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Graphical Techniques for Exploring Social Network Data

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Social network analysts study the structural patterning of the ties that link social actors. For the most part, they seek to uncover two kinds of patterns: (1) those that reveal subsets of actors that are organized into cohesive social groups, and (2) those that reveal subsets of actors that occupy equivalent social positions, or roles.

To uncover patterns of those kinds, network analysts collect and examine data on actor-to-actor ties. Such data record who is connected to whom and/or how closely they are connected. Typically, the data are organized into square, N-dimensional, N-by-N matrices where the N rows and the **N** columns both refer to the social actors being studied. Cell entries in these matrices indicate either the presence/absence or the strength of some social relationship linking the row actor to the column actor. In the present discussion, we will deal only with symmetric relationships where, given a connection from actor i to actor j, actor j is also connected to i in the same way.

Network analysts sometimes use standard statistical procedures in examining their actor-by-actor matrices. And there are several statistical modeling tools that have been developed specifically for network data (Holland and Leinhardt, 1981; Wasserman and Pattison, 1996). But these tools were designed primarily for testing hypotheses. They do not provide a simple direct way to explore the patterning of network data—one that will permit an investigator to “see” groups and positions.

The aim of the present paper is to introduce and illustrate such an exploratory device. In the next section, I will show some ways to create visual images that can be used to display the kinds of structure of interest to network analysts. Then, following that, I will show how those images can be adapted to help to uncover both the antecedents and the consequences of observed network structure.

Visual Images

Jacob Moreno (1932, 1934) was the first to use visual images to display the patterning of linkages among social actors. In Moreno' s images, each actor was represented by a point, and each link was shown by a line connecting a pair of points. One of his earliest images (Moreno 1932, p. 101) is reproduced as Figure 1. He characterized that image as showing "a group in which two dominating individuals are strongly united both directly and indirectly through other individuals." Thus, Moreno viewed that picture as a display of both cohesiveness ("strongly united") and social roles ("dominating individuals").

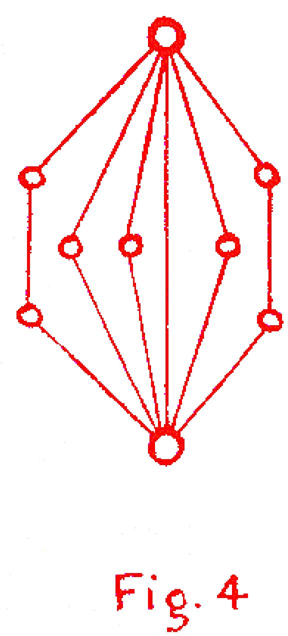

Figure 1. Moreno's Early Image

In this early work Moreno demonstrated “that variations in the locations of points could be used to stress important structural patterns in the data” (Freeman, 2000). Figure 2, for example, shows his image of friendship choices among fourth graders (Moreno 1934, p. 38). There he used triangles to designate boys, and circles to designate girls. He also used directed lines with arrowheads to show which child was the chooser and which the chosen. The important point, however, is that in order to stress the enormous tendency for children of that age to generate same-gender choices, Moreno located all the boys on the left of the picture and all the girls on the right.

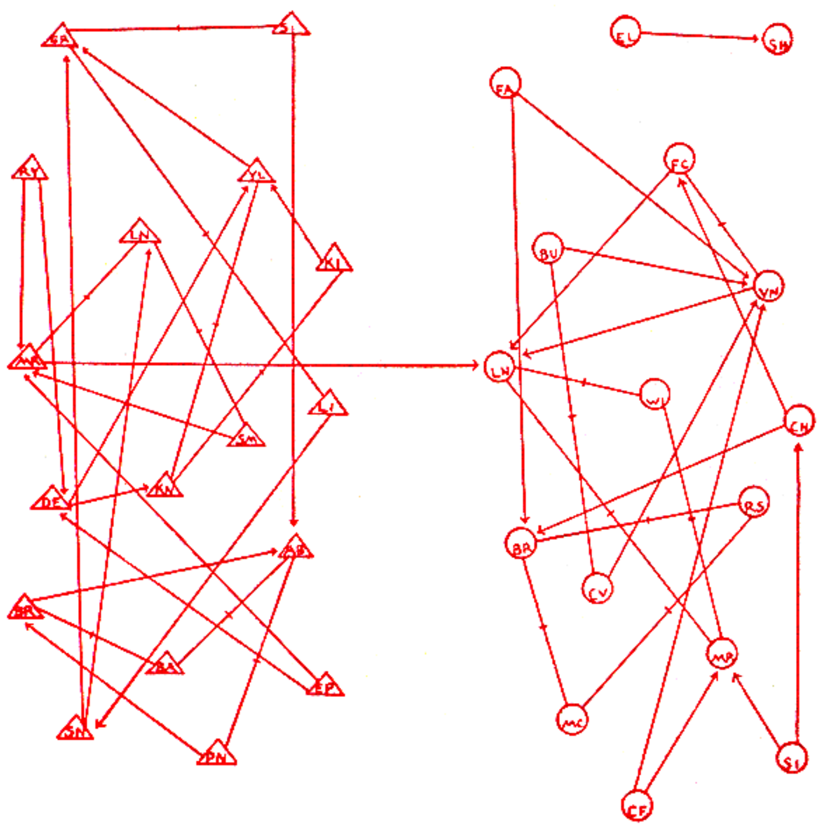

Figure 2. Moreno’s Image of Fourth Grade Friendship Choices

Moreno developed a great many procedures for arranging points that succeeded in emphasizing the structural features of the data that he wanted to stress. But those procedures were all essentially *ad hoc*. Moreno did not introduce any systematic general procedure for locating points in images. Instead, he developed different procedures—each tailored to the demands of each new data set. In any particular image, the placement of points depended on the point Moreno wanted to make about a particular data set.

Later analysts continue to use visual images and they continue to develop procedures for placing points in ways designed to reveal structural patterning. But a central aim of this newer work has been to develop *principled* procedures—procedures that are specified in exact terms and that will produce the same results when they are applied again and again or by

Most of this newer work embodies a fundamental assumption. It assumes that a display of a social pattern should preserve the pattern. Thus, the points in a visual image should be located in such a way that the observed strengths of the inter-actor ties are preserved. Those pairs that are socially closest in the observed data should be spatially closest in the graphic image. And those pairs that are the most socially remote in the data should be the farthest apart in the image.

This aim raises a non-trivial problem. I indicated above that network data come in the form an ***N***-by-***N*** matrix of observed social proximities. Such a matrix is ***N***-dimensional. That is, each social actor in the data set is at some specified closeness or social proximity to every actor in the set. We can assume that the actors are all closest to themselves. And an actor's proximity to each of the ***N***-1 other actors will take some smaller numeric value, based on reports, or observations. Thus, it is clear that each actor is assigned a score on each of ***N*** variables, and each of these scores specifies an inter- or intra-actor social proximity.

In general, then, to specify all these proximities exactly, we need to use ***N*** dimensions—as many as there are actors. But, if we are dealing with more than three actors, this might raise a problem. We can actually view a picture of spatial proximities in a collection of points only if they are arrayed in one-, two-, or three-dimensions. So, in order to create a visual display, we need a way of simplifying the social proximities recorded in the data—of reducing its dimensionality. What we are seeking, therefore, is some systematic procedure that will specify a location for each point in a picture with no more than three dimensions. Moreover, the pattern of spatial proximities of the points in that picture must reflect, as closely as possible, the pattern of social proximities of the actors in the original ***N***-dimensional data matrix.

Two main approaches are used to construct such images. The first is based in a search algorithm. It is called *multidimensional scaling*, *smallest space analysis* or *spring embedding*. These are simply variations on a common approach. They are simply variations on a common theme. So, here I will lump them all together and refer to them simply as multidimensional scaling (MDS).

MDS requires that the investigator specify a desired dimensionality—typically, one, two or three. Then, given that specified number of dimensions, MDS uses a search procedure to try to find optimal locations at which to place the points. Optimal locations are either (1) those that come closest to reproducing the pattern of the original ***N***-dimensional social proximities contained in the data matrix (metric MDS), or (2) those that come closest to reproducing the order, but not necessarily the exact magnitudes, of the original proximities (non-metric MDS).

A number of different procedures have been developed to search for optimal locations for points (Krempel, 1999). And there are several ways to evaluate how closely the pattern of a given set of MDS proximities corresponds to the pattern of proximities in the original data matrix (Kruskal and Wish, 1978)[i]. But all of the MDS procedures share a general approach; all involve a search for an optimal arrangement.

The second approach is determinate. It is based on an algebraic procedure, *singular value decomposition* (SVD)[ii]. SVD transforms the ***N*** original variables into ***N*** new variables, or dimensions. These new dimensions are ordered from largest to smallest in terms how much of the variance, or patterning, in the original data is associated with each. The most variance is always associated with the first dimension. Each succeeding dimension is, in turn, associated with progressively less of the variance.

If a one, two or three dimensional visual image is going to be useful, the hope is that the first two or three of these new dimensions will be associated with virtually all of the variance contained in the original data (Weller and Romney, 1990). If, in contrast, the first few dimensions are associated with very little of the original variance, SVD will not yield useful results.

As was the case with MDS, there are several ways of getting SVD solutions. SVD itself is always calculated the same way, but there are differences in the ways the data are pre-processed before SVD is run. One standard pre-processor removes the effects of differences in the sizes of the row and column totals. When that approach is taken, the results are said to be produced by *correspondence analysis*. Another pre-processor—perhaps the best known one—removes the effects of differences in means and the variances in rows and columns. When that is done, the results are described as produced by *principal components analysis*.

The Search for Structure

In every case, whether we use MDS or SVD to explore data, the first problem will always be to determine whether the data embody any interesting patterning at all. To examine this question, I will draw upon a data set collected on a beach by Freeman, Freeman and Michaelson (1988). We asked 43 regular beach goers to sort cards naming beach people into piles in terms of who was socially close to whom. These sorts were used to produce a matrix in which each cell contained a tally of the number of times the row person had been grouped together with the column person. This matrix of judged social proximities was used as input to MDS and the two-dimensional image reproduced in Figure 3 was produced.

The arrangement of points in Figure 3 divides most of the points into two fairly dense clusters on the right and the left. Each of these clusters has core members located near the center of the cluster. And each has peripheral points that surround the core. In addition, several points (27, 30, 32, 40 and 43) fall in the center, between the two main clusters. Thus, this image seems to display social groups as clusters. Moreover, it places individuals in core and peripheral positions within each group, and it suggests that some actors occupy “bridging” positions between the two groups. This arrangement is completely consistent with the ethnographic data and the systematic observations originally reported by Freeman, Freeman and Michaelson.

Beyond shape, another feature of this MDS output is important. Most MDS programs report an index of “stress.” Higher values of stress indicate that the proximities calculated by MDS do not correspond very well to the original ***N***-dimensional proximities. In this case, the stress = .17. This is reasonable for a 43 by 43 data matrix.

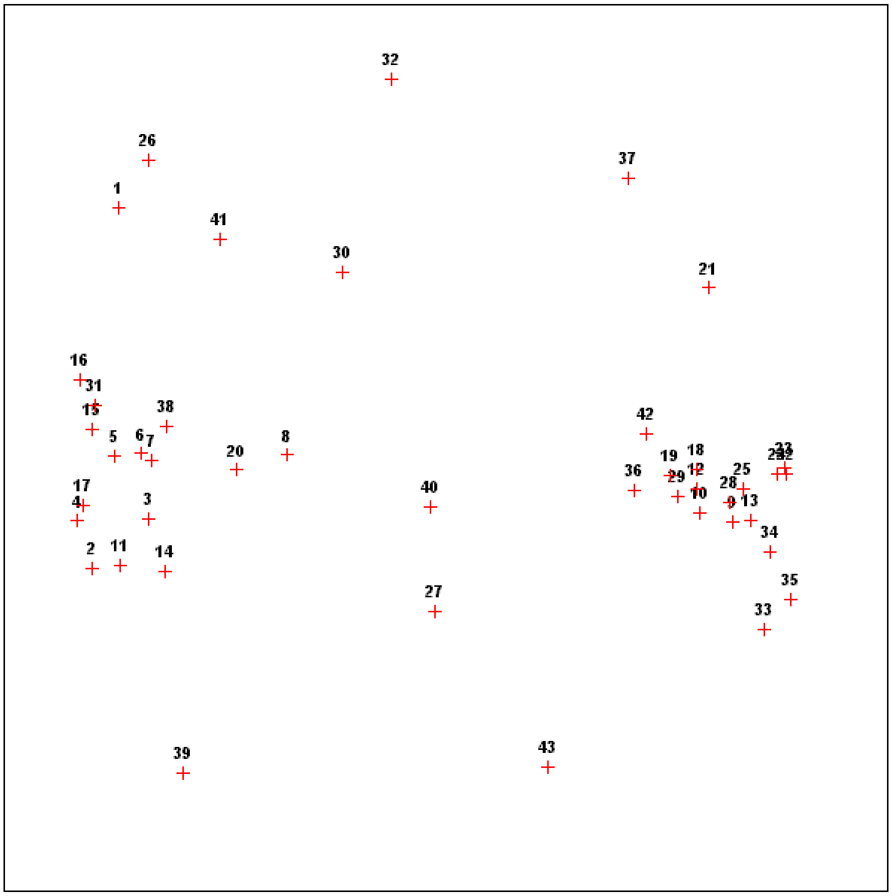

Figure 3. MDS of Freeman, Freeman and Michaelson's Beach Data

Now let us compare that image with one in which there is no systematic social patterning. We can construct such an image from the data that produced Figure 3. We first remove all the entries from the 43 by 43 data matrix and save them. Then we return each of these frequencies to a randomly chosen cell—preserving symmetry. The result is a new matrix in which the overall distribution of cell entries is identical to that of the original data. But in this new matrix actors are paired at random.

The result of applying MDS to this new matrix is shown in Figure 4. There, the points form into an almost circular disk. This shape is critical. Generally, any MDS image that is shaped like a disk in two dimensions or a sphere in three, suggests that the links are unpatterned. Moreover, the stress index is .36. This high value confirms that there is little of patterning here.

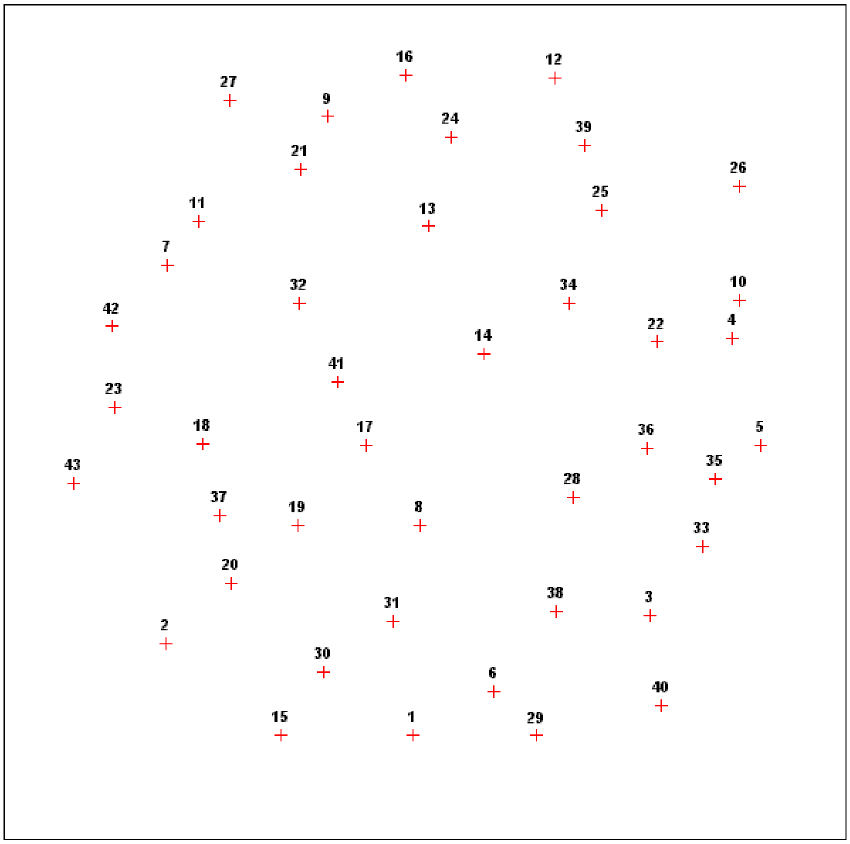

Figure 4. MDS of Randomized Data

SVD can be applied to the same data—with similar results. See, for example, the image in Figure 5. The same beach data that produced Figure 3 were used to produce Figure 5. They were preprocessed (using correlations) to remove the effects of differences in means and variances. Then they were processed using SVD. The result is called principle components analysis.

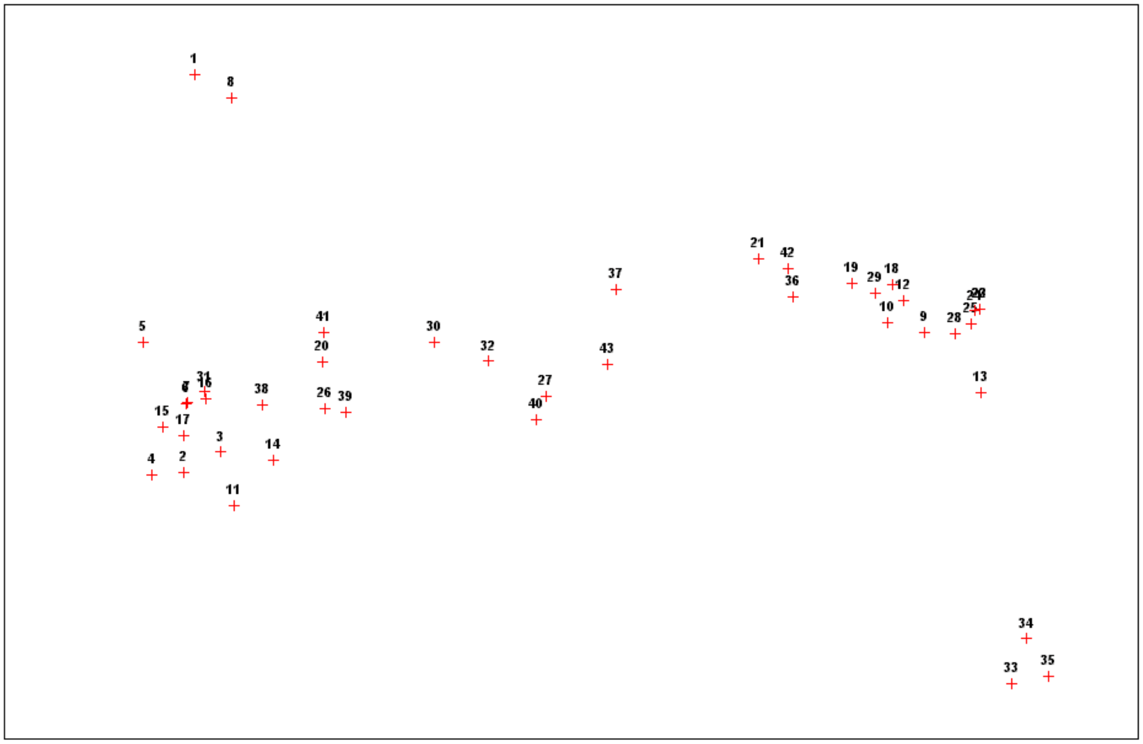

Figure 5. SVD of the Beach Data Using Principle Components

This SVD image of the beach data yields an even more dramatic display of the two main groups of beach goers. Core and peripheral group members are still shown, as are the bridging members. Note that which actors are clustered together and which are pulled apart is consistent with the MDS image.

The proportion of variance associated with the first two dimensions here provides further evidence that structure is present. For these data, the first two dimensions are associated with 36% of the variance. This is a substantial proportion. Clearly, SVD has captured the structure in these data.

When the random data are entered into SVD we again see a disk-like pattern. This time the pattern is somewhat more irregular than the one produced by MDS, but it is still essentially an amorphous disk. And, in the present case, somewhat less than 11% of the total variance is displayed in the two dimensions shown in the figure. This is a relatively small proportion and, because it is so small, it provides further evidence that the image contains little important structural information.

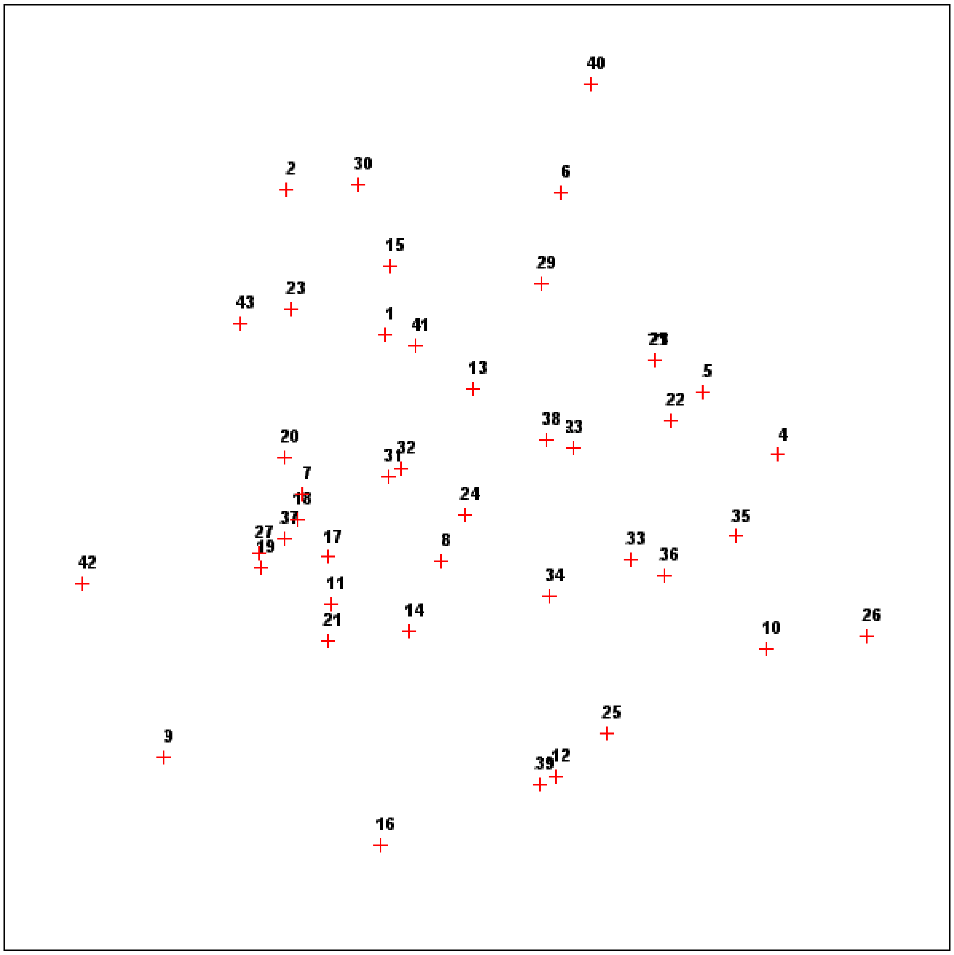

Figure 6. SVD of the Randomized Beach Data

Thus, in the general case—using either MDS or SVD—it is relatively simple to determine whether a data set has, or does not have interesting structural properties. If the plot produces an image that is shaped like a disk or a globe, it is generally not interesting from a structural perspective. But, to the degree that it departs from these forms, it displays important structural properties. This approach, then, can be used for the first step in the exploratory analysis of network data.

Finding Correlates of Structural Patterns

When we uncover a data set that has an interesting structural form, we are just beginning. We are simply ready for the next step in exploratory analysis. The really interesting questions involve finding the antecedents and the consequences of observed structural patterns.

The basic approach I will use to finding these features is not new. Bock and Husain (1952) used it to show how a class of ninth graders chose partners for an assignment. They asked each of the 16 members of a ninth grade class to rank all of the others in terms of their desirability as collaborators on a joint research project. Then they calculated principle components and produced the image shown in Figure 7.

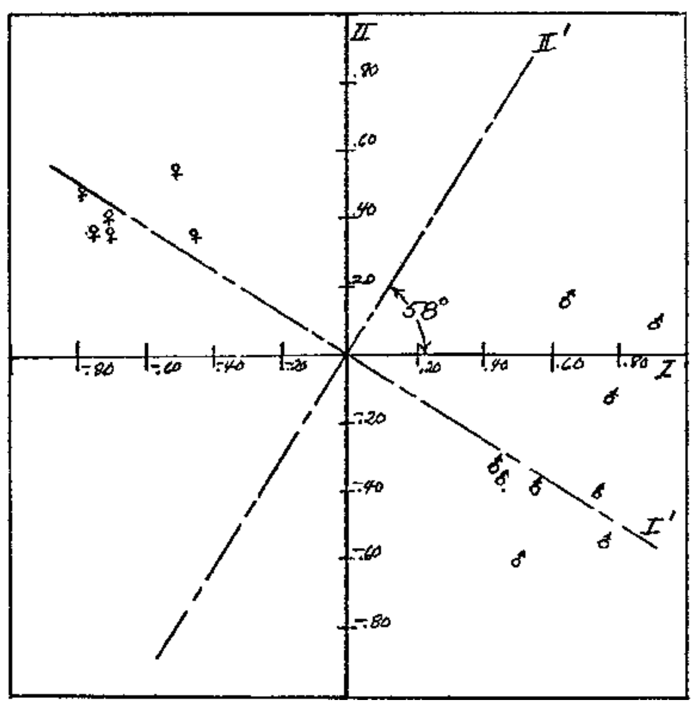

Figure 7. Bock and Husain's Ninth Graders

Bock and Husain plotted the student's partner choices in two dimensions. Moreover, they used gender symbols to emphasize the differences between the choices made by females and those made by males. In this case, the males and females formed distinct clusters in which males chose other males and females, other females. The point of the labeling was to call attention to the fact that the main basis for partner choice was gender.

In the 1950s this device of identifying subsets of points in a structural display according to the various characteristics of the actors involved was difficult. It involved manually specifying the locations of points, hiring a draftsman and photographically reproducing the final drawing for printing.

Today, the whole process has been simplified with the use of personal computers. Using standard computer programs we can automatically produce images that call attention to particular subsets of points by assigning distinct symbols or colors to identify them. In the work described below I have used a program called MAGE (Richardson and Richardson, 1992).[iii] It is excellent for exploratory work in social network analysis (Freeman, Webster and Kirke, 1998). Like the picture produced by Bock and Husain, images produced by MAGE can be used to communicate findings in published reports.[iv] But, more important, they can be generated with such ease that investigators can use them for exploratory work. Images in which subsets of points are identified can be used to explore the impact of any number of external variables on a structural pattern.

In the next three sections, I will show how MAGE has been used to explore these questions. These sections will illustrate three applications of visual analysis. They will show how graphic techniques can help in: (1) pure exploratory research, (2) examining an *a priori* hunch and (3) validating a model. Finally, in the last section I will illustrate another approach. There I will show how animation can be used to generate new *post hoc* structural insights.

Exploratory Research

One of my students, Marbella Canales, worked in the cosmetics department of an upscale department store. She asked each of her fellow employees to list any of the others with whom she or he spent leisure time. This produced a binary, on/off, matrix of social links. That matrix was used to calculate the lengths of the shortest paths—from actor, through social link, to actor, through link, etc.—linking each pair of employees. Those distances were entered into the MDS program. And a three-dimensional MDS produced the arrangement shown in Figure 8.

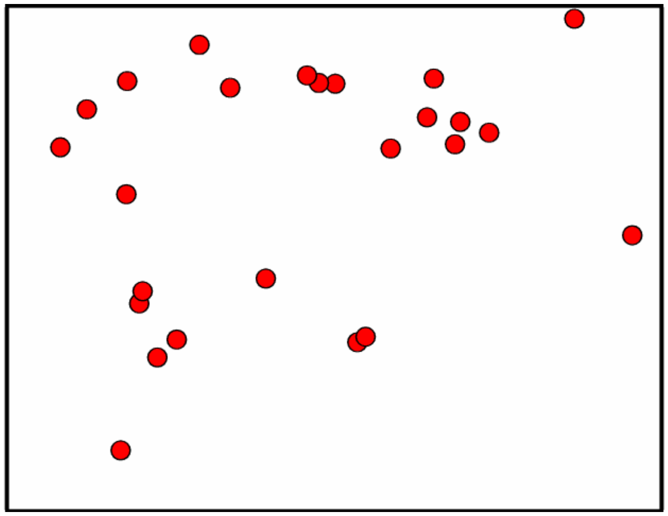

Figure 8. MDS of Department Store Data

Figure 8 is not a disk. It shows that patterning is present in these data. That patterning is even more evident when we add the actor-to-actor ties reported by the employees. See Figure 9. There the pattern of linkages forms a horseshoe shape. This is commonly seen in MDS; it indicates that the actors are laid out into an almost-linear string.

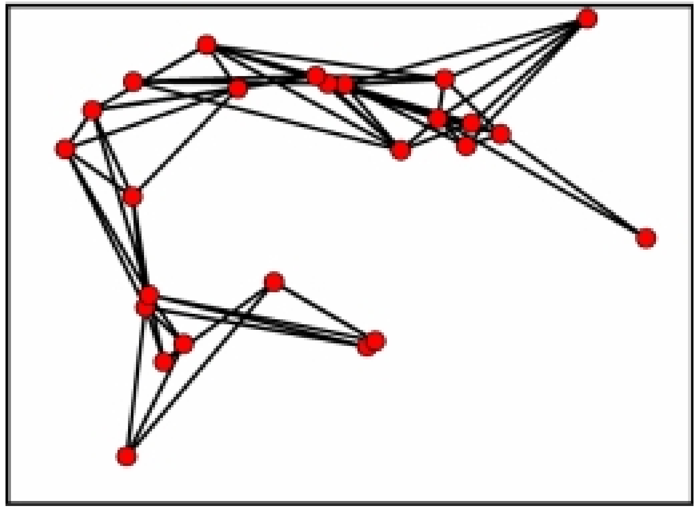

Figure 9. MDS of Department Store Data Showing Ties

Canales had collected the usual sociological "face sheet" data from her co-workers. She was interested in the degree to which age, gender, ethnicity and so on might be entailed in the choices of partners for leisure time interaction. To answer these questions, she colored points in the display so that she could pinpoint the locations of actors who possessed particular attributes. In Figure 10, for example, all the actors who had middle-eastern ethnic backgrounds were colored blue. Clearly, the blue points are distributed all over the figure, and partner choices are not based on that ethnic factor.

The same was true for other ethnicities. In Figure 11, the two employees with Asian backgrounds are shown in green. They are widely separated. Marital status seems also to have had no effect. In Figure 12 married actors are colored yellow. And they too turn out to be widely separated in the image.

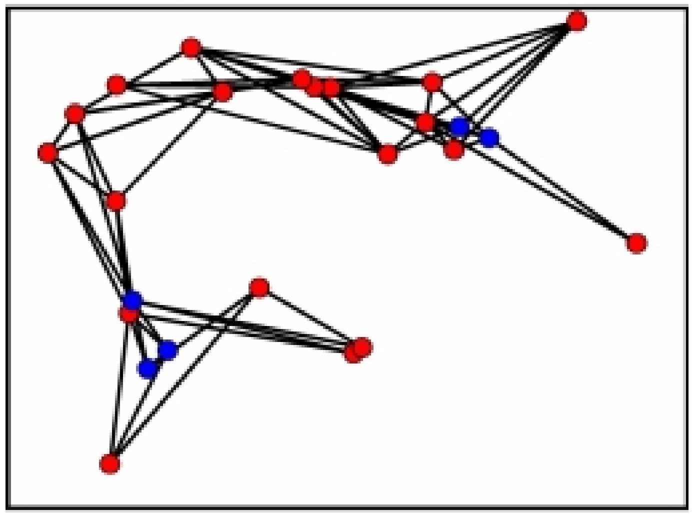

Figure 10. MDS of Department Store Data Showing Actors with Middle-Eastern Ethnic Backgrounds

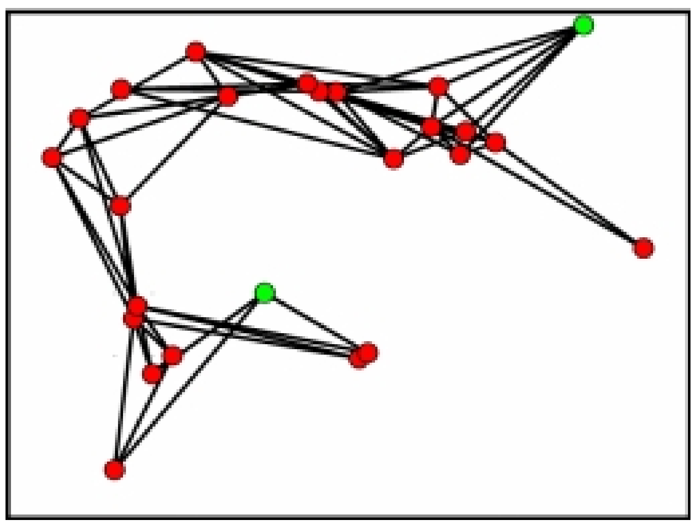

Figure 11. MDS of Department Store Data Showing Actors with Asian Backgrounds

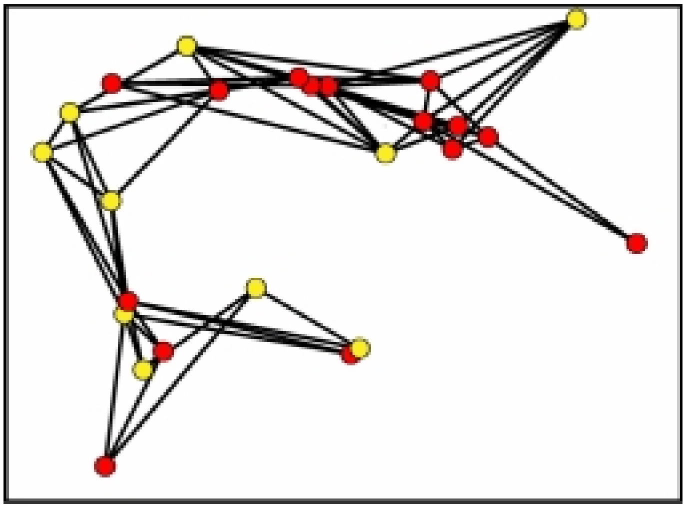

Figure 12. MDS of Department Store Data Showing Married Actors

Age, however, turned out to be important. In Figure 13, those actors who were aged 30 or less are blue, those more than 30 but 40 or less are yellow and those more than 40 are red. These three categories are distinctly separated in the image. Thus, age turns out to be one characteristic that is important to these individuals when it comes to choosing partners for interaction. It was the only face-sheet variable to display a systematic patterning. Using strictly visual techniques, then, Canales was able to discover an important correlate of interaction among her coworkers.

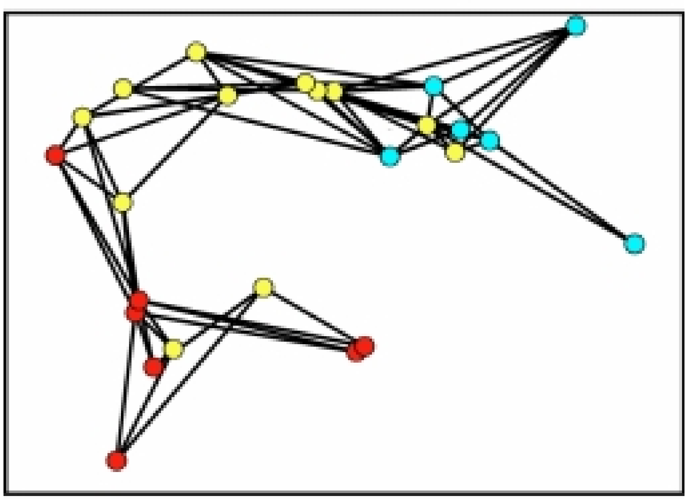

Figure 13. MDS of Department Store Data Showing Actors' Age Grades

Examining an *a priori* Hunch

Another of my students, Laticia Oseguera, was a collegiate basketball star. She had an intuitive idea that athletes would confide in their teammates more or less according whether theirs was a team sport like basketball or an individual sport like tennis. Co-participants in individual sports, she thought, would be more willing to confide in teammates.

Oseguera collected data among 191 athletes in thirteen sports at her university. All members of the men's and women's basketball teams, the men's and women's soccer teams, the men's water polo team, the women's volleyball team, the men's and women's tennis teams, the men's and women's track teams, the men's and women's swimming teams, and the men's golf team were surveyed. Each was asked to name any other athletes with whom he or she had discussed important personal problems. Then the resulting matrix was used as input for the principal components version of SVD. The two-dimensional result is shown in Figure 14.

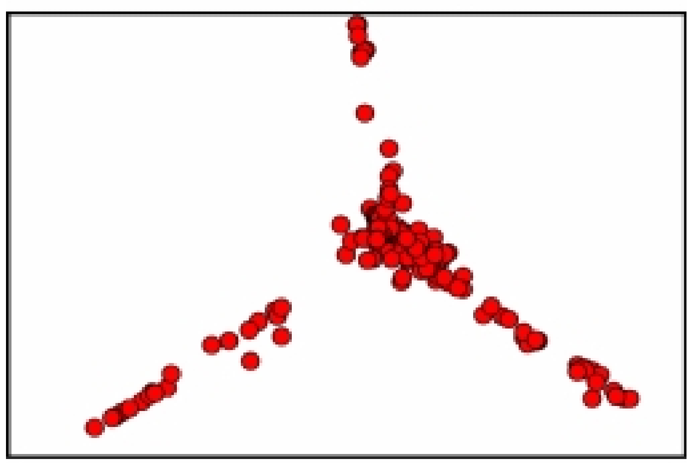

Figure 14. SVD of Athletes

Although there is a somewhat globe-like clump in the center, the three long arms show a dramatic structural patterning in this data set. Athletes on these arms chose one another along the arm; those near the center were apparently less exclusive. If Oseguera's idea is correct athletes from all the individual sports should fall along the arms and the team-sport athletes should cluster near the middle of the image. She explored this notion by coloring individuals in terms of their sport.

In Figure 15, members of the men's tennis team are colored blue. Tennis is an individual sport and their position at the extreme periphery suggests that Oseguera's idea was correct for them. Most of their confidants are fellow tennis players, but they are also adjacent to another cluster of athletes with whom they apparently sometimes communicate.

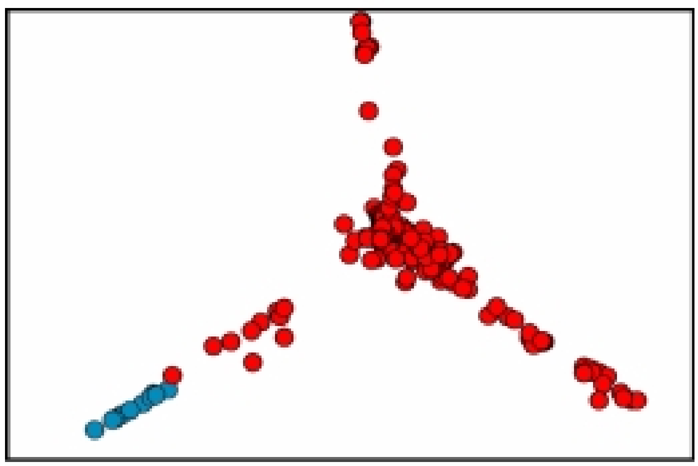

Figure 15. SVD of Athletes; Male Tennis Players are Blue

That other collection is colored yellow in Figure 16. They turn out to be members of the female tennis team. Like their male counterparts, they are involved in an individual sport, and they are peripheral. Among the tennis players, the women are not as peripheral as the men, but they are still distinctly separated from the main body of athletes. This provides further support for Oseguera's idea.

But the really interesting feature here is that the female tennis players are in a position where they bridge between their male tennis counterparts and the rest of the athletes. Certainly their bridging position is consistent with the observation that women usually provide the links between otherwise unconnected social networks (Bernard, 19**).

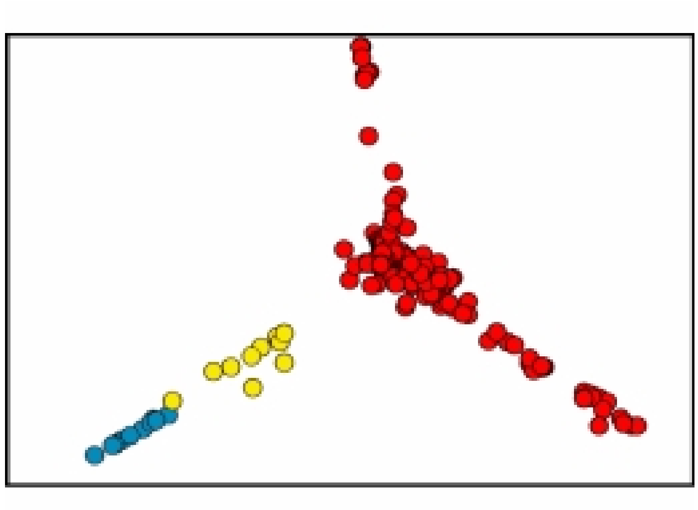

Figure 16. SVD of Athletes; Female Tennis Players are Yellow

In Figure 17, the green points are the male soccer players. They are involved in a team sport, and their position, at the end of an arm contradicts Oseguera's idea. Apparently they confide in one another.

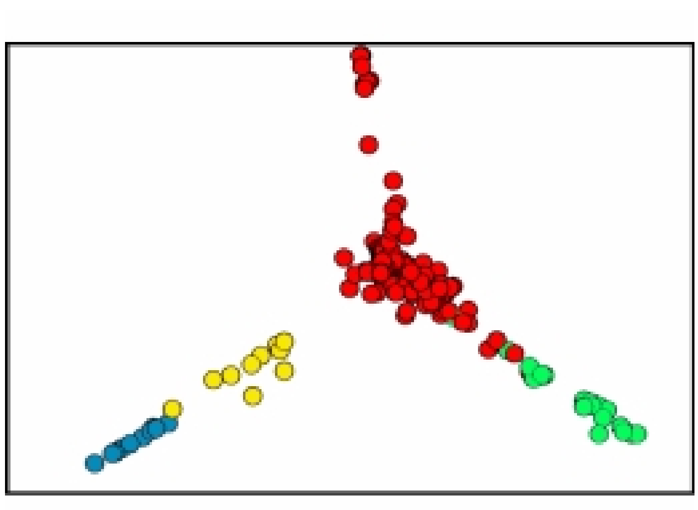

Figure 17. SVD of Athletes; Male Soccer Players are Green

The points colored purple in Figure 18 are the members of the women's soccer team. And, like the male soccer players, they contradict Oseguera's idea by being both involved in a team sport and confiding in their fellow team members. But, like the female tennis players, they occupy an intermediate position on the same arm as their male counterparts and they are a bridge between the members of the men's soccer team and the center.

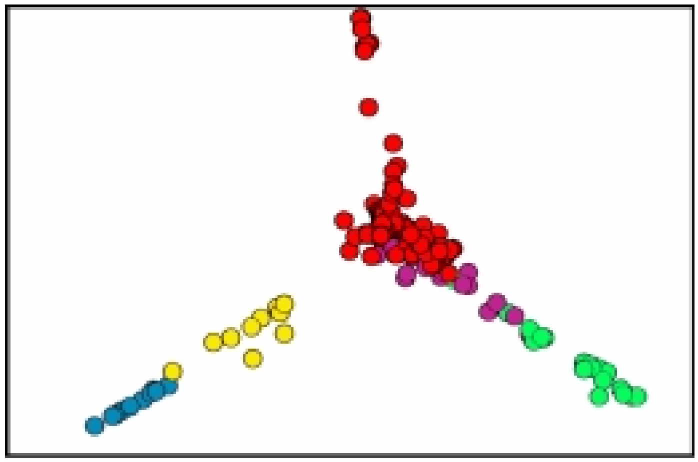

Figure 18. SVD of Athletes; Female Soccer Players are Purple

The gold points in Figure 19 are members of the men's golf team. They are involved in an individual-sport and their peripheral position is, again, consistent with Oseguera's original idea.

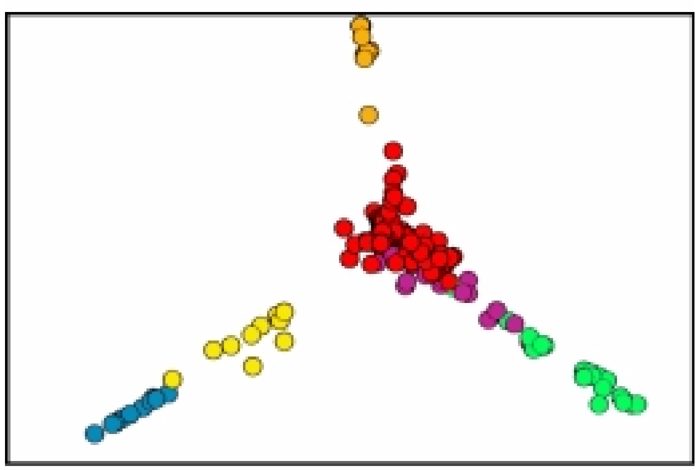

Figure 19. SVD of Athletes; Male Golfers are Gold

And finally, the dark blue points in Figure 20 are members of the men's water polo team. This is another team-sport and its position contradicts Oseguera's original idea. Moreover, since there is no female golf team, the bridging position with respect to the golfers is occupied by the water polo players.

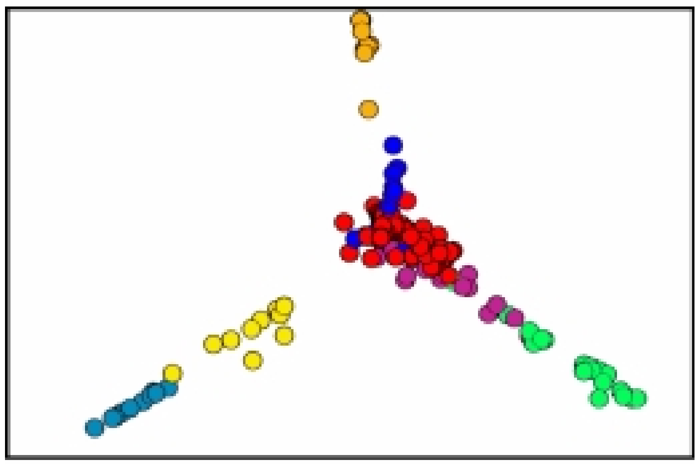

Figure 20. SVD of Athletes; Male Water Polo Players are Dark Blue

The remaining athletes, male and female basketball players, members of the men's and women's swimming team, the male and female track team members and the women's volleyball team are all clustered closely together in the center. Since some of these athletes are involved in team sports and some in individual sports, and since the athletes found in peripheral positions also represent each of these categories, Oseguera ended up rejecting her intuitive idea.

But, after a look at the data, she was able to come up with a new *post-hoc* idea. She was able to demonstrate a tendency for female athletes to bridge between the male athletes who were involved in the same sport and the main body of athletes from other sports.

Validating a Model

Cynthia Webster had been working on the development of a new procedure for uncovering small close-knit groups in social network data. She wanted to determine how well it worked when applied to data. She had already collected a large data set on friendship in an Australian residential college. In that study, she had interviewed all 217 residents individually and asked them to name their friends within the college. The residents had also indicated the strength of each friendship tie. In all, five levels of friendship were designated (5=best friend, 4=close friend, 3=friend, 2=friendly acquaintance, 1=acquaintance).

Webster symmetrized that original matrix and then applied her new method to uncover all the tightly connected subsets of residents. She assigned each group a name based on her ethnographic experience in the setting.

Webster reasoned that in order to validate her new procedure she had to demonstrate that her groups were tightly knit when the data were analyzed using an independent procedure. She set about, then, to determine the relation between the proximity structure of her data as displayed by SVD and the groups she had uncovered using her new method.

She pre-processed the data to remove the effects of means and variances and calculated a three dimensional SVD (Freeman, Webster and Kirke, 1998). The first two axes are shown in Figure 21.

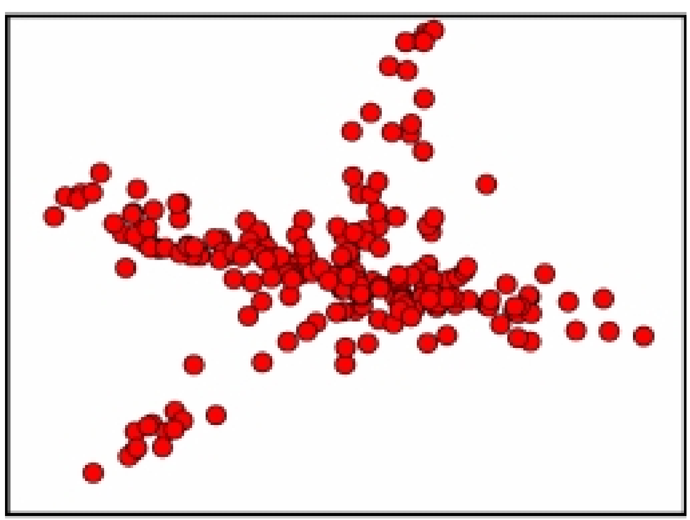

Figure 21. SVD of Friendships in a Residence Hall

The points in the image are clearly arranged into a four-pronged propeller-like object. Webster reasoned that if her method agreed with the SVD result, each of her groups would be found together in a tight cluster of points in the image. In particular, the four outlying clusters in the image would correspond to distinct groups she had uncovered with her new method.

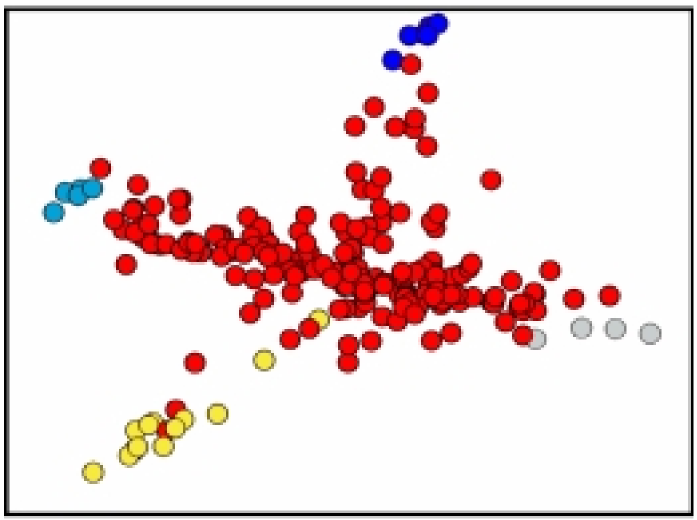

Figure 22. The Outlying Points in the Residence Hall

So she colored points according to group memberships and discovered that the outlying clusters were easily identifiable in terms of her groups. Figure 22 shows in dark blue the points included in a group she named “the grunges.” They were a collection of rebellious “hippie” students. A group of students who were preoccupied with religion are pictured in yellow. And the interesting feature is that they are bi-polar to the grunges. This polarity makes a certain amount of sense. A group colored light blue identifies a third extreme in the image. Webster called these students “the women.” They were the somewhat-proper female social leaders in the community. And finally, the fourth extreme in the image is occupied by the students Webster called “math heads.” They are gray. These were the non-social “nerds” in this student residence. And again, it makes sense that these “math heads” would fall at the opposite pole from “the women.”

All in all, then, this exercise shows that, at least so far as the extremes are concerned, Webster's grouping method produces groups that are consistent with the spatial patterns displayed by SVD.

A *Post hoc* Analysis

The final example involves a network study by Freeman and Freeman (1980). In the late 1970s, we examined the impacts of EIES, a computer communication system that worked much as the internet does today. It facilitated an email-like message transmission and the development of conferences, or discussion groups. Subjects were from the US and Canada and all were involved in the study of social networks.

Before the computer hookup was inaugurated, the participants were given a questionnaire in which they identified those others whom they knew about, those they had met, those who were friends and those they considered to be close personal friends. Then, after eight months of computer connection, they were queried again.

The fact that we had two waves of data permitted us to study the changes in interpersonal ties during the six months of computer communication. So we stacked the two matrices—before and after—normalized to remove the effects of differences in row and column totals and entered the combined data into SVD. The resulting image showed the changes in the proximities between pairs of network analysts that occurred during the six-month period.

To examine these changes, I used an animation program, MOVIEMOL.[v] The initial proximities are shown in Figure 23. They are patterned in a way that suggests the presence of two main clusters.

But in this case I was primarily concerned with change. So I examined the before-after transition using MOVIEMOL animation. And I began to see a pattern; the points could be divided into four distinct categories according to the direction of their movement. Some moved greater distances and some smaller distances, but the directions were patterned. These directions are shown in Figure 24.

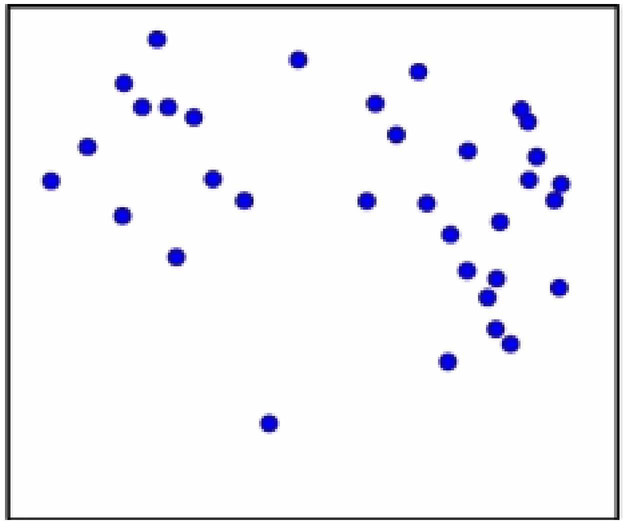

Figure 23. Initial Proximities among Network Investigators

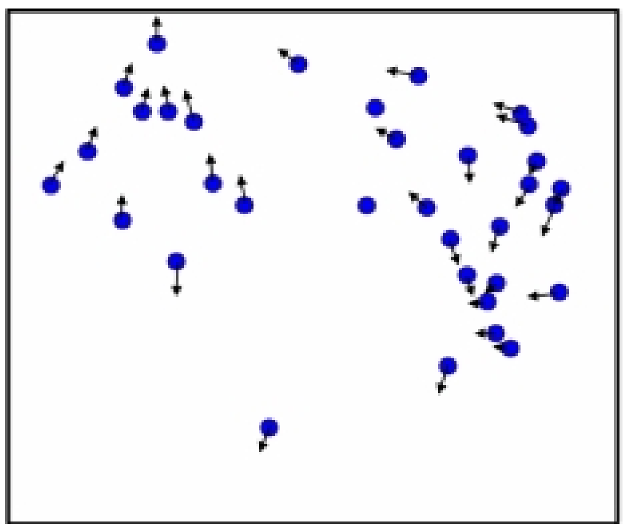

Figure 24. Directions of Movement among Network Investigators

So I colored those points according to their directions of movement. Those that moved up and to the left were colored yellow. Those that moved down and to the right were green. Those that dropped toward the lower left were red. And the remaining two points that did not move remained blue. You can see their final locations in Figure 25.

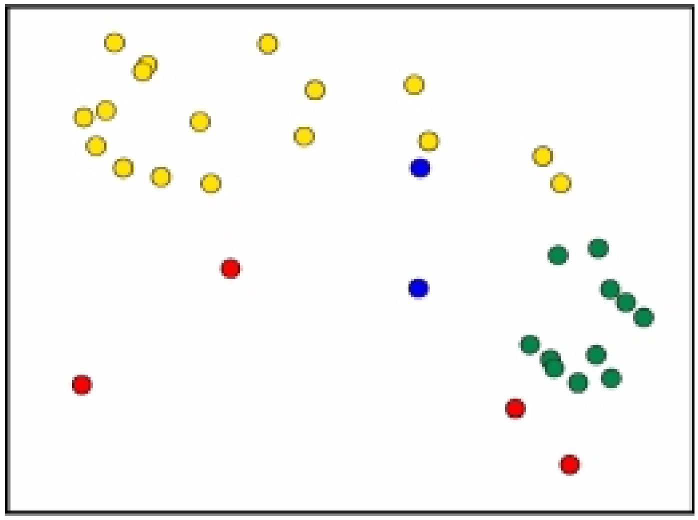

Figure 25. Movement Classes among Network Investigators

After identifying the points of various colors, it was clear what the various directions of movement implied. The red points were individuals who did not participate and who dropped out of network research during the experimental period. The blue pair did not participate in the internet at all, but they did remain in the network research area. The gold points represented individuals from several fields who at that time were in the process of organizing an interdisciplinary social networks specialty. And the green points were sociologists who objected to forming a new specialty and who were anxious to define network research simply as a sub-area of sociology. In this case, then, watching the animation yielded a new *post*-hoc insight that helped to make sense of a data set.

Conclusions

In this paper, I have demonstrated a simple and straightforward approach to exploratory analysis of social network data. This approach uses a search procedure (MDS) and/or an algebraic data reduction scheme (SVD) along with easily available programs for graphic display (MAGE and MOVIEMOL). With these tools, an investigator can determine whether or not a given data set contains any interesting structural features. These features are revealed simply by looking at visual images. This approach makes it simple to develop new insights based on characteristics of the data. In addition, it can be used to conduct preliminary tests of *a priori* ideas, to explore the fit of models to data and, using animation, to examine dynamic processes.

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Footnotes

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[i] In the present paper I used the procedures built in to the MDS program that is part of the UCINET 5 package (Borgatti, Everett and Freeman, 1999). Similar MDS programs are included in many standard statistical packages.

[ii] I have used the SVD program in UCINET 5 (Borgatti, Everett and Freeman, 1999). But any other standard statistical package might just as well have been used.

[iii] This program can be downloaded free from: ftp://kinemage.biochem.duke.edu/

[iv] MAGE is designed to make it easy to construct and manipulate network images on a computer screen, but it is limited in its ability to produce images for the printed page. Therefore, although the work described below was done using MAGE, it is presented here using bitmap images produced another program that generates XML.

[v] MOVIEMOL can be downloaded free from the following url: http://www.fos.su.se/moviemol.html