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A SYNTACTIC CHARACTERIZATION OF BOUNDED-RANK DECISION TREES IN TERMS OF DECISION LISTS (*)

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Abstract. – *We define syntactically a sub-class of decision lists* (tree-like decision lists) *and we show its equivalence with the class of bounded rank decision trees. As a by-product, the main theorem provides an alternate and easier proof of the Blum's containement Theorem* [1]. *Furthermore we give an inversion procedure for Blum's derivation of a decision list from a bounded rank decision tree.*

Résumé. – *Nous définissons syntactiquement une sous-classe de listes de decision* (tree-like decision lists) *et nous montrons son équivalence avec la classe des arbres de décision de rang borné. Comme sous-produit, le théorème principal fournit une preuve alternative et plus simple du Théorème d'inclusion de Blum* [1]. *En plus, nous donnnons une procédure d'inversion pour la dérivation de Blum d'une liste de décision à partir d'un arbre de décision de rang borné.*

1. INTRODUCTION

Decision lists have been introduced by Rivest in [3] as a representation of boolean functions. He showed that k-decision lists, *i.e.* decision lists in which any term has at most k literals, are (1) a generalization of $k\text{-}CNF$, $k\text{-}DNF$ and of depth-k decision trees and (2) are polynomially learnable under PAC model. [2] showed that constant rank decision trees are also polynomially PAC learnable and [1] showed that rank-k decision trees are a sub-class of k-decision lists, thus providing to an improvement of the result of [2] since constant rank decision trees can be polynomially PAC-learned using Rivest's algorithm for k-decision lists as subroutine.

Here we define a sub-class of decision lists - the class of *tree-like decision lists*. For the lists of this class we define the *rank* measure and we show that the class of rank-k decision trees is equivalent to the class of rank-k tree-like

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decision lists. As a by-product of Theorem 3.1, we provide an alternate proof of Blum's containement theorem.

In the final section we give an algorithm such that given a decision list L it builds a corresponding decision tree. Also when L is the list that the main Theorem of [1] produces when applied to a rank-k *reduced* decision tree T, it allows us to recover exactly T.

2. PRELIMINARIES

Let $\mathcal{V}_n$ be a set of n boolean variables $v_1, v_2, \ldots, v_n$. A *literal* ℓ_i denotes a variable v_i or its negation. Boolean *constants* are denoted by $a, b, \ldots$ A *term* or *monomial* t is a *conjunction* of literals. Terms are supposed to be strings of literals and we refer to a *prefix* of length k of a term t as the term built from the conjunction of the first (from left to right) k literals of t, with $k \leq |t|$.

A *decision list* L on a family $\{F_i\}$ of boolean functions over n variables is a sequence $(F_1, b_1), \ldots, (F_{m-1}, b_{m-1}), (1, b_m)$, with $m > 0$. On input $\vec{x} \in \{0,1\}^n$, it computes the boolean function f_L defined as b_j where j is the least number less than $m - 1$ such that $F_j(\vec{x}) = 1$, if such j exists, and b_m otherwise. Here we limit the boolean functions F_i to monomials on $\mathcal{V}_n$ like in [3]. L is a *k-decision list* if for each monomial t, $|t| \leq k$. The length $|L|$ of a decision list L is the number of monomials. A couple of the form (t, a) will be called *item* and by $(t, a)_i$ we denote the i-th item in L. Given $L = (t_1, b_1), \ldots, (t_{m-1}, b_{m-1}), (1, b_m)$ and a literal ℓ we denote by $(\ell \wedge L)$ the list $(\ell \wedge t_1, b_1), \ldots, (\ell \wedge t_{m-1}, b_{m-1}), (\ell, b_m)$.

A *decision tree* T is a binary tree such that the internal nodes are labelled with a variable of $\mathcal{V}_n$, the leaves are labelled with boolean constants and each right (respectively left) arc is labelled with 1 (respectively 0). Note that the same variable can label several internal nodes on the same path; if there is no such repetition, then the tree is said to be *reduced*. The boolean function f_T computed by T is defined in the following way: if T is a constant a then $f_T = a$, otherwise if $T = (v_i, T_1, T_2)$, then $f_T = (v_i \wedge f_{T_1}) \vee (\bar{v}_i \wedge f_{T_1})$.

The *rank* $r(T)$ of a decision tree T is the height of the largest complete binary tree that can be embedded in T. It is defined by:

$$r(T) = \begin{cases} 0 & \text{if } T = a \\ \max(r(T_1), r(T_2)) & \text{if } T = (v_i, T_1, T_2) \text{ and } r(T_1) \neq r(T_2) \\ r(T_1) + 1 & \text{if } T = (v_i, T_1, T_2) \text{ and } r(T_1) = r(T_2) \end{cases}$$

The size $|T|$ of a decision tree T is the number of its internal nodes. We refer to $\mathcal{T}_k$ as the class of rank k decision trees.

3. MAIN RESULT

First we define the class $\mathcal{L}_k$ of tree-like decision lists with rank k, proving some key properties they satisfy. Then we show the equivalence between $\mathcal{L}_k$ and $\mathcal{T}_k$.

3.1. Tree-like decision lists

To reader's convenience we state the Lemma (proved below) that guarantees the soundness of the definition of tree-like decision list.

LEMMA 3.1: *Given a tree-like decision list L, with* $|L| > 1$, *there exists a unique decomposition of L in* $(\ell \wedge L_1)$ *and* L_2 *such that* $L = (\ell \wedge L_1), L_2$, *and* L_1 *and* L_2 *are tree-like decision lists.*

DEFINITION 3.1: *A tree-like decision list (tdl) is defined inductively by:*

- $(1, a)$ *is a tdl for any* $a \in \{0, 1\}$;
- *given two tdl's* L_1 *and* L_2, *the decision list* $(\ell \wedge L_1), L_2$ *is a tdl for any literal* ℓ.

The rank $\rho(L)$ of a tdl L is 0 if $L = (1, a)$, and is obtained from $\rho(L_1)$ and $\rho(L_2)$, as for the decision trees, otherwise. $\mathcal{L}_k$ is the class of tdl's having rank k.

Observe that a rank-k tdl is not necessarily a k-decision list. For example, the 3-decision list $((v_1 \wedge v_2 \wedge v_3, 1), (v_1 \wedge v_2, 1), (v_1, 1), (1, 0))$ has rank 1.

It is easy to see that in a tdl L of length greater than 1 there is always a first item having a term t such that $|t| = 1$ (so $t = \ell$) and all t_i's in the previous items of L, if any, start with ℓ and have length at least 2. This observation allows us to prove the key property (Lemma 3.1) of the tdl's, namely: from a tdl L, there is a unique way to recover the two sub-tdl's L_1 and L_2 and the literal ℓ that define it.

Proof of Lemma 3.1: The decomposition of L is as follows:

- Starting from the leftmost item of L, search for the first term t such that $|t| = 1$;
- define $(\ell \wedge L_1)$ by taking all the items of L up to t, define L_2 as the remaining items of L.

Suppose that this decomposition is not unique so that L can be written as $(\ell' \wedge L_1'), L_2'$. By hypothesis, by the decomposition and by the previous observation we have that ℓ and ℓ' must be the same literal and they must be in the same item of L. Since the items in $(\ell' \wedge L_1'), L_2'$ and in $(\ell \wedge L_1), L_2$

are the same, it follows immediately that $L'_2 = L_2$ and therefore $L'_1 = L_1$. So the decomposition of L with respect to its sub-tdl's is unique. □

We define the boolean function ϕ_L associated with a tdl L in terms of the tree structure as follows: $\phi_L = a$ if $L = (1, a)$ and $\phi_L = (\ell \wedge \phi_{L_1}) \vee (\bar{\ell} \wedge \phi_{L_2})$ otherwise. Then the previous property allows us to show that the boolean function f_L computed by L is ϕ_L.

LEMMA 3.2: *For any tree-like decision list L, $f_L = \phi_L$.*

Proof: By induction on $|L|$. Suppose $|L| > 1$, since if $|L| = 1$ the result is trivial. By Lemma 3.1 we find uniquely ℓ, L_1 and L_2 such that $L = (\ell \wedge L_1), L_2$ and by inductive hypothesis $\phi_{L_i} = f_{L_i}$ for $i = 1, 2$. If $\ell = 1$, then $f_L = f_{L_1} = \phi_{L_1}$, since the last term of L_1 is the true term. On the other hand, if $\ell = 0$, then all terms in $(\ell \wedge L_1)$ are falsified and so $f_L = f_{L_2} = \phi_{L_2}$. So $f_L = (\ell \wedge \phi_{L_1}) \vee (\bar{\ell} \wedge \phi_{L_2}) = \phi_L$. □

3.2. Equivalence result

THEOREM 3.1: *For any decision tree $T \in \mathcal{T}_k$, there is an equivalent tdl $L \in \mathcal{L}_k$, moreover L is k-decision list and and the size of L is equal to the number of leaves of T.*

Proof: By double induction on the height and on the rank of T. If $r(T) = 0$ and $T = a$, then $L = (1, a)$ and the result is immediate. Now, Let $r(T) = k$ and suppose that ℓ is the literal at the root of T and that T_1 and T_2 are respectively the right and the left sub-trees of T. By definition of rank at least one between T_1 and T_2 has rank at most $k - 1$. Assume without loss of generality that T_1 has this property. Let L_1 and L_2 be the two tdl's associated respectively with T_1 and T_2, having their same rank and granted by the inductive hypothesis. The list L we associate with T is therefore $(\ell \wedge L_1), L_2$. Thus $r(T) = \rho(L)$ and $f_T = f_L$ since by inductive hypothesis we have $r(T_i) = \rho(L_i)$ and $f_{T_i} = f_{L_i}$ for $i = 1, 2$. Observe that the role of L_1 and L_2 is compulsory if we want to obtain a k-decision list. □

Observe that the proof of this Theorem, suggested by one of the Referees, implicitly defines another way to obtain Theorem 1 of [Bl]. Here we give a sketch of its original proof since it will be useful in the next section.

THEOREM 3.2 ([1]): *For any decision tree $T \in \mathcal{T}_k$ of m leaves there exists an equivalent k-decision list of size at most m.*

Proof: By induction on m. If $m = 1$ or $m = 2$ the result is easy. Suppose $m > 2$, observe that if $r(T) = k$, then there is a path of length at most k

ending in a leaf a. Consider the item (t, a) where t is the term associated to this path and consider the tree $\overline{T} = T - t$ obtained by by-passing T with respect to t, *i.e.* eliminating the node in T corresponding to the last variable in t and attaching the brother sub-tree of the leaf a to the node above it. Since $\overline{T}$ has at most $m - 1$ leaves, by inductive hypothesis we have that $L_{\overline{T}}$ is the list associated to $\overline{T}$. The list L is therefore $(t, a), L_{\overline{T}}$. Since the length of each term is bounded by the rank of T, L is a k-decision list; and, since we repeat the above procedure for each leaf in T, the length of L is at most m. □

The reverse inclusion is given by the following Theorem.

THEOREM 3.3: *For any tdl $L \in \mathcal{L}_k$, there is an equivalent decision tree $T \in \mathcal{T}_k$.*

Proof: By induction on $|L|$. If $|L| = 1$, then $L = (1, a)$ so $T = a$. If $|L| > 1$, then by Lemma 3.1 we can identify uniquely ℓ, L_1 and L_2 such that $L = (\ell \wedge L_1), L_2$. Given T_1 and T_2 associated respectively with L_1 and L_2, we build the tree $T = (\ell, T_1, T_2)$ according to the sign of ℓ. Then $r(T) = \rho(L)$ and $f_T = f_L$ since by inductive hypothesis we have $r(T_i) = \rho(L_i)$ and $f_{T_i} = f_{L_i}$, for $i = 1, 2$. □

Given $L \in \mathcal{L}_k$ the number of steps required to build $T \in \mathcal{T}_k$ is $O(|L| \log |L| + (|L| - 2^k)^2)$. To see this we first discuss the case in which T is a complete binary decision tree of depth k, then we consider the general case.

Consider the algorithm implicitly defined by the previous Theorem subdivided in phases as follows. At the *first phase* we search for the first term in L from the left having size 1, in $|L|$ items, using the decomposition algorithm of Lemma 3.1. We have thus identified the literal at the root of T and the two sub-tdl's L_1 and L_2 of L. At the *second phase* we search sequentially in L_1 and L_2 for two terms of size 1 in only $|L| - 1$ items, since $|L_1| + |L_2| = |L|$ and we can exclude from the search the term identified at the previous phase. In general, at the j-th *phase*, we search for 2^{j-1} terms of size 1 in $(|L| - (2^{j-1} - 1))$ items.

Observe that after j phases such that $\sum_{i=0}^{j} 2^i = |L|$ we have identified all the terms in L. Thus the number of phases is $j = O(\log |L|)$. The total number of steps required to build (a binary complete decision tree) T is $\sum_{i=1}^{j} (|L| - (2^{i-1} - 1))$ and this is $O(|L| \log |L|)$.

Observe that if $T \in \mathcal{T}_k$, then a complete binary tree T_c of depth k is always embedded in T. This means that in the general case of a not necessarily complete decision tree $T \in \mathcal{T}_k$, at some point the algorithm will recover

T_c. By previous observation, this part requires at most $O(|L| \log |L|)$ steps and eliminates 2^k items from L. For the remaining $|L| - 2^k$ items in L we can only say that in each phase the algorithm eliminates at least one item. So in the worst case this second part requires $O((|L| - 2^k)^2)$ steps. Therefore the total number of steps is $O(|L| \log |L| + (|L| - 2^k)^2)$. Observe that when L corresponds to a complete decision tree our algorithm runs in time $O(|L| \log |L|)$.

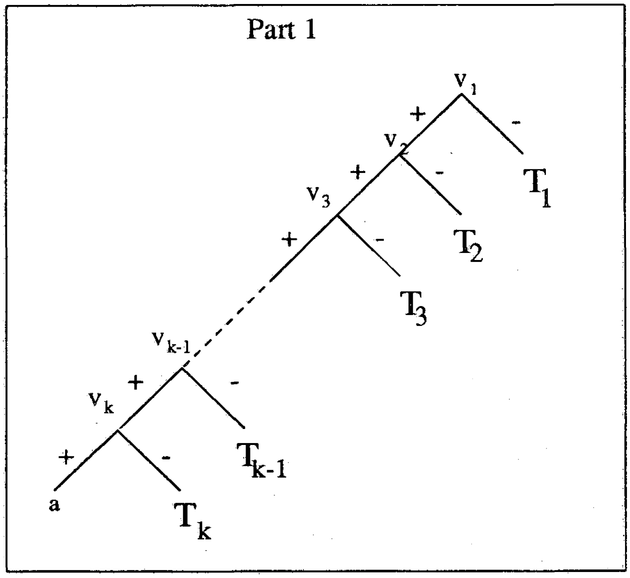
As remarked in Lemma 1 of [2], for any decision tree T, $r(T) \leq \log(|T| + 1)$ since the smallest decision tree of rank k is the complete binary tree of depth k. This means that a decision tree of size n can be represented by a tdl $L \in \mathcal{L}_{\lceil \log(n+1) \rceil}$. On the other hand, since the minimal decision tree computing the parity function over n variables requires a complete binary decision tree with 2^n leaves, the minimal tdl computing the parity function belongs to $\mathcal{L}_n$ but must have length no less than 2^n.

Moreover it is obvious that a k-rank tdl can be represented by a k-decision list (Theorems 3.3 and 3.2). For the reverse inclusion we can only say that, since a k-decision list L has a trivial representation as a decision tree of size $\leq k^{|L|}$, then L can be represented by an equivalent tdl $L' \in \mathcal{L}_{\lceil \frac{|L|}{\lfloor \log k \rfloor} \rceil}$ but of length $k^{|L|}$.

4. RECOVERING BOUNDED RANK REDUCED DECISION TREES

The procedure converting a rank k tdl into an equivalent rank-k decision tree is straightforward. On the other side recovering a rank-k decision tree from the k-decision list produced by Blum's procedure requires some more work. In this section we present an algorithm, *Rec-Tree*, to recover decision trees from decision lists. Moreover if L_T is the decision list produced by Theorem 3.2 when applied to the reduced decision tree T we have that *Rec-Tree*$(L_T) = T$.

Let $path(T)$ be the set of terms associated with paths of T. Let $t = \ell_1 \wedge \ldots \wedge \ell_k$ be a term in $path(T)$, ending with leaf a. In order to view T as in Part 1 of Figure 1, for each variable in t we define $+, - \in \{0, 1\}$ according to the sign (respectively the negated sign) of ℓ_i in t. Moreover if $T = (v_i, T_1, T_2)$ we denote T_1 by T^{i^+}, T_2 by T^{i^-} and $(T^{i^+})^{j^-}$ by $T^{i^+j^-}$ (with $+$ and $-$ submitted to the restrictions above). A simple relation between T and $\overline{T} = T - t$ is given by the following Remark.



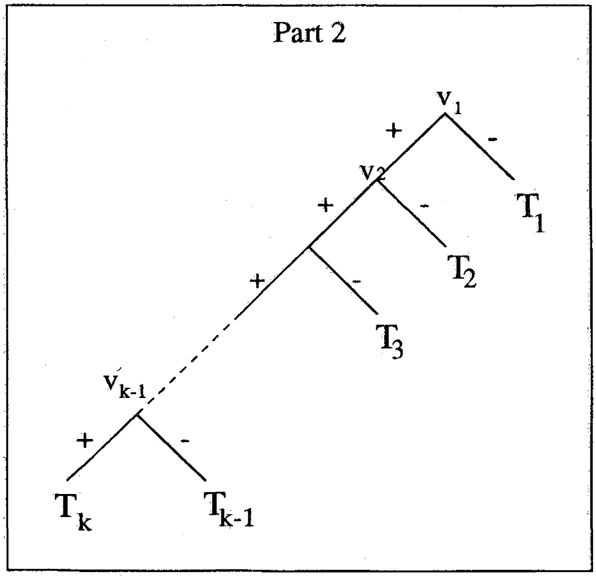


Figure 1. – Part 1: the decision tree T **wrt** $t = \ell_1 \wedge \ldots \wedge \ell_k$**;**
Part 2: the decision tree $\overline{T} = T - t$ **wrt** t**.**

REMARK 4.1: *Let T be a decision tree as in Part 1 of Figure 1 and let $t \in path(T)$ be a term $\ell_1 \wedge \ldots \wedge \ell_k$ with $1 \leq k \leq r(T)$ ending with leaf a:*

- *if $|t| = 1$, then $T_1 = \overline{T}$;*
- *if $|t| > 1$, then for any $1 \leq i \leq k-1$, $T_i = \overline{T}^{1^+2^+\ldots(i-1)^+i^-}$ and $T_k = \overline{T}^{1^+2^+\ldots(k-2)^+(k-1)^+}$.*

On a given decision list L, *Rec-Tree* works as follows: at the first step it recovers the constant decision tree T_1 from the default term of L; at the i-th step it recovers T_i by: (1) taking the $(|L|-i+1)$-th item $(t,a)_{|L|-i+1}$ of L; (2) building the trivial decision tree consistent with the term t and the constant a and putting the tree T_{i-1}, recovered at the previous step, at the unused nodes of this tree; (3) reducing each one of the T_{i-1}'s according to the path followed to reach it.

In what follows we provide more details about the algorithm. In order to have a more efficient reduction step and to simplify the proof of the theorem we merge the second and the third step, reducing the T_{i-1}'s as soon as they have to be attached to a node and working at each node on the previously reduced T_{i-1}.

Let $sgn(\ell,t)$ and $nsgn(\ell,t)$ be two functions computing respectively the sign and the negated sign of ℓ in t and let $root(T)$ be a function giving the variable at the root of T. Consider the following sub-routines:

1. BTV (Build a Tree wrt to a Variable), that takes as inputs a variable v_i, a term t and two decision trees T_1 and T_2 and outputs the tree $T = (\ell_i, T_1, T_2)$ according to the sign of v_i in t;
2. RT (Reduce Tree), that takes as inputs a variable v_i, $sg \in \{0,1\}$ and a decision tree T and outputs the decision tree T^* as follows:
   if $(T = a)$ **or** $(Root(T) \neq v_i)$
   then $T^* = T$;
   else T^* is the sub-tree of T chosen according to sg;
3. BTT (Build Tree wrt a Term), a recursive sub-routine that takes as input an item of the form (t,a) and a decision tree T, outputs the decision tree T^* as follows:
   if $|t| = 1$
   then $T^* = BTV(t^{=1}, t, a, T)$;
   else
   $T^+ = RT(t^{=1}, sgn(t^{=1}, t), T)$;
   $T^- = RT(t^{=1}, nsgn(t^{=1}, t), T)$;
   $T^* = BTV(t^{=1}, t, BTT((t^{>1}, a), T^+), T^-)$;

4. Finally *Rec-Tree*, that takes as input a decision list L, outputs a decision tree T, defined recursively as follows
if $L = (1, a)$
then $T = a$;
else $T = BTT((t, a)_1, \textit{Rec-tree}(L - (t, a)_1))$;

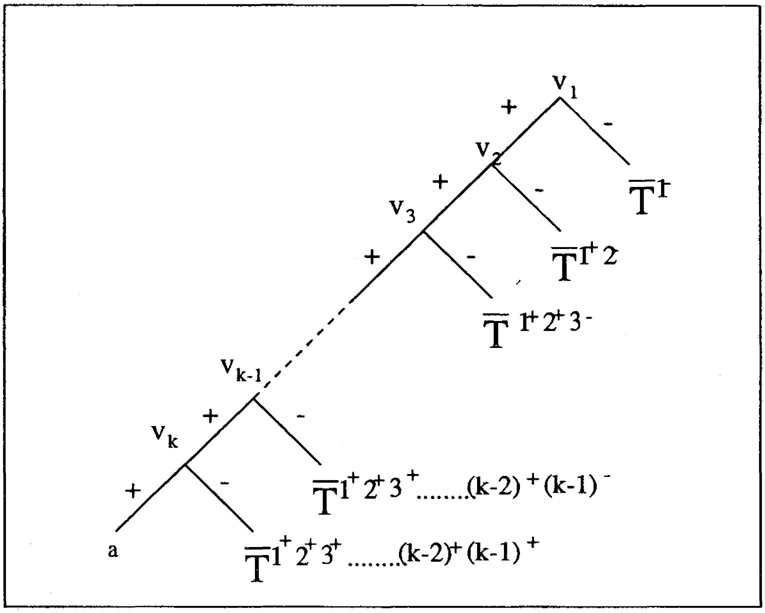


Figure 2. – The output of BTT **on inputs** $t = \ell_1 \wedge \ldots \wedge \ell_k$ **and** $\overline{T} = T - t$.

THEOREM 4.1: *For any reduced tree* $T \in \mathcal{T}_k$, *Rec-Tree*(L_T) *outputs* T *in* $O(|L|k)$ *steps.*

Proof: By induction on the number m of leaves of T. Let $m > 1$, since the case $m = 1$ is immediate by definition of *Rec-Tree*. Let $t = \ell_1 \wedge \ldots \wedge \ell_k \in path(T)$ be the term chosen ending with leaf a and let $\overline{T} = T - t$. By inductive hypothesis $Rec-Tree(L_{\overline{T}}) = \overline{T}$ and by Theorem 3.2 $L_T = (t, a), L_{\overline{T}}$. The theorem follows showing that $BTT((t, a), \overline{T}) = T$ and this is obtained by cases on $|t|$: if $|t| = 1$, then $t = \ell_k$ for some ℓ_k. Since v_k is the root label of T and T is a reduced tree, then v_k does not occur as label of any node of $\overline{T}$ (so we have no need to reduce it in BTT). By definition of BTV we obtain T. If, otherwise, $t = \ell_1 \wedge \ldots \wedge \ell_k$ with

$k > 1$, then the result follows by Remark 4.1 observing that, in this case, BTT outputs the tree of Figure 2.

Observe that if $T \in \mathcal{T}_k$, then every term in L_T has length bounded by k, so for each term in L, BTT calls itself at most k times. Since *Rec-tree* calls BTT $|L| - 1$ times, the total number of steps to output T is $O(|L|k)$. □

Observe that *Rec-tree* can be used to recover decision trees from any decision list. Suppose that we modify *Rec-tree* by eliminating the reduction sub-routine, and that we run the modified algorithm on a k-decision list L. It is easy to see that in $O(|L|k)$ steps, *Rec-tree* outputs a decision tree T consistent with L of depth $\leq k|L|$ but of size $\leq k^{|L|}$. On the other hand, supposing that $k^{|L|} \gg |\mathcal{V}_n|$ and that the minimal decision tree consistent with L has size, for example, polynomial in $|L|$, it could be interesting to study under what kind of hypothesis and what kind of modifications of *Rec-tree*, such a decision tree can be obtained, using, for istance, a fully reducing subroutine that, for each variable in the currently analyzed term, always explores the whole tree produced at the previous step.

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