in the term is true or false. The AND gate evaluates to 1 iff the values of the wires to the AND gate are such that the corresponding clause in σ_j contributes 1. The value of the term is 1 iff the value of the AND gate is 1. The value of $\sigma_j(x)$ is the same as the value of $\sigma_j(x)$ modulo m . A term with value zero modulo m has value zero, so connecting everything to a single AND gate gives the result for all j and x .

The circuits in turn can be regarded as polynomial “probabilistic arguments” and r “random arguments.” This shows that Tarui’s convenient formalism using distributions and polynomials can be converted to a deterministic simulation of probabilistic arguments.

For the case $m = 2$, there is a deterministic simulation of the probabilistic arguments given in Theorem 12 given above.

Proposition 12.2 ([All89, AH90]). *If the probabilistic polynomial σ given in Proposition 12.1 can be converted to a deterministic circuit C' that has $c2^r$ AND gates, each of fan-in c and fan-out r , then the circuit C' has success probability $> 1/2$, and the circuit C' has success probability $> 1/2$.*

Proof. This follows from the simulation of a MAJ of u -many Parity gates, where each Parity has fan-in at most m (an even number), by a depth-2 circuit comprised of $um + 1$ MAJ gates [All89, AH90]. \square

Håstad and Goldmann [HG91] proved that any depth-3 circuit of this kind (even with the MAJORITY gates replaced by arbitrary unweighted threshold gates) that computes the GF(2) polynomial $\sum_{i=1}^n \prod_{j=1}^d x_{ij}$ must have size at least $2^{\Omega(n/(d+1)4^{d+1})}$, which translates to $2^{n^{\Omega(1)}}$ if $d \leq (1/3) \log n$. Razborov and Wigderson [RW93] showed that any such circuit that computes the GF(2) polynomial $\sum_{i=1}^n \prod_{j=1}^{\log n} \sum_{k=1}^n x_{ijk}$ must have $n^{\Omega(\log n)}$ size, regardless of the bottom fan-in d . This still leaves open the possibility of achieving polynomial size in the depth-3 construction for functions in (uniform) AC⁰, or for achieving polynomial size with a higher constant depth (cf. [HHK91]).

Now we look concretely at polynomials for OR. First note that under the sign output representation, OR is trivially represented over \mathbf{Z} by the degree-one polynomial $\sum_{i=1}^n x_i$. Under strong representation, however, the degree jumps all the way to n , over \mathbf{Z}_m as well as \mathbf{Z} . For probabilistic polynomials, however, strong representation is much less costly.

Theorem 13 ([ABFR94]). *OR is strongly represented over \mathbf{Z} within error ϵ by probabilistic polynomials of degree $O(\log(1/\epsilon) \log n)$.*

Proof. We vary somewhat from the proof in [ABFR94]: Let $\ell = \lceil \log_2 n \rceil$. For each k , $0 \leq k \leq \ell$, let $R_k \subseteq \{1, \dots, n\}$ be randomly selected by independently placing $i \in R_k$ with probability $1/2^k$. This gives us for each k a randomly-selected polynomial $\rho_k(x_1, \dots, x_n) = \sum_{i \in R_k} x_i$. Finally define

$$\sigma(x_1, \dots, x_n) = 1 - \prod_{k=0}^{\ell} (1 - \rho_k(x_1, \dots, x_n)). \quad (8)$$

Now when all x_i are 0, with probability 1 this polynomial gives 0. When the set S of x_i that are 1 is nonempty, an easy analysis of the two values of k that straddle $\log_2 |S|$ shows that with probability at least $1/4$, some ρ_k takes value 1, so the product is zero, so σ takes value 1. Finally, to amplify the $1/4$ to $1 - \epsilon$, replace the product in (8) by a product of $\lceil \log_2(4/\epsilon) \rceil$ independent copies of $\prod_k (1 - \rho_k(x_1, \dots, x_n))$. \square

This uses $O(n \log(1/\epsilon))$ random bits. As is well known, one only needs the random variables defining the sets R_k to be pairwise-independent, and a standard universal hashing construction needs only $O(\log n)$ random bits for the success probability $1/4$, hence $O(\log n \log(1/\epsilon))$ random bits overall. This construction works for probabilistic strong representation over \mathbf{Z}_m as well as \mathbf{Z} .

The question we ask is: Can one do better in the degree and random-bits measures? We show that the answer is *yes* for polynomials over any finite field, including \mathbf{Z}_p with p prime, by a construction involving error-correcting codes. Such codes were

used by Tarui [Tar93] in non-constructive arguments, and by Naor and Naor [NN93] in other contexts. Probabilistic polynomials are constructed from the first show how the basic ‘‘parity trick’’ of Naor and Naor can eliminate the product over k in (8): Using $\ell + 1$ random bits

$$\sigma(x_1, \dots, x_n) = \sum_{k=0}^{\ell} b_k \rho_k(x_1, \dots, x_n)$$

Then $\sigma(\vec{0}) = 0$ with probability one. For all arguments, σ gives value 1. The bit b_k alters the overall sum by 1 with probability at least $1/8$, $\sigma(\vec{x}) = 1 \pmod{2}$. Thus a probabilistic polynomial achieving constant success probability needs $O(\log(1/\epsilon))$ trials to degree $O(\log(1/\epsilon))$ for success probability of $1 - \epsilon$ on random bits. Hence this saves an $O(\log n)$ factor on the number of bits, although we have strong representation over \mathbf{Z}_2 in this case.

Open Problem 1. *Can \vee be strongly represented by probabilistic polynomials of degree $\log(1/\epsilon) \cdot o(\log n)$?*

This relates to whether the randomized reduction of Valiant and Vazirani [VV86] can be made as efficient as optimized in [NRS95] (see also [NN93, Gup93]).

The construction via error-correcting codes that we use here gives better constants in the bounds compared to the standard construction. The degree-one representation over \mathbf{Z}_2 is improved from $O(\log n)$ to $O(\log(\log n))$, and the minimal effect on the other bounds. The number of $2 \log n$ random bits needed for pairwise independence, i.e. for a universal₂ hash function, is reduced to $O(\log(\log n))$ random bits.

7.1 Error-Correcting Codes

In this subsection, let Σ be an alphabet whose cardinality is $|\Sigma|$. The Hamming distance $d_H(x, y)$ of two strings $x, y \in \Sigma^N$ is the number of positions in which x and y differ. The set of codewords over Σ is a set $C \subseteq \Sigma^N$ such that for all distinct $x, y \in \Sigma^N$, $d_H(x, y) \geq 2$. The elements of C are called *codewords*. We identify Σ with the vector space $\mathbb{F}_{|\Sigma|}^N$, where $\mathbb{F}_{|\Sigma|}$ is the field with $|\Sigma|$ elements. Then Σ^N can be regarded as a vector space of dimension N over $\mathbb{F}_{|\Sigma|}$. The elements of C are called *codewords*. We identify Σ with the vector space $\mathbb{F}_{|\Sigma|}^N$, where $\mathbb{F}_{|\Sigma|}$ is the field with $|\Sigma|$ elements. Then Σ^N can be regarded as a vector space of dimension N over $\mathbb{F}_{|\Sigma|}$.

Definition 6. *A linear code over \mathbb{F} with parameters $[N, K, \delta]$ is a linear subspace $C \subseteq \Sigma^N$ that forms a vector subspace of Σ^N of dimension K . The parameters are the rate $R = K/N$, and the density δ is the minimum distance d_C .*

The use of $[N, K, \delta]$ to distinguish linear codes is standard. The intent is clear we write $[N, K, \delta]$ in place of $[N, K, d]$. The minimum distance of a linear code $C \subseteq \Sigma^N$, denote by d_C , the maximum distance of a codeword from the origin.

and write $\delta_C = d_C/N$. Thus d_C equals $\min\{d_H(x, y) : x, y \in C, x \neq y\}$, and so is called the *minimum distance* of the code C . The *weight* $wt(x)$ of a string $x \in \Sigma^N$ is the number of nonzero entries, which is the same as $d_H(x, 0)$. A well-known fact is that in a linear code C , the minimum distance is equal to the minimum weight of a non-zero codeword. This is because for all $x, y \in C$, $x - y$ is also in C . Thus the density δ_C gives the minimum proportion of non-0 entries in any non-zero codeword. Where intent is clear we write just d and δ for d_C and δ_C .

Definition 7. A generator matrix G for an $[N, K, d]$ code C is a $K \times N$ matrix over \mathcal{F} whose rows $G(i, \cdot)$, $1 \leq i \leq K$, form a basis for C .

Now we indicate how we intend to make N and K scale with our input lengths n .

Definition 8. Let $[C_n]_{n=1}^\infty$ be a sequence of $[N_n, K_n, d_n]$ codes over \mathcal{F} . Then the C_n are said to be *small codes* if $N_n = n^{O(1)}$, and *large codes* if they are not small and $N_n = 2^{n^{O(1)}}$.

For probabilistic polynomials we use small codes, with $K_n = n$:

Proposition 13.1. Let G generate an $[N, n, \delta]$ code over \mathcal{F} . Then the probabilistic polynomial σ with sample space the columns of G , defined by

$$\sigma_j(x_1, \dots, x_n) = \sum_{i=1}^n G(i, j)x_i, \quad (9)$$

represents $OR(x_1, \dots, x_n)$ over \mathcal{F} with success probability at least δ .

Proof. If all x_i are 0, then for all j , $\sigma_j(x_1, \dots, x_n) = 0$, so this probabilistic polynomial gives one-sided error. Now let $S = \{i : x_i = 1\}$ be nonempty. To S there corresponds the unique codeword $w_S = \sum_{i \in S} G(i, \cdot)$. Since w_S is nonzero, with probability at least δ over j sampled uniformly from $\{1, \dots, N\}$, $w_S(j) \neq 0$. And $w_S(j) = \sigma_j(x_1, \dots, x_n)$. \square

Note that σ has the columns of G as its sample space and is linear. Also, $1 - \sigma$ represents NOR, $\sigma(1 - x_1, \dots, 1 - x_n)$ represents NAND, and $1 - \sigma(1 - x_1, \dots, 1 - x_n)$ represents AND. These probabilistic polynomials are also linear with constant success probability. The number r of random bits used is $\lceil \log_2 N \rceil$. Expressed in terms of the rate $R = K/N$, with $K = n$, $r = \log n + \log(1/R)$. Thus if the rate is constant, $r = \log n + O(1)$, while if N is polynomial in K , $r = O(\log n)$. This motivates the next definition, part (a) of which is standard in coding theory.

Definition 9. (a) A sequence $[C_n]_{n=1}^\infty$ of codes over \mathcal{F} is *asymptotically good* if there are constants $R, \delta > 0$ such that $(\forall^\infty n) R_n \geq R \wedge \delta_n \geq \delta$.

(b) The sequence is *almost-good* if $\delta > 0$ exists giving $(\forall^\infty n) \delta_n \geq \delta$, and the lengths N_n are polynomial in K_n .

The emphasis in Proposition 13.1 is on the computation of individual entries $G(i, j)$. This stands in contrast to the main focus of coding theory, which is to take a plaintext message w , encode it into a codeword $x = wG$, transmit x over a channel that adds noise, and receiver x' to recover w . So long as $d_H(x, x') \leq R$, a decoding algorithm given x' will find x and then w . The more R is above d , and R , the more erroneous symbols one can correct before the decoding fails. In recent breakthrough work, Spielman and Srivastava [SS16] have shown that there are good codes with $K_n = N_n = O(n)$ that give encoding and decoding in (uniform) AC^0 . The codes used by Sudan and Sudan [SS96] and the results of [ALM⁺92] are almost-good, and put G into AC^0 . They suffice for the next result.

Theorem 14. There are AC^0 -uniform linear probability distributions σ over $GF(2)$ with constant success probability δ .

Proof. We scale down the main theorem in section 13.1 to the case of “small codes” with $K = n$ as follows: Let $h = \lceil \log_2 n \rceil$. That is, we identify $\{1, \dots, K\}$ with $(a subset of \{0, 1\}^h)$. We break each $i \in \{0, 1\}^h$ into m strings $i_1 \dots i_m$, where $m = \lceil \log_2 n \rceil$. We suppose that the last one, i_m , is padded out to length m . Note that each such i corresponds to a monomial in m variables $z_1^{i_1} \dots z_m^{i_m}$, where now i_1, \dots, i_m are regarded as non-negative integers. Note that all such monomials are distinct and have total weight n .

Now let $\eta > 0$ be arbitrary, let $s = \lceil \log_2(m/\eta) \rceil$, and let $v \in GF(2^s)$. The column space of our matrix G over $GF(2^s)$ is

$$J = \{(a_1, \dots, a_m, v) : a_1, \dots, a_m \in \{0, 1\}^h\}$$

which is in 1-1 correspondence with strings j of length m and columns $j = (a_1, \dots, a_m, v)$ we define:

$$G(i, j) = (a_1^{i_1} \dots a_m^{i_m} v)$$

where the powers and products are over \mathcal{F} , but the v is a $GF(2^s)$ scalar. This is a $GF(2^s)$ -linear map from binary strings, which brings the final result down to $GF(2^s)$. The columns of G in (10) are binary strings of length only $2 \log \log n + O(1)$. The AC^0 circuits in (10) yield uniform AC^0 circuits (and we suspect that the AC^0 circuit in (10) is optimal, as treated in [BIS90]). The number of random bits used is $\lceil \log_2 n \rceil$.

$$\frac{h}{\log h} \log\left(\frac{h^2}{\eta \log h}\right) = 2h - \frac{h \log \log h}{\log h} + O(1)$$

Hence the codes are almost-good, with length $N_n = 2^{n^{O(1)}}$.

We claim that G generates a code of the required dimension and density. Since the distinct monomials are linearly independent in $\mathcal{F}[z_1, \dots, z_m]$, they generate a space of dimension K over \mathcal{F} . For the density we use the key lemma from the aforementioned “PCP” papers, often ascribed to Schwartz [Sch80] but anticipated by Zippel [Zip79]: For every two distinct polynomials p and q of total degree at most D over a field \mathcal{F} , and every $I \subseteq \mathcal{F}$,

$$|\{ \vec{a} \in \mathcal{F}^m : p(\vec{a}) = q(\vec{a}) \}| \leq D|I|^{m-1}.$$

With $I = \mathcal{F}$, it follows that every nonzero polynomial p in our space takes on at least $|\mathcal{F}|^m - D|\mathcal{F}|^{m-1}$ nonzero values. Dividing by $|\mathcal{F}|^m$ says that the proportion of nonzero values is at least $1 - D/|\mathcal{F}| = 1 - mh/2^s = 1 - \eta$. Now consider the codeword w_p corresponding to p , and consider a nonzero value $p(a_1, \dots, a_m) = u$. This corresponds to a range of 2^s -many columns indexed by (a_1, \dots, a_m, v) over all $v \in \mathcal{F}$. Since $u \neq 0$, exactly half of those v give $u \bullet v = 1$. Hence the density of the codeword w_p is at least $(1 - \eta)/2$, and this fulfills the claim made about the code. (Technically, G is the “concatenation” of the code over \mathcal{F} with the so-called binary “Hadamard code” defined by the dot-product function over $GF(2)$.)

Finally, Proposition 13.1 gives us the desired linear probabilistic polynomials, for AND, NOR, NAND as well as OR, with constant one-sided error arbitrarily close to $1/2$, and with polynomial sample-space size. \square

We do not know of a sequence of *good* small codes that is AC^0 -uniform. B.-Z. Shen [She93] shows how to construct asymptotically good binary codes by an algebraic technique that (in an analogous situation) chops many columns out of J without reducing the density of the code, but we do not know how uniform the “chops” are.

In the case of large codes with $K = 2^n$, the computation of $G(i, j)$ in (10) involves field elements of size $O(\log n)$. Since both the sequences (a_1, \dots, a_m) and (i_1, \dots, i_m) can be read left-to-right, the entire computation can be done in one-way log-space. Thus NL random-logspace reduces to $\oplus L$, and this immediately implies Wigderson’s theorem that $NL/poly \subseteq \oplus L/poly$ [Wig94]. We would like to know whether this computation can be done in TC^0 .

Matters become more complex when the error tolerance ϵ is not constant but shrinks rapidly with n . A example application is simulating AC^0 circuits of depth b and size n^c within a target error e . We may suppose that each gate is a NAND gate of fan-in at most n . The idea is to substitute “the same” probabilistic polynomial σ of degree d and error ϵ_n for each gate. Composing these polynomials then yields a single probabilistic polynomial τ of degree d^b in the input variables x_1, \dots, x_n of the circuit that computes it with error at most $\epsilon_n n^c$. This works even though the “errors at each gate” are not independent; note that τ has the same sample space as σ . Thus we wish to arrange $\epsilon_n \leq e/n^c$.

We could do $O(\log(1/\epsilon_n))$ independent trials in this example, thus making $d \simeq c \log n$ and using $r(n) = O(\log n \log(1/\epsilon_n)) = O(\log^2 n)$ random bits. Plugging this in to the construction in Theorem 14 improves the original degree bounds of Beigel,

Reingold, and Spielman [BRS91a, BRS95], and S. Gupta [Gup93], but still falls well short of the optimal argument of Tarui [Tar93].

However, there is a very interesting possibility to compute OR in a uniform manner by using larger fields \mathcal{F} . It is known that there exist sequences of good codes over \mathcal{F} with $\delta_n \geq \delta$ exponentially many, then the argument of Proposition 13.1 immediately gives a probabilistic polynomial τ over $GF(2^k)$ that computes OR using $O(\log n)$ random bits. The following then gives an alternative way to compute OR for OR . Let or_k be the unique polynomial that computes OR over $GF(2)$.

Proposition 14.1. *Let G be an $n \times N$ generator matrix over $GF(2^k)$, and let G' be the straightforward way of computing OR over $GF(2^k)$. Then the probabilistic polynomial σ defined by*

$$\sigma_j(x_1, \dots, x_n) = or_k \left(\sum_{i=1}^n G'(i, kj - k + j) \right)$$

represents $OR(x_1, \dots, x_n)$ over $GF(2)$ with error ϵ and sample space $\{1, \dots, N\}$.

Note that σ has the same sample space as τ . The error of σ is the same as that of G' over $GF(2)$, but the difference between the two is much smaller.

Now we want to ask: What happens to “good” probabilistic polynomials as n grows upward with n ? What must at least happen to the error ϵ ? The answer is given by a coding-theory bound called the *Singleton bound*: For a code of length n over a field \mathcal{F} , $K + d \leq N + 1$. Written another way with $\epsilon = 1 - \delta$, this says that $\delta \geq (K - 1)/n$, and putting $K = n$, this says that $\delta \geq (1 - \epsilon)/n$. This means that ϵ must satisfy

$$r(n) \geq \log_2(n - 1) + \log_2(1 - \epsilon)$$

This is much better than the $r(n) = \log(n) \log(1 - \epsilon)$ bound for AC^0 circuits. There are codes that meet this bound—such codes are called *Maximum Distance Separable* (MDS). The question now becomes: Can we construct probabilistic polynomials of high density over $GF(2^k)$? This and the question of whether R_k for good codes in Definition 9 may scale with n are the main open problems in the theory, for which [MS77] is a standard reference. The theory of probabilistic polynomials over larger fields of the same characteristic (here, $GF(2^k)$) is not well understood, but it is believed that there is room in the theory of error-correcting codes over larger fields that will add to our knowledge about complexity theory.

8 Other Combinatorial Structures

If we blur the distinction between a language L and its complement $\sim L$, we can regard L as a “two-coloring” of Σ^* . We seek connections to a powerful body of mathematics that is bound up with generalizations of a familiar theorem about two-colorings of the plane:

Any map formed by simple closed curves and infinite straight lines in the plane can be colored with two colors, so long as all intersections are “general”—meaning that for every pair of curves or lines, the intersections (if any) between them form a collection of isolated crossing points.

Versions of this theorem extend to higher dimensions. To use them, we need to identify Σ^* with a subset of real space. We decide to take $\Sigma = \{0, 1\}$ and identify Σ^n with the vertices of the unit cube in \mathbf{R}^n , for each n .

The generalization of “infinite straight line” to \mathbf{R}^n is a *hyperplane*, meaning an affine translation of an $(n-1)$ -dimensional subspace of \mathbf{R}^n . Every hyperplane is defined by an equation of the form $\sum_{i=1}^n x_i w_i = t$. The (upper) *open half space* associated to the hyperplane consists of points \vec{x} satisfying $\sum_{i=1}^n x_i w_i > t$. Note that this inequality defines a threshold gate. A *polytope* is an intersection of open half-spaces that defines a bounded nonempty region of space, together with its *surface* consisting of those points belonging to the hyperplanes that are added in forming the topological closure of this region. (This wording makes all polytopes “full-dimensional.”) Every polytope is convex. Familiar examples of polytopes in \mathbf{R}^3 are the tetrahedron, cube, octahedron, and prism, but not a cylinder, cone, or sphere.

For simplicity, we will not work with the theories of algebraic curves and algebraic topology that provide full generalizations of simple closed curves in the plane, but will confine attention to polytopes. Say a collection of polytopes is in “general position” if no polytope has a hyperplane that goes through a vertex of the unit n -cube, and no two polytopes share a hyperplane nor any lower-dimensional facet. (See [MP68] for more on this.) Then we have an analogue of the above two-coloring theorem:

Every finite collection of polytopes in general position defines a two-coloring of \mathbf{R}^n , and every vertex of the unit n -cube has a well-defined color.

Definition 10. A language L belongs to *PALT* if there are polynomial-sized collections \mathcal{P}_n of polytopes in general position, with each member of \mathcal{P}_n defined by polynomially-many half-spaces, such that for all n , all points in $L^{=n}$ have one color, and all points in $\sim L^{=n}$ have the other color.

By definition, PALT is closed under complements. If we want to distinguish “the language of $\{\mathcal{P}_n\}$ ” from its complement, we may exploit the fact that the partition

of \mathbf{R}^n by \mathcal{P}_n has only one infinite region, and does not have a unit cube that have the same color as this region. By adding one polytope that encloses the unit cube.

Now we can characterize this idea in terms of circuits. This completes the proof of Theorem 3.

Proposition 14.2. A language L belongs to PALT if and only if it is polynomial-sized Parity \circ AND \circ LT circuits.

Proof. Let L in PALT, and let \mathcal{P}_n define $L^{=n}$. Each member of \mathcal{P}_n is a collection of LT gates. By a standard lemma in [MP68], each member of \mathcal{P}_n is a collection of LT gates that gives the same outputs on the vertices of the unit cube. Note that the weights and threshold for the latter gate are polynomial in n . By [MP68], the circuits obtained by attaching a single parity gate to each member of \mathcal{P}_n are polynomial-size P \circ A \circ LT circuits. Now we can prove the claim by induction on n . If $n = 1$, then the vertices of the unit cube have different colors iff the number of hyperplanes passing through x is odd. If $n = 2$, then exactly one of x, y belongs to the interior of P is colored 1. By [MP68], a P \circ A \circ LT circuit computes the same language as the corresponding P \circ A \circ LT circuit. Now we prove the general case. Consider the straight line segment ℓ from x to y . If ℓ intersects the surfaces of polytopes are isolated, for instance, if ℓ is a line segment in the interior of a polytope, then some hyperplane involved would have to pass through a vertex of the unit cube. By [MP68], this contradicts the general position. Two different polytopes may share a hyperplane, but this does not affect the total number of intersections, counting multiplicity. If ℓ intersects the surfaces of polytopes in general position, then each intersection, counting this kind of multiplicity, has both or neither of x, y in its interior. This completes the proof of the claim.

Going the other way, given a P \circ A \circ LT circuit that computes the language of PALT, we can find a collection of polytopes in general position whose intersection of open half spaces is the language of PALT. By adding some assignments in $\{0, 1\}^n$, we can make this intersection of open half spaces the language of PALT. The lemma from [MP68] can also be used to tweak the circuit to make it a PALT circuit without changing any values on the unit cube.

Thus PALT is a small-depth, polynomial-size circuit class. It is “small-depth” in the sense that it is “above” the polynomial-size circuit classes for which the membership problem is known, such as those treated in [HG91, GHR92]. It is “polynomial-size” in the sense that the known classes are contained in polynomial-size TC^0 depth-2 circuits. The proof of Theorem 14.2 depends on the problem of whether $\text{NC}^1 = \text{TC}_3^0$. We find that $\text{NC}^1 = \text{TC}_3^0$ implies PALT. Since $\text{PALT} \subseteq \text{TC}_4^0$ by the obvious simulation of Parity by two AND gates and the known simulation of Parity by two Midbit gates, we find that $\text{NC}^1 = \text{TC}_4^0$ implies PALT. However, we do not know whether TC_4^0 is a small-depth circuit class. The depth simulation we know was furnished by Alexander Goldvarg, and the proof of Theorem 14.2 was communicated with Maciel and Mikael Goldvarg.

Theorem 15. For any $m > 0$, $\text{Mod}_m \circ \text{AND} \circ \text{LT}$ circuits are polynomial-sized and closed under complements. They consist of a Midbit gate connected to one layer of Mod_m gates.

particular, $\text{PALT} \subseteq q\text{TC}_3^0$, where the “ q ” indicates quasipolynomial size.

Proof. As shown in [CSV84], by using iterated addition to simulate the weights in an LT gate, $\text{LT} \subseteq \text{AC}^0 \circ \text{MAJ}$. Thus

$$\text{Mod}_m \circ \text{AND} \circ \text{LT} \subseteq \text{Mod}_m \circ \text{AC}^0 \circ \text{MAJ}.$$

Now by Theorem 12, $\text{Mod}_m \circ \text{AC}^0 \subseteq q(\text{Midbit} \circ \text{AND}_{\text{small}})$, where all AND gates in the corresponding level are *small*, i.e., have polylog fan-in. Now each MAJ gate involved has fan-in at most $r = n^{O(1)}$. We want to simulate each small-AND of MAJ by a single SYM gate of quasipolynomial fan-in. Theorem 3.6 of [Mac95], which is a slight extension of the relevant special case of results in [Bei94b] and [HHK91], does this by brute-force coding of all $(r+1)^{\text{polylog}(n)}$ possible vectors of sums of the input bits to the $\text{polylog}(n)$ -many MAJ gates, with a different integer for each vector. The coding produces a function of these integers, which becomes a symmetric function of $n^{\text{polylog}(n)}$ -many input lines. The codings used in [Bei94b, Mac95] do not produce a threshold function of these integers, so they do not yield a single MAJ gate. However, because all of the MAJ and small-AND gates above can be normalized to have the same fan-in via “dummy inputs,” the number k of values on which each new SYM gate outputs *true* can be the same for all SYM gates in the circuit. Thus

$$\text{Mod}_m \circ \text{AND} \circ \text{LT} \subseteq q(\text{Midbit} \circ \text{SYM}).$$

By a lemma of Hájnal et al. [HMP⁺87], every symmetric 0-1 valued function h in m “own” variables can be written as

$$h(z_1, \dots, z_m) = g(M_1(z_1, \dots, z_m), \dots, M_{2k}(z_1, \dots, z_m)),$$

where (1) $i_1 < i_2 < \dots < i_k$ are the k values of $z_1 + \dots + z_m$ on which h outputs 1, (2) for each j , $1 \leq j \leq k$, $M_{2j}(z_1, \dots, z_m) = 1 \iff z_1 + \dots + z_m \geq i_j$ and $M_{2j-1}(z_1, \dots, z_m) = 1 \iff z_1 + \dots + z_m \leq i_j$, and (3) g is the linear $2k$ -variable integer polynomial $g(r_1, \dots, r_{2k}) = r_1 + \dots + r_{2k} - k$. Each of the M_j functions is computable by a single MAJ gate using extra “dummy” inputs (and using the fact that negated inputs are available), so we can abbreviate this as $h = g \circ \text{MAJ}$. So the whole circuit is now a quasipolynomial-size Midbit $\circ g \circ \text{MAJ}$.

Now finally we claim that since g is *linear*, the Midbit $\circ g$ portion of the circuit can be replaced by a single Midbit gate. This is because the original single Midbit gate M outputs the middle bit of the binary sum of its inputs, and each input line $g(r_1, \dots, r_{2k})$ is itself a sum, minus k . Hence we can gather all the inputs to all g ’s into a “positive section” of inputs to a new gate M' , and all of the “ $-k$ ”s into a “negative section,” so that the new M' outputs the middle bit of the *gap* between the number of inputs in its positive section that are on and the number of inputs in its negative section, all of which are on. Here we are helped for ease of verification by the fact that we have made k the same for each of the quasipolynomial-many

inputs g_1, \dots, g_q to the original M , so that the

$$\left(\sum_{i=1}^q \sum_{j=1}^{2k} r_{j,i} \right) -$$

Analogous to the way that the class MidbitP is related to the middle bit of a GapP function, this M' can be used to produce a quasipolynomial-size Midbit $\circ \text{MAJ}$ circuit. Finally, applying the same construction to the symmetric gate M' produces a quasipolynomial-size MidbitP circuit, which is clearly in $q\text{TC}_3^0$.

PALT seems to be worthy of further research. Is it contained in polynomial-size TC^0 depth-3? Does it have a quasipolynomial-size circuit? Does it have a quasipolynomial-size circuit that given collections \mathcal{P}_1 defining L_1 and \mathcal{P}_2 defining L_2 , produces a collection \mathcal{P}_3 defining $L_1 \cap L_2$ by taking all pairwise intersections of \mathcal{P}_1 and \mathcal{P}_2 . However, the size blowup in the collection \mathcal{P}_3 makes this question difficult to answer. The real technical matter is whether the quasipolynomial-size circuit of projections can be done from \mathbf{R}^n to \mathbf{R}^m with $m = n$.

A simpler class PLT can be defined in terms of collections of hyperplanes alone. Similar to PALT, it is contained in polynomial-size Parity $\circ \text{LT}$ circuits, which are contained in polynomial-size TC^0 circuits. The class of languages defined by a single hyperplane is contained in polynomial-size TC^0 circuits, and this is contained in LT_1 by Agrawal and Arvind [AA95], who show that the class of languages defined by a single hyperplane is contained in polynomial-size TC^0 circuits, and this is contained in LT_1 , then $\text{NP} = \text{P}$. Clearly, the class of languages defined by a single hyperplane reduces to LT_1 , but this reduction is neither bounded by a polynomial nor contained in it. So even the stronger results in [AA95] seem not to help. The question is whether PALT relates to P and NP. A truth-table reduction of PALT to P is not possible, but it is contained in polynomial-size *linear decision tree*, as studied by Agrawal and Arvind [AA95]. The exponential size lower bounds in [BLY92] and [AA95] apply to linear decision trees, but not to arbitrary points in \mathbf{R}^n , however, and we do not know whether PALT is contained in polynomial-size TC^0 circuits. The promise that geometrical methods of the kind used in [AA95] can be brought to bear on Boolean complexity via linear decision trees is still there.

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