Testing ± 1-Weight Halfspaces

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Abstract. We consider the problem of testing whether a Boolean function $f : \{-1,1\}^n \to \{-1,1\}$ is a ± 1-*weight halfspace*, i.e. a function of the form $f(x) = \mathrm{sgn}(w_1x_1+w_2x_2+\cdots+w_nx_n)$ where the weights w_i take values in $\{-1,1\}$. We show that the complexity of this problem is markedly different from the problem of testing whether f is a general halfspace with arbitrary weights. While the latter can be done with a number of queries that is independent of n [7], to distinguish whether f is a ± 1-weight halfspace versus ϵ-far from all such halfspaces we prove that nonadaptive algorithms must make $\Omega(\log n)$ queries. We complement this lower bound with a sublinear upper bound showing that $O(\sqrt{n}\cdot \mathrm{poly}(\frac{1}{\epsilon}))$ queries suffice.

1 Introduction

dfgfghdfg this is the best i can get it asdf to do it doens't seem to make much difference as far as I can tell

This is the best I can get it to to do i I don't know how to change $\frac{3}{4} \cdot \sum_{i}^{n}$ of

A fundamental class in machine learning and complexity is the class of halfspaces, or functions of the form $f(x) = (w_1x_1 + w_2x_2 + \cdots + w_nx_n - \theta)$. Halfspaces are a simple yet powerful class of functions, which for decades have played an important role in fields such as complexity theory, optimization, and machine learning (see e.g. [5, 12, 1, 9, 8, 11]).

Recently [7] brought attention to the problem of *testing* halfspaces. Given query access to a function $f : \{-1,1\}^n \to \{-1,1\}$, the goal of an ϵ-testing algorithm is to output YES if f is a halfspace and NO if it is ϵ-far (with respect to the uniform distribution over inputs) from all halfspaces. Unlike a learning algorithm for halfspaces, a testing algorithm is not required to output an approximation to f when it is close to a halfspace. Thus, the testing problem can be viewed as a relaxation of the proper learning problem (this is made formal in [4]). Correspondingly, [7] found that halfspaces can be tested more efficiently than they can be learned. In particular, while $\Omega(n/\epsilon)$ queries are required to learn halfspaces to accuracy ϵ (this follows from e.g. [6]), [7] show that ϵ-testing halfspaces only requires $\mathrm{poly}(1/\epsilon)$ queries, *independent of the dimension* n.

In this work, we consider the problem of testing whether a function f belongs to a natural subclass of halfspaces, the class of ± 1-*weight halfspaces*. These are functions of the form $f(x) = \mathrm{sgn}(w_1 x_1 + w_2 x_2 + \cdots + w_n x_n)$ where the weights w_i all take values in $\{-1, 1\}$. Included in this class is the majority function on n variables, and all 2^n "reorientations" of majority, where some variables x_i are replaced by $-x_i$. Alternatively, this can be viewed as the subclass of halfspaces where all variables have the same amount of influence on the outcome of the function, but some variables get a "positive" vote while others get a "negative" vote.

For the problem of testing ± 1-weight halfspaces, we prove two main results:

1. **Lower Bound.** We show that any nonadaptive testing algorithm which distinguishes ± 1-weight halfspaces from functions that are ϵ-far from ± 1-weight halfspaces must make at least $\Omega(\log n)$ many queries. By a standard transformation (see e.g. [3]), this also implies an $\Omega(\log \log n)$ lower bound for adaptive algorithms. Taken together with [7], this shows that testing this natural subclass of halfspaces is more query-intensive then testing the general class of all halfspaces.
2. **Upper Bound.** We give a nonadaptive algorithm making $O(\sqrt{n} \cdot \mathrm{poly}(1/\epsilon))$ many queries to f, which outputs (i) YES with probability at least $2/3$ if f is a ± 1-weight halfspace (ii) NO with probability at least $2/3$ if f is ϵ-far from any ± 1-weight halfspace.
   We note that it follows from [6] that *learning* the class of ± 1-weight halfspaces requires $\Omega(n/\epsilon)$ queries. Thus, while some dependence on n is necessary for testing, our upper bound shows testing ± 1-weight halfspaces can still be done more efficiently than learning.

Although we prove our results specifically for the case of halfspaces with all weights ± 1, we remark that similar results can be obtained using our methods for other similar subclasses of halfspaces such as $\{-1, 0, 1\}$-weight halfspaces (± 1-weight halfspaces where some variables are irrelevant).

Techniques. As is standard in property testing, our lower bound is proved using Yao's method. We define two distributions D_{YES} and D_{NO} over functions, where a draw from D_{YES} is a randomly chosen ± 1-weight halfspace and a draw from D_{NO} is a halfspace whose coefficients are drawn uniformly from $\{+1, -1, +\sqrt{3}, -\sqrt{3}\}$. We show that a random draw from D_{NO} is with high probability $\Omega(1)$-far from every ± 1-weight halfspace, but that any set of $o(\log n)$ query strings cannot distinguish between a draw from D_{YES} and a draw from D_{NO}.

Our upper bound is achieved by an algorithm which uniformly selects a small set of variables and checks, for each selected variable x_i, that the magnitude of the corresponding singleton Fourier coefficient $|\hat{f}(i)|$ is close to to the right value. We show that any function that passes this test with high probability must have its degree-1 Fourier coefficients very similar to those of some ± 1-weight halfspace, and that any function whose degree-1 Fourier coefficients have this property must be close to a ± 1-weight halfspace. At a high level this approach is similar to some of what is done in [7], but in the setting of the current paper this approach incurs a dependence on n because of the level of accuracy that is required to adequately estimate the Fourier coefficients.

2 Notation and Preliminaries

Throughout this paper, unless otherwise noted f will denote a Boolean function of the form $f : \{-1,1\}^n \to \{-1,1\}$. We say that two Boolean functions f and g are *ϵ-far* if $\Pr_x[f(x) \neq g(x)] > \epsilon$, where x is drawn from the uniform distribution on $\{-1,1\}^n$.

We say that a function f is *unate* if it is monotone increasing or monotone decreasing as a function of variable x_i for each i.

Fourier analysis. We will make use of standard Fourier analysis of Boolean functions. The set of functions from the Boolean cube $\{-1,1\}^n$ to $\mathbf{R}$ forms a 2^n-dimensional inner product space with inner product given by $\langle f, g\rangle = \mathbf{E}_x[f(x)g(x)]$. The set of functions $(\chi_S)_{S\subseteq[n]}$ defined by $\chi_S(x) = \prod_{i\in S} x_i$ forms a complete orthonormal basis for this space. Given a function $f : \{-1,1\}^n \to \mathbf{R}$ we define its *Fourier coefficients* by $\hat{f}(S) = \mathbf{E}_x[f(x)x_S]$, and we have that $f(x) = \sum_S \hat{f}(S)x_S$. We will be particularly interested in f's *degree*-1 coefficients, i.e., $\hat{f}(S)$ for $|S| = 1$; for brevity we will write these as $\hat{f}(i)$ rather than $\hat{f}(\{i\})$. Finally, we have *Plancherel's identity* $\langle f, g\rangle = \sum_S \hat{f}(S)\hat{g}(S)$, which has as a special case *Parseval's identity*, $\mathbf{E}_x[f(x)^2] = \sum_S \hat{f}(S)^2$. It follows that for every $f : \{-1,1\}^n \to \{-1,1\}$ we have $\sum_S \hat{f}(S)^2 = 1$.

Probability bounds. To prove our lower bound we will require the Berry-Esseen theorem, a version of the Central Limit Theorem with error bounds (see e.g. [2]):

Theorem 1. *Let $\ell(x) = c_1x_1 + \cdots + c_nx_n$ be a linear form over the random ±1 bits x_i. Assume $|c_i| \leq \tau$ for all i and write $\sigma = \sqrt{\sum c_i^2}$. Write F for the c.d.f. of $\ell(x)/\sigma$; i.e., $F(t) = \Pr[\ell(x)/\sigma \leq t]$. Then for all $t \in \mathbf{R}$,*

$$|F(t) - \Phi(t)| \leq O(\tau/\sigma) \cdot \frac{1}{1+|t|^3},$$

where Φ denotes the c.d.f. of X, a standard Gaussian random variable. In particular, if $A \subseteq \mathbf{R}$ is any interval then $|\Pr[\ell(x)/\sigma \in A] - \Pr[X \in A]| \leq O(\tau/\sigma)$.

A special case of this theorem, with a sharper constant, is also useful (the following can be found in [10]):

Theorem 2. *Let $\ell(x)$ and τ be as defined in Theorem 1. Then for any $\lambda \geq \tau$ and any $\theta \in \mathbf{R}$ it holds that $\Pr[|\ell(x) - \theta| \leq \lambda] \leq 6\lambda/\sigma$.*

3 A $\Omega(\log n)$ Lower Bound for Testing ±1-Weight Halfspaces

In this section we prove the following theorem:

Theorem 3. *There is a fixed constant $\epsilon > 0$ such that any nonadaptive ϵ-testing algorithm $\mathcal{A}$ for the class of all ±1-weight halfspaces must make at least $(1/26)\log n$ many queries.*

To prove Theorem 3, we define two distributions D_{YES} and D_{NO} over functions. The "yes" distribution D_{YES} is uniform over all 2^n ± 1-weight halfspaces, i.e., a function f drawn from D_{YES} is $f(x) = \mathrm{sgn}(r_1 x_1 + \cdots r_n x_n)$ where each r_i is independently and uniformly chosen to be ± 1. The "no" distribution D_{NO} is similarly a distribution over halfspaces of the form $f(x) = \mathrm{sgn}(s_1 x_1 + \cdots s_n x_n)$, but each s_i is independently chosen to be $\pm\sqrt{1/2}$ or $\pm\sqrt{3/2}$ each with probability $1/4$.

To show that this approach yields a lower bound we must prove two things. First, we must show that a function drawn from D_{NO} is with high probability far from any ± 1-weight halfspace. This is formalized in the following lemma:

Lemma 1. *Let f be a random function drawn from D_{NO}. With probability at least $1 - o(1)$ we have that f is ϵ-far from any ± 1-weight halfspace, where $\epsilon > 0$ is some fixed constant independent of n.*

Next, we must show that no algorithm making $o(\log n)$ queries can distinguish D_{YES} and D_{NO}. This is formalized in the following lemma:

Lemma 2. *Fix any set $x^1, \dots, x^q$ of q query strings from $\{-1,1\}^n$. Let $\widetilde{D}_{YES}$ be the distribution over $\{-1,1\}^q$ obtained by drawing a random f from D_{YES} and evaluating it on $x^1, \dots, x^q$. Let $\widetilde{D}_{NO}$ be the distribution over $\{-1,1\}^q$ obtained by drawing a random f from D_{NO} and evaluating it on $x^1, \dots, x^q$. If $q = (1/26)\log n$ then $\|\widetilde{D}_{YES} - \widetilde{D}_{NO}\|_1 = o(1)$.*

We prove Lemmas 1 and 2 in subsections 3.1 and 3.2 respectively. A standard argument using Yao's method (see e.g. Section 8 of [3]) implies that the lemmas taken together prove Theorem 3.

3.1 Proof of Lemma 1.

Let f be drawn from D_{NO}, and let $s_1, \dots, s_n$ denote the coefficients thus obtained. Let T_1 denote $\{i : |s_i| = \sqrt{1/2}\}$ and T_2 denote $\{i : |s_i| = \sqrt{3/2}\}$. We may assume that both $|T_1|$ and $|T_2|$ lie in the range $[n/2 - \sqrt{n \log n}, n/2 + \sqrt{n \log n}]$ since the probability that this fails to hold is $1 - o(1)$. It will be slightly more convenient for us to view f as $\mathrm{sgn}(\sqrt{2}(s_1 x_1 + \cdots + s_n x_n))$, that is, such that all coefficients are of magnitude 1 or $\sqrt{3}$.

It is easy to see that the closest ± 1-weight halfspace to f must have the same sign pattern in its coefficients that f does. Thus we may assume without loss of generality that f's coefficients are all $+1$ or $+\sqrt{3}$, and it suffices to show that f is far from the majority function $\mathrm{Maj}(x) = \mathrm{sgn}(x_1 + \cdots + x_n)$.

Let Z be the set consisting of those $z \in \{-1,1\}^{T_1}$ (i.e. assignments to the variables in T_1) which satisfy $S_{T_1} = \sum_{i \in T_1} z_i \in [\sqrt{n/2}, 2\sqrt{n/2}]$. Since we are assuming that $|T_1| \approx n/2$, using Theorem 1, we have that $|Z|/2^{|T_1|} = C_1 \pm o(1)$ for constant $C_1 = \Phi(2) - \Phi(1) > 0$.

Now fix any $z \in Z$, so $\sum_{i \in T_1} z_i$ is some value $V_z \cdot \sqrt{n/2}$ where $V_z \in [1,2]$. There are $2^{n-|T_1|}$ extensions of z to a full input $z' \in \{-1,1\}^n$. Let $C_{\mathrm{Maj}}(z)$ be the fraction of those extensions which have $\mathrm{Maj}(z') = -1$; in other words, $C_{\mathrm{Maj}}(z)$ is the fraction of strings in $\{-1,1\}^{T_2}$ which have $\sum_{i \in T_2} z_i < -V_z\sqrt{n/2}$. By Theorem 1, this fraction is $\Phi(-V_z) \pm o(1)$. Let $C_f(z)$ be the fraction of the $2^{n-|T_1|}$ extensions of z which have $f(z') = -1$. Since the variables in T_2 all have coefficient $\sqrt{3}$, $C_f(z)$ is the fraction of strings in $\{-1,1\}^{T_2}$ which have $\sum_{i \in T_2} z_i < -(V_z/\sqrt{3})\sqrt{n/2}$, which by Theorem 1 is $\Phi(-V_z/\sqrt{3}) \pm o(1)$.

There is some absolute constant $c > 0$ such that for all $z \in Z$, $|C_f(z) - C_{\mathrm{Maj}}(z)| \geq c$. Thus, for a constant fraction of all possible assignments to the variables in T_1, the functions Maj and f disagree on a constant fraction of all possible extensions of the assignment to all variables in $T_1 \cup T_2$. Consequently, we have that Maj and f disagree on a constant fraction of all assignments, and the lemma is proved. $\square$

3.2 Proof of Lemma 2.

For $i = 1, \ldots, n$ let $Y^i \in \{-1,1\}^q$ denote the vector of $(x_i^1, \ldots, x_i^q)$, that is, the vector containing the values of the i^{th} bits of each of the queries. Alternatively, if we view the n-bit strings $x^1, \ldots, x^q$ as the rows of a $q \times n$ matrix, the strings $Y^1, \ldots, Y^n$ are the columns. If $f(x) = \mathrm{sgn}(a_1x_1 + \cdots + a_nx_n)$ is a halfspace, we write $\mathrm{sgn}(\sum_{i=1}^n a_iY^i)$ to denote $(f(x^1), \ldots, f(x^q))$, the vector of outputs of f on $x^1, \ldots, x^q$; note that the value $\mathrm{sgn}(\sum_{i=1}^n a_iY^i)$ is an element of $\{-1,1\}^q$.

Since the statistical distance between two distributions D_1, D_2 on a domain $\mathcal{D}$ of size N is bounded by $N \cdot \max_{x \in \mathcal{D}} |D_1(x) - D_2(x)|$, we have that the statistical distance $\|\widetilde{D}_{YES} - \widetilde{D}_{NO}\|_1$ is at most $2^q \cdot \max_{Q \in \{-1,1\}^q} |\Pr_r[\mathrm{sgn}(\sum_{i=1}^n r_iY^i) = Q] - \Pr_s[\mathrm{sgn}(\sum_{i=1}^n s_iY^i) = Q]|$. So let us fix an arbitrary $Q \in \{-1,1\}^q$; it suffices for us to bound

$$\left| \Pr_r[\mathrm{sgn}(\sum_{i=1}^n r_iY^i) = Q] - \Pr_s[\mathrm{sgn}(\sum_{i=1}^n s_iY^i) = Q] \right|. \tag{1}$$

Let InQ denote the indicator random variable for the quadrant Q, i.e. given $x \in \mathbf{R}^q$ the value of $\mathrm{InQ}(x)$ is 1 if x lies in the quadrant corresponding to Q and is 0 otherwise. We have

$$(1) = \left| \mathbf{E}_r[\mathrm{InQ}(\sum_{i=1}^n r_iY^i)] - \mathbf{E}_s[\mathrm{InQ}(\sum_{i=1}^n s_iY^i)] \right| \tag{2}$$

We then note that since the Y^i vectors are of length q, there are at most 2^q possibilities in $\{-1,1\}^q$ for their values which we denote by $\widetilde{Y}^1, \ldots, \widetilde{Y}^{2^q}$. We lump together those vectors which are the same: for $i = 1, \ldots, 2^q$ let c_i denote the number of times that $\widetilde{Y}^i$ occurs in $Y^1, \ldots, Y^n$. We then have that $\sum_{i=1}^n r_iY^i = \sum_{i=1}^{2^q} a_i\widetilde{Y}^i$ where each a_i is an independent random variable which is a sum of c_i independent ± 1 random variables (the r_j's for those j that have $Y^j = \widetilde{Y}^i$). Similarly, we have $\sum_{i=1}^n s_iY^i = \sum_{i=1}^{2^q} b_i\widetilde{Y}^i$ where each b_i is an independent random variable which is a sum of c_i independent variables distributed as the s_j's (these are the s_j's for those j that have $Y^j = \widetilde{Y}^i$). We thus can re-express (2) as

$$\left| \mathbf{E}_a[\mathrm{InQ}(\sum_{i=1}^{2^q} a_i\widetilde{Y}^i)] - \mathbf{E}_b[\mathrm{InQ}(\sum_{i=1}^{2^q} b_i\widetilde{Y}^i)] \right|. \tag{3}$$

Let us define a sequence of random variables that hybridize between $\sum_{i=1}^{2^q} a_i \widetilde{Y}^i$ and $\sum_{i=1}^{2^q} b_i \widetilde{Y}^i$. For $1 \leq \ell \leq 2^q + 1$ define

$$Z_\ell := \sum_{i<\ell} b_i \widetilde{Y}^i \ + \ \sum_{i \geq \ell} a_i \widetilde{Y}^i, \qquad \text{so} \quad Z_1 = \sum_{i=1}^{2^q} a_i \widetilde{Y}^i \quad \text{and} \quad Z_{2^q+1} = \sum_{i=1}^{2^q} b_i \widetilde{Y}^i. \tag{4}$$

As is typical in hybrid arguments, by telescoping (3), we have that (3) equals

$$\begin{aligned}\left|\mathbf{E}_{a,b}[\sum_{\ell=1}^{2^q} \mathrm{InQ}(Z_\ell) \ - \ \mathrm{InQ}(Z_{\ell+1})]\right| &= \left|\sum_{\ell=1}^{2^q} \mathbf{E}_{a,b}[\mathrm{InQ}(Z_\ell) - \mathrm{InQ}(Z_{\ell+1})]\right| \\ &= \left|\sum_{\ell=1}^{2^q} \mathbf{E}_{a,b}[\mathrm{InQ}(W_\ell + a_\ell \widetilde{Y}^\ell) - \mathrm{InQ}(W_\ell + b_\ell \widetilde{Y}^\ell)]\right| \end{aligned} \tag{5}$$

where $W_\ell := \sum_{i<\ell} b_i \widetilde{Y}^i \ + \ \sum_{i>\ell} a_i \widetilde{Y}^i$. The RHS of (5) is at most

$$2^q \cdot \max_{\ell=1,\ldots,2^q} |\, \mathbf{E}_{a,b}[\mathrm{InQ}(W_\ell + a_\ell \widetilde{Y}^\ell) - \mathrm{InQ}(W_\ell + b_\ell \widetilde{Y}^\ell)]|.$$

So let us fix an arbitrary ℓ; we will bound

$$\left|\mathbf{E}_{a,b}[\mathrm{InQ}(W_\ell + a_\ell \widetilde{Y}^\ell) - \mathrm{InQ}(W_\ell + b_\ell \widetilde{Y}^\ell)]\right| \leq B \tag{6}$$

(we will specify B later), and this gives that $\|\widetilde{D}_{YES} - \widetilde{D}_{NO}\|_1 \leq 4^q B$ by the arguments above. Before continuing further, it is useful to note that W_ℓ, a_ℓ, and b_ℓ are all independent from each other.

Bounding (6). Let $N := (n/2^q)^{1/3}$. Without loss of generality, we may assume that the the c_i's are in monotone increasing order, that is $c_1 \leq c_2 \leq \ldots \leq c_{2^q}$. We consider two cases depending on the value of c_ℓ. If $c_\ell > N$ then we say that c_ℓ is *big*, and otherwise we say that c_ℓ is *small*. Note that each c_i is a nonnegative integer and $c_1 + \cdots + c_{2^q} = n$, so at least one c_i must be big; in fact, we know that the largest value c_{2^q} is at least $n/2^q$.

If c_ℓ is big, we argue that a_ℓ and b_ℓ are distributed quite similarly, and thus for any possible outcome of W_ℓ the LHS of (6) must be small. If c_ℓ is small, we consider some $k \neq \ell$ for which c_k is very big (we just saw that $k = 2^q$ is such a k) and show that for any possible outcome of a_ℓ, b_ℓ and all the other contributors to W_ℓ, the contribution to W_ℓ from this c_k makes the LHS of (6) small (intuitively, the contribution of c_k is so large that it "swamps" the small difference that results from considering a_ℓ versus b_ℓ).

Case 1: Bounding (6) when c_ℓ is big, i.e. $c_\ell > N$. Fix any possible outcome for W_ℓ in (6). Note that the vector $\widetilde{Y}^\ell$ has all its coordinates ± 1 and thus it is "skew" to each of the axis-aligned hyperplanes defining quadrant Q. Since Q is convex, there is some interval A (possibly half-infinite) of the real line such that for all $t \in \mathbf{R}$ we have $\mathrm{InQ}(W_\ell + t\widetilde{Y}^\ell) = 1$ if and only if $t \in A$. It follows that

$$|\Pr_{a_\ell}[\mathrm{InQ}(W_\ell + a_\ell \widetilde{Y}^\ell) = 1] - \Pr_{b_\ell}[\mathrm{InQ}(W_\ell + b_\ell \widetilde{Y}^\ell) = 1]| = |\Pr[a_\ell \in A] - \Pr[b_\ell \in A]|. \tag{7}$$

Now observe that as in Theorem 1, a_ℓ and b_ℓ are each sums of c_ℓ many independent zero-mean random variables (the r_j's and s_j's respectively) with the same total variance $\sigma = \sqrt{c_\ell}$ and with each $|r_j|, |s_j| \leq O(1)$. Applying Theorem 1 to both a_ℓ and b_ℓ, we get that the RHS of (7) is at most $O(1/\sqrt{c_\ell}) = O(1/\sqrt{N})$. Averaging the LHS of (7) over the distribution of values for W_ℓ, it follows that if c_ℓ is big then the LHS of (6) is at most $O(1/\sqrt{N})$.

Case 2: Bounding (6) when c_ℓ is small, i.e. $c_\ell \leq N$. We first note that every possible outcome for a_ℓ, b_ℓ results in $|a_\ell - b_\ell| \leq O(N)$. Let $k = 2^q$ and recall that $c_k \geq n/2^q$. Fix any possible outcome for a_ℓ, b_ℓ and for all other a_j, b_j such that $j \neq k$ (so the only "unfixed" randomess at this point is the choice of a_k and b_k). Let W'_ℓ denote the contribution to W_ℓ from these $2^q - 2$ fixed a_j, b_j values, so W_ℓ equals $W'_\ell + a_k\widetilde{Y}^k$ (since $k > \ell$). (Note that under this supposition there is actually no dependence on b_k now; the only randomness left is the choice of a_k.)

We have

$$\begin{aligned} &|\Pr_{a_k}[\mathrm{InQ}(W_\ell + a_\ell\widetilde{Y}^\ell) = 1] - \Pr_{a_k}[\mathrm{InQ}(W_\ell + b_\ell\widetilde{Y}^\ell) = 1]| \\ =\ &|\Pr_{a_k}[\mathrm{InQ}(W'_\ell + a_\ell\widetilde{Y}^\ell + a_k\widetilde{Y}^k) = 1] - \Pr_{a_k}[\mathrm{InQ}(W'_\ell + b_\ell\widetilde{Y}^\ell + a_k\widetilde{Y}^k) = 1]| \quad (8)\end{aligned}$$

The RHS of (8) is at most

$$\Pr_{a_k}[\text{the vector } W'_\ell + a_\ell\widetilde{Y}^\ell + a_k\widetilde{Y}^k \text{ has any coordinate of magnitude at most } |a_\ell - b_\ell|]. \quad (9)$$

(If each coordinate of $W'_\ell + a_\ell\widetilde{Y}^\ell + a_k\widetilde{Y}^k$ has magnitude greater than $|a_\ell - b_\ell|$, then each corresponding coordinate of $W'_\ell + b_\ell\widetilde{Y}^\ell + a_k\widetilde{Y}^k$ must have the same sign, and so such an outcome affects each of the probabilities in (8) in the same way – either both points are in quadrant Q or both are not.) Since each coordinate of $\widetilde{Y}^k$ is of magnitude 1, by a union bound the probability (9) is at most q times

$$\max_{\text{all intervals } A \text{ of width } 2|a_\ell - b_\ell|} \Pr_{a_k}[a_k \in A]. \quad (10)$$

Now using the fact that $|a_\ell - b_\ell| = O(N)$, the fact that a_k is a sum of $c_k \geq n/2^q$ independent ± 1-valued variables, and Theorem 2, we have that (10) is at most $O(N)/\sqrt{n/2^q}$. So we have that (8) is at most $O(Nq\sqrt{2^q})/\sqrt{n}$. Averaging (8) over a suitable distribution of values for $a_1, b_1, \ldots, a_{k-1}, b_{k-1}, a_{k+1}, b_{k+1}, \ldots, a_{2^q}, b_{2^q}$, gives that the LHS of (6) is at most $O(Nq\sqrt{2^q})/\sqrt{n}$.

So we have seen that whether c_ℓ is big or small, the value of (6) is upper bounded by

$$\max\{O(1/\sqrt{N}), O(Nq\sqrt{2^q})/\sqrt{n}\}.$$

Recalling that $N = (n/2^q)^{1/3}$, this equals $O(q(2^q/n)^{1/6})$, and thus $\|\widetilde{D}_{YES} - \widetilde{D}_{NO}\|_1 \leq O(q2^{13q/6}/n^{1/6})$. Recalling that $q = (1/26)\log n$, this equals $O((\log n)/n^{1/12}) = o(1)$, and Lemma 2 is proved.

4 A Sublinear Algorithm for Testing ± 1-Weight Halfspaces

In this section we present the **± 1-Weight Halfspace-Test** algorithm, and prove the following theorem:

Theorem 4. *For any $36/n < \epsilon < 1/2$ and any function $f : \{-1,1\}^n \to \{-1,1\}$,*

- *if f is a ± 1-weight halfspace, then* **± 1-Weight Halfspace-Test**(f, ϵ) *passes with probability $\geq 2/3$,*
- *if f is ϵ-far from any ± 1-weight halfspace, then* **± 1-Weight Halfspace-Test**(f, ϵ) *rejects with probability $\geq 2/3$.*

The query complexity of **± 1-Weight Halfspace-Test**(f, ϵ) *is $O(\sqrt{n}\frac{1}{\epsilon^6}\log\frac{1}{\epsilon})$. The algorithm is nonadaptive and has two-sided error.*

The main tool underlying our algorithm is the following theorem, which says that if most of f's degree-1 Fourier coefficients are almost as large as those of the majority function, then f must be close to the majority function. Here we adopt the shorthand Maj_n to denote the majority function on n variables, and $\hat{\mathsf{M}}_n$ to denote the value of the degree-1 Fourier coefficients of Maj_n.

Theorem 5. *Let $f : \{-1,1\}^n \to \{-1,1\}$ be any Boolean function and let $\epsilon > 36/n$. Suppose that there is a subset of $m \geq (1-\epsilon)n$ variables i each of which satisfies $\hat{f}(i) \geq (1-\epsilon)\hat{\mathsf{M}}_n$. Then $\Pr[f(x) \neq \mathrm{Maj}_n(x)] \leq 32\sqrt{\epsilon}$.*

In the following subsections we prove Theorem 5 and then present our testing algorithm.

4.1 Proof of Theorem 5.

Recall the following well-known lemma, whose proof serves as a warmup for Theorem 5:

Lemma 3. *Every $f : \{-1,1\}^n \to \{-1,1\}$ satisfies $\sum_{i=1}^n |\hat{f}(i)| \leq n\hat{\mathsf{M}}_n$.*

Proof. Let $G(x) = \mathrm{sgn}(\hat{f}(1))x_1 + \cdots + \mathrm{sgn}(\hat{f}(n))x_n$ and let $g(x)$ be the ± 1-weight halfspace $g(x) = \mathrm{sgn}(G(x))$. We have

$$\sum_{i=1}^n |\hat{f}(i)| = \mathbf{E}[fG] \leq \mathbf{E}[|G|] = \mathbf{E}[G(x)g(x)] = \sum_{i=1}^n \hat{\mathsf{M}}_n,$$

where the first equality is Plancherel (using the fact that G is linear), the inequality is because f is a ± 1-valued function, the second equality is by definition of g and the third equality is Plancherel again, observing that each $\hat{g}(i)$ has magnitude $\hat{\mathsf{M}}_n$ and sign $\mathrm{sgn}(\hat{f}(i))$. $\square$

Proof of Theorem 5. For notational convenience, we assume that the variables whose Fourier coefficients are "almost right" are $x_1, x_2, ..., x_m$. Now define $G(x) = x_1 +$

$x_2 + \cdots x_n$, so that $\mathrm{Maj}_n = \mathrm{sgn}(G)$. We are interested in the difference between the following two quantities:

$$\mathbf{E}[|G(x)|] = \mathbf{E}[G(x)\mathrm{Maj}_n(x)] = \sum_S \hat{G}(S)\hat{\mathrm{Maj}}_n(S) = \sum_{i=1}^{n} \hat{\mathrm{Maj}}_n(i) = n\hat{\mathsf{M}}_n,$$

$$\mathbf{E}[G(x)f(x)] = \sum_S \hat{G}(S)\hat{f}(S) = \sum_{i=1}^{n} \hat{f}(i) = \sum_{i=1}^{m} \hat{f}(i) + \sum_{i=m+1}^{n} \hat{f}(i).$$

The bottom quantity is broken into two summations. We can lower bound the first summation by $(1-\epsilon)^2 n\hat{\mathsf{M}}_n \geq (1-2\epsilon)n\hat{\mathsf{M}}_n$. This is because the first summation contains at least $(1-\epsilon)n$ terms, each of which is at least $(1-\epsilon)\hat{\mathsf{M}}_n$. Given this, Lemma 3 implies that the second summation is at least $-2\epsilon n\hat{\mathsf{M}}_n$. Thus we have

$$\mathbf{E}[G(x)f(x)] \geq (1-4\epsilon)n\hat{\mathsf{M}}_n$$

and hence

$$\mathbf{E}[|G| - Gf] \leq 4\epsilon n\hat{\mathsf{M}}_n \leq 4\epsilon\sqrt{n} \tag{11}$$

where we used the fact (easily verified from Parseval's equality) that $\hat{\mathsf{M}}_n \leq \frac{1}{\sqrt{n}}$.

Let p denote the fraction of points such that $f \neq \mathrm{sgn}(G)$, i.e. $f \neq \mathrm{Maj}_n$. If $p \leq 32\sqrt{\epsilon}$ then we are done, so we assume $p > 32\sqrt{\epsilon}$ and obtain a contradiction. Since $\epsilon \geq 36/n$, we have $p \geq 192/\sqrt{n}$. Let k be such that $\sqrt{\epsilon} = (4k+2)/\sqrt{n}$, so in particular $k \geq 1$. It is well known (by Stirling's approximation) that each "layer" $\{x \in \{-1,1\}^n : x_1 + \cdots + x_n = \ell\}$ of the Boolean cube contains at most a $\frac{1}{\sqrt{n}}$ fraction of $\{-1,1\}^n$, and consequently at most a $\frac{2k+1}{\sqrt{n}}$ fraction of points have $|G(x)| \leq 2k$. It follows that at least a $p/2$ fraction of points satisfy both $|G(x)| > 2k$ and $f(x) \neq \mathrm{Maj}_n(x)$. Since $|G(x)| - G(x)f(x)$ is at least $4k$ on each such point and $|G(x)| - G(x)f(x)$ is never negative, this implies that the LHS of (11) is at least

$$\frac{p}{2} \cdot 4k > (16\sqrt{\epsilon}) \cdot (4k) \geq (16\sqrt{\epsilon})(2k+1) = (16\sqrt{\epsilon}) \cdot \frac{\sqrt{\epsilon n}}{2} = 8\epsilon\sqrt{n},$$

but this contradicts (11). This proves the theorem. □

4.2 A Tester for ± 1-Weight Halfspaces.

Intuitively, our algorithm works by choosing a handful of random indices $i \in [n]$, estimating the corresponding $|\hat{f}(i)|$ values (while checking unateness in these variables), and checking that each estimate is almost as large as $\hat{\mathsf{M}}_n$. The correctness of the algorithm is based on the fact that if f is unate and most $|\hat{f}(i)|$ are large, then some *reorientation* of f (that is, a replacement of some x_i by $-x_i$) will make most $\hat{f}(i)$ large. A simple application of Theorem 5 then implies that the reorientation is close to Maj_n, and therefore that f is close to a ± 1-weight halfspace.

We start with some preliminary lemmas which will assist us in estimating $|\hat{f}(i)|$ for functions that we expect to be unate.

Lemma 4.

$$\hat{f}(i) = \Pr_x[f(x^{i-}) < f(x^{i+})] - \Pr_x[f(x^{i-}) > f(x^{i+})]$$

where x^{i-} and x^{i+} denote the bit-string x with the i^{th} bit set to -1 or 1 respectively.

We refer to the first probability above as the *positive influence* of variable i and the second probability as the *negative influence* of i. Each variable in a monotone function has only positive influence. Each variable in a *unate* function has only positive influence or negative influence, but not both.

Proof.(of Lemma 4) First note that $\hat{f}(i) = \mathbf{E}_x[f(x)x_i]$, then

$$\begin{aligned}\mathbf{E}_x[f(x)x_i] = &\Pr_x[f(x) = 1, x_i = 1] + \Pr_x[f(x) = -1, x_i = -1] \\ &- \Pr_x[f(x) = -1, x_i = 1] - \Pr_x[f(x) = 1, x_i = -1].\end{aligned}$$

Now group all x's into pairs (x^{i-}, x^{i+}) that differ in the i^{th} bit. If the value of f is the same on both elements of a pair, then the total contribution of that pair to the expectation is zero. On the other hand, if $f(x^{i-}) < f(x^{i+})$, then x^{i-} and x^{i+} each add $\frac{1}{2^n}$ to the expectation, and if $f(x^{i-}) > f(x^{i+})$, then x^{i-} and x^{i+} each subtract $\frac{1}{2^n}$. This yields the desired result. □

Lemma 5. *Let f be any Boolean function, $i \in [n]$, and let $|\hat{f}(i)| = p$. By drawing $m = \frac{3}{p\epsilon^2} \cdot \log \frac{2}{\delta}$ uniform random strings $x \in \{-1, 1\}^n$, and querying f on the values $f(x^{i+})$ and $f(x^{i-})$, with probability $1 - \delta$ we either obtain an estimate of $|\hat{f}(i)|$ accurate to within a multiplicative factor of $(1 \pm \epsilon)$, or discover that f is not unate.*

The idea of the proof is that if neither the positive influence nor the negative influence is small, random sampling will discover that f is not unate. Otherwise, $|\hat{f}(i)|$ is well approximated by either the positive or negative influence, and a standard multiplicative form of the Chernoff bound shows that m samples suffice.

Proof.(of Lemma 5) Suppose first that both the positive influence and negative influence are at least $\frac{\epsilon p}{2}$. Then the probability that we do not observe any pair with positive influence is $\leq (1 - \frac{\epsilon p}{2})^m \leq e^{-\epsilon pm/2} = e^{-(3/2\epsilon)\log(2/\delta)} < \frac{\delta}{2}$, and similarly for the negative influence. Therefore, the probability that we observe at least some positive influence and some negative influence (and therefore discover that f is not unate) is at least $1 - 2\frac{\delta}{2} = 1 - \delta$.

Now consider the case when either the positive influence or the negative influence is less than $\frac{\epsilon p}{2}$. Without loss of generality, assume that the negative influence is less than $\frac{\epsilon p}{2}$. Then the positive influence is a good estimate of $|\hat{f}(i)|$. In particular, the probability that the estimate of the positive influence is not within $(1 \pm \frac{\epsilon}{2})p$ of the true value (and therefore the estimate of $|\hat{f}(i)|$ is not within $(1 \pm \epsilon)p$), is at most $< 2e^{-mp\epsilon^2/3} = 2e^{-\log \frac{2}{\delta}} = \delta$ by the multiplicative Chernoff bound. So in this case, the probability that the estimate we receive is accurate to within a multiplicative factor of $(1 \pm \epsilon)$ is at least $1 - \delta$. This concludes the proof. □

Now we are ready to present the algorithm and prove its correctness.

±1-Weight Halfspace-Test (inputs are $\epsilon > 0$ and black-box access to $f : \{-1,1\}^n \to \{-1,1\}$)

1. Let $\epsilon' = (\frac{\epsilon}{32})^2$.
2. Choose $k = \frac{1}{\epsilon'} \ln 6 = O(\frac{1}{\epsilon'})$ many random indices $i \in \{1, ..., n\}$.
3. For each i, estimate $|\hat{f}(i)|$. Do this as in Lemma 5 by drawing $m = \frac{24 \log 12k}{\hat{\mathsf{M}}_n \epsilon'^2} = O(\frac{\sqrt{n}}{\epsilon'^2} \log \frac{1}{\epsilon'})$ random x's and querying $f(x^{i+})$ and $f(x^{i-})$. If a violation of unateness is found, reject.
4. Pass if and only if each estimate is larger than $(1 - \frac{\epsilon'}{2})\hat{\mathsf{M}}_n$.

Proof. (of Theorem 4) To prove that the test is correct, we need to show two things: first that it passes functions which are ±1-weight halfspaces, and second that anything it passes with high probability must be ϵ-close to a ±1-weight halfspace. To prove the first, note that if f is a ±1-weight halfspace, the only possibility for rejection is if any of the estimates of $|\hat{f}(i)|$ is less than $(1 - \frac{\epsilon'}{2})\hat{\mathsf{M}}_n$. But applying lemma 5 (with $p = \hat{\mathsf{M}}_n$, $\epsilon = \frac{\epsilon'}{2}$, $\delta = \frac{1}{6k}$), the probability that a particular estimate is wrong is $< \frac{1}{6k}$, and therefore the probability that any estimate is wrong is $< \frac{1}{6}$. Thus the probability of success is $\geq \frac{5}{6}$.

The more difficult part is showing that any function which passes the test whp must be close to a ±1-weight halfspace. To do this, note that if f passes the test whp then it must be the case that for all but an ϵ' fraction of variables, $|\hat{f}(i)| > (1 - \epsilon')\hat{\mathsf{M}}_n$. If this is not the case, then Step 2 will choose a "bad" variable – one for which $|\hat{f}(i)| \leq (1 - \epsilon')\hat{\mathsf{M}}_n$ – with probability at least $\frac{5}{6}$. Now we would like to show that for any bad variable i, the estimate of $|\hat{f}(i)|$ is likely to be less than $(1 - \frac{\epsilon'}{2})\hat{\mathsf{M}}_n$. Without loss of generality, assume that $|\hat{f}(i)| = (1 - \epsilon')\hat{\mathsf{M}}_n$ (if $|\hat{f}(i)|$ is less than that, then variable i will be even less likely to pass step 3). Then note that it suffices to estimate $|\hat{f}(i)|$ to within a multiplicative factor of $(1 + \frac{\epsilon}{2})$ (since $(1 + \frac{\epsilon'}{2})(1 - \epsilon')\hat{\mathsf{M}}_n < (1 - \frac{\epsilon'}{2})\hat{\mathsf{M}}_n$). Again using Lemma 5 (this time with $p = (1 - \epsilon')\hat{\mathsf{M}}_n$, $\epsilon = \frac{\epsilon'}{2}$, $\delta = \frac{1}{6k}$), we see that $\frac{12}{\hat{\mathsf{M}}\epsilon'^2(1-\epsilon')} \log 12k < \frac{24}{\hat{\mathsf{M}}\epsilon'^2} \log 12k$ samples suffice to achieve discover the variable is bad with probability $1 - \frac{1}{6k}$. The total probability of failure (the probability that we fail to choose a bad variable, or that we mis-estimate one when we do) is thus $< \frac{1}{6} + \frac{1}{6k} < \frac{1}{3}$.

The query complexity of the algorithm is $O(km) = O(\sqrt{n}\frac{1}{\epsilon'^3} \log \frac{1}{\epsilon'}) = O(\sqrt{n} \cdot \frac{1}{\epsilon^6} \log \frac{1}{\epsilon})$. □

5 Conclusion

We have proven a lower bound showing that the complexity of testing ±1-weight halfspaces is is at least $\Omega(\log n)$ and an upper bound showing that it is at most $O(\sqrt{n} \cdot \mathrm{poly}(\frac{1}{\epsilon}))$. An open question is to close the gap between these bounds and determine the exact dependence on n. One goal is to use some type of binary search to get a $\mathrm{poly}\log(n)$-query adaptive testing algorithm; another is to improve our lower bound to $n^{\Omega(1)}$ for nonadaptive algorithms.

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