Answer Set Solving in Practice

Torsten Schaub University of Potsdam torsten@cs.uni-potsdam.de





Potassco Slide Packages are licensed under a Creative Commons Attribution 3.0 Unported License.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018 1 / 538

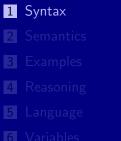
Introduction: Overview





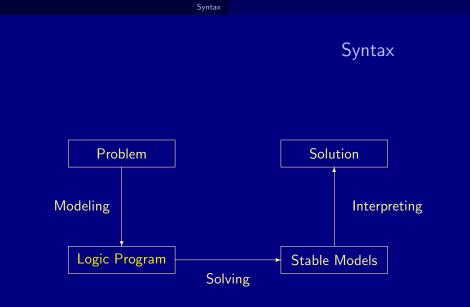
Torsten Schaub (KRR@UP)

Outline





Torsten Schaub (KRR@UP)



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

Potassco

34 / 538

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 $0 \le i \le n$

$$h(r) = a_0$$

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

A literal is an atom or a negated atom A program P is positive if $B(r)^- = \emptyset$ for all $r \in P$

Torsten Schaub (KRR@UP)



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

$$a_0 := a_1, \ldots, a_m$$
, not a_{m+1}, \ldots , not a_n .
where $0 \le m \le n$ and each $a_i \in \mathcal{A}$ is an atom for $0 \le n$

Notation

$$h(r) = a_0$$

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

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

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

A literal is an atom or a negated atom
 A program P is positive if B(r)⁻ = Ø for all r ∈ P

Potassco

35 / 538

< n

October 20, 2018

Torsten Schaub (KRR@UP)

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 $0 \le i \le n$ Notation

$$h(r) = a_0$$

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

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

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

A literal is an atom or a negated atom
 A program P is positive if B(r)⁻ = ∅ for all r ∈ P

Torsten Schaub (KRR@UP)



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 $0 \le i \le n$ Notation

$$h(r) = a_0$$

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

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

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

$$A(P) = \bigcup_{r \in P} (\{h(r)\} \cup B(r)^+ \cup B(r)^-)$$

$$B(P) = \{B(r) \mid r \in P\}$$

$$h(P) = \{h(r) \mid r \in P\}$$

Torsten Schaub (KRR@UP)



• A logic program, P, over a set \mathcal{A} of atoms is a finite set of rules \blacksquare 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 $0 \le i \le n$ Notation

$$\begin{array}{l} h(r) &= a_0 \\ B(r) &= \{a_1, \dots, a_m, \sim a_{m+1}, \dots, \sim a_n\} \\ B(r)^+ &= \{a_1, \dots, a_m\} \\ B(r)^- &= \{a_{m+1}, \dots, a_n\} \end{array}$$

A literal is an atom or a negated atom

October 20, 2018

35 / 538

Torsten Schaub (KRR@UP)

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 $0 \le i \le n$ Notation

$$\begin{array}{l} h(r) &= a_0 \\ B(r) &= \{a_1, \dots, a_m, \sim a_{m+1}, \dots, \sim a_n\} \\ B(r)^+ &= \{a_1, \dots, a_m\} \\ B(r)^- &= \{a_{m+1}, \dots, a_n\} \end{array}$$

A literal is an atom or a negated atom
A program P is positive if B(r)⁻ = Ø for all r ∈ P

Torsten Schaub (KRR@UP)



Examples

Example rules

- \bullet $a \leftarrow b, \sim c$
- $\blacksquare a \leftarrow \sim c, b$
- $a \leftarrow$
- \bullet a \leftarrow b
- $a \leftarrow \sim c$
- $bachelor(joe) \leftarrow male(joe), \sim married(joe)$

Example literals

a, b, c, bachelor(joe), male(joe), married(joe) ∼c, ∼married(joe)



Torsten Schaub (KRR@UP)

Examples

• Example rules • $a \leftarrow b, \sim c$ • $a \leftarrow \sim c, b$ • $a \leftarrow$ • $a \leftarrow b$ • $a \leftarrow -c$

 $\blacksquare bachelor(joe) \leftarrow male(joe), \sim married(joe)$

Example literals

a, b, c, bachelor(joe), male(joe), married(joe) ∼c, ∼married(joe)



Torsten Schaub (KRR@UP)

Examples

Example rules a ← b, ~c a ← ~c, b a ← a ← b a ← ~c bachelor(joe) ← male(joe), ~married(joe)

Example literals

a, b, c, bachelor(joe), male(joe), married(joe) ∼c, ∼married(joe)



Torsten Schaub (KRR@UP)

Examples

Example rules a \leftarrow b, \sigma c a \leftarrow -c, b a \leftarrow b a \leftarrow b a \leftarrow c bachelor(joe) \leftarrow male(joe), \sigma married(joe)

Example literals

- a, b, c, bachelor(joe), male(joe), married(joe)
- ~*c*, ~*married(joe)*



Torsten Schaub (KRR@UP)

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	\bot, \top	\rightarrow	\wedge	\vee	\leftrightarrow	\sim	_



Torsten Schaub (KRR@UP)

Outline

1 Syntax

- 2 Semantics
- 3 Example
- 4 Reasoning



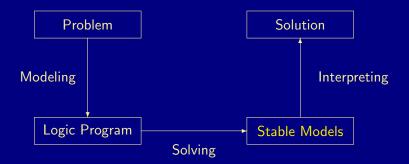
6 Variables



Torsten Schaub (KRR@UP)









Answer Set Solving in Practice

October 20, 2018

Stable models of positive programs

A set of atoms X is closed under a positive program P iff for any r ∈ P, h(r) ∈ X whenever B(r)⁺ ⊆ 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



Stable models of positive programs

A set of atoms X is closed under a positive program P iff for any r ∈ P, h(r) ∈ X whenever B(r)⁺ ⊆ 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



Stable models of positive programs

A set of atoms X is closed under a positive program P iff for any r ∈ P, h(r) ∈ X whenever B(r)⁺ ⊆ 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



Stable models of positive programs

A set of atoms X is closed under a positive program P iff for any r ∈ P, h(r) ∈ X whenever B(r)⁺ ⊆ 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



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



Torsten Schaub (KRR@UP)

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



Torsten Schaub (KRR@UP)

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



Torsten Schaub (KRR@UP)

Consider the logical formula Φ and its three



October 20, 2018

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

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

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

Formula Φ 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



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

Φ

 $q \land (q \land \neg r \rightarrow p)$

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

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

Formula Φ has one stable model, often called answer set: p +

 $\{p,q\}$

p	\mapsto	1	
q	\mapsto	1	
r	\mapsto	0	

$$P_{\Phi} \left[\begin{array}{ccc} q & \leftarrow & \\ p & \leftarrow & q, \ \sim r \end{array} \right]$$

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



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

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

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

if all atoms in X are justified by some rule in P



October 20, 2018

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

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

Formula Φ has one stable model. often called answer set:

 $\{p,q\}$

• if all atoms in X are justified by some rule in P

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

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

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

 $\Phi \mid q$

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

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

Formula Φ 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

 $(q \land \neg r \rightarrow p)$

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

October 20, 2018

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

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

Formula Φ 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

> October 20, 2018 42 / 538

Torsten Schaub (KRR@UP)

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

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

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

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

Formula Φ 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

Torsten Schaub (KRR@UP)

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

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

Stable models of normal programs

■ The reduct, *P^X*, of a program *P* relative to a set *X* of atoms is defined by

$$P^X = \{h(r) \leftarrow B(r)^+ \mid r \in P ext{ and } B(r)^- \cap X = \emptyset\}$$

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

Remarks $Cn(P^X)$ is the \subseteq -smallest (classical) model of P^X Each atom in X is justified by an "applying rule from P" Set X is stable under "applying rules from P"



Stable models of normal programs

■ The reduct, *P^X*, of a program *P* relative to a set *X* of atoms is defined by

$${\mathcal P}^X = \{ {\mathit{h}}(r) \leftarrow {\mathcal B}(r)^+ \mid r \in {\mathcal P} ext{ and } {\mathcal B}(r)^- \cap X = \emptyset \}$$

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

Remarks $Cn(P^X)$ is the \subseteq -smallest (classical) model of P^X Each atom in X is justified by an *"applying rule f* Set X is stable under *"applying rules from P"*



Stable models of normal programs

■ The reduct, *P^X*, of a program *P* relative to a set *X* of atoms is defined by

$$\mathcal{P}^X = \{\mathit{h}(r) \leftarrow \mathcal{B}(r)^+ \mid r \in \mathcal{P} ext{ and } \mathcal{B}(r)^- \cap X = \emptyset\}$$

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

Remarks

• $Cn(P^X)$ is the \subseteq -smallest (classical) model of P^X

Each atom in X is justified by an *"applying rule from P"*

Set X is stable under "applying rules from P'



Torsten Schaub (KRR@UP)

Stable models of normal programs

■ The reduct, *P^X*, of a program *P* relative to a set *X* of atoms is defined by

$$\mathcal{P}^X = \{\mathit{h}(r) \leftarrow \mathcal{B}(r)^+ \mid r \in \mathcal{P} ext{ and } \mathcal{B}(r)^- \cap X = \emptyset\}$$

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

Remarks

• $Cn(P^X)$ is the \subseteq -smallest (classical) model of P^X

■ Each atom in X is justified by an *"applying rule from P"*

■ Set X is stable under *"applying rules from P"*



A closer look at P^X

- Alternatively, 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
 - all negative atoms of the form ~a in the bodies of the remaining rules
- Note Only negative body literals are evaluated

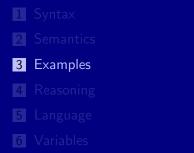


A closer look at P^X

- Alternatively, 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
 - all negative atoms of the form ~a in the bodies of the remaining rules
- Note Only negative body literals are evaluated



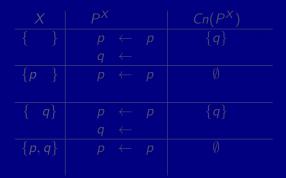
Outline





Torsten Schaub (KRR@UP)

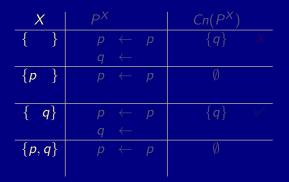
$P = \{p \leftarrow p, \ q \leftarrow {\sim}p\}$





Torsten Schaub (KRR@UP)

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





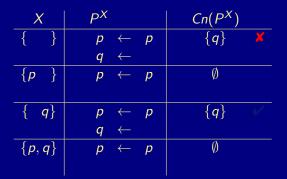
Torsten Schaub (KRR@UP)

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

Potassco October 20, 2018 46 / 538

Torsten Schaub (KRR@UP)

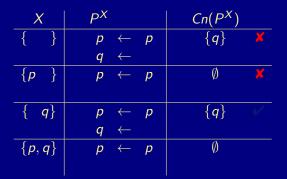
$$P = \{p \leftarrow p, \ q \leftarrow {\sim}p\}$$



Potassco October 20, 2018 46 / 538

Torsten Schaub (KRR@UP)

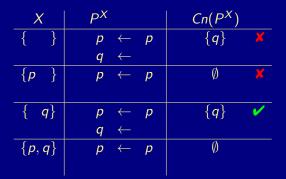
$$P = \{p \leftarrow p, \ q \leftarrow {\sim}p\}$$





Torsten Schaub (KRR@UP)

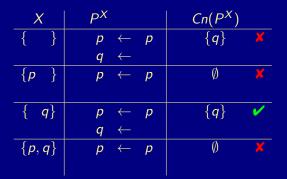
$$P = \{p \leftarrow p, \ q \leftarrow {\sim}p\}$$



Potassco October 20, 2018 46 / 538

Torsten Schaub (KRR@UP)

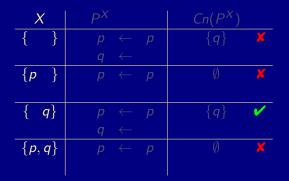
$$P = \{p \leftarrow p, \ q \leftarrow {\sim}p\}$$





Torsten Schaub (KRR@UP)

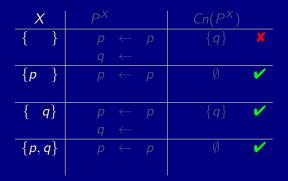
$P = \{p \leftarrow p, \ q \leftarrow {\sim}p\}$





Torsten Schaub (KRR@UP)

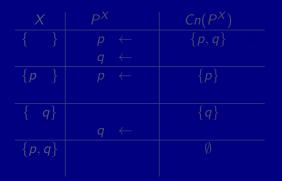
$P = \{ p \leftarrow p, \ q \leftarrow \neg p \}$





Torsten Schaub (KRR@UP)

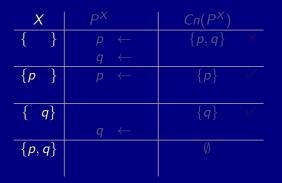
$P = \{ p \leftarrow \neg q, \ q \leftarrow \neg p \}$





Torsten Schaub (KRR@UP)

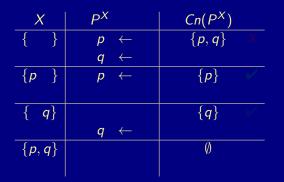
$P = \{p \leftarrow \neg q, \ q \leftarrow \neg p\}$





Torsten Schaub (KRR@UP)

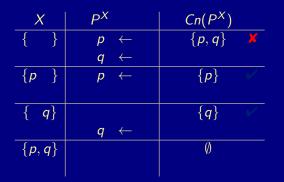
$P = \{ p \leftarrow \neg q, \ q \leftarrow \neg p \}$





Torsten Schaub (KRR@UP)

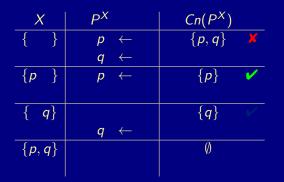
$P = \{p \leftarrow {\sim}q, \ q \leftarrow {\sim}p\}$





Torsten Schaub (KRR@UP)

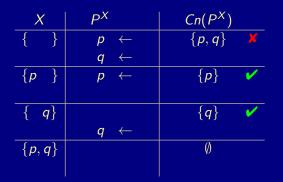
$P = \{p \leftarrow {\sim}q, \ q \leftarrow {\sim}p\}$





Torsten Schaub (KRR@UP)

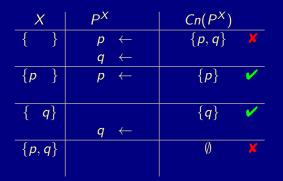
$P = \{p \leftarrow {\sim}q, \ q \leftarrow {\sim}p\}$



Potassco October 20, 2018 47 / 538

Torsten Schaub (KRR@UP)

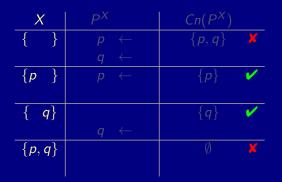
$P = \{p \leftarrow {\sim}q, \ q \leftarrow {\sim}p\}$



Potassco October 20, 2018 47 / 538

Torsten Schaub (KRR@UP)

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



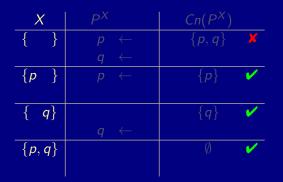


Torsten Schaub (KRR@UP)

Examples

Example two

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





Torsten Schaub (KRR@UP)

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





Torsten Schaub (KRR@UP)

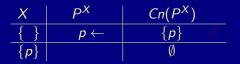
$P = \{p \leftarrow \sim p\}$





Torsten Schaub (KRR@UP)

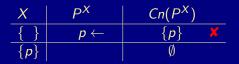
 $P = \{p \leftarrow \neg p\}$





Torsten Schaub (KRR@UP)

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





Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

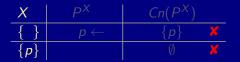
 $P = \{p \leftarrow {\sim} p\}$





Torsten Schaub (KRR@UP)

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





Torsten Schaub (KRR@UP)

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





Torsten Schaub (KRR@UP)

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

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



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

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



- A logic program may have zero, one, or multiple stable models
- If X is a stable model of a logic program P, then X ⊆ h(P)
- If X is a stable model of a logic program P, then X is a (classical) model of P
- If X and Y are stable models of a *normal* program P, then $X \not\subset Y$



- A logic program may have zero, one, or multiple stable models
- If X is a stable model of a logic program P, then X ⊆ h(P)
- If X is a stable model of a logic program P, then X is a (classical) model of P
- If X and Y are stable models of a *normal* program P, then $X \not\subset Y$



Exemplars

Logic program		Answer sets
a.		{a}
a :- b.		{}
a :- b.	b.	{a,b}
a :- b.	b :- a.	{}
a :- not c.		{a}
a :- not c.	с.	{c}
a :- not c.	c :- not a.	{a}, {c}
a :- not a.		



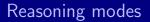
Torsten Schaub (KRR@UP)

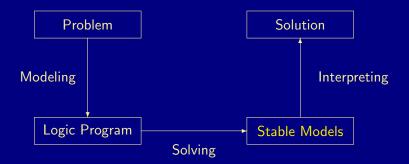
Outline

Syntax Semantics Examples Reasoning Language Variables



Torsten Schaub (KRR@UP)







Answer Set Solving in Practice

October 20, 2018

Reasoning modes

- Satisfiability
- Enumeration[†]
- Projection[†]
- Intersection[‡]
- Union[‡]
- Optimization
- and combinations of them

[†] without solution recording

without solution enumeration



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018 53 / 538

Outline

1 Syntax

- 2 Semantic
- 3 Examples
- 4 Reasoning

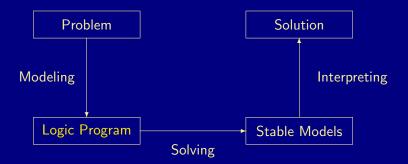


6 Variables



Torsten Schaub (KRR@UP)







Torsten Schaub (KRR@UP)

p(X) :- q(X)
p :- q(X) : r(X)
p(X) ; q(X) :- r(X)
:- q(X), p(X)
2 { $p(X,Y) : q(X)$ } 7 :- $r(Y)$
:- r(Y), 2 #sum{ X : $p(X,Y)$, $q(X)$ } 7
$:\sim$ q(X), p(X,C) [C] #minimize { C : q(X), p(X,C) }



October 20, 2018 56 / 538

Torsten Schaub (KRR@UP)

 Variables 	p(X) :- q(X)
	p := q(X) : r(X)
	p(X) ; q(X) := r(X)
	ts :- q(X), p(X)
	2 { $p(X,Y) : q(X)$ } 7 :- $r(Y)$
	(Y) :- r(Y), 2 #sum{ X : p(X,Y), q(X) } 7
	$:\sim$ q(X), p(X,C) [C] #minimize $\{$ C : q(X), p(X,C) $\}$



October 20, 2018 56 / 538

Torsten Schaub (KRR@UP)

 Variables 	p(X) :- q(X)
Conditional litera	ls $p := q(X) : r(X)$
	p(X) ; q(X) :- r(X)
	nts :- q(X), p(X)
	2 { $p(X,Y) : q(X)$ } 7 :- $r(Y)$
	s(Y) :- r(Y), 2 #sum{ X : p(X,Y), q(X) } 7
	$:\sim$ q(X), p(X,C) [C] #minimize $\left\{ \begin{array}{c} C \ : \ q(X), \ p(X,C) \end{array} \right\}$



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018 56 / 538

 Variables 	p(X) := q(X)
 Conditional literals 	p := q(X) : r(X)
 Disjunction 	p(X) ; q(X) := r(X)
	:- q(X), p(X)
	2 { $p(X,Y)$: $q(X)$ } 7 :- $r(Y)$
	<pre>T) := r(Y), 2 #sum{ X : p(X,Y), q(X) } 7</pre>
	$:\sim$ q(X), p(X,C) [C] #minimize $\left\{ \ C \ : \ q(X), \ p(X,C) ight\}$



October 20, 2018 56 / 538

Torsten Schaub (KRR@UP)

 Variables 	p(X) := q(X)
 Conditional literals 	p := q(X) : r(X)
 Disjunction 	p(X) ; q(X) := r(X)
Integrity constraints	:- q(X), p(X)
	2 { $p(X,Y)$: $q(X)$ } 7 :- $r(Y)$
) :- r(Y), 2 #sum{ X : p(X,Y), q(X) } 7
	$:\sim$ q(X), p(X,C) [C] #minimize { C : q(X), p(X,C) }



Answer Set Solving in Practice

October 20, 2018 56 / 538

 Variables 	p(X) := q(X)
 Conditional literals 	p := q(X) : r(X)
 Disjunction 	p(X) ; q(X) :- r(X)
Integrity constraints	:- q(X), p(X)
■ Choice	2 { $p(X,Y) : q(X)$ } 7 :- $r(Y)$
) :- r(Y), 2 #sum{ X : p(X,Y), q(X) } 7
	:~ q(X), p(X,C) [C] #minimize { C : q(X), p(X,C) }



 Variables 	p(X) :- q(X)
Conditional literals	p := q(X) : r(X)
 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 #sum{ X : p(X,Y), q(X) } 7
	$: \sim q(X), p(X,C) [C]$ #minimize { C : q(X), p(X,C) }



 Variables 	p(X) :- q(X)
 Conditional literals 	p := q(X) : r(X)
 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 #sum{ X : $p(X,Y)$, $q(X)$ } 7
 Optimization 	
	$\label{eq:constraint} \begin{array}{l} :\sim \mbox{ q(X), p(X,C) [C]} \\ \mbox{ \#minimize } \left\{ \mbox{ C } : \mbox{ q(X), p(X,C) } \right\} \end{array}$



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018 56 / 538

 Variables 	p(X) := q(X)
 Conditional literals 	p := q(X) : r(X)
 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 #sum{ X : p(X,Y), q(X) } 7
 Optimization Weak constraints Statements 	:~ q(X), p(X,C) [C] #minimize { C : q(X), p(X,C) }



October 20, 2018 56 / 538

Torsten Schaub (KRR@UP)

 Variables 	p(X) :- q(X)
 Conditional literals 	p := q(X) : r(X)
 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 #sum{ X : $p(X,Y)$, $q(X)$ } 7
 Optimization Weak constraints Statements 	:~ q(X), p(X,C) [C] #minimize { C : q(X), p(X,C) }



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018 56 / 538

 Variables 	p(X) :- q(X)
Conditional literals	p := q(X) : r(X)
 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 #sum{ X : $p(X,Y)$, $q(X)$ } 7
 Multi-objective optimization Weak constraints :~ q(X), p(X,C) [C@42] Statements #minimize { C@42 : q(X), p(X,C) } 	



Outline

1 Syntax

- 2 Semantic
- 3 Example
- 4 Reasoning
- 5 Language
- 6 Variables



Torsten Schaub (KRR@UP)

Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$



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 constructible from \mathcal{T}
- A variable-free atom is also called ground
- 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; θ is a (ground) substitution
- Ground instantiation of P: ground $(P) = \bigcup_{r \in P} ground(r)$



59 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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 constructible from *T* (also called alphabet or Herbrand base)
- A variable-free atom is also called ground
- 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; θ is a (ground) substitution

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

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

59 / 538

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 constructible from \mathcal{T}
- A variable-free atom is also called ground
- 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; θ is a (ground) substitution

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



59 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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 constructible from \mathcal{T}
- A variable-free atom is also called ground
- 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; θ is a (ground) substitution

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



59 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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 constructible from \mathcal{T}
- A variable-free atom is also called ground
- 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; θ is a (ground) substitution

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



59 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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

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

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

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

Grounding aims at reducing the ground instantiation



Torsten Schaub (KRR@UP)

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

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

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

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



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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

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

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

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



Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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

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

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

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

Grounding aims at reducing the ground instantiation



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

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

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

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

Grounding aims at reducing the ground instantiation



Torsten Schaub (KRR@UP)

Safety

- A normal rule is safe, if each of its variables also occurs in some positive body literal
- A normal program is safe, if all of its rules are safe



Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X, \overline{Z}) \leftarrow p(X, Y), p(Y, \overline{Z})$ q(a)q(b) $q(X) \leftarrow \sim r(X)$ $r(X) \leftarrow \sim q(X), \overline{d(X)}$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$

Potassco October 20, 2018 62 / 538

Torsten Schaub (KRR@UP)

Example

Safe ?

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X, \overline{Z}) \leftarrow p(X, Y), p(Y, \overline{Z})$ q(a)q(b) $q(X) \leftarrow \sim r(X)$ $r(X) \leftarrow \sim q(X), \overline{d(X)}$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$



Torsten Schaub (KRR@UP)

Example

Safe ?

V

1

1

V

1

1

V

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$

Potassco October 20, 2018 62 / 538

Torsten Schaub (KRR@UP)

Example

Safe ?

V

1

1

V

1

1

V

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$

Potassco October 20, 2018 62 / 538

Torsten Schaub (KRR@UP)

Example

Safe ?

V

1

1

V

1

V

1

1

V

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$



Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$



October 20, 2018 62 / 538

Example

Safe ?

V

1

V

V

1

V

V

V

V

~

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$

October 20, 2018 62 / 538

Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$

1 V V 1 V V V V ~

Safe ?

V

Potassco October 20, 2018 62 / 538

Torsten Schaub (KRR@UP)



Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$







Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$





Example

d(a)d(c)d(d)p(a,b)p(b,c)p(c, d) $p(X,Z) \leftarrow p(X,Y), p(Y,Z)$ q(a)q(b) $q(X) \leftarrow \sim r(X), d(X)$ $r(X) \leftarrow \sim q(X), d(X)$ $s(X) \leftarrow \sim r(X), p(X, Y), q(Y)$





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 $Cn(ground(P)^X) = X$



Torsten Schaub (KRR@UP)

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)^X) = X



Torsten Schaub (KRR@UP)

- Y. Babovich and V. Lifschitz. Computing answer sets using program completion. Unpublished draft, 2003.
- C. Baral. *Knowledge Representation, Reasoning and Declarative Problem Solving.* Cambridge University Press, 2003.
- 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.
- 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 <u>Potass</u>

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018 538 / 538

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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

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.

 M. D'Agostino, D. Gabbay, R. Hähnle, and J. Posegga, editors. Handbook of Tableau Methods.
 Kluwer Academic Publishers, 1999.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

 [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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

[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.



538 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

[27] M. Gebser, R. Kaminski, B. Kaufmann, M. Lindauer, M. Ostrowski, J. Romero, T. Schaub, and S. Thiele. *Potassco User Guide.* <u>University of Potsdam</u>, 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.



538 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice



538 / 538

[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 Hoeve and J. Hooker, editors, *Proceedings of the Sixth International Conference on Integration of AI and OR Techniques in Constraint Programming for Combinatorial Optimization Problems*

Potassco

538 / 538

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

(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. Truszczyński, 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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

[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.



538 / 538

Answer Set Solving in Practice

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. Anzeiger der Akademie der Wissenschaften in Wien, page 65–66, 1932.
- [48] A. Heyting.



538 / 538

Torsten Schaub (KRR@UP)

Die formalen Regeln der intuitionistischen Logik.

In *Sitzungsberichte der Preussischen Akademie der Wissenschaften*, page 42–56. Deutsche Akademie der Wissenschaften zu Berlin, 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?

Torsten Schaub (KRR@UP)



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. Artifical 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.

Torsten Schaub (KRR@UP)



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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice

October 20, 2018

[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,

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.



538 / 538

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. Soininen. 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.

Torsten Schaub (KRR@UP)

Answer Set Solving in Practice



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 R. Ernst, editor, *Proceedings of the International Conference on Computer-Aided Design (ICCAD'01)*, pages 279–285. IEEE Computer Society Press, 2001.

