A TWO-WAY APPROACH FOR PROBABILISTIC GRAPHICAL MODELS STRUCTURE LEARNING AND ONTOLOGY ENRICHMENT

Mouna Ben Ishak[1], Philippe Leray[2] and Nahla Ben Amor[1]
[1]*LARODEC Laboratory, ISG, University of Tunis, 2000 Tunis, Tunisia*
[2]*Knowledge and Decision Team, LINA Laboratory UMR 6241, Polytech'Nantes, Nantes, France*

Keywords: Ontologies, Probabilistic graphical models (PGMs), Machine learning, Ontology enrichment.

Abstract: Ontologies and probabilistic graphical models are considered within the most efficient frameworks in knowledge representation. Ontologies are the key concept in semantic technology whose use is increasingly prevalent by the computer science community. They provide a structured representation of knowledge characterized by its semantic richness. Probabilistic Graphical Models (PGMs) are powerful tools for representing and reasoning under uncertainty. Nevertheless, both suffer from their building phase. It is well known that learning the structure of a PGM and automatic ontology enrichment are very hard problems. Therefore, several algorithms have been proposed for learning the PGMs structure from data and several others have led to automate the process of ontologies enrichment. However, there was not a real collaboration between these two research directions. In this work, we propose a two-way approach that allows PGMs and ontologies cooperation. More precisely, we propose to harness ontologies representation capabilities in order to enrich the building process of PGMs. We are in particular interested in object oriented Bayesian networks (OOBNs) which are an extension of standard Bayesian networks (BNs) using the object paradigm. We first generate a prior OOBN by morphing an ontology related to the problem under study and then, we describe how the learning process carried out with the OOBN might be a potential solution to enrich the ontology used initially.

1 INTRODUCTION

Ontologies are the key concept in semantic web, they allow logical reasoning about concepts linked by semantic relations within a knowledge domain. Probabilistic graphical models (PGMs), from their side, provide an efficient framework for knowledge representation and reasoning under uncertainty. Even though they represent two different paradigms, Ontologies and PGMs share several similarities which has led to some research directions aiming to combine them. In this area, Bayesian networks (BNs) (Pearl, 1988) are the most commonly used. However, given the restrictive expressiveness of BNs, proposed methods focus on a restrained range of ontologies and neglect some of their components. To overcome this weakness, we propose to explore other PGMs, significantly more expressive than standard BNs, in order to address an extended range of ontologies.

We are in particular interested in *object oriented Bayesian networks* (Bangsø and Wuillemin, 2000) (OOBN), which are an extension of standard BNs. In fact, OOBNs share several similarities with ontologies and they are suitable to represent hierarchical systems as they introduce several aspects of object oriented modeling, such as inheritance. Our idea is to define the common points and similarities between these two paradigms in order to set up a set of mapping rules allowing us to generate a prior OOBN by morphing ontology in hand and then to use it as a starting point to the global OOBN learning algorithm, this latter will take advantages from both semantical data, derived from ontology which will ensure its good start-up and observational data. We then capitalize on the final structure resulting from the learning process to carry out the ontology enrichment. By this way, our approach ensures a real cooperation, in both ways, between ontologies and OOBNs.

The remainder of this paper is organized as follows: In sections 2 and 3 we provide a brief representation of our working tools. In section 4, we introduce our new approach. In section 5, we look over the related work. The final section summarizes conclusions reached and outlines directions for future research.

Ben Ishak M., Leray P. and Ben Amor N..
A TWO-WAY APPROACH FOR PROBABILISTIC GRAPHICAL MODELS STRUCTURE LEARNING AND ONTOLOGY ENRICHMENT.
DOI: 10.5220/0003634801890194
In *Proceedings of the International Conference on Knowledge Engineering and Ontology Development* (KEOD-2011), pages 189-194
ISBN: 978-989-8425-80-5

2 ONTOLOGIES

For the AI community, an ontology is *an explicit specification of a conceptualization* (Gruber, 1993). That is, an ontology is a description of a set of representational primitives with which to model an abstract model of a knowledge domain. Formally, we define an ontology $\mathcal{O} = \langle \mathcal{C}p, \mathcal{R}, \mathcal{I}, \mathcal{A} \rangle$ as follows:

- $\mathcal{C}p = \{cp_1, \ldots cp_n\}$ is the set of n concepts (classes) such that each cp_i has a set of k properties (attributes) $\mathcal{P}_i = \{p_1, \ldots p_k\}$.
- $\mathcal{R}$ is the set of binary relations among elements of $\mathcal{C}p$ which consists of two subsets:
  - $\mathcal{H}_{\mathcal{R}}$ which describes the inheritance relations among concepts.
  - $\mathcal{S}_{\mathcal{R}}$ which describes semantic relations among concepts. That is, each relation $cp_i s_R cp_j \in \mathcal{S}_{\mathcal{R}}$ has cp_i as a domain and cp_j as a range.
- $\mathcal{I}$ is the set of instances, representing the knowledge base.
- $\mathcal{A}$ is the set of the axioms of the ontology. $\mathcal{A}$ consists of constraints on the domain of the ontology that involve $\mathcal{C}p$, $\mathcal{R}$ and $\mathcal{I}$.

During the last few years, increasing attention has been focused on ontologies and ontological engineering. By ontological engineering we refer to the set of activities that concern the ontology life cycle, covering its design, deployment, up to its maintenance which is becoming more and more crucial to ensure the continual update of the ontology toward possible changes. The ontology evolution process (Stojanovic et al., 2002) is defined as *the timely adaptation of an ontology in response to a certain change in the domain or its conceptualization*. Evolution can be of two types (Khattak et al., 2009):

- **Ontology Population Process.** consists in introducing new instances of the ontology concepts and relations.
- **Ontology Enrichment Process.** consists in adding (removing) concepts, properties and (or) relations in the ontology or making some modifications in the already existing ones because of changes required in the ontology definition itself, and then populate it for its instances. Ontology enrichment techniques are automatic processes, which generate a set of the possible modifications on the ontology and propose these suggestions to the ontology engineers.

This paper proposes to harness PGMs structure definition in order to improve the process of ontologies enrichment. We are in particular interested in object oriented Bayesian networks. Before introducing our method, we give basic notions on this framework.

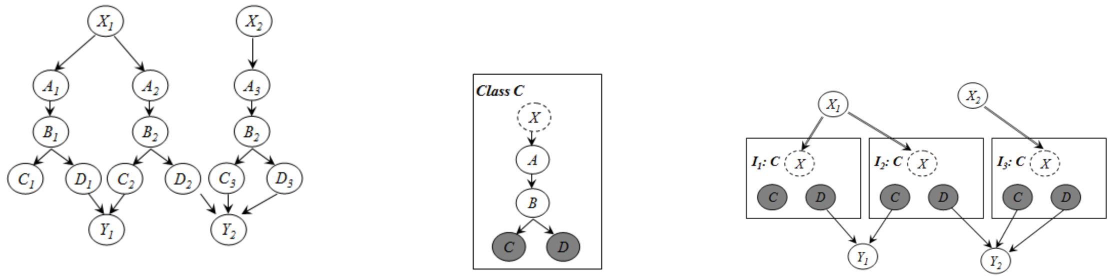
3 OBJECT ORIENTED BAYESIAN NETWORKS

Probabilistic graphical models (PGMs) provide an efficient framework for knowledge representation and reasoning under uncertainty. *Object oriented Bayesian networks* (OOBNs) (Bangsø and Wuillemin, 2000) (Koller and Pfeffer, 1997) are an extension of standard Bayesian networks (BNs) (Pearl, 1988) using the object paradigm. They are a convenient representation of knowledge containing repetitive structures. So they are a suitable tool to represent some special relations which are not obvious to represent using standard BNs (e.g., examine a hereditary character of a person given those of his parents). Thus an OOBN models the domain using fragments of a Bayesian network known as classes. Each class can be instantiated several times within the specification of another class. Formally, a class T is a DAG over three, pairwise disjoint sets of nodes $(\mathcal{I}_T, \mathcal{H}_T, \mathcal{O}_T)$, such that for each instantiation t of T:

- $\mathcal{I}_T$ is the set of input nodes. All input nodes are references to nodes defined in other classes (called referenced nodes).
- $\mathcal{H}_T$ is the set of internal nodes including instantiations of classes which do not contain instantiations of $\mathcal{T}$.
- $\mathcal{O}_T$ is the set of output nodes. They are nodes from the class usable outside the instantiations of the class. An output node of an instantiation can be a reference node if it is used as an output node of the class containing it.

Internal nodes (expect classes instantiations) and output nodes (except those which are reference nodes) are considered as real nodes and they represent variables. In an OOBN, nodes are linked using either directed links (i.e., links as in standard BNs) or reference links. The former are used to link reference or real nodes to real nodes, the latter are used to link reference or real nodes to reference nodes. Each node in the OOBN has its potential, i.e. a probability distribution over its states given its parents. To express the fact that two nodes (or instantiations) are linked in some manner, we can also use construction links $(- - -)$ which only represent a help to the specification.

When some classes in the OOBN are similar (i.e. share some nodes and potentials), their specification



(a) The standard BN. (b) The class definition. (c) The OOBN representation.

Figure 1: An OOBN example.

can be simplified by creating a class hierarchy among them. Formally, a class S over $(\mathcal{I}_S, \mathcal{O}_S, \mathcal{H}_S)$ is a subclass of a class T over $(\mathcal{I}_T, \mathcal{O}_T, \mathcal{H}_T)$, if $\mathcal{I}_T \subseteq \mathcal{I}_S, \mathcal{O}_T \subseteq \mathcal{O}_S$ and $\mathcal{H}_T \subseteq \mathcal{H}_S$.

In the extreme case where the OOBN consists of a class having neither instantiations of other classes nor input and output nodes we collapse to standard BNs.

Example 1. *In figure 1, assume that in the BN of 1(a) X_1 and X_2 have the same state space and the conditional probability tables (CPTs) associated with all nodes labeled A_i as well as nodes labeled B_i,C_i and D_i, where $i = \{1,2,3\}$ are identical. Hence, we have three copies of a same structure. Thus, when modeling an OOBN such a repetitive structure will be presented by a class 1(b), where the dashed node X is the input node (an artificial node having the same state space as X_1 and X_2), the shaded nodes C and D are output nodes, and A and B are the encapsulated nodes. Thus, we can represent the BN of figure (a) using an OOBN model (c). The class C is instantiated three times and the nodes X_1, X_2, Y_1 and Y_2 are connected to the appropriate objects labeled $I.1, I.2$ and $I.3$.*

4 A NEW APPROACH FOR OOBN-ONTOLOGY COOPERATION: 2OC

In this section, we expose our two-way approach that integrates the ontological knowledge in the OOBN learning process by morphing an ontology into a prior OOBN structure then, the final structure derived from the learning process is used to provide a set of possible extensions allowing the enrichment of the ontology used initially.

4.1 The Morphing Process

We associate ontology concepts to classes of the OOBN framework and concept properties to their sets of random variables (real nodes). Concepts that are connected by a subsumption relationship in the ontology will be represented by a class hierarchy in the prior OOBN, and semantic relations, which we assume that they follow a causal orientation (Ben Ishak et al., 2011), are used to specify classes interfaces and instantiations organization in the OOBN.

To provide the morphing process, we assume that the ontology conceptual graph is a directed graph whose nodes are the concepts and relations (semantic and hierarchical ones) are the edges. Our target is to accomplish the mapping of this structure into a prior OOBN structure while browsing each node once and only once. To this end, we adapt the generic Depth-First Search (DFS) algorithm for graph traversing. The idea over the Depth-First Search algorithm is to traverse a graph by exploring all the vertices reachable from a source vertex: If all its neighbors have already been visited (in general, color markers are used to keep track), or there are no ones, then the algorithm backtracks to the last vertex that had unvisited neighbors. Once all reachable vertices have been visited, the algorithm selects one of the remaining unvisited vertices and continues the traversal. It finishes when all vertices have been visited. The DFS traversal allows us to classify edges into four classes that we use to determine actions to do on each encountered concept:

- **Tree Edges:** are edges in the DFS search tree. They allow to define actions on concepts encountered for the first time.
- **Back Edges:** join a vertex to an ancestor already visited. They allow cycle detection, in our case these edges will never be encountered. As our edges respect a causal orientation having a cycle of the form $X_1 \rightarrow X_2 \rightarrow X_3 \rightarrow X_1$means that X_1 is

the cause of X_2 which is the cause of X_3 so this latter cannot be the cause of X_1 at the same instant t but rather at an instant $t+\varepsilon$. We are limited to ontologies that do not contain cycles, because such relationships invoke the dynamic aspect which is not considered in this work.

- **Forward and Cross Edges:** all other edges. They allow to define actions to do on concepts that are already visited crossing another path and so having more than one parent.

A deep study of the similarities between ontologies and the OOBN framework and a more detailed description of the morphing process can be find in (Ben Ishak et al., 2011).

4.2 The Learning Process

Few works have been proposed in the literature to learn the structure (Bangsø et al., 2001) (Langseth and Nielsen, 2003) of an OOBN. (Langseth and Nielsen, 2003) proposed the OO-SEM algorithm which consists of two steps. First, they take advantages from prior information available when learning in object oriented domains. Thus, an expert is asked about a partial specification of an OOBN by grouping nodes into instantiations and instantiations into classes. Having this prior model, the second step starts by learning the interfaces of the instantiations. Then, the structure inside each class is learned based on the candidate interfaces founded previously. Thanks to the morphing process described above, we are not in need of expert elicitation as our process allowed us to take advantage of the semantic richness provided by ontologies to generate the prior OOBN structure. This later will be used as a starting point to the second step which will be done as described in (Langseth and Nielsen, 2003).

4.3 The Change Detection Process

To get the final OOBN structure we have gathered both ontology semantic richness and observational data. Yet, in some cases, data may contradict the ontological knowledge which leads us to distinguish two possible working assumptions:

- **A Total Confidence in the Ontology.** Any contradiction encountered during the learning process is due to data. The conflict must be managed while remaining consistent with the ontological knowledge. The enrichment process will be restrained to the addition of certain knowledge (relations, concepts, etc.) while preserving the already existing ones and what was regarded as truth remains truth.
- **A Total Confidence in the Data.** Any contradiction encountered during the learning process is due to the ontology. The conflict must be managed while remaining faithful to the data. In this case, changing the conceptualization of the ontology will be allowed, not only by adding knowledge, but also by performing other possible changes, such as deleting, merging, etc. This means that the data will allow us to get new truths that may suspect the former. In the following we will adopt this assumption.

As described above, the OO-SEM algorithm starts by learning the interface of each class then learns the structure inside each class. We can benefit of these two steps in order to improve the ontology granularity. In fact, the first step allows us to detect the possible existence of new relations and / or concepts which might be added to the ontology at hand. The second step may affect the definition of the already existing concepts and / or relations.

4.3.1 Interfaces Learning vs Relations and/or Concepts Adding or Removing

Remove Relations. When we have generated the OOBN, concepts related by a semantic relations were represented by instances of classes encapsulated in each other, and we have expect that the learning process will identify the variables that interact between the two instances. If no common interface is identified, then these two concepts should be independent. So their semantic relation have to be checked.

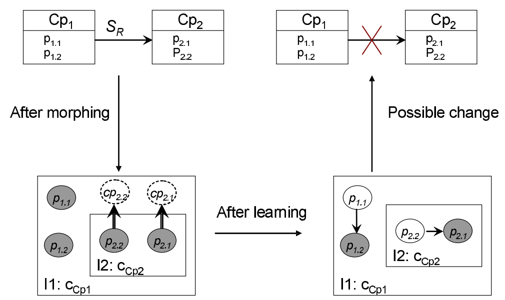


Figure 2: Enrichment process: an example of removing a relation (S_R is a semantic relation). Here we suppose that after performing the learning process, we didn't find nodes from C_{cp_1} that reference nodes from C_{cp_2}. Thus, we can propose to delete the semantic relation which appears in the ontology.

Add Concepts/Relations. A class c_i communicates via its interface with a set S_c of classes. If S_c is a singleton then we can simply propose to add a new relation between concepts representing these classes in the underlying ontology. Otherwise, we can use this exchange between classes whether by translating it into relations or concepts allowing the factorization of some other ones already present in the ontology. If some classes in S_c similar sets of nodes and have similar structures, then we can extract a super-concept over them. Otherwise, these relations may be translated into relations in the ontology.

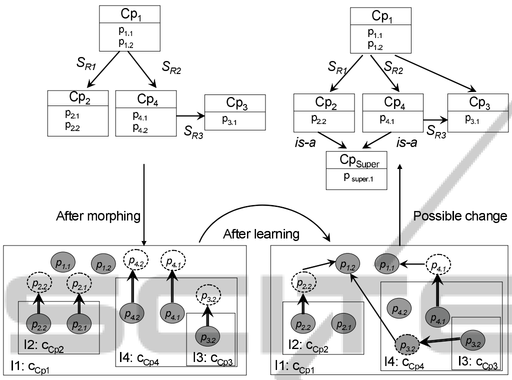


Figure 3: Enrichment process: an example of adding concepts and relations (S_{R1}, S_{R2} and S_{R3} are semantic relations). Here we suppose that $p_{2.1}$ and $p_{4.2}$ have the same state space and their respective classes C_{cp_2} and C_{cp_4} communicate with the same class C_{cp_1}. Thus, in the ontological side, we can define a super-concept over cp_2 and cp_4 having p_{super} as property which substitute both $p_{2.1}$ and $p_{4.2}$. Note that C_{cp_3} communicates also with C_{cp_1}, but as it doesn't represent shared properties with the other classes, then we will simply add a new relation between cp_3 and cp_1 in the ontology.

4.3.2 Classes Learning vs Concepts Redefinition

As defined above, each class c in the OOBN is a DAG over its three sets of nodes $\mathcal{I}_c, \mathcal{H}_c$ and $\mathcal{O}_c$. Suppose that the result of the learning process, was a disconnected graph (as the example of figure 4), this means that $\mathcal{I}_c, \mathcal{H}_c$ and $\mathcal{O}_c$ are divided into multiple independent connected components (two in figure 4). Thus, nodes of each component are not really correlated with those of the other components. This can be translated in the ontological side by proposing to deconstruct the corresponding concept into more refined ones, where each concept represents a component of the disconnected graph.

The possible changes are then communicated to an expert via a warning system which detects the changes and allows the expert to state actions to be done. If he chooses to apply the change, he shall first denominate the discovered relations and / or concepts.

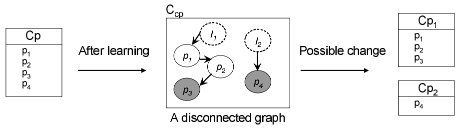


Figure 4: Enrichment process: an example of concept redefinition.

5 RELATED WORK

In recent years, a panoply of works have been proposed in order to combine PGMs and ontologies so that one can enrich the other.

One line of research aims to extend existing ontology languages, such as OWL[1], to be able to catch uncertainty in the knowledge domain. Proposed methods (Ding and Peng, 2004), (Yang and Calmet, 2005), (Costa and Laskey, 2006) use additional markups to represent probabilistic information attached to individual concepts and properties in OWL ontologies. Other works define transition actions in order to generate a PGM given an ontology with the intention of extending ontology querying to handle uncertainty while keeping the ontology formalism intact (Bellandi and Turini, 2009).

On the other hand, some solutions proposed the use of ontologies to help PGMs construction. Some of them are designed for specific applications (Helsper and van der Gaag, 2002), (Zheng et al., 2008), while some others give various solutions to handle this issue (Fenz et al., 2009), (Ben Messaoud et al., 2011).

However, all these solutions are limited to a restrained range of PGMs, usually BNs. So, they neglect some ontology important aspects such as representing concepts having more than one property, non taxonomic relations, etc. Moreover, the main idea behind these methods was to enhance ontology reasoning abilities to support uncertainty. However, we cannot provide a good basis for reasoning while we do not have a well defined ontology, which takes into consideration changes of its knowledge domain.

Thanks to the mapping process found between ontologies and OOBNs, our 2OC approach allowed us to deal with ontologies without significant restrictions. We focused on concepts, their properties, hierarchical as well as semantic relations and we showed how these elements would be useful to automatically generate a prior OOBN structure, this latter is then learned using observational data. This mixture of semantical data provided by the ontology and observational data presents a potential solution to discover

[1]ttp://www.w3.org/TR/2004/REC-owl-features-20040210/

new knowledge which is not yet expressed by the ontology thus, our idea was to translate new relations discovered by the learning process into knowledge which may be useful to enrich the initial ontology.

6 CONCLUSIONS AND FUTURE WORKS

In this paper, we have proposed a new two-way approach, named OOBN-Ontology Cooperation (2OC) for OOBN structure learning and automatic ontology enrichment. The leading idea of our approach is to capitalize on analyzing the elements that are common to both tasks with the intension of improving their state-of-the-art methods. In fact, our work is considered as an initiative aiming to set up new bridges between PGMs and ontologies. The originality of our method lies first, on the use of the OOBN framework which allowed us to address an extended range of ontologies, second, on its bidirectional benefit as it ensures a real cooperation, in both ways, between ontologies and OOBNs.

Nevertheless, this current version is subject to several improvements. As a first line of research, we aim to implement our method and test it on real world applications based on ontologies, furthermore, in this work, our aim was to provide a warning system able to propose a set of possible changes to the ontology engineers. The discovered relations and / or concepts have to be denominated so, as possible research direction, we will be interested in natural language processing (NLP) methods to allow the automation of this process. Our last perspective concerns the use of another PGM, Probabilistic Relational Models (Getoor et al., 2007),whose characteristics are similar to OOBNs.

REFERENCES

Bangsø, O., Langseth, H., and Nielsen, T. D. (2001). Structural learning in object oriented domains. In *Proceedings of the 14th International Florida Artificial Intelligence Research Society Conference*, pages 340–344.

Bangsø, O. and Wuillemin, P.-H. (2000). Object oriented bayesian networks: a framework for top-down specification of large bayesian networks with repetitive structures. Technical report, Aalborg University.

Bellandi, A. and Turini, F. (2009). Extending ontology queries with bayesian network reasoning. In *Proceedings of the 13th International Conference on Intelligent Engineering Systems*, pages 165–170, Barbados.

Ben Ishak, M., Leray, P., and Ben Amor, N. (2011). Ontology-based generation of object oriented bayesian networks. In *Proceedings of the 8th Bayesian Modelling Applications Workshop*, pages 12–20, Barcelona, Spain.

Ben Messaoud, M., Leray, P., and Ben Amor, N. (2011). Semcado: a serendipitous strategy for learning causal bayesian networks using ontologies. In *Proceedings of the 11th European Conference on Symbolic and Quantitative Approaches to Reasoning with Uncertainty*, pages 182–193, Belfast, Northern Ireland.

Costa, P. and Laskey, K. (2006). PR-OWL: A framework for probabilistic ontologies. *Frontiers In Artificial Intelligence and Applications*, 150:237–249.

Ding, Z. and Peng, Y. (2004). A probabilistic extension to ontology language OWL. In *Proceedings of the 37th Hawaii International Conference On System Sciences*.

Fenz, S., Tjoa, M., and Hudec, M. (2009). Ontology-based generation of bayesian networks. In *Proceedings of the 3rd International Conference on Complex, Intelligent and Software Intensive Systems*, pages 712–717, Fukuoka, Japan.

Getoor, L., Friedman, N., Koller, D., Pfeffer, A., and Taskar, B. (2007). Probabilistic relational models. In Getoor, L. and Taskar, B., editors, *An Introduction to Statistical Relational Learning*, pages 129–174. MIT Press.

Gruber, T. (1993). A translation approach to portable ontology specifications. *Knowledge Acquisition*, 5(2):199–220.

Helsper, E. M. and van der Gaag, L. C. (2002). Building bayesian networks through ontologies. In *Proceedings of the 15th European Conference on Artificial Intelligence*, pages 680–684, Amsterdam.

Khattak, A. M., Latif, K., Lee, S., and Lee, Y.-K. (2009). Ontology evolution: A survey and future challenges. In *The 2nd International Conference on u-and e- Service, Science and Technology*, pages 285–300, Jeju.

Koller, D. and Pfeffer, A. (1997). Object-oriented bayesian networks. In *Proceedings of the 13th Conference on Uncertainty in Artificial Intelligence*, pages 302–313, Providence, Rhode Island, USA. Morgan Kaufmann.

Langseth, H. and Nielsen, T. D. (2003). Fusion of domain knowledge with data for structural learning in object oriented domains. *Journal of Machine Learning Research*, 4:339–368.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems*. Morgan Kaufmann, San Franciscos.

Stojanovic, L., Maedche, A., Stojanovic, N., and Motik, B. (2002). User-driven ontology evolution management. In *Proceedings of the 13th International Conference on Knowledge Engineering and Knowledge Management*, pages 285–300, Siguenza, Spain.

Yang, Y. and Calmet, J. (2005). Ontobayes: An ontology-driven uncertainty model. In *The International Conference on Intelligent Agents, Web Technologies and Internet Commerce*, pages 457–463, Vienna, Austria.

Zheng, H., Kang, B.-Y., and Kim, H.-G. (2008). An ontology-based bayesian network approach for representing uncertainty in clinical practice guidelines. In *ISWC International Workshops, URSW 2005-2007, Revised Selected and Invited Papers*, pages 161–173.