Comparing Multiple Social Networks Using Multiple Dimensional Scaling

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Abstract

This paper explores the comparison of social networks and gives a description of a method I developed for comparing many social networks. I developed this new technique by using multi-dimensional scaling to differentiate between several social networks. Others have used various methods and factors for comparing these social networks, such as descriptive network statistics, triads census and network similarities. These other methods compare only one feature of the given networks and are numerical in output. This new method has the advantage of comparing several network features and being an easy graphical method for the end user to compare multiple social networks.

Key words: Network comparison, social network analysis, multi-dimensional Scaling.

Introduction

In this methodological paper I use multidimensional scaling, a graphical technique, to compare and differentiate between several social networks in different locations. I first review other researchers’ work on comparing social networks and identify the data sets used in the paper. It is difficult to compare networks as there are several network variables, sometimes conflicting, that can be used to analyse and differentiate between networks. I next explore different variables that identify the differences between networks, before giving an example of a new technique I have developed using multi-dimensional scaling to differentiate graphically between seven social networks. This new method has the advantage that it combines in a mathematically proven way several variables and gives a graphical output. In the final section of this paper I highlight and summarise my findings.

Previous Work

The majority of social network studies have been case studies of a single group or setting. Relatively less attention has been paid to comparisons using networks from multiple settings or to longitudinal comparisons. Studies employing multiple settings focus on one of two distinct general questions. The first asks whether a
network of a specific relational content, in aggregate, exhibits common structural tendencies. The second
enquires as to what structural features are distinguished among different kinds of social relations. In
approaching the first sort of question, some studies have examined the same relation measured in multiple
settings. Empirical examples include friendships in schools or classrooms, including Bearman, et al., (1997),
Hallinan (1974) and Leinhardt (1972).

Exponential random graph models, as explored by Wasserman and Patterson (1996), compare the direction
and magnitudes of parameters characterizing local networks in graphs. These models allow for calculated
measures of dissimilarity between graphs for a variety of social networks. Results have shown the differences
in the ‘structural signatures’ of different kinds of relations, notably antagonistic relations such as fighting and
dominance on the one hand, and relations of affection (friendship, liking) and affiliation on the other.
Differences between species became apparent only for the first kind of relation, where humans showed
tendencies toward mutuality and in-stars and away from transitivity, compared to non-human primates, which
showed tendencies in the opposite direction on these properties (see Skvoretz & Faust 2002). More recent
work continues this line of inquiry using the triples or triad census of Holland and Leinhardt (1976) as a
vehicle for comparisons of local structural similarities among a collection of 51 networks of different
relational contents and measured for different species. The method of triad census was also used in Faust and
Skvoretz (2007) to study 42 networks from 4 types of species: humans, nonhuman primates, nonprimate
mammals, and birds. Their aim was to assess whether two, three or many differing networks were similarly
structured despite their surface differences.

Faust (2006) also uses a triad census ‘to compare different social networks of, amongst other species,
chimpanzees’. She comes to the conclusion that ‘caution should be taken in interpreting higher order
structural properties when they are explained by local network features’. This method does not fulfil my
requirements for comparing many networks.

Methods

I examined several different network variables, including the number of nodes in a network, the density of
networks, the average shortest path length, network centralization and finally betweenness. I produced this data
using UCINET to compare the results. I then analysed this data using techniques described in Marsh (1988)
and in Upton and Cook (1996). These techniques are implemented in SPSS, and it was the failure to discern a
single comparator variable that led me to investigate the following methods.

Secondly, to compare several different social networks, I produced a metadata table detailing five network
variables across all 7 datasets. Theses data were then analysed using multi-dimensional scaling techniques that
are implemented in SPSS and described in Coxon (1982). All multi-dimensional scaling techniques standardise the data before plotting those data on two dimensions. The metadata table is an input to the
following procedures implemented in SPSS. The ALSCAL multi-dimensional scaling procedure is
implemented as part of SPSS. I discounted this procedure, as it has two main problems: firstly, it allows for
the plotting of rows and columns in the same model space, which is confusing for the viewer, and secondly
this procedure has its faults with small value differences in the data identified in Ramsey (1982). I similarly
discounted the next two multidimensional scaling procedures, Proxscal and Minissa, as they are designed to
work only on square matrix and not rectangle matrix data. I finally chose to use the multi-dimensional scaling
techniques of Prefmap (detailed in Busing 2006) and Hiclus, as these are implemented in SPSS for ease of
use. The scaling procedure Prefmap, although designed for preference data, gives a virtually identical output
to the multi-dimensional scaling procedure used by Minirsa (detailed in Van Deun, et al., 2007). In the past I
found it preferable, as it is intended for a more general use, but it is not implemented in SPSS. I then integrated the respective outputs using techniques described in Coxon (1982).

Data Sets

A brief description of the data sets used within this paper is given below.

**Urban and Rural housing social network**

The rural estate consisted of 98 properties built during the late 1970s. To collect acquaintanceship network data, I randomly sampled 25 properties and attempted to collect data from residents at these properties through face-to-face interviews. I then delivered self-complete/post back questionnaires to the remaining properties with return addresses and reply paid envelopes. The acquaintanceship network data used for the urban estate was collected using the same techniques as used for the rural estate. I randomly sampled 25 properties for face-to-face interviews, and again delivered self-complete questionnaires to the remaining households. Three households returned partial questionnaires. As Table 1 shows, the urban sample covers a comparable 24.8% of households.

**Table 1. Rural and Urban estate sample and response**

|                              | Rural | Urban |
|------------------------------|-------|-------|
| No. Properties               | 98    | 137   |
| No. Face-to-face interviews  | 15    | 7     |
| No. Self-completed questionnaires | 9   | 27    |
| No. Incomplete questionnaires | 1    | 3     |

(The face-to-face interviews were pilot studies)

**Student social network waves 1, 2 and 3**

The longitudinal data sets used in this paper were collected as part of my M.A. dissertation (Stevens 2008), and I had good access to students. These three surveys (waves) are a very near duplicate between waves, with only minor modifications of titles and dates. The student network is more transient than the staff network. An M.A. student studies on campus for an average of 1 year, and a student studies on campus for an average of just over 2 years (2.04). The sample size of the data collected is shown below in Table 3. The response rate was 92.3% for wave 1 and 100% for wave 2 and wave 3.
Figure 1. Student friendships by wave (65 students)

![Graph showing student friendships by wave](image)

The basic descriptive statistics of the longitudinal student data set for a given week is shown below in Table 2.

Table 2. Student response rates

|                  | Wave 1 | Wave 2 | Wave 3 |
|------------------|--------|--------|--------|
| Data Collection week no. | 1      | 7      | 14     |
| No. Completed questionnaires | 60     | 65     | 64     |
| No. Acquaintances    | 252    | 371    | 796    |
| Average             | 4.20   | 5.71   | 12.43  |

Staff and Student email social networks

Work email network

The first email friendship network I investigate is a University based staff network. By its nature this is a complete sample. The set has information on 1,910 different members of staff who sent or received email to other members of staff in a one-week period. In comparison with the student email network that I describe next, the email volume of the staff email network is less affected by term dates. This is shown below in Figure 2.
Figure 2. Internal staff email volume by week (2,582 staff with 110 redirects)

(Source: Data collected by University of Essex computer service and detailed in Stevens, John, (19-20 February 2009a))

The basic descriptive statistics of the staff email data set for a given week are shown below in Table 3.

Table 3. Staff email response rates

| No. Staff email originators | 1910 |
| No. Emails                  | 40071 |
| Average                    | 20.97 |

**Student email network**

The second email friendship network I investigate is a university-based student email network. The set has information on 819 different students who sent email to other students or received email from other students, in a one-week period. Unlike the staff email network which I described previously, students’ attendance and the email volume of the student email network are affected by term dates. This is shown in Figure 3.
Figure 3. Internal student email volume by week (8,591 students with 254 redirects)

(Source: Data collected by University of Essex computer service)

The basic descriptive statistics of the student email data set for a given week are shown below in Table 4.

Table 4. Student email response rates

| No. Student email originators | 891 |
|-------------------------------|-----|
| No. Emails                    | 10106 |
| Average                       | 11.34 |

Variables that Affect the Comparison of Social Networks

I investigated the comparison of social networks by concentrating on which variables would be most useful to differentiate among social networks and their structures. The five social network variables I compare are (1) the number of nodes (i.e., size of network), (2) the degree of a node, (3) the density of a social network, (4) the shortest path length between nodes, (5) network centralisation and (6) betweeness.

Number of Nodes

The first and most obvious variable to investigate when comparing social Networks is the size of the social network (number of nodes). Table 5 gives the number of nodes in each of the social networks used in the paper.
Table 5. Degree of node within social Networks

| Data set                              | No. of nodes |
|---------------------------------------|--------------|
| Rural housing social network          | 24           |
| Urban housing social network          | 27           |
| Student social network wave 1         | 60           |
| Student social network wave 2         | 65           |
| Student social network wave 3         | 64           |
| Surname data                          | 95           |
| Student email social network          | 324          |
| Staff email social network            | 833          |
| Mean                                  | 186.5        |

(Source: Figures given by UCINET for all the paper’s data sets)

Displaying the data contained in Table 5 as a figure would be pointless, as there is only one dimension to the data. This output is only of very limited use for comparing the structure of social networks.

Density

The density of a social network is a commonly used concept within social network analysis. Many researchers, such as Fararo and Sunshine (1968), Anderson et al. (1999) and Lin et al. (1999), have studied the density of social networks to see how tight or weak a community is. Some authors also use the term ‘reciprocity amongst friends’ to refer to density. Fischer (1982: 139-143) introduces the concept of multistrandedness, which seems very similar if not identical to density.

A commonly used measure of the density of a friendship social network is the clustering coefficient. This paper uses the clustering coefficient interchangeably with density. Clustering coefficients are representations of a person, but shaped as triangles: X has friends called Y and Z who know each other as well. The clustering coefficient is used regularly when describing friendship and social Networks, e.g., in Scott (1991:73-84) and Wassermann and Frast (1994:101-103).

Scott (1991: 77) argues that the clustering coefficient is unable to scale for differing sizes of social networks. I take the view that the clustering coefficient can be used for comparing social networks of ± 10% in sizes. Table 6 lists the number of nodes in each of my real world social networks with its corresponding social network density.

Table 6. Comparing social network size and density

| Data set                              | No. of nodes | Density of social Networks |
|---------------------------------------|--------------|----------------------------|
| Rural housing social network          | 24           | 0.0451                     |
| Urban housing social network          | 27           | 0.0116                     |
| Student social network wave 1         | 60           | 0.0370                     |
| Student social network wave 2         | 65           | 0.0938                     |
| Student social network wave 3         | 64           | 0.1796                     |
| Student email social network          | 324          | 0.0118                     |
| Staff email social network            | 833          | 0.0051                     |
| Mean                                  | 199.5        | 0.048                      |

(Source: Calculated using UCINET using all the papers datasets)
It should be noted from Table 6 that the mean density does not increase linearly with the number of nodes in a network. However, an experimenter could compare two social networks of similar sizes that have been collected using the same data collection technique and methodology. It can also be seen from Figure 4 that the average degree of a node is not relative to the size of the social network.

**Figure 4. Number of nodes against social network density**

(Source: Output from MS EXCEL XP when plotting no nodes against social network density)

**Path Length (small world social networks)**

The next variable is the shortest path length that is unrelated to network density between 2 nodes. This is also a popular area for social network studies. The research area for this section is also called small world social network studies, and was first detailed in Milgram (1967). Table 8 details some of these studies.

**Table 7. Summary Details of Selected Small World Studies**

|                     | 1967 (Milgram) | 1989 (Tjaden) | 2000 (Wiseman) | 2002 (Dobbs) |
|---------------------|----------------|---------------|----------------|--------------|
| **Type of experiment** | Post out/post back | Database       | Post out / post back | Internet     |
| **Number of targets**      | 1 per sample group | N/A           | 1              | 18           |
| **Size of community**      | 180 million    | 35,000        | 56 million     | 1 billion    |
| **Initial sample size**    | 128            | N/A           | 500            | 24,163       |
| **Completed chains**       | 18             | 1             | 50 (approx)    | 384          |
| **Mean links in chains**   | 5.5            | 2.53          | 4              | 6            |
The small world literature contains some significant gaps; no published work on the sampling for small world studies addresses the question of how many cases must be collected to make a reasonable model from the data. Likewise, I found no published work that examines the effects of response rates of data or resulting model quality. Watts and Strogatz (1998) show that the addition of a handful of “random links” can turn a disconnected social network into a highly connected one. These “links” can generate social networks with significant social consequences (as has happened through the spread of infectious disease such as AIDS and SARS). Similarly, key people may facilitate constructive links, such as the extensive fundraising achieved by the political outsider Howard Dean through Internet social networks rather than conventional advertising in the 2004 U.S. presidential election. Gladwell (2000) argues that the six-degree phenomenon is dependent on a few extraordinary people (connectors) with large social networks of contacts and friends. These people mediate the connections between the vast majorities of otherwise weakly connected individuals. To this extent, these “connectors” can mediate social network interactions-- a process Gladwell calls “funnelling.” The opposite of the shortest path between 2 nodes is the less used average longest path, as referred to in Alon et al. (1994). This measurement gives a good approximation of the maximum distance across a social network by taking an average to remove the return path. I used both measurements in Table 8.
Table 8. Number of nodes and path length

| Data set                     | No of nodes | Shortest Path |
|------------------------------|-------------|---------------|
| Rural housing social network | 24          | 3.160         |
| Urban housing social network | 27          | 1.547         |
| Student social network wave 1| 60          | 2.924         |
| Student social network wave 2| 65          | 2.535         |
| Student social network wave 3| 64          | 2.053         |
| Student email social network | 324         | 4.442         |
| Staff email social network  | 833         | 3.618         |
| Mean                         | 199.5       | 2.534         |

(Source: Calculated using UCINET using all the papers datasets)

It can also be seen from Figure 6 that the average degree of a node is not relative to the shortest or longest path length in the social network.

Figure 6. Number of nodes against path lengths

(Source: Output from MS EXCEL XP when plotting no nodes against average shortest path length)
The next variable to be investigated was centrality. Table 9, as above, gives the network centrality for the 7 datasets I collected.

Table 9. Number of nodes and network centrality

| Data set                        | No of nodes | Mean centralization | Network % centralization |
|---------------------------------|-------------|---------------------|--------------------------|
| Rural housing social network    | 24          | 7.737               | 19.84                    |
| Urban housing social network    | 27          | 3.250               | 5.78                     |
| Student social network wave 1   | 60          | 3.157               | 14.80                    |
| Student social network wave 2   | 65          | 6.514               | 20.12                    |
| Student social network wave 3   | 64          | 12.000              | 32.80                    |
| Student email social network    | 324         | 3.834               | 18.06                    |
| Staff email social network      | 833         | 4.223               | 4.88                     |
| Mean                            | 199.5       | 5.852               | 16.60                    |

(Source: Calculated using UCINET using all the papers datasets)

The data in Table 6 is represented in Figure 7 as a graph plotting the number of nodes against the network centrality.

Figure 7. Number of nodes against Network % centralization

(Source: Output from MS EXCEL XP when plotting no nodes against centrality)
It can also be seen from Figure 7 that, similar to the previous comparisons, the degree of a node is not relative to the centrality of the social network.

**Betweeness**

The next natural step to be investigated is the network variable of betweeness, which once again also appears to have been overlooked by researchers working on comparing networks. Table 10 provides the values for the average betweeness for the 7 data sets.

**Table 10. Number of nodes and betweeness**

| Data set                          | No of nodes | Betweeness  |
|-----------------------------------|-------------|-------------|
| Rural housing social network      | 24          | 20.404      |
| Urban housing social Network      | 27          | 0.604       |
| Student social network wave 1     | 60          | 75.458      |
| Student social network wave 2     | 65          | 91.200      |
| Student social network wave 3     | 64          | 63.373      |
| Student email social Network      | 324         | 221.775     |
| Staff email social Network        | 833         | 1072.264    |
| Mean                              | 199.5       | 220.725     |

(Source: Calculated using UCINET using all the papers dataset)

This data is represented differently in Figure 8. It can be seen from this figure that the average degree of a node is not relative to betweeness in the social network. Betweeness is affected by at least 2 variables, the age of the social network and the physical location of its nodes. This variability is highlighted in Figure 8, which plots the number of nodes against betweeness.

**Figure 8. Number of nodes plotted against betweeness**

(Source: Output from MS EXCEL XP when plotting no nodes against betweeness)
Summary of presented data sets

There are many possible factors to think about when comparing social networks. These include the average degree of node, the social network density and the number of triads. These plots are very similar, as the variables chosen are all related to the density of the social network. The graphs describing the network variables’ network centralization and the shortest path length are quite different and are not related to network density. But Figures 1, 3, and 4, which represent network density, shortest path length and network centrality, all show a similar profile to the trend line: an inverted ‘V’ with a peak between 100 and 300 nodes. Although they are similar for the range of nodes, I will be including these in my further analysis, as these variables provide a destination between networks when larger and smaller networks are to be differentiated.

The variables that I have chosen, as the above sections highlight, are the most relevant variables when comparing these networks, i.e., the number of nodes, density of the graph, the shortest path length and network centrality. I will use these network variables in the following section of this paper. I am certain this is not a complete list of variables but it should be clear from the above work that no one network variable is the best for comparing social networks.

Comparing Many Social Networks

Traditionally the most commonly used quantitative way of comparing social networks was to compare the density of different social networks, but this is a very broad-brush approach. As a way forward, Faust and Skvoretz (2007) compared the number of triads between different social networks (triads being cliques of 3 nodes). I chose to ignore cliques, as I anticipated using the multi-dimensional scaling technique as described by Coxon (1982) because it is a way of analysing several variables of the social network together and not just the number of cliques.

Metadata table

To compare many social networks, I used multi-dimensional scaling procedures on a metadata table of variables, which I selected. I followed on from this by using the multi-dimensional scaling tools of Prefmap and Hiclus on the metadata table. This produced a graphical output to compare the social networks when the procedures’ outputs are combined together.

Table 11. Metadata table

| Data set                   | No. of nodes | Density of social network | Average Shortest Path | Network % centralization | Betweenness |
|----------------------------|--------------|----------------------------|------------------------|--------------------------|-------------|
| Rural housing social network | 24           | 0.0451                     | 3.160                  | 19.84                    | 20.404      |
| Urban housing social network | 27           | 0.0116                     | 1.547                  | 5.78                     | 0.604       |
| Student social network wave 1 | 60           | 0.0370                     | 2.924                  | 14.80                    | 75.458      |
| Student social network wave 2 | 65           | 0.0938                     | 2.535                  | 20.12                    | 91.200      |
| Student social network wave 3 | 64           | 0.1796                     | 2.053                  | 32.80                    | 63.373      |
| Student email social network | 324          | 0.0118                     | 4.442                  | 18.06                    | 221.775     |
| Staff email social network   | 833          | 0.0051                     | 3.618                  | 4.88                     | 1072.264    |

(Source: Values calculated using UCINET using all the papers dataset)
As can easily be seen from this table, I found there is no single variable that can be used for comparing social networks. As can be seen, it is very hard for the casual observer to notice any trends or classifications from Table 11.

**Prefmap**

The multi-dimensional scaling technique I explore is the Prefmap procedure that is also implemented in SPSS14 (and up). Figure 9, shown below, shows the output for this procedure. This procedure has the notable advantage that the user can select to output rows or columns in the model space and use a rectangular input data matrix.

**Figure 9. Prefmap output**

(Final Stress: 0.0000; Penalty 4.5677)
(Source: Scaling output of Prefmap as implemented in SPSS when computing metadata Table 11)
Interpreting results

Multi-dimensional scaling by its nature does not easily allow for a scale to be applied to its output, as the procedure folds multi-dimensions into a 2 dimensional workspace. To interpret the output, I do not combine the results of the Prefscal and Hierarchical, the techniques as described in Coxon, APMC (1982), as I found this technique added nothing to the results. Instead I will assign descriptions to the three distinct clusters. This graph is shown below in Figure 10.

A. The first cluster contains only row 2 (Urban estate), as it is distantly different from the other networks, being a chain in structure.

B. The second cluster contains rows 3 (Wave 1), 4 (Wave 2) and 7 (Student email). This cluster is a group of 3 less interconnected and more diverse networks.

C. The third and final cluster contains rows 1 (Rural estate), 5 (Wave 3) and 6 (Staff email). This cluster is a group of 3 more interconnected and more homogeneous networks.

This new method identifies three distinct typological types of social networks. The first is a network made up of a chain of nodes; the second grouping of networks consists of less interconnected networks; and the final type is a grouping of more interconnected networks.

Figure 10. Prefmap output

(Final Stress: 0.0000: Penalty 4.5677)
(Source: Scaling output of Prefmap as implemented in SPSS when computing metadata Table 11)
Comparing social networks using multi-dimensional scaling on a meta-data table is one way that works well when many social networks need to be compared. A minimum of 3 social networks should be compared using this method. An area for further investigation would be to assess the accuracy of the minimum number of social networks to be compared.

Summary

As I have already stated in the previous sections, there are many factors to consider when comparing social networks. Others have used various methods and factors for comparing these social networks, such as comparing degree of node, density of the social network, path length and the number of triads in a network. The technique I developed, which was far more successful for comparing several social networks, was achieved by creating a Metadata table of several social network variables and using multi-dimensional scaling techniques such as Prefscal. A graphical representation of the differences between several social networks is shown. This technique works better if more than three social networks are compared. To summarize, this technique is not perfect, but it does provide a more comprehensive and systematic method of comparing social networks.

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Biography
John Stevens is a PhD student at The University of Essex. His areas of research include; Community (inclusion and exclusion), disability, research methods, and medical sociology.