# Answer Set Solving in Practice

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#### Motivation: Overview

- 1 Motivation
- 2 Nutshell
- 3 Evolution
- 4 Foundation
- 5 Workflow
- 6 Engine
- 7 Usage
- 8 Summary



# Outline

#### 1 Motivation

- 2 Nutshel
- 3 Evolution
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# Informatics

"What is the problem?" versus "How to solve the problem?"



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## Informatics

"What is the problem?" versus "How to solve the problem?"



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# Traditional programming

"What is the problem?" versus "How to solve the problem?"



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# Traditional programming

"What is the problem?" versus "How to solve the problem?"



#### Declarative problem solving

"What is the problem?"

versus "How to solve the problem?"



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#### Declarative problem solving

"What is the problem?"

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# Declarative problem solving

"What is the problem?" versus "How to solve the problem?"





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# What is the benefit?





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# What is the benefit?





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## What is the benefit?

#### + Transparency

+ Flexibility + Maintainability + Reliability

+ Generality
+ Efficiency
+ Optimality
+ Availability





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#### What is the benefit?





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#### What is the benefit?





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# Outline

#### 1 Motivation



#### 3 Evolution













# Answer Set Programming (ASP)

What is ASP? ASP is an approach for declarative problem solving



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# Answer Set Programming (ASP)

What is ASP?

ASP is an approach for declarative problem solving

#### ■ Where is ASP from?

- Databases
- Logic programming
- Knowledge representation and reasoning
- Satisfiability solving



# Answer Set Programming (ASP)

- What is ASP?
  ASP = DB+LP+KR+SAT !
  ASP is an approach for declarative problem solving
- Where is ASP from?
  - Databases
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  - Satisfiability solving


What is ASP?
 ASP is an approach for declarative problem solving

 What is ASP good for? Solving knowledge-intense combinatorial (optimization) problems



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What is ASP?
 ASP is an approach for declarative problem solving

- What is ASP good for?
  Solving knowledge-intense combinatorial (optimization) problems
- What problems are this?
  Problems consisting of (many) decisions and constraints



What is ASP?
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- What is ASP good for?
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- What problems are this?
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  Examples Sudoku, Configuration, Diagnosis, Music composition, Planning, System design, Time tabling, etc.



What is ASP?
 ASP is an approach for declarative problem solving

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 Solving knowledge-intense combinatorial (optimization) problems

 What problems are this? — And industrial ones?
 Problems consisting of (many) decisions and constraints
 Examples Sudoku, Configuration, Diagnosis, Music composition, Planning, System design, Time tabling, etc.



What is ASP?

ASP is an approach for declarative problem solving

What is ASP good for?

Solving knowledge-intense combinatorial (optimization) problems

What problems are this? — And industrial ones?

- Debian, Ubuntu: Linux package configuration
- Exeura: Call routing
- Fcc: Radio frequency auction
- Gioia Tauro: Workforce management
- Nasa: Decision support for Space Shuttle
- Siemens: Partner units configuration
- Variantum: Product configuration



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Over 13 months in 2016–17 the US Federal Communications Commission conducted an "incentive auction" to repurpose radio spectrum from broadcast television to wireless internet. In the end, the auction yielded §19.8 billion \$10.05 billion of which was paid to 175 broadcasters for voluntarily relinquishing their licenses across 14 UHF channels. Stations that continued broadcasting were assigned potentially new channels to fit as densely as possible into the channels that remained. The government netted more than §7 billion (used to pay down the national debt) after covering costs. A crucial element of the auction design was the construction of a sofver, dubbed SATFC, that determined whether sets of stations could be "repacked" in this way; it needed for run every time a station was given a price quote. This



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What is ASP?
 ASP is an approach for declarative problem solving

- What is ASP good for?
  Solving knowledge-intense combinatorial (optimization) problems
- What problems are this?
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- What are ASP's distinguishing features?
  - High level, versatile modeling language
  - High performance solvers



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- Any industrial impact?
  - ASP Tech companies: dlv systems and potassco solutions



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- Any industrial impact?
  - ASP Tech companies: dlv systems and potassco solutions
- Anything not so good for ASP?
  - Number crunching

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■ '70/'80 Capturing incomplete information



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#### '70/'80 Capturing incomplete information

- Databases Closed world assumption
- Logic programming Negation as failure
- Non-monotonic reasoning Auto-epistemic and Default logics, Circumscription



#### ■ '70/'80 Capturing incomplete information

- Databases Closed world assumption
  - Axiomatic characterization
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  - Axiomatic characterization
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  - Herbrand interpretations
  - Fix-point characterizations

 Non-monotonic reasoning Auto-epistemic and Default logics, Circumscription



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  - Herbrand interpretations
  - Fix-point characterizations

Non-monotonic reasoning

- Auto-epistemic and Default logics, Circumscription
  - Extensions of first-order logic
  - Modalities, fix-points, second-order logic



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- '90 Amalgamation and computation



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#### '90 Amalgamation and computation

- Logic programming semantics
  Well-founded and stable models semantics
- ASP solving "Stable models = Well-founded semantics + Branch"



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  - Stable models semantics derived from non-monotonic logics
  - Alternating fix-point theory

#### ASP solving

"Stable models = Well-founded semantics + Branch"



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  - "Stable models = Well-founded semantics + Branch"
    - Modeling Grounding Solving
    - Icebreakers: lparse and smodels



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    - Bio-informatics, Linux Package Configuration, Music composition, Robotics, System Design, etc
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    - Roots: Logic of Here-and-There , G3



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#### Theorem Proving based approach (eg. Prolog)

Provide a representation of the problem
 A solution is given by a derivation of a quer

Model Generation based approach (eg. SATisfiability testing)

Provide a representation of the problemA solution is given by a model of the representation

#### Automated planning, Kautz and Selman (ECAI'92)

Represent planning problems as propositional theories so that models not proofs describe solutions



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Represent planning problems as propositional theories so that models not proofs describe solutions



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# Model Generation based Problem Solving

Representation	Solution
constraint satisfaction problem	assignment
propositional horn theories	smallest model
propositional theories	models
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auto-epistemic theories	expansions
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Prolog program

on(a,b). on(b,c).

above(X,Y) := on(X,Y).
above(X,Y) := on(X,Z), above(Z,Y).

Prolog queries

```
?- above(a,c).
true.
```

```
?- above(c,a).
```

no.

```
Prolog program
```

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```

Prolog queries (testing entailment)

```
?- above(a,c).
true.
```

```
?- above(c,a).
```

no.

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#### Shuffled Prolog program

on(a,b). on(b,c).

```
above(X,Y) :- above(X,Z), on(Z,Y).
above(X,Y) :- on(X,Y).
```

#### Prolog queries

?- above(a,c).

Fatal Error: local stack overflow.



#### Shuffled Prolog program

on(a,b). on(b,c).

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above(X,Y) :- on(X,Y).
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Prolog queries (answered via fixed execution)

?- above(a,c).

Fatal Error: local stack overflow.



## Paradigm shift

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#### Formula

- on(a, b)
- $\land on(b, c)$
- $\land \quad (\textit{on}(X,Y) \rightarrow \textit{above}(X,Y))$
- $\land \quad (\textit{on}(X,Z) \land \textit{above}(Z,Y) \rightarrow \textit{above}(X,Y))$

#### Herbrand model

 $( on(a, b), on(b, c), on(a, c), on(b, b), \\ above(a, b), above(b, c), above(a, c), above(b, b), above(c, b) <math>)$ 



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#### Formula

- on(a, b)
- $\land on(b, c)$
- $\land \quad (\mathit{on}(X,Y) \rightarrow \mathit{above}(X,Y))$
- $\wedge \quad (\textit{on}(X,Z) \land \textit{above}(Z,Y) \rightarrow \textit{above}(X,Y))$

#### Herbrand model

$$\left\{ \begin{array}{cc} on(a,b), & on(b,c), & on(a,c), & on(b,b), \\ above(a,b), & above(b,c), & above(a,c), & above(b,b), & above(c,b) \end{array} \right\}$$



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#### Formula

- on(a, b)
- $\wedge on(b, c)$
- $\land \quad (\textit{on}(X,Y) \rightarrow \textit{above}(X,Y))$
- $\land \quad (on(X,Z) \land above(Z,Y) \rightarrow above(X,Y))$

#### Herbrand model (among 426!)

 $\left\{ \begin{array}{cc} on(a,b), & on(b,c), & on(a,c), & on(b,b), \\ above(a,b), & above(b,c), & above(a,c), & above(b,b), & above(c,b) \end{array} \right\}$ 



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## Paradigm shift

#### Theorem Proving based approach (eg. Prolog)

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 A solution is given by a derivation of a query

Model Generation based approach (eg. SATisfiability testing)

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## ➡ Answer Set Programming (ASP)



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## Answer Set Programming at large

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## Answer Set Programming commonly

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first-order theories	stable models
first-order theories	Herbrand models
auto-epistemic theories	expansions
default theories	extensions

#### first-order programs

stable Herbrand models Potassco

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Logic program

on(a,b). on(b,c).

above(X,Y) := on(X,Y).above(X,Y) := on(X,Z), above(Z,Y).



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```
Logic program
on(a,b).
on(b,c).
above(X,Y) :- on(X,Y).
above(X,Y) :- on(X,Z), above(Z,Y).
```

#### Stable Herbrand model

 $\{ on(a, b), on(b, c), above(b, c), above(a, b), above(a, c) \}$ 



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```
Logic program
on(a,b).
on(b,c).
above(X,Y) :- on(X,Y).
above(X,Y) :- on(X,Z), above(Z,Y).
```

#### Stable Herbrand model (and no others)

 $\{ on(a, b), on(b, c), above(b, c), above(a, b), above(a, c) \}$ 



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Logic program

on(a,b). on(b,c).

```
above(X,Y) :- above(Z,Y), on(X,Z).
above(X,Y) :- on(X,Y).
```

Stable Herbrand model (and no others)

 $\{ on(a, b), on(b, c), above(b, c), above(a, b), above(a, c) \}$ 



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#### ASP versus LP

ASP	Prolog
Model generation	Query orientation
Bottom-up	Top-down
Modeling language	Programming language
Rule-based format	
Instantiation	Unification
Flat terms	Nested terms
(Turing +) $NP(^{NP})$	Turing



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ASP ver	sus SAT
---------	---------

ASP	SAT
Model generation	
Bottom	-up
Constructive Logic	Classical Logic
Closed (and open) world reasoning	Open world reasoning
Modeling language	—
Complex reasoning modes	Satisfiability testing
Satisfiability	Satisfiability
Enumeration/Projection	—
Intersection/Union	—
Optimization	—
(Turing +) $NP(^{NP})$	<b>NP</b> ∰ Potas

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## Outline

#### 1 Motivation



#### 3 Evolution













#### Propositional Normal Logic Programs

• A logic program P is a set of rules of the form

$$\underbrace{a}_{\text{head}} \leftarrow \underbrace{b_1, \ldots, b_m, \neg c_1, \ldots, \neg c_n}_{\text{body}}$$

- **a** and all  $b_i, c_j$  are atoms (propositional variables)
- $lacksim \leftarrow$ , ,, eg denote if, and, and negation
- intuitive reading: head must be true if body holds
- Semantics given by stable models, informally, models of P justifying each true atom by some rule in P



#### Logic Programs

■ A logic program *P* is a set of rules of the form

$$\underbrace{a}_{\text{head}} \leftarrow \underbrace{b_1, \ldots, b_m, \neg c_1, \ldots, \neg c_n}_{\text{body}}$$

a and all b<sub>i</sub>, c<sub>j</sub> are atoms (propositional variables)
 ←, ,, ¬ denote if, and, and negation
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Semantics given by stable models, informally, models of P justifying each true atom by some rule in P



#### Normal Logic Programs

■ A logic program *P* is a set of rules of the form

$$\underbrace{a}_{\text{head}} \leftarrow \underbrace{b_1, \ldots, b_m, \neg c_1, \ldots, \neg c_n}_{\text{body}}$$

a and all b<sub>i</sub>, c<sub>j</sub> are atoms (propositional variables)
 ←, ,, ¬ denote if, and, and negation
 intuitive reading: head must be true if body holds

Semantics given by stable models, informally, models of P justifying each true atom by some rule in P

Disclaimer The following formalities apply to normal logic programs



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а	b	С	$( eg b  ightarrow a) \ \land \ (b  ightarrow c)$
F	F	F	$F \land (F  o F)$
F	F	Т	$F \land (F  ightarrow T)$
F	Т	F	$(F  ightarrow F) \ \land \ F$
F	Т	Т	$(F  ightarrow F) \ \land \ (T  ightarrow T)$
Т	F	F	$(T  ightarrow T) \ \land \ (F  ightarrow F)$
Т	F	Т	$(T  ightarrow T) \ \land \ (F  ightarrow T)$
Т	Т	F	$(F  ightarrow T) \ \land \ F$
Т	Т	Т	$(F  ightarrow T) \land (T  ightarrow T)$



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а	b	С	$( eg b  ightarrow a) \ \land \ (b  ightarrow c)$
F	F	F	$F \land (F  ightarrow F)$
F	F	Т	$F \land (F  ightarrow T)$
F	Т	F	$(F  ightarrow F) \ \land \ F$
F	Т	Т	$({f F}  ightarrow {f F}) \ \land \ ({f T}  ightarrow {f T})$
Т	F	F	$(T  ightarrow T) \ \land \ (F  ightarrow F)$
Т	F	Т	$(T  ightarrow T) \ \land \ (F  ightarrow T)$
Т	Т	F	$({f F}  ightarrow {f T}) \ \land \ {f F}$
Т	Т	Т	$({f F}  ightarrow {f T}) \ \wedge \ ({f T}  ightarrow {f T})$



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а	b	С	$( eg b  ightarrow a) \ \land \ (b  ightarrow c)$
F	F	F	F $\wedge$ T
F	F	Т	FΛT
F	Т	F	ΤΛF
F	Т	Т	$T \land T$
Т	F	F	T $\wedge$ T
Т	F	Т	ΤΛT
Т	Т	F	ΤΛF
Т	Т	Т	$T \land T$



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• We get four models:  $\{b, c\}, \{a\}, \{a, c\}, and \{a, b, c\}$ 



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$$\begin{array}{c|cccc} a & b & c & (\neg b \rightarrow a) \land (b \rightarrow c) \\ \hline F & F & F & (\neg F \rightarrow a) \land (b \rightarrow c) \\ F & F & T & (\neg F \rightarrow a) \land (b \rightarrow c) \\ F & T & F & (\neg T \rightarrow a) \land (b \rightarrow c) \\ F & T & T & (\neg T \rightarrow a) \land (b \rightarrow c) \\ \hline T & F & F & (\neg F \rightarrow a) \land (b \rightarrow c) \\ T & F & T & (\neg F \rightarrow a) \land (b \rightarrow c) \\ T & T & F & (\neg T \rightarrow a) \land (b \rightarrow c) \\ \hline T & T & T & (\neg T \rightarrow a) \land (b \rightarrow c) \\ \end{array}$$



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а	b	С	$( eg b  ightarrow a) \wedge (b  ightarrow c)$
F	F	F	$a \wedge (b  ightarrow c)$
F	F	Т	$a \wedge (b  ightarrow c)$
F	Т	F	${\sf T} \wedge (b  o c)$
F	Т	Т	${\sf T} \wedge (b  o c)$
Т	F	F	$a \wedge (b  ightarrow c)$
Т	F	Т	$a \wedge (b  ightarrow c)$
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Т	Т	Т	${f T} \wedge (b  o c)$



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а	b	С	$( eg b  ightarrow a) \wedge (b  ightarrow c)$
F	F	F	$a \wedge (b  ightarrow c)$
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F	Т	F	(b  ightarrow c)
F	Т	Т	(b  ightarrow c)
Т	F	F	$a \wedge (b  ightarrow c)$
Т	F	Т	$a \wedge (b  ightarrow c)$
Т	Т	F	(b  ightarrow c)
Т	Т	Т	(b  ightarrow c)
			Reduct



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а	b	С	$( eg b  ightarrow a) \wedge (b  ightarrow c)$
F	F	F	$a \wedge (b  ightarrow c)$
F	F	Т	$a \wedge (b  ightarrow c)$
F	Т	F	(b  ightarrow c)
F	Т	Т	(b  ightarrow c)
Т	F	F	$a \wedge (b  ightarrow c)$
Т	F	Т	$a \wedge (b  ightarrow c)$
Т	Т	F	(b  ightarrow c)
Т	Т	Т	(b  ightarrow c)
			Reduct



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а	b	С	$( eg b  ightarrow a) \wedge (b  ightarrow c)$
F	F	F	$a \wedge (b  ightarrow c)$
F	F	Т	$a \wedge (b  ightarrow c)$
F	Т	F	(b ightarrow c)
$\mathbf{F}_{i}$	Т	Т	$(b  ightarrow c) \models$
$\mathbf{T}_{i}$	$ \mathbf{F} $	F	$a \wedge (b  ightarrow c) \models a$
$\mathbf{T}_{i}$	$ \mathbf{F} $	Т	$a \wedge (b  ightarrow c) \models a$
Т	Т	F	(b ightarrow c)
$\mathbf{T}_{i}$	Т	Т	$(b  ightarrow c) \models$
			Reduct



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а	b	С	$( eg b  ightarrow a) \wedge (b  ightarrow c)$	
F	F	F	$a \wedge (b  ightarrow c)$	
F	F	Т	$a \wedge (b  ightarrow c)$	
F	Т	F	(b ightarrow c)	
F	Т	Т	(b  ightarrow c)	Þ
Т	F	F	$a \wedge (b  ightarrow c)$	⊨ a
Т	F	Т	$a \wedge (b  ightarrow c)$	⊨ a
Т	Т	F	(b  ightarrow c)	
Т	Т	Т	(b  ightarrow c)	⊨
			Reduct	



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а	b	С	$( eg b  ightarrow a) \wedge (b  ightarrow c)$
F	F	F	$a \wedge (b  ightarrow c) \models a$
F	F	Т	$a \wedge (b  ightarrow c) \models a$
F	Т	F	$(b  ightarrow c) \models$
F	Т	Т	$(b  ightarrow c) \models$
Т	F	F	$a \wedge (b  ightarrow c) \models a$
Т	F	Т	$a \wedge (b  o c) \models a$
Т	Т	F	$(b  ightarrow c) \models$
Т	Т	Т	$(b  ightarrow c) \models$
			Reduct



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• We get one stable model:  $\{a\}$ 

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■ We get one stable model: {*a*}

■ Stable models = Smallest models of (respective) reducts

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# Outline

#### 1 Motivation

- 2 Nutshell
- 3 Evolution
- 4 Foundation
- 5 Workflow
- 6 Engine
- 7 Usage
- 8 Summary



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# ASP modeling, grounding, and solving



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# Rooting ASP solving





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# Rooting ASP solving



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# Outline

#### 1 Motivation

- 2 Nutshell
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# Outline

#### 1 Motivation

- 2 Nutshell
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  - 8 Summary



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#### ASP as High-level Language

- Express problem instance as sets of facts
- Encode problem class as a set of rules
- Read off solutions from stable models of facts and rules

#### ASP as Low-level Language

- Compile a problem into a set of facts and rules
- Solve the original problem by solving its compilation

#### ASP and Imperative language

Control continuously changing logic programs



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- Express problem instance as sets of facts
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#### ASP as "Low-level" Language

- Compile a problem instance into a set of facts
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#### ASP and Imperative language

Control continuously changing logic programs



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#### Two and a half sides of a coin

#### ASP as High-level Language

- Express problem instance as sets of facts
- Encode problem class as a set of rules
- Read off solutions from stable models of facts and rules

#### ASP as "Low-level" Language

- Compile a problem instance into a set of facts
- Encode problem class as a set of rules
- Solve the original problem by solving its compilation

#### ASP and Imperative language

Control continuously changing logic programs


# Outline

### 1 Motivation

- 2 Nutshell
- 3 Evolution
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- 5 Workflow
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- 7 Usage





# Upcoming experience

ASP is a viable tool for Knowledge Representation and Reasoning

- Integration of DB, LP, KR, and SAT techniques
- Combinatorial search problems in the realm of NP and NP<sup>NP</sup>
- Succinct, elaboration-tolerant problem representations

rapid application development tool

- Easy handling of knowledge-intensive applications
  - data, defaults, exceptions, frame axioms, reachability etc
- ASP offers efficient and versatile off-the-shelf solving technology
  - http://potassco.org
  - winning ASP, CASC, MISC, PB, and SAT competitions
- ASP has a growing range of applications, and its's good fun!



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# ASP = DB + LP + KR + SAT



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# Upcoming experience

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# $ASP = DB + LP + KR + SMT^n$



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