Answer Set Programming, the Solving Paradigm for Knowledge Representation and Reasoning

Martin Gebser Torsten Schaub

University of Potsdam

Outline

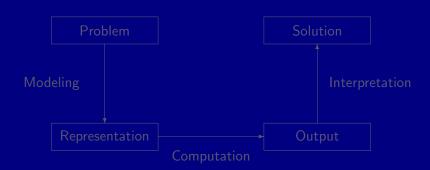
- 1 Motivation
- 2 Introduction
- 3 Modeling by Example
- 4 Conflict-Driven Answer Set Solving
- 5 Potassco
- 6 Summary

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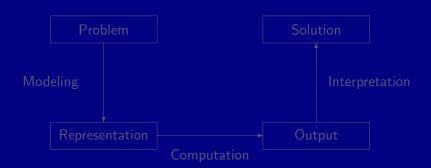
Goal: Declarative problem solving

- "What is the problem?" instead of
- "How to solve the problem?"



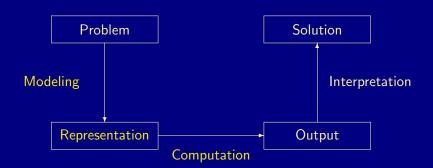
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- ASP is an approach to declarative problem solving, combining
 - a rich yet simple modeling language
 - with high-performance solving capacities
- ASP has its roots in
 - (logic-based) knowledge representation and reasoning
 - (deductive) databases
 - constraint solving (in particular, SAT solving)
 - logic programming (with negation
- ASP allows for solving all search problems in NP (and NP^{NP}) in a uniform way (being more compact than SAT)
- The versatility of ASP is reflected by the ASP solver clasp, winning first places at ASP'09, PB'09, and SAT'09
- ASP embraces many emerging application areas

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Consider the logical formula Φ and its three (classical) models:

$$\Phi \ \boxed{ q \ \land \ (q \land \neg r \to p)}$$

$$\{p,q\},\{q,r\}, \text{ and } \{p,q,r\}$$

This formula has one stable model, called answer set:

$$\{p,q\}$$

Informally, a set X of atoms is an answer set of a logic program Π if X is a (classical) model of Π and if all atoms in X are justified by some rule in Π

rooted in intuitionistic logics HT (Heyting, 1930) and G3 (Gödel, 1932)

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■ Syntax

 \blacksquare A rule, r, is an expression of the form

$$a \leftarrow b_1, \ldots, b_m, not \ c_1, \ldots, not \ c_n$$

where $0 \le m, n$ and each a, b_i, c_i is an atom

- A logic program is a finite set of rules
- Semantics

The reduct, Π^X , of a program Π relative to a set X of atoms is defined by

$$\Pi^X = \{ a \leftarrow b_1, \dots, b_m \mid r \in \Pi \text{ and } \{c_1, \dots, c_n\} \cap X = \emptyset \}$$

The \subseteq -smallest model of Π^X is denoted by $Cn(\Pi^X)$ A set X of atoms is an answer set of a program Π , if

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Variables (over the Herbrand Universe)

$$p(X) := q(X)$$
 over constants $\{a,b,c\}$ stands for $p(a) := q(a)$, $p(b) := q(b)$, $p(c) := q(c)$

Conditional Literals

Disjunction

$$p(X) ; q(X) := r(X)$$

Integrity Constraints

$$:= q(X), p(X)$$

Choice

$$2 \{ p(X,Y) : q(X) \} 7 := r(Y)$$

Aggregates

■ Variables (over the Herbrand Universe)

```
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- Aggregates
 - \blacksquare s(Y) :- r(Y), 2 #count { p(X,Y) : q(X) } \top
 - also: #sum, #times, #avg, #min, #max, #even, #od

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 - p :- q(X) : r(X) given r(a), r(b), r(c) stands for p :- q(a), q(b), q(c)
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$$\blacksquare$$
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Integrity Constraints

$$=$$
 :- $q(X)$, $p(X)$

Choice

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Disjunction

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- Integrity Constraints

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Choice

$$1$$
 2 $\{ p(X,Y) : q(X) \} 7 := r(Y)$

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$$p(X,Y) : q(X)$$
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Reasoning Modes

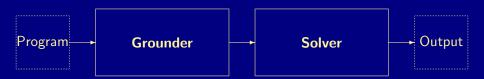
- Satisfiability
- Enumeration[†]
- Projection[†]
- Intersection[‡]
- Union[‡]
- Optimization
- Sampling

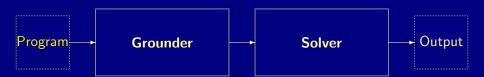
- † without solution recording
- t without solution enumeration

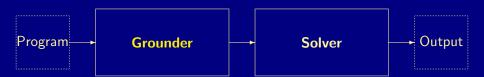
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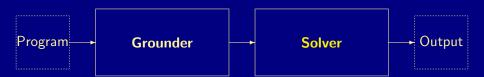
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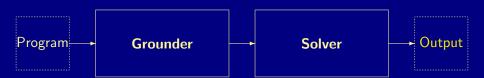
ASP Solving Process

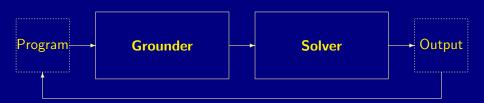












node(1..6).

```
node(1..6).
edge(1,2).
            edge(1,3).
                        edge(1,4).
edge(2,4).
            edge(2,5).
                        edge(2,6).
edge(3,1).
            edge(3,4).
                        edge(3,5).
edge(4,1).
            edge(4,2).
edge(5,3).
            edge(5,4).
                       edge(5,6).
edge(6,2).
            edge(6,3).
                        edge(6,5).
```

```
node(1..6).
edge(1,2).
           edge(1,3).
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edge(2,4).
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                       edge(2,6).
edge(3,1).
           edge(3,4).
                       edge(3,5).
edge(4,1).
           edge(4,2).
edge(5,3).
           edge(5,4). edge(5,6).
edge(6,2).
           edge(6,3).
                       edge(6,5).
col(r). col(b). col(g).
```

```
node(1..6).
edge(1,2).
           edge(1,3).
                       edge(1,4).
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           edge(2,5). edge(2,6).
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edge(4,1).
           edge(4,2).
edge(5,3).
           edge(5,4). edge(5,6).
edge(6,2).
           edge(6,3). edge(6,5).
col(r). col(b). col(g).
1 \{ color(X,C) : col(C) \} 1 : - node(X).
:- edge(X,Y), color(X,C), color(Y,C).
```

Graph Coloring: Grounding

\$ gringo -t color.lp

Graph Coloring: Grounding

\$ gringo -t color.lp

```
node(1). node(2). node(3). node(4). node(5). node(6).
edge(1,2).
            edge(1,3).
                        edge(1,4).
                                    edge(2,4).
                                                edge(2,5).
                                                             edge(2,6).
                                                edge(4,2).
edge(3,1).
            edge(3.4).
                        edge(3.5).
                                    edge(4.1).
                                                             edge(5,3).
edge(5.4).
            edge(5.6).
                        edge(6.2).
                                    edge(6.3).
                                                edge(6.5).
col(r). col(b). col(g).
1 { color(1,r), color(1,b), color(1,g) } 1.
1 { color(2,r), color(2,b), color(2,g) } 1.
1 { color(3,r), color(3,b), color(3,g) } 1.
1 { color(4,r), color(4,b), color(4,g) } 1.
1 { color(5,r), color(5,b), color(5,g) } 1.
1 { color(6,r), color(6,b), color(6,g) } 1.
 :- color(1,r), color(2,r).
                             :- color(2,g), color(5,g). ...
                                                              :- color(6,r), color(2,r).
 :- color(1,b), color(2,b).
                             :- color(2,r), color(6,r).
                                                              :- color(6,b), color(2,b).
 :- color(1,g), color(2,g).
                             :- color(2.b), color(6.b).
                                                              :- color(6,g), color(2,g).
 :- color(1,r), color(3,r).
                             :- color(2,g), color(6,g).
                                                              :- color(6,r), color(3,r).
 :- color(1.b), color(3.b).
                             :- color(3.r), color(1.r),
                                                              :- color(6,b), color(3,b).
 :- color(1,g), color(3,g).
                             :- color(3.b), color(1.b).
                                                              :- color(6,g), color(3,g).
 :- color(1,r), color(4,r).
                             :- color(3,g), color(1,g).
                                                              :- color(6,r), color(5,r).
 :- color(1,b), color(4,b).
                             :- color(3,r), color(4,r).
                                                              :- color(6,b), color(5,b).
 :- color(1,g), color(4,g).
                             :- color(3.b), color(4.b).
                                                              :- color(6.g), color(5.g),
 :- color(2,r), color(4,r).
                             :- color(3,g), color(4,g).
 :- color(2,b), color(4,b).
                             :- color(3,r), color(5,r).
 :- color(2,g), color(4,g).
                             :- color(3,b), color(5,b).
```

Graph Coloring: Solving

\$ gringo color.lp | clasp 0

Graph Coloring: Solving

\$ gringo color.lp | clasp 0

```
clasp version 1.2.1
Reading from stdin
               : Done(0.000s)
Reading
Preprocessing: Done(0.000s)
Solving...
Answer: 1
\operatorname{color}(1,b) \operatorname{color}(2,r) \operatorname{color}(3,r) \operatorname{color}(4,g) \operatorname{color}(5,b) \operatorname{color}(6,g) \operatorname{node}(1) ... \operatorname{edge}(1,2) ... \operatorname{col}(r) ...
Answer: 2
color(1,g) color(2,r) color(3,r) color(4,b) color(5,g) color(6,b) node(1) ... edge(1,2) ... col(r) ...
Answer: 3
color(1,b) color(2,g) color(3,g) color(4,r) color(5,b) color(6,r) node(1) ... edge(1,2) ... col(r) ...
Answer: 4
color(1,g) color(2,b) color(3,b) color(4,r) color(5,g) color(6,r) node(1) ... edge(1,2) ... col(r) ...
Answer: 5
\operatorname{color}(1,r) \operatorname{color}(2,b) \operatorname{color}(3,b) \operatorname{color}(4,g) \operatorname{color}(5,r) \operatorname{color}(6,g) \operatorname{node}(1) ... \operatorname{edge}(1,2) ... \operatorname{col}(r) ...
Answer: 6
color(1,r) color(2,g) color(3,g) color(4,b) color(5,r) color(6,b) node(1) ... edge(1,2) ... col(r) ...
Models
               : 6
               : 0.000 (Solving: 0.000)
Time
```

```
node(1..6).
edge(1,2;3;4).
                edge(2,4;5;6).
                                 edge(3,1;4;5).
                                 edge(6,2;3;5).
edge(4,1;2).
                edge(5,3;4;6).
```

```
node(1..6).
edge(1,2;3;4).
                edge(2,4;5;6).
                                 edge(3,1;4;5).
edge(4,1;2).
                edge(5,3;4;6).
                                 edge(6,2;3;5).
cost(1,2,2).
              cost(1,3,3).
                             cost(1,4,1).
cost(2.4.2).
              cost(2.5.2).
                             cost(2.6.4).
cost(3,1,3).
              cost(3.4.2).
                             cost(3.5.2).
cost(4,1,1).
              cost(4.2.2).
cost(5,3,2).
              cost(5,4,2).
                            cost(5,6,1).
cost(6,2,4).
              cost(6,3,3).
                            cost(6.5.1).
```

```
1 { cycle(X,Y) : edge(X,Y) } 1 :- node(X).
1 { cycle(X,Y) : edge(X,Y) } 1 :- node(Y).

reached(Y) :- cycle(1,Y).
reached(Y) :- cycle(X,Y), reached(X).

:- node(Y), not reached(Y).

#minimize [ cycle(X,Y) : cost(X,Y,C) = C ].
```

```
1 { cycle(X,Y) : edge(X,Y) } 1 :- node(X).
1 { cycle(X,Y) : edge(X,Y) } 1 :- node(Y).
reached(Y) :- cycle(1,Y).
reached(Y) :- cycle(X,Y), reached(X).
:- node(Y), not reached(Y).
#minimize [ cycle(X,Y) : cost(X,Y,C) = C ].
```

```
1 { cycle(X,Y) : edge(X,Y) } 1 :- node(X).
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```

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1 { cycle(X,Y) : edge(X,Y) } 1 :- node(X).
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reached(Y) :- cycle(1,Y).
reached(Y) :- cycle(X,Y), reached(X).
:- node(Y), not reached(Y).
#minimize [ cycle(X,Y) : cost(X,Y,C) = C ].
```

```
reviewer(r1). paper(p1). classA(r1,p1). classB(r1,p2). coi(r1,p3).
reviewer(r2). paper(p2). classA(r1,p3). classB(r1,p4). coi(r1,p6).
```

```
reviewer(r1). paper(p1). classA(r1,p1). classB(r1,p2). coi(r1,p3).
reviewer(r2). paper(p2). classA(r1,p3). classB(r1,p4). coi(r1,p6).
3 { assigned(P,R) : reviewer(R) } 3 :- paper(P).
```

```
reviewer(r1). paper(p1). classA(r1,p1). classB(r1,p2). coi(r1,p3).
reviewer(r2). paper(p2). classA(r1,p3). classB(r1,p4). coi(r1,p6).
3 { assigned(P,R) : reviewer(R) } 3 :- paper(P).
 :- assigned(P,R), coi(R,P).
 :- assigned(P,R), not classA(R,P), not classB(R,P).
 :- 9 { assigned(P,R) : paper(P) } , reviewer(R).
 :- { assigned(P,R) : paper(P) } 6, reviewer(R).
```

```
reviewer(r1). paper(p1). classA(r1,p1). classB(r1,p2). coi(r1,p3).
reviewer(r2). paper(p2). classA(r1,p3). classB(r1,p4). coi(r1,p6).
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 :- 9 { assigned(P,R) : paper(P) } , reviewer(R).
 :- { assigned(P,R) : paper(P) } 6, reviewer(R).
assignedB(P,R) :- assigned(P,R), classB(R,P).
 :- 3 { assignedB(P,R) : paper(P) }, reviewer(R).
```

```
reviewer(r1). paper(p1). classA(r1,p1). classB(r1,p2). coi(r1,p3).
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 :- { assigned(P,R) : paper(P) } 6, reviewer(R).
assignedB(P,R) :- assigned(P,R), classB(R,P).
 :- 3 { assignedB(P,R) : paper(P) }, reviewer(R).
#minimize { assignedB(P,R) : paper(P) : reviewer(R) }.
```

Simplistic STRIPS Planning

```
fluent(p).
             fluent(q).
                         fluent(r).
action(a). pre(a,p).
                         add(a,q).
                                      del(a,p).
action(b).
         pre(b,q).
                         add(b,r).
                                      del(b,q).
init(p).
             query(r).
```

Simplistic STRIPS Planning

```
fluent(p).
             fluent(q).
                         fluent(r).
action(a). pre(a,p).
                         add(a,q).
                                      del(a,p).
action(b). pre(b,q).
                         add(b,r).
                                      del(b,q).
init(p).
             query(r).
time(1..k).
          lasttime(T) :- time(T), not time(T+1).
```

Simplistic STRIPS Planning

```
fluent(p). fluent(q). fluent(r).
action(a). pre(a,p). add(a,q). del(a,p).
action(b). pre(b,q). add(b,r). del(b,q).
init(p). query(r).
time(1..k). lasttime(T): - time(T), not time(T+1).
holds(P,0) := init(P).
1 \{ occ(A,T) : action(A) \} 1 : - time(T).
 := occ(A,T), pre(A,F), not holds(F,T-1).
ocdel(F,T) := occ(A,T), del(A,F).
holds(F,T) := occ(A,T), add(A,F).
holds(F,T) :- holds(F,T-1), not ocdel(F,T), time(T).
 :- query(F), not holds(F,T), lasttime(T).
```

```
#base.
```

```
fluent(p).
             fluent(q).
                          fluent(r).
action(a). pre(a,p).
                         add(a,q).
                                      del(a,p).
         pre(b,q).
                          add(b,r).
                                      del(b,q).
action(b).
init(p).
             query(r).
holds(P,0) := init(P).
```

```
#base.
```

```
fluent(p). fluent(q). fluent(r).
action(a). pre(a,p). add(a,q). del(a,p).
action(b). pre(b,q).
                          add(b,r). del(b,q).
init(p).
            query(r).
holds(P,0) := init(P).
#cumulative t.
1 { occ(A,t) : action(A) } 1.
 :- occ(A,t), pre(A,F), not holds(F,t-1).
ocdel(F,t) := occ(A,t), del(A,F).
holds(F,t) := occ(A,t), add(A,F).
holds(F,t) := holds(F,t-1), not ocdel(F,t).
```

```
#base.
```

```
fluent(p). fluent(q). fluent(r).
action(a). pre(a,p). add(a,q). del(a,p).
action(b). pre(b,q). add(b,r). del(b,q).
init(p). query(r).
holds(P,0) := init(P).
#cumulative t.
1 { occ(A,t) : action(A) } 1.
 :- occ(A,t), pre(A,F), not holds(F,t-1).
ocdel(F,t) := occ(A,t), del(A,F).
holds(F,t) := occ(A,t), add(A,F).
holds(F,t) := holds(F,t-1), not ocdel(F,t).
#volatile t.
 :- query(F), not holds(F,t).
```

What is ASP good for?

- Combinatorial search problems (some with substantial amount of data):
 - For instance, auctions, bio-informatics, computer-aided verification, configuration, constraint satisfaction, diagnosis, information integration, planning and scheduling, security analysis, semantic web, wire-routing, zoology and linguistics, and many more
- My favorite: Using ASP as a basis for a decision support system for NASA's space shuttle (Gelfond et al., Texas Tech)
- Our own applications:
 - Automatic synthesis of multiprocessor systems
 - Inconsistency detection in large biological networks
 - Home monitoring for risk prevention in assisted living
 - General game playing

What does ASP offer?

- Integration of KR, DB, and search techniques
- Compact, easily maintainable problem representations
- Rapid application development tool
- Easy handling of dynamic, knowledge intensive applications (including: data, frame axioms, exceptions, defaults, closures, etc.)

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$$ASP = KR + DB + Search$$

Outline

- 1 Motivation
- 2 Introduction
- 3 Modeling by Example
- 4 Conflict-Driven Answer Set Solving
- 5 Potassco
- 6 Summary

■ Idea

■ View inferences in Answer Set Programming (ASP) as unit propagation on nogoods.

(A nogood expresses a constraint violated by any solution.)

Benefits

- A uniform constraint-based framework for different kinds of inferences in ASP
- Advanced techniques from the areas of CSP and SAT
- Highly competitive implementation
- Nogoods from Logic Programs are
 - nogoods from Clark's Completion,
 - nogoods from Unfounded Sets, and
 - nogoods from Aggregates.

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O(n)

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(A nogood expresses a constraint violated by any solution.)

Benefits

- A uniform constraint-based framework for different kinds of inferences in ASP
- Advanced techniques from the areas of CSP and SAT
- Highly competitive implementation

■ Nogoods from Logic Programs are

■ nogoods from Clark's Completion,	O(n)
■ nogoods from Unfounded Sets, and	$O(2^n)$
and the first Annual Control of the	O(2n)

nogoods from Aggregates.

Nogoods from Clark's Completion

■ For example, for body $\{x, not y\}$, we obtain 3 nogoods

```
\{F\{x, not y\}, Tx, Fy\}\{\{T\{x, not y\}, Fx\}, \{T\{x, not y\}, Ty\}\}
```

- For nogood $\{\mathbf{F}\{x, not y\}, \mathbf{T}x, \mathbf{F}y\}$, the signed literal
 - $\mathsf{T}\{x, not y\}$ is unit-resulting wrt assignment $(\mathsf{T}x, \mathsf{F}y)$ and
 - Ty is unit-resulting wrt assignment ($\mathbf{F}\{x, not y\}, \mathbf{T}x$)
- Similarly, there are atom-oriented nogoods (see IJCAI'07)

Nogoods from Clark's Completion

■ For example, for body $\{x, not y\}$, we obtain 3 nogoods

```
 \begin{array}{c|c} \dots \leftarrow x, \textit{not } y \\ \vdots \\ \dots \leftarrow x, \textit{not } y \end{array} \qquad \qquad \{ \mathbf{F}\{x, \textit{not } y\}, \mathbf{T}x, \mathbf{F}y \} \\ \{ \{ \mathbf{T}\{x, \textit{not } y\}, \mathbf{F}x\}, \{ \mathbf{T}\{x, \textit{not } y\}, \mathbf{T}y \} \} \end{array}
```

- For nogood $\{F\{x, not y\}, Tx, Fy\}$, the signed literal
 - $T\{x, not y\}$ is unit-resulting wrt assignment (Tx, Fy) and
 - **T**y is unit-resulting wrt assignment ($\mathbf{F}\{x, not y\}, \mathbf{T}x$).
- Similarly, there are atom-oriented nogoods (see IJCAI'07).

Nogoods from Clark's Completion

■ For example, for body $\{x, not y\}$, we obtain 3 nogoods

- For nogood $\{F\{x, not y\}, Tx, Fy\}$, the signed literal
 - $T\{x, not y\}$ is unit-resulting wrt assignment (Tx, Fy) and
 - **T**y is unit-resulting wrt assignment ($\mathbf{F}\{x, not y\}, \mathbf{T}x$).
- Similarly, there are atom-oriented nogoods (see IJCAI'07).

Basic Decision Algorithm

```
loop
```

```
Propagate // (Boolean) constraint propagation

if no conflict then

if all variables assigned then return solution

else Decide // pick and assign some free literal

else if top-level conflict then

return unsatisfiable

else

Analyze // resolve conflict and record a conflict constraint

Backjump // undo assignments until conflict constraint is unit
```

Algorithm 1: Nogood Propagation

```
: A logic program \Pi, a set \nabla of nogoods, and an assignment A.
    Output: An extended assignment and set of nogoods.
 1 U \leftarrow \emptyset
                                                                                   // set of unfounded atoms
 2 loop
          repeat
 3
                if \delta \subseteq A for some \delta \in \Delta_{\Pi} \cup \nabla then return (A, \nabla)
                                                                                                         // conflict
 4
                \Sigma \leftarrow \{\delta \in \Delta_{\Pi} \cup \nabla \mid (\delta \setminus A) = \{\sigma\}, \overline{\sigma} \notin A\} // unit-resulting nogoods
 5
               if \Sigma \neq \emptyset then
 6
                     let \sigma \in (\delta \setminus A) for some \delta \in \Sigma in
                     8
          until \Sigma = \emptyset
 9
          if \Pi is tight then return (A, \nabla) // no unfounded set \emptyset \subset U \subseteq (atom(\Pi) \setminus A^{\mathsf{F}})
10
          else
11
                U \leftarrow (U \setminus A^{\mathsf{F}})
12
               if U = \emptyset then U \leftarrow UnfoundedSet(\Pi, A)
13
               if U = \emptyset then return (A, \nabla) // no unfounded set \emptyset \subset U \subset (atom(\Pi) \setminus A^{\mathsf{F}})
14
                let p \in U in
15
                 \nabla \leftarrow \nabla \cup \{\lambda(p, U)\} // record unit-resulting or violated loop nogood
16
```

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Potassco, the Potsdam Answer Set Solving Collection, bundles tools for ASP developed at the University of Potsdam, for instance:

- Grounder: Gringo, pyngo
- Solver: clasp, claspD, claspar
- *Grounder+Solver*: Clingo, iClingo, Clingcon
- Further Tools: claspfolio, coala, inca, plasp, sbass, xorro

Benchmarking: http://asparagus.cs.uni-potsdam.de

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- clasp is a native ASP solver for extended logic programs
- clasp can also be run as SAT or PB solver
 - From version 1.3, input formats are recognized and distinguished
 - Search engine unmodified
- clasp's search algorithm relies on conflict-driven learning, featuring:
 - Conflict Analysis via First-UIP Scheme
 - Conflict Constraint Recording and Deletion
 - Backjumping
 - Restarts
 - Lookback-based Decision Heuristics
 - **Progress Saving**
 - Unit Propagation via Watched Literals
 - Dedicated Propagation of Binary and Ternary Constraints
 - Dedicated Propagation of Cardinality and Weight Constraints
 - Equivalence Reasoning and Resolution-based Preprocessing

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Solving the 2009 ASP Competition (NP)

Benchmark	#	clasp	clasp ⁺	cmodels[m]	smodels
15Puzzle	16 (16/0)	33.01 (0)	20.18 (0)	31.36 (0)	600.00 (48)
BlockedNQueens	29 (Ì5/14)	5.09 (0)	4.91 (O)	9.04 (0)	29.37 (0)
ChannelRouting	10 (6/4)	120.13 (6)	120.14 (6)	120.58 (6)	120.90 (6)
EdgeMatching	29 (29/0)	0.23 (0)	0.41 (0)	59.32 (0)	60.32 (0)
Fastfood	29 (10/19)	1.17 (0)	0.90 (0)	29.22 (0)	83.93 (3)
GraphColouring	29 (9/20)	421.55 (60)	357.88 (39)	422.66 (57)	453.77 (63)
Hanoi	15 (15/0)	11.76 (0)	3.97 (0)	2.92 (0)	523.77 (39)
HierarchicalClustering	12 (8/4)	0.16 (0)	0.17 (0)	0.76 (0)	1.56 (0)
SchurNumbers	29 (13/16)	17.44 (0)	49.60 (0)	75.70 (0)	504.17 (72)
Solitaire	27 (22/5)	204.78 (27)	162.82 (21)	175.69 (21)	316.96 (36)
Sudoku	10 (10/0)	0.15 (0)	0.16 (0)	2.55 (0)	0.25 (0)
WeightBoundedDomSet	29 (29/0)	123.13 (15)	102.18 (12)	300.26 (36)	400.84 (51)
$\varnothing(\varnothing)$ (tight)	264 (182/82)	78.22 (9)	68.61(6.50)	102.50 (10)	257.99(26.50)
ConnectedDomSet	21 (10/11)	40.42 (3)	36.11 (3)	7.46 (0)	183.76 (15)
GeneralizedSlitherlink	29 (29/0)	0.10 (0)	0.22 (0)	1.92 (0)	0.16 (0)
GraphPartitioning	13 (6/7)	9.27 (0)	7.98 (0)	20.19 (0)	92.10 (3)
HamiltonianPath	29 (29/0)	0.07 (0)	0.06 (0)	0.21 (0)	2.22 (0)
KnightTour	10 (10/0)	124.29 (6)	91.80 (3)	242.48 (12)	150.55 (3)
Labyrinth	29 (29/0)	123.82 (12)	82.92 (6)	142.24 (6)	594.10 (81)
MazeGeneration	29 (10/19)	91.17 (12)	89.89 (12)	90.41 (12)	293.62 (42)
Sokoban	29 (9/20)	0.73 (0)	0.80 (0)	3.39 (0)	176.01 (15)
TravellingSalesperson	29 (29/0)	0.05 (0)	0.06 (0)	317.82 (7)	0.22 (0)
WireRouting	23 (12/11)	42.81 (3)	36.36 (3)	175.73 (12)	448.32 (45)
$\varnothing(\varnothing)$ (nontight)	241 (173/68)	43.27(3.60)	34.62(2.70)	100.19(4.90)	194.11(20.40)
Ø(Ø)	505 (355/150)	62.33(6.55)	53.16(4.77)	101.45(7.68)	228.95(23.73)

clasp (version 1.3.1) clasp + clasp -sat-prepro -trans-ext=dynamic

cmodels[m] (version 3.79 with minisat 2.0)
smodels (version 2.34 with option -restart)

Solving the 2009 ASP Competition (NP)

Benchmark	#	clasp	clasp ⁺	cmodels[m]	smodels
15Puzzle	16 (16/0)	33.01 (0)	20.18 (0)	31.36 (0)	600.00 (48)
BlockedNQueens	29 (15/14)	5.09 (0)	4.91 (O)	9.04 (0)	29.37 (0)
ChannelRouting	10 (6/4)	120.13 (6)	120.14 (6)	120.58 (6)	120.90 (6)
EdgeMatching	29 (29/0)	0.23 (0)	0.41 (0)	59.32 (0)	60.32 (0)
Fastfood	29 (10/19)	1.17 (0)	0.90 (0)	29.22 (0)	83.93 (3)
GraphColouring	29 (9/20)	421.55 (60)	357.88 (39)	422.66 (57)	453.77 (63)
Hanoi	15 (15/0)	11.76 (0)	3.97 (0)	2.92 (0)	523.77 (39)
HierarchicalClustering	12 (8/4)	0.16 (0)	0.17 (0)	0.76 (0)	1.56 (0)
SchurNumbers	29 (13/16)	17.44 (0)	49.60 (0)	75.70 (0)	504.17 (72)
Solitaire	27 (22/5)	204.78 (27)	162.82 (21)	175.69 (21)	316.96 (36)
Sudoku	10 (10/0)	0.15 (0)	0.16 (0)	2.55 (0)	0.25 (0)
WeightBoundedDomSet	29 (29/0)	123.13 (15)	102.18 (12)	300.26 (36)	400.84 (51)
$\varnothing(\varnothing)$ (tight)	264 (182/82)	78.22 (9)	68.61(6.50)	102.50 (10)	257.99(26.50)
ConnectedDomSet	21 (10/11)	40.42 (3)	36.11 (3)	7.46 (0)	183.76 (15)
GeneralizedSlitherlink	29 (29/0)	0.10 (0)	0.22 (0)	1.92 (0)	0.16 (0)
GraphPartitioning	13 (6/7)	9.27 (0)	7.98 (0)	20.19 (0)	92.10 (3)
HamiltonianPath	29 (29/0)	0.07 (0)	0.06 (0)	0.21 (0)	2.22 (0)
KnightTour	10 (10/0)	124.29 (6)	91.80 (3)	242.48 (12)	150.55 (3)
Labyrinth	29 (29/0)	123.82 (12)	82.92 (6)	142.24 (6)	594.10 (81)
MazeGeneration	29 (10/19)	91.17 (12)	89.89 (12)	90.41 (12)	293.62 (42)
Sokoban	29 (9/20)	0.73 (0)	0.80 (0)	3.39 (0)	176.01 (15)
TravellingSalesperson	29 (29/0)	0.05 (0)	0.06 (0)	317.82 (7)	0.22 (0)
WireRouting	23 (12/11)	42.81 (3)	36.36 (3)	175.73 (12)	448.32 (45)
Ø(Ø) (nontight)	241 (173/68)	43.27(3.60)	34.62(2.70)	100.19(4.90)	194.11(20.40)
Ø(Ø)	505 (355/150)	62.33(6.55)	53.16(4.77)	101.45(7.68)	228.95(23.73)

clasp (version 1.3.1) clasp + clasp -sat-prepro -trans-ext=dynamic

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Outline

- 1 Motivation
- 2 Introduction
- 3 Modeling by Example
- 4 Conflict-Driven Answer Set Solving
- 5 Potassco
- 6 Summary

Summary

- ASP is emerging as a viable tool for Knowledge Representation and Reasoning
- ASP offers efficient and versatile off-the-shelf solving technology
 - http://potassco.sourceforge.net
 - ASP'09, PB'09, and SAT'09
- ASP offers an expanding functionality and ease of use
 - Rapid application development tool
- ASP has a growing range of applications

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$$ASP = KR + DB + Search$$

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