

Inductive Logic Programming
Lecture 1.2
Meta-Interpretive Learning of Grammars

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Papers for this lecture

Paper03: S.H. Muggleton, D. Lin, N. Pahlavi, and A. Tamaddoni-Nezhad. Meta-interpretive learning: application to grammatical inference. Machine Learning, 94:25-49, 2014.

Motivation

Logic Program (Kowalski, 1980)

Inductive Logic Programming (Muggleton, 1991)

Machine Learn arbitrary programs

State-of-art ILP systems cannot learn grammars. Why?

Predicate Invention and Recursion (Muggleton et al, 2011)

Parity example

Finite acceptor	Definite Clause Grammar (DCG)	Positive examples
<pre> graph LR start(()) --> q0(((q0))) q0 -- 0 --> q0 q0 -- 1 --> q1((q1)) q1 -- 0 --> q1 q1 -- 1 --> q0 style start fill:none,stroke:none </pre>	$q_0([], []) \leftarrow$ $q_0([0 A], B) \leftarrow q_0(A, B)$ $q_0([1 A], B) \leftarrow q_1(A, B)$ $q_1([0 A], B) \leftarrow q_1(A, B)$ $q_1([1 A], B) \leftarrow q_0(A, B)$	λ 0 11 00 101

DCG general form

$$Q([], []) \leftarrow$$

$$Q([C|x], y) \leftarrow P(x, y)$$

Meta-Interpreter version of Parity

Predicate invention via higher-order abduction?

$$\begin{aligned} Q([], []) &\leftarrow \\ Q([C|x], y) &\leftarrow P(x, y) \end{aligned}$$

Meta-Interpreter (Regular)	Ground facts
$parse(S) \leftarrow parse(q0, S, []).$ $parse(Q, [], []) \leftarrow acceptor(Q).$ $parse(Q, [C X], Y) \leftarrow$ $\quad\quad\quad delta1(Q, C, P),$ $\quad\quad\quad parse(P, X, Y).$	$acceptor(q0) \leftarrow$ $delta1(q0, 0, q0) \leftarrow$ $delta1(q0, 1, q1) \leftarrow$ $delta1(q1, 0, q1) \leftarrow$ $delta1(q1, 1, q0) \leftarrow$

Meta-Interpretive Learning (MIL) setting

Input	$\langle B, E \rangle$ where $B = \langle B_M, B_A \rangle$, B_M is Meta-Interpreter and B_A is Atomic background $E = \langle E^+, E^- \rangle$ are positive and negative examples
Output	$H \in \mathcal{H}_{B,E}$ where H is higher-order existentially-quantified Datalog atoms such that $B, H \models E^+$ and B, E^- consistent
Inverse Entailment	$B, \neg E^+ \models \neg H$ where $\neg E^+, \neg H$ are Universally-quantified denials

MIL examples for Parity

E^+	$\neg E^+$	E^-
$parse([]) \leftarrow$	$\leftarrow parse([],$	$\leftarrow parse([1])$
$parse([1, 1]) \leftarrow$	$parse([1, 1]),$	$\leftarrow parse([0, 1])$
$parse([0, 1, 1]) \leftarrow$	$parse([0, 1, 1]),$	$\leftarrow parse([1, 0])$
$parse([1, 0, 1]) \leftarrow$	$parse([1, 0, 1]),$	$\leftarrow parse([0, 0, 1])$
$parse([1, 1, 0]) \leftarrow$	$parse([1, 1, 0]).$	$\leftarrow parse([1, 1, 1])$

Hypothesis Ordering and properties

Definition ($\succeq_{B,E}$ relation in MIL) Within the MIL setting we say that $H \succeq_{B,E} H'$ in the case that $H, H' \in \mathcal{H}_{B,E}$ and $\neg H' \succeq_{\theta} \neg H$.

Proposition (Lattice) $\langle \mathcal{H}_{B,E}, \succeq_{B,E} \rangle$ forms a lattice.

Proposition (Unique \top) There exists $\top \in \mathcal{H}_{B,E}$ such that $\top \succeq_{B,E} H$ for each $H \in \mathcal{H}_{B,E}$ and \top is unique up to renaming of Skolem constants.

Proposition (Unique \perp) For finite $\mathcal{H}_{B,E}$ there exists \perp such that $H \succeq_{B,E} \perp$ for each $H \in \mathcal{H}_{B,E}$ and \perp is unique up to renaming of Skolem constants.

Meta-Interpreter for Context-Free Grammars

$parse(S) \leftarrow start(Q), parse(Q, S, []).$

$parse(Q, X, X) \leftarrow acceptor(Q).$

$parse(Q, [C|X], Y) \leftarrow delta1(Q, C, P), parse(P, X, Y).$

$parse(Q, X, Y) \leftarrow delta2(Q, P, C), parse(P, X, [C|Y]).$

$parse(Q, X, Y) \leftarrow delta3(Q, P, R), parse(P, X, Z), parse(R, Z, Y).$

Metagol_R implementation in Prolog

parse(S,G1,G2) :- parse(s(0),S,[],G1,G2).

parse(Q,X,X,G1,G2) :- abduce(acceptor(Q),G1,G2).

parse(Q,[C|X],Y,G1,G2) :- skolem(P), abduce(delta1(Q,C,P),G1,G3),
parse(P,X,Y,G3,G2).

abduce(X,G,G) :- member(X,G).

abduce(X,G,[X|G]) :- not(member(X,G)).

skolem(s(0)). skolem(s(1)). ...

Prolog query and answer for Metagol_R

Query

```
:- parse([],[],G1), parse([0],G1,G2), parse([0,0],G2,G3),    % Positive
   parse([1,1],G3,G4), parse([0,0,0],G4,G5),
   parse([0,1,1],G5,G6), parse([1,0,1],G6,G),
   not(parse([1],G,G)), not(parse([0,1],G,G)).                % Negative
```

Answer

```
G = [delta1(s(1),0,s(1)), delta1(s(1),1,s(0)),
     delta1(s(0),1,s(1)), delta1(s(0),0,s(0)),
     acceptor(s(0))]
```

Experiments

Null Hypothesis 1.1 Metagol_R cannot learn randomly chosen Regular languages.

Null Hypothesis 1.2 Metagol_R cannot outperform a state-of-the-art ILP system on learning randomly chosen Regular languages.

Null Hypothesis 2.1 Metagol_{CF} cannot learn randomly chosen Context-Free languages.

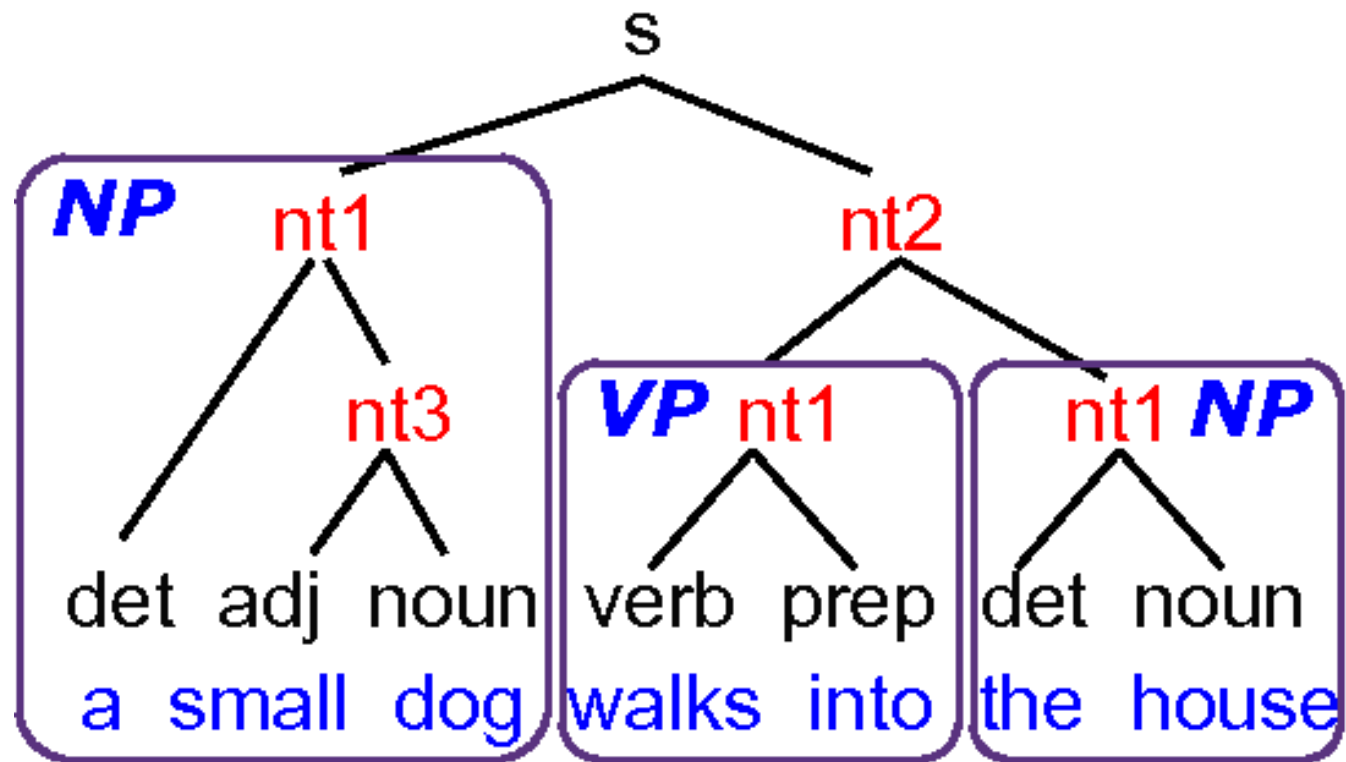
Null Hypothesis 2.2 Metagol_{CF} cannot outperform a state-of-the-art ILP system on learning randomly chosen Context-Free languages.

Null Hypothesis 3 Metagol_{RCF} cannot improve performance by changing representation from Regular to Context-Free languages.

Results

Null	Predictive accuracy	Running time
1	<p>Predictive Accuracy (%)</p> <p>No. of training examples</p> <p>Metagol_R MC-TopLog Default</p>	<p>Time (ms)</p> <p>No. of training examples</p> <p>Metagol_R MC-TopLog</p>
2	<p>Predictive Accuracy (%)</p> <p>No. of training examples</p> <p>Metagol_CF MC-TopLog Default</p>	<p>Time (ms)</p> <p>No. of training examples</p> <p>Metagol_CF MC-TopLog</p>
3	<p>Predictive Accuracy (%)</p> <p>No. of training examples</p> <p>Metagol_RCF Metagol_CF Default</p>	<p>Time (ms)</p> <p>No. of training examples</p> <p>Metagol_RCF Metagol_CF</p>

MIL invention in natural grammars



Related work

Meta-level abduction Propositional predicate invention by abduction (Inoue et al, 2009/2010) applied to biochemical networks and cello playing.

Grammatical inference Learning of grammars from examples (Higuera, 2010).

Automata learning Studied since 1950s (Moore, 1956). Provably efficient algorithms for deterministic finite state acceptors.

Learnability Both regular and CF learnable in the limit from positive/negative presentations. Regular languages PAC-learnable, but CF not known to be.

Context-free Efficient and complete approach (Sakakibara, 2002). Only heuristic approaches (Langley and Stromsten, 2000) for learning CF from positive and negative examples.

Summary and limitations

Meta-Interpretive Learning Theory, implementation and experiments.

Grammar application MIL outperforms MC-TopLog in accuracy and speed.

Predicate invention and recursion MIL ease in implementing predicate invention through Higher-order Datalog constructs.

Declarative bias Learn bias for MIL hypothesis space in first-order logic.

Further work Answer Set Programming (ASP), chart parsing, natural grammars, non-empty ground background knowledge, meta-interpreters for other first-order fragments such as Monadic and Dyadic logic.