# Examining the Impacts of Key Influencers on Community Development

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**Abstract:** In this research, we aim to identify and investigate the impacts of key influencers on community formations and developments. We assess the impacts of key influencers by analyzing the activities and structure of the social media presence of a local community. Results of our analysis show that key influencers play important roles in connecting the community, transferring information, and improving overall sentiment of the community members. Our findings suggest that community practitioners can apply social network analysis to identify value-added influencers and discover strategies for improving the community and keeping leadership roles.

**Keywords:** Social networks, network analysis, community development, network graph, influencer analysis.

## 1 Introduction

Organizations have increasingly used social media in community development to share information with a wide audience and improve the quality of communications. On social media platforms community practitioners can actively engage with community members and establish relationships with them. Meanwhile, social media provide rich data for practitioners to understand community members' concerns and thus devise and launch new strategies to solve community issues. In addition, social network data provide the opportunity for practitioners to understand how a community is formed and maintained online. Understanding how community members interact with each other and share information overtime can help practitioners to effectively engage community members and promote community development initiatives.

Form network perspectives, communities can be viewed as sets of individuals and organizations and their relationships. Community development is to strengthen and extend networks of relationships between individuals and organizations. Network analysis can provide valuable information about how networks expand and grow more interconnected over time. Within a community, active members create influence by generating traffic or connecting the network. Strategically employing influencers in the network can enhance the leadership capacity of community leaders. Community practitioners can analyze social networks to identify central individuals in a network who are best placed to diffuse

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information or connect the network. Moreover, these central individuals can be utilized so that they can subsequently influence other members in their network.

To examine the impacts of key influencers on community development, we collected Twitter data on a local community-Brooklyn Tech Triangle. We analyze the Twitter data to identify key influencers in the network based on centralities and visualize the network structure with network graphs. Results of our analysis suggest that key influencers in the community played important roles in sharing information, promoting positive sentiment and connecting community members. By applying a proactive approach to find and engage with key influencers, community practitioners can more effectively scale and accelerate community development initiatives.

In the next section, we provide a review of related works done in this area. Then we introduce the context and our methodology. Later, we present our analysis and findings, and we provide discussions and recommendations based on our results.

## 2 Related works

Community practitioners increasingly use social media platforms to communicate with members, promote community development initiatives and build relationships with community members and leaders [Ennis and West (2010)]. Social media and social networks offer a rich set of platforms and means of participation, communication, engagement and connectedness for development and social impact: they enable the support of community development efforts [Matthews (2016)]. Social media facilitates two-way interactions between community practitioners and members through direct connections. Social platforms act as a connective space for communication and information sharing. As a result, social media becomes a major part of practitioners' communication strategies [Oh, Eom and Rao (2015)].

Social media simplifies access and information sharing. Since most social media platforms are free to join, they have become cost effective outlets for communication and marketing. Moreover, organizations employ data analytics and knowledge management techniques to develop insights into what their target audience wants and needs. The data analytics and knowledge management sharing technologies allow these organizations to be more responsive and strategic by adjusting existing strategies or developing new ones to meet their customers' needs [Zeng, Chen, Lusch et al. (2010)].

Community practitioners can utilize social media platforms to share content and opinions and build online identities and networks. With information on social media they can actively engage in monitoring and understanding the issues and opportunities facing the community. In addition, through networking community practitioners can enhance their leadership capacity within the community by being adaptive problem solvers to achieve a desired set of objectives [Hoppe and Reinelt (2010)]. Therefore, previous research suggests community leaders to include social media in their community development practices and establish effective communication through social media tools [Ang (2011)].

Social network analysis is a methodology for discovering patterns of relationships, interactions, and social structure in network communities [Chau and Xu (2012)]. Social network data provide the opportunity for understanding how a community is formed and maintained online: the social networks depict the interconnections of community members. The network graphs are model representations of the social networks and the graph characteristics yields invaluable information on how the community is centralized on certain subgroups, if such subgroups exist, or otherwise isolated from each other. Thus, integrating social media analytics into community development practice is a useful way to assess the impacts of community development works [Ennis and West (2010)].

Community practitioners can obtain a comprehensive profile of community members by interacting with them and listening to their specific needs on social media platforms. By engaging with the audience via interactions and exchanges, social media empowers organizations to establish an adaptive collaborative ecosystem which promotes positive relationships with customers [Patino, Pitta and Quinones (2012)]. Organizations can benefit from targeting members to effectively share and promote valuable information [Matthews (2016)]. Therefore, organizations increasingly analyze social networks to identify members who are influential in their networks [Bakshy, Hofman, Mason et al. (2011)].

Key influencers play a very important role in community formation and development. Community practitioners should engage with them during all stages of community initiatives and promotions. The appearance of conviction and integrity are crucial to making the influencers persuasive role models for influencing and directing community users' attitude toward community initiatives. Key influencers can be identified by measuring the centrality of the community members. The centrality of each member in a network is a metric that captures the importance of each individual member in the overall network structure [Poulin, Boily and Masse (2000)]. Individuals with high centrality scores are often more likely to be leaders, key canals of information, and early adopters of products or promotions. Computing centrality scores and finding out central member(s) are important in that these central members could help spread information faster or protect the network from breaking. For example, they can be used to stop rumors.

There are different approaches to measure centrality. Some of these measures include indegree, betweenness, closeness, and eigenvector. Centrality measurements, such as indegree and betweenness have been used to obtain analysis for different purposes. Hubs are individuals in a network that are highly sought-after by other network members as defined by Freeman et al. [Freeman, Roeder and Mulholland (1979)]. Indegree centrality is used to measure and identify hubs in a network by counting how many relationships point towards an individual. The indegree centrality of a vertex $v$, for a given graph $G:=(V,E)$ with $|V|$ vertices (individuals) and $|E|$ edges (relationships), is defined as $CD(v)=deg(v)$.

Bridgers are individuals in a network who have connections to different clusters [Freeman, Roeder and Mulholland (1979)]. Because bridgers have access to clusters that are otherwise unknown to most network members, they play a very important role in the transfer of information through the network. Betweenness centrality is used to measure and identify bridgers in a network. The betweenness centrality of a vertex $v$ in a graph $G:=(V,E)$ with $V$ vertices (individuals) and $|E|$ edges (relationships), is computed as:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Finding out members with high betweenness centrality scores is important because they could help spread information in the social network faster, and they could also help protect the network from breaking [Bakshy, Hofman, Mason et al. (2011)]. In addition, understanding how information flows through networks is valuable for practitioners to determine how to strategically access it [Banerjee, Chandrasekhar, Duflo et al. (2017)].

## 3 Context and methodology

We collect and analyze social media data on a local community - Brooklyn Tech Triangle to identify and examine the impacts of key influencers on community development. The Brooklyn Tech Triangle is made up of three key practitioners: Downtown Brooklyn, DUMBO, and Brooklyn Navy Yard. The three practitioners share the task to promote an active and cohesive community, attract entrepreneurs and investment, and connect the local community with the economic opportunities and resources.

**Table 1:** Twitter data of Brooklyn Tech Triangle

| Search Term | Number of Tweets |
|---|---|
| #DowntownBrooklyn | 1832 |
| #DumboBid | 1308 |
| #BrooklynNavyYard | 1388 |
| Total | 4528 |

Recognizing the importance of social media in community development, the practitioners all have their individual social media presences. Using related keywords (Twitter hashtags as shown in Tab. 1), a total of 4528 tweets were collected from Twitter through dashDB on IBM's BlueMix platform from April 2014 to November 2016, over a thirty-two-month span. The diverse twitter users provide valuable information from their stream of tweets as an important source of real-time web information [Gayo-Avello (2013)]. In addition, the simplicity of Twitter is important for fast news sharing and just-in-time updates [Jansen, Zhang, Sobel et al. (2009)].

Network analysis offers important metrics that community practitioners should seek to understand. Ang [Ang (2011)] proposes examining connectivity and conversations to understand how social media facilitates the formation of relationships among community users. Network analysis can help describing the connectivity of participating members, identifying the patterns of interactions, and tracing how information flows within the community. These can be particular key measures of the health of a community in terms of reducing disconnectedness and receiving quick responses from community members. Thus, in this research we focus on investigating the connectivity of the community with network analysis and examining the conversations to discover the relationships and impacts.

## 4 Analysis and results

We first visualize the community with network graphs, as shown in Fig. 1, whose layouts are done by Fruchterman et al.'s [Fruchterman and Reingold (1991)] algorithm. We observe that the online networks grew in terms of both size and density from 2014 to 2016. The number of unique active members in the network increased to 814 in the year of 2016 from 214 in 2014. The network graphs help us visualize the emergence of leaderships and the change of influence over time. As shown in Fig. 1, the network grew to more interconnected by a higher number of clusters in 2016 from its more centralized state in 2014. In 2014, two of the practitioners, Downtown Brooklyn and DUMBO, functioned as major hubs of the network, and in 2016 the function was shared by more leaders and influencers as they emerged in the network.


**Figure 1:** Network graphs of Brooklyn Tech Triangle 2014-2016

### *4.1 The impacts of hubs on community development*

Indegree centrality is calculated to identify key influencers in the community who serve as hubs in a network. These influencers are important accounts for the diffusion of community initiatives and generating traffic in the network. The key influencers (hubs) in the community are listed in Tab. 2, and all of the practitioners ranked top in the list. The key influencers are highly sought-after by other community members, and each of them has a large number of followers in the network, as shown in Tab. 2. The influencers are also more vocal than other accounts in the network, and on average they contributed 15% of tweets generated by the community monthly.

**Table 2:** Indegree centrality scores of key accounts

| Account | Indegree score | | | Count of Followers |
|---|---|---|---|---|
| | 2014 | 2015 | 2016 | |
| DowntownBklyn | 139 | 271 | 102 | 11356 |
| DUMBOBID | 99 | 128 | 82 | 12835 |
| BklynNavyYard | - | 31 | 34 | 661 |
| BLDG92 | 40 | 36 | 27 | 2731 |
| TechTriangleU | 36 | 54 | - | 274 |
| BEIN_BK | - | 10 | 49 | 145 |

Examining the centrality scores, we also discover the changes of influence over-time in the community. For example, *BLDG92* and *BklynNavyYard* are both Twitter handlers of Brooklyn Navy Yard. During the early development of the industry park in 2014 and 2015, *BLDG92* was more vocal in the community in promoting office buildings to host tech-driven manufacturers and companies. Starting from 2015 *BklynNavyYard* became increasingly more active in the network as the practitioner switched to the focus on creating quality jobs in the modern industrial sector and connecting local community to resources and economic opportunities. Another example is *BE.IN*-The Brooklyn Education Innovation Network. *BE.IN* is a consortium of institutions, students, and faculty in Brooklyn. It aims to promote collaboration between local colleges and universities in Brooklyn. By examining the centrality scores, we can discover that since 2016 *BE.IN* has emerged as a major hub and took over the leadership role of some other influencers.

Hubs in a network are also important accounts to promote positive attitudes of community members. We conducted sentiment analysis of the tweets generated by the influencers and community members. Sentiment analysis is the process to determine the attitude of a content creator with respect to specific topics [Deng, Sinha, Zhao et al. (2017)]. Sentiment analysis empowers organizations by providing extensive, insightful information regarding their target audiences' sentiments. In the past few years, abundant machine learning algorithms have been developed for natural language processing and sentiment analysis (e.g., [Zhang, Wang, Li et al. (2018)]. In this research we used *text2vec* and *glmnet* R packages to train a model with 1.6 million labelled tweets [Go, Bhayani and Huang (2009)], and then we conducted sentiment scoring of our Twitter data using the trained model. The model generated sentiment scores of every tweet in a range of values from 0 (completely negative) to 1 (completely positive). Human annotation of 500 sampled tweets suggests that the model achieved an accuracy of 91%. We measure the attitude of community members towards the influencers with the sentiment scores of their comments and retweets on the influencers' posts. As shown in Fig. 2, the sentiment of community members towards the influencers is significantly (*p-value*=0.03) more positive than the overall sentiment of the community as a whole.

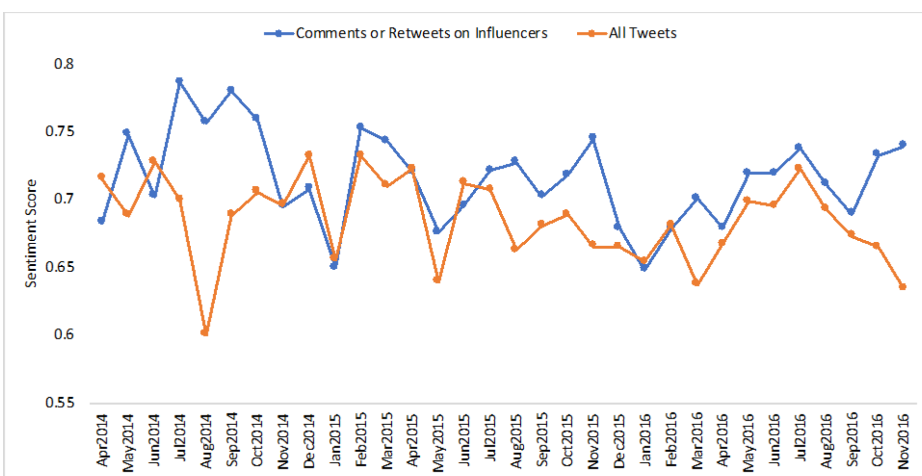


**Figure 2:** Monthly average sentiment scores of tweets 2014-2016

### *4.2 The impacts of bridgers on community development*

Betweenness centrality is calculated to identify bridgers in the community who have connections to different clusters in the community. These key influencers play important roles in the transfer of information through the network and keep the network from breaking. The key influencers (bridgers) in the community are listed in Tab. 3. It is not a surprise that all of the practitioners ranked top in this list. Meanwhile, certain accounts who are not very central in the network also receive high scores of betweenness centrality, such as *TuckerDBP*, *EntrepreneurSFC* and *explorebrooklyn*, as shown in Tab. 3.

**Table 3:** Betweenness centrality scores of key accounts

| Account | Indegree score | | |
|---|---|---|---|
| | 2014 | 2015 | 2016 |
| DowntownBklyn | 2849 | 6663 | 1292 |
| DUMBOBID | 2110 | 2733 | 1148 |
| BklynNavyYard | - | 492 | 123 |
| BLDG92 | 406 | 39 | 117 |
| TechTriangleU | 148 | 244 | - |
| TuckerDBP | 195 | 359 | - |
| EntrepreneurSFC | 134 | - | - |
| explorebrooklyn | 68 | 42 | - |

We further investigate these key influencers with network graphs shown in Fig. 3, and the network graphs help visualize the interconnection of the influencers. Network graphs of the whole data set present large graphs with many small clusters as previously shown in Fig. 1. To reduce dimensionality, we exclude small clusters in the network. The key influencers in the network are labelled in the pruned network graphs (Fig. 3) based on their Brandes's betweenness centrality scores [Brandes (2001)]. We discover that some key influencers in the network play important roles in connecting the community. For example, our network graphs reveal no direct link between two practitioners, Downtown Brooklyn and DUMBO, in the social network from 2014 to 2015. Several accounts functioned as bridgers to connect the two practitioners in the network. The personal account of a community leader, *TuckerDBP*, was active in tweeting about the development of Brooklyn; *EntrepreneurSFC,* a college's entrepreneurship center, promoted its incubator in the network to engage with entrepreneurs and practitioners; *explorebrooklyn*, the tourism promotion department for Brooklyn's travel and tourism sector, was active in tweeting to promote the borough as a destination for tourism. Those accounts played expected (as for *TuckerDBP* and *EntrepreneurSFC*) or unexpected roles (as for *explorebrooklyn*) in connecting the community and transferring information through social networks. Such value-added influencers help the practitioners to promote the community development initiative and enhance their leaderships.

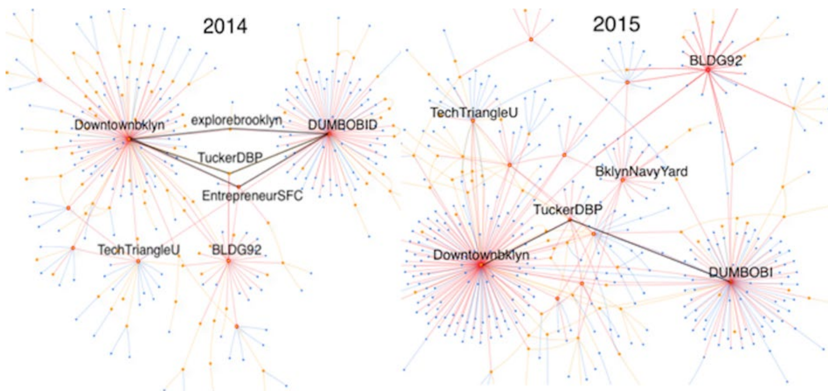


**Figure 3:** Pruned network graphs 2014-2015

## 5 Discussion

Social network analysis provides a new way to investigate the interconnection and relationships between community members, key influencers, and practitioners. Results of our analysis show that key influencers in the network have a number of impacts on community development. First, the key influencers are active in generating contents and traffics, and thus they attract members to follow community development and engage in community activities. Community practitioners can employ key influencers to promote community development initiatives and increase membership. Second, the key influencers also help promote positive attitudes of community members. The benefit of community practitioners tracking the sentiment of community members is that it allows quantifying perceptions about their leaderships, community initiatives, engagement and campaigns. Therefore, it is important for community practitioners to maintain positive relationship with key influencers and foster positive sentiment of key influencers' tweets on community development initiatives. Third, the influences of community members change dynamically over time. In addition to actively engaging with community members in social networks, practitioners should also constantly examine how users are networked. For example, in our study *explorebrooklyn* played an unexpected 'brokering' roles in transferring information between practitioners in the social network. It is important for practitioners to recognize these key influencers and their 'brokering' impact [Morgan-Trimmer (2014)]. Community practitioners should effectively collaborate with key influencers to enhance their leadership along with strategic alliances.

A variety of techniques of social network analysis can be useful for community practitioners to devise social networks as a means to improve community development practices. Social media data can be collected from different data sources, and different analytic techniques can be applied on the data. In this research our analysis generates beneficial insight for community practitioners who want to know the structure, connections and influencers of a social network. Besides identifying key influencers and their impacts, community practitioners can also assess community members' attitude and concerns overtime. Analyzing social networks helps organizations to have better understanding about their customers' feedbacks and opinions, attitudes, perceptions and behavior.

Community practitioners can use the information for devising effective communication strategies and can therefore, improve their reputation and leadership.

## 6 Conclusion

In this research we analyze the social network of a local community to demonstrate how community practitioners can apply network analysis to improve their community development strategies. Our analysis suggests that key influencers play important roles in generating traffics, transferring information, and improving overall sentiment of the community members. Community practitioners can use network analysis to identify and evaluate key influencers to accomplish their development objectives and strengthen their leadership roles. Furthermore, network analysis can be used for validation of the leadership roles that influencers play by tracking the metrics of the community initiatives and campaigns.

Our findings are based on analysis of a local community that has a relatively small size. Future research applied in different contexts are needed to validate the analysis and interpretation of the data. In our future work we will include data from other social media sources to examine the variance of network structures and user activities. In addition to the centrality analysis we conduct in this research, other major types of social network analysis, such as topological analysis and cluster analysis, can also be applied in future research.

In conclusion, our research exhibits that social networks become a common venue for community practitioners to engage with community members and promote community initiatives. Community practitioners should utilize social network analysis to evaluate online activities and identify and examine key influencers in the community. Insights generated from network analysis can provide community practitioners great advantage in building leaderships and understanding target audience to develop strategic community development practices.

## References

**Ang, L.** (2011): Community relationship management and social media. *Journal of Database Marketing & Customer Strategy Management*, vol. 18, no. 1, pp. 31-38.

**Bakshy, E.; Hofman, J. M.; Mason, W. A.; Watts, D. J.** (2011): Everyone’s an influencer: quantifying influence on Twitter. *Proceedings of the 4th ACM International Conference on Web Search and Data Mining*, pp. 65-74.

**Banerjee, A.; Chandrasekhar, A. G.; Duflo, E.; Jackson, M. O.** (2017): *Using Gossips to Spread Information: Theory and Evidence from Two Randomized Controlled Trials.* MIT Department of Economics Working Paper, no. 14-15.

**Brandes, U.** (2001): A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, vol. 25, no. 2, pp. 163-177.

**Chau, M.; Xu, J.** (2012): Business intelligence in blogs: understanding consumer interactions and communities. *MIS Quarterly*, vol. 36, no. 4, pp. 1189-1216.

**Deng, S.; Sinha, A. P.; Zhao, H.; Wu, J.** (2017): Adapting sentiment analysis to domain-specific social media texts. *Decision Support Systems*, vol. 94, no. C, pp. 65-76.

**Ennis, G.; West, D.** (2010): Exploring the potential of social network analysis in asset-based community development practice and research. *Australian Social Work*, vol. 63, no. 4, pp. 404-417.

**Freeman, L. C.; Roeder, C.; Mulholland, R.** (1979): Centrality in social networks: II. experimental results. *Social Networks*, vol. 2, no. 2, pp. 119-141.

**Fruchterman, T.; Reingold, E.** (1991): Graph drawing by force-directed placement. *Software Practice & Experience*, vol. 21, no. 11, pp. 1129-1164.

**Gayo-Avello, D.** (2013): Nepotistic relationships in Twitter and their impact on rank prestige algorithms. *Information Processing & Management*, vol. 49, no. 6, pp. 1250-1280.

**Go, A.; Bhayani, R.; Huang, L.** (2009): Twitter sentiment classification using distant supervision. *CS224N Project Report, Stanford*, vol. 1, no. 12.

**Hoppe, B.; Reinelt, C.** (2010): Social network analysis and the evaluation of leadership networks. *Leadership Quarterly*, vol. 21, no. 4, pp. 600-619.

**Jansen, B. J.; Zhang, M.; Sobel, K.; Chowdury, A.** (2009).: Twitter power: tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, vol. 60, no. 11, pp. 2169-2188.

**Matthews, P.** (2016): Social media, community development and social capital. *Community Development Journal*, vol. 51, no. 3, pp. 419-435.

**Morgan-Trimmer, S.** (2014): It's who you know: community empowerment through network brokers. *Community Development Journal*, vol. 49, no. 3, pp. 458-472.

**Oh, O.; Eom, C.; Rao, H. R.** (2015): Research note-role of social media in social change: an analysis of collective sense making during the 2011 Egypt revolution. *Information Systems Research*, vol. 26, no. 1, pp. 210-223.

**Patino, A.; Pitta, D. A.; Quinones, R.** (2012): Social media's emerging importance in market research. *Journal of Consumer Marketing*, vol. 29, no. 3, pp. 233-237.

**Poulin, R.; Boily, M. C.; Masse, B. R.** (2000): Dynamical systems to define centrality in social networks. *Social Networks*, vol. 22, pp. 187-220.

**Zeng, D.; Chen, H.; Lusch, R.; Li, S. H.** (2010): Social media analytics and intelligence. *IEEE Intelligent Systems*, vol. 25, no. 6, pp. 13-16.

**Zhang, Y.; Wang, Q.; Li, Y.; Wu, X.** (2018): Sentiment classification based on piecewise pooling convolutional neural network. *Computers, Materials & Continua*, vol. 56, no. 2, pp. 285-297.