

---

# Bayesian Ontologies in AI Systems

---

**Paulo C. G. da Costa, Kathryn B. Laskey**

C4I Center - George Mason University  
4400 University Drive  
Fairfax, VA 22030-4400  
[pcosta, klaskey]@gmu.edu

**Ghazi AlGhamdi**

Royal Saudi Air Forces  
P.O. Box 56819  
Riyadh 11564 Saudi Arabia  
ghazi.alghamdi@gmail.com

## Abstract

Ontologies have become ubiquitous in current-generation information systems. An ontology is an explicit, formal representation of the entities and relationships that can exist in a domain of application. Following a well-trodden path, initial research in computational ontology has neglected uncertainty, developing almost exclusively within the framework of classical logic. As appreciation grows of the limitations of ontology formalisms that cannot represent uncertainty, the demand from user communities increases for ontology formalisms with the power to express uncertainty. Support for uncertainty is essential for interoperability, knowledge sharing, and knowledge reuse. Bayesian ontologies are used to describe knowledge about a domain with its associated uncertainty in a principled, structured, sharable, and machine-understandable way. This paper considers Multi-Entity Bayesian Networks (MEBN) as a logical basis for Bayesian ontologies, and describes PR-OWL, a MEBN-based probabilistic extension to the ontology language OWL. To illustrate the potentialities of Bayesian probabilistic ontologies in the development of AI systems, we present a case study in information security, in which ontology development played a key role.

## 1 INTRODUCTION

The term ontology came from Philosophy and was applied to Information Systems in the late seventies to characterize the formalization of a body of knowledge describing a given domain. One of the major drivers for the popularity of that concept was the realization that many of the most challenging problems in the information technology field (e.g. interoperability among systems) cannot not be solved without considering the semantics intrinsically embedded in each particular knowledge system. In other words, addressing issues such as *type consistency* or *consistency of format* might sometimes work in very controlled environments, but successful knowledge sharing requires *semantic interoperability*, a much stronger requirement. For example, consider the sentence, “Washington voiced strong objections to the UN Resolution proposed by the European Union.”

Semantic interoperability means not just that two distinct knowledge systems are able to exchange data in a given format (e.g., the character string “Washington”), but also that the *referent* of the token must have the same meaning for both parties (e.g., “Washington” refers to the United States as an agent, and not to the first President of the United States, a state in the Pacific Northwest, or a baseball team).

Commonly touted as a promising solution to the problem of semantic interoperability (e.g., Chandrasekaran *et al.* 1999), ontologies are formal representations of knowledge about a given domain, typically expressed in a manner that can be processed by machines. Specifically, an ontology explicitly represents the types of entities that can exist in the domain, the properties these entities can have, the relationships they can have to one another, the roles they can play with respect to one another, how they are decomposed into parts, and the events and processes in which entities can participate. Ontologies are useful for ensuring that producer and consumer share a common interpretation of data, especially in situations in which ownership boundaries are crossed.

Standard representation languages for ontologies such as the OWL Web ontology language (Patel-Schneider *et al.* 2004) and publicly available ontologies can greatly facilitate the development of interoperable systems, but the process of integrating and reusing ontologies remains fraught with difficulty (see Valente *et al.* 1999 for discussion of some of the difficulties in the context of a case study in air campaign planning). Ontologies are developed with a focus and from a point of view. This means that gaps, overlaps, and inconsistencies will continue to exist when independently developed ontologies are used together. Developers and users may have little incentive to participate in the tedious process of constructing ontologies. Furthermore, service providers may have incentive to “game” the system by designing ontologies to show their product in a good light as compared with competitors, at the expense of information that would help consumers to make meaningful comparisons between the merits of different providers. Methods for automated discovery of metadata and construction of ontologies can help to overcome the tedium and mitigate non-compliance but gaps and inconsistencies

are unavoidable. Automation can also help to control gaming, but each closed loophole spurs innovation to discover another. Additionally, the infeasibility of enforcing a single global standard ontology means that semantic interoperability will continue to be a difficult objective to achieve in an environment in which capabilities are controlled by a diverse and heterogeneous set of agents.

A major shortcoming of ontologies is their inability to represent and reason with uncertain, incomplete data. Due to various factors (see Costa 2005) virtually all current ontology formalisms are based on classical logic, and thus provide no support for plausible reasoning. In the example above, a standard ontology might enumerate several possible senses for the word “Washington,” but would have no ability to grade their relative plausibility in a given context. This is inadequate for an open world environment in which noisy and incomplete information is the rule. Not surprisingly, as ontology engineering research has achieved a greater level of maturity, the need for representing uncertainty in ontologies in a principled way has become clear. There is increasing interest in extending traditional ontology formalisms to include sound mechanisms for representing and reasoning with uncertainty (Costa *et al.* 2005).

## 2 RELATED RESEARCH

One of the main reasons why research in ontology languages is still focused on deterministic approaches has been the limited expressivity of traditional probabilistic languages. There is a current line of research focused on extending OWL so it can represent probabilistic information contained in a Bayesian Network (e.g. Ding & Peng 2004, Gu *et al.* 2004). The approach involves augmenting OWL semantics to allow probabilistic information to be represented via additional markups. The result would be a probabilistic annotated ontology that could be translated to a Bayesian network (BN). Such a translation would be based on a set of translation rules that would rely on the probabilistic information attached to individual concepts and properties within the annotated ontology. BNs provide an elegant mathematical structure for modeling complex relationships among hypotheses while keeping a relatively simple visualization of these relationships. Yet, the limited attribute-value representation of BNs makes them unsuitable for problems requiring greater expressive power.

Another option for representing uncertainty in OWL is to focus on OWL-DL, a decidable subset of OWL that is based on Description Logics (Baader *et al.* 2003). Description Logics are a family of knowledge representation formalisms that represent the knowledge of an application domain (the “world”) by first defining the relevant concepts of the domain (its terminology), and then using these concepts to specify properties of objects and individuals occurring in the domain (the world description). Description Logic divides a knowledge base into two components: a terminological box, or T-Box, and

the assertional box, or A-Box. The first introduces the terminology (i.e. the vocabulary) of an application domain, while the latter contains assertions about instances of the concepts defined in the T-Box. Description Logic is a subset of FOL that provides a very good combination of decidability and expressiveness, and is the basis of OWL-DL. Probabilistic extensions have been developed for description logics (e.g. Jaeger 1994, Koller *et al.*, 1997, Giugno & Lukasiewicz 2002) Description logics are highly effective and efficient for the classification and subsumption problems they were designed to address. However, their ability to represent and reason about other commonly occurring kinds of knowledge is limited. An example of a restrictive aspect of DL languages is their limited ability to represent constraints on the instances that can participate in a relationship.

Although the above approaches are promising where applicable, a definitive solution for the generic semantic mapping problem requires a general-purpose formalism that gives ontology designers a range of options to balance tractability against expressiveness. Pool and Aiken (2004) developed an OWL-based interface for the relational probabilistic toolset Quiddity\*Suite, developed by IET, Inc. Their constructs provide an expressive method for representing uncertainty in OWL ontologies. Their work is similar in spirit to ours, but is specialized to the Quiddity\*Suite toolset. We employ MEBN as our underlying logical basis, thus providing full first-order expressiveness. Costa (2005) presents rules for constructing PR-OWL ontologies in a manner that can be translated into Quiddity\*Suite, and for performing the translation.

## 3 REPRESENTING UNCERTAINTY

Initial attempts to represent uncertainty in ontology languages tend to begin with constructs for attaching probabilities as attributes of entities. This approach is clearly inadequate, in that it fails to account for structural features such as conditional dependence (or independence), double counting of influence on multiply connected graphs, and context-specific independence. Many researchers have pointed out the importance of structural information in probabilistic models (e.g. Shafer 1986, Pearl, 1988, Schum 1994, Kadane & Schum 1996). It is well known that some questions about evidence can be answered entirely in structural terms (e.g., 1994, page 271). In short, annotating an ontology with numerical probabilities is just not enough, as too much information is lost to the lack of a representational scheme that can capture structural nuances of the probabilistic information.

### 3.1 PROBABILISTIC ONTOLOGIES

Probabilistic ontologies expand standard ontologies by providing logically sound constructs for representing statistical regularities and probabilistic interrelationships in a domain of application.

**Definition 1** (from Costa 2005): A *probabilistic ontology* is an explicit, formal knowledge representation that expresses knowledge about a domain of application. This includes:

- 1a. Types of entities that exist in the domain;
- 1b. Properties of those entities;
- 1c. Relationships among entities;
- 1d. Processes and events that happen with those entities;
- 1e. Statistical regularities that characterize the domain;
- 1f. Inconclusive, ambiguous, incomplete, unreliable, and dissonant knowledge related to entities of the domain; and
- 1g. Uncertainty about all the above forms of knowledge;

where the term entity refers to any concept (real or fictitious, concrete or abstract) that can be described and reasoned about within the domain of application. ■

Any representational scheme that attempts to convey all the details and idiosyncrasies of a complex domain must be highly expressive. Although tractability requirements often motivate restrictions on the ability of reasoning engines to process highly expressive representations, if ontologies are to be general-purpose repositories of shared knowledge, then restrictions on reasoners must not dictate what it is possible to say about a domain. As a logical basis for our ontology language, we used Multi-Entity Bayesian Networks (MEBN) because of its ability to represent probability distributions over interpretations of arbitrary first-order domain theories (Laskey 2006).

### 3.2 THE UNDERLYING LOGIC

MEBN is a first-order Bayesian logic that integrates classical first-order logic with probability theory. Classical first-order logic (FOL) is by far the most commonly used, studied and implemented logical system, serving as the logical basis for most current-generation AI systems and ontology languages. MEBN logic provides the basis for extending the capability of these systems by introducing a sound mathematical basis for representing and reasoning under uncertainty.

MEBN represents the world as comprised of entities that have attributes and are related to other entities. Knowledge about the attributes of entities and their relationships to each other is represented as a collection of *MEBN fragments* (MFrag) organized into *MEBN Theories*. An MFrag represents a conditional probability distribution for instances of its resident random variables given their parents in the fragment graph and the context nodes. An *MEBN Theory* is a set of MFrag that collectively satisfies consistency constraints ensuring the existence of a unique joint probability distribution over instances of the random variables represented in each of the MFrag within the set. MEBN semantics integrates the standard model-theoretic semantics of classical first-

order logic with random variables as formalized in mathematical statistics.

As a full integration of first-order logic and probability, MEBN provides: (1) a means of expressing a globally consistent joint distribution over models of any consistent, finitely axiomatizable FOL theory; (2) a proof theory capable of identifying inconsistent theories in finitely many steps and converging to correct responses to probabilistic queries; and (3) a built in mechanism for adding sequences of new axioms and refining theories in the light of observations.

## 4 BAYESIAN ONTOLOGIES IN PR-OWL

PR-OWL is a probabilistic extension to the OWL Web ontology language. The OWL specification is a Recommendation issued by the Worldwide Web Consortium (W3C). An active OWL user community has grown up, and there is growing interest in probabilistic extensions to OWL (Costa, et al., 2005). PR-OWL provides constructs for writing ontologies containing probabilistic information that could be processed by diverse tools (e.g. Netica, Hugin, Quiddity\*Suite, JavaBayes, etc.) employing different representation formalisms (e.g. PRMs, BNs, OOBNs, etc). That level of flexibility can only be achieved using the underlying semantics of first-order Bayesian logic, which is not a part of the standard OWL semantics and abstract syntax.

Ideally, specification of a probabilistic ontology language would follow the steps defined by the W3C (Jacobs, 2003) to issue an official standard. New tools would need to be developed to support the extended syntax and implied semantics of the probabilistic extensions. Such an effort would require commitment from diverse developers and workgroups, which falls outside our present scope. For this reason, PR-OWL was written as an upper OWL ontology. DaConta *et al.* define an upper ontology as a set of integrated ontologies that characterizes a set of basic commonsense knowledge notions (2003, page 230). In our initial definition of PR-OWL as an upper ontology, these basic commonsense notions are related to representing uncertainty in a principled way using OWL syntax.

PR-OWL consists of a set of classes, subclasses and properties that collectively form a framework for building probabilistic ontologies. The first step toward building a probabilistic ontology in compliance with our definition is to import into any OWL editor an OWL file containing the PR-OWL classes, subclasses, and properties. An overview of the general concepts involved in the definition of a MEBN Theory in PR-OWL is depicted in Figure 1. In this diagram, the ovals represent general classes; and arrows represent major relationships between classes. A probabilistic ontology must have at least one individual of class *MTheory*, which is a label linking a group of MFrag that collectively form a valid MEBN Theory. In actual PR-OWL syntax, that link is expressed

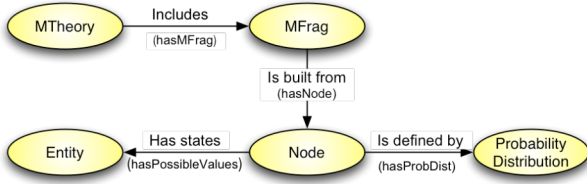


Figure 1 – Major PR-OWL Concepts / Classes

via the object property *hasMFrag* (which is the inverse of object property *isMFragIn*).

Individuals of class MFrag are comprised of nodes, which can be resident, input, or context nodes (not shown in the picture). Each individual of class Node is a random variable and thus has a mutually exclusive and collectively exhaustive set of possible states. In PR-OWL, the object property *hasPossibleValues* links each node with its possible states, which are individuals of class Entity. Finally, random variables (represented by the class Nodes in PR-OWL) have unconditional or conditional probability distributions, which are represented by class Probability Distribution and linked to its respective nodes via the object property *hasProbDist*.

The scheme in Figure 1 is intended to present just a general view and omits many details of an actual PR-OWL representation of a MEBN Theory. Figure 2 shows an expanded version conveying the main elements in Figure 1, their subclasses, the secondary elements that are needed for representing a MEBN Theory and the reified relationships that were necessary for expressing the complex structure of a Bayesian probabilistic model using OWL syntax. Reification is the treatment of an analytic or abstract relationship as though it were a real entity. Use of reification is necessary in PR-OWL because properties in

OWL are binary relations (i.e. link two individuals or an individual and a value), while many of the relations in a probabilistic model include more than one individual (i.e. N-ary relations). The use of reification for representing N-ary relations on the Semantic Web is covered by a working draft from the W3C's Semantic Web Best Practices Working Group (Noy & Rector 2004).

Although the scheme in Figure 2 shows all the elements needed to represent a complete MEBN Theory, it is clear that any attempt at a complete description would render the diagram cluttered and incomprehensible. A complete account of the classes, properties and the code of PR-OWL that define an upper ontology for probabilistic systems is given in Costa (2005). These definitions can be used to represent any MEBN Theory as formalized in Laskey (2006).

Probabilistic ontologies written using the PR-OWL upper ontology achieve a principled representation of uncertainty and allow for the use of different probabilistic reasoning systems as a means to perform plausible reasoning and learning from data on the MEBN Theories represented in PR-OWL format. The advances presented here in terms of writing PR-OWL Bayesian Ontologies can be directly applied to AI systems, increasing their potential for knowledge sharing, reusability, and interoperability.

To illustrate the power of probabilistic ontologies, consider an example from the information security domain. A system for reasoning about threats to a secure information system might need to integrate two ontologies that classify threats differently. One ontology might have a very coarse classification system for attack types, whereas another ontology might have a much more

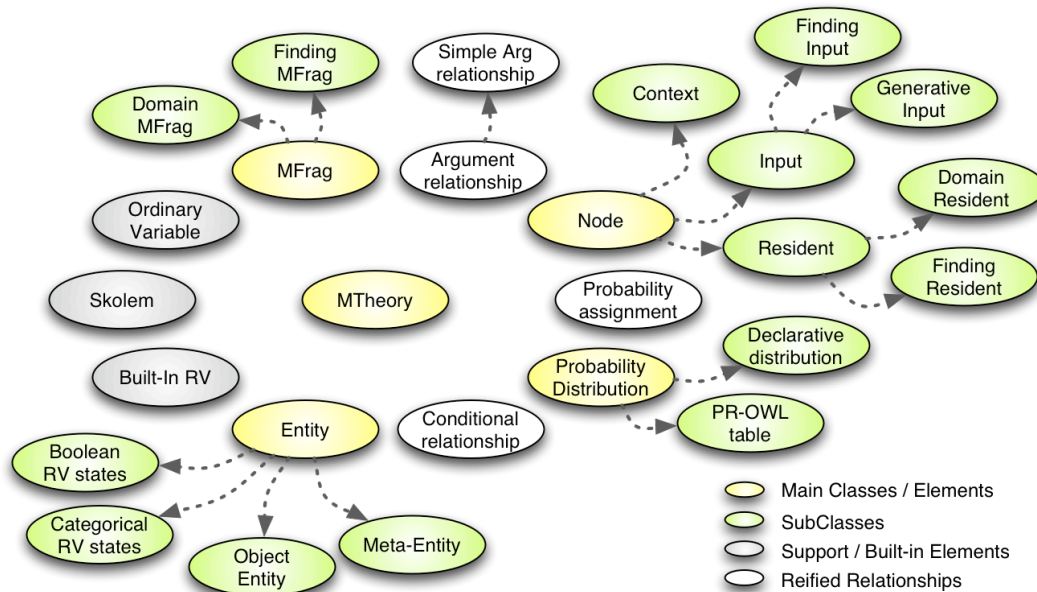


Figure 2 – Elements of a MEBN-based Bayesian Ontology written in PR-OWL

finely differentiated system with separate subtypes for minor variants of a given attack type. An attack instance might be classified by a system based on the first ontology, and passed for further processing to a system that makes use of the second ontology. In the simplest case, the second ontology is a refinement of the first, but in more complex cases, there may not be a neat mapping of leaf classes in the first ontology to non-leaf classes in the second. A probabilistic ontology provides a way to use classification information from the first system as evidence to rule out some classes in the second ontology and infer probabilities for others.

Although some ontology languages do offer constructs that help to import one ontology into another, they lack a principled means for grading the similarity between concepts or to make plausible inferences about the mapping between them. Providing such a means is an important step towards making the semantic mapping problem a less expensive, tedious, error-prone process. In short, the lack of a principled representation for uncertainty in the field of ontological engineering is a major weakness hindering efforts towards better solutions for the semantic mapping problem. More generally, lack of support for uncertainty management is a serious impediment to reaping the potential benefits of formal ontologies.

## 5 CASE STUDY: THE DTB PROJECT

DTB stands for Detection of Threat Behavior, a project initially funded by ARDA<sup>1</sup> and conducted jointly by IET<sup>2</sup> and GMU. The project focused on a particularly insidious threat: that posed by individuals who misuse their privileges to gain access to sensitive information in order to make it available to unauthorized parties (e.g.: other states, terrorists), or to manipulate it with the purpose of producing misleading analysis (AlGhamdi *et al.* 2004).

The overall idea of the DTB project is to model user queries and detect situations in which users in sensitive positions may be accessing documents outside their assigned areas of responsibility. This novel approach to insider threats assumes a controlled environment in which rules for accessing information are clearly defined and, ideally, tightly enforced. Although such environments provide little encouragement to insider threats, unusual access patterns are not easily detected given current technology. In fact, documented cases in which insiders used unsophisticated tactics to outsmart standard security systems (e.g. CNN.com, 1998) leave a very uncomfortable open question: what about the sophisticated ones?

---

<sup>1</sup> ARDA – Advanced Research and Development Activity ([www.ic-arda.org](http://www.ic-arda.org))

<sup>2</sup> IET – Information Extraction and Transport, Inc. ([www.iet.com](http://www.iet.com))

Catching more elaborate patterns that might be characteristic of users attempting illegal activities such as disclosure of classified information is a daunting task that must be tackled with a powerful inference method capable of dealing with the uncertainty involved in the process. The flexible modeling framework provided by multi-entity Bayesian networks makes it an obvious candidate to model the intricacies of security-controlled environments. Its natural ability to capture a domain with the richness of details required for feeding its inference engine is a major strength, but poses a well known challenge to modelers: how to make the model interoperable among different agencies and systems. This requirement implies conflicting objectives. There is a need to define concepts precisely enough to capture the subtlest hints of suspicious behavior under a given agency's rules. Yet, there is also a need to construct a model that is sufficiently general to be reused, with appropriate modification, by other agencies. This is a common dilemma for system developers.

The project's final product is intended for a community with many possible users, both inside the Intelligence community and outside it. This leads to diverse (although similar) vocabularies, policies, organization culture, etc, with a great potential of invalidating the initial model. Like most complex domains, the Intelligence community does not have a commonly accepted set of rules, policies, or vocabulary; deeming sophisticated, detail-rich systems unlikely to achieve interoperability without extra effort devoted specifically to this end. In the DTB project, ontologies were employed as a means to address the above issues. Because different views of a domain have to be represented by different ontologies, any interoperable system built upon ontologies must have a means of dealing with the ontology mapping problem. The project started with a focus on building a user behavior model for detecting suspicious user activities, and on devising data mining algorithms capable of extracting document relevance data to feed the user behavior model. At the same time, two ontologies were developed as a formal representation of aspects of the domain relevant to the user behavior model and the data mining algorithms. Both ontologies were developed with the open source ontology tool Protégé. The first, the *Insider Behavior ontology (IB)*, describes the entities, attributes and relationships represented in the MEBN model of insider threat behavior. The second, the *Organization and Task Ontology (OT)*, represents features of an organization such as internal rules, security clearance categories, such "need to know" rules, and compartment types (and these terms' respective meanings with regard to data access), the topic classifications used by the data mining algorithms we use to capture document relevance, and other domain-relevant information.

It is important to emphasize the role of ontologies as a tool for enforcing semantic consistency of the models. Since both ontologies were made "in sync" with the

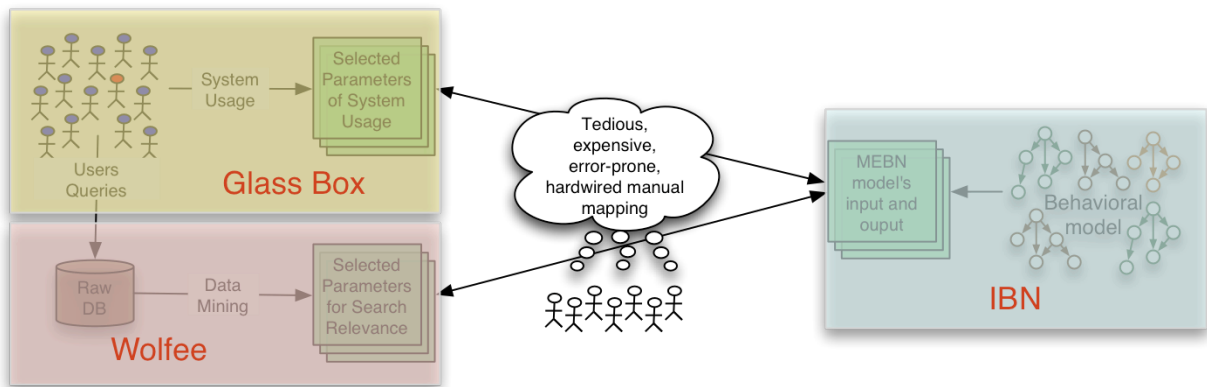


Figure 3 – The Insider Threat Detection Process with no use of Ontologies

development phase of their subjects, the modelers were forced not only to think about the specific model details but also about ensuring that each variable and its semantic meaning is consistent with the models and with the domain's concepts.

Once the behavioral model and the data mining algorithms were ready, the next step was to extract the actual data to be used for assessing the relevance of each user's search with respect to his/her assigned task. For this task, the project adopted the software Glass Box, a Java-based user monitoring application available to researchers on ARDA's Novel Intelligence from Massive Data project (NIMD) (<http://glassbox.labworks.org>). Glass Box was used to capture the actions of users and then extract the information needed for the data mining algorithms. Since our focus now is on the flow of knowledge within the system, the reader is referred to Shackelford (2005) for details on the data mining algorithms.

The flow, which is depicted in figure 3, starts with a set of users (top left), whose queries and general system usage is analyzed. User queries are passed to data mining algorithms that infer the degree of relevance of user queries to various topics. Results of data mining are fed to the behavioral MEBN model. System usage refers to general parameters that can be used by the MEBN model to make inferences about unusual patterns (e.g. user login time, copy and paste actions, etc). The three bigger, translucent boxes in the figure represent the system's software modules, while the arrows represent their respective integration requirements. Glass Box is used for capturing all data, of which some will be discarded, some will feed the MEBN model directly, and some will go through the data mining process, which will capture the relevance of a given user's searches with respect to his/her assigned task. The results of the data mining process will also feed the behavioral model, as further

information for assessing each user's likelihood of being an insider threat or not.

As highlighted above, the communication between software packages has to be "hardwired" via their respective APIs, in a tedious, manual, expensive, error-prone process that has to be repeated for every change in any parameter of any software package, for any additional feature in the system, and for every change of policy inside the agency in which the system is installed. This inflexible scheme also hinders interoperability. For every agency where the system is to be installed we would have to repeat this whole process and little if any of the previous setup efforts could be reused.

The approach used for solving the DTB project's interoperability problem was to use ontologies as information brokers between software applications, as depicted in Figure 4. By doing so, the parameters are "hardwired" between each application and its respective ontology, instead of between applications as in the original scheme depicted in Figure 3. Therefore, if (say) there were a change in working hours of a given agency, there would be no need to search all APIs for variables using this information. Instead, only a single ontology has to be changed and the others will be updated via the Integration Ontology (IO).

It is important to note the nature of the IO. Contrary to most approaches in semantic mapping, the work in the DTB project is not towards a "merged", "coarser", bigger ontology containing domain information represented in GB, IB, or OT ontologies. Instead, IO is a domain-free, meta-ontology carrying only information about the semantic mapping between each of the domain ontologies in the system. The structure, classes, and slots of the IO will not represent the domain in which the system being applied. Domain information will appear only in the instances of IO, which convey the actual relationships among the domain ontologies' concepts.

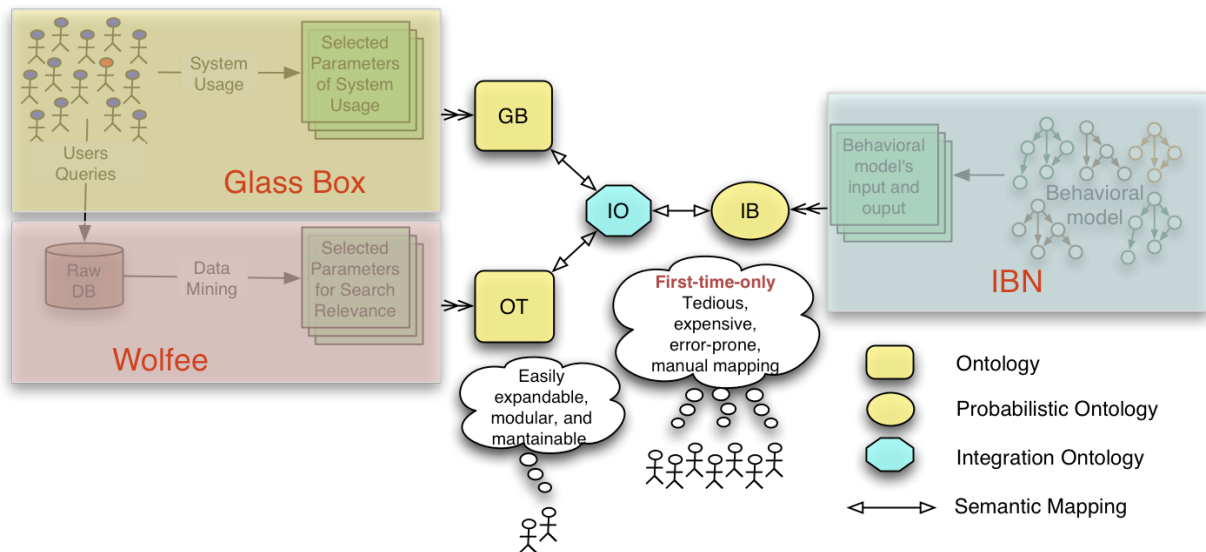


Figure 4 – The Insider Threat Detection Process using a Probabilistic Ontology

This approach to integration provides an elegant way of conveying semantic mapping information. Avoiding domain-related knowledge in the IO makes it much easier to maintain and to expand, as modifications in the ontologies being mapped will affect only the mappings (i.e. the instances of IO) and not the IO itself. Some common problems arise from such a scheme, for example: how can we measure the commonality between any two concepts in different ontologies? These are issues that confront any semantic mapping approach. Our probabilistic approach promises to provide new insights for tackling these difficult questions.

## 6 DISCUSSION AND FUTURE WORK

Semantic interoperability is a major objective in general IT system development and a necessary ingredient for AI systems seeking improved knowledge sharing and reuse. In this work, we discussed the role of ontologies in general and probabilistic ontologies in particular as a means to achieve semantic interoperability. We presented a Bayesian ontology language based on MEBN logic that provides a means to express first-order probabilistic theories. As a tool for writing probabilistic ontologies, PR-OWL has the potential to greatly improve the development of AI systems. Finally, the DTB project was introduced as an example of how Bayesian ontologies can improve knowledge sharing in an AI system.

Probabilistic ontologies are an increasingly important topic in forums devoted to best practices in systems development. Given the nature of the domain knowledge embedded in their systems, AI system developers would profit most from the advantages of being able to convey such knowledge with a principled treatment for uncertainty.

## Acknowledgments

Grateful acknowledgement is due to Ken Laskey for insightful comments and discussions on semantic interoperability and data exchange issues, to Mike Pool for helpful discussions on probabilistic ontologies, and to Ed Wright for many valuable discussions and insights. Kathryn Laskey's work was partially supported by the Advanced Research and Development Activity (ARDA), under contract NBCHC030059, issued by the Department of the Interior. Additional support was provided by the US Navy. The views, opinions, and findings contained in this paper are those of the author(s) and should not be construed as an official position, policy, or decision, of ARDA, the Department of the Interior, or the US Navy unless so designated by other official documentation.

## References

- AlGhamdi, G., Laskey, K. B., Wang, X., Barbara, D., Shackleford, T., Wright, E. J., et al. (2004). Detecting Threatening Behavior Using Bayesian Networks, Conference on Behavioral Representation in Modeling and Simulation - BRIMS. Arlington, VA, USA.
- Baader, F., et al., eds. (2003) *The Description Logic Handbook: Theory, Implementation and Applications*. First edition ed., Cambridge University Press: Cambridge, UK. 574
- Chandrasekaran, B., Josephson, J.R., and Benjamins, V. R. (1999). What are Ontologies and Why Do We Need Them? *IEEE Intelligent Systems* 14(1).
- CNN.com. (1998). Rationalizing Treason: An Interview with Aldrich Ames. Cold War Experience - Espionage Series Retrieved January 20, 2005, from

- <http://www.cnn.com/SPECIALS/cold.war/experience/spies/interviews/ames/>.
- Costa, P. C. G. (2005). *Bayesian Semantics for the Semantic Web*. Doctoral Dissertation. Department of Systems Engineering and Operations Research, George Mason University: Fairfax, VA, USA. p. 312. <http://hdl.handle.net/1920/455>.
- Costa, P. C. G., Laskey, K.B., Laskey, K.J., and Pool, M. (2005) *Proceedings of the Workshop on Uncertainty Reasoning in the Semantic Web, International Semantic Web Conference*, November 2005.
- Costa, P. C. G.; Laskey, K. B.; and Laskey, K. J. (2005a) PR-OWL: A Bayesian Framework for the Semantic Web. *Proceedings of the first workshop on Uncertainty Reasoning for the Semantic Web (URSW 2005)*, held at the Fourth International Semantic Web Conference (ISWC 2005). November, 6-10 2005, Galway, Ireland.
- Costa, P. C. G.; Fung, F.; Laskey, K. B.; Pool, M.; Takikawa, M.; and Wright, E. (2005b). MEBN Logic: A Key Enabler for Network-Centric Warfare. *Proceedings of the 10<sup>th</sup> International Command and Control Research and Technology Symposium*. [http://mason.gmu.edu/~pcosta/pc\\_publ.html#](http://mason.gmu.edu/~pcosta/pc_publ.html#)
- DaConta, M. C., Obrst, L. J., & Smith, K. T. (2003). *The Sematic Web: A Guide to the Future of Xml, Web Services, and Knowledge Management*. Indianapolis, IN, USA: Wiley Publishing, Inc.
- Ding, Z., and Y. Peng. (2004). A probabilistic extension to ontology language OWL. in *37th Annual Hawaii International Conference on System Sciences (HICSS'04)*. Big Island, Hawaii.
- Giugno, R. and T. Lukasiewicz. (2002) P-SHOQ(D): A probabilistic extension of SHOQ(D) for probabilistic ontologies in the Semantic Web. in *European Conference on Logics in Artificial Intelligence (JELIA 2002)*. Cosenza, Italy: Springer.
- Gu, T., P.H. Keng, and Z.D. Qing (2004). A Bayesian approach for dealing with uncertainty contexts. in *Second International Conference on Pervasive Computing*. Vienna, Austria: Austrian Computer Society.
- Jacobs, I., ed. (2003). World Wide Web Consortium Process Document. Retrieved March 03, 2005, from <http://www.w3.org/2003/06/Process-20030618/cover.html>.
- Laskey, K.B. (2006) *MEBN: A Logic for Open-World Probabilistic Reasoning*. <http://ite.gmu.edu/~klaskey/index.html>.
- Kadane, J. B., & Schum, D. A. (1996). *A Probabilistic Analysis of the Sacco and Vanzetti Evidence*. New York, NY, USA: John Wiley & Sons.
- Koller, D., Levy, A. Y., & Pfeffer, A. (1997). P-CLASSIC: A Tractable Probabilistic Description Logic. Paper presented at the Fourteenth National Conference on Artificial Intelligence (AAAI-97), July 27-31. Providence, RI, USA.
- Mahoney, S. M., & Laskey, K. B. (1998). Constructing situation specific networks. *Uncertainty in Artificial Intelligence: Proceedings of the Fourteenth Conference*, San Mateo, CA: Morgan Kaufmann.
- Noy, N.F. and A. Rector (2004). *Defining N-ary relations on the Semantic Web: Use with individuals*, in *W3C Working Draft*. 2004, World Wide Web Consortium: Boston, MA. p. W3C Working Draft.
- Patel-Schneider, P. F., Hayes, P., & Horrocks, I. (2004, February 10). OWL Web Ontology Language - Semantics and Abstract Syntax. W3C Recommendation. Retrieved March 03, 2006, from <http://www.w3.org/TR/owl-semantics/>.
- Pearl, J. (1988) *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, San Mateo, CA: Morgan Kaufmann.
- Pool, M. and Aikin, J. (2004) KEEPER: and Protégé: An elicitation environment for Bayesian inference tools, in *Workshop on Protégé and Reasoning* held at the Seventh International Protégé Conference: Bethesda, MD, USA.
- Shackelford, T. (2005). *Using Data Mining Techniques to Develop Measures of Document Relevance*. Doctoral Dissertation. George Mason University: Fairfax, VA, USA.
- Shafer, G. (1986). The Construction of Probability Arguments. *Boston University Law Review*, 66(3-4), 799-816.
- Schum, D. A. (1994). *Evidential Foundations of Probabilistic Reasoning*. New York, NY, USA: Wiley.
- Valente, A., Russ, T., MacGregor, R. and Swartout, W. (1999). Building and (Re)Using an Ontology of Air Campaign Planning. *IEEE Intelligent Systems* 14(1).
- Takikawa, M., d'Ambrosio, B., & Wright, E. (2001). Real-time inference with large-scale temporal Bayes nets. *Uncertainty in Artificial Intelligence: Proceedings of the Seventeenth Conference*, San Mateo, CA: Morgan Kaufmann.