Three-year Trends in YouTube Video Content and Encoding

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Abstract: Despite the dominance of YouTube streaming traffic, there have been few studies focusing on characterizing YouTube videos over time. Given the sheer volume of YouTube videos, we created a custom crawler which took snapshots of popular YouTube channels and ran the crawler daily for the past 3 years. This provides YouTube video trends from 2018–2020 for over 160k videos, considering media type, duration, bit rate, resolution, codec, encoding format, and popularity. Analysis of the data shows YouTube videos have increased frame rates, resolutions and durations over this time, with the biggest clips consuming over 200 Mb/s and being over 3 hours long, accompanied by corresponding changes in encoding rates and codecs. Our analysis and the resulting dataset we make public should be beneficial for traffic shaping or CDN deployment strategies.

1 Introduction

Video use on the Internet has grown tremendously over the past decade, with video (business and consumer) projected to consumed 79% of all Internet traffic in 2020 (Cisco Inc, 2016), up from 63% in 2015. Among the myriad video applications, YouTube is perhaps the most successful with 2 billion monthly users and 500 hours of video uploaded every minute (MerchDope, 2020). On mobile networks, YouTube makes up more than 22% of the traffic (Li et al., 2018b). Understanding the video characteristics of YouTube can help network traffic management, engineering and optimization.

The increased deployment of end-to-end encryption, such as HTTP3/QUIC (Langley et al., 2017), has made it harder for Internet Service Providers (ISPs) to detect and manage traffic over their networks (Kakhki et al., 2016). While various detection mechanisms for encrypted traffic have been proposed (Dimopoulos et al., 2016; Li et al., 2018a; Tsilimantos et al., 2018), most require video flow data, such as duration and data rate, for training. If designers of such algorithms had longitudinal data – video characteristics over time – they could develop algorithms that are resilient to the evolution video characteristics.

With this in mind, we established a "video crawler" project that monitors video characteristics mined from popular YouTube channel lists and launched it several years ago. We expect to observe and record the evolution of YouTube video technologies, provide "ground truth" data to improve video detection algorithms, and capture some social characteristics of popular videos based on their views.

To provide a better understanding of Internet video over time, this paper presents an in-depth measurement study on video statistics from the world's leading provider – YouTube – for three years (2018-2020), with statistics for over 160,000 distinct videos, accounting for 3.2 million media clips. Analysis shows YouTube videos have changed significantly from earlier studies (Cheng et al., 2008; Li et al., 2005) in their durations, bitrates, and codecs used, affirming the need for more recent data. Analysis of social use shows viral view patterns where a small set of videos are viewed a lot more than others, indicating opportunities for new caching strategies to enhance YouTube service quality over edge networks.

The rest of the paper is organized as follows: Section 2 presents related research; Section 3 depicts our measurement architecture; Section 4 analyzes the statistics collected; and Section 5 summarizes our conclusion and presents possible future work.

2 Related Work

While YouTube dominates Internet traffic in terms of volume, most YouTube measurement work has focused on social aspects (Bärtl, 2018; Brodersen et al., 2012; Wattenhofer et al., 2012), such as popularity and number of views.

Cheng et al. (Cheng et al., 2008) crawled 3 millions distinct videos, but since their 2007 work, video codecs have evolved from H.263 to H.264, YouTube started using HTML5 and Dynamic Adaptive Streaming over HTTP (DASH), and Internet network capacities have greatly increased.

Krishnappa et al. (Krishnappa et al., 2013) analyze the trade-offs of using DASH by examining streaming traces from YouTube. Although they notice that YouTube needs to generate multiple clips with different encoding rates to support DASH, they only collect data on a small portion of YouTube videos.

Our work provides recent video statistics – e.g., median video durations and encoding rates – while also providing a logitudinal view of video content and encoding, showing evolution of the same over the past 3 years.

3 Methodology

Given the sheer volume of YouTube traffic (500 hours of video uploaded every minute (MerchDope, 2020)), it is not feasible to monitor the statistics of all videos from the edge. Instead, we built a *YouTube crawler* that samples Internet videos by selecting and crawling through several video channels each day.

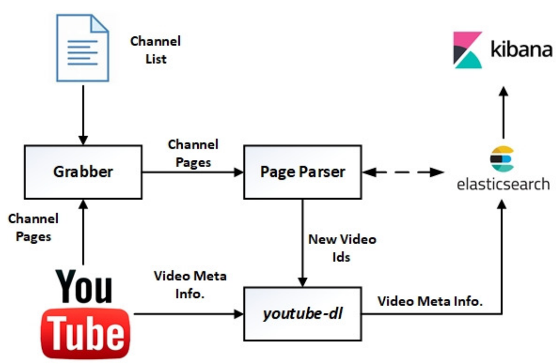


Figure 1: YouTube Crawler General Architecture

Our crawler architecture is depicted in Figure 1. The Grabber imports the Channel List and uses that to select the YouTube Pages. The Channel Pages are fed into the Page Parser which gathers the video id, which is used by `youtube-dl` to download meta-data on each video. This, in turn, is used by `elasticsearch` and `kibana` to gather and analyze the video statistics.

For the channel list, as of 2020 there are around 37 million YouTube channels worldwide, making it impractical to monitor all of them. However, most popular videos (see Table 1) are listed on the YouTube web page.[1] We use these videos as a sample of YouTube videos at that point in time.

Before taking each daily sample, we clear all cookies and do not login to a Google account to avoid YouTube's "recommended" videos so as to keep the crawler content neutral.

Since YouTube deploys rate limiters to dissuade robotic crawling (see Section 3.1), we only gather new meta-data each day, about 100–300 new videos daily.

A key element of our video crawler uses `youtube-dl`[2] with the "-j" option to retrieve video formats in `json`, without actually streaming the video clips.

3.1 Thwarting Anti-Crawling

When developing in late 2017, we noticed YouTube imposed rate limiting to deter crawling. Upon detecting frequent requests from one host (e.g., more than one day of crawling), YouTube would blacklist the host's IP address. To avoid this, we tried adding a random delay after every request, but our host was still blacklisted within a few days. Thus, we reboot our host daily to get a new dynamic IP address and avoid a blacklist.

3.2 Re-crawling Popular Videos

Since our primary research goal is to ascertain encoding and content information, we only collect data once upon discovery. However, as of January 6th, 2020, we also gather trends in popularity by selecting the top 100 videos based on view count and retrieving their statistics daily. As a validation of our crawling approach, we find our top 10 list exactly matches the top 10 list on Wikipedia (Wikipedia, 2004).

We have observed that the time span between video upload time and first discovery time is relatively short (7 days, on average). So, since August 1st, 2020, we also re-crawl the top 100 videos discovered both 1 month and 1 year earlier to provide a more complete picture on social characteristics of the videos.

Finally, with respect to YouTube user privacy, our crawler does not collect videos marked "private" or "paid", or those removed by uploaders or moderators

[1] https://www.youtube.com/

[2] https://youtube-dl.org/

Table 1: Monitored YouTube Channels

Main Page	https://www.youtube.com
Music	https://www.youtube.com/channel/UC-9-kyTW8ZkZNDHQJ6FgpwQ
Sports	https://www.youtube.com/channel/UCEgdi0XIXXZ-qJOFPf4JSKw
Game	https://www.youtube.com/channel/UCOpNcN46UbXVtpKMrmU4Abg
News	https://www.youtube.com/channel/UCYfdidRxbB8Qhf0Nx7ioOYw
Spotlight	https://www.youtube.com/channel/UCBR8-60-B28hp2BmDPdntcQ
VR 360	https://www.youtube.com/channel/UCzuqhhs6NWbgTzMuM09WKDQ
Trends	https://www.youtube.com/feed/trending
Movie Trailers	https://www.youtube.com/user/movieclipsTRAILERS/videos

(e.g., for copyright violation). Moreover, our crawler does not retrieve any personal user information – all information collected is solely based on each video's public metadata.

4 Results

Starting from an Amazon Web Service (AWS) Elastic Cloud (EC2) instance from US-East on December 11, 2017, we obtained a daily snapshot using our YouTube crawler, except for a handful of times our dynamic IP address was blacklisted and a few YouTube outrages (e.g., October 17, 2018). The information the crawler gathered is a snapshot of the web page of channels listed in Table 1 and the content and encoding data on videos listed in these channels. By October 31st 2020, this comprises *160,156* unique videos, including *5472* live videos.[3] While our dataset is not large compared to the entire YouTube repository, since it is obtained from the most popular videos from YouTube home page channels, it likely represents accessed videos.

Some of the video statistics gathered are static, fixed when the video is uploaded (e.g., display id, date uploaded, and duration), while other statistics are dynamic and may change each time crawled (e.g., number of views, supported format). In this paper, we consider the dynamic information to be static since the last crawl, except for the number of views over time.

4.1 Video Category

When uploading videos, the user can choose one of 15 pre-set categories to describe the content of their videos, or enter a custom content type. Figure 2(a) shows the distribution of all categories discovered by our crawler on the y-axis, with the x-axis showing the number of videos (bottom) and percentage of the total (top). Comparing our results with the 12 categories used in 2007 (Cheng et al., 2008), YouTube has added three new categories: "Education", "Science & Technologies", and "Nonprofit & Activism". YouTube also renamed "Gadgets & Games" to be "Gaming", perhaps because games have become more popular over the past five years. Videos that do not have a category provided are listed as "Unspecified". Three categories, "Trailer", "Show" and "News", are not shown in the current set of upload pages and have less than 100 videos each.

From the figure, the distribution of video categories is highly skewed: the most populous category, "News & Politics", has about 27% of all videos, the second largest category, "Sports", has about 21%, and the third, "Gaming", about 17%.

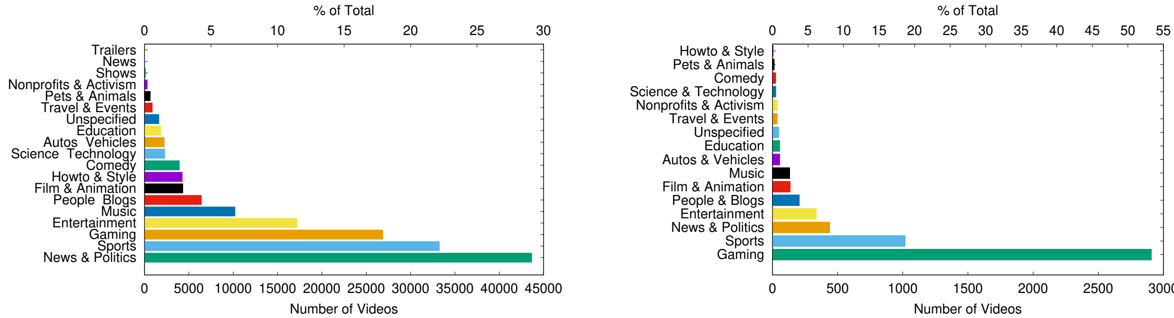
The "Gaming" category ("Gadgets & Games" in 2007) has moved from the 7th largest category (7.4%) in 2007 (Cheng et al., 2008) to the 3rd largest category (17%) in our data set. Moreover, about 54% of the live streaming sessions are gamers broadcasting through YouTube Live – a higher fraction even than YouTube live sports broadcasting.

Figure 3 shows a histogram of the normalized, non-live video categories by upload year. The COVID pandemic and U.S. presidential election likely elevated the popularity of "News & Politics" videos towards the end of 2020.

4.2 Video Length

Figure 4 shows distributions of the video durations, broken down by year. Compared to 2005 (Li et al., 2005) and 2008 (Cheng et al., 2008), videos have gotten longer. In 2008, 97.9% of YouTube videos were under 600 seconds, and 99.1% were under 700 seconds, while in 2020, 25% of videos were longer than 931 seconds and 5% of videos were longer than 11,600 seconds (3 hours, 12 minutes). The median duration of uploaded videos in 2018 is 296 seconds, and increased to 440 seconds in 2020. While there is a

[3] Publicly available at http://perform.wpi.edu/downloads/#youtube-crawler.



(a) Pre-recorded Videos

(b) Live Videos

Figure 2: Distribution of Video Categories

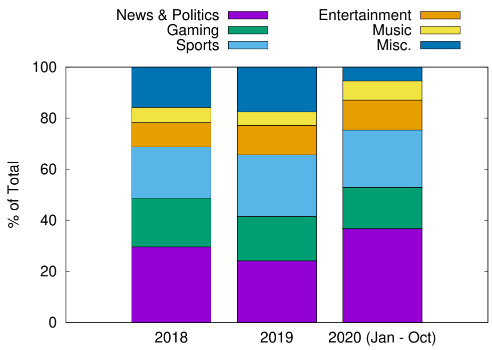


Figure 3: Normalized Histogram of Video Categories

default limit of 900 seconds for regular user uploads, YouTube allows authorized users to upload videos up to 12 hours in length.

Figure 4(b) compares the video lengths for the most popular categories. 90% of “News & Politics” and “Music” videos are less than 900 seconds long, compared to only 74% for “Entertainment” and “Sports”. “Gaming” videos are the longest, with nearly 60% over 900 seconds.

4.3 Multiple Clips per Video

YouTube video streaming supports two different approaches (Krishnappa et al., 2013; Dimopoulos et al., 2016): *progressive downloading* for low quality videos (144p, 240p, 360p, and 480p) and *HTTP adaptive streaming (HAS)* for high definition (HD) videos (720p and 1080p). Both methods require YouTube to post-process the uploaded video to generate multiple clips.[4] As Figure 5 shows, YouTube generates 20 or more clips on average, each of different quality (resolution and encoding rate) for the same video content. Having clips with different qualities allow video players to adapt the streaming data rate to the available bandwidth. YouTube Live even generates 5-6 streams (144p to 1080p) using the HTTP Live Streaming (HLS) protocol.

Figure 6 shows the cumulative distribution of the total file sizes of non-live streaming videos. The distribution of sizes is heavy tailed, similar to that of video length. In our crawled data, the median total file size is 420 Mbytes, the average is 3.6 Gbytes and 5% of videos are more than 19 Gbytes. With an average duration of 2047 seconds, YouTube needs at least 12 Mbytes of storage for every minute of video. So, for the 500 hours of videos uploaded every minute, YouTube needs a minimum 350 Gbytes/minute for storage on each edge server on which they are placed.

Figure 6 depicts the size of the clip with the best quality for each video in our dataset. This distribution is similar to the total file size and distributions. The median of the size of the best quality clip is 90 Mbytes, and the average is 759 Mbytes. Although Google imposes a maximum limit of 120 Gbytes, the largest is only 81 Gbytes, and only 1.4% of videos have a clip larger than 10 Gbytes.

4.4 Resolution

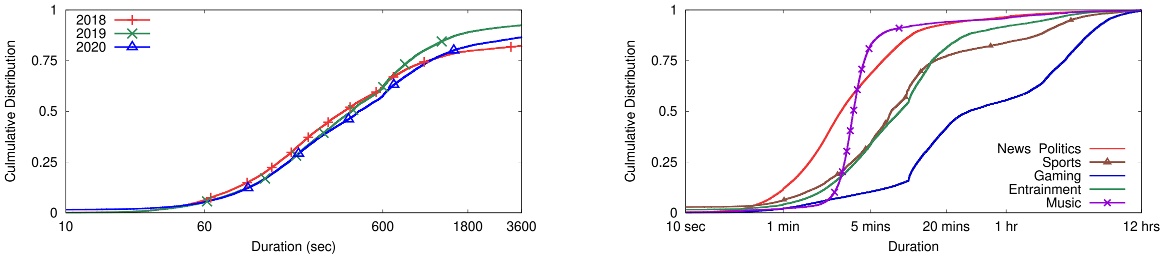
In addition to live streaming, YouTube videos can be classified into regular (2D) videos and virtual reality (VR, 3D or 360°) videos. At present, the maximum resolution supported on YouTube is 4320p for 2D videos and 4320s for 3D videos. The ‘p’ designation stands for ‘progressive scan’, and the ‘s’ for ‘spherical’. The number preceding it is the number of vertical pixels. Intuitively, 3D videos have higher data rates than 2D videos with the same resolution.

The highest data rate observed is 226 Mb/s for an 8K 360°(4320s)[5] clip of the video “Expedition Everest: The Science - 360 | National Geographic”.[6] Note,

[4] We call one encoding of a video a “clip”.

[5] 4320p and 4320s videos are considered as 8K resolutions.

[6] https://www.youtube.com/watch?v=twVdBzQM-gc



(a) Video Duration by Year

(b) Video Duration by Category

Figure 4: Video Durations

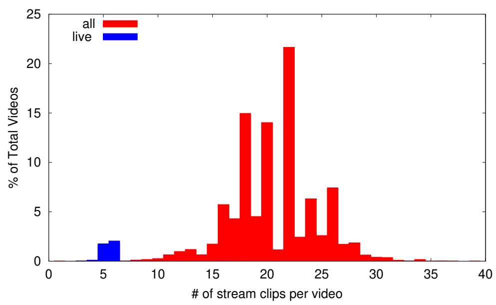


Figure 5: Distribution of Number of Clips per Video

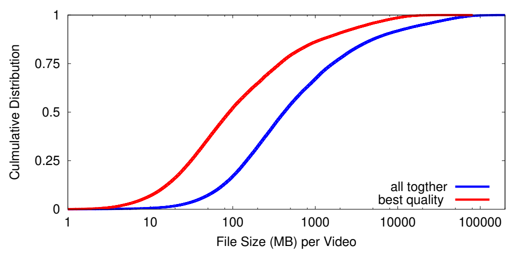


Figure 6: Total Stream File Size per Video

this data rate is a challenge for residential broadband networks and 4G/LTE networks in the U.S.

Figure 7(a) compares data rates for different resolutions for regular (2D) video clips. Not surprisingly, video clips with higher resolution usually have higher data rates. However, the distribution of data rates for DASH audio overlaps with the 144p videos. Thus, rate-based video detection algorithms (Li et al., 2018a) may fail to differentiate audio from low bitrate video streams based only on measured data rates.

Figure 7(b) compares data rates for different resolution 3D (360°) clips. Similar to 2D video clips, 3D videos with larger resolutions have higher data rates than videos with lower resolutions. Table 2 provides statistics for data rates for different resolution clips. This information could be used for passive video detection algorithms (Dimopoulos et al., 2016; Li et al., 2018a; Orsolic et al., 2017) to better differentiate video flows.

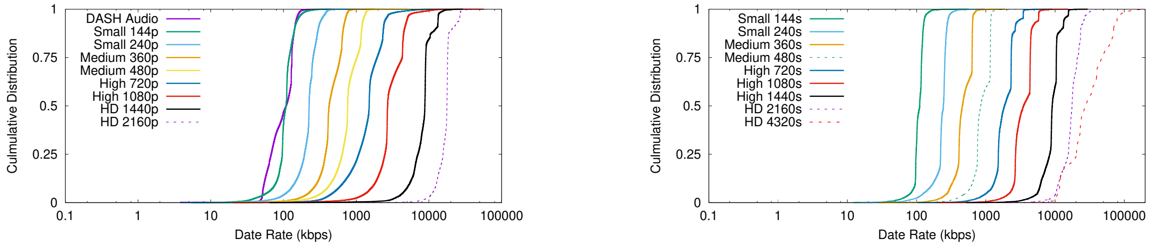
4.5 Frame Rate

Video frame rates also impact video data rates. Figure 8 shows a distribution of the best quality clips for each video in our dataset. YouTube supports multiple format videos with different resolutions and frame rates. However, as observed, the maximum frame rate for most videos is in one of two categories: 30 f/s (standard) and 60 f/s (high motion). High frame rates (60 f/s) are usually used for videos that might benefit from the extra frames, (e.g., game streams), whereas low frame rates (30 f/s or lower) are usually for more stationary scenes (e.g., talking news broadcasts).

From Figure 8, about a quarter of videos have a maximum frame rate of less than 25 f/s. On the other end, only 24% of videos support up to 60 f/s. Most 60 f/s videos are from "Gaming" and "Sports", and nearly 74% of "Gaming" videos support 60 f/s format compared to 38% for "Sports".

Figure 9 compares the cumulative distributions of video encoding rates with the same resolutions but different frame rates. 720p with 60 f/s videos have similar data rates as 1080p with 30 f/s videos, although distributions are distinguishable by frame rate. This indicates that Machine Learning based approaches (Dimopoulos et al., 2016; Li et al., 2018a; Orsolic et al., 2017) may be inaccurate if they rely on only measured data rates to infer video quality.

Figure 10 compares the trend in the average encoding bitrates and average frame rates for the past three years. Both x-axes show the average number of distinct clips per video. The left graph compares the trend in average encoding rate, and the right the trend in average frame rate. The error bars in both graphs are 95% confidence intervals round the means. Over the past 3 years, the average number of clips per video has dropped from 22.2 clips per video to 18.7 clips per video. However, the average encoding rate has increased from 841 kb/s in 2018 to 991 kb/s in 2020, while the average frame rate has remained relatively constant, 30.2 f/s in 2018 and 30.3 f/s in 2020.



(a) 2D Videos (b) VR (3D) Videos

Figure 7: Video Data Rate

Table 2: Popular YouTube Video Stream Encoding Rates

Quality	#	median (kbps)	mean ± stdev (kbps)	min (kbps)	max (kbps)	CI (95%) of mean (kb/s) left	right
Dash Audio	435522	108.82	102.50 ± 38.84	3.84	5005.42	102.40	102.60
Small 144p	322424	108.25	108.77 ± 31.46	5.55	993.32	108.68	108.86
Small 240p	318460	225.10	225.89 ± 65.84	6.51	1431.89	225.70	226.08
Medium 360p	379571	423.92	467.50 ± 152.57	8.43	4974.63	467.09	467.90
Medium 480p	314544	761.89	805.75 ± 289.38	9.33	10255.67	804.91	806.60
High 720p	350445	1507.20	1554.80 ± 828.74	4.01	26112.00	1551.83	1556.44
High 1080p	212538	2801.81	3180.81 ± 1512.22	20.36	56738.24	3175.41	3186.20
HD 1440p	8555	8790.81	8490.40 ± 2581.42	64.20	29496.66	8444.49	8536.32
HD 2160p	7254	17695.02	17261.33 ± 4023.76	1045.18	72333.43	17183.60	17339.05
HD 4320p	58	21727.62	24066.20 ± 12927.65	10252.97	74515.99	21273.48	26858.92
VR Small 144s	5538	110.75	108.77 ± 20.17	12.35	565.06	108.32	109.21
VR Small 240s	5536	243.62	233.82 ± 51.74	15.23	974.30	232.68	234.97
VR Medium 360s	5875	459.32	492.51 ± 137.89	28.28	1889.39	489.55	495.47
VR Medium 480s	5535	844.72	911.30 ± 246.81	52.92	2901.47	905.84	916.76
VR High 720s	6833	1857.584	1956.88 ± 637.87	103.23	9155.10	1944.19	1969.58
VR High 1080s	6535	3501.62	3625.00 ± 1117.28	206.09	15433.90	3602.26	3647.74
VR High 1440s	6479	9094.60	9361.51 ± 2456.44	522.83	29529.80	9311.30	9411.72
VR HD 2160s	6386	17577.32	17941.50 ± 5080.15	1291.31	62149.85	17836.91	18046.09
VR HD 4320s	808	27443.38	36293.75 ± 24554.87	4762.67	226340.49	34872.55	37714.95

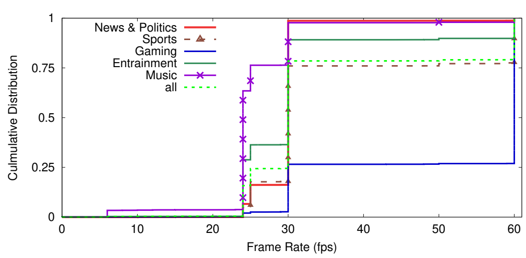


Figure 8: Max Frame Rate

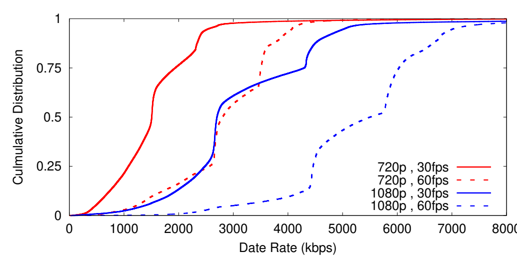
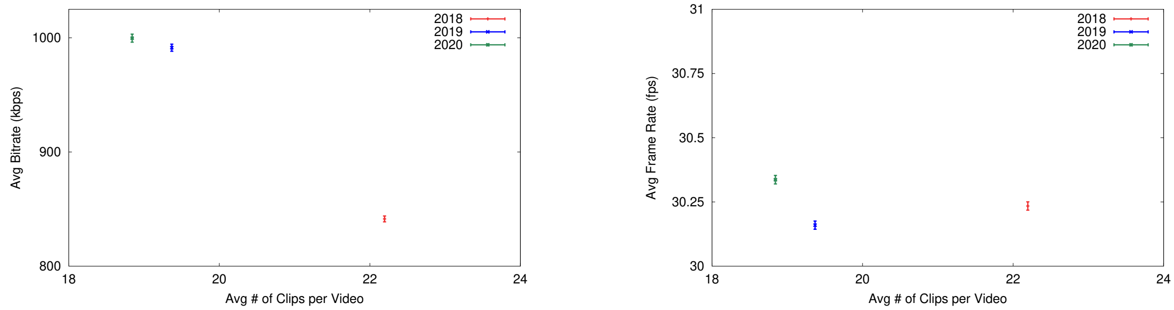


Figure 9: Encoding Rates for Video with Different Frame Rates

4.6 Video Codecs

To support different client capabilities, YouTube generates video clips with the same resolution but using different codecs. Figure 11 shows the distribution of video codecs. YouTube primarily supports two codec types: MPEG-4/H.264 (avc1) and WebM (vp9 and vp8). 90% of videos have two 144p video clips – one is using the H.264 codec (avc1.4d400c), and the other the WebM codec (vp9). Similarly, other popular quality clips, 240p, 360p, 480p, 720p, and 1080p, also have one clip encoded with H.264 and another with WebM. For WebM, vp9 is the dominate codec, widely used by videos of all quality.

Note, the H.264 codecs used by YouTube can be grouped into three categories: i) *baseline*: avc1.42E0xx used by 360p videos, ii) *main*: avc1.4DE0xx used by 144p, 240p, 360p, 480p and 720p videos, and iii) *high*: avc1.6400xx used by 720p and 1080p videos, where xx is the Advance Video Coding (AVC) level. The *main* category of H.264 has



(a) Encoding Rate (b) Frame Rate

Figure 10: Encoding Rate and Frame Rate

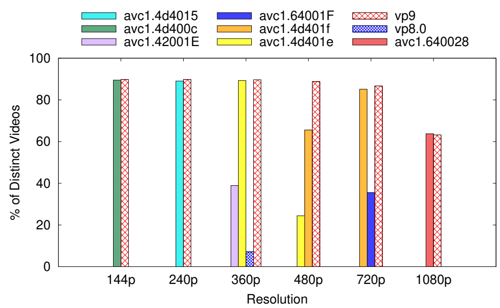


Figure 11: Video Codecs Used in 2D Videos

been used by clips from 144p to 720p.

4.7 Social Statistics

In addition to YouTube video statistics, we also measure social statistics for some videos based on number of views. Figure 12 shows our crawler detects many popular music videos (more than 1 billion views) which were uploaded far earlier than our first crawl. Given the temporal relevance of “News & Politics”, only a small portion are detected before our crawler runs (i.e., recent news has not been viewed).

Figure 13 compares cumulative views for different video categories. Although all the distributions are heavy tailed, only 0.2% of “News & Politics” videos (75 out of 43,733) have more than 10 million views, compared to 23.8% “Music” videos (2264 out of 26,915) that have more than 10 millions views. Among the 109 videos with more than 1 billion views, 105 are “Music”, 2 are “Education”, 1 is “Autos & Vehicles” and 1 is “Entertainment”. “Gaming” and “Sports” videos are similar to “News & Politics” in that they only have 1.3% and 1.4%, respectively, of videos with more than 10 million views. However, the median views for “Gaming” and “Sports” are 95.2K and 80.1K, respectively – much higher than “News & Politics” which has a median of only 23.9K.

From January 6, 2020, we crawl the 100 most viewed videos in our dataset to get the daily view changes. Figure 14 compares the five most viewed videos’ daily view count. Our five most viewed videos follow the same as the top five videos in Wikipedia[7] at the same time.

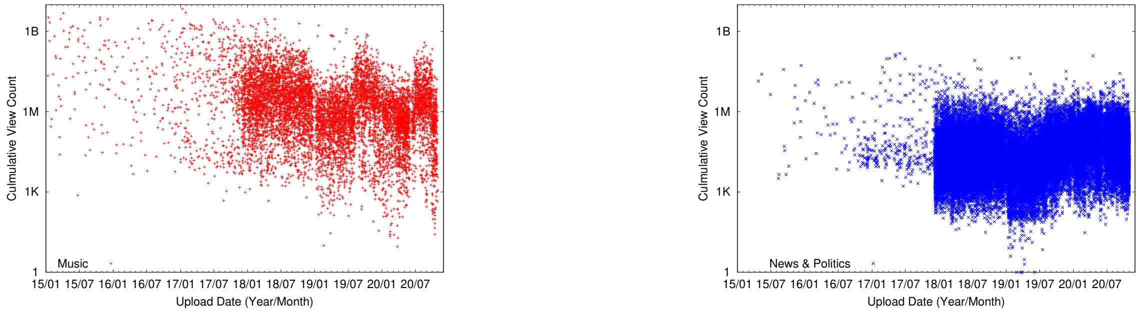
In January 2020, “Despacito” was the most viewed video with more than 6.6 billion views, and ‘Baby Shark Dance” the 4th most with 4.3 billion views. However, as Figure 14 shows, “Baby Shark Dance” has around 6 million daily views, much higher than the 2 million daily views for other popular videos. “Baby Shark Dance” surpassed “Despacito” after reaching 7.0 billion views on Oct 31st, 2020.

The peak in “Baby Shark Dance” between March 15 and April 15 corresponds to the start of the COVID lockdown in the U.S. Similar trends can be observed for “Masha and the Bear”, the 5th most popular video in 2020. Note, “Baby Shark Dance” and “Masha and the Bear” are classified as “Education” videos.

5 Conclusions

This paper presents a detailed investigation of the characteristics of YouTube videos, the most popular video sharing site to date. As a highlight, based on analysis of over 160 thousand videos (over 3 million clips) collected over the past three years, YouTube videos are longer (median duration of 440 seconds) than they were a decade ago (Cheng et al., 2008), with an average of 20 different media clips for each video, requiring considerable storage space. “News & Politics” and “Sports” are the most popular pre-recorded video categories, while “Gaming” is the most popular live category. Future work includes crawling throughout 2021, CDN server deployment strategy design, and developing new traffic classification methods.

[7]https://en.wikipedia.org/wiki/List_of_most-viewed_YouTube_videos



(a) Music

(b) News & Politics

Figure 12: # of Views of "Music" and "News & Politics" Video

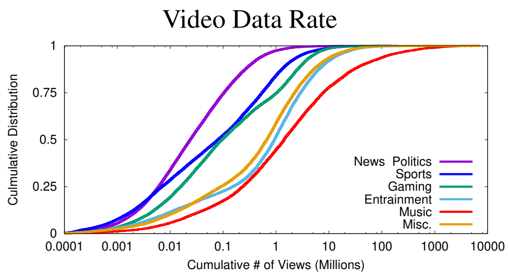


Figure 13: Distribution of Cumulative Number of Views

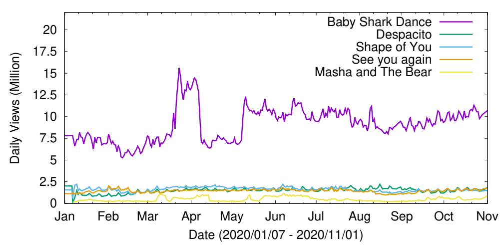


Figure 14: Daily View Trend of Top 5 Videos (2020)

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