Incorporating Social Theories in Computational Behavioral Models

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Abstract. Computational social science methodologies are increasingly being viewed as critical for modeling complex individual and organizational behaviors in dynamic, real world scenarios. However, many challenges for identifying, representing and incorporating appropriate socio-cultural behaviors remain. Social theories provide rules, which have strong theoretic underpinnings and have been empirically validated, for representing and analyzing individual and group interactions. The key insight in this paper is that social theories can be embedded into computational models as functional mappings based on underlying factors, structures and interactions in social systems. We describe a generic framework, called a Culturally Infused Social Network (CISN), which makes such mappings realizable with its abilities to incorporate multi-domain socio-cultural factors, model at multiple scales, and represent dynamic information. We explore the incorporation of different social theories for added rigor to modeling and analysis by analyzing the fall of the Islamic Courts Union (ICU) regime in Somalia during the latter half of 2006. Specifically, we incorporate the concepts of homophily and frustration to examine the strength of the ICU's alliances during its rise and fall. Additionally, we employ Affect Control Theory (ACT) to improve the resolution and detail of the model, and thus enhance the explanatory power of the CISN framework.

Keywords: Socio-cultural behavioral models, Computational social science, Social networks, Group stability, Somalia

1 Introduction

Computational models are useful for analyzing behavior in social systems. What is lacking is a generalizable method for incorporating essential details from a real-world scenario into a computational model. The critical aspects of our social environment that affect the decisions and actions we take can be thought of as culture – any information or behavior learned from our social setting. Incorporating culture into a computational model can represent the unseen motivations that dictate the actions we take, and thus add realism to actors' actions within that model. However, there are a number of challenges that need to be overcome. Most simulations apply social behavioral rules in an ad hoc manner, often coding a standard set of behavior rules into the model to be applied for all actors in all situations. This is an opportunity missed, as there are many empirically-proven social theories in the literature which could provide theoretic underpinnings to actor behavior. Developing a computational model with the exceptional ability to incorporate pragmatic social theories would contribute greatly to the field of computational social modeling. This is precisely what we endeavor to achieve in our latest research.

In this paper, we employ a computational framework called a Culturally Infused Social Network (CISN) [1] for incorporating both culture and social theories into a complex simulation. CISNs leverage a probabilistic reasoning framework to represent various socio-cultural factors and relationships. Actors and entities in a CISN are embedded in social networks that model social interactions. Bridging the gap that exists between social theoretic methods and computational models is critical. One of the key insights is to mathematically represent the culture-dependent behavior using a probabilistic framework. Such a framework should expose critical factors and relations in the form of random variables (rv_s) and probabilistic rules. Mapping social theories into the computational framework can then be concretely reduced to the formulation of these rv_s and rules. Social theories can also be used to inform mathematical methods for combining the effects of the variables and rules. Mapping of social theories also involves formulation and interpretation of networks that represent social interaction. CISNs overcome the challenge of incorporating social theories through a unique architecture with separate components to represent the two fundamental aspects of any social interaction between two social actors, namely their contact opportunity and their cultural affinity. Both of these aspects are represented using social networks and cultural fragments. A cultural fragment, which is represented using a probabilistic reasoning network framework called Bayesian Knowledge Base (BKB), models a specific behavior of an actor or group. The CISN architecture defines infusion points where interactions prescribed by social theories can be incorporated into the model using Bayesian fusion algorithms. CISNs also represent the multi-scale organization of social systems by including networks to represent social structures at different levels (group, community, nation, etc.). Bayesian fusion algorithms help to combine the individual behaviors to form behaviors of groups at higher levels in the social system. For model validation, we continue with the investigation of group stability of major players in the 2006 Somali civil war. The initial results for this scenario [2] utilized only homophily theory to provide analysis of the interactions between the different groups and its impact on group stability. In order to demonstrate the generality of our methodology, we extend the initial results by applying Affect Control Theory (ACT) [3] and landscape theory [4] along with homophily, and show how a more nuanced analysis of the scenario can be conducted. In the following section, we provide a background on foundational concepts, and then follow it with a description of the approach used to construct CISNs incorporating elements of culture and social theories. Finally, we detail the application of our framework to the Somali scenario.

2 Background

Homophily [5], a prominent social theory, hypothesizes that actors of similar beliefs and goals will be attracted to each other and inclined to cooperate. We employ homophily to model the cohesion of clans within alliances. On the other hand, we have the notion of frustration, which we adapted from Axelrod and Bennett's landscape theory of aggregation [4]. In our reinterpretation, frustration suggests that actors taking mutually threatening actions will align against each other. At first glance it seems that high homophily should imply low frustration. This will usually be correct, but much can depend on influential variables. Two actors could have mostly identical beliefs, goals, and reasoning rules, which suggests they should want to work together, but a single difference could disproportionately influence them to take opposing actions, driving them apart. Affect Control Theory (ACT) [3] is a widely applied social theory with a mathematical formulation which proposes that individuals shape their impressions about other entities through social interactions, where they conduct themselves in a way such that the generated feelings are appropriate to the situation. By considering that an individual's goals/intents vary with the social event, we apply ACT in our framework to tune it based on actions and reactions, thus better reflecting complex real-world scenarios. Existing microsimulation based methods such as MoSeS [6] provide frameworks for incorporating social theories. However, actor behavior is usually kept linear, making them ill-suited to simulating social theories with dependence on actors' thoughts and choices. This is a major drawback that we address in our methodology by using BKBs [7] to model nonlinear actor behavior.

3 Approach

Before going into a deeper discussion on how social theories can be incorporated into real world scenarios using a CISN, we discuss some of the underlying representations and behavioral concepts used to incorporate culture into our models.

Bayesian Knowledge Bases (BKBs), Intent and Culture: The unique advantage of BKBs, unlike Bayesian networks, is that they do not require a complete probability distribution for all rv_s. A BKB is essentially a set of conditional probability rules (CPRs) linking rv_s in an "if-then" fashion. BKBs can be graphically represented as directed graphs with two types of nodes: (1) instantiation-nodes (I-nodes), which represent the states of rv_s; and (2) support-nodes (S-nodes), which represent CPR probability values. Representing culture in our model is essential because it can impact intentions, decisions and actions [1]. For use in our model, analysts can generate cultural fragments, which are BKBs representing actor behaviors and their cultural influences. We connect underlying cultural factors to actor behavior using the notion of intent [8]. The instantiation of rv_s, as represented by I-nodes, is used to represent four essential components of the intent framework: 1) Beliefs (B) – beliefs about others; 2) Axioms (X) – beliefs about self; 3) Goals (G); and 4) Actions (A). Multiple cultural fragments can be combined into a single BKB using the Bayesian fusion algorithm [9]. This is critical for modeling dynamism, as fragments, representing real-time changes, can be added during simulation. Reasoning over the BKBs can help in predictions (e.g. belief updating) and explanations (e.g. contribution analysis).

CISN Framework: CISN (**Fig. 1**) [2] has a flexible, plug-n-play architecture that allows for multi-scale modeling of actors, groups, social structures, and interactions. At each level, behavior can be incorporated in the form of cultural fragments. The components of the framework deal with various aspects of social systems, including physical interactions, social influences, and perceptions. The component-based architecture allows for plug-n-play of methodologies and representations. Functional mappings between components combine information and analyses across the various methods. One key insight of the architecture is that social influence is a function of not only the similarities of the actors, but also of their physical interactions. An ideology network represents the ideological proximity of actors. In contrast, a contact network represents their communication proximity.

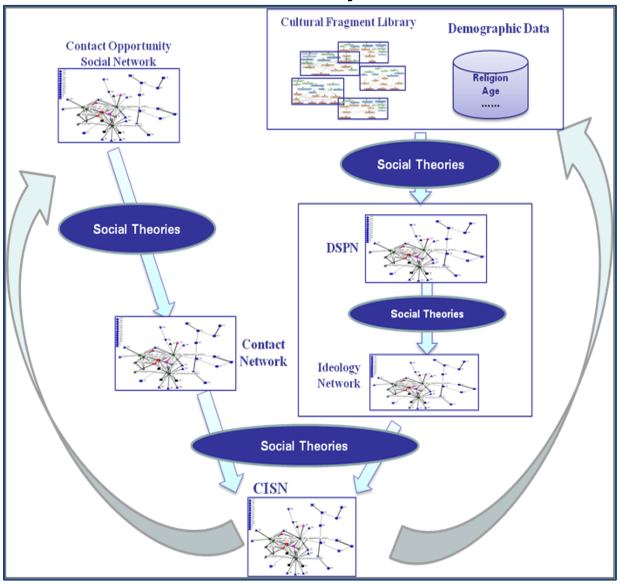

Fig. 1. CISN Architecture

An ideology network is comprised of nodes representing actors, goals, and actions. A weighted link between an actor and an action or goal indicates the calculated probability of the actor taking that action or setting that goal. Links between actors, indicating the similarity of the actors' culture and ideology, are calculated based on the actors' probability to pursue similar goals or actions. It is expected that actors with similar ideology will be more likely to collaborate, given the opportunity. Thus ideology networks help assess the desire or will to collaborate. Contact networks indicate the opportunity for actors to interact with other actors in the model. There can be a number of ways actors might interact: virtually, physically, financially, etc. Each of these interactions can be individually represented using contact opportunity social networks. A contact network is formed by combining all the contact opportunity social networks. The contact network and the ideology network are combined to form the CISN.

Changes in behavior can occur when an actor's perception of other actors changes [3]. Social perception has an impact on the role and status of an actor in a social system. This in turn will affect how he is treated or what social influence he has. The perception of the actors towards each other is represented in the Distributed Social Perception Network (DSPN), where the nodes represent actors, and edges represent perceptions. Note that the edges are bidirectional, as the sentiment that actor *a* has towards actor *b* may not be reciprocal. In a CISN, a DSPN provides input for generation of the ideology network. We can use social theories to inform the perception process. **Fig. 1** indicates where social theories can be incorporated into the CISN.

4 Application

Table 1. Simulation Time Line

	Date	Major Events
1	08/16/2006	ICU seizes multiple ports that were supporting piracy.
2	09/30/2006	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	11/01/2006	Puntland aligns with ICU against Somaliland.
6	11/26/2006	Ethiopian convoy in Baidoa is attacked by Pro-ICU forces.
7	12/02/2006	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.

For validation, we analyzed the conflict in Somalia during the latter half of 2006--a complex, rapidly-evolving, and well-documented scenario [10]. We explored the composition and dynamics of groups involved in the conflict, with the aim of explaining the Islamic Courts Union's (ICU's) sudden rise to, and even more sudden fall from, power. During this period, the main adversary of ICU was the Transitional Federal Government (TFG), which was devised during one of many peace conferences to stabilize the region. This conflict was framed by the ICU's successful occupation of Mogadishu in early June 2006 and the dissolution of the ICU in December of 2006. Since ICU was composed of multiple sub-groups, each with their own interests, goals and beliefs, understanding the stability of these groups is critical to determining the factors leading to the rise and fall of ICU. Most models in group stability focus on the cohesive forces of homophily and neglect the repulsive forces of frustration. We construct two competing models, based on: 1) only homophily; and 2) homophily and frustration combined. By comparing the stability analysis provided by the models with the actual events in the scenario, we validate our ability to embed social theories in computational frameworks and compare the efficacy of the two models. To further demonstrate the versatility of CISN, we analyze the same scenario through the lens of ACT. ACT has mathematical/statistical underpinnings. Applying ACT helps us understand the correlation between group stability and the change in other actors' perceptions of ICU.

Experimental Setup: For our simulation, we considered events during ICU's ascent and decline: June – Dec 2006. The major events included in our model are provided in . For each time step in , our simulation performs three major actions [14]: 1) Process Social Networks: We construct social networks to highlight relationships between actors affecting TFG and the ICU. We include both static and dynamic social networks, which are combined to form a single network using a weighted scheme. 2) Generate CISN: Actors are selected based on information extracted from the social networks. For each actor, relevant fragments are fused to form the actor's overall cultural fragment. Probability values for plausible actions are also calculated. The ideology network is constructed from all actors and plausible actions. Contact potentials from the various social networks are used to construct the final CISN. 3) Stability Analysis: As new alliances are made, the ideologies of the sub-groups are fused with the core ICU and TFG ideologies to generate the overall group ideologies in the ideology network. Variance in the support among the subgroups is captured using an instability metric calculated from the deviation of each sub-group ideology from the group ideology. After the CISN is generated, we measure the instability metric for a selected target *rv*. A large instability value indicates that the group is likely to fragment.

The CISN is used to compute the degree to which each subactor influences the organization's overall decisions. A "super-fused" BKB, modeling the entire organization, is built by fusing all subactors' BKBs. Fragment contribution is used to calculate each subactor's contribution to the instantiations of a chosen target variable. In our simulations we chose *rv* "(A) Invade TFG territory" as the target variable. Finally, we find the variance of the contributions to the target variable across all the subactors by calculating the variance of the ratio of the contributions to each variable instantiation. This variance figure is our measure of instability. We employ ACT social theory to update individual perspectives based on unfolding events. Each sentiment is taken from an observer's point of view toward the participants involved. Three entities are considered for a situation: actors, events, and objects. An observer will assign *Evaluation-Potency-Activity* (EPA) values to the entities. The observer either finds the situation is consistent with cultural norms, or that it represents a deflection. In the case of deflection, the observer will modify its initial sentiment to conform to the situation. The EPA values are rated between [-3, 3] [11]. We use equations derived from ACT[1] to formulate the sentiment changes. To incorporate EPA values into the model, we select actors' goals, intentions, and behaviors that are related to each of the EPA components and build EPA fragments. The EPA fragments are fused with basic culture fragments to represent an actor's composite cultural influence. Since potency reflects how a region perceives the strength of ICU, the *potency* EPA value may serve as an indicator of the group instability.

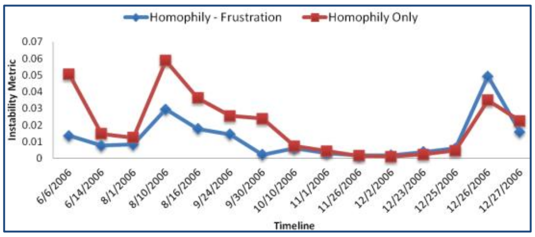

Fig. 2. Stability with Homophily and Frustration

Results and Analysis: Referring to **Fig. 1**, we can see that there is a social theory plug-in that feeds into the box containing the DSPN and ideology network. It is here that we applied Landscape Theory to gauge group stability by incorporating the concepts of homophily and frustration. Homophily contributes towards group cohesion, while frustration acts as a force of dissolution. In **Fig. 2**, we can observe the refinement provided by the incorporation of frustration. Without frustration, there is a maximum in the calculated instability of the group on 8/10/2006 that seems to indicate that the ICU should have fragmented and dissolved at this early stage. With the addi-

[1] http://www.indiana.edu/~socpsy/ACT/interact/subcultures/sex_averages.htm

tion of frustration, we see that our results agree more closely with the actual timeline, where additional friction is apparent by a *local* maximum at 8/10/2006, but the timeline maximum now occurs properly at 12/26/2006. Thus we have a clear instance demonstrating how the incorporation of the social concept of frustration has greatly improved the accuracy of our results. It may seem counter-intuitive that adding frustration to the homophily model decreases instability. However, note that, mathematically, instability metric is measured using the variance of the contributions of the subactors to ICU's behavior, specifically contributions to the *rv* "(A) Invade TFG territory". Take for example 08/10/2006 when the strategic region of Beledweyne was incorporated into ICU. Since the start of this conflict Beledweyne, which borders the territories controlled by TFG and Ethiopia, was split between allies supporting ICU and TFG. Some extremist allies within ICU supported complete takeover of this region while moderate allies feared further escalation in violence. This variance is more pronounced when only homophily is considered. When we also include the frustration of the subactors with the ICU's efforts to attack TFG (from both moderate and extremist points of view), the variance of the contributions to ICU's behavior reduces, leading to lower instability values. In non-mathematical terms, the decrease in instability can be seen as disengagement of a set of subactors leading to lower conflicts within the ICU alliance.

On examining the changes in the instability values in the homophily-frustration model, we see that the instability of ICU is high during its expansionist phase in the early part of the timeline. This can be explained by new groups with different socio-cultural make-up aligning themselves to ICU. However ICU's successful military operations contribute to its stabilization over time. This continues until Ethiopia initiates hostilities and starts gaining the upper hand. Military reversals increases the rift among the ICU allies, especially on the issues of resisting TFG, as indicated by the spike in ICU's instability metric around 12/26/2006. This eventually leads to the disintegration of ICU.

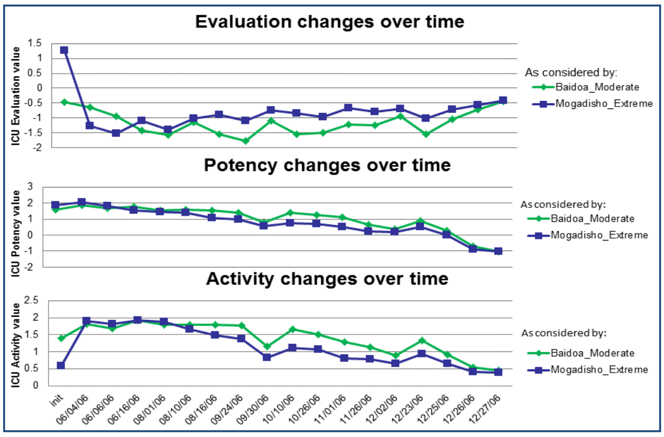

Fig. 3. Applying ACT to Stability Analysis – EPA Values

We model the important effects of perception and sentiment change using ACT. ACT argues that when presented with a conflict between an actor's EPA values and that actor's reactions to a particular event, an observer will respond by modifying his estimation of the actor's EPA values, either temporarily by associating modifiers for the actor (e.g. angry, eager, patient, etc.), or by assigning entirely new EPA values for the actor. At this point in our model, we explore the use of modifiers, and leave value reassignment for future research. **Fig. 3** shows how EPA values toward ICU from two different groups, extremist and moderate, change over time. As we can see, the potency values for the ICU from both groups increase in the beginning as ICU seizes more regions and gains power, but decreases below zero after 12/25/06. This happens when Ethiopia and TFG get the upper hand, and ICU loses most of the territory they had gained. Thus, ACT provides additional explanation for the decline of ICU.

5 Conclusion

In this work, we provided key insights to incorporating social theories into computational models, and presented CISN as a generic framework that embodies these insights. We validated the viability of CISN by analyzing the stability of ICU during the 2006 conflict using landscape theory and ACT theory. We demonstrated the ability of CISN to compare social theories by showing the added accuracy provided by employing frustration and homophily for stability analysis. With ACT, we provided more details in the model in the form of actor perception and added explanation to the breakup of ICU. This work represents only the first step in embedding social theories in computational frameworks. Our next steps will be to embed different social theories and to pose a relevant categorization scheme for those theories.

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