

# $\varepsilon$ -discrepancy sets and their applications for interpolation of sparse polynomials

Noga Alon\*

Yishay Mansour†

February 22, 2002

## Abstract

We present a simple explicit construction of a probability distribution supported on  $(p-1)^2$  vectors in  $Z_p^n$ , where  $p \geq n/\varepsilon$  is a prime, for which the absolute value of each nontrivial Fourier coefficients is bounded by  $\varepsilon$ . This construction is used to derandomize the algorithm of [Man92] that interpolates a sparse polynomial in polynomial time in the bit complexity model.

## 1 Introduction

Given a set  $A \subset Z_p^n$ , for each  $\alpha \in Z_p^n$  define

$$DISC_A(\alpha) = \frac{1}{|A|} \left| \sum_{z \in A} \omega^{\langle \alpha, z \rangle} \right|,$$

where  $\omega$  is the  $p$ th root of unity over the complex numbers, i.e.  $\omega = e^{2\pi i/p}$ .

**Definition 1** A set  $A \subset Z_p^n$  is an  $\varepsilon$  discrepancy set if for any  $\alpha \neq \vec{0}$ ,  $DISC_A(\alpha) \leq \varepsilon$ .

In this note we present a simple explicit construction as follows.

**Theorem 1.1** For any prime  $p$  and any  $n > 1$  there exists an explicit set  $A_p^n \subset Z_p^n$ , such that  $|A_p^n| = (p-1)^2$  and  $A_p^n$  is an  $\frac{n-1}{p-1}$  discrepancy set.

The construction is a *mod p* variant of one of the binary constructions presented in [AGHP90]. Another construction with related properties appears in [AMN90]. The main advantage of the present construction is its simplicity and the elementary proof of its properties.

---

\*Department of Mathematics, Raymond and Beverly Sackler Faculty of Exact Sciences, Tel-Aviv University, Tel-Aviv, Israel. Research supported in part by a USA-Israeli BSF grant and by the Fund for Basic Research administered by the Israel Academy of Sciences.

†Department of Computer Science, Raymond and Beverly Sackler Faculty of Exact Sciences, Tel-Aviv University, Tel-Aviv, Israel. Research supported in part by a grant of the Israeli Ministry of Science and Technology and by The Israel Science Foundation administered by The Israel Academy of Science and Humanities.

Our main application for  $\varepsilon$  discrepancy sets is the derandomization of the interpolation algorithm of [Man92]. Using an  $\varepsilon$  discrepancy set we can test whether a sparse multivariate polynomial is identically zero, which is a major task in any multivariate interpolation algorithm. Other possible applications are mentioned as well.

Other previous works on sparse multi-variate polynomial interpolation include the work of Zippel [Zip79], which gives a probabilistic algorithm, that of Grigoriev and Karpinski [GK87], for interpolation of a sparse permanent, and the work of Ben-Or and Tiwari [BOT88].

Our construction of  $\varepsilon$ -discrepancy sets can be viewed as a real-value analog of the “ $\varepsilon$ -bias” distribution [NN90, AGHP90], which is defined over boolean variables and guarantees that the absolute value of each of its nontrivial Fourier coefficients is bounded by  $\varepsilon$ .

## 2 Construction of an $\varepsilon$ discrepancy set

Let  $p$  be a prime and let  $Z_p^*$  denote the multiplicative group of the finite field  $Z_p$ . For  $x, y \in Z_p^*$  put  $v_{x,y} = (y, yx, yx^2, \dots, yx^{n-1})$ . Define  $A_p^n = \{v_{x,y} \mid x, y \in Z_p^*\}$ . Note that the size of the set  $A_p^n$  is  $(p-1)^2$ .

For  $a \in Z_p$  and  $\alpha \in Z_p^n$  define  $n_{a,\alpha}$  by

$$n_{a,\alpha} = |\{v_{x,y} \mid x, y \in Z_p^*, \langle v_{x,y}, \alpha \rangle = a\}|$$

**Claim 2.1** *Let  $\alpha \neq \vec{0}$ . If  $a, b \neq 0$  then  $n_{a,\alpha} = n_{b,\alpha}$ . In addition,  $n_{0,\alpha} \leq (n-1)(p-1)$*

**Proof:** Consider the inner product,

$$\langle v_{x,y}, \alpha \rangle = \sum_{i=0}^{n-1} yx^i \alpha_i = yP_\alpha(x)$$

where  $P_\alpha(x)$  is the polynomial with  $\vec{\alpha}$  as the vector of its coefficients, i.e.  $P_\alpha(x) = \sum_i \alpha_i x^i$ . We are interested in the number of solutions  $x, y$  of the equation

$$yP_\alpha(x) = a.$$

Fix  $x \in Z_p^*$ . Clearly, if  $P_\alpha(x) \neq 0$  then for each  $y \in Z_p^*$  there is a different nonzero value to  $yP_\alpha(x)$ . Hence, each value in  $Z_p^*$  is generated by a unique  $y$  (in this case). On the other hand if  $P_\alpha(x) = 0$ , then  $\langle v_{x,y}, \alpha \rangle = 0$  for every  $y \in Z_p^*$ . Since  $P_\alpha(x) = 0$  for at most  $n-1$  different  $x \in Z_p^*$ , we conclude that  $n_{0,\alpha} \leq (n-1)(p-1)$ .  $\square$

**Theorem 2.2**  *$A_p^n$  is an  $\frac{n-1}{p-1}$  discrepancy set.*

**Proof:** By the construction of  $A_p^n$ ,

$$DISC_{A_p^n}(\alpha) = \frac{1}{(p-1)^2} \left| \sum_{x,y \in Z_p} \omega^{\langle \alpha, v_{x,y} \rangle} \right|.$$

We can rewrite this as,

$$DISC_{A_p^n}(\alpha) = \frac{1}{(p-1)^2} \left| \sum_{a \in Z_p} n_{a,\alpha} \omega^a \right|.$$

Recall that  $\sum_{i=0}^{p-1} \omega^i = 0$ . Since for  $a \neq 0$ ,  $n_{a,\alpha} = k$  is the same, the only non-zero contribution is from  $a = 0$ , showing that  $\sum_{a \in Z_p} n_{a,\alpha} \omega^a = n_{0,\alpha} - k$ . Since  $n_{0,\alpha} \leq (n-1)(p-1)$  and  $0 \leq k \leq p-1$ , we have that,

$$DISC_{A_p^n}(\alpha) \leq \frac{n-1}{p-1},$$

completing the proof of the theorem. □

## 3 Applications

### 3.1 Interpolation of Multivariate Polynomials

Let  $P(x_1, \dots, x_n) = \sum_{i=0}^t c_i x_1^{e_{i,1}} \cdots x_n^{e_{i,n}}$  be a multivariate polynomial with  $t$  integer coefficients. Let  $L_1(P)$  denote the sum of the absolute values of the coefficients of  $P$ , i.e.  $L_1(P) = \sum_{i=0}^t |c_i|$ .

**Lemma 3.1** *Let  $A$  be an  $\varepsilon$  discrepancy set, and  $P(x_1, \dots, x_n) = c_0 + \sum_{i=1}^t c_i x_1^{e_{i,1}} \cdots x_n^{e_{i,n}}$ . Then,*

$$|E_{(z_1, \dots, z_n) \in A} [P(\omega^{z_1}, \dots, \omega^{z_n})] - c_0| \leq \varepsilon L_1(P)$$

where  $E$  is the expectation over the uniform distribution of vectors from  $A$ .

**Proof:** Let  $\vec{e}_i = (e_{i,1}, \dots, e_{i,n})$ . By the linearity of expectation,

$$E_{\vec{z}=(z_1, \dots, z_n) \in A} [P(\omega^{z_1}, \dots, \omega^{z_n})] = c_0 + \sum_{i=1}^t c_i E[\omega^{\langle \vec{z}, \vec{e}_i \rangle}].$$

Since  $A$  is an  $\varepsilon$  discrepancy set and  $\vec{e}_i \neq \vec{0}$ ,

$$|E[\omega^{\langle \vec{z}, \vec{e}_i \rangle}]| \leq \varepsilon,$$

and the assertion of the lemma follows. □

By the same argument one can show the following.

**Claim 3.2** *Let  $A$  be an  $\varepsilon$  discrepancy set, and  $P(x_1, \dots, x_n) = \sum_{i=0}^t c_i x_1^{e_{i,1}} \cdots x_n^{e_{i,n}}$ . Then,*

$$\left| E_{(z_1, \dots, z_n) \in A} \left[ \|P(\omega^{z_1}, \dots, \omega^{z_n})\|^2 \right] - \sum_{i=0}^t c_i^2 \right| \leq \varepsilon L_1^2(P)$$

where  $E$  is the expectation over the uniform distribution of vectors from  $A$ .

The above claim gives an immediate tool to test if a sparse multivariate polynomial is zero (assuming that its coefficients are integers and bounded). Since the coefficients are integers, then either  $\sum_{i=0}^t c_i^2$  is at least one or it is zero. By choosing  $p > 2nL_1^2(P)$  we guarantee that the error is less than  $1/2$ , and therefore, by the above claim, we can distinguish between the two cases.

We next demonstrate the derandomization on the algorithm of [Man92]. The idea, as in [Zip79], is to interpolate the variables one by one. Since we have an upper bound, say  $t$ , on the number of non-zero coefficients, there would be at most  $t$  terms to consider. The assumption here is that we have a black box that outputs the value of  $P(x_1, \dots, x_n)$  for any desired  $(x_1, \dots, x_n)$ , and our objective is to determine the coefficients of  $P$ . From the analysis it follows that this is possible even if our black box only outputs (sufficiently accurate) approximations of the values of  $P$ .

Initially, we can rewrite  $P$  as,

$$P(x_1, \dots, x_n) = \sum_{j=0}^d x_1^j P_j(x_2, \dots, x_n).$$

We are interested in determining which of the  $P_j$ 's are not the zero polynomial. To perform this we note that, for a prime  $p > d$ ,

$$P_j(x_2, \dots, x_n) = \frac{1}{p} \sum_{k=0}^{p-1} P(\omega^k, x_2, \dots, x_n) \omega^{-kj}.$$

For each  $\vec{z} = (z_2, \dots, z_n) \in A_p^{n-1}$  we can compute  $P_j(z_2, \dots, z_n)$  by using the above identity, and then compute  $E_z[\|P_j(z)\|^2]$ .

In general we define  $P_{e_1, \dots, e_k}$  as follows,

$$P(x_1, \dots, x_n) = \sum_{e_1=0}^d \cdots \sum_{e_k=0}^d x_1^{e_1} \cdots x_k^{e_k} P_{e_1, \dots, e_k}(x_{k+1}, \dots, x_n),$$

i.e.  $P_{e_1, \dots, e_k}(x_{k+1}, \dots, x_n)$  has all the terms that include  $x_1^{e_1} \cdots x_k^{e_k}$ . By the properties of the discrete Fourier transform we have that,

$$P_{e_1, \dots, e_k}(x_{k+1}, \dots, x_n) = \frac{1}{p^k} \sum_{j_1=0}^{p-1} \cdots \sum_{j_k=0}^{p-1} P(\omega^{j_1}, \dots, \omega^{j_k}, x_{k+1}, \dots, x_n) \omega^{-e_1 j_1} \cdots \omega^{-e_k j_k}.$$

In order to test whether  $P_{e_1, \dots, e_k} \neq 0$ , we estimate its norm by computing,

$$E_{(z_{k+1}, \dots, z_n) \in A_p^{n-k}} \left[ \left\| E_{(z_1, \dots, z_k) \in A_p^k} [P(\omega^{z_1}, \dots, \omega^{z_k}) \omega^{-\sum_{j=1}^k e_j z_j}] \right\|^2 \right].$$

The interpolation works in phases. At the  $k$ th phase we determine all the vectors  $(e_1, \dots, e_k)$ , such that  $P_{e_1, \dots, e_k} \neq 0$ , given all the the vectors  $(e_1, \dots, e_{k-1})$ , such that  $P_{e_1, \dots, e_{k-1}} \neq 0$ . Since the polynomial  $P$  has only  $t$  non-zero coefficients, at any phase we need to maintain at most  $t$  vectors. At the end we have all the terms, i.e.  $\vec{e}_i$ , and need only to determine the coefficients.

### 3.2 Univariate polynomials

In [Kat89, AIK<sup>+</sup>90] and, more explicitly, in [RSW93] it is shown how to construct explicitly a set  $B \subset Z_p$ , such that  $|B| = O((\log p/\varepsilon)^c)$ , for some constant  $c$ , and such that for any  $\alpha \neq 0, \alpha \in Z_p$ ,

$$\frac{1}{|B|} \left| \sum_{z \in B} \omega^{\alpha z} \right| \leq \varepsilon.$$

We can use the set  $B$  to interpolate any sparse univariate polynomial of (high) degree  $d (\leq p)$ . Recall that if  $P(x) = \sum_{i=0}^p a_i x^i$  then  $a_k = (1/p) \sum_{j=0}^p P(\omega^j) \omega^{-kj}$ . Hence, averaging over  $B$  would add an additive error of at most  $\varepsilon L_1(P)$  to any coefficient.

Using such constructions we can reduce the size of  $A_p^n$  when  $\varepsilon \gg 1/p^{1/c}$  to  $O(\frac{n}{\varepsilon} (\log p/\varepsilon)^c)$ . To do so, simply modify the construction above by letting  $x$  vary over an arbitrary subset of cardinality  $n/\varepsilon$  of  $Z_p$  and by letting  $y$  vary over a subset  $B \subset Z_p$ , that has the above properties. It is easy to check that the discussion in Section 2 implies that the modified set is a  $2\varepsilon$ -discrepancy set in  $Z_p^n$ . By Proposition 7' in [AR94], for  $\epsilon > p^{-n/2}$  the size of any  $\epsilon$  discrepancy set for  $Z_p^n$  is at least  $\Omega(\frac{n \log p}{\epsilon^2 \log(n \log p/\epsilon^2)})$  showing that the last construction is not far from the optimum.

### 3.3 Axis Parallel boxes

The sets  $A_p^n$  can be used to approximate the expectation of any function  $P$  with a small value of  $L_1(P)$ . As an illustration, consider the function  $f_a(x) = 1$  if  $x < a$  and  $f_a(x) = 0$  otherwise, where  $x \in Z_p$ . For the intersection of  $k$  such functions, i.e.  $F(\vec{x}) = \prod_{j=1}^k f_{a_j, i_j}(\vec{x})$ , one can show that  $L_1(F) = O(\log^k p)$ , and hence the set  $A_p^n$  can be used to approximate the expectation of  $F$  (which is the fraction of the volume of the corresponding box in  $Z_p^n$ ) within an additive error of  $O(\frac{n \log^k p}{p})$ . In fact, by replacing  $F$  by a smooth function that approximates it this error term can be improved to  $O(\frac{n \log^k(p/n)}{p})$ . Since for this example this is a weaker estimate than those obtained by the constructions in [EGL<sup>+</sup>92] and [CRS94] we omit the details.

## 4 Conclusion and Open questions

We showed that the set  $A_p^n$  is an  $\frac{n-1}{p-1}$  discrepancy set, and  $|A_p^n| = O(p^2)$ . The modified construction described in Subsection 3.2 provides an  $\epsilon$ -discrepancy set of size polynomial in  $\log p/\varepsilon$  and linear in  $n$ .

For the interpolation problem we need that  $p$  is larger than the degree of the polynomial in each variable. Therefore, the modified set can be useful here. It is not difficult to check (see Proposition 6' in [AR94]) that a random set of  $\Theta(\frac{n}{\varepsilon^2} \log p)$  vectors from  $Z_p^n$  would almost surely be an  $\varepsilon$  discrepancy set, and as mentioned above this is nearly best possible. However the problem of finding an explicit construction of such a small  $\varepsilon$ -discrepancy set remains open.

**Acknowledgment** We would like to thank Avi Wigderson for helpful comments and suggestions.

## References

[AGHP90] Noga Alon, Oded Goldreich, Johan Hastad, and Rene Peralta. Simple constructions of almost  $k$ -wise independent random variables. In 31<sup>th</sup> *Annual Symposium on Foundations*

- of Computer Science, St. Louis, Missouri*, pages 544–553, October 1990. Also: *Random Structures and Algorithms* 3 (1992), 289–304.
- [AIK<sup>+</sup>90] M. Ajtai, H. Iwaniec, J. Komlós, J. Pintz, and E. Szemerédi. Construction of a thin set with small fourier coefficients. *Bull. London Math. Soc.*, 22:583–590, 1990.
- [AMN90] Y. Azar, R. Motwani, and J. Naor. Approximating arbitrary probability distributions using small sample spaces. Manuscript, 1990.
- [AR94] N. Alon and Y. Roichman. Random cayley graphs and expanders. *Random Structures and Algorithms*, 5:271–284, 1994.
- [BOT88] M. Ben-Or and P. Tiwari. A deterministic algorithm for sparse multivariate polynomial interpolation. In *Proceedings of the 20<sup>th</sup> Annual ACM Symposium on Theory of Computing*, pages 301–309, May 1988.
- [CRS94] Suresh Chari, Pankaj Rohatgi, and Aravind Srinivasan. Improved algorithms via approximations of probability distributions. In *Proceedings of the 26<sup>th</sup> Annual ACM Symposium on Theory of Computing*, pages 584–592, May 1994.
- [EGL<sup>+</sup>92] G. Even, O. Goldreich, M. Luby, N. Nisan, and B. Velickovic. Approximations of general independent distributions. In *Proceedings of the 24<sup>th</sup> Annual ACM Symposium on Theory of Computing*, pages 10–16, May 1992.
- [GK87] D. Y. Grigoriev and M. Karpinski. The matching problem for bipartite graphs with polynomially bounded permanents is in NC. In *28<sup>th</sup> Annual Symposium on Foundations of Computer Science, Los Angeles, California*, pages 166–172, October 1987.
- [Kat89] N. M. Katz. An estimate for character sums. *J. AMS* 2:197–200, 1989.
- [Man92] Yishay Mansour. Randomized approximation and interpolation of sparse polynomials. In *ICALP*, pages 261–272, July 1992.
- [NN90] Joseph Naor and Moni Naor. Small bias probability spaces: efficient construction and applications. In *Proceedings of the 22<sup>nd</sup> Annual ACM Symposium on Theory of Computing, Baltimore, Maryland*, pages 213–223, May 1990.
- [RSW93] A. Razborov, E. Szemerédi, and A. Wigderson. Constructing small sets that are uniform in arithmetic progressions. *Combinatorics, Probability and Computing* 2:513–518, 1993.
- [Zip79] R. E. Zippel. Probabilistic algorithms for sparse polynomials. In *EUROSAM*, pages 216–226. Springer Lecture notes in computer science, vol. 72, 1979.