The International Center for Research on the Management of Technology

Relational Data in Organizational Settings: An Introductory Note for Using AGNI and Netgraphs to Analyze Nodes, Relationships, Partitions and Boundaries

Varghese P. George
Thomas J. Allen

January, 1993 **WP # 85-93**

Sloan WP# 3526

Sloan School of Management
Massachusetts Institute of Technology
38 Memorial Drive, E56-390
Cambridge, MA 02139-4307

Relational Data in Organizational Settings:

An Introductory Note for Using AGNI* and Netgraphs to Analyze Nodes, Relationships, Partitions and Boundaries

Varghese P. George and Thomas J. Allen

4th January 1993

Individuals have their place in organizations. But, it is the synergy from the interdependence of individuals and groups in organizations that make the whole bigger than its parts. Beyond the obvious, however, any review of scholarly studies on organizations would show that researchers have had, on the whole, a hard time understanding and interpreting the *relational* nature of organizations. Perhaps there is a historic reason for this. Since the publication of "The American Soldier" (Stouffer, 1949) after World War II, in which a large body of data was effectively summarized and communicated to the reader using statistical techniques, survey analysis has become the mainstay of empirical researchers. Over the years, survey research evolved, "possessing its own rules for forming basic concepts, and combining them into meaningful propositions" (Rosenberg, 1968). Unfortunately, the research methods and statistical techniques that have become predominant in this genre are incapable of analyzing relational data.

On the positive side, however, during the same time several network analytic tools (Burt, 1989b; Richards, 1986; Borgatti, Everett, & Freeman, 1992) became available, mostly incorporating graph theoretic or clustering algorithms of various kinds. These tools have become popular among a small set of "network researchers," a handful of whom have been investigating organizational issues. While all these tools have certain algorithmic sophistication, much remains to be done for data management, visualization, ease of export of data (for further statistical analyses), and general user-friendliness. Further, none of them, to our knowledge, allow *user-specified* boundaries or partitions *within* networks, a feature to which, as the reader will notice in the design of the analytic tool described in this paper, the authors of this paper are very partial.

In this paper we describe the features of a network analytic tool, designed and being built to make interpreting relational data easier and more intuitive. We will show you how one would start with a full set of variables that your theory and hypotheses call for, and simply progress through the network and statistical analyses without the back-breaking, life-stopping data manipulations.

REDUCTIONIST VERSUS RELATIONAL APPROACH

A reader relatively new to the field might ask rightly why archetypal statistical procedures would not suffice, and what advantage analysis of relational data would provide. There are simple answers to these questions.

First, if you can avoid relational data, stay away from them. The data are difficult to collect, and usually too large to comfortably manage.[1] Second, if you really need to incorporate relational

*A Graphic Network Interpreter

[1]If you are studying n entities, you have to track $n \times n$ potential relationships and the variables associated with *each* of these. Alternately, as some tools require, you may have to account for *several* $n \times n$ matrices, each representing one type of relationship.

data, try to get away with adequately justifiable reductionist variables.[2] Finally, if your research questions really require relational data, do not hesitate to use them. Archetypal statistical procedures can just about handle dyadic relations, and they have no means of handling triads, tetrads, pentads and beyond. For the latter, we have to roll in network analytic techniques, to summarize each node's relative "position" in a network (in *multiple* ways) or to classify its membership in a "cluster." The algorithms used for such computations are not enormously complicated.

Perhaps the most important thing to bear in mind is that in any sophisticated analysis, in *organizational* contexts, it is becoming increasingly difficult *not* to account for the relational aspect. Examples in organizational research abound. Indeed, while Venkatraman's (1990) "holistic approach" in strategy may be considered as a precursor, in marketing, Iacobucci recently identified the need for full-fledged network models (1992).

RELATIONAL DATA IN ORGANIZATIONAL STUDIES

The use of relational data in *organizational* studies can be found only in certain special niches. One finds *explicit* examples in the research on organizational communication networks (Allen, 1984; Rice, 1984; Rogers & Kincaid, 1981) and on interlocking corporate directorates (Burt, 1982; Mintz & Schwartz, 1981, 1985; Mizruchi & Schwartz, 1987; Pennings, 1980). But beyond these two classes, use of relational data has been modest.[3]

Organizational scholars have considered *implicitly* an extraordinary range relational phenomena ranging from the interaction of technology and markets (Clark, 1985), to competition among firms (Caves, 1980; Porter, 1980, 1985). In the latter case, quite often, singularly relational data (relationships of firms with current and potential competitors, suppliers, buyers and market forces) are forced to fit to the "non-relational" tools and techniques derived from the field of economics of industrial organizations. Curiously though, globalization and cooperation among firms have kindled an interest in relational data and techniques to analyze them. A small number of studies that use them in this context have appeared recently (Barley, Freeman, & Hybels, 1991; Ghoshal & Bartlett, 1990; Nohria & Garcia-Pont, 1991; Powell & Brantley, 1991).

One does not have to turn to scholarly studies to find organizational, relational data. In every day life, the simple organizational chart is perhaps the most visible, and used, relational data. Further, managers also worry about interdependence among "functions," and interdependence across geographical distances, as the example in Figure 1 starkly shows. Tools for encoding, visualizing and analyzing such data have been rather rudimentary. It is this gap that AGNI (A Graphic Network Interpreter) is designed to fill.[4]

The reader is cautioned not to consider this note as a tutorial for network analytic methods, for which one would have to turn elsewhere. We hope to provide an introduction to *AGNI*'s design philosophy and features through this note. Some previous familiarity and appreciation for relational data and phenomena would be helpful. A modest bibliography on network methods is available at the end of this note.

NETWORK ANALYSIS

The conceptual underpinnings of social network analysis go back to Cooley (1902) at the turn of the century. Theoretical focusing was helped along by Simmel (1955). But it was Moreno's research from the early 1930s (Moreno, 1978), which developed into what became known as *sociometry*, that

[2]For example, Roberts reports in his study (1991) of high technology entrepreneurs that the *number* of founders is strongly correlated with the long term success the newly founded companies. The implication, of course, is that, greater the number of founders, larger the resource network for the company, and better the odds for its survivability and success. There was no need to painfully recreate the individual networks of the founders. Reductionism can be efficient and defensible.

[3]This is not to deny that there are several bodies of literature in psychology and sociology that rely heavily on relational data. However, organizational scholars have been slow in embracing the methods, inspite of their obvious applicability.

[4]Though AGNI has been designed principally to handle *organizational* data, it is flexible enough to handle any relational data.

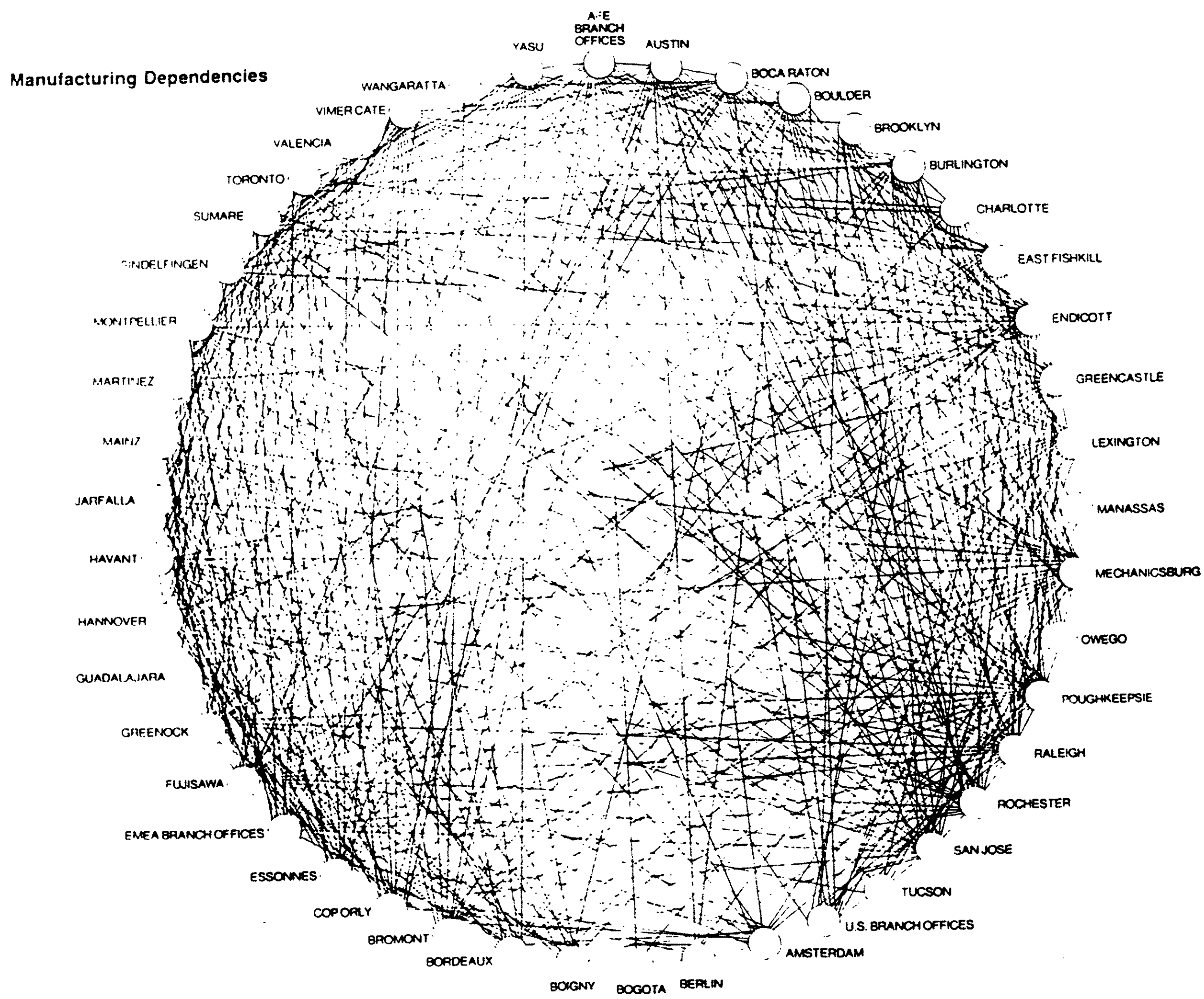


Figure 1: IBM's Manufacturing Interdependencies. (Bhambri, Wilson, & Vancil, 1979).

Note: This is a reproduction of an original company document that graphically shows the extent of interdependencies of IBM's manufacturing plants around the world.

provided the greatest impetus to the formation and the growth of the field known today as network analysis. Harary and colleagues (1965, 1990), and Flament (1963) made substantial contributions by developing the mathematical (graph theoretic) measures that characterize network structure. Several augmented or adapted algorithms for these measures, a few clustering algorithms, and some statistical routines form the bag of tricks for the currently popular analytic tools (Burt, 1989b; Richards, 1986; Borgatti et al., 1992).

It would be impossible to summarize, within the scope of this paper, even the most important measures of network structure. The reader is pointed to some excellent references: (Buckley & Harary, 1990; Burt, Minor, & Associates, 1983; Burt, 1980c, 1982; Harary et al., 1965; Rice & Richards, 1985; Knoke & Kuklinski, 1982; Scott, 1991). We note, however, the consequences of computing these structural measures: (a) each node in the network can be assigned a series of network-based "values" and "memberships" in subgroups (e.g., relative centralities, cliques, etc.), (b) each subgroup, culled from the overall network, can be given "indices," characterizing each one relative to others (e.g., centralizations), and, (c) each relationship can be given network-based "weights" (e.g., path distances). The gist of all these is that the algorithms generate a set of new structural variables that can be used to describe the nodes and relationships, in a network and its sub-networks. Therefore, we can simply roll them back with the other descriptive measures and proceed with further statistical testing. As the reader will find out later, this simple feature, of taking account of the network structure by rolling back the computed network measures, will be extensively and painlessly used in AGNI.

Before we turn to describe the design features of AGNI, let us first examine the network visualization scheme that we have implemented.[5] We use a matrix-based network visualization scheme, described in detail in the next section. The scheme embodies some of AGNI's design philosophy. An understanding of the visualization scheme will be helpful in understanding AGNI itself.

NETGRAPHS FOR NETWORK MATRIX VISUALIZATION

For long, the basic graphical tool for network analysis had been the sociograms, borrowed from Moreno's (1978) sociometry. In the typical sociogram, each node represents a person and the branches from the node represent some form relationship between nodes. Due to the difficulty in generating and understanding large sociograms, this form of analysis has been generally restricted to small social systems. Worse yet, even for such small systems, once the graphic image was achieved it became impossible to understand the relationships in what often resembled a dish of spaghetti. Many a graduate student labored long hours to produce *by hand* these spaghetti-like graphic outputs of somewhat suspect interpretive value.[6]

Alternatively, networks can be graphically represented by their matrices. This is the basic approach that Netgraph has. In its most fundamental form, we convert an adjacency matrix to a graphic grid. On a large square lattice, Netgraphs simply record the 'ones' (that is, the contacts), wherever they appear in the matrix, as minuscule filled ('lit up') tile. In other words, the complete picture will look like a large square grid that is selectively filled in to indicate contacts.[7]

Once you have such diagrams, it is apparent that the information in the images can be enhanced considerably if a capability to permute the rows and columns of adjacency matrix is built into them. The first suggestion, therefore, is to permute the rows and columns of the adjacency matrix based on a key variable (such as a demographic variable, a metric of physical or organizational distance, types of different roles, different cliques, etc.) and to provide boundaries within the Netgraph to visually delineate the 'different values' of the variable.

[5] The reader might know that for a network of any appreciable size, the graph representation on the computer is an intractable problem. Attempts to circumvent this has met with only limited success. New techniques, and relaxation of some of the stringent conditions (e.g., no crossing lines, minimum area, no overlapping nodes, etc.), have succeeded in generating graphs of acceptable visual quality (Marks, 1991b, 1991a; Kosak, Marks, & Shieber, 1991b, 1991a). The computational burden still limits their applicability to small sizes of networks. This also rules out their use in exploratory data anlysis.

[6] Researchers have been severely critical of sociograms (Rogers & Kincaid, 1981; Forsyth & Katz, 1960).

[7] This is the simplest version. Others too have (Burt, 1989a; Rogers & Kincaid, 1981) generated such rudimentary pictures.

To further aid in understanding a network, the adjacency matrix can be 'sorted.' For example, the columns and rows of a communication matrix may be permuted on the basis of the number of individuals with whom any given individual communicates. In other words, the row and column for the lowest communicator is positioned in the upper left hand corner of the Netgraph, the next lowest is assigned the next row and column below and to the right, and so on. Such sorting by number of contacts yields several valuable results. First, it usually brings about an order ('high' to 'low') to the data being presented. Second, it provides a quick visual impression about (degree-based) *relative centralities* and *group centralizations*. Finally, by pulling the high communicators to one corner, it becomes easier to get a visual sense for the *density* of the network as well.

The use of color (or shades of gray) adds a third dimension to the graph. The basic unit of analysis in the graph is a pair (of individuals or organizational units). Pairs can have many characteristics. Characteristics of pairs are derived from corresponding individuals either sharing or not sharing certain characteristics. For example, both members of a pair could be managers or engineers, or one might be a manager, the other an engineer. These three types of a pair can be assigned different colors, thereby showing the different patterns that develop for communication among managers, communication among engineers and communication between the two types.

In Figures 2 and 3, we show how the technique described above can yield useful information. Both the figures are based on the same network.[8] That is, in both cases, the relationships are identical. In Figure 2 we show a "unpermuted" Netgraph. The nodes are arranged in no particular order, and a tile of any shade indicates the *presence* of a relationship. In Figure 3, however, the nodes are permuted to bring together the ones that belong to the same group. Lines are also drawn to delineate the groups. Further, within each group, the nodes are sorted by the number of their relationships (that is, by their *relative centralities*). There are four shades differentiating the relationships: three for relationships within each of the three groups, and one for inter-group relationships. By comparing the two figures, the reader can see how these manipulations have helped display some of the underlying patterns within the network.

It does not take very much imagination to think of many possible applications. One could examine communication patterns at and between different hierarchical levels, among and between different professions (eg. hardware and software engineers) and so on. The analysis is constrained only by the shades of grey or the number of colors available for printing. Further, the third dimension (z) can be used to represent, say, path distances or strengths of ties. Configurations revealed in such diagrams will provide significant insights on second order effects of networks.

In summary, a Netgraph is a pictorial representation of networks that keeps the unit of analysis at the level of each individual (node) while retaining comparative information with regard to all other relevant individuals (nodes). It enables us to understand the structural, demographic and attitudinal influences on networks. It aggregates and delineates data, thereby helping in visually estimating some crucial network parameters. For the same reason, they can also be used in prescriptive modes. And, unlike sociograms, once simply programmed, computers will do *quickly* all the work in generating them, no matter how large the sample.

We turn to comment briefly on internal partitions of networks, of the kind in Figure 3, and on the need to consider them explicitly in organizational settings.

BOUNDARIES AND PARTITIONS OF NETWORKS

Any researcher embarking on network analysis would have surely come across the problem of boundary specification. From their review of sociological literature, Laumann, Marsden and Prensky (1983), developed a typology of boundary specification strategies. Under each of two metatheoretical perspectives, *realist* and *nominalist*,[9] they identify four "definitional foci" used for delimiting actors

[8]For pedagogic reasons, we use simulated data for the examples in this paper.

[9]The reader might find the following excerpt useful to clarify the distinction:

> In the realist approach, the investigator adopts the presumed vantage point of the actors themselves in defining

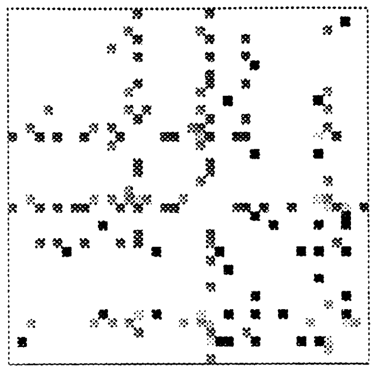


Figure 2: Example of an "Unpermuted" Netgraph

Note: The network represented here is the same as the one in Figure 3. The nodes are arranged in no particular order, and a tile of any shade represents the *presence* of a relationship.

within a network: (a) nodal attributes, (b) relations, (c) participation in event or activity, and (d) multiple foci. Laumann et al. clearly favor a nominalist view and argue that there is "*no sense in which social networks must 'naturally' correspond to social systems.*" (Emphasis theirs.)

Though we fully agree with the above view, we would stress an additional point that is of particular relevance in an organizational context. Just as the "outer" boundary specification has to be undertaken carefully, "inner boundaries" or partitions too have to be carefully specified in analytical strategies. For example, in Figure 4, we present again the same network shown in Figures 2 and 3. The nodes here have been just sorted by degree-based relative centralities. The Netgraph is *not* partitioned. Clearly, network measures attributable to a node will be different for computations based on the *overall* graph and the *sub*graphs. Both types of measures would be useful to describe the network structure, and to understand the effect of these "inner boundaries" or partitions. The latter aspect is of considerable relevance to organizational scholars since boundary spanning is of great practical and theoretical importance (Adams, 1980; Aldrich & Herker, 1977; Ancona, 1990; Taylor & Moghaddam, 1987; Tushman, 1977; Van de Ven & Walker, 1984).

Just as for "outer" boundaries, we favor a nominalist view for the partitions, and believe that algorithmic (cliquing and clustering) disaggregation or partitioning should be left as the last resort, to fall back after strategies for specifying the partitions fail. Next we turn to describing AGNI's

the boundaries of social entitites. That is, the network is treated as social fact only in that it is consciously experienced as such by the actors composing it. . . .

⋮

The second major approach used to define network closure is the nominalist perspective on social reality. Here, an analyst self-consciously imposes a conceptual framework constructed to serve his own analytic purposes. Delineation of network boundaries is analytically relative to the purposes of the investigator, and thus network closure has no ontologically independent status. There is no assumption that reality itself will naturally conform to the analyst's distinction; the perception of reality is assumed to be mediated by the conceptual apparatus of the analyst, be he (or she) an active participant in the social scene under study or an outside observer. . . . (Laumann et al., 1983)

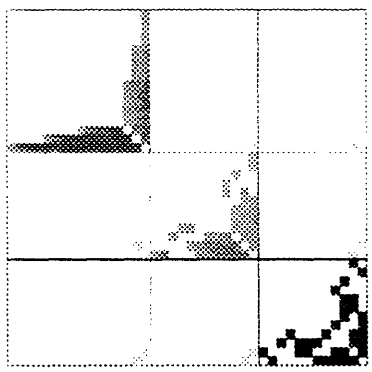


Figure 3: Example of a "Partitioned" Netgraph — After Permuting Nodes, Delineating Groups, and Assigning "Shades" to Relationships

Note: The network represented here is the same as the one in Figure 2. However, the nodes are permuted to bring together the ones that belong to the same group. This essentially "partitions" the graph into three subgraphs, but keeps the information about ties among these subgraphs. Lines are also drawn to delineate the groups. Further, within each group, the nodes are sorted by the number of their relationships (that is, by their *relative centralities*). There are four shades differentiating the relationships: three for relationships within each of the three groups, and one for inter-group relationships. By comparing the two figures, the reader can see how these manipulations have helped display some of the underlying patterns within the network.

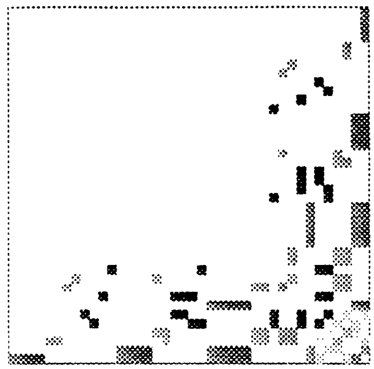


Figure 4: Example of a Netgraph — After Permuting Nodes, *Without* Delineating Groups, and Assigning "Shades" to Relationships

Note: The network represented here is the same as the one in Figures 2 and 3. Within the graph, the nodes are permuted ("sorted") by the number of their relationships (that is, by their *relative centralities*). However, they are *not* permuted to bring together the ones that belong to the same group. That is, the graph is not "partitioned." As before, there are four shades differentiating the relationships: three for relationships within each of the three groups, and one for inter-group relationships. It is easy to see that group "partitions" have a strong influence on the structure of the network, and useful information can be gleaned from structural measures computed on the whole graph as well as the subgraphs.

features.

AGNI — A GRAPHIC NETWORK INTERPRETER

AGNI is a network analytic software currently under development at MIT. A partial prototype is now available for demonstrating the basic features.[10] AGNI's computational module will incorporate a superset of the algorithms available in currently popular social network tools. However, in almost all other features, such as data input/output, user interface, data management and visualization, AGNI is designed to offer considerable enhancements compared to other software of its genre. Even with regard to the implementation of the algorithms, as we suggested in the previous section, there are useful features like the option to carry out simultaneously computations on an entire graph as well as on its partitions.

In Figure 6 we provide a schematic representation of AGNI's features. Brief descriptions about the features follow.

Data Input

AGNI accepts multiple datasets. This permits comparative analysis. Two input files, one for the characteristics of nodes and a second for their relationships, constitute an AGNI dataset. There

[10]AGNI is written in C, with its graphics and user interface using X and Motif. Currently it runs on UNIX machines.

is no restriction on the number of nodes or on the size of the network.[11]

It is important to note that *both* the "nodal" and the "relational" files carry their respective characteristic variables. By carrying the characteristics of relationships as attached variables, AGNI avoids the need to carry around separate matrices, each representing a separate network of a particular *type* of relationship. As shown in Figure 5, the input files principally consist of *columnar* ASCII data. After stripping the header and the trailer, they can be easily fed to any other package.[12] At the top of Figure 5, we show a base dataset with n nodal and k relational characteristic variables. There is also no restriction on the number or type of these variables.

As we saw earlier in the description of Netgraphs, coloring the tiles of a network matrix based on selected variables can be an effective technique in exploratory analysis. But principally, the variables can be used in rigorous network analysis to partition the network and to examine their influence on the network structure.

User Interface

AGNI has a state-of-the-art user interface. A user is stepped through various analytic procedures using appropriate menus, icons, windows for help, and the like. But the most important feature is that any data icon can be used as an "input" to any other basic operation (under data management, algorithms, visualization, etc.), which would result in a new icon. If the new icon is also a data icon (as would result from a data management or algorithmic operation), then it can be used again as an input to further operations. This iterative feature permits an analyst to collect a complete set of desired structural variables, of various kinds, before moving onto statistical analysis.

Data Management

The data management module allows an extensive set of data manipulations. In addition to a complete set of "database" operations, it provides network aggregation routines of various kinds. For example, given a network of relationships among a group *firms*, the module can return a network among the *product classes* (to which the firms belong) by aggregating the links among the firms. This technique can be very useful in various types of research to span levels of analysis.

Visualization

Interactive Netgraphs

In our earlier description of Netgraphs, we showed their *graphical* effectiveness as an exploratory network data analytic tool. As a matter of fact, Netgraphs are more than just graphical tools. A user can query, for example, after placing the mouse-cursor on a selected tile, for the details of a particular relationship. Alternately, a user can also ask the Netgraph to identify selected nodes' relationships.

Exploratory Data Analysis

AGNI will also have a set EDA tools (histograms, stem and leaf plots, etc.) that would permit the user to quickly plot the distributions of variables.

Algorithms

As we suggested before, AGNI's graph theoretic algorithms are implemented with same design philosophy as its visualization technique. Numerical parameters are computable simultaneously on the complete network as well as on its partitions. This feature allows the user to analyze the influence of selected internal boundaries. When completed, AGNI will have a superset of the most

---

[11] If a user ends up excessively taxing the resources of a given machine, AGNI can be moved up and recompiled on a more powerful machine. In our experience so far, AGNI has been fully portable.

[12] The header and the trailer are needed just to tell AGNI which is the nodal data and which the relational.

used algorithms. Algorithms currently in place, under development, and being planned are shown in Table 1.

Table 1: Algorithms For AGNI

Class	Type	References
Currently implemented		
Centrality	In-degree Out-degree In- and out-degree	Freeman (1979). Burt et al. (1983). Burt et al. (1983). Burt et al. (1983).
	Geodesics betweenness Information	Freeman (1979). For shortest paths: Cormen, Leiserson, and Rivest (1990). Stephenson and Zelen (1989). For matrix inversion: Press, Flannery, Teukolsky, and Vetterling (1988).
	Eccentricity Connectivity Closeness Prominence	Buckley and Harary (1990). For breadth-first search: Cormen et al. (1990). Burt et al. (1983). For breadth-first search: Cormen et al. (1990). Freeman (1979). For breadth-first search: Cormen et al. (1990). Burt et al. (1983). For breadth-first search: Cormen et al. (1990).
	Eigenvector centrality Reflected centrality Derived centrality	Mizruchi, Mariolis, Schwartz, and Mintz (1986). For eigenvector computations: Strang (1988). Mizruchi et al. (1986). Mizruchi et al. (1986).
	Power	Bonacich (1987). For matrix inversion: Press et al. (1988).
Distance	Breadth-first search Euclidean distance Manhattan distance Ordinal distance	Cormen et al. (1990). Strang (1988). Strang (1988). Derived from "location" variables of network nodes.
Under development		
Centrality	Group based Flow betweenness	Bonacich (1991). For eigenvector computations: Strang (1988). Freeman, Borgatti, and White (1991). For flow computations: Cormen et al. (1990).
Cliques	Maximal clique "All Cliques"	Buckley and Harary (1990). Reingold, Nievergelt, and Deo (1977).
To be developed		
Centrality	For non-binary data	See under currently implemented algorithms for centrality.
Distance	Shortest paths for non-binary data	Cormen et al. (1990).
Positional Analysis	Hierarchical and non-hierarchical methods: fuzzy clustering, multidimensional scaling, concor, linkage methods, centroid partitioning, blockmodeling, etc.	Burt (1982). Burt (1984). Burt (1980c). Burt (1980b). Burt (1977a). (Burt, 1977b). (Burt, 1976). (Burt, 1980a). Burt (1988b). Burt (1982). Burt (1988a). (Burt, 1979). Aldenderfer and Blashfield (1984). Kaufman and Rousseeuw (1990). Trauwaert (1988). Breiger, Boorman, and Arabie (1975). Etc.
Cliques	Complexes, clubs, clans	Seidman and Foster (1978). Mokken (1979).

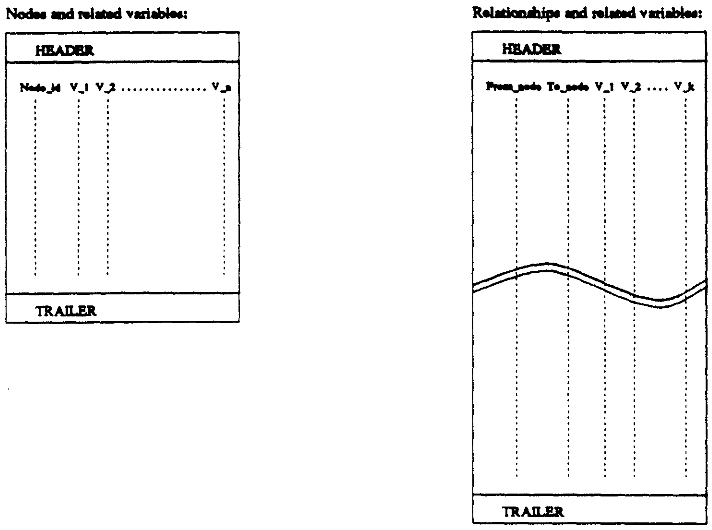
In addition to the set of sophisticated algorithms referred to above, AGNI also computes several types of simple 'counts' and 'densities.' For example, 'number of partners' at the node-level inside and outside partitions, as well as intra- and inter-group 'densities' can be computed. As the reader might agree, these straightforward statistics are sometimes more helpful for exploring the patterns of a network than the results of some of the complicated algorithms.

At the bottom of Figure 5, we show what happens *automatically* after AGNI has been asked to carry out selected algorithms. We see that additional p "nodal" and q "relational" structural variables, generated by the algorithms, get appended to the side of the original dataset. The new dataset can be subjected to further analysis by AGNI, or moved over for statistical analyses external to it.

Data Output

Data output from AGNI takes various forms. From Netgraphs come Postscript files that can be merged with most types of documents. After data manipulations and computations, new AGNI datasets or ASCII columnar files for other packages can be generated. AGNI is also designed to have a direct seamless link to the statistical package S, so that a user, with access to S, can continue with statistical analyses without intermediate data handling.

Basic structure of AGNI's ASCII input files:



The dataset after "network" parameters computed by AGNI's algorithms have been added:

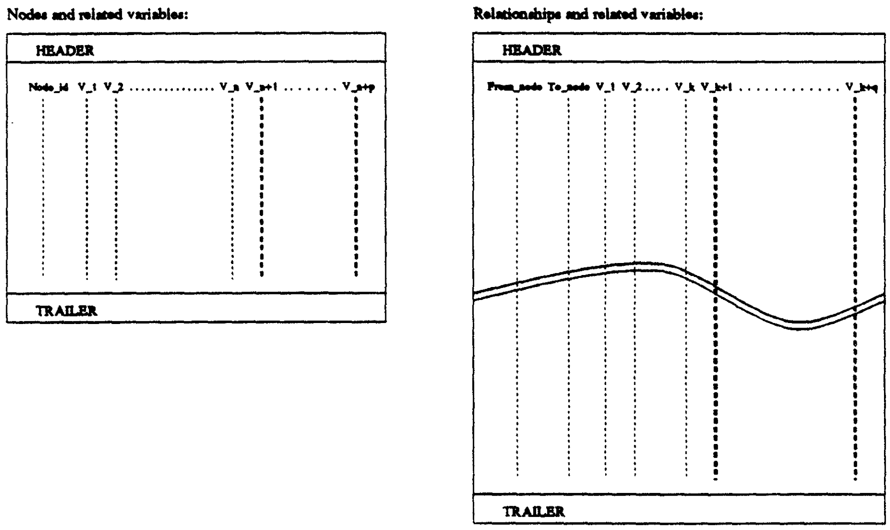


Figure 5: AGNI's Input File Structure and Rolling Back of Network Parameters

Note: AGNI's input files consist of *columnar* ASCII data that can be easily fed to any other package after stripping the header and the trailer. The header and the trailer are needed just to distinguish between the "nodal" and "relational" data. At the top, we show a base dataset with n nodal and k relational variables. There is no restriction on the number and type of these variables. At the bottom, we show what happens *automatically* after AGNI has been asked to carry out chosen algorithms. We see additional p "nodal" and q "relational" structural variables that are generated by the algorithms. The new dataset can be subjected to further analysis by AGNI, or moved over for statistical analyses external to it.

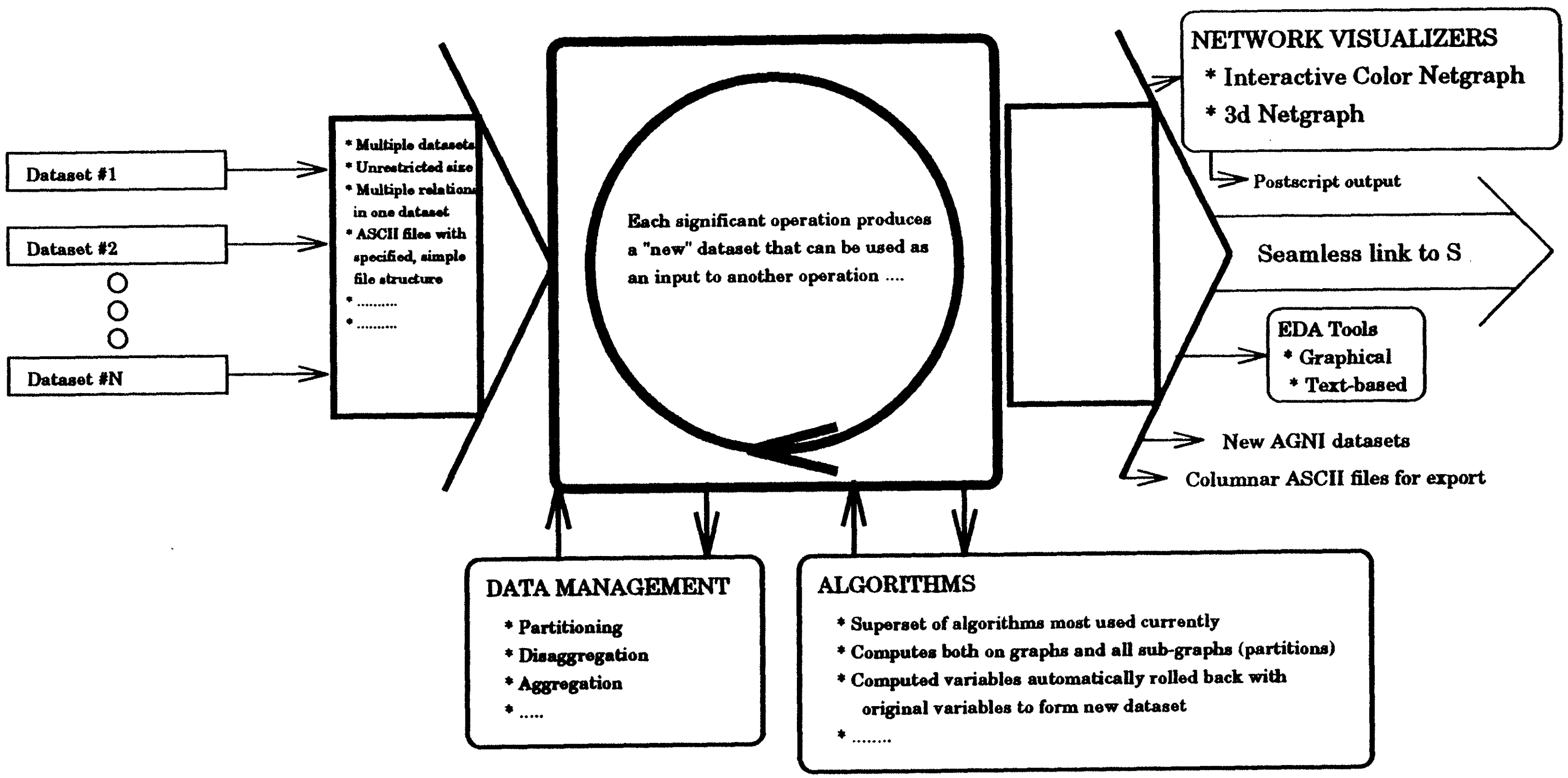


Figure 6: A Graphic Network Interpreter (AGNI) — A Schematic Diagram

REFERENCE

Adams, J. S. (1980). Interorganizational Processes and Organizational Boundary Activities. In Staw, B. M., & Cummings, L. L. (Eds.), *Research in Organizational Behavior*. Greenwich:JAI Press Inc.

Aldenderfer, M. S., & Blashfield, R. K. (1984). *Cluster Analysis*. London: Sage Publications.

Aldrich, H., & Herker, D. (1977). Boundary spanning roles and organization structure. *Academy of Management Review*, *2*(2).

Allen, T. J. (1984). *Managing the Flow of Technology*. Cambridge, MA: The MIT Press.

Ancona, D. G. (1990). Outward bound: Strategies for team survival in an organization. *Academy of Management Journal*, *33*(2), 334–365.

Barley, S. R., Freeman, J., & Hybels, R. C. (1991). Strategic alliances in commercial biotechnology. Unpublished manuscript.

Bhambri, A., Wilson, J. L., & Vancil, R. F. (1979). IBM Corporation: Backround Note. Harvard Business School, Published by the President and Fellows of Harvard College. # 180-034.

Bonacich, P. (1987). Power and centrality: A family of measures. *American journal of sociology*, *92*, 1170–1182.

Bonacich, P. (1991). Simultaneous group and individual centralities. *Social networks*, *13*, 155–168.

Borgatti, S., Everett, M., & Freeman, L. (1992). *UCINET IV Version 1.0*. Columbia: Analytic Technologies.

Breiger, R. L., Boorman, S. A., & Arabie, P. (1975). An algorithm for clustering relational data with applications to social network analysis and comparison with mutlidimensional scaling. *Journal of mathematical psychology*, *12*, 323–383.

Buckley, F., & Harary, F. (1990). *Distance in graphs*. Addison-Wesley Publishing Company.

Burt, R. S. (1976). Positions in networks. *Social Forces*, *6*, 93–122.

Burt, R. S. (1977a). Positions in multiple network systems, part one: a general conception of stratification and prestige in a system of actors cast as a social topology. *Social Forces*, *6*, 106–131.

Burt, R. S. (1977b). Positions in multiple network systems, part two: stratification and prestige among elite decision makers in the community of altneustadt. *Social Forces*, *56*, 551–575.

Burt, R. S. (1978/1979). Stratification and prestige among elite experts in methodological and mathematical sociology circa 1975. *Social networks*, *1*, 105–158.

Burt, R. S. (1980a). Cooptive corporate actor networks: A reconsideration of interlocking directorates involving american manufacturing. *Administrative Science Quarterly*, *25*, 557–582.

Burt, R. S. (1980b). Innovations as a structural interest: Rethinking the impact of network position on innovation adoption. *Social Networks*, *2*, 327–355.

Burt, R. S. (1980c). Models of network stucture. *Annual Review of Sociology*, *6*, 79–141.

Burt, R. S. (1982). *Toward a structural theory of action: Network models of social structure, perception, and action*. New York: Academic Press.

Burt, R. S. (1984). Network items and the general social survey. *Social Networks*, *6*, 293–339.

Burt, R. S. (1988a). Some properties of structural equivalence measures derived from sociometric choice data. *Social networks, 10*, 1–28.

Burt, R. S. (1988b). The stability of american markets. *American Journal of Sociology, 94*(2), 356–395.

Burt, R. S. (1989a). *Structure Assistant, Version 2.0*. Research Program in Structural Analysis, Center for the Social Sciences, Columbia University.

Burt, R. S. (1989b). *Structure, Version 4.1*. Research Program in Structural Analysis, Center for the Social Sciences, Columbia University.

Burt, R. S., Minor, M. J., & Associates (1983). *Applied Network Analysis*. Newbury Park, CA: SAGE Publications.

Caves, R. E. (1980). Industrial organization, corporate strategy and structure. *Journal of Economic Literature, XVIII*, 64–92.

Clark, K. B. (1985). The interaction of design hierarchies and market concepts in technological evolution. *Research Policy, 14*.

Cooley, C. H. (1902). *Human Nature and the Social Order*. Republished by Schocken Books in 1964.

Cormen, T. H., Leiserson, C. E., & Rivest, R. L. (1990). *Introduction to Algorithms*. The MIT Press and McGraw-Hill.

Flament, C. (1963). *Applications of Graph Theory to Group Structure*. Prentice Hall.

Forsyth, E., & Katz, L. (1960). A Matrix Approach to Analysis of Sociometric Data: Preliminary Report. In Moreno, J., et al. (Eds.), *The Sociometry Reader*. The Free Press.

Freeman, L. C. (1979). Centrality in social networks: I. conceptual clarification. *Social networks, 1*, 215–239.

Freeman, L. C., Borgatti, S. P., & White, D. R. (1991). Centrality in valued graphs: A measure of betweenness based on network flow. *Social networks, 13*, 141–154.

Ghoshal, S., & Bartlett, C. A. (1990). The multinational corporation as an interorganizational network. *Academy of Management Review, 15*(4), 603–625.

Harary, F., Norman, R. Z., & Cartwright, D. (1965). *Structural Models: An Introduction to the Theory of Directed Graphs*. John Wiley & Sons, Inc.

Iacobucci, D., & Hopkins, N. (1992). Modeling dyadic interactions and networks in marketing. *Journal of Marketing Research, XXIX*, 5–17.

Kaufman, L., & Rousseeuw, P. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. New York: Wiley.

Knoke, D., & Kuklinski, J. H. (1982). Network Analysis. Series: Quantitative applications in the social sciences 28, SAGE Publications, Inc.

Kosak, C., Marks, J., & Shieber, S. (1991a). New approaches to automating network-diagram layout. Tech. rep. TR-22-91, Center For Research In Computing Technology: Harvard University.

Kosak, C., Marks, J., & Shieber, S. (1991b). A parallel genetic algorithm for network-diagram layout. In Kaufmann, M. (Ed.), *Proceedings of the Fourgh International Conference on Genetic Algorithms*, pp. 458–465. San Diego, California.

Laumann, E. O., Marsden, P. V., & Prensky, D. (1983). *Applied network analysis*, chap. The boundary specification problem in network analysis.

Marks, J. (1991a). The competence of an automated graphic designer. In *Proceedings of the 1991 Long Island Conference on Artificial Intelligence and Computer Graphics*, pp. 52–61. NYIT,New York.

Marks, J. (1991b). A formal specification scheme for network diagrams that facilitates automated designs. *Journal of Visual Languages and Computing*, *2*, 395–414.

Mintz, B., & Schwartz, M. (1981). Interlocking directorates and interest group formation. *American Sociological Review*, *46*, 851–869.

Mintz, B., & Schwartz, M. (1985). *The Power and Structure of American Business*. Chicago, IL: The University of Chicago Press.

Mizruchi, M. S., Mariolis, P., Schwartz, M., & Mintz, B. (1986). *Sociological methodology*, chap. Techniques for disaggregating centrality scores in social networks. Washington, D.C.: American Sociological Association.

Mizruchi, M. S., & Schwartz, M. (Eds.). (1987). *Intercorporate Relations: The Structural Analysis of Business*. New York, NY: Cambridge University Press.

Mokken, R. J. (1979). Cliques, clubs, and clans. *Quality an quantity*, *13*, 161–173.

Moreno, M.D., J. (1978). *Who Shall Survive? Foundations of Sociometry, Group Psychotherapy and Sociodrama*. Beacon House Inc.

Nohria, N., & Garcia-Pont, C. (1991). Global strategic linkages and industry structure. *Strategic Management Journal*, *12*, 105–124.

Pennings, J. M. (1980). *Interlocking Directorates: Origin and Consequences of Conections Among Organizations' Boards of Directors*. Jossey-Bass Publishers.

Porter, M. E. (1980). *Competitive strategy: Techniques for analyzing industries and competitors*. New York: Free Press.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. New York: Free Press and London: Collier Macmillan.

Powell, W. W., & Brantley, P. (1991). Competitive cooperation in biotechnology: Learning through networks?. Unpublished manuscript.

Press, W., Flannery, B., Teukolsky, S., & Vetterling, W. (1988). *Numerical Recipies in C*. Cambridge University Press.

Reingold, E. M., Nievergelt, J., & Deo, N. (1977). *Combinatorial Algorithms: Theory and Practice*. Prentice-Hall.

Rice, R. E. (1984). *The New media: Communication, research, and technology*. Beverly Hills: Sage Publications.

Rice, R. E., & Richards, W. D. (1985). An Overview of Network Analysis Methods and Programs. In Dervin, B., & Voight, M. J. (Eds.), *Progress in Communication Sciences*. ABLEX Publishing Corporation.

Richards, W. D. (1986). *The NEGOPY Network Analysis Program*. Laboratory for Computer and Communications Research, Simon Fraser University, Burnaby, B.C. Canada.

Roberts, E. B. (1991). *Entrepreneurs in high technology: lessons from M.I.T. and beyond.* New York: Oxford University Press.

Rogers, E. M., & Kincaid, D. L. (1981). *Communication Networks: Toward a New Paradigm for Research*. New York: The Free Press.

Rosenberg, M. (1968). *The Logic of Survey Analysis*. New York: Basic Books.

Scott, J. (1991). *Social Network Analysis: A Handbook*. London: Sage Publications.

Seidman, S. B., & Foster, B. L. (1978). A graph-theoretic generalization of the clique concept. *Journal of mathematical sociology*, *6*, 139–154.

Simmel, G. (1955). *Conflict and the Web of Group-Affiliations*. Free Press of Glencoe. Translated by Kurt H. Wolff and Reinhard Bendix.

Stephenson, K., & Zelen, M. (1989). Rethinking centrality: Methods and examples. *Social networks*, *11*, 1–37.

Stouffer, S. A. (1949). *The American Soldier*. Princeton: Princeton University Press.

Strang, G. (1988). *Linear Algebra and its Applications*. Harcourt Brace Jovanovich.

Taylor, D. M., & Moghaddam, F. M. (1987). *Theories of Intergroup Relations*. Praeger.

Trauwaert, E. (1988). On the meaning of dunn's partition coefficient for fuzzy clusters. *Fuzzy Sets and Systems*, *?*, 217–238.

Tushman, M. (1977). Special boundary roles in the innovation process. *Administrative Services Quarterly*, *22*.

Van de Ven, A. H., & Walker, G. (1984). The dynamics of interorganizational coordination. *Administrative Science Quarterly*, *29*, 598–621.

Venkatraman, N., & Prescott, J. E. (1990). Environment strategy coalignment: An empirical test of its performance implications. *Strategic Management Journal*, *11*, 1–23.