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Social Network Analysis and Estimating the Size of Hard-to-Count Subpopulations[1]

Daniel Jackson, John Kirkland[2], Barry Jackson and David Bimler
Massey University, Palmerston North, New Zealand

Social Network Analysis (SNA) is a social research tool that investigates both individuals and their relationships within a population. Complete network analysis is used to examine closed populations, while personal network analysis examines the set of people ('alters') that an individual ('informant') is connected to. Personal network analysis may be performed in the context of a survey to provide information on a larger group of individuals than a traditional survey of the same sample size. This review of the literature discusses the need for networks to be carefully defined and generated to reflect the population of interest, and examines the issue of informant accuracy in social network data. It also discusses an SNA model for estimating subpopulation sizes and how subpopulation characteristics may affect these estimates. Finally, it suggests some guidelines for potential SNA researchers.

INTRODUCTION

Traditionally, when researchers have sought to investigate the characteristics of society the focus has been on the use of polls or surveys of individuals. The combined data over all participants is then scaled up in order to generalise about the size of and demographic make-up of subpopulations. However, any population is more than just the sum of its individuals. The relationships and interactions between individuals are also important elements of a population. Traditional survey methods may identify groups within the population, but tell us little about how individuals within these groups are related to and affect one other. For example, a traditional survey may tell us that girls are outperforming boys at a school, but cannot tell us about the social influences that contributed to this outcome. A method that specifically examines relationships may explain more about subgroups in the population.

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[2] Correspondence concerning this article should be addressed to John Kirkland, Department of Health and Human Development, Massey University, Private Bag 11-222, Palmerston North. E-mail: j.kirkland@massey.ac.nz

Social Network Analysis (SNA) is an alternative method of gathering data about populations. Social network researchers come from a diverse range of backgrounds and are interested in many different relationships and populations. These differences have led to the creation of two basic kinds of network analysis, reflecting two different kinds of data: complete (sociocentric) network analysis, and personal (egocentric) network analysis (Marsden, 1990).

Researchers interested in a small group such as an office or a classroom commonly use complete network analysis. Researchers attempt to obtain all the relationships among a set of respondents, such as all the friendships among employees of a given company. Statistical techniques are then employed in order to identify subgroups (cliques), power bases, whether relationships are reciprocated, how well respondents know each other and other network properties.

Personal network analysis examines the open-ended group of people (known as 'alters') that an individual (known as an 'informant') knows. Each informant is asked about the people they interact with, and about the relationships among those people. Personal network analysis is extremely convenient because it can be used with random sampling in the context of a traditional survey. Standard statistical techniques can then be used to generalise the results to describe the characteristics of the greater population and the distribution of relationships within it. However, because of the open-ended nature of personal networks, it is not possible to verify every detail. Findings from complete network studies are often used to build theories that personal network studies draw from. For example, studies of informants' forgetting allow researchers to modify their models of personal networks (Brewer & Webster, 1999).

An emerging field of personal network analysis is the use of social network data in the estimation of hard-to-count subpopulations. A sample of informants provides information about the members of their personal social networks. This social network data serves as a substitute for directly interviewing these network members ('alters'). Each informant provides information on many alters, so a small sample leads to a large data set. Bernard, Johnsen, Killworth & Robinson (1989) reasoned that the proportion of alters in an informant's network that are members of a subpopulation, averaged over all informants should give an approximation of the proportion (and hence the number) of people in the greater population who are members of the subpopulation. This can be expressed as $m/c=e/t$, where m is the average number of alters that informants know in the subpopulation, c is the average size of an informant's network, e is the total size of the subpopulation and t is the total population.

The value of c needs to be determined in order to estimate the size of e (Bernard & Killworth, 1997). One method of estimating personal network sizes is through the use of network generators. The average number of subpopulation members known m is determined by informant reports and therefore depends on informants' accuracy of recall.

Additionally, this simple model of the network scale-up method ($m/c=e/t$) works only under three assumptions (Killworth, McCarty, Bernard, Shelley, & Johnsen, 1998a):

1. Everyone has an equal chance of knowing someone in a given subpopulation.
2. ‘c’ (network size) is a constant.
3. Everyone has ‘perfect’ knowledge about the members of their network.

These assumptions are not met for all subpopulations (Johnsen, Bernard, Killworth, Shelley, & McCarty, 1995; Killworth, Johnsen, McCarty, Shelley, & Bernard, 1998b; Laumann, Gagnon, Michaels, Michael, & Schumm, 1993), so future models must take specific subpopulation effects into account (Killworth, McCarty, et al., 1998a).

SOME FEATURES OF NETWORK SURVEYS

A number of approaches have been made to determine the size of rare and concealed populations . Kalton, for instance, identified a number of practical methods for sampling rare and mobile populations (Kalton, G, 2003). Other approaches have been adopted; the multiplicity method (Rothbart, Fine, & Sudman ,1982), geographical clustering method (Kalton & Anderson, 1986) and network sampling, "Locating the seriously ill," (Sudman & Freeman, 1988) and "Estimating incidence of missing children," (Sudman, 1986).

Sampling errors common to traditional survey methods are also present in network surveys. The problem of non-response bias (where certain individuals are less likely to complete the survey than others) is compounded in the alter generation process. However, a small sample of informants can provide information on a much larger section of the population than a traditional survey of the same size. Although the cost of interviewing each informant is higher, the increased data yield reduces the overall cost of the survey. Network surveys provide information about the relationships between individuals as well as about the individuals themselves.

Informants may be more willing to identify alters who are members of a stigmatic subpopulation than they are to identify themselves. However, informants may not be aware that an alter is a subpopulation member. There are unknown errors in the estimates of network sizes, which carry through to the analysis of network properties, and subpopulation estimates.

NETWORK GENERATION

There are several different possible definitions of personal networks used by social network analysts. The total personal network of an informant is the set of people that he/she has known over the course of his/her lifetime. It is obviously impossible to enumerate anyone's total personal network. And even if an informant were to successfully recall everyone he/she had ever met, he/she would not be able to supply detailed information about each alter. Informants are more likely to recall, and to have detailed knowledge of the members of their active personal networks.

The relationships in personal networks can be defined in either situational or conceptual terms. Situationally defined relationships such as 'family', 'co-workers', 'classmates' and 'neighbours' are consistently defined, leading to a reliable network generator, but at the expense of including other sectors of an informant's network. Conceptual relationships such as 'acquaintances', 'friends', 'close friends' and 'best friends', may be considered as being like successive layers of total personal networks, with relationship strengths and alter knowledge increasing as each layer is removed.

Personal networks of alters can be elicited by using one or more 'name generators'. The number of names generated by an informant is taken as a measure of his/her network size 'c'. McCallister and Fischer (1978) were unsatisfied with previous methods of network generation. They noted that asking informants to list 'friends' excluded network alters from other social contexts, and that there were individual differences between informants' interpretation of terms like 'best friend' or 'close friend'. As an alternative, they asked informants to name alters who they interacted with in several unambiguously defined situations. They also observed that informants had poor recall of the people they know, and that extensive probing could help to generate more alters.

McCallister and Fischer (1978) limited their study to core personal networks, that is those alters who most influenced informants' attitudes and behaviour, so they used a variety of name generators centring on important interactions. McCallister and Fischer emphasised the importance of carefully specifying what properties of networks are of interest and using name generators that capture a representative sample of the relevant alters.

Fischer (1982) noted that the concept of 'friend' was central to studies of social networks. Noting the ambiguity of dictionary definitions, 'class' and cultural differences in interpretation, Fischer investigated 1050 informants' interpretations of the term 'friend', and found significant variation between informants. There was variation between informants as to whether they included family members, co-workers or neighbours as 'friends'. Fischer's study demonstrated the importance of clearly defined terms in network generation.

Two network generators were considered particularly important in determining the size of "hard-to-count" subpopulations: The (American) General Social Survey (GSS); and the Reverse Small World (RSW) technique. The General Social Survey (GSS) is a nationally representative, cross-sectional survey that has been conducted almost every year since 1972. The General Social Survey includes information on American demographics, beliefs, attitudes and participation in social life. The Reverse Small World (RSW) technique was developed by a group of researchers notably Killworth and Bernard (1978), Bernard, Killworth and Sailer (1981) and Bernard, Killworth, and McCarty (1982). The two approaches were compared by Bernard, Shelley & Killworth (1987) in order to estimate how many people are in an average network, to attempt to understand what the differences in network size depend on and to look for the rules governing whom people know and why they know each other. The GSS question asked informants to simply name as alters those who they had "talked about important matters with in the last six months". In the RSW task, informants were asked to name alters that they would use to get in touch with 500 fictional 'targets'. Informants generated an average of 160 alters in the RSW and were limited to 5 in the GSS. These researchers admitted that although networks produced by the RSW were much larger, they did not know whether they were any more useful than networks produced using the GSS. They found some overlap between the networks elicited by the two techniques but speculated that they were tapping into different cognitive sets of alters: intimate alters and instrumental alters.

Freeman and Thompson (1989) noted that the RSW technique seemed to be estimating a different parameter to personal network size, so they adapted the phonebook approach to network generation first used by Pool and Kochen (1978, cited in Freeman & Thompson, 1989). Three hundred and five surnames were randomly selected from a phonebook and presented to 247 informants who generated an average of 15 alters. Scaling up to match the total number of names in the phonebook yielded a 'c' of 5500. Freeman and Thompson acknowledged that it was an order of magnitude larger than that estimated by Killworth and Bernard (1978, cited in Freeman & Thompson, 1989) and Killworth, Bernard and McCarty (1984), but note that the RSW mode is concerned with social contacts and not total personal networks. Freeman and Thompson believed that their estimate was merely a lower bound for informants' total personal networks due to errors of recall.

In a second investigation of different network generators, Bernard, Johnsen, Killworth, McCarty, Shelley, & Robinson (1990) compared the networks generated by the GSS 'important matters' technique, the RSW method, a social support instrument and Freeman and Thompson's (1989) phonebook method. Bernard et al. acknowledged that their RSW technique does not produce alters who are representative of informants' total personal networks, and that the RSW did not elicit key social support alters either. Bernard et al. found that the phonebook method yielded a network that was the most representative of an informant's total personal network.

Killworth, Johnsen, Bernard, Shelley & McCarty (1990) had a closer look at the phonebook method. They found that if only the 7 most common names in the phonebook were used, a correlation of 0.81 was found with the data for 305 names. They also found that a phonebook for a part of the area had a good correlation with the full version. This indicated that the phonebook instrument could be reduced to a smaller size and still retain its reliability. However, they found that some unusual names that were similar to more conventional names elicited many responses even though there were few listings in the phone book, leading them to predict that the Freeman and Thompson (1989) estimate of network size was an overestimate.

Campbell and Lee (1991) investigated the consequences of name generators for network data. They considered network size, age and education heterogeneity and found that the average tie characteristics were strongly affected by the name generator used. In particular, they found that racial and sexual heterogeneity were the least affected by name generator choice. Campbell and Lee also found that network data gathered using name generators tend to reflect stronger ties, stronger role relations or ties associated with local geographical areas.

In order to elicit a representative sample of any informant's network, cues are required that stimulate unbiased recall of alters in that network. McCarty, Bernard, Killworth, Shelley, & Johnsen (1997) examined the use of 50 first names common to both blacks and whites in the United States. However, Asians respondents were biased against selection because there were no Asian names on the list. Some names on the list were more common in older or younger people which resulted in an alter selection bias. An alter selection bias was also found against females because of the wider range of female names. The seven most popular male first names in the US accounted for 7.9% of the population compared to only 3% for female first names. McCarty et al. suggest that both the respondent selection bias and alter selection bias could be rectified by randomly assigning respondents to a unique list drawn from a larger pool of names, with a probability of a name being drawn equal to its prevalence in the population. McCarty et al. believe that the first-name method captures a more representative sample of the personal network than other methods. The proportion of alters recalled with a given first name agreed well with the prevalence in the greater population. This was not found to be the case for the phonebook method (Killworth et al., 1990).

Brewer (1997) re-examined the McCarty et al. (1997) data looking for associative biases in the network generation process. Associative biases occur when the recollection of an alter prompts the recollection of a contextually related alter. Recall of a workmate may prompt the recall of another workmate, for instance. The informants in the McCarty et al. study had been asked whether various pairs of alters knew each other. Brewer found that successively recalled alters were no more likely to know each other than separately recalled alters. Brewer speculated that the presentation of first name cues served to restart the recall process because the informant could not control or anticipate the order of cue presentation.

The average number of people known to an individual is far from measured. Informants are fallible and as a result the size of a personal network can never be measured directly, and so a useful proxy for personal network size has to be determined instead. The first-name method does not require the informant to make a subjective judgement about 'friendship' and with the improvements to their method proposed by McCarty et al. (1997) seems well designed to elicit a representative sample of alters from informants' total personal networks.

Name generators are complex instruments that not only require a consistent interpretation by informants but also need to be consistently applied by interviewers. Marsden (2003) examined interviewer effects on the network size of informants participating in the 1998 General Social Survey (GSS) in the United States. Although Marsden found no strong effects of interviewer characteristics on network size, he did find significant variation in network sizes between interviewers. Marsden suggested interviewer effects may be limited by providing extensive interviewer training, 'probing' guidelines for the elicitation of additional alters and computer assisted interviewing. Such improvements would increase the consistency and reliability of a network generation instrument.

INFORMANT ACCURACY

The accuracy of social network data depends upon the accuracy of informant reports in the data collection process. If the network data is skewed significantly by informant inaccuracy then the nature of this error must be understood in order to draw meaningful conclusions from the data. However, there are several possible sources of informant inaccuracy such as forgetting, cognitive schemas, biases and, as discussed in the next section, the properties of certain subpopulations.

In the first of a series of informant accuracy studies, Killworth and Bernard (1976) examined a partial network of 32 deaf informants who communicated with each other using Teletype machines. The informants logged their interactions with each other and were later asked to rank each other by the amount of communication with them in the study period. Overall they found that informants tended to communicate more with the people they ranked higher, but surprisingly they also found that the person ranked as being communicated with the most was only in the top four 52% of the time. This disparity between perceived interactions and observed interaction led Killworth and Bernard to speculate that informants' interactions are interpreted through a cognitive structure that systematically distorts informant recall.

In a review of their informant accuracy studies, Bernard, Killworth, Kronenfeld & Sailer (1984) found that informants who recorded their behaviour were no more accurate than those who didn't, and that informant accuracy decreased as the time elapsed increased. Over all their datasets they found that informants could recall or predict less than 1/2 of their communications. No demographic differences were found between accurate and inaccurate individuals.

Many studies have found poor informant accuracy in a wide range of situations. Some researchers have also found specific factors that affect accuracy. Hyett (1979, cited in Bernard et al., 1984) surveyed 354 telephone users and found that infrequent users over reported the number of calls made while frequent users under reported the number of calls made. Young and Young (1961, cited in Bernard et al., 1984) found greater accuracy and agreement amongst informants in Mexico when asked about publicly available information compared to private information. Kronenfeld (1972, cited in Bernard et al., 1984) asked informants who were leaving restaurants to describe what the waiters and waitresses were wearing. Informants showed much higher agreement about the waiters' clothes than the waitresses' despite the fact that there were no waiters in the restaurant! Kronenfeld suggested that without specific memories of the waiters, informants turned to cultural norms for descriptions of what they had 'seen'. It is clear that if social scientists wish to use recall data about actions and interactions as a substitute for those actions and interactions, then they must understand something of how informants' cognition affects the storage and retrieval of information.

Why should informants' cognitive processes conflict with accurate recall? Freeman and Romney (1987) believed that long-term social structure was not well represented by any particular set of recorded interactions. Instead, they asserted that social structure might be a relatively stable pattern of interpersonal relations that is well represented by informants' cognitive structures. When asking informants to recall information about a particular event there are two main sources of recall error: some facts are lost, and the remainder are supplemented with pseudo-facts. Freeman and Romney asked informants who attended a series of weekly meetings about the attendees of the final meeting. Informants were inaccurate about the attendees of the final meeting. They forgot those who attended few prior meetings and falsely recalled those who were the most regular attendees. This was a systematic bias towards the social structure norm showing that informant recall may be a better measure of long-term social structure than is a single observation. In addition, recall data is much easier and less costly to collect than observational data, especially for large or open-ended networks.

In a follow-up study investigating attendance recall of a series of University meetings Freeman, Romney & Freeman (1987) found that just under half of the attendees of the final meeting were forgotten and there were a small number of false recalls leading to an error ratio of 52%. However, the correlation between recall and attendance at all sessions was greater than the correlation between attendance at the final session and attendance at the previous sessions. Therefore Freeman et al. concluded that recall provides a better index of the long-term pattern of social structure than that derived from direct observation. Based on their cognitive outlook of recall Freeman et al. hypothesised that those informants who were in the in-group (faculty members with central offices) were more experienced and had developed complex internal mental structures that represented social structure and would therefore forget fewer attendees but also falsely recall more attendees. They also hypothesised that those who have attended more sessions would be seen as more typical elements of the sessions and would therefore be less likely to be forgotten and more likely to be falsely recalled. Both of the hypotheses were supported by the data indicating that informant recall is mediated by cognitive structure. At the same time as supporting the Bernard et al. (1984) figures for informant accuracy (around 50%), the results of this study indicated that the problem of informant inaccuracy is not as great as originally supposed.

The persons recalled in a network elicitation task are only a sample of the possible set of persons who could be named. Sudman (1985) examined five closed groups (3 work departments and 2 church groups) varying in size from 18 to 283 members. He compared recall, recognition and numerical estimation (guessing) of acquaintances and friends as different methods for estimating personal network size. He found that recognition procedures produced substantially larger estimates of network size than recall. However, he also found that the numerical estimates of network size, though highly variable, were closer to recognition estimates than recall estimates were. Sudman found that as group size increased the accuracy of recall estimates decreased. Sudman cautioned against simply asking an informant to name everyone they know because of the variation between informants' power of recall and also their interpretation of the term 'knowing'.

Brewer and Webster (1999) examined the effects of the forgetting of friends on the measurement of personal social networks. They asked 217 residents at a student hall to recall their friends in the hall and then presented them with a list of all residents at the hall from which they were asked to recognise any additional friends. On average, they found that 20% of friends had been forgotten. Informant characteristics were found to have no correlation with forgetting and no difference was found between those recalled and those recognised. However, relationship strength was found to be slightly stronger for recalled friends. A higher proportion of best (97%) and close (91%) friends was recalled than 'just friends' but 26% of those with a best or close friend forgot at least one of them. However, 21% of informants didn't forget any friends. Recalled friendships were slightly more likely to be reciprocated than recognised ones, but this difference was slight. Recognised friends were slightly more peripheral (distant) in an informant's network than recalled friends. Recall data was found to correlate very strongly (r=0.92) with combined (recall + recognition) data regarding personal network density. In addition, recall data correlated strongly (r=0.89) with combined data in the measurement of network size. Brewer and Webster concluded that although estimates of personal network sizes using recall data were underestimates due to forgetting, they were still good proxies for the combined data estimates of personal network sizes and should retain the network size order of informants.

In a study of social support in the social networks of 8 classes of 31 17-year old high school students Ferligoj and Hlebec (1999) also investigated the difference between free recall and recognition network data. In a different approach to that of Brewer and Webster (1999), Ferligoj and Hlebec separated informants into recall or recognition groups. They found that in their study (where informants knew each other well) that free recall had as high a test-retest reliability as recognition.

However, they found that the recognition task yielded more and weaker relationships than the recall task. Although recall was found to be a stable method, they concluded that if a full list of membership is available then the recognition method should be used in order to include weaker relationships.

As already noted, informants have imperfect recall of their interactions. However, in addition to memory errors, informants may also exhibit various biases in the reporting of their interactions. Some informants may over/understate the characteristics of their relationships, and others may have different minimum requirements for reporting a relationship to exist. Feld and Carter (2002) define this tendency to over/underreport others as "expansiveness bias". Informants may also tend to exaggerate their relationship strength and interactions with desirable people and/or overlook their relationships with undesirable people. This is defined as "attractiveness bias". Feld and Carter re-examined a 1960 dataset of 930 college students to examine these biases and found evidence for expansiveness bias but not for attractiveness bias. This suggests that the cumulative reports about each informant yield better network data than informants' reports about themselves, which may be exaggerations/understatements. Although it is not possible to collect reciprocated data for each informant in an open network design, a sample of informants could be studied to give a general indication of expansiveness bias. In order to reduce expansiveness bias in further studies, Feld and Carter suggest minimising the variation in individual interpretation by asking solid practical questions that minimise distortion.

SUBPOPULATION EFFECTS

The network scale-up method of estimating the size of hard-to-count subpopulations produced good initial results. Laumann, Gagnon, Michaels, Michael & Coleman (1989) and Laumann et al. (1993) found very good agreement between their estimate of the number of homicide victims and the FBI official statistics for the United States.

McCarty, Killworth, Bernard, Johnsen and Shelley (2000) also compared two methods for estimating the size of personal networks using a nationally representative sample of the United States. Both methods rely on the ability of respondents to estimate the number of people they know in specific subpopulations of the U.S. (e.g., diabetics, Native Americans) and people in particular relation categories (e.g., immediate family, coworkers). The results demonstrate a remarkable similarity between the average network sizes generated by both methods (approximately 291). Similar results were obtained with a separate national sample.

Homicide statistics are considered to be the most reliably reported of the FBI index of seven serious crimes (Gove et al., 1985, cited in Johnsen et al., 1995). Homicide victims were found to have personal networks of similar size to the general population, and because the knowledge of their homicides propagated throughout their networks quickly and thoroughly, it was therefore used as a benchmark subpopulation for comparative purposes (Johnsen et al., 1995).

However, when network scale-up methods were used to estimate the seropositive (HIV+) subpopulation and then checked against the benchmark (homicides) Johnsen et al. (1995) found an over-count by a factor of 3.7. This implied that the social network size of a seropositive individual was only 27% of the size of the population average. Although seropositive individuals have been hypothesised to cut back their networks, the definition of an acquaintance used in the alter generation process specified contact within the last two years, therefore limiting the possible shrinkage of a seropositive's network. Johnsen et al. concluded that the most likely explanation was that due to the stigmatising nature of HIV infection that information about an individual's HIV status was limited to about 1/3 of their active personal network.

The difficulty in estimating seroprevalence highlights the limitations of Bernard and Killworth's model, which makes three main assumptions (Killworth, McCarty, et al., 1998):

1. Everyone has an equal chance of knowing someone in a given subpopulation.
2. Network size 'c' is a constant.
3. Everyone has ‘perfect’ knowledge about the members of their network.

It is clear that these assumptions are not met in the case of HIV+ individuals. The demographic makeup of the HIV+ subpopulation in the USA is different to that of the general population, with homosexual males and intravenous drug users making up a disproportionate number of cases. Given that similar individuals are likely to interact more with each other, this means that a male homosexual or an IV drug user has a greater chance of knowing an HIV+ individual than do other individuals. This is referred to as a 'barrier' effect or as a 'buried' subpopulation (Killworth, Johnsen, et al., 1998; Killworth, McCarty, et al., 1998). Where certain demographics are related to subpopulation membership it is preferable to include a representative number of individuals with those demographics. However, some linked demographic variables may be of a sensitive or private nature (i.e. sexuality). Given a fairly large sample, though, the distribution of most demographics would be expected to be representative, and the chance of missing any 'buried' populations would be low.

Data from Johnsen et al. (1995) suggest that network size of HIV+ individuals is smaller than the norm, and/or that information about HIV status is limited in the network. This imperfect knowledge of HIV status is called a transmission effect (Killworth, Johnsen, et al., 1998; Killworth, McCarty, et al., 1998). For some subpopulations (first name "Michael" for instance) membership is immediately apparent and informants can be considered to have 'perfect' knowledge. For other subpopulations, information of subpopulation status may be limited by one or more transmission errors. There are three main sources of transmission errors (McCarty, Killworth, Bernard, Johnsen & Shelley, 2001):

1. Doesn't come up in conversation (e.g. left-handedness, twin).
2. Stigma (e.g. HIV+ or drug use).
3. Personal information (e.g. weight, IQ, income)

In order to make a more accurate estimate of seroprevalence the characteristics of HIV+ social networks need to be more explored (Johnsen et al., 1995; Killworth, Johnsen, et al., 1998; Laumann et al., 1993; Shelley, Bernard, Killworth, Johnsen & McCarty, 1995). The composition of relationship types within the social networks of both HIV+ and 'normals', as well as the relationship paths that HIV status information propagate through need to be more thoroughly investigated. Any barriers that surround the networks of HIV+ individuals and the difference in network size between HIV+ individuals and 'normals' must also be identified. If these properties are better understood, then the simple model of the network scale-up method can be modified to give weightings to:

1. The probability of knowing someone in the HIV+ subpopulation, given an individual’s demographic information.
2. The ratio of HIV+ network size to 'normal' network size.
3. The proportion of alters in an HIV+ person’s network that know of their status.

The problem of transmission errors is perhaps the largest obstacle in the estimation of hard-to-count subpopulations. There are two potential methods of accounting for transmission errors. The first method is to investigate the networks of subpopulation members, in order to determine the proportion of their alters that know of their subpopulation status. The second method is to seek to quantify the stigma level of the subpopulation. Either method produces a scaling factor for the subpopulation.

In an effort to better understand the characteristics of the personal networks of HIV+ individuals, Shelley et al. (1995) interviewed 70 HIV+ patients. They found that their sample of HIV+ patients did have smaller personal networks than the control group, and that they also limited information about their HIV status within their networks. Shelley et al. also investigated the socio-demographic characteristics that govern who receives HIV status information and found that medical personnel and support group members have the most knowledge of HIV status. Friends and former lovers had the next best knowledge followed by relatives and acquaintances. Males and whites were found to have slightly more knowledge of HIV status than women and blacks.

Shelley et al. (1995) speculated that if informants were to know information that was less well known than HIV status then maybe they would also know HIV status. However, they found that informants could not accurately judge how difficult a given piece of information was to know, and also that black men had the greatest knowledge of alters' blood types (the hardest piece of information to know) but had the worst knowledge of alters' HIV status.

Exploring the possibility of quantifying transmission and barrier errors, Killworth, Johnsen, McCarty, Bernard and Shelley (2003) found that informants may be responding based on imperfect knowledge. Although Killworth et al. were unable to assign a scaling factor to estimate the actual size of a hard-to-count subpopulation, they found that it is possible to determine an effective subpopulation size. This effective size could be used to compare different geographical areas or demographics sectors in the population to find relative differences in subpopulation membership. The validity of the probabilty model in describig the distribution of peoples' personal networks to improve the estimate has been undertaken by Bernard, Johnsen, Killworth and S. Robinson (1989).

APPLYING SOCIAL NETWORK ANALYSIS

Care must be taken to obtain a sample of alters that represent the population. The first step is to collect a representative sample of informants. If the sample of informants is skewed, then any resultant pool of alters will also be skewed. Some groups of informants are more likely to respond than are others and some demographic groups are over/under represented in some subpopulations. Attention must be paid to the respective merits of targeted samples (better validity) and of random samples (less costly).

A network generation method that elicits alters that are representative of each informant's personal network is also vitally important. A network generator such as the first-name method is a reliable instrument because informants are not required to interpret terms, and there is no bias towards alters from certain social contexts.

Although suitable in other respects the first-name method has been criticised for its ethnic bias. It has been suggested by McCarty et al. (1997) that each informant be presented with a list of 50 names that have been randomly selected from a greater pool of names that is representative of all ethnic groups in the greater population. In New Zealand for instance special care must be taken to ensure that Maori are represented in the sample. Interviewers need to be trained to administer the network generation method consistently. Interviewers must follow a set procedure in the initial generation of alters, a set of guidelines must be developed for the probing for additional alters also for the recording and interpretation of informant responses. Ideally, interviewers would be tested for consistency in a trial phase before interviewing their first informant in the study group.

Network size 'c' is estimated by multiplying the number of alters generated from the list of first names by the ratio of names in the population to names on the list. It is reasonable to use this number as a proxy for 'c' without further modification. Those informants who generate more alters can justifiably be seen as having larger networks than those informants who generate fewer alters.

The standard approach of investigating alters is to ask the informant about each alter as he/she is generated. Although identifying information is not sought about alters, some informants may be unwilling to label an alter as a subpopulation member. As an alternative, after the generation process, informants could be asked, "How many of the people that you have listed meet these criteria?" This would reassure informants that they weren't 'dobbing in' any of their alters.

Transmission effects have been found to interfere with the estimation of some hard-to-count subpopulations such as HIV+ individuals in the US. Investigation of the social networks of the members of different stigma-bearing subpopulations of known size may allow for the quantification of stigma that can then be applied to unknown subpopulations with equivalent levels of stigma.

Although the estimation of exact subpopulation sizes may in some cases be unobtainable, relative differences between areas, demographic groups and related subpopulations may still be obtained. Any investigation would need to take into consideration a number of factors. The final research method will depend upon the subpopulation of interest.

One possible avenue for future research is the use of computer modelling to investigate the effects of informant accuracy, biases, barrier effects and transmission effects on network data. Such a model may help in the design of subsequent experiments and to identify distortions in future network data.

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