On Using Subjective Logic to Build Consistent Merged Ontologies

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Abstract. Ontologies encode a community's understanding of a domain and are thus subjective. Different communities may create different models of overlapping domains. If they need to be integrated, this may cause problems: combining subjective knowledge from diverse ontologies into a merged model may make it inconsistent. We provide a Subjective Logic-based approach to support users in creating a consistent merged ontology reflecting a commonly trusted view of the domain.

Keywords: Ontology merging . Consistency . Subjective Logic

1 Introduction

Ontologies represent domain knowledge. They are subjective with regards to the creators' view of the domain. This can cause problems, when ontologies need to be merged: while each of them models a consistent view of the world, their combination may be inconsistent. Whereas inconsistencies in single ontologies that result from modeling errors are comparatively easy to resolve automatically [8,10], inconsistencies that arise due to differing views of the world are difficult to deal with. In order to resolve them, the subjective beliefs about the world and how trustworthy they are need to be taken into consideration.

A formal approach to capture beliefs and trustworthiness is *Subjective Logic* [6], which consists of a belief model called opinion and a set of operations for combining opinions. It is applicable in situations with considerable uncertainty and incomplete knowledge. This formalism has been successfully applied to a number of Semantic Web related tasks, e.g., for ontology alignment [7], recommendation systems [9], and inconsistency handling in single ontology development environments [10].

We propose to use Subjective Logic theory for inconsistency resolution in ontology merging. More precisely, the problem that we are addressing is the following: Given an inconsistent ontology that is the result of merging several consistent source ontologies, determine which changes should be made to make the ontology consistent. These changes should preserve the most trusted point of view on the shared domain. A first evaluation shows that this approach is promising.

2 Applying Subjective Logic to Achieve Consistency

We call an ontology $\mathcal{O}$ *inconsistent* iff there is no model of $\mathcal{O}$, i.e., $\mathcal{O}$ is unsatisfiable [2]. A first step to resolving inconsistency in a merged ontology is to pinpoint its origin. To do so, the ontology is evaluated using an off-the-shelf reasoner. If the consistency test fails, the conflicting axioms set that cause inconsistencies are extracted using the reasoner. In the next step, the trustworthiness of each axiom is computed using our Subjective Logic-based approach. For the least trustworthy axioms, a suggested revised axioms' set (following the approach from [8]) will be represented to the user.

Subjective Logic. Subjective opinions express beliefs of agents about the truth of propositions with degrees of uncertainty [6]. In our approach we use binary subjective logic and regard the source ontologies as agents, as they represent their communities' beliefs about the domain. Let $\mathcal{P}$ be a proposition such as "Axiom x is trustworthy in the merged ontology $\mathcal{O}_M$". Following [6], the *opinion* w of agent $\mathcal{O}_i$ about the proposition $\mathcal{P}$ is equivalent to a beta distribution for the information source x as the combination of belief $b_x^{\mathcal{O}_i}$, disbelief $d_x^{\mathcal{O}_i}$, uncertainty $u_x^{\mathcal{O}_i}$, and base rate (atomicity) $a_x^{\mathcal{O}_i}$ with a tuple $w_x^{\mathcal{O}_i} = (b_x^{\mathcal{O}_i}, d_x^{\mathcal{O}_i}, u_x^{\mathcal{O}_i}, a_x^{\mathcal{O}_i})$, where $b_x^{\mathcal{O}_i} + d_x^{\mathcal{O}_i} + u_x^{\mathcal{O}_i} = 1$.

Opinions are formed on the basis of positive r and negative s evidence about x available to agent $\mathcal{O}_i$. Then, $b_x^{\mathcal{O}_i}, d_x^{\mathcal{O}_i}$, and $u_x^{\mathcal{O}_i}$ are:

$$b_x^{\mathcal{O}_i} = \frac{r_x^{\mathcal{O}_i}}{r_x^{\mathcal{O}_i} + s_x^{\mathcal{O}_i} + W},\ d_x^{\mathcal{O}_i} = \frac{s_x^{\mathcal{O}_i}}{r_x^{\mathcal{O}_i} + s_x^{\mathcal{O}_i} + W},\ u_x^{\mathcal{O}_i} = \frac{W}{r_x^{\mathcal{O}_i} + s_x^{\mathcal{O}_i} + W} \tag{1}$$

where, W is the default non-informative prior weight that in binomial opinions is defined as $W = 2$. Thus, the opinion's probability expectation value is computed by $t_x^{\mathcal{O}_i} = b_x^{\mathcal{O}_i} + a_x^{\mathcal{O}_i} \times u_x^{\mathcal{O}_i}$ as the trustworthiness of x by agent $\mathcal{O}_i$. This requires that we determine $r_x^{\mathcal{O}_i}$, $s_x^{\mathcal{O}_i}$ (to calculate $b_x^{\mathcal{O}_i}, d_x^{\mathcal{O}_i}, u_x^{\mathcal{O}_i}$) and $a_x^{\mathcal{O}_i}$.

Positive and negative evidence. To determine the positive evidence r of an axiom x_j, we use provenance information. Each axiom in $\mathcal{O}_M$ is derived from one or several input ontologies $\mathcal{O}_i$. Therefore, r for x_j from agent $\mathcal{O}_i$ is calculated in Eq. 2 as (i) the existence of axiom x_j in $\mathcal{O}_i$ (*provenance information*), and (ii) the impact of the axiom's elements (*effect*), to reflect how much the ontology gets affected if axiom x_j is altered. By axiom's elements, we mean those elements which are involved in an axiom, e.g., A and B in the axiom $x_1 : A \sqsubseteq B$. To this end, we determine how often elements of axiom x_j have been referenced in other axioms in the ontology. Let $c(\mathcal{O}_i)$ be the total number of axioms in $\mathcal{O}_i$ and $c_{x_j}(\mathcal{O}_i)$ be the number of axioms in $\mathcal{O}_i$ that contain elements of x_j. Then $f_{x_j}(\mathcal{O}_i) = \frac{c_{x_j}(\mathcal{O}_i)}{c(\mathcal{O}_i)}$ is the fraction of axioms in $\mathcal{O}_i$ that contain elements of x_j. The provenance of the axioms is represented by the α and β parameters; if $x_j \notin \mathcal{O}_i$, but the elements of the axioms exist in $\mathcal{O}_i$, then $f_{x_j}(\mathcal{O}_i)$ multiplies with β, otherwise, it multiplies with α.

$$r_{x_j}^{\mathcal{O}_i} = \begin{cases} \alpha \times f_{x_j}(\mathcal{O}_i) & \text{if } x_j \in \mathcal{O}_i \\ \beta \times f_{x_j}(\mathcal{O}_i) & \text{if } x_j \notin \mathcal{O}_i \end{cases} \tag{2}$$

A justification is a minimal subset of an ontology that causes it to be inconsistent. Let $\mathcal{O}$ be an ontology entailing axiom x ($\mathcal{O} \models x$). $\mathcal{J}$ is a *justification* for x in $\mathcal{O}$ if $\mathcal{J} \subseteq \mathcal{O}$, and $\mathcal{J} \models \alpha$, and for all $\mathcal{J}' \subsetneq \mathcal{J}$ $\mathcal{J}' \nvDash \alpha$ [4]. The ontology justification set $\mathcal{J}$ is the set of all justifications, $\mathcal{J} = \{\mathcal{J}_1, \mathcal{J}_2, ..., \mathcal{J}_l\}$, where there may be multiple, potentially overlapping justifications in $\mathcal{J}$. Each justification $\mathcal{J}_k \in \mathcal{J}$ includes several axioms, denoted by $\mathcal{J}_k = (x_1, x_2, ..., x_z)$. In this follow, to determine the negative observations s, we use the axiom frequency $c_{x_j}(\mathcal{J})$ in the justification set $\mathcal{J}$ divided by the number of the conflicting axioms set that cause inconsistencies $c(X)$ which belong to $\mathcal{O}_i$ in Eq. 3 (to reflect the view of $\mathcal{O}_i$). This metric is already used in the [8], to accelerate the process of getting rid of unsatisfiable concepts.

$$s_{x_j}^{\mathcal{O}_i} = \frac{c_{x_j}(\mathcal{J})}{c(X)} \tag{3}$$

Base Rate. In the absence of evidence for belief, disbelief, and uncertainty, the base rate plays an important role. It reflects prior knowledge about the phenomenon at hand. In our case, using the centrality measure [1] of elements e_{x_j} seems a suitable indicator. The base rate for axiom x_j with t elements $x_j = \{e_1, e_2, ..., e_t\}$ is given by Eq. 4. This is determined by the number of super- and subclasses of the elements divided by the total number of elements $|e|$ in $\mathcal{O}_i$.

$$a_{x_j}^{\mathcal{O}_i} = \frac{1}{|e| \in \mathcal{O}_i} \times \sum_{k=1}^{t} |SubClass(e_k) \cup SuperClass(e_k)|, e_k \in x_j \tag{4}$$

Combining Opinions and Conditional Opinions. The Subjective Logic operator *consensus* $\oplus$ [6] combines the opinions in such a way, that the more trustworthiness opinions will be those that are agreed upon by multiple agents. Let $w_x^{\mathcal{O}_1} = (b_x^{\mathcal{O}_1}, d_x^{\mathcal{O}_1}, u_x^{\mathcal{O}_1}, a_x^{\mathcal{O}_1})$ and $w_x^{\mathcal{O}_2} = (b_x^{\mathcal{O}_2}, d_x^{\mathcal{O}_2}, u_x^{\mathcal{O}_2}, a_x^{\mathcal{O}_2})$ be opinions respectively held by $\mathcal{O}_1$ and $\mathcal{O}_2$ about the same proposition x. Then the consensus for these two opinions is $w_x^{\mathcal{O}_1\mathcal{O}_2} = w_x^{\mathcal{O}_1} \oplus w_x^{\mathcal{O}_2}$ [6], it reflects the opinion of an imaginary agent representing both $\mathcal{O}_1$ and $\mathcal{O}_2$. In principle, this operator can be used in our approach to combine opinions by different agents and reach a consensus.

However, this would have a drawback: it does not consider the effect of the calculated ranked values for axioms in $\mathcal{J}_k$ on $\mathcal{J}_l$, $k \neq l$. To overcome this issue, we use conditional theory of Subjective Logic [6], which reflects the effect of the dependent opinions. Let us consider an example: $\mathcal{J} = \{\mathcal{J}_1, \mathcal{J}_2, \mathcal{J}_3\}$ is a set of justifications, where axioms are repeated in multiple $\mathcal{J}$s, as $\mathcal{J} = \{(x_1, x_2, x_3), (x_4, x_5, x_6, x_7), (x_3, x_4, x_5, x_7, x_8)\}$. The opinions for $\mathcal{J}_1$'s axioms can be calculated as independent opinions. However, some elements of $\mathcal{J}_3$ have already obtained some ranked values from $\mathcal{J}_1$ and $\mathcal{J}_2$. Here, we can use the previous ranked values from $\mathcal{J}_1$ and $\mathcal{J}_2$ for x_3, x_4, x_5, x_7 in $\mathcal{J}_3$, but it might happen that these axioms compared to the remaining axioms in $\mathcal{J}_3$ get different ranked values. Therefore, in an incremental process, we calculate a new value in each $\mathcal{J}$, but we also consider the effect of the previous ranked values for axioms

Table 1: Inconsistencies and their resolution in merged ontologies

id	Input ont. $\mathcal{O}_i$				$\mathcal{T}, \mathcal{A} \in \mathcal{O}_M$		Result	$\|C_{un}\|$	$\|\mathcal{J}\|$	$c(X)$	*Detect*	*Rank*	*Plan*
d1	cmt	conference			488	0	FAILED	21	95	695	15442	93575	17
d2	edas	confOf			777	115	FAILED	11	24	122	18071	7295	5
d3	sigkdd	ekaw			332	0	PASSED	-	-	-	-	-	-
d4	confOf	conference			434	0	FAILED	21	88	536	14559	60173	53
d5	cmt	conference	confOf		631	0	FAILED	22	110	692	18115	247050	20
d6	confOf	sigdd	edas		867	115	FAILED	16	68	384	36050	111888	6
d7	cmt	ekaw	confOf		562	0	PASSED	-	-	-	-	-	-
d8	cmt	edas	ekaw	sigkdd	1113	115	FAILED	32	148	946	104923	1099466	23
d9	cmt	confOf	sigkdd	edas	1051	115	FAILED	23	103	569	28768	393748	7
d10	human	mouse			6645	6449	PASSED	-	-	-	-	-	-

in other $\mathcal{J}s$. Thus, we enrich our method by using the conditional *deduction* operator $\circledcirc$ introduced in [6] to express this.

3 Related Work

To handle inconsistencies in one ontology, various researches such as [8] have been done, where the authors ranked the justification with a single metric. In [10], Subjective Logic is used to solve ontology inconsistencies in a single ontology process, not applying Subjective Logic to ontologies merging process, where the agent's opinions from the input ontologies play a serious role. Moreover, no agent's opinion combination has been considered, and the authors only utilized the atomicity value and omitted the belief, disbelief and uncertainty values. To deal with multiple ontologies, the authors in [5] considered multiple ontologies that are networked via mappings for distributed environments, only. To the best of our knowledge, this is the first work that by using the Subjective Logic theory considers the knowledge of input sources to handle the inconsistencies on a merged model. As a whole, we differ from other works in three key respects: we solve inconsistencies in the ontology merging process; we combine several criteria to rank the conflicting axioms set that cause inconsistencies with belief, disbelief and atomicity values; we consider the combination of agents' opinions and we employ conditional ranking when the conflicting axioms are dependent.

4 Preliminary Evaluation

As a preliminary evaluation, the proposed workflow has been implemented within our merge framework [3] [1]. We conducted a series of tests [2] on the OAEI benchmark [3]. Table 1 shows the TBox $\mathcal{T}$ and Abox $\mathcal{A}$ size of the merged ontologies. In a first step, we use the reasoner to determine whether the merged ontology is consistent (PASSED) or not (FAILED). For the ontologies

[1] http://comerger.uni-jena.de/

[2] on Intel Core i7 with 12 GB internal memory; Pellet reasoner; $\alpha = 1$, $\beta = 0.5$

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

that do not pass the consistency check, we then determine the unsatisfiable classes C_{un} and the justification set $\mathcal{J}$. Afterwards, our method processes all axioms $c(X)$ of the justification set, and ranks them. Table 1 shows the size of $C_{un}, \mathcal{J}$ and $c(X)$ for each inconsistent merged ontology. The axioms with the lowest trustworthiness are presented to the user together with a suggested resolution. The rightmost columns of the table show the runtime (in millisecond) for detecting the inconsistencies (i.e., extracting $C_{un}, \mathcal{J}$ and $c(X)$), ranking and generating the resolution plan respectively. Given that ontology merging is a complex, time consuming task overall, they seem acceptable.

5 Conclusion and Future Work

We propose a novel approach using Subjective Logic to estimate the trustworthiness of axioms that cause inconsistencies within a merged ontology. We use provenance information and structural relevance to assess the opinions of the input ontologies. With the consensus operator, conflicting opinions can be combined. Moreover, we adopted conditional theory in the Subjective Logic to reflect the opinion of an axiom which is dependent on another opinion. A first evaluation shows that the approach is promising. A pretty straightforward extension of this work that we are pursuing already, is to determine root causes of inconsistencies and restrict the approach to those. Also, using domain knowledge might improve the estimation of an opinion's probability expectation.

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