I Tube, You Tube, Everybody Tubes: Analyzing the World's Largest User Generated Content Video System

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ABSTRACT

User Generated Content (UGC) is re-shaping the way people watch video and TV, with millions of video producers and consumers. In particular, UGC sites are creating new viewing patterns, social interactions, empowering users to be more creative, and developing new business opportunities. To better understand the impact of such UGC systems, we have analyzed YouTube, the world-largest UGC VoD system. Based on a large amount of data collected, we provide an in-depth study of YouTube and other similar UCG systems. In particular, we study the popularity life-cycle of videos, the intrinsic statistical properties of requests and their relationship with video age, and the level of content aliasing or of illegal content in the system. We also provide insights on the potential for more efficient UCG VoD systems (e.g., utilizing P2P systems or making better use of caching). Finally, we discuss the opportunities to leverage the latent demand for niche videos that are not reached today due to information filtering effects or other system scarcity distortions. Overall, we believe that the results presented in this paper are crucial in understanding UGC systems and their inefficiencies, which can have tremendous commercial and technical consequences.

Keywords

User-generated contents, VoD, P2P, Caching, Popularity analysis, Content aliasing

1. INTRODUCTION

Video content in standard Video-on-Demand (VoD) systems has been historically created and supplied by a limited number of media producers, such as licensed broadcasters and production companies. Content popularity was somewhat controllable through professional marketing campaigns. The advent of user-generated content (UGC) has re-shaped the online video market enormously. Nowadays, hundreds of millions of Internet users are self-publishing consumers. The content length is shortened by two orders of magnitude and so is the production rate. Wired magazine refers to this small-sized content pop culture as "bite-size bits for high-speed munching" [31].

The scale, dynamics, and decentralization of the UGC videos makes the old mode of content popularity prediction impractical. UGC popularity is more ephemeral and has a much more unpredictable behavior. As opposed to the early days of TV where everyone watched the same program at the same time, such strong reinforcement of popularity (or unpopularity) is much more diluted in UGC. Constant waves of new videos and the convenience of the Web is quickly personalizing the viewing experience, leading to a great variability in user behavior and attention span. At the same time, the corresponding lack of editorial control in UGC is creating problems of copyright infringement, which seriously threatens the future viability of such systems.

Understanding the popularity characteristics is important because it can bring forward the latent demand on UGC created by bottlenecks that distort the popularity distribution. It also greatly affects the strategies for marketing, target advertising, recommendation, and search engines.

To understand the nature and the impact of UGC systems, in this paper, we analyze YouTube, the world-largest UGC VoD system. The main contribution of this paper is an extensive trace-driven analysis of UGC video popularity distributions. We have collected a large amount of data from YouTube and another UGC system, Daum. Our analysis reveals very interesting properties regarding the distribution of requests across videos, the evolution of viewer's focus, and the shifts in popularity. Such analysis is pivotal in understanding some of the most pressing questions regarding UGC opportunities. Our analysis also reveals key results regarding the level of piracy and the level of content duplication in such systems, which could have major implications in the deployment of future UGC services.

The highlights of our work could be summarized as follows:

1. We compare some prominent UGC systems with

[*] The data traces used in this paper will be shared for the wider community use in due time at `http://an.kaist.ac.kr/YouTube_Trace_2007.html`.

other standard VoD systems such as Netflix and Lovefilm. We highlight the main differences between the two systems and point out very interesting properties regarding content production, consumption patterns, and user participation.

2. By analyzing the popularity distributions from various categories of UGC services and by tracking the time evolution of it, we show that the popularity distribution of UGC exhibits power-law with truncated tails. We discuss several filtering mechanisms that create truncated power-law distribution. Based on this, we estimate the potential benefits arising from leveraging the latent demand that is hidden due to the filtering effects

3. The increase amount of traffic generated by UGC is a pressing issue for both ISPs and content providers due to the exploding mass of videos. We provide insights into more efficient UGC VoD systems by making a better use of caching and utilizing a peer-to-peer (P2P) technique in UGC distribution.

4. Content aliasing and illegal uploads are critical problems of today's UGC systems, since they can hamper the efficiency of UGC systems and cause costly lawsuits respectively. We measure the prevalence of content duplication and illegal uploads in UGC, and their impact in various system's characteristics.

The rest of the paper is organized as follows. §2 describes our trace methodology and the key characteristics of UGC. In §3, we analyze the popularity distribution of UGC and the forces that shape it. §4 investigates how popularity of videos evolve over time. §5 considers the performance potential of server workload and bandwidth savings via caching and P2P techniques. §6 focuses on the level of content duplication and illegal uploads in UGC. Finally, we present related works in §7 and in §8, we conclude.

2. METHODOLOGY AND PROPERTIES

This section introduces our data collection process and the general properties of the measured UGC videos.

2.1 Data Collection

Our dataset consists of meta-information about user-generated videos from YouTube and Daum UGC services. **YouTube**, the largest UGC site world-wide, serves 100 million distinct videos and $65,000$ uploads daily [6]. **Daum UCC)**, the most popular UGC service in Korea, is well-known for its high-quality videos (streaming as high as at 800 kb/s) and serves 2 million visitors and 35 million views weekly [1].

We crawled YouTube and Daum sites and collected meta information about videos by visiting their indexed pages that link all videos belonging to a category. Due to the massive scale of YouTube, we limited our data collection to two of the categories: 'Entertainment' and 'Science & Technology' (now called 'Howto & DIY'). Throughout this paper, we simply refer to them as `Ent` and `Sci`. For Daum, we have collected video information from all the categories. Each video record contains fixed information, such as the uploader, the upload time, and the length, and time-varying information, such as views, ratings, stars, and links. *Views* and *ratings* indicate the number of times the video has been played or evaluated by users. *Stars* indicate the average score from rating, and *links* indicate the list of external web pages hyper-linking the video. Our trace includes multiple snapshots of video information taken daily across 6 days for `Sci`. These multiple snapshots give insights on the actual request patterns and the popularity evolution of UGC videos. Table 1 summarizes our datasets with basic statistics.

Our trace does not contain information about individual user requests. However, our analysis focuses on video popularity evolution, aggregated request distribution, and other statistics that do not require detailed knowledge of such individual user's behavior.

2.2 UGC versus Non-UGC

To begin with, we present several distinctive features of our UGC video trace. To put things in perspective, we highlight the key differences and similarities between UGC and non-UGC (or professionally generated contents). For comparison purposes, we use data from three representative non-UGC services. **Netflix**, a popular online video rental store, make customer ratings of their 17,770 videos publicly available at [4] and we include this data in our comparison. We additionally crawled the web site of **Lovefilm** [3], Europe's largest online DVD rental store, and **Yahoo! Movies** [5] for meta-information about their movie collections. Our Lovefilm dataset contains the video length and the director. Our Yahoo dataset contains the daily top ten US Box Office Chart from 2004 to March 2007, and their theater gross. Table 2 summarizes the non-UGC dataset.

Table 2: Summary of non-UGC traces

Trace	# Videos	Period	Description
`Netflix`	17,770	Oct 2006	Customer ratings
`Lovefilm`	39,447	Jan 2007	Length and director
`Yahoo`	361	2004 - 2007	Theater gross income

2.2.1 Content Production Patterns

One key characteristic of UGC is the fast content production rate. As we have reported in [28], the scale of production for UGC shows a striking difference with non-UGC. IMDb, the largest online movie database,

Table 1: Video trace summary and statistics.

Name	Category	# Videos	Tot. views	Tot. length	Data collection period
YouTube	Ent	1,687,506	3,708,600,000	15.2 years	Dec 28, 2006 (crawled once)
YouTube	Sci	252,255	539,868,316	1.8 years	Jan 14 - 19, '07 (daily), Feb 14, '07, Mar 15, '07 (once)
Daum	All	196,037	207,555,622	1.0 year	Mar 1, 2007 (crawled once)

carries 963,309 titles of movies and TV episodes produced since 1888, up until now [2]. In contrast, YouTube enjoys 65,000 daily new uploads – which means that it only takes 15 days in YouTube to produce the same number of videos as in IMDb.

UGC requires less production efforts, compared to non-UGC. Accordingly, the number of distinct publishers is massive for UGC. The average number of posts per publisher, however, is similar for UGC and non-UGC (e.g., 90% of film directors publish less than 10 movies). Interestingly, there exist extremely heavy publishers in UGC, who post over 1,000 videos over a few years. In contrast, the largest number of movies produced by a single director scales only up to a hundred movies over half a century.

Next, length of UGC videos varies across categories. Daum CF category shows the shortest median length of 30 seconds, while Daum Music Video shows the longest median length of 203 seconds. Compared with non-UGC, the UGC video length is much shorter by two orders of magnitude. The median movie length in Lovefilm is 94 minutes.

2.2.2 User Participation

The video popularity and ratings (i.e., the number of viewers who evaluated the video) show a strong linear relationship for both UGC and non-UGC, with the correlation coefficient of 0.8 for YouTube and 0.87 for Yahoo. This is an interesting observation, because it indicates that users are not biased towards rating popular videos more than unpopular ones.

Despite the Web2.0 features to encourage user participation, the level of active user participation is very low in YouTube. While 54% of all videos are rated, the aggregate ratings only account for 0.22% of the total views. Comments, a more active form of participation, account for mere 0.16% of total views. While we are not able to verify this from VoD traces, other Web 2.0 sites also report similar trends on relatively low user involvements [11].

2.2.3 How Content Is Found?

We will now examine at the pages that link to YouTube videos. Based on Sci trace, 47% of all videos have incoming links from external sites. The aggregate views of these linked videos account for 90% of the total views, indicating that popular videos are more likely to be linked. Nevertheless, the total clicks derived from these links account for only 3% of the total views, indicating that views coming from external links is not very significant. We have identified that the top five web sites linking to videos in YouTube Sci are myspace.com, blogspot.com, orkut.com, Qooqle.jp, and friendster.com; four of them from social networking sites, and one on video recommendation.

3. IS UGC TRAFFIC POWER-LAW?

Analyzing the exact form of probability distribution does not only help us to understand the underlying mechanism, but also help us answer important design questions in UGC services. This is true in multiple other areas, for instance, the study of the scale-free nature of Web requests has brought insights into improving search engines and advertising. Similarly, understanding the distributions from book sales in an online store helps online retailers estimate their lost opportunities due to poor item categorization or description, or naïve recommendation engines [10, 20, 34].

The power-law has been increasingly used to model various statistics appearing in the computer science and its applications. A distinguished feature of power-law is a straight line in the log-log plot of views versus frequency. However, there are some distributions (e.g., log-normal) that show almost straight line waist across a few orders in a log-log plot. Therefore it is entirely a non-trivial task to determine whether a certain distributions is power-law or log-normal, unless the plot shows a clear straight line across several orders of magnitude [16,18,30,32,35]. The shape of a distribution implies the underlying mechanism that generates it. Normally, the power-law distribution arises from *rich-get-richer principle*, while the log-normal distribution arises from the law of proportionate effect[1].

In a real-world, the shape of the natural distribution can be affected due to various reasons (e.g., bottlenecks in the system). In fact, many distributions whose underlying mechanism is power-law fail to show clear power-law patterns, especially at the both end of the distribution: the most popular and the least popular items. In the case of movies in cinemas [9], the distortion may come from the lack of enough movie theaters, where niche content is not seen as much as it should. This is a *distribution bottleneck* and bringing such content online removes the distribution bottleneck.

However, this is not the only bottleneck that modifies the shape of a distribution. For example, NetFlix data

[1] The log-normal distribution is very similar to the normal distribution; the difference is at is multiplicative process, not additive.

(Figure 1) does not show a power-law pattern for the non-popular videos. This is an *information bottleneck*, and relates to the fact that users cannot easily discover niche content, or content is not properly categorized or ranked[2]. The latent demand for products, that cannot be reached by inefficiencies in system, can have tremendous commercial and technical consequences [10]. No wonder, NetFlix recently launched the $1 million netflix prize to improve their recommendation engine [4].

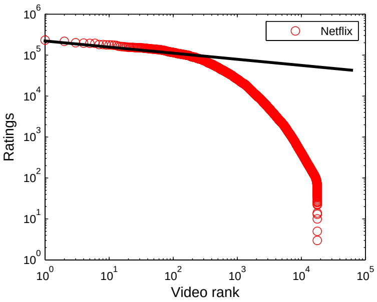


Figure 1: Empirical plot of ranks against ratings, with a synthetic power-law plot for ranks [1 100].

In this section, we study the statistical properties of YouTube video popularity. We first examine how skewed requests are across videos. Then we delve deeper into the actual statistical properties of the system, focusing on how user requests are distributed across popular and non-popular content, and discuss the potential factors that shape such distributions. To provide different comparison points of view, we will use traces from both UGC and non-UGC services.

3.1 Pareto Principle

The Pareto Principle (or 80-20 rule) is widely used to describe the skewness in distribution. Such skewness tells us how niche-centric the service is and is useful in re-adjusting the design principle of the system. To test the Pareto Principle, we count the number of views for the least r-th popular videos and show it in Figure 2. The horizontal axis represents the videos sorted from the most popular to the least popular, with video ranks normalized between 0 and 100. The graph shows that 10% of the top popular videos account for nearly 80% of views, while the rest 90% of videos account for less than 20% of views. This result is quite surprising, since in the other online systems, the 90% of least popular files contributes much larger portion to the total number of views. For instance, analysis of a large VoD system in China, PowerInfo, shows that 90% of least popular VoD files account for 40% of all requests [36]. It is expected that more broader availability of videos enhances the diversity of user's requests and results in more spread of requests across files. However, counter-intuitively, the requests on YouTube seem to be highly skewed towards popular files.

A nice immediate implication of this skewed distribution is that caching can be made very efficient since storing only a small set of objects can produce high hit ratios. That is, by storing only 10% of long-term popular videos, a cache can serve 80% of requests. We revisit this issue in §5.1, where we hypothesize a global cache for YouTube and assess its performance. Another implication is that YouTube is not so niche-centric and serves mostly popular content. It is disputable whether this phenomenon is a signature characteristic of UGC, as opposed to commercial videos, or a consequence of the YouTube's video categorization or recommendation. We expect that a better recommendation engine would mitigate the strong dominance of the popular content and shift the user's requests toward non-popular content. High skewness in popularity is also confirmed from Daum data as shown in Figure 2.

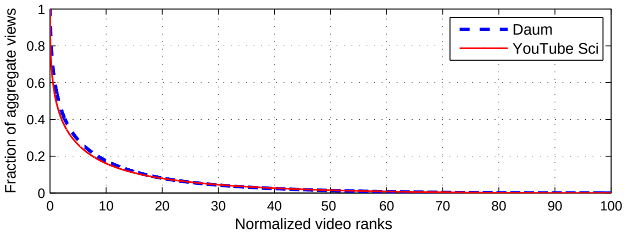


Figure 2: Skewness of user interests across videos

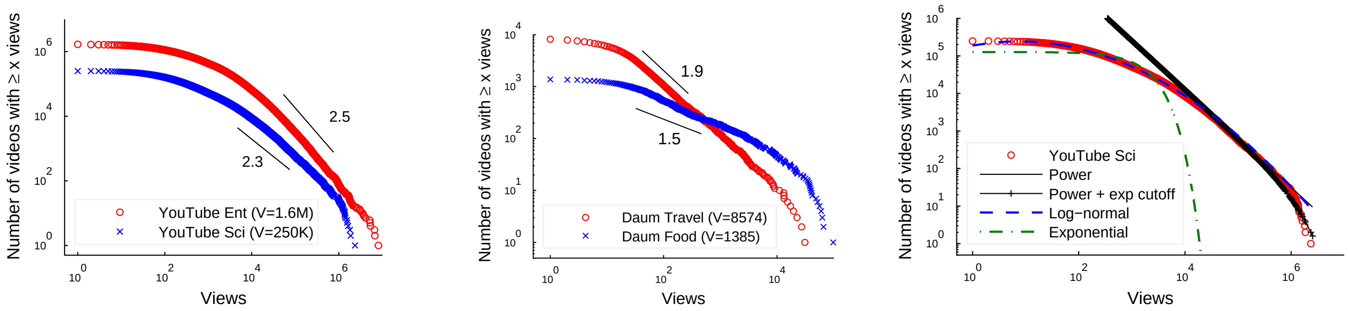
3.2 Statistical Properties

We now analyze the intrinsic statistical properties of UGC video popularity. Here we will use two different representations of the popularity distribution. Each representation will serve to analyze the behavior of different types of videos. In particular, we use a plot of views against the complementary cumulative number of views (i.e., frequency) and a plot of video ranks against views. The first representation focuses on the most popular videos and has been widely used to determine whether a given distribution exhibits certain statistical properties or not (e.g., power-law) by many researchers. The second representation shows the behavior of unpopular videos and has recently been used to understand the behavior and so-called "the Long Tail" potential of the non-popular content by Anderson [10]. These two plots in fact are transposed versions of one another and represent the same quantity [34].

3.2.1 Popular Content Analysis

Figures 3(a) and (b) display the popularity distribution of videos of four representative categories from YouTube and Daum. All of them exhibit power-law be-

[2] Note that we plot customer ratings rather than views since this was the only data available [4]. However, we have observed from other VoD and UCG sites that ratings and views are related by a linear relationship (see §2.2.2). Thus the general distribution presented in this plot should not differ greatly when plotting rank against views.



(a) YouTube empirical plot (b) Daum empirical plot (c) Curve fitting for YouTube

Figure 3: Video popularity distribution of YouTube and Daum follows power-law in the waist, with varying exponent from 1.5 to 2.5. YouTube `Sci` and Daum `Food` exhibit sharp decay in the tail of hot content.

havior (a straight line in a log-log plot) across for more than two orders of magnitude. The fitted power-law exponents are also shown in the figure. However YouTube `Sci` and Daum `Travel` categories show a sharp decay for the most popular content. To examine the truncation in detail, Figure 3(c) shows the plot of `Sci` with the best-fit curves of power-law, log-normal, exponential, and power-law with an exponential cutoff. A log-normally distributed quantity is one whose logarithm is normally distributed. Power-law with an exponential cutoff has an exponential decay term $e^{-\lambda x}$ that overwhelms the power-law behavior at large values of x. For $x < \frac{1}{\lambda}$, it is almost identical to a normal power-law, and for $x > \frac{1}{\lambda}$, a normal exponential decay.

Our fitting result suggests that truncation at the tail follows power-law with an exponential cutoff. Daum `Travel` shows a similar result. Video popularity also seems *category-dependent*. Popularity distributions of other Daum categories (not shown here) showed high variability; some do not follow power-law distribution, the others follow power-law distribution but in which the exponent varies. Nonetheless, all of them showed *power-law waist*, with most of them having *a truncated tail* that fits best by power-law with an exponential cutoff.

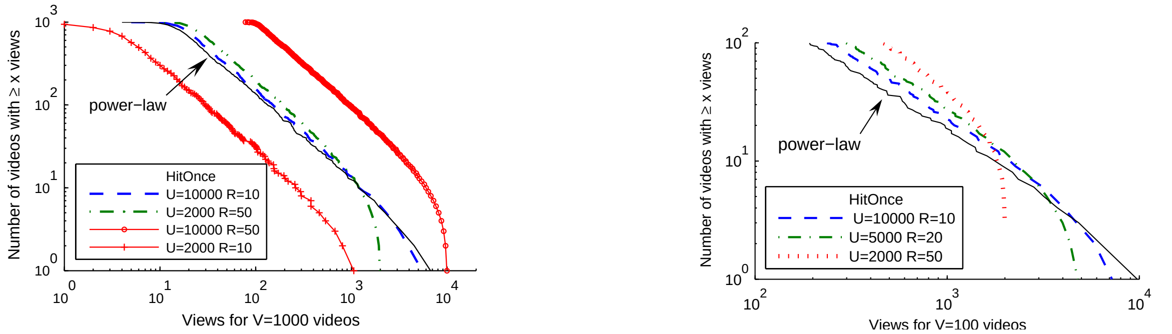
While there exists significant difficulty in determining whether a certain distribution is power-law or not, here, we will next consider the case where the innate shape of popularity distribution is power-law, and that the exponential cutoff arises from the limitation on the number of videos and the user's behavior. There are several mechanisms that generate power-law distributions, but the simplest and the most convincing one is the *Yule process* (also rephrased as *preferential attachment* or *rich-get-richer principle*) [12, 27, 37]. In UGC, this process can be translated as following: if k users have already watched a video, then the rate of other users watching the video is proportional to k. We will now investigate why a power-law distribution can have a sharp decay for the most popular content.

Power-law with a truncated tail appears frequently in the degree distributions of various real-world networks such as WWW, protein networks, e-mail networks, actor networks, and scientific collaboration networks [19, 33]. Several models have been suggested to explain the cause of this truncation. We will review two models and investigate whether they are applicable to our case.

First, Amaral *et. al* [8] suggested that the aging effect can yield truncation. Consider a network of actors, where every actor will stop acting, in time. This means that even a very highly connected vertex will, eventually, stop receiving new links. However, the aging effect does not apply to our case, because videos across all ages shows truncated tail. In fact, as we will see later in the paper, our daily trace shows that 80% of the videos requested on a given day are older than 1 month, contradicting the hypothesis of aging effect in our case.

Second, Mossa *et. al.* [33] suggested a network model to explain the degree distribution of WWW. Along with the preferential attachment, the model adopts the concept of information filtering, which means that a user cannot regard all the information but receive information from only a fraction or a fixed number of existing pages. Due to this information filtering process, the preferential attachment is hindered and the exponential cutoff appears. The information filtering is surely present also in both UGC and standard VoD services. However, highly popular videos are prominently featured within these VoD services to attract more viewers, and thus it is unlikely that information filtering causes truncation for our case.

A study by Gummadi et al. [23] gives us some hints on the truncated tail. In their study of file popularity in P2P downloads, they suggest the cause of distortion from "fetch-at-most-once" behavior of users. That is, unlike in the WWW traffic where a single user fetches a popular page (e.g., CNN) many times, P2P users fetch each object at most once. Given a fixed number of users, U, the videos, V, and the average number of requests per user, R, the authors simulate P2P down-



(a) Varying the requests per user (R) and the number of users (U)

(b) Varying the number of videos (V)

Figure 4: Numerical simulation on the impact of "fetch-at-most-once" on the tail distribution

loads with two types of user populations: *Power* and *HitOnce*. Both user groups make requests based on the same initial Zipf file popularity. However, Power group may request videos multiple times, and HitOnce group, at most once. HitOnce user will make multiple draws until a new item is requested. The resulting popularity graph for HitOnce users appears truncated, compared to a straight line for Power users [23].

UGC also has "Fetch-at-most-once"-like behavior; since video content does not change (i.e., immutable), viewers are not likely to watch the same video multiple times, as they do for mutable web objects. Expanding the work in [23], we suggest that other system characteristics such as R and V, in combination with "fetch-at-most-once", have a major impact in forming the truncated tail. To numerically verify this, we repeat the simulation described above, but with varying parameters for U, R, and V. In our setting, the Zipf parameter is set as 1.0 for the initial video popularity.

Figure 4 shows the resulting video popularity in a plot of views against the cumulative number of videos. We make several observations from Figure 4(a). First, compared with Power, HitOnce shows in a truncated tail, as expected. Interestingly, the truncated tail gets amplified as the number of requests per user, R, increases. If R is small, then the "fetch-at-most-once" effect does not take place. With increased R, "fetch-at-most-once" effect starts playing a bigger role, since there is a higher chance the a particular user is geared towards the same popular file multiple times. Second, adding more users in the system, U, increases views per videos (shifting the plot in the x-axis). However, the overall shape of the graph does not change, indicating that the U has little impact in the tail truncation. Finally, increasing both R and U (from $U = 2000, R = 10$ to $U = 10000, R = 50$), the tail shape changes in a similar way as when R increases. Note that larger R and U values represents the case where new users are added to the system and old users make more and more requests (thus R increases). This intuitively captures what happens in the real UGC systems. In fact, our trace also shows similar trends. Figure 5 shows the popularity distribution of `Sci`, over a short and long-term window. Having a long-term window represents large R and U values. The plot of popularity during one day (i.e., small R) exhibits a clear power-law decay, while for longer terms, the distribution exhibits a truncated tail as in Figure 4(a).

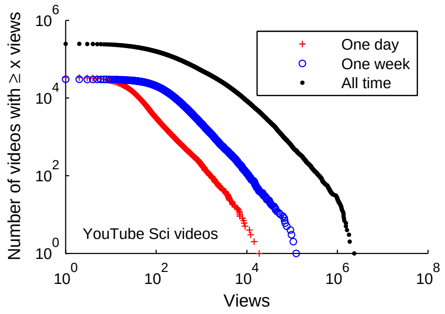


Figure 5: Tail shape over different time-windows

Another factor that can greatly impact the shape of a distribution is the number of videos, V. Figure 4(b) shows the same simulation results, repeating for a smaller number of videos ($V = 100$). If V is small, "fetch-at-most-once" effect becomes amplified since there is only a small number of videos to choose from. This results in a highly truncated tail, as shown in Figure 4(b) for the case of $U = 2000, R = 50$. We can also empirically verify this from our plots of YouTube and Daum data. Let us revisit the plots in Figures 3(a) and (b). We observe that the tail cutoff is much more pronounced for categories with smaller number of videos, such as `Sci` in the case of YouTube and `Food` in the case of Daum.

So far, we focused on the popularity distribution of popular content and showed, via numerical simulations and empirical validation, that the tail truncation is affected by both the average requests per users and the number of videos in a category. Next, we move on to the non-popular portion of the distribution.

3.3 Studying The Long Tail

Anderson, in his book [10], asserted that there exist huge opportunities in the unlimited number of non-popular items, or so he calls this the economics of "the Long Tail." Here we will investigate the Long Tail opportunities in UGC services. In particular, the following questions are of our interest: what is the underlying distribution of non-popular items, what shapes the distribution in one way or another, and how much benefit the Long Tail can bring for UGC services.

Let us look into the distribution of the non-popular content. We use a plot of video ranks against views, where unpopular videos are put at the tail. This representation, suggested by Zipf, has been used to observe Zipf's law. Figure 6(a) shows such empirical plot of `Sci` videos, on a log-log scale. The figure shows a Zipf-like waist (a straight line in a log-log plot) with a truncated tail. When we perform goodness-of-fit test with several distributions, the truncated tail fits best with Zipf with an exponential cutoff, as clearly shown in the figure. Log-normal is the second best fit.

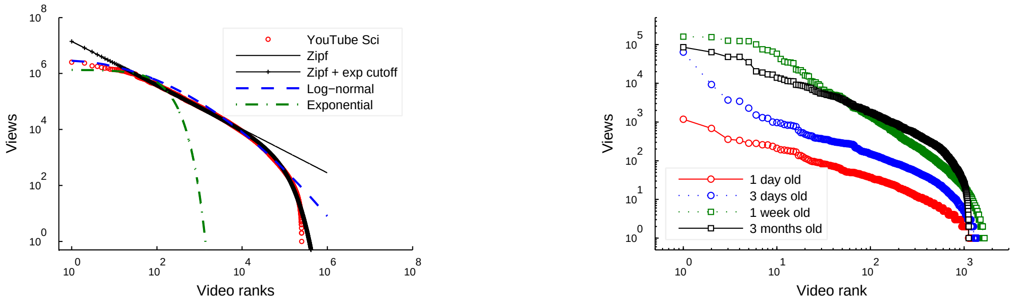
However, as stressed before, it is hard to decide whether it is a Zipf distribution modulated by a removable bottleneck, or it is just a natural log-normal distribution. Identifying the true nature of the distribution is hugely important because it can affect strategies for marketing, target advertising, recommendation, and search engines. In the following, we list the potential causes for the truncated tail and discuss how they apply to our scenario:

- Natural shape of UGC is truncated: User-generated content, by definition, varies widely in its quality. One may argue that the natural shape of the popularity distribution of UGC is truncated, since significant fraction of videos in UGC are produced for small audiences (e.g., family members), as opposed to professionally generated content, which is produced for much wider audiences. For most of the UGC categories we examined, goodness-of-fit suggests Zipf with an exponential cutoff as the best-fit, rather than a log-normal. However, it is unlikely that such this distribution captures the natural user behavior. Zipf (so as power-law) is *scale-free* in nature, while exponential is a distribution that is *scaled* or *limited* in size. Therefore the two will rarely appear coherently and naturally as a single mechanism. Rather, a more likely scenario is that the underlying mechanism is Zipf, but a bottleneck in the system truncates the tail.

- Sampled publishing (pre-filters): The plot of Netflix in Figure 1 shows a sharp decay in the tail. This can be explained by sampling bias. Even though NetFlix provides an enormous online catalog of DVDs world-wide, their videos are a set of movies that are sampled from all the movies ever made; only a small portion of movies world-wide are made into DVD titles. In UGC services, publishes post videos sampled from the video pool in their possession. However, they may only upload those that they consider most interesting. The following process explains how such pre-filtering affects the shape of a distribution: Consider a complete list of N videos, whose popularity distribution follows Zipf. Then let us remove h videos from the set, such that the probability of a video removed is proportional to the inverse order of their ranks. The remaining $N - h$ videos will have truncated tail.

- Information filtering (post-filters): Search or recommendation engines typically return a small number of *hits*, compared with the total number of items that are indexed as relevant [15, 33]. The impact of these post-filters has been extensively analyzed by Fortunato *et al.* [20], where they show post-filters yield truncated distributions. If we assume that UGC too is truncated in the non-popular items due to post-filters, then older videos should have more pronounced truncation than the younger ones (as older videos have been exposed longer to the filtering effect). Indeed, we are able to observe this from our trace. Figure 6(b) shows the popularity distributions of `Sci` videos of different ages. Videos aged 1 day are clearly less truncated in tail than older ones. The graphs for older videos show: popular items gaining more views; the slop at the waist becoming steeper; and the tail becoming more truncated. This reinforces the case for post-filtering, where top videos are more likely to be favored in the way they are presented to the users, and this impact gets amplified as time passes, since non-popular videos will rarely be brought to user's attention.

The above discussion reflects an important observation, since it suggests that the truncated Long Tail represents a latent demand that could potentially be brought forward with adequate recommendation and search engines, better tagging techniques, and the ease of video posting. If Zipf is the natural shape and the truncated tail is due to some removable bottlenecks (e.g., filtering), then in the system with no bottleneck, the videos in the truncated region would gain deserved views, offering the better chances to discover rare niche videos to users and potential business opportunities to the company. We estimate the benefit from the removal of the bottleneck of system. The estimation is defined as the ratio of aggregated additional views against the existing total views. Table 3 shows the measured benefits for the four UGC video categories. We also present the number of videos that may benefit. YouTube `Ent` and `Sci` show great opportunities in the Long Tail eco-



(a) YouTube tail fitting of non-popular videos

(b) Popularity distribution of videos with varying ages

Figure 6: Ranks versus views plot for YouTube `Sci` videos.

nomics (42-45% potential improvement), due to the large number of videos that can benefit. While in Daum `Travel` and `Food`, the benefit is reduced due to a small number of videos that benefit. When the number of videos is small, the inefficiencies of the system (due to filtering effects) are smaller since information can be found easier.

Table 3: Potential gain from the Long Tail in terms of additional views and the number of beneficiary videos

	`Ent`	`Sci`	`Travel`	`Food`
Gain	45%(1.2M)	42%(240K)	4%(5K)	14%(400)

4. POPULARITY EVOLUTION OF UGC

As opposed to standard VoD systems where the content popularity fluctuation is rather predictable (via strategic marketing campaigns of movies), UGC video popularity can be ephemeral and have a much more unpredictable behavior. Similarly, as opposed to the early days of TV when most people watched the same program at the same time, such temporal correlation is much more diluted in UGC. Videos come and go all the time, and the viewing patterns also fluctuate based on how people get directed to such content, through RSS feeds, web reviews, blogs, e-mail or other recommendation networks. To better understand this temporal focus, in this section, we analyze the UGC video popularity evolution over time. Our analysis is conducted from two different angles. We first analyze whether requests concentrate on young or old videos. Then we investigate how fast or slow popularity changes for videos of different age, and further test if the future popularity of a video can be predicted. For the analysis, we use daily trace of YouTube `Sci` videos.

4.1 Popularity Distribution Versus Age

To examine the age distribution of requested videos, we first group videos by age (binned every five days) and count the total volume of requests for each age group. Figure 7 displays the maximum, median, and the average requests per age group. We only consider videos that are requested at least once during the trace period. The vertical axis is in log-scale. For very young videos (e.g., newer than 1 month), we observe slight increase in the average requests, which indicates viewers are mildly more interested in new videos, than the rest. However, this trend is not very pronounced, when we examine the plot of maximum requests. Some old videos too receive significant requests. In fact, our trace shows massive 80% of videos requested on a given day are older than 1 month and this traffic accounts to 72% of total requests. The plot becomes noisy for age groups older than 1 year, due to small number of videos. In summary, if we exclude the very new videos, user's preference seems relatively insensitive to video's age.

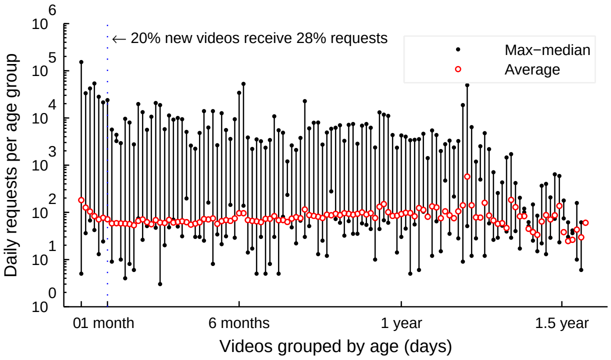


Figure 7: Distribution of request volume across video's age, based on `Sci` daily trace.

While user's interests is video-age insensitive in a gross scale, most of the top requests on a given day seem to target on recent videos in Figure 7. To further verify this, we look into the age distribution of top twenty most requested videos. Figure 8 shows the result for a different time-window of a day, a week, a month, and all time. For each plot, we used two snapshots, taken the corresponding periods apart, and ranked videos based on the increase in their views. For the plot of "all time", we assume the initial views of videos are zero. Over a one day period, roughly 50% of the top twenty videos are recent. However, as the time-window increases, the median age shifts towards older videos. This suggests ephemeral popularity of young videos. To better understand its effect, in the next section, we discuss the video popularity evolution over time.

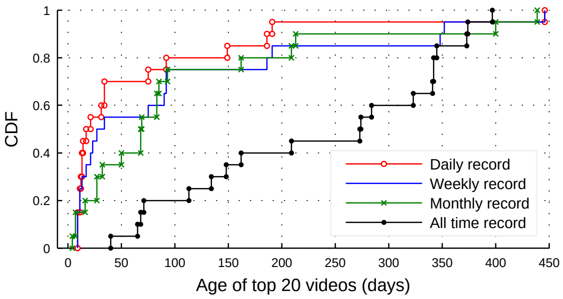


Figure 8: Age distribution of top 20 videos

4.2 Temporal Focus

We now continue our discussion on the video popularity and investigate how the popularity of individual UGC videos evolve over time, how fast or slow it changes, and whether the future popularity of a video can be predicted.

4.2.1 Probability of Videos Being Watched Over Time

When a video is posted, it has zero views; gradually videos will gain views over time. To capture this trend in UGC videos, in Figure 9, we show the percentage of videos aged $\leq X$ days having $\leq V$ views. We provide several view points by considering a range of V values from 0 to 10,000. The graph shows that after a day, 90% of videos are watched at least once, and 40% are watched over 10 times. After a longer period of time, more videos gain views, as expected. One noticeable trend in the graph is the consistent deeps at certain times (e.g. 1 day, 1 month, 1 year). These points seem to coincide with the time classification made by YouTube in their video categorization. From this plot, we can see that the slope of the graph seems to decay as time passes. Noting the log-scale in the horizontal axis, this indicates the probability of a given video to be requested decreases sharply over time. In fact, if we consider the case of $V = 10$, the probability that a give file gets more than 10 requests over the the duration of first 24 hours, 6 days, 3 weeks, and 11 months, is 0.43, 0.18, 0.17, and 0.14, respectively. This indicates that videos are more likely to get most of their requests soon after they are posted. Conversely, if a video did not get enough requests during its first days, then, it is unlikely that they will get many requests in the future. Based on these observations, we will next test if it is possible to predict a video's future popularity.

4.2.2 Predicting Near-Future Popularity

The ability to predict future popularity is immensely

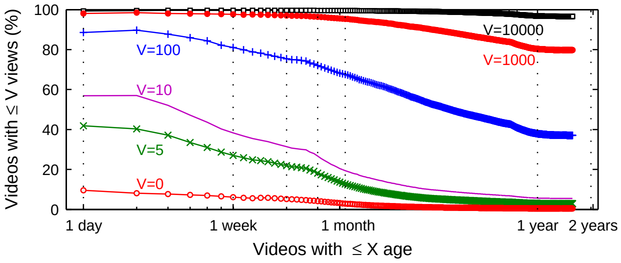


Figure 9: Probability of videos being watched over time, based on YouTube Sci trace

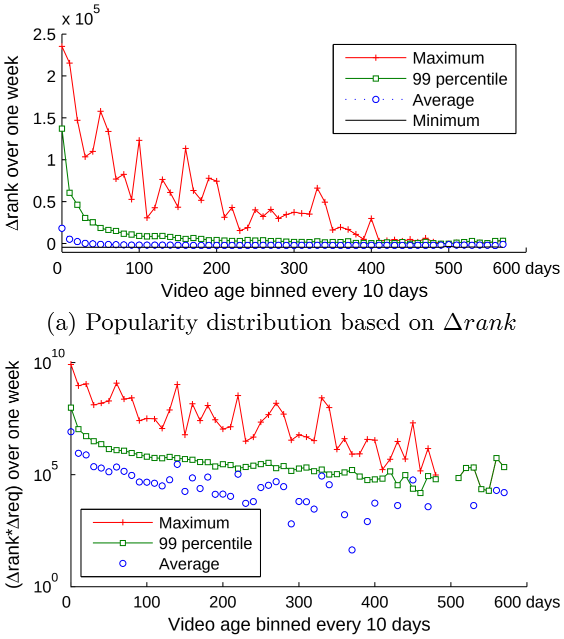
useful in many ways, because the service providers may pre-populate these videos within multiple proxies or caches and the content owners may use this fast feedback to better manage their contents (e.g., production companies releasing trailers to predict popularity). We now explore the possibility of using early views records in predicting near-future popularity. We compare the first few days' video views with those after some period of time (i.e., 5, 7, and 90 days). Table 4 shows the correlation coefficient of views for combinations of snapshots. We also present the number of videos used for sampling. Our results show that second day record gives a more accurate estimation than using the first day's records, in fact, at a relatively high accuracy (correlation coefficient above 0.8). This is due to the time it takes for videos to be known and start ramping up the popularity curve. Using the third day record improves the prediction accuracy, yet, only marginally. The result also shows a high correlation with the second day record even for more distant future popularity (e.g. three months afterwards).

Table 4: Correlation coefficient of video views in two snapshots (Number of videos analyzed)

Age (x_0)	x_0+5 days old	7 days old	90 days old
1 day old	0.5885 (7221)	0.8776 (3394)	0.5561 (11884)
2 days old	0.9665 (5185)	0.8793 (3394)	0.8425 (11215)
3 days old	0.9367 (3394)	0.9367 (3394)	0.8525 (9816)

4.2.3 Popularity Shifts

Now we examine how easy or hard it is for new and old videos to become very popular as a function of their age. To observe this, we will first look at how the video rank changes against the video age. In Figure 10(a), we use two snapshots from our 6-day trace, taken at day zero and day 5, and consider only those videos that appear on both of the snapshots. We group videos by their age (bin in units of ten days) and plot the change in ranks (i.e., $\Delta rank$) over age. For each age group, we plot the maximum, top 99 percentile, average, and the minimum change in $\Delta rank$. The vertical axis ranges from -4059 to 235132, which indicates that some videos decreased in their rank by 4059 during the trace period, while some jumped up 235132 ranks.



(a) Popularity distribution based on $\Delta rank$

(b) Popularity distribution based on $\Delta rank \cdot \Delta views$

Figure 10: Changes in ranking and popularity

We make several observations from Figure 10(a). First, young videos can change many rank positions very fast, while old videos have a much smaller rank fluctuation, indicating a more stable ranking classification for old videos. Still, some of the old videos also increased their ranks dramatically. This could indicate that old videos are able to ramp up the popularity ladder and become popular after a long time, e.g., due to the Long Tail effects and good recommendation engines. However, it is hard to conclude this from Figure 10(a) since a few requests may also result in major rank changes. We will revisit this issue at the end of this section.

The gap between the maximum and the top 99 percentile lines reflects that only a few young videos (e.g., less than 1%) make large rank changes, indicating that only a very small percentage of the young videos make it to the top popular list while the rest have much smaller ranking changes. We also see a consistent minimum $\Delta rank$ line at nearly -4000 across all age group. A detailed look at those videos reveals that those videos did not receive any request during the trace period, however their ranking was pushed back as other videos got at least one request. This shows that unpopular videos that do not receive any request will die in the ranking chart at a rate of 2000 positions per day.

As discussed before, when it comes to identifying major shifts in the popularity distribution, considering the actual change in views or ranks is not enough. Videos can get many requests but make a minor rank change, and vice versa; a large rank change could be due to a very few requests (e.g. from zero to five requests). To identify videos that made dramatic rank changes as well as received large number of requests, we propose using the product of ($\Delta rank \cdot \Delta views$) as in Figure 10(b). The vertical axis is in log scale. Now we observe more drastic popularity shifts for young videos; barely no single old video received a significant number of requests to make major upward shift in the popularity distribution. In short, revival-of-the-dead effect, where old videos are suddenly brought up to the top of the chart, does not seem to happen strongly in our trace.

5. EFFICIENT UGC SYSTEM DESIGN

With the increasing popularity of UGC, YouTube alone is estimated to carry astonishing 60% of all videos online, serving daily 100 million distinct videos [6]. This corresponds to, in our estimation, a massive 50 - 200 Gb/s of server loads as well as access bandwidth on a traditional server-client model. Accordingly network operators are reporting a rise in overall Web traffic and a rise in HTTP video streaming as a second aspect [7]. In this section, we provide insights on the potential for more efficient UCG system designs in terms of caching and Peer-to-Peer (P2P) techniques.

5.1 Better Use of Caching

Caching stores redundant copies of a file near the end user and has been proven to be extremely effective in many Web applications. Several factors affect the caching efficiency: the cache size, the number of users and videos, the correlation of requests, the shifts in popularity, and so on. In this section, we will hypothesize a global cache system for YouTube and assess its efficiency using our 6-day daily trace. Our interest is at investigating the cache performance, under massive new uploads and dynamic popularity evolution. We consider the following three simple caching schemes:

1. A *static finite* cache, where at day zero the cache is filled with long-term popular videos. The cache content is not altered during the trace period.

2. A *dynamic infinite* cache, where at day zero the cache is populated with all videos ever requested in `Sci` category, and thereafter stores any other videos requested during the trace period.

3. A *hybrid finite* cache, which works like the static cache, but where there is an extra cache portion that stores the daily most popular videos.

We populate the static cache with long-term popular videos accounting 90% of total traffic in the Pareto Principle. This corresponds to 16% of videos in `Sci`. Dynamic infinite cache simply stores all the videos ever requested. In hybrid finite cache, the cache is first populated with the top 16% of Sci videos, then the cache also allocates a small extra space to store the daily top 10,000 videos. We perform a trace-driven simulation to assess the cache performance in terms of the required cache size and the cache miss ratio. To do this, we replay the 6-day trace under our three cache scenarios and calculate the average the hit and miss ratios over multiple days. We simply use the number of videos cached as the cache size, because the video length and the encoding rate do not vary much across files. Table 5 summarizes the cache performance. The results indicate that about 40% of the videos are requested new each day. However, the volume of requests accounted for such videos is very small and they only account for about 20% of the requests. In fact, we see that a simple static cache that stores the top long-term popular files uses 84% less space than a dynamic infinite cache solution, at the cost of only 23% extra missed volume. We should also mention that, by adapting to changes in daily requests, a hybrid cache improves the cache efficiency about 10%, compared to the static cache.

Table 5: Synthetic cache efficiency

Type	Size	# Missed videos	Missed volume
Static	41,456	115,002 (48.8%)	5,093,832 (26.7%)
Dynamic	256,647	4,683 (1.9%)	648,376 (3.4%)
Hybrid	51,456	94,893 (40.3%)	3,271,649 (17.1%)

5.2 Potential for P2P

In this section we explore the potential benefits of a P2P technique in UGC distribution. In a P2P system, users (or peers) share videos they watched for a certain period of time. A new user may fetch videos from other peers who are concurrently online and have the content of interest, rather than fetching from the server. Inherently, P2P system is effective only when there are enough number of online peers sharing content – this is called a *torrent*. Here we investigate the potential benefits a P2P technique can bring to YouTube. However unlike the existing network environment where P2P has shown great efficiency [21], massive scale of videos, small-sized content, and the ephemeral popularity makes it unclear if P2P will be as effective in UGC. Therefore we first assess the feasibility of a P2P in UGC by examining how many files can benefit via P2P approach. We then perform a trace-driven analysis to measure how much server workload can be saved using P2P, compared to the traditional server-client model.

We commence by estimating the inter-arrival times of requests. Our trace provides granularity of requests up to a day and it shows that daily requests of individual video varies across the monitored period. We exploit this daily granularity and assume that requests within a single day are exponentially distributed *in time. Within a day, the inter-arrival time of requests has a mean of $\frac{1}{\lambda}$, where λ is the intensity of requests (i.e., the number of requests made that day). This inter-arrival time will be shortly used to calculate the number of concurrent users online. Figure 11 shows the CDF of the average inter-arrival times per video. We observe that over a quarter of videos are requested more frequent than every 10 minute.

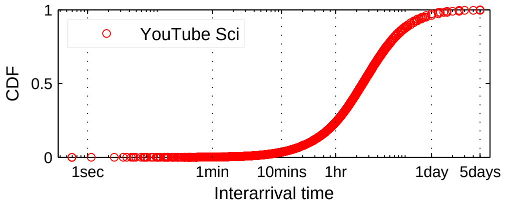
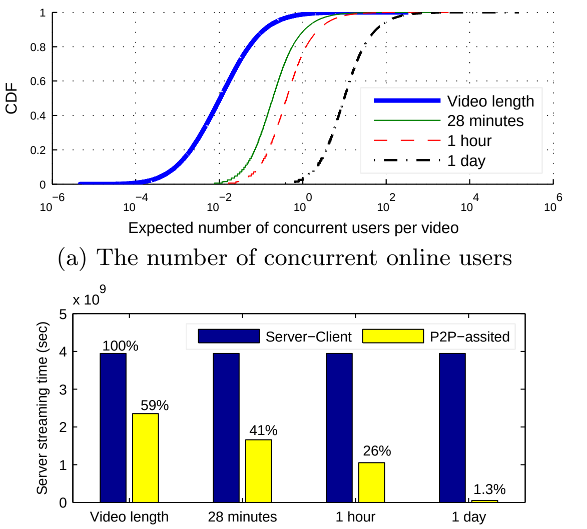


Figure 11: Inter-arrival times of requests

Next we calculate the number of concurrent users per video (e.g., torrent size). The torrent size depends on the duration and the frequency of users in the P2P system. The system time of a user is important because the P2P sharing may happen only when the user is online. We consider the following four cases of P2P system time: 1) length of the video user is watching, 2) duration of time user spends on YouTube, 3) one hour, and 4) one day. In the first case, users share videos only when they are watching them. In the second case, users will share videos while they are using YouTube. According to Nielsen/NetRatings [13], the average time spent by a user at YouTube is currently 28 minutes. We hence assume users may share videos for 28 minutes in our second case. In the last two cases, we consider users sharing videos even when they are no longer in the system. We mention that this may become a reality in the future (e.g., users equipped with always-on set-top boxes that run P2P).

Then for a given P2P system time of a user, t, and the inter-arrival time of requests, $\frac{1}{\lambda}$, the expected number of concurrent users is $\frac{\lambda}{t}$. Note that this value can be less than 1, indicating that there are times within that day with no users watching the video. We only consider P2P approach only when $\frac{\lambda}{t}$ is greater than one (i.e., more than one user watched a video). When $\frac{\lambda}{t} \leq 1$, we simply apply traditional server-client model. Figure 12(a) shows the CDF of the average concurrent users over the monitoring period per video. We observe that for most of the cases the expected number of concurrent users, $\frac{\lambda}{t}$, is less than 1, indicating that only few videos will benefit from P2P. However, when users share videos for a longer period of time (e.g, 1 day), P2P may assist 60% of videos with at least 10 current users all the time.

While the number of files that can benefit from P2P come out relatively small, this does not necessarily mean P2P is inefficient for UGC. As we have seen from the previous sections, UGC requests are highly skewed and



(a) The number of concurrent online users

(b) Server workload savings against server-client model

Figure 12: Potentials of a P2P system

temporal. Therefore, we investigate the benefits of P2P by comparing the estimated server workload between traditional client-server and P2P-assisted distribution approaches. In a client-server model, each request is directly served by the server. While in the P2P-assisted model, peers will participate in streaming only when there are concurrent users. As a measure of server workload, we use the total length of the streamed content. Figure 12(b) compares the server workload based on trace-driven analysis. Our results show that the potential of P2P is actually very large. The server workload is reduced by 41% even when users share only videos while they are watching. When users share videos for one day, the server workload reduces by tremendous 98.7%, compared to a client-server approach.

6. ALIASING AND ILLEGAL UPLOADS

Content aliasing and illegal uploads are critical problems of today's UGC systems, since they can hamper the efficiency of UGC systems as well as cause costly lawsuits. In this section, we study the prevalence of content duplication and illegal uploads in UGC, and their impact in various system's characteristics.

6.1 Content Aliasing

Traditional VoD services offer differently encoded versions of the same video, typically to support diverse downward streaming bandwidths. In UGC, there often exist multiple identical or very similar copies for a single popular event. We call this group of videos, *aliases*, and this new phenomenon *content aliasing*. Multiple copies of video for a single event dilute the popularity of the corresponding event, as the number of views is distributed over multiple copies. This has a direct impact on the design of recommendation and ranking systems, as it is no longer straightforward to track the popularity of an event from a single view count nor present users with unique videos, instead of numerous identical copies.

To estimate the prevalence of aliases, we have conducted the following experiment. We first sample 216 videos from the top $10,000$ videos of YouTube `Ent` category. Then we ask our 51 volunteers to view a few videos and read the title and description. After viewing some from our sample set, volunteers search YouTube using keywords of their choice and flag any video they deem pertaining to the same event as aliases[3] Our volunteers have identified $1,224$ aliases for 184 videos out of original 216. Most videos have 1 to 4 aliases, while the maximum number of aliases is 89. Out of all videos that pertain to the same event, we call the video with the earliest upload time *original*.

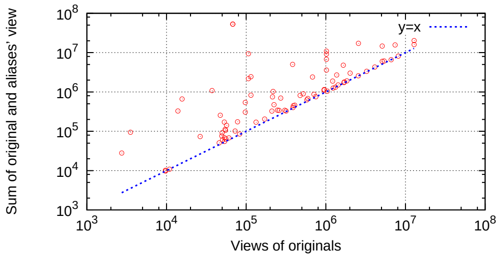


Figure 13: Sum of all views of the original and aliases versus views of original videos

Figure 13 shows the sum of views from all aliases and the original video against the number of views of the original videos. For a few videos, the sum of views from aliases grows more than two orders of magnitude than the views of the original. This clearly demonstrates the popularity dilution effect of content aliasing. Undiluted and augmented by the views of aliases, the original video could have been ranked much higher.

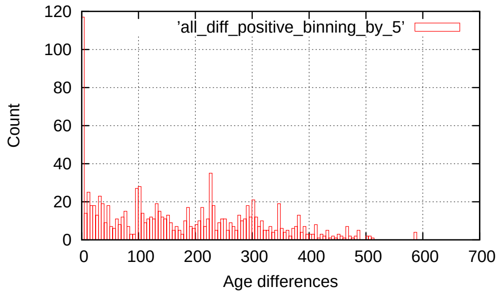


Figure 14: Number of aliases against age differences

Next, we analyze the time intervals between aliases. We plot the age differences between the original video

[3] We have created a webpage `http://beta.kaist.ac.kr` for volunteers to view the video along with the description, and then search for content aliases in YouTube.

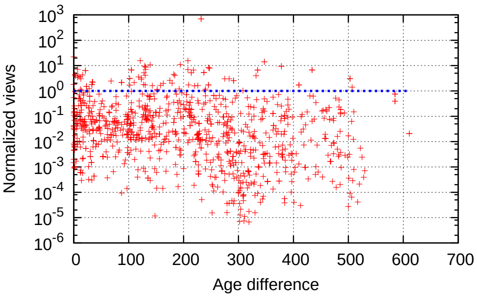


Figure 15: Normalized views against age differences

and its aliases in Figure 15 (the bin size is 5 days). A large number of aliases are uploaded on the same day as the original video or within a week. To examine how the number of views has changed, we plot the views of aliases normalized against that of the original against the age difference in Figure 15. One conspicuous point represents an alias that showed up more than 200 days later than the original and received almost 1000 times more views. This particular video was originally listed in the Music category, and later posted on the Comedy category with much more views. We find it rather surprising to see so many aliases still appear 100 or more days after the original video. As we dig deeper into those aliases that have 10 times or more views than the original and 100 days or more older. They are found to belong to different categories from the original and have been cross-posted over multiple categories. These aliases could be a potential reason for the flattened popularity tail. We leave further investigation behind this delayed popularity for future work.

Those aliases that turn up 100 days later with much fewer views are likely to serve personal archiving purposes. The Pearson correlation coefficient of the plot in Figure 15 is 0.004. It signifies little correlation or no decrease in the number of views over time. With a good number of aliases older than 100 and more views, we discern no clear trend in the aliases and their views over time.

Finally, we check for the existence of heavy alias uploaders. Suspecting their strong motivation for online popularity, we have wondered if they could post aliases of already popular videos. Our data, however, shows that over 80% of all aliases are by one-time uploaders and the maximum number of aliases by one uploader is 15.

6.2 Illegal Uploads

UGCs derived from copyrighted contents raise a serious legal dilemma for UGC service providers. In a sense, aliases can be considered to a great extent as a form of "video spam." A recent study from Vidmeter [25] suggests that nearly 10 percent of videos in YouTube are uploaded without the permission of the content owner. Vidmeter's report cover only the top ranked UGCs. We augment Vidmeter's work by looking not only at the top ranked videos, but all in `Ent`.

We get the list of all videos at two different times, and compare the two lists. The discrepancy represents the deleted videos. When we follow the links to the deleted videos, YouTube offers a notice about the reason behind deletion. Possible reasons are: removed by users, terms of use violation, copyright claim, and restricted access. From the the first set of videos $(1, 687, 506)$, the number of all deleted videos are $6, 843$ (0.4%). Only about 5% of deleted videos have violated the copyright law, which is a far smaller number than Vidmeter's.

7. RELATED WORK

We have already incorporated many of the references that closely relate to our work in the previous sections of the paper. As this work covers a broad spectrum of topics from popularity analysis to web caching and p2p streaming, we next briefly summarize related works.

Large-scale video on-demand streaming (or VoD) services have become popular in recent days, while UGC services have grown explosively. Among the numerous UGC sites, YouTube, MSN, Google Video, and Yahoo! Video are the notable ones. Due to relatively short history of UGC, little work has been done on the characteristics of UGC or comparisons to traditional VoD systems. One of the first related work on video popularity is that of Griwodz et al. using the video rental records [22]. Recently, Yu et al. [36] presented an in-depth analysis of access patterns and user behaviors in a centralized VoD system. Newman [34] carried out a good comprehensive study of power law distributions. He examined several examples of power-law: web hits, copies of books sold, telephone calls, etc. Also a paper by Alderson *et al.* develops an interesting and rich theory for scale-free networks [29].

The idea of P2P streaming has been extensively explored in recent works in the context of patch updates, VoD, etc [14, 21, 24, 26]. Most of existing work about P2P VoD [17, 24] systems was concentrated on the protocol design under various topological constraints and the analysis of simulation results. Our study considers the potential for P2P delivery in large scale UGC systems, which have unique characteristics in terms of user consumption patterns and video popularity distribution.

8. CONCLUSIONS

In this paper we have presented an extensive data-driven analysis on the popularity distribution, popularity evolution, and content duplication of user-generated video contents. To the best of our knowledge, this work is the first major stab at understanding the explosive growth of UGC and its implications on underlying infrastructures.

We have studied the nature of the user behavior and identified the key elements that shape the popularity distribution (e.g. what shapes the Long-Tail, alters the skewness of popularity, or breaks the power-law behavior for very popular contents). Our results indicate that information filtering factors are the likely cause for reducing niche content popularity, which if leveraged, could increase the total views by as much as 45%.

We have studied different UGC cache designs, and showed that simple policies that cache the most popular contents can offload server traffic by as much as 50%. Similarly, we have also demonstrate that a distribution system based on a P2P system can have great benefits, despite the diversity of requests and short video length.

Finally, we have tackled the impact of content aliasing and illegal uploads, which could hamper the future success of UGC services. Content aliasing is widely spread practise and has much impact on video ranking. Illegal uploads are more common amongst highly ranked videos. We believe that our work answers very critical and pressing questions, and lies the basis for the design of future UGC systems.

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