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Messaouda Fareh

LRDSI Laboratory, Department of Computer Science, Faculty of Sciences, University Blida1, Algeria

ABSTRACT

Interoperable ontologies already exist in the biomedical field, enabling scientists to communicate with minimum ambiguity. Unfortunately, ontology languages, in the semantic web, such as OWL and RDF(S), are based on crisp logic and thus they cannot handle uncertain knowledge about an application field, which is unsuitable for the medical domain. In this paper, we focus on modeling incomplete knowledge in the classical OWL ontologies, using Bayesian networks, all keeping the semantic of the first ontology, and applying algorithms dedicated to learn parameters of Bayesian networks in order to generate the Bayesian networks. We use EM algorithm for learning conditional probability tables of different nodes of Bayesian network automatically, contrary to different tools of Bayesian networks where probabilities are inserted manually. To validate our work, we have applied our model on the diagnosis of liver cancer using classical ontology containing incomplete instances, in order to handle medical uncertain knowledge, for predicting a liver cancer.

Introduction

It is always essential but difficult to capture incomplete, partial or uncertain knowledge using ontologies to conceptualize an application domain or to achieve semantic interoperability among heterogeneous systems.

Ontology is widely used to represent knowledge in many software applications. By default, ontology languages, such as OWL and RDF, are built on discrete logic, so that it cannot handle uncertain information about the domain.

Various approaches have been made to represent uncertainty in ontology, one of them is the probabilistic ontology based on Bayesian network. Bayesian Network is one of Directed Acyclic Graphs (DAG) model, which uses a set of random variables and probabilities function applied in DAG to model the relationship between nodes.

Models of Bayesian-based solutions for handling uncertainty in ontology use a variety of approaches. These approaches suggest a language of the

CONTACT Messaouda Fareh farehm@gmail.com LRDSI Laboratory, Faculty of Sciences, University Blida1, Algeria

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probabilistic ontologies based on Bayesian networks. And this later manages a statistical or random uncertainty. In this work, we describe the way we modeled the formal classical ontology with incomplete knowledge on Bayesian Network. Determining the conditional probability Table (CPT) is difficult without the user's help for introducing the prior probabilities in order to perform inference and reasoning.

Several approaches have been proposed for dealing with uncertainty in the Semantic Web (SW). Although the Bayesian network is one of the most promising approaches to model uncertainty in ontologies, no support has been offered to ontological engineers about the creation of this complex type of ontologies. This task has proven to be extremely difficult and hard (Carvalho et al. 2014). Notably in the case when we want to automate the construction process of probabilistic ontology.

In these works (Ding, Peng, and Pan 2006) (Yang and Calmet 2005) (Costa 2005), we find proposals of meta-models or upper ontology allowing to handle uncertainty in ontologies; the results of these meta-models are probabilistic languages which represent probabilistic ontologies. The problem is how to handle uncertainty in classical ontologies presented by incompleteness, this induces a number of problems:

(1) How to find the mapping rules between the concepts of ontology and those of a Bayesian network?
(2) How to evaluate and determine a prior probability value for the obtained Bayesian network without resorting the user, knowing that the probability term does not exist at the level of classical ontology.
(3) How to find the structure of a Bayesian network from a classical ontology and reasoning with uncertainty?

To deal with such problem, this paper presents a method that encompasses the general procedures of modeling incompleteness in ontologies, then reasoning under uncertainty, using Bayesian networks.

We have organized our paper as follows: Section 2 describes the categories for handling uncertainty in ontology; Section 3 represents the related work part. We have focused on the probabilistic approaches which based on Bayesian Network. Section 4 is made for the proposal process of modeling incompleteness in initial ontology detailing all its steps. An experiment and test, in the field of diagnostic prediction, were conducted to validate the proposed process presented in Section 5. We make conclusions and discuss the future work in Section 6.

Handling Uncertainty in Ontologies

In this section, we present two categories for handling uncertainty in ontology, the Bayesian Network and probabilistic ontologies.

Bayesian Network

An important issue, while modeling uncertain knowledge, is how to represent the probabilistic dependencies between the different elements of the knowledge base.

A Bayesian Network is the combination of the topology (graph) and the conditional probabilities of the variables (nodes). These are used together to explore the effects of various variables on each other.

Bayesian Networks (BNs) (Darwiche 2009) are probabilistic models that use a graphical structure to express conditional independence assumptions between the variables of the network. Over the years, BNs have been used to model probabilistic knowledge in many domains. In particular, they have been used in several biological applications (Ceylan and Peñaloza 2017). See (Scutari et al. 2014) (Friedman et al. 2000) for just two from many instances that can be found in the literature.

Determining the probabilities can be as simple as assigning them through joint probability distribution tables in some situations. However, for comprehensive Bayesian Networks, these probabilities are adapted (through learning) as more data is collected. Learning provides improved knowledge by combining prior knowledge with data (Heckerman 2008).

Inference is the task of computing the probabilities of unknown events in a Bayesian network given the data on known events. Inference is fundamental in determining the most probable values of the variables and then drawing conclusions from the values (Stephenson 2000).

Probabilistic Ontologies

Various approaches have been made to represent uncertainty in ontology; one of them was with a Bayesian approach. Many of these approaches focus especially on combining the web ontology language OWL with probabilistic formalisms based on Bayesian networks. Currently, there are four main published approaches: BayesOWL, OntoBayes, Multi-Entity Bayesian Networks (MEBN) and Probabilistic OWL (PR-OWL) (Costa et al., 2005).

BayesOWL: Ding et al. (Ding and Peng 2004) (Ding, Peng, and Pan 2006) propose a probabilistic generalization of OWL, called BayesOWL, which is based on standard Bayesian networks. BayesOWL is a framework, and to model uncertainty in semantic web ontologies based on Bayesian networks, it provides a set of rules and procedures for the direct translation of OWL ontology into a Bayesian network, and it also provides a method for incorporating available probability constraints while constructing the Bayesian network.

OntoBayes: Yang and Calmet (Yang and Calmet 2005) present an integration of the web ontology language OWL with Bayesian networks, called OntoBayes. This model makes use of probability and dependency-annotated OWL to represent uncertain information in BN structures. These extensions enhance knowledge representation in OWL and enable agents to act under uncertainty and complex structured opens environments at the same time.

Multi-Entity Bayesian Networks (MEBN): MEBN was first introduced by Laskey (2008). MEBN is a knowledge representation formalism that combines the power of first-order logic with uncertainty. MEBN provides syntax, a set of model construction and inference processes, and semantics; all of them provide means of defining probability distributions over unbounded and possibly infinite numbers of interrelated hypotheses.

Related Works

One of the main reasons that make the research in ontology languages focusing on deterministic approaches has limited expressiveness of traditional probabilistic languages. There is a current line of research focusing on extending OWL and combined with Bayesian networks, so it can represent probabilistic information contained in a Bayesian network.

The literature contains several works on probabilistic web ontology languages. Many of these approaches focus especially on language of combining the web ontology language OWL with probabilistic formalisms based on Bayesian networks.

In particular, (Yang and Calmet 2005) propose probability and dependency-annotated OWL extensions to construct Bayesian networks from ontologies. While their approach allows dealing with multivalued random variables in the CPT construction, the approach still requires the extension of the ontology with the proposed probabilistic OWL constructs.

Pool and Aikin (Pool and Aikin 2004) also provide a method for representing uncertainty in OWL ontologies, while Fukushige (Fukushige 2004) proposes a basic framework for representing probabilistic relationships in RDF.

In closely related work, Mitra et al. (Mitra, Noy, and Jaiswal 2005) describe an implemented technique, called OMEN, to enhance the existing ontology mappings by using a Bayesian network and to represent the influences between potential concept mappings across ontologies. More concretely, OMEN is based on a simple ontology model similar to RDF Scheme. It uses a set of meta-rules that capture the influence of the ontology structure and the semantics of ontology relations and matches nodes that are neighbors of already matched nodes in the two ontologies.

Devittet et al. (Devitt, Danev, and Matusikova 2006) have proposed a set of phases for building Bayesian networks automatically from an existing ontology: (a) the identification of random variables (nodes) (b) specifying different values for each variable (c) setting property between different variables. (d) Calculating the distribution of conditional probabilities.

Udrea et al. (Udrea, Subrahmanian, and Majkic 2006) present a probabilistic generalization of RDF, which allows representing terminological probabilistic knowledge about classes and assertion probabilistic knowledge about properties of individuals. They provide a technique for assertion probabilistic inference in acyclic probabilistic RDF theories, which is based on the notion of logical entailment in probabilistic logic, coupled with a local probabilistic semantics. They also provide a prototype implementation of their algorithms.

Ishak et al. (Ishak, Leray, and Amor 2011) developed a set of mapping rules which support the construction of an Object-Oriented Bayesian network structure by exploiting the knowledge stored within the ontology. The CPT construction is not considered by the proposed method.

Fenz (Fenz 2012) proposed an ontology-based approach for constructing Bayesian networks, the limitations of his proposed method are: (i) functions for calculating conditional probability tables are not provided by the ontology and have to be modeled externally (currently only the parent node weights and states are derived from the ontology), (ii) Boolean node assumption in the CPT construction, and (iii) human intervention is still necessary to some extent if the ontology does not provide a knowledge model that fits the domain of interest exactly.

In (Mouenis, Mohamed, and Souhaib 2014), a methodology was proposed to transform and encode a Bayesian network into ontology. For this purpose, the authors proposed a set of mapping rules where the nodes are transformed into a set of concepts in the ontology web language OWL, and the instances of each class are generated from the states of the corresponding node. As a key limitation of this proposal, there is no compatibility between the components of the ontology and the Bayesian network encoded within.

Hlel et al. (Hlel, Jamoussi, and Hamadou 2014) presented a process for integrating a Bayesian network on the ontology, they are defined a set of translation rules (1) the nodes of BN graph are transformed into a set of concepts (2) the possible values for each node are processed into instances concepts. (3) The prior probability P(a) (the probability of roots) is converted to a probability value (between 0 and 1) of a property of DataProperty type. In its recent work (Hlel, Jamoussi, and Hamadou 2017), the authors have proposed a method to construct the probabilistic ontologies, where they made a distinction between precise and probabilistic component of the ontology.

In contrast to existing approaches, the approach presented in this paper:

- Is designed as a generic approach and has been implemented as a prototype to construct a Bayesian network from formal ontology with incomplete knowledge.
- Conducts CPT computation without affect existing classes and individuals of the ontology.
- Preserves semantic constraints that have been defined in the initial ontology.
- Computes CPT an automatic manner, without the help of user for prior probabilities.
- Uses the ontology instance as a statistical base for obtaining the probability distribution.

Proposed Modeling

Bayesian networks are a very powerful way to represent the uncertainty of the web. However, finding the probability values automatically without the intervention of the expert to a prior probability is a difficult problem.

Our proposed method for creating a Bayesian network from a classical ontology with missing knowledge is shown in the following pseudo algorithm.

Pseudo algorithm for handling incompleteness using Bayesian network:
Input: Classical ontology OWL with incomplete knowledge
Output: Bayesian network
Begin:

- Extracting terminological and assertion parts.
- Constructing structure of Bayesian network.
- Constructing statistical table with incomplete knowledge.
- Learning parameter (EM).
- Inference in Bayesian network.

End.
Subsequently, we detail the steps of our modeling processes.

Extracting Terminological and Assertion Part of Ontology

An OWL ontology is characterized by (1) its terminological part, or the ontology scheme. We extract this part in order to apply mapping rules, for constructing Bayesian network. This part of OWL ontology contains:

concepts, properties and the constraints (Domain and Range) of property.

An OWL ontology is also characterized by (2) its assertion part; this part will be used to generate a statistical table in order to construct the probability tables, using the EM algorithm.

We extract terminological and assertion parts in order to import the classes, properties, relationships between properties, its domain and range, and assertions for constructing a Bayesian network.

Mapping between OWL and Bayesian Network

The first described issue was the lack of mapping between Bayesian networks and the concepts defined in OWL. In the literature, there is no consensus, and no explicit rules for mapping between the two languages OWL and Bayesian network. We propose mapping rules shown in Table 1, between OWL and Bayesian network, after studying each of its components.

Creating Structure of Bayesian Network

Learning structure of a Bayesian network consists of identifying the nodes and possible connections between these nodes from the OWL classical ontology.

To learn the structure of the Bayesian network, we applied the mapping rules mentioned in the previous section, which help the ontology engineer to create the structure of a Bayesian network in semi-automatic manner. The nodes are chosen among the concepts of the ontology and the arcs among the properties (object and data properties), according to the semantic of the initial ontology.

Constructing Statistics Table

We use the statistical table for learning parameters and settings the probability tables, applying the EM algorithm. We consider the statistics as

Table 1. Proposed mapping rules between OWL Ontology and Bayesian network.

	OWL	Bayesian network
Mapping	Ontology	Bayesian network
	Classes	nodes
	Property (Object and data property)	arcs
Comparison criterion	File .OWL	Graph of BN
	Standardized language for knowledge	Model of uncertain knowledge
	Deterministic language	Probabilistic sturcture
	Formal, it ignores the uncertainty	It takes account of the uncertainty
	Based on description logics	Based on Conditional Probablities Tables
	Inference in determinist knowledge	inference in uncertain knowledge

Fatigue	Joint pain	"Tabacoo"	Pain Abdomen	" Viral infection"	Jaundice	"Alcohol"	"Enlarger liver "	Gender	"livercancer"	Age>30	Overweight	Family history	
No	Yes	No	No	No	No	No	*	*	*	Yes	*	No	H
No	Yes	No	No	No	No	No	No	*	*	Yes	*	No	F
Yes	No	*	*	No	No	No	No	No	No	Yes	No	No	H
Yes	No	*	*	No	No	No	No	No	No	Yes	No	No	F
No	No	*	*	No	Yes	Yes	No	No	No	No	No	*	F
No	No	No	No	No	Yes	Yes	No	No	No	No	No	*	H
No	No	No	No	No	Yes	*	*	No	No	*	No	Yes	H
No	No	No	No	No	Yes	No	*	No	No	*	No	Yes	F
No	No	Yes	No	*	No	*	No	No	No	No	*	No	H
No	No	Yes	No	*	No	*	No	No	No	No	*	No	F
Yes	No	No		*	No	Yes	Yes	No	No	No	*	*	H
Yes	No	No		*	No	Yes	Yes	No	No	No	*	No	F
No	No	No	No	No	Yes	No	Yes	No	No	*	*	No	H
No	No	No	No	No	Yes	No	Yes	No	No	*	*	No	*

Figure 1. Part of statistical table.

incomplete because the instances of the ontology are incompletes. We used instances of the OWL ontology, as missing statistics (see Figure 1) to apply the EM algorithm.

The statistics table is an input parameter of the EM algorithm.

Applying EM Algorithm

An Expectation Maximization (EM) algorithm (Dempster, Laird, and Rubin 1977) is an iterative method for finding maximum likelihood or maximum posterior (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameters estimate are then used to determine the distribution of the latent variables in the next E step. Once we have the structure of the Bayesian network, and using statistics table, the EM algorithm handles learning the parameters of our Bayesian network, to get it ready for the inferences.

After executing the EM algorithm, it generates probability values estimated for missing data, from the statistics according to the data in the Bayesian network.

Experimentation and Test

We have developed an application to validate our modeling, in order to obtain a Bayesian network from a written ontology of OWL, with incomplete knowledge. Our tool is generic to model any ontology, one must first import this OWL ontology from any location, then, to extract the terminological and assertion parts of ontology to access the creation of Bayesian network.

For the learning parameter, we use the software Netica[1], Netica is currently one of the most diffused worldwide. Netica is used for diagnosis, accuracy or simulation in the areas of finance, and in many applications that require reasoning under uncertainty. A fully functional free version of the software is downloadable on the website of Norsys. The API Netica-J is a comprehensive library of Java classes for working with Bayesian networks. It contains functions to construct, learn data, modify, transform, perform testing, record and play networks, as well as a powerful engine of inference.

The EM algorithm has an input the CAS file of statistics table and DNE file of structure, and it gives us the parameters of the Bayesian network. In the rest of this section, we will perform a test on our implemented system. We used a method to test our system and to complete the steps of our modeling to create usable Bayesian network for predicting liver cancer.

The choice of the "Liver_Cancer" ontology is made because of the importance of this disease in the world because liver cancer is the most common type of cancer in the world and it causes major death (788 000 deaths/years), nearly 80% men (Cismef, descripteur MeSH: Tumeurs de foie, date of consultation 2018). Liver cancer is one of the most aggressive digestive cancers, but it is also one of those whose treatments have progressed most in recent years (Pakhale and Xaxa 2016).

Classical Ontology of Liver Cancer

The scheme of classical ontology for liver cancer is presented in Figure 2.

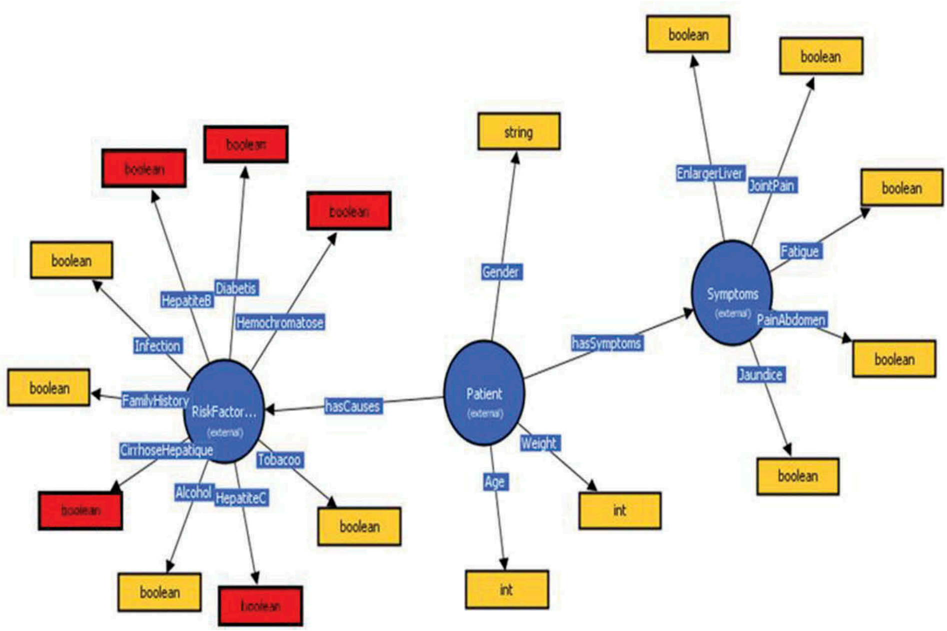

Figure 2. Liver cancer ontology.

Creating Bayesian Network for Liver Cancer

For constructing the structure of the Bayesian network, we have defined a set of rules which help the ontology engineer to create structure of the BN basing on the components of the classical ontology. Thus, the class liver cancer will be represented by a node in the BN. Also, all the symptoms and the risk factors classes are represented by nodes in the BN. The probabilistic relation among the concepts of the class symptoms and the liver cancer class will be represented by an arc in the BN. Also, the probabilistic relation among the concepts of the class risk-factors and the liver cancer class will be represented by an arc in the BN. The states of each node are created by the ontology engineer.

After creating the structure and parameters using EM algorithm, we find the Bayesian network presented in Figure 3 .

Validation

In this section, a quantitative evaluation of the prediction of a liver cancer, using our Bayesian network, is done by comparing the output result with the corresponding manually. To do so; we have evaluated separately the probabilistic inference with manual results by computing the outcome for each patient basing on its evidence. The evaluation parameters used are: True Positive (TP), True Negative (TN), False Negative (FN), and False Positive

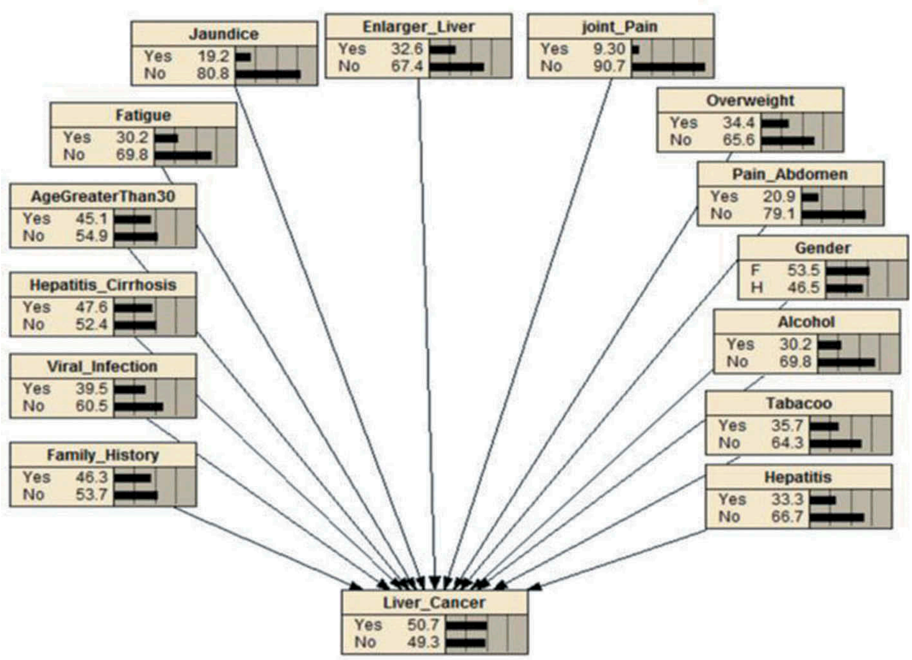

Figure 3. Liver cancer Bayesian network.

Table 2. The results obtained using probabilistic inference.

Parametrs	Inference in BN
Precision	0.89
Recall	0.91
F-measure	0.94

(FP). The quantitative evaluation in this paper based on calculating the precision, recall, and F-measure of the results obtained by the probabilistic inference, an illustration of these parameters can be found in Table 2.

It can be seen from Table 2 that the predictions for the probabilistic inference have the highest precision, recall, and F-measure and are, respectively, about 89%, 91%, and 94%, which signifies that the prediction basing on probabilistic inference is near to the prediction of the expert domain. Hence, these results are promising and give us good indications that reasoning in incomplete knowledge.

Conclusion

Across a wide range of domains, there is an urgent need for a well-founded approach to incorporate uncertain and incomplete knowledge into formal domain ontologies.

Ontologies are a powerful approach to allow knowledge sharing and support interoperability between people and computer systems. However, traditional or classical ontologies do not provide adequate support to the uncertainty, a fundamental characteristic of a complex environment in an open real world. It is proved that Bayesian networks are reliable methods to model uncertainty and to make predictions based on real facts even in the presence of uncertainty around these facts. We concluded that Bayesian networks can be applied in the semantic web to resolve the problem of uncertainty, and more particularly incompleteness.

We proposed for this modeling, a process that carries steps:

- Import OWL ontology: select ontology what we want to treat,
- Extract terminological and assertional part: extracting the classes, properties with constraints, and assertions.
- Constructing a statistical table from assertion part of ontology which contains incomplete values.
- Creating the structure of Bayesian network.
- Learning parameters by EM algorithm: learning parameters is to estimate the distribution parameters for all data according to the joint distribution of probabilities. EM algorithm uses the nodes of BN, and the instances of ontology which represent the missing data.

In the experimental and test section, we have applied our modeling on diagnostic ontology, for prediction a liver cancer, we obtained our Bayesian network, which contains the different nodes of symptoms and risk factor of liver cancer. We validate our modeling using probabilistic inference, which we obtain good values of precision and recall.

After modeling the incompleteness in the classical ontologies by Bayesian network and validate obtained inference, we envisage to learn the optimized structure using one of the algorithm to dedicate and to learn structure. In fact, how to find the optimal structure of a BN from a classical ontology, especially if there is a large classical ontology, containing a large number of concepts and properties, where the complexity of inference increases.

Note

1. http://www.norsys.com www.norsys.com.

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