Who's talking, who's listening: exploring social media use by community groups using social network analysis

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Abstract

Community participation in planning is generally considered crucial for the delivery of positive outcomes; however, the network structures of stakeholders such as community groups are not widely understood. This paper explores the use of social media, specifically Twitter, by five community groups. In the context of this study, community groups are self-created and organized groups of citizens that form to oppose a proposal to amend planning controls for a specific site. Utilizing the research technique of Social Network Analysis (SNA), this paper seeks to visualize the community group networks, as well as understand the connectedness and clustering of the networks. For the five community groups investigated, it was found that they are led by a small number of active people, which do not attract large numbers of friends and followers on Twitter and key stakeholders play a passive listening role in the networks.

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1 Introduction

Community participation in planning is generally considered crucial for the delivery of positive outcomes. While the literature acknowledges the formation of community groups and their intended goals (Dear 1992), knowledge of the structure of their networks are not widely understood. By visualizing their networks, we can gain an understanding of who their networks consist of and what keeps them working towards common goals (Innes and Booher 1999). Dempwolf and Lyles (2012) argue that although planning literature has begun to deal with network based research, the work is underdeveloped. While Innes (2005) advises that future research should consider linkages between stakeholders, the information content that flows through networks, who benefits from power in the network and what network patterns emerge and their productivity. This paper explores the use of social media, specifically Twitter, by five community groups in their opposition to proposed changes to planning controls in Sydney, Australia. In the context of this study, community groups are self-created and organized groups of citizens of various sizes that usually form to oppose a proposal to amend planning controls for a specific site or precinct. These groups usually try to sustain ongoing communication with the responsible planning authorities outside of the formal consultation periods or avenues. Traditional communication channels used by community groups include face-to-face meetings, letters, petitions and telephone calls (Dear 1992). In recent years, some community groups are now employing social media platforms, such as Facebook and Twitter to open up an additional communication channel. This paper concludes that social networks led by community groups do not attract large numbers of followers on Twitter, and although connected, key stakeholders and decision makers, including politicians and government agencies, play a passive listening role in the networks.

2 Literature Review

Healey (1993) refers to a shift from a modernist to a post-modernist view of planning as the communicative turn in planning theory, where formal community engagement is undertaken during the planning process. This shift is described by Harris (2002) as a re-orientation from technical planning models towards a more interactive understanding of planning activity.

Others have further developed the area of communicative planning and added terms such as deliberative planning (Forster 1999) to facilitate practical and timely participation and planning through consensus building (Innes 1996) as a form of negotiation and mediation in planning processes. The appearance of social media in recent years has potentially introduced another channel to facilitate communication in urban planning.

In the multi-disciplined field of urban planning and the Internet, much of the discussion has centered on the Internet's potential capacity to facilitate community participation and consultation (Evans-Cowley and Hollander 2010). More recently, focus has shifted to the role of social media as a way of engaging citizens in the planning process, with a focus on online forums and Facebook (Afzalan and Muller 2014; Afzalan and Evans-Cowley 2013). The use of social media can be broken into two separate groups of Government-initiated and Citizen-initiated social networks (Evans-Cowley 2010; Evans-Cowley and Hollander 2010). Citizen-initiated social networks focusing on planning issues form the majority of social networks found by Evans-Cowley (2010) and typically were organized to oppose a proposed development or draft plan.

Hampton and Wellman (2003) describe citizen-initiated social networks as communities consisting of far-flung kinship, workplace, friendship, interest group and neighborhood ties that form to provide networks of sociability, support and control. Hence, communities are not geographically defined groups, but loosely bounded networks. The utopian and dystopian claims the Internet will drastically alter communities remains largely unrealized. Furthermore, Hampton and Wellman (2003) argue the Internet has neither weakened nor transformed communities; rather it has enhanced existing relationships. Essentially, most online contacts are with the same friends, family, colleagues and neighbors that were in contact before the emergence of the Internet. However, it provides additional opportunity to communicate and sometimes replaces face-to-face and telephone contact.

To gain a better understanding of whether collective action can be assisted by the Internet, Hampton and Wellman (2003) conducted an extensive study of an Internet enabled community with access to email distribution lists, called Netville. This case study demonstrated that computer mediated communications were useful in reducing barriers to collective action. In a case study that pre-dates social media, email distribution lists were used to discuss property developer problems, organize in-person meetings, formulate strategies to pressure the developer and send representatives to town planning meetings with great effect. The Netville property developer noted that typically about 5% of new residents would mobilize to gather support via door knocking, petitions and letter writing to generate interest by approximately 20% of new residents. For the Netville development, the residents mobilized very quickly and over 50% of new residents got involved in protest activities. The activities were a combination of online discussions and organizing large scale community meetings. The property developer was also unprepared for the large volume of email communications from residents. Hampton and Wellman (2003) conclude the Internet intensifies the volume and range of community relations, rather than reducing or transforming them into an online only community.

More recently, Afzalan and Muller (2014) found that social media did not create a collaborative communications process in isolation, but integrated well with other communication methods. Moreover, Kavanaugh et al. (2007) found that an individual's use of the Internet within community groups increases over time and so does their level and types of involvement in the group. Hence, social media can provide a platform to quickly launch a community group's campaign and distribute information to a wide audience, but it also seems to cease functioning just as quickly. It could be argued that social media is a supplementary communication channel, that is being mobilized by community groups to support traditional mechanisms of community opposition (Williamson and Ruming 2015). Johnson and Halegoua (2014) identified the use of social media, particularly Facebook, would be beneficial to neighborhood communication, access to information, and participation, but also found mismatches between the perceived affordances of social media and the neighborhood context. Essentially, people are willing to experiment with or use social media to communicate with neighbors about neighborhood matters, but also encountered hesitations about using social media including the need for preexisting neighborhood ties and issues with accessibility.

It is acknowledge that recent social media studies have not returned results as positive as Hampton and Wellman (2003). To contribute to this growing area of research, this paper utilizes social network analysis of five community groups social media use to provide a snapshot of who in the community is participating and to what extent.

2.1 Social Network Analysis in planning literature

Dempwolf and Lyles (2012) note the use of Social Network Analysis (SNA) in planning literature is rare. The research that has been conducted under the broad banner of urban and environmental planning includes investigating opportunities to use social ties through dispersed low income housing (Kleit 2001), relationships between multi-organizational partnerships and community leaders (Provan et al. 2005), evaluation of social relationships in collaborative planning processes (Mandarno 2009), the role of planners in natural hazard mitigation (Lyles 2014) and the role of social networks in self organized communities (Afzalan and Evans-Cowley 2013). Dempwolf and Lyles (2012) argue that SNA research may have a positive influence on public participation in the planning process, and has the potential to uncover the presence of complex formal and informal relationships involving a wide array of stakeholders.

The literature has found several advantages of using SNA, including being a useful tool for evaluating community participation as a social capital builder (Mandarno 2009). Social capital refers to the value found within social networks. Social capital tends to be an intrinsic and instrumental notion of social networks. Research of social capital focuses on network structures such as strong and weak ties and dense clustering of nodes in a network. SNA can also reveal how internal and external factors influence participants capacity to build networks and understand the network structures (Mandarno 2009; Provan et al. 2005), however, simply increasing the network involvement is not an efficient strategy, due to added complexity. Notwithstanding, Innes and Booher (2002) argue the diversity and interdependence of stakeholders can be leveraged to produce better outcomes in planning processes.

Conversely, SNA research can be constrained to micro-level relationships due to the complexity of collecting inter-organizational data. Moreover, difficulties can be encountered when communicating SNA concepts to community leaders (Provan et al. 2005; Mandarno 2009). Dempwolf and Lyles (2012) argue that understanding the complexity associated with the diversity and interdependence of actors in a network is a challenge. Furthermore, although planning literature has begun to deal with network issues regarding the knowledge contained within networks and how the structure of networks enables or inhibits individuals, the work is underdeveloped.

Afzalan and Evans-Cowley (2013) found that although community groups believe online activities have the capacity to inform others of neighborhood issues, their online activities are rarely used for these purposes. Innes (2005) advises that future research should consider linkages between actors and the information content that flows through networks. While Afzalan and Evans-Cowley (2013) argues that in order to gain an understanding of online community activities, researchers also need to analyze the role of key members and their face-to-face activities with community group members.

These challenges are further amplified by Baum (2005) arguments that few planners' jobs require or allow interaction with community groups, and as a result, few planners are sufficiently involved to understanding the perspective and structure of community groups. Planners that do work with these groups tend to engage with readily accessible individuals rather than trying to understand the full extent of the community, organizations and institutions involved. Dempwolf and Lyles (2012) challenge planners to work at multiple spatial scales to engage with more precise definitions of community and place. SNA provides a framework and methods to visualize communities as relational networks separate from their geographic locations.

3 Case studies

The five case studies in the paper are based on community groups operating in Sydney, Australia, which are opposed to proposed changes to site specific planning controls. Table 1 provides general details of the planning proposal for each site. The sites are significant in size, ranging from 2000 square meters to 10 Hectares and all proposals are seeking to change the current non-residential land use to medium or high density residential use. This is consistent with the urban consolidation paradigm that has been pursued in Sydney for the past 30 years (Ruming et al. 2012), with a strong emphasis over the past decade (DPI 2013).

Table 1. Case study details

	Erskineville	**Bronte**	**Warriewood**	**Harold Park**	**Bondi**
Current land use	Warehousing	Registered club	Vacant lots and garden supplies	Horse racing track	Tennis courts
Size	7 Hectares	2,230 sq. meters	7.7 Hectares	10.5 Hectares	4,000 sq. meters
Proposed change(s) to planning controls	Rezone from Industrial to business and mixed use zones	Increase building height from 13 to 20 meters, increase floor space ratio from 1:1 to 2.1:1	Increase dwelling density from 25 to 80 dwellings per hectare	Rezone to mixed use zone and introduced various building heights up to 36 meters	Rezone from private recreation to residential
Proposed future use	Mixed use - retail and High density Residential	Mixed use - retail, registered club and residential	High density Residential	High density Residential	Medium density residential

Geographically, the Erskineville and Harold Park sites are in Sydney's inner western suburbs, Bronte and Bondi are in the eastern suburbs, while Warriewood is located in Sydney's Northern Suburbs.

The community group social media participants for each case study are presented in Fig. 1. For each group the researcher interrogated the Twitter followers list and categorized each follower into a defined group, where possible. The Erskineville group is the longest continuously operating case study, which was established in approx. 2005 and has been an active social media user since January 2012. Fifty-five percent of the Twitter followers are local residents and 10% are local business. The group is followed by Federal (1%), State (7%) and local politicians (4.5%). A further 12% of followers are journalist. The longevity of this group has attracted a significant number of followers (1323) and made 3450 tweets, which makes it the most active social media user of all the case studies (erskinevillevillage.org/).

The Bronte group formed to oppose redevelopment of a relatively small site and has the highest percentage of local residents following them (71%) and a significant representation by both state (9%) and local politicians (4%). The primary reason for this is the development being opposed by the community and is also opposed by the local politicians. Effectively, these three elements have joined together in their opposition to a planning process being undertaken by a state planning agency (savebrontevillage.com). The group has been active on social media since November 2012, has attracted 200 followers and made 1923 tweets.

The Warriewood group formed to oppose a planning proposal which quickly gained a significant amount of media attention due to the high profile property developer involved. While 35% of Twitter followers were residents, this was nearly matched by 30% being journalists and a further 12% being local politicians and local councils. Nine percent of followers were other community groups. The Warriewood proposal was refused relatively quickly and the community group ceased operations as quickly as they appeared (warriewoodbuild.wordpress.com). The group was active on social media from January to July 2014.

The Harold Park group formed to oppose one of Sydney's largest in-fill developments and represents the largest residential development of all five case studies. While 36% of followers are local residents, 19% are other community groups watching the planning process play out. Other groups with significant representation were journalists (11%), State (8%) and local (16%) politicians. This development represented a fundamental change to the suburb within which it is located, as the long standing horse racing facility ceased operation and the land was acquired by a property developer (flagharoldpark.com). The group commenced using social media in February 2012, has attracted 76 followers and made 200 tweets in 3 years.

The Bondi group was the second smallest proposed redevelopment in the case studies. The Twitter followers were predominantly local, with 68% being local residents and businesses. As with the Bronte site, this site has undergone a state planning agency process, which attracted other community groups (13%), journalists (7%) and state politicians (7%) to follow their Twitter account (rescuebondi.com). The group has been active on social media since September 2014.

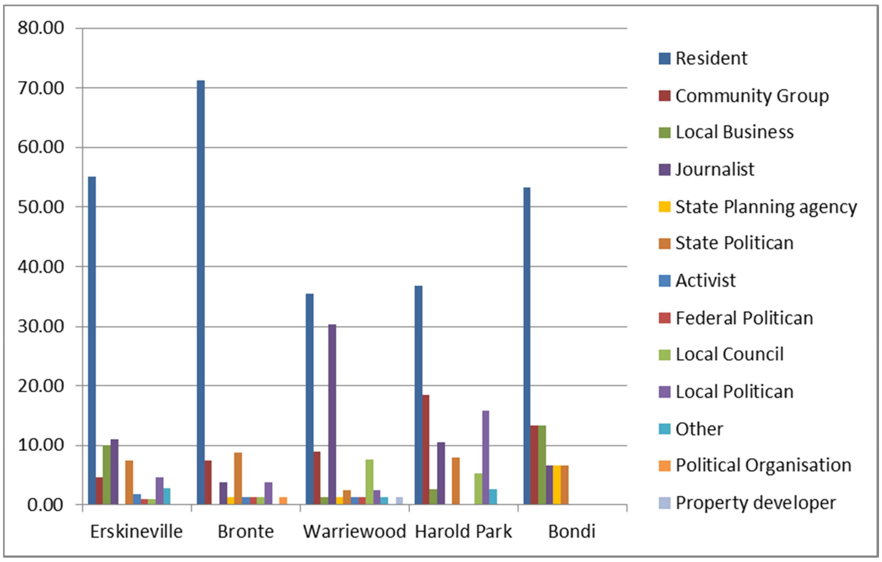

Fig. 1 Community group social media participants

4 Methodology

Utilizing the research technique of Social Network Analysis (SNA), this paper seeks to visualize the structure of community group networks, as well as investigate the connectedness of the networks. SNA is a quantitative analysis of relationships between individuals and organizations. By analyzing social structures it is possible to identify important individuals and group formations (Prell 2012:22). SNA does not consider individuals as a unit of analysis, but rather a set of individuals and their relationships. Wellman (1998) argues analysis of network structures offers a comprehensive approach to understanding the allocation of resources in a social system. Borgatti and Foster (2003) note recent growth in SNA research based on the digitization of everything, increased computing power and the free availability of large databases holding data.

SNA considered two distinct network types. The ego centered network consist of a network structure with a focal actor and a set of alters, who have ties to the ego. These networks are usually referred to as personal networks. Secondly, full networks are a collection of nodes and ties that are not driven by a focal actor (Wasserman and Faust 1994:42).

Social networks can be represented in mathematical or graphic form (Prell 2012). This paper seeks to describe social networks predominantly in graphic form, with further analysis of statistical measurements generated from the graphs. The network measurements include the analysis of degree (number of network connections), betweenness centrality (position within a network), tie strength and community detection methods.

5 Data Collection

Twitter data was collected directly from the Twitter application programming interface (API) using the TAGSv6 and Friends and Followers Google spreadsheets created by Hawksey (2011; 2013). The data was then manually converted into network data files, and finally, network analysis was performed using Gephi visualization software (http://gephi.org/).

Twitter is a service that allows people to publish short messages on the Internet and is commonly referred to as microblogging. Twitter allows people to subscribe, known as following other people they are interested in. A follower is notified every time someone they are following posts a new message. Twitter enables users to broadcast messages using hash tags (#) and send direct messages using the '@' symbol, however direct messages are still publically available (Java et al. 2007; Borgatti et al 2013:260). Java et al. (2007) considers the Twitter follower structure to be a social network. Moreover, Twitter is a directed social network, as someone who is followed by another Twitter user may not necessarily follow that user. Huberman et al. (2009) defines a friendship as two or more direct messages between Twitter users. By this definition, Twitter social networks are a fraction of the size of the dense friends and followers networks that can be observed. However, Huberman et al. (2009) also argues that although Twitter following may not define a social relationship, the number of followers may determine the role and importance of a person within a network. Accordingly, a person with a higher number of followers has a stronger communication function than someone with a small number of followers.

A major consideration for research design using network analysis is bounding the set of nodes to be included in the study. In some instances a clear boundary will appear around the study group, in others it is not so clear. The chosen boundary is primarily based on the research question(s), but is also based on two sets of actors: the egos personal network and the alters, which the ego have ties with. This does not imply the network does not have ties to the outside world. In the real world most groups have fuzzy boundaries. A common approach to approximating the network boundary is snowball or respondent driven sampling, when survey’s or interviews are being used to collect data (Borgatti et al. 2013:33-34).

For Twitter networks a boundary is clearly marked by the immediate friends and followers of the generic community groups Twitter account. In this instance the researcher has also chosen to take a sample of friends and followers of the community group’s followers. This approach was taken to allow the capture of all retweeting activities and to investigate how far this activity reaches through the network. This represents two degrees of separation from the community group. An artificial boundary must be set for social media data as the social networks are theoretically infinite.

6 Results

This section presents SNA results by firstly discussing the statistical measurements of the networks, and secondly, discussing the network structures of two of the five case studies. Network graphs for all five case studies can be viewed at www.wewilliamson.com

6.1 Network Properties

This section discusses the statistical measurements in Table 2 for all the case study networks. Network structures can be compared when they broadly have the same substantive meaning (Wasserman and Faust 1994:450), which is the case for this research. However, each network is unique and represents a snapshot in time. This analysis does not seek to identify the best or worst network structure in this set of case studies.

Centrality is a core concept of SNA, which is a measure of a nodes location within a network. Centrality measures are a group of concepts, with the simplest centrality measure being Degree. Degree is considered to be a measure of a person’s social activity and is measured by counting the number of direct relationship or interactions with other nodes. If a directed social network is being analyzed, degree can be separated into incoming and outing degree (Borgatti et al. 2013:164). Due to the large data sets used and the artificial boundary setting, the average degree in Table 2 for all case studies is low. This will be further discussed in the next section, where the nodes with the highest degree are identified using network graphs.

Social networks have a tendency to exhibit neighborhoods of nodes. Essentially, friends of a person will make connections to each other, and is referred to as clustering. The clustering coefficient identifies hub like structures within a social network and calculates the probability that two nodes within a hub are connected (Watts and Strogatz 1998). The cluster co-efficient was developed to capture the extent to which a network has areas of high and low density. The measure is based on calculating the density of each nodes personal network, which is then averaged to find an overall network co-efficient (Borgatti et al. 2013:156). With reference to Table 2, the clustering co-efficient was highest in the Bondi, Harold Park and Erskineville cases studies, which suggests people in these networks are more likely to embedded in more dense clusters, with a higher likelihood of cliques. Cliques are a subset of nodes where every node is connected to every other node in the subset (Borgatti et al 2013:183). The Bronte and Warriewood case studies exhibit lower clustering, which suggests there are a wider range of people involved that are not connected with others in the sub-group.

The basis for determining the diameter of a graph is the length of the shortest path between two nodes. In a directed network, the direction of edges is also taken into account (Wasserman and Faust 1994:134). For the Erskineville case study the average path length is 7 steps, while for the smaller groups the average path length is 3. This demonstrates the network size has a significant effect on the ability of information to traverse a network.

Community detection in networks is the identification of densely connected groups of nodes, with sparse connections with other sub-groups. These groups of nodes interact with each other to the extent that they could be considered a separate network. The identification of these groups can be of significant practical importance, as they identify social forces operating through direct contact among sub-group members, through indirect conduct transmitted by information brokers or relative cohesion compared to outside the sub-group (Wasserman and Faust 1994:251).

Community detection uses two key measurements. Firstly, modularity measures the strength of division of a network into communities. Networks with high modularity have dense connections between the nodes within a community, and sparse connections between nodes in different communities (Newman 2006). Essentially, modularity compares the number of internal links in the sub-groups to how many links would be expected if they were distributed at random (Borgatti et al. 2013:195). Modularity ranges between -1 and 1 to provide a measure of the density of links inside communities. Thus, the modularity values in Table 2 for the case studies are regarded as high.

Secondly, the community detection algorithm used by Gephi is a modularity optimization method developed by Blondel et al. (2008), which visualizes communities in non-geographic space. Comber et al. (2014) suggests using geographic attributes to provide greater insight in the sub-group network structures. However, community groups are typically aligned to a specific geographic location and geographic analysis has not been undertaken for these case studies. The visual results of community detection are in Fig. 7.

Table 2. Network level properties

	Erskineville	**Bronte**	**Warriewood**	**Harold Park**	**Bondi**
Nodes	108,678	58,852	45,762	39,531	6,085
Edges	207,910	90,783	55,218	72,090	10,789
Average Degree	1.91	1.54	1.21	1.83	1.77
Clustering Co-efficient	0.12	0.08	0.05	0.15	0.30
Average Path Length	7.08	3.66	3.15	3.23	3.32
Modularity	0.64	0.72	0.80	0.62	0.52
Communities	45	20	17	14	9

6.2 Network Structures

The following graphs are a visual representation of community group Twitter networks. In the graphs, a network consists of points which represent a person or organization and is referred to as a node. A connection between two nodes (people) is represented by a line and commonly referred to as an edge or vertices (Wasserman and Faust 1994:94). Various characteristics of the nodes and edges, such as size, shape and color, can be used to communicate information about the nodes and the relationships among them (Borgatti et al 2013:100). This analysis looks at graph results for 2 case studies.

The graphs in Fig. 2 are the result of loading raw twitter data into Gephi and applying the Force Atlas 2 layout algorithm, which is a force-directed layout algorithm that transforms raw data into a network map. The nodes with the highest degree have also been enlarged to identify their location within the network. High degree nodes are important for mobilizing the network and bring other stakeholders together. However, as high degree nodes must exert significant energy to maintain a large number of ties, their ties are often weak. Hence, high degree nodes can be trusted to use their links to diffuse information and potentially mobilize the network, but there is no guarantee that they can significantly influence those they are connected with (Prell et al 2009).

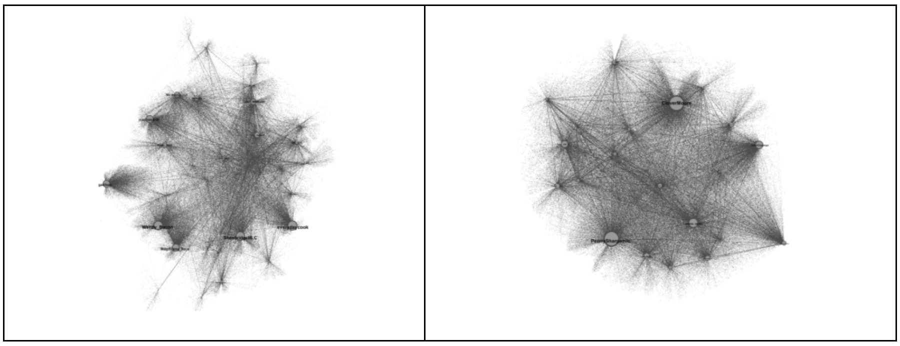

Fig. 2 Degree (left: Bronte, right: Harold Park)

There are various network structures depending on the network type, including small world, village, opinion leader and hierarchical networks (Lyles 2014). The networks depicted in Fig. 2 most closely resemble the opinion leader structure. Lyles (2014) analysis of network structures concludes that opinion leader network structures limit opportunities for the types of discourse and joint problem solving needed to engage with political issues. Notwithstanding, the opinion leader network structure seems a logical fit for community groups who are typically led by a small number of people who are seeking to distribute their opinions.

While Fig. 2 provides an overall view of the network structure, Fig. 3 represents the network of high degree nodes with all other nodes filtered out. Essentially, Fig. 3 identifies the nodes that have the potential to influence the network, due to their highly connected status. From a Twitter perspective, if these nodes tweet or retweet a message, it will be distributed further across the network. The node labels in Fig. 3 are mostly politicians, journalist, local residents and local businesses. The generic community group Twitter account does not appear in either of these graphs, as their degree is insignificant compared to the high degree nodes in the network.

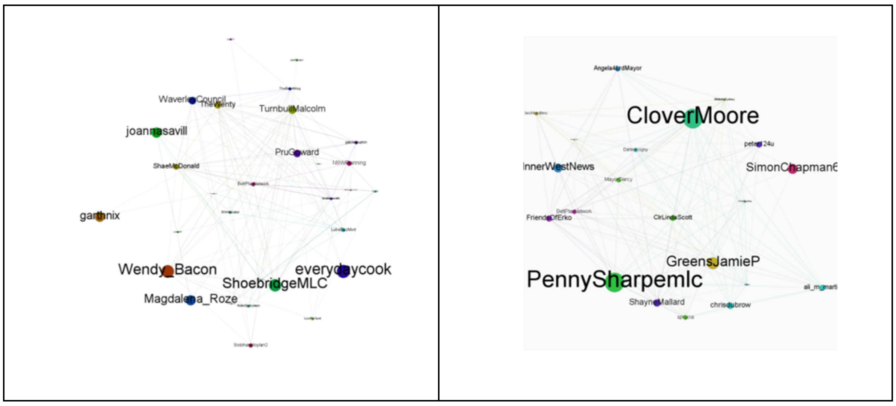

Fig. 3 Filtered Degree (left: Bronte, right: Harold Park)

Betweenness centrality measures the ability of a node to control the flow of communication in a network. Interactions between two non-adjacent nodes depend on other nodes to transmit a message. This can be considered important as certain nodes can perform an information broker role between disconnected segments of a network (Prell et al. 2009; Borgatti et al. 2013:188). Shortest path length is concerned with the number of nodes and edges used to find a route through a network. This measure is averaged for the entire network (Wasserman and Faust 1994:107). With slight exceptions, the graphs in Fig. 4 are almost identical to the high degree graphs in Fig. 2. In Twitter networks the high degree nodes are the nodes that are holding connections to large numbers of other nodes. Essentially, they are the bridges or information brokers to sub-groups within the broader network.

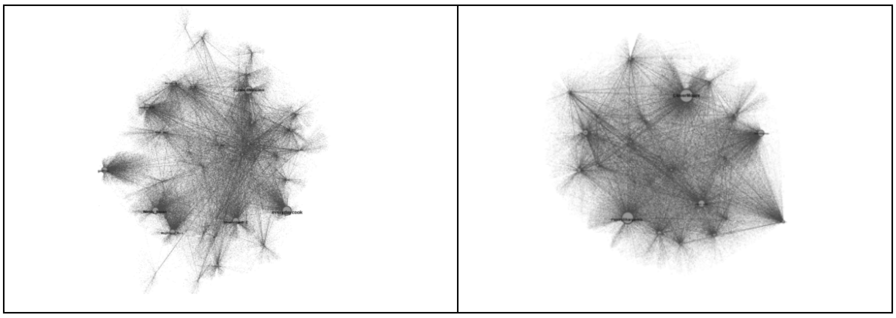

Fig. 4 Betweenness Centrality (left: Bronte, right: Harold Park)

Tie strength is displayed in network graphs by line thickness, which represents the portion of communications that has occurred between the nodes (Borgatti et al. 2013:112). Tie strength is closely associated with social capital, which refers to the value found within social networks and typically focuses on network structure attributers such as strong and weak ties and dense clustering of nodes (Wellman and Faust 2001). The graphs in Fig. 5 expose the strongest ties in the network, which also identifies the core network of the community group. By default, these are the people that are using the network on a regular basis. In both networks in Fig. 5 the strongest ties are centered on the node that is the community group's generic Twitter account, which plays the role of providing regular information, suggested activities and behaviors to its close ties, which are commonly the high degree nodes identified in Fig. 3.

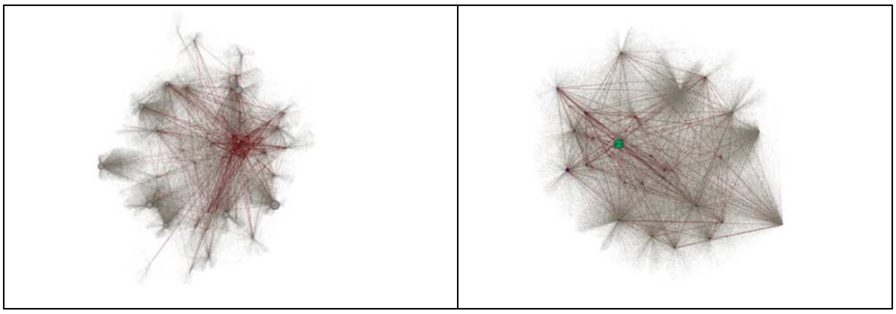

Fig. 5 Strong and weak ties (left: Bronte, right: Harold Park)

Fig. 6 is the network with a filter applied to remove all nodes that have not sent a tweet. The pattern of ties clustered around the generic community group node and the other nodes that have actually sent a tweet is a very close match with the strong ties in Fig. 5.

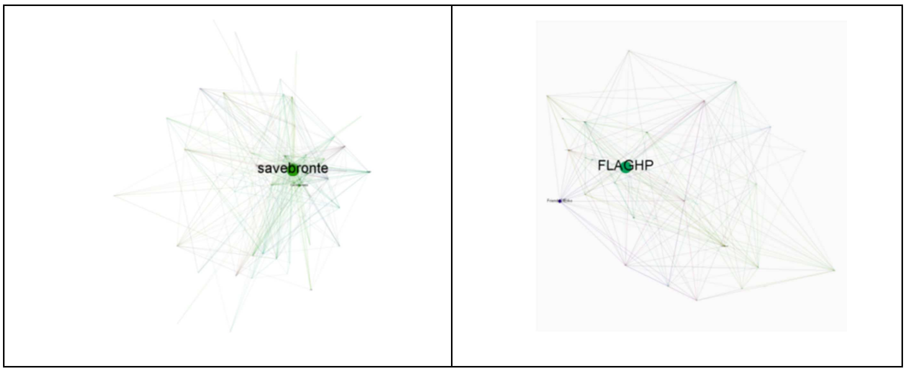

Fig. 6 Tweets (left: Bronte, right: Harold Park)

As discussed in the previous section, Gephi's community detection function was run to produce the graphs in Fig. 7. Essentially, the communities identified are sub-groups clustered around the highly connected nodes in the network.

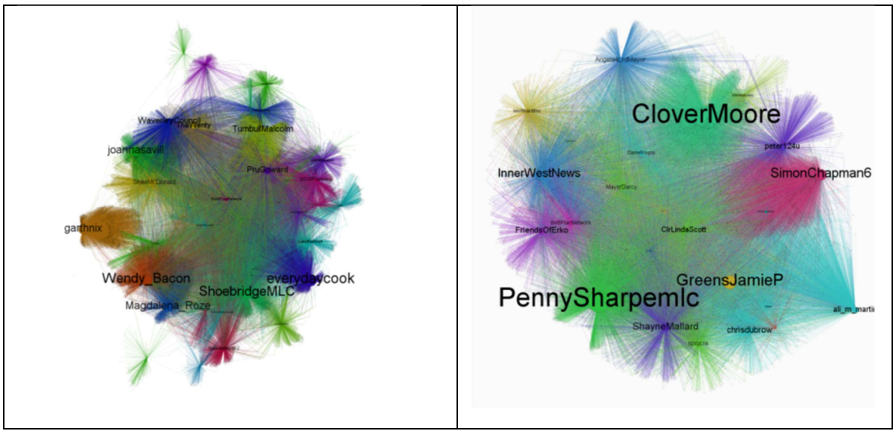

Fig. 7 Community detection (left: Bronte, right: Harold Park**)**

Finally, to gain a better understanding of what kind of reach retweeting would have on a network, the tweet and retweet data for the Bronte case study was investigated for the month of October 2014. This time period was relatively active for this community group as the proposed planning control changes were placed on public exhibition. Fig. 8 shows the daily activity for the month, which consisted of 287 tweets and 565 retweets. On 13 October, the community group organized a meeting at the local school hall for local residents to discuss the formal public exhibition and submissions process. This event resulted in the most active day of social media use, with 36 tweets and 75 retweets.

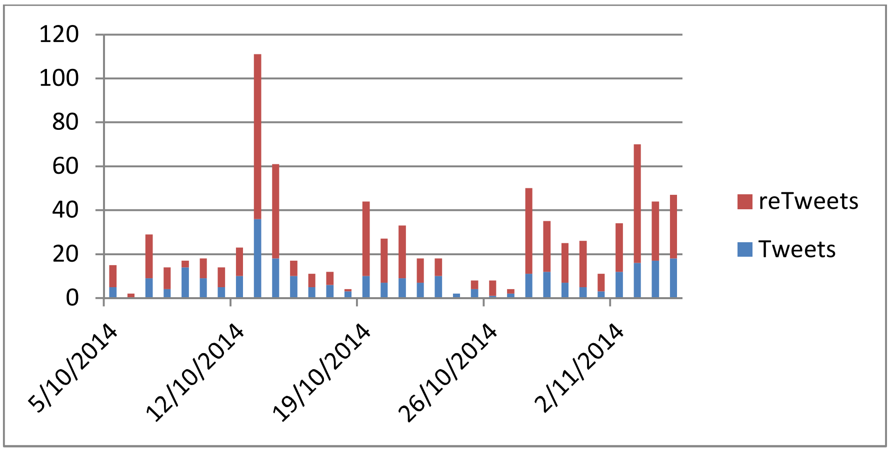

Fig. 8 Retweet activity during public exhibition

The Green nodes in Fig. 9 are the nodes that may have seen a retweet during this time, while the red nodes did not. The activity is concentrated in the center right portion of the network where the node that is the community group's generic Twitter account is located. This is a logical finding as the community group was communicating daily that the public exhibition was in motion and how people can make a formal submission. This graph also highlights which high degree nodes were not passing on the messaging. The nodes across the top of the network including the local council, the NSW Department of Planning and Environment, the Minister for Planning, a state member of parliament and 2 local newspapers did not retweet during this time. High degree nodes across the bottom of the network, being another state member of parliament, one citizen and one local business with significant degree were also silent.

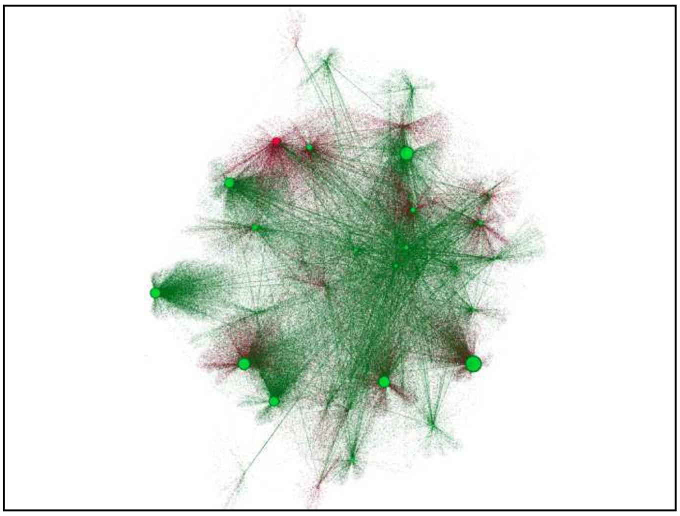

Fig. 9 Retweets (Bronte case study)

The nodes that did actively retweet during this time were local citizens, a local journalist and the Better Planning Network (BPN). The BPN is a volunteer-based organization founded in 2012 in response to the NSW Government's proposed planning reform package. The BPN claims to have affiliation with over 470 community groups across the State. This analysis suggests that although key stakeholders are connected to the network the community group has built on Twitter, they are passive listeners and do not necessarily promote the messaging that is being distributed across the network.

7 Discussion and Conclusion

This paper has presented an analysis of the Twitter networks of five community groups. The results from this study have provided the following findings.

Firstly, the community group social networks attract key stakeholders, such as politicians, planning authorities and local governments. Additional, journalist, news agencies, local business and other community groups are well represented. However, it was found that the community groups are led by a small number of active people in an opinion leader network structure, while the majority of people in the network have a low participation rate. Twitter's open nature allows interested parties to connect and potentially join the conversations. This analysis shows that even during the most important time periods in the planning process, numerous key stakeholders in the network did not participate. Further research on the perceived role of stakeholders and decision makers who link into a community group’s network, but chose not to participate during key time periods would be beneficial.

Second, while the community group’s generic Twitter accounts may not attract large numbers of friends and followers on Twitter, their combined network can become quite large and during periods of high tweeting and retweeting activity, information and comments can be distributed to a significant number of people.

Third, while graphs display a good representation of the networks, the unstructured nature of social media and the need for researchers to set an artificial boundary renders key SNA statistics, such as average degree inconclusive. However, SNA has identified significant clustering around high degree nodes and high modularity within sub-groups, which are logical findings for social media data analysis.

Fourth, a highly centralized network is characterized by a few individuals holding the majority of connections with others in the network. Lyles (2014) contends that centralized networks are good for building support for collective action, however, they are not so good for problem solving. A more decentralized structure provides better access to resources and stakeholders. Nonetheless, the goal of a community group is to generate collective action, thus the network structures found in this analysis seem appropriate. Furthermore, SNA illustrates the networks strongest ties are concentrated on the community group’s generic Twitter account and suggests there is social capital being generated within this segment of the social network.

Fifth, the Erskineville, Harold Park and Bronte community groups commenced using social media in 2012, while Warriewood and Bondi commenced in 2014. Each community groups social media profiles are followed by other community groups. This suggests that these groups are observing each other’s actions and potentially emulating them for their own cause. This echo’s Mergel (2013) suggestion that the key to the rapid diffusion of social media by local governments in the US can be attributed to the free and open nature of social media, and the fact that practices of others can be openly observed and emulated. It is difficult to identify social media use by community groups in Sydney prior to 2012, however, since 2012, numerous short and long term examples can be found.

Finally, this paper demonstrates that social network analysis is a satisfactory approach for investigating both statistical measures and visual patterns of community group social media use. This could be complimented by analysis of the messaging that is taking place between community group members and key stakeholders.

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