MULTI-AGENT VOTING FOR CONFLICT RESOLUTION
A Fuzzy Approach

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Abstract: Software agents that interpret the possible meaning of Semantic Web data differently should be able to resolve their differences i.e. resolve conflicts effectively. One typical use case is ontology mapping where different agents using different similarity measures create beliefs in the assessed similarities, which needs to be combined into a more coherent state. The combination of these contradicting beliefs can easily worsen the mapping precision and recall, which leads to poor performance of any ontology mapping algorithm. In these scenarios agents, which use different similarities and combine them into a more reliable and coherent view can easily become unreliable when these contradictions are not managed effectively between the different agents. In this paper we propose a solution based on the fuzzy voting model for managing such situations by introducing trust and voting between software agents that resolve contradicting beliefs in the assessed similarities.

1 INTRODUCTION

The continuously increasing semantic meta data on the Web will soon make it possible to deploy multi-agent systems on the Semantic Web that are able to integrate data from distributed and heterogeneous data sources. However a prerequisite for these systems is that agents deployed to different domains can develop a certain degree of understanding of their data and are able to map their data with other agents. Therefore ontology mapping (Euzenat and Shvaiko, 2007) is a key component of agent systems that need to integrate semantic data, which alone has several challenges(Shvaiko and Euzenat, 2008) before one can develop real word applications. One of these challenges is how to handle conflicting information that stems from the interpretation of Semantic Web data. The source of conflict can range from missing or insufficient information to the contradicting description of the same or similar terms. As an example consider two ontologies, which describe conferences. Both contain concepts about the location of the event where Ontology 1 contains the concept "Location" in the context of the "Event" whereas Ontology 2 contains "Place" in the context of the "Building", "Session room" or "Conference hall". Considering the extended contexts of these terms e.g. Wordnet hypernyms one can derive that both describes some kind of space or position of something. The trouble is that this information cannot be explicitly derived from the ontologies as "Place" refers to buildings and their parts, while "Location" refers to geographical region (country or city) where the conference is held. In order to resolve this contradiction human experts can discuss their point of view and reach a consensus if the mapping can be made or not. Multi-agent systems that create ontology mapping operate without human intervention therefore need to mimic the before mentioned conflict resolution process, which can improve the quality of the mapping if the contradiction can effectively be resolved. Our main contribution in this paper is managing conflicting beliefs using a fuzzy voting model and present a comparison using different membership functions for resolving conflict between beliefs in similarities, which is the core component of the DSSim ontology mapping system.

The paper is organized as follows. Section 2 provides the description of the problem and its context. Section 3 describes the voting model and how it is applied for determining trust during the ontology map-

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ping. Section 4 gives and overview of the related work. Finally, section 5 describes our future work.

2 BELIEF COMBINATION AND CONFLICTS

2.1 Combination of Similarity Measures

In the context of the Semantic Web it is envisioned that multi-agent systems can interpret and exchange the available data in order to achieve a specific task e.g. map concepts from different data sources before answering a user query. It is unlikely that one agent can have all the algorithms to determine similarities alone therefore more agents are neccessary with utilising different similarity measures that need to be combined into a more coherent view. This trend can be noticed in nearly all the systems that participate in the OAEI [1]. Most of the participating systems are not based on a multi-agent architecture however they all utilise different similarity measures. Once the different similarities have been assessed they are combined into a single measure which in turn is used to determine to select the best possible mapping pairs. The description of how mapping systems determine or built up beliefs in similarities and how systems determine semantic similarity are out of the scope of this paper nevertheless each system is described in the OAEI papers [2]. The system that inspired our work is called DSSim which uses a multi-agent architecture to build up beliefs in similarities and combines them using the Demster combination rule.

2.2 Source of Conflict

In our domain of interest namely ontology mapping several challenges had been identified by Shvaiko and Euzenat(Shvaiko and Euzenat, 2008), which are considered as major roadblocks for developing ontology mapping solutions that perform well on different domains. We have identified two problems that are the main source of contradictions when algorithms need to “interpret” the meaning of the data represented by the different ontologies. These problems are as follows:

1. **Representation Problems and Uncertainty.** Data on the semantic web is represented by ontologies, which typically consist of a number of classes, relations, instances and axioms. These elements are expressed using a logical language. The W3C has proposed RDF(S)(Beckett, 2004) and OWL(McGuinness and Harmelen, 2004) as Web ontology language however OWL has three increasingly-expressive sublanguages(OWL Lite, OWL DL, OWL Full) with different expressiveness and language constructs. In addition to the existing Web ontology languages W3C has proposed other languages like SKOS(Miles and Bechhofer, 2008), which is a standard to support the use of knowledge organization systems (KOS) such as thesauri, classification schemes, subject heading systems and taxonomies within the framework of the Semantic Web. SKOS are based on the Resource Description Framework (RDF) and it allows information to be passed between computer applications in an interoperable way. Ontology designers can choose between these language variants depending on the intended purpose of the ontologies. As a result of these representation differences ontology mapping systems will always need to consider the uncertain and conflicting aspects of how the semantic web data can be interpreted and processed by different similarity algorithms.
2. **Quality of Semantic Web Data.** Data quality problems (Wang et al., 1993) (Wand and Wang, 1996) in the context of database integration(Batini et al., 1986) have emerged long before the Semantic Web concept has been proposed. For every organisation or individual the context of the data, which is published can be slightly different depending on how they want to use their data. Therefore from the exchange point of view incompleteness of a particular data is quite common. The problem is that fragmented data environments like the Semantic Web inevitably lead to data and information quality problems causing the applications that process this data deal with ill-defined inaccurate or inconsistent information on the domain. In traditional integration scenarios resolving these data quality issues represents a vast amount of time and resources for human experts before any integration can take place. Software agents that operate on the Semantic Web need to resolve semantic data quality problems independently from the users.

As a result it is important that multi-agent systems on the Semantic Web can resolve their conflicting interpretation that stem from the above mentioned problems.

[1] http://oaei.ontologymatching.org/
[2] http://om2008.ontologymatching.org/

3 FUZZY VOTING MODEL FOR ONTOLOGY MAPPING

3.1 Voting and the Best Possible Alternative

The idea of individual voting in order to resolve conflict and choose the best option available is not rooted in computer but political science. Democratic systems are based on voting as Condorcet jury theorem (Austen-Smith and Banks, 1996) (Young, 1988) postulates that a group of voters using majority rule is more likely to choose the right action than an arbitrary single voter is. In these situations voters have a common goal, but do not know how to obtain this goal. Voters are informed differently about the performance of alternative ways of reaching it. If each member of a jury has only partial information, the majority decision is more likely to be correct than a decision arrived at by an individual juror. Moreover, the probability of a correct decision increases with the size of the jury. But things become more complicated when information is shared before a vote is taken. People then have to evaluate the information before making a collective decision. The same ideas apply for software agents especially if they need to reach a consensus on a particular issue. In case of ontology mapping where each agent can built up beliefs over the correctness of the mappings based on partial information we believe that voting can find the socially optimal choice. Software agents can use voting to determine the best decision for agent society but in case voters make mistakes in their judgments, then the majority alternative (if it exists) is statistically most likely to be the best choice. The application of voting for software agents is a possible way to make systems more intelligent i.e. mimic the decision making how humans reach consensus decision on a problematic issue.

3.2 Fuzzy Voting Model

In ontology mapping the conflicting results of the different beliefs in similarity can be resolved if the mapping algorithm can produce an agreed solution, even though the individual opinions about the available alternatives may vary. Fuzzy voting model is detailed in (Nagy et al., 2008) can be utilised for reaching this agreement by evaluating trust between established beliefs through voting, which is a general method of reconciling differences. Voting is a mechanism where the opinions from a set of votes are evaluated in order to select the alternatives that best represent the collective preferences. Unfortunately deriving binary trust like trustful or not trustful from the difference of belief functions is not so straightforward since the different voters express their opinion as subjective probability over the similarities. For a particular mapping this always involves a certain degree of vagueness hence the threshold between the trust and distrust cannot be set definitely for all cases that can occur during the process. Additionally there is no clear transition between characterising a particular belief highly or less trustful. Therefore our argument is that the trust membership or belief difference values, which are expressed by different voters can be modeled properly by using fuzzy representation. Before each agent evaluates the trust in other agent's belief over the correctness of the mapping it calculates the difference between its own and the other agent's belief. Depending on the difference it can choose the available trust levels e.g. if the difference in beliefs is 0.2 then the available trust level can be high and medium. We model these trust levels as fuzzy membership functions. In fuzzy logic the membership function $\mu(x)$ is defined on the universe of discourse U and represents a particular input value as a member of the fuzzy set i.e. $\mu(x)$ is a curve that defines how each point in the U is mapped to a membership value (or degree of membership) between 0 and 1. Our ontology mapping system models the conflict resolution as a fuzzy system where the system components are described in the following sections:

3.3 Fuzzification of Input and Output Variables

Fuzzification is the process of decomposing a system input and/or output into one or more fuzzy sets. We have experimented different types of curves namely the triangular, trapezoidal and gauss shaped membership functions. Each fuzzy set spans a region of input (or output) value graphed with the membership. Our selected membership functions overlap to allow smooth mapping of the system. The process of fuzzification allows the system inputs and outputs to be expressed in linguistic terms so that rules can be applied in a simple manner to express a complex system.

Definition 1. *Belief difference is an input variable, which represents the agents own belief over the correctness of a mapping in order to establish mappings between concepts and properties in the ontology. During conflict resolution we need to be able to determine the level of difference.*

We propose three values for the fuzzy membership value $\mu(x) = \{small, average, large\}$.

Definition 2. *Belief is an input variable, which described the 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.*

$$belief_i(A) = \sum_{E_k \subseteq A} m_i(E_k) \qquad (1)$$

where m Demster's belief mass function represents the strength of some evidence i.e. $m(A)$ is our exact belief in a proposition represented by A. The similarity algorithms itself produce these assignment based on different similarity measures. We propose three values for the fuzzy membership value $\nu(x) = \{weak, strong\}$.

Definition 3. *Similarity is an input variable and is the result of some syntactic or semantic similarity measure. We propose three values for the fuzzy membership value $\xi(x) = \{low, average, high\}$.*

Definition 4. *Low, medium and high trusts are output variables and represent the level of trust we can assign to the combination of our input variables. We propose three values for the fuzzy membership value $\tau(x) = \{low, medium, high\}$.*

3.4 Rule Set

Fuzzy sets are used to quantify the information in the rule-base, and the inference mechanism operates on fuzzy sets to produce fuzzy sets. Fuzzy systems map the inputs to the outputs by a set of $condition- > action$ rules i.e. rules that can be expressed in $If - Then$ form. For our conflict resolution problem we have defined four simple rules that ensure that each combination of the input variables produce output on more than one output i.e. there is always more than one initial trust level is assigned to any input variables. As an example consider a rule for cases when the trust level is defined as low:

"IF (beliefdifference IS large OR beliefdifference IS average) AND belief IS weak AND (similarity IS low OR similarity IS average) THEN trust IS low"

The rules we have initially defined are the most general ones. In our future research we intend to investigate the impact of more fine grained rules (i.e. more rules could be defined to cover overlapping areas of our fuzzy sets) on our conflict resolution.

3.5 Defuzzification Method

After fuzzy reasoning we have the linguistic output variables, which need to be translated into a crisp (i.e. real numbers, not fuzzy sets) value. The objective is to derive a single crisp numeric value that best represents the inferred fuzzy values of the linguistic output variable. Defuzzification is such inverse transformation, which maps the output from the fuzzy domain back into the crisp domain. In our ontology mapping system we have selected the Center-of-Area (C-o-A) defuzzification method. The C-o-A method is often referred to as the Center-of-Gravity method because it computes the centroid of the composite area representing the output fuzzy term. In our system the trust levels are proportional with the area of the membership functions therefore other defuzzification methods like Center-of-Maximum (C-o-M) or Mean-of-Maximum (M-o-M) does not correspond well to our requirements.

Definition 5. *For representing trust in beliefs over similarities we have defined three membership functions, $\chi(x) = \{low, average, high\}$.*

3.6 Possible Membership Functions for Conflict Resolution

For our conflict resolution problem we have carried out experiments in order to select the best possible membership function combination that fit well to our problem. We have chosen the trapezodial, triangular and gauss membership function and their combinations to represent our input and output variables. For each test have generated 300 scenarios, which contain random input variables (belief difference, belief and similarity) that maps to a single trust level i.e. output variable(high, medium or low trust). In addition we have defined nine combination of membership functions that describes our input and output variables. We repeated our experiment 1000 times regenerating the 300 scenarios in each iteration.

3.7 Results on the Use of Different Memberships Functions

Experiments have shown that the the fuzzy conflict resolution is really sensitive on the input membership function. The best results can be achieved using triangular membership functions. In each experiments the average wrong answers are 121 and the minimum wrong answers are 109 whereas the maximum are 134 when choosing triangular input functions. The results are promising as we are able to resolve conflict in nearly 2/3 of the cases. In practice the real improvements in the ontology mapping quality can be foreseen where the number of conflict for the candidate mapping set is high. These situation of course likely to occur where both source and target ontologies contain large number (up to 10.000) of concepts and properties. The selection of the output function does not influence the end result of the conflict resolution.

4 CASE STUDY

We have carried out experiments with the benchmark ontologies of the Ontology Alignment Evaluation Initiative(OAEI) [3], which is an international initiative that has been set up for evaluating ontology matching algorithms. The experiments were carried out to assess how trust management influences results of our mapping algorithm. Our main objective was to evaluate the impact of establishing trust before combining beliefs in similarities between concepts and properties in the ontology. The OAEI 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 benchmark tests were created and grouped by the following criteria:

- Group 1xx: simple tests such as comparing the reference ontology with itself, with another irrelevant ontology 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, hierarchy that can be suppressed, expanded or flattened.
- Group 3xx: four real-life ontologies of bibliographic references that were found on the web e.g. BibTeX/MIT, BibTeX/UMBC.

As the benchmark is the only test-set in the OAEI tracks where the results are also available we have run first our experiments where DSSim applies the fuzzy voting model for evaluating trust and one without it. Therefore as a basic comparison we have modified our algorithm (without trust), which does not evaluate trust before conflicting belief combination just combine them using Dempster's combination rule. The recall and precision graphs for the algorithm with trust and without trust over the whole benchmarks are depicted on Fig. 1, 2. Experiments have proved that with establishing trust one can reach higher average precision and recall rate.

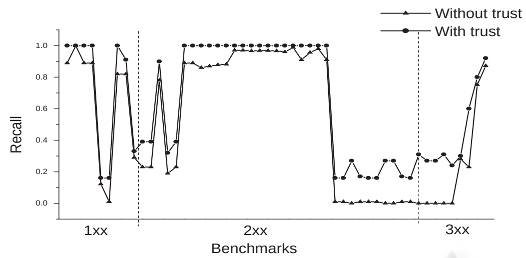

Figure 1: Recall graph with and without applying fuzzy voting.

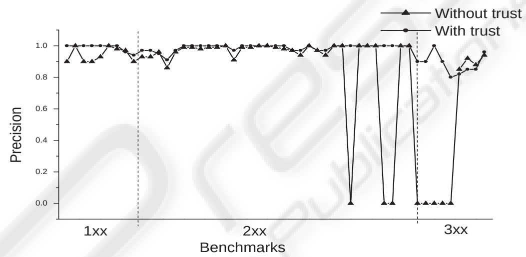

Figure 2: Precision graph with and without applying fuzzy voting.

5 RELATED WORK

Different approaches to eliminate contradictions for ontology mapping have been proposed by the ontology mapping community. These approaches can be classified into two distinct categories. First group include solution that considers uncertainty and fuzziness as an inherent nature of the ontology mapping and tries to describe it accordingly. Ferrera et. al. (Ferrara et al., 2008) models the whole ontology mapping problem as fuzzy where conflicts can occur. Their solution use fuzzy Description Logic theories to the problem of mapping validation as a different way of handling mapping uncertainty with respect to probabilistic approaches. As a result, they propose a mapping validation algorithm based on fuzzy interpretation of mappings in order to detect inconsistencies. Tang et.al. (Tang et al., 2006) formalises the ontology mapping problem as the problem of Bayesian decision making as strategy. Their sytem RiMOM has participated in the OAEI competition since 2006. Their solution do consider two kinds of conflicts in metadata heterogeneity, structure conflict and name conflict. However they use thesaurus and statistical techniques to resolve them before combining the results. The second group however differ conceptually because they mainly utilise data mining and logic reasoning techniques in pre and post processing stages of

[3]http://oaei.ontologymatching.org/

the mapping. Liu et.al. (Liu et al., 2006) proposes a four-stage ontology mapping approach with integrating the available information of labels, instances, past experiences, and the structures in different stages gradually. Besides, reusing the past experiences, reducing the aggregation-level mismatch before iteration, mining the logic relation of attributes account for the improvement of mapping results thus eliminating the available contradictions. Similar solution has been proposed by the ASMOV system (Jean-Mary and Kabuka, 2008) , which automates the ontology alignment process using a weighted average of measurements of similarity along four different features of ontologies, and performs semantic validation of resulting alignments. This system acknowledges that conflicting mappings are produced during the mapping process but they use an iterative post processing logic validation in order to filter out the conflicting mappings.

6 CONCLUSIONS

In this paper we have shown how the fuzzy voting model can be used to resolve contradictory beliefs before combining them into a more coherent state by evaluating fuzzy trust. The main contribution of this paper is managing conflicting beliefs using different fuzzy variables and to present a comparison using different membership functions and fuzzy variables for resolving conflict between beliefs in similarities, which is the core component of the DSSim ontology mapping system. We have proposed new levels of trust for resolving these conflicts in the context of ontology mapping, which is a prerequisite for any systems that makes use of information available on the Semantic Web. Our system is conceived to be flexible because the membership functions for the voters could be changed dynamically in order to influence the outputs according to the different similarity measures that can be used in the mapping system. We have described initial experimental results with the benchmarks of the Ontology Alignment Initiative, which demonstrates the effectiveness of our approach through the improved recall and precision rates. There are many areas of ongoing work, with our primary focus considering the effect of the changing number of voters and the impact on precision and recall or applying our algorithm in different application areas. We also aim to measure the proportion of the obvious and difficult conflicts that can occur during the mapping process and how these affect the overall performance of our solution.

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