

Answer Set Solving in Practice

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ASP modulo theories: Overview

- 1 Theory language
- 2 Low-level semantics
- 3 Intermediate Format
- 4 Theory propagation
- 5 Experiments
- 6 Acyclicity checking
- 7 Constraint Answer Set Programming

Motivation

- Input ASP = DB+KRR+LP+SAT
- Output ASPmT = DB+KRR+LP+S
- ASP solving *ground* | *solve*
 - ↳ **logic programs with elusive theory atoms**
- Application areas
Agents, Assisted Living, Robotics, Planning, Scheduling,
Bio- and Cheminformatics, etc

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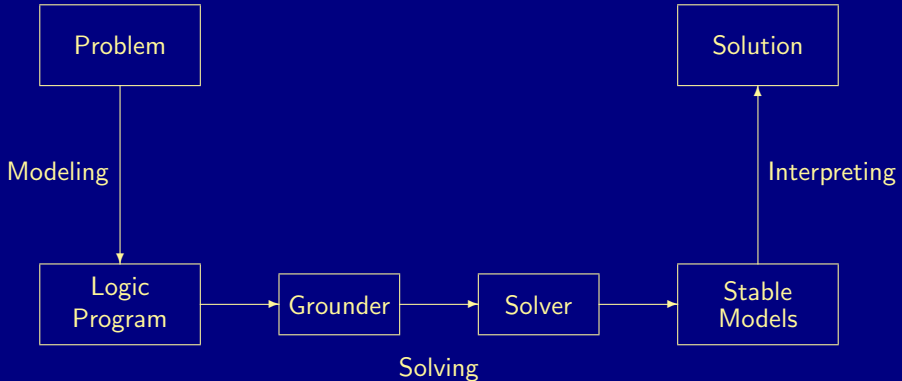
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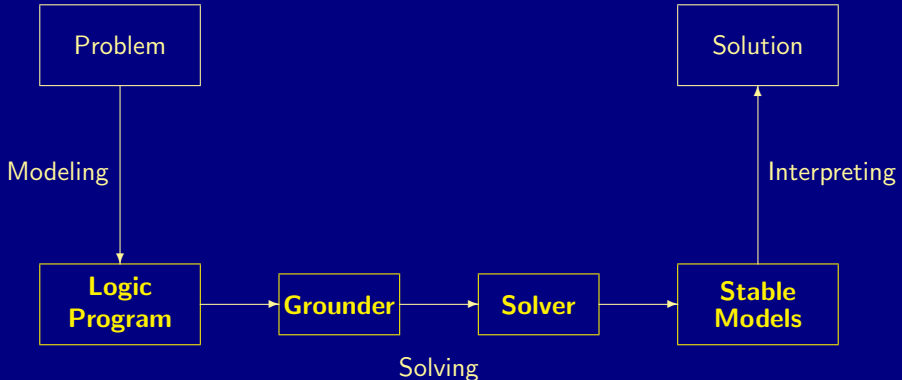
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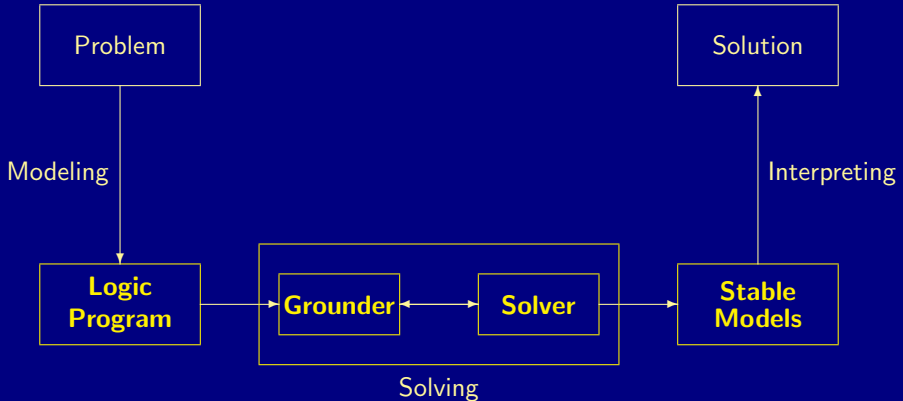
ASP solving process



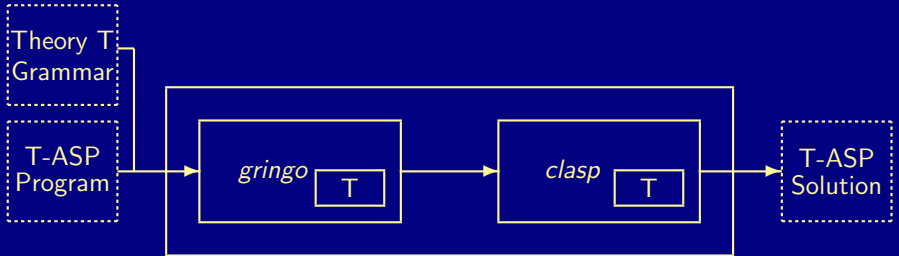
ASP solving process **modulo theories**



ASP solving process modulo theories

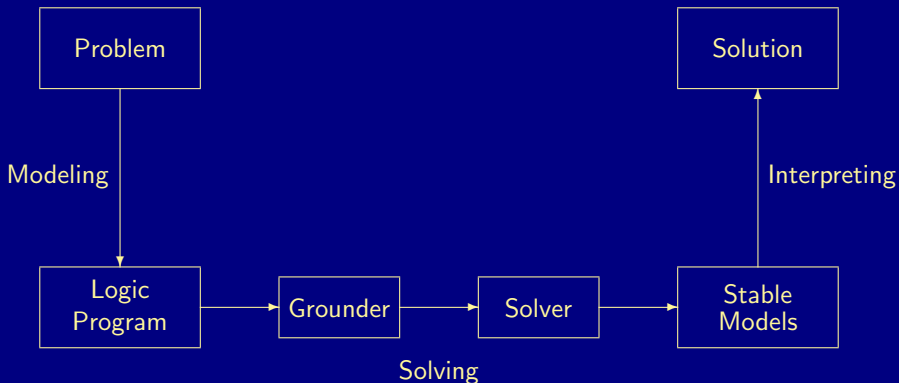


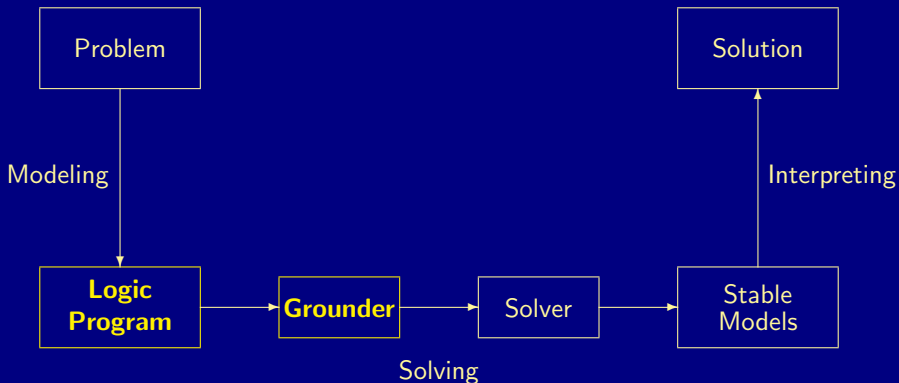
clingo's approach



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ASP solving process **modulo theories**

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Linear constraints

```

#theory csp {
  linear_term {
    + : 5, unary;
    - : 5, unary;
    * : 4, binary, left;
    + : 3, binary, left;
    - : 3, binary, left
  };

  dom_term {
    + : 5, unary;
    - : 5, unary;
    .. : 1, binary, left
  };

  show_term {
    / : 1, binary, left
  };

  minimize_term {
    + : 5, unary;
    - : 5, unary;
    * : 4, binary, left;
    + : 3, binary, left;
    - : 3, binary, left;
    @ : 0, binary, left
  };

  &dom/0 : dom_term, {=}, linear_term, any;
  &sum/0 : linear_term, {<=,=,>=,<,>,!}, linear_term, any;
  &show/0 : show_term, directive;
  &distinct/0 : linear_term, any;
  &minimize/0 : minimize_term, directive
}.

```

send + more = money

$$\begin{array}{rcccc}
 & s & e & n & d \\
 + & m & o & r & e \\
 \hline
 m & o & n & e & y
 \end{array}$$

Each letter corresponds exactly to one digit and all variables have to be pairwise distinct

$$\begin{array}{rcccc}
 & 9 & 5 & 6 & 7 \\
 + & 1 & 0 & 8 & 5 \\
 \hline
 1 & 0 & 6 & 5 & 2
 \end{array}$$

The example has exactly one solution

$$\{ s \mapsto 9, e \mapsto 5, n \mapsto 6, d \mapsto 7, m \mapsto 1, o \mapsto 0, r \mapsto 8, y \mapsto 2 \}$$

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$$\{ s \mapsto 9, e \mapsto 5, n \mapsto 6, d \mapsto 7, m \mapsto 1, o \mapsto 0, r \mapsto 8, y \mapsto 2 \}$$

send+more=money

```

#include "csp.lp".

digit(1,3,s). digit(2,3,m). digit(sum,4,m).
digit(1,2,e). digit(2,2,o). digit(sum,3,o).
digit(1,1,n). digit(2,1,r). digit(sum,2,n).
digit(1,0,d). digit(2,0,e). digit(sum,1,e).
                                digit(sum,0,y).

base(10).
exp(E) :- digit(_,E,_).

power(1,0).
power(B*P,E) :- base(B), power(P,E-1), exp(E), E>0.

number(N) :- digit(N,_,_), N!=sum.
high(D) :- digit(N,E,D), not digit(N,E+1,_).

&dom {0..9} = X :- digit(_,_,X).

&sum { M*D : digit(N,E,D), power(M,E), number(N);
      ~M*D : digit(sum,E,D), power(M,E)          } = 0.

&sum { D } > 0 :- high(D).

&distinct { D : digit(_,_,D) }.

&show { D : digit(_,_,D) }.

```

send+more=money

```

#include "csp.lp".

digit(1,3,s). digit(2,3,m). digit(sum,4,m).
digit(1,2,e). digit(2,2,o). digit(sum,3,o).
digit(1,1,n). digit(2,1,r). digit(sum,2,n).
digit(1,0,d). digit(2,0,e). digit(sum,1,e).
                                digit(sum,0,y).

base(10).
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      -M*D : digit(sum,E,D), power(M,E)          } = 0.

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send+more=money

```
digit(1,3,s). digit(2,3,m). digit(sum,4,m).
digit(1,2,e). digit(2,2,o). digit(sum,3,o).
digit(1,1,n). digit(2,1,r). digit(sum,2,n).
digit(1,0,d). digit(2,0,e). digit(sum,1,e).
                                digit(sum,0,y).
```

```
base(10).
exp(0). exp(1). exp(2). exp(3). exp(4).
```

```
power(1,0).
power(10,1). power(100,2). power(1000,3). power(10000,4).
```

```
number(1). number(2).
high(s). high(m).
```

```
&dom{0..9}=s. &dom{0..9}=m. &dom{0..9}=e. &dom{0..9}=o. &dom{0..9}=n. &dom{0..9}=r. &dom{0..9}=d. &dom{0..9}
```

```
&sum{ 1000*s; 100*e; 10*n; 1*d;
      1000*m; 100*o; 10*r; 1*e;
      -10000*m; -1000*o; -100*n; -10*e; -1*y } = 0.
```

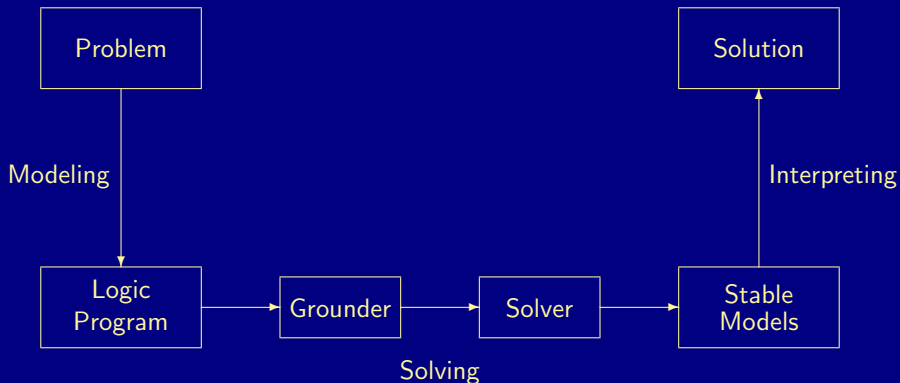
```
&sum{s} > 0. &sum{m} > 0.
```

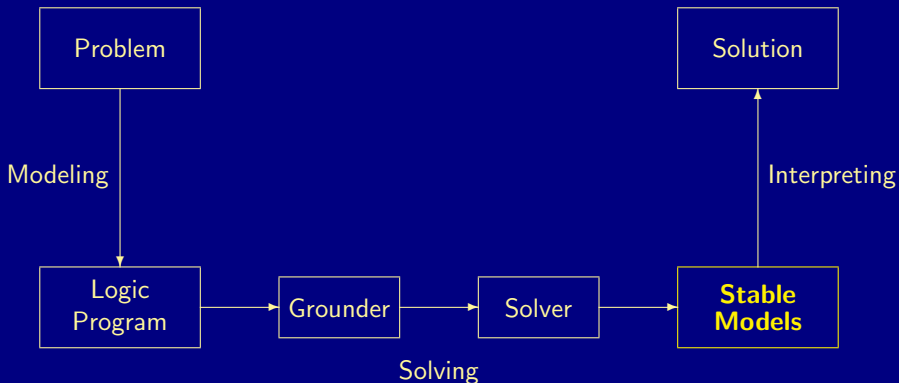
```
&distinct{s; m; e; o; n; r; d; y}.
```

```
&show{s; m; e; o; n; r; d; y}.
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ASP solving process **modulo theories**

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ASP modulo theories

- We distinguish theory atoms depending upon whether they are
 - defined via rules in the logic program, or
 - external otherwise, or
 - strict being equivalent to the associated constraint, or
 - non-strict only implying the associated constraint.
- Informally, a set $X \subseteq \mathcal{A} \cup \mathcal{T}$ of atoms is a \mathbb{T} -stable model of a program P if there is some \mathbb{T} -solution \mathcal{S} such that X is a (regular) stable model of the program

$$\begin{aligned}
 & P \cup \{a \leftarrow \mid a \in (\mathcal{T}_e \setminus \text{head}(P)) \cap \mathcal{S}\} \\
 & \cup \{\leftarrow \sim a \mid a \in (\mathcal{T}_e \cap \text{head}(P)) \cap \mathcal{S}\} \\
 & \cup \{\{a\} \leftarrow \mid a \in (\mathcal{T}_i \setminus \text{head}(P)) \cap \mathcal{S}\} \\
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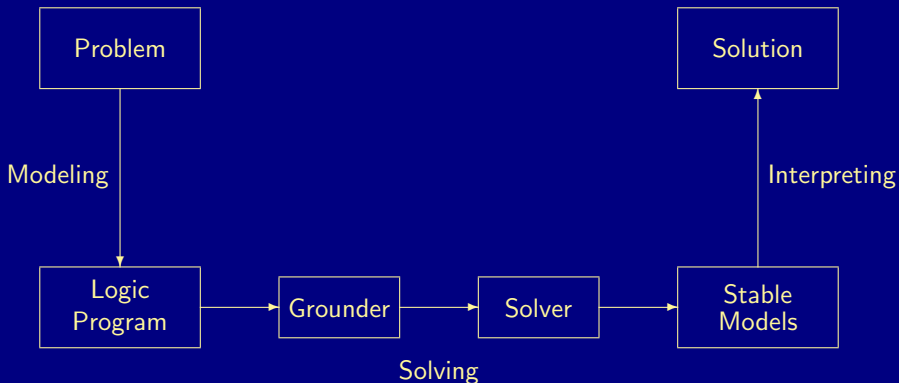
ASP modulo theories

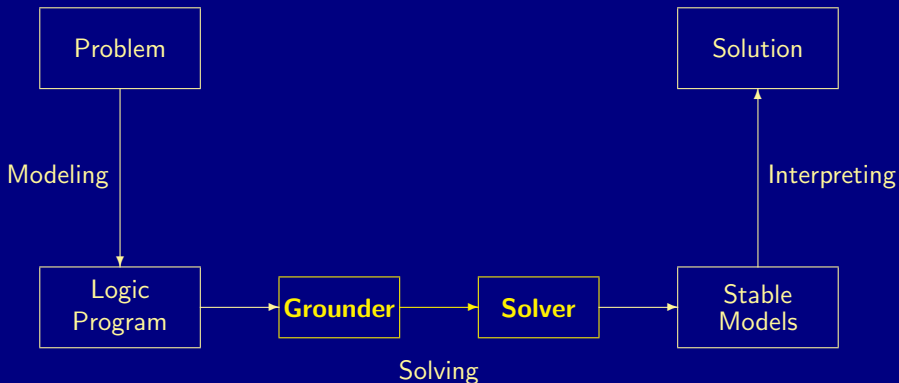
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aspif example`{a}.``b :- a.``c :- not a.``asp 1 0 0``1 1 1 1 0 0``1 0 1 2 0 1 1``1 0 1 3 0 1 -1``4 1 a 1 1``4 1 b 1 2``4 1 c 1 3``0`

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aspif overview

- Rule statements
- Minimize statements
- Projection statements
- Output statements
- External statements
- Assumption statements
- Heuristic statements
- **Edge statements**
- **Theory terms and atoms**
- Comments

aspif theory example

```

task(1).
task(2).

duration(1,200).
duration(2,400).

&dom {1..1000} = beg(1).
&dom {1..1000} = end(1).
&dom {1..1000} = beg(2).
&dom {1..1000} = end(2).

&diff{end(1)-beg(1)}<=200.
&diff{end(2)-beg(2)}<=400.

&show{ beg/1; end/1 }.

```

```

asp 1 0 0
1 0 1 1 0 0
1 0 1 2 0 0
1 0 1 3 0 0
1 0 1 4 0 0
1 0 1 5 0 0
1 0 1 6 0 0
4 7 task(1) 0
4 7 task(2) 0
4 15 duration(1,200) 0
4 15 duration(2,400) 0
9 0 1 200
9 0 3 400
9 0 6 1
9 0 11 2
9 1 0 4 diff
9 1 2 2 <=
9 1 4 1 -
9 1 5 3 end
9 1 8 3 beg
9 2 7 5 1 6
9 2 9 8 1 6
9 2 10 4 2 7 9
9 2 12 5 1 11
9 2 13 8 1 11
9 2 14 4 2 12 13
9 4 0 1 10 0
9 4 1 1 14 0
9 6 5 0 1 0 2 1
9 6 6 0 1 1 2 3
0

```

aspif theory example

```

task(1).
task(2).

duration(1,200).
duration(2,400).

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```

```

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1 0 1 1 0 0
1 0 1 2 0 0
1 0 1 3 0 0
1 0 1 4 0 0
1 0 1 5 0 0
1 0 1 6 0 0
4 7 task(1) 0
4 7 task(2) 0
4 15 duration(1,200) 0
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9 0 1 200
9 0 3 400
9 0 6 1
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9 1 0 4 diff
9 1 2 2 <=
9 1 4 1 -
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9 2 7 5 1 6
9 2 9 8 1 6
9 2 10 4 2 7 9
9 2 12 5 1 11
9 2 13 8 1 11
9 2 14 4 2 12 13
9 4 0 1 10 0
9 4 1 1 14 0
9 6 5 0 1 0 2 1
9 6 6 0 1 1 2 3
0

```


aspif theory example

```

task(1).
task(2).

duration(1,200).
duration(2,400).

&dom {1..1000} = beg(1).
&dom {1..1000} = end(1).
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&diff{end(1)-beg(1)}<=200.
&diff{end(2)-beg(2)}<=400.

&show{ beg/1; end/1 }.

```

```

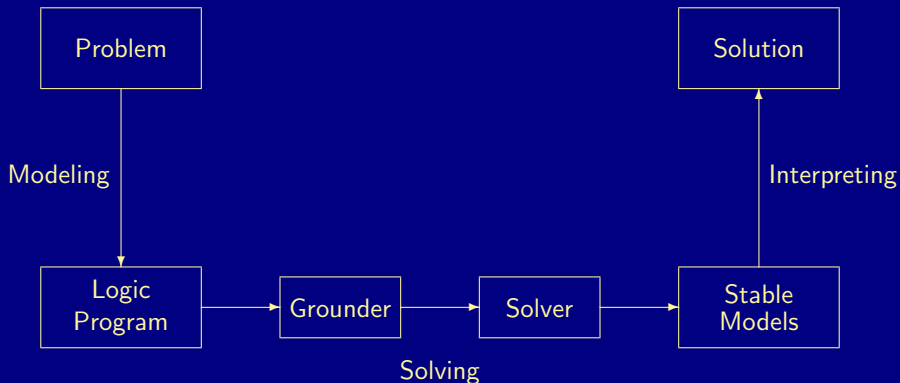
asp 1 0 0
1 0 1 1 0 0
1 0 1 2 0 0
1 0 1 3 0 0
1 0 1 4 0 0
1 0 1 5 0 0
1 0 1 6 0 0
4 7 task(1) 0
4 7 task(2) 0
4 15 duration(1,200) 0
4 15 duration(2,400) 0
9 0 1 200
9 0 3 400
9 0 6 1
9 0 11 2
9 1 0 4 diff
9 1 2 2 <=
9 1 4 1 -
9 1 5 3 end
9 1 8 3 beg
9 2 7 5 1 6
9 2 9 8 1 6
9 2 10 4 2 7 9
9 2 12 5 1 11
9 2 13 8 1 11
9 2 14 4 2 12 13
9 4 0 1 10 0
9 4 1 1 14 0
9 6 5 0 1 0 2 1
9 6 6 0 1 1 2 3
0

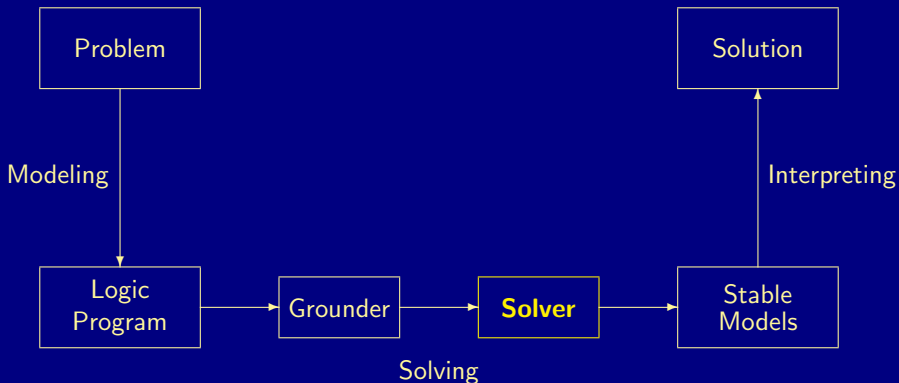
```

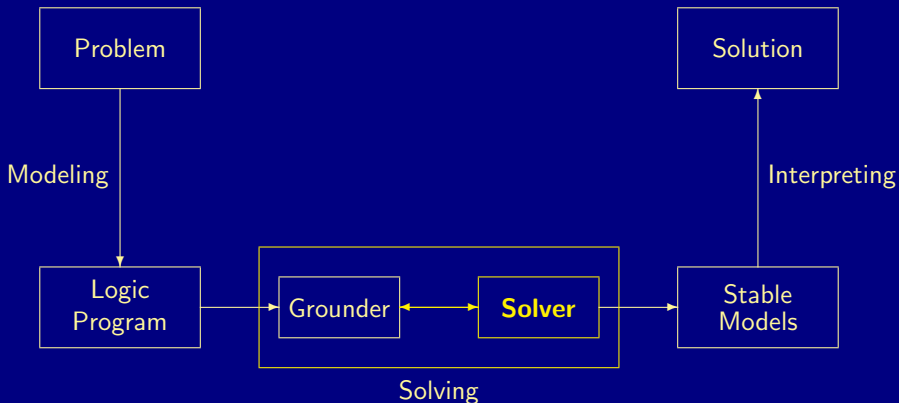
Only 6 (theory) atoms!

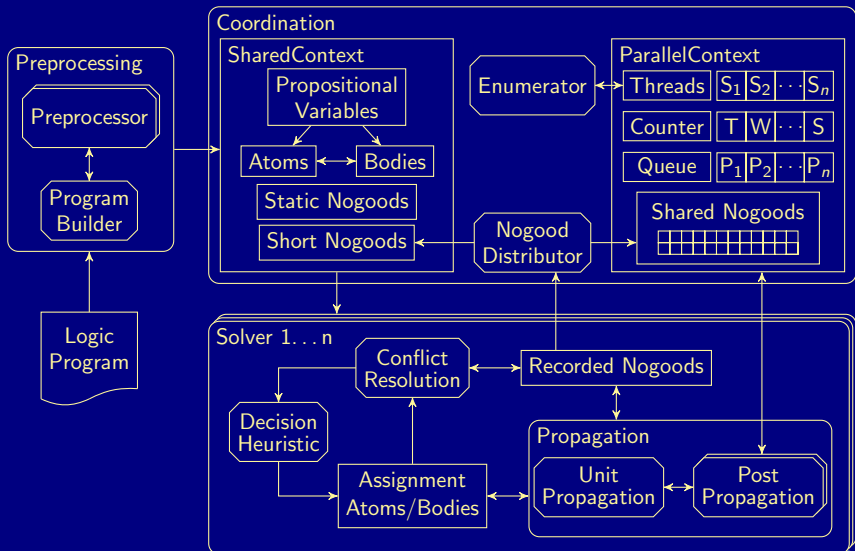
Outline

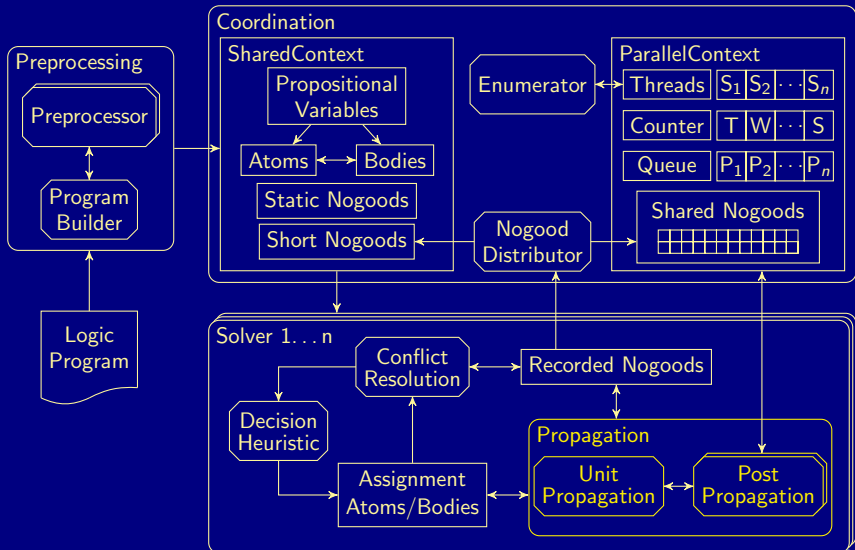
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Architecture of *clasp*

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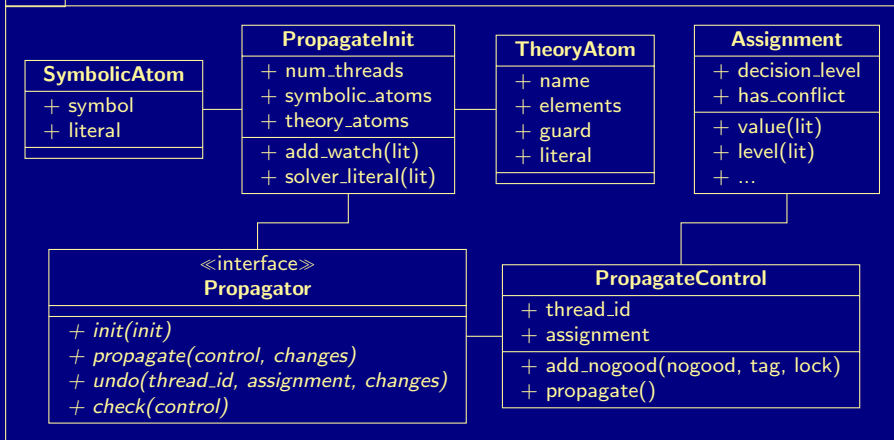
Conflict-driven constraint learning modulo theories

```

(I) initialize // register theory propagators and initialize watches
    loop
        propagate completion, loop, and recorded nogoods // deterministically assign literals
        if no conflict then
            if all variables assigned then
(C)         if some  $\delta \in \Delta_T$  is violated for  $T \in \mathbb{T}$  then record  $\delta$  // theory propagator's check
                else return variable assignment //  $\mathbb{T}$ -stable model found
            else
(P)         propagate theories  $T \in \mathbb{T}$  // theory propagators may record theory nogoods
                if no nogood recorded then decide // non-deterministically assign some literal
            else
                if top-level conflict then return unsatisfiable
            else
                analyze // resolve conflict and record a conflict constraint
(U)         backjump // undo assignments until conflict constraint is unit
  
```


Propagator interface

clingo



The *dot* propagator

```

#script (python)

import sys
import time

class Propagator:
    def init(self, init):
        self.sleep = .1
        for atom in init.symbolic_atoms:
            init.add_watch(init.solver_literal(atom.literal))

    def propagate(self, ctl, changes):
        for l in changes:
            sys.stdout.write(".")
            sys.stdout.flush()
            time.sleep(self.sleep)
        return True

    def undo(self, solver_id, assign, undo):
        for l in undo:
            sys.stdout.write("\b \b")
            sys.stdout.flush()
            time.sleep(self.sleep)

def main(prg):
    prg.register_propagator(Propagator())
    prg.ground(["base", []])
    prg.solve()
    sys.stdout.write("\n")

#end.

```

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Difference logic propagation

Problem	#	ASP		ASP modulo <i>DL</i> (stateless)				ASP modulo <i>DL</i> (stateful)			
		T	TO	defined		external		defined		external	
				T	TO	T	TO	T	TO	T	TO
Flow shop	120	569	110	283	40	382	70	177	30	281	50
Job shop	80	600	80	600	80	600	80	37	0	43	0
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Total	260	525	230	366	140	398	170	72	30	109	50

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- defined versus external amounts to the difference between
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Difference logic propagation

Problem	#	ASP		ASP modulo <i>DL</i> (stateless)				ASP modulo <i>DL</i> (stateful)			
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Outline

- 1 Theory language
- 2 Low-level semantics
- 3 Intermediate Format
- 4 Theory propagation
- 5 Experiments
- 6 Acyclicity checking**
- 7 Constraint Answer Set Programming

Builtin acyclicity checking

- Edge statement

$$\#edge(u, v) : l_1, \dots, l_n. \quad (3)$$

- A set X of atoms is an acyclic stable of a logic program P , if

- 1 X is a stable model of P and
- 2 the graph

$$(\{u, v \mid X \models l_1, \dots, l_n, (3) \in P\}, \{(u, v) \mid X \models l_1, \dots, l_n, (3) \in P\})$$

is acyclic

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Constraint Satisfaction Problem

- A **constraint satisfaction problem (CSP)** consists of
 - a set V of variables,
 - a set D of domains, and
 - a set C of constraints

such that

- each variable $v \in V$ has an associated domain $dom(v) \in D$;
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Example

$$\begin{array}{r}
 \\
 s \\
 + m \\
 \hline
 m
 \end{array}$$

Each letter corresponds exactly to one digit and all variables have to be pairwise distinct

$$V = \{s, e, n, d, m, o, r, y\}$$

$$D = \{dom(v) = \{0, \dots, 9\} \mid v \in V\}$$

$$\begin{aligned}
 C = \{ & (\vec{V}, \text{allDistinct}(V)), \\
 & (\vec{V}, s \times 1000 + e \times 100 + n \times 10 + d + \\
 & \phantom{(\vec{V},} m \times 1000 + o \times 100 + r \times 10 + e == \\
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 m o e y
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Each letter corresponds exactly to one digit and all variables have to be pairwise distinct

$$\begin{array}{r}
 \\
 9 5 6 7 \\
 + 1 0 8 5 \\
 \hline
 1 0 6 5 2
 \end{array}$$

The example has exactly one solution

$$\{ s \mapsto 9, e \mapsto 5, n \mapsto 6, d \mapsto 7, m \mapsto 1, o \mapsto 0, r \mapsto 8, y \mapsto 2 \}$$

Constraint satisfaction problem

- Notation We use $S(c) = S$ and $R(c) = R$ to access the scope and the relation of a constraint $c = (S, R)$
- For an assignment $A : V \rightarrow \bigcup_{v \in V} \text{dom}(v)$ and a constraint (S, R) with scope $S = (v_1, \dots, v_k)$, define

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Constraint Answer Set Programming

- A **constraint logic program** P is a logic program over an extended alphabet $\mathcal{A} \cup \mathcal{C}$ where
 - \mathcal{A} is a set of **regular atoms** and
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- Given a set of literals B and some set \mathcal{B} of atoms, we define
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- We identify constraint atoms with constraints via a function

$$\gamma : \mathcal{C} \rightarrow \mathcal{C}$$

- Furthermore, $\gamma(Y) = \{\gamma(c) \mid c \in Y\}$ for any $Y \subseteq \mathcal{C}$
- Note Unlike regular atoms \mathcal{A} , constraint atoms \mathcal{C} are not subject to the unique names assumption, eg.

$$\gamma(x < y) = \gamma(((-y - 1) \leq -(x + 1)) \wedge (x \neq y))$$

- A constraint logic program P is associated with a CSP as follows
 - $C[P] = \gamma(\text{atom}(P) \cap \mathcal{C})$,
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- Let P be a constraint logic program over $\mathcal{A} \cup \mathcal{C}$ and let $A : V[P] \rightarrow D[P]$ be an assignment, define the **constraint reduct** of P wrt A as follows

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 - extension of ASP solver *smodels*
- *clingcon*
 - extension of ASP system *clingo* (viz. *gringo* and *clasp*)
 - lazy approach
- *aspartame*
 - translational approach (independent of ASP system)
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- *aspmt*, *dlvhex*, *ezcsp*, *gasp*, *inca*, ...

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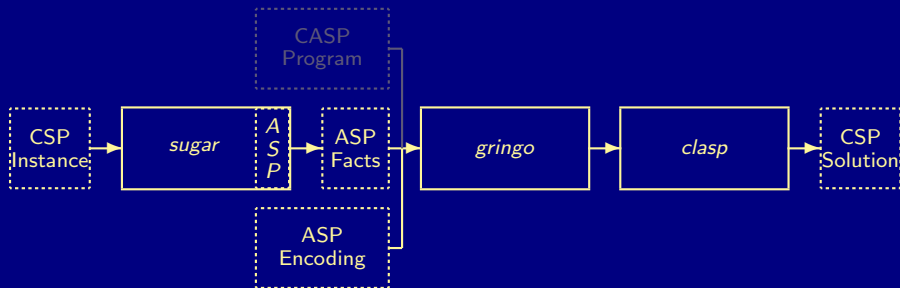
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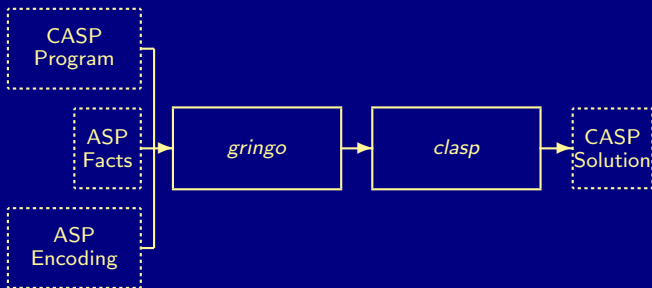
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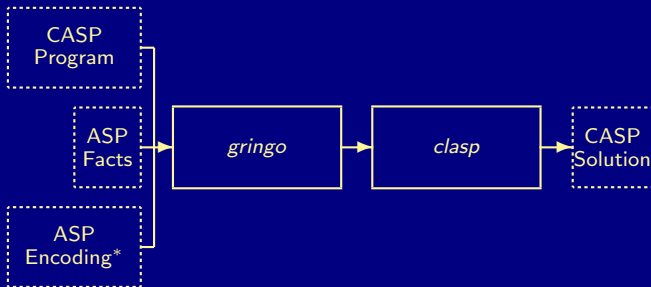
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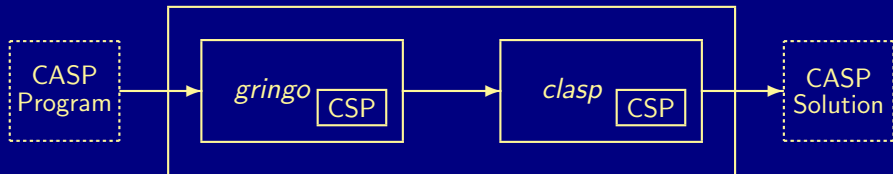


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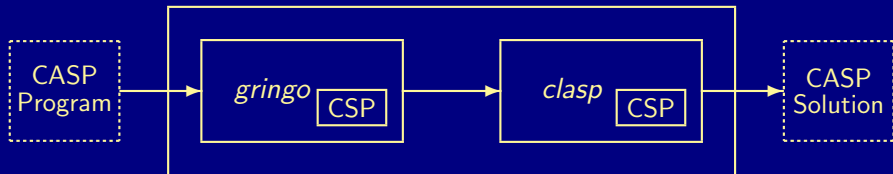
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■ *clingcon 3*

language specification
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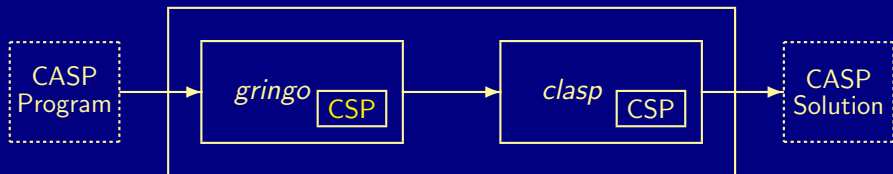
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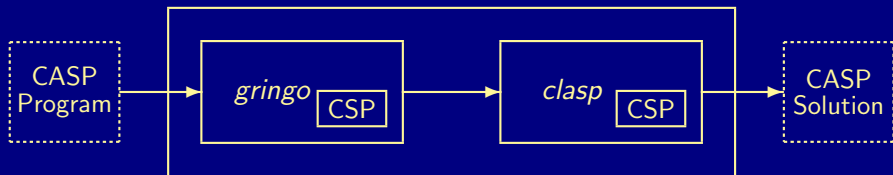
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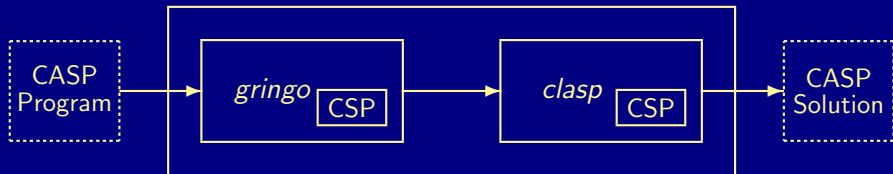
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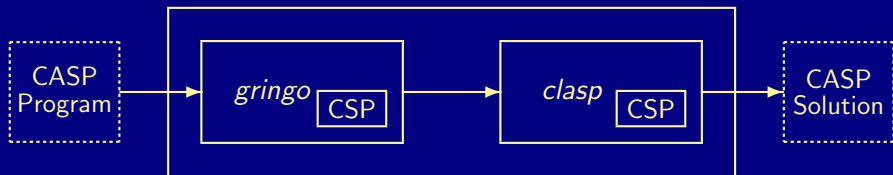
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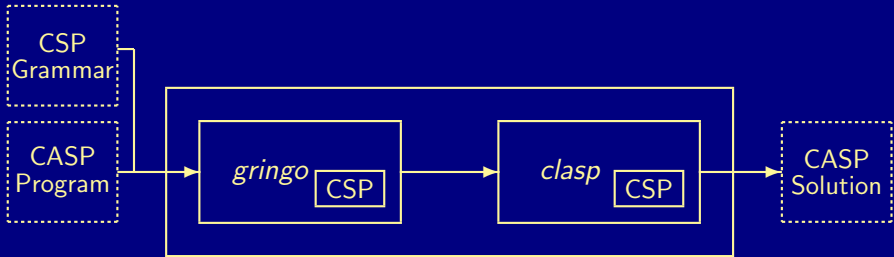
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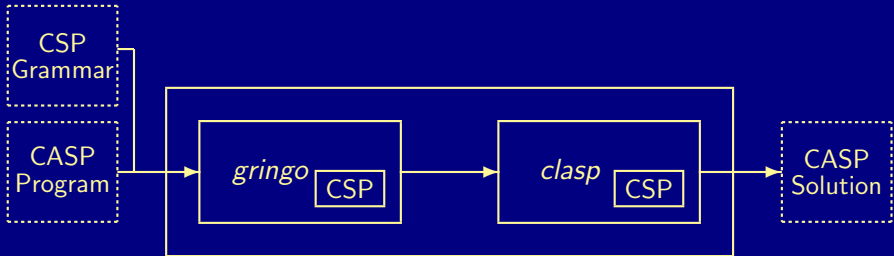
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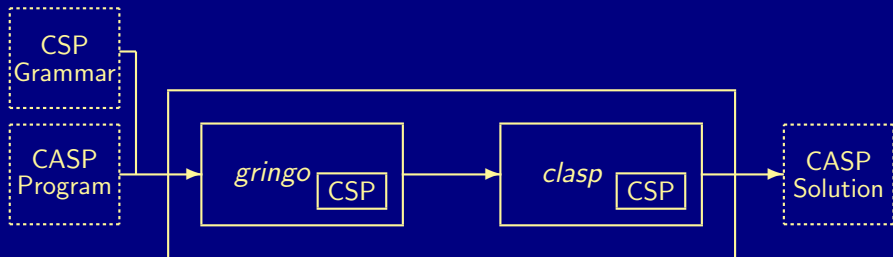
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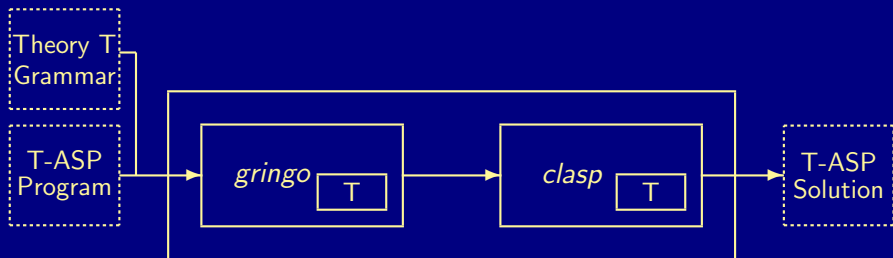
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clingcon instantiates *clingo*

- [1] Y. Babovich and V. Lifschitz.
Computing answer sets using program completion.
Unpublished draft, 2003.
- [2] C. Baral.
Knowledge Representation, Reasoning and Declarative Problem Solving.
Cambridge University Press, 2003.
- [3] C. Baral, G. Brewka, and J. Schlipf, editors.
Proceedings of the Ninth International Conference on Logic Programming and Nonmonotonic Reasoning (LPNMR'07), volume 4483 of *Lecture Notes in Artificial Intelligence*. Springer-Verlag, 2007.
- [4] C. Baral and M. Gelfond.
Logic programming and knowledge representation.
Journal of Logic Programming, 12:1–80, 1994.
- [5] S. Baselice, P. Bonatti, and M. Gelfond.
Towards an integration of answer set and constraint solving

In M. Gabbrielli and G. Gupta, editors, *Proceedings of the Twenty-first International Conference on Logic Programming (ICLP'05)*, volume 3668 of *Lecture Notes in Computer Science*, pages 52–66. Springer-Verlag, 2005.

[6] A. Biere.

Adaptive restart strategies for conflict driven SAT solvers.

In H. Kleine Büning and X. Zhao, editors, *Proceedings of the Eleventh International Conference on Theory and Applications of Satisfiability Testing (SAT'08)*, volume 4996 of *Lecture Notes in Computer Science*, pages 28–33. Springer-Verlag, 2008.

[7] A. Biere.

PicoSAT essentials.

Journal on Satisfiability, Boolean Modeling and Computation, 4:75–97, 2008.

[8] A. Biere, M. Heule, H. van Maaren, and T. Walsh, editors.

Handbook of Satisfiability, volume 185 of *Frontiers in Artificial Intelligence and Applications*.

IOS Press, 2009.

- [9] G. Brewka, T. Eiter, and M. Truszczyński.
Answer set programming at a glance.
Communications of the ACM, 54(12):92–103, 2011.
- [10] G. Brewka, I. Niemelä, and M. Truszczyński.
Answer set optimization.
In G. Gottlob and T. Walsh, editors, *Proceedings of the Eighteenth International Joint Conference on Artificial Intelligence (IJCAI'03)*, pages 867–872. Morgan Kaufmann Publishers, 2003.
- [11] K. Clark.
Negation as failure.
In H. Gallaire and J. Minker, editors, *Logic and Data Bases*, pages 293–322. Plenum Press, 1978.
- [12] M. D'Agostino, D. Gabbay, R. Hähnle, and J. Posegga, editors.
Handbook of Tableau Methods.
Kluwer Academic Publishers, 1999.

- [13] E. Dantsin, T. Eiter, G. Gottlob, and A. Voronkov.
Complexity and expressive power of logic programming.
In *Proceedings of the Twelfth Annual IEEE Conference on Computational Complexity (CCC'97)*, pages 82–101. IEEE Computer Society Press, 1997.
- [14] M. Davis, G. Logemann, and D. Loveland.
A machine program for theorem-proving.
Communications of the ACM, 5:394–397, 1962.
- [15] M. Davis and H. Putnam.
A computing procedure for quantification theory.
Journal of the ACM, 7:201–215, 1960.
- [16] E. Di Rosa, E. Giunchiglia, and M. Maratea.
Solving satisfiability problems with preferences.
Constraints, 15(4):485–515, 2010.
- [17] C. Drescher, M. Gebser, T. Grote, B. Kaufmann, A. König, M. Ostrowski, and T. Schaub.

Conflict-driven disjunctive answer set solving.

In G. Brewka and J. Lang, editors, *Proceedings of the Eleventh International Conference on Principles of Knowledge Representation and Reasoning (KR'08)*, pages 422–432. AAAI Press, 2008.

- [18] C. Drescher, M. Gebser, B. Kaufmann, and T. Schaub.

Heuristics in conflict resolution.

In M. Pagnucco and M. Thielscher, editors, *Proceedings of the Twelfth International Workshop on Nonmonotonic Reasoning (NMR'08)*, number UNSW-CSE-TR-0819 in School of Computer Science and Engineering, The University of New South Wales, Technical Report Series, pages 141–149, 2008.

- [19] N. Eén and N. Sörensson.

An extensible SAT-solver.

In E. Giunchiglia and A. Tacchella, editors, *Proceedings of the Sixth International Conference on Theory and Applications of Satisfiability Testing (SAT'03)*, volume 2919 of *Lecture Notes in Computer Science*, pages 502–518. Springer-Verlag, 2004.

- [20] T. Eiter and G. Gottlob.
On the computational cost of disjunctive logic programming:
Propositional case.
Annals of Mathematics and Artificial Intelligence, 15(3-4):289–323,
1995.
- [21] T. Eiter, G. Ianni, and T. Krennwallner.
Answer Set Programming: A Primer.
In S. Tessaris, E. Franconi, T. Eiter, C. Gutierrez, S. Handschuh,
M. Rousset, and R. Schmidt, editors, *Fifth International Reasoning
Web Summer School (RW'09)*, volume 5689 of *Lecture Notes in
Computer Science*, pages 40–110. Springer-Verlag, 2009.
- [22] F. Fages.
Consistency of Clark's completion and the existence of stable models.
Journal of Methods of Logic in Computer Science, 1:51–60, 1994.
- [23] P. Ferraris.
Answer sets for propositional theories.

In C. Baral, G. Greco, N. Leone, and G. Terracina, editors, *Proceedings of the Eighth International Conference on Logic Programming and Nonmonotonic Reasoning (LPNMR'05)*, volume 3662 of *Lecture Notes in Artificial Intelligence*, pages 119–131. Springer-Verlag, 2005.

[24] P. Ferraris and V. Lifschitz.

Mathematical foundations of answer set programming.

In S. Artëmov, H. Barringer, A. d'Avila Garcez, L. Lamb, and J. Woods, editors, *We Will Show Them! Essays in Honour of Dov Gabbay*, volume 1, pages 615–664. College Publications, 2005.

[25] M. Fitting.

A Kripke-Kleene semantics for logic programs.

Journal of Logic Programming, 2(4):295–312, 1985.

[26] M. Gebser, A. Harrison, R. Kaminski, V. Lifschitz, and T. Schaub.

Abstract Gringo.

Theory and Practice of Logic Programming, 15(4-5):449–463, 2015.

Available at <http://arxiv.org/abs/1507.06576>.

- [27] M. Gebser, R. Kaminski, B. Kaufmann, M. Lindauer, M. Ostrowski, J. Romero, T. Schaub, and S. Thiele.
Potassco User Guide.
University of Potsdam, second edition edition, 2015.
- [28] M. Gebser, R. Kaminski, B. Kaufmann, M. Ostrowski, T. Schaub, and S. Thiele.
A user's guide to gringo, clasp, clingo, and iclingo.
- [29] M. Gebser, R. Kaminski, B. Kaufmann, M. Ostrowski, T. Schaub, and S. Thiele.
Engineering an incremental ASP solver.
In M. Garcia de la Banda and E. Pontelli, editors, *Proceedings of the Twenty-fourth International Conference on Logic Programming (ICLP'08)*, volume 5366 of *Lecture Notes in Computer Science*, pages 190–205. Springer-Verlag, 2008.
- [30] M. Gebser, R. Kaminski, B. Kaufmann, and T. Schaub.

On the implementation of weight constraint rules in conflict-driven ASP solvers.

In Hill and Warren [49], pages 250–264.

[31] M. Gebser, R. Kaminski, B. Kaufmann, and T. Schaub.

Answer Set Solving in Practice.

Synthesis Lectures on Artificial Intelligence and Machine Learning.
Morgan and Claypool Publishers, 2012.

[32] M. Gebser, B. Kaufmann, A. Neumann, and T. Schaub.

clasp: A conflict-driven answer set solver.

In Baral et al. [3], pages 260–265.

[33] M. Gebser, B. Kaufmann, A. Neumann, and T. Schaub.

Conflict-driven answer set enumeration.

In Baral et al. [3], pages 136–148.

[34] M. Gebser, B. Kaufmann, A. Neumann, and T. Schaub.

Conflict-driven answer set solving.

In Veloso [74], pages 386–392.

- [35] M. Gebser, B. Kaufmann, A. Neumann, and T. Schaub.
Advanced preprocessing for answer set solving.
In M. Ghallab, C. Spyropoulos, N. Fakotakis, and N. Avouris, editors, *Proceedings of the Eighteenth European Conference on Artificial Intelligence (ECAI'08)*, pages 15–19. IOS Press, 2008.
- [36] M. Gebser, B. Kaufmann, and T. Schaub.
The conflict-driven answer set solver clasp: Progress report.
In E. Erdem, F. Lin, and T. Schaub, editors, *Proceedings of the Tenth International Conference on Logic Programming and Nonmonotonic Reasoning (LPNMR'09)*, volume 5753 of *Lecture Notes in Artificial Intelligence*, pages 509–514. Springer-Verlag, 2009.
- [37] M. Gebser, B. Kaufmann, and T. Schaub.
Solution enumeration for projected Boolean search problems.
In W. van Hoes and J. Hooker, editors, *Proceedings of the Sixth International Conference on Integration of AI and OR Techniques in Constraint Programming for Combinatorial Optimization Problems*

(CPAIOR'09), volume 5547 of *Lecture Notes in Computer Science*, pages 71–86. Springer-Verlag, 2009.

[38] M. Gebser, M. Ostrowski, and T. Schaub.

Constraint answer set solving.

In Hill and Warren [49], pages 235–249.

[39] M. Gebser and T. Schaub.

Tableau calculi for answer set programming.

In S. Etalle and M. Truszczynski, editors, *Proceedings of the Twenty-second International Conference on Logic Programming (ICLP'06)*, volume 4079 of *Lecture Notes in Computer Science*, pages 11–25. Springer-Verlag, 2006.

[40] M. Gebser and T. Schaub.

Generic tableaux for answer set programming.

In V. Dahl and I. Niemelä, editors, *Proceedings of the Twenty-third International Conference on Logic Programming (ICLP'07)*, volume 4670 of *Lecture Notes in Computer Science*, pages 119–133. Springer-Verlag, 2007.

- [41] M. Gelfond.
Answer sets.
In V. Lifschitz, F. van Harmelen, and B. Porter, editors, *Handbook of Knowledge Representation*, chapter 7, pages 285–316. Elsevier Science, 2008.
- [42] M. Gelfond and Y. Kahl.
Knowledge Representation, Reasoning, and the Design of Intelligent Agents: The Answer-Set Programming Approach.
Cambridge University Press, 2014.
- [43] M. Gelfond and N. Leone.
Logic programming and knowledge representation — the A-Prolog perspective.
Artificial Intelligence, 138(1-2):3–38, 2002.
- [44] M. Gelfond and V. Lifschitz.
The stable model semantics for logic programming.

In R. Kowalski and K. Bowen, editors, *Proceedings of the Fifth International Conference and Symposium of Logic Programming (ICLP'88)*, pages 1070–1080. MIT Press, 1988.

[45] M. Gelfond and V. Lifschitz.

Logic programs with classical negation.

In D. Warren and P. Szeredi, editors, *Proceedings of the Seventh International Conference on Logic Programming (ICLP'90)*, pages 579–597. MIT Press, 1990.

[46] E. Giunchiglia, Y. Lierler, and M. Maratea.

Answer set programming based on propositional satisfiability.

Journal of Automated Reasoning, 36(4):345–377, 2006.

[47] K. Gödel.

Zum intuitionistischen Aussagenkalkül.

In *Anzeiger der Akademie der Wissenschaften in Wien*, page 65–66. 1932.

[48] A. Heyting.

Die formalen Regeln der intuitionistischen Logik.

In *Sitzungsberichte der Preussischen Akademie der Wissenschaften*, page 42–56. 1930.

Reprint in *Logik-Texte: Kommentierte Auswahl zur Geschichte der Modernen Logik*, Akademie-Verlag, 1986.

- [49] P. Hill and D. Warren, editors.
Proceedings of the Twenty-fifth International Conference on Logic Programming (ICLP'09), volume 5649 of *Lecture Notes in Computer Science*. Springer-Verlag, 2009.
- [50] J. Huang.
The effect of restarts on the efficiency of clause learning.
In Veloso [74], pages 2318–2323.
- [51] K. Konczak, T. Linke, and T. Schaub.
Graphs and colorings for answer set programming.
Theory and Practice of Logic Programming, 6(1-2):61–106, 2006.
- [52] J. Lee.

A model-theoretic counterpart of loop formulas.

In L. Kaelbling and A. Saffiotti, editors, *Proceedings of the Nineteenth International Joint Conference on Artificial Intelligence (IJCAI'05)*, pages 503–508. Professional Book Center, 2005.

- [53] N. Leone, G. Pfeifer, W. Faber, T. Eiter, G. Gottlob, S. Perri, and F. Scarcello.

The DLV system for knowledge representation and reasoning.

ACM Transactions on Computational Logic, 7(3):499–562, 2006.

- [54] V. Lifschitz.

Answer set programming and plan generation.

Artificial Intelligence, 138(1-2):39–54, 2002.

- [55] V. Lifschitz.

Introduction to answer set programming.

Unpublished draft, 2004.

- [56] V. Lifschitz and A. Razborov.

Why are there so many loop formulas?

ACM Transactions on Computational Logic, 7(2):261–268, 2006.

- [57] F. Lin and Y. Zhao.
ASSAT: computing answer sets of a logic program by SAT solvers.
Artificial Intelligence, 157(1-2):115–137, 2004.
- [58] V. Marek and M. Truszczyński.
Nonmonotonic logic: context-dependent reasoning.
Artificial Intelligence. Springer-Verlag, 1993.
- [59] V. Marek and M. Truszczyński.
Stable models and an alternative logic programming paradigm.
In K. Apt, V. Marek, M. Truszczyński, and D. Warren, editors, *The Logic Programming Paradigm: a 25-Year Perspective*, pages 375–398. Springer-Verlag, 1999.
- [60] J. Marques-Silva, I. Lynce, and S. Malik.
Conflict-driven clause learning SAT solvers.
In Biere et al. [8], chapter 4, pages 131–153.
- [61] J. Marques-Silva and K. Sakallah.

GRASP: A search algorithm for propositional satisfiability.

IEEE Transactions on Computers, 48(5):506–521, 1999.

[62] V. Mellarkod and M. Gelfond.

Integrating answer set reasoning with constraint solving techniques.

In J. Garrigue and M. Hermenegildo, editors, *Proceedings of the Ninth International Symposium on Functional and Logic Programming (FLOPS'08)*, volume 4989 of *Lecture Notes in Computer Science*, pages 15–31. Springer-Verlag, 2008.

[63] V. Mellarkod, M. Gelfond, and Y. Zhang.

Integrating answer set programming and constraint logic programming.

Annals of Mathematics and Artificial Intelligence, 53(1-4):251–287, 2008.

[64] D. Mitchell.

A SAT solver primer.

Bulletin of the European Association for Theoretical Computer Science, 85:112–133, 2005.

- [65] M. Moskewicz, C. Madigan, Y. Zhao, L. Zhang, and S. Malik.
Chaff: Engineering an efficient SAT solver.
In *Proceedings of the Thirty-eighth Conference on Design Automation (DAC'01)*, pages 530–535. ACM Press, 2001.
- [66] I. Niemelä.
Logic programs with stable model semantics as a constraint programming paradigm.
Annals of Mathematics and Artificial Intelligence, 25(3-4):241–273, 1999.
- [67] R. Nieuwenhuis, A. Oliveras, and C. Tinelli.
Solving SAT and SAT modulo theories: From an abstract Davis-Putnam-Logemann-Loveland procedure to DPLL(T).
Journal of the ACM, 53(6):937–977, 2006.
- [68] K. Pipatsrisawat and A. Darwiche.
A lightweight component caching scheme for satisfiability solvers.

In J. Marques-Silva and K. Sakallah, editors, *Proceedings of the Tenth International Conference on Theory and Applications of Satisfiability Testing (SAT'07)*, volume 4501 of *Lecture Notes in Computer Science*, pages 294–299. Springer-Verlag, 2007.

- [69] L. Ryan.
Efficient algorithms for clause-learning SAT solvers.
Master's thesis, Simon Fraser University, 2004.
- [70] P. Simons, I. Niemelä, and T. Soinen.
Extending and implementing the stable model semantics.
Artificial Intelligence, 138(1-2):181–234, 2002.
- [71] T. Son and E. Pontelli.
Planning with preferences using logic programming.
Theory and Practice of Logic Programming, 6(5):559–608, 2006.
- [72] T. Syrjänen.
Lparse 1.0 user's manual, 2001.
- [73] A. Van Gelder, K. Ross, and J. Schlipf.

The well-founded semantics for general logic programs.

Journal of the ACM, 38(3):620–650, 1991.

[74] M. Veloso, editor.

Proceedings of the Twentieth International Joint Conference on Artificial Intelligence (IJCAI'07). AAAI/MIT Press, 2007.

[75] L. Zhang, C. Madigan, M. Moskewicz, and S. Malik.

Efficient conflict driven learning in a Boolean satisfiability solver.

In *Proceedings of the International Conference on Computer-Aided Design (ICCAD'01)*, pages 279–285. ACM Press, 2001.