Modeling Complex Social Scenarios Using Culturally Infused Social Networks

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***Abstract*—Modeling complex real world scenarios require representing and analyzing information from multiple domains including social, economic and political aspects. However, most of the current frameworks in social networks are not generic enough to incorporate multi-domain information or to be applied in different scenarios. Current frameworks also make simplifications in other modeling aspects such as incorporating dynamism and providing multi-scale analyses. Representing culture is critical to truly capture the nuances of various social processes. It also helps to make the framework generic enough to be applied in multiple application domains. We will leverage a novel framework called the Culturally Infused Social Network (CISN) to represent culture using probabilistic reasoning networks called Bayesian Knowledge Bases (BKBs), in representations known as cultural fragments. Cultural fragments model the intent of actors by relating their actions to underlying beliefs and goals. CISN also supports analysis algorithms to make predictions and provide explanations. We validate CISN by simulating the 2006 Somali conflict involving the Islamic Court Union(ICU). The Somali conflict is a complex scenario requiring deep understanding of myriad factors. We focus on analyzing the group stability of ICU, how changing alliance caused conflicts and led to its ultimate demise. We define a metric to measure instability in a group, identify critical factors that led to instability in ICU and provide analyses.**

***Index Terms*—Socio-cultural behavioral models, Computational social science, Social networks, Group stability, Somalia**

I. Introduction

Computational social science [1] has been useful in incorporating large data sets in social models, simulating a wide range of social scenarios and providing analyses. Social network techniques, which are central to computational science, represent social information as network graphs consisting of nodes and edges. The nodes denote the social units such as individuals and edges represent the relationships between the nodes. Social Network Analysis (SNA) [2] leverages existing graph theoretic algorithms and metrics to classify and analyze network structures. Analyzing structure using metrics such as connectivity and resilience, can provide insights into network properties and node functionalities. Although SNA and other traditional computational social science methods have provided a better understanding of social systems, there are a number of challenges that need to be solved when it comes to modeling real world scenarios. The behavior of social systems depends on complex, inter-connected multi-domain factors. Making simplifications in the form of addressing only a small set of important factors may be fine for some but unacceptable in others. For example, modeling the radicalization process in a society should not only take into account religious factors but also the political, economic and community aspects. Therefore a generic framework to represent, integrate and analyze varied factors from multiple domains, is required. Realistic modeling frameworks should also incorporate realistic assumptions about dynamism and represent its various nuances. One such nuance of dynamism is the multi-scalar nature of social processes. Social networks can represent nodes at multiple scales such as individual actors at the most basic level to social groups such as family units and communities at higher levels. Due to the multi-scale structure of social organizations, dynamism at one level can affect the nodes at other levels. Therefore, social network frameworks must have the ability to represent multi-scalarity of social processes and support relevant analyses.

In this paper, we propose a generic framework for modeling such complex social scenarios, called the Culturally Infused Social Networks (CISN) [3]. The key idea in CISN is that in order to truly incorporate the richness of social behavior, it is important to represent culture. Cultural factors are responsible to the uniqueness of behavior seen in societies in different parts of the world. For example, some societies such as in Iraq and Somalia are clan-based where the clan loyalty takes precedence over nationalistic identity. Social norms, identities and beliefs also vary in different parts of the world. It is clear that culture provides a way to formulate a generic framework which can be tailored to a specific region or social structure by configuring the specific cultural factors. Although, there has been some work in incorporating culture in social simulations and analyses [4], [5], there are significant challenges such as coming up with a comprehensive list of cultural factors relevant to the model. Another challenge is representing the transition of cultural factors over time in a computational model. CISN utilizes the probabilistic reasoning framework of Bayesian Knowledge Bases (BKBs) [6] to represent cultural factors (in the form of cultural fragments) and its influence on behavior. CISN also supports multi-scale analyses as the nodes can represent either individuals or organization. Cultural fragments of individuals to represent the culture of their communities and so on. These fragments can also be used to incorporate new information and behaviors, thus simulating dynamism.

CISN is a mature framework that has been applied to challenging scenarios [3], [7]. As such the goal of the paper is to present a methodology, based on CISN, to model dynamic multi-scale social processes and validate it by applying it to understand group stability in large and heterogeneous groups through incorporation of multi-domain modeling information. Group stability is a critical problem in computational social science and has potential applications in understanding international conflicts. We use the Somali conflict of 2006 as a case study to validate the framework and its capability to model and measure group stability, and provide explanations for the stability or instability. The novel concepts that we introduce are constructing cultural fragments as part of organizational behavior, designing algorithms to identify conflicts and providing explanations. We will also show how the ideology of sub-groups affect the overall ideology of a super group that they belong to. In the next section, we will provide a brief background on related methodologies and a discussion of the strengths of the CISN framework. We will then give a detailed description of the framework along with background material on its various components and analysis methodology. The scenario, used to validate the framework, is then described along with the simulation setup. The results are then presented along with analyses.

II. Background

The goal of this paper is to present a generic social network framework that can deal with real world dynamism, incorporate multi-domain information and provide multi-scale analyses. There has been previous work on developing models to incorporate dynamism in social networks. In the Dynamic Network Analysis [8] model, dynamism is represented by relations between classes of network parameters. However, the drawback is that it is a challenge to come up with rigorous definitions for these relations. Multiplex network models [9] in SNA incorporate multi-domain information by using different types of network edges. However, dynamic multiplex networks are a challenge to construct because changes in one social relationship represented in the network may have an effect on others. One of the research domains that has to deal with the type of complex social scenarios that we are trying to tackle, is nation reconstruction modeling. Stabilization and Reconstruction Organizational Model (SROM) [10] simplifies nation-scale modeling by constructing sub-models for each region and integrating them by specifying the interaction between them. These regional sub-models incorporate heterogeneous specifications from multiple domains. However the drawback for such models is that the interactions between the sub-models are rigid and is specific to this application domain. The main reason for the limitations of current models is the absence of a flexible, generic framework for representing cultural factors while supporting in-depth analyses. Without an adequate cultural model, critical relations may remain hidden and important insights lost. Current methods in group stability are based on structural properties with a focus on network connectivity. Needless to say, leaving out cultural factors or even limited cultural modeling will reduce their effectiveness greatly.

Moreover, in current models, all variables have to be defined beforehand. This means that unforeseen information, which is common in dynamic situations, cannot be easily added to the simulation. CISN works well with this type of situations because new variables can be added on the fly. The ability of CISN to represent various types of information from multiple sources and to integrate multiple social networks makes it a powerful generic framework. CISN is a prescriptive methodology capable of making predictions while providing explanations behind the prediction. This is realized through reasoning algorithms that utilize the probabilistic representation of the cultural fragments to identify plausible outcomes and then trace the variables that are most responsible for this behavior. This allows the analyst to go beyond just making a prediction and come up with a narrative behind the prediction which is supported by the evidence.

III. Modeling Framework

Culture has a fundamental impact on how the person perceives the world, his/her decision making process and reactions to events. The way people greet each other and relationships with family and friends are only some of the consequences of culture. Modeling culture by a fixed set of parameters is limiting due to the broad spectrum of behavior that can be attributed to people, even in a narrow social group. There is also added complexity due to individual variations in cultural factors that causes uncertainty in how culture eventually manifests as behavior. Additionally, cultural understanding by the modeler is usually subjective. Therefore, any realistic framework must acknowledge and deal with this uncertainty too. Our goal is to develop a prescriptive framework to model culture which can be validated against observable events. Simply developing a cultural model without relating it to behavior is not very useful. Therefore, it is necessary to model the connections between perceptions and beliefs of a person or groups of people with their intent, actions and behaviors. We will leverage our previous work [6], [11] on intent modeling and probabilistic networks, where the beliefs and goals are linked with the actions through demonstrable causal chains. This goes to our core modeling philosophy of providing explanations to emergent behavior in complex social networks. We will explicitly represent the uncertainty in socio-cultural information by leveraging our work in Bayesian Knowledge Bases (BKBs).

BKBs are used to represent the cultural information of the nodes in the social network. They are a generalization of Bayesian Networks (BNs) where the states of the system, being modeled, are represented by a set of random variables (rvs). The relationships between the rvs are represented in a probabilistic network as a set of Conditional Probability Rules (CPR). The BKB network consists of I-nodes and S-nodes, connected by directed edges. Each I-node represents a particular state of some random variable. S-nodes may have zero or more incoming edges and only one outgoing edge. Each S-node encodes the *if-then* rule consisting of these I-nodes.

Unlike BNs, BKBs can work with incomplete information. BNs require knowledge of the complete probability distribution of all the variables and this is impractical in many real world scenarios where complete information is rarely possible.

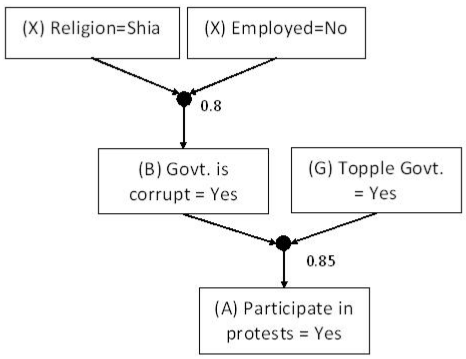

Fig. 1. A Sample BKB

A. Culturally Infused Social Network

One of the objectives of the Culturally Infused Social Network(CISN) framework is to incorporate fine grained behavior in the network nodes. We do this by modeling individual and group intent. We leverage the previous work in the Adversarial Intent Inferencing (AII) model [11] in categorizing the important components of intent as beliefs, goals and actions. Intent of an individual and group is manifested in observable actions, which are influenced by the entity's goals and beliefs. Cultural traits will influence the beliefs, goals and actions. For rendering the intent in BKBs, we use the following types of I-nodes in the BKBs: 1) Beliefs (B): represent what the entity believes about other entities, 2) Axioms (X): represent what the entity believes about themselves, 3) Goals (G): capture the aims and goals that the entity seeks to achieve, and 4) Actions (A): represent the possible actions that the entity can take to achieve the goals.

By connecting observable actions with the underlying beliefs and motivating goals, we not only provide predictions in terms of plausible behavior but also explanations. Cultural information is used to generate the various beliefs, axioms, goals and actions nodes in the BKBs. The BKBs that represent cultural information are called cultural fragments. Fig. 1 shows a cultural fragment for a scenario from the 2011 demonstrations in Bahrain[1] by the local Shia majority. According to the BKB, men who are unemployed are more likely to view the government as corrupt. This view combined with the goal to remove the government is more likely to lead them to participate in protests. Typically, it is a challenge to represent the entire cultural information using a single cultural fragment. As can be seen from the Bahrain scenario, gender and religious beliefs are not the only factors involved. In fact, cultural factors for even simple scenarios can be extensive. Also, the information about culture is subjective. It is difficult to even come up with a common definition for culture that is accepted by all sociologists. There might also be differences in opinion on what constitutes the important cultural factors in a particular scenario, leading to different analysts wanting to represent potentially contradictory information in the BKBs. Our framework has the ability to allow modelers to represent different pieces of informations for an entity, as separate cultural fragments. These fragments can then be fused, using a process called Bayesian knowledge fusion [12], to form larger and more complete cultural BKBs. Therefore, competing views of multiple modelers need not be discarded, and can be taken into account in the final analysis. BKB fusion grants analysts the ability to incrementally model complex scenarios, allowing them to focus on a smaller subset of factors at a time. The modelers create a library of cultural fragments for a scenario that can be used for multiple entities.

[1]http://en.wikipedia.org/wiki/2011_Bahraini_protests

Cultural fragments capture the behavior of individual actors. We still need to understand how individual cultural characteristics lead to change in social relations and how the resultant social interactions lead to changes in behavior. SNA methods have been widely used to represent relations between actors. However, due to the lack of a generic way to incorporate culture in the social networks, their effectiveness is limited. The Culturally Infused Social Network(CISN) is a novel and generic framework to seamlessly incorporate culture in SNA. The process of generating CISNs (Fig. 2), consists of generating three intermediate networks called the Ideology Network, Contact Opportunity Network and Contact Constrained Ideology Network.

The Ideology Network represents behavioral and cultural similarities between the actors. It is created from cultural analyses of the actors in the particular scenario. Cultural analyses involve looking at databases such as census, to determine demographic characteristics such as age, religious affiliations, etc. of the actors. Based on these characteristics, appropriate and relevant cultural fragments are chosen from the library for individual actors. These fragments are fused to create a cultural fragment for the actor. A bimodal network called the Cultural Analysis Network is generated and consists of two types of nodes: actor and action nodes. The edges in the Cultural Analysis Network, existing only between nodes of different types, represent the probability of an actor taking a particular action and is calculated by applying reasoning algorithms on the cultural fragment of the actor. This focus on observable actions is consistent with our objective of modeling actor behavior by relating it to their beliefs and goals. We use the social theory of homophily [13], which states that social ties are more likely between actors with similar behavior, to generate edges between actors in the Ideology Network. We generate the weights for the edges between two actors in the Ideology Network by comparing their plausible actions in Cultural Analysis Network. If m is the number of actions being considered, $p_{i,j}$ is the probability for person i to take action/goal j then we use a vector $L_x = (p_{x,1}, ..., p_{x,m})$ to denote the probabilities for a node/actor x to take the actions $1..m$. The normalized weight of the edge $g_{x,y}$ between any two actors x and y is given by

$$g_{x,y} = \frac{\sum_{l=1}^{m} p_{x,l} p_{y,l}}{max(g_{i,j})} \tag{1}$$

However, just because they have similar behavior, as represented in the Ideology Network, does not mean that they will have social interaction. The probabilities for actual interactions would depend on what social groups they move in. In our framework, this is represented in the Contact Opportunity Network, which is generated from available social information. This may be in the form of lists of friends on social networking sites, memberships in professional societies like IEEE, religious affiliations, etc. Our framework has the capability to extract information from multiple social networks and combine them to a single Contact Opportunity Network. If m is the number of social networks used for extracting contact information, $O^i_{x,y}$ is the contact opportunity between distinct nodes x and y in network i, w_i is the weight for network i, then the normalized contact opportunity between x and y is given by

$$O_{x,y} = \frac{\sum_{i=1}^{m} w_i O^i_{x,y}}{max(O_{ij})} \tag{2}$$

By combining the information from the Ideology and Contact Opportunity Networks, we have a more realistic picture of the potential social interaction between the actors. This network is called the Contact Constrained Ideology Network. Using the notations in Eqn. 1 and Eqn. 2, the weight of the edge $d_{x,y}$ between any two nodes x and y in Contact Constrained Ideology Network is

$$d_{x,y} = \frac{O_{x,y} \cdot g_{z,y}}{max(d_{i,j})} \; where \; x \neq y \tag{3}$$

Finally, the CISN is obtained by combining the Contact Constrained Ideology Network with the combined social network.

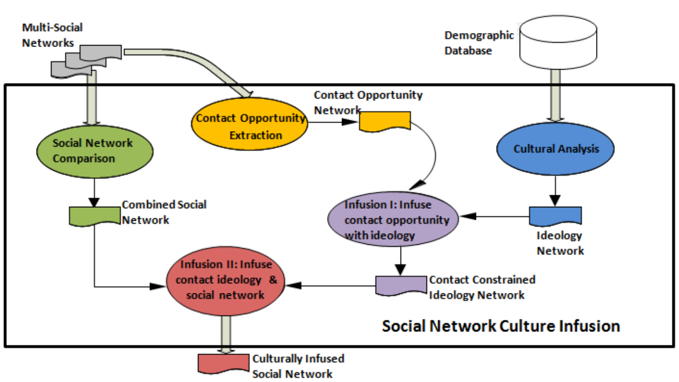

Fig. 2. Generating Culturally Infused Social Networks

B. Analyses

Since the behavioral characteristics in CISN are represented as a BKB, reasoning algorithms can be used to provide analyses at specific time steps and over a time period. Variables and factors critical to observed behavior can also be identified.

1) Reasoning Algorithms: Bayesian inference algorithms such as Bayesian updating [6], [14] can be applied on BKBs to identify probable states and their probabilities. This will change as new information(represented by new fragments or new evidence) is incorporated. Bayesian updating calculates the probability of a rv having a certain state, given the evidence. However, they do not provide explanations for the same nor do they detect and quantify change over time. This is done using the notion of variable contributions.

2) Contributions: BKBs explicitly model the causal chains, linking various pieces of information. By back tracking on the causal chain, we can pinpoint variables that are responsible for the observed phenomena and provide explanations. As part of providing explanations, we select variables of interest (also, termed target variables) in the BKBs and calculate how other variables *contribute* towards its value.In calculating the contributions for a target variable q by a variable r, denoted as $c^t_q(r)$, for the BKB B_t, we look at all possible worlds or inference graphs [6] where q has the specified states. Out of this, the probabilities of those worlds containing r are summed to calculate the contribution. The method for calculating the contribution is given in Algorithm 1.

Algorithm 1 CONTRIB-COMPUTE(B_t, t, q)

Determine $W^t_q(r)$={$(w^r_{q,i}(q), p^t_{q,i}(r))$}
▷ $w^t_{q,i}(r)$: world containing r in which q is true
▷ $p^t_{q,i}(r)$: probability of $w^t_{q,i}(r)$
$c^t_q(r) = \sum_{i=1}^{m} p^t_{q,i}(r)$ ▷ Contribution of r towards q

3) Fragment Propagation: The CISN framework captures the dynamism with its ability to incorporate new information in the model, as required. New information is introduced in the form of new fragments and are fused with the existing knowledge bases of the actors. This will lead to changes in the probability distributions of the rvs in the BKBs, possibly leading to new output states. Understanding the factors behind the changes in the behavior is critical in providing explanations.

In the previous section, we explained how contributions can be used to provide explanations for actor behavior at a particular point. However, the notion of contributions can be extended to understand changes across time steps. In the algorithm that we developed (outlined in Algorithm 2), the significant contributing factors for a target variable are identified for each time step in the scenario. At any time step t,a factor whose contribution changes by at least a certain amount α, from the previous time $t-1$, is considered to be significant. By correlating the increase or decrease of significant contributing factors with the changes in the probability of the target variable, we can provide explanations for the observed changes in actor behavior over time. We have used contributions to explain opinion changes in the 2008 South Carolina primary elections for the Democratic Party [7].

Social interactions can also lead to changes in a person's beliefs, goals and actions. For example, interactions of an atheist with a deeply religious family member can lead to him/her imbibing some of the religious idealism and/or vice versa. This is represented in our framework by the exchange of relevant cultural fragments between actors. The new fragments are fused with the existing knowledge base of the actor leading to changes in the probability distributions of their beliefs, goals and actions. Since edges in CISN represents both contact probabilities and closeness in ideology, they determine who interacts with whom and guides the propagation of fragments between the actors. The reliability factors for these fragments play an important role in the propagation as it determines how it impacts the behavior of the actor. The weights of the edges in CISN can be used as a guide to set the reliability measure of the fragments. However, social influence tends to fade with time or with the introduction of new fragments. We simulate this effect on actor behavior, by decreasing the reliability factor of the cultural fragments and re-fusing it in the actor knowledge base. By decreasing the reliability factor we are reducing the impact or effect these fragments have on the actor behavior.

Algorithm 2 SIGNIFICANT-CONTRIB(B_t, t, q)

for all I-nodes $r \neq q$ in BKB B_t **do**
  ▷ B_t is the given BKB
  $c_q^t(r) \leftarrow$ CONTRIB-COMPUTE(B_t, t, q)
  $\delta_q^t(r) = abs(c_q^t(r) - c_q^{t-1}(r))$
end for
Normalize values of $\delta_q^t(r)$ with max as 1
for all values of $\delta_q^t(r)$ **do**
  if $\delta_q^t(r) > \alpha$ **then**
    State r is a significant contributor to q at time t
  end if
end for

4) Group Stability Analysis: When we deal with heterogeneous groups that contain people from different cultural backgrounds with differing (or even conflicting) beliefs and goals, there are chances for conflict. Conflict can lead to intra-group tensions, open hostilities and even violence creating instabilities in the group. Instability is an important issue when dealing with large groups such as nations with disparate cultural groups, a continent-size organization such as the European Union or even a large business conglomerate. In our framework, we model conflict and instability as differences in beliefs, goals and actions. In large groups that consist of smaller sub-groups, we measure instability in terms of differing support for certain critical aspects of the overall group ideology by the sub-groups. Though the group ideology is really a combination of the various sub-group ideologies, depending on the factors such as number and size of the sub-groups, certain beliefs and behaviors may dominate. The instability metric in our framework is measured in terms of the standard deviation of the *fragment contributions* of the sub-group towards an important target variable in the group ideology. Fragment contribution, described in Algorithm 3, is an extension of variable contribution. Given a sub-group fragment $B^i_{SG,t}$ and a target variable q in the group fragment $B_{G,t}$, we look at all the worlds supported by $B_{G,t}$ and the given evidence, where q is true. Out of these worlds, only those containing at least one S-node of $B^i_{SG,t}$ are selected and their probabilities are summed to arrive at the fragment contribution. In other words, fragment contribution is measuring how Conditional Probability Rules(CPRs) of a sub-group fragment is influencing the overall group behavior. Since the fusion algorithm preserves the source information of the individual fragments, the sub-group fragments can be easily identified in the group BKB. Fragment contribution is a novel concept that that we introduce and validate in this paper.

Algorithm 3 FRAG-CONTRIB-COMPUTE($B_{G,t}, t, q, B^i_{SG,t}$)

Determine $W_q^t(B^i_{SG,t})$=$\{(w^r_{q,i}(B^i_{SG,t}), p^t_{q,i}(B^i_{SG,t}))\}$
  ▷ $w^t_{q,i}(B^i_{SG,t})$: world supported by $B_{G,t}$ in which q is true and contains at least one S-node of $B^i_{SG,t}$
  ▷ $p^t_{q,i}(B^i_{SG,t})$: probability of $w^t_{q,i}(B^i_{SG,t})$
$c_q^t(B^i_{SG,t}) = \sum_{i=1}^{m} p^t_{q,i}(B^i_{SG,t})$ ▷ Contribution of $B^i_{SG,t}$ towards q

IV. Validation

We have described the CISN framework and touched upon its capability to model and analyze dynamic social processes. In order to validate the framework, we model the 2006 Somali conflict. In this section, we describe in detail the knowledge engineering and the simulation setup. Our emphasis in the analyses is to identify ideology conflicts in the group ideology due to changing circumstances and explain how that effects group stability.

A. The Somalia Scenario

Somalia has been in a state of civil war since 1991, due to the bitter rivalry between clans and warlords. Somalia has 5 major clans [15], which are in turn divided into multiple sub-clans and sub-subclans. The clans are geographically distributed, with different clans dominating different regions in Somalia. Clans have significant differences in terms of political affiliations and occupation - northern clans are more rural and southern clans are more urban. The inter-clan and warlord rivalry is mainly about fighting for scarce resources such as fertile land, grazing rights and economic infrastructure such as valuable towns and ports. Due to the civil war, the country has been divided into three main regions - Somaliland, Puntland and South-South Central regions.

The conflict in Somalia encompasses a large number of social, political, economic, ecological and strategic factors. The situation is extremely dynamic characterized by fickle alliances among clans and warlords. Modeling all these factors and providing analyses is a challenge. The two major organizations that were involved in the 2006 conflict were the Transitional

Federal Government (TFG) and the Islamic Courts Union (ICU). TFG was formed out of one of the many peace conferences that tried to resolve the conflict. ICU, on the other had its genesis with the Islamists groups in Mogadishu. In order to counter the lawlessness caused by the absence of a central government, Islamic courts based on *Sharia* law had sprung in multiple places, under the protection of local clans [16]. In 2006, these independent courts in Mogadishu combined to form the Islamic Court Union (ICU), leading to the establishment of an alternate power center to the TFG. Towards the end of 2006, with the intervention of Ethiopia, ICU disintegrated. The rise and fall of ICU, within a space of a year, is truly representative of the highly dynamic conditions in Somalia and provides a suitable scenario to validate our modeling philosophy and bring out the strengths of the CISN modeling framework. The central question that we analyze here is: why did ICU have such a quick rise and an even quicker demise?

Both TFG and ICU were complex organizations composed of multiple sub-groups with their own interests, goals and beliefs. TFG was essentially a nebulous set of warlords and other leaders whose stated goals included preventing the formation of an Islamic nation. Although, ICU was essentially a religious organization, there were moderate and extremists elements. ICU and TFG were fragile organizations with expedient sub-groups providing support or opposition based on prevailing conditions. It is clear that understanding the cohesion and stability of these groups is critical to our analysis. In addition to warring warlords, there were other factors such as regional economy, geography and public support that contributed to the dynamism of these groups. The public support was also fragmented. Clan loyalties also further exacerbated the division in the population. All in all, the resultant dynamic situation creates a challenge for computational social science models. The main hypothesis that we prove through analysis in this paper is that as the extreme elements gained more prominence and power within the Islamic Courts Union (ICU), the stability of ICU was affected which resulted in their decline.

B. Simulation Setup

The initial step in setting up the testbed for validating our framework is to identify the specific events we want to model. Since our hypothesis revolved around the rise and fall of ICU, we decided to use the events related to TFG and ICU that occurred in the months from June to December 2006. Some of the major events from this scenario that were modeled in our framework are highlighted in Table I. Let it be noted that the events listed, occurred on and around the specific dates mentioned. For this testbed, we generated a library of cultural fragments from information and data collected from open source. 73 data sources, consisting of news portals, think tank reports and government reports, were used.

For each time step in the scenario time line, we go through the following process sequence to generate CISNs and conduct analyses.

1) Process Social Networks and Cultural Fragments: Using the information from open sources, we construct social networks to understand relationships between important factors affecting TFG and ICU. We use both static and dynamic social networks in our simulations. Static networks depict information that do not change over the simulation time line. An example is the *Region-to-Region* network where the nodes depict the main regions in Somalia and the edges exist between regions if they are geographical neighbors. The dynamic networks are updated at each time step based on the events and the resultant changes. *Org-to-Org* and *Region-to-Org* are dynamic social networks that are used in the simulations. Although ICU and TFG are the primary organizations in these networks, other organizations such as Puntland and Jubaland play a part in the events and are also represented. In *Org-to-Org* networks, two organizations are connected if they are allied in that time step. *Region-to-Org* is a bimodal network with the nodes representing the regions and organizations. An edge can only connect a region node to the organization node if the former is being occupied by the latter. It is evident that these networks will change through the time line as new alliances are made and the old ones are broken, and as the organizations lose or gain ground. By using a weighted scheme, we combine these networks to form a single social network.

Relationship of the actors with the regions and other organizations can be gleaned from the social network graphs. Based on these relationships, we can select relevant cultural fragments that will be fused to form the overall cultural fragment for the actor, thus inherently modeling the dynamism of the actor behavior. For example, as ICU gains new allies it is to be expected that their overall behavior will now encompass the goals and beliefs of their allies. Similarly, the overall behavior of TFG will change as it gains or loses allies and regions. We simulate this by having a BKB represent overall group ideology into which the allies or sub-group ideologies (represented by their cultural fragments) are fused or removed.

2) Generate CISN: In this stage, the cultural fragments for the actors are selected using the dynamically changing social networks. Our simulation uses two types of fragments: Persistent and Event. Persistent fragments for an actor represent their core values and goals, that do not change over the simulation. Event fragments, on the other hand, represent new beliefs, goals and actions that are acquired by the actor due to the events unfolding over the time line. The event fragment in Fig. 3 is inserted in the model for the time step 08/16/06, when ICU captures the piracy supporting ports, in their efforts to stabilize the regions and establish the legitimacy of their regime.

At each time step, the relevant persistent and event fragments for each actor are fused and the probability values for all plausible actions are calculated. The Ideology Network consisting of all actors and all plausible actions are created. We use the contact potential from the various social networks such as the *Org-to-Org* network along with the information from the Ideology Network to construct the Contact Constrained Ideology Network. The Contact Constrained Ideology Network is combined with social networks to create the final CISN.

3) Stability Analysis: Using the underlying social networks to select cultural fragments to construct the Ideology Network is an important innovation that helps to realistically model the dynamism in the scenario. The dynamic *Org-to-Org* network represents the changing alliances with TFG and ICU. As new alliances are made, the ideology of the sub-groups are fused with the core ICU and TFG ideology to generate the overall group ideology. Although the overall behavior might tilt towards accepting certain beliefs or promoting certain actions, there might be a large variance of support among the sub-groups. We measure this using the instability metric which calculates how much each sub-group ideology deviates from the group ideology. At each time step, after the CISN is generated, we measure the instability metric for a selected target variable. If the instability values are large, it means that the group is highly unstable and likely to split. Since our hypothesis for the reason behind ICU's quick demise is the sharp disagreement of its allies, measuring the instability is key for the validation of the CISN framework

TABLE I
TIME LINE FOR THE SCENARIO

	Date	Major Events
1	8/16/2006	ICU seizes multiple ports that were supporting piracy.
2	9/30/2006	Minor skirmishes between ICU and Ethiopian troops. Some warlords defect to ICU.
3	10/10/2006	ICU captures complete annexation of Jubaland. More clans open negotiations with ICU.
4	10/26/2006	ICU declares Jihad against Ethiopian soldiers in Somalia.
5	11/1/2006	Puntland aligns with ICU against Somaliland.
6	11/26/2006	Ethiopian convoy in Baidoa is attacked by Pro-ICU forces.
7	12/2/2006	Multiple defections of groups both from and into ICU. ICU forces surround Baidoa and cuts off all support.
8	12/23/2006	Ethiopia deploys tanks and more soldiers near Baidoa.
9	12/25/2006	Ethiopia and TFG get the upper hand and push ICU back.
10	12/26/2006	ICU loses most of the territory gained since June. They are pushed back to Mogadishu.
11	12/27/2006	ICU surrenders most of the town without a fight. ICU leaders flee. TFG and Ethiopia captures Mogadishu.

C. Results and Analyses

The hypothesis that we validate is that as ICU gained more allies and took over more regions, they aggregated sub-groups that had varied views that failed to coexist and this led to the ultimate demise of ICU. This conflict was most evident in their support for hostilities against TFG. We will analyze the sub-group support for ICU's campaign against TFG and measure the instability related to their contributions to the rv x_k with the label "(A) Invade TFG territory". We will then identify specific groups that are strong and weak supporters and analyze the contributing factors.

CISNs are generated for each time step as described in the previous section. The instability metric is measured for ICU at each time step using the CISN and the values are plotted. The graph in Fig. 4 shows the values from Oct 10 onwards as it contains the results most relevant to our hypothesis. We see that

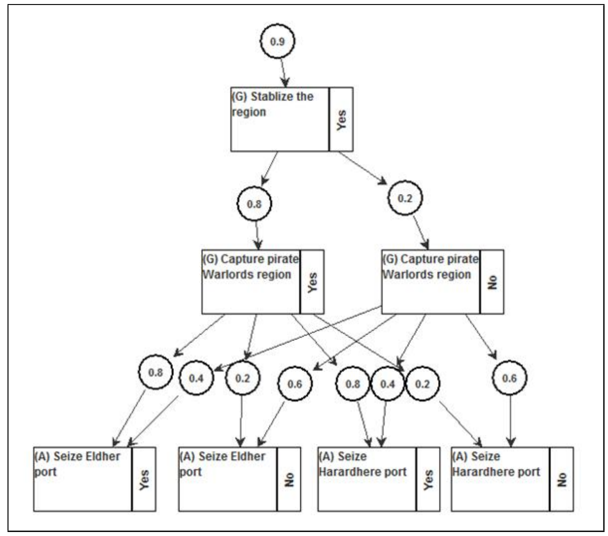

Fig. 3. Event Fragment

the instability values remain low in the beginning. However it starts to increase, modestly at first (Dec 23 and 25) and then a sharp spike on Dec 26 and 27. When we compare the instability values with the group size (number of sub-groups in ICU), we see that the group size decreases sharply when the instability is high. This means that the instability is leading to the disintegration of the ICU. When ICU lost support from its key allies, its demise was rapid.

For further analyses of the causes for this instability, we look at the deviation of specific groups and identify the groups that are strong supporters of the ICU's intent to attack TFG and invade their territory as represented by target rv x_k. For example, the region Mogadishu has a low fragment contribution towards x_k. Mogadishu's main contributions towards its low desire to fight TFG are from the following rvs: (B) Ethiopia is strong, (B) Ethiopia reinforces Baidoa, (B) Ethiopia started using air power and heavy artillery, and (G) Form a legitimate government. These contributing factors help in constructing an explanation for Mogadishu's behavior. It is clear that Ethiopia was a big factor for Mogadishu not wanting to fight TFG. When Ethiopia reinforces Baidoa with tank and artillery in December, it marked a turning point in the conflict. Till then Ethiopia had been a passive supporter and did not reveal an intention to invade interior parts of Somalia to crush the ICU. Ethiopia reinforcing Baidoa is significant as it is the seat of the TFG government and had been surrounded by ICU. Ethiopia also started to openly support TFG by deploying their soldiers to attack ICU. All these factors resulted in low enthusiasm for war with TFG in Mogadishu and ICU lost support here. However, the entry of Ethiopia did not deter other regions such as Wanla Weyn. The variable contributing highly to x_k is "(B) ICU territory is stable/secure". This region believes that ICU is good for security and is therefore is a strong supporter.

We have validated our hypothesis behind ICU's demise by showing the correlation between the increase in instability metric and breakup of the group. We also identified the reason behind the instability to be the entry of Ethiopia and subsequent polarization of support for conflict with TFG.

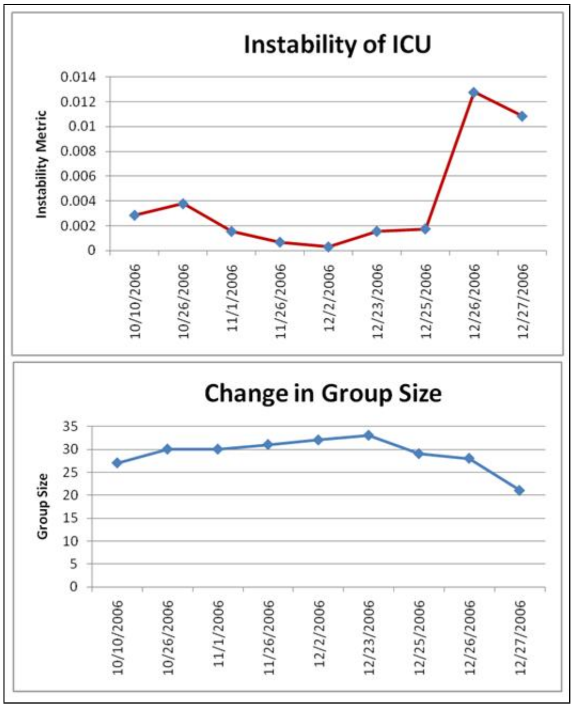

Fig. 4. Comparing Group Instability and Group Size

V. Conclusion

Embedding culture in social networks is crucial for designing modeling and simulation frameworks for real world scenarios. However, cultural information can be subjective and difficult to obtain. We proposed the Culturally Infused Social Network (CISN) as a way to model fine grained behavioral traits in individual nodes using culture, represented as Bayesian Knowledge Bases. We demonstrated how reusable cultural fragments can be generated from heterogeneous information sources. One of the novelties of the framework is its ability to link together cultural factors such as beliefs, norms, goals etc with observable actions, by using the concept of actor intent. We also demonstrated how information from multiple social networks can be subsumed in CISNs and how the social networks themselves can be used to select appropriate cultural fragments for the actors. A key result of the work presented here is the ability to realistically model dynamism, through the ability to incorporate new information and observe the emergence of new behavior. We also demonstrated the ability of CISN to support multi-scale analyses by looking at group stability and the effect of sub-group behaviors on overall behavior. The 2006 Somali conflict was used to validate the framework and the group stability metric. The set of events in the conflict, that we simulated, were fast moving. The scenario also had various interlocking factors from various domains and, as such, provided a suitable testbed to bring out the strengths of the CISN framework.

One avenue for future work is to model more intricately the multi-scale process of opinion change in the sub-group due to interactions with other sub-groups. This is supported in CISN and can be simulated as the spread of fragments in the sub-group population. Incorporation of multiple agents in the sub-groups will help in simulating this spread and also incorporate heterogeneity in sub-group behaviors. By having such fine grained simulations of sub-group populations, more in-depth explanations for predictions are possible.

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