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ANALYSIS OF SOCIAL INTERACTIONS IN A SOCIAL NEWS APPLICATION

Paul Alpar, University of Marburg, and Steffen Blaschke, University of Hamburg

Abstract

We analyze the interactions within a social news application. In such applications participants post “news” that usually contain a link to another web site which carries the actual story and they vote for news they like. News that receive a required amount of votes make it to the front page, usually the home page, and receive more attention in this way. Other news get buried by the pile of incoming news. Given the big number of such applications all over the world and the impact that some of these applications have on the diffusion of news, it is important to understand their operation. The paper examines the activities of the members of a particular social news site, and examines which news submitters are successful in contributing news that reach the front page. The sites support what has been called citizen journalism but they can also become targets of manipulation attempts and spamming. Therefore, it is also important for operators of such sites to be able to easily recognize such attempts. The paper offers an approach based on social network analysis for this purpose.

Keywords: social news, social network analysis, web 2.0, voting manipulation

1 INTRODUCTION

A new set of Internet applications and services, commonly referred to as the *Social Web* or *Web 2.0* (O'Reilly, 2005), has become extremely popular in the first decade of the new millennium. The respective sites are among the most visited on the entire world-wide web (cf. the traffic monitoring service *Alexa* at www.alexacom.com for up-to-date statistics). Social network sites are used to stay in contact with friends (*Facebook*), to search for new job opportunities (*LinkedIn*), or to share photos (*Flickr*) and videos (*YouTube*) with family and others (see Boyd & Ellison, 2008, for a comprehensive definition and further examples). People often read wikis (such as *Wikipedia* or *Wikia*) to get some first knowledge on a subject, and many people keep blogs (e.g., using systems like *Wordpress*, or *Typepad*) to tell others what they do, think, or feel. Microblogging, i.e., posting (and reading) of short text messages has become a leisure activity of millions of users world-wide. One common denominator of these sites and services is that their content is generated by the users themselves.

A social news site is a web application that allows its users to raise attention to news, images, or videos from other sites, rate or comment on them, and eventually discover interesting and new themes and topics. Such websites are important for two reasons. First, they can support a quick distribution of news or help promote a product. For example, the publication of the AACS encryption key and its temporary removal on *Digg* (www.digg.com), currently the most popular social news site, sparked a widespread publication of the “secret” key (Wikipedia, n.d.). Another example is the sell-out of box rivets used to build playing constructions from cardboard boxes after they were mentioned on *Digg* (Warren & Jurgensen, 2007). Second, they are often (mis)used to raise the popularity of another website through incoming links. The effectiveness of such attempts depends on the popularity of the social news site itself, on some technical issues (e.g., the specification of nofollow links) and how quickly the social news site recognizes and removes spam. A visit to various social news sites reveals that such spam submissions are a common practice (and a problem).

There are many social news sites in many countries and in many languages, but this is much less than the millions of blogs around the world. They receive much less traffic and have a much smaller number of registered users than social network sites such as Facebook or Twitter. The smaller scale may be one reason that research has concentrated so far on social networking and blogging while social news applications have received little attention despite their relative popularity. Among the few scholars who studied social news are Lerman (2007a), who takes a closer look at the process of collaborative rating and the impact of “friend”-relationships in *Digg*, and Goode (2009), who reasons about the relationship of social news to citizen journalism and their contribution to democracy.

This paper examines, based on data from a small social news site operated in Germany, questions that have been raised in the analyses of other social web sites; for example: What is the distribution of participation with respect to content generation? It also analyzes the occurrence and detection of manipulation attempts in social news, though it takes a different approach than Lerman (2007a). The specific questions are: Are there attempts to manipulate rankings? Can manipulation attempts be automatically detected? Finally, it raises questions that are specific to social news applications; for example: Which users submit most top stories?

Since there is little research on these questions so far, our research is data-driven and exploratory rather than an attempt to test hypotheses for which there may be not enough theoretical background yet. To answer the questions, we apply social network analysis and some simple statistical procedures.

The paper is structured as follows. In the next section, the functions of a social news site are discussed in detail in order to identify social interactions that take place and segment users by the functions they utilize. In the third section, the data is described that has been used for quantitative analyses. It also contains some first answers to the above questions. Social networks analysis is carried out in the fourth section. This is followed by statistical analyses of most frequent news contributors. The last section summarizes the results and gives our intentions for future research.

2 SOCIAL NEWS APPLICATIONS

2.1 Functions

A social news application enables its users to post, read, vote, and comment on news items. Actually, the items are usually not the news itself but a link to the news on another website, often accompanied by a short description or comment on the news by the item contributor. Pointing to other websites resembles social bookmarking like in *Delicious* (www.deli.cio.us). However, social bookmarking sites are neither designed for comments on specific items of a website nor for threaded discussions of these items. Except for counting of the occurrence of bookmarks in different bookmark collections, approving or disapproving of websites does not usually take place. In contrast, the goal in social news is not to assemble a collection of (shareable) bookmarks but to point to specific items on a website. On a social news site, a user reads the news description and if interested in the news he has to click on the link to get to the target website carrying the news. Some applications also allow the posting of “original” items that do not link to any other website. In general, users must register to be able to submit news, but everyone can read them. New items are entered into a queue in chronological order with the most recent item on top.

Readers can express whether they like or dislike the news items. Depending on the system, they either must register to do so or can vote anonymously. In any case, each user can vote only once for an item. The votes are called points, diggs, or something else. The most popular items according to the voters are displayed on the home page of the social news application. The popularity can be calculated by simply counting the number of users who voted for the item and subtracting the number of users who voted against it. However, more complex algorithms are also in use. For example, each vote can be given a user-dependent weight depending on the past activity of the user.

The past activity of the user is reflected by a figure often referred to as “karma,” by the number of stars, or by the level (e. g., “expert”) that the user achieved. This user status may be displayed next to the member name or in his profile. Karma or another indication of user status is often calculated based on a complex algorithm that takes into account the number of news submissions, the number of news items that made it to the home page, the number of votes given to other items, time elapsed since last activity, and so on. The exact algorithms for the calculation of item popularity or user level are often kept secret in order to prevent manipulation.

2.2 Manipulation attempts

Various forms of manipulation occur. First, news items are submitted which are just an advertisement for a website. This is not desired by most news applications and it is usually ruled out in the terms of use. Such advertisements are submitted not just to attract users from the news application to the website but also to boost the search engine score of the advertised website. Even if no user clicks on the link, the submitters expect some benefit from posting the link and continue spamming the news application as long as they are not prevented from it. The latter happens when the administrator of the news application puts the advertised uniform resource identifier (URI) on the application’s black list. The administrator can also delete items that violate the stated policies.

Another form of manipulation occurs when a person creates several accounts for himself (i.e., fake identities) in order to vote several times for his own contributions or those of his friends. A variation of this behaviour is possible if anonymous voting is allowed. In that case, applications just record the IP address under which the user voted. If he enters the Internet with another IP address, he can vote again. Social news applications suffer from these manipulations because the quality of news items deteriorates and, often enough, the voting process puts news items up on the home page that are of little interest to the majority of users. There are even services which offer to push a submission to the front page for money (Newitz, 2007; Arrington, 2008). The natural process of social filtering or sorting out “garbage” in the case of advertisement, hate items, or similar items fails in such cases. Therefore, administrators are fighting spam and manipulation by manual actions and software routines (e. g., automatic filtering of posts that contain abusive language).

2.3 Social Interactions in Social News

In social networks direct communication among members occurs but it can be questioned what makes social news sites “social”, i.e., which interactions take place. There are a number of ways that interactions among social news users occur. Reading of a news item can already be considered an interaction (like reading a blog post; cf. Blanchard, 2004). A vote for or against the news item is a reaction to the submission. A comment to a post or to a comment is an even stronger form of interaction. Choosing a user as a “friend” clearly expresses some form of positive attitude towards that user. This can occur because the users know each other offline, because of common interest in the same type of news, because a user is attracted by a photo of another user, because the “friends” want to game the system, or for some other reasons. A request to be notified when a user submits a new item (e.g., via RSS) is a form of interaction that usually expresses common interest. In this paper, we concentrated on posting and voting as will be explained in section 3.

2.4 User Segmentation

A number of studies classify users of social communities based on their social roles within the community (see Turner & Fisher (2006) for an overview). Brush et al. (2005) classify users of Usenet discussion groups based on a survey as *key contributors*, *low volume repliers*, *questioners*, *readers*, or *disengaged observers*. We classify users of social news applications based on the activity they perform in the application. We call users who post news items, but rarely rate other users’ posts, *Posters*. *Voters* rate news items, but they rarely post. *Community builders* post and rate news items. They make the community thrive since both activities are necessary for the community to function. *Spammers* are posters who only post to promote their own web sites or voters who only vote for posts that they submitted under another identity. *Readers* are users who only read posts and comments to posts but (almost) never post or vote. They are sometimes referred to as *lurkers* (Nonnecke & Preece, 2001). While in other settings lurkers may generate value only for themselves, here, they may also generate value for owners of the social news application or owners of the websites that posts are pointing to. If these websites carry advertisements or direct e-commerce offers, then readers may click on them and generate revenues for the website owners. Therefore, although their free-riding does not foster the processes of news selection and relationship building, they may have a value for website owners. Note that spammers, posters, or voters may perform their activities without reading any news items or comments. Figure 1 displays the user segments and their relationships (where S stands for spammer).

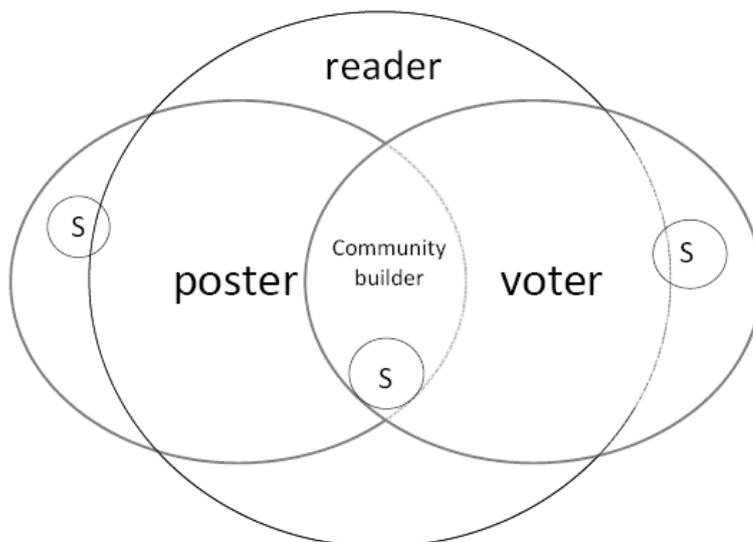


Figure 1. User segments in social news applications

Users who post and vote but do not read are not shown in the figure to keep it simple. The correct assignment of each user to a segment is difficult on sites where reading is possible without registration and login. The exact size of some of the segments in our case will be given in the analysis below.

3 EMPIRICAL DATA

We received empirical data from a small social news site named *Colivia* (www.colivia.de) for a period of six months in 2009. The site was launched in 2007 as an experiment but started promotion activities in 2009. Thus, our data stem from its early operation. The site had about 32,000 registered users at the beginning of 2011. We received anonymous data without any personal data of users such as age, gender, or email address. However, all activity relevant to community building on the news website that the users performed after logging in as a registered user was on record and available to us. We concentrated on the following interactions in our analyses: posting of news and voting for posts. We did not consider reading posts because a precise tracking of this activity is not possible. First, reading posts can be done anonymously by registered and non-registered users. This means, posters and voters may also visit the community unnoticed if they do not engage in any activity for which a login is required. Second, it is not always known what readers have actually read. Several post introductions are displayed on one webpage. We can only assume that a reader read an introduction if he clicks on it to see the whole post. We do not know whether he read introductions on which he did not click. Therefore, even if we had received log files of the website, which we did not, we neither would have been able to clearly distinguish visits by readers from visits by other user segments, nor is there any reliable way of determining actual reading in the first place. The only way to find out more information about reading would be to interview users. Comments were also omitted from further analyses because they occur relatively seldom compared to votes. The majority of comments complemented a vote or they originated from the original poster as a reply to another user's comment. Friend selections and RSS subscriptions rarely occurred.

4 DATA ANALYSIS

4.1 Concentration Analysis

We started our analyses with statistics on the concentration of activities. Figure 2 displays the concentration of posts in the observed period.

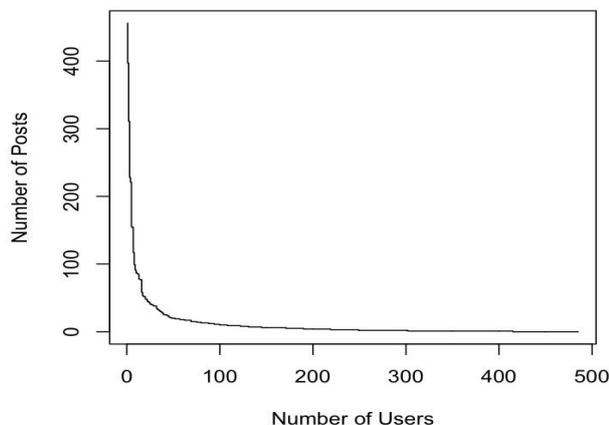


Figure 2. *Distribution of posts by users*

A few users post often while the majority of users never posts. This behavior resembles the behavior of users in other social communities (e.g., Kittur, Chi, Pendelton, Suh, & Mytkowicz, 2007). Lerman (2007b) analyzed a large sample of “popular” news items (i.e., those that made it to the homepage) on

Digg and found out that from the top 1000 users 3% contributed 33% of the weekly posts, 21% of votes and 60% of the news items that made it to the homepage. In comparison, Figure 3 displays the distribution of votes by users.

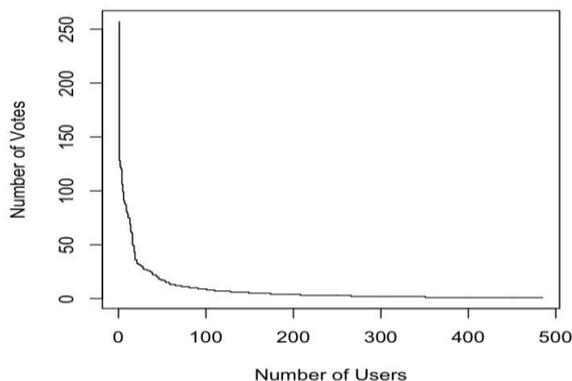


Figure 3. *Distribution of votes by users*

The concentration of votes on a small number of (registered) users reveals that many users either visit the site rarely or just for a short time or remain passive even if they visit it often. The latter group seems only to be reading posts and perhaps the original news without any further action on the social news website. A more exact analysis of this behavior is not possible without server logs. Since reading is possible without registration, it is not clear why they register at all. Perhaps just to have the option to take a more active role when so desired.

4.2 Manipulation Analysis

Manipulation attempts can be analyzed on the basis of (indirect) interaction among community members by using social network analysis. It enjoys a long-standing tradition as a rigorous methodology in sociology (Scott, 1991; Wasserman & Faust, 1999), though it nowadays receives ample use throughout all social sciences (Borgatti, Mehra, Brass, & Labianca, 2009; Kilduff & Brass, 2010). Social network analysis has originally been developed to study social interactions among members of formal (e.g., companies) or non-formal communities (e.g., neighbourhoods). There, social interactions are based on communication (i.e., an exchange of verbal or written messages). However, other forms of social interaction can also lead to the development of social communities. For example, modifications of Wikipedia articles were analyzed to determine power relationships among its users (Kittur et al., 2007). Mutual blog links in blogrolls and trackbacks, comments to blog entries, and reading of block entries have been analyzed to determine whether communities develop in the blogosphere (Chin & Chignell, 2006; Blanchard, 2004; Efimova & Hendrick, 2005) or which blogs are the most popular (Lin & Kao, 2010). In the context of software creation, participation in open source software development has been considered social interaction and analyzed via social network analysis (Long & Siau, 2007).

Here, we concentrate on votes as the social interaction. These are explicit expressions of (dis)agreement while in blog analyses blogroll links, comments, or citations are used as indicators of positive attitude towards a blog (Tayebi et al., 2007; Lin & Kao, 2010). We obtain a social network of interacting users on the social news site by querying the underlying database. Our query yields a directed graph (G) of 485 registered users (V , vertices) and 2.098 relations (E , edges) among them. The actual number of users was higher already at that time but those users whose posts did not receive any vote have been excluded. This is also true for some users and spam that have been manually deleted. Each user accounts for a particular number of posts to the social news site, which we use to determine its vertex size in the graph. Similarly, each relation denotes one or more votes of a user for

the post(s) of another. We use the particular number of votes to determine the weight of the relation between any pair of users.

There are 290 posters who account for 3.351 posts, 70 voters without posts, and 125 community builders with 2.353 posts. Here, we define posters precisely as members who never voted for a post and voters as members who never posted a news item. Figure 3 shows the entire directed graph with posters and voters in light grey color, and community builders in dark grey color. In addition, we use a k -core decomposition, which repeatedly deletes all vertices with less than k relations until the maximal connected network component is found (for details on the algorithm and its interpretation, see Seidman, 1983; Moody & White, 2003), to identify the core of the graph (k -core=17). Unsurprisingly, the core comprises of 27 users, all of whom are community builders. However, only 22 of these users share mutual relations, which is why we consider these users the absolute core of the community.



Figure 4. User graph of the social news application

The graph has one large component of completely connected vertices ($V=460$) and six smaller ones ($V=9, 5, 4, 3, 2,$ and 2). The fact that the six smaller components are not connected to the larger social network suggests that the respective users in these smaller components are either random drop-bys with only a few votes at their hand or manipulation attempts.

A qualitative assessment of the users outside the main component and their posts reveals that, for example, the smallest component of two users is merely a single post by a user who attracted a single vote by another user. Obviously, this situation is hardly a manipulation attempt. In contrast, another small and isolated component of nine users in the lower part of Figure 4 is likely to be such a manipulation attempt. A user accounts for three posts and receives votes from eight other users, none of who has voted or posted otherwise. Moreover, they exhibit almost consecutive user IDs, which

indicates that the accounts were established shortly one after another. Lastly, the qualitative check of the content of the posts hardens the doubt of genuine information to begin with.

Manipulation attempts cannot be easily detected through database queries alone, mostly because their patterns vary considerably. The “fork” in the upper part of Figure 4 that is connected to the largest component turns out to be a manipulation attempt upon investigation, although one user who does not seem to be part of the game voted for a manipulative post. A quick visual analysis of the components of a social network may thus serve as a first indicator of manipulation attempts. A closer look at the respective users, the relations among them, and their posts usually provides enough evidence of manipulation attempts such that administrators of the social news site may use this kind of information to maintain black lists of both users and web pages they promoted.

Next to database queries, visual data mining (Keim, 2002) of social networks is a fruitful approach to identify manipulation attempts or other relational irregularities. Unfortunately, it is only feasible in small networks of a size up to a few thousand vertices and edges. By observing the site at its beginning, we were able to look at all relevant users. In case of networks beyond the size limitations of a computer display or a printout, we must apply appropriate filters to scale down these networks to a manageable size. We may either choose to look only at parts of a network (e.g., a single component, a community, or a clique) within a given time, or take account of the whole network for only part of the time (e.g., a month, a day, or a year). For example, Fazeen et al. (2011) used for some of their analyses a random sample network of 500 actors from a database of over 440,000 actors in Twitter. Visual data mining can also serve to first discover manipulation patterns. Then, appropriate data base queries can be formulated to automate the detection of manipulation in the complete social network, even if it has millions of users.

Lerman (2007a) has analytically identified that users dig stories their friends submit or their friends dig. Users of Digg made also the observation that top users who were well connected through friend links often achieved that their stories climbed to the front page. Their protest led to a change of the algorithm that calculates the popularity of a story so that now “diversity” also plays a role in the calculations on Digg. The updated algorithm reduces the weight of group votes, i.e., the votes of connected users (Hoffman, 2008). Our approach helps to recognize gaming even when users are not connected via friend links.

Within the largest component of 460 vertices, we are particularly interested in the social network defined by mutual relations, that is, users who voted for one another. Figure 5 displays the respective undirected graph of mutual dyads. Most noteworthy, there are two users (IDs 10 and 34) who are in close relation with others, partly because the number of their posts attracts many followers. However, another user (ID 226) who has also a big number of posts has only a single relation. Isolated dyads could also constitute manipulation attempts.

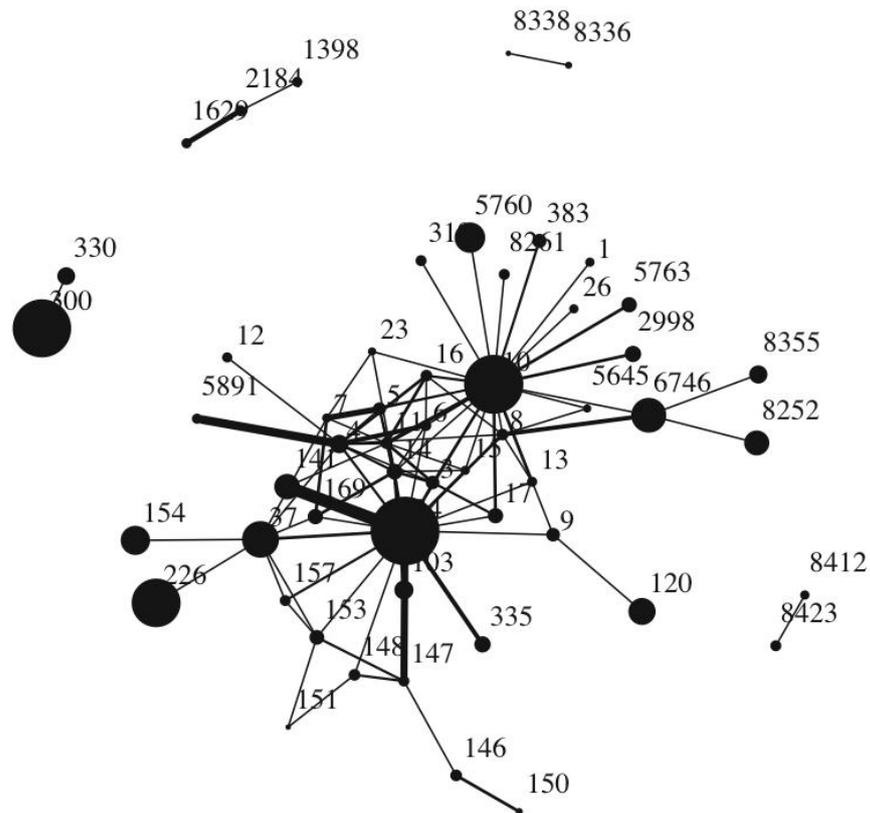


Figure 5. Mutual dyads in the user graph

Social network analysis offers a number of centrality measures such as betweenness and closeness (Freeman, 1979). The causal implications of the centrality measures, however, hold true only for social networks involving communication or some derivative of social interaction (friendship, trust, etc.). Since social news are largely driven by votes with respect to the visibility of posts (i.e., vertex size), we refrain from tempting computations of such measures that yield little theoretical and practical insight into the structures and dynamics of social news sites.

4.3 Analysis of Successful Posting

Here, we turn to the question about the characteristics of popular posters. These characteristics relate to their activity within the social news application rather than their personal traits, which are unknown to us. Frequent posters become known in the community so that community members may be more willing to read their posts. The question arises whether their posts are also frequently voted for and whether their posts often reach the top page. Note that in our case friend links barely existed and, therefore, could not be used to vote posts to top ranks. Also, posts of frequent spammers including their activities were deleted. To account for the different number of news items contributed by different users, we calculate the ratio of news items that reached the top page divided by the total number of items submitted. Since reaching the top page is a rational goal of most submitters, we call this ratio the “success rate” of a submitter. We concentrated on posters who submitted more than 30 news items ($n=30$) within the observed time frame.

Result 1: There is no significant correlation between the total number of posts and the success rate.

Frequent posting is obviously no guarantee for the popularity of contributions. There is, perhaps not surprisingly, a highly significant correlation between the total number of votes received and the success rate ($r=0.444$, $p=0.014$). This is also true for the correlation between the average number of

votes received and the success rate ($r=0.766$, $p<0.001$). The basic results also hold if we consider all users who posted more than 10 ($n=69$) or 5 ($n=120$) posts. This means that contributors of top stories do not reach the top page with only one or a few news items but seem to repeatedly contribute popular items.

When users submit a post to Colivia they must assign it to one of five categories (society and politics, sports, technology and knowledge, entertainment and arts, economics). Users who mainly submit to one category may be experts in this area and may, therefore, attract many votes. Therefore, we examine whether posters that concentrate their posts on a category achieve a higher success rate. For this analysis, we observed the percentage of posts in each category for each frequently posting user (more than 30 posts). Then, we recorded the maximum percentage of each user independently of the category in which this percentage occurred and correlated it with the success rate as calculated above.

Result 2: There is no significant correlation between concentration on a news category and the success rate.

In other words, users who were posting more or less equally in several categories contributed as many top stories as users who mainly or exclusively contributed to one category. This was independent of the category in which users specialized in (in terms of their posting) although this result may be due to too few observations per category. A plausible interpretation of these results would be that voters of the specific social news site have varied interests so that “specialists” in one category have no advantage in the voting process as might be the case on a site that is mainly (but not exclusively) devoted to technical issues, for example.

5 CONCLUSIONS

Our research shows that in the analysed social news application, like in many other social software applications, relatively few very active participants are driving the site. In this case, these are not just the generators of content but also those who rate the content as they ensure that interesting content receives more attention and bad content, especially spam, remains unnoticed. The lurkers may contribute to the revenues generated on the site but they are of no direct value to the development of the community. Social network analysis can help to automatically identify possible spamming as described above. This is important since the more successful a site is the more spam it attracts, which can tremendously deteriorate its quality. Frequent posters may become identifiable on the website but it does not guarantee top spots to their posts. Whether our results hold for other social news sites, esp. those with a much larger membership, should be subject of further research. However, the needed data must be made available.

One promising avenue for future research is the analysis of the dynamics of network interaction, which promises a better understanding of network growth, member activity, and manipulation attempts over time. For example, by looking at the network at different points in time, we may statistically infer the effects that drive the evolution of interaction (Snijders, 2001). Although time-coded data is a necessary prerequisite to conduct this kind of analysis, it is at close hand for many online social networks. Again, such research hinges on the availability of necessary data.

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