An Introduction to Statistical Inference With Network Data

In: Social Network Analysis and Education: Theory, Methods & Applications

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Pub. Date: 2013
Access Date: July 15, 2021
Publishing Company: SAGE Publications, Inc.
City: Thousand Oaks
Print ISBN: 9781412999472
Online ISBN: 9781452270104
DOI: https://dx.doi.org/10.4135/9781452270104
Print pages: 171-184

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Objectives

In this chapter, you will learn about the difference between the mathematical and statistical approaches to social network analysis. In Part II, many social network measures for concepts related to both complete and ego networks were presented. These measures reflect a mathematical approach that focuses on what a network of actors "looks like." This approach does not, however, consider whether a certain configuration is predictable and normal, how one relation is associated with another relation among the same set of actors, or whether one network structure could be thought of as "better" than another. To attend to these important issues, in this chapter, you will learn about the ways in which statistical inference has evolved in order to move social network analysis beyond the social scientific goal of description and closer to explanation and ultimately prediction. It is assumed that you have a basic understanding of probability and statistical inference.

Making and Testing Predictions

Is there a relationship between the frequency of collaboration between school leaders and how often they turn to each other to discuss issues of a confidential nature? Do school leaders prefer to collaborate with those with whom they have collaborated in the past, or is there some other reason? Could it be that gender or some other individual attribute predicts confidential exchanges between school leaders, or does some previous relation have a stronger effect? Does collaboration between leaders explain one's level of trust in one's administrative colleagues? Can we distinguish among different groups of school leaders based on how frequently they collaborate, and if so, are these groupings related to the level at which they work (school versus district)?

The chapters in Part II focused on ways in which different algorithms can be used to describe properties related to ego or complete networks. This chapter moves beyond these static snapshots and provides an introduction to the ways in which recent advances in inferential statistics can be used to make predictions from social network data and address the questions in the previous paragraph. Other introductions to statistical network models can be found in Wasserman and Faust (1994), Scott (2000), and Goldenberg, Zheng, Fienberg, and Airoldi (2009). Unlike these other introductions, the ideas to be presented in this chapter are intentionally presented in a nontechnical manner, avoiding the use of formulas and focusing on a conceptual understanding rather than calculation. The primary aim of this chapter is to convey the importance of statistical models and how they can be used to test whether some network features were expected and normal or whether one network configuration could be thought of as “better” than another.

This chapter begins by describing the critical differences between mathematical and statistical approaches to social network analysis and how these approaches reflect the important analytic difference between description and prediction. While recognizing that most social network analysis is descriptive and, therefore, implicitly relies on the mathematical approach, this chapter lays the foundation for some of the newer and exciting ways in which statistics can be applied to the study of social networks in and around education. The goal of this chapter is not to provide a comprehensive overview of the logic and mechanics of statistical inference with network data but rather introduce you to how statistics have been adapted to further strengthen the inferential claims emanating from social network studies. Consequently, as a result of these techniques, social network analysis has moved beyond description and toward prediction, a direction in which most network analyses in education are headed.

The development of these statistical tools and their application to social network analysis can be traced to two general dissatisfactions with earlier social network studies. First, the measures presented throughout Part II were merely descriptive, with networks being described by creating indicators for their structure (e.g., density, reciprocity, etc.) and the members of networks characterized by their position (e.g., centrality). These measures convey the image of a fixed network with attitudes or behaviors passing through it, much like airplanes flying to and from different airports. In reality, unlike airports, networks change, and in some instances quickly. Teachers confer with new colleagues and no longer do so with old ones. Some students seek extra help for the first time, while others quit after receiving that help for some time. Relationships may change because of the behavior change, while in other cases people change behaviors or attitudes because those closest to them have changed theirs (Valente, 2010). For example, if a teacher favors a certain instructional approach, he or she may form friendships with other teachers who prefer that same approach. Alternatively, a teacher may adopt an instructional approach because his or her friend has adopted it. Consequently, we need a way to simultaneously analyze changes in networks and behaviors. These issues surrounding the co-evolution of behavior and social networks have been addressed through the development of statistical models that estimate the likelihood that two actors form ties in a network based on their existing relationships and behaviors (Valente, 2010).

In addition to earlier studies not accounting for network dynamics, thereby limiting the types of questions that could be asked, they also did not account for the dependencies between a network's actors. For example, associations among network exposure (e.g., attitudes of one's peers), network indicators (e.g., size, transitivity), and individual attributes are nonindependent—a critical assumption that provides the foundation for most conventional statistical tests. For example, let's say a statistical analysis reveals that two high-achieving students are more likely than low achievers to have high-achieving friends. This association, however, may be the result of both the focal student and the network alters being connected to a third student who is also a high achiever. Therefore, a different statistical approach was needed that did not assume the independence of a network's actors. Because of these two issues, there has been a marked shift toward a statistical approach that can test propositions about network-related properties rather than simply relying on descriptive statements. This statistical approach not only avoids the assumption of independence but also provides ways to model a network's change over time and test hypotheses related to these changes.

Mathematical versus Statistical Approaches

Social network analysis is more a branch of "mathematical" social science than of "statistical or quantitative analysis," though social network analysts often reflect both approaches (Hanneman & Riddle, 2005). The distinction between the two, however, is not clear cut. Mathematical approaches tend to regard the measured relationships and their strengths as accurately reflecting the "real," "final," or "equilibrium" status of the network. In addition to this deterministic thinking, the mathematical approach also assumes that the observations are not a "sample" of some larger population of possible observations; rather, as is the case with complete network studies, the observations are usually regarded as *the* population of interest. That is, the sample in these instances is the same as the population.

Statistical analysts, on the other hand, tend to regard the particular scores on relationship strengths as stochastic or probabilistic realizations of an underlying true tendency or probability distribution of relationship strengths. Statistical analysts also tend to think of a particular set of network data as sampled from some larger class or population of such networks or network elements. The concern of the statistical approach, therefore, is on the reproducibility in a subsequent study of similar samples (Hanneman & Riddle, 2005).

It should be evident that the chapters in Part II were concerned with the mathematical rather than the statistical side of network analysis. Before moving on to the statistical analysis of social networks, there are a few main points about the relationship between the material in this chapter and the main statistical approaches employed in educational research.

In one way, there is little apparent difference between conventional statistical approaches and network approaches (Hanneman & Riddle, 2005). Univariate, bivariate, and even many multivariate descriptive statistical tools are commonly used in describing, exploring, and modeling social network data. Social network data are, as pointed out in Chapter 3, easily represented as arrays of numbers—just like other types of actor-by-attribute data. As a result, the same kinds of operations can be performed on network data as on other types of data. Algorithms from statistics are commonly used to describe characteristics of individual observations (e.g. the mean tie strength of Student A with all other alters in his or network) and the network as a whole (e.g. the mean of all tie strengths among all students in the network). Statistical algorithms are often used in assessing the degree of similarity among actors and in finding patterns in network data (e.g., factor analysis, cluster analysis, multidimensional scaling). Even the tools of predictive modeling are commonly applied to network data (e.g. correlation and regression).

Inferences with Network Data

Descriptive statistical tools such as those in Part II are really just algorithms—some, admittedly, complicated—for summarizing characteristics of the distributions of scores. That is, they are mathematical operations. Where statistics really become "statistical" is on the inferential side, that is, when attention turns to assessing the reproducibility or likelihood of an observed pattern. Inferential statistics can be and are applied to the analysis of network data. Hanneman and Riddle (2005) note that there are several important differences between the flavors of inferential statistics used with network data and those that are most commonly taught in basic courses in statistics courses.

Probably the most common emphasis in the application of inferential statistics to social science data is to answer questions about the stability, reproducibility, or generalizability of results observed in a single sample (Hanneman & Riddle, 2005). According to this emphasis, the main question asked is: If a study is repeated on a different sample (drawn by the same method), how likely is it that you would get the same answer about what is going on in the whole population from which both samples have been drawn? This is a really important question because it helps you evaluate the confidence (or lack of it) that you should have in assessing theories and giving advice. This use of inferential statistics represents a majority of the quantitative work done in contemporary educational research.

To the extent the observations used in a network analysis are drawn by probability sampling methods from some identifiable population of actors and/or ties, the same kind of question about the generalizability of sample results applies. Often, however, this type of inferential question is of little interest to social network researchers. In many cases, network analysts are studying a particular network or set of networks and have no interest in generalizing to a larger population of such networks (either because there isn't any such population or because they simply do not care about generalizing to it in any probabilistic way). For example, how attitudes about a new school reform initiative diffuse through one school's faculty and staff doesn't mean the process plays out in the same way at another school. In some other cases, however, there may be an interest in generalizing, but samples are typically not drawn through probability methods. Network analysis often relies on artifacts, direct observation, laboratory experiments, and documents as data sources, and usually there are no plausible ways of identifying populations and drawing samples by probability methods.

The other major use of inferential statistics in educational research is for testing hypotheses. In many cases, the same or closely related tools are used for questions of assessing generalizability and for hypothesis testing. The underlying logic of hypothesis testing is to compare an observed result in a sample to some null hypothesis value relative to the sampling variability of the result under the assumption that the null hypothesis is true. If the sample result differs greatly from what was likely to have been observed under the assumption that the null hypothesis is true, then the null hypothesis can confidently be rejected.

The key link in the inferential chain of hypothesis testing is the estimation of the standard errors of statistics—that is, estimating the expected amount that the value a statistic would "jump around" from one sample to the next simply as a result of accidents of sampling (Hanneman & Riddle, 2005). Rarely, of course, can standard errors be directly observed or calculated because there are no replications. Instead, information from a sample is used to estimate the sampling variability.

Hanneman and Riddle (2005) go on to note that with many common statistical procedures, it is possible to estimate standard errors through validated approximations (e.g., the standard error of a mean is usually estimated by the sample standard deviation divided by the square root of the sample size). These approximations, however, only hold when the observations are drawn through independent random sampling. Network observations are almost always by definition nonindependent (except, of course, ego-level network studies from which egos have been randomly drawn from some target population). Consequently, conventional inferential formulas do not apply to network data (though formulas developed for other types of dependent sampling may apply). It is particularly erroneous to assume that such formulas do apply, because the nonindependence of network observations will often underestimate the true sampling variability and result in having too much confidence in your results.

Permutations Tests for Network Data

The approach of most network analysts interested in statistical inference for testing hypotheses about network properties is to work out the probability distributions for statistics directly. This approach is used because (1) no one has developed approximations for the sampling distributions of most of the descriptive statistics used by network analysts and (2) interest often focuses on the probability of an estimate relative to some theoretical baseline (usually randomness) rather than on the probability that a given network is typical of the population of all networks. So, how does this actually work?

Network analysts make use of a form of nonparametric tests referred to as permutations (there are others, too). This is just a fancy way that mathematicians refer to a reordering of numbers. Prell (2012) offers the following example, which shows the permutations of the numbers 1 through 5:

{1, 2, 3, 4, 5}

{1, 3, 4, 5, 2}

{2, 3, 1, 5, 4}

{3, 2, 5, 1, 4}

{4, 5, 3, 1, 2}

In this example, each permutation that follows the original ordering has the same numbers but in a different order. Of course, there any many more permutations possible (5! = 120 total permutations). Contrasted with mathematicians, statisticians use the term *permutation* to refer to rearrangements of data. The connection to social networks is that the data that are rearranged are matrices. These matrices are rearranged over and over again, providing a distribution against which the observed data can be measured. These permutations—hundreds and even thousands of them—are used for testing levels of significance, or the likelihood of an observed network property occurring by chance.

So, let's say you are interested in the number of collaborative exchanges that occur between teachers from two different grade levels in a complete network of teachers within one elementary school. First, you count the number of times these types of exchanges occur in the observed network and then permute these relational data lots and lots of times. With each permutation, you calculate the number of times this type of tie (collaborative exchanges between teachers from two different grade levels) occurs and compare this result to the original observed network. After this process of permuting and comparing, you can see how often the results of these permutations are the same as the original observed results: The more often the results of the permutations are the same as your observed data, the more likely that the pattern of exchanges in the observed data was due to chance. If, however, the results from the observed data are so unlikely when compared to the results of the permutations, then you are to conclude that your results are not the byproduct of chance. Therefore, this result would be considered statistically significant.

Here is a second example of how this works. Suppose you were interested in the proportion of seventh-grade students in a middle school who were members of cliques (or any other network-derived group structure). Recall that the notion of a clique implies a rigid structure—nonrandom connections among students. Assume you have relational data from all 100 students in the seventh-grade class, in which there are 60 symmetric ties among students (i.e., Student A nominates Student B and vice versa), and it is observed that there are 15 cliques containing at least four students. The inferential question might be posed as: How likely is it, if ties among students were purely random events, that a network composed of 100 students and 60 symmetric ties would display 15 cliques of size four or more? If it turns out that cliques of size four or more in random networks of this size and degree are quite common, you would be very cautious in concluding that you have uncovered a “real structure” or nonrandomness. If it turns out that such cliques (or more numerous or more inclusive ones) are very unlikely under the assumption that ties are purely random, then it is very plausible to reach the conclusion that there is a “true” social structure present.

Exponential Random Graph Models

But how can you determine this probability? The method used is one of simulation. Like most simulation, a lot of computer resources and (maybe) some programming skills are often necessary. In the current case, you might use a table of random numbers to distribute 60 ties among 100 actors and then search the resulting network for cliques of size four or more. If no clique is found, a 0 for the trial is recorded; if a clique is found, a 1 is recoded. The rest is simple. Just repeat the simulation several thousand times and add up what proportion of the “trials” result in “successes.” The probability of a success across these simulations is a good estimator of the likelihood that you might find a network of this size and density to have a clique of this size “just by accident” when the nonrandom causal mechanisms that you think cause cliques are not, in fact, operating.

Valente (2010) notes that the big development in the use of simulations in network studies—that is, the probability that a network measure would occur by chance—was the use of exponential random graph models (ERGMs). These models were first developed (Frank & Strauss, 1986; Holland & Leinhardt, 1981) in order to provide a way to determine whether network properties (e.g., reciprocity) occur by chance as a result of other network properties (e.g., density) or whether the observed properties are unlikely given other parameters in the network (Valente, 2010). In addition to providing a probability distribution against which an observed network parameter can be compared, ERGMs have matured in such a way that they also permit actor attributes to be incorporated into model estimation. So, not only did the use of ERGMs allow hypothesis testing, they also evolved in ways that permitted formal statistical tests that included actor-level covariates such as those related to individuals' demographic (e.g., gender) or behavioral (e.g., class attendance) characteristics.

This development may sound odd, and it is certainly a lot of work (most of which, thankfully, is done by social network applications). But, in fact, it is not really that different from the logic of hypothesis testing with nonnetwork data. Social network data tend to differ from more "conventional" actor-by-attribute survey data in some key ways: Network data are often not drawn from probability samples, and the observations of individual actors are not independent. These differences are important for the generalization of findings and for the mechanics of hypothesis testing. There is, however, nothing fundamentally different about the logic of the use of descriptive and inferential statistics with social network data.

The application of statistics to relational data can be quite complicated and is one that is currently at the forefront of social network analysis. Despite these complications, there are several reasons why it is desirable and often necessary to move beyond the mathematical approach and its emphasis on description and toward the statistical approach and its emphases on explanation and inference (Robins, Pattison, Kalish, & Yusher, 2007). For example, statistical models allow you to understand the uncertainty associated with observed outcomes and more accurately reflect the complexity of social processes. In addition, statistical models allow inferences about whether certain network substructures (e.g., groups of teachers within a school) are more commonly observed in the network than might be expected by chance. Hypotheses about the social processes that might produce these structural properties can then be formally tested. Finally, different social processes may make similar qualitative predictions about network structures, and it is only through careful quantitative modeling that the differences in predictions can be evaluated. For example, clustering in networks might emerge from endogenous (self-organizing) structural effects (e.g., structural balance), or through node-level effects (e.g., homophily).

ERGMs are the primary building blocks of statistically testing network structural effects. Increasingly, researchers are not only interested in describing an ego or complete network but rather in whether an observed network property is significant. ERGMs generate (random) networks derived from features of the observed network, which provide a way to compare the observed and simulated networks. Statistical analysis is then conducted to test whether the ties in the simulated network match those generated by the simulations.

Here is how an ERGM generally works. Suppose an empirical network consists of 100 teachers and 1,000 ties among them, for a density value of 10%. We might be interested in examining whether there is a tendency for reciprocity: If Teacher A nominated B, was B more likely to nominate A? To figure out whether there is a tendency toward reciprocal relations, hundreds or perhaps even thousands of networks are generated with the same number of actors and ties as in the empirical network—100 actors and 1,000 ties. The average of the simulated distribution of reciprocal ties is calculated and then compared to the value in the empirical (observed) network. Then, if the reciprocity in the empirical network differs from the average reciprocity in the simulated networks more than it would be expected to by chance, we can conclude that there is indeed a tendency towards reciprocity. One feature that makes newer ERGMs even more powerful is that they are even flexible enough to allow you to elect which structural parameters (reciprocity, density, transitivity, *K*-star configurations, among others) to include in the simulation, but these choices should be made with great caution.

In addition to ERGMs, many models in the network literature are important tools for simulation, hypothesis generation, and "thought experiments." However, since this text focuses on more basic and commonplace uses of network analysis in educational research, the following chapter provides a brief and succinct introduction to some of these ideas—many of which have a logic similar to that of ERGMs—with an emphasis on how certain research questions can be addressed through statistical inference without getting mired in technical details.

ERGM Example: Friendship Formation in School

To further demonstrate the logic and utility of ERGMs, consider the example provided by Goodreau, Kitts, and Morris (2009), who used this approach to identify the determinants of friendship formation that lead to pervasive regularities in friendship structure among adolescent students. Or, stated more succinctly, why do similar types of students always seem to become friends? Data were drawn from the first wave of National Longitudinal Survey of Adolescent Health (Add Health). The "in-school" questionnaire asked students to identify their five best male and five best female friends in order of closeness. From this, they focus solely on mutual friendships, those dyads in which students nominate each other. Because they are reciprocated, mutual friendships are cross-validated and thus more likely to be stronger than one-way friendship nominations. In addition, the Add Health survey also collected substantial information on students' sociodemographic attributes and behaviors.

Goodreau, Kitts, and Morris used ERGMs to identify the mechanisms that lead to the formation of these within-school friendships. Specifically, they consider students' overall propensity to make friends (sociality), as well as their propensity to make friends based on their own attributes (selective mixing) and based on their friends' choice of friends (triad closure). ERGMs allow them to tease out which of these three mechanisms or combination of mechanisms is most closely associated with friendship formation and how these mechanisms vary across students with different sociodemographic backgrounds. A common model was applied to all 59 schools and estimates, (and their standard errors) were aggregated to determine whether the effects generalize across schools (Snijders & Baeveldt, 2003). This enabled them to examine whether there were any idiosyncratic variations within schools as well as make comparisons across all sampled schools.

A number of interesting results are reported. First, there is evidence that both selective mixing (associating with same-attribute others) and triad closure (a friend's friends are more likely to become friends) operate across a wide range of sociodemographic settings to structure the process of mutual friendship formation. These processes interact, generating a complex set of effects. The attributes of grade and sex always generate both strong assortative mixing and within-category triad closure. The effects of students' race vary: white, black, and Asian students typically exhibit assortative mixing and within-category triad closure, representing structural cohesion within their subpopulations, but other categories are more complicated. Hispanic students (by far the most numerous of remaining categories) can display random (i.e., unbiased) or even disassortative mixing. Even when Hispanics exhibit assortative mixing, it is often coupled with a relative lack of within-category triad closure, reducing their higher-order cohesion.

In addition, they also find that the higher-order processes governing friendship formation can depend on the school's overall demographic profile. For example, the extent of Hispanic cohesion appears to be partly shaped by the homogeneity of the school's non–Hispanic population: the more homogeneous the non–Hispanic population, the more cohesive the Hispanic friendships. Similarly, the strength of assortative mixing for whites is inversely related to their relative share of the student body: The more they are in the minority, the more segregated their friendships become. This relation does not hold for blacks: Assortative mixing is strongest for blacks when they compose an intermediate proportion of the population. Perhaps blacks are less assortative than whites when they are a small minority because this status is familiar to them.

The modeling goal of Goodreau, Kitts, and Morris (2009) was to move beyond network description to uncover the generative processes that underlie network tie formation. Generative processes refer to those micro-level mechanisms that produce a higher-level network structure: interaction between two actors that leads to a bigger pattern among a larger set of actors. The ERGM framework offers a general set of tools to aid in this goal, and the Add Health survey (with 59 replicate schools) has a unique structure for exploiting these new capabilities. By focusing on personal attributes (race, sex, and grade), they were able to identify some of the demographic correlates of friendship formation and rule out the kind of endogenous feedback processes between friendship choices and personal attributes found in other contexts. By estimating all models within the relatively small units of schools, they were able to get closer to ensuring that all pairs of students are equally able to form friendships, so their choices are less confounded by gross heterogeneities in opportunity. In addition, by simultaneously estimating effects at the individual, dyadic, and triadic levels, they were able to disentangle the effects of each level from the others. This modeling strategy moves the field closer to quantitatively comparing the strength of effects within and across the levels on which student friendship preferences operate.

Two notes of caution about these permutation-based tests are warranted (Prell, 2012). Fortunately, these permutation-based tests of statistical significance, such as ERGMs, are available through both general and specialized social-network software packages and programs (reviewed in Chapter 12). But, depending on the size of your network, these tests can be very demanding of your computer's computational capabilities. If the data require many permutations, it might take quite some time for your computer to calculate a test statistic. Second, while many permutation-based tests can be used to derive probability values, they do not work so well for calculating confidence intervals.

Summary

Like most quantitative social science, we are often interested in making an inference about some sample estimate to a larger population. The process through which this is typically done is predicated on two assumptions: first, the sampling distribution—the distribution of estimates from many samples—is normal and; second, observations within and between samples are independent. This nonindependence of observations often underestimates the true sampling variability and results in inflated standard errors that give you too much confidence in your results. Therefore, you would be more likely to commit what is often referred to as Type I error: rejecting a null hypothesis when it is actually true.

To address the inherent way in which network data violate the assumption of independence, network researchers have developed means to test the likelihood of a network property that do not rely on this assumption of normality. The key has been the development of simulation. These simulated networks provide the basis for comparing an observed network property against what would happen by chance. Some of the first network models to make use of simulation were of exponential random graph models (ERGMs). Used only for cross-sectional data, these models can be used to determine whether an observed network is a function of properties based on the algorithms covered in Part II, including density, reciprocity, transitivity, and so on. ERGMs can help determine whether properties occur by chance as a result of other network properties or whether the observed properties are unlikely given other network parameters.

This chapter ended with an example of how ERGMs were used to examine friendship formation in adolescents within schools. In addition to demonstrating the logic of simulation and its application to estimating the likelihood of a friendship tie between two students, this example also showed how individual attributes (e.g., race and grade level) can be incorporated into model estimation. In general, these models provide a basis for statistical inference and hypothesis testing, but, more specifically, they can (1) describe a network in terms of its structural properties; (2) determine if individual attributes are associated with network structural properties; and (3) determine if individual attributes are associated with behaviors and attitudes while controlling both 1 and 2. For example, an ERGM can be used to estimate whether help-seeking behavior between teachers is likely to be reciprocated if that reciprocation is greater than expected by chance and if it is associated with the grade level that one is assigned to teach (same grade-level teachers are more likely to give and receive help). We can include a behavior or attitude in the model to determine if, for example, teachers with high job satisfaction are more likely to seek and receive help, controlling for grade level and reciprocity.

ERGMs are one class of models that have been developed by network analysts to make inferences from network data and are considered the “building blocks” of statistical estimation with network data (Valente, 2010). The next chapter builds on this introduction and surveys a number of other different modeling approaches that have been developed to account for the inherent dependency of relational data. While these approaches are varied and perhaps even complicated, the key is that they are predicated on the idea of comparing an observed network property to a whole bunch of simulated networks. The earliest variations of these simulated networks (e.g., Bernoulli graphs and Markov random graphs) are based on simple rules and may not result in satisfactory simulated network distributions. Recent developments have resulted in programs that generate better and, therefore, more realistic simulated networks that provide a more reasonable basis for comparison. While these developments are exciting, they are beyond the scope of this introduction. Suffice it to say, the critical idea in this chapter is that simulations permit inferences and hypothesis testing using network data that are by definition nonindependent observations. The next chapter introduces several of these different approaches, all of which have evolved from this idea of using simulations to generate the distributions against which observed properties are tested.

Chapter Follow-Up

Why are these simulations necessary in order to make probabilistic inferences with network data?
Explain in plain language how simulations are used to create a probability distribution that enables you to make a statistical inference with network data.
Contrast the aims of the mathematical and statistical approaches to social network analysis. For what reasons would educational researchers prefer one approach versus the other?

Critical Questions to Ask about Network Studies that Make Statistical Inferences

How were the simulated networks, also known as the dependence graphs, generated?
Did these simulations properly and adequately account for the nonindependence of the data?
How many simulated networks were generated?
What hypotheses were being tested?
Is the difference between the observed and simulated networks statistically significant? If so, what does this mean?

Essential Reading

Goldenberg, A.Zheng, A.Fienberg, S.Airoldi, E. A survey of statistical network models. *Foundations and Trends in Machine Learning,*(2009).2(2),129–233.

Goodreau, S. M.Kitts, J. M.Morris, M. Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. *Demography,*(2009).46(1),103–125.

Scott, J.(2000). Social network analysis: A handbook (2nd ed.). Thousand Oaks, CA: Sage Publications.

http://dx.doi.org/10.4135/9781452270104.n8