## 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

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<ul><li>clasp</li><li>dlv</li></ul>	http://potassco.sourceforge.net http://www.dlvsystem.com					
smodels	http://www.tcs.hut.fi	and the second secon				
<ul><li>gringo</li><li>Iparse</li></ul>	http://potasso http://www.tcs.hut.fi	co.sourceforge.n i/Software/smode				
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## 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
- http://potassco.sourceforge.net/teaching.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.



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## Introduction: Overview



#### 2 Semantics



4 Variables

5 Language constructs

#### 6 Reasoning modes

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## Outline







4 Variables

5 Language constructs

#### 6 Reasoning modes

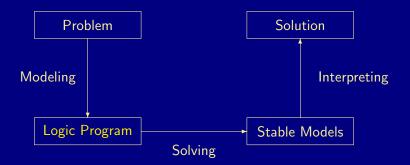


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## Problem solving in ASP: Syntax





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## Normal logic programs

A logic program, P, over a set A of atoms is a finite set of rules
A (normal) rule, r, is of the form

$$a_0 \leftarrow a_1, \ldots, a_m, \sim a_{m+1}, \ldots, \sim a_n$$

where  $0 \le m \le n$  and each  $a_i \in \mathcal{A}$  is an atom for  $0 \le i \le n$ 

$$head(r) = a_0$$
  

$$body(r) = \{a_1, \dots, a_m, \sim a_{m+1}, \dots, \sim a_n\}$$
  

$$body(r)^+ = \{a_1, \dots, a_m\}$$
  

$$body(r)^- = \{a_{m+1}, \dots, a_n\}$$
  

$$atom(P) = \bigcup_{r \in P} (\{head(r)\} \cup body(r)^+ \cup body(r)^-)$$
  

$$body(P) = \{body(r) \mid r \in P\}$$
  
program P is positive if  $body(r)^- = \emptyset$  for all  $r \in P$   $\textcircled{Potas}$ 

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where  $0 \le m \le n$  and each  $a_i \in \mathcal{A}$  is an atom for  $0 \le i \le n$ Notation

$$\begin{aligned} head(r) &= a_0 \\ body(r) &= \{a_1, \dots, a_m, \sim a_{m+1}, \dots, \sim a_n\} \\ body(r)^+ &= \{a_1, \dots, a_m\} \\ body(r)^- &= \{a_{m+1}, \dots, a_n\} \\ atom(P) &= \bigcup_{r \in P} (\{head(r)\} \cup body(r)^+ \cup body(r)^-) \\ body(P) &= \{body(r) \mid r \in P\} \\ program P \text{ is positive if } body(r)^- &= \emptyset \text{ for all } r \in P \end{aligned}$$

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## Rough notational convention

We sometimes use the following notation interchangeably in order to stress the respective view:

						default	classical
	true, false	if	and	or	iff	negation	negation
source code		:-	,			not	-
logic program		$\leftarrow$				$\sim$	_
formula	$\perp, \top$	$\rightarrow$	$\wedge$	$\vee$	$\leftrightarrow$	$\sim$	-



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Semantics

## Outline

#### 1 Syntax

- 2 Semantics
- 3 Examples
- 4 Variables
- 5 Language constructs
- 6 Reasoning modes

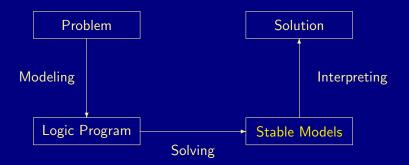


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## Problem solving in ASP: Semantics





Stable models of positive programs

A set of atoms X is closed under a positive program P iff for any r ∈ P, head(r) ∈ X whenever body(r)<sup>+</sup> ⊆ X
 X corresponds to a model of P (seen as a formula)

The smallest set of atoms which is closed under a positive program P is denoted by Cn(P)

• Cn(P) corresponds to the  $\subseteq$ -smallest model of P (ditto)

The set Cn(P) of atoms is the stable model of a *positive* program P



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## Some "logical" remarks

Positive rules are also referred to as definite clauses

Definite clauses are disjunctions with exactly one positive atom:

 $a_0 \vee \neg a_1 \vee \cdots \vee \neg a_m$ 

#### A set of definite clauses has a (unique) smallest model

Horn clauses are clauses with at most one positive atom

- Every definite clause is a Horn clause but not vice versa
- Non-definite Horn clauses can be regarded as integrity constraints
- A set of Horn clauses has a smallest model or none

This smallest model is the intended semantics of such sets of clauses
 Given a positive program P, Cn(P) corresponds to the smallest model of the set of definite clauses corresponding to P

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# Consider the logical formula $\Phi$ and its three (classical) models:

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

Formula  $\Phi$  has one stable model, often called answer set:

 $\{p,q\}$ 

Informally, a set X of atoms is a stable model of a logic program P if X is a (classical) model of P and if all atoms in X are justified by some rule in P (rooted in intuitionistic logics HT (Heyting, 1930) and G3 (Gödel, 1932))



$$\begin{array}{cccc} P_{\Phi} & q & \leftarrow & \\ p & \leftarrow & q, \ \sim r \end{array}$$

 $\Phi \quad q \quad \land \quad (q \land \neg r \to p)$ 

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Stable model of normal programs

■ The reduct, *P*<sup>X</sup>, of a program *P* relative to a set *X* of atoms is defined by

 $P^X = \{head(r) \leftarrow body(r)^+ \mid r \in P \text{ and } body(r)^- \cap X = \emptyset\}$ 

A set X of atoms is a stable model of a program P, if  $Cn(P^X) = X$ 

Note Cn(P<sup>X</sup>) is the ⊆-smallest (classical) model of P<sup>X</sup>
 Note Every atom in X is justified by an "applying rule from P"



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## A closer look at $P^X$

In other words, given a set X of atoms from P,

 $P^X$  is obtained from P by deleting

- 1 each rule having  $\sim a$  in its body with  $a \in X$ and then
- 2 all negative atoms of the form ~a in the bodies of the remaining rules

 $\blacksquare$  Note Only negative body literals are evaluated wrt X



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## Outline











#### 6 Reasoning modes

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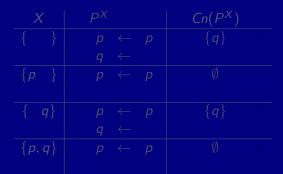
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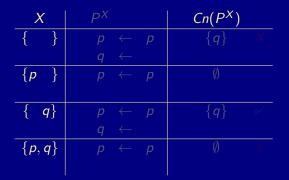
## A first example

### $P = \{p \leftarrow p, \ q \leftarrow \neg p\}$



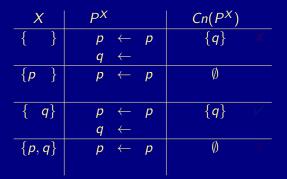


#### $P = \{ p \leftarrow p, \ q \leftarrow \neg p \}$





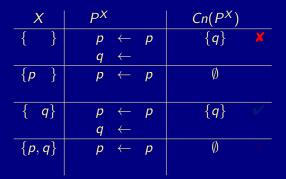
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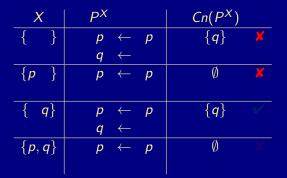
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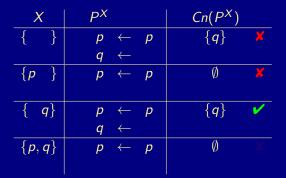
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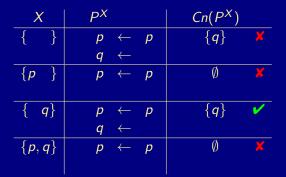
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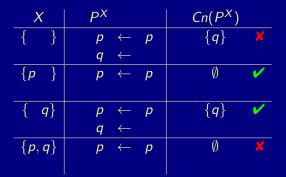
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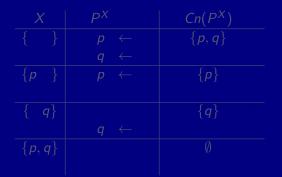


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#### $P = \{p \leftarrow {\sim}q, \ q \leftarrow {\sim}p\}$

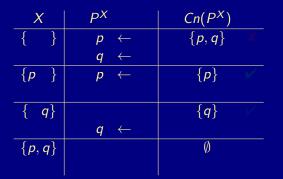




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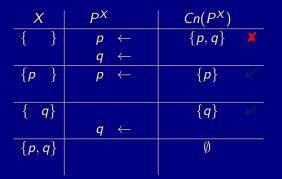
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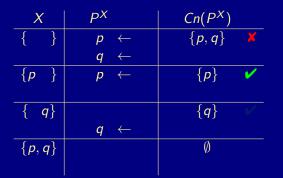
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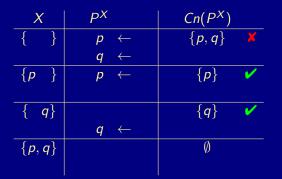
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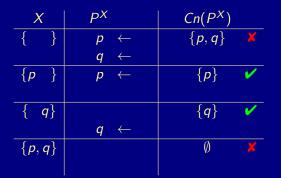
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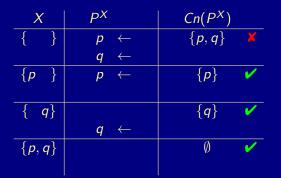


$$P = \{p \leftarrow {\sim}q, \ q \leftarrow {\sim}p\}$$





$$P = \{p \leftarrow \neg q, \ q \leftarrow \neg p\}$$





## A third example

#### $P = \{p \leftarrow {\sim} p\}$





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## Some properties

#### A logic program may have zero, one, or multiple stable models!

- If X is a stable model of a logic program P, then X is a model of P (seen as a formula)
- If X and Y are stable models of a *normal* program P, then  $X \not\subset Y$



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Variables

## Outline

#### 1 Syntax

- 2 Semantics
- 3 Examples
- 4 Variables
  - 5 Language constructs

#### 6 Reasoning modes

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#### Let P be a logic program

- Let  $\mathcal{T}$  be a set of (variable-free) terms
- Let  $\mathcal{A}$  be a set of (variable-free) atoms constructable from  $\mathcal{T}$
- Ground Instances of  $r \in P$ : Set of variable-free rules obtained by replacing all variables in r by elements from T:

 $ground(r) = \{r\theta \mid \theta : var(r) \rightarrow \mathcal{T} \text{ and } var(r\theta) = \emptyset\}$ 

where var(r) stands for the set of all variables occurring in r;  $\theta$  is a (ground) substitution

Ground Instantiation of P:  $ground(P) = \bigcup_{r \in P} ground(r)$ 



#### Let P be a logic program

- Let  $\mathcal{T}$  be a set of variable-free terms (also called Herbrand universe)
- Let *A* be a set of (variable-free) atoms constructable from *T* (also called alphabet or Herbrand base)
- Ground Instances of  $r \in P$ : Set of variable-free rules obtained by replacing all variables in r by elements from T:

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Let P be a logic program

- Let  $\mathcal{T}$  be a set of (variable-free) terms
- $\blacksquare$  Let  $\mathcal A$  be a set of (variable-free) atoms constructable from  $\mathcal T$

Ground Instances of  $r \in P$ : Set of variable-free rules obtained by replacing all variables in r by elements from T:

 $ground(r) = \{r\theta \mid \theta : var(r) \rightarrow \mathcal{T} \text{ and } var(r\theta) = \emptyset\}$ 

where var(r) stands for the set of all variables occurring in r;  $\theta$  is a (ground) substitution

Ground Instantiation of *P*: ground(*P*) =  $\bigcup_{r \in P}$  ground(*r*)

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# An example

$$P = \{ r(a, b) \leftarrow, r(b, c) \leftarrow, t(X, Y) \leftarrow r(X, Y) \}$$
  

$$\mathcal{T} = \{a, b, c\}$$
  

$$\mathcal{A} = \begin{cases} r(a, a), r(a, b), r(a, c), r(b, a), r(b, b), r(b, c), r(c, a), r(c, b), r(c, c), \\ t(a, a), t(a, b), t(a, c), t(b, a), t(b, b), t(b, c), t(c, a), t(c, b), t(c, c) \end{cases}$$
  

$$ground(P) = \begin{cases} r(a, b) \leftarrow, \\ r(b, c) \leftarrow, \\ t(a, a) \leftarrow r(a, a), t(b, a) \leftarrow r(b, a), t(c, a) \leftarrow r(c, a), \\ t(a, b) \leftarrow r(a, b), t(b, b) \leftarrow r(b, b), t(c, b) \leftarrow r(c, b), \\ t(a, c) \leftarrow r(a, c), t(b, c) \leftarrow r(b, c), t(c, c) \leftarrow r(c, c) \end{cases}$$

Intelligent Grounding aims at reducing the ground instantiation



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$$\mathcal{T} = \{a, b, c\}$$
  

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#### Stable models of programs with Variables

#### Let P be a normal logic program with variables

A set X of (ground) atoms is a stable model of P,
 if Cn(ground(P)<sup>X</sup>) = X



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## Outline

#### 1 Syntax

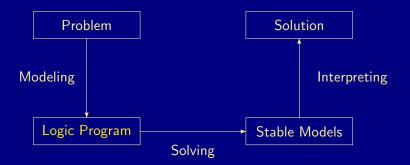
- 2 Semantics
- 3 Examples
- 4 Variables
- 5 Language constructs
  - 6 Reasoning modes



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#### Problem solving in ASP: Extended Syntax





# Language Constructs

Variables (over the Herbrand Universe)

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

Conditional Literals

p :- q(X) : r(X) given r(a), r(b), r(c) stands for p :- q(a), q(b), q(c)

Disjunction

= p(X) | q(X) :- r(X)

Integrity Constraints

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

Choice

■ 2 { p(X,Y) : q(X) } 7 :- r(Y)

Aggregates

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

also: #sum, #avg, #min, #max, #even, #odd

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## Language Constructs

#### ■ Variables (over the Herbrand Universe)

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

p :- q(X) : r(X) given r(a), r(b), r(c) stands for p :- q(a), q(b), q(c)

Disjunction

= p(X) | q(X) := r(X)

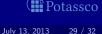
- Integrity Constraints
  - = :- q(X), p(X)
- Choice

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

Aggregates

■ s(Y) := r(Y), 2 #count { p(X,Y) : q(X) } 7

also: #sum, #avg, #min, #max, #even, #odd



# Language Constructs

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

p :- q(X) : r(X) given r(a), r(b), r(c) stands for p :- q(a), q(b), q(c)

Disjunction

p(X) | q(X) :- r(X)

Integrity Constraints

■ :- q(X), p(X)

Choice

**2** { p(X,Y) : q(X) } 7 :- r(Y)

Aggregates

s(Y) :- r(Y), 2 #count { p(X,Y) : q(X) } 7

also: #sum, #avg, #min, #max, #even, #odd

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Variables (over the Herbrand Universe)

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## Variables (over the Herbrand Universe) $\mathbf{p}(\mathbf{X}) := \mathbf{q}(\mathbf{X})$ over constants {a, b, c} stands for p(a) := q(a), p(b) := q(b), p(c) := q(c)Conditional Literals $\blacksquare$ p :- q(X) : r(X) given r(a), r(b), r(c) stands for p := q(a), q(b), q(c)Integrity Constraints $\blacksquare$ :- q(X), p(X) Choice **2** { p(X,Y) : q(X) } 7 :- r(Y)Aggregates ■ s(Y) := r(Y), 2 #count { p(X,Y) : q(X) } 7 ■ also: #sum, #avg, #min, #max, #even, #odd M. Gebser and T. Schaub (KRR@UP) July 13, 2013

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# Outline

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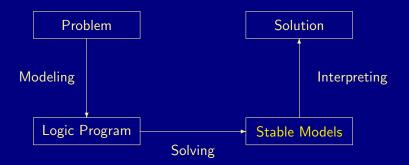
#### 6 Reasoning modes



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## Problem solving in ASP: Reasoning Modes





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# **Reasoning Modes**

- Satisfiability
- Enumeration<sup>†</sup>
- Projection<sup>†</sup>
- Intersection<sup>‡</sup>
- Union<sup>‡</sup>
- Optimization
- and combinations of them

<sup>†</sup> without solution recording

<sup>‡</sup> without solution enumeration



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