Adaptive Information Fusion in Asymmetric Sensemaking Environment

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12th ICCRTS, Newport, RI, June 2007
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Motivation

• Asymmetric battlespace environments call for strategy rethink
  – Complex and “wicked” environment
  – Disparate information sources coupled with Uncertainty, ambiguity and dynamicity
• Deliberate MDMP is not sufficient
  – Linearity assumptions for non-linear asymmetric situations
• Generating COA must be progressive and opportunistic
  – Recalibration of the usual prescriptive-normative models of judgment and choice to fight unknown adversaries
• SENSEMAKING: Precursor to MDMP
  – “Connecting dots” to disparate information
  – Seeking explanations to unexpected evolving situations
  – Dynamic re-planning and re-tasking based on prospective and retrospective analysis
Sensemaking in the Context of C2

- How battle staff reduce uncertainty or ambiguity during decision making processes
- Aggregation of fragmentary battle space information (deriving meaning from fragmentary cues)
- Dynamic re-planning and re-tasking to account for the evolving asymmetric battlespace environments
- Aiding the commanders situation awareness by capturing the evolving states of battle dynamics, the information equivocality and the commander’s intent.
A hypothetical scenario: Analyzing the Iraq insurgency

- The Battlestaff start out with various hypotheses regarding a perceived desired end state of an insurgent operation, $H_o$
- To achieve this end state, the insurgents have various operational foci, $h_i$. Examples of this could be funneling money and weapons to a particular cell, attacking soft targets to draw out coalition forces etcetera.
- For each operational focus there is a motive $X_i$ or motives that avail themselves to the insurgents
- The operational focus and the motivation are uniquely effected by a pre-identified influence pathway, $S_i$. The influence pathway is a unique action or sets of actions that will be used to influence operations to achieve the desired end state
Illustration by Example

• In this case, an *influence pathway* could be the use of inflammatory religious sermons, political pressure—Al Sadr withdrawing from the unity government, arming militias, etcetera.

• For each of the unique *influence pathways* there is a specific set of *targets, m*, to be attacked and *targeted actions* designed to collectively bring about the desired *end state* (Mosques, Bridges, Coalition Ops Bases, Kidnappings, etcetera)

  – Figure 1 illustrates this example
Illustration by Example

Figure 1
Illustration by Example

Construct a *network* to represent all the *variables* in the scenario.

Issues for analytical sensemaking:

- For a simple hypothetical scenario note the *multiplicity* of causal linkages!!
- **Complexity** increases with *increasing variables*; in real life battle space environments we expect a large number of variables and multiple linkages; We may not even be able to identify all of them; Some are interrelated, some are latent
Illustration by Example

Of interest for C2 sensemaking:
• What happens when new information arrives to the intelligent analyst?
• How does the network behave?
• What variables are affected?
• Are the effects serious enough to warrant immediate changes in the existing COA?
Illustration by Example

- Examples: The adversaries change their attack methods (armor penetrating IEDS);
- What is the most likely *target*?
- What is the *influencing* factor? (Sourced from Iran?);
- What is the likely change in *operational focus*? (From soft targets to armored coalition patrols).
- Does it represent an operational shift from low level attritional attacks to bold guerilla style hit and run tactics?
- If so, what *end state* does the adversary hope to achieve by focusing on these particular variables?
Bayesian Abduction Model

- The existing COA and planning models not flexible to handle the types of scenario described above
- We have proposed the Bayesian abduction model that combines sensemaking with Peircean abduction reasoning to model complex situations where information ambiguity, equivocality and dynamicity are dominant.
- Using this model, an intelligence analyst is able to fuse information from disparate sources in real time to identify variables and causal links of interest from the multiplicity of factors in the complex battlespace environment.
- The analyst can then use abductive reasoning to form plausible explanations for the situation of interest
Bayesian Abduction Model

Features:

- Generates a list of **exhaustive and mutually exclusive** hypotheses regarding a scenario of interest.
- Represents all the variables of interest in the scenario as **nodes** to generate a belief network. Links from a parent node to a child node are **causal links**.
- Uses **Bayesian analysis** to evaluate all the possible states (solutions) for the network.
- Applies **Peircean abduction** reasoning to infer to the best explanation. (*E* is your collection of evidence; Hypothesis *h_i* explains *E*; No other explanation explains *E* as well as *h_i*; therefore *h_i* is probably correct)
Bayesian Abduction Model

- Uses Genetic algorithm (GA) to perform fast and efficient search for plausible alternatives presented as possible states of the network.
- The analyst makes a judgment call based on: How strong $h_i$ as compared to other alternatives; independent of all $h$, how good is $h_i$? How confident are you in the accuracy of $E$?; How thorough is the search for other plausible alternatives?.
Bayesian Abduction Model

Bayesian Analysis
Belief Network formulation

Generate initial population:
(initial sampling)
Instantiation done according to pre-specified rules.

Selection:
According to the probability metric, set a threshold probability value for selection

Reproduction:
Possible solutions are combined (Different paths are taken to evaluate all possible states of the network)

Mutation:
Low frequency random changes provides diversity and avoids premature convergence

Convergence?

Solutions (States of the Network)
Convergence to high probability states of the network.

Abductive Inference for sensemaking
Bayesian Probabilistic Reasoning

Rationale:

- Intelligence analysts assign subjective conditional probabilities to variables of interest in order to analyze their impact in a given scenario.
- The conditional probabilities are based on the “belief state” of the analyst, not classical probability.
- The analyst starts by assigning a conditional probability to hypothesis $h$ apriori based on his/her expertise and knowledge. Upon obtaining some new evidence $D$, the apriori epistemic state $P$ (state of knowledge) is revised by Bayes theorem into a conditional probability given by
Bayesian Probabilistic Reasoning

\[
P(h \mid D) = \frac{P(D \mid h)P(h)}{P(D)}
\]

- \(P(h)\) denotes the initial probability that hypothesis \(h\) holds, before we incorporate any new data.
- \(P(D)\) denotes the probability that evidence data \(D\) will be observed. \(P(D)\) represents the probability of evidence \(D\) given no knowledge about which hypothesis holds.
- \(P(D|h)\) denotes 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 \(D\).
Peircean Abduction Reasoning

A process of reasoning that tries to form a plausible explanation for new and anomalous data.

- Classification of a given data set into potentially relevant elementary explanatory hypotheses.
- Given an observation $d$ and the knowledge that $h$ causes $d$, it is an abduction to hypothesize that $h$ occurred.
- Given a proposition $q$ and the knowledge that $p \rightarrow q$, it is an abduction to conclude $p$.
- Is inherently uncertain since information or data supporting abduction process is dynamic in nature, leading to human construction of multiple and often competing hypotheses.
Modeling Approach

- We have a certain problem space or world $P(w)$ comprising of certain events of interest $P(E)$.
  - Let $P(w) = \sum P(E)$ where $E$ is an explanation of world $W$
- Assuming independent events

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

$$P(w | E) = \frac{P(w \& E)}{P(E)}$$

- The Abduction process in sensemaking is: Given $E$, explain $E$, then try to infer $w$ from these explanations
- Extend the model to account for uncertain information. An uncertain consequence corresponds to an event $E$, along with the probability $\alpha$ that $E$ did not happen,

$$P(w | E, \alpha) = \alpha P(w | E) + (1 - \alpha) P(w | \overline{E})$$
Modeling Approach

- In the case of a set of alternatives $E_i, i = 1, 2 \ldots n$, one of which is true, we extend the above equation thus:

$$P(w | \{E_i, \alpha_i\}_{i=1\ldots n}) = \sum_{i=1\ldots n} \alpha_i P(w | E_i)$$

- Formulate the problem as a belief network showing all the causal linkages together with the associated conditional probabilities.
- Once the state of the network is determined with all the instantiated variables determined, it is straightforward to perform backward or forward inference.
- Use a fast search algorithm such as the genetic algorithm (GA) to perform the search and computation for the most probable hypothesis-Abductive inference in belief networks is \textit{NP-hard}; The more complex the network, the harder the computation.
Modeling Approach

- A Genetic algorithm is an adaptation procedure based on the mechanics of natural genetics and natural selection. GA’s search from a population, not a single point and use randomized operators as opposed to deterministic rules.
- GA’s can handle very complex network problems.
  - Perform fast and efficient computation over large search spaces
  - Inference is performed as a search in a large discrete multi-dimensional space
  - Adaptive search facilitates the discovery of network states with high probability instantiations
  - Represent multiple states for each variable depending on the cardinality we select for the genetic coding.
Consider the hypothetical scenario previously described

- **Code** all the variables as a **finite length** string (in this case, **cardinality 2** so that the set \{0,1\} is sufficient to represent all the states of the variables)

- At any instance, the state of the network is fully determined by a vector \(a\), where

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

- The resulting **network representation** for all nodes is a binary pair \(\{C_j, a\}\) 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

  See Figure 2
Simulation

Figure 2
Simulation

- Subject the initial population to genetic operators {mutation, crossover, reproduction}
- The fitness function to determine propagation is calculated based on the defined Bayesian operators
- Start by assigning some apriori conditional probabilities such as
  
  \[ P(H_o) = 0.4 \]

  Implying we are only 40% confident that our chosen hypothesis regarding the end state is plausible.

- Similarly prior probabilities of all instantiated variables can be determined by straightforward application of Bayes theorem, for example
  
  \[ P(m_i) = \sum_{S_{i=1}} P(m_i \mid S_1, S_2, S_3, ... S_r) \]
Sample Results

Array 1: $P(h_i | H_o)$

<table>
<thead>
<tr>
<th>$h_i$</th>
<th>$H_o$</th>
<th>$H_o = 1$</th>
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<tbody>
<tr>
<td>$H_1 = h_1$</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>$H_2 = h_2$</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>$H_3 = h_3$</td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>$H_4 = h_4$</td>
<td>0.9</td>
<td></td>
</tr>
</tbody>
</table>

Array 2: $P(X_i | h_i)$

<table>
<thead>
<tr>
<th>$x_i$</th>
<th>$h_i$</th>
<th>$H_1 = h_1$</th>
<th>$H_2 = h_2$</th>
<th>$H_3 = h_3$</th>
<th>$H_4 = h_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1 = x_1$</td>
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<td>0.2</td>
<td>0.6</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>$X_2 = x_2$</td>
<td>0.3</td>
<td>0.4</td>
<td>0.5</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>$X_3 = x_3$</td>
<td>0.9</td>
<td>0.3</td>
<td>0.6</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>$X_4 = x_4$</td>
<td>0.1</td>
<td>0.9</td>
<td>0.7</td>
<td>0.5</td>
<td></td>
</tr>
</tbody>
</table>

Array 3: $P(S_i | X_i)$

<table>
<thead>
<tr>
<th>$S_i$</th>
<th>$X_i = x_i$</th>
<th>$X_1 = x_1$</th>
<th>$X_2 = x_2$</th>
<th>$X_3 = x_3$</th>
<th>$X_4 = x_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1 = s_1$</td>
<td>0.5</td>
<td>0.6</td>
<td>0.9</td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>$S_2 = s_2$</td>
<td>0.1</td>
<td>0.0</td>
<td>0.5</td>
<td>0.4</td>
<td></td>
</tr>
<tr>
<td>$S_3 = s_3$</td>
<td>0.9</td>
<td>0.1</td>
<td>0.3</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td>$S_4 = s_4$</td>
<td>0.5</td>
<td>0.6</td>
<td>0.7</td>
<td>0.4</td>
<td></td>
</tr>
</tbody>
</table>

Array 4: $P(m_i | S_i)$

<table>
<thead>
<tr>
<th>$m_i$</th>
<th>$S_i$</th>
<th>$S_1 = s_1$</th>
<th>$S_2 = s_2$</th>
<th>$S_3 = s_3$</th>
<th>$S_4 = s_4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_1 = m_1$</td>
<td>0.6</td>
<td>0.3</td>
<td>0.8</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td>$M_2 = m_2$</td>
<td>0.3</td>
<td>0.5</td>
<td>0.4</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>$M_3 = m_3$</td>
<td>0.1</td>
<td>0.9</td>
<td>0.2</td>
<td>0.6</td>
<td></td>
</tr>
</tbody>
</table>
Sample Results

1000 generations from GA

Sample GA run. Variable $h_1$ is instantiated for different values and the resultant steady state probabilities of variable $m_i$ are displayed.
Results Discussion

- 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 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. In this case, it is left to the analyst to look at other contributing factors before making inference.

See Venn Diagram in Figure 4
Sample results

Solution space showing the feasible solutions for the sample problem
Conclusion

• This paper proposes an analytical sensemaking model to aid the C2 decision making process that combines Bayesian formalism with Peircean abduction reasoning.
• The Bayesian abduction model (BAM) has been implemented using GA. The developed model and algorithms will improve the design of sensemaking support systems for the Future Combat Force.
• The aim of the modeling process is twofold: Foremost, retrospectively discovering or identifying variables or combinations therefore that can adequately explain observed adversary COA and secondly; Identifying variables and causal linkages that can aid in predicting an adversary’s set of COA.
• The model provides an advantage to information fusion in a system characterized by dynamicity and complexity—evolving system states.
Questions??