The Dynamics of Web-based Social Networks: Membership, Relationships, and Change

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Abstract

Social networks on the web are growing dramatically in size and number. The huge popularity of sites like MySpace, Facebook, and others has drawn in hundreds of millions of users, and the attention of scientists and the media. The public accessibility of web-based social networks offers great promise for researchers interested in studying the behavior of users and how to integrate social information into applications. However, to do that effectively, it is necessary to understand how networks grow and change. Over a two-year period we have collected data on every social network we could identify, and we also gathered daily information on thirteen networks over a forty-seven day period. In this article, we present the first comprehensive survey of web-based social networks, followed by an analysis of membership and relationship dynamics within them. From our analysis of these data, we present several conclusions on how users behave in social networks, and what network features correlate with that behavior.

1. Introduction and Background

Social Networking is one of the biggest trends on the web, with hundreds of millions of people participating. While social interaction and community organization on the web is not new, the scale at which people are forming explicitly social connections in public forums is unique to social networks in the last couple years.

There are hundreds of web-based social networks. Some websites are dedicated specifically to social networking (e.g. Facebook, Friendster, and MySpace), while others support social networks, but they are secondary to other features and purposes (e.g. YouTube, Spout, and Tickle). Their purposes vary from religious to political to entertainment, and membership in a given network can be as small as a few dozen users to over 100,000,000.

Thirteen social networks were included in this study, ranging from small (about 1,000 members) to very large (over 10,000,000 members). Where available for each network, we gathered statistics on total membership, day-to-day changes in the size and relationships, and activity patterns for each user.

In web-based social networks (WBSNs), users state directly who they are friends with. Since collecting social network data in the real world is so difficult, WBSNs offer an attractive data alternative. They are dramatically larger than network models that are built by hand, and they are active and changing, rather than a fixed one-time view.

In this paper, we present an analysis of the growth patterns and dynamics of web-based social networks. This is addressed on two levels: a world wide web level trend, where we examine the growth in the number of sites and overall membership, and a network level trend, where we show for each network the membership growth, members who leave, relationships added and removed, and analyze the clustering. We conclude with a discussion of major patterns of behavior in WBSNs and lessons that can be drawn from this analysis.

1.1. Related Work

Social networks based on real world connections have been studied extensively. These studies have relied on data gathered by surveying people, studying family trees and historical documents, or extrapolating from observable behavior. Even previous work examining *online* social networks (Garton *et al.*, 1997) recommends a survey-based approach for extracting social information about users. Similarly, the growth and activity patterns, design, and behavior(Preece, 2000) in online communities is the subject of a vast literature. In this work, however, we study the explicitly stated social connections, rather than social interactions of users. While that differentiates our approach from the body of work on online communities, many suggestions we present in the conclusions echo suggestions for the design of these communities in existing work (Preece, 2000).

(Kumar *et al.*, 2006a) looks at structural patterns of web-based social networks, including an analysis of LiveJournal, a network we use in this study. The authors are primarily interested in predicting the participation of users in different communities within the social networks, a topic not addressed in this article. We believe that their work fits well with the results we present, describing finer-grained internal behavior within web-based social networks, one level more specific than we analyze here.

(Kumar *et al.*, 2006b) performed an analysis of the social networks in flickr and Yahoo! 360 to develop a model of network growth. They studied the growth in membership, and how users were connected in the network. However, the networks used in their work are not typical of most web-based social networks. Flickr is primarily a photo sharing site, with the social network playing a very small role. Yahoo! 360 is integrated into most of the Yahoo! services, rather than existing as a stand-alone network, so connections can tend to be sporadic and isolated. As we discuss in section 3.4.1, the purpose of the websites have a significant impact on the characteristics of their social networks. Even though the behavior in these networks cannot be considered representative of other websites that are entirely dedicated to social networking, the paper does identify several features that our results support. Namely, we also describe the distribution of members as friendless (i.e. singletons), outsiders (isolated clusters, which they call the "middle region"), and a large central component.

2. Web Level Trends

2.1. Definition of Web-based Social Networks

There are many ways in which social networks can be automatically derived on the web: users connected through transactions in online auctions, users who post within the same thread on a news group or discussion forum (e.g. as in (Yeung, 2005)), or even members of groups listed in HTML documents can be turned into a social network. Many online communities and forums contain, by this loose definition, an implicit social network. In this work, we are only interested in websites that have an explicit representation of the social network, and where connections between people represent conscious statements of a relationships.

For inclusion in our survey, a web-based social network must meet the following criteria:

1. It is accessible over the web with a web browser. This excludes networks where users would need to download special software in order to participate and social networks based on other technologies, such as mobile devices.

2. Users must explicitly state their relationship with other people qua stating a relationship. Although social networks can be built from many different interactions, a WBSN is more than just a potential source of social network data; it is a website or framework that has the development of an explicit social network as a goal. This criteria rules out building social networks from auction transactions, co-postings, or similar events that link people when a connection is created as a side effect of another process.

3. The system must have explicit built-in support for users making these connections. The system should be specifically designed to support social network connections. This means that a group of friends who each maintain a simple HTML page with a list of his or her friends would not qualify as a WBSN because HTML itself does not have explicit built-in support for making social connections. There must be some greater over-arching and unifying structure that connects the data and regulates how it is presented and formatted.

4. Relationships must be visible and browsable. The data does not necessarily have to be public (i.e. visible by anyone on the web) but should be accessible to at least the registered users of a system. For example, some websites allow users to bookmark the profiles of other users and others allow users to maintain address books. Even when these lists are explicit expressions of social connections, they would not qualify a system as a WBSN if they cannot be seen and browsed by other users.

These criteria qualify most of the major social networking websites like MySpace, Facebook, Orkut, and CyWorld while ruling out many dating sites, like Match.com, and other online communities that connect users, such as Craig's List or MeetUp.com. Sites that require users to pay for membership are included as long as they meet the criteria above.

2.2. Growth in Number and Membership

As part of this project, we have been building and maintaining a list of networks at http://trust.mindswap.org/. In December, 2004 we completed our first list of WBSNs. Our goal was to find and list every website that met the criteria defined in section 2.1 and, where possible, to include an estimate of the number of members. Since 2004, we have added new sites as they come online and regularly updated membership statistics. Comparing the numbers from when we first completed the study to now, two years later, illustrates the growth in number and size of social networks on the web.

The number of social networking websites we discovered has almost doubled over the two year period, from 125 to 223. For each network we tracked the number of members. The total number of members among all sites grew four-fold from 115 million to 490 million.

The size of individual networks ranges widely from a few dozen members to over 100 million members. In 2006, the largest site (mySpace with more than 150 million members) is nearly an order of magnitude larger than the largest site in 2004 (Tickle with 18 million members). As would be expected with this kind of growth, the number of WBSNs with over a million members has increased sharply from eighteen in late 2004 to 41 in late 2006. While the number of sites has doubled and the total membership has increased manyfold, the *pattern* of distribution of members, as shown in figure 1, is basically the same.

3. Network Level Trends

Analyzing patterns in individual networks provides insight into the behavioral patterns of users. In this section, we look at the rates at which users join and leave the network, and at which they add and

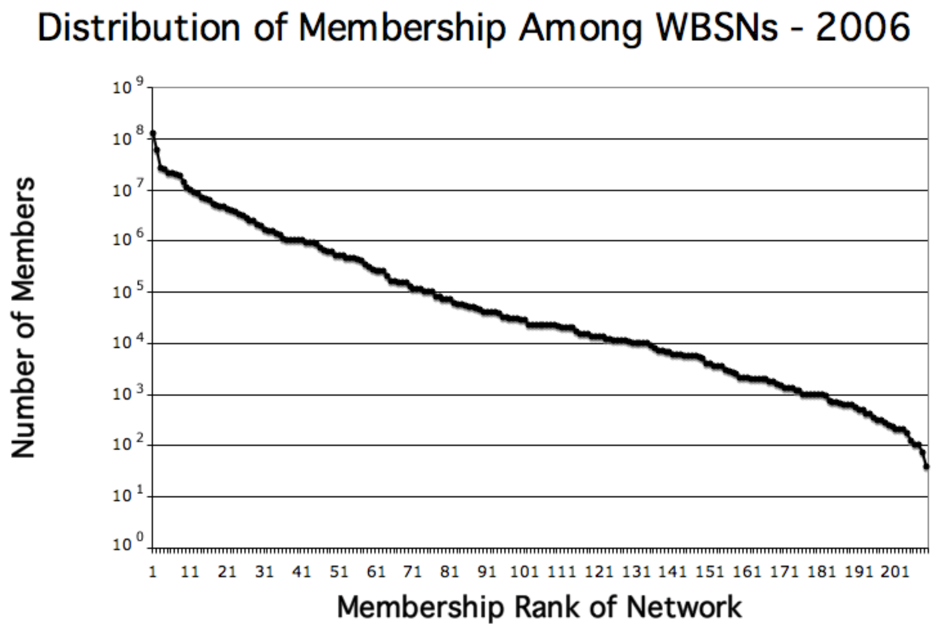


Figure 1: Distribution of members among social networking websites in 2004. Sites are ranked from the most populated to least. Note the y-axis is a logarithmic scale.

remove relationships, patterns of relationship formation, and how time and activity relate to the user's position in the network.

3.1. Networks Studied

We included thirteen social networks in our study. Some had user identification systems that allowed us to find information about all of the users. In others, we had to spider the central cluster of users to collect the data. Seven of these networks made the relationships of their members available in FOAF format (a machine processable Semantic Web vocabulary for representing social networks), which made it very straightforward to build adjacency lists.

For the networks where it was possible, we collected data every day, beginning at midnight, for forty-seven days. To the best of our knowledge, this is the first study to examine day-to-day patterns of membership and relationship dynamics in WBSNs. We were also interested in when members joined the network, and the last time they were active in the network. Some of the websites we used in this study provided that information and others did not.

In this section, we give a brief introduction to each network and explain what data we collected.

1. Buzznet

Table 1: Information collected for each social network in this study.

Network	URL	Number of Members	All Members	Join Date	Last Active Date	Adjacency Lists	Daily Adjacency Lists
Buzznet	http://buzznet.com	32,000		X		X	X
dogster	http://dogster.com	179,000	X	X		X	
Ecademy	http://ecademy.com	100,000	X	X	X	X	X
FilmTrust	http://trust.mindswap.org/FilmTrust	1,000	X	X		X	X
Fotothing	http://fotothing.com	8,400				X	X
Friendster	http://friendster.com	32,000,000	X			X	
GreatestJournal	http://greatestjournal.com	1,600,000		X		X	
HAMSTERster	http://hamsterster.com	1,350	X	X		X	X
Hipstir	http://hipstir.com	15,300		X	X	X	
LiveJournal	http://livejournal.com	11,000,000		X		X	
Mobango	http://mobango.com	1,100,000	X	X		X	
tribe	http://tribe.net	215,000		X	X	X	X
Worldshine	http://worldshine.com	5,500	X			X	X

Buzznet is a user-content oriented site, with movies, music, photos, and blogs. We collected join dates and a daily adjacency list for the central cluster.

2. dogster

   Dogster is a social network for dogs. Pet owners create profiles for their dogs, just like people do on typical social networking sites, and dogs make connections to “Pup Pals”. We gathered join dates for all dogs on the site, as well as a one-time adjacency list.

3. Ecademy

   Ecademy is a business oriented social network with 100,000 members. We gathered and adjacency lists, and join dates and last active dates for all members. Note that while Ecademy reports 100,000 members, we were only able to extract information for about 70,000. The rest of the profiles came up blocked, private, or with an error page when we were conducting our study.

4. FilmTrust

   FilmTrust is a social network where users rate movies, write reviews, and also rate the trustworthiness of their friends. This network was created as part of our related work (Golbeck, 2005), (Golbeck, 2006). Since the inception of the network we have logged every change in membership and relationships.

5. Fotothing

   Fotothing is a photo blogging website combined with a social network. Little information was available for individual users, but we collected daily adjacency lists of the central cluster.

6. GreatestJournal

   GreatestJournal is a blogging and photo sharing site based on the LiveJournal source code (see item 10). We were able to obtain the number of members who joined each day to see the growth pattern over three years.

7. Friendster

   Frendster was one of the original massively popular social networks, with nearly 32,000,000 users. Though it has recently lost popularity to mySpace.com, it is still an actively growing community. Because of the size, we could not collect daily information. We were able to gather a full adjacency list and member list to use in some of our analyses.

8. HAMSTERster

   HAMSTERster is a social network for hamsters. It is a small network, with less than 1,500 hamster-members. While the behavior in this network, like dogster, is not necessarily expected to be the same as what would be seen in normal human networks, we believe it will be in line with normal web-based social network behavior. We were able to collect join dates for all members and daily adjacency lists that include all members.

9. Hipstir

   Hipstir is a now defunct social network. It was originally a general social networking site. When we began this study, we spidered and collected the adjacency list of the central cluster, as well as the join date and last active date of all members in that cluster.

10. LiveJournal

    LiveJournal is a blogging website with an underlying social network. Because of the size - over 10,000,000 members - it was impossible to build daily adjacency lists. However, LiveJournal gathers and makes available data about the number of new members who have joined each day. We also collected a one-time adjacency list of the central cluster for analysis.

11. Mobango

    Mobango advertises itself as "The complete way to discover mobile media and share it with friends". The site is designed to search, share, and download media for mobile phones, such as ringtones and backgrounds. While media sharing is its main purpose, a social network is layered on top of the site. We were able to gather a full member list with the join date for each member, as well as a full adjacency list.

12. tribe

    Tribe is a community-oriented social network, with over 45,000 communities (or "tribes"). Because we did not have access to the full membership list, we had to collect information on only the central cluster of users. Foe them we collected join dates, last active dates, and daily adjacency lists.

13. Worldshine

    Worldshine is a travel site. It provides tools to book flights and hotels, and find information about destinations. The social networking component is an additional feature. We have collected a full member list and adjacency list from the site.

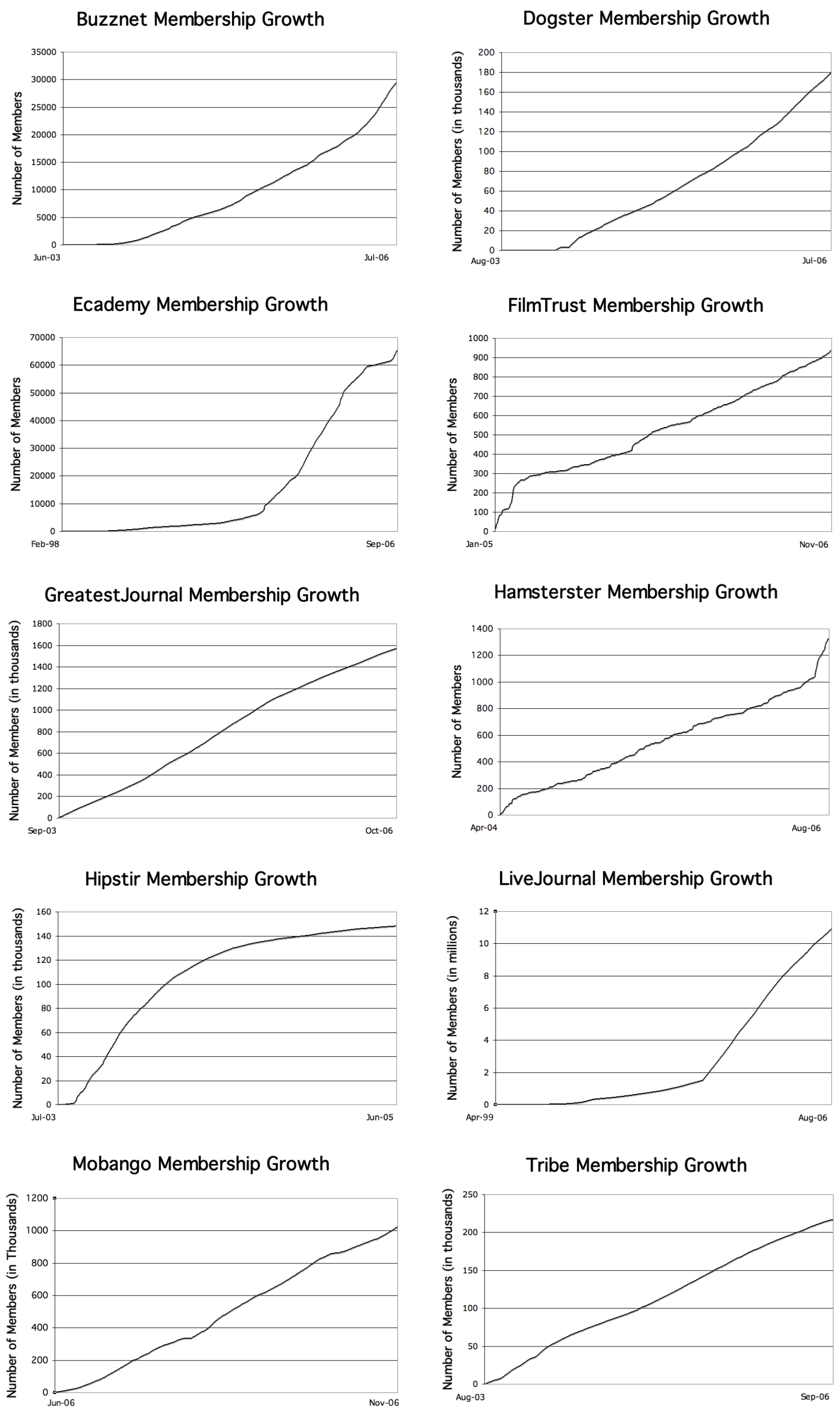
3.2. Patterns of Network Growth

For ten networks, we obtained data on the number of new members who joined each day over the network's history. As can be seen in the figures in table 2, there are simple trends in the growth patterns. Most networks have a linear growth rate.

In some networks, there are points where there is a clear shift in the slope. For example, LiveJournal shows a sharp increase in December of 2003 where the number of new members jumped from around 2,000-2,500 per day to around 10,000 - 12,000 new members per day. That sharp change occurred precisely when LiveJournal started airing commercials in Regal Cinemas during the Lord of the Rings movies[1]. Hamsterster also shows a significant increase in the rate of growth toward the last couple months in the chart. That corresponds with a brief mention in the July 17th, 2006 issue of Newsweek(Hamwi, 2006). FilmTrust, on the other hand, decreased its rate of growth after March, 2005. FilmTrust was designed as part of the author's dissertation project, and users were actively recruited until the April 1, 2005 defense. Since that point, it has been growing on its own, but at a lower rate than where there was active recruiting.

[1]http://news.livejournal.com/73540.html

Table 2: Membership growth patterns in ten web-based social networks



Ecademy's growth rates shift at several points. From its inception until 2002, Ecademy pitched itself as a business education network. In 2002, it changed its focus to business networking, and saw a sharp increase in the rate that members joined. That rate remained relatively steady until recently. There was a lag in membership growth from November, 2005 to June, 2006, followed by another sharp increase. The drop in growth in November corresponds with a site redesign[2], and the resumption of the previous higher growth rate in June, 2006 corresponds with a package of new features, such as integration with Skype, Google Maps, and the release of some user guides. However, for both of these changes, it is unclear whether the items we have identified or some other factor is responsible.

Hipstir, on the other hand, shows a different pattern, with membership growth that was logarithmic. This is a sign of a dying network, where members stop participating, stop inviting friends, and fewer new people are joining. Note that the data we have on Hipstir only goes to mid-2005, unlike all the other networks where we have more current numbers. This is because Hipstir went offline sometime in mid-2006. Our inquiries to site administrators and domain owners were not answered, so the reasons for closing the site are uncertain, but the decline in new members was almost certainly a factor.

These networks range widely in their purpose (business to blogging to pets) and size (from around 1,000 members to 10 million members). However, this analysis shows that regardless of these issues, living networks tend to grow at a linear rate, which is affected up or down mostly by publicity and recruitment. Most people are simply unaware of most of these sites (who knew that there was even a possibility for a hamster social networking site?). Discovery in a place like a major magazine movie trailer opens up the number of people aware of a network, and as they join, there is an increase in invitations and awareness spread by word of mouth.

3.3. Profile Deletion

The figures in section 3.2 are based on the new members who joined each day. A question that is relevant to growth, and potentially more interesting, is the rate at which members *leave* a network. It takes some effort to delete an account from a social network, and a common intuition is that it is easier to just abandon the account and never use it. Understanding the rate at which people leave informs how to treat analysis of the network.

In Buzznet, Ecademy, FilmTrust, Fotothing, and Tribe, we tracked the number of accounts that disappeared during our 47-day observation. For three of the observed networks - Ecademy, FilmTrust, and Fotothing - no members left. In fact, we were able to look at the *full* history of Ecademy and

[2] http://www.ecademy.com/node.php?id=39557&seen=1

Table 3: Net change in relationships in social networks over a 47 day period

Network	*Removed*		*Added*		*Net Growth*	
Buzznet	6,418	(1.82%)	135,158	(38.38%)	128,740	(36.56%)
Ecademy	1,774	(0.66%)	26,751	(9.92%)	24,977	(9.26%)
Fotothing	2,059	(2.73%)	11,314	(14.98%)	9,255	(12.26%)
Tribe	11,211	(0.50%)	180,936	(8.08%)	169,725	(7.58%)
FilmTrust	1	(0.001%)	399	(31.7%)	398	(31.6%)

FilmTrust. In Ecademy, we did not find any completely missing accounts beyond fourteen of the original twenty-five, indicating that essentially no users have terminated their accounts in the eight years that the site has been active. Similarly, only eight members left FilmTrust in the two years it was active.However, there were no instructions we could find in any of these websites on what a user needed to do in order to cancel an account. We believe this is the main factor for not losing any members. The next two websites seem to support that.

Buzznet and Tribe both saw some members leave. Tribe lost 569 members over the 47 day period, or an average of about 12 members per day. This represents 0.23% of the population removed over the time we surveyed. However, with 9,666 new members joining in the same period, the members who left had only a small impact on the growth rate of the network. Buzznet also saw 77 members, or 0.24% of the membership, leave. We believe these networks saw more members leave because, unlike the others, both have easy to find instructions on how to delete profiles.

3.4. Relationships

Relationship formation is the "social" part of social networking. Just as we saw memberships increase, the number of relationships also grew significantly in all the networks we considered.

When we compare the growth in relationships to the growth in membership, we see that for Buzznet, FilmTrust, Fotothing, and Tribe, the increase in relationships outpaced the growth in membership significantly (by 1.86, 2.51, 2.71, 1.68, and times respectively). This would suggest that the networks are becoming more densely connected as they grow. In Ecademy, growth in relationships grew more slowly than membership, at a ratio of 0.76.

The removal of relationships is easier than removing a whole profile from the network. All the websites we studied had very straightforward mechanisms for removing friends, usually with a link on the friend's profile page. However, the social implications of deleting friends can discourage users from doing so. Furthermore, little is gained by deleting friends; indeed, many people strive to get as many friends as possible. As a result, we see a much slower rate of relationship removal than relationship

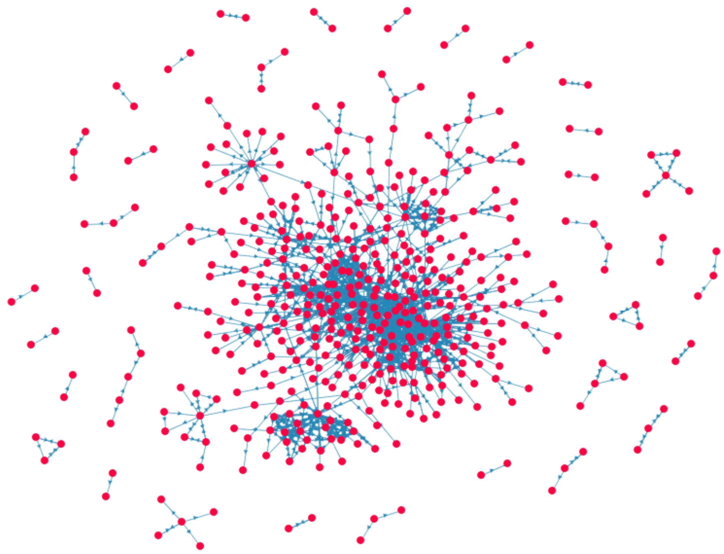


Figure 2: The FilmTrust social network. Users who are not connected into the main component and are seen in the small clusters scattered around the edges.

Table 4: Number of Friendless and Outsiders given as a percentage of the total number of members, and the actual number of members

Network	*Membership*	*Friendless*	*Outsiders (including Friendless)*
Dogster	184,875	10.4% (19227)	10.6% (19597)
Ecademy	11,805	30.7% (3403)	32.0% (3547)
FilmTrust	954	45.8% (437)	56.8% (524)
HAMSTERster	1,321	13.7% (181)	27.8% (368)
Mobango	1,029,047	99.7% (1,025,509)	99.7% (1,026,438)
Worldshine	5,250	98.7% (5,181)	98.7% (5,181)

addition.

Table 3 shows the total number of relationships that we found removed in the networks over the 47 day period where collected daily trends. For all the networks, the number of removed relationships is a very small percentage of the overall number of relationships in the network. Furthermore, the number of removed relationships many times smaller than the number of new relationships. These numbers indicate that users will add new friends, but delete people who are no longer friends much less frequently.

3.4.1. The Friendless and the Outsiders

The study of social networks focuses on connections between people. In web-based social networks, much of the services and features are also based around social connections. However, it is not uncommon for people to join these sites and make no friends. The extent to which these friendless members exist has not been addressed.

For the six networks in this study where we had a full member list as well as an adjacency list (Ecademy, Dogster, FilmTrust, Friendster, HAMSTERster, and Worldshine), we computed the number of friendless members.

As shown in table 4, the percentages of friendless users vary widely from network to network. This is explained by how much of non-networking functionality each site has. The lowest percentage of friendless members are among the pet sites, where the purpose is entirely social and there are few factors preventing people from connecting (i.e. it carries fewer implications to say "my dog wants to be friends with your dog" than to say "I want to be friends with you"). The next level are more traditional social networking sites, Ecademy and Friendster, where the purpose is to make social connections. The friendless rates in these sites is about 30%. FilmTrust, with a friendless rate of 44%, is much higher. We believe that is because the site has a purpose other than social networking. Members can join just for the movie information. Mobango and Worldshine have basically no social activity in their social networks but have other rich functionality. Worldshine is primarily a suite of travel tools and information and Mobango is a site where users download ringtones and pictures for their mobile phone. In both sites, members are most likely joining for the features, and have little motivation to participate in the social network.

We also consider a slightly larger group: the *outsiders*. Outsiders include all the friendless, plus members who have some social connections, but who are only members of small groups that are not connected in to the main central cluster. Essentially, the outsiders are people who are not connected into the large main group in the social network. For example, figure 2 shows a visualization of the FilmTrust network. Friendless members are not shown, but from this picture, it is easy to identify the small clusters of outsiders scattered around the main central group.

In the two smaller networks, FilmTrust and HAMSTERster, the number of outsiders is significantly larger than the number of friendless members. In the other networks, there is a small increase, but nearly all outsiders are totally friendless.

3.5. Centrality

Figure 2 shows a typical clustering pattern of a social network. The large central cluster contains a majority of the users. For each node, centrality measures how close it is to the center. Centrality is an important measure of influence and activity in social networks(Freeman, 1979),(Wasserman & Faust,

Table 5: Rank Correlation of Centrality with Join Date, Last Activity, and Activity Duration

Network	*Join Date*	*Last Activity*	*Activity Duration*	*Number of Friends*
Ecademy	0.11	-0.29	-0.47	-0.72
Hipstir	-0.07	-0.51	-0.55	-0.90
tribe	0.04	-0.29	-0.39	-0.50

1994), and we are interested in what factors affect the centrality of nodes in WBSNs.

We were particularly interested in the role played by the age of a node, the last active date of a node, and its centrality. We measured centrality as the average shortest path length. There are many measures of centrality, but we were interested in how close nodes were to the center of the main cluster; average path length (APL) is a good measure of this.

Three networks made join and last activity dates available for their users: Ecademy, Hipstir, and tribe. Using the adjacency lists we computed the APL for each node in these networks. We collected several parameters for each person in the network:

1. Join date: When the person joined the network.
2. Last Activity: The last time the person logged into the network.
3. Centrality: The average shortest path length between the person and everyone else in the network, computed using the network adjacency list.
4. Length of Activity: The time between the join date and the last active date indicates how long the user has actively been using the network.
5. Number of Friends: The number of friends a person has.

To see the relationship between centrality and the temporal measures, we computed the rank correlation (Spearman's ρ) of APL and join date, last active date, and duration of activity. Rank correlation was more appropriate than a standard Pearson correlation because the growth patterns of Ecademy and Hipstir were not linear, and thus we may not expect a linear relationship between dates and other features.

As table 5 shows, there is no significant correlation between centrality and join date in any of the networks. Last activity correlates more strongly with centrality, but duration of activity has a highest correlation of the temporal measures. Note that this and the other measures have a negative correlation, indicating that as the time measure increases , APL decreases (indicating a more central node).These results indicate that active members tend to be more central than members who have not logged in recently. Furthermore, the longer users have been active, regardless of the actual date they joined or their date of last activity, the more central they are. All three networks show a medium strength correlation with centrality and activity duration.

These results have intuitive explanations. Being active in the network means more opportunities to create social connections. The more social connections a person has, the more likely they are to lower their average shortest path length. If users stop participating in the network, they have no chance to grow closer to newer members. Users who have joined more recently have a greater chance of connecting to people close to the center, and thus having a smaller APL. Members who have been active longest tend to have the lowest APL (and thus highest centrality) because they have had the longest amount of time participating in the network to make connections. For all three networks, the number of friends a member has is the variable that correlates most strongly with centrality.

3.6. Conclusions

This network-level analysis provides insights into many aspects of web-based social network dynamics. The general conclusions we draw are as follows:

- Membership Growth: As a rule, the membership of networks will grow at a linear rate. The rate of growth can be affected positively or negatively by publicity. The only exception we found was Hipstir, where the network was in decline.
- Profile Deletion: Members rarely delete their profiles from social networks. When there is a clear and easy mechanism for deletion, some people will take advantage of it, but they represent a tiny fraction of the population of the network.
- Relationship Dynamics: Users add relationships frequently, and in most of the networks we looked at, the networks grew denser, with relationships growing more quickly than the number of new members. Users will also delete relationships, but at rates that are orders of magnitude less frequent than they add relationships.
- Social Disconnection: The percentage of users who are disconnected from the main cluster, or who are completely socially isolated, varies widely among social networks. As non-social features of the website are more important, the percentage of socially disconnected users increases.
- Centrality: The users who tend to be toward the center of the cluster, not surprisingly, are the users with the most number of friends. They also tend to be users who have been active longer

in the network.

4. Discussion and Future Work

In this article we present a study of web-based social network growth and dynamics, using many networks and data collected over two years. Our work shows a dramatic growth in the number and size of social networks. We have also shown the patterns of users joining and leaving networks, forming and breaking relationships, and their role and position in the network.

Many differences among networks can be explained by the design of the network. We saw that the number of friendless and socially disconnected people is much higher when networks have some other purpose than social networking. Mobango, for instance, has over a million users but only a few thousand participate in the social network. Unlike pure social networking websites (e.g. Dogster, Ecademy), where users only join if they are interested in using the network, websites with other motivations need to offer incentives for users to participate. Ideally, this would integrate the social network into features of the website, as is done with FilmTrust. In FilmTrust, users can choose to ignore the social network, but they are given additional features (e.g. ranked movie reviews and recommended ratings on movies) if they participate.

When extracting the explicit social network information from a site for analysis, it is important to consider these design features. How the site is designed, how it encourages the formation of social connections, and what the other features of the site are will all affect how the social network evolves. Furthermore, dynamics and behavior of members change based on how straightforward it is to perform certain actions. For example, our results suggest that there are big differences in how frequently profiles are deleted due largely to how easy the process is explained. This connection between usability and action is important to consider when studying behavior and dynamics of WBSNs, and especially when comparing different networks.

We have analyzed the patterns of network growth and dynamics of networks on the web level and the network level. We did not look at community behavior within the networks, nor at egocentric trends, such as when users are more likely to add relationships, what network features correlate with the number of friends a person has, and how the number of friends each person has correlates with profile features (and with reality). As mentioned earlier, (Kumar *et al.*, 2006a) presents results on factors that cause users to join and leave communities. We are in the process of examining egocentric trends, which we will address in future work.

5. Acknowledgements

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