Volume 5, Issue 1
January 2012
ISSN: 1946-1836

JOURNAL OF INFORMATION SYSTEMS APPLIED RESEARCH

In this issue:

The **Journal of Information Systems Applied Research** (JISAR) is a double-blind peer-reviewed academic journal published by **EDSIG,** the Education Special Interest Group of AITP, the Association of Information Technology Professionals (Chicago, Illinois). Publishing frequency is currently quarterly. The first date of publication is December 1, 2008.

JISAR is published online (http://jisar.org) in connection with CONISAR, the Conference on Information Systems Applied Research, which is also double-blind peer reviewed. Our sister publication, the Proceedings of CONISAR, features all papers, panels, workshops, and presentations from the conference. (http://conisar.org)

The journal acceptance review process involves a minimum of three double-blind peer reviews, where both the reviewer is not aware of the identities of the authors and the authors are not aware of the identities of the reviewers. The initial reviews happen before the conference. At that point papers are divided into award papers (top 15%), other journal papers (top 30%), unsettled papers, and non-journal papers. The unsettled papers are subjected to a second round of blind peer review to establish whether they will be accepted to the journal or not. Those papers that are deemed of sufficient quality are accepted for publication in the JISAR journal. Currently the target acceptance rate for the journal is about 45%.

Questions should be addressed to the editor at editor@jisar.org or the publisher at publisher@jisar.org.

JOURNAL OF INFORMATION SYSTEMS APPLIED RESEARCH

Editors

JISAR Editorial Board

Measuring Propagation in Online Social Networks: The Case of YouTube

Amir Afrasiabi Rad
a.afrasiabi@uOttawa.ca
School of Electrical Engineering and Computer Science

Morad Benyoucef
Benyoucef@Telfer.uOttawa.ca
Telfer School of Management

University of Ottawa
Ottawa, Ontario K1N 6N5, Canada

Abstract

We conducted a propagation analysis on an open social network, i.e., YouTube, by crawling one of its friendship networks and one of its subscribers (followers) networks. Our study is unique because it investigates the two main types of connections (i.e., friends and followers) within the same environment and interaction features. We observed that the effect on propagation of people who are not either in a friendship network or a subscription network is higher than that of friends or subscribers. Meanwhile, we found that even though the network of subscribers was denser than the network of friends, the magnitude of propagation in the subscription network was less than in the friendship network. We also noticed a low correlation between the popularity of content and its propagation in general, with a greater correlation in subscription networks than that in friendship networks.

Keywords: Social Network, Social Link Type, Information Propagation, Viral Marketing, YouTube

1. INTRODUCTION

Social networking websites, such as MySpace, Facebook, Twitter, Flickr, Orkut, YouTube, etc. are becoming more and more popular. To illustrate this popularity, it is enough to refer to social networks' usage statistics. In the US alone, social networks attracted more than 90% of all teenagers and young adults (Trusov, Bodapati, & Bucklin, 2010). More than 35 hours of videos are uploaded on YouTube every minute (YouTube LLC., 2010); and over 750 million active Facebook users share more than 30 billion pieces of content, and spend over 23 billion minutes on Facebook every month (Facebook Inc., 2011). The increase in the user population of social networks leads to a rise in user interaction, and ultimately higher volumes of generated and distributed content. This massive popularity of social networks, and their high user-base and user participation rates, along with the enormity and variety of user generated content turned social networking sites into hubs of social activity, and shaped them into a new generation of information mediums. Moreover, the interconnectivity of users in online social networks allows user generated content to be easily propagated through the whole social network.

The above mentioned facts attracted the attention of the marketing community. These unique characteristics of social networks provide the opportunity to harness the collective opinions of the population in order to shape user behavior and design marketing campaigns while

gaining insights about future market trends (Asur & Huberman, 2010; Bearden, Calcich, Netemeyer, & Teel, 1986; Leskovec, Adamic, & Huberman, 2007). Furthermore, the possibility of content propagation along the social links builds a huge community of users who can be seen as viral advertisers. Many studies have been conducted to analyze the opportunities of viral advertisement on social networks (Bearden et al., 1986; Van den Bulte & Joshi, 2007; Domingos & Richardson, 2001; Duan, Gu, & Whinston, 2008; Evans, 2009; Hu, Tian, Liu, Liang, & Gao, 2011; Kempe, Kleinberg, & Tardos, 2005; Kim & Srivastava, 2007; Stephen & Toubia, 2009). Most of these studies analyzed the advertisement value (aka influence) of a user on his friends. However, knowing that word-of-mouth is not distributed in the absence of propagation, only a few studies investigated the information propagation and its patterns. Meanwhile, some papers relied on the results of studies on propagation in offline social networks (Van den Bulte & Joshi, 2007), but these results are not necessarily valid in online environments (Howison, Wiggins, & Crowston, 2011). In general, while the cascade of information in social networking websites is generally observed, there is little data available on viral propagation in the online world, and studies on how and why the propagation occurs have received little focus. At the same time, little attention has been dedicated to measuring and characterizing the propagation of information in online social networks.

As mentioned earlier, online social networks are different and most probably follow different information dissemination patterns compared to offline social networks. Three of the major differences that affect propagation, are (a) the fact that communication can be either one-way or two-way - one-way communication is not usually seen in offline social networks; (b) due to the ease of information transmission on online networks, nodes have access to more friends instantly, so a broadcast message can easily be transmitted to many friends at once; and (c) there is more than one definition for links between nodes, as they can be defined as friendship links (those who mutually follow each other), and follower links (those who follow others without the others necessarily following them). There is, nonetheless, another important difference that deals not with the structure of the network, but with the online environment: information on online social networks is easily and readily available, whereas gathering offline social network data takes much more effort and time (Howison et al., 2011). The abundance of information gives us the opportunity to analyze online social networks for understanding the speed and magnitude of information propagation. We are also interested in evaluating the role of friends as opposed to followers in the information propagation. In order to achieve this, we evaluated information propagation on the YouTube social network. We chose YouTube because it provides the opportunity to analyze the role of friends and followers in the context of content propagation without switching between different environments and different features. The results of our study may be of interest to the online marketing community since the results may guide online marketers in choosing the more suitable social network (friendship or follower) for their viral marketing campaigns.

The rest of the paper is organized as follows. The next section reviews previous studies on content propagation. Section 3 describes the YouTube social network and its characteristics. In Section 4 we explain our data extraction method, and describe our collected data. In Section 5 we analyze the propagation magnitude on YouTube. In Section 6 we investigate the correlation of propagation and popularity. Discussion and conclusion are provided in Sections 7 and 8.

2. BACKGROUND AND MOTIVATION

There is abundant literature on the theory of propagation and new product diffusion in marketing science research (Bakshy, Karrer, & Adamic, 2009). Some models, such as the Bass model (Bass, 2004), focus solely on the behavioral aspect of propagation, and leave out the structural component of social networks. They suggest that a greater number of content generators, independent of where in the network they are located, lead to a higher propagation rate. On the other hand, models that studied the structure of social networks (Chatterjee & Eliashberg, 1990) have not been tested extensively in different networks with various structures (Bakshy et al., 2009). Therefore, those studies are still in the theoretical phase. Our current research, along with others mentioned in this section, tries to provide some empirical results on top of the theory to help in understanding social propagation and developing more realistic theoretical models.

Among the few studies that had focused on propagation patterns in social networks is the study of Flickr to measure the propagation of photos (Cha, Mislove, & Gummadi, 2009). The authors collected and analyzed a large longitude of user interactions on Flickr. They found that popularity has a loose relationship with propagation, as the popular photos were not propagated more than an average of three hops in the social network. They also observed that the propagation takes a much longer time than what is expected by marketing research. However, they could conclude that more interaction accounts for an important factor in the extent of propagation and can also expedite the propagation process. However, the study only considers friendship relations (two-way relations), and leaves out follower relations (one-way relations), which are found in abundance in online social networks.

In a different study (Huberman, Romero, & Wu, 2008), the dissemination of information on the Twitter social network is analyzed from a friendship point of view. The authors analyzed a large dataset of Twitter data to find posts, friendships, and interactions among users. The findings show a strong relationship between the number of posts and the number of followers meaning that more followers result in more encouragement for posting. However, the number of posts eventually saturates. The interesting finding is that in case of friends (who have a two-way relationship), the number of posts follows the same pattern, but it never saturates. It is also important to note that the number of friends may saturate, but the number of followers may grow indefinitely. Therefore, the authors conclude that the visible network of interactions is not the true representative of the actual hidden network that influences the propagation.

In another study, Yoganarasimhan (Yoganarasimhan, 2010) studied the effects of network structure on propagation, and discovered that in addition to the effect of neighbors' behavior, the size and structure of the initiator's network (initiator here means initiator of the content) have a great effect on the magnitude of propagation. The author calculated the centrality metrics for YouTube users, and discovered that as the size of a community increases, the central nodes of that community have a better chance of propagating their videos.

On the other hand, Cheng et al. (Xu Cheng, Dale, & Jiangchuan Liu, 2008) evaluated the relationships between YouTube videos. According to the authors, the statistics related to YouTube videos are very different from statistics of other video sharing websites. They related these differences to the social nature of YouTube, and their analysis of relations between YouTube videos confirmed this hypothesis by showing a "small world" network between YouTube videos. Although Cheng et al. evaluated the role of each YouTube video in the propagation of similar videos; they did not investigate the role of the underlying social network of video uploaders (initiators) in this propagation.

Baluja et al. (Baluja et al., 2008) conducted a similar study but took a different direction. They developed an algorithm to facilitate the propagation of preferences in social communities. They applied their algorithm on YouTube considering it a network of videos. They, therefore, reached similar results as Cheng et al. (Xu Cheng et al., 2008), confirming that YouTube's graph of videos is an effective system to propagate videos online. But they did not measure the effects of user social networks on video propagation.

On the other hand, studies such as the one by Lange (Lange, 2007) pointed out the importance of user social networks on YouTube video propagation. The author extracted user behaviors from the network of users based on video preferences, and discovered a similarity of behavior among friends, and suggested a potential for propagation in such social networks.

3. THE YOUTUBE SOCIAL NETWORK

YouTube, a subsidiary of Google, is the largest video sharing website containing about 43% of all videos found on the Internet (comScore 2010). Since its launch in 2005, the popularity of YouTube has consistantly increased, and more web users, from various demographics, registered on this video sharing website to benefit from its contents and features. Statistics from 2010 state that more than 35 hours of video are uploaded to YouTube every minute (YouTube LLC., 2010). But YouTube is not just a video sharing website. It also accounts for being a social network since it has a large number of registered users (i.e., channels) who can upload videos, follow other channels (i.e., subscribe),

Table 1. Statistics of collected data for friendship network

Data Description	*Statistics*
#Users	8,984
#Videos	113,562
#Friendship-links	8,986

Table 2. Statistics for collected data for subscribers' network

Data Description	*Statistics*
#Users	9,633
#Videos	332,296
#Subscription-links	40,358

and be friends with other channels. Thus, there are many channels in YouTube with millions of friends and subscribers (YouTube LLC., 2010). Most importantly, in order to fully qualify as a social network, YouTube has to enable users to communicate with each other. YouTube satisfies this requirement by implementing a broad infrastructure that allows users to communicate with each other in many different ways which resulted in users commenting on nearly 50% of YouTube videos (YouTube LLC., 2010). YouTube's communication infrastructure includes the following features:

- Private messaging: channels can send private messages to each other
- Commenting on channels: channels can comment on other channels
- Commenting on videos: channels can comment on videos posted by themselves or other channels
- Marking a video as favorite (favorite marking): channels can favorite uploaded videos
- Publishing video descriptions: the uploader channel can write a video description for its uploads
- Liking or disliking a video description or a comment (rating): channels can like or dislike video descriptions or comments that are posted by other channels
- Replying to a comment: every channel can reply to a comment. This is simply the act of commenting on comments.

YouTube provides the advantage of allowing two types of relationships between channels: friendship, which creates a two-way relationship for channels, and subscription, which allows channels to get updates on any other channel while having a one-way relationship with those channels. This feature allows us to evaluate our model on friendship and subscription on the same social network with the same communication features. Note that since private messages are not extractable, from an external observer's view point, the communication features are the same for both friends and subscribers. The existence of this feature is very important as it gives the opportunity to analyze the behavior and communication patterns of friends and subscribers, as well as their influence on content propagation.

4. DATA COLLECTION

Google (YouTube owner) published a library of APIs and tools that enable developers to connect their applications with Google products. APIs are a set of message formats that facilitate communication between different applications. In order to collect data we used YouTube APIs (http://code.google.com/apis/youtube/overview.html), and crawled a subset of the YouTube network. We randomly selected a YouTube video and chose its uploader as our starting point. In addition to recording all publicly available communications, uploads, and their information, we located the uploader's friends and subscribers. We continued crawling by performing the same tasks for the friends and subscribers. Note that we conducted this operation separately for friends and subscribers, as each has its own network hierarchy. In this way, only for the friendship network, we collected a subset of 9000 users, which resulted in data on 110 thousand videos and 16 million interactions in a snowball sampling method. We should mention that we collected the interactions as signs of content propagation because YouTube has a system that reveals recent activities of friends and subscribers, so every comment is visible to all neighboring nodes. We did not evaluate the content of comments, so spam might be among our collected data. However, considering that we are mainly interested in comments made by friends or subscribers or their networks, the amount of spam can be small compared to meaningful comments, the small error created by spam can be ignored. Table 1 and Table 2 contain the statistics of our collected data.

YouTube Statistics

Analysis of the extracted network of YouTube (from this point on, we refer to the extracted subset of YouTube as simply YouTube network) users shows that with the extraction of about

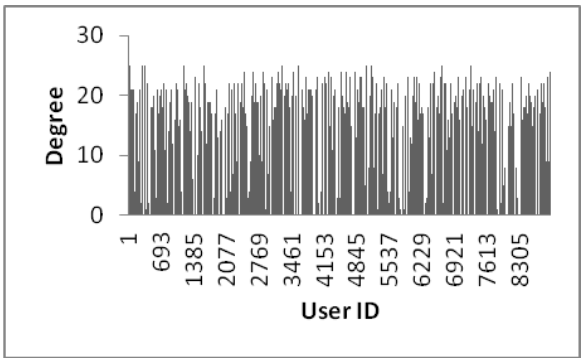

Figure 1. Degree distribution in friendship network

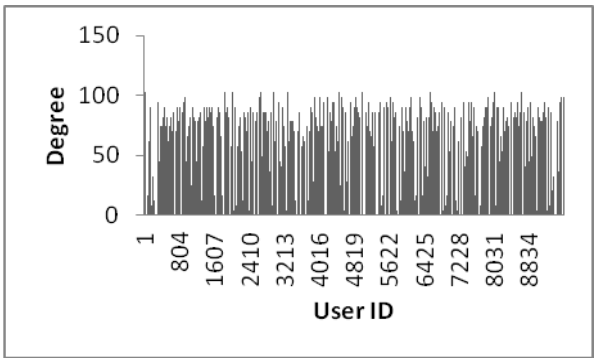

Figure 2. Degree distribution in subscription network

9000 friends using snowball sampling, we reached a maximum of 5 hops from the seed user. This shows the connectedness rate in the friendship network in the YouTube social network. Each user has an average degree of 2, with variance of 16.28, and 8301 users having only one friend, and the highest number of friends for a user in our sample is 26 (Figure 1). These statistics mean that users tend to have a small number of friends on YouTube.

On the other hand, statistics for the subscription network are different. Every user is subscribed to an average of 7 channels, with a maximum of 103 subscriptions (Figure 2). However, the number of users with zero subscription is still high and is equal to 3046. This means that the ease of subscription and lack of necessity to be approved by the other user are factors that encourage users to subscribe to other channels rather than create a friendship link. These statistics help us understand the underlying network structure of the crawled data.

Table 3. Video propagation Methods in YouTube

Propagation Method	*Description*
Sharing	Users can share YouTube videos by email, posting on blog, etc.
Recommended Videos	Videos that are recommended by YouTube based on user's previous visits.
Featuring	YouTube features some videos on its first page.
Suggested Videos	Videos that are similar to the video that the user is watching
Search Results	Videos that appear in search results
Recent Activities	Videos that were involved in recent activities of user's

Figure 1 and Figure 2 reveal an interesting fact about the networks of friendship and subscription. On the charts, the two networks seem to have similar distributions. We normalized the variances of both datasets, and the close values of variance (18.54 and 16.28) confirm this observation. Therefore, without considering the type of social network, the distribution of links follows a similar trend.

Limitations in data collection

Unfortunately, YouTube does not keep track of more than 7500 comments for each video, so we could not evaluate the speed of propagation. However, the most popular video was uploaded in 2006, and still receives comments. All the first thousand popular videos received their last comment on the day of data collection in 2011.

Moreover, this limitation may affect our results if friends and subscribers were among the people who commented first on the videos. To measure this effect, we selected a smaller dataset of videos with less than 7500 comments and ran the analysis on them. Our analysis, nevertheless, showed similar results on propagation magnitude, and its correlation with popularity.

5. PROPAGATION IN YOUTUBE

YouTube data can be propagated by different means, and is not restricted to commenting inside the YouTube network. These methods range from inside network propagation to exporting the video on a personal blog or website. Table 3 provides a set of methods that contribute to content propagation in YouTube.

Table 4. Propagation of videos in friendship network

Propagation Magnitude	*#Videos*	*%Propagated Videos*	*%Total Videos*
1 hop	1289	96.84%	1.14%
2 hop	40	3.00%	0.04%
3 hop	2	0.16%	0.01%

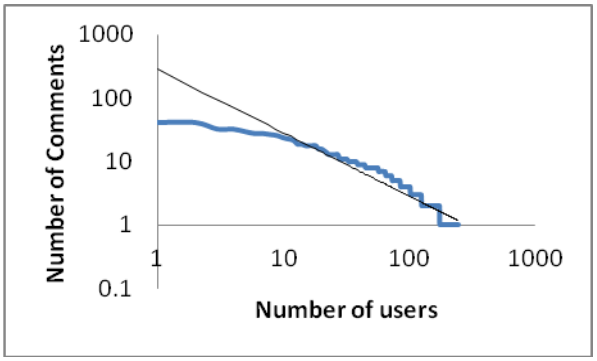

Figure 3. Distribution of comments per

Since we are interested in content propagation on YouTube that is generated by friends or subscribers, we are interested in the users' recent activities (i.e., five most recent uploads, commenting, rating, etc. that appear on every user's profile page) that are visible to friends and subscribers. Rating, favorite marking, Commenting on a video, and uploading a new video are the commonly observed recent activities, with rating being the most common one. As YouTube does not allow access to ratings or favorite markings per user, we only extracted the networks of users who commented on each others' videos. These networks include data on comments that are made on videos by users who have a path through friendship or subscription to the uploader. In other words, we eliminated from our analysis comments that were not made by friends, subscribers, and their networks.

Propagation Magnitude in YouTube

The first step in analyzing the propagation is to analyze the magnitude, or the longest hop, by which data propagates. Our dataset of 5 hops shows interesting results. We discuss them in the friendship and subscription datasets.

Propagation Magnitude in Friendship Network

We recorded a total 16.4 million interactions on videos that are posted in our friendship dataset.

Table 5. Propagation of videos in subscription network

Propagation Magnitude	*#Videos*	*%Propagated Videos*	*%Total Videos*
1 hop	269	96.76%	0.88%
2 hop	9	3.24%	0.03%

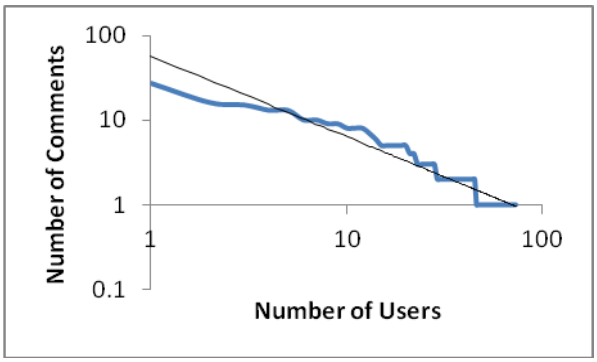

Figure 4. Distribution of comments in

Since we are only interested in interactions between friends, we pre-processed our data to extract the underlying network of interactions between friends. This resulted in a huge reduction in our sample graph. This illustrates our first finding: in an open social network, the amount of interactions between strangers accounts for a high percentage of the total interactions.

This finding is verified by a reduction of our captured interactions to 133 thousand interactions, a reduction rate of 98.76%, when we filtered out the interactions between channels that do not have a friendship path to the uploader node.

Analysis of propagation in the friendship network revealed that videos are propagated at most to three hops of friends (a hop denotes a link between two levels of friendship). Meanwhile, the distribution of propagation reveals that only a small fraction of the videos is propagated to the second and third levels of friends (Table 4). The propagation of videos through friendship is not significant. However, looking at the users involved in propagating the videos suggests that a huge part of propagation is carried out by a small number of users. We observed that the commenting pattern in the friendship network follows a power law distribution with the exponent of 0.90, meaning that the contents are highly propagated through a small number of highly active users (Figure 3).

Propagation Magnitude in Subscription Network
In the same way, we recorded a total 44.7 million interactions on videos that are posted in our subscription dataset. Since we are only interested in interactions between subscribers, we pre-processed our data to extract only the interactions between subscribers. Similar to the friendship network, this resulted in a huge reduction in our sample graph. The captured interactions were reduced to 27 thousand, much less than the interactions in the friendship network. This reduction has a rate of 99.93%, which means that almost all interactions happen between users who do not have a path through subscription. This was a surprise because since the connectedness of the subscription network is far higher than the friendship network, it was expected that subscribers have more effect on propagation than friends. The low effect on propagation may be due to lower personal connection between subscribers, hence subscribers are less inclined to leave comments. Meanwhile, our analysis of propagation in the subscription network revealed that videos are propagated at most to two hops of subscribers. Moreover, the distribution of propagation suggests that only a small fraction of the videos are propagated to the second level of subscribers.

Similar to the friendship network, the propagation of videos through subscription is not significant. However, looking at the users who are involved in propagating the videos still suggests that a huge part of propagation is carried out by a small number of subscribers. We observed that the commenting pattern in the subscription network follows a power law distribution with the exponent of 0.93, meaning that the content is highly propagated through a small number of highly active users (Figure 4).

6. PROPAGATION AND POPULARITY

In the next step, we investigated the popularity of videos in relation to their propagation, in order to understand whether the popularity of videos drives or is driven by propagation, or if friends and subscribers choose the videos to comment on based on other considerations. To do so, we selected a set of ten highly propagated videos in addition to ten highly popular videos from each dataset, and evaluated the correlation of popularity and propagation of videos. We measure the popularity of a video by its view count and ratings. Table 6 shows statistics of the five most popular videos in our datasets. These videos may or may not be propagated by network members, and these statistics show general popularities of videos without considering their propagation. Note that three of five popular videos are common in both networks. This infers the similarity of growth patterns in both networks.

Propagation and popularity in friendship network

To measure the correlation between popularity and propagation in the friendship network, we extracted the five most popular and the five longest propagated nodes from the network of friendship interactions, i.e., the friends who commented on each other's posts (Table 7). In our first observation, none of the videos that appeared in the network's most popular videos (Table 6) appeared in the most popular and deepest propagated set in the friendship interaction network, and the most popular video in the friendship interaction network was, in

Table 6. Statistics of popular videos

Dataset	*View Count*	*Rating*
Friendship	$1.8 * 10^8$	4.68
	$8.6 * 10^7$	4.91
	$4.8 * 10^7$	4.83
	$4.6 * 10^7$	4.54
	$3.8 * 10^7$	4.93
Subscription	$1.8 * 10^8$	4.68
	$4.8 * 10^7$	4.83
	$3.8 * 10^7$	4.93
	$3.4 * 10^7$	4.91
	$3.6 * 10^7$	4.50

Table 7. The deepest propagated, and the most popular videos in friendship network

Type	*Propagation Depth (hops)*	*View Count*	*Rating*
Longest Propagated	3	575	5
	3	231	3.67
	2	71953	3.78
	2	61429	3.95
	2	30914	4.75
Most Popular	1	562261	4.94
	1	558523	4.89
	1	78220	4.94
	1	78074	4.93
	1	76163	4.39

Table 8. The deepest propagated, and the most popular videos in subscription network

Type	*Propagation Depth (hops)*	*View Count*	*Rating*
Longest Propagated	2	72001	3.78
	2	61429	3.95
	2	30935	4.75
	2	7262	4.43
	2	5072	3.96
Most Popular	1	562611	4.94
	2	72001	3.78
	2	61429	3.95
	1	37201	4.82
	2	30935	4.75

fact, ranked 1570 out of 113 thousand videos in the total friendship network. Meanwhile, the longest propagated videos had average popularities in the friendship network. These figures mean that the propagation of videos by friends does not affect the popularity of videos, and vice versa.

Propagation and popularity in subscription network

We applied the methodology that we used for the friendship network on the subscription network. The analysis of the subscription network shows that the most popular video (Table 8) ranked 747 out of 332 thousand videos in the total subscription network (Table 6). On the other hand, videos that are propagated the most in the subscription network are also subscription network's most popular videos. Therefore, there is a correlation between the popularity and the level of propagation by subscribers, meaning that more propagated videos by subscribers become popular at least among the subscribers and their network or vice versa.

7. DISCUSSION

Advertisement is a costly process for businesses, and in some cases, it takes a considerable amount of the business budget. Businesses have always looked into ways to advertise their products and services at a lower cost. Viral marketing and advertisement on social networks provided a solution for this requirement. However, there is still a considerable cost associated with viral marketing even though it is lower than, say, banner ads. This cost is mainly associated with influencing the first person and encouraging him/her to spread the word, in addition to making sure that the word will be spread to the next levels in the network. Therefore, businesses may be interested in finding the most appropriate person and the most appropriate network to do the advertisement. The low propagation rate among friends and followers in an open social network suggests that open social networks are not generally well suited for businesses that need to spread the word in communities. Meanwhile, the better propagation rate among friends (compared to followers) suggests that the focus of businesses should be on friendship networks. At the same time, our research suggests that in friendship networks, the popularity of the message does not affect its propagation, while in follower networks it does. Therefore, businesses may need to focus on making the message itself interesting (popular) within follower networks more than they do within friendship networks.

8. CONCLUSION

There are many studies on the effects of social networks on viral marketing and diffusion of information. However, few studies have focused on propagation in social networks. Moreover, to the best of our knowledge, there is no study that analyses propagation in friendship and follower networks as two different entities in the same environment, and at the same time. Therefore, we felt a need for a study of propagation, its trends, and magnitude. We conducted a propagation analysis on an open social network, i.e., YouTube. We believe that the fact that everyone can view the contents uploaded by a user, and post a comment, rate, or share that content contribute to YouTube's openness.

We crawled two subsets of the YouTube user network for friendship and subscription and analyzed the propagation, and the role of friends and subscribers in content dissemination. We observed that the effect on propagation of people who are not either in a friendship network or a subscription network is higher than that of friends or subscribers. Meanwhile, we discovered that even though the network of subscribers was denser than the network of friends, the propagation in the subscription network was lower. This might imply that when the relationship is one-way, users are less inclined to contribute to the content.

Although our extracted data did not initially include user relations to the level of more than 5 hops, this limitation did not affect our study of the magnitude of propagation, and the correlation of propagation and popularity as even the most popular videos did not propagate more than three hops in their networks. Our result shows a low correlation between popularity and propagation in general. However, the correlation of popularity and propagation in the friendship network is more than what exists in the subscription network. This may be due to the fact that friends feel more obliged than subscribers to contribute comments about the contents posted by their peers. On the other hand, subscribers may, most of the time, only comment on what interests them.

As future work, we intend to extract a larger dataset, and combine the networks that are common in both friendship and subscription datasets in order to analyze the effects of propagation in the existence of both friends and followers at the same time. Analyzing the resulting network will lead to a better understanding of social networks as a marketing channel, and will lead marketers to a more suitable choice of network for their marketing campaigns.

9. ACKNOWLEDGEMENT

We would like to acknowledge Mr. Hamid Poursepanj for his invaluable insights and efforts that were put in this project.

10. REFERENCES

Asur, S., & Huberman, B. A. (2010). Predicting the Future with Social Media. SSRN eLibrary. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1579522

Bakshy, E., Karrer, B., & Adamic, L. A. (2009). Social influence and the diffusion of user-created content (p. 325). ACM Press. doi:10.1145/1566374.1566421

Baluja, S., Seth, R., Sivakumar, D., Jing, Y., Yagnik, J., Kumar, S., Ravichandran, D., et al. (2008). Video suggestion and discovery for youtube: taking random walks through the view graph. Proceeding of the 17th international conference on World Wide Web, WWW '08 (pp. 895–904). Beijing, China: ACM. doi:10.1145/1367497.1367618

Bass, F. M. (2004). Comments on "A New Product Growth for Model Consumer Durables": The Bass Model. Management Science, 50(12), 1833-1840.

Bearden, W. O., Calcich, S. E., Netemeyer, R., & Teel, J. E. (1986). An Exploratory Investigation Of Consumer Innovativeness And Interpersonal Influences. Advances in Consumer Research, 13(1), 77-82.

Cha, M., Mislove, A., & Gummadi, K. P. (2009). A measurement-driven analysis of information propagation in the flickr social network. Proceedings of the 18th international conference on World wide web, WWW '09 (pp. 721–730). New York, NY, USA: ACM. doi:10.1145/1526709.1526806

Chatterjee, R., & Eliashberg, J. (1990). The Innovation Diffusion Process in a Heterogeneous Population: A Micromodeling Approach. Management Science, 36(9), 1057-1079.

Domingos, P., & Richardson, M. (2001). Mining the network value of customers. Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining, KDD '01 (pp. 57–66). New York, NY, USA: ACM. doi:10.1145/502512.502525

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? - An empirical investigation of panel data. Decis. Support Syst., 45(4), 1007-1016.

Evans, D. C. (2009, January 15). Beyond Influencers: Social Network Properties and Viral Marketing. Psychster Inc. Retrieved from http://www.slideshare.net/idealistdave/beyond-influencers-social-network-properties-and-viral-marketing-presentation

Facebook Inc. (2011). Facebook Statistics. Retrieved July 9, 2011, from http://www.facebook.com/press/info.php?statistics

Howison, J., Wiggins, A., & Crowston, K. (2011). Validity Issues in the Use of Social Network Analysis for the Study of Online Communities. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.157.9237

Hu, N., Tian, G., Liu, L., Liang, B., & Gao, Y. (2011). Do Links Matter? An Investigation of the Impact of Consumer Feedback, Recommendation Networks, and Price Bundling on Sales. Engineering Management, IEEE Transactions on, PP(99), 1-12. doi:10.1109/TEM.2010.2064318

Huberman, B. A., Romero, D. M., & Wu, F. (2008). Social networks that matter: Twitter under the microscope. 0812.1045. Retrieved from http://arxiv.org/abs/0812.1045

Kempe, D., Kleinberg, J., & Tardos, É. (2005). Influential Nodes in a Diffusion Model for Social Networks. Automata, Languages and Programming (pp. 1127-1138). Retrieved from http://dx.doi.org/10.1007/11523468_91

Kim, Y. A., & Srivastava, J. (2007). Impact of social influence in e-commerce decision making. Proceedings of the ninth international conference on Electronic commerce (pp. 293-302). Minneapolis, MN, USA: ACM. doi:10.1145/1282100.1282157

Lange, P. G. (2007). Publicly Private and Privately Public: Social Networking on YouTube. Journal of Computer-Mediated Communication, 13(1), 361-380. doi:10.1111/j.1083-6101.2007.00400.x

Leskovec, J., Adamic, L. A., & Huberman, B. A. (2007). The dynamics of viral marketing. ACM Trans. Web, 1(1), 5+. doi:10.1145/1232722.1232727

Stephen, A. T., & Toubia, O. (2009). Deriving Value from Social Commerce Networks. SSRN eLibrary. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1150995

Trusov, M., Bodapati, A. V., & Bucklin, R. E. (2010). Determining Influential Users in Internet Social Networks. Journal of Marketing Research, XLVII(August), 643-658. doi:10.2139/ssrn.1479689

Van den Bulte, C., & Joshi, Y. V. (2007). New Product Diffusion with Influentials and Imitators. MARKETING SCIENCE, 26(3), 400-421. doi:10.1287/mksc.1060.0224

Xu Cheng, Dale, C., & Jiangchuan Liu. (2008). Statistics and Social Network of YouTube Videos. 16th International Workshop on Quality of Service, 2008. IWQoS 2008 (pp. 229-238). Presented at the 16th International Workshop on Quality of Service, 2008. IWQoS 2008, IEEE. doi:10.1109/IWQOS.2008.32

Yoganarasimhan, H. (2010). Impact of Social Network Structure on Content Propagation: A Study using YouTube Data. University of California, Davis.

YouTube LLC. (2010). YouTube - Press Statistics. Retrieved July 9, 2011, from http://www.youtube.com/t/press_statistics

Editor's Note:

This paper was selected for inclusion in the journal as a CONISAR 2011 Meritorious Paper. The acceptance rate is typically 15% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2011.