DynASP2.5: Dynamic Programming on Tree Decompositions in Action

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Abstract

Efficient, exact parameterized algorithms are a vibrant theoretical research area. Recent solving competitions, such as the PACE challenge, show that there is also increasing practical interest in the parameterized algorithms community. An important research question is whether such algorithms can be built to efficiently solve specific problems in practice, that is, to be competitive with established solving systems. In this paper, we consider Answer Set Programming (ASP), a logic-based declarative modeling and problem solving framework. State-of-the-art ASP solvers generally rely on SAT-based algorithms. In addition, DynASP2, an ASP solver that is based on a classical dynamic programming on tree decompositions, has recently been introduced. DynASP2 outperforms modern ASP solvers when the goal is to count the number of solutions of programs that have small treewidth. However, for quickly finding one solutions, DynASP2 proved uncompetitive. In this paper, we present a new algorithm and implementation, called DynASP2.5, that shows competitive behavior compared to state-of-the-art ASP solvers on problems like Steiner tree for low-treewidth graphs, even when the task is to find just one solution. Our implementation is based on a novel approach that we call multi-pass dynamic programming.

1998 ACM Subject Classification I.2.8 Problem Solving, Control Methods, and Search · D.1.6 Logic Programming · F.4.1 Mathematical Logic · I.2.3 Deduction and Theorem Proving · I.2.4 Knowledge Representation Formalisms and Methods

Keywords and phrases Parameterized algorithms; Fixed-parameter linear time; Tree decompositions; Multi-pass dynamic programming

Digital Object Identifier 10.4230/LIPIcs.IPEC.2017.17

1 Introduction

Answer set programming (ASP) is a logic-based declarative modeling language and problem solving framework [13], where a program is defined by a set of rules over propositional atoms and is interpreted under an extended stable model semantics [15]. Problems are usually modeled in ASP in such a way that the solutions (called answer sets) of a program directly correspond to the solutions of the considered problem instance. Computational problems for disjunctive, propositional ASP, such as deciding whether a program has an answer set, are complete for the second level of the polynomial hierarchy [8]. In consequence, finding answer sets usually involves a SAT part (finding a model of the program) and an UNSAT part (minimality check). A variety of ASP solvers based on techniques of SAT solvers are readily available [3, 11] and have proven to be very successful in solving competitions.
Recently, a dynamic programming based solver (DynASP2) that builds upon ideas from parameterized algorithms has been proposed [9]. The running time of the underlying algorithm is double exponential in the treewidth of the input program and linear in its size (a so-called fixed-parameter linear algorithm). DynASP2 roughly works as follows. First, it computes a tree decomposition of the incidence graph of the given input program. Second, it solves the program via dynamic programming (DP) on the tree decomposition, traversing the tree exactly once bottom-up. Both the SAT and UNSAT tasks are considered in a single pass. Once the root node has been reached, complete solutions for the input program can be constructed, if any exist. The exhaustive nature of DP algorithms, where all potential solutions are computed locally for each node of the tree decomposition, works well when all solutions are indeed needed, e.g., for counting answer sets. However, this approach is not competitive when the task is to construct just one answer set, since space requirements can be quite extensive, resulting in long running times. Another downside is the fact that DP algorithms on tree decompositions may exhibit running times that vary considerably, even on tree decompositions of the exact same width [1].

In this paper, we propose a multi-pass algorithm, called M-DP\textsubscript{SINC}, for dynamic programming on tree decompositions, as well as a new implementation (DynASP2.5). In contrast to classical DP algorithms for problems on the second level of the polynomial hierarchy, M-DP\textsubscript{SINC} traverses the given tree decomposition multiple times in a bottom-up fashion. During the first pass, it computes and stores sets of atoms that are relevant for the SAT part (finding a model of the program) up to the root. In the second pass, it computes and stores sets of atoms that are relevant for the UNSAT part (checking for minimality). Finally, in the third pass, it links those sets from past two passes together that might lead to an answer set. This allows us to discard candidates that do not lead to answer sets early on.

In addition, we present technical improvements (including working on non-nice tree decompositions) and employ dedicated customization techniques for selecting tree decompositions. These improvements are the main ingredients to speed up the solving process for DP algorithms. Experiments indicate that DynASP2.5 is competitive, even for quickly finding some answer set, when solving the Steiner tree problem on graphs of low treewidth. In particular, DynASP2.5 are able to solve instances that have an upper bound on the incidence treewidth of 14 (whereas DynASP2 could solve instances of treewidth at most 9) on our benchmark set\textsuperscript{1}.

**Contributions.** Our main contributions can be summarized as follows:

1. We establish a novel fixed-parameter linear algorithm (M-DP\textsubscript{SINC}), which works in multiple passes and computes SAT and UNSAT parts separately.
2. We present an implementation (DynASP2.5)\textsuperscript{2} and an experimental evaluation.

**Related Work.** An ASP solver (DynASP2) that is based on single pass DP on tree decompositions was recently introduced [9]. The solver is dedicated to counting answer sets for the full ground ASP language. The present paper extends these results by a multi-pass DP algorithm. In contrast to systems that use encodings in Monadic Second-Order (MSO) [14], our approach directly treats ASP. Bliem et al. [4] introduced a multi-pass approach and an implementation (D-FLAT\textsuperscript{2}) for DP on tree decompositions solving subset minimization tasks. Their approach allows to specify DP algorithms by means of ASP. In D-FLAT\textsuperscript{2} one

\textsuperscript{1} The set is available at https://github.com/daajoe/dynasp_experiments/tree/ipec2017.

\textsuperscript{2} The sources of our solver are available at https://github.com/daajoe/dynasp/releases/tag/v2.5.0.
can see ASP as a meta-language to describe what needs to be done at each node of the tree decomposition, whereas our work presents an algorithm dedicated to find some answer set of a program. Further, we require specialized adaptations to the ASP problem semantics, including three valued evaluation of atoms, handling of non-nice tree decompositions, and optimizations in join nodes to be competitive. We use in our solver the heuristic tree decomposition library htd [2]. For other systems we refer to the PACE challenge [7].

2 Formal Background

Tree Decompositions. Let $G = (V, E)$ be a graph, $T = (N, F, n)$ a rooted tree, and $\chi : N \rightarrow 2^V$ a function that maps each node $t \in N$ to a set of vertices. We call the sets $\chi(\cdot)$ bags and $N$ the set of nodes. Then, the pair $T = (T, \chi)$ is a tree decomposition (TD) of $G$ if the following conditions hold: (i) for every vertex $v \in V$ there is a node $t \in N$ with $v \in \chi(t)$; (ii) for every edge $e \in E$ there is a node $t \in N$ with $e \subseteq \chi(t)$; and (iii) for any three nodes $t_1, t_2, t_3 \in N$, if $t_2$ lies on the unique path from $t_1$ to $t_3$, then $\chi(t_1) \cap \chi(t_3) \subseteq \chi(t_2)$.

We call max\{\text{tw}(t) - 1 | t \in N\} the width of the TD. The treewidth $\text{tw}(G)$ of a graph $G$ is the minimum width over all possible TDs of $G$. For some arbitrary but fixed integer $k$ and a graph of treewidth at most $k$, we can compute a TD of width $\leq k$ in time $2^{O(k^3 \cdot |V|)}$ [6].

Answer Set Programming (ASP). ASP is a declarative modeling and problem solving framework that combines techniques of knowledge representation and database theory. Two of the main advantages of ASP are its expressiveness and, when using non-ground programs, its advanced declarative problem modeling capability. Prior to solving, non-ground programs are usually compiled into ground ones by a grounder. There are classes of non-ground programs that preserve the treewidth of the input instance after grounding [5]. In this paper, we restrict ourselves to ground ASP programs. For a comprehensive introduction, see, e.g., [13]. Let $\ell, m, n$ be non-negative integers such that $\ell \leq m \leq n$, $a_1, \ldots, a_n$ distinct propositional atoms, and $\ell \in \{a_1, \neg a_1\}$. A choice rule is an expression of the form $\{a_1; \ldots; a_\ell\} \leftarrow a_{\ell+1}, \ldots, a_n, \neg a_{m+1}, \ldots, \neg a_n$ with the intuitive meaning that some subset of $\{a_1, \ldots, a_\ell\}$ is true if all atoms $a_{\ell+1}, \ldots, a_n$ are true and there is no evidence that any atom of $a_{m+1}, \ldots, a_n$ is true. A disjunctive rule is of the form $a_1 \lor \cdots \lor a_\ell \leftarrow a_{\ell+1}, \ldots, a_n, \neg a_{m+1}, \ldots, \neg a_n$, which, intuitively, means that at least one atom of $a_1, \ldots, a_\ell$ must be true if all atoms $a_{\ell+1}, \ldots, a_n$ are true and there is no evidence that any atom of $a_{m+1}, \ldots, a_n$ is true. A rule $r$ is either a disjunctive or a choice rule. Let $H_r := \{a_1, \ldots, a_\ell\}$, $B_r^+ := \{a_{\ell+1}, \ldots, a_m\}$, and $B_r^- := \{a_{m+1}, \ldots, a_n\}$. Usually, for a rule $r$, if $B_r^- \cup B_r^+ = \emptyset$, we simply write $H_r$ instead of $H_r \leftarrow$. For a rule $r$, let $\text{at}(r) := H_r \cup B_r^+ \cup B_r^-$ denote its atoms and $\text{body} := B_r^+ \cup \{\neg b \mid b \in B_r^-\}$ its body. A program $P$ is a set of rules, where $\text{at}(P) := \bigcup_{r \in P} \text{at}(r)$ denotes its atoms. A set $M \subseteq \text{at}(P)$ satisfies a rule $r$ if (i) $r$ is a disjunctive rule and $(H_r \cup B_r^-) \cap M \neq \emptyset$ or $B_r^+ \not\subseteq M$ or (ii) $r$ is a choice rule. Note that choice rules are always satisfied. $M$ is a (classical) model of $P$, denoted by $M \models P$, if $M$ satisfies every rule $r \in P$. The reduct
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The set $P = \{ \text{each bag-program in turn, storing results in tables for each TD node.} \}$ works as $\text{DynASP2} \ [9]$, a dynamic programming-based algorithm for ASP. The algorithm works by iteratively refining the program $P$ to $P'$, where $P'$ is a proper subset of $P$ with respect to $M$. A set $M \subseteq \text{at}(P)$ is an answer set of $P$ if $M \models P$ and there does not exist a proper subset $M' \subsetneq M$, such that $M' \models P_M$.

**Example 1.** Consider program $P$, consisting of the following nine rules:

$P = \{ \{e_{ab}\}; \{e_{cd}\}; \{e_{ad}\}; \{e_{bc}\}; a \leftarrow e_{ab}; \ a_d \leftarrow e_{cd}; \ a_c \leftarrow e_{bc}; \ a_e \leftarrow a_d, e_{cd}; \ a_e \leftarrow a_d, e_{cd}; \ a_e \leftarrow a_d, e_{cd}. \}$

The set $A = \{e_{ab}, e_{bc}, a_d, a_e\}$ is a minimal model of the reduct $P^A = \{e_{ab} \leftarrow ; e_{bc} \leftarrow ; a_d \leftarrow e_{cd}; a_c \leftarrow e_{bc}; a_e \leftarrow a_d, e_{cd}\}$. Now, consider program $R = \{a \lor c \leftarrow b; b \leftarrow c, \neg g; c \leftarrow a; b \lor c \leftarrow c; h \lor i \leftarrow g, \neg c; a \lor b; g \leftarrow \neg i; c; \{d\} \leftarrow g\}$. The set $B = \{b, c, d, g\}$ is an answer set of $R$, since $B$ is a minimal model of the reduct $R^B = \{a \lor c \leftarrow b; c \leftarrow a; b \lor c \leftarrow c; a \lor b; g; c; d \leftarrow g\}$.

In this paper, we mainly consider the output answer set problem, that is, output an answer set for an ASP program. The decision version of this problem is $\Sigma^P_2$-complete.

**Graph Representations of Programs.** In order to use TDs for ASP solving, we need dedicated graph representations of programs. The incidence graph $I(P)$ of $P$ is the bipartite graph that has the atoms and rules of $P$ as vertices and an edge $ar$ if $a \in \text{at}(r)$ for some rule $r \in P$ [9]. The semi-incidence graph $S(P)$ of $P$ is a graph that has the atoms and rules of $P$ as vertices and (i) an edge $ar$ if $a \in \text{at}(r)$ for some rule $r \in P$ as well as (ii) an edge $ab$ for distinct atoms $a, b \in H_r$ where $r \in P$ is a choice rule. Since, for every program $P$, the incidence graph $I(P)$ is a subgraph of the semi-incidence graph, we have that $\text{tw}(I(P)) \leq \text{tw}(S(P))$. Further, by definition of TDs and the construction of a semi-incidence graph, head atoms of each choice rule occur together in at least one bag of the TD.

Sub-programs. Let $T = (T, \chi)$ be a nice TD of the semi-incidence graph $S(P)$ of a program $P$. Also, let $T = (N, \cdot, n)$ and $t \in N$. The bag-program is defined as $P_t := P \cap \chi(t)$. The set $\text{at}_{\leq t} := \{a \mid a \in \text{at}(P) \cap \chi(t'), t' \in \text{post-order}(T, t)\}$ is called atoms below $t$, the program below $t$ is defined as $P_{\leq t} := \{r \mid r \in P_t, t' \in \text{post-order}(T, t)\}$, and the program strictly below $t$ is $P_{< t} := P_{\leq t} \setminus P_t$. Since $\chi(n) = \emptyset$, it holds that $P_{\leq n} = P_{< n} = P$ and at_{< n} = at(P).

3 A Single Pass DP Algorithm

DynASP2 [9], a dynamic programming-based ASP solver, splits the input program $P$ into bag-programs based on the structure of a given nice tree decomposition for $P$ and evaluates each bag-program in turn, storing results in tables for each TD node. The algorithm works as shown in Figure 1 (following the red DynASP2 arrow) and executes the following steps:

1. Construct a graph representation $G(P)$ of the given input program $P$. 


2. Compute a TD $T$ of the graph $G(P)$ by means of some heuristic, thereby decomposing $P$ into several smaller bag-programs and fixing an ordering in which $P$ will be evaluated.

3. Algorithm $\text{DP}_A(T)$ (see Listing 1 above) specifies the general scheme for this step, assuming that an algorithm $A$, which strongly depends on the graph representation, is given. Such an algorithm $A$ is called a table algorithm that specifies, how the individual bag-programs for each tree node are evaluated. $\text{DP}_A(T)$ works as follows: Traverse the tree decomposition $T$ in post-order. For every node $t \in T$ in the tree decomposition $T = (T, E, n, \chi)$, run $A$ to compute the table for node $t$ (denoted $A$-Tabs[$t$]). Intuitively, each tuple, which we refer to as row, in the table represents a witness for the existence of a solution for the bag-program at node $t$. $A$-Tabs[$t$] is computed by taking, as input, the tables of the child nodes of $t$, and extending them according to the bag-program $P_t$. Each row in $A$-Tabs[$t$] consists of a witness set (a set of atoms relevant for the SAT part of the problem), and a family of counter-witness sets (sets of atoms relevant for the UNSAT part) [9]. This directly follows the definition of answer sets, namely, being models of $P$ and subset-minimal with respect to $P^M$.

4. For root node $n$, check if a “solution row” exists in table $A$-Tabs[$n$] and print the solution to the output ASP problem.

With the above general algorithm in mind, we are now ready to propose $\text{SINC}$, a new table algorithm for solving ASP on the semi-incidence graph (see Listing 2). $\text{DP}_{\text{SINC}}$ merges two earlier algorithms for the primal and incidence graph [9].

As in the general approach, $\text{SINC}$ computes and stores witness sets, and their corresponding counter-witness sets. However, in addition, for each witness set and counter-witness set, respectively, we need to store so-called satisfiability states (or sat-states, for short), since the atoms of a rule may no longer be contained in one single bag of the TD of the semi-incidence graph. Therefore, we need to remember in each TD node, how much of a rule is already satisfied. The following describes this in more detail.

By definition of TDs and the semi-incidence graph, for every atom $a$ and every rule $r$ of a program, it is true that if atom $a$ occurs in rule $r$, then $a$ and $r$ occur together in at least one bag of the TD. As a consequence, the table algorithm encounters every occurrence of an atom in any rule. In the end, on removal of $r$, we have to ensure that $r$ is among the rules that are already satisfied. However, we need to keep track of whether a witness set satisfies a rule, because not all atoms that occur in a rule occur together in a bag. Hence, when
We use the binary operator \( local-program \) witnesses, which we will discuss in more detail below. The sat-state program, i.e., \( \dot{\sigma} \) to sat-states, we need to keep track of a representative of a rule. We achieve this by removing all literals \( M \)

For set \( R \)

For set \( S \) and element \( s \), we denote \( S^+_s \triangleq S \cup \{s\} \) and \( S^-_s \triangleq S \setminus \{s\} \).

our algorithm traverses the TD and an atom is removed we still need to store this sat-state, as setting this atom to a certain truth value influences the satisfiability of the rule. Since the semi-incidence graph contains a clique on every set \( A \) of atoms that occur together in a choice rule head, those atoms \( A \) occur together in a bag in every TD of the semi-incidence graph. For that reason, we do not need to incorporate choice rules into the satisfiability state, in contrast to the algorithm for the incidence graph [9].

In Algorithm \( \text{SINC} \) (detailed in Listing 2), a row \( u \) in the table \( \tau_u \) is a triple \( \langle M,\sigma,C \rangle \). The set \( M \subseteq \text{at}(P) \cap \{\chi(t)\} \) represents a witness set. The family \( C \) of rows represents counter-witnesses, which we will discuss in more detail below. The sat-state \( \sigma \) for \( M \) represents rules of \( \chi(t) \) satisfied by a superset of \( M \). Hence, \( M \) witnesses a model \( M' \supseteq M \) where \( M' \leftarrow P_{\text{at}} \cup \sigma \). For that reason, a witness set together with its sat-state is called a \emph{witness}. We use the binary operator \( \cup \) to combine sat-states, which ensures that rules satisfied in at least one operand remain satisfied. For a node \( t \), our algorithm considers a local-program depending on the bag \( \chi(t) \). Intuitively, this provides a local view on the program.

**Definition 2.** Let \( P \) be a program, \( T = (\chi,\tau) \) a TD of \( S(P) \), \( t \) a node of \( T \) and \( R \subseteq P_t \). The local-program \( R^{(t)} \) is obtained from \( R \cup \{r \mid r \in R \) is a choice rule, \( H_r \subseteq \text{at}_{\langle t \rangle} \) by removing all literals \( a \) and \( \lnot a \) from every rule where \( a \notin \chi(t) \).

**Example 3.** Observe \( P^{(t)}_{t_4} = \{e_{bc},r_b\} \) and \( P^{(t_5)}_{t_5} = \{c \leftarrow \} \) for \( P_{t_4} \) and \( P_{t_5} \) of Figure 2.

Since the local-program \( P^{(t)} \) depends on the considered node \( t \), we may have different local-programs for for node \( t \) and its child \( t' \). In particular, the programs \( \{r\}^{(t)} \) and \( \{r\}^{(t')} \) might already differ for a rule \( r \in \chi(t) \cap \chi(t') \). In consequence for satisfiability with respect to sat-states, we need to keep track of a representative of a rule. We achieve this by a function \( \hat{R}^{(t)} : R \rightarrow 2^{R^{(t)}} \) that maps a rule in \( R \subseteq P_{t} \) for bag-program \( P_{t} \) to its local-program, i.e., \( \hat{R}^{(t)}(r) := \{r\}^{(t)} \) for \( r \in R \). When we compute newly satisfied rules for witness set \( M \) and a set \( R \) of rules, we use the function \( \hat{R}^{(t)} \). Formally, \( \text{SatPr}(\hat{R}^{(t)}(M),M) := \{r \mid (r,S) \in \hat{R}^{(t)},M \models S\} \) for \( M \subseteq \chi(t) \setminus P_{t} \) using program \( S = \hat{R}^{(t)}(r) \) constructed by \( \hat{R}^{(t)} \) and \( r \in R \).

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3 We require to add \( \{r \mid r \in R \) is a choice rule, \( H_r \subseteq \text{at}_{t_1} \) in order to decide satisfiability for corner cases of choice rules involving counter-witnesses of Line 3 in Listing 2.
Example 4 provides an explanation of the part of \( \text{SINC} \) that deals with witnesses only. Therefore, the resulting algorithm \( \text{MOD} \) computes only models and is obtained from \( \text{SINC} \), by taking only the first two row positions into account (red and green text in Listing 2). The remaining position (blue text) can be seen as an algorithm \( \text{CMOD} \) that computes counter-witnesses (see [10, Ex. 4]). Note that we discuss selected cases, and we assume that each row in a table \( \tau \) is identified by a number, i.e., row \( i \) corresponds to \( u_{i,t} = \langle M_{t,i}, \sigma_{x,i} \rangle \).

**Example 4.** Consider program \( P \) from Example 1, TD \( T = \langle ., \chi \rangle \) in Figure 2, and the tables \( \tau_1, \ldots, \tau_34 \), which illustrate computation results obtained during post-order traversal of \( T \) by \( \text{MOD} \). Figure 2 (left) does not show every intermediate node of TD \( T \). Table \( \tau_1 = \{\{\emptyset, \emptyset\} \} \) as type\((t_1) = \text{leaf} \) (see Line 1 in Listing 2). Table \( \tau_3 \) is obtained via introducing rule \( r_{ab} \), after introducing atom \( e_{ab} \) (type\((t_2) = \text{int} \) = int). It contains two rows due to two possible truth assignments using atom \( e_{ab} \) (Line 3–5). Observe that rule \( r_{ab} \) is satisfied in both rows \( M_{3,1} \) and \( M_{3,2} \), since the head of choice rule \( r_{ab} \) is in \( \text{at} \subseteq t_3 \) (see Line 7 and Definition 2). Intuitively, whenever a rule \( r \) is proven to be satisfied, sat-state \( \sigma_{x,i} \) marks \( r \) as satisfied since an atom of a rule of \( S(P) \) might only occur in one TD bag. Consider table \( \tau_4 \) with type\((t_4) = \text{rem} \) and \( r_{ab} \notin \chi(t_3) \setminus \chi(t_4) \). By definition of TDs of \( S(P) \), we have encountered every occurrence of any atom in \( r_{ab} \). Thus, \( \text{MOD} \) enforces that only rows where \( r_{ab} \) is marked satisfied in \( \tau_4 \), are considered for table \( \tau_4 \). The resulting table \( \tau_4 \) consists of rows of \( \tau_3 \) with \( \sigma_{x,i} = \emptyset \), where rule \( r_{ab} \) is proven satisfied \( (r_{ab} \in \sigma_{3,1}, \sigma_{3,2}, \text{see Line 11}) \). Note that between nodes \( t_6 \) and \( t_{10} \), an atom and rule remove as well as an atom and rule introduce node is placed. Observe that the second row \( u_{6,2} = \langle M_{6,2}, \sigma_{6,2} \rangle \) in \( \tau_6 \) does not have a “successor row” in \( \tau_{10} \), since \( t_6 \notin \sigma_{6,2} \). Intuitively, join node \( t_{34} \) joins only common witness sets in \( \tau_{17} \) and \( \tau_{33} \) with \( \chi(t_{17}) = \chi(t_{33}) = \chi(t_{34}) \). In general, a join node marks rules satisfied, which are marked satisfied in at least one child (see Line 13–14).

Since we already explained how to obtain models, we only briefly describe how to compute counter-witnesses. Family \( C \) consists of rows \( (C, \rho) \), where \( C \subseteq \text{at}(P) \cap \chi(t) \) is a counter-witness set to \( M \). Similar to the sat-state \( \sigma \), the sat-state \( \rho \) for \( C \) under \( M \) represents whether rules of the GL reduct \( P_t^M \) are satisfied by a superset of \( C \). A counter-witness set
where the associated witness does not lead to a solution at the root node. In addition, there

The classical DP algorithm

for DP on TDs presented in [4]. Our novel algorithm allows for an early cleanup (purging)

implementation (DynASP2.5), which tackles this issue by adapting and extending concepts

doing both witnesses and counter-witnesses in one step by traversing the given TD

exactly once. In particular, it exhaustively stores all potential counter-witnesses, even those

can be a high number of duplicates among the counter-witnesses, which are stored separately.

Definition 5. \( R \subseteq M \)' satisfying \( C' \models (P_{ct} \cup P)^M \) since \( M \) witnesses a model \( M' \geq M \) where \( M' \neq P_{ct} \).

In consequence, there exists an answer set of \( P \) if the root table contains \( \emptyset, \emptyset, \emptyset \).

In order to decide the satisfiability of counter-witness sets, we require local-reducts similar
to local-programs (see Definition 2 and below).

Definition 5. Let \( P \) be a program, \( T = (\cdot, \chi) \) be a TD of \( S(P) \), \( t \) be a node of \( T \), \( R \subseteq P_t \) and \( M \subseteq \mathcal{A}(P_t) \). We define local-reduct \( R^{(t,M)} \) as \( [R^{(t,M)}]M \) and \( \tilde{R}^{(t,M)} : R \rightarrow 2^{R^{(t,M)}} \) as \( \tilde{R}^{(t,M)}(r) := \{ \tilde{r}^{(t,M)} \} \) for any \( r \in R \).

Note that one can now easily refine \( \text{SatPr}_{\{1\},·} \) such that it takes as first argument
arbitrary functions mapping from rules to programs. In particular, one can then pass the
function \( R^{(t,M)} \) for a set \( R \) of rules, and a witness set \( M \subseteq \mathcal{A}(P_t) \), as used in Listing 2.

Proposition 6 (\( * \), c.f. [9]). Let \( P \) be a program and \( k := bw(S(P)) \). Then, the algorithm \( \text{DynASP2.5} \) runs in time \( O(2^{M_{max}} \cdot ||S(P)||) \) and is correct.

DynASP2.5: Implementing a III Pass DP Algorithm

The classical DP algorithm \( \text{DynASP2.5} \) (Step 3 of Figure 1) follows a single pass approach. It
computes both witnesses and counter-witnesses in one step by traversing the given TD
exactly once. In particular, it exhaustively stores all potential counter-witnesses, even those
where the associated witness does not lead to a solution at the root node. In addition, there
can be a high number of duplicates among the counter-witnesses, which are stored separately.
In this section, we propose a multi-pass algorithm, \( \text{MDynASP2.5} \), for DP on TDs and a new
implementation (DynASP2.5), which tackles this issue by adapting and extending concepts
for DP on TDs presented in [4]. Our novel algorithm allows for an early cleanup (purging)

\footnote{Due to space limitations, proofs of statements marked with “*” have been omitted.}
of witnesses that do not lead to answer sets. As a consequence, this (i) avoids to construct expendable counter-witnesses. Moreover, multiple passes enable us to store witnesses and counter-witnesses separately which, in turn, (ii) avoids storing duplicates of counter-witnesses and (iii) allows for highly space-efficient data structures (pointers) in practice when linking witnesses and counter-witnesses together. Figure 1 (following the blue arrows) presents the control flow of the new multi-pass approach $DynASP2.5$, where $M$-$DP_{SINC}$ introduces a much more elaborate computation in Step 3 (cf. Figure 1).

4.1 The Algorithm

Algorithm $M$-$DP_{SINC}$ executed as Step 3 runs $DP_{MOD}$, $DP_{CMOD}$ and new Algorithm $DPL_{MOD,CMOD}$ in three respective passes (3.I, 3.II, and 3.III) as follows:

3.I. First, we run the algorithm $DP_{MOD}$, which computes, via a bottom-up traversal, a table $MOD$-Tabs[$t$] of witnesses for every node $t$ in the tree decomposition. Then, via a top-down traversal, it purges those witnesses from tables $MOD$-Tabs[$t$] that do not extend to a witness in the table for the parent node; these witnesses can never be used to construct a model (nor answer set).

3.II. For this step, let $CMOD$ be a table algorithm computing only counter-witnesses of $SINC$ (blue parts of Listing 2). We execute $DP_{CMOD}$, which computes all counter-witnesses for all the witnesses at once and stores the resulting tables in $CMOD$-Tabs[$t$]. For every node $t$, table $CMOD$-Tabs[$t$] contains possible counter-witnesses for subset-minimality. Again, irrelevant rows are purged.

3.III. Finally, via a bottom-up traversal, for every node $t$ in the TD, witnesses and counter-witnesses are linked using algorithm $DPL_{MOD,CMOD}$ (see Listing 3). $DPL_{MOD,CMOD}$ takes previous results and maps rows in $MOD$-Tabs[$t$] to a set of rows in $CMOD$-Tabs[$t$].

We already explained the table algorithms $DP_{MOD}$ and $DP_{CMOD}$ in the previous section. The main part of our multi-pass algorithm is the algorithm $DPL_{MOD,CMOD}$ based on the general algorithm $DPL_{W,C}$ (Listing 3) with $W = MOD$, $C = CMOD$, which links those separate tables together. Before we quickly discuss the core of $DPL_{W,C}$ in Line 5–7, note that Line 2–4 introduce auxiliary definitions. Line 2 combines rows of the child nodes of given node $t$, which is achieved by a product over sets where we drop the order and keep sets only.

The rules $r_2,\ldots,r_k$ simulate that only specific subsets of ${a_1,\ldots,a_k}$ are allowed. Rules $r_f$ and $r_{cf}$ enforce that $f$ is set to true. Let $T = (T, \chi, t_0)$ be a TD of the semi-incidence graph $S(P_k)$ of program $P_k$ where $T = (V, E)$ with $V = \{t_1,t_2,t_3\}$, $E = \{(t_1,t_2),(t_2,t_3)\}$, $\chi(t_1) = \{a_1,\ldots,a_k,f,r,cf\}$, $\chi(t_2) = \{a_1,\ldots,a_k,r_2,\ldots,r_k,f\}$, and $\chi(t_3) = \emptyset$. Figure 3 (left) illustrates the tables for program $P_2$ after $DP_{SINC}$, whereas Figure 3 (right) presents tables after $M$-$DP_{SINC}$ was run, which, mainly due to cleanup, are exponentially smaller in $k$. Observe that in Pass 3.II, $M$-$DP_{SINC}$ “temporarily” materializes counter-witnesses for $r_1$. 

**Example 7.** Let $k$ be some integer and $P_k$ be the program that consists of the rules $r_c := \{a_1,\ldots,a_k\} \leftarrow f$, $r_2 := \leftarrow a_2,\ldots,r_k := \leftarrow a_k$, and $r_f := \leftarrow f$ and $r_{cf} := \{f\} \leftarrow$. The rules $r_2,\ldots,r_k$ simulate that only specific subsets of ${a_1,\ldots,a_k}$ are allowed. Rules $r_f$ and $r_{cf}$ enforce that $f$ is set to true. Let $T = (T, \chi, t_0)$ be a TD of the semi-incidence graph $S(P_k)$ of program $P_k$ where $T = (V, E)$ with $V = \{t_1,t_2,t_3\}$, $E = \{(t_1,t_2),(t_2,t_3)\}$, $\chi(t_1) = \{a_1,\ldots,a_k,f,r,cf\}$, $\chi(t_2) = \{a_1,\ldots,a_k,r_2,\ldots,r_k,f\}$, and $\chi(t_3) = \emptyset$. Figure 3 (left) illustrates the tables for program $P_2$ after $DP_{SINC}$, whereas Figure 3 (right) presents tables after $M$-$DP_{SINC}$ was run, which, mainly due to cleanup, are exponentially smaller in $k$. Observe that in Pass 3.II, $M$-$DP_{SINC}$ “temporarily” materializes counter-witnesses for $r_1$.
only, presented in table $\tau_1^{\text{CMOD}}$. Hence, using multi-pass algorithm $\mathcal{M}\text{-DP}_{\text{SINC}}$ results in an exponential speedup. Note that we can extend the program such that we have the same effect for a TD of minimum width and even if we take the incidence graph. The program $P_k$ and the TD $\mathcal{T}$ also reveal that a different TD of the same width, where $f$ occurs very early in the bottom-up traversal, would result in a smaller table $\tau_1$ even when running $\text{DP}_{\text{SINC}}$.

$\triangleright$ **Theorem 8 (⋆).** For a program $P$ of semi-incidence treewidth $k = \text{tw}(P)$, the algorithm $\mathcal{M}\text{-DP}_{\text{SINC}}$ is correct and runs in time $O(2^{2^{k+2}} \cdot \|P\|)$.

### 4.2 Implementation Details

Efficient implementations of dynamic programming algorithms on TDs are not a by-product of computational complexity theory and involve tuning and sophisticated algorithm engineering. For that reason, we present additional details about implementing the $\mathcal{M}\text{-DP}_{\text{SINC}}$ algorithm into our prototypical multi-pass solver DynASP2.5.

Even though normalizing a TD (computing a nice TD) can be achieved without increasing its width, a normalization may artificially introduce additional atoms. Normalization causes several additional intermediate join nodes among such artificially introduced atoms requiring a significant amount of total unnecessary computation in practice. That is why, we use non-nice tree decompositions. In order to still ensure the theoretical runtime bounds, we limit the number of children per node to a constant. Moreover, linking counter-witnesses to witnesses efficiently is crucial. The main challenge is to deal with situations where a witness might be linked to a different family of counter-witnesses depending on different predecessors of the row (hidden in set notation of Line 9 in Listing 3). In these cases, DynASP2.5 eagerly creates a “clone” in form of a very light-weighted proxy to the original row and ensures that only the original row (if at all required) serves as a counter-witness during Pass 3. Together with efficient caches of counter-witnesses, DynASP2.5 reduces the overhead caused by clones in practice.

Dedicated data structures are vital. In DynASP2.5, sets of witnesses and satisfied rules are represented via constant-size bit vectors. We use 32-bit integers to represent whether an atom is set to true or a rule is satisfied in the respective bit positions according to the bag. A restriction to 32-bit integers seems reasonable as we assume, because of practical memory limitations, that our approach works well on TDs of width $\leq 20$. Since state-of-the-art computers handle constant-sized integers extremely efficiently, DynASP2.5 allows for
efficient projections and joins of rows, as well as subset checks. In order to not recompute counter-witnesses (in Pass 3.II) for different witnesses, we use a three-valued notation of counter-witness sets consisting of atoms set to true (T), false (F), or false but true in the witness set (TW) to build the reduct. Note that only atoms occurring in negations or choice rules are among the (TW)-atoms, since only these atoms “affect” the corresponding reducts.

Minimum width is not the only optimization goal when computing TDs by means of heuristics. Instead, using customized TDs that not only optimize the width, but also some other, relevant feature, works seemingly well in practice [1]. While DynASP2.5 (M-DP, SINC) does not take additional TD features into account, we also implemented a variant (DynASP2.5 depgraph), which prefers one out of ten TDs that intuitively speaking avoids to introduce head atoms of some rule \( r \) in node \( t \), without having encountered every body atom of \( r \) below \( t \), similar to atom dependencies in the program [12]. The variant DynASP2.5 joinsize minimizes bag sizes of child nodes of join nodes, c.f. [2].

### 4.3 Experimental Evaluation

We performed experiments to investigate the runtime behavior of DynASP2.5 and its variants, in order to evaluate whether our multi-pass approach can be beneficial and has practical advantages over the classical single pass approach (DynASP2). Further, we considered the dedicated ASP solver clasp 3.3.0. Clearly, we cannot hope to solve programs with graph representations of high treewidth. However, programs involving real-world graphs such as graph problems on transit graphs admit TDs of acceptable width to perform DP on TDs.

To get a first intuition, we focused on the Steiner tree problem (St) for our benchmarks. We mainly inspected the CPU time using the average over five runs per instance (five fixed seeds allow for some variance in the heuristic TD computation). For each run, we limited the environment to 16 GB RAM and 1200 seconds CPU time. We used clasp with improvements for unsatisfiable cores [3] enabled and solution printing/recording disabled. We also benchmarked clasp with branch-and-bound, which, however, timed out on almost every instance. The left plot in Figure 4 shows the result of always selecting the best among five TDs, whereas the right plot shows the average running time. The table in Figure 4 reports average running times (TD computation and Passes 3.I, 3.II, 3.III) among the solved instances and the total number of timeouts (TO). We consider an instance to time out when all five TDs exceeded the limit. For the variants depgraph and joinsize, runtimes for computing and selecting among ten TDs are included. Our empirical benchmark results confirm that DynASP2.5 exhibits competitive runtime behavior even for TDs of treewidth around 14. Compared to clasp, DynASP2.5 is capable of additionally delivering the number of optimal solutions. In particular, the depgraph variant shows promising runtimes.

![Figure 4: Cactus plots showing best and average runtime among five TDs (left). Number of Timeouts (TO) and average runtime among solved instances (right).](image-url)
Conclusion

In this paper, we presented a novel approach for ASP solving based on ideas from parameterized complexity. Our algorithms run in linear time assuming bounded treewidth of the input program. Our solver applies DP in three passes, thereby avoiding redundancies. Experimental results indicate that our ASP solver is competitive for certain classes of instances with small treewidth, where the latest version of the well-known solver clasp hardly keeps up. An interesting question for future research is whether a linear amount of passes (incremental DP) can improve the runtime behavior.

References