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Title	Social Modelling in Support of Planning and Intelligence
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Social Modelling in Support of Planning and Intelligence

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Abstract

Mathematical and computer models for optimised courses of action, conventional threat assessment and logistic planning support have become accepted tools in modern military headquarters. However, it is clear that many of the issues faced by planners and intelligence analysts require a better understanding of political, cultural and social issues. By this reasoning their support tool set should include a social modelling capability to represent and analyse social systems, relations and processes in the form of mathematical or conceptual models.

Modelling such processes is a complex enterprise that involves integration of mathematical methods and computational techniques with knowledge that is domain- and context-specific. This mathematisation of social phenomena, which we shall term *social modelling*, also requires using different theories from social science, depending on the methodologies and approaches used. Our research approach is therefore underpinned by social theory. It is specifically focussed on identifying the socio-cultural conditions of social processes and movements; identifying groups and patterns of social relations; modelling systemic and structural factors that may affect social behaviour; understanding social actors' motivation to belong to particular social movements and how they might be influenced. In this paper we look at some of these techniques and their application to problems encountered in the Defence arena.

Introduction: Rationale for this approach

The current national security environment is complicated and dynamic. Increasingly, national threats are not constrained to conventional military systems but arise from diverse systems that might be generalised as networked social systems. It is clearly important to understand how these systems are structured and how they might evolve over time, as well as identify the crucial processes that drive them. However, the threats we face from global terrorism and unconventional warfare are not easily defined. Moreover, most events that occur in human systems are typically the result of many factors. Multiple ill-defined concepts that might explain terrorism or collective violence makes this a complex area to model.

Mathematical and computer models for optimised courses of action, conventional threat assessment and logistic planning support have become accepted tools in modern military headquarters. However, it is clear that many of the issues faced by planners and intelligence analysts require a better understanding of political, cultural and social issues. Potential adversaries are not always "part of an organized, conventional military force, but have formed highly adaptive organizational webs based on tribal or religious affinities" (Popp, 2005). A large part of intelligence analysis involves understanding such situations in order to support strategic decision making and operational planning, and to avert threat. In the current climate it has become even more important for our decision-makers, at both the tactical and strategic levels, to understand these threats and try to prevent them. Popp (2005) points out that this requires a high level of social, political, and cultural awareness as well as military expertise and outlines a DARPA initiative to address this requirement. By this reasoning an intelligence analysis support tool set should include a social modelling capability to represent and analyse social systems, relations and processes in the form of mathematical or conceptual models. Appropriate decision support tools for this complex environment rely on the formal conceptualisation of specific social phenomena.

In this paper we advocate a multi-disciplinary approach to the development of a spectrum of social models. It describes the salient elements of research aimed at developing a coherent framework to encompass social modelling tools and analytic techniques to support intelligence analysis and planning for Australian Defence and National Security more generally.

Mathematical modelling of social phenomena

"Mathematics is needed especially and primarily for helping coax social phenomena sufficiently into view to permit the sorts of reconstruing, manipulation and measurement on which productive insight depends." (White, 1997)

Social modelling is still a relatively underdeveloped area. Social Network Analysis (SNA), probably the most developed and best-known branch of mathematical sociology, was developed early in the 20th century by collaborators from the sociology and mathematics disciplines. It utilises mathematical graph theory to represent and analyse the structural properties of networks; algebraic representations of networks and blockmodelling to describe social positions and roles; and statistical analysis to study the evolution of networks. Other modelling approaches include simulation and probabilistic models; statistical analysis; algebraic models; demographic analysis; and event history analysis.

Two categories of models we will investigate are stochastic and structural models. Rapaport (1983) describes the former as models which are rooted in probability theory. They are better suited to model social concepts than deterministic models as they avoid the problem of exact measurement and exact prediction by relying on statistical laws to produce probabilistic predictions. Structural models are those in which relations play a central role, such as, networks of relations and organisational structures. Techniques from set theory and graph theory are typically used to analyse these models.

Mathematical models of social phenomena are often constructed in order to investigate interesting aspects of social behaviour (or results of conceptual experiments), such as conditions for instability in a population or the underlying structure of a system, rather than as accurate predictors of such behaviour or system manifestation. Special care must be taken with these models because there are no axioms analogous to the fundamental physical laws in the social sciences. However an axiomatic approach is useful to ensure that the models are internally consistent and to enable concise definition of the elements within the modelling structure. A framework based on hypothetical assumptions is constructed instead. Another difficulty that arises when constructing models of social phenomena relates to the model parameters. In contrast to physical systems where the variables of interest are defined precisely and are usually measurable, social systems typically involve an enormous number of variables which are usually much too difficult to measure (Rapaport 1983). Quantification also requires that the model builder specifies what is to be observed and how it should be measured.
"In the interest of formulating a tractable problem, the mathematical model builder must confine the model to a small number of parameters related to the dynamics of the process. Sociologists who formulate theories verbally are not bound by these constraints. They can include as many factors into their theories as they can think of, thereby forestalling any criticism to the effect that they have not considered this or that. Unfortunately the more 'complete' a theory is the more difficult it is to put it to a test." (Rapaport, 1983, p 200)

A crucial part of this work will be to develop specialised techniques for the analysis and systematic storage of sociological, socioeconomic, and demographic data.

Networked Social Systems

Increasingly, research in disciplines ranging from physics to social and organizational science has started to recognize the value of network approaches as a way of understanding the behaviour of complex systems. Of particular interest have been social and organizational phenomena. The network perspective conceptualises social organisations as a collection of individuals or actors and the relational ties among them. Relational ties can be thought of as channels for transfer of material and other resources (e.g. information, knowledge or influence).

There are a number of reasons for this increased interest in networks. The first is the view that adopting a network model of the world enables us to utilise a powerful set of techniques that are constantly improving. The following quote from Emirbayer (1997) illustrates the point. *"This perspective [of social network analysis] is not primarily a theory or even a set of complicated research techniques, but rather a comprehensive new family of analytical strategies, a paradigm for the study of how resources, goods, and even positions flow through particular figurations of social ties."* The second reason is the growing evidence to support the validity of this perspective as we elaborate below.

Networks are crucial to the understanding of social phenomena. Granovetter (1990) argues that "no part of social life can be properly analyzed without seeing how it is fundamentally embedded in networks of social relations." Castells (1997) refers to a 'network society' induced by the information revolution and the restructuring of

capitalism in the 20th century, and characterised by globalization and the new social movements trying to resist it. New forms of interactive worldwide media such as the Internet are used by the various movements to aid their struggles against strategic global trends. Arquilla & Ronfeldt (1999) coin the term 'netwar' to define a new form of conflict (and crime) involving networks of non-state actors, "who are able to organize into sprawling multiorganizational networks". The networks link individuals and groups through various types of relation, and are able to modify their structures and strategies as circumstances dictate. Networked structures trade the control and efficiency of rigid hierarchically structured systems for increased adaptability and flexibility. According to Arquilla and Ronfeldt (1999), having a networked enterprise structure provides more than simply the ability "to keep from being suppressed, it now allows them [non-state actors] to compete in more nearly equal terms with states and other hierarchically oriented actors".

An increased focus on network approaches to understanding social systems and organisations allows us to understand a variety of important outcomes at multiple levels. It has been recognised (Duke et al., 2006) that networks spanning various domains (social, cognitive, information, physical) "directly impact vital national problems". Moreover current understanding of complex interactive networks that typically represent social systems of interest is limited.

The structure of organisations of interest is potentially revealed by analysis of relevant social networks. However, in the case of covert networks these might be difficult to detect and analysts might need to rely on raw data, such as communications traffic or observed interactions, to put the pieces together. It is important in this case to have a good understanding of these organisations; how they operate and what a typical network might look like. Wolters (2002) uses social and anthropological research to describe the direct ties between members of covert networks or secret societies as being based on "trusted prior contacts" such as kinship, school friendship, comrade-ship, religious and community ties etc. Members tend to be organised in cohesive cells or action-sets. These cells are only loosely linked for conducting operations, usually through a liaison. Contact between cells and the central organising group are set up for a specific activity and purposely kept brief in order to avoid detection. Although communications networks are necessary for operations to be planned, financed, resourced and executed, they are typically only in existence for short periods of time. However, although they might not give us much information about the whole organisational structure, they could reveal the contacts between action-sets and the central leadership.

Social Network Analysis

A social network is simply a network consisting of a set of actors between whom relational ties are defined (Wasserman & Faust, 1994). It can be mathematically represented as a graph whose nodes and links correspond to actors and relational ties respectively. A social network might be mapped according to observed communications traffic or resource or information flows. The resulting network could inform us on network structure. It might also serve to map known relationships that could reveal an individual's position, functional role and importance to the organisation. Network analysis provides a set of formal definitions, measures and descriptions to evaluate organisational characteristics.

Network structure is determined from regularities or patterns in the linkages among the network nodes. Mathematical analysis can be employed to quantify network characteristics to determine how the network behaves under varying conditions.

Intelligence agencies understand the value of structuring large quantities of collected data as entities and the relationships between them, and value the ability to visualise these data as link charts to aid analysis. However, current intelligence analysis is often limited to intuitive sense-making which takes place wholly in the analyst's mind and does not take advantage of the powerful techniques from social modelling (Sparrow, 1991). In dealing with data about large networked organisations, intelligence analysts often need to integrate data from multiple incidents and multiple sources to determine the organisational structures and transactions that occur in these networks (Xu & Chen, 2005). This requires that information on entities and events is categorised and structured systematically and that data collection and analysis is based on a coherent theoretical foundation.

Robins and Pattison (2006) define social networks as "patterns that arise through human social processes" and multiple social networks as "several different types of social networks operating simultaneously". They argue that multiple networks should be analysed *jointly* in order to get a better understanding of the organisation under investigation. In order to understand how networks evolve it is important to study how different networks influence and reshape each other from a dynamic perspective; transfers and exchanges among the actors lead to dependencies across multiple networks.

In order to make sense of intelligence data we need information on both the dynamic transactions and interactions, and the relatively static relationship structures.

SNA Measures

In this section we present a simple example, which illustrates potential analyses for a single connected network. The network we consider (shown in Figure 1) consists of 753 individual actors connected to each other on the basis of some association. The analysis has been conducted in the manner of a mathematical exercise – the resulting measures have not been interpreted in their social context but have been considered mathematically to reveal patterns in the data. Typically, social network analysis is conducted on data with at least partial information on node types, node attributes, and relationship types, as well as information on the limitation of the data collection. Analysts might have an initial hypothesis to work from and a set of investigative questions to answer. In this case we have only anonymous nodes and abstract connections between them. In one sense this means that we can make totally objective observations, however it makes the job of making any sense out of the results much more difficult as we rely solely on identifying patterns. There is a danger that we might miss important results simply because we have incomplete information.

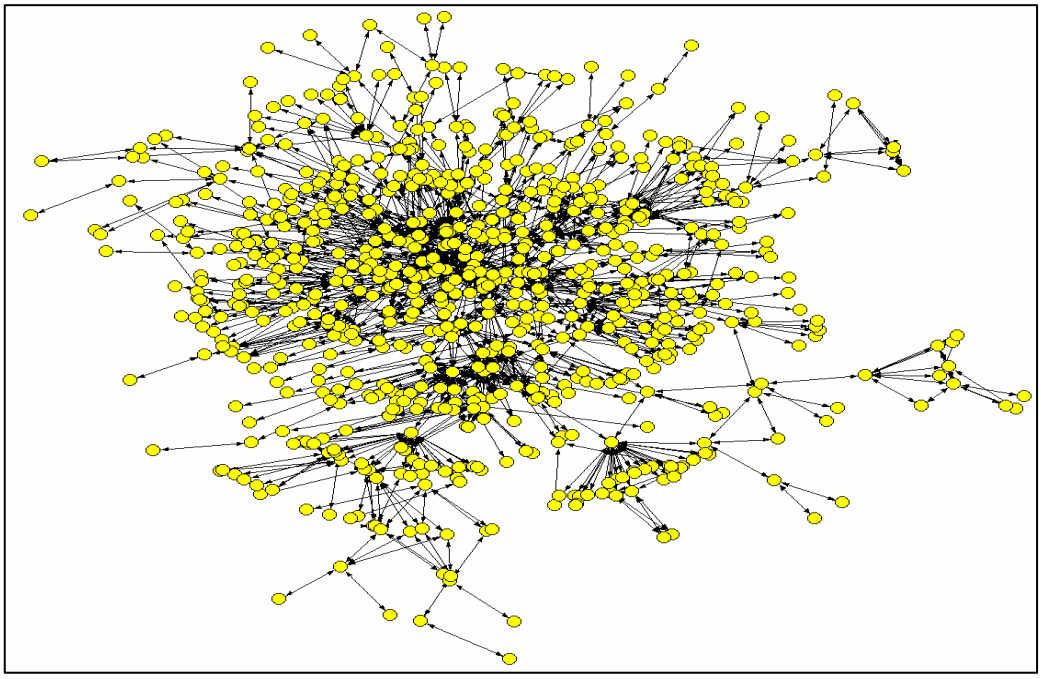

Figure 1: A dense and complicated network

In a typical analysis we investigate two sets of measures. The first set describes individual node measures: degree and eigenvector centrality tell us something about an individual's local connectedness in the network; while betweenness centrality and closeness describe a node's strategic position. The second set of measures focus on regularities or patterns in the linkages among the network nodes. Depending on the nature of the data we might also determine some structural properties (Newman, 2003) of the network: resilience, transitivity, mixing patterns, reachability, group structure, and so on. Importantly dynamic data, such as communications data might give indications of imminent events or even describe changes in the underlying group structures.

Network analysis provides a set of formal definitions, measures and descriptions to evaluate organisational characteristics. It does this by viewing these characteristics as arising out of the structural properties of relational information. An initial set of questions to help focus the analysis might come from the study of criminal networks. McAndrew (2000) proposes that criminals form networks through their interactions with other criminals. The main area of implicit structural analysis has been in drug trafficking networks, which typically require various roles for both individuals and teams, and the criminal groups involved are often transnational and associated with various kinds of crime. The aspects that are usually studied include the degree of hierarchy or flexibility in the structure, the types of roles identified by the level of organisation and importance of cohesiveness. Investigators might be interested in getting answers to the following questions:

- Who is central and peripheral in the network?
- Which individuals are crucial to the operation of the network?
- What individuals have access to more information?
- What is the overall structure of the network?
- What subgroups exist in the network?

- What are the different roles and jobs in the network?
- What are the important communications and methods of communicating?

Individual node measures that might help answer the first three questions listed above include: degree centrality, which compares the number of direct connections an actor has to the other nodes in the network; eigenvector centrality, which takes into account the centrality of the actor's direct neighbours; betweenness, which gives an indication of an actor's ability to act as a broker or conduit in the network; and closeness, which considers the average number of links separating an actor from all other nodes in the network. These measures help determine the key people in the network.

The other questions are best answered by studying the network structure. Social network literature suggests that characteristics of social networks may relate to individual and group behaviour in complex ways. Furthermore, network characteristics can be determined from structural properties such as the similarity of network position of members or the presence of cohesive subsets or subgroups. The size and nature of these subgroups might help us to better understand the behaviour of the whole network. For example, subgroup properties can help determine how fast and to what extent information or influence or even conflict might move across the network and they can tell us about the nature of group affiliations.

In any human organisation in which individuals interact with each other regularly, groups emerge quite naturally and often deliberately. The group structure in a network gives us new insight into the dynamics of the organisation. Ethnographers have traditionally defined human groups as collections of individuals linked to each other by regular interaction. The ethnographic description of a group is based on intuitive ideas and does not help us determine how to systematically partition a network into meaningful subnetworks with as little human intervention as possible. As a result social network researchers have made many attempts to formalise the group concept (Freeman, 1996). One definition considers the concept of a *clique*, which is defined as a maximal subnetwork containing three or more actors all of whom are connected to each other. In this particular network, there are 169 cliques, and they consist of 185 nodes from the network, i.e. there are many overlaps between these cliques.

Typically, an individual may belong to many different cliques, making the segmentation into subnetworks an almost impossible task. In particular, in a dense and complex network as this one there is too much overlap to make sense of the structure. For this reason researchers have attempted to relax the definition of a clique in order to describe subgraphs that are "clique-like". These definitions have known graph theoretic properties while also capturing important intuitive and theoretic properties of cohesive subgroups. Two approaches are described below: using properties of reachability and path distance to extend the clique definition; and using nodal degree as the basis for the definition.

Subgroups based on reachability: The underlying hypothesis behind this definition is that important social processes (such as diffusion of information or influence) occur through intermediaries. Hence paths connecting subgroup members should be

relatively short. For example, an ***n*-clique** is a maximal subgraph in which the largest geodesic distance between any two nodes in the subgroup is no larger than *n*, $d(i,j) \le n \forall n_i, n_j \in N_s$, where N_s is the node set of the subgraph. Note that we can describe *n*-cliques in which the intermediaries in a geodesic between a pair of *n*-clique members are not themselves clique members. In order to get around this problem we define an ***n*-clan** as an *n*-clique in which the geodesic distance *d(i,j)* between all nodes in the subgraph is no greater than *n* for paths *within* the subgraph. The *n*-clans in a graph are those *n*-cliques that have diameter less than *n*.

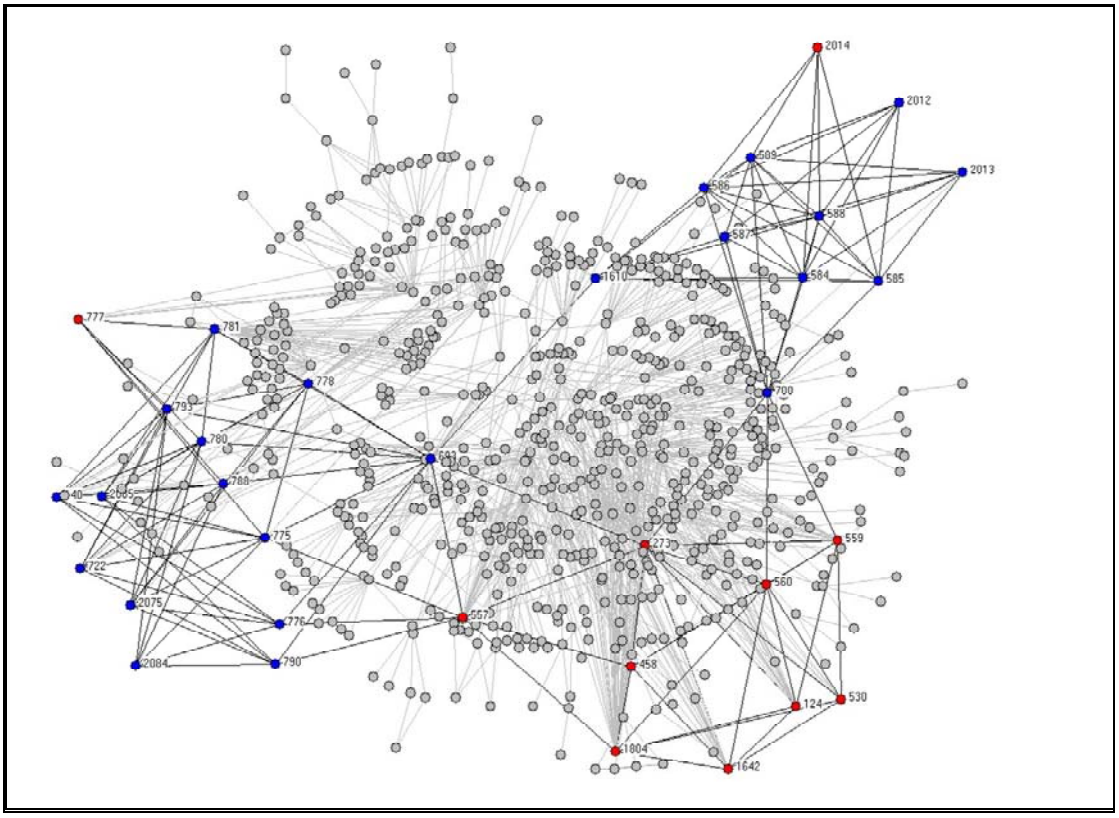

Figure 2: Two 6-cores (blue) and one 5-core (red)

Subgroups based on nodal degree: These approaches focus on adjacency between actors rather than on paths and geodesics. The rationale used here is that network processes require direct contact among actors or even repeated direct contact among several actors. These alternatives require that all subgroup members be adjacent to a minimum number of other subgroup members rather than all of them. This also increases the subgraph's robustness (where we define robustness as the "degree to which the structure is invulnerable to the removal of any given individual"). For example, a *k-core* is a subgraph in which each node is adjacent to a minimum number, *k*, of other nodes in the subgraph. The definition of a *k*-core is less restrictive than a clique and is therefore useful for detecting larger non-overlapping clusters. The maximum *k* determined in our network's *k*-cores is 6. Figure 2 highlights two 6-cores (in blue) and one 5-core (in red). *K*-cores with lower values of *k* have been omitted for clarity. This representation of the network highlights the clustered nature of these three subgroups. We might attempt to interpret these clusters as executive or managing committees, whose members require direct contact among several actors.

Another way to determine network structure is to use a top-down approach and identify substructures that are locally dense. This approach attempts to find lines of division in the larger network as a way of decomposing the network into subgroups. We can define partitions of the network by grouping together actors based on the concentration of ties within the group compared to ties between groups. The faction detection algorithm used here attempts to partition the network by maximising this ratio. Procedures exist to compare the goodness-of-fit of this partitioning to an ideal partitioning in which actors within each group have maximum connection while actors across groups have minimum connection.

The faction detection algorithm requires you to specify the number of factions to use in partitioning the network. In our case, after trial and error, we specified six factions. The rationale for this decision is as follows. Our starting assumption was that the three clusters determined by the k-core technique should remain as clusters existing in a single faction. On inspection it was evident that most of the nodes from the three densest *k*-cores exist in three of these factions, suggesting that there may be at least three groups existing. However, partitioning on three factions meant that all three clusters were splintered across the factions. Similar results were obtained for four and five factions. Six was the smallest number of factions for which our clusters retain their nature. Of course, these starting assumptions might be inappropriate; in reality, members of the same core could be split across factions. The only way to resolve this is to examine node attribute data and link types in order to determine whether the faction partitions we have here makes sense.

Figure 3, which shows the whole network, highlights the links connecting the members of the three k-cores. The structures of these factions (if they are indeed meaningful substructures) might point at useful organisational attributes. For example, the pink faction seems to be very hierarchical, while the red one appears to be a hierarchy with a flat "executive" team. Group detection techniques help us make sense of dense complicated networks.

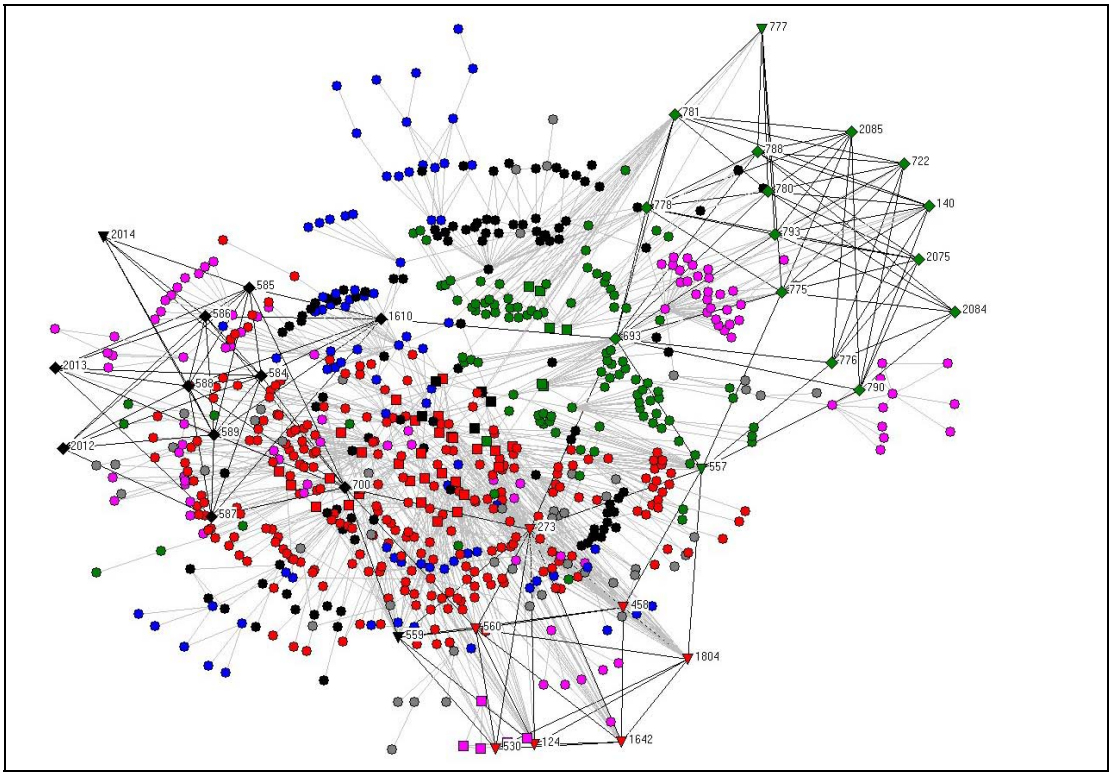

Figure 3: Showing six factions and three k-cores

Stochastic Models

Mathematical models that involve probability distributions and uncertain or ill-defined data are termed stochastic to distinguish them from deterministic models. They include stochastic process models, which describe the development of a process over time according to probabilistic laws and often form the basis of a computer simulation model. These techniques have been successfully applied to the physical and biological sciences. Application to social processes has been more problematic owing to the difficulty associated with measurement of social parameters (Bartholomew, 1967). The approach taken is the traditional mathematical approach as it is applied to modelling of physical systems: taking relevant (for the problem at hand) aspects of the modelled system and representing them mathematically (e.g. as a set of equations) in order to understand facts about the behaviour of the system under certain conditions. Uncertainty in the system is handled by treating the mathematical variables as a probability distribution.

A powerful class of models in this area are simulations of evolving social processes and movements. These models may be used to develop experimental scenarios that allow decision-makers to gain insight about a particular situation. MacKerrow (2003) presents an intelligent-agent based model for simulating the spread of social grievances. The agents in the model simulate people in specific societies with statistically similar demographics. They are subjected to social and political pressures that may cause them to change their behaviour and attitudes. The objective is not to "predict specific events" but to gain an insight of social perceptions (of personal

hardship, social disadvantage etc) and allegiances through the analysis of various evolving scenarios. MacKerrow makes the important point that "the underlying social processes cannot be understood by a simple linear combination" of relevant sub processes, since every society has a unique history and cultural make up. The sheer number of potential factors that might impact on society clearly points to a need for a multi-disciplinary approach to these models.

Another illustrative example of a multi-disciplinary approach to agent-based simulation of social phenomena is a study of violence and revenge in virtual egalitarian societies (Younger, 2005). In this study rule-based simulation models based on anthropological investigations of real-life egalitarian cultures are used to test assumptions and identify characteristics of violence in a controlled environment. The analysis discussed by Younger, which includes comparisons of simulation results with ethnographic data, demonstrates the utility of such models. The ability to experiment by varying the simulation conditions or model variables can lead to insights that might not be obvious from ethnographic observations alone.

Social simulations are particularly useful for modelling the spread of influence and information in specific societies. Wragg (2006) presents a comprehensive study of the applicability of agent-based simulations to the analysis of social influence. The study includes an investigation of the spread of public opinion and the impact on an individual's stance from media, religious and local neighbourhood influences. It features, as a case study, a simulation using cellular automata of a polio vaccination information campaign and its acceptance by the simulated population. The analysis illustrates how opinion polarisation and clustering as well as large-scale attitude change may emerge as a result of public information campaigns. An important consideration in this work is the concept of social distance, which is a crucial factor in information diffusion or the spread of influence and opinion. One aspect is physical distance: spatial remoteness or closeness, and geographical dispersion. Technology can bridge this physical gap to some extent via modern communications methods, travel and the Internet. However, other aspects of social distance are harder to bridge. These might be characterised by such objective factors as power, rank and different life conditions of minority groups as well as by subjective attitudes towards members of other groups.

A more detailed simulation of resource flows and communication patterns can be performed using stochastic methods for process modelling. Stochastic characterisation and analysis of network flows based on observed resource or information flows, transactions and behaviours form the basis of an illustrative model. Once the structural frameworks in which the relevant social processes take place are understood, refined dynamic models representing, for example, operational processes, resource transactions or information flows can be developed. These modelled processes can be run with different variables and under different initial conditions to conduct "what if" analysis and determine viable courses of action.

Yet another powerful class of stochastic models for analysing social phenomena is that of Bayesian networks, which are probabilistic constructs for modelling knowledge frameworks and decision support systems. They may be used to represent causal relations in a particular social domain on the basis of economic,

political or socio-cultural theories. They have already been used successfully to support centre of gravity analysis in military planning (Falzon, 2006) as well as to support situation assessment for operations other than war. A Bayesian network is represented by a directed acyclic graph whose nodes correspond to variables, which can take on two or more values, and which are linked by causal or functional dependencies. A node may represent any kind of variable: an observed measurement, a parameter, a latent variable, or a hypothesis. Sociological or other factors contributing to a particular situation are represented as primary or more indirect (secondary tertiary, etc) causes according to the topology of the directed graph that defines the conditional independence relationships among the variables modelled in the network. The probabilistic nature of the models enables uncertainty in the data to be represented explicitly, making them ideal situation assessment and hypothesis testing tools for uncertain intelligence.

Conclusion

In this paper we looked at a suite of modelling techniques to model social phenomena. The problem space that concerns analysts and decision-makers in today's National Security arena is vast and ill-defined. It is clear that there is not a single modelling technique that fits the whole space. There are still many gaps in our current modelling suite.

The research approach is necessarily multi-disciplinary. Rather than focussing all our effort on an adversary's military capability the tenets of Effects Based Operations require us to "creat[e] effects across all dimensions of the strategic environment" (Atkinson & Moffat, 2005). This includes the socio-cultural, ideological and political, as well as the military dimension. This is particularly the case in the face of an unconventional opponent. Planning needs to focus more on the opponent's intentions, which in turn requires that decision-makers have a good understanding of salient aspects of the adversary, such as: organisation type and structure; group dynamics and factional formations; demographic attributes; social motivations and influence; socio-cultural norms and values; underlying principles and modes of operation; as well as access to resources. No one modelling technique will be appropriate to analyse this social system. An integrated spectrum of theoretical concepts and modelling methods drawing from the social sciences, mathematics and the natural sciences are necessary.

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