Efficiently Encoding Meta-Interpretive Learning by Answer Set Programming (*Work in Progress*)

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LOGICAL METHODS IN COMPUTER SCIENCE

Inter-University Research Institute Corporation / Research Organization of Information and Systems

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Meta-Interpretive Learning [Muggleton *et al.*, 2015]

MIL is an elegant yet powerful approach

- Efficient realization of *Predicate Invention*
  - *Essential feature* for explicitly learning “hidden” concepts
  - Hard problem due to *high combinatorial complexity*
- Enables learning of *recursive rules and programs*
- Meta-rules *constrain search space* effectively

Setting of MIL

Example (MIL-Problem)

Meta-rules $\mathcal{R}$:

- $P(x, y) \leftarrow Q(x, z), R(z, y)$ (*chain-rule*)
- $P(x, y) \leftarrow Q(x, y), R(y)$ (*postcon-rule*)

Background knowledge B:

- $remove([X|R], R) \leftarrow .$ (*drops the first element from a list*)
- $empty([]) \leftarrow .$ (*checks if a list is empty*)

Positive and negative examples:

- $E^+ = \{p([a, a], []), p([b, b], [])\}$
- $E^- = \{p([a, a, a], [a]), p([b, b, b], [])\}$

Possible solution:

$p(x, y) \leftarrow remove(x, z),\ p1(z, y).$
$p1(x, y) \leftarrow remove(x, y), empty(y).$

Metagol [Cropper and Muggleton, 2016]

MIL-solver based on classical Prolog meta-interpreter

Example (Induction Based on Positive Examples)

```
prove([PExample|R],BK,BK_H) :-
     metarule(Name,MetaSub,(PExample :- Body)),
     save_subst(metasub(Name,MetaSub),BK,BK_Mod),
     prove(Body,BK_Mod,BK_H).
```

- Efficient by exploiting *query-driven* mechanism
- Negative examples trigger backtracking only in the end

Motivation: Using Answer Set Programming for MIL

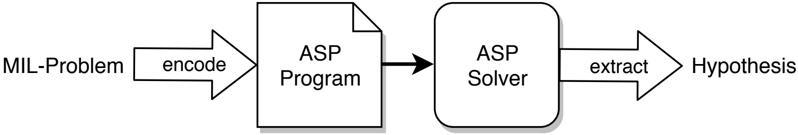
ASP well-suited as MIL is essentially *combinatorial search problem*

1. **Purely declarative formalism**
   - High *flexibility* and modularity
   - Non-termination is *not an issue*

2. **Performance gains**
   - Leverage *efficient* ASP solvers
   - *Conflict propagation* and *learning*

3. **Optimization capabilities**
   - Finding *minimal* solutions
   - Handling *noisy* data

Our Approach



Challenge 1: Grounding explodes due to background knowledge!

- HEX extends ASP by *external atoms* $\&g[\vec{p}](\vec{c})$ [Eiter *et al.*, 2008]

$\Rightarrow$ Only import *relevant* background knowledge (assuming forward-chained meta-rules)

Challenge 2: Straightforward encoding yields huge search space!

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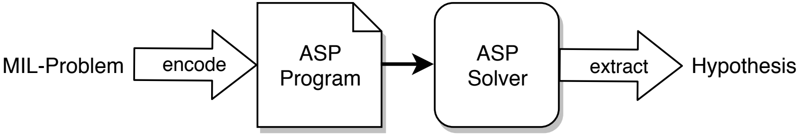

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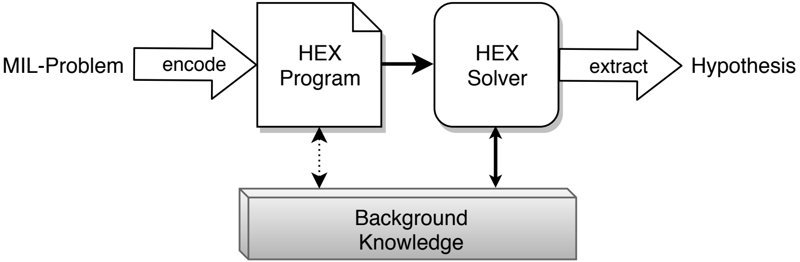

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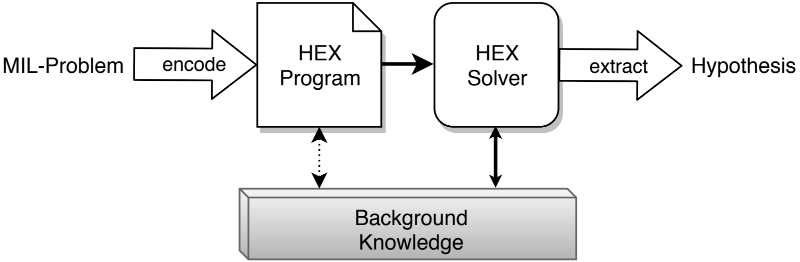

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Basic Encoding

Example (Guess-and-check encoding)

```
% import
 unary_bg(empty,X) :- &empty[ded](X).
 binary_bg(remove,X,Y) :- &remove[ded](X,Y).

% guess
 { meta(post,P1,P2,P3)  } :- sig(P1), sig(P2), sig(P3).
 { meta(chain,P1,P2,P3) } :- sig(P1), sig(P2), sig(P3).

% derive
 ded(P,X,Y)  :- binary_bg(P,X,Y).
 ded(P1,X,Y) :- meta(post,P1,P2,P3), ded(P2,X,Y), unary_bg(P3,Y).
 ded(P1,X,Y) :- meta(chain,P1,P2,P3), ded(P2,X,Z), ded(P3,Z,Y).

% check
 :- pos_ex(P,X,Y), not ded(P,X,Y).
 :- neg_ex(P,X,Y), ded(P,X,Y).
```

Extremely many possible combinations of meta-substitutions!

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Bottom-Up Encoding [ICLP'18]

- Interleave *guessing* and *derive* part ⇒ avoid many redundant rules

Example (Restricting Guesses)

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% import
 unary_bg(empty,X) :- &empty[ded](X).
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% guess
 { meta(post,P1,P2,P3)  } :- sig(P1), ded(P2,X,Y), unary_bg(P3,Y).
 { meta(chain,P1,P2,P3) } :- sig(P1), ded(P2,X,Z), ded(P3,Z,Y).

% derive
 ded(P,X,Y)  :- binary_bg(P,X,Y).
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Still guesses rules not needed for deriving any positive example!

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 ded(P,X,Y)  :- binary_bg(P,X,Y).
 ded(P1,X,Y) :- meta(post,P1,P2,P3), ded(P2,X,Y), unary_bg(P3,Y).
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 :- pos_ex(P,X,Y), not ded(P,X,Y).
 :- neg_ex(P,X,Y), ded(P,X,Y).
```

Still guesses rules not needed for deriving any positive example!

Novel Top-Down Encoding

- *Goal-driven* guessing of rules, starting with positive examples

Example (Restricting guesses to relevant meta-rules)

```
% ... import, derive and check part as before

% remove guess for meta-substitutions!

% new sub-goals
 goal(P,X,Y) :- pos_ex(P1,X,Y).
 goal(Q,X,Y) :- ded_u(post,P,Q,R,X,Y,_).
 goal(Q,X,Z) :- ded_u(chain,P,Q,R,X,Y,Z).
 goal(R,Z,Y) :- ded_u(chain,P,Q,R,X,Y,Z).

% one rule for each sub-goal
 {ded_u(post,P,Q,R,X,Y,_) : ord(P,Q),unary_bg(R,Y);
 ded_u(chain,P,Q,R,X,Y,Z) : ord(P,Q),ord(P,R),state(Z)}=1 :- goal(P,X,Y).

% collect meta-substitutions
 meta(M,P,Q,R) :- ded_u(M,P,Q,R,X,Y,Z), M != bg.
```

Novel Top-Down Encoding

- *Goal-driven* guessing of rules, starting with positive examples

Example (Restricting guesses to relevant meta-rules)

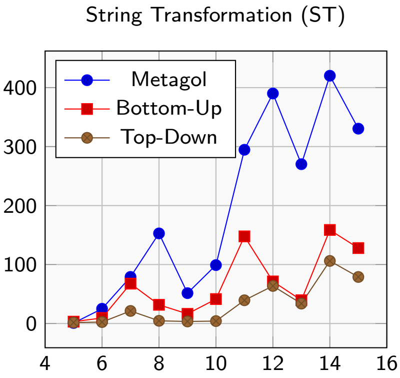
```
% all possible rule instances
 ded_a(bg,P,n,n,X,Y,n) :- binary_bg(P,X,Y).
 ded_a(post,P,Q,R,X,Y,n) :- ord(P,Q),ded_a(_,Q,_,_,X,Y,_),unary_bg(R,Y).
 ded_a(chain,P,Q,R,X,Y,Z) :- ord(P,Q),ord(P,R),ded_a(_,Q,_,_,X,Z,_),
                                                  ded_a(_,R,_,_,Z,Y,_).
% new sub-goals
 goal(P,X,Y) :- pos_ex(P1,X,Y).
 goal(Q,X,Y) :- ded_u(post,P,Q,R,X,Y,_).
 goal(Q,X,Z) :- ded_u(chain,P,Q,R,X,Y,Z).
 goal(R,Z,Y) :- ded_u(chain,P,Q,R,X,Y,Z).

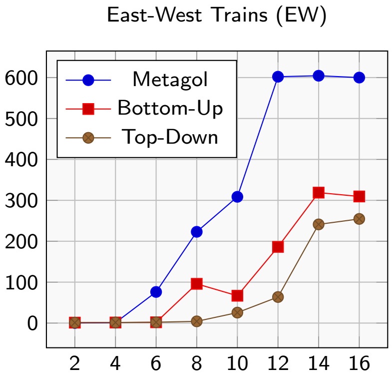
% one rule for each sub-goal
 {ded_u(M,P,Q,R,X,Y,Z) : ded_a(M,P,Q,R,X,Y,Z)} = 1 :- goal(P,X,Y).


% collect meta-substitutions
 meta(M,P,Q,R) :- ded_u(M,P,Q,R,X,Y,Z), M != bg.
```

First Experiments

- *Average runtimes* in sec. over 20/10 instances, timeout 600 s
- Use *hexlite* solver with *clingo* as backend





Conclusion

- Novel HEX-encodings of Meta-Interpretive Learning
  - Speedup due to efficient propagation of negative examples
  - Grounding feasible due to limited import of BK
- *State abstraction* further reduces grounding [ICLP'18]
- Techniques possibly *applicable* to other approaches (e.g. *ILASP*)?
- Future work:
  - *Formalize* top-down encoding, combine with state abstraction
  - *Solver-implementation* based on HEX-encodings

Thank You for Your Attention!

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