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Title: Adaptive Information Fusion in Asymmetric Sensemaking Environment
Topic: Modeling & Simulation

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We present the characteristics of sensemaking as an information fusion model based on Pierceean abduction logic. We use Bayesian network to model abduction logic primitives from a kernel of disparate information sources. We propose information fusion models for prospective and retrospective sensemaking conditions to simulate the ways commanders and the battle staffs process information. By using a constructive information network from Iraq conflict, we demonstrate our models in terms of robustness when compared to the traditional Bayesian model alone.
Specifically, the challenge for sensemaking is: *what happens when new information unexpectedly arrives to the intelligent analyst? For instance: (1) the adversaries change their attack methods; (2) new targets are exploited by the adversaries; (3) new adversary sponsors emerge (e.g., Iran, Syria, etc.); and (4) a coalition partner decides to withdraw from protecting a city.* The existing courses of action planning rarely survive the kinds of information described above. By combining the abduction process and Bayesian probability network formalisms, we propose a Bayesian Abduction Models (BAM) to support in the performance analysis of the sensemaking process such as illustrated in the sample case above.

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 system lacks analytical models that can capture the evolving states of battle dynamics and its information equivocality.This proposal seeks to minimize this problem by developing a probabilistic abduction model for the 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 *Ho* will represent an end state which is a composite hypothesis, for example, we can hypothesize that the Iran is responsible for the sectarian violence. The variables h_i form a subset of *Ho* and will represent the operational focus (Funneling money and weapons to insurgents, Covert operations in Iraq etcetera).The Variables X_i may represent a perceived motive for the operational focus while *Si* may represent the influence path(example: using the Al-Sadr militia, using Al-Qaeda).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; 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 or making the best inference from the given evidence.

The existing courses of action planning 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 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 of the sensemaking process such as illustrated in the sample case above

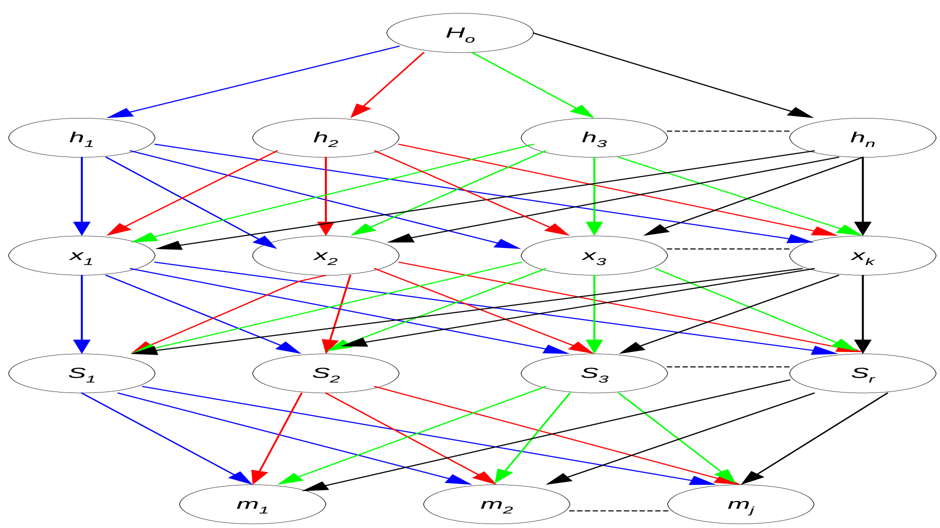

Fig 1:Example network where $\{h_i, x_i, S_i, m_i\}$ represent the *Endstate,Operational Focus,Influence path*and the *Target* variables respectively.

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 of 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, an 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 inferencing processes:

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

Abduction is 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.

Bayes Theory

We have alluded to the use of Bayesian theory in our proposed work. Without oversimplification,lets debrief our readers on the foundation of the Bayesian approach(Pearl,1990).In any situation in which we have to make decisions we are often interested in determining the best hypothesis from some space H, given observed data D. So far, there has been no substantive study on the application of Bayesian networks in sensemaking. There are several reasons why applications of the Bayesian models to sensemaking are often not of interest. First, equation (i) above cannot handle well hypotheses of multiple disorders-since Bayesian models are well grounded in diagnostics decision making process (pearl,1988).For example, given two independent hypotheses,h_1 and h_2 and a common data set D1,D2,…,Dm, the computation P(Dj|h1^h2) 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 explanation to take place in a sensemaking information network. The relationship between Bayesian reasoning and abduction is governed by the assertion that issues affecting reasoning, e.g., semantics is abductive in nature, thereby, a set of plausible explanations of a proposition characterizing the context of interest can be derived (Prakken, 2004).Simply

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

E is an explanation of world w

$$P(E) = \prod_{h \in E} P(h)$$

$$P(w \mid E) = \frac{P(w \,\&\, E)}{P(E)} \quad \begin{matrix} \leftarrow \text{explains w \&E} \\ \leftarrow \text{explains E} \end{matrix}$$

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 can compute the prior probabilities of all variables as follows

$P(h_1)= P(h_1|H_o)P(H_o) +P(h_1|H_a)P(H_a)= (0.9)(0.4)+(0.8)(0.6)=0.84$
$P(x_1)= P(x_1|h_1)P(h_1) + P(x_1|h_2)P(h_2)=(0.7)(0.84)+(0.4)(0.16) =0.652$
$P(S_1)=P(S_1|x_1)P(x_1) +P(S_1|x_2)P(x_2)=(0.5)(0.652) +(0.6)(0.348) =0.5348$

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

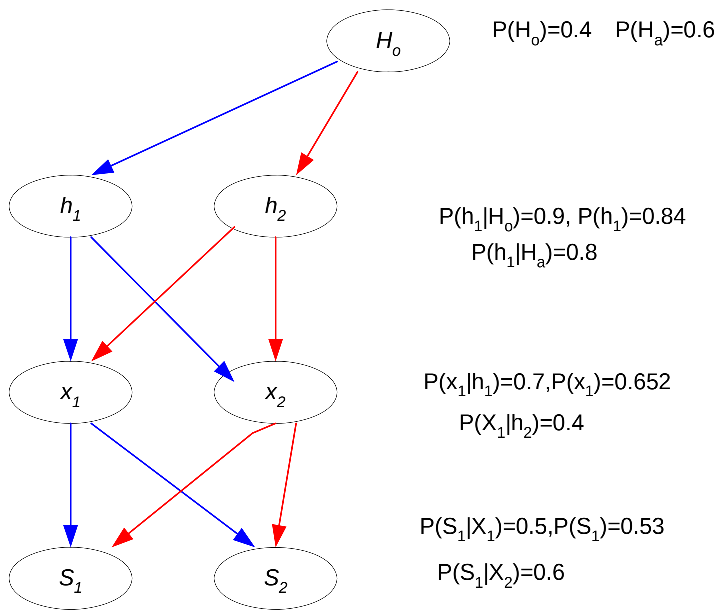

Fig 2 :Example network where $\{h_i, x_i, S_i\}$ represent the Endstate,*Operational Focus and Motivation* and the *Influence Path* variables respectively

$$
\begin{aligned}
P(h_1|H_o) &= 0.9\\
P(x_1|H_o) &= P(x_1|h_1,H_o)P(h_1|H_o) + (P(x_1|h_2,H_o)P(h_2|H_o)\\
&= P(x_1|h_1)P(h_1|h_o)+P(x_1|h_2)P(h_2|H_o)\\
&= (0.7)(0.9) + (0.4)(0.1) =0.67\\
P(x_2|H_o) &= P(x_2|h_2,H_o)P(h_2|H_o) +P(x_2|h_1,H_o)P(h_1|H_o)\\
&=P(x_2|h_2)P(h_2|H_o) + P(x_2|h_1)P(h_1|H_o)\\
&=(0.6)(0.1) +(0.4)(0.9)\\
&= 0.42\\
P(S_1|H_o) &= P(S_1|x_1,h_1)P(x_1|H_o)+P(S_1|x_2,h_2)P(x_2|H_o)\\
&= P(S_1|x_1)P(x_1|H_o)+P(S_1|x_2)P(x_2|Ho)\\
&= (0.8)(0.67) + (0.6)(0.42)= 0.734
\end{aligned}
$$

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(h1|S1), 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(S1|h1). That is

$$
\begin{aligned}
P(S_1|h_1) &= P(S_1|x_1)P(x_1|h_1)P(S_1|x_2) + P(S_1|x_2)P(x_2|h_1)P(x_2|h_2)\\
&=(0.5)(0.7)(0.6) +(0.6)(0.3)(0.6)\\
&=0.318
\end{aligned}
$$

$P(h_1|S_1) = 0.504$

We then compute the probability P (S1|Ho) and P(Ho|S1) in a sequence as follows

$P(S_1|H_o) = P(S_1|h_1)P(h_1|H_o)+P(S_1|h_2)P(h_2|H_o)$

$= (0.53)(0.9)+(0.47)(0.1)$

$=0.524$

Which gives us a probable explanation for prospective sensemaking.

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, this gives us a probable explanation for retrospective sensemaking.
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 $\{S_1,S_2, S_3..S_r\}$,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 obtained by the analyst, the analyst is interested in determining the possible effect on his most probable hypothesis, *Ho*. 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 post in a previously secure part of the country. This would definitely require a level of sophistication, challenging the analysts previous hypothesis about the end state of the insurgency. Using 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. By posing inference as search in a large discrete multi-dimensional space where the metric (phenotype) is the probability of each c hypothesis, GA can be conditioned to serve as an inferencing engine. More over GA's adaptive searching characteristic facilitates the search for 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. GA's use probabilistic transition rules, not deterministic ones and are amenable to probabilistic reasoning methods such Bayesian methods. 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 cardinality two for the variables so that the set {0,1} is sufficient to represent all the states of the variables. In this case,{0 } represents a variable (or node) in the network that is not instantiated while {1} represents an instantiated node. 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 straight 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:

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

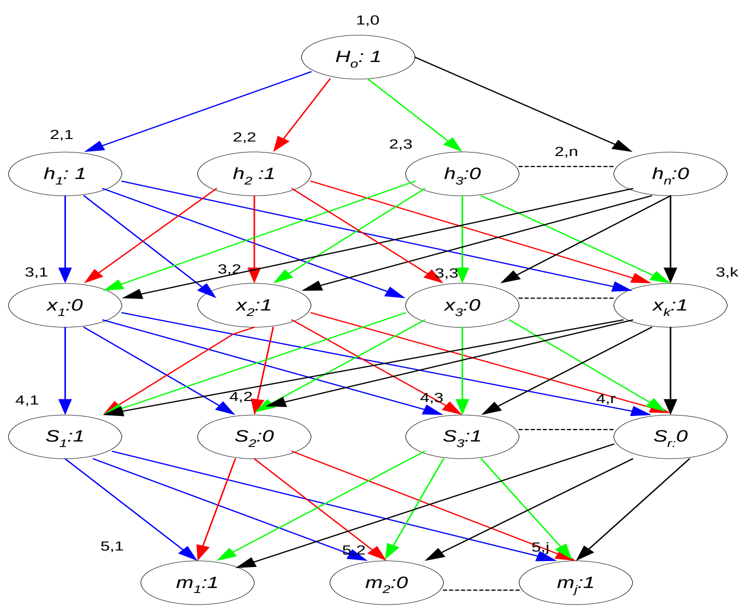

Fig 3:The network with all the instantiated variables coded {1}.the nodes are given position coordinates for the search process

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, we use a hypothetical network, an array of conditional probability tables was generated using Bayesian abduction inference.

Exhibit 1: Sample calculations using MathLab 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 some new information arrives to the analyst, a variable is 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 problem outcome (Most probable explanation).As mentioned before, this can be prospective or retrospective. Figure 4 illustrates the sample results using 1000 generations. The red line shows the most probable explanation and blue showing the least probable. The converging of the two lines occurs at 3000 generations. Note the probability (Y) scale is multiplied by 10. For this example, given the information, with probability of 0.4, the two hypotheses are equally likely to be accepted—this result is still being verified; may be happenstance or chance variability may be responsible for this convergence—something we are suspicious!!

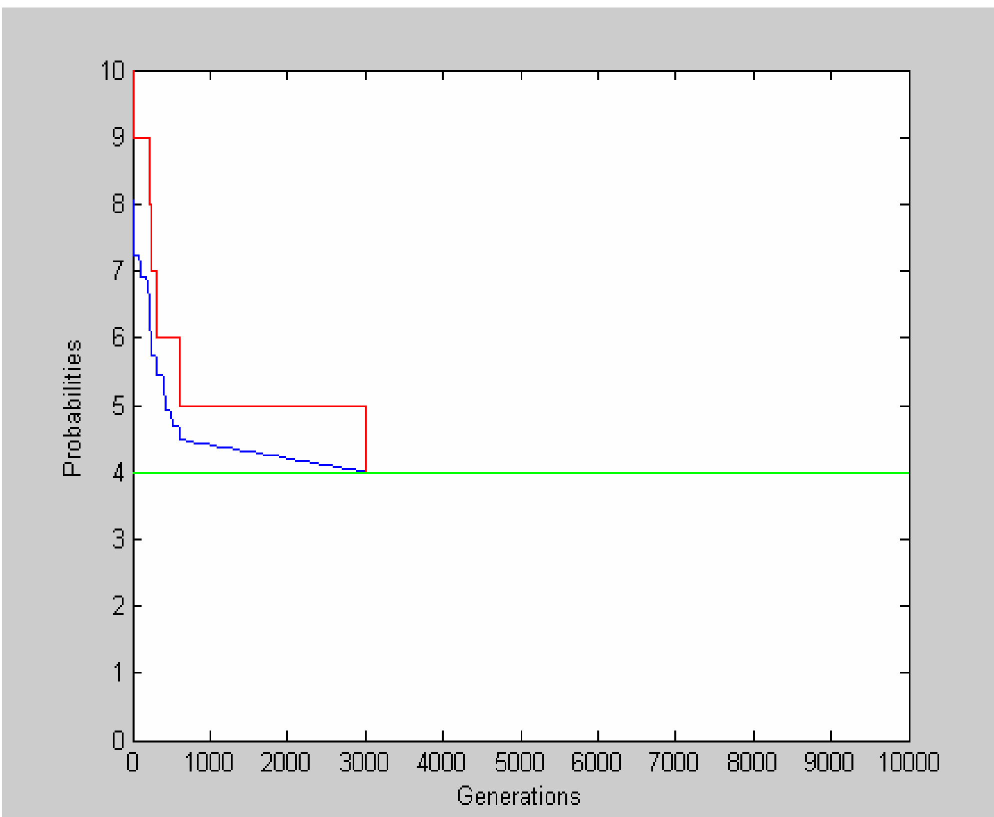

Figure 4: A graph showing a sample GA run (the red line shows the most probable explanation and blue showing the least probable).

Conclusion:

In this paper we present a computational model of adductive inference using Bayesian techniques. Sample simulation runs with networks of medium complexities have been undertaken and the model has been shown to provide approximate abductive inference for different two hypotheses test scenarios. Efficient and fast computation is accomplished by the use GA in the model. The BAM model is still being refined and future task include developing a user interface for the BAM that can be used by intelligence analysts.

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