A Framework for a Fuzzy Matching between Multiple Domain Ontologies

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Abstract. The paper proposes an alignment framework for a set of domain ontologies in order to enable their interoperability in a number of information retrieval tasks. The procedure starts by anchoring the domain ontologies concepts to the concepts of a generic reference ontology. This allows the representation of each domain concept as a fuzzy set of reference concepts or instances. Next, the domain concepts are mapped to one another by using fuzzy sets relatedness criteria. The match itself is presented as a fuzzy set of the reference concepts or instances, which allows the comparison of a new ontology directly to the already calculated matches. The paper contains a preliminary evaluation of the approach.

1 Introduction

With the growing demand and acceptance of ontology-based applications, we have witnessed the creation of multiple ontologies describing similar or even identical fractions of real world knowledge. These ontologies, (partly) complementary or (partly) redundant, have an impaired collaborative functionality, because of the decentralized nature of their conception, their different scopes and application purposes, or because of mismatches in terms of syntax and terminology. More than rarely, however, the sharing, integration and interoperability of these resources is required in real life application scenarios.

Ontology matching provides mechanisms for the alignment of (the components of) various knowledge resources. The different ontology matching approaches can be classified w.r.t. the object on which this alignment relies [10]: *terminological approaches* measure the similarity of the concept names and their lexical definitions, *extensional* approaches use instance data to discover matches, *structural* approaches rely on the relations that hold between the different concepts and *semantic* approaches are based on logical methods. These different approaches are often complemented by the use of background knowledge provided by a *reference ontology*, allowing to deal with realistic matching cases (e.g. weakly structured models) [2, 16, 15]. Another current issue in realistic case ontology matching is the handling of imprecise information and the resulting matching imperfections [12].

The paper suggest a procedure for alignment of the concepts of several domain ontologies, referred to as source ontologies, by the help of a generic reference ontology. The reference ontology is a pre-existing knowledge body which provides common knowledge about a given domain of interest. The choice of a reference therefore depends on the sources: this can be a broader domain ontology (for instance FMA in the domain of medicine or biology) or a more generic knowledge source (such as populated WordNet or Wikipedia). In the current study, we focus on text-populated hierarchies (e.g. web-directories) describing similar or complementary domains, using Wikipedia as a reference ontology. We apply the idea of anchoring a set of source ontologies onto a reference ontology [15], but in contrast to previous techniques, we rely on the uniformity in the matching criteria for the whole set of input ontologies as well as the semantic nature of these matchings as a main advantage of the anchoring. Based on this anchoring, we redefine the source concepts as fuzzy sets of reference concepts or, consequently, instances. This enables the application of a whole set of similarity measures defined on fuzzy sets. An important and difficult question is how a concept is defined, how many and what instances are included in its extension. This uncertainty in concept definition is embedded by entering the realm of fuzzy set representations. In consequence, uncertainty in concept matching is addressed as well. The match itself is presented as a fuzzy set of the reference concepts or instances, which plays in favor of the scalability of the approach.

As we shall see in the sequel, certain analogies between our approach and topic modeling [5] can be drawn. Our results particularly relate to the LDA approach taken by Rosen-Zvi *et al* [17], who determine the similarity of authors based on topic vectors which describe the respective authors publications. In contrast to their approach, our design decision was to use pre-existing knowledge in the form of a reference ontology for the topics. After computing the topic scores for the source ontologies, our approach is able to compute new "topic models" for the matches, without using the instances any more.

In next section, we discuss related work. Section 3 provides background in the problem of ontology heterogeneity and describes standard measures for extensional concept mapping, as well as a novel ontology matching algorithm. The framework of the alignment approach that we propose is presented in Section 4 followed by a preliminary evaluation in Section 5.

2 Background and Related Work

Fuzzy set theory has been introduced as a generalization of classical set theory [22]. A fuzzy set A is defined on a given domain of objects X by the function f_A which expresses the degree of membership of every element of X to A by assigning to each $x \in X$ a value from the interval $[0, 1]$. This allows to deal with imprecise and vague data. A way of handling imprecise information in ontologies is to incorporate fuzzy logic into them. Several papers by Sanchez, Calegari and colleagues [7], [8], [18] form an important body of work on fuzzy ontologies. The authors have been motivated by the observation that crisp reasoning through two valued logic, although machine processable, is not suited to deal with uncertain or imprecise information available in real world knowledge. Each ontology concept is defined as a fuzzy set on the domain of instances and relations on the domain of instances and concepts are defined as fuzzy relations.

Work on fuzzy ontology matching can be classified in two families : (1) approaches extending crisp ontology matching to deal with fuzzy ontologies and (2) approaches addressing imprecision of the matching of (crisp or fuzzy) concepts. Based on the work on approximate concept mapping by Stuckenschmidt [19] and Akahani *et al.* [1], Xu *et al.* [21] suggested a framework for the mapping of fuzzy concepts between fuzzy ontologies. With a similar idea, [4] propose a framework to define similarity relations among fuzzy ontology components. The other family of fuzzy matching approaches is motivated by the representation of imprecision of the matching itself, even with crisp ontologies. For instance, in [11], a fuzzy approach is proposed to handling mapping uncertainty. A new ontology mapping approach based on fuzzy conceptual graphs and rules is proposed in [6]. To define new intra-ontology concept similarity measures, Cross *et al.* [9] model a concept as a fuzzy set of its ancestor concepts and itself. As a membership degree function, the authors use the Information Content (IC) of concept with respect to its ontology. IC can be measured by using external text corpus or by using the ontology structure.

3 Matching Heterogeneous Ontologies

An ontology consists of a set of *concepts* and *relations* defined on these concepts, which provide in an explicit and formal manner knowledge about a given domain. We are particularly interested in ontologies, whose concepts come equipped with a set of associated instances, referred to as populated ontologies and defined as tuples of the kind $O = \{C, \texttt{is\_a}, R, I, g\}$, where C is a set whose elements are called concepts, `is_a` is a partial order on C, R is a set of other relations holding between the elements of C, I is a set whose elements are called instances and $g : C \rightarrow 2^I$ is a mapping from the set of concepts to the set of subsets of I. In this way, a concept is *intensionally* modeled by its relations to other concepts, and *extensionally* by a set of instances assigned to it via the mapping g. By assumption, all instances can be represented as real-valued vectors of uniform dimension.

Ontology heterogeneity occurs when two or more ontologies are created independently from one another over similar domains. Heterogeneity may be observed on a *linguistic or terminological* level (use of vocabulary), on a *conceptual* level (level of detail, coverage or scope) [10] or on *extensional* level (population). Whenever heterogeneity of any of these kinds is observed over a set of ontologies, these ontologies will be referred to as *heterogeneous*.

Ontology matching addresses the heterogeneity problem by providing a set of assertions on the relations holding between the elements of two (or more) heterogeneous ontologies. In a narrower understanding of this definition, we will be interested in measuring the degree of equivalence of any two concepts from two distinct ontologies. Under a given choice of similarity criteria, various measures of concept relatedness can be applied. We have proposed several extensional concept similarity measures for document populated ontologies in [20].

Let us consider two ontologies $O_1 = (C_1, \texttt{is\_a}, R_1, I_1, g_1)$ and $O_2 = (C_2, \texttt{is\_a}, R_2, I_2, g_2)$. For the purposes of the current study, we have relied on the straightforward idea that determining the similarity $sim(A, B)$ of two concepts $A \in C_1$ and $B \in C_2$ consists in comparing their instance sets $g_1(A)$ and $g_2(B)$. For doing so, we need a similarity measure for instances $\mathbf{i}^A$ and $\mathbf{i}^B$, where $\mathbf{i}^A \in g_1(A)$ and $\mathbf{i}^B \in g_2(B)$. We can use, for instance, the scalar product and the cosine $s(\mathbf{i}^A, \mathbf{i}^B) = \frac{\langle \mathbf{i}^A, \mathbf{i}^B \rangle}{\|\mathbf{i}^A\| \|\mathbf{i}^B\|}$. Based on this similarity measure for elements, the similarity measure for the sets can be defined by computing the similarity of the mean vectors corresponding to class prototypes, i.e.

$$sim_{proto}(A, B) = s\Big(\frac{1}{|g_1(A)|} \sum_{j=1}^{|g_1(A)|} \mathbf{i}_j^A, \frac{1}{|g_2(B)|} \sum_{k=1}^{|g_2(B)|} \mathbf{i}_k^B\Big). \tag{1}$$

This method underlies the Caiman approach [14] in which concepts are assumed to be represented by their mean vector. The theory of hierarchical clustering (e.g., [3]) provides alternative methods for defining similarities for pairs of sets. Examples are the similarity measures sim_{min}, sim_{max}, sim_{avg}, which use the minimum, maximum, and average similarity of concept vectors, respectively.

Using the prototype corresponds to developping a simple topic model, in which the topics correspond to the word weights in the prototype. More elaborate topic modelling like LDA [5] and PLSI [13] could be applied, which are able to determine the underlying, "hidden" topics of the documents in a concept. However, in our experiments, using the prototype vector already worked well. It is also computationally much less expensive, than, for instance, PLSI. Note that our fuzzy approach, to be introduced later, consists in **providing** a hierarchical set of topics in the form of a reference ontology. The semantics of the reference topics is described by their instances.

A *matching algorithm* based on a concept similarity measure like one of the suggested above, is given in Alg. 1. The algorithm operates implicitly on the product graph of two input ontologies and it takes into account all given relations in these ontologies (the `is_a` relation and the relations in R are treated in the same manner). The algorithm has a quadratic runtime, since it is greedy and operates on the product graph.

4 A Two-level Multiple Ontologies Matching Architecture

Let $\Omega = \{O_1, ..., O_n\}$ be a set of ontologies that will be referred to as the set of *source* ontologies and let their concepts be referred to as *source concepts*, denoted by C_Ω. Let $O_{ref} = (X, \texttt{is\_a}, R_{ref}, I_{ref}, g_{ref})$, be an ontology, called the *reference* ontology whose concepts will be called *reference concepts*. The set Ω is characterized as a set of ontologies which share similar functionalities and application focuses, but are heterogeneous as discussed in Section 3. A certain complementarity of these ontologies can be assumed: they could be defined with

```
procedure Map(M, O1, O2)
// M is the set of matches that are still possible
// The function returns a set of mappings for the concepts of O1 and O2
begin
    Find (A, B) ∈ M that maximizs sim(A, B)
    // The parameter θ specifies the acceptable minimum similarity
    If sim(A, B) < θ then return ∅
    // Because of the ISA-relationships and the ones in R, the match (A, B)
    // constrains the remaining set of potential matches:
    Remove the following from M:

      – every pair (a, b) such that one of the following conditions is true for some
        r ∈ (R1 ∩ R2) ∪ {isa}:
        r(a, A) ∧ ¬r(b, B), r(b, B) ∧ ¬r(a, A), r(A, a) ∧ ¬r(B, b), r(B, b) ∧ ¬r(A, a)
      – every pair (a, b) for which A = a, B = b //in order to enforce a 1:1 mapping

    return {(A, B)} ∪ Map(M, O1, O2)

procedure Main(O1, O2)
begin
    return Map(C1 × C2, O1, O2)
```

Algorithm 1: A greedy algorithm for matching ontologies O_1 and O_2.

the same application scope, but on different levels, treating different and complementary aspects of the same application problem. The ontology O_{ref} is assumed to be application independent, generic knowledge source. Finally, we posit that the ontologies in Ω and O_{ref} are populated as described in section 3. We are interested in identifying the degree of relatedness of any two concepts taken from any two ontologies from the set Ω. We propose the following matching architecture.

Phase one. The source ontologies are first matched independently from one another to the reference ontology by the help of the concept similarity measures and the algorithm introduced in Section 3. As a result, every concept from each of the source ontologies can be represented as a set of similarity scores calculated for this concept and all the concepts in the reference ontology (the *score* in our case is one of the *sim* functions introduced in the previous section).

The considered concept representation gives rise to the following fuzzy set interpretations. Let $score_A(x)$ be the similarity between a concept $x \in X$ and A, a random concept from the set of source ontologies. The concept A will be defined as a fuzzy set in X which has a membership function f_A given by

$$f_A(x) = score_A(x), \forall x \in X. \tag{2}$$

Alternatively, we propose to define the membership function on the set of *instances* of the reference ontology concepts. We will be looking for a fucntion of some domain element, $\mathbf{i}$, in A which maximizes the scores of those concepts in the reference ontology that contain $\mathbf{i}$ as an instance. We start by presenting the reference ontology as an ontology of fuzzy concepts with respect to its instances.

In our case, this will be trivialized to a two-valued membership function: for every instance $\mathbf{i}$ from the reference ontology the function $f_x(\mathbf{i}) = 1$, if $\mathbf{i} \in x$ and 0 otherwise. Thus, we define a source concept A as

$$f_A(\mathbf{i}) = max_{x \in X} T(f_x(\mathbf{i}), f_A(x)), \tag{3}$$

where T is the t-norm of two fuzzy membership functions defined as $T(f_A, f_B) = min(f_A, f_B)$. Recall that in fuzzy set theory the t-norm and the t-conorm (defined as $S(f_A, f_B) = max(f_A, f_B)$) carry the sense of intersection and union of fuzzy sets. As required, (3) amounts to finding the concept x that contains the instance $\mathbf{i}$ and has the maximum score with respect to A. We note that this formulation can be potentially extended to fuzzy reference ontologies with standard membership functions in the full interval $[0, 1]$.

Phase two. We will rely on the fuzzified versions of the concepts of the source ontologies in order to judge on their relatedness. Consider two concepts A and B defined by their fuzzy membership functions f_A and f_B. A straightforward measure of the closeness of these concepts can be given as $\rho_{base}(f_A, f_B) = \max_{x \in X} |f_A(x) - f_B(x)|$ or, alternatively, by their Euclidean distance:

$$\rho_{diff}(f_A, f_B) = \|f_A - f_B\|_2 \,, \tag{4}$$

where $\|x\|_2 = \left(\sum_{x \in X} |x|^2\right)^{1/2}$ is the l^2-norm.

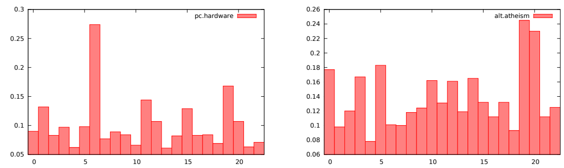
Many measures of fuzzy set compatibility known from fuzzy set theory can be applied, as well [9]. Zadeh's partial matching index between two fuzzy sets A and B is given by $\rho_{sup-min}(f_A, f_B) = \sup \min_{x \in X}(f_A(x), f_B(x))$. We also consider the standard Jaccard coefficient $\rho_{jacc}(f_A, f_B) = \sharp T(f_A, f_B)/\sharp S(f_A, f_B)$, where $\sharp$ returns fuzzy set cardinality.

Once we have represented our source concepts as fuzzy sets, we can measure concept similarities directly on the set of fuzzified concepts C_Ω. Alternatively, in order to take the semantical structure of the ontologies into account, one can apply the matching algorithm described in Alg. 1 by taking as input any two given fuzzified source ontologies and using one of the similarity measures introduced above. Fuzzufied versions of the relationships can be used in a modified version of the algorithm, as well, but this remains out of the scope of this paper.

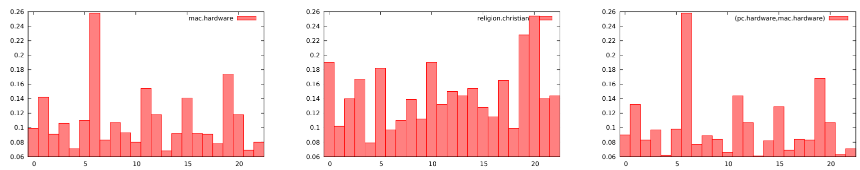
Finally, note that it is possible to define the match itself as a fuzzy set on the reference concepts or their instances (alternative choices given definitions (2) and (3). This will play in favour of the scalability of our approach, since the concepts of every new ontology can be compared to the match directly. One natural possibility of defining the match would be to use again the t-norm. If we know that a source concept A is mapped to a source concept B (information that is made available by the measures introduced earlier in this section), the match will be defined as the fuzzy set

$$f'_{(A,B)}(x) = T(f_A(x), f_B(x)), \forall x \in X. \tag{5}$$

We can easily compare the concepts of a new ontology, represented as well as fuzzy sets on the same space X, with the calculated matches.



(a) Scores for *pc.hardware* (b) Scores for *alt.atheism*



(c) Scores for *mac.hardware* (d) Scores *religion.christian* (e) *(pc.hardw.,mac.hardw.)*

Fig. 1. Fuzzy membership functions: Scores w.r.t. the Inex 2007 Wikipedia Ontology. (a)–(d) represent single concept scores, while (e) represents the scores of the match of two concepts.

5 Experiments

We provide a preliminary evaluation of the proposed approach as a proof of concept. Note that the current section does not aim at comparing the approach to other matching techniques, as this has been done in [20]. It aims to prove, by performing these matchings, that the transition to a fuzzy framework is successful.

As a reference ontology, we consider the 23 categories that form Wikipedia's main topic classifications. For each topic category, we included a set of matching documents from the Inex 2007 corpus which directly belong to this category, or to one of its direct subcategories in the Wikipedia category tree. Thus we arrived at the following 23 concepts: *law (745 documents), technology (293), arts(319), society(2050), agriculture(530) social_sciences(1695) computing(1902) health(341) education(515) mathematics(1903) people(136) business(1202) science(547), history(445), politics(896), applied_sciences(1302), geography(164), chronology(303), environment(467), nature(234), humanities(537), language(427), culture(765)*. Note that there exist `is_a` relationships between some of the concepts, e.g., *politics* and *society*.

The two source ontologies were constructed from the 20 Newsgroup dataset and consist of the following hierarchically organized classes: O_1 = {*sci.med (990), rec.autos (990), alt.atheism (799), sport.baseball (994), pc.hardware(982)*} and O_2 = {*sci.space (987), rec.motorcycles (993.7), religion.christian (997), sport.hockey (999), mac.hardware (961)*}.

By applying the techniques described in Section 3, we match these concepts to the reference ontology in order to acquire their fuzzy representations. We then proceed to apply the similarity measures suggested in Section 4 on the set

A from O_1	B from O_2	ρ_{diff}
sci.med	sci.space	0.23
rec.autos	rec.motorcycl.	0.173
alt.atheism	religion.christ.	0.078
sport.baseball	sport.hockey	0.068
pc.hardware	mac.hardware	0.05

A from O_1	B from O_2	sim_{proto}
sci.med	religion.christ.	0.359
rec.autos	rec.motorcycl.	0.471
alt.atheism	religion.christ.	0.537
sport.baseb.	sport.hockey	0.559
pc.hardware	mac.hardware	0.716

Fig. 2. (a) Fuzzy match determined by smallest distances ρ_{diff}. (b) Crips match determined using largest similarities sim_{proto} (larger values are better)

of source concepts. Finally, we also measure their similarity by using the crisp matching measure used in the first step and compare the results achieved by both. In what follows, we will focus on instance-based concept similarities.

In the crisp matching step and also for directly matching O_1 and O_2, we considered sim_{proto}, sim_{min}, sim_{max}, and sim_{avg}. Since the prototype method worked best and is the most efficient to compute, we will only present the results for this method. In order to compute the prototype similarity, we first transformed the documents into TF-IDF vectors. The prototype method then computes a single prototype (mean vector) for each class. For a pair of classes, their similarity corresponds to the cosine of their prototype vectors.

The diagrams in Fig. 1 show the scores with respect to the Inex 2007 Wikipedia ontology. It can be seen that the membership functions of *pc.hardware* and *mac.hardware* are quite similar, as are those of *alt.atheism* and *religion.christian*. In contrast, *alt.atheism* and *religion.christian* are quite dissimilar to the hardware classes. The two religion-related concepts have their two highest peaks at the Wikipedia concepts *humanities* and *nature*. For the two hardware classes, the Wikipedia concept with the highest score is *computing*.

Using the Euclidean distance $\rho_{diff}(f_A, f_B)$ for selecting the best-matching concept pairs in O_1 and O_2, we arrive at the match in Fig. 2(a). The fuzzy matching method is obviously able to map the related yet different concept pairs. Even the less obvious match between *sci.med* and *sci.space* is found by the method. Note that it is possible to define a fuzzy membership function of the matched concept *(computers1,computers2)*, which is obtained as the minimum of the respective scores. The one for the match *(pc.hardware,mac.hardware)* is shown in Fig. 1(e). Fig. 2(b) shows the match that is found by comparing the prototypes of the respective concepts (higher values are better), i.e., the result of the crisp match between O_1 and O_2. The match is quite similar to the fuzzy one which proves the correctness of the latter. The crisp method fails to map *sci.med* to *sci.space*.

Mathematically speaking, both the fuzzy matching approach and the prototype approach describe each concept by a single feature vector that is somehow obtained from the document vectors. The one for the fuzzy method corresponds to the scores with respect to the reference concepts, whereas the concept prototype is the average of the document vectors. However, the concept prototype refers to the document *word content* only, whereas the membership function refers to the reference concepts that can be assumed to be of a more *semantic* nature, and to contain only relevant information.

Our fuzzy approach for comparing two concepts scales well, since each concept is described by a number of scores, i.e., a single vector whose length only depends on the number of concepts in the reference ontology, which is assumed to be fixed. In the experiments, we based the scores on the concept prototypes, which is a simple yet efficient method. Using other distances like single, complete and average link models or similarities based on variable selection will result in a higher complexity, but potentially more accurate results. The complexity of the matching algorithm depends on the densities of the graphs and the setting of θ. It can be reduced by forcing the algorithm to descend on the `is_a` relationship, similar to the levelwise algorithm described in [20].

6 Conclusion and Future Work

We have proposed a technique for alignment of the concepts of a set of domain ontologies by using a fuzzy set formulation and a generic reference ontology as a mediator. Fuzziness helps to embed uncertainty in concept definition and representation while the use of a reference ontology provides uniform semantic criteria for this representation. The computation of the match itself is inexpensive.

The suggested approach consists in a change of perspective: we enter the realm of fuzzy reasoning, in which we do not have to use the documents any more. In future work, we will be investigating the idea of building a combined knowledge body on the basis of the redefined fuzzy concepts (taken from the whole set of source ontologies) by exploring the possible fuzzy relations between them, instead of using a pairwise concept matching approach.

In contrast to approaches from the topic modeling theory, in our framework the topic space is defined in the very beginning by the reference ontology; we do not try to induce it from corpora by discovering hidden semantics, but we have clearly defined topics, which are not only word probabilities. This is a different perspective which has as an advantage that depending on the domain of interest, different semantics can be considered by the user with respect to the choice of a reference ontology, i.e. the user can introduce certain bias independent on the latent semantical contents of the instances. In future work, it would be interesting to explore, given a set of source ontologies, how the matching results will differ with respect to different choices of a reference ontology.

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