

¹ **Fixed-Parameter Tractability of**
² **Learning Small Decision Trees**
³ **(full paper)**

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⁶ —— **Abstract** ——

⁷ We consider the NP-hard problem of finding a smallest decision tree which represents a given partially
⁸ defined Boolean formula. We establish fixed-parameter tractability of the problem with respect to
⁹ the NLC-width of the instance. We formulate a dynamic programming procedure which utilizes
¹⁰ the NLC-decomposition of the instance. For this to work, we establish a succinct representation
¹¹ of partial solutions, so that the space and time requirements of each dynamic programming step
¹² remain bounded in terms of the NLC-width.

¹³ **2012 ACM Subject Classification** Theory of computation → Design and analysis of algorithms →
¹⁴ Parameterized complexity and exact algorithms → Fixed parameter tractability

¹⁵ **Keywords and phrases** parameterized complexity, NLC-width, rank-width, decision trees, partially
¹⁶ defined Boolean formulas

17 **1 Introduction**

18 Decision trees have proved to be extremely useful tools for the describing, classifying,
 19 generalizing data [18, 22, 25]. In this paper, we consider decision trees for *classification*
 20 *instances (CIs)*, consisting of a finite set E of *examples* (also called *feature vectors*) over a
 21 finite set F of *features*. Each example $e \in E$ is a function $e : F \rightarrow \{0, 1\}$ which determines
 22 whether the feature f is true or false for e . Moreover, E is given as a partition $E^+ \uplus E^-$ into
 23 positive and negative examples. For instance, examples could represent medical patients and
 24 features diagnostic tests; a patient is positive or negative corresponding to whether they have
 25 been diagnosed with a certain disease or not. CIs are also called *partially* or *incompletely*
 26 *defined Boolean functions*, as we can consider the features as Boolean variables, and examples
 27 as truth assignments that evaluate to 0 (for positive examples) or 1 (for negative examples).
 28 CIs have been studied as a key concept for the logical analysis of data and in switching
 29 theory [4, 6, 5, 7, 8, 17, 20].

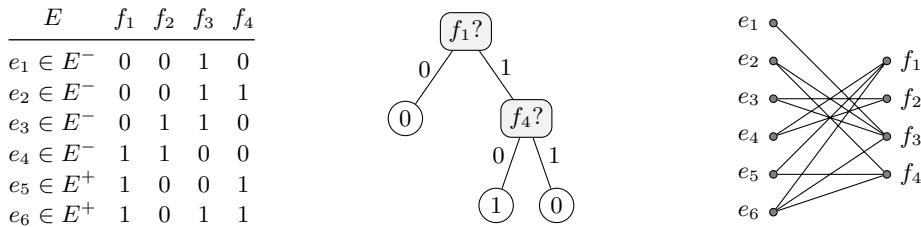
30 Because of their simplicity, decision trees are particularly attractive for providing in-
 31 terpretable models of the underlying CI, an aspect whose importance has been strongly
 32 emphasized over the recent years [10, 12, 15, 19, 21]. In this context, one prefers *small trees*,
 33 as they are easier to interpret and require fewer tests to make a classification. Small trees
 34 are also preferred in view of the parsimony principle (Occam's Razor) since small trees are
 35 expected to generalize better to new data [2]. However, finding a small decision tree, as
 36 formulated in the following decision problem, is NP-complete [16].

37 MINIMUM DECISION TREE SIZE (DTS): given a CI $E = E^+ \uplus E^-$ and an integer s ,
 38 is there a decision tree with at most s nodes for E ?

39 Given this complexity barrier, we propose a fixed-parameter algorithm for the problem,
 40 which exploits the input CI's hidden structure. The *incidence graph* of a CI is the bipartite
 41 graph $G_I(E)$ whose vertices are the examples on one side and the features on the other,
 42 where an example e is adjacent with a feature f if and only if $e(f) = 1$. Figure 1 shows a CI
 43 and a smallest decision tree for it, as well as the incidence graph.

44 Key to our algorithm are new notions for succinctly representing decision trees that
 45 correspond to subtrees of the incidence graph's tree decomposition. Based on that, we can
 46 carry out a dynamic programming (DP) procedure along the tree decomposition.

47 While the DP approach using treewidth is quite well understood and can often be quite
 48 easily designed for problems on graphs (or more generally problems whose solutions can be
 49 represented in terms of the graph for which the tree decomposition is given), the same DP
 50 approach can become rather involved if applied to problems whose solutions have no or only
 51 minor resemblance to the graph for which one is given a tree decomposition. Probably the
 52 most prominent example for this is the celebrated result by Bodlaender [3], where he uses a



■ **Figure 1** A CI $E = E^+ \uplus E^-$ with six examples and four features (left), a decision tree with 5 nodes that classifies E (middle), the incidence graph $G_I(E)$ (right).

53 DP approach on an approximate tree decomposition to compute the exact treewidth of a
 54 graph; here, the solutions are tree decompositions, which are complex structures that cannot
 55 easily be represented in terms of the graph. Other prominent examples include a DP approach
 56 to compute the exact treedepth [26] or clique-width [14] using an optimal tree decomposition.
 57 We face a similar problem, since solutions in our case are decision trees that do not bear
 58 any resemblance to the incidence graph for which we are given the tree decomposition. The
 59 main obstacle to overcome, therefore, is the design of the DP-records for our DP algorithm.
 60 That is, a record for a node b in a tree decomposition for the incidence graph of E needs
 61 to provide a compact representation of partial solutions, i.e. partial solutions in the sense
 62 that they represent the part of the solution for the whole instance E that corresponds to the
 63 sub-instance induced by all features and examples contained in the bags in the subtree of
 64 the tree decomposition rooted at the current node b . We overcome this obstacle in Section 3,
 65 where we also provide intuitive descriptions and motivation for the definition of the records
 66 (Subsection 3.1).

67 2 Preliminaries

68 2.1 Parameterized Complexity

69 We give some basic definitions of Parameterized Complexity and refer for a more in-depth
 70 treatment to other sources [9, 13]. Parameterized complexity considers problems in a two-
 71 dimensional setting, where a problem instance is a pair (I, k) , where I is the main part
 72 and k is the parameter. A parameterized problem is *fixed-parameter tractable* if there exists
 73 a computable function f such that instances (I, k) can be solved in time $f(k)\|I\|^{O(1)}$.

74 2.2 Graphs and NLC-width

75 We will assume that the reader is familiar with basic graph theory (see, e.g. [11, 1]). We
 76 consider (vertex and edge labelled) undirected graphs. Let $G = (V, E)$ be an undirected
 77 graph. We write $V(G) = V$ and $E(G) = E$ for the sets of vertices and edges of G , respectively.
 78 We denote an edge between $u \in V$ and $v \in V$ as $\{u, v\}$. For a set $V' \subseteq V$ of vertices we let
 79 $G[V']$ denote the graph induced by the vertices in V' , i.e. $G[V']$ has vertex set V' and edge
 80 set $E \cap \{\{u, v\} \mid u, v \in V'\}$ and we let $G - V'$ denote the graph $G[V \setminus V']$. For a set $E' \subseteq E$
 81 of edges we let denote $G - E'$ the graph with vertex set V and edge set $E \setminus E'$.

82 A *k-graph* is a pair (G, λ) , where $G = (V, E)$ is an undirected graph and $\lambda : V \rightarrow [k]$ is a
 83 *vertex label mapping* that labels every vertex $v \in V$ with a label $\lambda(v)$ from $[k]$. We call the
 84 *k-graph* consisting of exactly one vertex v (say, labeled by i) an *initial k-graph* and denote it
 85 by $i(v)$.

86 Node label control-width (*NLC-width*) is a graph parameter, defined as follows [28]: Let
 87 $k \in \mathbb{N}$ be a positive integer. An *k-NLC-expression tree* of a graph $G = (V, E)$ is a subcubic
 88 tree B , where every node b of B is associated with a *k-graph* (denoted by (G_b, λ_b)), such
 89 that:

- 90 1. Every leaf represents an initial *k-graph* $i(v)$ with $i \in [k]$ and $v \in V$.
- 91 2. Every non-leaf node b with one child c is a *relabeling node* and is associated with a
 92 relabelling function $R_b : [k] \rightarrow [k]$. Moreover, G_b is obtained from G_c after relabelling all
 93 vertices of G_c with label i to label $R_b(i)$ for every $i \in [k]$.
- 94 3. Every non-leaf node b with two children, i.e., a left child l and a right child r , is a *join*
 95 *node* and is associated with a *join matrix*, i.e., a binary $k \times k$ matrix M_b . Moreover,

96 (G_b, λ_b) is obtained from the disjoint union of (G_l, λ_l) and (G_r, λ_r) after adding an edge
 97 from all vertices labeled i in G_l to all vertices labeled j in G_r whenever $M_b[i, j] = 1$.

98 4. G is equal to the G_r for the root node r of B .

99 The NLC-width of a graph G , denoted by $nlcw(G)$, is the minimum k for which G has
 100 a k -NLC-expression tree. A k -NLC-expression tree is *nice* if every relabelling node has a
 101 relabelling function $R : [k] \rightarrow [k]$ such that for some $i, j \in [k]$, $R(i) = j$ and $R(\ell) = \ell$ for all
 102 $\ell \in [k] \setminus \{i\}$. Clearly, given a k -NLC-expression tree, a nice k -NLC-expression tree can be
 103 found in polynomial time; simply replace every relabelling node (that relabels more than one
 104 label at a time) by a sequence of relabelling nodes.

105 Let b be a node in a k -NLC-expression tree of a graph G . We denote by V_b the set of
 106 vertices of G_b . By the definition of a k -NLC-expression tree, if $u, v \in V_b$ have the same label
 107 in (G_b, λ_b) and $w \in V(G) \setminus V_b$, then u is adjacent to w in G if and only if v is.

108 Computing the NLC-width of a graph is NP-hard [?]. However, it is sufficient to use the
 109 algorithm of Seymour and Oum [?], which returns a c -expression for some $c \leq 2^{3cw(G)+2} - 1$
 110 in $O(n^9 \log n)$ time, or the later improvements of Oum [24] and Hliněný and Oum [?]
 111 that provide cubic-time algorithms which yield a c -expression for some $c \leq 8^{cw(G)} - 1$ and
 112 $c \leq 2^{cw(G)+1} - 1$, respectively.

113 should it be $nlcw$, or should we define cw and say it's approximation?

114 2.3 Classification Problems

115 An *example* e is a function $e : \text{feat}(e) \rightarrow \{0, 1\}$ defined on a finite set $\text{feat}(e)$ of *features*. For
 116 a set E of examples, we put $\text{feat}(E) = \bigcup_{e \in E} \text{feat}(e)$. We say that two examples e_1, e_2 *agree*
 117 on a feature f if $f \in \text{feat}(e_1)$, $f \in \text{feat}(e_2)$ and $e_1(f) = e_2(f)$. If $f \in \text{feat}(e_1)$, $f \in \text{feat}(e_2)$
 118 but $e_1(f) \neq e_2(f)$, we say that the examples *disagree on* f .

119 A *classification instance* (CI) (also called a *partially defined Boolean function* [17])
 120 $E = E^+ \uplus E^-$ is the disjoint union of two sets of examples, where for all $e_1, e_2 \in E$ we have
 121 $\text{feat}(e_1) = \text{feat}(e_2)$. The examples in E^+ are said to be *positive*; the examples in E^- are
 122 said to be *negative*. A set X of examples is *uniform* if $X \subseteq E^+$ or $X \subseteq E^-$; otherwise X is
 123 *non-uniform*.

124 Given a CI E , a subset $F \subseteq \text{feat}(E)$ is a *support set* of E if any two examples $e_1 \in E^+$
 125 and $e_2 \in E^-$ disagree in at least one feature of F . Finding a smallest support set, denoted
 126 by $\text{MSS}(E)$, for a classification instance E is an NP-hard task [17, Theorem 12.2].

127 We define the *incidence graph* of E , denoted by $G_I(E)$, as the bipartite graph with
 128 partition $(E, \text{feat}(E))$ having an edge between an example $e \in E$ and a feature $f \in \text{feat}(e)$ if
 129 $f(e) = 1$.

130 2.4 Decision Trees

131 A *decision tree* (DT) (or *classification tree*) is a rooted tree T with vertex set $V(T)$ and arc
 132 set $A(T)$, where each non-leaf node (called a *test*) $v \in V(T)$ is labelled with a feature $\text{feat}(v)$,
 133 each non-leaf node v has exactly two out-going arcs, a *left arc* and a *right arc*, and each leaf
 134 is either a *positive* or a *negative* leaf. We write $\text{feat}(T) = \{v \in V(T) \mid \text{feat}(v)\}$.

135 Consider a CI E and a decision tree T with $\text{feat}(T) \subseteq \text{feat}(E)$. For each node v of T we
 136 define $E_T(v)$ as the set of all examples $e \in E$ such that for each left (right, respectively)
 137 arc (u, v) on the unique path from the root of T to v we have $e(\text{feat}(v)) = 0$ ($e(\text{feat}(v)) = 1$,
 138 respectively). T *correctly classifies* an example $e \in E$ if e is a positive (negative) example
 139 and $e \in E_T(v)$ for a positive (negative) leaf. We say that T *classifies* E (or simply that T is

¹⁴⁰ a DT for E) if T correctly classifies every example $e \in E$. See Figure 1 for an illustration of
¹⁴¹ a CI, its incidence graph, and a DT that classifies E .

¹⁴² The size of T is its number of nodes, i.e. $|V(T)|$. We consider the following problem.

MINIMUM DECISION TREE SIZE (DTS)

¹⁴³ Input: A classification instance E and an integer s .
¹⁴⁴ Question: Is there a decision tree of size at most s for E ?

¹⁴⁵ We now give some simple auxiliary lemmas that are required by our algorithm.

¹⁴⁶ ▶ **Lemma 1.** *Let A be a set of features of size a . Then the number of DTs of size at most s that use only features in A is at most a^{2s+1} and those can be enumerated in $\mathcal{O}(a^{2s+1})$ time.*

¹⁴⁷ **Proof.** We start by counting the number of trees T with n nodes that can potentially underlie
¹⁴⁸ a DT with n nodes. Note that there is one-to-one correspondence between trees T that
¹⁴⁹ underlie a DT with n nodes and unlabelled rooted ordered binary trees with n nodes (where
¹⁵⁰ ordered refers to an ordering of the at most 2 child nodes). Since it is known that the number
¹⁵¹ of unlabelled rooted ordered binary trees with n nodes is equal to the n -th Catalan number
¹⁵² C_n and that those trees can be enumerated in $\mathcal{O}(C_n)$ time [27], we already obtain that we
¹⁵³ can enumerate all of the at most C_n possible trees T underlying a DT of size n in $\mathcal{O}(C_n)$
¹⁵⁴ time. Therefore, there are at most sC_s possible trees of size at most s that can underlie a
¹⁵⁵ DT with at most s nodes and those can be enumerated in $\mathcal{O}(sC_s)$ time. It now remains
¹⁵⁶ to bound the number of possible feature assignments $feat(f)$ for these trees as well as the
¹⁵⁷ number of possibilities for the leave nodes that can be either labelled positive or negative.
¹⁵⁸ Since we can assume that $a \geq 2$, we obtain that the number of possible feature assignments
¹⁵⁹ (and labellings of leaf-nodes) of a tree T with n nodes is at most a^n . Taking everything
¹⁶⁰ together, we obtain that there are at most $sC_s a^s \leq s4^s a^s \leq a^{2s+1}$ many DTs of size at most
¹⁶¹ s using only features in A and those can be enumerated in $\mathcal{O}(a^{2s+1})$ time. ◀

¹⁶² ▶ **Lemma 2.** *Let A be a set of features of size a . There are at most $a^{2^{a+1}+3}$ inclusion-wise
¹⁶³ minimal DTs using only features in A and these can be enumerated in $\mathcal{O}(a^{2^{a+1}+3})$ time.*

¹⁶⁴ **Proof.** Note that an inclusion-wise minimal DT T that uses only features in A has at most
¹⁶⁵ $2^a + 1$ nodes; this is because every feature appears at most once on every path T . Therefore, we
¹⁶⁶ obtain from Lemma 1 that the number of choices for T is at most $a^{2(2^a+1)+1} = a^{2^{a+1}+3}$. ◀

¹⁶⁷ ▶ **Lemma 3.** *Let E be a CI. Then one can decide whether E has a DT and if so output a
¹⁶⁸ DT of minimum size for E in time $\mathcal{O}((2^{|E|})^{4|E|-1})$.*

¹⁶⁹ **Proof.** Note first that $|feat(E)| \leq 2^{|E|}$ since we can assume that E does not contain two
¹⁷⁰ equivalent features. Moreover, E has a DT if and only if $feat(E)$ is a support set, which can be
¹⁷¹ checked in time $\mathcal{O}(|E|^2 |feat(E)|)$ by checking, for every pair of positive and negative examples
¹⁷² in E , whether there is a feature that distinguishes them. If this is not the case, we output **NO**,
¹⁷³ so assume that E has a DT. Note that any inclusion-wise minimal DT for E has at most $|E|$
¹⁷⁴ leaves and therefore size at most $2|E| - 1$. We can therefore employ Lemma 1 to enumerate
¹⁷⁵ all inclusion-wise minimal potential DTs for E in time $\mathcal{O}((2^{|E|})^{2(2|E|-1)+1}) \in \mathcal{O}((2^{|E|})^{4|E|-1})$.
¹⁷⁶ For every such tree we then check whether it is indeed a DT for E and return a DT for E of
¹⁷⁷ minimum size found during this process. ◀

178 **3 An FPT-Algorithm for NLC-width**

179 In this section, we present our main result, i.e. we will show that DTS is fixed-parameter
 180 tractable parameterized by NLC-width.

181 ▶ **Theorem 4.** *Let E be a CI, let B be an NLC-decomposition of width ω for $G_I(E)$, and
 182 let s be an integer. Then, deciding whether E has a DT of size at most s is fixed-parameter
 183 tractable parameterized by ω .*

184 ▶ **Corollary 5.** *DTS is fixed-parameter tractable parameterized by NLC-width.*

todo: Due to
proposition ...

185 In principle, we will use a dynamic programming algorithm along the NLC-decomposition
 186 (B, χ) of $G_I(E)$ that computes a set of records for every node b of B in a bottom-up manner.
 187 Each record will represent an equivalence class of solutions (DTs) for the whole instance
 188 restricted to the examples and features contained in the current subtree rooted in b , i.e.
 189 the examples and features contained in $\chi(b)$. Before we continue with the formal notions
 190 and definitions required to define the records, we want to illustrate the main ideas and
 191 motivations. In what follows let B be an NLC-decomposition of $G_I(E)$ of width k . For
 192 $b \in V(B)$, we write $\text{feat}(b)$ and $\text{exam}(b)$ for the sets $\chi(b) \cap \text{feat}(E)$ and $\chi(b) \cap E$, respectively.

193 **3.1 Description of the Main Ideas Behind the Algorithm**

194 Consider a node b of B . To simplify the presentation, we will sometime refer to the features
 195 and examples in $\chi(B_b) \setminus \chi(b)$ as *forgotten* features and examples and we refer to the features
 196 and examples in $(\text{feat}(E) \cup E) \setminus \chi(B_b)$ as *future* features and examples. We start with some
 197 simple observations that follow immediately from the properties of tree decompositions.

198 ▶ **Observation 6.(1)** *$e(f) = 0$ for every forgotten example $e \in \text{exam}(B_b) \setminus \text{exam}(b)$ and
 199 future feature $f \in \text{feat}(E) \setminus \text{feat}(B_b)$,*
 200 (2) *$e(f) = 0$ for every future example $e \in E \setminus \text{exam}(B_b)$ and forgotten feature $f \in \text{feat}(B_b) \setminus
 201 \text{feat}(b)$;*

202 **Proof.** Towards showing (1), let e be an example in $\text{exam}(B_b) \setminus \text{exam}(b)$ and let f be a
 203 feature in $\text{feat}(E) \setminus \text{feat}(B_b)$. We claim that because (T, χ) is a tree decomposition of $G_I(E)$,
 204 the graph $G_I(E)$ cannot contain an edge between e and f , which implies that $e(f) = 0$.
 205 Suppose for a contradiction that this is not the case, i.e. $\{e, f\} \in E(G_I(E))$. Then, because
 206 of property (T1) of a tree decomposition, there must exist a node b' such that $e, f \in \chi(b')$.
 207 But then, if $b' \in V(B_b)$ we obtain that $f \notin \chi(b')$. Similarly, if $b' \in V(B \setminus B_b)$, we obtain
 208 that $e \notin \chi(b')$ since otherwise e would violate property (T2) of a tree decomposition. This
 209 completes the proof for (1); the proof for (2) is analogous. ◀

210 Informally, Observation 6 shows that forgotten examples cannot be distinguished by
 211 future features and future examples cannot be distinguished by forgotten features. Consider
 212 a DT T for E and a node b of B . For a set W containing features and examples from E , we
 213 denote by $E[W]$ the sub-instance of E induced by the features and examples in W . Our aim
 214 is to obtain a compact representation (represented by records) of the partial solution for the
 215 sub-instance $E[\chi(B_b)]$ of E induced by the features and examples in $\chi(B_b)$ represented by T .

216 Intuitively, such a compact representation has to (1) represent a partial solution (DT)
 217 for the examples in $\text{exam}(B_b)$ and (2) retain sufficient information about the structure of T
 218 in order to decide whether it can be extended to a DT that also classifies the examples in
 219 $E \setminus \text{exam}(B_b)$.

todo: adjust to
NLC-width

220 For illustration purposes let us first consider the simplified case that $\text{exam}(b) = \emptyset$. Because
 221 of Observation 6 (1), this implies that every forgotten example goes to the left child of
 222 any node t in T that is assigned a future feature. Therefore, under the assumption that
 223 $\text{exam}(b) = \emptyset$ the DT T' obtained from T after:

- 224 ■ removing the subtree T_r of T for every right child r of a node t of T with $\text{feat}(t) \in$
 225 $\text{feat}(E) \setminus \text{feat}(B_b)$ and replacing t with an edge from its parent in T to its left child in T

226 is a DT for $E[\chi(B_b)]$. Note that this means that under the rather strong assumption
 227 that $\text{exam}(b) = \emptyset$, the part of T that takes care of the sub-instance $E[\chi(B_b)]$ is itself a DT
 228 using only features in $\text{feat}(B_b)$; we will see later that unfortunately this is no longer the case
 229 if $\text{exam}(b) \neq \emptyset$. Note that even though T' is a DT for $E[B_b]$, it does not yet constitute a
 230 compact representation, since the number of features it uses in $\text{feat}(B_b) \setminus \text{feat}(b)$ is potentially
 231 unbounded. However, we obtain from Observation 6 (2) that every future example will end
 232 up in the left child of every node t of T' that is assigned a forgotten feature. This means
 233 that to decide whether T' can be extended to a DT for the whole instance, the nodes that
 234 are assigned forgotten features are not important. In fact, the only nodes in T' that can be
 235 important for the classification of future examples are the nodes that are assigned features
 236 in $\text{feat}(b)$. That is, it is sufficient to remember the DT T'' obtained from T' after:

- 237 ■ removing the subtree T_r of T' for every right child r of a node t of T' with $\text{feat}(t) \in$
 238 $\text{feat}(B_b) \setminus \text{feat}(b)$ and replacing t with an edge from its parent in T' to its left child in T' .

239 Since the number of possible DT T'' is clearly bounded in terms of the number of features
 240 in $\text{feat}(b)$ (and therefore in terms of the treewidth of $G_I(E)$), this would already give us the
 241 compact representation that we are looking for. However, this only works in the case that
 242 $\text{exam}(b) = \emptyset$, which is clearly not the case in general.

243 So let us now consider the general case with $\text{exam}(b) \neq \emptyset$. The first difference now is
 244 that the part of T that takes care of the sub-instance $E[\chi(B_b)]$ is no longer a DT that only
 245 uses features in $\text{feat}(B_b)$. In fact, it could even be the case that $E[\chi(B_b)]$ does not have a
 246 DT, because there could exist examples in $\text{exam}(b)$ that can only be distinguished using
 247 the features in $\text{feat}(E) \setminus \text{feat}(B_b)$. This means that we have to allow our partial solution for
 248 $E[\chi(B_b)]$ to use future features. Fortunately, we do not need to know which exact future
 249 feature is used by our partial solution but it suffices to know that a future feature is used and
 250 how it behaves w.r.t. the examples in $\text{exam}(b)$; this is because Observation 6 (1) implies that
 251 a future feature is used in a partial solution only for the purpose of distinguishing examples
 252 in $\text{exam}(b)$. Moreover, because every forgotten example ends up in the left child of any node
 253 t of T that uses a future feature, we only need to remember the left child for those nodes.
 254 Also, we only need to remember occurrences of those nodes (using future features) if at least
 255 one example in $\text{exam}(b)$ ends up in the right child of such a node; otherwise the node has
 256 no influence on the classification of examples in $\text{exam}(B_b)$. Finally, we cannot simply forget
 257 nodes that use forgotten features (as we could in the case that $\text{exam}(b) = \emptyset$). This is because
 258 we need to know exactly where the examples in $\text{exam}(b)$ end up at. For instance, if such
 259 an example in $\text{exam}(b)$ ends up in the right child of a node using a future feature, we need
 260 to know that this is the case because this means that the example has to be classified in
 261 this place at a later stage of the algorithm. Nevertheless, we do not need to remember all
 262 occurrences of nodes using forgotten features, but only those for which there is at least one
 263 example in $\text{exam}(b)$ that ends up in the right child of the node. Similarly, we do not need
 264 to remember the exact forgotten feature that is used but only how it behaves towards the
 265 examples in $\text{exam}(b)$. In summary, we only need to remember the full information about

266 the nodes of T that use a feature in $\text{feat}(b)$. For all other nodes, i.e. nodes that use either
 267 forgotten or future features, we only need to remember such a node, if at least one example
 268 in $\text{exam}(b)$ ends up in its right child. Moreover, even if this is the case, we only need to
 269 remember the following for such nodes:

- 270 ■ whether it uses a future or a forgotten feature and
 271 ■ how it behaves w.r.t. the examples in $\text{exam}(b)$.

272 With these ideas in mind, we are now ready to provide a formal definition of the compact
 273 representation of the part of T that takes care of the sub-instance $E[\chi(B_b)]$.

274 3.2 Formal Definition of Records and Preliminary Results

275 In the following, let E be a CI and let B be a k -NLC-expression tree for $G_I(E)$. Consider a
 276 node b of B . Recall that b is either a leaf node associated with a k -graph $i(v)$, a relabelling
 277 node with 1 child and with relabelling function R_b , or a join node with a left child, a right
 278 child and a join matrix M_b . Moreover, recall that (G_b, λ_b) is the k -graph associated with b
 279 (whose unlabeled version is a subgraph of G) and V_b is the set of vertices of G_b . Additionally,
 280 we will use the following notation. We denote by $\text{feat}(b)$ the set $V_b \cap \text{feat}(E)$ of features in
 281 V_b and by $\text{exam}(b)$ the set $V_b \cap E$ of examples in V_b .

282 Consider a node b of B . Let L be a set of labels (usually $L = [k]$). For a subset $L' \subseteq L$,
 283 we denote by $\overline{L'}$ the set $L \setminus L'$. For a label $l \in L$, we introduce a new feature f_l , which we
 284 will call a *forgotten feature*. Moreover, for a subset $L' \subseteq L$ of labels, we introduce a new
 285 feature $f_{L'}$, which we call an *future (or introduce) feature*. Let $F_L = \{f_l \mid l \in L\}$ be the set
 286 of all forgotten features and let $I_L = \{f_{L'} \mid L' \subseteq L\}$ be the set of all future features w.r.t.
 287 L . To distinguish features in $\text{feat}(E)$ from forgotton and future features, we will sometimes
 288 refer to them as *real features*.

289 Let T be a DT and $t \in V(T)$. We say that a node t_A is a *left (right) ancestor* of t
 290 if t is contained in the subtree of T rooted at the left (right) child of t_A . We denote by
 291 $\text{anc}_T^L(t)$ ($\text{anc}_T^R(t)$), or simply $\text{anc}^L(t)$ ($\text{anc}^R(t)$) if T is clear from the context, the set of all
 292 left (right) ancestors of t in T . We denote by $\text{anc}(t)$ the set of all *ancestors* of t in T , i.e.,
 293 $\text{anc}(t) = \text{anc}^L(t) \cup \text{anc}^R(t)$.

294 Let T be a DT and $t \in V(T)$ be an inner node of T with left child l , right child r , and
 295 parent p . We say that T' is obtained from T after *left (right) contracting* t if T' is the DT
 296 obtained from T after removing t together with all nodes in T_r/T_l and adding the edge
 297 between p and l/r ; if t has no parent then no edge is added.

298 We say that T is a *DT for b* , if T is a DT for $\text{exam}(b)$ that uses only the features in $\text{feat}(b)$.
 299 We say that an inner node $t \in V(T)$ is *left (right) redundant* in T if $\text{feat}(t) \in \text{feat}(\text{anc}^L(t))$
 300 ($\text{feat}(t) \in \text{feat}(\text{anc}^R(t))$). We say that t is redundant if it is either left redundant or right
 301 redundant. Intuitively, a node t is left (right) redundant if all examples that end up at t ,
 302 i.e., the examples in $E_T(t)$, go the left (right) child of t in T . Therefore, if t is left (right)
 303 redundant in T , then the tree obtained after left (right) contracting t is still a DT.

304 We say that T is a *DT template* for b if T is a DT for $\text{exam}(b)$ that can additionally
 305 use the future features in $I_{[k]}$. Here, we assume that a future feature $f_{L'} \in I_{[k]}$ for some
 306 $L' \subseteq [k]$ is 1 at an example $e \in \text{exam}(b)$ if $\lambda_b(e) \in L'$ and otherwise it is 0. We say that
 307 a DT template is *complete* if it does not use any features in $I_{[k]}$, otherwise we say that it
 308 is *incomplete*. Informally, the role of the future features in a DT template is to provide
 309 spaceholders for the features in $\text{feat}(E) \setminus \text{feat}(b)$. Because all of those features behave the
 310 same w.r.t. to examples in $\text{exam}(b)$ having the same label, they can be charactericed by the
 311 set of labels for which those features are 1. Let T be a DT template for b and let $t \in V(T)$.

312 We denote by $A_T(t)$ (or short $A(t)$) if T is clear from the context) the set of *filtered labels* for t ,
 313 i.e., $A(t) = (\bigcap_{f_{L'} \in \text{feat}(\text{anc}_L(t)) \cap I_{[k]}} \overline{L'}) \cap (\bigcap_{f_{L'} \in \text{feat}(\text{anc}_R(t)) \cap I_{[k]}} L')$. Informally, $A(t)$ is the set
 314 of all labels $l \in [k]$ such that an example e with label l would end up at t , if only the effect of
 315 the future features on the path to t is considered. We say that t with $f_{L'} = \text{feat}(t) \in I_{[k]}$ is
 316 *left (right) redundant* in T if $A(t) \subseteq L'$ ($A(t) \subseteq \overline{L'}$). We say that t is *redundant* if it is either
 317 left redundant or right redundant. Intuitively, t is left (right) redundant if all examples that
 318 can reach t (considering the influence of the future features only) end up in the left (right)
 319 child of t . This also implies that if t is left (right) redundant, then the DT template obtained
 320 after left (right) contracting t is equivalent with T (all examples end up in the same leaves).
 321 Finally, let us extend the definition $E_T(t)$ from DTs to DT templates. That is, for a DT
 322 template T for a node b , a node $t \in V(T)$, and a set of examples $E' \subseteq \text{exam}(b)$, we denote
 323 by $E_T(E', t)$ (or $E_T(t)$ if $E' = \text{exam}(b)$) the set of examples $e \in E'$ with $\lambda_b(e) \in A(t)$ and
 324 $e \in E'[\tau(t)]$, where $\tau(t)$ is the assignment of the features in $\text{feat}(b)$ along the path from the
 325 root of T to t .

define τ in prelims

326 We say that T is a *DT skeleton* for b if T is a DT that can only use features in $F_{[k]} \cup I_{[k]}$.
 327 Note that because of the features $F_{[k]}$, whose behaviour w.r.t. the examples in $\text{exam}(b)$ is
 328 not defined, the behaviour w.r.t. the examples in $\text{exam}(b)$ of such a DT skeleton is not
 329 necessarily defined. Nevertheless, the behaviour of a feature f_l in $F_{[k]}$ is well-defined w.r.t.
 330 to the examples in $\text{exam}(E) \setminus \text{exam}(b)$, i.e., it behaves the same as any feature in $\text{feat}(b)$
 331 with label l . Intuitively, DT skeletons are obtained from DT templates after replacing every
 332 feature f in $\text{feat}(b)$ with the forgotten feature $f_{\lambda_b(f)}$. This allows us to further compress the
 333 information contained in DT templates, while still keeping the information about how the
 334 DT template behaves w.r.t. future examples in E . In particular, DT skeletons will form the
 335 main information stored by our records.

336 Let T be a DT skeleton and $t \in V(T)$. Similarly as we did for DT templates, we say that
 337 T is *complete* if it uses no future features and otherwise we say that it is incomplete. We say
 338 that an inner node t with $f_l = \text{feat}(t) \in F_{[k]}$ is *left (right) redundant* in T if $f_l \in \text{feat}(\text{anc}^L(t))$
 339 ($f_l \in \text{feat}(\text{anc}^R(t))$). Similarly, as for DT (templates), if t with $\text{feat}(t) \in F_{[k]}$ is left (right)
 340 redundant, then we can left (right) contract t without changing the properties of T .

341 Let T be a DT (skeleton/template). Then, we denote by $r(T)$ the DT obtained from T
 342 after left (right) contracting every left (right) redundant node of T . The following lemma
 343 shows that $r(T)$ is well-defined, i.e., the order in which the left (right) contractions are
 344 performed does not influence the result.

345 ▶ **Lemma 7.** *Let T be a DT (skeleton/template), let $t \in V(T)$ be a left (right) redundant node
 346 in T , and let T' be the DT (skeleton/template) obtained from T after left (right) contracting
 347 t . Then, a node $t' \in V(T')$ is left (right) redundant in T' if and only if t' is left (right)
 348 redundant in T .*

349 **Proof.** Clearly, if t' is left (right) redundant in T' , then the same is true in T ; this is because
 350 if t'' is a left (right) ancestor of t' in T' , then the same holds in T . So suppose that t' is
 351 left (right) redundant in T . If $\text{feat}(t')$ is a real or forgotten feature, then t' is left (right)
 352 redundant in T because of some left (right) ancestor t_A of t' in T with $\text{feat}(t_A) = \text{feat}(t')$.
 353 If $t_A \neq t$, then t' is also left (right) redundant in T' (because t_A is also in T'). Otherwise,
 354 $t_A = t$ and therefore t must also be left (right) redundant in T ; because otherwise t' was
 355 removed when t was contracted. Therefore, t is left (right) redundant in T because of some
 356 left (right) ancestor t'_A of t in T with $\text{feat}(t'_A) = \text{feat}(t) = \text{feat}(t')$, which implies that t' is
 357 left (right) redundant in T' because of t'_A .

358 If, on the other hand, $\text{feat}(t')$ is a future feature $f_{L'}$, then $A_T(t') \subseteq \overline{L'}$ ($A_T(t') \subseteq L'$).
 359 We will show that $A_T(t') = A_{T'}(t')$, which shows that t' remains left (right) redundant in

360 This clearly holds if $\text{feat}(t)$ is not a future feature. So suppose that $\text{feat}(t) = f_L$. Then,
 361 because t is left (right) redundant in T (because otherwise t' would have been removed from
 362 T when contracting t), we have that $A_T(t) \subseteq \bar{L}$ ($A_T(t) \subseteq L$). Therefore, $A_T(t) = A_T(t) \cap \bar{L}$
 363 ($A_T(t) = A_T(t) \cap L$), which shows that t has no influence on $A_T(t')$ and therefore implies
 364 that $A_T(t') = A_{T'}(t')$. \blacktriangleleft

365 We now show that $r(T)$ shares certain properties with T . In particular, the first observation
 366 shows that if T is a DT template for b , then so is $r(T)$.

367 **► Observation 8.** *Let T be a DT template for b , then so is $r(T)$.*

368 **Proof.** It suffices to show that if t is left (right) redundant in T and e is in $E_T(t)$, then e
 369 goes to the left (right) child of t in T . If $\text{feat}(t) \in \text{feat}(b)$, then t is left (right) redundant
 370 because of some left (right) ancestor t' with $\text{feat}(t') = \text{feat}(t)$. Moreover, because $e \in E_T(t)$,
 371 e went to the left (right) child of t' and therefore e goes to the left (right) child of t (because
 372 $\text{feat}(t) = \text{feat}(t')$). If, on the other hand, $\text{feat}(t)$ is some future feature f_L , then $A(t) \subseteq \bar{L}$
 373 ($A(t) \subseteq L$) and because $e \in E_T(t)$, also $\lambda_b(e) \in A(t)$. Therefore, e goes to the left (right)
 374 child of t . \blacktriangleleft

375 The second observation shows the similarity in behaviour of T and $r(T)$ with respect to
 376 future examples in $E \setminus \text{exam}(b)$.

377 **► Observation 9.** *Let T be a DT (skeleton/template) for b , and let e be an example in
 378 $E \setminus \text{exam}(b)$ that is correctly classified by T . Then, e is also correctly classified by $r(T)$.*

379 **Proof.** The proof is very similar to the proof of Observation 8. That is, again it suffices to
 380 show that if t is left (right) redundant in T and e goes to t , then e goes to the left (right) child
 381 of t in T . The proof is essentially the same as the proof in Observation 8 for the case that
 382 $\text{feat}(t)$ is a real feature or a future feature. Moreover, if $\text{feat}(t)$ is a forgotten feature f_L , then
 383 t is left (right) redundant because of some left (right) ancestor t' with $\text{feat}(t') = \text{feat}(t) = f_L$.
 384 Moreover, because e goes to t , e went to the left (right) child of t' and therefore e goes to
 385 the left (right) child of t (because e behaves in the same way w.r.t. every feature in V_b that
 386 has the same label). \blacktriangleleft

387 Before we define our records and their semantics, we first show a bound on the number
 388 of DT skeletons (and the time to enumerate those) as this will allow us to obtain a similar
 389 bound for the number of records. We say that T is *reduced* if $r(T) = T$.

390 **► Observation 10.** *Let T be a reduced DT skeleton whose forgotten features use a set of at
 391 most k_F labels and whose future features use a set of at most k_I labels. Then, T has height
 392 at most $k_F + k_I + 1$ and size at most $2^{k_F+k_I+1}$.*

393 **Proof.** Consider a root-to-leaf path P in T . Then, every forgotten feature appears at most
 394 once on P ; because the second occurrence of such a feature would necessarily be redundant.
 395 Therefore, P can contain at most k_F forgotten features. Similarly, P can contain at most
 396 k_I future features, since otherwise one of the future features on P would be redundant.
 397 Therefore, T has height at most $k_F + k_I + 1$ and therefore size at most $2^{k_F+k_I+1}$. \blacktriangleleft

398 We obtain the following corollary as a special case.

399 **► Corollary 11.** *Let T be a reduced DT skeleton for a node $b \in V(B)$. Then, T has height at
 400 most $2k + 1$ and size at most 2^{2k+1} .*

401 ► **Observation 12.** The are at most $(k_F + 2^{k_I})^{2^{k_F+k_I+2}+1}$ reduced DT skeletons whose
 402 forgotten features use a set of at most k_F labels and whose future features use a set of at
 403 most k_I labels. Moreover, those can be enumerated in time $\mathcal{O}((k_F + 2^{k_I})^{2^{k_F+k_I+2}+1})$.

404 **Proof.** Because of Observation 10 such a DT skeleton has height at most $k_F + k_I + 1$ and
 405 size at most $2^{k_F+k_I+1}$. Therefore, the statement of the lemma follows from Lemma 1 by
 406 setting $a = k_F + 2^{k_I}$ and $s = 2^{k_F+k_I+1}$. ◀

407 We obtain the following corollary as a special case.

408 ► **Corollary 13.** The are at most $(k + 2^k)^{2^{2k+2}+1}$ reduced DT skeletons for a node $b \in V(B)$
 409 and those can be enumerated in time $\mathcal{O}((k + 2^k)^{2^{2k+2}+1})$.

410 Let T be a DT (template/skeleton) using only features in $\text{feat}(E) \cup F_L \cup \text{SoIFL}$ for some
 411 set L of labels (usually $L = [k]$). A *feature relabeling* is a function $\alpha : \text{feat}(E) \cup F_L \rightarrow F_{L'} \cup I_{L'}$,
 412 where L' is some set of labels (usually $L' = L$). With a slight abuse of notation, we denote
 413 by $\alpha(T)$, the decision tree obtained after relabeling all features used by T according to α ,
 414 i.e., $\alpha(T)$ is obtained from T after replacing the feature assignment function $\text{feat}_T(t)$ for T
 415 with the function $\text{feat}_{\alpha(T)}(t)$ defined by setting $\text{feat}_{\alpha(T)}(t) = \alpha(\text{feat}_T(t))$ if α is defined for
 416 $\text{feat}(t)$ and $\text{feat}_{\alpha(T)}(t) = \text{feat}_T(t)$, otherwise. We say that two feature relabellings α_1 and α_2
 417 are *compatible* if they agree on their shared domain.

418 We denote by α_b^s the *standard feature relabelling* for b , i.e., the function $\alpha_b^s : \text{feat}(b) \rightarrow F_{[k]}$
 419 defined by setting $\alpha_b^s(f) = f_{\lambda_b(f)}$ for every $f \in \text{feat}(b)$.

420 We now show an important property on the interchangeability of feature relabelings and
 421 reductions. That is, we show in Lemma 15 below that the effect of any sequence of feature
 422 relabellings and reductions that ends with the reduction operation ($r()$) is the same as the
 423 effect of the sequence that contains the same relabelling operations followed by one reduction
 424 operation at the end. To show this property, we need the following auxiliary lemma.

425 ► **Lemma 14.** Let T be a DT (template/skeleton) for a node $b \in V(B)$ and let α be a
 426 feature relabelling. If a node $t \in V(T)$ is left (right) redundant in T , then it is also left (right)
 427 redundant in $\alpha(T)$.

428 **Proof.** We distinguish the following two cases. If $\text{feat}(t) \in \text{feat}(b) \cup F_{[k]}$, then t is left (right)
 429 redundant in T because of some left (right) ancestor t' of t in T with $\text{feat}(t) = \text{feat}(t')$.
 430 Because $\alpha(\text{feat}(t)) = \alpha(\text{feat}(t'))$, we obtain that t is also left (right) redundant in $\alpha(T)$
 431 because of t' . If, on the other hand, $\text{feat}(t) \in I_{[k]}$, then t is left (right) redundant in T
 432 because of some set A of ancestors t_A with $\text{feat}(t_A) \in I_{[k]}$. Because the domain of α does
 433 not include future features, it follows that α does not change the feature assignment for t
 434 nor for its ancestors in A , and therefore t is also left (right) redundant in $\alpha(T)$. ◀

435 ► **Lemma 15.** Let T be a DT (template/skeleton) and let α be a feature relabelling. Then,
 436 $r(\alpha(T)) = r(\alpha(r(T)))$.

437 **Proof.** Let T' be the DT (template/skeleton) obtained from $\alpha(T)$ after left (right) contracting
 438 every node t that is left (right) redundant in T ; note that such a node t is also left (right)
 439 redundant in $\alpha(T)$ because of Lemma 14. Then, $T' = \alpha(\text{red}(T))$ and moreover because of
 440 Lemma 7 (and using the fact that every node t that is left (right) redundant in T is so
 441 in $\alpha(T)$), a node $t \in V(T')$ is left (right) redundant in T' if and only if it is so in $\alpha(T)$.
 442 Therefore, a node t is left (right) redundant in $\alpha(T)$ if and only if it is left (right) redundant
 443 in T or in $\alpha(r(T)) = T'$, which shows that $r(\alpha(T)) = r(\alpha(r(T)))$. ◀

444 We are now ready to define the records and their semantics. A *record* for b is a pair
 445 (T, s) such that T is a reduced decision tree skeleton for b and s is a natural number. We
 446 say that a record (T, s) is *semi-valid* for b if there is a (reduced) DT template T' for b such
 447 that $r(\alpha_b^s(T')) = T$ and $s = |V(T') \setminus V(T)|$. We say that a record (T, s) is *valid* for b if s is
 448 the minimum number such that (T, s) is semi-valid. We denote by $\mathcal{R}(b)$ the set of all valid
 449 records for b . The following corollary follows immediately from Corollary 13.

450 ▶ **Corollary 16.** $|\mathcal{R}(b)| \leq (k + 2^k)^{2^{2k+2}+1}$

451 Note that E has a DT of size at most s if and only if $\mathcal{R}(r)$ for the root r of B contains a
 452 record (T, s) such that T is complete.

453 3.3 Proof to the Main Result

454 We will now show that we can compute $\mathcal{R}(b)$ for every of the 3 node types of a nice k -NLC
 455 expression tree provided that $\mathcal{R}(c)$ has already been computed for every child c of b .

456 ▶ **Lemma 17** (leaf node). *Let $b \in V(B)$ be a leaf node. Then $\mathcal{R}(b)$ can be computed in time
 457 $\mathcal{O}(k(1 + 2^k)^{2^{k+3}+1})$.*

458 **Proof.** Let $i(v)$ be the initial k -graph associated with b . If v is a feature, then $\mathcal{R}(b)$ contains
 459 all records $(T, 0)$ such that T is a reduced DT skeleton for b using only the features in
 460 $\{f_{\lambda(v)}\} \cup I_{[k]}$. The correctness in this case follows because V_b contains no examples and
 461 therefore every reduced DT skeleton constitutes a valid record for b . Moreover, the run-time
 462 follows from Observation 12, since the time required to enumerate all those reduced DT
 463 skeletons is at most $\mathcal{O}((1 + 2^k)^{2^{k+3}+1})$.

464 If, on the other hand v is an example, then $\mathcal{R}(b)$ contains all records $(T, 0)$ such that T
 465 is a reduced DT skeleton for b using only the features in $I_{[k]}$ and which correctly classify v .
 466 Because of Observation 12, those can be enumerated in time $\mathcal{O}((1 + 2^k)^{2^{k+3}+1})$ and checking
 467 for each of those whether it correctly classifies v can be achieved in time $\mathcal{O}(k)$ because of
 468 Observation 10. ◀

469 Before we present the corresponding lemmas for the join-node and the relabelling node, we
 470 first need to introduce the so-called plugin operation that allows us to reverse the reductions
 471 applied to a DT (skeleton/template).

472 Let T and T' be two DT (templates/skeletons). Let $P = (t, p_1, \dots, p_\ell, t')$ be the path from
 473 t to t' in T such that t is an ancestor of t' in T , for some integer ℓ . Moreover, let $e = (p, c)$ be
 474 an edge in T' such that p is the parent of c in T' . We say that the DT (template/skeleton)
 475 T'' is obtained by *plugging in the path P into T' at edge e* if T'' is obtained from T' by doing
 476 the following. For an inner vertex p_i of P , let $T(P, p_i)$ be the subtree of T rooted at the
 477 unique child c of p_i that is not on P . Let P' be the induced subtree of T containing all
 478 vertices of P plus all vertices of $T(P, p_i)$ for every i with $1 \leq i \leq \ell$. Then, T'' is obtained
 479 from T' by removing the edge $e = (p, c)$, adding P' , and adding the edge from p to p_1 as
 480 well as the edge from p_ℓ to c . Moreover, T'' inherits all feature assignments as well as the
 481 left (right) child relation from T and T' .

482 The significance of the plugin operation comes from the fact that it allows us to reverse
 483 the reduction that has been applied to a DT (template/skeleton). For instance, consider a
 484 node b of B and let T be a DT skeleton for b and let T' be a DT template for b such that
 485 $T = r(\alpha_b^s(T'))$. Then, we can use the plugin operation to reverse the direction or in other
 486 words obtain T' from T as follows. Let $z : V(T) \rightarrow V(T')$ be the injective function mapping
 487 every node in T to its original node in T' . Then, we first use z to reverse the relabelling

488 given by $\alpha_b^s(T')$, i.e., let T^0 be the DT obtained from T by setting $\text{feat}_{T^0}(t) = \text{feat}_{T'}(z_H(t))$
 489 for every $t \in V(T^0)$. We now add back the nodes in $V(T') \setminus V(T)$ with the help of our plugin
 490 operation. In particular, for every edge $e = (p, c)$ in T^0 , where p is the parent of c in T^0 , let
 491 $P(e)$ be the path in T' between $z(p)$ and $z(c)$. Let T^1 be the DT template obtained from T^0
 492 after plugin in the path $P(e)$ into T^0 at edge e , for every edge $e = (p, c)$ of T^0 . Then, it is
 493 easy to see that $T^1 = T'$.

todo: simplify the
 run-time
 expressi⁴⁹⁴₄₉₅

► **Lemma 18 (join node).** *Let $b \in V(B)$ be a join node. Then $\mathcal{R}(b)$ can be computed in time $\mathcal{O}(2^{3k+1}(2k + 2^k)^{2^{3k+2}+1})$.*

496 **Proof.** Let b_L and b_R be the left and right child of b in B , respectively. Let M_b be the
 497 join matrix for the node b , i.e., M_b is a $k \times k$ binary matrix. For every label $i \in [k]$, let
 498 $A_{i,*} = \{j \in [k] \mid M_b[i, j] = 1\}$ and $A_{*,i} = \{j \in [k] \mid M_b[j, i] = 1\}$.

499 To distiguish between forgotten features from the left and the right subtree, we introduce
 500 the left i_L and the right version i_R for every label $i \in [k]$. With a slight abuse of notation,
 501 we also denote by $[k_L]$ be the set $\{1_L, \dots, k_L\}$ of (left) labels and we denote by $[k_R]$ be the
 502 set $\{1_R, \dots, k_R\}$ of (right) labels.

503 To compute the set $\mathcal{R}(b)$ of valid records for b , we first enumerate all reduced DT skeletons
 504 T using features in $[k_L] \cup [k_R] \cup I_{[k]}$. Because of Observation 12, those can be enumerated in
 505 time $\mathcal{O}((2k + 2^k)^{2^{3k+2}+1})$. For every such reduced DT skeleton T , we now do the following in
 506 order to decide whether T gives rise to a valid record for b . Let $\alpha_{LR \rightarrow} : F_{[k_L]} \cup F_{[k_R]} \rightarrow F_{[k]}$
 507 be the feature relabeling that relabels every (left/right) feature $f_{i_H} \in F_{[k_L]} \cup F_{[k_R]}$ (for some
 508 $H \in \{L, R\}$) to its original feature f_i .

509 Let $\alpha_L : F_{[k_R]} \rightarrow I_{[k]}$ be the feature relabeling that relabels every forgotten feature
 510 $f_{i_R} \in F_{[k_R]}$ to the future feature $f_{A_{*,i}}$. Let T_L be the reduced DT skeleton obtained from T
 511 after applying the relabelling using α_L followed by $\alpha_{LR \rightarrow}$ and then reducing the resulting
 512 DT skeleton, i.e., $T_L = r(\alpha_{LR \rightarrow}(\alpha_L(T)))$.

513 Similarly, let $\alpha_R : F_{[k_L]} \rightarrow I_{[k]}$ be the feature relabeling that relabels every forgotten feature
 514 $f_{i_L} \in F_{[k_L]}$ to the future feature $f_{A_{i,*}}$. Let T_R be the reduced DT skeleton obtained
 515 from T after applying the relabelling using α_R followed by $\alpha_{LR \rightarrow}$ and then reducing the
 516 resulting DT skeleton, i.e., $T_R = r(\alpha_{LR \rightarrow}(\alpha_R(T)))$.

517 Let $\hat{T} = r(\alpha_{LR \rightarrow}(T))$ and $\hat{s} = |V(T) \setminus V(\hat{T})|$. We now check whether there are records
 518 $(T_L, s_L) \in \mathcal{R}(b_L)$ and $(T_R, s_R) \in \mathcal{R}(b_R)$. If not we discard T and if yes, then we add the
 519 record $(\hat{T}, s_L + s_R + \hat{s})$ to $\mathcal{R}(b)$. This completes the description about how the records
 520 $\mathcal{R}(b)$ are computed. Moreover, the run-time for computing $\mathcal{R}(b)$ can be obtained as follows.
 521 First, because of Observation 12, we can enumerate all reduced DT skeletons T in time
 522 $\mathcal{O}((2k + 2^k)^{2^{3k+2}+1})$. Moreover, computing \hat{T} and \hat{s} can be done in time $\mathcal{O}(|T|) = \mathcal{O}(2^{3k+1})$
 523 (using Observation 10). Finally, computing T_L and T_R and checking the existence of the
 524 records $(T_L, s_L) \in \mathcal{R}(b_L)$ and $(T_R, s_R) \in \mathcal{R}(b_R)$ can be achieved in time $\mathcal{O}(|T|) = \mathcal{O}(2^{3k+1})$;
 525 here we assume that the records in $\mathcal{R}(b)$ are stored in an array whose key is \hat{T} . Therefore,
 526 we obtain $\mathcal{O}(|T|(2k + 2^k)^{2^{3k+2}+1}) = \mathcal{O}(2^{3k+1}(2k + 2^k)^{2^{3k+2}+1})$ as the total run-time for
 527 computing $\mathcal{R}(b)$.

528 We now show the correctness of our construction for $\mathcal{R}(b)$, i.e., we have to show that
 529 a record is valid if and only if we have added such a record according to our construction
 530 above. For this it suffices to show that a record is semi-valid if and only if we have added
 531 such a record according to our construction above. This is because, a valid record (T, s) can
 532 be obtained from the set of all semi-valid records (T, s') , where s is the minimum s' among
 533 all semi-valid records for T .

534 Towards showing the forward direction, suppose that (\hat{T}, s) is a semi-valid record for b .
 535 Therefore, there is a DT template T' for b such that $\hat{T} = r(\alpha_b^s(T'))$ and $s = |V(T') \setminus V(T)|$.

536 Let $\alpha_{\rightarrow R} : F_{[k]} \rightarrow F_{[k_R]}$ ($\alpha_{\rightarrow L} : F_{[k]} \rightarrow F_{[k_L]}$) be the feature relabeling that relabels
 537 every forgotten feature $f_i \in F_{[k]}$ to its corresponding forgotten feature in $[k_R]$ ($[k_L]$), i.e.,
 538 $\alpha_{\rightarrow R}(i) = i_R$ ($\alpha_{\rightarrow L}(i) = i_L$) for every $i \in [k]$.

539 Let $T = r(\alpha_{\rightarrow R}(\alpha_{b_R}^s(\alpha_{\rightarrow L}(\alpha_{b_L}^s(T')))))$ and let $\hat{s} = |V(T) \setminus V(\hat{T})|$. Because $\alpha_b^s = \alpha_{LR \rightarrow} \circ$
 540 $\alpha_{\rightarrow R} \circ \alpha_{b_R}^s \circ \alpha_{\rightarrow L} \circ \alpha_{b_L}^s$, we obtain from Lemma 15 that $\hat{T} = r(\alpha_{LR \rightarrow}(T))$.

541 Let $T_L = r(\alpha_{LR \rightarrow}(\alpha_L(T)))$ and $T_R = r(\alpha_{LR \rightarrow}(\alpha_R(T)))$. It remains to show that there
 542 are s_L and s_R with $s = s_L + s_R + \hat{s}$ such that $(T_L, s_L) \in \mathcal{R}(b_L)$ and $(T_R, s_R) \in \mathcal{R}(b_R)$.

543 Let $T'_L = r(\alpha_L(\alpha_{\rightarrow R}(\alpha_{b_R}^s(T'))))$ and $T'_R = r(\alpha_R(\alpha_{\rightarrow L}(\alpha_{b_L}^s(T'))))$. Note that T'_H is a DT
 544 template for b_H because so is T' .

545 Note that $T_L = r(\alpha_{b_L}^s(T'_L))$ because of Lemma 15 and the observation that the sequence
 546 $\alpha_{LR \rightarrow} \circ \alpha_L \circ \alpha_{\rightarrow R} \circ \alpha_{b_R}^s \circ \alpha_{\rightarrow L} \circ \alpha_{b_L}^s$ of relabellings to obtain T_L via T has the same total
 547 effect as the sequence $\alpha_{b_L}^s \circ \alpha_L \circ \alpha_{\rightarrow R} \circ \alpha_{b_R}^s$ of relabellings to obtain T_L via T'_L . Using a
 548 similar argument, we obtain that $T_R = r(\alpha_{b_R}^s(T'_R))$. Let $s_H = |V(T'_H) \setminus V(T_H)|$ for every
 549 $H \in \{L, R\}$. Then, T'_H shows that (T_H, s_H) is a semi-valid record for b_H .

550 It remains to show that $s_L + s_R + \hat{s} = s$. Note first that $s = |V(T') \setminus V(\hat{T})| =$
 551 $|V(T') \setminus V(T)| + |V(T) \setminus V(\hat{T})| = |V(T') \setminus V(T)| + \hat{s}$ and it therefore suffices to show that
 552 $s_L + s_R = |V(T') \setminus V(T)|$. Towards showing this, let t be a node in $|V(T') \setminus V(T)|$. First note
 553 that $\text{feat}_{T'}(t) \in \text{feat}(b_H)$ for some $H \in \{L, R\}$, because all nodes with future features in T'
 554 are also in T . Therefore, t is in $V(T'_H) \setminus V(T_H)$, which shows that t is either in $V(T'_L) \setminus V(T_L)$
 555 or in $V(T'_R) \setminus V(T_R)$, as required.

556 Towards showing the reverse direction, suppose that our construction adds the record
 557 $(\hat{T}, s_L + s_R + \hat{s})$ and let T , T_L , and T_R be as defined in the construction. Recall that:

- 558 ■ T is reduced and $\hat{T} = r(\alpha_{LR \rightarrow}(T))$,
- 559 ■ $T_L = r(\alpha_L(T))$ and (T_L, s_L) is semi-valid for b_L ,
- 560 ■ $T_R = r(\alpha_R(T))$ and (T_R, s_R) is semi-valid for b_R .

561 Let T'_L be the reduced DT template for b_L such that $T_L = r(\alpha_{b_L}^s(T'_L))$ and $s_L =$
 562 $|V(T'_L) \setminus V(T_L)|$, which exists because (T_L, s_L) is semi-valid for b_L . Similarly, let T'_R be the
 563 reduced DT template for b_R such that $T_R = r(\alpha_{b_R}^s(T'_R))$ and $s_R = |V(T'_R) \setminus V(T_R)|$, which
 564 exists because (T_R, s_R) is semi-valid for b_R .

565 We now show how to construct a witness T' (from T , T'_L , and T'_R) for the semi-validity of
 566 the record $(\hat{T}, s_L + s_R + \hat{s})$, i.e., T' is a reduced DT template for b such that $\hat{T} = r(\alpha_b^s(T'))$
 567 and $s_L + s_R + \hat{s} = |V(T') \setminus V(\hat{T})|$.

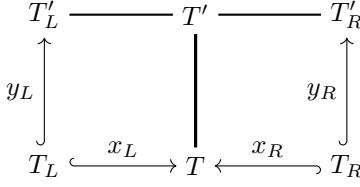
568 Informally, we obtain T' from T after reversing the relabelling and reduction operations
 569 applied to T'_L and T'_R to obtain T_L and T_R , respectively; recall that $T_H = r(\alpha_{b_H}^s(T'_H))$ for
 570 $H \in \{L, R\}$. That is, we will reverse the labelling for the nodes in T and add back the nodes
 571 to T that have been removed from T'_L and T'_R .

572 Let $H \in \{L, R\}$. Because T_H is obtained from T by reduction, every node in T_H
 573 corresponds to a unique node in T . Therefore, there is an injective function $x_H : V(T_H) \rightarrow$
 574 $V(T)$ mapping every node in T_H to its original node in T . Similarly, because T_H is obtained
 575 from T'_H by reduction, there is an injective function $y_H : V(T_H) \rightarrow V(T'_H)$ mapping every
 576 node in T_H to its original node in T'_H . See also Figure 2 for an illustration of these mappings.

577 In order to obtain T' from T , we will essentially need to be able to reverse the reduction
 578 operation $T_H = r(\alpha_{b_H}^s(T'_H))$ that has been applied to T'_H to obtain T_H for every $H \in \{L, R\}$.
 579 To do so we will make use of the plugin operation.

580 Our first order of business is to rename all forgotten features in T to their real features
 581 as given by T'_L and T'_R . That is, for every node t in T assigned to a forgotten feature, i.e.,
 582 $\text{feat}_T(t) \in F_{[k_L]} \cup F_{[k_R]}$, we do the following. If $\text{feat}_T(t) \in F_{[k_H]}$ for $H \in \{L, R\}$, then t is also
 583 in T_H and hence also in T'_H . Therefore, we can change $\text{feat}_T(t)$ to the real feature assigned

maybe a longer explanation



■ Figure 2

584 to t in T'_H . Let T^0 be the DT obtained from T after renaming all forgotten features to real
585 features in this manner.

586 Consider an edge $e = (p, c)$ in T_L such that p is the parent of c in T_L . Then, e corresponds
587 to a path $P'_L(e)$ between $y_L(p)$ and $y_L(c)$ in T'_L . Similarly, e corresponds to a path $P_L(e)$
588 between $x_L(p)$ and $x_L(c)$ in T^0 .

589 Our next order of business is now to add all nodes to T^0 that have been removed when
590 going from T'_L to T_L (via the reduction $r(\alpha_{b_L}^s(T'_L))$). To achieve this, we go over every edge
591 $e = (p, c)$ of T_L such that p is the parent of c in T_L and plugin the path $P'_L(e)$ (from T'_L)
592 into the last edge on the path $P_L(e)$ (from T^0). Let T^1 be the tree obtained from T^0 after
593 doing this operation for every edge of T_L .

594 Consider an edge $e = (p, c)$ in T_R such that p is the parent of c in T_R . Then, e corresponds
595 to a path $P'_R(e)$ between $y_R(p)$ and $y_R(c)$ in T'_R . Similarly, e corresponds to a path $P_R(e)$
596 between $x_R(p)$ and $x_R(c)$ in T^1 . Similarly to above, we now add all nodes to T^1 that have
597 been removed when going from T'_R to T_R (via the reduction $r(\alpha_{b_R}^s(T'_R))$). To achieve this,
598 we go over every edge $e = (p, c)$ of T_R such that p is the parent of c in T_R and plugin the
599 path $P'_R(e)$ (from T'_R) into the last edge on the path $P_R(e)$ (from T^1). Let T' be the tree
600 obtained from T^1 after doing this operation for every edge of T_R .

601 We now show that T' is indeed a witness for the semi-validity of the record $(\hat{T}, s_L + s_R + \hat{s})$,
602 i.e., T' is a reduced DT template for b such that $\hat{T} = r(\alpha_b^s(T'))$ and $s_L + s_R + \hat{s} = |V(T') \setminus V(\hat{T})|$.

603 We start by showing that T' is reduced. First note that because T is reduced so is T^0 .
604 Consider a node $t \in V(T')$. If $\text{feat}_{T'}(t) \in \text{feat}(b_H)$ for some $H \in \{L, R\}$, then t is also in
605 $V(T'_H)$. Therefore, if t were redundant in T' , it would also be redundant in T'_H , which cannot
606 be the case because T'_H is reduced. Moreover, if on the other hand, $\text{feat}_{T'}(t) \in I_{[k]}$, then t is
607 in T^0 and therefore cannot be redundant because T^0 is reduced. Therefore, T' is reduced and
608 it obviously only uses features in $\text{feat}(b) \cup F_{[k]}$. We show next that T' is a DT template for
609 b , i.e., T' classifies all examples in $\text{exam}(b)$ correctly. Towards showing this, let $e \in \text{exam}(b)$,
610 then $e \in \text{exam}(b_H)$ for some $H \in \{L, R\}$. Because T'_H is a DT template for b_H , we know
611 that e is correctly classified by T'_H . Let l be the leaf in T'_H that contains e , i.e., $e \in E_{T'_H}(l)$
612 and let Q be the path from the root of T'_H to l . Then, l also exists in T' and moreover the
613 path P from the root of T' to l contains all nodes of Q . Note furthermore that if a node t in
614 Q has its left/right child on Q , then the same holds on P . We will show that e follows along
615 the path P in T' and therefore ends up in l , which shows that e is correctly classified by T' .

616 Let t be a node of P . If t is also in Q , then e will be sent to the child of t in P . Otherwise,
617 t is either in $V(T) \setminus V(T_H)$ or t is in $T'_H \setminus T_{\bar{H}}$, where $\bar{H} = L$ if $H = R$ and $\bar{H} = R$ otherwise.

618 In the former case, $\text{feat}_{T'}(t) \in I_{[k]}$ or $\text{feat}_{T'}(t) \in \text{feat}(b_{\bar{H}})$, which implies that t behaves
619 towards e in the same manner as some future feature $f_L \in I_{[k]}$, i.e., if $\text{feat}_{T'}(t) \in I_{[k]}$, then
620 $f_L = \text{feat}_{T'}(t)$ and if $\text{feat}_{T'}(t) \in \text{feat}(b_{\bar{H}})$, then $f_L = \alpha_L(\text{feat}_T(t))$. Moreover, t is redundant
621 in $\alpha_L(T)$ because of its ancestors in T_H , i.e., either $A_{\alpha_L T}(t) \subseteq L$ or $A_{\alpha_L T}(t) \subseteq \bar{L}$. Because
622 all these ancestors are in T_H and therefore on Q , $\lambda_{b_L}(e) \in A_{\alpha_L T}(t)$, which implies that e is
623 send to the non-redundant child of t . Finally, since P contains l it follows that P contains

624 also the non-redundant child of t in $\alpha_L(T)$ and therefore e is send to the child of t on P , as
625 required.

626 In the latter case, i.e., the case that t is in $V(T'_H) \setminus V(T_H)$, t is redundant in $\alpha_{b_H}^s(T'_H)$
627 because of some ancestor $t' \in V(T_H)$ with $\alpha_{b_H}^s(feat_{T'}(t)) = \alpha_{b_H}^s(feat_{T'}(t'))$. Therefore,
628 $feat_{T'}(t')$ behaves in the same manner towards e as $feat_{T'}(t)$, which because t' is on Q
629 (because $t' \in V(T_H)$) implies that e is send to the (non-redundant) child of t on P .

630 It remains to show that $\hat{T} = r(\alpha_b^s(T'))$ and $s_L + s_R + \hat{s} = |V(T') \setminus V(\hat{T})|$. Towards
631 showing this, we first show that $T = r(\alpha_{T' \rightarrow T}(T'))$, where $\alpha_{T' \rightarrow T} = \alpha_{\rightarrow L} \circ \alpha_{b_R}^s \circ \alpha_{\rightarrow L} \circ \alpha_{b_L}^s$.
632 In other words, we need to show that the set of redundant nodes in $\alpha_{T' \rightarrow T}(T')$ is equal to
633 $V(T') \setminus V(T) = V(T') \setminus V(T^0)$. Because, as shown above T' is reduced, it follows that if
634 a node t is redundant $\alpha_{T' \rightarrow T}(T')$, then $t \in feat_{T'}(b_H)$ for some $H \{L, R\}$. Because all such
635 nodes, i.e., nodes t in T' with $t \in feat_{T'}(b_H)$ are also in T'_H , we obtain that t is redundant in
636 $\alpha_{T' \rightarrow T}(T')$ if and only if it is redundant in $\alpha_{b_H}^s(T'_H)$. Therefore, $\bigcup_{H \in \{L, R\}} V(T'_H) \setminus V(T_H)$ is
637 the set of all redundant nodes in $\alpha_{T' \rightarrow T}(T')$, which is equal to $V(T') \setminus V(T^0)$ by construction
638 of T' , as required. Note that $|V(T') \setminus V(T^0)| = s_L + s_R$ because of the construction of T' .
639 Now, because $\hat{T} = r(\alpha_{LR \rightarrow}(T))$ and $\alpha_b^s = \alpha_{LR \rightarrow} \circ \alpha_{T' \rightarrow T}$, we obtain from Lemma 15 that
640 $\hat{T} = r(\alpha_b^s(T'))$. Finally, because $|V(T') \setminus V(T^0)| = s_L + s_R$ and $|V(T^0) \setminus V(\hat{T})| = \hat{s}$, it follows
641 that $|V(T') \setminus V(\hat{T})| = s_L + s_R + \hat{s}$, as required. ◀

642 ▶ **Lemma 19** (relabel node). *Let $b \in V(B)$ be relabeling node in B . Then $\mathcal{R}(b)$ can be
643 computed in time $\mathcal{O}(2^{2k+1}(k + 2^k)^{2^{2k+2}+1})$.*

644 **Proof.** Let c be the unique child of b in B and let $R_b : [k] \rightarrow [k]$ be the relabelling function
645 associated with b . Because B is nice, it holds that there are labels i and j with $i \neq j$ such
646 that $R(i) = j$ and $R(\ell) = \ell$ for every $\ell \in [k] \setminus \{i\}$.

647 We say that a future feature $f_L \in I_{[k]}$ is *good* if it does not distinguish between i and j , i.e.,
648 $i \in L$ if and only if $j \in L$, and *bad* otherwise. For a bad future feature f_L , we denote by $g(f_L)$
649 the good future feature $f_{g(L)}$, where $g(L) = L \cup \{i\}$ if $j \in L$ and $g(L) = L \setminus \{i\}$, otherwise,
650 i.e., informally, $g(f_L)$ is the good feature corresponding to f_L that sends all examples with
651 label i to the same side as f_L sends all examples with label j .

652 To obtain the set $\mathcal{R}(b)$ of valid records for b , we first enumerate all reduced DT skeletons
653 T for b . Let $\alpha_{i \rightarrow j}^I : I_{[k]} \rightarrow I_{[k]}$ be the function defined by setting $\alpha_{i \rightarrow j}^I(f_L) = g(f_L)$ for every
654 bad future feature $f_L \in I_{[k]}$, i.e., $\alpha_{i \rightarrow j}^I$ relabels every bad feature f_L to its corresponding
655 good feature $g(f_L)$. Let $T^c = r(\alpha_{i \rightarrow j}^I(T))$. We now check whether $\mathcal{R}(c)$ contains a record of
656 the form (T^c, s^c) . If not, then we disregard T . Otherwise, let $\alpha_{i \rightarrow j}^F$ be the feature relabelling
657 that relabels the forgotten feature f_i to the forgotten feature f_j . Let $\hat{T} = r(\alpha_{i \rightarrow j}^F(T))$ and
658 $\hat{s} = |V(T) \setminus V(\hat{T})|$. We now distinguish two cases. If we have not yet added any record of
659 the form (\hat{T}, s') to $\mathcal{R}(b)$, then we add the record $(\hat{T}, s^c + \hat{s})$ to $\mathcal{R}(b)$. Otherwise we replace
660 the unique existing record (\hat{T}, s') with the record $(\hat{T}, \min\{s', s^c + \hat{s}\})$. This completes the
661 construction of the set $\mathcal{R}(b)$ of valid records.

662 Note that computing $\mathcal{R}(b)$ in this manner can be achieved in the stated run-time.
663 This is because due to Corollary 13 we can enumerate all possible choices for T in time
664 $\mathcal{O}((k + 2^k)^{2^{2k+2}+1})$ and for every such choice T we can compute T^c and \hat{T} and check
665 the existence of a record (T^c, s) in $\mathcal{R}(c)$ in time at most $\mathcal{O}(|T|) = \mathcal{O}(2^{2k+1})$ (because of
666 Corollary 11).

667 It remains to show the correctness of our construction for $\mathcal{R}(b)$, i.e., we have to show that
668 a record is valid for b if and only if we have added such a record according to our construction
669 above. For this it suffices to show that a record is semi-valid for b if and only if we have
670 added such a record according to our construction above. This is because, a valid record

671 (T, s) can be obtained from the set of all semi-valid records (T, s') , where s is the minimum
 672 s' among all semi-valid records for T .

673 Towards showing the forward direction, suppose that the record (\hat{T}, s) is semi-valid for b .
 674 Then, there is a reduced DT template T' for b such that $\hat{T} = \alpha_b^s(T')$ and $s = |V(T') \setminus V(\hat{T})|$.

675 Let $T = r(\alpha_c^s(T'))$. Then, $\hat{T} = r(\alpha_{i \rightarrow j}^F(T))$ because of Lemma 15 together with the
 676 observation that $\alpha_{i \rightarrow j}^F \circ \alpha_c^s = \alpha_b^s$. Note that T corresponds to the reduced DT skeleton
 677 considered by our construction. Let $T^c = r(\alpha_{i \rightarrow j}^I(T))$, let $\hat{s} = |V(T) \setminus V(\hat{T})|$, and let $s^c = s - \hat{s}$.
 678 It remains to show that the record (T^c, s^c) is semi-valid for c . Let $T'' = r(\alpha_{i \rightarrow j}^I(T'))$. Then,
 679 T'' is a reduced DT template for c , because so is T' for b and moreover all examples, in
 680 particular those with label i , in $\text{exam}(c)$ end up in the same leaf in T'' as they do in
 681 T' ; because of the relabelling $\alpha_{i \rightarrow j}^I$ that relabelled all bad future features in T' into their
 682 corresponding good future features in T'' . Moreover, $T^c = r(\alpha_c^s(T''))$ because of Lemma 15
 683 and furthermore $s^c = s - \hat{s} = |V(T'') \setminus V(T^c)|$. Therefore, T'' shows that (T^c, s^c) is semi-valid
 684 for c .

685 Towards showing the reverse direction, suppose that we have added the record $(\hat{T}, s^c + \hat{s})$
 686 using our construction. Then, there is a DT skeleton T for b with $\hat{T} = r(\alpha_{i \rightarrow j}^F(\hat{T}))$ and
 687 $\hat{s} = |V(T) \setminus V(\hat{T})|$ and a record $(T^c, s^c) \in \mathcal{R}(c)$ with $T^c = r(\alpha_{i \rightarrow j}^I(T))$.

688 We have to show that the record $(\hat{T}, s^c + \hat{s})$ is semi-valid for b . Because $(T^c, s^c) \in \mathcal{R}(c)$,
 689 there is a reduced DT template T' for c such that $T^c = r(\alpha_c^s(T'))$ and $s^c = |V(T') \setminus V(T^c)|$.
 690 Informally, we now construct a witness T''' for the semi-validity of $(\hat{T}, s^c + \hat{s})$ for b from T'
 691 by reversing the reduction $T^c = r(\alpha_{i \rightarrow j}^I(T))$.

692 Let $a : V(T^c) \rightarrow V(T')$ be the injective function that maps every node in T^c to its
 693 corresponding node in T' ; which exists because $T^c = r(\alpha_c^s(T'))$. First Let $b : V(T^c) \rightarrow V(T)$
 694 be the injective function that maps every node in T^c to its corresponding node in T ;
 695 which exists because $T^c = r(\alpha_{i \rightarrow j}^I(T))$. First we relabel every future feature in T' in
 696 to its corresponding future feature. Let T'' be the DT template obtained from T' by
 697 setting $\text{feat}_{T''}(a(b^{-1}(t))) = \text{feat}_T(t)$ for every node $t \in V(T^c)$ with $\text{feat}_T(t) \in I_{[k]}$ and
 698 $\text{feat}_{T''}(t) = \text{feat}_{T'}(t)$ otherwise. Moreover, let T''' be the DT template obtained from T''
 699 by doing the following for every edge $e = (p, c)$ in T^c , where p is the parent of c in T^c . Let
 700 $P(e)$ be the path from $b(p)$ to $b(c)$ in T . Then, we plugin the path $P(e)$ into T'' at the edge
 701 $(p', a(c))$, where p' is the parent of $a(c)$ in T'' .

702 Then, T''' is a DT template for b , because T' is a DT template for c and we only changed
 703 where examples with label i go, which are not present in $\text{exam}(b)$. Moreover, $T = r(\alpha_c^s(T'''))$
 704 and therefore $\hat{T} = r(\alpha_b^s(T'''))$. Finally, because $|V(T''') \setminus V(T)| = |V(T') \setminus V(T^c)| = s^c$, it
 705 holds that $|V(T''') \setminus V(\hat{T})| = s^c + \hat{s}$, which shows that the record $(\hat{T}, s^c + \hat{s})$ is semi-valid for
 706 b . ◀

there is one
problem
remaining: T'''
could now have
some forgotten
features from T ,
those should be
replaced by
arbitrary rea
features with the
same label; but
only if such
examples also
exist; maybe there
is a better way???

4 An FPT-Algorithm for bounded solution size and δ_{max} .

707 In the following, let E be a CI and $q \notin \text{feat}(E)$. A *decision tree pattern*, or simply a *DT*
 708 *pattern*, T is a rooted subcubic tree, where every leaf node is either a *positive* or *negative* leaf
 709 and every non-leaf node is labelled with a feature in $\text{feat}(E) \cup \{q\}$. For every node v of a
 710 DT pattern T , we indicate with $\text{feat}_T(v)$ the label associated to that node. Finally we say
 711 that an inner node $v \in V(T)$ is a *fixed node* if $\text{feat}_T(v) \in \text{feat}(E)$ and *non-fixed* otherwise.

712 A DT pattern T' is an *improvement* for a DT pattern T if $T' = T$ as rooted trees and
 713 $\text{feat}_{T'}(v) = \text{feat}_T(v)$ for every fixed node v of T . A *complete improvement* T' of T is an
 714 improvement such that $\text{feat}(T') \subseteq \text{feat}(E)$. A *threshold assignment* for a DT pattern T is a

717 function th that maps every fixed node $v \in V(T)$ to a natural number $th(v)$. Note that any
 718 complete improvement T' of a DT pattern T can be made to a decision tree with a threshold
 719 assignment.

720 Let T be a DT pattern and th be a threshold assignment for T , for each node v of T we
 721 define the set of examples that arrive at node v , $E_T(v)$ as follows: $E_T(v)$ is the set of all
 722 examples $e \in E$ such that for each left (right, respectively) arc (u, w) on the unique path from
 723 the root of T to v either u is a fixed node and $(feat(u))(e) \leq th(u)$ ($(feat(u))(e) > th(u)$,
 724 respectively) or u is a non-fixed node. A DT pattern T is *valid* for a set of examples $E' \subseteq E$
 725 if there is threshold assignment for the fixed nodes such that for every positive (negative)
 726 example e , $e \in E_T(v)$ for a positive (negative) leaf v .

727 The definition of $E_T(v)$ is an indication of the behaviour of feature q and of non-fixed
 728 nodes. Informally, if any example reaches at a non-fixed node of T then it reach both his
 729 children. While no feature in $feat(E)$ can simulate such behaviour for any threshold, q
 730 simultaneously cover the two cases a feature with his threshold does not distinguish any two
 731 examples.

732 4.1 Preprocess

733 Let E be a CI and T be a DT pattern. For every $v \in V(T)$, we define the set of *expected*
 734 *examples* E_v as follows:

- 735 ■ if v is the root, then $E_v = E$;
- 736 ■ if v is the left child of a fixed node v_p , then $E_v = E_{v_p}[feat(v_p) \leq th_L(v_p) + 1]$;
- 737 ■ if v is the right child of a fixed node v_p , then $E_v = E_{v_p}[feat(v_p) > th_R(v_p) - 1]$;
- 738 ■ if v is a child of a non-fixed node v_p , then $E_v = E_{v_p}$.

739 Note that the definition of E_v is strictly related with the following: if v is a fixed node,
 740 let c_ℓ and c_r be the left, resp. right, child of v , we define two values $th_L(v)$ and $th_R(v)$ as
 741 follows:

- 742 ■ let $th_L(v)$ be the maximum value in $D_E(feat(v))$ such that T_{c_ℓ} is valid for $E_v[feat(v) \leq$
 743 $th_L(v)]$;
- 744 ■ let $th_R(v)$ be the minimum value in $D_E(feat(v))$ such that T_{c_r} is valid for $E_v[feat(v) >$
 745 $th_R(v)]$.

746 Before formally proving in Lemma 22 that we are able to compute E_v and $th_L(v)$, $th_R(v)$
 747 (when v is a fixed node) for every $v \in V(T)$, we want to describe the role of E_v in the proof
 748 of Lemma 24.

749 Let us consider the following situation. Suppose we are trying to find a DT of minimum
 750 size for a CI E using at least the features in a given support set S . The first step would be
 751 to compute a minimum size DT T^* for E such that $feat(T^*) = S$. Next we analyse the case
 752 an optimal DT for E uses not only every feature from S but some additional feature: for
 753 this reason we consider DT patterns T of size at most s and such that $feat(T) = S \cup \{q\}$.

754 Let E be a CI, S be a support set for E and T be a DT pattern of size at most s such
 755 that $feat(T) = S \cup \{q\}$. If T is a valid DT pattern for E , then T , and every T' obtained
 756 after left/right-contracting every non-fixed node v of T , can be easily extended to a solution.

757 The following two lemmas cover the case T is not a valid DT pattern for E .

758 ▶ **Lemma 20.** *Let T be a DT pattern that is not valid for E . For every node v of T it holds
 759 that T_v is not valid for E_v .*

760 **Proof.** Let T be a DT pattern that is not valid for E . We show this statement in a root-to-leaves fashion: first we show the statement holds for the root; then we prove it holds for every other node, given the fact it holds for each of its ancestors (or its parent). Let r be the root of T . By definition $E_r = E$ and $T_r = T$ and so the statement follows directly from the assumption.

765 Let v be the left child of a fixed node v_p . By the definition of $th_L(v_p)$, the DT pattern T_v is not valid for $E_v = E_{v_p}[feat(v_p) \leq th_L(v_p) + 1]$. Similarly if v is the right child of a fixed node v_p , the DT pattern T_v is not valid for $E_v = E_{v_p}[feat(v_p) > th_R(v_p) - 1]$.

768 Let v be a child of a non-fixed node v_p . Suppose by contradiction that T_v is valid for E_v . We show that T_{v_p} is valid for E_{v_p} and consequently reaching a contradiction with the assumption: any threshold assignment for the fixed nodes of T_v that is a witness of the validity of T_v for E_v is also threshold assignment for the fixed nodes of T_{v_p} that is a witness of the validity of T_{v_p} for $E_{v_p} = E_v$; note this is true because v_p is a non-fixed node. ◀

773 ▶ **Lemma 21.** *Let T be a DT pattern that is not valid for E . For every fixed node v of T it holds that $th_L(v) < th_R(v)$.*

775 **Proof.** Let T be a DT pattern that is not valid for E . Suppose by contradiction that there is a fixed node v^* such that $th_L(v^*) \geq th_R(v^*)$. Let c_ℓ and c_r be the left and right child of v^* . We can set the threshold for $feat(v^*)$ as $th_L(v^*)$ and note that, by definition and the assumption, T_{c_ℓ} is valid for E_{c_ℓ} and T_{c_r} is valid for E_{c_r} . This is a contradiction with Lemma 20 as for every node $v \in V(T)$, T_v is not valid for E_v . ◀

780 Now we are finally ready to prove we can efficiently compute E_v , $th_L(v)$ and $th_R(v)$ for every node $v \in V(T)$.

782 ▶ **Lemma 22.** *Let E be a CI, let T be a DT pattern of depth at most d . Then there is an algorithm that runs in time $\mathcal{O}(2^{d^2/2} n^{1+o(1)} \log n)$ and computes the set E_v and thresholds $th_L(v)$ and $th_R(v)$ for every node $v \in V(T)$.*

785 **Proof.** The idea is to use the recursive algorithm **findLR** illustrated in Algorithm 1. That is, given E , T , the algorithm **findLR** attempts to find the triple $(E_v, th_L(v), th_R(v))$ for every node $v \in V(T)$. Lines 3 to 4: if T consists of a leaf node, the algorithm just report $(E, \text{nil}, \text{nil})$. Let c_ℓ and c_r be the left, resp. right, child of the root v . Lines 6 to 11: if the root of T is a non-fixed node, the algorithm calls itself recursively to compute on (E, T_{c_ℓ}) and (E, T_{c_r}) . Lines 13 to 15: if the root of T is a fixed node v , the algorithm computes the pair (t_ℓ, t_r) for the root using the algorithm **binarySearch** and then calls itself recursively to compute the triple for $(E[feat(v) \leq t_\ell + 1], T_{c_\ell})$ and $(E[feat(v) > t_r - 1], T_{c_r})$.

793 A key element for the correctness of **findLR** is the algorithm **binarySearch** illustrated in Algorithm 2. Given E , T , f , c_ℓ and c_r , this algorithm computes the pair (t_ℓ, t_r) for the root of T that has feature f . This sub-routine performs a standard binary search procedure on the array D containing all the values in $D_E(f)$ in ascending order to find maximum t_ℓ and minimum t_r such that T_{c_ℓ} and T_{c_r} can be extended to DT for $E[f \leq t_\ell]$ and for $E[f > t_r]$ respectively. To achieve this, the sub-routine makes at most $\log|E|$ calls to **findTH**; note that each of those calls is made for a tree of smaller depth. Lines 3 to 12: the algorithm finds the maximum t_ℓ by calling algorithm **findTH** in Line 6 repeatedly. Lines 13 to 22: the algorithm finds the minimum t_r by calling algorithm **findTH** in Line 16 repeatedly.

802 A sub-routine used for **binarySearch** is the algorithm **findTH** illustrated in Algorithm 3. This algorithm is very similar to Algorithm 1 but the output is some way much simpler.

804 The running time of Algorithm 1 can now be obtained by multiplying the number of recursive calls to **findLR** with the time required for one recursive call. To obtain the number

806 of recursive calls first note that if **findLR** is called with DT pattern of depth d , then it makes
 807 at most $(2 \log n) + 2$ recursive calls to **findLR** with a pattern of depth at most $d - 1$, where
 808 $n = |E|$. Therefore the number $T(n, d)$ of recursive calls for a pattern of depth d is given
 809 by the recursion relation $T(n, d) = (2(\log n) + 2)T(n, d - 1)$ starting with $T(n, 0) = 0$. This
 810 implies that $T(n, d) \in \mathcal{O}((\log n)^d)$. Finally, the runtime for one recursive call is easily seen to
 811 be at most $\mathcal{O}(n \log n)$. Hence, the total runtime of the algorithm is at most $\mathcal{O}((\log n)^d n \log n)$,
 812 which because (see also [9, Exercise 3.18]):

813 $(\log n)^d \leq 2^{d^2/2} 2^{\log \log d^2/2} = 2^{d^2/2} n^{o(1)}$

814 is at most $\mathcal{O}(2^{d^2/2} n^{1+o(1)} \log n)$. ◀

Algorithm 1 Algorithm to compute the triple $(E_v, th_L(v), th_R(v))$ for every node $v \in V(T)$.

Input: CI E , DT pattern T

Output: a triple $(E_v, th_L(v), th_R(v))$ for every node $v \in V(T)$.

```

1: function findLR( $E, T$ )
2:    $r \leftarrow$  “root of  $T$ ”
3:   if  $r$  is a leaf then
4:     return  $(E, \text{nil}, \text{nil})$ 
5:    $c_\ell, c_r \leftarrow$  “left child and right child of  $r$ ”
6:   if  $r$  is a non-fixed node then
7:      $\lambda_\ell \leftarrow \text{FINDLR}(E, T_{c_\ell})$ 
8:      $\lambda_r \leftarrow \text{FINDLR}(E, T_{c_r})$ 
9:     if  $\lambda_\ell \neq \text{nil}$  and  $\lambda_r \neq \text{nil}$  then
10:      return  $(E, \text{nil}, \text{nil}) \cup \lambda_\ell \cup \lambda_r$ 
11:    return nil
12:    $f \leftarrow \text{feat}(r)$ 
13:    $(t_\ell, t_r) \leftarrow \text{BINARYSEARCH}(E, T, f, c_\ell, c_r)$ 
14:    $\lambda_\ell \leftarrow \text{FINDLR}(E[f \leq t_\ell + 1], T_{c_\ell})$ 
15:    $\lambda_r \leftarrow \text{FINDLR}(E[f > t_r - 1], T_{c_r})$ 
16:   return  $(E, t_\ell, t_r) \cup \lambda_\ell \cup \lambda_r$ 
```

4.2 The algorithm

816 Now we have computed a set E_v for every node $v \in V(T)$, whether it is a leaf, fixed or
 817 non-fixed node. A *pool set* for node $v \in V(T)$ is a set $\Pi(v) \subseteq E_v$, such that if $\Pi(v) \subseteq E_T(v)$
 818 then either

- 819 ■ T_v is not valid for E_v , or
 820 ■ for any complete improvement T'_v for T_v that is valid for E_v , there are two elements
 821 $e, e' \in \Pi(v)$ and there is a non-fixed node u for T such that $\text{feat}_{T'}(u)$ must distinguish e
 822 and e' .

823 For every node $v \in V(T)$, we define $\Pi(v)$ in a leaves-to-root fashion as follows. If v is
 824 a negative leaf then $\Pi(v) = \{e^+\}$, where e^+ is any example in $E^+ \cap E_v$; similarly, if v is a
 825 positive leaf then $\Pi(v) = \{e^-\}$, where e^- is any example in $E^- \cap E_v$. Let c_ℓ and c_r be the
 826 left, resp. right, child of v , then $\Pi(v) = \Pi(c_\ell) \cup \Pi(c_r)$.

827 Now we want to show that the construction of Π is correct, that is:

828 ▶ **Lemma 23.** $\Pi(v)$ is a pool set for v for every node $v \in V(T)$.

Algorithm 2 Algorithm to compute the pair $(th_L(r), th_R(r))$ for the root r of T

Input: CI E , DT pattern T , feature f of the root of T , left child c_ℓ of the root of T , right child c_r of the root of T

Output: maximum threshold t_ℓ in $D_E(f)$ for f such that (T_{c_ℓ}, α) can classify every example in $E[f \leq t_\ell]$ and minimum threshold t_r in $D_E(f)$ for f such that (T_{c_r}, α) can classify $E[f > t_r]$

```

1: function binarySearch( $E, T, f, c_\ell, c_r$ )
2:    $D \leftarrow$  “array containing all elements in  $D_E(f)$  in
      ascending order”
3:    $L \leftarrow 0; R \leftarrow |D_E(f)| - 1; b \leftarrow 0$ 
4:   while  $L \leq R$  do
5:      $m \leftarrow \lfloor (L + R)/2 \rfloor$ 
6:     if FINDTH( $E[f \leq D[m]], T_{c_\ell}$ ) = TRUE then
7:        $L \leftarrow m + 1; b \leftarrow 1$ 
8:     else
9:        $R \leftarrow m - 1; b \leftarrow 0$ 
10:    if  $b = 1$  then
11:       $t_\ell \leftarrow D[m]$ 
12:     $t_\ell \leftarrow D[m - 1]$                                  $\triangleright$  assuming that  $D[-1] = D[0] - 1$ 
13:     $L \leftarrow 0; R \leftarrow |D_E(f)| - 1; b \leftarrow 0$ 
14:    while  $L \leq R$  do
15:       $m \leftarrow \lfloor (L + R)/2 \rfloor$ 
16:      if FINDTH( $E[f > D[m]], T_{c_r}$ ) = TRUE then
17:         $R \leftarrow m - 1; b \leftarrow 1$ 
18:      else
19:         $L \leftarrow m + 1; b \leftarrow 0$ 
20:    if  $b = 1$  then
21:       $t_r \leftarrow D[m]$ 
22:     $t_r \leftarrow D[m + 1]$                                  $\triangleright$  assuming that  $D[|D_E(f)|] = D[|D_E(f)| - 1] + 1$ 
23:    return  $(t_\ell, t_r)$ 

```

829 **Proof.** We show this by induction on the depth of T and let v be the root of T . Since
 830 $E_T(v) = E$ it is trivial to note that $\Pi(v) \subseteq E_T(v)$. We start proving the base case: let T be
 831 a pattern of depth 0. Suppose v is negative leaf. Since $E_v = E$ is not uniform, there is an
 832 example $e^+ \in E^+ \cap E_v$. The case where v is a positive leaf can be proved in a symmetrical
 833 manner.

834 Now, let T be a pattern of depth at least one and let c_ℓ and c_r be the left and right
 835 child of v . Suppose first that v is a fixed node and let $f = \text{feat}(v)$. Thanks to Lemma 20,
 836 for every $e_\ell \in \Pi(c_\ell)$ and $e_r \in \Pi(c_r)$, we know that $f(e_\ell) < f(e_r)$. This means that either
 837 $\Pi(c_\ell) \subseteq E_T(c_\ell)$ or $\Pi(c_r) \subseteq E_T(c_r)$, say that $\Pi(c_i) \subseteq E_T(c_i)$, for $i \in \{\ell, r\}$. Since T_{c_i} has
 838 depth smaller than $T_v = T$, by the inductive hypothesis $\Pi(c_i)$ is a pool set for c_i .

839 Finally suppose v is a non-fixed node. Let us consider any complete improvement T'_v for
 840 T_v . For any threshold assignment for T'_v , we have one of the following three cases: either
 841 $\Pi(c_\ell) \subseteq E_{T'}(c_\ell)$ or $\Pi(c_r) \subseteq E_{T'}(c_r)$ or there is an example $e_\ell \in \Pi(c_\ell)$ and an example
 842 $e_r \in \Pi(c_r)$ such that $e_\ell \in E_{T'}(c_r)$ and $e_r \in E_{T'}(c_\ell)$. In the first two cases the statement is
 843 again proven thanks to the inductive hypothesis since T_{c_ℓ} and T_{c_r} have depth smaller than
 844 T_v . In the third case, v is a non-fixed node for T such that $\text{feat}_{T'}(v)$ distinguishes e_ℓ and
 845 e_r . \blacktriangleleft

846 In particular, let us consider the pool set $\Pi(r)$ for the root r of T , we define $\Pi(T) := \Pi(r)$.
 847 In this way given T , we are able to compute the corresponding pool set.

Algorithm 3

Input: CI E , pattern T

Output: TRUE if T can classify all examples in E , FALSE otherwise

```

1: function FINDTH( $E, T$ )
2:    $r \leftarrow$  “root of  $T$ ”
3:   if  $r$  is a leaf then
4:     if  $E$  is not uniform then
5:       return FALSE
6:     return TRUE
7:    $c_\ell, c_r \leftarrow$  “left child and right child of  $r$ ”
8:   if  $r$  is a non-fixed then
9:      $\lambda_\ell \leftarrow$  FINDTH( $E, T_{c_\ell}$ )
10:     $\lambda_r \leftarrow$  FINDTH( $E, T_{c_r}$ )
11:    if  $\lambda_\ell =$  TRUE and  $\lambda_r =$  TRUE then
12:      return TRUE
13:    return FALSE
14:    $f \leftarrow \text{feat}(r)$ 
15:    $t \leftarrow \text{BINARYSEARCH}(E, T, f, c_\ell, c_r)$ 
16:    $\lambda_\ell \leftarrow \text{FINDLR}(E[f \leq t_\ell + 1], T_{c_\ell})$ 
17:    $\lambda_r \leftarrow \text{FINDLR}(E[f > t_r - 1], T_{c_r})$ 
18:   if  $\lambda_r =$  FALSE then
19:     return FALSE
20:   return TRUE

```

848 Let S be a support set for a CI E , we say that $B \subseteq \text{feat}(E)$ is a *branching set* for S if
 849 for every minimal DT T for E such that $S \subset \text{feat}(T)$ then $B \cap (\text{feat}(T) \setminus S) \neq \emptyset$.

850 ▶ **Lemma 24.** *There is a $\mathcal{O}(2^{d^2/2} s^{2s+1} n^{1+o(1)} \log n)$ time algorithm that given a support set
 851 S computes a branching set R_0 for S of size at most $s^{2s+3} \delta_{\max}$.*

852 **Proof.** Let E be a CI, a support set S for E and an integer s . We start by enumerating all
 853 DT patterns T of size at most s such that $\text{feat}(T) = S \cup \{q\}$. For every such DT pattern
 854 T , thanks to Lemma 22, we are able to obtain the set E_v for every node $v \in V(T)$ in time
 855 $\mathcal{O}(2^{d^2/2} n^{1+o(1)} \log n)$. In a leaves-to-root fashion, we are able to compute the set $\Pi(v)$ for
 856 every node $v \in V(T)$ and ultimately $\Pi(T)$.

857 Let $R(T)$ be the set of all the features in $\text{feat}(E) \setminus S$ that distinguish at least two examples
 858 in $\Pi(T)$. The algorithm returns the set of features R_0 obtained by considering the union of
 859 the sets $R(T)$ over all these DT patterns T of size at most s . By Lemma 1 this algorithm
 860 runs in time $\mathcal{O}(2^{d^2/2} s^{2s+1} n^{1+o(1)} \log n)$.

861 Now we show the size of R_0 is bounded. By construction $|\Pi(T)| \leq |T| \leq s$; for every two
 862 distinct elements of $\Pi(T)$, by definition, there are at most δ_{\max} features that distinguish
 863 such two examples. This means that $|R(T)| \leq s^2 \delta_{\max}$ and so R_0 has size at most $s^{2s+3} \delta_{\max}$.

864 We are left to show that R_0 is a branching set for S . Let T be a minimal DT for E such
 865 that $S \subset \text{feat}(T)$ and suppose by contradiction that $R_0 \cap (\text{feat}(T) \setminus S) = \emptyset$. In particular we
 866 have that $R(T) \cap (\text{feat}(T) \setminus S) = \emptyset$. This means that for every feature f of T that does not
 867 belong to S , f does not distinguish any two elements in $\Pi(T)$. By Lemma 23, $\Pi(T) = \Pi(r)$,
 868 where r is the root of T , is a pool set and so T is not valid for E , which is a contradiction. ◀

869 ▶ **Lemma 25 ([23]).** *Let E be a CI and let k be an integer. Then there is an algorithm that
 870 in time $\mathcal{O}(\delta_{\max}(E)^k |E|)$ enumerates all (of the at most $\delta_{\max}(E)^k$) minimal support sets of
 871 size at most k for E .*

872 ▶ **Lemma 26** ([23]). Let T be a DT of minimum size for E and let S be a support set
 873 contained in $\text{feat}(T)$. Then, the set $R = \text{feat}(T) \setminus S$ is useful.

874 ▶ **Observation 27** ([23]). Let T be a DT for a CI E , then $\text{feat}(T)$ is a support set of E .

875 **Proof.** Suppose for a contradiction that this is not the case and there is an example $e^+ \in E^+$
 876 and an example $e^- \in E^-$ such that e^+ and e^- agree on all features in $\text{feat}(T)$. Therefore,
 877 e^+ and e^- are contained in the same leaf node of T , contradicting our assumption that T is
 878 a DT. ◀

879 ▶ **Theorem 28** ([23]). Let E be a CI, $S \subseteq \text{feat}(E)$ be a support set for E , and let s and
 880 d be integers. Then, there is an algorithm that runs in time $2^{\mathcal{O}(s^2)} \|E\|^{1+\mathcal{o}(1)} \log \|E\|$ and
 881 computes a DT of minimum size among all DTs T with $\text{feat}(T) = S$ and $\text{size}(T) \leq s$ if such
 882 a DT exists; otherwise **nil** is returned.

883 ▶ **Theorem 29.** MINIMUM DECISION TREE SIZE is fixed-parameter tractable parametrized
 884 by $\delta_{\max} + s$.

885 **Proof.** We start by presenting the algorithm for MINIMUM DECISION TREE SIZE, which is
 886 illustrated in Algorithm 4 and Algorithm 5.

887 Given a CI E and an integer s , the algorithm returns a DT of minimum size among all
 888 DTs of size at most s if such a DT exists and otherwise the algorithm returns **nil**. The
 889 algorithm **minDT** starts by computing the set \mathcal{S} of all minimal support sets for E of size
 890 at most s , which because of Lemma 25 results in a set \mathcal{S} of size at most (\cdot) . In Line 4
 891 the algorithm then iterates over all sets S in \mathcal{S} and calls the function **minDTS** given in
 892 Algorithm 5 for E , s , and S , which returns a DT of minimum size among all DTs T for E
 893 of size at most s such that $S \subseteq \text{feat}(T)$. It then updates the currently best decision tree B
 894 if necessary with the DT found by the function **minDTS**. Moreover, if the best DT found
 895 after going through all sets in \mathcal{S} has size at most s , it is returned (in Line 9), otherwise
 896 the algorithm returns **nil**. Finally, the function **minDTS** given in Algorithm 5 does the
 897 following. It first computes a DT T of minimum size that uses exactly the features in S using
 898 Lemma 28. It then tries to improve upon T with the help of useful sets. That is, it uses
 899 Lemma 24 to compute the branching set R_0 . It then iterates over all (of the at most (\cdot))
 900 features $f \in R_0$ (using the for-loop in Line 4), and calls itself recursively on the support set
 901 $S \cup \{f\}$. If this call finds a smaller DT, then the current best DT is updated. Finally, after
 902 the for-loop the algorithm either returns a solution if its size is less than s or **nil** otherwise.

903 Towards showing the correctness of Algorithm 4, consider the case that E has a DT
 904 of size at most s and let T be a such a DT of minimum size. Because of Observation 27,
 905 $\text{feat}(T)$ is a support set for E and therefore $\text{feat}(T)$ contains a minimal support set S of size
 906 at most s . Because the for-loop in Line 4 of Algorithm 4 iterates over all minimal support
 907 sets of size at most s for E , it follows that Algorithm 5 is called with parameters E , s , and
 908 S . If $\text{feat}(T) = S$, then B is set to a DT for E of size $|T|$ in Line 2 of Algorithm 5 and the
 909 algorithm will output a DT of size at most $|T|$ for E . If, on the other hand, $\text{feat}(T) \setminus S \neq \emptyset$,
 910 then because T has minimum size and S is a support set for E with $S \subseteq \text{feat}(T)$, we obtain
 911 from Lemma 26 that the set $R = \text{feat}(T) \setminus S$ is useful for S . Therefore, because of Lemma 24,
 912 R has to contain a feature f from the set R_0 computed in Line 3. It follows that Algorithm 5
 913 is called with parameters E , s , and $S \cup \{v\}$. From now onwards the argument repeats and
 914 since $R_0 \neq \emptyset$ the process stops after at most $s - |S|$ recursive calls after which a DT for E of
 915 size at most $|T|$ will be computed in Line 2 of Algorithm 5. Finally, it is easy to see that if
 916 Algorithm 4 outputs a DT T , then it is a valid solution. This is because, T must have been

917 computed in Line 2 of Algorithm 5, which implies that T is a DT for E . Moreover, T has
 918 size at most s , because of Line 8 in Algorithm 4.

919 To analyse the run-time of the algorithm, we first remark that the whole algorithm can
 920 be seen as a bounded-depth search tree algorithm, i.e., a branching algorithm with small
 921 recursion depth and few branches at every node. In particular, every recursive call adds at
 922 least one feature to the set of features bounding the recursion depth to at most s . Moreover,
 923 every feature that is added is either added in Line 2 of Algorithm 4, when enumerating
 924 all minimal support sets, in which case there are at most $\delta_{\max}(E)$ branches or the feature
 925 is added in Line 5 of Algorithm 5, in which case there are at most $|R_0| \leq s^{2s+3}\delta_{\max}(E)$
 926 branches. It follows that the algorithm can be seen as a branching algorithm of depth
 927 at most s with at most $s^{2s+3}\delta_{\max}(E) = \max\{s^{2s+3}\delta_{\max}(E), \delta_{\max}(E)\}$ branches at every
 928 step. Therefore, the total run-time of the algorithm is at most the number of nodes in
 929 the branching tree, i.e., at most $(s^{2s+3}\delta_{\max}(E))^s$, times the maximum time required in
 930 one recursive call. Now the maximum time required for one recursive call is dominated
 931 by the time spend in Line 2 of Algorithm 5, i.e., the time required to compute a DT of
 932 minimum size using exactly the features in S with the help of Theorem 28, which is at
 933 most $2^{\mathcal{O}(s^2)}\|E\|^{1+o(1)}\log\|E\|$. Therefore, we obtain $(s^{2s+3}\delta_{\max}(E))^s 2^{\mathcal{O}(s^2)}\|E\|^{1+o(1)}\log\|E\|$
 934 as the total run-time of the algorithm, which shows that DTS is fixed-parameter tractable
 935 parameterized by $s + \delta_{\max}(E)$. \blacktriangleleft

■ **Algorithm 4** Main method for finding a DT of minimum size.

Input: CI E and integer s

Output: DT for E of minimum size (among all DTs of size at most s) if such a DT exists, otherwise
 nil

```

1: function minDT( $E, s$ )
2:    $\mathcal{S} \leftarrow$  "set of all minimal support sets for  $E$  of size at most  $s$  using Lemma 25"
3:    $B \leftarrow \text{nil}$ 
4:   for  $S \in \mathcal{S}$  do
5:      $T \leftarrow \text{MINDTS}(E, s, S)$ 
6:     if ( $T \neq \text{nil}$ ) and ( $B = \text{nil}$  or  $|B| > |T|$ ) then
7:        $B \leftarrow T$ 
8:     if  $B \neq \text{nil}$  and  $|B| \leq s$  then
9:       return  $B$ 
10:    return  $\text{nil}$ 
```

936 5 Conclusion

937 We have initiated the study of the parameterized complexity of learning DTs from data. Our
 938 main tractability result provides novel insights into the structure of DTs and is based on
 939 the NLC-width parameter that seems to be well suited to measure the complexity of input
 940 instances for the problem.

941 The problem of learning DTs comes in many variants and flavors, which opens up a wide
 942 range of new research directions to explore. For instance:

- 943 ■ What other (structural) parameters can be exploited to efficiently learn DTs? Is learning
 944 DTs of small size fixed-parameter tractable parameterized by the rank-width of $G_I(E)$?
- 945 ■ Instead of learning DTs of small size, one often wants to learn DTs of small height.
 946 Therefore, it is natural to ask whether our approach can be also used in this setting.
 947 While one can adapt our approach to obtain an XP-algorithm for learning DTs of small

■ **Algorithm 5** Method for finding a DT of minimum size using at least the features in a given support set S .

Input: CI E , integer s , support set S for E with $|S| \leq s$
Output: DT of minimum size among all DTs T for E of size at most s such that $S \subseteq \text{feat}(T)$; if no such DT exists, **nil**

```

1: function minDTS( $E, s, S$ )
2:    $B \leftarrow$  “compute a DT of minimum size for  $E$  using exactly the features in  $S$  using Theorem ??”
3:    $R_0 \leftarrow$  “compute the branching set  $R_0$  for  $S$  using Lemma 24”
4:   for  $f \in R_0$  do
5:      $T \leftarrow \text{MINDTS}(E, s, S \cup \{f\})$ 
6:     if  $T \neq \text{nil}$  and  $|T| < |B|$  then
7:        $B \leftarrow T$ 
8:     if  $|B| \leq s$  then
9:       return  $B$ 
10:    return nil

```

948 height parameterized by NLC-width, it is not clear to us whether the problem also allows
949 for an fpt-algorithm.

950 ■ Can we extend our approach to CIs, where features range over an arbitrary domain? In
951 this case, one usually still uses DTs that make binary decisions (i.e. whether a feature is
952 smaller equal or larger than a given threshold). While it is relatively easy to see that our
953 approach can be extended if the domain’s size (for every feature) is bounded or used as
954 an additional parameter, it is not clear what happens if the size of the domain is allowed
955 to grow arbitrarily.

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