Network Analysis in Marketing

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Abstract

Understanding relationships is fundamental to marketing. Research has moved beyond simple dyadic relations to examine how networks of relations influence behaviour. While network theory is frequently drawn upon in marketing, few researchers apply the formal network analytical techniques developed. The aim here is to make network analysis more accessible. In this paper we discuss the basic data requirements and use a large business-to-business communication network to demonstrate a number of network measures and theories that have been applied in marketing studies.

Keywords: Network analysis, Marketing relationships, Communication networks

1. Introduction

Whether it is business-to-business, business-to-consumer or consumer-to-consumer, much of marketing revolves around relationships. Creating and fostering supplier and customer relationships, coordinating cross-functional links within an organisation, knowing how competitors are positioned within an industry, and understanding when and to what degree consumers make use of their personal and professional contacts are fundamental issues in the field. Complex issues such as collaboration, trust, power and choice involve more than simple dyadic relationships, most are embedded in networks of relationships.

Since understanding the structure and function of networks, in both business-to-business and consumer markets is essential to marketing (Arabie and Wind 1994; Iacobucci 1996; Wilkinson 2001), it is not surprising that network theories have been readily accepted. Network theories have been applied to a wide range of marketing issues. These areas include: word-of-mouth (WOM) communication (Duhan, Johnson, Wilcox and Harrell 1997; Goldenberg, Libai and Muller 2001), relationship marketing (Achrol 1997; Brodie, Coviello, Brookes and Little 1997; Iacobucci and Ostrom 1996; Mattsson 1997), information acquisition (Moorman and Matulich 1993; Rindfleisch and Moorman 2001), and diffusion and adoption of new products and services (Midgley, Morrison and Roberts 1992; Morrison, Roberts and Midgley 2000; Rogers 1995).

Although there is a substantial literature on network theories, relatively few marketing studies have employed the formal network quantitative techniques that are associated with the theories. While analytic tools are available, texts have been written (Scott 1991; Wasserman and Faust 1994; Wellman and Berkowitz 1997) and computer programs developed (Borgatti, Everett and Freeman 2002; Krackhardt, Blyth and McGrath 1994; Boer, Huisman, Snijders, and Zeggelink 2001), only a few marketing researchers have used them. Notable exceptions include, but are not limited to: Iacobucci, Henderson, Marcati and Chang's (1996) article on brand switching behaviour; Iacobucci and Hopkins' (1992) discussion of network models in marketing; Ronchetto, Hutt and Reingen's (1989) study of organisational buying behaviour. The general avoidance of quantitative network analysis within marketing is most likely due to three factors: 1) the special data requirements needed to perform network analysis, 2) the terminology used to define the network analytic models, and 3) the cumbersome computer programs that were first developed.

In this paper we propose to make network analysis more accessible. We begin with a brief introduction to social network analysis and discuss the basic data formats available, with a large business-to-business communication network as an illustrative example. Next, we review the marketing studies that investigate network theories with formal structural measures. With each network theory discussed, we use one of the latest computer programs, Ucinet 6 (Borgatti, Everett and Freeman 2002), to calculate formal measures for our business-to-business network example. Overall, the purpose of this paper is to stimulate novel directions for marketing research in terms of structural comparisons.

2. The Network Perspective

The focus of network analysis is in understanding how *structural properties* of a network affect behaviour (Wellman 1983). Many marketing studies interested in relationships, however, simply gather information on the characteristics of network members such as network size (e.g., number of strategic alliances), frequency of interaction (e.g., number of times a month information is sought from a personal source), or relationship type (e.g., whether a strong or weak recommendation source is used). Such information is useful but limited in determining how the structure of a network affects network members.

Information on the inter-relationships among network members is required to investigate structural issues. Issues, such as whether decentralised or centralised networks promote trust amongst network members, or how influential are reference groups within dense versus sparse networks, or whether lead-edge users are positioned within the core or on the periphery of networks, call for data on both direct and indirect linkages which provide differential opportunities and constraints for the network members involved. Social network analysis, therefore, investigates quantitative structural properties that cannot be realised from the study of individuals' characteristics or from simple dyadic relationships.

3. Network Data

3.1 Network Elements

Networks consist of members, referred to as *actors*, and their *relationships. Actors* within a network are distinct individuals (e.g., peers within a social group) or collective units (e.g., organisations within a specific industry). *Relational ties* link network members. These linkages may differ in *direction* (symmetric or asymmetric), *valence* (positive, neutral or negative), *strength* (weak, moderate or strong), and *content* (e.g., advice seeking, resource sharing, informal communication and so on).

3.2 Relational Data Matrix

A standard dataset includes a set of informants (the rows of the matrix) and their responses to a set of questions about their attributes in regards to specific issues (the columns of the matrix). The result is an actor-by-attribute matrix. A relational dataset used in network analysis also includes a set of informants (the rows of the matrix), but their responses are to a set of questions about their relationships to specific actors. The result is an actor-by-actor matrix, not an actor-by-attribute matrix.

Typically, relational information is obtained for a single set of actors (e.g., resource sharing among all libraries within Australia). This is referred to as a *one-mode network.* The relational information is entered in a square matrix in which the actors for the rows and columns are the same. Not all relations involve the same set of actors (e.g., buyer/supplier relationships, consumer brand loyalty). In this case relational information is obtained on two different sets of actors, where the actors on the rows differ from the actors on the columns. This type of network is called a *two-mode network.*

The existence of a tie between two actors is entered in a *binary* adjacency relational data matrix as a '1' if present or '0' if absent. For relationships in which *valued* information has been obtained (frequency of interaction, strength, duration, intimacy) a real number is entered. Valued data may be entered as either *similarity* data, where larger numbers in the cells of the matrix represent stronger ties (e.g., duration of the relationship), or *distance* data, which is like a road map where smaller numbers indicate closeness or stronger ties (e.g., rank order from "1", most important, to "5", least important).

Table 1 is an example of an adjacency data matrix for communication flow among 27 Australian laboratories that are early adopters of a particular technology. Reading across the rows shows that Actor 4 reports a communication tie with Actor 25, but note that Actor 25 does not report a communication tie with Actor 4. Since theoretically communication is a mutual relationship, this example brings up concerns of validity and reliability. As with attribute data, data quality issues with relational data must be considered (Marsden 1990). Research has shown that, overall, people are better at reporting their general interactions and typical relationships than they are at reporting specific connections that occur during restricted time periods

Table 1: Communication Network for 27 Early Adopter Laboratories

Actor Labels	4	6	7	8	10	18	20	22	25	26	46	48	64	76	78	106	110	131	140	144	152	170	173	175	177	202	210
4	0	1	0	0	1	0	0	0	1	0	0	1	0	1	1	0	1	0	1	1	1	0	0	0	0	0	0
6	1	0	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
8	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0
10	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0
20	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
46	1	0	0	1	1	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
48	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
64	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
76	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
78	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
106	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
110	1	0	1	0	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
131	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
140	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
144	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
152	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	1
170	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
173	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
175	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
177	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
202	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	1	1	0	0	0	0	0	1
210	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0

(Bernard, Killworth, Kronenfeld and Sailer 1984; Freeman, Romney and Freeman 1987).

3.3 Data Collection

All of the standard data collection techniques of surveys, interviews, observations, experiments, documentary analysis, and diaries can be used to obtain network data. The main difference is in the level of specificity. Relational studies in marketing mostly have asked informants to indicate the *types* of actors with which they have some relation (e.g., When searching for information on holiday destinations, which of the following sources do you use: friends, family, colleagues, and/or professional travel agents?). These studies then analyse the data in the standard way and report categorical findings (e.g., More people use strong tie sources, family and friends, for information concerning holiday destinations than weak ties.). The key to conducting a network study is to elicit information pertaining to the specific relations among explicit actors, not types of actors (e.g., List the initials or first names of all the people you would go to for information on holiday destinations.). Once the specific actors are identified, then additional relational information (e.g., Which of the listed actors are friends of yours? Which have social contact with one another?), as well as attribute information pertaining to each actor can be obtained (e.g., Which actors are male? Which are female?).

Data collection also depends on the focus of the research. Is the goal to explore a single, bounded network in which all actors that have meaningful relationships can be identified (e.g., the diffusion of an innovation among all research laboratories in Australia)? Or is the research concerned with comparing networks among actors involved in separate networks (e.g., Consumers of cosmetic surgery do not necessarily have connections to one another, though a study may investigate to what extent consumers' personal networks influence their decision of which cosmetic surgeon or procedure to choose.)? When the goal is to map the complete network consisting of the relational ties among members of a single bounded community, it is referred to as a *socio-centric* study. Relevant relational data are obtained for each actor in the network. This allows for a complete analysis of the overall network structure as well as a positional analysis for each actor embedded in the network. *Ego-centric* or personal networks are centred on a focal actor (*ego*) and ego's relationships to a set of others (ego's *alters*), plus the relationships among these alters. Without information on the inter-relationships among ego's alters, little structural analysis can be performed as the only information obtained is ego's dyadic ties to a limited number of alters (McCarty 2002).

Informants' verbal reports are by far the most common way to collect relational information. For small (50 actors or less) socio-centric studies *saturation surveys* are used. Relational data are obtained from multiple, if not all, actors within the network. Informants are given some type of recognition task and are asked to identify those with whom s/he has a particular relation (see Weller and Romney 1988 for descriptions of various techniques). The most popular recognition technique is to provide informants with a roster of names of all actors in the network. Each informant then indicates the dyadic ties with whom s/he is connected. This results in a single vector of relational information for each informant. These vectors are then combined to form a square actor-by-actor relational matrix. Data can be obtained by having informants use some type of ranking or rating scale (e.g., full rank order, paired comparisons, triads or likert scales). With the roster method, informants report their ties without considering how other network members are interconnected. To obtain each informants' global perspective of the network, pile sort techniques (Webster 1994) and the Cognitive Social Structure method can be used (Krackhardt 1987).

For relatively large networks (Burt and Ronchi 1994) and for ego-centric networks, recognition tasks are not possible. Instead, informants are asked to recall their specific relations. Two methods of data collection aid in the recall of network ties: *name generators* and *position generators* (for a list of questions and procedures see: Burt 1984; Killworth, McCarty, Bernard, Johnsen, Domini and Shelley 2003; McCallister and Fischer 1978; van der Poel 1993). With name generators, informants are asked to recall actors (e.g., people, organisations, departments or whatever the unit of analysis is) with whom they have a particular relation, such as 'discusses important issues with'. Names also can be used as probes. A name is stated (e.g., Sue or the Red Cross or Accounting) and informants are asked whether they know or have a particular relationship with an actor of that name. With position generators, roles or positions (e.g., doctor, politician, teenager or a charity organisation, a financial institution ...) are used as stimuli and informants are asked whether they have a connection to someone or some organisation in that role.

4. Network Analysis

4.1 Visual Representations: Graphs.

Among the major advantages of network analysis is its use of graph theory. Graphs allow for a visual representation of the structural and relational positions of network members (Freeman 1984; Hage and Harary 1983; Moreno 1953). In a graph network actors are displayed as points (called nodes) and the relations between actors are shown as lines connecting the nodes. When a relation is mutual, the ties between actors are shown with arrows headed at both ends. A relation that is headed by a single arrow indicates a tie directed from one actor to another.

Figure 1 is a graph of the communication network for the 27 Australian laboratories in Table 1. A visual exploration of the network structure quickly reveals that the majority of the communication ties are directed at only six labs: labs 4, 8, 10, 76, 78 and 106. Most of the remaining labs receive fewer than three ties, with five labs – 20, 22, 173, 175, 177 – receiving no reported ties. This suggests a core-periphery structure to the network with certain labs being preferred communication

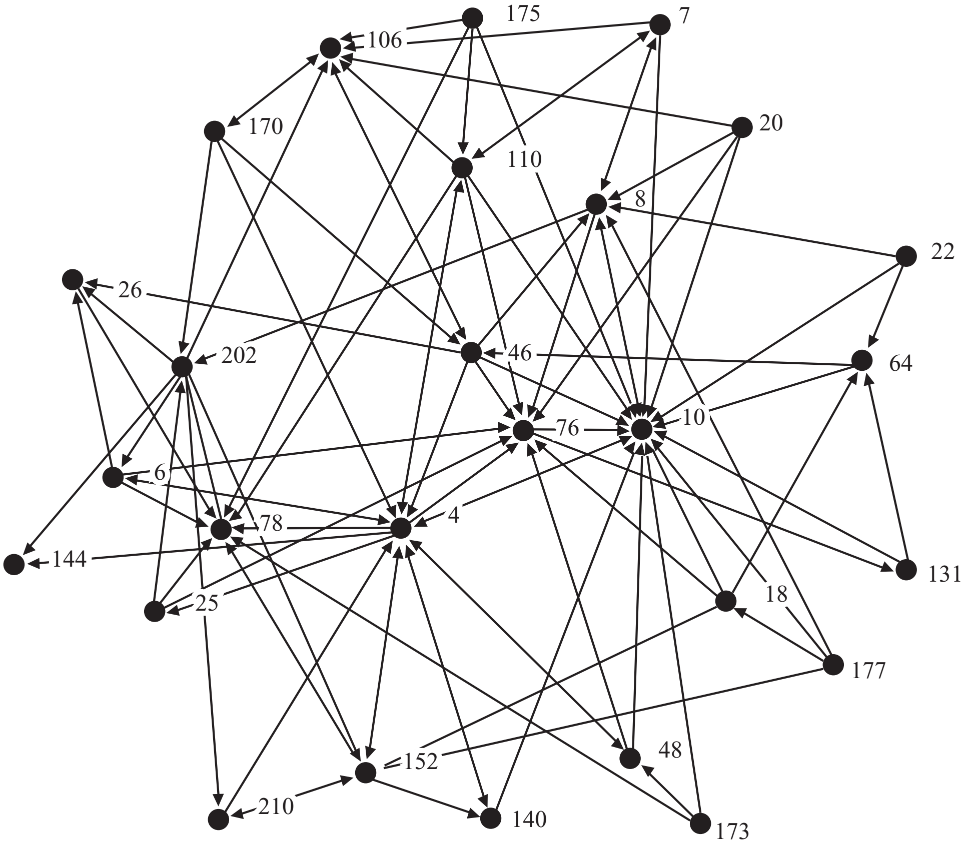

Figure 1: Communication Network for 27 Australian Laboratories

partners or more important to the communication structure than others.

Incorporating attribute information of the actors can reveal further insights. For example, labs 10 and 202 adopted a particular technology much earlier than the other network members. These two labs, however, are not directly connected to one another and are in very different positions within the network. Many labs report a communication tie with lab 10, two of which are mutual, one to lab 8 and one to lab 4. Lab 202 reports seven ties, but none are mutual and only three labs report having a tie to 202. Four labs - 8, 76, 18, and 152 - adopted the technology within three years following the two innovators. Note lab 8 is the only lab that reports having communication ties to both labs 10 and 202. All the others have ties to either 10 or 202, but not both. In the following year labs 4, 110, 25, 177 and 48 adopted the technology. Again, these labs have direct ties to only one of the first adopters, not both. These findings point to a division within the network that possibly stems from the two innovator labs.

4.2 Network Measures

Once a network involves more than twenty actors, it becomes very difficult to adequately analyse the network visually. Quantification is required. Two basic lines of inquiry in network analysis are that of cohesive subgroups and actor positions and roles. Since over 50 network measures exist, we review those that have been used in marketing and discuss the relevant theories. All of the network measures and visual displays are generated by the network software program *Ucinet 6* (Borgatti, Everett and Freeman 2002).

4.2.1 Cohesion and Clustering

Density is the most common measure of network cohesion. It measures the extent to which all possible ties are present for any one network. It is the number of actual ties present divided by the total possible number of ties. Density can be calculated for the entire network as a whole as well as for each actor's personal network. The overall density for the communication network example is 22.79%, indicating a relatively loose-knit network. The density for lab 210's network is 66.67%. Lab 210 has direct ties to labs 4, 152, 202 but the possible tie between labs 4 and 202 is not present. So for lab 210's network there are two ties present (4, 152 and 152, 202) out of a possible three giving a density of 66.67%.

Dense networks are thought to encourage cooperation and collaboration among the actors involved because everyone is directly invested in one another. Along with cooperation comes pressure to conform to established systems and norms. Loose-knit networks benefit actors that choose to operate differently. Cadeaux's (1997) paper on product assortment qualifies this line of thinking. He observed that dense, horizontal networks led to product standardisation, but this in turn enhanced supply diversity. He also cautioned that networks with low densities can be quite rigid and only those actors with sufficient status were able to negotiate their exchange relations.

Network subgroup detection has been of continuing interest in marketing. In an early study Wilkinson (1976) compared two methods of identifying subgroups to explore power and influence relations in distribution channels. Reingen, Foster, Brown and Seidman (1984) found that friendship cliques had a significant impact on brand choice behaviour. *Clique* (Luce and Perry 1949) is a longstanding, robust measure of network subgroups. A clique is a subset of actors who all have direct connections to one another and no additional network member can be added who also has direct connections to everyone in the subset. Due to the strict definition of a clique, typical networks consist of a relatively large

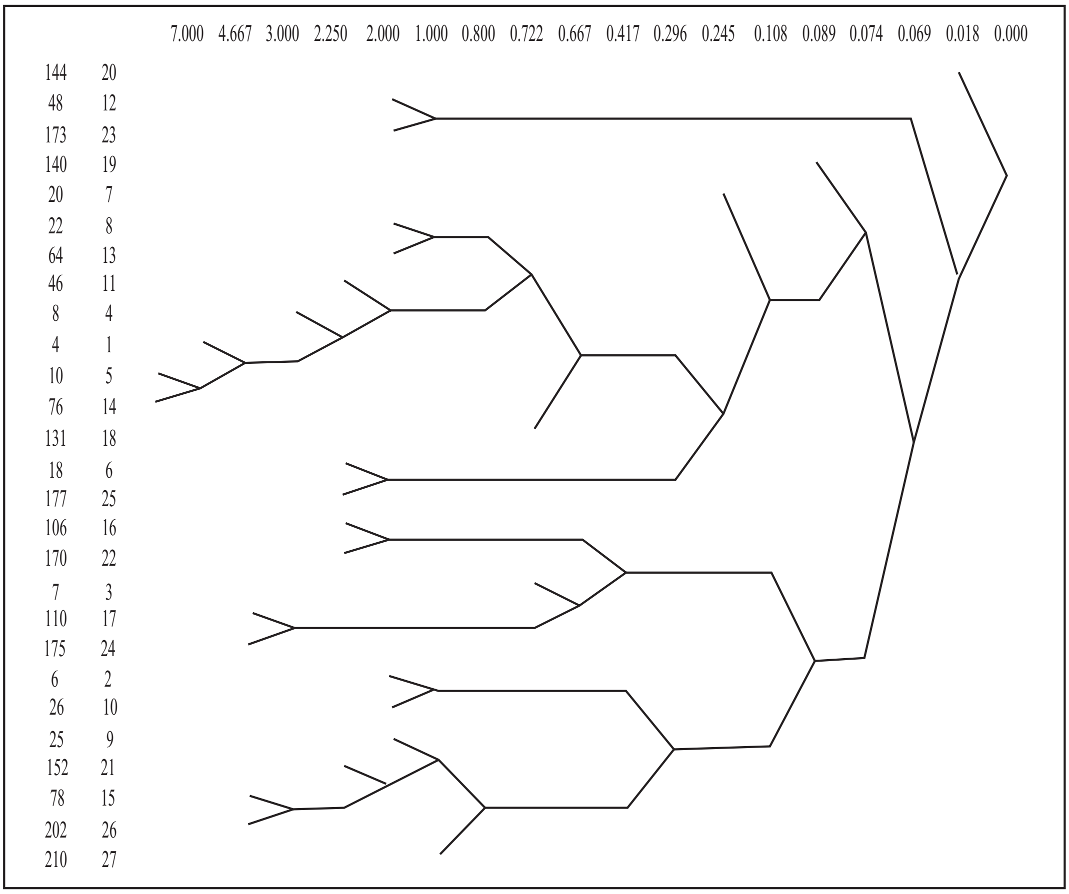

Figure 2: Hierarchical Clustering of Clique Co-membership

number of cliques that are small in size with a fair amount of overlap in membership.

In total 38 cliques are identified in the Australian laboratory communication network. Lab10 is a member of 19 of the 38 cliques while lab 202 is involved in 5 cliques. Note the overlap in the 5 cliques: {C1 = 202, 78, 26, 6; C2 = 202, 78, 25; C3 = 202, 78, 152; C4 = 202, 152, 210; C5 = 202, 106, 170}. A hierarchical clustering of the clique co-membership, shown in Figure 2, reveals the general subgroup structure for the entire network (Freeman 1996). There are clearly two main subgroups, with the two innovator labs located in separate ones.

Probably the best known network theory in marketing, *strength-of-weak-ties* (Granovetter 1973,1983), combines the notions of cohesion and clustering. Strength-of-weak-ties proposes that individual actors within a network tend to gain novel information from their less intimate relationships rather than from their close ties. The reasoning behind this argument is that actors who are strongly connected tend to share their information with one another and hence possess the same knowledge. Since the knowledge within a closely-knit group of actors is homogeneous, new information tends to come from sources with external connections which are likely to be weak. This suggests that weak ties act as "bridges" disseminating novel information from one dense portion of a network to another.

Reingen and colleagues were the first to use formal network measures to test hypotheses related to the *strength of weak ties* theory within a service marketing environment (Brown and Reingen 1987; Reingen and Kernan 1986). In addition to the general support for the strength-of-weak-ties theory, that weak ties advance the flow of information throughout a network by acting as bridges between dense subgroups, they found that strong ties were more numerous and more influential as information sources but were less likely to be actively sought out. Apparently, much of the information from strong ties is gained through everyday, casual interaction not from purposeful search.

Strength-of-weak-ties has been extended further to include the type of information exchanged. Frenzen and Nakamoto's (1993) experimental results showed that individuals tended to allow valued information, that had the potential to provide limited positive benefits, to flow to strong ties only. As information became inexpensive and benefits were permitted to become common, weak ties are developed. Their findings indicate that motivation can moderate the ways in which actors use their personal networks.

4.2.2 Position or Role

Where actors are located in a network can have a large impact on their performance. The notion of centrality has attracted research in marketing for some time. *Centrality* has been equated with popularity, independence, influence, prominence and power (Bonnacich 1987; Freeman 1979; Katz 1953; Taylor 1969). It is thought that actors in highly central positions have access to more resources and typically are able to control the flow of resources, to a large extent, throughout the network. Peripheral actors are vulnerable because they are dependent on only a few ties.

Degree Centrality is the most basic centrality measure and indicates activity level or popularity. It can be calculated for both ties that are incoming, the total number of ties received, and outgoing, total number of ties reported. Czepiel (1974, 1975) used the concept of centrality, measured by the number of ties received, to investigate innovation diffusion and found that centrality was associated with early adoption, although the relationship was not significant. He noted that firm size was associated with both the number of ties received and adoption time, larger firms tended to receive more ties but were later adopters, and recommended the inclusion of both actor and context level characteristics in any network study.

The communication network example (Figure 1) shows lab 10 to be by far the most central with incoming ties, receiving 16, with labs 4, 76 and 78 next, receiving 9 ties. The centrality ranking differs for sent ties with lab 4 most central sending a total of 10 ties, lab 202 next with 7 ties sent and labs 46 and 110 sending 6 ties. Lab 10 reports only 2 communication ties to network members. Clearly lab 10 is the most popular while lab 4 is the most active network member. Pearson correlations of lab size, centrality and time of adoption indicate significant associations for adoption time and centrality with labs that are more central to the communication network adopting earlier (adoption time by incoming ties pearson's $r = -.278$, $p<.05$; outgoing ties pearson's $r = -.280$, $p<.05$). For this example there is no significant relationship between size, with number of full-time employees and budget as proxies, and centrality (employees by incoming ties = .097; by outgoing = .044; budget by incoming = -.081; budget by outgoing = -.121).

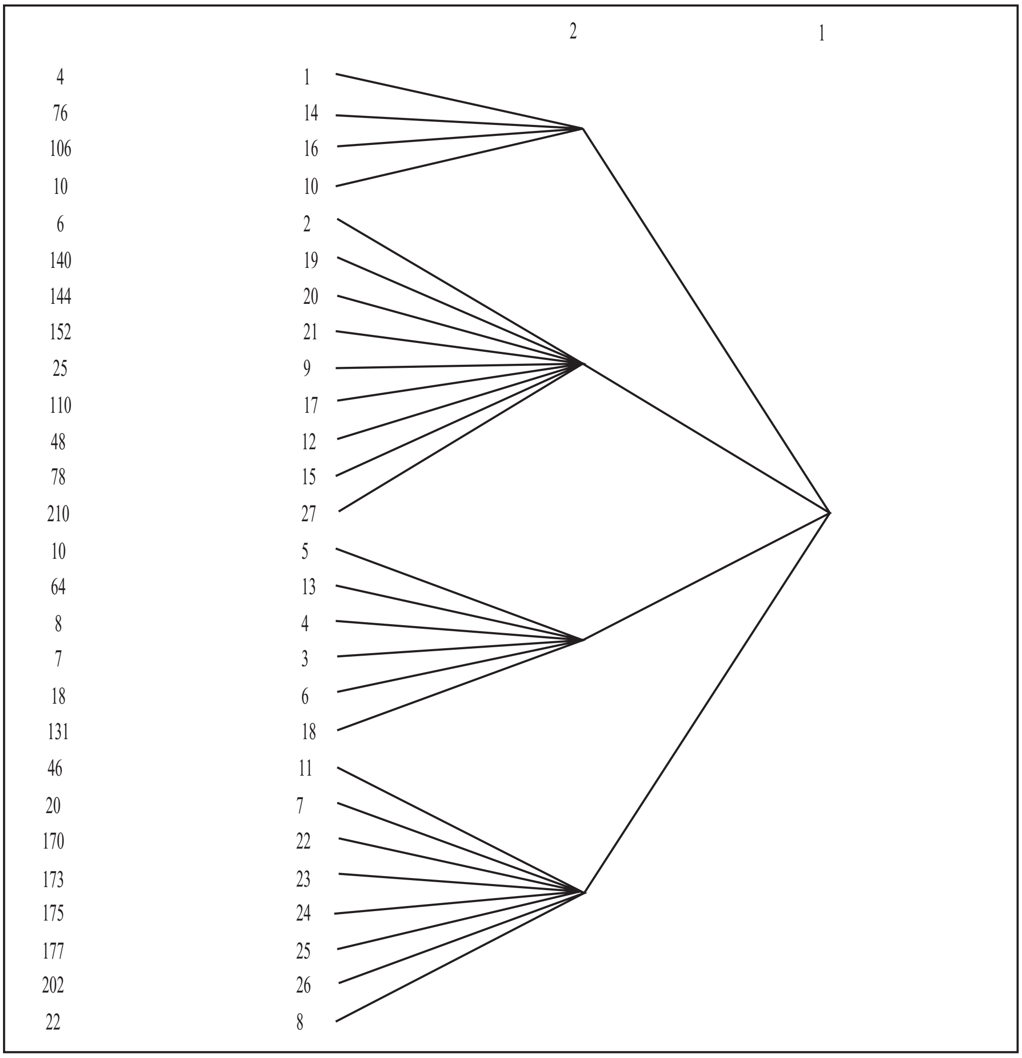

Figure 3: CONCOR Structural Equivalence Results for Incoming Ties

Structural Equivalence (Lorrain and White 1971) is a positional measure that identifies actors whose relations are structured identically. Structurally equivalent actors are substitutable, occupy the same role in the network, not because they are directly connected to one another but because they have exactly the same connections to exactly the same others. Resource exchange does not occur directly, but through accessing the same third parties. An example where we might expect structural equivalence to hold is in highly competitive situations where competitive businesses gain information from the same third party suppliers rather than directly from competitors (Burt 1987).

Ward and Reingen (1990) used CONCOR (Breiger, Boorman and Arabie 1975) to measure structurally equivalent actors in their study of group decision making. CONCOR (based on the CONvergence of iterated CORrelations) places network actors into structurally equivalent sets, or structural roles, based upon the convergence of iterated correlations. Basically the network's relational data are entered as an actor by actor adjacency matrix. CONCOR repeatedly correlates the rows or the columns or both of the data matrix until there is convergence resulting in each entry being a 1 or –1. This matrix is used to divide network actors into two equivalence sets such that members of the same set are positively correlated and members of different equivalence sets are negatively correlated. Subsequent divisions are then applied to the separate sets.

Figure 3 shows the results for the received communication ties using CONCOR. The numbers in the far left column represent the same actors as shown in Figure 1. Four equivalence sets are identified. One of these role sets consists of labs 4, 76, 106 and 26. While these labs are not directly connected to one another, they have received ties from some of the same others, especially labs 6, 46, and 110. Note labs 10 and 202 do not occupy the same network role. Even though they are the two innovators in the network, structurally they are not substitutable because they are connected to different others. This result puts into question the usefulness of structural equivalence as a measure to determine network roles. In their reanalysis of Coleman, Katz and Menzel's (1966) classic *Medical Innovation* data set, van den Bulte and Lilien (2001) incorporate marketing variables along with structural equivalence and conclude that network effects disappear when marketing tactics are taken into account. Their results call attention to the importance of including situational variables in all research.

5. Discussion

Network theories have been widely used in marketing. Although network measures are nonstandard and the collection of network data is demanding, researchers have found network analysis to complement and extend traditional methods. We have reviewed only a few of the available network analytical techniques. Many more exist that have yet to be applied to marketing situations. The marketing studies reviewed have exposed the limitations to taking a purely structural approach. Characteristics of the actors, of the relationships and of the situation all should be considered to ensure a comprehensive investigation is performed.

References

Achrol, R.S., 1997. Changes in the theory of interorganizational relations in marketing: Toward a network paradigm. Journal of the Academy of Marketing Science 25 (1), 56-71.

Arabie, P. and Wind, Y., 1994. Marketing and Social Networks. In Advances in Social Network Analysis, S. Wasserman and Galaskiewicz, J. (Eds.), Sage Publications, Thousand Oaks.

Bernard, H.R., Killworth, P.D., Kronenfeld, D. and Sailer, L., 1984. The problem of informant accuracy: The validity of retrospective data. Annual Review of Anthropology 13, 495-517.

Boer, P., Huisman, M., Snijders, T.A.B., and Zeggelink, E.P.H. 2001. StOCNET: An Open Software System for the Advanced Statistical Analysis of Social Networks, ProGAMMA / ICS, Groningen.

Bonnacich, P., 1987. Power and centrality: A family of measures. American Journal of Sociology 92, 1170-1182.

Borgatti, S.P., Everett, M.G. and Freeman, L.C., 2002. Ucinet for Windows: Software for Social Network Analysis. Analytic Technologies, Harvard.

Breiger R, Boorman, S. and Arabie, P., 1975. An algorithm for clustering relational data, with applications to social network analysis and comparison with multi-dimensional scaling. Journal of Mathematical Psychology 12, 328-383.

Brodie, R.J., Coviello, N.E., Brookes, R.W. and Little, V., 1997. Toward a paradigm shift? An examination of contemporary marketing practices. Journal of Marketing Management 13 (5), 383-406.

Brown, J.J. and Reingen, P.H., 1987. Social ties and word-of-mouth referral behavior. Journal of Consumer Research 4, 350-362.

Burt, R.S., 1984. Network items and the general social science survey. Social Networks 6, 293-339.

Burt, R.S., 1987. Social cohesion and innovation: Cohesion versus social equivalence. American Journal of Sociology 92, 1287-1335.

Burt, R.S. and Ronchi, D., 1994. Measuring a large network quickly. Social Networks 16, 91-135.

Cadeaux, J., 1997. Channel network structure and the product assortment function. Journal of Marketing Channels 6 (2), 17-33.

Coleman, J.S., Katz, E. and Menzel, H., 1966. Medical Innovation: A Diffusion Study, Bobbs-Merrill, Indianapolis.

Czepiel, J.A., 1974. Word of mouth processes in the diffusion of a major technological innovation. Journal of Marketing Research 11, 172-180.

Czepiel, J.A., 1975. Patterns of interorganizational communications and the diffusion of a major technological innovation in a competitive industrial community. Academy of Management Journal 18, 6-24.

Duhan, D.F., Johnson, S.D., Wilcox, J.B., and Harrell, G.D., 1997. Influences on consumer use of word-of-mouth recommendation sources. Journal of the Academy of Marketing Science 25 (4), 283-295.

Freeman, L.C., 1979. Centrality in social networks: Conceptual clarification. Social Networks 1, 215-239.

Freeman, L.C., 1984. Turning a profit from mathematics: The case of social networks. Journal of Mathematical Sociology 10, 343-360.

Freeman, L.C., 1996. Cliques, gallois lattices and the structure of human social groups. Social Networks 18, 173-187.

Freeman, L.C., Romney, A.K., and Freeman, S., 1987. Cognitive structure and informant accuracy. American Anthropologist 89, 310-325.

Frenzen, J. and Nakamoto, K., 1993. Structure, cooperation, and the flow of market information. Journal of Consumer Research 20, 360-375.

Goldenberg, J., Libai, B., and Muller, E., 2001. Talk of the network a complex systems look at the underlying process of word-of-mouth. Marketing Letters 12 (3), 211-223.

Granovetter, M.S., 1973. The strength of weak ties. American Journal of Sociology 78 (6), 1360-1380.

Granovetter, M.S., 1983. The strength of weak ties: A network theory revisited. Sociological Theory 1, 201-233.

Hage, P. and Harary, F., 1983. Structural models in anthropology. Cambridge: Cambridge University Press.

Iacobucci, D., 1996. Networks in Marketing. Sage Publications, Thousand Oaks.

Iacobucci, D., and Ostrom, A., 1996. Commercial and interpersonal relationships: Using the structure of interpersonal relationships to understand individual-to-individual, individual-to-firm, and firm-to-firm relationships in commerce. International Journal of Research in Marketing 13, 53-72.

Iacobucci, D., Henderson, G., Marcati, A. and Chang, J., 1996. Network analyses of brand switching behavior. International Journal of Research in Marketing 13, 415-429.

Iacobucci, D. and Hopkins, N., 1992. Modeling dyadic interactions and networks in marketing. Journal of Marketing Research 29, 5-17.

Katz, L., 1953. A new status index derived from sociometric data analysis. Psychometrika 18, 34-43.

Killworth, P.D., McCarty, C., Bernard, H.R., Johnsen, E.C., Domini, J. and Shelley, G.A., 2003. Two interpretations of reports of knowledge of subpopulation sizes. Social Networks 25, 141-160.

Krackhardt, D., 1987. Cognitive social structures. Social Networks 9, 109-134.

Krackhardt, D., Blyth, J., and McGrath, C., 1994. KrackPlot 3.0: An improved network drawing program. Connections 17 (2) 53-55.

Lorrain, F. and White, H.C., 1971. Structural equivalence of individuals in social networks. Journal of Mathematical Sociology 1, 49-80.

Luce, R.D. and Perry, A.D., 1949. A method of matrix analysis of group structure. Psychometrika 14, 95-116.

Marsden, P.V., 1990. Network data and measurement. Annual Review of Sociology 16, 435-463.

McCallister, L. and Fischer, C., 1978. A procedure for surveying personal networks. Sociological Methods and Research 7, 131-148.

McCarty, C., 2002. Structure in personal networks. Journal of Social Structure 3, 1. Available online at http://zeeb.library.cmu.edu:7850/JoSS/McCarty.htm.

Mattsson, L., 1997. 'Relationship Marketing' and the 'Markets-as-Networks Approach' – A comparative analysis of two evolving streams of research. Journal of Marketing Management 13, 447-461.

Midgley, D.F., Morrison, P.D. and Roberts, J.H., 1992. The effect of network structure in industrial diffusion processes. Research Policy 21 (6), 533-552.

Moreno, J.L., 1953. Who Shall Survive? New York: Beacon House Inc.

Morrison, P.D., Roberts, J.H. and Midgley, D.F., 2000. Opinion leadership amongst leading edge users. Australasian Marketing Journal 8 (1), 5-14.

Moorman, C. and Matulich, E., 1993. A model of consumers' preventive health behaviors: The role of health motivation and health ability. Journal of Consumer Research 20, 208-228.

Reingen, P.H., Foster, B.L., Brown, J.J., and Seidman, S.B., 1984. Brand congruence in interpersonal relations: A social network analysis. Journal of Consumer Research 11, 771-783.

Reingen, P.H. and Kernan, J.B., 1986. Analysis of referral networks in marketing: Methods and illustration. Journal of Marketing Research 23, 370-378.

Rindfleisch, A. and Moorman, C., 2001. The acquisition and utilization of information in new product alliances: A strength-of-ties perspective. Journal of Marketing 65 (2), 1-18.

Rogers, E.M., 1995. Diffusion of Innovations, 4th edition. The Free Press, New York.

Ronchetto, J.R., Hutt. M.D. and Reingen, P.H., 1989. Embedded influence patterns in organizational buying systems. Journal of Marketing 53, 51-62.

Scott, J., 1991. Social Network Analysis: A Handbook. Sage Publications, Newbury Park.

Taylor, M., 1969. Influence structures. Sociometry 32, 490-502.

van den Bulte, C. and Lilien, G.L., 2001. Medical innovation revisited: Social contagion versus marketing effort. American Journal of Sociology 106 (5), 1409-35.

van der Poel, M.G.M., 1993. Delineating personal support networks. Social Networks 15, 49-70.

Ward, J.C. and Reingen, P.H., 1990. Sociocognitive analysis of group decision making among consumers. Journal of Consumer Research 17, 245-262.

Wasserman, S. and Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge.

Webster, C.M., 1994. Data type: A comparison of observational and cognitive measures. Journal of Quantitative Anthropology 4, 313-328.

Weller, S.C. and Romney, A.K., 1988. Systematic Data Collection. Sage, Newbury Park.

Wellman, B., 1983. Network Analysis: Some basic Principles. In R. Collins (Ed.) Sociological Theory. 155-199. Jossey-Bass, San Francisco.

Wellman, B. and Berkowitz, S.D. 1997. Social Structures: A Network Approach. JAI Press, Greenwich, CT.

Wilkinson, I.F., 2001. A history of network and channels thinking in marketing in the 20th Century. Australasian Marketing Journal 9 (2), 23-52.

Wilkinson, I.F., 1976. An Exploration of methodologies for detecting subgroups, subsystems, and cliques of firms in distribution channels. Journal of the Academy of Marketing Science 4 (2), 539-553.

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