Journal of Social Structure

JoSS Article: Volume 16

Using *Lord of the Flies* to Teach Social Networks

jimi adams
Associate Professor, Department of Health & Behavioral Sciences, University of Colorado Denver
jimi.adams@ucdenver.edu

Abstract
Lord of the Flies is commonly assigned reading for high school and college students. The novel about shipwrecked boys is often analyzed thematically to examine how the boys' perceived isolation on the island effects their attitudes and behavior. However, what is similarly apparent is that the society they develop while on the island establishes certain patterns, and is governed by collective rules (some more explicit than others). Here I demonstrate how those behavioral patterns and norms are useful for interpreting the concepts and analytic tools found in social network literature. I describe how I used the novel as a "capstone" project in four sections of an undergraduate Social Networks course. This demonstrates how students' readings of the text revealed several common families of social network measures leveraged in the book's plot.

I would like to thank Ryan Light, David Schaefer and Skye Bender-deMoll for helpful comments in preparing this manuscript. Any errors that remain are my own.

"I'll give the conch to the next person to speak. He can hold it when he's speaking … And he won't be interrupted … We'll have rules! … Lots of rules! Then when anyone breaks 'em—"

(Golding, 1954; p.33)

1. Introduction

One of the best courses that I remember taking as an undergraduate was a general education geography requirement in which the instructor did not use a textbook, but instead relied entirely on a collection of novels. Once I began teaching sociology courses I hearkened back to that experience and resolved that somewhere along the way I would find a way to use that approach in my teaching. When I began teaching a substantively oriented course on social networks, I decided it was a prime opportunity to draw on that experience.[1] While I didn't yet have the courage to take the plunge fully, and rely solely on novels for the course, I aimed to find a book that we could use at the end of the term as a means to pull together much of what we had covered. I would ask the students to read the book, and we would use class discussions of it to think about how network concepts were illustrated, and examine how these network ideas drove key elements of the book's plot.

After some consideration, I settled on William Golding's *Lord of the Flies* (hereafter *LotF*) as a book that would be especially useful for illustrating a wide range of the concepts our course covered.[2] While *LotF* is a book that many of the students likely would have prior exposure to, we would take a fundamentally different approach to reading and interpreting it—through the social network perspective we had developed in the course. This article draws on that experience to describe the utility of *LotF* in demonstrating both the descriptive elements of the social network perspective, as well as showing how Golding's plot (potentially unwittingly) leveraged several of social network researchers' key theoretical ideas.

For the last several course meetings of a substantively oriented Social Networks course, students were assigned to read *LotF*. These concluding class sessions—and some portion of their respective final exams—were organized as a discussion of: (1) what network elements that we covered in the course the students saw represented in the book's text, and (2) identifying how those network features served to advance the novel's plot and/or character development. Each of the examples provided below is selected from those course discussions and assignments, presented according to the organization of the course.[3]

[1] Often in departments where there are social network researchers, the first course to be offered is one on Social Network Analysis (SNA). Since SNA relies heavily on mathematical and computational aspects (Freeman, 2004), courses are often limited to upper division. However, it seemed to me that social networks was a great opportunity to expand sociological course offerings for undergrads, and even provide a potential alternative introductory course to recruit students to the perspective sociology has to offer—through a set of ideas that are increasingly close at hand to most of todays undergrads (but see Hargittai, 2010).

[2] After asking a number of colleagues for suggestions of books that would be useful for these aims, I thank Bernie Hogan in particular for pointing me to *Lord of the Flies*.

[3] Space limitations require that I leave out numerous additional examples that arose in these discussions.

2. Talking about & Gathering Social Network Data

As a means for understanding societal phenomena, the social network perspective shifts analytic focus from single entities and their characteristics—e.g., individuals' race, gender and class; organizations' size, location and institutions; nations' development or political environments—to instead focus on the patterning of **relational** connections between them (Wellman, 1988).[4] While these analyses can apply to such varied units of analyses, the theoretical and methodological development has identified patterns of relational structure independent of such potential differences—even explicitly claiming that the same analytic ideas ought to apply regardless of the types of actors to which they are applied (Wasserman and Faust, 1994).

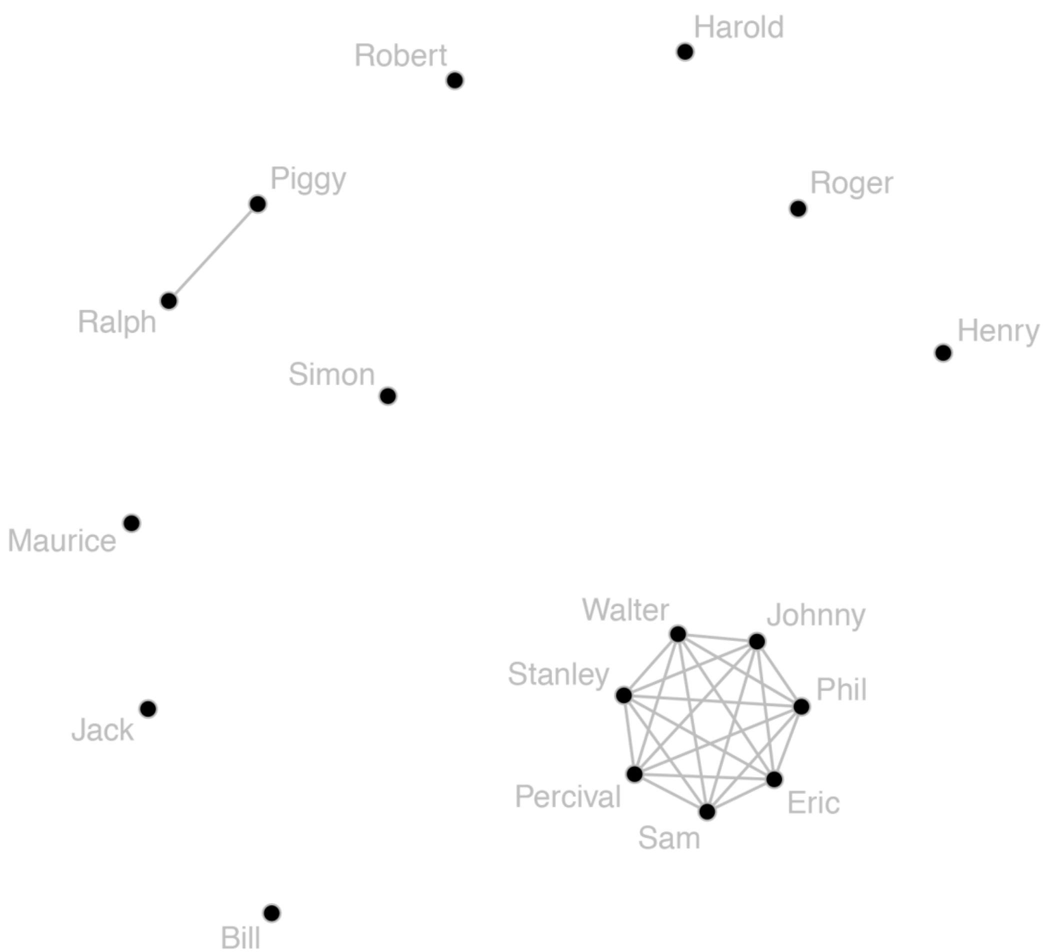

Figure 1. Network of Prior Relationships
In this figure, nodes represent each of the boys in *Lord of the Flies*, and ties represent those relationships that can be inferred to have existed before the book's events began.

[4] Given the introductory nature of the course and material here, the discussion that follows assumes no prior knowledge of SNA. This may lead some definitions and explanations to be moderately redundant for some readers of *JoSS*.

2.1 Relational Terminology

Social network ideas rely heavily on graph theory, and therefore concepts in the field borrow many terms and tools from graph theorists. From this tradition, those entities described above are generally referred to as **nodes** or **vertices** and are represented in network visualizations by points. These nodes can represent actors of various types—individual, institutional, nations, etc. Below, I will frequently refer to "individuals" but this is merely shorthand, and readers should keep in mind that nodes could represent actors of different sorts. For example, in Figure 1, the labeled points represent the named characters in *LotF*. Lines connecting the points represent the **ties** or **relationships** between those nodes. These lines can represent any number of relational types. In the Appendix network "movie" I visualize the evolving multiplex network structure for the entire plot of *LotF*.[5]

A key distinction among social network relationships is between those that are **directed** (which in graph theory are described as 'arcs') from those that are **undirected** (termed 'edges') (Knoke and Song, 2007). A **directed** relationship is one that is fundamentally different when perceived from either end of the relationship; i.e., it involves sender and receiver roles. For example ties of social support can differentiate those who provide support, from those who receive and potentially benefit from it. Contrastingly, some relationships are **undirected** in that the different roles are relationally indistinguishable from one another—e.g., a pair of siblings, or participants in a conversation. Figure 1 presents an undirected tie of prior knowledge among the characters in *LotF* before the book begins. While many of the characters are seemingly strangers to one another before the events of the book (e.g., Piggy and Ralph), others clearly have pre-existing relationships (e.g., the choir or Sam and Eric). A **network** (or **graph**) includes the entire collection of nodes and ties among the studied population, which can be represented by a "graph" as in the example network in Figure 1.

While *LotF* is often analyzed thematically, using these observational network data also provides an engaging example from which to interpret the concepts and analytic tools found in social network literature. Before doing so, an (admittedly overly-brief) summary of the novel is in order. *LotF* provides an account of a group of boys stranded on a deserted island; most of the boys seem to first meet following their plane crash, with the exception of a pair of twins (Sam-n-Eric) and a choir (lead by Jack), The boys initially establish rules to govern their island society (with Ralph as their chief)—perhaps best exhibited in the expectation that passing the conch restricts who is permitted to speak when they gather in assemblies (see epigraph)—with these rules focused primarily on the boys' survival (e.g., hunting for food and building shelters) and rescue (e.g., maintaining a signal fire). As the book progresses, their society increasingly devolves as they spend more time pursuing immediate pleasures (e.g., hunting and swimming). Thematic interpretations of the book see this shift as representing the boys' regression to a primitive state—reaching its apex when during a ritualistic dance, the group kills one of the boys (Simon).

[5] The video is available from www.youtube.com/watch?v=xwV9K_Hm_mY. Additionally, as patterns are described in the text, I provide hyperlinks to the moment in that video where the pattern can be seen. In the paper's Appendix, I provide a complete list of these timestamps along with a timeline of the book.

2.2 Gathering and Coding Network Data

As mentioned above, social network analysis (SNA) can describe relational structure over a variety of relationship types. In the examples that follow, I rely on undirected ties that capture individuals' co-presence in the same location, and directed ties variably representing relationships of: speaks to, physical aggression, or passes the conch.[6] Considerable attention has been devoted to strategies for collecting network data. The vast majority of existing strategies employ some combination of survey and/or observational data gathering techniques (Marsden, 2011), with various forms of "breadcrumb" data also becoming increasingly common (Borgatti and Everett, 1997; Eagle, Pentland and Lazer, 2009). The classes' approach, where students noted from actions described in the text of *LotF*, is most similar to strategies for recording observational network data (e.g., Schaefer et al., 2010).

Before network data such as these from *LotF* can be analyzed, researchers must address how nodes and ties are to be sampled, a concern known as the **boundary specification** problem (Laumann, Marsden and Prensky, 1994). There are three primary strategies for determining which nodes and ties to include ego, partial and "complete" network designs (Morris, 2004). An **ego network** approach takes the strategy of sampling a set of nodes, then enumerating the connections they have to some set of other individuals (referred to as **alters**). The respondent (or **ego**) is then asked to detail characteristics of those alters, and the features of the relationships they have with each (e.g., strength of the tie or frequency of contact). Occasionally egos are also asked to provide their own estimation of relationships among their alters. An ego network design does not attempt to connect that collected information between sampled egos. This means that any analyses can describe characteristics of the network surrounding an ego, but does not provide any indications of the potential linkages among those egos or between the alters that sampled egos report about.

A **partial network** design follows the basic strategy of an ego network design, but then in turn attempts to recruit some proportion of each egos' alters as respondents themselves (e.g., adams et al., 2012). This chain-referral system can trace one, some or all of an egos' alters, and can be repeated followed for any number of rounds, which provides the basis for principled approaches to sampling hidden populations (Mouw and Verdery, 2012; Salganik and Heckathorn, 2004).

Contrastingly, a "**complete**" network design identifies a population of nodes to study, then attempts to enumerate all of the relationships among that set of nodes. In most settings the boundaries for identifying who (and ties to/from whom) are to be included involves some arbitrariness to the boundary determination—hence "complete" being somewhat of a misnomer. While each of these strategies could be proxied in recording social network data from *LotF*,[7] in practice, the examples below follow a complete network approach, using presence on the island as the analytic boundary.

---

[6] These tie types also reflect a recent distinction in the literature between "state" based ties that endure (e.g., friendship) compared to "event" based dies that are momentary (e.g., a phone call) (Butts, 2008). While a majority of social network theory has been developed from the former, structural patterns from both can be important for revealing group structure. All of the ties used here are "event" ties.

[7] For example, we could take an ego network approach by focusing only on the ties that focal characters experience. Or we could apply a partial network design by tracing the flow of speculation about the "beastie" from Harold to others

3. I have Network Data; What Can I do with It?

There is a variety of ways to organize the types of metrics used to describe network characteristics. Here—as with our course's organization—I use the unit of analysis to organize the presentation of these metrics, and how *LotF* is helpful in representing each. I begin with metrics focused on relational patterns applied to the individual or node level; I then address metrics that focus on the relationship level as the unit of analysis. From there, I expand the focus to detail metrics that apply to groups of various sizes—starting with the entire network, then addressing smaller subsections within the complete network. Finally, I address metrics that compare nodes (or subsets of nodes) in a pairwise fashion, and introduce how temporal change is captured in network analyses. The metrics described below do not provide an exhaustive list of concepts used in the field, but do represent several key families of relational structure measures commonly found in the theoretical and empirical social network literature. For more complete coverage, see Wasserman and Faust (1994) or Scott and Carrington (2011).

3.1. Node Level Metrics

Probably the simplest way to incorporate network ideas into sociological thinking is to identify relational attributes of individual actors. That is, what makes a person's position within a network particularly informative? Among the most common network metrics computed is the number of ties a node has, which graph theorists refer to as a node's **degree**. In addition to looking at degree for any one node, a recent explosion of literature has taken the degree distribution (see Figure 2) as a first opportunity to summarize relationship patterns among a population. Before the book began, each of the choirboys knew substantially more others in the book's population (making up all of those with D=6) than anyone else, and most characters did not appear to have any prior relationships (D=0). A frequently observed feature of many networks is a skewed degree distribution, with **scale free** networks of particular interest especially among those examining very large networks (Barabasi, 2009).[8] While some networks exhibit common distributions, many, like the one presented in Figure 2 do not. Moreover, even those scholars who have most stridently championed the gains from this feature of networks have come to recognize that "no approach to complex systems can succeed unless it exploits the network topology" (Barabasi, 2009: 413)—a feature about which the degree distribution alone provides very little information. In other words, key features visible from Figure 1 cannot be determined from only the information conveyed in Figure 2's degree distribution.

on the island. Each of these would provide an incomplete representation of the island network—both in momentary snapshots and in any attempt to aggregate across them.

[8] A scale free network is one with a degree distribution that follows a power-law: $P(k)\sim k^{-\gamma}$, where γ is scale invariant (Barabasi, 2009). This pattern can most readily be seen by plotting the degree distribution on a log-log plot, with the distribution following a negative linear pattern, with slope γ.

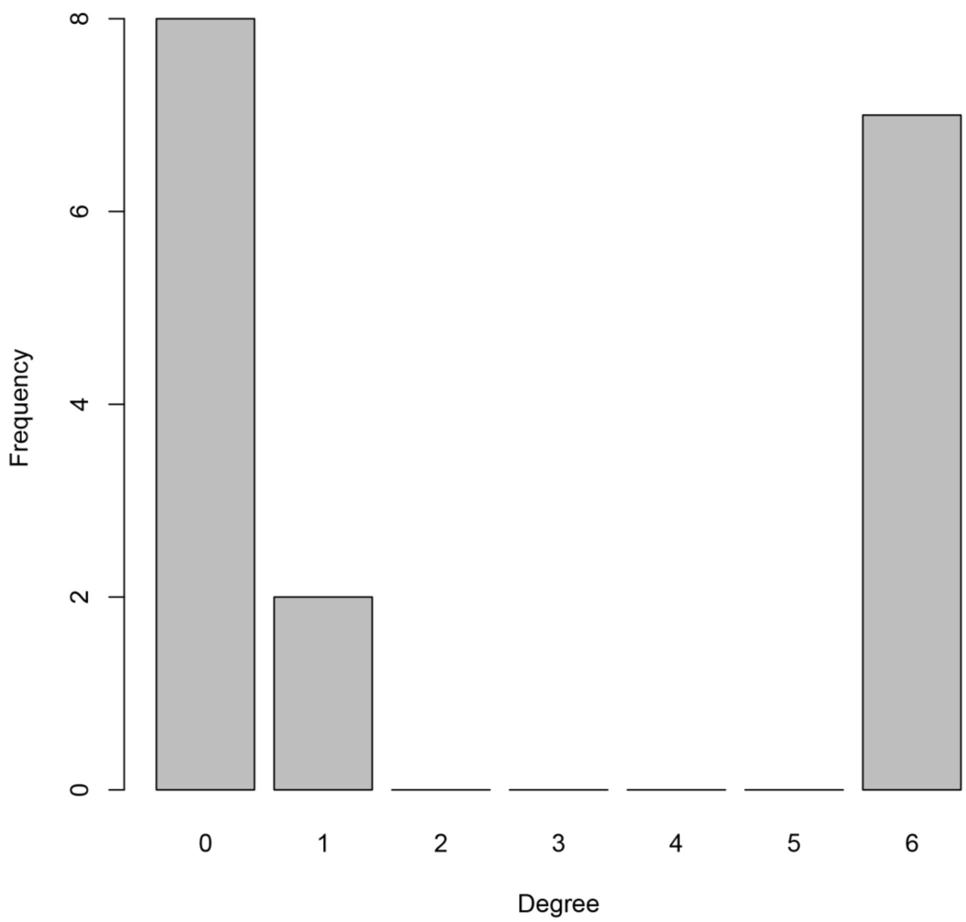

Figure 2. Degree distribution of Prior Ties
This frequency distribution accounts for nodes' degree corresponding to the network visualized in Figure 1.

A central question for sociologists is one of who wields power over others in various social settings. SNA provides a variety of **centrality** measures as a strategy for identifying relational positions that facilitate such individual advantages. Degree can be thought of as one such metric—having more ties can be an advantage over having fewer. However, this is a simplistic notion of how relational structure determines power, and has lead to the proliferation of numerous metrics for capturing centrality. The two other most commonly used approaches for estimating relational centrality can be thought of as deriving power from one's reach in a network or one's ability to constrain a network (Borgatti and Everett, 2006).

Closeness centrality C_c for node i is computed as:

$$C_c(n_i) = [\sum_{j=1}^{g} d(n_i, n_j)]^{-1} \qquad (1)$$

—where d is the distance (see elaboration in Section 3.5) from i to all other nodes j in the graph (size g) (Freeman, 1979). Conceptually, this metric captures of how readily someone in a network could potentially distribute information to everyone else in the graph—i.e., power is defined by a person's reach. Through most of the first half of *LotF*, Ralph would have very high closeness centrality on the coded "speaks to" tie, due to his proximity to both biguns and littluns on the island (video link).[9] Alternatively, relational power can be determined by one's ability to constrain others' actions (Burt, 2001). **Betweenness centrality** is the most common approach to capturing this version of power, which is computed for node i as:

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk} \qquad (2)$$

where g_{jk} denotes the shortest (or geodesic) path between the pair of nodes j, k, and n_i denotes the number of those paths that i falls on. This proportion is then summed over all ordered pairs ($j<k$) in the network, not including i (Freeman, 1979). Conceptually, the more often that a node sits between other pairs of nodes, the more power that node has, from its capacity to constrain the others' communication. Near the end of *LotF*, when the boys have split into two tribes, on both the "speaks to" and "co-presence" ties Sam-n-Eric have substantial betweenness centrality because they are the only members who bridge between the group lead by Jack and the one including Ralph and Piggy (video link). In fact, at points they even explicitly use this position as leverage to avoid being more ostracized within Jack's camp. Simon plays a similar role earlier in the book—especially as exemplified by the "speaks to" tie—when he brokers information flow between the littluns (receiving information from them about their fears) and the biguns (to whom he conveys some of that information).

Some might ask why the boys on the island pay any attention to Piggy at all, since so few of them appear to hold him in any esteem. This is where another major centrality measure can be revealing——eigenvector centrality aligns with closeness to recognize that reach matters in a population, but differs by noting that not all reach is equal. Eigenvector centrality therefore weights the contributions to centrality computation by the centrality of the other nodes to whom one is connected (Bonacich and Lloyd, 2001; Bonacich, 1987)—i.e., *whose* ear can a person bend? Eigenvector centrality thus recognizes the differential importance of ties in computing centrality, an intuition that forms the basis of Google's Page Rank (Brin, 1998). This is where Piggy derives his power; he may only really have the respect of one other boy on the island, but Ralph is himself well connected (video link). Among the ties represented here, we can think of receipt of the "speaks to" tie as conveying some willingness of one boy to devote attention to another. When aggregating the "speaks to" tie over the first four chapters, we find that Piggy—compared to other nodes—receives a disproportionate proportion of "speaks to" ties from Ralph.

[9] Students frequently pointed out Ralph's high centrality early in the book, which would be similar if we explored other tie types they inferred from the text, e.g., directed "respects" ties and/or undirected "friendship" ties.

3.2. Tie Level Metrics

While SNA can capture metrics that identify structural features that (dis-)advantage individuals, the nature of relational analysis is such that there are numerous other levels at which analyses are informative. At the next highest level of aggregation are metrics that apply to the ties themselves. We frequently think of ties as binary (i.e., limited to either their presence or absence). However, ties can also have **value** (e.g., to express the strength of a relationship; Granovetter, 1973), **frequency** (e.g., to identify how often nodes exchange emails; Kossinets and Watts, 2006), or be **signed** (e.g., differentiating alliances from antagonisms among political actors; Neal, 2014). In the *LotF* case, instead of looking at the "speaks to" tie only at one moment, we could aggregate over some time period (e.g., a chapter) to estimate weighted "communication" ties between each pair of boys.

For directed ties, **reciprocity** captures the proportion of the time when a directed tie is present that the opposite relationship is also found—e.g., if *i* says *j* is their friend, recording whether *j* says the same about *i* (Cartwright, 1956). Reciprocity is easily summarized for a full network by recording the number of **M**utual (reciprocal), **A**cyclic (un-reciprocated) and **N**ull (neither directed tie being present) ties for all dyads in the graph (known as MAN notation). While the presentation here did not systematically code a "respects" relationship (an additional tie type students often mentioned), it is clear in the book that examining this tie between Jack and Ralph would reveal it as reciprocated early in the book, acyclic by some point in the middle of it (Jack apparently having lost respect for Ralph), and null by the end of the book.

Up to now, we have only considered network features for one type of tie at a time. However, important relational features are often the product of how multiple types of ties overlap within a network. This network **multiplexity** can be analyzed to reveal how certain types of ties: reinforce one another via redundancy (e.g., when people communicate over multiple platforms; Wellman et al., 2001) or are complementary (e.g., when sexual ties provide different risk potential for transmitting sexually transmitted diseases than do needle-sharing ties; adams, Moody and Morris, 2013). Another revelation of relational power in *LotF* is apparent through simultaneously examining the "speaks to" and "passes conch" ties coded here. The norm was established that to speak one should first be passed the conch. This norm is largely followed in the assembly during Chapter 2 (video link). However, by Chapter 5, a number of boys can be seen speaking without having first been passed the conch—especially if Piggy was the speaker preceding them, an indicator of his lack of authority (video link).

A final tie-level pattern often examined in a network is known as **homophily**, which is the tendency to form ties with others like oneself at a rate greater than chance (McPherson et al., 2001). Metrics for estimating network homophily are complex and therefore numerous, varying most substantially on the baseline assumptions for determining what comprises random association patterns against which empirical networks are compared (Bojanowski and Corten, 2014). Given the relative homogeneity among the characters in *LotF*, homophily is not as common a feature in this book as it is in many real world networks. However, it can still be seen in certain situations—most clearly in examining the "co-presence" tie early in the book when there is frequent sorting by age, with the littluns and biguns spending time separately (video link).

3.3. Network Level Metrics

Now, let's turn from highly localized measures to those that summarize patterns for the entire network. Network **density** indicates the extent to which a collection of nodes is connected to one another and is computed as the observed ties expressed as a proportion of all potential ties (Knoke and Song, 2007). Density is rarely observed at its maximum in empirical networks, but in *LotF* it is maximized for the "co-presence" tie when the boys gather for an assembly (video link). The same tie can exhibit some meaningful variation in *LotF*, for example when small numbers of the group head off to explore other parts of the island (in Chapter 3, video link), or when they are milling about on the beach in separate groups (in Chapter 2); each event would reduce the graph density well below its potential maximum.

Network **clustering** captures the general degree of "clumpiness" in a network,[10] which relies on identifying how often there are smaller groups of the network where ties are more often within than across group.[11] Graph clustering is estimated with a wide variety of conceptual and algorithmic approaches (Fortunato, 2010aa; Porter, 2009aa). Clustering may be the most important plot device in *LotF*, providing the simplest strategy for identifying the "tribal" break that occurs in the latter portion of the book. At any one moment in this point of the book, or aggregating over these chapters, graph clustering over the "co-presence" and "speaks to" ties readily reveals the separation of the boys into two distinct groups (though the composition of those groups varies, as additional boys secede from the group led by Ralph to the one led by Jack, video link). This pattern is even observed earlier in the book, when Jack and the other choirboys go off on hunting excursions (see Figure 3).

[10] Given the variety of disciplines that have contributed to network analyses, there are often concepts that are shared across disciplines but described by different terms, and situations where the same term is used by different disciplines to describe different concepts. Clustering is among the most problematic of the latter of these—where the same term is variously used to describe several closely related, but not equivalent, concepts. Here, I follow the sociological approach to defining graph clustering, which is often referred to as "community structure" in other disciplines.

[11] This differs from homophily in that group membership is identified *purely* by observed structural patterns of the network, not by any exogenous attributes.

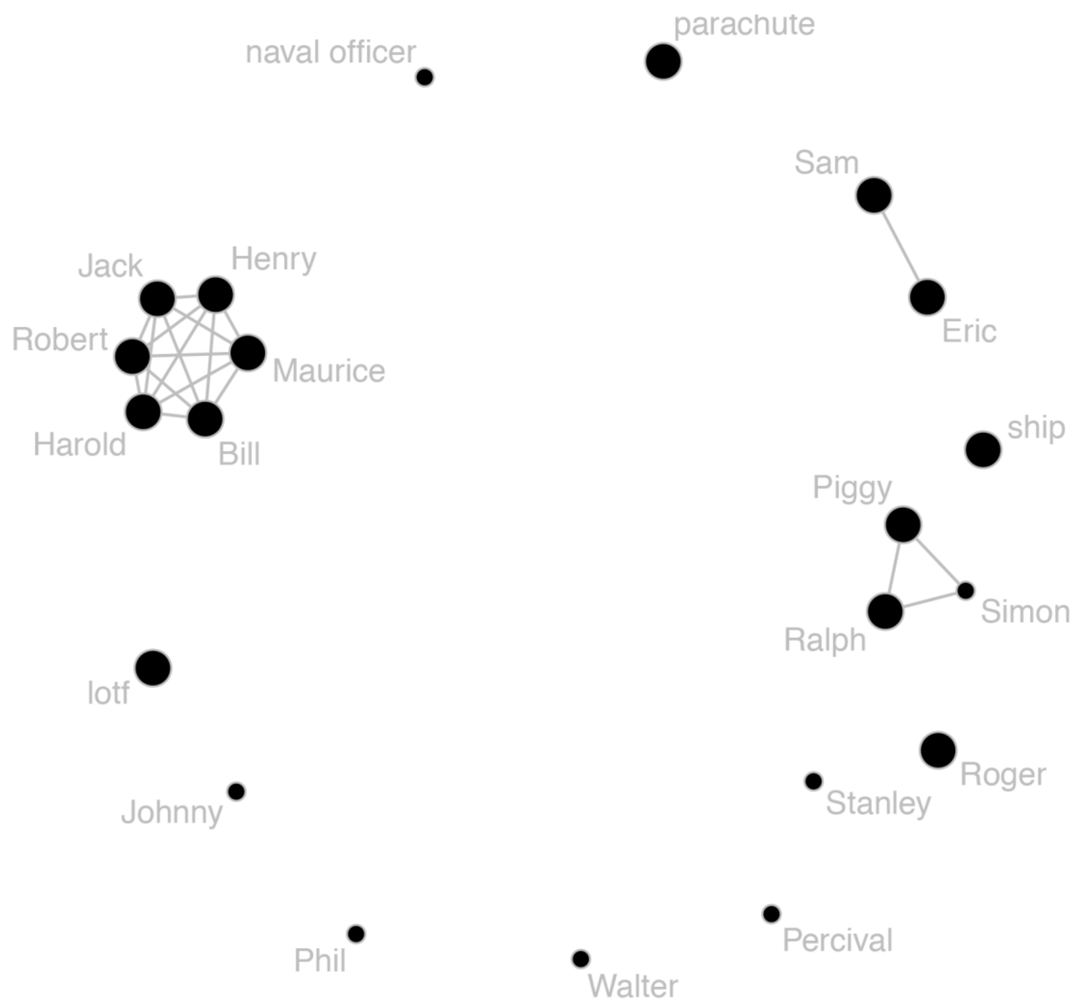

Figure 3. Clustered Network
This figure represents the "co-presence" tie during one of the choirboys' hunting excursions. Node size is determined by whether the boy is a "littlun" (smaller) or not (larger).

3.4. Subgroup Level Metrics

In between a focus at the purely local and full network levels, there are also families of measures that explore features of subgroups within a network. Subgroup **cohesion** estimates how closely knit together is a subsample of the network's population; this is estimated by balancing between the notions of clustering and density described above (Freeman, 1992). In essence, cohesion asks about internal group density among the members of the subgroup, while also estimating the separation of the group's members from all other nodes in the graph (Moody and White, 2003). As with many of the metrics described here, cohesion is estimated by a range of algorithms that differentially capture the concept's balance between internal cohesion and external segmentation. One approach is based on each member of the group having some minimum amount of connectivity (e.g., degree) to others within the subgroup; other approaches focus on minimizing the distance between members of the group (Borgatti et al., 1990), while still others focus on how fragile a subgroup's connection is to other nodes in the population who are not part of the group (e.g., by identifying how many ties would need to be dropped to separate the group from the rest of the network; Moody and White, 2003).

Returning to Figure 3, subgroup cohesion provides some informative interpretations about this observed "co-presence" network. First, the subgroup of choirboys/hunters exhibit maximal subgroup cohesion: they each are simultaneously directly connected to each other member of the subgroup, and none of them are connected to any other boys outside the group. Comparing this subgroup to others in this moment of the story would depend on how we identify the other groups against which to compare the cohesive hunters. By relying on purely structural features, we could readily identify two other subgroups—the one involving Ralph, Piggy and Simon and another including only Sam-n-Eric. Comparing between these various subgroups reveals that while each of these others are substantially smaller than the hunters group (1/2 and 1/3 of the size of the hunters, respectively), all three groups exhibit maximal *internal* subgroup cohesion. Alternatively, if we identified the other group for comparison via some attribute (e.g., those who remained behind at the beach), the comparison group would be considerably larger than the hunter group (involving 11 compared to 6 of the boys), but is a much less internally cohesive subgroup than is the hunters' (video link).

The smallest subgroup larger than the dyads discussed in Section 3.2 is a **triad**—potential groups consisting of 3 nodes. While reciprocity provides one dimension of social balance (Festinger, 1957), a more general application of the concept can be examined among triads. For undirected graphs, this corresponds to the colloquial notion of "a friend of a friend is a friend." That is, if two people (*i* and *j*) share a third person (*k*) in common as a friend (i.e., the *ik* and *jk* ties both exist) we would expect a higher likelihood than otherwise of also observing the *ij* tie—a pattern known as triadic closure. Undirected triadic closure can be extended to apply to directed graphs. A first step towards estimating this is to summarize the "dyad census" (in MAN notation, as described above). We can then summarize for all combinations of dyads over the triad whether it is balanced or not, identifying the presence or absence of social balance at the level of the triad—a concept generally described as **transitivity** (Moody, 1998).

Again, drawing from an inferred set of directed "respects" ties among the Ralph, Jack and Piggy triad early in the book we could examine the social balance between them. At this time, Jack and Ralph appear to each respect the other, Piggy respects Ralph, and regardless of whether we consider Ralph to respect Piggy (resulting in 2 mutual dyads and 1 null) or not (1 mutual, 1 acyclic[12] and 1 null), the result would be unbalanced. As in theoretical predictions (Holland and Leinhardt, 1970) and empirical observations (Hummon and Doreian, 2003), this imbalanced triad tends toward changing into some other form that is balanced; in the book leading to Jack ultimately losing respect for Ralph, and vice versa later on.

[12] Those used to the "triad census" format will note that the direction of the acyclicity differentiates the between relevant triad isomorphisms. In this case, it us a 'U' pattern, pointing away from the mutual dyad. However, for the 111 triad, both the U and D variants are unbalanced.

3.5. Pairwise Metrics

One of the most proliferated network findings is the so-called "Six Degrees of Separation" which purports that any randomly chosen pair of people in the world could be connected by a path of no more than six steps (Milgram, 1967).[13] This finding popularized the notion of network **distance**, which is simply the number of steps between a pair of nodes in a graph—a pair of nodes directly connected are at distance one; one's partner's partner is at distance 2, etc. A few particularities of the measure are worth mentioning: people are defined to be distance zero from themselves, and nodes that are unreachable from one another (e.g., Stanley and Roger in Figure 3) are defined as having infinite or undefined distances between them. In the childhood game of "telephone" the imprecision with which messages are passed is often a function of the network distance they had to travel (the message loses accuracy the further it has to travel). In the same way, the various murmurings in *LotF* about "the beast" on the island became increasingly distorted and reported with exaggerated confidence with each step they were passed, ultimately spreading fear throughout most of the boys.

The reason to save pairwise measures until this point in the discussion is because of how the last measure is estimated. Network **equivalence** is a notion of how structurally similar the position is between a pair of nodes. Two nodes are structurally equivalent (one specific operationalization of the equivalence concept) when they are *identical* on *all* network structural measures that can be computed; i.e., they are structurally indistinguishable from one another. Formally:

$$\forall x : G_{a,x} = G_{b,x}, x \neq a, b \tag{3}$$

That is, if a and b are equivalent, whenever there is a tie from x to a, there is also a tie from x to b and the same goes for ties from a (b) to x. Additionally, x is neither a nor b. Equivalence measures can be computed over a single tie type, or over multiple tie types at once (White, Boorman and Breiger, 1976). Throughout *LotF* it is rare that Sam-n-Eric are not seen together. This would result in them being structurally equivalent nodes on almost all ties at almost any point in the book (e.g., video link), with the occasional exception of the directed "speaks to" and "passes conch" ties. While structural equivalence looks for exactly matching pairs of nodes, other variants look for more relaxed notions of *similar*, not exact, equivalence (Borgatti and Everett, 1992).

3.6. Dynamics on Networks & Dynamics of Networks

Each of the metrics described above are measured on static networks. However, networks change (ties can be added or dropped), as does their composition (people alter their behaviors). For example, preschoolers' networks become increasingly marked by homophily and transitivity over the school year (Schaefer et al., 2010). Researchers have increasingly focused on theorizing, empirically capturing, and modeling these sorts of dynamic network properties (Moody, 2009). When examining dynamics *on* networks, scholars are interested in capturing how behaviors change over a static network. For example, this perspective captures how sexually transmitted diseases spread through a population's sexual and needle sharing partnerships (Darrow et al., 1999), or how fads can cascade over online connections (Centola, 2010). From an alternative theoretical orientation, scholars can

[13] That is, for the pair *ij*, person *i* knows someone who knows someone who knows someone who knows someone who knows someone who knows person *j*, and vice versa.

focus on how and why networks change over time (i.e., dynamics *of* networks). Such dynamics have demonstrated for example that network segregation on depression status appears to evolve not from homophilous preference, but rather from avoidance and withdrawal (Schaefer, Kornienko and Fox, 2011). While these processes function in theoretically separable ways, as with most complex systems, both network ties and actors' behaviors dynamically each influence the other as they coevolve over time (Kossinets and Watts, 2006; Schaefer et al., 2010). Researchers are increasingly interested in statistically modeling—and disentangling—these processes (Steglich, Snijders and Pearson, 2010).

In *LotF*, more of the readily observable dynamics are *of* network change. For example, the "co-presence" tie is increasingly clustered over time. On "co-presence" and "speaks to" ties, Simon is more isolated (less central), especially within the choirboys/hunters subgroup as the book progresses. The number of observed "aggression" ties increases later in the book.

4. Did *LotF* Reflect Student Mastery?

Our use of *LotF* was relatively simply structured. I asked students to read the novel, and as they did to be on the lookout for any ways they saw concepts we had covered during the semester. Second, I asked them to consider how these patterns served to advance the plot and/or character development, especially as resulting from the (in-)consistencies of the observed patterns with empirical findings we had covered. Class sessions were free-flowing discussions of the students observations. We would draw network diagrams on the board, and discuss the concepts, application, and (in-)consistencies with empirical patterns as a class. A writing assignment required students to individually elaborate these ideas for a few concepts.[14]

From this approach, I rely on two strategies for evaluating whether this exercise actually facilitated/reflected)[15] student's understanding of core social network ideas. First is based on unsystematic descriptive observations from my experience employing this exercise for four class sections with 95 cumulative students (ranging in size from 8 to 35 students). Second, I briefly discuss the correlation of performance derived specifically from this material with performance in the remainder of the course.

In each of the class sections where I used *LotF* as a "capstone" experience for an undergraduate course on social networks, we spent the bulk of class time for the last two weeks discussing how *LotF* reflected the concepts we had covered during the semester. Across all courses, these were the class sessions where students were most engaged in class discussions. Moreover, in each of the sections, students were able to identify moments in the book that reflected concepts from each of the "families" of measures the course had covered. *All* of the examples described above are drawn from one (or more) of these discussions and/or students' writings. Perhaps most informatively, while for each of these class sessions I came in with a list of potential examples for us to discuss, in three of the course sections students identified tie types and/or reflected social

[14] It varied between the course sections whether this assignment was part of their final exam, or a "capstone" paper assignment.

[15] As will be clear below, from the metrics used here it is not possible to distinguish whether *LotF* lead to improved student performance, or merely reflected their competence on course material. In other words, the evaluation criteria presented here have sensitivity, but cannot establish causal direction.

network patterns that I had not myself considered. And in each case, while the student initiating the discussion of these new ideas did not necessarily fully identify how the tie type reflected patterns we had discussed (e.g., whether it was consistent with or different from prevalent empirical findings), class discussions were able to generate resolution.

Given that the *LotF* section of each course was intended as a "capstone" experience for the course, it is difficult to distinguish whether performance on the corresponding material facilitated students' understanding of social concepts or merely reflected it. However, it is informative that across all four sections, the correlation was high (~0.72)[16] between student performance on the final exam/paper section devoted to *LotF* and their performance on all other course material.[17]

5. Conclusion

Scholars have recognized the presence of social network patterns in popular media (Freeman, 2000), including some relatively complex ones (adams, 2015). Here, I have discussed how I followed this lead to use *Lord of the Flies* as a capstone experience for students in four sections of an undergraduate social networks course. I showed how the book reflects many of the key ideas covered in the course. *LotF* proved useful for demonstrating the basic terminology and theoretical orientations underpinning social network research. There are numerous strategies available for collecting social network data, and coding the relational data available in the text provided opportunities to demonstrate the comparative strengths and weaknesses of each.

In addition to social network data being available within *LotF*, it also provided examples of many of the key analytic concepts used by social network researchers. While not every specific concept covered in the course was identifiable in the text, some examples of *each* of the major families of measures were. It was possible to estimate aspects of personal network composition from the text, including (age) homophily in the ties among boys on the island. Other micro-dynamics (particularly social balance) not only were visible in the book, but drove major plot points—e.g., the imbalanced triad between Ralph, Piggy and Jack was an early source of plot tension and was resolved in the novel's climax. Different boys exhibited the various features associated with different measures of centrality intended to capture social "importance" from varied theoretical bases (examples presented above include different aspects variably demonstrating the importance of Jack, Ralph, Piggy, Simon or Sam-n-Eric). Visualizing network change helped to identify how group structures—both clustering of the whole network and cohesion within subgroups—was important to driving aspects of the novel's plot. Finally, Sam-n-Eric are identical not only in the sense of being twins, but also in their relational signatures for virtually the entire book.

---

16 Additionally, this correlation is deflated by two countervailing patterns. First, four students failed to properly engage both portions of the question prompt and therefore had scores less than 50% for the relevant assignment. Second, one of the sections was an honors section, with a median course grade of A-, introducing a floor-effect for this section. Given that the overall correlation is strong while including both of these, I chose not to discard them.

17 This was comprised of an essay question asking students to apply multiple network concepts to interpreting plot events from *LotF*. While I did not explicitly employ it as a rubric, the evaluation criteria for this item were similar to the "Level of Abstraction Scale" (Britton et al., 1975; Collett, Kelly and Sobolewski, 2010)

Not only were these patterns visible in the book, students' ability to identify and accurately describe them coincided with their general performance in the course, suggesting that this exercise provided a useful way to evaluate social network mastery developed in the course. While I have yet to take the plunge to teach a sociological course *entirely* from novels, this experience suggests the potential utility of drawing on popular media material as a useful resource for conveying key ideas in the social sciences.

6. References

adams, j. (2015). Glee's McKinley High: Following Middle America's Sexual Taboos. *Network Science* 3, 2: 293-295.

adams, j., Moody, J., and Morris, M. (2013). Sex, Drugs, and Race: How Behaviors Differentially Contribute to Sexually Transmitted Infection Risk Network Structure. *American Journal of Public Health* 103, 2: 322-329.

adams, j., Moody, J., Muth, S. Q., and Morris, M. (2012). Quantifying the Benefits of Link-Tracing Designs for Partnership Network Studies. *Field Methods* 24, 2: 175-193.

Barabasi, A.-L. (2009). Scale-Free Networks: A Decade and Beyond. *Science* 325: 412-413.

Bender-deMoll, S. (2013). ndtv: Network Dynamic Temporal Visualization Package.

Bojanowski, M. and Corten, R. (2014). Measuring Segregation in Social Networks. *Social Networks* 39: 14-32.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology* 92: 1170-1182.

Bonacich, P. and Lloyd, P. (2001). Eigenvector-like Measures of Centrality for Asymmetric Relations. *Social Networks* 23, 3: 191-201.

Borgatti, S. P. and Everett, M. G. (1992). Notions of Position in Social Network Analysis. Sociological *Methodology* 22: 1-35.

Borgatti, S. P. and Everett, M. G. (1997). Network Analysis of 2-Mode Data. *Social Networks* 19: 243-269.

Borgatti, S. P. and Everett, M. G. (2006). A Graph-Theoretic Perspective on Centrality. *Social Networks* 28: 466-484.

Borgatti, S. P., Everett, M. G., and Shirey, P. R. (1990). LS Sets, Lambda Sets, and Other Cohesive Subsets. *Social Networks* 12: 337-357.

Brin, S. and Page, L. (1998). The Anatomy of a Large-Scale Hypertextual Web Search Engine. In *Proceedings of the 7th World-Wide Web Conference*. Brisbane, Australia.

Britton, J., Burgess, T., Martin, N., McLeod, A., and Rosen, H. (1975). *The Development of Writing Abilities*. MacMillan Education, London, England.

Burt, R. S. (2001). Structural Holes versus Network Closure as Social Capital. Pp. 31-56 in *Social Capital: Theory and Research*. Aldine de Gruyter.

Butts, C. T. (2008). A Relational Event Framework for Social Action. *Sociological Methodology* 38, 1: 155-200.

Cartwright, D. and Harary, F. (1956). Structural Balance: A Generalization of Heider's Theory. *Psychological Review* 63: 277-293.

Centola, D. (2010). The Spread of Behavior in an Online Social Network Experiment. *Science* 329, 5996: 1194-1197.

Collett, J. L., Kelly, S., and Sobolewski, C. (2010). Using *Remember the Titans* to Teach Theories of Conflict Reduction. *Teaching Sociology* 38, 3: 258-266.

Darrow, W. W., Potterat, J. J., Rothenberg, R. B., Woodhouse, D. E., Muth, S. Q., and Klovdahl, A. S. (1999). Using Knowledge of Social Networks to Prevent Human Immunodeficiency Virus Infections: The Colorado Springs Study. *Sociological Focus* 32: 143-158.

Eagle, N., Pentland, A. S., and Lazer, D. (2009). Inferring Friendship Network Structure by Using Mobile Phone Data. *Proceedings of the National Academy of Science* 106, 36: 15274-15278.

Festinger, L. (1957). *A Theory of Cognitive Balance*. Row, Peterson and Co., Evanston, IL.

Fortunato, S. (2010). Community Detection in Graphs. *Physics Reports* 486: 75-174.

Freeman, L. C. (1979). Centrality in Social Networks: Conceptual Clarification. *Social Networks* 1: 215-239.

Freeman, L. C. (1992). The Sociological Concept of Group: An Empirical-Test of 2 Models. *American Journal of Sociology* 98, 1: 152-166.

Freeman, L. C. (2000). See You in the Funny Papers: Cartoons and Social Networks. *Connections* 23, 1: 32-42.

Freeman, L. C. (2004). *The Development of Social Network Analysis: A Study in the Sociology of Science*. Empirical Press, Vancouver, BC.

Golding, W. (1954). *Lord of the Flies*. Perigree Books.

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology* 78, 6: 1360-1380.

Hargittai, E. (2010). Digital na(t)ives? Variation in Internet skills and Uses Among Members of the 'Net Generation. *Sociological Inquiry* 80, 1: 92-113.

Holland, P. W. and Leinhardt, S. (1970). A Method for Detecting Structure in Sociometric Data. *American Journal of Sociology* 70: 492-513.

Hummon, N. P. and Doreian, P. (2003). Some Dynamics of Social Balance Processes: Bringing Heider Back into Balance Theory. *Social Networks* 25: 17-49.

Knoke, D. and Yang, S. (2007). *Social Network Analysis*, Volume 154 of Quantitative Applications in the Social Sciences. Sage.

Kossinets, G. and Watts, D. J. (2006). Empirical Analysis of an Evolving Social Network. *Science* 311, 5757: 88—90.

Laumann, E. O., Marsden, P. V., and Prensky, D. (1994). The Boundary Specification Problem in Network Analysis. In *Research Methods in Social Network Analysis*, edited by L.C. Freeman, D.R. White, and A.K. Romney. New Brunswick, NJ: Transaction Publishers.

Marsden, P. V. (2011). Survey Methods for Network Data. Chapter 5 in *The Sage Handbook of Social Network Analysis*, edited by John Scott and Peter J. Carrington. Los Angeles, CA: Sage.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology* 27: 415-444.

Milgram, S. (1967). The Small World Problem. *Psychology Today* 1:61-67.

Moody, J. (1998). Matrix Methods for Calculating the Triad Census. *Social Networks* 20, 4: 291-299.

Moody, J. (2009). Network Dynamics. Chapter 19 in *The Sage Handbook of Social Network Analysis*, edited by John Scott and Peter J. Carrington. Los Angeles, CA: Sage.

Moody, J. and White, D. R. (2003). Structural Cohesion and Embeddedness: A Hierarchical Concept of Social Groups. *American Sociological Review* 68, 1: 103-127.

Morris, M. (2004). *Network Epidemiology: A Handbook for Survey Design and Data Collection*. Oxford University Press, London.

Mouw, T. and Verdery, A. M. (2012). Network Sampling with Memory: A Proposal for More Efficient Sampling from Social Networks. *Sociological Methodology* 42, 1: 206-256.

Neal, Z. (2014). The Backbone of Bipartite Projections: Inferring Relationships from Co-authorship, Co-sponsorship, Co-attendance and other Co-behaviors. *Social Networks* 39: 84-97.

Porter, M. A., Onnela, J.-P., and Mucha, P. J. (2009). Communities in Networks. *Notices of the AMS* 56, 9: 1082-1097, 1164-1166.

R, Development Core Team. (2006). R: A Language and Environment for Statistical Computing.

Salganik, M. J. and Heckathorn, D. D. (2004). Sampling and Estimation in Hhidden Populations Using Respondent Driven Sampling. *Sociological Methodology* 34: 193-240.

Schaefer, D., Light, J. M., Fabes, R. A., Hanish, L. D., and Martin, C. L. (2010). Fundamental Principles of Network Formation among Preschool Children. *Social Networks* 32: 61-71.

Schaefer, D. R., Kornienko, O., and Fox, A. M. (2011). Misery Does Not Love Company: Network Selection Mechanisms and Depression Homophily. *American Sociological Review* 75, 5: 764-785.

Scott, J. and Carrington, P. J. (2011). *The Sage Handbook of Social Network Analysis*. Sage.

Steglich, C., Snijders, T. A. B., and Pearson, M. (2010). Dynamic Networks and Behavior: Separating Selection from Influence. *Sociological Methodology* 40, 1: 329-393.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Volume 8 of Structural Analysis in the Social Sciences. Cambridge University Press, New York.

Wellman, B. (1988). Structural Analysis: From Method and Metaphor to Theory and Substance. Pp. 19-61 in *Social Structures: A Network Approach*. Volume 2 of Structural Analysis in the Social Sciences, edited by Barry Wellman and S. D. Berkowitz. Cambridge University Press.

Wellman, B., Haase, A. Q., Witte, J., and Hampton, K. (2001). Does the Internet Increase, Decrease or Supplement Social Capital? Social Networks, Participation, and Community Commitment. *American Behavioral Scientist* 45: 436-455.

White, H. C., Boorman, S. A., and Breiger, R. L. (1976). Social Structure from Multiple Networks 1: Blockmodels of Roles and Positions. *American Journal of Sociology* 81: 730-780.

Appendix I

A. Network Movie Description

An accompanying video visualizes the complete evolving multiplex event network for the full plot of *LotF*. That video can be found at (www.youtube.com/watch?v=xwV9K_Hm_mY). The movie was produced with the ndtv package (version 0.5.1; Bender-deMoll, 2013) implemented in R (version 3.1.3; R, 2006). Within the video, the following conventions are used: Node color-coding: green=possesses conch, black=deceased; Line color-coding: black=knows, blue=speaks to, green=passes conch, red=strikes.

B. Network Pattern Time Stamps

Below, I provide a complete listing for each of the patterns described above in the text as timestamps (in minutes and seconds), where those patterns are visualized in the linked social network movie.

Section 2

- **visualization**: the baseline figure in Figure 1 … **0** m **0** s
- **degree distribution**: the degree distribution in Figure 1 … **0** m **0** s

Section 3.1

- **closeness**: Ralph's high centrality/importance … **0** m **7** s to **0** m **44** s
- **betweenness**: Sam-n-Eric's high centrality/importance on "co-presence" tie … **7** m **15** s
  eigenvector: Piggy's high centrality/importance on co-presence tie … **0** m **45**

Section 3.2

- **multiplexity**: *complementarity* of "passes conch" and "speaks to" ties … **0** m **55** s to **1** m **26** s
- **multiplexity**: *disjuncture* of "passes conch" and "speaks to" ties … **3** m **45** s to **4** m **20** s
- **homophily**: age similarity in "co-presence" tie … **2** m **49** s

Section 3.3

- **density**: maximal density on "co-presence" tie … **0** m **7** s
- **density**: lower density on "co-presence" tie … **2** m **27** s
- **clustering**: low clustering on "co-presence" tie … **0** m **7** s
- **clustering**: high clustering on "co-presence" tie … **6** m **40** s

Section 3.4

- **cohesion**: high cohesion among choir boys & low cohesion among other boys on "co-presence" tie … **2** m **41** s

Section 3.5

- **distance**: Stanley & Roger unreachable "co-presence tie" … **2** m **49** s
- **equivalence**: Sam-n-Eric *identical* on "co-presence tie" … **2** m **43** s

C. Novel Chronology Time Stamps

Additionally, the video can be used to extract a simple timeline from the book. To assist with that, here is a time-stamped Table of Contents.

D. Data Availability

The data used to generate the Appendix video is available as a single networkDynamic class object in the R environment, available for download at goo.gl/YWMSXQ. Within the object, there are 473 unique time slices, each corresponding to an individual event change; these are temporally ordered. Also encoded in the object are the durations accounting for node (dis-)appearances, durations for "co-presence" ties to enter/exit the visualization, and node attributes for possessing the conch and deaths.