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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 millions of YouTube videos. The *socialness* of a video is quantified by classifying the referrer sources for video views as *social* (e.g. an emailed link, Facebook referral) or *non-social* (e.g. a link from related videos). We find that viewership patterns of highly social videos are very different from 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. By using our insights on viral videos we are able develop a method for ranking blogs and websites on their ability to spread viral videos.

Keywords Viral videos · Internet sharing · YouTube · Social media · Ranking blogs · Data mining · Logs mining · Weblogs

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1 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 do not 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 provide viewing choices. They are more likely to watch videos that are distributed from person to person across social networking sites, blogs, emails and instant messaging. Videos that become popular through such sharing have become known as *viral videos* (Urban Dictionary 2010; Wikipedia 2010; Encyclopedia 2010; Hyperdictionary 2010; Viral Videos 2010a, b, c, d).

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 (Leskovec et al. 2009; Cha et al. 2007). A study on new media versus old media, published in May 2010 (Journalisms 2010) 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 User Generated Content (UGC) make traditional content popularity prediction unsuitable (Cha et al. 2007). The opportunity to leverage these shared views comes early in a video's life. [Around 25.0% of the daily views on YouTube come from person-to-person sharing. Yet if we just look at views on the first day of the video, this number is 34% (see Table 1 and Fig. 1). Then it drops down to 16% by the end of the third month.] Marketing organizations and researchers are working hard to figure out how to capitalize on these time sensitive opportunities (dmiracle 2010; Marketing Experiments 2010; Kempe et al. 2003).

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 2008 and the November 2008

Table 1 Cumulative percent of social views as a function of video age

Day 1	Week one	First month	Two months	Three months
34%	31%	27%	25%	23%

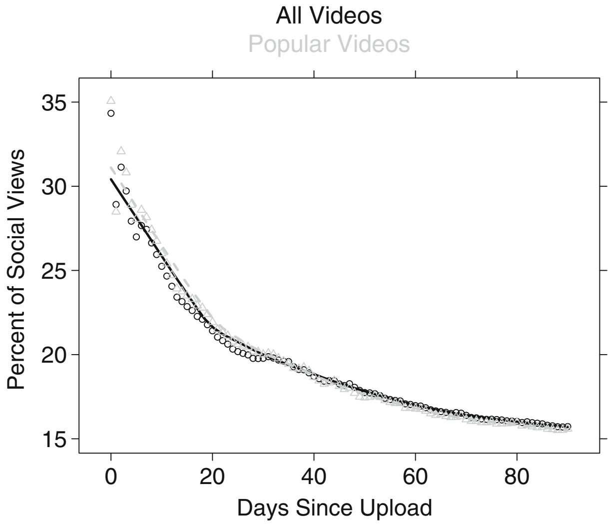


Fig. 1 Daily percent of social views as a function of the number of days since the video was uploaded. There is no significant difference between all the videos and popular videos

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 (YouTube 2008), and by November 2008, it had been viewed over 10 million times. Wallsten (2008) 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. Cheng et al. (2007) 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 of its success, and they also note that linking, rating and favoriting make videos popular in a very organic fashion. Crane and Sornette (2008) 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 and decayed around the peak. Adams et al. (2008) 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 media 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 drive a rapid increase in attention. In a previous study (Cha et al. 2007) 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. (2009) studied distribution chains and large-scale cascades across Facebook. 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. Note that we would have loved to study cascade behaviour of the sharing of videos but we do not have access to the type of data. Most of the video sharing happens outside YouTube.

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. 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. With this definition we are able to detect viral videos very early on and use this information in various places on the site. We are able to quantify the socialness of categories of videos, observe differences in the behavior of social referrals (such us Twitter and Facebook), and determine the effectiveness of viral videos in generating views across longer intervals of time.

Section 2 describes the *social* and *non-social* classification of referrer sources. Section 3 describes the application of this classification to video segmentation and demonstrates the relationship between socialness and the dynamics of video growth. Section 4 highlights differences in the socialness of video categories and the referrals from Twitter and Facebook. Section 5 shows the behavior of two specific videos, one that is viral and one that is not. Section 6 describes the behavior of *popular* videos, which we define to be videos that are in the top 1 percentile in terms of views generated. Section 7 proposes a methodology for ranking websites and blogs on their propensity to spread viral videos. Finally, Section 8 contains a brief summary of our results.

2 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. The results on the Popular Video Section were generated using all popular videos in the same period. 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.

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 applied to the video level so that videos can be characterized by their "socialness". Videos with an extremely low number of views do not provide a useful sense of their socialness. Consequently, we excluded videos with less than 100 views within their first 30 days of viewing, although our primary results are not sensitive to this particular cutoff. 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 viewing, the aggregate fraction of social views is 27%. Figure 2 shows how the fraction of social views varies across our (filtered) set of videos. However, there are a significant number of videos with higher levels of sharing. Twenty percent 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

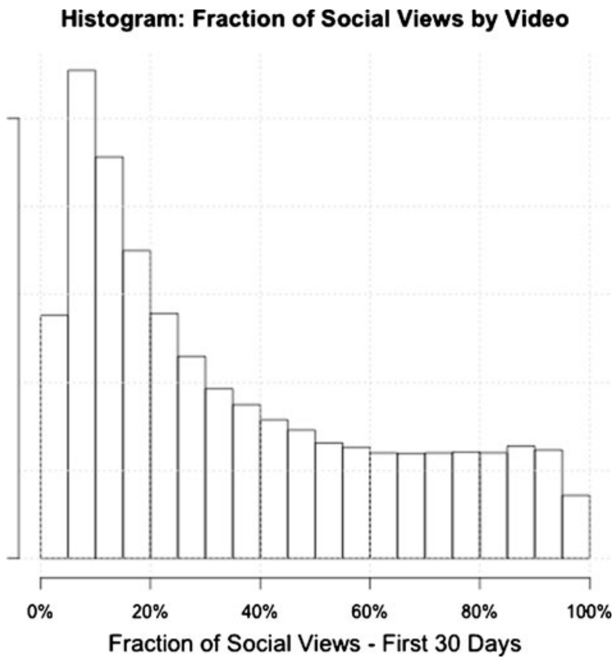


Fig. 2 Histogram of the fraction of social views for each video. These social view fractions are calculated using views from the first 30 days since video upload

fraction of social views is 34%, but this fraction drops over time to 16% (see Table 1 and Fig. 1). Overall, 25% of the daily views on YouTube are the result of person-to-person sharing.

3 Social segmentation and video growth

In this section we discuss the relationship between socialness and the dynamics of video growth. We learn 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.

We segments videos by using the fraction of social views during the first 30 days of viewing. 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 3a shows the growth of views within three segments with very different fractions of social views: the lowest tenth percentile, the 50–60th percentile, and the top tenth percentile. All of these videos peaked on their fifth 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 than the least shared segment.

The difference in behavior across segments is not limited to relative growth. Figure 3b shows that the absolute number of views is also much greater for the video segment with the highest rate of sharing (90–100%). On the day of upload, this segment starts out with half of the views than 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 Fig. 4a. 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. Figure 4b indicates the degree to which the fraction of 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,

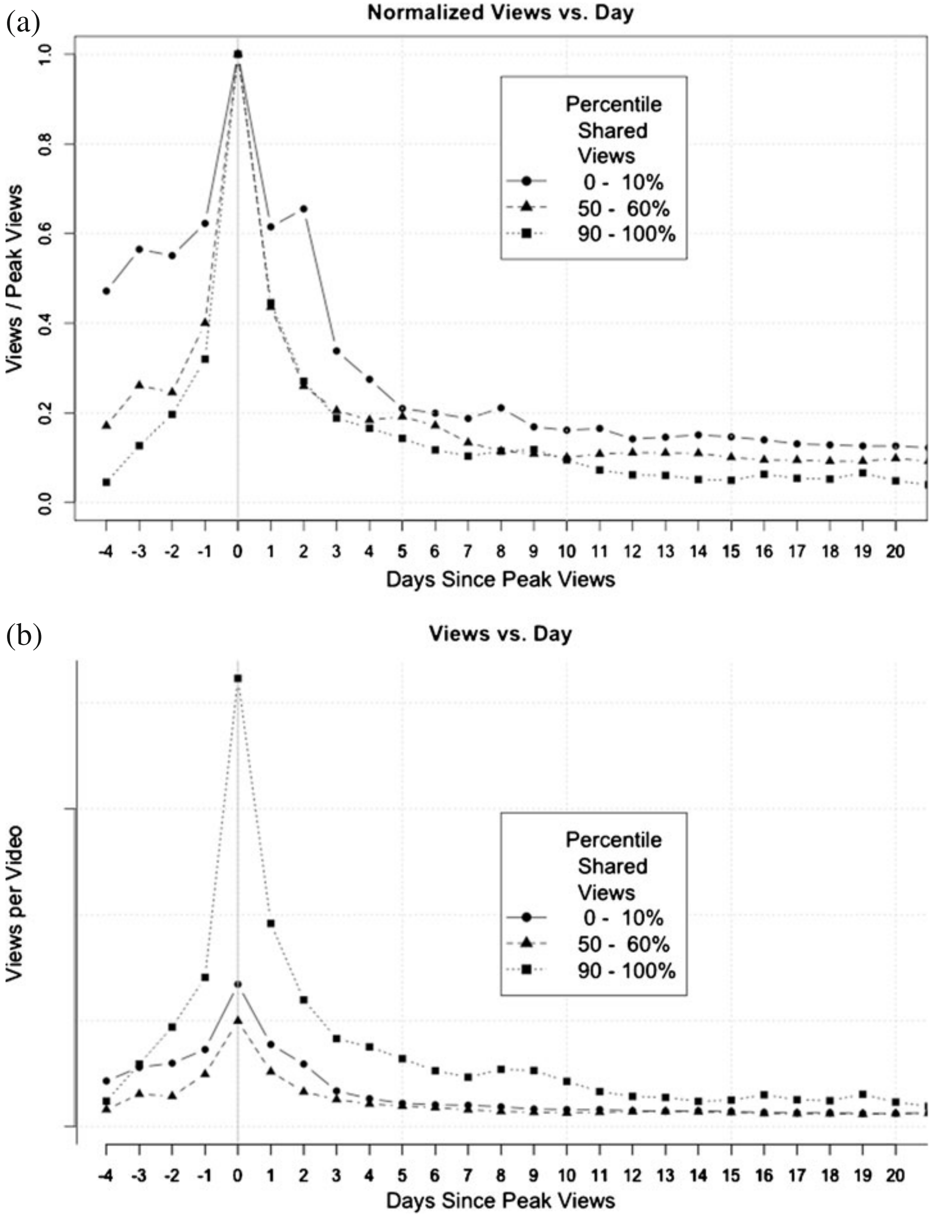


Fig. 3 **a** Relative growth of views from three video segments with very different levels of sharing. All of the videos considered peaked on their fifth day of viewing. The segment with the highest level of sharing has the highest (relative) rate of growth, as well as a steep post-peak decline. **b** Absolute number of views as a function of day for the three segments of videos

and a fairly steady decrease in the level of sharing afterwards. There is less 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

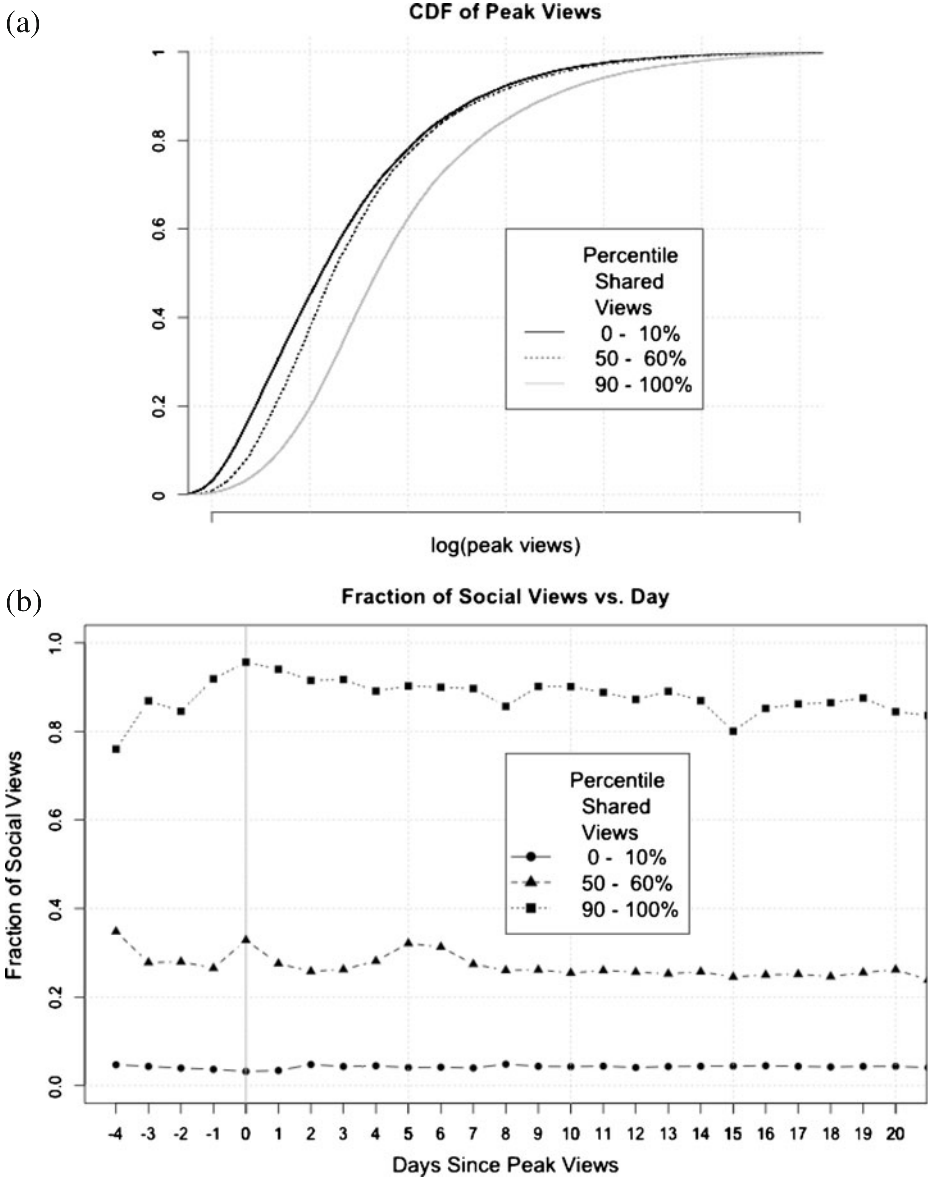


Fig. 4 **a** CDF for the log of the peak views for three video segments. **b** Fraction of social views by day for the three video segments for videos that peaked on their fifth day of viewing

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 Fig. 3b is similar to the behavior described by Crane and Sornette (2008). After looking at the views profile, Crane and Sornette classify videos into viral, quality and junk. Although their approach is interesting but it is not useful at classifying videos in real time. In this paper we propose a definition that is actionable, where we can classify videos as they become viral and use this information is various places on YouTube.

4 Socialness of video categories & views

4.1 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. In this section we discuss the question of what is the composition of viral videos in terms of categories.

Using the first 30 days of viewing, Table in Fig. 5 shows three ways in which the socialness of a video category can be quantified. The second column shows 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." Figure 6a and b 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 but that is because Music comprises a large percent of the daily activity on YouTube.

4.2 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

Fig. 5 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

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

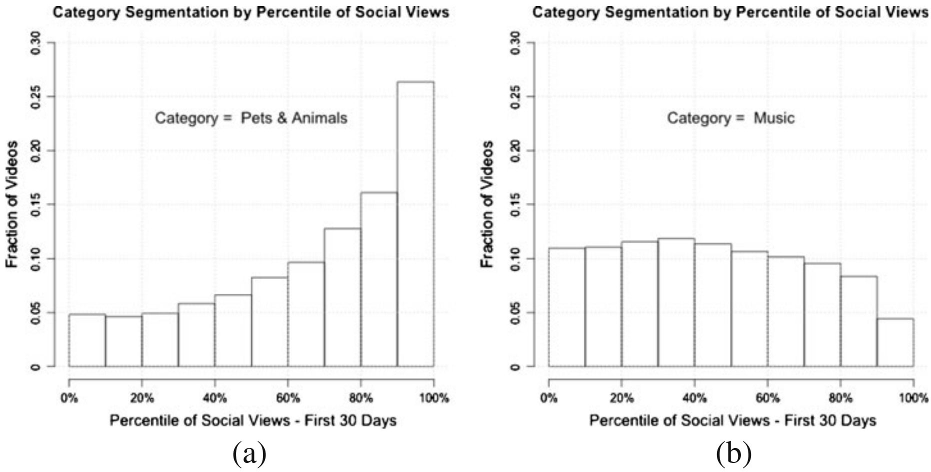
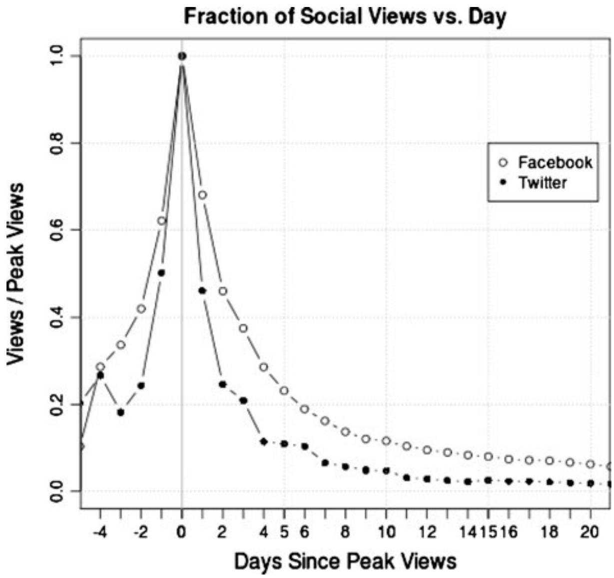


Fig. 6 **a** Segmentation by percentage of social views from the pets category. For this category, 42.3% of the videos have a level of sharing that is above the 80th percentile. **b** Segmentation by percentage of social views of the music category. For this category, 12.8% of the views have a level of sharing that is above the 80th percentile

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 Fig. 7 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

Fig. 7 Relative growth of views from Facebook and Twitter referrals. All views were for videos that peaked on their sixth day of viewing. In this plot, for each curve, the views are normalized by dividing by the views at the peak



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. Figure 8a and b are analogous to the category figures for “Pets” and “Music” (Fig. 6a and b). 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

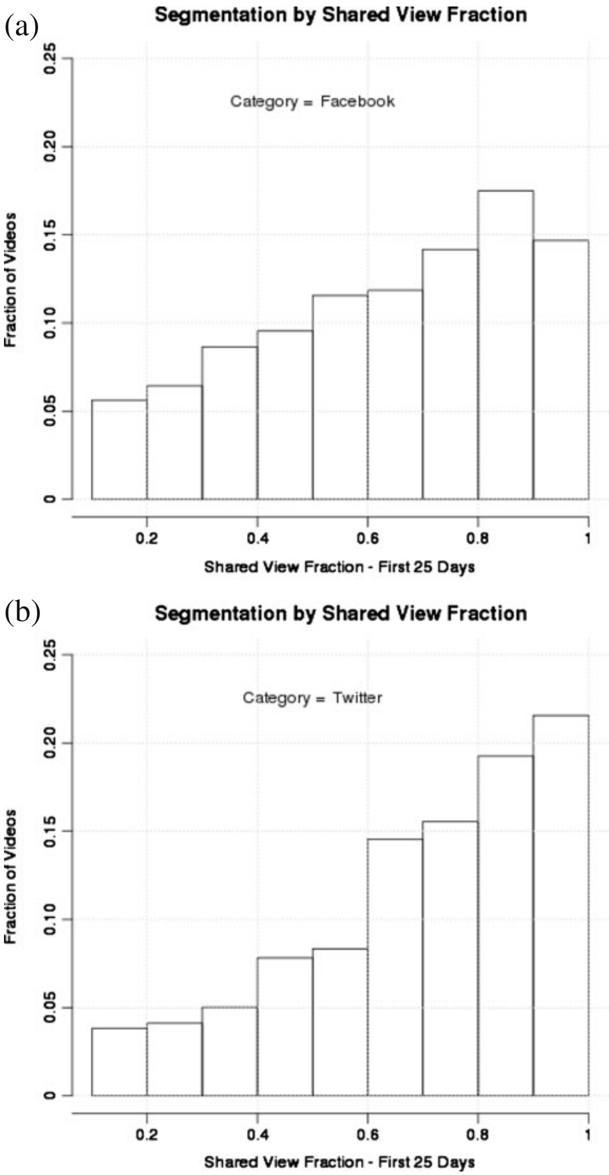


Fig. 8 **a** Segmentation of Facebook referrals by the associated video’s fraction of social views. **b** Segmentation of Twitter referrals by the associated video’s fraction of social views

these plots also indicate that Twitter views are more likely to be associated with highly shared videos than Facebook views are.

5 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.

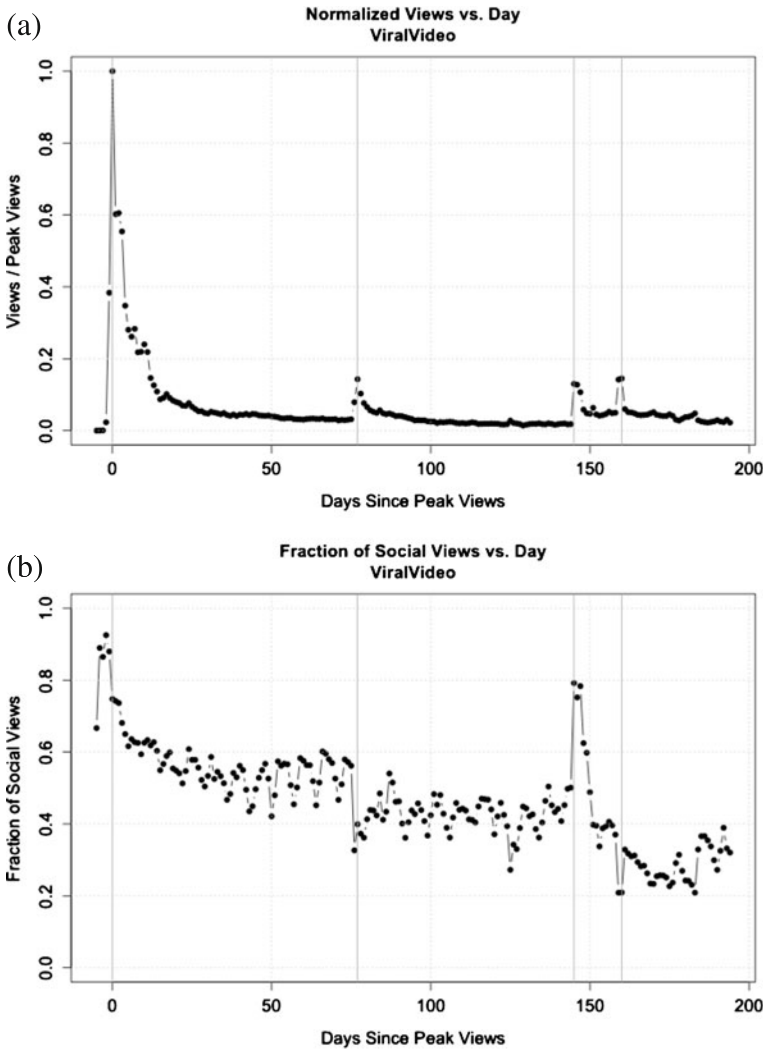


Fig. 9 **a** Relative growth of views for the "ViralVideo" video. The primary peak for this video occurs on the sixth day of viewing. Secondary peaks occur on days 78, 146, and 161. **b** Fraction of social views by day for the "ViralVideo" video. This fraction declines rather steadily over time. Although it declines rapidly at days 77 and 160, and there is a brief resurgence in sharing starting at day 145

We found that the patterns on an aggregated level are similar to patterns on some individual videos.

For our analysis, we took two popular, recently uploaded videos. One is a music video (denoted *MusicVideo*), 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.

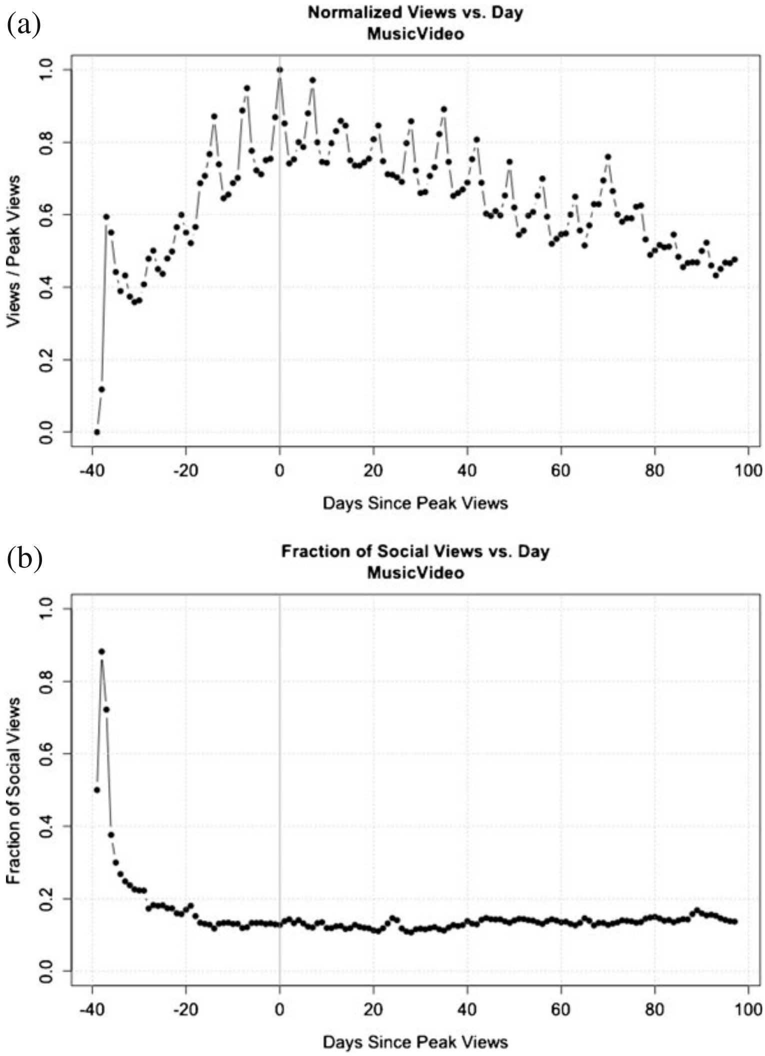


Fig. 10 **a** Relative growth of views for the "MusicVideo" video. The primary peak for this video occurs on the 38th day of viewing. **b** Fraction of social views by day for the "MusicVideo" video. This fraction declines rapidly over the first several weeks until it reaches a relatively low and somewhat constant level

The “ViralVideo” is a very popular video that has generated tens of millions of views. Figure 9a shows the normalized views over time for this video. The video peaked on its sixth 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, making it a viral video.

Figure 9b 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 Fig. 9a. 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 from YouTube searches for this video. In contrast, the third peak in Fig. 9a 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 10a 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. We do not consider this video viral, 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, Fig. 10b shows that 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.

6 Popular videos

6.1 Socialness of popular videos

Previous sections of this paper have focused on the full spectrum of YouTube videos. 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. The majority of videos become popular through related videos and search.

Figure 11a shows the distribution of the percentage of social views among popular videos in the first 30 days. Note that the distribution is bimodal. That is, it has two peaks, showing that most videos are either viral (peak around 90%) or non-viral (peak around 10%). The peak at 10% is much higher than the one at 90%. If we consider viral videos those with at least 60% of social views, 23% of the videos in this plot are viral. Figure 11b shows the distribution of percentage of views form YouTube search and related videos. This distribution it is still bimodal but it is much more uniform than the previous one, 37% of the videos have at least 60% of their views coming from YouTube search and related.

The bimodal distribution (Fig. 11a, b) means that videos have many views that originate either from YouTube or from external websites/sharing. This pattern can be explained by the fact that viral videos do not seem to make it very often into the YouTube discovery mechanisms such us related videos or YouTube search. We have

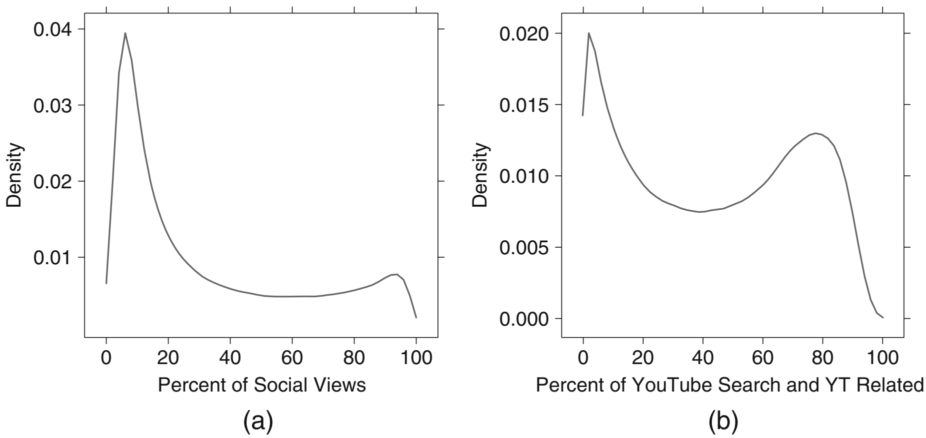


Fig. 11 **a** Distribution of percent of social views for popular videos. Most videos have a low percentage of social views and therefore are non-viral. **b** Distribution of percent of views from YouTube search and related

a couple of hypotheses to explain that. Related videos rely on co-visitation data[1] almost exclusively over a certain period of time. But most viral videos have views in a short period of time and their users are often casual YouTube users (Ulges et al. 2011). These factors may prevent viral videos from making it into the related list of any other videos. On the other hand, videos that make it into the related video list of other videos have a stable source of views; even if it decays, it is sustained for a longer period of time. These hypotheses also suggest that they way we compute related videos today does not apply very well to viral videos.

6.2 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. In this section, we want to understand the relationship between "viralness" and "long term popularity" of a video. In order to understand this relationship, define popularity ratio (PR) as:

$$PR(video) = \frac{\text{Views in the Second Month}}{\text{Views in the First Ten Days}}$$

A good percentage of viral videos have most of their views in the first week that they are uploaded to YouTube. A large PR means that the video had also kept generating views in its second month. We call videos with large PR "long-term popular" and videos with low PR "short-term popular".

[1] Co-visitation between video A and B is the number of people that watch A and B.

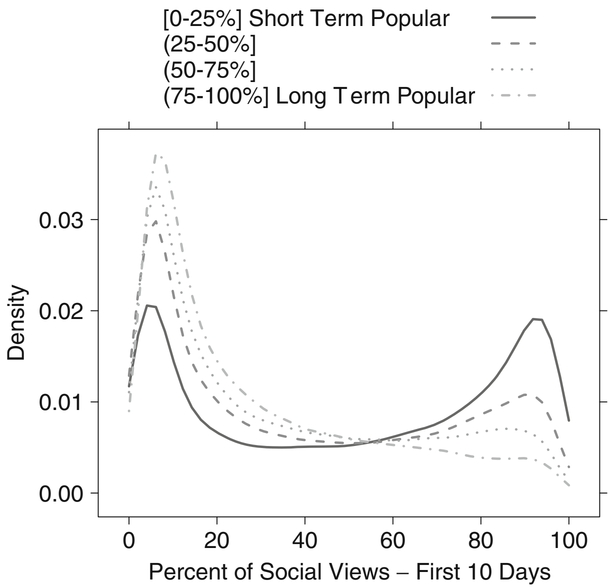


Fig. 12 Density of percent of social views for popular videos in the first ten days. The videos are segmented by their "long-term popularity

In Fig. 12 we segment videos by PR percentile. The [0–25%] percentile corresponds to "short-term popular" and the [75–100%] to the "long-term popular" videos. From Fig. 12 we see again a clear bimodal distribution of social views for popular videos. That is, videos tend to be either viral or non-viral. The "short-term popular" videos, represented by the solid black line, shows the density of viral and non-viral videos is approximately the same. By contrast, the density of "long-term popular" videos, represented by the dashed light-gray line, shows almost no viral videos. The intermediate percentile groups perform in between the two extremes as expected. Once again, the plot indicates that viral videos do well at generating views over short periods of time, but this level of success is not sustained.

7 Ranking viral video blogs

In this section we address the problem of ranking websites and blogs that embed videos. Intuitively, we would like a ranking function that measures the propensity of a website or a blog to spread viral videos. Also, we want to rank websites on their ability to discriminate good viral videos from unpopular videos. We need to be able to discard websites, such as Facebook, which refer good videos as well as unpopular videos. Having a ranking with such properties could be useful in many applications. For example, we can use highly ranked blogs to predict, in real time, which videos would become viral.

For this application, we define:

– **Popular videos:** videos with more than $views_{\text{cutoff}}$ views in the first 30 days since the video upload. Where $views_{\text{cutoff}}$ is defined such that popular videos are the

top 1% of videos in terms of views. This translates to videos with at least several thousands of views.
- **Viral videos:** popular videos with at least 60% of social views in the first month.
- **Viral video measure:** (used in url ranking) sum of embedded views on that url coming from viral videos.
- **Unpopular videos:** videos with less than 100 views in the first 30 days.

Let $\mathcal{V}_p$ be the set of viral popular videos and $\mathcal{V}_u$ as the set of unpopular vdeos. For each url u, let $\mathcal{W}_{100}(u)$ be the set of videos in with at least 100 views coming from url u. We use the ratio $r(u)$ between viral and unpopular videos to discard outliers with very low ratios, such as Facebook.

$$r(u) = \frac{\left|\mathcal{V}_p \cap \mathcal{W}_{100}(u)\right|}{\left|\mathcal{V}_p \cup \mathcal{V}_u\right|}$$

Also, for each url u and each video $v \in \mathcal{V}_p$, let views(u, v) be the number of views from video v coming from url u. After we filter urls u such us $r(u) < r_{low}$ for some small constant r_{low}. We use as a ranking function $\mathcal{R}(u)$ the sum of views on that url coming from viral videos.

$$\mathcal{R}(u) = \sum_{v \in \mathcal{V}_p} views(u, v) \tag{1}$$

7.1 Validating the ranking function

In order to validate our ranking function, we compare it with the popular blog ranking technorati.com (technorati 2011).[2] This ranking site only considers websites classified as blogs, so sites such us sports.yahoo.com, www.reddit.com, thedailywh.at are not ranked while sites like www.huffingtonpost.com and www.gizmodo.com are. While Technorati has a different basis other than video referrals for ranking blogs, its overall goal of finding popular, fast changing content on the internet matches our criteria.

We take the top 100 sites ranked by our algorithm and compare it with the rank on technorati.com. Out of our top 100 blogs, 49 were listed by technorati.com. Of these 49 blogs, 40% had ranks less than 50 in technorati.com, 53% had ranks less than 100, and 71% had ranks less than 200. This suggests a very good correlation. Table 2 shows the top 25 urls ranked by our algorithm. The "NA" is used in cases in which technorati.com did not provide a ranking.

[2]From Technorati: Technorati Rank is a site's rank among the Technorati Authority of all sites. Authority is calculated based on a site's linking behavior, categorization and other associated data over a short, finite period of time. A site's authority may rapidly rise and fall depending on what the blogosphere is discussing at the moment, and how often a site produces content being referenced by other sites.

Table 2 Viral video rank for top 25 urls

	technorati_rank	viral_video_rank
sports.yahoo.com	NA	1
rivals.yahoo.com	NA	2
huffingtonpost.com	1	3
reddit.com	NA	4
perezhilton.com	122	5
new.music.yahoo.com	NA	6
news.yahoo.com	NA	7
gizmodo.com	5	8
sportsillustrated.cnn.com	NA	9
boston.barstoolsports.com	1580	10
breitbart.tv	162	11
thedailywh.at	NA	12
kotaku.com	18	13
engadget.com	2	14
popeater.com	17	15
deadspin.com	76	16
thisis50.com	NA	17
buzzfeed.com	24	18
mmo-champion.com	NA	19
drudgereport.com	NA	20
theblaze.com	NA	21
i-am-bored.com	13347	22
gawker.com	6	23
boingboing.net	8	24
hotair.com	14	25

NA is used in cases in which technorati.com didn't provide a ranking

8 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 its 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. Our viral video insights can be used to rank websites and blogs on their propensity to spread viral videos. Our ranking correlates well with the popular blog ranking site Technorati.

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