Infusing Social Networks With Culture

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Abstract—Social Network Analysis (SNA) is a powerful tool for analyzing social phenomena that is based on studying how actors are connected or interact with each other. All Social Networks (SNs) are inherently embedded in particular cultures. However, the effect of cultural influence is often missing from SNA techniques. Moreover, to incorporate culture, modeling approaches have to deal with inaccurate, unrealistic, and incomplete cultural data. In order to address this problem, we propose a generic approach to systematically represent culture in the form of relevant factors and relationships, while leveraging relevant social theories, and to infuse them into SNs in order to obtain more realistic and complete analyses. Using two sets of experiments, we validate the effectiveness of our approach and demonstrate the significant advantages obtained through culturally infused SNA.

Index Terms—Bayesian knowledge bases (BKBs), culturally infused social network (CISN), culture, social network analysis (SNA).

I. INTRODUCTION

STRUCTURE affects function. Social Network Analysis (SNA) is a set of techniques developed to study the structural information contained in social entities' interactions (e.g., communication and relationships). In the original definition of Social Networks (SNs), each node represents a social entity (a person, a group of persons, or an organization), and an edge between two nodes represents an interaction between the corresponding entities. In general, SNs can be used to study many types of interactions between different types of entities. Understanding how entities interact with each other can provide significant insights into a myriad of social processes. In fact, SNA has been studied and applied in a broad range of fields, including sociology, epidemiology, criminology, economics, and so forth [1], [6].

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Modern SNA has been studied for more than 70 years [3]. Network analysis approaches have attracted a great amount of research interest, and there have been many computer software tools and methodologies developed to perform this analysis [1], [4], [5]. These analysis tools and techniques can comprehensively analyze SNs and provide insights. However, development of sophisticated SNA methods still faces many challenges. Compared with the great strides made in SNA approaches over the years, research into SN construction (i.e., gathering, using, and combining data for SNs) has been lagging. SN-based modeling frameworks are typically built for a particular domain (e.g., geographic, religious, and application specific), which cannot be readily mapped to other domains. Furthermore, many complex applications require the combination of multiple SNs across various domains. As such, the problem of effectively handling a mass of social data gathered from multiple domains is one of the pressing problems faced by SNA researchers.

Another serious problem is that SNs are focused only on interactions between social entities and not on the possible behavior of the entities within the network. Most analyses done on SNs identify the characteristics of the entities' interactions [5], group entities with similar structural patterns [7], and map interaction patterns to potential roles/positions (e.g., broker and core/periphery) [1], [6]. Thus, it is clear that SNA is more descriptive; that is, it is typically used to answer the "what is" questions: "Which social entity is important or popular?," "Which entities are core or periphery actors in an organization?," "Which groups of entities will have similar behaviors?," etc. However, in many applications, such as antiterrorism and emergency preparedness, SNA users are also interested in details about how social entities will act/react in a particular situation, as well as explanations behind observed social phenomena and emergent social structures. Therefore, SN-based models should have the ability to provide more comprehensive behavioral insights and predictions for social phenomena. Some SNA researchers have already worked to address one or more parts of these problems [8], [9]; however, these approaches are designed for specific applications and have their own individual foci.

Although a link in an SN can provide information about the strength of the relationship between two nodes, it does not provide a "context" to the relationship. Cultural cues can provide such a context. Culture is a broad umbrella term that includes, among other things, norms, roles, attitudes, beliefs, etc. Infusing cultural influences into SNs is a way to provide context to social relationships. Culture not only highlights the uniqueness in a social system but also provides explanations for observations of decisions, social changes, etc. Modeling culture and its influences is a key step toward representing the inherent dynamism in social systems. However, coming up with

an overarching framework for incorporating culture has many challenges, such as inherent uncertainty and incompleteness of sociocultural data. Uncertainty and incompleteness may be due to subjective biases of respondents or intentional concealment of information [1], [6]. Additionally, simply including cultural factors does not provide insights into social behavior at individual and group levels. It is important to link sociocultural factors to behavior. The Culturally Infused SN (CISN) structure will provide a framework to make those links and test the resulting consequences. Exactly how and where to make those links will require domain expertise from Subject Matter Experts (SMEs) and social scientists. Our goal for CISNs is to define mathematical structures and mappings to allow crossover of social information/theories/relations into the computational domain for a generic scenario. It should also be noted that our goal is not to define or identify culture.

The main goal of this paper is to demonstrate how culture can be realistically represented using the CISN framework.[1] It is a domain-independent framework that takes into account the inherent uncertainty and incompleteness of cultural data. Our framework will also seamlessly link cultural factors to entity behavior. Since a CISN leverages probabilistic reasoning networks and intent-based behavioral models, it has a rigorous foundation. Because of the varied meaning and significance of culture across domains of social science, we employ a very broad definition of culture and focus on representing culture in a manner relevant to the model, as identified by the SMEs and domain experts. In addition to infusion of culture, the CISN has the capability to model and analyze social processes at multiple scales in social systems [45]. We will validate our framework using a terrorism network and show how cultural information can help uncover previously hidden relationships. This paper is organized as follows: Sections II and III introduce current issues in SN construction and potential methods to solve them. Section IV provides a concise introduction to cultural models. Section V concentrates on the design of our approach to infuse SNs with cultural influences, followed by details of the initial implementation and experimental results in Section VI. Conclusion and discussion of future work are provided in Section VII.

II. BACKGROUND AND CURRENT ISSUES OF SN CONSTRUCTION

The SN research field can be generally decomposed into two major areas: SN construction and SNA methods. SNA methods are focused on identifying the structural characteristics of interactions of individual persons, organizations, or the whole network. SN construction is concerned with how to gather, interpret, compare, and combine SN data. Currently, there are two main types of approaches to gathering SN data, namely, elicitation and registration [11]. We will describe both of these data-gathering approaches and also show how uncertainty and incompleteness are the two main issues with the

social data. In elicitation, interaction information is acquired via questionnaires or surveys. Data obtained by elicitation are inherently inaccurate and subjective [1], [12]. Respondents may be from different backgrounds, leading them to have a different understanding of a question. For example, people from the USA will have a different understanding of friendship than that of Chinese people. It is hard to compare or combine the friendship network of a Chinese person with that of someone from the USA. In addition, in some applications, such as antiterrorism and homeland security, malicious respondents may intentionally make an effort to hide their true actions/relations from detection.

SNA researchers have already noticed this problem and developed approaches to study and refine SN data sets. These approaches are mainly focused on analyzing data collection factors' effects on SNs [13], [14] and optimizing data-gathering approaches for specific applications to achieve better data sets [8], [9]. To the best of our knowledge, however, the questions of how to generically and systematically refine network data and then pinpoint the relevant data, which themselves are potentially incomplete, inaccurate, or completely missing, have yet to be addressed.

The second method of data gathering, i.e., registration, acquires interactions by extracting them from registered information, such as membership lists, email records, and authorship records of published materials. It would seem that registration data should be more accurate and objective; however, registration data can be difficult to interpret. The numbers obtained may convey different meanings in different contexts. Taking phone call lists as an example: two people who call each other once a week may be normal and therefore unremarkable in a developed country, but quite abnormal and potentially of interest in a developing country, where the use of telephones is not so extensive. Interaction information is usually domain specific, but network data may be collected from various domains. Every domain has particular circumstances and unique characteristics. Thus, each domain can be so different that the data obtained from different contexts are not directly comparable or easily combinable. At issue is the fact that, in many real-world applications, SNA users face the task of analyzing multiple SNs from various domains, each of which only contains a part of the big picture of the underlying mechanism they wish to explore. A full understanding of the phenomena cannot be obtained by simply "summing" the results obtained from each interaction together. Most SNA approaches focus on SNs in particular domains and employ different doctrines to generate separate sets of insights [15], [16]. They leave the combination of analytical results to human intelligence. Thus, the absence of a generic approach to handle SNs across domains prevents a deeper understanding of the underlying mechanisms of social phenomena and prevents currently obtained insights from being generalized and utilized across different disciplines.

III. CULTURE IS THE KEY

In order to effectively address the issues discussed in the previous section, we claim that culture is the key. Culture has been studied and used in many fields and has multiple definitions due

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[1]A preliminary formulation of the CISN framework was presented in [10]. This paper significantly refines the CISN, providing new ideas and foundational algorithms.

to varied understandings and different foci of researchers. We consider culture to be broad enough to encompass all learned notions (including cultural norms, social roles, beliefs, and social customs), sociocultural attributes, and behaviors.

First of all, culture provides and defines the SN structure. Infusing cultural influences into SNs can shed light on connections whose relevance would not have been as apparent, or may have even been missed, otherwise. For example, suppose Tom is an actor within an SN. Tom's known acquaintances are represented in the network. We know that Tom is planning to build a research company focused on computer science technologies. Suppose we are trying to determine which persons Tom is most likely to collaborate with or recruit while building his company. Without any other data, it is difficult to determine whom Tom will select. Consider how the use of cultural elements can provide insight into the SN. If, for each person in Tom's SN, we know their technological background, wealth, and degree of satisfaction with their current job, infusing this cultural information into the SN will strengthen the links with acquaintances that have computer science backgrounds, are not satisfied with their current job, or who want to make more money. Furthermore, infusing SNs with cultural elements would also highlight ties that may not have been directly represented in the original network, e.g., a friend of Tom's happens to be an expert in a promising field of computer science. Thus, by infusing cultural elements into SNs, we can potentially obtain more realistic and complete data sets for SNA.

Moreover, culture significantly affects an actor's behavior, serving to limit, determine, and even help predict it. In order to identify and evaluate potential behaviors in SNA, cultural analysis is indispensable. Behavior is not simply about passing information and making ties—it is heavily affected by an actor's intent, worldview (e.g., values and beliefs), and context (e.g., behavior history, capability, and opportunity). It is rare, if not impossible, for two individuals to have the exact same reactions in identical situations. Intentions, values, perceptions, and opportunities are not solely determined by the present situation but are also based on one's history, context, and circumstances. In essence, they are determined by the cultural environment from which the individuals or groups originated and within which they are currently embedded. In order for SNA techniques to be able to provide more useful behavioral insights, it is vital to infuse cultural influences into SNs.

Furthermore, culture constrains communication and interaction among actors and can help determine the underlying similarity between domains. Taking a kinship network as an example: compared with Americans, Chinese have a quite different and more complicated definition of kinship. For example, in China, a brother's son and a sister's son are referred to differently, but in the USA, they would both be called nephew. Thus, it is not surprising that the kinship network of those from the USA and those from China may be significantly different. As a result, it is hard to compare the analysis results obtained from each network or to extrapolate insights from one type of network to the other. Additionally, a kinship network may consist of people from both the USA and China. Such a network will inevitably be skewed by biased understandings and definitions of kinship. Fortunately, culture can help bridge the gap between domains. By carefully studying U.S. and Chinese cultures, we have the ability to estimate the differences and similarities between different types of kinship. This enables us to potentially eliminate, or at least relieve, the underlying biases and inconsistencies.

Most, if not all, SNs are constrained and affected by, or perhaps even derived from, culture. Cultural awareness should be a significant element of SNA. However, current SNA methods either do not consider cultural elements or have been specialized to focus on a specific culture either implicitly or explicitly [15], [17]–[20]. In order to effectively and generically construct more realistic, complete, and behaviorally informative SNs, it is crucial to formally model cultural influences and incorporate these models into SNA.

IV. MODELING CULTURE

There are many definitions of culture. A common thread in these definitions is that culture deals with those things that are influenced by or learned through social processes and that it can have a significant impact on behavior [21]. This motivates the desire to utilize cultural information in refining SN data sets, particularly if the behavior of the actors in the network is of interest. In order to make use of culture in a broad range of domains and applications, a method of systematically modeling cultural influences is required. However, attempts to form a comprehensive computational model for representing culture and its influence are rare at this current time [22].

Attempts to model culture allow for only a small number of cultural variables to be considered and employ simplistic assumptions [23]–[25]. Axelrod [23], who broadly defined culture as a "set of individual attributes that are subject to social influence," leveraged multiagent simulation to understand change in cultural traits due to influence of neighbors and analyzed convergence over time. However, their simulation does not link culture to actor behavior and is therefore limited in its utility. This work does provide a precedent for applying a broad definition of culture in computational social science. A model by Harrison and Carroll [24] looks at culture in organizations. Although this work deals with transmission of culture, it is representative of models where one or more discrete values are used to represent cultural attributes, and these values are changed using analytical equations. Coming up with suitable values for culture is a challenge, and the values used in the model represent the subjective view of the modeler. It does not support multiple viewpoints. This is particularly detrimental in a field where finding a unified interpretation of cultural attributes is a challenge. The cultural model by Hofstede *et al.* [26] uses a multidimensional space to quantify cultural values. The shortcomings of this model are evident: inflexibility in adding new cultural factors and an ad hoc approach to coming up with the values of the cultural attributes. Models in areas such as role-playing simulations [27] are more expressive but have not been applied to SNs. Fuhse [22] proposed a theoretical framework for modeling culture in SNs but provided no practical implementation. Our approach can model all relevant cultural variables and allows their effects to be combined in a probabilistic framework.

Other frameworks based on Multi-Agent Systems (MAS) and game theory have been widely used to incorporate sociocultural influences. Multigames [41] is an interesting framework for representing social interactions in complex scenarios such as economic games. The advantages of multigames include explicit representation of multiscalar aspects of social systems and incorporation of social aspects such as roles. However, approaches such as multigames provide very little in the way of explanations for observed behavior. In MAS [42], social processes are represented as interaction rules between agents, and emergence of collective behavior is studied through simulation of the agents. A relatively recent survey of MAS is provided in [43]. More relevant to the paper's theme are multiagent models for complex social scenarios that incorporate cultural influence. Kuznar and Sedlmeyer [44] formulated a MAS-based framework for understanding the interaction between cattle herders and agriculturist communities in Darfur and studied the emergent collective actions that destabilized the region. The model incorporates relevant social, cultural, geographical, and economic factors. Although this framework has been used to study pastoralist–agriculturist interactions in other regions, it would be a challenge to apply it to more generic situations.

To summarize, current cultural models use ad hoc approaches to assign and change the quantitative values of the cultural attributes. In addition, the models are restrictive and cannot be easily applied to multiple domains. Finally, the cultural factors are not explicitly linked to the behavior of the entities. We acknowledge that sociocultural data are highly subjective and, in most real-world scenarios, incomplete and uncertain. Our framework does not get around this by making simplifications but by making our assumptions explicit. We do this by leveraging a probabilistic reasoning framework called Bayesian Knowledge Bases (BKBs) [28]. BKBs can represent a wide range of cultural information by employing an intent-based behavioral model. The intent model plays the critical role of relating cultural parameters to observable behavior, whereas BKBs provide the capability to employ sophisticated reasoning algorithms, including Bayesian updating and revision [28], [29]. We will now explain the main concepts in our framework in more detail.

A BKB is basically a collection of rules. These rules can specify a probability distribution over a set of random variables in an "if–then" fashion that is natural for use by SMEs. The only condition imposed on these rules is that they must be mutually exclusive. BKBs are graphically represented as directed bipartite graphs with two types of nodes: 1) I-nodes, which represent instantiations of random variables (RVs); and 2) S-nodes, which represent rules. For a detailed description and formal definition of BKBs, refer to [28]. To understand how BKBs successfully deal with the uncertainty and incompleteness of modeling information, and how this is unique in the probabilistic modeling domain, we compare BKBs with the widely used probabilistic reasoning framework called Bayesian Networks (BNs). It may be noted that probabilistic reasoning networks have been used to represent uncertainty in various domains such as decision making, knowledge engineering, etc. Although BNs incorporate uncertainty in modeling data, the framework requires a complete description of the probability space, which means that it requires complete knowledge of the
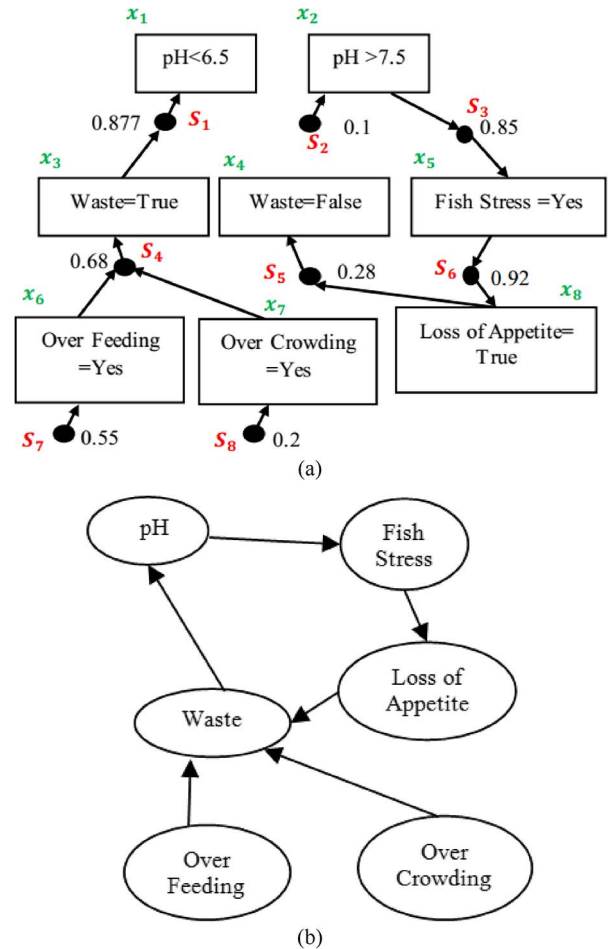

Fig. 1. Comparing BKBs and BNs. (a) BKB with eight rules. (b) A corresponding BN cannot be built due to incompleteness and cyclic information.

modeling scenario. Unlike BNs, BKBs do not require a full conditional probability table for each random variable and the set of variables it depends on. The rules that are needed may be included as Conditional Probability Rules (CPRs), and the ones that are not needed or unknown are left out. Fig. 1(a) has an example of a BKB, where the boxes represent I-nodes (with labels x_i) and the small black circles (with labels S_i in red) represent the S-nodes. Each S-node represents a rule. The S-node S_4 has a rule that reads "if the RV OverFeeding is Yes and the RV OverCrowding is Yes, then the RV waste is Yes with a probability of 0.68." Fig. 1(a) provides an example of a set of rules that can be represented by a BKB but not by a BN [see Fig. 1(b)] due to its incompleteness and underlying random variable cycle. Allowing incompleteness facilitates the representation of information in domains, such as social science, where complete knowledge may not be possible to obtain. It also alleviates the problem of having to fill in large conditional probability tables whose size can be exponential in the number of dependent variables for each random variable. BKBs also allow for the inclusion of potentially contradictory and cyclic information, which is not possible in BNs.

Although BKBs can work with uncertain and incomplete information, forming rules from sociocultural information that can be used in BKBs is a challenge. We employ the behavioral modeling paradigm of the adversarial intent inferencing model
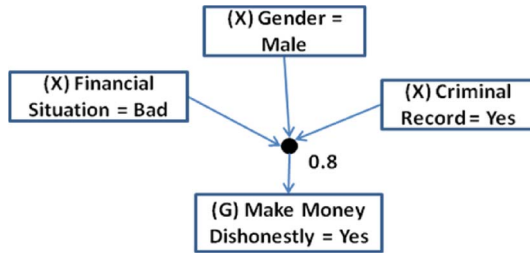
Fig. 2.   Example of a cultural fragment.

(henceforth referred to as the intent model), formulated by Santos [30] and Santos and Zhao [31], to encode the sociocultural information in relation to the actors and entities. This model was designed to capture actor/entity behavior in the form of intent, which is a combination of its goals, intentions, biases, beliefs, and perceptions, and can be easily extended to accommodate any other cultural information deemed relevant. Although the intent model notions of beliefs, goals, and actions are similar to the Belief–Desire–Intent (BDI)-based software model [32], BDI models are mainly used for agent planning. The intent model, on the other hand, focuses on providing explanations for observed behavior. Since the intent model utilizes BKBs, well-defined reasoning algorithms are also available for analysis under uncertainty, which is not the case with BDI.

Information about the actor being modeled is divided into four categories.

1) *Axioms:* what the actors believe about themselves.
2) *Beliefs:* what the actors believe about others.
3) *Goals:* what the actors hope to achieve.
4) *Actions:* the actions the actors may carry out to achieve their goals.

Random variables of each of these types are defined, and each of their possible states is included as an I-node in the BKB.

Relationships between the axioms, beliefs, goals, and actions are included as S-nodes (or CPRs) in the BKB. BKBs that represent sociocultural information are termed cultural fragments. An example is shown in Fig. 2, which illustrates how one could encode the rule that if someone is a male with a criminal record and a bad financial situation, then there is a probability of 0.8 that he has a goal to make money dishonestly.

Most cultural influences are classified as axioms or beliefs and will impact the actor's likely goals and actions. This framework allows for the representation of cultural influences at various levels of granularity, with a formal method for combining the effect of all the cultural variables that are thought to impact the situation of interest. Reasoning algorithms such as Bayesian updating and revision [28] allow the determination of likely goals and actions based on the available cultural information.

Since cultures are so varied, no single cultural fragment is able to capture all the information that might be useful in a given scenario. In addition, in each scenario, the amount of knowledge available about the actors in the network may change. In order to address these challenges, a library of cultural fragments is maintained. Each fragment is a BKB that contains one piece of cultural information. When a new actor needs to be modeled, all the information that is available about them is used to select the appropriate cultural fragments. Selection

can be done using a decision tree, and the selected fragments are merged into one large BKB, using a process of BKB fusion [33]. Information specific to the actor being modeled is set as evidence in this BKB so that reasoning can be performed.

Usability is a key issue for an overarching computational framework that will be used by experts from various disciplines such as anthropology, sociology, and political science. Although the framework's theoretical foundations in computational science and probability theory may hinder its acceptance by modelers in some of these fields, software tools can be developed to make it more user-friendly. The framework has certain unique features that will help simplify its use. The cultural fragments consist of if–then rules that can be generated even by novices to Bayesian probability. In the absence of quantitative cultural statistics (which is normally the case), the probability measures represent subjective opinions and intuitions of the SMEs. Here also, detailed knowledge of probability theory is not required. Moreover, the process for representing complex cultural influences can be simplified, as "elemental" cultural fragments can be combined in an incremental fashion. Software tools can be produced with an intuitive graphical interface to help ease and speed up the process of generating the fragments.

V. INFUSING SNs WITH CULTURE

Cultural fragments are powerful tools that can provide detailed behavioral information about the actors. By reasoning over the cultural fragments, we can obtain a prediction of their potential behaviors. It may be noted that under the intent model, behavior encompasses not only observable actions but also beliefs and goals. These behavioral insights provide significant clues to help answer the "what," "how," and "why" questions of tie formation between individuals. Thus, cultural information can be used to refine SN data sets by strengthening, weakening, or removing existing links (ties) and by bringing to light new and potentially covert ties within the network, which is the major focus of this paper.

The main challenge in the culture infusion process is to map the complex sociocultural information from the cultural fragments to an SN. The main idea behind our methodology (see Fig. 3) is to take into account two aspects of the social processes that are represented in SNs, namely, social and communication.

The social aspects of the SNs include all relevant factors related to individual behavior. First, an individual's behavior can be affected by the behavior of others. We find that the behaviors of actors in an SN usually fall into one of two high-level categories: those that raise the probability that the actors will communicate or collaborate, and those that lower it. We propose that major behaviors can be coarsely classified, as shown in Table I. Second, an actor's behavior may be also affected by other actors' attributes, such as personality, educational background, etc. For example, when we analyze the propagation of innovation, we find that different people give credit to different types of sources. Some people believe scientific experts, whereas others place more trust in what celebrities say.

Therefore, based on individuals' properties, attributes, and potential behaviors, we can estimate the probabilities for different social interaction between actors. We use a network
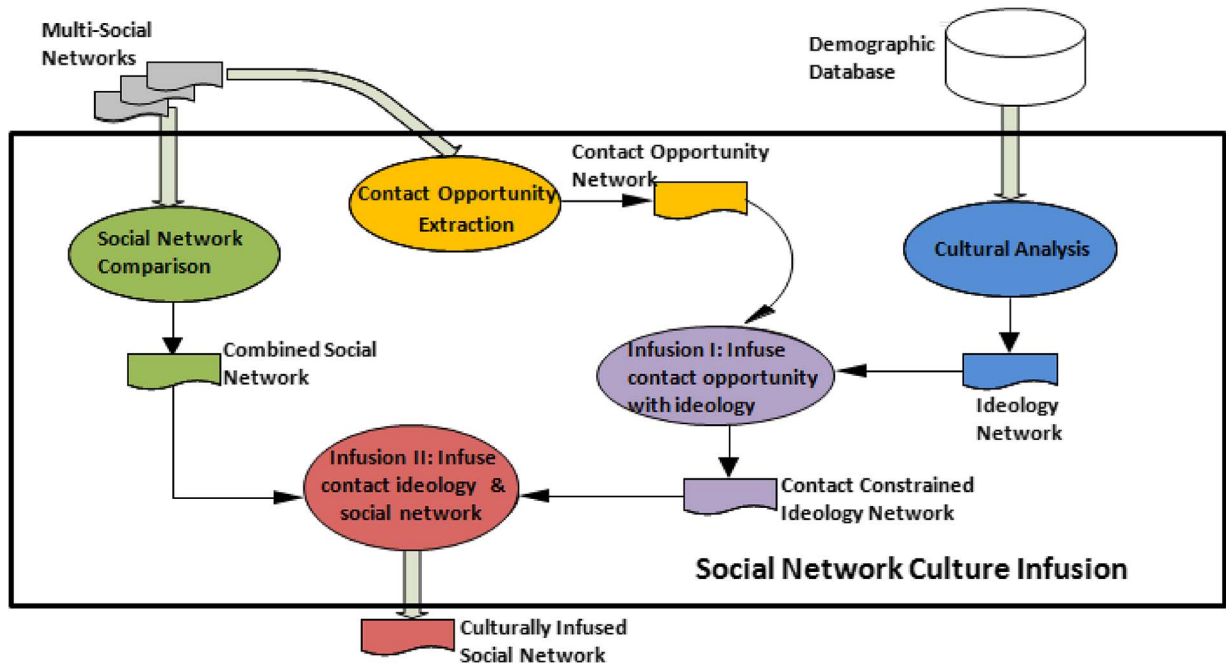
Fig. 3.   SN culture infusion architecture.

TABLE I
MAJOR TYPES OF BEHAVIORS

Raise Prob. Of Collaboration		Lower Prob. Of Collaboration	
Cooperative	The actors will cooperate to achieve a shared goal or action (e.g. group to-gether and have a street demonstration)	*Competitive*	Actors compete with each other and are less likely to collaborate (e.g. two people are selling the same part to a small market)
Complementary	Different goals/actions, but these goals/actions complement each other (e.g. someone wants to buy a certain part and someone else wants to sell the same part)	*Conflictive*	Radically opposed. Not possible to cooperate. (e.g. people from two groups that hate each other)

to encode the cultural and ideological similarity of actors in an SN and call it an Ideology Network (IN). An IN is an intermediate network that is used in the generation of the final CISNs. In an IN, there are two types of nodes: individual actors and beliefs/goals/actions. Ties between actors in the network indicate the strength of ideological agreement with respect to the beliefs/goals/actions nodes in the network (thus indicating their propensity to form ties in an SN given the opportunity). A tie between an actor and a belief/goal/action represents the probability that the actor will take the action or have the goal. Different subsets of the goals and actions found in the actors' BKBs can be used to form multiple INs, each representing the actors' similarity with respect to a different set of possible behaviors. An example of an IN can be found in the experimental results in Section VI.

We now discuss the communication aspects that need to be modeled in the CISNs. INs tend to group people together based solely on similarity. One important element missing here is the opportunity for individuals to make contact with each other—a necessary condition for social ties. Here, the term "contact" does not only imply physical contact. It represents any means that actors may use to communicate, pass information, and, in essence, interact with each other. In the real world, people interact with others not only because they have similar or matched intentions but also because they have the opportunity to interact.

For example, after the cultural analysis, we may find that two people have extremely matched goals, e.g., selling and buying a specific product. In the IN, there will be a high probability for these two individuals to collaborate (sell and buy). However, if in the real world there is no way for these two people to get to know each other, the collaboration between them will likely never happen. Thus, in order to obtain a more realistic estimation of actors' behaviors and interactions, it is critical to take into account the opportunity for actors to interact with each other. Contact opportunity can be estimated by analysis of individuals' interactions with others and are represented in a Contact Opportunity Network (CON), which is another intermediate network that is generated in our framework.

The architecture of our approach to infusing culture into SNs is shown in Fig. 3. In this figure, each circle represents a functional component, which is a plug-and-play module, thus allowing component functions to be modified according to the particular requirements posed by specific applications. More importantly, by constructing the model in a plug-and-play manner, algorithms and methods (such as specific methods to combine an IN and a contact network) can be swapped into the framework. In real-world applications, users are faced with the task of understanding complex phenomena that relate to multiple types of interactions between actors. Thus, in our system, the output from these components would be combined

together according to their significance in the application being studied and according to various social theories, which can then be compared and contrasted. To explain the culture infusion, we will now describe the sequence of steps in the process (see Fig. 3).

A. Contact Opportunity Extraction

This component generates the CON that represents the communication aspects that we seek to model in the final CISN. Contacts between entities can be formed in a number of ways, and each way may be represented by an SN. For example, networks representing membership in a club, transportation networks (roads, rails), etc., can be used to calculate contact opportunity in the form of edge weights in the CON. This component consists of algorithms to extract and combine information from multiple networks.

B. Cultural Analysis

The cultural analysis component generates the IN. The first step in generating the IN is to select the relevant cultural fragments for the actors/entities. We do this by using demographic information relevant to the scenario being modeled. For example, if the actor is old and wealthy, then the fragments that represent the cultural information for old and wealthy people should be chosen. The selected fragments are then merged using a process of BKB fusion (described later) to form a single large fragment to represent the actor behavior. We also calculate the weight of the edges between the actor and beliefs/goals/actions nodes by applying the Bayesian updating algorithm on the cultural fragments of the actors. These values are used to calculate the weights of the connections between the actors.

C. Infusion I

In this component, the IN is combined with the CON, which represents the capacities and opportunities of individuals to form social ties with each other, yielding a Contact Constrained Ideology Network (CCIN). After combining the CON and the IN, we obtain a more realistic estimation of the probability that an actor may exhibit certain types of behaviors and build particular ties to other actors. The specific method to combine the IN and the CON is not specified by the framework and is decided based on the scenario being modeled.

D. Social Network Comparison

Our framework basically takes SNs as input, infuses culture, and generates a combined SN. Since there may be multiple SNs, they are combined into one SN in this component. Again, the specific method to combine the networks is not fixed in the framework and may be informed by the scenario and relevant social theories.

E. Infusion II

Finally, a CISN is obtained by combining the CCIN with the combined SN. The infused cultural information from the CCIN will help in strengthening the relevant ties, discovery of new relationships, and weakening of the nonrelevant ties, in the final CISN.

It should be pointed out that this methodology is highly scalable due to the strengths of the underlying BKB representations. Any number of cultural factors or pieces of information in the form of cultural fragments can be included in the model. Our model also allows multiple analysts to work together to build a common model. This is facilitated by the BKB fusion algorithms. Therefore, any cultural fragment created by an analyst can be easily added to the model and analyzed. The overriding limiting factor on size of the framework is computational power. We discuss the challenge of computational speed in the future work portion of Section VII.

VI. Initial Implementation, Experimental Results, and Analysis

In order to validate our methodology of representing and infusing cultural elements, and to demonstrate the significant advantages of infusing SNs with culture, we implemented our current formulation of CISN and conducted experiments using SN culture infusion. In our experiment, we demonstrate how cultural elements can provide significant insights that may not be available using existing SNs. Furthermore, we demonstrate how to infuse SNs with cultural influence and validate in detail the advantages of CISNs.

A. Objective

For this particular experiment, we will show the following in the CISN.

1) Actors are connected by edges with various strengths, although the original SNs are unweighted.
2) Insights into an individual's potential goals and actions are provided.
3) Most importantly, the network connection structure is changed, and the information relevant to the application at hand becomes prominent.

B. Experimental Scenario

Assume we are dealing with the hypothetical case that international financiers are funding people in the USA to perform a terrorist act targeting a U.S. nuclear plant. The analysts have a set of networks (including a financial transaction network, a friendship network, and a contact network) containing 50 individuals and the demographic information of each individual (including age, religion, education, financial status, and criminal record). The contact network has information on how frequently the actors meet with each other. The people in this scenario are classified into the following categories based on their function.

1) Funders:
    a) International persons with significant financial assets who are willing to fund terrorism.
    b) Typical demographic characteristics: extreme religious belief, good financial status, young, and high education.
2) Planners:
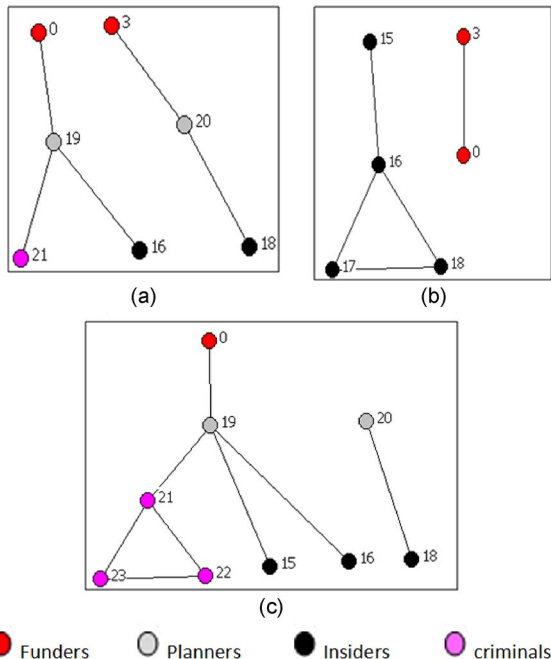   a) Persons in the USA receiving funding from international sources and planning terrorist acts in the USA.

Fig. 4. Core connection in the various networks.

b) Typical demographic characteristics: extreme religious belief, bad financial status, young, and high education.

3) Insiders:

a) U.S. nuclear plant workers who may cooperate with terrorists.

b) Typical demographic characteristics: extreme religious belief, bad financial status, young, high education, and working in a nuclear plant.

4) Criminals:

a) Criminals who will do anything if they get paid.

b) Typical demographic characteristics: bad financial status, young, low education, and criminal records.

5) Normal international persons and normal persons in the USA:

a) Demographic characteristics are set randomly, tending toward moderate religious belief and no criminal records.

Additionally, the analysts are informed that, in the SNs, there are two funders who intend to provide money for terrorists in the USA. The tasks for analysts are to determine the following.

1) Which individuals should analysts pay attention to in order to monitor or prevent the potential terrorist actions?

2) What are the probable behaviors of the actors (particularly the important persons defined in the previous step) in the network?

3) How will funders, planners, insiders, and criminals potentially interact with each other in this scenario to perform the terrorist act?

C. Test Bed

Assume there are 50 people in total in our test bed and they are distributed as follows:

1) funders: persons 0–3;
2) planners: persons 19 and 20;
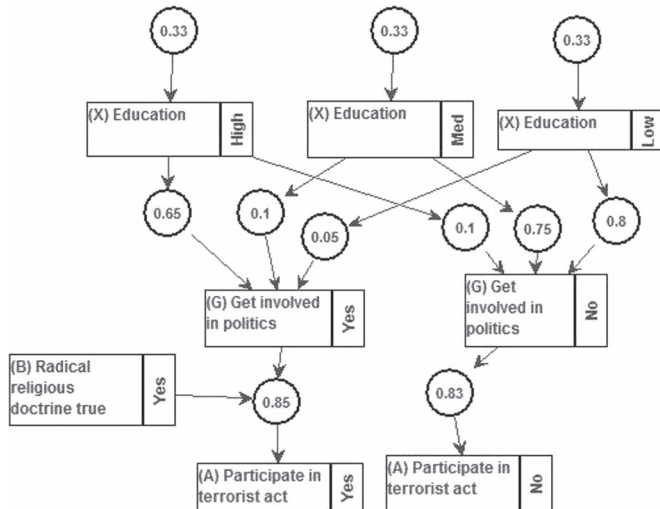
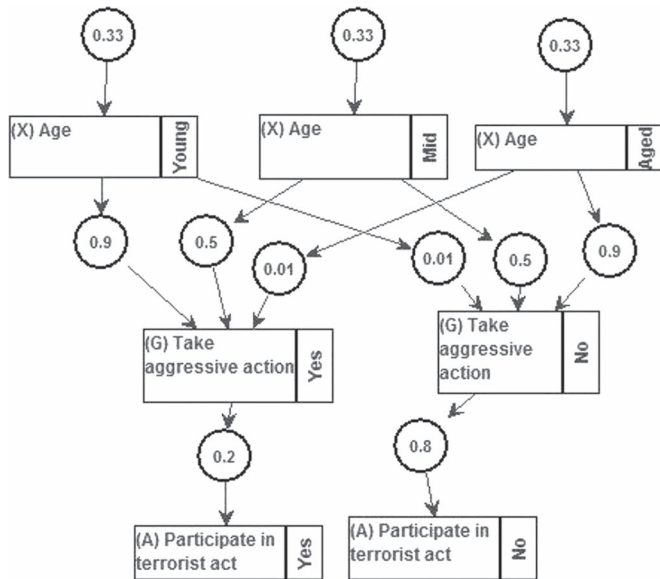Fig. 5. Fragment for all actors (All1) based on educational level.

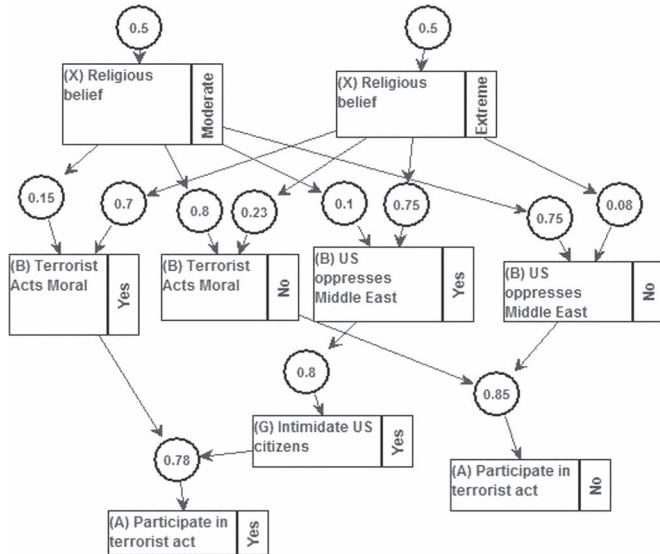Fig. 6. Fragment for all actors (All2) based on age.

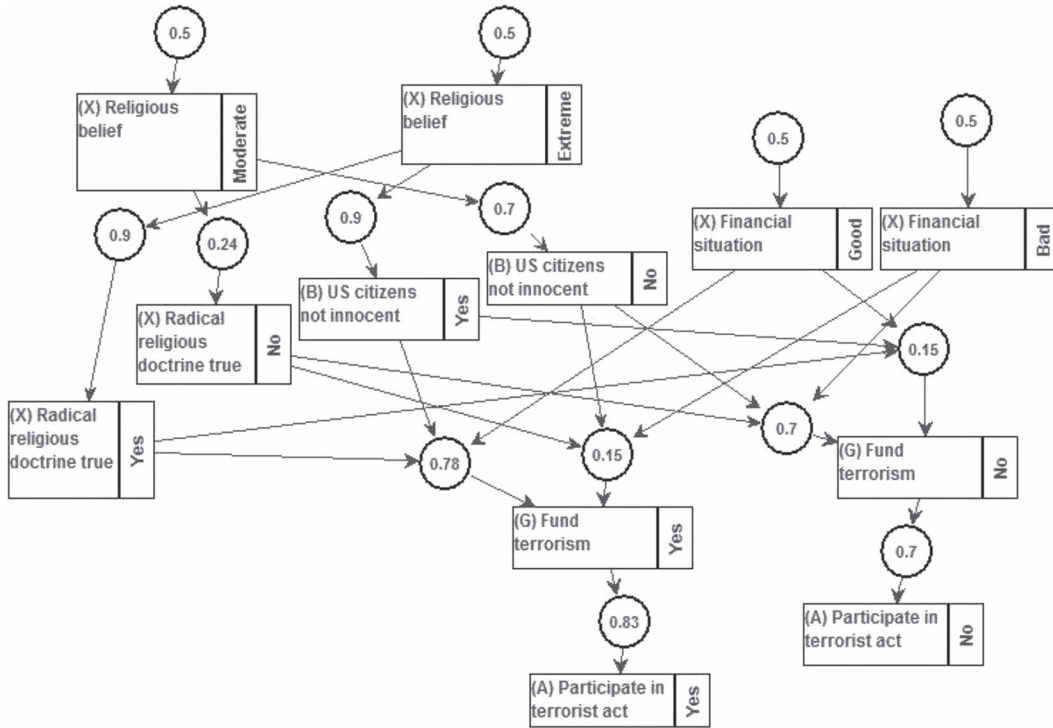Fig. 7. Fragment used only for non-U.S. actors (INT1) [36].

Fig. 8.   Fragment used only for non-U.S. actors (INT2) [36].

  3) insiders: persons 15–18;
  4) criminals: persons 21–23;
  5) normal persons: all others.

SNA analysts are given three different types of social inter-actions: financial, friendship, and contact. In order to study how our approach performs under different conditions, for each type of interaction, we generate a set of four networks with average degrees of 2, 4, 6, and 8. All of these SNs are unweighted symmetric networks.

Based on studies of current terrorist groups' actual behaviors, a commonly observed phenomenon is that outside funders send money to planners in the USA, and planners find and cooperate with insiders and criminals to carry out the terrorist act [38], [39]. Thus, in order to make sure that the SNs contain some interactions from the scenario we designed, a set of probable connections between critical individuals is set in the SNs. These connections are called core connections and are shown in Fig. 4. In these figures, and all other figures, blue nodes represent normal persons, red nodes represent funders, gray nodes represent planners, black nodes represent insiders, and pink nodes represent criminals. The analysts also have demographic information about individuals contained in the test bed. This demographic information includes the following: age (young, middle, or aged), religion (moderate or extreme), education (low, medium, or high), financial status (good or bad), and criminal record (yes or no).

1) Cultural Fragments: In order to represent the cultural information, several cultural fragments were constructed. These were derived from expert source material. If our methodology were to be used in the real world, an expert would construct the fragments (or choose them from a library of predefined fragments) and tailor them to the situation being modeled.
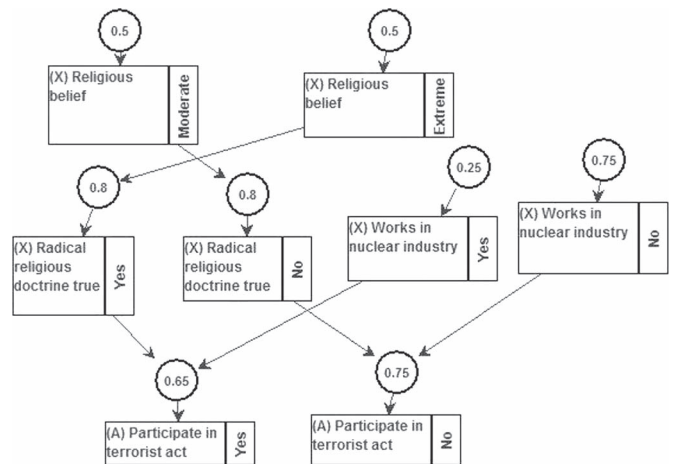

Fig. 9.   Fragment used only for U.S. actors (US1).

Two fragments were built that could be applied to all people in the network. The first fragment addresses the typical level of education of a terrorist [34], and the second describes the typical age of a terrorist [35] (see Figs. 5 and 6). Note that the item within brackets in the figure caption is its tag and is used in the decision tree in Fig. 12.

Since there are actors from multiple geographic regions in the network, it is no surprise that the cultural aspects of these actors may differ substantially. As a result, there are some fragments that apply only to actors in the network from outside the USA (see Figs. 7 and 8) and some that only apply to those from the USA (see Figs. 9 and 10). It may be noted that fragments representing the general behavior of a population of actors can be combined with fragments representing some specific behavior of an individual in the population to provide variability.
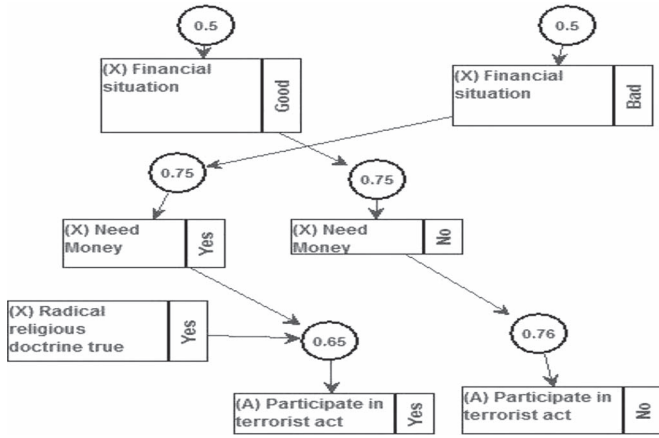
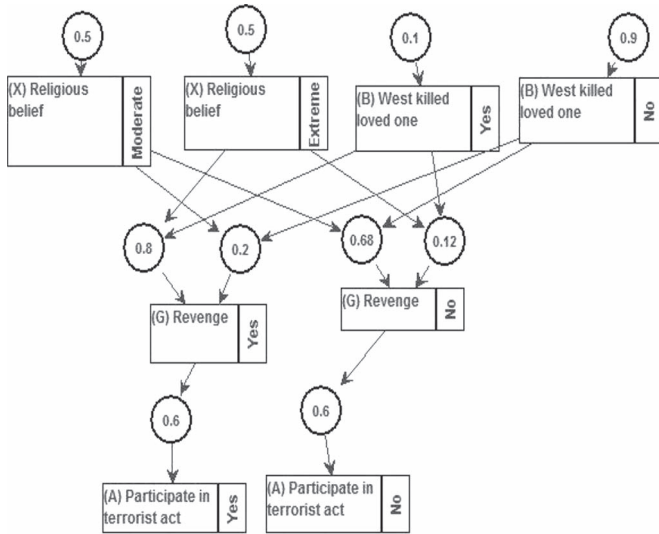Fig. 10. Fragment used only for U.S. actors (US2).

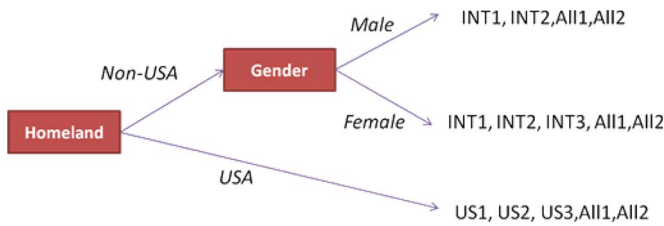Fig. 11. Gender-based actor fragment for non-U.S. actors (INT3).

Fig. 12. Decision tree for choosing cultural fragments.

A final criterion for selecting which fragments to use for which actors in the network was gender [37] (see Fig. 11). The entire process of choosing which fragments to use for which actors can be summed up in the decision tree shown in Fig. 12 This method provides a concise description of the selection process and is sufficient for many situations. However, as models become more intricate, a more sophisticated selection process will be required.

Once the desired fragments have been chosen for each actor, these fragments must be fused into one large BKB that can be used to infer likely goals and actions. Fusion of fragments is not a trivial task, as there may be inconsistencies between the rules in the fragments or, if special care is not taken to

avoid it, the resultant fused network could be probabilistically invalid. We have formulated a fusion algorithm that combines multiple BKBs and generates a fused BKB that is consistent with the axioms of the BKB theory [28]. The algorithm for fusing fragments is described in detail by Santos *et al.* [33].

The main idea in fusion is to consider each input BKB fragment to be from a particular source. Each source is given a reliability rating, so that if conflicting information should arise, more weight will be given to the source that is considered to be more reliable. Reliability measures used in the fusion process can be also used to model the impact of the cultural fragment on an actor. By using different reliability measures, a variance in the behavior of actors can be simulated. It may be noted that CISNs also support multiagent simulations where Monte Carlo methods are used to generate and analyze convergent behaviors of actor populations. Reasoning can be performed on the BKB to determine which sources are most influential for any particular prediction made by the BKB. Using the decision tree and fragment-sourcing techniques, BKBs were built for each actor in the network. Using the BKBs, the likelihood of each actor taking each action or having each goal can be computed. This information was used to create an IN for all the actors in the scenario, representing their degree of ideological agreement.

2) Infusing Culture: Recalling the infusion process described in Section V, a CISN is generated from a number of intermediate networks. The intermediate networks are a CON, an IN, and a CCIN. We will now look at the specific methodology used to generate these networks.

CON: Information about potential contact between actors can be extracted from the existing SNs. In this scenario, we use multiple SNs, such as financial and friendship networks. Assuming the total number of SNs is k, an edge weight in the CON is defined as

$$w_{xy} = \begin{cases} 1, & \text{if } \sum_{i=1}^{k} w_{xy}^i > 0 \\ 0, & \text{otherwise} \end{cases}$$

where

w_{xy} edge weight between actors x and y in the CON;
w_{xy}^i edge weight between actors x and y in the ith SN.

Note that, in our validation scenario, $k = 3$.

The actual contact opportunity between actors x and y is measured by their geodesic distance, which is labeled 0_{xy}, in the CON. The geodesic distance between two nodes in a network is the number of hops required to move from one node to the other.

IN: An IN is used to represent the behavioral similarity between actors. In our model, behavior is represented using the concept of intent, i.e., axioms, beliefs, goals, and actions, which are in turn gathered from sociocultural data, as represented in the cultural fragments. Using the cultural fragments, we can obtain an estimation of potential behaviors for each actor. In this particular implementation, we focus only on I-nodes that represent *action* as indicators of behavior. The use of belief and goal nodes will be included in future work. Each actor has a fused BKB that consists of all relevant cultural fragments. We select a set of actions that are most relevant to the scenario and calculate the probabilities of the actors selecting the actions. This is done using the Bayesian updating algorithm [28].

An IN is essentially a two-mode network, containing two types of nodes (actors and actions). An IN is generated in two stages. In the first stage, connections are only built between different types of nodes, i.e., actors and actions. The weight of an edge between an actor and an action represents the probability that an actor will take that action. For each actor–action edge, the probabilities are calculated using the following method. Consider an actor, in the IN, to be represented as a vector $= (p_{x1}, p_{x2}, \ldots, p_{xk})$, where k is the number of actions contained in the network, and p_{xi} is the probability that actor x will take action i. The similarity between actors x and y is measured using the dot product, i.e.,

$$g_{xy} = \sum_{i=1}^{k} p_{xi} \cdot p_{yi}.$$

By the definition of the dot product, the preceding equation takes into account not only the magnitudes of the vectors but also how far apart they are in the vector space (represented by the cosine of the angle between them). Therefore, two identical vectors with small magnitudes will have a lower similarity than two other identical vectors with large magnitudes. This is consistent with our notion of uncertainty, as a lower magnitude (probability) means that uncertainty is high. Therefore, two identical vectors with low magnitudes (and high uncertainty) should have a low similarity compared to identical vectors with high magnitudes.

In the second phase, edges are constructed between actor nodes, representing how likely the actors are to take similar actions. Recall that under the notions of the intent model and for the current work, taking similar actions is equivalent to displaying similar behavior.

The final IN is obtained by setting the edge weight between actors to the normalized measure of their behavioral similarity. More precisely, assume there are n actors in the network, the edge weight between actors x and y (represented as d_{xy}) in the IN is calculated as

$$g_{xy} = \frac{g'_{xy}}{\max \left(g'_{ij} \right)}, \qquad \text{where } i, j = 1 \text{ to } n \quad \text{and} \quad i \neq j.$$

CCIN: After obtaining the IN, we combine it with the CON and generate the CCIN.

Weights of the contact opportunity and ideological networks are combined in the following way:

$$d'_{xy} = r^{-(0_{xy}-1)} \cdot g_{xy}, \qquad \text{where } x \neq y$$
$$d_{xy} = \frac{d'_{xy}}{\max \left(d'_{ij} \right)}, \qquad \text{where } i, j = 1 \text{ to } n, \quad i \neq j$$

where

d'_{xy} weight of the edge connecting actors x and y in the CCIN;
d_{xy} normalized d'_{xy};
n number of actors contained in the CCIN;
r constant greater than 1;
0_{xy} geodesic distance between x and y.

In our experiment, $n = 50$, and r, essentially a fading constant, is set to 2.

CISNs: When facing multiple SNs, our method first combines these SNs into a single network before combining them with the CCIN. The combination of multiple SNs is formulated as

$$C'_{xy} = \sum_{i=1}^{k} w^i_{xy}$$
$$C_{xy} = \frac{C'_{xy}}{\max \left(C'_{ij} \right)}, \qquad \text{where } i, j = 1 \text{ to } n \quad \text{and} \quad i \neq j$$

where
C^i_{xy} edge weight between actors x and y in the combined SN;
C_{xy} normalized C'_{xy};
w^i_{xy} edge weight between actors x and y in the ith SN.

Note that although the CON is derived from the SNs, it is different from the combined SN. The CON has weights 1 or infinity and is used to modulate the effect of ideological similarity in the CCIN.

Finally, we infuse the cultural information depicted in the CCIN into the final CISN using the following formulation:

$$e'_{xy} = a \cdot C_{xy} + b \cdot d_{xy}$$
$$e_{xy} = \frac{e'_{xy}}{\max \left(e'_{ij} \right)}, \qquad \text{where } i, j = 1 \text{ to } n \quad \text{and} \quad i \neq j$$

where
e'_{xy} edge weight between actors x and y in the CISN;
e_{xy} normalized e'_{xy};
a, b constants with values greater than 0.

Constants a and b represent the importance of the SNs and the cultural information, respectively. In our experiment, $a = b = 1$.

In order to study how well our method performs in various conditions, we test our SN culture infusion approach on four sets of SNs with average degrees of 2, 4, 6, and 8. Each set contains three SNs with different types of interactions (financial, friendship, and contact). Within each set, the SNs have the same average degree. Since we obtained similar results on all sets, here, we will present in detail the experimental results and analysis for the set of SNs with an average degree of 2 and briefly provide a summary of our experiments on SNs with other average degrees.

Experimental Results of Social Networks With an Average Degree of 2: The generated SNs, namely, financial, friendship, and contact, are shown in Figs. 13–15, respectively.

From these figures, we can see that a single SN contains incomplete interaction information. Each SN has some critical interactions missing. For example, without studying the contact network, the analysts are very unlikely to identify the interaction between person 19 (planner) and person 15 (insider). In addition, when we look at any one SN, there is usually a large connected component that includes persons 0 and 3 (who are known funders), which contains more than 80% of the total population. This means that all people in the large component *may* be involved in the terrorist act and that all interactions in the large component *may* be important for successfully planning or carrying out a terrorist act in the USA. This type of traditional analysis is clearly not productive. We conclude that based on a single SN, the analysis results can often be
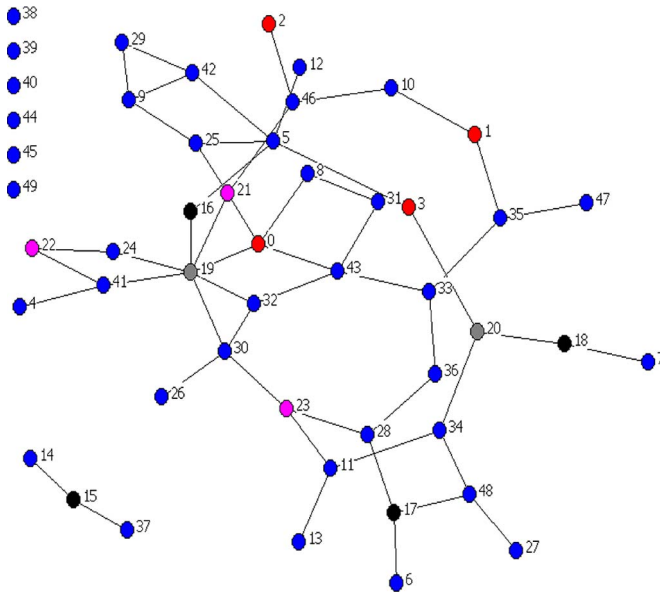
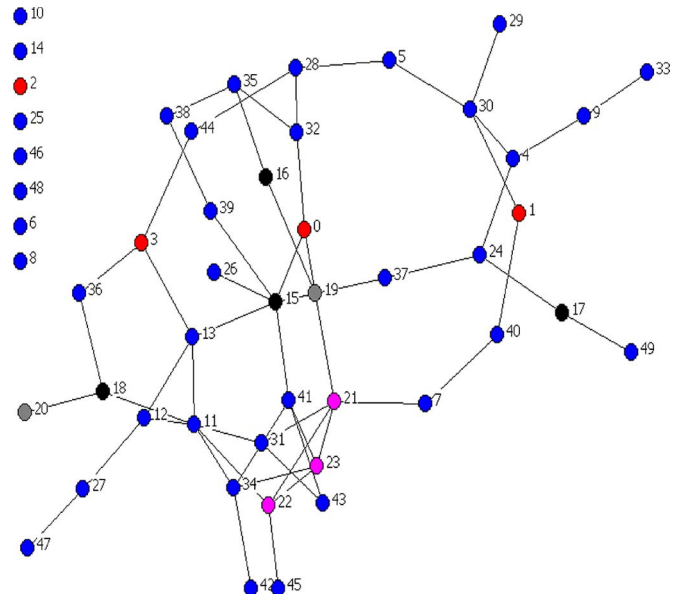Fig. 13. Financial network with an average degree of 2.

Fig. 15. Contact network with an average degree of 2.
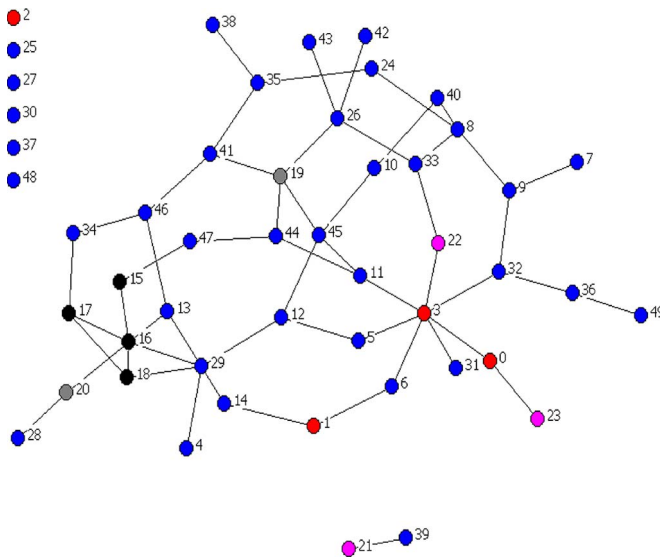

Fig. 14. Friendship network with an average degree of 2.
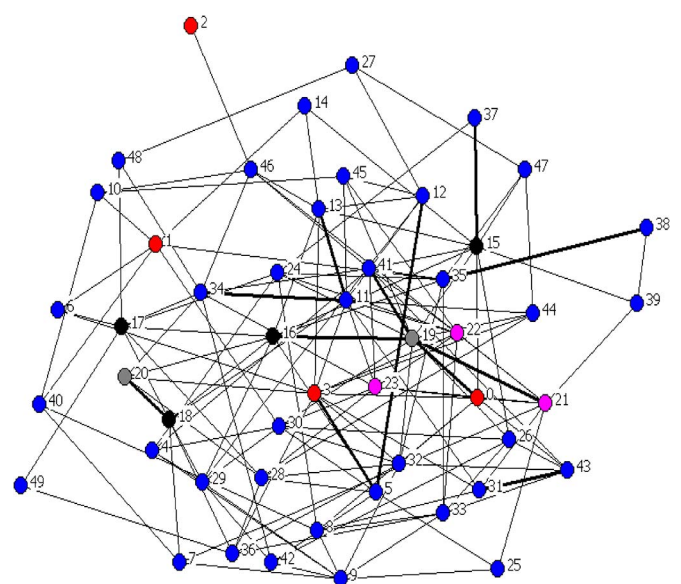

Fig. 16. Combination of SNs with an average degree of 2.

inaccurate or inconclusive. Moreover, analysts will inevitably lose focus on relevant information since it is overwhelmed by noise (irrelevant connections).

Combine these three SNs, however, and a network with more relevant information can be obtained. The combined SN is shown in Fig. 16. This figure shows that the combined SN contains more complete information than any single original SN. The combined SN contains only one connected component, which means that all individuals and interactions in the network could be involved in the terrorist act. In the combined SN, relevant information is again overwhelmed by noise. This is not surprising since the network contains all existing ties, no matter how strong. Normally, SNA users are more interested in the small subset of important interactions relevant to the scenario. In real-world applications, SNA users usually focus on strong ties first to identify the backbone of interactions between individuals and thus avoid wasting time on detailed
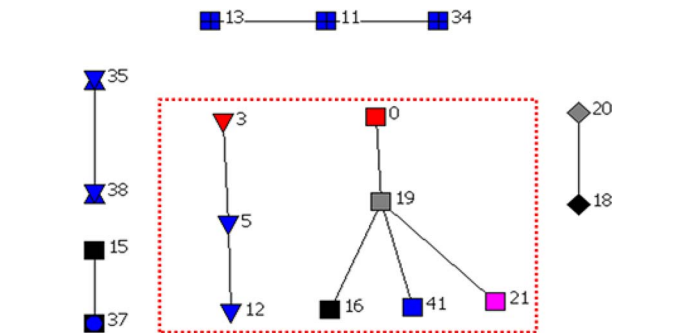

Fig. 17. Combined SN focused on strong ties (average degree of 2).

but unimportant information. As shown in Fig. 16, edges in the combined SN have different weights. The subnetwork, consisting only of strong ties, is shown in Fig. 17.
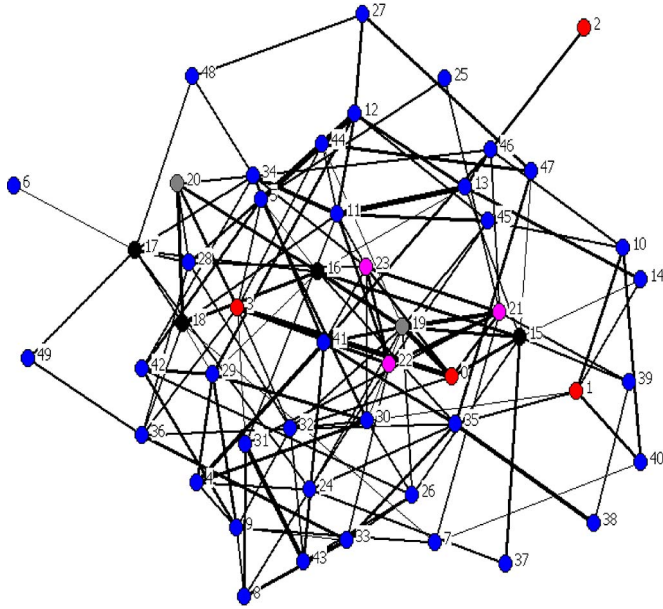
Fig. 18.   CISN for an average degree of 2.

In this figure, and all figures that describe networks with a focus on strong ties, different connected components are represented by different node shapes. The region enclosed by the red dashes contains the connected components that include the known funders (persons 0 and 3). From this figure, we can see that when we focus on strong ties in the combined SN, a lot of relevant information will be lost. Only three relevant individuals (out of a total of six) who may be involved in the terrorist act are detected. They are persons 19 (planner), 16 (insider), and 21 (criminal). The interactions between insiders and criminals, and those between funder (person 3) and planner (person 20), are missing.

The CISN obtained in our experiment is shown in Fig. 18. In this figure, we can see that, similar to the combined SN, actors are connected by edges with various weights, and all actors contained in the CISN are contained in one connected component. This means that if we use all the detailed information provided in the cultural analysis, we may again lose our focus on the relevant information.

Let us see what we obtain when focusing on strong ties. The CISN focused on strong ties (edge weight larger than 0.5) is shown in Fig. 19. When we include the relevant action nodes (the ones used in the generation of the IN) and reinsert the edges between the actor and action nodes (by using the IN), Fig. 20 is obtained. From Figs. 19 and 20, we can see that relevant information about the scenario is prominent in the CISN. In this network, a more complete set of relevant actors is obtained (only person 17, who is an insider, is not detected). In addition, the set of detected actors is quite accurate as only one actor (person 37) in the set is not relevant. Moreover, some covert interactions are detected, such as the interaction between funders and insiders (e.g., the connection between persons 0 and 15, which only appears once in the contact network) and the interaction between funders and planners (e.g., the connection between persons 3 and 20, which only appears once in the financial transaction network). In the CISN, the structure of interactions between relevant actors is prominent. Fig. 20 also helps us confirm our
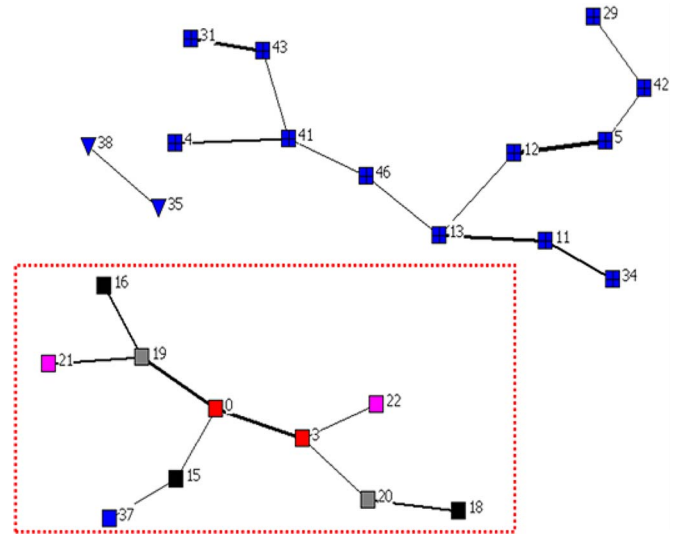

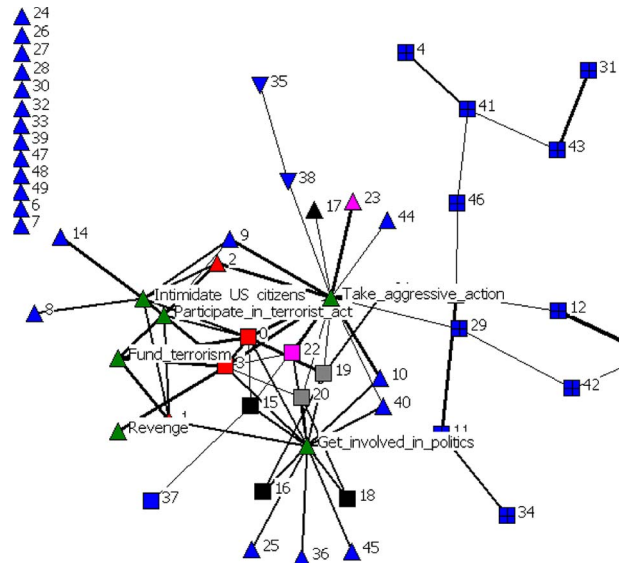Fig. 19.   CISN focused on strong ties (average degree of 2).

Fig. 20.   CISN with action nodes (average degree of 2).

suspicions of the malevolent nodes because these nodes are strongly linked to action nodes that are connected with terrorist activities. Notice that the benign normal nodes (in blue) are not strongly connected to these action nodes. Therefore, using this network, we not only identify the relevant nodes but also get a prediction of their potential goals and actions.

Experimental Results for Social Networks With Other Average Degrees: In the experiments on SNs with average degrees of 4, 6, and 8, we find that the analysis results obtained from single SNs and untrimmed (containing all existing edges) combined SNs have exactly the same characteristics as SNs with an average degree of 2. Thus, we do not include these results in this paper. In this section, we focus on networks with strong ties only. The combined networks for SNs with average degrees of 4, 6, and 8 are shown in Figs. 21–23, respectively.

From these figures, we can see that, in these networks, the relevant information is either missing (degree of 4) or overwhelmed by noise (degrees of 6 and 8).
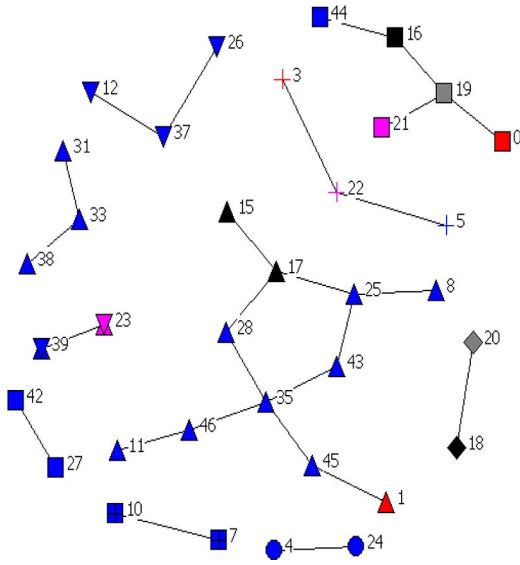
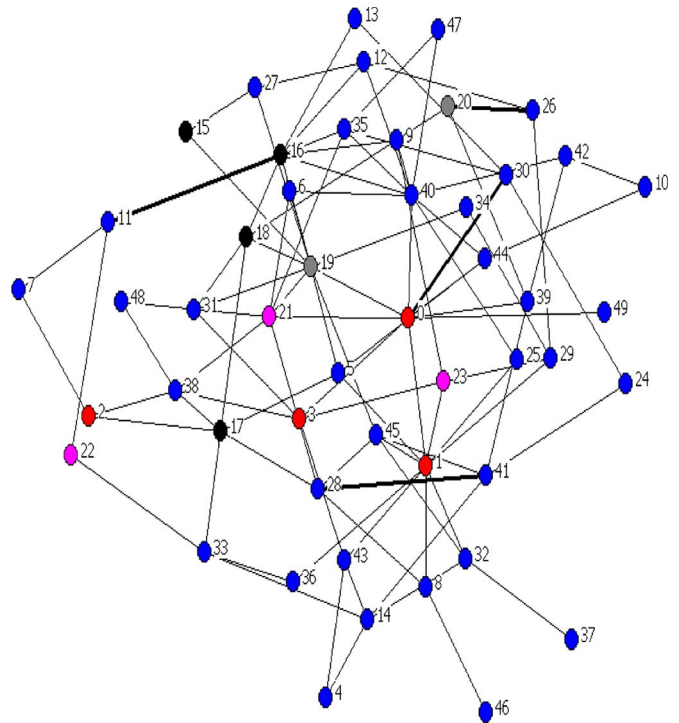Fig. 21. Combined SN focused on strong ties (average degree of 4).

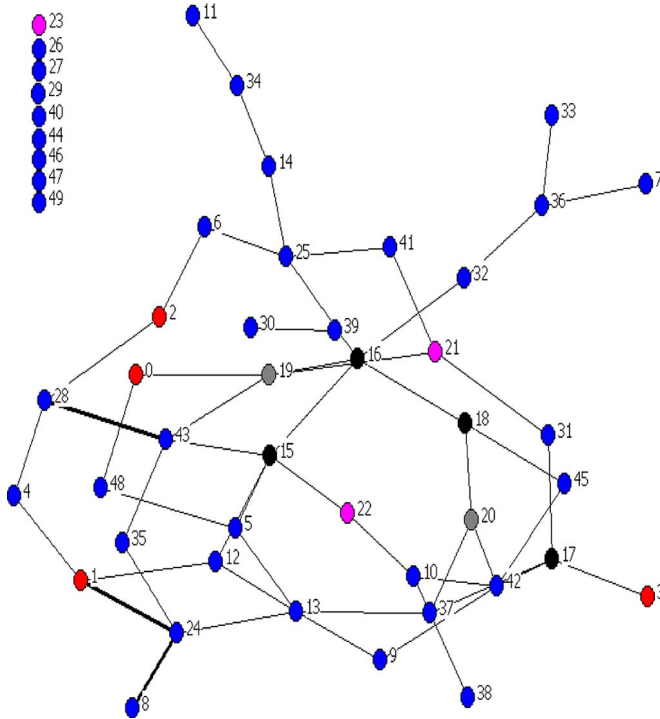Fig. 23. Combined SN focused on strong ties (average degree of 8).

Fig. 22. Combined SN focused on strong ties (average degree of 6).

Fig. 24. CISN (average degree of 4, strong ties only).

The resultant networks that are obtained from the CISNs by focusing on the strong ties for average degrees of 4, 6, and 8 are shown in Figs. 24–26, respectively.

From Figs. 27–29, where we include the action nodes in the CISN for average degrees of 4, 6, and 8, respectively, we see how the nodes we are interested in are connected with relevant behaviors.

Summary of Results: From our experiment, we conclude the following.

1) For complex real-world scenarios, single SNs can provide incomplete and, therefore, misleading information, whereas relevant information contained in the network
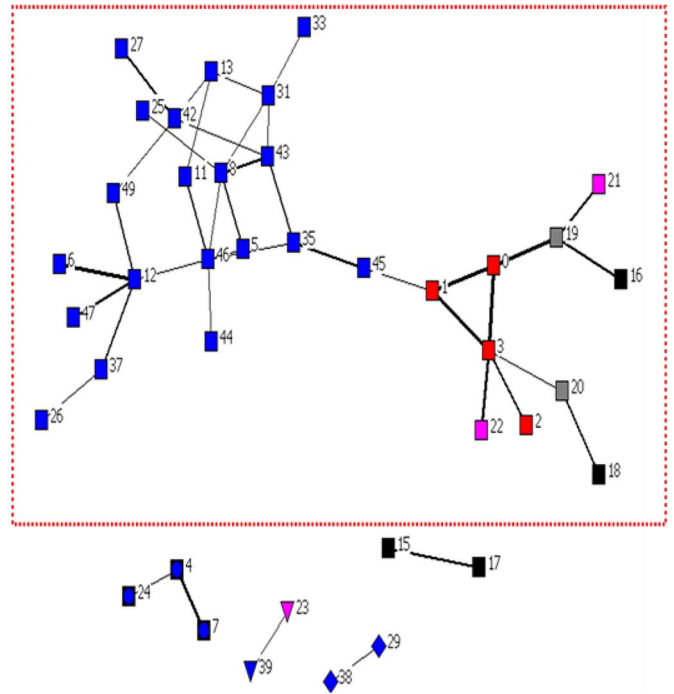
may be overwhelmed by noise. The root of this problem stems from all the relevant connections that do not exist in a single SN.

2) Similarly, in a combined SN, relevant information may be either missing or overwhelmed by noise. In essence, this problem is due to a lack of context or detail concerning the exact nature of observed connections.

3) By infusing SNs with culture, relevant information becomes prominent. Cultural infusion can often provide us
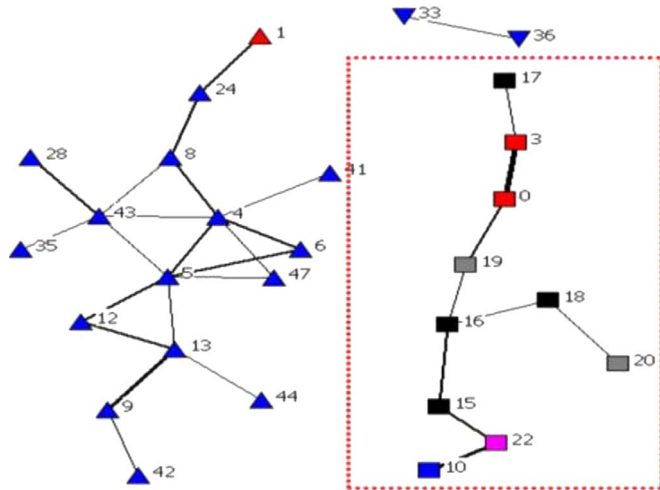
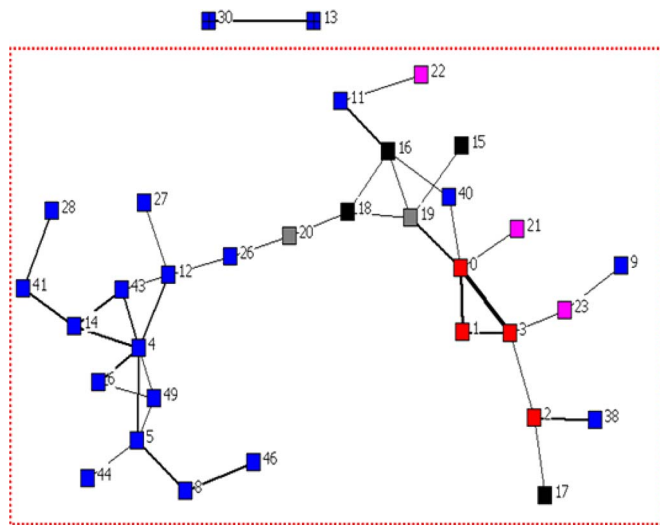Fig. 25. CISN (average degree of 6, strong ties only).

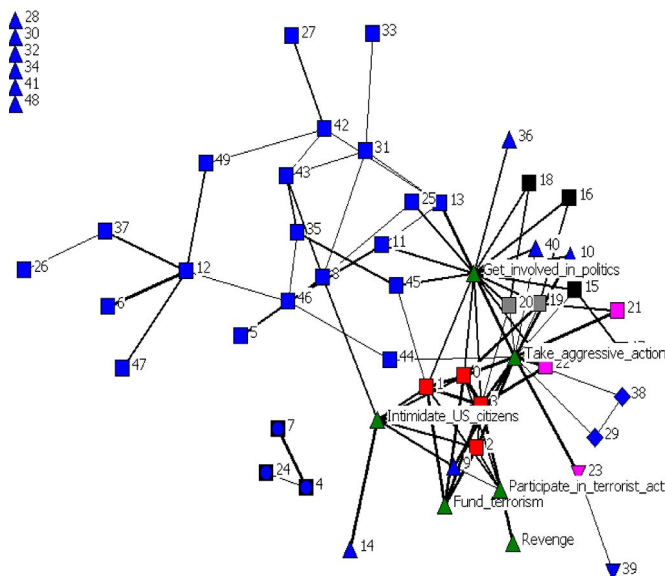Fig. 26. CISN (average degree of 8, strong ties only).

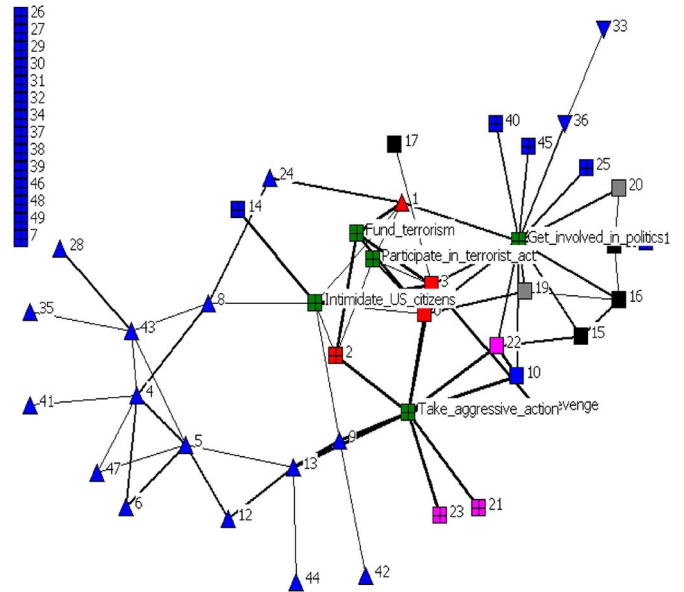Fig. 27. CISN with action nodes (average degree of 4).

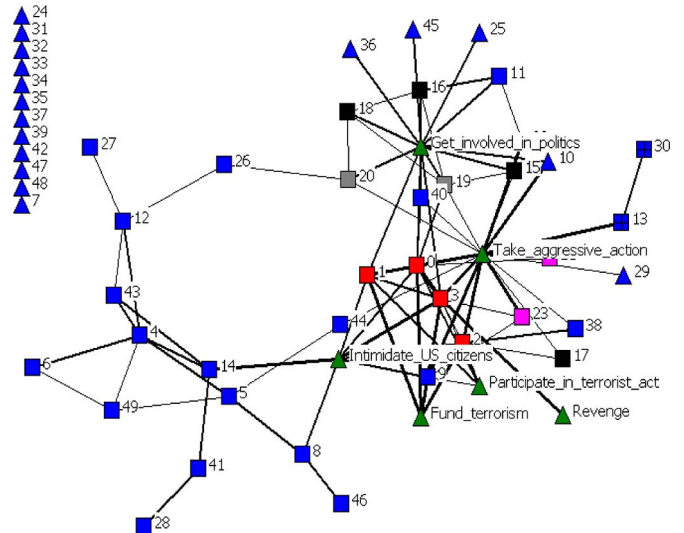Fig. 28. CISN with action nodes (average degree of 6).

Fig. 29. CISN with action nodes (average degree of 8).

a more complete and accurate set of relevant actors. In addition, due to the ability to detect covert interactions, CISNs can provide a more realistic picture of the true structure of interactions between actors. Moreover, infusing SNs with cultural influences can provide significant insights into people's potential goals and actions.

VII. CONCLUSION AND FUTURE WORK

Currently, SNA users are often faced with incomplete and skewed SN data sets because of missing cultural elements. In this paper, we present a generic approach that can be used to systematically model cultural influences and infuse them into SNs. We implemented our approach and tested it with two sets of experiments. Based on the analysis of our experimental results, we validated the effectiveness of our approach and demonstrated that infusing SNs with culture is a promising technology to aid SN analysts in identifying significant groups and ties in the face of data overload.

The work discussed in this paper presents a fundamental framework for infusing SNs with cultural influence. The CISN has the capability to represent sociocultural characteristic at various scales (ranging from community scale to larger scales and from states to entire nations) and can be used to analyze multiscale social dynamics. This has been demonstrated in our work in modeling interclan dynamics, and the resultant political instability in Somalia during the 2006 civil war using the CISN framework was documented in [45]. Moreover, the notion of using cultural fragments has been employed to represent migration dynamics of a large population in the modeling of cross-border epidemics with emphasis on the 2009 H1N1 outbreak in Mexico [46].

The detailed design of each component in our framework will be described further in future work. One important future task is to study how to systematically store, select, and fuse BKFs in order to build cultural fragments. Currently, the infusion of cultural information into SNs is done based on linear combination. Another significant task for us is to research the most effective methods for infusion in various applications. In the future, we will continue to develop the framework in a plug-and-play fashion and then explore the use of various (and sometimes competing) social theories, both to add rigor to the modeling of an actor's intent and actions, and to compare and contrast the effects and validity of those theories. Scalability becomes an important issue in real-world scenarios, where numerous actors and large social networks are the norm. We will leverage previous work on parallel/distributed anytime-anywhere algorithms [4], [40] to build scalable algorithms for analyzing CISNs. We will also improve the scalability of the CISN model by developing parallel/distributed methodologies for Bayesian reasoning.

Acknowledgment

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