Analyzing Factors Impacting Revining on the Vine Social Network

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Abstract. Diffusion of information in the Vine video social network happens via a *revining* mechanism that enables accelerated propagation of news, rumors, and different types of videos. In this paper we aim to understand the revining behavior in Vine and how it may be impacted by different factors. We first look at general properties of information dissemination via the revining feature in Vine. Then, we examine the impact of video content on revining behavior. Finally, we examine how cyberbullying may impact the revining behavior. The insights from this analysis help motivate the design of more effective information dissemination and automatic classification of cyberbullying incidents in online social networks.

Keywords: Information diffusion · Vine · Cyberbullying

1 Introduction

Online social networks such as Facebook, Twitter, YouTube, and Vine are attracting more users every day, and they have become an important source of information sharing and propagation [1]. Vine is a video-based online social network and has become increasingly popular recently in the Internet community. There are almost 40 million registered Vine users as of April 2, 2015 while the total number of Vines played everyday is 15 billion [2]. Using a mobile application, Vine users can record and edit six-second looping videos, which they can share on their profiles for others to see, like, and comment upon. An example of the Vine social network is shown in Figure 1. All user profiles in Vine are public by default unless users change their privacy policies. In the public setting, posts are accessible by all Vine users, not only followers. Using the privacy setting, Vine users can limit the access to their posts to their followers only. Users can also limit who can find them or message them. In the home feed page, featured Vine videos in different categories are provided to a user when logged in.

Due to the wide popularity of online social networks, they have been used for sharing news, art, politics [3–5] and have been researched from different areas,

such as marketing and sociology [5]. Vine videos are getting more popular, as they can be easily embedded in Twitter, and the auto-loop feature makes it funny and interesting [6]. One of the most interesting characteristics of Vine is the revining behavior. That is, spreading information in Vine happens via revining a shared 6-second video referred to as a "vine". Users can easily share a video by pressing the revining button provided below the video. Figure 1 also illustrates the revining behavior.

Previous work [7,8] provided detailed characterization of Twitter, looking at the interaction among the users and the temporal behavior of users in Twitter. Other works have looked at the retweeting behavior in Twitter [3,9–12]. Pezzoni et al. measured the influence of a user based on the average number of times that his/her originated tweets have been retweeted [12]. Beside user properties, they also considered the position of the tweet in the feed as a factor impacting retweeting behavior. The authors of [13,14] have considered the number of times a recent seed tweet has been retweeted as the influence of the post, and used this to estimate the total influence and influence score of the user, and then examined a network of influencers. Further, [14] observed that URLs that were rated as having more positive feelings have

Fig. 1. An example of the Vine social network with revining.

been spread more. The authors evaluated the impact of Twitter users in different topics, instead of labeling them as influencer or not influencer. While they built the propagation tree by looking at the followers retweeting, [15] looked at the retweeting methods other than formal retweeting mechanism of Twitter. Looking at different domains, they observed the percentage of retweets coming from non-followers is higher than that from followers. Zhao et al. in [16] considered two types of retweets, coming from direct and indirect followers of the user who originated a tweet. They proposed that looking at the influence of the followers is also important for predicting the number of retweets. There are also considerable amount of works trying to predict the number of retweets [16–20]. In [20], the authors used image features to predict the number of retweets by looking at the image link tweets. Another work [21] analyzed the behavior of the tweets that have been retweeted many times and tried to detect two classes of tweets, first the group of tweets that have been retweeted less than 30 times, and second the group of tweets that have been retweetd more than 100 times. Our work differs
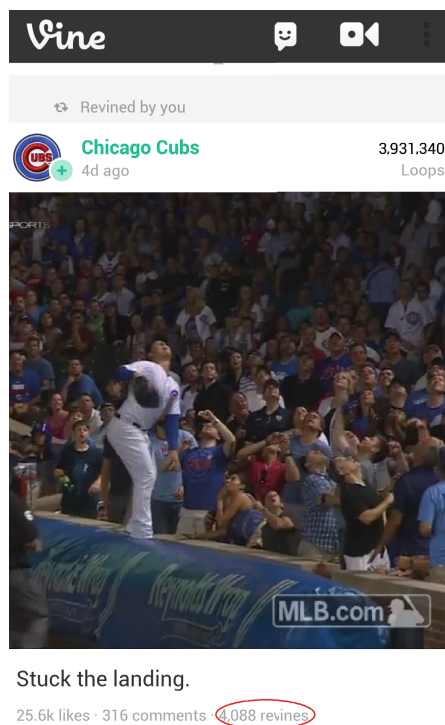
from previous works in terms of examining the revining behavior of video-based vines, but leverages prior works in that determining how far a vine has been propagated can be useful as a sense of how influential the post has been.

To date, there has been little prior work examining video-based social networks like Vine. One paper [22] has labeled a small set of about a thousand Vine videos as cyberbullying or not, for the purposes of detecting cyberbullying incidents in Vine. That work does not investigate how vines propagate via revining in the social network, which is the focus of our paper.

This paper makes the following contributions. It is the first paper to provide a detailed characterization of key properties of Vine, a video-based social network. Second, we labeled the content and emotion of a small set of videos and explore their relationship to revining behavior. Third we reveal the difference in revining behavior between vine videos labeled as cyberbullying, and those that are not.

In the following, we first describe our data collection efforts, basic analysis and then provide more characteristics regarding revining. We then analyze the revining behavior of videos both in terms of their labeled video content and cyberbullying content.

2   Dataset

Vine is a 6-second short video sharing platform, launched in 2012. Users can create videos recorded by their mobile phone camera, and apply edits provided by the mobile app. Using snowball sampling, we collected the complete profile information of 55,744 users in Vine. Specifically, starting from 5 random seed users, we collected data for all users within two tops of the seed users, i.e., followers of the seed users, and users who follow those followers. This gives us in total 390,463 unique seed videos generated by these users (approximately 7 vines for each user). For each user we collected their total number of followers, followings, total number of videos created by the user (seed videos) and total

Table 1. Collected features for users and seed vines.

Follower	list of followers of user
Following	list of followings of user
uSeedPost	number of posted videos originated by a user
uPost	number of total posted videos by a user (originated plus revined)
uLoop	number of times all posted videos by a user have been played
uLike	number of times all originated videos by a user have been liked
PostDate	the exact date and time the seed video was originated
Description	the attached caption and tags to the posted video
Revinee	list of all the users who shared the seed video
pLoop	number of times the seed video has been played
pLike	number of times the seed video has been liked
pComment	number of comments the seed video has been liked
pRevine	number of times the seed video has been revined

number of videos revined by the user. We also collected the total number of likes, revines, and loops (# of times video has been played) for each user.

For each of the seed videos, we collected the total number of likes and comments associated with the posed video. Also we collected the creation day, how many times the video has been played (i.e., loop counts) in July 2015. Also we looked at how many times each video has been revined by collecting the user id of all the users who have revined it, along with the time stamp when it has been revined. The complete list of users who have revined a video is accessible directly by collecting information associated to the seed video itself. Table 1 summarizes the features that were collected for users and their seed videos.

3   User Behavior on Vine

3.1   Basic Analysis

We first examine the general behavior of users in Vine, including the number of followers and following, which are user based features, and the number of comments, likes, revines and loops of a video, which are post based features. Figure 2 shows the distributions of the number of followers and following of 55,744 users as complementary cumulative distribution functions (CCDFs). Compared with previous work that reported the following and follower distributions in Twitter [8], there is a much larger gap between the distribution of the number of followers and the number of followings of Vine users. Only 1.3% of the Vine users follow more than 10,000 users, however 19.27% have more than 10,000 followers.
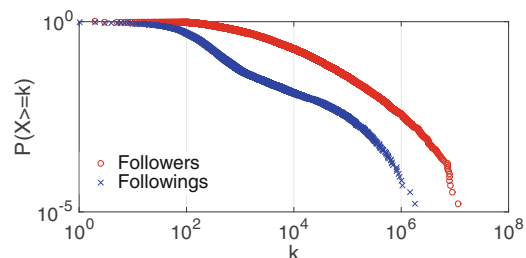

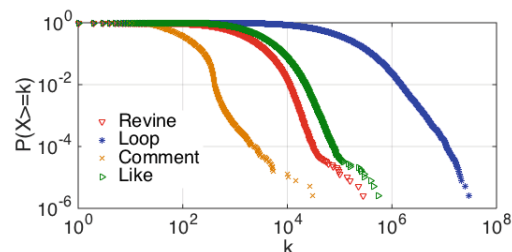**Fig. 2.** CCDFs of the number of followers and followings in Vine.

Fig. 3. CCDFs of the number of revines, loops, comments, and likes in Vine.

Figure 3 provides the CCDFs for the number of times a seed video has been played as a loop, has been shared as a revine, has been liked and has been commented upon. The curve for looping is much higher than the other three (i.e., there is a long tail), possibly due to the auto-looping feature. Revining and liking have lower and very similar distributions. Commenting has the distinctly lowest CCDF curve among the features considered for a post.

Table 2 provides the mean, median and maximum values for all user features, including the total number of followers and followings, total number of

Table 2. Statistics on the Vine dataset, for 55,744 users.

	Follower	Following	uLoop	uSeedPost	uLike	uPost
Mean	23,571.14	1,459.0	5.67×10^5	147.2	3,630.0	705.6
Median	1,434.0	99.0	2.97×10^5	52.0	826.0	160.0
Maximum	1.16×10^7	1.83×10^6	2.10×10^9	1.9×10^4	2.10×10^6	7.10×10^4

posts originated by a user (uSeedPost), total number of videos posted by a user (originated+shared), total number of likes a user has received (uLike) and total number of times all his/her posts have been looped (uLoop). We observed that there are outliers that are a large distance from the mean. Namely, the substantial deviation of the mean from the median for nearly every category shows there are a set of Vine users whose feature values are much higher than the behaviors of most of the population. For example, we noticed celebrities provide such a distortive effect, e.g., one celebrity had 12 million followers.

Table 3. Pearson correlation between the collected Vine features. Only for the vines with ∗ is the p-value larger than 0.001, while for the rest the p-value is smaller than 0.001.

	pLike	pComment	pRevine	pLoop	Follower	Following	uLoop	uSeedPost	uLike	uSharedPost
pLike	1.000	**0.672**	**0.840**	**0.596**	**0.473**	-0.009	0.246	-0.018	-0.034	-0.060
pComment	0.672	1.000	**0.692**	0.408	0.209^*	0.000	0.131	-0.010	-0.007	-0.03
pRevine	0.840	0.692	1.000	**0.421**	0.295	-0.005	0.144	-0.017	-0.051	-0.046
pLoop	0.596	0.408	0.421	1.000	0.25	-0.006	0.164	-0.033	-0.038	-0.042
Follower	0.473	0.209	0.295	0.256	1.000	0.011	**0.378**	0.141	0.022	0.043
Following	-0.009	0.000^*	-0.005	-0.006	0.011	1.000	-0.006	-0.013	0.002^*	-0.004^*
uLoop	0.246	0.131	0.144	0.164	0.378	-0.006	1.000	0.156	0.030	0.069
uSeedPost	-0.018	-0.010	-0.017	-0.033	0.141	-0.013	0.156	1.000	0.199	**0.512**
uLike	-0.034	-0.007	-0.051	-0.038	0.022	0.002^*	0.030	0.199	1.000	0.203
uSharedPost	-0.060	-0.032	-0.046	-0.042	0.043	-0.004^*	0.069	0.512	0.203	1.00

Table 3 displays the correlations among different user and post based features. pLike, pComment, pRevine and pLoop are post features and uLoop, uLike, uSeedPost (# posts originated by user) and uSharedPost (# posts revined by user) are user features. The highest correlation is among revines and likes for posts, as was seen in Figure 3 where their CCDFs were also very similar. Revining is also correlated with the number of comments. The correlation of revines for a post with the loop feature is high but is the lowest among post based features. In terms of correlation of the revining with user based features, there is a positive correlation between revining of a post and number of followers that the poster of the seed vine has. There is a very small negative correlation between the number of revines and followings.

There is no correlation between the number of followings a user has and the other user features. The number of followers has considerable correlation with the total number of loops for all seed videos posted by the user (uLoops).

Also the correlation between user's seed post and user's shared post (uShared-Post) is about 0.5, showing users who tend to share more videos also generate more seed videos.

In total, from all posts, there were 366,517 tags in total and 83,147 unique hashtags. As Figure 4 illustrates, only 8.25% of the posts have more than 3 tags and the highest number of tags for a video is 20.
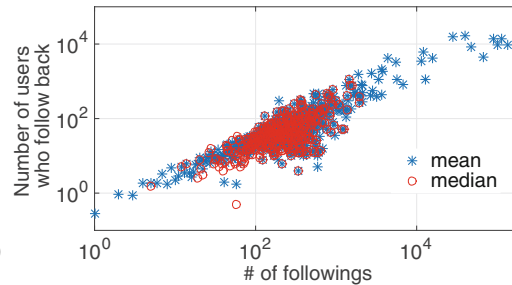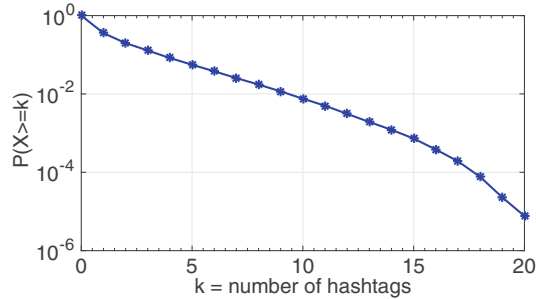

Fig. 4. CCDF of the number of tags.

Fig. 5. Mean and median number of users who follow back a user versus number of followings.

As another property of the Vine social network, we investigated the number of users who follow back their following users. Figure 5 shows a positive correlation between the number of followings and the mean number of users who follow back their following users.

3.2   Revining Behavior and Followers and Following

In this subsection, we explore in more detail the relationship between revining behavior and the numbers of followers and following. First, we establish a baseline for originated videos. Figure 6 plots the correlation between the number of originated vine videos and the number of followers. For up to about 1000 followers, there is a linear relation between the log number of followers and log number of mean videos and after that there is no positive trend. We also provide the mean and median for the log scale bins in solid and dash lines, [8]. The mean is clearly above the median, indicating again there are outliers who send original vines much more than other users. In Figure 7, we plot the correlation between the number of originated vines and the number of followings. Up to about a value of 665, the line is linear and after that there is a negative trend between mean value of vine and followings.

In terms of revines, Figure 8 shows the relation between the number of followers and the mean number of revines. Figure 8 demonstrates that as the number of followers increases, the mean number of revinings increases. For up to 245 followers there is positive correlation, and as followers increase the variance of the mean number of revines increase. On Figure 9 it can be seen that as the number
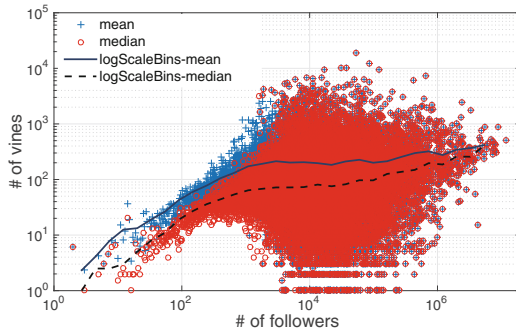
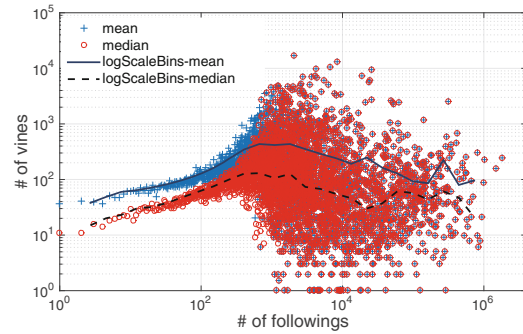**Fig. 6.** Mean and median number of original vines versus number of followers.

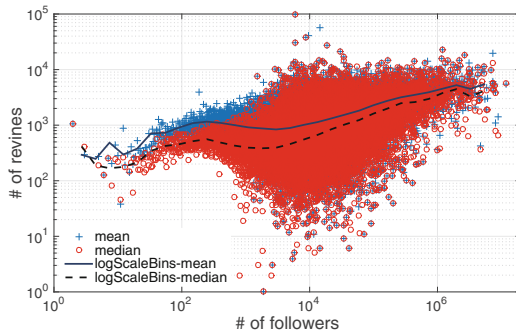**Fig. 7.** Mean and median number of original vines versus number of followings.

Fig. 8. Mean and median number of revines of the original vines versus number of followers.
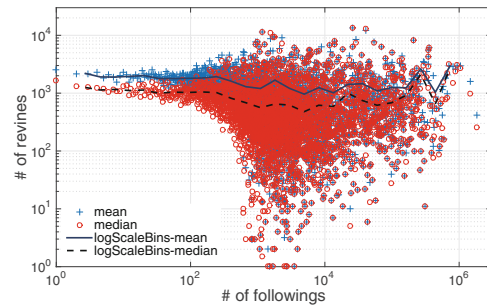

Fig. 9. Mean and median number of revines of the original vines versus number of followings.

of following increase the mean number of revines is approximately constant for values close to 245 and after that the variance starts to increase. But there is no positive correlation between number of followings and the number of revines for a post.

3.3   Revining and Temporal Behavior

Next, we explore temporal properties of revining. Figure 10 provides the CCDF of the maximum number of times a seed vine has been revined per day. 19% of the vine videos have reached the maximum revining of more than 1000 times a day. A few seed videos have been revined more than a maximum of 10,000 times in a day.

Figure 11 shows the time difference between the first revine occurring after an original vine has been posted. 48% of the first revines have occurred within one minute and 93% have happened within one hour.

Figure 12 shows the activity of users in terms of posting seed vine videos during the seven days of the week, and across 24 hours. The minimum fraction
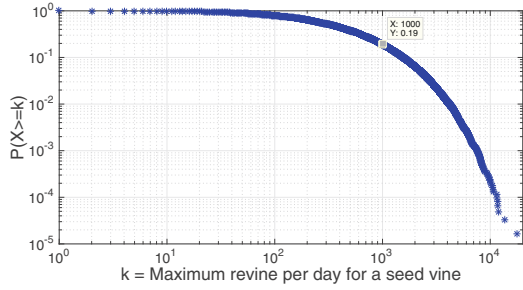
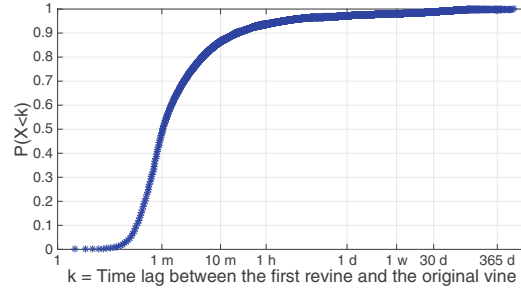**Fig. 10.** CCDF of maximum number of times a seed vine has been revined per day.

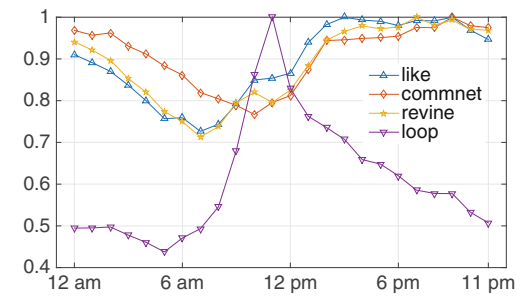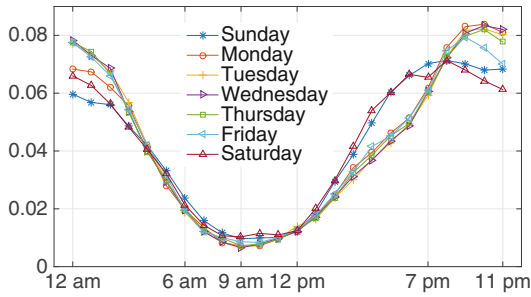**Fig. 11.** The time lag between the first revine and the original vine.

Fig. 12. (left) Percentage of vines posted at time x during a day. (right) Normalized number of likes, revines, comments and loops for posts received at time x in a day. Each graph has been normalized to one by dividing to its highest value.

of the seed videos were posted during the morning, 6am-12pm. The activity increases after that until reaching its peak around 10pm-11pm. The trend of the posting behavior differs somewhat for the weekend, shifting to a higher fraction of posts earlier in the evening, with high proportion of user activity from about 6pm to midnight. On the right side figure, we provide the mean number of likes, comments, revines and loops for the videos posted at time x during a day. It is interesting to see a pattern, showing the videos posted in the evening received on average more likes, comments and are revined more. However, the number of loops shows a completely different behavior and the highest average number of loops belongs to the videos posted at 11am.

3.4 Revining and Hash Tags

Another factor we are interested to explore is the correlation between the post's hash tags and the number of times it has been revined. Table 4 provides the tags with the highest frequency in four different bins of revining. The hash tags are ordered so that the tags on the left have the highest frequency. Each bin contains a quarter of the seed Vine videos. For example 1-bin contains one fourth of the media sessions with the lowest amount of revining. Comedy is the top tag in all four bins. Football is among the top 10 most frequent tags only in the highest

Table 4. The tags with highest frequency in 4 different bins of revining.

1-bin	comedy	funny	remake	6secondcover	lol	loop	revine	music	singing	videoshop
2-bin	comedy	remake	funny	lol		loop	revine	6secondcover	onedirection	teamsour	howto
3-bin	comedy	remake	funny	onedirection	loop	lol	revine	howto	teamsour	6secondcover
4-bin	remake	comedy	funny	onedirection	loop	lol	revine	howto	blackranked	football

Fig. 13. Visualization of the tags associated with the vines

quadrant of the number of revines. Also music and singing only occur in the lowest quadrant of revining. The top ten tags for 2-bin and 3-bin are the same, except reordered.

A visualization of the tags depicted in Figure 13 shows that comedy, funny and remake have the highest frequency and have been seen among the top three tags for all 4 bins.

3.5   Revining and Followers

Figure 14 provides the CCDF for the percentage of revines that have been made by the followers of the user who posted the original Vine video. Since all users in our dataset have public profiles and their profiles and seed vines are accessible by all Vine users, revines are not just limited to their followers. In fact, for 1.67% of the seed vines, none of the revinings have been by the followers of the poster of the original vine. For 58% of the users, more than 90% of the propagation takes place by users who are not direct followers of the users. These include celebrities, sports pages, local singer pages, fun-related pages, etc. Previous work [15] has reported non-follower retweets range from 78.7% to 98.5% for four different domains "Fundraiser", "News", "Petitions" and "YouTube".

Figure 15 displays the relation between the number of additional recipients of the Vine video (users other than the original poster's followers) and the number of followers. There is a positive correlation which shows the higher the number of followers a user has, the greater are the number of users other than followers who access the video post.
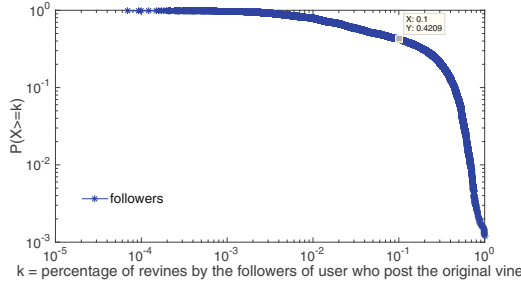
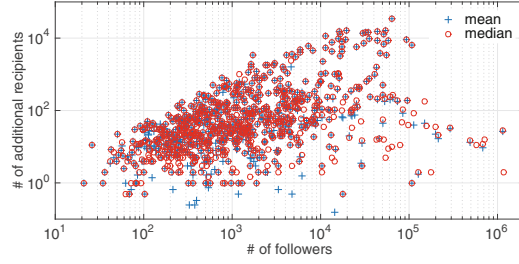**Fig. 14.** CCDF of the percentage of the reviners who are the followers of the source of the original vine

Fig. 15. Mean and median number of additional recipients of the vine via revining

3.6   Revine Tree

Figure 16 shows the number of hops a video gets propagated in Vine. For this purpose we collected the user name of all the users who revined a seed video. We then find the ones who are followers of the poster of the seed video and named them as first hop users. At the next step we collected the followers of the first hop users and compared them with the remaining users in the revining list. The common users, if they exist, are named as second hop users. We continued the process until there are no more users

Fig. 16. CCDF of number of hops a video get propagated through the network.

in the x-hop user list. 6.7% of the videos have been propagated 0 hops, meaning none of the revining users have been among their followers. The most common number of hops is 3, i.e., 24.96% of the videos have been propagated 3 hops by their followers. In comparison, for Twitter, the most common number of hops reported is 1 for 85% of the tweets [8]. Also they show the highest number of hops is 10 in tweet propagation, while for Vine the largest number of hops we have discovered is 16. Hence, Vine videos are propagated more on average, and also more in the extreme.
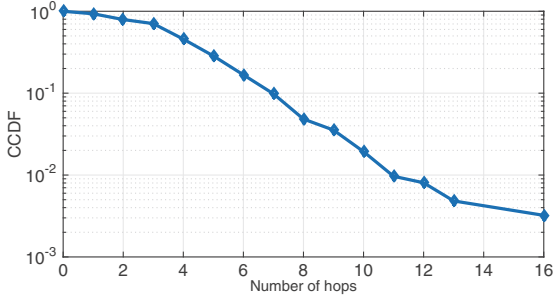
Figure 17 shows an example of a revine tree. The seed video has been revined 8401 times. Looking at the links among these 8401 users, 4501 users have connection with at least one of the 8401 users, with 4595 links. This means that around half of the users that were not among the followers of the original poster have revined the video. As the poster of this Vine video has a public profile, other users who do not follow this user also can see his/her profile content and share the seed video. The dark blue nodes in the right side shows a propagation of video in the network in a community that is not at all connected to the main
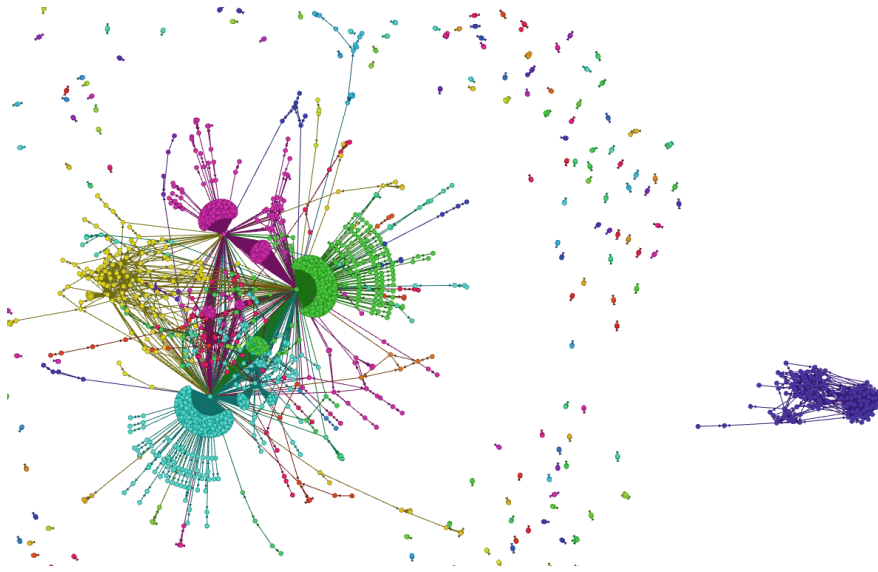
Fig. 17. Revine tree of followers of a seed Vine video who revined the post.

network component. Most of the nodes who are not followers of the original poster are single node components that have not lead to more revining.

The node with highest degree in the pink group is the original poster. Looking at the revining time of the other two nodes with highest in-degree (light blue and green groups), both revined the video in the first 24 hours, one being the first user who revined and the other being the 5th user who revined the video. These later reviners have been more influential than the original poster in the propagation of this vine. Previous work [16] has also observed that real propagation in tweeter happen with a pattern similar to Figure 17.

4   Labeled Data Analysis

In this work, we are specifically interested in how revining behavior is affected by the content of the videos as well as the presence of cyberbullying in the vines. This requires that we label various Vine videos. We selected a set of 983 vines, and collected the appropriate user features of the seed video posters, and the feature set of the posts. Using CrowdFlower, a crowd-sourced website, we labeled the video content and emotions of these vines according to the methodology from [23]. For the video content, People, Person, Indoor, Outdoor, Cartoon, Text, Activity, Animal and Other were provided as categories in multiple choice format to CrowdFlower contributors. Next, the contributors were asked to identify the emotions expressed in the video, given the following options to choose from: Neutral, Joy, Sad, Love, Surprise, Fear and Anger. The same set of videos were labeled for cyberbullying according to the methodology from [22]. Each media session (including a video and its associated comments) was labeled by five different contributors.

4.1   Revining and the Content/Emotion of Vines

We wanted to determine the relationship between the content/emotion of the video and the number of times it gets revined. Figure 18 illustrates the mean and median number of times a seed vine is revined for each of the categories we labeled for the vines. We observed "car", "activity" and "outdoor" have the highest mean. However there is big gap between their mean and median, showing there are outliers with a large amount of revining for these categories. For categories like "food", "fashion" or "cartoon" the mean is close to the median, revealing the lack of significant outliers. For these categories, our analysis found that in terms of the mean number of hops that the "car" category had been propagated on average 5 hops, which was the highest mean among other categories. Next highest was the "text" category, which was propagated with an average 4.4 hops. The category "activity" and "other" had the minimum average number of hops around 2.7.
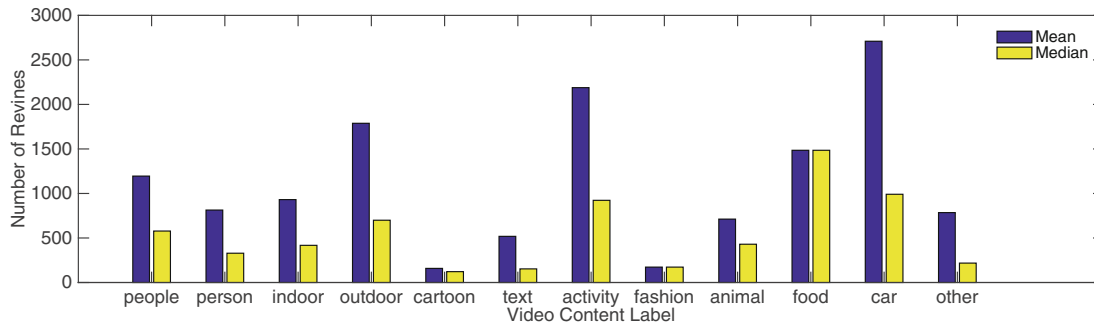

Fig. 18. Mean and median of number of times a video has been revined versus the content of the video.

Figure 19 illustrates the mean and median number of times a seed video has been revined versus the emotional content of the video. We find that "anger" and "sad" have the highest difference between the median and the mean. Positive emotions such as "love", "joy" and "surprised" have higher mean number of revines compared to negative emotion categories such as "sad", "fear" and "anger". "Neutral" behavior seems to behave closer to negative feelings than positive emotions. *In terms of the mean number of hops of revining propagation for different emotions, we found that "love" had the highest mean value 4.4 hops on average and "sad" had the lowest mean value of 2.8 hops.* Previous work [14] also observed that URLs that were rated as having more positive feelings have been spread more. For the rest of the emotion categories the mean value of the category is close to the mean number of hops 3.5.

4.2   Revining and Cyberbullying Vines

Looking at the first revining of the videos for each group, the lag between an original seed vine and its first revine is less than 1 minute for 40% of cyberbullying
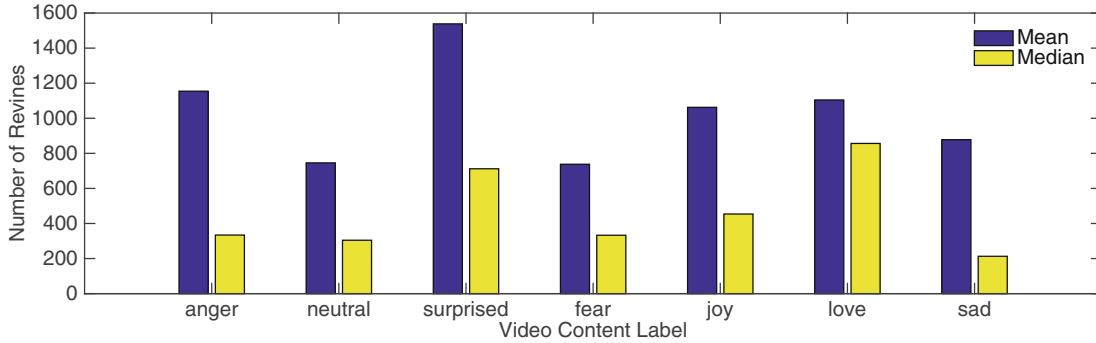
Fig. 19. Mean and median number of times a seed video has been revined versus the emotional content of the video.

vine videos and 50% for non-cyberbullying vine videos. The average time that a cyberbullying vine was revined is 4.01 days versus a mean of 1.27 days for non-cyberbullying vines (p-value 0.05 for t-test). This means the first revines happen faster for the non-cyberbullying group. We also looked at the longest time between two consecutive revining of a seed post for cyberbullying and non-cyberbullying Vine sessions. The average value over the longest inactivity period for cyberbullying is 94.91 days versus a mean of 111.15 days for non-cyberbullying (p-value 0.01 for t-test).

We found that the mean number of revining hops for cyberbullying videos was 3.21 while the mean number of hops for non-cyberbullying videos is 3.78 (p-value 0.003 for t-test). *Not only are non-cyberbullying videos shared more, but they also propagate through the network more deeply compared to cyberbullying videos.*

Tables 5 and 6 provide the mean values for the two different classes of cyberbullying and non-cyberbullying versus user and post features. The owner of cyberbullying video sessions have fewer followers and they also follow fewer users. They have lower number of total likes for their posted videos and the total number of loops is also smaller. However they have shown more activity in terms of posting seed Vine videos compare to non-cyberbullying class users.

Table 5. Mean of user features for cyberbullying and non-cyberbullying class.

	Follower	Following	uLike	uLoop	uSeedPost	uPost
cyberbullying	9.10×10^4	2.27×10^3	5.97×10^3	1.5×10^3	5.12×10^2	1.53×10^3
non-cyberbullying	1.07×10^5	3.03×10^3	7.35×10^3	4.15×10^7	4.44×10^2	1.38×10^3

Table 6 shows that cyberbullying labeled vines have been revined less, though they have been looped more. Also they receive more comments though fewer likes compared to the mean value of the non-cyberbullying labeled vines.

Table 6. Mean of post features for cyberbullying and non-cyberbullying class.

	pRevine	pLoop	pComment	pLike
cyberbullying	719.97	139,534.5	88.5	5,973.3
non-cyberbullying	1,095.6	118,326.2	76.3	7,355.8

5   Conclusions

As far as we are aware, this paper is the first to present a detailed analysis of user behavior in the Vine social network. We analyzed 55,744 profiles of Vine users, along with 390,463 seed Vine videos generated by these users. There are six key findings. First, the number of followers has a positive correlation with the number of seed vines for up to 1000 followers, then the variance of the number of seed vines grows too large. There is also a positive correlation between the number of followers and those revining. Second, for 42% of the users, only 10% of the revines come from the followers, meaning they are responsible for only a small percentage of the propagation of the posts. Third, there is a positive correlation between the number of additional recipients and the followers, supporting the first two statements. Fourth, Vine users are most active in the late evening hours; they are most likely to post original videos after 10pm and receive the greatest number of likes, comments and revines. However the peak of the loops belong to the videos posted at 11am. Fifth, using a smaller set of labeled videos based on their content and emotions, we observed that the videos containing the emotion of "love" have been propagated more deeply, and videos containing the emotion of "sadness" have traveled the lowest number of hops in the network compared with the other emotions. Finally, when examining the differences between videos identified as cyberbullying and those that were not, we found that cyberbullying video sessions were revined less, traveled lower hops in the network, but looped more and receive more comments. Additionally, users who posted cyberbullying videos have less followers and following, but they are more active in posting seed videos. We plan to incorporate these findings into the design of more effective information dissemination and automatic classification of cyberbullying incidences in online social networks.

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