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Backdoors to tractable answer set programming ☆



Johannes Klaus Fichte a,b, Stefan Szeider a,*

- ^a Vienna University of Technology, Favoritenstrasse 9-11, 1040 Vienna, Austria
- ^b University of Potsdam, August-Bebel-Strasse 89, 14482 Potsdam, Germany

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ABSTRACT

Answer Set Programming (ASP) is an increasingly popular framework for declarative programming that admits the description of problems by means of rules and constraints that form a disjunctive logic program. In particular, many AI problems such as reasoning in a nonmonotonic setting can be directly formulated in ASP. Although the main problems of ASP are of high computational complexity, complete for the second level of the Polynomial Hierarchy, several restrictions of ASP have been identified in the literature, under which ASP problems become tractable.

In this paper we use the concept of backdoors to identify new restrictions that make ASP problems tractable. Small backdoors are sets of atoms that represent "clever reasoning shortcuts" through the search space and represent a hidden structure in the problem input. The concept of backdoors is widely used in theoretical investigations in the areas of propositional satisfiability and constraint satisfaction. We show that it can be fruitfully adapted to ASP. We demonstrate how backdoors can serve as a unifying framework that accommodates several tractable restrictions of ASP known from the literature. Furthermore, we show how backdoors allow us to deploy recent algorithmic results from parameterized complexity theory to the domain of answer set programming.

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1. Introduction

Answer Set Programming (ASP) is an increasingly popular framework for declarative programming [115,122]. ASP admits the description of problems by means of rules and constraints that form a disjunctive logic program. Solutions to the program are so-called stable models or answer sets. Many important problems of AI and reasoning can be succinctly represented and successfully solved within the ASP framework. It has been applied to several large industrial applications, e.g., social networks [97], match making [74], planning in a seaport [129], optimization of packaging of Linux distributions [69], and general game playing [145].

The main computational problems for ASP (such as deciding whether a program has a solution, or whether a certain atom is contained in at least one or in all solutions) are complete for the second level of the Polynomial Hierarchy [41]; thus, ASP problems are "harder than NP" and have a higher worst-case complexity than CSP and SAT. In the literature, several restrictions have been identified that make ASP tractable, most prominently the **Horn** fragment and the stratified fragment [78,2], for a detailed trichotomy (tractable, first level, second level of PH) see [148].

E-mail addresses: fichte@kr.tuwien.ac.at (J.K. Fichte), stefan@szeider.net (S. Szeider).

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^{*} Corresponding author.

1.1. Contribution

In this paper we use the concept of *backdoors* to identify new restrictions that make propositional ASP problems tractable. Small backdoors are sets of atoms that represent "clever reasoning shortcuts" through the search space and represent a hidden structure in the problem input. Backdoors were originally introduced by Williams, Gomes, and Selman [152,153] as a tool to analyze the behavior of DPLL-based SAT solvers. Backdoors have been widely used in theoretical investigations in the area of propositional satisfiability [152,135,138,103] and constraint satisfaction [84], and also for abductive reasoning [125], argumentation [40], and quantified Boolean formulas [137]. A backdoor is defined with respect to some fixed *target class* for which the computational problem under consideration is polynomial-time tractable. The size of the backdoor can be seen as a distance measure that indicates how far the instance is from the target class.

In this paper we develop a rigorous theory of backdoors for answer set programming. We show that the concept of backdoors can be fruitfully adapted for this setting, and that backdoors can serve as a *unifying framework* that accommodates several tractable restrictions of propositional ASP known from the literature.

For a worst-case complexity analysis of various problems involving backdoors such as finding a small backdoor or using it to solve the problem, it is crucial to investigate how the running time depends on the size of the backdoor, and how well running time scales with backdoor size. *Parameterized Complexity* [35,55,85] provides a most suitable theoretical framework for such an analysis. It provides the key notion of *fixed-parameter tractability* which, in our context, means polynomial-time tractability for fixed backdoor size, where the order of the polynomial does not depend on the backdoor size. We show how backdoors allow us to deploy recent algorithmic results from parameterized complexity theory to the domain of answer set programming.

Parameterized complexity provides tools for a rigorous analysis of *polynomial-time preprocessing* in terms of *kerneliza-tion* [7,58]. A kernelization is a polynomial-time self-reduction of a parameterized decision problem that outputs a decision equivalent problem instance whose size is bounded by a function f of the parameter (the kernel size). It is known that every decidable fixed-parameter tractable problem admits a kernelization, but some problems admit small kernels (of size polynomial in the parameter) and others do not. We provide upper and lower bounds for the kernel size of the problems backdoor evaluation and backdoor detection for disjunctive answer set programs. These bounds provide worst case guarantees and limits for polynomial-time preprocessing for the considered problems.

Several algorithms in the literature are defined for disjunction-free (i.e., normal) programs only. We introduce a general method for *lifting* these parameters to disjunctive programs, preserving fixed-parameter tractability under certain conditions. Although our main focus is on a theoretical evaluation, we present some experimental results where we consider the backdoor size of structured programs and random programs of varied density.

1.2. Background and related work

Complexity of ASP problems Answer set programming is based on the stable-model semantics for logic programs [78,79]. The computational complexity of various problems arising in answer set programming has been subject of extensive studies. Eiter and Gottlob [41] have established that the main decision problems of (disjunctive) ASP are complete for the second level of the Polynomial Hierarchy (Σ_2^P - or Π_2^P -complete, respectively). Moreover, Bidoít and Froidevaux [5] and Marek and Truszczyński [114] have shown that the problems are NP-complete (co-NP-complete respectively) for disjunction-free (so-called *normal*) programs. Several fragments of programs where the main reasoning problems are polynomial-time tractable have been identified, e.g., Horn programs [78], stratified programs [2] and programs without even cycles [156]. Dantsin et al. [27] survey the classical complexity of the main reasoning problems for various semantics of logic programming, including fragments of answer set programming.

ASP solvers Various ASP solvers have been developed in recent years. Many of them utilize SAT solvers as black boxes or search techniques from SAT. There are solvers that deal with one or more fragments of disjunctive programs (normal, tight, or head-cycle-free), e.g., Smodels [141], Assat [111], Cmodels2 [82], and Clasp2 [71]. There are also solvers that deal with the full set of disjunctive programs, e.g., Clasp3 [37], Cmodels3 [108], DLV [107], and GnT [92]. Compilations to other problem domains and respective solvers have been considered for normal programs, e.g., propositional satisfiability [91], mixed integer programming [112], satisfiability modulo theories [93,76]. We would like to point out that these solvers use heuristics without non-trivial worst-case performance guarantees. In contrast we provide for the main reasoning problems of answer set programming theoretical worst-case time bounds that take certain hidden structures in disjunctive programs into account

Preprocessing techniques and unit propagation used in solvers might be considered in a wider sense as implicitly exploiting Horn fragments. Grounders like Gringo [64] already solve Horn programs simply by propagating atoms which trivially (do not) belong to the minimal model, e.g., atoms that occur in the head of rules with an empty body, atoms that occur in the head of rules where all atoms in the positive body already belong to the minimal model, atoms that cannot belong to the minimal model according to some constraint, and atoms that cannot belong to the minimal model as they occur in no head. Moreover, SAT-based solvers like Clasp [62] transform the program into a propositional formula using Clark's completion (see e.g., [73]) where the resulting formula characterizes the classical models and necessary conditions for atoms to belong to a model. If the program contains no cycles in its positive dependency graph, unit propagation (as part of a

DPLL-based algorithm) already solves Horn fragments. Otherwise, loop formulas are added which prevent the solver from assigning true to atoms that occur on a cycle unless some atom from outside is set to true. If there is an atom from outside that has been assigned to true, atoms on the cycle are set again to true by unit propagation and so forth.

Parameterizations of ASP So far there has been no rigorous study of disjunctive ASP within the framework of parameterized complexity. However, several results known from the literature can be stated in terms of parameterized complexity and provide fixed-parameter tractability. The considered parameters include the number of atoms of a normal program that appear in negative rule bodies [4], the number of non-Horn rules of a normal program [4], the size of a smallest feedback vertex set in the dependency digraph of a normal program [85], the number of cycles of even length in the dependency digraph of a normal program [90,119], and a combination of two parameters: the length of the longest cycle in the dependency digraph and the treewidth of the interaction graph of a head-cycle-free programs [3]. Very recently we established [48] an fpt-reduction that reduces disjunctive ASP to normal ASP; in other words, a reduction from the second level of the Polynomial Hierarchy to the first level. However, these results do not provide fixed-parameter tractability of the ASP reasoning problems, and hence are not directly comparable to the results presented in this paper. A general theoretical framework to classify parameterized problems on whether they admit an fpt-reduction to SAT or not has lately been introduced in [28]. Similar to our result in [48] this does not provide fixed-parameter tractability of the ASP reasoning problems, but in certain cases fixed-parameter tractability of the reduction to SAT.

Backdoors The concept of a backdoor originates in SAT/CSP and was introduced by Williams et al. [152,153]. Since then, backdoors have been used frequently in the literature for theoretical investigations. The study of the parameterized complexity of backdoor detection was initiated by Nishimura et al. [123] who considered satisfiability backdoors for the base classes Horn and 2CNF. Since then, the study has been extended to various other base classes, including clustering formulas [124], renamable Horn formulas [128], QHorn formulas [59], Nested formulas [56], acyclic formulas [54], and formulas of bounded incidence treewidth [57]; for a survey, see [55]. Several results extend the concept of backdoors to other problems, e.g., backdoor sets for constraint satisfaction problems [152], quantified Boolean formulas [137], abstract argumentation [40], and abductive reasoning [125]. Samer and Szeider [136] have introduced backdoor trees for propositional satisfiability which provide a more refined concept of backdoor evaluation and take the interaction of variables that form a backdoor into account. Dilkina et al. [31,32] have considered strong backdoors with "empty clause detection" (empty clauses trivially yield satisfiability). Empty clause detection is present in many modern SAT solvers and often leads to much smaller backdoors in practice. However, they have also established that backdoor detection for the base classes Horn and 2CNF is already harder than NP when empty clause detection is added. Moreover, Szeider [144] has shown that (strong) backdoor detection is W[1]-hard for almost all base classes when empty clause detection is added and thus unlikely to be fixed-parameter tractable.

1.3. Prior work and paper organization

This paper is an extended and updated version of the papers that appeared in the proceedings of the 22nd International Joint Conference on Artificial Intelligence [47] and in the selected papers proceedings of the Student Session of the 23rd European Summer School in Logic, Language, and Information [49]. The present paper provides a higher level of detail, in particular full proofs and more examples. Furthermore, the paper extends its previous versions in the following way: additional attention is payed to the minimality check (Lemma 3.7). Theorem 5.13 is extended to entail some very recent results in parameterized complexity theory. A completely new section (Section 6) is devoted to a rigorous analysis of preprocessing methods for the problems of backdoor detection and backdoor evaluation. We present a general method to lift parameters from rules of normal programs to disjunctive programs (Section 7). We extend the section on the theoretical comparison of parameters (Section 8) by additional comparisons to other parameters, e.g., weak feedback width and interaction graph treewidth, and to other classes of programs, e.g., head-cycle-free and tight programs. Additionally, we provide some empirical data on backdoor detection and discuss the evaluation of backdoors in a practical setting in Section 4.1.

2. Preliminaries

2.1. Answer set programming

We consider a universe U of propositional atoms. A literal is an atom $a \in U$ or its negation $\neg a$. A disjunctive logic program (or simply a program) P is a set of rules of the following form

$$x_1 \vee \ldots \vee x_l \leftarrow y_1, \ldots, y_m, \neg z_1, \ldots, \neg z_n$$

where $x_1, \ldots, x_l, y_1, \ldots, y_m, z_1, \ldots, z_n$ are atoms and l, m, n are non-negative integers. Let r be a rule. We write $\{x_1, \ldots, x_l\} = H(r)$ (the head of r), $\{y_1, \ldots, y_m\} = B^+(r)$ (the positive body of r) and $\{z_1, \ldots, z_n\} = B^-(r)$ (the negative body of r). We denote the sets of atoms occurring in a rule r or in a program P by $at(r) = H(r) \cup B^+(r) \cup B^-(r)$ and $at(P) = \bigcup_{r \in P} at(r)$,

respectively. A rule r is negation-free if $B^-(r) = \emptyset$, normal if $|H(r)| \le 1$, a constraint if |H(r)| = 0, constraint-free if |H(r) > 0|, Horn if it is normal and negation-free or a constraint, positive if it is Horn and constraint-free, tautological if $B^+(r) \cap (H(r) \cup B^-(r)) \ne \emptyset$, and non-tautological if it is not tautological. We say that a program has a certain property if all its rules have the property. Horn refers to the class of all Horn programs. We denote the class of all normal programs by Normal. Let P and P' be programs. We say that P' is a subprogram of P (in symbols $P' \subseteq P$) if for each rule $r' \in P'$ there is some rule $r \in P$ with $H(r') \subseteq H(r)$, $B^+(r') \subseteq B^+(r)$, $B^-(r') \subseteq B^-(r)$. We call a class C of programs hereditary if for each $P \in C$ all subprograms of P are in C as well. Note that many natural classes of programs (and all classes considered in this paper) are hereditary.

A set M of atoms satisfies a rule r if $(H(r) \cup B^-(r)) \cap M \neq \emptyset$ or $B^+(r) \setminus M \neq \emptyset$. M is a model of P if it satisfies all rules of P. The Gelfond–Lifschitz (GL) reduct of a program P under a set M of atoms is the program P^M obtained from P by first removing all rules r with $B^-(r) \cap M \neq \emptyset$ and second removing all $\neg z$ where $z \in B^-(r)$ from the remaining rules r [79]. M is an answer set (or stable model) of a program P if M is a minimal model of P^M . We denote by AS(P) the set of all answer sets of P.

Example 2.1. Consider the program *P* consisting of the following rules:

```
\begin{array}{lll} d \leftarrow a, e; & a \leftarrow d, \neg b, \neg c; & e \lor c \leftarrow f; \\ f \leftarrow d, c; & c \leftarrow f, e, \neg b; & c \leftarrow d; \\ b \leftarrow c; & f. & \end{array}
```

The set $M = \{b, c, f\}$ is an answer set of P, since $P^M = \{d \leftarrow a, e; f \leftarrow d, c; b \leftarrow c; e \lor c \leftarrow f; c \leftarrow d; f\}$ and the minimal models of P^M are $\{b, c, f\}$ and $\{e, f\}$.

In this paper we generally assume that programs contain no tautological rules since one can simply remove tautological rules from a program without effecting the answer sets, i.e., AS(P) = AS(P') where P' is a program obtained from P' by removing all tautological rules [13, The. 5.5] or [42]. In one case we allow tautological rules and state that explicitly (Proposition 5.10). Moreover, we generally assume that programs contain no rules r where $H(r) \cap B^-(r) \neq \emptyset$ since one can simply remove from those rules the head atoms in $H(r) \cap B^-(r)$ without effecting the answer sets, i.e., AS(P) = AS(P') where P' is a program obtained from P' by setting $H(r) := H(r) \setminus B^-(r)$ for every rule r where $H(r) \cap B^-(r) \neq \emptyset$ [42].

It is well known that normal Horn programs have a unique answer set or no answer set and that this set can be found in linear time. Van Emden and Kowalski [149] have shown that every constraint-free Horn program has a unique minimal model. Dowling and Gallier [33] have established a linear-time algorithm for testing the satisfiability of propositional Horn formulas which easily extends to Horn programs. In the following we state the well-known linear-time result.

Lemma 2.1. Every Horn program has at most one minimal model which can be found in linear time.

2.2. ASP problems

We consider the following fundamental ASP problems.

CHECKING

Given: A program P and a set $M \subseteq at(P)$.

Task: Decide whether M is an answer set of P.

CONSISTENCY

Given: A program P.

Task: Decide whether P has an answer set.

BRAVE REASONING

Given: A program P and an atom $a \in at(P)$.

Task: Decide whether a belongs to some answer set of P.

SKEPTICAL REASONING

Given: A program P and an atom $a \in at(P)$.

Task: Decide whether a belongs to all answer sets of P.

COUNTING

Given: A program P.

Task: Compute the number of answer sets of *P*.

ENUM

Given: A program P.

Task: List all answer sets of P.

We denote by $Asp\mathcal{R}eason$ the family of the reasoning problems Checking, Consistency, Brave Reasoning, and Skeptical Reasoning. We denote by $Asp\mathcal{T}ull$ the family of all the problems defined above. The family $Asp\mathcal{R}eason$ consists of decision problems, and $Asp\mathcal{T}ull$ adds to it a counting and an enumeration problem. In the sequel we will occasionally write L_{Normal} to denote a problem $L \in Asp\mathcal{T}ull$ restricted to input programs from **Normal**.

CHECKING is co-NP-complete in general [41], but CHECKING_{Normal} is polynomial [14]. Consistency and Brave Reasoning are Σ_2^P -complete, Skeptical Reasoning is Π_2^P -complete [41]. Both reasoning problems are NP-complete (or co-NP-complete) for normal programs [113], but are polynomial-time solvable for Horn programs [78]. Counting is easily seen to be #P-hard¹ as it entails the problem #SAT.

2.3. Parameterized complexity

Problem instances that originate from practical applications are often structured in a certain way that facilitates to obtain a solution relatively fast. Such instances seem to be harder in theory, where worst-case running times are given in terms of the input size in bits, than they are in practice. The framework of *parameterized complexity*, introduced by Downey and Fellows [34], takes structural properties of problem instances in form of a parameter into account. In consequence, it offers a framework for a more detailed theoretical analysis that is closer to the practical hardness of problems. In recent years parameterized complexity theory has become a very active research area. Since there are many ways of defining and capturing structure in a problem instance, there are various ways to parameterize a problem. A main concept of parameterized complexity theory is *fixed-parameter tractability* which relaxes classical polynomial-time tractability in such a way that all non-polynomial parts depend only on the size of the parameter and not on the size of the input.

We briefly give some background on parameterized complexity. For more detailed information we refer to other sources [34,35,50,84,120]. An instance of a parameterized problem L is a pair $(I,k) \in \mathcal{L}^* \times \mathbb{N}$ for some finite alphabet \mathcal{L} . For an instance $(I,k) \in \mathcal{L}^* \times \mathbb{N}$ we call I the main part and k the parameter. $\|I\|$ denotes the size of I. L is fixed-parameter tractable if there exist a computable function f and a constant c such that we can decide whether $(I,k) \in L$ in time $\mathcal{O}(f(k)\|I\|^c)$. Such an algorithm is called an fpt-algorithm. If L is a decision problem, then we identify L with the set of all yes-instances (I,k). FPT is the class of all fixed-parameter tractable decision problems.

Let $L\subseteq \Sigma^*\times \mathbb{N}$ and $L'\subseteq \Sigma^*\times \mathbb{N}$ be two parameterized decision problems for some finite alphabets Σ and Σ' . An fpt-reduction r from L to L' is a many-to-one reduction from $\Sigma^*\times \mathbb{N}$ to $\Sigma'^*\times \mathbb{N}$ such that for all $I\in \Sigma^*$ we have $(I,k)\in L$ if and only if $r(I,k)=(I',k')\in L'$ and $k'\leq g(k)$ for a fixed computable function $g:\mathbb{N}\to\mathbb{N}$ and there is a computable function f and a constant f0 such that f1 is computable in time $\mathcal{O}(f(k)\|I\|^c)$. Thus, an fpt-reduction is, in particular, an fpt-algorithm. It is easy to see that the class FPT is closed under fpt-reductions. It is clear for parameterized problems f1, and f2 that if f3 there is an fpt-reduction from f3 to f4, then f5 the first f5 the first f6 there is an fpt-reduction from f7 then f8 the first f8 that if f9 the first f9 then form f1 then f1 then f2 that if f3 the first f4 that if f5 the first f5 then form f6 then first f6 then first f6 then first f7 then f8 then first f8 then first f8 then first f9 then first f1 then f1 then f2 that if f1 then f2 that if f1 then f1 then f2 then first f1 then f1 then f1 then f2 that if f1 then f1 then f1 then f2 then f1 then f1 then f1 then f1 then f2 then f1 then f2 then f3 then f1 then f3 then

The Weft Hierarchy consists of parameterized complexity classes $W[1] \subseteq W[2] \subseteq \cdots$ which are defined as the closure of certain parameterized problems under parameterized reductions. There is strong theoretical evidence that parameterized problems that are hard for classes W[i] are not fixed-parameter tractable. A prominent W[2]-complete problem is HITTING SET [34,35] defined as follows:

HITTING SET

Given: A family of sets (S, k) where $S = \{S_1, \dots, S_m\}$ and an integer k.

Parameter: The integer k.

Task: Decide whether there exists set H of size at most k which intersects with all the S_i (H is a hitting set of S).

The class XP of *non-uniform* tractable problems consists of all parameterized decision problems that can be solved in polynomial time if the parameter is considered constant. That is, $(I,k) \in L$ can be decided in time $\mathcal{O}(\|I\|^{f(k)})$ for some computable function f. The parameterized complexity class paraNP contains all parameterized decision problems L such that $(I,k) \in L$ can be decided *non-deterministically* in time $\mathcal{O}(f(k)\|I\|^c)$ for some computable function f and constant c. A parameterized decision problem is paraNP-complete if it is in NP and NP-complete when restricted to finitely many parameter values [50]. By co-paraNP we denote the class of all parameterized decision problems whose complement (yes and no instances swapped) is in paraNP. Using the concepts and terminology of Flum and Grohe [50], co-paraNP = para-coNP.

2.4. Graphs

We recall some notations of graph theory. We consider undirected and directed graphs. An undirected graph or simply a graph is a pair G = (V, E) where $V \neq \emptyset$ is a set of vertices and $E \subseteq \{\{u, v\} \subseteq V : u \neq v\}$ is a set of edges. We denote an

¹ #P is the complexity class consisting of all the counting problems associated with the decision problems in NP.

edge $\{v, w\}$ by uv or vu. A graph G' = (V', E') is a subgraph of G if $V' \subseteq V$ and $E' \subseteq E$ and an induced subgraph if additionally for any $u, v \in V'$ and $uv \in E$ also $uv \in E'$. A path of length k is a graph with k+1 pairwise distinct vertices v_1, \ldots, v_{k+1} , and k distinct edges v_iv_{i+1} where $1 \le i \le k$ (possibly k=0). A cycle of length k is a graph that consists of k distinct vertices v_1, v_2, \ldots, v_k and k distinct edges $v_1v_2, \ldots, v_{k-1}v_k, v_kv_1$. Let G = (V, E) be a graph. G is bipartite if the set V of vertices can be divided into two disjoint sets U and W such that there is no edge $uv \in E$ with $u, v \in U$ or $u, v \in W$. G is complete if for any two vertices $u, v \in V$ there is an edge $uv \in E$. G contains a clique on $V' \subseteq V$ if the induced subgraph (V', E') of G is a complete graph. A connected component C of G is an inclusion-maximal subgraph $C = (V_C, E_C)$ of G such that for any two vertices $u, v \in V_C$ there is a path in C from U to V.

A directed graph or simply a digraph is a pair G = (V, E) where $V \neq \emptyset$ is a set of vertices and $E \subseteq \{(u, v) \in V \times V : u \neq v\}$ is a set of directed edges. A digraph G' = (V', E') is a subdigraph of G if $V' \subseteq V$ and $E' \subseteq E$ and an induced subdigraph if additionally for any $u, v \in V'$ and $(u, v) \in E$ also $(u, v) \in E'$. A directed path of length k is a digraph with k+1 pairwise distinct vertices v_1, \ldots, v_{k+1} , and k distinct edges (v_i, v_{i+1}) where $1 \leq i \leq k$ (possibly k = 0). A directed cycle of length k is a digraph that consists of k distinct vertices v_1, v_2, \ldots, v_k and k distinct edges $(v_1, v_2), \ldots, (v_{k-1}, v_k), (v_k, v_1)$.

We sometimes denote a (directed) path or (directed) cycle as a sequence of vertices. Please observe that according to the above definitions, the length of an undirected cycle is at least 3, whereas the length of a directed cycle is at least 2.

A strongly connected component C of a digraph G = (V, E) is an inclusion-maximal directed subgraph $C = (V_C, E_C)$ of G such that for any two vertices $u, v \in V_C$ there are paths in C from u to v and from v to u. The strongly connected components of G form a partition of the set V of vertices, we denote this partition by SCC(G).

For further basic terminology on graphs and digraphs we refer to a standard text [30,11].

2.5. Satisfiability backdoors

We also need some notions from propositional satisfiability. A literal is an atom or its negation and a clause is a finite set of literals A CNF formula is a finite set of clauses. A truth assignment is a mapping $\tau: X \to \{0, 1\}$ defined for a set $X \subseteq U$ of atoms. For $x \in X$ we put $\tau(\neg x) = 1 - \tau(x)$. By 2^X we denote the set of all truth assignments $\tau: X \to \{0, 1\}$. The truth assignment reduct of a CNF formula F with respect to $\tau \in 2^X$ is the CNF formula F_τ obtained from F by first removing all clauses C that contain a literal set to 1 by T, and second removing from the remaining clauses all literals set to 0 by T. T satisfies T if T is satisfiable if it is satisfied by some T.

The following is obvious from the definitions:

Observation 2.2. Let F be a CNF formula and X a set of atoms. F is satisfiable if and only if F_{τ} is satisfiable for at least one truth assignment $\tau \in 2^{X}$.

This leads to the definition of a strong backdoor relative to a class $\mathcal C$ of polynomially solvable CNF formulas: a set X of atoms is a strong $\mathcal C$ -backdoor of a CNF formula F if $F_{\tau} \in \mathcal C$ for all truth assignments $\tau \in 2^X$. Assume that the satisfiability of formulas $F \in \mathcal C$ of size $\|F\| = n$ can be decided in time $\mathcal O(n^c)$. Then we can decide the satisfiability of an arbitrary formula F for which we know a strong $\mathcal C$ -backdoor of size F in time $\mathcal O(2^k n^c)$ which is efficient as long as F remains small.

A further variant of backdoors are deletion backdoors defined by removing literals from a CNF formula. F-X denotes the formula obtained from F by removing all literals x, $\neg x$ for $x \in X$ from the clauses of F. Then a set X of atoms is a deletion C-backdoor of F if $F-X \in C$. In general, deletion C-backdoors are not necessarily strong C-backdoors. If all subsets of a formula in C also belong to C (C is clause-induced), then deletion C-backdoors are strong C-backdoors.

Before we can use a backdoor we need to find it first. What we call the *backdoor approach* is a process consisting of the following two phases:

- finding a backdoor (backdoor detection) and
- using the backdoor to solve the problem (backdoor evaluation).

For most reasonable target classes C the detection of a strong C-backdoor of size at most k is NP-hard if k is part of the input. However, as we are interested in finding *small* backdoors, it makes sense to parameterize the backdoor search by k and consider the parameterized complexity of backdoor detection. Indeed, with respect to the classes of Horn CNF formulas and 2-CNF formulas, the detection of strong backdoors of size at most k is fixed-parameter tractable [123]. The parameterized complexity of backdoor detection for many further target classes has been investigated [55].

The purpose of this paper is to develop a backdoor approach for answer set programming. It turns out that the evaluation problem is more complicated than for propositional satisfiability (see Section 3.3) and various target classes for answer set programming require new algorithms for backdoor detection (see Section 5).

3. Answer set backdoors

3.1. Strong backdoors

In order to translate the notion of backdoors to the domain of ASP, we first need to come up with a suitable concept of a reduction with respect to a truth assignment. The following is a natural definition which generalizes a concept of Gottlob et al. [85].

Definition 3.1. Let *P* be a program, *X* a set of atoms, and $\tau \in 2^X$. The *truth assignment reduct* of *P* under τ is the logic program P_{τ} obtained from *P* by

- 1. removing all rules r with $H(r) \cap \tau^{-1}(1) \neq \emptyset$ or $H(r) \subseteq X$;
- 2. removing all rules r with $B^+(r) \cap \tau^{-1}(0) \neq \emptyset$;
- 3. removing all rules r with $B^-(r) \cap \tau^{-1}(1) \neq \emptyset$;
- 4. removing from the heads and bodies of the remaining rules all literals $a, \neg a$ with $a \in X$.

Definition 3.2. Let C be a class of programs. A set X of atoms is a *strong* C-backdoor of a program P if $P_{\tau} \in C$ for all truth assignments $\tau \in 2^{X}$.

By a *minimal* strong C-backdoor of a program P we mean a strong C-backdoor of P that does not properly contain a smaller strong C-backdoor of P; a *smallest* strong C-backdoor of P is one of smallest cardinality.

Example 3.1. We consider the program of Example 2.1. The set $\{b,c\}$ is a strong **Horn**-backdoor since all four truth assignment reducts $P_{\bar{b}\bar{c}} = P_{b=0,c=0} = \{d \leftarrow a,e; \ a \leftarrow d; \ e \leftarrow f; \ f\}$, $P_{\bar{b}c} = \{d \leftarrow a,e; \ f \leftarrow d; \ f\}$, $P_{b\bar{c}} = \{d \leftarrow a,e; \ e \leftarrow f; \ f\}$, and $P_{bc} = \{d \leftarrow a,e; \ f \leftarrow d; \ f\}$ are in the class **Horn**.

3.2. Deletion backdoors

Next we define a variant of answer set backdoors similar to satisfiability deletion backdoors. For a program P and a set X of atoms we define P-X as the program obtained from P by deleting a, $\neg a$ for $a \in X$ from the rules of P. The definition gives rise to deletion backdoors. We will see that finding deletion backdoors is in some cases easier than finding strong backdoors.

Definition 3.3. Let \mathcal{C} be a class of programs. A set X of atoms is a *deletion* \mathcal{C} -backdoor of a program P if $P-X \in \mathcal{C}$.

In general, not every strong C-backdoor is a deletion C-backdoor, and not every deletion C-backdoor is a strong C-backdoor. But we can strengthen one direction requiring the base class to satisfy the very mild condition of being hereditary (see Section 2) which holds for all base classes considered in this paper.

Lemma 3.4. If C is hereditary, then every deletion C-backdoor is a strong C-backdoor.

Proof. Let P be a program, $X \subseteq \operatorname{at}(P)$, and $\tau \in 2^X$. Let $r' \in P_\tau$. It follows from Definition 3.1 that r' is obtained from some $r \in P$ by deleting $a, \neg a$ for all $a \in X$ from the head and body of r. Consequently $r' \in P - X$. Hence $P_\tau \subseteq P - X$ which establishes the proposition. \square

3.3. Backdoor evaluation

An analogue to Observation 2.2 does not hold for ASP, even if we consider the most basic problem Consistency. Take for example the program $P = \{x \leftarrow y; \ y \leftarrow x; \leftarrow \neg x\}$ and the set $X = \{x\}$. Both reducts $P_{x=0} = \{z\}$ and $P_{x=1} = \{y\}$ have answer sets, but P has no answer set. However, we can show a somewhat weaker asymmetric variant of Observation 2.2, where we can map each answer set of P to an answer set of P_{τ} for some $\tau \in 2^X$. This is made precise by the following definition and lemma (which are key for a backdoor approach to answer set programming).

Definition 3.5. Let P be a program and X a set of atoms. We define

$$\mathsf{AS}(P,X) = \big\{ M \cup \tau^{-1}(1) : \tau \in 2^{X \cap \mathsf{at}(P)}, \, M \in \mathsf{AS}(P_\tau) \big\}.$$

In other words, the sets in AS(P, X) are answer sets of P_{τ} for truth assignments τ to $X \cap at(P)$ extended by those atoms which are set to true by τ . In the following lemma we will see that the elements in AS(P, X) are "answer set candidates" of the original program P.

Lemma 3.6. $AS(P) \subseteq AS(P, X)$ holds for every program P and every set X of atoms.

Proof. Let $M \in AS(P)$ be chosen arbitrarily. We put $X_0 = (X \setminus M) \cap at(P)$ and $X_1 = X \cap M$ and define a truth assignment $\tau \in 2^{X \cap at(P)}$ by setting $\tau^{-1}(i) = X_i$ for $i \in \{0, 1\}$. Let $M' = M \setminus X_1$. Observe that $M' \in AS(P_\tau)$ implies $M \in AS(P, X)$ since $M = M' \cup \tau^{-1}(1)$ by definition. Hence, to establish the lemma, it suffices to show that $M' \in AS(P_\tau)$. We have to show that M' is a model of $P_\tau^{M'}$, and that no proper subset of M' is a model of $P_\tau^{M'}$.

In order to show that M' is a model of $P_{\tau}^{M'}$, choose $r' \in P_{\tau}^{M'}$ arbitrarily. By construction of $P_{\tau}^{M'}$ there is a corresponding rule $r \in P$ with $H(r') = H(r) \setminus X_0$ and $B^+(r') = B^+(r) \setminus X_1$ which gives rise to a rule $r'' \in P_{\tau}$, and in turn, r'' gives rise to $r' \in P_{\tau}^{M'}$. Since $B^-(r) \cap X_1 = \emptyset$ (otherwise r would have been deleted forming P_{τ}) and $B^-(r) \cap M' = \emptyset$ (otherwise r'' would have been deleted forming $P_{\tau}^{M'}$), it follows that $B^-(r) \cap M = \emptyset$. Thus, r gives rise to a rule $r^* \in P^M$ with $H(r) = H(r^*)$ and $B^+(r) = B^+(r^*)$. Since $M \in AS(P)$, M satisfies r^* , i.e., $H(r) \cap M \neq \emptyset$ or $B^+(r) \setminus M \neq \emptyset$. However, $H(r) \cap M = H(r') \cap M'$ and $H(r) \cap M = H(r') \cap M'$ are a model of $H(r) \cap M = H(r') \cap M'$ and $H(r) \cap M = H(r') \cap M'$ are a model of $H(r) \cap M = H(r') \cap M'$. Let $H(r) \cap M = H(r') \cap M'$ are a model of $H(r) \cap M' = H(r) \cap M'$. Since $H(r) \cap M' = H(r) \cap M'$ are a model of $H(r) \cap M' = H(r) \cap M'$. Since $H(r) \cap M' = H(r) \cap M'$ and $H(r) \cap M' = H(r) \cap M'$ are a model of $H(r) \cap M' = H(r) \cap M'$. Let $H(r) \cap M' = H(r) \cap M' = H(r) \cap M'$ and $H(r) \cap M' = H(r) \cap M'$ are a model of $H(r) \cap M' = H(r) \cap M'$. Since $H(r) \cap M' = H(r) \cap M'$ and $H(r) \cap M' = H(r) \cap M'$ are a model of $H(r) \cap M' = H(r) \cap M'$. Since $H(r) \cap M' = H(r) \cap M'$ and $H(r) \cap M' = H(r)$ and $H(r) \cap M' = H(r)$ and

In order to show that no proper subset of M' is a model of P_{τ}^M choose arbitrarily a proper subset $N' \subseteq M'$. Let $N = N' \cup X_1$. Since $M' = M \setminus X_1$ and $X_1 \subseteq M$ it follows that $N \subseteq M$. Since M is a minimal model of P^M , N cannot be a model of P^M . Consequently, there must be a rule $r \in P$ such that $B^-(r) \cap M = \emptyset$ (i.e., r is not deleted by forming P^M), $B^+(r) \subseteq N$ and $H(r) \cap N = \emptyset$. However, since M satisfies P^M and since $B^+(r) \subseteq N \subseteq M$, $H(r) \cap M \neq \emptyset$. Thus, r is not a constraint. Moreover, since $H(r) \cap M \neq \emptyset$ and $M \cap X_0 = \emptyset$, it follows that $H(r) \setminus X_0 \neq \emptyset$. Thus, since $H(r) \cap X_1 = \emptyset$, $H(r) \setminus X \neq \emptyset$. We conclude that r is not deleted when forming P_{τ} and giving rise to a rule $r' \in P_{\tau}$, which in turn is not deleted when forming $P_{\tau}^{M'}$, giving rise to a rule r'', with $H(r'') = H(r) \setminus X_0$, $B^+(r'') = B^+(r) \setminus X_1$, and $B^-(r'') = \emptyset$. Since $B^+(r'') \subseteq N'$ and $H(r'') \cap N = \emptyset$, N' is not a model of $P_{\tau}^{M'}$.

Thus, we have established that M' is a stable model of P_{τ} , and so the lemma follows. \square

In view of Lemma 3.6 we shall refer to the elements in AS(P, X) as "answer set candidates."

Example 3.2. We consider program P of Example 2.1 and the strong **Horn**-backdoor $X = \{b, c\}$ of Example 3.1. The answer sets of P_{τ} are $AS(P_{b\bar{c}}) = \{\{e, f\}\}$, $AS(P_{b\bar{c}}) = \{\{e, f\}\}$, $AS(P_{b\bar{c}}) = \{\{e, f\}\}$, and $AS(P_{bc}) = \{\{f\}\}$ for $\tau \in 2^{\{b, c\}}$. We obtain the set $AS(P, X) = \{\{e, f\}, \{c, f\}, \{b, e, f\}, \{b, c, f\}\}$.

In view of Lemma 3.6, we can compute AS(P) by (i) computing $AS(P_{\tau})$ for all $\tau \in 2^X$ (this produces the set AS(P, X) of candidates for AS(P)), and (ii) checking for each $M \in AS(P, X)$ whether it is an answer set of P. The check (ii) entails (ii.a) checking whether $M \in AS(P, X)$ is a model of P and (ii.b) whether $M \in AS(P, X)$ is a minimal model of P^M . We would like to note that in particular any constraint contained in P is removed in the truth assignment reduct P_{τ} but considered in check (ii.a). Clearly check (ii.a) can be carried out in polynomial time for each M. Check (ii.b), however, is co-NP-complete in general [113], but polynomial for normal programs [14].

Fortunately, for our considerations it suffices to perform check (ii.b) for programs that are "close to **Normal**," and so the check is fixed-parameter tractable in the size of the given backdoor. More precisely, we consider the following parameterized problem and establish its fixed-parameter tractability in the next lemma.

Strong C-Backdoor Asp Check

Given: A program P, a strong C-backdoor X of P and a set $M \subseteq at(P)$.

Parameter: The size |X| of the backdoor.

Task: Decide whether M is an answer set of P.

Lemma 3.7. Let \mathcal{C} be a class of normal programs. The problem Strong \mathcal{C} -Backdoor Asp Check is fixed-parameter tractable.

Proof. Let C be a class of normal programs, P a program, and X a strong C-backdoor X of P with |X| = k. We can check in polynomial time whether M is a model of P and whether M is a model of P^M . If it is not, we can reject M, and we are done. Hence assume that M is a model of P^M . In order to check whether $M \in AS(P)$ we still need to decide whether M is a minimal model of P^M . Recall that P contains no tautological rules.

Let $X_1 \subseteq M \cap X$. We construct from P^M a program $P^M_{X_1 \subseteq X}$ by (i) removing all rules r for which $H(r) \cap X_1 \neq \emptyset$, and (ii) replacing for all remaining rules r the head H(r) with $H(r) \setminus X$, and the positive body $B^+(r)$ with $B^+(r) \setminus X_1$.

Claim. $P_{X_1 \subset X}^M$ is Horn.

To show the claim, consider some rule $r' \in P^M_{X_1 \subseteq X}$. By construction, there must be a rule $r \in P$ that gives raise to a rule in P^M , which in turn gives raise to r'. Let $\tau \in 2^X$ be the assignment that sets all atoms in $X \cap H(r)$ to 0, and all atoms in $X \setminus H(r)$ to 1. Since r is not tautological, it follows that r is not deleted when we obtain P_τ , and it gives rise to a rule $r^* \in P_\tau$, where $H(r^*) = H(r) \setminus X$. However, since $\mathcal C$ is a class of normal programs, r^* is normal. Hence $1 \ge |H(r^*)| = |H(r) \setminus X| = |H(r')|$, and the claim follows.

To test whether M is a minimal model of P^M , we run the following procedure for every set $X_1 \subseteq M \cap X$.

Find C-backdoor Apply Determine answer sets Check candidates Solutions $X \subseteq \operatorname{at}(P)$ $\tau_i: X \to \{0,1\}$ of simplified programs candidates $T_{\tau_i}: X \to \{0,1\}$ of simplified programs $T_{\tau_i}: X \to \{0,1\}$ of $T_{\tau_i}: X \to \{0,1\}$ of simplified programs $T_{\tau_i}: X \to \{0,1\}$ of $T_{\tau_i}: X$

Fig. 1. Exploit pattern of ASP backdoors if the target class \mathcal{C} is normal and enumerable where n denotes the input size of P.

If $P_{X_1 \subset X}^M$ has no model, then stop and return TRUE.

Otherwise, compute the unique minimal model L of the Horn program $P_{X_1 \subseteq X}^M$. If $L \subseteq M \setminus X$, $L \cup X_1 \subsetneq M$, and $L \cup X_1$ is a model of P^M , then return FALSE. Otherwise return TRUE.

For each set $X_1 \subseteq M \cap X$ the above procedure runs in linear time by Lemma 2.1. As there are $\mathcal{O}(2^k)$ sets X_1 to consider, we have a total running time of $\mathcal{O}(2^k n)$ where n denotes the input size of P and k = |X|. It remains to establish the correctness of the above procedure in terms of the following claim.

Claim. *M* is a minimal model of P^M if and only if the algorithm returns True for each $X_1 \subseteq M \cap X$.

 (\Rightarrow) Assume that M is a minimal model of P^M , and suppose to the contrary that there is some $X_1 \subseteq M \cap X$ for which the algorithm returns False. Consequently, $P^M_{X_1 \subseteq X}$ has a unique minimal model L with $L \subseteq M \setminus X$, $L \cup X_1 \subseteq M$, and where $L \cup X_1$ is a model of P^M . This contradicts the assumption that M is a minimal model of P^M . Hence the only-if direction of the claim is shown.

(\Leftarrow) Assume that the algorithm returns True for each $X_1 \subseteq M \cap X$. We show that M is a minimal model of P^M . Suppose to the contrary that P^M has a model $M' \subseteq M$.

We run the algorithm for $X_1 := M' \cap X$. By assumption, the algorithm returns True. There are two possibilities: (i) $P_{X_1 \subseteq X}^M$ has no model, or (ii) $P_{X_1 \subseteq X}^M$ has a model, and for its unique minimal model L the following holds: (ii.a) L is not a subset of $M \setminus X$, or (ii.b) $L \cup X_1$ is not a proper subset of M, or (ii.c) $L \cup X_1$ is not a model of P^M .

We show that case (i) is not possible by showing that $M' \setminus X$ is a model of $P_{X_1 \subseteq X}^M$.

To see this, consider a rule $r' \in P^M_{X_1 \subseteq X}$, and let $r \in P^M$ such that r' is obtained from r by removing X from H(r) and by removing X_1 from $B^+(r)$. Since M' is a model of P^M , we have (a) $B^+(r) \setminus M' \neq \emptyset$ or (b) $H(r) \cap M' \neq \emptyset$. Moreover, since $B^+(r') = B^+(r) \setminus X_1$ and $X_1 = M' \cap X$, (a) implies $\emptyset \neq B^+(r) \setminus M' = B^+(r) \setminus X_1 \setminus M' = B^+(r') \setminus M' \subseteq B^+(r') \setminus (M' \setminus X)$, and since $H(r) \cap X_1 = \emptyset$, (b) implies $\emptyset \neq H(r) \cap M' = H(r) \cap (M' \setminus X_1) = H(r) \cap (M' \setminus X) = (H(r) \setminus X) \cap (M' \setminus X) = H(r') \cap (M' \setminus X)$. Hence $M' \setminus X$ satisfies r'. Since $r' \in P^M_{X_1 \subseteq X}$ was chosen arbitrarily, we conclude that $M' \setminus X$ is a model of $P^M_{X_1 \subseteq X}$.

Case (ii) is not possible either, as we can see as follows. Assume $P^M_{X_1\subseteq X}$ has a model, and let L be its unique minimal model. Since $M'\setminus X$ is a model of $P^M_{X_1\subseteq X}$, as shown above, we have $L\subseteq M'\setminus X$. Case (ii.a): We have $L\subseteq M\setminus X$ since $L\subseteq M'\setminus X$ and $M'\setminus X\subseteq M\setminus X$. Case (ii.b): Further we have $L\cup X_1\subseteq M$ since $L\cup X_1\subseteq (M'\setminus X)\cup X_1=(M'\setminus X)\cup (M'\cap X)=M'\subseteq M$. Case (ii.c): And finally $L\cup X_1$ is a model of P^M , as can be seen as follows. Consider a rule $r\in P^M$. If $X_1\cap H(r)\neq\emptyset$, then $L\cup X_1$ satisfies r; thus, it remains to consider the case $X_1\cap H(r)=\emptyset$. In this case there is a rule $r'\in P^M_{X_1\subseteq X}$ with $H(r')=H(r)\setminus X$ and $H(r')=H(r)\setminus X$. Since L is a model of L is a model of L is an another in L i

Since neither case (i) nor case (ii) is possible, we have a contradiction, and we conclude that M is a minimal model of P^{M} .

Hence the second direction of the claim is established, and so the lemma follows. □

Fig. 1 illustrates how we can exploit a strong C-backdoor to find answer sets. For a given program P and a strong C-backdoor X of P we have to consider $|2^X|$ truth assignments to the atoms in the backdoor X. For each truth assignment $\tau \in 2^X$ we reduce the program P to a program P_{τ} and compute the set $\mathsf{AS}(P_{\tau})$. Finally, we obtain the set $\mathsf{AS}(P)$ by checking for each $M \in \mathsf{AS}(P_{\tau})$ whether it gives rise to an answer set of P.

Example 3.3. We consider the set $AS(P, X) = \{\{e, f\}, \{c, f\}, \{b, e, f\}, \{b, c, f\}\}$ of answer set candidates of Example 3.2 and check for each candidate $L = \{e, f\}, M = \{c, f\}, N = \{b, e, f\}$, and $O = \{b, c, f\}$ whether it is an answer set of P. Therefore we solve the problem Strong Horn-Backdoor Asp Check by means of Lemma 3.7.

First we test whether the sets L, M, N and O are models of P. We easily observe that N and O are models of P. But L and M are not models of P since they do not satisfy the rule $c \leftarrow e$, f, $\neg b$ and $b \leftarrow c$ respectively, and we can drop them as candidates. Then we positively answer the question whether N and O are models of its GL-reducts P^N and P^O respectively.

Next we consider the minimality and apply the algorithm of Lemma 3.7 for each subset of the backdoor $X = \{b, c\}$. We have the GL-reduct $P^N = \{d \leftarrow a, e; e \lor c \leftarrow f; f \leftarrow d, c; c \leftarrow d; b \leftarrow c; f\}$. For $X_1 = \emptyset$ we obtain $P^N_{X_1 \subseteq X} = \{d \leftarrow a, e; e \leftarrow f; f \leftarrow d, c; \leftarrow d; \leftarrow c; f\}$. The set $L = \{e, f\}$ is the unique minimal model of $P^N_{X_1 \subseteq X}$. Since $L \subseteq N \setminus X$, $L \cup X_1 \subseteq N$, and $L \cup X_1$ is a model of P^N , the algorithm returns FALSE. We conclude that N is not a minimal model of P^N and thus P^N is not an answer set of P^N .

We obtain the GL-reduct $P^0 = \{d \leftarrow a, e; e \lor c \leftarrow f; f \leftarrow d, c; c \leftarrow d; b \leftarrow c; f\}$. For $X_1 = \emptyset$ we have $P^0_{X_1 \subseteq X} = \{d \leftarrow a, e; e \leftarrow f; f \leftarrow d, e; \leftarrow d; \leftarrow c; f\}$. The set $L = \{e, f\}$ is the unique minimal model of $P^0_{X_1 \subseteq X}$. Since $L \cup X_1 \subsetneq O$, the algorithm returns True. For $X_2 = \{b\}$ we get $P^0_{X_2 \subseteq X} = \{d \leftarrow a, e; e \leftarrow f; f \leftarrow d, e; \leftarrow d; f\}$ and the unique minimal model $L = \{e, f\}$. Since $L \subseteq O \setminus X$, the algorithm returns True. For $X_3 = \{c\}$ we obtain $P^0_{X_3 \subseteq X} = \{d \leftarrow a, e; f \leftarrow d; \leftarrow f\}$ and no minimal model. Thus, the algorithm returns True. For $X_4 = \{b, c\}$ we have $P^0_{X_4 \subseteq X} = \{d \leftarrow a, e; f \leftarrow d; f\}$ and the unique minimal model $L = \{f\}$. Since $L \cup X_1 \subsetneq O$, the algorithm returns True. Since only $\{b, c, f\} \in AS(P, X)$ is an answer set of P, we obtain $AS(P) = \{\{b, c, f\}\}$.

In view of Lemmas 3.6 and 3.7, the computation of AS(P) is fixed-parameter tractable for parameter k if we know a strong C-backdoor X of size at most k for P, and each program in C is normal and its stable sets can be computed in polynomial time. This consideration leads to the following definition and result.

Definition 3.8. A class C of programs is *enumerable* if for each $P \in C$ we can compute AS(P) in polynomial time. If AS(P) can be computed in linear time, then the class C is *linear-time enumerable*.

Please note, that this is a stronger property than being enumerable with polynomial-time delay; the latter is usually used in the context of enumeration problems and also mentioned in Section 8.4 for a certain parameter.

Theorem 3.9. Let C be an enumerable class of normal programs. The problems in AspFull are all fixed-parameter tractable when parameterized by the size of a strong C-backdoor, assuming that the backdoor is given as input.

Proof. Let X be the given backdoor, k = |X| and n the input size of P. Since $P_{\tau} \in \mathcal{C}$ and \mathcal{C} is enumerable, we can compute $\mathsf{AS}(P_{\tau})$ in polynomial time for each $\tau \in 2^X$, say in time $\mathcal{O}(n^c)$ for some constant c. Observe that therefore $|\mathsf{AS}(P_{\tau})| \leq \mathcal{O}(n^c)$ for each $\tau \in 2^X$. Thus, we obtain $\mathsf{AS}(P,X)$ in time $\mathcal{O}(2^k n^c)$, and $|\mathsf{AS}(P,X)| \leq \mathcal{O}(2^k n^c)$. By Lemma 3.6, $\mathsf{AS}(P) \subseteq \mathsf{AS}(P,X)$. By means of Lemma 3.7 we can decide whether $M \in \mathsf{AS}(P)$ in time $\mathcal{O}(2^k n)$ for each $M \in \mathsf{AS}(P,X)$. Thus, we determine from $\mathsf{AS}(P,X)$ the set of all answer sets of P in time $\mathcal{O}(2^k \cdot n^c \cdot 2^k \cdot n + 2^k \cdot n^c) = \mathcal{O}(2^{2k} n^{c+1})$. Once we know $\mathsf{AS}(P)$, then we can also solve all problems in $\mathcal{AspFull}$ within polynomial time. \square

Theorem 3.9 identifies conditions under which a small backdoor indeed reduces the search space for the main ASP reasoning problems, that is, to be exponential only in the backdoor size and not in the size of the entire instance. Hence under these conditions a small backdoor can be considered as a "clever reasoning shortcut" through the search space.

Remark. If we know that each program in C has at most one answer set, and P has a strong C-backdoor of size k, then we can conclude that P has at most 2^k answer sets. Thus, we obtain an upper bound on the number of answer sets of P by computing a small strong C-backdoor of P.

3.4. Backdoor detection

Theorem 3.9 draws our attention to enumerable classes of normal programs. Given such a class C, is the detection of C-backdoors fixed-parameter tractable? If the answer is affirmative, we can drop in Theorem 3.9 the assumption that the backdoor is given as an input for this class.

Each class \mathcal{C} of programs gives rise to the following two parameterized decision problems:

Strong C-Backdoor Detection

Given: A program P and an integer k.

Parameter: The integer *k*.

Task: Decide whether P has a strong C-backdoor X of size at most k.

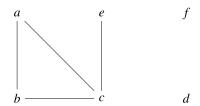


Fig. 2. Negation dependency graph N_P of the program P of Example 2.1.

Deletion C-Backdoor Detection

Given: A program P and an integer k.

Parameter: The integer *k*.

Task: Decide whether P has a deletion C-backdoor X of size at most k.

By a standard construction, known as self-reduction or self-transformation [139,34,35], one can use a decision algorithm for Deletion C-Backbook Detection to actually find the backdoor. We only require the base class to be hereditary.

Lemma 3.10. Let C be a hereditary class of programs. If DELETION C-BACKDOOR DETECTION is fixed-parameter tractable, then also finding a deletion C-backdoor of a given program P of size at most k is fixed-parameter tractable (for parameter k).

Proof. We proceed by induction on k. If k=0 the statement is clearly true. Let k>0. Given (P,k) we check for all $x \in \operatorname{at}(P)$ whether $P-\{x\}$ has a deletion \mathcal{C} -backdoor of size at most k-1. If the answer is NO for all x, then P has no deletion \mathcal{C} -backdoor of size k. If the answer is YES for x, then by induction hypothesis we can compute a deletion \mathcal{C} -backdoor X of size at most k-1 of P-x, and $X \cup \{x\}$ is a deletion \mathcal{C} -backdoor of P. \square

Remark. One could consider also target classes where empty rules are detected (an analogy to "empty clause detection" [31, 32] in the SAT setting) which would yield smaller backdoors. However, backdoor detection is already W[1]-hard for almost all base classes, including Horn, in the SAT setting when empty clause detection is added [144]. These W[1]-hardness results carry over to the ASP setting if empty rule detection is added.

4. Target class Horn

In this section we consider the important case **Horn** as the target class for backdoors. As a consequence of **Lemma 2.1**, **Horn** is linear-time enumerable. The following lemma shows that strong and deletion **Horn**-backdoors coincide.

Lemma 4.1. A set X is a strong **Horn**-backdoor of a program P if and only it is a deletion **Horn**-backdoor of P.

Proof. Since **Horn** is hereditary, Lemma 3.4 establishes the if-direction. For the only-if direction, we assume for the sake of a contradiction that X is a strong **Horn**-backdoor of P but not a deletion **Horn**-backdoor of P. Hence there is a rule $r' \in P - X$ that is neither tautological nor Horn. Let $r \in P$ be a rule from which r' was obtained in forming P - X. We define $\tau \in 2^X$ by setting all atoms in $X \cap (H(r) \cup B^-(r))$ to 0, all atoms in $X \cap B^+(r)$ to 1, and all remaining atoms in $X \setminus \operatorname{at}(r)$ arbitrarily to 0 or 1. Since r is not tautological, this definition of τ is sound. It follows that $r' \in P_{\tau}$, contradicting the assumption that X is a strong **Horn**-backdoor of P. \square

Definition 4.2. Let P be a program. The *negation dependency graph* N_P is the graph defined on the set of atoms of the given program P, where two distinct atoms x, y are joined by an edge xy if there is a rule $r \in P$ with $x \in H(r)$ and $y \in H(r) \cup B^-(r)$.

Example 4.1. Fig. 2 visualizes the negation dependency graph N_P of the program P of Example 2.1.

The following lemma states how we can use recent results on the vertex cover problem to find deletion backdoors for the target class **Horn**. A *vertex cover* of a graph G = (V, E) is a set $S \subseteq V$ such that for every edge $uv \in E$ we have $\{u, v\} \cap S \neq \emptyset$.

Lemma 4.3. Let P be a program. A set $X \subseteq at(P)$ is a deletion **Horn**-backdoor of P if and only if X is a vertex cover of the negation dependency graph N_P .

Proof. Let $X \subseteq at(P)$ be a deletion **Horn**-backdoor of P. Consider an edge uv of N_P . By construction of N_P there is a corresponding rule $r \in P$ with (i) $u, v \in H(r)$ and $u \neq v$ or (ii) $u \in H(r)$ and $v \in B^-(r)$. Since X is a deletion **Horn**-backdoor,

 $|H(r) - X| \le 1$ and $B^-(r) - X = \emptyset$. Thus, if case (i) applies, $\{u, v\} \cap X \ne \emptyset$. If case (ii) applies, again $\{u, v\} \cap X \ne \emptyset$. We conclude that X is a vertex cover of N_P .

Conversely, assume that X is a vertex cover of N_P . Consider a rule $r \in P - X$ for proof by contradiction assume that r is not Horn (in particular r is not a constraint). If $|H(r)| \ge 2$ then there are two variables $u, v \in H(r)$ and an edge uv of N_P such that $\{u, v\} \cap X = \emptyset$, contradicting the assumption that X is a vertex cover. Similarly, if $B^-(r) \ne \emptyset$ then we take a variable $u \in B^-(r)$ and a variable $v \in H(r)$; such v exists since v is not a constraint. Thus, v contains the edge v with v is a vertex cover. Hence the claim holds. v

Example 4.2. For instance, the negation dependency graph N_P of the program P of Example 2.1 consists of the triangle $\{a, b, c\}$ and a path (c, e). Then $\{b, c\}$ is a vertex cover of N_P . We observe easily that there exists no vertex cover of size 1. Thus, $\{b, c\}$ is a smallest strong **Horn**-backdoor of P.

Remark. Note that the unparameterized version² of STRONG **Horn**-BACKDOOR DETECTION is NP-hard. Since the reduction presented in the proof of Lemma 4.3 can be used straightforward as a reduction of the unparameterized version of the vertex cover problem to STRONG **Horn**-BACKDOOR DETECTION.

Theorem 4.4. Strong **Horn**-Backboor Detection is fixed-parameter tractable. In fact, given a program with n atoms we can find a strong **Horn**-backboor of size at most k in time $\mathcal{O}(1.2738^k + kn)$ or decide that no such backboor exists.

Proof. Let P be a given program. Let N_P be the negation dependency graph of P. According to Lemma 4.3, a set $X \subseteq \operatorname{at}(P)$ is a vertex cover of N_P if and only if X is a deletion **Horn**-backdoor of P. Then a vertex cover of size at most k, if it exists, can be found in time $\mathcal{O}(1.2738^k + kn)$ by Chen et al. [22]. By Lemma 4.1 this vertex cover is also a strong **Horn**-backdoor of P. \square

Now we can use Theorem 4.4 to strengthen the fixed-parameter tractability result of Theorem 3.9 by dropping the assumption that the backdoor is given.

Corollary 4.5. All the problems in AspFull are fixed-parameter tractable when parameterized by the size of a smallest strong **Horn**-backdoor of the given program.

4.1. Horn-backdoors of benchmark instances

The underlying idea for fixed-parameter tractability is that problem instances for which the parameter is small can be solved efficiently. It is therefore natural to ask how the values of a parameter are distributed in various problem instances. Hence, we investigate the size of backdoors for various benchmark programs, focusing on the target class **Horn**. As expected, structured programs, originating from application domains, have smaller backdoors than random instances. Since the direct implementation of our backdoor-based algorithms seems impracticable.

We have determined strong **Horn**-backdoors for various benchmark programs by means of encodings into answer set programming, integer linear programming (ILP), local search (LS), and propositional satisfiability (SAT). We use the connection stated in Lemma 4.3 and compile the problem of finding a minimum vertex cover (k-vertex cover) into the respective domain. The encodings are straightforward: Let P be a program (without constraints or tautological rules) and let $N_p = (V, E)$ be its negation dependency graph. For the ASP encoding we proceed as follows: Among the atoms of our ASP program will be atoms $\{e_{uw}: uw \in E\}$ and atoms $C = \{c_v: v \in V\}$. The truth values of the atoms in C represent a subset $S \subseteq \operatorname{at}(P)$ such that c_v is true if and only if $v \in S$ (a vertex cover). We introduce for every edge $vw \in E$ a constraint $\leftarrow e_{vw}$, $\neg c_v$, $\neg c_w$ and a choice rule $1\{c_u, c_v\} \leftarrow e_{u,v}$ Moreover, we add a statement to minimize the number of atoms in C that belong to an answer set (see [141,73] for choice rules and minimize statements). For the ILP encoding we proceed as follows: We introduce for every vertex $v \in V$ a binary variable b_v , we add for every edge $vw \in E$ a constraint $b_v + b_w \ge 1$, and minimize the sum $\sum_{v \in V} b_v$. For LS we ran designated local search based vertex cover solvers [15, 17,16] on the graph N_p . For the SAT encoding we used an encoding similar to the encoding presented in [53]. We introduce for every edge $uv \in E$ a binary clause and add a sequential unary counter [142] to express that at most k vertices belong to a vertex cover.

The answer set program that solves backdoor detection was generated by means of ASP meta programming [70] and solved using Clasp [71,72] version 3.0.5 with an unsatisfiable-core based optimization strategy (the command line parameter "-opt-strategy=5" yields the behavior) [1]. The integer linear program was generated using the open source mathematics framework Sage [44] with Python [150], solved using ILOG CPLEX 12 [89] and Gurobi [87].

² Given a parameterized problem L on some finite alphabet Σ . The unparameterized version of L is the classical problem $\{l\#u^k: (I,k)\in L\}$ where u denotes an arbitrary symbol from Σ and # is a new symbol not in Σ .

Table 1Size of smallest strong **Horn**-backdoors (bd) for various benchmark sets, given as % of the total number of atoms (# atoms) by the mean over the instances.

Domain	Instance set	Disj.	#instances	#atoms	Horn bd(%)	stdev
AI	HanoiTower	_	60	32 956.7	4.28	0.08
	StrategicCompanies	+	15	2002.0	6.03	0.04
	MinimalDiagnosis	+	551	111856.5	10.74	1.71
Graph	GraphColoring	_	60	3544.4	19.47	0.79
Planning	MSS/MUS	+	38	49 402.3	3.80	0.70
	ConformantPlanning	+	24	1378.2	8.43	2.12
Cryptography	Factoring	_	10	3336.8	25.76	1.30
Puzzle	Labyrinth	_	261	55 604.9	3.42	0.82
	KnightTour	_	10	23 156.9	33.08	0.20
	Solitaire	_	25	11 486.8	38.88	0.20
Random	RandomQBF	+	15	160.1	49.69	0.00
	RLP	_	282	200.0	67.26	5.42
	RandomNonTight	_	220	200.0	89.85	0.24

ConformantPlanning: secure planning under incomplete initial states [147]; instances provided by Gebser and Kaminski [60]. Factoring: factorization of a number where an efficient algorithm would yield a cryptographic attack by Gebser [38]; for instances see [61]. HanoiTower: classic Towers of Hanoi puzzle by Truszczynski, Smith and Westlund; for instances see [18]. GraphColoring: classic graph coloring problem by Lierler and Balduccini; for instances see [18]. KnightTour: finding a tour for the knight piece traveling any square following the rules of chess by Zhou, Calimeri, and Santoro; for instances see [18]. Labyrinth: classical Ravensburger's Labyrinth puzzle by Gebser; for instances see [18]. MinimalDiagnosis: an application in systems biology [67]; for instances see [18]. MSS/MUS: problem whether a clause belongs to some minimal unsatisfiable subset [94]; instances provided by Gebser and Kaminski [60]. Solitaire: classical Peg Solitaire puzzle by Lierler and Balduccini; for instances see [18]. StrategicCompanies: encoding the Σ_2^P -complete problem of producing and owning companies and strategic sets between the companies [63]. RandomQBF: translations of randomly generated 2-QBF instances using the method by Chen and Interinal [20]; for instances see [63]. RLP: Randomly generated normal programs, of various density (number of rules divided by the number of atoms) [155]; for instances see [63]. RandomNonTight: Randomly generated normal programs in [61] with n=40, 50, and 60 variables, respectively with 40 instances per step instances.

The results obtained with ILP methods using modern solvers like CPLEX and Gurobi come along with a certain inaccuracy (see e.g., [25,24,140]). Therefore, we ran Clasp on the structured instances using the encoding of k-vertex cover problem described above to obtain optimality.

Table 1 illustrates our results on the size of small strong **Horn**-backdoors of the considered benchmark instances. We mainly used benchmark sets from the first three Answer Set Programming Competitions [18,29,63], because most of the instances contain only normal and/or disjunctive rules and no extended rules (cardinality/weight-constraints).³ We reference in the caption of Table 1 from where the instances have been taken and indicate in the table the number of instances of each benchmark set.

The structured instances have, as expected, significantly smaller strong **Horn**-backdoors than the random instances. We would like to mention that the random programs from the ASP competitions contain a rather small number of atoms. So far we have no good evidence why in particular the sets <code>KnightTour</code> and <code>Solitaire</code> have rather large strong **Horn**-backdoors compared to other structured instances.

5. Target classes based on acyclicity

There are two causes for a program to have a large number of answer sets: (i) disjunctions in the heads of rules, and (ii) certain cyclic dependencies between rules. Disallowing both yields enumerable classes.

In order to define acyclicity we associate with each disjunctive program P its dependency digraph D_P and its (undirected) dependency graph U_P . The dependency digraph was defined by Apt et al. [2] which slight differs from our notion as no additional edges on head atoms are introduced. The following definition is closely related to the notion suggested by Gottlob et al. [85].

Definition 5.1. Let P be a program. The *dependency digraph* is the digraph D_P which has as vertices the atoms of P and a directed edge (x, y) between any two distinct atoms x, y for which there is a rule $r \in P$ with $x \in H(r)$ and $y \in B^+(r) \cup B^-(r)$ or $x, y \in H(r)$. We call the edge (x, y) *negative* if there is a rule $r \in P$ with $x \in H(r)$ and $y \in B^-(r)$ or $x, y \in H(r)$.

Definition 5.2. Let P be a program. The (undirected) dependency graph is the graph U_P obtained from the dependency digraph D_p

- 1. by replacing each negative edge e = (x, y) with two edges xv_e , v_ey where v_e is a new negative vertex, and
- 2. by replacing each remaining directed edge (u, v) with an edge uv.

³ We are aware that one can preprocess extended rules and compile them into normal rules. Even though recent versions of the solver Clasp provide such an option [66], those compilations blow up the instances significantly. Hence we omitted it for pragmatic reasons.

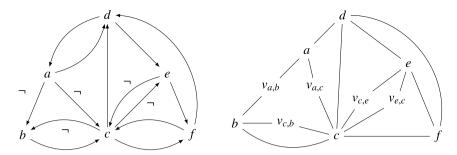


Fig. 3. Dependency digraph D_P (left) and dependency graph U_P (right) of the program P of Example 2.1.

Example 5.1. Fig. 3 visualizes the dependency digraph D_P and the dependency graph U_p of the program P of Example 2.1.

Definition 5.3. Let *P* be a program.

- 1. A directed cycle of P is a directed cycle in the dependency digraph D_P .
- 2. A directed cycle is bad if it contains a negative edge, otherwise it is good.
- 3. A directed cycle is even if it contains an even number of negative edges, otherwise it is odd.
- 4. A cycle of P is a cycle in the dependency graph U_P .
- 5. A cycle is bad if it contains a negative vertex, otherwise it is good.
- 6. A cycle is even if it contains an even number of negative vertices, otherwise it is odd.

Definition 5.4. The following classes of programs are defined in terms of the absence of certain kinds of cycles:

- no-C contains all programs that have no cycles,
- no-BC contains all programs that have no bad cycles,
- no-DC contains all programs that have no directed cycles,
- no-DC2 contains all programs that have no directed cycles of length at least 3 and no directed bad cycles,
- no-DBC contains all programs that have no directed bad cycles,
- no-EC contains all programs that have no even cycles,
- no-BEC contains all programs that have no bad even cycles,
- no-DEC contains all programs that have no directed even cycles, and
- no-DBEC contains all programs that have no directed bad even cycles.

We let Acyc denote the family of all the nine classes defined above. We also write \mathcal{D} -Acyc to denote the subfamily {**no-DC**, **no-DBC**, **no-DBC**, **no-DBC**, **no-DBC**} $\subseteq Acyc$.

Example 5.2. Consider the dependency graphs of the program P of Example 2.1 as depicted in Fig. 3. For instance the sequence (d, e, f) is a cycle, (d, a) is a directed cycle (of length 2), (d, e, f) and (c, e, f) are directed cycles (of length 3), $(a, v_{(a,c)}, c, d)$ is a bad cycle, (b, c) is a directed bad cycle. The sequence (d, e, f) is an even cycle and a directed even cycle, (c, e) is a directed bad even cycle.

The set $X = \{c\}$ is a strong **no-DBEC**-backdoor since the truth assignment reducts $P_{c=0} = P_0 = \{d \leftarrow a, e; a \leftarrow d, \neg b; e \leftarrow f; f\}$ and $P_1 = \{d \leftarrow a, e; f \leftarrow d; b; f\}$ are in the target class **no-DBEC**. X is also a strong **no-BEC**-backdoor, since $P_0 \in \text{no-BEC}$ and $P_1 \in \text{no-BEC}$. The answer sets of P_τ are $AS(P_{\bar{c}}) = \{\{e, f\}\}$ and $AS(P_c) = \{\{b, f\}\}$. Thus, $AS(P, X) = \{\{e, f\}, \{b, c, f\}\}$, and since only $\{b, c, f\}$ is an answer set of P, we obtain $AS(P) = \{\{b, c, f\}\}$.

The dependency and dependency digraphs contain bad even cycles through head atoms for non-singleton heads. This has the following consequence.

Observation 5.5. $C \subseteq Normal$ holds for all $C \in Acyc$.

If we have two programs $P \subseteq P'$, then clearly the dependency (di)graph of P is a sub(di)graph of the dependency (di)graph of P'. This has the following consequence.

Observation 5.6. All $C \in Acyc$ are hereditary.

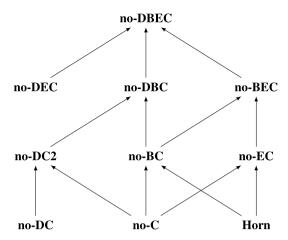


Fig. 4. Relationship between classes of programs with respect to their generality. A directed path from a class \mathcal{C} to a class \mathcal{C}' indicates that $\mathcal{C} \subseteq \mathcal{C}'$. If there is no path between two classes \mathcal{C} and \mathcal{C}' , then neither $\mathcal{C} \subseteq \mathcal{C}'$ nor $\mathcal{C}' \subseteq \mathcal{C}$ and we say \mathcal{C} and \mathcal{C}' are incomparable.

The following is a direct consequence of the definitions of the various classes in Acyc.

Observation 5.7. If $C, C' \in Acyc \cup \{\text{Horn}\}$ such that the digraph in Fig. 4 contains a directed path from the class C to the class C', then $C \subseteq C'$. If no inclusion between two classes is indicated, then the classes are in fact incomparable.

Proof. We first consider the acyclicity-based target classes. By definition we have **no-DC** \subsetneq **no-DBC** and **no-C** \subsetneq **no-BC** \subsetneq **no-DBC**; it is easy to see that the inclusions are proper. However, contrary to what one expects, **no-C** \nsubseteq **no-DC**, which can be seen by considering the program $P_1 = \{x \leftarrow y, y \leftarrow x\}$. But the class **no-DC2** which requires that a program has no directed cycles but may have directed good cycles of length 2 (as in P_1) generalizes both classes **no-C** and **no-DC**. By definition we have **no-DBC** \subsetneq **no-DBEC**, **no-DEC**, **no-DBEC**, **no-DEC**, **no-BEC**, **no-EC**, **no-EC**, **no-EC**, **no-DEC**.

Next we consider the target class **Horn**. Let $C \in \{\text{no-C}, \text{no-DC}, \text{no-DC}\}$. We easily observe that **Horn** $\nsubseteq C$ by considering the program $P_2 = \{a \leftarrow b; b \leftarrow c; c \leftarrow a\}$ which is obviously Horn but does not belong to C. Conversely, we observe that $C \nsubseteq \text{Horn}$ by considering the program $P_3 = \{a \leftarrow \neg b\}$ which belongs to C but is obviously not Horn. Thus, C and **Horn** are incomparable. We observe that **Horn** $\subsetneq \text{no-BC}$ by again considering the program P_3 which belongs to **no-BC**, but is obviously not Horn, and by considering the fact that all rules C in a Horn program C satisfy C and C and C which yields that the dependency graph C contains no bad vertices and hence gives us that C contains no bad cycles. C

The class **no-DBC** coincides with the well-known class of *stratified* programs [2,77,19]. A normal program P is *stratified* if there is a mapping $str : at(P) \to \mathbb{N}$, called *stratification*, such that for each rule r in P the following holds: (i) if $x \in H(r)$ and $y \in B^+(r)$, then $str(x) \le str(y)$ and (ii) if $x \in H(r)$ and $y \in B^-(r)$, then str(x) < str(y).

Lemma 5.8. (See Apt et al. [2].) **Strat** = **no-DBC**.

The class **no-DBEC**, the largest class in $\mathcal{A}cyc$, has already been studied by Zhao and Lin [156,110], who showed that every program in **no-DBEC** has at most one answer set, and this answer set can be found in polynomial time. For **no-DBC** the unique answer set can even be found in linear time [121].

In our context this has the following important consequence.

Proposition 5.9. All classes in Acyc are enumerable, the classes $C \in Acyc$ with $C \subseteq$ **no-DBC** are even linear-time enumerable.

In view of Observation 5.5 and Proposition 5.9, all classes in $\mathcal{A}cyc$ satisfy the requirement of Theorem 3.9 and are therefore in principle suitable target classes of a backdoor approach. Therefore we will study the parameterized complexity of Strong \mathcal{C} -Backdoor Detection and Deletion \mathcal{C} -Backdoor Detection for $\mathcal{C} \in \mathcal{A}cyc$. As we shall see in the next two subsections, the results for Strong \mathcal{C} -Backdoor Detection are throughout negative, however for Deletion \mathcal{C} -Backdoor Detection there are several (fixed-parameter) tractable cases.

5.1. Strong backdoor detection

Proposition 5.10. Assume that the input program may contain tautological rules. Then, for every target class $C \in Acyc$, the problem Strong C-Backdoor Detection is W[2]-hard, and hence unlikely to be fixed-parameter tractable.

Proof. We give an fpt-reduction from the W[2]-complete problem HITTING SET (see Section 2.3) to STRONG \mathcal{C} -BACKDOOR DETECTION. Let (S,k) be an instance of this problem with $S = \{S_1,\ldots,S_m\}$. We construct a program P as follows. As atoms we take the elements of $U = \bigcup_{i=1}^m S_i$ and new atoms a_i^j and b_i^j for $1 \le i \le m$, $1 \le j \le k+1$. For each $1 \le i \le m$ and $1 \le j \le k+1$ we take two rules r_i^j , s_i^j where $H(r_i^j) = \{a_i^j\}$, $B^-(r_i^j) = S_i \cup \{b_i^j\}$, $B^+(r_i^j) = S_i$ (which is a tautological rule); $H(s_i^j) = \{b_i^j\}$, $B^-(s_i^j) = \{a_i^j\}$, $B^+(s_i^j) = \emptyset$.

We show that S has a hitting set of size at most k if and only if P has a strong C-backdoor of size at most k.

(⇒) Let H an hitting set of S of size at most k. We choose an arbitrary truth assignment $\tau \in 2^H$ and show that $P_{\tau} \in C$. Since H is a hitting set, each rule r_i^j will be removed when forming P_{τ} . Hence the only rules left in P_{τ} are the rules s_i^j , and so $P_{\tau} \in \mathbf{no-DC} \cap \mathbf{no-C} \subseteq \mathcal{C}$. Thus, H is a strong \mathcal{C} -backdoor of P.

(⇐) Let X be a strong \mathcal{C} -backdoor of P of size at most k. We show that $H = X \cap U$ is a hitting set of S. Choose $1 \le i \le m$ and consider S_i . We first consider the case **no-DC** ⊆ \mathcal{C} . For each $1 \le j \le k+1$ the program P contains a bad even directed cycle (a_i^j, b_j^i) . In order to destroy these cycles, X must contain an atom from S_i , since otherwise, X would need to contain for each $1 \le j \le k+1$ at least one of the atoms from each cycle, but then $|X| \ge k+1$, contradicting the assumption on the size of X. Hence H is a hitting set of S. Now we consider the case **no-C** ⊆ C. For each $1 \le j \le k+1$ the program P contains a bad even cycle $(a_i^j, v_{a_i^j, b_i^j}, v_{b_i^j, a_i^j})$. In order to destroy these cycles, X must contain an atom from S_i , since otherwise, X would need to contain an atom from each cycle, again a contradiction. Hence H is a hitting set of S. Consequently, the WI21-hardness of Strong C-Backdoor Detection follows. \square

For the target classes in \mathcal{D} -Acyc we can avoid the use of tautological rules in the reduction and so strengthen Proposition 5.10 as follows (it would be interesting to know if this is also possible for the remaining classes mentioned in Proposition 5.10).

Theorem 5.11. For every target class $C \in \mathcal{D}$ -Acyc, the problem Strong C-Backdoor Detection is W[2]-hard, and hence unlikely to be fixed-parameter tractable.

Proof. In order to show that Strong \mathcal{C} -Backdoor Detection is W[2]-hard for $\mathcal{C} \in \mathcal{D}$ -Acyc when we forbid tautological rules in the input, we modify the reduction used in the proof of Proposition 5.10 from Hitting Set by redefining the rules r_i^j , s_i^j . We put $H(r_i^j) = \{a_i^j\}$, $B^-(r_i^j) = S_i \cup \{b_i^j\}$, $B^+(r_i^j) = \emptyset$; $H(s_i^j) = \{b_i^j\}$, $B^-(s_i^j) = \{a_i^j\}$, $B^+(s_i^j) = U$. By the very same argument as in the proof of Proposition 5.10 we can show that S has a hitting set of size at most k if and only if P has a strong C-backdoor of size at most k. We would like to mention that this reduction does not work for the undirected cases as it yields undirected cycles $(b_i^j, u, b_i^{j'}, u')$ for any $u, u' \in U$. \square

For the class **no-DBEC** we can again strengthen the result and show that detecting a strong **no-DBEC**-backdoor is already co-NP-hard for backdoor size 0; hence the problem is co-paraNP-hard (see Section 2.3).

Theorem 5.12. The problem Strong **no-DBEC**-Backdoor Detection is co-paraNP-hard, and hence not fixed-parameter tractable unless P = co-NP.

Proof. Recall that a path does not visit the same vertex twice. We reduce from the following problem, which is NP-complete [52,104],

DIRECTED PATH VIA A NODE

Given: A digraph G and $s, m, t \in V$ distinct vertices.

Task: Decide whether G contains a directed path from s to t via m.

Let G = (V, E) be a digraph and $s, m, t \in V$ distinct vertices. We define a program P as follows: For each edge $e = (v, w) \in E$ where $w \neq m$ we take a rule r_e : $w \leftarrow v$. For each edge e = (v, m) we take a rule r_e : $m \leftarrow \neg v$. Finally we add the rule $r_{s,t}$: $s \leftarrow \neg t$. We observe that the dependency digraph of P is exactly the digraph we obtain from G by adding the "reverse" edge (t, s) (if not already present), and by marking (t, s) and all incoming edges of m as negative.

We show that G has a path from s to t via m if and only if $P \notin \mathbf{no-DBEC}$. Assume G has such a path. Then this path must contain exactly one incoming edge of m, and hence it contains exactly one negative edge. The path, together with the negative edge (t, s), forms a directed bad even cycle of P, hence $P \notin \mathbf{no-DBEC}$. Conversely, assume $P \notin \mathbf{no-DBEC}$. Hence the dependency digraph of P contains a directed bad even cycle, i.e., a cycle that contains at least two negative edges. As it can contain at most one incoming edge of m, the cycle contains exactly one incoming edge of m and the reverse edge (t, s). Consequently, the cycle induces in G a directed path from s to t via m. \square

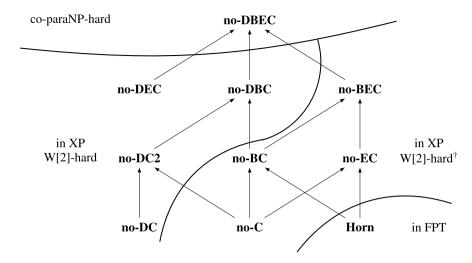


Fig. 5. Known complexity of the problem Strong C-Backdoor Detection. † When we allow tautologies in the input program, see Theorem 5.11.

Fig. 5 illustrates the known complexity results of the problem Strong \mathcal{C} -Backdoor Detection. An arrow from \mathcal{C} to \mathcal{C}' indicates that \mathcal{C}' is a proper subset of \mathcal{C} and hence the size of a smallest strong \mathcal{C}' -backdoor is at most the size of a smallest strong \mathcal{C} -backdoor.

Remark. Note that the unparameterized version of STRONG C-BACKDOOR DETECTION for the acyclicity-based target classes C is NP-hard since W[2]-hardness implies NP-hardness and co-paraNP-hardness also implies co-NP-hardness. Moreover, the reduction presented in the proof of Proposition 5.10 and Theorems 5.11, 5.12 can be used straightforward as a reduction of the unparameterized version of Hitting Set, Directed Path VIA a Node respectively, to STRONG C-BACKDOOR DETECTION.

5.2. Deletion backdoor detection

The W[2]-hardness results of Theorems 5.11 and 5.12 suggest to relax the problem and to look for *deletion backdoors* instead of strong backdoors. In view of Lemma 3.4 and Observation 5.6, every deletion backdoor is also a strong backdoor for the considered acyclicity-based target classes, hence the backdoor approach of Theorem 3.9 works.

Fortunately, the results of this section show that the relaxation indeed gives us fixed-parameter tractability of backdoor detection for most considered classes. Fig. 6 illustrates these results that we obtain by making use of very recent progress in fixed-parameter algorithmics on various variants of *feedback vertex set* and *cycle transversal* problems.

Consider a graph G = (V, E) and a set $W \subseteq V$. A cycle in G is a W-cycle if it contains at least one vertex from W. A set $T \subseteq V$ is a W-cycle transversal of G if every W-cycle of G is also a T-cycle. A set $T \subseteq V$ is an even-length W-cycle transversal of G if every W-cycle of G of even length is also a T-cycle. A V-cycle transversal is also called a feedback vertex set.

We give analog definitions for a digraph G = (V, E) and $W \subseteq V$. A directed cycle in G is a directed W-cycle if it contains at least on vertex from W. A set $T \subseteq V$ is a directed W-cycle transversal of G if every directed W-cycle of G is also a directed G-cycle. A set G is an directed even-length G if every directed G-cycle of G of even length is also a directed G-cycle. A directed G-cycle transversal is also called a directed feedback vertex set.

Theorem 5.13. The problem Deletion C-Backdoor Detection is fixed-parameter tractable for all $C \in Acyc \setminus \{\text{no-DEC}, \text{no-DBEC}\}$.

Proof. Let P be a program and $k \ge 0$. Let U_p be the dependency graph and D_p the dependency digraph of P, respectively. Next we consider the various target classes C mentioned in the statement of the theorem, one by one, and show how we can decide whether P has a deletion C-backdoor of size at most k.

First we consider "undirected" target classes. Downey and Fellows [34,35] have shown that finding a feedback vertex set of size at most k is fixed-parameter tractable. We apply their algorithm to the dependency graph U_p . If the algorithm produces a feedback vertex set S of size at most k, then we can form a deletion $\operatorname{no-C-backdoor}$ of P of size at most k by replacing each negative vertex in S by one of its two neighbors, which always gives rise to an atom of P. If U_p has no feedback vertex set of size at most k, then P has no deletion $\operatorname{no-C-backdoor}$ of size at most k. Hence Deletion $\operatorname{no-C-Backdoor}$ Detection is fixed-parameter tractable. Similarly, Deletion $\operatorname{no-BC-Backdoor}$ Detection is fixed-parameter tractable by finding a W-feedback vertex set of U_p , taking as W the set of bad vertices of U_p . Cygan et al. [26] and Kawarabayashi and Kobayashi [102] showed that finding a W-feedback vertex set is fixed-parameter tractable, hence so is Deletion $\operatorname{no-BC-Backdoor}$ Detection.

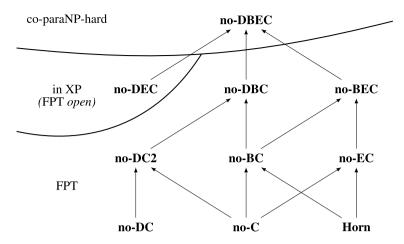


Fig. 6. Relationship between classes of programs and known complexity of the problem Deletion C-BackDoor Detection. An arrow from C to C' indicates that deletion C-backdoors are smaller than deletion C'-backdoors. The FPT-results are established in Theorems 4.4 and 5.13. The XP-result is established in Theorem 5.15. The co-paraNP-hardness result is established in Theorem 5.16.

In order to extend this approach to Deletion **no-EC**-Backdoor Detection, we would like to use fixed-parameter tractability of finding an even W-cycle transversal, which was established by Misra et al. [116] for W=V, and by Kakimura et al. [98] for general W. In order to do this, we use the following trick of Aracena, Gajardo, and Montalva [117] that turns cycles containing an even number of bad vertices into cycles of even length. From D_p we obtain a graph U_p' by replacing each negative edge e=(x,y) with three edges xu_e , u_ev_e , and v_ev_e where v_e and v_ev_e are new negative vertices, and by replacing each remaining directed edge (u,v) with two edges uw_e and w_ev_e where w_e is a new (non-negative) vertex. We observe that U_p' can be seen as being obtained from D_p by subdividing edges. Hence there is a natural 1-to-1 correspondence between cycles in U_p and cycles in U_p' . Moreover, a cycle of U_p containing an even number of negative vertices corresponds to a cycle of U_p' of even length, and a bad cycle of U_p corresponds to a bad cycle of U_p' . Thus, when we have an even cycle transversal S of U_p' , we obtain a deletion **no-EC**-backdoor by replacing each negative vertex $v \in S$ by its non-negative neighbor. Hence Deletion **no-EC**-Backdoor Detection is fixed-parameter tractable. For Deletion **no-BEC**-Backdoor Detection we proceed similarly, using a even W-cycle transversal of U_p' , letting W be the set of negative vertices of U_p' .

We now proceed with the remaining "directed" target classes no-DC, no-DC2, and no-DBC.

Let G = (V, E) be a digraph. Evidently, the directed feedback vertex sets of D_p are exactly the deletion **no-DC**-backdoors of P. Hence, by using the fixed-parameter algorithm of Chen et al. [21] for finding directed feedback vertex sets we obtain fixed-parameter tractability of Deletion **no-DC**-Backdoor Detection.

To make this work for Deletion **no-DC2**-Backdoor Detection we consider instead of D_p the digraph D_p' obtained from D_p by replacing each negative edge e = (u, v) by two (non-negative) edges (u, w_e) , (w_e, v) , where w_e is a new vertex. The directed cycles of D_p and D_p' are in a 1-to-1 correspondence. However, directed cycles of length 2 in D_p' correspond to good cycles of length 2 in D_p . Bonsma and Lokshtanov [12] showed that finding a directed feedback vertex set that only needs to cut cycles of length at least 3 is fixed-parameter tractable. Applying this algorithm to D_p' (and replacing each vertex w_e in a solution with one of its neighbors) yields fixed-parameter tractability of Deletion **no-DC2**-Backdoor Detection.

The approach for Deletion **no-DC**-Backdoor Detection extends to Deletion **no-DBC**-Backdoor Detection by considering directed W-feedback vertex sets of the digraph D_p' obtained from D_p using a simple construction already mentioned by Cygan et al. [26] where we replace each negative edge e = (u, v) by two (non-negative) edges (u, w_e) , (w_e, v) and $W = \{w_e : e \text{ is a negative edge}\}$. The directed W-cycles of D_p' and the directed bad cycles of D_p are obviously in a 1-to-1 correspondence. Thus, when we have a directed W-feedback vertex set S of D_p' , we obtain a deletion **no-DBC**-backdoor by replacing each vertex $v \in S \cap W$ by its neighbor. The fixed-parameter tractability of finding a directed W-feedback vertex set was shown by Chitnis et al. [23]. \square

According to Observation 5.6, the classes mentioned in Theorem 5.13 are hereditary. Hence using Theorem 5.13 we can drop the assumption in Theorem 3.9 that the backdoor is given. We obtain directly the following results:

Theorem 5.14. For all $C \in Acyc \setminus \{$ **no-DEC** $\}$ all problems in AspFull are fixed-parameter tractable when parameterized by the size of a smallest deletion C-backdoor.

Let us now turn to the two classes **no-DEC**, **no-DBEC** excluded in Theorem 5.13. We cannot establish that DELETION **no-DEC**-BACKDOOR DETECTION is fixed-parameter tractable, as the underlying even cycle transversal problem seems to be currently out of reach to be solved. However, in Theorem 5.15 below, we can at least show that for every constant k, we

can decide in polynomial time whether a strong **no-DEC**-backdoor of size at most k exists; thus, the problem is in XP. For DELETION **no-DBEC**-BACKDOOR DETECTION the situation is different: here we can rule out fixed-parameter tractability under the complexity theoretical assumption $P \neq \text{co-NP}$ (Theorem 5.16).

Theorem 5.15. The problem Deletion **no-DEC-**Backdoor Detection is in XP.

Proof. Let P be a program, n the input size of P, and k be a constant. We are interested in a deletion **no-DEC**-backdoor of P of size at most k. We loop over all possible sets $X \subseteq \operatorname{at}(P)$ of size at most k. Since k is a constant, there is a polynomial number $\mathcal{O}(n^k)$ of such sets X. To decide whether X is a deletion **no-DEC**-backdoor of P, we need to check whether $P - X \in$ **no-DEC**. For the membership check $P - X \in$ **no-DEC** we have to decide whether D_{P-X} contains a bad even cycle. We use a directed variant of the trick in the proof of Theorem 5.13 (in fact, the directed version is slightly simpler). Let D_{P-X} be the dependency digraph of P - X. From D_{P-X} we obtain a new digraph D'_{P-X} by subdividing every non-negative edge, i.e., we replace each non-negative edge e = (x, y) by two (non-negative) edges (x, u_e) , (u_e, y) where u_e is a new vertex. Obviously, directed even cycles in D_{P-X} are in 1-to-1 correspondence with directed cycles of even length in D'_{P-X} . Whether a digraph contains a directed cycle of even length can be checked in polynomial time by means of the following results: Vazirani and Yannakakis [151] have shown that finding a cycle of even length in a digraph is equivalent to finding a so-called Pfaffian orientation of a graph. Robertson, Seymour, and Thomas [133] have shown that a Pfaffian orientation can be found in polynomial time, hence the test works in polynomial time.

Theorem 5.16. The problem Deletion **no-DBEC**-Backdoor Detection is co-paraNP-hard, and hence not fixed-parameter tractable unless P = co-NP

Proof. The theorem follows from the reduction in the proof of Theorem 5.12. \Box

Remark. We note that the unparameterized version of Deletion C-Backdoor Detection for the acyclicity-based target classes C is NP-hard and co-NP-hard respectively, since the reduction presented in the proof of Theorems 5.13 and 5.15 can be used straightforward as a reduction of the unparameterized version of the variants of the minimal feedback vertex set problem, Directed Path via a Node respectively, to Deletion C-Backdoor Detection.

5.3. Backdoors of benchmark instances

For the acyclicity based target classes $C \in Acyc$ we have computed small deletion C-backdoors only for very few selected instances with moderate size since the currently available algorithms can only deal with rather small instances within a reasonable computation time. The size of small deletion **no-C**-backdoors of selected instances of Solitaire was about half of the size of small strong **Horn**-backdoors.

6. Kernelization

If we want to solve a hard problem, then in many settings, it is beneficial to first apply a polynomial preprocessing to a given problem instance. In particular, polynomial-time preprocessing techniques have been developed in ASP solving (see e.g., [45,65,68]). However, polynomial-time preprocessing for NP-hard problems has mainly been subject of empirical studies where provable performance guarantees are missing, mainly due to the fact, that if we can show that we can reduce in polynomial-time a problem instance by just one bit, then by iterating this reduction we can solve the instances in polynomial time. In contrast, the framework of parameterized complexity offers with the notion of kernelization a useful mathematical framework that admits the rigorous theoretical analysis of polynomial-time preprocessing for NP-hard problems. A kernelization is a polynomial-time reduction that replaces the input by a smaller input, called a "kernel", whose size is bounded by some computable function of the parameter only. A well known result of parameterized complexity theory is that a decidable problem is fixed-parameter tractable if and only if it admits a kernelization [36]. The result leads us to the question of whether a problem also has a kernelization that reduces instances to a size which is polynomially bounded by the parameter, so-called polynomial kernels. Indeed, many NP-hard optimization problems admit polynomial kernels when parameterized by the size of the solution [134]. In the following we consider kernelizations for backdoor detection and backdoor evaluation in the context of ASP. We establish that for some target classes, backdoor detection admits a polynomial kernel. We further provide strong theoretical evidence that for all target classes considered, backdoor evaluation does not admit a polynomial kernel.

We will later use the following problem:

VERTEX COVER

Given: A graph G = (V, E) and an integer k.

Parameter: The integer *k*.

Task: Decide whether there is a vertex cover $S \subseteq V$ (see Section 4) of size at most k.

Next we give a more formal definition of kernelization. Let $L, L' \subseteq \Sigma^* \times \mathbb{N}$ be parameterized problems. A *bi-kernelization* is a polynomial-time many-to-one reduction from the problem L to problem L' where the size of the output is bounded by a computable function of the parameter. That is, a bi-kernelization is an algorithm that, given an instance $(I,k) \in \Sigma^* \times \mathbb{N}$ outputs for a constant c in time $\mathcal{O}((\|I\|+k)^c)$ a pair $(I',k') \in \Sigma^* \times \mathbb{N}$, such that (i) $(I,k) \in L$ if and only if $(I',k') \in L'$ and (ii) $\|I'\|+k' \leq g(k)$ where g is an arbitrary computable function, called the size of the kernel. If L'=L then the reduction is called a *kernelization*, the reduced instance a *kernel*. If g is a polynomial then we say that L admits a *polynomial bi-kernel*, or *polynomial kernel* if in addition L=L'. For instance, the problem Vertex Cover has a kernel of at most 2k vertices and thus admits a polynomial kernel [22]. L is called *compressible* if it admits a polynomial bi-kernel.

The following proposition states the connection between fixed-parameter tractable problems and kernels, as observed by Downey, Fellows, and Stege [36]:

Proposition 6.1. (See Downey et al. [36], Flum and Grohe [50].) A parameterized problem is fixed-parameter tractable if and only if it is decidable and has a kernelization.

Thus, our fixed-parameter tractability results of Theorems 3.9, 4.4, and 5.13 immediately provide that the mentioned problems admit a kernelization. In the following we investigate whether these problems admit polynomial kernels.

6.1. Backdoor detection

The first result of this section is quite positive.

Theorem 6.2. For $C \in \{\text{Horn, no-C}\}\)$ the problem Deletion C-Backdoor Detection admits a polynomial kernel. For C = Horn the kernel has a linear number of atoms, for C = no-C the kernel has a quadratic number of atoms.

Proof. First consider the case $C = \mathbf{Horn}$. Let (P,k) be an instance of Deletion **Horn**-Backdoor Detection. We obtain in polynomial time the negation dependency graph N_p of P (see Definition 4.2) and consider (N_p,k) as an instance of Vertex Cover. We use the kernelization algorithm of Chen et al. [22] for Vertex Cover and reduce in polynomial time (N_p,k) to a Vertex Cover instance (G,k') where G = (V,E) with at most 2k many vertices. It remains to translate G into a program P' where $N_{p'} = G$ by taking for every edge $xy \in E$ a rule $x \leftarrow \neg y$. Now (P',k') is a polynomial kernel with a linear number of atoms.

Second consider the case $C = \mathbf{no}$ -C. Let (P,k) be an instance of Deletion \mathbf{no} -C-Backdoor Detection. We obtain in polynomial time the dependency graph U_p of P and consider (U_p,k) as an instance of Feedback Vertex Set (see Section 5.2). We use the kernelization algorithm of Thomassé [146] for Feedback Vertex Set and reduce in polynomial time (U_p,k) to a Feedback Vertex Set instance (G',k') with at most $4k^2$ vertices. As above we translate G=(V,E) into a program P' where $U_{p'}=G$ by taking for every edge $xy\in E$ a rule $x\leftarrow \neg y$. Now (P',k') is a polynomial kernel with a quadratic number of atoms. \square

Similar to the construction in the proof of Theorem 5.13 we can reduce for the remaining classes the backdoor detection problem to variants of feedback vertex set. However, for the other variants of feedback vertex set no polynomial kernels are known.

We would like to point out that the kernels obtained in the proof of Theorem 6.2 are equivalent to the input program with respect to the existence of a backdoor, hence the kernels can be used to find a backdoor. However the obtained kernels are not equivalent with respect to the decision of the problems in AspReason, in consequence the kernel cannot be used for backdoor evaluation. In the next subsection we consider kernels with respect to problems in AspReason.

6.2. Backdoor evaluation

Next we consider the problems in $Asp\Re eason$. We will see that neither of them admits a polynomial kernel when parameterized by the size of a strong C-backdoor for the considered target classes, subject to standard complexity theoretical assumptions.

Our superpolynomial lower bounds for kernel size are based on a result by Fortnow and Santhanam [51] regarding satisfiability parameterized by the number of variables.

SAT[VARS]

Given: A CNF formula *F*.

Parameter: The number k of variables of F. Task: Decide whether F is satisfiable.

Proposition 6.3. (See Fortnow and Santhanam [51].) If SAT[VARS] is compressible, then NP \subseteq co-NP/poly.

The complexity class NP/poly consists of all problems that can be solved non-deterministically in non-uniform polynomial time, i.e., by a non-deterministic polynomial-time Turing machine with an additional polynomial-bounded input that depends only on the length of the input, but not on the input itself (advice function), for details see e.g., [100]. It is well-known from Yap's Theorem [154] that if NP \subseteq co-NP/poly then the Polynomial Hierarchy collapses to its third level $(\Sigma_3^P = \Pi_3^P)$ which is considered unlikely by standard complexity theoretical assumptions.

The following theorem extends a result for normal programs [58]. We need a different line of argument, as the technique used in [58] only applies to problems in NP or co-NP.

Theorem 6.4. Let $C \in Acyc \cup \{\text{Horn}\}\$. Then no problem in AspReason admits a polynomial kernel when parameterized by the size of a smallest strong C-backdoor or deletion C-backdoor, unless $NP \subseteq \text{co-NP/poly}$.

Proof. We show that the existence of a polynomial kernel for any of the above problems implies that SAT[VARS] is compressible, and hence by Proposition 6.3 the collapse would follow.

First consider the problem Consistency. From a CNF formula F with k variables we use a reduction of Niemelä [122] and construct a program P_1 as follows: Among the atoms of our program P_1 will be two atoms a_x and $a_{\bar{x}}$ for each variable $x \in var(F)$, an atom b_C for each clause $C \in F$. We add the rules $a_{\bar{x}} \leftarrow \neg a_x$ and $a_x \leftarrow \neg a_{\bar{x}}$ for each variable $x \in var(F)$. For each clause $C \in F$ we add for each $x \in C$ the rule $b_C \leftarrow a_x$ and for each $x \in C$ the rule $b_C \leftarrow a_{\bar{x}}$. Additionally, for each clause $C \in F$ we add the rule $c \leftarrow \neg b_C$. Now it is easy to see that the formula $c \in C$ is satisfiable if and only if the program $c \in C$ has an answer set. We observe that $c \in C$ and $c \in C$ has an answer set. We observe that $c \in C$ has an answer set.

For the problem Brave Reasoning we modify the reduction from above. We create a program P_2 that consists of all atoms and rules from P_1 . Additionally, the program P_2 contains an atom t and a rule r with $H(r) = \{t\}$, $B^+(r) = \emptyset$, and $B^-(r) = \emptyset$. We observe that the formula F is satisfiable if and only if the atom t is contained in some answer set of P_2 . Since X is still a backdoor of size k (2k), and a polynomial kernel for Brave Reasoning, again it would yield that SAT[VARS] is compressible.

Let UnSat[Vars] denote the problem defined exactly like Sat[Vars], just with yes and no answers swapped. A bi-kernelization for UnSat[Vars] is also a bi-kernelization for Sat[Vars] (with yes and no answers swapped). Hence Sat[Vars] is compressible if and only if UnSat[Vars] is compressible. An argument dual to the previous one for Brave Reasoning shows that a polynomial kernel for Skeptical Reasoning, parameterized by backdoor size, would yield that UnSat[Vars] is compressible, which, as argued above, would yield that Sat[Vars] is compressible.

7. Lifting parameters

In this section we will introduce a general method to lift ASP-parameters that are defined for normal programs to disjunctive programs. Thereby we extend several algorithms that have been suggested for normal programs to disjunctive programs. The lifting method also gives us an alternative approach to obtain some results of Section 5.

The following definition allows us to speak about parameters for programs in a more abstract way.

Definition 7.1. An *ASP-parameter* is a function p that assigns to every program P some non-negative integer p(P) such that $p(P') \le p(P)$ holds whenever P' is obtained from P by deleting rules or deleting atoms from rules. If p is only defined for normal programs, we call it a *normal ASP-parameter*. For an ASP parameter p we write p^{\downarrow} to denote the ASP-parameter obtained by restricting p to normal programs.

We impose the condition $p(P') \le p(P)$ for technical reasons. This is not a limitation, as most reasonable parameters and all parameters considered in this paper satisfy this condition.

There are natural ASP-parameters associated with backdoors:

Definition 7.2. For a class \mathcal{C} of programs and a program P let $\operatorname{sb}_{\mathcal{C}}(P)$ denote the size of a smallest strong \mathcal{C} -backdoor and $\operatorname{db}_{\mathcal{C}}(P)$ denote the size of a smallest deletion \mathcal{C} -backdoor of P.

We will "lift" normal ASP-parameters to general disjunctive programs as follows.

Definition 7.3. For a normal ASP-parameter p we define the ASP-parameter p^{\uparrow} by setting, for each disjunctive program P, $p^{\uparrow}(P)$ as the minimum of |X| + p(P - X) over all inclusion-minimal deletion **Normal**-backdoors X of P.

The next lemma shows that this definition is compatible with deletion C-backdoors if $C \subseteq \mathbf{Normal}$. In other words, if C is a class of normal programs, then we can divide the task of finding a deletion C-backdoor for a program P into two parts: (i) to find a deletion \mathbf{Normal} -backdoor X, and (ii) to find a deletion C-backdoor of P - X.

Lemma 7.4 (Self-lifting). Let \mathcal{C} be a class of normal programs. Then $db_{\mathcal{C}}(P) = (db_{\mathcal{C}}^{\downarrow})^{\uparrow}(P)$ for every program P.

Proof. Let \mathcal{C} be a class of normal programs, and P a program. Let X be a deletion \mathcal{C} -backdoor of P of size $\mathrm{db}_{\mathcal{C}}(P)$. Thus, $P-X\in\mathcal{C}\subseteq \mathbf{Normal}$. Hence X is a deletion \mathbf{Normal} -backdoor of P. We select an inclusion-minimal subset X' of X that is still a deletion \mathbf{Normal} -backdoor of P (say, by starting with X'=X, and then looping over all the elements X' of X, and if $X'\setminus\{X\}$ is still a deletion \mathcal{C} -backdoor, then setting $X':=X'\setminus\{X\}$. What we end up with is an inclusion-minimal deletion \mathbf{Normal} -backdoor X' of P of size at most $\mathrm{db}_{\mathcal{C}}(P)$. Let P'=P-X' and $X''=X\setminus X'$. P' is a normal program. Since P'-X''=P-X, it follows that $P'-X''\in\mathcal{C}$. Hence X'' is a deletion \mathcal{C} -backdoor of P. Thus, by the definition of $\mathrm{db}_{\mathcal{C}}^{\uparrow}(P)$ we have that $\mathrm{db}_{\mathcal{C}}^{\uparrow}(P)\leq |X'|+|X''|=\mathrm{db}_{\mathcal{C}}(P)$.

Conversely, let $\mathrm{db}_{\mathcal{C}}^{\uparrow}(P) = k$. Hence there is a deletion **Normal**-backdoor X' of P such that $|X'| + \mathrm{db}_{\mathcal{C}}(P - X') = k$. Let P' = P - X'. Since $\mathrm{db}_{\mathcal{C}}(P') \leq k - |X'|$, it follows that P' has a deletion \mathcal{C} -backdoor X'' of size k - |X'|. We put $X = X' \cup X''$ and observe that $P - X = P' - X'' \in \mathcal{C}$. Hence X is a deletion \mathcal{C} -backdoor of P. Since $\mathrm{db}_{\mathcal{C}}(P) \leq |X| \leq |X'| + |X''| \leq \mathrm{db}_{\mathcal{C}}^{\uparrow}(P) \leq k$, the lemma follows. \square

Example 7.1. Consider the program P of Example 2.1 and let #neg(P) denote the number of atoms that appear in negative rule bodies of a normal program (we will discuss this parameter in more detail in Section 8.2).

We determine $\# neg^{\uparrow}(P) = 2$ by the following observations: The set $X_1 = \{c\}$ is a deletion **Normal**-backdoor of P since $P - X_1 = \{d \leftarrow a, e; a \leftarrow d, \neg b; e \leftarrow f; f \leftarrow d; \leftarrow f, e, \neg b; \leftarrow d; b; f\}$ belongs to the class **Normal**. The set $X_2 = \{e\}$ is a deletion **Normal**-backdoor of P since $P - X_2 = \{d \leftarrow a; a \leftarrow d, \neg b, \neg c; c \leftarrow f; f \leftarrow d, c; c \leftarrow f, \neg b; c \leftarrow d; b \leftarrow c; f\}$ belongs to the class **Normal**. Observe that X_1 and X_2 are the only inclusion-minimal deletion **Normal**-backdoors of the program P. We obtain $\# neg^{\uparrow}(P, X_1) = 2$ since $\# neg(P - X_1) = 1$. We have $\# neg^{\uparrow}(P, X_2) = 3$ since $\# neg(P - X_2) = 2$. Thus, $\# neg^{\uparrow}(P) = 2$.

For every ASP-parameter p we consider the following problem.

Bound[p]

Given: A program P and an integer k.

Parameter: The integer k.

Task: Decide whether p(P) ≤ k holds.

For a problem $L \in \mathcal{A}sp\mathcal{Full}$ and an ASP-parameter p we write L[p] to denote the problem L parameterized by p. That is, the instance of the problem is augmented with an integer k, the parameter, and for the input program P it holds that $p(P) \leq k$. Moreover, we write $L[p]_N$ to denote the restriction of L[p] where instances are restricted to normal programs P. Similarly, BOUND $[p]_N$ is the restriction of BOUND[p] to normal programs. For all the problems $L[p]_N$, p only needs to be a normal ASP-parameter.

Next we state the main result of this section.

Theorem 7.5 (Lifting). Let p be a normal ASP-parameter such that $BOUND[p]_N$ and $ENUM[p]_N$ are fixed-parameter tractable. Then for all $L \in \mathcal{AspFull}$ the problem $L[p^{\uparrow}]$ is fixed-parameter tractable.

We need some definitions and auxiliary results to establish the theorem.

Definition 7.6. Let P be a disjunctive program. The *head dependency graph* H_P of the program P is the graph which has as vertices the atoms of P and an edge between any two distinct atoms if they appear together in the head of a rule of P.

Lemma 7.7. Let P be a disjunctive program. A set $X \subseteq at(P)$ is a deletion **Normal**-backdoor of P if and only if X is a vertex cover of the head dependency graph H_P .

Proof. Let X be a deletion **Normal**-backdoor of P. Consider an edge uv of H_P , then there is a rule $r \in P$ with $u, v \in H(r)$ and $u \neq v$. Since X is a deletion **Normal**-backdoor of P, we have $\{u, v\} \cap X \neq \emptyset$. We conclude that X is a vertex cover of H_P .

Conversely, assume that X is a vertex cover of H_P . We show that X is a deletion **Normal**-backdoor of P. Assume to the contrary, that P-X contains a rule r whose head contains two variables u,v. Consequently, there is an edge uv in H_P such that $\{u,v\} \cap X = \emptyset$, contradicting the assumption that X is a vertex cover. \square

Lemma 7.8. Let G = (V, E) be a graph, n = |E|, and let k be a non-negative integer. G has at most 2^k inclusion-minimal vertex covers of size at most k, and we can list all such vertex covers in time $\mathcal{O}(2^k n)$.

Proof. We build a binary search tree T of depth at most k where each node t of T is labeled with a set S_t . We build the tree recursively, starting with the root r with label $S_r = \emptyset$. If S_t is a vertex cover of G we stop the current branch, and t becomes a "success" leaf of T. If t is of distance k from the root and S_t is not a vertex cover of G, then we also stop the current branch, and t becomes a "failure" leaf of T. It remains to consider the case where S_t is not a vertex cover and t is of distance smaller than k from the root. We pick an edge $uv \in E$ such that $u, v \notin S_t$ (such edge exists, otherwise S_t would be a vertex cover) and add two children t', t'' to t with labels $S_{t'} = S_t \cup \{u\}$ and $S_{t''} = S_t \cup \{v\}$. It is easy to see that for every inclusion-minimal vertex cover S of G of size at most k there is a success leaf t with $S_t = S$. Since T has $\mathcal{O}(2^k)$ nodes, the lemma follows. \square

From Lemmas 7.7 and 7.8 we immediately obtain the next result.

Proposition 7.9. Every disjunctive program of input size n has at most 2^k inclusion-minimal deletion **Normal**-backdoors of size at most k, and all these backdoors can be enumerated in time $\mathcal{O}(2^k n)$.

Proof of Theorem 7.5. Let p be a normal ASP-parameter such that $\text{Enum}[p]_N$ and $\text{Bound}[p]_N$ are fixed-parameter tractable. Let P be a given disjunctive program of input size n and k an integer such that $p^{\uparrow}(P) \leq k$. In the following, when we say some task is solvable in "fpt-time", we mean that it can be solved in time $\mathcal{O}(f(k)n^c)$ for some computable function f and a constant c.

By Proposition 7.9 we can enumerate all inclusion-minimal deletion **Normal**-backdoors of size at most k in time $\mathcal{O}(2^k n)$. We can check whether $p(P-X) \le k - |X|$ for each such backdoor X in fpt-time since BOUND[p]_N is fixed-parameter tractable by assumption. Since $p^{\uparrow}(P) < k$, there is at least one such set X where the check succeeds.

We pick such set X and compute AS(P,X) in fpt-time. That this is possible can be seen as follows. Obviously, for each truth assignment $\tau \in 2^X$ the program P_τ is normal since P-X is normal, and clearly $p(P_\tau) \le p(P-X) \le k$ by Definition 7.1. We can compute $AS(P_\tau)$ in fpt-time since ENUM[p]_N is fixed-parameter tractable by assumption. Since there are at most 2^k such programs P_τ , we can indeed compute the set AS(P,X) in fpt-time.

By Lemma 3.6 we have $AS(P) \subseteq AS(P, X)$, hence it remains to check for each $M \in AS(P, X)$ whether it gives rise to an answer set of P. Since X is a deletion **Normal**-backdoor of P, and since one easily observes that **Normal** is hereditary, it follows by Lemma 3.4 that X is a strong **Normal**-backdoor of P. Hence Lemma 3.7 applies, and we can decide whether $M \in AS(P)$ in time $\mathcal{O}(2^k n)$. Hence we can determine the set AS(P) in fpt-time. Once we know the set AS(P), we obtain for every problem $P \in Aspfull$ that $P \in Aspful$

Example 7.2. Consider the program P of Example 2.1 with the deletion **Normal**-backdoor $X_1 = \{c\}$ from Example 7.1. We want to enumerate all answer sets of P. We obtain with Ben-Eliyahu's algorithm [4] the sets $AS(P_{\bar{c}}) = \{\{e, f\}\}$ and $AS(P_c) = \{\{b, f\}\}$, and so we get the set $AS(P, X) = \{\{e, f\}\}$, $\{b, c, f\}\}$ of answer set candidates. By means of the algorithm that solves the problem Strong C-Backdoor ASP CHECK (see Lemma 3.7) we observe that $\{b, c, f\}$ is the only answer set of P.

Remark. Please note that Definitions 4.2 and 5.1 introduce additional edges or certain cycles, respectively, on head atoms for non-singleton heads in the constructed graphs. This construction has the same effect on the size of smallest deletion backdoors into Horn or acyclicity-based target classes as the lifting of corresponding parameters from normal to disjunctive programs.

8. Theoretical comparison of ASP-parameters

In this section we compare several ASP-parameters in terms of their *generality*. Fig. 7 illustrates the results in terms of a lattice. Let p and q be ASP-parameters. We say that p dominates q (in symbols $p \le q$) if there is a function f such that $p(P) \le f(q(P))$ holds for all programs P. The parameters p and q are *similar* (in symbols $p \sim q$) if $p \le q$ and $q \le p$. The parameter p strictly dominates q (in symbols p < q) if $p \le q$ but not $q \le p$, and p and p are incomparable (in symbols $p \bowtie q$) if neither $p \le q$ nor $q \le p$.

Observation 8.1. Let p and q be ASP-parameters and $L \in \mathcal{A}sp\mathcal{F}ull$. If p dominates q and $L[p] \in FPT$, then also $L[q] \in FPT$.

Observation 8.2. Let p and q be normal ASP-parameters and $o \in \{ \leq, \prec, \bowtie \}$. Then $p \circ q$ if and only if $p^{\uparrow} \circ q^{\uparrow}$.

Proof. Let p and q be normal ASP-parameters. We will show that $p^{\uparrow} \leq q^{\uparrow}$ iff $p \leq q$. Since \prec and \bowtie can be defined in terms of \prec , this shows the claimed observation.

Assume $p^{\uparrow} \leq q^{\uparrow}$. Hence there is a function f such that for all programs P we have $p^{\uparrow}(P) \leq f(q^{\uparrow}(P))$. In particular, if P is normal we have by Definition 7.3 that $p(P) = p^{\uparrow}(P)$ and $q(P) = q^{\uparrow}(P)$, hence $p(P) \leq q(P)$, and so $p \leq q$.

Now assume $p \le q$. Hence there is a function f such that for all normal programs P we have $p(P) \le f(q(P))$. Let f', f'' be the monotonic functions on non-negative integers defined by $f'(n) = \max_{0 \le i \le n} f(n)$ and f''(n) = f'(n) + n. Let P be a

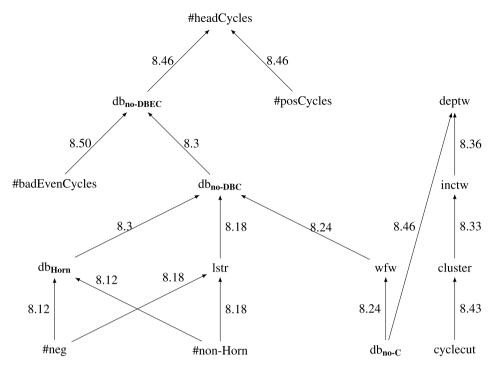


Fig. 7. Domination Lattice (relationship between ASP-parameters when restricted to normal programs). An arrow from p to p' indicates that p' strictly dominates p. Please recall that deptw does not yield tractability (Proposition 8.36). When we do not restrict the parameters to normal programs and apply lifting (Observation 8.60) the parameter #headCycles is not strictly more general. A label i of an edge indicates that Proposition i establishes the result.

program and X a minimal deletion **Normal**-backdoor of P. We have $|X| + p(P - X) \le |X| + f(q(P - X)) \le |X| + q(P - X) + f'(q(P - X)) \le |X| + q(P - X) + f'(|X| + q(P - X)) \le f''(|X| + q(P - X))$. Hence $p^{\uparrow} \le q^{\uparrow}$ follows by Definition 7.3. \square

Let \mathcal{C} be a class of programs. In the following, we omit \cdot^{\downarrow} (see Definition 7.1) for the parameters $db_{\mathcal{C}}$ and $sb_{\mathcal{C}}$ whenever it is clear from the context that we compare $db_{\mathcal{C}}$ or $sb_{\mathcal{C}}$ with a normal ASP-parameter.

In the following we define various auxiliary programs which we will use as examples, to separate the parameters from each other and establish incomparability or strictness results.

Example 8.1. Let m and n be some large integers. We define the following programs:

$$\begin{split} P_{1}^{n} &:= \{a \leftarrow \neg b_{1}, \dots, \neg b_{n}\}, \\ P_{2}^{n} &:= \{a_{i} \leftarrow \neg b: 1 \leq i \leq n\}, \\ P_{31}^{n} &:= \{b_{i} \leftarrow \neg a; \ a \leftarrow \neg b_{i}: 1 \leq i \leq n\}, \\ P_{32}^{n} &:= \{b_{i} \leftarrow a; \ a \leftarrow b_{i}: 1 \leq i \leq n\}, \\ P_{33}^{n} &:= P_{31}^{n} \cup \{a \leftarrow d_{1}; \ d_{i} \leftarrow d_{i+1}: 1 \leq i < n\} \cup \{c_{i} \leftarrow b_{i}; \ d_{i} \leftarrow c_{i}; \ d_{i} \leftarrow b_{i}: 1 \leq i \leq n\}, \\ P_{34}^{n} &:= P_{33}^{n} \cup \{d_{i} \leftarrow \neg b_{i}: 1 \leq i \leq n\}, \\ P_{35}^{n} &:= P_{33}^{n} \setminus \{a \leftarrow \neg b_{i}; \ b_{i} \leftarrow \neg a: 1 \leq i \leq n\} \cup \{a_{0} \leftarrow \neg a\} \cup \{b_{i} \leftarrow a_{0}: 1 \leq i \leq n\}, \\ P_{4}^{n} &:= \{c_{i} \leftarrow \neg a_{i}; \ c_{i} \leftarrow b_{i}; \ b_{i} \leftarrow \neg a_{i}; \ a_{i} \leftarrow e_{i}; \ e_{i} \leftarrow d_{i}; \ d_{i} \leftarrow a_{i}: 1 \leq i \leq n\}, \\ P_{51}^{n} &:= \{b_{i} \leftarrow \neg a_{i}; \ a_{i} \leftarrow \neg b_{i}: 1 \leq i \leq n\}, \\ P_{53}^{n} &:= \{b_{i} \leftarrow a_{i}; \ a_{i} \leftarrow b_{i}: 1 \leq i \leq n\}, \\ P_{53}^{n} &:= \{b_{i} \leftarrow a_{i}; \ c_{i} \leftarrow b_{i}; \ a_{i} \leftarrow c_{i}: 1 \leq i \leq n\}, \\ P_{54}^{n} &:= \{b_{i} \leftarrow a_{i}; \ c_{i} \leftarrow b_{i}; \ a_{i} \leftarrow c_{i}: 1 \leq i \leq n\}, \\ P_{6}^{n} &:= \{a \leftarrow b_{1}, \dots, b_{n}, c_{i}: 1 \leq i \leq n\}, \\ P_{7}^{n} &:= \{a_{j} \leftarrow a_{i}: 1 \leq i < j \leq n\}, \\ \end{split}$$

$$P_8^{m,n} := \{b \leftarrow a_1, \dots, a_m\} \cup \{c_i \leftarrow c_{i+1} : 1 \le i \le n\} \cup \{c_{n+1} \leftarrow c_1\},$$

$$P_9^n := \{a_2 \leftarrow \neg a_1; \ a_3 \leftarrow \neg a_2\} \cup \{b_i \leftarrow a_3; \ a_1 \leftarrow b_i : 1 \le i \le n\}, \text{ and }$$

$$P_{11}^n := \{a_i \lor b \leftarrow c; \ c \leftarrow b; \ b \leftarrow a_i : 1 \le i \le n\}.$$

8.1. ASP-parameters based on backdoor size

Backdoor-based ASP-parameters can be related to each other in terms of their underlying base classes. We just need a very weak assumption stated in the following which holds for all target classes considered in the paper. Therefore, we need the following definition: A class C of programs is closed under the union of disjoint copies if for every $P \in C$ and disjoint copies P_1, \ldots, P_i of P also $P \cup P_1 \cup \ldots \cup P_i \in \mathcal{C}$. We say a program P' is a disjoint copy of P if P' is isomorphic to P and $at(P) \cap at(P') = \emptyset$.

Proposition 8.3. Let C, C' be classes of programs that are closed under the union of disjoint copies. If $C \subseteq C'$, then $db_{C'} \prec db_C$ and $\operatorname{sb}_{\mathcal{C}'} \prec \operatorname{sb}_{\mathcal{C}}$, even $\operatorname{db}_{\mathcal{C}'}(P) < \operatorname{db}_{\mathcal{C}}(P)$ and $\operatorname{sb}_{\mathcal{C}'}(P) < \operatorname{sb}_{\mathcal{C}}(P)$ for every program P. If $\mathcal{C}' \setminus \mathcal{C}$ contains a program with at least one atom, then $C \subseteq C'$ implies $db_{C'} \prec db_C$ and $sb_{C'} \prec sb_C$.

Proof. The first statement is obvious. For the second statement, let $P \in \mathcal{C}' \setminus \mathcal{C}$ with |at(P)| > 1. We construct the program P^n consisting of *n* disjoint copies of *P* and observe that $P^n \in \mathcal{C}'$ but $db_{\mathcal{C}}(P^n)$, $sb_{\mathcal{C}}(P^n) \ge n$. \square

Hence the relationships between target classes as stated in Observation 5.7 carry over to the corresponding backdoorbased ASP-parameters that is, if $\mathcal{C} \subseteq \mathcal{C}'$ then a smallest strong (deletion) \mathcal{C}' -backdoor is at most the size of a smallest strong (deletion) C-backdoor.

According to Lemma 3.4 every deletion \mathcal{C} -backdoor is a strong \mathcal{C} -backdoor if \mathcal{C} is hereditary, hence it also holds for smallest backdoors and we immediately get from the definitions:

Observation 8.4. *If* C *is hereditary, then* sb_C *dominates* db_C .

According to Lemma 4.1, every strong Horn-backdoor of a program is a deletion Horn-backdoor and vice versa. Hence we obtain the following statement:

Observation 8.5. $sb_{Horn} \sim db_{Horn}$.

Observation 8.6. We make the following observations about programs from Example 8.1.

- 1. Consider program P_{31}^n and P_{32}^n and let $P \in \{P_{31}^n, P_{32}^n\}$. Since $P \{a\}$ is Horn and contains no cycle and no directed cycle, we obtain $\mathsf{db}_{\boldsymbol{Horn}}(P) \leq 1, \ \mathsf{db}_{\boldsymbol{no-C}}(P) \leq 1, \ \mathit{and} \ \mathsf{db}_{\boldsymbol{no-DC}}(P) \leq 1. \ \mathit{According to Observation 8.3, we have } \ \mathsf{db}_{\mathcal{C}}(P^n_{31}) \leq 1 \ \mathit{and} \ \mathsf{db}_{\mathcal{C}}(P^n_{32}) \leq 1$ where $C \in \{\mathbf{Horn}\} \cup \mathcal{A}cyc$.
- 2. Consider program P_{33}^n . Since $P_{33}^n \{a\}$ is Horn and contains no directed cycle and no bad cycle, we obtain $db_{\mathbf{Horn}}(P_{33}^n) = 0$, $db_{\mathbf{no-DC}}(P_{33}^n) \leq 1$, and $db_{\mathbf{no-BC}}(P_{33}^n) \leq 1$. According to Observation 8.3, we have $db_{\mathcal{C}}(P_{33}^n) \leq 1$ where $\mathcal{C} \in \{\mathbf{Horn}, \mathbf{no-BC}, \mathbf{no-BC},$
- Consider program Pⁿ₃₄. Since Pⁿ₃₄ − {a} contains no even cycle, db_{no-EC}(Pⁿ₃₄) ≤ 1.
 Consider program Pⁿ₄. The negation dependency graph of Pⁿ₄ contains 2n disjoint paths a_ib_i and a_ic_i. Thus smallest deletion Horn-backdoor are of size at least n. Pⁿ₄ contains n disjoint bad cycles, n directed cycles of length at least 3, and n directed even cycles. Hence smallest deletion C-backdoors are of size at least n and thus $db_{\mathcal{C}}(P_{A}^{n}) \geq n$ where $\mathcal{C} \in$ {Horn, no-C, no-BC, no-DC, no-DC2, no-EC, no-BEC, no-DEC}.
- 5. Consider program P_{51}^n . The negation dependency graph of P_{51}^n contains n disjoint paths and thus $db_{\text{Horn}}(P_{51}^n) = n$. P_{51}^n contains n disjoint directed bad even cycles and thus $db_{\text{no-DBEC}}(P_{51}^n) = n$. According to Observation 8.3, we obtain $db_{\mathcal{C}}(P_{51}^n) \geq n$ where
- 6. Consider program P_{52}^n . Since P_{52}^n contains n disjoint directed bad cycles, $db_{no-DBC}(P_{52}^n) = n$.
- 7. Consider program P_{54}^n . Since P_{54}^n contains n disjoint even cycles, n disjoint directed cycles of length at least 3, and n disjoint directed even cycles, we obtain by Observation 8.3 $db_{\mathcal{C}}(P_{54}^n) \geq n$ where $\mathcal{C} \in \{\text{no-C}, \text{no-DC}, \text{no-DC}, \text{no-DC}, \text{no-DCC}\}$.
- 8. Consider program P_6^n . Since P_6^n is Horn and contains no cycle and no directed cycle, $db_{\mathbf{Horn}}(P_6^n) = db_{\mathbf{no-C}}(P_6^n) = db_{\mathbf{no-DC}}(P_6^n) = 0$. According to Observation 8.3, we have $db_{\mathcal{C}}(P_6^n) = 0$ where $\mathcal{C} \in \{\text{Horn}\} \cup \mathcal{A}cyc$.
- 9. Consider program P_7^n . Since P_7^n is Horn and contains no bad cycle and no directed cycle, $db_{Horn}(P_7^n) = db_{no-BC}(P_7^n)$
- db_{no-DC}(P₇ⁿ) = 0. According to Observation 8.3, we have db_C(P₇ⁿ) = 0 where C ∈ {Horn, no-BC, no-BEC} ∪ D-Acyc.

 10. Consider program P₈^{m,n}. Since P₈^{m,n} is Horn and P₈^{m,n} − {c₁} contains no cycle and no directed cycle, we obtain db_{Horn}(P₈^{m,n}) = 0, db_{no-C}(P₈^{m,n}) ≤ 1, db_{no-DC}(P₈^{m,n}) ≤ 1. According to Observation 8.3, we have db_C(P₈^{m,n}) ≤ 1 where C ∈ {Horn} ∪ Acyc.

 11. Consider program P₉ⁿ. Since P₉ⁿ − {a₂} is Horn and P₉ⁿ − {a₁} contains no cycle and no directed cycle, we have db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1, decording to Observation 8.3 are larged db_{Horn}(P₉ⁿ) ≤ 1 are larged
- $db_{\mathbf{no-C}}(P_0^n) \leq 1$, and $db_{\mathbf{no-DC}}(P_0^n) \leq 1$. According to Observation 8.3, we have $db_{\mathcal{C}}(P_0^n) \leq 1$ where $\mathcal{C} \in \{\mathbf{Horn}\} \cup \mathcal{A}_{\mathcal{CVC}}$.

- 12. Consider program P_{11}^n and let $X = \{b\}$. Since $P_{11}^n X$ is normal, X is a deletion **Normal**-backdoor of P_{11}^n . Since $P_{11}^n X$ is Horn, X is a deletion **Horn**-backdoor of P_{11}^n and $\mathrm{db}_{\mathbf{Horn}}(P_{11}^n X) = 1$. Since $P_{11}^n X$ contains no cycle, no even cycle, and no directed cycle, we have $\mathrm{db}_{\mathcal{C}}(P_{11}^n X) = 1$ where $\mathcal{C} \in \mathcal{A}$ cyc. Consequently, $\mathrm{db}_{\mathcal{C}}(P_{11}^n X) = 1$ where $\mathcal{C} \in \mathcal{C}$ is the program of \mathcal{C} in the program of \mathcal{C} is a deletion \mathcal{C} in the program of \mathcal{C} in the program of \mathcal{C} is a deletion \mathcal{C} in the program of \mathcal{C} in the program of \mathcal{C} is a deletion \mathcal{C} in the program of \mathcal{C} in the program of \mathcal{C} is a deletion \mathcal{C} in the program of \mathcal{C} in the program of \mathcal{C} in the program of \mathcal{C} is a deletion \mathcal{C} in the program of \mathcal{C} in
- 8.2. ASP-parameters based on the distance from Horn

Our backdoor-based ASP-parameter dbHorn can be considered as a parameter that measures the distance of a program from being a Horn program. In the literature some normal ASP-parameters have been proposed, that also can be considered as distance measures from Horn. In this section we compare them with dbHorn. Since the ASP-parameters considered in the literature are normal, we compare the parameters for normal programs only. However, in view of Observation 8.2 the results also hold for the lifted parameters to disjunctive programs.

Definition 8.7. (See Ben-Eliyahu [4].) Let P be a normal program. Then

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\# \operatorname{neg}(P) := |\{a \in \operatorname{at}(P) : a \in B^-(r) \text{ for some rule } r \in P\}|,
\#non-Horn(P) := |\{r \in P : r \text{ is not Horn }\}|.
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Proposition 8.8. (See Ben-Eliyahu [4].) For each $L \in Asp \mathcal{F}ull$, $L[\#neg]_N \in FPT$ and $L[\#non-Horn]_N \in FPT$.

Since BOUND[p]_N for $p \in \{\text{#neg}, \text{#non-Horn}\}$ is clearly solvable in polynomial time and thus fixed-parameter tractable, we can use the Lifting Theorem (Theorem 7.5) to obtain the following result.

Corollary 8.9. For each $L \in AspFull$, $L[\#neg^{\uparrow}] \in FPT$ and $L[\#non-Horn^{\uparrow}] \in FPT$.

Observation 8.10. We make the following observations about programs from Example 8.1.

- 1. Consider program P_1^n which contains n atoms that occur in $B^-(r)$ for some rule $r \in P$ and exactly one non-Horn rule. Thus, $\# \operatorname{neg}(P_1^n) = n$ and $\# \operatorname{non-Horn}(P_1^n) = 1$.
- 2. Consider program P_2^n which contains only the atom b that occurs in $B^-(r)$ for some rule $r \in P_2^n$ and n non-Horn rules. Thus, $\# \operatorname{neg}(P_2^n) = 1$ and $\# \operatorname{non-Horn}(P_2^n) = n$.
- 3. Consider program P_{31}^n which contains for $1 \le i \le n$ the atoms a and b_i that occur in $B^-(r)$ for some rule $r \in P_{31}^n$ and the non-Horn rules $b_i \leftarrow \neg a$ and $a \leftarrow \neg b_i$. Hence, $\# \operatorname{neg}(P_{31}^n) = n + 1$ and $\# \operatorname{non-Horn}(P_{31}^n) = 2n$.

 4. Consider program P_{32}^n which is Horn. Thus, $\# \operatorname{neg}(P_{32}^n) = \# \operatorname{non-Horn}(P_{32}^n) = 0$.

 5. Consider program P_{35}^n which contains only the atom a that occurs in $B^-(r)$ for some rule $r \in P_{35}^n$ and exactly one non-Horn rule.
- So $\#neg(P_{35}^n) = \#non-Horn(P_{35}^n) = 1.$
- 6. Consider program P_4^n which contains for $1 \le i \le n$ the atoms a_i that occur in $B^-(r)$ for some rule $r \in P_4^n$ and the non-Horn rules $b_i \leftarrow \neg a_i$ and $c_i \leftarrow \neg a_i$. Thus, $\# neg(P_4^n) = n$ and $\# non-Horn(P_4^n) = 2n$.
- 7. Consider program $P_{5,1}^n$ which contains for $1 \le i \le n$ the atoms a_i and b_i that occur in $B^-(r)$ for some rule $r \in P$ and the non-Horn rules $b_i \leftarrow \neg a_i$ and $a_i \leftarrow \neg b_i$. Hence, $\# neg(P_{51}^n) = \# non-Horn(P_{51}^n) = 2n$.
- 8. Consider the program P_{52}^n which contains the atoms b_i that occur in $B^-(r)$ for some rule $r \in P_{52}^n$ and the non-Horn rules $a_i \leftarrow \neg b_i$. Hence, $\# neg(P_{52}^n) = \# non-Horn(P_{52}^n) = n$.
- 9. Consider programs P_{54}^n , P_6^n , P_7^n , and $P_8^{m,n}$ which are Horn. Thus, $\# neg(P_{54}^n) = \# non-Horn(P_{54}^n) = \# neg(P_6^n) = \# non-Horn(P_6^n) = \# neg(P_7^n) = \# non-Horn(P_8^n) = \# non-Horn(P_8^n) = 0.$ 10. Consider the program P_9^n which contains only the atoms a_1 and a_2 that occur in $B^-(r)$ for some rule $r \in P_9^n$ and only the non-Horn
- rules $a_2 \leftarrow \neg a_1$ and $a_3 \leftarrow \neg a_2$. Hence, $\# neg(P_9^n) = \# non-Horn(P_9^n) = 2$. 11. Consider the program P_{11}^n . The set $X = \{b\}$ is a deletion **Normal**-backdoor of P_{11}^n . Since $P_{11}^n X$ is Horn, we have $\# \operatorname{neg}(P_{11}^n - X) = \# \operatorname{non-Horn}(P_{11}^n - X) = 0.$ Thus, $\# \operatorname{neg}^{\uparrow}(P_{11}^n) = |X| + \# \operatorname{neg}(P_{11}^n - X) = 1$ and $\# \operatorname{non-Horn}^{\uparrow}(P_{11}^n) = |X| + \# \operatorname{neg}(P_{11}^n - X) = 1$ $|X| + \# \text{non-Horn}(P_{11}^n - X) = 1.$

Proposition 8.11. #neg and #non-Horn are incomparable.

Proof. The proposition directly follows from considering P_1^n and P_2^n where $\# neg(P_1^n) = n$ and $\# non-Horn(P_1^n) = 1$; and $\# neg(P_2^n) = 1$ and $\# non-Horn(P_2^n) = n$ by Observation 8.10. \square

However, it is easy to see that db_{Horn} dominates both parameters.

Proposition 8.12. db_{Horn} strictly dominates #neg and #non-Horn. $db_{\mathcal{C}}$ and #neg; and $db_{\mathcal{C}}$ and #non-Horn are incomparable where $C \in \{\text{no-C}, \text{no-DC}, \text{no-DC2}, \text{no-EC}, \text{no-DEC}\}.$

Proof. For a normal program P define the sets $B^-(P) = \{a \in \mathsf{at}(P) : a \in B^-(r) \text{ for some rule } r \in P\}$ and $H(P) = \{a \in \mathsf{at}(P) : a \in \mathsf{at}(P) : a \in \mathsf{at}(P) : a \in \mathsf{at}(P) : a \in \mathsf{at}(P)\}$ $H(r): r \in P, r$ is not Horn}. We observe that $B^-(P)$ and H(P) are deletion **Horn**-backdoors of P, hence $db_{Horn}(P) \le P$ # neg(P) and $db_{Horn}(P) \le \# non-Horn(P)$. To show that db_{Horn} strictly dominates the two parameters, consider $P_{3,1}^n$ where $db_{\mathbf{Horn}}(P_{31}^n) \le 1$, but $\#neg(P_{31}^n) = n+1$ and $\#non-Horn(P_{31}^n) = 2n$ by Observations 8.6 and 8.10.

The second statement follows from considering the programs P_{31}^n and P_{54}^n where $db_{\mathcal{C}}(P_{31}^n) \le 1$ and $p(P_{31}^n) \ge n+1$; and $db_{\mathcal{C}}(P_{54}^n) \ge n$ and $p(P_{54}^n) = 0$ for $\mathcal{C} \in \{\text{no-C, no-DC, no-DC2, no-EC, no-DEC}\}\$ and $p \in \{\text{#neg, #non-Horn}\}\$ by $Observations\ 8.6$ and 8.10. Hence $db_C \bowtie \#nog\ and\ db_C \bowtie \#non-Horn\ for\ C \in \{no-C, no-DC, no-DC2, no-EC, no-DEC\}.$

8.3. ASP-parameters based on the distance from being stratified

Ben-Eliyahu [4] and Gottlob et al. [85] have considered ASP-parameters that measure in a certain sense how far away a program is from being stratified. In this section we will investigate how these parameters fit into our landscape of ASP-parameters. Similar to the last section the parameters have been considered for normal programs only, hence we compare the parameters for normal programs only. Again, in view of Observation 8.2 the results also hold for the lifted parameters to disjunctive programs.

Recall from Section 2.4 that SCC(G) denotes the partition of the vertex set of a digraph into strongly connected components.

Definition 8.13. (See Ben-Eliyahu [4].) Let P be a normal program, D_P its dependency digraph, and $A \subseteq at(P)$. P_{A} denotes the program obtained from P by (i) deleting all rules r in the program P where $H(r) \cap A = \emptyset$ and (ii) removing from the bodies of the remaining rules all literals $\neg a$ with $a \notin A$ (this corresponds to the well-known concept of a reduct). Then

$$\mathsf{lstr}(P) := \sum_{C \in \mathsf{SCC}(D_P)} \min \big\{ \# \mathsf{neg}(P_{/C}), \# \mathsf{non\text{-}Horn}(P_{/C}) \big\}.$$

lstr(P) is called the *level of stratifiability* of P.

Proposition 8.14. (See Ben-Eliyahu [4].) For each $L \in AspFull$, $L[lstr]_N \in FPT$.

Since BOUND[lstr]N is clearly solvable in polynomial time and thus fixed-parameter tractable, we can use the Lifting Theorem (Theorem 7.5) to obtain the following result.

Corollary 8.15. For each $L \in AspFull$, $L[lstr^{\uparrow}] \in FPT$.

Observation 8.16. We make the following observations about programs from Example 8.1.

- 1. Consider program P_{31}^n and let $P=P_{31}^n$. The partition $SCC(D_P)$ contains only the set C=at(P) and thus $P_{/C}=P$. By Observation P_{31}^n and P_{31}^n are P_{31}^n . tion 8.10 #neg(P) = n + 1 and #non-Horn(P) = 2n and hence $lstr(P_{31}^n) = n + 1$.
- 2. Consider program P_{32}^n and let $P = P_{32}^n$. The partition $SCC(D_P)$ contains only the set C = at(P) and $P_{/C} = P$. Since #neg(P) = 0 by Observation 8.10, we have $lstr(P_{32}^n) = 0$.

 3. Consider program P_{35}^n and let $P = P_{35}^n$. The partition $SCC(D_P)$ contains only the set C = at(P). Thus, $P = P_{/C}$. Since $\#neg(P_{35}^n) = 1$.
- 1 by Observation 8.10, we conclude $\operatorname{lstr}(P_{35}^n) \leq 1$.
- 4. Consider program P_4^n and let $P = P_4^n$. We have $SCC(D_P)$ contains exactly the sets $A_i = \{a_i, e_i, d_i\}$, $B_i = \{b_i\}$, and $C_i = \{c_i\}$ where $1 \le i \le n$. Hence $P_{A_i} = \{a_i \leftarrow e_i; e_i \leftarrow d_i; d_i \leftarrow a_i\}$ and $P_{B_i} = \{b_i\}$ and $P_{C_i} = \{c_i; c_i \leftarrow b_i\}$. Since $\#neg(P_{C}) = 0$ for every $C \in SCC(D_P)$, we have $lstr(P_4^n) = 0$.
- 5. Consider program P_{51}^n and P_{52}^n and let $P \in \{P_{51}^n, P_{52}^n\}$. The partition $SCC(D_P)$ contains exactly the sets $C_i = \{a_i, b_i\}$ where $1 \le i \le n$ and hence $P_{/C_i} = \{b_i \leftarrow \neg a_i; \ a_i \leftarrow \neg b_i\}$ and $P_{/C_i} = \{b_i \leftarrow a_i; \ a_i \leftarrow \neg b_i: 1 \le i \le n\}$, respectively. Since $\#neg(P_{/C_i}) = \{b_i \leftarrow a_i; \ a_i \leftarrow \neg b_i: 1 \le n\}$, respectively. #non- $Horn(P_{/C_i}) = 2$, respectively #neg $(P_{/C_i}) = \#$ non- $Horn(P_{/C_i}) = 1$, and there are n components we obtain $lstr(P_{51}^n) = 2n$ and $Istr(P_{52}^n) = n$.
- 6. Consider program P_6^n and let $P = P_6^n$. The partition $SCC(D_P)$ contains exactly the sets $A = \{a\}$, $B_i = \{b_i\}$, and $C_i = \{c_i\}$ where $1 \leq i \leq n. \ Hence \ P_{/A} = \{a \leftarrow b_1, \ldots, b_n, c_i : 1 \leq i \leq n\} \ and \ P_{/B_i} = P_{/C_i} = \emptyset \ where \ 1 \leq i \leq n. \ Since \ \#neg(P_{/C}) = 0 \ for \ every \ C \in A$ $SCC(D_P)$, we have $Istr(P_6^n) = 0$.
- 7. Consider program P_7^n and let $P = P_7^n$. The partition $SCC(D_P)$ contains exactly the sets $C_i = \{a_i\}$ where $1 \le i \le n$. Thus, $P_{C_i} = \{a_i\}$ $\{a_i \leftarrow a_j : 1 \le j < i\}$. Hence $\# neg(P_{/C_i}) = 0$ for every $C \in SCC(D_P)$. We obtain $lstr(P_7^n) = 0$.
- 8. Consider program $P_8^{m,n}$ and let $P = P_8^{m,n}$. The partition $SCC(D_P)$ contains exactly the sets $A_i = \{a_i\}$ where $1 \le i \le m$, $B = \{b\}$, and $C = \{c_i : 1 \le i \le n\}. \text{ Hence } P_{/A_i} = \emptyset \text{ where } 1 \le i \le m, \ P_{/B} = \{b \leftarrow a_1, \dots, a_m\}, \text{ and } P_{/C} = \{c_i \leftarrow c_{i+1} : 1 \le i \le n\} \cup \{c_{n+1} \leftarrow c_{n+1} \in C_n\} \cup \{c_{n+1} \in C_n\}$ c_1 }. Since $\# \operatorname{neg}(P_{/A_i}) = 0$ where $1 \le i \le m$, $\# \operatorname{neg}(P_{/B}) = 0$, and $\# \operatorname{neg}(P_{/C}) = 0$, we obtain $\operatorname{lstr}(P_8^{m,n}) = 0$.

 9. Consider program P_9^n and let $P = P_9^n$. The partition $\operatorname{SCC}(D_P)$ contains only the set $C = \operatorname{at}(P)$. Hence $P_{/C} = P$. Since $\# \operatorname{neg}(P) = P$.
- #non-Horn(P) = 2, we have $lstr(P_q^n) = 2$.

10. Consider program P_{11}^n . The set $X = \{b\}$ is a deletion **Normal**-backdoor of P_{11}^n by Observation 8.6. We have $P = P_{11}^n - X = \{a_i \leftarrow c; c; \leftarrow a_i : 1 \le i \le n\}$. The partition $SCC(D_P)$ contains the sets $A_i = \{a_i\}$, where $1 \le i \le n$, and $C = \{c\}$. Hence $P_{A_i} = \{a_i \leftarrow c\}$, where $1 \le i \le n$, and $P_{C} = \{c\}$. Since $\# neg(P_{C}) = 0$ for every $C \in SCC(D_P)$, we obtain Istr(P) = 0. Consequently, $Istr(P_{11}^n) = |X| + Istr(P_{11}^n - X) = 1$.

Observation 8.17. Istr strictly dominates #neg and #non-Horn.

Proof. Let P be a normal program. We first show that $\sum_{C \in SCC(D_P)} \#neg(P_{/C}) \le \#neg(P)$. Define the set $B^-(P) = \{a \in at(P) : a \in B^-(r) \text{ for some rule } r \in P\}$. By definition $B^-(P_{/A}) \subseteq B^-(P)$ for some $A \subseteq at(P)$; thus, $\bigcup_{C \in SCC(D_P)} B^-(P_{/C}) \subseteq B^-(P)$. Let $C, C' \in SCC(D_P)$ and $C \ne C'$. By definition of a strongly connected component we have $C \cap C' = \emptyset$ and by definition we have that $B^-(P_{/C}) \subseteq C$ and $B^-(P_{/C'}) \subseteq C'$. Hence $B^-(P_{/C}) \cap B^-(P_{/C'}) = \emptyset$. Consequently $\sum_{C \in SCC(D_P)} \#neg(P_{/C}) \le \#neg(P)$. A similar argument shows that $\sum_{C \in SCC(D_P)} \#non-Horn(P_{/C}) \le \#non-Horn(P)$. Since $lstr(P) = \sum_{C \in SCC(D_P)} \min\{\#neg(P_{/C}), \#non-Horn(P_{/C})\}$, we have $lstr(P) \le \#neg(P)$ and $lstr(P) \le \#non-Horn(P)$. To show that lstr strictly dominates the two parameters, consider program P_4^n where $lstr(P_4^n) = 0$, but $\#neg(P_4^n) \ge n$ and $\#non-Horn(P_4^n) \ge 2n$ by Observations 8.10 and 8.16. Hence the observation is true. \square

Proposition 8.18. db_{no-DBC} strictly dominates lstr. Moreover, $db_{\mathcal{C}}$ and lstr are incomparable for the remaining target classes namely $\mathcal{C} \in \mathcal{A}cyc \setminus \{no-DBC, no-DBEC\} \cup \{Horn\}$.

Proof. We first show that db_{no-DBC} dominates lstr. For a normal program P define the sets $B^-(P) = \{a \in at(P) : a \in B^-(r) \text{ for some rule } r \in P\}$ and $H(P) = \{a \in H(r) : r \in P, r \text{ is not Horn}\}$. Let $C \in SCC(D_P)$, we define

$$X_C = \begin{cases} B^-(P_{/C}), & \text{if } |B^-(P_{/C})| \le |H(P_{/C})|; \\ H(P_{/C}), & \text{otherwise} \end{cases}$$

and $X = \{X_C : C \in SCC(D_P)\}$. We show that X is a deletion **no-DBC**-backdoor of P. By definition for every directed bad cycle $c = (x_1, \ldots, x_l)$ of D_P the atom $x_i \in C'$ where $1 \le i \le l$ and $C' \in SCC(D_P)$ (all vertices of c belong to the same strongly connected component). Moreover, by definition we have for every negative edge $(x_i, x_j) \in D_P$ of the dependency digraph D_P a corresponding rule $r \in P$ such that $x_j \in H(r)$ and $x_i \in B^-(r)$. Since X_C consists of either $B^-(P/C)$ or H(P/C), at least one of the atoms x_i, x_j belongs to X_C . Thus, for every directed bad cycle c of the program P at least one atom of the cycle belongs to X. Hence $P - X \in$ **no-DBC** and X is a deletion **no-DBC**-backdoor of P. We obtain $db_{\textbf{no-DBC}}(P) \le lstr(P)$. To show that $db_{\textbf{no-DBC}}$ strictly dominates lstr, consider program P_{31}^n where $db_{\textbf{no-DBC}}(P_{31}^n) \le 1$ and $lstr(P_{31}^n) = n + 1$ by Observations 8.6 and 8.16. Hence $db_{\textbf{no-DBC}} < lstr$.

Then we show that the parameters $\mathrm{db}_{\mathcal{C}}$ and lstr are incomparable. Consider the programs P_3^n and P_4^n where $\mathrm{db}_{\mathcal{C}}(P_{31}^n) \leq 1$ and $\mathrm{lstr}(P_{31}^n) = n+1$; and $\mathrm{lstr}(P_4^n) = 0$ and $\mathrm{db}_{\mathcal{C}}(P_4^n) \geq n$ for $\mathcal{C} \in \{\mathbf{Horn}, \mathbf{no-C}, \mathbf{no-BC}, \mathbf{no-DC}, \mathbf{no-BC}, \mathbf{no-BC}, \mathbf{no-BEC}, \mathbf{no-DEC}\}$ by Observations 8.6 and 8.16. We conclude $\mathrm{db}_{\mathcal{C}} \bowtie 1$ lstr. \square

Definition 8.19. (See Gottlob et al. [85].) Let P be a normal program, D_P its dependency digraph, U_P its dependency graph, and $A \subseteq \operatorname{at}(P)$. $\hat{P}_{/A}$ denotes the program obtained from $P_{/A}$ by removing from the bodies of every rule all literals a with $a \notin A$. $\operatorname{at}^+(P)$ denotes the maximal set $W \subseteq \operatorname{at}(P)$ such that there is no bad W-cycle in the dependency graph U_P , in other words the set of all atoms that do not lie on a bad cycle of P. Then

$$fw(P) := \min\{|S| : S \text{ is a feedback vertex set of } U_P\} \text{ and } wfw(P) := fw(\{r \in \hat{P}_{/C} - at^+(\hat{P}_{/C}) : C \in SCC(D_P), \hat{P}_{/C} \notin \mathbf{no-DBC}\}).$$

fw(P) is called the *feedback-width* of P, and wfw(P) is called the *weak-feedback-width* of P.

Observation 8.20. Let P be a normal program and D_P its dependency digraph. Then $fw(P) = db_{no-C}(P)$ and hence

$$\mathsf{wfw}(\mathsf{P}) = \mathsf{db}_{\mathbf{no-C}}\big(\big\{r \in \hat{P}_{/C} - at^+(\hat{P}_{/C}) : C \in \mathsf{SCC}(D_P), \, \hat{P}_{/C} \notin \mathbf{no-DBC}\big\}\big).$$

Proposition 8.21. (See Gottlob et al. [85].) For each $L \in Asp \mathcal{F}ull$, $L[fw]_N \in FPT$ and $L[wfw]_N \in FPT$.

Since $Bounp[fw]_N$ and $Bounp[wfw]_N$ is fixed-parameter tractable, we can use the Lifting Theorem (Theorem 7.5) to obtain the following result.

Corollary 8.22. For each $L \in AspFull$, $L[fw^{\uparrow}] \in FPT$ and $L[wfw^{\uparrow}] \in FPT$.

Observation 8.23. We make the following observations about programs from Example 8.1.

- 1. Consider the program P_{31}^n and let $P = P_{31}^n$. The partition $SCC(D_P)$ contains only the set C = at(P). For every atom $a \in C$ the program P contains a bad {a}-cycle and thus at⁺($\hat{P}_{/C}$) = \emptyset . Consequently, $\hat{P}_{/C}$ – at⁺($\hat{P}_{/C}$) = $\hat{P}_{/C}$ = P. As P \notin **no-DBC**, $\{r \in \hat{P}_{/C} - \operatorname{at}^+(\hat{P}_{/C}), C \in SCC(D_P), \hat{P}_{/C} \notin \mathbf{no\text{-}DBC}\} = P$. We have $\operatorname{db}_{\mathbf{no\text{-}C}}(P) = 1$ by Observation 8.6 and according to Observa*tion 8.20, we obtain* wfw(P_{31}^n) = 1.
- 2. Consider program P_{32}^n and let $P = P_{32}^n$. The partition $SCC(D_P)$ contains only the set C = at(P), $\hat{P}_{/C} = P$. For every atom $a \in C$ we have $\hat{P}_{/C} \in \mathbf{no\text{-}DBC}$ and thus $\{r \in \hat{P}_{/C} - \operatorname{at}^+(\hat{P}_{/C}) : C \in SCC(D_P), \hat{P}_{/C} \notin \mathbf{no\text{-}DBC}\} = \emptyset$. Consequently, wfw $(P_{32}^n) = 0$.
- 3. Consider the programs P_{33}^n , P_{34}^n , and P_{35}^n and let $P \in \{P_{33}^n, P_{34}^n, P_{35}^n\}$. We first observe that the dependency digraph of P contains only one strongly connected component. Hence the partition $SCC(D_P)$ contains only the set C = at(P). For every atom $a \in C$ program P contains a bad {a}-cycle and thus $\operatorname{at}^+(\hat{P}_{/C}) = \emptyset$. Consequently, $\hat{P}_{/C} - \operatorname{at}^+(\hat{P}_{/C}) = \hat{P}_{/C} = P$. Since $P \notin \operatorname{\mathbf{no-DBC}}$, we obtain $\{r \in \hat{P}_{/C} - at^+(\hat{P}_{/C}), C \in SCC(D_P), \hat{P}_{/C} \notin \mathbf{no}\text{-}\mathbf{DBC}\} = P$. We have $db_{\mathbf{no}\text{-}\mathbf{C}}(P) = n$ since P contains n disjoint $\{b_i\}$ -cycles. According to Observation 8.20, we conclude $wfw(P_{33}^n) = wfw(P_{34}^n) = wfw(P_{35}^n) = n$.
- 4. Consider program P_4^n and let $P = P_4^n$. The partition $SCC(D_P)$ contains exactly the sets $A_i = \{a_i, d_i, e_i\}$, $B_i = \{b_i\}$, and $C_i = \{c_i\}$, for $1 \le i \le n$. Hence $\hat{P}_{/A_i} = \{a_i \leftarrow e_i; e_i \leftarrow d_i; d_i \leftarrow a_i\}$, $\hat{P}_{/B_i} = \{b_i\}$ and $\hat{P}_{/C_i} = \{c_i\}$. For every $C \in SCC(D_P)$ the program $\hat{P}_{/C} \in SCC(D_P)$ the program $\hat{P}_{/C} \in SCC(D_P)$ **no-DBC**. Consequently, $\{r \in \hat{P}_{/C} - \operatorname{at}^+(\hat{P}_{/C}), C \in SCC(D_P), \hat{P}_{/C} \notin \operatorname{\textbf{no-DBC}}\} = \emptyset$ and we obtain $\operatorname{wfw}(P_4^n) = 0$. 5. Consider program P_{51}^n and let $P = P_{51}^n$. The partition $SCC(D_P)$ contains exactly the sets $C_i = \{a_i, b_i\}$, for $1 \le i \le n$, and thus
- $\hat{P}_{/C_i} = \{a_i \leftarrow \neg b_i; b_i \leftarrow \neg a_i\}$. Since $db_{\mathbf{no-C}}(\hat{P}_{/C_i}) = 1$ and there are n components we obtain $wfw(P_{5_1}^n) = n$.
- 6. Consider program P_{52}^n and let $P = P_{52}^n$. We observe that the partition $SCC(D_P)$ contains exactly the sets $C_i = \{a_i, b_i\}$. For every atom $a \in C_i$ where $1 \le i \le n$ there is a bad $\{a\}$ -cycle in the dependency graph of $\hat{P}_{/C_i}$ and thus $\operatorname{at}^+(\hat{P}_{/C_i}) = \emptyset$. Consequently, $\hat{P}_{/C_i} - \operatorname{at}^+(\hat{P}_{/C_i}) = \hat{P}_{/C_i}$. Since $\hat{P}_{/C_i} \notin \operatorname{\textbf{no-DBC}}$, $\{r \in \hat{P}_{/C} - \operatorname{at}^+(\hat{P}_{/C}) : C \in \operatorname{SCC}(D_P), \hat{P}_{/C} \notin \operatorname{\textbf{no-DBC}}\} = P$. We observe that $\operatorname{db}_{\operatorname{\textbf{no-C}}}(P) = n$ and according to Observation 8.20, we obtain $\operatorname{wfw}(P^n_{52}) = n$.
- 7. Consider program P_6^n and let $P = P_6^n$. The partition $SCC(D_P)$ contains exactly the sets $A = \{a\}$, $B_i = \{b_i\}$, and $C_i = \{c_i\}$ where $1 \le i \le n$. Hence $\hat{P}_{/A} = \{a\}$ and $\hat{P}_{/B_i} = \hat{P}_{/C_i} = \emptyset$ where $1 \le i \le n$. Since $db_{\mathbf{no-C}}(\hat{P}_{/C}) = 0$ for every $C \in SCC(D_P)$, we obtain $wfw(P_6^n) = 0.$
- 8. Consider program P_7^n and let $P = P_7^n$. Since the partition $SCC(D_P)$ contains exactly the sets $\{a_i\}$ where $1 \le i \le n$, $\hat{P}_{/\{a_i\}} = \{a_i\}$ and thus $wfw(\hat{P}_{/\{a_i\}}) = 0$. We obtain $wfw(P_7^n) = 0$.
- 9. Consider program $P_8^{m,n}$ and let $P=P_8^{m,n}$. The partition $SCC(D_P)$ contains exactly the sets $A_i=\{a_i\}$ for $1 \leq i \leq m$, $B=\{b\}$, and $C = \{c_i : 1 \le i \le n\}$. Hence $\hat{P}_{/A_i} = \emptyset$ for $1 \le i \le m$, $\hat{P}_{/B} = \emptyset$, and $\hat{P}_{/C} = \{c_i \leftarrow c_{i+1} : 1 \le i \le n\} \cup \{c_{n+1} \leftarrow c_1\}$. The programs $\hat{P}_{/A_i}$, $\hat{P}_{/B}$, and $\hat{P}_{/C}$ belong to the class **no-DBC** for $1 \le i \le m$. Consequently $\{r \in \hat{P}_{/C} - at^+(\hat{P}_{/C}) : C \in SCC(D_P), \hat{P}_{/C} \notin S$ **no-DBC**} = \emptyset . Hence we conclude that wfw($P_8^{m,n}$) = 0.
- 10. Consider program P_9^n and let $P = P_9^n$. The partition $SCC(D_P)$ contains only the set C = at(P). For every atom $a \in C$ there is a bad {a}-cycle in the dependency graph of P and thus $at^+(\hat{P}_{/C}) = \emptyset$. Consequently, $\hat{P}_{/C} - at^+(\hat{P}_{/C}) = \hat{P}_{/C} = P$. Since $P \notin \mathbf{no-DBC}$, $\{r \in \hat{P}_{/C} - \operatorname{at}^+(\hat{P}_{/C}) : C \in SCC(D_P), \hat{P}_{/C} \notin \operatorname{\textbf{no-DBC}}\} = P.$ By Observation 8.6 $\operatorname{db}_{\operatorname{\textbf{no-C}}}(P) \le 1$ and according to Observation 8.20, we obtain $wfw(P_0^n) \leq 1$.
- 11. Consider program P_{11}^n and let $P = P_{11}^n$. The set $X = \{b\}$ is a deletion **Normal**-backdoor of P_{11}^n by Observation 8.6 and $P = P_{11}^n$ $X = \{a_i \leftarrow c; c; \leftarrow a_i : 1 \le i \le n\}$. The partition $SCC(D_P)$ contains exactly the sets $\{a_i\}$ for $1 \le i \le n$ and $\{c\}$. Hence $\hat{P}_{/\{a_i\}} = \{a_i\}$ for $1 \le i \le n$ and $\hat{P}_{/\{c\}} = \{c\}$. We observe that $db_{no-c}(\hat{P}_{/C}) = 0$ for every $C \in SCC(D_P)$ and according to Observation 8.20, we obtain wfw(P) = 0. Consequently, wfw $^{\uparrow}(P_{11}^n) = |X| + \text{wfw}(P_{11}^n - X) = 1$.

In the following proposition we state the relationship between the parameter wfw and our backdoor-based ASP parameters. The first result (dbno-DBC strictly dominates wfw) was anticipated by Gottlob et al. [85].

Proposition 8.24. wfw strictly dominates db_{no-DBC} and db_{no-DBC} strictly dominates wfw. Moreover, db_C and wfw are incomparable for the remaining target classes namely $C \in \{\text{Horn}, \text{no-BC}, \text{no-DC}, \text{no-BC}, \text{no-BEC}, \text{no-DEC}\}$.

Proof. We first show that wfw strictly dominates db_{no-C} . Let P be a normal program and X be a deletion no-C-backdoor of *P*. Define $P = \{P/C - at^+(P/C) : C \in SCC(D_P), P/C \notin \textbf{no-DBC}\}$. Since $P \subseteq P$ and **no-C** is hereditary (Observation 5.6), $\hat{P} - X \in \mathbf{no-C}$ and hence X is a deletion $\mathbf{no-C}$ -backdoor of \hat{P} . Consequently, $\mathrm{wfw}(P) \leq \mathrm{db}_{\mathbf{no-C}}(\hat{P})$. To show that wfw is strictly more general than db_{no-C} , consider the program P_4^n where $wfw(P_4^n) = 0$ and $db_{no-C}(P_4^n) = n$. Hence $wfw < db_{no-C}(P_4^n) = n$. by Observations 8.3 and 8.23.

Next, we show that db_{no-DBC} strictly dominates wfw. Let P be a normal program and $\hat{P} = \{\hat{P}_{/C} - at^+(\hat{P}_{/C}) : C \in P\}$ $SCC(D_P)$, $\hat{P}_{/C} \notin \mathbf{no\text{-}DBC}$. According to Observation 8.20, $wfw(P) = db_{\mathbf{no\text{-}C}}(\hat{P})$ and thus it is sufficient to show that $db_{\mathbf{no-DBC}}(P) < db_{\mathbf{no-C}}(\hat{P})$. Let X be an arbitrary deletion $\mathbf{no-C}$ -backdoor of \hat{P} . Since $\mathbf{no-C} \subseteq \mathbf{no-DBC}$ Observation 8.3 yields that X is also a deletion **no-DBC**-backdoor of \hat{P} . Let c be an arbitrary directed bad cycle of D_P . As all vertices of c belong to the same partition $C \in SCC(D_P)$, $at(\hat{P}/C) \subseteq C$, and $D_{\hat{P}/C}$ is an induced subdigraph of D_P on $at(\hat{P}/C)$, we obtain c is a directed bad cycle in $D_{\hat{P}/C}$. Since $\hat{P} = \{\hat{P}/C - at^+(\hat{P}/C) : C \in SCC(D_P), \hat{P}/C \notin \textbf{no-DBC}\}$ and by definition there is no $at^+(\hat{P}/C)$ -cycle in U_P , there is no directed bad at $(\hat{P}_{/C})$ -cycle in D_P and hence c is also a directed bad cycle in $D_{\hat{P}_{/C}}$. Since X is a deletion

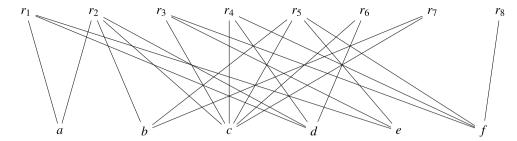


Fig. 8. Incidence graph I_P of the program P of Example 2.1.

no-DBC-backdoor of $D_{\hat{P}/C}$ and c is a directed bad X-cycle in $D_{\hat{P}/C}$, X is also a deletion **no-DBC**-backdoor of P. Consequently, $db_{\mathbf{no-DBC}}(P) \leq db_{\mathbf{no-C}}(\hat{P}) = wfw(P)$. To show that $db_{\mathbf{no-DBC}}$ is strictly more general than the parameter wfw, consider the program P_{33}^n where $db_{\mathbf{no-DBC}}(P_{33}^n) \leq 1$ and $wfw(P_{33}^n) = n$ by Observations 8.6 and 8.23. Hence $db_{\mathbf{no-DBC}} \prec lstr$.

The third statement follows from considering the programs P_{33}^n , P_{34}^n , and P_4^n where $db_{\mathcal{C}}(P_{33}^n) \leq 1$ for $\mathcal{C} \in \{\text{Horn}, \text{no-BC}, \text{no-DC}, \text{no-DC}, \text{no-DC}\}$ and $db_{\text{no-EC}}(P_{34}^n) \leq 1$ and $wfw(P_{33}^n) = wfw(P_{34}^n) = n$; and $wfw(P_4^n) = 0$ and $db_{\mathcal{C}}(P_4^n) = n$ by Observations 8.6 and 8.23. Hence $db_{\mathcal{C}} \bowtie wfw$ for $\mathcal{C} \in \{\text{Horn}, \text{no-BC}, \text{no-DC}, \text{no-DC}, \text{no-DC}, \text{no-BEC}, \text{no-DEC}\}$. \square

Observation 8.25. *If* $p \in \{\text{#neg, #non-Horn, lstr}\}$, then p and wfw are incomparable.

Proof. To show that p and wfw are incomparable consider the programs P_{31}^n and P_{35}^n where $p(P_{31}^n) \ge n+1$ and $wfw(P_{31}^n) = 1$; and $p(P_{35}^n) \le 1$ and $wfw(P_{35}^n) = n$ by Observations 8.10, 8.16 and 8.23. \square

8.4. Incidence treewidth

Treewidth is graph parameter introduced by Robertson and Seymour [130–132] that measures in a certain sense the tree-likeness of a graph. See [8–10,86] for further background and examples on treewidth. Treewidth has been widely applied in knowledge representation, reasoning, and artificial intelligence [39,86,90,118,126].

Definition 8.26. Let G = (V, E) be a graph, $T = (N, E_T)$ a tree, and χ a labeling that maps any node t of T to a subset $\chi(t) \subseteq V$. We call the sets $\chi(\cdot)$ bags and denote the vertices of T as nodes. The pair (T, χ) is a tree decomposition of G if the following conditions hold:

- 1. for every vertex $v \in V$ there is a node $t \in N$ such that $v \in \chi(t)$ ("vertices covered");
- 2. for every edge $vw \in E$ there is a node $t \in N$ such that $v, w \in \chi(t)$ ("edges covered"); and
- 3. 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 $\chi(t_1) \cap \chi(t_3) \subseteq \chi(t_2)$ ("connectivity").

The width of the tree decomposition (T, χ) is $\max\{|\chi(t)| - 1 : t \in V(T)\}$. The treewidth of G, denoted by $\mathsf{tw}(G)$, is the minimum taken over the widths of all possible tree decompositions of G.

We will use the following basic properties of treewidth.

Lemma 8.27. (Folklore, e.g., [132].) Let G be a graph and C_1, \ldots, C_l its connected components, then $\mathsf{tw}(G) = \mathsf{max}\{\mathsf{tw}(C_i) : 1 \le i \le l\}$.

Lemma 8.28. (Folklore, e.g., [6].) Let G be a graph. If G has a feedback vertex set size at most k, then $tw(G) \le k + 1$.

Treewidth can be applied to programs by means of various graph representations.

Definition 8.29. (See Jakl et al. [90].) Let P be a normal program. The *incidence graph* I_P of P is the bipartite graph which has as vertices the atoms and rules of P and where a rule and an atom are joined by an edge if and only if the atom occurs in the rule. Then $inctw(P) := tw(I_P)$. The parameter inctw(P) is called the *incidence treewidth* of P.

Fig. 8 illustrates the incidence graph I_P of the program P of Example 2.1.

Proposition 8.30. (See Jakl et al. [90].) For each $L \in Asp\mathcal{Full} \setminus \{Enum\}$, $L[inctw]_N \in FPT$ and for $Enum[inctw]_N$ the solutions can be enumerated with fixed-parameter linear delay between any two consecutive solutions.

Observation 8.31. We make the following observations about programs from Example 8.1.

- 1. Consider the programs P^n_{32} and P^n_{51} . We observe that incidence graph of P^n_{32} consists of the cycles a, r_i, b_i, r_{2i} for $1 \le i \le n$ and the incidence graph of P^n_{51} consists of the cycles a_i, r_i, b_i, r_{2i} for $1 \le i \le n$. According to Lemma 8.28, a cycle has treewidth at most 2 and according to Lemma 8.27, we have inctw $(P^n_{32}) \le 2$ and inctw $(P^n_{51}) \le 2$.
- 2. Consider the programs P_6^n and P_7^n . Its incidence graph contains a clique on n vertices. Thus, by definition inctw(P_6^n) $\geq n-1$ and $\operatorname{inctw}(P_7^n) \ge n - 1$.
- 3. Consider program $P_8^{m,n}$. The incidence graph consists of a tree on the vertices r_0, b, a_1, \ldots, a_m and a cycle $r_1, c_1, \ldots, r_n, c_n, r_{n+1}$, c_{n+1} , r_{n+2} . By definition a tree has treewidth 1, according to Lemma 8.28, a cycle has treewidth at most 2, and according to *Lemma 8.27, we obtain* $inctw(P_8^{m,n}) \leq 2$.

The following observation states why we cannot apply our lifting theorem and extend the parameter treewidth from normal to disjunctive programs.

Observation 8.32. ENUM[inctw]_N \notin FPT.

Proof. Consider the program P_{51}^n where inctw $(P_{51}^n) \le 2$. Let $M \subseteq at(P)$ such that either $a_i \in M$ or $b_i \in M$. According to the definitions, we obtain the GL-reduct $P^M = \{a_i : a_i \in M\} \cup \{b_i : b_i \in M\}$. Since M is a minimal model of P^M , M is also an answer set of P. Thus, the program P has 2^n many answer sets. Consequently, enumerating the answer sets of P takes time $\Omega(2^n)$. \square

Proposition 8.33. If $C \in \{\text{Horn}\} \cup \mathcal{A}_{CVC} \text{ and } p \in \{\text{db}_{C}, \#\text{neg}, \#\text{non-Horn}, \text{lstr}, \text{wfw}\}, \text{ then } p \text{ and inctw are incomparable.}$

Proof. We observe incomparability from the programs P_{51}^n and P_6^n where $p(P_{51}^n) \ge n$ and inctw $(P_{51}^n) = 2$; and $p(P_6^n) \le 1$ and inctw $(P_6^n) \ge n - 1$ by Observations 8.6, 8.10, 8.16, 8.23, and 8.31. \square

8.5. Dependency treewidth

One might ask whether it makes sense to consider restrictions on the treewidth of the dependency graph. In this section we show that the dependency treewidth strictly dominates the incidence treewidth and backdoors with respect to the target class no-C, but unfortunately parameterizing the main ASP problems by the dependency treewidth does not yield fixed-parameter tractability.

Definition 8.34. Let P be a program, then $deptw(P) = tw(U_P)$. We call deptw(P) the dependency treewidth of P.

Observation 8.35. We make the following observations about programs from Example 8.1.

- 1. Consider programs P^n_{32} and P^n_6 where the dependency graph is a tree. Thus, $\operatorname{deptw}(P^n_{32}) = \operatorname{deptw}(P^n_6) = 1$. 2. Consider program P^n_{51} . We observe that its dependency graph consists of n disjoint cycles b_i , v_{b_i,a_i} , a_i , v_{a_i,b_i} for $1 \le i \le n$. According to Lemma 8.28, a cycle has treewidth at most 2 and according to Lemma 8.27, we obtain deptw $(P_{51}^n) \le 2$.
- 3. Consider program P_n^n . Its dependency graph contains a clique on n vertices as a subgraph. Hence deptive $(P_n^n) > n 1$.

Proposition 8.36. deptw strictly dominates inctw and db_{no-C} . Let $C \in \{Horn\} \cup Acyc \setminus \{no-C, no-EC\}$ and $p \in \{db_C, \#neg\}$, #non-Horn, lstr, wfw}, then p and deptw are incomparable.

Proof. Let P be a normal program, and I_P its incidence graph. Let (T, χ) be an arbitrary tree decomposition of I_P . We create a tree decomposition (T, χ') for U_P as follows: For every $r \in P$ let v_r be the corresponding vertex in I_P . We replace the occurrence of a $v_r \in \chi(t)$ by H(r) for all nodes $t \in V(T)$. Then the pair (T, χ') satisfies Conditions 1 and 2 of a tree decomposition of U_P . Since all edges of I_P are covered in (T, χ) for every $r \in P$ there is a $t \in V(T)$ such that $v_r \in \chi(T)$ and $h \in \chi(T)$ where $H(r) = \{h\}$. Because all v_r are connected in the bags of the tree decomposition (T, χ) and all corresponding elements h are connected in (T, χ) , Condition 3 holds for (T, χ') . Thus, (T, χ') is a tree decomposition of the dependency graph U_P . Since the width of (T, χ') is less or equal to the width of (T, χ) it follows $\mathsf{tw}(U_P) \leq \mathsf{tw}(I_P)$ for a normal program P. To show that deptw strictly dominates inctw, consider the program P_n^n where $\operatorname{deptw}(P_n^n) \leq 1$ and $\operatorname{inctw}(P_n^n) \geq n$. Hence deptw \prec inctw.

Let P be a normal program and X a deletion **no-C**-backdoor of P. Thus, X is a feedback vertex set of the dependency graph U_P . According to Lemma 8.28, $tw(U_P) \le k+1$. Hence deptw $\le db_{no-c}$. To show that deptw strictly dominates db_{no-c} consider the program P_{51}^n where $\operatorname{deptw}(P_{51}^n) \leq 2$ and $\operatorname{db}_{\mathbf{no-C}}(P_{51}^n) \geq n$. Consequently, $\operatorname{deptw} \prec \operatorname{db}_{\mathbf{no-C}}$ and the proposition

To show the last statement, consider again the programs P_{51}^n and P_7^n where $\operatorname{deptw}(P_{51}^n) \leq 2$ and $p(P_{51}^n) \geq n$; and $\operatorname{deptw}(P_7^n) \geq n-1$ and $p(P_7^n) = 0$ by Observations 8.6, 8.16, 8.23, and 8.35. \square

Proposition 8.37. For each $L \in \mathcal{A}sp\mathcal{R}eason$, L_N is NP-hard, even for programs that have dependency treewidth 2.

Proof. First consider the problem Consistency. From a 3-CNF formula F with k variables we construct a program P as follows: Among the atoms of our program P will be two atoms a_x and $a_{\bar{k}}$ for each variable $x \in var(F)$ and a new atom f. We add the rules $a_{\bar{k}} \leftarrow \neg a_x$ and $a_x \leftarrow \neg a_{\bar{k}}$ for each variable $x \in var(F)$. For each clause $\{l_1, l_2, l_3\} \in F$ we add the rule $f \leftarrow h(l_1), h(l_2), h(l_3), \neg f$ where $h(\neg x) = a_x$ and $h(x) = a_{\bar{k}}$. Now it is easy to see that the formula F is satisfiable if and only if the program P has an answer set. Let U_P be the undirected dependency graph of P. We construct the following tree decomposition (T,χ) for U_P : the tree T consists of the node t_f and for each $x \in var(F)$ of the nodes t_{fx} , $t_{x\bar{k}}$, and $t_{\bar{k}x}$ along with the edges $t_f t_{fx}$, $t_f t_x t_{x\bar{k}}$, and $t_{x\bar{k}} t_{\bar{k}x}$. We label the nodes by $\chi(t_f) := \{f, v_f\}$ and for each $x \in var(F)$ by $\chi(t_{fx}) := \{a_x, a_{\bar{k}}, f_f, \chi(t_{x\bar{k}}) := \{a_x, a_{\bar{k}}, v_{a_x}a_{\bar{k}}\}$. We observe that the pair (T,χ) satisfies Condition 1. The rules $a_{\bar{k}} \leftarrow \neg a_x$ and $a_x \leftarrow \neg a_{\bar{k}}$ yield the edges $a_x v_{a_x}a_{\bar{k}}$, $v_{a_x}a_{\bar{k}}$, and $v_{\bar{k}}a_{\bar{k}}$

8.6. Interaction treewidth

In this section we consider two parameters investigated by Ben-Eliyahu and Dechter [3]: the interaction treewidth introduced under the term "clique width", and the feedback width of the interaction graph introduced under the term "cycle-cutset size". The interaction graph represents "interactions" between head atoms and related body atoms (similar to the Gaifman graph). The interaction treewidth measures in a certain sense the tree-likeness of the interaction graph and the feedback width the distance of the interaction graph from being acyclic. Both parameters are considered together with the length of the longest cycle in the positive dependency digraph (which states dependencies between atoms in the head and atoms in the positive body).

Definition 8.38. (See Ben-Eliyahu and Dechter [3].) Let P be a normal program. The *interaction graph* is the graph A_P which has as vertices the atoms of P and an edge xy between any two distinct atoms x and y for which there are rules $r, r' \in P$ such that $x \in at(r)$, $y \in at(r')$, and $H(r) \cap H(r') \neq \emptyset$.

Definition 8.39. (See Kanchanasut and Stuckey [99], Ben-Eliyahu and Dechter [3].) Let P be a program. The positive dependency digraph D_P^+ of P has as vertices the atoms at(P) and a directed edge (x, y) between any two atoms $x, y \in at(P)$ for which there is a rule P0 with P1 with P2 with P3 with P4 with P5 with P6 with P6 with P8 with P9 w

Let G = (V, E) be a graph and $c = (v_1, ..., v_l)$ a cycle of length l in G. A chord of c is an edge $v_i v_j \in E$ where v_i and v_j are not connected by an edge in c (non-consecutive vertices). G is chordal (triangulated) if every cycle in G of length at least 4 has a chord.

Definition 8.40. (See Ben-Eliyahu and Dechter [3].) Let G be a digraph and G' a graph. Then

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lc(G) := \max\{\{2\} \cup \{|c| : c \text{ is a cycle in } G\}\},\
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 $cs(G') := \{w : G' \text{ is a subgraph of a chordal graph with all cliques of size at most } w\},$ and

 $fw(G') := min\{|S| : S \text{ is a feedback vertex set of } G'\}.$

lc is the length of the longest cycle. cs is the clique size.⁷

Let P be a normal program, A_P its interaction graph, and D_P^+ its positive dependency digraph. Then

$$cluster(P) := cs(A_P) \cdot log lc(D_P^+)$$

$$cyclecut(P) := fw(A_P) \cdot log lc(D_P^+)$$

cluster(P) is called the size of the tree clustering, cyclecut(P) is called the size of the cycle cutset decomposition.

⁴ Today the term "clique-width" is predominately used to refer to a different graph parameter, see, e.g., [83].

⁵ This definition is equivalent to the original definition in [3] which is given in terms of cliques: the interaction graph is the graph where each atom is associated with a vertex and for every atom a the set of all literals that appear in rules that have a in their heads are connected as a clique.

⁶ Ben-Eliyahu and Dechter [3] used the term dependency graph while the term positive dependency graph was first used by Kanchanasut and Stuckey [99] and became popular by Erdem and Lifschitz [43].

⁷ The original definition is based on the length of the longest acyclic path in any component of *G* instead of the length of the longest cycle and the term clique width is used instead of clique size.

In fact the definition of cs(G) is related to the treewidth:

Lemma 8.41. (See Robertson and Seymour [132].) Let G be a graph. Then tw(G) = cs(G) + 1.

Corollary 8.42. Let P be a normal program, A_P its interaction graph, and D_P^+ its dependency digraph. Then

```
cluster(P) = (tw(A_P) - 1) \cdot log lc(D_P^+)
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Proposition 8.43. (See Ben-Eliyahu and Dechter [3].) For each $L \in \mathcal{A}sp\mathcal{F}ull$, $L[\text{cluster}]_N \in \text{FPT}$ and $L[\text{cyclecut}]_N \in \text{FPT}$.

Observation 8.44. We make the following observations about programs from Example 8.1.

- Consider programs Pⁿ₅₁ and Pⁿ₅₃ and let P ∈ {Pⁿ₅₁, Pⁿ₅₃}. The interaction graph A_p contains n disjoint paths a_i, b_i, for 1 ≤ i ≤ m. Hence A_P contains no cycles and fw(A_P) = 0 and according to Lemma 8.28, we obtain tw(A_P) ≤ 1. Moreover, the positive dependency digraph D⁺_P contains no edges, n disjoint cycles of length exactly 2 respectively. Thus, lc(D⁺_P) = 2. Consequently, cluster(Pⁿ₅₁) ≤ 1 and cyclecut(Pⁿ₅₁) ≤ 1; and cluster(Pⁿ₅₃) ≤ 1 and cyclecut(Pⁿ₅₃) ≤ 1.
 Consider program P^{m,n}₈ and let P = P^{m,n}₈. The interaction graph A_P contains a clique on m vertices and thus tw(A_P) ≥ m − 1.
- 2. Consider program $P_8^{m,n}$ and let $P = P_8^{m,n}$. The interaction graph A_P contains a clique on m vertices and thus $tw(A_P) \ge m-1$. According to Lemma 8.41, we obtain $cs(A_P) \ge m-2$. According to Lemma 8.28, we have $fw(A_P) \ge m-2$. Moreover, the positive dependency digraph D_P^+ contains the cycle $c_1, c_2, \ldots, c_n, c_{n+1}$. Thus, $lc(D_P^+) = n$. Consequently, $cluster(P_8^{m,n}) \ge (m-2) \cdot log n$ and $cyclecut(P_8^{m,n}) \ge (m-2) \cdot log n$.

Observation 8.45. cluster strictly dominates cyclecut.

Proof. Let P be a normal program and A_P its interaction graph. According to Lemma 8.28, we obtain $tw(A_P) \le fw(A_P) + 1$. Hence $cluster(P) \prec cyclecut(P)$. \Box

Proposition 8.46. inctw strictly dominates cluster. If $C \in \{\text{Horn}\} \cup \mathcal{A}_{Cyc} \text{ and } p \in \{\text{db}_{\mathcal{C}}, \#\text{neg}, \#\text{non-Horn}, \text{lstr}, \text{wfw}\}$, then p and cluster are incomparable; and p and cyclecut are incomparable.

Proof. We first show that inctw dominates cluster. Let P be a normal program, I_P its incidence graph, and A_P its interaction graph. Let (T, χ) be an arbitrary tree decomposition of A_P . We create a tree decomposition (T, χ') for I_P as follows: For every $r \in P$ let v_r be the corresponding vertex in I_P . By definition for every $r \in P$ there is a bag $\chi(t)$ where $t \in V(T)$ such that $\operatorname{at}(r) \subset \chi(t)$. We set $\chi'(t) = \chi(t) \cup \{v_r\}$. Then the pair (T, χ') clearly satisfies Conditions 1 and 2 of a tree decomposition of I_P by definition. Since every v_r occurs in exactly one bag Condition 3 holds for (T, χ') . Thus, (T, χ') is a tree decomposition of the interaction graph A_P . Since the width of (T, χ') is less or equal to the width of (T, χ) plus one it follows $\operatorname{tw}(I_P) \leq \operatorname{tw}(A_P) + 1$. To show that inctw strictly dominates cluster, consider the program $P_8^{m,n}$ where $\operatorname{inctw}(P_8^{m,n}) \leq 2$ and cluster $(P_8^{m,n}) = (m-2)\log n$ by Observations 8.31 and 8.44. Hence inctw \prec cluster. Let $p \in \{\operatorname{db}_{\mathcal{C}}, \#\operatorname{neg}, \#\operatorname{non-Horn}, \operatorname{lstr}, \operatorname{wfw}\}$ and $\mathcal{C} \in \{\operatorname{Horn}\} \cup \mathcal{A}_{CyC}$. We show the incomparability of the parameter p and

Let $p \in \{\text{db}_{\mathcal{C}}$, #neg, #non-Horn, lstr, wfw} and $\mathcal{C} \in \{\text{Horn}\} \cup \mathcal{A}cyc$. We show the incomparability of the parameter p and cyclecut. In fact we show something stronger, there are programs P where p is of constant size, but both $\operatorname{tw}(D_P^+)$ and $\operatorname{fw}(D_P^+)$, respectively, and $\operatorname{lc}(I_P)$ can be arbitrarily large, and there are programs where the converse sustains. Therefore we consider the programs $P_{5_1}^n$ and $P_{5_1}^{m,n}$ where $p(P_{5_1}^n) \geq n$ and $\operatorname{cluster}(P_{5_1}^n) \leq 1$ and $\operatorname{cyclecut}(P_{8_1}^{m,n}) \geq (m-2) \cdot \log n$ and $\operatorname{cluster}(P_{8_1}^{m,n}) \geq (m-2) \cdot \log n$ by Observations 8.6, 8.10, 8.16, 8.23, and 8.44. Consequently, the second statement holds. \square

8.7. Number of bad even cycles

Lin and Zhao [110] have considered the number of directed bad even cycles of a given program as a parameter which measures in a certain sense the distance of a program from being acyclic with respect to bad even cycles. This parameter relates to our notion of deletion **no-DEC**-backdoors and deletion **no-DBEC**-backdoors.

Definition 8.47. (See Lin and Zhao [110].) Let P be a normal program. Then

 $\text{\#badEvenCycles}(P) := |\{c : c \text{ is a directed bad even cycle of } P\}|$

Proposition 8.48. For each $L \in AspFull$, $L[\#badEvenCycles]_N \in FPT$.

Observation 8.49. We make the following observations about programs from Example 8.1.

1. Consider program P_A^n which contains no directed bad even cycle. Hence #badEvenCycles $(P_A^n) = 0$.

- 2. Consider program P_{51}^n which contains n disjoint directed bad even cycles. Thus, $\#badEvenCycles(P_{51}^n) = n$. 3. Consider programs P_{52}^n , P_7^n , and $P_8^{m,n}$ which contain no directed bad even cycle. Consequently we obtain $\#badEvenCycles(P_{52}^n) = n$. #badEvenCycles($P_7^{m,n}$) = #badEvenCycles($P_8^{m,n}$) = 0.
- 4. Consider program P_0^n which contains the directed bad even cycles a_1, a_2, a_3, b_i for $1 \le i \le n$. Since there are n of those directed bad even cycles we obtain #badEvenCycles(P_0^n) = n.

Proposition 8.50. $db_{no-DBEC}$ strictly dominates #badEvenCycles. Moreover, db_C and #badEvenCycles are incomparable for the remaining target classes $C \in Acyc \setminus \{\text{no-DBEC}\} \cup \{\text{Horn}\}$. If $p \in \{\text{#neg, #non-Horn, lstr, wfw, inctw, deptw, cluster, cyclecut}\}$, then pand #badEvenCycles are incomparable.

Proof. To see that $db_{no-DBEC}$ strictly dominates #badEvenCycles. Let P be a normal program. If P has at most k directed bad even cycles, we can construct a deletion \mathbf{no} -DBEC-backdoor X for P by taking one element from each directed bad even cycle into X. Thus, $db_{no-DBEC}(P) \le \#badEvenCycles(P)$. If a program P has a deletion **no-DBEC**-backdoor of size 1, it can have arbitrarily many even cycles that run through the atom in the backdoor, e.g. program P_0^n where $db_{no-DBEC}(P_0^n) \leq 1$ and #badEvenCycles(P_q^n) = n by Observations 8.6 and 8.49. It follows that $db_{no-DBEC} \prec \#$ badEvenCycles and the proposition holds.

To show the second statement, consider the programs P_4^n , P_{52}^n , and P_9^n where $db_{\mathcal{C}}(P_9^n) = 1$ for $\mathcal{C} \in \mathcal{A}\mathit{cyc} \cup \{\mathbf{Horn}\}$ and #badEvenCycles(P_9^n) = n; conversely $db_C(P_4^n) \ge n$ for $C \in \{Horn, no-C, no-BC, no-DC, no-DC, no-DC, no-DEC, no-BEC\}$, $\mathrm{db_{no\text{-}DBC}}(P^n_{52}) \geq n$, and $\mathrm{\#badEvenCycles}(P^n_4) = \mathrm{\#badEvenCycles}(P^n_{52}) = 0$. Hence $\mathrm{db}_{\mathcal{C}} \bowtie \mathrm{\#badEvenCycles}$ for $\mathcal{C} \in \mathit{Acyc} \setminus$ $\{no\text{-DBEC}\} \cup \{Horn\}$ by Observations 8.6 and 8.49.

To show the third statement, consider the programs P_{51}^n , P_{52}^n , P_{7}^n , and $P_{8}^{m,n}$, P_{9}^n where $\operatorname{inctw}(P_{7}^n) \geq n-1$ and $\operatorname{deptw}(P_{7}^n) \geq n-1$, $p(P_{52}^n) \geq n$ for $p \in \{\text{#neg, #non-Horn, lstr, wfw}\}$, $\operatorname{cyclecut}(P_{8}^{m,n}) \geq (m-2)\log n$, $\operatorname{cluster}(P_{8}^{m,n}) \geq (m-2)\log n$, and $\operatorname{#badEvenCycles}(P_{7}^n) = \operatorname{#badEvenCycles}(P_{8}^{m,n}) = \operatorname{#badEvenCycles}(P_{52}^n) = 0$; $\operatorname{conversely}(P_{51}^n) \leq 2$ for $p \in \{\text{#neg, #non-Horn, lstr, wfw}\}$, and $\operatorname{#badEvenCycles}(P_{51}^n) = \operatorname{#badEvenCycles}(P_{51}^n) = \operatorname{#badEvenCycles}(P_$ #badEvenCycles(P_n^n) = n by Observations 8.6, 8.10, 8.16, 8.23, 8.31, 8.35, 8.44, and 8.49. Hence $p \bowtie$ #badEvenCycles for $p \in \{\text{#neg, #non-Horn, lstr, wfw, inctw, deptw, cluster, cyclecut}\}$. \square

8.8. *Number of positive cycles (loop formulas)*

Fages [46], Lin and Zhao [109], and Lee and Lifschitz [105] have introduced compilations of normal programs and disjunctive programs to SAT, respectively. Fages [46] has established the notion of being acyclic with respect to the positive dependency digraph of a given program, so-called tight programs. Lin and Zhao [109] have extended this to non-tight programs by adding additional formulas that prevent cycles in the positive dependency graph, so-called loop formulas. We would like to mention that loop formulas are used in some ASP solvers, e.g., Clasp3 [37] and Cmodels3 [108]. The concept of loop formulas is based on the observation that cycles in the positive dependency digraph yield additional models in the SAT formula which are in fact not answer sets and can be eliminated by forbidding a "circular justification" of atoms without having a "justification from outside". The number of loop formulas depends on the number of cycles of the positive dependency digraph and yields the following parameter that measures in a certain sense the distance of a program from being tight.

Definition 8.51. (See Fages [46].) Let P be a normal program and D_p^+ its positive dependency digraph. Then

```
posCycles := |\{c : c \text{ is a directed cycle in } D_p^+\}|
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The program P is called *tight* if #posCycles = 0.8

The parameter has been generalized to disjunctive programs by Lee and Lifschitz [105].

Proposition 8.52. (See Fages [46].) For $L \in \mathcal{A}sp\mathcal{R}eason$, $L[\#posCycles]_N$ is NP-hard or co-NP-hard, even for tight programs.

Observation 8.53. We make the following observations about programs from Example 8.1.

- 1. Consider programs P_{32}^n and P_{53}^n where the positive dependency digraphs contain n directed cycles. Hence $\#posCycles(P_{32}^n) = P_{53}^n$ $\#posCycles(P_{53}^n) = n.$
- 2. Consider program P_{51}^n and P_7^n where the positive dependency digraphs contain no cycle. Hence $\#posCycles(P_{51}^n) = P_7^n$ $\#posCycles(P_7^n) = 0.$
- 3. Consider program $P_8^{m,n}$. Its positive dependency digraph contains only the cycle $c_1, c_2, \ldots, c_n, c_{n+1}$; thus, $\text{\#posCycles}(P_8^n) = 1$.

⁸ Fages [46] used the term positive-order consistent instead of tight.

Proposition 8.54. If $C \in \{\text{Horn}\} \cup \mathcal{A}_{CVC} \text{ and } p \in \{\text{db}_C, \#\text{neg}, \#\text{non-Horn}, \text{lstr}, \text{wfw, inctw, deptw, cluster, cyclecut, } \#\text{badEven-horn}\}$ Cycles}, then p and #posCycles are incomparable.

Proof. We observe incomparability from the programs P_{32}^n , P_{51}^n , P_{53}^n , P_7^n , and $P_8^{n,m}$. We have $p(P_{51}^n) \geq n$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 1\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 2\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 2\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 3\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 3\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 3\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\}, 4\}$ for $p \in \{\mathrm{db}_{\mathcal{C}} \in \{0,1\},$ the proposition holds.

8.9. Head-cycles

Ben-Eliyahu and Dechter [3] have considered programs that do not contain certain cycles in their positive dependency digraph, so-called head-cycle-free programs. Head-cycle-free programs can be compiled into normal programs in polynomial time. We would like to mention that connections to head-cycle-free programs are exploited in the implementation of ASP solvers (see e.g., [106]). In the following we consider the number of head cycles as a parameter which then measures in a certain sense the distance of a program from being head-cycle-free.

Definition 8.55. (See Ben-Eliyahu and Dechter [3].) Let P be a program and D_P^+ its positive dependency digraph. A headcycle of D_P^+ is an $\{x, y\}$ -cycle where $x, y \in H(r)$ for some rule $r \in P$. The program P is head-cycle-free if D_P^+ contains no

One might consider the number of head-cycles as a parameter to tractability.

Definition 8.56. Let P be a program and D_P^+ its positive dependency digraph. Then

```
#headCycles := |\{c : c \text{ is a head-cycle of } D_p^+\}|
```

But as the following proposition states that the ASP-reasoning problems are already NP-complete for head-cycle-free programs.

Proposition 8.57. (See Ben-Eliyahu and Dechter [3].) Each $L \in AspReason$ is NP-hard or co-NP-hard, even for head-cycle-free programs.

Observation 8.58. We make the following observations about programs from Example 8.1.

- 1. Consider program P_{51}^n . Since the positive dependency digraph of P_{51}^n contains no cycle, #headCycles $(P_{51}^n) = 0$. 2. Consider program P_{11}^n . The positive dependency digraph of P_{11}^n contains the head cycles a_ibc for $1 \le i \le n$. Thus, #headCycles $(P_{11}^n) = n$.

Even though the parameter #headCycles does not yield tractability for the ASP-reasoning problems we are interested in the relationship between our lifted parameters and the parameter #headCycles. We will first restrict the input programs to normal programs in Observation 8.59 and then consider disjunctive programs Observation 8.60.

Observation 8.59. If $C \in \{\text{Horn}\} \cup \mathcal{A}_{CYC}$ and $p \in \{\text{db}_{C}, \#\text{neg}, \#\text{non-Horn}, \text{lstr}, \text{wfw}, \text{inctw}, \text{deptw}, \text{cluster}, \text{cyclecut}, \}$ #badEvenCycles, #posCycles}, then #headCycles strictly dominates p^{\downarrow} .

Proof. By definition every normal program is head-cycle-free, hence #headCycles strictly dominates p. \Box

Observation 8.60. If $C \in \{\text{Horn}\} \cup \mathcal{A}_{CVC}$, then db_C and #headCycles are incomparable. Moreover, if $p \in \{\#\text{neg}, \#\text{non-Horn}, \text{lstr}, \text{wfw}\}$, then p^{\uparrow} and #headCycles are incomparable.

Proof. To see that the parameters are incomparable consider the programs P_{51}^n and P_{11}^n where $\mathrm{db}_\mathcal{C} \geq n$ as well as $p(P_{51}^n) \geq n$ and $p(P_{11}^n) = 1$ and $p(P_{11}^n) = 1$

 $^{^9}$ See Section 5.2 for the definition of a W-cycle.

9. Summary and future work

We have introduced the backdoor approach to the domain of propositional answer set programming. In a certain sense, the backdoor approach allows us to augment known tractable classes and makes efficient solving methods for tractable classes generally applicable. Our approach makes recent progress in fixed-parameter algorithmics applicable to answer set programming and establishes a unifying approach that accommodates several parameters from the literature. This framework gives rise to a detailed comparison of the various parameters in terms of their generality. We introduce a general method of lifting parameters from normal to disjunctive programs and establish several basic properties of this method. We further studied the preprocessing limits of ASP rules in terms of kernelization taking backdoor size as the parameter.

The results and concepts of this paper give rise to several research questions. For instance, it would be interesting to consider backdoors for target classes that contain programs with an exponential number of answer sets, but where the set of all answer sets can be succinctly represented. A simple example is the class of programs that consist of (in)dependent components of bounded size. It would be interesting to enhance our backdoor approach to extended rules in particular to weight constraints.

An interesting further research direction is to study whether and how backdoors can be used to control modern heuristics in ASP solvers to obtain a speed-up. We do not expect a practically competitive heuristic that is purely based on backdoors and does not take other aspects of ASP solving into account. Therefore, a conclusive evaluation requires a rigorous experimental setup that takes the interaction of various heuristic methods into account (e.g., interaction of solver techniques [101] and tuning of parameter values [88], modifying the branching heuristic by caching truth values of atoms and reusing them [127], modifying the atom score initially, or while learning conflict clauses, or at a certain depth of the search). So far various studies and theoretical considerations on the effect of restricting decision heuristics to a subset of variables based on structural properties have been carried out in the context of SAT and ASP, where both positive [80,81, 143,75] and negative effects [96,95] have been observed.

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