Catching a Viral Video

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***Abstract*—The sharing and re-sharing of videos on social sites, blogs e-mail, and other means has given rise to the phenomenon of viral videos – videos that become popular through internet sharing. In this paper we seek to better understand viral videos on YouTube by analyzing sharing and its relationship to video popularity using 1.5 million YouTube videos. The *socialness* of a video is quantified by classifying the referrer sources for video views as *social* (e.g. an emailed link) or *non-social* (e.g. a link from related videos). By segmenting videos according to their fraction of social views, we find that viewership patterns of highly social videos is very different than less social videos. For example, the highly social videos rise to, and fall from, their peak popularity more quickly than less social videos. We also find that not all highly social videos become popular, and not all popular videos are highly social. And, despite their ability to generate large volumes of views over a short period of time, only 21% of the most popular videos (in terms of 30-day views) can be classified as viral. The observations made here lay the ground work for future work related to the creation of classification and predictive models for online videos.**

I. Introduction and Related Work

Historically, videos have been distributed by very large media organizations directly to consumers, whose choices were limited to switching to another centralized media organization or turning off the TV. These organizations acted, to some extent, as arbiters of taste, and they determined which videos were good enough to be broadcast. In doing so, they impacted what would, or could, become popular.

This situation has changed due to the emergence of online video sharing sites and social networking. Now, many short videos that don't have the quality or format necessary to make them suitable for broadcast on more traditional media are readily available for viewing. The sheer volume of available videos makes it difficult for users to decide what to watch or, perhaps, if to watch. As a result, people have come to rely on their social networks to make their viewing choices. They are more likely to watch videos that are distributed from person to person across social networking sites and blogs and via email and instant messaging. Videos that become popular through such sharing have become known as *viral videos* [11], [19], [5], [4], [12], [13], [14], [15].

Characteristics of viralness. Stories and videos that gain traction in social media do so quickly, often within hours of initial reports, and they fade quickly as well [8], [1]. A study on new media versus old media, published in May 2010 [6] indicates that just 5% of the top five stories on Twitter remained among the top stories in the following week. This was true of 13% of the top stories on blogs and 9% on YouTube. In the mainstream press, on the other hand, 50% of the top five stories remained a top story a week later. Spotting those viral stories and trends early on has value, both in conferring status on the people who first shared them and in providing monetization opportunity for the networks on which they are shared. However, the scale, dynamics and decentralisation of UGC (User Generated Content) make traditional content popularity prediction unsuitable [1]. Currently, 25.0% of the views on YouTube come from person-to-person sharing. Yet if we just look at views that come in the first week since video upload, this number increases to 45.1% (see Table 1). So, the opportunity to leverage these shared views comes early in a video's life. Marketing organizations and researchers are working hard to figure out how to capitalize on these time sensitive opportunities [16], [17], [7].

Viralness beyond monetization. The impact of videos with high levels of sharing extends beyond the opportunity for monetization. One example of this extension is the dissemination of political thought. Between July 1, 2008 and the November 2008 US Presidential Election, the Obama campaign posted almost 800 videos on YouTube, and the McCain campaign posted just over 100. The pro-Obama Will.i.am's video ”Yes we can” went viral after being uploaded to YouTube on February 2008 [20], and by November 2008, it had been viewed over 10 million times. Wallsten [18] tracked the views, blog posts, and mentions of this video in the traditional media and concluded that blog posting, (i.e. personal communication) was the driving force in viewing this pro-Obama video.

Further related work. Several papers characterise different aspects of UGC videos, as well as the networks that contain them, to better understand why and how some videos become popular. Xu Cheng et al. [2] note the differences in length, lifespan and content of YouTube videos compared to traditional media. They conclude that the social networking aspect of the site is a key driving force to its success, and they also note that linking, rating and favoriting make videos popular in a very organic fashion. Crane and Sornette [3] examined daily view data from a cross-section of videos on YouTube. Videos containing a peak in viewership were classified as “viral”, “quality”, or “junk”, depending on how rapidly the views increased leading up to the peak and how rapidly they decayed after the peak. Meeyoung Cha

Day 1	Week One	First Month	Two Months	Three Months
46.5%	45.1%	42.2%	39%	35.9%

Table I
PERCENT OF SOCIAL VIEWS AS A FUNCTION OF VIDEO AGE.

et al. [9] used data from Flickr, a photo sharing site, to compare the dissemination of user generated content across social networks with the spread of infectious disease in human populations. They conclude that social networks are efficient transmission mediums and online content can be very infectious. They also note that, along with direct social dissemination, other sharing mechanisms, such as linking from external sites, also drives a rapid increase in attention. In a previous study [1] the authors found that 47% of all videos on YouTube have incoming links from external sites, and the aggregate views of these linked videos account for 90% of the total views, indicating that popular videos are more likely to be linked. Sun et al. [10] studied distribution chains and large-scale cascades across the facebook social networking site. They concluded that such cascades typically start with many initiators rather than individual points and that chains formed can be very long, much longer than those involved in non-internet settings.

Our approach to studying viral videos. Our approach to understanding the importance and impact of sharing on video dissemination is different from the ones described above. Instead of following the traffic across a network, we track the growth of individual YouTube videos across time and study this growth after segmenting videos by their level of "socialness". In this way, we can understand the behavior of viral videos, their prominence, and their relationship to less shared and/or less popular counterparts. It also gives us the ability to quantify the socialness of categories of videos, observe differences in the behavior of social referrals, like Twitter and Facebook, and determine the effectiveness of viral videos in generating views across longer intervals of time.

Section II describes the *social* and *nonsocial* classification of referrer sources. Section III describes the application of this classification to video segmentation and demonstrates the relationship between socialness and the dynamics of video growth. Section IV highlights differences in the socialness of video categories and the referrals from Twitter and Facebook. Section V shows the behavior of two specific videos, one that is viral and one that is not. Section VI describes the behavior of *popular* videos, which we, somewhat arbitrarily, define to be videos that are in the top 1 percentile in terms of views generated. Finally, section VII contains a brief summary of our results.

II. VIDEO DATA & VIEW CLASSIFICATION

The results presented below were generated using 1.5 million videos that were randomly selected from the set of videos uploaded to YouTube between April 2009 and March 2010. Restricting the analysis to this time frame allows us to capture the influence of sharing from social sites that have become prominent more recently, such as Facebook, Twitter, and various blogs. Using a one year window provides a set of videos than span all seasons of the year.

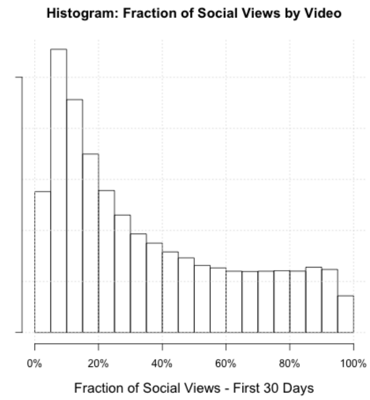

Figure 1. Histogram of the fraction of social views for each video. These social view fractions are calculated using views from the first 30 days since video upload.

The data available for each video included the video category (e.g., "Pets", "Music", "News") and the number of views by referrer at the daily level. Here the term 'referrer' is used to describe how the user came to watch a particular video. These referrer sources were classified as "social" or "non-social":

- **External Links and Embeds** ***(social)*** The user viewed the video as the result of clicking on a link that is external to YouTube. These links may be in blogs, emails, instant messages, etc. Or, the view came from a video that was embedded directly into a blog, email, etc. In this situation, the user is able to watch the video without getting redirected to YouTube.
- **Unknown** ***(social)*** The user typed or copied a URL directly into the browser leaving the referrer unknown.
- **YouTube Internal** ***(non-social)*** The user found the video using a discovery mechanism internal to YouTube. These sources include related videos, videos featured on browse pages, and video ads and promotions.
- **Search** ***(non-social)*** The user found the video using YouTube search or an external search engine.

This classification of views can be rolled up to the video level so that videos can be characterized by their "socialness". Videos with an extremely low number of views don't provide a useful sense of their socialness. Consequently, we excluded videos that do not have at least 100 views within their first 30 days of viewing, although our primary results are not sensitive to this particular choice. Videos with a higher fraction of views coming from social sources are more social than videos with a lower fraction. Using the first 30 days of views since video upload, the aggregate fraction of social views is 42.2%. Figure 1 shows how the fraction of social views varies across our (filtered) set of videos. The median fraction of social views is 27%, and the mode is closer to 10%. However, there are a significant number of videos with higher levels of sharing. 20% of the videos have a fraction of social views greater than 65%.

Of course the socialness of a video evolves over time. In fact, if we look at all videos and just count views that happened within the first day since video upload, the fraction of social views is more than 46%, but this fraction drops over time (see Table I). Overall, only 25% of views on YouTube are the result of person-to-person sharing.

III. Social Segmentation and Video Growth

In this section, the set of videos is segmented to demonstrate the relationship between socialness and the dynamics of video growth. We'll see that not all highly shared videos generate a large number of views. However, highly shared videos do tend to generate more views over a shorter period of time than less shared videos.

Video segments were generated using the fraction of social views during the first 30 days of viewing after video upload. Ten segments were created; each with an, approximately, equal number of videos (i.e. segmentation was done across socialness percentiles.) The least social segment contains videos with 0.0 to 6.1% social views, and the most social segment contains 81.8 to 100% social views.

The first step in analyzing the growth of these video segments was to time-align their viewing history using the day of peak views for each video as a reference. The views within each segment were then aggregated to provide an overall picture of video growth. To avoid the complication of missing data for videos that peak earlier than others, and potential differences in growth behavior for videos peaking on different days, the results shown below are limited to videos that peaked on the same viewing day.

Figure 2 shows the growth of views within three segments with very different fractions of social views; the lowest 10th percentile, the 50-60th percentile, and the top 10th percentile. All of these videos peaked on their 5th day of viewing. The number of views for each day-segment combination has been normalized by the number of views for the segment on the peak day. This figure indicates that the segment of videos with the highest rate of sharing has the highest rate of (relative) growth leading up to the peak. It also has a much sharper decline from it peak than the least shared segment.

The difference in behavior across segments is not limited to relative growth. Figure 3 shows that the absolute number of views is also much greater for the video segment with the highest rate of sharing. On the day of upload, this segment

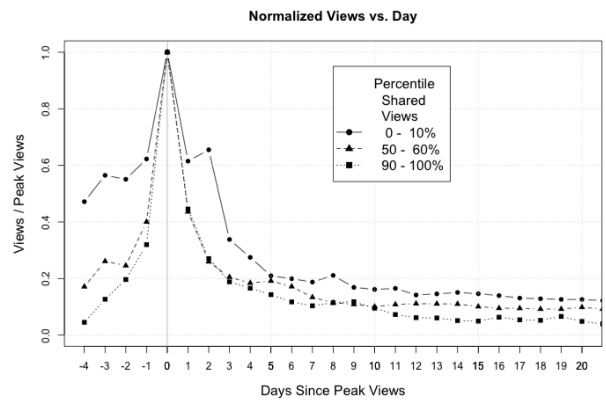

Figure 2. Relative growth of views from three video segments with very different levels of sharing. All of the videos considered peaked on their 5th day of viewing. The segment with the highest level of sharing has the highest (relative) rate of growth, as well as a steep post-peak decline.

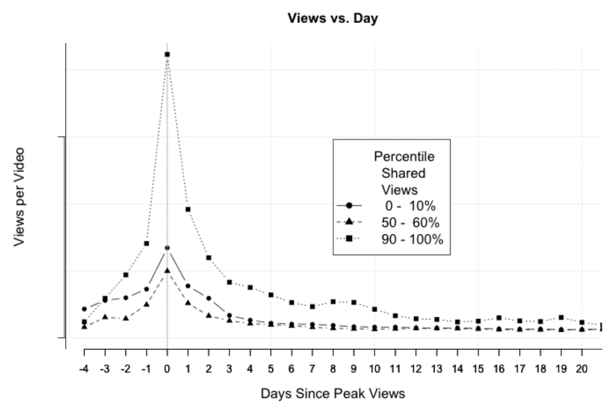

Figure 3. Absolute number of views as a function of day for the three segments of videos. Again, all of the videos considered peaked on their 5th day of viewing.

starts out with half of the views as the segment with the lowest fraction of social views. On the peak day, the number of views is several times as great.

Because views were aggregated within each video segment, it is possible that the observed differences in peak views were driven by a small number of videos with a large number of views. To check for this possibility, the CDF of the log of the peak views within each segment is plotted in Figure 4. The curve corresponding to the peak views for the most social segment is shifted considerably to the right of the least social segment, indicating that the more social videos have peaks that are systematically higher than less shared videos.

It is also possible that the dramatic growth in views for highly shared videos is not just due to the high level of sharing, but also due to an increase in the rate of sharing itself. Figure 5 indicates the degree to which the fraction of

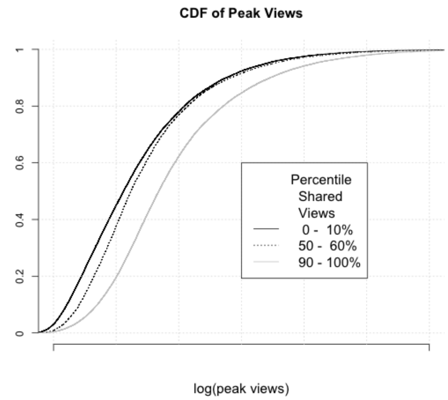

Figure 4. CDF for the log of the peak views for three video segments.

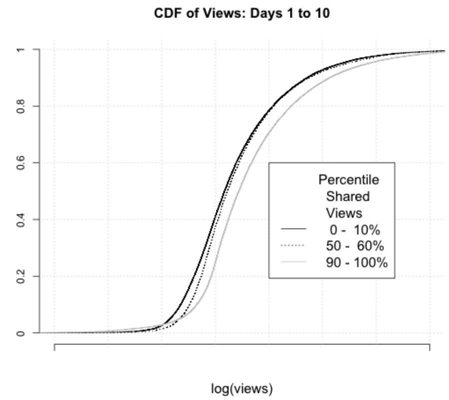

Figure 6. CDF of the log of views (days 1 to 10) for three video segments.

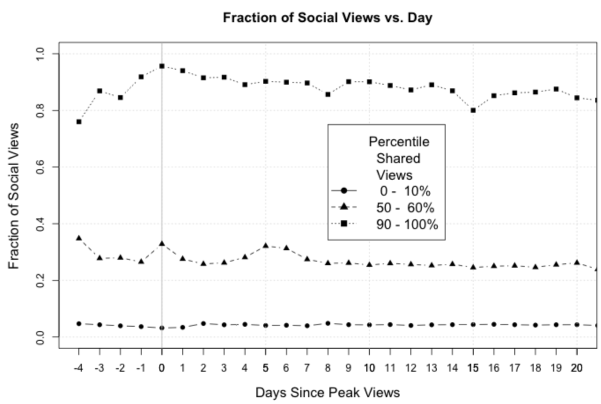

Figure 5. Fraction of social views by day for the three video segments for videos that peaked on their 5th day of viewing.

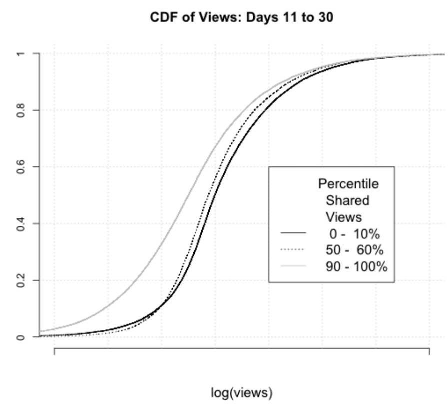

Figure 7. CDF of the log of views generated from days 11 to 30 for three video segments.

social views within the video segments evolves over time. There is about a 25% increase in the sharing for the segment with the highest fraction of social views leading up to the peak day, and a fairly steady decrease in the level of sharing afterwards. There is a lesser change in the level of sharing in the other two segments. The increase in the sharing rate of highly shared videos suggests that someone who views a video as a result of sharing is more likely to share that video with someone else. Future attempts to model or predict video growth due to sharing should take this evolution into account.

The growth in absolute views across video segments shown in Figure 3 is similar to the behavior described by Crane and Sornette [3]. However, the diversity in video growth seems more aptly explained by the inherent level of sharing within each group of videos, rather than the viral, quality, and junk descriptors suggested.

We saw from Table I that the overall level of sharing decreases with video age. The advantage that highly shared videos have in terms of gaining views decreases even more quickly over time. Figure 6 shows the CDF for views generated from days 1 to day 10 for three video segments. The highest shared videos definitively gain more views than the least shared videos across all levels of video popularity. However, over the next 20 days the margin diminishes significantly for the most popular videos, and among the less popular videos the least shared videos gained more views than the highly shared videos (see Figure 7). Highly shared videos effectively gain views over short periods of time, but this ability to gain views is not sustained.

IV. Socialness of Video Categories & Views

A. *Video Categories*

Considering the relationship between social views and video growth, it is natural to ask which categories of videos are the most social. The answer depends on how the level of sharing is measured, as well as the time frame for the measurement. Using the first 30 days since video upload, Table 8 shows three ways in which the socialness of a video category can be quantified. The first column shows

Category Name	Highly Shared Video %	Category Social View %	Overall Social View %
Pets & Animals	**42.3**	48.4	1.3
Nonprofits & Activism	38.8	54.7	1.4
News & Politics	31.7	47.2	6.6
Travel & Events	29.5	46.0	1.1
Education	28.8	**61.3**	2.9
Science & Technology	28.4	50.6	2.9
Sports	28.1	39.7	7.9
People & Blogs	26.7	43.8	11.4
Autos & Vehicles	23.8	42.0	2.2
Comedy	20.0	42.9	10.3
Howto & Style	19.7	38.8	2.6
Entertainment	15.6	32.4	16.9
Gadgets & Games	15.3	36.8	6.3
Film & Animation	14.0	33.3	5.0
Music	12.8	29.9	**18.2**
Shows	9.8	34.1	3.0

Figure 8. Three measures for ranking the level of sharing within video categories: the fraction of videos within the category that are highly social, the fraction of views within the category that are social, and the absolute number of social views generated by the category.

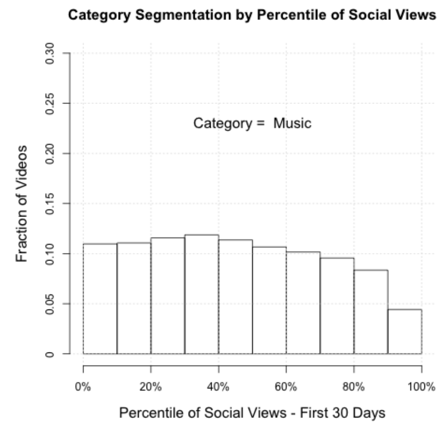

Figure 10. Segmentation by percentage of social views of the music category. For this category, 12.8% of the views have a level of sharing that is above the 80th percentile.

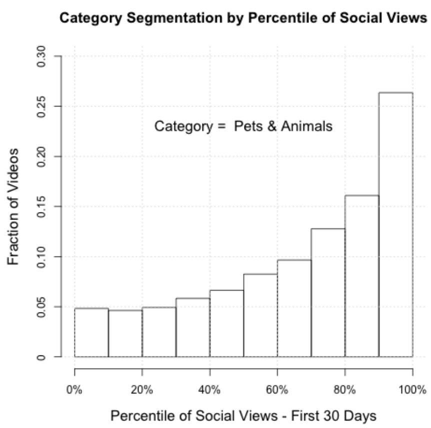

Figure 9. Segmentation by percentage of social views from the pets category. For this category, 42.3% of the videos have a level of sharing that is above the 80th percentile.

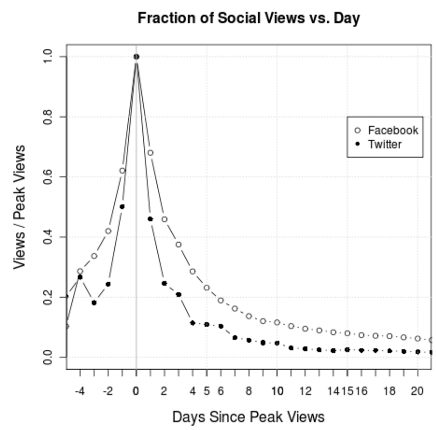

Figure 11. Relative growth of views from Facebook and Twitter referrals. All views were for videos that peaked on their 6th day of viewing.

the ***fraction of videos*** that exceed the 80th percentile in sharing within each category. In this case, the category with the highest level of socialness is ”Pets”, and the lowest is ”Shows”. Figures 9 and 10 show the fraction of videos that fall into each video segment.

On the other hand, if the ***fraction of views*** that are social is used to rank the categories, then the category with the highest level of sharing is ”Education”. Finally, if we look at the absolute number of social views generated, then the ”Music” category has the highest level of sharing. This category generated 18.2% of all social views that occurred within the first 30 days. The reason that ”Music” jumps to the top for this measure is the large number of views associated with music videos. This category generates a lot of social views, but these videos don’t typically rely on these views to become popular.

B. Views

In this study, views are classified as either social or non-social. However, social views from different referral sources can behave differently. As an example, consider the social networking sites Facebook and Twitter. We classify the referrals generated by these sites as social, and the views generated by these sites follow the same pattern of growth as the views generated by the highly social video segment. But, as Figure 11 indicates, the behavior of the Twitter views is more extreme. During the two days prior to peak viewing the Facebook views increased by a factor of 2.4. For Twitter, the increase was a factor of 4.5. The Twitter views are more highly concentrated near the day of peak viewing. This behavior is consistent with the real-time nature of sharing on Twitter.

The distribution of Facebook and Twitter referrals across video segments also differs. Figures 12 and 13 are analogous

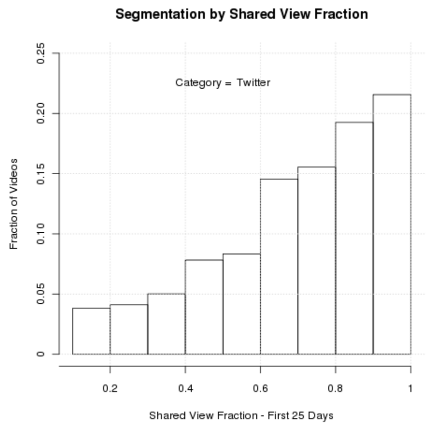

Figure 12. Segmentation of Twitter referrals by the associated video's fraction of social views. 35.9% of these views are associated with videos that have a level of sharing that is above the 80th percentile.

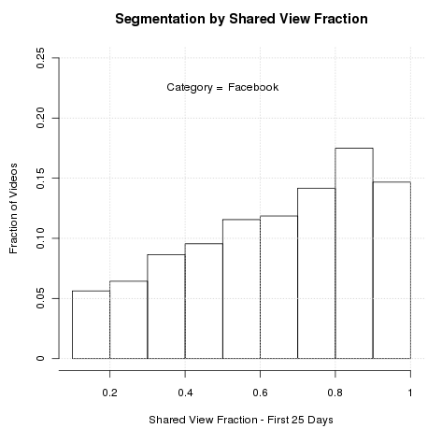

Figure 13. Segmentation of Twitter referrals by the associated video's fraction of social views. 35.9% of these views are associated with videos that have a level of sharing that is above the 80th percentile.

to the category figures for "Pets" and "Music" (Figures 9 and 10). These figures indicate that Twitter and Facebook referrals are more likely to be associated with videos that have a high fraction of social views. Since Twitter and Facebook referrals are considered social, this behavior is expected. But, these plots also indicate that Twitter views are more likely to be associated with highly shared videos than Facebook views, which is consistent with Figure 11.

V. Video Examples

Up to this point we have focused on the aggregate behavior of videos within video segments. But, analyzing the behavior of individual videos is instructive as well. We will see that the patterns we found on an aggregated level hold for individual videos as well.

For our analysis we take two popular, recently uploaded videos. One is a music video (denoted *PopularVideo*), which got most of its views from searches, as is quite typical for music videos. The other one is a popular entertainment video (denoted *ViralVideo*) which has a large percentage of social views and thus classifies as a viral video.

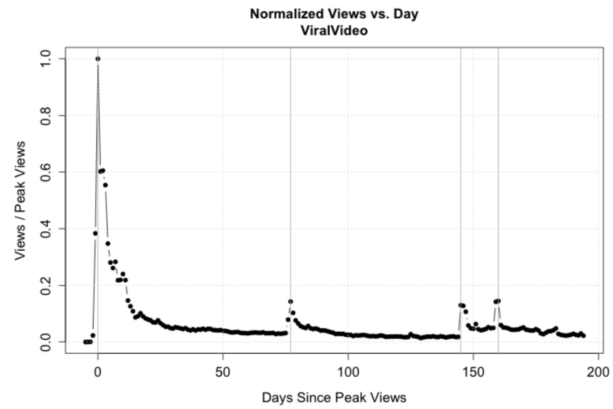

Figure 14. Relative growth of views for the "ViralVideo" video. The primary peak for this video occurs on the 6th day of viewing. Secondary peaks occur on days 78, 146, and 161.

The "ViralVideo" is a very popular video that has generated tens of millions of views. Figure 14 shows the normalized views over time for this video. The video peaked on its 6th day and the level of sharing within the first 30 days puts it in the 80th-90th percentile video segment. This is a very popular video that relied heavily on social views to become popular. It is a viral video. However, the most interesting behavior occurs after the primary viral spike.

Figure 15 shows the fraction of social views across time for this video. This fraction increases sharply just prior to the first viral peak, and then drops steadily before cycling through a pattern of increases and decreases with a weekly period. Then, quite suddenly, the fraction of social views drops significantly on day 77. This drop occurs one day prior to the secondary peak seen in Figure 14. And, this spike coincides with the airing of a popular TV show, which featured a take-off on this video. The sudden drop in the fraction of social views was caused by an increase in referrals due to YouTube searches for this video.

In contrast, the third peak in Figure 14 coincides with a spike in the fraction of social views. This viral spike was sparked by referrals from a blog post containing an end of year summary of popular YouTube videos.

The "MusicVideo" is a very popular video that has also generated tens of millions of views. Figure 16 shows the normalized views over time for this video. The video peaked on its 38th day and the level of sharing within the first 30 days puts it in the 30-40th percentile video segment. This is not a viral video, although the video does have a viral-like spike on its third day of viewing. After this spike, the number of views increases steadily with a regular weekly pattern superposed. On the other hand, Figure 17 shows that

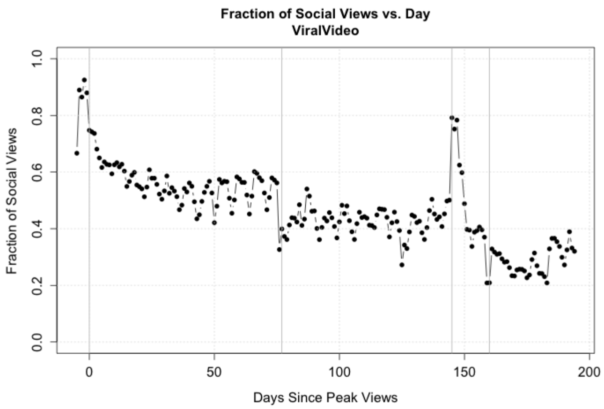

Figure 15. Fraction of social views by day for the "ViralVideo" video. This fraction declines rather steadily over time. Although it declines rapidly at days 77 and 160, and there is a brief resurgence in sharing starting at day 145.

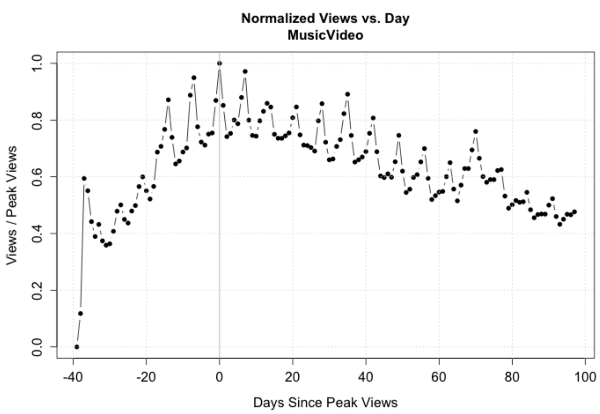

Figure 16. Relative growth of views for the "MusicVideo" video. The primary peak for this video occurs on the 38th day of viewing.

the fraction of social views spikes within the first few days before dropping to a low and somewhat constant level that is between 10 and 15%. "ViralVideo" and "MusicVideo" are both very popular videos, but the driving force behind this popularity is clearly very different in these two examples.

VI. Popular Videos

A. Socialness of Popular Videos

Previous sections of this paper have focused on the full spectrum of YouTube videos. In doing so, we have seen that not all highly social videos are popular. This section focuses on popular videos, which we define to be the top 1% of videos in terms of views. We find that not all popular videos are highly social. In fact, the majority of videos that become popular do so without being highly social.

Within the first 30 days since upload, 44% of popular video views are social. This fraction is higher than the corresponding 42.2% for the overall video population reported

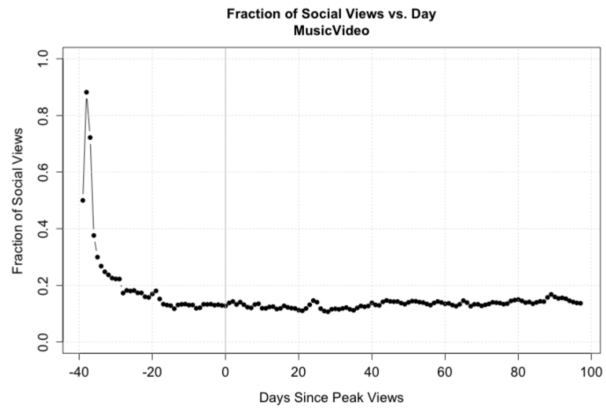

Figure 17. Fraction of social views by day for the "MusicVideo" video. This fraction declines rapidly over the first several weeks until it reaches a relatively low and somewhat constant level.

Day 1	Week One	First Month	Two Months	Three Months
39%	43%	44%	41%	37%

Table II
Percent of social views as a function of video age for popular videos.

in Table I. And, unlike the overall population, the fraction of social views increases over the first month before decreasing over time (see Table II). After 60 days, the fraction drops to 41%, and after 90 days it is 37%.

Just as we observed the fraction of videos that belong to each social view video segment for certain categories of videos (Figures 9 and 10), the fraction of popular videos that belong to each social view video segment are shown in Figure 18. The highest shared segment contains the highest fraction of popular videos, 11.9%. However, only 21% of the popular videos have a level of sharing that is above the 80th percentile. And, only 30% of popular videos received more than half of their views from a social referral. So, most popular videos do not rely heavily on social views to become popular.

Although most popular videos do not rely on social referrals to become popular, it is still possible that viral videos (those that are both highly shared and popular) generate a significant fraction of the popular video views. Figure 19 shows that this is not the case. 23% of views come from the two most social segments (above 80th percentile in sharing). So, even in the first 30 days when they are most prominent, viral videos are not responsible for the majority of popular video traffic on YouTube.

In Figure 19 the video segment with 40-50th percentile social views generates the most views. These views are primarily due to videos in the categories "Music" and "Entertainment". For comparison, the views from the highest social segment are primarily due to videos in the categories

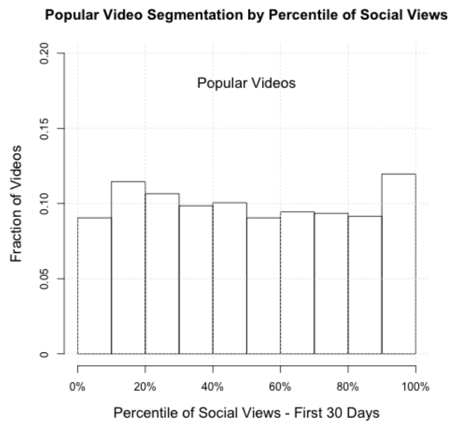

Figure 18. Segmentation by fraction of social views for the set of popular videos. About 21% of the popular videos have a level of sharing that is above the 80th percentile.

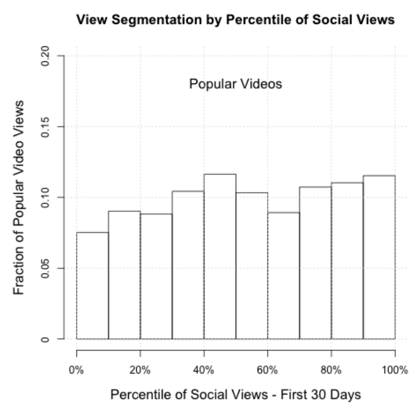

Figure 19. Segmentation by fraction of social views for the views associated with popular videos. About 12% of the popular video views are from the segment of videos with the highest level of sharing, and about another 12% are from the segment with fraction of social views in the 40-50th percentile

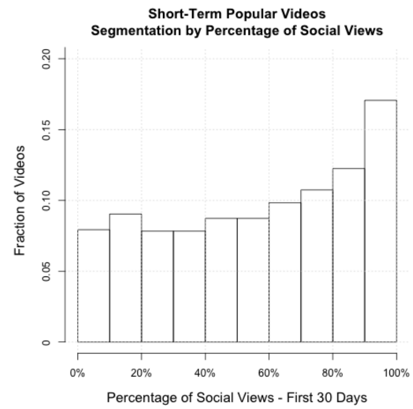

Figure 20. Segmentation by percentage of social views for the set of videos that are ”short-term” popular. Many of these videos come from the more social video segments.

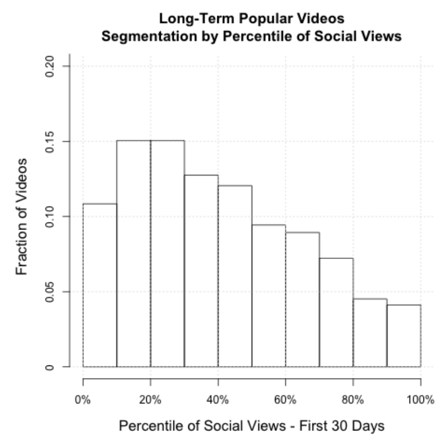

Figure 21. Segmentation by percentage of social views for the set of videos that are ”long-term” popular. Many of these videos come from the less social video segments.

”People & Blogs”, ”Comedy”, and ”Entertainment”.

B. Staying Power of Viral Videos

The observed decline in the fraction of social views over time for popular videos suggests that viral videos do not continue to generate social views across longer periods of time. However, we would also like to know if viral videos tend to generate non-social views over longer periods of time. So, for each popular video, we compute the ratio of views in the second month after upload to views in the first month. Videos with a high ratio (above the 50th percentile) are are classified as “long-term popular” videos. Videos with a low ratio (below the 50th percentile are classified as ”short-term popular”.

Figure 20 shows the distribution of ”short-term popular” videos across the video segments. Many of these videos come from the more social video segments. On the other hand, Figure 21 shows that many of the ”long-term popular” videos come from the less social video segments. Once again, the indication is that viral videos do well at generating views over short periods of time, but this level of success is not sustained.

This last comparison is perhaps a bit unfair. Viral videos start out by generating more views than their less social popular video counterparts, and then we require them to maintain this higher viewing rate over time in order to make it into the long-term popular category. So, we also look at CDFs of video views, as in Figures 6 and 7, but now using only popular videos. Figures 22 and 23 show the CDF of the log of views generated by popular videos for three social view segments. As was the case in the larger population of videos, the highly social videos tend to generate more views early in their lives. But, in days 11-30 these more

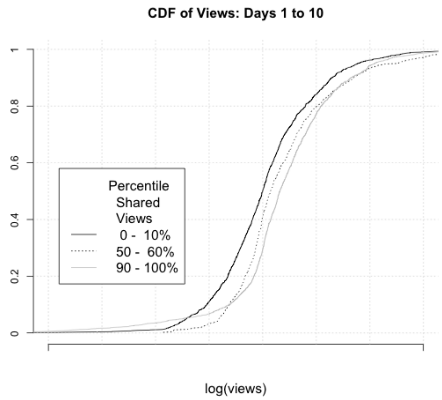

Figure 22. CDF of the log of the views generated from days 1 to 10 for three video segments.

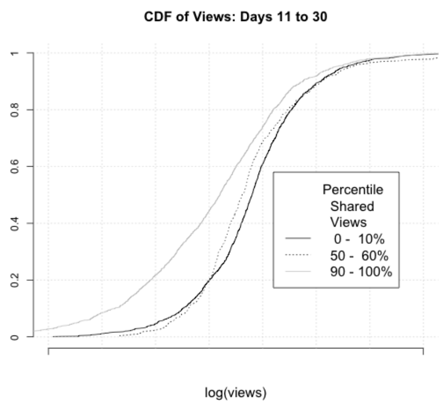

Figure 23. CDF of the log of the views generated from days 11 to 30 for three video segments.

social videos cannot keep pace with those that rely less on sharing. So, as compelling as viral videos are in the short term, they are less capable of gaining views over the long term.

VII. Summary

Highly social videos behave differently than less social videos. They tend to peak more sharply and wane more rapidly. While they tend to generate more views in the short-term, they cannot keep up with less shared videos over the long-term. Viral videos are a subset of these highly social videos that rise to extreme levels of popularity. These videos demonstrate the power of sharing, and it's role in shaping video viewing habits. However, as appealing and interesting as viral videos are, they have not replaced less social methods of video discovery. The insights generated in this paper will be used as the basis for future work related to the creation of classification and predictive models for online videos.

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