The purpose of social network analysis is to investigate complex relationships and interactions amongst entities within a network. Advanced social network analysis techniques can be used to answer question such as:

* With whom will an individual develop relationships?
* How does an individual interact with others via such relationships?
* Who is central or an opinion leader in the social network to which an individual belongs?

Social network analysis techniques can be categorized as either descriptive techniques or statistical inference techniques. One of the main limitations of descriptive techniques is that it is difficult to analyze certain characteristics of social networks in a relative sense. For example, if a particular social network has a certain number of ties among the members, with descriptive methods we can hardly determine the degree to which the members of the network are densely connected. On the other hand, statistical inference techniques enable us to produce appropriate conclusions about network data that goes beyond the immediate scope of the data.

The aim of this tutorial is to give you a basic introduction to statistical inference of network data with RStudio. The tutorial will be structured as follows (still in progress):

* Understanding network data in relation to statistics.
* Analysing the dataset.
* Describing one network.
* Exercise one: calculating the density of networks against a hypothesis.
* Understanding the questions – how to compare datasets to get characteristics such as density, how to do regression with datasets.
* Answering the question 1.
* Answering question 2.

UNDERSTANDING NETWORK DATA IN RELATION TO STATISTICS

Before we start, there are two essential concepts that you must understand about applying statistics to network data.

Firstly, social network analysis is about relations among actors, not about relations between variables. This is extremely important to understand because it means that rather than describing distributions of attributes of actors (or “variables), we are describing the distributions of relations among actors. Therefore, in applying statistics to network data, we are concerned with issues like the average strength of relations between actors, for example:

*“Is the strength of ties between actors in a network correlated with the centrality of the actors in the network?”*

Secondly, many of the standard inferential statistic tools that are concerned with the distribution of attributes cannot be applied directly to network data. This is because, unlike attribute analysis, the observations in network data are not independent samplings from populations. For example, in network data, we might observe Chad’s tie with Darren, while another observation might be Darren’s tie with Ryan. Network analysis says that we cannot suppose that these relations are independent because Darren is involved in two of the observations and there is a strong likelihood that we will infer another observation which depicts Chad’s tie with Ryan. Standard inferential tests assume independent observations and therefore, if we apply standard inferential statistics to observations that are not independent, it will produce seriously misleading results.

In order to overcome these challenges, when applying statistics to network data, we need to use alternative numerical approaches. These approaches are known as “bootstrapping” and permutations but for now, let’s start with the tutorial.

UNDERSTANDING THE DATA

This tutorial is purely for introductory purposes and so, the following sections’ objective is to walk you through two exercises which will give you a basic understanding of how to apply inferential statistics to network data.

For this tutorial, we will be using the Knoke and Knoki datasets which describes two relations; the exchange of information and the exchange of money among 10 organizations. The following code exhibits the money exchange matrix and the information exchange matrix:

*Put Matrices here .*

As you can see, network data matrices consist of a square array of measurements. The rows of the array are the same set of observations, while each cell of the array describes a relationship between actors. In our dataset, each cell represents either the exchange of money or information between two organisations as a 1 or no exchange as a 0. By comparing rows of the array we can see which actors are similar to which other actors in whom they choose to exchange information or money. By looking at the columns, we can see who is similar to whom in terms of being chosen by others. This helps us to see which actors have similar positions in the network which brings us to the first major emphasis of network analysis: how are actors located or embedded within the overall network?

However, a network analyst will also look at the data in a more holistic way. For example, they may notice that there are about equal numbers of ones and zeros in the matrix which suggests that there is a moderate density of liking overall. However, the analyst may want to test prior made hypotheses about the density or mean tie strength of a network. For example, we might want to test:

* Whether the hypothesis that, the proportion of binary ties present, differs from .50?
* Whether the hypothesis that, the average strength of a valued tie, differs from 3?

This will bring us to the first exercise which involves finding the degree to which the members of a network are densely connected.

DESCRIBING ONE NETWORK

Before we start with the first exercise, let’s do an in-depth analysis of one of the matrices, we will use the Knoke matrix, in order to solidify our understanding of the various statistical values which we may observe.

*Knoke dataset*

Firstly, it is important to note that this particular dataset is asymmetric and binary. The scale of measurement, binary or valued, matters in making proper choices about interpretation and application of many statistical tools. The data which we are observing is the relations between the actors. So, in each matrix we have 10 x 10 = 100 observations or cases. For many analyses, the ties of actors with themselves (the main diagonal) are not meaningful and so there is actually N \* N-1 = 90 observations. If the data were symmetric (Xij = Xji), half of the observations would be redundant and so there would be N \* N-1 / 2 = 45 observations, however, this is not the case for our dataset.

The first thing we are going to do is summarise some of the most basic characteristics of the distribution of these scores. To do this, we are going to generate the most commonly used statistical measures for the Knoke matrix.

*Show the mean, SD, sum , variance, Minimum, Maximum and Num of observations for the Knoke matrix.*

By looking at the data we can see that the number of observations is 90 which range from a minimum score of 0 to a maximum score of 1. The sum of the ties is “x” and the average value (mean) of the ties is x/90 = i. Due to the fact that our relations have been coded as a “dummy” variables (0 for no relation, 1 for a relation), the mean is also the proportion of possible ties that are present (or the density) within the network. What we can also calculate is the coefficient of variation, SD / mean x 100 = “t”. This suggests quite a lot of variation as the percentage of the average score.

Adding onto this, we might also want to examine the distribution of ties for each actor, opposed to the distribution of ties for the entire network.

*Show the mean for each actor in Knoke matrix (specify row network and column network)*

By analysing the network of rows for the Knoke matrix we can see that actor 1 has a mean (or density) of tie sending of “x”. This means that the actor sent 4 ties to the available 9 actors- this can also be inferred by looking at the sum for actor 1 in the row network. If we look at the column network we can see that actor 1 received somewhat more money than they sent because their column mean is “y”. Adding onto this, if we scan down the column of means we can see that there is a considerable amount of variability across actors for sending and receiving money- some send more money while others get more money. It may be helpful to note that if we were working with valued data, rather than binary data, the measure of variability would be more informative across actors. This is because the variability of binary data is strictly a function of its mean. The main objective of this section was to emphasise the first essential concept that when we use statistics to describe network data, we are describing properties of the distribution of relations (or ties among actors) rather than properties of the distribution of attributes across actors.

FIRST EXERCISE

Now that we have a better understanding of a single network, and the general statistical measures of that network, we can begin with the first exercise. As previously mentioned, network analysts are usually interested in a more holistic view of the network which usually involves the density, or average tie strength, of the network. It is typical for an analyst to want to prove or disprove a theory about the density of a network and for this we need to create a hypothesis (for the purpose of this exercise we will be working with the Knoki matrix):

*Hypothesis: “Let’s suppose that we think that all organisations have the tendency to want to directly distribute information to all other organisations in the network, as a way of legitimizing themselves.”*

This hypothesis suggests that all the organisations will exchange information with all other organisations and therefore each cell in the matrix will = 1. Therefore, if this hypothesis/theory is correct, then the density of the Knoki network should be 1.0. We are now able to compare the true value of the network density, or average tie strength, against a test value (density = 1.0).

*Calculate mean of Knoki*

We can see that this theory is not true because the true network density of Knoki is not equal to 1.0, it is equal to “x”. However, perhaps the difference between what we see (density = “x”) and what the theory predicts (density = 1.0) is due to random variation (which occurs when the information is collected). Therefore, we need to find a way to ask the data to convince us that we can be confident in rejecting the hypothesis. To do this, we need to be able to compare the network to a randomly generated network of the same size. By comparing our network to a randomly generated network, we can determine the degree to which our network has the same density compared to a network generated by chance, allowing us to reduce the effect of random variation. This brings us back to the numerical approaches of “bootstrapping” and permutations.

Bootstrapping calculates random sub-samples from our network, for a specified number of times, to produce a sample distribution of density measures. We know that the difference between the test value (1,00) and the observed value (“x”) = (“i”). Now, using the sample distribution of density measures, we can observe how often a difference this large (“i”) happens by random sample variation if the null hypothesis (density = 1.0) was really true in the population.

*Run the Noki network against the randomly generated networks and explain the code.*

TO BE CONTINUED

The analyst might also compare the cells above and below the diagonal to see if there is reciprocity in choices (e.g. Bob chose Ted, did Ted choose Bob?). This is the second major emphasis of network analysis: seeing how the whole pattern of individual choices gives rise to more holistic patterns.