

# Answer Set Solving in Practice

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# Rough Roadmap

- 1 Introduction
- 2 Language
- 3 Modeling
- 4 Grounding
- 5 Foundations
- 6 Solving
- 7 Systems
- 8 Applications

# Resources

## ■ Course material

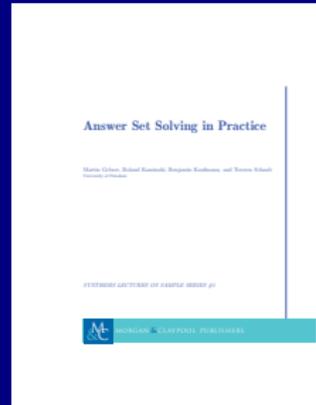
- <http://www.cs.uni-potsdam.de/wv/lehre>
- <http://moodle.cs.uni-potsdam.de>
- <http://potassco.sourceforge.net/teaching.html>

## ■ Systems

- **clasp** <http://potassco.sourceforge.net>
- **dlv** <http://www.dlvsystem.com>
- **smodels** <http://www.tcs.hut.fi/Software/smodels>
- **gringo** <http://potassco.sourceforge.net>
- **lparse** <http://www.tcs.hut.fi/Software/smodels>
- **clingo** <http://potassco.sourceforge.net>
- **iclingo** <http://potassco.sourceforge.net>
- **oclingo** <http://potassco.sourceforge.net>
  
- **asparagus** <http://asparagus.cs.uni-potsdam.de>

# The Potassco Book

1. Motivation
2. Introduction
3. Basic modeling
4. Grounding
5. Characterizations
6. Solving
7. Systems
8. Advanced modeling
9. Conclusions



## Resources

- <http://potassco.sourceforge.net/book.html>
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# Literature

Books [4], [29], [53]

Surveys [50], [2], [39], [21], [11]

Articles [41], [42], [6], [61], [54], [49], [40], etc.

# Constraint Answer Set Programming: Overview

- 1 Motivation
- 2 Preliminaries
- 3 Modeling Language
- 4 Algorithms

# Outline

- 1 Motivation
- 2 Preliminaries
- 3 Modeling Language
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# Motivation

- Observation Certain applications are more naturally modeled by mixing Boolean with non-Boolean constructs, eg., accounting for
  - resources,
  - fine timings, or
  - functions over finite domains
- Approach Extend ASP with CP capacities
  - propositional semantics
  - CDCL-style solving capacities
    - following the approach of SMT solving
  - off-the-shelf CP solvers

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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  $dom(v) \in D$ ;
- a constraint  $c$  is a pair  $(S, R)$  consisting of a  $k$ -ary relation  $R$  on a vector  $S \subseteq V^k$  of variables, called the scope of  $R$
- Note For  $S = (v_1, \dots, v_k)$ , we have  $R \subseteq dom(v_1) \times \dots \times dom(v_k)$

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## Example

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

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

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

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

$$\begin{aligned}
 C = \{ & (\vec{V}, \text{allDistinct}(V)), \\
 & (\vec{V}, s \times 1000 + e \times 100 + n \times 10 + d + \\
 & \quad m \times 1000 + o \times 100 + r \times 10 + e == \\
 & \quad m \times 10000 + o \times 1000 + n \times 100 + e \times 10 + y), \\
 & ((m), m == 1) \}
 \end{aligned}$$

## Example

$$\begin{array}{r}
 \phantom{+} \phantom{m} \phantom{o} \phantom{r} \phantom{e} \\
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 + \phantom{s} m \phantom{o} \phantom{r} \phantom{e} \\
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$$\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

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

# 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

$$\text{sat}_C(A) = \{c \in C \mid A(S(c)) \in R(c)\}$$

where  $A(S) = (A(v_1), \dots, A(v_k))$

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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
  - $\mathcal{C}$  is a set of **constraint atoms**,such that  $head(r) \in \mathcal{A}$  for each  $r \in P$
- Given a set of literals  $B$  and some set  $\mathcal{B}$  of atoms, we define
$$B|_{\mathcal{B}} = (B^+ \cap \mathcal{B}) \cup \{\sim a \mid a \in B^- \cap \mathcal{B}\}$$

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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
  - $C[P] = \gamma(\text{atom}(P) \cap \mathcal{C})$ ,
  - $V[P]$  is obtained from the constraint scopes in  $C[P]$ ,
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# Constraint Answer Set Programming

- 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

$$P^A = \{ \text{head}(r) \leftarrow \text{body}(r)|_{\mathcal{A}} \mid r \in P, \\ \gamma(\text{body}(r)|_{\mathcal{C}^+}) \subseteq \text{sat}_{\mathcal{C}[P]}(A), \\ \gamma(\text{body}(r)|_{\mathcal{C}^-}) \cap \text{sat}_{\mathcal{C}[P]}(A) = \emptyset \}$$

- A set  $X \subseteq \mathcal{A}$  of (regular) atoms is a constraint answer set of  $P$  wrt  $A$ , if  $X$  is an answer set of  $P^A$ .

That is, if  $X$  is the  $\subseteq$ -smallest model of  $(P^A)^X$

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- 2 Preliminaries
- 3 Modeling Language**
- 4 Algorithms

# Modeling Language

## Note

Although our semantics is propositional, the atoms in  $\mathcal{A}$  and  $\mathcal{C}$  are constructible from a multi-sorted, first-order signature given by:

- a set  $\mathcal{P}_{\mathcal{A}} \cup \mathcal{P}_{\mathcal{C}}$  of **predicate symbols** such that  $\mathcal{P}_{\mathcal{A}} \cap \mathcal{P}_{\mathcal{C}} = \emptyset$ ,
- a set  $\mathcal{F}_{\mathcal{A}} \cup \mathcal{F}_{\mathcal{C}}$  of **function symbols** (including constant symbols),
- a set  $\mathcal{V}_{\mathcal{A}}$  of **regular variable symbols**, and
- a set  $\mathcal{V}_{\mathcal{C}} \subseteq \mathcal{T}(\mathcal{F}_{\mathcal{A}})$  of **constraint variable symbols**, where  $\mathcal{T}(\mathcal{F}_{\mathcal{A}})$  denotes the set of all ground terms over  $\mathcal{F}_{\mathcal{A}}$

As usual, the atoms in  $\mathcal{A} \cup \mathcal{C}$  are obtained by a grounding process

## An Example

$$\begin{array}{l}
 \text{time}(0..t_{max}) \\
 \text{bucket}(a) \quad \text{bucket}(b) \\
 1 \{ \text{pour}(B, T) : \text{bucket}(B) \} 1 \quad \leftarrow \text{time}(T), T < t_{max} \\
 1 \leq^{\$} \text{amt}(B, T) \quad \leftarrow \text{pour}(B, T), T < t_{max} \\
 \text{amt}(B, T) \leq^{\$} 3 \quad \leftarrow \text{pour}(B, T), T < t_{max} \\
 \text{amt}(B, T) =^{\$} 0 \quad \leftarrow \sim \text{pour}(B, T), T < t_{max} \\
 \text{vol}(B, T+1) =^{\$} \text{vol}(B, T) +^{\$} \text{amt}(B, T) \quad \leftarrow \text{time}(T), T < t_{max} \\
 \text{down}(B, T) \quad \leftarrow \text{vol}(C, T) <^{\$} \text{vol}(B, T) \\
 \text{up}(B, T) \quad \leftarrow \sim \text{down}(B, T) \\
 \text{vol}(a, 0) =^{\$} 0 \quad \text{vol}(b, 0) =^{\$} 1 \\
 \leftarrow \text{up}(a, t_{max})
 \end{array}$$

## An Example

- Consider the signature of our exemplary program:

$$\begin{aligned} \{B, C, T\} &\subseteq \mathcal{V}_A \\ \{0, \dots, t_{max}, +, a, b, amt, vol\} &\subseteq \mathcal{F}_A \\ \{<, time, bucket, pour, up, down\} &\subseteq \mathcal{P}_A \\ \{0, 1, 3, +^{\$}\} &\subseteq \mathcal{F}_C \\ \{=^{\$}, <^{\$}, \leq^{\$}\} &\subseteq \mathcal{P}_C \end{aligned}$$

- With substitution  $\{B \mapsto b, T \mapsto 1, t_{max} \mapsto 2\}$ , we get:

$$\begin{aligned} amt(b, 1) =^{\$} 0 &\leftarrow \sim pour(b, 1) \\ vol(b, 2) =^{\$} vol(b, 1) +^{\$} amt(b, 1) &\leftarrow \end{aligned}$$

and, among others, our signature hence contains

$$\begin{aligned} \{amt(b, 1), vol(b, 1), vol(b, 2)\} &\subseteq \mathcal{V}_C \\ \{pour(b, 1)\} &\subseteq \mathcal{A} \\ \{amt(b, 1) =^{\$} 0, vol(b, 2) =^{\$} vol(b, 1) +^{\$} amt(b, 1)\} &\subseteq \mathcal{C} \end{aligned}$$

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## An Example

- For  $t_{max} = 2$ , our program has eleven constraint answer sets, summarized as follows

$up(a, 0)$	$pour(a, 0)$	$amt(a, 0)$	$up(a, 1)$	$pour(a, 1)$	$amt(a, 1)$	$up(a, 2)$
T	T	1	T	T	1, 2, 3	F
T	T	2, 3	F	T	1, 2, 3	F
T	T	3	F	F	0	F
T	F	0	T	T	3	F

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T	T	2, 3	F	T	1, 2, 3	F
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T	F	0	T	T	3	F

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# SAT modulo theories

## SAT modulo theories (SMT)

- logical formulas with respect to combinations of background theories
- real numbers, integers, lists, arrays, bit vectors ...

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## SAT

$$(x \vee y \vee z) \wedge (\neg x \vee \neg y \vee \neg z)$$

# SAT modulo theories

## SAT modulo theories (SMT)

- logical formulas with respect to combinations of background theories
- real numbers, integers, lists, arrays, bit vectors ...

## SMT

$$(\sin(x)^3 = \cos(\log(y) \cdot x) \quad \vee b \quad \vee -x^2 \geq 2.3y)$$

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## SMT

(  $a \quad \vee b \quad \vee -x^2 \geq 2.3y$  )

# SAT modulo theories

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- logical formulas with respect to combinations of background theories
- real numbers, integers, lists, arrays, bit vectors ...

## SMT

(  $a \vee b \vee c$  )

## Main Algorithm

**loop**

PROPAGATE

**if** no conflict **then**    **if** partial assignment **then** DECIDE    **else return** solution**else if** some decisions made **then**

ANALYZE CONFLICT

RECORD REASON

BACKJUMP

**else exit**

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## ASP Propagation

## Propagation Algorithm

**loop**

UNIT-PROPAGATION

**if** conflict **then return****else if** UNFOUNDED-SET **then**

RECORD LOOP-NOGOOD

**if** conflict **then return****else return**

# Constraint ASP Propagation

## Propagation Algorithm

**loop**

UNIT-PROPAGATION

**if** conflict **then return**

**else if** UNFOUNDED-SET **then**

RECORD LOOP-NOGOOD

**if** conflict **then return**

**else if** CONSTRAINT-PROPAGATION **then**

**if** conflict **then return**

**else return**

## Main Algorithm

**loop**

PROPAGATE

**if** no conflict **then**    **if** partial assignment **then** DECIDE    **else return** solution**else if** some decisions made **then**

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**else exit**

## Constraint CDNL

## Main Algorithm

**loop**

PROPAGATE

**if** no conflict **then**    **if** partial assignment **then** DECIDE    **else if** CSP-SOLVE **then return** solution    **else**

ANALYZE CONFLICT

RECORD REASON

BACKJUMP

**else if** some decisions made **then**

ANALYZE CONFLICT

RECORD REASON

BACKJUMP

**else exit**

## Conflict and reason determination

- Design Goal Use off-the-shelf CP solvers
- Problem Off-the-shelf CP solvers do not provide reasons for conflicts
- Idea Approximate reasons in various ways
  - lazy learning versus early learning
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