

Experiencing Answer Set Programming at Work Today and Tomorrow

Torsten Schaub

University of Potsdam



Outline

- 1 Introduction
- 2 Modeling
- 3 Solving
- 4 Optimizing
- 5 Reacting
- 6 Summary

Outline

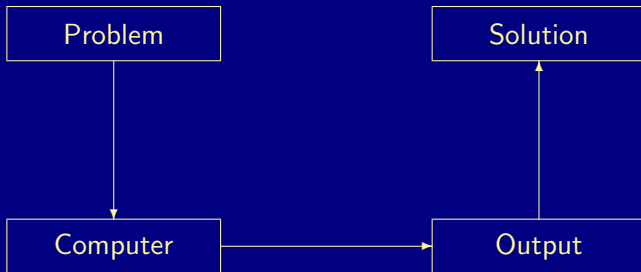
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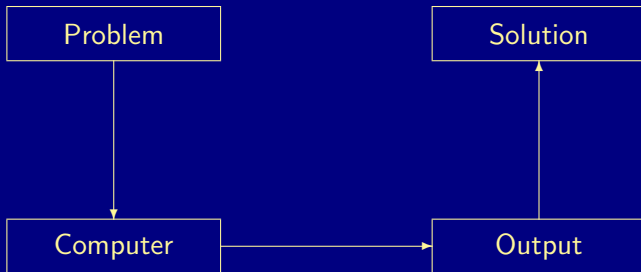
Informatics

“What is the problem?” versus *“How to solve the problem?”*



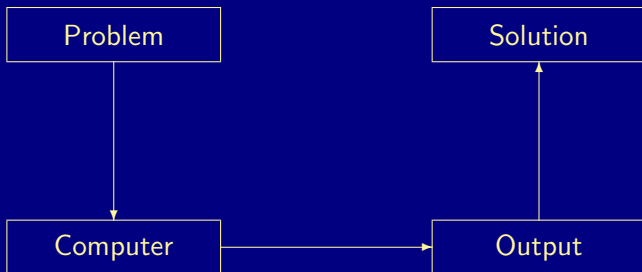
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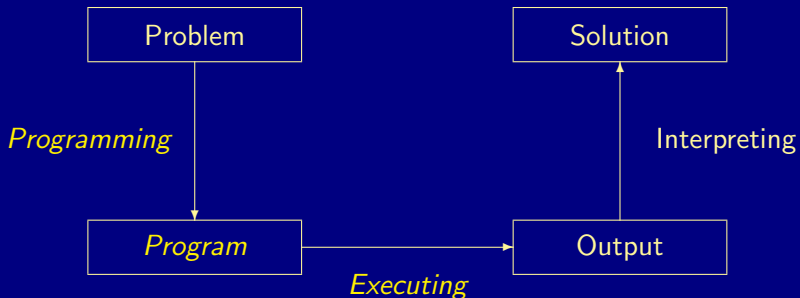
Traditional programming

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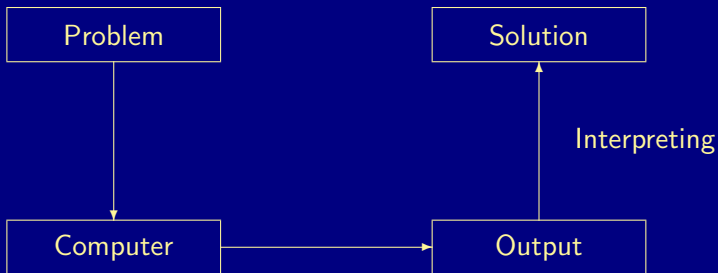
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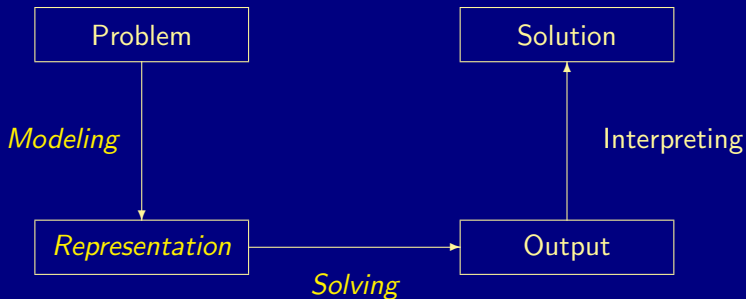
Declarative problem solving

“What is the problem?” versus *“How to solve the problem?”*



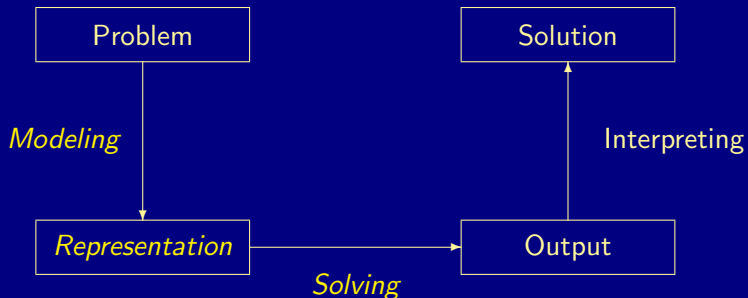
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Declarative problem solving

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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

- (deductive) databases

- logic programming (with negation)

- (logic-based) knowledge representation and (nonmonotonic) reasoning
- constraint solving (in particular, SATisfiability testing)

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, CASC, MISC, PB, and SAT competitions

ASP embraces many emerging application areas, and users

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KR's shift of paradigm

Theorem Proving based approach (eg. Prolog)

- 1 Provide a representation of the problem
- 2 A solution is given by a derivation of a query

Model Generation based approach (eg. SATisfiability testing)

- 1 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
propositional programs	stable models
first-order theories	models
first-order theories	minimal models
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first-order theories	Herbrand models
auto-epistemic theories	expansions
default theories	extensions

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Model Generation based Problem Solving

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Answer Set Programming *in general*

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Answer Set Programming *in practice*

Representation	Solution
constraint satisfaction problem	assignment
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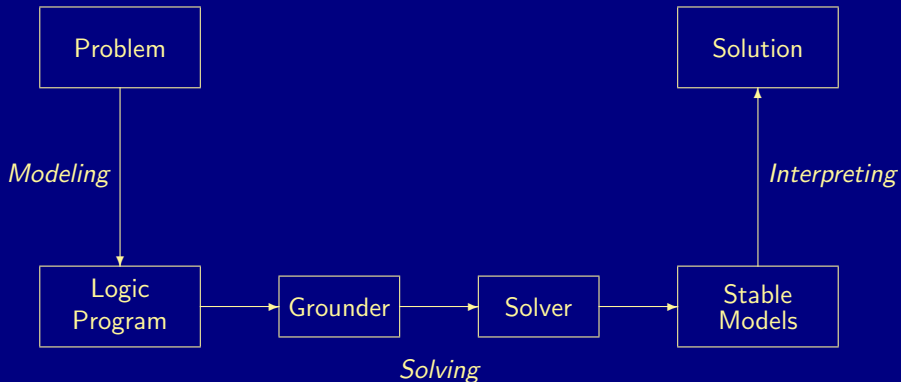
ASP versus LP

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

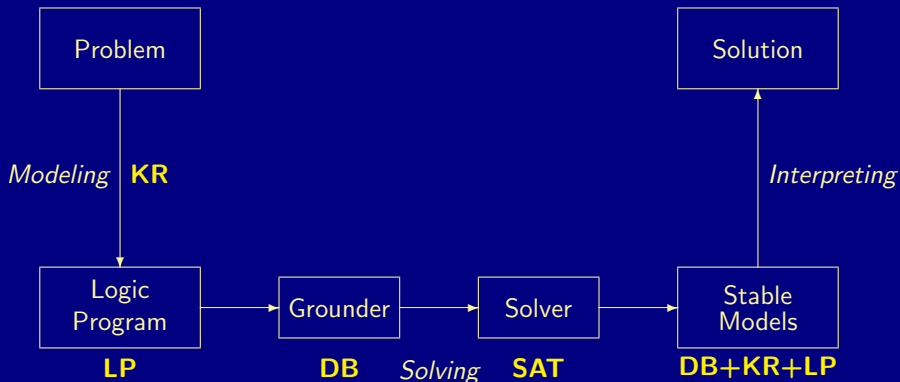
ASP versus SAT

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	—
Intersection/Union	—
Optimization	—
(Turing +) $NP(NP)$	NP

ASP solving



Rooting ASP solving



Answer Set Programming

in a Hazelnutshell

- ASP is an approach to **declarative problem solving**, combining
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- tailored to **Knowledge Representation and Reasoning**

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ASP = DB+LP+KR+SAT

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$$\mathbf{ASP = DB + LP + KR + SMT}^n$$

Declarativity versus Scalability

Declarativity

ASP does separate a problem's representation from the algorithms used for solving it

Scalability

- 1 ASP does not separate a problem's representation from its induced combinatorics
- 2 Boolean constraint technology is rather sensitive to search parameters

Followup to: M. Gebser, R. Kaminski, B. Kaufmann, and T. Schaub. Challenges in Answer Set Solving. In *Essays Dedicated to Michael Gelfond on the Occasion of His 65th Birthday*, pages 74–90. Springer, 2011

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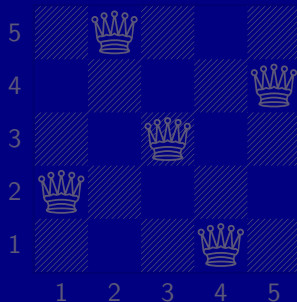
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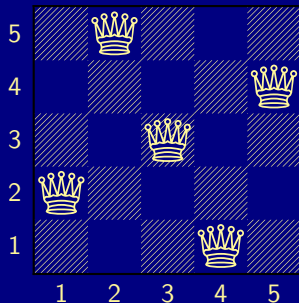
The n-queens problem



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

The n-queens problem

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



Basic encoding

queensB.lp

```
{ queen(1..n,1..n) }.
```

```
:- not { 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.
```

Advanced encoding

queensA.lp

```
{ queen(I,1..n) } == 1 :- I = 1..n.  
{ 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.
```

Corrupted encoding

queensC.lp

```
{ queen(1..n,1..n,1..n) }.
```

```
:- not { queen(I,J,K) } == n.
```

```
:- queen(I,J,K), queen(I,JJ,K), J != JJ.
```

```
:- queen(I,J,K), queen(II,J,K), I != II.
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```
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```

```
:- queen(I,J,K), queen(II,JJ,K), (I,J) != (II,JJ), I+J == II+JJ.
```

```
queen(I,J) :- queen(I,J,K).
```

Grounding size

via `wc --lines`

n	queensB.lp	queensA.lp	queensC.lp
10	3053	310	30413
20	25493	830	509613
30	87333	1550	2619613
40	208573	2470	8342413
50	409213	3590	20460013
60	709253	4910	42554413
70	1128693	6430	79007613
80	1687533	8150	135001613
90	2405773	10070	217255513
100	3303413	12190	331350013

Challenge one

Fact

ASP Modeling (still) requires Craft, Experience, and Knowledge

Challenge

Theory and Tools for Non-Ground Pre-processing

Challenge one

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Theory and Tools for Non-Ground Pre-processing — *Just like SQL !*

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Towards conflict-driven search

Boolean constraint solving algorithms pioneered for SAT led to:

- Traditional DPLL-style approach
(DPLL stands for 'Davis-Putnam-Logemann-Loveland')
 - (Unit) propagation
 - (Chronological) backtracking
 - in ASP, eg *smodels*
- Modern CDCL-style approach
(CDCL stands for 'Conflict-Driven Constraint Learning')
 - (Unit) propagation
 - Conflict analysis (via resolution)
 - Learning + Backjumping + Assertion
 - in ASP, eg *clasp*

DPLL-style solving

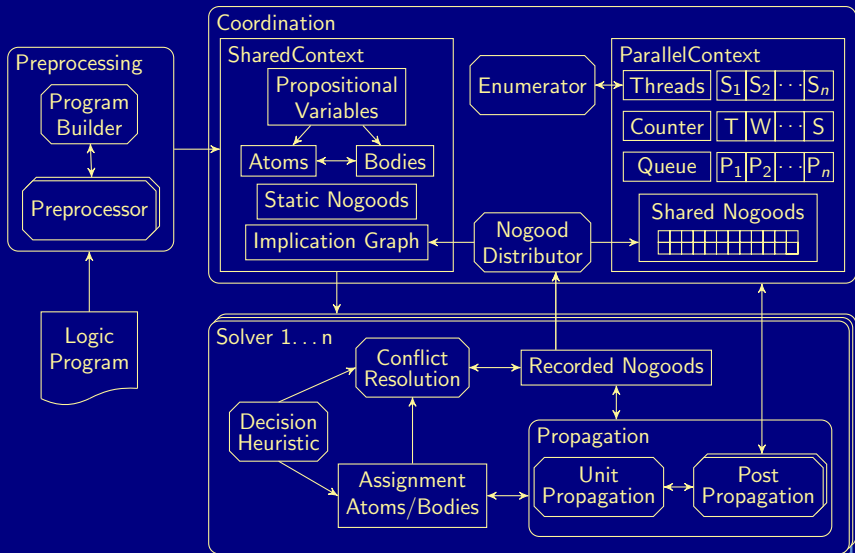
loop

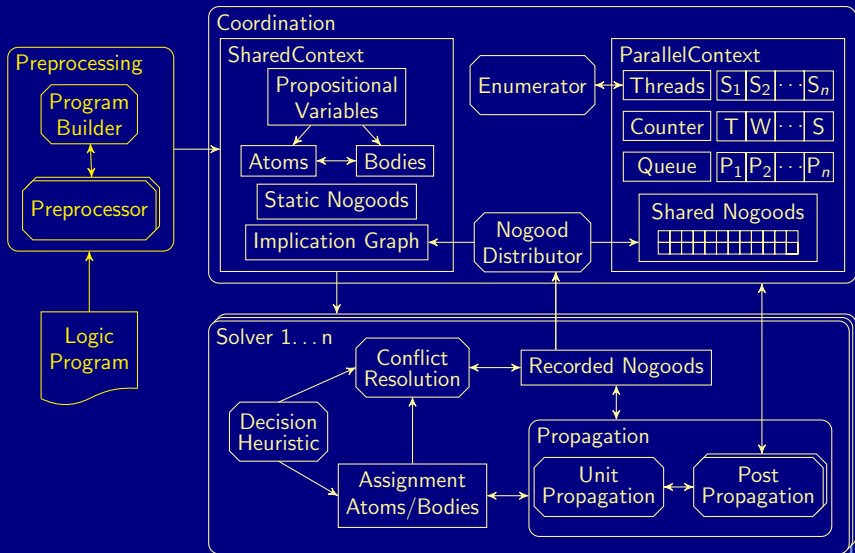
```
propagate // deterministically assign literals
if no conflict then
    if all variables assigned then return solution
    else decide // non-deterministically assign some literal
else
    if top-level conflict then return unsatisfiable
    else
        backtrack // unassign literals propagated after last decision
        flip // assign complement of last decision literal
```

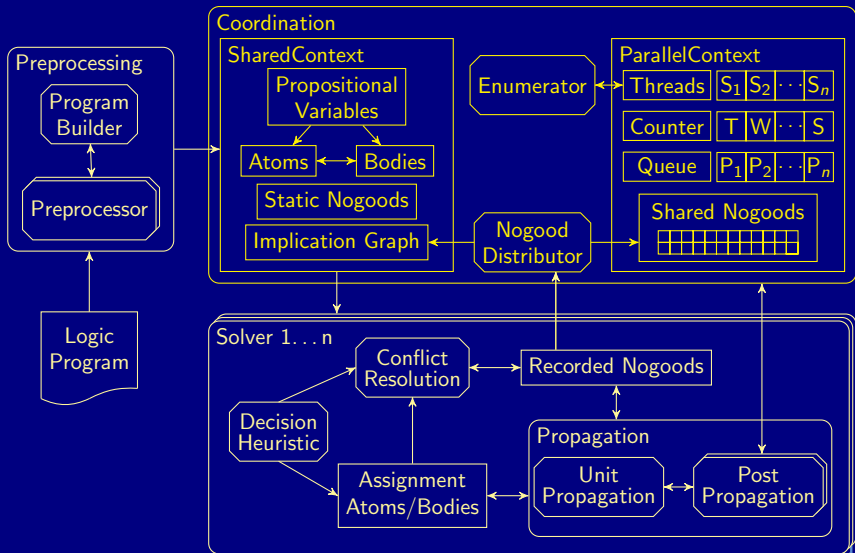
CDCL-style solving

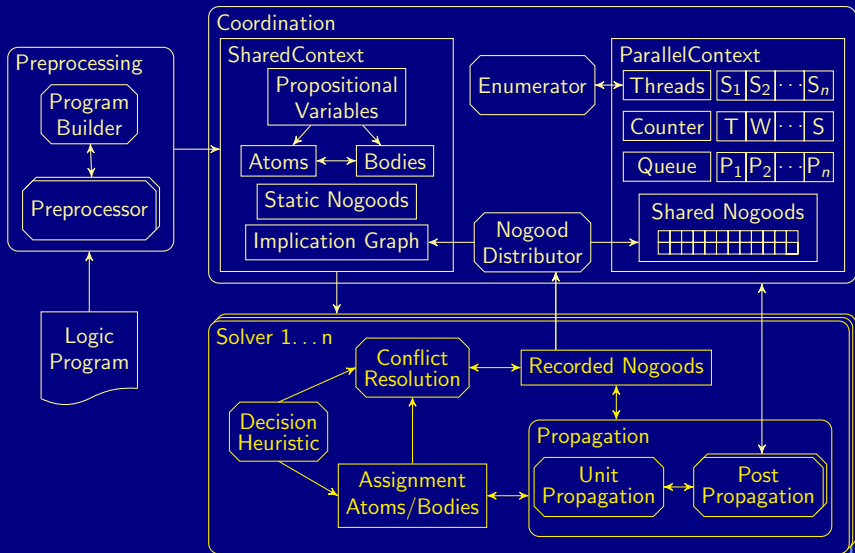
loop

```
propagate // deterministically assign literals
if no conflict then
  if all variables assigned then return solution
  else decide // non-deterministically assign some literal
else
  if top-level conflict then return unsatisfiable
  else
    analyze // analyze conflict and add conflict constraint
    backjump // unassign literals until conflict constraint is unit
```

Multi-threaded architecture of *clasp*

Multi-threaded architecture of *clasp*

Multi-threaded architecture of *clasp*

Multi-threaded architecture of *clasp*

Challenge two

Fact

Boolean constraint technology is rather sensitive to search parameters

Challenge

Robust ASP solving technology

Challenge two

Fact

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Robust ASP solving technology

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Challenge

Robust ASP solving technology — *Taming the oracle !*

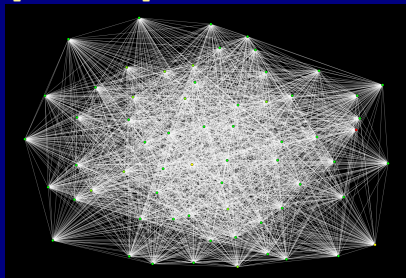
Inside *clasp*, or the encoding's impact

queens{B,A}.lp, n=8

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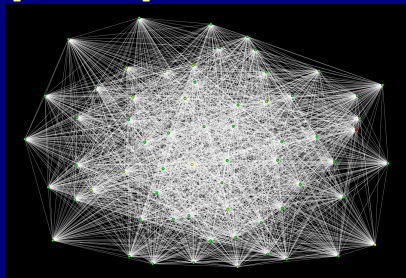
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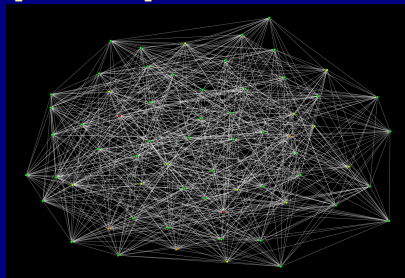
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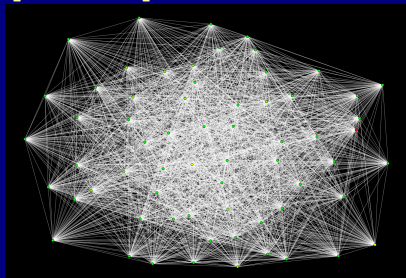
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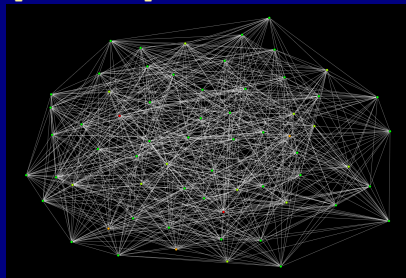
Inside *clasp*, or the encoding's impact

queens{B,A}.lp, n=8

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queensA.lp



Like the pictures...?

➡ Check out Arne König's talk on Tuesday at 16:00+ during TechComm 3

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Configurations

clasp version 2.1.3

```
--configuration=<arg>    : Configure default configuration [frumpy]
  <arg>: frumpy|jumpy|handy|crafty|trendy|chatty
    frumpy: Use conservative defaults
    jumpy  : Use aggressive defaults
    handy  : Use defaults geared towards large problems
    crafty : Use defaults geared towards crafted problems
    trendy : Use defaults geared towards industrial problems
    chatty : Use 4 competing threads initialized via the default portfolio
```

Comparing configurations

on queensA.lp

n	--frumpy	--jumpy	--handy	--crafty	--trendy	--chatty
50	0.063	0.023	3.416	0.030	1.805	0.061
100	20.364	0.099	7.891	0.136	7.321	0.121
150	60.000	0.212	14.522	0.271	19.883	0.347
200	60.000	0.415	15.026	0.667	32.476	0.753
500	60.000	3.199	60.000	7.471	60.000	6.104

(times in seconds, cut-off at 60 seconds)

Comparing configurations

on queensA.lp

n	--frumpy	--jumpy	--handy	--crafty	--trendy	--chatty
50	0.063	0.023	3.416	0.030	1.805	0.061
100	20.364	0.099	7.891	0.136	7.321	0.121
150	60.000	0.212	14.522	0.271	19.883	0.347
200	60.000	0.415	15.026	0.667	32.476	0.753
500	60.000	3.199	60.000	7.471	60.000	6.104

(times in seconds, cut-off at 60 seconds)

Comparing configurations

on queensA.lp

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150	60.000	0.212	14.522	0.271	19.883	0.347
200	60.000	0.415	15.026	0.667	32.476	0.753
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(times in seconds, cut-off at 60 seconds)

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clasp's default portfolio for parallel solving via `clasp --print-portfolio`

```
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[TRENDY]: --heuristic=vsids --restarts=d,100,0.7 --deletion=3,50 --del-init=500,19500 --del-grow=1.1,20.0,x,100
[FRUMPY]: --heuristic=berkmin --restarts=x,100,1.5 --deletion=1,75 --del-init-r=200,40000 --del-max=400000 --de
[JUMPY]: --heuristic=vsids --restarts=l,100 --del-init-r=1000,20000 --del-algo=basic,2 --deletion=3,75 --del-g
[STRONG]: --heuristic=berkmin --restarts=x,100,1.5 --deletion=1,75 --del-init-r=200,40000 --del-max=400000 --de
[HANDY]: --heuristic=vsids --restarts=d,100,0.7 --deletion=2,50,20.0 --del-max=200000 --del-algo=sort,2 --del
[S2]: --heuristic=vsids --reverse-arcs=1 --otfs=1 --local-restarts --save-progress=0 --contraction=250 --counte
[S4]: --heuristic=vsids --restarts=l,256 --counter-restart=3 --strengthen=recursive --update-lbd --del-glue=2 --
[SLOW]: --heuristic=berkmin --berk-max=512 --restarts=f,16000 --lookahead=atom,50
[VMTF]: --heuristic=vmtf --str=no --contr=0 --restarts=x,100,1.3 --del-init-r=800,9200
[SIMPLE]: --heuristic=vsids --strengthen=recursive --restarts=x,100,1.5,15 --contraction=0
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[LOCAL-R]: --berk-max=512 --restarts=x,100,1.5,6 --local-restarts --init-w=2 --contr=0
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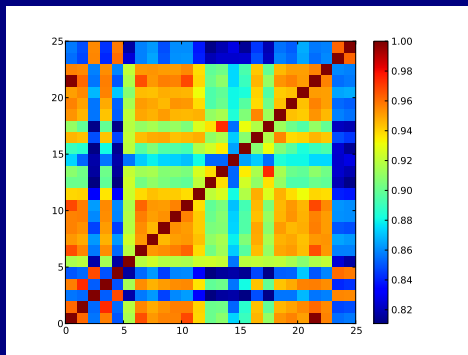
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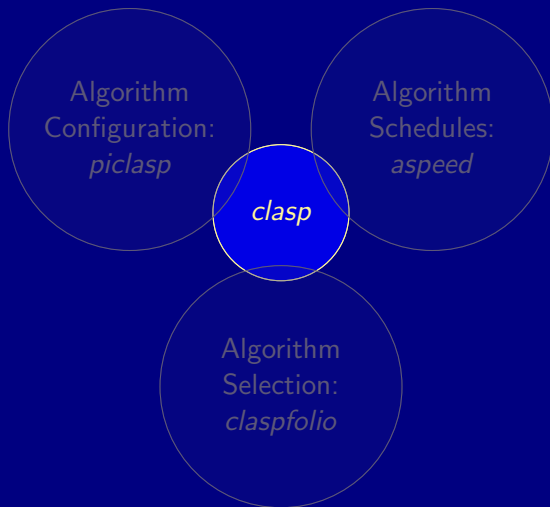
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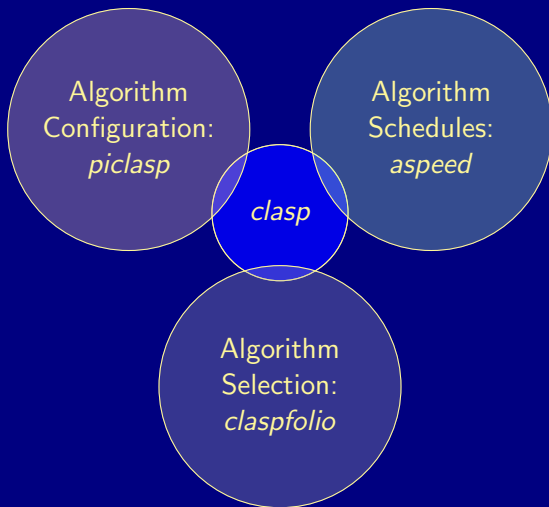
Correlation of *clasp* configurations



Algorithm engineering



Algorithm engineering



piclasp

Task

Identify an individual **configuration** for solving a specific problem class (having a homogeneous instance set)

Approach

Use an algorithm configurator (eg *SMAC* or *ParamILS*) for finding a well performing configuration

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piclasp's search space

Clasp - Search Options:

```

--heuristic=<arg>      : Configure decision heuristic
  <arg>: Berkmin|Vmtf|Vsids|Unit|None
    Berkmin: Apply BerkMin-like heuristic
    Vmtf   : Apply Siegf-ike heuristic
    Vsids  : Apply Chaff-like heuristic
    Unit   : Apply Smodels-like heuristic (Default if --no-lookback)
    None   : Select the first free variable
--[no-]init-moms       : Initialize heuristic with MOMS-score
--score-other=<n>     : Score 0=no|1=loop|2=all other learnt nogoods
--sign-def=<n>        : Default sign: 0=type|1=no|2=yes|3=rnd
--[no-]sign-fix       : Disable sign heuristics and use default signs only
--berk-max=<n>        : Consider at most <n> nogoods in Berkmin heuristic
--[no-]berk-huang     : Enable/Disable Huang-scoring in Berkmin
--[no-]berk-once      : Score sets (instead of multisets) in Berkmin
--vmtf-mtf=<n>        : In Vmtf move <n> conflict-literals to the front
--vsids-decay=<n>     : In Vsids use 1.0/<n> as decay factor
--[no-]nant           : In Unit count only atoms in NAnt(P)
--opt-heuristic[=0..3]: Use opt. in 1=sign|2=model|3=both heuristics
--save-progress[=<n>] : Use RSat-like progress saving on backjumps > <n>
--rand-freq=<p>       : Make random decisions with probability <p>
--init-watches=0..2  : Configure watched literal initialization [1]
  Watch 0=first|1=random|2=least watched literals in nogoods
--seed=<n>            : Set random number generator's seed to <n>

--lookahead[=<arg>|no] : Configure failed-literal detection (fld)
  <arg>: <type>[,<n 1..umax>] / Implicit: atom
    <type>: Run fld via atom|body|hybrid lookahead
    <n>    : Disable fld after <n> applications ([-1]=no limit)

```

aspeed

Task

Synthesize a timeout- and time-minimal **schedule** of configurations for solving a heterogeneous set of problem instances

Approach

Use ASP (and runtime data) for finding such a schedule

aspeed

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aspeed's basic encoding

```

solver(S) :- time(_,S,_).
time(S,T) :- time(_,S,T).
unit(1..N) :- units(N).

{ slice(U,S,T) : time(S,T) : T <= K : unit(U) } 1 :- solver(S), kappa(K).

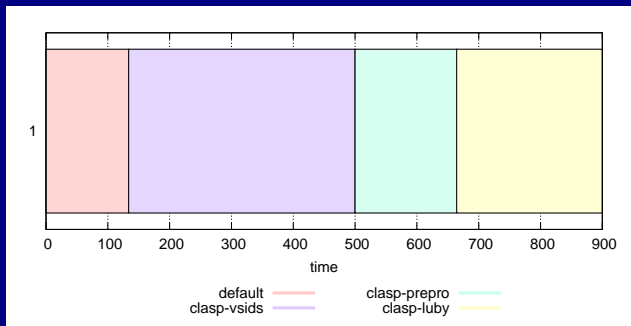
:- not [ slice(U,S,T) = T ] K, kappa(K), unit(U).

slice(S,T) :- slice(_,S,T).
solved(I,S) :- slice(S,T), time(I,S,T).
solved(I,S) :- solved(J,S), order(I,J,S).
solved(I) :- solved(I,_).

#maximize { solved(I) @ 2 }.
#minimize [ slice(S,T) = T*T @ 1 ].

```


A resulting schedule



claspfolio

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Select an individual **configuration** for solving a specific problem instance (from a heterogeneous instance set)

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Use instance features to select a promising configuration from a portfolio via trained classifiers

claspfolio

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claspre features

- Plain instance features
 - Number of atoms
 - Number of rule types
 - ...
- Features after preprocessing
 - Tightness
 - Equivalences between atoms and bodies
 - Number of constraint types
 - ...
- Search features after restarting
 - Number of choices
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All in all $32 + 25 \cdot 2$ features are calculated

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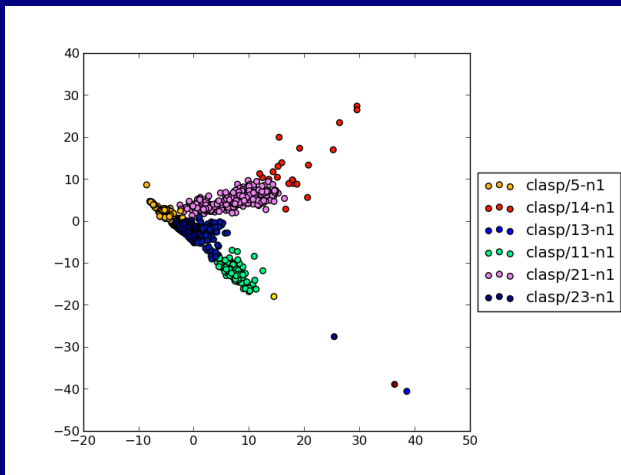
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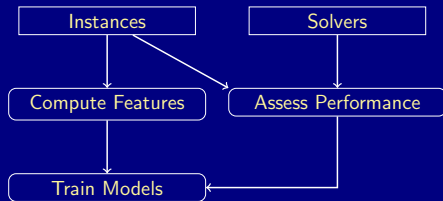
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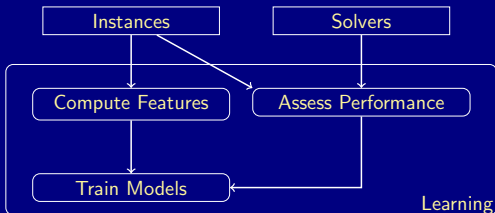
Feature space in practice

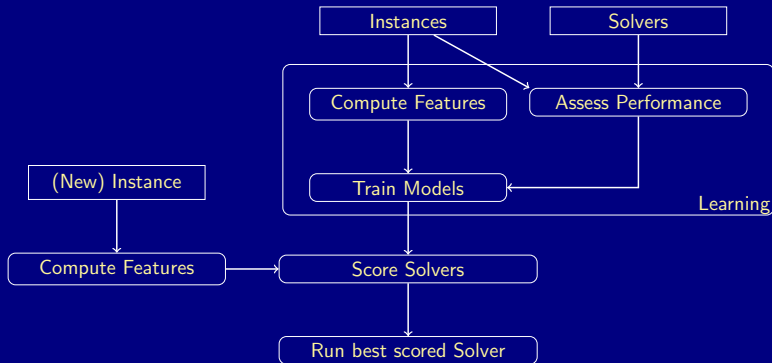


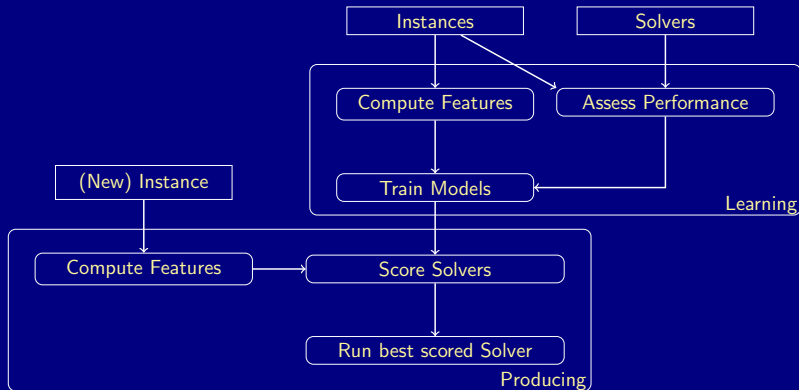
claspfolio's architecture



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hclasp

- *hclasp* allows for incorporating domain-specific heuristics
 - input language for expressing domain-specific heuristics
 - solving capacities for integrating domain-specific heuristics

- Example

- Extend your encoding, `enc.lp`, by a heuristic rule like

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_heuristic(occ(A,T),factor,T) :- action(A),time(T).
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and the heuristic information via a `#show` statement

Ground the program (as usual) and make `hclasp` notice your heuristic modifications

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loop

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propagate // compute deterministic consequences
if no conflict then
    if all variables assigned then return variable assignment
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else
    if top-level conflict then return unsatisfiable
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        analyze // analyze conflict and add a conflict constraint
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Inside *decide*

■ Heuristic functions

$$h : \mathcal{A} \rightarrow [0, +\infty) \quad \text{and} \quad s : \mathcal{A} \rightarrow \{\mathbf{T}, \mathbf{F}\}$$

■ Algorithmic scheme

$$\mathbf{1} \quad h(a) := \alpha \times h(a) + \beta(a)$$

for each $a \in \mathcal{A}$

$$\mathbf{2} \quad U := \mathcal{A} \setminus (A^{\mathbf{T}} \cup A^{\mathbf{F}})$$

$$\mathbf{3} \quad C := \operatorname{argmax}_{a \in U} h(a)$$

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Heuristic language elements

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- Heuristic modifiers (atom, a , and integer, v)
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holds(P,0) :- init(P).

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

holds(F,T) :- holds(F,T-1), not nolds(F,T), time(T).
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:- query(F), not holds(F,t).

_heuristic(A,level,V) :- _heuristic(A,true, V).
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```

Simple STRIPS planner

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Planning Competition Benchmarks

```

_heuristic(holds(F,T-1),true, t-T+1) :- holds(F,T).
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```

Problem	<i>base configuration</i>	<i>_heuristic</i>	<i>base c. (SAT)</i>	<i>heur. (SAT)</i>
<i>Blocks'00</i>	134.4s (180/61)	9.2s (239/3)	163.2s (59)	2.6s (0)
<i>Elevator'00</i>	3.1s (279/0)	0.0s (279/0)	3.4s (0)	0.0s (0)
<i>Freecell'00</i>	288.7s (147/115)	184.2s (194/74)	226.4s (47)	52.0s (0)
<i>Logistics'00</i>	145.8s (148/61)	115.3s (168/52)	113.9s (23)	15.5s (3)
<i>Depots'02</i>	400.3s (51/184)	297.4s (115/135)	389.0s (64)	61.6s (0)
<i>Driverlog'02</i>	308.3s (108/143)	189.6s (169/92)	245.8s (61)	6.1s (0)
<i>Rovers'02</i>	245.8s (138/112)	165.7s (179/79)	162.9s (41)	5.7s (0)
<i>Satellite'02</i>	398.4s (73/186)	229.9s (155/106)	364.6s (82)	30.8s (0)
<i>Zenotravel'02</i>	350.7s (101/169)	239.0s (154/116)	224.5s (53)	6.3s (0)
<i>Total</i>	252.8s (1225/1031)	158.9s (1652/657)	187.2s (430)	17.1s (3)

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- 1 Introduction
- 2 Modeling
- 3 Solving
 - Conflict-driven search
 - Solver configurations
 - Parallel solving
 - Automatic solver engineering
 - Domain-specific heuristics
- 4 Optimizing
- 5 Reacting
- 6 Summary

Challenge three (or: one+two)

Fact

Many real-world applications involve optimization

Challenge

Theory and Tools for versatile optimization methods

Challenge three (or: one+two)

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Theory and Tools for versatile optimization methods

Alternative ways of optimization

- Branch-and-Bound optimization in *clasp*
- Hierarchical Branch-and-Bound optimization in *clasp*
- Unsatisfiability-based optimization in *unclasp*
- Incremental optimization in *iclingo*

- Saturation-based optimization in *metasp* (via *claspD*)
- Heuristic-driven optimization in *hclasp*

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Challenge four (or: one+one+two)

Fact

Intelligence is build around us and in our pockets

Challenge

Incremental and reactive ASP solving technology

Challenge four (or: one+one+two)

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Incremental and reactive ASP solving technology

Going online

- Planning and reasoning about action with *iclingo*
- Sliding windows in stream reasoning with *oclingo*
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- Cognitive robotics with *ROSoClingo*

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“Ke Jia” robots
(X. Chen, UST China)

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Summary

Declarativity

ASP separates a problem's representation from the algorithms used for solving it

Challenges

- Modeling
- Solving
- Optimizing
- Reacting

Scalability

There is no free lunch !

Visit us !

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- open source software
- teaching material

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Mona Gharib ◦ Susanne Grell ◦ Jean Gressmann ◦ Torsten Grote ◦
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