Learning Efficient Constraints in Answer Set Programming

Alice Tarzariol, Martin Gebser, Konstantin Schekotihin

Alpen-Adria-Universität Klagenfurt, Austria

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Overview

1. Answer Set Programming
2. Practical Issues with Symmetries
3. Learning Efficient Constrains
4. Extension for Optimization Problems
5. Conclusions and Future Works

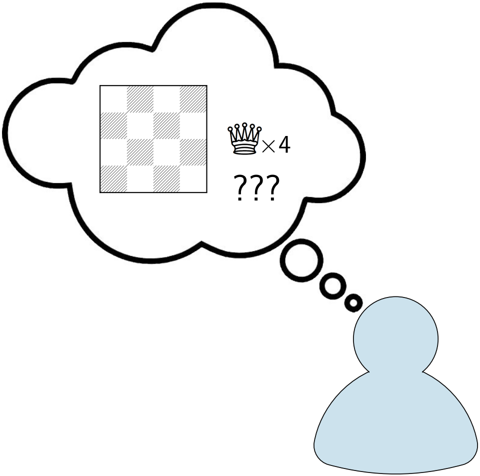
Answer Set Programming

Introduction

- Declarative programming paradigm, based on logic
- Suited for combinatorial search and optimization problems
- For examples:
  - $\rightarrow$ Configurations
  - $\rightarrow$ Scheduling
  - $\rightarrow$ Planning
  - $\rightarrow$ $\dots$
- Strengths: flexible, intuitive, expressive, efficient systems

ASP Declarative Approach

"Describe the problem/solutions" VS "List the steps to solve it"



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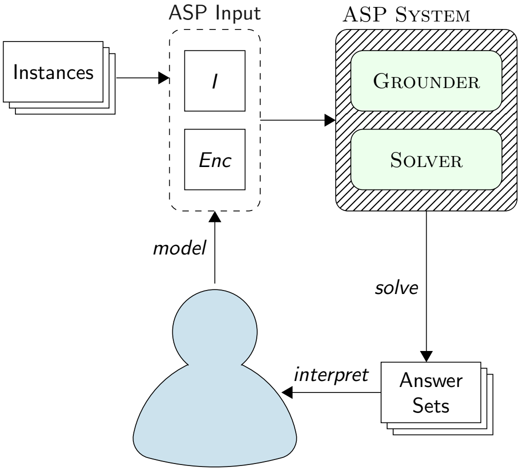
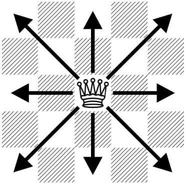


ASP Input

When the users model a problem, they define two elements:

- **Encoding:**
  - → General rules
  - → Describe objects and relations in the problem
  - → E.g., grid, queens attack

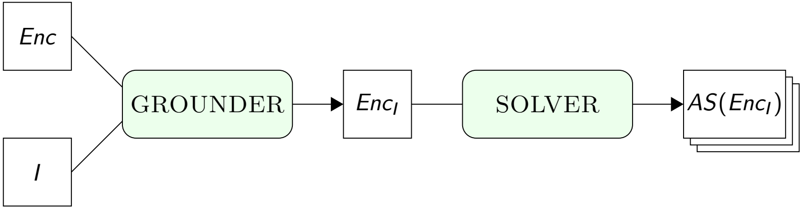


$\times n$

- **Instance:**
  - → Specific input
  - → Drawn from a set of valid instances
  - → Number(s), graph, etc.

$$n = 4$$

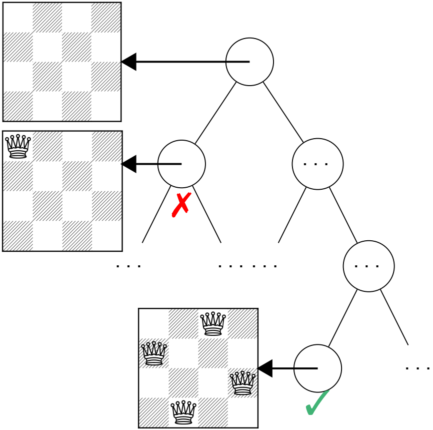
ASP System



1. GROUNDER:
   - → Combines the information between *Enc* and *I*
   - → Result: Enc_I, which defines concrete elements and conditions

2. SOLVER
   - → Searches for the truth assignments that are answer sets (solutions)

(Intuitive) Solving Procedure



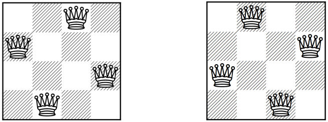
Practical Issues with Symmetries

Issues with Industrial Applications

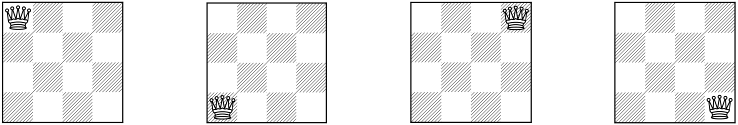
- Huge instances, no answer
- Several techniques for coping with different issues
- In this talk: symmetries!
- The encoding *Enc* highly influences the search performance
- It should avoid symmetries, exploit invariants of instances, etc.

What is a Symmetry?

- A symmetry entails equivalent characteristics to another object, e.g., truth assignments
- Symmetric solutions



- Symmetric (partial) interpretations



How do we deal with symmetries?

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- Automatically identify symmetric solutions and extend a given model with constraints discarding them
  - → Instance-specific
  - → Model-oriented

Instance-Specific Approaches to Symmetry Breaking

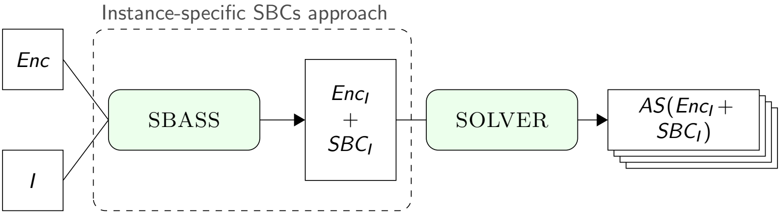
Remove the symmetries according to syntactic properties of the current problem instance [4] by adding *Symmetry Breaking Constraints (SBCs)*

Instance-Specific SBCs

1. Define a reduction to graph automorphism problem
2. Use tools to find symmetric vertex permutations, e.g. SAUCY [2]
3. Derive symmetries of the original problem from vertex permutations
4. Add SBCs according to a certain criterion (e.g., lexicographic order)

Symmetry Breaking Answer Set Solving

SBASS [3] implements automatic symmetry detection and breaking for ground ASP programs



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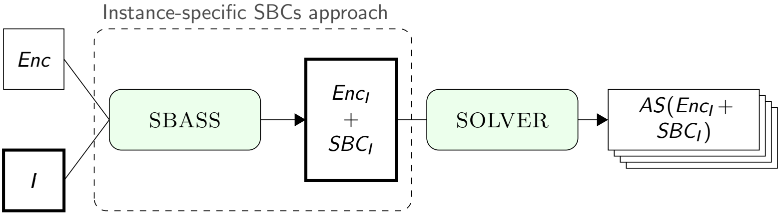

Limitations of instance-specific SBCs approaches

1. No generalisation

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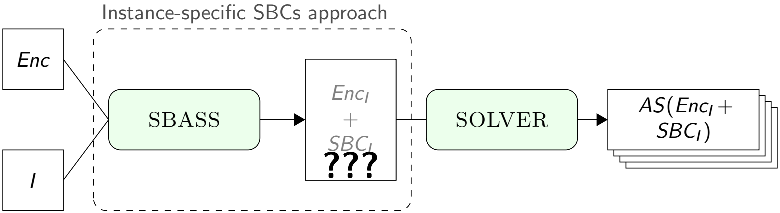

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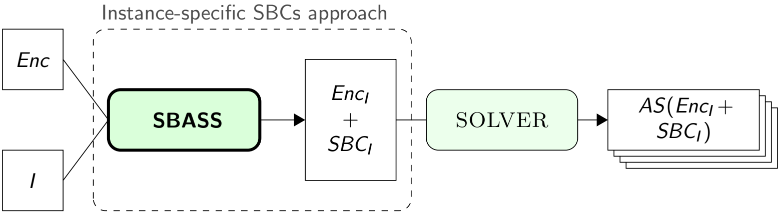

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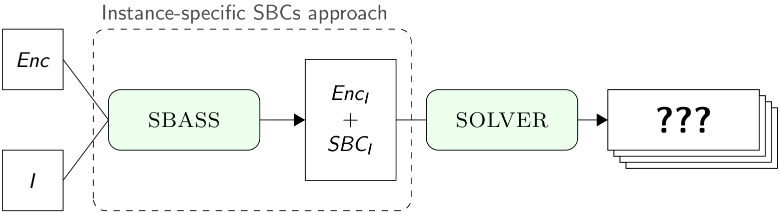
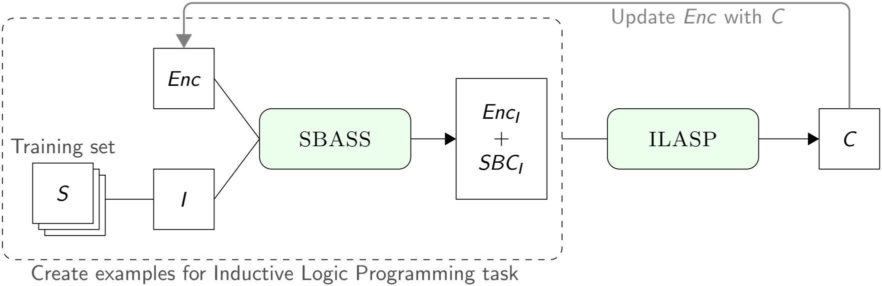


Limitations of instance-specific SBCs approaches

1. No generalisation
2. Interpretability
3. Pre-processing overhead
4. Redundancy

Model-Oriented Approach



Learning Framework

Input: "naive" encoding Enc, set of representative satisfiable instances S

$\rightarrow$ Identify symmetries of each instance in S

$\rightarrow$ Use the symmetries to create examples for an ILP task

Output: constraints C pruning redundant parts of the search space

Learning Efficient Constrains

Learning Efficient Constraints in ASP

Version 1	Version 2	Version 3
Simple Decision Problems	Complex Decision Problems	Optimization Problems
IJCAI 2021 [5] & MLJ 2022 [6]	ICLP 2022 [8]	AAAI 2023 [7]

Research Goals

1. Define a model-oriented approach capable of lifting symmetries and obtaining first-order constraints (for a target distribution)
2. Investigate extensions to enable learning constraints for advanced combinatorial problems
3. Extend the expressiveness of the learning framework to analyse the symmetries of optimization problems

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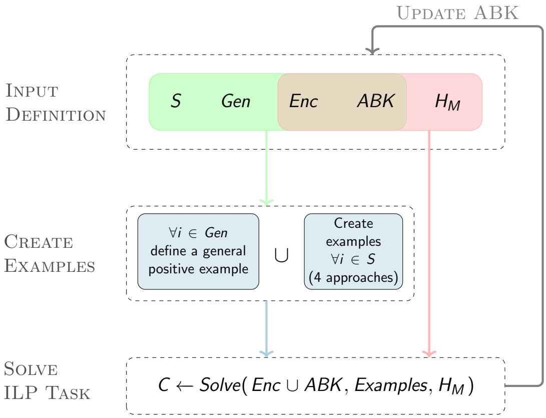

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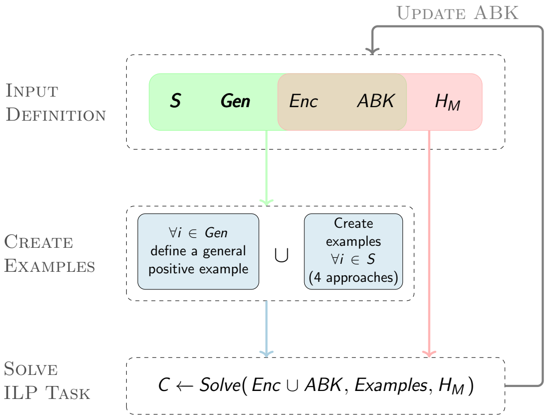

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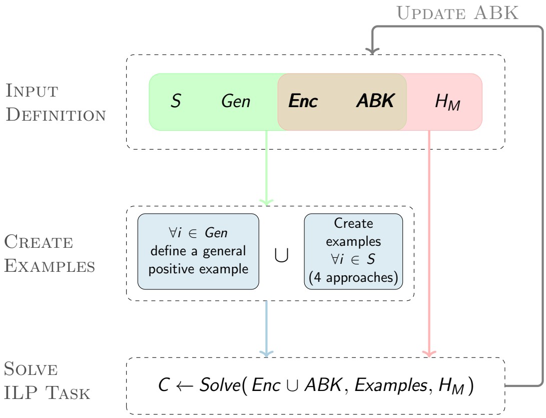

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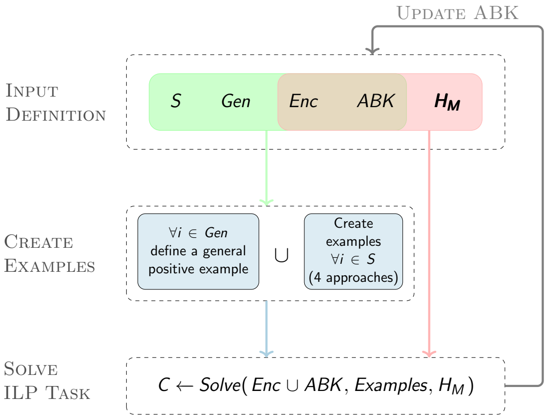
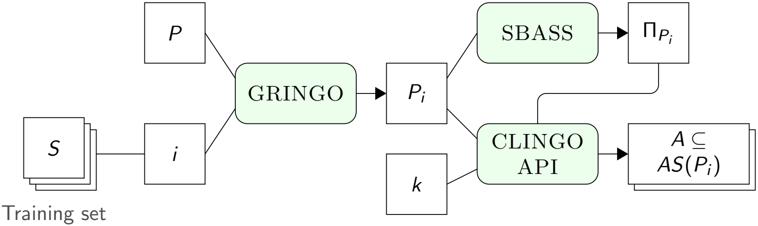


Scalable Approach for Creating Examples



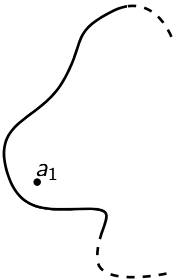
Scalable Full-SBCs

- Exploit CLINGO API with the symmetries Π_{P_i} to explore only k cells from the partition of $AS(P_i)$
- For each cell, the smallest element is a positive example, then create MAX negative examples

Scalable Approach for Creating Examples (Cont.)

For each instance $i \in S$ (set of representative satisfiable instances in input):

1. SBASS(P_i) returns Π_{P_i}
2. CLINGO returns $a_1 \in AS(P_i)$



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1. $\textsc{Sbass}(P_i)$ returns Π_{P_i}
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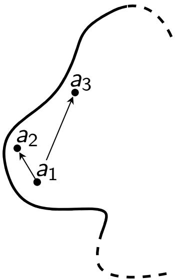
3. Apply Π_{P_i} to a_1 to identify its symmetries



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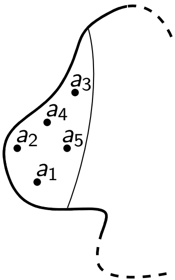

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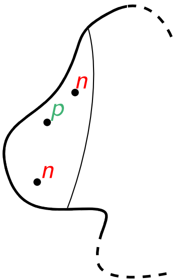

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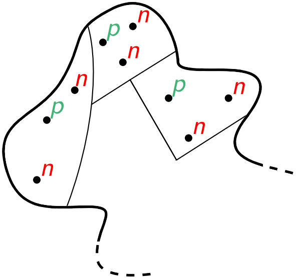
3. Apply Π_{P_i} to a_1 to identify its symmetries
4. One positive example, MAX sampled negative examples
5. Repeat the previous steps k times or until no new solutions are found



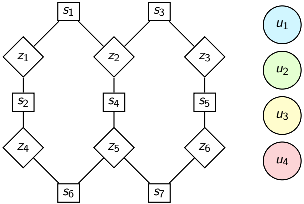
Partner Units Problem (PUP)

- Abstract representation of a configuration problem originating from a railway safety system of Siemens
- Extremely hard to solve this problem with real, large-scale instances
- “Naive” encoding + “standard” instances $\rightarrow$ 99% symmetric candidate solutions

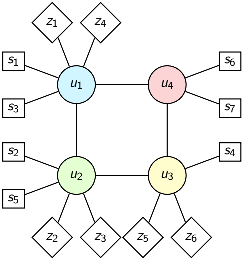
Simple ASP Encoding for PUP [1]

```
% Input
zone(Z) :- zone2sensor(Z,D).
sensor(D) :- zone2sensor(Z,D).
comUnit(1..n).

% Generate
1 { unit2zone(U,Z) : comUnit(U) } 1 :- zone(Z).
1 { unit2sensor(U,S) : comUnit(U) } 1 :- sensor(S).

% Constraint UCAP
:- comUnit(U), ucap+1 { unit2zone(U,Z): zone(Z) }.
:- comUnit(U), ucap+1 { unit2sensor(U,S): sensor(S) }.

% Constraint IUCAP
partnerunits(U,P) :- unit2zone(U,Z), zone2sensor(Z,S),  unit2sensor(P,S), U!=P.
partnerunits(U,P) :- partnerunits(P,U), comUnit(U), comUnit(P).
:- comUnit(U), iucap+1 { partnerunits(U,P): comUnit(P) }.
```

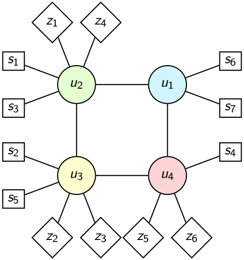
PUP Example



(a) Partner Units Problem instance with $UCAP = IUCAP = 2$



(b) A solution for the instance



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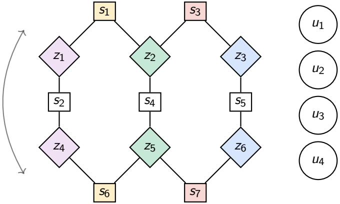

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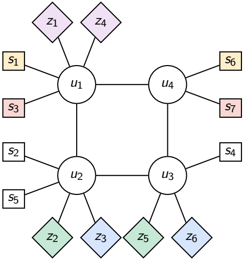

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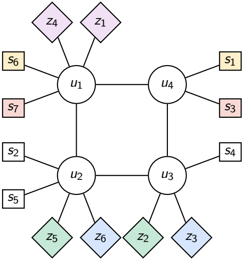

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Experiments

	Enc	SBASS	Enc+SBCs(i)	Enc+ABK	Adv
dbl-10	0.02	0.04	0.02	**0.01**	**0.01**
un-dbl-10*	505.91	0.03	TO	**0.01**	0.16
dbl-20	1.06	0.31	1.40	**0.08**	0.53
un-dbl-20*	TO	0.28	TO	**0.34**	TO
dbl-30	1.70	3.12	0.91	**0.46**	2.21
un-dbl-30*	TO	3.19	TO	**19.97**	TO
dbl-40	TO	14.58	482.17	**5.50**	11.50
un-dbl-40*	TO	9.52	TO	**65.54**	TO
dbl-50	TO	57.91	TO	**54.89**	542.09

- Three distributions of PUP instances: **double**, doublev, triple.
- **Enc+ABK**: the most efficient constraints obtained from the samples.
- **Adv**: advanced encoding containing static symmetric breaking and ordering rules.

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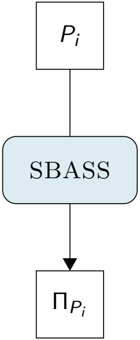
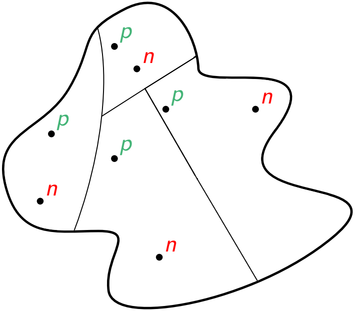
Extension for Optimization Problems

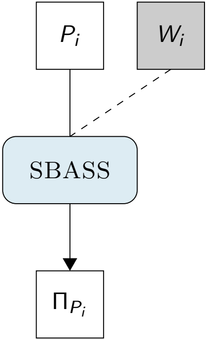
Decision vs Optimization Problems

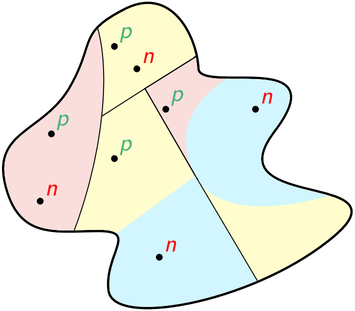




- For decision problems, correct partition and representative solutions

Decision vs Optimization Problems





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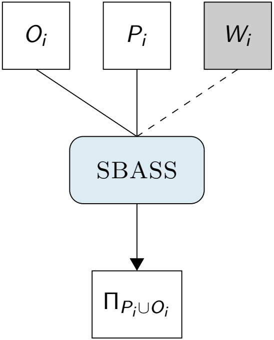
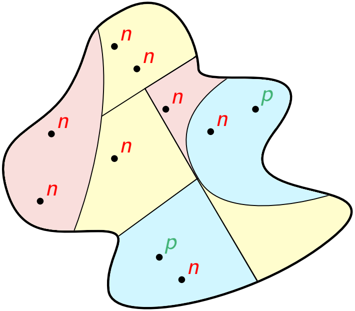




- For decision problems, correct partition and representative solutions
- SBASS doesn't parse weak constraints, thus incorrect examples
- *Solution*: add auxiliary normal rules defining a finer partition

Conclusions and Future Works

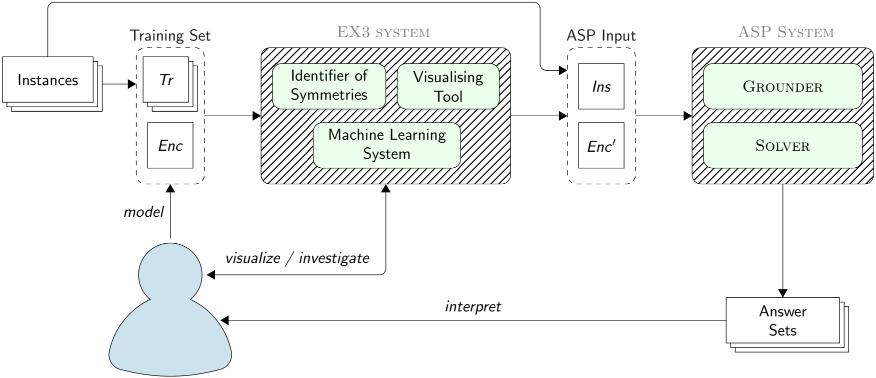
Conclusions

- Design and implement a model-oriented approach for lifting SBCs
- Test it over some simple and advanced combinatorial problems (decision and optimization)
- The learned constraints:
  - $\rightarrow$ are general and easier to interpret than ground SBCs
  - $\rightarrow$ obtain better-solving performance than the original program, the online application of instance-specific SBCs approaches, and SBCs designed by experts (for some type of instances)
- But wait ... there's more!

Current Limitations

- Instances labelling has a critical impact on the framework applicability
  - $\rightarrow$ Automatically extract features and generalise them
- No transferable knowledge/no insights from the problem or instance distribution
  - $\rightarrow$ Exploit the properties learned to define language bias (i.e., auxiliary predicates)
- Interpretability of the learned constraints
  - $\rightarrow$ Explain to the user the meaning of the constraints learned

EX3 – EXtract, EXploit and EXplain Knowledge



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