# Modeling and Solving in Answer Set Programming

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# Outline

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- 2 Introduction
- 3 Basic modeling
- 4 (Language extensions)
- 5 Solving
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# Bias

#### Focus

Answer Set Programming as Boolean Constraint Satisfaction Problem
 Answer Set Solving as a Boolean Constraint Solving
 Answer Set Systems at http://potassco.sourceforge.net

#### Further resources

http://potassco.sourceforge.net/teaching.html

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## Motivation: Overview

#### 1 Motivation

- 2 Nutshell
- 3 Shifting paradigms
- 4 Rooting ASP
- 5 Problem solving

#### 6 Use

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# Informatics





# Informatics



# Traditional programming



# Traditional programming



# Declarative problem solving



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## Answer Set Programming in a Nutshell

ASP is an approach to declarative problem solving, combining

a rich yet simple modeling language

with high-performance solving capacities

ASP has its roots in

(logic-based) knowledge representation and (nonmonotonic) reasoning

(deductive) databases

constraint solving (in particular, SATisfiability testing)

logic programming (with negation)

ASP allows for solving all search problems in NP (and  $NP^{NP}$ ) in a uniform way

ASP is versatile as reflected by the ASP solver clasp, winning first places at ASP'07/09/11, CASC'11, MISC'11, PB'09/11, and SAT'09/11

ASP embraces many emerging application areas

Torsten Schaub et al. (KRR@UP)

Modeling and Solving in ASP

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tailored to Knowledge Representation and Reasoning

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# ASP = KR + DB + SAT + LP

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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 problem.
- 2 A 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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# Model Generation based Problem Solving

Representation	Solution
constraint satisfaction problem	assignment
propositional horn theories	smallest model
propositional theories	models
propositional theories	minimal models
propositional theories	stable models
propositional programs	minimal models
propositional programs	supported models
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first-order theories	models
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first-order theories	Herbrand models
auto-epistemic theories	expansions
default theories	extensions

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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).
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no.

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#### Formula

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

#### Herbrand model

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

#### Formula

on(a, b)  $\land on(b, c)$   $\land (on(X, Y) \rightarrow above(X, Y))$  $\land (on(X, Z) \land above(Z, Y) \rightarrow above(X, Y))$ 

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## SAT-style playing with blocks

#### Formula

- on(a, b) ∧ on(b, c)
- $\land (on(X, Y) \rightarrow above(X, Y))$  $\land (on(X, Z) \land above(Z, Y) \rightarrow above(X, Y))$
- Herbrand model (among 426!)

```
\{on(b, b), on(a, b), on(b, c), on(a, c), above(b, b), above(c, b), above(a, b), above(b, c), above(c, c), above(a, c) \}
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## KR's shift of paradigm

Theorem Proving based approach (eg. Prolog)

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➡ Answer Set Programming (ASP)

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## Answer Set Programming at large

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## Answer Set Programming in practice

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#### first-order programs

#### stable Herbrand models

#### ASP-style playing with blocks

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#### Stable Herbrand model

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Stable Herbrand model (and no others)

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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	

## ASP versus 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			
Optimization			
Intersection/Union			
(Turing +) $NP(^{NP})$	NP		

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## ASP solving









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Torsten Schaub et al. (KRR@UP)

Use

#### What is ASP good for?

 Combinatorial search problems in the realm of P, NP, and NP<sup>NP</sup> (some with substantial amount of data), like

- Automated Planning,
- Code Optimization,
- Composition of Renaissance Music,
- Database Integration,
- Decision Support for NASA shuttle controllers,
- Model Checking
- Product Configuration,
- Robotics,
- System Biology,
- System Synthesis,
- (industrial) Team-building,
- and many many more.

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■ Integration of KR, DB, and SAT techniques

Succinct, elaboration-tolerant problem representations

- Rapid application development tool
- Easy handling of dynamic, knowledge intensive applications
  - including: data, frame axioms, exceptions, defaults, closures, etc.

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## ASP = KR + DB + SAT + LP

#### Introduction: Overview





- 9 Examples
- 10 Variables
- 11 Language Constructs
- 12 Reasoning Modes

#### Introduction: Overview



#### 11 Language Constructs

#### 12 Reasoning Modes

#### Problem solving in ASP: Syntax



#### Normal logic programs

■ A (normal) rule, r, is an ordered pair of the form

$$A_0 \leftarrow A_1, \ldots, A_m$$
, not  $A_{m+1}, \ldots$ , not  $A_n$ ,

where  $n \ge m \ge 0$ , and each  $A_i$   $(0 \le i \le n)$  is an atom. • A (normal) logic program is a finite set of rules.

Notation

$$head(r) = A_0$$
  

$$body(r) = \{A_1, \dots, A_m, not \ A_{m+1}, \dots, not \ A_n\}$$
  

$$body(r)^+ = \{A_1, \dots, A_m\}$$
  

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

A program is called positive if  $body(r)^- = \emptyset$  for all its rules.

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## (Rough) notational convention

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

				negation	classical
	if	and	or	as failure	negation
source code	:-	,		not	-
logic program	$\leftarrow$			not/ $\sim$	_
formula	$\rightarrow$	$\wedge$	$\vee$	$\sim/(\neg)$	_

#### Introduction: Overview



#### 8 Semantics

9 Examples

10 Variables

Language Constructs

12 Reasoning Modes

#### Problem solving in ASP: Semantics



## Answer set: Formal Definition Positive programs

- A set of atoms X is closed under a positive program  $\Pi$  iff for any  $r \in \Pi$ ,  $head(r) \in X$  whenever  $body(r)^+ \subseteq X$ .
  - $\rightarrow$  X corresponds to a model of  $\Pi$  (seen as a formula).
- The smallest set of atoms which is closed under a positive program  $\Pi$  is denoted by  $Cn(\Pi)$ .
  - →  $Cn(\Pi)$  corresponds to the  $\subseteq$ -smallest model of  $\Pi$  (ditto).
- The set  $Cn(\Pi)$  of atoms is the answer set of a *positive* program  $\Pi$ .

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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:

 $A_0 \lor \neg A_1 \lor \cdots \lor \neg A_m$ 

#### 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 set of clauses.

Given a positive program  $\Pi$ ,  $Cn(\Pi)$  corresponds to the smallest model of the set of definite clauses corresponding to  $\Pi$ .

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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:

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 $egamma_{\Phi} \quad q \quad \leftarrow \\
p \quad \leftarrow \quad q, \ \textit{not } r$ 

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

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$$egin{array}{ccc} p & \mapsto & 1 \ q & \mapsto & 1 \ r & \mapsto & 0 \end{array}$$

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

$$eggar{}
eggar{}
egg$$

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

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

 $\{p,q\}$ 

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

$$\begin{array}{rrrr} \Pi_{\Phi} & q & \leftarrow \\ p & \leftarrow & q, \ \textit{not} \ r \end{array}$$

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

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

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

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

- Note:  $Cn(\Pi^X)$  is the  $\subseteq$ -smallest (classical) model of  $\Pi^X$ .
- Note: Every atom in X is justified by an "applying rule from  $\Pi$ "
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# A closer look at $\Pi^X$

In other words, given a set X of atoms from  $\Pi$ ,

#### $\Pi^X$ is obtained from $\Pi$ by deleting

- **1** each rule having a *not* A in its body with  $A \in X$  and then
- 2 all negative atoms of the form *not* A in the bodies of the remaining rules.

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X	$\Pi^X$	$Cn(\Pi^X)$
Ø	$p \leftarrow p$	$\{q\}$ X
	$q \leftarrow$	
{ <i>p</i> }	$p \leftarrow p$	Ø×
{ <b>q</b> }	$egin{array}{ccc} p &\leftarrow p \ q &\leftarrow \end{array}$	$\{q\}$ $\checkmark$
{ <i>p</i> , <i>q</i> }	$p \leftarrow p$	Ø×



X	П <sup>X</sup>	$Cn(\Pi^X)$
Ø	$p \leftarrow p$	{q} X
	$q \leftarrow$	
{ <i>p</i> }	$p \leftarrow p$	Ø×
<i>{q}</i>	$egin{array}{ccc} p &\leftarrow p \ q &\leftarrow \end{array}  onumber \ q &\leftarrow \end{array}$	{q}
{ <i>p</i> , <i>q</i> }	$p \leftarrow p$	Ø×

X	П <sup>X</sup>	$Cn(\Pi^X)$
Ø	$p \leftarrow p$	{q} X
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{ <i>p</i> }	$p \leftarrow p$	Ø 🗡
{ <b>q</b> }	$egin{array}{cccc} p &\leftarrow p \ q &\leftarrow \end{array} \end{array}$	$\{q\}$
{ <i>p</i> , <i>q</i> }	$p \leftarrow p$	Ø 🗶

X	П <sup>X</sup>	$Cn(\Pi^X)$
Ø	$p \leftarrow p$	{q} X
	$q \leftarrow$	
{ <i>p</i> }	$p \leftarrow p$	Ø 🗡
<i>{q}</i>	$p \leftarrow p$	{q} 🖌
	$q \leftarrow$	
{ <i>p</i> , <i>q</i> }	$p \leftarrow p$	Ø 🗶

X	П <sup>X</sup>	$Cn(\Pi^X)$
Ø	$p \leftarrow p$	{q} X
	$q \leftarrow$	
{ <i>p</i> }	$p \leftarrow p$	Ø 🗡
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	$q \leftarrow$	
{ <i>p</i> , <i>q</i> }	$p \leftarrow p$	Ø 🗡





X	$\square^X$	$Cn(\Pi^X)$
Ø	$p \leftarrow$	$\{p,q\}$ X
	$q \leftarrow$	
{ <i>p</i> }	$p \leftarrow$	{ <i>p</i> }
<i>{q}</i>	$q \leftarrow$	{q}
{ <i>p</i> , <i>q</i> }		ØX

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Ø	$p \leftarrow$	$\{p,q\}$ X
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{ <i>p</i> }	$p \leftarrow$	{ <i>p</i> } ✓
<i>{q}</i>	$q \leftarrow$	{q}
{ <i>p</i> , <i>q</i> }		Ø×





#### $\Pi = \{p \leftarrow \textit{not } p\}$



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### Answer set: Some properties

#### A logic program may have zero, one, or multiple answer sets!

- If X is an answer set of a logic program Π, then X is a model of Π (seen as a formula).
- If X and Y are answer sets of a *normal* program  $\Pi$ , then  $X \not\subset Y$ .

#### Answer set: Some properties

- A logic program may have zero, one, or multiple answer sets!
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Let  $\Pi$  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  $r \in \Pi$ : Set of variable-free rules obtained by replacing all variables in r by elements from T:

 $ground(r) = \{r\theta \mid \theta : var(r) \to \mathcal{T}\}$ 

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

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

Let  $\Pi$  be a logic program.

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

# An example

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

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

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

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

Intelligent Grounding aims at reducing the ground instantiation.

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Modeling and Solving in ASP

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### Answer sets of programs with Variables

Let  $\Pi$  be a normal logic program with variables.

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### Problem solving in ASP: Extended Syntax



Variables (over the Herbrand Universe)

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

**Conditional Literals** 

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

Disjunction

 $p(X) \mid q(X) := r(X)$ 

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)

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

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Disjunction

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

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### Problem solving in ASP: Reasoning Modes



# **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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#### **13** ASP Solving Process

14 Problems as Logic ProgramsGraph Coloring

#### 15 Methodology

- Satisfiability
- Queens
- Reviewer Assignment
- Planning

### Modeling and Interpreting



# Modeling

For solving a problem class P for a problem instance I, encode

- **1** the problem instance I as a set C(I) of facts and
- 2 the problem class P as a set C(P) of rules

such that the solutions to P for I can be (polynomially) extracted from the answer sets of  $C(I) \cup C(P)$ .

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### Basic Modeling: Overview

#### ASP Solving Process

# 14 Problems as Logic Programs■ Graph Coloring

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- Satisfiability
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#### ASP Solving Process



#### node(1..6).

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

col(r). col(b). col(g).

```
1 {color(X,C) : col(C)} 1 :- node(X).
```

```
:- edge(X,Y), color(X,C), color(Y,C).
```

node(1..6).

```
edge(1, 2).
            edge(1,3).
                         edge(1, 4).
edge(2, 4).
            edge(2,5).
                         edge(2,6).
edge(3, 1).
            edge(3, 4).
                         edge(3,5).
edge(4, 1).
            edge(4, 2).
edge(5,3).
            edge(5,4).
                         edge(5,6).
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#### ASP Solving Process



#### Graph Coloring: Grounding

#### \$ gringo -t color.lp

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```
node(1). node(2). node(3). node(4). node(5). node(6).
edge(1,2).
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                                    edge(6.3).
                                                 edge(6.5).
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1 {color(6,r), color(6,b), color(6,g)} 1.
 :- color(1,r), color(2,r).
                             :- color(2,g), color(5,g). ...
                                                              := color(6,r), color(2,r).
 :- color(1,b), color(2,b).
                             :- color(2,r), color(6,r).
                                                              := color(6,b), color(2,b),
 :- color(1,g), color(2,g).
                             := color(2,b), color(6,b).
                                                              :- color(6,g), color(2,g).
 :- color(1,r), color(3,r).
                             :- color(2,g), color(6,g).
                                                              :- color(6,r), color(3,r).
 := color(1,b), color(3,b).
                             :- color(3,r), color(1,r).
                                                              := color(6,b), color(3,b),
 :- color(1,g), color(3,g).
                             := color(3,b), color(1,b).
                                                              :- color(6,g), color(3,g).
 :- color(1,r), color(4,r).
                             :- color(3,g), color(1,g).
                                                              := color(6,r), color(5,r).
 :- color(1,b), color(4,b).
                             :- color(3,r), color(4,r).
                                                              := color(6,b), color(5,b).
 :- color(1,g), color(4,g).
                             := color(3,b), color(4,b).
                                                              := color(6.g), color(5.g).
 :- color(2,r), color(4,r).
                             := color(3,g), color(4,g).
 := color(2,b), color(4,b).
                             := color(3,r), color(5,r).
 :- color(2,g), color(4,g).
                             := color(3,b), color(5,b).
 Torsten Schaub et al. (KRR@UP)
                                          Modeling and Solving in ASP
```

#### ASP Solving Process



#### Graph Coloring: Solving

#### \$ gringo color.lp | clasp 0

```
Clasp version 1.2.1

Reading from stdin

Reading : Done(0.000s)

Preprocessing: Done(0.000s)

Solving...

Answer: 1

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

Answer: 2

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

Answer: 3

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

Answer: 4

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

Answer: 5

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

Answer: 6

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

Models : 6
```

Fime : 0.000 (Solving: 0.000)

#### Graph Coloring: Solving

#### \$ gringo color.lp | clasp 0

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

#### Basic Modeling: Overview

#### ASP Solving Process

Problems as Logic ProgramsGraph Coloring

#### 15 Methodology

- Satisfiability
- Queens
- Reviewer Assignment
- Planning

#### Basic Methodology

Generate and Test (or: Guess and Check) approach

Generator Generate potential answer set candidates (typically through non-deterministic constructs) Tester Eliminate invalid candidates (typically through integrity constraints)

#### Nutshell

## Logic program = Data + Generator + Tester (+ Optimizer)

#### Basic Methodology

Generate and Test (or: Guess and Check) approach

Generator Generate potential answer set candidates (typically through non-deterministic constructs) Tester Eliminate invalid candidates (typically through integrity constraints)

#### Nutshell

# Logic program = Data + Generator + Tester (+ Optimizer)

## Satisfiability

• Problem Instance: A propositional formula  $\phi$  in CNF.

Problem Class: Is there an assignment of propositional variables to true and false such that a given formula φ is true.

Example: Consider formula  $(a \lor \neg b) \land (\neg a \lor b)$ .

Logic Program:



## Satisfiability

• Problem Instance: A propositional formula  $\phi$  in CNF.

Problem Class: Is there an assignment of propositional variables to true and false such that a given formula φ is true.

• Example: Consider formula  $(a \lor \neg b) \land (\neg a \lor b)$ .

■ Logic Program:

Generator	Tester	Stable models
${a,b} \leftarrow$	$\leftarrow$ not a, b	$X_1 = \{a,b\}$
	$\leftarrow$ a, not b	$X_2 = \{\}$

#### Queens

## The n-Queens Problem



- Place *n* queens on an  $n \times n$ chess board
- Queens must not attack one another



## Defining the Field

#### queens.lp

row(1..n). col(1..n).

- Create file queens.lpDefine the field
  - n rows
  - n columns

#### Defining the Field

Running . . .

```
$ clingo queens.lp -c n=5
Answer: 1
row(1) row(2) row(3) row(4) row(5) \
col(1) col(2) col(3) col(4) col(5)
SATISFIABLE
```

Models	:	1
Time	:	0.000
Prepare	:	0.000
Prepro.	:	0.000
Solving	:	0.000

## Placing some Queens

```
queens.lp
```

```
row(1..n).
col(1..n).
{ queen(I,J) : row(I) : col(J) }.
```

• Guess a solution candidate

Place some queens on the board

## Placing some Queens

Running ...

```
$ clingo queens.lp -c n=5 3
Answer: 1
row(1) row(2) row(3) row(4) row(5) \setminus
col(1) col(2) col(3) col(4) col(5)
Answer: 2
row(1) row(2) row(3) row(4) row(5) \setminus
col(1) col(2) col(3) col(4) col(5) queen(1,1)
Answer: 3
row(1) row(2) row(3) row(4) row(5) \setminus
col(1) col(2) col(3) col(4) col(5) queen(2,1)
SATISFIABLE
```

#### Models : 3+

## Placing some Queens: Answer 1



# Placing some Queens: Answer 2



# Placing some Queens: Answer 3



#### Queens

## Placing *n* Queens

```
queens.lp
```

```
row(1..n).
col(1..n).
{ queen(I,J) : row(I) : col(J) }.
:= not n { queen(I,J) } n.
```

#### Place exactly n queens on the board

## Placing *n* Queens

Running . . .

```
$ clingo queens.lp -c n=5 2
Answer: 1
row(1) row(2) row(3) row(4) row(5) \setminus
col(1) col(2) col(3) col(4) col(5) 
queen(5,1) queen(4,1) queen(3,1) \setminus
queen(2,1) queen(1,1)
Answer: 2
row(1) row(2) row(3) row(4) row(5) \setminus
col(1) col(2) col(3) col(4) col(5) \setminus
queen(1,2) queen(4,1) queen(3,1) \setminus
queen(2,1) queen(1,1)
```

. . .

Queens

## Placing *n* Queens: Answer 1



Queens

## Placing *n* Queens: Answer 2



#### Horizontal and vertical Attack

queens.lp

```
row(1..n).
col(1..n).
{ queen(I,J) : row(I) : col(J) }.
:- not n { queen(I,J) } n.
:- queen(I,J), queen(I,JJ), J != JJ.
:- queen(I,J), queen(II,J), I != II.
```

Forbid horizontal attacks

Forbid vertical attacks

#### Horizontal and vertical Attack

queens.lp

```
row(1..n).
col(1..n).
{ queen(I,J) : row(I) : col(J) }.
:- not n { queen(I,J) } n.
:- queen(I,J), queen(I,JJ), J != JJ.
:- queen(I,J), queen(II,J), I != II.
```

Forbid horizontal attacks

Forbid vertical attacks

#### Horizontal and vertical Attack

Running . . .

. . .

```
$ clingo queens.lp -c n=5
Answer: 1
row(1) row(2) row(3) row(4) row(5) \
col(1) col(2) col(3) col(4) col(5) \
queen(5,5) queen(4,4) queen(3,3) \
queen(2,2) queen(1,1)
```

# Horizontal and vertical Attack: Answer 1



## Diagonal Attack

queens.lp

```
row(1..n).
col(1..n).
\{ queen(I,J) : row(I) : col(J) \}.
:= not n { queen(I,J) } n.
:- queen(I,J), queen(I,JJ), J != JJ.
:- queen(I,J), queen(II,J), I != II.
:- queen(I,J), queen(II,JJ), (I,J) != (II,JJ),
   I-J == II-JJ.
:- queen(I,J), queen(II,JJ), (I,J) != (II,JJ),
   I+J == II+JJ.
```

#### Forbid diagonal attacks

## **Diagonal Attack**

Running ...

```
$ clingo queens.lp -c n=5
Answer: 1
row(1) row(2) row(3) row(4) row(5) \
col(1) col(2) col(3) col(4) col(5) \
queen(4,5) queen(1,4) queen(3,3) \
queen(5,2) queen(2,1)
SATISFIABLE
```

Models	:	1+
Time	:	0.000
Prepare	:	0.000
Prepro.	:	0.000
Solving	:	0.000

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#### Queens

## Diagonal Attack: Answer 1



## Optimizing

queens-opt.lp

- 1 { queen(I,1..n) } 1 :- I = 1..n. 1 { queen(1..n,J) } 1 :- J = 1..n. :- { queen(D-J,J) } 2, D = 2..2\*n. :- { queen(D+J,J) } 2, D = 1-n..n-1.
  - Encoding can be optimized
  - Much faster to solve
  - See Section *Tweaking N*-*Queens*
reviewer(r1). paper(p1). classA(r1,p1). classB(r1,p2). coi(r1,p3). reviewer(r2). paper(p2). classA(r1,p3). classB(r1,p4). coi(r1,p6). ...

3 { assigned(P,R) : reviewer(R) } 3 :- paper(P).

```
:- assigned(P,R), coi(R,P).
:- assigned(P,R), not classA(R,P), not classB(R,P).
:- 9 { assigned(P,R) : paper(P) } , reviewer(R).
:- { assigned(P,R) : paper(P) } 6, reviewer(R).
```

```
assignedB(P,R) :- classB(R,P), assigned(P,R).
:- 3 { assignedB(P,R) : paper(P) }, reviewer(R).
```

#minimize { assignedB(P,R) : paper(P) : reviewer(R) }

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

#### 3 { assigned(P,R) : reviewer(R) } 3 :- paper(P).

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```

```
assignedB(P,R) :- classB(R,P), assigned(P,R).
:- 3 { assignedB(P,R) : paper(P) }, reviewer(R).
```

```
#minimize { assignedB(P,R) : paper(P) : reviewer(R) }
```

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

3 { assigned(P,R) : reviewer(R) } 3 :- paper(P).

```
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```

```
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Torsten Schaub et al. (KRR@UP)

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

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:- { assigned(P,R) : paper(P) } 6, reviewer(R).
```

```
assignedB(P,R) :- classB(R,P), assigned(P,R).
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```

```
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```

Torsten Schaub et al. (KRR@UP)

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

3 { assigned(P,R) : reviewer(R) } 3 :- paper(P).

```
:- assigned(P,R), coi(R,P).
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```

```
assignedB(P,R) :- classB(R,P), assigned(P,R).
:- 3 { assignedB(P,R) : paper(P) }, reviewer(R).
```

```
#minimize { assignedB(P,R) : paper(P) : reviewer(R) }.
```

## Simplistic STRIPS Planning

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

time(1..k). lasttime(T) :- time(T), not time(T+1).

```
holds(P,0) :- init(P).
```

```
1 { occ(A,T) : action(A) } 1 :- time(T).
:- occ(A,T), pre(A,F), not holds(F,T-1).
```

```
ocdel(F,T) :- occ(A,T), del(A,F).
holds(F,T) :- occ(A,T), add(A,F).
holds(F,T) :- holds(F,T-1), not ocdel(F,T), time(T).
```

:- query(F), not holds(F,T), lasttime(T).

## Simplistic STRIPS Planning

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

## Simplistic STRIPS Planning

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

## Language Extensions: Overview

- 16 Motivation
- 17 Integrity Constraints
- 18 Choice Rules
- **19** Cardinality Constraints
- 20 Weight Constraints
- 21 Optimization statements
- 22 Conditional literals
- 23 smodels format

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#### Language extensions

- The expressiveness of a language can be enhanced by introducing new constructs
- To this end, we must address the following issues:
  - What is the syntax of the new language construct?
  - What is the semantics of the new language construct?
  - How to implement the new language construct?
- A way of providing semantics is to furnish a translation removing the new constructs, eg. classical negation
- This translation might also be used for implementing the language extension

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# Integrity Constraints

Idea Eliminate unwanted solution candidates
Syntax An integrity constraint is of the form

 $\leftarrow A_1, \ldots, A_m, not \ A_{m+1}, \ldots, not \ A_n,$ 

where  $n \ge m \ge 1$ , and each  $A_i$   $(1 \le i \le n)$  is a atom

Example :- edge(X,Y), color(X,C), color(Y,C).
 Embedding For a new symbol x, map

 $\begin{array}{cccc} \leftarrow & A_1, \dots, A_m, \, not \, A_{m+1}, \dots, \, not \, A_n \\ \mapsto & x \ \leftarrow & A_1, \dots, A_m, \, not \, A_{m+1}, \dots, \, not \, A_n, \, not \, x \end{array}$ 

Another example  $\Pi = \{p \leftarrow not \ q, \ q \leftarrow not \ p\}$ versus  $\Pi' = \Pi \cup \{\leftarrow p\}$  and  $\Pi'' = \Pi \cup \{\leftarrow not \ p\}$ 

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■ Another example  $\Pi = \{p \leftarrow not \ q, \ q \leftarrow not \ p\}$ versus  $\Pi' = \Pi \cup \{\leftarrow p\}$  and  $\Pi'' = \Pi \cup \{\leftarrow not \ p\}$ 

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## Choice rules

Idea Choices over subsetsSyntax

$$\{A_1,\ldots,A_m\} \leftarrow A_{m+1},\ldots,A_n, not A_{n+1},\ldots, not A_o,$$

- Informal meaning If the body is satisfied in an answer set, then any subset of {A<sub>1</sub>,..., A<sub>m</sub>} can be included in the answer set
   ■ Example 1 {color(X,C) : col(C)} 1 :- node(X).
- Another Example Program Π = { {a} ← b, b ← } has two answer sets: {b} and {a, b}

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# Embedding in normal logic programs

A choice rule of form

$$\{A_1,\ldots,A_m\} \leftarrow A_{m+1},\ldots,A_n, not A_{n+1},\ldots, not A_o$$

can be translated into 2m + 1 rules

$$A \leftarrow A_{m+1}, \dots, A_n, \text{ not } A_{n+1}, \dots, \text{ not } A_o$$
  
$$A_1 \leftarrow A, \text{ not } \overline{A_1} \quad \dots \quad A_m \leftarrow A, \text{ not } \overline{A_m}$$
  
$$\overline{A_1} \leftarrow \text{ not } A_1 \quad \dots \quad \overline{A_m} \leftarrow \text{ not } A_m$$

by introducing new atoms  $A, \overline{A_1}, \ldots, \overline{A_m}$ 

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# Cardinality constraints

Syntax A (positive) cardinality constraint is of the form

 $I \{A_1,\ldots,A_m\} u$ 

 Informal meaning A cardinality constraint is satisfied in an answer set X, if the number of atoms from {A<sub>1</sub>,..., A<sub>m</sub>} satisfied in X is between l and u (inclusive) More formally, if l ≤ |{A<sub>1</sub>,..., A<sub>m</sub>} ∩ X| ≤ u
 Example 2 {hd(a),...,hd(m)} 4

Conditions  $I \{A_1 : B_1, \dots, A_m : B_m\} u$ where  $B_1, \dots, B_m$  are used for restricting instantiations of variables occurring in  $A_1, \dots, A_m$ 

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# Cardinality rules

Syntax

$$A_0 \leftarrow I \{A_1, \ldots, A_m, not \ A_{m+1}, \ldots, not \ A_n\}$$

Informal meaning If at least *l* elements of the "body" are true in an answer set, then add A<sub>0</sub> to the answer set

I is a lower bound on the "body"

• Example Program  $\Pi = \{ a \leftarrow 1\{b, c\}, b \leftarrow \}$  has answer set  $\{a, b\}$ 

#### Embedding in normal logic programs

Replace each cardinality rule

$$A_0 \leftarrow I \{A_1, \ldots, A_m\}$$
 by  $A_0 \leftarrow cc(A_1, I)$ 

where atom  $cc(A_i, j)$  represents the fact that at least j of the atoms in  $\{A_i, \ldots, A_m\}$ , that is, of the atoms that have an equal or greater index than i, are in a particular answer set

■ The definition of *cc*(*A<sub>i</sub>*,*j*) is given by the rules

$$egin{array}{rll} cc(A_i,j{+}1) &\leftarrow cc(A_{i+1},j),A_i\ cc(A_i,j) &\leftarrow cc(A_{i+1},j)\ cc(A_{m+1},0) &\leftarrow \end{array}$$

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### ... and vice versa

#### A normal rule

$$A_0 \leftarrow A_1, \ldots, A_m$$
, not  $A_{m+1}, \ldots$ , not  $A_n$ ,

can be represented by the cardinality rule

$$A_0 \leftarrow n \{A_1, \ldots, A_m, not A_{m+1}, \ldots, not A_n\}$$

# Cardinality rules with upper bounds

A rule of the form

$$A_0 \leftarrow I \{A_1, \ldots, A_m, not \ A_{m+1}, \ldots, not \ A_n\} \ u$$

stands for

 $\begin{array}{rcl} A_0 & \leftarrow & B, \ not \ C \\ B & \leftarrow & I \ \{A_1, \dots, A_m, \ not \ A_{m+1}, \dots, \ not \ A_n\} \\ C & \leftarrow & u+1 \ \{A_1, \dots, A_m, \ not \ A_{m+1}, \dots, \ not \ A_n\} \end{array}$ 

#### Cardinality constraints as heads

A rule of the form

$$I \{A_1,\ldots,A_m\} \ u \leftarrow A_{m+1},\ldots,A_n, not \ A_{n+1},\ldots, not \ A_o,$$

stands for

$$B \leftarrow A_{m+1}, \dots, A_n, \text{ not } A_{n+1}, \dots, \text{ not } A_o$$
  
$$\{A_1, \dots, A_m\} \leftarrow B$$
  
$$C \leftarrow l \{A_1, \dots, A_m\} u$$
  
$$\leftarrow B, \text{ not } C$$

#### Full-fledged cardinality rules

#### A rule of the form

 $I_0 S_0 u_0 \leftarrow I_1 S_1 u_1, \ldots, I_n S_n u_n$ 

where  ${\cal A}$  is the underlying alphabet

#### Full-fledged cardinality rules

#### A rule of the form

 $I_0 S_0 u_0 \leftarrow I_1 S_1 u_1, \ldots, I_n S_n u_n$ stands for 0 < i < n $B_i \leftarrow I_i S_i$  $C_i \leftarrow u_i + 1 S_i$  $A \leftarrow B_1, \ldots, B_n, not C_1, \ldots, not C_n$  $\leftarrow$  A. not  $B_0$  $\leftarrow A, C_0$  $S_0 \cap \mathcal{A} \leftarrow \mathcal{A}$ where  $\mathcal{A}$  is the underlying alphabet

# Language Extensions: Overview

- 16 Motivation
- **17** Integrity Constraints
- 18 Choice Rules
- 19 Cardinality Constraints
- 20 Weight Constraints
- 21 Optimization statements
- 22 Conditional literals
- 23 smodels format

### Weight constraints

• Syntax / 
$$[A_1 = w_1, ..., A_m = w_m,$$
  
not  $A_{m+1} = w_{m+1}, ..., not A_n = w_n] u$ 

 Informal meaning A weight constraint is satisfied in an answer set X, if

$$l \leq \left(\sum_{1 \leq i \leq m, A_i \in X} w_i + \sum_{m < i \leq n, A_i \notin X} w_i\right) \leq u$$

➡ Generalization of cardinality constraints
 ■ Example 80 [hd(a)=50,...,hd(m)=100] 400

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Torsten Schaub et al. (KRR@UP)
## Optimization statements

- Idea Compute optimal answer sets by minimizing (or maximizing) a weighted sum of given elements
- Syntax

■ #minimize 
$$[A_1 = w_1, ..., A_m = w_m,$$
  
not  $A_{m+1} = w_{m+1}, ...,$  not  $A_n = w_n]$   
■ #maximize  $[A_1 = w_1, ..., A_m = w_m,$   
not  $A_{m+1} = w_{m+1}, ...,$  not  $A_n = w_n]$ 

### Example

Multi-criteria optimization can be accomplished by adding priority levels to weighted literals, that is, by replacing  $L_i = w_i$  by  $L_i = w_i @P_i$ 

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Example

■ #minimize [road(X,Y) : length(X,Y,L) = L]

Multi-criteria optimization can be accomplished by adding priority levels to weighted literals, that is, by replacing L<sub>i</sub> = w<sub>i</sub> by L<sub>i</sub> = w<sub>i</sub>@P<sub>i</sub>

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# Conditional literals

- Idea Encode the contents of a (multi-)set without enumerating its elements
- Syntax  $A_0: A_1: \ldots: A_m: not A_{m+1}: \ldots: not A_n$
- Informal meaning List all ground instances of A<sub>0</sub> such that corresponding instances of A<sub>1</sub>,..., A<sub>m</sub>, not A<sub>m+1</sub>,..., not A<sub>n</sub> are true
- Example Given 'p(1). p(2). p(3). q(2).' the choice
  - ${r(X) : p(X) : not q(X)}.$
  - is instantiated to
    - ${r(1), r(3)}.$

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# smodels format

Logic programs in *smodels* format consist of

- normal rules
- choice rules
- cardinality rules
- weight rules
- optimization statements

Such a format is obtained by grounders *lparse* and gringo

# Conflict-Driven Answer Set Solving: Overview

### 24 Motivation

25 Boolean Constraints

#### 26 Nogoods from Logic Programs

- Nogoods from program completion
- Nogoods from loop formulas

#### 27 Conflict-Driven Nogood Learning

- CDNL-ASP Algorithm
- Nogood Propagation
- Conflict Analysis

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# Motivation

 Goal Approach to computing answer sets of logic programs, based on concepts from

- Constraint Processing (CP) and
- Satisfiability Checking (SAT)
- Idea View inferences in ASP as unit propagation on nogoods

Benefits

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

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• An assignment A over  $dom(A) = atom(\Pi) \cup body(\Pi)$  is a sequence

 $(\sigma_1,\ldots,\sigma_n)$ 

of signed literals  $\sigma_i$  of form  $\mathsf{T}p$  or  $\mathsf{F}p$  for  $p \in dom(A)$  and  $1 \le i \le n$ .  $\square$   $\mathsf{T}p$  expresses that p is *true* and  $\mathsf{F}p$  that it is *false*.

The complement,  $\overline{\sigma}$ , of a literal  $\sigma$  is defined as  $\overline{\mathbf{T}p} = \mathbf{F}p$  and  $\overline{\mathbf{F}p} = \mathbf{T}p$ .

 $\blacksquare$   $A \circ B$  denotes the concatenation of assignments A and B.

Given  $A = (\sigma_1, \ldots, \sigma_{k-1}, \sigma_k, \ldots, \sigma_n)$ , we let  $A[\sigma_k] = (\sigma_1, \ldots, \sigma_{k-1})$ .

We sometimes identify an assignment with the set of its literals. Given this, we access *true* and *false* propositions in A via

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 $\mathcal{A}^\mathsf{T} = \{ p \in \mathit{dom}(A) \mid \mathsf{T}p \in A \} \; \; \mathsf{and} \; \; \mathcal{A}^\mathsf{F} = \{ p \in \mathit{dom}(A) \mid \mathsf{F}p \in A \} \; .$ 

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- A nogood is a set {σ<sub>1</sub>,...,σ<sub>n</sub>} of signed literals, expressing a constraint violated by any assignment containing σ<sub>1</sub>,...,σ<sub>n</sub>.
- An assignment A such that  $A^{\mathsf{T}} \cup A^{\mathsf{F}} = dom(A)$  and  $A^{\mathsf{T}} \cap A^{\mathsf{F}} = \emptyset$ is a solution for a set  $\Delta$  of nogoods, if  $\delta \not\subseteq A$  for all  $\delta \in \Delta$ .
- For a nogood  $\delta$ , a literal  $\sigma \in \delta$ , and an assignment A, we say that  $\overline{\sigma}$  is unit-resulting for  $\delta$  wrt A, if

1 
$$\delta \setminus A = \{\sigma\}$$
 and  
2  $\overline{\sigma} \notin A$ .

For a set  $\Delta$  of nogoods and an assignment A, unit propagation is the iterated process of extending A with unit-resulting literals until no further literal is unit-resulting for any nogood in  $\Delta$ .

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via program completion

The completion of a logic program  $\Pi$  can be defined as follows:

$$\{p_{\beta} \leftrightarrow p_{1} \wedge \dots \wedge p_{m} \wedge \neg p_{m+1} \wedge \dots \wedge \neg p_{n} \mid \\ \beta \in body(\Pi), \beta = \{p_{1}, \dots, p_{m}, not \ p_{m+1}, \dots, not \ p_{n}\}\}$$

 $\cup \quad \{p \leftrightarrow p_{\beta_1} \lor \cdots \lor p_{\beta_k} \mid \\ p \in atom(\Pi), body(p) = \{\beta_1, \dots, \beta_k\}\},$ 

where  $body(p) = \{body(r) \mid r \in \Pi, head(r) = p\}$ .

via program completion

Let  $\beta = \{p_1, \ldots, p_m, not \ p_{m+1}, \ldots, not \ p_n\}$  be a body.

The equivalence

$$p_{\beta} \leftrightarrow p_1 \wedge \cdots \wedge p_m \wedge \neg p_{m+1} \wedge \cdots \wedge \neg p_n$$

can be decomposed into two implications.

### 1 We get

$$p_{\beta} \rightarrow p_1 \wedge \cdots \wedge p_m \wedge \neg p_{m+1} \wedge \cdots \wedge \neg p_n$$

which is equivalent to the conjunction of

$$\neg p_{\beta} \lor p_1, \ldots, \neg p_{\beta} \lor p_m, \neg p_{\beta} \lor \neg p_{m+1}, \ldots, \neg p_{\beta} \lor \neg p_n$$

This set of clauses expresses the following set of nogoods:

 $\Delta(\beta) = \{ \{ \mathsf{T}\beta, \mathsf{F}p_1 \}, \dots, \{ \mathsf{T}\beta, \mathsf{F}p_m \}, \{ \mathsf{T}\beta, \mathsf{T}p_{m+1} \}, \dots, \{ \mathsf{T}\beta, \mathsf{T}p_n \} \}$ 

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can be decomposed into two implications.

2 The converse of the previous implication, viz.

$$p_1 \wedge \cdots \wedge p_m \wedge \neg p_{m+1} \wedge \cdots \wedge \neg p_n \rightarrow p_\beta$$

gives rise to the nogood

 $\delta(\beta) = \{\mathsf{F}\beta, \mathsf{T}p_1, \ldots, \mathsf{T}p_m, \mathsf{F}p_{m+1}, \ldots, \mathsf{F}p_n\}$ 

Intuitively,  $\delta(\beta)$  is a constraint enforcing the truth of body  $\beta$ , or the falsity of a contained literal.

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via program completion

Proceeding analogously with the atom-based equivalences, viz.

 $p \leftrightarrow p_{\beta_1} \lor \cdots \lor p_{\beta_k}$ 

we obtain for an atom  $p \in atom(\Pi)$  along with its bodies  $body(p) = \{\beta_1, \dots, \beta_k\}$  the nogoods

 $\Delta(p) = \{ \{ \mathsf{F}p, \mathsf{T}\beta_1 \}, \dots, \{ \mathsf{F}p, \mathsf{T}\beta_k \} \} \text{ and } \delta(p) = \{ \mathsf{T}p, \mathsf{F}\beta_1, \dots, \mathsf{F}\beta_k \}.$ 

atom-oriented nogoods

For an atom p where  $body(p) = \{\beta_1, \ldots, \beta_k\}$ , recall that

$$\delta(p) = \{\mathsf{T}p, \mathsf{F}\beta_1, \dots, \mathsf{F}\beta_k\}$$
  
$$\Delta(p) = \{\{\mathsf{F}p, \mathsf{T}\beta_1\}, \dots, \{\mathsf{F}p, \mathsf{T}\beta_k\}\}.$$

For example, for atom x with  $body(x) = \{\{y\}, \{not \ z\}\}$ , we obtain

For nogood  $\delta(x) = \{Tx, F\{y\}, F\{not z\}\}$ , the signed literal Fx is unit-resulting wrt assignment (F{y}, F{not z}) and T{not z} is unit-resulting wrt assignment (Tx, F{y})

atom-oriented nogoods

For an atom p where  $body(p) = \{\beta_1, \ldots, \beta_k\}$ , recall that

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For a body  $\beta = \{p_1, \dots, p_m, not \ p_{m+1}, \dots, not \ p_n\}$ , recall that

$$\begin{aligned} \delta(\beta) &= \{ \mathsf{F}\beta, \mathsf{T}p_1, \dots, \mathsf{T}p_m, \mathsf{F}p_{m+1}, \dots, \mathsf{F}p_n \} \\ \Delta(\beta) &= \{ \{ \mathsf{T}\beta, \mathsf{F}p_1 \}, \dots, \{ \mathsf{T}\beta, \mathsf{F}p_m \}, \{ \mathsf{T}\beta, \mathsf{T}p_{m+1} \}, \dots, \{ \mathsf{T}\beta, \mathsf{T}p_n \} \} . \end{aligned}$$

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$$\begin{vmatrix} \dots \leftarrow x, \text{ not } y \\ \vdots \\ \dots \leftarrow x, \text{ not } y \end{vmatrix} \delta(\{x, \text{ not } y\}) = \{ \mathsf{F}\{x, \text{ not } y\}, \mathsf{T}x, \mathsf{F}y \} \\ \Delta(\{x, \text{ not } y\}) = \{ \{\mathsf{T}\{x, \text{ not } y\}, \mathsf{F}x\}, \{\mathsf{T}\{x, \text{ not } y\}, \mathsf{T}y\} \} \end{vmatrix}$$

For nogood δ({x, not y}) = {F{x, not y}, Tx, Fy}, the signed literal
T{x, not y} is unit-resulting wrt assignment (Tx, Fy) and
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# Characterization of answer sets for tight logic programs

#### Let $\Pi$ be a logic program and

 $\begin{aligned} \Delta_{\Pi} &= \{\delta(p) \mid p \in atom(\Pi)\} \cup \{\delta \in \Delta(p) \mid p \in atom(\Pi)\} \\ &\cup \{\delta(\beta) \mid \beta \in body(\Pi)\} \cup \{\delta \in \Delta(\beta) \mid \beta \in body(\Pi)\} . \end{aligned}$ 

#### Theorem

Let  $\Pi$  be a tight logic program. Then,  $X \subseteq atom(\Pi)$  is an answer set of  $\Pi$  iff  $X = A^{\mathsf{T}} \cap atom(\Pi)$  for a (unique) solution A for  $\Delta_{\Pi}$ .

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Torsten Schaub et al. (KRR@UP)

## Nogoods from logic programs via loop formulas

Let  $\Pi$  be a normal logic program and recall that:

For L ⊆ atom(Π), the external supports of L for Π are
 ES<sub>Π</sub>(L) = {r ∈ Π | head(r) ∈ L, body(r)<sup>+</sup> ∩ L = ∅}.
 The (disjunctive) loop formula of L for Π is

$$LF_{\Pi}(L) = (\bigvee_{A \in L} A) \to (\bigvee_{r \in ES_{\Pi}(L)} body(r))$$
  
$$\equiv (\bigwedge_{r \in ES_{\Pi}(L)} \neg body(r)) \to (\bigwedge_{A \in L} \neg A)$$

The loop formula of L enforces all atoms in L to be *false* whenever L is not externally supported.

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## ■ The external bodies of L for $\Pi$ are $EB(L) = \{body(r) \mid r \in ES_{\Pi}(L)\}$

For a logic program Π and some Ø ⊂ U ⊆ atom(Π), define the loop nogood of an atom p ∈ U as λ(p, U) = {Tp, Fβ₁,..., Fβk} where EB(U) = {β₁,..., βk}.
In all, we get the following set of loop nogoods for Π: Λ<sub>Π</sub> = ⋃<sub>Ø⊂U⊆atom(Π)</sub>{λ(p, U) | p ∈ U}
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For a logic program Π and some Ø ⊂ U ⊆ atom(Π), define the loop nogood of an atom p ∈ U as λ(p, U) = {Tp, Fβ₁,..., Fβk} where EB(U) = {β₁,..., βk}.
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The set Λ<sub>Π</sub> of loop nogoods denies cyclic support among *true* atoms.

## Example

#### Consider

$$\Pi = \left\{ \begin{array}{ll} x \leftarrow not \ y & u \leftarrow x \\ y \leftarrow not \ x & u \leftarrow v \\ y \leftarrow not \ x & v \leftarrow u, y \end{array} \right\}$$

For u in the set  $\{u, v\}$ , we obtain the loop nogood:

$$\lambda(u, \{u, v\}) = \{\mathsf{T}u, \mathsf{F}\{x\}\}$$

Similarly for v in  $\{u, v\}$ , we get:

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### Characterization of answer sets

#### Theorem

Let  $\Pi$  be a logic program. Then,  $X \subseteq atom(\Pi)$  is an answer set of  $\Pi$  iff  $X = A^{\mathsf{T}} \cap atom(\Pi)$  for a (unique) solution A for  $\Delta_{\Pi} \cup \Lambda_{\Pi}$ .

#### Some remarks

Nogoods in Λ<sub>Π</sub> augment Δ<sub>Π</sub> with conditions checking for unfounded sets, in particular, those being loops.
 While |Δ<sub>Π</sub>| is linear in the size of Π, Λ<sub>Π</sub> may contain exponentially many (non-redundant) loop nogoods

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# Conflict-Driven Answer Set Solving: Overview

#### 24 Motivation

25 Boolean Constraints

26 Nogoods from Logic Programs

- Nogoods from program completion
- Nogoods from loop formulas

27 Conflict-Driven Nogood Learning

- CDNL-ASP Algorithm
- Nogood Propagation
- Conflict Analysis

## Conflict-driven search

Boolean constraint solving algorithms pioneered for SAT led to:

- Traditional DPLL-style approach
  - (Unit) propagation
  - (Chronological) backtracking

Modern CDCL-style approach

- (Unit) propagation
- Conflict analysis (via resolution)
- Learning + Backjumping + Assertion

# DPLL-style solving

#### loop

propagate // compute deterministic consequences
if no conflict then
 if all variables assigned then return variable assignment
 else decide // non-deterministically assign some literal
else
 if top-level conflict then return unsatisfiable
 else
 backtrack // undo assignments made after last decision

// undo assignments made after last decision
// assign complement of last decision literal

flip

# CDCL-style solving

#### loop

propagate // compute deterministic consequences
if no conflict then
 if all variables assigned then return variable assignment
 else decide // non-deterministically assign some literal
else
 if top-level conflict then return unsatisfiable
 else
 analyze // analyze conflict and add a conflict constraint
 backjump // undo assignments until conflict constraint is unit

## Outline of CDNL-ASP algorithm

#### Keep track of deterministic consequences by unit propagation on:

- Program completion
- Loop nogoods, determined and recorded on demand
  - Dedicated unfounded set detection !
- Dynamic nogoods, derived from conflicts and unfounded sets

When a nogood in  $\Delta_{\Pi} \cup 
abla$  becomes violated:

- Analyze the conflict by resolution
- (until reaching a Unique Implication Point, short: UIP)
- E Learn the derived conflict nogood  $\delta$
- Backjump to the earliest (heuristic) choice such that the complement of the UIP is unit-resulting for  $\delta$
- Assert the complement of the UIP and proceed (by unit propagation)
- Terminate when either:
  - Finding an answer set (a solution for  $\Delta_{\Pi} \cup \Lambda_{\Pi}$ )
  - Deriving a conflict independently of (heuristic) choices

[Δ<sub>Π</sub>]

 $|\Lambda_{\Pi}|$ 

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#### Algorithm 1: CDNL-ASP

Input : A logic program П. Output : An answer set of  $\Pi$  or "no answer set".  $A \leftarrow \emptyset$ // assignment over  $atom(\Pi) \cup body(\Pi)$  $\nabla \leftarrow \emptyset$ // set of (dynamic) nogoods  $dl \leftarrow 0$ // decision level loop  $(A, \nabla) \leftarrow \mathsf{NogoodPropagation}(\Pi, \nabla, A)$ if  $\varepsilon \subset A$  for some  $\varepsilon \in \Delta_{\Pi} \cup \nabla$  then if dl = 0 then return no answer set  $(\delta, k) \leftarrow \text{ConflictAnalysis}(\varepsilon, \Pi, \nabla, A)$  $\nabla \leftarrow \nabla \cup \{\delta\}$ // learning  $A \leftarrow (A \setminus \{\sigma \in A \mid k < dl(\sigma)\})$ // backjumping  $dl \leftarrow k$ else if  $A^{\mathsf{T}} \cup A^{\mathsf{F}} = atom(\Pi) \cup body(\Pi)$  then return  $A^{\mathsf{T}} \cap atom(\Pi)$ // answer set else  $\sigma_d \leftarrow \text{Select}(\Pi, \nabla, A)$ // heuristic choice of  $\sigma_d \notin A$  $dl \leftarrow dl + 1$  $A \leftarrow A \circ (\sigma_d)$  $// dl(\sigma_d) = dl$ 

## Observations

- Decision level dl, initially set to 0, is used to count the number of heuristically chosen literals in assignment A.
- For a heuristically chosen literal  $\sigma_d = \mathbf{T}p$  or  $\sigma_d = \mathbf{F}p$ , respectively, we require  $p \in (atom(\Pi) \cup body(\Pi)) \setminus (A^{\mathsf{T}} \cup A^{\mathsf{F}})$ .
- For any literal  $\sigma \in A$ ,  $dl(\sigma)$  denotes the decision level of  $\sigma$ , viz. the value dl had when  $\sigma$  was assigned.
- A conflict is detected from violation of a nogood  $\varepsilon \subseteq \Delta_{\Pi} \cup \nabla$ .
- A conflict at decision level 0 (where *A* contains no heuristically chosen literals) indicates non-existence of answer sets.
- A nogood  $\delta$  derived by conflict analysis is asserting, that is, some literal is unit-resulting for  $\delta$  at a decision level k < dl.
  - After learning  $\delta$  and backjumping to decision level k,
    - at least one literal is newly derivable by unit propagation.
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dl	$\sigma_d$	$\overline{\sigma}$	δ
1	Тu		
2	$\mathbf{F}$ {not x, not y}		
		Fw	$\{Tw,F\{\textit{not }x,\textit{not }y\}\} = \delta(w)$
3	$\mathbf{F}\{not y\}$		
		Fx	$\{Tx,F\{not \ y\}\} = \delta(x)$
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Torsten Schaub et al. (KRR@UP)
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Derive deterministic consequences via:

- Unit propagation on  $\Delta_{\Pi}$  and  $\nabla$ ;
- Unfounded sets  $U \subseteq atom(\Pi)$ .
- Note that U is unfounded if  $EB(U) \subseteq A^{\mathsf{F}}$ .
  - ${}^{\hspace*{-0.5ex} {\scriptscriptstyle \mathbb{S}}}$  For any  $p\in U$ , we have  $(\lambda(p,U)\setminus\{{\sf T}p\})\subseteq A.$
- An "interesting" unfounded set *U* satisfies:

 $\emptyset \subset U \subseteq (\mathit{atom}(\Pi) \setminus A^{\mathsf{F}})$ .

Wrt a fixpoint of unit propagation, such an unfounded set contains some loop of Π.
Tight programs do not yield "interesting" unfounded sets !
Given an unfounded set U and some p ∈ U, adding λ(p, U) to ∇ triggers a conflict or further derivations by unit propagation.
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#### Algorithm 2: NogoodPropagation : A logic program $\Pi$ , a set $\nabla$ of nogoods, and an assignment A. Input Output : An extended assignment and set of nogoods. $U \leftarrow \emptyset$ // set of unfounded atoms loop repeat if $\delta \subseteq A$ for some $\delta \in \Delta_{\Pi} \cup \nabla$ then return $(A, \nabla)$ // conflict $\Sigma \leftarrow \{\delta \in \Delta_{\Pi} \cup \nabla \mid (\delta \setminus A) = \{\sigma\}, \overline{\sigma} \notin A\}$ // unit-resulting nogoods if $\Sigma \neq \emptyset$ then let $\sigma \in (\delta \setminus A)$ for some $\delta \in \Sigma$ in $| A \leftarrow A \circ (\overline{\sigma}) // dl(\overline{\sigma}) = max(\{dl(\rho) \mid \rho \in (\delta \setminus \{\sigma\})\} \cup \{0\})$ until $\Sigma = \emptyset$ if $\Pi$ is tight then return $(A, \nabla) / /$ no unfounded set $\emptyset \subset U \subset (atom(\Pi) \setminus A^{\mathsf{F}})$ else

 $\begin{bmatrix} U \leftarrow (U \setminus A^{\mathsf{F}}) \\ \text{if } U = \emptyset \text{ then } U \leftarrow \mathsf{UnfoundedSet}(\Pi, A) \\ \text{if } U = \emptyset \text{ then return } (A, \nabla) / / \text{ no unfounded set } \emptyset \subset U \subseteq (atom(\Pi) \setminus A^{\mathsf{F}}) \\ \text{let } p \in U \text{ in} \\ \Box \nabla \leftarrow \nabla \cup \{\lambda(p, U)\} / / \text{ record unit-resulting or violated loop nogood} \end{bmatrix}$ 

## Requirements for UnfoundedSet

Implementations of UnfoundedSet must guarantee the following for a result U

- 1  $U \subseteq (atom(\Pi) \setminus A^{\mathsf{F}})$
- 2  $EB(U) \subseteq A^{\mathsf{F}}$
- **3**  $U = \emptyset$  iff there is no nonempty unfounded subset of  $(atom(\Pi) \setminus A^{\mathsf{F}})$

Beyond that, there are various alternatives, such as:

- Calculating the greatest unfounded set
- Calculating unfounded sets within strongly connected components of the positive atom dependency graph of Π

Usually, the latter option is implemented in ASP solvers

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#### Example: NogoodPropagation

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		$T{v}$	$\{Tu,F\{x,y\},F\{v\}\}=\delta(u)$
		$T{u, y}$	$\{F\{u, y\}, Tu, Ty\} = \delta(\{u, y\})$
		Tν	$\{Fv,T\{u,y\}\}\in\Delta(v)$
			$\{Tu,F\{x\},F\{x,y\}\}=\lambda(u,\{u,v\})$

## Outline of ConflictAnalysis

- Conflict analysis is triggered whenever some nogood δ ∈ Δ<sub>Π</sub> ∪ ∇ becomes violated, viz. δ ⊆ A, at a decision level dl > 0.
  - Note that all but the first literal assigned at *dl* have been unit-resulting for nogoods ε ∈ Δ<sub>Π</sub> ∪ ∇.
  - If σ ∈ δ has been unit-resulting for ε, we obtain a new violated nogood by resolving δ and ε as follows:

 $(\delta \setminus \{\sigma\}) \cup (\varepsilon \setminus \{\overline{\sigma}\})$ .

Resolution is directed by resolving first over the literal  $\sigma \in \delta$  derived last, viz.  $(\delta \setminus A[\sigma]) = \{\sigma\}$ .

Iterated resolution progresses in inverse order of assignment.

- Iterated resolution stops as soon as it generates a nogood  $\delta$  containing exactly one literal  $\sigma$  assigned at decision level dl.
  - This literal  $\sigma$  is called First Unique Implication Point (First-UIP).
  - All literals in  $(\delta \setminus \{\sigma\})$  are assigned at decision levels smaller than dl.

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#### Algorithm 3: ConflictAnalysis

- **Input** : A violated nogood  $\delta$ , a logic program  $\Pi$ , a set  $\nabla$  of nogoods, and an assignment A.
- **Output** : A derived nogood and a decision level.

#### loop

$$\begin{array}{l} \textbf{let } \sigma \in \delta \text{ such that } (\delta \setminus A[\sigma]) = \{\sigma\} \text{ in} \\ k \leftarrow \max(\{dl(\rho) \mid \rho \in \delta \setminus \{\sigma\}\} \cup \{0\}) \\ \textbf{if } k = dl(\sigma) \text{ then} \\ \mid \textbf{let } \varepsilon \in \Delta_{\Pi} \cup \nabla \text{ such that } (\varepsilon \setminus A[\sigma]) = \{\overline{\sigma}\} \text{ in} \\ \mid & \buildrel \delta \leftarrow (\delta \setminus \{\sigma\}) \cup (\varepsilon \setminus \{\overline{\sigma}\}) \\ \textbf{else return } (\delta, k) \end{array}$$

// resolution

Consider

$$\Pi = \begin{cases} x \leftarrow not \ y & u \leftarrow x, y & v \leftarrow x & w \leftarrow not \ x, not \ y \\ y \leftarrow not \ x & u \leftarrow v & v \leftarrow u, y \end{cases}$$



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dl	$\sigma_d$	$\overline{\sigma}$	$\delta$	
1	Тu			
2	$F\{not x, not y\}$			
		Fw	$\{Tw, F\{not x, not y\}\} = \delta(w)$	
3	<b>F</b> {not y}			
		Fx	$\{Tx,F\{not \ y\}\} = \delta(x)$	
		<b>F</b> { <i>x</i> }	$\{T\{x\},Fx\}\in\Delta(\{x\})$	$\{\mathbf{T}u, \mathbf{F}x\}$
		$\mathbf{F}\{x, y\}$	$\{T\{x,y\},Fx\}\in\Delta(\{x,y\})$	$\{Tu, Fx, F\{x\}\}$
		$T{not x}$	$\{\mathbf{F}\{not \ x\}, \mathbf{F}x\} = \delta(\{not \ x\})$	
		Тy	$\{\mathbf{F}\{not \ y\}, \mathbf{F}y\} = \delta(\{not \ y\})$	
		$T\{v\}$	$\{Tu,F\{x,y\},F\{v\}\}=\delta(u)$	
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		Tv	$\{Fv,T\{u,y\}\}\in\Delta(v)$	
			$\{Tu,F\{x\},F\{x,y\}\}=\lambda(u,\{u,v\})$	×

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$$\Pi = \begin{cases} x \leftarrow not \ y & u \leftarrow x, y & v \leftarrow x & w \leftarrow not \ x, not \ y \\ y \leftarrow not \ x & u \leftarrow v & v \leftarrow u, y \end{cases}$$



There always is a First-UIP at which conflict analysis terminates.

- In the worst, resolution stops at the heuristically chosen literal assigned at decision level *dl*.
- The nogood  $\delta$  containing First-UIP  $\sigma$  is violated by A, viz.  $\delta \subseteq A$ .
- We have  $k = max(\{dl(\rho) \mid \rho \in \delta \setminus \{\sigma\}\} \cup \{0\}) < dl$ .
  - After recording  $\delta$  in  $\nabla$  and backjumping to decision level k,  $\overline{\alpha}$  is unit-resulting for  $\delta$
  - Such a nogood  $\delta$  is called asserting.

Asserting nogoods direct conflict-driven search into a different region of the search space than traversed before,

without explicitly flipping any heuristically chosen literal !

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## Effective Modeling: Overview

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- Hamiltonian Cycle
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Encoding Methodology
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Do's and Dont's

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## Modeling and Interpreting



## Problems as Logic Program

For solving a problem class P for a problem instance I, encode

- **1** the problem instance I as a set C(I) of facts and
- 2 the problem class P as a set C(P) of rules

such that the solutions to P for I can be (polynomially) extracted from the answer sets of  $C(I) \cup C(P)$ .

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#### Problem Instance as Facts

#### Given: a (directed) graph G



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node(4). node(5). node(6).

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atural Language	Logical Language	
<b>1</b> Each node has a unique color.	<pre>color(X,C) :- iscol(C), node(X), not other(X,C).</pre>	
	<pre>other(X,C) :- iscol(C), color(X,D), D != C.</pre>	
Any two connected nodes must not have the same color.	<pre>2 :- color(X,C), color(Y,C), edge(X,Y).</pre>	
Let there be three colors.	<pre>3 #const n=3. iscol(1n).</pre>	
A solution is a coloring.	4 #hide. #show color/2.	

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- 3 #const n=3. iscol(1..n).
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Any two connected nodes
must not have the same color.
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Logical Language

- 1 1 #count{ color(X,C) :
   iscol(C) } 1
   :- node(X).
- 2 :- color(X,C), color(Y,C), edge(X,Y).
- 3 #const n=3. iscol(1..n).
- 4 #hide. #show color/2.

Recapitulation I

```
Instance as Facts (in graph.lp)
```

node(1). node(2). node(3). node(4). node(5). node(6).

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

# N-Colorability Recapitulation II

#### Uniform Encoding (in color.lp)

```
% DOMAIN
#const n=3. iscol(1..n).
```

```
% GENERATE
1 #count{ color(X,C) : iscol(C) } 1 :- node(X).
% color(X,C) :- iscol(C), node(X), not other(X,C).
% other(X,C) :- iscol(C), color(X,D), D != C.
```

```
% TEST
:- color(X,C), color(Y,C), edge(X,Y).
```

```
% DISPLAY
#hide. #show color/2.
```

# N-Colorability Let's Run it!

#### gringo graph.lp color.lp | clasp 0

# N-Colorability Let's Run it!

```
gringo graph.lp color.lp | clasp 0
```

```
clasp version 2.0.2
Reading from stdin
Solving...
Answer: 1
color(6,2) color(5,3) color(4,2) color(3,1) color(2,1) color(1,3)
Answer: 2
color(6,1) color(5,3) color(4,1) color(3,2) color(2,2) color(1,3)
Answer: 3
color(6,3) color(5,2) color(4,3) color(3,1) color(2,1) color(1,2)
Answer: 4
color(6,1) color(5,2) color(4,1) color(3,3) color(2,3) color(1,2)
Answer: 5
color(6,3) color(5,1) color(4,3) color(3,2) color(2,2) color(1,1)
Answer: 6
color(6,2) color(5,1) color(4,2) color(3,3) color(2,3) color(1,1)
```

- **Found:** 3-coloring(s)
- Answer: 1
- color(1,3) color(5,3)
- color(2,1) color(3,1)
- color(4,2) color(6,2)



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- color(1,3) color(5,3)
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### **Found:** 3-coloring(s)

Answer: 1

color(1,3) color(5,3)

color(2,1) color(3,1)

color(4,2) color(6,2)



### **Found:** 3-coloring(s)

Answer: 1

color(1,3) color(5,3)

color(2,1) color(3,1)

color(4,2) color(6,2)



## Interlude: Answer Set(s) Computation



## Interlude: Answer Set(s) Computation



# N-Colorability Grounding

#### gringo -t graph.lp color.lp

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

```
iscol(1). iscol(2). iscol(3).
```

```
1 #count{ color(1,1), color(1,2), color(1,3) } 1.
1 #count{ color(2,1), color(2,2), color(2,3) } 1.
1 #count{ color(3,1), color(3,2), color(3,3) } 1.
1 #count{ color(4,1), color(4,2), color(4,3) } 1.
1 #count{ color(5,1), color(5,2), color(5,3) } 1.
1 #count{ color(6,1), color(6,2), color(6,3) } 1.
```

```
:- color(1,1), color(2,1).
:- color(1,2), color(2,2).
:- color(1,3), color(2,3).
```

# N-Colorability Grounding

```
gringo -t graph.lp color.lp
node(1). node(2). node(3). node(4). node(5). node(6).
edge(1,2). edge(1,3). edge(1,4). edge(2,4). edge(2,5). ...
iscol(1). iscol(2). iscol(3).
1 \text{ #count} \{ \text{ color}(1,1), \text{ color}(1,2), \text{ color}(1,3) \} 1.
1 #count{ color(2,1), color(2,2), color(2,3) } 1.
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1 #count{ color(5,1), color(5,2), color(5,3) } 1.
1 \text{ #count} \{ \text{ color}(6,1), \text{ color}(6,2), \text{ color}(6,3) \} 1.
:= color(1,1), color(2,1).
:= color(1,2), color(2,2).
:- color(1,3), color(2,3). ...
```

# N-Colorability Solving

#### gringo graph.lp color.lp | clasp --stats 0

Models		
		(Solving: 0.00s 1st Model: 0.00s Unsat: 0.00s)
CPU Time	0.000s	
Choices		
Conflicts		
Restarts		
Atoms	63	
Rules	113	(1: 95 2: 12 3: 6)
Bodies		
Equivalences		(Atom=Atom: 31 Body=Body: 6 Other: 69)
Tight		
Variables	63	(Eliminated: 0 Frozen: 30)
Constraints		(Binary: 73.3% Ternary: 0.0% Other: 26.7%)
		(Binary: 0.0% Ternary: 0.0% Other: 0.0%)

# N-Colorability Solving

#### gringo graph.lp color.lp | clasp --stats 0

Models		6	
Time		0.001s	(Solving: 0.00s 1st Model: 0.00s Unsat: 0.00s)
CPU Time		0.000s	
Choices		5	
Conflicts		0	
Restarts		0	
Atoms		63	
Rules		113	(1: 95 2: 12 3: 6)
Bodies		64	
Equivalences	5:	106	(Atom=Atom: 31 Body=Body: 6 Other: 69)
Tight		Yes	
Variables		63	(Eliminated: 0 Frozen: 30)
Constraints		45	(Binary: 73.3% Ternary: 0.0% Other: 26.7%)
Lemmas		0	(Binary: 0.0% Ternary: 0.0% Other: 0.0%)

# N-Colorability Solving

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Models		6	
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CPU Time		0.000s	
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Conflicts		0	
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## Hamiltonian Cycle

#### Problem Instance as Facts

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# Hamiltonian Cycle Engineering an Encoding

#### **Problem Specification**

A (directed) graph G = (V, E) is Hamiltonian if it contains a cycle C that visits every node of V exactly once.

C traverses exactly one incoming and one outgoing edge per node. C traverses every node of V (starting from an arbitrary node in V).

#### Problem Encoding

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

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**Problem Specification** 

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**Problem Specification** 

A (directed) graph G = (V, E) is Hamiltonian if it contains a cycle C that visits every node of V exactly once.

 $\square C$  traverses exactly one incoming and one outgoing edge per node.  $\square C$  traverses every node of V (starting from an arbitrary node in V).

Problem Encoding

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

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C traverses exactly one incoming and one outgoing edge per node. C traverses every node of V (starting from an arbitrary node in V).

Problem Encoding

```
reach(X) :- first(X).
reach(Y) :- reach(X), cycle(X,Y).
```

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Problem Encoding

reach(X) :- first(X).
reach(Y) :- reach(X), cycle(X,Y).

The definition of reach is recursive!

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reach(X) :- first(X).
reach(Y) :- reach(X), cycle(X,Y).

first(X) := X = #min[node(Y) = Y].

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Problem Encoding

```
reach(X) :- first(X).
reach(Y) :- reach(X), cycle(X,Y).
```

```
:- node(Y), not reach(Y).
```

### Hamiltonian Cycle The Complete Picture

#### Uniform Encoding (in cycle.lp)

```
% DOMAIN
first(X) :- X = \#\min[ node(Y) = Y ].
```

```
% GENERATE
1 #count{ cycle(X,Y) : edge(X,Y) } 1 :- node(X).
1 #count{ cycle(X,Y) : edge(X,Y) } 1 :- node(Y).
% DEFINE
reach(X) :- first(X).
reach(Y) :- reach(X), cycle(X,Y).
% TEST
:- node(Y), not reach(Y).
```

```
% DISPLAY
#hide. #show cycle/2.
```

Torsten Schaub et al. (KRR@UP)

# Hamiltonian Cycle Let's Run it!

#### gringo graph.lp cycle.lp | clasp --stats

Answer: 1
cycle(6,5) cycle(5,3) cycle(4,2) cycle(3,1) cycle(2,6) cycle(1,4)
SATISFIABLE

Models									
			(Solving:	0.00s		Model:	0.00s		0.00s)
CPU Time		0.000s							
Choices									
Conflicts									
Restarts									
Atoms									
Rules				21 3:	12)				
Bodies		81							
Equivalences:			(Atom=Ator		Body=	=Body: 3	12 Othe	er: 126)	
Tight			(SCCs: 1 1						

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SATISFIABLE

Models : 1+ : 0.001s (Solving: 0.00s 1st Model: 0.00s Unsat: 0.00s) Time CPU Time : 0.000s Choices : 3 Conflicts : 0 Restarts : 0 Atoms : 84 Rules : 117 (1: 84 2: 21 3: 12)Bodies : 81 Equivalences: 174 (Atom=Atom: 36 Body=Body: 12 Other: 126) Tight : No (SCCs: 1 Nodes: 20)

### Found: Hamiltonian cycle

Answer: 1



### Found: Hamiltonian cycle

Answer: 1



### Found: Hamiltonian cycle

Answer: 1



### Found: Hamiltonian cycle

Answer: 1



### Found: Hamiltonian cycle

Answer: 1



### Found: Hamiltonian cycle

Answer: 1



### Found: Hamiltonian cycle

Answer: 1



### Mr Hamilton as Traveling Salesperson Problem Instance as Facts

#### **Given:** a directed graph *G* plus edge costs

node(1). node(2). node(3). node(4). node(5). node(6).

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



## Mr Hamilton as Traveling Salesperson Problem Instance as Facts

#### Given: a directed graph G plus edge costs

```
cost(1,2,2).
cost(1,3,3). cost(3,1,3).
cost(1,4,1). cost(4,1,1).
cost(2,4,2). cost(4,2,2).
cost(2,5,2).
cost(2,6,4). cost(6,2,4).
cost(3,4,2).
cost(3,5,2). cost(5,3,2).
cost(5,4,2).
cost(5,6,1). cost(6,5,1).
cost(6,3,3).
```



**Optimization Objective** 

A Hamiltonian cycle is optimal if its accumulated edge costs are minimal.

Use #minimize (and/or #maximize) to associate each answer set with objective value(s).

**Optimization Encoding** 

% OPTIMIZE
#minimize[ cycle(X,Y) : cost(X,Y,C) = C@1 ]

Target: minimal sum of costs C (at priority level 1) associated with instances of cycle in an answer set

Torsten Schaub et al. (KRR@UP)

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Torsten Schaub et al. (KRR@UP)

## Mr Hamilton as Traveling Salesperson Let's Run it!

#### gringo graph.lp costs.lp cycle.lp price.lp | clasp --stats 0

### Mr Hamilton as Traveling Salesperson Let's Run it!

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```
Answer: 1
cycle(6,5) cycle(5,3) cycle(4,2) cycle(3,1) cycle(2,6) cycle(1,4)
Optimization: 13
Answer: 2
cycle(6,5) cycle(5,3) cycle(4,1) cycle(3,4) cycle(2,6) cycle(1,2)
Optimization: 12
Answer: 3
cycle(6,3) cycle(5,6) cycle(4,1) cycle(3,4) cycle(2,5) cycle(1,2)
Optimization: 11
OPTIMUM FOUND
Models : 1
 Enumerated: 3
 Optimum : yes
Optimization: 11
Time
      : 0.004s (Solving: 0.00s 1st Model: 0.00s Unsat: 0.00s)
CPU Time : 0.000s
```

## Mr Hamilton as Traveling Salesperson Let's Interpret it!

### Found: optimal Hamiltonian cycle

Answer: 1



## Mr Hamilton as Traveling Salesperson Let's Interpret it!

### Found: optimal Hamiltonian cycle

Answer: 2

cycle(1,2)
cycle(2,6)
cycle(6,5)
cycle(5,3)
cycle(3,4)
cycle(4,1)



## Mr Hamilton as Traveling Salesperson Let's Interpret it!

### Found: optimal Hamiltonian cycle

Answer: 3

cycle(1,2)
cycle(2,5)
cycle(5,6)
cycle(6,3)
cycle(3,4)
cycle(4,1)



### For solving a problem (class) in ASP, provide

- 1 facts describing an instance and
- **2** a (uniform) encoding of solutions.

#### Encodings are often structured by the following logical parts:

Domain information (by deduction from facts)
 Generator providing solution candidates (choice rules)
 Define rules analyzing properties of candidates (normal rules)
 Tester eliminating invalid candidates (integrity constraints)
 Display statements projecting answer sets (onto characteristic atoms)
 Optimizer evaluating answer sets (#minimize/#maximize)
 n a Nutshell
 Logic Program 

 (Data + Deduction) + (Generation + Analysis) +
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Torsten Schaub et al. (KRR@UP)

Modeling and Solving in ASP

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 $\subset$ 

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 $\subset$ 

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Logic Program

(Data + Deduction) + (Generation + Analysis) +Selection + Projection [+ Optimization]

(normal rules)

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(#minimize/#maximize)

## Effective Modeling: Overview

### 28 Problems as Logic Programs (Revisited)

- Graph Coloring
- Hamiltonian Cycle
- Traveling Salesperson

29 Encoding Methodology
■ Tweaking N-Queens
■ Do's and Dont's

### 30 Hints

### ASP offers

- 1 rich yet easy modeling languages
- 2 efficient instantiation procedures
- 3 powerful search engines

### Question: Anything left to worry about?

- Answer: Yes! (unfortunately)
- Even in declarative programming, the problem encoding matters.

### Consider sorting [4, 7, 2, 5, 1, 8, 6, 3]

- divide-and-conquer (Quicksort)
- permutation guessing

 $\sim 8(\log_2 8) = 16$  "operations"  $\sim 8!/2$  = 20,160 "operations"

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$$\label{eq:solution} \begin{split} &\sim 8(\log_2 8) = 16 \qquad \text{``operations''} \\ &\sim 8!/2 \qquad = 20,160 \ \text{``operations''} \end{split}$$

## **N**-Queens Problem

### Problem Specification

### Given an $N \times N$ chessboard,

place N queens such that they do not attack each other (neither horizontally, vertically, nor diagonally).

### *N* = 4



Placement



## **N**-Queens Problem

### **Problem Specification**

Given an  $N \times N$  chessboard, place N queens such that they do not attack each other (neither horizontally, vertically, nor diagonally).

#### *N* = 4



Placement



#### 1 Each square may host a queen.

2 No row, column, or diagonal hosts two queens.

3 A placement is given by instances of queen in an answer set.

```
queens_0.lp
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- queen(X1,Y1), queen(X1,Y2), Y1 < Y2.
% property</pre>
```

```
#hide. #show queen/2.
```

```
    Each square may host a queen.
    No row, column, or diagonal hosts two queens.
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```

```
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% TEST
:- queen(X1,Y1), queen(X1,Y2), Y1 < Y2.
% DISPLAY</pre>
```

```
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```

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```
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% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- queen(X1,Y1), queen(X2,Y1), X1 < X2.
% DISPLAY
#biddle_ftable_property(0)</pre>
```

```
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% DISPLAY</pre>
```

#hide. #show queen/2.

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2 No row, column, or diagonal hosts two queens.

**3** A placement is given by instances of queen in an answer set.

```
queens_0.lp
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
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% TEST
[...]
% DISPLAY
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```

1 Each square may host a queen.

2 No row, column, or diagonal hosts two queens.

**3** A placement is given by instances of queen in an answer set.

```
queens_0.lp
% DOMAIN
                                   Anything missing?
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
[...]
% DISPLAY
#hide. #show queen/2.
```

**1** Each square may host a queen.

2 No row, column, or diagonal hosts two queens.

3 A placement is given by instances of queen in an answer set.

4 We have to place (at least) N queens.

```
queens_0.lp
% DOMATN
#const n=4. square(1..n, 1..n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
[...]
:- not n #count{ queen(X,Y) }.
% DISPLAY
#hide. #show queen/2.
Torsten Schaub et al. (KRR@UP)
                                Modeling and Solving in ASP
```

# A First Encoding Let's Place 8 Queens!

#### gringo -c n=8 queens\_0.lp | clasp --stats

```
Answer: 1
queen(1,6) queen(2,3) queen(3,1) queen(4,7)
queen(5,5) queen(6,8) queen(7,2) queen(8,4)
SATISFIABLE
```

Models								
Time	0.006s	(Solving:	0.00s	1st	Model:	0.00s	Unsat:	0.00s)
CPU Time	0.000s							
Choices	18							
Conflicts								
Restarts								
Variables	793							
Constraints	729							

## A First Encoding Let's Place 8 Queens!

```
gringo -c n=8 queens_0.lp | clasp --stats
```

```
Answer: 1
queen(1,6) queen(2,3) queen(3,1) queen(4,7)
queen(5,5) queen(6,8) queen(7,2) queen(8,4)
SATISFIABLE
```

Models	1+							
Time	0.006s	(Solving:	0.00s	1st	Model:	0.00s	Unsat:	0.00s)
CPU Time	0.000s							
Choices	18							
Conflicts	13							
Restarts	0							
Variables	793							
Constraints	729							

#### Let's Place 8 Queens!



#### Let's Place 8 Queens!



# A First Encoding Let's Place 22 Queens!

#### gringo -c n=22 queens\_0.lp | clasp --stats

Answer: 1
queen(1,10) queen(2,6) queen(3,16) queen(4,14) queen(5,8) ...
SATISFIABLE

Models								
Time	150.531s	(Solving:	150.37s	1st	Model:	150.34s	Unsat:	0.00s)
CPU Time	147.480s							
Choices	594960							
Conflicts	574565							
Restarts	19							
Variables	17271							
Constraints	16787							

# A First Encoding Let's Place 22 Queens!

```
gringo -c n=22 queens_0.lp | clasp --stats
```

```
Answer: 1
queen(1,10) queen(2,6) queen(3,16) queen(4,14) queen(5,8) ...
SATISFIABLE
```

Models	1+							
Time	150.531s	(Solving:	150.37s	1st	Model:	150.34s	Unsat:	0.00s)
CPU Time	147.480s							
Choices	594960							
Conflicts	574565							
Restarts	19							
Variables	17271							
Constraints	16787							

```
queens_0.1p
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
:- queen(X1,Y1), queen(X1,Y2), Y1 < Y2.
:- queen(X1,Y1), queen(X2,Y1), X1 < X2.
:- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|.
:- not n #count{ gueen(X,Y) }.
```

#### % DISPLAY #hide. #show queen/2.

At least *N* queens?

Exactly one gueen per row and column!

```
queens_0.1p
% DOMAIN
#const n=4. square(1...n,1...n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- queen(X1,Y1), queen(X2,Y1), X1 < X2.
:- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|.
```

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0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|.
```

% DISPLAY #hide. #show queen/2.

At least *N* queens?

```
At least N queens?
```

Exactly one queen per row and column!

queens\_1.lp

```
% DOMAIN
#const n=4. square(1..n,1..n).
```

```
% GENERATE
```

```
0 #count{ queen(X, Y) } 1 :- square(X, Y).
```

```
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|.</pre>
```

% DISPLAY #hide. #show queen/2.

# A First Refinement Let's Place 22 Queens!

#### gringo -c n=22 queens\_1.lp | clasp --stats

Answer: 1
queen(1,18) queen(2,10) queen(3,21) queen(4,3) queen(5,5) ...
SATISFIABLE

Models								
Time	0.113s	(Solving:	0.00s	1st	Model:	0.00s	Unsat:	0.00s)
CPU Time	0.020s							
Choices	132							
Conflicts	105							
Restarts								
Variables	7238							
Constraints	6710							

A First Refinement Let's Place 22 Queens!

```
gringo -c n=22 queens_1.lp | clasp --stats
```

```
Answer: 1
queen(1,18) queen(2,10) queen(3,21) queen(4,3) queen(5,5) ...
SATISFIABLE
```

Models	1+							
Time	0.113s	(Solving:	0.00s	1st	Model:	0.00s	Unsat:	0.00s)
CPU Time	0.020s							
Choices	132							
Conflicts	105							
Restarts	1							
Variables	7238							
Constraints	6710							

# A First Refinement Let's Place 122 Queens!

#### gringo -c n=122 queens\_1.lp | clasp --stats

Answer: 1
queen(1,24) queen(2,52) queen(3,37) queen(4,60) queen(5,76) ...
SATISFIABLE

Models								
Time	79.475s	(Solving:	1.06s	1st	Model:	1.06s	Unsat:	0.00s)
CPU Time	6.930s							
Choices	1373							
Conflicts	845							
Restarts								
Variables	1211338							
Constraints	1196210							

A First Refinement Let's Place 122 Queens!

```
gringo -c n=122 queens_1.lp | clasp --stats
```

```
Answer: 1
queen(1,24) queen(2,52) queen(3,37) queen(4,60) queen(5,76) ...
SATISFIABLE
```

Models	1+							
Time	79.475s	(Solving:	1.06s	1st	Model:	1.06s	Unsat:	0.00s)
CPU Time	6.930s							
Choices	1373							
Conflicts	845							
Restarts	4							
Variables	1211338							
Constraints	1196210							

A First Refinement Let's Place 122 Queens!

```
gringo -c n=122 queens_1.lp | clasp --stats
```

```
Answer: 1
queen(1,24) queen(2,52) queen(3,37) queen(4,60) queen(5,76) ...
SATISFIABLE
```

Models	1+							
Time	79.475s	(Solving:	1.06s	1st	Model:	1.06s	Unsat:	0.00s)
CPU Time	6.930s							
Choices	1373							
Conflicts	845							
Restarts	4							
Variables	1211338							
Constraints	1196210							
Where Time Has Gone

#### time(gringo -c n=122 queens\_1.lp | clasp --stats

1241358 7402724 24950848

real 1m15.468s user 1m15.980s svs 0m0.090s

Where Time Has Gone

#### time(gringo -c n=122 queens\_1.lp | wc

1241358 7402724 24950848

real 1m15.468s user 1m15.980s sys 0m0.090s

Where Time Has Gone

#### time(gringo -c n=122 queens\_1.lp | wc)

1241358 7402724 24950848

real 1m15.468s user 1m15.980s sys 0m0.090s

### Just kidding :)

Where Time Has Gone

#### time(gringo -c n=122 queens\_1.lp | wc)

1241358 7402724 24950848

real 1m15.468s user 1m15.980s sys 0m0.090s

Where Time Has Gone

#### time(gringo -c n=122 queens\_1.lp | wc)

#### 1241358 7402724 24950848

real 1m15.468s user 1m15.980s sys 0m0.090s

Where Time Has Gone

time(gringo -c n=122 queens\_1.lp | wc)

1241358 7402724 24950848

real 1m15.468s user 1m15.980s sys 0m0.090s

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n). % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y). % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$ :- queen(X1, Y1), queen(X2, Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y). % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$ :- queen(X1, Y1), queen(X2, Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y). % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$ :- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y). % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$ :- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y).  $O(n \times n)$ % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$ :- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y).  $O(n \times n)$ % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $O(n \times n)$  $O(n \times n)$ :- Y = 1...n, not 1 #count{ queen(X,Y) } 1. :- queen(X1, Y1), queen(X2, Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens_1.lp	
% DOMAIN #const n=4. square(1n,1n).	$O(n \times n)$
% GENERATE O #count{ queen(X,Y) } 1 :- square(X,Y).	$O(n \times n)$
<pre>% TEST :- X = 1n, not 1 #count{ queen(X,Y) } 1. :- Y = 1n, not 1 #count{ queen(X,Y) } 1. :- queen(X1,Y1), queen(X2,Y2), X1 &lt; X2, X2-X1 ==  Y2-Y1 .</pre>	$egin{array}{c} O(n{ imes}n) \ O(n{ imes}n) \ O(n{ imes}n) \ O(n^2{ imes}n^2) \end{array}$
% DISPLAY #hide. #show queen/2.	

queens_1.lp	
% DOMAIN #const n=4. square(1n,1n).	$O(n \times n)$
% GENERATE 0 #count{ queen(X,Y) } 1 :- square(X,Y).	$O(n \times n)$
<pre>% TEST :- X = 1n, not 1 #count{ queen(X,Y) } 1. :- Y = 1n, not 1 #count{ queen(X,Y) } 1. :- queen(X1,Y1), queen(X2,Y2), X1 &lt; X2, X2-X1 ==  Y2-Y1 .</pre>	$egin{array}{c} O(n{ imes}n) \\ O(n{ imes}n) \\ O(n^2{ imes}n^2) \end{array}$
% DISPLAY #hide. #show queen/2.	

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y).  $O(n \times n)$ % TEST :- X = 1..n, not 1 #count{ queen(X,Y) } 1.  $O(n \times n)$  $O(n \times n)$  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$  $O(n^2 \times n^2)$ :- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY #hide. #show queen/2.

queens_1.lp	
% DOMAIN #const n=4. square(1n,1n).	$O(n \times n)$
% GENERATE O #count{ queen(X,Y) } 1 :- square(X,Y).	$O(n \times n)$
<pre>% TEST :- X = 1n, not 1 #count{ queen(X,Y) } 1. :- Y = 1n, not 1 #count{ queen(X,Y) } 1. :- queen(X1,Y1), queen(X2,Y2), X1 &lt; X2, X2-X1 ==  Y2-Y1 .</pre>	$egin{array}{c} O(n{ imes}n) \ O(n{ imes}n) \ O(n{ imes}n) \ O(n^2{ imes}n^2) \end{array}$
% DISPLAY #hide. #show queen/2.	

queens\_1.lp % DOMAIN #const n=4. square(1..n,1..n).  $O(n \times n)$ % GENERATE 0 #count{ queen(X, Y) } 1 :- square(X, Y).  $O(n \times n)$ % TEST  $:- X = 1..n, not 1 #count{ queen(X,Y) } 1.$  $O(n \times n)$  $O(n \times n)$  $:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.$  $O(n^2 \times n^2)$ :- queen(X1, Y1), queen(X2, Y2), X1 < X2, X2-X1 == |Y2-Y1|. % DISPLAY Diagonals cause trouble! #hide. #show gueen/2.

#### *N* = 4



#diagonal $_1 =$ (#row + #column) - 1



#diagonal<sub>2</sub> = (#row – #column) + N

 $\approx$  #diagonal<sub>1/2</sub> can be determined in this way for arbitrary N.

#### *N* = 4



#diagonal<sub>1</sub> = (#row + #column) - 1



#diagonal<sub>2</sub> = (#row – #column) + N

#diagonal<sub>1/2</sub> can be determined in this way for arbitrary N.

#### *N* = 4



#diagonal<sub>1</sub> = (#row + #column) - 1



#diagonal<sub>2</sub> = (#row - #column) + N

 $\mathbb{I}$  #diagonal<sub>1/2</sub> can be determined in this way for arbitrary *N*.

#### *N* = 4







#diagonal<sub>2</sub> = (#row - #column) + N

 $\mathbb{R}$  #diagonal<sub>1/2</sub> can be determined in this way for arbitrary N.

```
queens_1.lp
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- queen(X1,Y1), queen(X2,Y2), X1 < X2, X2-X1 == |Y2-Y1|.</pre>
```

% DISPLAY #hide. #show queen/2.

```
queens_1.lp
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
:- X = 1...n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X+Y)-1 }. % Diagonal 1
% DISPLAY
#hide. #show queen/2.
```

```
queens_1.lp
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X+Y)-1 }. % Diagonal 1
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X-Y)+n }. % Diagonal 2
```

% DISPLAY #hide. #show queen/2.

```
queens_2.1p
% DOMAIN
#const n=4. square(1..n,1..n).
% GENERATE
0 #count{ queen(X, Y) } 1 :- square(X, Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X+Y)-1 }. % Diagonal 1
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X-Y)+n }. % Diagonal 2
```

% DISPLAY #hide. #show queen/2.

## A Second Refinement Let's Place 122 Queens!

#### gringo -c n=122 queens\_2.1p | clasp --stats

Answer: 1
queen(1,98) queen(2,54) queen(3,89) queen(4,83) queen(5,59) ...
SATISFIABLE

Models								
Time	2.211s	(Solving:	0.13s	1st	Model:	0.13s	Unsat:	0.00s)
CPU Time	0.210s							
Choices	11036							
Conflicts	499							
Restarts								
Variables	16098							
Constraints	970							

A Second Refinement Let's Place 122 Queens!

```
gringo -c n=122 queens_2.lp | clasp --stats
```

```
Answer: 1
queen(1,98) queen(2,54) queen(3,89) queen(4,83) queen(5,59) ...
SATISFIABLE
```

Models	1+							
Time	2.211s	(Solving:	0.13s	1st	Model:	0.13s	Unsat:	0.00s)
CPU Time	0.210s							
Choices	11036							
Conflicts	499							
Restarts	3							
Variables	16098							
Constraints	970							

A Second Refinement Let's Place 122 Queens!

```
gringo -c n=122 queens_2.lp | clasp --stats
```

```
Answer: 1
queen(1,98) queen(2,54) queen(3,89) queen(4,83) queen(5,59) ...
SATISFIABLE
```

Models	1+							
Time	2.211s	(Solving:	0.13s	1st	Model:	0.13s	Unsat:	0.00s)
CPU Time	0.210s							
Choices	11036							
Conflicts	499							
Restarts	3							
Variables	16098							
Constraints	970							

## A Second Refinement Let's Place 300 Queens!

#### gringo -c n=300 queens\_2.lp | clasp --stats

Answer: 1
queen(1,62) queen(2,232) queen(3,176) queen(4,241) queen(5,207) ...
SATISFIABLE

Models								
Time	35.450s	(Solving:	6.69s	1st	Model:	6.68s	Unsat:	0.00s)
CPU Time	7.250s							
Choices	141445							
Conflicts	7488							
Restarts								
Variables	92994							
Constraints	2394							

A Second Refinement Let's Place 300 Queens!

```
gringo -c n=300 queens_2.1p | clasp --stats
```

```
Answer: 1
queen(1,62) queen(2,232) queen(3,176) queen(4,241) queen(5,207) ...
SATISFIABLE
```

Models	1+							
Time	35.450s	(Solving:	6.69s	1st	Model:	6.68s	Unsat:	0.00s)
CPU Time	7.250s							
Choices	141445							
Conflicts	7488							
Restarts	9							
Variables	92994							
Constraints	2394							

A Second Refinement Let's Place 300 Queens!

```
gringo -c n=300 queens_2.1p | clasp --stats
```

```
Answer: 1
queen(1,62) queen(2,232) queen(3,176) queen(4,241) queen(5,207) ...
SATISFIABLE
```

Models	1+							
Time	35.450s	(Solving:	6.69s	1st	Model:	6.68s	Unsat:	0.00s)
CPU Time	7.250s							
Choices	141445							
Conflicts	7488							
Restarts	9							
Variables	92994							
Constraints	2394							

#### Let's Precompute Diagonals!

queens\_2.1p

```
% DOMAIN
#const n=4. square(1..n,1..n).
diag1(X,Y,(X+Y)-1) :- square(X,Y). diag2(X,Y,(X-Y)+n) :- square(X,Y).
% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X+Y)-1 }. % Diagonal 1
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X-Y)+n }. % Diagonal 2
```

#### % DISPLAY #hide. #show queen/2.

#### Let's Precompute Diagonals!

queens\_2.1p

```
% DOMAIN
#const n=4. square(1..n,1..n).
diag1(X,Y,(X+Y)-1) :- square(X,Y). diag2(X,Y,(X-Y)+n) :- square(X,Y).
% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X+Y)-1 }. % Diagonal 1
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : D == (X-Y)+n }. % Diagonal 2
```

#### % DISPLAY #hide. #show queen/2.

#### Let's Precompute Diagonals!

queens\_2.1p

```
% DOMAIN
#const n=4. square(1..n,1..n).
diag1(X,Y,(X+Y)-1) :- square(X,Y). diag2(X,Y,(X-Y)+n) :- square(X,Y).
% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : diag1(X,Y,D) }. % Diagonal 1
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : diag2(X,Y,D) }. % Diagonal 2
```

#### % DISPLAY #hide. #show queen/2.

#### Let's Precompute Diagonals!

queens\_3.1p

```
% DOMAIN
#const n=4. square(1..n,1..n).
diag1(X,Y,(X+Y)-1) :- square(X,Y). diag2(X,Y,(X-Y)+n) :- square(X,Y).
% GENERATE
0 #count{ queen(X,Y) } 1 :- square(X,Y).
% TEST
:- X = 1..n, not 1 #count{ queen(X,Y) } 1.
:- Y = 1..n, not 1 #count{ queen(X,Y) } 1.
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : diag1(X,Y,D) }. % Diagonal 1
:- D = 1..2*n-1, 2 #count{ queen(X,Y) : diag2(X,Y,D) }. % Diagonal 2
```

#### % DISPLAY #hide. #show queen/2.

### A Third Refinement Let's Place 300 Queens!

#### gringo -c n=300 queens\_3.lp | clasp --stats

Answer: 1 queen(1,62) queen(2,232) queen(3,176) queen(4,241) queen(5,207) ... SATISFIABLE

Models								
Time	8.889s	(Solving:	6.61s	1st	Model:	6.60s	Unsat:	0.00s)
CPU Time	7.320s							
Choices	141445							
Conflicts	7488							
Restarts								
Variables	92994							
Constraints	2394							
A Third Refinement Let's Place 300 Queens!

```
gringo -c n=300 queens_3.1p | clasp --stats
```

```
Answer: 1
queen(1,62) queen(2,232) queen(3,176) queen(4,241) queen(5,207) ...
SATISFIABLE
```

Models	1+							
Time	8.889s	(Solving:	6.61s	1st	Model:	6.60s	Unsat:	0.00s)
CPU Time	7.320s							
Choices	141445							
Conflicts	7488							
Restarts	9							
Variables	92994							
Constraints	2394							

A Third Refinement Let's Place 300 Queens!

```
gringo -c n=300 queens_3.1p | clasp --stats
```

```
Answer: 1
queen(1,62) queen(2,232) queen(3,176) queen(4,241) queen(5,207) ...
SATISFIABLE
```

Models	1+							
Time	8.889s	(Solving:	6.61s	1st	Model:	6.60s	Unsat:	0.00s)
CPU Time	7.320s							
Choices	141445							
Conflicts	7488							
Restarts	9							
Variables	92994							
Constraints	2394							

# A Third Refinement Let's Place 600 Queens!

#### gringo -c n=600 queens\_3.lp | clasp --stats

Answer: 1
queen(1,477) queen(2,365) queen(3,455) queen(4,470) queen(5,237) ...
SATISFIABLE

Models								
Time	76.798s	(Solving:	65.81s	1st	Model:	65.75s	Unsat:	0.00s)
CPU Time	68.620s							
Choices	869379							
Conflicts	25746							
Restarts	12							
Variables	365994							
Constraints	4794							

A Third Refinement Let's Place 600 Queens!

```
gringo -c n=600 queens_3.1p | clasp --stats
```

```
Answer: 1
queen(1,477) queen(2,365) queen(3,455) queen(4,470) queen(5,237) ...
SATISFIABLE
```

Models	1+							
Time	76.798s	(Solving:	65.81s	1st	Model:	65.75s	Unsat:	0.00s)
CPU Time	68.620s							
Choices	869379							
Conflicts	25746							
Restarts	12							
Variables	365994							
Constraints	4794							

# gringo -c n=600 queens\_3.lp | clasp --stats

```
Answer: 1
queen(1,477) queen(2,365) queen(3,455) queen(4,470) queen(5,237) ...
SATISFIABLE
```

Models	1+							
Time	76.798s	(Solving:	65.81s	1st	Model:	65.75s	Unsat:	0.00s)
CPU Time	68.620s							
Choices	869379							
Conflicts	25746							
Restarts	12							
Variables	365994							
Constraints	4794							

# gringo -c n=600 queens\_3.lp | clasp --stats --heuristic=vsids --trans-ext=dynamic

Answer: 1 queen(1,477) queen(2,365) queen(3,455) queen(4,470) queen(5,237) ... SATISFIABLE

76.798s	(Solving:	65.81s	1st	Model:	65.75s	Unsat:	0.00s)
68.620s							
869379							
25746							
12							
365994							
4794							
	: 1+ : 76.798s : 68.620s : 869379 : 25746 : 12 : 365994 : 4794	: 1+ : 76.798s (Solving: : 68.620s : 869379 : 25746 : 12 : 365994 : 4794	: 1+ : 76.798s (Solving: 65.81s : 68.620s : 869379 : 25746 : 12 : 365994 : 4794	: 1+ : 76.798s (Solving: 65.81s 1st : 68.620s : 869379 : 25746 : 12 : 365994 : 4794	: 1+ : 76.798s (Solving: 65.81s 1st Model: : 68.620s : 869379 : 25746 : 12 : 365994 : 4794	: 1+ : 76.798s (Solving: 65.81s 1st Model: 65.75s : 68.620s : 869379 : 25746 : 12 : 365994 : 4794	: 1+ : 76.798s (Solving: 65.81s 1st Model: 65.75s Unsat: : 68.620s : 869379 : 25746 : 12 : 365994 : 4794

```
gringo -c n=600 queens_3.lp | clasp --stats
--heuristic=vsids --trans-ext=dynamic
```

```
Answer: 1
queen(1,422) queen(2,458) queen(3,224) queen(4,408) queen(5,405) ...
SATISFIABLE
```

Models	1+							
Time	37.454s	(Solving:	26.38s	1st	Model:	26.26s	Unsat:	0.00s)
CPU Time	29.580s							
Choices	961315							
Conflicts	3222							
Restarts	7							
Variables	365994							
Constraints	4794							

# gringo -c n=600 queens\_3.lp | clasp --stats --heuristic=vsids --trans-ext=dynamic

Answer: 1 queen(1,422) queen(2,458) queen(3,224) queen(4,408) queen(5,405) ... SATISFIABLE

Models								
Time	37.454s	(Solving:	26.38s	1st	Model:	26.26s	Unsat:	0.00s)
CPU Time	29.580s							
Choices	961315							
Conflicts	3222							
Restarts								
	265004							
variables	365994							
Constraints	4794							

```
gringo -c n=600 queens_3.lp | clasp --stats
--heuristic=vsids --trans-ext=dynamic
```

```
Answer: 1
queen(1,90) queen(2,452) queen(3,494) queen(4,145) queen(5,84) ...
SATISFIABLE
```

Models	1+							
Time	22.654s	(Solving:	10.53s	1st	Model:	10.47s	Unsat:	0.00s)
CPU Time	15.750s							
Choices	1058729							
Conflicts	2128							
Restarts	6							
Variables	403123							
Constraints	49636							

#### Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber).
pro(asparagus,cheap). pro(cucumber,cheap).
pro(asparagus,fresh). pro(cucumber,fresh).
pro(asparagus,tasty). pro(cucumber,tasty).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber). pro(asparagus,cheap). pro(cucumber,cheap). pro(asparagus,fresh). pro(cucumber,fresh). pro(asparagus,tasty). pro(cucumber,tasty).

buy(X) :- veg(X), pro(X,cheap), pro(X,fresh), pro(X,tasty).

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Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber).
pro(asparagus,cheap). pro(cucumber,cheap).
pro(asparagus,fresh). pro(cucumber,fresh).
pro(asparagus,tasty). pro(cucumber,tasty).
pro(asparagus,clean).

buy(X) :- veg(X), pro(X,cheap), pro(X,fresh), pro(X,tasty), pro(X,clean).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber).
pro(asparagus,cheap). pro(cucumber,cheap).
pro(asparagus,fresh). pro(cucumber,fresh).
pro(asparagus,tasty). pro(cucumber,tasty).
pro(asparagus,clean).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber). pro(asparagus,cheap). pro(cucumber,cheap). pre(cheap). pro(asparagus,fresh). pro(cucumber,fresh). pre(fresh). pro(asparagus,tasty). pro(cucumber,tasty). pre(tasty). pro(asparagus,clean).

buy(X) :- veg(X), pro(X,P) : pre(P).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber).
pro(asparagus,cheap). pro(cucumber,cheap). pre(cheap).
pro(asparagus,fresh). pro(cucumber,fresh). pre(fresh).
pro(asparagus,tasty). pro(cucumber,tasty). pre(tasty).
pro(asparagus,clean). pre(clean).

buy(X) :- veg(X), pro(X,P) : pre(P).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber). pro(asparagus,cheap). pro(cucumber,cheap). pre(cheap). pro(asparagus,fresh). pro(cucumber,fresh). pre(fresh). pro(asparagus,tasty). pro(cucumber,tasty). pre(tasty). pro(asparagus,clean).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber). pro(asparagus,cheap). pro(cucumber,cheap). pre(cheap). pro(asparagus,fresh). pro(cucumber,fresh). pre(fresh). pro(asparagus,tasty). pro(cucumber,tasty). pre(tasty). pro(asparagus,clean).

buy(X) :- veg(X), not bye(X). bye(X) :- veg(X), pre(P), not pro(X,P).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change
 use variable-sized conjunction (via ':') ... adapts to changing facts
 use negation of complement ... adapts to changing facts

#### **Example:** vegetables to buy

veg(asparagus). veg(cucumber). pro(asparagus,cheap). pro(cucumber,cheap). pre(cheap). pro(asparagus,fresh). pro(cucumber,fresh). pre(fresh). pro(asparagus,tasty). pro(cucumber,tasty). pre(tasty). pro(asparagus,clean). pre(clean).

buy(X) :- veg(X), not bye(X). bye(X) :- veg(X), pre(P), not pro(X,P).

Goal: identify objects such that ALL properties from a "list" hold

check all properties explicitly ... obsolete if properties change X
 use variable-sized conjunction (via ':') ... adapts to changing facts ✓
 use negation of complement ... adapts to changing facts ✓

#### Example: vegetables to buy

veg(asparagus). veg(cucumber).
pro(asparagus,cheap). pro(cucumber,cheap). pre(cheap).
pro(asparagus,fresh). pro(cucumber,fresh). pre(fresh).
pro(asparagus,tasty). pro(cucumber,tasty). pre(tasty).
pro(asparagus,clean). pre(clean).

buy(X) :- veg(X), not bye(X). bye(X) :- veg(X), pre(P), not pro(X,P).

# Running Example: Latin Square

#### **Given:** an $N \times N$ board

#### Wanted: assignment of 1, . . . , N



#### represented by facts:

<pre>square(1,1).</pre>	<pre>square(1,6).</pre>
square(2,1).	<pre>square(2,6).</pre>
<pre>square(3,1).</pre>	<pre>square(3,6).</pre>
square(4,1).	<pre>square(4,6).</pre>
square(5,1).	<pre>square(5,6).</pre>
square(6,1).	square(6,6).



#### represented by atoms:

	num(1,2,2)	num(1,6,6)
	num(2,2,3)	
num(3,1,3)	num(3,2,4)	num(3,6,2)
num(4,1,4)		num(4,6,3)
num(5,1,5)	num(5,2,6)	num(5,6,4)
num(6.1.6)	num(6.2.1)	num(6.6.5)

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# Running Example: Latin Square

#### **Given:** an $N \times N$ board





represented by facts:

<pre>square(1,1).</pre>	<pre>square(1,6).</pre>
square(2,1).	<pre>square(2,6).</pre>
square(3,1).	<pre>square(3,6).</pre>
square(4,1).	<pre>square(4,6).</pre>
square(5,1).	<pre>square(5,6).</pre>
square(6,1).	square(6,6).

1	1	2	3	4	5	6
2	2	3	4	5	6	1
3	3	4	5	6	1	2
4	4	5	6	1	2	3
5	5	6	1	2	3	4
6	6	1	2	3	4	5
	1	2	3	4	5	6

represented by atoms:

num(1,1,1)	num(1,2,2)	num(1,6,6)
num(2,1,2)	num(2,2,3)	num(2,6,1)
num(3,1,3)	num(3,2,4)	num(3,6,2)
num(4,1,4)	num(4,2,5)	num(4,6,3)
num(5,1,5)	num(5,2,6)	num(5,6,4)
num(6.1.6)	num(6.2.1)	 num(6.6.5)

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#### A Latin square encoding

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
```

 $1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- square(X,Y).$ 

```
% TEST
:- square(X1,Y1), N = 1..n, not num(X1,Y2,N) : square(X1,Y2).
:- square(X1,Y1), N = 1..n, not num(X2,Y1,N) : square(X2,Y1).
```

```
unreused "singleton variables"
```

```
      gringo latin_0.lp | wc
      gringo latin_1.lp | wc

      105480 2558984 14005258
      42056 273672 1690522

      Torsten Schaub et al. (KRR@UP)
      Modeling and Solving in ASP
```

#### A Latin square encoding

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

#### % GENERATE

 $1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- square(X,Y).$ 

# % TEST :- square(X1,Y1), N = 1..n, not num(X1,Y2,N) : square(X1,Y2). :- square(X1,Y1), N = 1..n, not num(X2,Y1,N) : square(X2,Y1).

#### unreused "singleton variables"

# gringo latin\_0.lp | wc gringo latin\_1.lp | wc 105480 2558984 14005258 42056 273672 1690522 Torsten Schaub et al. (KRR@UP) Modeling and Solving in ASP

#### A Latin square encoding

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- square(X1,Y1), N = 1..n, not num(X1,Y2,N) : square(X1,Y2).
:- square(X1,Y1), N = 1..n, not num(X2,Y1,N) : square(X2,Y1).
```

#### unreused "singleton variables"

```
      gringo latin_0.lp | wc
      gringo latin_1.lp | wc

      105480 2558984 14005258
      42056 273672 1690522

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      Modeling and Solving in ASP
```

#### A Latin square encoding

```
% DOMAIN
#const n=32. square(1..n,1..n).
squareX(X) :- square(X,Y). squareY(Y) :- square(X,Y).
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
% TEST
:- squareX(X1) , N = 1..n, not num(X1,Y2,N) : square(X1,Y2).
:- squareY(Y1) , N = 1..n, not num(X2,Y1,N) : square(X2,Y1).
```

#### unreused "singleton variables"

```
      gringo latin_0.lp | wc
      gringo latin_1.lp | wc

      105480 2558984 14005258
      42056 273672 1690522

      Torsten Schaub et al. (KRR@UP)
      Modeling and Solving in ASP
```

#### A Latin square encoding

```
% DOMAIN
#const n=32. square(1..n,1..n).
squareX(X) :- square(X,Y).
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
% TEST
:- squareX(X1) , N = 1..n, not num(X1,Y2,N) : square(X1,Y2).
:- squareY(Y1) , N = 1..n, not num(X2,Y1,N) : square(X2,Y1).
```

#### unreused "singleton variables"

gringo latin_0.lp   wc	gringo latin_1.lp   wc
105480 <b>2558984</b> 14005258	42056 273672 1690522
Torsten Schaub et al. (KRR@UP)	Modeling and Solving in ASP

```
Another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

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```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 != Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 != X2.
```

duplicate ground rules (swapping Y1/Y2 and X1/X2 gives the "same")

```
      gringo latin_2.lp | wc
      gringo latin_3.lp | wc

      2071560 12389384 40906946
      1055752 6294536 21099558
```

Modeling and Solving in ASP

```
Another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 != Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 != X2.
```

☞ duplicate ground rules (swapping Y1/Y2 and X1/X2 gives the "same")



```
Another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 != Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 != X2.
```

☞ duplicate ground rules (swapping Y1/Y2 and X1/X2 gives the "same")

gringo latin_2.lp   wc	
2071560 12389384 40906946	1055752 6294536 21099558

```
Another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 < Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 < X2.
```

🖾 duplicate ground rules (swapping Y1/Y2 and X1/X2 gives the "same")

gringo latin_2.lp   wc	
2071560 12389384 40906946	1055752 6294536 21099558

```
Another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 < Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 < X2.
```

 $^{\circ\circ}$  duplicate ground rules (swapping Y1/Y2 and X1/X2 gives the "same")

gringo latin_2.lp   wc	gringo latin_3.lp   wc
2071560 12389384 40906946	1055752 6294536 21099558

```
Still another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 < Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 < X2.
```

uniqueness of N in a row/column checked by ENUMERATING PAIRS!



```
Still another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 < Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 < X2.
```

Iniqueness of N in a row/column checked by ENUMERATING PAIRS!

 gringo latin\_3.lp | wc
 gringo latin\_4.lp | wc

 1055752 6294536 21099558
 228360 1205256 4780744

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```
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```

```
Still another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- num(X1,Y1,N), num(X1,Y2,N), Y1 < Y2.
:- num(X1,Y1,N), num(X2,Y1,N), X1 < X2.</pre>
```

In uniqueness of N in a row/column checked by ENUMERATING PAIRS!

```
    gringo latin_3.lp | wc
    gringo latin_4.lp | wc

    1055752 6294536 21099558
    228360 1205256 4780744

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```

```
Still another Latin square encoding
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% DEFINE + TEST
gtX(X-1,Y,N) := num(X,Y,N), 1 < X.
                                           gtY(X,Y-1,N) := num(X,Y,N), 1 < Y.
gtX(X-1,Y,N) := gtX(X,Y,N), 1 < X.
                                           gtY(X,Y-1,N) := gtY(X,Y,N), 1 < Y.
    uniqueness of \mathbb{N} in a row/column checked by ENUMERATING PAIRS!
gringo latin_3.lp | wc
1055752 6294536 21099558
Torsten Schaub et al. (KRR@UP)
                               Modeling and Solving in ASP
                                                                            197 / 226
```

```
Still another Latin square encoding
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% DEFINE + TEST
gtX(X-1,Y,N) := num(X,Y,N), 1 < X.
                                         gtY(X,Y-1,N) := num(X,Y,N), 1 < Y.
gtX(X-1,Y,N) := gtX(X,Y,N), 1 < X.
                                          gtY(X,Y-1,N) := gtY(X,Y,N), 1 < Y.
 := num(X,Y,N), gtX(X,Y,N).
                                           := num(X,Y,N), gtY(X,Y,N).
gringo latin_3.lp | wc
```

1055752 6294536 21099558

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Modeling and Solving in ASP
### Linearizing Existence Tests

```
Still another Latin square encoding
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% DEFINE + TEST
gtX(X-1,Y,N) := num(X,Y,N), 1 < X.
                                          gtY(X,Y-1,N) := num(X,Y,N), 1 < Y.
gtX(X-1,Y,N) := gtX(X,Y,N), 1 < X.
                                          gtY(X,Y-1,N) := gtY(X,Y,N), 1 < Y.
 := num(X,Y,N), gtX(X,Y,N).
                                           := num(X,Y,N), gtY(X,Y,N).
```

 gringo latin\_3.lp | wc
 gringo latin\_4.lp | wc

 1055752 6294536 21099558
 228360 1205256 4780744

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```
Yet another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
sigma(S) :- S = #sum[ square(X,n) = X ].
```

% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).

```
% DEFINE + TEST
occX(X,N,C) :- X = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) :- Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- occX(X,N,C), C != 1. :- occY(Y,N,C), C != 1.
```

% DISPLAY
#hide. #show num/3. #show sigma/1.

gringo latin\_5.lp | wc gringo latin\_6.lp | wc

```
Yet another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
sigma(S) :- S = #sum[ square(X,n) = X ].
```

% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).

```
% DEFINE + TEST
occX(X,N,C) :- X = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) :- Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- occX(X,N,C), C != 1. :- occY(Y,N,C), C != 1.
```

% DISPLAY
#hide. #show num/3. #show sigma/1.

gringo latin\_5.lp | wc gringo latin\_6.lp | wc

```
Yet another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
sigma(S) :- S = #sum[ square(X,n) = X ].
```

% GENERATE 1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).

```
% DEFINE + TEST
occX(X,N,C) :- X = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) :- Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- occX(X,N,C), C != 1. :- occY(Y,N,C), C != 1.
```

% DISPLAY
#hide. #show num/3. #show sigma/1.

gringo latin\_5.lp | wc gringo latin\_6.lp | wc

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10102 070720 0105010

```
Yet another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
sigma(S) :- S = #sum[ square(X,n) = X ].
% GENERATE
```

```
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- square(X,Y).
```

```
% DEFINE + TEST
occX(X,N,C) :- X = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) :- Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- occX(X,N,C), C != 1. :- occY(Y,N,C), C != 1.
```

% DISPLAY
#hide. #show num/3. #show sigma/1.

gringo latin\_5.lp | wc gringo latin\_6.lp | wc

Torsten Schaub et al. (KRR@UP)

10196 979760 0106010

```
Yet another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
sigma(S) :- S = #sum[ square(X,n) = X ].
```

% GENERATE 1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).

```
% DEFINE + TEST
occX(X,N,C) :- X = 1..n, N = 1..n, C #count{ num(X,Y,N) } C, C = 0..n.
occY(Y,N,C) :- Y = 1..n, N = 1..n, C #count{ num(X,Y,N) } C, C = 0..n.
:- occX(X,N,C), C != 1. :- occY(Y,N,C), C != 1.
```

% DISPLAY
#hide. #show num/3. #show sigma/1.

#### internal transformation by gringo

```
Yet another Latin square encoding
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
sigma(S) :- S = #sum[ square(X,n) = X ].
```

% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).

```
% DEFINE + TEST
occX(X,N,C) :- X = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) :- Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- occX(X,N,C), C != 1. :- occY(Y,N,C), C != 1.
```

% DISPLAY
#hide. #show num/3. #show sigma/1.

#### gringo latin\_5.lp | wc gri:

Modeling and Solving in ASP

х

```
Yet another Latin square encoding
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 # count \{ num(X,Y,N) : N = 1...n \} 1 :- square(X,Y).
% DEFINE + TEST
occX(X,N,C) := X = 1...n, N = 1...n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) := Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- \text{occX}(X,N,C), C != 1. :- \text{occY}(Y,N,C), C != 1.
% DISPLAY
#hide. #show num/3.
gringo latin_5.lp | wc
 Torsten Schaub et al. (KRR@UP)
                               Modeling and Solving in ASP
```

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```
Yet another Latin square encoding
% DOMATN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% DEFINE + TEST
occX(X,N,C) := X = 1...n, N = 1...n, C = #count{ num(X,Y,N) }.
occY(Y,N,C) := Y = 1..n, N = 1..n, C = #count{ num(X,Y,N) }.
:- \text{occX}(X,N,C), C != 1. :- \text{occY}(Y,N,C), C != 1.
% DISPLAY
#hide. #show num/3.
gringo latin_5.lp | wc
304136 5778440 30252505
 Torsten Schaub et al. (KRR@UP)
                                Modeling and Solving in ASP
```

Modeling and Solving in ASP

### Assigning Aggregate Values

```
Yet another Latin square encoding
% DOMATN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
% DISPLAY
#hide. #show num/3.
gringo latin_5.lp | wc
                                        gringo latin_6.lp | wc
304136 5778440 30252505
```

```
Yet another Latin square encoding
% DOMATN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
% DISPLAY
#hide. #show num/3.
gringo latin_5.lp | wc
                                         gringo latin_6.lp | wc
304136 5778440 30252505
                                         48136 373768 2185042
 Torsten Schaub et al. (KRR@UP)
                               Modeling and Solving in ASP
```

#### The ultimate Latin square encoding?

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
```

% DISPLAY #hide. #show num/3.

### The ultimate Latin square encoding?

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
```

% DISPLAY #hide. #show num/3.

#### many symmetric solutions (mirroring, rotation, value permutation)

### The ultimate Latin square encoding?

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
```

% DISPLAY #hide. #show num/3.

#### easy and safe to fix a full row/column!

```
The ultimate Latin square encoding?
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
```

```
:- square(1,Y), not num(1,Y,Y). % Symmetry Breaking
```

```
% DISPLAY
#hide. #show num/3.
```

easy and safe to fix a full row/column!

### The ultimate Latin square encoding?

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- square(1,Y), not num(1,Y,Y). % Symmetry Breaking
```

% DISPLAY #hide. #show num/3.

#### Let's compare enumeration speed!

### The ultimate Latin square encoding?

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
```

% DISPLAY #hide. #show num/3.

```
gringo -c n=5 latin_6.lp | clasp -q 0
```

### The ultimate Latin square encoding?

```
% DOMAIN
#const n=32. square(1..n,1..n).
```

```
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
```

```
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
```

```
% DISPLAY
#hide. #show num/3.
gringo -c n=5 latin_6.lp | clasp -q 0
Models : 161280 Time : 2.078s
```

```
The ultimate Latin square encoding?
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 #count{ num(X,Y,N) : N = 1..n } 1 :- square(X,Y).
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- square(1,Y), not num(1,Y,Y). % Symmetry Breaking
```

```
% DISPLAY
#hide. #show num/3.
```

```
gringo -c n=5 latin_7.lp | clasp -q 0
```

Models : 161280 Time : 2.078s

```
The ultimate Latin square encoding?
```

```
% DOMAIN
#const n=32. square(1..n,1..n).
% GENERATE
1 \text{ #count} \{ \text{ num}(X,Y,N) : N = 1...n \} 1 :- \text{ square}(X,Y).
% TEST
:- X = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- Y = 1..n, N = 1..n, not 1 #count{ num(X,Y,N) } 1.
:- square(1,Y), not num(1,Y,Y). % Symmetry Breaking
% DISPLAY
#hide. #show num/3.
```

```
gringo -c n=5 latin_7.lp | clasp -q 0
```

```
Models : 1344 Time : 0.024s
```

### Effective Modeling: Overview

#### 28 Problems as Logic Programs (Revisited)

- Graph Coloring
- Hamiltonian Cycle
- Traveling Salesperson

#### 29 Encoding Methodology

- Tweaking N-Queens
- Do's and Dont's

### 30 Hints

### 1 Create a working encoding

- Q1: Do you need to modify the encoding if the facts change?
- Q2: Are all variables significant (or statically functionally dependent)?
- Q3: Can there be (many) identic ground rules?
- Q4: Do you enumerate pairs of values (to test uniqueness)?
- Q5: Do you assign dynamic aggregate values (to check a fixed bound)?
- Q6: Do you admit (obvious) symmetric solutions?
- Q7: Do you have additional domain knowledge simplifying the problem?
- Are you aware of anything else that, if encoded, would reduce grounding and/or solving efforts?

#### 2 Revise until no "Yes" answer!

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- Q1: Do you need to modify the encoding if the facts change?
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- Q7: Do you have additional domain knowledge simplifying the problem?
- Q8: Are you aware of anything else that, if encoded, would reduce grounding and/or solving efforts?
- 2 Revise until no "Yes" answer!
  - If the format of facts makes encoding painful (for instance, abusing grounding for "scientific calculations"), revise the fact format as well.

### Kinds of errors

syntactic ... follow error messages by the grounder
 semantic ... (most likely) encoding/intention mismatch

#### Ways to identify semantic errors (early)

- develop and test incrementally
- prepare toy instances with "interesting features"
- build the encoding bottom-up and verify additions (eg. new predicates)
- compare the encoded to the intended meaning
  - check whether the grounding fits (use gringo -t)
  - if answer sets are unintended, investigate conditions that fail to hold if answer sets are missing examine integrity constraints (add heads)

ask tools (eg. http://www.kr.tuwien.ac.at/research/projects/mmdasp/)

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# **Overcoming Performance Bottlenecks**

### Grounding

monitor time spent by and output size of gringo

 system tools (eg. time(gringo [...] | wc))
 profiling info (eg. gringo --gstats --verbose=3 [...] > /dev/null)

### Solving

check solving statistics (use clasp --stats) if great search efforts (Conflicts/Choices/Restarts), then try auto-configuration (offered by claspfolio) try manual fine-tuning (requires expert knowledge!) if possible, reformulate the problem or add domain knowledge ("redundant" constraints) to help the solver

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### Grounding

monitor time spent by and output size of gringo

 system tools (eg. time(gringo [...] | wc))
 profiling info (eg. gringo --gstats --verbose=3 [...] > /dev/null)

 <sup>IIII</sup> once identified, reformulate "critical" logic program parts

### Solving

check solving statistics (use clasp --stats)
if great search efforts (Conflicts/Choices/Restarts), then
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### Solving

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#### Grounding

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#### Grounding

#### Solving

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Torsten Schaub et al. (KRR@UP)

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#### Grounding

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## Systems: Overview

- 31 Potassco
- 32 gringo
- 33 clasp
- 34 Siblings
  - claspfolio
  - clingcon
  - iclingo
  - oclingo

#### 35 Book

# Systems: Overview

#### 31 Potassco

32 gringc

#### <mark>33</mark> clasp

34 Siblings

- claspfolio
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#### 35 Book

### http://potassco.sourceforge.net

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

- *Grounder*: gringo, pyngo
- Solver: clasp, claspd, claspar
- *Grounder+Solver*: clingo, iclingo, oclingo, clingcon
- *Further Tools*: claspfolio, coala, inca, plasp, sbass, xorro

Benchmark repository: http://asparagus.cs.uni-potsdam.de

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## Systems: Overview

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#### 35 Book

# gringo

- Accepts safe programs with aggregates
- Tolerates unrestricted use of function symbols (as long as it yields a finite ground instantiation :)
- Expressive power of a Turing machine
- Basic architecture of gringo:



## Systems: Overview



32 gringo



#### 34 Siblings

- claspfolio
- clingcon
- iclingo
- oclingo

#### 35 Book

# clasp

Native ASP solver combining conflict-driven search with sophisticated reasoning techniques:

- Advanced preprocessing including, e.g., equivalence reasoning
- Lookback-based decision heuristics
- Restart policies
- Nogood deletion
- Progress saving
- Dedicated data structures for binary and ternary nogoods
- Lazy data structures (watched literals) for long nogoods
- Dedicated data structures for cardinality and weight constraints
- Lazy unfounded set checking based on "source pointers"
- Tight integration of unit propagation and unfounded set checking
- Reasoning modes
- Multi-threaded search
- • •

# Reasoning modes of *clasp*

Beyond deciding answer set existence, *clasp* allows for:

- Optimization
- Enumeration
- Projective Enumeration

[without solution recording] [without solution recording]

- Brave and Cautious Reasoning determining the
  - union or
  - intersection
  - of all answer sets by computing only linearly many of them
- and combinations thereof
- clasp also allows for solving
  - propositional CNF formulas (extended *dimacs*)
  - pseudo-Boolean formulas (opb and wbo)

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clasp



Torsten Schaub et al. (KRR@UP)

Modeling and Solving in ASP

clasp



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Modeling and Solving in ASP

## Systems: Overview

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#### 35 Book

# claspfolio

- Automatic selection of *clasp* configuration among 22 configuration via (learned) classifiers
- Basic architecture of *claspfolio*:



# clingcon

- Hybrid grounding and solving
- Solving in hybrid domains, like Bio-Informatics
- Basic architecture of *clingcon*:



### Pouring Water into Buckets on a Scale

 time(0..t).
 \$domain(0..500).

 bucket(a).
 volume(a,0) \$== 0.

 bucket(b).
 volume(b,0) \$== 100

1 { pour(B,T) : bucket(B) } 1 :- time(T), T < t.

```
1 $<= amount(B,T) :- pour(B,T), T < t.
amount(B,T) $<= 30 :- pour(B,T), T < t.
amount(B,T) $== 0 :- not pour(B,T), bucket(B), time(T), T < t.</pre>
```

```
volume(B,T+1) $== volume(B,T) + amount(B,T) :- bucket(B), time(T), T < t.</pre>
```

down(B,T) := volume(C,T) \$< volume(B,T), bucket(B;C), time(T)
up(B,T) := not down(B,T), bucket(B), time(T).</pre>

:- up(a,t).

#### Pouring Water into Buckets on a Scale

 time(0..t).
 \$domain(0..500).

 bucket(a).
 volume(a,0) \$== 0.

 bucket(b).
 volume(b,0) \$== 100.

 $1 \{ pour(B,T) : bucket(B) \} 1 :- time(T), T < t.$ 

```
1 $<= amount(B,T) :- pour(B,T), T < t.
amount(B,T) $<= 30 :- pour(B,T), T < t.
amount(B,T) $== 0 :- not pour(B,T), bucket(B), time(T), T < t.</pre>
```

volume(B,T+1) \$== volume(B,T) + amount(B,T) :- bucket(B), time(T), T < t.</pre>

down(B,T) := volume(C,T) \$< volume(B,T), bucket(B;C), time(T). up(B,T) := not down(B,T), bucket(B), time(T).

:- up(a,t).

# iclingo

- Incremental grounding and solving
- Offline solving in dynamic domains, like Automated Planning
- Basic architecture of *iclingo*:




































# Simplistic STRIPS Planning

#base.

# Simplistic STRIPS Planning

#### #base.

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

# oclingo

- Reactive grounding and solving
- Online solving in dynamic domains, like Robotics
- Basic architecture of *oclingo*:











































### **Elevator Control**

```
#base.
```

```
floor(1..3).
atFloor(1,0).
#cumulative t.
#external request(F,t) : floor(F).
1 { atFloor(F-1;F+1,t) } 1 :- atFloor(F,t-1), floor(F).
:- atFloor(F,t), not floor(F).
requested(F,t) :- request(F,t), floor(F), not atFloor(F,t).
requested(F,t) :- requested(F,t-1), floor(F), not atFloor(F,t).
goal(t) :- not requested(F,t) : floor(F).
```

#volatile t

```
:- not goal(t).
```

#### **Elevator Control**

```
#base.
```

```
floor(1..3).
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requested(F,t) :- requested(F,t-1), floor(F), not atFloor(F,t).
goal(t) :- not requested(F,t) : floor(F).
```

#volatile t.

:- not goal(t).

#### oClingo acts as a server listening on a port waiting for client requests

To issue such requests, a separate controller program sends online progressions using network sockets

#### For instance,

- #step 1.
- request(3,1).
- #endstep.

# This process terminates when the client sends

#stop.

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#### For instance,

```
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request(3,1).
#endstep.
```

#### This process terminates when the client sends #stop.

#### Systems: Overview

- 31 Potassco
- 32 gringo
- 33 clasp
- 34 Siblings
  - claspfolio
  - clingcon
  - iclingo
  - oclingo

#### 35 Book

# The (forthcoming) Potassco Book

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



#### http://potassco.sourceforge.net/teaching.html
#### Summary

- ASP is emerging as a viable tool for Knowledge Representation and Reasoning
- ASP offers efficient and versatile off-the-shelf solving technology
  - http://potassco.sourceforge.net
  - ASP'07/09/11, CASC'11, MISC'11, PB'09/11, and SAT'09/11
- ASP offers an expanding functionality and ease of use
  - Rapid application development tool
- ASP has a growing range of applications

### ASP = KR + DB + SAT + LP

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