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Title: Adaptive Information Fusion in Asymmetric Sensemaking Environment

Topic: Modeling & Simulation

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Abstract

The existing sensemaking models for traditional force-on-force battlefield information management rarely survive the kinds of information in asymmetric battlespace environments. By combining the abduction process and Bayesian probability network formalisms, we propose a Bayesian Abduction Models (BAM) to support in the sensemaking process of evaluating multiple hypotheses in the context of changing information. This paper describes a Bayesian network that captures abduction logic primitives from a kernel of disparate information sources. We use a genetic learning algorithm to solve BAM information fusion problems. We show how the model can be used in prospective and retrospective sensemaking conditions to simulate the ways commanders and the battle staffs process information.

Introduction

Consider the current military conflicts in Iraq and Afghanistan. The adversary environment is known to be complex, " wicked" and completely asymmetric--the adversaries are barely known, and their tactics keep changing against the coalition forces. The deliberate military decision making processes (MDMP) with all their linearity assumptions collapse immediately in contact with asymmetric information environments. Generating courses of action must be progressive and opportunistic--the usual analytical models of judgment and choice that fit force-on-force tactics must be recalibrated to fight against unknown enemies. Sensemaking, the process of connecting dots to disparate information and seeking explanation to potentially unexpected evolving situations, has been suggested as an embellishment or precursor to existing MDMP. Unfortunately, these nascent decision systems lack analytical models that can capture the evolving states of battle dynamics and its information equivocality. The proposed method seeks to minimize this problem by developing a probabilistic abduction model for sensemaking process.

To help elucidate our point of discourse, consider a fictitious case in the current conflict in Iraq. We can use a hypothetical network depicted below to illustrate an example of analyzing the Iraq insurgency. The top most variable H_o will represent a composite hypothesis for a desired end state problem. For example, we can hypothesize that, according to intelligent speculations, that Iran is responsible for the sectarian violence. The variables h_i form a subset of H_o and will represent the operational focus (e.g., funneling money and weapons to insurgents, covert operations in Iraq, etc.); X_i may represent the perceived motives f; S_i may represent the influence path (example: Al-Sadr militia cell, Al-Qaeda cell, etc.) responsible for attacking targets m_i (e.g., mosques, coalition forces, kidnapping, etc.). Figure 1 shows the network of the information described above.

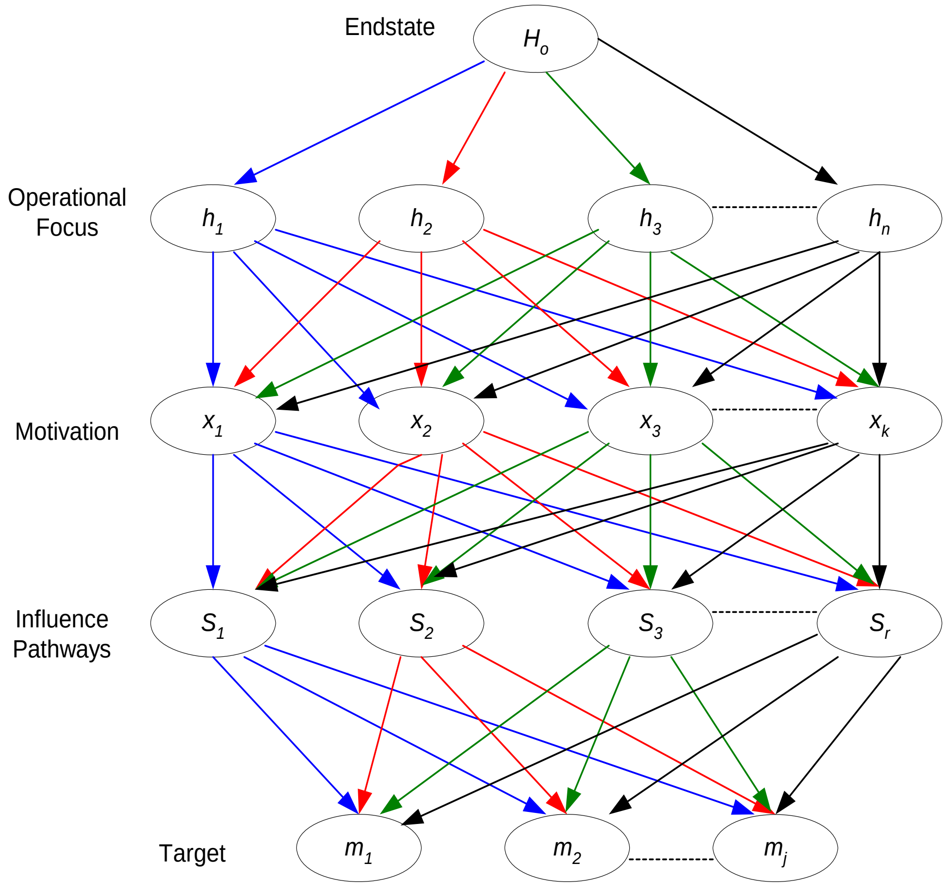

Figure 1: Example network where { h_i,x_i,S_i,m_i} represent the *End state*, *Operational Focus*, *Motivation*, *Influence Pathways*, and the *Target* variables, respectively.

From a sensemaking perspective we are interested in knowing what happens when new information unexpectedly arrives to the intelligent analyst. For instance:
1) The adversaries change their attack methods; and
2) New targets are exploited by the adversaries.
From the list of possible hypotheses and variables, the analyst is interested in determining the most probable explanation, and/or making the best inference from the given evidence. The existing courses of action and planning models rarely survive the kinds of information described above. Sensemaking is suggested as a model for situations with ambiguities such as the one in the above case; more so, abductive reasoning is suggested as its supporting tool. Abduction is a reasoning process that tries to form plausible explanations for abnormal observations. A typical abduction task is a classification of a given data set into potentially relevant elementary explanatory hypotheses. By combining the abduction task and Bayesian probability formalisms, we have developed a Bayesian Abduction Model (BAM) to support in the performance analysis during a sensemaking process such as illustrated in the sample case above.

Theoretical Foundation

Developing an abduction driven Bayesian model of sensemaking begs for an important question: "Can sensemaking with all its tacit dimensions of knowledge be represented mathematically (and computationally)? Our answer is definitely yes, but with a caution about avoiding over generalization.

Let us review some of the existing models developed to either target sensemaking or its pseudo-variances. Computationally, Schmidt (1994) view sensemaking as a symbolic system of human communication when he notes that "in systems that hold and manipulate information, it is possible for a system to hold and manipulate information that represents the system itself, in such a way that there is a causal link in both directions between the system and the information; if the system changes the information, the system itself changes accordingly. These (conditions) are self reference that make goal directed (sensemaking) systems symbolic and computational reflective systems." Schank (1982) observes that sensemaking is a system of actions, symbols and processes that enables an organization to transform information into valued knowledge which in turn increases its long run adaptive capacity (1982; pp.8). Weick (1995) notes that sensemaking is a theory and a process of how people reduce uncertainty or ambiguity…during decision making. In DARPA's Information Awareness Project initiatives, sensemaking is considered an important tool for the Future Combat Force because, with fragmentary battle space information, "meaning has to be derived from these fragmentary cues".

Peircean philosophy provides a foundation for understanding human reasoning and capturing behavioral characteristics of decision makers due to cultural, physiological, and psychological effects. Peirce's theory focuses on a system of logic that can achieve the best possible conclusions based on the available information. Pierce (1877) first described abductive inference by providing two intuitive characterizations: given an observation *d* and the knowledge that *h* causes *d, it* is an abduction to hypothesize that *h* occurred; and given a proposition *q* and the knowledge that $p \rightarrow q$, it is an abduction to conclude *p*. In either case, abduction is uncertain because something else might be the actual cause of *d, or* because the reasoning pattern is the classical fallacy of "affirming the consequent" and is formally invalid. Additional difficulties can exist because *h* might not always cause *d*, or because *p* might imply *q* only by default. Generally, we can say that *h explains d* and *p explains q* and we shall refer to *h* and *p* as *hypotheses* and *d* and *q* as data. Peirce (1877) further defined the process of inquiry or discovery as including three fundamental inference processes:

1) Abduction generation of hypotheses to explain new anomalous data.
2) Deduction performs the function of making a prediction as to what would occur if the hypotheses were to turn out to be the case.
3) Induction finds the ratio of the frequency by which the necessary results of deduction does in fact occur.

Abduction is then, a reasoning process that tries to form plausible explanations for abnormal observations. It is distinct from deduction and induction in that it is inherently uncertain since information or data supporting abduction process is dynamic in nature, leading to human construction of multiple and often competing hypotheses.

Bayes Theory

We have alluded to the use of Bayesian theory in our proposed work. What follows is a short summary on the foundation of the Bayesian approach (Pearl, 1995). In any situation in which we have to make decisions we are often interested in determining the best hypothesis from some construct space H, given observed data D. Bayes theorem provides a way to calculate the probability of a hypothesis based on its prior probability, the probabilities of observing various data given the hypothesis and the observed data itself. To define Bayes theorem precisely, we first need to define the notations used. Let *P(h)* denote the initial probability that hypothesis *h* holds, before we incorporate any new data. *P(h)* is the prior probability of *h* and may reflect any background knowledge we have about the chance that *h* is our atypical belief or a correct hypothesis. If no such prior knowledge exists, let *P(D)* denote the probability that evidence data *D* will be observed. *P(D)* represents the probability of evidence *D* given no knowledge about which hypothesis holds. Let *P(D|h*) denote the probability of observing data *D* given some world in which hypothesis *h* holds. We are interested in the probability *P(h|D)* that *h* holds given the observed data *D*. P(D) serves to confirm, reject, or modify our initial belief about h. *P(h|D*) is called the posterior probability of *h* because it reflects our confidence that *h* holds after we have seen some evidence *D*.

Bayes theorem provides a way to calculate the posterior probability *P(h|D)*, from prior probability *P(h)*,together with *P(D)* and *P(D|h)* and can be mathematically stated as,

$$P(h \mid D) = \frac{P(D \mid h)P(h)}{P(D)} \quad \ldots\ldots\ldots\ldots\ldots\text{(i)}$$

In previous studies, Pate-Cornell (2001) used Bayesian analysis to study intelligence fusion. McLaughlin and Pate-Cornell (2005) used Bayesian techniques to provide an analytical illustration of Iraq's nuclear program intelligence. Sticha, Buede and Rees (2005) developed APOLLO, an analytical tool for predicting a subject's decision making. Starr and Shi (2004) conducted a study on Bayesian belief networks and their applications to land operations for the Australian military. So far, there has been no substantive study of the application of Bayesian networks in sensemaking. There are several reasons for this. First, equation (i) above cannot handle well hypotheses of multiple disorders since Bayesian models are more grounded in diagnostics decision making process (Pearl,1988). For example, given two independent hypotheses h_1 and h_2 and a common data set $D_1, D_2, \ldots, D_m$, the computation $P(D_j|h_1 \wedge h_2)$ presents a serious logical analysis challenge. Secondly, it is difficult to handle causal chaining where there is no direct influence; note that the success of Bayesian Belief Networks (BBN), e.g. Pearl (2000), is based on the availability of direct conditional influences.

Abduction and Bayesian Model

The existing models of abduction are purely from the logical approach (Konolige, 1992).Our model is not for logical reasoning. We are interested in the probabilistic models of uncertainties that allow some causal inference to take place in a sensemaking information network. In this case, the relationship between Bayesian reasoning and abduction is governed by the assertion related only to a set of plausible explanations (Prakken, 2004). Simply

Let $P(w) = \sum P(E)$ *(ii)*

Where E is an explanation of world w

$$P(E) = \prod_{h \in E} P(h) \text{ (Assuming independent events E)---(iii)}$$

$$P(w \mid E) = \frac{P(w \,\&\, E)}{P(E)} \begin{array}{l} \leftarrow \text{explains w \&E} \\ \leftarrow \text{explains E} \end{array} \qquad \text{(iv)}$$

P(w|E) may represent, say, mass demonstration by Iraqi citizens because of bombing of a mosque by the coalition force. The abduction problem in sensemaking is: given *E*, explain *E*, then try to explain *w* from these explanations.

Mathematical Illustration

We briefly demonstrate the Bayesian abductive inference using a mathematical illustration. For simplicity, inference is performed only for a part of the network as shown in Figure 2 below. We define an end state of the network as a composite hypothesis H_o and to this we assign a prior probability. The prior probability can be assumed based on the level of past information that we have about a particular situation that is of interest. For example, H_o could be maintaining stability operations in Bagdad. The estimated probability could be from the news media, intelligence briefings, or simply the commander's estimate. We can write, $P(H_o) = 0.4$

This means that we are only 40% confident that our chosen hypothesis is plausible. By the axioms of probability, the probability of an alternative hypothesis $P(H_a)$ representing any other end state is therefore, $P(H_a) = 0.6$ and we need not explicitly state this. Similarly we can assign apriori probabilities for the conditional probabilities of interest representing the probabilities of the children events, given the parents.

Next, we can compute the prior probabilities of all the instantiated variables as follows

$$P(h_1)= P(h_1|H_o)P(H_o) +P(h_1|H_a)P(H_a)= (0.9)(0.4)+(0.8)(0.6)=0.84$$

$$P(x_1)= P(x_1|h_1)P(h_1) + P(x_1|h_2)P(h_2)=(0.7)(0.84)+(0.4)(0.16) =0.652$$

$$P(S_1)=P(S_1|x_1)P(x_1) + P(S_1|x_2)P(x_2)=(0.5)(0.652) + (0.6)(0.348) = 0.5348$$

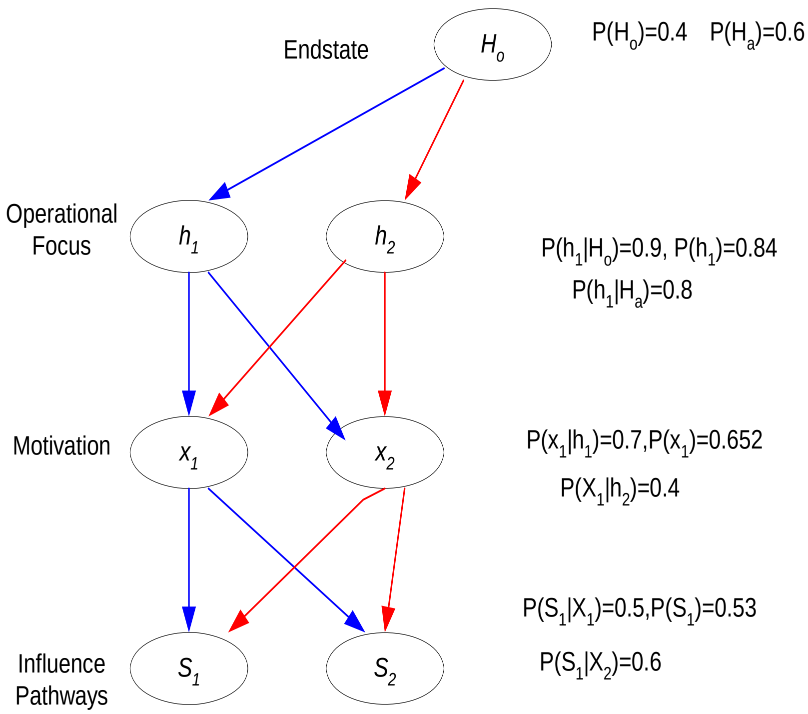

Figure 2: Example network where $\{h_i, x_i\ S_i\}$ represent the *End state*, *Operational Focus*, *Motivation* and the *Influence Pathways* variables respectively

Now suppose the variable X is instantiated for x_1. Since the Markov condition entails that each variable is conditionally independent of the next variable given its parents, we can compute

$$P(h_1|H_o)=0.9$$

$$\begin{aligned}P(x_1|H_o) &= P(x_1|h_1,H_o)P(h_1|H_o) + (P(x_1|h_2,H_o)P(h_2|H_o)\\ &= P(x_1|h_1)P(h_1|h_o)+P(x_1|h_2)P(h_2|H_o)\\ &= (0.7)(0.9) + (0.4)(0.1) = 0.67\end{aligned}$$

$$\begin{aligned}P(x_2|H_o) &= P(x_2|h_2,H_o)P(h_2|H_o) + P(x_2|h_1,H_o)P(h_1|H_o)\\ &= P(x_2|h_2)P(h_2|H_o) + P(x_2|h_1)P(h_1|H_o)\\ &= (0.6)(0.1) + (0.4)(0.9) = 0.42\end{aligned}$$

$$\begin{aligned}P(S_1|H_o) &= P(S_1|x_1,h_1)P(x_1|H_o)+P(S_1|x_2,h_2)P(x_2|H_o)\\ &= P(S_1|x_1)P(x_1|H_o)+P(S_1|x_2)P(x_2|Ho)\\ &= (0.8)(0.67) + (0.6)(0.42) = 0.734\end{aligned}$$

Applying abductive inference, we can compute

$$P(x_1|S_1) = \frac{P(S_1 \mid x_1)P(x_1)}{P(S_1)} = \frac{(0.5)(0.652)}{0.5348} = 0.60$$

To compute $P(h_1|S_1)$, we again apply Bayes theorem

$$P(h_1|S_1) = \frac{P(S_1 \mid h_1)(P(h_1)}{P(S_1)}$$

But we need to first compute the $P(S_1|h_1)$. That is

$$P(S_1|h_1) = P(S_1|x_1)P(x_1|h_1)P(S_1|x_2) + P(S_1|x_2)P(x_2|h_1)P(x_2|h_2)$$
$$= (0.5)(0.7)(0.6) + (0.6)(0.3)(0.6) =0.318$$

$$P(h_1|S_1) = 0.504$$

We then compute the probability $P\ (S_1|H_o)$ and $P(H_o|S_1)$ in a sequence as follows

$$P(S_1|H_o) = P(\ S_1|h_1)P(h_1|H_o)+P(S_1|h_2)P(h_2|H_o)$$
$$= \ (0.53)(0.9)+(0.47)(0.1) = 0.524$$

The value of 0.524 gives the numerical probability that we may assign to our degree of belief that event S_1 will happen given a world in which the hypothesis H_o holds plus all the other instantiated variables. Referring to our fictitious scenario network, we can say with a 52% certainty that the end state represented by hypothesis H_o will influence event $S_{1.}$ In terms of prospective sensemaking S_1 is therefore the most probable explanation for hypothesis H_o.

Again, by using Bayes theorem

$$P(H_o \mid S_1) = \frac{P(S_1 \mid H_o)P(H_o)}{P(S_1)} = \frac{(0.524)(0.4)}{0.53} = 0.395$$

Similarly, given the influence path S_1 ,we can perform a backward inference and say that S_1 will influence the desired end state H_o only 39% of the time (i.e., probably not a very significant influence path for this hypothesis). This backward inference corresponds to the consequent→antecedent reasoning or the retrospective sensemaking of the network scenario.

Considering the network shown in Figure (1) above

$$P(m_1) = \sum_{S_1,..s_r} P(m_1 \mid S_1, S_2, S_3,..S_r)$$

Because of the independence of {S_1, S2, S_3...S_r}, we can write

$$P(m_1) = \sum_{S_1..S_r} P(m_1 \mid S_1..S_r)P(S_1)P(S_2)P(S_3)...P(S_r)$$

$$P(m_1) = P(m_1 \mid S_1)P(S_1) + P(m_1 \mid S_2)P(S_2) + P(m_1 \mid S_3)P(S_3).......P(m_1 \mid S_r)P(S_r)$$

Clearly, the complexity of the computation, even for a relatively simple network can be seen. When new evidence is introduced, the analyst is interested in determining the possible effects on his most probable hypothesis, H_o. Suppose the new evidence points to a new target to be exploited by the insurgents. The new target may be a coalition command and control (C2)post in a previously secure part of the country. This would definitely require a level of sophistication, challenging the analyst's previous hypothesis about the end state of the insurgency. Using a Bayesian abduction inference, we can compute the state of the network with variable X_i instantiated as follows:

$$P(H_o \mid X_i) = \frac{P(X_i \mid H_o)P(H_o)}{P(X_i)}$$

$$P(X_i \mid H_o) = \sum_{h_1..h_n} (X_i \mid h_n, H_o)P(h_n \mid H_o)$$

$$P(X_i \mid H_o) = P(X_1 \mid h_1, H_o)P(h_1 \mid H_o) + P(X_1 \mid h_2, H_o)P(h_2 \mid H_o).........P(X_1 \mid h_n, H_o)P(h_n \mid H_o)$$

$$P(X_i \mid H_o) = P(X_1 \mid h_1)P(h_1 \mid H_o) + P(X_1 \mid h_2)P(h_2 \mid H_o)......P(X_1 \mid h_n)P(h_n \mid H_o)$$

Once the state (solution) of the network is determined, it is straightforward to perform forward or backward inference. It is easy to see also that the more complex the network, the more difficult the computation. Unfortunately abductive inference in belief networks belongs to the class of NP-hard problems (Cooper, 1990). Complexity increases drastically as a function of the number of undirected cycles, discrete states per variable and variables in the network. Approximate solution techniques which reduce calculation time and generate rankings of possible hypotheses have been introduced as an alternative.

In order to overcome the problem of computational complexity, the BAM uses a genetic algorithm (GA) to perform the search and computation for the most probable hypothesis. GA's can handle very complex network problems and perform efficient and fast computation over large search spaces. Using GA, inference is performed as a search in a large discrete multi-dimensional space of competition hypotheses. Generally, GA can conduct a search adaptively and thus facilitates the discovery of a hypothesis path with a high probability instantiations.

One major advantage of GA is that we can represent multiple states for each variable depending on the cardinality that we choose for the genetic coding. Our GA model uses probabilistic transition rules to propagate search along the direction of “best” fit in the Bayesian network, making use of Bayesian characteristics that conditionally explore or prune nodes based on their probabilistic scores.

The first step in applying GA to our BAM model is to code all the variables in our hypothetical network as a finite length string. The simplest scheme is to use two-variable cardinality so that the set {0,1} is sufficient to represent all the states of the variables. At any instance, the state of the network can be fully determined by using a vector *a*, where

$$a = \begin{cases} 1 \text{ if a node } C_{kj} \text{ is instantiated} \\ 0 \text{ otherwise} \end{cases}$$

At each level *k* of the network, we have N_k nodes such that $C_{kj} \in N_k$, $j = 1,2,3..,n$.

The resulting network representation for all nodes is a binary pair $\{Cj, a\}$ for all nodes *k*. The initial population is generated by coding each of the variables with a {0,1} depending on the state of the instantiation. The initial population is then subjected to genetic operators {mutation, crossover, reproduction}. The fitness function to determine reproduction is calculated based on classical Bayesian operators. Figure 3 below represents the network with the instantiated variables (nodes) coded by {1}. The generated string for all the parameters to be manipulated is represented as:

H_o	H_a	h_1	h_2	h_3	h_n	X_1	X_2	X_3	X_k	S_1	S_2	S_3	S_r	m_1	m_2	m_j
1	0	1	1	0	0	0	1	0	1	1	0	1	0	1	0	1

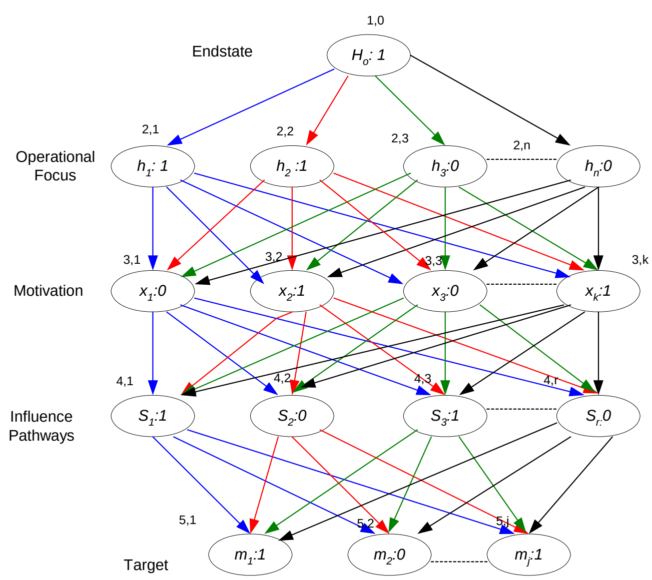

Figure 3: The network with all the instantiated variables coded {1}.the nodes are given position coordinates for the search process

In a previous work, Gelsema (1995) applied a GA to abductive reasoning in Bayesian belief networks. Gelsema used a two level network depicting a classical diagnostic problem. Our approach differs significantly from Gelsema's approach in two ways. Foremost, Gelsema's goal was to find the states of the network (solutions) with the highest overall posteriori probability. To do this, the fitness function was straightforwardly calculated as a product of *n* multipliers, one for each of the *n* nodes in the network. This could be seen as more of a search for an optimal solution. The BAM model does not search for the optimal solution; rather it searches for the most probable outcome (hypothesis) given the evidence in the prospective sensemaking phase using abductive inference. In retrospective sensemaking, the BAM model searches for the evidence, given a probable outcome (hypothesis).

Sample Results

To clarify the approach, using a hypothetical network, an array of conditional probability tables was generated using Bayesian abduction inference. The results of the sample calculations are shown in Table 1 below.

Table 1: Sample calculations using MatLab software

Array 1: *$P(h_i|H_o)$*

$h_i \mid H_o$	$H_o = 1$
$H_1 = h_1$	0.8
$H_2 = h_2$	0.5
$H_3 = h_3$	0.3
$H_4 = h_4$	0.9

Array 2: *$P(X_i|h_i)$*

$x_i \mid h_i$	$H_1 = h_1$	$H_2 = h_2$	$H_3 = h_3$	$H_4 = h_4$
$X_1 = x_1$	0.7	0.2	0.6	0.1
$X_2 = x_2$	0.3	0.4	0.5	0.8
$X_3 = x_3$	0.9	0.3	0.6	0.1
$X_4 = x_4$	0.1	0.9	0.7	0.5

Array 3: *$P(S_i|X_i)$*

$S_i \mid x_i$	$X_1 = x_1$	$X_2 = x_2$	$X_3 = x_3$	$X_4 = x_4$
$S_1 = s_1$	0.5	0.6	0.9	0.3
$S_2 = s_2$	0.1	0.0	0.5	0.4
$S_3 = s_3$	0.9	0.1	0.3	0.5
$S_4 = s_4$	0.5	0.6	0.7	0.4

Array 4: ***P(m_i|S_i)***

$m_i \mid S_i$	$S_1 = s_1$	$S_2 = s_2$	$S_3 = s_3$	$S_4 = s_4$
$M_1 = m_1$	0.6	0.3	0.8	0.1
$M_2 = m_2$	0.3	0.5	0.4	0.9
$M_3 = m_3$	0.1	0.9	0.2	0.6

The variable names in the arrays are replaced with the position coordinates representing the variables. When a new information arrives to the analyst, the corresponding information a variable is either defined or instantiated, and coded by a {1} in the string. The GA model then performs the abductive inference by performing the computation for all possible states of the instantiated network variables and giving the approximate inference. The result is then output as the most probable explanation.

Figure 4 illustrates the sample results using 1000 generations from a genetic algorithm. The graph shows how the most probable outcome varies as we manipulate the value of one variable h_1 .For example if the analyst believes there is a 70% chance that the Operational Focus of the adversary is node h_1 then there is a 30% chance that the targeted node is m_3. If on the other hand the analyst has reason to totally discount the possibility of the Operational Focus being node h_1 (in other words,0% chance for node h_1),then the node with the highest probability of being targeted would be m_2 (26% chance). Notice also that with a 30% chance of occurrence for node h_1 both m_1 and m_3 are equally likely targets. If the probability of h_1 occurring is increased to 0.4 then both m_1 and m_2 are equally likely targets. With h_1 instantiated with probability 0.35, m_2 and m_3 are equally likely to be targeted and it would be left to the analyst to look at other contributing factors before making further inference. Figure 5 is a Venn diagram to capture the above result explanations. Similarly, backward inferences can be made, starting with apriori probabilities for the targets and inferring most probable outcomes for any of the other network variables.

Conclusion

In this paper we have presented a computational model of adductive inference using Bayesian techniques. We use a genetic algorithm to solve a BAM directed information fusion problem that deal with a multiple hypotheses sensemaking problem. By using a constructive information network from Iraq conflict, we demonstrate our model in terms of robustness when compared to the traditional Bayesian model alone. Sample simulation experiments with a small information network were used to demonstrate the model efficacy. The BAM model is still being refined and future tasks include developing a user interface for the BAM that can be used by intelligence analysts and comparing the current results to decision tree approaches.

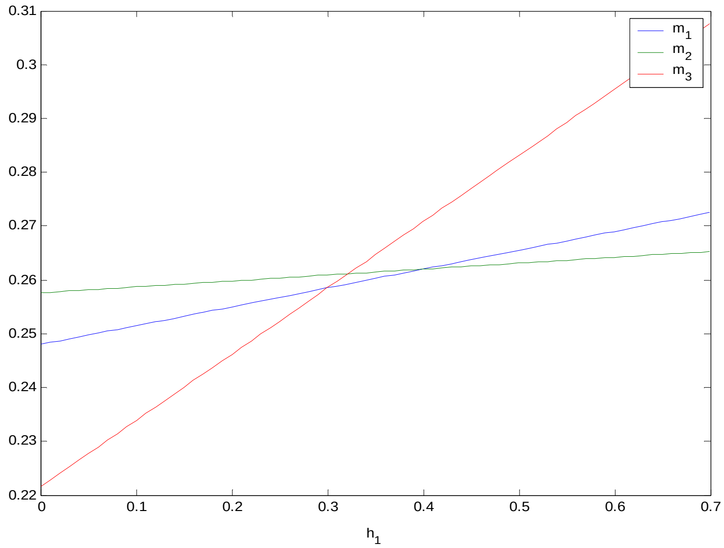

Figure 4: A graph showing a sample GA run. Variable h_1 is instantiated for different values and the resultant steady state probabilities of variable m_3 are displayed.

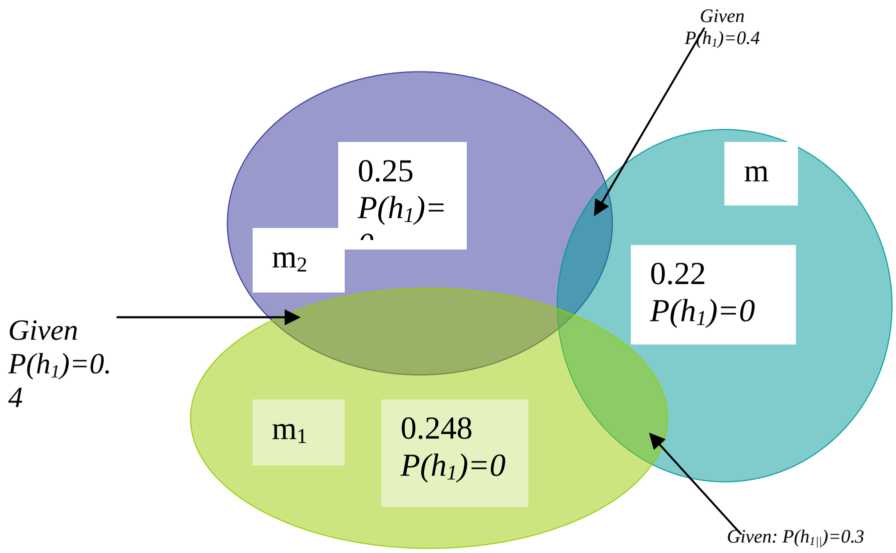

Figure 5: Solution space showing the feasible solutions for the sample run in figure 4 above

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