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Inductive Learning of Answer Set Programs

Mark Law, Alessandra Russo and Krysia Broda

Inductive Logic Programming

The task of Inductive Logic Programming (ILP) is to find a hypothesis *H* which “explains” a set of positive and negative examples (E^+ and E^-) with respect to a background knowledge *B*.

The work on nonmonotonic ILP under the Answer Set/Stable Model semantics has mostly been limited to learning normal logic programs and is usually restricted to **either** brave **or** cautious reasoning.

Our new learning task, Learning from Answer Sets, incorporates **both** brave **and** cautious reasoning with the aim of learning Answer Set Programs containing normal rules, choice rules and constraints.

Sudoku Example

$+ve$

4		1	2
2			
		4	1
1			3

(a)

$-ve$

		3	
2			
	3		
1		1	

(b)

$-ve$

1		4	
	2	3	
			1
1			2

(c)

$complete$

4	3	1	2
2	1	3	4
3	2	4	1
1	4	2	3

(d)

```
1 { value(1, C), value(2, C), value(3, C), value(4, C) } 1 :- cell(C).
:- value(V, C1), value(V, C2), same_row(C1, C2).
:- value(V, C1), value(V, C2), same_block(C1, C2).
:- value(V, C1), value(V, C2), same_col(C1, C2).
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Comparison with related works under the Answer Set semantics

Learning Task	Normal Rules	Choice Rules	Constraints	Classical negation	Brave	Cautious	Algorithm for optimal solutions
Brave Induction [Sakama, Inoue 2009]	✔	✔	✘	✔	✔	✘	✘
Cautious Induction [Sakama, Inoue 2009]	✔	✔	✘	✔	✘	✔	✘
XHAIL [Ray 2009] & ASPAL [Corapi, Russo, Lupu 2011]	✔	✘	✘	✘	✔	✘	✔
Induction of Stable Models [Otero 2001]	✔	✘	✘	✘	✔	✘	✘
Induction from Answer Sets [Sakama 2005]	✔	✘	✔	✔	✔	✔	✘
LAS	✔	✔	✔	✘	✔	✔	✔

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Learning from Answer Sets

A partial interpretation E is a pair of sets of atoms $\langle E^{inc}, E^{exc}\rangle$ called the *inclusions* and *exclusions* respectively.

An Answer Set A *extends* $\langle E^{inc}, E^{exc}\rangle$ if and only if: $E^{inc} \subseteq A$ and $E^{exc} \cap A = \emptyset$.

A *Learning from Answer Sets task* is a tuple $T = \langle B, S_M, E^+, E^-\rangle$ where B is an ASP program, S_M is the search space defined by a language bias M, E^+ and E^- are sets of partial interpretations.

A hypothesis $H \in ILP_{LAS}\langle B, S_M, E^+, E^-\rangle$ if and only if:

1. $H \subseteq S_M$
2. $\forall e^+ \in E^+ \ \exists A \in AS(B \cup H)$ st A extends e^+
3. $\forall e^- \in E^- \ \nexists A \in AS(B \cup H)$ st A extends e^-

Inductive Learning of Answer Set Programs

A hypothesis $H \in positive\_solutions\langle B, S_M, E^+, E^- \rangle$ if and only if:

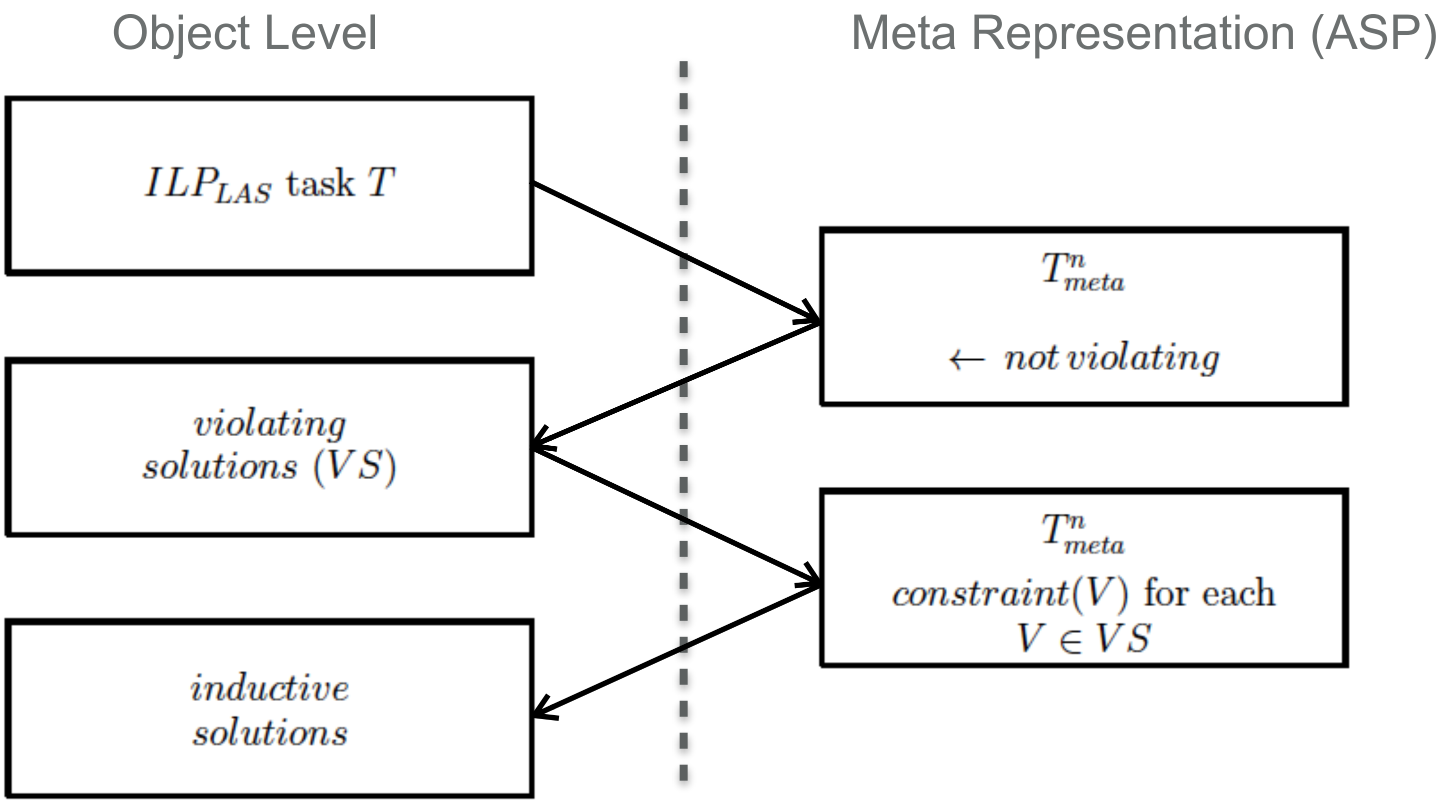
1. $H \subseteq S_M$
2. $\forall e^+ \in E^+ \; \exists A \in AS(B \cup H)$ st A extends e^+

A hypothesis $H \in violating\_solutions\langle B, S_M, E^+, E^- \rangle$ if and only if:

1. $H \subseteq S_M$
2. $\forall e^+ \in E^+ \; \exists A \in AS(B \cup H)$ st A extends e^+
3. $\exists e^- \in E^- \; \exists A \in AS(B \cup H)$ st A extends e^-

$$ILP_{LAS}\langle B, S_M, E^+, E^- \rangle$$
$$= positive\_solutions\langle B, S_M, E^+, E^- \rangle \backslash violating\_solutions\langle B, S_M, E^+, E^- \rangle$$

Inductive Learning of Answer Sets



n: a given hypothesis length

T^n_{meta}: ASP task program (a meta representation of the task T)

Inductive Learning of Answer Sets

Algorithm 1 ILASP

procedure ILASP(T)
    $solutions = []$
    for $n = 0$; $solutions.empty$; $n{+}{+}$ **do**
        $vs = AS(T^n_{meta} \cup \{\leftarrow \text{ not } violating; \quad ex(negative).\})$
        $ps = AS(T^n_{meta} \cup \{constraint(meta^{-1}(V)) : V \in vs\})$
        $solutions = \{meta^{-1}(A) : A \in ps\}$
    end for
    return $solutions$
end procedure

T^n_{meta}: ASP task program (a meta representation of the task T)
vs: violating solutions
ps: positive solutions

Comparison with related works

$$ILP_{brave}\langle B, E\rangle$$

$$\Downarrow$$

$$ILP_{ASPAL/XHAIL}\langle B, \langle E, \emptyset\rangle\rangle$$

$$ILP_{ASPAL/XHAIL}\langle B, \langle E^{+}, E^{-}\rangle\rangle$$

$$\Downarrow$$

$$ILP_{stable\_models}\langle B, \{\langle E^{+}, E^{-}\rangle\}\rangle$$

$$ILP_{stable\_models}\langle B, \{\langle E_1^{+}, E_1^{-}\rangle \ldots \{\langle E_n^{+}, E_n^{-}\rangle\}\rangle$$

$$\Downarrow$$

$$ILP_{LAS}\langle B, \{\langle E_1^{+}, E_1^{-}\rangle \ldots \{\langle E_n^{+}, E_n^{-}\rangle\}, \emptyset\rangle$$

$$ILP_{LAS}\langle B, E^{+}, E^{-}\rangle$$

Comparison with related works

$$ILP_{cautious}\langle B, \{e_1, \ldots, e_n\}\rangle$$

$$\Downarrow$$

$$ILP_{LAS}\langle B, \emptyset, \{\langle\emptyset, \{e_1\}\rangle \ldots \langle\emptyset, \{e_n\}\rangle\}\rangle$$

Current work: modification of ILASP

- For some classes of problem there could be many violating solutions before we find an inductive solution.
- The sudoku example is one such problem, with 413044 before the first inductive solution it takes over 14 minutes to solve with ILASP.
- In fact, many of these are violating for the same reason (they share Answer Sets which extend negative examples).
- With our new system based on ruling out classes of hypothesis, we need only 7 classes and the problem is solved in less than a second.

Other current work

- Expand the subset of ASP that we can learn
  - conditions, weighted aggregates etc.
  - weak constraints/optimisation statements

- Real applications
  - Ideally not achievable by other ILP tasks
  - Will motivate the work from a practical point of view
  - Measure the accuracy of the learning task