A New Lower Bound Technique for Decision Trees [1]

by

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ABSTRACT In this paper, we prove two general lower bounds for algebraic decision trees which test membership in a set $S \subseteq \mathbb{R}^n$ which is defined by linear inequalities. Let $rank(S)$ be the maximal dimension of a linear subspace contained in the closure of S.

First we prove that any decision tree which uses multilinear functions (i.e. arbitrary products of linear functions) must have depth at least $n - rank(S)$. This solves an open question raised by A.C. Yao ([Y89]) and can be used to show that multilinear functions are not really more powerful than simple comparisons between the input variables when computing the largest k elements of n given numbers. Yao could only prove this result in the special case when products of at most two linear functions are used. Our proof is based on a dimension argument. It seems to be the first time that such an approach yields good lower bounds for nonlinear decision trees.

Surprisingly, we can use the same methods to give an alternative proof for Rabin's fundamental Theorem ([Rab]), namely that the depth of any decision tree using arbitrary analytic functions is at least $n - rank(S)$. Since we show that Rabin's original proof is incorrect, our proof of Rabin's Theorem is not only the first correct one but also generalizes the Theorem to a wider class of functions.

1. Introduction

Among other algebraic complexity measures (e.g. [MST], [ST]), the algebraic decision tree and algebraic computation tree models have have turned out to be very useful in proving lower bounds for elementary combinatorial or geometric problems like maximum finding, set equality, set disjointness and sorting (see [Be] for more examples) or even more complicated problems like convex polygon inclusion ([Ram]) and motion planning ([OD]).

The algebraic decision tree model is an abstraction of "real" algorithms where only comparisons between input variables or functions of input variables are counted whereas all other time-consuming operations like data-management, function evaluation or other control structures have zero cost. For complex problems, this simplification can make the problem considerably easier; for example, the knapsack problem which is known to be NP-complete has a polynomial solution in the decision tree model (e.g. [MadH]). Therefore, lower bounds in the decision tree model can only be tight for quite simple problems.

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A *decision problem* is a disjoint partition $\mathbb{R}^n = S_1 \cup \cdots \cup S_q$ of $\mathbb{R}^n$ into arbitrary sets S_i. A *decision tree* T for a decision problem is a binary tree whose internal nodes are labeled by predicates defined on $\mathbb{R}^n$, whose outgoing edges of an internal node are labeled by $true$ or $false$, and whose leaves are labeled by one of the S_i (Fig. 3.1 shows an example). The evaluation of T on input $x \in \mathbb{R}^n$ starts at the root and then proceeds downwards by evaluating the predicate at an internal node and taking the appropriate of the two outgoing edges. Finally, a leaf with label S_x is reached. S_x is the result of the computation, the path x followed is the *computation path* of x, and T is correct if $x \in S_x$ for all x. The worst-case running time of T is the length of the longest computation path in T.

T is called an *algebraic decision tree* if all functions evaluated at internal nodes are defined by polynomials. The most restricted algebraic decision trees are *comparison trees* where only comparisons between two input variables are allowed ([FG], [MT]). *Linear decision trees* ([Sn82]) where linear functions of the input variables can be used ([BLY], [DL], [FG], [MT], [RY]) are more powerful. Products of linear functions were used in [Y89]) and arbitrary polynomials of bounded degree in [Be] and [Y92]. Finally, arbitrary analytic functions were allowed in [Ja] and [Rab]. Of course, this classification of algebraic decision trees is not exhaustive and many less natural restrictions on the functions can be found in the literature (e.g. [DL], [MMS]).

In our paper, we only prove lower bounds for algebraic decision trees, but we also want to mention the *algebraic computation tree* model where additional computing nodes exist which evaluate elementary functions on all input variables and previously computed functions ([Be], [OD]). Of course, this can be simulated by an algebraic decision tree which uses polynomials of increasing degree, but this model is much closer to the model of "real" algorithms (e.g. [PS]). Probabilistic and nondeterministic decision trees have also been studied ([MT], [Sn85]).

From now on, we assume that the decision problem is a membership problem, i.e. we want to decide whether an input $x \in \mathbb{R}^n$ is in a set $S \subseteq \mathbb{R}^n$ (we call S the *target set*), but the lower bounds mentioned below can easily be transformed into similar bounds for arbitrary decision problems. Several lower bound techniques are known for algebraic decision trees. One of the first and most widely used arguments was that the logarithm of the number of connected components of S is a lower bound for the depth of linear decision trees ([DL]. This was generalized in [Be] to bounded degree decision trees. And recently Ramanan has shown how this technique can sometimes give strong lower bounds even for sets S which do not have many connected components by intersecting S with another easily computable set and thus increasing the number of components ([Ram]). Another old approach is to use an adversary argument to show that there must be at least one long path in the tree ([DL]) or proving the existence of many disjoint subtrees ([FG]).

An interesting topological lower bound, at least for linear decision trees, was proved by Rivest and Yao. They showed that the logarithm of the number of s-dimensional faces of S for arbitrary s is a lower bound ([RY]). And very recently, Yao et. al. have found a way to exploit even a much more complex topological property of S, i.e. they showed that the logarithm of the Euler characteristic of S is a lower bound not only for linear decision trees ([BLY]) but also for bounded degree decision trees ([Y92]).

The only known results about analytic decision trees are due to Rabin ([Rab]) and Jaromczyk ([Ja]). Rabin proved the fundamental Theorem that any analytic decision tree for S must have depth $|H|$ if S is defined by a set H of independent linear inequalities. Jaromczyk tried to generalize Rabin's Theorem to sets S defined by arbitrary polynomial inequalities but faced heavy problems concerning real algebraic varieties which he could not solve adequately. Unfortunately, Rabin's proof is not correct (see Section 3). The same is probably true for Jaromczyk's generalization because Rabin's error lies in a basic definition which is also used by Jaromzyk.

Surprisingly, we can give an alternative (and hopefully correct) proof of Rabin's Theorem by using a new lower bound technique which we have developed to solve an open question raised by Yao. In [Y92], Yao showed that median tests are not really more powerful than simple comparisons between the input variables when computing the largest k elements of n given numbers. He raised the question whether this can be generalized to functions which are arbitrary products of linear functions (the median test can be written as the product of only two linear functions).

We show in this paper that it can be generalized. Our proof technique is based on a dimension argument and works only for sets S defined by linear inequalities. Let $rank(S)$ be the maximal dimension of a linear subspace contained in the closure of S. We show that, for any computation path p in the decision tree, the closure of the set of inputs x which have computation path p always contains a linear subspace of dimension $n - length(p)$. Hence $length(p) \geq n - rank(S)$.

It seems to be the first time that a dimension argument is used to derive good lower bounds for nonlinear decision trees. And it seems to be the first time that someone has looked carefully in Rabin's proof and, finding it incorrect, gives a correct proof. This is even more important because no other lower bounds for this most general model are known.

This paper is organized as follows. In Section 2 we give some geometric definitions and Lemmas. In Section 3 we define certificates and proofs, an abstraction of the decision tree model, and show why we consider Rabin's proof incorrect. The generalization of Yao's Theorem and Rabin's corrected Theorem follow in Sections 4 and 5, respectively. And we conclude with some remarks in Section 6.

2. Geometric Preliminaries

In this Section we will give some elementary definitions. We use the notations $\overline{B} = cl\, B$ and $B^0 = int\, B$, where $B \subseteq \mathbb{R}^n$ is any set. $B_n(z, \epsilon)$ denotes the n–dimensional ball of radius ϵ centered at z.

A *linear variety (flat)* in $\mathbb{R}^n$ is a subset $G \subseteq \mathbb{R}^n$ of the form $G = v + L$ where $L \subseteq \mathbb{R}^n$ is a linear subspace and $v \in \mathbb{R}^n$. The flat has dimension $dim\, G := dim\, L$.

Let $L_n := \{\lambda_0 + \sum_{i=1}^{n} \lambda_i x_i \mid \lambda_0, \ldots, \lambda_n \in \mathbb{R}\}$ be the set of linear functions in n real variables $x = (x_1, \ldots, x_n)$. Let $L_n^{(j)} := \{l_1 \cdots l_j \mid l_i \in L_n, \forall i\}$ be the set of *multilinear functions* of degree j in n variables which is a proper subset of the set of all polynomials of degree j in n variables and $L_n^* := L_n^\infty = \bigcup_{j=1}^{\infty} L_n^{(j)}$.

Each $l \in L_n$ induces an oriented hyperplane $h = \{x \in \mathbb{R}^n \mid l(x) = 0\}$ with normal vector n. Let $\Delta := \{>, \geq, =, \neq\}$ be the set of all comparison operators and $\Delta_> := \{>, \geq\}$. For a set $L = \{l_1, \ldots, l_m\} \subset L_n$ of linear functions we usually denote the set of its corresponding hyperplanes by $H = \{h_1, \ldots, h_m\}$. $Arr(H)$ is the arrangement of the hyperplanes in H (see [Ed] for details of arrangements). If $Op = \{op_1, \ldots, op_m\}$, $op_i \in \Delta$, is a set of comparison operators then we define the set of simultaneous solutions of L with respect to Op as $S_{L,Op} := \{x \in \mathbb{R}^n \mid l_i(x)\ op_i\ 0,\ i = 1, \ldots, m\}$; if $L = \emptyset$ then $S_{L,Op} := \mathbb{R}^n$. We omit the index Op whenever it is clear from the context which Op should be used.

To measure the degree of independence of the linear functions in L we introduce the rank of L : $rank(L) := n - dim\, span(n_1, \ldots, n_m)$ where n_i is the normal vector of the hyperplane h_i defined by l_i. The following Lemma shows that $rank(L)$ is the maximal dimension of a linear variety contained in $\overline{S_L}$.

Lemma 2.1 Let $L = \{l_1, \ldots, l_m\} \subset L_n$ be a set of linear functions and let $Op \in \Delta_>^m$ be arbitrary. Let H be the set of hyperplanes defined by L. If $S_L \neq \emptyset$ then

(a) S_L contains a linear variety of dimension $rank(L)$;

(b) $\overline{S_L}$ does not contain a linear variety of dimension $rank(L) + 1$;

(c) $rank(L) = \min\{k \mid Arr(H)$ contains a k-face$\}$, and there is a $rank(L)$-face of $Arr(H)$ contained in $\overline{S_L}$.

Proof : Let h_i be the hyperplane corresponding to the function l_i with normal vector n_i.

(a) Let $z \in S_L$ be arbitrary and let V be a linear subspace of dimension $rank(L)$ such that $span(V, n_1, \ldots, n_m) = \mathbb{R}^n$. Then V is perpendicular to all normal vectors n_i and therefore parallel to all hyperplanes h_i; hence $z + V \subseteq S_L$.

(b) If V is any linear variety contained in $\overline{S_L}$ then V must be parallel to all hyperplanes h_i, i.e. perpendicular to all normal vectors n_i. Hence $dim\, V \leq n - dim\, span(n_1, \ldots, n_m)$.

(c) Any k-face in $Arr(H)$ is a k-dimensional subset of the intersection of $n - k$ linearly independent hyperplanes of H ([Ed]). Since there are at not more than $span(n_1, \ldots, n_m)$ linearly independent hyperplanes in H, $Arr(H)$ contains only k-faces for $k \geq n - dim\, span(n_1, \ldots, n_m) = rank(L)$. Furthermore, all cells in $Arr(H)$ are bounded by at least one $rank(L)$-face. $\square$

Let $L \subset L_n$ be a set of linear functions and H the set of hyperplanes defined by L. Then $Arr(H)$ induces a *signature* on the points $x \in \mathbb{R}^n$: $sig(x) := (\epsilon_1, \ldots, \epsilon_m)$ where $\epsilon_i = -, 0, +$ iff x lies under, on, above h_i, respectively. We call L *sign-independent* if all possible signatures are realized in $Arr(H)$. The notion of sign-independence was introduced by Rabin ([Rab]) but he failed to observe the following simple characterization of sign-independence in terms of $rank(L)$.

Lemma 2.2 Let $L = \{l_1, \ldots, l_m\} \subset L_n$ and let h_i be the hyperplane defined by l_i. Then

$$L \text{ is sign-independent} \iff dim \bigcap_{i=1}^{m} h_i = n - m \iff rank(L) = n - m.$$

Proof : Elementary geometry, or see [Ed]. □

The definitions above will mainly be used in the next Section for defining the target set, i.e. the subset of $\mathbb{R}^n$ which is computed by the decision tree. But we also need some definitions concerning the functions which are used at internal nodes of the decision tree. Yao restricted the internal functions to products of linear functions, whereas Rabin allowed arbitrary analytic functions. We give a more general framework by defining the functions by means of the properties they should have (to make our proofs work). Theorem 2.4 shows that our model includes the models of Yao and Rabin.

Let $F = (F_n)_{n=1,2,3,\ldots}$ be a family of sets of real-valued functions in n real variables with the following properties :

Let $f_n, g_n \in F_n$ and h be a hyperplane in $\mathbb{R}^n$.

(F1) f_n is continuous.

(F2) $f_n \cdot g_n \in F_n$, i.e. F_n is closed under multiplication.

(F3) F_n is closed under translations and rotations of the coordinate system.

(F4) If there is an open set $U \subseteq \mathbb{R}^n$ with $f_n\big|_U \equiv 0$ then $f_n \equiv 0$.

(F5) $f_n\big|_{(x_n = 0)} \in F_{n-1}$.

(F6) If $f_n\big|_h \equiv 0$ then there exists an $g_n \in F_n$ such that $f_n = l \cdot g_n$, where l is the linear function defining h.

Lemma 2.3 Then the following properties are also satisfied for $f_n \in F_n$:

(F7) If h is a hyperplane in $\mathbb{R}^n$ then $f_n\big|_h \in F_{n-1}$.

(F8) Let V be a linear subspace of $\mathbb{R}^n$ of dimension $k < n$. If a relatively open set $U \subseteq V$ exists with $f_n\big|_U \equiv 0$ then also $f_n\big|_V \equiv 0$.

Proof : (F7) follows from F(3) and (F5).

(F8) V can be defined as the intersection of $n-k$ hyperplanes : $V = \bigcap_{i=1}^{n-k} h_i$.

Successive application of (F7) yields a function $f_k = f_n\big|_V \in F_k$. Now (F4) proofs the claim. $\square$

Theorem 2.4 *The following classes of functions satisfy (F1)–(F6) : The linear functions L_n, L_n^*, real polynomials and analytic functions.*

Proof : (F1)–(F5) are obviously true. Only (F6) needs a closer look if we deal with polynomials, so let f_n be a polynomial and h a hyperplane in $\mathbb{R}^n$ (with defining linear function l) such that $f_n\big|_h \equiv 0$. From the Hilbertsche Nullstellensatz (see [vdW], page 164, formula (2)) it follows that a $q \in \mathbb{N}$ and a polynomial f_n' exist such that $f_n^q = f_n' \cdot l$. But l is prime and hence divides f_n. $\square$

3. Certificates and Proofs

In this Section we recall Yao's definition of certificates ([Y89]), give a definition of complete proofs which slightly differs from Rabin's definition ([Rab]) and show how these definitions are related to decision trees. Then we prove some simple geometric Lemmas and show why Rabin's model is not so useful when proving lower bounds for decision trees.

Let $L = \{l_1, \ldots, l_m\} \subset L_n$ be a set of linear functions, and let $Op_L \in \Delta_>^m$ be a set of comparison operators for L. Then the pair (L, Op_L) defines the *target set* $S_L = S_{L,Op_L}$. Let $F = (F_n)_{n=1,2,3,\ldots}$ be a class of functions satisfying (F1)–(F6). This is the universe of functions which can be used at internal nodes of the decision tree.

Let $G = \{g_1, \ldots, g_k\}$ be a set of functions with either $g_i \in F_n$ or $\frac{1}{g_i} \in F_n$ (in fact, since we are only interested in the sign of g_i, we can w.l.o.g. assume that $g_i \in F_n$), and let $Op_G \in \Delta^k$ be a set of comparison operators for G. Then $S_G = S_{G,Op_G}$ is defined as before (where all g_i had been linear functions). We call the pair $Z = (G, Op_G)$ a *certificate* for (L, Op_L) if $S_G \subseteq S_L$. The size of the certificate is defined to be $|Z| := k$, i.e. the number of defining functions of G. Z is called *strict* if $Op_G = \{>\}^k$. In this case we write for short $(G, >)$ or $S_{G,>}$ instead of $(G, \{>\}^k)$ or $S_{G,\{>\}^k}$, respectively. Similarly, we call the target set *strict* if $Op_L = \{>\}^m$ and we then also write $S_{L,>}$. Analogously, we write $S_{g,=}$ for the set of zeros of a function $g \in L_n^*$. Since all functions in F_n are continous, if $S_{G,>} \neq \emptyset$ then $S_{G,>}$ is an open set and hence truly n-dimensional.

Let $0 \not\equiv Q \in F_n$ be an arbitrary function and let $Z = \{Z_1, \ldots, Z_p\}$ be a set of certificates. Z is a *complete proof* for (L, Op_L) with respect to Q if

(C1) Each Z_i is a certificate for L, i.e. $\forall x \forall i : x \in S_{Z_i} \Rightarrow x \in S_L$.

(C2) S_L is covered by $S_{Q,=}$ and the S_{Z_i}, i.e. $\forall x, Q(x) \neq 0 : (x \in S_L \Rightarrow \exists i : x \in S_{Z_i})$.

The size of Z is the maximal size of one of its certificates, i.e. $|Z| := \max_i |Z_i|$. If all Z_i are strict then we call Z a *strict complete proof.*

There is a strong correspondence between certificates and complete proofs on the one hand and decision trees on the other hand. Given a decision tree which decides membership in a set S_{L,Op_L} the set of functions evaluated along any 1-path (i.e. a path which gives the answer "is member") is a certificate for (L, Op_L). And the collection of all certificates corresponding to all 1-paths is a complete proof for (L, Op_L) w.r.t. any function Q. Hence any lower bound on the size of a certificate or complete proof is also a lower bound for decision trees.

Also, each certificate can easily be transformed into an equivalent path of a decision tree. However, the transformation of an arbitrary complete proof into a whole decision tree can result in a rather complicated and nonoptimal decision tree.

The next two Lemmas show that we can restrict our lower bound proofs to strict complete proofs. Here we differ from Rabin who only allowed nonstrict inequalities (i.e. $\geq$) in the definition of S_G and S_L.

Lemma 3.1 Let $Z = (G, >)$ be a strict certificate for (L, Op), $Op \in \Delta^m_>$ arbitrary. Then Z is also a certificate for $(L, >)$.

Proof : W.l.o.g. is $S_G \neq \emptyset$. Assume that there exists a $z \in S_G$ with $l_i(z) = 0$. But since S_G is an open set there exists an $\epsilon > 0$ such that $B_n(z, \epsilon) \subseteq S_G$ which means that also $B_n(z, \epsilon) \subseteq S_L$, a contradiction to $l_i(z) = 0$. □

Lemma 3.2 Let Z be a complete proof for (L, Op_L) w.r.t. Q. Then there exists a set of certificates Z' and a $0 \not\equiv Q' \in F_n$ such that $|Z'| \leq |Z|$ and Z' is a strict complete proof for $(L, >)$ w.r.t. Q'.

Proof : Assume that $Z = \{Z_1, \ldots, Z_p\}$ with $Z_i = (G_i, Op_i)$, $G_i = \{g_{i1}, \ldots, g_{ik}\}$ and $Op_i = \{op_{i1}, \ldots, op_{ik}\}$. We first define $Q' := Q \cdot \prod_{i,j} g_{ij}$ where the product is taken over all $g_{ij} \not\equiv 0$. Then we define Z' by

(1) Replacing all predicates "$g_{ij} \neq 0$" by "$g_{ij}^2 > 0$".

(2) Throwing away all Z_i with $op_{ij} =$ '$=$' for some j.

(3) And then defining all remaining $op'_{ij} :=$ '$>$'.

Obviously, $|Z'| \leq |Z|$ and all certificates are strict. It remains to show that Z' is a complete proof for $(L, >)$. Step (1) did not change anything except the degree of some functions which is irrelevant for us. So suppose w.l.o.g. that Z did not contain any $op_{ij} =$ '$\neq$'.

(C1) Since $S_{Z'_i} \subseteq S_{Z_i}$ for all Z'_i remaining after step (2), the Z'_i are also certificates for (L, Op_L) and hence for $(L, >)$ by Lemma 3.1.

(C2) If there is an $x \in S_{L,>}$ with $Q'(x) \neq 0$ then in particular $x \in S_L$ and $Q(x) \neq 0$. By (C2) there must be an i such that $x \in S_{Z_i}$, i.e. $\forall j$: $g_{ij}(x)\ op_{ij}\ 0$, $op_{ij} \in \{>, \geq, =\}$. From $Q'(x) \neq 0$ follows $op_{ij} \in \{>, \geq\}$ and