AMCIS 2022 Proceedings

VCC - Virtual Communities and Collaboration

Aug 10th, 12:00 AM

The Difference between Offline and Online Ties in Twitter

Youngsoo Kim
Texas Tech University, youngsoo.kim@ttu.edu

Alireza Sheikh-Zadeh
Texas Tech University, alireza.zadeh@ttu.edu

The Difference between Offline and Online Ties in Twitter

Emergent Research Forum (ERF)

Youngsoo Kim
Jerry S. Rawls College of Business
Texas Tech University
703 Flint Avenue, Lubbock, TX 79409
youngsoo.kim@ttu.edu

Alireza Sheikh-Zadeh
Jerry S. Rawls College of Business
Texas Tech University
703 Flint Avenue, Lubbock, TX 79409
alireza.zadeh@ttu.edu

Abstract

Social network sites (SNSs) not only strengthens an existing offline relationship, but also facilitates the formation of a new online relationship. As a result, there coexist the online ties between offline friends and online ties between two users who do not have any offline interactions and connection in SNSs. We investigate the nature of offline ties and its roles on tweet diffusion. We observe some interesting findings: (1) people can spread more efficiently (with fewer hops) their tweet on their offline friends' local network; (2) offline ties play an essential intermediary role in facilitating pairwise tweet dissemination on each other's local network; (3) As either in-degree centrality of a network or the number of community clusters increases, the information flow efficiency and edge-between centrality increase.

Introduction

The computer-mediated communication (CMC) field observes many prominent theories in the area of online communication (Fermented and Hiltz, 1998). Media richness theory (Daft and Lengel, 1986; Sproull and Kiesler, 1986) initially pointed to CMC limitations such as text-only based communication, which does not allow for non-verbal emotional cues, and the medium's limited social presence. But the current consensus is that CMC has advanced to a point where it is well capable of delivering a higher communication quality (McKenna et al., 2002). For example, in a phenomenon called hyper-personal communication, CMC exhibits ubiquitous attributes and draws higher levels of intimacy, closeness, and ties than face-to-face communication (Walther, 1996). Therefore, CMC not only strengthens an existing offline relationship, but also facilitates the formation of a new online relationship (Mesch and Talmud, 2007). Given these facts, easy and frequent movements of social groups formed in the offline world into the online world have been observed.

Among diverse social network sites, Twitter is primarily treated as an instant personal messaging application that is also a broadcast news medium. In a group setting, it is a preferred groupcast medium that connects to others who are in close relationships and positively maintains social relationships (Crawford, 2009; Hofer and Aubert, 2013). As Twitter can augment offline relationships and information dissemination (Dunbar et al., 2015), it is also be treated as a complementary groupware that supports a group continuity going offline to online (Wellman et al., 1996; Choi and Im, 2015).

Since Twitter's debut, there have been many studies on its utility and application. The literature has posited substantial knowledge and understanding of Twitter and its capabilities. However, one area that is yet to be unveiled is the nature of ties and its impacts on tweet diffusion, particularly with the focus on the comparison of the ties between offline friends (hereafter, we call it offline friend ties or offline ties) with the just online ties between two users who do not have any offline interactions and connection. That is, we pursue a clear understanding and more commanding knowledge about the nature and role of offline friend ties in Twitter.

There is a paucity in the number of studies that explore how offline ties influence online networking behavior. Moreover, most studies on the topic are limited to event-based social media (Meetup, Douban and Plancast), which mostly function as an online platform for offline activity. Liu et al. (2012) and Zuo et al. (2012) studied the offline to and from online interactions through a mobile application used in a conference among the conference attendees. Zuo et al. (2012) indicated the importance of offline interactions, which they found functioned as the background reference for users as they choose their online communications. At least 50% of people who had online interactions also had offline encounters with one another. Also, offline to online transfer flow was more dominant than online to offline transfer flow. Liu et al. (2012) showed that event-based social medium helped people revolve around social events and post about social events and activities. Yin et al. (2016) evaluate Meetup dataset to answer whether there is a correlation between offline and online interactions. They report that there is no correlation between offline and online interactions after an offline meeting. That is, the offline meeting does not lead to significant online activities.

The exploration of this topic (the nature of offline ties and its roles on tweet diffusion) provides significant insights into the way offline and online ties can influence the Twitter network. We develop the following research questions focusing on two specific domains: (1) tie feature and (2) tweet propagation.

First, the foremost question is “how do offline and online ties differ in the nature of ties?” Both (1) establishing online relationship with offline friends and (2) seeking new online acquaintances are common in Twitter. In the literature, there are few studies that answer this particular engaging question. Dunbar et al. (2015) studied the mirroring phenomenon of offline to online, but not the comparative analysis between the two types of ties (offline and online ties) on social network structure. More specifically, given reciprocity and triadic closure, the most popular two concepts in the network theory literature, we examine whether there is a significant difference in the rate of reciprocity and follower overlap induced from the triadic closure mechanism between offline and online ties.

Second, we aim to investigate the difference in the role of offline and online ties in tweet diffusion. Given two users *i* and *j*, we measure (1) information flow efficiency (IFE) to calibrate how efficiently user *i* disseminates information on user *j*’s local network and (2) edge betweenness centrality (EBC) to identify the role of a tie between users *i* and *j* in information diffusion on user *j*’s local network. We examine the causal relationship between the relationship type (offline versus online ties) to both IFE and EBC.

Third, given our first hypothesis of there being a significant difference in the rates of reciprocity and follower overlap between offline and online ties, we attempt to analyze how the proportion of offline ties, which is characterized by higher reciprocity and follower overlap induced from triadic closure, affects IFE and EBC at diverse network structures. Previous studies emphasized that the network performance (e.g., information flow or epidemics) closely depends on (1) network structures (Bampo et al., 2008; Barabási, 2009; Freeman, 1979; Lazer & Friedman, 2007) and (2) structural properties such as *network centrality* and *community structures* (Dodds et al., 2003; Freeman, 1979; Moody, 2001; Sallaberry et al., 2013; Wasserman and Faust, 1994; Wejnert, 2002). *Network centrality* indicates how a single or few users are more popular (e.g., possessing a higher number of followers) than the other users in the network (Freeman, 1979). Network centrality is often shown to be advantageous for innovation diffusion (Freeman, 1979; Ibarra, 1993). In marketing, campaign managers prefer central networks and use hub members as seeds (Hinz et al., 2011). In the context of virtual R&D groups, Ahuja et al. (2003) found that the centrality of a person is a stronger predictor of performance than personal characteristics. Unlike network centrality, *community structure* reflects the division of users into densely connected communities while they withhold only a few connections to or from the users of the other communities (Newman, 2010; Sytch and Tatarynowicz, 2014). Previous studies showed that the community structure enhances information diffusion and builds cohesion within community clusters (Nematzadeh et al., 2014; Rogers, 2010; Sytch and Tatarynowicz, 2014). We examine whether and how the impacts of offline tie proportion on IFE and EBC are moderated by the network structure, including in-degree network centrality, community structure, and their interaction.

Fourth, we aim to understand the comparative impact of reciprocity and triadic closure on information flow performances at different network structures. Despite highlighting the importance of network structures in information flow, previous studies have not clearly explained how reciprocity and triadic closure affect the information diffusion (i.e., tweet) and on what condition. In general, reciprocity exists in online social networks as online users often know each other in the offline world, or they seek to improve their online social capital by creating reciprocal - follow and follow back – connections (Gaudeul and Giannetti, 2013; Lou et al., 2013). Former studies inconsistently showed that reciprocity could accelerate or decelerate information diffusion (Granovetter, 1973; Zhu et al., 2014). Zhu et al. (2014) showed that reciprocal ties enhance the network's connectivity, reduce the average inter-node distances, and (resultantly) promote the coverage and speed of information diffusion. This result was in contrast with the weak tie theory as Granovetter (1973) found that weaker ties (nonreciprocal ties) are more effective in spreading information—for example, people usually find jobs through their relationship with others, rather than their friends.

Regarding triadic closure, previous studies showed that the triadic relationship in social networks could weaken or strengthen the relationship between the users (Caplow, 1968; Simmel, 1950). Huang et al. (2018) found that triadic closure weakens the frequency of interactions between the first two ties despite strengthening the network's overall communication rate. Song et al. (2019) showed that the higher rate of triadic closure (in a directed network) between the content providers in Youtube increases the reciprocity (i.e., strengthening the relationship) between the nodes with higher follower overlap. However, they show that homophily and triadic closure negatively moderate the benefit of reciprocation because of reduced information benefit.

Method

Regression Model

We amassed a total of 2,176 Twitter users from (1) Amazon Mechanical Turk where the accounts are public and (2) a university student body pool.

For the data cleaning, the first step is to eliminate the outliers. The accounts that are only unidirectional, such as spammers, celebrities, politicians, and mass media accounts where they broadcast or push their news only, are eliminated (Kwak et al., 2010; Zipkin, 2013). Additionally, as a rule, a user account with more than 1,000 followers is considered as the unidirectional account type and is to be eliminated (Ghosh et al., 2012). For example, a celebrity, typically, who has over hundreds of followers rarely holds bidirectional communication with each of those followers. For other data cleaning steps, we excluded those user accounts that (1) are private accounts (because we need to access the account for information), (2) are created before January 1, 2011 (because this study's data collection started on that date), (3) have more than 15 followers, (4) follows more than 20 other Twitter accounts, and (5) have not tweeted in the last three previous months from the survey date (to exclude dormant accounts).

After applying these criteria and screening out the unqualified accounts, the final dataset of 13,924 pairs is secured for the analysis of tie structures and information propagation. A total of 6,288 pairs are people who are offline friends as well as online friends. Treating each account as a local network, we extracted the data about alters (other Twitter users who are directly connected to the user, i.e., followers and/or followees). This information is publicly available online. The offline friendship information was gathered through a survey that had a question of "Who do you know in real life?" for the user's Twitter friends.

Simulation Model

Considering the constrained sample from which our empirical dataset has been drawn, we adopt a *simulation* approach to address the third and fourth research questions. The collected dataset does not allow us to explore the impact of different network structures, such as the varying combinations of offline tie proportions, in-degree centrality, and the number of community clusters. In particular, to explore the causal effects and further generalize our empirical findings, we simulate a series of controlled experiments to uncover the sensitivity of information flow performance measures (IFE and EBC) to different rates of offline ties and various network structures as well as the causal impact of reciprocity and triadic closure.

In order to investigate the role of offline ties in heterogeneous Twitter scenarios, we implement simulation models. Our simulation follows two simultaneously constructed network formation mechanisms: (1) scale-free network formation to control the in-degree centrality and community structure and (2) tie formation mechanism to incorporate the nature of ties, whether a tie is reciprocal or formed based on triadic closure.

Networks in nature are not entirely random, and they may follow a specific formation pattern. Research shows that many self-organizing systems, such as online social networks, naturally follow a scale-free network structure where most nodes possess only a few ties, linked together by a few highly central hubs (Aparicio et al., 2015; Barabási, 2009; Ebel et al., 2002; Goel et al., 2016; Johnson et al., 2014; Wu et al., 2004). Scale-free networks grow based on a preferential attachment mechanism implying that a new user usually prefers to connect with the most popular users (Barabási and Albert, 1999; Johnson et al., 2014; Bampo et al., 2008). The magnitude of preferential attachment, however, might differ across various networks. A higher coefficient of preferential attachment increases the centrality of the former users where at the end, the node degree (or in-degree) of the resultant networks may follow a highly skewed distribution (Barabási and Albert, 1999; Ebel et al., 2002). Following the aforementioned setting, the resultant network develops heterogeneous users' ego networks and enjoys withholding some critical statistical properties of online social networks such as stationary power-law in-degree distribution (Johnson et al., 2014) and stationary average pairwise distances despite the changes in the network size (Andriani & McKelvey, 2009).

Preliminary Results and Discussion

The regression results show that two users who are offline friends are more likely to (1) have a reciprocal relationship (β_1=0.283 p<0.001 for $Reciprocity_{ij}$) and (2) share followers in Twitter (β_1=0.014, p<0.001 for $FollowerOverlap_{ij}$), supporting Hypotheses 1 and 2. Construing this result, we provide two plausible explanations below.

One plausible explanation is the extension of offline friendship into Twitter network. Social network sites not only allow a user to create new friends and new relationships but also enable a user to augment and revitalize dormant relationships (Ofcom, 2008). Offline friends who use Twitter will have their mutual friends naturally drawn into the online Twitter network, where this process leads to higher reciprocity and follower overlap (Ellison et al., 2007; Ofcom, 2008; Hlebec et al., 2006). Kraut et al. (2002) reported that the technology and Internet empower the person to ubiquitously manage the relationships and gain a greater social benefit by reinforcing the ties with offline friends. Vergeer and Pelzer (2009) reported that online and offline network capitals are positively associated, suggesting that online network is a supplement to offline friend network. This extension of offline friend network into online network is also supported by the tantalizing technological attributes provided on Twitter (e.g., easy thumb navigation, portability, ubiquity, and touch technology) (Choi and Im, 2015).

Another explanation is based on a new tie formation principle called *triadic closure*, one of the fundamental principles of network formation (Schaefer et al., 2010). Triadic closure means two people are likely to become friends because they share a mutual friend. Suppose that users *i* and *j* know user *k,* respectively, and users *i* and *j* do not know each other. Users *i* and *j* can build online friendships on Twitter. Triadic closure would occur among offline friends going online rather than among online friends. That is, when users *i* (or *j*) and *k* are offline friends, users *i* and *j* are more likely to build online friendship on Twitter. There are several reasons. First, offline friends are more closely connected through a high reciprocity level, so they may introduce their friends to each other. This "openness" propels the formation of a triadic closure on Twitter. Second, our analyses show that offline friends are more likely to retweet and interact with each other within Twitter networks (to be discussed later). As a result, high retweeting behavior among offline friends makes them share more mutual friends, producing a high overlap of followers among offline friends.

Triadic closure happening among offline friends on Twitter can also be explained by the concept of the structural hole introduced in the social relatedness approach in social network theory by Granovetter (1973; 1983; 1985). A structural hole happens when a user is connected to other users who do not have connections to each other. This situation would give more power and autonomy to the (ego) user whom other users are following in controlling new information. A structural hole may impede communication. As a result, alters may choose to become direct followers rather than acquiring the information from an ego user. That is, users *i* and *j* want to directly send or receive each other's tweets rather than having user *k* retweets user *j*'s (user *i*'s) tweets to user *i* (user *j*).

In sum, there are two possible explanations for higher reciprocity and follower overlap between offline friends: (1) as the transfer of offline friendship network into Twitter or (2) as internal evolution process of network structure based on triadic closure in Twitter. Our results show that face-to-face interaction is important for the formation of a Twitter network as a social network.

The coefficients of NCR_{ij} show that offline friends can distribute information more independently in his friend's ego network than online friends can. In information flow efficiency, we consider not only the number of reachable users but also the distance of the reachable users. The positive and significant coefficient of IFE_{ij} shows that a user can more likely and quickly distribute information in an offline friend's ego network. The regression results of EBC_{ij} show that the edge between offline friends can facilitate all communications in a Twitter ego network. This implies that offline ties play a role help all the users in an ego network share the same information via tweets and retweets. In sum, all the results show that as a user establishes online connections with more offline friends, the user may effectively leverage Twitter network in distributing information.

Our findings highlight an important role of a strong tie based on the assumption that offline ties are stronger compared to online ties – the assumption is empirically supported by the higher reciprocity and overlap of followers. Given the layers of connections (followers) through which information can propagate, offline ties play a critical role in disseminating and gathering new information that may first be disseminated by the weaker ties (online ties), as shown in our empirical results in NCR_{ij}, IFE_{ij}, and EBC_{ij}. Along with the results from Panovich et al. (2012), these results highlight the importance of offline friends for information exchange in the online social network.

The simulation model provides an abstract yet exhaustive demonstration of real-world network dynamics and enables us to explore how the empirical network differs from other possible networks predicted by simulation. Although we empirically found that the coverage and efficiency of information flow of individual user *i* on user *j*'s ego network according to their relationship (offline versus online friends), it remained a question, how information flow varies across diverse network configuration depending on centrality, community structures, and the nature of tie formation (reciprocity vs. triadic closure ties). In particular, we show that the information flow performance measures do not necessarily follow a linear pattern of change depending on the proportion of offline ties.

SELECTED REFERENCES

Ahuja, M. K., Galletta, D. F., & Carley, K. M. (2003). Individual centrality and performance in virtual R&D groups: An empirical study. Management Science, 49(1), 21-38.

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). Developing theory through simulation methods. Academy of Management Review, 32(2), 480-499.

Ghosh, S., Viswanath, B., Kooti, F., Sharma, N. K., Korlam, G., Benevenuto, F., & Gummadi, K. P. (2012). Understanding and combating link farming in the twitter social network. In *Proceedings of the 21st international conference on World Wide Web*. Lyon, France.

Granovetter, M. (1973). The strength of weak ties. *American Journal of sociology*, 78(6),1360-1380.

Granovetter, M. (1983). The strength of weak ties: A network theory revisited. *Sociological theory*, 1, 201-233.

Granovetter, M. (1985). Economic Action and Social Structure: A Theory of Embeddedness. *American Journal of Sociology, 19.*

Katz, N., Lazer, D., Arrow, H., & Contractor, N. (2004). Network theory and small groups. *Small group research*, 35(3), 307-332.

Krackhardt, D., Nohria, N., & Eccles, B. (2003). The strength of strong ties. In R. Cross, A. Parker, & L. Sasson, (Eds.), Networks in the knowledge economy, (pp. 82, Ch.3). Oxford University Press.

Myers, S. A., Sharma, A., Gupta, P., & Lin, J. (2014). *Information network or social network? The structure of the twitter follow graph*. In Proceedings of the companion publication of the 23rd international conference on World wide web companion, Seoul, Republic of Korea.

Newman, M. (2010). *Networks: an introduction*. Oxford university press.

Suh, B., Hong, L., Pirolli, P., & Chi, E. H. (2010). *Want to be retweeted? large scale analytics on factors impacting retweet in twitter network*. In 2010 IEEE Second international conference on social computing. Minneapolis, MN, USA