Culturally Infused Social Network Analysis

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Abstract - *Social networks are an important way to represent and analyze social phenomena. One aspect that is critical in order to provide relevant and useful analyses is the capability to infuse culture systematically. Cultural elements are typically either lacking or implicitly (and sometimes unintentionally) embedded in social network construction. Thus, current SNA approaches must deal with imprecise, un-realistic, and incomplete data. In this paper, we propose a generic approach to systematically model culture and infuse it into social networks to obtain more realistic and complete social network data sets that can provide insight into the probable intentions and behaviors of the actors in the network. In fact, in this paper we will introduce the concept of culturally-infused social networks, their construction, and their capability to provide fuller and more relevant social network analyses.*

Keywords: Bayesian Knowledge Base, Culture, Culturally-Infused Social Network, Social Network Analysis.

1 Introduction

Social Network Analysis (SNA) is a set of techniques developed to study the information contained in the interactions (e.g. communications and relationships) of social entities. Understanding how entities interact with each other will provide significant insights into a myriad of phenomena originating from multiple fields. In fact, SNA has been studied and applied in a broad range of fields, including sociology, epidemiology, criminology, economics, etc [1, 2].

One critical aspect that affects the relevancy of current analyses is culture. Culture pervades every part of our life as social beings and factors into just about every decision we make. However, SNA, a methodology that endeavors to provide a framework to explain and rigorously analyze social systems and phenomena, lacks a formal methodology to consider culture in its analyses. In order to fully understand complex social systems, the next generation of SNA techniques needs to provide more accurate structural information and provide insights into the behavior of actors in the network. Current SNA techniques face two major problems in achieving these goals: 1) the data they start with is likely to be incomplete and incorrect and 2) they either do not consider the effects of culture or embed it implicitly in the analysis in an ad hoc manner. Thus, it is critical to develop culturally-infused social networks to make culture explicit and exploitable in social network analysis.

As such, in this paper we introduce the concept of culturally-infused social networks which are social networks that explicitly and formally embed critical cultural elements and factors in order to ultimately provide a more realistic and richer network for analysis. Also, we propose a novel and generic approach for modeling and infusing culture within social networks in order to provide more realistic, prescriptive (i.e. able to predict individual's potential behaviors), and useful data sets for SNA. In our approach, culture is systematically modeled and depicted with Bayesian Knowledge Bases [3]. Demographic data is provided as input and predictions of actors' potential behaviors are obtained through cultural analysis. The infusion of culture into social networks is achieved by combining the insights obtained from individuals' behaviors with the social network data. For brevity, only key results and discussion are provided in this paper. Further information regarding our framework can be found in [4].

This paper is organized as follows. Sections 2 and 3 introduce current issues in social network construction and the potential methods to solve them. Section 4 provides a brief introduction to cultural models. Section 5 concentrates on the design of our approach to infuse social networks with culture. The next section presents an initial implementation of our approach and the experimental results. Concluding remarks are provided in Section 7.

2 Background and Current Issues

Modern SNA has been a field of study for more than 70 years [5] and there have been many computer software tools and methodologies developed to perform analysis [1, 6, 7]. However, one of the crucial problems which SNA users face is that in real-world applications the social networks to be analyzed are usually imprecise and incomplete. In addition, they cannot provide significant insights into actors' behavior due to a lack of socio-cultural awareness in social network analyses. This seriously degrades, possibly even destroys, the usefulness of obtained results or analysis. To the best of our knowledge, the question of how to explicitly, generically, and systematically consider socio-cultural knowledge in order to refine network data, pinpoint the relevant data, and provide insights into actors' behaviors has still not been addressed.

Currently, there are a limited number of approaches to gathering social network data (mainly consisting of elicitation and registration) [8]. In elicitation, interaction information is acquired via questionnaires or surveys. All respondents are embedded in particular cultures such that data obtained by elicitation is inherently imprecise and subjective [1, 9]. Respondents may be from different circumstances leading them to have a different understanding of the survey questions. Also, in some applications, such as anti-terrorism 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 social network data sets. These approaches are mainly focused on analyzing data collection factors' effects on social networks [10, 11] and optimizing data gathering approaches for specific applications to achieve better data sets [12, 13]. However, these approaches are designed with specific applications in mind and have their own individual foci. Thus, these approaches and the insights obtained from them cannot be generalized such that they are useful across disciplines.

The second method of data gathering, registration, acquires interactions by extracting them from registered information, such as membership lists, email records, and authorship records of scientific articles. It seems that registration data should be more accurate and objective. However the numbers obtained may convey different meanings in different contexts. It is difficult to interpret, compare, and combine registration data without considering the context/domain, in essence the cultural environment, of this data. Taking phone call lists as an example, two people who call each other once a week may be normal in a developed country but quite abnormal in a developing country where the use of telephones is not so extensive. Usually, interaction information data is domain-specific, but network data may be collected from various domains (e.g. geographic spaces, circumstances, and applications). Most SNA approaches focus on social networks with particular domains in mind and employ different doctrines to generate separate sets of insights [14, 15]. They leave the combination of analysis results to human intelligence. The absence of a generic approach to handle social networks across domains prevents deeper understanding of the underlying mechanisms of social phenomena and prevents currently obtained insights from being generalized and utilized across different disciplines.

Providing behavioral insights is one of the most important goals of SNA. SNA techniques should be able to help analysts predict potential actions/goals of social entities under particular circumstances. However, that has not been the case. This is mainly because social networks are constructed based on social entities' interactions. SNA results are focused on identifying the characteristics of social entities' interaction patterns and mapping these patterns to their potential roles. Thus, the analysis results obtained from current social networks are more descriptive and usually can only be used to answer specific types of questions; such as: which social entity is important/popular?, which entities are core/periphery actors in an organization?, which groups of entities will have similar behaviors?, etc. Human behavior (e.g. attitudes, actions, and goals) is not influenced simply by interactions with others, but is heavily affected by an individual's history, context, and, in essence, cultural environment. The lack of cultural knowledge in current social network analysis approaches seriously limits their ability to provide behavioral insights.

3 Culture Is the Key

In order to effectively address the issues discussed in the previous section, we posit that culture is the key. Culture has been studied and used in many fields and has multiple definitions due to the varied understandings and different foci of researchers. In this paper, culture is taken to be as broad as all learned notions and behaviors.

First, culture has a significant impact on social network structure. Infusing culture into social networks can shed light on connections that would not have been apparent, or may have even been missing altogether otherwise. For example, suppose Tom is an actor in a social network. Tom's known set of acquaintances are represented in the network. We know that Tom is planning to build a research company focused on computer 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 who Tom will tend to recruit. Consider how the use of culture can provide insights into the social network. If, for each of the people in Tom's social network, we know their technical background, wealth, and the degree of satisfaction with their current job, infusing this cultural information into the social network will strengthen the links with acquaintances that have a computing background, are not satisfied with their current job, or want to make money. Furthermore, infusing social networks with culture would also highlight ties that may not have been directly represented in the original network, e.g. a friend of Tom's friend happens to be an expert in a promising computing field. Thus, by infusing culture into social networks, we can potentially obtain more realistic and complete data sets for SNA.

Moreover, culture significantly affects, limits, and determines actors' behavior and can also be used to predict it. In order to make SNA more prescriptive, cultural analysis is indispensible. Behavior is not simply about passing information and making ties, it is heavily affected by an actor's intent, viewpoint (e.g. values, beliefs, etc.) and context (e. g. behavioral history, capability, opportunity, etc.). It is rare that two individuals will take the same actions or have the exact same reactions in identical situations. Intentions, values, perceptions, and opportunities are not only determined by the present day situation, but also based on one's history, context, and circumstances. In essence they are determined in part by the cultural environment that individuals or groups originated from and are currently embedded within. In order for SNA techniques to be able to provide more significant behavioral insights, it is vital to infuse culture into social networks.

Furthermore, culture constrains communication and interaction among actors and can help to potentially determine the underlying similarity between domains. Taking kinship networks as an example, consider the varying relation types and structures that can be formed simply based on language. For example, in the Chinese language, a brother's son and a sister's son are referred to differently. In English, both would be considered nephews. As a result, it is harder to compare the analysis results obtained from each network or to extrapolate potential insights from one type of network to the other. Also, in some complex applications a kinship network may consist of people who consider differing sets of kinship. The network will inevitably be skewed by the biased understandings and definitions of kinship. Fortunately, culture can help to bridge the gap between domains. For example, by carefully studying specific cultures, we have the ability to estimate the differences and similarities between different types of kinships. This enables us to potentially eliminate, or at least relieve, the underlying biases.

Most, if not all, social networks are constrained and affected by, or even originate from, culture. Cultural awareness is critical and should be a significant element of SNA. However, current SNA methods either do not consider cultural elements or focus on specific cultures either implicitly or explicitly [14, 16-18]. In order to effectively and generically construct more complete, realistic, and behaviorally informative social networks, it is crucial to strictly and formally model culture in a principled manner and infuse culture into social network analyses.

4 Modeling Culture

There are many definitions of culture, but a common thread in these definitions is that culture deals with those things that are influenced through social processes and that culture can have a significant impact on behavior [19]. This motivates the desire to utilize cultural information in refining social network data sets, especially 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 culture is required. However, attempts to form a comprehensive computational model of culture are rare at the current time. Current attempts to model culture in social networks allow for only a small number of cultural variables to be considered and employ simplistic means of combining the effect of these variables [20, 22]. Models in areas such as role playing simulations [23] are more expressive but have not been applied to the domain of social networks and still do not contain the expressive and explanatory power necessary to fully capture culture. Our approach models relevant cultural variables and allows their effects to be combined in a rigorous probabilistic framework.

In order to create a generic framework to model culture, a representation of cultural knowledge is needed. Cultures vary greatly from region to region and person to person. In order to accommodate this diversity, a library of cultural fragments is employed. It contains a structured collection of information about the beliefs, attitudes, and possible behaviors of actors from a variety of cultures. Each fragment is a modularized piece of cultural information that is applicable to actors embedded within a specific culture. When an actor needs to be modeled, the information about them that is available is used to select to the set of cultural fragments that best represents their situation. These are then aggregated to form a comprehensive representation of the cultural context of the actor. An example of a simple fragment is shown in Figure 1.

Figure 1. An example of a cultural fragment

The fragments cannot contain all possible information about each actor, in fact, even if we wanted to include all possible information it would not be available due to practical issues. As a result it is important to include the right kind of information in the fragments. They should focus on the cultural background of the actors, their attributes and beliefs, and how these impact their likely intentions and behaviors. When studying a particular situation it is necessary to further restrict the information that is considered and carefully choose the fragments from the library that are most relevant to the types of behaviors and interactions that are of interest.

5 Culturally-Infused Social Networks

Cultural fragments are powerful tools that can provide valuable behavioral information about the actors in existing social networks. By reasoning over the cultural fragments, we can obtain an estimation/prediction of the potential behaviors of actors in the network (e.g. attitudes, beliefs, goals and actions). These behavioral insights convey significant clues to answer the "what", "how", "when" and "why" questions of tie formation between individuals. Thus cultural information can be used to refine social network data sets by strengthening, weakening, or removing existing links (ties) and bringing light to new and potentially covert ties within the network. Furthermore behavioral information can be included in the visualization of network data providing insights into the potential goals and actions of an individual actor or group of actors depicted in the network.

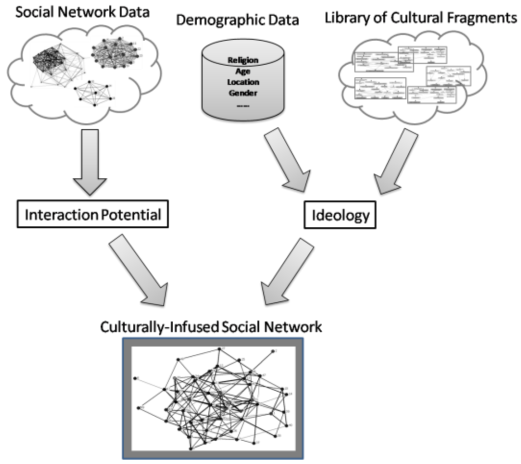

Figure 2. High level description of architecture

Our cultural analysis component takes actors' demographic information as input and uses cultural fragments to estimate their potential beliefs and behaviors. Based on these behavioral insights, we build an *ideology network* that depicts the ideological and cultural similarity of the actors. However we note that similar ideology is not sufficient to guarantee that two actors will interact with one another. For example they may simply have no acquaintances in common and have never had the chance to meet. Therefore we also consider the *interaction potential* of actors in the network which represents the capacities and opportunities of individuals to form social ties with each other. Finally, a *culturally-infused social network* is obtained by considering both the ideology of the actors in the network along with their potential to form ties. Figure 2 gives a high level view of the process of constructing a culturally-infused social network.

It is critical to consider an individual's cultural context and potential behaviors in order to effectively estimate the probability of interaction between actors. We use a network to encode the cultural and ideological similarity of actors in a social network and call it an ideology network. In an ideology network there are two types of nodes; individual actors and behavior nodes which represent beliefs, goals, and actions. Ties between actors in the network indicate the strength of ideological agreement with respect to the behavior nodes in the network (and in turn indicate the propensity of actors to form ties in a social network given the opportunity). Ties between actors and behavior nodes represent the probability that the actor will take the action or have the goal or belief corresponding to the node.

The culturally infused social network is obtained by considering both the cultural and ideological similarity of actors, represented in the ideology network, and the potential of actors to interact with one another, which is determined by analyzing social networks. The behavior nodes from the ideology network can be included in the culturally infused social network in order to provide information about actors' beliefs, intentions and other critical criteria.

6 Experimental Results and Analysis

In order to validate our design and demonstrate the significant insights provided by including cultural elements in social networks, we implemented a preliminary method of infusing social networks with culture and performed a set of experiments.

6.1 Experiment Scenario

Our experiment is designed for the scenario in which it is known that person *X* is involved in a bank robbery and we want to know who his likely accomplices are and how they interact with each other. Assume the bank robbery is done in the way that the planner (person *X*) cooperates with criminals and insiders (who are working in or familiar with the bank and willing to participate in the robbery). In our experiment, the test-bed contains 30 people who are split into several categories: person 0 is the planner, persons 1 to 8 are criminals, person 9 is the insider, and persons 10 to 29 are regular persons whose demographic data (including education, age, financial status, criminal record, and gender) are generated randomly. The available data are a set of social networks (including financial transaction network, kinship network, and contact network) of these 30 people and the demographic information of each individual. However, assume that users do not know the categorization of the people in the network described above. The tasks for users are to study:

1. Which are the important people to study in order to prevent or monitor the robbery?
2. What are the probable behaviors of the individuals (especially the important people identified in task 1)?
3. How will the important people interact with each other in order to perform the robbery?

6.2 Input Data

In our experiment, there are three types of social networks, a financial network, a kinship network, and a contact network. In order to make sure that the social networks contain at least some important information about the interactions in the scenario, a set of probable connections between critical individuals are mandatorily set in these social networks. Using *i-j* to represent the edge connecting person *i* and person *j*, these connections are: financial transactions between the planner and a criminal (edge 0-2) and between criminals (edge 4-6); kinship connections between a criminal and a regular person who is working in a bank (edge 2-10) and between a criminal and an insider (edge 6-8); contact connections between a planner and criminals (edge 0-1 and 0-6), between criminals (edge 5-6 and 6-7), and between a criminal and an insider (edge 6-8). In addition to these critical connections, random connections between individuals are inserted in each social network. These random connections are generated by the random graph function provided in Pajek [8] by setting the network's average degree to 2. All three social networks in our experiment are symmetric and unweighted graphs. Due to space limitations, we only present the financial transaction social network and provide key results.

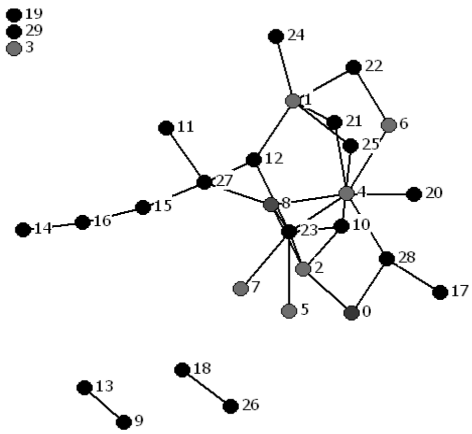

Figure 3. Financial transaction social network in our experiment.

As shown in Figure 3, a single social network usually contains incomplete interaction information. Some critical interactions are missing, such as the connection between node 6 (a criminal) and 8 (the insider) which may only be observed in the kinship network. Thus, it is important to combine multiple social networks together to obtain more complete information. In this experiment, the three social networks are combined using a linear combination in which each social network has the same weight.

With the social networks in hand, cultural fragments are needed to represent the cultural information relevant to each actor in the network. For this, we employ Bayesian Knowledge Bases (BKBs) [3]. A BKB is a collection of conditional probability rules (CPRs) that specify a probability distribution over a set of random variables in an "if-then" fashion that is natural for use by experts. BKBs are represented graphically as directed graphs with two types of nodes: (1) I-nodes which represent instantiations of random variables and (2) S-nodes with represent CPRs.

The adversarial intent inferencing (AII) model [25] of Santos was utilized to create the BKBs. According to [25], the AII model was designed to "capture the goals, intentions, biases, beliefs, and perceptions" of an adversary, and we find that it can be easily extended to accommodate other cultural information that is deemed relevant. This information is included as I-nodes in the BKB. Relationships between these items (e.g. beliefs, goals, and actions) are included as S-nodes (or CPRs) in the BKB.

This framework allows for the representation of culture at varied levels of granularity with a formal way of combining the effect of all the cultural variables that are thought to impact the situation of interest. Statistical inference allows the determination of likely goals and actions based on the available cultural information

For the experiment, several BKBs were built and used to populate a library of cultural fragments. Then, based on the demographic input data, a full BKB was built for each actor in the network by fusing several of the cultural fragments together. An example of a fused BKB is shown in Figure 4.

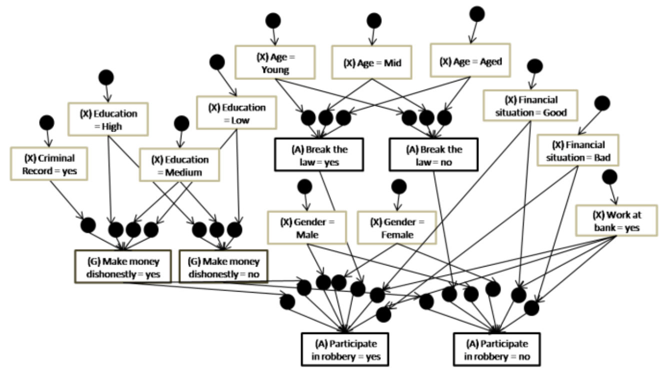

Figure 4. A BKB that is the fusion of several cultural fragments

The BKBs then take actors' demographic information as input and estimate their potential behaviors. The demographic data used in our experiment includes: age (young, middle, or aged), gender (male or female), education (low, medium, or high), criminal record (yes or no), and financial status (good or bad).

Based on the behavioral insights obtained from the cultural analysis, an ideology network is generated. The ideology network is further refined based on the interaction potential of the actors in the network. In this experiment, the interaction potential was found using the actors' contact opportunities in order to obtain a Contact Constrained Ideology Network (CCIN). Tie strength in the CCIN is a function of tie strength in the ideology network and the actors' contact opportunities. In this case contact opportunity is computed using a decaying function of the geodesic distance between actors in the social networks. Finally, the culturally-infused social network is obtained by combining the CCIN and the combination of the original social networks. In our experiment, these two networks are combined with equal weight given to each. The obtained culturally-infused social network is shown in Figure 5. In this network, the important individuals and their interactions are isolated in the small connected component which contains the planner (node 0). In figure 5 we also can see that the planner cooperates with some criminals (nodes 4 to 7), some of whom have the connections to the insider (node 8). The structure of these important individuals' interactions matches the setup of our experimental scenario.

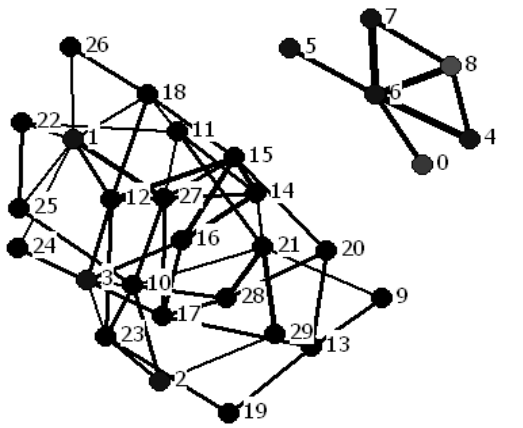

Figure 5. Culturally-infused social network on strong ties

The culturally-infused social network with actors' potential behaviors is shown in Figure 6. In this figure, each individual's potential behaviors are shown. Based on individual's behaviors we can see that some criminals (nodes 1 to 3) are not included in the component containing the planner and other important individuals since they do not have similar potential behaviors to the planner.

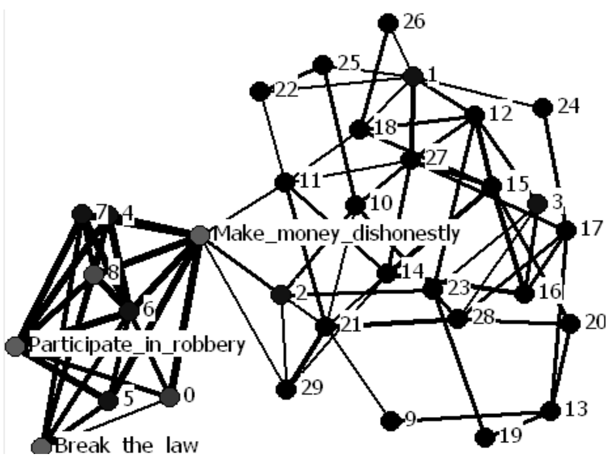

Figure 6. Culturally infused social network on strong ties (with behavior nodes)

6.3 Summary

Comparing the results we obtained for single social networks (Figure 3), and the culturally-infused social network (Figures 5 and 6), we can conclude that

1. Single social networks usually contain incomplete and imprecise information;
2. The important information (actors, interactions, and behaviors) that is relevant to the scenario becomes prominent in the culturally-infused social network. In other social networks, it is either overwhelmed by noise, or missed.

7 Conclusion and Future Work

Currently, SNA users are usually faced with incomplete and imprecise social network data sets because of the absence of cultural elements. In this paper, we present a generic approach that can be used to systematically model culture and infuse it into social networks. We implement our approach and test it in a set of experiments. Based on the analysis of experimental results, we validate the effectiveness of our approach and demonstrate that infusing culture into networks is a promising technology to aid social network analysts in identifying cultural groups and suspicious ties in the face of a data overload.

The initial work discussed in this paper presents a fundamental framework for infusing social networks with culture, and spotlights the strong capabilities that are inherent within its design. The detailed design of each component in our framework was necessary in order to provide a realistic experimental validation. For brevity, we have provided only key results and discussion. Further information can be found in [4]. One important future task is to study how to systematically store, select, and fuse BKBs for building culture fragments. Currently, the infusion of cultural information into social networks is done based on a linear combination and future work will refine this process. Another significant task for us is to research the proper methods of infusion for various applications.

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