Introduction to Causal Modeling, Bayesian Theory and Major Bayesian Modeling Tools for the Intelligence Analyst

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This work introduces concepts behind Bayesian Causal Networks and their applicability in intelligence data analysis. This work briefly surveys Bayesian modeling tools and provides pointers for further investigation. Bayesian Causal Networks combine graphical representation with causal modeling techniques and Bayesian probability theory to provide a useful technique for event modeling and forecasting.

Key terms: temporal reasoning, Bayesian networks, Bayesian Belief Networks, causation, Causal modeling, conditional probability, probabilistic models, decision analysis, correlation, Bayes Law, Bayes Theorem, graph theory, probabilistic inference, influence diagrams.

1. Introduction

Bayesian Causal Networks combine graphical representation with causal modeling and Bayesian probability to provide a useful tool for intelligence analysis. They allow probabilistic causal models to be constructed to accomplish probabilistic forecasts of future events and situations. This paper introduces some concepts which are necessary to apply to causal modeling in an intelligence analysis context. It will provide some understanding of the principles of causation, principles of probability, the Bayes Theorem and an exposure to some Bayesian modeling tools available for use. This document is intended to be the first iteration of an evolving training guide for intelligence analysts.[2]

2. Causality, General Concept

The concepts of causality and causation, though loaded with a fair amount of philosophical baggage, are straightforward.[3] Causation, or the working of causes, refers to the

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[2] Another very good introduction to Bayesian Networks can be found in Eugene Charniak, “Bayesian Networks without Tears,” AI Magazine

[3] See Wikipedia entry for Causation at URL: < http://en.wikipedia.org/wiki/Causality >.

set of all particular "causal" or "cause-and-effect" relations. Most generally, causation is a relationship that holds between events, properties, variables, or states of affairs. Causality always implies at least some relationship of dependency between the cause and the effect. For example, deeming something a cause may imply that, all other things being equal, if the cause occurs, occurs the effect does as well or at least that the probability of the effect occurring increases. It is also usually presumed that the cause chronologically precedes the effect.

Causality is sometimes a confusing concept. Typically, conceptions of causality tend to be simplified and fail to grasp the underlying nature of things. One academic describes a taxonomy of causalities, going from basic to complex: (1) underlying causality, (2) relational causality, (3) probabilistic causality, and (4) Emergent causality. [4]

3. Causal Modeling and Its Utility

Described by Wikipedia, a causal model is an abstract model that uses cause and effect logic to describe the behavior of a system.[5] The logic can be as simple as a Boolean, "if-then" model or as complicated as Bayesian. A causal model is a specific type of model focusing on causal factors. Typically models will refer only to some aspects of the phenomenon in question, and two models of the same phenomenon may be essentially different, that is in which the difference is more than just a simple renaming. This may be due to differing requirements of the model's end users or to conceptual or esthetic differences by the modelers and decisions made during the modeling process.[6] Differences may also reflect some unique subject matter expertise available from individual analysts. Such differences highlight the utility of collaboration, provided by some causal modeling tools.

Causal modeling is related to but not the same as a variety of other mathematical techniques such as multiple regression. Multiple regression, for example, treats only one item as a dependent variable and tends to over-emphasis factors which are only limited impact.[7]

The utility of causal modeling ought to be fairly obvious in intelligence analysis, especially when considering military courses of action. A military commander is compelled to plan around likely or most likely situations. Typically an intelligence assessment for that commander contains an assessment of the most likely scenario as well as the most dangerous scenario. But beyond this, commanders would it useful to know the probabilities of enemy

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[4] Tina A. Grotzer and David N. Perkins, "A Taxonomy of Causal Models: The Conceptual Leaps Between Models and Students' Reflections on Them," Harvard University, URL: <http://www.pz.haIyard.edu/Research/UCppapers/taxNARST.pdf >, accessed on 25 October 2006.

[5] See Wikipedia entry for "Causal Model" at URL: < http://en.wikipedia.org/wiki/Causal_model>, accessed on 25 October 2006.

[6] See Wikipedia entry for "Scientific Model at URL: http://en.wikipedia.org/wiki/Scientific_modeling, accessed on 25 October 2006.

[7] See James Alan Neff, "Stmctural Equation Modeling: Introduction and Application to HIV Risk Behayiors ... and other stuff ...," at URL <www.utexas.edu/research/cswr/nida/images/Neff.PPT>, accessed on 25 October 2006. Techniques related to causal modeling include path analysis, structural equation modeling, LISREL (Linear Structural Relations), and Covariance Structure Analysis.

courses of action based on specific conditions. For instance, given a specifically important bridge, the only means of crossing a river, what would be the likely enemy courses of action if that bridge were damaged or destroyed? What would be the likely enemy courses of action if I attacked at a specific location, or made him think I was attacking him there? The Australian Defence Science and Technology Organisation (DSTO) incorporates a Bayesian modeling tool called COGNET, for example, to assist with center of gravity analysis.[8] Causal modeling provides another tool for the arsenal of operations research.[9]

Consider the conjecture that "if it rains, I will get wet." Clearly, if it does not rain, I will not get wet. But, on the other hand, whether or not I get wet also depends on whether or not I go outside, whether or not I have an umbrella and use it, whether or not it is raining when I go outside, and maybe some other factors. This example illustrates that typically there is a chain of causal factors and also typically a combination of causal factors. As Figure 1 shows, even simple causal models can take on a variety of structures.[10]

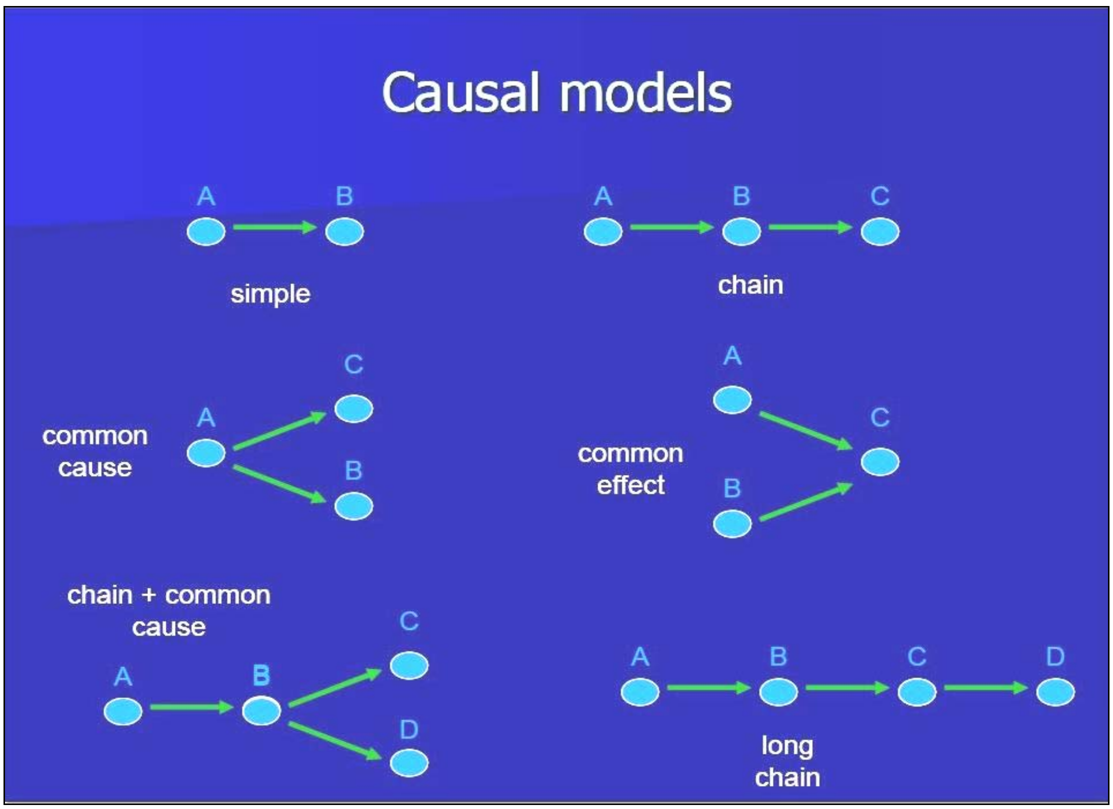

Figure 1: Various Simple Causal Models

[8] Lucia Falzon, "Using Bayesian Network Analysis to Support Centre of Gravity Analysis in Military Planning," *European Journal of Operational Research* 170 (2006): 629-643.

[9] Ronald D. Anderson and Gyula Vastag, "Causal Modeling Alternatives in Operations Research: Overview and Application," *European Journal of Operational Research* 156 (2004): 92-109.

[10] Figure adapted from David Lagnado, "Beyond Covariation: Cues to Causal Structure," Slide 64, at URL: < http://www.psychol.ucl.ac.uk/ljdm/talkppt/LagnadoLJDM.pdf >, accessed on 24 October 2006.

Figure 1 represents merely one type of causal model, the graphical causal model. Graphical causal models are a relatively new field and experienced huge theoretical growth during the 1990s.[11] Such models have some roots in graph theory and use some of the concepts of graph theory. Graphical causal models provide the benefit of a visual representation of the model.[12]

The model creator must understand enough of the relevant factors and relationships involved in the model for it to be a credible model. This leads to a premise:

> *Premise* 1: *Subject Matter Expertise* is *necessary for credible and accurate causal modeling.*

In an ideal world, or at least an ideal model, the collection of factors is "collectively exhaustive and mutually exclusive." That is to say, in this perfect model all the relevant factors are known and are completely independent of each other. In real life, very few problems allow such analytical luxuries. In the analytical experience, especially in the context of intelligence, a model is merely an approximation of what exists in real life, the causal factors are typically ambiguous and overlapping, and the model must be continuously modified once further (and hopefully better) data is available.

It is also critical to understand the difference between coincidence, correlation and causality. Two events may occur simultaneously, or coincide, and still be completely independent of each other. To a statistician there is high correlation between the two events, but in fact there may be absolutely no causal relationship.[13] This leads to another premise:

> *Premise* 2: *In causal modeling, care must be taken* to *distinguish between coincidence, correlation and causality.*

To illustrate, one of the most common errors we find in the press is the confusion between *correlation* and *causation* in scientific and health-related studies. In theory, these are easy to distinguish - an action or occurrence can *cause* another (such as smoking causes lung cancer), or it can *correlate* with another (such as smoking is correlated with alcoholism). If one action causes another, then they are most certainly correlated. But just because two things occur together does not mean that one caused the other, even if it seems to make sense. Unfortunately, our intuition can lead us astray when it comes to distinguishing between causality and correlation. For example, eating breakfast has long been correlated with success

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[11] Judea Pearl, "Influence Diagrams-Historical and Personal Perspectives," *Decision Analysis* 2, no. 4 (December 2005): 232-234; and Craig Boutilier, "The Influence of Influence Diagrams on Artificial Intelligence," *Decision Analysis* 2, no. 4 (December 2005): 229-231.

[12] Sander Greenland and Babette Brumback, "An Overview of Relations Among Causal Modelling Methods," *International Journal of Epidemiology* 31 (2002): 1030-1037.

[13] It is said that a statistician on his death bead will utter the words "Correlation is not," waiting for the reply "Causation." This repeats the mantra that "correlation is not causation," central to the study of statistics.

in school for elementary school children. It would be easy to conclude that eating breakfast *causes* students to be better learners. It turns out, however, that those who don't eat breakfast are also more likely to be absent or tardy - and it is absenteeism that is playing a significant role in their poor performance. When researchers retested the breakfast theory, they found that, independent of other factors, breakfast only helps undernourished children perform better.

If a cause and effect, for example have an absolute relationship then the probability of this cause and its effect has a value of "1," or absolute certainty. But, few things in life are this way. Consider the conjecture that "if it rains, I will get wet." Clearly, if it does not rain, I will not get wet. But, on the other hand, whether or not I get wet also depends on whether or not I go outside, whether or not I have an umbrella and use it, whether or not it is raining when I go outside, and probably other factors.

Bayesian methodology is based on conditional probabilities: if variables *A* and *B* are not independent then the belief in *A* given that *B* is known is the conditional probability $P(A|B) = P(A, B) / P(B)$.[14] This formula simply shows the degree of belief in the state of *A* when the state of *B* is known. Likewise, the probability of B given A can be calculated in the same manner, yielding what has come to be known as Bayes Law or Bayes theorem:

$$P(A|B) = P(B|A)\,P(A) / P(B)$$

This rule is at the very heart of Bayesian analysis. It allows information updating in response to new information.[15] Three steps are involved in Bayesian modeling: (1) developing a probability model that incorporates existing knowledge about event probabilities, (2) updating the knowledge by adjusting the probabilities according to observed data, and (3) evaluating the model with respect to the data and the sensitivity of the conclusions to the assumptions.

Perhaps stated in more basic terms, a succinct working explanation of Bayes' rule has been provided in an Economist article:[16]

> *"The essence of the Bayesian approach is to provide a mathematical rule explaining how you should change your existing beliefs in the light of new evidence. In other words, it allows scientists to combine new data with their existing knowledge or expertise. The canonical example is to imagine that a precocious newborn observes his first sunset, and wonders whether the sun will*

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[14] In this nomenclature, P (*A*|*B*) means the probability of *A* given *B*, P (*B*|*A*) means the probability of *B* given *A*, P (*A*) means the probability of A and P (*B*) means the probability of *B*. *A* and *B* can be events, states, conditions or anything to which a probability can be assigned.

[15] Research in Bayesian causal modeling involves the process of building causal models automatically from data and modifying the causal model once new data is received. Such rigor is far beyond what is typically necessary for a causal model in the general intelligence context although rigor is always welcome when possible.

[16] “In Praise of Bayes,” *Economist* 356, no. 8190 (30 September 2000): 83-84. Extract found on URL <http://www.cim.mcgill.ca/-friggi/bayesfbayesrule/>, accessed on 26 September 2006. Another useful Economist article is “Bayes Rule,” *Economist* 378, no. 8459 (17 January 2006): 70-71.

rise again or not. He assigns equal prior probabilities to both possible outcomes, and represents this by placing one white and one black marble into a bag. The following day, when the sun rises, the child places another white marble in the bag. The probability that a marble plucked randomly from the bag will be white (i.e., the child's degree of belief in future sunrises) has thus gone from a half to two-thirds. After sunrise the next day, the child adds another white marble, and the probability (and thus the degree of belief) goes from two-thirds to three-quarters. And so on. Gradually, the initial belief that the sun is just as likely as not to rise each morning is modified to become a near certainty that the sun will always rise. "

The process of adjusting the causal model is often referred to as "truth maintenance."

4. Building Causal Models[17]

Authors Nadkarni and Shenoy, in a paper in the Decision Support Systems journal, propose a four-step procedure to construct Bayesian causal maps: [18]

1. Data elicitation (gathering and consolidation),
2. Derivation of causal maps,
3. Modification of causal maps to construct Bayesian causal maps, and
4. Derivation of the parameters of Bayesian Causal maps.

In the first step, qualitative information is gathered (or documented) concerning the topic in question. On approach, perhaps for a completely new topic, is an interview with a subject-matter expert. The responses to such an interview are gathered and transcribed in textual fashion to get a "narrative." Two approaches to this are useful, structured and unstructured. Structured methods are useful for confirming or validating expert knowledge rather than gathering knowledge for domains that are not clearly defined. Unstructured approaches, such as "what are the factors relevant to the decision?" yield important insights into general knowledge held by a variety of individuals.

Four parts are involved in the second step, derivation of causal maps: (1) identifying causal steps from the knowledge acquired in step 1, (2) building raw (Rough) causal maps, (3) constructing a coding scheme (naming the factors), and (4) converting the raw causal maps into code causal maps (linking the factors and what they are believed to cause).

The third step, modifying the causal maps, involves the consideration of four major modeling issues: (1) identifying conditional independencies, (2) discerning the underlying links between concepts, (3) distinguishing between direct and indirect relationships, and (4)

[17] A causal model is also referred to as a causal map and other terms. The developers of the Java Causal Analysis Tool (JACT), for example, refer to them as "plans." A Bayesian causal model is also known as a Bayesian Belief Network (BBN), once appropriate values are assigned.

[18] Suchete Nadkarni and Prakash P. Shenoy, "A Causal Mapping Approach to Constructing Bayesian Networks," *Decision Support Systems* 38 (2004): 259-281. The four steps are annotated and commented on here.

eliminating circular relations.[19] One widely used method to accomplish this is the use of adjacency matrices. Nadkarni and Shenoy provide an example matrix factors considered when selecting a car to purchase. In the matrix shown in Table 1, a '0' means there is no relationship, a '+' means there is a positive relationship and a '-' means there is a relationship between case and effect.

	Mileage	Age	Fuel Efficiency	Performance	Brand Quality
Mileage		+	0	0	0
Age	0		0	0	0
Fuel Efficiency	-	-		0	+
Performance	-	-	+		+
Brand Quality	0	0	0	0	

Table 1: Illustration of an Adjacency Matrix

Using JCAT, the corresponding network would appear as shown in Figure 2, where solid lines act as causes ('+' values above) and dashed lines act as inhibitors ('-' values above). Where the above matrix contains a '0', there is no connection.

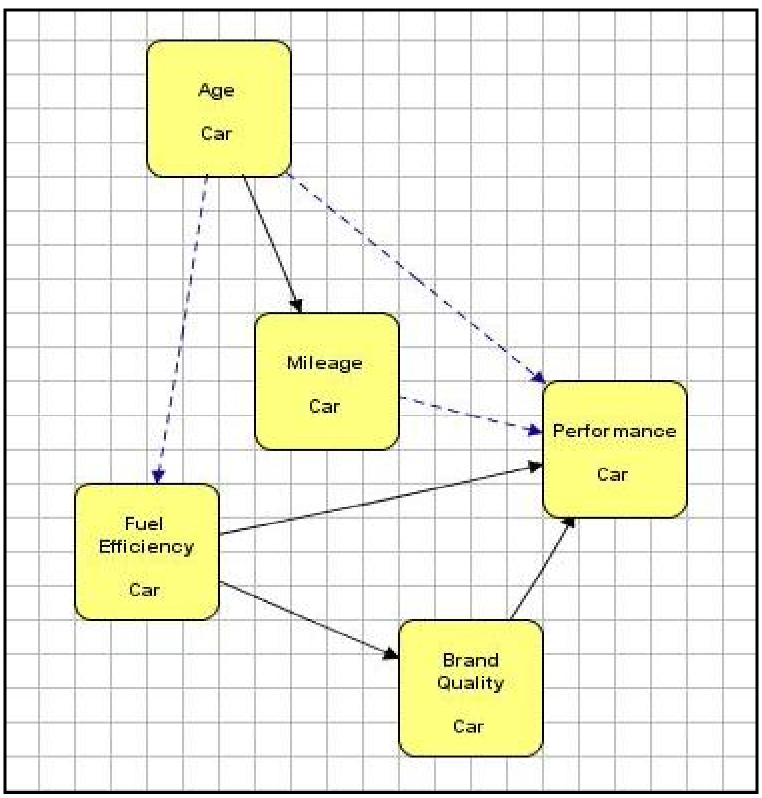

Figure 2: Automobile Comparison Causal Model

[19] Circular dependencies are verboten in causal diagrams, although some tools allow for such "feedback" if the items are independent in time.

From the diagram it should be apparent that fuel efficiency and a quality brand act to increase the performance or merit of the vehicle. Efficiency and Brand have direct causal effect on the performance. At the same time, the age of the vehicle and the mileage act as inhibiting causes on the vehicles performance. Age also indirectly affects performance through mileage and fuel efficiency. This causal model is just a section of a larger causal model by Nadkarni and Shenoy which includes performance as well as price and car condition as factors in a decision model for car purchase.[20]

Once the structure of the Bayesian causal map has been constructed, numerical parameters of the network need to be assessed so that results can be calculated. Fortunately, these calculations are typically embedded inside Bayesian modeling tools. Figure 3 shows the results of a simple JCAT simulation.

Figure 3 – Simulation of Car Performance Model

With the additional factor of setting an initial mileage value, the causal model shows how the performance or value of the car decreases over time. While this causal model is largely notional, it does illustrate one additional feature of the JCAT tool, the ability to model over time. In this model, initial mileage is kept at a constant value. In more complicated simulations values can increase or decrease over time. Historical models have been built, for example, showing the rise and fall of civil unrest among specific Southeast Asian population groups.[21]

Consider a more complicated example, a planned air attack against a hypothetical enemy. We will model the likelihood of a successful attack based on (1) the timing of our planned attack, (2) inclement weather and (3) the operational status of enemy air defenses. Success here will simply be defined as a weather-enabled attack with no resistance. For an attack to be successful, it must occur, air defenses must not be operational (by whatever means) and the weather must be good. Eight different combinations of the three factors occur, which will "schedule." Figure 4 shows this simple air attack Bayesian causal model. Figures 5, 6 and 7 show the "scheduling" of Operational Air Defense Assets (only operational during intervals 4 through 7), Inclement Weather and Our Air Attack. Figure 8 shows the results of the causal model, showing, as expected that success is more likely when the weather is good, air defenses are disabled and we actually attack. Obviously, when we do not attack, success has a zero

[20] Nadkarni and Shenoy, p. 263.

[21] See unpublished JCAT models for Aceh and for Thailand, but by Keith Anthony and USAFR Maj Joel Montgomery.

probability. Given an attack, success is least likely when the weather is bad and air defenses are operational.

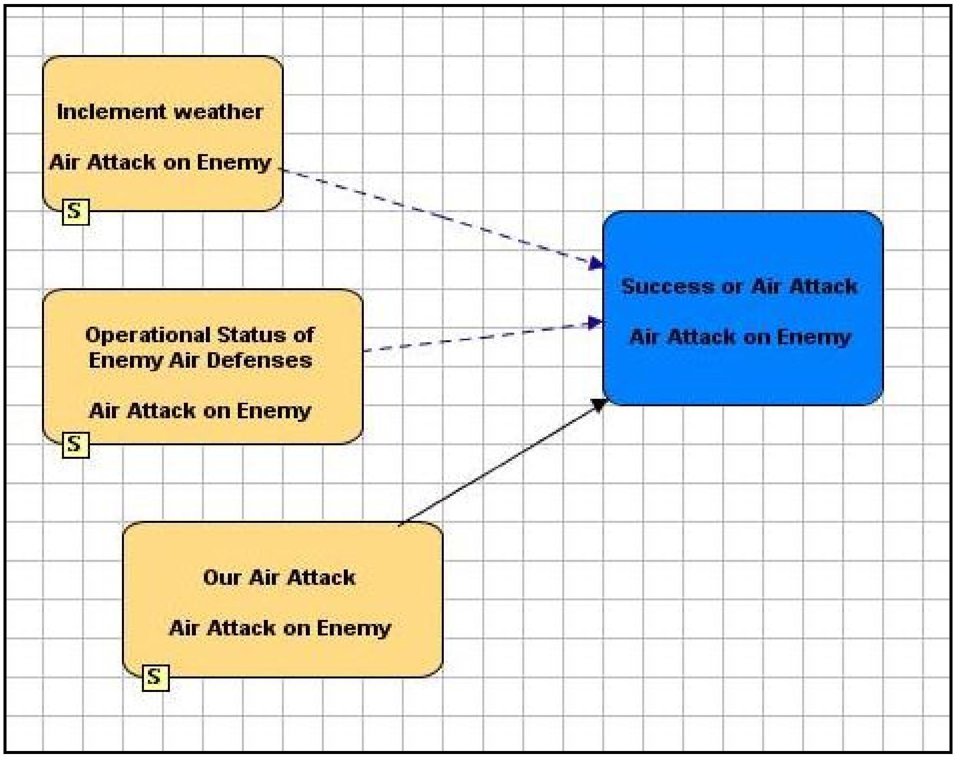

Figure 4 – Air Attack Bayesian Causal model in JCAT

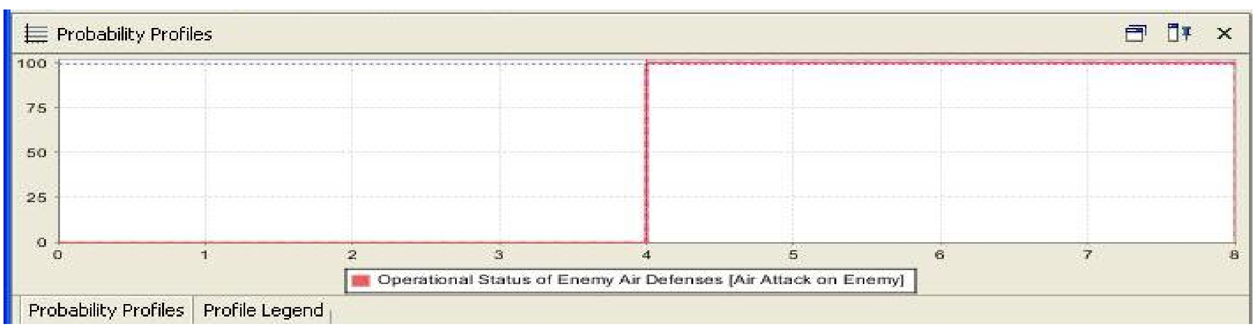

Figure 5 – Scheduling of Operational Air Defense Causal Factor

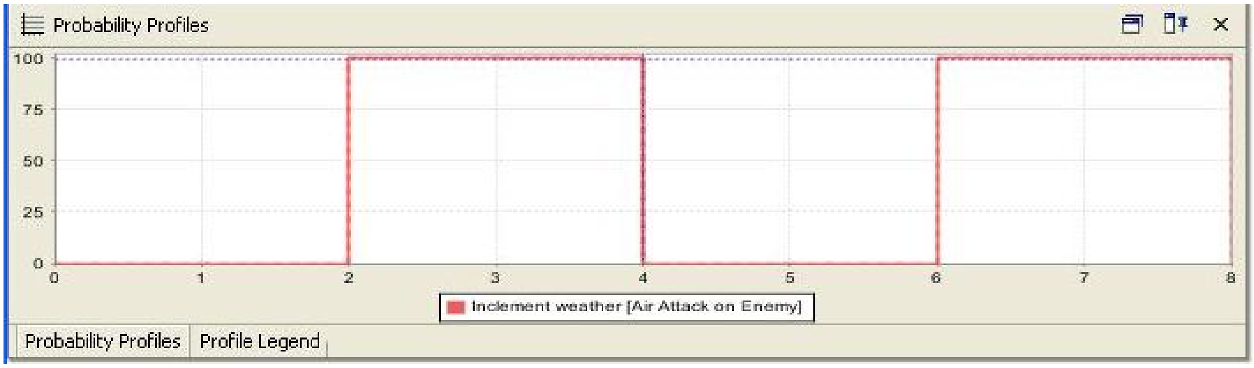

Figure 6 – Scheduling of Inclement Weather Causal Factor

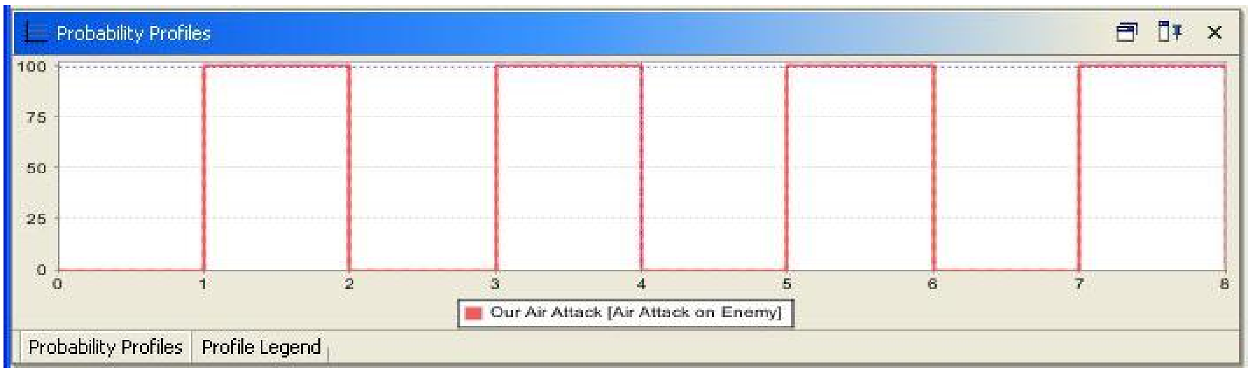

Figure 7 – Scheduling of Air Attack Causal Factor

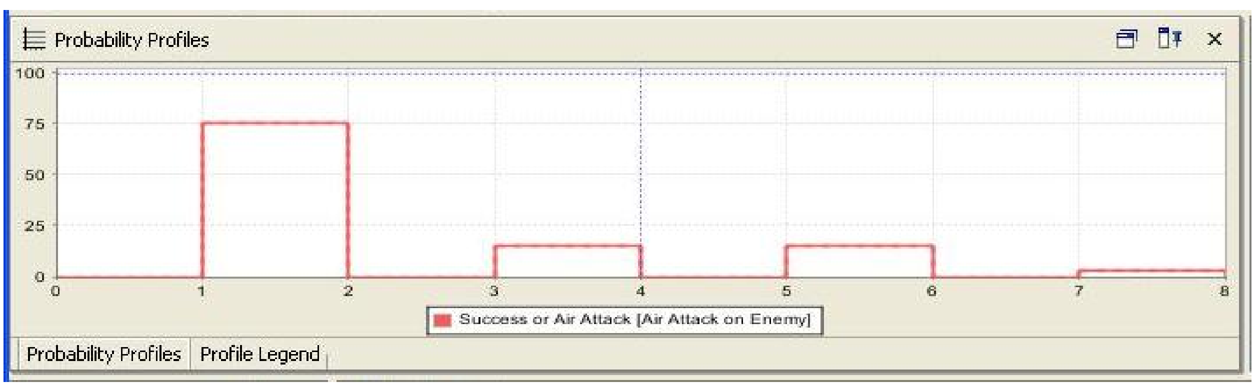

Figure 8 – Simulation of Resultant Success Causal Factor

JCAT provides another feature, the ability to specify synergy between causal factors. Factors may have specific causal factors when acting alone , but different ones when acting with other factors. In such manner, this gives the ability to model "tipping point" factors for a specific problem. This JCAT model could be modified to show the effects of specific operations to disable the enemy air defense system or made more complicated with other possible actions to accomplish overall mission objectives, with an air attack being merely one possible mission option.

Causal maps, also called cause maps or even cognitive maps, are connected to graph theory in that they are directed acyclical graphs (DAGs) that represent cause-effect relationships. Causal maps express judgments, or beliefs, that certain events, actions or conditions will lead to particular outcomes. Causal maps have three major components: causal concepts, causal connections and causal values. Causal values may be constant, instantaneous, sporadic or persistent. JACT allows models to give a causal factor persistence – although a factors value may be momentary, the effects of that factor can be felt for a certain time period afterwards in a diminishing fashion. For instance, although the Acehen tsunami of December 2004 was over in a very short time period, its effects are still being experienced now, almost two full years later.

5. Refining Causal Models

Models, of course, are only representations of real-life and are even in the best case, limited, inaccurate and evolving. MIT Professor Sterman has observed that "All models are wrong!'[22] So, it is likely that even the best, most thought-out causal model, using the best tool available, will need to be modified. The probabilities will need to be adjusted. Previously hidden, unknown or even-nonexistent factors will emerge. Existing factors will become irrelevant and need to be eliminated. Bayesian theory provides the facility to do this automatically in a mathematical context (and result in a mathematically precise and correct result). For our graphical models and use with tools, such as JCAT, simply adjusting the model will suffice.

6. Causal Modeling Tools

A variety of Bayesian causal modeling tools are available, some from commercial vendors and some in the public-domain. A tool produced at the Air Force Research Laboratory facilities at Rome Labs, NY, known as the Java Causal Analysis Tool (JCAT), has been used to produce the model described and displayed above. JCAT, being Government Off-the-Shelf (GOTS) is freely available for use. JCAT differs from other available tools in that it provides the capability to produce time-sequenced models, it allows synergistic combinations of causal factors and its calculations are a rigorous implementation of Bayes theory. Other tools in common use include Netica and BNet.

[22] John D. Sterman, "All Models are Wrong: Reflections on Becoming a Systems Scientist," *System Dynamics Review* 18, no. 4 (Winter 2002): 501-531. The phrase actually has an earlier origin in George E. P. and Norman R. Draper, *Empirical Model-Building and Response Surfaces* (New York, New York: Wiley, 1987): 74, 424, and has two variants: (1) "Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful" and (2) "Essentially, all models are wrong, but some are useful."

#. Causal Modeling File formats[23]

A variety of file formats have been created for use with Bayesian causal tools. Of major importance is the Bayesian Interchange Format (BIF), an XML-based proposal for interchange of Bayesian file data.

Name	File Name Suffix	Description
Bayesian Interchange Format	.bif	The goal of the current effort is to specify a XML-based format that is very simple to understand and yet can represent directed acyclic graphs with probabilistic relations, decision variables and utility values. The current format is referred to as XMLBIF version 0.3. The proposed interchange format. I am following Fabio Cozman's version of the format, which is similar to the original proposal.
MSBN	.dsc	Microsoft's BN tool format. See the MSBN page.
Hugin	.hugin	File format used by the HUGIN BN tool.
Ideal	.ideal	A format that is based on the one used in the IDEAL toolkit.
Ergo	.ergo	File format used by the ERGO BN tool.

[23] Found at “Bayesian Network Repository,” URL: <http://www.cs.huji.ac.il/labs/compbio/Repository/ > , accessed on 27 October 2006.

#. For Further Research

A number of professional journals and publications provide papers concerning causal modeling, Bayesian networks and related topics. The scope of these publications ranges from the imminently practical to theoretical mathematics:

- AI Magazine
- Causal Modeling
- Cognitive Science
- Computational Intelligence
- Decision Analysis
- Decision Support Systems
- European Journal of Operational Research
- IEEE Transactions on Systems, Man and Cybernetics
- International Journal of Approximate Inference
- International Journal on Artificial Intelligence Tools
- International Journal of Forecasting
- International Journal of Pattern Recognition and Artificial Intelligence
- Journal of Applied Probability
- Journal of Artificial Intelligence Research
- Journal of Experimental & Theoretical Artificial Intelligence
- Journal of Machine Learning Inference
- Journal of Machine Learning Research
- Journal of Uncertainty, Fuzziness and Knowledge-Based Systems
- Knowledge-Based Systems
- Mathematical and Computer Modelling
- Military Operations Research
- Risk Analysis
- Simulation Modelling Practice and Theory

Moreover, the Internet provides a number of quite useful resources on the topic of Bayesian methods (this list is by nature incomplete, but includes some notable items):

- A Primer on Bayesian Statistics in Health Economics and Outcomes Research

- Judea Pearl's publication site
- Judea Pearl's lecture The Art and Science of Cause and Effect
- Judea Pearl's lecture on Reasoning with Cause and Effect
- Judea Pearl's book, Causality: Models, Reasoning, and Inference
-
- Publications by Prakash Shenoy

- Homepage for Decision Analysis

- AI Magazine article by E. Charniak, "Bayesian Networks Without Tears"

#. Bayesian Tools [24]

This table presents and describes a sampling of some Bayesian models. URLs are provided for more information. There is no distinction here between commercial tools and public-domain tools.

Analytica	Analytica is a Macintosh-based, visual environment for creating, analyzing and communicating probabilistic models for business, risk and decision analysis. It is the successor to Lumina's Demos decision modeling system for the Macintosh. (see http://www.lumina.com/index.html)
BayesiaLab	A complete set of Bayesian network tools, including supervised and unsupervised learning, and analysis toolbox. (see http://www.bayesia.com/)
B-Course	Software tool useful for analyzing multivariate probabilistic dependencies and building the corresponding Bayesian networks.[25] (see http://b-course.hiit.fi/)
Bayes Net Toolbox for Matlab	(see http://bnt.sourceforge.net/) The Bayes Net Toolboc is designed as a plugin toolkit for Matlab.
BNet	A family of tools for building, using and embedding belief networks in your own software. (see http://www.cra.com/commercial-products-services/belief-network-modeling.asp) BNet is embedded in a variety of larger systems.
Cleverset	Bayesian-based tools to analyze past and current behaviors of customers. (see http://www.cleverset.com/solution/howitworks.html)
COGNET	COG (Center of Gravity) Network Effects Tool, in use by the Australian Defence Science and Technology Organisation (DSTO).[26] COGNET uses HUGIN as its Bayesian engine.
Ergo	Erg0 is a Bayesian network editor and solver produced by Noetic systems (see http://www.noeticsystems.com/ergo/)
GeNie	Decision modeling environment implementing influence diagrams and Bayesian networks (Windows). Has over 2000 users. SMILE (Structural Modeling, Inference, and Learning Engine) is a fully portable library of C++ classes implementing graphical decision-theoretic methods, such as Bayesian net-works and influence diagrams, directly amenable to inclusion in intelligent systems. Its Windows user interface, GeNie is a

[24] This is probably not an all-inclusive list – tools will be added as be become aware of them.

[25] "B-Course: A Web-Based Tool for Bayesian and Causal Data Analysis," *International Journal on Artificial Intelligence Tools* 11, no. 3 (2002): 369-387.

[26] Lucia Falzon, "Using Bayesian Network Analysis to Support Centre of Gravity Analysis in Military Planning," *European Journal of Operational Research* 170 (2006): 629-643.

	versatile and user-friendly development environment for graphical decision-theoretic models. Both modules, developed at the Decision Systems Laboratory, University of Pittsburgh, have been made available to the community in July 1998 and have now several thousand users worldwide. (see http://genie.sis.pitt.edu/)
HUGIN	Full suite of Bayesian Network reasoning tools (see http://www.hugin.com/).
JavaBayes	Builds Bayesian Networks in Java. See < http://www.cs.cmu.edu/~javabayes/Home/ >.
JCAT	Java Causal Analysis Tool is a Java-based implementation of the Causal Analysis Tool (CAT) developed by Dr. John Lemmer at AFRL/IF.
jNBC	**jBNC** is a Java toolkit for training, testing, and applying Bayesian Network Classifiers. Implemented classifiers have been shown to perform well in a variety of artificial intelligence, machine learning, and data mining applications. (see http://jbnc.sourceforge.net/)
MIM	MIM is a tool for graphical modeling applied in many different fields. It is designed to help you understand complex multivariate data, by facilitating graphical representations of the dependencies between the variables under study. MIM is based on a comprehensive class of statistical models for discrete and continuous data. The dependence properties of the models can be displayed in the form of a graph. MIM implements a full range of statistical techniques based on the models, including maximum likelihood estimation, hypothesis testing, model selection and much more. MIM can be downloaded for free. (see http://www.aisee.com/apps/mim.htm)
MSBNx	MSBNx is a component-based Windows application for creating, assessing, and evaluating Bayesian Networks, created at Microsoft Research. The application's installation module includes complete help files and sample networks. Bayesian Networks are encoded in an XML file format. The application and its components run on Windows 98, Windows 2000, and Windows XP. (see http://research.microsoft.com/adapt/MSBNx/default.aspx)
Netica	Netica, the world's most widely used Bayesian network development software, was designed to be simple, reliable, and high performing. For managing uncertainty in business, engineering, medicine, or ecology, it is the tool of choice for many of the world's leading companies and government agencies. (see http://www.norsys.com)
Precision Tree	An add-in for Microsoft Excel for building decision trees and influence diagrams directly in the spreadsheet (see http://www.palisade.com/)
SIAM	SIAM is a powerful software application designed to assist people in analyzing complex problems and issues, especially when empirical information is sparse or uncertain. SIAM can be used in a range of operational situations, from corporate decision making to national security planning. (see http://www.inet.saic.com/inet-public/siam.htm)
XBAIES	XBAIES is a Windows-based system for Bayesian network inference and learning. See < http://www.staff.city.ac.uk/~rgc/webpages/xbpage.html >

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