How people interact in evolving online affiliation networks

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The study of human interactions is of central importance for understanding the behavior of individuals, groups and societies. Here, we observe the formation and evolution of networks by monitoring the addition of all new links and we analyze quantitatively the tendencies used to create ties in these evolving online affiliation networks. We first show that an accurate estimation of these probabilistic tendencies can only be achieved by following the time evolution of the network. For example, the actions that are attributed to the usual friend of a friend mechanism through a statistical analysis of a static snapshot of the network are overestimated by a factor of two. A detailed analysis of the dynamic network evolution shows that half of those triangles were generated through other mechanisms, in spite of the characteristic static pattern. Inferences about the reason for the existence of links using statistical analysis of network snapshots must therefore be made with great caution. Here, we start by characterizing every single link when the tie was established in the network. This information allows us to describe the probabilistic tendencies of tie formation and extract sociological conclusions as follows. The tendencies to add new links differ significantly from what we would expect if they would have not been affected by the individuals’ structural position in the network, i.e., from random link formation. We also find significant differences in behavioral traits in the social tendencies among individuals according to their degree of activity, gender, age, popularity and other attributes. For instance, in the particular datasets analyzed here, we find that women reciprocate connections three times as much as men and that this difference increases with age. Men tend to connect with the most popular people more often than women across all ages. On the other hand, triangular ties tendencies are similar, independent of gender, and show an increase with age. Our findings can be useful to build models of realistic social network structures and to discover the underlying laws that govern establishment of ties in evolving social networks.

I. INTRODUCTION

Uncovering patterns of human behavior addresses fundamental questions about the structure of the society we live in. The choices made at the individual level determine the emergent complex global network underlying a given social structure. Conversely, the structure of the social network that constitutes an individual’s community also affects to a large extent the individual’s ability to act. For instance, the position in the network structure may facilitate one’s ability to interact with others by providing information of possible choices and their consequences, or by supplying the individual with different kinds of material and immaterial resources. On the other side, this structure may also limit this individual’s ability to act by excluding information through local social norms and through social control.

Detecting regularities and motifs in the development of social networks provides significant tools for the understanding of the structure of society. Thus, a number of statistical association models have been proposed to link a social network structure to a statistically significant social mechanism of interaction. Social theoretical frameworks, like the MultiTheoretical MultiLevel (MTML) formalism, have proposed a set of mechanisms of social interaction to describe the probabilistic tendencies of creation, maintenance, dissolution, and reconstitution of interpersonal ties during the evolution of a social network. Examples of mechanisms include (see Fig.1): 1) reciprocity (named social exchange after the most likely social mechanism), 2) friend of a friend ties or closing triangles (balance), 3) exploration of distant network areas which require at least 3 steps from the position of the person in the current network (self-interest theories), 4) ties facilitating dissemination of information by linking to well-connected people (named collective action or preferential attachment), and 5) links that act as bridges between two sub-networks that are not directly linked (structural hole mechanism). Contractor et al. have further identified a set of probabilistic tendencies for ties to be present or absent in networks that the different families of theoretical mechanisms may cause. One important conclusion is that a given family of theoretical mechanisms may generate different probabilistic tendencies for ties to be present or absent. Furthermore, the same probabilistic tendency may be caused by several different families of theoretical mechanisms. In the present study we aim to unravel significant patterns in these social mechanisms of human interaction by monitoring and analyzing the time evolution of the actions of members of two online affiliation networks. The term affiliation refers to data based on co-membership or co-participation in events, where here members use the Internet to interact with each other through the online sites. A connection in such sites may indicate underlying social ties.
FIG. 1. (a) The five probabilistic tendencies we used to classify the interactions. Black arrows indicate existing links and red arrows are the possible options for a new link, according to the following tendencies: 1. Social exchange, which corresponds to establishing a reciprocal link, i.e. add as favorite someone who has already added us to their favorite lists, 2. Balance, where we select a favorite who is in the list of one of our existing favorites (friend of a friend), 3. Distant connection, where the connection is to a member with whom there is no proximity, i.e., one needs at least three links to reach this member, 4. Collective action, where we connect to a person whose connectivity is well above the average connectivity in the community (we quantify this behavior by examining whether the total degree of the receiving agent belongs to the upper 5% of the degree distribution at the given time), and 5. Structural hole, where a link connects two otherwise not connected clusters of at least 3 members each, and which are otherwise not directly linked to each other (in the picture this link would connect the cluster of people in hats with the red-haired cluster). (b,c) Why we cannot extract tendencies from a static snapshot: in the presented example a triangle relation is built from time \( t - 2 \) to time \( t \) under two different scenarios that lead to the same resulting triangle. (b) The ties X-Y and Y-Z can be formed, at times \( t - 2 \) and \( t - 1 \) respectively, via distant mechanisms resulting in a balance mechanism for the formation of X-Z at time \( t \). Here X uses a friend of a friend to be introduced to Z. (c) A different path, though, would classify the X-Z tie differently. If X connected to Z before connecting to Y, then the X-Z link represents a distant tendency, since there is no close connections between them. A static network analysis would suggest that X used balance to connect to Z, instead.

In principle, a formal statistical analysis, such as exponential random graph models [4, 10] would search for regularities or motifs in the social structure by comparing a static snapshot of the network with a suitable ensemble of equiprobable random configurations. However, this approach cannot characterize the decisions taken (consciously or not) at the individual level on the type of mechanism used for an established connection. A direct application of a statistical analysis to evolving networks may not be able to resolve the full spectrum of human interactions. This is due to the inherent history-dependent nature of social interactions, i.e., the interaction mechanisms determine the evolving network, which, in turn, conditions the human choices of interaction. Figures 1b and 1c illustrate this point during the generation of a hypothetical triangular XYZ relation at time \( t \). This static pattern may be associated with a balance mechanism for the tie XZ (friend of a friend) as a result of closing the triangle as shown in Fig. 1a. However, a closer inspection of the time evolution of tie formation reveals the possibility of a different classification of the XZ link, where agent X has used the distant mechanism at time \( t - 2 \) to connect with Z as in Fig. 1c. As we show later, in Fig. 2, the actual number of balance links is over-estimated by a factor of 2 when we use static snapshots of real communities.

The above example can be generalized to the global network level. For instance, an agent may decide to connect to agents that are far away in the network (distant mechanism). Eventually, individuals are brought closer to each other to form a tightly connected cluster. The evolving nature of the network may change those initial distant interactions into balance, as new relations are created in the network. Therefore, the precise knowledge of the time evolution of each tie in the network is crucial to unravel the relevant behavioral mechanisms in a real community.

Here, we present a microscopic and temporal statistical analysis of the evolution of two online social networks; one from its original inception and the other after it is well developed. We aim to uncover how the combination of different social mechanisms eventually shapes the interaction network. Our longitudinal approach focuses on characterizing each interpersonal tie at the time when it is established. The knowledge of the order in which each link was formed allows us to characterize social patterns that cannot be derived from statistical analysis of static snapshots of the networks.

II. DATASETS AND METHODS

We study the affiliation networks of two online social networking sites in Sweden, pussokram.com [11] and qx.se [12]. Both datasets were de-identified in their source. The pussokram community (POK for brevity) is used mainly by Swedish young adults for friendship, including dating and non-romantic relations. Activity in the community was recorded for 512 consecutive days, starting
on the day that the site was created in 2001. At the end of recording, the community had 28,876 members with a mean user age of 21 years who have performed \( \sim 190,000 \) interactions. The QX site is the Nordic region’s largest and most active web community for homosexual, bisexual, transgender, and queer people. The site is also frequently used by heterosexual men and women. Activity among the users was recorded during two months starting November, 2005. At that time there were \( \sim 180,000 \) registered members; 80,426 of them were active during the recording period establishing more than 1 million ties.

There are many types of interactions between members in the two communities under study, but we focus on those which imply a firmer commitment than, e.g., simply sending a message \( \text{[13]} \). Such interactions are (a) the favorites list in QX, and (b) the guestbook signing in QX and POK. The former interaction represents a clear declaration of approval and/or interest, while the latter is a communication publicly accessible to all community members where a link does not necessarily indicate a particularly close relationship. We compare two means of interaction in one community (favorites list and guestbook signing in QX) and the same type of interaction (guestbook signing) in two communities (QX and POK). We use the guestbook signing to test consistent trends in the results.

In the QX dataset, it is possible that a user can remove a contact at any point. There was a small number of such links, in total less than 1% of the total links, that were removed during our monitoring window. It may be interesting to study the conditions of ties removal in parallel with the addition process, but the small number of removed contacts does not influence our results here, and we do not further pursue this topic.

Each individual knows the following structural information from the affiliation network: (a) who has added her in their favorites list or who has written in her guestbook, (b) the members that she has added in her favorites list and, (c) the friends of her friends since the user can access the favorite list of friends. This subnetwork defines the immediate neighborhood of a member. Actions involving this neighborhood are captured by social exchange and balance mechanisms. The members situated farther away than this immediate neighborhood are considered to belong to the rest of the network for which the user has no direct information. Interactions with these members are classified as distant. A collective action can also be a conscious choice, since a member can assess the popularity of others through access to their favorite list, but it is also possible that this action may not be conscious. Structural hole requires a much wider knowledge of the network structure, and thus is the only mechanism that a member does not realize that is using.

Our analysis can be readily extended to treat more general situations. For simplicity, though, here we will not evaluate exogenous mechanisms where interactions are based on attributes of the actors, such as homophily, common interests, etc \( \text{[6]} \). We will further not study the effect of focus constraints, i.e., the increased likelihood of a tie being present among people that share a social context, for example, living close to each other geographically or working at the same office \( \text{[14]} \). The crux of the matter is to quantify the different probabilistic tendencies about the actions of the users as they are determined by the knowledge of the user about the structure of the affiliation network that is the vital part of his/her social life in the community.

The detailed quality of our longitudinal data allows us to identify the precise probabilistic tendencies for tie formation that a newly established link corresponds to, when an actor adds a new favorite in his list (or signs a guestbook). Every interaction that occurred between two members was recorded together with the timestamp when the event took place. We create the evolving network of interacting agents by adding the directed links in sequential order. For example, at the time when a member X adds a member Y in the favorite list of X, we create a directional link from X to Y. Similarly, in guestbook signing, the directional link from X to Y corresponds to X writing in Y’s guestbook (we take into account only the first time X signs Y’s guestbook and ignore repeated signings). Every time we add a link, we characterize this action according to the probabilistic tendencies described in Fig. 1h, as dictated by the network configuration at the given moment. Every link is therefore assigned to one or more probabilistic tendencies: exchange, balance, distant, collective action, and structural hole. We define the probabilities of each tendency \( P_{\text{exc}}, P_{\text{bal}}, P_{\text{dis}}, P_{\text{ca}}, \) and \( P_{\text{sh}} \) respectively, as the number of links that were created using the corresponding tendency normalized by the total number of links created up to a given time \( t \).

A newly formed link is assigned to the exchange tendency when it is established in the opposite direction of an existing link. The balance tendency corresponds to a directed network distance \( \ell = 2 \), i.e. when a link points to a friend of a friend (\( \ell \) is the directed distance between two nodes just before the link is formed - defined as the shortest path with all arrows pointing to the same direction, so that a directed path exists between these two nodes). If the distance between the two nodes is \( \ell \geq 3 \), the link represents the distant tendency. A link is considered as collective action when the chosen node is a hub. We define a hub as a node whose total degree (counting both incoming and outgoing links) belongs to the upper 5% of the degree distribution as measured at the time of link formation. A link represents the structural hole tendency when this link connects two clusters of at least three members each that would otherwise be disconnected. Table 1 summarizes these definitions.

In general, the increase in the probability of a tie forming under a given tendency will not necessarily be compensated for by a tie with decreased probability under another tendency. The relative probabilities between tendencies do not necessarily present competing risks and different tendencies may act at the same time. It is then possible that one link jointly represents more than one
type of tendency in tie formation. In this case, we assign this action to all involved tendencies. For instance, a balance tie could be also catalogued as collective action if the agent closes a triangle by connecting to a hub. Based on the definitions, only balance and distant tendencies are complementary to each other \( P_{\text{bal}} + P_{\text{dis}} = 1 \) so that the presence of one excludes the presence of the other. The other tendencies are normalized as, e.g., \( P_{\text{ca}} + P_{\text{not-ca}} = 1 \) \( (P_{\text{not-ca}} \text{ is the probability of not performing a collective action}).

By establishing all links in the order they appeared, we can recreate the entire history of the directed network of interactions. While POK starts at \( t = 0 \) from an empty network, QX has a large part of the network already in place at \( t = t_0 \), our initial recording date. In this case, we know all the existing links at \( t = t_0 \). Thus, in QX, we characterize only the network links that were added during the monitoring period.

Figure 2 presents the fraction of appearance of each tendency when considering all recorded interactions in the studied datasets, QX and POK, and the means of interaction, guestbook and favorite list.

The results are fairly independent of the specific community and the means of interaction. The probabilities \( P_{\text{exc}}, P_{\text{bal}}, \text{and } P_{\text{ca}} \) appear each at approximately 15-30% of all actions. The distant mechanism is dominant, with \( P_{\text{dis}} \approx 80\% \) of the established links. Collective action remains low at \( P_{\text{ca}} \approx 20\% \) considering that this tendency is considered the main driver in some models of network formation through preferential attachment \( [7, 15] \). A very small fraction of links \( P_{\text{sh}} \) ‘fills’ the structural holes. This is a result of the small number of clusters that exist in each community, so that the chances to connect isolated clusters are small. In particular, comparison to the random case (where the same members act at each time step, but instead of the established link they choose a random connection, Fig. 2 yellow bars) reveals that the structural hole tendency is more probable when an agent connects to a random member. In other words, although there exist opportunities for structural hole, the members tend to stay within their own sub-networks, despite the lack of knowledge on the global structure. The percentages for the other tendencies are also very different from random selections. This implies that community members follow social criteria when adding new favorite members (or sign guestbooks). We verified the robustness of our results by comparing the percentages of the links at the early stages of network formation with those of the links that were established later in the process. For example, in QX favorites the first half of the actions dataset gives practically the same result as the second half: exchange was 13.8% for the first half and 13.9% for the second, balance was used 22.1% versus 22.4%, and collective action was used 18.8% versus 19.7%. Furthermore, the stability of this result over the evolution of the links is verified later, in Fig. 4.

Our analysis has shown that the direct calculation of the tendencies of link formation from the time evolution of the network provides a consistent characterization of the social mechanisms involved, which is different from a static snapshot. Furthermore, the present analysis allows to determine if the found tendencies are influenced by important actor attributes that are hypothesized to have an association with ties formation \( [16] \). These attributes include age, gender, popularity and activity intensity measured as the number of links developed at a given time. Next, we incorporate these attributes in our analysis to attempt to understand how different factors influence the behavior of the actors. We show that the

| Tendency        | Indicator | Directionality |
|-----------------|-----------|----------------|
| \( P_{\text{exc}} \) | Social Exchange | \( \ell = 1 \), mutual link | directed |
| \( P_{\text{bal}} \) | Balance | \( \ell = 2 \) | directed |
| \( P_{\text{dis}} \) | Distant | \( \ell \geq 3 \) | directed |
| \( P_{\text{ca}} \) | Collective Action | link to a hub | undirected |
| \( P_{\text{sh}} \) | Structural Hole | connect two clusters | undirected |

FIG. 2. The relative appearance of the five probabilistic tendencies in the actions of the community members in QX using favorites (red), in QX using guestbook (green), and in POK using guestbook (blue). These tendencies are compared to a completely random selection (yellow). Exchange and balance are practically non-existent in random selections, but carry significant weight in the interactions of the real communities. Connecting to distant members appears in the community much less frequently than in random, while the preference towards well-connected agents (collective action) is significantly more prominent. Finally, structural hole is significantly suppressed in the real communities compared to the randomized case.
III. RESULTS

A. Gender influence

Our analysis reveals that gender is an important attribute determining the social tendencies. Analysis of the QX community (the only one reporting gender) reveals that men do not use some mechanisms in the same way as women (Fig. 3). Using the gender information in the QX favorite lists, we find that a female member is almost three times more probable to have an exchange tendency compared to male members and three times more probable to fill structural holes (men, on the other side, perform distant and collective actions at higher percentages). The significant difference in exchange, for example, reveals a different approach of online communication between men and women [17]. Our result is in agreement with the self-reported tendency of women users to exchange more private e-mails than participating in public discussions [18]. The stronger preference for exchange of female users in the QX community can also be seen as a similar trait where women tend to develop stronger inter-personal relations by frequently reciprocating friendships.

B. Age influence

In the databases that we studied, members of different age tend to present different behaviors. In Fig. 4 we calculate the fraction of actions that correspond to a tendency as a function of the self-reported age of the QX members. In the insets, we separate the corresponding probabilities for male and female members. We find that while reciprocity in women remains high as they age, men instead reduce it by a factor of 2 as they reach 40. This shows that younger male members are more eager to reciprocate their connections. In contrast, the level of balance is roughly constant for both genders and independently of age, with an important exception at the youngest ages, where members younger than 20 years old are using systematically less balance links. This could be because it is more difficult for them to develop a stable local network in an adult-oriented community. There are no significant trends with age for collective action or structural hole, although the latter tendency is rarely used. The gender-based trends shown in Fig. 3 are consistent with the age-based results. Women of a given age are always using more exchange and less collective action tendencies than men of the same age ( insets of Fig. 4).

C. Activity influence

Communities include members of varying activity [13]. In order to study the effect of the different activity levels, we address the question of whether a higher involvement in a community is accompanied by a different pattern in the probabilistic tendencies of social mechanisms. We calculate the different probabilities of social mechanisms as a function of the number of $k_{out}$ outgoing links for
each member. For instance, \( P_\alpha(k_{\text{out}}) \) (where \( \alpha \) denotes exchange, balance, etc) measures the probability that the next action will correspond to \( \alpha \), when the member has \( k_{\text{out}} \) outgoing links. We measure \( P_\alpha(k_{\text{out}}) \) through all the actions of members when they increase the number of outgoing links from \( k_{\text{out}} \) to \( k_{\text{out}} + 1 \), irrespectively of the time that the action was performed. Interestingly, we find that a member typically modifies his/her behavior according to its current degree of activity \( k_{\text{out}} \). As a member becomes more involved in the community and, as a consequence, increases the size of his/her favorites list or signs more guestbooks, the member switches to a different relative percentage of using each tendency.

We identify the following pattern which is very consistent across the two datasets and different types of interactions (see Fig. 5). The first tie of a new member is always distant since the member has no network established. However, even at this stage, 20-30\% of these links are also exchange— meaning that a new member readily 'responds' to the incoming link by established members— and collective action, meaning that the member immediately searches for popular members in the community. At this earlier stage, balance tendency is suppressed, since linking to friends of friends requires first a firm establishment of the immediate neighborhood.

An interesting crossover appears when the members arrive to a size \( k_{\text{out}} \approx 10 \) in their favorites list (see for example Fig. 5a for QX favorites). The percentage of all tendencies up to that value is approximately constant. At around 10 interactions in QX favorites, balance overtakes both exchange and collective action in the behavioral tendencies. As the members keep adding more links, the distant mechanism drops significantly to approximately 60\% after \( k_{\text{out}} \approx 100 \), and the balance tendency grows increasingly stronger consequently. Similarly, the exchange tendency declines steadily towards 0 as the size of the favorites list increases towards the hundreds. Collective action leading to preferential attachment seems to be the most stable over a longer \( k_{\text{out}} \)-range. Finally, the relative probability of \( P_{\text{sh}}(k_{\text{out}}) \) peaks at low and large values of \( k_{\text{out}} \). The structural holes are filled mainly by either new members or well-established members, with a significantly smaller fraction of structural holes performed in the intermediate \( k_{\text{out}} \) regime. This interesting behavior reveals trends in the social tendencies across the individual users as they enter the network.

The choice of different tendencies is, thus, shown to have a complex dependence on the individual’s level of activity. In addition to external attributes, such as gender and age, we find that very active members have different tendencies than the less active ones. Such features can only be extracted by following the entire time evolution of each member’s connections.

**FIG. 5.** Fraction of the appearance of a tendency as a function of the adding member’s list size, at the time of addition. Qualitatively, all three datasets are in agreement with each other. The small quantitative differences may be due to the different means of interaction and/or the design of each platform.

**D. Popularity attributes**

So far, our analysis focused on quantifying the different probabilistic tendencies as seen from the member that establishes a link. We characterized the outgoing links which can be controlled by their initiator, in the sense that any member can choose where, when, and how often connects to other members. However, the popularity (or attractiveness) of a member cannot be adjusted at will. We characterize the popularity based on the number of incoming links. Using the same methodology as above, we can now study how different tendencies determine the popularity of a member.

For each relationship between two people we assign the initiator, i.e. the member who contacted the other
member first, and the receiver, i.e. the member who was contacted. In the case of a reciprocal relation we only characterize the link that was established first. Given the list of a member’s connections, we can then know what fraction of those connections is due to the initiative of this member and what fraction originated from the other side. Thus, if someone very often reciprocates but seldom initiates links, she will have a small value of initiated links although she may have a large number of incoming and/or outgoing links.

In Fig. 6a we present the histogram of how many members fall into each category. The diagram is roughly divided into three areas: a) Members who initiate a lot of connections but are first contacted by very few members (‘spammers’) b) Members who on average equally initiate and receive contacts, and c) Members who receive many more contacts than they initiate (‘popular’).

The importance of using the time evolution of probabilistic tendencies to determine behavior is reflected in this popularity classification. In Figs. 6b-d we present the average percentage for each category and for each tendency that the members use when they add friends themselves. The exchange tendency shows a clear variation with respect to this classification. The ‘popular’ members in the upper diagonal part of the distribution use a lot of exchange, which can be understood since they respond to friendship requests but rarely start new connections. As we move towards the ‘spammers’ the exchange tendencies almost disappear, since very few people approach those members and therefore they have small chance to use exchange. On the contrary, the spammers tend to use balance more, i.e. they connect to friends of friends, since they try to access the largest possible number of the accessible members (Fig. 6c). Finally, connecting to distant parts of the network (Fig. 6d) has a more uniform behavior, although the popular members seem to use it more, pointing to a “rich-club” phenomenon [19].

The above described trends demonstrate the richness of information that becomes accessible by following the evolution of link formation. Nevertheless, we next show that even in the absence of the network history, we can still deduce some useful conclusions on the probabilistic tendencies.

E. Neighborhood landscape change

As discussed above, the presented analysis would not be possible without continuously monitoring the time evolution of the links. The characteristics of a given link with time do not remain necessarily the same as when the connection was established, but they can change due to the addition of more links or the removal of existing ones. For example, a friendship that starts between two isolated individuals may evolve into a densely connected neighborhood, so that a link that started as distant may eventually switch with time to either balance, exchange, collective action, structural hole, or any combination of them.

In order to study how significant the evolution of the link formation tendencies is, we compare the probabilistic tendencies obtained above following the time evolution with those obtained by a statistical analysis of a snapshot of the network. The statistical analysis of the static snapshot is done by characterizing all existing links at the time when the link was established. Thus, we remove a link and characterize it as if it was just established, and

FIG. 6. (a) Histogram of the number of members as a function of the links that they initiated (x-axis) and the links that were pointed to them but initiated at the partner’s side (y-axis). (b-d) Average percentage of exchange, balance, and distant mechanisms as a function of the links initiated and received.

FIG. 7. Comparison of the probabilistic tendencies fraction, where links are characterized either at the time of addition (solid lines) or at the time of observation (dashed lines) in the POK community.
immediately re-insert it back in the network. Thus, each link is assigned to the specific probabilistic tendencies according to the current neighborhood environment of each agent, independently of the time it was established. We repeat this process for all links in the static snapshot and we calculate the relative percentage for each mechanism.

In Fig. 7 we compare the running percentages for each tendency at the moment of addition, such as those measured in Fig. 2 to those of the corresponding static network. All tendencies are different in these two measurements. Exchange is the only predictable tendency, since by definition it appears two times more at the time of observation compared to the time of addition. The other tendencies cannot be predicted from the static measurements. For example, although a member is typically using the balance tendency to add links at a percentage of around 10%, if she tries to evaluate her neighborhood at any point in time she will find out that now approximately 20% of her acquaintances fall under the balance theory. Similarly, the central hubs seem to be reinforced, since collective action is used in less than 30% of the total actions, but eventually more than 45% of the links are directed towards the biggest hubs. In other words, members are ultimately attached to hubs more often than we could conclude from characterizing their original actions only, due to the dynamic environment. This quantifies and generalizes the situation depicted in Figs. 1d and 1f: the knowledge of the network structure at a given time is not sufficient for characterizing the probabilistic tendencies.

Another aspect of this plot (Fig. 7) is that the tendencies at the time of addition reach their asymptotic values quite fast and they remain roughly constant with time. The corresponding values extracted from the static networks are also quite robust and follow closely the variations of the values in the evolving networks, creating a constant gap between the two curves. Since there is currently no method to estimate the magnitude of the difference between the two cases by static information only, it is still not possible to extract the percentage of the probabilistic tendencies without following the network evolution.

Next, we compare our results with other directed social interaction networks from the literature, such as the Epinions [20], SlashDot [21] and LiveJournal [22] communities. The datasets were downloaded from http://snap.stanford.edu/data The Epinions dataset is a directed network of trust from epinions.com, where a user can declare her trust towards another user, based on submitted reviews. This trust creates a directed link between the two users. The network has 75879 nodes and 508837 links. Slashdot.com is a technology-oriented news site, where users can tag each other as friends or foes. In our analysis we only use the friendship links. We use two snapshots of the network, on November 6, 2008 (77360 nodes and 905468 links) and on February 2, 2009 (82168 nodes and 948464 links) [21]. Finally, LiveJournal.com is a social networking site, where users can declare who they consider as their friends. The network that we use has 4847571 nodes and 68993773 links. For these networks we only have the static snapshots. Therefore, we can only study the exchange tendency, which is the only one that remains unmodified in a static network (we can always measure the existence of reciprocity, independently of the time it was established).

The probability to use the exchange tendency among the different social networks (Fig. 8) depends on the specific features of each community. For example, in the SlashDot and in the LiveJournal communities, where a link shows that a user declares another user as being his/her friend, there is a large degree of the exchange tendency because mutual relations are favored in these social networking environments. In contrast, in the QX database the exchange tendency is quite smaller due to the nature of this community. Similarly, in the Epinions database a link shows that a member trusts the tech reviews of the other member, but this relation is usually not mutual (if I trust the reviews of an expert reviewer, this reviewer may not necessarily trust my reviews).

FIG. 8. Probabilistic exchange tendencies extracted from static network snapshots for several directed networks.

IV. DISCUSSION

The wealth of information obtained by our longitudinal analysis can complement other statistical analysis for probabilistic tendencies [6, 10]. The family of exponential random graph models [23] (p*), and in particular the logit p* models [4], have been very successful in analyzing network snapshots at a given moment in time. These methods detect network patterns that appear more frequently than a random null hypothesis would assume. In this way, the underlying mechanisms of network creation are inferred from the resulting motifs. Our present analysis goes beyond this approach by directly facing a number of key issues: we can follow the entire network evolution, we can characterize individual actions, and we
can also assign known mechanisms to any given action. The results of these actions often yield network patterns where an individual contribution may be lost in the static snapshot pattern, due to the effect of subsequent connections. In broad terms, our analysis compared to exponential random graph models may be considered to be the analogue of a microscopic statistical physics description compared to a macroscopic thermodynamic approach.

Here, we have shown that following the order of links establishment at the microscopic level in a social network provides a direct measurement of the probabilistic tendencies. This allows both the quantification of the relative strength between tendencies in a given community, and the extraction of useful sociological conclusions. For example, in the communities that we studied, we show that women tend to use the exchange mechanism more frequently than men. This tendency is more pronounced with age since reciprocity in older men largely declines while in women it remains stable across all ages. In these communities, also, men tend to connect to the hubs more often than women, independently of age. The use of triadic closures is almost constant for both genders and all ages, except for the youngest members with ages below 20. This may be a consequence of the more adult-oriented character of the community. Similarly, we capture a different use of the tendencies between the more active and less active members. The basis of our findings is that these results cannot be derived analyzing a snapshot of a static network. As shown in Figs. 1b and 1c and quantified in the preceding section, it is not possible to make assumptions of why a link exists a long time after the link was established.

Our findings reflect the behavior of users in the online networking sites that we studied. The suggested method of following the dynamic evolution, though, represents a consistent method which can be applied to other networks. Further studies in different online communities should elaborate on whether the trends reported here with respect to sex, age, etc, are generic to other types of networks.

The present analysis complements other approaches in the literature [24] by focusing on individual actions and the study of how the underlying mechanisms behind these actions are driving the evolution of the large-scale social network. The ability to isolate individual actions can be also very useful in studying behaviors that are unusual, and help characterize idiosyncratic ways of building the friendship network. The present analysis can be extended to exogenous mechanisms, as well, by incorporating information from other aspects of the activity in the community (e.g., joining specific clubs, participating in forum discussions, communities, etc).

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