Hybrid Learning of Ontology Classes

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Outline

1. Introduction to Description Logics, OWL, and the Learning Problem
2. Solving the Learning Problem with Genetic Programming (GP)
3. Genetic Refinement Operators
4. Preliminary Evaluation
5. Conclusions & Future Work

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Introduction to Description Logics

- Description Logics (DL) is the name of a family of languages for knowledge representation
- fragment of first order predicate logic
- less expressive power than predicate logic, but decidable inference problems
- intuitive variable free syntax
- basis of the ontology language OWL (W3C recommendation)
- OWL ontology convertable to DL knowledge base and vice versa

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\texttt{Man} &\equiv \texttt{Person} \sqcap \neg\texttt{Female} \\
\texttt{Mother} &\equiv \texttt{Woman} \sqcap \exists\texttt{hasChild}.\top \\
\texttt{Person} &\equiv \texttt{Man} \sqcup \texttt{Woman} \\
\bot &\equiv \texttt{Male} \sqcap \texttt{Female}
\end{aligned}
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$\mathcal{ALC}$ Description Logic knowledge base

TBox - terminological knowledge

The Learning Problem in DLs

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$\texttt{hasChild(JOHN,MARIA)}$
$\texttt{hasChild(ANNA,JASON)}$

$\texttt{Male(JOHN)}$
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$\texttt{Male(STEPHEN)}$
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$\mathcal{ALC}$ Description Logic knowledge base
ABox - assertional knowledge

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positive examples: $\{\mathtt{STEPHEN}, \mathtt{MARC}, \mathtt{JOHN}\}$

negative examples: $\{\mathtt{JASON}, \mathtt{ANNA}, \mathtt{MARIA}, \mathtt{MICHELLE}\}$

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positive examples: $\{\texttt{STEPHEN}, \texttt{MARC}, \texttt{JOHN}\}$

negative examples: $\{\texttt{JASON}, \texttt{ANNA}, \texttt{MARIA}, \texttt{MICHELLE}\}$

possible solution: $\texttt{Target} \equiv \texttt{Male} \sqcap \exists\texttt{hasChild}.\top$

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Genetic Programming (GP)

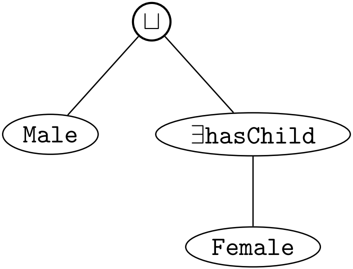
Algorithm (Genetic Programming)

- *create population*
- *while the termination criterion is not met:*
  - *select a subset of the population based on their fitness*
  - *produce offspring using genetic operators on selected individuals*
  - *create a new population from the old one and the offspring*

- genetic operators: crossover, mutation, editing
- selection: rank selection, FPS, tournament selection
- tree representation common in GP

Applying Standard GP

- representing $\mathcal{ALC}$ concepts:
  - terminal set
    $T = N_C \cup \{\top, \bot\}$
  - function set
    $F = \{\sqcup, \sqcap, \neg\} \cup \{\forall r \mid r \in N_R\}$
    $\cup \{\exists r \mid r \in N_R\}$



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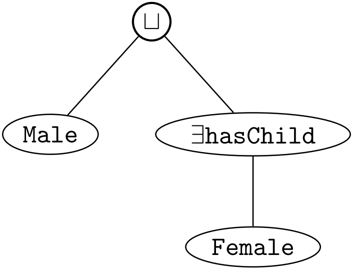

- possible fitness function:

$$f_{\mathcal{K}}(C) = -\frac{|E^+ \setminus pos_{\mathcal{K}}(C)| + |neg_{\mathcal{K}}(C)|}{|E^+| + |E^-|} - a \cdot |C| \quad (0 < a < 1)$$

  - $pos_{\mathcal{K}}(C)$ ... set of covered positive examples
  - $neg_{\mathcal{K}}(C)$ ... set of covered negative examples
  - a ... concept length penalty

Advantages&Disadvantages of the Standard GP Approach

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- Advantages:
  - very flexible learning method (can handle other description languages)
  - parallelisable algorithms
  - GP is robust to noise
- Disadvantages:
  - crossover operator too destructive: small syntactic changes - drastic semantic changes
  - does not use all of the available background knowledge: no exploitation of the subsumption hierarchy of concepts

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Refinement Operators

- idea: combine refinement operators and GP
- definition of refinement operators:
  - consider quasi-ordered space $(\mathcal{ALC}, \sqsubseteq)$
  - $\mathcal{ALC}$ downward (upward) refinement operator ρ is a mapping from S to 2^S such that for any $C \in S$:

$$C' \in \rho(C) \text{ implies } C' \sqsubseteq C \quad (C \sqsubseteq C')$$

  - example: $\top$

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- refinement operators ...
  - ... can make use of the generality order of concepts w.r.t. $\mathcal{K}$
  - ... are less destructive w.r.t. the semantics of a concept
  - ... can use the (precomputed) subsumption hierarchy

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$$\phi_{\mathcal{K}}(C) = \begin{cases} \text{rand}(\phi_{\downarrow}(C)) & \text{with probability } \dfrac{\frac{|neg_{\mathcal{K}}(C)|}{|E^-|}}{1+\frac{|neg_{\mathcal{K}}(C)|}{|E^-|}-\frac{|pos_{\mathcal{K}}(C)|}{|E^+|}} \\ \text{rand}(\phi_{\uparrow}(C)) & \text{with probability } \dfrac{1-\frac{|pos_{\mathcal{K}}(C)|}{|E^+|}}{1+\frac{|neg_{\mathcal{K}}(C)|}{|E^-|}-\frac{|pos_{\mathcal{K}}(C)|}{|E^+|}} \end{cases}$$

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- we created a complete and proper operator based on a full property analysis [Lehmann et. al, ILP 2007]

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Evaluation - Uncle Problem

- learn definition of uncle from FORTE family data set (337 assertions, 86 examples)
- problem is challenging - relatively complex solution and no search space restrictions

possible solution:

$$\mathtt{Uncle} \equiv \mathtt{Male} \sqcap (\exists\, \mathtt{sibling}.\exists\, \mathtt{parent}.\top \sqcup \exists\, \mathtt{married}.\exists\, \mathtt{sibling}.\exists\, \mathtt{parent}.\top)$$

Evaluation - Uncle Problem

- learn definition of uncle from FORTE family data set (337 assertions, 86 examples)
- problem is challenging - relatively complex solution and no search space restrictions
- compare against state of the art DL learning system YinYang
- compare improvement over standard GP

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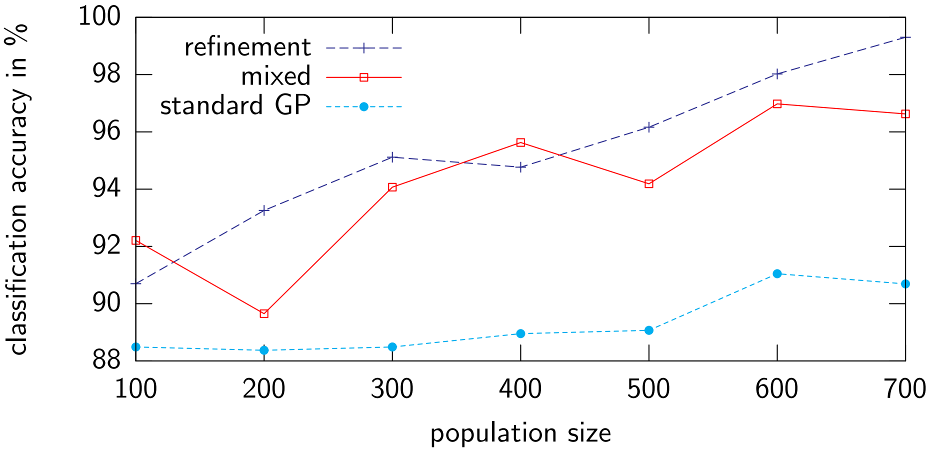
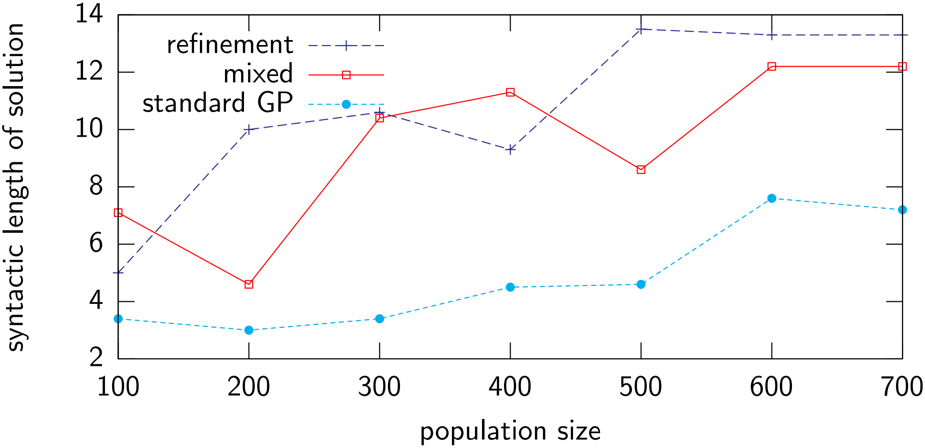
Evaluation - Accuracy



YinYang: 73.5%

Evaluation - Concept Length



YinYang: 12.2

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Contributions to the State of the Art

- first time to apply evolutionary techniques to learning problem in DLs
- first framework for combining refinement operators and GP directly
- creation of a concrete operator based on a full property analysis
- implemented in a system called DL-Learner and shown to be feasible in a preliminary evaluation

Future Work

- more evaluation examples, e.g. asses performance on noisy or inconsistent data
- create (more) benchmarks to assess scalability and enable easier comparison between different algorithms
- tests on real world data, e.g. DBpedia
- embed learning algorithm in ontology editor e.g. OntoWiki
- extend algorithm to other description languages (cardinality restrictions, datatype integer)

Thank you for your attention.

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