

Semantic Enrichment in OWL Knowledge Bases

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ABSTRACT

The Semantic Web is still growing and the availability of large knowledge graphs increased over the past years. In spite of the growing number of knowledge bases there exist very few with a sophisticated schema. Often they only consist of a collection of facts with no consistent structure. Other knowledge bases contain only schema information without instances of the defined schemata.

But only the combination of both of these extremes, sophisticated schema and available instance data can enable powerful reasoning, easier checking for consistency and improved queryability.

This article shows two methods for the semantic enrichment of large OWL knowledge bases. The first method focuses on finding and creating class expressions in an automatic or semiautomatic approach based on given knowledge in the graph. Whereas the second method enriches knowledge bases with different types of OWL2 axioms.

General Terms

Theory

Keywords

Ontology engineering, Supervised machine learning, Knowledge Base Enrichment, OWL, Heuristics

1. INTRODUCTION

- semantic web: growing, bigger knowledge graphs

- Open data Initiative, Protégé ontology etc -> hard to maintain, debug / find error inconsistencies

- lack sophisticated schema (only schema no instances, only facts)

- combination good schema + instance data -> powerful reasoning, consistency, improved query

- Example: Person birthplace + Benefits + missing info + semi-automated

2. ENRICHMENT OVERVIEW

The term enrichment in this context describes the extension of the (semantic) schema of a knowledge base. The process of knowledge base enrichment increases the semantic richness and the expressiveness of the knowledge base. The goal of the enrichment process is to find axioms, which can be added to the existing ontology. A special case is to find definitions of classes and subclasses. This is closely related to the Inductive Logic Programming (ILP) as it is described later in this article. Ontology enrichment methods usually depend on machine learning or on applying heuristics to find additional axioms in the knowledge graph.[1]

As stated before, knowledge base enrichment usually works on existing data to improve the semantic schema. This supports the so-called *grass-root* approach for creating ontologies. Here the whole ontology structure is not created upfront, but evolves over time and with every part of data that is added to the knowledge base.[1]

- description logic: least common subsumer - top-down, refinement operator for ALER - combine in YINYANG tool

- knowledge base completion (well-defined sense) classes <-> subclasses

- CELOE (heuristics and adaptation), described later

3. CLASS LEARNING

Motivation

The class learning approach is one method of enrichment of knowledge bases. It aims at finding new definitions of classes to extend the semantic schema. For the motivation of the method consider the following example.

Example 1. For this example consider a knowledge base containing a class *President of the United States* with instance data like Abraham Lincoln, John F. Kennedy, Bill Clinton and Barack Obama. A class learning algorithm may suggest that the President class is equivalent to the following two class expressions:

Person and born in the USA

American citizen and born in the USA¹

¹The class 'American citizen' is here a subclass of 'Person',

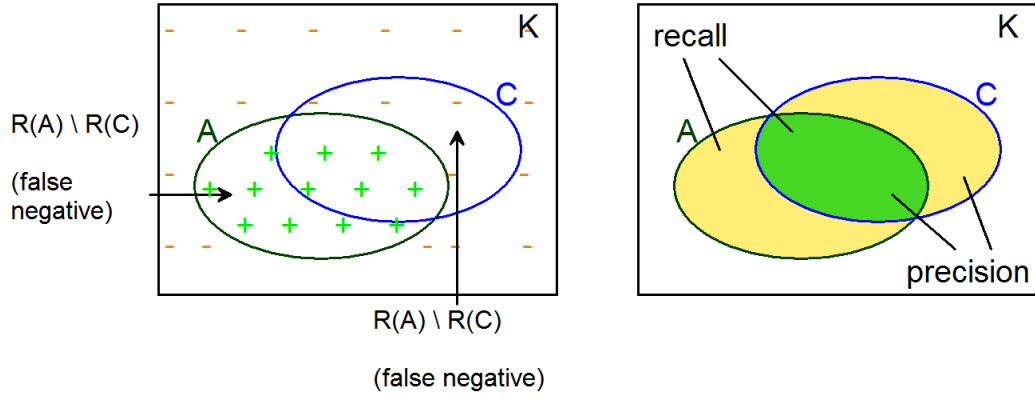


Figure 1: recall precision

These suggestions would then be presented to a knowledge engineer who then can decide if they are plausible and should be added to the knowledge graph. Should the engineer for instance choose the second statement he could check if there are instances of the class president, where the individual is not of type American citizen. This could indicate an error or missing information in the knowledge graph which could be fixed by this semi-automated approach by the knowledge engineer.

Learning Problem

The problem of learning class definitions for given data depend on the so called inductive reasoning as opposed to inference or deductive reasoning. [2] Inductive Reasoning is also a key concept in Inductive Logic Programming.

Definition 1. We are searching for a formal description of the class A , which has existing instances in the examined ontology. A possible class expression C then contains axioms of the form $A \subseteq C$ or $A \equiv C$.

This means that the learned expression C is a description of the individuals of A . In our president example, the individuals are the presidents John F. Kennedy, Barack Obama etc. whereas C can be one of the suggested expression. In many cases there will be no exact solution for C , but rather an approximation. This can be the case, if the knowledge base contains false class assignments or missing information. In our example the birthplace of Thomas Jefferson might be missing in the ontology. However, if most of the other presidents have the correct birthplace the learning algorithm may still suggest the expressions. Again, missing information may be completed by the knowledge engineer.

In a complex knowledge base a class learning algorithm may find many new class definitions and often different expressions for the same class. Based on Occam's razor [?] simple solutions are preferred over complex ones, because they are more readable and thus easier for the knowledge engineer to evaluate. Simplicity is measured in a straightforward

which makes the second statement more specific.

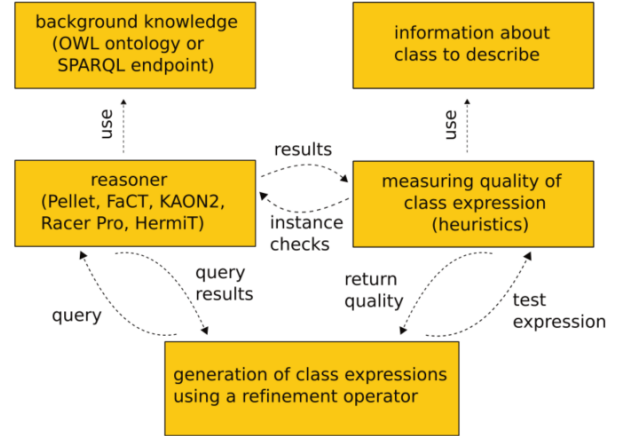


Figure 2: CELOE[2]

way: the length of an expression, which consists of role, concept and quantifiers. The algorithm is biased towards shorter expressions. [2]

Algorithm

One algorithm for solving the learning problem is called CELOE (Class Expression Learning for Ontology Engineering). It is described in [2]. An brief overview of CELOE is given in Figure 2. The algorithm follows the “generate and test” approach which is the common concept in ILP. In the learning process many class expressions are created and tested against the background knowledge. Each of these class expressions is evaluated using different heuristics, which are described in detail in a separate section.

To find appropriate class expression to describe existing classes CELOE uses a so called *refinement operator*. The idea of these operator is based on the work in [3],[4] and [5]. Refinement operators are used to search in the space of expressions. It can be seen as a top-down algorithm as it is illustrated in Figure 3. As an example consider the following path (\rightsquigarrow indicates a refinement step):

$T \rightsquigarrow Person \rightsquigarrow Person \sqcap takesPartIn.T \rightsquigarrow Person \sqcap$

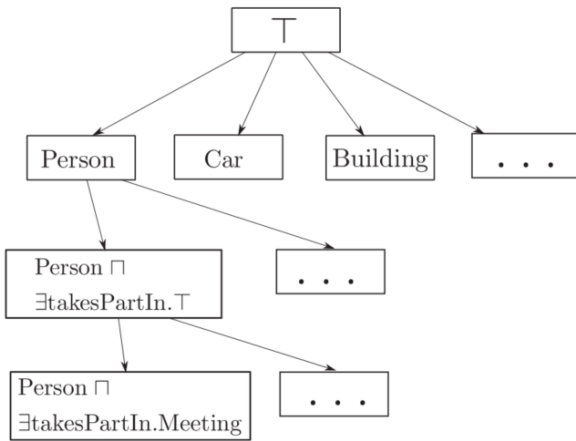


Figure 3: Tree[2]

takesPartIn.Meeting

4. ENRICHMENT WITH OWL AXIOMS

- more

- more

- more

5. HEURISTICS

5.1 Finding the right Heuristic

5.2 Efficient heuristic computation

- more

- more

- more

6. EVALUATION HEURISTICS

- more

- more

- more

7. EVALUATION ON ONTOLOGY ENRICHMENT

- more

- more

- more

8. RELATED WORK

- more [2]

- more [1]

- more [3, 4, 5]

- more [6]

9. CONCLUSIONS

- more

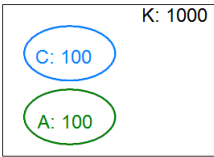
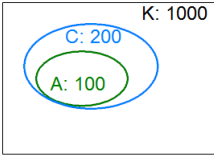
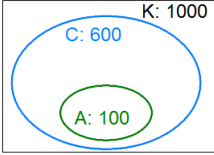
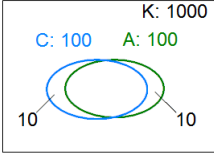
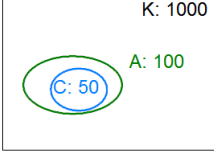
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10. REFERENCES

- [1] L. Bühmann and J. Lehmann. Universal owl axiom enrichment for large knowledge bases. *EKAW*, pages 57–71, 2012.
- [2] J. Lehmann, S. Auer, L. Bühmann, and S. Tramp. Class expression learning for ontology engineering. *Journal of Web Semantics*, pages 71–81, 2011.
- [3] J. Lehmann and P. Hitzler. Foundations of refinement operators for description logics. *LNCS*, 4894, 2007.
- [4] J. Lehmann and P. Hitzler. A refinement operator based learning algorithm for the alc description logic. *LNCS*, 4894, 2007.
- [5] J. Lehmann and P. Hitzler. Concept learning in description logics using refinement operators. *Machine Learning Journal*, 78:203–250, 2010.
- [6] S.-H. Nienhuys-Cheng and R. d. Wolf. *Foundations of Inductive Logic Programming*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 1997.

Table 1: Heuristics

Illustration	accuracy & recall		pred. acc.	F-Measure	A-Measure	Jaccard
 <p>K: 1000 C: 100 A: 100</p>	accuracy	0%	0 %	0 %	0 %	0 %
	recall	0%				
 <p>K: 1000 C: 200 A: 100</p>	accuracy	50%	0 %	0 %	0 %	0 %
	recall	100%				
 <p>K: 1000 C: 600 A: 100</p>	accuracy	16.7%	0 %	0 %	0 %	0 %
	recall	100%				
 <p>K: 1000 C: 100 A: 100 10 10</p>	accuracy	90%	0 %	0 %	0 %	0 %
	recall	90%				
 <p>K: 1000 C: 50 A: 100</p>	accuracy	50%	0 %	0 %	0 %	0 %
	recall	100%				