Multi-Agent Ontology Mapping with Uncertainty on the Semantic Web

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Abstract

The increasing number of ontologies of the Semantic Web poses new challenges for ontology mapping. Ontology mapping in the context of Question Answering can provide more correct results if the mapping process can deal with uncertainty effectively that is caused by the incomplete and inconsistent information used and produced by the mapping process. We present a novel approach of how Dempster-Shafer belief functions can be used to represent uncertain similarities created by both syntactic and semantic similarity algorithms. For ontology mapping in the context of Question Answering on the Semantic Web we propose a multi agent framework where agents create dynamic ontology mappings in order to integrate information and provide precise answers for the users query. We also discuss the problems which can be encountered if we have conflicting beliefs between agents in a particular mapping.

1. Introduction

The problem of mapping two ontologies effectively and efficiently is a necessary precondition to integrate information on the Semantic Web. During recent years different research communities have proposed[1] a wide range of methods for creating such mappings. The proposed methods usually combine syntactic and semantic measures by introducing different techniques ranging from heuristics to machine learning. While these methods perform well in certain domains the quality of the produced mappings can differ from domain to domain depending on the specific parameters defined in the methods e.g. tuning similarity threshold.

Our objective was to produce a method that does not depend on any fine tuned internal parameters for a specific domain or does not assume having large amount of data samples a-priory for machine learning or Bayesian probability assessment. Our hypothesis is that the correctness of different similarity mapping algorithms is always heavily dependent on the actual content and conceptual structure of these ontologies which are different even if two ontologies have been created on the same domain but with different purpose. Therefore from the mapping point of view these ontologies will always contain inconsistencies, missing or overlapping elements and different conceptualisation of the same terms which introduces a considerable amount of uncertainty into the mapping process. In this paper we introduce a novel method how these uncertainties can be harnessed in order to improve the correctness of the mappings and how the problem of conflicting beliefs can be handled by introducing trust between the agents.

The paper is organized as follows: In the section 2 we describe the context of our research. In the section 3 we introduce our method, how uncertainty and similarities has been interpreted and used in our algorithm. Section 4 details how conflicting beliefs are combined in our system. In section 5 we show how our system compares with other ontology mapping algorithms and point out the strengths and weaknesses of the system. Section 6 reviews the similar solutions and in section 7 we draw our conclusions of our research.

2. Motivation: Question Answering on the Semantic Web

The Semantic Web holds the promise of allowing computer systems to integrate information from disparate sources to achieve the goals of end users e.g. Question-Answering over web based databases or resources. In this context it is hardly imaginable that isolated applications will be able to serve successfully the users' ever growing requirements since the information available to human decision makers continues to grow beyond human cognitive capabilities. In such an environment a single agent or application limited by its knowledge, perspective and its computational resources cannot cope with the before mentioned scenarios effectively. Our novel approach utilizes a multi agent framework to create dynamic mappings between the different ontology concepts that describe the heterogeneous data sources of different domains.

The usefulness and correctness of the response of Question Answering systems like AQUA [2, 3] are extremely dependent on the how heterogeneous sources described by their ontologies can semantically be mapped using different conceptual models. For ontology mapping in the context of Question Answering over heterogeneous sources we propose a multi agent architecture[4] because as a particular domain becomes larger and more complex, open and distributed, a set of cooperating agents are necessary in order to address the ontology mapping task effectively. In real scenarios, ontology mapping can be carried out on domains with large number of classes and properties. Without the multi agent architecture the response time of the system can increase exponentially when the number of concepts to map increases. An overview of our system is depicted on Fig. 1. The two real word ontologies[1][2] describe BibTeX publications from the University of Maryland, Baltimore County (UMBC) and from the Massachusetts Institute of Technology (MIT) . The AQUA system and the answer composition component is described just to provide the context of our work (our overall framework) but these are not our major target in this paper. The user poses a natural language query to the AQUA system which converts it into FOL (First Order Logic) terms. The main components and its functions of the system are as follows:

1. Broker agent receives FOL term, decomposes it(in case more than one concepts are in the query) and distributes the sub queries to the mapping agents.

2. Mapping agents retrieve sub query class and property hypernyms from WordNet.

3. Mapping agents retrieve ontology fragments from the external ontologies which are candidate mappings to the received sub-queries. Mapping agents use WordNet as background knowledge in order to enhance their beliefs on the possible meaning of the concepts or properties in the particular context.

4. Mapping agents build up coherent beliefs by combining all possible beliefs over the similarities of the sub queries and ontology fragments. Mapping agents utilize both syntactic and semantic similarity algorithms build their beliefs over the correctness of the mapping.

5. Broker agent passes the possible mappings into the answer composition component for particular sub-query ontology fragment mapping in which the belief function has the highest value.

6. Answer composition component retrieves the concrete instances from the external ontologies or data sources which will be included into the answer.

7. Answer composition component creates an answer to the user's question.

2.1. Example scenario

Based on the architecture depicted on Fig. 1 we present the following simplified example which will be used in the following sections of the paper in order to demonstrate our algorithm. We consider the following user query and its FOL representation as an input to our mapping component framework: List all papers with keywords uncertain ontology mapping?

$(\exists x)\, paper\,(x)\, and$
$hasKeywords\,(x, [uncertain, ontology\ mapping])$

- Step 1: Broker agent distributes(no decomposition is necessary in this case) the FOL query to the mapping agents.

- Step 2: Mapping agents 1 and 2 consult WordNet in order to extend the concepts and properties with their inherited hypernym in the query. These hypernyms will serve as variables in the hypothesis. For the concepts "paper" e.g. we have found that "article" and "communication" or "publication" are possible concepts that can appear in any of the external ontologies.

- Step 3: Mapping agents iterate through all concepts and properties from the ontologies and create several hypothesises that must be verified with finding evidences e.g.

$$Agent1 : H_n(\textit{mapping}) =$$
$$\textit{Query}\,\{\ \textit{paper,article,communation,publication}\} \Longleftrightarrow$$
$$\textit{Ontology}_{\text{MIT}}\,\{\ \textit{Article}\}$$
$$and$$
$$Agent2 : H_n(\ \textit{mapping}) =$$
$$\textit{Query}\,\{\ \textit{paper,article,communation,publication}\}$$
$$\Leftrightarrow\ \textit{Ontology}_{\text{UMBC}}\,\{\ \textit{Publication}\}$$

where H is the hypothesis for the mapping.

Further we try to find supporting evidences for the hypothesises. In this phase different syntactic and semantic similarity measures (see subsection 3.2-3) are considered as different experts are used which will determine belief mass functions for the hypothesis. The

[1] http://ebiquity.umbc.edu/ontology/publication.owl
[2] http://visus.mit.edu/bibtex/0.01/bibtex.owl

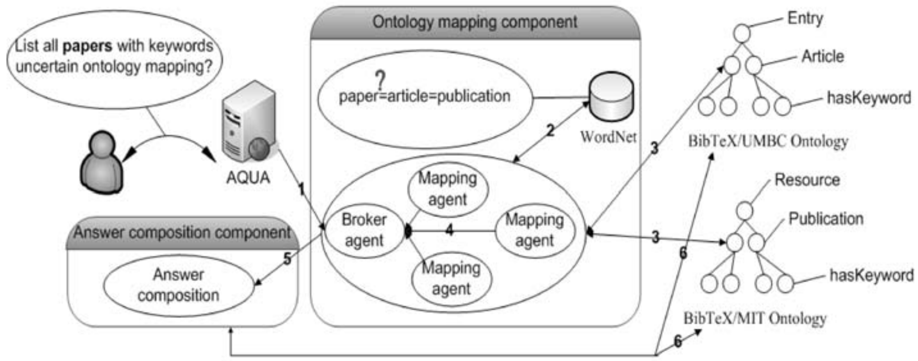


Figure 1. Overview of the system

last phase of this step is to combine the belief mass functions using Dempster's combination rule in order to form a coherent belief of the different experts on the hypothesises.

- Step 4: Mapping agents select the hypothesis in which they believe in most and sent it back to the broker agent. In our example the following mappings have been established:

$$Mapping_{\text{Query, MIT ontology}}(paper \leftrightarrow article)$$
$$Mapping_{\text{Query, UMBC ontology}}(paper \leftrightarrow publication)$$

- Step 5-6: The answer is composed for the user's query which includes the relevant instances from the ontologies.

3. Belief Function for Uncertain Similarity Assessment

3.1. Uncertainty

In our ontology mapping framework each agent carries only partial knowledge of the domain and can observe it from its own perspective where available prior knowledge is generally uncertain. Our main argument is that knowledge cannot be viewed as a simple conceptualization of the world, but it has to represent some degree of interpretation. Such interpretation depends on the context of the entities involved in the process. This idea is rooted in the fact the different entities' interpretations are always subjective, since they occur according to an individual schema, which is than communicated to other individuals by a particular language. In order to represent these subjective probabilities in our system we use the Dempster-Shafer theory of evidence [7], which provides a mechanism for modeling and reasoning uncertain information in a numerical way, particularly when it is not possible to assign belief to a single element of a set of variables. Consequently the theory allows the user to represent uncertainty for knowledge representation, because the interval between support and plausibility can be easily assessed for a set of hypothesizes. Missing data (ignorance) can also be modeled by Dempster-Shafer approach and additionally evidences from two or more sources can be combined using Dempster's rule of combination. The combined support, disbelief and uncertainty can each be separately evaluated. The main advantage of the Dempster-Shafer theory is that it provides a method for combining the effect of different learned evidences to establish a new belief by using Dempster's combination rule.

The following elements have been used in our system in order to model uncertainty:

Frame of Discernment(Θ) :finite set representing the space of hypothesizes. It contains all possible mutually exclusive context events of the same kind.

$$\Theta = \{H_1, ..., H_n, ...H_N\} \tag{1}$$

Evidence:available certain fact and is usually a result of observation. Used during the reasoning process to choose the best hypothesis in Θ.

Belief mass function (m): is a finite amount of support assigned to the subset of Θ. It represents the strength of some evidence and

$$\sum_{A \subseteq \Theta} m_i(A) = 1 \tag{2}$$

where m_i(A) is our exact belief in a proposition represented by A that belongs to agent *i*. The similarity algorithms itself produce these assignment based on different similarity measures. As an example consider the query fragment that contains the concept "paper". Based on the Word-

Net we identify that the concept "article" is one of the inherited hypernyms of the "paper" so after similarity assessment our variables will have the following belief mass value:

$$- m_1(Query\{paper, article, communication, publication\}, Ontology_{\text{MIT}}\{Article\}) = 0.85$$
$$- m_2(Query\{paper, article, communication, publication\}, Ontology_{\text{MIT}}\{Article\}) = 0.91$$

In practice we assess up to 8 inherited hypernyms similarities with different algorithms (considered as experts) which can be combined based on the combination rule in order to create a more reliable mapping. Once the combined belief mass functions have been assigned the following additional measures can be derived from the available information.

Belief: amount of justified support to A that is the lower probability function of Dempster, which accounts for all evidence E_k that supports the given proposition A.

$$belief_i(A) = \sum_{E_k \subseteq A} m_i(E_k) \tag{3}$$

An important aspect of the mapping is how one can make a decision over how different similarity measures can be combined and which nodes should be retained as best possible candidates for the match. To combine the qualitative similarity measures that have been converted into belief mass functions we use the Dempster's rule of combination and we retain the node where the belief function has the highest value.

Dempster's rule of combination:Suppose we have two mass functions $m_i(E_k)$ and $m_j(E_{k'})$ and we want to combine them into a global $m_{ij}(A)$. Following Dempster's combination rule

$$m_{ij}(A) = m_i \oplus m_j = \sum_{E_k E_{k'}} m_i(E_k) * m_j(E_{k'}) \tag{4}$$

where *i* and *j* represent two different agents.

This process called belief revision which is rearranging a cognitive state in order to embody new information while preserving the global consistency. This process is computationally very expensive and from an engineering point of view, this means that it not always convenient or possible to build systems in which the belief revision process is performed globally by a single unit. Therefore, applying multi agent architecture is an alternative and distributed approach to the single one, where the belief revision process is no longer assigned to a single agent but to a group of agents, in which each single agent is able to perform belief revision and communicate with the others. Our algorithm takes all the concepts and its properties from the different external ontologies and assesses similarity with all the concepts and properties in the query graph.

3.2. Syntactic Similarity

To assess syntactic similarity between ontology entities we use different string-based techniques to match names and name descriptions. These distance functions map a pair of strings to a real number, which indicates a qualitative similarity between the strings. To achieve more reliable assessment and to maximize our system's accuracy we combine different string matching techniques such as edit distance like functions e.g. Monger-Elkan [5] to the token based distance functions e.g. Jaccard [6] similarity. To combine different similarity measures we use Dempster's rule of combination. Several reasonable similarity measures exist however, each being appropriate to certain situations. At this stage of the similarity mapping our algorithm takes one entity from Ontology 1 and tries to find similar entity in the extended query. The similarity mapping process is carried out on the following entities:

- Concept name similarity
- Property name and set similarity

The use of string distances described here is the first step towards identifying matching entities between query and the external ontology or between ontologies with little prior knowledge. However, string similarity alone is not sufficient to capture the subtle differences between classes with similar names but different meanings. Therefore we work with WordNet in order to exploit hypernymy at the lexical level. Once our query sting is extended with lexically hypernym entities we calculate the string similarity measures between the query and the ontologies. In order to increase the correctness of our similarity measures the obtained similarity coefficients need to be combined. Establishing this combination method was our primary objective that had been included into the system. Further once the combined similarities have been calculated we have developed a simple methodology to derive the belief mass function that is the fundamental property of Demster-Shafer framework.

3.3. Semantic Similarity

For semantic similarity between concept, relations and the properties we use graph-based techniques. We take the extended query and the ontology input as labeled graphs. The semantic matching is viewed as graph like structures containing terms and their inter-relationships. The similarity comparison between a pair of nodes from two ontologies is based on the analysis of their positions within the graphs. Our assumption is that if two nodes from two ontologies are similar, their neighbours might also be somehow similar. We consider semantic similarity between nodes of the graphs based on similarity of leaf nodes, which represent properties. That is, two non leaf schema elements are semantically similar if their leaf sets are highly similar, even if their immediate children are not. The main reason why semantic heterogeneity occurs in the different ontology structures is because different institutions develop their data sets individually, which as a result contain many overlapping concepts. Assessing the above mentioned similarities in our system we adapted and extended the SimilarityBase and SimilarityTop algorithms [2] used in the current AQUA system for multiple ontologies. Our aim is that the similarity algorithms (experts in terms of evidence theory) would mimic the way a human designer would describe a domain based on a well established dictionary.

What also needs to be considered when the two graph structures are obtained from both the user query fragment and the representation of the subset of the source ontology is that there can be a generalization or specialization of a specific concepts present in the graph which was obtained from the external source and this needs to be handled correctly. In our system we adapted and extended the before mentioned SimilarityBase and SimilarityTop algorithms, which has been proved effective in the current AQUA system for multiple ontologies.

4. Conflicting Beliefs and Trust

Based on our experiments with the OAEI benchmarks(see section 5) we have investigated why in some cases the belief combination produced incorrect result even thought before the combination a correct mapping could have been derived for the particular case based on individual beliefs. The problem occurs when the different experts' similarity assessment produces conflicting beliefs over the correctness of a particular mapping. A conflict between two beliefs in Dempster-Shafer theory can be interpreted qualitatively as one source strongly supports one hypothesis and the other strongly supports another hypothesis, where the two hypotheses are not compatible. In this scenario applying Dempster's combination rule to conflicting beliefs can lead to an almost impossible choice with a very low degree of belief which due to the normalisation will result in the most possible outcome with a very high degree of belief [8, 9]. The combination rule strongly emphasizes the agreement between multiple sources and ignores all the conflicting evidence through a normalization factor.

The counter-intuitive results that can occur with Dempsters rule of combination are well known and have generated a great deal of debate within the uncertainty reasoning community. Different variants of the combination rule[13] have been proposed to achieve more realistic combined belief. Instead of proposing an additional combination rule we turned our attention to the root cause of the conflict itself namely how the uncertain information was produced in our model. Imagine the following scenario where Θ frame of discernment has three mapping elements e_1, e_2, e_3 and the assigned belief masses on the correctness of the particular mappings are as described in Table 1.

Table 1. Belief mass functions

(a) Before normalisation

EXPERT	BELIEF MASS FUNCTIONS
Expert 1	$m_1(e_1)$=0;$m_1(e_2)$=0.01; $m_1(e_3)$=0
Expert 2	$m_2(e_1)$=0.74;$m_2(e_2)$=0.35; $m_2(e_3)$=0.24
Expert 3	$m_3(e_1)$=0.69;$m_3(e_2)$=0.3; $m_3(e_3)$=0.21

(b) After normalisation

EXPERT	BELIEF MASS FUNCTIONS
Expert 1	$m_1(e_1)$=0;$m_1(e_2)$=1; $m_1(e_3)$=0
Expert 2	$m_2(e_1)$=0.55;$m_2(e_2)$=0.26; $m_2(e_3)$=0.19
Expert 3	$m_3(e_1)$=0.57;$m_3(e_2)$=0.25; $m_3(e_3)$=0.18

In this scenario the belief of "Expert 1" is in conflict with the other experts' belief and due to the normalization of the hypothesis set(Table 1(b)) a week possibility is transformed into strong support which would result in an incorrect mapping. In our ontology mapping framework the belief functions are considered as a method to model an expert's beliefs, therefore the belief function defined by an expert can also be viewed as a way of expressing the expert's preferences over choices, with respect to masses assigned to different hypotheses. The larger the mass assigned to a hypothesis is the more preferred the hypothesis will be. In this context the problem is how we handle the experts' conflicting individual preferences that need to be aggregated in order to form a collective preference. Therefore instead of modifying the combination rule we need to revise the conflicting information itself since this is what poses the problem and not the combination rule. Additionally the similarity algorithm hence expert which contributes the conflicting belief can vary from mapping to mapping. Our proposed solution is based on the degree of trust what stems from the reputation model [10] between the individual experts' belief over the correctness of the mapping. In our framework we propose a trust based model because in our case, historical information about how a particular expert performed in the past does not help to determine the actual level of trust, since it differs from case to case.

In our scenario the modified reputation model is particularly appealing because it can be defined as the collective opinion or view about the mapping where this view can be mainly be derived from an aggregation of individual preferences. In our ontology mapping framework we assess trust between the experts' beliefs and determine which expert's belief cannot be trusted, reevaluating the one which contradicts with the majority of the beliefs. Figure 2 shows the improvement in precision we have achieved by applying our trust model for combining contradictory evidences.

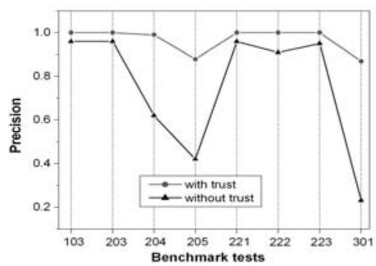


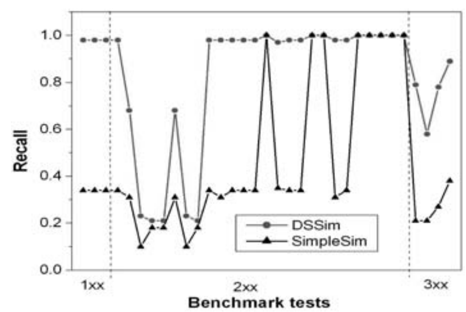
Figure 2. Precision graph

5. Evaluation of the mapping algorithm

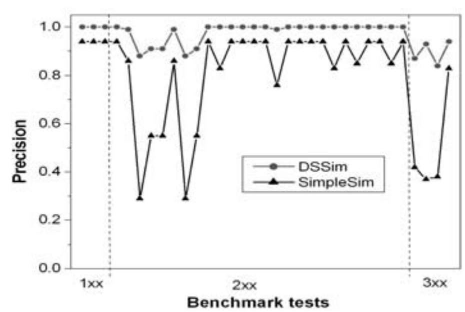
5.1. Experiments with the OAEI 2006 benchmarks

We have participated in the Ontology Alignment Evaluation Initiative contest [3] which is an international initiative that has been set up for evaluating ontology matching algorithms. We have used the provided ontologies in the systematic benchmarks and compared our mapping results to the contestant's results. For the complete list of alignment results one can refer to Ontology Alignment Initiative web-site[4]. The experiments were carried out to assess the efficiency of the mapping algorithms themselves. The experiments of the question answering (AQUA) using our mappings algorithms are out of the scope of this paper. Our main objective was to compare our system and algorithms to existing approaches on the same basis and to allow drawing constructive conclusions. The benchmark contains tests which were systematically generated starting from some reference ontology and discarding a number of information in order to evaluate how the algorithm behave when this information is lacking. The bibliographic reference ontology (different classifications of publications) contained 33 named classes, 24 object properties, 40 data properties. Further each generated ontology was aligned with the reference ontology. The evaluation was measured with recall and precision which are useful measures that have a fixed range and are easy to compare across queries and engines. By definition precision is a measure of the usefulness of a hitlist where hitlist is an ordered list of hits in decreasing order of relevance to the query. Recall is a measure of the completeness of the hitlist and shows how well the engine performs in finding relevant entities. The most important factor in building better mapping algorithms is to increase precision without worsening the recall.

As a basic comparison we have modified our algorithm (SimpleSim) which does not consider the similarity assessment uncertain just combine them using simple average of the three different results. The recall and precision graphs for the DSSim(with uncertainty) and SimpleSim(without uncertainty) over the whole benchmarks are depicted on Fig. 3. Experiments have proved that with utilizing uncertainty one can reach high precision rate since our main objective was to increase mapping precision with incorporating uncertainty into the process.



(a) Recall



(b) Precision

Figure 3. Recall and Precision graphs

Several systems participated in the OAEI 2006 contest. From those we have selected two relevant systems Falcon-AO[5],PRIOR[6] (top of the competition) for our comparison table as depicted on Table 2. The benchmark tests were created and grouped by the following criterias:

- Group 1xx: simple tests such as comparing the reference ontology with itself, with another irrelevant on-

[3]http://oaei.ontologymatching.org/
[4]http://oaei.ontologymatching.org/2006/results/
[5]Falcon-AO [11]
[6]PRIOR [12]

Table 2. Comparison of different algorithms

algo	DSSim		falcon		prior	
test	Prec.	Rec.	Prec.	Rec.	Prec.	Rec.
1xx	1	0.98	1	1	1	1
2xx	0.99	0.49	0.91	0.85	0.95	0.58
3xx	0.9	0.78	0.89	0.78	0.85	0.8
H-mean	0.98	0.55	0.92	0.86	0.95	0.63

tology or the same ontology in its restriction to OWL-Lite.

- Group 2xx: systematic tests that were obtained by discarding some features from some reference ontology e.g. Name of entities replaced by random strings, synonyms, name with different conventions, strings in another language than english, comments that can be suppressed or translated in another language, hierarchy that can be suppressed, expanded or flattened, properties that can be suppressed or having the restrictions on classes discarded, and classes that can be expanded, i.e., replaced by several classes or flattened.

- Group 3xx: four real-life ontologies of bibliographic references that were found on the web e.g. BibTeX/MIT, BibTeX/UMBC.

Considering mapping precision our system performs well compared to other systems. We believe that this is due to the fact that we augment the mapping terms with other possible alternatives from WordNet and assess subjective probabilities on the correctness of the mappings. This results in a process where correct mappings can be produced without using any domain specific heuristics in the process. Considering recall our system does not perform as well as the other systems because our algorithm (DSSim) always considers the whole *rdf:ID* tag in the ontologies therefore any additional information like comments or the language element is omitted. Not considering the language element can be considered as a weakness. However, we believe that comments in ontologies can work well when the ontologies originate from a well controlled environment with strong academic background like universities or research institutions. From the another side if we consider the nature of the semantic web where any private company can place its ontology to the web to support its own web enabled data it can lead to really different comments even for the same concepts or properties.

5.2. Strengths and weaknesses of the system

Most of the benchmark tests proved that when different similarity assessments have to be combined handling uncertainty can lead to a high precision rate which is a definite strength of our system. Another strength of our system is that the produced mappings are not very dependent on the structure and hierarchy of the concepts and properties in the ontology (see group 2xx). The reason is our mapping algorithm takes mainly concepts (classes) and properties (object and data type) to capture the specific restrictions in the particular ontologies and converts them into directed graph fragments. As a consequence our method is not heavily dependent on subclass, sub property, disjointness or equivalency relationships among classes and properties hence on the logical constraints imposed by the ontology language itself. Additionally the query terms are extended with their inherited hypernyms from WordNet so the uncertainty can be distributed sufficiently that can lead to a large number of possibly valid choices. However since Dempser's combination rule is computationally really expensive operation we need to reduce the problem space therefore the number of additional variables per query fragment. This can lead to the loss of valuable information and consequently more irrelevant mappings.

6. Related work

In recent years, a number of different mapping approaches have evolved from the different research communities e.g. knowledge base or database systems where researchers have developed algorithms and tools for finding these mappings in a semi or fully automated fashion. Unfortunately the mappings produced by these systems are usually imprecise. Most automatic ontology-mapping tools use heuristics or machine-learning techniques, which can produce different mapping accuracy on different domains. Ontology mapping systems that consider uncertainty on the Semantic Web are dominantly based on Bayesian networks.

The idea of automatic ontology mapping based on BayesOWL [14], a probabilistic framework that has been developed for modeling uncertainty in Semantic Web uses source and target ontologies which are first translated into Bayesian networks (BN) then the concept mapping between the two ontologies are treated as evidential reasoning between the two translated BNs. In order to obtain probabilities needed for constructing conditional probability tables, machine learning techniques are used. Other system GLUE [15] also employs machine-learning techniques to find mappings where multiple learners exploiting information in concept instances and taxonomic structure of ontologies. GLUE uses a Bayesian network to combine results of different learners. OMEN [16] uses a Bayesian network as well and enhances existing ontology mappings by deriving missed matches and invalidating existing false matches where domain knowledge of mapping are described by using simple meta-rules.

Our approach described in this paper is complementary to the existing approaches and provides an alternative to the Bayesian solutions however performance issues with the belief combination needs to be addressed in order to achieve acceptable response time of the system.

7. Conclusions

Inconsistency and incompleteness are important problems that affect the Semantic Web therefore ontology mapping systems that operate in this environment should have the appropriate mechanisms to cope with these issues. In this complex environment different scientific disciplines need to be utilized together to achieve better results for answering user queries and create mappings within an acceptable response times. We think that in our implementation we have made an encouraging step towards a well established mapping framework but the different key system components such as similarity measure or the scalability of uncertainty handling part needs to be investigated further.

The main contribution of this paper and our research is the application of Dempster-Shafer theory for the ontology mapping problem on the Semantic Web. Our preliminary results have shown that using Dempster-Shafer theory is a promising approach and needs to be investigated further in ontology mapping context since it has not been done so far. We believe that this is because Dempste-Shafer combination rules can be unfeasible in domains with large number of variables. In our future research we will investigate how these optimization methods can be adapted and applied in our scenario with a dynamic multi agent environment where each agent has partial knowledge of the domain.

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