YouTube Video Characteristics: Survey and Updates

Xianhui Che, Barry Ip, Ling Lin

***Abstract*—Given the impact of YouTube on Internet services and social networks, a healthy quantity of research have been conducted over the past few years. The majority of studies on traffic capture and evaluation were carried out prior to Google's acquisition of YouTube in 2007. Since then, there have been some changes made on the user policy and service infrastructure, such as limit of video duration, file size, and resolutions. This paper endeavors to depict the latest YouTube traffic profiles and deliver updated and valuable information for future researchers. In order to obtain a detailed understanding of YouTube video characteristics, a customized web spider was employed to crawl across over a million YouTube videos. The study demonstrates consistency with previous research for major video streams whilst new categories of features have emerged within the YouTube service provision. Compared with traditional video repositories, YouTube exhibits many unique characteristics that may introduce novel challenges and opportunities for optimizing the performance of short video sharing services. Existing research in the relevant field is briefly summarized in this paper, and the YouTube video characteristics are analyzed in the aspect of video category, duration, resolution, file size, and data rate.**

***Index Terms*—YouTube, Online Video, Traffic Analysis.**

I. Background and Existing Work

Traffic produced by YouTube has a significant impact on both fixed and mobile networks. The study and evaluation of YouTube content features will benefit network traffic engineering for the sustainable development of video delivery services and traffic regulation in the network, particularly in the area of network cache engineering for network operators where existing cache algorithms can be refined and optimized to better adapt to YouTube video traffic patterns.

The main objective of this paper is to depict the latest YouTube traffic profiles and deliver updated and valuable information for future researchers. There have been a healthy amount of research on YouTube video analysis over the past few years, most of which were conducted prior to 2007. Following Google's acquisition of YouTube in 2008, several major aspects of network and service framework restructuring were undertaken. Since then, some changes have been made on the user policy and service infrastructure, such as limit of video duration, file size, and resolutions. This paper is to deliver the latest reflection of YouTube video characteristics under the impact of such changes. The previous studies of a similar type were conducted more than six years ago ([1], [2], [3], [4]), hence the findings of this article will also provide a comparative insight into how YouTube videos have developed over recent years.

Xianhui Che and Barry Ip work as Assistant Professor and Associate Professor respectively in University of Nottingham Ningbo Campus (UNNC). Ling Lin is a chartered engineer and acts as a research consultant for UNNC. Emails: {cherry.che, barry.ip}@nottingham.edu.cn., linglin_unnc@outlook.com.

Statistics from the work of Cheng et al [1], Gill et al [2], Cheng et al [3], and Abhari et al [4] will be compared with the findings of this article, since there are similar scopes of investigation such as video categories, video durations, file size, and bit rate. Since all four existing publications were based on statistics prior to the Google's acquisition of YouTube, a comparative analysis will be given to depict how YouTube videos have developed over recent years based on the collective statistics as shown in Table I. The work of Cheng et al [1] and [3] emanate from the same research group.

TABLE I: Collective Statistics Overview

Publication	Collection Time	Total Collection
[1]	Early 2007	2,676,388 Video Contents
[2]	Jan-Apr, 2007	23,250,438 HTTP Transactions
[3]	Early 2007	3,269,030 Video Contents
[4]	2007 and 2008	60,544 Video Contents
This paper	Apr-May, 2013	1,245,700 Video Contents

In terms of YouTube traffic analysis, a variety of research has been performed with different approaches and objectives. Ameigeiras et al [5] collects statistics from the most viewed video clips, studies the impact of video encoding rate on traffic generation mode, and proposes a traffic model that can be used for feasible and effective simulation. The study of video duration and bit rate by Ameigeiras et al [5] was based on a total trace of 32,860 video contents and was analyzing traffic from a different perspective, hence the work of Ameigeiras et al [5] will not be used as a reference for point of comparison in this research. Adhikari et al [6] discovers that YouTube does not take users' location into account whilst serving video content - the same point is ascertained by Zink et al [7].

II. Measurement Methodology

A. *YouTube Video Meta Data*

After a video is uploaded and converted, YouTube randomly assigns a unique 64-bit number to the video, which is represented in base-64 encoding algorithm by an 11 character alphanumeric ID. For all video records collected in this paper, a check function was implemented to confirm every record in the dataset is distinct, by removing records with duplicated ID. Each record in the dataset contains intuitive meta-data and the first 2KB of the content. A typical example of the meta-data for a YouTube video is shown below.

- YouTube ID: aZpD0btOZx8
- Video Title: Super Mario
- Video Category: Music
- Content Length: 4163902 Bytes

- Resolutions: 34/640x360/9/0/115, 18/640x360/9/0/115, 5/320x240/7/0/0
- Video Duration: 64 seconds
- Total Views: 36383401

The main difference between YouTube's video service and other traditional video services is that YouTube's videos are not streamed to end users, but are instead downloaded over several normal HTTP-over-TCP connections. Except for possibly stopping the download, YouTube end-users have no control over the download speed. The data rate of HTTP connections are not controlled in the same pace as the video playback rate, but rather, video contents are sent at the maximum data rate of the network capacity which may overload the underlying network.

B. Customized Web Spider

The crawling approach has been a popular methodology for collecting and characterizing YouTube videos. It has been effectively used in [1] [3] [4], as well as in [2] where a multi-level approach was built on the crawling technique. In this paper, a customized web spider has been developed to collect meta-data information of YouTube video contents. The YouTube content item (i.e. video web page) is linked to other content items that have similar titles, descriptions, or tags, which are chosen by the uploader. A YouTube content item may have hundreds of YouTube content related links, although the YouTube web page only shows the top 20 related links at any given time. Hence the relationship between YouTube videos can be considered as a directed spider-web graph, where each video is a node on the graph and videos are linked to each other via the top 20 related links. The web spider will follow the recursive links among YouTube videos and capture video dataset using a breadth-first search technique [8].

The sample space for this project focused primarily on popular and active YouTube content. This is pertinent since rarely accessed or unpopular YouTube content have relatively low impact on traffic optimization strategy. Thus, the initial YouTube URLs are loaded from *http://www.youtube.com/videos?s=pop*, which is the front page for popular content on YouTube. The web spider operates with several different IP addresses which are changed on a regular basis and restarted once a day to bypass YouTube's restrictions. This is necessary as YouTube blocks access from the same IP address through which a large amount of YouTube content items have been accessed in a given time period. The legitimacy issue will be discussed in Section III-C.

The YouTube web spider works on 11-thread actions to achieve maximum performance. Two URL tables are maintained by the system with one recording visited URLs and the other one listing new URLs. Upon the system startup, the spider loads all stored YouTube IDs into the visited URL table to avoid URL duplication. Thread 0 adds a new URL retrieved from the YouTube front page to the new URL table every 30 minutes since new links are regularly updated by the YouTube server. The remaining 10 threads (thread 1-10) are worker threads for YouTube information retrieval, each of which will carry out this process repeatedly: visit one URL that is randomly selected from the new URL table, retrieve content meta-data, download the first 2KB of YouTube content, save the meta-data and 2KB content to database, add 20 new URL to the new URL table and filter out duplicated URLs, add the visited URL to the visited URL table. During this process there are three HTTP transactions involved.

The aim of the first transaction is to acquire the YouTube meta-data video information. YouTube only allows users to view videos online and does not allow videos to be downloaded. Thus, the actual links for HTTP video streaming are encoded in YouTube's HTML and Javascript pages and are updated periodically. Hence, one of the major challenges for this project is to decode HTTP streaming links in order for the required data to be retrieved for the analysis. Issues concerning copyright will be discussed in Section II-C.

The second HTTP transaction is responsible for downloading actual video content. In order to save bandwidth and storage space, only the first 2KB of YouTube content is downloaded and stored in a MySQL database for further processing, which is sufficient for the final analysis. The video downloading is necessary for two reasons. First, the length of the video is a critical parameter for content analysis, which does not exist in the video's HTML web page, but only in the header of the HTTP download stream. Secondly, the audio and video encoding schema only exists within video content.

The third and final transaction is to retrieve the viewing history for the relevant videos. The viewing history represents a data summary of daily visits to the video, starting from the day that it was uploaded to the day that the web spider accesses it. The history also indicates how the video's popularity has grown (or otherwise) and the lifespan of YouTube video (in the case of videos which are removed from YouTube). The view history is returned in the body of the HTTP response.

C. Copyright and Access Issues

Factors regarding copyright and access have scarcely been addressed in existing academic publications, hence a consideration of these issues will be made in this paper. Numerous debates and discussions are available in various selections of texts and online sources with regard to the legality of downloading and the potential copyright infringement of YouTube videos.

YouTube provides free video content for users who, in return, register website hits to increase the popularity and, ultimately, the profits of the site. By downloading videos for offline viewing, users would therefore circumvent their exposure to advertising placed on YouTube beyond the initial viewing, and hence remove any money-making potential in subsequent viewings. Naturally, therefore, YouTube does not want users to side-step advertising by engaging in video downloads. However, avoiding advertising is not inherently illegal, in the same sense that it is legal to use in-browser advert blockers and skipping adverts on TV sites. These discussions reflect the common arguments on the issue.

Despite the ongoing confusion and debate, the research carried out in this paper can be justified for two major reasons:

first, YouTube video contents are not fully downloaded, instead only the first 2KB of the content is extracted since the header contains all the necessary meta-data information for this research. Second, the research conduct complies with the Fair Use policy of the World Intellectual Property Organization (WIPO), which states "the fair use of a copyright work, for purposes such as criticism, comment, news reporting, teaching, scholarship, or research, is not an infringement of copyright" [9].

III. YouTube Video Characteristics

All 1,245,700 dataset records were saved as raw data in a MySQL database. Each record represents a unique YouTube video content item. A data processing application was developed using c# programming language to analyze each record. The results generated by the data processing application will be discussed in this section.

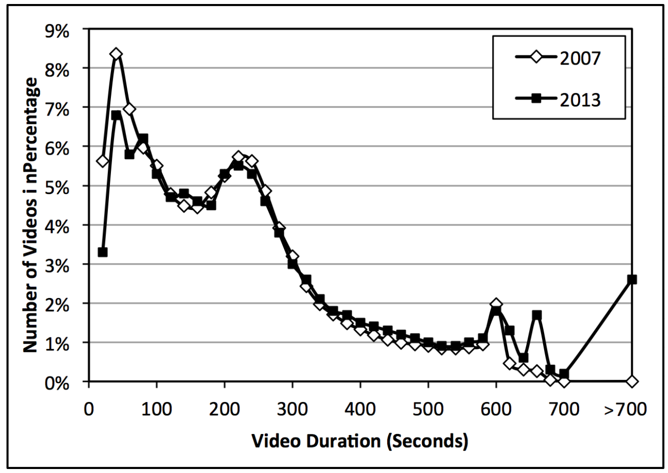
A. Video Category Distribution

Upon uploading a video, YouTube server selects one of 18 predefined video categories. Table II compares the video category ranking for 2007 and 2013. The data for 2007 is taken from the existing work of Cheng et al [1] while 2013 represents the primary data collected in this research via the customized web spider. The percentage in the table refers to the occupancy of the category in the whole collection of the dataset. As can be seen, a few popular categories occupy significantly large percentages, while numerous less popular categories account for lightweight percentage shares. Here, popularity is reflected in the percentage share of each video category.

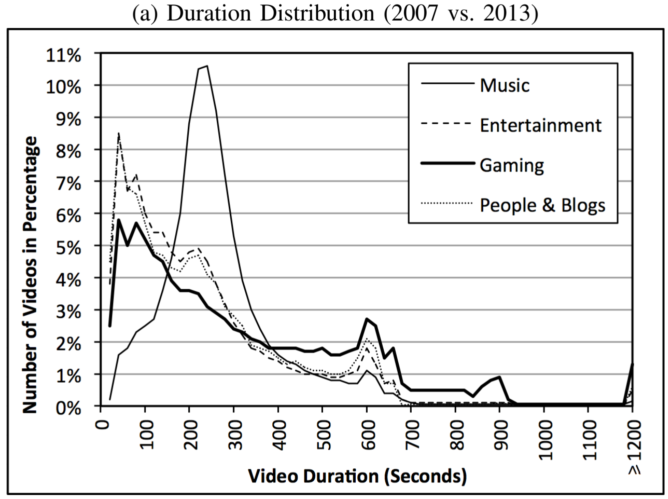
TABLE II: YouTube Video Category Rankings, 2007 and 2013

	2007 Categories		2013 Categories	
1	Music	22.9%	Music	22.8%
2	Entertainment	17.8%	Entertainment	16.0%
3	Comedy	12.1%	Gaming	8.5%
4	Sports	9.7%	People & Blogs	8.1%
5	Film & Animation	8.4%	Sports	8.0%
6	People & Blogs	7.4%	Comedy	5.9%
7	Gaming	7.3%	Film & Animation	5.9%
8	News & Politics	4.3%	How to & Style	5.1%
9	Autos & Vehicles	2.5%	News & Politics	4.6%
10	Travel & Places	2.2%	Cars & Vehicles	3.9%
11	How to & DIY	2.0%	Science & Technology	2.9%
12	Pets & Animals	1.9%	Education	2.9%
13			Travel Events	2.2%
14			Pets & Animals	1.8%

Compared to 2007, Music and Entertainment remain as the two most popular categories in 2013 with respect to the proportion of content, and two new categories have been added: Science & Technology and Education. The third largest category in 2007 was Comedy (dropped from 12.1% to 5.9%), which is now replaced by the Gaming category (risen from 7.3% to 8.5%) in 2013. In the other categories, two have slightly decreased: Sports (from 9.7% to 8.0%), and Film & Animation (from 8.4% to 5.9%), whilst other growing categories include People & Blogs (from 7.4% to 8.1%), Cars & Vehicles (from 2.5% to 3.9%), and, most markedly, How to & Style (from 2.0% to 5.1%).



(a) Duration Distribution (2007 vs. 2013)



(b) Duration Distribution of Major Categories (2013)

Fig. 1: YouTube Video Duration Distribution

B. Video Duration Distribution

Generally speaking, the duration of YouTube videos is shorter than that of traditional media videos (such as films and TV programs), mostly comprising of videos that are relatively short in length. The results from the dataset reveal that more than 96% of the videos retrieved in this analysis are under 600 seconds in length. This is mainly due to the limit of 10 minutes imposed by YouTube in March 2006, which was increased to 15 minutes in July, 2010 [10]. Partner users of YouTube and users with verified status are able to upload videos longer than the set limit [10].

Figure 1a depicts the histogram of the distribution of YouTube video duration for 2007 and 2013, in which the x-axis represents the video duration range while the y-axis refers to the number of videos for all categories. As above, 2007 data is taken from existing research of Cheng et al [1] and 2013 data is collected via the customized web spider. Figure 1b illustrates and compares the YouTube video duration distribution of the top four most popular categories of 2013: Music, Entertainment, Gaming and People & Blogs. The x-axis represents the video duration range in every 20 seconds while the y-axis refers to the percentage of the number of videos in the category.

From the 2013 data alone, the duration distribution exhibits four peaks and the overlapped contour of Figure 1b resembles the shape of Figure 1a. The 2007 dataset only shows the first three peaks. The first peak is within 1 minute which has an occupancy of around 16% in 2013 and 21% in 2007. YouTube has been comprehended as an outlet for short videos since 2005, although the decrease in the percentage of short videos indicates that YouTube is gradually catering to those wishing to upload videos of greater length.

The second peak and the third peak are consistent over the past five years, as shown in the comparison of 2007 and 2013 figures. The second peak is within the range of 200 to 240 seconds, which occurs because the Music category has been a long-standing popular category on YouTube and the typical length of music videos is often within this range. The third peak is near the duration of between 580 and 600 seconds due the duration limit imposed by YouTube. Users often tend to divide long videos into several pieces with each fitting the boundary of 10 minutes.

The fourth peak in the 2013 figure is caused by the number of videos that exceed 700 seconds in length. This peak is missing from the 2007 figure because of the previous 10-minute boundary. In July 2010, YouTube raised the video uploading limit to 15 minutes, and a further five months later enabled verified users to upload videos longer than 15-minutes in length. Users have, since 2010, consequently taken advantage of this new facility as evidenced in Figure 1a which shows approximately 2.6% occupancy of the fourth peak among all collected YouTube videos.

Statistics in this research indicate Gaming is the major category for long videos (i.e. those longer than 700 seconds). As shown in Figure 1b, 6.3% of videos in this category are 700 - 900 seconds in length while other categories all have less than 1% in this duration (except for the Entertainment category which has 1.2%). There are barely any videos with a duration of between 15 minutes and 20 minutes for the four categories outlined in Figure 1b, with a maximum of 0.65% from the Music category. For videos that are longer than 20 minutes, the order of the four major categories is – Gaming: 1.3%, People & Blogs: 0.6%, Entertainment: 0.5%, Music: 0.15%.

C. Resolution Distribution

There have been no research data available in existing publications regarding YouTube video resolution. The analysis of YouTube video resolutions are important for two reasons: one, it gives a definitive indication of video qualities in the system; two, it offers a indicative reflection of end users' uploading capabilities. The original YouTube service only offered videos with one resolution level at 320 $\times$ 240 which solely utilized Macromedia's proprietary Flash technology. With the dramatic growth of smart phones in recent years, YouTube offered support for MP4 format in 2007 for devices that do not offer Flash, such as Apple's iPhone and iPad, in the meantime also allowing for higher quality videos to be uploaded. Further, starting from March 2008, a wider range of resolutions are permitted by YouTube [10]. Such expansions to YouTube services illustrates the company's willingness to adapt to an evolving market, enabling end users to choose suitable video resolutions and formats according to their available bandwidth, requirements, and devices.

The current observation in 2013 of YouTube HTML source code reveals that YouTube's video playback technology is based on both Flash (.FLV) and MPEG4 (.MP4). FLV and MP4 do not refer to video quality but the types of containers of video codecs. In fact, YouTube accepts a variety of video formats such as WMV, AVI, MOV and MPEG, which are automatically converted into .FLV and .MP4 format in different resolutions upon uploading. Many YouTube videos will also play using HTML5 in supported browsers where formats such as WebM VP8 and H.264 are permitted.

When the same video content is being uploaded to YouTube servers, each unique upload is transcoded into a variety of different formats and resolutions so as to support streaming requirements [11], hence several sources (i.e. files) are saved on the server, each corresponding to one resolution. A total of 1,245,700 unique YouTube video are recorded in this dataset and the sum of all resolution sources for all these videos are 4,264,696, which means, on average, each YouTube content item has approximately 3.4 resolution sources. The ranking of various YouTube video resolutions of 2013 is shown below.

(1)	320$\times$240 (FLV)	100%
(2)	640$\times$360 (MP4)	74%
(3)	640$\times$360 (FLV)	66%
(4)	854$\times$480 (FLV)	40%
(5)	320$\times$240 (MP4)	26%
(6)	320$\times$240 (others)	20%
(7)	1280$\times$720 (total)	14%
(8)	1920$\times$1080 (total)	3%

The percentages in the above statistics refer to the proportion of YouTube video contents that have enabled the corresponding resolution. For example, the percentage for 320$\times$240 (FLV) is exactly 100%, which means that all YouTube contents contain a resolution of 320$\times$240 in Macromedia's Flash format. The statistics show that the original resolution 320$\times$240 which was originally introduced by YouTube, is still by far the leading resolution. Currently the two most popular resolutions in YouTube are 320$\times$240 and 640$\times$360.

D. Video File Size Distribution

Video file size distributions have been investigated in existing publications [1][2][4] where the analyses of file sizes were based on all collected YouTube videos and did not offer a perspective on specific video resolutions. Figure 2 shows the video file size distributions for video contents with resolutions of 640×360 (FLV) and 320×240 (FLV) of 2013. The x-axis represents the range of YouTube video file sizes and the y-axis refers to the proportion of the YouTube contents with respective ranges. The statistical results and analysis focus on two popular resolutions in Flash format - 640×360 (FLV) and 320×240 (FLV) which are representative of high quality and low quality videos [10].

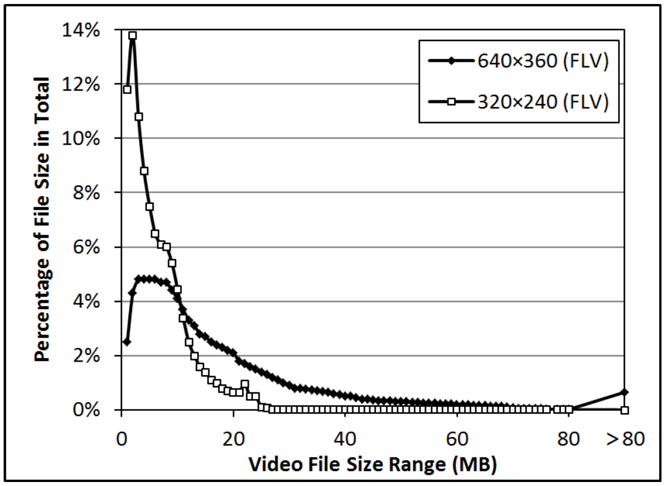


Fig. 2: YouTube Video File Size Distributions (2013)

TABLE III: Video File Size Range

	2007	2013	640×360 FLV (2013)	320×240 FLV (2013)
<30MB	98.8% [1]	90.1%	84.5%	99.2%
30MB–100MB	1.0% [4]	6.7%	14.6%	0.8%
> 100MB	0.1% [2]	0.5%	0.9%	0.1%
Average File Size	8.4MB [1] 9.8MB [4]	13.8MB	17.6MB	6.5MB

Table III compares the file size ranges collected in this paper with statistics from existing research. YouTube's policy on the size limit of video files was 100 MB when previous studies were carried out prior to 2008. The current file size limit is 2 GB for uploading via YouTube web or 20 GB if up-to-date browser versions are used [10]. Due to this policy change, the average file size has increased over the past few years as can be seen from the statistics.

Cheng et al [1] states that the distribution of file sizes is similar to video lengths, and Abhari et al [4] discovers the file size distribution can be modeled by a Gamma distribution. Both articles have given an approximate estimation of YouTube file size distribution using all collected YouTube videos in the dataset. A more precise analysis should take video resolutions into account. As discussed in the previous section, a range of different resolution options have been offered by YouTube since 2008, which have a direct impact on file sizes. When the same YouTube content is uploaded with different resolutions, file size varies accordingly. As shown in Figure 2, file sizes of resolution 640×360 (FLV) are notably higher than those of 320×240 (FLV).

One of the significant aspects of investigating YouTube file sizes is to help with cache management from the network carrier's perspective. The average YouTube video file size is around 17.6 Megabytes for resolution 640×360 (FLV) and 6.5 Megabytes for resolution 320×240 (FLV). Therefore, if 1 million YouTube videos were to be cached, the total disk space required for storage would be approximately 17.6 Terabytes for resolution 640×360 (FLV) and 6.5 Terabytes for resolution 320×240 (FLV).

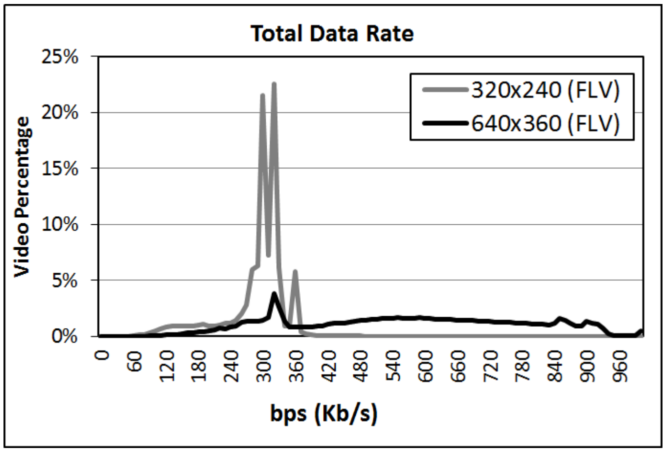
The first peak (also the main peak) of file size distribution can still be described using the Gamma model. There is a slight rise of percentage after the long tail. Around 0.69% of YouTube video files in 640×360 (FLV) are more than 100 Megabytes, and around 0.34% of YouTube video files in 320×240 (FLV) are more than 50 Megabytes. Despite the remarkable increase of file size allowance from YouTube, the maximum file size that users can upload is still affected by the video resolution choice and video duration limit. Take 640×360 for example, the maximum video bit rate of standard quality uploads is 1000 kbps and the maximum audio bit rate is 197 Kb/s [10], hence the maximum possible file size for this resolution would be (1+0.197) Megabits multiplying by 15 minutes which equals to roughly 134 Megabytes.

E. Data Rate Distribution

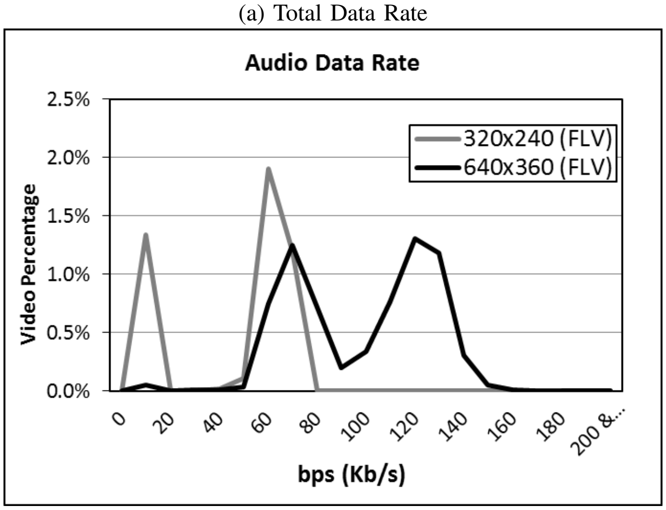
Gill et al [2] estimated the YouTube video play-back data rate based on the calculation of video file size divided by video duration. In the dataset collected in this research, the data rate can be easily observed from the FLV header that is retrieved from the meta data. The value of total data rate is in the format of IEEE 754-2008, IEEE Standard for Floating-Point Arithmetic.

It is found that over 99.9% of the YouTube videos accessed contain FLV meta-data specifying the content's total data rate, video data rate and audio data rate. (The FLV headers of fewer than 1000 YouTube records from a total of 1,245,700 records in the dataset are corrupted, therefore are unable to parse). This indicates that virtually all YouTube videos are transmitted as constant bit rate (CBR). Compared with variable bit rate (VBR) which is suitable for high quality video download and certain high-bandwidth streaming environments, CBR is a more reliable choice for streaming videos to any bandwidth that users may have. Figure 3 depicts the distributions of play-back total data rate and audio data rate for two most popular resolutions: 320×240 (FLV) and 640×360 (FLV). The x-axis represents the bit rate of YouTube contents in Kb/s and the y-axis refers to the proportion of the YouTube contents.

As shown in Figure 3a, YouTube video total data rate in 320×240 (FLV) format reaches its peak at 300 Kb/s and 320 Kb/s in 2013 data, which is consistent with the result of Cheng et al [3] where 300 Kb/s and 360 Kb/s data rates were observed as a peak period in 2007. The total data rate for 640×360 (FLV) also reaches its peak at 320 Kb/s. The peak data rates for two different resolutions fall into the same range which implies the most common data rate budget for today's users are around 320 Kb/s. The total data rate for more than 98% of YouTube videos in 320×240 (FLV) format is within 360Kb/s



(a) Total Data Rate



(b) Audio Data Rate

Fig. 3: YouTube Video Data Rate Distributions (2013)

while the total data rate for 640×360 (FLV) is ranging up to 960 Kb/s. Both ranges are within the data rate limits set by YouTube [10].

In terms of audio data rate, Figure 3b indicates that both distributions of the two resolutions evidence two peaks which coincide with the two audio bit rates that YouTube recommends for 640×360 resolution [10]: the mono audio bit rate is 64 Kb/s and the stereo audio bit rate is 128 Kb/s. Although no data is shown for the recommended data rate of 320×240 in [10], based on the Figure 4b the mono audio bit rate should be 16 Kb/s and the stereo audio bit rate should be 64 Kb/s.

IV. Conclusions

The majority of existing studies on traffic capture and evaluation were conducted prior to Google's acquisition of YouTube in 2007. This paper depicts the latest YouTube traffic profiles and deliver updated and valuable information for future researchers, and can be regarded as complementary research to previous publications since no major discrepancy has been found as a result of the acquisition. The study has mostly demonstrated consistency with former findings for major video streams whilst new features have emerged within the YouTube service provision. Compared with traditional video repositories, YouTube exhibits many unique characteristics that may introduce novel challenges and opportunities for optimizing the performance of short video sharing services.

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