10-1-2018

Strategic Players for Identifying Optimal Social Network Intervention Subjects

Miles Q. Ott
Smith College, mott@smith.edu

John M. Light
Oregon Research Institute

Melissa A. Clark
University of Massachusetts Medical School

Nancy P. Barnett
Brown University

HHS Public Access
Author manuscript
Soc Networks. Author manuscript; available in PMC 2020 January 14.

Published in final edited form as:
Soc Networks. 2018 October ; 55: 97–103. doi:10.1016/j.socnet.2018.05.004.

Strategic Players for Identifying Optimal Social Network Intervention Subjects

Miles Q. Ott,
Smith College 44 College Lane, Northampton, MA 01063

John M. Light,
Oregon Research Institute, 1776 Millrace Dr., Eugene, OR 97403

Melissa A. Clark,
University of Massachusetts Medical School, 55 Lake Avenue North, Worcester, MA, 01655

Nancy P. Barnett
Brown University, Box G-S121-5, Brown University, Providence, RI 02912

Abstract

We present a method whereby social network ties are used to identify behavioral leaders who are situated in the network such that these individuals are: 1) able to influence other individuals who are in need of and most receptive to intervention, thereby maximizing the impact of the intervention; and 2) not embedded with ties that are likely to be behaviorally antagonistic to the intervention or that would compromise the optimal evaluation of intervention efficacy. In this study we developed a novel method which we call Strategic Players, which is a solution for identifying a set of players who are close to a target subset of the network (i.e., the targeted group), and far away from the subset we wish to avoid (i.e. the avoidance group). This solution seeks to maximize the diffusion of the behavior to the targeted group while minimizing contact and influence from the avoidance group. We apply this method to two different social networks.

Keywords

Social Networks; diffusion of influence; centrality; key players; strategic players

Introduction

Social network interventions (SNIs) target individuals who, by virtue of their status in the network, are influential in the behavior of others. Such interventions are specifically designed to consider social connections when attempting to change health behaviors, in large part because social networks provide a way to spread information and healthy behavior (Centola, 2010; Latkin, Donnell, et al., 2013; Latkin, German, Vlahov, & Galea, 2013; Pilowsky et al., 2007; Smith & Christakis, 2008; Tobin & Latkin, 2008; Valente, 2012). One common SNI approach involves engaging peer educators or influential individuals (commonly called "opinion leaders") who communicate within their communities and serve as role models, thus conveying behavior change goals to others. HIV prevention is one area in which the efficacy of SNIs has been established (Amirkhanian et al., 2005; Broadhead et al., 1998; Latkin, Davey-Rothwell, et al., 2013), and there is evidence that greater behavior change occurs among those with close proximity to the peer model (Li, Weeks, Borgatti, Clair, & Dickson-Gomez, 2012).

SNIs rely on diffusion of innovation theory (Rogers, 2002). According to this theory, individuals are more likely to adopt innovative methods, products, or ideas when they see them adopted by others with whom they have close, credibility-enhancing relationships. There is evidence that health-enhancing behaviors spread through networks via similar mechanisms, such that individuals are more likely to adopt health-enhancing behaviors when their close associates have adopted similar behaviors (Smith & Christakis, 2008; Valente, 2010). Close connections are therefore typically assumed to be central to the efficacy of network interventions (Fujimoto & Valente, 2012).

Borgatti uses social network metrics to identify network members who have the “most important” positions in the network, which he refers to as the set of key players (KPP-Pos; Borgatti, 2006). The approach to identifying a KPP-Pos set differs from, for instance, centrality scores (e.g. Bonacich, 1972; Freeman, 1979) by its focus on the importance of nodes to network *cohesion*, where cohesion is measured by some variant of path length or reachability in the network as a whole. For example, it is easy to construct networks where the most central nodes can be removed without much effect on average path lengths. By shifting the criterion from centrality to cohesion, the KPP-POS approach identifies a minimal set of nodes that serve as the most important members of the network in terms of linking nodes to each other through the shortest average paths (though other definitions of cohesion apply as well).

The KPP-POS approach is arguably an improvement over centrality measures for identifying sets of influential network members. Influential network members are arbiters of important resources (information, support, etc.) which are assumed to flow through network linkages, for example, by behavioral modeling or interpersonal interaction. However, KPP-POS does not take into account non-linkage-related node characteristics that may affect inclusion in the KPP-POS set. An example of such a situation, for purposes of this paper, is a behavioral intervention, where a primary at-risk subset of the members of some network (e.g., a community or organization) is targeted for the intervention in such a way that other secondary at-risk members will be maximally exposed to the primary at-risk intervention recipients, and thus be helped indirectly. Such contagion effects are of interest because maximizing them can dramatically amplify the effect of the original intervention (e.g., Aral & Walker, 2011).

The foregoing discussion suggests a need to broaden the goal of methods like KPP-POS. Not only do we need to identify opinion leaders who optimally reach those individuals in the network who would be targeted for intervention, but we may also want to avoid exposing other individuals to the intervention. For example, an intervention designed to reduce smoking risk among susceptible adolescents (e.g., who had begun an intermittent pattern of smoking) would need to include or exclude potential opinion leaders and secondary targets of the intervention based on whether they show the target behavioral pattern. Another example is an intervention in which one wishes to avoid targeting members who are unlikely to be responsive to the intervention, or could even be openly antagonistic, in order to avoid reducing the overall efficacy of the intervention within the network. Current methods do not address this important objective to avoid wasting resources on network members who are known *a priori* to be at little or no risk or are not likely to be responsive to the intervention.

An additional circumstance that requires a modification to the methods for identifying key players refers to an intervention design feature (as opposed to a participant characteristic as above) in which an intervention is being tested within a community of smaller networks. For example, consider a social network intervention at an elementary school in which one class is identified as the control group, and another class is identified as the intervention group. While social connections will primarily be formed within the classes, there will also be the potential for across-class social ties. For optimal internal validity and to provide the best test of an intervention relative to a control, it is important to (a) avoid the transmission of intervention effects to the control group, and (b) avoid suppression of the intervention effects from contact with the (presumably less effective) control condition (called leakage and contamination, respectively in some contexts; Aral & Walker, 2011; 2012). This circumstance requires similar optimization of the identification of key players referred to above, but also requires attending to ties between sub-networks, such that we may avoid transmission or suppression of effects.

In summary, there is a need to extend the Key Player identification whereby social network ties are used to identify individuals who are situated in the network such that these opinion leaders are 1) able to influence those individuals who are in need of and most receptive to intervention; and 2) are not embedded with ties that are likely to be behaviorally antagonistic to the intervention or that would compromise the optimal evaluation of intervention efficacy.

Method: Strategic Players

The objective of this study was to develop a solution for identifying a set of players who are close to a target subset of the network (i.e., targeted group), and far away from the non-targeted subset (i.e., avoidance group). Under the assumption that the directness of relationships predicts amount of influence transmission (Mundt, 2011; Rosenquist, Murabito, Fowler, & Christakis, 2010; Valente, Hoffman, Ritt-Olson, Lichtman, & Johnson, 2003), this solution should maximize the diffusion of the behavior to the targeted group while minimizing contact and influence from the avoidance group.

In the KPP-POS method, where there are n members of the network, the set K of key players (with pre-specified size |K|) is identified as the set of network members for which the average of the inverse minimum distance d_{Kj} for all network nodes j to any member of the set K is maximized. Thus, this method seeks to maximize:

$$D = \frac{\sum_j \frac{1}{d_{Kj}}}{n} \qquad \text{(Eq 1)}$$

which is equation 14 in the original Key Players paper (KP-Pos; Borgatti, 2006). KPP-POS is an excellent way to identify a subset of network members to intervene upon in the absence of other covariate information, in the sense that the KPP-POS set optimally "connects" the network.

If we know the subset T of the network who are the targets we want *maximum* diffusion to, and the subset A of the network who we seek to *minimize* diffusion to, then, by extending the KPP-POS method (Eq 1), we identify the Strategic Player set or SP set as the set of the members of T we should provide the intervention to so that we maximize:

$$D = \theta\frac{\sum_j \frac{1}{d_{Tj}}}{t} - (1-\theta)\frac{\sum_j \frac{1}{d_{Aj}}}{a} \quad \text{(Eq 2)}$$

Where t is the number in the targeted group, a is the number of individuals in the avoidance group, and θ is a user-supplied parameter quantifying the tradeoff between maximizing reachability to the target population, and minimizing reachability to the avoidance population. When θ=1, reaching all the targets is the only priority, the avoidance group does not affect the selection of players. When θ=0, reaching the target population does not affect the selection of players, and maximizing the distance to the avoidance group is the sole priority.

The path definition on which the distance metric is calculated is flexible and may be defined to refer to distance across directed or undirected ties. The choice of which path definition to use will depend on the situation at hand. For example, in the case in which the researchers believe influence will only spread through reciprocated relationships (such as close friendships), the path definition should be calculated over the undirected network of reciprocated ties. However, if the intervention will spread from influential individuals, such as individuals that others look up to, the path definition should allow for these directed relationships.

Implementation: Strategic Players

As with other methods of selecting an optimal subset of players, the process of finding the solution can be computationally intensive. For example, if there were 200 targets and 50 players to be identified, Equation 2 would have to be evaluated approximately 4.5 × 10^47 times to be certain that an optimal set was found, which is not tractable with current computing capabilities. However, an optimization technique such as gradient descent or a greedy optimization (Cormen, Leiserson, Rivest, & Stein, 2001) can be used so that the method of selecting strategic players (SP) can be tractably implemented. Following the optimization method suggested for Key Players (KP; Borgatti, 2006), we have utilized the greedy optimization as follows:

a. A random sample of s network members is randomly chosen from the target group, and is the initial SP set.

b. The distance measure is calculated (Equation 2). Recall this process balances *minimizing* the distance between the SP set and other targeted network members while also *maximizing* the distance between the SP set and the network members who are to be avoided, while ignoring those who are neither targeted members nor those who are to be avoided.

c. For every combination of the s members of the SP set, and (t-s) remaining members of the target group, the pair is swapped and the distance measure is recalculated.

d. If all of the distances from step c are not an improvement over the distances for the previous set, we stop. Otherwise, the swap from step c that results in the biggest increase in the distance measure is retained.

e. We repeat steps c and d until there is no improvement from swapping.

Because the final SP set identified in the above algorithm depends on the initial set of players that are randomly selected, we recommend completing the above procedure many times, to ensure that the solution is not merely a local maximum. The number of times to complete the above procedure will depend on the size of the target group and number of players. If there are few players, or a small target group, then a smaller number of iterations will be sufficient to find the optimal SP set. However, if there are many players, or a large target group, then a larger number of iterations will be necessary. An R package that implements strategic players can be found on CRAN (Ott, 2016).

Example 1: A simple network

Consider an illustrative example in which we have 13 individuals in our network, six of whom are targets by virtue of some characteristic (e.g., tobacco users who would like to quit using tobacco) (Figure 1; t=6, IDs=1,2,5,7,8,12), two are individuals we want to avoid (i.e., tobacco users who are strongly opposed to quitting the use of tobacco) (a=2, IDs=3,10), and the other five are neutral (i.e., non-smokers). While we do not seek to either target or avoid neutral group members, they nevertheless may serve as bridges from one target group member to another (or from an avoidance group member to a target group member). For example, consider node 6, a member of the neutral group, and for the purposes of this example a non-smoker who will not directly benefit from the intervention. If node 5 is given the intervention, node 6 could tell other smokers they are connected to (such as node 7) about the intervention, thereby potentially transmitting the effect of the intervention. Avoidance group members could actively work against the goals of the intervention, thereby restricting the transmission of the intervention. For example, if node 2 were to be given the anti-tobacco intervention, node 3 might actively work against the goals of the intervention, thus preventing the effect of the intervention to be transmitted to other targets connected to node 2.

We want to identify an SP set of size 3 (s=3) from the 6 targets such that the members of the SP set are as close as possible to the other targets, and as far as possible from the avoidance group, with θ dictating the extent to which we prioritize being near the other targets as opposed to being far from the avoidance group.

First we use the KPP-POS method to identify the set of size three from this network. Due to the symmetry in the network, there are multiple sets that are equally optimal for a 3-set of KPP-POS. These sets are: {(2,6,11), (2,7,11), (3,6,11), (3,7,11), (3,7,12), (3,8,11), (3,8,12)}.

Next, we use the SP method to identify a set of size three, but treat the avoidance group (3,10) as members of the neutral group. Since there is no avoidance group, the value of θ will not impact the choice of the SP set. In this situation when the target group is equal to those with IDs (1,2,5,7,8,12), and all other members of the network are deemed neutral, the strategic players algorithm identifies the SP set as (1,7,12).

Next we use the SP method to identify a set of size three, taking into account membership in the target group and the avoidance group. In this example, we use the values 0.5 and 0.9 for θ. The strategic players algorithm identifies the optimal SP set as (1,5,7), when θ=.5, and (1,7,12) when θ=.9. It is not surprising that we identify the same SP set when treating the avoid group as neutral, and when we use θ=.9. In effect, the closer that θ is to one, the less emphasis is placed on limiting reachability to the avoid group, and when θ=1, the avoid group is, in effect, considered neutral. It is evident that members 1, 7, and 12 as a set maximize access to other nodes if distances to the avoid set are not weighted heavily. In other words, when the priority is to improve proximity in the network to the target set, and there is little concern of decreasing proximity to the avoid set, more central members (such as 1,7,12 in this network) will be chosen. Whereas members 1, 5, and 7 achieve more separation from the avoid set by being much further, on average, from network member 10.

We can contrast these results to the KPP-POS sets for this network. Notice that the sets identified by SP were not identified by the KPP-POS method because KPP-POS only considers position in the network, and is not designed to account for any other characteristics of the network members. In this example, we wish to avoid choosing network members 3, 10 as well as those who are in close proximity to network members 3 and 10; KPP-POS does not take this into account, and in fact considers it optimal to include ID 3. Likewise, although we want to prioritize choosing network members near those with IDs (1,2,5,7,8,12), KPP-POS again does not account for this preference and instead finds the set(s) of nodes to optimize proximity to *all* members of the network, rather than just the members of the network that we wish to target.

Demonstration

Example 2: Zachary's karate club network

In another example with a slightly larger and more complicated network, we identify both the KPP-POS and SP sets of size 3 in Zachary's karate club network (Zachary, 1977). This network represents social interactions among 34 members of a karate club with two factions (Figure 2) labeled for our purposes as the target and avoid groups. For the purposes of this example we also identified network members labelled 11, 8, 29, 33, and 34 as neutral.

For the KPP-POS set of size 3, there are two equally optimal KPP-POS sets: {(1,26,34), (1,25,34)}. For the purposes of this example, we will use (1,26,34) as the KPP-POS set. For the SP set of size 3, we specify that θ=.3, which prioritizes choosing target network members who are far away from avoidance network members. There are two equally optimal SP sets: {(7,13,18), (7,13,22)}. Notice that the network members labelled 18 and 22 have identical positions in the network in that they both only have ties with the network members labelled 1 and 2. We proceed to use (7,13,18) as the SP set for simplicity.

Both the SP and KPP-POS sets are displayed in Figure 3. As noted, the KPP-POS set is more likely to include network members that the SP set is designed to avoid. In this example, the KPP-POS set includes network member 25, which is in the “avoid” group. Further the KPP-POS set does not prioritize proximity to the target groups, as the SP set does.

In order to gain further insight in the differences between the KPP-POS and SP methods, we contrast betweenness centrality and degree for the SP and KPP-POS sets from Karate club example. In the KPP-POS set (1,25,34) we find that 1 and 34 have the first and second highest levels of betweenness in the network, while 25 has the median level of betweenness. This is in sharp contrast to the betweenness centrality of the SP set (7,13,18), in which 13 and 18 are tied for the lowest level of betweenness, and 7 has a betweenness that is just above the median. Next we compare the degrees of the members of the KPP-POS and SP sets. Members of the KPP-POS set have much higher degree than members of the SP set. For the KPP-POS set, the degrees are 16, 3, and 17, whereas for the SP set, the degrees are 4, 2, and 2. In general, we conclude that the KPP-POS set will tend to maximize reach to the entire network that is being considered, while the SP set will strategically maximize reach to the target members (balanced with minimizing reach to the avoidance members) of the network. Consequently, the KPP-POS set will often choose members of the network that have higher degree and higher betweenness centrality than the SP set, especially when the target group for the SP set is a small subset of the entire network. Importantly, in the event that the target group includes every member of the network, the KPP-POS and SP sets will be identical.

Example 3: The UrWeb Network

The UrWeb sample is composed of residents of two university dormitories that are physically connected to each other, but are separate entities (Barnett et al., 2014). Here we use a subset (n=44) of the full dataset (N=129) to provide a simple demonstration of the SP method. Participants are categorized as being a member of Dorm 1 or Dorm 2, and are further categorized as being a heavy drinker (reported drinking 5 or more drinks on two or more occasions in the last month). There are 14 residents in Dorm 1, of whom 7 are heavy drinkers, and 30 residents of Dorm 2, of whom 18 are heavy drinkers (Figure 4).

We wish to target the heavy drinkers in Dorm 1 for an intervention, with the heavy drinkers in Dorm 2 as controls. For this reason, we want to choose for the SP set (i.e., those responsible for conveying behavior change) a subset of the heavy drinkers in Dorm 1 who are maximally connected to other heavy drinkers in Dorm 1, while minimally connected to the heavy drinkers in Dorm 2.

We apply the SP method and report the proportion of the targets (i.e., heavy drinkers in Dorm 1) and the proportion of the avoidance group (heavy drinkers in Dorm 2) reached in one, two, or three steps for varying the size of the SP set (s), and varying levels of θ (0, .25, .5, .75, 1) in Figure 5. Here “step” applies to the number of social network ties that are traversed from someone identified in the SP set to others in the target group or avoidance group. Figure 5a and 5b presents the results for one step, 5c and 5d for two steps, and Figure 5e and 5f for three steps to the target group and the avoidance group respectively.

We can see in Figure 5, that for that any given value of s, as θ increases (rows), so too does the percent of the targets reached in the given number of steps; however, as θ increases, the percent of avoids reached (see maps b,d,f) also increases. Of course this is because as θ increases there is a higher priority on having the members of the SP set near to the targets and a lower priority on having members of the SP set far from the avoidance group. Additionally, for a given value of θ, as s increases (columns), the percent of targets reached in a given number of steps also increases.

This example shows how the choice of θ and the choice of s (the size of the SP set) will impact the reach to the targets as well as the reach to avoiders. In this specific example, there is a large degree of separation between the targets and avoiders in the network, so when θ <1, the one step reach to avoiders is 0% (Figure 5). If the researcher is only concerned with contamination that travels at most one step, a θ of .75 with s=4 should be chosen to maximize reach to the targets and minimize reach to avoiders, since 100% of the target group is reached, and 0% of the avoidance group is reached within one step. However, by examining Tables 2 and 3, we can see how the choice of θ affects the two- and three-step reach to avoiders. If the researcher is concerned with contamination that travels further than one step, the choice of θ would depend on the researcher's priorities of maximizing reachability to the target group while minimizing reachability to the avoid group.

Discussion

We introduce the Strategic Player (SP) method for identifying an optimal subset of individuals to use for targeted interventions on social networks. We first demonstrate the SP method on two social networks and show how prioritizing reachability to the target group versus minimizing reachability to the avoidance group through the choice of the θ parameter will result in different SP sets. We also demonstrate this method on a social network of college students living in two dormitories, showing that choice of the size of the SP set and the choice of the θ parameter impacts reachability to the target and avoidance groups within this social network. Researchers using the SP method should carefully consider what levels of reachability to the target and avoidance groups are required for their intervention, and be aware that the best choice of the θ parameter and the size of the SP set will depend upon both of these considerations, as well as to the specific structure of the social network to which they are applying their intervention.

The SP method is an extension of the KPP-POS method in three important ways. First, the SP method allows researchers to identify the group of individuals in the network to which they want their intervention to spread (targets), whereas the KPP-POS addresses the situation in which all members of the network are targets. For example, in an intervention to reduce tobacco use in a network, the SP method would allow researchers to prioritize the intervention spreading to tobacco users, while the KPP-POS approach would be appropriate to maximize diffusion to tobacco users if the network was solely composed of tobacco users. Secondly, the SP method allows researchers to identify a group of individuals to which they do not want their intervention to spread (avoidance group), whereas the KPP-POS method is designed to maximize diffusion to all members of the network. For example, in a cluster-randomized controlled trial on a network, contagion of the intervention to the control group should be minimized. The KPP-POS method was not designed for such situations, whereas the SP method allows for researchers to identify which members of the network the intervention *should not* be spread to. Lastly, the SP method is flexible in that it allows researchers to decide the level to which they prioritize the diffusion of the intervention to the targets over the minimization of contagion to the avoidance group through the θ parameter. It is important to note that using the SP method, if the target group is defined as every member of the network (which implies that there are no members of an avoidance group) the SP method reduces to the KPP-POS method, and will produce identical results.

The SP method will most readily achieve the goal of identifying the set of network members that maximizes diffusion to the target group and minimizes contagion to the avoidance group when these two groups are structurally separated in the network. In the situation that the members of the avoidance set are in close proximity to the members of the target set, we would not expect the SP set to perform well.

As yet, the SP approach has not been tested in prospectively collected network data; our presentation here provides proof-of-concept using selected secondary data sources. This approach therefore requires validation and further evaluation with larger and more complex networks. The SP approach could be particularly useful for applications involving behavioral health (e.g., for supporting behavior change in at-risk subgroups), and for other applications in which separation of subgroups is advantageous for information diffusion goals.

References

Amirkhanian YA, Kelly JA, Kabakchieva E, Kirsanova AV, Vassileva S, Takacs J, … Mocsonaki L (2005). A randomized social network HIV prevention trial with young men who have sex with men in Russia and Bulgaria. AIDS, 19(16), 1897–1905. doi:00002030-200511040-00019 [pii] [PubMed: 16227798]

Aral S, & Walker D (2011). Creating social contagion through viral product design: A randomized trial of peer influence in networks. Management Science, 57(9), 1623–1639. doi:10.1287/mnsc.1110.1421

Aral S, & Walker D (2012). Identifying influential and susceptible members of social networks. Science, 337(6092), 337–341. doi:10.1126/science.1215842 [PubMed: 22722253]

Barnett NP, Ott MQ, Rogers ML, Loxley M, Linkletter C, & Clark MA (2014). Peer associations for substance use and exercise in a college student social network. Health Psychology, 33(10), 1134–1142. doi:10.1037/a0034687 [PubMed: 24364375]

Borgatti SP (2006). Identifying sets of key players in a social network. Computational & Mathematical Organization Theory, 12(1), 21–34. doi:10.1007/s10588-006-7084-x

Broadhead RS, Heckathorn DD, Weakliem DL, Anthony DL, Madray H, Mills RJ, & Hughes J (1998). Harnessing peer networks as an instrument for AIDS prevention: results from a peer-driven intervention. Public Health Reports, 113 Suppl 1, 42–57. [PubMed: 9722809]

Centola D (2010). The spread of behavior in an online social network experiment. Science, 329(5996), 1194–1197. doi:10.1126/science.1185231 [PubMed: 20813952]

Cormen TH, Leiserson CE, Rivest RL, & Stein C (2001). Introduction to Algorithms: McGraw-Hill.

Fujimoto K, & Valente TW (2012). Decomposing the components of friendship and friends' influence on adolescent drinking and smoking. Journal of Adolescent Health, 51(2), 136–143. doi:10.1016/j.jadohealth.2011.11.013 [PubMed: 22824443]

Latkin CA, Davey-Rothwell MA, Knowlton AR, Alexander KA, Williams CT, & Boodram B (2013). Social network approaches to recruitment, HIV prevention, medical care, and medication adherence. Journal of Acquired Immune Deficiency Syndromes, 63 Suppl 1, S54–58. doi:10.1097/QAI.0b013e3182928e2a [PubMed: 23673888]

Latkin CA, Donnell D, Liu TY, Davey-Rothwell M, Celentano D, & Metzger D (2013). The dynamic relationship between social norms and behaviors: the results of an HIV prevention network intervention for injection drug users. Addiction, 108(5), 934–943. doi:10.1111/add.12095 [PubMed: 23362861]

Latkin CA, German D, Vlahov D, & Galea S (2013). Neighborhoods and HIV: A social ecological approach to prevention and care. American Psychologist, 68(4), 210–224. doi:10.1037/a0032704 [PubMed: 23688089]

Li J, Weeks MR, Borgatti SP, Clair S, & Dickson-Gomez J (2012). A social network approach to demonstrate the diffusion and change process of intervention from peer health advocates to the drug using community. Substance Use and Misuse, 47(5), 474–490. doi:10.3109/10826084.2012.644097 [PubMed: 22428816]

Mundt MP (2011). The impact of peer social networks on adolescent alcohol use initiation. Academy of Pediatrics, 11(5), 414–421. doi:10.1016/j.acap.2011.05.005

Ott M (2016). Strategic Players R Package version 1.0 https://CRAN.R-project.org/package=strategicplayers (Version).

Pilowsky DJ, Hoover D, Hadden B, Fuller C, Ompad DC, Andrews HF, … Latkin CA (2007). Impact of social network characteristics on high-risk sexual behaviors among non-injection drug users. Substance Use and Misuse, 42(11), 1629–1649. doi:10.1080/10826080701205372 [PubMed: 17934988]

Rogers EM (2002). Diffusion of preventive innovations. Addictive Behaviors, 27(6), 989–993. [PubMed: 12369480]

Rosenquist JN, Murabito J, Fowler JH, & Christakis NA (2010). The spread of alcohol consumption behavior in a large social network. Annals Of Internal Medicine, 152(7), 426. doi:10.7326/0003-4819-152-7-201004060-00007 [PubMed: 20368648]

Smith KP, & Christakis NA (2008). Social networks and health. Annual Review of Sociology, 34, 405–429.

Tobin KE, & Latkin CA (2008). An examination of social network characteristics of men who have sex with men who use drugs. Sexually Transmitted Infections, 84(6), 420–424. doi:10.1136/sti.2008.031591 [PubMed: 19028939]

Valente TW (2010). Social Networks and Health. New York: Oxford University Press.

Valente TW (2012). Network interventions. Science, 337(6090), 49–53. doi:DOI 10.1126/science.1217330 [PubMed: 22767921]

Valente TW, Hoffman BR, Ritt-Olson A, Lichtman K, & Johnson CA (2003). Effects of a social-network method for group assignment strategies on peer-led tobacco prevention programs in schools. American journal of public health, 93(11), 1837–1843. [PubMed: 14600050]

Zachary WW (1977). An information flow model for conflict and rission in small groups. Journal of Anthropological Research, 33(4), 452–473.

Author Manuscript

Author Manuscript

Author Manuscript

Highlights:

- A method to identify influential behavioral leaders is proposed
- The method balances proximity to targets for the innovation and distance from those who are antagonistic or need to be avoided for other reasons.
- This method may be used for identifying social network members for intervention studies

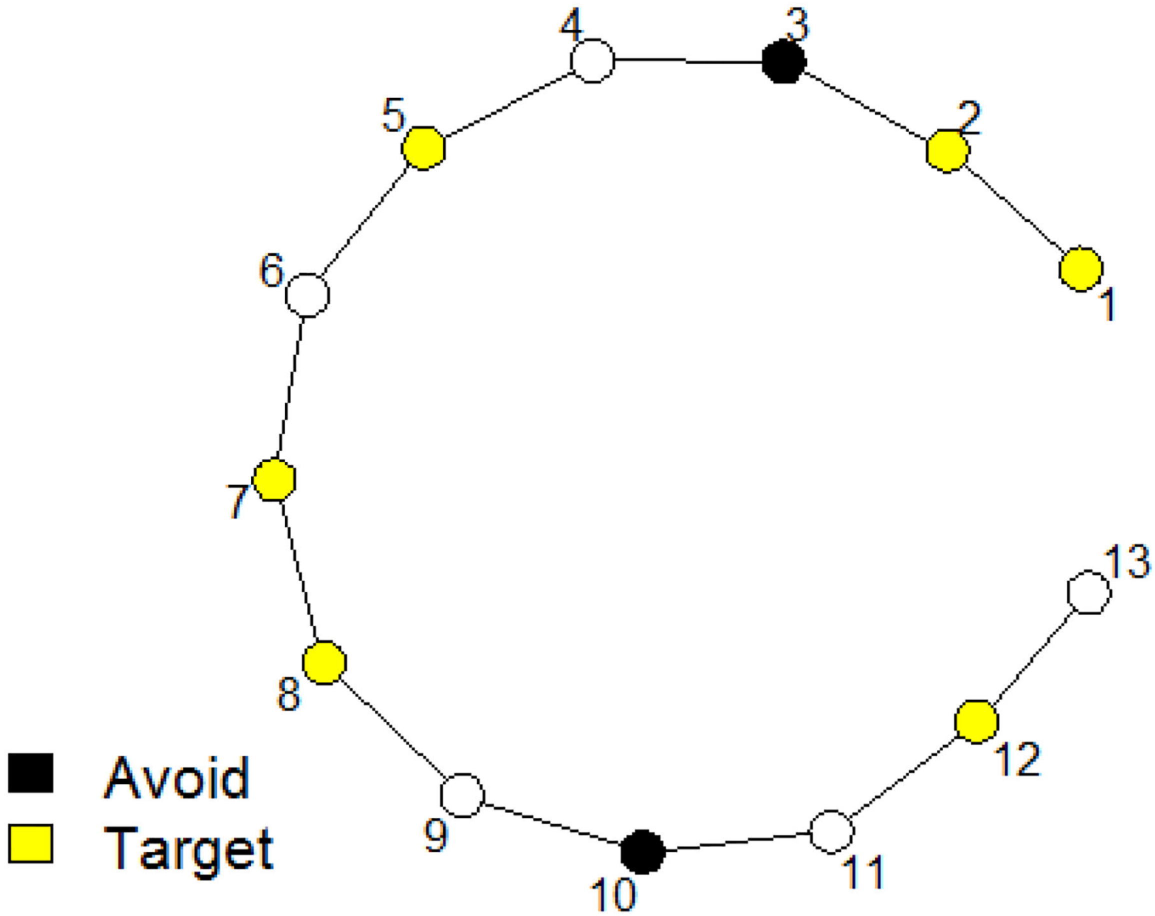

Figure 1.
Example of a simple social network with thirteen nodes, including six target nodes, two avoid nodes.

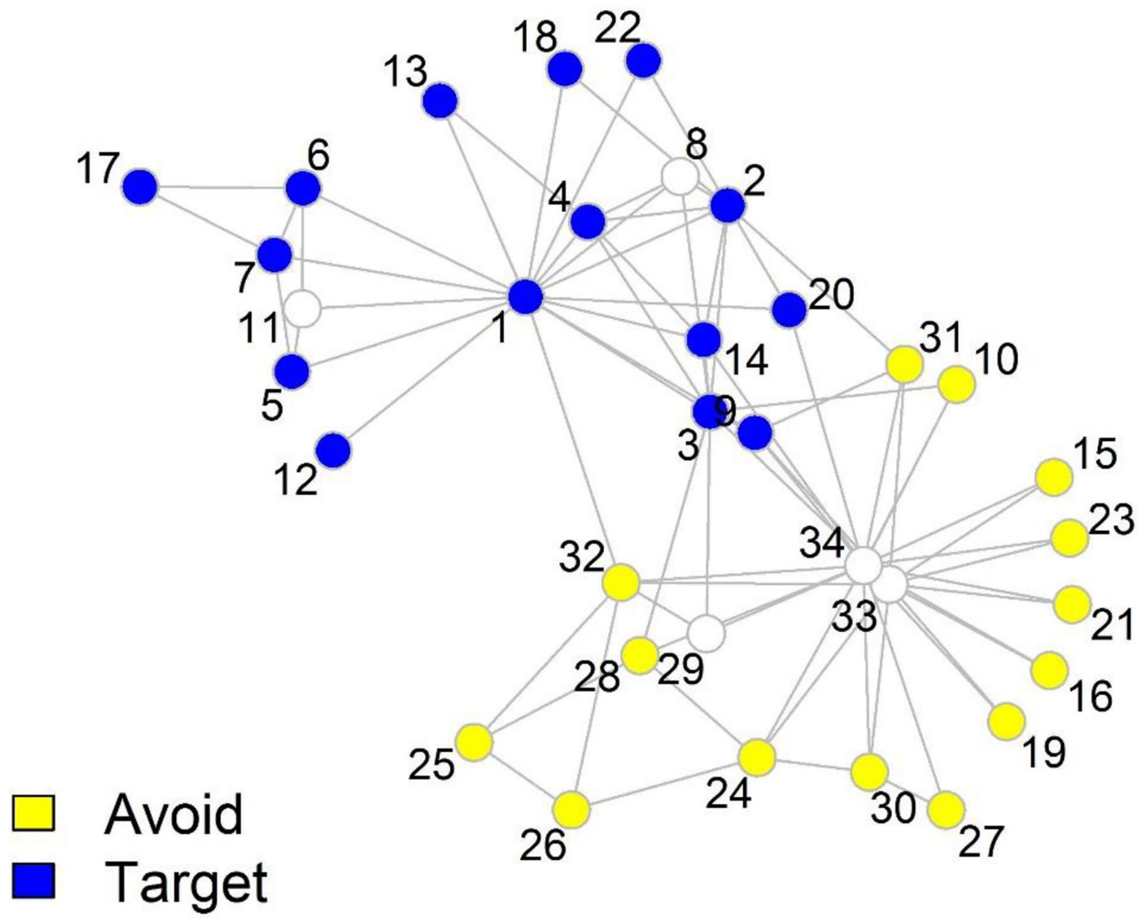

Figure 2.
Zachary's Karate club network with target and avoid groups.

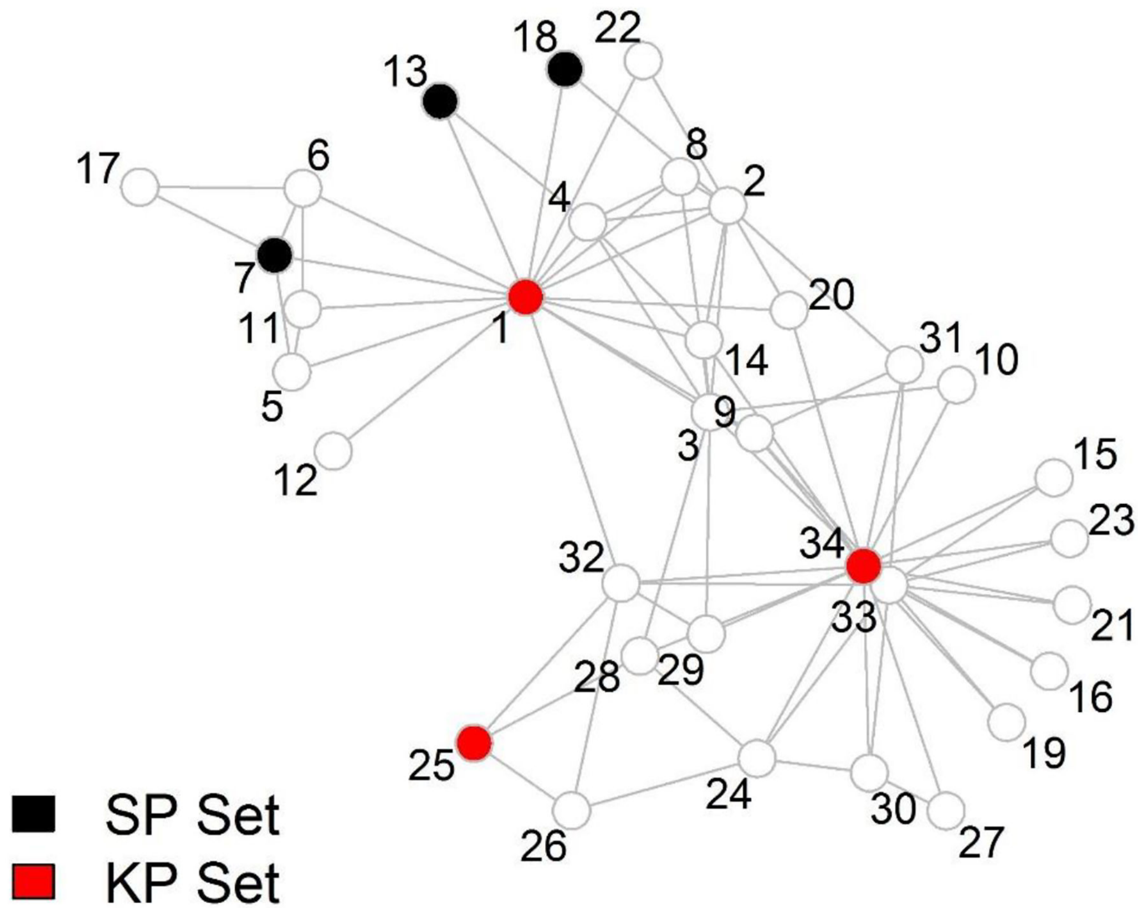

Figure 3.
Zachary’s Karate club network when set size = 3 and theta=0.3 for SP

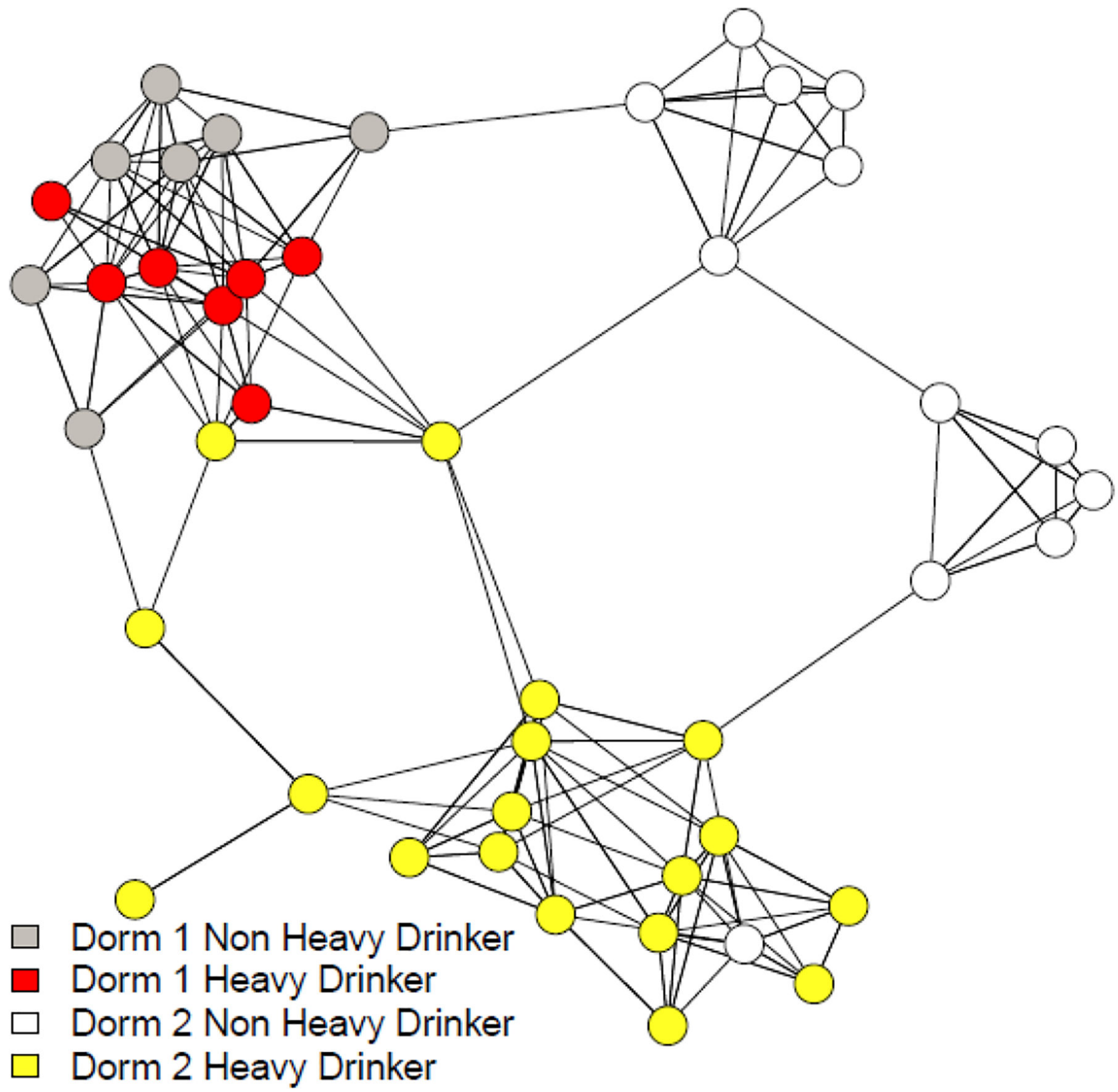

Figure 4.
Partial UrWeb Social Network

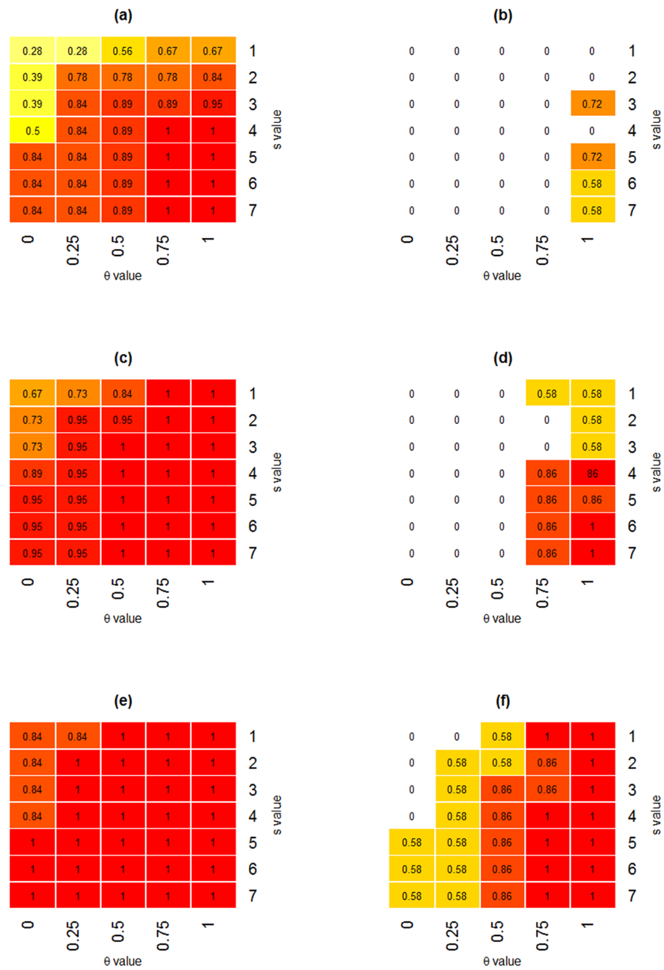

Figure 5.

Heatmaps of the proportion of the target group (a, c, e) and the avoidance group (b,d,f) reachable from the SP set within one step (a,b), two steps (c,d), and three steps (e,f) for varying θ, and size of the SP set (s).