**Bayesian Networks for the Human Element**

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### *Introduction*

Bayesian networks are powerful tools for knowledge representation and inference under conditions of uncertainty. Bayesian networks provide a traceable means of leveraging contextual expert knowledge to identify the causal structures surrounding two of the most elusive challenges currently facing the modeling, simulation and analysis community: the representation of human cognition and the representation of attitudes and behavior of the civilian population. The data to populate these structures is obtainable via knowledge elicitation methodologies or other sources of data like human experimentation.

We first provide background on Bayesian networks and their extensions. We then provide an introduction to machine learning, a method from the artificial intelligence community closely related to classification methods from statistics that can be used to construct Bayesian networks from an available data set. Next, we discuss the debate on Bayesian reasoning and argue that we can overcome the most serious objections. We then provide an overview of the use of Bayesian networks in modeling and make an argument for their use in the representation of decision making and behavior modeling in a military context.

### *Bayesian Networks*

A Bayesian network is a probabilistic graphical model that represents a set of variables and dependencies. Bayesian networks are directed acyclic graphs whose nodes represent variables, and whose edges represent conditional relationships between two variables. Nodes can represent a measured parameter, a latent variable or a hypothesis. A latent node in a learned Bayesian network is a variable that does not correspond to any input variable and is equivalent in a neural network to a node in the hidden layer. A Bayesian network is a complete model for the variables and their relationships and thus can be used to answer probabilistic queries about the variables.

A Bayesian network can be considered a mechanism for applying Bayes' rule to complex problems. Bayes' rule in terms of conditional and marginal probabilities for two variables is:

$$P(b|a) = \frac{P(a|b) \cdot P(b)}{P(a)}$$

Read this as the probability of event ‘b’ given the occurrence of ‘a’ is equal to the probability of event ‘a’ given the occurrence of ‘b’ times the probability of ‘b’ divided by the probability of ‘a’. This follows directly from the relationship between joint probability, conditional probability and marginal probability:

$$P(a \cap b) = P(a|b) \cdot P(b) = P(b|a) \cdot P(a)$$

Read this as the probability of the occurrence of ‘a’ and ‘b’ jointly is equal to the probability of the occurrence of ‘a’ conditioned on the occurrence of ‘b’ times the marginal probability of ‘b’, etc.

We use the term simple Bayesian network to distinguish the subset of methods under discussion from a variety of extensions to the basic methods. Likely the most familiar of these, influence diagrams, are an extension that adds decision and utility nodes to the simple Bayesian network. Influence diagrams are compact representations of decision trees. Influence diagrams are important models for Bayesian decision problems; however, our interest is in scientific inference.

Bayesian Knowledge Bases (BKBs) extend Bayesian networks by adding instance nodes to the random variable nodes, which are called support nodes in a BKB. Instance nodes represent known or estimated probabilities and function as a logical ‘and’ to compliment the logical ‘exclusive-or’ represented by the support nodes. BKBs do not require full specification of all probabilistic relationships between variables (Borghetti, Williams et al. 1996).

Bayesian networks by their nature support hierarchical modeling, which also takes advantage of the conditional independence property. Hierarchical models require that each node have at most one parent. Graphically, hierarchical models are trees. Hierarchical Bayesian Networks (HBNs) are an extension of Bayesian Networks for structured domains. In HBNs, a node is potentially an aggregation. An aggregate node is itself an HBN modeling independences inside a subset of the system (Gyftodimos and Flach 2002).

Object-oriented Bayesian networks (OOBNs) are an extension that leverages object oriented programming to allow complex domains to be described in terms of inter-related objects through the reuse of Bayesian network fragments. These fragments describe the probabilistic relations between the attributes of an object. Attributes can themselves be objects, providing a natural framework for encoding hierarchies. Classes provide a reusable probabilistic model which can be applied to similar objects and support inheritance of model fragments from a class to a subclass. OOBNs potentially provide an efficient means of modeling complex domains (Koller and Pfeffer 1997).

We restrict our discussion of simple Bayesian networks to models with a finite set of finite discrete variables (i.e., each variable has a finite set of possible states). This is not a serious limitation for most practical applications since through classification continuous data can be made discrete and discrete data can be categorized.

### ***Machine Learning***

Machine learning is one method for obtaining a Bayesian network from a set of data. Through machine learning it is possible to automatically produce through induction a complete model from data. Alternately, one can specify the structure of the model and machine learning can trivially estimate the parameters associated with the nodes. Netica by Norsys Software Corporation is a commercial product that can determine the parameters associated with the nodes even in data sets with missing data (Netica 2007).

Machine learning can be supervised, unsupervised, or semi-supervised. It can use reinforcement, transduction or learning-to-learn methods. Our simple Bayesian networks are essentially equivalent to those produced by a naive Bayes classifier, one of the most simple and robust methods for producing a Bayesian network from data.

Machine learning in artificial intelligence is closely related to data mining, classification or clustering methods in statistics, inductive reasoning, and pattern recognition. Statistical machine learning methods can apply the framework of Bayesian statistics; however, machine learning can employ a variety of classification techniques to produce models other than Bayesian networks. Common methods include Neural Networks, Support Vector Machines, k-Nearest Neighbors, Gaussian Mixture Models, Gaussian Classification, Decision Trees, and Radial Basis Functions (RBF).

We use WEKA, the open source machine learning software from the University of Waikato in New Zealand. WEKA version 3.4.13 contains 76 total classifier objects (some are base classes for one or more implemented classifiers) of which 12 are Bayesian network classifiers (Witten and Frank 2005).

### *Bayesian Reasoning*

It has been argued that Bayesian reasoning is counterintuitive. People do not employ Bayesian reasoning intuitively, find it very difficult to learn Bayesian reasoning when tutored, and rapidly forget Bayesian methods once the tutoring is over. This limitation seems to hold equally true for novices and highly trained professionals in a field (Yudkowsky 2009).

If people are particularly bad at reasoning about probabilities then it is natural to ask why we think one can elicit knowledge from experts to estimate distributions for a Bayesian network. First, we note that asking a person to estimate conditional probabilities is far more natural than the alternatives. Second, there is ample evidence that people can effectively draw conclusions from data and experience. That is, structural inference is intuitive. Thus humans are sufficiently skilled at translating subjective prior beliefs into a network model with appropriate prior probabilities. The challenge is to frame the knowledge elicitation strategy in a manner that avoids common human biases and failures related to probabilistic reasoning.

For example, one study has shown that some ways of phrasing story problems evoke more correct Bayesian reasoning (Gigerenzer and Hoffrage 1995). The most effective presentation of information uses natural frequencies. In a natural frequencies presentation the information about the prior probability is included in presenting the conditional probabilities.

Yudkowsky illustrates the use of natural frequencies with the following example (Yudkowsky 2009): Suppose that 40 out of 100 eggs contain pearls, 12 out of 40 eggs containing pearls are painted blue, and 6 out of 60 eggs containing nothing are painted blue. It is reasonably clear that blue eggs containing pearls occur twice as often as blue eggs containing nothing.

Many people are uncomfortable with the Bayesian approach. Often they question the use of automatic inference engines or contend that the subjective nature of the data used to develop the prior as arbitrary and subjective (Gelman 2008). The Bayesian approach can be subjective, but it is not arbitrary.

One may also use Bayesian networks without relying on subjective priors. One may, for example, use classical statistical methods including sampling to establish the prior distributions for a Bayesian network. In other words, the priors can be dominated by likelihoods. It is not necessary to fully embrace the Bayesian approach to benefit from using Bayesian networks.

Indeed, there are merits to the Bayesian approach in representing the human element. The model and prior are chosen based on our knowledge of the problem domain. These choices are not dictated by the amount of data collected or by the question we are interested in answering. We do not, for example, restrict the complexity of the model just because we have only a small amount of data (Neal 1998). Furthermore, probability is used to describe both physical randomness and uncertainty regarding the true values of the parameters.

Finally, the Bayesian approach exposes all aspects of the model for criticism. Box and Tiao describe a process of model building in statistical analysis where statistical analysis itself is a step in the iteration between entertaining a model and criticizing the model until the model is correct, given the data available. As new evidence is discovered the model may be revised (Box and Tiao 1973).

### *Conceptual Modeling*

The allure of simple Bayesian networks as a modeling methodology goes well beyond the computational aspects. We have used the term complete model to describe a Bayesian network consisting of nodes, arcs and associated probability distributions. We describe that portion of the Bayesian network consisting only of nodes and arcs as a conceptual model. One may think of this as the structure without the data for a given context. Context helps to focus effort onto elements of the probabilistic knowledge base that are of interest to the problem (Ngo and Haddawy 1995). When developing the Bayesian network as a conceptual model we typically omit discussion of the state space of the variables until the structure is defined.

Bayesian networks are a powerful and useful tool in conceptual modeling. We interpret the arc between two nodes as influence or cause for conceptual modeling and say that the predecessor node influences the state of the successor node. (Note that technically there may be no single 'correct' network structure for a complete model; even under the most strict set of assumptions a model may only have the same causal structure only up to what is termed d-separation equivalence (Pearl 2000).) Consider the set of parents (predecessor nodes) for a given node. The Bayesian network as conceptual model claims that knowing the state of the parent node(s) is sufficient to determine the state of the child node. The parents represent all that influences the child in the conceptual model. The corollary is much weaker—the state of the parent potentially influences the state of its children (successor nodes).

Analysis can be described as the process of breaking a complex system into smaller parts to better understand it. One important purpose of this process is to understand the relationship of the parts to the whole. Our ability to isolate a portion of the conceptual model by focusing on the parents of a given node is a powerful method for decomposing a system into manageable parts. The causal assumptions in the model are transparent and thus subject to debate and revision (Cheng and Greiner 2001). For this reason Bayesian networks provide great potential for modeling human decision making and the civilian populace.

### *Modeling Battle Command*

The human element remains preeminent in military operations. Modeling and analysis of future force operations demands increased attention to representing the Soldier, Marine, Sailor, and

Airman. The efficacy and value of concepts for emerging network-enabled operations cannot be adequately understood and assessed without accounting for how information and related technologies impact cognition and decision making.

Some excellent research has been accomplished, but the methods are often too sophisticated to apply directly or to transfer into contemporary military simulation models (Hudak 2008). Current work by the US Army TRADOC Analysis Center (TRAC) aims to address this capability gap for representing situational awareness and decision making in COMBAT XXI (Balogh and Harless 2003), the Army and USMC ground combat analytical model.

Cognitive scientists have identified six macrocognitive functions for Soldiers in future forces: naturalistic decision making, sensemaking, planning, adaptation/replanning, problem detection, and coordination. Supporting these functions are six macrocognitive processes: maintaining common ground, developing mental models, uncertainty management, turning leverage points into courses of action, attention management, and mental simulation story building (Baxter, Phillips, et. al 2004).

Bayesian networks (BN) are a natural method for representing situational awareness and decision making in general and recognition-primed decision making in particular. In recognition-primed decision making (RPD), cues are new perceptions (information) that trigger situation assessment which may alter situational awareness and trigger recognition that action is necessary. The recognition-action pair captures the unconscious action choice of the Soldier, an inherently intuitive process (Klein 1989).

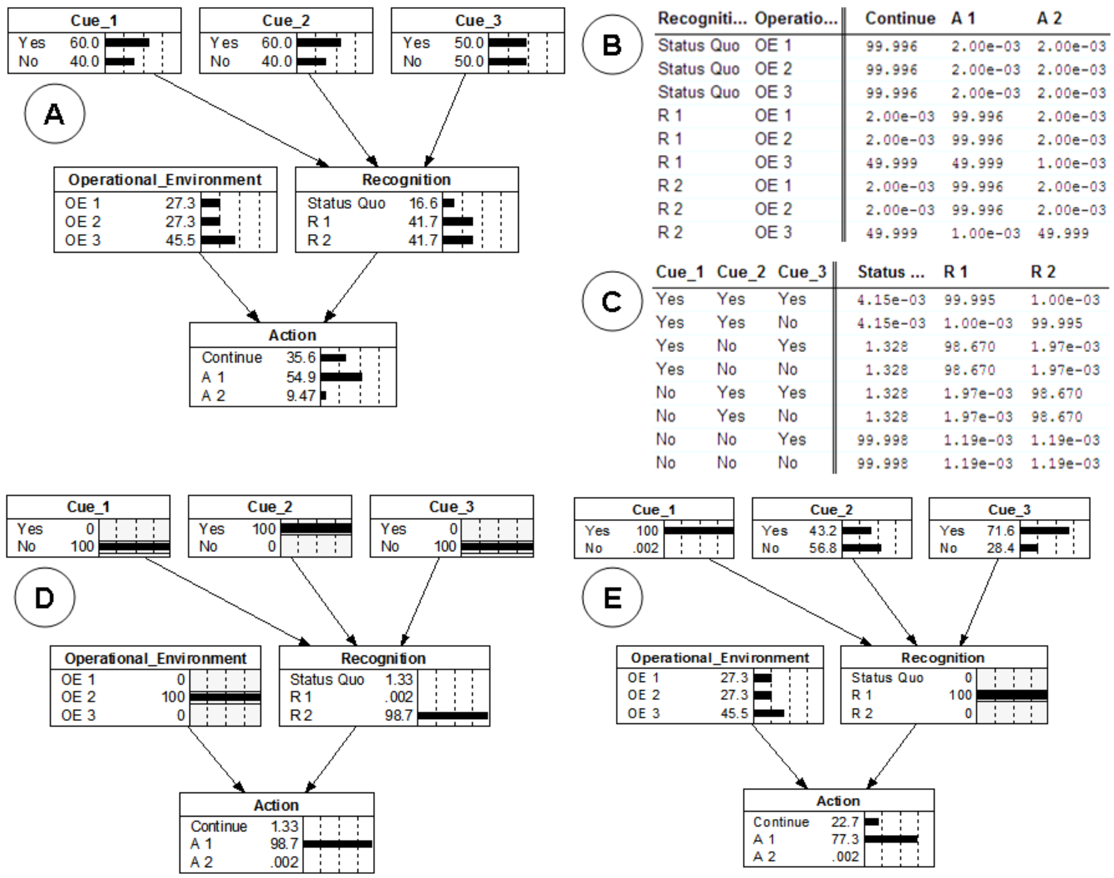


**Figure 1. (A) RPD example, (B) Conditional Probability Table (CPT) for Action, (C) CPT for Recognition, (D) BN with evidence, (E) BN exploring Recognition. (Netica, 2007)**

The Bayesian network in this case (see Figure 1) captures the Soldier's unconscious mental model for a given situation and context. It can serve as a component for a simulation model or be used to document and analyze knowledge about the decision situation. The set of situational awareness nodes influence the decision node directly or indirectly through intermediate nodes, which might represent recognition or other variables in the Soldier's mental model for the situation. In the Bayesian network model new information about the state of a given situational awareness node (e.g., setting the state of that node to one value in the model) may change the overall state of the nodes in the network and in particular may trigger a state change on the decision node representing a decision.

This example illustrates one method for using a Bayesian network. Here the Bayesian network is a complete model of Soldier understanding and reasoning for the given decision. This construct facilitates the use of expert knowledge in the domain area of interest to build the structure of the decision model. The network is used to answer probabilistic queries about one of the variables, the decision node. In particular, one course of action represented by one of the states of the node is selected after adjusting the state of situational awareness nodes.

The distribution of probability across the state of the decision node makes it possible to interpret the variable in various ways. A course of action might be triggered when the value of one state on the decision node exceeds some threshold. Alternately, some other factor or occurrence might trigger the evaluation of the decision node. In this case, the state with the highest probability might be selected or a probability draw might occur to select among the states based on their relative probability.

### ***Modeling Irregular Warfare***

Irregular warfare (IW) is defined as a violent struggle among state and non-state actors for legitimacy and influence over the relevant populations. The legitimacy of the conflict is judged primarily by the nation's population. Success in IW depends on our understanding of social dynamics of the civilian population such as tribal politics, social networks, religious influences, and cultural norms. The IW Joint Operating Concept (JOC) describes an objective Joint Force with enhanced capability for IW and a balanced approach to warfighting that allows it to be as compelling in IW as it is in conventional warfare (USSOCOM and MCCDC 2007). Modeling and analysis in support of IW requires an understanding and associated representation of the population in the area of operations. Bayesian networks are a natural choice to model the attitudes and behaviors of the population due to their ability to leverage expert knowledge and deal with subjective data and concepts.

The Bayesian network method can account for qualitative factors like norms, beliefs and perceptions that influence behavior of individuals and groups. Suppose that personal and social factors like beliefs, values, and interests influence the positions that individuals and groups in the population take on issues. The method can account for the influence of these factors on evolving population opinions about issues like legitimacy. Below we describe a sample Bayesian network that illustrates how norms, beliefs and perceptions influence the formation of behavioral intentions (see Figure 2). It can serve as a component in an agent-based model.

In this case we focus on the reasoned behavior of members of the population seeking an essential service in a conflict environment. The Theory of Planned Behavior describes how individuals form intentions to perform a reasoned behavior (Ajzen 1977). Intention reflects an entity's readiness to perform a behavior and is considered to be the immediate antecedent of behavior. Intention is based on the entity's *attitude* toward the behavior, the *subjective norm* in reference to the behavior, and the entity's *perceived behavioral control* regarding this behavior.

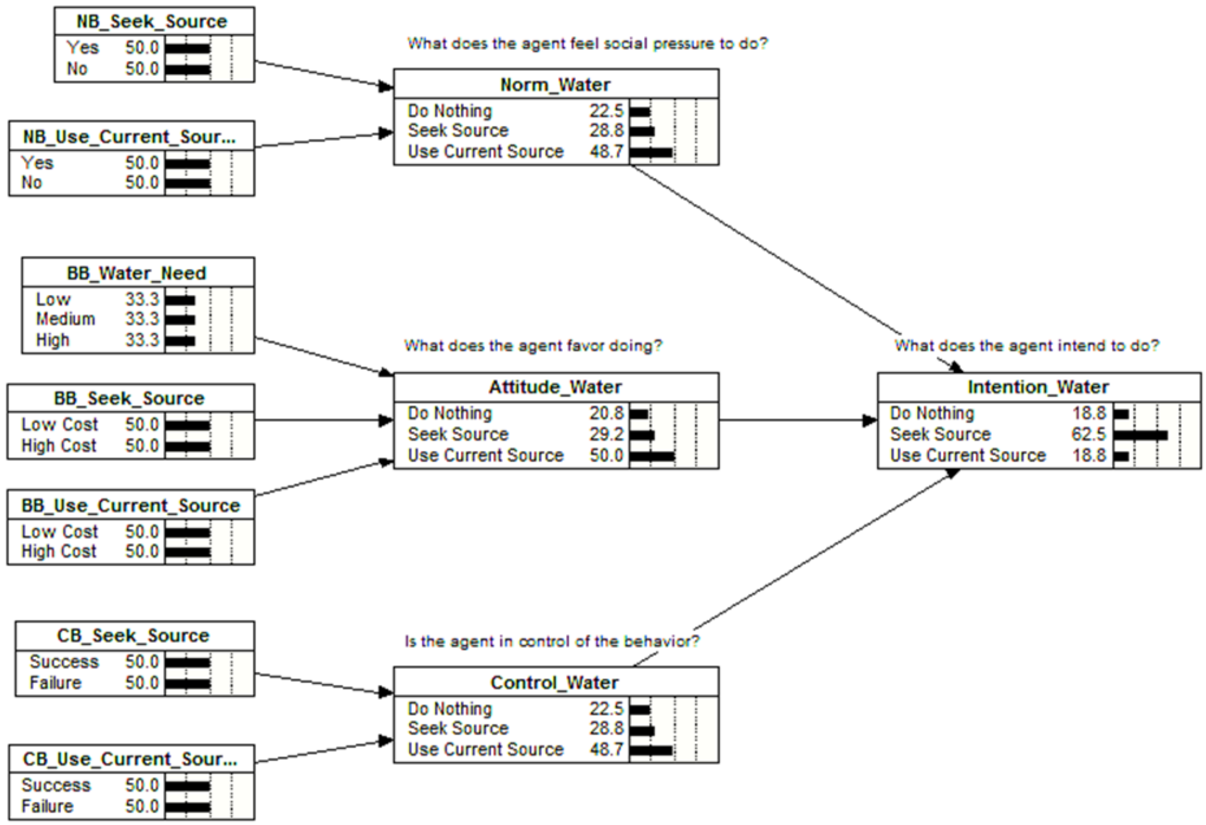


**Figure 1. TPB BN for Water as an Essential Service (Netica 2007).**

Behavioral beliefs link the attitude toward the behavior to expected outcomes through estimation that the behavior will produce a desired outcome. Attitude toward a behavior is the degree to which it is valued. The expectancy—value model links expected outcomes to the value of the outcomes. It implies that attitude toward a behavior is determined by the set of accessible behavioral beliefs linking the behavior to outcomes and other attributes.

Normative beliefs are perceived behavioral expectations of important referent individuals or groups. Normative beliefs in combination with the person's motivation to comply with the referents determine the subjective norm. Subjective norm is the perceived social pressure to engage in a behavior or not. The expectancy — value model implies that subjective norm is determined by the total set of accessible normative beliefs about the expectations of important referents.

Control beliefs concern the perceived presence of factors that may facilitate or impede performance of the behavior. Control beliefs in combination with the perceived power of each control factor determine perceived behavioral control. Perceived behavioral control refers to a person's perceptions of his ability to perform a behavior. The expectancy — value model of attitude implies that perceived behavioral control is determined by the total set of accessible control beliefs, which are the factors that may facilitate or impede performance of the behavior.

This example illustrates a second method for using a Bayesian network. The Bayesian network is still a complete model of an individual's understanding and reasoning for the given behavior. The network is still used to answer probabilistic queries about one of the variables, the intention node. In particular, one course of action represented by one of the states of the node is still selected. However, over the course of time the parameters of the Bayesian network are adjusted and new information about the beliefs is processed. The prior probabilities are replaced by posterior probabilities. This represents the individual learning from one's experience.

### *Conclusion*

We described how analysts can use simple Bayesian networks to represent critical aspects of the human element for modeling, simulation and analysis. We described a process for developing models and data using both expertise and available data. We described application of the method to modeling Soldier situational awareness and decision making in Battle Command and to modeling behavior of people and society in Irregular Warfare. Proof of principle implementations of Bayesian networks for the purposes described above are ongoing at TRADOC Analysis Center – Monterey.

### *Biographies*

***Leroy A. "Jack" Jackson*** *has served as senior operations research analyst and deputy director at the US Army Training and Doctrine Command (TRADOC) Analysis Center (TRAC) in Monterey, California since April 2002. He graduated with a BA in Mathematics from Cameron University in 1990 with high honors. He graduated from the Naval Postgraduate School in 1995 with an MS in Operations Research and was the distinguished Department of Defense graduate. He is a recipient of the US Army Chief of Staff's Award for Excellence in Operations Research. He served for 24 years in the US Army and earned the Legion of Merit. He currently conducts research in the areas of cognition and battle command, and society and irregular warfare.*

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