Watching Videos from Everywhere: A Study of the PPTV Mobile VoD System

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ABSTRACT

In this paper, we examine mobile users' behavior and their corresponding video viewing patterns from logs extracted from the servers of a large scale VoD system. We focus on the analysis of the main discrepancies that might exist when users access the VoD system catalog from WiFi or 3G connections. We also study factors that might impact mobile users' interests and video popularity. The users' behavior exhibits strong daily and weekly patterns, with mobile users' interests being surprisingly spread across almost all categories and video lengths, independently of the connection type. However, by examining the activity of users individually, we observed a concentration of interests and peculiar access patterns, which allows to classify the users and thus better predict their behavior. We also find a skewed video popularity distribution and then demonstrate that the popularity of a video can be predicted using its very early popularity level. We further analyzed the sources of video viewing and found that even if search engines are the dominant sources for a majority of videos, they represent less than 10% (resp. 20%) of the sources for the highly popular videos in 3G (resp. WiFi) network. We report that both the type of connections and mobile devices in use have an impact on the viewing time and the source of viewing. Based on our findings, we provide insights and recommendations that can be used to design intelligent mobile VoD systems and help improving personalized services on these platforms.

Categories and Subject Descriptors

C.2.4 [**Computer Applications**]: Distributed applications; C.4 [**Performance of Systems**]: Measurement techniques

General Terms

Measurement, Performance, Human Factors

Keywords

Mobile VoD, user behavior, video popularity, view source

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1. INTRODUCTION

The advanced wireless technologies (*e.g.* WiFi, 3G and 4G) and smart mobile devices (*e.g.* iPad, iPhone, Android systems) enable users to watch Internet videos from almost everywhere. Today video content providers often, if not always, offer client applications that can be installed on mobile users' tablets and smart phones, making the video viewing ubiquitous and contributing to the growing popularity of mobile video services.

A recent report [1] indicated an increase of 50% of the global mobile video traffic in 2011 compared to the previous year, and expected that the volume of video traffic will reach 25 times its current volume by 2016. Video providers naturally strive to meet such a huge demand through the design of better system architectures. Understanding the current system's artifacts, *e.g.* users' behavior, viewing patterns and trends of video popularity is of tremendous importance to design and optimize the efficiency of the systems, from the consumption of network resources to the economic models. User- and video-related trends are two key factors combining to influence the day-to-day performance of the VoD distribution network. Analyzing and predicting these factors is highly valuable to build scalable and robust distribution networks and caching systems.

There have been several measurement studies on landline based video systems, *e.g.* [15][14][5] for VoD systems, [10] for P2P VoD systems, [9] for P2P live streaming, [3] and [7] for IPTV systems. However, the observations reported so far may not be applicable to mobile video systems because of mobility-related constraints, limited bandwidth and small screen size of mobile devices. For example, Li *et al.* [12] found that viewing patterns in mobile TV systems are different from those observed in landline-based TV broadcast and VoD systems.

In this paper, we analyze the viewing behavior of mobile users and study the patterns of video consumptions using a unique dataset extracted from the log servers of PPTV, a leading video provider in China offering both live streaming and VoD services. The dataset spans over 14 days in December 2011 and consists in a collection of approximately 86 million videos requests generated by more than 3.5 million users. This unique dataset enables us to dig into both mobile users' behavior and video consumption patterns. From a user behavior perspective, we focus on temporal patterns, viewing time, user interests and individual users' activity, while for video-related patterns, we analyze the level of video popularity and sources of video viewing. We are particularly interested in identifying the impact of types of connection and mobile device on these metrics. Our main findings and observations are summarized as follows:

- We observe that the behavior of users shows strong daily and weekly patterns, with a relatively short viewing time. Longer viewing times are associated with the use of WiFi rather than 3G and with the use of tablets (*e.g.* iPad) compared to smart phones (*e.g.* iPhone). We also found a surprisingly high number of requests of long videos from 3G users. The completion rate (*i.e.* the viewing time normalized by the video length) for short videos is on average around 0.5, with lower rates observed for long videos. This is however varying with the time of the day, as we observed that completion rates are much higher in early morning.
- We analyze the activity of individual users by aggregating the number of views and find that it follows a stretched exponential distribution model. The stretched factor is correlated with the connection type. Interestingly, the users viewing videos through a mix of both WiFi and 3G connections watch a higher number of videos than those using exclusively one type of connection.
- We study the interests of users according to video category and found that such interests vary over the course of the day. The interests are also correlated with geo-locations. In general, individual users request and view videos from only a few categories, pointing to a high concentration of interests.
- We measure that 10% of the requested set of top popular videos attracted more than 80% of the views, in accordance with the Pareto principle ("a minor proportion of causes generate a major proportion of effects"). Although the observation period of 14 days is relatively short to assess general behavior of video popularity distributions, we find a high correlation between the amount of early viewing of videos and their near-future popularity, especially for animation videos and variety shows.
- We finally observe that even though the view source is dependent on the type of access to the network, overall the category page is the primary source of views and is often used to request highly popular videos. Another source is the PPTV video search engine which is the main source of views for more than half of the total video catalog, especially for low-popularity videos. The video search engine thus contributes to the diversity of video views.

In the light of these results, it is desirable that the research community investigates the inclusion of several features into the design of intelligent mobile VoD systems. Firstly, the Pareto principle of video popularity indicates that it might be necessary for content delivery networks (CDNs) to cache only the 10% top popular videos, since they contribute to more than 80% of the views. The high correlation coefficient between early view records of videos and their popularity can be used to decide whether a video should be cached just a few hours after its release. Secondly, it is important to notice that the effectiveness of the cache can be optimized by allocating most of the capacity to store the first chunks of videos, since the normalized viewing time of the vast majority of views is low. Thirdly, despite the variety of users' behaviors, users' interests reside in a few categories only, which could be leveraged to design efficient recommendation systems and targeted advertisement. Finally, the types of connection and mobile device should be considered as important factors. The CDN can better predict the peculiar behavior of its mobile users by taking these factors into account and thus optimize further the placement of servers and the routing strategies.

The remaining of this paper is organized as follows: Section 2 describes the dataset. In Section 3, we perform an in-depth analysis of users' behavior. Section 4 examines video popularity patterns, followed by an analysis of viewing source in Section 5. In section 6, we evaluate the design of a caching system that uses the observations we made. We discuss the related work in Section 7. Section 8 concludes our work.

2. DATASET

2.1 Dataset Description

Our dataset was collected from the log servers of PPTV[1], a leading video content provider offering live streaming and VoD services in China. PPTV provides free access to 22 categories of videos, including movies, TV series, animation or variety shows. Users can view videos either through a Web browser or through a free client application available for various types of mobile devices (*e.g.* iPad, iPhone, Android pads and Android phones).

Table 1: Main fields of logs

Field	Example
Timestamp	13:10:01 Dec. 4 2011
Geo-location	BJ, SH, overseas, etc.
Connection type	WiFi, 3G or unknown
User ID	33ab8c95437fd
File name	Tom and Jerry_episode1.mp4
Video category	Movie, TV series, animation
Device	iPhone, iPad, Android phone, etc.
Viewing time	55 seconds
Viewing source	video search, category page, etc.
Streaming type	VoD, live

Since most of the views of mobile accesses are generated by mobile devices-based software (as opposed to web browsers), we only consider the views records from the software. After a view is terminated, a record is pushed to the log servers. Table 1 lists an example of the main fields contained in the logs.

The timestamp field is formatted as GMT+8 (Beijing's time zone). The geo-location field can refer to one of the provinces in mainland China, HongKong-Macao-Taiwan or

[1]http://www.pptv.com/

an overseas location. Connection type has three possible values: WiFi, 3G and unknown. A unique user ID is generated when a client application is installed on a mobile device. Note that it is possible for some users to share a device (*e.g.* members of the same household) and as such a user in this paper relates to a client application which may correspond to different users sharing the same device. The video name field contains a unique identifier of the video. The viewing time field contains the duration of a view in seconds, not including the possible pauses in viewing. Finally, the viewing source field identifies how users discover videos, *i.e.* category page, video search, recent views, recommendation, favorite, top popular videos, cover and next episode.

We uniformly sampled the logs of VoD and live streaming requests that came from the client application on mobile devices for a period spanning two weeks from Dec. 1st, 2011 to Dec. 14th, 2011. Overall we collected 111,702,242 view logs, out of which 108,851,161 views are VoD requests. By filtering out the logs with unknown connection type, the data finally contained 86,521,403 logs, with a proportion of 92.58% access with a WiFi connection and 7.42% via a 3G connection. These views were generated by 3,759,129 users watching 427,316 unique videos. Hereafter, we will refer to this final filtered dataset as the `mobile dataset` and use it as the base of our analysis.

Table 2: Dataset statistics

Access method	% of views from		
	Tablets (iPad+aPad)	Smart phones (iPhone+aPhone)	others
3G	5.37	94.63	∼0
WiFi	44.89	55.10	0.01
WiFi+3G	42.08	57.91	0.01

Table 2 shows the distribution of views generated by different types of mobile devices. Almost all the views are from four types of mobile devices, *i.e.* iPad, iPhone, Android pad and Android phone (the latter two are abbreviated aPad and aPhone in this paper). The number of views from smart phones and tablets is similar when a WiFi connection is used while for 3G accesses most of the views come from smart phones.

2.2 Limitations

The dataset contains 14 days of viewing logs. This relatively short period of time does not allow us to fully observe users' behavior and videos' consumption patterns, as the series of viewing rates and video popularity trends usually span larger time scales. Besides, the dataset is a uniform sample and not a total collection of logs. We will thus focus on normalized values and avoid metrics that might be affected by a sampling bias.

Another limitation is that the dataset does not contain detailed video attributes, such as video length, video uploading time, video tags, bit rate or others. Among these attributes, video length is certainly one of the most important for the analysis of viewing time. In order to obtain this information, we used another large sample of viewing logs from the Web portal of PPTV (with 91 million entries, mostly from PCs). In this Web sample the video length is included, along with an identifier for the video file with the same format as in our `mobile dataset`. We were then able to obtain the corresponding length of 268,867 videos that were contained in both samples. Although these videos only cover 62.9% of the unique videos in `mobile dataset`, they still account for 95.8% of the views.

Finally, even though the viewing behavior during user's mobility would be of interest in this work, the dataset does not contain any relevant location information.

3. USERS' BEHAVIOR AND INTERESTS

We analyze in this section both aggregated viewing behavior and individual behavior of the users, and discuss the implications of our key observations.

3.1 Daily and Weekly Patterns

System designers need insights on the workload of the systems to perform adequate capacity design. In this article, we define workload as the number of video requests to the system. Figure 1 plots the variation of this workload over time, for both WiFi and 3G connection types. Each of the two curves is produced in the following way: we aggregate the number of views with a bin for each hour and counted the number of views of the same hour of week. Finally the number of views per hour is normalized by the total number of views through WiFi and 3G, respectively. Note that since the total number of views through WiFi is different from the number of views through 3G, one cannot quantitatively compare the two curves.

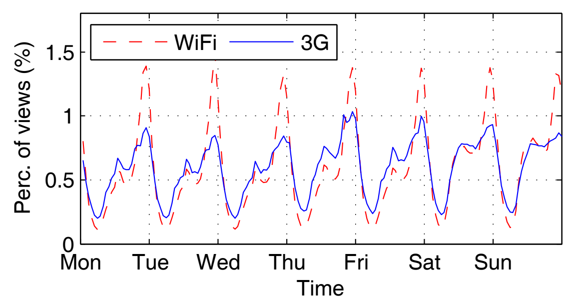


Figure 1: Weekly patterns of access using WiFi and 3G

Both WiFi and 3G workloads exhibit strong daily and weekly patterns. The lowest level of workload happens between 5AM and 7AM every day. The number of views reaches its first minor peak at 1PM in weekdays and at 2PM in weekends. The peak of day is observed around 11PM during both weekdays and weekends. We also observe that the number of views in the afternoon of the weekends is much higher than weekdays for both WiFi and 3G workloads.

Comparing 3G and WiFi workload patterns is also enlightening. The gap between the first minor peak (around 1PM) and the peak of the day (around 11PM) in WiFi network is much larger than that in 3G network, especially in weekends. The most probable reason is that the peak of the day happens during nights when users are most likely at home, thus favoring WiFi to obtain a better quality of video streaming and to save cost.

The daily pattern is similar to the one observed in landline-based VoD systems [10]. However the weekly pattern we observed is different from mobile TV systems [12], where for the 3G connections the viewing pattern of the weekend was almost the same as the pattern of the weekdays.

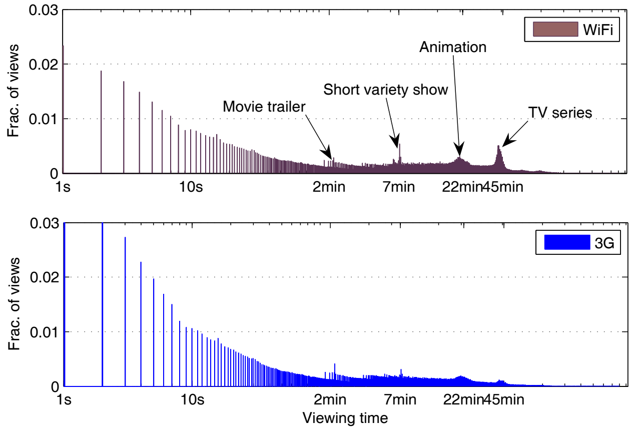


Figure 2: Distribution of viewing time via WiFi and 3G connections

3.2 Video Viewing Time

Viewing time is another indicator of workload, which can be also used for cache policy design. In particular, if most of the views last only a few minutes, it would be efficient to cache the first chunks of videos in content delivery networks (CDNs) so as to maximize the effectiveness of system storage.

Figure 2 shows the histogram distribution of viewing time for WiFi and 3G connection types. The y-axis is the normalized number of views. For both connection types, a considerable fraction of views last less than 10 seconds and generally, the number of views decreases with the growth of viewing time. There are noticeable peaks around 2 minutes, 7 minutes, 21 minutes and 45 minutes in both distributions. They correspond to typical video length for the following types of videos: movie trailer, short variety shows, animation and TV series. The peaks correspond to users watching entirely these types of videos. The variations in 3G viewing time distribution are not as marked as in the WiFi viewing time, indicating that there are fewer users watching full videos in 3G. A possible reason is that the 3G network has a relatively lower speed and obviously higher cost. Another possible reason is the limited power capacity of smart phones, which make up the most of the views via 3G connections as shown in Table 2.

Table 3: Cumulative distribution of viewing time

	0 s	10s	1 min	10 min	20 min
WiFi	23.9%	32.3%	48.7%	74.4%	83.8%
3G	42.7%	54.5%	67.5%	88.5%	94.1%

Table 3 summarizes the cumulative distribution of viewing time. The number of views with 0 seconds is considerably large, especially for views via 3G. 32.3% of the views via WiFi connections and 54.5% via 3G connections last less than 10 seconds. This can be due to the low access speed or to the poor rendering quality of mobile devices, with which users would quickly abandon the viewing of the video. Examining the views with longer durations, we find that only 26% of views via either WiFi or 3G last more than 10 minutes.

We further evaluate the impact of mobile devices on viewing time in Table 4. We only consider views via WiFi since views are more evenly distributed on tablets and smart phones as shown in Table 2. Views from tablets tend to last longer than those from smart phones. This may be explained by the smaller screen size and lower power capacity of smart phones. We also observe a small proportion of views with very long viewing time, often caused by the viewing of movies and TV series. Additionally, we find that views from Android phones last longer than the views from iPhones. While Android phones have various types of hardware with various screen sizes and battery capacities, all iPhones have the same type of hardware. Some Android phones with larger screens or longer battery life may offer better video streaming quality than iPhone, which in turn contributes to making the viewing time longer. We conclude that the type of connections and mobile devices impact the viewing time, with the larger screen size and longer battery life being possible factors lengthening the viewing time.

Table 4: Impact of devices on viewing time (WiFi)

Device	50th prctile (s)	95th prctile (min)
iPad	121	45.1
iPhone	44	34.7
aPad	80	45.8
aPhone	58	42.8

3.3 Normalized Viewing Time

The viewing time is also affected by video length, which varies from several seconds to more than 2 hours. In order to have a better grasp of how complete are the viewings, we define a rate of completion of a video as the *normalized viewing time (NVT)*, which is the ratio of the viewing time to the total length of the video. By definition, NVT can also be considered as a good indicator of the user's interest in a video.

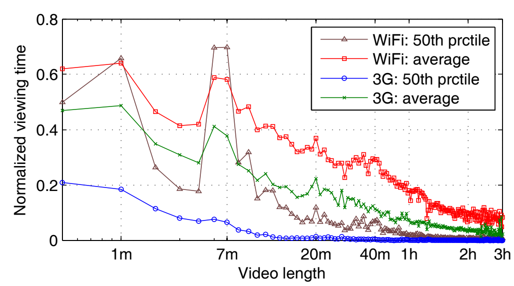


Figure 3: Normalized viewing time against video length

We bin the views by video length in minutes and compute the average and median NVT for each bin. Figure 3 shows the NVT against video length for WiFi and 3G connection types. As expected, the NVT for WiFi is larger than for 3G. It is however interesting to notice that the NVT for WiFi and 3G share similar patterns. In general, the NVT for shorter videos is higher than longer videos. For example with WiFi connections, while the NVT is around 0.4 for videos with length smaller than 12 minutes, it is only around 0.1 for those longer than 1.5 hours. We also observe several abrupt variations as the video length increases. The most noticeable is around the 7-minute length (the typical length for short variety shows). The median NVT value with length around 7 minutes even reaches 0.7 for WiFi connections.

Table 5: Average NVT against popularity of videos

Top	0.5%	1%	5%	10%	50%	100%
WiFi	0.205	0.222	0.275	0.284	0.304	0.336
3G	0.074	0.083	0.109	0.124	0.173	0.229

Yu *et al.* [15] found that in landline-based VoD systems, the viewing time is inversely proportional to the popularity of videos. We observe similar behavior in the PPTV mobile VoD systems as shown in Table 5. Regardless of the connection type, on average, the NVT grows with the decrease of video popularity. With WiFi connections the NVT grows from 0.205 for the top 0.5% of videos to 0.336 for all videos; with 3G connections the NVT grows from 0.074 for top 0.5% videos to 0.229 for all videos.

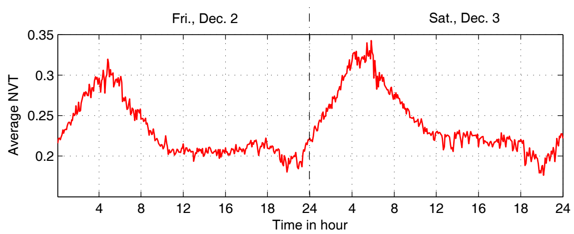


Figure 4: Normalized viewing time evolution over time of day

We further examine the evolution of NVT over time of days for WiFi connections in Figure 4. Note that the evolution of NVT for 3G networks exhibits the same trend as for the WiFi connections. Views are binned by 5-minute time frames and then the average of each bin is computed. Figure 4 shows the results for two days. We observe that the average NVT in early morning is higher than in other time of days, which is consistent with what was observed in mobile TV systems [12]. The NVT remains stable during day time and reaches its minimum in the evening.

3.4 User Interest

Internet video providers often store popular videos according to users' interest on CDN servers close to users. The storage locations of a video should be chosen by taking into account several factors, including the variation of users' interests over time and users' geo-locations. Here we measure user interest using the categories of the videos that the users watched.

3.4.1 User interests over time

Figure 5 depicts the popularity (measured by the proportion of views) of different categories over 2 days. Other days exhibit similar trends as shown in the figure. We bin the views by 5-minute time frames and compute the popularity for each category. For both WiFi and 3G connections, the top 4 categories, *i.e.* movies, TV series, animation and variety shows, make up about 94% of views. While TV series is the top category in terms of views for both connection types, we observe a rather unexpected fact that 3G users watch more movies than WiFi users. By further examining the movie views for 3G connections, we found that 58% of views were abandoned before playback. Several factors may contribute to explain this observation, including low speed of 3G connections, high connection costs, etc. We are unfortunately unable to investigate further these factors using the limited information contained in our dataset.

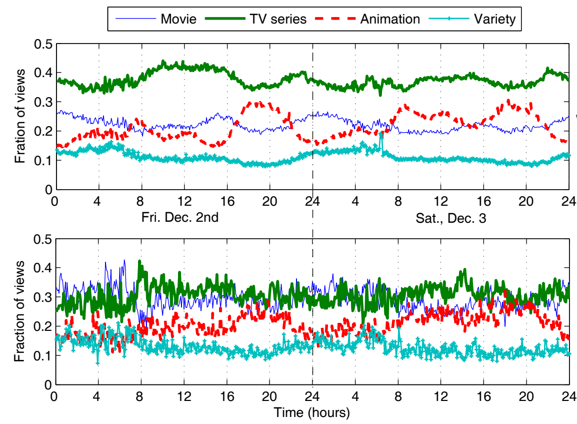


Figure 5: # of views from different categories over time

Looking at the evolution in time of the number of views, the curves for 3G connections are slightly less stable than those for WiFi connections. That may be however due to the fact that there are fewer samples in each time bin for the 3G connections, making the curves less smooth.

The popularity of movies and TV series share similar evolution trends: decreasing at early morning, remaining at a high level from 8AM to 4PM, decreasing again after 4PM, and climbing up from 8PM. The popularity trend of animation vidoes, as opposed to movies and TV series, exhibits a different shape. The popularity reaches its first peak around 8AM and grows fast from 4PM to reach a daily peak around 7PM. We believe the main reason behind these differences is that the majority of animation audiences are young students, who watch videos after study time.

The popularity of variety shows is less variable, but exhibits peaks around 6AM. A closer inspection of the data for this type of video revealed that at this time of day, the fraction of views from overseas reaches its peak. As shown later in this section, overseas users prefer to watch variety shows. By comparing the trends on Friday and Saturday, we observe a higher fraction of animation views in Saturday than in Friday. This might also be explained by the viewing of videos by young students.

3.4.2 User interest across locations

We first bin views by locations (*i.e.* provinces) and examine the popularity of categories for each location. We find that users from the provinces of mainland China share similar interests. However, the views from overseas and HongKong-Macao-Taiwan (HMT) show high discrepancies with mainland China on video categories. We thus further group the provinces of mainland China as one cluster and compared users' interests between mainland China, overseas and HMT in Figure 6. In the figure, "M-WiFi" is short for "Mainland China-WiFi", "O-WiFi" is short for "Overseas-WiFi".

Overall, about 7% (resp. 6%) of the views are from overseas (resp. HMT). We see different patterns of users'

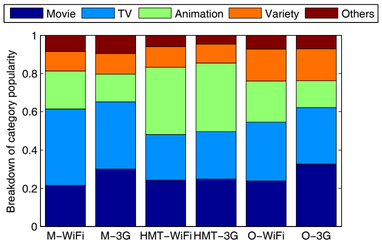


Figure 6: Popularity of categories across locations

interests in different locations. The users located in HMT are mainly interested in animation videos which represent 35.3% of the views, about twice as many as the percentage for other locations. Figure 6 also shows that overseas users tend to prefer videos of variety shows a little more than users from other locations. The users from mainland China on the other hand favor TV series.

While the impact of the connection type on HMT measurements seems very limited, it is clear that 3G users in mainland China and overseas favor viewing movies more than users with WiFi connections. This observation is consistent with the insight offered by Figure 5.

3.5 Activity of Individual Users

Understanding individual user behavior is important for the design of recommendation systems and targeted advertisement. In our dataset, users are identified by a unique user ID in the log entries. We divide users into 3 categories according to their connection types, *i.e.* WiFi, 3G and mixed-access users. WiFi and 3G users are defined as those viewing videos exclusively through either connection type during the observation period, while a mixed-access user is defined as one who accessed via each connection type at least once.

Table 6: Statistics for individual user activity

	% of users	# of views (percentile)	
		50th	95th
WiFi	83.57	6	89
3G	8.49	3	39
Mixed	7.94	27	186

Table 6 gives the number of users for the 3 categories and shows statistics for individual user activity. The number of views is aggregated for individual users from the dataset. We observe that the number of WiFi users is one order of magnitude greater than that of 3G and mixed-access users. WiFi users view twice as many videos as 3G users. For mixed-access users, the median number is about one order of magnitude larger than that for 3G users.

3.5.1 *Per user NVT analysis*

We now focus on the possible correlation between the number of views and the normalized viewing time for individual users. We bin users by their number of views and compute the average NVT for each bin. In Figure 7, the relationship between the number of views and the NVT shows an interesting feature. The measured NVT grows with the number of views but the growth seems to stop when the number of views reached a level of 100 views. Above this

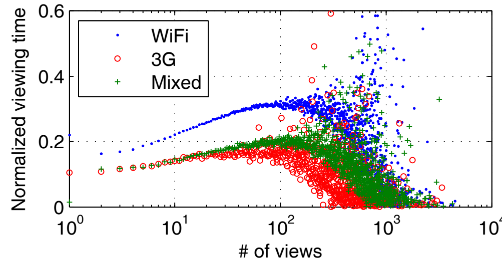


Figure 7: Average NVT against number of views

level the average NVT is more dispersed, but the relation is globally reversed as the average NVT decreases with the number of views.

3.5.2 *Distribution of user activity*

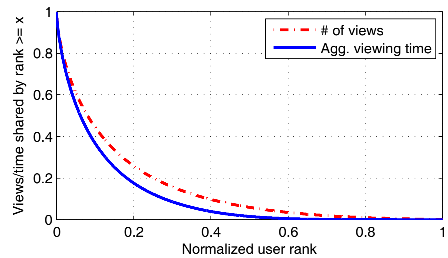


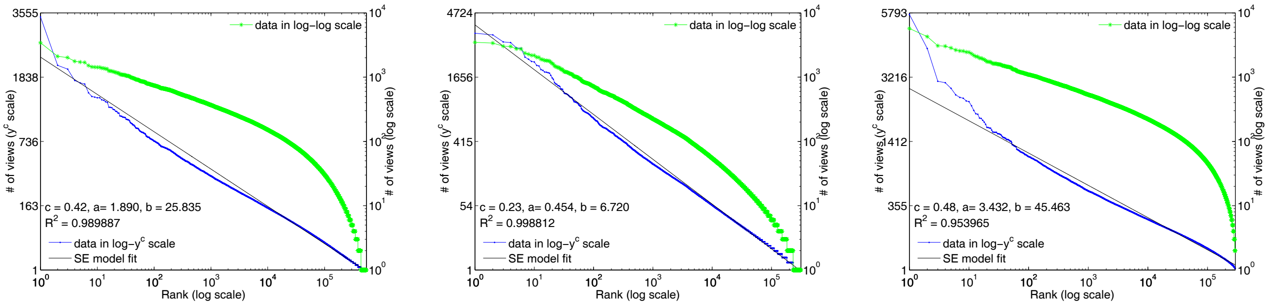
Figure 8: Rank distribution for users' activities

User activity can be quantified in our dataset through the per-user viewing time and the number of views. We examine the rank distribution of users for both viewing time and aggregated number of views and plot the results in Figure 8. The figure gives the important insight that the top 20% of the users generated 75% of the views and 80% of the viewing time. Since viewing time can be directly mapped to system workload, it means 80% of the workload is generated by 20% of users, following the Pareto principle.

We next examine the activity distribution per category of users. For each category, we sort the users according to the number of views in a descending order. We then plot the rank distribution of individual users' activity in Figure 9, *i.e.* rank index i versus the number of views made by the i-th ranked user. Note that the x-axis and the right y-axis are in logarithmic scale.

The well-known power law rank distribution would be observed as a straight line in log-log scale. It can be seen on Figure 9 that the rank distribution for the three connection types WiFi, 3G and mixed-access significantly deviate from such a straight line. We can clearly see a flat head and a thin tail, showing that the distributions do not follow a power law model.

Laherrere *et al.* [11] suggest a stretched exponential (SE) distribution, also known as the complementary Weibull distribution, to model such a deviation from the straight line in a log-log plot. The complementary cumulative distribution function (CCDF) of the SE distribution is given as $P(X \geq x) = e^{-(\frac{x}{x_0})^c}$, where c is the stretched factor and x_0 is a constant parameter. In the rank-ordering technique, N objects are ranked in a descending order of their reference



(a) WiFi (b) 3G (c) Mixed

Figure 9: Rank distribution of aggregated number of views for individual users

numbers. Then $P(X \geq x_i) = i/N$, where i $(1 \leq i \leq N)$ is the number of objects with reference numbers larger or equal to x_i. That is $\log(i/N) = -(\frac{x}{x_0})^c$. By substituting x_i for y_i, we have ${y_i}^c = -a \log i + b$, where $a = {x_0}^c$ and $b = {y_1}^c$. The log-y^c plot of ranked data following a SE distribution should be a straight line.

We leverage the SE fit method provided by Guo *et al.* [8], where the parameters for the distribution are obtained by maximum likelihood estimation. The goodness of fit is measured by the coefficient of determination, R^2. In Figure 9, the left y-axis is in y^c scale. As it can be seen the fit is very good for all 3 types of connections although exhibiting different stretched factors. The first several points in Figure 9c are significantly higher than the SE model predictions, which is known as the "King effect" [11].

Taking a closer look at the estimates of the distributions, the distribution for 3G connections has the smallest stretched factor, implying that it is more skewed towards (a few) core users. We further divide users in each category into subcategories by the type of mobile devices (*e.g.* iPad, iPhone, etc.). Although not shown here, we also observed SE distributions for each subcategory with a stretched factor equal to the factor measured for the category. For example, all the 3G subcategories are with the same stretched factor 0.23. We believe that different stretched factors for different types of users reflect the intrinsic characteristics of users' specific activities.

3.5.3 *Interests of individual users*

Internet video systems often rely on individual users' interests in videos for personalized recommendation. We investigate whether a user tends to watch videos from a small number of categories only. To this end we compute category entropy, which is introduced in [4] and defined for a user i as:

$$e_i = \frac{-\sum_{k=1}^{K} p_{ik} \times lnp_{ik}}{lnK} \tag{1}$$

where K is the number of categories, $p_{ik} = \frac{u_{ik}}{u_i}$, u_{ik} is the number of videos viewed by user i and belonging to category k, u_i is the total number of videos viewed by user i. The category entropy is a number between 0 and 1, with "0" corresponding to a user viewing videos of a single category only and "1" when the user watches videos uniformly chosen from all possible categories. PPTV offers $K = 22$ categories of videos for VoD streaming. We divide users into 2 groups, those viewing more than 1 video and those viewing more than 50 videos within 14 days. Figure 10 shows the distribution of the category entropy.

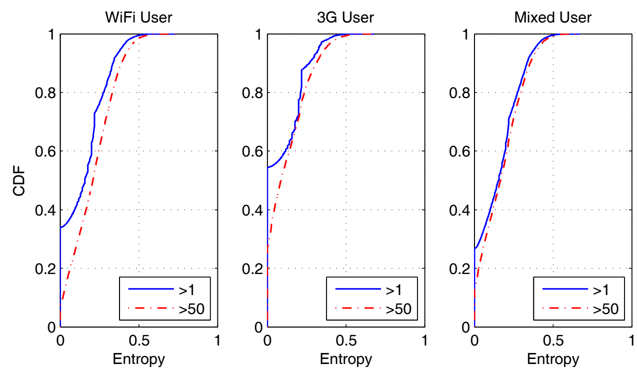


Figure 10: CDF of category entropy

Almost all users have a category entropy less than 0.5, independent of the number of viewed videos. Focusing on the users who view more than 50 videos, we observe as many as 29% of the users with 3G connections viewing videos of only 1 single category, which is larger than the WiFi (9%) and mixed users (15%). We conclude that individual users tend to view videos from a limited set of categories.

3.6 Summary and Implications

Our findings on user behavior are summarized as follows.

- Users' behavior through both WiFi and 3G connections shows strongly daily and weekly patterns. As opposed to previous work, we observed at large scale significantly different 3G and WiFi weekly patterns.
- In general, the viewing time is very short. Only about 25% of the views via either WiFi or 3G last longer than 10 minutes, and we note that a considerable fraction of views are abandoned before playback. The views via WiFi connections last longer than those via 3G. Mobile devices also have an impact on the viewing time, with larger screen sizes and longer battery life being possible factors explaining this longer viewing time.
- Longer videos have shorter normalized viewing time (NVT). The NVT is inversely proportional to the popularity of the videos and varies during the course of the day. The views taking place in the early morning have longer average NVTs.

- Movies and TV series account for 60% of views, independently from the connection type. There are surprisingly more views via 3G to request movies than via WiFi, although more than half of them are abandoned before playback. Users' interests also change over time and we observed different video "tastes" according to users' geolocation.
- Individual users' activity follows the Pareto principle: a minor proportion of causes generate a major proportion of effects. About 20% of users generate 80% of views and users requesting videos via both 3G and WiFi connections view a higher number of videos. The aggregated number of views per user follows a stretched exponential model with a stretched factor depending on the connection type. Besides, individual users and especially those using 3G connections tend to focus on videos from a limited set of categories.

These observations might prove useful for caching policy of CDNs, buffering policy in client software, system design, recommendation and advertisement systems:

- The system maintenance and upgrade operations should be scheduled between 5AM and 7AM to minimize the impact on users. Since the system's capacity is designed according to the peak workload, a major part of the system resources would be not used in the early morning.
- Short viewing time implies that the effectiveness of cache could be optimized by allocating most of the capacity to store the first chunks of videos on the CDN servers. The fact that the viewing time is also impacted by the connection type points to the need for different caching policies for different types of network access.
- A flexible buffering policy in the client application could consider the length, popularity of videos and the time of day to perform effective buffering, which is key for user engagement [5]. Firstly, client software should not aggressively buffer several chunks of videos, but rather adopt a more efficient adaptive caching policy. Secondly, video providers' customized client applications would benefit from the pre-fetching of more chunks of videos for buffering in the early morning, since views exhibit a high completion rate during this period. Finally, as noticed previously, buffering policies should take into account the type of connection and the type of mobile device used.
- Recommendation systems and content providers could exploit the patterns we observed to better fit users' variable interests across time and locations. A time-aware recommendation system could weight the candidate items based on the time of day, and for example propose to its users animation videos with a higher probability after school time. Advertisers could consider the fact that users with 3G connections are more likely to watch movies than those with WiFi connections.

4. VIDEO POPULARITY

In this section, we focus on the video popularity in the PPTV mobile VoD system. The video popularity characteristics not only help us to understand the underlying human collective behaviors, but also provide insights into optimization of the cache policy and deployment of CDNs.

Individual videos are identified by the unique file names of videos in the PPTV video system. Video popularity can be

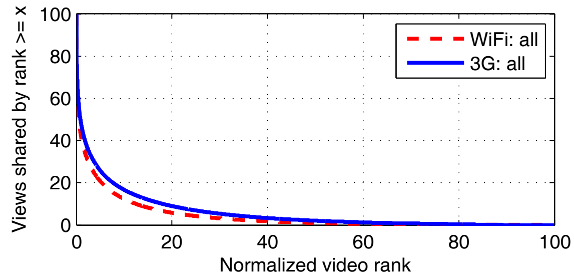


Figure 11: Pareto principle for video popularity

measured by either the number of views or the aggregated viewing time. We examine the correlation between these two popularity metrics with the Spearman rank correlation coefficient ρ. The coefficient ρ is defined as

$$\rho = 1 - \frac{6\sum(x_i - y_i)^2}{n(n^2-1)} \qquad (2)$$

where x_i and y_i are the ranks of the i-th video according to two different metrics, n is the total number of videos under consideration. It is a non-parametric measure of correlation, which quantifies how well an arbitrary monotonic function could describe the relationship between two variables. The coefficient lies in [-1,1], a value of "1" indicating perfect positive correlation and "-1" indicating perfect negative correlation.

The value of the correlation coefficient of the two popularity metrics is $\rho = 0.884$, indicating a high correlation. Thus, in the following we will use the number of views as the measure of video popularity. Unless otherwise specified, we consider the aggregated number of views to be the popularity of a video for the time period covered by our dataset.

4.1 Video Popularity Distribution

We examine the video popularity distribution by ranking videos by popularity. We normalize video ranks between 0 and 100 and compute the normalized aggregated views of the least x-th popular videos. Figure 11 shows a highly skewed distribution for both WiFi and 3G connections. The top 10% of the popular videos attract more than 80% of views. The distribution for 3G connections seems to be slightly less skewed than the WiFi's. The differences of viewing source between the two types of connections could be a contributing factor. As will be shown next, users with 3G connections are more likely to use search portals to discover videos than users with WiFi connections, which makes the video viewing of a more diverse origin. The skewed distribution indicates that the video popularity follows the Pareto principle, in this case that a very small number of top popular videos attract the majority of views.

Although not shown here, we found that the overlap rate of top ranked videos via WiFi and 3G connections is moderately high. For example, the overlap rate of the top 1,000 popular videos is 0.75.

These observations imply that by caching only the top 10% of popular videos on CDNs, more than 80% of requests can be satisfied. However, the popularity of videos changes overtime and is the object of the following subsection.

4.2 Video Rank Stability

We bin views of WiFi and 3G connections by 30-minute time frames. The rank stability coefficient for the top k popular videos in the i-th ($i > 1$) bin is defined as

$$R_k(i) = \frac{|S_k(i) \cap S_k(i-1)|}{k} \tag{3}$$

where S_i is the set of top k popular videos during the i-th time frame. The coefficient has values within [0, 1], where a value of "1" indicates no change and a value of "0" that all the videos in the top list change.

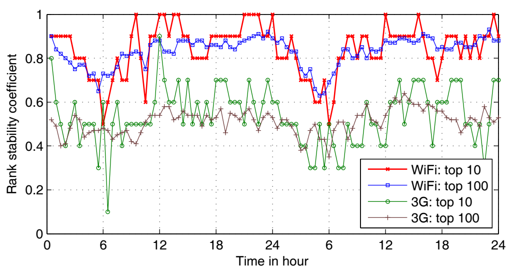


Figure 12: Video rank stability coefficient over time

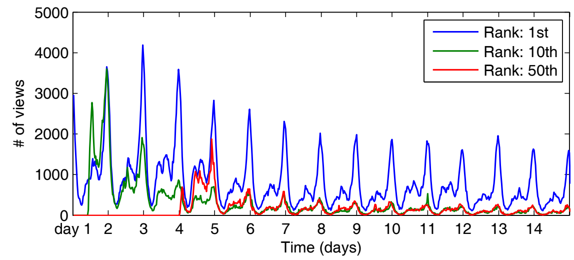
Figure 12 shows the change of the coefficient of the top 10 and top 100 popular videos over 2 days. Our first observation is that the top videos for WiFi connections have between 20% and 30% more stability than for 3G. This can be explained by the fact that there are fewer views in each bin for 3G and the difference in the number of views among popular videos is smaller. Thus a small variation of views would change the rank ordering of videos, which in turn results in a lower rank stability. We note that the top videos are less stable in the early morning and more stable after noon, which is the highest workload period of the day. This observation is consistent with the results in landline-based VoD systems [15] and mobile IPTV systems [12]. We also observed that the top 100 videos have similar stability as the top 10 videos, independently of the connection type, while in landline-based VoD systems [15], the top 100 videos are less stable than the top 10 videos.

The cache should adaptively change the top popular videos it stores to maximize efficiency. An important question at this point and that we examine in the following is whether it is possible to predict the near-future popularity of videos.

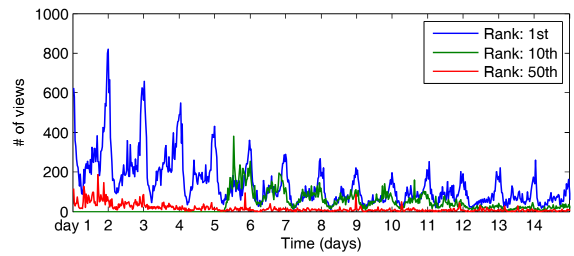
4.3 Video Popularity Evolution and Prediction

Focusing on the evolution of video popularity, we examine videos by ranking them in a descending order according to their popularity for WiFi and 3G connections. We select the 1st-ranked video (*i.e.* the most popular video), the 10th-ranked video and the 50th-ranked video for both types of connections and plot their popularity evolution trends over time in Figure 13. We note that popular videos watched via WiFi attract more views than via 3G, probably because of the higher number of views in WiFi network.

Figure 13 shows that both 3G and WiFi exhibit similar patterns in terms of video popularity evolution, including a strong daily pattern similar to the pattern of the total aggregated views of Figure 1. The figure shows that the number of views of popular videos has a clear decreasing



(a) WiFi



(b) 3G

Figure 13: Popularity over time for top videos

trend after the peak day and thus that a given video rarely belongs to the top list for a long time.

Another interesting finding is that the 10th-ranked videos for both WiFi and 3G connections experience a sharp increase in popularity immediately after their uploading, independently of when they were uploaded in the course of the day.

The above observation motivates us to examine whether it is possible to predict the near-future popularity of videos using their early views records. We unfortunately couldn't extract the exact upload time of videos from our data. We form an estimate of the upload time in the following way: we consider a video as being a fresh upload if it was not viewed in the three preceding days (*i.e.* from Dec. 1 to Dec. 3, 2011) and mark its upload time to be the first time it was viewed in our dataset. A drawback of this method is that it would consider the least popular videos uploaded before Dec. 1, 2011 to be freshly uploaded videos. In order to avoid this effect and since we are only interested in top popular videos, we further filter out the videos with less than 10 views.

Table 7: Pearson correlation coefficient between early views records and the popularity of videos

Network type	k hours after uploading				
	1h	2h	4h	8h	16h
WiFi (19,312)	0.542	0.836	0.841	0.813	0.888
3G (9,403)	0.049	0.777	0.926	0.944	0.961

With this method, we can estimate the upload time of videos uploaded after Dec. 3, 2011. We first focus on popularity prediction of videos uploaded on Dec. 4, 2011. Table 7 shows the Pearson correlation coefficient between the number of views a video attracted within k hours after its estimated upload time and the number of views of that video in the dataset. The Pearson correlation coefficient is a measure of the correlation (linear dependence) between two variables X and Y defined as

$$\rho_{X,Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \quad (4)$$

where E is the expected value operator, μ_X is the expected value of X and σ_X is its standard deviation.

We also present the number of videos under consideration in Table 7. For both WiFi and 3G connections, the first 4-hour viewing volume yields an accurate estimation with higher correlations. The early records of a longer duration only increase the correlations marginally, especially for WiFi connections.

Table 8: Pearson correlation coefficient between the first 4-hour viewing volume and the popularity on different days

	Dec. 4	Dec. 5	Dec. 6	Dec. 7
WiFi	0.841	0.630	0.880	0.913
3G	0.926	0.575	0.712	0.861

We also evaluate the Pearson correlation coefficient between the first 4-hour viewing volume and the near-future popularity for other days, including Dec. 5, Dec. 6 and Dec 7. The results are shown in Table 8. The coefficients are moderately high for all days: ranging from 0.63 to 0.913 for WiFi connections and from 0.575 to 0.926 for 3G. These results indicate that video popularity can be accurately predicted only with early views records.

We conjecture that such a high correlation is due to the fact that users are expecting the regular upload of new episodes of TV series, animation series and variety shows. To confirm our conjecture, we divide the videos by categories and compute the correlation coefficients between the first 4-hour viewing volume and the video popularity. The results are shown in Table 9.

Table 9: Correlation coefficient between the first 4-hour viewing volume and the popularity for different categories on Dec. 4

Category	WiFi (19,312)	3G (9,403)
Movie	0.304(2.9%)	-0.026(7.6%)
TV series	0.802(40.3%)	0.292(46.9%)
Animation	0.982(14.1%)	0.996(25.3%)
Variety	0.993(9.9%)	0.984(7.9%)
Others	0.884(32.8%)	0.822(12.3%)

We see a very high correlation for animation and variety videos for both types of connection, ranging from 0.982 to 0.996. While the correlation for TV series for WiFi connections is moderately high (0.802), it is very low for 3G. This difference suggests that users using 3G connections tend to not watch TV episodes just after their release date. The very low correlation for movies indicates that it is challenging to accurately predict the popularity of such content using only the very early viewing volume.

4.4 Summary and Implications

The key observations on video popularity are summarized below.

- Video popularity follows the Pareto principle. The top 10% of the popular videos attract more than 80% of views for both WiFi and 3G connection types. The overlap rate of the top ranked videos is moderately high for both connection types.
- The videos' popularity constantly changes overtime. The video rank stability for WiFi connections is between 20% and 30% higher than in 3G.
- Top popular videos exhibit a sharp increase of views several hours after their release. The early viewing volume of videos and their popularity are highly correlated, especially for animation videos and variety shows.

These observations have the following implications:

- Independently of the connection type, the quality of more than 80% of the views can be improved if the caching policy considers only the top 10% of popular videos.
- The popularity prediction can greatly benefit from the early viewing volume of the videos and can be used by designers to improve system performance.
- The flash crowd just after the release of popular videos, especially for TV episodes, animation videos, variety shows via WiFi connections, suggests an opportunity to leverage P2P techniques to reduce server loads.

5. VIEW SOURCE

The PPTV mobile VoD system provides 8 sources for users to discover videos: category page (*i.e.* the front page of each category), video search in PPTV, recent views (of the client), recommendation, favorites, top popular videos, cover (*i.e.* the first page of the client software) and next episode (of TV series or variety shows). An in-depth understanding of how users discover videos in WiFi and 3G networks and its correlation with video popularity is useful for both software developers and advertisers.

5.1 Sources of Views

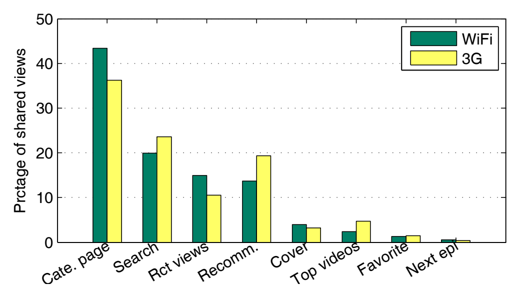


Figure 14: Percentage of views from different sources in WiFi and 3G networks

Figure 14 depicts the distribution of views from each source for WiFi and 3G connections. Category page and video search are the two main sources of views for both types of connections. They account for more than 60% of the views. We see that users with WiFi connections are more likely to use the category pages than those with 3G, while the latter use the search engine more often. These observations also show that users with 3G connections tend to find the videos of their interests directly rather than browse video pages.

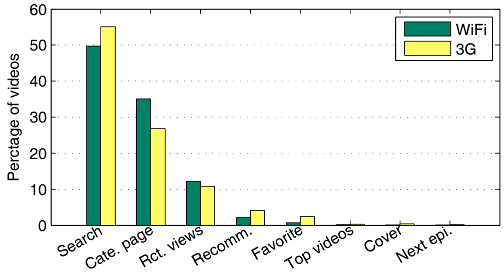


Figure 15: Percentage of videos dominated by different view sources

5.2 Dominant Sources for Individual Videos

We now look at the dominant sources for individual videos. We define the source which accounts for the largest proportion of views as a video's *dominant source* [16]. We extract the dominant source for each video and plot the result in Figure 15. We observe that the category page and the video search are the dominant view sources for 85% of the videos. However, in contrast to Figure 14, video search is the top source of views for individual videos. There are more individual videos dominated by search with 3G connections than with WiFi connections, which is consistent with our previous observation.

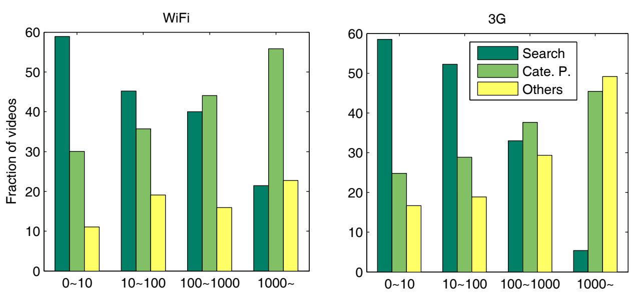


Figure 16: Percentage of videos for dominant sources with different views

Focusing on the view source of popular videos, we bin videos by their popularity and examine the dominant sources. Figure 16 shows the distribution of dominant sources for each bin for WiFi and 3G connections. All the other sources, except search and category page, are grouped as "Others".

With both types of connections, while video search is the dominant source for low-popularity videos, category pages are favored to access highly popular videos. Video searches represent less than 10% (resp. 20%) of the sources for the highly popular videos with 3G (resp. WiFi) connections. This observation suggests that videos are more likely to become popular if they are pushed to the category pages. It is also interesting to note that with 3G connections, half of the highly popular videos are not dominated by category pages as with WiFi connections but rather by a collection of other sources. Users with 3G connections would seem to carefully choose videos, before viewing from various sources.

5.3 The Impact of Search

We have found that video searches are the dominant source of viewing for individual videos, especially for low-popularity videos. Intuitively, one might consider that video search enables users to quickly find various videos matching their interests, which would result in an increase of the diversity of views. In order to verify this intuition, we use the Gini coefficient to measure statistical dispersion and examine the distributional inequality [16].

Sorting the videos in an ascending order according to their popularity, the Gini coefficient is defined as:

$$G = 1 - \sum_{k=1}^{n} (X_k - X_{k-1})(Y_k + Y_{k-1}) \qquad (5)$$

where n is the number of videos, X_k is the fraction of the first k videos, and Y_k is the fraction of the views attracted by the first k videos. A Gini coefficient of "0" indicates a perfect equality where views are uniformly shared by all videos, while "1" indicates a maximum inequality, *e.g.* one video alone attracts the entire views.

Table 10: Gini Coefficient with/without video search

Network type	w/ search	w/o search
Wifi	0.918	0.941
3G	0.884	0.930

In order to evaluate the impact of video search, we compute the Gini coefficient under two scenarios: when video search is present (*i.e.* the actual dataset) and when video search is removed. In order to evaluate the second scenario, we updated the popularity of each video by excluding the views from video search. The Gini coefficients with and without video search with WiFi and 3G connections are listed in Table 10.

The coefficients are above 0.88 for both types of connections, implying a dispersed distribution of video views. The 3G connections have a lower coefficient than the WiFi connections, indicating a lower dispersion. By removing the views from video search the coefficient increases by 0.023 for WiFi and 0.046 for 3G. This indicates that video search increases the diversity of viewing and that the video search plays a more important role with 3G than with WiFi connections.

5.4 Summary and Implications

Our two main findings of view source analysis can be summarized as follows.

- While category page is the primary source of views overall, video search is the dominant source of viewing for most of individual videos, especially for low-popularity videos. Users with 3G connections tend to use video search to discover videos more often than those with WiFi connections.
- Videos that are present on category pages are more likely to become popular, while video search increases the diversity of views.

Our findings offer insights on how video content is discovered in a large video repository. They emphasize the importance of different content discovery and give indications to content providers and advertisers on video promotions. The differences between WiFi and 3G connections should also be taken into account.

6. APPLICATION: DESIGN OF AN EFFICIENT CACHING SYSTEM

An efficient caching system typically stores replicas of videos as close as possible to end users, in order to improve user experience and alleviate server load. In the preceding sections we observed that caching the top 10% popular videos and the first few chunks of the videos could be part of a caching strategy to optimize the overall performance. In this section, we aim to evaluate such a performance gain using trace-driven simulations and comparing different caching strategies. We first assume a global virtual cache, where requests are first sent to the cache. Since we are primarily interested in the performance improvement potentially obtained by leveraging our findings, we do not assume any particular distribution for the locations of content cache servers. We assume that a video can be cached at chunks level and that it is divided in a set of 1-minute chunks. We consider the following 3 caching strategies:

1. Full caching: Each day the cache is refreshed with the top 10% popular videos as observed the day before. All the chunks of the selected videos are stored in the cache.
2. Partial caching: Each day the cache is refreshed with the top 10% popular videos as observed the day before. However as suggested by our findings, we only cache the first few chunks of each video. The fraction of cached chunks of each video is computed as a function of the normalized viewing time (NVT), as depicted on Figure 3. Specifically, considering the video lengths (in minutes), we estimate the expected video's viewing time with the average NVT. The number of chunks for each video to be cached corresponds then to the fraction of chunks covering the expected viewing time.
3. Full caching with limited size: In this strategy we further take into account the constraint of limited cache size. The daily cache size is set to the size used in the partial caching strategy of the same day. But all chunks of the selected videos are stored in the cache, which is populated with the top popular videos until it has reached it maximal capacity. Due to the limited cache size, less than 10% of the top popular videos will be stored.

For a viewing request i, let h_i denote the number of chunks' hits and let r_i denote the number of requested chunks, then the cache hit rate of the view i is defined as $C_i = \frac{h_i}{r_i}$. We perform the simulations by replaying the requests of 13 days, from Dec. 2 to Dec. 14. Table 11 shows the average cache hit ratio over all viewing requests. Note that the cache size is defined as the number of stored chunks in the cache. The table also shows the average value of each day's cache size.

Table 11: Cache performance

Cache scheme	avg. cache size	avg. hit rate
Full	658,630	75.3%
Partial	133,019	63.3%
Full+limited	133,019	52.6%

We observe a high average hit rate for the full caching strategy, showing the effectiveness of only caching the top 10% previously observed popular videos. Compared to the full caching strategy, the partial caching offers a reduction of 80% in cache size, at the expense of a reduction of only 12% of the hit rate. Our results also suggest that the variant of the full caching with limited size yields a lower hit rate when compared to the partial caching. This preliminary analysis indicates that the partial caching strategy provides a better tradeoff between cache size and hit rate.

7. RELATED WORK

User behavior and video consumption patterns in Internet video systems have been examined in the context of VoD [15][14] [5], IPTV [7][3], P2P VoD [10] and live streaming [9], including YouTube[2]. By measuring a VoD system, Yu *et al.* [15] made several observations on user arrival rate, video popularity and the impact of recommendation. Yin *et al.* [14] analyzed a live VoD system from the 2008 Olympics, focusing on how the dynamic nature of the system impacted user behavior. Dobrian *et al.* [5] examined the impact of video quality on user engagement and found that the buffering ratio is the most important factor. Guo *et al.* [8] modelized the video access patterns of several Internet video systems with stretched exponential distributions.

Another major type of video services is IPTV. Cha *et al.* [3] measured an IPTV system and analyzed the characteristics of viewing sessions and the patterns of channel popularity. Gopalakrishnan *et al.* [7] and Qiu *et al.* [13] modeled interactive usage and user activity in IPTV systems.

Measurement studies [10][9] on P2P-based VoD and live streaming systems emphasized the aspects of peer stability, chunk availability and scheduling mechanisms. We have discussed the possibility of using P2P techniques on mobile VoD systems in this paper. As a UGC (user-generated content) video system, YouTube constitutes a huge repository of short videos in the context of VoD streaming. Cha *et al.* [2] characterized the video popularity in YouTube. They identified several popularity distributions and gave suggestions on the design of caching and P2P content distribution.

Watching videos with mobile devices becomes more and more popular. Li *et al.* [12] analyzed traffic patterns and user behavior for a mobile TV system. They showed that the wireless connectivity allowed smooth video viewing with mobile devices and modeled the sojourn time in channels with two piecewise distributions. Finamore *et al.* [6] compared YouTube traffic generated by mobile devices with traffic generated by PCs. Their key observation is that aggressive buffering policies cause a considerable waste of bandwidth for mobile devices. In this paper, we observed the short viewing times and suggested adaptive caching policies which could be also leveraged in YouTube.

As opposed to previous research, to the best of our knowledge, our paper is among first to systematically analyze the user viewing behavior and the corresponding video consumption patterns for mobile VoD systems. We examined the impact of the connection type and the type of mobile device on viewing behavior, video popularity and viewing sources. We also compared our findings with landline-based VoD systems and mobile TV systems where applicable.

8. CONCLUSION

Understanding user behavior patterns in mobile video systems is of prime importance for content providers, system designers and researchers. In this paper, using a unique data from a mobile VoD system, we systematically analyzed users' behavior and the corresponding video popularity patterns, emphasizing the impact of the connection type (3G or WiFi) and the type of mobile device used (tablet or smart phone). We have made several key observations and discussed their implications on caching and buffering policies and the design of systems, software and on-line advertising. We observed short viewing times (especially via 3G), a stretched exponential distribution for user activity, a concentration of individual users' interests and that the video popularity conformed to the Pareto principle. We also highlighted several surprising findings: 3G users request more movies than other categories of videos; users requesting videos via both 3G and WiFi view a significantly higher number of videos; the early viewing volume of a video is a good predictor of popularity for animation and variety shows. These observations constitute useful insights for system designers, CDNs and developers alike.

Substantial study remains to address issues such as the impact of the type of client application (*e.g.* wired clients, web browsers and mobile clients) on video consumption patterns; the reasons underlying the differences in user behavior depending on whether they connect using WiFi or 3G; how to design better content delivery (*e.g.* P2P delivery) in mobile VoD systems as well as designing effective caching strategies in content delivery networks. Identifying the main discrepancies that might exist between the wired and wireless-based accesses to VoD content would also be worth investigating. In future work, we will study these potentially fundamental differences, exploiting both mobile and Internet-based VoD datasets.

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