Learning Sentences and Assessments in Probabilistic Description Logics

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URSW 2010

Outline

Motivation

- Representation of uncertainty in the semantic Web can be favoured by the use of learning techniques

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- Representation of uncertainty in the semantic Web can be favoured by the use of learning techniques
- Caveats in syntax and semantics in PDL have prevented them from spreading into several domains
- It can be hard to elicit the probability component of a particular set of sentences
- Focus in CR$\mathcal{ALC}$ language

Previous Efforts

Focus on Concept definitions

Using Noisy-OR classifiers

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Focus on Probabilistic inclusions

$C \equiv A \cup B \rightarrow P(C|A \cup B), P(C|A), P(C|B)$

Idea

Combined approach $\rightarrow$ an algorithm for learning concept definitions and probabilistic inclusions at once

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Mostly based on inductive logic programming techniques with a probabilistic twist

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Mostly based on inductive logic programming techniques with a probabilistic twist

- A search for the best concept description is performed.
- A decision is made as to whether to consider the concept definition found or to insert a probabilistic inclusion based on this concept

Probabilistic Description Logic CR$\mathcal{ALC}$

- CR$\mathcal{ALC}$ is a probabilistic extension of the DL $\mathcal{ALC}$.

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- CR$\mathcal{ALC}$ is a probabilistic extension of the DL $\mathcal{ALC}$.
- The following constructors are available in $\mathcal{ALC}$: *conjunction* ($C \sqcap D$), *disjunction* $C \sqcup D$, *negation* ($\neg C$), *existential* restriction ($\exists r.C$), and value restriction ($\forall r.C$).

Probabilistic Inclusions and their Semantics

- $P(\mathrm{A}|\mathrm{B}) = \alpha$

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- $\forall x \in \mathcal{D} \; : \; P(\mathrm{A}(\mathrm{x})|\mathrm{B}(\mathrm{x})) = \alpha$
- $P(\mathrm{Professor}(\mathrm{Maria})|\mathrm{Researcher}(\mathrm{Maria})) = 0.4$

Example

$P(\text{Animal}) = 0.9$,
$P(\text{Rational}) = 0.6$,
$P(\text{hasChild}) = 0.3$,
$\text{Human} \equiv \text{Animal} \sqcap \text{Rational}$,
$\text{Beast} \equiv \text{Animal} \sqcap \neg\text{Rational}$,
$\text{Parent} \equiv$
$\text{Human} \sqcap \exists\text{hasChild.Human}$,
$P(\text{Kangaroo}|\text{Beast}) = 0.4$,
$P(\text{Kangaroo}|\neg\text{Beast}) = 0.0$,
$\text{MaternityKangaroo} \equiv$
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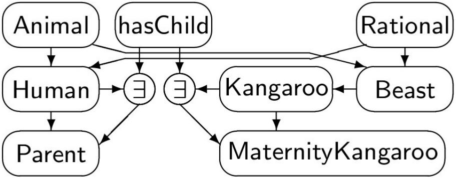

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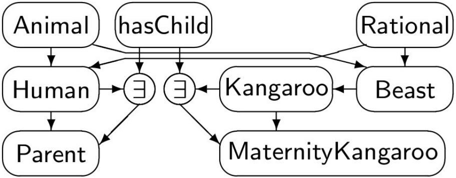

Inference

$$P(\text{Parent}(0)|\text{Human}(0)) = 0.232$$

Learning Description Logics

Goal

Find a correct concept with respect to given examples. A sound concept definition for Target must cover all positive examples and none of the negative examples

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- DL-Learner

Learning Steps

Refinement Operators

Generalization and specialization $\rightarrow$ θ-subsumption

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Score Function

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Search Algorithm

FOIL-based, genetic algorithms, horizontal expansion

Assumption

Deterministic

Father $\equiv$ Male $\sqcap$ hasChild.$\top$

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Probabilistic

$P(\text{FlyingBird}|\text{Bird}) = \alpha$

Assumption

Deterministic

Father $\equiv$ Male $\sqcap$ hasChild.$\top$

Probabilistic

P(FlyingBird|Bird) $= \alpha$

Assumption

Negative and positive examples underlie the choice of either a concept definition or a probabilistic inclusion

Proposal

- We expect to find concepts covering all positive examples which is not always possible $\rightarrow$ uncertainty

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- We expect to find concepts covering all positive examples which is not always possible $\rightarrow$ uncertainty
- When we are unable to find a concept definition that covers all positive examples we assume such hypothesis as candidates to be a probabilistic inclusion

Proposal II

Refinement Operators

Previous refinement operators

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Probabilistic score function

$$cover(e, \mathcal{K}, C) = P(e|\mathcal{K}, C).$$

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Search

- We start by searching a deterministic concept

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Search

- We start by searching a deterministic concept
- If after a set of iterations the score of the best candidate is below a given threshold, a search for a probabilistic inclusion is started

The Algorithm

Require: an initial knowledge base $\mathcal{K} =< \mathcal{T}, \mathcal{A} >$ and a training set E.

SearchTree with a node $\{C = \top, h = 0\}$
repeat
    choose node $N = \{C, h\}$ with highest probabilistic score in SearchTree
    expand node to length $h + 1$:
    add all nodes $D \in$ (refinementOperator(C)) with lenght $=h + 1$
    learn parameters for all nodes D
    $N = \{C, h + 1\}$
    expand alternative nodes according to horizontal expansion factor and $h + 1$[18]
until stopping criterion
$N' =$ best node in SearchTree
if score(N') $>$ threshold **then**
    return deterministic concept $C' \in N'$
else
    call ProbabilisticInclusion(SearchTree)
end if

Algorithm 1: Algorithm for learning probabilistic terminologies.

Probabilistic Inclusion Algorithm

Require: SearchTree previously computed

for each pair of candidates C_i, C_j in first k nodes of the SearchTree **do**
    compute the conditional mutual information $I(C_i, C_j|T)$
end for
build an undirected graph in which vertices are the k candidates
annotate the weight of an edge connecting C_i to C_j by the $I(C_i, C_j|T)$
build a maximum weight spanning tree from this graph
add T as parent for each C_i
learn probabilities for $P(C_i|Parents(C_i))$
return the highest probabilistic inclusion $P(T|C') = \alpha$

Algorithm 2: Algorithm for learning probabilistic inclusions.

Description Logic Learning Results

Table: Description logic learning results

Problem	axioms, examples	DL-learner correct (length)	Combined approach correct(length)
trains	252,10	100%(5)	100%(5)
arches	47,5	100%(9)	100%(10)
moral	31,43	100%(3)	100%(5)
poker(pair)	35,49	100%(8)	100%(8)
poker (straight)	45,55	100%(5)	100%(5)

A Real World Domain

Wikipedia

Wikipedia articles consist mostly of free text, but also contain various types of structured information in the form of Wiki markup

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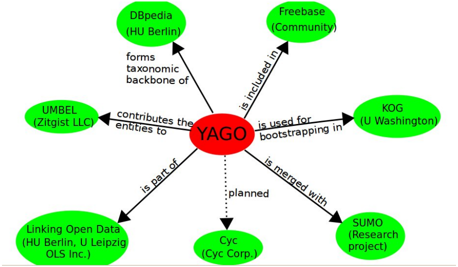
Several Projects

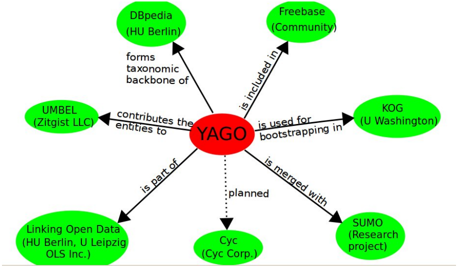
DBPedia and YAGO

YAGO



- YAGO knows more than 2 million entities (like persons, organizations, cities, etc.)

YAGO



- YAGO knows more than 2 million entities (like persons, organizations, cities, etc.)
- It knows 20 million facts about these entities: actedIn . . .

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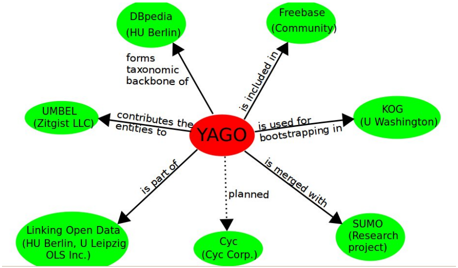

- YAGO knows more than 2 million entities (like persons, organizations, cities, etc.)
- It knows 20 million facts about these entities: actedIn . . .
- Scientists and film directors domains

Scientists Dataset

2008 potential scientists have been considered

$$
\begin{array}{ll}
 & P(\text{wrotes}) = 0.4 \\
 & P(\text{hasAcademicAdvisor}) = 0.80 \\
 & P(\text{interestedIn}) = 0.6 \\
 & P(\text{diedOnYear}) = 0.7 \\
 & P(\text{hasWonPrize}) = 0.4 \\
 & P(\text{worksAt}) = 0.85 \\
 & P(\text{influences}) = 0.6 \\
\text{Scientist} \equiv & \text{Person} \\
 & \sqcap(\exists \text{hasAcademicAdvisor.Person} \\
 & \sqcap \exists \text{wrotes.Text} \sqcap \exists \text{worksAt.EducationalInstitution}) \\
P(\text{InfluentialScientist} & \mid \text{Scientist} \sqcap \exists \text{influences.} \\
 & \exists \text{diedOnYear.Year}) = 0.85 \\
P(\text{Musician} & \mid \text{Person} \sqcap \exists \text{hasAcademicAdvisor.} \exists \text{wrote.Text}) = 0.1 \\
\text{HonoredScientist} \equiv & \text{Scientist} \\
 & \sqcap\ \exists \text{hasWonPrize.Prize}
\end{array}
$$

Scientists II

$$\begin{aligned} P(\text{Scientist}(0) \quad & |\text{Person}(0) \\ & \sqcap(\exists \text{wrote.Text}(1) \\ & \sqcap \exists \text{hasAcademicAdvisor.Person}(2)) = 0.5 \end{aligned}$$

Scientists II

$$
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P(\text{Scientist}(0) \quad & |\text{Person}(0) \\
& \sqcap(\exists \text{wrote.Text}(1) \sqcap \exists \text{hasAcademicAdvisor.} \\
& \exists \text{influences.Person}(3))) = 0.65
\end{aligned}
$$

Directors

5589 potential directors have been considered

$$
\begin{array}{ll}
 & P(\text{isMarriedTo}) = 0.1 \\
 & P(\text{influences}) = 0.35 \\
 & P(\text{hasWonPrize}) = 0.28 \\
 & P(\text{hasChild}) = 0.05 \\
 & P(\text{diedOnYear}) = 0.5 \\
 & P(\text{directed}) = 0.8 \\
 & P(\text{actedIn}) = 0.4 \\
\text{Actor} \equiv & \text{Person} \sqcap \forall \text{actedIn.Film} \\
P(\text{Director} & \mid \text{Person} \sqcap (\exists \text{directed.Film} \sqcap \exists \text{influences.} \\
 & \exists \text{actedIn.Film}) = 0.75 \\
P(\text{FomerActor} & \mid \text{Director} \sqcap \exists \text{actedIn.Film}) = 0.6 \\
\text{HonoredDirector} \equiv & \text{Director} \sqcap \exists \text{hasWonPrize.Prize} \\
\text{FamilyDirector} \equiv & \text{Director} \sqcap (\exists \text{isMarriedTo.Director} \sqcup \exists \text{hasChild.Director}) \\
P(\text{InfluentialDirector} & \mid \text{Director} \sqcap \exists \text{hasWonPrize.Prize} \sqcap \exists \text{influences.} \\
 & \exists \text{isMarriedTo.Director}) = 0.7 \\
P(\text{MostInfluentialDirector} & \mid \text{Director} \sqcap \exists \text{diedOnYear.Year} \sqcap \exists \text{influences.} \\
 & \exists \text{hasWonPrize.Prize}) = 0.8
\end{array}
$$

Directors II

$$P(\text{Actor}(0)|\text{Person}(0) \sqcap \exists \text{actedIn.Film}(1) \sqcap \exists \text{directed.Film}(2)) = 0.4$$

$$P(\text{Director}(0)|\text{Person}(0) \sqcap \exists \text{actedIn.Film}(1) \sqcap \exists \text{directed.Film}(2)) = 0.55$$

Directors II

$$P(\text{Actor}(0)|\text{Person}(0) \sqcap \exists\text{actedIn.Film}(1) \sqcap \exists\text{directed.Film}(2)) = 0.4$$

$$P(\text{Director}(0)|\text{Person}(0) \sqcap \exists\text{actedIn.Film}(1) \sqcap \exists\text{directed.Film}(2)) = 0.55$$

$$\begin{aligned} P(\text{Actor}(0) \quad & |\text{Person}(0) \\ & \sqcap(\exists\text{actedIn.Film}(1) \sqcap \exists\text{directed.Film}(2) \\ & \sqcap\exists\text{influences.Person}(3))) = 0.3 \end{aligned}$$

Conclusions

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- Initially, the search aims at finding deterministic concepts. If the score obtained is below a given threshold, a probabilistic inclusion search is conducted
- Preliminary results have focused a real-world domain —YAGO ontology based on Wikipedia

The End

Thank you