Chapter 18
Factors Enabling Information Propagation in a Social Network Site

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Abstract A relevant feature of Social Network Sites is their ability to propagate units of information and create large distributed conversations. This phenomenon is particularly relevant because of the speed of information propagation, which is known to be much faster than within traditional media, and because of the very large amount of people that can potentially be exposed to information items. While many general formal models of network propagation have been developed in different research fields, in this chapter we present the result of an empirical study on a Large Social Database (LSD) aimed at measuring specific socio-technical factors enabling information spreading in Social Network Sites.

18.1 Introduction

Social Network Sites (SNSs) constitute an efficient and effective platform to spread information, and can thus be seen as an alternative to traditional media. However in SNSs information flows are governed by different rules, because every user can (consciously or unconsciously) decide to facilitate information spreading. In this chapter we present the results of a research project aimed at investigating propagation paths in Friendfeed.

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Friendfeed, a microblogging service created in 2007 and acquired by Facebook in 2009, offers a very interesting case. On one side it can be considered as a classical microblogging service by allowing people to share short messages with a list of contacts. At the same time it allows users' contacts to comment directly under the original messages. While on Twitter conversations are spread through the network and traceable by the use of the reply sign @ and the re-tweet code RT [7] on Friendfeed conversations aggregate on fewer streams as comments on specific entries [6]: users spread conversations to a higher level of visibility simply by participating. A commented entry will be visible, in fact, to all the followers of the commenter in addition to all the followers of the original poster. In addition to these interesting and complex features, the majority of content produced inside this site is public and can be retrieved and analyzed, from the network of user contacts to most of the text entries and comments.

This large amount of user generated content by being persistent and searchable [1] allows us to access an unprecedented quantity of data to study the factors enabling or preventing information propagation. Even if the phenomenon appears to be of major interest when it involves breaking news such as the terror attack in Mumbai in 2008, that has been widely covered and reported live on Twitter, or the death of the pop star Michael Jackson, that created a massive amount of internet traffic both on Twitter and Facebook, the social web ceaselessly propagates information. Internet memes, units of cultural information able to spread through people retaining their informational content [4, 19], are an example of this on-line propagation of information.

The chapter is organized as follows. First, we discuss existing work on information propagation in social networks. In Sect. 18.3 we provide a brief description of the data used in our analysis, its acquisition and structure. In Sect. 18.4 we identify and classify a number of information propagation enablers, providing empirical data to highlight their role in the process. We conclude with a summary of the identified propagation patterns. This chapter extends our previous work [16] by applying our methodology to a new and larger dataset and by including additional analyses.

18.2 Related Work

The propagation of items through networks is a very abstract and general problem which has been studied in several fields. At the same time, different approaches have carefully exploited the specificities of their application fields according to the specific items traversing the network, e.g., viruses or Internet surfers, and developing specific solutions that worked well under those assumptions but are not meant to be general answers to this problem. Our goal here is not to explain in detail every approach that has been used but to highlight how previous researches and uses in different fields can provide insights into the topic. It is important to highlight that we are not going to move seamless ideas and concepts (such as *viral* or *propagation*) from a scientific field to another. Every discipline has its own specificity and moving concepts (and research methods) around would only generate greater confusion rather than real knowledge. Within this perspective being able to stress differences appears to be as important as stressing similarities.

Despite these necessary notes there is no doubt that contemporary studies on propagation are heavily related to the epidemiological studies. Epidemiology has tried to understand how *viruses* and other *pathogens* spread over the population. Although models assuming a standard rate of possible contacts have been used for a long time with overall good results [9,10] assuming random contacts was not considered good enough to reproduce our everyday experience. Some contacts are more probable than others and our daily experience is mostly based on a fixed number of recurrent social interactions. This leads to the methodological challenge of being able to observe and trace only what is relevant from a specific point of view, and highlights the role of social networks in *pathogens* propagation. Nevertheless there are many crucial differences between the propagation of an epidemic and the spreading of information in a SNS, that can be grouped in two major areas: differences related to the *available data* and differences in the nature of the *network nodes*.

In a closed SNS the problem of identifying what constitutes a *meaningful connection* is solved by the nature itself of the socio-technical environment. If we stay with the classical boyd-Ellison article about Social Network definition and scholarship [2]: a SNS is defined also by its feature of articulating a set of connections between users. The explicit connection between users, the *meaningful link* is part of the SNS itself and its establishment appears to be an explicit choice of the user. We are not claiming that every connection has the same value to the user, we are well aware of the differences and the nuanced reality of signification often constructed within on-line friendship and we will later provide empirical data supporting this heterogeneity; what we are claiming is that when we are dealing with SNSs the *basic level* of social connection is available in the technical structure of the system itself. Within this perspective the definition of the network is an easier task requiring less work from the researcher and implying a minor level of ambiguity.

The second difference when we shift our focus from viral diffusion to information/cultural spreading is about the nature of the *virus* itself and the nodes of the network. The metaphor of media virus [19] had (and still has) great success among the large audience. According to Jenkins [8], who is investigating how cultural contents spread through our society, there are many crucial differences in the way viruses and cultural content spread. The epidemiological metaphor, even if it is very attractive, should not be used. Jenkins' point stresses the role of end users in the propagation process. While in virus spreading people are almost passive carriers of viruses (they cannot choose if they want to be infected or not and, if infected, they have no choice between spreading the virus as it is or changing it) memes[1] need some kind of collaboration to their propagation. If it is obviously possible that someone is unintentionally exposed to any kind of *unit of information* the choice between spreading it or not and the way in which it has to be done is definitely

[1] Memes are described [19] as units of information capable of retaining their informational content, inducing people to reproduce the meme itself and staying alive as long as they are able to be reproduced.

up to the single person. This means that the spreading of specific information can be done also to pursue specific personal interests, to enforce personal relationships between users or according to a personal definition of relevance [7]. Information spreading in a socio-technical context is not only matter of what has the major chance of being replicated but also of how this replication is used by the members of a specific cultural context. This is why exposition $\neq$ contagion $\neq$ spreading. Within this perspective the *nodes* of a social network involved in the spreading of information, as well as those involved in the spreading of any kind of cultural object, are substantially different from those involved in the spreading of a viral agent.

The active role of media audiences has been part of any media spreading theory since long time [18] and a theoretically founded research on propagation in SNSs should not try to simply show how information propagates through a SNS but also understand what is the role of SNS structures and connections in the larger process of propagation of cultural information.

Another large body of work related to the analysis of networks regards the Internet. Intuitively propagation depends on the influence of users on other users, and well known approaches like HITS and Google's PageRank [3, 12] have been studied to associate weights to Internet nodes. The two main similarities of these approaches with SNS analysis techniques regard the awareness that some nodes may be more influential than others and the fact that direct connections are not sufficient to compute node weights. However the complexity of the information items traversing the network and the fact that nodes (often) represent real people give rise to a significantly different scenario. In Sect. 18.4 we provide some empirical evidence to support this claim.

Similarly, approaches to emphasize hidden structures of the Internet can be re-thought to be applied to SNSs, like k-shell decomposition [5, 11]. Also in this case, as well as in works dealing with other kinds of social networks [13], the specificities of the social relationships may induce a hidden network structure very different from the network defined by base connections. Therefore, while these approaches may be useful, it is important not to over-simplify social models mapping them to simple networks. In the remaining of this chapter we analyze some of these details, which are shown to play a fundamental role in information propagation.

18.3 Data Extraction and Summary

In Friendfeed users may open a new discussion by posting an **entry**. Every post will be visible to all users *following* the poster, who can **comment** on the original entry or *like* it. Therefore, for what concerns the content of this chapter a discussion consists in an *entry* followed by a chain of *comments*. In the following, we will indicate with *post* any text entry or comment posted by a user, with *entry* a new conversation started by a user, and with *comment* a comment to an entry.

To perform our analysis, we monitored the activity of Friendfeed from August 1, 2010, 00:00 AM to September 31, 2010, 12:00 PM. The service was monitored at a rate of about 1 update every 3 s to retrieve public user posts. At the end of the monitoring period we computed the network of users starting from the users in the sample and retrieving all the connected graph of followers.

The resulting database contained about 12.5 million entries, 3.7 million comments, 800,000 likes, and 28 million subscriptions (following relationships). All the data can be downloaded from the project website.[2]

Global services such as Friendfeed can be used in many different ways according to the socio-cultural contexts we are observing. As we have claimed before [6] the role that a specific social medium plays within a specific media system can be properly understood only if it is framed within a specific cultural context. Therefore, from this database we extracted the portion of the social network concerning a single cultural context, specifically the Italian network.

Since geographical identification is not provided by Friendfeed we adopted an ad hoc solution to identify Italian users. We started from a set I_1 of users certainly Italian, obtained by running a language identifier on the last posts of every user. However, this procedure could not be used to identify all Italian users, because some of them had private accounts (therefore their posts were not available) and some of them produced a large majority of their content in other languages (usually English). However, the Italian network tends to be very dense: 95 % of these users had at least 30 % of their followers recognized as Italian users. Therefore, we generated a new set I_2 including also those users not recognized as Italian at the first iteration, e.g., because we could not access their conversations, but with more than 30 % of contacts inside I_1. At this point there were some other users whose contacts marked as Italian became more than 30 % of their contacts. As a consequence, we reiterated the computation until when the set I_n did not increase in size with respect to I_{n-1}.

This procedure used to find the Italian network as a fix point is exemplified in Fig. 18.1, were we use a 50 % threshold: the identification of a first set of Italian users, represented in black (second graph clock-wise), allows us to mark three additional nodes as Italian (third graph, gray nodes). When these new nodes are added to the set of Italian (black) nodes, a new node starts satisfying the condition of having at least half black nodes as neighbors (bottom left graph). The process continues until we cannot mark additional nodes (bottom right).

Filtering all posts made by Italian users we obtained a database with about 350,000 entries, 400,000 comments, 50,000 likes and 700,000 subscriptions, that will be used in most of the following analyses.

General information about Friendfeed can be found in [6], where we presented a statistical and sociological description of this SNS. However, before focusing on the topic of information propagation it is interesting to look at the distribution of sources of entries. Figure 18.2 represents the percentage of entries coming from the top 10 most active services, obtained after a semi-automated discretization of source indications. If we observe the most active services extracted from the Italian subset of data (Fig. 18.3) instead of the global data we are going to see a significantly

[2] http://larica.uniurb.it/sigsna

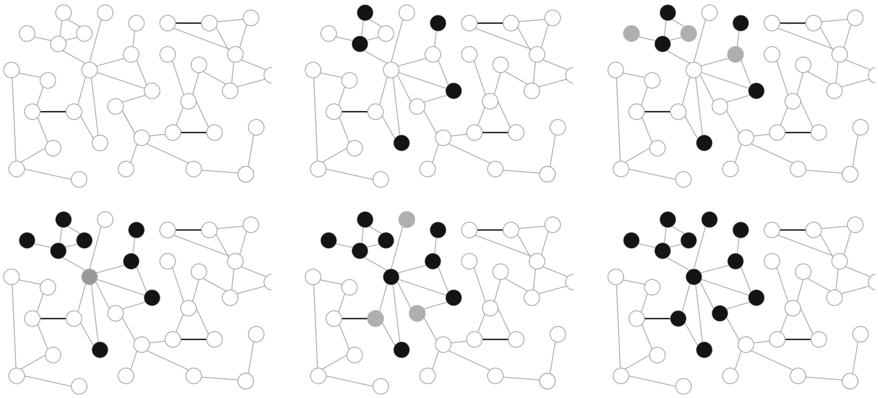

Fig. 18.1 Graphical explanation of the fix point procedure used to obtain the network of Italian users

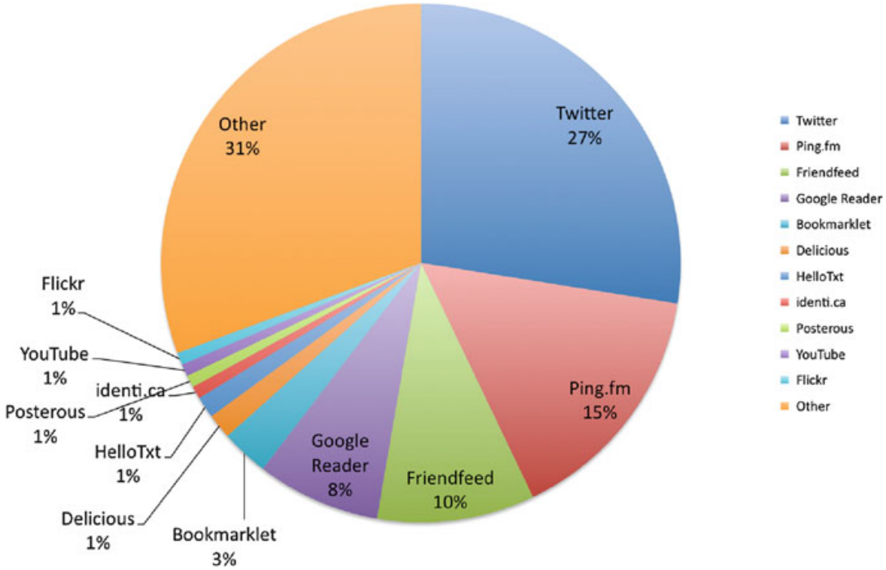

Fig. 18.2 Top 10 Sources of entries (all data set)

different picture. In Italy, where it exists a large online community of users that use Friedfeed as an online space for chat and discussion, the amount of entries produced directly in Friendfeed (and not imported into the system from an external service) increases from 10 % (global data) to 21 %. On the opposite side, due to the relatively small diffusion of Twitter in Italy entries imported from Twitter fall down from 27 % (global data) to 15 %. When we observe global online phenomena pointing out these local aspects is important because of their impact on more general processes like information propagation, that we are discussing in the following sections.

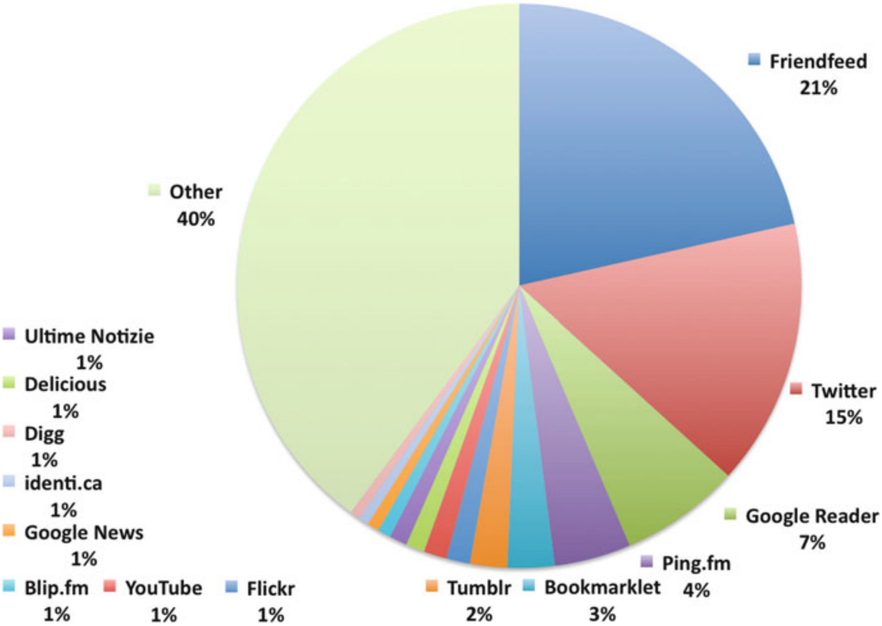

Fig. 18.3 Sources of entries (Italian data set)

18.4 Propagation Enablers

The discovery of factors enabling the spreading of memes and conversations should be based on a short list of well-defined metrics. In the following we focus on two main metrics: **number of interactions** (comments and likes), measuring the ability of a user or message to generate participation, and **audience**, counting the number of people exposed to a message.

In the following we discuss the factors influencing these metrics. These factors have been identified by analysing a large snapshot of the activity occurring inside Friendfeed. At a high level of abstraction a social data model is made of a *network* of *users* exchanging *messages*. We will organize the following discussion around these elements. This classification is only meant to simplify the complex picture drawn in the following, but does not indicate any independencies of these elements – on the contrary, we will see that they are strictly related one to the other.

18.4.1 User Modeling

The nodes of our network are not fixed entities, equal to each other. One important aspect differentiating them is their tendency to produce content.

Table 18.1 Basic statistics on entry production and comments received, Italian dataset, September 2010

	Min.	First qu.	Median	Mean	Third qu.	Max.
Entries (per day)	3,330	6,013	7,042	6,667	7,208	8,224
Comments (per day)	3,999	5,697	7,434	6,900	7,791	8,782
Daily Entries (per user per day)	0.03	0.07	0.2	0.79	0.60	116
Daily Comments (per user per day)	0.00	0.00	0.00	0.82	0.03	136

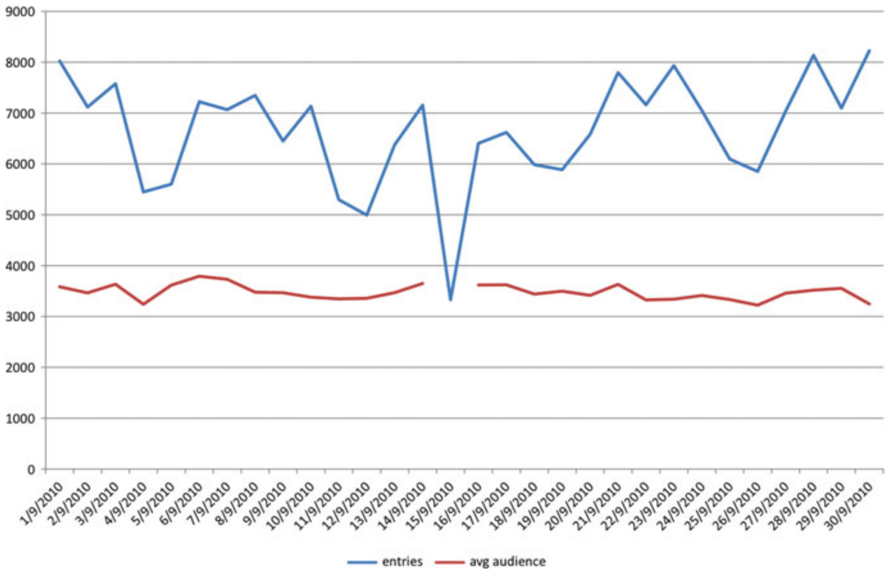

Fig. 18.4 Volume of daily activity (number of entries and comments per day, Italian subset), and average audience size

The entry production rate can be computed for each user and is indicated in Table 18.1. While these values approximate the long-term behavior (2 months) of each user, a more fine-grained analysis of the variations of this estimate highlighted that it can substantially vary depending on time and topic.

Observing the overall content production rate of the Italian community represented in Figs. 18.4 and 18.5 it is possible to describe a rather accurate time trend on a weekly base. As it clearly appears from the figure content production seems to have quite a cyclic behavior with lowest peaks during the weekend and a dull progression from Monday to Thursday.[3] The structural reason for that can be found in the high level of availability of Internet connections from most workplaces. On this point some sociological deduction is required. The weekly trend suggests a high

[3]On Sep. 15th the monitoring system had to be rebooted for maintenance, this explaining the missing values on that date.

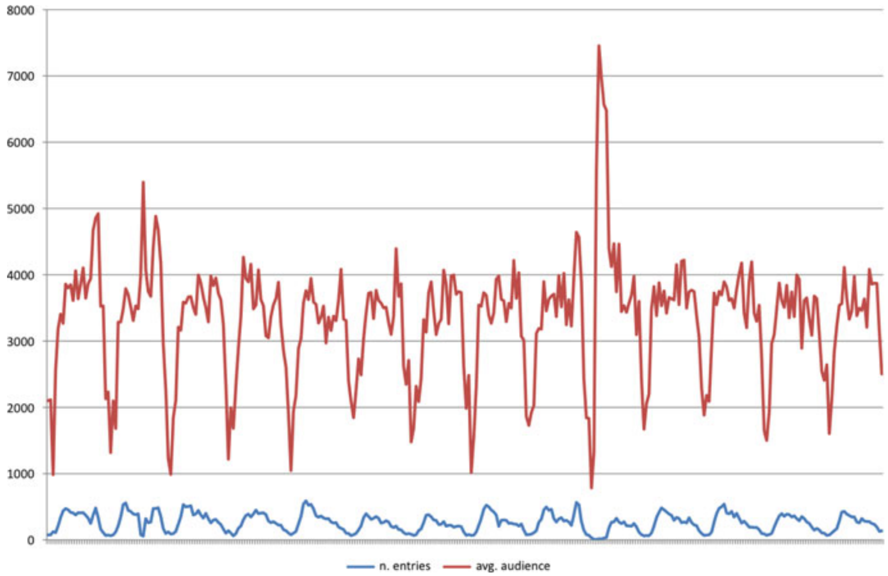

Fig. 18.5 Volume of hourly activity (number of entries and comments per hour, Italian subset, 2 weeks), and average audience size

level of routine with the social media use. These tools seem to be now part of a daily routine made of checking emails, browsing the Web and now updating and posting on social media. Within this routine daily issues can become topics of conversation and are often arisen by users. Weekends seem then, within the described scenario, points in time where the high level of connectivity and sharing is temporarily turned off or reduced.

The influence on propagation, and in particular the average number of users receiving an entry posted at a specific time, has been indicated at the bottom of Fig. 18.5 highlighting a daily trend similar to the one of entry and comment production.

Obviously contingency of life experience can induce a higher level of variability in average entry production rate. Even if, as we said, we can assume that social media use, and therefore content production, is part of daily routines of users, events can rapidly change them. This could be the case of a period of overwork that keeps users busy giving them less or zero time to share thoughts online, or – on the opposite side – it can be the case of an illness that forcing the users to stay at home would probably rise up his/her social media usage. A few examples taken from our qualitative observations should then be able to explain these points: during summer, when vacation time reaches its highs, many users post short entries to inform the community of their upcoming absence: [J.] *On monday I am leaving for summer holidays. No internet for two weeks. ...* In a similar way when user H. writes: [H.] *today I'm kind of sick ... May you sing me a little tune?* she is asking for some kind

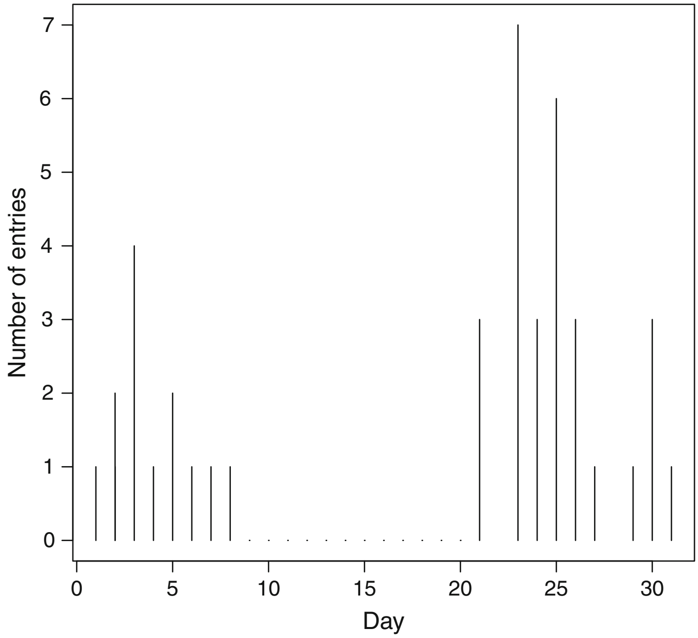

Fig. 18.6 Number of entries produced by user J. during August

of emotional support and alerting that she will be on-line and active in the social media context more that it is expected (or at different times).

Both examples suggest on one side the high level of contingency that can impact individual content production rate in a social media context and on the other side highlight the high level of relational use that social media have. Asking for emotional support during hard times or feeling the duty to inform people that you are not going to be available on-line because of vacation time shows, once more, the level of intimacy that social media can offer. In Fig. 18.6 we show the number of entries produced by the first user in August as one of many examples of specific entry production trends – in this case the message was posted at the beginning of the month.

18.4.2 Network Modeling

The analysis of how the network structure impacts on the propagation of messages can be described as the analysis of all the factors implied in the process that leads from the production of a message (exposition to a message on the network) to the choice, made by other users, to interact with that message and spread it.

Table 18.2 Connection network vs. communication network

Edges in connection network	692,668
Edges in communication network	52,913
Common edges	31,845

According to the final goal of this work we are assuming that aside the network made of established connections it is possible to observe a closer network made of most important connections that are technically equal to the others but much more used. Those connections can be established between off-line friends and then moved on-line but also between on-line friends that feel themselves very close. A link in this *communication* network indicates that the connected users exchanged at least one direct message, i.e., a comment.

The existence of a *communication network* alongside with the *connection network* can be proved by observing the existence, within the single user's network, of specific nodes much more active than others. As it can be observed in Table 18.2 not every existing connection is used in the same way. Some users seem to comment or interact with a far higher frequency than others and those two networks are only partially overlapping. This suggests that interaction here is not merely related to a simple exchange of information about specific topics but involves a more complex relational context made of friendship and empathy. Modeling network propagation should therefore keep into consideration the existence of such preferred paths and the existence of many of them can give to a single message a higher probability of being commented and having its visibility increased.

The relational aspect of *communication links* appears to be evident if we observe the relationship between the number of entries produced and the number of comments received. In fact, we could expect that the more entries a user posts, the more comments he/she will generate and those comments would spread the messages toward a larger audience. However, Fig. 18.7 shows an opposite behaviour. Automated programs or services that post on-line a large quantity of messages usually get zero or very few comments: there is no conversation or real interaction going on between those services and users. Those services can surely be used, with an informative purpose, by a large number of people but they do not seem to be able to generate any kind of conversation therefore, in a network such as Friendfeed, their messages will not propagate out of the first set of direct followers.

Even more interestingly the analysis of users with less than 20 entries posted per day shows that also for nodes plausibly representing real users and not *spammers* the correlation between number of posts and received comments is not evident. On the contrary, we can distinguish a large number of users whose entries are not commented ($y = 0$), and among commented users a positive correlation up to a certain posting rate, with the number of comments then diminishing again toward 0.

To conclude our analysis of the factors influencing the tendency of a connection to generate comments, consider Table 18.3 where we grouped all entries by their original sources. Entries coming from Friendfeed show an average comment rate higher than all other sources. This suggests that even if Friendfeed has the ability to

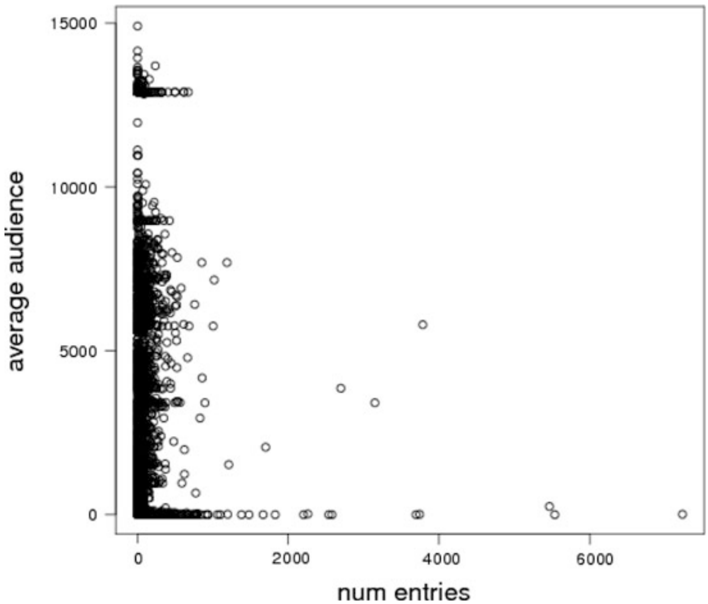

Fig. 18.7 Number of daily entries per user (x) and average audience (y)

Table 18.3 Number of comments received per posted entry, evaluated over different sources

	Twitter	Friendfeed	Facebook	Flickr	YouTube
AVG	0.49	3.41	0.22	0.28	0.18
MAX	197	787	2	163	75

aggregate many different sources the entries that have been created specifically for Friendfeed have a greater ability to induce conversations.

18.4.3 Conversation Modeling

Conversations in Friendfeed take place in a highly competitive environment. The technical structure of the service generates a social space where the visibility of published messages is defined by two opposite forces. Trying to describe how visibility happens in Friendfeed is important to stress once more that the probability for a message to be seen outside of the original network of followers is determined by the interactions (comments or likes) that it will be able to generate. Within this perspective the general visibility of a message seems to be related to the number of on-line users (belonging to the poster's network); if many of them are on-line there

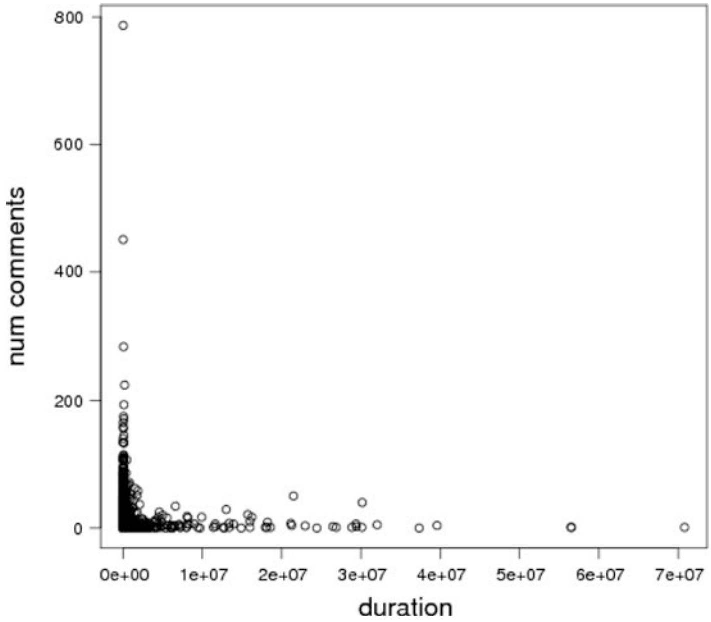

Fig. 18.8 Duration of discussions (x, minutes) and number of comments composing them (y)

will be a higher chance of visibility. At this level one could assume that a message sent while there are many on-line users has a higher probability to be commented and then propagated. Nevertheless at the same time users will produce, while they are on-line, concurrent messages that will move other messages out of the first page (where they would have had greater visibility).

The number of on-line users is therefore to be considered as a double direction force, able to push up the level of visibility of messages (and to spread them out of their original network) and to push down the same level of visibility by producing concurrent messages that will have the chance to move other messages out of the pages with the highest level of visibility.

The analysis of the average lifetime and of the lifetime distribution of conversations in Friendfeed gives us some additional insights on this issue. Observing Fig. 18.8 it is possible to see how on one side the largest part of conversation has a relatively short life span and on the other side there is no clear correlation between the number of comments in a discussion and its life time as it is shown in Fig. 18.9. This short life time indicates an average use of the service as a tool for informal conversation with no (or few) big topics addressed. Conversations seem to be made of interconnected comments that hardly have the ambition of creating more complex, structured and stable discussions. On the opposite of what one could think many of the most commented entries in our sample have an extremely short life time. This suggests that many of the most commented entries are due to a high emotional answer to the first original entry. This could be the case, as we suggested in recent

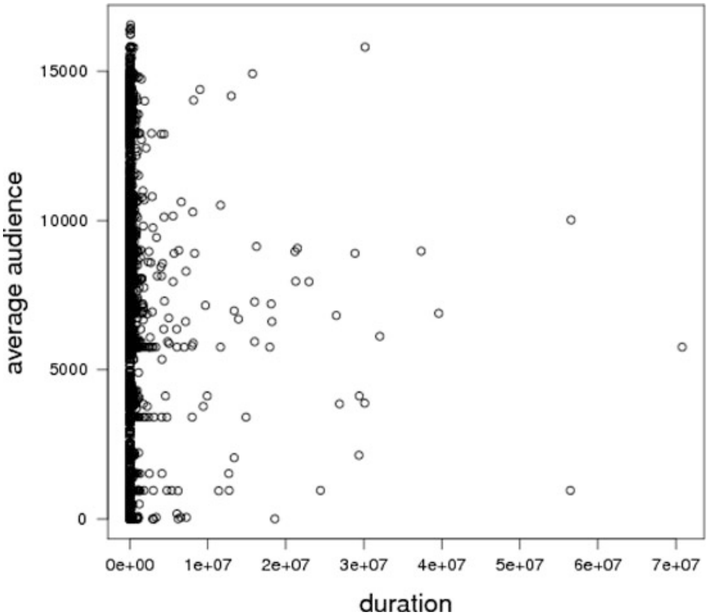

Fig. 18.9 Duration of discussions (x, minutes) and average audience (y)

work [17] of breaking news announcing something happened. In that case a highly emotional response will generate a massive amount of comments that will burst into the network but, at the same time, will be extinguished in a very short time (this relation between posting frequency and emotional involvement can also be used as a ranking parameter in search engines for social media [14, 15]). In addition to that, as illustrated in Fig. 18.9, the ability to reach a large audience is not directly related to the life time of the conversation. This is coherent to what we said in the introduction of this article and it confirms the ability of microblogging sites to spread messages to large audiences in a short time.

18.5 Summary and Concluding Remarks

In this work we provided an in depth description of the SNS Friendfeed and of some of its inner dynamics, investigating some major elements involved in the process of information propagation. The following is a list of our main findings:

- Users active inside Friendfeed generate much more comments than external users importing their messages into the service.
- Content production rate follows specific time-trends.
- These trends are locally affected by contingent events (both private and public).

- The average audience of an entry depends on its posting time with specifically identified trends.
- Information spreads on communication networks only partially overlapping the network of contacts.
- Automated users tend not to generate discussions.
- The number of comments received by users with more limited entry production rates increases only up to some threshold (what is often called *information overload*).
- Most conversations have a very quick growth and an evolution that usually ends within a few hours.
- This is particularly evident for highly commented entries – the presence of many comments often implies a shorter discussion.

These results show how the problem of information spreading in SNSs is influenced by many factors, and cannot be studied in depth reducing it to simpler network models – although this does not prevent simplified models from highlighting interesting features of these complex environments.

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