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A Cultural Belief Network Simulator

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Abstract. This paper describes a tool for anticipating cultural behavior called, "CulBN." The tool uses Bayesian belief networks to represent distributions of causal knowledge spread across members of cultural groups. CulBN simulations allow one to anticipate how changes in beliefs affect decisions and actions at the cultural level of analysis. An example case from a study of Afghan decision making is used to illustrate the functionality of the tool.

Keywords: cultural network analysis, CNA, cultural model, belief network, Bayesian modeling

1 Introduction

The purpose of this paper is to describe a prototype tool for simulating cultural behavior; the "Cultural Belief Network Simulation Tool" (CulBN). We use an example case from a study of Afghan decision making to illustrate key features of the tool and associated process for building cultural models. The tool"s functionality derives from a principled, cognitive approach to culture. We first define and discuss this view of culture, prior to discussing specific details of CulBN.

The cognitive approach to culture begins by defining culture in terms of the widely shared concepts, causal beliefs, and values that comprise a shared symbolic meaning system [1, 2]. Shared meaning systems imply that members of a culture tend to perceive, interpret, and respond to events in similar ways. The cognitive approach to culture is often combined with an epidemiological metaphor from which researchers seek to explain the prevalence and spread of ideas in populations [3].

Working from this perspective, we previously developed cultural network analysis (CNA), a method for describing ideas that are shared by members of cultural groups, and relevant to decisions within a defined situation [4]. CNA discriminates between three kinds of ideas: concepts, values, and beliefs about causal relations. The cultural models resulting from CNA use belief network diagrams to show how the set of relevant ideas relate to one another. The CNA approach also includes the full set of techniques needed to build cultural model diagrams. This consists of specific methods to elicit the three kinds of ideas from native people in interviews or survey instruments, extract the ideas from interview transcripts or other texts, analyze how common the ideas are between and within cultural groups, align and assemble the common ideas into complete maps. CNA offers a unique set of theoretical constraints which distinguishes the cultural models it produces from other ways of modeling culture [5]. These aspects include an emphasis on ensuring the relevance of cultural models to *key decisions* to provide a more direct link to actual behavior, focus on the cultural insider or *emic perspective*, modeling interrelated *networks of ideas* rather than treating ideas as independent entities, and by seeking to directly estimate the actual *prevalence of ideas* in the network rather than relying on more nebulous notions of sharedness.

This overall conception and approach to cultural analysis ideally suits simulations using Bayesian normative modeling, though with a slight twist. In typical applications of Bayesian belief networks (BNs), one elicits expert structural and probability inputs to get best possible representation of a physical system [6]. The aim in such cases is to accurately predict key physical outcomes based on expert understanding of influences within that physical system. That is, the ultimate concern is for physical reality. In contrast, the objective here is to represent human cultural knowledge as the system of interest. That is, the aim is to accurately anticipate the perceptions and decisions of groups within a specified context based on relevant culturally shared conceptions, causal reasoning, and appraised values. The key principles for application of BNs to cultural modeling are:

- BN focuses on population, rather than individual psychological level of analysis
- Nodes represent concepts held in common by some percentage of the population
- Edges represent causal beliefs, also distributed across members of the population
- Probabilities denote prevalence of ideas in the population, not strength of belief

In principle, concept nodes also contain associated value information. However, values are left implicit in the current instantiation. Next, we describe the CNA approach to building and simulating cultural models as a two step process. First, a data step is necessary to translate from raw qualitative data to structured inputs to be used in the second, modeling step. The modeling step incorporates the inputs to build executable models in CulBN. We walk through the two steps in the context of a concrete example of Afghan decision making.

2 Data Step

CulBN simulations, as a component of CNA, are grounded in the kinds of data people from a wide variety of cultures, including non-western and non-literate cultures, have been shown capable of providing in natural communications, interviews and field experiments. The first step in a CNA collection is to determine the target population and critical decision or behavior of interest. These elements are often captured in brief scenarios that provide some additional context, such as the following:

> *A unit of American soldiers in Afghanistan's Uruzgan Valley was engulfed in a ferocious fire fight with the Taliban. Only after six hours, and supporting airstrikes, could they extricate themselves from the valley. The Americans were surprised in the battle by the fact that many local farmers spontaneously joined in, rushing home to get their weapons. The farmers sided with the Taliban, fighting against the Americans. Asked later why they'd done so, the villagers insisted that they didn't support the Taliban's ideological agenda, nor were they particularly hostile toward the Americans.*

2.1 Interview Process

CNA interviews are structured around short scenarios that describe the critical decision of interest for a cultural group, such as the Afghan farmers‟ decision to join the fighting in the scenario above. The information basis for the modeling effort described in this paper was a set of CNA interviews conducted with Afghans as part of a larger cultural study [7]. Each participant was interviewed individually using the same CNA interview guide. The interview guide consisted of open-ended questions to elicit participants‟ overall explanations of the situation, as well as their perspectives regarding the Afghan protagonists‟ intentions, objectives, fundamental values, and the causal links between them.

2.2 Coding and analysis

Two independent coders read through all of the transcripts and identified segments that contained concept-causal belief-value (CBV) chains. Next, the two analysts coded each segment by identifying the antecedent, the consequent, and the direction of the relationship between the antecedent and consequent for each causal belief. For example: *"Americans bring security"* (concept) *"decreases the likelihood that"* (causal belief) *"Farmers join the Taliban side of the fight"* (concept). The coders then collaborated to resolve overlaps and redundancies between their respective lists. Percent agreement for the coding was 81% for the Farmers scenario. Prevalence information was then derived by tallying the number of times a CBV chain was mentioned across all three interviews. We converted the frequencies to proportions by using the count of the most prevalent idea as the upper bound. Finally, we created a frequency table for all ideas. The CBV chains were then integrated into a network diagram of the Afghan Farmers' decisions leading to their behavior in the scenario.

3 Modeling Step

In the modeling step, we construct the cultural belief network in CulBN, and use it as a starting point from which to perform simulations of concept and causal belief change on the decision of interest. The model is initialized with the empirical data that was collected above in the data step. The full cultural belief network for the Afghan Farmers is shown in Figure 1. Recall that these models represent how the cultural group perceives reality. They do not attempt to model physical reality. Hence, we can change various parameters of the model to simulate effects of changes in the distribution of ideas on cultural decisions and behavior. The remainder of this section describes the elements and process of the modeling step in more detail.

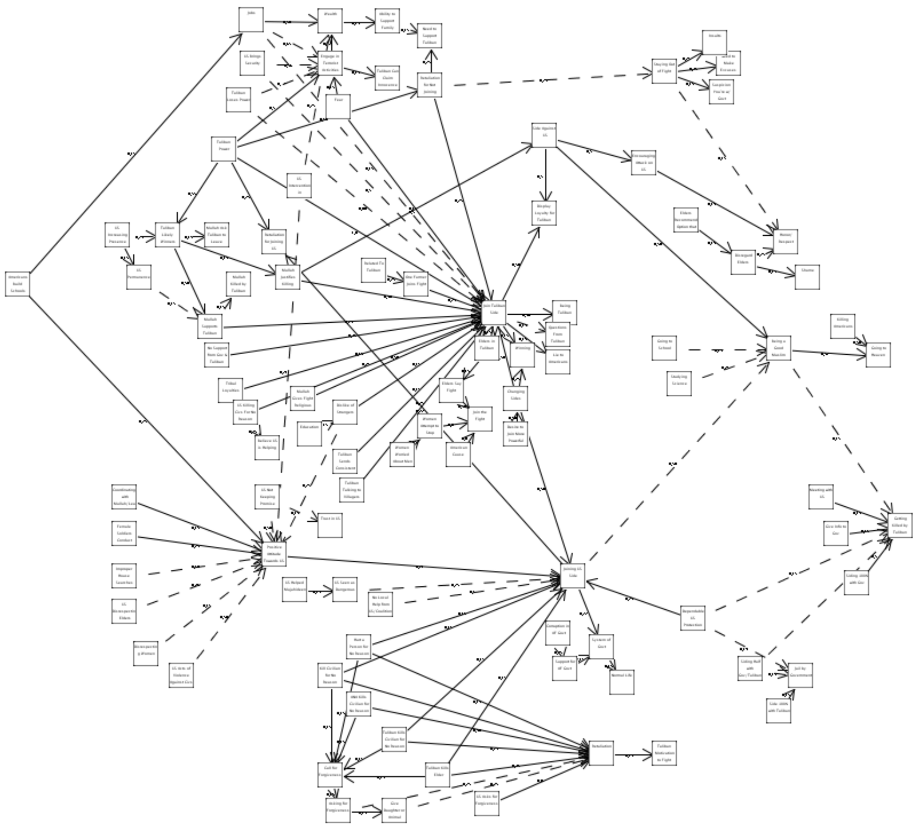

Figure 1. Cultural belief network of Afghan Farmers‟ decision making in a conflict scenario as implemented in CulBN.

3.1 Diagram Semantics in CulBN

A subset of the full model is illustrated in Figure 2 to enhance readability. In these diagrams, nodes represent culturally-shared concepts, and the probability on the node signifies the prevalence of the concept in Afghan thinking in the scenario context. The solid arrows represent perceived positive causal relationships and dotted arrows represent negative ones. Probabilities on the lines denote prevalence of the causal beliefs. As shown in Figure 2, for example, the prevalence of the causal belief that jobs increase wealth for Afghans is 38%.

The values the model takes as input are initially determined empirically. These values represent the current state of the cultural model, as derived from the text data. To perform a simulation, the user revises the inputs with hypothetical values. The distinction is visualized in Figure 2. Here, the prevalence of the concept 'US Brings Security' is low, based on the data. However, we may wish to explore the consequences of a case where the concept in much more prevalent in the cultural group (as a result of radio announcements about security, for example). In Figure 2, we see the initial empirical value is represented by the dotted level on the node and the hypothesized values are represented with the solidfill.

After specifying input values, the user runs the simulator to acquire the probability values of the dependent nodes[1]. An output probability can be interpreted as the prevalence of the concept in the cultural group given the input values specified. For example, in Figure 2 we see that 'Join Taliban Side' is less prevalent with the increased perceptions that the „US brings security."

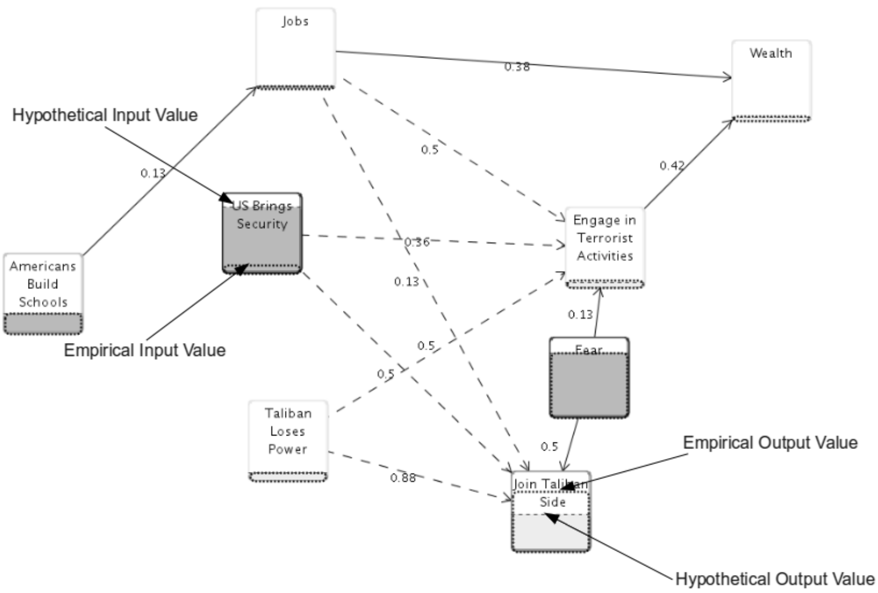

Figure 2. Hypothetical and empirical values in CulBN

3.2 Interaction with Cultural Models in CulBN

CulBN contains a user interface that allows for creation, visualization, and manipulation of input values in a CNA-type cultural model. Combining this capability with the simulation engine allows the user to easily interact with a cultural model by supplying hypothetical data and visualizing the changes produced in the model. Figure 3 demonstrates this in the Afghan Farmer example. In the top left, we see a model initialized with only empirical data being run (the small dialog is the sample count). To the right, we see the output of the model that 75% of Afghan farmers are expected to join the Taliban in the scenario. In the bottom panels, we explore the effects of hypothesized changes to cultural concepts and causal beliefs related to perceptions of the extent that Americans are building schools locally. First, we hypothesize an increase in the prevalence of perceptions of school-building in the population (see the bottom left of Figure 3). Note that this does not result in much change in the percentage of farmers who decide to join the Taliban (notice that the solid fill on the 'Join Taliban Side' node is

1 CulBN currently relies on the Java Causal Analysis Tool (JCAT) as its simulation engine 8. Lemmer, J. *Uncertainty management with JCAT*. 2007 [cited 2010; Available from: www.au.af.mil/bia/events%5Cconf-mar07%5Clemmer_jcat.pdf.. JCAT back-end uses a Monte Carlo Markov Chain (MCMC) sampler to stochastically generate the outcome likelihoods.

almost the same as the dotted fill). The implication here is that, based on the current model, influencing perceptions that schools are being built is not an effective strategy, in and of itself. However, if we incorporate an additional presumed influence on the *causal belief* that American school building leads to more jobs, then we will notice an impact on the decision to join the Taliban (see the bottom right of Figure 3). This example shows that subtle distinctions in the specific cultural ideas targeted for influence can yield sizable differences in the predicted effects on the decisions underlying cultural behavior.

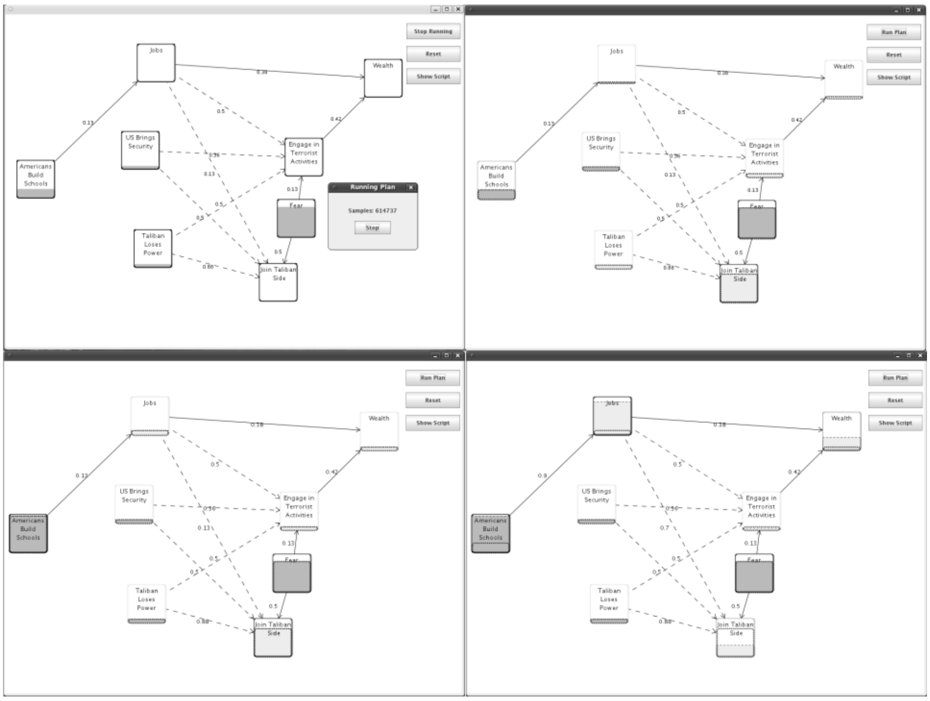

Figure 3. Inputting hypothetical data and running the simulator in CulBN. Top left- running the empirical model, top right- result of empirical model, bottom left-result of a run with hypothetical input to a concept, bottom right- result of second run with hypothetical input added to links

4 Discussion

4.1 Practical implications

CulBN and its underlying principles are likely to prove useful in a wide array of applications. Here, we describe benefits of the tool for supporting analysts who need to understand the behavior of groups from other cultures. First, CulBN p*rovides a coherent approach for constraining and making sense of a vast array of concepts, causal beliefs, and values, as they are relevant within particular situations*. CulBN, relying on the CNA process, begins with a group‟s key decisions, attitudes, or behaviors of interest in a given context. It then provides a systematic approach for identifying and linking the most relevant concepts, causal beliefs, and values from the group‟s own perspective to the key decisions. Secondly, CulBN y*ields a nuanced perspective of the thinking in diverse cultural groups. This is especially helpful to analysts who have little immersive experience within the culture.* By providing an explicit map of the group‟s perceived associations between concepts, the analyst has a ready reference that describes “what else members of the group would be thinking” in a given situation. Thus, it provides direct support for taking the group‟s perspective in that situation. Thirdly, CulBN i*ncreases the systematicity and credibility of analyst recommendations, while maintaining flexible analysis processes.* CulBN introduces a rigorous process for structuring available information regarding the cognitive content shared among members of a group, allowing analysts to freely explore the cognitive effects of hypothetical influences on the cultural group of interest. Fourthly, CulBN a*ids in promoting analysts' cultural expertise across teams and organizations*. The cultural model representations are useful knowledge products that can be shared among analysts to provide a concrete basis for discussions, including helping novice analysts get up to speed on specific topics relevant to their area of study. In addition, CulBN could be used to monitor changes in a group‟s, organization‟s, or wider society‟s attitudes and behaviors over time. That is, cultural models provide a basis for representing long-term cultural shifts in attitude and belief.

4.2 Theoretical implications

The current work extends past developments in cultural network analysis by deriving quantitative cultural models from qualitative data, and incorporating them into a BN framework that enables simulated influence on cultural perceptions, decisions, and behavior. There are several advantages of the current approach to achieve cultural simulations. First, cultural agents that do not have the empirical grounding that comes by incorporating quantitative cultural models cannot be guaranteed to behave in culturally authentic ways. The performance of any model is bound by the data used to inform it. Second, a BN fits closely with the representational commitments made within CNA, allowing for the specific interpretations of elements and parameters that fit neatly within the epidemiological view of culture. Also, the quantitative cultural models incorporated into CulBN address the cultural “levels of analysis problem” that exists with many agent-models that aim to represent culture [9]. The problem is that the “cultural” level of analysis describes population characteristics, whereas cognitive agents represent individual people. By building and simulating quantitative cultural network models that estimate population-level characteristics of cultural groups, we can avoid building agents that stereotype the culture of interest. That is, CNA, combined with tools like CulBN, provides a coherent, grounded, and feasible means to model and simulate effects of changes in the distribution of mental representations in a population, as an alternative to stereotyped cultural agents that represent a canonical form of the culture.

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