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 knowlege bases there exist very few with a sophisticated schema. Often they only consist of a collection of facts with no consistant structure. Other knowlege 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 show two methods for the semantic enrichment of large OWL knowlege bases. The first method focuses at finding and creating class expressions in an automatic or semiautomatic approach based on given knowlege in the graph. Whereas the second method enrichs knowlege 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, Protoge ontologie etc -> hard to maintain, debug / find error inconsitencies

- 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 knowlege base. The process of knowlege base enrichment increases the semantic richness and the expressiveness of the knowlege base. The goal of the enrichment progress is to find axioms, witch can be added to the existing ontology. A special case is to find definition 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 knowlege graph.[1]

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

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

- knowlege base completetion (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 knowlege bases. It aims at finding new definition of classes to extend the semantic schema. For the motivation of the method consider the following example.

Example 1. For this example consider a knowlegde 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 USA[1]
```

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

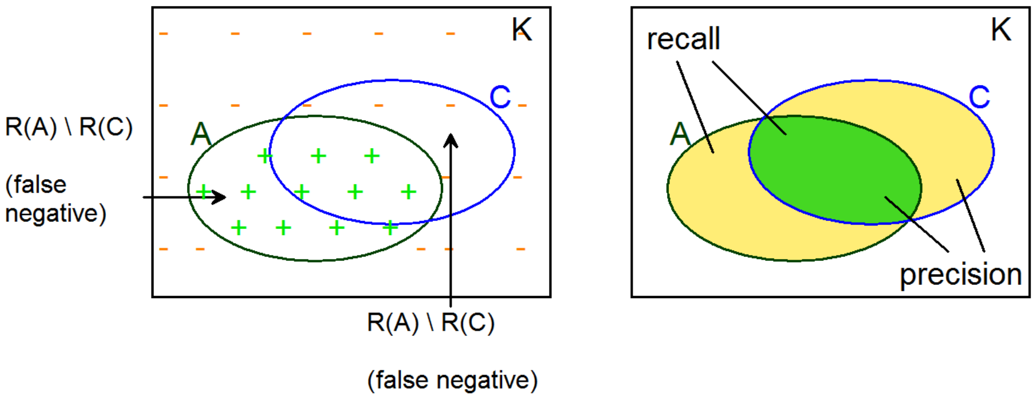

Figure 1: recall precision

These suggestions would then be presented to a knwolege engineer who than can decide if they are plausible and should be added to the knowlege 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 knowlege graph witch could be fixed by this semi-automated approach by the knowlege 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 approximotion. This can be the case, if the knowlege 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 knowlege engineer.

In a complexe knowlege base a class learning algorithm may find many new class definition and often different expression for the same class. Based on Occam's razor [**?**] simple solutions are preferred over complex ones, because they are more readable an thus easier for the knowlege engineer to evalueate. Simplicity is measured in an straight forward

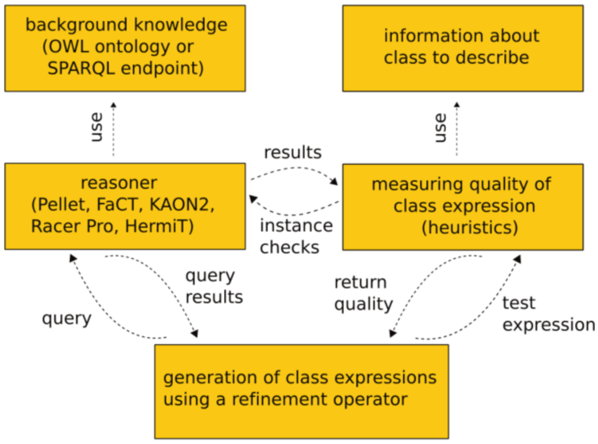

Figure 2: CELOE[2]

way: the lenght of an expression, which consists of role, concept and quatifiers. 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 expression are created and tested against the background knowlege. Each of these class expressions is evalued using diffenrent heuristics, which are described in detail in a separate section.

To find appropiate 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-downl algorithm as it is illustrated in Figure 3. As an example consider the following path ($\rightsquigarrow$ indicates a refinement step):

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

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witch makes the second statement more specific.

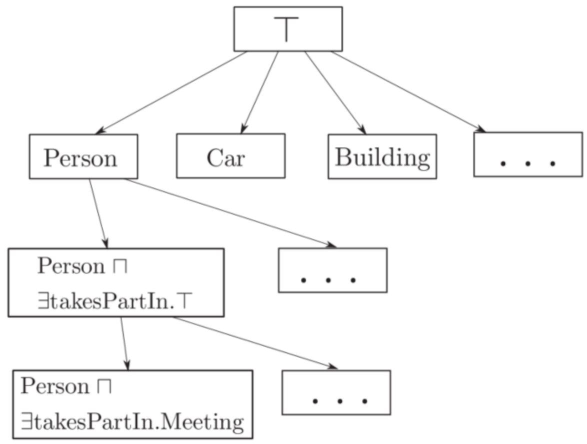


Figure 3: Tree[2]

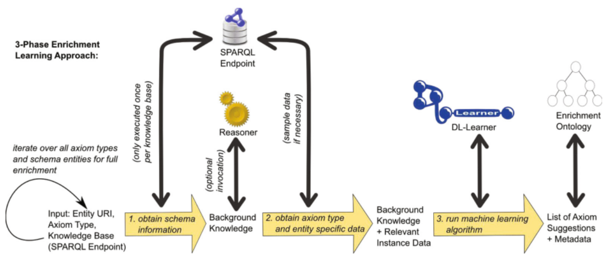


Figure 4: 3-Phase Enrichment Workflow[1]

takesPartIn.Meeting

4. ENRICHMENT WITH OWL AXIOMS

OWL offers many different types of axioms for a method to enrich the knowlege base. Figure 4 shows the 3 steps in the enrichment workflow as described in [1]:

1. The first phase is about obtaining general information about the knowlege base, in particular axioms, which define the class hierarchy are obtained. The schema queried via SPARQL, but is loaded only once.
2. In the second phase data is again obtained via SPARQL. These background checks allows the method to learn and test new axioms. Examples for axiom types are explained in the following text.
3. The score of axiom candidates is computed and the result is returned.

The algorithm for suggestion of new axioms is based on checking and counting RDF triples. In the following example we want to learn if the class A is an appropiate domain of a predicate p. For that we count the triples that match this statement to obtain a score.

Example 2. Lets look at the predicate `onto:attendsMeeting` and check if we can find a suitable candidate for a domain. Note that `onto:Manager` is a subclass of `onto:Employee`.

Listing 1: Triples written in turtle syntax

```
onto:Software_Engineer
        onto:attendsMeeting      onto:TeamMeeting;
        rdf:type                 onto:Employee.
onto:Software_Architekt
        onto:attendsMeeting      onto:TeamMeeting;
        rdf:type                 onto:Employee.
onto:Project_Manager
        onto:attendsMeeting      onto:ManagerMeeting;
        rdf:type                 onto:Manager.

onto:Manager    rdfs:subClassOf  onto:Employee.
```

Looking at this example we would abtain a score of 33.3 % (1 out of 3) for the class `onto:Manager` and 100 % (3 out of 3) for the class `onto:Employee`.
Obviously this extrem simple and straightforward method of calculating the score for the domain of a predicate p has some limitation. Mainly the method doesn't discriminate between a score calculated by having 100 out of 100 correct observations or only 3 out of 3. Different methods, for example the Wald method [?], overcome that problem. More involved heuristics are shown in the next section.

Obtaining Axioms via SPARQL queries

This section explains how SPARQL queries are used to extract information in step 2 of the enrichment workflow.

Subclass and Disjointness of classes

This query evaluates all individuals (`?ind`) and checks if they are instance of the user defined class definition in `$class`. In this query higher count indicates a better candidate for a superclass. Lower value indicates a disjointness.

```
SELECT ?type (COUNT(?ind ) AS ?count ) WHERE {
    ?ind a <$class >.
    ?ind a ?type .
} GROUP BY ?type
```

Subsumption and Disjointness of properties

A pretty simular query can be used to learn subsumption and disjointness of predicates.

```
SELECT ?p (COUNT(? s ) AS ?count ) WHERE {
    ?s ?p ?o .
    ?s <$property> ?o .
} GROUP BY ?p
```

Domain and Range of properties

A query for the domain of a property counts the occurrences subjects of type `?type` having the property `$property`.

```
SELECT ?type COUNT(DISTINCT ?ind ) WHERE {
    ?ind <$property> ?o .
    ?ind a ?type .
} GROUP BY ?type
```

The query for the range of `$property` is analog. It can be also distinguished between object and data properties. Here only the queries for object properties are listed.

```
SELECT ?type (COUNT(DISTINCT ?ind ) AS ?cnt ) WHERE {
    ?s <$property> ? ind .
    ?ind a ?type .
} GROUP BY ?type
```

Inverse of Properties
To check if a property is inverse we check the `$property` with subject and object and in swapped position. As always we count how often the expression holds.

```
SELECT ?p (COUNT(*) AS ?count ) WHERE {
    ?s <$property> ?o .
    ?o ?p ?s .
} GROUP BY ?p
```

5. HEURISTICS

5.1 Finding the right heuristic

A heuristic measures how well a given class expression fits the learning problem. [2] To test an algorithm we must have positive and negative examples. As we want to descibe class A with C we can consider every instance of A as a positive and everything else as negative examples. The predictive accuracy can be described as:

$$predacc(C) = 1 - \frac{|R(A) \setminus R(C)| + |R(C) \setminus R(A)|}{n} \quad n = |Ind(K)|$$

Here, Ind(K) stands for the set of individuals in the knowlege base. $R(A) \setminus R(C)$ are the false negatives whereas $R(C) \setminus R(A)$ are the false positives.
As you can see in Figure 2 for the term *precision* we consider the intersection of A and C ($R(A) \cap R(C)$) and the false positive. In other words, how many individuals are rightfull considered with our class expression C.
For the other term *recall* we consider again the intersection of A and C and the false negative. This score tells us how many individuals of A we can describe with our class expression C.

Table 5 compares the score of four different heuristics. They are:

- **pred. acc.** The formula for the predictive accuracy was shown above.
- **F-Measure** The F-Measure is defined as harmonic mean of precision and recall. It can be weighted by a factor β, [2] choose 3 for β for learning super classes, wich gives recall a higher weight than precision.
  $F\text{-}Measure = \frac{\beta+1}{\frac{\beta}{rec} + \frac{1}{acc}}$
- **A-Measure** For the A-Measure we choose the arithmetic mean of precision and recall.
  $A\text{-}Measure = \frac{prec \times acc}{2}$
- **Jaccard** The Jaccard index is well known to compare two sets. It is defined as the size of the intersection divided by the size of the union of the sets.
  $Jaccard(A, B) = \frac{|A \cap C|}{|A \cup C|}$

5.2 Efficient heuristic computation

- more

- more

- more

6. EVALUATION

- more

- more

- more

7. RELATED WORK

- more [2]

- more [1]

- more [3, 4, 5]

- more [6]

8. CONCLUSIONS

- more

- more

- more

9. 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.

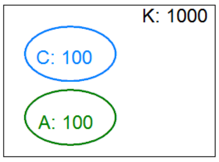
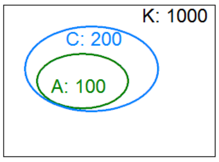
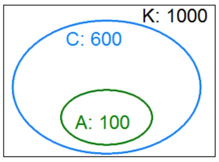
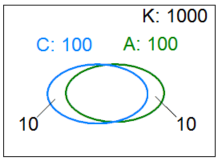
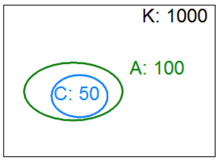
[3] J. Lehmann and P. Hitzler. Foundations of refinement operators for description logics. *LNCS*, 4894, 2007.

[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
	accuracy 0% recall 0%	80 %	0 %	0 %	0 %
	accuracy 50% recall 100%	90 %	66.7 %	75 %	50 %
	accuracy 16.7% recall 100%	50 %	28.6 %	58.3 %	16.7 %
	accuracy 90% recall 90%	98 %	90 %	90 %	81.8 %
	accuracy 50% recall 100%	95 %	66.7 %	75 %	50 %