

Ontology Learning from Interpretations in Lightweight Description Logics

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Ontologies

Ontology: a formal conceptualization of a domain of interest.

Mother \equiv Woman $\sqcap \exists$ hasChild. \top

Father \equiv Man $\sqcap \exists$ hasChild. \top

Father_of_boy \equiv Father $\sqcap \exists$ hasChild.Man

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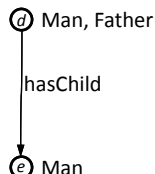
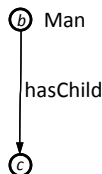
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Instance data + *inference*:

ⓐ Mother



Ontologies

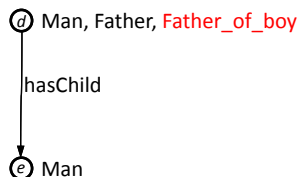
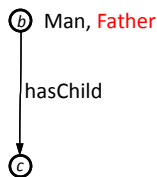
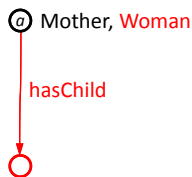
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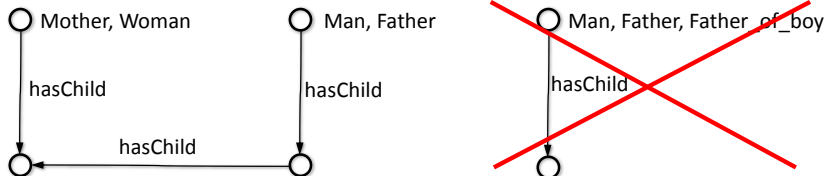
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Models: datasets satisfying all axioms in the ontology:



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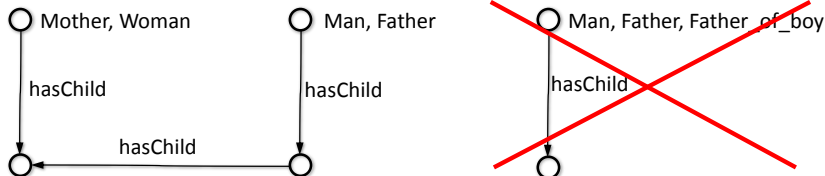
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Models: datasets satisfying all axioms in the ontology:



Can we *learn ontologies from models without supervision*?

Motivation

- *ontologies* and the *Semantic Web technologies* have become a prominent knowledge management paradigm
- the data is abundant and good ontologies are ever more important
- traditional knowledge acquisition bottleneck (building ontologies ex-ante) turns into *knowledge re-engineering bottleneck*:

How to *elicit ontological commitments implicitly present on the data-level*?

Description Logics: syntax

The \mathcal{EL} family of *Description Logics* (underpinning OWL 2 EL) used for modeling large taxonomies (e.g., SNOMED).

Language consists of (atomic) concepts (e.g., Man), roles (e.g., hasChild), and constructors:

$$C, D ::= \underbrace{\top \mid A \mid C \sqcap D}_{\mathcal{L}^\square} \mid \exists r.C$$

An ontology (TBox) is a set of formulas of type: $C \sqsubseteq D$, where:

\mathcal{EL} : C and D in \mathcal{EL}

$\mathcal{EL}^{\text{rhs}}$: C in \mathcal{L}^\square and D in \mathcal{EL}

$\mathcal{EL}^{\text{lhs}}$: C in \mathcal{EL} and D in \mathcal{L}^\square

Example:

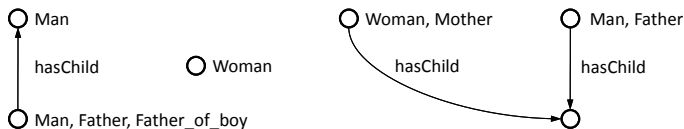
$\mathcal{EL}^{\text{rhs}}$: $\text{Father_of_boy} \sqsubseteq \text{Man} \sqcap \exists \text{hasChild.Man}$

$\mathcal{EL}^{\text{lhs}}$: $\text{Man} \sqcap \exists \text{hasChild.Man} \sqsubseteq \text{Father_of_boy}$

Description Logics: semantics

An *interpretation* $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$ consists of:

- $\Delta^{\mathcal{I}}$ non-empty domain of individuals,
- interpretation function $\cdot^{\mathcal{I}}$, which encodes a labelled graph, e.g.:



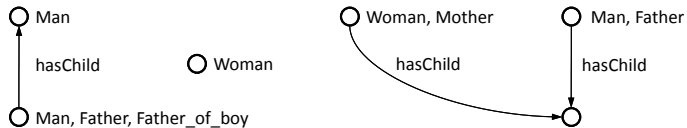
An interpretation \mathcal{I} is a *model* of an ontology iff $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ for every $C \sqsubseteq D$ in the ontology.

Note: An ontology has infinitely many (possibly) infinite models.

Learning model

Is it possible to *correctly identify an ontology* in an *unsupervised manner* from a *finitely presentable sample of models*?

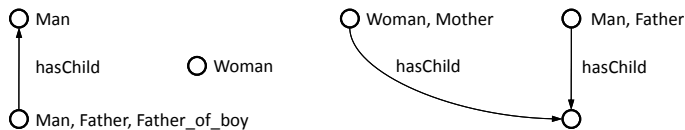
Teacher: provides a finite *learning set*, e.g.:



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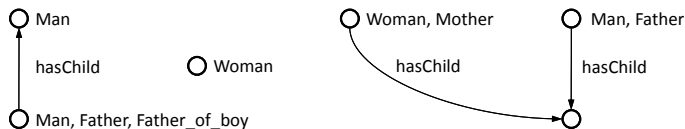
Learner: guesses the *correct ontology*, e.g.:

Mother	≡	Woman \sqcap \exists hasChild.⊤
Father	≡	Man \sqcap \exists hasChild.⊤
Father_of_boy	≡	Father \sqcap \exists hasChild.Man

Learning model

Is it possible to *correctly identify an ontology* in an *unsupervised manner* from a *finitely presentable sample of models*?

Teacher: provides a finite *learning set*, e.g.:



Learner: guesses the *correct ontology*, e.g.:

$$\begin{aligned}
 \text{Mother} &\equiv \text{Woman} \sqcap \exists \text{hasChild} . \top \\
 \text{Father} &\equiv \text{Man} \sqcap \exists \text{hasChild} . \top \\
 \text{Father_of_boy} &\equiv \text{Father} \sqcap \exists \text{hasChild} . \text{Man}
 \end{aligned}$$

Admissibility condition: the learning set is reach enough to refute every wrong guess (e.g., there exists a man who is not a woman).

Results

- 1 There does not exist a finite learning set for \mathcal{EL} .
- 2 There always exist finite learning sets for $\mathcal{EL}^{\text{rhs}}$ and $\mathcal{EL}^{\text{lhs}}$.
 - The learner can succeed easily *using an equivalence oracle*.
 - In case of $\mathcal{EL}^{\text{rhs}}$, the learner can succeed *without the oracle*.

Impossibility result for \mathcal{EL}

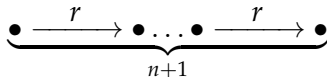
\mathcal{EL} : $\exists \text{hasUncle}.\top \sqsubseteq \exists \text{hasParent}.\exists \text{hasSibling}.\text{Man}$

Theorem: There does not exist a finite learning set for \mathcal{EL} .

For every axiom:

$$\underbrace{\exists r.\dots\exists r.\top}_n \sqsubseteq \underbrace{\exists r.\dots\exists r.\exists r.\top}_{n+1}$$

the learning set must contain a finite chain of individuals of length exactly $n + 1$, as depicted below:

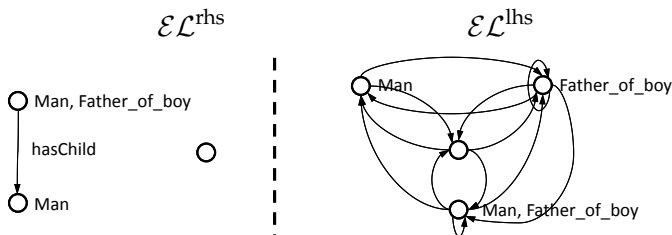


Learning in $\mathcal{EL}^{\text{rhs}} / \mathcal{EL}^{\text{lhs}}$ with an equivalence oracle

$\mathcal{EL}^{\text{rhs}}$: Father_of_boy \sqsubseteq Man $\sqcap \exists \text{hasChild}. \text{Man}$

$\mathcal{EL}^{\text{lhs}}$: Man $\sqcap \exists \text{hasChild}. \text{Man}$ \sqsubseteq Father_of_boy

Theorem: There always exist finite learning sets for $\mathcal{EL}^{\text{rhs}}$ and $\mathcal{EL}^{\text{lhs}}$ (shown by an application of the type construction method.)



Learning in $\mathcal{EL}^{\text{rhs}} / \mathcal{EL}^{\text{lhs}}$ with an equivalence oracle

For every ontology of size n , consistent with the learning set, ask the oracle if it is correct:

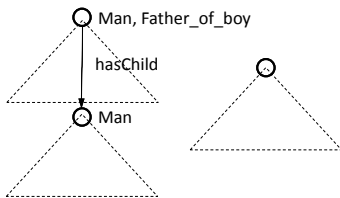
Yes: we're done.

No: increase n by 1.

Unsupervised learning in $\mathcal{EL}^{\text{rhs}}$

$\mathcal{EL}^{\text{rhs}}$: $\text{Father_of_boy} \sqsubseteq \text{Man} \sqcap \exists \text{hasChild}.\text{Man}$

“Good” candidate axioms can be directly extracted from the learning set in $\mathcal{EL}^{\text{rhs}}$.



The algorithm runs in double exponential time and can generate ontologies of double exponential size w.r.t. data (but there might exist more optimal solutions).

Note: We conjecture a similar result to hold for $\mathcal{EL}^{\text{lhs}}$...

Related work

Ontology learning by query (in Angluin's framework):

Konev, B., Lutz, C., Ozaki, A., Wolter, F. **Exact learning of lightweight description logic ontologies.** In: *Proc. of KR-14*, 2014.

Konev, B., Ozaki, A., Wolter, F. **Exact Learning Description Logic Ontologies from Data Retrieval Examples.** In: *Proc. of DL-15*, 2015.

Learning DL concepts via different operators:

Cohen, W.W., Hirsh, H. **Learning the classic description logic: Theoretical and experimental results.** In: *Proc. of KR-94*, 1994.

Lehmann, J., Hitzler, P. **A refinement operator based learning algorithm for the \mathcal{ALC} description logic.** In: *ILP*, 2008.

Applications of concept analysis for enriching ontologies:

Baader, F., Ganter, B., Sertkaya, B., Sattler, U. **Completing description logic knowledge bases using formal concept analysis.** In: *Proc. of IJCAI-07*, 2007.

Conclusions

The presented approach offers a theoretical foundation for the problem of unsupervised ontology learning from data.

Immediate open problem:

- is unsupervised learning possible also in the case of $\mathcal{EL}^{\text{lhs}}$?

Other questions:

- what other feasible conditions could be used to warrant unsupervised learnability in particular languages?
- can we define practical learning algorithms?