Understanding Social Effects in Online Networks

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***Abstract*—Understanding the motives behind people's interactions online can offer sound bases to predict how a social network may evolve and also support a host of applications. We hypothesize that three offline social factors, namely, stature, relationship strength, and egocentricity may also play an important role in driving users' interactions online. Therefore, we study the influence of these three social factors in online interactions by analyzing the transitivity in triads or three-way relationships among users. Analyzing transitivity through the lens of triad census for four popular social networks, namely, Facebook, Twitter, YouTube and Slashdot, we find that: (i) users' interactions are largely influenced by intermediary relations, which enhances the mediators' stature; (ii) the strength of offline relationships plays a salient role in transitivity of relations online; and (iii) egocentricity, embodied in over-active and popular users, has a significant effect on the dynamics of online interactions.**

I. Introduction

Over the past few years, Online Social Networks (OSNs) such as Facebook and Twitter have become an integral part of our society. People constantly use these networks to connect, express, and share information [1]. OSNs offer new communication mechanisms that have had a massive influence on how people form and maintain relationships. Several OSNs have emerged in the past decade; each one provides a unique way to socialize, along with its own motivations and reasons for usage. Users, on the other hand, also bring their own motives and reasons to use and contribute to each network. For example, Facebook users may be motivated to form friendships for social sharing, whereas Twitter users may be interested in attracting new followers. Because of these distinct reasons, it is essential to understand users' motives in interacting on OSNs as the popularity and adoption of OSNs hinges not only on the strength of their current user population, but also on the level of involvement of these users in their relationships [2].

Extensive sociological studies have identified three factors, namely, stature, relationship strength, and egocentricity that drive people to socialize and interact in conventional, offline networks [3]–[5]. Several studies have modeled the patterns of structural interactions among users in online networks [6], [7], however, very few have sought to understand what motivates users to share and interact online. Some efforts suggest that users' motives may depend on their individual preferences [8], or may be based on fulfilling their existence [9].

Triadic or three-way relationships have been regarded as the core of social network research for nearly half a century [10]. Social scientists have considered such triadic interactions as important building blocks for social network analysis [11]. They contend that compared to two actors in dyads, the three actors in triads and the pairwise relationships among them may allow different social behaviors to be observed that cannot be present in two-person context [11]. For example, the third actor in a three-way relationship can play the role of a mediator and help the conflicting parties to reach an acceptable solution [12]. Alternatively, the third actor can also undermine relationships between the other two actors; ultimately causing one member to feel unwanted or disconnected [12]. Social studies also indicate that triadic configurations and interactions are vital in analyzing the network structure. In fact, the local configuration underlying triadic relationships has implications for the global structure of the network [5]. Thus, theories such as structural balance, clusterability, ranked clusters, and transitivity are analyzed and expressed in triadic terms [13]. Because of the key role of triadic structures, the influence of the three social forces in offline relationships is explored through the lens of triadic analysis. The analysis of online social networks, however, overwhelmingly considers only dyadic or two-way interactions. As a result, these analyses can rarely explain the reasons that may have caused the structural and interaction patterns that they reveal.

In this paper, we examine transitivity in triadic relationships on four popular online social networks, namely, Facebook, Twitter, YouTube and Slashdot. Examining transitivity through the lens of triad census [12], we examine how three social effects, namely, stature, relationship strength, and egocentricity can explain users' interactions on these online networks. Our analysis suggests that: (i) relationship strength is equally important on all four networks; (ii) social stature significantly affects YouTube more than the other three networks; and (iii) the effect of egocentricity is more prominent on Slashdot and Twitter than on Facebook and YouTube.

This paper is organized as follows. Section II presents an overview of triadic analysis. Section III briefly describes the data sets used in this study. Results from our analysis are discussed in Section IV. Section V reviews related work. Section VI offers conclusions and directions for future work.

II. Triadic Analysis

In this section, we introduce triad census, explain how it can be linked to transitivity; and how it can ultimately reveal users' motives for interacting online.

A. Triad Census

A triad is a subgraph of three nodes and links between them. A network of n nodes contains $O(n^3)$ triads. Triads can be of sixteen different types as shown in Fig. 1. Triad types can be labeled according to M-A-N scheme; where each type has a label of three to four digits that respectively represent the number of **mutual (M)**, **asymmetric (A)**, and **null (N)** dyads [14] and the direction of ties among them. A mutual dyad refers to a two-way interaction where one user initiates the connection and the other user reciprocates. An asymmetric dyad constitutes one-way interaction where a user initiates a connection to another user, which is not reciprocated. Null dyad entails no interaction between the two users. When two triad types contain an equivalent number of dyads, the fourth digit is used to distinguish the direction of the ties: **D** for downward, **U** for upward, **T** for transitive and **C** for cyclic [15]. To elucidate the usage of the fourth digit, triad T.021U in Fig. 1 contains two asymmetric connections that point upwards, whereas two asymmetric connections in T.021D point downwards, and in T.021C the two connections are cyclic. A triad census is a census of all the possible types of triads in a given network [16].

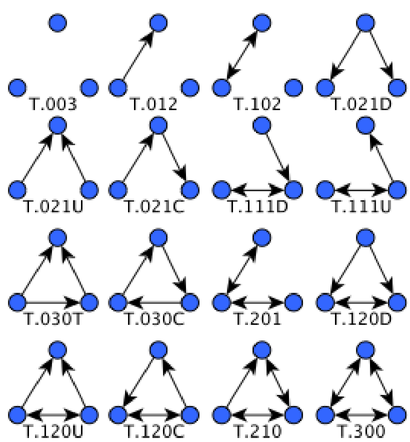

Fig. 1. Isomorphic Triad Types with MAN Scheme

B. *Transitivity in Triads*

Transitivity is a key concept that links many social theories to triadic structures [17]. A social relation among three users A, B, and C is transitive if the relations $A \rightarrow B$, $B \rightarrow C$, and $A \rightarrow C$ are present [18]. Based on the concept of transitivity, a triad can be classified into three categories, transitive, intransitive and vacuously transitive. A triad is said to be transitive if every three-way relation it contains is also transitive [17]. For instance, the mutual dyad in T.120D in Fig. 1 results in two possible three-way relationships among its users A, B, and C: (i) $A \rightarrow B$, $A \rightarrow C$, $B \rightarrow C$; or (ii) $A \rightarrow B$, $A \rightarrow C$, $C \rightarrow B$. Both of these sets of relations are transitive; therefore, T.120D is a transitive triad. Conversely, T.120C is intransitive because it contains the intransitive three-way relation $A \rightarrow B$, $B \rightarrow C$, $C \rightarrow A$. Finally, triads that do not feature a directed path including their three users are vacuously transitive. Fig. 2 classifies the 16 triad types according to the transitivity of their underlying relationships. We next describe social theories ascribed to each of these three classes of triads.

1. Intransitive Triads - Social Stature: Intransitive triads typically emerge due to social effects that encourage users to

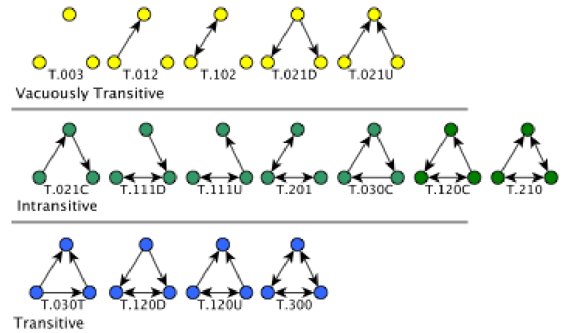

Fig. 2. Vacuous, Intransitive, and Transitive Triads

interact through a middle man, rather than establish a direct relationship. Thus, information shared across the triads hinges upon the control of users in intermediary positions, bestowing them with power that raises their social stature [19]. Such triads are uncomfortable and can be a source of distress to at least one user [20], because they open opportunities for intermediary users to hide secret information and relationships. To eliminate this discomfort and distress and avoid inequality in the dyadic relationships, intransitive triads exhibit a natural tendency towards transitivity. Consequently, intransitive structures seldom occur in offline networks [21] and represent three users who intentionally choose to withhold interaction.

2. Transitive Triads - Relationship Strength: While the effect of social stature diminishes in transitive triads, the strength of relationships sculptures such interactions. Accordingly, transitive triads are abundant in a network of close personal friends due to the existence of strong underlying relationships among them [22]. This is because sustaining multi-way relationships requires significant investment of emotions and time to which only few would commit, unless the relationships are strong and valuable [5]. Thus, transitive triads dominate networks in which users exhibit homophily, whether it occurs naturally (e.g. race and gender) and/or by choice (e.g. organization, religion, and club). For example, when three people belong to an organization, one member may introduce his friend to another, inducing the transitive relation.

3. Vacuously Transitive Triads - Egocentricity: Every vacuously transitive triad except for T.021U and T.021D is uninteresting because these include only dyadic relationships and unrelated outsiders. Users in vacuous triads T.021U and T.021D, however, exhibit egocentric tendencies, and are only concerned about themselves with little regard for their social network [23]. In these triads, the two asymmetric connections either point towards or away from the egocentric users. T.021D features an egocentric user who interacts with many others, but does not receive reciprocal responses. T.021U, on the other hand, represents an egocentric user who receives attention from many others, but never reciprocates.

III. DATA DESCRIPTION

We study Facebook, Twitter, YouTube and Slashdot because of their popularity and unique features as summarized below. This collection allows us to investigate the impact of the social effects on diverse types of relationships.

1. Facebook: This is the most prevalent online social network in the world [24]; and it has one billion monthly active users [25]. This OSN allows users to create personal profiles with information such as name, birthday, status, and personal interests [26]. A friendship on Facebook is bi-directional, where users cerate social links by "friending" other users. Also, once the friendship is established, users can exchange messages as wall posts, upload photos, and tag their friends' photos [1]. The Facebook data set was collected from the New Orleans regional network [27]. It includes $876,993$ wall posts exchanged between $46,952$ users [28], where a link is created from user A to user B, if user A posts a message on the wall of user B.

2. Twitter: This is one of the most popular microblogging service [29] for posting short messages up to 140 characters in length. Its structure mirrors the combined features of social and information network [30]. Social ties on Twitter are attention-based [31]. Twitter encourages users to pay attention to each another through the follower-followee concept as well as by mentioning others in their tweets. In addition, a common practice is "retweeting" other users' messages to direct attention to them [32]. The Twitter data set contains $81,306$ users and $1,768,149$ follower-followee links [33]. It was provided by the Stanford Large Network Dataset Collection [34].

3. YouTube: This network is considered as the leader in online video sharing; every day people watch hundreds of millions of videos and upload another hundreds of thousands [35]. This purpose-driven [36] OSN allows users to upload and share videos through websites, e-mails, and mobile devices [35]. Friendships are based on users' interests in videos [36]; users can share their own videos and add comments on others' videos. The data set obtained from online social networks research [37] consists of $1,157,827$ users and $4,945,382$ user-to-user links [38].

4. Slashdot is a technology news site, which allows users to submit stories and encourages other users to comment on them. It is one of the few online networks that offers both positive and negative relationships [39]. In 2002, Slashdot introduced the Slash-dot Zoo, which lets users rate others as "friend" (like) or "foe" (dislike). Thus, the relationship between Slashdot users is either a friend or a foe; friend means the user likes the other user's comment, while a foe relation means the user dislikes the comment [6]. The Slashdot data set consists of $82,168$ nodes and $948,464$ friend/foe links [40].

Initially, we processed each of these data sets using the sub-quadratic census computation algorithm [41], which we implemented in Python on 12 Intel Xeon $X5650$ Westmere cores with 2.67 GHz per core and 4 GB memory for each core. The complete census for Facebook and Slashdot data sets was computed in 1:39 hours and 13:15 hours respectively, but the census for the Twitter and YouTube data could not be computed exhaustively. Exhaustive census can be computed only for Slashdot and not for Twitter, although both OSNs have about the same number of nodes because the connectivity of Twitter is significantly higher compared to Slashdot. Therefore, we sampled the Twitter and YouTube data sets using the Forest Fire Sampling (FFS) algorithm, which is known to produce the most representative samples [42]. The sampled YouTube data set consists of $69,465$ nodes and $255,542$ edges, while the sampled Twitter data set consists of $56,914$ nodes and $980,266$ links.

TABLE I. UMAN FREQUENCIES OF TRIAD TYPES

Triad	Expected Frequency	Triad	Expected Frequency
T.003	N^3	T.030T	$3/4A^3$
T.012	$3AN^2$	T.030C	$1/4A^3$
T.102	$3MN^2$	T.201	$3NM^2$
T.021D	$3/4NA^2$	T.120D	$3/4MA^2$
T.021U	$3/4NA^2$	T.120U	$3/4MA^2$
T.021C	$3/2NA^2$	T120C	$3/2MA^2$
T.111D	$3MAN$	T210	$3MA^2$
T.111U	$3MAN$	T300	M^3

IV. Result and Analysis

For each OSN, we compared the proportions of each type of triad against those expected in a random network with the same number of mutual (**M**), asymmetric (**A**), and null (**N**) dyads computed using the expressions for the uniform graph or UMAN distribution [43] listed in Table I [14]. The actual and UMAN proportions are listed in Table II. If the actual proportion of any type of triad is higher than that expected by chance, the social dynamic of that type of triad dominates. Otherwise, the dynamic of that triad type has relatively little influence on the network.

A. Intransitive Triads - Social Stature

Table II shows that intransitive triads are higher than what would be expected by chance. This finding avers that users in powerful, intermediary positions have a significant effect on the interactions on all the four networks. Such powerful intermediaries arise because a majority of OSNs promote one-way information exchange [29]. Moreover, because relationships hold less value online compared to offline networks, online connections may lead to lower stress and tension [44]. Hence, intransitive triads may be common and stable online as compared to offline networks. Finally, users on online networks may interact with intermediaries intentionally, because they may believe that such interactions can improve their popularity. In fact, the relationships on all four OSNs explain this conjecture.

1. Facebook: Users may want to increase the visibility of their wall posts by interacting with intermediaries.

2. Twitter: Users may tend to link with intermediaries in order to conserve their own time and attention. They exploit "retweeting", which is a common practice on Twitter, where users forward those tweets that interest them to their followers [32]. In the process of retweeting, these intermediary users screen their tweets. For example: if A follows B, and B follows C, B as a mediator filters quality tweets from C and passes them to A. In this case, A may choose not to follow C, because A has already received the best of C's tweets. In addition, the primary motive on Twitter is to gain knowledge of C's activities rather than to seek a relationship with C. Thus, Twitter intermediaries play an important role as supervisors by rebroadcasting only quality tweets to their followers.

3. YouTube: Intermediary users may serve as channels [36] to those who interact with them to improve the popularity of their uploaded videos.

TABLE II. TRIAD CENSUS: PROPORTIONS IN OSNS AND UMAN

Triad Type	UMAN-FB	FB Prop.	UMAN-SDot	SDot Prop.	UMAN-Tw	Tw Prop.	UMAN-YT	YT Prop.
Intransitive								
T.021C	$1.44E-08$	$2.27E-08$	$2.52E-09$	$1.03E-08$	$8.80E-08$	$2.38E-07$	$9.02E-11$	$2.33677E-10$
T.111D	$2.26E-08$	$5.07E-08$	$1.33E-08$	$1.06E-07$	$1.32E-07$	$4.04E-07$	$1.14E-09$	$3.3482E-09$
T.111U	$2.26E-08$	$5.61E-08$	$1.33E-08$	$8.11E-08$	$1.32E-07$	$3.30E-07$	$1.14E-09$	$9.36E-09$
T.030C	$2.35E-13$	$2.20E-11$	$1.72E-14$	$9.95E-13$	$3.56E-12$	$4.29E-10$	$1.17E-16$	$1.79E-14$
T.201	$1.77E-08$	$5.52E-08$	$3.52E-08$	$5.05E-07$	$9.88E-08$	$3.01E-07$	$7.32E-09$	$6.35E-08$
T.120C	$1.11E-12$	$4.25E-10$	$2.73E-13$	$1.11E-10$	$1.60E-11$	$8.06E-09$	$4.43E-15$	$6.27E-13$
T.210	$1.73E-12$	$2.14E-09$	$1.44E-12$	$8.36E-10$	$2.39E-11$	$3.86E-08$	$5.60E-14$	$9.34E-12$
Transitive								
T.030T	$7.05E-13$	$1.20E-09$	$5.16E-14$	$1.44E-10$	$1.07E-11$	$2.34E-08$	$3.50E-16$	$3.58E-14$
T.120D	$5.53E-13$	$1.56E-09$	$1.36E-13$	$8.18E-10$	$7.99E-12$	$1.55E-08$	$2.21E-15$	$5.91E-13$
T.120U	$5.53E-13$	$7.77E-10$	$1.36E-13$	$2.00E-10$	$7.99E-12$	$2.46E-08$	$2.21E-15$	$3.76E-13$
T.300	$4.53E-13$	$1.54E-09$	$1.27E-12$	$4.39E-09$	$5.98E-12$	$3.07E-08$	$1.18E-13$	$6.15E-11$
Vac. Transitive								
T.003	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
T.012	$2.94E-04$	$2.93E-04$	$1.23E-04$	$1.12E-04$	$7.26E-04$	$7.02E-04$	$2.33E-05$	$1.8875E-05$
T.102	$2.30E-04$	$2.30E-04$	$3.25E-04$	$3.24E-04$	$5.44E-04$	$5.43E-04$	$1.47E-04$	$1.47E-04$
T.021D	$7.20E-09$	$4.29E-08$	$1.26E-09$	$4.76E-08$	$4.40E-08$	$1.58E-07$	$4.51E-11$	$5.48E-10$
T.021U	$7.20E-09$	$1.98E-08$	$1.26E-09$	$2.41E-08$	$4.40E-08$	$5.73E-07$	$4.51E-11$	$6.77E-10$

4. Slashdot: The relationship on this OSN is friend/foe [45]; an intermediary user could be a friend or a foe of one or both of the other two users. When an intermediary has a friend relation with one user and a foe relation with the other user, the two users might not seek interaction with each other because there is no stress or tension that forces them to approach closer. For example, consider $A \rightarrow B$ and $B \rightarrow C$ where A and B are friends, and B and C are enemies, it is less natural for A to be a friend or a foe to C [39], as there is no stress or tension in the interaction, thus leading to a higher than expected frequency of intransitive triads.

B. Transitive Triads - Relationship Strength

Table II shows that almost every transitive triad is more than expected by chance. Moreover, intransitive triads are more abundant than transitive ones. These findings rationalize the interactions on all four networks as follows:

1. Facebook: Transitive triads are higher than expected, suggesting that these offline social bonds are notable in the interactions on Facebook. Such Facebook friendships, which reflect offline ties [26] are mainly formed among users who maintain existing offline relationships rather than total strangers leading to a lower count of transitive compared to intransitive triads.

2. Twitter: Users may show a tendency to follow those that their followees follow, leading to a higher occurrence of transitive interactions. Thus, considering the interaction $A \rightarrow B$, and $B \rightarrow C$, A may then want to follow C because of B's influence. In other words, B provides the social proof that C may be worth following [31]. Transitive triads may be infrequent compared to intransitive triads because of the nature of the social tie on Twitter, more friends demand more time and attention to read and filter tweets. Thus, users who feel that they already have enough friends may show a lower tendency to add new friends [31].

3. YouTube: Users on this video sharing network tend to form clusters with those who like similar videos. Indeed, the tendency towards "friend of my friend is my friend" can be seen, leading to a higher than expected frequency of transitive triads. Transitive triads are less frequent than intransitive triads because users may be more dedicated to their existing links rather than forming new ones.

4. Slashdot: Positive or friend relations on this network cause stress on other relations to turn positive [39], which may explain the higher than expected transitive frequencies. For example, the strength of the positive relation between B and C and B and A exerts stress on A and C that forces them to form a relation. Similarly, if B is a foe of both A and C, it may encourage both A and C to form a friendship. Thus, both the tendencies, namely, "friend of my friend is my friend" and "enemy of my enemy is my friend" can be seen on Slashdot, leading to a higher than chance frequency of transitive triads. Finally, if B is a foe of A and a friend of C, B would not be able to exert enough pressure to cultivate a relation between A and C, which may explain why transitive triads are less frequent compared to intransitive ones.

C. Vacuously Transitive Triads - Egocentricity

Table II shows that vacuously transitive triads T.021D and T.021U are more frequent relative to chance, which can explain the interactions on all four networks.

1. Facebook: Triad T.021D may correspond to overactive users who spam the walls of others [46] with no regard to whether the receivers are interested in their information. This type of triad occurs more frequently than expected, suggesting that these overactive users can cause others discomfort and may threaten overuse of public wall posts. Triads T.021U represent users who consume or benefit from the shared information but do not return the favor, perhaps to gain popularity or to maintain their self-image. This suggests that extremely popular users, as defined both by friendship count and levels of interactions are more frequent than expected [38].

2. Twitter: Triads T.021D on Twitter represent users who tend to follow others without reciprocity. They are likely to represent celebrities, opinion leaders, or users that are simply popular because people like their ideas. These users, however, do not bother to follow others in return. Both types of triads are more frequent than chance, meaning that information spreads away from a single user, rather than circulating through multiple users. Thus, information on Twitter flows in one direction and communication occurs in the form of a spread rather than in the form of sharing [29].

3. YouTube: T.021D triads correspond to users' tendency to create links without consideration of reciprocity or friendship, because they are only interested in the videos. On the other hand, triads T.021U represent users who upload more videos perhaps to get the attention of other users and be chosen as friends, but they do not reciprocate these friendships. Thus, on YouTube, users who initiate or receive friend requests from other users, but without reciprocation, are more frequent than expected. This explains how YouTube users build friendships based on their interest in videos [36].

Slashdot: Triads T.021D may correspond to trolls who post offensive comments to bother other users. These trolls tag serious users, who really contribute to the discussion as foes and other trolls as friends [47]. Thus, Slashdot may be more affected by trolls. Triads T.021U represent popular users who receive a high number of "friend" or "foe" endorsements [45]. These users bask in their popularity and do not bother to reciprocate friend or foe links leading to higher than expected proportion of T.021U triads.

In summary, our analysis illuminated a number of interesting observations regarding the underlying social forces that drive online social network interactions. The mediating role of triplet relationships aggrandizes the social stature of these role occupants that allows them to oversee the sharing of information. More interestingly, intransitive relations are more stable in online networks than offline ones due to the absence of discomfort and stress. The influence of relationship strength is driven by different facets in OSNs. Case in point, the strength of relationships on YouTube is highly likely determined by akin interests, while on Facebook it is encapsulated by offline interactions. Finally, popularity plays a potential role in defining the path of interactions such as in Twitter. Hence, the effect of egocentricity is evident in the formation of relations in certain OSNs.

V. Related Work

Triad census has been used to study theoretical principles underlying social interactions such as the correlation between presence/absence of a particular network structure and triadic properties [15] and examining personal networks of strong and weak ties [48]. Triads have also been used to investigate negative as well as positive relationships in online networks [6], [49], and explore the effects of classical sociological theories such as social balance and stature on the strength of relationships [7]. Recently, they have been used to predict links on Twitter by analyzing network status and reciprocity [31] and to investigate the behavior and network structure of YouTube groups [36]. We extend our recent work, which used triadic analysis to investigate interaction patterns on Facebook [50] to study the patterns on Twitter, YouTube, and Slashdot. Expanding our analysis allowed us to understand how these social factors can explain the interactions on these three networks despite their diverse characteristics, features, and relationships.

VI. Conclusions and Future Research

In this paper, we used triadic analysis to unveil three social influences that can explain users' interactions on four popular networks with diverse and unique features, namely, Facebook, Twitter, YouTube and Slashdot. Using triad census to examine transitivity, we identified that: (i) social stature significantly affects online relationships, which is contrary to offline relations; (ii) strength of relationships is equally important in both offline and online networks; and (iii) egocentricity can potentially have a greater impact on online socializations compared to offline ones. In the future, we will evaluate temporal features to study the transition of stature over time. Additionally, the outcomes will be amalgamated into methods for information diffusion and structural evolution.

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