DISCOVERING SOCIAL NETWORKS USING A MOBILE PHONE GAME

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ABSTRACT

This paper is part of a larger project, which applies a social medicine approach to complex Aboriginal health issues in Northern Australia. A major component of this project is the construction and use of multiplex social networks, both with Aboriginal communities and associated health care worker networks. In an attempt to overcome difficulties with language diversity and poor survey response, a mobile computer game is under development for determination of the social networks. This paper discusses simulations of the game developed to optimize the server-side processing required to elucidate the network.

Keywords: social network analysis, simulation, norm change, gamification, cell phones, health, Australia, Northern Territory, Aboriginal, health

1. INTRODUCTION

There is increasing interest in the use of social network analysis (SNA) to understand patterns of interactions that may provide for more efficient health delivery systems. This is particularly so when practices and communication of prevention can be used by the community in conjunction with medical advice and treatments (Kothari, Hamel, MacDonald, Meyer, Cohen, & Bonnenfant, 2014; Shakya, Christakis, & Fowler, 2014). As these papers show, the use of SNA is also useful in the design and delivery and health programs in developing countries, where existing medical infrastructure and public health practices may be lacking. A similar issue can also exist in developed economies like Australia, where populations have different levels of access to medical services and may lack sufficient social networks of health prevention and information. An example discussed in this paper is Aboriginal health in Northern Australia.

There are several aspects of Aboriginal health, where poor outcomes may necessarily are be related to the lack of medical technology, drugs or treatment protocols. They may arise instead through issues of *social medicine*, where communication shortcomings frustrate prevention and treatment goals (see for example Preston-Thomas, Fagan, Nakata, & Anderson, 2013). In this project we focus on social networks, specifically *network resilience,* merging the latest theories in social network analysis and computer simulation with qualitative research and a leadership-development training program.

Network resilience is the capacity of a network to recover from threats and shocks. However, in the health domain, network resilience may have effects that can be positive and/or negative:

- **It is beneficial** when it helps a community to support its members, such as in providing food and assistance to the sick, or emotional support to those who have suffered loss or mental health difficulties.
- **It may be harmful** if it impairs the reduction of social contact needed to control a dangerous infection (for example, the Ebola epidemic in Africa in 2014) or the drug resistant forms of tuberculosis (Andre, Ijaz, Tillinghast, Krebs, Diem, Metchock, Crisp, & McElroy, 2007).
- **It may also be harmful** if in that it may obstruct leadership and community empowerment to break adverse social practices/norms (Carsten, Uhl-Bien, West, Patera, & McGregor, 2010).

Young & Burke (2009) show that social norms may emerge which result in some people receiving adverse medical treatment:

> *...a 75 year old heart patient is more likely to receive an invasive treatment either coronary angioplasty or bypass surgery in Tallahassee, a city with a relatively high pro- portion of younger cardiac patients (62 and under), than in Fort Lauderdale, a city with a comparatively older patient population. Since surgery becomes riskier with age, 75 year olds in Tallahassee are likely to have worse outcomes than 75 year olds in Fort Lauderdale, even with no differences in the average competence of physicians or other quality factors across the locations.*

Thus social norms, which can be deleterious, are difficult to break, and ways of bringing about a *tipping point* to another more productive norm are eagerly sought (Young & Burke, 2009) . For the spread of epidemics, such as H1N1 Spanish Flu, computer simulation has now reached the level of modelling every person in a community, 280 million agents in the case of the Los Alamos *Epicast* model for the USA (Germann, Kadau, Longini, & Macken, 2006). We aim to construct similar models to those aimed at epidemic threats, such as Extensive Drug Resistant TB, for which the methodologies are both well established. Gardy, Johnston, Sui, Cook, Shah, Brodkin, Rempel, Moore, Zhao, & Holt (2011) concluded that had Social Network Analysis (SNA) been conducted in association with historical data screening, TB outbreaks could have been prevented.

The project aims to investigate the important relationship (for an example see Fuller, Hermeston, Passey, Fallon, & Muyambi, 2012) between understanding the complexity of the networks within communities and Aboriginal Community Health (ACH) Centers and their associated care workers (ACHWs) and to elucidate thus understanding that highlight the flow of not pathogens, but ideas, information and influence, along social networks. It targets widespread health problems, such as hepatitis B (increases liver cancer risk), scabies (also increases liver cancer risk), renal failure and cardio-rheumatology. In all these cases the drugs and treatments are well established and cheap, subsidized to make them easily accessible. (Preston-Thomas et al., 2013) for example, highlight the need for "culturally appropriate patient education resources" for chronic hepatitis B. Figure 1 shows the overall project framework.

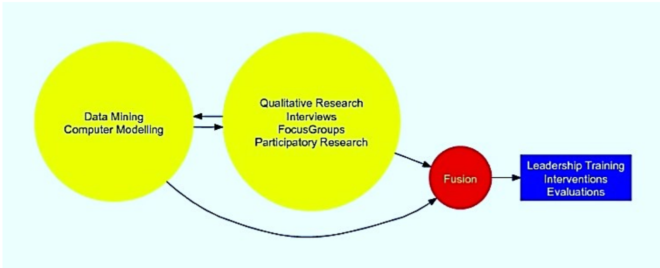

Figure 1: Project Structure

An essential requirement of the project is to ascertain the networks links between community members, ACHWs (Associated Health Care Workers) and the cross links between the two groups. A new mobile phone game is under development for building these networks, and this paper describes a simulation model for how it does so.

2. PROJECT BACKGROUND

For infection diseases, such as pandemic flu, and currently Ebola, simulation plays a major role in predicting spread of the disease and testing intervention strategies, in the *Epicast* model (Germann et al., 2006) with an computer agent for every person in the United States. The network of connections among individuals, through schools, shops, public transport are explicitly represented to get as accurate estimate as possible of the infection trajectory.

2.1. Social network analysis for health

In chronic diseases networks are equally important, but they are *social networks*, where the infective agents are not the pathogens, but information and influence. From the early days of network thinking, when Watts (1999) introduced *small world networks* to explain the six degrees of separation phenomenon, through the rapid growth in understanding scale free networks, introduced by (Barabási & Frangos, 2014) to the exponential random graphs (Pattison & Robins, 2002) which underlie many social phenomena, the structure of networks has emerged as a key driver of social dynamics.

Social networks focus on the relational and interactional ties between units (Wasserman, 1994). Christakis & Fowler (2009) cite numerous examples of network effects in medicine, such as the influence of friends of friends of friends (three degrees of separation) on obesity. Centrality is the key concept from graph theory needed in SNA. From the node level point of view can be measured in terms of degree (the number of ties to and from an actor). Structurally, centrality is measured in terms of closeness (the extent to which an actor is close to all others in the network) and betweenness (the extent to which an actor lies in the shortest path to all others in the network). So, it is implied that *degree centrality* shows the strength of actors' communication activity while *betweenness centrality* indicates an actor's control of communication (power and influence) and *closeness centrality* shows actors the minimum time and efficiency for communicating with other actors in the network (or communication efficiency, see Chung & Hossain, 2010). Granovetter (1973) introduced the idea of the strength of weak ties, as the first influential study on the importance of relations of actors in social networks, arguing that individuals obtain new and novel information from weak ties rather than from strong ties within the individual's group structure. If *i* has a strong tie with *j* and *k*, then *j* and *k* themselves are likely to become friends (the *homophilly* principle). Thus, strong ties will tend to cluster into cliques. The bridge *ij* in Figure 2 is a weak tie that brings novel information to each group.

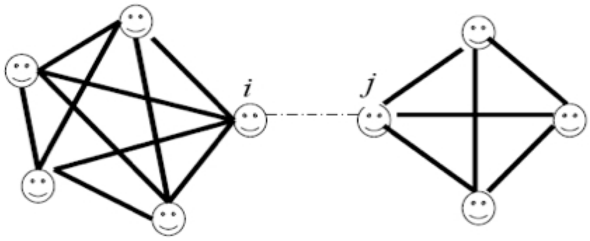

Figure 2: Weak vs.Strong Ties

As an individual's personal network grows over time, the extent of information coming from closely knit clusters ends to become redundant (Chung & Hossain, 2010). Actors are in a better position to benefit from interactions with others, who are not well connected themselves or are not well organized. Based on this idea Burt (2009) introduced the idea of structural holes. Holes in the network refers to the absence of ties that would otherwise connect unconnected clusters together. For instance, as it is shown in Figure 3, the network on the left contains many structural holes while the one on the right contains few. In other words, the lack of connections among unconnected nodes in a network form the holes in the structure. Individuals who bridge these holes attain an advantageous position that yields information and control benefits (Chung & Hossain, 2010).

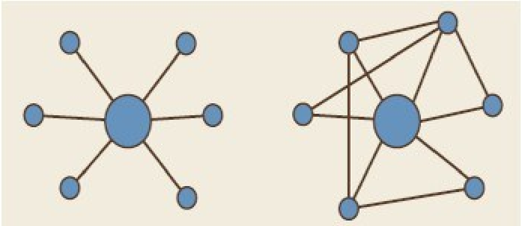

Figure 3: Two ego networks with different structures

Network effects on an individual's ability to perform better have been documented in studies on community health, communications, sociology and social psychology (Coleman, 1988; Guetzkow & Simon, 1955; Leavitt, 1951) and actors with a dense social network perform better (Oh, Chung, & Labianca, 2004; Reagans & McEvily, 2003). Furthermore, actors who are rich in structural holes (connections to social clusters or groups who are themselves not well connected) are better situated in their social network to obtain, control and broker information (Burt, 2009). In the field of medical innovation, Social Network Analysis (SNA) proved useful for understanding the diffusion of innovation among physicians (Coleman, Katz, & Menzel, 1957). It also proved fruitful for understanding the social processes which intervened during the initial trials of the drug gammanym, from the time when it was adopted by a few local innovators to the time when it was ultimately used by the entire medical community.

2.2. Australian Aboriginal health issues

Several major health problems within Aboriginal communities are essentially Non-Communicable Diseases (NCDs), such as renal failure and liver cancer. The primary causal factors include pathogens for which there are straightforward treatments and vaccines. The solutions lie therefore not in conventional but in social medicine, which involves lifestyle choices and effective communication and influence. Thus understanding social networks is essential to addressing questions in social medicine.

In network epidemiology studies traditional SNA has been widely used to understand mental health (Perrucci & Targ, 1982), social network and health status (Seeman, Seeman, & Sayles, 1985) and the spread of HIV disease (Morris, 1993). Little is known about how the social immunity and resilience which is embedded in social networks of Aboriginal Communities.

Recent developments in network theory surround *multiplex networks* (Bianconi & Dorogovtsev, 2014). In such a network, there is one set of nodes (usually people, but could include animals or other agents), but with multiple layers, each layer connected by a different mechanism. So, for example, a community may have school, work and sport networks, each connecting its members in different ways. Such multiplex networks have quite different properties compared to single layer networks, and are often more difficult to break apart.

There are five levels of the multiplex network, each targeted by a separate mission of the game:

- The kinship network of family ties
- The peer network of friends of similar age and occupation, such as teenage groups;
- The cultural / community ties, spreading out hierarchically from the community elders.
- The information links, which defines the trust network for data about health risks and treatments.

There are two coupled social networks involved: the networks of the Aboriginal Health Care Workers; and the networks of the individuals within the communities themselves. The nature of this coupling and the associated dynamics are significant in improving existing, and identifying new, interventions. Better health outcomes require changing social norms. We propose the use of leadership training will help bring about change, with effects continuing beyond the lifetime of the project (Evans & Sinclair, 2015).

Building computational models of social systems often hits the major difficulty of taking qualitative data from interviews, focus groups and other tools, and creating quantitative, algorithmic decision procedures to put into the computer model. Yet this data flow is critical to building better agent-based models of socio-economic systems. Numerous findings, such as Preston-Thomas et al. (2013) highlight the significance of communication and information dissemination in Aboriginal Health. Understanding the way influence travels along social networks within Aboriginal communities is essential to formulating the most effective leadership training protocols. The overarching project integrates agent-based computer modelling and social network analysis, underpinned by extensive qualitative research applied to Aboriginal health. It also features the incorporation of the research findings into leadership training as its capstone health intervention.

3. SIMULATION TO MODEL NORM CHANGE

This project features a new hybrid approach to overcoming immunity to change (Keagan & Lahey, 2009). It will use computer simulation, infused by the network data, to determine the drivers and key network properties of social norms. It will then simulate various interventions to create tipping points (Young & Burke, 2009) in these norms. Such interventions could range from turning an influential individual, to adding financial incentives to alternative behaviors. The computer models require a decision process for the agents and a network model for the communication between them. The latter is inferred from the qualitative and historical studies. The decisions use the Quantal response model (McKelvey & Palfrey, 1998), common in choice modelling. Such models require a utility, ui, corresponding to each possible action and temperature parameter, T = 1 , which governs how much noise there is in the choice. At high temperatures, the choice is random. At low temperatures, only the choice with maximal utility is chosen. A simple implementation, where Pi is the probability of making choice i, from a set of M choices is:

$$P_i = \frac{exp^{(\beta u_i)}}{\sum_i^k exp^{(\beta u_k)}} \qquad (1)$$

Such models need both verification and validation (Midgley, Marks, & Kunchamwar, 2007). Verification is the process of establishing that the software will perform as required. It will be accomplished using: independent code reading by team members; testing system level conservation quantities; checking for expected trends; and sensitivity analysis. Graphs and networks are visualized with standard software such as *Pajek* and *Matlab*. To detect tipping points, however, we will get some parameter values where the model is very sensitive. To check that these are genuine tipping points (as opposed to numerical instabilities or in- felicities), we use a battery of established techniques (Scheffer, Carpenter, Lenton, Bascompte, Brock, Dakos, Van De Koppel, Van De Leemput, Levin, & Van Nes, 2012): increased variatiance; long correlation lengths; flickering; and maxima in mutual information and transfer entropy (Barnett, Lizier, Harré, Seth, & Bossomaier, 2013; Bossomaier, Barnett, & Harre, 2013; Harré & Bossomaier, 2009).

The Community Health Simulation Model (CHSM) embeds the social network and the choice mechanism in an Agent Based Model (ABM) with one agent per person for at least two communities, the associated Aboriginal Health Care Workers and other stakeholders. To determine its validity it will simulate a range of health outcomes as presently observed and parametrization and network structure fine-tuned accordingly. The validated model will then be run for various scenarios suggested by current health priorities and the data from the social network analysis. It will determine which links need to be strengthened or broken in order to achieve better health outcomes.

4. THE GAME

This game is single player, but uses a web site and server-side processing to elucidate the SNAs. There are three levels. Each level corresponds to one of the components of the multiplex network.

There are prizes at each level. At the first level, everybody wins a small prize, say around $50, typical of the cost for an experimental subject. The second level involves a smaller number of larger prizes and the third a single new smartphone.

The game starts with a random network on the server. Each player gets a challenge, to link two faces, say A to C, via other faces presented as an option, say, a,b,c,d. The player, Leesha, say, has to choose a person which will give the shortest path to C. Suppose Leesha chooses b. The server now increases the strength of link b, and generates a new set, x,y,z, C. Leesha chooses again and again, until she chooses C.
At the beginning, Leesha gets a score just for completing the task, so it's easy to begin with The server meanwhile has added strengthened her links. Future guesses from other players get higher scores and the link strength goes up slightly super linear with number of hits. Thus the network gets more and more realistic as the game progresses.

A strategy already used in games is employed to increase engagement. Everybody is trying to maximize his/her score and can see a league table. But everybody effectively has to cooperate to open the next level. This would occur when the network is stable (details to be worked out about how to measure this.) At this point all links which never received reinforcement are deleted. To help with this collective goal, the growing network could be visualized in the game.

An important aspect to this: all the people in the game do not need to play. In fact, one could restrict players to a target age group, so that we get the network as perceived by that group. Not sure about whether this is a good thing. The game is only weakly language dependent, requiring just a hundred words or so of text at the start of the game. This is especially important for remote Aboriginal communities where English may sometimes be a second, third of fourth language.

5. SIMULATION MODEL

First we consider the need for the simulation model and then go on to provide the details.

5.1. Need for the simulation model

Running tests with human players is very time consuming, both before during and after the experimental run. Yet there are numerous game parameters and algorithmic details to optimize:

- Players can enter a link with various levels of certainty, say, definite, strongly believe, and unsure. Each decision needs to assign a lower candidate weight to the link. The weights of these links determine the ratio of false positive (high weight to unsure) and true negative (low weight to unsure).
- The number of games needs to be set for the human trials, or at least some maximum value needs to be imposed. But the network will asymptote to the correct set of links, so the convergence needs to be examined to determine the most effective stopping point.
- AT the outset it is not known what the fine structure of the networks will be. They may be assortative, homophilic and so, and each network will present different learning challenges. Thus the server needs to predict and adapt to these structures to optimize the presentation of faces for refining the links. These issues can all be addressed by simulation.

6. DETAILS OF THE GAME AND SIMULATION

The simulation model first generates a network, either random or small world, for the community. For each player, it then generates a reduced network and adds noise. So each player has a network which connects everybody in the community (all nodes of the graph), but with varying strength according to how well they know somebody.

At each time step each player works out the shortest path between the target faces, given their own network knowledge. This path is inversely weighted by their certainty of each link. So, the shortest path may be longer than the number of actually steps needed to get from one node to the other, because this reduced number of links has greater uncertainty. In more detail, each player has a set of links comprising:

- Their direct links, which have value 1, since they are certain;
- Their next neighbor links, in other words, the links of their friends; these are less certain and have a value q_{nnn}, which is set to 5;
- Their remote links, which are random, but biased towards the correct network, which have a weight q_{rem}, currently set to 20.

The larger values of the next neighbor and remote links means that shortest paths will avoid these links if possible. The game is then iterated for a number of rounds, with each player playing once in round. Each time a link is used by a player, the learned network is updated on the server. But the link strength is updated by the reciprocal of the link value. Thus a remote link (player uncertain about it) contributes less to the growing network.
The game simulation is built in Matlab R2012b, using the *matlab$_b$ gl* toolbox available from Matlab Central on the Mathworks website (www.mathworks.com.au/matlabcentral/).

7. RESULTS

The community size was set at 200, as above. The number of players, 50, was varied along with the number of nodes. Figure 4 shows the results for a random graph. The green line shows the number of links correctly identified on the server. The red (solid) line shows false positives, which increase slowly as the games progress. The blue line (major dashed) shows the true negatives, which decrease as the game progresses.
To play a game, defined here as one face set, could probably be completed in around 10 seconds. If we say that an average of 5 are completed per minute, the total time would be 200 minutes, which is quite feasible for a play anywhere anytime mobile phone game.

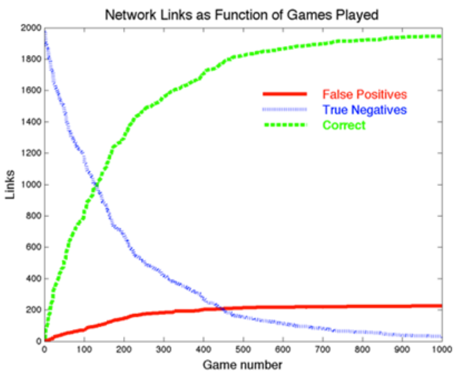

Figure 4: Simulation results showing true positives (descending curves) and false positives (rising curves) for a random graph.

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Figure 5 shows the same plots for a small-world (Watts, 1999) network. The number of direct neighbors was 20 and the probability of rewiring 0.1. This gives approximately the same number of links as the random graph case. The two networks are quite similar, although the small world is slightly easier to learn. This is fortunate, since it is more representative of likely community structures. It is also fortunate that the differences are not too great, since it suggests the game will be robust to the actual community structure.

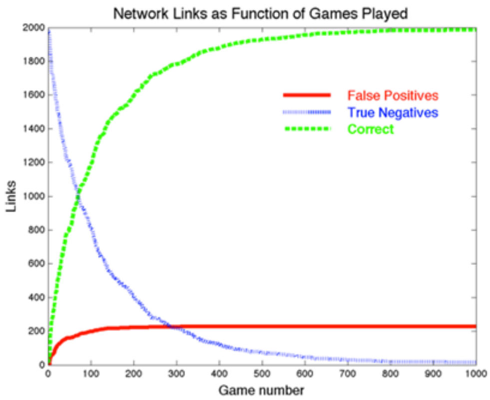

Figure 5: Simulation results showing true positives (descending curves) and false positives (rising curves) for a small world network.

8. CONCLUSIONS AND FURTHER WORK

The simulation model described here demonstrates that it should be possible to get good network estimates within an acceptable timeframe. The next stage of the project is to test the effectiveness within actual cohorts of players. Pre-testing of the game will be carried out on two student cohorts, form quite different social structures: a regional university in NSW; and the University of Hong Kong. The student cohorts will contain 200 students matched to similarly sized Aboriginal communities. For these cohorts the networks determined by the game will be validated by surveys, focus groups and interviews.

Furthermore we believe the use of a mobile game methodology outline in this paper has much to offer the field of SNA. SNA relies on extensive interviews, where respondent ability to describe a network may vary, along with other members of that network (Bader & Schuster, 2015; Gummerus, Liljander, Weman, & Pihlström, 2012; Xu, 2011). The use of secondary information to describe social networks, may also be limited in that to what extent respondents' value or actively use a network encapsulated by events or online linkages may be difficult to determine without directly questioning them. In short, the use of the game methodology as outlined in this paper may be an important addition to a social network analysis, which relates directly back to the demonstration of a social network as a communication channel of importance to respondents.

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