Transferable Belief Model for the Semantic Web

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Abstract

For all the potential and actual benefits of the Semantic Web, it "remains largely unrealized", as stated by Tim Berners-Lee. Apart from practical issues that still must be tackled by the community, there are theoretical issues still present in the Semantic Web standards. One of such theoretical issues is the representation and reasoning using imprecise or uncertain information. The foundation of the Semantic Web is the assertion of relations between entities, but these relations usually do not carry a degree or level of relationship. The relations either are or are not. Using a simple subject-predicate-object tuple we can say that Alice (subject) likes (predicate) Rock music (object), but we can not say that she does so with a confidence of 80%. This is important because representing and reasoning with imprecise information is essential to dealing with real world information. We propose the use of the Transferable Belief Model (TBM), an elaboration of the Dempster-Shafer Theory, as a way to achieve this. It will be particularly applied to the visual surveillance domain. This is relevant because computer algorithms to detect objects on scenes are not fully reliable, and representing this unreliability in the system is desirable. Exhaustive testing must be performed on the system, but early empirical tests show the feasibility of using the TBM as a model for reasoning with uncertainty in the semantic web.

1 Introduction

Recently, research on semantically enriched knowledge models for surveillance and forensic use is intensifying. They are seen as an alternative to ad-hoc systems that offer little interoperability and do not adhere to any standard. Using semantic web technologies for Smart Surveillance Systems offers several advantages:

- The World Wide Web is large. It is comprised of millions upon millions of documents, hosted in an equally large network of computers. This means that any development towards the semantic web must ensure operability in such a large scale.
- Semantic Web has still an active research community tackling different issues, including modelling, indexing, querying, and reasoning. Key aspects for the surveillance task.
- Standard compliance allows the easy exchange of information between different data sources. Expanding the available knowledge for the reasoning task.

Additionally, when dealing with information from the real world (such as in the surveillance domain), one has to take into account the 'ignorance' inherent in the data-sources. Ignorance can be defined of three types[2]:

- **Incompleteness** Not all the data is known
- **Imprecision** Data is available with an imprecise measurement
- **Uncertainty** The data may be wrong

One of the open issues in Semantic Web technologies is the representation of imprecise and uncertain data. The semantic tuples (inferred or otherwise) and rules are binary only. That is, one can not assert, in a standard compliant way, degrees or levels for the predicates or relations between the entities. This causes that tuples asserted can only be binary and the information inferred from rules can only either be (when it is explicitly stated in the relations) or not be (when there's no relationship), but there is no degree of confidence or the accuracy of the extracted or inferred information.

It would be desirable to be able to encode and reason using relative (as opposed to absolute) information in the semantic web, mostly because information in the real world is usually flexible or relative and computer systems are imprecise or unreliable when dealing with the real world. For this we propose to use subjective logic, and more specifically, the Dempster-Shaffer Theory of Evidence and it's Transferable Belief Model (TBM) elaboration. We intend to apply this specifically in the forensic and surveillance domain, but the model is generic and can be applied to any other domain. Exhaustive explanation of the TBM falls outside the scope of this paper. For a more complete theoretical explanation behind the model, please refer to [2].

The Dempster-Shafer (DS) Theory of Evidence is a framework for reasoning under uncertainty. It was developed by Glenn Shafer to represent uncertain knowledge, starting from the works of his advisor, Arthur Dempster. It allows to combine evidence from different sources and arrive to a degree of belief which takes into account all the sources of information.

To be able to use the DS framework in the semantic web, two issues must be tackled: encoding the information in a semantic framework and reasoning with this information to create new knowledge. In the next chapters we will introduce briefly the DS framework and its concepts and we will propose ways to deal with the encoding and reasoning issues in the semantic web. The rest of this document follows the next structure: Section 2 presents previous attempts at representing probability and uncertainty in the semantic web. The TBM is introduced in section 3. In section 4, the proposed ontology is presented. Section 5 deals with the operations of the TBM to be implemented for the reasoning task. Finally, section 6 presents final remarks and future work.

2 Literature Review

There are already some efforts for encoding probabilistic information in the semantic web using OWL and/or RDF. These efforts usually handle some other form of uncertainty handling or offer a general way to encode any probabilistic information in the semantic web. In [6] for example, an approach is proposed for modelling and reasoning with Bayesian networks for the task of ontology mapping. [4] also focuses on Bayesian Networks, but not just for ontologies mapping. It proposes a vocabulary to model Multi-Entity Bayesian Networks. The actual task of reasoning is left for specific tools. In [5] both a model and a probabilistic reasoning engine using Markov Logic is proposed. The W3C has also started evaluating the standardisation of probabilistic ontologies, as can be seen in the efforts expressed in [13] and [7]. A review of some of these efforts and some others can be seen in [12].

In the forensic and surveillance domain, Han *et al.* attempted first to use subjective logic to handle uncertainty and subjective logic to handle incompleteness using semantic web technologies. In [8] several forensic questions are tried to answer like 'who is the suspect of the event?' and 'who is the most probable witness of the suspect of the event?'. Data is modelled in OWL and in this first approach, data is annotated manually. This framework is then successfully tested on the detection of simple events like two people speaking.

Han *et al.* further explore the feasibility of subjective logic for surveillance and forensic scenarios in [10] and default reasoning is considered for dealing with incompleteness. Here, appropriate operators for dealing with surveillance data using subjective logic and default reasoning (but not specific to semantic web technologies) are introduced. Successful examples are presented for identity inference and theft inference, with and without contextual cues. Details about the implementation, if any, are not reported.

This approach is extended in [9] for estimating whether one person could serve as a witness of another person in a public area scene. To deal with the uncertainty, a reputational subjective opinion function for the spatial-temporal relations is developed. In addition, the acquired opinions are accumulated over time using subjective operators. A preliminary test case is performed on a airport surveillance manually annotated one minute video. Logic Programming with the CLIPS rule engine is used. Large scale and more complex scenarios test are still missing.

Others have attempted to include ignorance handling (particularly Imprecision and Uncertainty) extensions to web semantic languages (albeit not specific to surveillance or forensic scenarios). In [3], Ceolin *et al.* proposed three extensions and applications of subjective logic in the Semantic Web, namely: the use of semantic similarity measures for weighing subjective opinions, a way for accounting for partial observations, and the new concept of 'open world opinion', i.e. subjective opinions based on Dirichlet Processes, which extend multinomial opinions. Finally, [1] proposes fuzzy ontologies using OWL 2 annotation properties along with constructs particular to fuzzy logic, which would allow to handle imprecise data on a regular semantic framework.

None of these approaches are tailored for the TBM or the DS theory.

3 Introduction to the Transferable Belief Model

We will use a single variable example based on one presented in [2] to introduce one by one the concepts of the Transferable Belief Model. In this example, we are tasked with finding the name of Johns wife, which we know can be either Mary, Jane or Sabrina. This leads us to the first concept: frame of discernment.

Frame of discernment (Ω) The frame of discernment is the finite set which holds all the hypothesis of the task. In our example, $\Omega = \{Mary, Jane, Jill\}$. In a closed world context, the truth must be inside this frame of discernment. In an open world context, the truth may be somewhere else. For this example, we will use the closed world assumption, but it must be noted that OWL and related ontology languages use the open world assumption.

Suppose now that an old person remembers John's wife being either Mary or Jane, but he's not sure. This now leads us to the next three concepts: Potential (Evidence), Mass function, and focal elements.

Potential is a known fact about the task in the frame of discernment. It can be the result of an observation, a measurement, or in our case, a testimony. Every time new evidence is known, the system must be updated to account for the new information.

Mass function The mass (m) is a quantifiable amount of support to a group of hypothesis in Ω. This support is introduced by the Evidence. Assigning a mass $m(A)$ to a subset A of Ω, gives support to exactly that subset A. The mass function for particular evidence must verify that $\sum_{A \subseteq \Omega} m(A) = 1$. In our case, we subjectively select the value of 0.8 to the confidence of the testimony of the old person. This means that $m(Mary, Jane) = 0.8$. We need to include the fact that this person might be wrong, but we should be careful not to assign the rest of the mass to $Jill$, because the testimony does not support directly the fact that John's wife is Jill. This means that $m(Mary, Jane, Jill) = 0.2$.

Focal elements are the subsets of Ω having non-null mass. The set of focal elements is called Focal Set (FS). In our case, $FS = \{\{Mary, Jane\}, \{Mary, Jane, Jill\}\}$.

We now learn from another person that he knows John's wife has short hair, and we know that only Jane and Jill have short hair. We now must combine the new information with the current state of the knowledge base. For this we must introduce two new concepts: Potential and Dempster's Rule of Combination.

Potential is the formal way of defining the evidence available to the system. It is the mass function induced by particular evidence. In our case, we have two potentials produced by the two testimonies we have right now.

$$t_1 = \{\{Mary, Jane\}[0.8], \{Mary, Jane, Jill\}[0.2]\}$$

$$t_2 = \{\{Jane, Jill\}[0.9], \{Mary\}[0.1]\}$$

Dempster's Rule of Combination currently we have two potentials t_1 and t_2, each with its own mass functions m_{t1} and m_{t2}. The goal is to get single, combined potential $t_{1\oplus 2}$ with a joint mass function $m_{t1} \oplus m_{t2}$. Dempster's Rule of Combination relies on the intuition that the product $m_1(X) * m_2(Y)$ supports $X \cap Y$. This means that:

$$m_{1,2}(A) = (m_1 \oplus m_2)(A) = \sum_{B \cap C = A \neq \oslash} m_1(B) * m_2(C)$$

For the current state of our knowledge base, we get the following generated Focal Elements:

$$FE_{t1\oplus t2} = \{\{Jane\}, \{Mary\}, \{Jane, Jill\}\}$$

and the following masses:

$$m(\{Jane\}) = 0.8 * 0.9 = 0.72$$

$$m(\{Mary\}) = 0.8 * 0.1 + 0.2 * 0.1 = 0.1$$

$$m(\{Jane, Jill\}) = 0.2 * 0.9 = 0.18$$

for a combined potential of:

$$t_{1\oplus 2} = \{\{Jane\}[0.72], \{Mary\}[0.1], \{Jane, Jill\}[0.18]\}$$

A situation arises when we introduce new evidence that contradicts the currently available potentials. Let us now assume that a person tells us that one day they saw John in a romantically compromising situation with Mary. The newly introduced potential (with the subjectively selected values of 0.8 and 0.2 to the confidence of the information) is:

$$t_3 = \{\{Mary\}[0.8], \{Jane, Jill\}[0.2]\}$$

If we try to combine this potential into the knowledge base we will notice that $\{Jane\} \cap \{Mary\} = \oslash$ and $\{Mary\} \cap \{Jane, Jill\} = \oslash$. This means we have a conflict. This is evident when we combine the new potential and get empty focal elements and this happens because one potential is strictly supporting a set of hypothesis, and the other one supports a completely disjoint set of hypothesis. In TBM, we can quantify this contradiction, known as the **conflict** k as the sum of the product of the masses of the conflicting focal elements:

$$k_{1,2} = \sum_{B \cap C = \oslash} m_1(B) * m_2(C)$$

In our case:

$$k = 0.72 * 0.8 + 0.1 * 0.2 + 0.18 * 0.8 = 0.74$$

Under the open world assumption, a conflict means that the truth lies outside the current frame of discernment. In that case, the conflicting mass would go to $\oslash$ ($m(\oslash) = k$). In an closed world assumption, to keep the mass functions adding to 1, the produced mass function must be normalised with the conflicting mass. This means that the combination becomes:

$$m_{1,2}(A) = (m_1 \oplus m_2)(A) = \frac{1}{1 - k_{1,2}} \sum_{B \cap C = A \neq \oslash} m_1(B) * m_2(C)$$

In our closed world example, this means that:

$$FE_{t1\oplus t2\oplus t3} = \{\{Jane\}, \{Mary\}, \{Jane, Jill\}\}$$

$$m(\{Jane\}) = \frac{0.72 * 0.2}{1 - 0.74} \approx 0.55$$

$$m(\{Mary\}) = \frac{0.1 * 0.8}{1 - 0.74} \approx 0.3$$

$$m(\{Jane, Jill\}) = \frac{0.2 * 0.18}{1 - 0.74} \approx 0.14$$

$$t_{1\oplus 2\oplus 3} = \{\{Jane\}[0.55], \{Mary\}[0.3], \{Jane, Jill\}[0.14]\}$$

The goal of the task is to find John's wife according to the evidence we have. We will now introduce some functions that will allow us to quantify our knowledge of the case according to the available evidence.

Belief is the justified amount of support given to any subset of Ω. Any mass that includes a given subset, supports that subset. It could be interpreted as the lower probability that the solution is the subset. Mathematically:

$$bel(A) = \sum_{B | B \subseteq A} m(B)$$

For this exercise we are interested in knowing our belief, according to the evidence, that each of the elements in the frame of discernment is John's wife:

$$bel(\{Mary\}) = 0.3$$

$$bel(\{Jane\}) = 0.55$$

$$bel(\{Jill\}) = 0$$

Plausibility is the total amount of support given to A at least partially. More specifically, is the support not given strictly to $\overline{A}$. It could be seen as the upper probability that the solution is the subset A.

$$pls(A) = 1 - bel(\overline{A}) = \sum_{B|B \cap A \neq \emptyset} m(B)$$

In our example:

$$pls(\{Mary\}) = 0.3$$

$$pls(\{Jane\}) = 0.55 + 0.14 = 0.69$$

$$pls(\{Jill\}) = 0.14$$

It can be seen intuitively that $bel(A) \leq pls(A)$.

Ignorance is the difference between $pls(A)$ and $bel(A)$. It's the support that is only given partially to A. Intuitively we can see that these are masses allocated not exclusively to A, which means that we do not have enough information to discriminate between the support to A and all the other members of the focal elements where A is present.

$$ign(A) = pls(A) - bel(A)$$

Doubt is the degree of support that will never be assigned to A.

$$dou(A) = 1 - pls(A) = bel(\overline{A})$$

So far, what has been done is simply asserting beliefs. But the goal of all of this is to make a decision. These are the two levels of the TBM:

- **Credal** level (from Latin Credo "I Believe") is where beliefs are assessed, updated, and combined.
- **Pignistic** level (from Latin Pignus "Bet") is where decisions must be made.

Once the knowledge base is updated with all the available information, all the potentials are combined, and all the beliefs are updated, we must select from Ω the best hypothesis or group of hypothesis. There is no standard rule for this, and usually rules are created for specific problems, commonly involving the belief and plausibility functions mentioned before. For example, selecting the maximum of belief or plausibility, or a combination of both. More advanced rules are available but will not be discussed here.

In our example, we can see that Jane is likely John's wife, as is not only the hypothesis with the highest amount of support, it is also the most plausible.

Extensions exists to handle domains where the hypothesis lie in multiple variables. In John's wife example, we might be interested in finding also the age of John's wife, or the colour of her hair. In the surveillance example, we want to infer the type of events given the actors and their actions. Although this extensions will not be explained here, they will be taken into account for the actual work concerning this project.

4 Transferable Belief Model Ontology

The first task towards implementing the TBM in the semantic web, is defining it's vocabulary or taxonomy in a standard compliant way. For this, we identify the important and relevant concepts for the reasoning task and encode them in an OWL ontology. A first version of this ontology is presented in Figure 1.

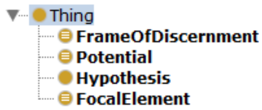

Figure 1. The proposed Transferable Belief Model ontology

- **TBM:Hypothesis** is the first concept and it is basically a variable in the domain of the problem we want to address.
- **TBM:FrameOfDiscernment** is the collection of possible **TBM:Hypothesis** in the domain.
- **TBM:FocalElement** consists of a collection of **TBM:Hypothesis** and a **Mass** property which is a float numeric value.
- **TBM:Potential** is an observation or measurement and consists of a collection of **TBM:FocalElements**.

It does not seem necessary to model FocalSets, as it's simply an intermediate step to the potentials.

Under this paradigm, a domain would define it's own concepts and inherit the variables from the TBM ontology. A reasoning engine would then perform the reasoning with the variables. For example for a surveillance ontology, the variables or hypothesis, would be the events and the objects. The visual analysis would feed the knowledge base with the levels of confidence of the detection task (i.e. a given blob is a person with a reliability of 70%).

5 Reasoner

The reason why the concepts of **Combination**, **Belief**, **Plausibility**, **Ignorance**, and **Doubt** where not included in the ontology, is because these are actually operations, and the main tasks involved in the actual reasoning. The reasoning engine will be the implementation of these operations. In particular:

Combination will be the main operation. The first time the knowledge base is instantiated, it will look for all the instances of potentials and they will be sequentially combined in a new instance of a potential with all the combined Focal Elements and masses. Every time a new potential is added, it will be combined into the "global" potential. Given the complexity of Dempster's Rule of Combination [11], special care must be had in the implementation. Big-data models for large scale processing like Map-Reduce and Google's Pregel, are being evaluated.

Belief, Plausibility, Ignorance, and Doubt will be built-in functions. This functions can be used by the user either in SPARQL queries, SWRL rules, or client applications. No specific function for the selection of hypothesis will be implemented. This will allow the client applications to implement their own selection using their own rules, aided by the implemented functions. This functions will also require the use of Big-data processing models.

6 Conclusions and Future Work

We have presented in this paper a framework for reasoning with imprecise and uncertain data using the Transferable Belief Model of the Dempster-Shafer Theory. This framework consists of an ontology to model de concepts of a domain, and a reasoning engine to infer new information. The framework must be exhaustively tested, but early empirical tests show the feasibility of the framework and the use of the TBM to reason on the semantic web with uncertain data. The tests are being performed on the surveillance domain, where metadata extracted from CCTV recordings is indexed in the repository, along with the certainty of the data. This information is then combined to create new hypothesis and potentials. The user can then perform queries to extract the new knowledge and act on it.

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References

[1] Fernando Bobillo and Umberto Straccia. Fuzzy ontology representation using owl 2. *Int. J. Approx. Reasoning*, 52(7):1073–1094, October 2011.

[2] Nicolas Burrus and David Lesagne. *Theory of Evidence*. 2003.

[3] Davide Ceolin, Archana Nottamkandath, and Wan Fokkink. Subjective logic extensions for the semantic web. In *8th International Workshop on Uncertainty Reasoning for the Semantic Web*, 2012.

[4] Paulo Cesar G da Costa, Kathryn B Laskey, and Kenneth J Laskey. Pr-owl: A bayesian ontology language for the semantic web. In *ISWC-URSW*, pages 23–33, 2005.

[5] Pedro Carvalho de Oliveira. Probabilistic Reasoning in the Semantic Web using Markov Logic. Master's thesis, University of Coimbra, 2009.

[6] Zhongli Ding, Yun Peng, and Rong Pan. Bayesowl: Uncertainty modeling in semantic web ontologies. In Zongmin Ma, editor, *Soft Computing in Ontologies and Semantic Web*, volume 204 of *Studies in Fuzziness and Soft Computing*, pages 3–29. Springer Berlin Heidelberg, 2006.

[7] Yoshio Fukushige. Representing probabilistic knowledge in the semantic web. http://www.w3.org/2004/09/13-Yoshio/PositionPaper.html, April 2015.

[8] Seunghan Han, A. Hutter, and W. Stechele. Toward contextual forensic retrieval for visual surveillance: Challenges and an architectural approach. In *Image Analysis for Multimedia Interactive Services (WIAMIS), 2009 10th International Workshop on*, pages 201–204, 2009.

[9] Seunghan Han, Bonjung Koo, A. Hutter, and W. Stechele. Forensic reasoning upon pre-obtained surveillance metadata using uncertain spatio-temporal rules and subjective logic. In *Image Analysis for Multimedia Interactive Services (WIAMIS), 2010 11th International Workshop on*, pages 1–4, 2010.

[10] Seunghan Han, Bonjung Koo, and W. Stechele. Subjective logic based approach to modeling default reasoning for visual surveillance. In *Semantic Computing (ICSC), 2010 IEEE Fourth International Conference on*, pages 112–119, 2010.

[11] Pekka Orponen. Dempster's rule of combination is #p-complete. *Artificial Intelligence*, 44(12):245 – 253, 1990.

[12] Livia Predoiu and Heiner Stuckenschmidt. Probabilistic models for the semantic web: A survey. *The Semantic Web for Knowledge and Data Management: Technologies and Practices. Information Science Reference, Hershey, PA, USA*, 2008.

[13] W3C Incubator Group. Uncertainty reasoning for the world wide web. http://www.w3.org/2005/Incubator/urw3/XGR-urw3-20080331/, April 2015.