Logic programs with monotone abstract constraint atoms∗

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Abstract

We introduce and study logic programs whose clauses are built out of *monotone constraint atoms*. We show that the operational concept of the one-step provability operator generalizes to programs with monotone constraint atoms, but the generalization involves nondeterminism. Our main results demonstrate that our formalism is a common generalization of (1) normal logic programming with its semantics of models, supported models and stable models, (2) logic programming with weight atoms (*lparse* programs) with the semantics of stable models, as defined by Niemelä, Simons and Soininen, and (3) of disjunctive logic programming with the possible-model semantics of Sakama and Inoue.

1 Introduction

In this paper, we introduce and study logic programs whose clauses are built of generalized atoms expressing constraints on sets. We propose a generalization of normal logic programming to this extended setting. Our generalization uses the assumption of the monotonicity of constraints and it employs the nondeterminism in deriving ways to satisfy constraints. In our approach the basic concepts, methods, semantics and results of normal logic programming generalize to the proposed context. Our work provides a theoretical framework to a recent extension of logic programming with weight constraints (also known as *pseudo-boolean constraints*) (Niemelä et al. 1999; Simons et al. 2002), and to an earlier formalism of disjunctive logic programs with the semantics of possible models (Sakama and Inoue 1994), but applies to a much broader class of programs.

In the 1990s researchers demonstrated that normal logic programming with the

∗ Parts of this paper appeared earlier in conference papers (Marek et al. 2004; Marek and Truszczyński 2004).

stable-model semantics is an effective knowledge representation formalism. It provides solutions to problems arising in such contexts as planning, reasoning about actions, diagnosis and abduction, product configuration, and modeling and reasoning about preferences. Moreover, due to the emergence of fast methods to compute stable models (Niemelä and Simons 1997; Babovich and Lifschitz 2002; Lin and Zhao 2002; Leone et al. 2004), the importance of the formalism increased significantly as it became possible to use it not only as a modeling language but also as a practical computational tool. The contributions of (Baral 2003; Gelfond and Leone 2002) provide a detailed discussion of the formalism and its applications.

In the last few years, researchers proposed extensions of the language of normal logic programming with means to model constraints involving *aggregate* operations on sets. (Simons et al. 2002) proposed a formalism integrating logic programming with *weight constraints*, known in the SAT community as *pseudo-boolean* constraints, generalized the concept of stable models to this extended setting, and developed fast algorithms to compute them. (Denecker et al. 2001; Pelov et al. 2004), introduced a formalism allowing for more general aggregates. They extended to this new setting several semantics of normal logic programs, including the stable-model semantics and the well-founded semantics. A related recent work (Dell'Armi et al. 2003; Faber et al. 2004; Calimeri et al. 2005), incorporated aggregates into the formalism of *disjunctive* logic programs with the *answer-set semantics*. Yet another extension of normal logic programming has been proposed in (Marek and Remmel. 2004) as set-based constraints. Such extensions are important as they simplify the task of modeling problem specifications, typically result in more direct and concise encodings, and often significantly improve the computational effectiveness of the formalism as a problem-solving tool.

Our goal is to propose an abstract formalism of logic programs extended with means to model constraints on sets, preserving as much as possible analogies between our theory and *normal* logic programming. We introduce the notion of an *abstract constraint* and its linguistic counterpart — an *abstract constraint atom*. We then use abstract constraint atoms as building blocks of program clauses in the same way propositional atoms form clauses of normal logic programs. For the most part, we restrict our attention to *monotone* constraints, as monotonicity is essential for preserving the notion of a logic program as a computational device. We show that basic concepts, techniques, and results of normal logic programming have direct generalizations for the class of programs built of monotone abstract constraints. What distinguishes our work from other recent approaches to integrating logic programming with aggregates is that we allow constraint atoms in the heads of clauses, while formalisms proposed and studied in (Denecker et al. 2001; Pelov et al. 2004; Dell'Armi et al. 2003; Faber et al. 2004; Calimeri et al. 2005) do not.

In many respects the theory we built in this paper mirrors closely an operator-based treatment of normal logic programs. There is, however, a basic difference. Abstract constraint atoms are inherently nondeterministic. They can be viewed as shorthands for certain disjunctions and, in general, there are many ways to make an abstract constraint atom true. This nondeterminism has a consequence. The one-step provability operator, which generalizes the one-step provability operator of (van

Emden and Kowalski 1976) defined for normal programs, is no longer deterministic. It assigns to an interpretation M a *set* $T(M)$ of interpretations. Each interpretation in the set $T(M)$ is regarded as possible and equally likely outcome of applying the operator to M.

The nondeterministic one-step provability operator is a key tool in our work. It generalizes the one-step provability operator of (van Emden and Kowalski 1976). Thanks to close parallels between these two concepts, we are able to reconstruct operator-based characterizations of models, supported models, and the concept of a *bottom-up* computation for programs with abstract constraints that generalize Horn programs. We then extend to programs with abstract monotone constraints the definitions of the *Gelfond-Lifschitz* reduct and a stable model (Gelfond and Lifschitz 1988). We also distinguish and discuss the class of *deterministic* programs (programs with clauses whose heads can be satisfied in one way only). For these programs the one-step provability operator becomes deterministic and the theory of normal logic programming extends to deterministic programs without *any* significant change. In particular, it follows that normal logic programming with all its major 2-valued semantics can be viewed as a special case of logic programming with monotone abstract constraints.

In addition, we show that programs with abstract constraints provide a formal account of a class of logic programs with weight (pseudo-boolean) atoms introduced in (Simons et al. 2002). We call programs in the syntax proposed in that paper *lparse programs*. (Simons et al. 2002) defined for lparse programs the notion of a *stable model* and showed that lparse programs generalize normal logic programming with the stable-model semantics of Gelfond and Lifschitz (Gelfond and Lifschitz 1988). However, the notion of the reduct underlying the definition of a stable model given in (Simons et al. 2002) is different from that proposed in (Gelfond and Lifschitz 1988) and the precise nature of the relationship between normal logic programs and lparse programs was not clear.

Our work explicates this relationship. On one hand, the formalism of programs with abstract constraints parallels normal logic programming. In particular, major concepts, results and techniques in normal logic programming have counterparts in the setting of programs with abstract constraints. On the other hand, under some simple transformations, lparse programs can be viewed as a special case of programs with abstract constraints. Thus, through this connection, the theory of normal logic programming can be lifted to the setting of lparse programs leading, in particular, to new characterizations of stable models of lparse programs.

Finally, we show that programs with monotone abstract constraints generalize the formalism of disjunctive logic programs with the semantics of *possible* models (Sakama and Inoue 1994). In fact, as we point out, several ideas that are stated in abstract terms in our paper have their roots in (Sakama and Inoue 1994).

2 Basic concepts, motivation, examples

We consider a language determined by a fixed set At of *propositional atoms*. An *abstract constraint* is a collection $C \subseteq \mathcal{P}(At)$ (if X is a set, by $\mathcal{P}(X)$ we denote the family of all subsets of X). We say that elements of C *satisfy* the constraint C or have the property C. An *abstract constraint atom* (or *ac-atom*, for short) is an expression $C(X)$, where $X \subseteq At$ is *finite* and C is an abstract constraint. An *ac-literal* is an expression of the form $C(X)$ or $\mathbf{not}(C(X))$, where $C(X)$ is an ac-atom. We call X the *atom set* of an ac-literal A of the form $C(X)$ or $\mathbf{not}(C(X))$ and denote it by $aset(A)$.

An intended meaning of an ac-atom $C(X)$ is to represent a requirement on subsets of X that they must satisfy the constraint C. Formally, we interpret ac-atoms by means of propositional interpretations (truth assignments), which we represent as subsets of At: an atom is *true* in an interpretation $M \subseteq At$ if $p \in M$, otherwise, p is *false* in M. An interpretation $M \subseteq At$ *satisfies* an ac-atom $C(X)$, written $M \models C(X)$, if $M \cap X \in C$ (that is, if the set of atoms in X that are true in M satisfies the constraint C). Otherwise, M does not satisfy $C(X)$, written $M \not\models C(X)$. In that case, we also say that M satisfies the *ac-literal* $\mathbf{not}(C(X))$ and write $M \models \mathbf{not}(C(X))$. An ac-atom $C(X)$ is *consistent* if there is an interpretation M such that $M \models C(X)$ or, equivalently, if C contains at least one subset of X. We will now illustrate these concepts with several examples of common constraints.

Pseudo-boolean constraints. These constraints are also known as *weight constraints*. Given a real number w and a function W, assigning to each atom in At a real number (its *weight*), a *pseudo-boolean* constraint $PB(w, W, \leq)$ imposes a restriction that "the total weight of atoms in a set is at least w". Formally, we set $PB(w, W, \leq) = \{A \subseteq At\colon w \leq \sum_{a\in A} W(a)\}$ (comparison relations $<$, $>$, $\geq$ give rise to other types of weight constraints).

Cardinality constraints. They are pseudo-boolean constraints in which a bound w is a non-negative integer and a weight of every atom is 1. Throughout the paper, we use cardinality constraints to illustrate concepts we study. To simplify the notation and to make it consistent with the notation used in (Simons et al. 2002), we write kX to denote an ac-atom $C(X)$, where $C = PB(k, W, \leq)$ and $W(a) = 1$ for every $a \in At$.

Product constraints. They differ from weight constraints in that they restrict the product of individual weights of atoms in allowed sets, depending on the type of the comparison relation used. Selecting the relation $\leq$ and assuming the same notation as before, we express product constraints as abstract constraints of the form $\Pi(w, W, \leq) = \{A \subseteq At\colon w \leq \Pi_{a\in A} W(a)\}$.

Maximum constraints. Given a weight function W on the set of atoms and a real bound w, the maximum constraint restricts allowed sets of atoms to those with the maximum weight at least w. Formally, we express them as abstract constraints of the form $Max(w, W, \leq) = \{A \subseteq At\colon w \leq \max\{W(a)\colon a \in A\}\}$ (or its variants, depending on the comparison relation).

Even- and odd-cardinality constraints. They impose a parity requirement on the cardinality of allowed sets. Formally, we express them as abstract constraints $E = \{A \subseteq At\colon |A| \text{ is even}\}$ and $O = \{A \subseteq At\colon |A| \text{ is odd}\}$.

Containment constraints. Such constraints require that allowed sets contain some prespecified configurations (subsets). We capture them by abstract constraints

$C(\mathcal{A})$ that consist of all subsets of At that contain at least one set from a prespecified collection $\mathcal{A}$ of finite subsets of At.

Each of these constraints determines associated ac-atoms. Let $At = \{p_1, p_2, \ldots\}$ and let us consider a weight function W such that for every integer $i \geq 1$, $W(p_i) = i$. The expression $PB(6, W, \leq)$ is an example of a pseudo-boolean constraint. If we denote it by C_1, then $C_1(\{p_1, p_2, p_5, p_6\})$ is an example of a pseudo-boolean constraint atom. A set $M \subseteq At$ satisfies $C_1(\{p_1, p_2, p_5, p_6\})$ if and only if the total weight of atoms in $M \cap \{p_1, p_2, p_5, p_6\}$ is at least 6 (that is, if and only if M contains p_6, or p_5 together with at least one other atom). Similarly, $Max(5, W, \leq)$ is an example of a maximum constraint and, if we denote it by C_2, $C_2(\{p_2, p_4, p_6, p_8\})$ is a maximum constraint atom that enforces the restriction on sets of atoms to contain p_6 or p_8. An abstract constraint atom $E(\{p_1, p_7\})$ (E stands for the even-cardinality constraint) forces allowed sets of atoms to contain none or both of p_1 and p_7. All these constraint atoms are consistent. An atom $C_3(\{p_1, p_2, p_3\})$, where $C_3 = PB(7, w, \leq)$ is an example of an inconsistent constraint atom. No selection of atoms from $\{p_1, p_2, p_3\}$ satisfies it and, consequently, it has no models.

These examples demonstrate that abstract constraints and abstract constraint atoms express a broad range of common constraints. In this paper, we show that abstract constraint atoms can be combined into logic program clauses to represent even more complex constraints, and that much of the theory of normal logic programs generalizes to the extended setting.

3 Logic programs built of $\mathcal{F}$-atoms

Let $\mathcal{F}$ be a class of abstract constraints over At. By an *$\mathcal{F}$-atom* we mean an abstract constraint atom $A(X)$ such that $A \in \mathcal{F}$ and $X \subseteq At$. An *$\mathcal{F}$-literal* (or simply, a *literal*, if the context is clear) is an expression of the form $A(X)$ or $\mathbf{not}(A(X))$, where $A(X)$ is an $\mathcal{F}$-atom. An *$\mathcal{F}$-clause* is an expression

$$A(X) \leftarrow B_1(X_1), \ldots, B_m(X_m), \mathbf{not}(C_1(Y_1)), \ldots, \mathbf{not}(C_n(Y_n)) \tag{1}$$

where $A(X)$, $B_i(X_i)$ and $C_j(Y_j)$ are $\mathcal{F}$-atoms. An $\mathcal{F}$-clause (1) is called a *constraint clause* if $A(X)$ is not consistent. An *$\mathcal{F}$-program* is a finite collection of $\mathcal{F}$-clauses[1].

If r is a clause of the form (1), $A(X)$ is the *head* of r, denoted by $hd(r)$, and X is the *head set* of r, denoted by $hset(r)$. We also call the conjunction of literals $B_1(X_1), \ldots, B_m(X_m), \mathbf{not}(C_1(Y_1)), \ldots, \mathbf{not}(C_n(Y_n))$, the *body* of r and denote it by $bd(r)$. Occasionally, we use the same term to denote the *set* of all literals in the body of a clause. Finally, for an $\mathcal{F}$-program P, we define $hset(P)$ to be the union of sets $hset(r)$, for $r \in P$.

An interpretation $M \subseteq At$ *satisfies* a set (conjunction) L of literals, if it satisfies every literal in L. We say that M *satisfies* an $\mathcal{F}$-clause r if M satisfies the head of the clause whenever it satisfies the body of r. Finally, M *satisfies* an $\mathcal{F}$-program P

[1] We note that the assumption of the finiteness of programs is not essential. The entire theory of $\mathcal{F}$-programs extends to the case when we admit infinite programs. However, additional means of proof, such as Zorn Lemma, may be required in some arguments (for instance, in the argument for the existence of minimal models of $\mathcal{F}$-programs).

if it satisfies all clauses in P. We write $M \models L$, $M \models r$ and $M \models P$ to denote these three types of the satisfaction relation. We will often write "*is a model of*" instead of "satisfies". $\mathcal{F}$-programs that have models are called *consistent*.

Clauses of normal logic programs are typically regarded as computational devices: *assuming that preconditions of a clause have been established, the clause provides a justification to establish (compute) its head*. Crucial concepts behind formal accounts of that intuition are those of a Horn program, the corresponding *bottom-up* computation, and a least Herbrand model, which defines the *result* of the computation. Computations and their results are well defined due to the *monotone* behavior of Horn programs.

To extend normal logic programming to the class of programs with abstract constraint atoms, one needs a generalization of the class of Horn programs supporting an appropriate notion of a computation, with the results of computations playing the same role as that played by the least Herbrand model. In order to accomplish that, it is not enough simply to disallow the negation operator in the bodies of $\mathcal{F}$-clauses. It is also necessary to restrict the class of constraints to those that are *monotone* (that is, intuitively, once true in an interpretation, they remain true in every superset of it). Without that assumption, the monotonicity of normal Horn programs does not generalize and there is no straightforward way to define the concept of a computation. (We refer to (Marek 2005) for a study of properties of monotone constraints.)

Formally, we say that an abstract constraint C is *monotone* if for every $A, A' \subseteq At$, if $A \in C$ and $A \subseteq A'$ then $A' \in C$ (in other words, monotone constraints are precisely upward-closed families of subsets of At). An abstract constraint atom $C(X)$ is monotone if its constraint C is monotone.

Proposition 1

Let C be an abstract monotone constraint over At, $X \subseteq At$, and let $M, M' \subseteq At$ be two interpretations. If $M \models C(X)$ and $M \subseteq M'$, then $M' \models C(X)$.

We note that if all the individual weights used by a weight function are non-negative, the corresponding pseudo-boolean constraints are monotone. The maximum constraints are monotone for *every* weight function. On the other hand, we note that some common constraints, for instance, even- and odd-cardinality constraints E and O, are not monotone.

¿From now on we restrict our attention to constraints that are *monotone*. We will write a *monotone* $\mathcal{F}$-clause and a *monotone* $\mathcal{F}$-program to make it explicit that all constraints in $\mathcal{F}$ are monotone.

An important consequence of the monotonicity assumption is that monotone $\mathcal{F}$-programs without constraint clauses have models (and so, also minimal models).

Proposition 2

Let P be a monotone $\mathcal{F}$-program without constraint clauses. Then the set At of all atoms in the language is a model of P.

Proof
Let $r \in P$. Since the constraint $hd(r)$ is consistent, there is a set of atoms $M \subseteq At$ such that $M \models hd(r)$. By the monotonicity of constraints in $\mathcal{F}$, $At \models hd(r)$. Thus, $At \models P$. $\square$

Another important consequence of the monotonicity assumption is that the concept of a Horn program has an obvious direct generalization.

Definition 1
A monotone $\mathcal{F}$-program that contains no occurrences of the operator **not** is a *Horn $\mathcal{F}$-program.* $\square$

Horn $\mathcal{F}$-programs defined in this way have many properties that generalize well-known properties of *normal* Horn programs. We will state and prove several of them later in the paper.

4 Nondeterministic one-step provability operator

Following a fundamental idea underlying normal logic programming, we assign to $\mathcal{F}$-clauses a procedural interpretation, which views them as derivation clauses. In the discussion that follows we do not assume that constraints in $\mathcal{F}$ are monotone.

Intuitively, if an $\mathcal{F}$-clause r has its body satisfied by some set of atoms M, then r provides *support* for deriving from M any set of atoms M' such that

1. M' consists of some atoms from the headset of r (r provides *no* grounds for deriving atoms that do not appear in its headset)
2. M' satisfies the head of r (since r "fires", the constraint imposed by its head must hold).

Clearly, the process of deriving M' from M by means of r is *nondeterministic* in the sense that, in general, there are several sets that are supported by r and M.

This interpretation of $\mathcal{F}$-clauses extends to $\mathcal{F}$-programs. Given an $\mathcal{F}$-program P and a set of atoms M, each clause $r \in P$ such that M satisfies the body of r provides a support for a subset of the head set of r. The union, say M', of such sets — each supported by *some* clause r, with r ranging over those clauses in P whose body is satisfied by M — can be viewed as "derived" from M by means of P. In general, given P and M, there may be several such derived sets. Thus the notion of derivability associated with a program is nondeterministic, as in the case of individual clauses.

We describe formally this intuition of derivability in terms of a nondeterministic one-step provability operator. Before we give a precise definition, we note that by a *nondeterministic operator* on a set D we mean any function $f\colon D \rightarrow \mathcal{P}(D)$. One can view the set $f(d)$ as the collection of all possible outcomes of applying f to d one of which, if $f(d) \neq \emptyset$, can be selected nondeterministically as the *actual* outcome of f. We emphasize that we allow $f(d)$ to be empty, that is, nondeterministic operators are, in general, *partial* — for some elements of the domain they do not assign any possible outcomes.

Definition 2
Let $\mathcal{F}$ be a class of constraints (not necessarily monotone). Let P be an $\mathcal{F}$-program and let $M \subseteq At$.

1. A clause $r \in P$ is *M-applicable*, if $M \models bd(r)$. We denote by $P(M)$ the set of all M-applicable clauses in P.
2. A set M' is *nondeterministically one-step provable* from M by means of P, if $M' \subseteq hset(P(M))$ and $M' \models hd(r)$, for every clause r in $P(M)$.
3. The *nondeterministic one-step provability operator* T_P^{nd}, is a function from $\mathcal{P}(At)$ to $\mathcal{P}(\mathcal{P}(At))$ such that for every $M \subseteq At$, $T_P^{nd}(M)$ consists of all sets M' that are nondeterministically one-step provable from M by means of P. □

Since an abstract constraint forming the head of an $\mathcal{F}$-clause may be inconsistent, there exist programs P and interpretations $M \subseteq At$ such that $T_P^{nd}(M)$ is empty.

The concepts introduced above have especially elegant properties for *monotone* $\mathcal{F}$-programs. First, to illustrate them, let us consider a simple example involving a program with cardinality constraints (cf. Section 2). The program discussed in this example is not a Horn program.

Example 1
Let P be a program with cardinality constraints consisting of the following clauses:

$$\begin{aligned} r_1 = &\quad 2\{a\} \leftarrow 2\{b, d\} \\ r_2 = &\quad 1\{b, c\} \leftarrow \mathbf{not}(1\{e\}) \\ r_3 = &\quad 1\{a, d\} \leftarrow 2\{b, c\} \end{aligned}$$

We note that the cardinality atom in the head of the first clause is inconsistent.

Let us consider a set $M = \{b, c, e\}$. Since $M \not\models 2\{b, d\}$, r_1 is not M-applicable. Similarly, $M \not\models \mathbf{not}(1\{e\})$ and r_2 is not M-applicable, either. On the other hand, $M \models 2\{b, c\}$ and so, r_3 is M-applicable.

There are three subsets of $\{a, d\}$ that satisfy the constraint $1\{a, d\}$ in the head of the clause r_3: $\{a\}$, $\{d\}$ and $\{a, d\}$. Thus, each of these sets is nondeterministically one-step provable from M and, consequently,

$$T_P^{nd}(M) = \{\{a\}, \{d\}, \{a, d\}\}.$$

We also note that if $|M| = 1$ and $e \notin M$ then r_2 is the only M-applicable clause in P. For such sets M, $T_P^{nd}(M) = \{\{b\}, \{c\}, \{b, c\}\}$. On the other hand, if M contains both b and d, then r_1 is M-applicable and since the head of r_1 is inconsistent, $T_P^{nd}(M) = \emptyset$ (no set is nondeterministically one-step provable from such a set M). □

The example shows, in particular, that it may be the case that $T_P^{nd}(M) = \emptyset$. If, however, P is a *monotone* $\mathcal{F}$-program without constraint clauses, then it is never the case.

Proposition 3
Let P be a monotone $\mathcal{F}$-program without constraint clauses. For every $M \subseteq At$, $hset(P(M)) \in T_P^{nd}(M)$. In particular, $T_P^{nd}(M) \neq \emptyset$.

Proof
Let us consider $r \in P(M)$. Then, $hset(P(M)) \cap hset(r) = hset(r)$. Since $hd(r)$ is consistent, it follows by the monotonicity of constraints in $\mathcal{F}$ that $hset(r) \models hd(r)$. Thus, $hset(P(M)) \models hd(r)$ and, consequently, $hset(P(M)) \in T_P^{nd}(M)$. $\square$

The operator T_P^{nd} plays a fundamental role in our research. It allows us to formalize the procedural interpretation of $\mathcal{F}$-clauses and identify several classes of models.

Our first result characterizes models of monotone $\mathcal{F}$-programs. Models of a normal logic program P are prefixpoints of the one-step provability operator T_P (van Emden and Kowalski 1976). This characterization lifts to the class of monotone $\mathcal{F}$-programs, with the operator T_P^{nd} replacing T_P.

Theorem 1
Let P be a monotone $\mathcal{F}$-program and let $M \subseteq At$. The set M is a model of P if and only if there is $M' \in T_P^{nd}(M)$ such that $M' \subseteq M$.

Proof
Let M be a model of P and $M' = M \cap hset(P(M))$. Let $r \in P(M)$. Since M is a model of r, $M \models hd(r)$. Clearly, $hset(r) \subseteq hset(P(M))$. Thus, $M \cap hset(r) = M' \cap hset(r)$ and, consequently, $M' \models hd(r)$. It follows that $M' \in T_P^{nd}(M)$. Since $M' \subseteq M$, the assertion follows.

Conversely, let us assume that there is $M' \in T_P^{nd}(M)$ such that $M' \subseteq M$. Let $r \in P$ be a clause such that $M \models bd(r)$. Since $M' \in T_P^{nd}(M)$, $M' \models hd(r)$. We recall that the constraint involved in $hd(r)$ is monotone (as we consider only monotone constraints). Thus, by Proposition 1, $M \models hd(r)$, as well. It follows that M is a model of every clause in P and, consequently, of P. $\square$

5 Supported models of $\mathcal{F}$-programs

For a set M of atoms, we say that M-applicable clauses in an $\mathcal{F}$-program P provide *support* to atoms in the heads of these clauses. In general, a model M of an $\mathcal{F}$-program may contain elements that have no support in a program and M itself, that is, cannot be derived from M by means of clauses in the program.

Example 2
Let P be a program with cardinality constraints consisting of a single clause:

$$1\{p, q\} \leftarrow \mathbf{not}(1\{q\}),$$

where p and q are two different atoms. Let $M_1 = \{q\}$. Clearly, M_1 is a model of P. However, M_1 has no support in P and itself. Indeed, $T_P^{nd}(M_1) = \{\emptyset\}$ and so, P and M_1 do not provide support for any atom. Similarly, another model of P, the set $M_2 = \{p, s\}$, where $s \in At$ is an atom different from p and q, has no support in P and itself. We have $T_P^{nd}(M_2) = \{\{p\}, \{q\}, \{p, q\}\}$ and so, p has support in P and M_2, but s does not. Finally, the set $M_3 = \{p\}$, which is also a model of P, *has support* in P and itself. Indeed, $T_P^{nd}(M_3) = \{\{p\}, \{q\}, \{p, q\}\}$ and there is a way to derive M_3 from P and M_3. $\square$

For M to be a model of P, M must satisfy the heads of all applicable clauses. To this end, M needs to contain some of the atoms appearing in the headsets of these clauses (atoms with support in M and P) and, possibly, also some atoms that do not have such support. Models that contain *only* atoms with support form an important class of models generalizing the class of supported models for normal logic programs (Clark 1978; Apt 1990).

Definition 3

Let $\mathcal{F}$ be a class of constraints (not necessarily monotone) and let P be an $\mathcal{F}$-program. A set of atoms M is a *supported model* of P if M is a model of P and $M \subseteq hset(P(M))$. □

Supported models have the following characterization generalizing a characterization of supported models of normal logic programs as fixpoints of the the van Emden-Kowalski operator (the characterizing condition is commonly used as a definition of a *fixpoint* of a nondeterministic operator).

Theorem 2

Let $\mathcal{F}$ be a class of constraints (not necessarily monotone). Let P be an $\mathcal{F}$-program. A set $M \subseteq At$ is a supported model of P if and only if $M \in T_P^{nd}(M)$.

Proof

If M is a supported model of P then it is a model of P (by the definition). Moreover, $M \subseteq hset(P(M))$. Thus, $M \in T_P^{nd}(M)$. Conversely, if $M \in T_P^{nd}(M)$, then $M \subseteq hset(P(M))$ and $M \models hd(r)$, for every $r \in P(M)$. Thus, $M \models r$, for every $r \in P(M)$. If $r \in P \setminus P(M)$, then $M \not\models bd(r)$ and so, $M \models r$. Thus, M is a model of P. Since $M \in T_P^{nd}(M)$ also implies $M \subseteq hset(P(M))$, M is a supported model of P. □

In Section 8 we show that the use of the term *supported* for the class of models defined in this section is not a misnomer; supported models of $\mathcal{F}$-programs generalize supported models of normal logic programs.

6 Horn $\mathcal{F}$-programs

For the concepts of the one-step provability and supported models we did not need a restriction to monotone constraints. To properly generalize the notion of a stable model, however, this restriction is essential. Thus, from this point on, we will consider only monotone $\mathcal{F}$-programs.

First, we will study Horn $\mathcal{F}$-programs (we recall that the notion of a Horn $\mathcal{F}$-program assumes that $\mathcal{F}$ consists of monotone constraints only) viewing them as representations of certain nondeterministic computational processes. We will later use the results of this section to extend to the class of $\mathcal{F}$-programs the concept of a stable model.

Definition 4
Let P be a Horn $\mathcal{F}$-program. A *P-computation* is a sequence $(X_n)_{n=0,1,\ldots}$ such that $X_0 = \emptyset$ and, for every non-negative integer n:

1. $X_n \subseteq X_{n+1}$, and
2. $X_{n+1} \in T_P^{nd}(X_n)$.

Given a computation $t = (X_n)_{n=0,1,\ldots}$, we call $\bigcup_{n=0}^{\infty} X_n$ the *result* of the computation t and denote it by R_t. $\square$

Our stipulations that P-computations have length ω does not restrict the generality. Since atom sets of ac-atoms are finite, if a clause is applicable with respect to the result of the computation, it is applicable at some step n of the computation. Consequently, like in the case of normal Horn programs, all possible results of computations of arbitrary transfinite lengths can be reached in ω steps, even in the case of infinite programs.

Results of computations are supported models.

Theorem 3
Let P be a Horn $\mathcal{F}$-program and let t be a P-computation. Then R_t is a supported model of P, that is, R_t is a model of P and $R_t \subseteq hset(P(R_t))$.

Proof
Let $t = (X_n)_{n=0,1,\ldots}$. Clearly $X_0 = \emptyset \subseteq hset(P(R_t))$. Let n be a non-negative integer. Since $X_{n+1} \in T_P^{nd}(X_n)$, $X_{n+1} \subseteq hset(P(X_n))$. Since P is a Horn $\mathcal{F}$-program, it follows that if $r \in P$, $X \subseteq Y$ and $X \models bd(r)$, then $Y \models bd(r)$. Thus, since $X_n \subseteq R_t$, we have

$$X_{n+1} \subseteq hset(P(X_n)) \subseteq hset(P(R_t)).$$

By induction, $R_t = \bigcup_{n=0}^{\infty} X_n \subseteq hset(P(R_t))$.

Conversely, let us consider a clause $r \in P$. If $R_t \not\models bd(r)$ then $R_t \models r$. Let us then assume that $R_t \models bd(r)$. Since r has finitely many $\mathcal{F}$-atoms in the body, and since each $\mathcal{F}$-atom is of the form $C(X)$, where X is *finite*, there is a non-negative integer i such that $X_i \models bd(r)$. By the definition of a P-computation, $X_{i+1} \in T_P^{nd}(X_i)$. Thus, $X_{i+1} \models hd(r)$ and, since $X_{i+1} \subseteq R_t$, $R_t \models hd(r)$ (by the monotonicity of $hd(r)$). It follows that $R_t \models r$ in the case when $R_t \models bd(r)$, as well. Thus, R_t is a model of P. Since R_t is a model of P and $R_t \subseteq hset(P(R_t))$, R_t is a supported model of P. $\square$

We will now show that having a model (being consistent) is a necessary and sufficient condition for a Horn $\mathcal{F}$-program to have a computation. To this end, we will first introduce a certain class of computations.

Definition 5
Let M be a model of P. A *canonical P-computation with respect to M* is a sequence $t^{P,M} = (X_n^{P,M})_{n=0,1,\ldots}$ defined as follows:

1. $X_0^{P,M} = \emptyset$ and,
2. $X_{n+1}^{P,M} = hset(P(X_n^{P,M})) \cap M$, for every $n \geq 0$. $\square$

We observe that canonical computations involve no nondeterminism. At each stage there is exactly one way in which we can continue. This continuation is determined by the model M. Before we proceed further, we illustrate the concept of a canonical computation with a simple example.

Example 3
Let us assume that $At = \{a, b, c, d\}$ and let us consider a Horn program with cardinality constraints, say P, consisting of the following clauses:

$r_1 = \quad 1\{a, d\} \leftarrow 2\{b, d\}$
$r_2 = \quad 1\{b, c\} \leftarrow$
$r_3 = \quad 1\{a\} \leftarrow 2\{b, c\}$

Let $M = \{a, b, c, d\}$. It is easy to check that M is a model of P (it also follows from Proposition 2, as the constraint atoms in the heads of clauses in P are consistent).

We will now construct a canonical P-computation with respect to M. By the definition $X_0^{P,M} = \emptyset$. The only $X_0^{P,M}$-applicable clause in P is r_2. Since $\{b, c\} \cap M = \{b, c\}$, $X_1^{P,M} = \{b, c\}$. The clauses r_2 and r_3 are $X_1^{P,M}$-applicable and r_1 is not. Since $\{a\} \cap M = \{a\}$ and $\{b, c\} \cap M = \{b, c\}$, $X_2^{P,M} = \{a, b, c\}$. Since r_2 and r_3 are the only $X_2^{P,M}$-applicable clauses in P, it follows that $X_k^{P,M} = X_2^{P,M}$, for $k = 3, 4, \ldots$.

By the definition, the union of all sets in the canonical computation is included in M. Our example demonstrates that canonical computations with respect to M, in general, do not reconstruct all of M. $\square$

The use of the term P-computation in Definition 5 is justified. The following theorem shows that the sequence $t^{P,M}$ is indeed a P-computation.

Theorem 4
Let P be a Horn $\mathcal{F}$-program and let $M \subseteq At$ be a model of P. Then the sequence $t^{P,M}$ is a P-computation.

Proof
We need to show that the conditions (1) and (2) from the definition of a P-computation hold for the sequence $t^{P,M}$. To prove (1), we proceed by induction on n. For $n = 0$, the condition (1) is, clearly, satisfied. Let us assume that for some non-negative integer n, $X_n^{P,M} \subseteq X_{n+1}^{P,M}$ holds. Then

$$hset(P(X_n^{P,M})) \subseteq hset(P(X_{n+1}^{P,M})).$$

It follows that

$$X_{n+1}^{P,M} = hset(P(X_n^{P,M})) \cap M \subseteq hset(P(X_{n+1}^{P,M})) \cap M = X_{n+2}^{P,M}.$$

To prove (2), let us consider a non-negative integer n. By the definition, $X_{n+1}^{P,M} \subseteq hset(P(X_n^{P,M}))$. It remains to prove that $X_{n+1}^{P,M} \models P(X_n^{P,M})$. Let $r \in P(X_n^{P,M})$. Then $X_n^{P,M} \models bd(r)$ and, since $X_n^{P,M} \subseteq M$, $M \models bd(r)$. We recall that M is a model of P. Thus, $M \models hd(r)$. It follows that $M \cap hset(r) \models hd(r)$ and, consequently, $M \cap hset(P(X_n^{P,M})) \models hd(r)$. Since $X_{n+1}^{P,M} = M \cap hset(P(X_n^{P,M}))$, it follows that $X_{n+1}^{P,M} \models P(X_n^{P,M})$. $\square$

We now have the following corollary to Theorems 3 and 4 that characterizes Horn $\mathcal{F}$-programs that have computations.

Corollary 1
Let P be a Horn $\mathcal{F}$-program. Then, P has a model if and only if it has a P-computation. In particular, every Horn $\mathcal{F}$-program P without constraint clauses possesses at least one P-computation.

Proof
If M is a model of P then the canonical computation $t^{P,M}$ is a P-computation (Theorem 4). Conversely, if P has a P-computation t, then R_t is a model of P (Theorem 3). The second part of the assertion follows from the fact that Horn $\mathcal{F}$-programs without constraint clauses have models (Proposition 2). □

We use the concept of a computation to identify a certain class of models of Horn $\mathcal{F}$-programs.

Definition 6
Let P be a Horn $\mathcal{F}$-program. We say that a set of atoms M is a *derivable model* of P if there exists a P-computation t such that $M = R_t$. □

Derivable models play in our theory a role analogous to that of the least model of a normal Horn program. The basic analogy is that they are the results of bottom-up computations, as is the case for the least model of a normal Horn program.

Theorems 3 and 4 entail several properties of Horn $\mathcal{F}$-programs, their computations and models. We gather them in the following corollary. Properties (1) and (3) - (6) generalize properties of the least model of a normal Horn logic program.

Corollary 2
Let P be a Horn $\mathcal{F}$-program. Then:

1. If P is consistent then P has at least one derivable model.
2. For every model M of P there is a largest derivable model M' of P such that $M' \subseteq M$.
3. A model M of P is derivable if and only if $M = R_{t^{P,M}}$.
4. If P contains no constraint clauses then P has a largest derivable model.
5. Every minimal model of P is derivable.
6. Every derivable model of P is a supported model of P.

Proof
(1) Since P has a model, it has a P-computation (Theorem 4). The result of this computation is a model of P (Theorem 3). By the definition, this model is derivable.
(2) Let M be a model of P and let $t = (X_n)_{n=0,1,\ldots}$ be the canonical P-computation for M. Then, R_t is a derivable model of P and $R_t \subseteq M$. Let $s = (Y_n)_{n=0,1,\ldots}$ be a P-computation such that $R_s \subseteq M$. Clearly, we have $Y_0 \subseteq X_0$. Let us consider an integer $n > 0$ and let us assume that $Y_{n-1} \subseteq X_{n-1}$. Since $R_s \subseteq M$, $Y_n \subseteq M$. Thus, by the definition of a P-computation,

$$Y_n \subseteq hset(P(Y_{n-1})) \cap M\cdot$$

Since P is a Horn $\mathcal{F}$-program and since $Y_{n-1} \subseteq X_{n-1}$, $hset(P(Y_{n-1})) \subseteq hset(P(X_{n-1}))$. Thus,

$$Y_n \subseteq hset(P(X_{n-1})) \cap M = X_n.$$

It follows now by induction that $R_s \subseteq R_t$. Thus, R_t is the largest derivable model contained in M.
(3) Let M be a model of P. The argument we used in (2) shows that the result of the canonical computation from P with respect to M is the greatest derivable model contained in M. If M is derivable, then $M = R_{t^{P,M}}$. The converse implication follows by the definition.
(4) The set At is a model of P. Let R be the result of the canonical P-computation for At. Clearly, R is a derivable model of P. We will show that every derivable model of P is a subset of R. Let M be a derivable model of P. By (3), M is the result of a canonical computation for M. Since $M \subseteq At$, it follows by an induction argument that for every non-negative integer n, $X_n^{P,M} \subseteq X_n^{P,At}$ (we omit the details, as the argument is similar to that in the proof of (2)). Consequently, $M \subseteq R$.
(5) This assertion follows directly from (2).
(6) This assertion follows directly from Theorem 3. □

Despite analogies with the least model of a normal Horn program, derivable models are not, in general, minimal. For instance, a program with cardinality constraints consisting of a single clause

$$1\{a, b\} \leftarrow$$

has three derivable models: $\{a\}$, $\{b\}$ and $\{a, b\}$, only two of which are minimal.

Horn $\mathcal{F}$-programs generalize Horn normal logic programs (see Section 8 for details.). For a Horn $\mathcal{F}$-programs without constraint clauses, the canonical computation with respect to the set of all atoms is a counterpart to the bottom-up computation determined by a normal Horn program.

7 Stable models of monotone $\mathcal{F}$-programs

We will now use the results of the two previous sections to introduce and study the class of *stable* models of monotone $\mathcal{F}$-programs.

Definition 7
Let P be a monotone $\mathcal{F}$-program and let $M \subseteq At$. The *reduct* of P with respect to M, P^M in symbols, is a Horn $\mathcal{F}$-program obtained from P by (1) removing from P every $\mathcal{F}$-clause containing in the body a literal $\mathbf{not}(A)$ such that $M \models A$, and (2) removing all literals of the form $\mathbf{not}(A)$ from all the remaining clauses in P. A set of atoms M is a *stable* model of P if M is a derivable model of the reduct P^M. □

The following result is easy to show (and so we omit its proof) but useful.

Lemma 1
Let P be a monotone $\mathcal{F}$-program. If M is a model of P, then M is a model of P^M.
□

Example 4
We illustrate the concept of stable models of monotone $\mathcal{F}$-programs with examples underlining some aspects of their properties. The class $\mathcal{F}$ we use in this example consists of *all* cardinality constraints which, we recall, are monotone (Section 2).

Let P be a program consisting of the following two clauses:

$1\{a,b\} \leftarrow 1\{d\}, \mathbf{not}(1\{b,c\})$
$1\{a,d\} \leftarrow$

We will now investigate properties of some sets with respect to this program.
(1) The set $M_1 = \emptyset$ is not a model of our program P. As we will see soon (Proposition 4), stable models are supported models and, consequently, also models. Thus $\emptyset$ is not a stable model of P.
(2) The set $M_2 = \{a,b,c\}$ is a model of P. But M_2 is not a stable model of P. Indeed, let us compute P^{M_2}. It consists of just one clause: $1\{a,d\} \leftarrow$. Since M_2 is not a derivable model of P^{M_2} (it contains an atom not occurring in any head of the clause of P^{M_2}), M_2 is not a stable model of P
(3) The set $M_3 = \{a,d\}$ is a stable model of P. The reduct P^{M_3} consists of two clauses:

$1\{a,b\} \leftarrow 1\{d\}$
$1\{a,d\} \leftarrow$

The sequence $\emptyset, \{a,d\}, \{a,d\}, \ldots$ is a P^{M_3}-computation. Thus, M_3 is a derivable model of P^{M_3} and hence M_3 is a stable model of P
(4) The set $M_4 = \{a\}$ is a stable model of P. The reduct P^{M_4} consists of two clauses:

$1\{a,b\} \leftarrow 1\{d\}$
$1\{a,d\} \leftarrow$

The sequence $\emptyset, \{a\}, \{a\}, \ldots$ is a P^{M_4}-computation. Thus $\{a\}$ is a stable model of P.

In our example $M_4 \subset M_3$. Thus, in contrast to normal logic programs (but not to lparse programs), stable models of abstract constraint programs can nest. That is, they do not satisfy the antichain (minimality with respect to inclusion) property.

The program P that we considered above has stable models. It is easy to construct examples of programs that have no stable models. For instance, a program consisting of just one clause: $2\{a,b,c\} \leftarrow \mathbf{not}(1\{a,b\})$ has models but no stable models. □

Stable models of a monotone $\mathcal{F}$-program P are indeed models of P. Thus, the use of the term "model" in their name is justified. In fact, a stronger property holds: stable models of monotone $\mathcal{F}$-programs are supported. This again generalizes a well-known property of normal logic programs[2].

[2] Incidentally, in the case of programs with weight constraints in the lparse syntax, no such property has been established as supported models have not been defined for that formalism.

Proposition 4
Let P be a monotone $\mathcal{F}$-program. If $M \subseteq At$ is a stable model of P then M is a supported model of P.

Proof
First, it follows directly from the corresponding definitions that $T_P^{nd}(M) = T_{P^M}^{nd}(M)$. Next, since M is a derivable model of P^M, M is a supported model of P^M (Corollary 2(6)). Thus, by Theorem 2, $M \in T_{P^M}^{nd}(M)$ and, consequently, $M \in T_P^{nd}(M)$. It follows that M is a supported model of P. $\square$

With the notion of a stable model in hand, we can strengthen Theorem 3.

Theorem 5
Let P be a Horn $\mathcal{F}$-program. A set of atoms $M \subseteq At$ is a derivable model of P if and only if M is a stable model of P.

Proof
The assertion is a direct consequence of the fact that for every Horn $\mathcal{F}$-program P and for every set of atoms M, $P = P^M$. $\square$

We will now prove yet another result that generalizes a property of stable models of normal logic programs (cf. work on extending the semantics of stable models to logic programs with integrity constraints (Lifschitz 1996)).

Proposition 5
Let P and Q be two monotone $\mathcal{F}$-programs.

1. If M is a stable model of P and a model of Q then M is a stable model of $P \cup Q$.
2. If Q consists of constraint clauses and M is a stable model of $P \cup Q$ then M is a stable model of P.

Proof
(1) Since M is a stable model of P, M is a derivable model of P^M. By Corollary 2(3), M is the result of the canonical P^M-computation with respect to M. Since M is a model of $P \cup Q$, by Lemma 1 M is a model of $(P \cup Q)^M = P^M \cup Q^M$. Therefore, the canonical $(P^M \cup Q^M)$-computation with respect to M is well defined. Its result is clearly contained in M. On the other hand, it contains the result of the canonical P^M-computation with respect to M, which is M. Therefore, the result of the canonical $(P^M \cup Q^M)$-computation with respect to M is M. Thus, M is a derivable model of $(P \cup Q)^M$ and a stable model of $P \cup Q$.
(2) Since M is a stable model of $P \cup Q$, M is the result of a $(P \cup Q)^M$-computation, say t. Since Q consists of constraint clauses, t is a P^M-computation (constraint clauses, having inconsistent heads, do not participate in computations). Thus, M is also a result of a P^M-computation, that is, M is a stable model of P. $\square$

8 Monotone $\mathcal{F}$-programs and normal logic programming

A main goal of this paper is to propose a way to integrate abstract constraints into normal logic programming. In this section, we show that our formalism of $\mathcal{F}$-programs *contains* normal logic programming (modulo a very simple encoding) so that all major two-valued semantics are preserved.

To this end, let us consider an abstract constraint:

$$PB = \{X \subseteq At \colon X \neq \emptyset\}\cdot$$

We note that PB is identical with the pseudo-boolean constraint (we introduced pseudo-boolean constraints in Section 2):

$$PB = PB(1, W, \leq),$$

where W is a weight function on At such that $W(a) = 1$, for every $a \in At$. Clearly, the constraint PB is monotone. We will show that normal logic programs can be encoded as $\{PB\}$-programs or, more generally, as monotone $\mathcal{F}$-programs, for every class $\mathcal{F}$ of monotone abstract constraints such that $PB \in \mathcal{F}$. In what follows, if $a \in At$, we will write $PB(a)$ for a $\{PB\}$-atom $PB(\{a\})$.

We note that for every $a \in At$ and every interpretation $M \subseteq At$, $M \models a$ if and only if $M \models PB(a)$. That is, a propositional atom a is logically equivalent to an abstract constraint atom $PB(a)$. This equivalence suggests an encoding of a normal logic program P as $\{PB\}$-program P^{pb}. Namely, if r is a normal logic program clause

$$a \leftarrow b_1, \ldots, b_m, \mathbf{not}(c_1), \ldots, \mathbf{not}(c_n)$$

we define r^{pb} to be a $\{PB\}$-clause

$$PB(a) \leftarrow PB(b_1), \ldots, PB(b_m), \mathbf{not}(PB(c_1)), \ldots, \mathbf{not}(PB(c_n))\cdot$$

For a normal logic program P, we define $P^{pb} = \{r^{pb} \colon r \in P\}$. By our earlier comments, P^{pb} is a *monotone* $\mathcal{F}$-program, for every class of monotone constraint atoms containing the constraint PB.

We note that due to the equivalence of a and $PB(a)$, which we noted above, for every interpretation $M \subseteq At$ we have

$$M \models bd(r) \ \text{ if and only if } \ M \models bd(r^{pb})\cdot \tag{2}$$

(here and in other places we use symbols such as $bd(r)$, $hd(r)$ and $hd(P)$ also in the context of normal logic programs, and assume their standard meaning).

Our first result involves operators associated with programs. Let P be a normal logic program. We recall that the one-step provability operator T_P (van Emden and Kowalski 1976) is defined as follows: for every $M \subseteq At$,

$$T_P(M) = \{hd(r) \colon r \in P \text{ and } M \models bd(r)\}\cdot$$

We have the following basic property of the translation $P \mapsto P^{pb}$.

Proposition 6

Let P be a normal logic program. Then for every $M \subseteq At(P)$, $T^{nd}_{P^{pb}}(M) = \{T_P(M)\}$.

Proof
We will write r and r' for a pair of corresponding clauses in P and P^{pb}. That is, if $r \in P$ then $r' = r^{pb}$ is the counterpart of r in P^{pb}. Conversely, if $r' \in P^{pb}$, r is the clause in P such that $r^{pb} = r'$. Clearly, we have $hset(r') = \{hd(r)\}$.

By the equivalence (2), a clause $r \in P$ is M-applicable if and only if r' is M-applicable. Thus, we have

$$hset(P^{pb}(M)) = hd(P(M)) = T_P(M)\cdot \tag{3}$$

Let $r' \in P^{pb}(M)$ and let $a = hd(r)$. It follows that $r \in P(M)$ and $a \in T_P(M)$. Since $hd(r') = PB(a)$, $T_P(M) \models hd(r')$. Thus, $T_P(M)$ is one-step nondeterministically provable from M and P^{pb}, that is, $T_P(M) \in T^{nd}_{P^{pb}}(M)$.

Next, let us consider $M' \in T^{nd}_{P^{pb}}(M)$. By the definition, $M' \subseteq hset(P^{pb}(M))$. Thus, by (3), we have $M' \subseteq T_P(M)$. Let us now consider $a \in T_P(M)$. It follows that there is a clause $r \in P(M)$ such that $hd(r) = a$. Consequently, $r' \in P^{pb}(M)$ and $hd(r') = PB(a)$. Since $M' \in T^{nd}_{P^{pb}}(M)$, $M' \models hd(r')$. Thus, $a \in M'$. It follows that $M' = T_P(M)$ and, consequently, $T^{nd}_{P^{pb}}(M) = \{T_P(M)\}$. □

This result entails a proposition concerning Horn programs.

Proposition 7
Let P be a normal Horn logic program. Then M is a least model of P if and only if M is a derivable model of P^{pb}.

Proof
We first observe that the sequence $\{T_P \uparrow n(\emptyset)\}_{n=0,1,\ldots}$ is a P^{pb}-computation (one can show this by an easy inductive argument, using the relationship between T_P and $T^{nd}_{P^{pb}}$ established by Proposition 6). Since M is the limit of the sequence $\{T_P \uparrow n(\emptyset)\}_{n=0,1,\ldots}$, M is a derivable model of P^{pb}.

Conversely, if M is a derivable model of P^{pb}, then M is the result of a derivation $\{X_n\}_{n=0,1,\ldots}$ from P^{pb}. Thus, for every $n = 0, 1, \ldots$, $X_{n+1} \in T^{nd}_{P^{pb}}(X_n)$. By Proposition 6, $X_{n+1} = T_P(X_n)$. Since $X_0 = \emptyset$, it follows that for every $n = 0, 1, \ldots$, $X_n = T_P \uparrow n(\emptyset)$. Consequently, $M = \bigcup_{n=0}^{\infty} T_P \uparrow n(\emptyset)$ and so, M is the least model of P. □

We can now prove the main result of this section demonstrating that the embedding $P \mapsto P^{pb}$ preserves all the semantics considered in the paper.

Theorem 6
Let P be a normal logic program and let M be a set of atoms. Then M is a model (supported model, stable model) of P if and only if M is a model (supported model, stable model) of P^{pb}.

Proof
It is well known that M is a model of P if and only if $T_P(M) \subseteq M$ (Apt 1990). By Proposition 6, the latter condition is equivalent to the condition that there is $M' \in T^{nd}_{P^{pb}}(M)$ such that $M' \subseteq M$. By Theorem 1, this last condition is equivalent

to M being a model of P^{pb}. Thus, M is a model of P if and only if M is a model of P^{pb}.

The proof for the case of supported models is essentially the same. It relies on the fact that M is a supported model of P if and only if $M = T_P(M)$ (Apt 1990) and uses Proposition 6 and Theorem 2.

Let us assume now that M is a stable model of P. It follows that M is the least model of P^M. By Proposition 7, M is a derivable model of $[P^M]^{pb}$. It follows from the definitions of the reducts of normal logic programs and $\{PB\}$-programs that $[P^M]^{pb} = [P^{pb}]^M$. Thus, M is a stable model of P^{pb}. The converse implication can be proved in the same way. □

There are other ways to establish a connection between normal logic programs and programs with abstract constraints. We will now define a class of monotone $\mathcal{F}$-programs, which offers a most direct extension of normal logic programming.

Definition 8
An $\mathcal{F}$-atom $C(X)$ is *definite* if X is a minimal element in C. An $\mathcal{F}$-clause r is *definite* if $hd(r)$ is a definite $\mathcal{F}$-atom. An $\mathcal{F}$-program is *definite* if every clause in P is definite. □

We use the term definite following the logic programming tradition (cf. (van Emden and Kowalski 1976), for instance), where it is used for clauses whose heads provide "definite" information (as opposed to being disjunctions and so listing several possible alternatives).

Example 5
Let $\mathcal{F}$ consist of two monotone constraints, C_1 and C_2 where:

$$C_1 = \{X \subseteq At\colon \{a, b\} \subseteq X \text{ or } \{a, c\} \subseteq X \text{ or } |X| \text{ is infinite}\}$$

and

$$C_2 = \{X \subseteq At\colon \{d, e\} \subseteq X\}.$$

The constraint C_1 has two minimal elements: $\{a, b\}$ and $\{a, c\}$. The constraint C_2 has just one minimal element: $\{d, e\}$.

These constraints generate three definite atoms $C_1(\{a, b\})$, $C_1(\{a, c\})$, and $C_2(\{d, e\})$. An $\mathcal{F}$-program consisting of the following clauses is definite:

$C_1(\{a, b\}) \leftarrow$
$C_1(\{a, c\}) \leftarrow C_1(\{a, b, c\}), \mathbf{not}(C_2(\{a, b, d, e\})$
$C_2(\{d, e\}) \leftarrow$

We note that some monotone constraints do not yield any definite constraint atoms. It happens when they have no finite minimal elements. A constraint C consisting of all infinite subsets of At offers a specific example. □

Definite $\mathcal{F}$-atoms have the following simple properties.

Proposition 8
Let $X \subseteq At$ and let $C(X)$ be a definite $\mathcal{F}$-atom. Then $C(X)$ is consistent and, for every $M \subseteq At$, $M \models C(X)$ if and only if $X \subseteq M$.

Proof
If $M \models C(X)$ then $M \cap X \in C$. Since $C(X)$ is a definite $\mathcal{F}$-atom, X is a minimal element in C. It follows that $M \cap X = X$ and so, $X \subseteq M$. Conversely, if $X \subseteq M$ then $M \cap X = X$. Since $X \in C$, $M \cap X \in C$. Thus, $M \models C(X)$. This argument proves the second part of the assertion. In particular, it follows that $X \models C(X)$. Thus, $C(X)$ is consistent. $\square$

The intuition behind the notion of a definite $\mathcal{F}$-atom is now clear. Given a definite $\mathcal{F}$-program and an interpretation M, there is always a way to satisfy the heads of all M-applicable clauses (due to consistency of definite $\mathcal{F}$-atoms). Moreover, there is only *one* way to do so if we want only to use atoms appearing in the headsets of M-applicable clauses (due the the second property from Proposition 8). Thus, computing with definite $\mathcal{F}$-programs does not involve nondeterminism. Indeed, we have the following result.

Proposition 9
Let P be a definite $\mathcal{F}$-program. Then, for every set of atoms M, $|T_P^{nd}(M)| = 1$.

Proof
Let $r \in P(M)$. Since $hd(r)$ is a definite $\mathcal{F}$-atom, then $hset(r) \models hd(r)$. We now observe that $hset(r) \subseteq hset(P(M))$. Thus, for every $r \in P(M)$, $hset(P(M)) \models hd(r)$. By the definition of the one-step nondeterministic provability, $hset(P(M)) \in T_P^{nd}(M)$. Thus, $|T_P^{nd}(M)| \geq 1$.

Next, let us consider $M' \in T_P^{nd}(M)$. From the definition of $T_P^{nd}(M)$, it follows that $M' \subseteq hset(P(M))$. To prove the converse inclusion, let $r \in P(M)$. Again by the definition of $T_P^{nd}(M)$, we have that $M' \models hd(r)$. Since $hd(r)$ is a definite $\mathcal{F}$-atom, Proposition 8 implies that $hset(r) \subseteq M'$. Thus, $hset(P(M)) \subseteq M'$.

It follows that $hset(P(M)) = M'$ and so, $|T_P^{nd}(M)| = 1$. $\square$

Thus, for a definite $\mathcal{F}$-program P, the operator T_P^{nd} is deterministic and, so, can be regarded as an operator with both the domain and codomain $\mathcal{P}(At)$. We will write T_P^d, to denote it. Models, supported models and stable models of a definite monotone $\mathcal{F}$-program (for supported models we do not need the monotonicity assumption) can be introduced in terms of the operator T_P^d in *exactly* the same way the corresponding concepts are defined in normal logic programming. In particular, the algebraic treatment of logic programming developed in (Fitting 2002; Przymusinski 1990; Denecker et al. 2000) applies to definite $\mathcal{F}$-programs and results in a natural and direct extension of normal logic programming. We note that this comment extends to 3- and 4-valued semantics of partial models, supported models and stable models (including the Kripke-Kleene semantics and the well-founded semantics)[3].

We will explicitly mention just one result on definite monotone $\mathcal{F}$-programs (in fact, definite Horn programs) here, as it will be used later in the paper.

[3] Results in (Denecker et al. 2001; Pelov et al. 2004; Pelov. 2004) are related to this observation. They concern programs with aggregates, whose clauses have heads consisting of *single* atoms and so, are definite.

Proposition 10
Let P be a definite Horn $\mathcal{F}$-program. Then P has exactly one derivable model and this model is the least model of P.

Proof
Since P is definite, it contains no constraint clauses and so, it has a model (Proposition 2). Thus, it has at least one P-computation. Let $(X_n)_{n=0,1,\ldots}$ and $(Y_n)_{n=0,1,\ldots}$ be two P-computations. By the definition, $X_0 = \emptyset = Y_0$. Let us assume that for some $n \geq 0$, $X_n = Y_n$. By the definition of P-computations,

$$X_{n+1} \in T_P^{nd}(X_n) \text{ and } Y_{n+1} \in T_P^{nd}(Y_n).$$

By the induction hypothesis, $X_n = Y_n$. Thus, $T_P^{nd}(X_n) = T_P^{nd}(Y_n)$. Since P is definite, $|T_P^{nd}(X_n)| = |T_P^{nd}(Y_n)| = 1$ and so, $X_{n+1} = Y_{n+1}$. Thus, both computations coincide and P has exactly one P-computation and so, exactly one derivable model. Since every model of P contains a derivable model, it follows that the unique derivable model of P is also a least model of P. $\square$

9 Encoding lparse programs as monotone $\mathcal{F}$-programs

We will now investigate the relation between lparse programs (Niemelä et al. 1999; Simons et al. 2002) and programs with monotone abstract constraints. We start by reviewing the syntax and the semantics of lparse programs.

A *weighted set of literals* is a function $W : X \to \{\ldots, -1, 0, 1, \ldots\}$, where $X \subseteq At \cup \{\mathbf{not}(a) \mid a \in At\}$ is finite. We call X the *literal set* of W and denote it by $lset(W)$. The set of atoms that appear in literals in $lset(W)$ is the *atom set* of W. We denote it by $aset(W)$. Sometimes it will be convenient to write W explicitly. To this end, we will write W as

$$\{a_1 = w_1, \ldots, a_m = w_m, \mathbf{not}(b_1) = w_1', \ldots, \mathbf{not}(b_n) = w_n'\}, \quad (4)$$

where the domain of the function W is $\{a_1, \ldots, a_m, \mathbf{not}(b_1), \ldots \mathbf{not}(b_n)\}$, and $w_1 = W(a_1), \ldots, w_n' = W(\mathbf{not}(b_n))$, loosely following the lparse notation. Thus, when the domain of W is $\{a, b, c\}$ and $W(a) = 1$, $W(b) = 2$, and $W(c) = 1$, then we write W as $\{a = 1, b = 2, c = 1\}$.

An *lparse atom* (*l-atom*, for short) is an expression of the form kWl, where W is a weighted set of literals, and k and l are integers such that $k \leq l$. By the *literal set* of an l-atom $A = kWl$ we mean $lset(W)$ and write $lset(A)$ to denote it (in a similar way, we extend the definition and the notation of the atoms set to the case of l-atoms).

We say that a set of atoms (interpretation) M satisfies an l-atom kWl if

$$k \leq \sum_{\substack{p \in lset(W) \\ p \in M}} W(p) + \sum_{\substack{\mathbf{not}(p) \in lset(W) \\ p \notin M}} W(p) \leq l$$

($M \models kWl$, in symbols). We note that it is easy to give an example of an inconsistent l-atom. For instance, $2\{a = 1\}2$ is inconsistent. We will use I to denote any inconsistent constraint (it does not matter which, as all are equivalent to each other).

An *lparse clause* (l-clause, for short) is an expression r of the form

$$A \leftarrow B_1, \ldots, B_n,$$

where A and B_i, $1 \leq i \leq n$, are l-atoms. We call A the *head* of r and $\{B_1, \ldots, B_n\}$ the *body* of r. We denote them by $hd(r)$ and $bd(r)$, respectively. An *lparse program* is a finite set of l-clauses.

We say that a set $M \subseteq At$ *satisfies* an l-clause r if M satisfies $hd(r)$ whenever it satisfies each l-atom in the body of r. We say that M satisfies an lparse program P if M satisfies each l-clause in P. We write $M \models r$ and $M \models P$ in these cases, respectively.

We note that lparse programs allow both negative literals and negative weights in l-atoms. However, in (Simons et al. 2002) it is argued that negative weights can be expressed using negative literals and vice versa and, hence, one is inessential when the other is available. In fact, in (Simons et al. 2002) an l-atom with negative weights is treated simply as a shorthand for the corresponding constraint with non-negative weights. We follow this approach here and from now on consider only l-atoms kWl, where W assigns non-negative weights to literals.

Before we continue, let us define $\mathcal{PB}$ to be a set of all pseudo-boolean constraints of the form $PB(k, W, \leq)$, where k is a non-negative integer and W a weight function assigning to elements of At non-negative integers (cf. Section 2). Directly from the definition it follows that every constraint in $\mathcal{PB}$ is monotone.

Let us consider an l-atom lW which contains no negative literals (and, as it is evident from the notation, no upper bound). In particular, $lset(W) = aset(W)$. Let W' be an extension of W, which assigns 0 to every atom $p \in At \setminus aset(W)$. We observe that a set $M \subseteq At$ is a model of lW if and only if M is a model of the $\mathcal{PB}$-atom $A(X)$, where $A = PB(l, W', \leq)$ and $X = aset(W)$. Therefore, we will regard such an l-atom lW as a $\mathcal{PB}$-atom or, speaking more formally (but with some abuse of notation) we will denote by lW the $\mathcal{PB}$-atom $A(X)$.

If $W = \{a = 1\}$ and $l = 2$, then the corresponding $\mathcal{PB}$-atom is inconsistent (it is one of many inconsistent $\mathcal{PB}$-atoms). As in the case of l-atoms, we will write I to denote (any) inconsistent $\mathcal{PB}$-atom.

This discussion suggests that lparse programs built of l-atoms without negative literals and upper bounds can be viewed as Horn $\mathcal{PB}$-programs. We will exploit that relationship below in the definition of the reduct, and will subsequently extend it to all lparse programs.

Let P be an lparse program and let $M \subseteq At$. An *lparse-reduct* of P with respect to M is a $\mathcal{PB}$-program obtained by:

1. eliminating from P every clause r such that $M \not\models B$, for at least one l-atom $B \in bd(r)$.
2. replacing each remaining l-clause $r = kWl \leftarrow k_1 W_1 l_1, \ldots, k_n W_n l_n$ with $\mathcal{PB}$-clauses of the form

$$1\{a = 1\} \leftarrow k_1' W_1', \ldots, k_n' W_n',$$

where $a \in lset(W) \cap M$, W_i' is W_i restricted to $lset(W_i) \cap At$, and

$$k_i' = k_i - \sum_{\substack{\mathbf{not}(p) \in lset(W_i) \\ p \notin M}} W_i(\mathbf{not}(p))$$

(by our comments above, expressions of the form $l'\,W'$ denote here $\mathcal{PB}$-atoms). With some abuse of notation, we denote the reduct of P with respect to M by P^M (the type of the program, an lparse program or a $\mathcal{PB}$-program, determines which reduct we have in mind). By our comments above, P^M can be regarded as a definite Horn $\mathcal{PB}$-program. Thus, P^M has a least model, $lm(P^M)$ (Proposition 10). This model is the result of the canonical computation from P^M with respect to M.

Definition 9
Let P be an lparse program. A set $M \subseteq At$ is an *lparse-stable model* of P if $M = lm(P^M)$ and $M \models P$. □

We will now show that *all* lparse programs can be viewed as $\mathcal{PB}$-programs. This task involves two steps. First, we show how to translate lparse programs to **not**-free lparse programs so that lparse-stable models are preserved. Second, we show that for **not**-free lparse programs the two definitions of stable models presented in the paper (Definitions 7 and 9) are equivalent.

An lparse program P can be translated in the following way to a **not**-free lparse program P', where for each l-atom kWl, $aset(W) \subseteq At$. We recall that by our earlier comments, we need to consider only lparse programs with no negative weights. For each negated literal $\mathbf{not}(b)$ appearing in P, introduce a new propositional atom $\bar{b}$ and an l-clause $\bar{b} \leftarrow 0\{b = 1\}0$. Then we replace each l-atom kWl where the weighted set of literals W is of the form (4) with an l-atom

$$k\{a_1 = w_1, \ldots, a_m = w_m, \bar{b_1} = w_1', \ldots, \bar{b_n} = w_n'\}l.$$

It is straightforward to show that this transformation preserves lparse-stable models in the following sense.

Proposition 11
Let P be an lparse program, P' a **not**-free lparse program obtained by the translation above, and B the set of new atoms introduced in the translation. Then,

- if M is an lparse-stable model of P then $M \cup \{\bar{b} \mid b \in B \setminus M\}$ is a lparse-stable model of P' and
- if M' is a lparse-stable model of P' then $M = M' \setminus B$ is an lparse-stable model of P. □

Now we show that **not**-free lparse programs can be translated to $\mathcal{PB}$-programs. To simplify the description of the encoding and make it uniform, we assume that all bounds are present. Let r be an l-clause

$$kWl \leftarrow k_1\,W_1\,l_1, \ldots, k_m\,W_m\,l_m.$$

We represent this l-clause by a *pair* of $\mathcal{PB}$-clauses, $e_1(r)$ and $e_2(r)$ that we define as

$$kW \leftarrow k_1\,W_1, \ldots, k_m\,W_m, \mathbf{not}((l_1 + 1)\,W_1), \ldots, \mathbf{not}((l_m + 1)\,W_m),$$

and

$$I \leftarrow (l+1)\,W, k_1\,W_1, \ldots, k_m\,W_m, \mathbf{not}((l_1+1)\,W_1), \ldots, \mathbf{not}((l_m+1)\,W_m),$$

respectively. We recall that the symbol I, appearing in the clause $e_2(r)$, stands for the inconsistent $\mathcal{PB}$-atom introduced above.

Now, given a **not**-free lparse program P, we translate it into a $\mathcal{PB}$-program

$$e(P) = \bigcup_{r \in P} \{e_1(r), e_2(r)\}.$$

Theorem 7
Let P be a **not**-free lparse program. A set $M \subseteq At$ is an lparse-stable model of P if and only if M is a stable model of $e(P)$, as defined for $\mathcal{PB}$-programs.

Proof
In the proof we will use the notation:

$$P_1 = \bigcup\{e_1(r)\colon r \in P\} \quad \text{and} \quad P_2 = \bigcup\{e_2(r)\colon r \in P\}.$$

Let us assume first that M is an lparse-stable model of a **not**-free lparse program P. We will show that M is a stable model of the $\mathcal{PB}$-program $e(P)$, which in our terminology is equal to $P_1 \cup P_2$.

Since M is an lparse-stable model of P, it is a model of P (Definition 9). Consequently, M is a model of P_2. By Proposition 5 to complete this part of the proof, it suffices to show that M is a stable model of the program P_1. To this end, we note that the definitions of the respective reducts imply that a clause

$$1\{a = 1\} \leftarrow k_1\,W_1, \ldots k_m\,W_m$$

belongs to the lparse-reduct P^M if and only if the reduct P_1^M contains a clause

$$kW \leftarrow k_1\,W_1, \ldots k_m\,W_m$$

such that $a \in aset(W)$ and $M \models k_i\,W_i$ for all $1 \leq i \leq m$.

¿From this relationship it follows that the results of the canonical computations from P^M and P_1^M with respect to M coincide (we recall that both reducts are Horn $\mathcal{PB}$-programs). Since M is the least model of P^M, it is the result of the canonical computation from P^M with respect to M. Thus, M is also the result of the canonical computation from P_1^M with respect to M. In other words, M is a derivable model of P_1 and, consequently, a stable model of P_1.

Conversely, let us assume that M is a stable model of $P_1 \cup P_2$. It follows that M is a model of $P_1 \cup P_2$ and, consequently, a model of P. Next, we note that since M is a stable model of $P_1 \cup P_2$, it is a stable model of P_1 (by Proposition 5). Thus, it is a derivable model of its reduct P_1^M and, therefore, it is also the result of the canonical computation from P_1^M with respect to M. Our observation about the relationship between the reducts P_1^M of and P^M holds now, as well. Consequently, M is the result of the canonical computation from P^M with respect to M. Thus, M is a derivable model of P^M. Since P^M is a definite Horn $\mathcal{PB}$-program, it has only one derivable model — its least model. It follows that M is the least model of P^M and, consequently, an lparse-stable model of P. $\square$

Theorem 7 shows that $\mathcal{PB}$-programs can express arbitrary **not**-free lparse programs with only linear growth in the size of the program. The converse relationship holds, too: **not**-free lparse programs can represent arbitrary $\mathcal{PB}$-programs without increasing the size of the representation. Let r be a $\mathcal{PB}$-clause

$$kW \leftarrow k_1\, W_1, \dots, k_m\, W_m, \mathbf{not}(l_1\, V_1), \dots, \mathbf{not}(l_n\, V_n).$$

We define $f(r)$ as follows. If there is i, $1 \le i \le n$, such that $l_i = 0$, we set $f(r) = \;\; kW \leftarrow kW$ (in fact any tautology would do). Otherwise, we set

$$f(r) = \;\; kW \leftarrow k_1\, W_1, \dots, k_m\, W_m, 0\, V_1(l_1 - 1), \dots, 0\, V_n(l_n - 1).$$

Given a $\mathcal{PB}$-program P, we define $f(P) = \{f(r) \colon r \in P\}$.

Theorem 8
Let P be a $\mathcal{PB}$-program. A set of atoms M is a stable model of P (as defined for $\mathcal{PB}$-programs) if and only if M is an lparse-stable model of $f(P)$.

Proof
First, we observe that P and $f(P)$ have the same models. Next, similarly as before, we have that the lparse-reduct $[f(P)]^M$ contains a clause

$$1\{a = 1\} \leftarrow k_1\, W_1, \dots k_m\, W_m, 0\, V_1, \dots, 0\, V_n$$

if and only if P^M contains a clause of the form

$$kW \leftarrow k_1\, W_1, \dots k_m\, W_m$$

such that $a \in aset(W)$ and $M \models k_i\, W_i$ for all $1 \le i \le m$. Since in the clauses of the first type l-atoms V_i are always true, as before, the results of the canonical computations from P^M and $[f(P)]^M$ with respect to M of P coincide (we recall that both reducts are Horn $\mathcal{PB}$-programs). Using this observation one can complete the proof by reasoning as in the previous proof. $\square$

Theorems 7 and 8 establish the equivalence of **not**-*free lparse* programs and $\mathcal{PB}$-programs with respect to the stable model semantics. The translations e and f also preserve models. The equivalence between **not**-*free lparse* programs and $\mathcal{PB}$-programs extends to supported models under the following concept of supportedness for lparse-programs.

Definition 10
Let P be a **not**-free lparse program. A set of atoms M is a supported model of P if M is a model of P and if for every atom $a \in M$ there is an l-clause $A \leftarrow B_1, \dots, B_n$ in P such that $a \in aset(A)$ and $M \models B_i$, $1 \le i \le n$.

Indeed, we have the following two theorems (we only sketch a proof of one of them; the proof of the other one is similar).

Theorem 9
Let P be a **not**-free lparse program. A set $M \subseteq At$ is an lparse-supported model of P if and only if M is a supported model of $e(P)$, as defined for $\mathcal{PB}$-programs.

Proof

Let us denote $Q = e(P)$. Let M be an lparse-supported model of P. We will show that M is a supported model of Q. By our earlier observations, P and Q have the same models. Thus, M is a model of Q. To complete the argument, we need to show that $M \subseteq hset(Q(M))$. Let $a \in M$. Since M is an lparse-supported model of P, there is an l-clause $r \in P$ such that $r = A \leftarrow B_1, \ldots, B_n$, $a \in aset(A)$ and $M \models B_i$ for every i, $1 \leq i \leq n$. It follows that $a \in aset(hd(e_1(r)))$ and that $M \models bd(e_1(r))$. Since $e_1(r) \in Q$, $e_1(r) \in Q(M)$. Thus, $a \in hset(Q(M))$. It follows that $M \subseteq hset(Q(M))$ and so M is a supported model of Q.

Conversely, let us assume that M is a supported model of Q. Then M is a model of Q and so M is a model of P, as well. Let $a \in M$. It follows that $a \in hset(Q(M))$. Since each clause of the form $e_2(r)$ $(r \in P)$ is a constraint, there is an l-clause $r \in P$ such that clause $e_1(r) \in Q$ such that $M \models bd(e_1(r))$ and $a \in hset(hd(e_1(r)))$. Let $r = A \leftarrow B_1, \ldots, B_n$. It follows that $a \in aset(A)$ and that $M \models B_i$, $1 \leq i \leq n$. Thus, M is an lparse-supported model of P. □

Theorem 10

Let P be a $\mathcal{PB}$-program. A set of atoms M is a stable model of P (as defined for $\mathcal{PB}$-programs) if and only if M is an lparse-stable model of $f(P)$.

It follows from the results in this section that the translations e and f uniformly preserve basic semantics of **not**-free lparse and $\mathcal{PB}$-programs, and allow us to view **not**-free lparse programs as $\mathcal{PB}$-programs and *vice versa*.

We also note that this equivalence demonstrates that lparse programs with the semantics of stable models as defined in (Niemelä et al. 1999) can be viewed as a generalization of normal logic programming. It follows from Theorems 6 and 8 that the encoding of normal logic programs as lparse programs, defined as the composition of the translation $P \mapsto P^{pb}$ described in Section 8 (we note that the constraint PB belongs to the class $\mathcal{PB}$) and the translation f, preserves the semantics of models, supported models and stable models (an alternative proof of this fact, restricted to the case of stable models was first given in (Simons et al. 2002) and served as a motivation for the class of lparse programs and its stable-model semantics). This result is important, as it is not at all evident that the reduct used in (Simons et al. 2002), leads to fixpoints that generalize the semantics of stable models as defined in (Gelfond and Lifschitz 1988).

Given that the formalisms of **not**-free lparse and $\mathcal{PB}$-programs are equivalent, it is important to stress what differentiates them. The advantage of the formalism of **not**-free lparse programs is that it does not require the negation operator in the language. The strength of the formalism of $\mathcal{PB}$-programs lies in the fact that its syntax so closely resembles that of normal logic programs, and that the development of the theory of $\mathcal{PB}$-programs so closely follows that of the normal logic programming.

10 Monotone $\mathcal{F}$-programs and disjunctive logic programs

(Sakama and Inoue 1994) introduced and investigated a semantics of *possible models* of disjunctive logic programs. It turns out that this semantics is different from the semantics proposed by Minker (Minker 1982) and from that of Gelfond and Lifschitz (Gelfond and Lifschitz 1991; Przymusinski 1991). In this section, we will show that the formalism of monotone $\mathcal{F}$-programs generalizes the semantics of possible models. For the purpose of our discussion, we will extend the use of the terms *head*, *body*, M-applicability, and notation P^M, $hd(r)$, $bd(r)$ to the case of disjunctive programs.

Definition 11
(Sakama and Inoue 1994) Let P be a disjunctive logic program. A *split* program for P is any normal logic program that can be obtained by the following procedure. First, we select for each clause r in P, a set $S_r \subseteq hd(r)$. Next, we replace r with clauses of the form $A \leftarrow body$, where $A \in S_r$, if $S_r \neq \emptyset$, and with the (constraint) clause $\leftarrow bd(r)$, if $S_r = \emptyset$.

A set M of atoms is a *possible* model of P if M is a stable model (in the sense of Gelfond and Lifschitz (Gelfond and Lifschitz 1988)) of a split program for P. □

We point out that we allow for disjunctive clauses to have empty heads (that is, we allow constraint clauses). We also allow that sets S_r be empty. Consequently, split programs may contain constraints even if the original program does not.

Example 6
Let P be the disjunctive program:

$$P = \{a \vee b \vee c \leftarrow, \quad a \vee c \leftarrow \mathbf{not}(b), \quad b \leftarrow \mathbf{not}(c), \quad c \leftarrow \mathbf{not}(a)\}\cdot$$

Then, the program Q:

$$Q = \{a \leftarrow, \quad a \leftarrow \mathbf{not}(b), \quad c \leftarrow \mathbf{not}(b), \quad b \leftarrow \mathbf{not}(c), \quad \leftarrow \mathbf{not}(a)\}\cdot$$

is an example of a split program for P (given by the following subsets of the sets of atoms in the heads of the clauses: $\{a\}$, $\{a, c\}$, $\{b\}$ and $\emptyset$, respectively). Moreover, since $\{a, b\}$ is a stable model of Q, $\{a, b\}$ is a possible model of P. □

If M is a model of a disjunctive program P, by $s(P, M)$ we denote the split program of P determined by sets $S_r = M \cap hd(r)$. We have the following simple characterization of possible models.

Proposition 12
Let P be a disjunctive program. A set of atoms M is a possible model of P if and only if M is a stable model of the split program $s(P, M)$.

Proof
If M is a possible model of P, then M is a stable model of a split program of P, say Q. Let us assume that Q is determined by sets $S_r \subseteq hd(r)$, where $r \in P$.

For every clause $r \in P$, if r is M-applicable then all clauses it contributes to Q

are M-applicable, too, as they have the same body as r. Since M is a model of Q (being a stable model of Q), we obtain that $S_r \subseteq M$. Thus, $Q(M) \subseteq s(P, M)$.

Directly from the definition of $s(P, M)$ we obtain that M is a model of $s(P, M)$. Thus, M is a model of $[s(P, M)]^M$ and, consequently, $lm([s(P, M)]^M)$ exists. Moreover, it follows that $lm([s(P, M)]^M) \subseteq M$ (indeed, all non-constraint clauses in $s(P, M)$ have heads from M).

Since M is a stable model of Q, $M = lm(Q^M)$. Thus, it follows that $M = lm([Q(M)]^M)$ and so, we obtain:

$$M = lm([Q(M)]^M) \subseteq lm([s(P, M)]^M) \subseteq M\cdot$$

Thus, $lm([s(P, M)]^M) = M$ or, in other words, M is a stable model of $s(P, M)$. The converse implication follows by the definition. □

Let r be a disjunctive logic program clause of the form:

$$c_1 \vee \ldots \vee c_k \leftarrow a_1, \ldots, a_m, \mathbf{not}(b_1), \ldots, \mathbf{not}(b_n),$$

where all a_i, b_i and c_i are atoms. We encode this clause as a program clause with cardinality atoms:

$$r^{ca} = \quad 1\{c_1, \ldots, c_k\} \leftarrow 1\{a_1\}, \ldots, 1\{a_m\}, \mathbf{not}(1\{b_1\}), \ldots, \mathbf{not}(1\{b_n\})\cdot$$

(If all a_i and b_i are distinct, the following translation could be used instead: $1\{c_1, \ldots, c_k\} \leftarrow m\{a_1, \ldots, a_m\}, \mathbf{not}(1\{b_1, \ldots, b_n\})$.) We note that if $k = 0$, that is, the head of r is empty, the rule r^{ca} has the constraint $1\emptyset$ in the head, which is inconsistent. In this case, r^{ca} is a constraint clause.

For a disjunctive logic program P, we define $P^{ca} = \{r^{ca} \colon r \in P\}$ (ca in the subscript stands for "cardinality atoms"). Since cardinality constraints are monotone, the concept of a stable model of the program P^{ca} is well defined. We have the following theorem.

Theorem 11
Let P be a disjunctive logic program. A set of atoms M is a possible model of P if and only if M is a stable model of the program P^{ca} (in the sense, we defined in this paper).

Proof
We first note that $[s(P, M)]^M = s(P^M, M)$. Thus, by Proposition 12, it follows that M is a possible model of P if and only if M is a least model of $s(P^M, M)$. We also note that $[P^{ca}]^M = [P^M]^{ca}$. Thus, M is a stable model of P^{ca} if and only if M is a derivable model of $[P^M]^{ca}$.

It follows that in order to prove the assertion it suffices to show that for every positive (no negation in the bodies of clauses) disjunctive program P, M is a least model of $s(P, M)$ if and only if M is a derivable model of P^{ca}. We will now prove this claim. To simplify notation, we will write Q instead of P^{ca}.

First, we note P and Q have the same models. Thus, each side of the equivalence implies that M is a model of Q. In particular, it follows (no matter which implication we are proving) that Q has a canonical computation $t^{Q,M} = (X_n^{Q,M})_{n=0,1,\ldots}$. Next, we observe that for every $X \subseteq M$, the definitions of Q and $s(P, M)$ imply that

$$hset(Q(X)) \cap M = hd(s(P, M)(X)) = T_{s(P,M)}(X).$$

In particular, since $X_{n+1}^{Q,M} = hset(Q(X_n^{Q,M})) \cap M$, for every $n = 0, 1, \ldots$, we have

$$X_{n+1}^{Q,M} = T_{s(P,M)}(X_n^{Q,M}).$$

These identities imply that the result of the canonical Q-computation for M and the least model of $s(P, M)$ coincide. Consequently, M is a derivable model of Q if and only if M is a least model of $s(P, M)$ as claimed. □

11 Discussion

In the paper, we introduced and studied the formalism of $\mathcal{F}$-programs. When all constraints in $\mathcal{F}$ are monotone, this formalism offers an abstract framework for integrating constraints into logic programming. It exploits and builds on analogies with normal logic programming. Most concepts and techniques for monotone $\mathcal{F}$-programs are closely patterned after their counterparts developed there and so, normal logic programming can be viewed as a fragment of the theory of monotone $\mathcal{F}$-programs. Importantly, the same is the case for other nonmonotonic systems namely, the disjunctive logic programming with the possible-model semantics of (Sakama and Inoue 1994), and for the formalism of logic programs with weight constraints (Simons et al. 2002). For these two formalisms, monotone $\mathcal{F}$-programs help to explain the nature of their relationship with normal logic programming, hidden by their original definitions.

In this paper, we developed the foundation for the theory of monotone $\mathcal{F}$-programs. Recently, the theory of monotone $\mathcal{F}$-programs was developed further. (Liu and Truszczyński 2005b) demonstrated that Fages lemma (Fages 1994), and the concepts of the program completion and a loop formula extend to the setting of monotone $\mathcal{F}$-programs. The latter two properties allow one to reduce stable-model computation for programs with weight constraints to the problem of computing models of propositional theories extended with weight atoms (referred to as *pseudo-boolean* constraints in the satisfiability community). (Liu and Truszczyński 2005a) exploited this reduction and developed an algorithm to compute stable models of programs with weight constraints by using off-the-shelf solvers of pseudo-boolean constraints such as those described in (Barth 1995; Walser 1997; Aloul et al. 2002; Liu and Truszczyński 2003; East and Truszczyński 2004).

There are strong analogies between the approach we propose and develop here and some of the *techniques* discussed in (Sakama and Inoue 1994) in the context of disjunctive programs with the semantics of possible models. One way to look at the results of our paper is that it extends the way (Sakama and Inoue 1994) handles nondeterminism, inherent in disjunctive logic programs, to the abstract setting of monotone $\mathcal{F}$-programs. In particular, (Sakama and Inoue 1994) presents a computational procedure for disjunctive programs without negation, which can be shown to be closely related to our notion of a P-computation. That paper also introduces a nondeterministic provability operator, defined for *positive* disjunctive programs. Three aspects differentiate our work from (Sakama and Inoue 1994). Most importantly, we study here a much broader class of programs than disjunctive ones. Secondly, we define a provability operator on the class of *all* monotone $\mathcal{F}$-programs and not just positive ones. Finally, we consistently exploit properties of this operator, and align our approach with the standard operator-based development of normal logic programming (Apt 1990; Fitting 2002).

The emergence of a nondeterministic one-step provability operator warrants additional comments. Nondeterministic provability operators were considered before in the context of logic programming. We already noted that (Sakama and Inoue 1994) proposed a provability operator similar to the one we introduced here (although only for the class of *positive* disjunctive programs). (Sakama and Inoue 1995) proposed another operator designed to capture a different computational process arising in the context of paraconsistent systems. Finally, (Pelov and Truszczynski. 2004) presented a characterization of answer sets of disjunctive logic programs in terms of yet another nondeterministic provability operator. However, the operator we proposed here exhibits the closest parallels with the van Emden-Kowalski operator and opens up a possibility of generalizing the approximation theory proposed in (Denecker et al. 2000) to the case of monotone $\mathcal{F}$-programs. However, for that to happen, one will need techniques for handling nondeterministic operators on lattices, similar to those presented for the deterministic operators in (Denecker et al. 2000; Denecker et al. 2004). Developing such techniques is an open problem.

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