A Genuinely Bayesian Tool for Managing Uncertainty in Plans

John Lemmer
Buster McCrabb

Air Force Research Laboratory (AFRL) has developed a true Bayesian tool for managing uncertainty in temporal plans. The tool is principled, rich in supported modeling details, and feasible both for humans to use and for PCs to compute.

During conflict, risk is a continuous concern for commanders. A major source of risk is uncertainty about future outcomes of their presently planned and executing actions. Another source of uncertainty is trying to understand how the outcomes commanders do see relate to actions they have previously taken or were taken by others, including the adversary. The US Air Force Research Laboratory Information Directorate (AFRL/IF) Rome Research Site is developing a technology to address each of these problems.

Temporal plans are plans which evolve over time. Such plans present Bayesian analysis with many challenges, both humanistic and computational. True Bayesian analysis, with its voracious appetite for numbers, can overwhelm both analyst and computer.

In order to tame this voracious appetite, current Bayesian tools often resort to extreme approximations. These approximations render the potential power of Bayesian reasoning almost ineffective, and result in an analysis little different from one performed with Fuzzy Sets or heuristics. The result is that plans are modeled and analyzed with limited, often almost useless levels of fidelity.

The AFRL tool avoids overwhelming both the model builder and computer without resorting to extreme, unjustified approximations. It allows the analyst to provide exactly the model parameters she thinks important while estimating the remaining using *causal* (*not* statistical) reasoning. This approach allows known causal correlations to be input while avoiding burdening the human with details. The tool also allows the computer to avoid being overwhelmed by computations by avoiding marginally useful computations. The result is a tool which does not need to assume away the power of true Bayesianism.

The Problem

The temporal aspects of plans arise from three major sources. First the actions under the control of the planner are scheduled over a period of time, not necessarily all taking place at once. Second, there are often delays in the effects produced by these scheduled planned actions, and, third, the direct and indirect effects which are produced may last for only a finite period of time. The uncertainties in these plans arise because the scheduled actions will not always produce the desired effects, length of delays may vary, as may periods of persistence. Moreover, multiple causes acting in temporal relation with each other may be required to produce some effects.

Large uncertain temporal plans are notoriously difficult for humans to accurately understand. Local cause/effect uncertainties seem to be significantly easier to understand and estimate than are the uncertainties of indirect effects propagated across a plan from many local sources. For example, if a bomb of a certain kind strikes a particular type of bridge, the probability that the bridge will be unusable after the strike is understandable and can be determined, at least in principle, by empirical testing. Suppose, however, that the purpose of bombing the bridge is not simply to disrupt road transportation but also to disrupt the electrical power transmitted on cables carried by the bridge. Suppose further, that these effects are desired for their indirect effects on both food supply and morale. It is hoped that these in turn will cause civil unrest. In any reasonable plan it is likely that many other actions will also be taken with the ultimate goal of achieving civil unrest. In such a case it becomes much more difficult for humans to assess the overall effect of successfully (or not) having destroyed a particular bridge.

The purpose of the AFRL tool is to integrate and to propagate local probabilistic assessment of plan elements into an overall assessment of global plan uncertainty. The primary output of the tool is the probability over time that particular effects will be achieved. (See Figure 2a.) This propagation is carried out in a principled way using models of the (uncertain) cause/effect relationships forming the basis of a plan. It is the principled, genuinely Bayesian, methods that differentiates the AFRL tool from its competitors. Because of its principled methods and lack of unrealistic assumptions, the results have clear meaning which can be understood, analyzed and debated.

The uncertain analysis is done on causal models built by planning domain experts .The local probabilities associated with elements of the plan (e.g. the probability of closing a bridge as the result of an air attack) are also provided to the tool. One of the main benefits accruing from the tool's principled approach is how it facilitates user provision of probabilities.

The Tool

How does the AFRL tool differ from other superficially similar tools? With our tool, the modeler constructs a model graphically, as in many other tools. Like other tools the modeler provides numbers related to the uncertainty of the various cause effect relations. All tools then perform computations to provide an overall assessment of uncertainty.

But here the similarities end. Once the AFRL tool's hood is raised, the differences from other tools are as notable as the differences between raising the hood on a NASCAR machine and its look-alike production model:

1) The model is temporal not static: events can begin and end over time; effects can be delayed; effects, once achieved, may have only finite persistence. 2) The edges strictly mean "causes", not "is conditionally dependent on", "influences", or some other, non-causal perhaps ill-defined meaning. Causal nodes in the graph can have relations to each other besides "independent". Causes can be, for example, synergistic or jointly necessary. 'AND' relations among causes can be modeled. Such relationships allow the user to build higher fidelity models. 3) Causal relationships can also reduce the number of probability estimates the user need provide. 4) Observations of actual events can be used, over time, to update predictive results. 5) Large models with many temporal connections spanning significant time lengths are computationally feasible.

Yet with all these features, the *meaning* of the model and of the calculated probabilities remains unchanged. To those familiar with modeling uncertainty, these are large claims, and require a closer look.

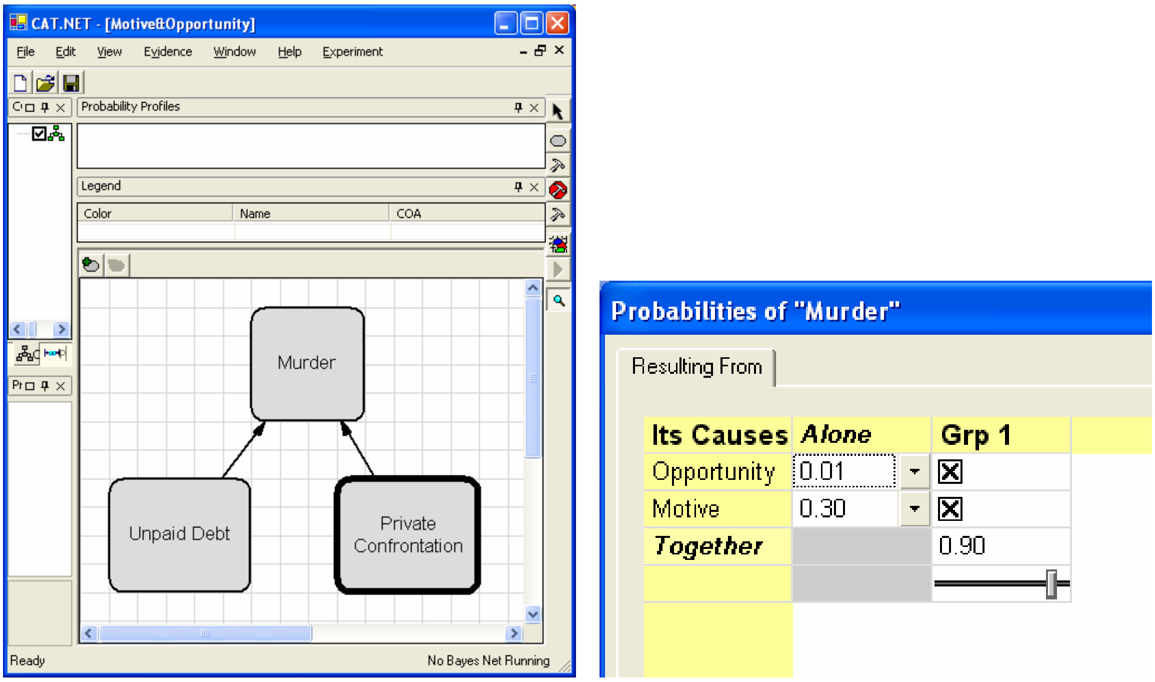

Figure 1: a)Causal Model, b)Mechanisms Uncertainly Causing Murder

In the CAT model shown in Figure 1a, an unpaid debt provides the motive for murder, and a private confrontation provides the opportunity. For a particular individual, whom we will call Tony, the table in Figure 1b provides the probabilities that the causes, both motive and opportunity, will actually result in murder. Opportunity alone provides only 1 in 100 chance. Motive alone, without a good opportunity gives a 30% chance. But both together make murder almost a certainty (.9 probability). So far, this is essentially a static model.

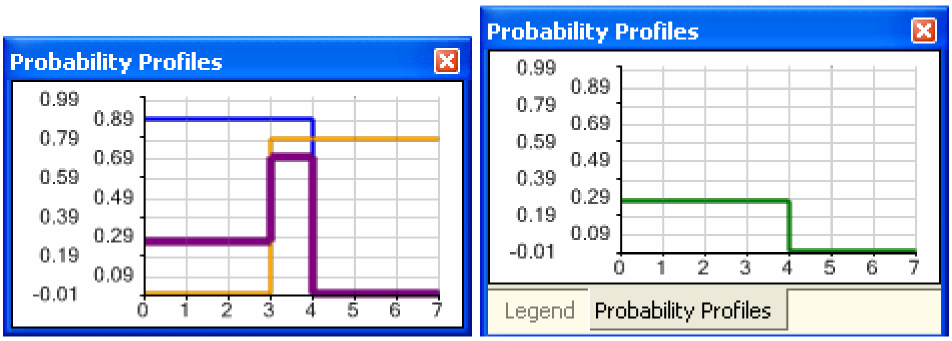

Figure 2: a) Correlated Cause, b), Independent Causes

The model becomes temporal by adding delays, start times, and persistence to the events in the model. Such values are not illustrated here, but their effects are apparent in Figure 2.

The blue line in Figure 2a shows that that we expect a bad debt to almost certainly occur (probability .9, vertical axis) at time 0 (horizontal axis) and persist for four weeks. During the third week, as shown by the gold line, we are expecting Tony to have an opportunity to “do something” about the debt. So, based on our model of Tony, we think (the purple line) there is low probability that a murder will occur during the first three weeks, but is quite likely during the third week. However, once the debt is paid, murder probability drops almost to zero.

Most existing Bayesian tools, including some popular in DOD, cannot model probabilities over time as in the example above, nor can they model the interaction between separate causes such as motive and opportunity. In one popular tool, (if it could do temporal prediction at all), it would probably produce a murder prediction such as the green line in Figure2b. This is this because the tool can deal only with probabilities associated with individual causes, not interacting groups of causes. To predict differently with this tool, it would probably be necessary to assert that Tony has a relatively high likelihood of committing murder, given opportunity alone but no motive.

Because the mathematics underlying CAT preserve the probabilistic semantics of the input, we are justified in claiming that the probability of murder in the third week is 70%. If, like some tools, the probabilistic interpretation of computations was not preserved, we might be able to say no more than that there are more influences indicating murder in the third week. CAT offers users a clear definition of the parameters that they are estimating. The value, .90, shown in Figure 1(b) means exactly what we expect: that with 90% probability Tony given both motive an opportunity, will murder. All parameters entered into CAT can be the product of such small *gedanken* experiments.

CAT provides superior prediction and inference because it provides more accurate probabilistic models of domains. Bayes’ rule is only as good as the probabilistic models to which it applies. So Bayes’ rule is never more powerful than when applied within the context of CAT.