BeliefOWL: An Evidential Representation in OWL Ontology

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Abstract. *The OWL is a language for representing ontologies but it is unable to capture the uncertainty about the concepts for a domain. To address the problem of representing uncertainty, we propose in this paper, the theoretical aspects of our tool BeliefOWL which is based on evidential approach. It focuses on translating an ontology into a directed evidential network by applying a set of structural translation rules. Once the network is constructed, belief masses will be assigned to the different nodes in order to propagate uncertainties later.*

1 Introduction

Many ontology definition languages have been developed to define ontologies in a formal way. Among them the OWL [3] which is based on crisp logic. This language suffers from its lack to represent real domains containing incomplete knowledge or uncertain information. To overcome this, an extension of the OWL seems to be a convenient solution. Many researches find this extension important and try to propose approaches for handling uncertainty in ontology field. For that purpose, two main mathematical theories have been applied: the probability theory ([2],[7]) and the fuzzy sets theory ([4],[6]).

However not all the problems of uncertainty lend themselves to one of these theories. We can find ourselves faced to situations where we are called to represent the total ignorance or the partial one about information concerning classes. This can be resolved by applying the Dempster-Shafer theory [5]. At this stage, we are interested to use this theory and especially we are encouraged to work with the directed evidential networks [1] which are viewed as effective and appropriate graphical representation for uncertain knowledge. Adding to that, the use of conditional belief functions provides a well representation of the uncertainty in the relationships among the variables of a graph.

In this position paper we present our tool BeliefOWL as an approach for extending an OWL ontology with belief functions as well as the translation of this ontology into an evidential network.

[3] http://www.w3.org/2001/sw/webOnt

2 Uncertainty in OWL

The OWL is an expressive language for representing classes and the relations between them for a domain of discourse. However the source of information itself can suffer from giving a sufficient information of a concept. Sometimes we can find ourselves unable to express the exact relation existing between classes because of an incomplete knowledge about the domain of discourse or missed values. Uncertainty extension to the OWL is starting to know a considerable focus during the last years.

To cope with uncertain information in OWL extension, we propose the use of the Dempster-Shafer theory [5]. In fact this theory allows assigning beliefs not only to a single element but to a set of elements. Furthermore, it gives the experts the possibility to represent the total ignorance or the partial one about information concerning the classes of an ontology and the relations that may exist between them. Besides, this theory provides a method for combining several pieces of evidence from different sources to establish a new belief by using Dempster's rule of combination.

One of our goal is to translate an OWL taxonomy into a directed evidential network (DEVN). The DEVN is a model introduced in [1] to represent knowledge under uncertainty by using the belief functions. It is defined as a directed acyclic graph (DAG) where the nodes represent variables and the directed arcs linking nodes describe conditional dependence relations between these variables. These relations are expressed by conditional belief functions for each variable given its parents. Two kinds of belief functions are depicted to represent uncertainty in the DEVN: the prior belief function and the conditional belief function. The former concerns the root node and the latter expresses the belief function of a node given the value taken by its parents.

3 Presentation of the BeliefOWL

The figure 1 resumes the different steps followed leading to our tool. In fact the BeliefOWL has as input an OWL ontology and as output a directed evidential network (DEVN).

Step 1: A Belief Extension to OWL: An OWL ontology can define classes, properties and individuals. In this paper we will focus on attributing belief masses to the different classes of an OWL taxonomy. For this purpose, we define some new classes able to represent and to introduce this uncertain information.

– **Prior evidence**: We define two classes to express the prior evidence <*belief-Distribution*> and<*priorBelief*>. The former is used to enumerate the different masses related to the different classes of an OWL taxonomy. It has an object property <*hasPriorBelief*> that specifies the relation between classes

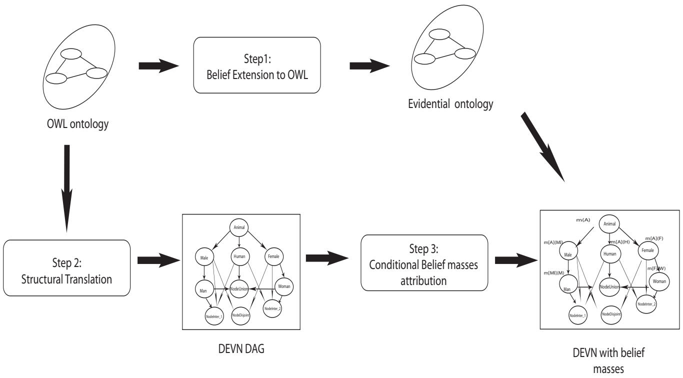

Fig. 1. BeliefOWL Framework

<*beliefDistribution*> and <*priorBelief*>. The latter expresses the prior evidence and has a datatype property <*massValue*> which enables to assign a mass value between 0 and 1.

– **Conditional evidence**: It is defined through two main classes <*beliefDistribution*> and<*condBelief*>. The former is the same as in the case of prior evidence but has an object property <*hasCondBelief*>. The latter identifies the conditional evidence and has a datatype property<*massValue*>.

Step 2: Constructing an Evidential Network: Given an OWL ontology, we translate it in a DAG by specifying the different nodes to be created as well as the relations existing between these nodes. The construction of the DAG interests some of the OWL statements those related to classes.

– <*owl:class*>: It is represented as a variable node in the translated DEVN.
– <*rdfs:subClassOf*>: When a class is a subclass of another one, a directed arc is drawn from the superclass node to the child subclass node.
– <*owl:disjointWith*>,<*owl:equivalentClass*>:When two classes are related to each other by one of these statements, a new node is created in the translated DEVN and a directed arc is drawn between the two classes and the node added.
– <*owl:intersectionOf*>: A class C may be defined as the intersection of some classes C_i(i,. . . ,n). This can be represented in the translated DEVN by an arc from each C_i to C and another one from C and each C_i to a new node created for representing the intersection.
– <*owl:unionOf*>: A class C may be defined as the union of some classes C_i(i,. . . ,n). This can be represented in the translated DEVN by an arc from C to each C_i to C and another one from C and each C_i to a new node created for representing the union.

Step 3: Evidence Attribution: Once the DAG of our network is constructed, the remaining issue is to assign masses for each node of the network. Considering the DAG that we have got, we can depict two kinds of nodes:

- **ClassesNodes**: are the nodes representing the different classes of our taxonomy and defined by <owl:class>. To this kind of nodes we attribute the prior belief functions and the conditional ones given into the evidential ontology.
- **ConstNodes**: are those related to the constructors of our taxonomy without considering <rdfs:subClassOf> because this kind of constructor is not represented by a specific node. Concerning the constNodes, masses will be attributed according to the constructor we are talking about. In fact if we have a node created to depict an intersection between two classes, the mass will be attributed by applying the Dempster's rule of combination. Concerning the node representing an union, the disjunctive rule of combination will be applied in that case.

Once our evidential network is constructed and the masses are assigned to each node a propagation process can be performed.

4 Conclusion

In this paper, we have presented the beliefOWL which is a new approach for representing uncertainty in an OWL ontology. We considered only the case for including uncertainty in classes. This uncertainty is modeled via the Dempster-Shafer theory of evidence. We have presented the theoretical aspects of our tool which consists on translating an OWL ontology into a network. For this purpose, we extend the OWL ontology classes with belief masses, then we apply structural translation rules in order to get a DAG of a directed evidential network. The masses added to the ontology will be extracted and will be attributed to the network's nodes classes.

Further work can carry about the properties and the individuals. The prior beliefs assigned to the different nodes of the network are given by an expert, in the future the assignment can be done automatically through a learning process.

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