

# Probabilistic Ontologies for Knowledge Fusion

**Kathryn Blackmond Laskey, Paulo C. G. Costa**

Center of Excellence in C4I  
George Mason University, MS 4B5  
Fairfax, VA 22030-444 U.S.A.  
{klaskey, pcosta}@gmu.edu

**Terry Janssen**

Lockheed Martin Corporation, IS&GS/GSS  
13560 Dulles Technology Drive  
Herndon, VA 20171 USA  
terry.janssen@lmco.com

*Abstract – To cope with asymmetric threats in an increasingly network centric environment, today's command support systems must interoperate with a diverse collection of other systems. As a natural consequence, the focus is changing from data fusion to knowledge fusion. This new reality creates the need for advanced techniques that exploit not only the syntactic structure of knowledge bases, but also the semantic content. Ontologies play a major role in semantically aware systems, providing a means for highly effective knowledge sharing. However, they lack a standardized treatment of uncertainty, a ubiquitous feature of multi-source fusion problems. This paper discusses the applicability of Probabilistic Ontologies designed in Probabilistic OWL (PR-OWL) to address this unmet need. The potential of PR-OWL probabilistic ontologies is demonstrated through a case study in the counterterrorism domain. A simple PR-OWL ontology for the case study was implemented using a recently released PR-OWL knowledge representation and reasoning system.*

**Keywords:** Probabilistic Ontologies, Bayes Theorem, Semantic Systems, Multi-Entity Bayesian Networks.

## 1 Introduction

Until recently, computers were used primarily as media for storing, exchanging, and working with data. As the volume and bandwidth of available information has skyrocketed, the data deluge has become unmanageable, generating an urgent need for technologies to transform volumes of data into usable knowledge.

As an example, today's command and control systems are seeing a constant increase in data influx from multiple, diverse, and usually geographically dispersed sensors. This situation is not new. In 1985, Crevald observed, "The history of command can thus be understood in terms of a race between the demand for information and the ability of command systems to meet it," ([1], page 265). Modern sensor and communication technology has largely removed the data bottleneck, creating a knowledge bottleneck in its place. Replacing the word "information" in Crevald's assertion to the word "knowledge" generates a perfect description of today's situation.

The task of fusing data from different sensors has evolved to become a task of fusing knowledge from different

systems. Attempts to perform this task by simply matching syntax conventions from diverse systems are doomed to failure. The realization is growing that sharing knowledge among distinct information systems requires first arriving at a common understanding of their respective semantics, and then formalizing that semantics in computable representations.

That is, interoperating systems should interpret terminology in a consistent way. If organizational and/or technology constraints make this infeasible, then appropriate translations must be established between vocabularies used by different systems. Techniques for making semantic information explicit and computationally accessible are key to effective exploitation of data from diverse sources. Shared formal semantics enables systems with different internal representations to exchange information, and provides a means to enforce business rules such as access controls for security.

When heterogeneous systems are required to interoperate in an open world, vocabularies that are developed for individual stand-alone applications break down. Ontologies provide shared representations of the entities and relationships characterizing a domain, into which vocabularies of legacy systems can be mapped. However, a major limitation of traditional ontology formalisms is the lack of consistent support for uncertainty. Because uncertainty is a fundamental aspect of knowledge fusion, this is a serious deficiency. Current ontology formalisms provide no principled means to ensure semantic consistency with respect to issues of uncertainty or data quality.

This paper discusses the applicability of Probabilistic Ontologies [2] as a key element for knowledge fusion among diverse systems. The paper organized as follows. Section 2 introduces Multi-Entity Bayesian Networks (MEBN) [3], the expressive Bayesian logic that underlies the PR-OWL language. Section 3 introduces PR-OWL, an extension of the OWL language that provides constructs for representing probabilistic ontologies. Section 4 presents UnBBayes-MEBN, a system for entering, storing, and reasoning with PR-OWL probabilistic ontologies. Finally, Section 5 uses a counterterrorism case study to demonstrate the power of PR-OWL ontologies for multi-source fusion.

## 2 MEBN

Uncertainty is ubiquitous to knowledge fusion. Almost any source of primary data carries some degree of uncertainty. Bayesian probability is a principled formalism for representing uncertainty and drawing inferences in the presence of uncertainty. Bayesian methods have been widely applied in multi-sensor data fusion systems (e.g. [4, 5]). Bayesian networks (BNs) [6, 7] are popular models for representing and reasoning about problems involving many related hypotheses. BNs have been widely applied to information and knowledge fusion, but are fundamentally limited in their expressive power (see [3] for details). Specifically, in a standard Bayesian network, all the hypotheses and relationships are fixed in advance, and only the evidence can vary from problem to problem. Many multi-source fusion problems involve uncertain numbers of interacting entities related to each other in ways that cannot be known in advance. For example, there may be an indeterminate number of weakly discriminatory reports coming from an unknown number of objects, and there may be uncertainty about which report should be associated with which object. This kind of fusion problem produces an exponential set of association hypotheses that require special hypothesis management methods [c.f. 5, 8]. MEBN logic combines the flexibility of Bayesian Networks with the representational power of First-Order Logic. Among other features, MEBN logic can represent and reason with association uncertainty, and thus provides a sound logical foundation for hypothesis management in multi-source fusion [8].

MEBN represents the world as made up 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 (MFragments) organized into MEBN Theories (MTheories). An MFragment represents a conditional probability distribution of the instances of its resident random variables (RVs) given the values of instances of their parents in the fragment graphs and given the context constraints. RVs are graphically represented in an MFragment either as resident nodes, which have distributions defined in their home fragment, or as input nodes, which have distributions defined elsewhere. Context nodes are the third type of MFragment nodes, and represent conditions assumed for definition of the local distributions.

Typically, MFragments are small, because their main purpose is to model “small pieces” of domain knowledge that can be reused in any context that matches the context nodes. This is a very important feature of the logic for modeling complex, intricate situations and is one that can be seen as the knowledge representation version of the “divide and conquer” paradigm for decision-making. While the latter breaks a hard, complex decision problem in a set of smaller ones, the former uses a similar decomposition approach for representing intricate, complex military situations. This decomposition is accomplished by modeling a complex situation as a collection of small

MFragments, each representing some specific element of a simpler situation. The additional advantage of MEBN modeling is the ability to reuse these “small pieces” of knowledge, combining them in many different ways in different scenarios.

Indeed, MFragments provide a flexible means to represent knowledge about specific subjects within the domain of discourse, but the true gain in expressive power is revealed when aggregating these “knowledge patterns” to form a coherent model of the domain of discourse that can be instantiated to reason about specific situations and refined through learning. It is important to note that just collecting a set of MFragments that represent specific parts of a domain is not enough to ensure a coherent representation of that domain. For example, it would be easy to specify a set of MFragments with cyclic influences (i.e. a random variable which has its probability distribution influencing itself), or one having multiple conflicting distributions for a random variable in different MFragments (i.e. a random variable with more than one home MFragment, each defining a different distribution).

In order to build a coherent model it is important to make sure that a set of MFragments collectively satisfies consistency constraints ensuring the existence of a unique joint probability distribution over instances of the random variables mentioned in the MFragments. Such a coherent collection of MFragments is called an MTheory, and it represents a joint probability distribution for an unbounded, possibly infinite number of instances of its random variables. This joint distribution is specified implicitly through the local and default distributions within each MFragment, together with the conditional independence relationships implied by the fragment graphs.

A generative MTheory summarizes statistical regularities that characterize a domain. These regularities are captured and encoded in a knowledge base using some combination of expert judgment and learning from observation. To apply a generative MTheory to reason about particular scenarios, one needs to provide the system with specific information about the individual entity instances involved in the scenario. On receipt of this information, Bayesian inference can be used both to answer specific questions of interest (e.g., how likely is it that a terrorist is planning to perform a specific attack?) and to refine the MTheory (e.g., each new tactical situation includes additional statistical data about the likelihood of a given attack for that set of circumstances). Bayesian inference is used to perform both problem-specific inference and learning in a sound, logically coherent manner.

MEBN logic provides a sound mathematical basis for representing and reasoning under uncertainty. PR-OWL uses MEBN’s strengths to provide a framework for building probabilistic ontologies (PO), a major step towards semantically aware, probabilistic knowledge fusion systems.

### 3 Probabilistic Ontologies

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. [9]), and it is well known that some questions about evidence can be answered entirely in structural terms (e.g., [9], page 271). Indeed, Shafer ([11], pages 5-9) argues that probability is more about structure than it is about numbers.

This is particularly true in domains such as intelligence analysis and Human Intelligence (HUMINT), in which chains of evidential reasoning and argument structures play a key role [9,10]. Structural information also plays a major role in the way evidence collected from multiple sensors with different degrees of reliability and trust is evaluated. In most cases, distinct aspects of the same piece of information have to be analyzed and weighed based on incomplete knowledge about the source of the information. Structural information is a key asset to provide an in depth analysis of what each piece of knowledge means in the overall context being assessed. Effective sharing of uncertain knowledge between applications requires communicating structure as well as conclusions. The recipient of a communication must be provided enough information about how a conclusion was reached to evaluate its credibility, to use it in the proper context, and to perform the bookkeeping required to prevent double counting. Semantics is key to ensuring that sender and receiver attach the same meaning to the information being communicated.

State-of-the-art systems are increasingly adopting ontologies as a means to ensure formal semantic support for knowledge sharing. In many cases, uncertainty is becoming recognized as an important aspect to be represented and reasoned upon. A common error is to provide support for uncertainty representation by just annotating ontologies with numerical probabilities. This is a weak approach that leads to fragile intelligence systems, as too much information is lost due to the lack of a representational scheme that can capture structural nuances of the probabilistic information. Clearly, more expressive representation formalisms are needed. Probabilistic ontologies [2] have been proposed as a means of meeting this need.

**Definition 1** (from [2]): 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.

Probabilistic ontologies are used for the purpose of comprehensively describing knowledge about a domain and the uncertainty associated with that knowledge in a principled, structured and sharable way, ideally in a format that can be read and processed by a computer. They also expand the possibilities of standard ontologies by introducing the requirement of a proper representation of the statistical regularities and the uncertain evidence about entities in a domain of application.

PR-OWL was developed as an extension enabling OWL ontologies to represent complex Bayesian probabilistic models in a way that is flexible enough to be used by diverse Bayesian probabilistic tools (e.g. Netica, Hugin, Quiddity\*Suite, JavaBayes, etc.) based on different probabilistic technologies (e.g. probabilistic relational models, BNs, etc.). More specifically, PR-OWL is an upper ontology for probabilistic systems that can be used as a framework for developing probabilistic ontologies (as defined above) that are expressive enough to represent even the most complex probabilistic models. DaConta et al. define an upper ontology as a set of integrated ontologies that characterizes a set of basic commonsense knowledge notions ([12], page 230). In PR-OWL, these basic commonsense notions are related to representing uncertainty in a principled way using OWL syntax (itself a specialization of XML syntax), providing a set of constructs that can be employed to build probabilistic ontologies.

Figure 1 shows the main concepts involved in defining an MTheory in PR-OWL.

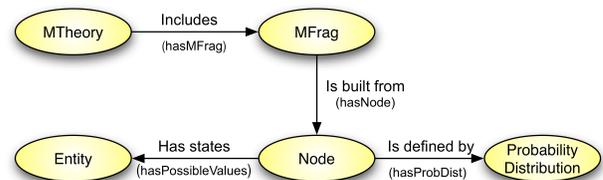


Figure 1 – Main Elements of PR-OWL

In the diagram, ellipses represent general classes while arrows represent the main relationships between these classes. A probabilistic ontology (PO) has to have at least one individual of class MTheory, which is basically a label linking a group of MFrag that collectively form a valid MTheory. In actual PR-OWL syntax, that link is expressed 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 (RV), and thus has a mutually comprehensive, 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 `ProbabilityDistribution` and linked to its respective nodes via the object property `hasProbDist`. Figure 2 depicts the main elements of the PR-OWL language, its subclasses, and the secondary elements necessary for representing an MTheory. The relations necessary to express the complex structure of MEBN probabilistic models using the OWL syntax are also depicted. In addition to [2], the interested reader will find more information on the PR-OWL language at <http://www.pr-owl.org>.

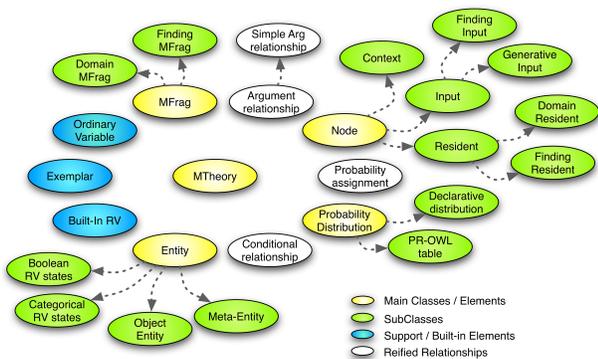


Figure 2 – PR-OWL Elements

The first step towards building a probabilistic ontology in compliance with our Definition 1 is to import into any OWL editor an OWL file containing the PR-OWL classes, subclasses, and properties (one is available at <http://www.pr-owl.org/pr-owl.owl>). After importing the PR-OWL definitions, the next step in ontology design is to construct domain-specific concepts, using the PR-OWL definitions to represent uncertainty about their attributes and relationships. Using this procedure, an ontology engineer is not only able to build a coherent generative MTheory and other probabilistic ontology elements, but also make it compatible with other ontologies that use PR-OWL concepts.

## 4 UnBBayes-MEBN

At its current stage of development, PR-OWL contains only the basic representation elements that provide a means of representing any MEBN theory. Such a representation could be used by a Bayesian tool (acting as a probabilistic ontology reasoner) to perform inferences to answer queries and/or to learn from newly incoming evidence via Bayesian learning.

However, building MFrag in a probabilistic ontology is a manual, error prone, and tedious process. Avoiding errors or inconsistencies requires deep knowledge of the logic

and of the data structures of PR-OWL, since the user would have to know all technical terms such as `hasPossibleValues`, `is-NodeFrom`, `isResidentNodeIn`, etc. In an ideal scenario, many of these terms could be omitted and filled automatic by a software application projected to enforce the consistency of a MEBN model.

The development of UnBBayes-MEBN [13, 14], an open source, Java-based application that is currently in alpha phase (public release March 08), is an important step towards this objective, as it provides both a GUI for building probabilistic ontologies and a reasoner based on the PR-OWL/MEBN framework.

UnBBayes-MEBN was designed to allow building POs in an intuitive way without having to rely on a deep knowledge of the PR-OWL specification. Figure 3 brings a snapshot of the UnBBayes-MEBN user interface. In the figure, a click on the “R” icon and another click anywhere in the editing panel will create a resident node, for which a description can be inserted in the text area at the lower left part of the screen. Clicking on the arrow icon and dragging the cursor from one node to another defines probabilistic relations between nodes, in a manner similar to any number of Bayesian network packages. In response to these actions, the system defines the respective PR-OWL tags (syntactic elements that denote particular parts of a PR-OWL ontology) in the background.

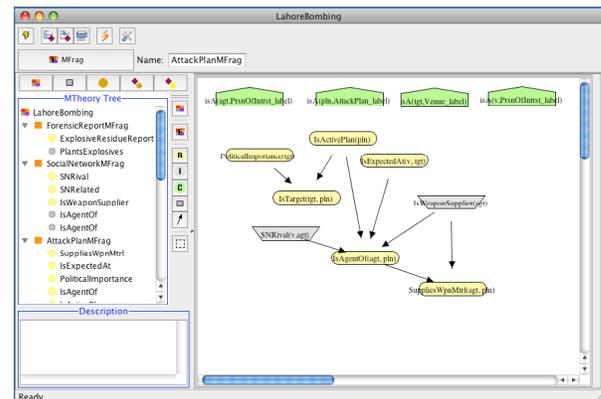


Figure 3 – The UnBBayes-MEBN GUI

Probabilistic Ontologies in UnBBayes-MEBN are saved in PR-OWL format (\*.owl file), while application-specific data is stored in a text file with the \*.ubf extension. Support for MEBN input/output operations is provided via the Protégé-OWL API, which is based on the class `JenaOWLModel`. By using a common API, UnBBayes-MEBN ensures that MTheories created using its GUI can be opened and edited in the popular ontology editor Protégé (and vice-versa). This compatibility is important because it ensures that files created in UnBBayes-MEBN can be opened and edited not only in Protégé, but also in any OWL-compliant application (although these applications will not be able to understand the ontology’s probabilistic characteristics). In addition, ontologies that have already been defined using an OWL-compliant editor can be extended to the PR-OWL format in a quick and direct way. All that is needed is to open the OWL file

in UnBBayes-MEBN, create an MTheory for the ontology, and save the result.

## 5 Case Study : Attack in Lahore

To illustrate the capabilities of PR-OWL to represent the kinds of knowledge fusion problems faced by today’s net-centric systems, we consider a counter-terrorism case study. Our simple illustrative scenario concerns an attempted attack on a high-profile meeting in Pakistan that is detected and prevented through collaboration between two intelligence analysts and interoperation of diverse fusion systems. The case study illustrates the role of semantic technology and probabilistic reasoning in enabling this intelligence success.

*The analysts.* Intelligence analyst IA1 has been assigned the task of compiling and maintaining social networks of persons-of-interest in Pakistan. Over time, he has developed a social network that includes a known arms dealer (AD) in Islamabad and his associates. Meanwhile, intelligence analyst IA2 has been tasked with compiling and maintaining an intelligence profile of the city of Lahore. In this role, IA2 has access to all intelligence reports associated with people, events, communications, etc within his area of responsibility (AOR).

*The meeting.* At present, IA2 is aware of, and is monitoring, a conference of six Tribal Leaders (TL1 – TL6) which is occurring in Lahore. This is a high-profile meeting that is receiving heavy coverage by news agencies all over the world, and is therefore of concern as a potential terrorist target.

*The arrest.* At the Lahore airport, a canine unit has detected explosive residue on a Lahore resident (P) attempting to leave the city. Upon receiving this report, IA2 declares P a person-of-interest. This declaration initiates an automatic interaction to add P to the scope of IA1’s social network, and to alert IA1 to report any significant results concerning P coming from the social network analysis. IA1’s analysis uncovers a third-order relationship between P and AD: P’s brother, BP, has the same religious advisor, C, as AD.

Figure 4 shows a set of MFrag that could be used to support the above analysis. These MFrag are shown as screenshots from the UNBBayes-MEBN system. The MFrag involve reasoning about entities of different types and the relationships among them.

In an operational analyst support system, the PR-OWL ontology that represented the uncertain aspects of this problem would import existing upper ontologies and domain ontologies. For this illustration, we constructed a simple, stand-alone PR-OWL ontology.

*Plan Agent and Target.* This MFrag represents basic information about attacks using explosives. The context random variables, drawn as pentagons at the top of the MFrag, represent logical conditions assumed to hold when the probability distributions are assigned. In this case, the context random variables state that *pln* represents an attack plan, *agt* and *v* represent persons-of-interest, and *tgt* represents a venue that might be targeted by the attack. In

our simple example, we take a venue to denote a localized space-time region that might be the focus of an attack. The MFrag contains two input random variables, whose distributions are defined in other MFrag. These are shown as trapezoids in the figure. They represent whether *agt* is a weapons supplier and whether *v* and *agt* are rivals in the social network. Root nodes in the MFrag are random variables representing whether the plan is active, the political importance of the target, and whether *v*, the potential victim, is expected to be present at the venue.

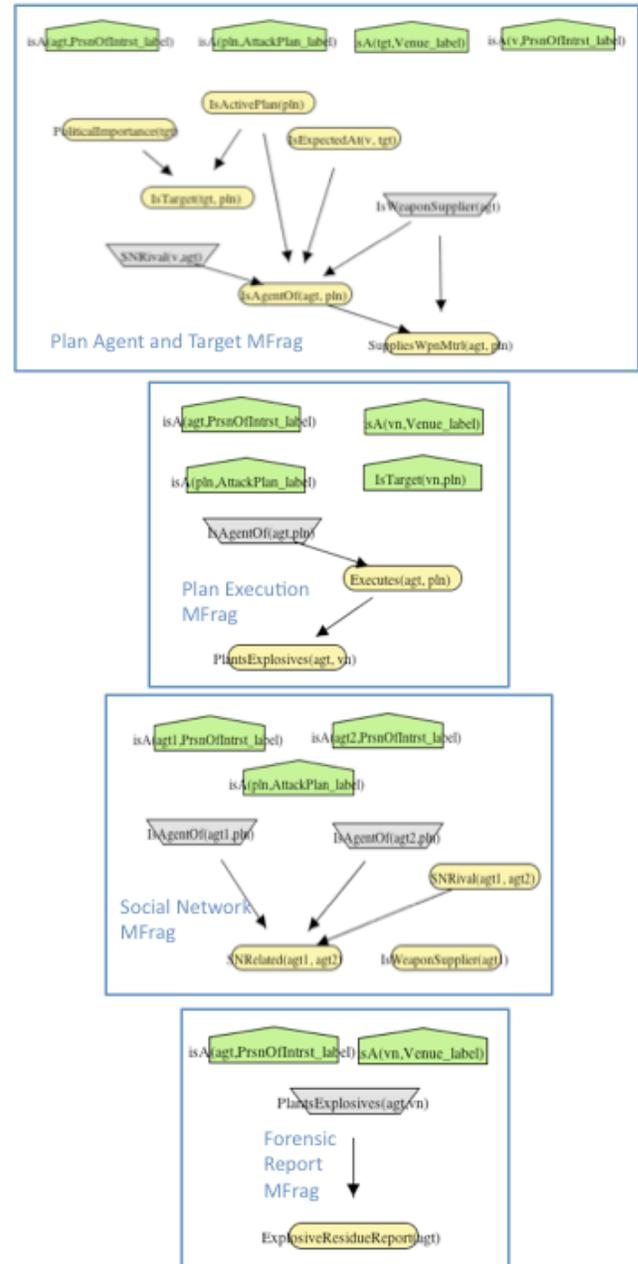


Figure 4 – MFrag for the First SSBN

Whether the venue is targeted depends on whether the plan is active (if the plan is not active, then no venue is targeted by the plan), and the political importance of the venue (important venues are more likely to be targeted).

Whether *agt* is an agent of the plan, i.e., is actively involved in bringing it about, depends on whether the plan is active, whether a rival of *agt* is expected to be at the venue (individuals may try to target their rivals), and whether the *agt* is a weapons supplier (weapons suppliers are more likely to be agents in attacks that use explosives). Finally, whether *agt* plays the role of supplying weapons depends on whether *agt* is an agent of the plan and whether *agt* is a weapons supplier.

**Plan Execution.** This MFrag represents the knowledge that an agent of a plan may execute the plan, and one of the activities a plan executor might perform is to plant explosives at the targeted venue.

**Social Network.** This MFrag represents the actors and their relationships. Its context variables state that *agt1* and *agt2* are persons-of-interest and *pln* is an attack plan. It represents the knowledge that two agents of the same plan are likely to be related in the social network. It also represents the hypothesis that *agt1* and *agt2* are rivals and that a *agt1* is a weapons dealer.

**Forensic Report.** This MFrag represents the possibility that an individual who plants explosives may be apprehended and explosive residues detected.

Each of these MFrag is a template for a fragment of a Bayesian network, and can be instantiated by substituting actual instances for the placeholder variables. For example, instantiating the social network MFrag by substituting AD for *agt1* and C for *agt2* would create random variables *SNRelated(AD,C)*, *SNRival(AD,C)*, and *IsWeaponSupplier(AD)*, representing the hypotheses that AD and C are related in the social network, that they are rivals, and that AD is a weapon supplier. An MFrag may be instantiated any number of times for a given problem, resulting in any number of instances of each of its resident random variables.

Of course, the MTheory described here is highly simplified. Its purpose is to illustrate the capabilities of the language and not to provide a sophisticated representation of terrorist attacks. In particular, our ability to represent the problem is limited by the inability of the alpha implementation of UNBBayes-MEBN to represent subtypes. We expect this limitation to be removed in future versions.

We could not use UNBBayes-MEBN to construct a situation-specific Bayesian network (SSBN) for IA2's analysis problem, because the current alpha implementation is limited to the special case of a single query node with no evidence below the query node, and our model does not meet that limitation. Nevertheless, we did construct a SSBN by hand for this problem.

The prior probability of an arbitrary venue being targeted for an attack was set at 0.02%. For an event of high political importance such as the conference in question, the prior probability was set to 0.3%. After incorporating the information that AD is a weapons dealer who is related in the social network to both C and P, and that explosive residues were detected on P, the probability that

the conference has been targeted for attack becomes about 10%.

As part of his continuing analysis, IA2 has been monitoring the system for current intelligence information related to the conference. A query for the current locations of TL1 through TL6 reveals a SIGINT report that a cell phone call was received by a cell phone owned by TL6, and that the cell phone was geo-located in the city of Karachi. A query for IMINT change detection indicates that a vehicle that was present during the course of the conference is now missing from the conference location. A further analysis of the SIGINT report reveals that the cell phone call to TL6 originated from C. Finally, a query to the social network system reveals that TL6 and TL5 are bitter rivals.

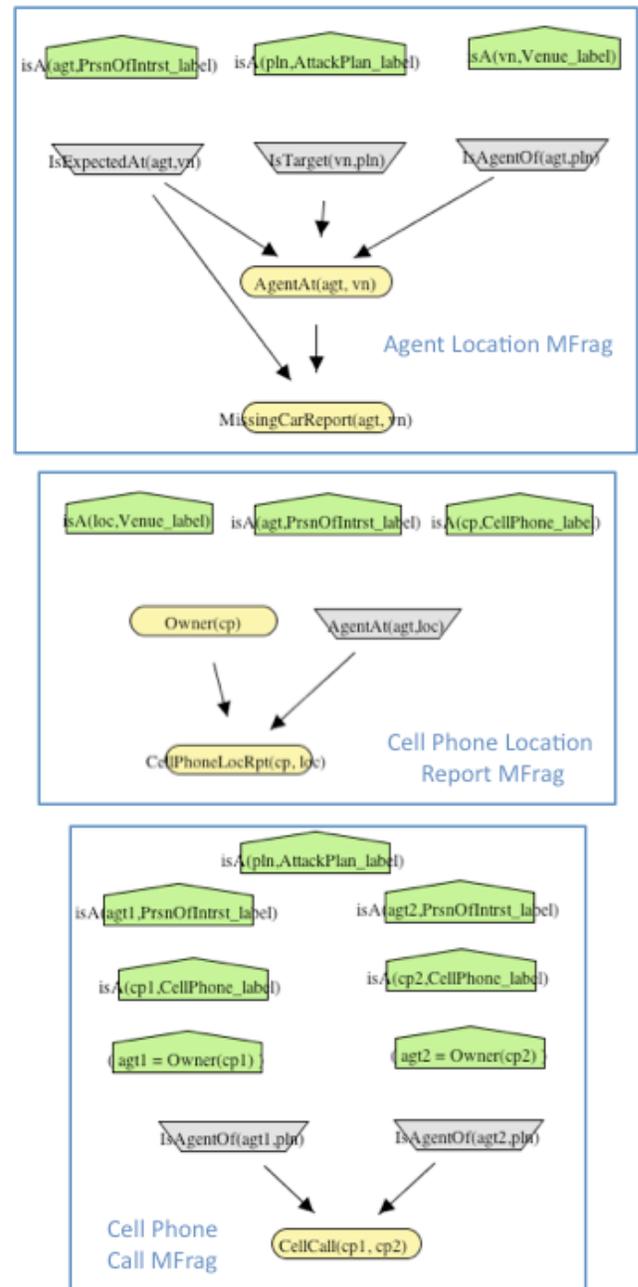


Figure 5 – MFrag for the Second SSBN

Figure 5 shows additional MFrag that represent this new information.

- *Agent Location.* This MFrag represents the knowledge that an individual who is expected at a venue is likely to be at the venue unless the individual is an agent of a plan that targets the venue.
- *Cell Phone Call.* This MFrag represents the knowledge that agents of a plan may call each other to coordinate the plan.
- *Cell Phone Localization.* This MFrag represents knowledge about geolocation of cell phones, and that the location of a cell phones typically indicates the location of its owner.

After constructing the situation-specific Bayesian network and adding the evidence that there was a call from TL6's cell phone to C's cell phone, that TL6's cell phone was geo-located at a location other than the conference, that TL6 and C are related in the social network (inferred by logical reasoning from the cell phone call) that TL6's car was missing from the conference, and that TL6 and TL5 are rivals, the probability has increased to about 88% that the conference has been targeted for an attack.

Figure 6 shows the SSBN constructed by hand using the Netica® Bayesian network software package. We are currently extending the SSBN construction algorithm in UnBBayes-MEBN to be capable of constructing the SSBN for this problem.

This problem requires bringing knowledge to bear about events in space and time, how agents own and use objects such as cell phones and cars, social interactions among agents, and other sophisticated kinds of reasoning. Many

of these reasoning patterns are reusable across a wide variety of problems. Examples include the knowledge that individuals are usually at the same location as their cell phones, that they may call each other to coordinate joint activities, and that they use cars for transportation. In an operational system, these kinds of reasoning would make use of available ontologies. PR-OWL allows the user of such an ontology to add probabilistic information to represent relationships that fall short of certainty.

To conclude our case study, after using PR-OWL and Bayesian reasoning to explore the implications of the evidence, IA2 appreciates the significance of the combined Multi-INT data, and issues an Actionable Intelligence Report to interdict the possible terrorist attack.

## 6 Conclusion

Ontologies provide the “semantic glue” to enable knowledge sharing among distinct systems cooperating in data rich domains such as Intelligence Analysis, but fail to provide adequate support for uncertainty, an ubiquitous characteristic of open world environments. Effective multi-INT fusion requires uncertainty management to be effective, and recent advances in research on probabilistic ontologies have the potential to make uncertainty management to work smoothly with semantic technology.

The case study presented in this work has shown that such research, albeit in its infancy, can help to support interoperability among Intelligence systems in an open environment, addressing issues of fusing multiple sources of noisy information into a coherent overall situation picture.

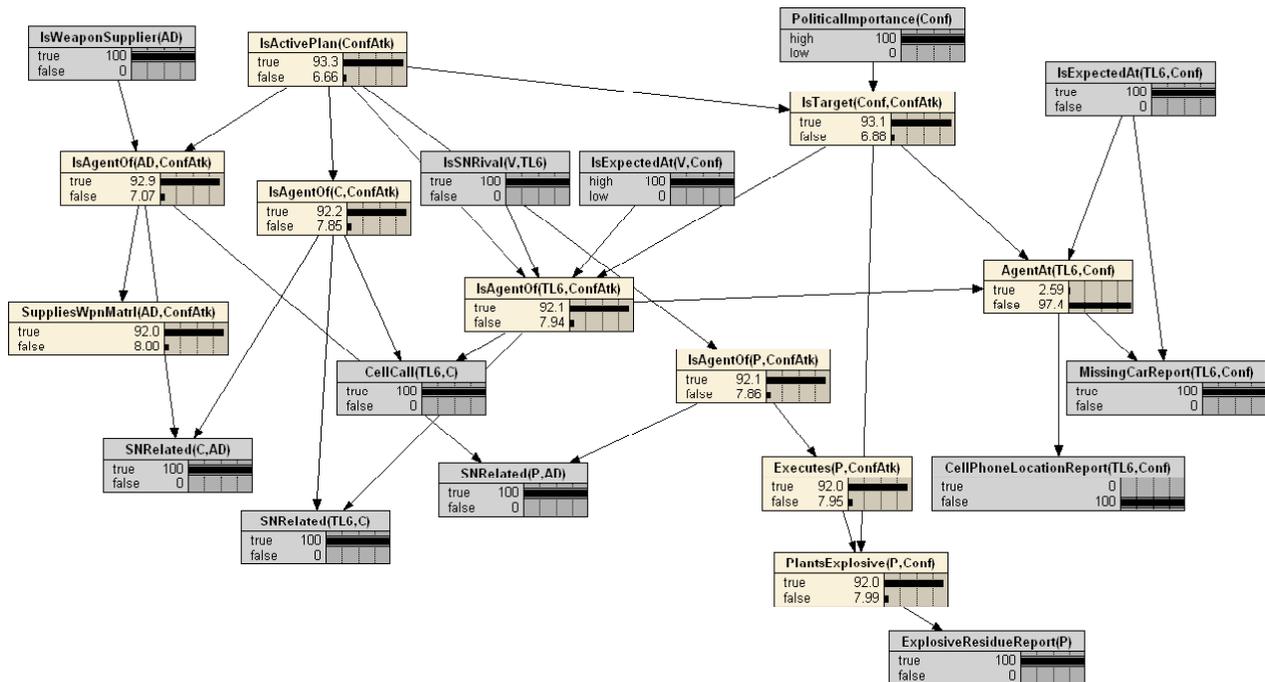


Figure 6 –SSBN for Conference Bombing

Exactly how ontologies should work with probabilities is still an open research issue. The Intelligence Analysis knowledge sharing use case presented in this work has shown how probabilistic ontologies can be used to address that issue. UnBBayes-MEBN, which was used to support the use case, is still in alpha phase and should see various improvements in the near future. This system constitutes a promising environment for building probabilistic ontologies to support knowledge sharing in open world environments.

## Acknowledgments

Kathryn Laskey gratefully acknowledges partial support from Lockheed Martin Corporation for the research reported in this paper.

## References

- [1] Martin Van Creveld, *Command in War* (1987 Reprint edition). Harvard University Press Cambridge, MA, USA, 1985.
- [2] Paulo C. G. Costa, Bayesian Semantics for the Semantic Web. PhD Diss. Department of Systems Engineering and Operations Research, George Mason University. 315p, July 2005, Fairfax, VA, USA.
- [3] Laskey, K.B., MEBN: A Language for First-Order Bayesian Knowledge Bases, *Artificial Intelligence*, 172(2-3), 2007.
- [4] Paulo C. G. Costa, The Fighter Aircraft's Autodefense Management Problem: A Dynamic Decision Network Approach. Master of Science Thesis, School of Information Technology and Engineering, George Mason University. May 1999, Fairfax, VA, USA.
- [5] Larry D. Stone, Charles A. Barlow, and Thomas L. Corwin, *Bayesian Multiple Target Tracking*. 1999, Artech House, Boston, MA, USA.
- [6] Stephen L. Lauritzen; and David J. Spiegelhalter, Local computation and probabilities on graphical structures and their applications to expert systems. 1988, *Journal of Royal Statistical Society*, 50(2), 157-224.
- [7] Judea Pearl. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. 1988, Morgan Kaufmann Publishers, San Mateo, CA, USA.
- [8] Laskey, K.B., Mahoney, S.M., and Wright, E., "Hypothesis Management in Situation-Specific Network Construction." *Uncertainty in Artificial Intelligence: Proceedings of the Seventeenth Conference*, 2001, San Mateo, CA, Morgan Kaufman.
- [9] David A. Schum, *Evidential Foundations of Probabilistic Reasoning*, 1994, John Wiley & Sons, Inc., New York, NY, USA.
- [10] Jay B. Kadane, and David A. Schum, *A Probabilistic Analysis of the Sacco and Vanzetti Evidence*. 1996, John Wiley & Sons, New York, NY, USA.
- [11] Glenn Shafer, Combining AI and OR. University of Kansas School of Business, April 1988, Working Paper No. 195.
- [12] Michael C. DaConta, Leo J. Obrst, and Kevin T. Smith, *The Semantic Web: A Guide to the Future of XML, Web Services, and Knowledge Management*. 2003, Wiley Publishing, Inc. Indianapolis, IN, USA.
- [13] Rommel N. Carvalho, Laécio L. Santos, Marcelo Ladeira, and Paulo C. G. Costa, A Tool for Plausible Reasoning in the Semantic Web using MEBN. In *Proceedings of the Seventh International Conference on Intelligent Systems Design and Applications*, 2007, pp. 381-386. IEEE Press.
- [14] Paulo C. G. Costa, Marcelo Ladeira, Rommel N. Carvalho, Kathryn B. Laskey, Laécio L. Santos, and Shou Matsumoto, A First-Order Bayesian Tool for Probabilistic Ontologies. In *Proceedings of the 21st Florida FLAIRS UNBBayes-MEBN*, May 2008, Coconut Grove, FL, USA.